# Constructing and Understanding Bayesian Networks for Legal Evidence with Scenario Schemes

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## ABSTRACT

In a criminal trial, a judge or jury needs to reach a conclusion about 'what happened' based on the available evidence. Often this includes probabilistic evidence. Whereas Bayesian networks form a good tool for analysing evidence probabilistically, simply presenting the outcome of the network to a judge or jury does not allow them to make an informed decision. In this paper, we propose to combine Bayesian networks with a narrative approach to reasoning with legal evidence, the result of which allows a juror to reason with alternative scenarios while also incorporating probabilistic information. The proposed method aids both the construction and the understanding of Bayesian networks, using scenario schemes. We make three distinct contributions: (1) we propose to use scenario schemes to aid the construction of Bayesian networks, (2) we propose a method for producing scenarios in text form from the resulting networks and (3) we propose a format for reporting the alternative scenarios and their relations to the evidence (including strength).

## 1. INTRODUCTION

In a criminal trial, the collection of evidence often includes probabilistic evidence (e.g. DNA profiling) as well as non-probabilistic evidence (e.g. witness testimonies). In forensic science, Bayesian networks have become popular as a probabilistic tool that is particularly suitable for working with multiple pieces of evidence (see e.g. [21, 9]). A Bayesian network models the relations between variables in a graph, and the underlying probabilities are specified in probability tables. From a Bayesian network any prior or posterior probability after observing evidence can be computed.


*ICAIL'15,* June 8–12, 2015, San Diego, CA, USA

ACM 978-1-4503-3522-5/15/06 ...$15.00.
http://dx.doi.org/10.1145/2746090.2746097.

Although a Bayesian network is a good tool for analysing probabilistic evidence, it can be difficult to work with. This difficulty lies in two tasks: (1) constructing a network modelling a case and (2) understanding the results of a network. Regarding (1), finding the structure of the network and the numbers is not straightforward. In previous research, methods were developed that can help find the structure of a Bayesian network for legal evidence (see e.g. [11, 10, 25] specifically for legal applications) and for eliciting the numbers (see e.g. [19] for elicitation techniques in general). Regarding (2), an understanding of a Bayesian network is needed for a judge or jury to use the results. Methods for understanding or explaining Bayesian networks are less well-developed (some work on explaining Bayesian networks for legal evidence can be found in [22, 15, 26]). In this paper, we propose a method that assists both the construction and the understanding of a Bayesian network modelling legal evidence.

We propose to use a combination of Bayesian networks and scenarios. The narrative approach to legal reasoning is a natural way for a judge or jury to organize the evidence as part of a coherent whole [18]. This coherent perspective can aid the construction of a network by providing the variables relevant for the model, as well as the understanding since it connects to an intuitive way of thinking for a judge or jury. We propose to report not only the posterior probability of scenarios but also how the evidence supports or attacks each scenario. This way, a juror can understand the content of the network and make their own decision using methods from typical narrative approaches to reasoning with legal evidence (such as [18, 27]), while also incorporating the probabilistic information. Ultimately, our goal is to develop a method that can take several alternative scenarios, model them in a Bayesian network that functions behind the scenes to evaluate any probabilistic evidence in a case, and present the results in a verbal report, which can be used for reasoning with scenarios by a judge or jury.

In this paper, we build upon previous work from [25], in which a method was proposed to construct a Bayesian network based on scenarios, and [26], in which scenarios were extracted from a Bayesian network as explanations for a judge or jury. In this paper, we extend the construction method from [25] with scenario schemes. As a result, coherent scenarios are now clearly present in the network and can be extracted to understand the content of the network.

Our contributions are threefold: (1) we extend the method from [25] with the use of scenario schemes, which provides yet more structure to the construction process (Section 3), (2) we propose a method for producing scenarios in text form from a Bayesian network built with scenario schemes (Section 4), and (3) we propose a format for verbally reporting alternative scenarios and their relations to the evidence as they can be found in a Bayesian network (Section 5).

# 2. PREREQUISITES

## 2.1 Bayesian networks

A Bayesian network consists of a directed acyclic graph and probability tables [12]. Each node in the graph represents a variable that can have certain values (e.g. true and false, though more than two values is possible). A probability table for a node $V$ gives the conditional probability of $V$ conditioned on its parents. For a node with two parents $U$ and $W$ the table holds $\Pr(V|U,W)$ for all configurations of values of $V$, $U$ and $W$. If $V$ has no parents, the probability table specifies $V$'s prior probability. Together, the graph and the probability tables are a compact representation of a joint probability distribution.

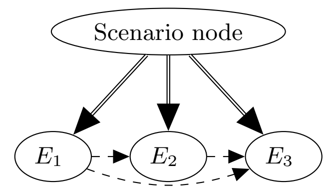
Information about the (in)dependencies between variables is modelled by the arrows in the graph. The arrows can be but are not necessarily causal relations [5]. From the structure of the graph it can be read which variables possibly have an influence on each other. When there is an *active chain* between variables $A$ and $B$, there is possibly an influence and they are said to be *d-connected*. If there is no active chain, there can be no influence and $A$ and $B$ are *d-separated*. For a serial connection $A \to C \to B$ or a diverging connection $A \leftarrow C \to B$, the chain is active when $C$ is not observed, and $A$ and $B$ are d-connected. As soon as $C$ is observed, the chain becomes inactive and when there are no other active chains between $A$ and $B$, they are d-separated. The converging connection $A \to C \leftarrow B$ is an exception: the chain between $A$ and $B$ is blocked when $C$ is not observed, yielding $A$ and $B$ d-separated. As soon as $C$ is observed, the chain becomes active and $A$ and $B$ are d-connected.

## 2.2 Constructing Bayesian networks

The construction of a Bayesian network modelling a case is not straightforward. In the legal field in particular, each case will require a custom model. To simplify the task of modelling a case in a Bayesian network, Hepler, Dawid and Leucari [11] listed several recurrent structures that could be used throughout various cases. This effort was continued by Fenton, Neil and Lagnado [10], who compiled a list of *legal idioms*. This comprises, for instance, the typical structure of connecting evidence to a hypothesis, and of modelling an alibi. In [25], four idioms were proposed to complement the idioms from Fenton et al. These new idioms are specifically intended for capturing scenarios in a Bayesian network. Based on these idioms a procedure is proposed for constructing a Bayesian network incrementally by *unfolding* a scenario into more and more detail. In this procedure, several alternative scenarios serve as a starting point to construct a Bayesian network capturing these scenarios. In the subsections below we briefly summarize the ideas from [25]. In Section 3, these ideas will be extended with the use of scenario schemes to further assist the construction process.

### 2.2.1 *The narrative idioms*

The four narrative idioms from [25] provide the basic structure for capturing a scenario as a whole (the scenario idiom), a scenario with subscenarios (the subscenario idiom), small variations within a scenario (the variation idiom) and several alternative scenarios in one network (the merged scenarios idiom). In this section the scenario idiom and the subscenario idiom will be discussed. For more details and further information about the other idioms, see [25].




| Scenario node | T | F |
| --- | --- | --- |
| $E_1$ =T | 1 | ... |
| $E_1$ =F | 0 | ... |

**Figure 1: The scenario idiom from [25]. Double arrows signify a special relation between the scenario node and an element node. Probabilities for element nodes are partially fixed as shown in the table. Dashed arrows show some possible connections.**

The scenario idiom and the subscenario idiom capture the coherence of a scenario and a subscenario, respectively. A scenario is not just any collection of states and events, it is a coherent collection in the sense that the elements of a scenario 'belong together'. For example, after finding a broken window in our home, we not only hypothesize that the window was broken by someone somehow, but we also hypothesize about the entire scenario of a burglary in which someone broke the window to steal things. Due to a scenario's coherence, observing evidence about one element of the scenario (a broken window) influences our belief in the scenario as a whole (a burglary) and therefore all other elements of that scenario. In [25], this is called *transfer of evidential support*. The scenario idiom provides the required structure for representing this phenomenon in a Bayesian network.

With the scenario idiom, each element of a scenario is modelled as a separate boolean node (in Figure 1: $E_1$, $E_2$,...). Between these nodes there can be connections (shown as dashed arrows in the image). A boolean *scenario node* representing the scenario as a whole has arrows pointing to each element of the scenario. These arrows are shown as double arrows in Figure 1, since they signify special relations between the scenario node (the scenario as a whole) and the element nodes (which are part of the scenario). The underlying idea here is that when the scenario as a whole is true (`Scenario Node = true`) then each element of the scenario must be true. As a result, some probabilities for the element nodes are fixed as shown in the table in Figure 1.

Due to the structure of the scenario idiom, the elements of the scenario are always d-connected via the scenario node (since the scenario node itself is never instantiated), and influence can pass between the nodes of the scenario. Additionally, by partially fixing the probabilities of the element nodes, in the absence of other influences it will always be the case that an increase in the probability of one element of the scenario will lead to an increase of the probability of all other elements of the scenario. The idiom structure in combination with the partially fixed probability tables thus models the transfer of evidential support.

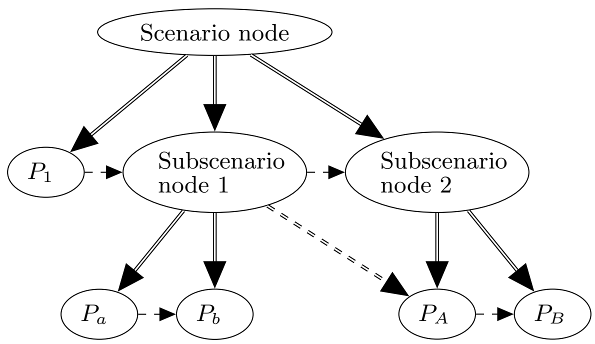



**Figure 2: The subscenario idiom from [25]. Double arrows signify a special relation between the (sub)scenario node and an element node. Dashed arrows show some possible connections.**

When there is a subscenario within a scenario, this subscenario itself has coherence and transfer of evidential support within the subscenario. For example, a burglary could be a subscenario within a larger scenario in which the thief was later found by the police. Such a subscenario can be modelled with the subscenario idiom (Figure 2). In the subscenario idiom, each subscenario has its own subscenario node, similar to a scenario node. These subscenario nodes are themselves part of the scenario as a whole. The probabilities are specified similar to those for the scenario idiom.

#### *2.2.2 The design method*

In [25], a procedure is proposed for constructing a Bayesian network for a case using the narrative idioms. Starting with a collection of alternative scenarios, these scenarios are each represented in a network structure, and merged to form one Bayesian network. Using the method of *unfolding*, a modeller gradually works through each scenario, using subscenarios to add more details when necessary. At first only an initial scenario is modelled with the scenario idiom. As soon as more details are needed about a certain element of that scenario, that element is 'unfolded' to become a subscenario node with more detailed elements of that subscenario attached to it. Constructing a Bayesian network then consists of the following steps, which can be repeated when needed:

1. Collect the relevant scenarios;
2. Unfold each scenario to the required level of detail using the idioms;
3. Merge all scenario structures to form one Bayesian network;
4. Include evidence and connect it to the nodes in the scenarios.

## 3. CONSTRUCTING A NETWORK WITH SCENARIO SCHEMES

In this section, we add the notion of a scenario scheme to the method from [25] as discussed in the previous section. A scenario scheme represents the abstract structure of a scenario. Whereas the scenario and subscenario idiom from Section 2.2 are meant to capture the general structure of *any* scenario in a Bayesian network, a scenario scheme is used to capture the typical structure of a certain type of scenario. For example, there can be a scenario scheme for a typical burglary, or a typical murder case. A scenario scheme thus specifies the structure of a scenario to a greater extent than the general scenario idiom from Section 2.2.

Adding the use of scenarios schemes can thus enhance the construction method from Section 2.2 by providing the modeller with more specific structures in which scenarios can be modelled. Furthermore, by using scenario schemes during the building process, some additional information is put into the Bayesian network that can later be used to explain the content of the network using scenarios.

### 3.1 Scenario scheme idioms

In order to use scenario schemes to build Bayesian network models, we use a scenario scheme idiom for each scenario scheme. Such a scenario scheme idiom is a specification of a general scenario idiom from Section 2.2, making it more context-specific. For example, for a typical murder scheme, the idiom will look as shown in Figure 3. Other scenario scheme idioms are, for example, in Figures 4 and 5 which will be used in the example case from Section 3.2.

There will be many different scenario scheme idioms for various scenario schemes. Ideally, a database of scenario scheme idioms is available to the modeller. A scenario scheme idiom can also be used as a subscenario within a larger scenario, using the subscenario idiom from Figure 2.

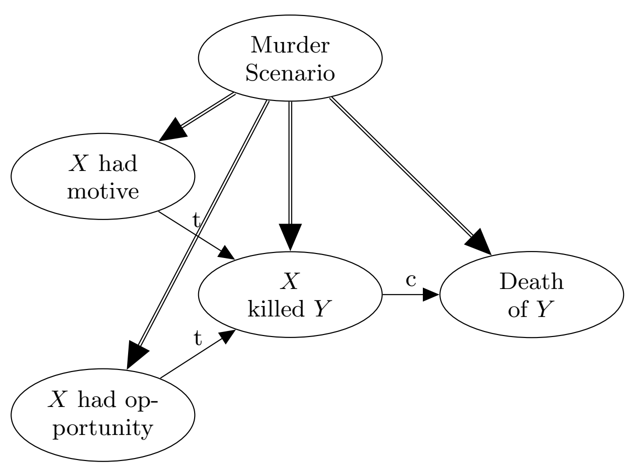



**Figure 3: The murder scheme idiom. Double arrows signify that the underlying probabilities are fixed.**

The nodes of the scenario scheme idiom are boolean nodes with values true and false, formulated as propositions ('X killed Y'). This makes it possible to translate to a scenario with propositions of the type 'Joe killed Pete', which then corresponds to the value-assignment 'Joe killed Pete = true'. The arrows between elements of the scenario are annotated with either 'c' (causal) or 't' (temporal) for later use when explaining the scenario. For now we only distinguish between these two labels, although in the future these could be extended to include other types of connections as well, such as distinction between physical causation and intentionality.

Using the labelled arrows, the Bayesian network structure shows how the propositions for each node relate to each other. For example, when nodes $A$ and $B$ are connected with a 'c'-arrow, the intended meaning is 'A causes B'. To ensure that this is what the Bayesian network model represents, the probabilities should be such that any arrow between nodes in the scenario represent a positive connection (namely, $\Pr(B = \texttt{true} | A = \texttt{true}, \texttt{Scenario Node = false})$ $\geq 0.5$. For `Scenario Node = true`, the numbers are fixed by the scenario idiom from [25]). By formulating the propositions in the scenario scheme idiom correctly, this restriction on the numbers should be satisfied naturally.

## 3.2 An example

Using the ideas from the previous sections, we can model an example case. We model part of a well-known Dutch case[1], with fictitious names Mary (the victim) and John (the suspect). Mary was found in a meadow, molested and killed. DNA traces were found on her body. From the autopsy, it became clear that the perpetrator attempted to strangle her, but failed and used a knife to cut her throat instead. There was also other evidence related to the molestation, which is beyond the scope of this example. Early in the investigation, two asylum seekers from the nearby asylum seeker's center were suspects, but were exonerated since there was no DNA match. Years later, an extensive DNA screening of the local population led to John as a suspect. He confessed and showed the knife with which he had killed Mary. John was convicted for the crime.

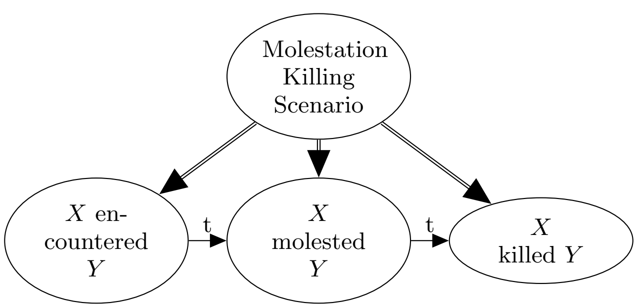



**Figure 4: A scenario scheme idiom for molestation and subsequent killing**

In the model in Figure 6, a Bayesian network for this case is shown. On the left hand side, the scenario about an asylum seeker (AS) was modelled, using a scenario scheme about molestation and then killing, shown in Figure 4. Since the DNA evidence quickly led to exoneration, the scenario does not need to be modelled in more detail. On the right hand side, a scenario about John was modelled with the same scenario scheme. The event 'John killed Mary' is now expanded (using the concept of unfolding from [25]) to a subscenario using a scenario scheme about a failed strangulation followed by cutting someone's throat, shown in Figure 5.

[1]The case can be found on www.rechtspraak.nl using identifier NJFS 2013/155

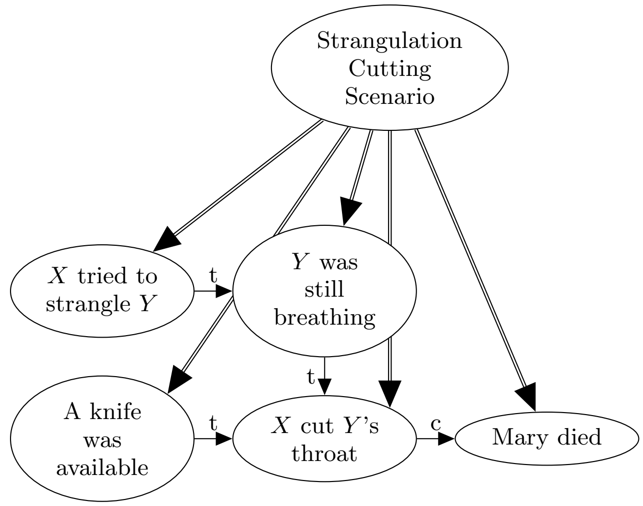



**Figure 5: A scenario scheme idiom for strangulation followed by cut throat**

# 4. PRODUCING SCENARIOS IN TEXT

In a network constructed with the method from Section 3, each scenario is modelled as a structure with a scenario node at the top. The nodes connected directly to this scenario node make up the scenario. In this section, it will be discussed how a scenario associated with a scenario node can be put into text form. Below, it will first be discussed how a scenario in a Bayesian network could be represented as a text (Section 4.1), which is then followed by a procedure that could produce such a text from a Bayesian network structure (Section 4.2).

## 4.1 From Bayesian network to text form

In order to produce a scenario in text form, the main idea is to take the proposition expressed by each node in a scenario and to put them in an appropriate order depending on the connections in the scheme, using the labels to formulate appropriate conjunctions ('therefore' for label 'c' and 'then' for label 't') between elements of the scenario. The main question addressed in this section is how to put the elements of a scenario in an appropriate linear order.

Consider the example from Figure 6. The scenario scheme underlying both main scenarios is shown in Figure 4. This scheme has a linear order, so it is straightforward to produce a a text for the scenario about the asylum seeker:

> AS encountered Mary. *Then* AS molested Mary. *Then* AS killed Mary.

However, in the scenario about John there is a subscenario (with subscenario node `John killed Mary`) with a non-linear structure. This means there are two issues to deal with:

1. How to put the subscenario into text within the larger scenario; and

2. How to produce a linear account of the non-linear subscenario about John killing Mary.

Regarding (1), we propose to maintain the short description of the subscenario ('John killed Mary') that is in the

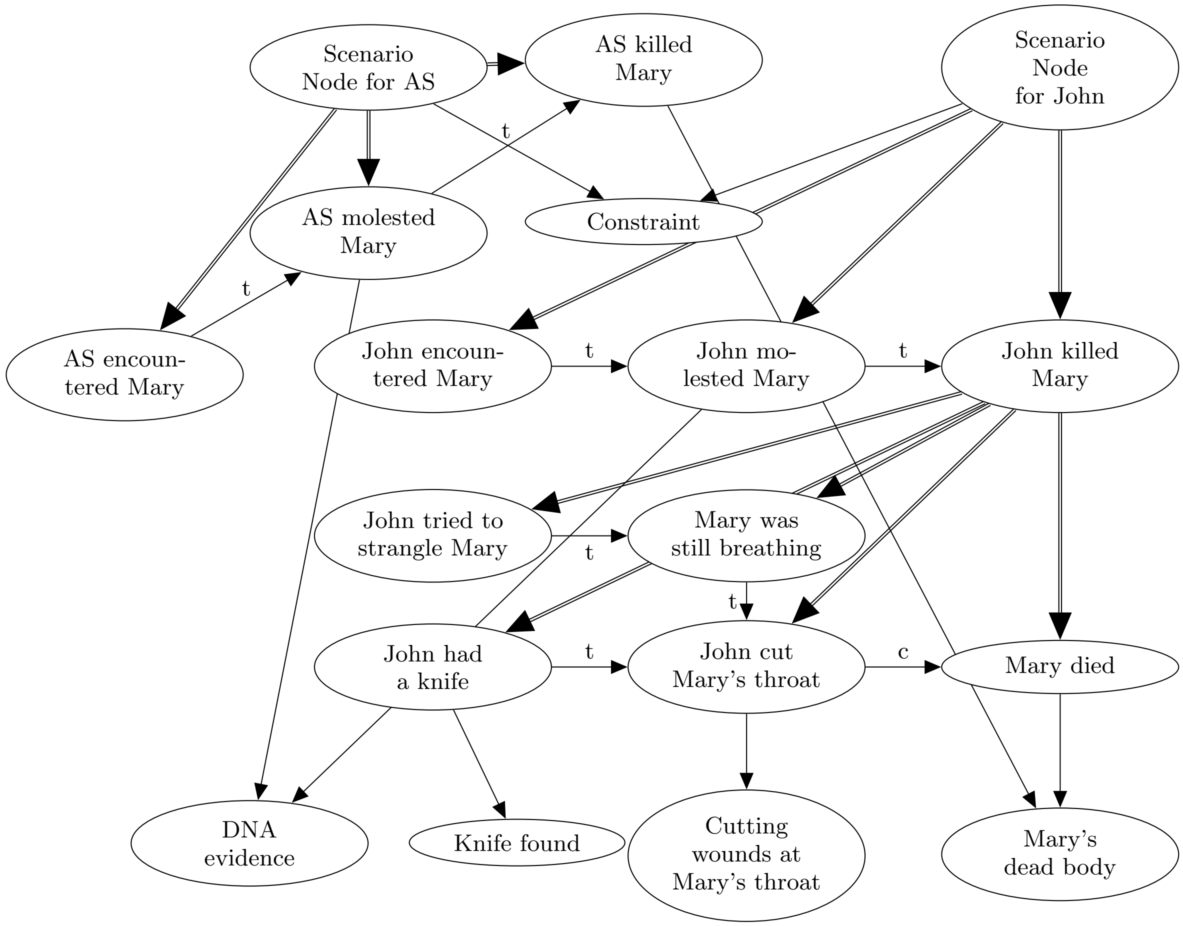



**Figure 6: An annotated Bayesian network structure for the example case with two scenarios**

subscenario node, as well as the detailed description of the elements of that subscenario. This way, the text that is presented to a judge or jury can incorporate the concept of 'unfolding', in which information about subscenarios can be provided upon request. In this example, the presented text would at first only describe the subscenario with the proposition 'John killed Mary', but after zooming in on this proposition, a more detailed description would be revealed.

Regarding (2), we propose to translate to a linear account of the scenario such that the direction of arrows in the network are respected. Whenever for nodes $X$ and $Y$ there is an arrow $X \rightarrow Y$ (labelled $c$ or $t$), the proposition corresponding to $X$ will appear in the text before the proposition for $Y$. Since a Bayesian network is acyclic, such a linear ordering is always possible.

In what follows, we discuss several non-linear structures as they might occur in a scenario, see Figure 7. For producing scenarios we are not concerned with influence between nodes changing as a result of observations in the network, since we are simply interested in reporting the scenarios that are in the network without taking the evidence into account yet.

The structure in 7(a) is an example of a node with two parents. In order to respect both arrows, the nodes A and B need to precede C in the text. We propose to do this by making groups of propositions (with 'and' or 'or') whenever a node has multiple incoming arrows: "A and B. Therefore C." In this example the two arrows have different labels. We propose to use conjunction 'therefore' whenever at least one of the arrows is labelled 'c'.

Whether 'and' or 'or' is used, depends on the underlying probabilities. Default is to use 'and', but there is an exception when 'or' is more appropriate, namely when the so-called 'explaining away' effect occurs [28]. When A and B are interpreted as causes, knowing that A is true and thereby caused C can reduce the need to know about an alternative cause B of C. For example, let A be 'Joe had a knife with him' and let B be 'a knife was lying nearby', both with arrows to C: 'Joe stabbed Pete'. In this case, knowing A (Joe had a knife) reduces the need to assume B (a knife was lying nearby) to explain the effect C (Joe stabbed Pete). In such cases, it makes more sense to combine A and B with 'or'. To be precise, parents A and B of C will be combined with 'or' when the following holds, which determines the 'explaining away' effect as described in [28]:

$$\frac{\Pr(C = \mathrm{T}|A = \mathrm{T}, B = \mathrm{T})}{\Pr(C = \mathrm{T}|A = \mathrm{T}, B = \mathrm{F})} \leq \frac{\Pr(C = \mathrm{T}|A = \mathrm{F}, B = \mathrm{T})}{\Pr(C = \mathrm{T}|A = \mathrm{F}, B = \mathrm{F})}$$

Similar to such a situation with multiple parents, when a node has multiple children we group the children together using 'and'. For multiple children, no distinction needs to

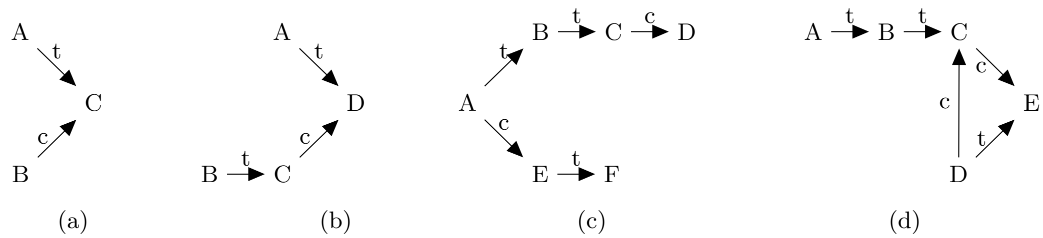



**Figure 7: Some typical structures**

be made between 'and' and 'or', since children are not conditioned on each other unless there is a connection between them, which leads to a different situation (see below).

In Figures 7(b) and (c), two situations are shown in which groups of parents or children need to be formed, but where one path is longer than the other. In Figure 7(b), two alternative translations could be (where 'and' is used as a default for groups of multiple parents):

1. "B then C, and A. Therefore D."
2. "B. Then C and A. Therefore D."

We propose to use the second translation since in the first, the combination of 'B then C' in one sentence quickly becomes complicated for longer paths (e.g. "K then L therefore M then N, and O. Therefore P"). The second translation deals better with a structure as shown in Figure 7 (c). There, the translation would be: "A. Therefore B and E. Then C and F. Therefore D." We thus go with a translation that groups nodes together that are at the same distance from the common ancestor or descendant. However, this may lead to some ambiguity, since different structures (e.g. with additional arrows) will be translated to the same text.

Finally, there could be a situation such as the one in Figure 7 (d), where a parent of E is also the parent of a parent of E (namely, D is a parent of C). When this is the case, in order to respect the arrows, D needs to precede C. We propose the following translation: "D. Therefore C. Therefore E". In this translation, the arrow from D to E is respected, but is not explicitly mentioned in the text. Including the remainder of the graph, the translation becomes: "A. Then B and D. Therefore C. Therefore E." Nodes B and D are grouped together because they are at the same distance from common descendant C.

## 4.2 Producing a text

To produce the translations as proposed in Section 4.1, we now propose an algorithm that can produce a text on the basis of a Bayesian network structure, incorporating the ideas from Section 4.1. Most importantly, this procedure respects the direction of arrows in the graph and groups multiple parents or multiple children together when possible.

We start with the nodes that have no parents within the scenario, tracing paths in the network for each of these starting nodes. As soon as a common descendant is found, the sequences for different starting nodes are integrated to form one sequence such that nodes at the same distance of the common descendant are grouped together. Similarly, when paths split, children are grouped together, and the children of those children, etcetera.

1. Start with all nodes that have no parents within the scenario.
2. For a starting node X, find all children and the label ('c' or 't') of their connection to X. Write down a sequence starting with 'X.' followed by 'Then' when all children are connected with a 't'-connection and 'Therefore' when there is at least one 'c'-connection. When there are multiple children of X, add these to the sequence conjoined with 'and'. For a parent X with children Y and Z (where at least one connection is labelled 'c'), this becomes: "X. Therefore Y and Z."
3. For the set of children of the previous step, find all children of these nodes and conjoin them with 'and'. Place this at the end of the sequence, preceded by 'Therefore' if there is at least one 'c'-connection, and 'Then' otherwise.
4. As soon as a node is encountered that also occurs elsewhere in the sequence or in another sequence for that network, this is a common descendant. Integrate sequences pairwise as follows, repeating to form one sequence:
   (a) Each sequence consists of groups of nodes (possibly consisting of one node, or several nodes combined with 'and' or 'or'), separated by connectives 'therefore' or 'then'. Count the length of the sequences by counting the number of groups. Suppose sequence 1 is of length $n$ and sequence 2 is of length $k$. Without loss of generalization, assume $n \geq k$. Then $d = n - k$ is the difference in length.
   (b) Merge the sequences by starting with the first $d$ nodes of sequence 1, and whatever connectives are between them.
   (c) After that, group the $d+1$st group of sequence 1 with the first group of sequence 2 (conjoined with 'and' or 'or', depending on the probabilities, see Section 4.1), the $d+2$nd group of sequence 1 with the second group of sequence 2, etcetera, until the $n-1$st group of sequence 1 is grouped with the $k-1$st group of sequence 2.
   (d) Connectives in the new sequence are of type $c$ whenever there is at least one $c$-connection between elements in one of the sequences, and otherwise $t$.
   (e) The last node of each sequence will be the common descendant, place this node in the sequence only once.

5. Repeat the process by expanding each sequence by finding child nodes and integrate whenever a common descendant is found.

This procedure gives the required results for the examples from Section 4.1. To see this, consider the structures from Figure 7 once again (where 'and' is used as a default for multiple parents, since probabilities are not considered here):

7(a) There are two start nodes: A and B. This leads to two initial sequences 'A. Then C.' and 'B. Therefore C'. Node C is in both sequences, so they are integrated to obtain 'A and B. Therefore C'.

7(b) Again, A and B are the two start nodes. Two sequences 'A. Then D.' and 'B. Then C. Therefore D' are formed. These are of different lengths, so the final sequence becomes: 'B. Then A and C. Therefore D.'

7(c) There is one start node, A. Children of A are grouped together, and children of the set of children of A are again grouped together. This leads to 'A. Therefore B and E. Then C and F. Therefore D.'

7(d) In this structure, A and D are both start nodes. Two sequences are formed to find one common descendant C: 'A. Then B. Then C.' and 'D. Therefore C'. These are integrated to obtain 'A. Then B and D. Therefore C.' Proceeding with this sequence, the last node E is added to obtain: 'A. Then B and D. Therefore C. Therefore E.'

When applying this procedure above to the subscenario about John killing Mary, the following result is obtained:

> John tried to strangle Mary. *Then* Mary was still breathing *and* John had a knife. *Then* John cut Mary's throat. *Therefore* Mary died.

Using the procedure described above, inevitably some information about the structure of the scenario is lost. For example, the temporal connection between 'John had a knife' and 'John cut Mary's throat' is not in the text produced by the procedure. And multiple nodes are connected with 'and', in two distinct cases: when a node has two incoming arrows, the parents are conjoined with 'and', and when a node has two outgoing arrows, the children are conjoined with 'and'. In the resulting text, there is thus no distinction between these two situations. We believe this is not a problem, since the main goal of our scenarios in text form is to convey the main scenarios present in the network, not their precise internal connections.

The subscenario about John killing Mary is part of the larger scenario about John. As discussed in Section 4.1, we propose to have the short description from the subscenario node ('John killed Mary') in the larger scenario such that, upon request, the detailed subscenario can be provided. This way, the scenario in text form maintains the concept of unfolding as used during the construction of a network. In a software environment, one could think of a hyper link:

> John encountered Mary. *Then* John molested Mary. *Then* John killed Mary.

Clicking the text 'John killed Mary' could give the following result:

> John encountered Mary. *Then* John molested Mary. *Then* [John killed Mary: John tried to strangle Mary. *Then* Mary was still breathing *and* John had a knife. *Then* John cut Mary's throat. *Therefore* Mary died.].

# 5. REPORTING THE RESULTS

After scenarios in text form have been produced, an informative presentation of the evidence related to these scenarios is needed. In the narrative approach to legal reasoning, choices between scenarios are typically made by comparing the evidential support for each scenario (see e.g. [18] and [3]) and which evidence distinguishes between scenarios (see e.g. [23]). This section is about how probabilistic information can be used to present information on evidential support and distinguishing evidence in relation to the scenarios.

A traditional narrative approach has no way to measure the strength of evidential support, other than, for example, counting how many pieces of evidence support each scenario. However, some pieces of evidence will provide stronger support than others, which can be captured in a probabilistic approach. In Section 5.1 we discuss how the strength of evidential support can be found in the network, and how to deal with multiple pieces of evidence (Section 5.2). This is followed by a concluding section with an example of how a verbal report on scenarios and their evidential support can be created (Section 5.3).

In the sections below we assume that the roles of various variables in the network are known. In principle, any node that does not represent evidence will be either a scenario node or part of a scenario (and hence connected to a scenario node or a subscenario node). The remaining nodes, those not directly connected to a scenario node or a subscenario node, are the evidential nodes.

## 5.1 Reporting evidence strength

Often, the strength of evidence is stated in terms of likelihood ratios (see e.g. [21]). However, a likelihood ratio is only meaningful when two mutually exclusive and exhaustive hypotheses are compared [8]. Here we want to list the evidence for each scenario separately, to adhere to the narrative approach. What matters for evidential support is whether the probability of the scenario as a whole changes when the evidence is observed [8]: $\Pr(s|e)$ changes relative to $\Pr(s)$. As a measure of evidential support, we thus use:

$$\frac{\Pr(s|e)}{\Pr(s)}.$$

Although there are several other measures of evidential support that compare the posterior and the prior probability, nearly all are ordinally equivalent to this one, including $\frac{\Pr(e|s)}{\Pr(e)}$ (which is equal, as follows from Bayes' theorem), see also [4]. The fraction above measures the change in probability of $s$. When this fraction is larger than 1, the evidence supports the scenario, and when the fraction has value smaller than 1, the evidence attacks the scenario. The larger (smaller) the value, the stronger the evidential support (attack).

With this measure, for each scenario supporting evidence ($>1$) and attacking evidence ($<1$) can be found and reported with a strength (translated to a qualitative account). In deciding between scenarios, crucial are the pieces of evidence

| | | | |
|---|---|---|---|
| | $x <$ | 0.001 | Very strong evidence to attack |
| 0.001 | $\leq x <$ | 0.01 | Strong evidence to attack |
| 0.01 | $\leq x <$ | 0.1 | Moderate evidence to attack |
| 0.1 | $\leq x <$ | 1 | Limited evidence to attack |
| 1 | $< x \leq$ | 10 | Limited evidence to support |
| 10 | $< x \leq$ | 100 | Moderate evidence to support |
| 100 | $< x \leq$ | 1000 | Strong evidence to support |
| 1000 | $< x$ | | Very strong evidence to support |

**Table 1: A qualitative scale for evidential support**

that *distinguish* between scenarios: a piece of evidence that supports one scenario more than the other. We propose to report the two strengths of support and add the remark that a piece of evidence is distinguishing evidence.

Finally, a feature of working with scenarios to analyse a case is that a scenario can also make 'predictions' about evidence that is yet to be found. Such a 'prediction' is called a scenario consequence in [3]. It is a piece of evidence that can be expected as a consequence of the scenario, but has not been observed yet. In the example from Figure 6, the potential evidence 'knife found' is a scenario consequence for the scenario about John (as long as it has not been observed yet). Such evidence can also be reported with a strength according to the measure proposed above, to reveal how strong that evidence would support the scenario if it were found.

### 5.2 Combining multiple pieces of evidence

When multiple pieces of evidence are involved, a different order by which evidence is entered into the network can lead to different strengths for one piece of evidence. An ordering $e_1, e_2, e_x, ...$, yields a different strength of evidential support for $e_x$ than ordering $e_x, e_1, e_2, ....$ Rather than imposing some ordering on the evidence, we propose to report the strength of each piece of evidence separately, as if it were the only evidence. For considering the combination of all evidence for a certain scenario, we compute one number for the measure of evidential support for the entire collection of evidence:

$$\frac{\Pr(s|e_1, ..., e_{n-1}, e_n)}{\Pr(s)}.$$

### 5.3 Presenting the results

Reporting the strength of evidence verbally requires some translation from the evidential support computed with the measure from Sections 5.1 and 5.2 to a qualitative report of evidential support. In what follows, we use a scale based on the standard qualitative scale published by the Association of Forensic Science Providers [2]. However, this scale needs to be slightly adapted since it was intended for likelihood ratios rather than evidential support. As a result, the scale from [2] has no translation for numbers smaller than 1, and only numbers higher than 1000 qualify as strong or very strong evidence. Since we are not (only) concerned with DNA evidence (which is typically associated with large likelihood ratios) but also with other types of evidence and their subjective probabilities, we expect our numbers to be lower. Our proposed scale is shown in Table 1.

Using the method described in Section 4, scenarios in text form can be produced from the Bayesian network. Each scenario is then accompanied by a list of all supporting evidence, attacking evidence, distinguishing evidence and scenario consequences, with a strength indicated for each piece of evidence separately according to the measure from Section 5.1 translated with the above scale. Furthermore, the combined strength of all evidence connected to that scenario is presented quantitatively (according to the same scale) and the posterior probability of the scenario node given all observed evidence is presented as a number. For the example network, the result looks as follows[2]:

- Scenario 1 (posterior probability: 0.0026): The asylum seeker encountered Mary. Then the asylum seeker molested Mary. Then the asylum seeker killed Mary.
  - Mary's dead body (Moderate evidence to support)
  - DNA evidence. (Limited evidence to attack)
  - Combined: Limited evidence to support.
- Scenario 2 (posterior probability: 0.8765): John encountered Mary. Then John molested Mary. Then [John killed Mary: John tried to strangle Mary. Then Mary was still breathing and John had a knife. Then John cut Mary's throat. Therefore Mary died.].
  - DNA evidence (Strong evidence to support)
  - Cutting wounds at Mary's throat (Limited evidence to support)
  - Mary's dead body (Moderate evidence to support)
  - Combined: Strong evidence to support
- Scenario consequence for scenario 2: knife found (Limited evidence to support)
- Distinguishing evidence: DNA evidence.

The strength of the DNA evidence for scenario 1 and scenario 2 might seem surprising. For the first scenario, the strength of the DNA evidence as attacking evidence is reported as limited. This is because the strength of a piece of evidence is calculated separate from the other evidence. When there is nu suspicion on the asylum seeker whatsoever (the prior probability is low), the DNA evidence has no strong effect. The evidential support of the DNA evidence for the second scenario is still not very high. This can be understood as a result of considering the scenario as a whole, rather than only a source level hypothesis that is supported by the DNA evidence. Since other parts of the scenario can still be false, the DNA evidence does not provide very strong support for the scenario, but strong support.

## 6. DISCUSSION

In this paper, we have proposed a method for both constructing and understanding a Bayesian network for legal evidence. Having a combined method has the advantage that the structure can be constructed such that the understanding becomes easier. Specifically, we proposed to use scenario schemes during the construction; by using scenario scheme idioms during the construction, the modelling process is more structured, while simultaneously it is ensured

[2] A network with specified probabilities is available from [website, anonymised for reviewing]

that all scenarios in the network are indeed coherent, and annotated with some structural properties (arrows labelled 'c' and 't'). This annotation is used for producing understandable scenarios in text form from the network. Finally, information about the relations of scenarios to the evidence is reported in a qualitative form.

The main advantage of this approach is that a judge or jury can make a decision using a scenario-based approach while also incorporating probabilistic information into their decision. As with any probabilistic approach, a disadvantage of this combination is that typically many numbers need to be specified in a Bayesian network. Methods for assisting the elicitation of probabilities are available (e.g. [19]). In addition, the use of scenario schemes provides some directions for the elicitation of numbers since the arrows in the scenario scheme idioms should always denote a positive influence.

Not all the numerical information from the network is used in the final verbal report, and not all the structural information from the network is taken into account when translating to scenarios in text form. Whether or not this is a disadvantage remains to be found in future applications to other cases; it can be an advantage to communicate only a limited amount of information to keep things understandable.

Another advantage of this approach lies in the understanding of the network: with the verbal report produced from the network, a judge or jury gains some understanding of the content of the network (the scenarios) as well as how the evidence changes the probabilities of these scenarios (communicated as qualitative strengths). In addition, the translation to scenarios in text form can be of help to a modeller as well: these scenarios can serve as feedback to find whether the network indeed models the scenarios as desired.

In the future we aim to test the method by means of a case study. Specifically, a case study can show what texts are produced for various scenarios and whether the labelling in the scenario scheme (with 'c' and 't') is satisfactory for the purpose of understanding these scenarios.

# 7. RELATED WORK

Pioneering work in modelling legal cases with Bayesian networks was done by Kadane and Schum [13]. Since then, the use of Bayesian networks to analyse legal cases has become popular (see e.g. [21, 9]) but it has become apparent that methods are needed for both constructing and understanding Bayesian networks for legal evidence. Below we discuss how the method proposed in this paper relates to previous work on constructing and understanding Bayesian networks.

One goal of the method proposed in this paper was to simplify the construction of a Bayesian network. Previous work on assisting the construction of Bayesian networks for modelling legal evidence was done by Hepler, Dawid and Leucari [11], who proposed the idea of working with often recurrent substructures. Fenton, Neil and Lagnado [10] extended these ideas with a list of six legal idioms, for modelling typical structures such as the relation between evidence and a hypothesis. In [25], this work was further extended with four idioms that were specifically intended for capturing scenarios. In the current paper, the use of scenario scheme idioms was proposed, building on the idea of scenario schemes as the underlying pattern of a scenario (see [18, 20, 3], all concerned with patterns underlying scenarios). This resulted in a specific idiom for each scenario scheme. Such a scenario scheme idiom is more context-dependent than the idioms previously proposed in [11, 10, 25] and thereby also provides more structure, simplifying the modelling process.

Another goal of the method was to understand Bayesian networks. Methods for understanding a Bayesian network can be focussed on various aspects, such as why certain modelling choices were made, or how the network leads to a conclusion (see [17] for an overview). Our goal was to communicate which scenarios are in the network, and their relations to the evidence. This goal was intended specifically for applications in the legal field. Related work in understanding Bayesian networks for legal cases was done by Keppens [15] and Timmer [22], who aimed to extract arguments from a network. Keppens also worked on generating crime scenarios in [16], but not applied to Bayesian networks. In [7], Druzdzel worked on extracting scenarios from a Bayesian network. There, a scenario is viewed as a configuration of nodes in the network. This approach leads to many more scenarios; for our example case, Druzdzel's approach would also produce scenarios such as 'AS did not encounter Mary, AS did not molest Mary, AS killed Mary'. In our current approach, the structure of a scenario plays an important role: not any collection of events can be a scenario (as opposed to Druzdzel's approach). Since the scenario scheme idiom always models a coherent scenario, what will be produced from the network is also a coherent scenario.

We also report the evidential support, including an associated strength. In [22], Timmer computes the strength of an argument with a measure similar to our measure of evidential support. Our qualitative reporting on evidence was inspired by typical narrative approaches, in which supporting evidence and distinguishing evidence for the scenario needs to be considered, see e.g. [18, 27, 3, 23].

This effort to combine Bayesian networks with scenarios was driven by a goal to better understand the various approaches to reasoning with legal evidence that exist in the literature, focussing on arguments, scenarios and probabilities respectively [14, 6, 1, 24]. One advantage of combining a probabilistic approach with a narrative approach is that various scenarios are compared, while the strength of evidential support for these scenario can be quantified on the basis of probabilities. As a result, a judge or jury can reason with scenarios while also incorporating probabilistic information about the evidence.

# 8. CONCLUSION

We have proposed a method for constructing and understanding a Bayesian network. Using scenario schemes as a basis, the construction of a network structure is assisted with typical substructures (idioms) for each scenario scheme. The resulting network contains clearly structured and annotated scenarios, which can then be extracted from the network and used to produce scenarios in text form. These scenarios then form the basis for a report in the style of traditional narrative approaches to reasoning with legal evidence, where several alternative scenarios and their relations to the evidence are reported. In addition to listing whether a piece of evidence supports or attacks a scenario, the probabilistic approach also allows for a strength of evidential support to be associated with each piece of evidence, and with the combination of all available evidence. This strength can be reported qualitatively to a judge or jury, which leads to a verbal report of alternative scenarios, their relations to the evidence and the strengths of evidential support.

By addressing both the construction and the understanding of a Bayesian network, the resulting scenarios produced from the network are guaranteed to be coherent scenarios, since they were modelled as such in the first place. By presenting not only the scenarios with their posterior probability as calculated by the network, but also the relations between the scenarios and the evidence, a judge or jury can make their own decision about a case in the style of traditional narrative approaches to legal reasoning.

In the future, we aim to test the method on a case study to find which results are produced for various scenarios.

## Acknowledgements

This work is part of the project "Designing and Understanding Forensic Bayesian Networks with Arguments and Scenarios" in the Forensic Science programme, financed by the Netherlands Organisation for Scientific Research (NWO).

## 9. REFERENCES

[1] T. Anderson, D. Schum, and W. Twining. *Analysis of Evidence*. Cambridge University Press, Cambridge, 2005.

[2] Association of Forensic Science Providers. Standards for the formulation of evaluative forensic science expert opinion. *Science & Justice*, 49(3):161 – 164, 2009.

[3] F. Bex. *Arguments, Stories and Criminal Evidence, a Formal Hybrid Theory*. Springer, Dordrecht, 2011.

[4] V. Crupi, K. Tentori, and M. Gonzales. On Bayesian measures of evidential support: Theoretical and empirical issues. *Philosophy of Science*, 74(2):229–252, 2007.

[5] A. Dawid. Beware of the DAG. In *Journal of Machine Learning Research: Workshop and Conference Proceedings*, volume 6, pages 59–86, 2009.

[6] A. P. Dawid, W. Twining, and M. Vasiliki, editors. *Evidence, Inference and Enquiry*. Oxford University Press, Oxford, 2011.

[7] M. Druzdzel. Qualitative verbal explanations in Bayesian belief networks. *Artificial Intelligence and Simulation of Behaviour Quarterly*, 94:43–54, 1996.

[8] N. Fenton, D. Berger, D. Lagnado, M. Neil, and A. Hsu. When 'neutral' evidence still has probative value (with implications from the Barry George Case). *Science & Justice*, 54(4):274 – 287, 2014.

[9] N. Fenton and M. Neil. Avoiding probabilistic reasoning fallacies in legal practice using Bayesian networks. *Australian Journal of Legal Philosophy*, 36:114 – 151, 2011.

[10] N. Fenton, M. Neil, and D. Lagnado. A general structure for legal arguments using Bayesian networks. *Cognitive Science*, 37:61 – 102, 2013.

[11] A. Hepler, A. Dawid, and V. Leucari. Object-oriented graphical representations of complex patterns of evidence. *Law, Probability & Risk*, 6:275–293, 2004.

[12] F. Jensen and T. Nielsen. *Bayesian Networks and Decision Graphs*. Springer, New York, 2007.

[13] J. Kadane and D. Schum. *A Probabilistic Analysis of the Sacco and Vanzetti Evidence*. John Wiley and Sons, New York, 1996.

[14] H. Kaptein, H. Prakken, and B. Verheij. *Legal Evidence and Proof: Statistics, Stories, Logic*. Ashgate Publishing Company, Aldershot, 2009.

[15] J. Keppens. On extracting arguments from Bayesian network representations of evidential reasoning. In K. Ashley and T. van Engers, editors, *The 13th International Conference on Artificial Intelligence and Law*, pages 141 – 150, New York, 2011. ACM.

[16] J. Keppens and J. Zeleznikow. A model based reasoning approach for generating plausible crime scenarios from evidence. In *Proceedings of the 9th International Conference on Artificial Intelligence and Law*, pages 51–59, New York, NY, USA, 2003. ACM.

[17] C. Lacave and F. Díez. A review of explanation methods for Bayesian networks. *The Knowledge Engineering Review*, 17(2):107–127, 2002.

[18] N. Pennington and R. Hastie. *Inside the Juror*, chapter The Story Model for Juror Decision Making, pages 192 – 221. Cambridge University Press, Cambridge, 1993.

[19] S. Renooij. Probability elicitation for belief networks: Issues to consider. *The Knowledge Engineering Review*, 16(3):255 – 269, 2001.

[20] R. Schank and R. Abelson. *Scripts, Plans, Goals and Understanding, An Inquiry into Human Knowledge Structures*. Lawrence Erlbaum, Hillsdale, 1977.

[21] F. Taroni, C. Aitken, P. Garbolino, and A. Biedermann. *Bayesian Networks and Probabilistic Inference in Forensic Science*. Wiley, Chichester, 2006.

[22] S. Timmer, J.-J. Meyer, H. Prakken, S. Renooij, and B. Verheij. Extracting legal arguments from forensic Bayesian networks. In R. Hoekstra, editor, *The 27th International Conference on Legal Knowledge and Information Systems (JURIX) 2014*, pages 71–80, Amsterdam, 2014. IOS Press.

[23] P. van Koppen. *Overtuigend Bewijs (Convincing Evidence)*. Nieuw Amsterdam, Amsterdam, 2011.

[24] B. Verheij. To catch a thief with and without numbers: Arguments, scenarios and probabilities. *Law, Probability & Risk*, 13(3-4):307–325, 2014.

[25] C. Vlek, H. Prakken, S. Renooij, and B. Verheij. Building Bayesian networks for legal evidence with narratives: a case study evaluation. *Artifical Intelligence and Law*, 22(4):375 – 421, 2014.

[26] C. Vlek, H. Prakken, S. Renooij, and B. Verheij. Extracting scenarios from a Bayesian network as explanations for legal evidence. In R. Hoekstra, editor, *The 27th International Conference on Legal Knowledge and Information Systems (JURIX) 2014*, pages 103–112, Amsterdam, 2014.

[27] W. Wagenaar, P. van Koppen, and H. Crombag. *Anchored Narratives: the Psychology of Criminal Evidence*. Harvester Wheatsheaf, Hemel Hempstead, 1993.

[28] P. Wellman and M. Henrion. Explaining 'explaining away'. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 15(3):287–292, 1993.