A Comparison of Two Hybrid Methods for Analyzing Evidential Reasoning

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Abstract. Reasoning with evidence is error prone, especially when qualitative and quantitative evidence is combined, as shown by infamous miscarriages of justice, such as the Lucia de Berk case in the Netherlands. Methods for the rational analysis of evidential reasoning come in different kinds, often with arguments, scenarios and probabilities as primitives. Recently various combinations of argumentative, narrative and probabilistic methods have been investigated. By the complexity and subtlety of the subject matter, it has proven hard to assess the specific strengths and points of attention of different methods. Comparative case studies have only recently started, and never by one team. In this paper, we provide an analysis of a single case in order to compare the relative merits of two methods recently proposed in AI and Law: a method using Bayesian networks with embedded scenarios, and a method using case models that provide a formal analysis of argument validity. To optimise the transparency of the two analyses, we have selected a case about which the final decision is undisputed. The two analyses allow us to provide a comparative evaluation showing strengths and weaknesses of the two methods. We find a core of evidential reasoning that is shared between the methods.

Keywords. Bayesian networks, case models

1. Introduction

Reasoning with evidence is difficult. This is especially pertinent in court, where reasoning correctly about evidence can mean the difference between a rightful conviction, or a wrongful imprisonment. To safeguard against errors, three tools for the rational analysis have been investigated in the literature: argument-based, scenario-based, and probabilistic [2,16,8,10]. In argumentative analyses, the emphasis is on argument structure, defeat and evaluation [29,4,14,20,24]. In scenario methods, with roots in legal psychology, the emphasis is on the construction and comparison of coherent explanatory scenarios and their relation to the evidence [3,19,28,18,1]. Probabilistic tools analyze how hypothetical events are probabilistically related to the evidence and to evidential updating, in particular by using Bayesian networks [15,12]. Hybrid approaches investigate, for instance, combinations of scenarios and arguments [5], evidential Bayesian networks [15,17,12], scenarios and probabilities [9,23]. Comparative case studies for assessing the relative merits of approaches are as yet rare. A recent valuable effort to this effect is the study of the Simonshaven case using different methods (upcoming issue 'Models of Rational Proof in Criminal Law' in the journal *Topics in Cognitive Science*, editors Henry Prakken, Floris Bex and Anne Ruth Mackor).

In this paper, two methods recently proposed in AI and Law are compared and evaluated: Bayesian networks with embedded scenarios [27], and case models that provide a formal analysis of argument validity [25]. For this, we develop two analyses of a murder case, one for each method. Since we are developing both analyses ourselves, we can aim for optimal similarity, increasing comparability (in contrast with the analyses in *Topics in Cognitive Science*, each developed by a separate team). The case is based on a real case,[1] simplified for present purposes. To improve transparency, we have selected a case with undisputed conclusion:

> On October first, 2002, N, a 25-year-old student is found dead in her apartment. There are signs of violence: bullet casings and blood. Before she died, she had called a friend. The friend reported a normal conversation, then heard a 'good morning', followed by yells and loud sounds, before the call dropped. A suspect was soon identified: P, the son of the landlord, who also lived in the apartment. He fled to Poland before he could be apprehended, and was only arrested in 2003. The court found P guilty of the murder of N in 2004.

2. Methods compared

2.1. Bayesian networks with embedded scenarios

A Bayesian network is a directed acyclic graph with associated conditional probabilities, and represents a joint probability distribution [22]. Bayesian networks can be used to avoid common fallacies in probabilistic reasoning [7]. The probability distribution can be found by elicitation techniques [21], although the lack of data makes objective priors difficult to find [11].

Probabilistic tools and the scenario approach are combined in [27] to construct a Bayesian network via scenario idioms. A scenario idiom consists of a boolean scenario node, and child-nodes representing aspects of that scenario. When the scenario node is true then all child-nodes must also be true. This ensures coherence, and transfer of evidential support. In the method, mutually exclusive scenarios are modeled via a constraint node (see [13]). Child nodes can represent abstract aspects that a court needs to prove, like motive or opportunity. Aspect nodes can be connected to other aspect nodes, and must be supported by evidence nodes. Evidence nodes are conditional on the aspect nodes.

2.2. Case Models

Case models are a formal tool for the analysis of coherent, presumptive and conclusive arguments using a preference ordering of cases [25]. The formalism is inspired by the connections between the three approaches to evidence. A case model can be constructed by adding evidence piecewise (argumentative) to construct coherent hypotheses (scenarios) of varying credibility (probabilistic).

A case model consists of a set of cases C, and their preference ordering $\leq$. Cases combine hypothetical events and evidence. The preference ordering depends on the coherence, conclusiveness, and presumptive validity of the arguments [25] of the cases.

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[1]Rechtbank Utrecht, see case ECLI:NL:RBUTR:2004:AO3150, also used in [6].
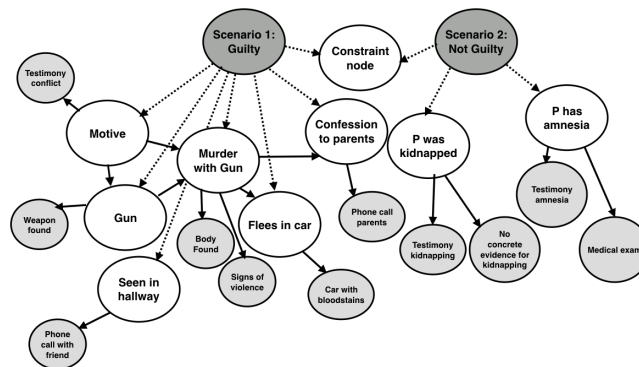
Figure 1. The Bayesian network of the case. The dark grey nodes are the scenario nodes: links between the scenario nodes and the aspect nodes are represented by dotted lines. The white nodes are the aspect nodes. The light grey, small nodes are the evidence nodes.

3. Models

In the following section, the methods for creating the Bayesian network and the case model are discussed.

3.1. Bayesian Networks

Following the method described by [27], two different scenarios of the case were constructed. The scenarios were modeled in a Bayesian network. The probability tables of each node were determined. The different nodes were turned off and on to see how each piece of evidence influences the probabilities in the scenario nodes.

3.1.1. Step 1: Create scenarios

Scenario 1   This scenario is based on the arguments of the prosecution. Suspect P murdered victim N with a gun. P had a motive, he was angry about an earlier conflict. He also had an illegal gun. N had been at home, on the phone with a friend. The friend testified that she heard N greet someone, followed by the sounds of gunfire and screaming. This greeting places P at the scene, as the other tenants had already left for work. After the murder, P flees in N's car, leaving blood traces behind. He flees to Poland. When he is in Poland, he makes several phone calls to his parents. In these phone calls, he confesses that he did something to N.

Scenario 2   This scenario is based on P's testimony. In this scenario P has been kidnapped, and he also has amnesia. P does not remember killing N, or where he was the morning of the crime.

3.1.2. Step 2: Creating the nodes and connections of the Bayesian Network

The complete network structure is shown in Figure 1. This is a diagram representation of the network that was created with GeNIe and AgenaRisk. The two scenario nodes were implemented first, connected by a constraint node.

	Probability of having a gun
Scenario1 and Motive	0.2
Scenario1 and ¬Motive	0
¬Scenario1 and Motive	0.2
¬Scenario1 and ¬Motive	0.06

Table 1. The probability table for `gun`. Numbers are based on the base rate of gun ownership, 6% in the Netherlands,[3] and the (debatable) assumption that people with a motive are more likely to own a firearm.

The aspect nodes for **scenario 1** are: `motive`, which represents the motive of P, supported by testimony of both his parents and N's friends about the conflict; `gun`, which represents the gun P had in his home, supported by the weapon being found, `seen in hallway`, which places P at the scene, and is supported by N's phone call with her friend. These three nodes are parent nodes of `murder with gun`, which represents P's murder of N, and is supported by N's body being found and signs of violence at the scene, like blood traces and bullet shells. The `murder with gun` node has two child-nodes: `flees in car`, representing how P flees, supported by N's car being found, which has been used after she died, and had her blood in it, and `confession to parents` node, representing P's confession to his parents over the phone, supported by his phone call. The node `motive` is also the parent of `gun`, as these are not two independent events: the probability of having a gun is not independent of the probability of having a motive.

The nodes for **scenario 2** are: the aspect node `kidnapped`, which represents P's kidnapping by unknown persons, which is supported by his testimony, evidence node `testimony P`, but detracted by evidence node: `no concrete evidence for kidnapping`, which represents that there is no concrete evidence, apart from P's testimony, that he was kidnapped. The aspect node `amnesia`, is supported by evidence node `P's testimony`, which represents P's testimony that he doesn't remember anything, and the node `medical investigation found no amnesia`, which represents the fact that there was no physical cause for amnesia as determined by a doctor.

3.1.3. Step 3: Creating the probability tables

Every node has an associated table, containing the probabilities of the node, conditioned on the values of the parents. Table 1 shows the probability table for the `gun` node, which depends on the value of the scenario node, and the motive node. The probabilities in the nodes are based on subjective choices. The constraint node has a value of NA when it was not the case that exactly one scenario was true.

3.1.4. Evidence flow through the network

By turning the evidence nodes off and on, the cumulative effect of different pieces of evidence on the probabilities of different scenarios is shown (Table 2). Presumption of innocence was modeled by having the prior probability of the guilty scenario node set to 50%, and the prior probability of the non-guilty scenario set to 50%, following [11].

3.2. Case Models

A case model (Figure 3) is created through a visual exploration of evidence (Figure 2). In this case study, evidence was collected from the court case. Then, the visual interpretation was created, where evidence was added step-by-step (in the same order as the nodes

Evidence	P(Scenario 1) in %	P(Scenario 2) in %
Start	50	50
Body found	43	56
Signs of violence	76	24
Weapon found	83	16
Phone call with friend	83	16
Testimony kidnapping	75	24
Testimony amnesia	64	35
Car with bloodstains	75	25
Testimony conflict	75	25
No concrete evidence of kidnapping	96	4
Medical investigation found no amnesia	99	1
Phone call parents	close to 100	close to 0

Table 2. Rounded down cumulative evidence in nodes for scenario 1, guilty and scenario 2, not guilty, evidence is turned on in the same order as evidence is added to the case model. The probability of one scenario does not affect the probability of the other scenario if there are no nodes that belong to both scenarios.

were turned on in (Table 2). From the visual interpretation, different hypotheses were collected. The hypotheses were then joined with maximally coherent evidence in order to create cases [25].

3.2.1. Step 1: Visual interpretation of the case model

A body is found. At this point, there is no evidence to assume a crime. However, there are (`signs_of_violence`), including bullet wounds and a found gun (`weapon_found`), so the victim was murdered with a gun.

Except for the victim, P was the only person in the house, and he was heard on the phone (`phone_call_with_friend`), so he is a suspect, and either guilty, or not guilty. P was then interviewed, and testified that he had been kidnapped, and that he had amnesia (`testimony_kidnapping`), (`testimony_amnesia`). The hypothesis of P not being guilty is further subdivided: either he is not guilty and he is telling the truth about the kidnapping and the amnesia, or he is not guilty and something else happened.

More evidence is added: N's (`car_with_bloodstains`) was found, moved after she was already dead, suggesting that P fled in her car. N's parents also testified about a conflict between P and N, which offers a motive (`testimony_conflict`). P's testimony conflicts with the results of a (`medical_examination`), which shows no physical cause for amnesia, as well as (`no_concrete_evidence`) of any kidnapping. The last piece of evidence is (`phone_call_parents`), he confesses that he did something to N in a phone call to his parents.

3.2.2. Step 2: Collect hypotheses

Every case in the case model has a hypothesis. This hypothesis can be found in the columns of the case model. This case model has the following three hypotheses:

1. `P_is_guilty`
2. `¬P_is_guilty` ∧ `P_was_kidnapped` $(\neg P \wedge K)$
3. `¬P_is_guilty` ∧ `¬P_was_kidnapped` $(\neg P \wedge \neg K)$
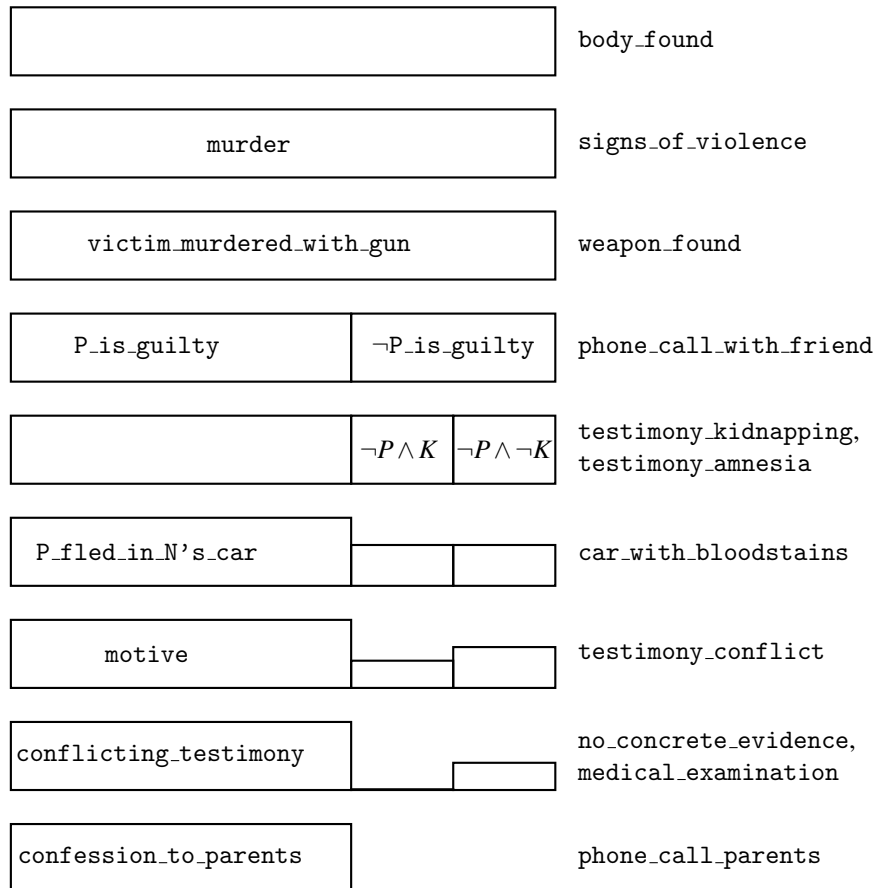
Figure 2. The case model creation, adding evidence chronologically

3.2.3. Step 3: Create cases by adding evidence to hypotheses

To create the cases, each hypothesis is extended with the subset of evidence that is coherent with the hypothesis. The evidence that is common to all three hypotheses: body_found ∧ signs_of_violence ∧ weapon_found ∧ phone_call_with_friend, is represented in these cases by E, for conciseness. There are 7 cases in total, shown in Figure 3.

1. P_is_guilty ∧ murder ∧ victim_murdered_with_gun ∧ P_fled_in_N's_car ∧ motive ∧ conflicting_testimony ∧ confession_to_parents ∧ E ∧ testimony_kidnapping ∧ testimony_amnesia ∧ car_with_bloodstains ∧ testimony_conflict ∧ no_concrete_evidence ∧ medical_examination ∧ phone_call_parents.

2. ¬P_is_guilty ∧ P_was_kidnapped ∧ murder ∧ victim_murdered_with_gun ∧ E ∧ testimony_kidnapping ∧ testimony_amnesia ∧ ¬ car_with_bloodstains.

Figure 3. The final case model creation

3. ¬P_is_guilty ∧ P_was_kidnapped ∧ murder ∧ victim_murdered_with_gun
   ∧ E ∧ testimony_kidnapping ∧ testimony_amnesia ∧ car_with_bloodstains
   ∧ ¬ testimony_conflict .
4. ¬P_is_guilty ∧ P_was_kidnapped ∧ murder ∧ victim_murdered_with_gun
   ∧ E ∧ testimony_kidnapping ∧ testimony_amnesia ∧ car_with_bloodstains
   ∧ testimony_conflict.
5. ¬P_is_guilty ∧ ¬P_was_kidnapped ∧ murder ∧ victim_murdered_with_gun
   ∧ E ∧ testimony_kidnapping ∧ testimony_amnesia ∧ ¬ car_with_bloodstains.
6. ¬P_is_guilty ∧ ¬P_was_kidnapped ∧ murder ∧ victim_murdered_with_gun
   ∧ E ∧ testimony_kidnapping ∧ testimony_amnesia ∧ car_with_bloodstains
   ∧ testimony_conflict ∧ ¬ no_concrete_evidence ∧ ¬ medical_examination.
7. ¬P_is_guilty ∧ ¬P_was_kidnapped ∧ murder ∧ victim_murdered_with_gun
   ∧ E ∧ testimony_kidnapping ∧ testimony_amnesia ∧ car_with_bloodstains
   ∧ testimony_conflict ∧ no_concrete_evidence ∧ medical_examination.

The preference ordering is, as represented by the areas of the different boxes: $1 > 2 \sim 4 \sim 5 \sim 7 > 3 \sim 6$.

The arguments (T, body_found) and (T, body_found ∧ signs_of_violence) are coherent, conclusive and presumptively valid, as everyone agrees that a body was found, and violence was committed.

The argument (body_found ∧ signs_of_violence ∧ testimony_conflict, P_is_guilty) is presumptively valid and coherent, but not conclusive, as (body_found ∧ signs_of_violence ∧ testimony_conflict, ¬P_is_guilty ∧ P_was_kidnapped) is also coherent.

The argument (body_found ∧ signs_of_violence ∧ weapon_found ∧ phone_call_with_friend ∧ testimony_kidnapping ∧ testimony_amnesia ∧ car_with_bloodstains ∧ testimony_conflict ∧ no_concrete_evidence ∧ medical_examination ∧ phone_call_parents, P_is_guilty) is coherent, conclusive, and presumably valid.

4. Comparative evaluation

We have provided two analyses of one case using very different formal methods. Also of the Simonshaven case, both a Bayesian network [11] (but not with embedded scenarios as we did here, following [27]) and a case model [26] were made. However, as these were prepared by separate authors, these analyses are based on rather different selections of what is modeled about the case and how. Here we have aimed to optimise similarity between the two models in order to allow for a more specific comparative evaluation. Also the Simonshaven case can be considered as a 'hard case' with a disputable outcome, whereas we selected a case with an undisputed outcome.

The Bayesian network with embedded scenarios (the BNS model) consists of a directed acyclic graph (with associated conditional probability tables) modeling the evidence/events and their probabilistic dependencies. In contrast, the case model (CM) con-

sists of sentences and a preference ordering modeling coherent combinations of evidence and hypothetical events. The ordering models comparative credibility of the cases and can be given a probabilistic interpretation. The two models hence provide very different ways to connect qualitative and quantitative modeling styles.

The two analyses provide a perspective on the stepwise influence of the evidence that is well aligned, as can be seen by comparing Table 2 and Figure 2. The design of the CM model (representing the stepwise construction of a theory about the case) influenced the choice of numbers for the BNS model, thereby optimizing the alignment.

The BNS model allows fine-grained numeric estimates of relevance and strength, where the CM model uses a cruder ordering. The effects of numeric propagation in the BN model are not easy to predict and interpret (cf. the influence of the CM model on the BNS model). For both methods, it is not obvious how to choose differences (numbers and ordering, respectively).

Both the BNS and the CM model can model conflicts of the evidence. In the BNS model, adding evidence can have a positive or negative effect on the probability of a scenario, and in the CM model evidence can match and exclude hypothetical scenarios.

The coherent clustering of events in scenarios is modeled in the BNS model using scenario nodes and constraint nodes (cf. [13]). In the CM model, clusters of evidence with scenarios are modeled by mutually exclusive cases.

The scenario nodes add to the explanation of the BNS model. Also turning evidence on and off (as in a BN software tool) helps to uncover the influence of the evidence on hypotheses. However the meaning of results and how they come about is not always transparent (why is an outcome 10%? why 50%?). The CM model's construction (Figure 2) allows for an explanation that as said could support alignment with Table 2. The final decision in the model has a transparent explanation, but the choice of ordering remains an issue.

For justifying a decision, the BNS model allows for a choice after picking a threshold posterior probability (e.g., 95%), providing a clean and precise model of justification. However, there is no obvious choice of threshold. In the CM model, justification of a decision has the form of coherence after exclusion of all alternatives considered. For both, the question remains whether there are unconsidered, unmodeled alternatives that could change the decision.

On ease of modeling, choosing dependencies and numbers for the BNS model was not easy, but once built, the role of the evidence on the hypothetical outcomes can be directly tested. The CM model was easy to construct. It seems positive that indeed consistency with the probabilistic BNS model was possible (as suggested by the theoretical fact that CM models allow for a numeric, probabilistic interpretation). At the same time, it is not clear whether the focus on only an ordering in the CM model reduces the expressiveness allowed by a BNS model, where subtle interaction effects can be modeled.

5. Summary and conclusion

Both Bayesian networks with embedded scenarios and case models can be used as hybrid tools to combine probabilistic, scenario and argumentation approaches to investigating hypotheses and evidence. In this paper, we have analyzed one case (with an undisputed outcome) using these two methods aiming for optimal similarity by using comparable modeling elements.

Evidence in Bayesian networks is relevant across the whole network, have a precise interpretation of evidence strength, and are straightforward in their use, once they have been created. Relations between different pieces of evidence is done by making subjective probabilities explicit, and truth is decided based on threshold probabilities. Coherence is not an inherent feature to Bayesian networks. Modelling a Bayesian network and deciding on the probabilities is a challenge.

In case models, evidence can be more local, confined to relevant cases. How to include quantitative data using only the ordering of cases is not clear. Coherence is inherent, and justification and explanation seem more similar to human reasoning than the conditional probabilities of the Bayesian network. Modelling a case model visually is straightforward, although extracting the cases and the ordering is not.

Both methods have limitations: the subjective probability assessment, especially in combination with nodes with a large probability table (nodes with many parents), is a problem in Bayesian networks. Coherency is similarly subjective, as well as the lack of expression of evidence strength in case models. However, both methods might help resolve inconsistent or incorrect reasoning with evidence by guiding the reasoners to consider conflicting pieces of evidence and overall coherence of each hypothesis or scenario.

We saw that the evidential progression modeled in two different ways (Table 2, Figure 2) could be well aligned, suggesting that such reasoning provides a shared core of evidential reasoning in the different methods. That progression is also at the heart of the modeling style in [7].

Reliable probability elicitation methods [21] are needed for the proper use of Bayesian networks. However, as the probabilities needed are often unobservable, giving appropriate probabilistic assessments can be very difficult. One idea to improve the understanding of probabilistic assessments would be to create a multi-agent simulation, with certain known incidences of different crimes. Then, different ranges of probabilities, based on those in this simulation, can be used in Bayesian networks to test different scenarios inside these worlds.

The case model theory does not exclude the possibility of quantification. However, it is unclear how this would work in practise: would this mean that every part of the case model is quantified, or can there be a mixed approach? Modelling a case that is more reliant on statistical inferences (for example, with DNA evidence), would be useful in finding the limitations of quantification in case models.

A useful, stricter evaluation of the methods could come from a systematic comparative analysis of other cases, more complex than the present one, like in the Simonshaven case studies, but then with carefully guarded model similarity.

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