Demonstration of a Structure-guided Approach to Capturing Bayesian Reasoning about Legal Evidence in Argumentation

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Reasoning about statistics and probabilities can, when not treated with cautiousness, lead to reasoning errors.Over the last decades the rise of forensic sciences has led to an increase in the availability of statistical evidence. To facilitate the correct explanation of such evidence we investigate how argumentation models can help in the interpretation of statistical information. Uncertainties are by forensic experts often expressed numerically, but lawyers, judges and other legal experts have notorious difficulty interpreting these results [3, 1, 2, 5]. In this demonstration of our main paper [6] we focus on the connection between formal models of argumentation and Bayesian belief networks (BNs). We use BNs because they are a well-known model to represent and reason with complex probabilistic information. We introduce the notion of a *support graph* as an intermediate structure between Bayesian networks and argumentation models. A support graph captures the inferences modelled in a Bayesian network but disentangles the complicating graphical properties of such models and instead emphasises its intuitive understanding. Moreover, we show that this intermediate model can function as a template to generate different arguments based on the data.

A BN is a graphical model that not only represents a probability distribution but also its independence relation between the variables. Independence between variables is conceptually important but it also means that the number of model parameters can be reduced. It has been shown by Pearl [4] that *inter-causal interactions* should be taken into account in reasoning under uncertainty. An inter-causal interaction arises when two causes can independently cause (part of) the observed evidence. In such a situation it is often the case that belief in both causes is increased because of the diagnostic value of the evidence even though only one of the causes is sufficient to explain that evidence. This means that observing one cause 'explains away' the elevated belief in the other. These interactions are challenging to reason correctly about, but BNs can inherently model them correctly because they can model both causality and independence.

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A support graph is an intermediate structure between a Bayesian network and arguments. The main idea is to define the structural part of the argumentation in a model that abstracts from actual instantiations. We say that a variable *supports* another variable if observing the former changes the probability of the latter. We need to consider how to efficiently represent the support between variables. A Bayesian network is a computationally very efficient representation of a probability distribution, but it lacks a clear and intuitive way to model argumentative support. The approach we take is to abstract away from the outcomes of variables at first and consider a graphical representation of the interactions between variables. In this way we represent the structural aspects of how a particular conclusion can be supported without looking at the outcomes of variables. We can do so because these outcomes influence the strengths of the influences but not the fact that there is a probabilistic correlation and therefore a possible argumentative inference for at least one of the outcomes.

What we aim to do is minimise the number of variables that we have to consider as possible premises by only looking at the variables that 'directly' influence the variable of interest. The so-called Markov blanket turns out to represent exactly this minimal set of directly influencing variables that we want to include as possible premises for a rule.

DEFINITION 1 (SUPPORT FACTORS OF X). *The set of support factors of a node X in a BN equals the Markov blanket of that node, i.e. parents of X, children of X and all other parents of children of X.*

With the support factors as premises we can build a support graph. During this process we have to take some special precautions to preclude circular argumentation and support via head-to-head connections since the former is a logical and the latter a probabilistic fallacy. The process starts by creating a node for the conclusion of interest and recursively adding sub-supporters while maintaining a *forbidden set* of variables that can no longer be used in further support because of these interactions.

A large benefit of support graphs lies in its capability to function as an argumentation template. Support graphs are generic models in the sense that they do not take into account a set of observed nodes. Observations can be added in an interactive manner without having to recompute the underlying support graph. We can even add instantiations to construct graphs with an argumentative interpretation. For the observed variables it should be clear that the observed outcome is also the outcome that we assign in the support graph. For other nodes we propose a method that is inspired by the likelihood ratio approach.

DEFINITION 2 (NUMERICAL SUPPORT). *We assign to every non-observed node S in the support graph an outcome s_i and a numerical support according to the following likelihood ratio:*

$$LR(S) = \frac{P(E_S|S = s_i)}{P(E_S|S = \overline{s_i})}$$

such that LR is greater than 1. where E_S denotes the set of observed outcomes of all descendants of S in the support graph and $\overline{s_i}$ is the other outcome of S. If the LR equals 1, the outcome is not determined.

We apply this method to the example shown in Figure 1. A suspect may or may not be the source of some forensic sample. A DNA profile match confirms that the DNA of this suspect is identical to DNA found on the sample which implies that the suspect is the source. Both inferential steps are prone to exceptional circumstances: a lab error may explain the lab result and an identical twin the DNA identity. The resulting support graph with the applied outcome- and LR labels is shown in Figure 2. What we can see in this example is that the inference from the profile match to a DNA match is quite strong ($LR = 400$), and that the uncertainty about the existence of a twin slightly reduces the strength of this conclusion, but that, all evidence considered, there is a high likelihood ratio in favour of the thesis that the suspect is the source of the sample.

If we further investigate the case and find that the suspect does have an identical twin we can update the labelling of the support graph as shown in Figure 2b. What happens is that the evidence still supports the conclusion but the strength has reduced a lot. The suspect is still very likely to have DNA identical to the source of the sample, but there is about 50 percent chance that he is not the source.

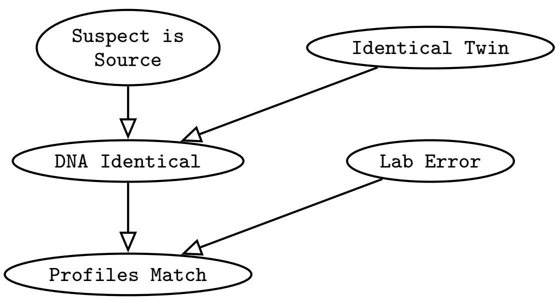
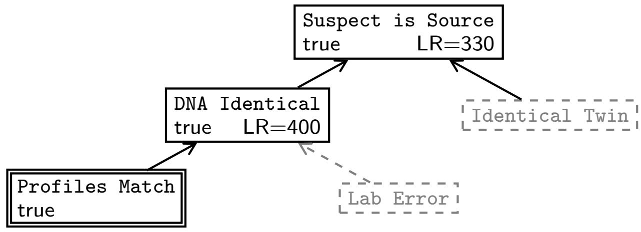
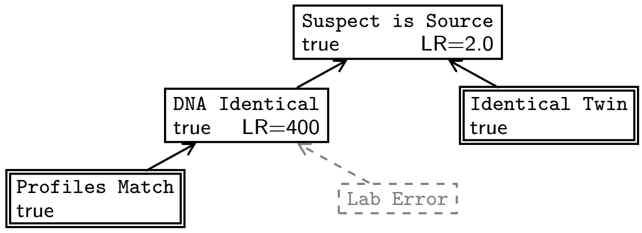


Figure 1: An example BN.



(a) The first piece of evidence is entered and the outcomes propagates through the graph.



(b) When a second piece of evidence is entered, the support graph does not need to be recomputed. We can simply redo the labelling.

Figure 2: Arguments can be constructed from a support graph by adding instantiations and propagating the outcomes according to the BN model of the probability distribution.

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