Building a Stronger Case: Combining Evidence and Law in Scenario-Based Bayesian Networks

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Abstract. Existing approaches to modelling legal cases in Bayesian networks focus either on correctly representing an empirical probabilistic model of evidence traces, or on modeling alternative scenarios that can explain what happened in a case. However, neither approach legally interprets, or qualifies, aspects of a scenario as a normative legal fact. Hence, the fact that a Bayesian network representing a scenario assigns a high posterior probability to a certain victim having been killed by a certain suspect, does not imply that that suspect is guilty of murder in the legal sense, because the events in the scenario cannot be qualified as legal facts.

This paper proposes an architecture for concrete legal fact idioms that qualify events in a narrative Bayesian network. This bridges the gap between the real world and the normative legal world through so-called counts-as rules. By modeling the legal facts explicitly in the Bayesian network, we can show whether a narrative completes one or more legal fact idioms. This is demonstrated using a case study. The proposed architecture may help judges and lawyers decide on which narratives they should investigate further and which narratives are stronger than others with regard to both the evidence and the legal facts.

Keywords. Bayesian networks, Legal Modelling, Decision Support, Narrative Legal Bayesian networks

1. Introduction

Judges have to combine information from different sources and consider alternative explanations in order to come to a conclusion about a criminal case. They also have to qualify the (possible) events that have occurred as legal facts. Probabilistic reasoning using Bayesian Networks is one way in which this can be done coherently. This paper proposes a first step towards such an approach.

Bayesian networks have been used to model different criminal cases [1,2,3]: The networks combine the events that might have happened (scenario) and the evidence in a case, altogether resulting in a probability of guilt for the defendant. However, existing approaches to constructing these networks have focused on how to represent the stories

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presented by the prosecution and the defense, and not on how these stories are interpreted, or qualified, by a judge. The judge needs to be sure beyond a reasonable doubt that the defendant's acts are criminal. A criminal act consists of criminal elements. We can consider these as legal facts, in the sense that they are facts that have to be proven to legal standards. One example of such legal facts is made explicit in the definition of murder, which is the 'premeditated intentional killing of another person' (we here stay close to the phrasing in Dutch law). If a scenario is not complete with regards to the legal facts, e.g., if it does not show 'premeditation', the defendant cannot be convicted for murder, and the suspect is acquitted, even if the scenario is otherwise highly convincing.

In this paper we propose a hybrid approach to modelling criminal cases, where the normative and explicit knowledge structure of criminal law is embedded into scenario-based Bayesian networks, to show whether a scenario is complete with regards to the legal facts it aims to prove. By making the elements of the crime explicit, we can explicitly consider their probability given the evidence. In this way it can be expressed whether the probability of a legal fact is low due to a lack of evidence, or due to the scenario being incomplete. This allows both prosecution and defense to know whether their resources should go into finding stronger evidence to support part of a narrative, or to argue for or against a qualification of a (sub)-scenario as a legal fact.

The remainder of the paper is structured as follows: In Section 2, the preliminaries on Bayesian networks and narrative and probabilistic approaches to modelling criminal cases are introduced. Section 3 introduces our hybrid Bayesian network model architecture. In Section 4, the method is illustrated using an example case study. Section 5 is a discussion of the method that compares and contrasts it with other approaches.

2. Preliminaries and State of the Art

A Bayesian network (BN) is a tuple $B = \langle G, \Pr \rangle$, where G is a directed acyclic graph (DAG) that captures a joint probability distribution Pr over random variables [4]. The independences among the variables are coded in the DAG and serve for factorizing the joint distribution into conditional distributions for each variable (or node) given its parents in G: $\Pr(V_1, ..., V_n) = \prod_{i=1}^{n} \Pr(V_i | parents(V_i))$. From a Bayesian network, any prior or posterior probability of interest over a subset of the variables can be computed.

Bayesian networks have been used to model criminal cases, or aspects thereof. Existing networks range from those modelling just the interpretation and reliability of forensic evidence [5,6,7], to models including witness or expert testimonies [8], and even entire court cases including competing alternative scenarios [3,1,9]. To aid the construction of such networks, *idioms* can be used, which are BN fragments that represent reoccurring sub-structures and can be used as generic building blocks [10]. For example, the *evidence idiom* links an observation variable to an unobservable hypothesis variable in order to provide evidence for that hypothesis.

In this paper we will illustrate our proposed architecture for a criminal case described in [11]. This case has been modelled before using a non-probabilistic, argumentation-based method [12]. The latter work also studies the connection between the factual story and the legal story using constitutive rules, or *count-as rules*, to qualify events in the world as legal facts. Count-as rules have been used [13] and analysed [14,15] before. To the best of our knowledge, however, the connection to legal facts has not been addressed with Bayesian networks before.

3. A Hybrid Layered Bayesian Network Architecture

We propose a generic method for building Bayesian network models of criminal cases that combine three aspects of the case by means of three layers: (I) the narrative layer, (II) the evidence layer, and (III) the legal layer. The Bayesian network $B = \langle G, \Pr \rangle$ as a whole combines a directed acyclic graph (DAG) $G = \langle V, A \rangle$ with nodes V and arcs A, and conditional probability tables (CPTs) for each node. The set of nodes $V = V_S \cup V_E \cup V_L$ consists of three disjoint subsets of nodes, one for each layer. More specifically, the narrative layer is a sub-Bayesian network B_S of B with graph $G_S = \langle V_S, A_S \rangle$, where $A_S = A \cap (V_S \times V_S)$. The evidence layer consists of nodes V_E and arcs $A_E = (A \cap (V_E \times V_E)) \cup (A \cap (V_S \times V_E))$, that is, it includes arcs among the nodes in V_E as well as arcs going from V_S to V_E. Finally, the legal layer consists of nodes V_L and arcs $A_L = (A \cap (V_L \times V_L)) \cup (A \cap (V_S \times V_L))$, that is, arcs within the layer as well as incoming arcs from the narrative layer. We will now describe the different layers in more detail.

3.1. The Narrative Layer and the Evidence Layer

The narrative layer represents one or more scenarios in $G_S = \langle V_S, A_S \rangle$. A scenario is a sequence of events that attempts to explain the evidence found in the case. A scenario can correspond to a story scheme, which is a generalized pattern of events. Alternative scenarios can be presented by the prosecution and the defense. The scenarios themselves are hypothesized and not directly observed. For example, once investigators have found a dead body, but no other evidence, one scenario could be a story scheme that concludes death by natural causes, another a scheme that concludes murder, another a scheme that concludes suicide. The specific elements of the story scheme are then converted into variables V_S that represent the valuation of the events, in cases of boolean variables as being true or false. The variables are then ordered temporally by A_S. Finally, the CPTs are specified. The result is the narrative layer in which each node represents an element of a story scheme and the nodes V_S together represent all plausible scenarios that are considered by the modeller [12,2].

The evidence layer represents the evidence that was found in the specific case. It consists of nodes V_E, each modelling an observable piece of evidence in the real world, and forms an unconnected subgraph G_E of G. By means of evidence idioms, nodes V_E are connected to the narrative layer to either support or attack the events that are specified in the narrative layer. All nodes V_E will have at least one parent in the narrative layer. For example, if one of the events in the narrative is that the suspect and the victim were seen together at some location at some time, a node in the evidence layer could be whether the suspect and victim were seen by a witness or on camera images of that location at that time. The probabilities of the events in the narrative layer should be interpreted as subjective degrees of belief, not as frequentist probabilities, because it is unclear how we should instantiate probabilities for unique cases from frequentist statistics [16]. Hence, any probabilities chosen to define the CPT will depend on the subjective degrees of belief of the modellers or investigators. The probabilities of the events in the evidence layer can be a combination of subjective degrees of belief, as well as frequentist probabilities. For events such as DNA-traces or soil recognition, there exist statistical methods that can be used to establish empirical probabilities [5]. However, for other types of more contextual evidence, subjective degrees of belief may be necessary.

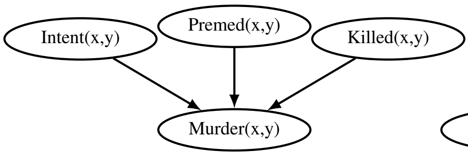

Figure 1. Legal idiom for murder

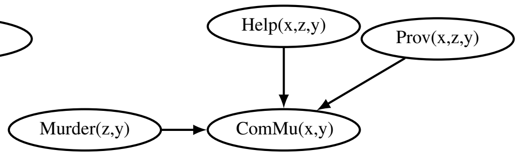

Figure 2. Legal idiom for complicity in murder

3.2. The Legal Layer

The legal layer represents through its nodes V_L the normative legal facts that need to be established in order to convict a suspect of a crime. The bridge between the normative legal facts V_L in the legal layer and the hypothetical scenarios in the narrative layer, can be made using count-as rules such as of the type defined in [15,13]. This means that for each legal fact $V_l \in V_L$, we need to consider whether there are one or more nodes $V_s \in V_S$ in the narrative layer that have at least one valuation such that that valuation would result in the (dis-)qualification of that event as a legal fact. The nodes V_s are then taken as parents for the node V_l that represents that legal fact. The CPT of V_l is then filled out based on the values of its parents in V_S. Then V_l can serve as a definition: given that the nodes in V_s have a certain valuation, this causes the node V_l to take on a certain value: either the events in that valuation of V_S count as $V_l = \mathit{true}$, or they do not. If there is no relevant node in the narrative layer, then V_l has no parents. In this case, the prior probability of V_l is set to a low value in order to simulate the presumption of innocence. We propose to cast this general pattern for legal facts in crime definitions into a Bayesian network idiom. These idioms can help us to construct the legal layer.

3.2.1. Constructing the Legal Fact Idioms

In this section, we demonstrate the design of legal fact idioms for two examples based on the Dutch criminal code for murder (Article 289 Sr) and for complicity in murder (Art 48 Sr + 289 Sr).

We can formulate the legal facts for *Murder* as predicates for intentional action *Intent* (x,y) and premeditation $\mathit{Premed}(x,y)$ and $\mathit{Killed}(x,y)$ which lead to $\mathit{Murder}(x,y)$, where x,y are a human suspect and a victim, as based on Article 289.[2] The structure of the legal fact idiom for *Murder* is shown in Figure 1.

For x,y, the CPT for the node $\mathit{Murder}(x,y)$ in the murder idiom is defined by $\Pr(\mathit{Murder}(x,y) = \mathit{true}|v_1) = 1$ for parent valuation $v_1 = (\mathit{Intent}(x,y) = \mathit{true} \wedge \mathit{Premed}(x,y) = \mathit{true} \wedge \mathit{Killed}(x,y) = \mathit{true})$, and $\Pr(\mathit{Murder}(x,y) = \mathit{true}|v) = 0$ for all other parent valuations $v \neq v_1$. This corresponds to the legal rule that can be expressed as: $(\mathit{Intent}(x,y) \wedge \mathit{Premed}(x,y) \wedge \mathit{Killed}(x,y)) = \mathit{Murder}(x,y)$.

To define *Complicity in Murder* (*ComMu*), we need to represent Article 48; the suspect either purposefully helped the murderer (Help), or provided aid to the murderer (*Prov*) (materials, information and such), and that the victim has been murdered (*Murder*). We can define predicates $\mathit{Murder}(z,y)$, $\mathit{Help}(x,z,y)$, $\mathit{Prov}(x,z,y)$, where x is the human suspect (of complicity), y is the victim, and z is the murderer; we assume in this case that this murderer cannot also be the suspect of complicity.[3] The structure of this idiom is shown in Figure 2. The CPT for com-

[2]Further exceptions outlined in 348/350Sv in the Dutch code of criminal procedure.

[3]Exceptions again in 348/350 Sv.

plicity in murder $ComMu(x,y)$, for all x,y,z, should correspond to the legal rule $(Murder(z,y) \wedge (Help(x,z,y) \vee Prov(x,z,y))) = ComMu(x,y,z)$. This means that for parent valuations $v_1 = (Murder(z,y) = true \wedge Help(x,z,y) = true \wedge Prov(x,z,y) = true)$, and $v_2 = (Murder(z,y) = true \wedge Help(x,z,y) = true \wedge Prov(x,z,y) = false)$, and $v_3 = (Murder(z,y) = true \wedge Help(x,z,y) = false \wedge Prov(x,z,y) = true)$, it is the case that $\Pr(ComMu(x,y,z) = true|v_i) = 1$, $i = 1,2,3$, and $\Pr = 0$ for other valuations.

4. Case Study: Murder in Wamel

In this section, we illustrate our approach to model construction for a real criminal case known as "Murder in Wamel" [11] and summarised as follows (from [12]):[4]

> There are three petty criminals: Kevin, the victim; Sander, the main witness and friend of Kevin's; and Francis, the prime suspect and an acquaintance of Kevin's. Kevin's body is found near two barns in the village of Wamel. He has been shot dead. Later that day, Sander contacts the police and states that he was also at the scene of the crime, allegedly trying to escape. According to Sander's initial, later denied, statements, Francis was also at the barns and an argument developed between Kevin and Francis (allegedly over a 5000 guilders debt that Francis owed Kevin). Francis then walked to the back of one of the barns. When Kevin followed him, there was a sudden firing of shots, after which Sander fled.

We note that Sander gave conflicting testimony: First he said that Francis shot Kevin but after some time he testified that he did not see anyone else at the barn. It was known by acquaintances of Sander that Francis had told Kevin and Sander to meet up at that barn to steal weed from a third party.

We are interested in the posterior probability that Francis is guilty of murder, as well as the posterior probability that Francis is guilty of complicity in murder, considering the evidence in the case. We model the provided scenario with events in the narrative layer, then provide evidence in the evidence layer using the evidence idiom [10]. The probabilities are assigned subjectively. The events in the narrative layer are then qualified as legal facts in the legal layer. The nodes per layer and their legal qualifications are shown in Table 1, and the resulting Bayesian network is shown in Figure 3.

We collect the relevant legal idioms: Murder and Complicity in Murder, in predicate form. The variables $x = Francis$, $y = Kevin$ are instantiated in both idioms. The CPTs of *Murder* and *ComMu* remain the same when the predicates are instantiated, as the definitions of murder and complicity in the network are not dependent on the identity of the suspect. The instantiated idioms function as propositional idioms and are specific to the identity of suspect and victim: We are only investigating whether Francis murdered, or was complicit in the murder of, Kevin.

The narrative layer is connected to the instantiated legal layer. All relevant parents in the narrative layer are qualified as one of the legal facts *Premed*, *Killed*, *Intent* for murder and *Murder*, *Prov*, *Help* for complicity. If for some legal fact no relevant nodes are found in the narrative layer, then that legal fact node remains parentless.

[4]The resulting Bayesian networks will are made available at `https://github.com/aludi/HHAI2024`

Narrative Layer	Evidence Layer	Legal Layer
DebtFightFK: Francis (F) and Kevin (K) have had history with each other, and had a fight.	TMathus: Testimony of witness Mathus; Sander (S) and K had both told him about F's plan to go to the barn.	`PlanBarnF` and `FightBarn` together count as `Premeditation`: given the situation, F had a motive to lure K to the barn.
PlanBarnF: F had a plan to lure K to a barn under the pretence of stealing weed.	TSLocation: Testimony of S that he and K were at the barn.	`ShootStenGun =` $\neg F$ and `KKilled` together count as `Murder(z,y)` in the *ComMu* idiom, because if someone killed K by shooting him and it was not F, then K was murdered and F might be complicit.
ShootStenGun: there are three options, either no-one killed K, or F killed him, or someone who was not F killed him.	TSF2: S's second testimony that he did not see F at the barn. TSF2 is conditioned on both a narrative element and on S's first testimony TSF1.	`ShootStenGun` and `KKilled` together count as `Killed`, because if you shoot at someone and they die, then you have killed them.
KBarn: K was at the barn at the time of the murder.	Body: The forensic report of K's body, showing cause of death.	`ShootStenGun = Francis` counts as `Intent` because shooting at someone with a stengun generally shows that you intend to kill them.
SBarn: S was at the barn at the time of the murder.	TStengun: Testimony that F attempted to buy springs that could be used to repair stenguns.	`PlanBarnF` counts as `Providing aid`, because the plan was necessary to lure K to the barn where he could be shot.
FStenGun: F was in possession of a stengun (murder weapon) before the time of the murder.	TSF1: S's first testimony that Francis was at the barn.	
FightBarn: F and K had a fight at the barn.		
FBarn: F was at the barn at the time of the murder.		
KKilled: K died due to the bullets from the stengun.		

Table 1. The nodes in the Narrative, Evidence and Legal layers. All nodes are boolean except *ShootStenGun*, which has 3 values.

4.1. Using the Bayesian Network

The resulting BN is shown in Figure 3. In this section we discuss how the posterior probability of guilt changes under different evidence valuations.

Without any instantiated evidence, the posterior probability of Francis' guilt is low: $\Pr(Murder = true) = 0.06$, $\Pr(Complicity = true) = 0.08$. We now consider the case evidence. There is combined testimony that supports that Francis had debts and lured Kevin to the barn under false pretense. Moreover, we believe that Francis has a stengun and that we found Kevin's body. However, the case hinges on Sander's testimony. Initially, he declared that he saw Francis at the barn (TSF1). However, he declared later that he did not see Francis at the barn (TSF2). We look at the implications of all evidence, combined with Sander's first testimony (e_1), then counterfactually if he had only provided TSF2 (e_1^*), and the combination TSF1 and TFS2 (e_2).

Given e_1 (Figure 3), we believe that Francis is at the barn, where he and Kevin fought. Therefore, the criminal-element nodes in the legal idiom for murder, premed-

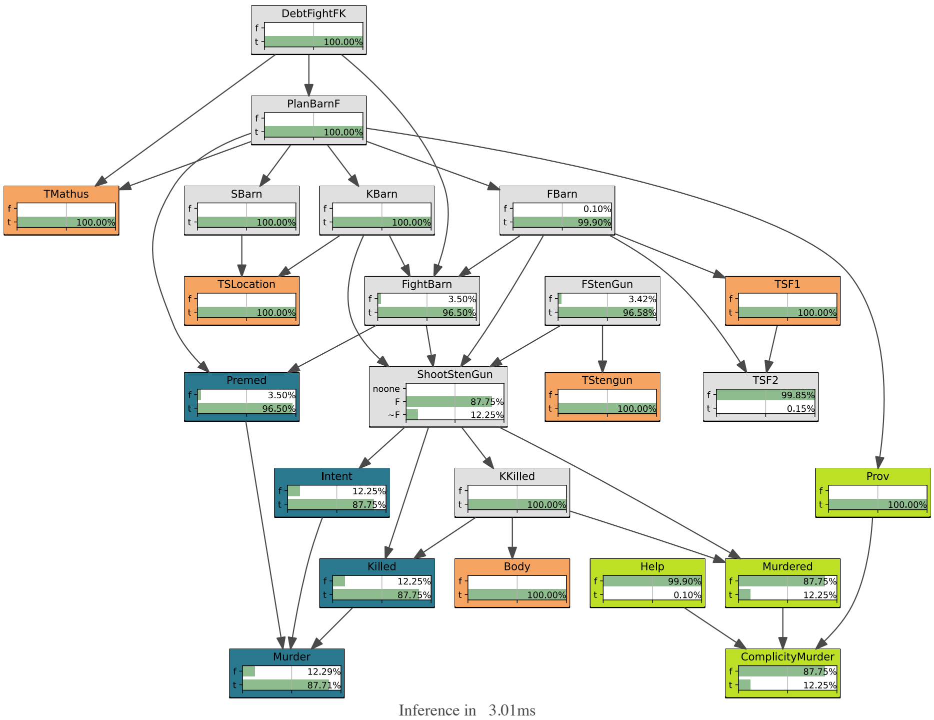

Figure 3. Combined BN with evidence as in the case that only considers Sander's first testimony. The orange nodes are instantiated evidence. The node `Murdered` represents `Murder(z,y)`. Screenshot from PyAgrum BN software used for computations.

itation, intent and killing of Kevin by Francis all have a high probability resulting in a posterior probability of murder of $\Pr(Murder = true \mid e_1) = 0.88$ compared to the lower posterior probability of complicity in murder of $\Pr(Complicity = true \mid e_1) = 0.12$, which still allows a possibility that someone other than Francis shot Kevin. The reason that we do not accept complicity in murder as a verdict, is the much higher probability that Francis himself was the murderer. Counterfactually, if Sander had only given his second testimony (e_1^*, no figure shown), the resulting probabilities would be $\Pr(Murder = true \mid e_1^*) = 0.02$ and $\Pr(Complicity = true \mid e_1^*) = 0.98$. In this case we assume that Francis was not at the barn and did not murder Kevin, and conclude that Francis was complicit in the murder due to providing information to the true murderer about Kevin's location.

Given e_2 (no figure shown), taking into account both Sander's testimonies, the resulting probability of guilt for either crime is not beyond reasonable doubt: $\Pr(Murder = true \mid e_2) = 0.59$ and $\Pr(Complicity = true \mid e_2) = 0.41$. Due to the conflicting testimony, we are unsure about whether Francis was at the barn and about who shot Sander.

5. Discussion

We have shown that we can use a legal idiom to model qualification of legal facts using counts-as rules in a Bayesian Network. The probability of the legal facts results from the narrative, which is supported by evidence. In the following, we compare this method with existing methods for probabilistic modelling in law and qualification of legal facts. Then, modelling choices are discussed, finishing with future research on hybrid methods.

Our proposed method explicitly models the legal facts that it aims to prove and qualifies events in the scenario as legal facts. In contrast, [2] models narratives as alternative scenarios, where the probability of the scenario node is implicitly equal to the probability of guilt. However, in this theory there are no restrictions on whether the scenario qualifies the relevant legal facts. In [3], legally relevant patterns of reasoning, such as opportunity and motive, are modelled with idioms. However, while opportunity and motive are useful tools in building plausible narratives, they are not legal facts. In both these methods there is no qualification of narrative facts as legal facts. In [12], elements of the factual story can be qualified as legal facts using qualification rules, modelled as count-as rules applied to arguments. The probability of the factual story is not represented explicitly but is instead represented using notions of internal coherence, completeness, and evidential support. In contrast, in our method, we can explicitly represent the probability of each aspect of the story, and hence of the legal facts at play, resulting in a probabilistic interpretation of evidential support.

This model is based on the case study presented in [12], with some additional evidence modelled based on [11]. As this is a proof of concept, the idioms and probabilities were not elicited from a domain expert. Further application of this method requires the non-trivial qualification from narrative to legal fact and translation from law to legal idiom, which should be done by domain experts. Additionally, in this model, it is always the case that there is a set of valuations of events specified in the narrative layer that is sufficient to count as a legal fact, hence, there is a probability of 1 in the CPT of the legal fact. For other valuations, the events do not count as legal fact and this results in probabilities of 0 in the CPT of the legal idiom. However, in actual cases there might be disagreement about whether a set of narrative events counts as a legal fact (cf the 'problem of the penumbra' in [15]).

The proposed method could be a first step towards a hybrid system, where Bayesian networks serve as a shared representation of the facts in a case. These networks could integrate perspectives from different experts, narratives from prosecution and defense, with calculated consequences of the assigned degrees of belief, integrating statistical reasoning from empirical forensic science. Such a model would allow different users to decide where their resources should go. For example, in Figure 3, there is a high degree of belief in the legal fact of $Premeditation(Francis, Kevin)$ and we are less sure about $Intent(Francis, Kevin)$ and $Killed(Francis, Kevin)$. Hence, it would be useful for a prosecutor to attempt to improve support for $Intent$ and $Killed$, and gather more evidence to make sure that it was Francis who shot the gun and not someone else. The defense should try to weaken the support for $Intent(Francis, Kevin)$ and $Killed(Francis, Kevin)$ by finding evidence to attack $TStengun$. In this case, specifying degrees of belief explicitly can help each side know where to aim for further investigation.

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