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# Planning and Action Organization in Ill-Defined Tasks: The Case of Everyday Activities

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## Abstract

Planning and organization of one's actions are crucial for successfully performing everyday activities such as setting the table. While existing research has addressed planning for well-defined tasks and control of already established sequences, little is known about how such sequences are planned in ill-defined tasks such as everyday activities. Initial attempts suggest that planning may be opportunistic, based on a number of environmental factors to minimize cognitive and physical effort. We address two questions arising from the existing work: First, to what extent is variation in human everyday activity behavior captured by the proposed opportunistic consideration of environmental factors? We address this question by employing machine learning baselines to gauge the proposed models explanatory scope. Second, to what extent are existing models of sequence control consistent with opportunistic action organization? We address this by investigating and discussing the implications opportunistic planning has for the mechanisms currently assumed for sequence control.

**Keywords:** spatial cognition; action sequence organization; opportunistic planning

## Introduction

Planning theory distinguishes between two domains of problem-solving: well-defined and ill-defined. Well-defined tasks are characterized by all the necessary information for problem-solving being clearly specified (initial state, solution means, and goal state), whereas ill-defined tasks lack specification in at least one of these areas (Simon, 1973). While planning and action organization in well-defined tasks has received considerable attention (see e.g. Newell & Simon, 1972; Morris & Ward, 2005; Botvinick & Plaut, 2004; Botvinick & Weinstein, 2014; Cooper, Ruh, & Mareschal, 2014; Kachergis, Berends, de Kleijn, & Hommel, 2016), little is known about how humans achieve planning and organization in ill-defined tasks and existing approaches (see e.g. Jiménez, De La Rosa, Fernández, Fernández, & Borrajo, 2012; Firby, 1987) are often ill-suited for everyday tasks.

In this contribution we shed further light on this issue by considering everyday activities, as they provide a unique and instrumental window for investigating the involved cognitive abilities. For one, everyday activities are ill-defined problems, as multiple possible solutions exist without defining the 'legal moves' allowed to achieve task success, which makes it computationally intractable to compare all possible solutions. At the same time, everyday activities are sufficiently circumscribed to allow systematic and controlled investigation and,

in fact, several suitable data sets have recently become available.

Early work suggests that planning in ill-defined domains such as everyday activities requires an opportunistic approach (Hayes-Roth & Hayes-Roth, 1979; Patsenko & Altmann, 2010). Specifically, recent modelling work indicates that problem-solving in everyday tasks follows a stepwise-optimal strategy (Wenzl & Schultheis, 2020a) and takes specific spatial constraints, such as distance, relational dependencies between items and dimensionality, into account (Wenzl & Schultheis, 2020b), while planning only one step ahead (Wenzl & Schultheis, 2020c). We will refer to this model as the *opportunistic planning model* (OPM) henceforth. Although the OPM provides important insight into action planning and organization in ill-defined domains, it also raises a number of questions, two of which we address in this contribution. One aspect that remains unclear from the existing work is to what extent the OPM captures the regularities and variations observed in human everyday activity behavior. Furthermore, the implications of the OPM for models of action sequence control remain to be clarified.

Accordingly, this contribution has two main objectives: First, by adopting the approach proposed in (Agrawal, Peterson, & Griffiths, 2019) we employ machine learning baselines to more precisely gauge the OPM's ability to capture aspects of human behavior and, second, to investigate and discuss implications of the OPM (and the specific qualities of everyday tasks it indicates) for the applicability of existing models of action sequence control.

The remainder of this paper is structured as follows: First, we give an overview of the difference between well- and ill-defined problem domains and existing models of action sequence organization. Subsequently, we evaluate the OPM using two machine learning models to compare the predictive power of each approach. We then highlight the implications of the OPM and its success for existing models of sequential action control. In closing, we discuss our results and highlight issues for future research.

## Sequential Action Organization

### Well- and Ill-Defined Domains of Problem-Solving

Planning theory divides the domain of problem-solving into two domains: *well-defined* and *ill-defined*. Well-defined do-

mains are characterized by the subject having all the information available that is required to solve the problem, i.e., the initial state, the desired goal state, and the rules or methods to reach the goal state. Finding a solution can then be described as searching the state space for a pathway that connects the start to the goal state. Planning strategies aim to minimize the extent of the search while providing a good chance of solving the problem or task successfully (Simon, 1973; Morris & Ward, 2005, Chap. 2).

Ill-defined problems are characterized by (one or more) of the components of the problem space being not fully specified. In the sense of Simon (1973), any problem or task with a large base of knowledge potentially relevant to the solution is ill-defined, as it becomes computationally intractable to consider all possible solutions.

We argue that everyday activities are ill-defined problems: In contrast to well-defined problems, where the allowable operations to reach the goal state are explicitly specified, there are no such constraints for everyday tasks – while one might argue that the initial state (no items on the table) and the goal state (required items on the table) are fully specified in a task such as table setting, the task can be solved with a multitude of potential solutions, i.e., the solution means are unspecified. While some everyday activities might require to do related actions in a specific order (e.g., following a recipe when cooking), this is not true for table setting, where all actions are unrelated and could thus be performed in an entirely arbitrary order.

As routine habits are highly optimized and require minimal cognitive effort, there is no clear ‘plan’ detailing which actions to perform in which order that is formulated beforehand, but instead, actions that serve the overall goal are chosen based on situational opportunities in each step (Wenzl & Schultheis, 2020c). We propose that, while people may have a ‘default plan’ available for highly habitualized actions such as table setting, planning is still required in a dynamically changing task environment (e.g., when performing several different everyday tasks simultaneously) or in a new environment, since in both cases, the preexisting plan needs to be adjusted to the new or changing conditions respectively.

## Models of Action Sequence Organization

Looking at existing approaches to planning and action organization reveals that most of them are tailored for well-defined problems and therefore not suited for ill-defined tasks: Models of classical planning theory, such as the General Problem Solver developed by Newell and Simon (1972), define problem-solving as a systematic search of the problem space by heuristics such as means-end analysis, which suggests that problem-solving is a rational, goal-directed, top-down approach to planning.

In existing models of sequential action organization, such as the recurrent connectionist approach of Botvinick and Plaut (2004), the assumption seems to be that the to be controlled sequence is completely known from the outset, i.e., finding a task solution consists in specifying the order of a fixed set

of actions. Building on this work, the goal circuit model implements an additional goal system next to the basic habit or routine system, which allows to perform action sequences in a flexible, goal-directed manner (Cooper et al., 2014), but while there is no fixed action set (sugar may or may not have to be opened dependent on the specific start state), all necessary subgoals for the action sequence are known in advance. In the case of hierarchical model-based reinforcement learning, the start and goal states of the to be solved navigation task are also fully specified, such that the problem solution is to find the lowest-cost pathway between both states (Botvinick & Weinstein, 2014). Similarly, the reinforcement learning model of Kachergis et al. (2016) provides an (unknown) fixed action sequence that needs to be learned by the subject, where the goal state (maximize the score) and the way to reach it (select the correct target in each timestep) are also fully specified.

While these models explicitly consider everyday tasks, they only include well-defined tasks – in ill-defined everyday tasks it is computationally intractable to choose the best path from start to goal state. Instead, it is beneficial to implement a planning strategy that does not try to plan the whole sequence choosing from a multitude of options, but that focuses on each step individually. Planning opportunistically allows changing subsequent decisions based on each interim decision, taking arising constraints or opportunities into account (Hayes-Roth & Hayes-Roth, 1979), thereby acting in a less planful and more situated manner (Patsenko & Altmann, 2010).

Hierarchical task network (HTN) planning in artificial intelligence deals with tasks in ill-defined domains by decomposing complex tasks into primitive subtasks and compound tasks, which are in turn decomposed into subtasks until a solution is found (Jiménez et al., 2012). However, HTN planning requires well-structured domain knowledge about the specific task, i.e., part of the solution needs to be known in advance and encoded. This is often unfeasible for real-world problems, as knowledge about the environment may be partial and goals may be underspecified (see e.g. Georgievski & Aiello, 2015). As people are able to perform everyday tasks efficiently even in unknown environments and without specific instructions (‘set the table’ does not specify required items), it is reasonable to assume that they rely more on general contextual knowledge (plates are normally stored in cupboards) than on specific knowledge about a certain environment. The OPM aims to be applicable also in unknown environments, which makes it infeasible to encode specific knowledge into the model itself.

Another way to deal flexibly with arising opportunities and constraints is to incorporate reactive planning strategies that continually monitor the world state and choose actions based on that state. While such a system is very flexible, it limits the possibility to plan ahead, which may lead to inefficiency or even dangerous situations, as strategic planning is required to detect possibly negative future states before they occur

(Firby, 1987). Reactive planning may therefore be helpful to monitor task execution during everyday tasks, but would need to be complemented with some sort of strategic planning in order to achieve task success without encountering detrimental situations. Concerning its opportunistic approach, the OPM has similarities with affordance theory, as both rely on the individual making use of opportunities for action provided by the environment (Gibson, 1979). However, whereas affordances in the original Gibsonian interpretation can be directly perceived and therefore render mental representations of the environment unnecessary (see also Chong & Proctor, 2020), the OPM assumes at least some kind of mental representation of the spatial environment.

To evaluate how well an opportunistic model can explain observed human behavior in everyday tasks, we consider the OPM for table setting (Wenzl & Schultheis, 2020a).

## Opportunistic Planning in Table Setting

### The Opportunistic Planning Model

Previous modeling work indicates that humans prefer specific action orderings while setting the table: The next item to be picked up and taken to the table is assumed to be chosen based on the current location and the perceived cost of each possible action, with the lowest-cost action being chosen (Wenzl & Schultheis, 2020a, 2020c, 2020b).

The OPM takes the influence of the following spatial aspects of the task environment on action organization during table setting into account:

- *Distance*: minimizing traversed distance,
- *relational dependencies*: e.g., saucer goes below cup and should therefore be taken first, so both items have to be moved to and placed on the table only once, and
- *topology (containment)*: picking up items from, e.g., a counter top, is considered less effortful than picking up items stored in a closed cupboard.

The OPM approximates opportunistic planning by determining the lowest-cost next action for each step from episode start (no items on the table, subject at starting position) to task success (all required items on the table and, if specified, in the target position, subject standing at the table).

Each cost  $C_{p,q}$  is calculated by determining the Euclidean distance between two item locations  $p(x_1, y_1, z_1)$  and  $q(x_2, y_2, z_2)$  in a  $nD$  representation of the specific environment, where  $n$  is either 1, 2, or 3. This distance is further qualified by relational dependencies (parameter  $k$ ) and containment (parameter  $c$ ) yielding a weighted cost computed as given in Eq. 1, where  $d$  is the Euclidean distance.

$$C_{p,q} = d(p, q)^k \cdot c \quad (1)$$

Consistent with previous research on *strong spatial cognition* (Freksa, 2015), relational dependencies are defined as constraints that favor putting one item on the table earlier or later in the action sequence, e.g., either because the first

Table 1: Parameter categories for items

Category	Items	Value range
strong k	tray, placemat, table cloth	$0.0 < k < 0.9$
medium k	plate (empty), napkin	$0.1 < k < 1.0$
food k	plate with food prepared during sequence	$1.0 < k < 2.0$
no k	all other items	$k = 1.0$
c	items stored in closed locations	$1.0 < c < 2.0$

item is supposed to be placed below the second item (saucer and cup, etc.), the item is used to define the place setting (placemat, plate), or the item is reserved for the food prepared during the action sequence and can thus only be taken once preparations are done. As the actions themselves are not directly related, i.e., there is no fixed order in which specific actions need to be performed, all actions are considered individually, without any dependencies on other actions. Containment indicates whether an item can be accessed directly or if it is stored in a closed location, such as a cupboard, that has to be opened first.

The weighted cost for each possible action also depends on which dimensions are considered when calculating the cost. Based on previous research indicating a preference for encoding distances in 2D ( $xy$ ) space (Wenzl & Schultheis, 2020c), we only consider 2D distances in this analysis.

All parameters are treated as free parameters and are estimated from the data.

### Simulation

Given a spatial layout with item coordinates, the task description (required items), and a sequence of current locations, simulations were conducted as follows: For each predicted next item, the prior location was taken as the current location, regardless of whether the corresponding action was a table setting action. In each step the cost for all next possible actions was calculated (Eq. 1,  $p$  = current location,  $q$  = item location), from which the action with the lowest associated cost was chosen. If there were multiple actions with the same associated cost, one action was chosen randomly.

Parameters  $k$  and  $c$  were estimated by grid search by finding the best-fitting model over all unique sequences of action orderings. Parameter  $k$  was estimated per item category (see Tab. 1),  $c$  was estimated for all objects in closed storage locations (e.g., cupboard, drawer). For each parameter combination, model accuracy was evaluated for  $n = 50$  iterations, considering the median prediction error over all iterations.

Values were tested in the ranges given in Tab. 1, in steps of 0.1. We applied the model on five different data sets, which are described in the following section.

### Data

Of the five data sets we employed, four were collected in laboratory settings and one in a real-world setting. An important commonality of all data sets is that setting the table in a solely habitual way was not possible, because the subjects

either were in a new environment or performed several everyday tasks simultaneously. In both cases, action sequence organization had to be adapted to the changed environment or conditions.

**TUM Kitchen** The TUM Kitchen Data Set (Tenorth, Bandouch, & Beetz, 2009) contains data from four subjects setting a table in different ways, each time using the same items in the same lab environment.

**EPIC-KITCHENS** EPIC-KITCHENS (Damen, D. et al., 2018) is a large-scale first-person vision data set collected by 32 participants in their native kitchens. Since each participant recorded their activities in their home kitchen, spatial environments and items vary between participants.

**Household Activities from Virtual Environments (HAVE) Dataset** The HAVE data set (Uhde, Berberich, Ramirez-Amaro, & Cheng, 2020) was recorded at the Automatica Trade Fair 2018 and consists of recordings for three scenarios, including 83 instances of table setting in a virtual environment. Each visitor could record one instance for each scenario, with each recording being limited to a maximum of 5 minutes. Each scenario was designed inside a 2-by-2-meter square environment and recorded using HTC Vive systems. All participants were new to the scenarios and had a brief adaptation phase before being given the scenario-specific activity goal. The virtual environment consisted of a table with two chairs and a cupboard in which the items were stored (see Fig. 1). For our analysis, 3 of the 83 sequences had to be discarded, as too few ( $n < 2$ ) items were on the table in the final state.<sup>1</sup>

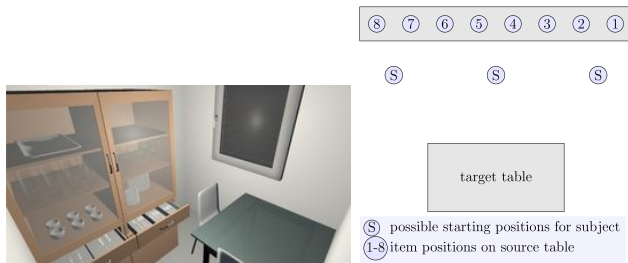


Figure 1: HAVE virtual environment (left) (Uhde et al., 2020), EASE-TSD layout (right)

**Virtual Reality Dataset** The data contains table setting sequences in a VR environment from a single participant. The virtual kitchen consisted of three separate regions (fridge, tray area, island area, each of which had to be visited at least once).

The participant was asked to set the table for one person having breakfast. The task was to first assemble all necessary items on the tray and then to carry the items to the table. The participant was familiar with the kitchen and knew the location of all required items well. Data from 39 trials was

collected. For action orderings we considered the order in which items were grasped and put on the tray.

**EASE Table Setting Dataset (EASE-TSD)** EASE-TSD (Meier, Mason, Porzel, Putze, & Schultz, 2018) is a data set collecting table setting instances in the context of the Everyday Science and Engineering (EASE) collaborative research center. Participants are given the task to ‘*set the table*’ while being recorded with a variety of sensors under various conditions (e.g., for a different number of people, different meals, and different degrees of formalism). Sensors include a mix of biosignal sensors (such as motion-capture systems) and video cameras. For the current analysis, we used a small subset of the recorded data consisting of 67 table setting instances. In the task, a predefined set of items (plate, spoon, knife, fork, cup, glass, bowl, bottle) had to be transferred from the source table to the target table, which was placed at approximately 2.5 meters distance (see Fig. 1). Items had to be transferred individually, but no other constraints, e.g., the order of items or a time limit, were specified. The initial location of the items on the source table as well as the starting position of the subject were randomized.

## Model Evaluation and Performance

### Evaluation Method

We evaluated the prediction accuracy of the OPM using a prequential approach (Dawid, 1984). For each step, the OPM predicted the next action in the sequence (i.e., which item to pick up next) based on the given parameters and the incorporated situational knowledge (location of items and subject). The predicted action was then compared to the observed action, resulting in a prediction error of either 0 (predicted = observed action) or 1 (predicted  $\neq$  observed action). This process was repeated for each sequence until  $length - 1$  for the observed sequence was reached – as that is the last point in the sequence where the OPM can choose from at least two actions –, resulting in a list of prediction errors for each step in each sequence, which were then accumulated.

To identify the parameter combination achieving the most accurate prediction, for each individual sequence the median accumulated error over all iterations was calculated (see Simulation) and the median error over all sequences was used to compare the OPM’s performance with different parameter combinations.

### Performance Baselines

Black-box machine learning models provide an estimate of how much variance in a certain type of behavior can be predicted. By continuously critiquing an interpretable cognitive model in regard to these black-box algorithms, it is thus possible to generate cognitive models that are both interpretable and accurate (Agrawal et al., 2019).

To evaluate the predictive power of the OPM, we implemented two machine learning models learning patterns from the data and generating predictions based on these patterns: a) a compact prediction tree (CPT) (Gueniche, Fournier-Viger,

<sup>1</sup>Excluded sequences: 79, 146, and 168.

Raman, & Tseng, 2015), and b) a recurrent neural network (RNN) (Gruber & Jockisch, 2020). Both methods are optimized for sequence prediction and are thus able to provide high prediction accuracy for sequential data.

As we also wanted to test how much of the OPM's prediction accuracy for behavioral sequences is based on underlying patterns and how much of is due to the encoded knowledge about the task environment, the machine learning models received just the action sequences as input, without any additional information. To the extent that the OPM outperforms the machine learning models, we can then infer that contextual knowledge about the task environment plays an important role in correctly prediction human behavior in everyday tasks.

Both models were trained on the whole data set, i.e., all action sequences. In each time step, the models were given the already seen actions to predict the next action; the predicted next action then being compared to the observed next action (same as for the model, see Evaluation Method). These steps were repeated until the observed sequence length was reached, as they did not get any information about which actions were expected in the specific sequence and thus always had multiple options to choose from. The RNN used a layer of gated recurrent units (GRUs), which outperform long short-term memory (LSTM) cells for low sample sizes and are less susceptible to overfitting (Gruber & Jockisch, 2020), and was trained for 300 epochs.

In contrast to the OPM, the machine learning models only received the action sequences during training, i.e., they had no additional contextual information about spatial locations, containment, or relational dependencies. Predicting the next action was thus equivalent to predicting the next element in a sequence solely based on the previously seen elements.

## Results

On average, the OPM outperforms both machine learning models. The best fit is achieved with parameters strong  $k = 0.2$ , mid  $k = 0.3$ , food  $k = 1.6$ ,  $c = 1.5$  and distances calculated in 2D space ( $xy$ ) (see Fig. 2). As there were multiple parameter combinations with the same median error (4.0), the best fit was chosen based on the average prediction error (4.127 for the best fit).

We compared optimal OPM performance with the machine learning models' performance using a Wilcoxon signed-rank test. Statistical analysis shows that the model performs significantly better than both the neural network ( $W = 3340.000, p < 0.001$ ) and the compact prediction tree ( $W = 112.000, p < 0.001$ ).

These results indicate the importance of task context: While the machine learning models learn patterns strictly from the observed sequences without any additional information, the OPM also gets information about the spatial environment (location of items and subject). As the OPM outperforms both the RNN and the CPT, it is reasonable to assume that this additional knowledge about the task environment is what allows the OPM to make more accurate predictions than

the machine learning models. This provides additional strong support to the OPM's assumptions: Human behavior in everyday tasks follows an opportunistic approach and takes specific (spatial) factors of the task environment into account.

Differences in prediction accuracy for different sequences in the OPM's performance resulted from a combination of factors: First, in some data sets, spatial environments were very small, which lead to multiple items having the same or a very similar spatial location. Second, whenever containment was given for all or none of the items, this factor became irrelevant; the same is true for relational dependencies, if only items without any relational dependencies were seen in the sequence. Especially in long sequences, and in combination with the first point, this lead to a number of items having nearly or exactly the same weighted distance. In these cases the OPM had to choose the next action randomly, resulting in a higher possibility of deviating from the observed sequence. In these cases, other still unknown factors may be relevant for action selection, which need to be considered in future work.

## Implications for Models of Sequential Action Control

The OPM's success indicates that problem-solving in ill-defined domains requires an opportunistic planning strategy. Previous models of action sequence control, such as planning a trajectory from start to goal state (Botvinick & Weinstein, 2014), learning a pre-defined sequence of actions by maximizing the achieved score (Kachergis et al., 2016), or learning the best action sequence for a known set of actions or goals (Botvinick & Plaut, 2004; Cooper et al., 2014), have no mechanisms for opportunistic behavior and are therefore not suitable for ill-defined domains.

While existing models of action sequence control are applicable for everyday tasks in which a finite number of solutions exists – i.e., when following a specific cooking recipe, or making coffee – a problem arises when no such constraints exist: What is the role of control in a task where no clear visualization of the plan, i.e., the allowed moves to reach each next step and the means to compare all solutions exist? If not the whole sequence is known from the start, but just a more or less specified goal state as well as the initial state, how can appropriate means to reach this goal state be extracted from an infinitely large search space? While other approaches, such as HTN planning, are generally able to deal with problems in ill-defined domains, they rely on an accurate descriptions of and knowledge about the planning task, which may not be given in an underspecified everyday task.

The OPM bridges this gap by implementing a strategy that relies heavily on the subject's immediate knowledge about the environment and implements a computationally tractable heuristic: The model reacts flexibly to arising opportunities or constraints in each step, taking knowledge about the (spatial) environment as well as the human preference to minimize effort into account while only comparing the possible options for each next step instead of the whole action sequence.

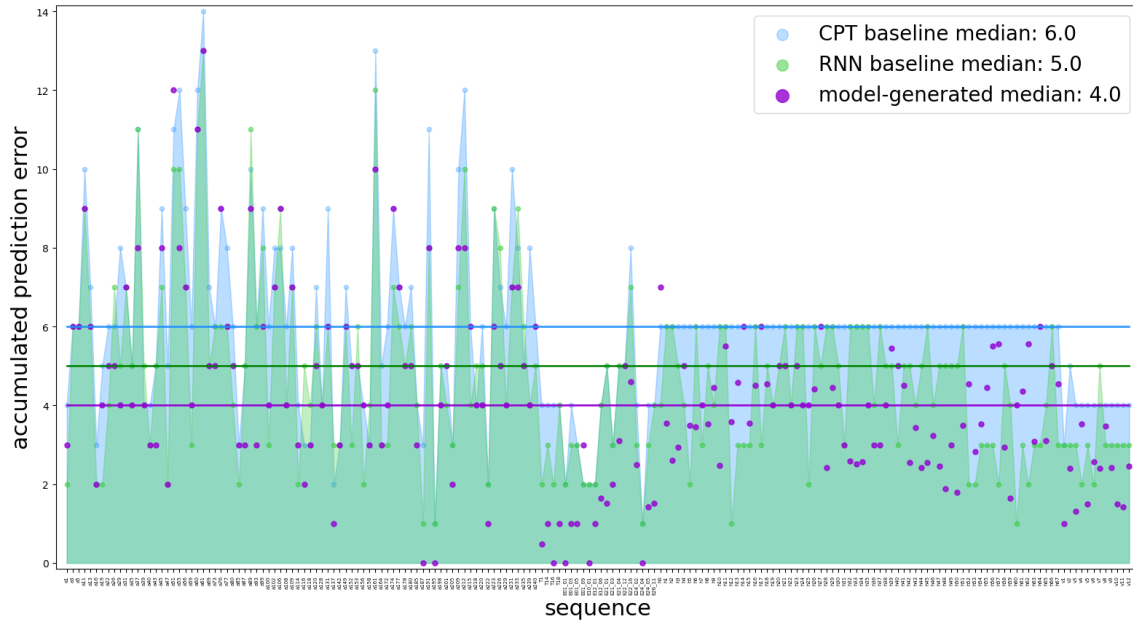


Figure 2: Best model simulation compared to RNN & CPT performance

In this regard, opportunistic planning and action sequence control models consider different cognitive mechanisms: While existing models of sequential action control focus on how sequential (routine) action with a finite problem space is controlled in order to minimize errors such as action slips during fixed sequences, opportunistic planning focuses on preference mechanisms that allow to explain human behavior observed during complex everyday tasks without a fixed set of actions. The role of action control is therefore less prominent in opportunistic planning models, such as the OPM, as they primarily consider how to narrow down the search space from a multitude of possible solutions.

In order to be suitable for complex everyday tasks with a large problem space, existing control models would need to integrate both of these levels by also considering mechanisms that decrease the number of possible solutions to a fixed set of actions, allowing to then implement control strategies.

### Conclusion and Future Work

The success of the OPM compared to black-box machine learning models lends support to the idea that situational context knowledge is of high importance to explain human behavior: The additional information the OPM has access to (location of items and subject) allows it to make more accurate predictions about human behavior than the black-box models learning patterns from the behavioral sequences without this additional knowledge. The importance of context knowledge may be pertinent for planning and action organization in ill-defined domains in general.

Regarding previous work on sequential action control, the OPM provides two important additions: First, it only compares possible solutions for each step to find the best option,

which makes it computationally tractable even in large problem spaces with a multitude of solutions, and second, considering the relational dependencies between actions and their implications concerning the required (cognitive) effort allows to better represent given constraints in real-world settings.

Future work includes applying the OPM on other everyday tasks in order to verify its ecological validity as a generative model that is not specific to the task of table setting. We also need to consider other potentially influential factors, which may be able to improve predictive power for the cases not yet fully explained by the OPM, such as sequences where spatial distances are very similar and relational dependencies and containment are only relevant for few or no items (see Results). Additionally, while modelling relational knowledge in a very abstract way has been sufficient for this first approach, modelling may profit from using a more expressive way to encode relations (see e.g. Gentner, 2010; Freksa, 1991).

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