Representing and Evaluating Legal Narratives with Subscenarios in a Bayesian Network*

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Abstract

In legal cases, stories or scenarios can serve as the context for a crime when reasoning with evidence. In order to develop a scientifically founded technique for evidential reasoning, a method is required for the representation and evaluation of various scenarios in a case. In this paper the probabilistic technique of Bayesian networks is proposed as a method for modeling narrative, and it is shown how this can be used to capture a number of narrative properties.

Bayesian networks quantify how the variables in a case interact. Recent research on Bayesian networks applied to legal cases includes the development of a list of legal idioms: recurring substructures in legal Bayesian networks. Scenarios are coherent presentations of a collection of states and events, and qualitative in nature. A method combining the quantitative, probabilistic approach with the narrative approach would strengthen the tools to represent and evaluate scenarios.

In a previous paper, the development of a design method for modeling multiple scenarios in a Bayesian network was initiated. The design method includes two narrative idioms: the scenario idiom and the merged scenarios idiom. In this current paper, the method of [34] is extended with a subscenario idiom and it is shown how the method can be used to represent characteristic features of narrative.

1 Introduction

In a criminal trial, narrative can provide a context for what happened. A story or scenario gives a coherent presentation of the states and events around a crime and (implicitly) how

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these led to the evidence that was found. It is then up to a judge or juror to evaluate whether there is a scenario sufficiently supported by evidence to believe that this is in fact what happened. In order to develop a scientifically founded method for reasoning with evidence in a legal case, we propose to represent and evaluate crime scenarios in a Bayesian network.

Narrative has been one of three dominant approaches in the literature on reasoning with evidence, next to argumentation and probability [17]. Recently, Verheij [33] proposed to integrate the three approaches. In a previous project [5, 4, 6, 8], a hybrid theory for stories and arguments in legal cases was developed. Currently, we are working on the connection between probabilistic models and narrative. We build upon the recent application of Bayesian networks to legal cases.
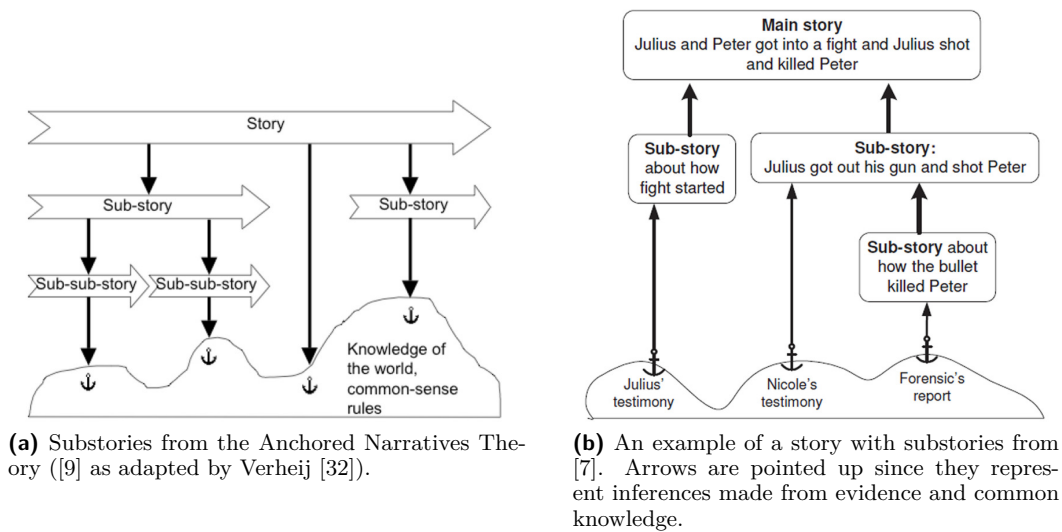
A Bayesian network represents a joint probability distribution over a collection of variables and consists of a graph, expressing the connections between variables in the domain, and underlying probability tables for these variables. As such, a Bayesian network can be used to represent the information that is available about a case, including evidence, hypothetical events and their connections.

In the legal field, the construction of a Bayesian network for a case is not at all straightforward. The network should include variables relevant to the case, but these differ from case to case. This contrasts with, for example, the medical field, where Bayesian networks have been used successfully to determine the most probable disease given a set of symptoms. For a given set of symptoms, a doctor knows in advance which tests will be relevant to perform and what their possible outcomes are, and a preconstructed Bayesian network can be selected. Unlike this relatively closed world of medical diagnoses, the legal field deals with a quite open world, where unpredictable relevant variables may turn up. For example, a yellow car passing by the evening before a burglary can seem irrelevant, until it turns out that it was driven by one of the suspects, inspecting the property before breaking in.

The application of Bayesian networks to legal cases has received quite some attention in recent research. Keppens [18] studied the combination of arguments and Bayesian networks in the context of law. Hepler, Dawid and Leucari [16] proposed the idea of often recurring substructures in the graph of a Bayesian network, which is also the basis of work by Fenton, Neil and Lagnado [14, 13, 20]. Fenton et al. developed a list of legal idioms, substructures that often occur in Bayesian networks for legal cases. Such idioms can be regarded as building blocks for a network, representing basic patterns in evidential reasoning. We intend to develop narrative idioms for representing scenarios in a legal case.

In our previous paper, we proposed to represent crime scenarios in a Bayesian network with the use of two narrative idioms: the scenario idiom for modeling scenarios, and the merged scenarios idiom for modeling multiple scenarios in one Bayesian network. Furthermore, we provided an initial sketch of a procedure for constructing such a Bayesian network. In this paper, we add a third idiom, the subscenario idiom, and we discuss how the scenario idiom and the subscenario idiom can be used to capture a number of narrative properties as they have been discussed in the literature. The contributions of this paper are threefold: (1) we give an analysis of characteristic features of narrative following recent work in the emerging field of computational narrative; (2) we extend the design method with a subscenario idiom; and (3) we show how the extended method can be used to represent the characteristic features from the analysis of narrative: structure, coherence, plausibility and the use of commonsense knowledge.

This paper is organized as follows: Section 2 is a literature study on narrative and its properties. In Section 3 some preliminaries on Bayesian networks are presented. In Section

(a) Substories from the Anchored Narratives Theory ([9] as adapted by Verheij [32]).

(b) An example of a story with substories from [7]. Arrows are pointed up since they represent inferences made from evidence and common knowledge.

Figure 1 Substories.

4 our design method and its development so far is presented. We extend this method with the new subscenario idiom in Section 5. Section 6 returns to the narrative properties, and the way in which these can be modeled with our extended design method. The paper is concluded in Section 7.

2   Narrative and its properties: a literature study

Literature on narrative spans a broad range of interests, from folk tales [27] to computer games [36] and TV-shows [22], and from determining the underlying plot of a story [21] to parsing and understanding a text [23]. This paper is concerned with legal stories, which we call scenarios: coherent collections of states and events, describing what can have happened around a supposed crime. Typically, there are multiple scenarios describing various accounts of what happened, and it is up to a judge or juror to find out which is true, based on the available and admissible evidence. Recent research on narrative in legal cases includes the development of a hybrid theory for stories and arguments [5] and simulating or animating a specific scenario with agents [31]. We focus on representing and evaluating various scenarios for a case.

The value of narrative in legal applications has been investigated in terms of various properties of narrative, such as a narrative's coherence, plausibility and the fact that it builds upon commonsense knowledge of the world. The sections below treat several properties of narrative that can be found in the literature, where reports on the 2009 workshop on the computational modeling of narrative [29, 15] served as a starting point.

2.1   Narrative structure

Three common denominators amongst representations of narrative are [15, 29]:
1. narratives have to do with sequences of events;
2. narratives have a hierarchical structure;
3. narratives are (eventually) grounded in commonsense knowledge of the world.

Following items (1) and (2), we take a scenario to be a collection of states and events with some coherent structure, either sequential or built up from subscenarios. Item (3), concerning commonsense knowledge, will be discussed in Section 2.4.

In a sequential structure, narrative is viewed as 'a succession of happenings' [29]. Schank and Abelson in their famous Script Theory [30] claim that for a proper text, a 'causal chain' can be constructed to represent it. Our case study [34] was done with this perspective in mind.

Alternatively, stories can be viewed as built up from substories. The idea of substories is prominently present in the Anchored Narratives Theory by Wagenaar et al. [35], see Figure 1a for their schematic representation of a story. There, the main story is ultimately anchored in commonsense generalizations. An example of a story with substories, taken from [7], is the following (see Figure 1b, where the anchoring is in evidence rather than in commonsense generalizations): Julius and Peter had a fight. This led to Julius firing a gun at Peter, who died as a result of this gunshot. This story consists of substories about Julius and Peter having a fight, Julius firing a gun at Peter and Peter dying of the gunshot.

2.2   Coherence

In the previous section, a scenario was said to be a collection of states and events with some *coherent structure.* In this section we further explore this notion of coherence, in light of scripts or story schemes (Section 2.2.1) and the transfer of evidential support as a consequence of narrative coherence (Section 2.2.2)

2.2.1   Scripts or story schemes

In an attempt to elucidate what makes a story or scenario coherent, one can study it from the perspective of Schank and Abelson's scripts [30]. Their scripts are used to explain how a listener can understand a story, and fill up the gaps that were left out when the story was told. Or as they say: "the meaning of a text is more than the sum of the meanings of individual sentences."

Schank and Abelson famously illustrated their theory with the example of a restaurant script: when a story is told about someone having dinner in a restaurant, the listener recognizes these events because he or she has a script of a typical restaurant visit in mind. This makes it possible for the listener to infer details that were omitted in the story. For example, when the story includes 'after ordering the food, he ate it', the listener will infer that between those two events, the waitress brought him his food.

A script is much like a 'template' for what elements a story (about a restaurant, for example), can or should contain. On the one hand, a listener uses this to make small inferences and fill up the gaps in a story. On the other hand, and this is not so much emphasized by Schank and Abelson [30], the storyteller makes sure that his story is perceived as *coherent* by adhering to a script. This idea of a template for what makes a complete story, can also be found in Pennington and Hastie's ideas on completeness [26] of a story, which led to Bex's story schemes [5].

Pennington and Hastie [25, 26] divide the coherence of narrative into three factors: consistency, completeness and plausibility. For them, the consistency of a story means that there should be no contradictions within the story. Plausibility is used to describe how well the story fits in with our knowledge of the real world. This will be discussed more elaborately in Section 2.3 below. Finally, completeness is 'the extent to which a story has all of its parts' [26] and can be regarded as a measure of how well a story follows a script.

In previous work by Bex and colleagues [5, 4, 6, 8], Pennington and Hastie's ideas on narrative coherence resurfaced in the formal setting of a hybrid theory for arguments and stories dealing with evidence in legal cases. There, a story is taken to be a coherent sequence of states and events. Arguments can be used to reason about the quality of the story: built upon evidential data available in the case, arguments can support states and events or causal connections in the story. Finally, arguments can also be used to reason about how well a story fits in and completes a so-called story scheme. The hybrid theory thereby implements the concept of a story's completeness.

Due to story schemes, a story for a legal case usually involves more states or events than what can be inferred directly from the available evidence. This is a valuable property in legal applications: it can lead to the finding of new evidence. In the hybrid theory, the notions of evidential gaps and story consequences are introduced. These refer to states or events that remain unsupported by evidence (evidential gaps) and new evidence that is found by trying to fill up these evidential gaps (story consequences).

2.2.2 Transfer of evidential support

A story or scenario is more than the sum of its parts. Separately, each state or event may seem uninteresting, or irrelevant to the case. By putting the states and events into a coherent whole and providing evidence for some of them, the scenario can be strong enough to make us believe in an event for which there is no direct evidence. This is illustrated by the following example:

▶ **Example 1.** We consider a famous Dutch case (known as 'De Deventer Moordzaak')[1], in which a widow was murdered. Her accountant was convicted for the murder, but according to some legal experts this was unjust. One of their arguments [11] presents an alternative scenario consisting of a number of small observations of the crime scene as it was found after the murder. In the original scenario for which the accountant was convicted, the suspect called the widow on the phone at 20:36 and drove to her home to kill her. In the alternative scenario, the killer must have been in the house much earlier than the accountant could have been given the phone call. In this scenario, the widow was doing the dishes and hadn't finished writing her shopping list when she was interrupted by the killer. Due to her strict routine this must have been shortly after the end of the eight o'clock news. The ingredients for this alternative scenario are small observations of seemingly unrelated details, such as an open notebook and pen on the table (she hadn't finished her shopping list) and the widow's apron on a chair in the conservatory (she was doing the dishes when she was interrupted by the doorbell). The neighbors testified that the widow always had a very strict routine, and together with the aforementioned details this leads to a coherent alternate scenario.

In this murder case example, the factor of interest is what time the killer entered the house. Given the time of the phone call, it would have taken the accountant quite some time to drive to the widow's house, giving her the time to finish her dishes and her shopping list. In the alternative scenario, someone else must have been the killer. There was no direct evidence for this specific event, but by presenting a coherent scenario with events for which evidence is available (such as, the widow was disturbed while she was doing the dishes), it can still become believable. It is this manifestation of coherence, which we shall refer to as *transfer of evidential support*, that we want to capture in our models.

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[1] Information about this case can be found on www.rechtspraak.nl with code LJN BA 1024.

2.3   Plausibility

Plausibility of a story is a term often discussed in literature on narrative and law (for example, in [26, 35, 5]. In a criminal trial, scenarios are often highly unlikely, such as an alibi that just seems hard to believe. But even a very implausible scenario can become probable when there is enough evidence to support it. It is then up to the judge or juror to take this evidence into consideration and decide which scenario is probable enough to assume that this is what happened.

Pennington and Hastie describe the plausibility of a story as "the extent to which the story is consistent which knowledge of real or imagined events in the real world" [26]. Bex formalizes this by expressing a story's plausibility in terms of how many elements of the story are supported by commonsense knowledge. The key idea of plausibility is that a story is plausible when as a whole, it seems credible to us given our knowledge of (and experience with) the real world.

2.4   Commonsense knowledge

In order to understand narrative, a listener needs commonsense knowledge about the world. This was already a factor in the idea of scripts to understand stories, and in the concept of plausibility as described above. The use of commonsense knowledge was mentioned as one of the three common denominators of narrative. According to Bex and Verheij [8, 7], commonsense knowledge can be captured in either story schemes or argument schemes.

Commonsense knowledge plays an important role in the Anchored Narratives Theory by Wagenaar et al. [35]. There, a story in a criminal trial should be firmly anchored in commonsense knowledge in the form of generalizations such as 'an expert witness usually speaks the truth'. Bex's hybrid theory [5] is centered around the idea that a story should be supported by evidence and commonsense knowledge.

2.5   Summarizing: properties of narrative

To summarize, the following properties of narrative have been discussed in this section:
1. Narrative structure: sequential or built up from substories;
2. Coherence, manifested in three key features:
    a. A script or story scheme that serves as a template for a story;
    b. Evidential gaps and story consequences: events unsupported by evidence (evidential gaps) and the finding of new evidence (story consequences) as a result of these gaps;
    c. Transfer of evidential support: evidence for one element of the story can increase the belief in the entire story and thereby all elements of the story;
3. Plausibility: the extent to which a story seems credible to us given our knowledge of (and experience with) the real world;
4. Commonsense knowledge: the basic knowledge needed to understand the story.

In Section 6, these properties will be further discussed, including how they are captured in the design method presented in this paper.

3   Bayesian networks in legal cases

A Bayesian network consists of a graph (such as in Figure 2) and probability tables (such as Tables 2a and 2b). The nodes in the graph represent variables in the domain: a Bayesian network for a legal case typically contains hypotheses (such as `Fingerprints X`, abbreviated as `FP X`, describing that X's fingerprints were found at the crime scene), intermediate nodes

Figure 2 Example of a Bayesian network.

Table 1 Examples of probability tables. `Fingerprints X` was abbreviated to `FP X`.

FP X = y	FP X = n
0.2	0.8

(a) Prior probability $P(\texttt{FP X})$.

	FP X = y	FP X = n
Fingerprint match = y	0.9	0.01
Fingerprint match = n	0.1	0.99

(b) CPT for $P(\texttt{Fingerprint match} \mid \texttt{FP X})$

and evidential nodes (in Figure 2, `Fingerprint match` describes that the police found a match between the fingerprints found at the crime scene and suspect X).

With the arrows between nodes, dependencies and independencies between variables are shown in the graph. These arrows are often thought of as representing causality, which can be helpful when constructing a Bayesian network [24]. However, the arrows represent correlation, not causality [10]. The conditional probability tables (CPT's) contain the probabilities for a node conditional on its predecessors (Table 2b shows the conditional probability table for `Fingerprint match`). A node with no predecessors contains the (unconditional) probabilities for each value of the variable (see Table 2a). Such probabilities are called *prior probabilities*.

A Bayesian network is a representation of a joint probability distribution (JPD) [19]. The JPD contains the probabilities for each combination of values of variables, such as $P(\texttt{Fingerprint match = n}, \texttt{Fingerprints X = y})$. From a Bayesian network, the numbers in the joint probability distribution can be retrieved, as well as any prior or posterior probability of interest.

After constructing the Bayesian network, the evidence nodes can be *instantiated* in the network: the probability of the appropriate value of the evidential nodes is set to 1, and this information is propagated through the network, leading to updated (posterior) probabilities for the other nodes. There are tools available for such calculations, such as GeNIe 2.0.[2]

Bayesian networks are often used as a compact representation of a joint probability distribution. An advantage of a Bayesian network is the insight that the graphical structure provides into the connections between the variables. Though a Bayesian network requires less numbers to be made explicit, both a JPD and a Bayesian network require full information about the probabilities in the domain. Eliciting these numbers is a known issue for Bayesian networks. A number of methods for finding these numbers, or guiding experts to find these numbers, are available [28].

There is an ongoing debate about the use of Bayesian methods in court. There has been a ruling by the Court of Appeal in the UK in 2010, stating that Bayes' theorem should not be used in evaluating evidence, except for DNA and 'possibly other areas where there is a firm statistical base' [12]. On the other hand, a member of the Supreme Court in the Netherlands, together with the Netherlands Forensic Institute (Nederlands Forensisch Instituut, NFI), recently advocated the use of Bayesian thinking [1, 2, 3].

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[2] GeNIe 2.0 is available for free on genie.sis.pitt.edu.

(a) The scenario idiom

(b) The scenario idiom for the burglary scenario
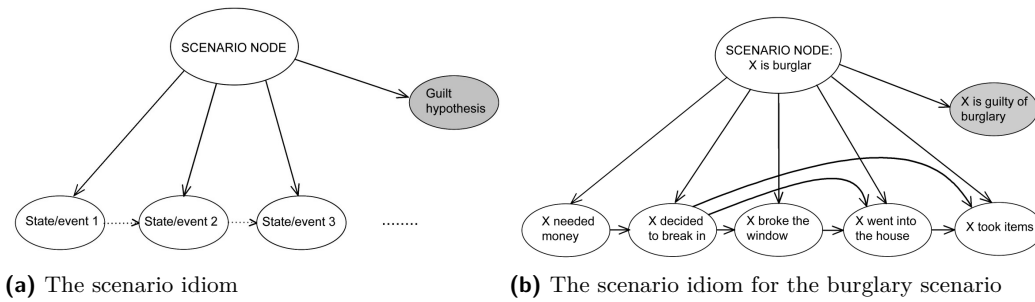
Figure 3 The scenario idiom. Dotted lines denote possible connections between states and events.

Arguments against the use of Bayesian networks in court concern the known problem of eliciting the numbers in the probability tables, and it is yet to be investigated how well the methods mentioned above can help in the specific area of legal applications. Another argument is that, even when these numbers are known, it is questionable whether they can be used to make decisions about one individual. Being aware of these arguments, we intend the Bayesian networks resulting from our method to be used as a tool to compare scenarios and their evidential support, rather than to calculate absolute numbers. Furthermore, we explicitly do not intend to make the decision for a judge or juror; the resulting network is meant to advise and provide insight into the case.

4 Representing scenarios in a Bayesian network

In this section we review our design method from [34] for modeling crime scenarios in a Bayesian network. The goal of this method is to represent multiple scenarios concerning a crime in one network. We focus on constructing the graph for the Bayesian network, modeling the relevant variables of a scenario in a coherent structure. Our design method as developed so far has two narrative idioms: the scenario idiom and the merged scenarios idiom. In Section 5, the design method will be extended with a third idiom.

The procedure from [34] for constructing a Bayesian network consists of the following four steps (more elaborately discussed in [34]): (1) collect all relevant scenarios, (2) model each scenario using the scenario idiom (or the subscenario idiom), (3) merge these idioms into one large Bayesian network with the merged scenarios idiom, and (4) add the evidence to the network. We assume that the admissibility of the evidence has been established before constructing this model. Evidential nodes are modeled using Fenton, Neil and Lagnado's evidence accuracy idiom and their idioms about dependency between evidence [14].

In Section 4.1 we review the scenario idiom, which was used in [34] to model a scenario as a sequence of states and events in a Bayesian network. In Section 4.2 we treat the merged scenarios idiom, and how it can be used to merge multiple scenarios in one network. [34] gives further details about the design method, including a case study.

4.1 The scenario idiom

The scenario idiom is intended to model a scenario as a whole, capturing its coherence as described in Section 2.2. To do this, we model connections between states and events in the scenario, and we include a scenario node to model the underlying coherence.

■ **Table 2** Probability tables for the scenario idiom. `Scenario Node` was abbreviated to `ScN`.

	ScN = y	ScN = n
Event = y	1	x
Event = n	0	1-x

(a) Conditional probability table for a node 'Event'

	ScN = y	ScN = n
Guilt hypothesis = y	1	0
Guilt hypothesis = n	0	1

(b) Conditional probability table for the guilt hypothesis
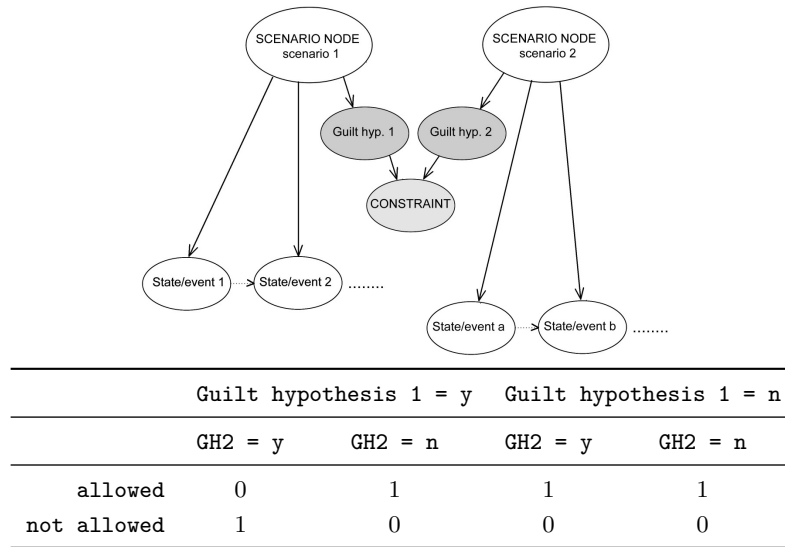
Consider the following scenario about a burglary:

Suspect X needed money, so X decided to break in. X broke the window of the house, went in and took some items from the house.

Figure 3b (from the case study in our previous paper [34]) shows how this scenario can be represented as a sequence of states and events. The figure illustrates the idea of the scenario idiom: the states and events are represented as nodes in the network, with connections between states and events drawn as arrows. The underlying probability tables express how certain these connections are. For example, a lack of money does not always lead to the decision to break in.

Furthermore, a scenario node is included, which is connected to all elements of the scenario. This scenario node is needed to model a scenario's coherence (see also Section 6.2). Finally, there is a node for the guilt hypothesis, describing who committed what crime: this node is included because this is ultimately the variable a judge or juror is interested in.

A general version of the scenario idiom is shown in Figure 3a. The idiom is constructed as follows:

1. Each state or event in the scenario is represented as a binary node with values 'yes' and 'no' in the network.
2. When there are connections between states or events in the scenario, arrows are drawn between the corresponding nodes (see [24] for what constitutes a connection between variables). Note that the connections between states and events within a scenario do not neccessarily need to form a sequence; one state or event can be connected to multiple elements of the scenario (not shown in Figure 3a). However, representing more complex connections within a scenario will be easier with the subscenario idiom (see Section 5).
3. A scenario node with values 'yes' and 'no' is included in the network. Arrows are drawn from this scenario node to each of the states or events in that scenario.
4. The probability table for the scenario node expresses the probability that the scenario is true without taking any of the evidence into account. This number corresponds to the plausibility of the scenario and is a subjective number that can be estimated by a judge or juror.
5. The conditional probability table for a state or event node depends on the connections of this state or event with the rest of the scenario. When the node is connected to other elements of the scenario, the numbers should be filled in accordingly. With no other connections, the probability table will look like Table 3a. The left column shows the logical relation that the event is an element in the scenario: when the scenario is true, all its elements must be true. The right column (when the scenario node is not true) is less straightforward. It expresses the probability that the event took place when the scenario as a whole is not true. These numbers in the right column are crucial for the evidential support: the higher the number for $P(\text{Event = yes} \mid \text{ScN = no})$ (x in the upper right of

	Guilt hypothesis 1 = y		Guilt hypothesis 1 = n	
	GH2 = y	GH2 = n	GH2 = y	GH2 = n
allowed	0	1	1	1
not allowed	1	0	0	0

Figure 4 The merged scenarios idiom and the conditional probability table for the constraint node. `Guilt hypothesis 2` was abbreviated to `GH2`.

the table), the *lower* the evidential support. This makes sense: when an event is quite likely to happen even when the scenario is not true, knowing that it happened has less of an influence on the probability of the entire scenario (see Section 6.2 for a more elaborate discussion of this point).

6. Finally, a guilt hypothesis is included, stating briefly what the scenario describes more elaborately: who committed what crime. Now that only one scenario is modeled (this will change when the merged scenarios idiom is used), the conditional probability table for the guilt hypothesis is straightforward: it follows logically from the scenario node. When the scenario node is true, the guilt hypothesis is true, and when the scenario node is not true, neither is the guilt hypothesis (see Table 3b).

4.2 The merged scenarios idiom

The merged scenarios idiom is used to combine multiple scenarios, in order to model them in one Bayesian network. The idiom puts a constraint on the guilt hypotheses, making sure that they cannot be true simultaneously. Therefore, a crucial step in the design method is to make sure that all guilt hypotheses are mutually exclusive or equal. Then when two scenarios are merged with the merged scenarios idiom, equal guilt hypotheses are represented by one node[3] and the constraint is put on mutually exclusive guilt hypotheses.

A constraint node is a common technique [19] to make sure that two or more nodes cannot be true simultaneously. It has values `allowed` and `not allowed` and there are arrows from the nodes that need to be constrained to the constraint node. The conditional probability table expresses logically that when more than one of the parent nodes is true, the constraint

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[3] All scenario nodes that were connected to any of the original nodes will now be connected to the one new node. The probability table for this new node expresses that the guilt hypothesis is true when at least one of the scenarios connected to it is true.
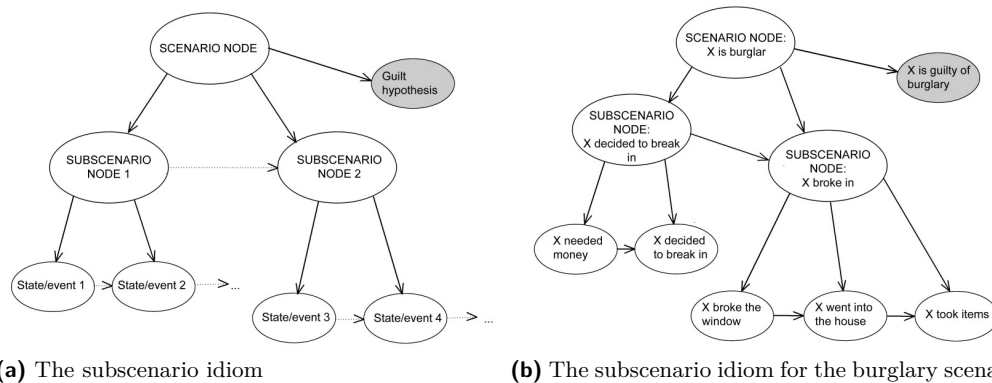
(a) The subscenario idiom

(b) The subscenario idiom for the burglary scenario

■ **Figure 5** The subscenario idiom. The dotted lines denote possible connections between states and events or between subscenarios.

node has value 'not allowed' (see the table in Figure 4). By instantiating the value to 'allowed', it can never be the case that more than one parent node is true at the same time.

When merging two scenarios, it may be the case that certain states or events in different scenarios contradict each other. In that case, a constraint needs to be put on these states or events; this constraint node is exactly like the constraint node from the merged scenarios idiom.

Furthermore, different scenarios may overlap, containing the same states or events, or even the same subscenario. When this happens, there will be separate nodes in different (sub)scenario idioms describing equal states, events or subscenarios. These will be replaced by one node describing this state, event or subscenario, which is then connected to all nodes that the original nodes were connected to.

The merged scenarios idiom in Figure 4 shows the merging of two scenario idioms. Analogously, the merged scenarios idiom can be used to merge two subscenario idioms or a combination of a subscenario idiom and a scenario idiom.

5   Extending the method: the subscenario idiom

In this section we introduce the scenario idiom in order to represent scenarios with a structure of subscenarios such as in Figure 1a.

5.1   The subscenario idiom

In the burglary example for the scenario idiom, the state 'X decided to break in' was connected to multiple states to express that it was the motive behind several actions of the burglar. With the subscenario idiom this can be modeled as in Figure 5b. There, the subscenario 'X needed money so X decided to break in' now serves as a motive for the subscenario 'X broke the window, went into the house and took some items'.

The ideas behind the subscenario idiom are closely related to the ideas behind the scenario idiom in the previous section. The coherence of an entire scenario is again modeled with use of a scenario node, which is connected to all elements of the scenario. In addition, there is now a level between the scenario node and the state or event nodes: the subscenario nodes. A general version of the subscenario idiom is shown in Figure 5a. It can be constructed in

▮ **Table 3** Conditional probability table for a subscenario node. `Scenario node` was abbreviated to `ScN`.

	ScN = y	ScN = n
`Subscenario node 1`= y	1	0
`Subscenario node 1`= n	0	1

▮ **Table 4** Conditional probability table for a subscenario node with a connection to another subscenario node. `Scenario node` was abbreviated to `ScN` and `Subscenario node 1` to `Sub1`.

	ScN = y		ScN = n	
	Sub1 = y	Sub1 = n	Sub1 = y	Sub1 = n
`Subscenario node 2`= y	1	0	0	0
`Subscenario node 2`= n	0	1	1	1

the same way as the scenario idiom, adding the following items to the list from Section 4.1 and changing items 3 and 5 from that list to read as below:

A. For a collection of states and events that form a subscenario, a subscenario node with values 'yes' and 'no' is included. An arrow is drawn from the subscenario to each state or event in the subscenario.
B. When there are connections between subscenarios, arrows are drawn between the corresponding subscenario nodes.
C. The conditional probability tables for the subscenario nodes express a logical relation: when the scenario node is true, all subscenario nodes must be true. When a scenario node is not true, none of the subscenario nodes are true. This leads to a probability table as in Table 3, or in the case of a connection between subscenarios, Table 4. In the case of the scenario node is false, we assume that a subscenario cannot be true in itself, but that it really needs the entire scenario to be true. This choice was made for technical reasons, to ensure that the subscenario idiom amounts to the same as the scenario idiom when all other connections are the same. See also Section 5.2.

3. (adapted) A scenario node with values 'yes' and 'no' is included in the network. Arrows are drawn from the scenario node to each of the subscenario nodes and any state or event in that scenario that is not connected to a subscenario node.
5. (adapted) The conditional probability table for a state or event node depends on the connections of this state or event with the rest of the scenario. When there is only a connection with the subscenario node, the numbers are filled in as follows: when the subscenario node is true, the state or event logically follows. When the subscenario node is not true, the numbers express the probability that this particular state or event would occur without the subscenario being true.

5.2   The subscenario idiom versus the scenario idiom

The scenario idiom and the subscenario idiom both represent states and events in a scenario as nodes, adding a scenario node to model the coherence of the scenario. However, the subscenario idiom includes another level in between the state and event nodes and the scenario node: the subscenario nodes. The subscenario nodes make it easily expressible that a collection of states or events (one subscenario) is connected to another collection in its
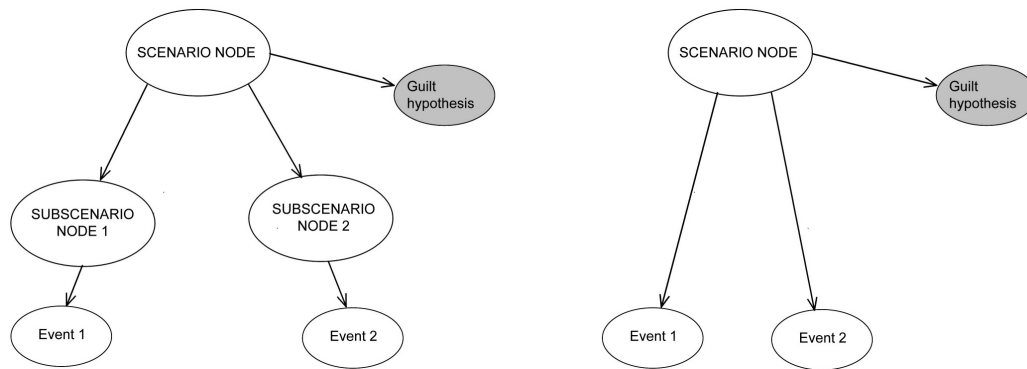
■ **Figure 6** A representation with the subscenario idiom (left) and one with the scenario idiom (right).

entirety: the decision to break in to a house can be connected to the entire subscenario of actually breaking in. Another advantage of using subscenarios is that when modeling multiple scenarios, the same subscenario can be connected to multiple scenario nodes.

When a scenario with no complicating connections between subscenario nodes (unlike the burglary example) is represented in the scenario idiom and in the subscenario idiom, there will be no difference in interpretation when calculating the probabilities. In particular, for a situation as shown in Figure 6, the probabilities $P(\texttt{Event1} \mid \texttt{Scenario node})$ for all values of the scenario node and Event1 will be the equal in both networks. For example, consider $P(\texttt{Event1=y} \mid \texttt{Scenario node=n})$ in both networks.

First note that by construction, the conditional probability tables for the state and event nodes in the subscenario idiom consist of the same numbers as in the scenario idiom (see Table 3a), now as probabilities conditional on the subscenario nodes. Furthermore, the probability tables for the subscenario idioms consist only of zeros and ones. Therefore, for $P(\texttt{Event1=y} \mid \texttt{Scenario node=n})$ in the left network, we have

$$
\begin{aligned}
&P(\texttt{Event1=y} \mid \texttt{Scenario node=n}) \\
={}& P(\texttt{Event1=y} \mid \texttt{Subscenario node1=y}) \\
&\quad \cdot P(\texttt{Subscenario node1=y} \mid \texttt{Scenario node=n}) \\
&+ P(\texttt{Event1=y} \mid \texttt{Subscenario node1=n}) \\
&\quad \cdot P(\texttt{Subscenario node1=n} \mid \texttt{Scenario node=n}) \\
={}& P(\texttt{Event1=y} \mid \texttt{Subscenario node1=y}) \cdot 0 + P(\texttt{Event1=y} \mid \texttt{Subscenario node1=n}) \cdot 1 \\
={}& P(\texttt{Event1=y} \mid \texttt{Subscenario node1=n})
\end{aligned}
$$

and this was set equal to $P(\texttt{Event1=y} \mid \texttt{Scenario node=n})$ (in the right network) in the probability tables.

Note that this calculation will not hold for the burglary example, since the connections between state and event nodes are not the same in the scenario idiom and the subscenario idiom. The connection from the event 'X decided to break in' to the event 'X broke a window' has now moved to the level of the subscenario nodes, which changes the interpretation of the scenario and thereby the probability tables. The subscenario version of the burgarly example is therefore really different from the example with the scenario idiom; this shows that the subscenario idiom can model a different interpretation of the scenario.
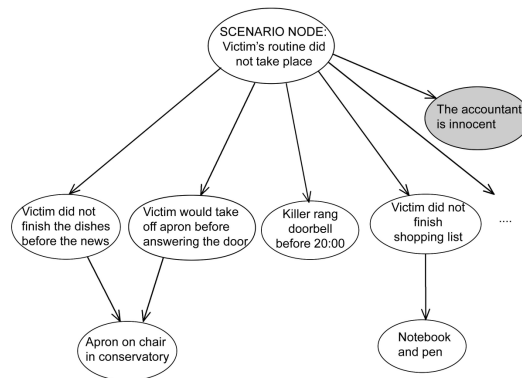
■ **Figure 7** Partial scenario idiom for the transfer of evidential support example.

6 Representing narrative properties with the design method

Returning to the discussion of narrative and its properties from Section 2, in this section we explain how each of the properties listed in Section 2.5 can be treated using the representational techniques from Sections 4 and 5.

6.1 Narrative structure

With our design method, the collection of states and events of which a scenario consists serves as a basis for the domain of the Bayesian network: each state or event was represented in the network with a node. The structure of narrative (item **1** from the list in Section 2.5) is captured with either the scenario idiom (best suited for sequential narrative representation) or the subscenario idiom (for modeling subscenarios). It depends on the interpretation of the scenario which idiom can best be used to represent it.

6.2 Coherence

In the construction of the scenario idiom and the subscenario idiom, the scenario node was intended to capture the coherence of a scenario. In this section we discuss how the structures of these idioms relate to scripts or story schemes and the transfer of evidential support.

6.2.1 Scripts or story schemes

The concept of a script or story scheme (item **2a**) inspired the idea of the scenario idiom and the subscenario idiom. They can be regarded as templates for representing a scenario in a Bayesian network. The idioms as presented in this paper can be the basis for scripts or schemes for specific crimes, such as a scheme prescribing what elements a typical murder case scenario has. However, crimes in particular are out of the ordinary, so a corpus of typical crime schemes will always be only the starting point of a specific model for a case. Further research is needed on the use of scripts and schemes for legal cases.

The idea of evidential gaps and story consequences (item **2b**) fits particularly well with the technique of Bayesian networks. By convention, Bayesian networks are usually constructed such that the arrows are directed from cause to effect. Intuitively, the elements of the scenario seem to 'predict' the evidence. When a predicted piece of evidence is not available, the evidential node is nonetheless included in the network, but it is left uninstantiated: it

is not fixed to have value 'yes'. This means there is an evidential gap. In the investigative process of a crime, such obvious absence of evidence may lead to a search for this particular piece of evidence. When this evidence is then found, the evidential node can be instantiated to 'yes', and we have found a story consequence.

6.2.2   Transfer of evidential support

The scenario idiom and the subscenario idiom are constructed such that they can capture the transfer of evidential support (item **2c**), namely, via the scenario node. Since there is no direct evidence about the scenario node, it is never fixed on a value (it is never instantiated), leaving a connection between any two elements of the scenario connected to the scenario node through which they can influence each other (any pair of states or events in the scenario is d-connected (see [19]) via the scenario node).

In Section 2.2, the concept of transfer of evidential support was introduced with the example of the murder case involving a scenario with seemingly unconnected states or events. However, since these elements together formed a coherent scenario, a transfer of evidential support was possible: by providing evidence for some elements the belief in all elements of the scenario increases.

The example scenario described the victim not finishing her usual evening routine, doing the dishes, writing a shopping list, etcetera (more details were involved in the actual case). Instead, she was disturbed by the killer ringing her doorbell shortly after the eight o'clock news. Figure 7 shows part of the scenario idiom for this scenario (the dots suggest that the scenario actually involved more elements).

There is no direct evidence for the event that the killer came in soon after the news. However, there is evidence for the fact that the victim was interrupted from doing the dishes (the apron) and that she did not finish her shopping list (the notebook and pen). The corresponding nodes for these evidential data can be instantiated to have value 'yes', which leads to a higher probability for these particular events in the scenario. Since we have no direct knowledge about the scenario node itself (it is never instantiated), a higher probability for one of the events will lead to a higher probability of the scenario node being true, leading to a higher probability of the killer ringing the doorbell shortly after the eight o'clock news.

The transfer of evidential support thus proceeds via the scenario node. This has to do with the evidential support of a piece of evidence for the entire scenario: as the posterior probability for the scenario node changes, due to the evidential support for it, the posterior probability for all events in that scenario change simultaneously: they logically follow from the scenario node.

When a piece of evidence supports an element of a scenario, the posterior probability $P(\texttt{ScN=y} \mid \texttt{Event=y})$ that the scenario node is true given that the event is true will be different from the prior probability $P(\texttt{ScN=y})$. The more $P(\texttt{ScN=y} \mid \texttt{Event=y})$ differs from $P(\texttt{ScN=y})$, the stronger the evidential support is for the scenario. We propose to use the fraction $\frac{P(\texttt{ScN=y} \mid \texttt{Event=y})}{P(\texttt{ScN=y})}$ as a measure of the evidential support.

As mentioned in Section 4.1, the strength of the evidential support depends on the conditional probability tables for the events in the scenario (as in Table 3a), and in particular the number $P(\texttt{Event=y} \mid \texttt{ScN=n})$, denoted as x in the table. When this number is high, this means that the event has a high probability of taking place when the scenario node is not true. This leads to a lower evidential support. In particular, the probability of the scenario node taking place is changes *less* when the number x is closer to 1. To see this, we expand the probability $P(\texttt{ScN=y} \mid \texttt{Event=y})$ using Bayes' rule:

$$
\begin{aligned}
P(\texttt{ScN=y} \mid \texttt{Event=y}) \;\; &= \;\; \frac{P(\texttt{Event=y} \mid \texttt{ScN=y}) \cdot P(\texttt{ScN=y})}{P(\texttt{Event=y})} = \frac{1 \cdot P(\texttt{ScN=y})}{P(\texttt{Event=y})} \\[2mm]
&= \;\; \frac{P(\texttt{ScN=y})}{P(\texttt{Event=y}|\texttt{ScN=y}) \cdot P(\texttt{ScN=y}) + P(\texttt{Event=y}|\texttt{ScN=n}) \cdot P(\texttt{ScN=n})} \\[2mm]
&= \;\; \frac{P(\texttt{ScN=y})}{1 \cdot P(\texttt{ScN=y}) + x \cdot P(\texttt{ScN=n})} \\[2mm]
\frac{P(\texttt{ScN=y} \mid \texttt{Event=y})}{P(\texttt{ScN=y})} \;\; &= \;\; \frac{1}{P(\texttt{ScN=y}) + x \cdot P(\texttt{ScN=n})}.
\end{aligned}
$$

When the number x is close to 1, then the fraction on the right is close to 1 (since the prior probabilities of the scenario node add up to 1). This means that $P(\texttt{ScN=y} \mid \texttt{Event=y})$ is almost equal to $P(\texttt{ScN=y})$, so there is less evidential support. The smaller x is, the smaller the denominator, so the larger the fraction and thereby the evidential support. This is in line with our intuition: when an event can perfectly well take place without the scenario node being true, then knowing that the event took place contributes less to our belief in the scenario node.

6.3   Plausibility

Plausibility (item **3**) can be interpreted in terms of probability as the probability of the scenario without taking any evidence into account. In our representation, this is the prior probability for the scenario node having value 'yes'. This number is a subjective estimate, which can be provided by a judge or juror, and it is taken up in the probability table for the scenario node.

6.4   Commonsense knowledge

Commonsense knowledge (item **4**) in the form of generalizations underlying a connection between two states or events in a scenario is expressed numerically as a number in the probability table in our method: the more 'common' the connection is (such as, 'when a suspect breaks a window, he might leave fingerprints'), the higher the conditional probability connecting the two states or events. As a consequence, scenarios that are close to our commonsense knowledge will have stronger connections in the Bayesian network.

7   Conclusion

In this paper, a design method for modeling crime scenarios in a Bayesian network has been presented and extended, and connections with literature on narrative have been discussed. In our previous paper [34], the development of the design method was started. There, a procedure for constructing a Bayesian network based on scenarios was introduced, including two narrative idioms: the scenario idiom and the merged scenarios idiom. In this current paper, the method was extended with a subscenario idiom, such that both sequential scenarios and scenarios built up from subscenarios could be represented in the Bayesian network.

    The notions of narrative coherence, plausibility and the use of commonsense knowledge have been interpreted in terms of the representational techniques developed. The transfer of evidential support (as a consequence of narrative coherence) is captured with the construction of the (sub)scenario idiom. The probabilities in the network reflect the plausibility and

the use of commonsense knowledge. By modeling these narrative properties, the Bayesian network can be used to evaluate and compare crime scenarios.

Further research is needed on the use of scripts and story schemes in the representation of a crime scenario. It deserves to be investigated how a corpus of schemes for crimes can serve as a starting point for the construction of specific models. Employing the concept of a scheme may help to systematize the construction of Bayesian networks for legal cases.

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