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Quantitative Pathway Modeling and Analysis in Cancer

by

Barbara Anna Novak

DISSERTATION

Submitted in partial satisfaction of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

Biological and Medical Informatics

in the

GRADUATE DIVISION

of the

UNIVERSITY OF CALIFORNIA, SAN FRANCISCO

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Abstract

Quantitative Pathway Modeling and Analysis in Cancer

Barbara A. Novak

Biological pathways describe the inter-relationships of genes, proteins, and molecules within a biological system. The study of specific pathways often requires painstaking research into each possible element of the network. Consequently, existing knowledge of gene regulatory networks is limited, resulting in hypotheses that are incomplete or at various levels of refinement. Computational modeling and quantitative analytical approaches seek to fill this information gap.

This dissertation describes the development of QPACA (**Q**uantitative **P**athway **A**nalysis in **Ca**ncer), a system for pathway visualization and analysis. QPACA addresses three aspects of the general problem: 1) representation and visualization of pathways in the context of biological data, 2) recognition of gene sets that are part of a pathway or coordinated process, and 3) augmentation of pathways by prediction of pathway membership. The pathway representation is designed to be flexible and extensible in order to enable the widest variety of pathway structures and components possible, while the analytical methods directly address the issues inherent in analysis of human systems without making limiting assumptions about the structure of pathways or discretizing data.

QPACA has been used to analyze a number of microarray data sets, employing both yeast and human samples. Four primary results are presented, each of which derives from aspects of QPACA's application to microarray data for analysis or visualization: 1) statistical analysis of differential expression patterns in the context of pathway

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representations supports the generation of biological hypotheses; 2) gene expression data are sufficient to support computational recognition of hypothesized pathway gene sets across a broad variety of biological processes; 3) gene expression data can be used to produce ranked lists of gene products that are enriched for proteins that interact with members of a predefined pathway; and 4) the surprising ubiquity of detectable signals in expression data that bear on human pathway structure appears to be due to largely nonannotated transcriptional programs present within established pathways.

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Chapter 1 Introduction

1.1. Systems Biology

One of the major goals of current biological research is the elucidation of the complex interactions and transformations in biological systems that drive their function and behavior. This systems-based approach utilizes high-throughput techniques in the realms of functional genomics, proteomics, metabolomics and transcriptomics to generate quantitative data for the construction and validation of computational models.

While previous efforts in identifying the genes and other components in an organism have provided a valuable list, it is not sufficient for understanding the fundamental complexity of the whole system. A simple catalogue misses information about how the parts assemble to form the organism, how they interact with each other, how the organism reacts to stimuli and malfunctions, and what design principles govern the organism. The answers to these questions are important both for a greater understanding of the system as a whole as well as for enabling any modifications for improved system behavior.

A system-wide understanding of a biological organism can be broken down into four fundamental areas: system structure (assembly and interaction of the system components), system dynamics (system behavior over time), control method (system control), and design method (system design principles). Progress in all of these areas requires breakthroughs in computational science, biology, and measurement technologies, as well as integration of any discoveries with existing knowledge.

Before tackling the more complex issues of system dynamics, control, and design, it is necessary to understand the basic structure of the system. Conventionally, the study of a specific biological pathway has required painstaking research into each possible element of the network, both by conducting new series of experiments and by surveying the existing literature to identify and describe interactions. This approach has resulted in a limited, though focused, knowledge of biological networks, with hypotheses about pathway interactions that are at various levels of refinement and completeness. Computational modeling and quantitative analytical approaches seek to fill this information gap. The use of high-throughput technologies, which make it possible to survey the behavior of thousands of elements at once, allows pathway interactions to be more easily examined. Gene expression microarrays have been used extensively in an attempt to elucidate the behavior of genes based on transcriptional regulation. Posttranscriptional and post-translational information, however, have been harder to measure with high accuracy or in high throughput.(Kitano 2002)

This work focuses on this fundamental aspect of systems biology by furthering the understanding of biological pathways through the development of a generalized system for pathway visualization and analysis. While the focus on pathways clearly

requires addressing aspects of pathway definition and representation, issues that surround the data available for analysis and predictions about pathway structure are also important. These issues include the experimental methods for generating high-throughput data, as well as the particular statistical problems inherent in using these techniques. The centrality of expression data for the modeling aspects of this work also requires some discussion of transcription factors and the computational methods used to study their behavior.

1.2. Modeling Pathways

Biological pathways model the inter-relationships of nucleic acids, proteins, small molecules, and processes within a biological system. They are useful constructs in studying the structure, dynamics and control of an organism. In a disease such as cancer, which is essentially a result of disorder within the structure of the system, the study of the relationships of genes to each other is particularly relevant.

Pathway models are fairly subjective, depending on the author's focus and intended objective. While they can describe biological processes down to the molecular level, including such information as rate constants and specific molecular interactions, they can also be fairly high-level, consisting merely of a set of interconnected elements. The level of detail can reflect either the author's intended use for the pathway (high level analyses don't necessarily require detailed knowledge of rate constants) or the actual level of knowledge about a particular pathway or pathway step (many holes still exist in the understanding of complex interactions in biological systems). Additionally, pathways tend to be descriptions of the general case; not all portions of a pathway may be active in a particular cell type or under a certain set of conditions.

Broadly, several major categories of biological pathways exist: metabolic pathways, molecular interaction networks, signal transduction networks, and gene regulatory networks. Metabolic pathways describe a series of enzyme catalyzed chemical reactions that form a metabolic product, which can then be used or stored by the cell. Molecular interactions networks depict actual physical binding interactions between cellular components. Signal transduction networks refer to the set of processes by which an organism senses both external and internal environmental cues and coordinates the behavior of individual cells to support the function of the organism as a whole. Finally, gene regulatory networks delineate the interactions that govern transcription of genes into mRNA and its subsequent translation into proteins.

Each pathway category comes with its own associated vocabulary, conventions, and (in some cases) exchange standards. The following chapter will go into greater detail on existing pathway models, efforts at pathway analysis and a discussion about standards for pathway data exchange.

1.3. Transcriptional Regulation Biology

Gene regulatory networks govern the execution of the genetic instructions for both the development and the functioning of an organism. These genetic instructions are encoded in the organism's genome, which is composed of strands of DNA sequence, consisting of a four-letter alphabet. Embedded within this sequence are relatively short stretches of DNA called genes, each of which encodes the specific information necessary to manufacture a particular protein. The working units of a cell are actually these proteins, which carry out the tasks necessary for the function and survival of the organism. Genes are first transcribed into messenger RNA, which is then translated into

proteins. Each gene in an organism has a specific set of functions, which are not necessarily relevant at all time points or in all cell types, thus control machinery must be present in the cell to determine which genes are turned "on" and at which times. Gene regulatory pathways describe this cellular machinery, known as transcriptional regulation. The two primary participants in this process are proteins known as transcription factors and transcription factor binding sites, 5-15 bp long DNA sequences often located in the gene promoter region. For a gene to be expressed (that is, translated into RNA and then protein), a specific set of transcription factors is required to bind to the gene's transcription factor binding sites. Each transcription factor is capable of binding to several binding sites whose sequences can differ by several bases. The correct set of transcription factors triggers binding of RNA polymerase and initiates transcription. A transcription factor can also inhibit gene expression by blocking RNA polymerase binding. Figure 1 shows the typical structure of a genetic sequence containing the gene, with its transcription and translation start sites, as well as several different transcription factor binding sites in the promoter region, which can be located several hundreds of bases upstream of the gene itself.



Figure 1. Participants in transcriptional regulation.

1.3.1. Motif finding

Understanding the control structure for a particular gene is dependent on knowing which transcription factor binding sites, and thus which transcription factors, are involved in driving its transcription. The process of finding these transcription factor binding sites, which are highly conserved and occur repeatedly throughout the genome, is known as motif finding. Traditional experimental methods to find binding sites for a particular transcription factor are labor intensive, resulting in many computational techniques for finding binding site sequences in promoter regions. Many different computational approaches exist in the field of motif finding, all roughly based on either pattern matching (finding new motifs based on known motifs) or pattern detection (finding overrepresented novel motifs). (Elnitski, Jin et al. 2006)

Chapter 7 will discuss using MaMF, a motif finder specifically geared toward finding the types of complex transcription motifs common in higher organisms, in combination with pathway analysis to examine the transcriptional programs present within established pathways.

1.4. Microarray technologies in cancer research

This section introduces the microarray technologies, including both expression and comparative genomic hybridization arrays, used in the development and testing of this work.

Microarrays provide a powerful method for simultaneously detecting and quantifying the relative amounts of thousands nucleic acid sequences in a heterogeneous mixture. Microarrays generally work in a fairly straightforward manner. DNA sequences corresponding to the desired probe DNA are attached to a solid substrate. Then, samples containing the target DNA are labeled with a fluorescent dye and hybridized to the array. Since binding affinities between particular probes and targets are not known, microarrays produce relative measurements of hybridization intensities.

Microarrays have generally been used to measure gene expression using cDNA derived from biological samples. Two major platforms exist for measuring gene expression: two-color spotted cDNA on glass slides and synthesized oligonucleotides on silicon. In recent years, microarrays have also been used to measure genomic aberrations in cancer. The platform used in this analysis uses a similar technology to that used in the two-color expression arrays.

1.4.1. Platforms for measuring gene expression

Two major platforms exist for measuring gene expression using microarrays: twocolor hybridization onto spotted arrays and lithographically deposited oligonucleotide arrays (Affymetrix). As can be seen in Figure 2, the first platform requires comparison of two biological samples. mRNA is isolated from each sample and used for the synthesis of first strand cDNA labeled with either Cy3 (green) or Cy5 (red) fluorescent dye. Then, these labeled samples are hybridized to a glass slide containing spots of purified cDNA representing individual genes. The ratio of red to green fluorescence can be used to measure the relative concentrations of the corresponding test or reference sample for each individual mRNA represented on the slide.



Figure 2. Overview of two-color spotted microarrays.

While this schematic shows a two-color expression microarray, the basic sequence of events is very similar for aCGH. In aCGH, instead of isolating RNA and then using RT/PCR to obtain fluorescently labeled DNA, DNA is isolated from the samples and fluorescently labeled. In the case of expression arrays, the probes on the array are gene-based DNA probes, while aCGH probes are generally a genome- or chromosome-wide set of bacterial artificial chromosomes intended to span the entire genomic space.

The Affymetrix platform, on the other hand, uses a set of ~20 bp long

oligonucleotide targets, instead of cDNA targets. These targets are deposited onto a

quartz slide using photolithography, a semiconductor manufacturing technique. Each

gene is represented by a carefully chosen set of oligonucleotide matches and mismatches

whose hybridization signals are then combined using a proprietary algorithm to form a

single mRNA expression value for that gene.

Two-color arrays were the first to be widely available and are still usually cheaper

to construct. They are also usually the only choice for less well-studied organisms that

don't justify commercial manufacture. Affymetrix style arrays have become more common due to generally better data quality (higher signal-to-noise ratio), better reproducibility (calculated expression values are absolute, not relative to a control sample), and decreasing costs.

1.4.2. Microarray-based comparative genomic hybridization

Comparative genomic hybridization (CGH) is a method for detecting copy number changes (gains, losses, or amplifications) in tumor cell genomic DNA. Traditionally, CGH has been performed by hybridizing fluorescently labeled DNA isolated from normal and cancerous tissue to a metaphase spread of normal chromosomes (FISH, or fluorescent in situ hybridization). The ratio of fluorescence intensity from these two samples indicates the gains or losses present at different physical locations in the genome. Due to the use of ratios, genomic aberrations resulting in balanced DNA content, such as tetraploidy, cannot be detected.

In array-based comparative genomic hybridization (aCGH), the samples are instead hybridized to probes printed on a glass slide, as in the two-color microarrays described above. These probes are derived both from known genes as well as from noncoding regions of the genome. The advantages of the array-based technique are improved resolution and dynamic range, as well as the ability to directly map aberrations to genomic sequence. (Pinkel, Segraves et al. 1998; Snijders, Nowee et al. 2003)

1.5. Statistical and other issues

In an ideal world, it would be possible to find easily manipulated cell lines or organisms in which one could measure the concentration of both expressed transcripts and translated proteins, both over time and under multiple conditions (such as knockouts, drug treatment, RNAi treatment, etc.). Given access to such data and including information about metabolite concentration and assuming that the data were at an appropriate granularity, it should be possible to work out a great deal of pathway biology. With such ideal data, many specific biochemical interactions and transformations could be identified. Data sets that approach this theoretical construct, however, are not even available in yeast and other lower organisms, much less in the human case.

The most readily available form of high-throughput data for these analyses has been microarray expression data. Even though this data is limited to the scope of transcriptional regulation as seen through mRNA expression levels, it has been a boon to research because it allows researchers to measure many different genes within the same experiment. This ability has, however, introduced problems of appropriate analysis, mainly having to do with statistical issues. Issues arising from the inherent noise in the measurement technology also limit these data. Additionally, the genes and, in large heterogeneous experiments, the samples that are actually involved in the process under study are outnumbered by those that are not involved.

1.5.1. Statistical issues of large data sets

In general, statistical measures help in determining whether or not a particular observation occurred by chance. For example, one commonly asked question in an expression microarray experiment as described above is which genes exhibit significantly highly coordinated behavior. On the surface, this question is fairly easily answered: simple calculate the correlation coefficients for all of the gene pairs and compare the results to a random permutation of the data (to assign a significance value). While this

technique would work on a smaller data set, the types of data sets encountered in microarray analysis run into something called the "multiple comparisons problem." Essentially, this problem arises whenever a large number of independent observations are evaluated using the same significance cutoff as would be used when considering one observation.

In order to understand the reason why large data sets have inherent statistical issues, it is first necessary to understand the underlying statistics involved in determining whether or not the observed data has occurred by chance.

This question falls into the statistical area of hypothesis testing, which seeks to differentiate between a null and an alternate hypothesis. The null hypothesis is defined as the theory, either believed to be true or used as a basis for argument, that there is no difference between two observations. The alternate hypothesis is that a difference does exist between the two observations. To carry out this test, a statistic is defined to measure the difference between the two observations. Then, this measurement is compared to a theoretically determined or empirically calculated distribution of that statistic under the null hypothesis. The probability value (p-value) of the hypothesis test is defined as the probability of arriving at a value of the test statistic as extreme or more extreme than those observed by chance alone. Small p-values suggest that the null hypothesis is unlikely to be true. Thus, a p-value of less than 0.05 indicates that 5% of the observed values could occur by chance.

Generally, a p-value ≤ 0.05 is considered to be significant. When considering 20 observations, one would expect to see one observation with a significant p-value purely by chance. A typical microarray experiment can contain tens of thousands of genes. An

uncorrected p-value would then result in hundreds of false positives. Several approaches have been used to calculate corrected p-values for high dimensional data sets. (Westfall and Young 1993; Jain, Chin et al. 2001; Tusher, Tibshirani et al. 2001; Olshen and Jain 2002; Segal, Dahlquist et al. 2003; Storey and Tibshirani 2003).

This work will discuss one way of avoiding the multiple comparisons problem by using orthogonal annotation and data sources to reduce the number of observations.

1.5.2. Issues with heterogeneous data sets

In the ideal case as described above, a data set used for examining a pathway would contain a carefully chosen set of perturbations that could be used to find new pathway elements and deduce the connections between them. In yeast and bacterial systems, such controlled perturbations of a system state have yielded biologically reasonable results (Friedman, Linial et al. 2000; Ideker, Thorsson et al. 2001; Paley and Karp 2002). This method relies on using prior knowledge of a pathway to generate hypotheses that can be tested using microarray data. The results can then be used to augment the pathway structure.

It has also been observed in yeast that only certain perturbations of a system are relevant to the corresponding pathways. In Hughes' yeast compendium, perturbations of genes in a particular pathway yielded the most informative changes in gene expression within that pathway, though not the largest. While deletion of erg genes, for example, had large effects on amino acid biosynthesis (as did many other deletions), the most specific (though smaller) effects were on the expression of genes in the erg pathway. (Hughes, Marton et al. 2000)

In higher organisms, it is frequently impossible or at least impractical to generate the types of controlled perturbations necessary for a systematic analysis of a pathway as described above. The data sets typically available for these organisms are fairly heterogeneous. Human cancer data sets, for example, frequently contain multiple instances of the cancer phenotype, across many individuals (and possibly multiple tumor types), each representing a unique experiment of nature. Given that each sample in such a data set has a different set of genomic, genetic, and epigenetic disregulations, there is no reason to expect, *a priori*, that all of the samples will be relevant to a quantitative study of a particular set of genes in a particular pathway.

Chapter 3 will describe a method for selecting relevant perturbations from the type of large heterogeneous data sets frequently encountered when studying higher organisms. Chapter 5 and Chapter 6 will validate this method using both yeast and human data sets and pathways.

Chapter 2 Review of Pathway Literature

2.1. Introduction

The last chapter briefly introduced the concept of biological pathways, the different types of pathways, and the types of data generally available for pathway analysis. This chapter will focus on existing efforts in modeling, storing and exchanging pathway information; in analyzing pathway structure; and in using pathways to further analysis of large data sets.

Pathway modeling can be conceptually divided into three main sub-areas: 1) representation and curation, 2) data analysis, and 3) model recognition and augmentation.

2.2. Pathway representation and curation

As discussed in Chapter 1, many different types of pathways exist, each with its own unique set of representational challenges as well as existing representational conventions, vocabulary and in some cases even exchange standards.

In terms of representing structure, pathways are complex both in the large number of possible interactions, the many possible variations of components and connections, and the different levels of known detail for different pathways. Pathway curation efforts are extensive and varied. Pathguide (Bader, Cary et al. 2006) lists over 200 biological pathway resources, ranging from organism specific pathway databases, such as EcoCyc (Karp, Riley et al. 2002), to multi-organism databases, such as KEGG (Kanehisa 1997; Kanehisa and Goto 2000) to pathway diagramming and analysis tools, such as GenMAPP (Dahlquist, Salomonis et al. 2002). In order for this data to be useful it needs to be accessible in a useful manner. For the casual browser, a visual representation of a pathway, such as the diagrams provided by BioCarta (http://www.biocarta.com/genes/index.asp), may be sufficient. In order to integrate pathways with data and perform complex analyses, however, it is necessary to extract the actual data from the databases and transform it into a representation that is computationally accessible.

One proposal for representing pathways, both as useful visual aides and as useful computational tools, is the Molecular Interaction Map (MIM). MIMs are a diagram convention that incorporate the following attributes: each molecular species should appear only once; multimolecular complexes should be represented concisely and extensibly; protein modifications should be represented uniquely, and any significant combination of molecular complexes should be represented (Kohn 1999). These attributes are important to consider when creating representations that are both rich in detail and computationally tractable.

Unfortunately, while many of the existing databases make their data accessible in computationally readable formats, each databases uses its own vocabulary and representational conventions. Frequently, two databases will have different names for the

same object or the same name for two different objects. Combining data from several different sources can be quite labor intensive.

2.2.1. Pathway exchange formats

Currently, there is no universally used standard for pathway exchange, though three formats have been proposed and are under development: PSI-MI (Proteomics Standards Initiative - Molecular Interaction), which focuses on representing protein interaction data; SBML (System Biology Markup Language), which focuses on biochemical network models, and BioPAX (Biological Pathway data exchange), which is the most general of the three and can encompass data from the other two. Table 1 shows a roadmap for the development and scope of the BioPAX format. As of this writing, BioPAX is at level 2, which allows for encoding all types of pathway elements, but is restricted to metabolic pathways and molecular interactions. Chapter 3 will further discuss the use of the BioPAX format in this work.

Development level	Scope of format	Sample data sources
Level 1	Metabolic pathways	aMAZE, BioCyc, KEGG, PUMA2
Level 2	Level 1 plus molecular interactions	BIND, HPRD, intAct, MINT
Level 3	Level 2 plus signaling pathways and gene regulation	CSNDB, INOH, PATIKA, Reactome, TRANSPATH
Level 4	Level 3 plus genetic interactions	FlyBase, MIPS
Future levels	Level 4 plus abstract associations	PubGene, GeneWays

Table	1.	BioPAX	road	map
			~	

For a complete list of the databases currently using the BioPAX format, see www.pathguide.org.

2.3. Pathway-based data analysis

Pathway-based data analysis can be either qualitative (using a pathway diagram to map out data values) or quantitative (combining pathway-based information with data analysis to reach a quantitative result). Many of the existing pathway databases allow the former type of analysis. Separate pathway analysis tools, such as Cytoscape (Shannon, Markiel et al. 2003), also exist for this type of analysis as well as for more complex qualitative and quantitative diagram-centered analyses.

Pathway-based quantitative data analysis, such as the Barkai 'transcription module' research (Ihmels, Friedlander et al. 2002), is an example of pathway-based quantitative data analysis. A transcription module is the set of genes and experimental conditions (data samples) that contribute to their co-regulation. They find these transcription modules by beginning with a set of genes suspected to belong to a transcription module (based on annotation or sequence similarity) and then using an algorithm to first choose relevant experiments and then refine the gene set to produce a common signature that can be used to identify these transcription modules. Similarly, Stuart *et. al.* (Stuart, Segal et al. 2003) showed that, by combining co-expression relationships found in many different experiments in several different organisms, it is possible to deduce functional relationships between genes.

2.4. Model recognition and induction

Attempts to induce pathway structure have remained separate from the efforts to represent already existing knowledge. While some of the representation efforts, like KEGG (Nakao, Bono et al. 1999), have also delved into the pathway prediction field, many have approached this problem from a different direction. Pathway representation and data visualization have been seen as ways of gathering knowledge for use by the scientific community, but pathway prediction efforts have focused on mathematical approaches to extracting interaction information from raw data.

Previous efforts to predict biological networks from expression data have relied on three major types of algorithms: pair-wise, equation-based, and network-based. While

each one has yielded important results, all of them have specific limitations. Pair-wise algorithms are based on correlations (Arkin, Shen et al. 1997) and are thus unable to determine causation. Equation-based algorithms, which can be linear (D'Haeseleer, Wen et al. 1999), non-linear (Weaver, Workman et al. 1999), or differential (Arkin, Ross et al. 1998), are either very coarse or require detailed knowledge of biochemical interactions. Finally, network-based algorithms are either Boolean (Liang, Fuhrman et al. 1998; Akutsu, Miyano et al. 2000), which requires discretization of data and thus loss of information, or Bayesian (Friedman, Linial et al. 2000; Hartemink, Gifford et al. 2001; Jansen, Yu et al. 2003), which can be biased toward more simple models in the absence of enough data (Smith, Jarvis et al. 2003). Many of these algorithms require making assumptions that are known to be untrue (e.g. that biological networks contain no feedback cycles). The validity of these different methods tends to be difficult to assess because many of the interactions have not been biologically tested, nor are common benchmarks yet available in this relatively young field. With the advent of comprehensive yeast expression datasets, some labs (Smith, Jarvis et al. 2003) have begun to try more data-driven approaches that rely less on mathematical formalisms.

2.5. Conclusion

The work differs from the aforementioned efforts in three ways. First, on a representational level, QPACA explicitly represents the objects and inter-relationships that comprise a pathway. The visual depiction is automatically generated. This is precisely the converse of efforts such as KEGG and BioCarta, where the diagrams are the primary representation and the pathway must be derived from the depiction. Second, while many curation-oriented efforts focus on comprehensive but static pathway

descriptions over a broad set of processes, this effort focuses on constructing tools that allow domain experts to rapidly construct and modify pathways for use in data exploration, which may itself feed back onto the original pathway structure. Third, many of the pathway recognition, induction, and network modeling approaches are rooted in formalisms that either restrict representational richness (no feedback cycles, etc.) or require substantial data reduction (binary or ternary states) that may limit their utility. QPACA's framework imposes no such limitations and introduces novel methodological development to address problems of pathway recognition and augmentation.

Chapter 3 QPACA: System Design

3.1. Introduction

The previous chapters demonstrate both the necessity for pathway-based analytical tools as well as the challenges inherent in the creation of these tools. QPACA, **Q**uantitative **P**athway **A**nalysis in **Ca**ncer, was developed with the goal of creating an easy to use system for the exploration (both visual and computational) of both fine- and coarse-grained pathway structure and of experimental data within the context of that structure. At the core of this system lies a simple and flexible pathway model. Using this model, it is possible to interrogate relationships between genes within a pathway as well as to visualize pathways and data. More importantly, QPACA also incorporates a set of analytical tools for pathway recognition and augmentation.



Figure 3. QPACA overview.

The QPACA system (b) accepts inputs in the form of pathway knowledge (BioPAX, KGML, or QPACA formatted text files) and data (tab-delimited text files). The system presents outputs as either a visual representation of the pathway input or as computational analysis results.

As can be seen in Figure 3, QPACA takes well-defined input (both pathways and data), feeds it through the pathway model and analysis tools, and then outputs pathway visualizations based on those inputs and a set of analysis parameters. This chapter begins with a discussion of the QPACA pathway model and how external pathway knowledge is translated and utilized by the system. Then, it discusses the optimization algorithm that forms the basis of QPACA's analytical tools. It concludes with a discussion of how these pieces fit together within the system architecture.

Application of the system to the exploration of three biological datasets will be discussed in Chapter 4, while Chapter 5 and Chapter 6 will discuss the development and testing of the QPACA analytical tools.

3.2. Pathway model

The development of pathway analysis tools was dependent on a solid pathway model that was ideally both intuitive and flexible. Specifically, QPACA's pathway model needed to be accessible to the average biologist as well as flexible enough to handle the myriad different types of pathways that exist in biology. At the time it was developed, no such pathway model existed.

QPACA models pathways as directed graphs, a computational structure composed of nodes connected by edges. Directed graphs offer the benefit of an existing body of algorithms for navigation, visualization and structure analysis. Within this structure, QPACA models physical entities and processes in pathways as nodes. The various types of interactions between these entities and processes are then modeled as edges connecting the nodes. To encompass the complexity inherent in pathway structure without losing the flexibility of the directed graph structure, QPACA's model also includes a special type of

node called the "event" node. Rather than representing a concrete concept in the pathway, this node type represents an event that occurs in the pathway, such as phosphorylation or the formation of protein complexes. In addition, each of these pathway components can be assigned any number of attributes stored as user-defined name-value pairs. Several different types of pathway interactions mapped to the QPACA representation can be seen in Figure 4.



Figure 4. QPACA pathway representation examples.

On the left are several typical pathway interactions. On the right are those interactions mapped to QPACA pathway components. QPACA nodes are indicated as boxes, while the edges are denoted as lines connecting the boxes. The direction of the arrows indicates the direction of the interaction. (a) and (b) show typical signaling interactions with no modifying event. QPACA stores this information as two nodes (representing each side of the signaling interaction) connected by an edge that has either a positive (activation) or negative (inhibition) edge type attribute. Note that, as in (b), nodes may have multiple edges connecting them, signifying different possible interactions, reversible reactions, etc. A more complex interaction (such as phosphorylation in (c)) is represented using an event node. The edges in this case do not have edge type modifiers. Any physical entities involved in aiding the interaction are connected to the event node with an undirected edge.

One further refinement that QPACA makes to the basic directed graph structure is

the notion of assemblies of pathway components. In Figure 4c, two pathway components,

A and phosphate, join together to form phosphorylated A. QPACA is capable of

representing this "assembly" of two items as a separate component composed of the two

original components. Assemblies are essentially any collection of pathway components that acts as one node in an interaction. This concept encompasses both the idea of physically assembled groups of objects, such as protein complexes, as well as interchangeable groups of objects, such as families of proteins that may act interchangeably at a particular node in the pathway structure.



Figure 5. QPACA pathway object model.

Figure 5 shows the pathway object model that corresponds to the QPACA pathway representation. This figure details the composition of each pathway object and

their relationships with each other. Each object in the model inherits from the PathwayComponent object, which ensures that each child object has an id, type and set of attributes. The id and type of each object serve to uniquely identify it and provide some basic information about its nature. The model supports arbitrary ids and types, though pre-defined types are necessary for accurate visualization and navigation. Attributes are a set of name-value pairs that store user-defined sets of annotations for each object. The smallest unit of the pathway is the PathwayElement, which represents a single physical element (such as a protein or molecule) or process within a pathway. PathwayAssemblies are containers of PathwayElements or other PathwayAssemblies that represent complexes or families of pathway elements. The PathwayEdge and PathwayVertex objects encode all information about the pathway relationships. PathwayVertices can be either simple nodes, which must contain a PathwayAssembly representing the object found at that node, or event nodes, which may contain a PathwayAssembly indicating an object that facilitates the event (such as a catalyst). PathwayEdges encode the relationships between different nodes. Finally, the Pathway object contains the PathwayVertices and PathwayEdges and provides methods for querying the pathway objects and navigating the pathway structure.

QPACA includes a set of filters for accessing pathway information from several different file formats: KEGG Markup Language (KGML)(Kanehisa, Goto et al. 2004), BioPAX (http://www.biopax.org) and the QPACA pathway language (see A.1.1). The explicit mapping between the different object models can be seen in Figure 6. The QPACA language allows biologists to directly enter their pathways into QPACA, and support for both BioPAX and KGML allow QPACA to be used with the existing pathway
databases. While BioPAX is being adopted as a pathway exchange standard by most of the public pathway databases (such as Reactome and KEGG) as well as by caBIG, at this writing it is still at level 2. Signaling pathways and gene regulation networks will not be fully supported until level 3. In order to facilitate use with all of the available KEGG pathways, the KGML filter was also added.



Figure 6. Mapping between QPACA, BioPAX and KGML object models.

The mappings between the three different object models are indicated in color and are fairly straightforward. All of these pathway models are based on the directed graphs with nodes and edges. Nodes and their corresponding physical entities are outlined in black. Edges, representing the different types of possible interactions are shaded in gray. Each model explicitly represents a pathway object, shaded in orange. Each model also has a parent object that represents a generic physical object (shaded in yellow) as well as an object that represents complex groups (shaded in green).

3.3. QPACA optimization method

Once a pathway model is in place, it can be used to provide support for pathway

based analytical analyses. QPACA's analytical methods take a set of pathway genes and

employ an optimization method to filter the data set such that it concentrates data that are most informative for that particular set of genes.

Chapter 1 (Section 1.5.2) discussed the specific example of the erg pathway in the Hughes yeast compendium, which showed that those samples with perturbations of genes in a particular pathway yielded the most informative changes in gene expression in that pathway. Similarly, given the general heterogeneity of the typical human cancer data set, it is unlikely that all samples in a given data set will be informative for a particular set of selected genes. QPACA resolves this issue by automatically selecting these relevant samples through the maximization of a scoring metric (see Figure 7). The goal of this method is to identify a specific subset of biological samples where the variation of gene expression across these samples conveys information about the function of the genes being studied. In simpler terms, this method can be used as a tool for pathway recognition, the ability to discriminate between real pathways and non-pathways.

A specific discussion of QPACA's ability to distinguish pathways from nonpathways using microarray expression data, given a set of genes hypothesized to be part of a pathway or coordinated process, can be found in Chapter 5.



Figure 7. QPACA optimization algorithm.

Sample subselection is achieved through the use of an optimization method that takes as input a large microarray data set, a set of genes, and a number of iterations. The method follows a simple hill-climbing optimization approach. Initially, a random subset of samples is chosen and scored. Then, in each subsequent iteration, a random sample is swapped into the subset and a new score is calculated. If the new score is better than the old score, the new subset is retained for the next iteration; otherwise the subset reverts to its previous state. The scoring metric was the median of the gene-gene correlations across all pairs of genes within a sample subset.

The optimization method employed in sample subselection follows a simple hillclimbing approach. A data set consists of a matrix of log-expression changes (denoted E) of a gene $g \in G\{1, ..., N\}$ over experimental samples $s \in S\{1, ..., M\}$, where N and M are the number of genes and samples, respectively. The optimization finds the optimal sample subset, S_{path} , for a specific subset of genes, G_{path} . To decide whether a set of genes is part of a pathway, G_{path} is composed of all genes in the data set that belong to that specific putative pathway. Figure 8 shows a pseudo-code representation of the optimization procedure.

```
procedure optimize(G<sub>path</sub>, E)
for i in (1:numStartPoints)
      randomly select subset of samples \text{S}_{\text{init}} \, \subset \, \text{S}
      numIter := 0
      S<sub>current</sub> := S<sub>init</sub>
      do until (no change in S<sub>current</sub>)
                or (numIter == maxIter)
             \mathbf{s}_{\text{new}} := pick random sample \mathbf{s}_{\text{new}} \in S \cap \mathbf{S}_{\text{current}}
             s_{old} := pick random sample s_{old} \in S_{current}
             s_{test} := (s_{current} - s_{old}) \cup s_{new}
             if (score(G<sub>path</sub>,S<sub>test</sub>,E) > score(G<sub>path</sub>,S<sub>current</sub>,E))
                   S<sub>current</sub> := S<sub>test</sub>
             ++numIter
      if (numIter == 0) or (score(G<sub>path</sub>,S<sub>current</sub>,E) > score(G<sub>path</sub>,S<sub>path</sub>,E))
             Spath := Scurrent
end
```

Figure 8. Pseudo-code for optimization algorithm.

score(gene subset, sample subset, expression matrix) is defined as the median of all gene-gene correlations (using Pearson's correlation) across all pairs of genes within the gene subset over the sample subset given the expression matrix. In the described experiments, maxIter was set to 600 and numStartPoints was set to 20 based on empirical evidence that these numbers ensure convergence.

One application of the method is to test whether a gene set is behaving in a coordinated fashion, and whether the coordination is relevant to our notion of a biological pathway. This test pertains to the common biological observation that some small set of genes appears to be behaving similarly (as in a hierarchical clustering of expression patterns), but where it is important to ask more quantitatively whether this gene set is also related through a common pathway. Chapter 5 reports on the algorithm's ability to yield high scores on sets of known pathway genes as compared with random sets of genes (to simulate false pathways) or randomized expression data (to simulate data with no signal).

The optimization method may also be applied to the question of biological pathway augmentation. Given a pathway for which the algorithm was able to recognize the gene set as a pathway, the scoring metric can then be used to rank the remaining nonpathway genes. Highly ranked genes could be hypothesized to also belong to the pathway. Chapter 6 reports on the algorithm's ability to find new pathway genes by conducting a series of cross-validation experiments in which a percentage of randomly chosen known pathway genes were held out during optimization and scoring of the pathway. Then, QPACA's scoring methodology was used to rank-order the held-out pathway genes and compare them to the background of non-pathway genes: those in other known pathways, those not known to belong to any other pathways and those in other closely related pathways.

However, ranking genes using the scoring metric described in Figure 8 (the median of all gene-gene correlations) results in many tied scores. As a result, Chapter 6 will also show the use of a refined scoring metric that substitutes the average of the top 10% of all gene-gene correlations, which reduces the number of tied genes.

3.4. System architecture

3.4.1. Design overview

At a basic level, QPACA can be seen as a black box that takes the pathway information and data that are input into the system and outputs a set of annotated images or data based on a set of user specified parameters (see Figure 3). This black box contains three basic modules: the pathway model (which controls input and output of pathway information), the visualization tools (which create annotated images) and the analysis tools (which generate pathway recognition and prediction results). The pathway model and associated code is responsible for input and output of pathway information. The visual and analysis tools both access the pathway model and share a common user interface, but are otherwise separate toolsets. Each of the modules can be accessed independently from the command-line.

The full system is organized in a 3-tier architecture (see Figure 10). This structure allows for the logical separation of user-facing client, the system's application logic, and the back-end database and tools. The user sees a set of dynamically generated web pages within a simple web-browser, removing the need for separate installation of QPACA for each user. These pages are dynamically generated by the application server based on inputs received from the user and information retrieved from the database and generated by the QPACA tools.

3.4.2. Implementation

3.4.2.1. Magellan

Magellan is a web-based system for the upload, storage, and analysis of multivariate data as well as annotations. It allows biologists to perform analyses of their data over the Internet through the use of a server-based system framework that interfaces with many different analytical systems. To maximize thee different types of information that the system can handle, data and annotations are treated as abstract entities with a user-defined type and value. Annotations may be used for analyses or visualization, as well as for intelligent subsetting of larger datasets. Analytical methods are deployed in a modular fashion that allows straightforward additions of new functionality or changes to existing functionality. Figure 9 diagrams the different components of the system and their interaction with each other.



Figure 9. Magellan UML component diagram.

This diagram shows the various interactions of the different components of Magellan. Magellan is roughly divided into a graphical user interface (GUI), a database, Java-based business logic, Java Server Pages (JSP) presentation pages, analytical methods, and NCI data sources. The JSP pages present information from the database and the analytical methods to the user via the web browser GUI. They directly contact the database for accessing user information as well as general data access and modification. The Java business logic is responsible for coordinating all interaction with the data for analyses as well as coordinating access to the outside NCI data sources. Analytical methods exist as separate modules, allowing straightforward modification of existing methods as well as addition of new methods.

3.4.2.2. QPACA as an analysis module

Figure 10 shows the structure of QPACA and its relationship to the different

components of the Magellan system. As a part of Magellan, the QPACA toolset is

available to researchers through a standard web browser. The specific interfaces between

the QPACA tools and Magellan are detailed in the sequence diagrams in Figure 11 and

Figure 12. Additionally, the QPACA tools can also be directly installed on the client

machine as stand-alone command-line programs. See Appendix B for further documentation.



Figure 10. QPACA system architecture overview.



Figure 11. Sequence diagram for QPACA visualization tools.

Interactions between the QPACA visualization tools and the Magellan GUI, Magellan database, and user are indicated as a series of lines denoting actions and boxes indicating duration. The blue boxes represent different possible actions based on pre-existing conditions. The actions shown encompass the different possible ways to view images within the QPACA system: (1) simply viewing the automatically generated image, (2) coloring an image based on a specified dataset or computed statistic, and (3) coloring an image based on pathway recognition results from the Analysis Tools (see Figure 12).



Figure 12. Sequence diagram for QPACA analytical tools. Interactions between the QPACA analysis tools and the Magellan GUI, Magellan database, and user are indicated as a series of lines denoting actions and boxes indicating duration. Two major actions are shown: (1) validatePathway, which performs the pathway recognition analysis task, and (2) predictInterestingGenes, which performs the pathway prediction analysis task.

3.4.3. QPACA toolset design

The QPACA toolset is composed of three separate modules: the pathway model, the visualization tools, and the analysis tools. The first two are written in Java, while the last is written in C for greater computational speed. The module containing the pathway model can be used to control input and output of pathway information as well as to navigate the pathway structure and answer basic questions based purely on the structure using standard graph-based algorithms. The model is built on the OpenJGraph open source Java library, which provides most of the basic graph functionality. Automatically generated visual graph output is provided using Graphviz (http://www.graphviz.org), open source graph visualization software. As discussed in Section 3.2, pathway input can come in three different file formats: BioPAX, KGML, or QPACA. QPACA's visualization module is also written in Java and provides classes and methods for coloring pathways based on data. This module can also calculate correlation and the F-statistic and color the pathway based on these computed values. Finally, the analysis module computes pathway recognition and augmentation results based on a dataset and gene lists derived from pathways. For further documentation of these software modules, see Appendix B.

3.5. Conclusion

This chapter introduced QPACA's system design, covering both the general architecture as well as specifics of both the pathway model and the analytical algorithms. QPACA is composed of three distinct modules: the pathway model, the visualization toolset, and the analysis toolset. The pathway model provides the basis for both the qualitative and quantitative analysis techniques. Chapter 4 will present several examples of using the visualization tools, while Chapter 5 and Chapter 6 will discuss the use and validation of the pathway recognition and pathway augmentation algorithms. Chapter 8 will explore combining these pathway analysis tools with analysis of transcription factor binding sites.

Chapter 4 Pathway Exploration and Visualization

4.1. Introduction

The previous chapter covered the design and implementation of QPACA. A working pathway model not only formalizes the representation of biological pathways, it also allows mapping from the experimental data space to the pathway space and enables researchers to ask questions about their data involving pathway structure and pathway-derived gene sets. One basic use for a pathway representation in data analysis is to simply reduce the dimensionality of a large data set to only those genes known to be involved in a known affected process, thereby avoiding the multiple comparisons problem outlined in Chapter 1. Additionally, a pathway representation can be used to provide a quick overview of the samples in a data set, creating a simple visual profile that can reveal differences in the types of samples. Finally, the gene/gene relationships of genes known to be closely related based on pathway structure can be easily queried and compared to mutational status or experimental conditions.

This chapter discusses three examples of using QPACA to explore and visualize data in the context of pathways that yield interesting insights into gene/gene relationships

in these data sets. Two pathways were used for these analyses: the receptor tyrosine kinase signaling (RTK) pathway, as defined by local experts (Figure 13), and the RAS subnetwork of the T-cell receptor signaling (TCR) pathway (Figure 14). These two pathways are representative of the different types of pathway elements and interactions that QPACA can model as well as of the different input types QPACA can handle (QPACA and BioPAX formats).



Figure 13. The receptor tyrosine kinase signaling (RTK) pathway.

The image was automatically generated by QPACA based on a description written in the QPACA pathway language. Black lines/arrows indicate excitatory interactions, while red lines/tees indicate inhibitory interactions. Nodes in the graph can represent gene products (rectangles), molecules (diamonds), or processes (green text). Joined rectangles indicate that a particular node can be represented by more than one gene product. Complexes of gene products are indicated by black dots with blue lines joining them to the members of the complex. The RTK pathway consists of the following 57 genes: *EGFR, ERBB2, EPHA2, HGFR, SRC, SOS1, GAP1IP4BP, RGL3, RALA, RAF1, MAP2K1, MAPK3, ELK1, CCND1, CDK4, CCND2, CDK6, RB1, E2F1, E2F2, E2F3, E2F4, CCNE1, CCNA2, CDK2, ARF1, MDM2, CDKN2A, CDKN1A, TP53, MYC, MYCN, HRAS, NRAS, GSK3B, CDKN1B, TNFSF6, MLLT7, BAD, AKT1, AKT2,*

RPS6KB1, PDK1, PTEN, PIK3CB, PIK3CD, PIK3R1, PIK3R2, PIK3CA, RACGAP1, PLCG1, DAG1, PKC, AP1M2, FOSB, RASGRP1, and *RAP1GDS1.*



Figure 14. The RAS subnetwork of the T-cell receptor signaling (TCR) pathway.

The image was automatically generated by QPACA based on a BioPAX level 2 formatted file downloaded from NCI-Nature Pathway Interaction Database (PID) (http://pid.nci.nih.gov). This diagram shows two pathway features not seen in Figure 13: 1) color-coding of activation/inhibition edges (green arrows indicate activation, red bars indicate inhibition (not seen)) and 2) use of event nodes as described in section 3.x (ovals). BioPAX level 2 is not able to encode certain commonly used pathway conventions. In this case, families of proteins are not encoded in the BioPAX output file, even though they are stored in the PID. Also, interactions with other pathways cannot be easily modeled, hence the presence of a generic "interaction" event node at the bottom of the diagram, which the PID lists as a link to the Calcium subnetwork of the TCR pathway. The RAS subnetwork consists of the following 11 genes: *BRAF, PRKCB (PKC beta), PRKCA (PKC alpha), RAF1, MAP2K1 (MEK1), MAP3K8 (COT), MAPK3 (ERK1), MAPK1 (ERK2), ELK1, FOS (c-FOS).*

4.2. Exploration of gene/gene relationships in an array-based comparative genomic hybridization experiment

Statistical analysis of microarray data can be aided by utilizing the context of a known pathway. In this instance, a set of array-based comparative genomic hybridizations (aCGH) derived from primary human bladder tumors were analyzed in the context of the Receptor Tyrosine Kinase (RTK) pathway (Figure 13). CGH measures the relative copy number of tumor DNA versus normal DNA. The data set consisted of 41 bladder tumors of different stages(Veltman, Fridlyand et al. 2003). Data was obtained from both high resolution (2000 clone) and oncogene focused (500 clone) arrays of bacterial artificial chromosomes (BACs). Using the pathway representation and focusing on gene/gene relationships in S-phase checkpoint control, several subsets of candidate genes for this analysis were formed. First, all genes within six steps upstream of S-phase checkpoint control (set 1) were found via graph traversal of the RTK pathway representation. Then two subsets were formed: a) all gene pairs within this set that are within three steps of each other or which target, or are targeted by, the same gene (set 2); b) all genes that are frequently changed in the data set (set 3). The first two subsets focused on genes pairs that were believed to be closely tied to a process known to be important in tumor growth and to consist of genes that were closely related to each other. Since knowledge of pathway membership is imperfect, the third set attempted to incorporate genes that might also be involved.

Two separate statistical analyses were performed: cross-locus correlation as well as complementation and concordance. In CGH data, closely mapping loci are expected to correlate in copy number, since large deletions and amplifications spanning many loci are

common. Strong correlations between loci that map far apart, however, can indicate nontrivial interactions. For this test, the correlations for all genes in sets 1 and 3 were computed. Significance was tested by permutation. Several pairs of distantly located genes were found to be highly correlated: gain of ERBB2 (17q12) and gain of CCNE1 (19q13.11) (p<0.05), loss of TP53 (17p13.3) and gain of CCND1 (11q13) (p<0.1), and gain of AIB1 (20q12) and loss of PTEN (10q23) (p<0.05). The last pair is particularly interesting because it incorporates a gene that was not included in the pathway description.



Figure 15. Correlation in aCGH of bladder tumors.

The genes highlighted in yellow in the pathway diagram represent all genes in set 1, that is, genes at least 6 steps upstream from S-phase checkpoint control. These genes, along with genes found to be frequently changed, were used in the correlation analysis. Highlighted in yellow in the red-green correlation plot on

the right are all correlations that were found to be statistically significant. Of special note are the correlations connected to the pathway diagram in blue. These are: gain of ERBB2 (17q12) and gain of CCNE1 (19q13.11) (p<0.05); gain of AIB1 (20q12) and loss of PTEN (10q23) (p<0.05); and loss of TP53 (17p13.3) and gain of CCND1 (11q13) (p<0.1). Of these, AIB1 was included in the analysis because it was frequently changed, not due to pathway membership.

In addition to correlation, complementation and concordance were also considered. Complementation is defined as change in one gene or locus occurring instead of change in another gene or locus. Concordance is the opposite, change in one gene or locus occurring along with change in another gene or locus. For this test, the test pairs (sets 2 and 3) were compared to a set of random pairs from a null population consisting of pairs of genes that change frequently and are not located on the same chromosome. Several complementary relationships were found to be significant: gain of CCND1 behaved complementarily with gain of both E2F3 (p<0.05) and CCNE1 (p<0.05); loss of CDKN2A was complementary to gain in CCND1 (p<0.1).

When examined in the context of the RTK pathway, gene pairs found in both sets of analyses fit the information known about the pathway. Additionally, specific statistically supported hypotheses for potential new interactions were made. It is important to note that, due to the problem of multiple comparisons, statistical significance cannot be achieved in the above data set by considering all-by-all locus correlations in performing these cross-locus comparisons.

4.3. Exploration of CGH phenotype of ERBB2 in expression of

RTK genes

The pathway representation can be used as a visual, as well as computational, tool. By coloring the nodes in the graph based on either data values (expression, copy number, etc.) or derived statistical values (correlation, F-test, etc.), it is possible to see these values changing across many samples.

In a set of breast cancer cell lines (Neve, Chin et al. 2006), statistical analysis showed that the data set could be divided into two subclasses based on ERBB2 amplification status. For these cell lines, both aCGH and expression data were available. While the original statistical analysis was done on the aCGH data, the two classes can also be seen in the RTK pathway when it is colored based on expression (Figure 16).

In this analysis, the statistical relationship between expression levels and a phenotype (panel A, expression versus ERBB2 amplified phenotype) or the correlation between genes (panels B and C) can be illustrated. Here, the visualization lends support to the notion of a biological switch that delineates two states, which are marked by both ERBB2 amplification at the genomic level and a host of coordinated changes in gene expression.



b) Correlations of genes to ERBB2 expression c) Correlations of

c) Correlations of genes to EPHA2 expression





In all images, white squares indicate missing values, from those genes either not being in the dataset or not passing the missing value threshold. Two classes of breast cell lines were previously identified using CGH data: ERBB2 amplifying and EPHA2 amplifying. a) The RTK pathway colored according to a computed F-statistic, which was based on these two classes. Brighter color indicates a higher discriminative value of the

gene. b) The RTK pathway colored according to each gene's correlation to ERBB2 using expression data. c) The RTK pathway colored according to each gene's correlation to EPHA2 using expression data. Images b and c are colored red/green with positive correlations in green and negative correlations in red. Uncorrelated genes are shown in black. All colors in the image are scaled to the maximum values of the statistic, i.e. the brightest colors correspond to the maximum actual value, not 1 or -1. The genes that showed a high discrimination ability between the two classes are outlined in blue. By comparing the correlation images to the f-statistic image, we can see that those genes with high f-statistics are highly correlated to either ERBB2 or EPHA2, and that these two genes are negatively correlated with each other.

4.4. Exploration of pancreatic cancer cell line data in the context of

the RAS subpathway

A similar analysis to that in the previous example was also performed on expression data gathered from several pancreatic cancer cell lines (Gysin, Rickert et al. 2005). This analysis focuses on the RAS subnetwork (Figure 14) since the most frequently mutated genes in pancreatic cancer are RAS genes (70-90%), mainly *KRAS2*.

The data set consisted of 22 pancreatic cancer cell lines, both treated and untreated with CI-1040, a MEK1/2 specific inhibitor, as well as 3 cultures of normal pancreatic ductal epithelial cells (PDEC) run on the Affymetrix U133 2.0 array. As an initial overview of the dataset, the data for each sample was plotted onto the pathway representation, showing that the cell lines did not have equivalent reactions to application of the inhibitor. Some typical samples can be seen in Figure 17. Next, the Student's t-test was used to determine if any genes were able to discriminate between the treated and untreated samples (Figure 18). Those genes that were obviously differentially expressed in the sample overview (MAP3K8 and FOS) were the only two that showed a statistically significant ability to discriminate between the treated and untreated samples.



Figure 17. Gene expression differences in cell lines treated and untreated with a MAP2K1 inhibitor. Gene expression data for two typical cell lines, both treated and untreated with CI-1040, coloring the RAS subnetwork. Expression ratios were computed for each gene by comparing to the average expression value for that gene. Red indicates down-regulation compared to the average and green indicates up-regulation compared to average. (a) and (b) show a cell line (Panc-1) which did not show noticeable differences in expression when treated with the inhibitor. (c) and (d) show the Hs cell line, which shows a large difference in expression, especially of MAP3K8(up-regulation) and FOS (down-regulation). There was also a slight down-regulation of MAP2K1 and a slight up-regulation of RAF1.



T-test between samples with and without CI1040

Figure 18. Discriminating between treated and untreated cell lines. T-test p-values for each gene are indicated in shades of green, with brighter colors indicating more significant p-values. Both FOS and MAP3K8 (both colored in the brightest green) have p-values ≤ 0.05 .

Interactions in pathways frequently rely on post-translational modifications, such as phosphorylation in the case of MAP2K1 in the RAS subnetwork. Even though the inhibitor specifically targets MAP2K1, it is not unusual that this gene is not the most differentially expressed between treated and untreated groups. Instead, treatment with the inhibitor tends to up-regulate MAP3K8, which phosphorylates MAP2K1. Additionally, one of the downstream effects of MAP2K1 is activation of FOS transcription. In the treated cell lines, FOS is frequently down-regulated. Of note in this analysis is the observation that not all samples behaved similarly in response to the same treatment. The sample subselection method described in Chapter 3 addresses this exact issue and will be discussed at greater length in the following chapter. This data set will also be revisited in Chapter 6 and Chapter 8.

4.5. Conclusion

Using QPACA to visually map both data and statistical values onto a visual representation of a pathway allowed for insights into several different types of data sets (both aCGH-based as well as expression-based studies). The context of the pathway was useful in both reducing the dimensionality of the data for improved statistical testing as well as for explanation of potential causality. The pathway visualization also reflects QPACA's ability to parse both locally defined pathways, as well as BioPAX formatted pathways downloaded from external databases.

Unlike other pathway visualization tools, QPACA also includes tools for displaying derived statistics (Sections 4.3 and 4.4) as well as tools for easily querying pathways for genes of potential interest (Section 4.2). The statistical tools allow biologists to make a quick qualitative assessment of the data in the context of the pathway, while the querying tools enable biologists to easily ask questions based on pathway structure.

The following chapters will deal with quantitative pathway analyses addressing the issues of both pathway recognition and pathway prediction.

Chapter 5 Computational Recognition of Pathways from Microarray Expression Data

5.1. Introduction

The previous chapter explored the use of QPACA as a qualitative analytical tool. This chapter introduces the use of QPACA as a quantitative analytical tool, focusing on addressing the issue of pathway recognition, which is the ability to discriminate between real pathways and non-pathways. In a biological context, this type of experiment can aide in answering the question of whether a set of genes identified through some procedure (such as differential expression between phenotypes) is likely to be part of a pathway or coordinated process, rather than simply a collection of genes that are parts of many tangentially related processes. Computationally, this type of experiment can be used as a feasibility proof for pathway augmentation. If a set of genes can confidently be identified as part of a pathway given an experimental data set, then it may be possible to make predictions of new pathway members given this data set. The following work was carried out in this second context, as a stepping-stone to pathway member prediction, which will be further discussed in Chapter 6. Given that the results were positive, inquiries motivated by the former context are also sensible in applying QPACA.

Chapter 1 and Chapter 2 discussed the problems and promises of rapidly accumulating gene expression data and the current methods for investigating pathways using that data. QPACA's analysis method directly addresses the issues inherent in analysis of human systems without discretizing data or making limiting assumptions about the structure of pathways. Given a set of genes hypothesized to be part of a pathway or coordinated process, QPACA is able to reliably distinguish true pathways from non-pathways using microarray expression data. As discussed in Chapter 1 (Section 1.5.2), only some of the experiments within a large data set are necessarily relevant to a specific biochemical pathway. By leveraging the optimization method described in Chapter 3 (Section 3.3), QPACA identifies the particular samples in an experimental data set that are particularly relevant to a specified set of genes and in so doing also assigns a coordination score to this set of genes (see Figure 8). This coordination score can then be used to determine whether a gene set represents a pathway or coordinated process.

This chapter presents data on all human and yeast pathways found in the KEGG pathway database. In 117 out of 191 cases (61%), QPACA was able to correctly identify these positive cases as *bona fide* pathways with p-values measured using rigorous permutation analysis. Success in recognizing pathways was dependent on pathway size, with the largest quartile of pathways yielding 83% success.

This work appeared previously in Novak and Jain 2006.

5.2. Materials and Methods

5.2.1. Data and data processing

Both human and yeast expression data sets were considered in developing and assessing QPACA. The Hughes compendium of yeast data (Hughes, Marton et al. 2000)(287 deletion mutants and 13 environmental conditions) was used primarily to develop and test the algorithm, while the NCI set of 60 human cancer derived cell lines (Staunton, Slonim et al. 2001) was used to validate the results in human data. The data sets contained expression levels for 6356 and 7071 genes, respectively. The data were processed to remove duplicates, genes with excessive missing values, and genes with insufficient annotations. Because the algorithm computes correlations across at most 20 samples, a fairly stringent measure of missing values was used. Each gene had to have signal for at least 80% of the total samples. In the NCI60 data set, this threshold eliminated roughly 3600 genes. The other genes were eliminated due to insufficient annotation (~700 genes) and consolidation of duplicates (~800 genes). The yeast data set had fewer issues with missing annotations and duplicated genes, as well as better general signal strength. After processing, 6163 genes remained in the yeast data set, while 1954 genes remained in the human data set. Raw expression values were converted to log2 ratios by taking the logarithm of each gene's value divided by the mean for that gene across all samples. Additionally, data were normalized by median centering within each sample (this is an automatic feature of QPACA's data processing, as it can influence results markedly if omitted). Both data sets were analyzed in the context of all pathways in the KEGG database with at least 5 genes in the corresponding data set. In the human data set, the receptor tyrosine kinase signaling (RTK) pathway, as defined by local

experts, was also analyzed. Figure 13 delineates the composition of this pathway. This resulted in a total of 83 yeast pathways and 108 human pathways. The pathways varied substantially in size, with the bottom half containing fewer than 20 genes, and the top quartile containing 30 genes or more.

5.2.2. Permutation testing and p-value calculation

The algorithm's ability to recognize pathway membership and to select samples relevant to a gene set was tested. Scores for each known pathway gene set (coupled with its experimental expression data) were compared to three distributions: 1) scores resulting from randomly chosen gene sets of the same size as the pathway set in question; and 2) scores resulting from randomizing the gene expression data itself; and 3) scores resulting from randomly chosen gene sets of the same size as the pathway set in question, restricted to genes represented within KEGG (see Figure 19 for a pseudo-code description of the methods). In each permutation test, the randomized data comes from the same microarray experiment as that used for the pathway case being tested. The first permutation method estimates the likelihood that any equal-sized gene set will find a sample subset which scores equal to or better than the test. If the probability is low, confidence of the metric's rationality increases. The second randomization method controls for the effects of the distribution of data values within a particular set of genes, which may yield unusual distributions of correlation values under certain degenerate conditions. Given a particular set of genes from a particular data set, data were randomized for each gene across all samples. The third method is a further control to test for the possibility that KEGG genes as a set may be biased.

Additionally, the optimized score(Gpath, Spath, E) was also compared to the

unoptimized score(Gpath, S, E) to determine if the optimization procedure actually

increased our ability to recognize pathways.

```
method 1: randomize pathway gene set, G<sub>path</sub>, without changing expression
matrix, E
for i in (1:maxPermutations)
    G<sub>random</sub> := randomly choose gene set from G of same size as G<sub>path</sub>
    S<sub>final</sub> := optimize(G<sub>random</sub>,E)
    ScoreArray[i] := score(G<sub>random</sub>,S<sub>final</sub>,E)
method 2: randomize expression matrix, E, without changing G<sub>path</sub>
    for i in (1:maxPermutations)
        E' := randomized matrix E
        S<sub>final</sub> := optimize(G<sub>random</sub>,E')
        ScoreArray[i] := score(G<sub>random</sub>,E')
```

 ${\tt method}\ {\tt 3:}$ same as method 1, but restrict ${\tt G}_{\tt path}$ to genes found in KEGG pathways

Figure 19. Pseudo-code for permutation methods.

In each case, the p-value for G_{path} was computed by comparing the score(G_{path} , S_{path} , E) to the distribution of the scores in ScoreArray where:

p-value := count(ScoreArray[i] > score(G_{path}, S_{path}, E)) / maxPermutations In the experiments described, maxPermutations was set to 500.

5.3. Results

Representative results for gene set recognition on a diverse and non-overlapping

set of yeast and human experimental data sets can be seen in Table 2 and Table 3.

			Number	Final	p-value w/	p-value w/o
Organism	PathwayID	Pathway	of genes	score	subselection	subselection
a) Yeast	sce00052	Galactose metabolism	30 / 30	0.826	<<0.01	<< 0.01
	sce00230	Purine metabolism	95 / 95	0.231	< 0.01	0.03
	sce04110	Cell cycle	100 / 100	0.227	0.01	< 0.01
	sce00100	Sterols biosynthesis	14 / 14	0.682	0.01	<< 0.01
	sce04020	Second messenger signaling	19 / 19	0.497	0.04	0.26
	sce04010	MAPK signaling	55 / 55	0.221	0.11	0.09
	sce04070	Phosphatidylinositol signaling	12 / 12	0.376	0.60	0.59
	sce00562	Inositol phosphate metabolism	32 / 32	0.12	0.96	0.55
b) Human	hsa00010	Glycolysis / Gluconeogenesis	24 / 60	0.253	<< 0.01	<< 0.01
	hsa00052	Galactose metabolism	13 / 28	0.377	< 0.01	0.01
	RTK	Receptor tyrosine kinase signaling	24 / 57	0.198	0.01	<< 0.01
	hsa04510	Integrin-mediated cell adhesion	25 / 82	0.161	0.01	<< 0.01
	hsa04010	MAPK signaling	41 / 287	0.1	0.01	0.09
	hsa04110	Cell cycle	30 / 120	0.131	0.02	0.05
	hsa04350	TGF-beta signaling	11 / 72	0.351	0.03	0.11r
	hsa04620	Toll-like receptor signaling	12 / 92	0.299	0.04	0.03
	hsa04210	Apoptosis	19 / 96	0.187	0.07	0.34
	hsa04070	Phosphatidylinositol signaling	13 / 70	0.217	0.29	0.47

.

Table 2. Results table for a representative set of pathways.

Each pathway is listed with its KEGG id, if available. The number of genes indicates those genes that both belonged to the pathway and were represented in the expression dataset over the total number of genes in that pathway. The final score is the median of all gene-gene correlations after optimization. Two empirically derived p-values are listed: 1) the probability that the subselection algorithm gave a better score than random and 2) the probability that a better score than random could be found without subselection. The p-values reported represent the most pessimistic p-value derived from each of the three random permutations, which can be seen in Table 3.

PathwayID	Randomized data p-value	Random gene set p-value	Random KEGG genes p-value
sce00052	<<0.01	<< 0.01	<<0.01
sce00230	<<0.01	<< 0.01	< 0.01
sce04110	<<0.01	<< 0.01	0.01
sce00100	<<0.01	0.01	<< 0.01
sce04020	<<0.01	0.02	0.04
sce04010	<<0.01	< 0.01	0.11
sce04070	0.03	0.60	0.02
sce00562	0.35	0.80	0.96
hsa00010	<<0.01	<< 0.01	<<0.01
hsa00052	<<0.01	< 0.01	<< 0.01
RTK	<<0.01	< 0.01	0.01
hsa04510	< 0.01	0.01	<< 0.01
hsa04010	< 0.01	0.01	< 0.01
hsa04110	<<0.01	0.02	0.01
hsa04350	< 0.01	0.03	<< 0.01
hsa04620	0.01	0.04	0.01
hsa04210	0.02	0.07	0.02
hsa04070	0.27	0.29	<< 0.01

Table 3. Breakdown of individual p-values with sample subselection for each pathway.

The individual p-values are: randomized data (scrambling the data for each gene in the pathway gene set), random gene set (gene sets of the same size as the pathway gene set randomly selected from the set of genes in the entire data set that are not part of the pathway gene set), and random KEGG gene set (gene sets of the same size as the pathway gene set randomly selected from the subset of genes in the entire data set that belong to other pathways in KEGG).

Table 2 reports the most pessimistic p-value computed from the three methods described above, while Table 3 provides the breakdown of all three individual p-values. A p-value of X can be interpreted as the probability that a random set of genes will yield a p-value of less than or equal to X. For this limited set of pathways, those for which subselection did not improve the significance of the score included the metabolic pathways (e.g. galactose metabolism) which are likely to show coordinated expression under many different conditions. In these pathways, the score was highly significant both with and without subselection. There were a few pathways, however, for which the score was not significant in either condition. In these cases (inositol phosphate metabolism and phosphatidylinositol signaling), it is possible that the perturbations in these pathways either did not show up in these particular data sets or that the effects were outside the scope of expression data, through post-translational modifications, for example. In none of these cases did the subselection process cause a significant result to become insignificant. Note, however, that significant variability in the p-values obtained using the three different methods was occasionally observed. These differences are expected, to the extent that each of the different permutation methods will yield different distributions of gene expression values. In the random data case, the distribution for the control is exactly the same as in the non-control. In the other two types of permutations, this is not so, and consequently, there were differences depending on the method used.



Figure 20. Comprehensive pathway recognition results from all 191 human and yeast pathways. (a) Cumulative histograms of permutation-based p-values for all analyzed pathways. Most pathways (117/191 or 61%) had significant scores ($p \le 0.05$) under the most stringent of these methods, indicating that this method is reproducible over a large and varied set of pathways. (b) Cumulative histograms of the p-values with optimization for all pathways (red), all pathways without optimization (blue), and for those pathways with ≥ 30 genes using optimization (green). For each case, the randomization permutation method was used. The optimization method clearly improves the p-value distribution over no optimization (p << 0.001 by Mann-Whitney), and restriction to larger gene set sizes also improves the p-value distribution (p << 0.001 by Mann-Whitney).

Figure 20 illustrates the comprehensive results obtained from all 191 human and yeast pathways. Panel A shows the cumulative histograms for the three different permutation methods. While there are some differences in the distributions, particularly at very low p-values, the three methods do not produce substantially different interpretations of the data. Using the most pessimistic values (as in Table 2), in 61% of all cases, we observed significant scores under optimization ($p \le 0.05$). For the reason of

distributional equivalence, we focused on the randomized data method. Panel B shows the effect of both the optimization procedure and larger gene set sizes for the data randomization permutation method. The optimization procedure clearly shifts the p-value distribution to the left, and the subset of pathways with larger gene set sizes also shifts the distribution to the left (both observations are highly statistically significant). Using the data randomization permutation method, for pathways with at least 30 genes, we observe 96% recognition at a false positive rate of 0.05. A more conservative test, using the most pessimistic of all permutation methods, yields a recognition rate of 83%.

5.4. Discussion and conclusion

The results detailed in this chapter address one aspect of computational structure elucidation using gene expression data. Given a gene set postulated to be part of a pathway or coordinated process, QPACA has demonstrated the ability to discriminate between real pathways and non-pathways. This problem is termed pathway recognition. Specifically, in 61% of cases known pathways (83% for larger pathways), QPACA was able to answer affirmatively while rejecting random pathways over 95% of the time.

By employing an automated method for identifying relevant sample subsets, QPACA has been able to analyze complex pathways relevant to major disease processes in humans. The next chapter covers the use of QPACA to address the other aspect of computational structure elucidation: pathway augmentation, or the ability to significantly enrich for pathway genes over non-pathway genes in making predictions about putative pathway members.

Chapter 6 Computational Prediction of New Pathway Members from Microarray Expression Data

6.1. Introduction

The previous chapter introduced the use of QPACA as a quantitative analytical tool in pathway recognition. Once a set of genes can reliably be distinguished as a true pathway or coordinated process, the next logical question is whether that set of genes can be augmented with new members.

This chapter will describe an approach to the pathway membership augmentation problem using the same optimization and scoring technique previously described for pathway recognition. Once a gene set has been recognized as a pathway or coordinated process, this method ranks non-pathway genes using the same scoring metric that was used for pathway recognition. Genes that increase the coordination score when added to the pathway gene set can reasonably be supposed to be related to the existing known pathway genes. This technique was tested with a series of cross-validation experiments in which QPACA was able to yield enrichments for predicted pathway genes over random genes at rates of 2-fold or better the majority of the time, with rates of 10-fold or better 10–20% of the time.

6.1.1. Cross-validation in biological pathway augmentation

Cross-validation is a common statistical technique that involves partitioning a data set into training and validation sets. In the holdout method, some observations, usually less than 1/3, are randomly chosen to form the validation set while the remaining observations form the training data. In the case of the QPACA augmentation algorithm, a randomly chosen 10% of the known pathway genes were held out during the initial recognition scoring/optimization of the pathway gene set. The augmentation algorithm was then used to rank both the held-out and non-pathway genes. If the algorithm successfully identifies potential pathway members, then the held out pathway genes should rank highly compared to the non-pathway genes.

The general fuzziness and interconnectedness of existing pathway definitions makes forming a true validation set of known non-pathway genes real data difficult. Certain broad generalizations can, however, be made. It is possible to subdivide the negative (i.e., non-pathway genes) into several general groups: (a) genes not known to belong to any pathway, (b) genes in other known KEGG pathways, and (c) genes in closely related pathways. It would be expected that enrichment for the held out known pathway genes would be greatest against the background of set (a) and least against that of set (c).

Construction of this third background of interrelated pathways was accomplished by subsetting large pathways. To some degree, all processes within an organism as interrelated. As a result, many of the most intensively studied pathways in existing pathway databases contain large numbers of genes (some number in the hundreds) and many different subprocesses. The RTK pathway in Figure 13, for example, contains several distinct processes. By choosing gene subsets of these large pathways, it was possible to examine the effect of genes in closely related pathways on pathway augmentation.

This chapter will first introduce the augmentation algorithm and scoring metric as well as the data sets used in the analysis. Then, it will discuss the results of the crossvalidation in two separate sections: first focusing on the data sets used in Chapter 5 and the first two backgrounds described above and then focusing on an ovarian data set and a background of closely related subpathways.

Portions of this work on cross-validation in the human and yeast data sets presented in Chapter 5 appeared previously in Novak and Jain 2006.

6.2. Materials and Methods

6.2.1. Augmentation algorithm and scoring metrics

The method used for pathway augmentation is described in Figure 21. In essence, each gene is scored based on the recognition score for the pathway with that gene added. Recall that the original scoring metric for pathway recognition was the median of all gene-gene correlations within the gene set (Figure 8). Unfortunately, due to its reliance on medians, this method results in a fair number of identical scores. In order to reduce the

number of ties, another scoring metric was also tested: the average of the top 10% of all

gene-gene correlations within the gene set.

```
procedure augmentPathway(G<sub>path</sub>,G<sub>notPath</sub>,E)
s<sub>path</sub> = optimize(G<sub>path</sub>,E)
pathScore = score(G<sub>path</sub>,s<sub>path</sub>,E)
foreach gene g in G<sub>notPath</sub>
G<sub>test</sub> = G<sub>path</sub> ∪ g
g<sub>score</sub> = score(G<sub>test</sub>,s<sub>path</sub>,E)
if (g<sub>score</sub> > pathScore)
results[g] = g<sub>score</sub>
```

end

```
Figure 21. Pseudo-code for augmentation algorithm.
Only those genes that improve the score for the pathway gene set are likely candidates for pathway membership.
```

6.2.2. Data and data processing

Three data sets were used to explore the utility of this augmentation algorithm. The initial set of experiments was conducted using the two data sets described in Chapter 5 (NCI60 cell line data and Hughes yeast compendium data). The 101 pathways for which all three permutation-based recognition p-values were less than 0.1 were used, eliminating those pathways for which prediction would be unlikely to work. This filtering matches the way in which a researcher would proceed in practice, where predicted augmentations of a pathway in which the recognition process failed would not be believed.

Sets of closely related subpathways were constructed using a data set of serous ovarian tumors. This data set included CGH as well as expression data, allowing for the formation of logical pathway submodules. The data set consisted of 50 snap-frozen serous ovarian tumors from the UAB/Duke Ovarian Cancer SPORE, comprised of 23 patients that survived >60 months (long survivors) and 27 that survived <36 months (short survivors)(Berchuck, Iversen et al. 2005). Samples in the data set were median-
centered and had a log2 ratio calculated for each value by taking the value divided by the average of all values for that gene and then taking the log base 2 of this ratio. To account for outliers that affect the calculation of Pearson's correlation, the data were assigned ranks prior to analysis. Specific pathways were chosen for the analysis from the KEGG database (Kanehisa and Goto 2000) that focused on EGFR, PI3K and TGF-beta, which are all implicated in ovarian cancer. These pathways were: MAPK signaling, calcium signaling, cytokine-cytokine receptor interaction, phosphatidylinositol signaling, cell cycle, TGF-beta signaling, focal adhesion, gap junction, and actin cytoskeleton regulation.

6.3. Cross-validation of pathway augmentation using human and yeast microarray data

For the 101 pathways from Chapter 5 where QPACA recognized the gene sets as pathways, cross-validation experiments were performed by holding out random subsets of known pathway genes and using QPACA's scoring methodology to rank-order the held-out pathway genes within a background of non-pathway genes (see Section 6.1.1 for additional details). Figure 22 summarizes the results using two background gene sets: one consisting of only of genes found in KEGG and the other of non-KEGG genes. Panel A shows smoothed histograms of scores for holdout RTK pathway genes and non-pathway genes (KEGG control gene set). The distributions are roughly normal, with the scores for the RTK pathway genes clearly shifted to the right. The RTK case was fairly typical in terms of enrichment of high scores within the pathway holdout set versus the nonpathway set. Panel B shows the corresponding representative receiver-operating characteristic (ROC) curve for the RTK pathway and for two other human pathways.

Panels C and D of Figure 22 summarize cross-validation results for the full set of 101 tested pathways with two different backgrounds. In Panel C, the cumulative distributions of ROC areas for the two control gene sets are shown. Both distributions are highly skewed to the right of 0.5 (p < 10-6 by exact binomial), indicating that positive enrichment for pathway genes over non-pathway genes occurs in the vast majority of cases. The non-KEGG control gene population yields a slightly stronger enrichment. Panel D shows cumulative histograms of maximal enrichment ratios for both control gene populations. Given a specific portion of the top-ranked genes in a ranked list, the enrichment reflects the ratio of the number of true positive genes found divided by the number of such genes expected by chance. The maximal enrichment ratio is the highest such ratio over the full range of possible proportions. Enrichments of 2-fold or better occur for 60% and 70% of the pathways using the KEGG and non-KEGG control gene sets, respectively. Enrichments of 10-fold or better occur in 12% and 20%, respectively. Note that all of the results in Figure 22 resulted from running the subset optimization procedure described previously. On the same set of 101 pathways, without running the optimization procedure, the chief difference in the results is a marked increase in the number of pathways for which the resulting ROC areas were significantly less than 0.5 (7% of non-optimized cross-validation runs yielded ROC areas < 0.485 compared with 0% of the runs with optimization).



Figure 22. Comprehensive pathway augmentation results from 101 human and yeast pathways. (a) Smoothed histogram of scores for holdout RTK pathway genes (solid line) and non-pathway genes (dashed line). The non-RTK-pathway genes were taken from the full set of KEGG genes that were not found in the annotated RTK pathway. The distributions are roughly normal, with the scores for the RTK pathway genes shifted to the right. (b) Three representative receiver-operating characteristic curves: RTK pathway (solid line), two KEGG human pathways (dashed lines). The shift of the RTK holdout distribution to the right of the non-pathway gene distribution yields a favorable ROC curve, with deflection into the upper left corner, with an area of 0.71. HSA00190 (Oxidative phosphorylation) also shows a favorable enrichment of known pathway genes against a background of non-pathway genes. HSA04020 (calcium signaling pathway) shows an atypical case, with no enrichment of pathway genes over non-pathway genes. (c) Cumulative distributions of ROC areas for all 101 pathways tested with two different backgrounds. The solid line shows results using the KEGG gene set as the source of non-pathway genes for each pathway holdout experiment. The dashed line shows similar results, but makes use of genes not annotated within KEGG as the source of non-pathway genes. Both distributions are highly skewed to the right of 0.5, indicating that positive enrichment for pathway genes over non-pathway genes occurs in the vast majority of cases. The non-KEGG control gene population yields a slightly stronger enrichment. (d) Cumulative histograms of maximal enrichment ratios for both control gene populations. Enrichments of 2-fold or better

occur for 60% and 70% of the pathways using the KEGG and non-KEGG control gene sets, respectively. Enrichments of 10-fold or better occur in 12% and 20%, respectively.

Recall that the RTK pathway (Figure 13) was a hand-curated representation of genes downstream of receptor-tyrosine-kinase signaling, particularly emphasizing pathways that affected cell-cycle regulation, proliferation, and apoptosis (each particularly important in cancer). Also, note the nominally better enrichments observed in using the non-KEGG genes as a control set as compared with the KEGG gene set. It is possible that the high-scoring control genes from the KEGG population of nominally non-RTK genes might, in fact, include genes that properly belonged to the RTK pathway, based on existing literature evidence. The top 30 highest-scoring genes (the right-hand tail of the "Other Genes" distribution from Figure 22a) were examined. Figure 23 depicts the documented relationships of 12 of these genes to the RTK pathway as originally curated. 15/30 of the highest-scoring KEGG genes (all nominal false positives in our cross-validation experiment) properly belong to the RTK or very closely related pathways.





This image shows the original annotated RTK pathway as in Figure 13 with the 15/30 top scoring genes that have documented links to the pathway. Interactions between highly scoring genes (yellow) with annotated RTK pathway genes (gray) are highlighted in green (Gulbins, Schlottmann et al. 1995; Hall, Bates et al. 1995; Yang, Zha et al. 1995; Hobert, Schilling et al. 1996; Watson, Robinson et al. 1997; Bertagnolo, Marchisio et al. 1998; Delcommenne, Tan et al. 1998; Nagata, Puls et al. 1998; Das, Shu et al. 2000; Liu, Dorow et al. 2000; Moores, Selfors et al. 2000; Ohtoshi, Maeda et al. 2000; Zhang, Ho et al. 2001; Humbert, Bryson et al. 2002; Weinmann, Yan et al. 2002). Three additional genes (IKBKE, PLCD1, and DYRK4) are shown unconnected to the existing diagram. These genes were members of closely related pathways (MAPK signaling, Calcium signaling and Phosphatidylinositol signaling). DYRK4 is also a tyrosine kinase (Becker, Weber et al. 1998; Zhang, Li et al. 2005).

6.4. Cross-validation of pathway augmentation using closely related

subpathways

As discussed in section 6.1.1, all processes within an organism are interrelated to

some degree. As a result, what KEGG curators have called a "pathway", especially in the

case of the larger pathways containing hundreds of genes, consists of modules that may

share a connection, but which may not behave as a coordinated process. In fact, when looking at heatmaps of expression data (such as Figure 24), it is possible to see distinct clusters of coordinated genes within the many genes in a large pathway.



samples

Figure 24. Expression heatmap of Cell Cycle pathway.

Image of ovarian data for the KEGG Cell Cycle pathway (hsa04110) with over-expression colored in green and under-expression colored in red. The image shows all of the genes in the pathway but only the 20 samples that most contribute to the coordination score as chosen by the QPACA optimization algorithm during pathway recognition. The red and blue colored bar at the top of the heatmap indicates survival status: short survivors in blue and long survivors in red. The genes in this pathway can be seen to form at least two fairly distinct coordination modules, divided into a large module which is largely down-regulated in the left half of the samples (all short survivors) and up-regulated on the right (mainly long survivors). There is a smaller cluster of genes at the bottom that shows the opposite behavior.

In light of these observations, it makes sense to consider smaller subsets of the pathway genes. These gene subsets also enable the formation of subpathways that are known to be closely related and can be used to further examine the efficacy of pathway membership augmentation using the QPACA algorithm.

This analysis will focus on subpathways in the ovarian data set that were formed based on both the defined structure of the pathway as well demonstrated relevance to ovarian cancer based on aCGH data.

6.4.1. Subpathway creation

Subpathways were defined based on the super-pathway's structure and a set of "core" genes. Since the data set contained both aCGH and expression data, it was possible to rigorously select several biologically interesting genes that were both highly deregulated on the genomic level in ovarian cancer and had expression levels that strongly correlated with the copy number variation. The first of these criteria ensures that the chosen genes are relevant to the genomic disturbances specific to ovarian cancer. The second criteria guarantees that the expression levels for these genes are related to these genomic disturbances.

Specifically, genes with (1) a corresponding CGH clone that had an absolute difference value of ≥ 0.2 in at least 30 samples and (2) an absolute value of the Pearson's correlation of aCGH to expression data of at least 0.5 were chosen. These selection criteria resulted in a list of 613 Affymetrix identifiers, corresponding to 443 unique annotated genes. Each of the selected pathways contained between one and four of these genes (see Table 4 for a complete list of pathways and core genes). Neighborhoods of 25-

60 genes (depending on the density of the surrounding pathway interactions) were chosen around these genes and defined as "subpathways". A sample image of the cell cycle pathway, highlighting the subpathways, can be seen in Figure 25. Core genes are highlighted in red.



Figure 25. Subpathways in the Cell Cycle pathway (hsa04110).

The large shaded areas indicate subpathways centered on 3 core genes (HDAC2, WEE1, and CDK7), which are colored red. The core genes are both highly deregulated at the genomic level in ovarian cancer and have expression levels that correlate strongly with the copy number variation. The subpathway centering on WEE1 is colored in pink; the one centering on HDAC2 is in yellow, and the one centering on CDK7 is in blue. The entire pathway as well as all three subpathways were correctly recognized as being significantly coordinated using the ovarian cancer expression data set, making them good candidates for exploration of QPACA's predictive ability.

6.4.2. Results

Prior to examining pathway augmentation in these subpathways, it is always necessary to determine pathway recognition using the data set. In the subpathways based on core genes, 76% had significant recognition scores, which is consistent with the proportion observed in the Chapter 5. Of note is that some subpathways derived from the same super-pathways are unrelated to each other in the sense of co-regulation. This observation is not unexpected given both the distinct coordination modules and the existence of distinct subprocesses in large curated pathways. Just as some samples in a large data set do not contribute equally to strong coordination between the genes, some genes in a large pathway may not show variance on the expression level. Results of the analysis can be seen in Table 4.

able 4. Results for pathway recognition in subpathways.				
	b) Core gene	c) Genes in	d) Recog.	e) Recog.
a) Super pathway name	name	subpath	p-value	score
	KRAS	45/54	0	0.115
hsa04010: MAPK signaling	PAK2	30/34	0	0.154
	MAP2K7	26/28	0.024	0.125
head/020: Calaium signaling	m signalingATP2B450/560.3060.044RYR139/4400.205		0.044	
lisa04020. Calciulii signaliig			0.205	
hsa04060: Cytokine-cytokine receptor interaction	TNFRSF10B	7/8	0.054	0.455
has 0.4070; Phase hat iduling a ital a isoling	BCR, DYRK4 23/27 0.032		0.136	
isao4070. Phosphatidyiniositoi signaning	PIP5K1A, PIK4CB	27/29	0.02	0.119
	CDK7	32/33	0	0.343
hsa04110: Cell cycle	HDAC2	36/38	0	0.274
	WEE1	32/38	0	0.413
hsa04350: TGF-beta signaling	PPP2CB	36/41	0	0.174
	KRAS	31/36	0	0.132
hea04510; Eccal adhesion	PAK2 32/38 0	0	0.121	
lisa04510. Focal adhesion	PTK2	TK2 46/49 0.32 0.049		
	CAPNS1	42/46	0.118	0.062
hsa04540: Gap junction	KRAS	34/38	0.002	0.126
	KRAS	37/39	0.01	0.088
hsa0/1810: Actin cutoskaleton regulation	PAK2 22/29 0.542 0.09		0.095	
iisa04610. Actin cytosketeton regulation	PTK2	30/36	0	0.161
	PIP5K1A	25/31	0.002	0.151

Table 4. Results for pathway recognition in subpathways.

Column (a) gives the pathway ID and name; column (b) specifies the subpathway core gene; column (c) indicates the number of genes that both belonged to the pathway and were represented in the expression data set over the total number of genes in the pathway; column (d) lists the p-value for pathway recognition and column (e) lists the recognition score.

Once a pathway has been determined to exhibit coordinated behavior based on a data set, non-pathway genes can then be assigned scores using the pathway augmentation algorithm (Figure 21). As in the previous cross-validation experiments in human and yeast data described above, holdout experiments were run on the subpathways in which a random 10% of genes were heldout during the optimization step. Then these heldout genes were scored along with the non-pathway genes. Enrichment was observed for known subpathway genes (Figure 26).



Figure 26. Comprehensive pathway augmentation results for all subpathways. Cumulative histograms of maximal enrichment ratios for all control gene populations: all genes found in the associated superpathway (dashed line), all genes found in other KEGG pathways(solid line), and all genes not found in KEGG (dotted line). Enrichments of 2-fold or better occur for about 40% of the pathways using any of the gene sets. Enrichments of 10-fold or better occur in 5% of the pathway gene set, 14% of the KEGG gene set and 24% of the non-KEGG gene set.

Of note is the effect of testing against a background of closely related

subpathways (denoted as "Pathway Control"). As predicted, the enrichment for heldout genes is lowest against this background, indicating that the more closely related a gene is to the pathway, the more likely it is that it will have a high coordination score.

6.5. Conclusion

Once a set of genes is known to represent a pathway and is recognized given a particular dataset, the next obvious avenue of research is computational augmentation of this pathway. This chapter addressed this problem and demonstrated QPACA's ability to significantly enrich for pathway genes over non-pathway genes in making predictions of putative pathway members. QPACA was able to yield enrichments for predicted pathway genes over random genes at rates of 2-fold or better the majority of the time, with rates of 10-fold or better 10–20% of the time, depending on the control gene set used. It was compared to three different control gene sets (genes not known to belong to any pathway, genes belonging to other pathways, and genes belonging to closely related subpathways) in several different data sets. While enrichment rates on the level of 2-fold may or may not be of practical significance, rates of 10-fold or higher are more likely to help prioritize experimental exploration of candidate genes for elaborating pathways of particular biological interest. Of particular note is the observation that genes known to be closely related to a pathway are more likely to score highly under the pathway augmentation algorithm.

The next chapter will explore the synergy that arises by combining sequencebased analytical methods (specifically, motif finding in gene promoter sets) with the information derived from measurements of variation in gene expression.

Chapter 7 The Relevance of Sequence Patterns to QPACA

The previous two chapters addressed two steps in pathway structure elucidation using gene expression data. First, given a gene set postulated to be part of a pathway or coordinated process, QPACA demonstrated the ability to discriminate between real pathways and non-pathways. Second, given a gene set known to represent part of a pathway, QPACA was then able to significantly enrich for pathway genes over nonpathway genes in making predictions of putative pathway members. The first problem was termed pathway recognition and the second pathway augmentation. Specifically, for the pathway recognition problem, in 61% of cases known pathways (83% for larger pathways), QPACA was able to answer affirmatively while rejecting random pathways over 95% of the time. For the pathway augmentation problem, QPACA was able to yield enrichments for predicted pathway genes over random genes at rates of 2-fold or better the majority of the time, with rates of 10-fold or better 10-20% of the time depending on the background used. While enrichment rates on the level of 2-fold may or may not be of practical significance, it is likely that rates of 10-fold or better may help prioritize experimental exploration of candidate genes for elaborating pathways of particular biological interest. Additionally, Chapter 6 also introduced the idea that gene sets are

recognized as pathways not because all genes within them are cross-correlated, but rather because individual genes grouped together to form highly coordinated expression modules.

The surprising feature of the results from the previous two chapters is that the results for pathway recognition and augmentation were made possible based on the patterns of variation in gene expression alone. No information regarding protein levels, phosphorylation states, or pairwise physical interactions was required. The natural question is *why* it was possible to deduce aspects of pathway structure, as defined by human curators based on knowledge of the experimental biological literature, from expression patterns. The most appealing answer is that the transcriptional programs that govern expression behave in a manner that frequently yields experimentally detectable patterns of co-variation among gene sets within pathways. If this were so, it should be possible to identify motifs and/or specific transcription factors that are present, at least within subsets of pathway genes that themselves exhibit the coordinated behavior that QPACA detects in differentiating true pathways from non-pathways and in yielding better than random enrichments in producing ranked lists of potential new pathway members.

In this chapter, this avenue is explored by combining sequence-based analytical methods (e.g. motif finding in gene promoter sets) with the information derived from measurements of variation in gene expression or protein levels. The remainder of this chapter will describe some preliminary data that supports the idea that simultaneously considering transcription factor analysis and pathway gene expression coordination may enhance the ability to make novel pathway membership predictions.

7.1. Introduction

As discussed previously in Chapter 6, gene sets are recognized as pathways not because all genes in them are cross-correlated, but because some genes form highly coordinated expression modules. These gene modules are evident in Figure 24.

Since this phenomenon does not appear to be strongly related to the curated pathway structure, the obvious question is which biological process or processes direct the expression clustering. Expression data directly measures the relative transcription of genes into mRNA, and it is reasonable to assume that transcription factors, which are instrumental to this process, may play a role in the composition of the expression modules. Common, and perhaps overlapping, transcription factors driving different genes could account for this observation.

To examine this hypothesis, a method for deterministic motif identification was used to identify putative transcription factor binding sites in the expression gene clusters. Several motifs known to affect the genes in question were identified. Additionally, tightly clustered genes were better at finding consistent motifs than randomly selected gene sets.

7.2. Methods

7.2.1. Data

Two separate data sets were used in this analysis: the ovarian data set described in Chapter 6 and the pancreatic cancer cell line data set introduced in Chapter 4, section 4.4. Recall that the pancreatic data set consisted of cell lines that were both treated and untreated with CI-1040, a selective MAP2K1 and MAP2K2 inhibitor.

The ovarian data set analysis focused on the Cell Cycle pathway, which had also been examined using the subpathway analysis in Chapter 6. The ovarian data set allowed a comparison to be made between using pathway structure-based gene sets (subpathways, see Section 6.4.1) and expression-based gene clusters.

The pancreatic data set was analyzed in the context of several pathways, chosen specifically for their relevance both to MAPK signaling as well as two well-characterized transcription factors: E2F and NF-kappaB. These pathways included MAPK signaling (hsa04010), natural killer cell mediated cytotoxicity (hsa04650), focal adhesion (hsa04510), cell cycle (hsa04010), and cytokine-cytokine receptor interaction (hsa04060). Focusing on pathways that incorporate well-known transcription factors allowed direct comparison of the MaMF derived motifs to the known motifs.

7.2.2. Cluster formation

First, the QPACA pathway recognition algorithm was run to generate a set of samples particularly relevant to overall coordination within the entire pathway gene set. Then, gene sets representing distinct expression modules were created using K-means clustering on the data sets limited to the selected samples. In the Cell Cycle pathway using the ovarian data set, for example, six clusters were formed (Table 5).

The number of clusters and the cluster size were constrained by several practical considerations. For this analysis, MaMF (Hon and Jain 2006) was used for motif identification. MaMF was chosen for its performance in mammalian motif finding, and in particular because it was designed for and evaluated against human data. MaMF requires that the input gene sets have at least three genes in order to form a coherent result. In addition, due to computational limitations, clusters of more than 50 genes were split into

smaller clusters. Given a set of promoter sequences, MaMF produces a ranked list of putative motifs, each with a numerical score that combines sequence similarity among the subsequences comprising the motif with the uniqueness of the subsequences given the background distribution of sequences within the organism under study.

As a result, each pathway split into different numbers of clusters to stay within these parameters (see Table 5 for a breakdown of pathway and cluster composition).

Table	5.	Pathway	clusters.
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Data set	Pathway	Genes in pathway	Number of clusters
Ovarian tumors	Cell cycle (hsa04110)	102	6
	Cell cycle (hsa04110)	102	5
Pancreatic cell lines	MAPK signaling (hsa04010)	236	13
	Natural killer cell mediated cytotoxicity (hsa04650)	61	6
	Focal adhesion (hsa04510)	154	11
	Cytokine-cytokine receptor interaction (hsa04060)	230	19

The larger the pathway, the more clusters needed to be created. The discrepancy between the number of clusters for the Cell Cycle pathway in the ovarian data set versus the pancreatic data set is attributable to the fact that dividing the genes into 6 clusters using the pancreatic data set resulted in a cluster that contained only one gene.

7.2.3. MaMF setup and evaluation

MaMF was used to find putative transcription factor binding sites that were common to each cluster of genes or subpathway. MaMF was used with the default set of parameters as described in (Hon and Jain 2006). Specifically, the following parameters were used: the width of the motif search was set to 11 bp; the nmer size used was 4 bp; and the number of seeds was set to 1000. Gene promoter sequences were gathered from the Database of Transcription Start Sites (DBTSS), Version 5.2.0 (Yamashita, Suzuki et al. 2006). The 14628 unique sequences consisted of –1000 and +200 bp around the transcription start site. This version was based on the UCSC hg17 genome sequence release and had already been repeat masked. A background distribution was constructed by MaMF based on the count with mutations method as used in (Hon and Jain 2006).

Putative binding sites for pathway based gene sets were evaluated in two ways: 1) qualitative comparison to known binding motifs found in the TransFac database of transcription factors (Matys, Kel-Margoulis et al. 2006) and 2) quantitative comparison to randomly selected gene sets. The random gene sets were selected to have the same number of genes as the pathway-based gene sets with no overlap between the two.

7.3. Results and discussion



7.3.1. Analysis of E2F binding sites in ovarian tumors

Figure 27. Cell cycle pathway (hsa04110) showing clustering, subpathways, and known E2F motifs. The large shaded areas indicate subpathways centered on core genes (CDK7:blue, WEE1:pink, HDAC7:yellow) as shown in Figure 25. The genes are colored based on a K-means clustering of their expression co-variation using a QPACA optimized subset of the ovarian data set. Circled genes are known targets of E2F (includes: CCNA2, CDC2, CDC6, CDC25A, CCND1, CCNE1, E2F1, E2F2, ORC1L, PCNA, RB1, RBL1). MAMF identified E2F motifs based on the whole collection of genes, either subnetwork, or the k-means cluster sets. The K-means motifs had the strongest match to known E2F motifs.

Figure 27 shows the distribution of the gene clusters in the pathway as well as the

location of the subpathways defined in Section 6.4.1. This pathway contains 12 known

E2F target genes, of which 11 are represented in the data set. The purple and yellow clusters contain four; the green cluster has two, and the orange cluster has one. Within each cluster, the expression is highly coordinated, but the clusters do not co-vary with one another. This is consistent with the finding that a large number of other motifs co-occur with E2F and are likely to be biologically active.(Hon and Jain 2006) Specifically, AhR, NF-1, EGR, SMAD, CREB, TBP, AP-2, SP1, MYC, ETS, and other transcription factors have been identified as being functional within the same promoter as E2F.

Using MaMF to survey all of the promoters of the genes in the Cell Cycle pathway, E2F is the top scoring motif found (see Table 6). It was also found using each of the three subpathways as well as the expression module clusters. The strongest match to the known E2F consensus sequence was found when considering those gene sets with the largest number of genes with known E2F binding sites. Additionally, the expression modules did far better at finding the known E2F binding motifs than the subpathways, supporting the idea that these expression modules are, in fact, related to transcription factor activity. Finally, in addition to matching known E2F motifs, the MaMF generated motifs also matched other known TransFac motifs, many of which are known to co-occur with E2F. Specifically, motifs matching AhR, NF-1, SMAD, and Sp-1 were often present in the top 30 generated motifs.

The gene sets that resulted in particularly good E2F matches also resulted in a larger number of matches to these co-occurring motifs. Although this is just a single example, it is instructive. While E2F is ubiquitous (and largely annotated as such) within the different parts of the Cell Cycle pathway, the clusters that were identified by QPACA showed strong co-variation among *intra*-cluster genes but not among *inter*-cluster genes.

A number of high-scoring motifs were identified that co-occurred with E2F within these clusters, but a large number of high-scoring motifs did not have an annotated known transcription factor associate with them within TRANSFAC. In Hon and Jain's original paper, a similar feature was noted, where it was shown that the high-scoring motifs were likely to be biologically important due to underlying coherent expression effects. Here, a different approach will be used, making use of the pancreatic cancer cell line data.

		Genes	Genes w/ known	Total E2F	Motif	Motif	
Gene	e set	in set	E2F BS	matches	similarity	rank	Motif consensus
	all	94	11	55	0.85	2	tt <u>cGCGCCAAac</u>
. 1	CDK7	33	8	26	0.64	7	gCGcCCGGGAArg
sub- nathways	HDAC2	38	9	30	0.74	25	CGsTccCGCCAccy
puilwuys	WEE1	35	3	17	0.66	5	tgcCGGCCAAa.
	1 red	2	0	7	0.78	28	TCTCCCGCCAGG
	2 blue	2	0	7	0.73	28	GTTCTCCCGCGGCCAGs
alustara	3 yellow	21	4	23	0.81	25	TtCGCGCCaAgm
clusters	4 green	35	2	30	0.78	11	TTCrCGcgAAAst
	5 orange	12	1	20	0.68	11	ggcgCGGGAAAct.G
	6 purple	22	4	31	0.83	1	TTCgCGcgAAA.
							ttCgCGCCAAac

 Table 6. Selected MaMF motifs that are similar to E2F.

Gene sets were derived from the Cell Cycle pathway and the ovarian data set (see Table 5 for composition). The discrepancy between the number of genes listed for each set in this table and in previous tables is due to mapping between Entrez Gene IDs and Refseq IDs. Genes with known E2F binding sites were derived from the TransFac database (version 7.0 - public). The motif shown is the best scoring motif in the top 30 motifs found by MaMF. Note that those gene sets with larger numbers of known E2F genes also had higher scoring E2F motifs found. Underlined sequence is the 11 bp motif found by MaMF; additional sequence was obtained from the surrounding sequence. Capitalized nucleotides are highly conserved (>50% of the contributing sequences contain that nucleotide at that position). The motif in bold at the bottom is the annotated E2F consensus sequence.

7.3.2. *Permutation analysis of MaMF generated motifs in pancreatic*

cancer cell lines

A more rigorous statistical analysis was performed using the pancreatic data set in order to explore two questions generated by the above analysis: (1) did the high scoring motifs found by MaMF using expression modules occur simply by chance and (2) did the use of QPACA generated sample subsets affect the performance of the expression modules (would expression modules generated from the entire data set have a harder time finding relevant motifs).



Figure 28. Distribution of MaMF score p-values for all expression modules. Using expression modules, MaMF is able to find better motifs than those found using random gene sets. The QPACA subsetting algorithm, however, does not seem to enhance MaMF's performance.

Given that a large number of the high-scoring motifs that MaMF found lacked any annotated known TF, it is natural to question whether motifs with competitive scores would have arisen by chance. To assess this probability, a null distribution of motifs was generated by MaMF using 100 random gene sets of the same size as the expression modules from the pancreatic cell line data set. The p-value for the motifs of a given module is the percentage of MaMF runs on random gene sets that resulted in higher scores than the corresponding expression module. Using this statistical measure, 75% of the expression modules were found to have significantly higher scores than random (see Figure 28). That is, the actual expression modules within the pancreatic cell line data set were strongly enriched for high-scoring motifs as detected by MaMF. In this particular case, it did *not* appear that the QPACA subsetting made a significantly impact on MaMF's ability to find high scoring motifs within expression modules identified without subsetting, but this is of less consequence. QPACA's subsetting algorithm is particularly powerful in fairly heterogeneous data sets because it is able to tease out signal from the noise of the uninvolved samples. In this case, all of the samples were related and this may have created a strong enough expression signal without a need for subsetting.

The key finding is that based on the enrichment for high-scoring motifs from the pathway expression modules, it seems likely that some significant fraction of the motifs that were found actually have biological significance. This argument can be strengthened by considering the fact that the pathways that were chosen for the pancreatic cancer analysis were enriched for genes known to contain E2F and NF-kappaB binding sites. Therefore, it is possible to compare which motifs were found for different pathways. Those pathways that were enriched for genes with E2F binding sites resulted in more E2F-like motifs than the pathways enriched for NF-kappaB genes and vice versa. So, analysis of the promoters of genes within the expression modules yielded both known TF motifs *and* high-scoring motifs of unknown provenance. Based on the enrichment of high-scoring motifs versus random gene sets, it appears that some interaction among the known TFs within these pathways as well as a significant number of additional, non-annotated TFs is responsible for some of the signal that QPACA is able to make use of in pathway recognition and augmentation tasks.

This preliminary data supports the idea that expression modules are related to transcription factor activity and that the involvement of transcription factors in gene expression may be useful in predicting pathway structure. Defining expression modules

was a bottleneck in this analysis, and a more automated approach to module selection would enhance future work in this direction. It is clear from the subpathway and cluster analyses that, just as not all samples are necessarily involved in an expression signature, not all genes are involved either. Thus, one possible approach to this issue is a modification of the QPACA subsetting algorithm to include gene subsetting as well as sample subsetting. This simultaneous optimization of gene set and sample set would identify more strongly coordinated transcriptional modules than studied here as the basis for further exploration.

Chapter 8 Conclusion and future directions

This work has described both the development and application of QPACA, a tool for pathway analysis. QPACA incorporates several facets of pathway analysis: pathway visualization and definition, visual analysis of experimental data, and computational pathway recognition and pathway membership prediction.

Chapter 1 and Chapter 2 introduced both the importance of pathway analysis for the elucidation of systems biology as well as current research efforts in this field. Pathway analysis is still expanding with many competing and sometimes overlapping pathway and data storage systems as well as many variations on algorithms to augment pathway membership and structure. While exchange standards such as BioPAX are emerging in an effort to unify the disparate pathway databases, these efforts are still not robust enough to cover all pathway types and instances.

Chapter 3 described the development of QPACA, covering the pathway model, the optimization algorithm at the heart of QPACA's analytical methods, and the system architecture. QPACA's pathway representation was designed to be flexible, extensible and accessible. It is integrated into the Magellan data analysis application for easy use by biologists and can import pathway data in three separate formats: BioPAX, KEGG, and the QPACA language. QPACA's utility in providing visual analysis of experimental data was demonstrated in Chapter 4 using several different types of human cancer data.

Chapter 5 and Chapter 6 addressed two steps in pathway structure elucidation using gene expression data. First, given a gene set postulated to be part of a pathway or coordinated process, QPACA demonstrated the ability to discriminate between real pathways and non-pathways. Second, given a gene set known to represent part of a pathway, QPACA was then able to significantly enrich for pathway genes over nonpathway genes in making predictions of putative pathway members. The first problem was termed pathway recognition and the second pathway augmentation. Specifically, for the pathway recognition problem, in 61% of cases known pathways (83% for larger pathways), QPACA was able to answer affirmatively while rejecting random pathways over 95% of the time. For the pathway augmentation problem, QPACA was able to yield enrichments for predicted pathway genes over random genes at rates of 2-fold or better the majority of the time, with rates of 10-fold or better 10-20% of the time depending on the background used. While enrichment rates on the level of 2-fold may or may not be of practical significance, it is likely that rates of 10-fold or better may help prioritize experimental exploration of candidate genes for elaborating pathways of particular biological interest. Additionally, Chapter 6 also introduced the idea that gene sets are recognized as pathways not because all genes within them are cross-correlated, but rather because individual genes form highly coordinated expression modules. By employing an automated method for identifying relevant sample subsets, QPACA has proved to be able to handle complex pathways relevant to major disease processes in humans.

There are several major areas for future work. First, the recognition and prediction algorithms can be extended to make use of new scoring metrics and optimization strategies. Given that the first, very simple, scoring metric yielded positive results, a more refined scoring metric would possibly be able to tease more information out of the data. The refined scoring metric presented at the end of Chapter 6 to deal with excessive prediction score ties is a simple example of this type of modification. Other metrics, which would allow both direction and magnitude to be taken into account in determining the score, can be considered that move beyond the simple correlation metric presented here. In particular, metrics that include pathway structure information could be particularly fruitful (e.g. by making use of graph-based algorithms that identify minimum spanning trees, maximum flow networks, etc.). Yet more challenging problems, including recognition and prediction of interactions (edges in the pathway graph) and full pathway induction (as opposed to just membership augmentation) are also areas for further research.

Chapter 7 explored the synergy that could arise by combining sequence-based analytical methods (e.g. motif finding in gene promoter sets) with the information derived from measurements of variation in gene expression or protein levels. The existence of the highly coordinated expression modules observed in Chapter 6 appears to stem, in part, from a set of common transcription factors that control the genes' regulation. Though many of the motif patterns that appear to be important within expression submodules of the pathways are not similar to known transcription factors.

This work has developed representational machinery for encoding knowledge about the biological networks that researchers conceptualize as "pathways." The

computational approaches developed for performing analyses and making predictions about the composition and structure of these pathways have yielded an unexpected result: that it is frequently possible, in a human cellular system, to detect aspects of pathway structure from patterns of variation in gene expression. The signal from these variations manifests as small groups of genes among which expression is strongly coordinated (within some set of experimental conditions or samples), where many of these groups comprise a pathway. There appears to be little relationship, however, between the membership of these transcriptional modules and physical interactions of the sort that are typically depicted in curated pathway representations. It appears that the influence of transcription factors may explain a significant fraction of this puzzle, but the degree of multi-factorial control through transcription factor binding motifs in human cell biology may be more complex than has been contemplated. By combining data analysis, pathway knowledge, expression data, and sequence data it should be possible to tease out more pieces of the puzzle.

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Appendix: Documentation of Code and Data

This section documents the use of the QPACA pathway language as well as the QPACA analytical methods initially referred to in Chapter 3 and later described in more detail in Chapter 5 and Chapter 6. This appendix should allow the reader to replicate the primary experiments and understand the software API. For specifics, such as data files and source code, the reader should consult the accompanying DVD.

Appendix A. QPACA Model

A.1.1. QPACA Pathway Language

The pathway language is composed of 3 sections: a) pathway specific information, such as the name and any other pathway attributes b) element information, and c) edge information.

```
pathway_name = "RTK Pathway Sample"
#pathway elements
pathway_elements {
  e10[type=geneProduct;name=ELK1;GeneID=2002]
  ell.a[type=geneProduct;name=CCND1;GeneID=595]
  e12.a[type=geneProduct;name=CDK4;GeneID=1019]
  #complex element type
  all[type=complex;objects=ell.a,el2.a]
  e13[type=geneProduct;name=RB1;GeneID=5925]
  e14.a[type=geneProduct;name=E2F1;GeneID=1869]
  e14.b[type=geneProduct;name=E2F2;GeneID=1870]
  e14.c[type=geneProduct;name=E2F3;GeneID=1871]
  e14.d[type=geneProduct;name=E2F4;GeneID=1874]
  a14[type=family;objects=e14.a,e14.b,e14.c,e14.d]
  e15.a[type=geneProduct;name=CCNE1;GeneID=898]
  e15.b[type=geneProduct;name=CCNA2;GeneID=890]
  #family element type
  a15[type=family;objects=e15.a,e15.b]
  e16[type=geneProduct;name=CDK2;GeneID=1017]
  e17[type=geneProduct;name=p14ARF;GeneID=1029]
  e18[type=geneProduct;name=MDM2;GeneID=4193]
  e19[type=geneProduct;name=CDKN2A;GeneID=1029;alt.name=p16]
  e20[type=geneProduct;name=CDKN1A;GeneID=1026;alt.name=p21]
  e21[type=geneProduct;name=TP53;GeneID=7157]
  #process element type
  e47[type=process;name=S-phase]
ļ
#pathway description
pathway {
  e10 -> e19 [weight=1]
  e10 -> a11 [weight=1]
  e19 - | all [weight=1]
  e10 -> e20 [weight=1]
  e20 -| a11 [weight=1]
  e20 -| e16 [weight=1]
  e13 - | a14 [weight=1]
  a14 -> a15 [weight=1]
  a15 -> e16 [weight=1]
  e16 -> e47 [weight=1]
  a14 -> e17 [weight=1]
  e17 - | e18 [weight=1]
  e18 - | e21 [weight=1]
  e21 -> e20 [weight=1]
  al1 - | e13 [weight=1]
```

Figure 29. Sample pathway description in QPACA Pathway Language.

Figure 29 shows a sample pathway description illustrating. All attributes are described using key-value pairs. Each pair is located on a separate line with an "=" separating the key from the value. Keys cannot contain any white space and values must

be delimited with quotation marks if they contain white space. Comment lines start with a "#".

The first section consists of a set of attribute values describing the pathway. The only required attribute is "pathway_name".

The "pathway_element" section defines all the components of the pathway. Each element must have a type and a unique ID. The ID is listed before the bracket. The allowed types are: geneProduct, family, complex, smallMolecule, and process. Elements of the "geneProduct" type must also have a GeneID, which denotes the Entrez Gene ID for that element. The "name" attribute governs the display name for the generated graph. Elements that group other elements (type "family" or "complex") must be defined after their constituent parts have been defined. "Family" denotes a group of elements which may all play the same role at a particular node in the graph. "Complex" denotes a group of elements that form a physical interaction and act together in the pathway.

The "pathway" section contains the interaction information for the pathway. The element IDs defined in the previous section are connected with symbols denoting edge type. Figure 29 shows the activation ("->") and inhibition ("-|") types. A neutral type ("--") is also currently supported.

A.1.2. Sample QPACA GUI Usage

Apple Comments	
	Select a Method of Analysis
Data types curren	tly available for analysis:
Data type:	Expression
Experimen	ıt: 4
Annotation	at Gene annotations for Staunton Affymetrix data
Data Operation	Annotate, Subselect, Project, or Export a Data Type. View
Documentation	
Select an method	of analysis:
Clustering of	Samples
Clustering of 3	Samples by R
Correlation/Per	rmutation
Genomic Con	relation Plot
Genomic Con	relation Plot in R
K Nearest Ne	ighbor Classification
Plot Data Aga	inst Chromosomal Position
O Plot Frequenc	y Against Chromosomal Position
O Differential E	cpression by 1-test
Colculate Mic	rise Valuer
Calculate Free	mency of Deviation A most Samples
OPACA Path	way Recognition
OOPACA Visu	al Pathway Analysis
Re-Select Dat	a Choose Another Data Set for Analysis
Analyze Data	

Figure 30. Analysis method selection in Magellan.

The Analysis Method Selection page in Magellan is the entry point for the QPACA analyses.



Figure 31. QPACA parameter selection

These pages present the user with a set of analysis parameters. On the first page, the top and left are Magellan specific parameters for data selection, while the column contains all of the QPACA parameters. The next page shows the automatically generated image for verification purposes and allows the user to choose the annotation types that match between the data in the Magellan database and the objects in the pathway.


Figure 32. QPACA data visualization results page.

This page shows visualization result page with a separate image for each selected sample in the data set. QPACA can also generate statistical summary images (such as correlations to a specified gene or F-statistic based on sample groups). The images are in SVG format and each one links to a larger version. The larger versions (also in SVG format) contain embedded links to the Entrez Gene database. The computational analysis results page (not shown) is presented as a simple directory listing of output files.

Appendix B. QPACA Analytical Module

B.1.1. PathwayAnalysis Usage

PathwayAnalysis runs the QPACA pathway recognition algorithm. It is necessary to run this prior to running PredictGenes. Data files should be tab-delimited text files with gene IDs in the first column and sample names (optional) across the top. edu.ucsf.qpaca.pathway.PathwayData generates appropriate pathway subsets data files given a pathway description file and a data set, though any file of the appropriate format can be used.

> PathwayAnalysis [option] ... datafile

Options:

-opt <n></n>	sets the number of optimization steps to n
	(default = 600)
-rgenes	perform random gene set permutation
-rdata	perform randomized data permutation
-inner <n></n>	sets the number of starting points to n
	(default = 20)
-outer <n></n>	sets the number of permutations to n
	(default = 1000)
-subsetsize <n></n>	sets the size of the subset of samples to be
	chosen to n (default = 20)
-header	if the datafile has a header line
	(containing sample names)

-datasize <n></n>	sets the number of genes in the data file to n (defaults to the number of data rows in the file)
-numsamples <n></n>	sets the number of total samples in the datafile to n (defaults to the number of data columns in the file)
-outputdir <directory_name></directory_name>	output directory
-outfile <filename></filename>	base name for output file
-help	this information

B.1.2. PredictGenes Usage

PredictGenes is responsible for identifying potential new pathway members. The

sample file for PredictGenes is derived from the PathwayAnalysis output.

> PredictGenes [-options] -samplefile samplefilename

-datafile datafilename -pathdatafile pathwaygenesfilename

Options:

-nsamples <n></n>	number of samples in the sample subset
-ntotalsamples	perform random gene set permutation
-outputdir <directory_name></directory_name>	output directory
-outfile <filename></filename>	base name for output file
-help	this information

The following three tab-delimited files are necessary:

samplefile	specifies which samples of the data set to use in predicting new pathway genes
datafile	should contain the data for those genes which are not known to belong to the pathway
pathdatafile	contains the data for the genes known to belong to the pathway

Appendix C.

Code Documentation

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QPACA Analytical Tools Code Documentation

PathwayAnalysis	pathway recognition module	
PredictGenes	pathway membership augmentation module	
PathwayUtil	a collection of utility functions for the PathwayAnalysis and PredictGenes modules	

PathwayAnalysis

PathwayAnalysis is QPACA's pathway recognition module. The output consists of a final score and a final, optimized subset of samples that were used to calculate that score.

Options		
-opt <i>n</i>	sets the number of optimization steps to n (default = 600)	
-rgenes	perform random gene set permutation	
-rdata	perform randomized data permutation	
-starts n	sets the number of starting points to n (default = 20)	
-perm <i>n</i>	sets the number of permutations to n (default = 1000)	
-subsetsize <i>n</i>	sets the size of the subset of samples to be chosen to n (default = 20)	
-header	if the datafile has a header line (containing sample names)	
-datasize <i>n</i>	sets the number of genes in the data file to n (defaults to the number of data rows in the file)	

Usage: > PathwayAnalysis [options] ... datafile

-numsamples <i>n</i>	sets the number of total samples in the datafile to n (defaults to the number of data columns in the file)
-corrout	print individual correlation values (useful for debugging)
-intOut <i>n</i>	determines which scores to print out. If $n == 0$, only reports the best overall score across all starting points, otherwise reports all scores (default).
-outputdir <i>directory_name</i>	output directory
-outfile filename	base name for output file
-selectgenes n	subselects <i>n</i> genes after subselecting samples
-help	print usage information

Functions

compute_correlation

Computes all correlations in a 2 dimensional array. <u>fisher_yates_shuffle</u>

Shuffles an array of size n in place. get_random_subset

Chooses a random sample subset.

<u>optimize</u>

Performs optimization of samples. <u>optimizeWithGenes</u>

Performs optimization of genes.

print_help

Prints out a short description of how to run the program.

random_int

Generates a random integer in [0,n).

random_subset

Chooses a random subset without replacement.

compute_correlation

Computes all correlations in a 2 dimensional array.

```
void compute_correlation(
    int colsize,
    int rowsize,
    int *cols,
    int *rows,
    double *correlations,
    double **data);
```

Parameter Description

colsize
number of columns in the dataset
rowsize
number of rows in the dataset
cols
the columns to use in computing the correlation
rows
the rows to use in computing the correlation
correlations
stores all of the correlation values
data
a 2-dimensional array containing the data

fisher_yates_shuffle

Shuffles an array of size n in place.

```
void fisher_yates_shuffle(
    double *array,
```

int n);

Parameter Description

array the array to shuffle n the size of the array

get_random_subset

Chooses a random sample subset.

```
void get_random_subset(
    int k,
    int n,
    int *set,
    int *rest);
```

Parameter Description

k	
	subset size
n	
_	total number of samples
set	int array holding the indices of the random subset
rest	int array holding the rest of the sample indices

Discussion

Generates a random sample subset of size k from a total sample set of size n and stores the subset in two arrays

optimize

Performs optimization of samples.

```
double optimize(
    int maxSteps,
    int subsetsize,
    int totalsize,
    int datasize,
    int corsize,
    int *genes,
    double *corr,
    double **data,
    int *subset);
```

Parameter Description

```
maxSteps
      maximum number of optimization steps
subsetsize
      size of the subset to optimize for
totalsize
      total number of columns in the dataset (samples)
datasize
      total number of rows in the dataset (genes)
corsize
      size of the output correlation array
genes
      array of which genes (indices) to optimize with
corr
      output correlation array
data
      2-dimensional array of data
subset
      final sample subset
```

function result the final score

optimizeWithGenes

Performs optimization of genes.

```
double optimizeWithGenes(
```

```
int maxSteps,
int nGenes,
int nSamples,
int nTotalSamples,
int nTotalGenes,
double **data,
int *sampleSubset,
int *geneSubset);
```

Parameter Description

```
maxSteps
maximum number of optimization steps
subsetsize
size of the subset to optimize for
nTotalSamples
total number of columns in the dataset (samples)
nTotalGenes
total number of rows in the dataset (genes)
corsize
size of the output correlation array
data
2-dimensional array of data
sampleSubset
array of which samples (indices) to optimize with
geneSubset
```

final sample subset

function result the final score

print_help

Prints out a short description of how to run the program.

```
void print_help(
    void);
```

random_int

Generates a random integer in [0,n).

```
int random_int(
    int n);
```

Parameter Description

n

the upper bound

function result a random integer in [0,n)

random_subset

Chooses a random subset without replacement.

```
void random_subset(
    int k,
    int n,
    int *arr);
```

Parameter Description

k	
	size of the subset
n	
	total size of the set
arr	
	array to store the chosen subset

#defines

FILESEP

The character used to separate parts of a filestring. <u>HEADER</u> default is no header <u>NUMBEROPTIMIZAIONS</u>

default value of n for -opt option <u>NUMBERPERMUTATIONS</u>

default value of n for -perm option **NUMBERSTARTINGPOINTS**

default value of n for -starts options <u>NUMGENES</u>

default value of *n* for -selectgenes option **SELECTGENES**

default is to not perform gene subselection **SUBSETSIZE**

default value of n for -subsetsize option

FILESEP

The character used to separate parts of a filestring.

/*Unix*/
#define FILESEP "/";

Discussion

When compiling for Unix-based systems use "/"; for Windows use "\\".

HEADER

default is no header

#define HEADER 0

NUMBEROPTIMIZATIONS

default value of *n* for -opt option

#define NUMBEROPTIMIZATIONS 600

NUMBERPERMUTATIONS

default value of n for -perm option

#define NUMBERPERMUTATIONS 1000

NUMBERSTARTINGPOINTS

default value of n for -starts option

#define NUMBERSTARTINGPOINTS 20

NUMGENES

default value of n for -selectgenes option

#define NUMGENES 20

SELECTGENES

default is to not perform gene subselection

#define SELECTGENES 0

SUBSETSIZE

default value of *n* for -subsetsize option

#define SUBSETSIZE 20

PredictGenes

PredictGenes is QPACA's pathway membership augmentation module.

Prior to running PredictGenes, it is necessary to ascertain pathway recognition using PathwayAnalysis. The sample subset and final score provided by PathwayAnalysis are then input into PredictGenes along with a list of non-pathway genes. PredictGenes assigns scores to the query genes based on the optimized sample subset and score from PathwayAnalysis.

Usage:

> PredictGenes [-options] -samplefile samplefilename -datafile datafilename -pathdatafile pathwaygenesfilename

Options		
-nsamples <i>n</i>	number of samples in the sample subset	
-ntotalsamples <i>n</i>	number total samples in the data set	
-outfile <i>filename</i>	desired name for the output file (default: root of the datafilename)	
-outputdir <i>directory_name</i>	output directory (default: current directory)	
-help	prints usage information	

The following three tab-delimited files are necessary:

samplefile	specifies which samples of the data set to use in predicting new pathway genes.	
datafile	should contain the data for those genes which are not known to belong to the pathway.	
pathdatafile	contains the data for the genes known to belong to pathway in question	

Functions

compute_correlation

Computes all correlations in a 2-dimensional array. <u>compute_original_score</u>

Calculates the score for the known pathway gene subset.

Computes the new scores. print_help Prints usage information. read_sample_file

Reads a sample file with no header.

compute_correlation

Computes all correlations in a 2-dimensional array.

```
void compute_correlation(
```

```
int colsize,
int rowsize,
int *cols,
double *correlations,
double **data);
```

Parameter Description

colsize
 number of columns in the dataset
rowsize
 number of rows in the dataset
cols
 the columns to use in computing the correlation
correlations
 stores all of the correlation values
data
 a 2 dimensional array containing the data

a 2-dimensional array containing the data

compute_original_score

Calculates the score for the known pathway gene subset.

See Also: <u>compute_scores</u>

```
double compute_original_score(
```

```
int nsamples,
int ntotalsamples,
int nsubsetRows,
int ndataRows,
int *sampleList,
double **subsetData,
double **data);
```

Parameter Description

```
nsamples
    the number of samples in the sample subset
ntotalsamples
    the total number of samples
nsubsetRows
    the number of rows in the known pathway gene
    subset
ndataRows
    the number of total data rows
sampleList
    the optimized sample subset
subsetData
    the data for the known pathway gene subset
data
    the data for the genes to be scored
```

function result

the score for the known pathway gene subset

compute_scores

Computes the new scores.

```
double* compute_scores(
    int nsubsetCols,
    int ndataCols,
    int nsubsetRows,
    int ndataRows,
    int *sampleList,
    double **subsetData,
    double **data);
```

Parameter Description

```
nsubsetCols
    the number of columns in the sample subset
ndataCols
    the number of total data columns
nsubsetRows
    the number of rows in the known pathway gene
    subset
ndataRows
    the number of total data rows
sampleList
    the optimized sample subset
subsetData
    the data for the known pathway gene subset
data
    the data for the genes to be scored
```

Discussion

The scoring function consists of the mean of the top 10% of all genegene correlations in the gene subset. This differs from the scoring function in PathwayAnalysis, which is the median of all gene-gene correlations.

print_help

Prints out a short description of how to run the program.

```
void print_help(
    void);
```

read_sample_file

Reads a sample file with no header.

```
void read_sample_file(
    FILE *fd,
    int *samples,
    int ncols);
```

Parameter Description

```
fd
    the sample file
ncols
    the number of columns in the file
samples
    an array used to store the sample information
```

PathwayUtil

A collection of utility functions for the the PathwayAnalysis and PredictGenes modules.

Functions

bcoeff2

Calculates the binomial coefficient for n choose 2. <u>compare_doubles</u> Compares two doubles.

count_cols

Counts the columns in a tab-delimited file.

<u>count_rows</u>

Counts the rows in a file.

doublearray_copy

Copies an array of doubles.

intarray_copy

Copies an array of ints.

lvector

Allocates an unsigned long vector with subscript range v[nl..

nh].

mean

Calculates the arithmetic mean of an array of doubles.

median

Finds the median of an array of doubles.

pearsons

Calculates the pearsons correlation coefficient between two arrays.

read_file_data

Reads a tab-delimited data file with no headers.

<u>read_file_data_ids</u>

Reads a tab-delimited data file with a header column.

read_file_with_headers

Reads a tab-delimited data file with a header column. select_kth_smallest

Selects the k-th smallest value in a double array.

<u>sort</u>

Sorts an array arr[0..n-1] into ascending numerical order. **variance**

Calculates the variance of an array.

bcoeff2

Calculates the binomial coefficient for n choose 2.

int bcoeff2(
 int n);

Parameter Description

n

function result the binomial coefficient

compare_doubles

Compares two doubles.

```
int compare_doubles(
    const void *a,
    const void *b);
```

Parameter Description

Parameter Description

a b

function result -1 if a < b, 1 if a > b, and 0 if they're equal

count_cols

Counts the columns in a tab-delimited file.

int count_cols(
 FILE *fd);

Parameter Description

fd

the file pointer to the file

function result the number of columns

count_rows

Counts the rows in a file.

```
int count_rows(
    FILE *fd);
```

Parameter Description

fd

the file pointer to the file

function result the number of rows

doublearray_copy

Copies an array of doubles.

void doublearray_copy(
 int n,
 double *src,
 double *dest);

Parameter Description

n the size of the array src the original array dest the new array

intarray_copy

Copies an array of ints.

```
void intarray_copy(
```

int n, int *src, int *dest);

Parameter Description

n the size of the array src the original array dest the new array

lvector

Allocates an unsigned long vector with subscript range v[nl..nh].

```
unsigned long *lvector(
    long nl,
    long nh);
```

Parameter Description

data the array n

the size of the array

function result the variance

mean

Calculates the arithmetic mean of an array of doubles.

```
double mean(
    unsigned long n,
    double arr[]);
```

Parameter Description

n the size of the array arr the array

function result the arithmetic mean

median

Finds the median of an array of doubles.

double median(
 unsigned long n,
 double arr[]);

Parameter Description

n the size of the array arr the array

function result the median

pearsons

Calculates the pearsons correlation coefficient between two arrays.

double pearsons(
 double *data1,
 double *data2,
 int n);

Parameter Description

data1 the first array data2 the second array n

the size of the arrays

function result

the pearsons correlation coefficient

read_file_data

Reads a tab-delimited data file with no headers.

```
void read_file_data(
    FILE *fd,
    double **data,
    int ncols);
```

Parameter Description

fd	
	a file pointer to the file
data	-
	a 2-dimensional array of doubles used to store the data
ncols	
	the number of columns in the file

Discussion

Stores the data in the file in a 2-dimensional array of doubles.

read_file_data_ids

Reads a tab-delimited data file with a header column containing IDs.

See Also: read_file_data

```
void read_file_data_ids(
    FILE *fd,
    double **data,
    char **ids,
    int ncols);
```

Parameter Description

fd a file pointer to the file data a matrix of doubles used to store the data ids the string array used to store ids ncols the number of columns in the file

Discussion

Just as the read_file_data function, this function stores the data in the file in a 2-dimensional array of doubles. In addition, the first column is assumed to contain data ids which are stored in a separate string array.

read_file_with_headers

Reads a tab-delimited data file with both a header column containing IDs and a header row containing sample names.

```
See Also: read_file_data, read_file_data_ids
void read_file_with_headers(
    FILE *fd,
```

double **data, char **samples,

char **ids, int ncols);

Parameter Description

```
fd
    a file pointer to the file
data
    a matrix of doubles used to store the data
samples
    a string array used to store sample names
ids
    the string array used to store ids
ncols
    the number of columns in the file
```

Discussion

Just as the read_file_data function, this function stores the data in the file in a 2-dimensional array of doubles. In addition, the first column is assumed to contain data ids which are stored in a separate string array. Also, the first row is assumed to contain sample names, which are stored in a separate string array.

select_kth_smallest

Selects the k-th smallest value in a double array.

```
double select_kth_smallest(
    unsigned long k,
    unsigned long n,
    double arr[]);
```

Parameter Description

k n the length of the array arr the array

function result the k-th smallest value

Discussion

Returns the k-th smallest value in the array arr[0..n-1]. The input array will be rearranged to have this value in location arr[k-2],with all smaller elements moved to arr[0..k-2] (in arbitrary order) and all large elements in arr[k..n-1] (also in arbitrary order). from "Numerical Recipes in C", pg. 342

sort

Sorts an array arr[0..n-1] into ascending numerical order.

```
void sort(
    unsigned long n,
    double arr[]);
```

Parameter Description

n the size of the array arr the array to sort

Discussion

Uses the Quicksort algorithm and replaces the input array with its sorted rearrangement.

variance

Calculates the variance of an array.

double variance(
 double *data,
 int n);

Parameter Description

data

the array

n

the size of the array

function result the variance

#defines

MAXLENGTH

Default length for allocating new strings.

SWAP

Swaps the location of two values.

MAXLENGTH

Default length for allocating new strings.

#define MAXLENGTH 3000

SWAP

Swaps the location of two values.

#define SWAP(a,b) temp=(a);(a)=(b);(b)=temp;

QPACA	
edu.ucsf.qpaca	QPACA (Quantitative Pathway Analysis in Cancer) provides the classes necessary to model pathways (edu.ucsf.qpaca.pathway) as well as the classes necessary for pathway input/output (edu.ucsf.qpaca.parser).

Pathway Modeling		
<u>edu.ucsf.qpaca.</u> <u>pathway</u>	Models a pathway and any associated data.	
edu.ucsf.qpaca. pathway. algorithm	Implements several graph-based algorithms for pathway model navigation.	

Pathway I/O	
<u>edu.ucsf.qpaca.</u> <u>parser</u>	Handles input/output of pathway information from the QPACA pathway model.
<u>edu.ucsf.qpaca.</u> parser.util	Supports the QPACA parser classes by defining language constants and providing parsing utility methods.

Package edu.ucsf.qpaca

QPACA (Quantitative Pathway Analysis in Cancer) provides the classes necessary to model pathways (edu.ucsf.qpaca.pathway) as well as the classes necessary for pathway input/output (edu.ucsf.qpaca.parser).

See:

Description

Class Summary	
FileUploadBean	A Java Bean that handles uploading files from a web page.
PathwayAnalysis	Runs the QPACA Pathway Analysis Tools within Magellan.

Package edu.ucsf.qpaca Description

QPACA (Quantitative Pathway Analysis in Cancer) provides the classes necessary to model pathways (edu.ucsf.qpaca.pathway) as well as the classes necessary for pathway input/output (edu.ucsf.qpaca.parser). This package includes two top-level classes used to implement the Magellan-based user interface. QPACA uses the following publicly available java libraries:

- OpenJGraph 0.9.2
- batik 1.6
- junit 3.8.1

Additionally, the user interface is dependent on edu.ucsf.Magellan and the Apache Tomcat java servlet container.

Package edu.ucsf.qpaca.pathway

Models a pathway and any associated data.

See:

Description

Interface Summary		
PathwayComponent	The base class for all pathway components, which specifies methods for getting and setting the various common attributes.	

Class Summary		
Pathway	A biological pathway represented as a directed graph.	
PathwayAssembly	An collection of objects in a pathway that can be found at a PathwayVertex.	
PathwayData	Container for data values that are used to color pathways.	
PathwayEdge	An edge in a pathway.	
PathwayElement	An element of a pathway.	
PathwayFactory	The factory for creating Vertices and Edges in a Pathway class.	
PathwaySVG	Handles manipulation and coloring (by data value) of SVG files generated by GraphViz.	
PathwayUtil	Static utility methods for manipulating data values.	
PathwayVertex	A vertex in a pathway.	

Package edu.ucsf.qpaca.pathway Description

Models a pathway and any associated data. The pathway model is based the on the OpenJGraph library, which provides classes for the creation and manipulation of graphs. At the root of the model is the PathwayComponent interface, which defines the base unit of each pathway model component. The model itself is composed of nodes (PathwayVertex) and edges (PathwayEdge) which belong to a pathway (Pathway). Each node can represent either a physical entity (PathwayAssembly or PathwayElement) or an event. Event nodes can also contain event modifier entities (either PathwayAssemblies or PathwayElements). Each PathwayAssembly is composed of one or many PathwayElements or other PathwayAssemblies. PathwayAssemblies can represent groups of PathwayElements that either act at the same node (but independently) or form a complex (with physical interactions).

In addition, this package also contains classes for manipulating data and pathway images (PathwayData and PathwaySVG). Finally, several classes (PathwayUtil, PathwayFactory, WeakPathway) include methods to facilitate use of the pathway model.

Package edu.ucsf.qpaca.pathway.algorithm

Implements several graph-based algorithms for pathway model navigation.

See:

Description

Class Summary		
PathwayMinimumSpanningTree	A concrete implementation of the minimum spanning tree algorithm using Kruskal's method specifically geared to Pathway objects.	
ShortestPathAlgorithm	Abstract class for implementing the shortest path algorithm.	
ShortestPathDijkstraAlgorithm	A concrete implementation of ShortestPathAlgorithm using Dijkstra's method.	

Package edu.ucsf.qpaca.pathway.algorithm Description

Implements several graph-based algorithms for pathway model navigation.
Package edu.ucsf.qpaca.parser

Handles input/output of pathway information from the QPACA pathway model.

See:

Description

Class Summary	
MapBioPAXtoQPACA	Maps between BioPAX keywords and QPACA keywords.
MapKGMLtoQPACA	Maps between KEGG KGML keywords and QPACA keywords.
ParseQPACALanguage	Creates QPACA pathways from files written in the QPACA Pathway language.
PathwayToDot	Translates Pathways into GraphViz .dot files.
TestBioPaxUtil	Tests the BioPaxUtil Class.
TestKGMLParsing	Tests the KGML-QPACA mapper.
TestKGMLUtil	Tests the KGMLUtil Class.
TestParsing	Tests the BioPAX-QPACA mapper.
TestPathLang	Tests the QPACA language parser.

Package edu.ucsf.qpaca.parser Description

Handles input/output of pathway information from the QPACA pathway model. ParseQPACALanguage parses the QPACA file format. MapBioPAXtoQPACA and MapKGMLtoQPACA parse BioPAX and KGML formats, respectively. PathwayToDot creates dot format files for parsing by the Graphviz graph visualization program.

Package edu.ucsf.qpaca.parser.util

Supports the QPACA parser classes by defining language constants and providing parsing utility methods.

See:

Description

Class Summary	
<u>BioPaxConstants</u>	BioPAX Constants.
<u>BioPaxUtil</u>	BioPax Utility Class.
KGMLConstants	KGML Constants.
KGMLUtil	KEGG KGML Utility Class.
OwlConstants	OWL (Web Ontology Language) Constants.
<u>QPACAConstants</u>	QPACA Constants.
QPACAUtil	QPACA Pathway language Utility Class.
<u>RdfConstants</u>	RDF (Resource Description Framework) Constants.
RdfQuery	Enables XPath-"lite" Queries on RDF Documents.
RdfUtil	Misc RDF Utilities.

Exception Summary	
BioPaxException	Exception thrown to indicate a syntax error in a BioPAX file.
KGMLException	Exception thrown to indicate a syntax error in a KGML file.
QPACAException	Exception thrown to indicate a syntax error in a QPACA file.

Package edu.ucsf.qpaca.parser.util Description

Supports the QPACA parser classes by defining language constants and providing parsing utility methods. Each file format throws it's own type of exception. Constants are defined in the Constants classes and utility methods in the Util classes. In addition, RdfConstants, RdfQuery, and RdfUtil enable more straightforward parsing of the XML-based formats.

edu.ucsf.qpaca Class FileUploadBean

java.lang.Object

edu.ucsf.qpaca.FileUploadBean

public class FileUploadBean

extends java.lang.Object

A Java Bean that handles uploading files from a web page.

Constructor Summary

FileUploadBean()

Method Summary		
void	<pre>doUpload(javax.servlet.http.HttpServletRequest request) Uploads the file specified on the HTML input page.</pre>	
java. lang. String []	getAllFieldValues(java.lang.String fieldName) Returns an array of String objects containing all of the values the given parameter has, or null if the parameter does not exist.	
java. lang. String	getContentType() Retrieves the content type of the uploaded file.	
java. util. Map	getFields() Retrieves the HTML input form's input elements.	
java. lang. String	getFieldValue (java.lang.String fieldName) Retrieves the value of an HTML input element	
java. lang. String	getFilename() Retrieves the filename of the uploaded file.	

java. lang. String	getFilepath () Retrieves the complete filepath on the client side of the uploaded file.
void	<pre>setSavePath(java.lang.String savePath) Sets the location that the file should be stored in on the server.</pre>

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll,
toString, wait, wait, wait
```

Constructor Detail

FileUploadBean

```
public FileUploadBean()
```

Method Detail

doUpload

Uploads the file specified on the HTML input page. First extracts the field names and values from the HTML form. Then extracts the uploaded file and saves it to the directory specified by the savePath and assigns the file's name, path, contentType to the filename, filepath and contentType fields.

Parameters:

request - the HTTP request that is needed to process the extracted HTML forms's element names-values and the uploaded file.

Throws:

java.io.IOException

getAllFieldValues

public java.lang.String[] getAllFieldValues(java.lang.String fieldName)

Returns an array of String objects containing all of the values the given parameter has, or null if the parameter does not exist.

Parameters: fieldName - name of the input element Returns: values of the input element

getContentType

public java.lang.String getContentType()

Retrieves the content type of the uploaded file.

Returns:

the content type

getFields

public java.util.Map getFields()

Retrieves the HTML input form's input elements.

Returns:

the input elements

getFieldValue

public java.lang.String getFieldValue(java.lang.String fieldName)

Retrieves the value of an HTML input element

Parameters:

fieldName - name of the input element Returns: value of the input element

getFilename

public java.lang.String getFilename()

Retrieves the filename of the uploaded file.

Returns: the filename

getFilepath

public java.lang.String getFilepath()

Retrieves the complete filepath on the client side of the uploaded file.

Returns:

the filepath

setSavePath

public void setSavePath(java.lang.String savePath)

Sets the location that the file should be stored in on the server.

Parameters:

savePath - server file location

edu.ucsf.qpaca Class PathwayAnalysis

java.lang.Object

L_edu.ucsf.Magellan.AnalysisThread

- edu.ucsf.qpaca.PathwayAnalysis

All Implemented Interfaces:

java.lang.Runnable

public class PathwayAnalysis

extends edu.ucsf.Magellan.AnalysisThread

Runs the QPACA Pathway Analysis Tools within Magellan. Handles creation of output directories and manages any errors generated during analysis.

Field Summary

Fields inherited from class edu.ucsf.Magellan.AnalysisThread

Analysis, application, running, sessionID

Constructor Summary

```
PathwayAnalysis(edu.ucsf.Magellan.AnalysisInfo analysis, java.lang.
String sessionID, javax.servlet.ServletContext application, javax.
servlet.ServletRequest request, Pathway path)
Initializes a new PathwayAnalysis thread given the provided parameters
```

```
PathwayAnalysis(edu.ucsf.Magellan.AnalysisInfo analysis, java.lang.
String sessionID, java.lang.String filepath, java.lang.
String annottype, java.lang.String pathAnnotType, Pathway path)
Initializes a new PathwayAnalysis thread given the provided parameters
```

Method Summary

boolean	deleteDir(java.io.File dir)
	Deletes all files and subdirectories under dir.
void	<u>run</u> ()
	Runs the analysis.
void	<pre>writeLog(java.io.File log, java.lang.String analysisType,</pre>
	edu.ucsf.Magellan.DataType dt) Writes out a log file detailing all of the analysis parameters.

Methods inherited from class edu.ucsf.Magellan.AnalysisThread

```
isRunning, setRunning
```

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll,
toString, wait, wait, wait
```

Constructor Detail

PathwayAnalysis

Initializes a new PathwayAnalysis thread given the provided parameters

Parameters:

analysis - the AnalysisInfo object storing the analysis parameters sessionID - the session identifier application - the ServletContext for this instance of PathwayAnalysis request - the client request information for this instance of PathwayAnalysis path - the pathway to analyze

PathwayAnalysis

java.lang.String filepath, java.lang.String annottype, java.lang.String pathAnnotType, Pathway path)

Initializes a new PathwayAnalysis thread given the provided parameters

Parameters:

analysis - the AnalysisInfo object storing the analysis parameters
sessionID - the session identifier
filepath - the data file path
annottype - the annotation type for the data
pathAnnotType - the matching annotation type in the pathway
path - the pathway to analyze

Method Detail

deleteDir

```
public boolean deleteDir(java.io.File dir)
```

Deletes all files and subdirectories under dir.

Parameters:

dir - the directory to delete Returns: true if all deletions successful, false otherwise.

run

```
public void run()
```

Runs the analysis.

Specified by:

run in interface java.lang.Runnable

Overrides:

run in class edu.ucsf.Magellan.AnalysisThread

writeLog

Writes out a log file detailing all of the analysis parameters.

Parameters:

log - the file analysisType - the type of analysis performed dt - the data type used in the analysis

Throws:

java.io.IOException - If any problems with file access occur.

edu.ucsf.qpaca.pathway Interface PathwayComponent

All Known Implementing Classes:

Pathway, PathwayAssembly, PathwayEdge, PathwayElement, PathwayVertex

public interface PathwayComponent

The base class for all pathway components, which specifies methods for getting and setting the various common attributes.

Method Summary	
java. lang. Object	getAttribute (java.lang.String type) Returns the attribute mapped to the specified attribute type.
java. util.Map	getAttributes () Returns the attributes of this Element.
java. lang. String	getID() Returns the ID of this PathwayComponent.
boolean	hasAttribute(java.lang.String type)Tests to see if this PathwayComponent has this type of attribute.
java. lang. Object	<u>removeAttribute</u> (java.lang.String key) Removes a specific attribute.
void	setAttribute (java.lang.String key, java.lang.Object value) Creates a new attribute.

Method Detail

getAttribute

java.lang.Object getAttribute(java.lang.String type)

Returns the attribute mapped to the specified attribute type.

Parameters: type - the attribute type Returns: the attribute specified by the type

getAttributes

java.util.Map getAttributes()

Returns the attributes of this Element.

Returns:

the attributes

getID

java.lang.String getID()

Returns the ID of this PathwayComponent.

Returns:

the ID

hasAttribute

boolean hasAttribute(java.lang.String type)

Tests to see if this PathwayComponent has this type of attribute.

Parameters:

type - the attribute typeReturns:true if this type of attribute exists;

removeAttribute

java.lang.Object removeAttribute(java.lang.String key)

Removes a specific attribute.

Parameters:

key - the attribute type

setAttribute

Creates a new attribute.

Parameters:

key - the attribute type value - the attribute

edu.ucsf.qpaca.pathway Class Pathway

java.lang.Object

L_salvo.jesus.graph.DirectedGraphImpl

edu.ucsf.qpaca.pathway.Pathway

All Implemented Interfaces:

<u>PathwayComponent</u>, java.io.Serializable, salvo.jesus.graph.DirectedGraph, salvo.jesus.graph.Graph, salvo.jesus.graph.WeightedGraph

public class Pathway

extends salvo.jesus.graph.DirectedGraphImpl implements salvo.jesus.graph.WeightedGraph, <u>PathwayComponent</u>, java.io.Serializable

A biological pathway represented as a directed graph.

See Also:

Serialized Form

Field Summary	
protected java. util. HashMap	attributes A HashMap of attributes.
Fields inherited from class salvo.jesus.graph.GraphImpl	

factory, traversal

Constructor Summary

Pathway()

N

Constructs a new, empty pathway.

lethod Summary	
void	addEdge(PathwayEdge pe)
	Adds a previously created edge.

salvo.jesus. graph. WeightedEdge	<pre>addEdge(salvo.jesus.graph.Vertex v1, salvo.jesus.graph.Vertex v2, double weight) Convenience method to add a WeightedEdge with a specified weight into the WeightedGraph.</pre>
<u>PathwayEdge</u>	<pre>addEdge(salvo.jesus.graph.Vertex v1, salvo.jesus.graph.Vertex v2, int newType) Adds a new edge connecting vertex v1 and vertex v2.</pre>
<u>PathwayEdge</u>	<pre>addEdge(salvo.jesus.graph.Vertex source, salvo.jesus.graph. Vertex sink, int newType, double newWeight) Adds a PathwayEdge with a specific weight to the Pathway.</pre>
java.util.Set	getAssemblies(java.util.Set vertices) Retrieves all Assemblies represented by the specified Vertices
java.lang. Object	getAttribute(java.lang.String type) Returns the attribute mapped to the specified attribute type.
java.util.Map	getAttributes () Returns the attributes of this Pathway.
salvo.jesus. graph.Vertex	getClosest(salvo.jesus.graph.Vertex v)Determines the Vertex that is 'closest' to the Vertex specified.
PathwayElement	<pre>getElement(java.lang.String input, java.lang.String inputType) Retrieves the PathwayElement represented by the input:inputType</pre>
java.util.Set	getElements () Retrieves all PathwayElements in this pathway
java.util.Set	getElements(java.util.Set vertices) Retrieves all PathwayElements represented by the specified Vertices.
java.lang. String	getID() Returns the unique ID of this PathwayComponent.
java.util.List	<pre>getPath(salvo.jesus.graph.Vertex v1, salvo.jesus.graph.Vertex v2) Retrieves the shortest path from Vertex v1 to Vertex v2.</pre>
PathwayVertex	<u>getVertex</u> (java.lang.String input, java.lang.String inputType) Retrieves the Vertex containing the PathwayElement represented by the input:inputType
PathwayVertex	<u>getVertexByID</u> (java.lang.String id) Retrieves the Vertex with the specified ID.
java.util.Set	getVertexSet(PathwayElement elem) Retrieves all Vertices containing the specified PathwayElement.
java.util.Set	<pre>getVertexSet(java.lang.String input, java.lang.String inputType) Retrieves all Vertices containing the PathwayElement represented by the input:inputType</pre>
boolean	hasAttribute(java.lang.String type) Tests to see if this PathwayComponent has the specified type of attribute.
salvo.jesus. graph. WeightedGraph	minimumSpanningTree () Determine a minimum spanning tree for the weighted graph.
java.util.Set	nConnected(salvo.jesus.graph.Vertex startVertex, int n, int dir) Retrieves all vertices that are within n steps from the starting Vertex
int	<pre>pathEffect(java.util.List path) Retrieves the overall effect of the specified path based on PathwayEdge types.</pre>

java.lang. Object	removeAttribute(java.lang.String key) Removes a specific attribute
void	<pre>setAttribute(java.lang.String key, java.lang.Object value) Creates a new attribute</pre>
void	setMinimumSpanningTreeAlgorithm(PathwayMinimumSpanningTree algo) Sets the algorithm used to determine the minimum spanning tree.
void	setShortestPathAlgorithm(ShortestPathAlgorithm algo) Sets the algorithm used to determine the shortest path spanning tree.
salvo.jesus. graph. WeightedGraph	<pre>shortestPath(salvo.jesus.graph.Vertex vertex) Determine a shortest path spanning tree for the weighted graph.</pre>

Methods inherited from class salvo.jesus.graph.DirectedGraphImpl

getEdge, getIncomingAdjacentVertices, getIncomingEdges, getOutgoingAdjacentVertices, getOutgoingEdges, isCycle, isPath

Methods inherited from class salvo.jesus.graph.GraphImpl

add, addEdge, addEdge, addGraphAddEdgeListener, addGraphAddVertexListener, addGraphRemoveEdgeListener, addGraphRemoveVertexListener, addListener, cloneVertices, containsEdge, containsVertex, forgetConnectedSets, getAdjacentVertices, getAdjacentVertices, getConnectedSet, getConnectedSet, getDegree, getDegree, getEdges, getEdgesCount, getEdgeSet, getGraphFactory, getTraversal, getVertexSet, getVertices, getVerticesCount, getVerticesIterator, isConnected, remove, removeEdge, removeEdges, removeGraphAddEdgeListener, removeGraphAddVertexListener, removeGraphRemoveEdgeListener, removeGraphRemoveVertexListener, removeListener, setGraphFactory, setTraversal, toString, traverse

Methods inherited from class java.lang.Object

clone, equals, finalize, getClass, hashCode, notify, notifyAll, wait, wait, wait

Methods inherited from interface salvo.jesus.graph.Graph

add, addEdge, addEdge, addGraphAddEdgeListener, addGraphAddVertexListener, addGraphRemoveEdgeListener, addGraphRemoveVertexListener, addListener, cloneVertices, getAdjacentVertices, getAdjacentVertices, getConnectedSet, getConnectedSet, getDegree, getDegree, getEdges, getEdgesCount, getEdgeSet, getGraphFactory, getTraversal, getVertexSet, getVertices, getVerticesCount, getVerticesIterator, isConnected, remove, removeEdge, removeEdges, removeGraphAddEdgeListener, removeGraphAddVertexListener, removeGraphRemoveEdgeListener, removeGraphRemoveVertexListener, removeListener, setGraphFactory, setTraversal, traverse

Field Detail

attributes

protected java.util.HashMap attributes

A HashMap of attributes.

Constructor Detail

Pathway

public Pathway()

Constructs a new, empty pathway.

Method Detail

addEdge

Adds a previously created edge. Calls DirectedGraphImpl.addEdge(edge).

```
Parameters:

pe - the edge to add

Throws:

java.lang.Exception
```

addEdge

Convenience method to add a WeightedEdge with a specified weight into the WeightedGraph. The default addEdge (v1, v2) will add a WeightedEdge with weight=1.0, after which you can call setWeight() to specify the weight.

Specified by:

addEdge in interface salvo.jesus.graph.WeightedGraph
Returns:

the new WeightedEdge

Throws:

java.lang.Exception

addEdge

public <u>PathwayEdge</u> addEdge(salvo.jesus.graph.Vertex v1, salvo.jesus.graph.Vertex v2, int newType) throws java.lang.Exception

> Adds a new edge connecting vertex v1 and vertex v2. Calls DirectedGraphImpl.addEdge(v1,v2) and sets the type of the edge to newType and the weight to 1.0.

Parameters:

v1 - Vertex that will be the source of the PathwayEdge v2 - Vertex that will be the sink of the PathwayEdge newType - the type of the new PathwayEdge **Returns:** the new PathwayEdge **Throws:**

java.lang.Exception

addEdge

public PathwayEdge addEdge(salvo.jesus.graph.Vertex source, salvo.jesus.graph.Vertex sink, int newType, double newWeight) throws java.lang.Exception

> Adds a PathwayEdge with a specific weight to the Pathway. Calls DirectedGraphImpl.addEdge(v1,v2) and sets the type of the edge to newType and the weight to newWeight.

Parameters:

source - Vertex that will be the source of the Edge sink - Vertex that will be the sink of the Edge newType - the type of the Edge newWeight - the weight of the Edge **Returns:** the new PathwayEdge

Throws:

java.lang.Exception

getAssemblies

public java.util.Set getAssemblies(java.util.Set vertices)

Retrieves all Assemblies represented by the specified Vertices

Parameters:

vertices - a Set of vertices **Returns:** a List of PathwayElements

getAttribute

public java.lang.Object getAttribute(java.lang.String type)

Returns the attribute mapped to the specified attribute type.

```
Specified by:

getAttribute in interface PathwayComponent
Parameters:

type - the attribute type
Returns:

the attribute specified by the type
```

getAttributes

```
public java.util.Map getAttributes()
```

Returns the attributes of this Pathway.

Specified by: <u>getAttributes</u> in interface <u>PathwayComponent</u> Returns: the attributes

getClosest

public salvo.jesus.graph.Vertex getClosest(salvo.jesus.graph.Vertex v)

Determines the Vertex that is 'closest' to the Vertex specified. The definition of the closest vertex in this context is a vertex that is directly adjacent to Vertex v where the edge has the least weight.

```
Specified by:
    getClosest in interface salvo.jesus.graph.WeightedGraph
Parameters:
    v - the starting vertex
Returns:
    the Vertex closes to v.
```

getElement

public <u>PathwayElement</u> getElement(java.lang.String input,

java.lang.String inputType)

Retrieves the PathwayElement represented by the input:inputType

Parameters:

input - the input value inputType - the input type Returns: a PathwayVertex, or null if no such Vertex found.

getElements

public java.util.Set getElements()

Retrieves all PathwayElements in this pathway

Returns: a Set of all PathwayElements

getElements

public java.util.Set getElements(java.util.Set vertices)

Retrieves all PathwayElements represented by the specified Vertices.

Parameters: vertices - a Set of vertices Returns: a List of PathwayElements

getID

public java.lang.String getID()

Returns the unique ID of this PathwayComponent. Since pathways do not have IDs, returns null

Specified by:

getID in interface PathwayComponent

Returns: null

getPath

Retrieves the shortest path from Vertex v1 to Vertex v2. Uses the shortest path spanning tree determined by shortestpath.

Parameters: v1 - start Vertex v2 - end Vertex Returns:

a list of the edges of the shortest path from v1 to v2 $% \left({{{\mathbf{v}}_{1}}} \right)$

getVertex

Retrieves the Vertex containing the PathwayElement represented by the input:inputType

```
Parameters:
```

input - the input value inputType - the input type Returns: a PathwayVertex, or null if no such Vertex found

getVertexByID

public <u>PathwayVertex</u> getVertexByID(java.lang.String id)

Retrieves the Vertex with the specified ID.

Parameters: id - the ID of the desired Vertex Returns: the PathwayVertex with the specified ID

getVertexSet

public java.util.Set getVertexSet(PathwayElement elem)

Retrieves all Vertices containing the specified PathwayElement.

Parameters: elem - the input PathwayElement Returns: a PathwayVertex

getVertexSet

Retrieves all Vertices containing the PathwayElement represented by the input:inputType

Parameters: input - the input value inputType - the input type Returns: a PathwayVertex

hasAttribute

public boolean hasAttribute(java.lang.String type)

Tests to see if this PathwayComponent has the specified type of attribute.

```
Specified by:

hasAttribute in interface PathwayComponent

Parameters:

type - the attribute type

Returns:

true if this type of attribute exists
```

minimumSpanningTree

public salvo.jesus.graph.WeightedGraph minimumSpanningTree()

Determine a minimum spanning tree for the weighted graph. There is no guarantee that the same method call will result in the same result, as long as it satisifies the property of a minimum spanning tree.

Specified by:

minimumSpanningTree in interface salvo.jesus.graph.WeightedGraph

Returns:

Subgraph connecting all the Vertices such that the sum of the weights of the Edges is at least as small as the sum of the weights of any other collection of Edges connecting all the Vertices.

nConnected

Retrieves all vertices that are within n steps from the starting Vertex

Parameters:

```
startVertex - the start Vertex
n - number of steps from the start Vertex
dir - the direction to search (1=downstream, -1=upstream, 0=both)
Returns:
a Set of vertices that are n-connected to the start Vertex
```

pathEffect

public int pathEffect(java.util.List path)

Retrieves the overall effect of the specified path based on PathwayEdge types.

Parameters:

path - a list of Pathway edges defining a path
Returns:
 1 if the overall effect is positive, -1 if negative

removeAttribute

public java.lang.Object removeAttribute(java.lang.String key)

Removes a specific attribute

```
Specified by:
```

<u>removeAttribute</u> in interface <u>PathwayComponent</u> **Parameters:** key - the attribute type

setAttribute

 Creates a new attribute

Specified by:

setAttribute in interface PathwayComponent

Parameters:

key - the attribute type value - the attribute

setMinimumSpanningTreeAlgorithm

public void setMinimumSpanningTreeAlgorithm(PathwayMinimumSpanningTree algo)

Sets the algorithm used to determine the minimum spanning tree.

setShortestPathAlgorithm

public void setShortestPathAlgorithm(ShortestPathAlgorithm algo)

Sets the algorithm used to determine the shortest path spanning tree.

shortestPath

public salvo.jesus.graph.WeightedGraph shortestPath(salvo.jesus.graph.Vertex vertex)

Determine a shortest path spanning tree for the weighted graph. Shortest path spanning tree need not be unique. Therefore, there is no guarantee that calling this method twice for the same weighted graph will return exactly the same shortest path spanning tree, unless there is only one shortest path spanning tree.

Also note that the graph returned by this method is a new instance of WeightedGraph. However, its vertices and edges will be the same instance as those of this WeightedGraph. Therefore, **do not** modify the contents of the returned WeightedGraph such that any of its vertices or edges are removed.

Specified by:

shortestPath in interface salvo.jesus.graph.WeightedGraph

Parameters:

vertex - The Vertex in the weighted graph that we want to get the shortest paths to all other vertices.

Returns:

Shortest spanning subgraph from the vertex parameter to all other vertices that are in the same connected set as the vertex.

edu.ucsf.qpaca.pathway Class PathwayAssembly

java.lang.Object

java.util.AbstractCollection<E>
 java.util.AbstractList<E>
 java.util.ArrayList
 du.ucsf.qpaca.pathway.PathwayAssembly

All Implemented Interfaces:

<u>PathwayComponent</u>, java.io.Serializable, java.lang.Cloneable, java.lang.Comparable, java.lang. Iterable, java.util.Collection, java.util.List, java.util.RandomAccess

public class PathwayAssembly

extends java.util.ArrayList implements java.io.Serializable, <u>PathwayComponent</u>, java.lang.Comparable

An collection of objects in a pathway that can be found at a PathwayVertex.

See Also:

Serialized Form

Field Summary	
protected java. util. HashMap	attributes A hashtable of attributes.
protected java. lang. String	<u>id</u> The unique id of the PathwayAssembly.

protected	
java.	type
lang.	The type of PathwayAssembly.
String	

Fields inherited from class java.util.AbstractList

modCount

Constructor Summary

PathwayAssembly()

Constructs a new, empty PathwayAssembly.

PathwayAssembly(java.lang.String newType, java.lang.String newID) Constructs a new PathwayAssembly object of the specified type.

PathwayAssembly(java.lang.String newType, java.lang.String newID, java.util.List 1)

Constructs a new PathwayAssembly object of the specified type with the specified list of PathwayElements.

PathwayAssembly(java.lang.String newType, java.lang.String newID,

java.util.List 1, java.util.Map newAttributes)

Constructs a new PathwayAssembly object of the specified type with the specified list of PathwayElements and attributes.

Method Summary		
int	compareTo(java.lang.Object o)Compares this PathwayAssembly to another Object.	
java. lang. Object	getAttribute (java.lang.String type) Returns the attribute mapped to the specified attribute type.	
java. util.Map	getAttributes () Returns the attributes of this PathwayAssembly.	
java. lang. String	getID() Returns the unique ID.	
java. lang. String	getType() Returns the type.	
boolean	hasAttribute(java.lang.String type) Tests to see if this PathwayComponent has this particular type of attribute.	
java. lang. Object	removeAttribute(java.lang.String key) Removes a specific attribute.	

void	<pre>setAttribute(java.lang.String key, java.lang.Object value) Creates a new attribute.</pre>
void	<pre>setType(java.lang.String newType) Sets the type.</pre>
java. lang. String	toString () Returns a String representation of this PathwayAssembly.

Methods inherited from class java.util.ArrayList

```
add, add, addAll, addAll, clear, clone, contains, ensureCapacity,
get, indexOf, isEmpty, lastIndexOf, remove, remove, removeRange, set,
size, toArray, toArray, trimToSize
```

Methods inherited from class java.util.AbstractList

equals, hashCode, iterator, listIterator, listIterator, subList

Methods inherited from class java.util.AbstractCollection

containsAll, removeAll, retainAll

Methods inherited from class java.lang.Object

finalize, getClass, notify, notifyAll, wait, wait, wait

Methods inherited from interface java.util.List

```
containsAll, equals, hashCode, iterator, listIterator, listIterator,
removeAll, retainAll, subList
```

Field Detail

attributes

protected java.util.HashMap attributes

A hashtable of attributes.

protected java.lang.String id

The unique id of the PathwayAssembly.

type

protected java.lang.String type

The type of PathwayAssembly. Indicates whether it's a set of aliases or a compound.

Constructor Detail

PathwayAssembly

public PathwayAssembly()

Constructs a new, empty PathwayAssembly.

PathwayAssembly

Constructs a new PathwayAssembly object of the specified type.

Parameters:

newType - the type of this PathwayAssembly newID - this PathwayAssembly's ID

PathwayAssembly

Constructs a new PathwayAssembly object of the specified type with the specified list of PathwayElements.

Parameters:

newType - the type of this PathwayAssembly newID - this PathwayAssembly's ID 1 - a List of PathwayElements that this PathwayAssembly contains

PathwayAssembly

Constructs a new PathwayAssembly object of the specified type with the specified list of PathwayElements and attributes.

Parameters:

newType - the type of this PathwayAssembly
newID - this PathwayAssembly's ID
1 - a List of PathwayElements that this PathwayAssembly contains
newAttributes - this PathwayAssembly's attributes

Method Detail

compareTo

```
public int compareTo(java.lang.Object o)
```

Compares this PathwayAssembly to another Object. If the Object is another PathwayAssembly, returns 0 if the two Assemblies have identical types and ids.

Specified by:

compareTo in interface java.lang.Comparable

Returns:

the value 0 if the argument is an equivalent PathwayAssembly

Throws:

java.lang.ClassCastException - if the argument is not a valid PathwayAssembly

getAttribute

public java.lang.Object getAttribute(java.lang.String type)

Returns the attribute mapped to the specified attribute type.

Specified by: getAttribute in interface PathwayComponent Parameters: type - the attribute type Returns: the attribute specified by the type

getAttributes

public java.util.Map getAttributes()

Returns the attributes of this PathwayAssembly.

Specified by: getAttributes in interface PathwayComponent Returns: the attributes

getID

public java.lang.String getID()

Returns the unique ID.

Specified by: getID in interface PathwayComponent Returns: the type

getType

public java.lang.String getType()

Returns the type.

Returns:

the type

hasAttribute

```
public boolean hasAttribute(java.lang.String type)
```

Tests to see if this PathwayComponent has this particular type of attribute.

Specified by: <u>hasAttribute</u> in interface <u>PathwayComponent</u> Parameters: type - the attribute type Returns: true if this type of attribute exists;

removeAttribute

public java.lang.Object removeAttribute(java.lang.String key)

Removes a specific attribute.

Specified by:

removeAttribute in interface PathwayComponent

Parameters:

key - the attribute type

setAttribute

public void setAttribute(java.lang.String key,

java.lang.Object value)

Creates a new attribute.

Specified by:

setAttribute in interface PathwayComponent

Parameters:

key - the attribute type value - the attribute

setType

public void setType(java.lang.String newType)

Sets the type.

Parameters: newType -

toString

public java.lang.String toString()

Returns a String representation of this PathwayAssembly.

Overrides:

toString in class java.util.AbstractCollection Returns: type.id and a list of objects contained in the Assembly

edu.ucsf.qpaca.pathway **Class PathwayData**

java.lang.Object

edu.ucsf.qpaca.pathway.PathwayData

public class PathwayData

extends java.lang.Object

Container for data values that are used to color pathways. Includes methods for some basic types of data manipulation.

Constructor Summary

PathwayData()

Creates an empty dataset.

PathwayData(java.io.File datafile, java.io.File annotFile, java.lang. String annotType, boolean logValues, double percentile, java.lang. String dupmethod, boolean calcRatios, double missingValueThreshold, double percAllowedMissing)

Creates a new PathwayData object using the specified dataset.

Method Summary		
protected double	calculateColor (double value) Calculates the color value for a particular data value.	
protected double	<pre>calculateColor(double value, double dMax, double dMin, double dMid) Calculates the color value for a particular data value given a defined data value range.</pre>	
Pathway	colorByCorrelation(Pathway path, java.lang.String pathAnnotType)Colors a pathway based on the correlations.	

<u>Pathway</u>	<pre>colorByPvalue(Pathway path, int pValueIndex, java.lang. String pathAnnotType, java.lang.String title)</pre>
Pathway	<pre>colorBySample(Pathway path, int sampleIndex, java.lang. String pathAnnotType) Colors a pathway based on the sample values for the given sample index.</pre>
Pathway	<pre>colorBySample(Pathway path, java.lang. String pathAnnotType) Colors a pathway based on the sample values for the first sample index.</pre>
int	<pre>createDataFiles(Pathway path, java.lang. String pathAnnotType, java.lang.String filepath, java. lang.String fileroot) Creates the pathway subset files for this dataset, given a pathway.</pre>
boolean	generateCorrelationData() Calculates the correlations of each gene to the gene with the specified correlationID.
java.util. Map	getCorrelationData()
java.lang. String	getCorrelationID() Returns the annotation ID used to calculate correlations.
double	getDataMax () Returns the largest data value in this dataset.
double	getDataMin() Returns the smallest data value in this dataset.
java.util. List	getSamplenames () Returns the samplenames.
int	getSize() Returns the number of data values in this dataset.
boolean	isEmpty () Returns true if this dataset contains no values.
static void	<pre>main(java.lang.String[] args) This method allows for testing the class on the command line.</pre>
void	<pre>readDataFile(java.io.File datafile, java.io. File annotFile, java.lang.String annotType, boolean logValues, double maxPercentile, java.lang. String dupmethod, boolean calcRatios, double missingValueThreshold, double percAllowedMissing) Reads in a datafile.</pre>
boolean	setCorrelationID(java.lang.String id) Sets the annotation ID for which to calculate correlations.

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll,
toString, wait, wait, wait
```

Constructor Detail

PathwayData

public PathwayData()

Creates an empty dataset.

PathwayData

```
public PathwayData(java.io.File datafile,
```

```
java.io.File annotFile,
java.lang.String annotType,
boolean logValues,
double percentile,
java.lang.String dupmethod,
boolean calcRatios,
double missingValueThreshold,
double percAllowedMissing)
throws java.io.FileNotFoundException,
java.io.IOException
```

Creates a new PathwayData object using the specified dataset. The dataset must be contained in a datafile with the following characteristics:

- o rows contain genes genes
- o columns contain samples
- the first column contains gene identifiers
- the first row contains the sample names
- o missing data is identified using the empty string or "NA"

Any additional gene annotations must be contained in a separate annotation file with the following characteristics:

- o the first column contains gene identifiers
- o additional columns contain the different gene annotations
- o annotation types are listed in the first row

Parameters:

datafile - the data file
annotFile - the annotation file
annotType - the annotation type in the annotation file that corresponds to an annotation type in the Pathway.

logValues - true if the datafile contains log values, false otherwise percentile - the percentile of the max/min threshold at which color is most intense

dupmethod - method used to resolve duplicates

calcRatios - if true, the values in the file need to have ratios calculated missingValueThreshold - the minimum threshold for valid data values percAllowedMissing - the percent of data values allowed to be missing for the gene to be considered not missing

Throws:

FileNotFoundException java.io.IOException

Method Detail

calculateColor

protected double calculateColor(double value)

Calculates the color value for a particular data value.

```
Parameters:
value - the data value
Returns:
```

the color value

calculateColor

protected double **calculateColor**(double value, double dMax, double dMin, double dMin,

Calculates the color value for a particular data value given a defined data value range.

Parameters:

value - the data value dMax - the largest data value dMin - the smallest data value dMid - the data value that represents 0

colorByCorrelation

Colors a pathway based on the correlations.

Parameters:

path - the pathway to color
 pathAnnotType - the annotation type of the pathway elements
Returns:
 the colored pathway

colorByPvalue

```
public <u>Pathway</u> colorByPvalue(<u>Pathway</u> path,
```

int pValueIndex, java.lang.String pathAnnotType, java.lang.String title)

colorBySample

Colors a pathway based on the sample values for the given sample index.

Parameters:

```
path - the pathway to color
sampleIndex - the index of the sample to use for coloring
pathAnnotType - the annotation type of the pathway elements
Returns:
```

the colored pathway

colorBySample

Colors a pathway based on the sample values for the first sample index.

Parameters: path - the pathway to color pathAnnotType - the annotation type of the pathway elements Returns: the colored pathway

createDataFiles

Creates the pathway subset files for this dataset, given a pathway.

Parameters: path - the Pathway for which to create the datafiles Returns: the number of data rows in the pathway subset file Throws: java.io.IOException

generateCorrelationData

```
public boolean generateCorrelationData()
```

Calculates the correlations of each gene to the gene with the specified correlationID.

Returns:

true if the correlation ID exists, false otherwise

getCorrelationData

public java.util.Map getCorrelationData()

getCorrelationID

public java.lang.String getCorrelationID()

Returns the annotation ID used to calculate correlations.

Returns:

the annotation ID

getDataMax

public double getDataMax()

Returns the largest data value in this dataset.

Returns: the maximum value

getDataMin

public double getDataMin()

Returns the smallest data value in this dataset.

Returns:

the minimum value

getSamplenames

public java.util.List getSamplenames()

Returns the samplenames.

Returns:

a List containing the samplenames.

getSize

public int getSize()

Returns the number of data values in this dataset.

Returns: size

isEmpty

public boolean isEmpty()

Returns true if this dataset contains no values.

Returns:

true if this dataset contains no values.

main

This method allows for testing the class on the command line. arguments to pass in: datafilename, annotfilename, annotType, logValues, maxPercentile, dupmethod, correlationID

Throws:

java.lang.Exception

readDataFile

Reads in a datafile.

Parameters:

datafile - the File to import.

annotFile - the File containing gene annotations of the data annotType - which annotation in the annotation file corresponds the gene annotation in the pathway logValues - true if the datafile contains log values, false otherwise maxPercentile - the data percentile at which the color is most intense dupmethod - method used to resolve duplicates calcRatios - if true, the values in the file need to have ratios calculated missingValueThreshold - the minimum threshold for valid data values percAllowedMissing - the percent of data values allowed to be missing for the gene to be represented

Throws:

java.io.FileNotFoundException - if the file cannot be found java.io.IOException - if the file cannot be read

setCorrelationID

public boolean setCorrelationID(java.lang.String id)

Sets the annotation ID for which to calculate correlations.

Parameters:

id - The annotation ID

Returns:

true if the ID exists in the dataset, false otherwise.

edu.ucsf.qpaca.pathway Class PathwayEdge

java.lang.Object

L salvo.jesus.graph.EdgeImpl L salvo.jesus.graph.DirectedWeightedEdgeImpl L edu.ucsf.qpaca.pathway.PathwayEdge

All Implemented Interfaces:

PathwayComponent, java.io.Serializable, salvo.jesus.graph.DirectedEdge, salvo.jesus.graph. DirectedWeightedEdge, salvo.jesus.graph.Edge, salvo.jesus.graph.GraphComponent, salvo.jesus. graph.LabeledEdge, salvo.jesus.graph.LabeledGraphComponent, salvo.jesus.graph. WeightedEdge

public class PathwayEdge

extends salvo.jesus.graph.DirectedWeightedEdgeImpl implements <u>PathwayComponent</u>, java.io.Serializable

An edge in a pathway.

See Also:

Serialized Form

Field Summary	
static int	ACTIVATION_TYPE PathwayEdge type: activation.
protected java. util. HashMap	attributes attributes describing this edge
static int	INHIBITION_TYPE PathwayEdge type: inhibition.

static int	NEUTRAL_TYPE
	PathwayEdge type: neutral.
protected int	typePathwayEdges can be either positive (ACTIVATION_TYPE), negative(INHIBITION_TYPE) or neutral (NEUTRAL_TYPE).

Fields inherited from class salvo.jesus.graph.EdgeImpl

str, vertexA, vertexB

Fields inherited from interface salvo.jesus.graph.DirectedEdge

DIRECTION_A_TO_B, DIRECTION_B_TO_A, NODIRECTION

Constructor Summary

PathwayEdge(salvo.jesus.graph.Vertex sourceVertex, salvo.jesus.graph. Vertex sinkVertex)

Creates a PathwayEdge object whose origin and destination vertices are specified by the method parameters.

PathwayEdge(salvo.jesus.graph.Vertex sourceVertex, salvo.jesus.graph. Vertex sinkVertex, double weight)

Creates a PathwayEdge object whose source and sink vertices and weight are specified by the parameters.

```
PathwayEdge(salvo.jesus.graph.Vertex sourceVertex, salvo.jesus.graph.
Vertex sinkVertex, int type)
```

Creates a PathwayEdge object whose origin and destination vertices are specified by the method parameters.

Method Summary

protected java. lang. Object	clone() Creates a clone of this Edge.
java. lang. Object	getAttribute (java.lang.String type) Returns the attribute mapped to the specified attribute type.
java. util.Map	getAttributes () Returns the attributes of this Edge.
java. lang. String	getID() Returns the ID of this PathwayComponent.
int	getType() Returns the type of the edge.

boolean	hasAttribute(java.lang.String type) Tests to see if this PathwayComponent has this particular type of attribute.
java. lang. Object	removeAttribute (java.lang.String key) Removes a particular attribute.
void	<pre>setAttribute(java.lang.String key, java.lang.Object value) Creates a new attribute.</pre>
void	setType(int type) Sets the type of the edge.
java. lang. String	toString() Returns a String representation of the Edge, using the the toString() methods of Vertex.

Methods inherited from class salvo.jesus.graph.DirectedWeightedEdgeImpl

getDirection, getSink, getSource, getWeight, setWeight

Methods inherited from class salvo.jesus.graph.EdgeImpl

```
getLabel, getOppositeVertex, getVertexA, getVertexB, hasLabel,
isFollowVertexLabel, setFollowVertexLabel, setLabel
```

Methods inherited from class java.lang.Object

```
equals, finalize, getClass, hashCode, notify, notifyAll, wait, wait, wait
```

Methods inherited from interface salvo.jesus.graph.Edge

getOppositeVertex, getVertexA, getVertexB

Methods inherited from interface salvo.jesus.graph.LabeledEdge

isFollowVertexLabel, setFollowVertexLabel

Methods inherited from interface salvo.jesus.graph.LabeledGraphComponent

getLabel, hasLabel, setLabel

Methods inherited from interface salvo.jesus.graph.Edge

getOppositeVertex, getVertexA, getVertexB

Methods inherited from interface salvo.jesus.graph.LabeledEdge

isFollowVertexLabel, setFollowVertexLabel

Methods inherited from interface salvo.jesus.graph.LabeledGraphComponent

getLabel, hasLabel, setLabel

Field Detail

ACTIVATION_TYPE

public static final int ACTIVATION_TYPE

PathwayEdge type: activation.

See Also: Constant Field Values

attributes

protected java.util.HashMap attributes

attributes describing this edge

INHIBITION_TYPE

public static final int **INHIBITION_TYPE**

PathwayEdge type: inhibition.

See Also:

Constant Field Values

NEUTRAL_TYPE

public static final int **NEUTRAL_TYPE**

PathwayEdge type: neutral.

See Also:

Constant Field Values

type

protected int type

PathwayEdges can be either positive (ACTIVATION_TYPE), negative (INHIBITION_TYPE) or neutral (NEUTRAL_TYPE).

Constructor Detail

PathwayEdge

Creates a PathwayEdge object whose origin and destination vertices are specified by the method parameters.

Parameters:

sourceVertex sinkVertex -

PathwayEdge

Creates a PathwayEdge object whose source and sink vertices and weight are specified by the parameters.

Parameters:

sourceVertex sinkVertex weight -

PathwayEdge

Creates a PathwayEdge object whose origin and destination vertices are specified by the method parameters.

Parameters:

sourceVertex sinkVertex type -

Method Detail

clone

protected java.lang.Object clone()

Creates a clone of this Edge. This calls the Edge constructor, thereby creating a new instance of Edge. However, the vertices in both endpoints of the Edge are not cloned.

Overrides:

clone in class salvo.jesus.graph.EdgeImpl

Returns:

A clone of an instance of Edge.

getAttribute

public java.lang.Object getAttribute(java.lang.String type)

Returns the attribute mapped to the specified attribute type.

Specified by:

getAttribute in interface PathwayComponent

Parameters:

type - the attribute type

Returns:

the attribute specified by the type

getAttributes

public java.util.Map getAttributes()

Returns the attributes of this Edge.

Specified by:

getAttributes in interface PathwayComponent

Returns:

the attributes

getID

public java.lang.String getID()

Returns the ID of this PathwayComponent. In this case...return null since PathwayEdges do not have IDs.

Specified by: getID in interface PathwayComponent Returns: null

getType

public int getType()

Returns the type of the edge.

Returns:

the type

hasAttribute

public boolean hasAttribute(java.lang.String type)

Tests to see if this PathwayComponent has this particular type of attribute.

Specified by: <u>hasAttribute</u> in interface <u>PathwayComponent</u> Parameters: type - the attribute type Returns: true if this type of attribute exists;

removeAttribute

public java.lang.Object removeAttribute(java.lang.String key)

Removes a particular attribute.

Specified by: <u>removeAttribute</u> in interface <u>PathwayComponent</u> Parameters:

key - the attribute type

setAttribute

Creates a new attribute.

Specified by:

setAttribute in interface PathwayComponent

Parameters:

key - the attribute type value - the attribute

setType

public void setType(int type)

Sets the type of the edge.

Parameters:

type - the new type

toString

public java.lang.String toString()

Returns a String representation of the Edge, using the the toString() methods of Vertex. Activation edges are represented as "-->"; inhibition edges are represented as "---|", and neutral edges are represented as "---".

Overrides:

toString in class salvo.jesus.graph.DirectedWeightedEdgeImpl Returns: The String representation of the Edge See Also: Vertex

edu.ucsf.qpaca.pathway Class PathwayElement

java.lang.Object

edu.ucsf.qpaca.pathway.PathwayElement

All Implemented Interfaces:

PathwayComponent, java.io.Serializable, java.lang.Comparable

public class PathwayElement

extends java.lang.Object implements <u>PathwayComponent</u>, java.lang.Comparable, java.io.Serializable

An element of a pathway. PathwayElements are the smallest unit in a pathway and may represents both any subprocess of the pathway (such as another pathway) and, more importantly, any physical object that participates in the pathway.

See Also:

Serialized Form

Field Summary	
protected java. util. HashMap	attributes A hashtable of attributes.
protected java. lang. String	<u>id</u> the unique id
protected java. lang. String	type the type of this element.

Constructor Summary

PathwayElement()

Constructs a new, empty element.

PathwayElement(java.lang.String newType, java.lang.String newID)
Constructs a new Element object with the specified name and type.

Method Summary		
int	compareTo(java.lang.Object o) Compares this Element to another Object.	
java. lang. Object	getAttribute (java.lang.String type) Returns the attribute mapped to the specified attribute type.	
java. util.Map	getAttributes () Returns the attributes of this Element.	
java. lang. String	getID() Returns this element's value.	
java. lang. String	getType() Returns this element's type.	
boolean	hasAttribute(java.lang.String type) Tests to see if this PathwayComponent has this type of attribute.	
java. lang. Object	removeAttribute(java.lang.String key) Removes a particular attribute	
void	<pre>setAttribute(java.lang.String key, java.lang.Object value) Creates a new attribute</pre>	
void	setType(java.lang.String newType) Sets this element's type.	
java. lang. String	toString() Returns the name of this element.	

Methods inherited from class java.lang.Object clone, equals, finalize, getClass, hashCode, notify, notifyAll, wait,

wait, wait

Field Detail

attributes

protected java.util.HashMap attributes

A hashtable of attributes.

id

protected java.lang.String id

the unique id

type

protected java.lang.String type

the type of this element. Such as "protein", "DNA", "small molecule", "process".

Constructor Detail

PathwayElement

public PathwayElement()

Constructs a new, empty element.

PathwayElement

Constructs a new Element object with the specified name and type.

Parameters:

newType - the type of this element

newID - the ID of this element

Method Detail

compareTo

public int compareTo(java.lang.Object o)

Compares this Element to another Object. If the Object is another Element, returns 0 if the two Elements have identical types and ids.

Specified by:

compareTo in interface java.lang.Comparable Returns: the value 0 if the argument is an equivalent Element Throws: java.lang.ClassCastException - if the argument is not a valid Element

getAttribute

public java.lang.Object getAttribute(java.lang.String type)

Returns the attribute mapped to the specified attribute type.

Specified by:

getAttribute in interface PathwayComponent

Parameters:

type - the attribute type

Returns:

the attribute specified by the type

getAttributes

public java.util.Map getAttributes()

Returns the attributes of this Element.

Specified by:

getAttributes in interface PathwayComponent

Returns:

the attributes

getID

public java.lang.String getID()

Returns this element's value.

Specified by: getID in interface PathwayComponent Returns: the value

getType

public java.lang.String getType()

Returns this element's type.

Returns:

the type

hasAttribute

public boolean hasAttribute(java.lang.String type)

Tests to see if this PathwayComponent has this type of attribute.

Specified by:

hasAttribute in interface PathwayComponent Parameters: type - the attribute type Returns: true if this type of attribute exists;

removeAttribute

public java.lang.Object removeAttribute(java.lang.String key)

Removes a particular attribute

Specified by: removeAttribute in interface PathwayComponent

Parameters:

key - the attribute type

setAttribute

Creates a new attribute

Specified by: <u>setAttribute</u> in interface <u>PathwayComponent</u> Parameters: key - the attribute type value - the attribute

setType

public void setType(java.lang.String newType)

Sets this element's type.

Parameters:

newType -

toString

```
public java.lang.String toString()
```

Returns the name of this element. If it does not have a specified name, returns the ID.

Overrides: toString in class java.lang.Object Returns: the "name" attribute or, if no name exists, the ID attribute

edu.ucsf.qpaca.pathway Class PathwayFactory

java.lang.Object

edu.ucsf.qpaca.pathway.PathwayFactory

All Implemented Interfaces:

java.io.Serializable, salvo.jesus.graph.GraphFactory

public class PathwayFactory

extends java.lang.Object implements salvo.jesus.graph.GraphFactory

The factory for creating Vertices and Edges in a Pathway class.

See Also:

Serialized Form

Constructor Summary

PathwayFactory()

Method Summary		
salvo. jesus. graph. Edge	<mark>createEdge</mark> (salvo.jesus.graph.Vertex v1, salvo.jesus.graph. Vertex v2)	
salvo. jesus. graph. Vertex	<u>createVertex</u> ()	

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll,
toString, wait, wait, wait
```

Constructor Detail

PathwayFactory

public PathwayFactory()

Method Detail

createEdge

Specified by:

createEdge in interface salvo.jesus.graph.GraphFactory

createVertex

public salvo.jesus.graph.Vertex createVertex()

Specified by:

createVertex in interface salvo.jesus.graph.GraphFactory

edu.ucsf.qpaca.pathway Class PathwaySVG

java.lang.Object

edu.ucsf.qpaca.pathway.PathwaySVG

public class PathwaySVG

extends java.lang.Object

Handles manipulation and coloring (by data value) of SVG files generated by GraphViz.

Constructor Summary

PathwaySVG()

PathwaySVG(java.lang.String uri)

PathwaySVG(java.lang.String uri, java.io.File datafile, java.io.File annotFile, java.lang.String annotType, boolean logValues, double percentile, java.lang. String dupmethod, boolean calcRatios, double missingValueThreshold, double percAllowedMissing) Creates a new PathwaySVG object with the specified SVG file and dataset

Creates a new Pathy	vaySVG object	with the specified	SVG file and dataset.
---------------------	---------------	--------------------	-----------------------

Method Summary		
protected double	calculateColor(double value)	
protected double	<u>calculateColor</u> (double value, double dMax, double dMin, double dMid)	
org.w3c. dom.svg. SVGDocument	<pre>color(java.util.Map dataForColoring, int index, java.lang. String titleString, double dMax, double dMin, double dMid, java.lang. String corrID) Colors the svg document based on values in at a specific index in the data list</pre>	
org.w3c. dom.svg. SVGDocument	<pre>colorByCorrelation()</pre>	
org.w3c. dom.svg. SVGDocument	<pre>colorBySample(int sampleIndex)</pre>	
boolean	generateCorrelationData()	

java.lang. String	getCorrelationID()
double	getDataMax()
double	getDataMin()
org.w3c. dom.svg. SVGDocument	getDocument()
boolean	<u>isTweaked</u> ()
static void	<pre>main(java.lang.String[] args) This method allows for testing the class on the command line.</pre>
void	<pre>readDataFile(java.io.File datafile, java.io.File annotFile, java.lang. String annotType, boolean logValues, double maxPercentile, java.lang. String dupmethod, boolean calcRatios, double missingValueThreshold, double percAllowedMissing) Reads in a datafile that will be used in generating colored images.</pre>
boolean	<pre>setCorrelationID(java.lang.String id)</pre>
void	<pre>setDocument(java.lang.String uri)</pre>
void	<pre>tweak(java.lang.String hreftag) Takes the svg file output by dot and separates the rectangles.</pre>
static void	<pre>writeSVGFile(org.w3c.dom.svg.SVGDocument doc, java.lang.String filename) Writes out the SVG document.</pre>

Methods inherited from class java.lang.Object

clone, equals, finalize, getClass, hashCode, notify, notifyAll, toString, wait, wait, wait

Constructor Detail

PathwaySVG

public PathwaySVG()

PathwaySVG

Parameters:

uri - the svg document URI

Throws:

java.io.IOException

PathwaySVG

```
public PathwaySVG(java.lang.String uri,
    java.io.File datafile,
    java.io.File annotFile,
    java.lang.String annotType,
    boolean logValues,
    double percentile,
    java.lang.String dupmethod,
    boolean calcRatios,
    double missingValueThreshold,
    double percAllowedMissing)
    throws java.io.FileNotFoundException,
    java.io.IOException
```

Creates a new PathwaySVG object with the specified SVG file and dataset. The data is contained a datafile (with genes in rows and samples in columns). Gene identifiers must be located in the first column. Missing data in the file is identified using the empty string or "NA". Gene annotations are in a corresponding annotation file, which also contains identifiers in the first column. The annotation type and list of samples further describe the data set.

Parameters:

uri - the svg document URI
datafile - the data file
annotFile - the data file
annotType - the annotation type that corresponds to the annotation type in the svg document hrefs.
logValues - true if the datafile contains log values, false otherwise
percentile - the percentile of the max/min threshold at which color is most intense
dupmethod - method used to resolve duplicates
calcRatios - if true, the values in the file need to have ratios calculated
missingValueThreshold - the minimum threshold for valid data values
percAllowedMissing - the percent of data values allowed to be missing for the gene to be represented
Throws:
FileNotFoundException
java.io.IOException

Method Detail

calculateColor

protected double calculateColor(double value)

calculateColor

protected double **calculateColor**(double value, double dMax, double dMax,

color

Colors the svg document based on values in at a specific index in the data list

Parameters:

dataForColoring - dataset index - index of sample color titleString - title of the svg plot dMax - data maximum dMin - data minimum dMid - data midpoint corrID - ID of correlation gene

colorByCorrelation

public org.w3c.dom.svg.SVGDocument colorByCorrelation()

colorBySample

public org.w3c.dom.svg.SVGDocument colorBySample(int sampleIndex)

generateCorrelationData

public boolean generateCorrelationData()

getCorrelationID

public java.lang.String getCorrelationID()

getDataMax

public double getDataMax()

getDataMin

public double getDataMin()

getDocument

public org.w3c.dom.svg.SVGDocument getDocument()

isTweaked

public boolean isTweaked()

main

This method allows for testing the class on the command line. args to pass in: svgfilename, datafilename, annotfilename,

Throws:

java.lang.Exception

readDataFile

```
throws java.io.FileNotFoundException, java.io.IOException
```

Reads in a datafile that will be used in generating colored images.

Parameters:

```
datafile - the File to import.
annotFile - the File containing gene annotations of the data
annotType - which annotation in the annotation file corresponds the gene annotation in the SVG file
logValues - true if the datafile contains log values, false otherwise
maxPercentile - the data percentile at which the color is most intense
dupmethod - method used to resolve duplicates
calcRatios - if true, the values in the file need to have ratios calculated
missingValueThreshold - the minimum threshold for valid data values
percAllowedMissing - the percent of data values allowed to be missing for the gene to be represented
Throws:
java.io.FileNotFoundException - if the file cannot be found
java.io.IOException - if the file cannot be read
```

setCorrelationID

public boolean setCorrelationID(java.lang.String id)

setDocument

Throws:

java.io.IOException

tweak

public void tweak(java.lang.String hreftag)

Takes the svg file output by dot and separates the rectangles.

Parameters:

hreftag - The portion of the hreftag that starts the gene id section.

writeSVGFile

public static void writeSVGFile(org.w3c.dom.svg.SVGDocument doc,

java.lang.String filename)
throws javax.xml.transform.TransformerConfigurationException,
 javax.xml.transform.TransformerException

Writes out the SVG document.

Parameters:

filename - the name of the output file

Throws:

javax.xml.transform.TransformerConfigurationException
javax.xml.transform.TransformerException

edu.ucsf.qpaca.pathway Class PathwayUtil

java.lang.Object

edu.ucsf.qpaca.pathway.PathwayUtil

public class PathwayUtil

extends java.lang.Object

Static utility methods for manipulating data values.

Constructor Summary

PathwayUtil()

Method Summary	
static java. lang.Object	arrayExpand(java.lang.Object a, int newLength) Resizes an array.
static java. util.List	indexOfNA(double[] values)Determines the index of all "NaN" values in an array of doubles.
static java. lang.String	joinDoubleArray(double[] tojoin, java.lang.String token) Join the values in an array of values into a string with the specified separator token.
static double	mean(double[] values) Determines the mean of the values in a double array.
static double	<pre>pearsons(double[] data1, double[] data2, int n) Calculates the pearson's correlation coefficient between two arrays data values of the length: data1 and data2 derived from "Numerical Recipes in C", pg 638-639</pre>
static double	randomizedSelect(double[] array, int begin, int end,int k)Selects the kth largest element from an array.

static double []	<pre>removeIndices(double[] values, java.util.Set indices) Removes the specified set of indices from an array of doubles.</pre>
static double []	removeNA(double[] values) removes the NaN values from an array of doubles.
static java.	removeNA(java.util.List values)
util.List	removes the NaN values from an List
static java.	removeNA(java.lang.String[] values)
lang.String[]	removes the null values from an array of Strings.

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll,
toString, wait, wait, wait
```

Constructor Detail

PathwayUtil

```
public PathwayUtil()
```

Method Detail

arrayExpand

Resizes an array.

Parameters:

a - the array to resize newLength - the length of the new array (if newLength < a.length, newLength is set to length+length/2).

Returns:

the new array or null if a was not an array.

indexOfNA

```
public static java.util.List indexOfNA(double[] values)
```

Determines the index of all "NaN" values in an array of doubles.

Parameters: values - the array Returns: a List of indices in the array

joinDoubleArray

Join the values in an array of values into a string with the specified separator token.

Parameters:

tojoin - the array token - the string separator **Returns:** the resulting string representation of the array

mean

public static double mean(double[] values)

Determines the mean of the values in a double array. If there are NaN values in the array, they are removed first and the mean is calculated without them.

Parameters:

values - an array of doubles Returns: the mean of the values

pearsons

public static double pearsons(double[] data1,

double[] data2, int n)

Calculates the pearson's correlation coefficient between two arrays data values of the length: data1 and data2 derived from "Numerical Recipes in C", pg 638-639

Parameters:

data1 - an array data2 - a second array n - the length of the two arrays **Returns:**

the pearson's correlation coefficient

randomizedSelect

Selects the kth largest element from an array. To calculate the median, set k=(end-begin)/2

Parameters:

array - the array to search begin - index of the first element in the array end - index of the last element in the array k - the index to select

Throws:

java.lang.IllegalArgumentException

removeIndices

Removes the specified set of indices from an array of doubles.

Parameters: values - the array indices - the indicies in the array to remove Returns:
the modified array

removeNA

public static double[] removeNA(double[] values)

removes the NaN values from an array of doubles.

Parameters:

values - the array to process
Returns:
the new double array

removeNA

public static java.util.List removeNA(java.util.List values)

removes the NaN values from an List
Parameters:
values - the List to process
Returns:
the new List

removeNA

public static java.lang.String[] removeNA(java.lang.String[] values)

removes the null values from an array of Strings.

Parameters:

values - the array to process
Returns:
the new String array

edu.ucsf.qpaca.pathway Class PathwayVertex

java.lang.Object

L salvo.jesus.graph.VertexImpl

edu.ucsf.qpaca.pathway.PathwayVertex

All Implemented Interfaces:

<u>PathwayComponent</u>, java.io.Serializable, java.lang.Comparable, salvo.jesus.graph. GraphComponent, salvo.jesus.graph.LabeledGraphComponent, salvo.jesus.graph.Vertex

public class PathwayVertex

extends salvo.jesus.graph.VertexImpl implements PathwayComponent, java.lang.Comparable, java.io.Serializable

A vertex in a pathway. This class encapsulates an object that the vertex will represent. Hence, a PathwayVertex can represent any object that extends java.lang.Object by simply calling setObject() or specifying the object in the constructor.

See Also:

Serialized Form

Field Summary	
protected java. util. HashMap	attributes

Fields inherited from class salvo.jesus.graph.VertexImpl

object

Constructor Summary

PathwayVertex()

Creates an empty PathwayVertex

PathwayVertex(java.lang.Object newobject)

Creates a new PathwayVertex that contains a specified object.

PathwayVertex(java.lang.Object newobject, java.lang.String newType) Creates a new PathwayVertex object that contains a specific object with a specific type.

PathwayVertex(java.lang.Object newobject, java.lang.String newType, java.util.Map newAttributes)

Creates a new PathwayVertex object that contains a specific object with a specific type and attributes.

PathwayVertex(java.lang.Object newobject, java.lang.String newType, java.util.Map newAttributes, java.lang.String newID)

Creates a new PathwayVertex object that contains a specific object with a specific type, attributes, and id.

PathwayVertex(java.lang.Object newobject, java.lang.String newType, java.lang.String newID)

Creates a new PathwayVertex object that contains a specific object with a specific type and id.

<u>PathwayVertex</u>(java.lang.String newType)

Creates an empty PathwayVertex with the specified type.

PathwayVertex(java.lang.String newType, java.lang.String newID) Creates an empty PathwayVertex with the specified type and id.

Method Summary	
int	compareTo(java.lang.Object o) Compares this PathwayVertex to another Object.
java. lang. Object	getAttribute (java.lang.String type) Returns the attribute mapped to the specified attribute type.
java. util.Map	getAttributes() Returns the attributes of this Vertex.
java. util.Set	getElements () Retrieves a List of all PathwayElements within this Vertex
java. lang. String	getID() Returns the ID of this PathwayComponent.
java. lang. String	getType() Returns the type of this PathwayVertex.
boolean	hasAttribute(java.lang.String type) Tests to see if this PathwayComponent has this type of attribute.

boolean	hasObject() Tests to see if this PathwayVertex contains an object.
boolean	hasType () Tests to see if this PathwayVertex has a type.
java. lang. Object	removeAttribute(java.lang.String key) Removes the specified attribute.
void	setAttribute (java.lang.String key, java.lang.Object value) Creates a new attribute.
java. lang. String	toString() Creates a string representation of this PathwayVertex: id:type:object

```
Methods inherited from class salvo.jesus.graph.VertexImpl
```

getLabel, getObject, hasLabel, setLabel, setObject

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll, wait,
wait, wait
```

Field Detail

attributes

protected java.util.HashMap attributes

Constructor Detail

PathwayVertex

public PathwayVertex()

Creates an empty PathwayVertex

PathwayVertex

public PathwayVertex(java.lang.Object newobject)

Creates a new PathwayVertex that contains a specified object.

Parameters: newobject -

PathwayVertex

Creates a new PathwayVertex object that contains a specific object with a specific type.

Parameters:

newobject - the object that the PathwayVertex will encapsulate newType - the new type

PathwayVertex

Creates a new PathwayVertex object that contains a specific object with a specific type and attributes.

Parameters:

newobject - the object that the PathwayVertex will encapsulate newType - the new type

PathwayVertex

Creates a new PathwayVertex object that contains a specific object with a specific type, attributes, and id.

Parameters:

newobject - the object that the PathwayVertex will encapsulate newType - the new type

PathwayVertex

Creates a new PathwayVertex object that contains a specific object with a specific type and id.

Parameters:

newobject - the object that the PathwayVertex will encapsulate newType - the new type

PathwayVertex

public PathwayVertex(java.lang.String newType)

Creates an empty PathwayVertex with the specified type.

Parameters:

newType - this vertex's type

PathwayVertex

Creates an empty PathwayVertex with the specified type and id.

Parameters:

newType - this vertex's type newID - this vertex's id

Method Detail

compareTo

```
public int compareTo(java.lang.Object o)
```

Compares this PathwayVertex to another Object. If the Object is another PathwayVertex, returns 0 if the corresponding Assemblies and types are equivalent.

Specified by: compareTo in interface java.lang.Comparable Parameters: o - the object to be tested. Returns: 0 if the argument is an equivalent PathwayVertex, 1 otherwise Throws: java.lang.ClassCastException - if the argument is not a valid PathwayVertex

getAttribute

public java.lang.Object getAttribute(java.lang.String type)

Returns the attribute mapped to the specified attribute type.

Specified by:

getAttribute in interface PathwayComponent

Parameters:

type - the attribute type

Returns:

the attribute specified by the type

getAttributes

public java.util.Map getAttributes()

Returns the attributes of this Vertex.

Specified by: getAttributes in interface PathwayComponent Returns: the attributes

getElements

public java.util.Set getElements()

Retrieves a List of all PathwayElements within this Vertex

Returns:

a List of PathwayElements

getID

public java.lang.String getID()

Returns the ID of this PathwayComponent.

Specified by:

getID in interface PathwayComponent
Returns:
the ID

getType

public java.lang.String getType()

Returns the type of this PathwayVertex.

Returns:

a String representing the type.

hasAttribute

```
public boolean hasAttribute(java.lang.String type)
```

Tests to see if this PathwayComponent has this type of attribute.

Specified by: <u>hasAttribute</u> in interface <u>PathwayComponent</u> Parameters: type - the attribute type Returns: true if this type of attribute exists;

hasObject

public boolean hasObject()

Tests to see if this PathwayVertex contains an object.

Returns:

true if the object exists;

hasType

public boolean hasType()

Tests to see if this PathwayVertex has a type.

Returns:

true if it has a type.

removeAttribute

public java.lang.Object removeAttribute(java.lang.String key)

Removes the specified attribute.

Specified by:

removeAttribute in interface PathwayComponent

Parameters:

key - the attribute type

setAttribute

Creates a new attribute.

Specified by:

setAttribute in interface PathwayComponent

Parameters:

key - the attribute type value - the attribute

toString

public java.lang.String toString()

Creates a string representation of this PathwayVertex: id:type:object

Overrides:

toString in class salvo.jesus.graph.VertexImpl Returns: String representation

edu.ucsf.qpaca.pathway.algorithm Class PathwayMinimumSpanningTree

java.lang.Object

edu.ucsf.qpaca.pathway.algorithm.PathwayMinimumSpanningTree

All Implemented Interfaces: java.io.Serializable

public class PathwayMinimumSpanningTree

extends java.lang.Object implements java.io.Serializable

A concrete implementation of the minimum spanning tree algorithm using Kruskal's method specifically geared to Pathway objects.

See Also:

Serialized Form

Constructor Summary

PathwayMinimumSpanningTree(Pathway path)

Creates an instance of PathwayMinimumSpanningTree

Method Summary		
salvo.jesus. graph. WeightedGraph	minimumSpanningTree() Determine the minimum spanning tree of a pathway using Kruskal's method.	

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll,
toString, wait, wait, wait
```

Constructor Detail

PathwayMinimumSpanningTree

public PathwayMinimumSpanningTree(Pathway path)

Creates an instance of PathwayMinimumSpanningTree

Parameters:

path - The Pathway where the minimum spanning tree will be determined.

Method Detail

minimumSpanningTree

public salvo.jesus.graph.WeightedGraph minimumSpanningTree()

Determine the minimum spanning tree of a pathway using Kruskal's method.

edu.ucsf.qpaca.pathway.algorithm Class ShortestPathAlgorithm

java.lang.Object

edu.ucsf.qpaca.pathway.algorithm.ShortestPathAlgorithm

All Implemented Interfaces: java.io.Serializable

Direct Known Subclasses: ShortestPathDijkstraAlgorithm

public abstract class ShortestPathAlgorithm

extends java.lang.Object implements java.io.Serializable

Abstract class for implementing the shortest path algorithm. Concrete subclasses must never modify the graph when it is computing the shortestpath.

See Also:

Serialized Form

Constructor Summary

ShortestPathAlgorithm(Pathway path)

Method Summary

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll, toString, wait, wait,
wait
```

Constructor Detail

ShortestPathAlgorithm

public ShortestPathAlgorithm(Pathway path)

Method Detail

shortestPath

public abstract salvo.jesus.graph.WeightedGraph shortestPath(salvo.jesus.graph.Vertex from)

Abstract method to be implemented by subclasses to determine a shortest path spanning tree from a given vertex in the form of a graph.

Returns:

A new Pathway that represents the shortest path spanning tree of the original Pathway. **Do not** modify the contents of the returned Pathway.

edu.ucsf.qpaca.pathway.algorithm Class ShortestPathDijkstraAlgorithm

java.lang.Object

edu.ucsf.qpaca.pathway.algorithm.ShortestPathAlgorithm

edu.ucsf.qpaca.pathway.algorithm.ShortestPathDijkstraAlgorithm

All Implemented Interfaces: java.io.Serializable

public class ShortestPathDijkstraAlgorithm

extends ShortestPathAlgorithm

A concrete implementation of ShortestPathAlgorithm using Dijkstra's method.

See Also:

Serialized Form

Constructor Summary

ShortestPathDijkstraAlgorithm(Pathway path, salvo.jesus.util.

HeapNodeComparator comparator)

Creates an instance of ShortestPathDijkstraAlgorithm.

Method Summary

salvo.jesus.shortestPath(salvo.jesus.graph.Vertex from)graph.Determines the shortest path from a given vertex to all other vertices that are in the same
connected set as the given vertex in the weighted graph using Dijkstra's algorithm.

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll, toString, wait,
wait, wait
```

Constructor Detail

ShortestPathDijkstraAlgorithm

public ShortestPathDijkstraAlgorithm(Pathway path,

salvo.jesus.util.HeapNodeComparator comparator)

Creates an instance of ShortestPathDijkstraAlgorithm.

Parameters:

path - The Pathway where a shortest path spanning tree will be determined. comparator - The HeapNodeComparator to be used to compare priorities of objects in the fringe/heap.

Method Detail

shortestPath

public salvo.jesus.graph.WeightedGraph shortestPath(salvo.jesus.graph.Vertex from)

Determines the shortest path from a given vertex to all other vertices that are in the same connected set as the given vertex in the weighted graph using Dijkstra's algorithm.

Specified by:

shortestPath in class ShortestPathAlgorithm

Parameters:

from - The Vertex from where we want to obtain the shortest path to all other vertices.

Returns:

A Pathway comprising of the shortest path spanning tree.

edu.ucsf.qpaca.parser Class MapBioPAXtoQPACA

java.lang.Object

edu.ucsf.qpaca.parser.MapBioPAXtoQPACA

public class MapBioPAXtoQPACA

extends java.lang.Object

Maps between BioPAX keywords and QPACA keywords.

Field Summary	
static java.	BIOPAX_EDGE_TYPE_ATTRIBUTE
lang.String	Pathway Attribute: BioPAX Edge Type.
static java.	BIOPAX_ID_ATTRIBUTE
lang.String	Pathway Attribute: BioPAX ID.
static java.	BIOPAX_NAME_ATTRIBUTE
lang.String	Pathway Attribute: BioPAX Name.
static java.	BIOPAX_NODE_TYPE_ATTRIBUTE
lang.String	Pathway Attribute: BioPAX Node Type.
static java.	COFACTOR
lang.String	Pathway Edge Attribute: COFACTOR
static java.	CONTAINS
lang.String	Pathway Edge Attribute: CONTAINS
static java.	CONTROLLED
lang.String	Pathway Edge Attribute: CONTROLLED
static java. lang.String	CONTROLLER Pathway Edge Attribute: CONTROLLER
static java. lang.String	Pathway Edge Attribute: LEFT

static java.	PARTICIPANT
lang.String	Pathway Edge Attribute: PARTICIPANT
static java. lang.String	RIGHT Pathway Edge Attribute: RIGHT

Constructor Summary

MapBioPAXtoQPACA (BioPaxUtil bpUtil, Pathway path) Initializes the mapping.

Method Summary

void	doMapping() Executes the Mapping.
java. util. ArrayList	getWarningList () Retrieves a list of all exceptions and warnings encountered during execution.

Methods inherited from class java.lang.Object

clone, equals, finalize, getClass, hashCode, notify, notifyAll, toString, wait, wait, wait

Field Detail

BIOPAX_EDGE_TYPE_ATTRIBUTE

public static final java.lang.String BIOPAX_EDGE_TYPE_ATTRIBUTE

Pathway Attribute: BioPAX Edge Type.

See Also:

Constant Field Values

BIOPAX_ID_ATTRIBUTE

public static final java.lang.String BIOPAX_ID_ATTRIBUTE

Pathway Attribute: BioPAX ID.

See Also:

Constant Field Values

BIOPAX_NAME_ATTRIBUTE

public static final java.lang.String BIOPAX_NAME_ATTRIBUTE

Pathway Attribute: BioPAX Name.

See Also:

Constant Field Values

BIOPAX_NODE_TYPE_ATTRIBUTE

public static final java.lang.String BIOPAX_NODE_TYPE_ATTRIBUTE

Pathway Attribute: BioPAX Node Type.

See Also: Constant Field Values

COFACTOR

public static final java.lang.String COFACTOR

Pathway Edge Attribute: COFACTOR

See Also:

Constant Field Values

CONTAINS

public static final java.lang.String CONTAINS

Pathway Edge Attribute: CONTAINS

See Also: Constant Field Values

CONTROLLED

public static final java.lang.String CONTROLLED

Pathway Edge Attribute: CONTROLLED

See Also: Constant Field Values

CONTROLLER

public static final java.lang.String CONTROLLER

Pathway Edge Attribute: CONTROLLER

See Also: Constant Field Values

LEFT

public static final java.lang.String LEFT

Pathway Edge Attribute: LEFT

See Also:

Constant Field Values

PARTICIPANT

public static final java.lang.String **PARTICIPANT**

Pathway Edge Attribute: PARTICIPANT

See Also: Constant Field Values

RIGHT

public static final java.lang.String **RIGHT**

Pathway Edge Attribute: RIGHT

See Also:

Constant Field Values

Constructor Detail

MapBioPAXtoQPACA

Initializes the mapping.

Parameters:

bpUtil - BioPAX Utility Class path - Pathway Object

Method Detail

doMapping

public void doMapping()

throws org.jdom.JDOMException, java.lang.Exception

Executes the Mapping.

Throws:

org.jdom.JDOMException - Error Parsing XML via JDOM. java.lang.Exception

getWarningList

public java.util.ArrayList getWarningList()

Retrieves a list of all exceptions and warnings encountered during execution.

Returns:

ArrayList of String Objects.

edu.ucsf.qpaca.parser Class MapKGMLtoQPACA

java.lang.Object

edu.ucsf.qpaca.parser.MapKGMLtoQPACA

public class MapKGMLtoQPACA

extends java.lang.Object

Maps between KEGG KGML keywords and QPACA keywords.

Constructor Summary

MapKGMLtoQPACA(KGMLUtil kgmlUtil, Pathway path) Initializes the mapping.

Method Summary

void	doMapping() Executes the Mapping.
java. util. ArrayList	getWarningList () Retrieves a list of all exceptions and warnings encountered during execution.

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll,
toString, wait, wait, wait
```

Constructor Detail

MapKGMLtoQPACA

Initializes the mapping.

Parameters:

kgmlUtil - KGML Utility Class. path - Pathway Object.

Method Detail

doMapping

Executes the Mapping.

Throws:

org.jdom.JDOMException - Error Parsing XML via JDOM. java.lang.Exception

getWarningList

public java.util.ArrayList getWarningList()

Retrieves a list of all exceptions and warnings encountered during execution.

Returns:

ArrayList of String Objects.

edu.ucsf.qpaca.parser Class ParseQPACALanguage

java.lang.Object

edu.ucsf.qpaca.parser.ParseQPACALanguage

public class ParseQPACALanguage

extends java.lang.Object

Creates QPACA pathways from files written in the QPACA Pathway language.

Constructor Summary

ParseQPACALanguage(java.io.Reader reader) Initializes the parser.

Method Summary

J	
Pathway	getPathway()
	Retrieves the Pathway.
java. lang. String	getPathwayID() Retrieves the pathway name.
java. lang. String	getPathwayLabel() Retrieves the pathway label.

Methods inherited from class java.lang.Object clone, equals, finalize, getClass, hashCode, notify, notifyAll, toString, wait, wait, wait

Constructor Detail

ParseQPACALanguage

Initializes the parser.

```
Parameters:
reader - Reader Object.
Throws:
java.io.IOException - Input/Output Error.
java.lang.Exception
```

Method Detail

getPathway

```
public <u>Pathway</u> getPathway()
```

Retrieves the Pathway.

Returns: Pathway

getPathwayID

public java.lang.String getPathwayID()

Retrieves the pathway name.

Returns: pathway name

getPathwayLabel

public java.lang.String getPathwayLabel()

Retrieves the pathway label.

Returns: pathway label

edu.ucsf.qpaca.parser Class PathwayToDot

java.lang.Object

edu.ucsf.qpaca.parser.PathwayToDot

public class PathwayToDot

extends java.lang.Object

Translates Pathways into GraphViz .dot files.

Constructor Summary

PathwayToDot()

Default Constructor

Method Summary	
void	<pre>createDotFile(Pathway path, java.lang.String fileName, java. lang.String linkID, java.lang.String linkBase) Creates a GraphViz.dot file.</pre>
protected java. util.List	<pre>writeAssemblies(java.util.Set assemblies, java.io. FileWriter out, java.lang.String linkID, java.lang. String linkBase) Writes out QPACA PathwayAssemblies, delegating the task to writeElement or writeRecord as necessary.</pre>
protected void	<pre>writeAttributes(java.util.Map atts, java.io.FileWriter out) Writes out label or name attributes.</pre>
protected void	writeHeader(java.io.FileWriter out) Writes out the header of the GraphViz file.

protected java. util.List	<pre>writeNodes(java.util.Set vertices, Pathway path, java.io. FileWriter out, java.lang.String linkID, java.lang. String linkBase) Writes out QPACA PathwayVertices, specifically handles the those of the QPACAConstants.EVENT type, delegating the task of writing out the other Vertices to writeAssemblies after extracting lists of PathwayAssemblies.</pre>
protected void	<pre>writeRecord(PathwayAssembly a, java.io.FileWriter out, java. lang.String linkID, java.lang.String linkBase) Writes out a GraphViz Record, which represents a collection of PathwayElements found at the same node (stored as a PathwayAssembly of type QPACAConstants.ALIAS or QPACAConstants.FAMILY).</pre>

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll,
toString, wait, wait, wait
```

Constructor Detail

PathwayToDot

```
public PathwayToDot()
```

Default Constructor

Method Detail

createDotFile

```
public void createDotFile(Pathway path,
```

java.lang.String fileName, java.lang.String linkID, java.lang.String linkBase)

Creates a GraphViz .dot file.

Parameters:

path - the pathway to output fileName - the output file linkID - attribute from which to create link linkBase - base of href link string

writeAssemblies

Writes out QPACA PathwayAssemblies, delegating the task to writeElement or writeRecord as necessary.

Parameters:

assemblies - all of the PathwayAssemblies out - the output FileWriter linkID - id of the element in the database link linkBase - the base URL of the database link

Throws:

java.io.IOException - if the file cannot be accessed.

writeAttributes

Writes out label or name attributes. Attributes for all PathwayComponents are handled the same way.

Parameters:

out - the output FileWriter atts - the attributes

Throws:

java.io.IOException - if the file cannot be accessed.

writeHeader

Writes out the header of the GraphViz file.

Parameters:

out - the output FileWriter

Throws:

java.io.IOException - if the file cannot be accessed.

writeNodes

Writes out QPACA PathwayVertices, specifically handles the those of the QPACAConstants. EVENT type, delegating the task of writing out the other Vertices to writeAssemblies after extracting lists of PathwayAssemblies.

Parameters:

vertices - all of the PathwayVertices
path - the pathway
out - the output FileWriter
linkID - id of the element in the database link
linkBase - the base URL of the database link
Throws:

java.io.IOException - if the file cannot be accessed.

writeRecord

Writes out a GraphViz Record, which represents a collection of PathwayElements found at the same node (stored as a PathwayAssembly of type QPACAConstants.ALIAS or QPACAConstants.FAMILY).

Parameters:

a - the PathwayAssembly out - the output FileWriter linkID - id of the element in the database link linkBase - the base URL of the database link

Throws:

java.io.IOException - if the file cannot be accessed.

edu.ucsf.qpaca.parser Class TestBioPaxUtil

java.lang.Object

__ junit.framework.Assert __ junit.framework.TestCase __ edu.ucsf.qpaca.parser.TestBioPaxUtil

All Implemented Interfaces: junit.framework.Test

public class TestBioPaxUtil

extends junit.framework.TestCase

Tests the BioPaxUtil Class.

Constructor Summary

TestBioPaxUtil()

Method Summary

void testUtil() Tests the BioPAX Utility Class using a sample biopax file located at sampleData/ biopax_sample1.owl

Methods inherited from class junit.framework.TestCase

```
countTestCases, createResult, getName, run, run, runBare, runTest,
setName, setUp, tearDown, toString
```

Methods inherited from class junit.framework.Assert

```
assertEquals, assertFalse, assertFalse, assertNotNull, assertNotNull, assertNotSame, assertTrue, assertTrue, fail, fail
```

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll, wait,
wait, wait
```

Constructor Detail

TestBioPaxUtil

public TestBioPaxUtil()

Method Detail

testUtil

Tests the BioPAX Utility Class using a sample biopax file located at sampleData/ biopax_sample1.owl

Throws:

java.lang.Exception - All Exceptions.

edu.ucsf.qpaca.parser Class TestKGMLParsing

java.lang.Object

L junit.framework.Assert L junit.framework.TestCase L edu.ucsf.qpaca.parser.TestKGMLParsing

All Implemented Interfaces: junit.framework.Test

public class TestKGMLParsing

extends junit.framework.TestCase

Tests the KGML-QPACA mapper.

Constructor Summary

TestKGMLParsing()

Method Summary

void testMapper1() Tests the KGML mapper using a sample KGML file located at sampleData/hsa00062. xml

Methods inherited from class junit.framework.TestCase

```
countTestCases, createResult, getName, run, run, runBare, runTest,
setName, setUp, tearDown, toString
```

Methods inherited from class junit.framework.Assert

```
assertEquals, assertFalse, assertFalse, assertNotNull, assertNotNull, assertNotSame, assertTrue, assertTrue, fail, fail
```

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll, wait,
wait, wait
```

Constructor Detail

TestKGMLParsing

public TestKGMLParsing()

Method Detail

testMapper1

Tests the KGML mapper using a sample KGML file located at sampleData/hsa00062.xml

Throws:

java.lang.Exception
edu.ucsf.qpaca.parser Class TestKGMLUtil

java.lang.Object

L junit.framework.Assert L junit.framework.TestCase L edu.ucsf.qpaca.parser.TestKGMLUtil

All Implemented Interfaces: junit.framework.Test

public class TestKGMLUtil

extends junit.framework.TestCase

Tests the KGMLUtil Class.

Constructor Summary

TestKGMLUtil()

Method Summary

void testUtil() Tests the KGML Utility Class using a sample KGML file located at sampleData/ hsa00190.xml

Methods inherited from class junit.framework.TestCase

```
countTestCases, createResult, getName, run, run, runBare, runTest,
setName, setUp, tearDown, toString
```

Methods inherited from class junit.framework.Assert

```
assertEquals, assertFalse, assertFalse, assertNotNull, assertNotNull, assertNotSame, assertTrue, assertTrue, fail, fail
```

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll, wait,
wait, wait
```

Constructor Detail

TestKGMLUtil

public TestKGMLUtil()

Method Detail

testUtil

Tests the KGML Utility Class using a sample KGML file located at sampleData/hsa00190.xml

Throws:

java.lang.Exception - All Exceptions.

edu.ucsf.qpaca.parser Class TestParsing

java.lang.Object

L junit.framework.Assert L junit.framework.TestCase L edu.ucsf.qpaca.parser.TestParsing

All Implemented Interfaces: junit.framework.Test

public class TestParsing

extends junit.framework.TestCase

Tests the BioPAX-QPACA mapper.

Constructor Summary

TestParsing()

Method Summary

void	testComplexMapping() Tests that we can map BioPAX Complexes Correctly.
void	testMapper1()
	Tests the Mapper on a valid BioPAX file located at sampleData/biopax_sample1.owl

Methods inherited from class junit.framework.TestCase

```
countTestCases, createResult, getName, run, run, runBare, runTest,
setName, setUp, tearDown, toString
```

Methods inherited from class junit.framework.Assert

```
assertEquals, assertFalse, assertFalse, assertNotNull, assertNotNull, assertNotSame, assertNotSame, assertTrue, fail, fail
```

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll, wait,
wait, wait
```

Constructor Detail

TestParsing

```
public TestParsing()
```

Method Detail

testComplexMapping

Tests that we can map BioPAX Complexes Correctly.

Throws:

java.lang.Exception - All Exceptions.

testMapper1

Tests the Mapper on a valid BioPAX file located at sampleData/biopax_sample1.owl

Throws:

java.lang.Exception - All Exceptions.

edu.ucsf.qpaca.parser Class TestPathLang

java.lang.Object

L junit.framework.Assert L junit.framework.TestCase L edu.ucsf.qpaca.parser.TestPathLang

All Implemented Interfaces: junit.framework.Test

public class TestPathLang

extends junit.framework.TestCase

Tests the QPACA language parser.

Constructor Summary

TestPathLang()

Method Summary

void testUtil() Tests the QPACA language parser using a valid QPACA file located at sampleData/ RTK.current.qpaca

Methods inherited from class junit.framework.TestCase

countTestCases, createResult, getName, run, run, runBare, runTest, setName, setUp, tearDown, toString

Methods inherited from class junit.framework.Assert

```
assertEquals, assertFalse, assertFalse, assertNotNull, assertNotNull, assertNotSame, assertTrue, assertTrue, fail, fail
```

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll, wait,
wait, wait
```

Constructor Detail

TestPathLang

public TestPathLang()

Method Detail

testUtil

Tests the QPACA language parser using a valid QPACA file located at sampleData/RTK.current. qpaca

Throws:

java.lang.Exception - All Exceptions.

edu.ucsf.qpaca.parser.util Class BioPaxConstants

java.lang.Object

L_edu.ucsf.qpaca.parser.util.BioPaxConstants

public class BioPaxConstants

extends java.lang.Object

BioPAX Constants.

Field Summary		
static java.	BIOCHEMICAL_REACTION	
lang.String	BioPAX Class: biochemicalReaction	
static org. jdom. Namespace	BIOPAX_LEVEL_1_NAMESPACE BioPAX Level 1 Namespace.	
static java.	BIOPAX_LEVEL_1_NAMESPACE_URI	
lang.String	BioPAX Level 1 Namespace URI.	
static org. jdom. Namespace	BIOPAX_LEVEL_2_NAMESPACE BioPAX Level 2 Namespace.	
static java.	BIOPAX_LEVEL_2_NAMESPACE_URI	
lang.String	BioPAX Level 2 Namespace URI.	
static java.	BIOPAX NAMESPACE PREFIX	
lang.String	BioPAX Namespace Prefix.	
static java.	CATALYSIS	
lang.String	BioPAX Class: catalysis	
static java.	COMPLEX	
lang.String	BioPAX Class: complex.	
static java. lang.String	COMPLEX_ASSEMBLY BioPAX Class: complexAssembly	
Namespace static java. lang.String static org. jdom. Namespace static java. lang.String static java. lang.String static java. lang.String static java. lang.String static java. lang.String	BIOPAX LEVEL 1 NAMESPACE URI BioPAX Level 1 Namespace URI. BIOPAX LEVEL 2 NAMESPACE BioPAX Level 2 Namespace. BIOPAX LEVEL 2 NAMESPACE URI BioPAX Level 2 Namespace URI. BIOPAX NAMESPACE PREFIX BioPAX Namespace Prefix. CATALYSIS BioPAX Class: catalysis COMPLEX BioPAX Class: complex.	

static java.	CONTROL
lang.String	BioPAX Class: control
static java.	CONTROL_TYPE_ACTIVATION
lang.String	Control Type: ACTIVATION
static java.	CONTROL_TYPE_ACTIVATION_ALLOSTERIC
lang.String	Control Type: ACTIVATION-ALLOSTERIC
static java.	CONTROL TYPE ACTIVATION NONALLOSTERIC
lang.String	Control Type: ACTIVATION-NONALLOSTERIC
static java. lang.String	CONTROL_TYPE_ACTIVATION_UNKMECH Control Type: ACTIVATION-UNKMECH
static java.	CONTROL_TYPE_INHIBITION
lang.String	Control Type: INHIBITION
static java.	CONTROL_TYPE_INHIBITION_ALLOSTERIC
lang.String	Control Type: INHIBITION-ALLOSTERIC
static java.	CONTROL_TYPE_INHIBITION_COMPETITIVE
lang.String	Control Type: INHIBITION-COMPETITIVE
static java.	CONTROL_TYPE_INHIBITION_IRREVERSIBLE
lang.String	Control Type: INHIBITION-IRREVERSIBLE
static java.	CONTROL_TYPE_INHIBITION_NONCOMPETITIVE
lang.String	Conrol Type: INHIBITION-NONCOMPETITIVE
static java.	CONTROL_TYPE_INHIBITION_OTHER
lang.String	Control Type: INHIBITION-OTHER
static java.	CONTROL_TYPE_INHIBITION_UNCOMPETITIVE
lang.String	Control Type: INHIBITION-UNCOMPETITIVE
static java.	CONTROL_TYPE_INHIBITION_UNKMECH
lang.String	Control Type: INHIBITION-UNKMECH
static java.	CONVERSION
lang.String	BioPAX Class: conversion
static java.	DNA
lang.String	BioPAX Class: dna
static java. lang.String	INTERACTION BioPAX Class: interaction.
static java.	MODULATION
lang.String	BioPAX Class: modulation
static java.	PATHWAY
lang.String	BioPAX Class: pathway
static java.	PHYSICAL ENTITY
lang.String	BioPAX Class: physicalEntity.

static java.	PHYSICAL_INTERACTION
lang.String	BioPAX Class: physicalInteraction.
static java.	PROTEIN
lang.String	BioPAX Class: protein
static java.	RNA
lang.String	BioPAX Class: rna
static java.	SMALL_MOLECULE
lang.String	BioPAX Class: smallMolecule.
static java.	TRANSPORT
lang.String	BioPAX Class: transport
static java. lang.String	TRANSPORT_WITH_BIOCHEMICAL_REACTION BioPAX Class: transportWithBiochemicalReaction
static java.	UXREF
lang.String	BioPAX Class: UnificationXref

Constructor Summary

BioPaxConstants()

Constructor.

Method Summary

java.util.Set	getInteractionSet() Gets a Set of all Interaction Entity Names.
java.util.Set	getPhysicalEntitySet() Gets a Set of all Physical Entity Names
static boolean	isActivation (java.lang.String controlType)
boolean	isControlInteraction (java.lang.String elementName) Determines if the Specified Element is of type: control.
boolean	isConversionInteraction (java.lang.String elementName) Determines if the Specified Element is of type: conversion.
static boolean	isInhibition (java.lang.String controlType)
boolean	isInteraction (java.lang.String elementName) Determines if the Specified Element is of type: interaction.
boolean	isPathway (java.lang.String elementName) Determines if the Specified Element is of type: pathway.
boolean	isPhysicalEntity (java.lang.String elementName) Determines if the Specified Element is of type: physical entity.

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll,
toString, wait, wait, wait
```

Field Detail

BIOCHEMICAL_REACTION

public static final java.lang.String BIOCHEMICAL_REACTION

BioPAX Class: biochemicalReaction

See Also: Constant Field Values

BIOPAX_LEVEL_1_NAMESPACE

public static final org.jdom.Namespace BIOPAX_LEVEL_1_NAMESPACE

BioPAX Level 1 Namespace.

BIOPAX_LEVEL_1_NAMESPACE_URI

public static final java.lang.String **BIOPAX_LEVEL_1_NAMESPACE_URI**

BioPAX Level 1 Namespace URI.

See Also: Constant Field Values

BIOPAX_LEVEL_2_NAMESPACE

public static final org.jdom.Namespace BIOPAX_LEVEL_2_NAMESPACE

BioPAX Level 2 Namespace.

BIOPAX_LEVEL_2_NAMESPACE_URI

public static final java.lang.String BIOPAX_LEVEL_2_NAMESPACE_URI

BioPAX Level 2 Namespace URI.

See Also: Constant Field Values

BIOPAX_NAMESPACE_PREFIX

public static final java.lang.String BIOPAX_NAMESPACE_PREFIX

BioPAX Namespace Prefix.

See Also: Constant Field Values

CATALYSIS

public static final java.lang.String CATALYSIS

BioPAX Class: catalysis

See Also: Constant Field Values

COMPLEX

public static final java.lang.String COMPLEX

BioPAX Class: complex.

See Also:

Constant Field Values

COMPLEX_ASSEMBLY

public static final java.lang.String COMPLEX_ASSEMBLY

BioPAX Class: complexAssembly

See Also:

Constant Field Values

CONTROL

public static final java.lang.String CONTROL

BioPAX Class: control

See Also: Constant Field Values

CONTROL_TYPE_ACTIVATION

public static final java.lang.String CONTROL_TYPE_ACTIVATION

Control Type: ACTIVATION

See Also: Constant Field Values

CONTROL_TYPE_ACTIVATION_ALLOSTERIC

public static final java.lang.String CONTROL_TYPE_ACTIVATION_ALLOSTERIC

Control Type: ACTIVATION-ALLOSTERIC

See Also: Constant Field Values

CONTROL_TYPE_ACTIVATION_NONALLOSTERIC

public static final java.lang.String CONTROL_TYPE_ACTIVATION_NONALLOSTERIC

Control Type: ACTIVATION-NONALLOSTERIC

See Also: Constant Field Values

CONTROL_TYPE_ACTIVATION_UNKMECH

public static final java.lang.String CONTROL_TYPE_ACTIVATION_UNKMECH

Control Type: ACTIVATION-UNKMECH

See Also: Constant Field Values

CONTROL_TYPE_INHIBITION

public static final java.lang.String CONTROL_TYPE_INHIBITION

Control Type: INHIBITION

See Also: Constant Field Values

CONTROL_TYPE_INHIBITION_ALLOSTERIC

public static final java.lang.String CONTROL_TYPE_INHIBITION_ALLOSTERIC

Control Type: INHIBITION-ALLOSTERIC

See Also:

Constant Field Values

CONTROL_TYPE_INHIBITION_COMPETITIVE

public static final java.lang.String CONTROL_TYPE_INHIBITION_COMPETITIVE

Control Type: INHIBITION-COMPETITIVE

See Also: Constant Field Values

CONTROL_TYPE_INHIBITION_IRREVERSIBLE

public static final java.lang.String CONTROL_TYPE_INHIBITION_IRREVERSIBLE

Control Type: INHIBITION-IRREVERSIBLE

See Also:

Constant Field Values

CONTROL_TYPE_INHIBITION_NONCOMPETITIVE

public static final java.lang.String CONTROL_TYPE_INHIBITION_NONCOMPETITIVE

Conrol Type: INHIBITION-NONCOMPETITIVE

See Also:

Constant Field Values

CONTROL_TYPE_INHIBITION_OTHER

public static final java.lang.String CONTROL_TYPE_INHIBITION_OTHER

Control Type: INHIBITION-OTHER

See Also: Constant Field Values

CONTROL_TYPE_INHIBITION_UNCOMPETITIVE

public static final java.lang.String CONTROL_TYPE_INHIBITION_UNCOMPETITIVE

Control Type: INHIBITION-UNCOMPETITIVE

See Also:

Constant Field Values

CONTROL_TYPE_INHIBITION_UNKMECH

public static final java.lang.String CONTROL_TYPE_INHIBITION_UNKMECH

Control Type: INHIBITION-UNKMECH

See Also: Constant Field Values

CONVERSION

public static final java.lang.String CONVERSION

BioPAX Class: conversion

See Also: Constant Field Values

DNA

public static final java.lang.String DNA

BioPAX Class: dna

See Also: Constant Field Values

INTERACTION

public static final java.lang.String INTERACTION

BioPAX Class: interaction.

See Also: Constant Field Values

MODULATION

public static final java.lang.String MODULATION

BioPAX Class: modulation

See Also:

Constant Field Values

PATHWAY

public static final java.lang.String **PATHWAY**

BioPAX Class: pathway

See Also:

Constant Field Values

PHYSICAL_ENTITY

public static final java.lang.String PHYSICAL_ENTITY

BioPAX Class: physicalEntity.

See Also: Constant Field Values

PHYSICAL_INTERACTION

public static final java.lang.String PHYSICAL_INTERACTION

BioPAX Class: physicalInteraction.

See Also: Constant Field Values

PROTEIN

public static final java.lang.String **PROTEIN**

BioPAX Class: protein

See Also: Constant Field Values

RNA

public static final java.lang.String RNA

BioPAX Class: rna

See Also: Constant Field Values

SMALL_MOLECULE

public static final java.lang.String SMALL_MOLECULE

BioPAX Class: smallMolecule.

See Also:

Constant Field Values

TRANSPORT

public static final java.lang.String TRANSPORT

BioPAX Class: transport

See Also: Constant Field Values

TRANSPORT_WITH_BIOCHEMICAL_REACTION

public static final java.lang.String TRANSPORT_WITH_BIOCHEMICAL_REACTION

BioPAX Class: transportWithBiochemicalReaction

See Also: Constant Field Values

UXREF

public static final java.lang.String **UXREF**

BioPAX Class: UnificationXref

See Also:

Constant Field Values

Constructor Detail

BioPaxConstants

public BioPaxConstants()

Constructor.

Method Detail

getInteractionSet

public java.util.Set getInteractionSet()

Gets a Set of all Interaction Entity Names.

Returns:

Set of Strings.

getPhysicalEntitySet

public java.util.Set getPhysicalEntitySet()

Gets a Set of all Physical Entity Names

Returns:

Set of Strings

isActivation

public static boolean isActivation(java.lang.String controlType)

isControlInteraction

public boolean isControlInteraction(java.lang.String elementName)

Determines if the Specified Element is of type: control.

Parameters: elementName - Element Name. Returns: boolean value.

isConversionInteraction

public boolean isConversionInteraction(java.lang.String elementName)

Determines if the Specified Element is of type: conversion.

Parameters: elementName - Element Name. Returns: boolean value.

isInhibition

public static boolean isInhibition(java.lang.String controlType)

isInteraction

public boolean isInteraction(java.lang.String elementName)

Determines if the Specified Element is of type: interaction.

Parameters: elementName - Element Name. Returns: boolean value.

isPathway

public boolean isPathway(java.lang.String elementName)

Determines if the Specified Element is of type: pathway.

Parameters: elementName - Element Name. Returns: boolean value.

isPhysicalEntity

public boolean isPhysicalEntity(java.lang.String elementName)

Determines if the Specified Element is of type: physical entity.

Parameters: elementName - Element Name. Returns: boolean value. edu.ucsf.qpaca.parser.util Class BioPaxUtil

java.lang.Object

edu.ucsf.qpaca.parser.util.BioPaxUtil

public class BioPaxUtil

extends java.lang.Object

BioPax Utility Class.

Constructor Summary

BioPaxUtil(java.io.Reader reader)
Constructor.

Method Summary		
java. util. ArrayList	getComplexList() Gets List of PhysicalEntity/complex Resources.	
java. util. ArrayList	getInteractionList() Gets List of Interaction Resources.	
java. util. ArrayList	getPathwayList() Gets list of Pathway Resources.	
java. util. ArrayList	getPhysicalEntityList () Gets List of Physical Entity Resources.	
java. util. HashMap	getRdfResourceMap() Gets HashMap of All RDF Resources, keyed by RDF ID.	
org. jdom. Element	getRootElement() Gets the Root Element of the BioPAX Tree.	

java. util. ArrayList Gets a List of all Pathways, Interactions, and Physical Entities.

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll,
toString, wait, wait, wait
```

Constructor Detail

BioPaxUtil

public BioPaxUtil(java.io.Reader reader)
 throws java.io.IOException,
 org.jdom.JDOMException,
 <u>BioPaxException</u>

Constructor.

```
Parameters:
reader - Reader Object.
Throws:
java.io.IOException - Input/Output Error.
org.jdom.JDOMException - XML Error.
<u>BioPaxException</u>
```

Method Detail

getComplexList

public java.util.ArrayList getComplexList()

Gets List of PhysicalEntity/complex Resources.

Returns:

ArrayList of JDOM Element Objects.

getInteractionList

public java.util.ArrayList getInteractionList()

Gets List of Interaction Resources.

Returns:

ArrayList of JDOM Element Objects.

getPathwayList

public java.util.ArrayList getPathwayList()

Gets list of Pathway Resources.

Returns:

ArrayList of JDOM Element Objects.

getPhysicalEntityList

public java.util.ArrayList getPhysicalEntityList()

Gets List of Physical Entity Resources.

Returns:

ArrayList of JDOM Element Objects.

getRdfResourceMap

public java.util.HashMap getRdfResourceMap()

Gets HashMap of All RDF Resources, keyed by RDF ID.

Returns:

HashMap of All RDF Resources, keyed by RDF ID.

getRootElement

public org.jdom.Element getRootElement()

Gets the Root Element of the BioPAX Tree.

Returns: JDOM Element Object.

getTopLevelComponentList

public java.util.ArrayList getTopLevelComponentList()

Gets a List of all Pathways, Interactions, and Physical Entities.

Returns:

ArrayList of JDOM Element Objects.

edu.ucsf.qpaca.parser.util Class KGMLConstants

java.lang.Object

edu.ucsf.qpaca.parser.util.KGMLConstants

public class KGMLConstants

extends java.lang.Object

KGML Constants.

Field Summary		
static java.	ACTIVATION	
lang.String	relation subtype: activation	
static java.	BINDING_ASSOCIATION	
lang.String	relation subtype: binding/association	
static java.	COMPLEX	
lang.String	entry type: complex of gene products	
static java.	COMPOUND	
lang.String	relation subtype: compound	
static java.	DEPHOSPHORYLATION	
lang.String	relation subtype: dephosphorylation	
static java.	DISSOCIATION	
lang.String	relation subtype: dissociation	
static java.	ECREL	
lang.String	relationship type: enzyme-enzyme.	
static java. lang.String	entry type: enzyme.	
static java. lang.String	EXPRESSION relation subtype: expression	

static java.	GENE
lang.String	entry type: gene
static java.	GEREL
lang.String	relationship type: gene expression (transcription factor-gene)
static java.	GLYCOSYLATION
lang.String	relation subtype: glycosylation
static java.	HIDDEN_COMPOUND
lang.String	relation subtype: hidden compound
static java. lang.String	INDIRECT_EFFECT Conrol Type: indirect effect
static java. lang.String	INHIBITION relation subtype: inhibition
static java. lang.String	IRREVERSIBLE reaction type: irreversible
static java. lang.String	MAPLINK relationship type: link to another pathway
static java. lang.String	METHYLATION relation subtype: methylation
static java.	ORTHOLOG
lang.String	entry type: ortholog.
static java.	PATHWAY
lang.String	entry type: linked pathway.
static java.	PCREL
lang.String	relationship type: protein-compound
static java.	PHOSPHORYLATION
lang.String	relation subtype: phosphorylation
static java.	PPREL
lang.String	relationship type: protein-protein.
static java. lang.String	REPRESSION relation subtype: repression
static java.	REVERSIBLE
lang.String	reaction type: reversible
static java. lang.String	SMALL_MOLECULE entry type: chemical compound
static java. lang.String	STATE_CHANGE relation subtype: state change
static java.	UBIQUINATION
lang.String	relation subtype: ubiquination

Constructor Summary

KGMLConstants()

Initializes the constants.

Method Summary		
static boolean	isActivation (java.lang.String subtype) Determines if an interaction is of an activation type	
static boolean	isInhibition (java.lang.String subtype) Determines if an interaction is of an inhibition type	

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll,
toString, wait, wait, wait
```

Field Detail

ACTIVATION

public static final java.lang.String ACTIVATION

relation subtype: activation

See Also:

Constant Field Values

BINDING_ASSOCIATION

public static final java.lang.String **BINDING_ASSOCIATION**

relation subtype: binding/association

See Also:

Constant Field Values

COMPLEX

public static final java.lang.String COMPLEX

entry type: complex of gene products

See Also: Constant Field Values

COMPOUND

public static final java.lang.String COMPOUND

relation subtype: compound

See Also: Constant Field Values

DEPHOSPHORYLATION

public static final java.lang.String **DEPHOSPHORYLATION**

relation subtype: dephosphorylation

See Also: Constant Field Values

DISSOCIATION

public static final java.lang.String **DISSOCIATION**

relation subtype: dissociation

See Also:

Constant Field Values

ECREL

public static final java.lang.String ECREL

relationship type: enzyme-enzyme.

See Also: Constant Field Values

ENZYME

public static final java.lang.String ENZYME

entry type: enzyme.

See Also: Constant Field Values

EXPRESSION

public static final java.lang.String **EXPRESSION**

relation subtype: expression

See Also: Constant Field Values

GENE

public static final java.lang.String **GENE**

entry type: gene

See Also: Constant Field Values

GEREL

public static final java.lang.String **GEREL**

relationship type: gene expression (transcription factor-gene)

See Also: Constant Field Values

GLYCOSYLATION

public static final java.lang.String GLYCOSYLATION

relation subtype: glycosylation

See Also: Constant Field Values

HIDDEN_COMPOUND

public static final java.lang.String HIDDEN_COMPOUND

relation subtype: hidden compound

See Also:

Constant Field Values

INDIRECT_EFFECT

public static final java.lang.String INDIRECT_EFFECT

Conrol Type: indirect effect

See Also: Constant Field Values

INHIBITION

public static final java.lang.String INHIBITION

relation subtype: inhibition

See Also: Constant Field Values

IRREVERSIBLE

public static final java.lang.String IRREVERSIBLE

reaction type: irreversible

See Also: Constant Field Values

MAPLINK

public static final java.lang.String MAPLINK

relationship type: link to another pathway

See Also:

Constant Field Values

METHYLATION

public static final java.lang.String **METHYLATION**

relation subtype: methylation

See Also:

Constant Field Values

ORTHOLOG

public static final java.lang.String **ORTHOLOG**

entry type: ortholog.

See Also: Constant Field Values

PATHWAY

public static final java.lang.String **PATHWAY**

entry type: linked pathway.

See Also: Constant Field Values

PCREL

public static final java.lang.String **PCREL**

relationship type: protein-compound

See Also:

Constant Field Values

PHOSPHORYLATION

public static final java.lang.String **PHOSPHORYLATION**

relation subtype: phosphorylation

See Also: Constant Field Values

PPREL

public static final java.lang.String **PPREL**

relationship type: protein-protein.

See Also: Constant Field Values

REPRESSION

public static final java.lang.String **REPRESSION**

relation subtype: repression

See Also:

Constant Field Values

REVERSIBLE

public static final java.lang.String REVERSIBLE

reaction type: reversible

See Also: Constant Field Values

SMALL_MOLECULE

public static final java.lang.String SMALL_MOLECULE

entry type: chemical compound

See Also: Constant Field Values

STATE_CHANGE

public static final java.lang.String STATE_CHANGE

relation subtype: state change

See Also:

Constant Field Values

UBIQUINATION

public static final java.lang.String UBIQUINATION

relation subtype: ubiquination

See Also:

Constant Field Values
Constructor Detail

KGMLConstants

public KGMLConstants()

Initializes the constants.

Method Detail

isActivation

public static boolean isActivation(java.lang.String subtype)

Determines if an interaction is of an activation type

Parameters:

subtype - the type of interaction to evaluate

Returns:

true if the subtype represents activation, false otherwise.

isInhibition

public static boolean isInhibition(java.lang.String subtype)

Determines if an interaction is of an inhibition type

Parameters:

subtype - the type of interaction to evaluate

Returns:

true if the subtype represents inhibition, false otherwise.

edu.ucsf.qpaca.parser.util Class KGMLUtil

java.lang.Object

edu.ucsf.qpaca.parser.util.KGMLUtil

public class KGMLUtil

extends java.lang.Object

KEGG KGML Utility Class.

Constructor Summary

KGMLUtil(java.io.Reader reader) Loads the KGML file.

Method Summary	
java. util. HashMap	getAllEntriesMap() Retrieves a list of all entries.
java. util. TreeMap	getComplexMap() Retrieves a list of complexes.
java. util. HashMap	getEntityMap () Retrieves a list of Entities.
java. lang. String	getPathwayID() Retrieves the pathway name.
java. lang. String	getPathwayLabel() Retrieves the pathway label.
java. util. ArrayList	getReactionList() Retrieves a list of Reactions.

java. util. ArrayList org. jdom. Element getRootElement() Retrieves the Root Element of the KGML Tree.

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll,
toString, wait, wait, wait
```

Constructor Detail

KGMLUtil

```
public KGMLUtil(java.io.Reader reader)
    throws java.io.IOException,
        org.jdom.JDOMException,
        java.lang.Exception
```

Loads the KGML file.

Parameters:

reader - Reader Object.

```
Throws:
```

java.io.IOException - Input/Output Error. org.jdom.JDOMException - XML Error. java.lang.Exception

Method Detail

getAllEntriesMap

public java.util.HashMap getAllEntriesMap()

Retrieves a list of all entries.

Returns:

ArrayList of JDOM Element Objects.

getComplexMap

public java.util.TreeMap getComplexMap()

Retrieves a list of complexes.

Returns:

ArrayList of JDOM Element Objects.

getEntityMap

public java.util.HashMap getEntityMap()

Retrieves a list of Entities.

Returns:

ArrayList of JDOM Element Objects.

getPathwayID

public java.lang.String getPathwayID()

Retrieves the pathway name.

Returns:

pathway name

getPathwayLabel

public java.lang.String getPathwayLabel()

Retrieves the pathway label.

Returns:

pathway label

getReactionList

public java.util.ArrayList getReactionList()

Retrieves a list of Reactions.

Returns:

ArrayList of JDOM Element Objects.

getRelationList

public java.util.ArrayList getRelationList()

Retrieves a list of Relations.

Returns: ArrayList of JDOM Element Objects.

getRootElement

public org.jdom.Element getRootElement()

Retrieves the Root Element of the KGML Tree.

Returns:

JDOM Element Object.

edu.ucsf.qpaca.parser.util Class OwlConstants

java.lang.Object

edu.ucsf.qpaca.parser.util.OwlConstants

public class **OwlConstants**

extends java.lang.Object

OWL (Web Ontology Language) Constants.

Field Summary		
static java. lang.String	OWL_IMPORTS_ELEMENT OWL Imports Element Name	
static org. jdom. Namespace	OWL_NAMESPACE RDF Namespace Object.	
static java.	OWL_NAMESPACE_PREFIX	
lang.String	OWL Namespace Prefix	
static java.	OWL_NAMESPACE_URI	
lang.String	OWL Namespace URI.	
static java.	OWL_ONTOLOGY_ELEMENT	
lang.String	OWL Ontology Element	

Constructor Summary

OwlConstants()

Method Summary

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll,
toString, wait, wait, wait
```

Field Detail

OWL_IMPORTS_ELEMENT

public static final java.lang.String OWL_IMPORTS_ELEMENT

OWL Imports Element Name

See Also: Constant Field Values

OWL_NAMESPACE

public static final org.jdom.Namespace OWL_NAMESPACE

RDF Namespace Object.

OWL_NAMESPACE_PREFIX

public static final java.lang.String OWL_NAMESPACE_PREFIX

OWL Namespace Prefix

See Also: Constant Field Values

OWL_NAMESPACE_URI

public static final java.lang.String OWL_NAMESPACE_URI

OWL Namespace URI.

See Also:

Constant Field Values

OWL_ONTOLOGY_ELEMENT

public static final java.lang.String OWL_ONTOLOGY_ELEMENT

OWL Ontology Element

See Also: Constant Field Values

Constructor Detail

OwlConstants

public OwlConstants()

edu.ucsf.qpaca.parser.util Class QPACAConstants

java.lang.Object

L_edu.ucsf.qpaca.parser.util.QPACAConstants

public class **QPACAConstants**

extends java.lang.Object

QPACA Constants.

Field Summary	
static java. lang.String	ACTIVATION PathwayEdge type: activation.
static java. lang.String	ALTAS PathwayAssembly type for families
static java. lang.String	COMPLEX PathwayAssembly type for complexes
static java. lang.String	COMPOUND PathwayAssembly type for complexes
static java. lang.String	CONVERSION PathwayEdge type: conversion.
static java. lang.String	DNA PathwayElement type: dna
static java. lang.String	EVENT PathwayVertex type: event
static java. lang.String	FAMILY PathwayAssembly type for families
static java. lang.String	GENE_PRODUCT PathwayElement type: gene product
static java. lang.String	INHIBITION PathwayEdge type: inhibition.

static java.	PHYSICAL_ENTITY
lang.String	PathwayVertex type: physicalEntity
static java.	PROCESS
lang.String	PathwayElement type: process
static java.	PROTEIN
lang.String	PathwayElement type: protein
static java.	RNA
lang.String	PathwayElement type: rna
static java.	SINGLE
lang.String	PathwayAssembly type for assemblies containing a single item.
static java. lang.String	SMALL_MOLECULE PathwayElement type: small molecule

Constructor Summary

<u>QPACAConstants</u>()

Constructor.

Method Summary		
static boolean	isControlInteraction (java.lang.String type) Determines if the type specifies a control interaction	
static boolean	isConversionlInteraction (java.lang.String type) Determines if the type specifies a conversion interaction	
static boolean	isNotSmallMolecule(java.lang.String type) Determines if the type specifies a dna/rna/protein/gene_product PathwayElement	

Methods inherited from class java.lang.Object

clone, equals, finalize, getClass, hashCode, notify, notifyAll, toString, wait, wait, wait

Field Detail

ACTIVATION

public static final java.lang.String **ACTIVATION**

PathwayEdge type: activation.

See Also:

ALIAS

public static final java.lang.String ALIAS

PathwayAssembly type for families

See Also: Constant Field Values

COMPLEX

public static final java.lang.String COMPLEX

PathwayAssembly type for complexes

See Also: Constant Field Values

COMPOUND

public static final java.lang.String COMPOUND

PathwayAssembly type for complexes

See Also: Constant Field Values

CONVERSION

public static final java.lang.String CONVERSION

PathwayEdge type: conversion.

See Also: Constant Field Values

DNA

public static final java.lang.String DNA

PathwayElement type: dna

See Also: Constant Field Values

EVENT

public static final java.lang.String EVENT

PathwayVertex type: event

See Also: Constant Field Values

FAMILY

public static final java.lang.String FAMILY

PathwayAssembly type for families

See Also: Constant Field Values

GENE_PRODUCT

public static final java.lang.String **GENE_PRODUCT**

PathwayElement type: gene product

See Also:

Constant Field Values

INHIBITION

public static final java.lang.String INHIBITION

PathwayEdge type: inhibition.

See Also: Constant Field Values

PHYSICAL_ENTITY

public static final java.lang.String PHYSICAL_ENTITY

PathwayVertex type: physicalEntity

See Also: Constant Field Values

PROCESS

public static final java.lang.String **PROCESS**

PathwayElement type: process

See Also: Constant Field Values

PROTEIN

public static final java.lang.String **PROTEIN**

PathwayElement type: protein

See Also: Constant Field Values

RNA

public static final java.lang.String RNA

PathwayElement type: rna

See Also: Constant Field Values

SINGLE

public static final java.lang.String **SINGLE**

PathwayAssembly type for assemblies containing a single item.

See Also:

Constant Field Values

SMALL_MOLECULE

public static final java.lang.String SMALL_MOLECULE

PathwayElement type: small molecule

See Also:

Constant Field Values

Constructor Detail

QPACAConstants

public **QPACAConstants**()

Constructor.

Method Detail

isControlInteraction

public static final boolean isControlInteraction(java.lang.String type)

Determines if the type specifies a control interaction

Parameters: type - type. Returns: boolean value.

isConversionlInteraction

public static final boolean **isConversionlInteraction**(java.lang.String type)

Determines if the type specifies a conversion interaction

Parameters: type - type. Returns: boolean value.

isNotSmallMolecule

public static final boolean isNotSmallMolecule(java.lang.String type)

Determines if the type specifies a dna/rna/protein/gene_product PathwayElement

Parameters:

type - type.

Returns:

boolean value.

edu.ucsf.qpaca.parser.util Class QPACAUtil

java.lang.Object

edu.ucsf.qpaca.parser.util.QPACAUtil

public class **QPACAUtil**

extends java.lang.Object

QPACA Pathway language Utility Class.

Constructor Summary

<u>QPACAUtil</u>(java.io.Reader reader) Initializes the parser.

Method Summary	
getAllEntriesMap() Retrieves a list of all entries.	
getComplexMap() Retrieves a list of complexes.	
getEntityMap() Retrieves a list of Entities.	
getPathway()	
getPathwayID() Retrieves the pathway name.	
getPathwayLabel () Retrieves the pathway label.	

java. util. ArrayList

getRelationList() Retrieves a list of Relations.

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll,
toString, wait, wait, wait
```

Constructor Detail

QPACAUtil

public **QPACAUtil**(java.io.Reader reader)
 throws java.io.IOException,
 java.lang.Exception

Initializes the parser.

Parameters:

reader - Reader Object. **Throws:** java.io.IOException - Input/Output Error. java.lang.Exception

Method Detail

getAllEntriesMap

public java.util.HashMap getAllEntriesMap()

Retrieves a list of all entries.

Returns:

ArrayList of JDOM Element Objects.

getComplexMap

public java.util.TreeMap getComplexMap()

Retrieves a list of complexes.

Returns:

ArrayList of JDOM Element Objects.

getEntityMap

public java.util.HashMap getEntityMap()

Retrieves a list of Entities.

Returns:

ArrayList of JDOM Element Objects.

getPathway

public <u>Pathway</u> getPathway()

getPathwayID

public java.lang.String getPathwayID()

Retrieves the pathway name.

Returns:

pathway name

getPathwayLabel

public java.lang.String getPathwayLabel()

Retrieves the pathway label.

Returns:

pathway label

getRelationList

public java.util.ArrayList getRelationList()

Retrieves a list of Relations.

Returns:

ArrayList of JDOM Element Objects.

edu.ucsf.qpaca.parser.util Class RdfConstants

java.lang.Object

edu.ucsf.qpaca.parser.util.RdfConstants

public class RdfConstants

extends java.lang.Object

RDF (Resource Description Framework) Constants.

Field Summary	
static java. lang.String	ABOUT_ATTRIBUTE RDF About Attribute
static java. lang.String	DATATYPE_ATTRIBUTE RDF Datatype Attribute
static java. lang.String	ID_ATTRIBUTE RDF ID Attribute
static org. jdom. Namespace	RDF_NAMESPACE RDF Namespace Object.
static java. lang.String	RDF_NAMESPACE_PREFIX RDF Namespace Prefix
static java. lang.String	RDF_NAMESPACE_URI RDF Namespace URI
static java. lang.String	RDF_ROOT_NAME RDF Root Name.
static java. lang.String	RDF Resource Attribute

Constructor Summary

RdfConstants()

Method Summary

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll,
toString, wait, wait, wait
```

Field Detail

ABOUT_ATTRIBUTE

public static final java.lang.String ABOUT_ATTRIBUTE

RDF About Attribute

See Also:

Constant Field Values

DATATYPE_ATTRIBUTE

public static final java.lang.String DATATYPE_ATTRIBUTE

RDF Datatype Attribute

See Also: Constant Field Values

ID_ATTRIBUTE

public static final java.lang.String ID_ATTRIBUTE

RDF ID Attribute

See Also:

Constant Field Values

RDF_NAMESPACE

public static final org.jdom.Namespace RDF_NAMESPACE

RDF Namespace Object.

RDF_NAMESPACE_PREFIX

public static final java.lang.String RDF_NAMESPACE_PREFIX

RDF Namespace Prefix

See Also: Constant Field Values

RDF_NAMESPACE_URI

public static final java.lang.String RDF_NAMESPACE_URI

RDF Namespace URI

See Also: Constant Field Values

RDF_ROOT_NAME

public static final java.lang.String RDF_ROOT_NAME

RDF Root Name.

See Also:

Constant Field Values

RESOURCE_ATTRIBUTE

public static final java.lang.String RESOURCE_ATTRIBUTE

RDF Resource Attribute

See Also:

Constant Field Values

Constructor Detail

RdfConstants

public RdfConstants()

edu.ucsf.qpaca.parser.util Class RdfQuery

java.lang.Object

edu.ucsf.qpaca.parser.util.RdfQuery

public class RdfQuery

extends java.lang.Object

Enables XPath-"lite" Queries on RDF Documents.

To make things really simple, this implementation ignore case, and ignores all Namespaces.

Constructor Summary

<u>RdfQuery</u>(java.util.HashMap rdfMap) A Hashmap of all XML Elements, keyed by RDF ID.

Method Summary	
org. jdom. Element	getNode (org.jdom.Element e, java.lang.String query) Gets First Node that match the XPath-"lite" Query.
java. util. ArrayList	<u>getNodes</u> (org.jdom.Element e, java.lang.String query) Gets all Nodes that match the XPath-"lite" Query.

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll,
toString, wait, wait, wait
```

Constructor Detail

RdfQuery

public RdfQuery(java.util.HashMap rdfMap)

A Hashmap of all XML Elements, keyed by RDF ID.

Parameters:

rdfMap - HashMap of RDF ID to XML Element.

Method Detail

getNode

Gets First Node that match the XPath-"lite" Query.

Parameters:

e - Target Element. query - XPath-"lite" Query.

Returns:

ArrayList of JDOM Elements, which match the query.

getNodes

Gets all Nodes that match the XPath-"lite" Query.

Parameters:

```
e - Target Element.
query - XPath-"lite" Query.
```

Returns:

ArrayList of JDOM Elements, which match the query.

edu.ucsf.qpaca.parser.util Class RdfUtil

java.lang.Object L edu.ucsf.qpaca.parser.util.RdfUtil

public class RdfUtil

extends java.lang.Object

Misc RDF Utilities.

Constructor Summary

RdfUtil()

Method Summary	
static java. lang.String	<pre>removeHashMark(java.lang.String referenceId) Strips out leading hash mark #, if necessary.</pre>

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll,
toString, wait, wait, wait
```

Constructor Detail

RdfUtil

public RdfUtil()

Method Detail

removeHashMark

public static java.lang.String removeHashMark(java.lang.String referenceId)

Strips out leading hash mark #, if necessary.

Parameters: referenceId - String with leading hash mark. Returns: String without hashmark.

edu.ucsf.qpaca.parser.util Class BioPaxException

java.lang.Object

L java.lang.Throwable
L java.lang.Exception
L edu.ucsf.qpaca.parser.util.BioPaxException

All Implemented Interfaces:

java.io.Serializable

public class BioPaxException

extends java.lang.Exception

Exception thrown to indicate a syntax error in a BioPAX file.

See Also:

Serialized Form

Constructor Summary

BioPaxException()

BioPaxException(java.lang.String msg)

Method Summary

Methods inherited from class java.lang.Throwable

```
fillInStackTrace, getCause, getLocalizedMessage, getMessage,
getStackTrace, initCause, printStackTrace, printStackTrace,
printStackTrace, setStackTrace, toString
```

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll, wait,
wait, wait
```

Constructor Detail

BioPaxException

public BioPaxException()

BioPaxException

public BioPaxException(java.lang.String msg)

edu.ucsf.qpaca.parser.util Class KGMLException

java.lang.Object

L java.lang.Throwable
L java.lang.Exception
L edu.ucsf.qpaca.parser.util.KGMLException

All Implemented Interfaces:

java.io.Serializable

public class KGMLException

extends java.lang.Exception

Exception thrown to indicate a syntax error in a KGML file.

See Also:

Serialized Form

Constructor Summary

KGMLException()

KGMLException(java.lang.String msg)

Method Summary

Methods inherited from class java.lang.Throwable

```
fillInStackTrace, getCause, getLocalizedMessage, getMessage,
getStackTrace, initCause, printStackTrace, printStackTrace,
printStackTrace, setStackTrace, toString
```

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll, wait,
wait, wait
```

Constructor Detail

KGMLException

public KGMLException()

KGMLException

public KGMLException(java.lang.String msg)

edu.ucsf.qpaca.parser.util Class QPACAException

java.lang.Object

L java.lang.Throwable
L java.lang.Exception
L edu.ucsf.qpaca.parser.util.QPACAException

All Implemented Interfaces:

java.io.Serializable

public class **QPACAException**

extends java.lang.Exception

Exception thrown to indicate a syntax error in a QPACA file.

See Also:

Serialized Form

Constructor Summary

<u>QPACAException</u>()

<u>QPACAException</u>(java.lang.String msg)

Method Summary

Methods inherited from class java.lang.Throwable

```
fillInStackTrace, getCause, getLocalizedMessage, getMessage,
getStackTrace, initCause, printStackTrace, printStackTrace,
printStackTrace, setStackTrace, toString
```

Methods inherited from class java.lang.Object

```
clone, equals, finalize, getClass, hashCode, notify, notifyAll, wait,
wait, wait
```

Constructor Detail

QPACAException

public **QPACAException()**

QPACAException

public **QPACAException**(java.lang.String msg)

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Bahalland June 6, 2007 Author Signature Date