Coherence and argument structure: An empirical comparison between plausible reasoning and the Bayesian approach to argumentation

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Abstract

Plausible reasoning has been proposed as an alternative to deductive and inductive norms of argument evaluation in informal logic. In this paper, we present the first systematic empirical contrast between the Bayesian account of argumentation and a plausible reasoning model. Results suggest that the Bayesian approach to argumentation provides a more precise picture of how people evaluate the strength of appeals to witness testimony when considering coherence and argument structure as relevant factors.

Keywords: Bayesian argumentation, plausible reasoning, argument evaluation.

Introduction

Imagine this situation: as part of a trial, someone reports having seen the defendant committing the crime he has been charged with. However, the eyewitness presence at the crime scene can only be corroborated by the testimony of a second witness. How should this fact influence the jury's decision? Now, consider another situation: two eyewitnesses, who do not know each other, declare they saw the person at the crime scene. How should the jury weigh up the testimonies in this case to decide whether the defendant is guilty? Is it possible to systematically describe the differences between these two cases and also determine the best way of combining the evidence to reach the best possible decision?

During the last decade, a research program has been proposed in the context of cognitive science in order to develop both a descriptive and normative model of argument evaluation, based on the concepts of subjective probability and Bayesian belief updating (Hahn & Oaksford, 2007; Oaksford, Chater & Hahn, 2008; Hahn & Oaksford, 2012). In parallel, some philosophers and AI researchers have questioned the normative status of the basic principles of Bayesian epistemology. In general, these critics describe a set of inference schemes as intuitively reasonable and then remark that these schemas cannot be reduced or properly understood from a probabilistic point of view. For example, Walton (2009) asserts that "defeasible arguments such as appeal to witness testimony are judged contextually in trials in a way that does not seem to conform to either deductive or inductive models of argument." (p. 33).In this vein, alternative models of inference have been proposed, such as defeasible reasoning(Pollock, 2006, 2008) or plausible reasoning (Rescher, 1976; Walton, 2008; Walton, Tindale & Gordon, in press).While plausible reasoning is a notion whose normative status is hotly debated (Hahn, Oaksford & Harris, 2013; Walton et al, in press), it is also a notion that is sufficiently formalised so as to afford testing of its descriptive adequacy (Rescher, 1976). Furthermore, plausibility is also a concept that has been invoked in the explanation of the origin of argumentation skills (Nussbaum, 2011). As far as we know, no empirical studies have been undertaken to contrast Bayesian and Plausibilist ideas as competing descriptive models of how people evaluate arguments. Argumentative scenarios as described in the first paragraph will provide the opportunity to make this comparison.

The main purpose of this paper is to undertake such a comparison between the Bayesian and the Plausibilist account in the context of an argument evaluation task. In what follows, the key features of each model are presented. We then offer a description of the situation that serves as the arena for the comparison between the models.

The Bayesian approach to argumentation

The basic principle of the Bayesian model of argument evaluation is that arguments can be understood as arrangements of premises and conclusions that have their respective subjective probabilities associated. These values express the agent's degree of belief in each premise and conclusion at a given time (Hahn & Oaksford, 2007).According to this account, the degree of belief in the conclusion is updated as a function of the degree of belief in the premises as prescribed by Bayes Theorem. Thus, the perceived argument strength,$\boldsymbol{P(H|E)}$, depends on the prior belief in the conclusion, $\boldsymbol{P(H)}$and the probabilities of the premises being true both in the case in which the conclusion is true$\boldsymbol{P(E|H)}$, and in the case in which it is not$\boldsymbol{P(E|\neg H)}$.The ratio between these values (likelihood ratio)provides an index of the degree of change of conclusion probability in light of the evidence (Hahn& Oaksford, 2012).

There are several characteristics that make the Bayesian approach a solid candidate to provide a good descriptive model of argument evaluation (Hahn et al, 2013). *Inter alia*, Bayesian models include specific parameters to represent different aspects of the quality and quantity of an argument's *content*. In fact, model parameterization makes it possible to derive both *ordinal* (e.g. Argument *X* will be better/worst evaluated than argument *Y*) and *point* predictions(e.g. Given the set of premises' probabilities, the degree of posterior belief in the conclusion *C* in light of the premises P_1 and P_2 will be *x*). This flexibility has allowed researchers to offer successful explanations of how people assess arguments from ignorance (*ad ignorantiam*), begging the question arguments (*petitioprincipii*) (Hahn & Oaksford, 2007), slippery slope situations (Corner, Hahn & Oaksford, 2011), and arguments against the person (*ad hominem*) (Harris, Hsu & Madsen, 2012). The evidence suggests that when people face an argumentation situation, they update their belief in the conclusion consistently with Bayesian standards.

What is plausible reasoning?

Pollock (2008) points out that there are several argumentation situations where the use of a probabilistic framework is, at least, misleading. For example, Pollock argues that it is counterintuitive that having an argument with several high probability independent premises might result in a low probability conclusion: the probability of the conclusion becomes weaker as 'stronger' evidence premises are added conjunctively. This kind of criticism has led some theorists to doubt the suitability of probability theory as the foundational ground for a theory of argumentation, and look to ideas like plausibility. In his seminal work, Rescher (1976) presents plausible reasoning as an inference framework that has been fashioned after a twofold purpose: 1) To analyse inferences made on the basis of information only supported by the 'trustworthiness', 'believability' or 'soundness' of the sources who offer the information; and 2) To provide a formal tool to make inferences in scenarios with informative inconsistency (i.e. when reports from different sources contradict each other), given that, according to Rescher, both deductive logic and probability calculus proscribe inference from contradictory premises. Thus, "the whole point of plausibility theory is to furnish a means for operating with the relative degrees of acceptability or presumptions in favor of diverse data" (Rescher, 1976, p.10).

In plausible reasoning, the concept of source refers not only to cognitive agents (witnesses, authorities, institutions) and concrete objects (records, documents, databases) but also to products of inference processes (theories, conjectures, suppositions, principles, rules, traditions, etc.). Other things equal, in the context of plausible reasoning, source reliability and the plausibility of a claim can be represented by the same index.

The plausibility of a set of premises, stated by a given source, can be expressed as a value in a scale ranging from 0 to 1 (where 1 is equal to absolute plausibility). Considering that plausibility is defined as an *ordinal* scale, Rescher clarifies that the purpose of his formalisation is not to create a quantitative device similar to probability calculus, but rather to provide a less restrictive "qualitative" calculus that enables direct comparison between plausibility values of different, and even contradictory, sets of propositions. In this spirit, taking a set of axioms as a starting point, Rescher (1976) derives a set of inference rules for plausible reasoning (see below rules MAX and MIN) which are not completely consistent with probability calculus, as it is shown below.

The case of appeal to witness testimony

In many argumentative contexts, people make use of testimonies as premises to support particular conclusions. Walton (2008) asserts that appeal to witness testimonies is an instance of a certain argumentative scheme called *argument from position to know*. In general, this kind of argument takes the following form:

> *Source X is in a position to know about a certain domain S containing proposition A.*
> *X claims that A (in domain S) is true/false*
> *Therefore, A is true/false.*

In the context of appeals to witness testimony in legal scenarios, Walton distinguishes two kinds of argumentative structures: convergent and corroborative (Walton, 2008). In convergent structures, two or more independent reports support the same conclusion. In corroboration arguments one or more testimonies support another testimony, in turn, giving support to a certain conclusion. According to plausible reasoning, in corroboration arguments, the conclusion must be as strong as the weakest premise (MIN rule), while in convergent structures, conclusion believability is at least as great as the strength of the most credible premise (MAX rule) (Walton; 2008).

From a probabilistic point of view, these structures can be represented by two different Bayesian networks (Figures 1 and 2). Each network conveys different dependence relationships between conclusion and premises. Thus, in a convergent structure such as the one represented in Figure 1, the argument strength can be expressed as the probability of a conclusion given the truth of the premises $A_2$and B_2,$P(C|A_2, B_2)$. By virtue of Bayes Theorem, this value can be calculated from $P(A_2|C)$ and $P(B_2|C)$. In the corroborative structure (Figure 2),interpreted as a causal Bayes net, the probability of the conclusion derives from$P(E_2|C)$by virtue of the causal Markov condition(the value of the variable is independent of other variables in the network, when conditioned on its parent values —direct causes (Pearl, 2000).

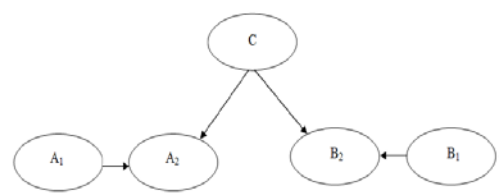

Figure1.Bayesian net of a convergent structure

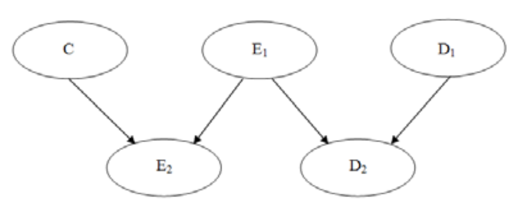

Figure2.Bayesian net of a corroborative structure.

One of the alleged features distinguishing the Bayesian account from plausible reasoning is the way inference from contradictions is addressed (Rescher, 1976). Therefore, coherence among testimonies is a key factor that must be considered in order to derive distinctive predictions, both for convergent and corroboration structures. In the remainder of this section, we show how coherence is incorporated in each model and its impact on the evaluation of appeal to witnesses.

Coherence and appeal to witness testimony

Harris and Hahn (2009) provide empirical evidence that people are sensitive to coherence among reports from different sources. They propose that people are able to weigh coherent information by the data about source reliability, following Bayesian prescriptions formulated by Bovens and Hartmann (2003). Specifically, in the experiments undertaken by Harris and Hahn (2009), people rated an argument based on multiple testimonies as better when more witnesses agreed on their reports, even though their individual reliability was the same. However, Harris and Hahn did not experimentally manipulate the argument structure, which prevented them from demonstrating whether the coherence effect disappears when reports rely on each other. In addition, their experimental design did not include a condition in which participants were faced with a total disagreement between sources, with equal or different reliability indexes. It is precisely for this particular scenario that Rescher (1976) and Walton (2008) suggested that the rules of plausible reasoning seem to be more appropriate than probabilistic ones.

In plausible reasoning, the strength of any appeal to witness testimony must be evaluated, taking into account independence among sources. If reports from each source do not rely on each other, they will form a convergent argument where the plausibility value of the conclusion will be at least as great as the most plausible report (MAX rule), regardless of whether all reports agree with each other. In contrast, if testimonies do rely on each other (as in corroborative arguments), they will connect together in a linked argument where the conclusion will be as plausible as the least plausible premise (MIN rule). If witnesses' reports are contradictory in a corroboration structure, premises will fail to support the conclusion.

To summarize, the predictions derived both from the Bayesian and the plausible reasoning models, only agree when arguments are linked and their premises are coherent. In these cases, both models predict that argument assessments might be stronger than the most reliable testimony. In the case of convergent and contradictory arguments, as well as corroboration arguments, plausible reasoning predictions tend to be higher, since Bayesian model penalizes further incoherence between premises.

In this experiment, participants assessed two appeals to witness testimony in which the following variables were directly manipulated: 1) argument structure (convergent vs. corroborative), 2) coherence among reports and 3) source reliability: This design allowed comparison between the descriptive fit of each model.

Method

Participants

289 undergraduate students (170 women), from four Colombian universities, with ages ranging from 16 to 30 (*M*= 20.06, s*d*.= 2.04). Some of them received extra credit in a class for participation in this study.

Design

A 2(convergent/corroboration structure) x 2(coherent/incoherent testimonies) x 2 (high/low reliability) factorial between-subjects design was used. The dependent variable was the numerical evaluation made by each participant of two appeals to witness testimony presented in two scenarios (car accident/burglary).

Materials and Procedure

The factors of interest (structure x coherence x reliability) gave place to eight conditions. Since each participant received two arguments, there were 64 possible combinations. As it was not possible to collect the dependent measure for all of them, 16 combinations of two arguments were randomly selected. In no case did the two arguments evaluated by one participant belong to the same experimental condition or to the same scenario. For example, if the hit and run argument was corroborative, coherent and had a low reliability, the second argument was a different condition. Scenarios were counterbalanced, so half of the participants had the burglary scenario first.

Each participant was provided with a booklet containing a set of general instructions, followed by the two cover stories, with the following general structure: first, a possible criminal incident was presented (hit-and-run accident/burglary) and the relevant authorities suspected two people of being responsible. Then, participants were told that the authorities had found either two witnesses who did not know each other (convergent structure) or someone asserting having witnessed the crime plus another witness confirming, or not, the presence of the former witness near the crime scene (corroboration structure). On the next page, the statement of each witness was presented, and it could be either coherent (coherent condition) or contradictory (incoherent condition). Immediately after this, participants were provided with results of a test performed to determine the visual acuity of each witness. This information was provided to define a reliability parameter for each report: in the low reliability condition both witnesses were just reliable: (positive hit rate = 0.6 and 0.65) (low reliability); in the high reliability condition, they are reliable enough (0.75 and 0.8) (high reliability). Variations in reliability were introduced to examine whether interactions between coherence and structure depended on reliability.

As an example, below is a reproduction of the hit and run cover story, with a convergent structure and based on reliable and contradictory testimonies (adapted from Kahneman & Tversky,1972):

Table 1.Evaluation means of appeals to witness testimony in each condition.

Structure	Coherence	Reliability	Predictions		
			Mean (S.D.)	Bayesian Model	Plausible Reasoning
Corroboration	Coherent	High	.65 (.16)	.73	.75
		Low	.55 (.16)	.59	.60
	Contradictory	High	.58 (.20)	.57	.25
		Low	.55 (.16)	.56	.40
Convergent	Coherent	High	.74 (.14)	.92	.8 – 1
		Low	.65 (.14)	.73	.65 – 1
	Contradictory	High	.63 (.18)	.57	.8 – 1
		Low	.54 (.16)	.55	.65 – 1

In a town there are two bus companies, the Green and the Red. One night very late, a bus is involved in an accident and drives away before the police arrive at the scene. The police find two people who had witnessed what had just happened. Witness A states that the bus was from the Green Company, while witness B says the opposite, that the bus was from the Red Company. Witnesses A and B did not know each other before the accident

To determine how reliable the witnesses are, the attorney who is dealing with the case, requests a visual acuity test for each of them, to be performed separately. The results show that witness A is able to correctly identify the color red and green 16 out of 20 times, in conditions similar to those present during the accident (lightning and distance). Results for witness B show that he is able to identify the colors correctly 15 out of 20 times in the same conditions.

To conclude, participants were asked to report, on a scale of 0 to 100, how confident they were that the suspect reported by the most reliable witness was guilty. That is, participants were asked to evaluate the conclusion of the stronger argument:

Based on this information, how confident would you be that the bus involved in the accident was Green? Please indicate your answer with a number between 0 and 100 where 0 means "I am completely sure the bus was NOT green" and 100 means "I am completely sure the bus was green"

Participants were tested in their classrooms in groups of 20 to 30 people. At the end of the task, demographic data was collected and participants were thanked and debriefed.

Results

Argument assessments for both scenarios were collapsed into a single score, since their means did not differ significantly. For ease of analysis, the original scale (0 to 100) was transformed into a 0 to 1 scale. Point predictions for both models were examined first, followed by ordinal predictions.

Point predictions for the Bayesian model were derived from eight Bayesian networks (one per condition) representing different combinations between convergent (Figure 1) and corroboration (Figure 2) structures as well as the coherence and reliability parameters specified in the design. Networks were implemented using GeNie[1] software. An example is depicted in Figure 3, where the conditional probability distributions have been set up according to the provided information on coherence and reliability.

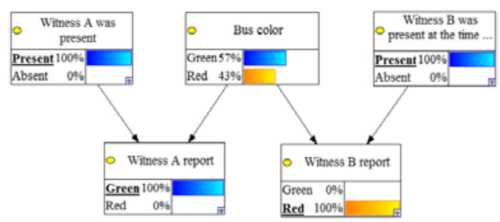

Figure 3.Bayesian network representing the convergent and contradictory argument with reliable testimonies.

Plausible reasoning predictions were calculated based on argument structure and reliability parameters. For instance, in the case of corroboration arguments with coherent and highly reliable witness testimonies, the predicted value is equal to the weaker testimony reliability (that from the witness accurately identifying the suspect 15 out of 20 times). In the case of convergent arguments with contradictory and less reliable testimonies, plausible reasoning predicts the judged strength of the conclusion will be equal or greater than that of the most reliable testimony (in this case, the testimony coming from the witness who identifies the suspect 13 out of 20 times).

Table 1 shows the predictions from each model along with the argument evaluation means. It should be noted that the values predicted by the Bayesian account fall within the confidence intervals predicted by the Plausibilist approach in 4 out of 8 experimental conditions.

[1]Available from http://genie.sis.pitt.edu/

The argument evaluation average was inferior to Bayesian predictions for coherent arguments with highly reliable testimonies as premises both in the case of convergent and of corroboration structure. In contrast, evaluations of convergent arguments with coherent and highly reliable witness reports were slightly greater than those prescribed by the Bayesian approach. Besides, plausible reasoning predictions only fall within the confidence interval of convergent and coherent argument evaluation means, showing a poorer descriptive fit of plausible reasoning compared to Bayesian predictions.

The second part of the analysis focused on comparing ordinal predictions both from plausible reasoning and the Bayesian model for each experimental condition. For this purpose, two different predictions were derived:

Coherence effect: Whereas the Bayesian approach predicts the perceived strength of the argument to be higher than the strongest testimony only in convergent structures with coherent premises, the plausible reasoning model does not predict a specific increase in the argument believability associated to coherence among testimonies.

Effect of structure on inconsistent arguments: According to the Bayesian model, both convergent and corroboration arguments will be evaluated in very similar ways when they have inconsistent premises (see Table 1). Plausible reasoning predicts that evaluation of convergent arguments with contradictory testimonies will be higher than that of the corroboration arguments with inconsistent testimonies, *ceteris paribus*. A three-way ANOVA was carried out where the dependent variable was the collapsed assessment rating for both scenarios. Main effects of every manipulated factor were found: structure, F (1, 570) = 18.21, p<.001, partial η^2 = .03, coherence, F (1, 570) = 27.02, p<.001, partial η^2 = .04, and reliability, F (1, 570) = 31.21, p<.001, partial η^2= .05. In particular, convergent and coherent arguments or arguments with highly reliable testimonies were consistently judged as stronger by our participants.

More importantly, there was a significant interaction between structure and coherence, F (1, 570) = 6.92, p<.01, partial η^2 = .01. There was not any other significant interaction between factors.

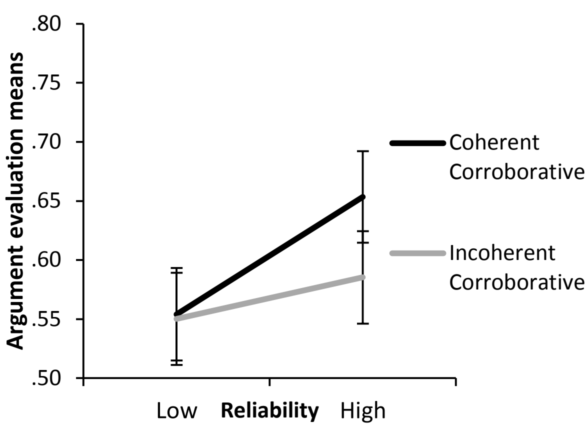

Figure 4.Corroboration argument evaluation mean ratings in each condition (CI 95%).

Post hoc analyses revealed that: 1) *Coherence effect*: arguments with coherent testimonies were better evaluated than those with incoherent ones in convergent structures, t(287) = 5.58, p< .001, but not in corroborative arguments t(287) = 1.72, p>.05, as predicted by the Bayesian model,. 2) On average, convergent and coherent arguments were judged to be stronger than corroboration and coherent arguments, t(281,34) = 5.04, p< .001. 3) *Effect of structure on inconsistent arguments*: Evaluations of arguments with contradictory testimonies were very similar, regardless of their structure, just as the Bayesian model predicts, t(286) = 1.06, p> .05. These findings are depicted in Figures 4 and 5.

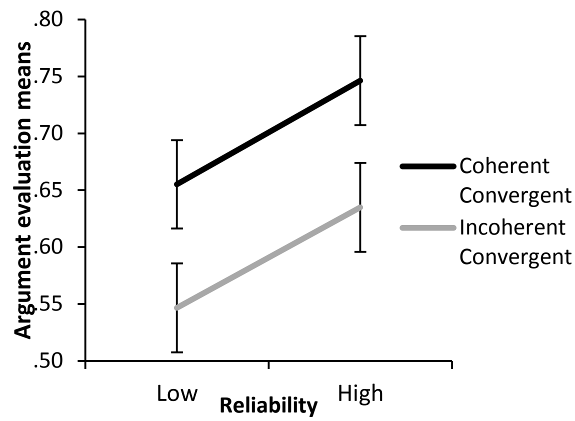

Figure 5.Convergent arguments' evaluation mean ratings for each condition.(CI 95%).

In conclusion, the results reported suggest that the Bayesian Model is superior to the Plausibilist approach, insofar as it describes more adequately participants' performance in tasks of assessment of testimony appeal. In this kind of situation, the perceived strength of the argument was lower than the most reliable testimony, both in convergent and corroboration structures *contra* the Plausibility hypothesis: people are not using anything like the MAX or MIN rules, as claimed by the Plausibilist approach. Additionally, only the Bayesian model can account for the combined effects of coherence and structure in the testimony appeals examined.

Discussion

Overall, results suggest that predictions derived from the Bayes nets, both point and ordinal, exhibit a better fit than predictions derived from the plausibility model. This trend is consistent even in the case of convergent arguments, where the Plausibilist model had an *a priori* advantage insofar as its predictions took the form of wide intervals, while the Bayesian model always generated discrete point predictions. However, participants consistently rated the strength of the argument conclusion (both for convergent and corroboration arguments) below what was predicted by the Bayesian model. This finding is consistent with *Bayesian conservatism*, a robust phenomenon reported in the literature on judgment and decision-making (Edwards, 1982). Generally, people tend to underestimate a hypothesis posterior probability, when compared to the prediction of the Bayes theorem. However, this systematic deviation from point predictions is also accompanied with superior ordinal fits. This highlights the need to further specifying the computational model that is required for the Bayesian approach to serve as a full psychological theory (though some advances have been made in this direction: see Corner, Harris & Hahn, 2010).

Recently, Fenton, Neil and Lagnado (2013) showed that the way people assess legal arguments, including alibi appeals, are well described by the prescriptions of a Bayes net. The findings reported in this paper add support to the Bayes model of legal argumentation, since it shows that people are sensitive to the interaction between structure of a testimony appeal and coherence between witnesses' reports.

Bowers and Davis (2012) have recently criticised Bayesian models of cognition, among other things, because they are seldom compared with simpler non-Bayesian models. This study can be considered a sample of one of those comparisons, as long as argumentation goes. There are, of course, other models proposed in informal logic (conductive reasoning, other forms of defeasible reasoning) that have not been contrasted with the Bayesian approach to argumentation. Our strategy in this paper, however, also reveals why these comparisons are rare. In the case of argumentation, pitting plausibility against a Bayesian model, involved a transition from an underspecified model to a set of concrete numerical predictions. By doing so, the theorist could always claim that the numerical version of the underspecified model is a caricature that does not represent the 'real' theory. This situation shows us that there is not much leeway when levelling the field in order to enable the comparison of alternative models of argumentation.

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