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A collection of idioms for modeling activity level evaluations in forensic science

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ABSTRACT

This paper presents a collection of idioms that is useful for modeling activity level evaluations in forensic science using Bayesian networks. The idioms are categorized into five groups: cause-consequence idioms, narrative idioms, synthesis idioms, hypothesis-conditioning idioms, and evidence-conditioning idioms. Each category represents a specific modeling objective. Furthermore, we support the use of an idiom-based approach and emphasize the relevance of our collection by combining several of the presented idioms to create a more comprehensive template model. This model can be used in cases involving transfer evidence and disputes over the actor and/or activity. Additionally, we cite literature that employs idioms in template models or case-specific models, providing the reader with examples of their use in forensic casework.

1. Introduction

In forensic casework, many relevant questions go beyond the source of the trace. Part of these questions, known as activity level questions [1], regard the manner of deposition of the trace and accordingly, the case hypotheses concern a dispute over an activity (or the actor) rather than a source. Forensic scientists must assess the likelihood of their findings concerning these activity level hypotheses. This assessment requires more information than source level evaluations, such as background distributions and probabilities of transfer, persistence, and recovery under different circumstances. The large amount of required information makes activity level evaluations a challenging practice. Some challenges include:

- a lack of knowledge on what variables influences the case findings
- a lack of available data on these variables
- a lack of uniformity in the evaluations, both between individual cases of the same expert and between different experts.

Activity level evaluations can be complex, but they can be invaluable for the legal process. Therefore, a more reliable and robust assessment framework is desired.

Aitken and Gammerman [2] were the first to mention the use of Bayesian networks (BNs) in forensic science. Nowadays, these networks are increasingly being used to model activity level evaluations in this field. BNs are probabilistic graphical models that use Bayes' theorem to calculate event probabilities. These networks consist of nodes and directed links, which represent random variables and conditional dependencies between the variables respectively. Each node has its own conditional probability table (CPT), containing the probabilities of the various states of a variable conditioned on its parent nodes. The model can be used to derive the probability of an event occurring given all the relationships that exist within the model. For further information on BNs and probabilistic reasoning in general, we recommend Aitken and Gammerman [2] and textbooks such as [3,4].

BNs are advantageous because of their ability to easily represent complex probabilistic relationships between variables. This makes them ideal for use in forensic science, where transparency and accurate results are required. Moreover, BNs are based on probability theory, which allows experts to revise probabilities for case propositions and uncertain variables. This helps them show how each piece of evidence affects their evaluation. Lastly, BNs are transparent, providing space for discussion and illustrating sources of uncertainty in the expert's reasoning.

Despite its potential benefits, the use of BNs within the legal framework has been limited. This is partly due to the complex, time-consuming and subjective nature of constructing an acceptable BN model for a legal case. And so the question is: how do we mitigate or eliminate these disadvantages?

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Neil et al. [5] propose an idiom-based approach to decrease the complexity of modeling BNs. The idiom-based approach divides the modeling process into smaller fragments, called idioms, that represent generic types of probabilistic reasoning [5,6]. They depict a set of variables and their probabilistic relationship, and can be modified and combined to form larger template or case models. Additional benefits include:

- Idioms can be constructed and reasoned about separately which makes them beneficial to the designer.
- Idioms give experts quick access to certain generic reasoning patterns, and they can choose which of these they want to integrate into a larger system.
- Idioms can easily be instantiated by transforming the node names into discipline- and case-specific variables.
- Idioms are advantageous for maintenance; modifying an idiom is much simpler than adjusting an entire template model.
- Idioms can be beneficial to (law) practitioners, as experts can explain their case model in a clear and concise manner.

Neil et al. [5] state that "idioms act as a library of patterns for the BN development process". Research domains such as legal reasoning and medical reasoning [7,8] have already developed a collection of idioms. Our goal is to present a collection of idioms particularly useful for modeling activity level evaluations in forensic casework. This paper combines a literature review of existing idioms (either generic or forensic) and our own suggestions of forensic idioms useful for activity level evaluations. Many of the perceived idioms are specified for other disciplines than forensic science. In such cases, we provide the generic version of the idiom as well as a forensic instantiation of that generic version. Furthermore, we extracted forensic reasoning patterns from template models and case models and translated them into idioms.

As a result, we provide the forensic expert with a collection of idioms consisting of five categories that are useful for activity level evaluations. Furthermore, we illustrate the idiom-based approach and the relevance of our collection by combining some of the presented idioms to create a larger template model. This model can be used for any kind of transfer evidence, in cases where the actor and/or the activity is disputed [9]. In addition, we provide concrete examples of how to use the idioms in forensic casework in Appendix A. We also refer to literature that utilizes the idioms in template models or case-specific models.

2. Methods

2.1. Scope of the review

A literature search was performed for the present study using two electronic databases, PubMed and Scopus. The initial search included three terms: 'Bayesian networks', 'Forensic' and 'Idioms'. The inclusion criteria were: research in English, research mentioning at least two out of three terms in the abstract, title and/or keywords, and research visually presenting Bayesian networks in figures.

Additional references were identified using our own personal collection and by a manual search among the citations in the reviewed papers. The list of potentially relevant literature contained 159 references. The list consisted of papers on **Bayesian networks in the forensic or legal domain** (n = 129) and papers on **the use of idioms in Bayesian networks within and outside of the forensic discipline** (n = 30). The first subset was utilized to extract forensic idioms from case models and to demonstrate the use of idioms in case models. The second set was used to identify generic idioms and idioms specifically relevant to forensic activity level evaluations.

2.2. Organizing and categorizing literature

2.2.1. Degree of specificity of Bayesian networks: idioms, instantiated idioms, template models and case models

The idiom-based approach is a bottom-up approach that pieces idioms together to construct more complex models - such as case models to evaluate activity level evaluations. We had to establish some criteria regarding the definition of an idiom to be able to identify idioms from larger case models and to investigate how they are being used in larger case models.

During our literature search, we identified four degrees of specificity of (BNs): idioms, instantiated idioms, template models and case models. We therefore believe that the idiom-based approach is a four-step method to advance the ladder of specificity: going from widely applicable models (idioms) to specific case models. Fig. 1 illustrates the four degrees of specificity and their applicability, which is represented by the width of the circles. To accurately distinguish between the different categories, we established a terminology based on acknowledged definitions from the literature as well as our own perspective. This enabled us to sort research papers according to the four degrees of specificity and to identify existing idioms from larger case models.

Generic idioms are usually transdisciplinary and can therefore be applied in a variety of areas. Idiom instantiations, on the other hand, are disciplinary versions of the generic idiom, which are more specific and are better suited for certain fields. Idioms are mostly qualitative, focusing on graphical structures rather than conditional probability tables (CPTs). Yet some exceptions exist where CPTs are essential to the utility of the idiom. Idioms are thus different from 'small' case models. Although the CPTs and/or variables may vary from case to case, the probabilistic reasoning of the idiom remains the same. Template models consist of more than one idiom (instantiation) and represent (multi) domain specific models, which are applicable to certain types of cases and scenarios. They may or may not include completed CPTs. Lastly, case models are an even more specific version of the template model, because these models contain completed CPTs and specific node names, and are therefore tailored to fit a certain case, limiting its applicability.

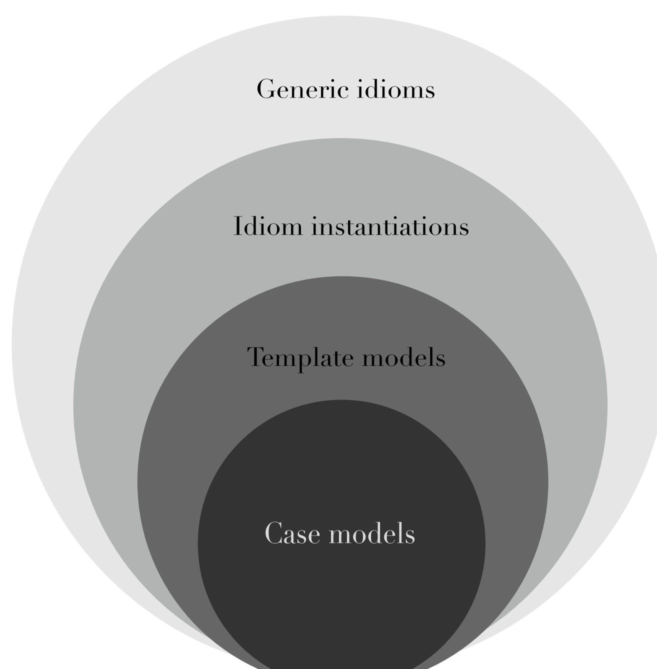


Fig. 1. From idioms to case models: the width of the circles represent the degree of applicability of Bayesian networks.

2.2.2. Final literature set

The 159 potentially relevant references were sorted into three categories: 29 references on case models, 49 on template models, and 30 on (instantiated) idioms. All references had to focus on **qualitative** modeling of BNs. Some references contain multiple levels of specificity and were added to all applicable categories accordingly. As this study focuses on idioms, we will only refer to template models and case models to illustrate the application of discussed idioms in practice. Since we focus on forensic activity level evaluation, not all research from our final literature set appears as references in this paper.

2.2.3. Grouping idioms

We identified the idioms, taking the terminology specified in 2.2.1 into consideration. The idioms were sorted by relevance, resulting in a final list of idioms valuable for forensic evaluations at activity level. These idioms were grouped into five categories that represent a particular modeling goal and purpose:

- Category A, *Cause-consequence idioms*: idioms modeling the relationship between cause(s) and effect(s)
- Category B, *Narrative idioms*: idioms concerning the storytelling coherence of the model
- Category C, *Synthesis idioms*: idioms combining multiple nodes into one node for organizational or computational purposes
- Category D, *Hypothesis-conditioning idioms*: idioms adding a precondition or postcondition to the case hypotheses
- Category E, *Evidence-conditioning idioms*: idioms adding a condition to the evidence and/or case findings

Table 1 presents the collection of idioms for modeling activity level evaluations in forensic science. The collection consists of generic (labeled G) types and (multiple) forensic (labeled F) instantiations. We have named the idioms presented in italic ourselves. These reasoning patterns are recognized in literature, but are not explicitly named. Chapter 3 is divided into sections that review each category in detail.

3. Collection of idioms

3.1. Category A: cause-consequence idioms

The *cause-consequence idiom* (labeled A.G1 in Fig. 2) [5,8] - also known as *cause-effect idiom* [10], *process-product idiom* [5,11] or *input-output idiom* [11] - models the probabilistic relationship of two variables: a cause and an (observed) effect. The cause node (parent node) and the consequence node (child node) are linked directly, meaning that observing the effect influences the probability of occurrence of the possible cause. The direction of the link is mathematically irrelevant. However, the direction tells us the line of reasoning (either from cause to effect or from effect to cause) and is therefore, in terms of semantics, highly important.

Table 1
The collection of idioms for modeling activity level evaluations in forensic science.

	Label	Name
Category A	A.G1	The cause-consequence idiom
	A.F1	The hypothesis-evidence idiom
	A.F2	The common cause idiom
	A.F3	The common effect idiom
Category B	B.G1	The scenario idiom
	B.G2	The subscenario idiom
	B.G3	The variation idiom
	B.F1	*The hypothesis-to-activity idiom*
	B.F2	*The hypothesis-to-transfer idiom*
Category C	C.G1	The synthesis idiom
	C.F1	*The LR-calculation idiom*
	C.F2	*The influencing-factor idiom*
	C.F3	*The trace-accumulation idiom*
	C.F4	*The case findings idiom*
Category D	D.F1	*The extended-likelihood-ratio idiom*
	D.F2	*The regrouping idiom*
	D.F3	*The hypothesis-precondition idiom*
Category E	E.G1	The measurement idiom
	E.F1	*The evidence-uncertainty idiom*

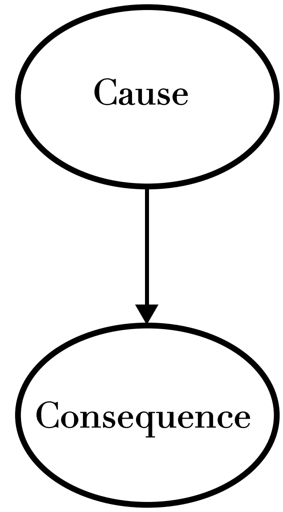


Fig. 2. A.G1: The generic idiom of category A, the cause-consequence idiom.

The usage is twofold: to predict an effect based on an event or to evaluate the probability of an event given a certain effect. The latter is common in forensic cases in which we observe an effect (the evidence) and wish to infer the probabilities of possible causes of the effect (the hypotheses). A common forensic instantiation of the cause-consequence idiom is the *hypothesis-evidence idiom* [6,7,12–17,17–19] (labeled A.F1 in Fig. 3). Hypotheses are also referred to as propositions. Hypotheses and propositions are used interchangeably in this paper.

One often associates the line of thought in the hypothesis-evidence idiom as causal because acts or activities leave or wipe traces. Even though this association is intuitive, causality (two simultaneous or consecutive events) is not a strict requirement. In fact, research is also non-uniform towards the definition of the connections. Some literature [7,19–22] refers to the connections as causal, whereas other research such as Vlek et al. [17] state that links represent “correlation rather than causality”. Although we prefer the latter, we chose not to rename this category as the purpose of the idiom is to model the line of reasoning from cause to effect.

There are two variations of the hypothesis-evidence idiom: the *common cause idiom* and the *common effect idiom* (labeled A.F2 and A.F3 in Fig. 3 respectively[1]). The common cause idiom [12,13,23] models the conjunction of two pieces of evidence. Conjunction is an overarching term for the relationship - which can either be conditionally independent or dependent - between the items of evidence. Due to the divergent connection between the two, the probability of finding Evidence 2 alters if and only if the true state of the hypothesis is unknown. If the true state of the hypothesis is known, information on Evidence 1 does not influence the probability on Evidence 2 and vice versa. The idiom may be modeled with an additional link - illustrated with a dashed link in Fig. 3 - between the evidence nodes, representing a common cause idiom with two conditionally dependent items of evidence.

The common cause idiom entails two items of evidence associated with one event, either both items are found on the same crime scene or are linked in a different way. For example, Taroni et al. [24] present an

[1] The idioms are labeled as forensic idioms but may as well be used in other disciplines. The same holds for the hypothesis-evidence idiom.

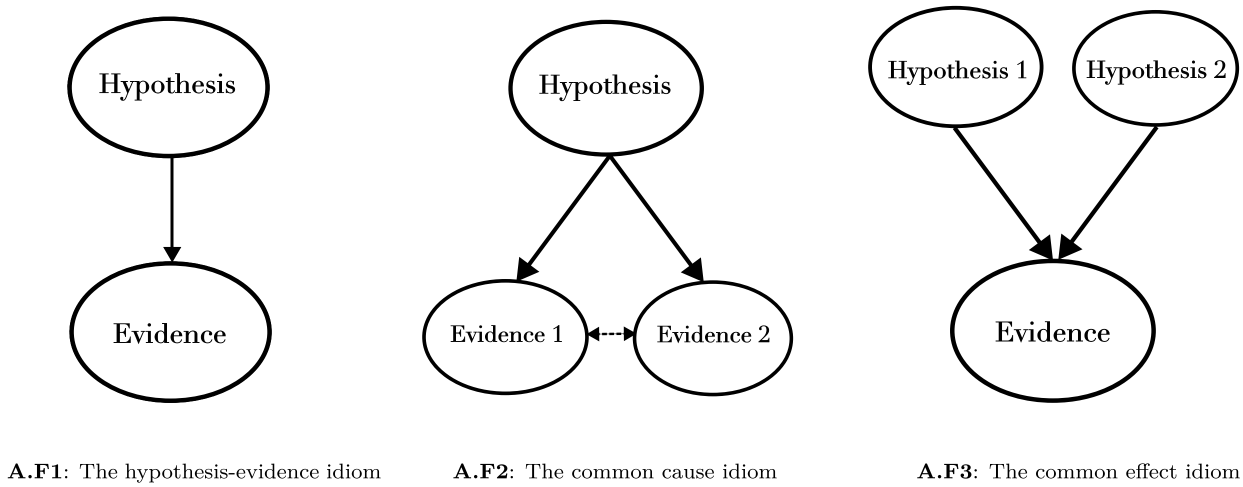


Fig. 3. Forensic instantiations of the cause-consequence idiom.

idiom for the evaluation of two items with no potential source found on two different scenes, aiming to infer a common source between the two of them, a so called forensic intelligence problem.

The common effect idiom [5,12,16] models two joined hypothesis-evidence idioms. The idiom models an effect with two possible causes and their intercausal relation. The common effect idiom is frequently used in medicine to assess the likelihood of possible causes of diseases or fatalities. If the effect is unknown, $P(\text{Cause 2} \mid \text{Cause 1}) = P(\text{Cause 2})$. In words, any information on cause 1 will not provide any information on cause 2 and vice versa. The probability of cause 2 will differ if both the presence of cause 1 and the effect is confirmed, also known as *explaining away* [3,5,7,16,25–32]. This idiom is particularly useful in forensic medical domains such as forensic pathology and forensic toxicology.

The common effect idiom models case hypotheses separately [19], using separate boolean nodes to represent each hypothesis. This is different from the hypothesis-evidence idiom, which uses a single node for all hypotheses, with states that correspond to each case hypothesis. In the next section we will discuss which idiom is best suited in which situation.

3.1.1. *Enforcing mutually exclusive hypotheses*

The choice of using either the hypothesis-evidence or the common effect idiom depends on the mutual exclusivity of the hypotheses. If the hypotheses are mutually exclusive, the hypothesis-evidence idiom can be used. This is because the states of the hypothesis node represent mutually exclusive events. However, if the hypotheses are not mutually exclusive, the common effect idiom is suitable since it uses separate boolean nodes for every hypothesis, allowing both hypotheses to be true at the same time [19].

The common effect idiom is necessary when attempting to model distinct causal pathways with different sets of evidence. However, a challenge arises when the competing arguments are mutually exclusive. In such cases, both the hypothesis-evidence idiom and the common effect idiom are inadequate to model this accurately. Mutually exclusive hypotheses will follow from the hypothesis-evidence idiom naturally, but the idiom cannot address different sets of evidence, information and their probabilistic relations to each of the propositions.[2] In contrast, the common effect idiom can model separate pathways, but the hypotheses are not mutually exclusive per se as the prior probabilities of the hypotheses being true do not necessarily add up to one. The question thus remains: how can we model competing forensic or legal arguments while ensuring mutually exclusive hypotheses?

Meester and Slooten [33] contemplate on several approaches proposed in the literature to enforcing mutually exclusive hypotheses within the common effect idiom. One of these proposals is to simply add an additional directed link between the boolean hypothesis nodes.

A second much discussed approach is to add a boolean constraint node as common child to the hypotheses [16–18,22,30,31,34] (Fig. 4). The CPT of constraint (Table 2) include probabilities such as $P(\text{Constraint} = \text{False} \mid H_2 = \text{True}, H_1 = \text{True}) = 1$ and $P(\text{Constraint} = \text{True} \mid H_2 = \text{True}, H_1 = \text{False}) = 1$. Meester and Slooten are particularly clear on problems arising from the constraint node: when the constraint node is set to true, the prior probabilities of the hypotheses change without adding any evidence to the model. Fenton et al. [30] agree with the criticism and offer an alternative solution that models an auxiliary node between the hypotheses and the constraint node. The auxiliary node includes an "NA" state that ensures the state of the hypotheses only focus on (True, False) and (False, True). As per Fenton et al. their suggested solution may not be perfect, but it is effective in achieving the desired results. Meester and Slooten, however, argue that the auxiliary nodes "lead to a rather arbitrary model based on a technical device rather than a modeling decision, or they are simply not needed.".

Meester and Slooten [33] also discuss the approach called *Bayesian*

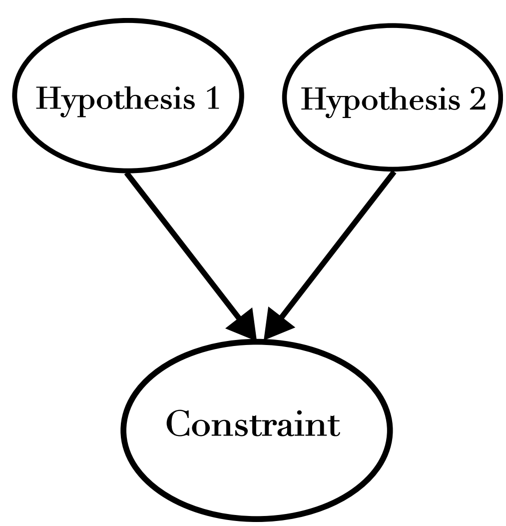


Fig. 4. The constraint solution to enforcing mutually exclusive hypotheses while modeling independent pathways.

[2] The hypothesis-evidence idiom is a basic Bayesian network with only two case variables. Forensic casework involves many variables and the path between hypothesis and evidence can be long and complex.

Table 2
The CPT for CONSTRAINT.

Constraint				
Hypothesis 1	False		True	
Hypothesis 2	False	True	False	True
False	1	0	0	1
True	0	1	1	0

network selection by Neil et al. [35]. Neil et al. suggest to model legal arguments, including different facts, (sources of) evidence and different thoughts on prior beliefs, separately. They illustrate that the models can be combined using 'switch nodes'. These switch nodes are able to include or exclude (disputed) facts or to alter assumptions on preconditions such as motive and opportunity. They argue that the combined model considers different arguments from both perspectives, but that it cannot account for different perspectives on the conditional dependencies between the nodes. As such, this approach feels incomplete, considering that the probabilistic relationship between the nodes can be disputed too.

Moreover, Meester and Slooten criticize that combining models lead to comprehensive and perplexing case models and question whether it is necessary at all to combine the models for H_1 and H_2. Neil et al. argue similar thoughts and believe that an integrated Bayesian model is redundant, that the models can be kept separate and that an expert can evaluate the plausibility of both. We also agree that keeping the models separate will decrease complexity, increase computational power and lessen the number of nodes that have no factual connection to the case such as the switch nodes. Often, the goal of the model is to calculate a Likelihood Ratio. Thus, we want to obtain $P(\text{Evidence} \mid \text{Hypothesis i} = \text{True})$ for $i = 1{,}2$. We can do this by constructing a network for each hypothesis separately, containing a 'combined evidence' node. See Van Dijk et al. [36] for an example.

For an in-depth discussion on the issue of modeling competing stories into one BN, we refer to Refs. [30,33,35].

3.1.2. Summary and applications

- Cause-consequence idioms model the probabilistic relationship of a cause and an effect. In forensic science, this is analogous to the probabilistic relationship between hypothesis and evidence (the hypothesis-evidence idiom).
- There are two variations of the hypothesis-evidence idiom: the common cause idiom and the common effect idiom. The common cause idiom includes more pieces of evidence that are either conditionally dependent or conditionally independent. The common effect idiom models an evidence node with multiple parent hypothesis nodes. The common effect idiom is advantageous when modeling two distinct pathways from hypothesis to evidence. One may also use separate BNs for each hypothesis.
- Cause-consequence idioms are frequently presented in forensic and legal research, whether in template models [3,9,13,26,27,37–63] or case models [16–19,64–76].

3.2. Category B: Narrative idioms

The second category is called *narrative idioms*. Narrative idioms are idioms that concern storytelling coherence in casework. Together, the idioms represent a top-down approach of repeatedly unfolding a scenario into smaller events to enhance communication between jurors and experts and to aid the expert in "gradually constructing a network in complex cases" [18].

The *scenario idiom*, the *(sub)scenario idiom* and the *variation idiom* (labeled B.G1, B.G2 and B.G3 in Fig. 5 respectively) are all narrative idioms and are investigated within a legal context by Vlek et al. [17,18,31,34]. The scenario idiom takes a scenario as parent node and unfolds it into smaller events, the child nodes. The scenario is fully covered by the events in the network and so, if the scenario is true, all events must have taken place. This translates to the conditional probabilities $P(\text{Event i} = \text{True} \mid \text{Scenario} = \text{True}) = 1$ for each i. Conversely, if the scenario is false, some of the events may still have occurred. The directed links between the scenario and the events ensure that information on the probability of one event affects not only the event itself but also the entire scenario. This active connection between each event through the scenario node is called *transfer of evidential* support [18]. The idiom can be further modeled with additional directed links between the nodes, representing dependencies between events. This applies to cases where two events cannot happen independently. Examples of such events are chronological events with event 1 occurring before event 2.

The scenario idiom can also be expanded to the subscenario idiom to further unfold the scenario and its events. This makes the events parent nodes themselves, creating a triple-layered model.

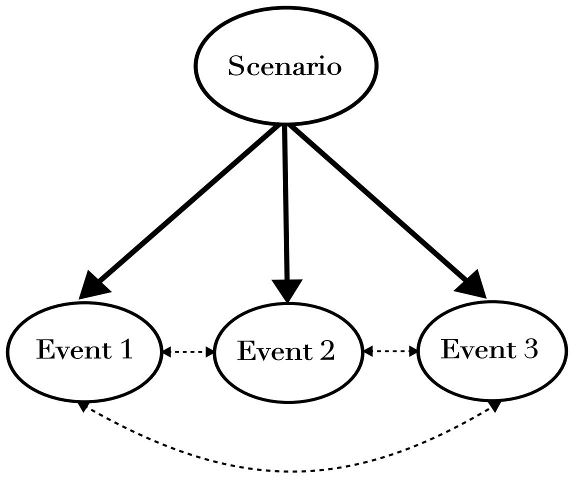
The variation idiom is a subconfiguration of the scenario idiom. This idiom represents a scenario which can be expressed in multiple variations. When the scenario holds, only one of the variations can be true (as opposed to all of them in the scenario idiom). The differences between the variation idiom and the scenario idiom are that the CPT values in the variation idiom (see for example the CPT of VARIATION 3 in Table 3) are assigned such that only one of the variations is true and that the directed links between the event nodes are optional in the scenario idiom but obligatory in the variation idiom.

The variation idiom is similar to the first approach of enforcing mutually exclusive hypotheses: it enforces mutually exclusive events by adding additional directed links between the variables. However, due to the directed links, VARIATION 1 and VARIATION 2 become part of the CPT of VARIATION 3. This is disadvantageous if one wants to model separate paths to each variation. Therefore, we advise against using the variation idiom if one desires to model distinct pathways from scenario to evidence.

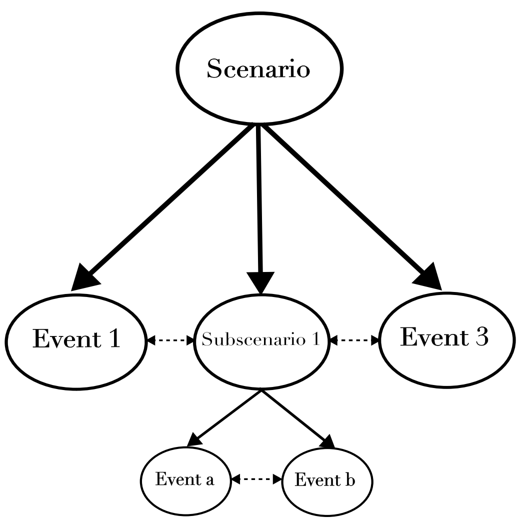
The scenario idiom, the subscenario idiom and the variation idiom all present ways to layer a story until one or more observable results follow. In forensic science, we have a similar structure: the *hypothesis-to-activity idiom* (labeled B.F1 in Fig. 6). Analogous to unfolding a scenario into smaller story lines, the hypothesis-to-activity idiom unfolds a proposition into multiple activities relevant to trace deposition. Unlike the event nodes in the scenario idiom, the activity nodes are not necessarily all 'true' if H_1 or H_2 is true. However, we believe the hypothesis-to-activity idiom is still part of the narrative category, as its goal remains the same: breaking down scenarios into smaller segments to help build the network and improve communication between the modeler and recipient.

HYPOTHESES is the parent node of the activity nodes and the CPTs of the child nodes represent the probability that an activity occurred considering one of the case hypotheses. The idiom can have additional directed links between the activities, as direct and secondary transfer activities are not mutually exclusive and may be conditionally dependent. In fact, Gill et al. [77] state that "there may be multiple opportunities for innocent and secondary transfer events to occur at different times".

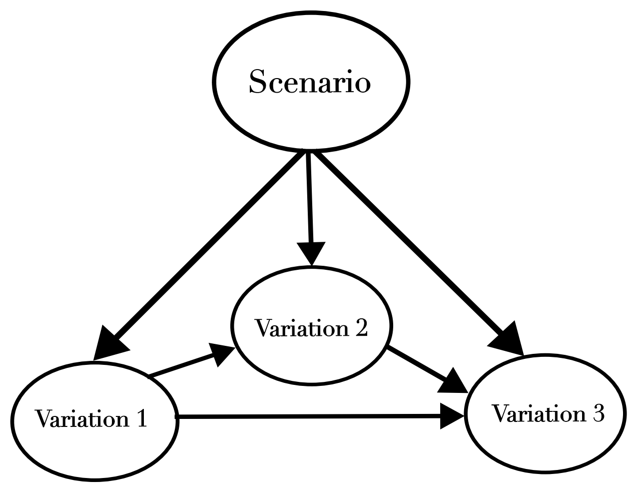
Kokshoorn et al. [9] showed that the dispute in forensic DNA activity level evaluations either concerns an activity or the actor's identity. They formulated multiple sets of relevant prosecution propositions (H_1) and relevant defense propositions (H_2). We translated this in four variables that cover all possible combinations of activity level propositions: suspect X, an alternative actor Y (this may be a known or unknown person), a criminal activity (hereafter activity 1), and an (innocent) alternative activity (hereafter activity 2). The prosecution states that suspect X did activity 1. The defense disputes this and their hypothesis is that an alternative (and often unknown) actor Y did activity 1 or that activity 1 never happened. Optionally, they may also state that suspect X did alternative activity 2. To consider all possible combinations, the hypothesis-to-activity idiom includes three boolean activity nodes: ACTIVITY 1 BY SUSPECT X, ACTIVITY 2 BY SUSPECT X and ACTIVITY 1 BY ALTERNATIVE ACTOR



B.G1: The scenario idiom



B.G2: The subscenario idiom



B.G3: The variation idiom

Fig. 5. Generic idioms of category B. Idiom B.F3, the variation idiom, is a substructure of the (sub)scenario idiom with entered CPTs. Every event in B.G1 must be true (if the scenario holds), whereas only one variation is true in B.G3.

Table 3
The CPT for VARIATION 3. We refer to Ref. [18] for the CPTs of the other two variations.

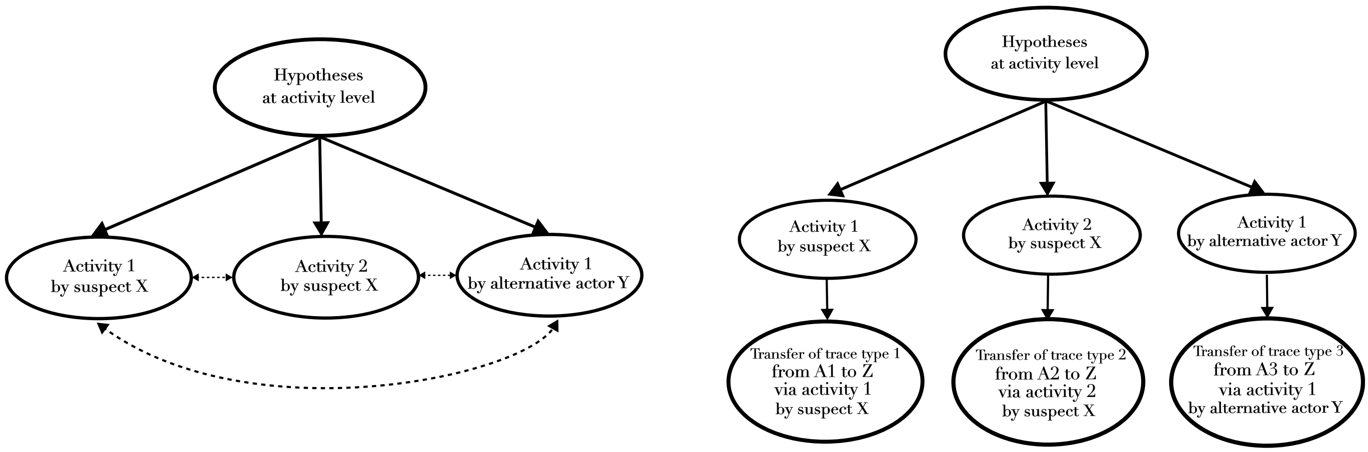
Variation 3								
Scenario	False				True			
Variation 1	False		True		False		True	
Variation 2	False	True	False	True	False	True	False	True
False	1	1	1	1	0	1	1	1
True	0	0	0	0	1	0	0	0

y. The irrelevant activity nodes can either be deleted or set to False. Node names may of course be further specified in casework to enhance interpretation. If the pathways interfere, for example in cases of secondary transfer, additional directed links may be needed between the transfer activities.

There are some modeling alternatives for the hypothesis-to-activity idiom. For example, one can combine all transfer activities in one node. Both model choices are mathematically equivalent. However, modeling a single node including all activities as states does not help the understanding of experts nor jurors in a complex case which is one of the major reasons to use BNs in the first place. Therefore, instead of grouping the activities, we prefer to group the findings related to the activities. We will elaborate on this matter in Section 3.3 about synthesis idioms.

Adding an additional layer between the hypothesis node and the activity nodes is a second possible modification to the hypothesis-to-activity idiom. This may be particularly useful when the case propositions consist of several parts and amount to scenarios more than to hypotheses. The extra layer does not portray the mechanisms that lead to the traces but rather breaks down the scenarios into smaller and more assessable parts. Idioms such as the subscenario idiom or the variation idiom can be used to model such extra layers.

The transfer nodes in the hypothesis-to-activity idiom can be further unfolded to become - as we label it - the *hypothesis-to-transfer idiom*



B.F1: The hypothesis-to-activity idiom **B.F2**: The hypothesis-to-transfer idiom

Fig. 6. Forensic instantiations of the sub(scenario) idiom. The dashed lines represent possible dependencies between the activities.

(labeled B.F2 in Fig. 6). Whereas the hypothesis-to-activity idiom unfolds the hypotheses into activities that could lead to the traces, the hypothesis-to-transfer idiom unfolds the mechanisms into expected transfer of traces considering those mechanisms. One may argue that the hypothesis-to-transfer idiom models two joined forensic instantiations of the scenario idiom rather than a single subscenario idiom: unfolding hypotheses into activities into transfer of traces. Both perceptions are technically correct. Yet, we believe it is more convenient to designate the hypothesis-to-transfer model as a single idiom since activity nodes and transfer nodes often appear together in forensic models that evaluate activity level questions.

When the transfer of traces are added to the model, the activities become parent nodes, analogous to the event nodes in the (sub)scenario idiom. There are two ways of modeling this idiom, method A and method B (also illustrated as B.F2 in Fig. 6) in Fig. 7 respectively. In method A, the child nodes of the activity nodes are named Transfer of trace type i, with $i = 1, 2, 3$ depending on the number of different trace types. Trace type may be defined as a trace plus possible source, for example DNA from suspect X or glass fragments from window X. Fig. 7 shows a case where each path has a different trace type (trace type 1, 2, and 3). The CPTs of the transfer nodes (Table 4) represent the probability of a trace transfer considering one or more activities - depending on the number of directed links between the activity nodes and the transfer of trace nodes. Multiple activities can lead to transfer of the same type of traces and hence, CPTs become very extensive and therefore difficult to fill in. Moreover, the CPTs now contain conditional probabilities such as P(transfer of trace of type 1 | Activity 1 by suspect X = False) that are impossible and irrelevant (marked as question mark in Table 4) for the expert to assess. The idiom varies in the number of activities, the number of expected traces and the number of directed links between transfer traces and activities. The size of the CPTs for transfer of trace type i equals 2^n, with n the number of directed links.

In method B, the child node of activity 1 by suspect x is named transfer of trace type 1 from A1 to Z via activity 1 by suspect X (A and Z are 'donor' and 'receptor', and can either be objects or individuals) instead of Transfer of trace type 1. In most cases, an activity node has only a single directed link to one transfer of trace node because the nodes name now include 'via activity 1 (or via activity 2)'. Consequently, the CPTs (Table 5) are often two dimensional. And if so, they only include the relevant probabilities. These probabilities can be assigned by the forensic expert using expert knowledge, literature and/or case-specific experiments. Moreover, method B appears to provide a solution for enforcing mutually exclusive hypotheses while modeling multiple pathways. Therefore, we recommend to use method B instead of method A for modeling the hypothesis-to-transfer idiom.

Both the hypothesis-to-activity idiom and the hypothesis-to-transfer idiom are essential in activity level evaluations and therefore appear in many forensic templates [9,48,54,58,59,61,62] and case models [32,64,65,67–76,78,79]. Although earlier research involving template models and case models such as [42] has also focused on activity level examinations, the use of the hypothesis-to-activity idiom is, to the best of our knowledge, only notably present in later work (2015 until now) - with the exception of Evett et al. [64].

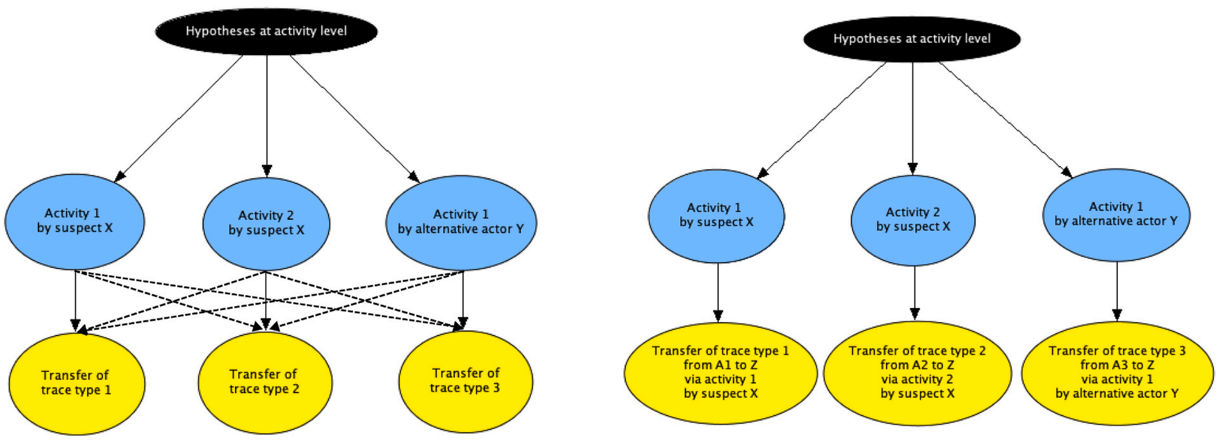
3.2.1. Summary and applications

- Narrative idioms are used for storytelling purposes. The generic idioms, the scenario idiom, the subscenario idiom, and the variation idiom are mainly studied in a legal context [17,18,31,34].
- Analogous to the scenario idiom, the forensic hypothesis-to-activity idiom focuses on pathways from hypothesis to activity related to trace deposition.
- Analogous to the subscenario idiom, the forensic hypothesis-to-transfer idiom focuses on pathways from hypothesis to the expected transfer of trace types.
- We recommend to use variable names such as 'transfer of trace type 1 from A1 to Z **via activity 1**' instead of 'transfer of trace type 1' for the transfer nodes in the hypothesis-to-transfer idiom to get relevant and assessable probabilities in the CPTs.

3.3. Category C: Synthesis idioms

The *synthesis idiom* [5,80,81] (labeled C.G1 in Fig. 8) - also known as the *definitional idiom* [8] or *accumulation idiom* [58] - models the synthesis, summary or combination of many nodes into one node: the synthesis node. Synthesis is defined by the states of its parent nodes. The purpose of the idiom is to organize the BN such that the overall structure and understanding is improved and/or the size of the CPTs is reduced [5].

Synthesis idioms can model definitional, hierarchical or combinatorial relations between variables. Definitional synthesis structures model deterministic relations, such as formulas and functions [5]. Hierarchical synthesis structures model the combination of similar variables with similar influence on some other node [5], which reduces the number of probability elicitations. Combinatorial synthesis structures reduce the size of the combinatorial space of the model, also known as 'parent divorcing' [5]. Whether to use it or not depends on how one would like to present the conditional probabilities: either by using nodes



(a) Method A (b) Method B

Fig. 7. Method A and B for modeling the hypothesis-to-activity idiom. The blue nodes and yellow nodes represent the activity and transfer nodes respectively. The dashed lines in method A illustrate possible directed links. The distinction between method A and B is found in the names of the transfer nodes. Method B is the recommended method. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 4
The CPT for TRANSFER OF TRACE TYPE 1.

Transfer of trace type 1		
Activity 1 by suspect X	False	True
False	?	(1-p)
True	?	p

Table 5
The CPT for TRANSFER OF TRACE TYPE 1 FROM A TO Z VIA ACT. 1 BY SUSPECT X.

Transfer of trace type 1 from A to Z via act. 1 by suspect X		
Activity 1 by suspect X	False	True
False	1	(1-p)
True	0	p

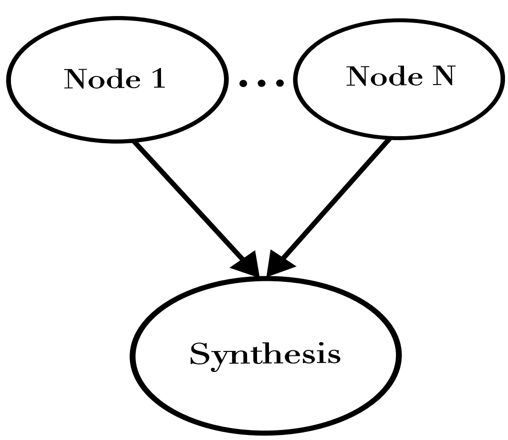


Fig. 8. C.G1: The generic idiom of category C: the synthesis idiom.

or CPTs. We prefer the former and think combinatorial synthesis idioms are essential for structuring a BN. Note that definitional and combinatorial synthesis idioms include non-causal relationships between nodes (see Section 3.1 for notes on causality in BNs).

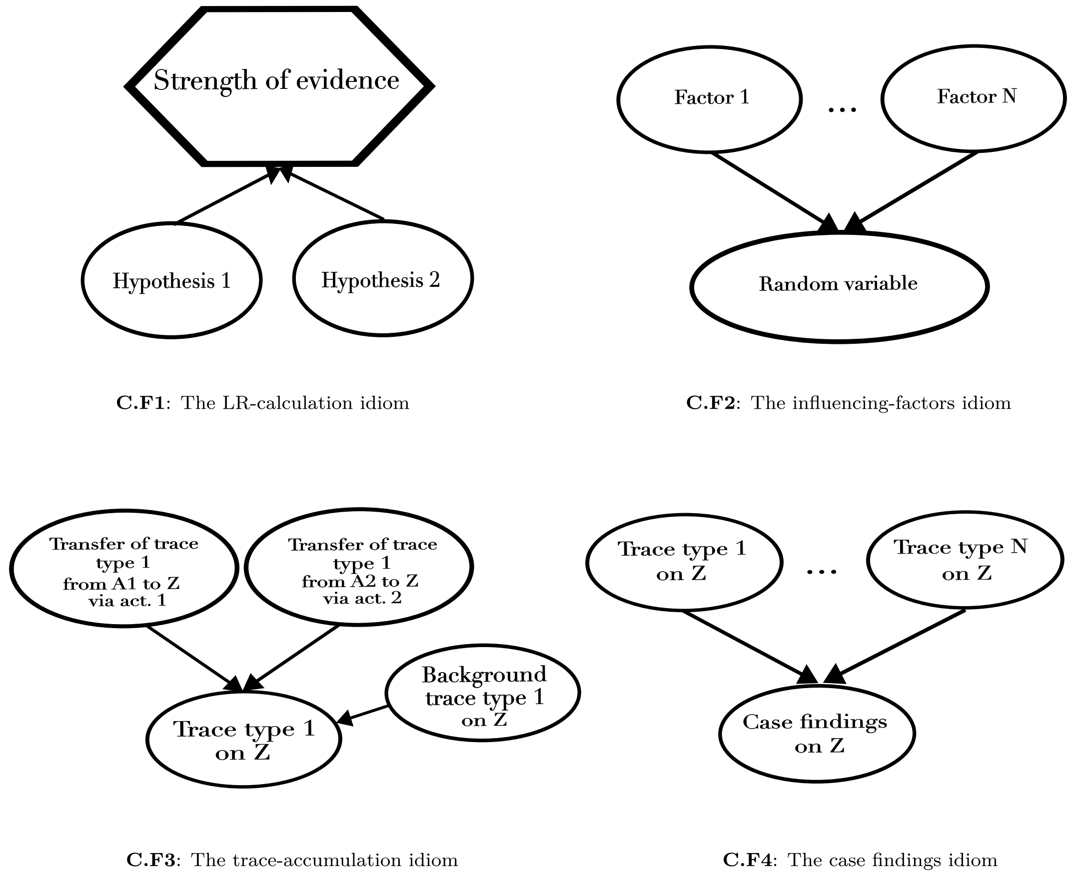
There are several ways in which synthesis idioms are being integrated into forensic BNs. This paper presents four of them. The *LR-calculation idiom* (C.F1 in Fig. 9) [58] is a definitional synthesis idiom and models the deterministic relationship between the case hypotheses H_1 and H_2, the case findings E and the strength of evidence, the LR. STRENGTH OF EVIDENCE is a function node that needs two states from the hypothesis nodes to calculate the LR (in the context of the BN). This idiom seems only for convenience as the strength of evidence can also be evaluated manually by instantiating H_1 and H_2 sequentially or by instantiating the case findings, with prior odds of the hypotheses equal to 1. The idiom should be used with caution, as it only works if the prior odds are (set to) 1. Furthermore, if one of the hypotheses is not simple but composite, prior probabilities of subhypotheses may affect the LR (see Section 3.5 for a discussion on multiple propositions).

The *influencing-factors idiom* (labeled C.F2 in Fig. 9) contains an hierarchical synthesis structure. Its structure is similar to a definitional synthesis idiom, but now the relation between child node and parent node is not deterministic. The synthesis node specifies a group of factors with similar influence on a variable of interest. The purpose of grouping is to reduce the number of parents of the variable of interest. In forensic science, these nodes do not concern any activities, but have a parental relation to either the transfer nodes or findings node [58]. Examples of such nodes are TIME BETWEEN DEPOSITION AND RECOVERY and *environmental conditions*, all affecting the final case findings. The influencing-factors idiom is related to a cause-consequence idiom because an unobservable consequence (the random variable) is defined as a probabilistic combination of factors influencing its causes [5].

The *trace-accumulation idiom* and the *case findings idiom* (e.g. in Refs. [58,68]) are examples of combinatorial synthesis idioms. The trace-accumulation idiom (labeled C.F3 in Fig. 9) fuses the results of multiple transfers and the background level[3] of the same trace type to item Z (for example, DNA from the same individual) [58,68]. Modeling-wise, the transfer nodes and background node will be combined using one synthesis node: TRACE TYPE i ON Z. If there are multiple traces of different sources and/or more items of interest, one must model multiple synthesis nodes.

The *case findings idiom* [58] (labeled C.F4 in Fig. 9) merges all nodes concerning traces on item Z into one case findings node. Only two states are necessary to model when using this idiom in a BN designed for a single case: 'case findings' and 'other'. The state 'case findings'

[3] Background is an ill-defined concept in forensic literature. Experts should always be clear on the definition of 'background' in their network.



C.F1: The LR-calculation idiom

C.F2: The influencing-factors idiom

C.F3: The trace-accumulation idiom

C.F4: The case findings idiom

Fig. 9. Forensic instantiations of the synthesis idiom. C.F1 is of definitional type, C.F2 is of hierarchical type, and C.F3 and C.F4 are of combinatorial type. C.F1 should be used with caution as it only applies to cases with prior odds equal to 1. An example of a forensic random variable in C.F2 is the persistence of traces.

summarizes all findings on item Z, for example DNA profiling results from multiple swabs from the same item [68]. The state 'other' defines any other possible result. When a BN is designed for a series of cases, the states of CASE FINDINGS ON Z should cover all possible findings.

Combining the trace-accumulation idiom and the case findings idiom is advantageous to probability elicitation. Consider the hypothesis-to-transfer idiom from Fig. 6 with three transfer nodes. If two of these transfer nodes concern traces of same type to Z, the synthesis node lessens the number of parents and reduces the size of the CPT of CASE FINDINGS ON Z.

3.3.1. Summary and applications

- Synthesis idioms model definitional, hierarchical or combinatorial relationships between variables. Forensic examples are the LR-calculation idiom, the influencing-factor idiom, the trace-accumulation idiom and the case findings idiom.
- The LR-calculation idiom should be used with caution as it only works if the prior odds are set to 1 and with two 'simple' hypotheses.
- Synthesis idioms are frequently integrated in forensic template models and case models, including [48,54,58,60,63,64,68,69,71,72,75,76,80,82]. To be more specific [48,54,58,68,69,72,75,76], illustrate models that use the trace-accumulation idiom (including the background level of trace material).

3.4. Intermezzo: adopting the idiom-based approach

Thus far, we have discussed cause-consequence, narrative, and synthesis idioms. As mentioned in the introduction, these can be combined to form template and case-specific models. To illustrate this approach, we present a template model (Fig. 10) that originates from merging the hypothesis-to-transfer idiom (B.F2 in Fig. 6), the trace-accumulation idiom (C.F3 in Fig. 9), and the case findings idiom (C.F4 in Fig. 9). Our template model is a generalization of the template model presented by Taylor et al. [58] for constructing BNs in forensic biology cases when considering activity level propositions. It also incorporates the ideas in Kokshoorn et al. [9] on propositions disputing the actor or activity in DNA evidence evaluation. The template model is available as Hugin file online at https://github.com/NetherlandsForensicInstitute/evaluation-of-transfer-evidence.

The template model illustrates the evaluation of transfer evidence regarding item Z by modeling the different possible pathways between trace deposition and the case findings on Z. The template model begins with a single node representing the case hypotheses, which is then divided into three activity nodes using the hypothesis-activity idiom. The hypothesis-to-transfer idiom is identical to the one illustrated in Section 3.2 on narrative idioms.

The template model is applicable to cases where activity 1 by suspect X and activity 1 by alternative actor Y lead to same type traces (for example in cases of indirect transfer) and to cases where these activities lead to different type of traces (i.e. DNA of suspect X and DNA of alternative actor Y respectively). Fig. 10 represents the latter and illustrates a case in which activity 1 and activity 2 by suspect X lead to trace type 1 on Z and activity 1 by alternative actor Y leads to trace type 2 on Z. The result of combining two transfer nodes into one node is the accumulation node TRACE TYPE 1 ON Z. This accumulation node is the expected evidence on Z considering the transfer activities and background material. Lastly, the case findings idiom merges all trace-accumulation nodes into a single node that summarizes the observed findings on item Z.

Our template model uses an integrated Bayesian approach to enforcing mutually exclusive hypotheses. TRANSFER OF TRACE TYPE 1 FROM A1

TO Z VIA ACTIVITY 1 BY SUSPECT X ensures that only the conditional probabilities given H_1 will follow that path. The mutually exclusive hypotheses are ensured by the CPT of CASE FINDINGS ON Z: it is only possible to observe the case findings through one of the routes. The expert may also choose to model each pathway using different BNs that are not joined (see Subsection 3.2.1 for further remarks on this issue).

The template model can be further expanded by including two categories: *hypothesis-conditioning* idioms (Section 3.5) and *evidence-conditioning* idioms (Section 3.6).

Traces on item Z are the central elements of Taylor et al.'s [58] template model and consequently the model only considers possible pathways from activity to these traces. Item Z is automatically linked to the activities stated in the hypotheses and is considered as a relevant item in the case for at least one of the hypotheses. If Item Z is found to be irrelevant, using the model would be meaningless. The relevance of item Z can be modeled explicitly as a separate relevance node (e.g. Ref. [64]) or as a subproposition node (e.g. Ref. [83]).

3.5. Category D: hypothesis-conditioning idioms

The fourth category involves idioms that allow hypotheses to be conditioned on a variable. We refer to this category as *hypothesis-conditioning idioms* (see Fig. 11). The purpose of this idiom is to limit which set of hypotheses are considered during evaluation, using conditional variables. We consider two types of such variables: *preconditions* and *postconditions*. preconditions are variables that make or break the relevance of a hypothesis, while postconditions partition and/or regroup hypotheses to form a set of propositions relevant to the case. In the latter, the hypotheses not considered can still be true, whereas in the former they cannot.

Fig. 11 illustrates the use of postconditional variables in two forensic idioms related to this category. The hypothesis-evidence idiom works well when there are two simple hypotheses to evaluate. Yet Buckleton et al. [14] claim that "it is often difficult to summarize all the issues of a real casework problem using two hypotheses". They proposed a structure that can handle three or more hypotheses: the *extended-likelihood-ratio idiom*. The idiom extends the hypothesis-evidence idiom by adding an extra node between HYPOTHESIS and EVIDENCE. In cases of multiple propositions contributing to the case hypotheses, the partitioning node recapitulates the hypotheses and/or divides them into two or more subhypotheses. Buckleton et al. illustrate this with a case example considering a simple prosecution proposition H_1 but a more complex defense proposition $H_2 = \{H_{2a}, H_{2b}\}$. The CPT of PARTITIONING (Table 6) include the relative contributions of the two subhypotheses H_{2a} and H_{2b} to the probability of the defense hypothesis H_2, $P(H_{2a}|H_2)$ and $P(H_{2b}|H_2)$ respectively. Note that this structure hides the fact that conditional priors need to be added to the model and that these priors affect the LR.

The second forensic idiom, the *regrouping idiom* [15], is the reverse of the extended likelihood ration idiom. The regrouping idiom extends the hypothesis-evidence idiom with a regrouping node conditioned on HYPOTHESES. Instead of two simple hypotheses, HYPOTHESES now considers multiple subhypotheses under H_1, H_2, or both. REGROUPING combines these subhypotheses to formulate H_1 and H_2 such that if either H_{1a} or H_{1b} is true H_1 is also true, and if either H_{2a} or H_{2b} is true H_2 must be true (see Table 7). The extended likelihood ratio idiom can be modeled similarly with a reversed directed link between REGROUPING and HYPOTHESES. Thus the regrouping idiom combines subhypotheses into one case hypothesis and the extended-likelihood-ratio idiom splits the case hypothesis into two or more subhypotheses. Both forensic idioms can be generalized by using terms such as cause and consequence (see Section 3.1). This allows them to be used in multiple domains.

The idioms may also be combined. De Koeijer et al. [83] presents a template model that divides the core propositions into two sets of subpropositions: one set that addresses the relation between a suspect and an item (S_1 and S_2) (also focused on by Taylor et al. [58]) and one set that addresses the relation between an item and the crime (A_1 and A_2). Fig. 12 illustrates this structure. Both sets are modeled as separate boolean nodes in the template model using the extended-likelihood-ratio idiom. The prosecution hypothesis and the three possible defense hypotheses are regrouped in CORE PROPOSITIONS using the regrouping idiom.Fig. 13 shows the *hypothesis-precondition*

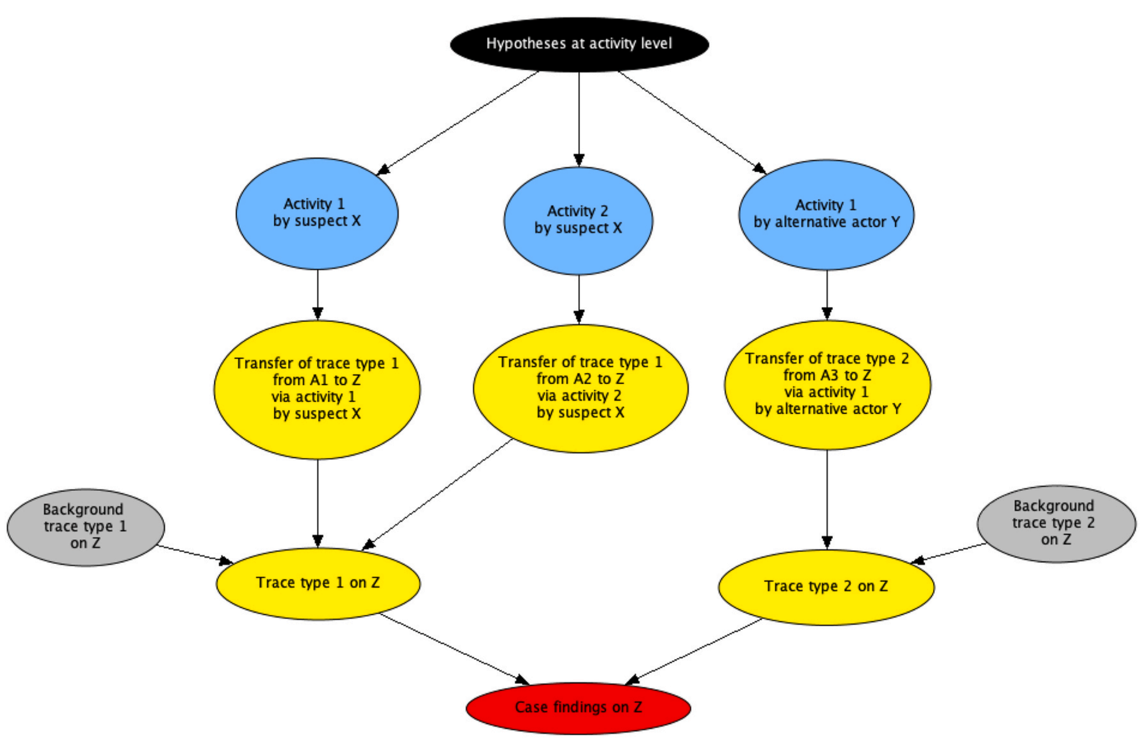
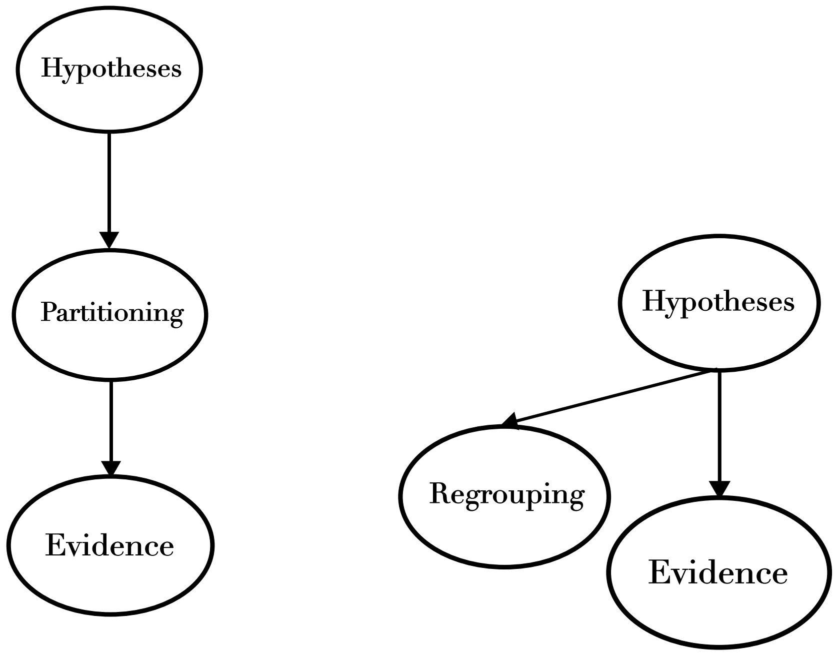


Fig. 10. A template model for assessing the strength of transfer evidence at activity level. The template model is a combination of the hypothesis-to-transfer idiom (B.F2 in Fig. 6), the trace-accumulation idiom (C.F3 in Fig. 9), and the case-findings idiom (C.F4 in Fig. 9).



D.F1: The extended-likelihood-ratio idiom

D.F2: The regrouping idiom

Fig. 11. The use of postconditional variables in two forensic idioms.

Table 6
The CPT for PARTITIONING.

Partitioning		
Hypotheses	H_1	H_2
H_1	1	0
H_{2a}	0	p
H_{2b}	0	(1-p)

Table 7
The CPT for REGROUPING.

Regrouping				
Hypotheses	H_{1a}	H_{1b}	H_{2a}	H_{2b}
H_1	1	1	0	0
H_2	0	0	1	1

idiom, using preconditions for the hypotheses in HYPOTHESES. These conditions are necessary requirements for a hypothesis to be true, or conditions that influence the prior probability of one of the hypotheses [16]. For example, in legal cases, opportunity is a necessary requirement for a defendant's guilt, while motive increases the prior probability of the prosecution hypothesis [6,7,16,22]. Alibi evidence [6,7,16], also a precondition, is directly proportional to opportunity and may contradict the prosecution proposition.

Modeling-wise, PRECONDITION is a boolean root node and is structured as a parent node of HYPOTHESES [7,16,22]. The conditional probabilities in the CPT of HYPOTHESES are entered such that the hypotheses are true (or false) if the condition holds or that the prior probability of the hypotheses change. The idiom can be instantiated using terms such as opportunity, motive, alibi and/or capability and can be expanded using multiple preconditions. Thus far, the idiom has shown up only in template models and case models evaluating source level hypotheses [43,84] but may be used for networks that evaluate activity level evaluations too.

3.5.1. *Summary and applications*

- Hypothesis-conditioning idioms allow hypotheses to be conditioned on a variable. This variable can be a precondition or a postcondition.
- Preconditional variables represent crucial factors for the relevance of a hypothesis. They are modeled as root node of the hypotheses node in the hypothesis-precondition idiom. This idiom is particularly prevalent in legal casework.
- Postconditional variables form a set of hypotheses that are relevant to the case. These variables can be modeled as either a partitioning node or a regrouping node. The partitioning node divides at least one of the hypotheses into several subpropositions, while the regrouping node combines the subpropositions to form a single set of hypotheses.
- The hypothesis-conditioning idiom is not very prominent in forensic casework. [40,41,53,83,85] show applications of the extended-likelihood-ratio idiom and the regrouping idiom.

3.6. *Category E: evidence-conditioning idioms*

Evidence-conditioning idioms consist of root nodes that represent uncertain factors in the evidence evaluation or strict preconditions for the evidence to be taken into account. Idioms in this category make it clear that observations or evaluations may be inaccurate, unreliable or irrelevant.

The evidence-uncertainty idiom (E.F1 in Fig. 14) descends from the generic idiom, the *measurement* idiom [8,11,16]. The measurement idiom (E.G1 in Fig. 14) indicates that any measurement of variable X can be uncertain and may not accurately reflect its true value. The idiom is structured as MEASUREMENT OF X as child node with two parent nodes TRUE VALUE OF X and UNCERTAINTY. In the evidence-uncertainty idiom, TRUE VALUE OF X and MEASUREMENT OF X are replaced by ACTUAL EVIDENCE and OBSERVED EVIDENCE respectively. UNCERTAINTY can be substituted with any uncertain factor related to the evidence (evaluation). Common modeled uncertainties regarding the evidence in forensic activity level evaluations are the relevance of an item (if modeled as uncertainty root node) [3], sufficient recovery of the trace material [48,54,58,60,75] and correct interpretation of the evidence [47]. All these variables can be

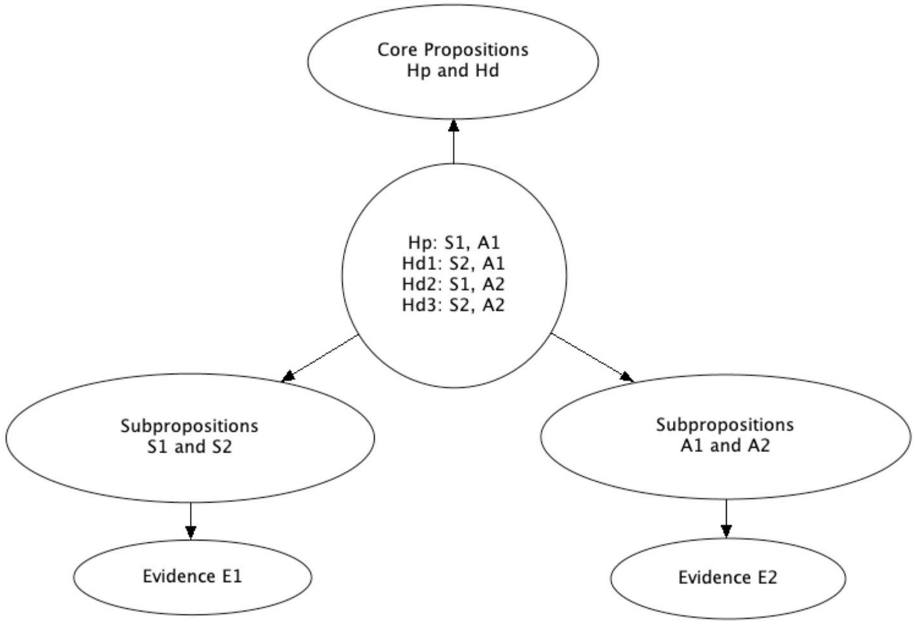


Fig. 12. Template model for evaluating activity level propositions [83]. The template model is a combination of the extended-likelihood-ratio idiom and the regrouping idiom.

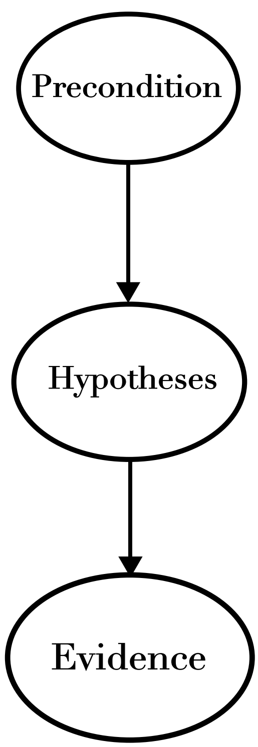


Fig. 13. D.F3: The hypothesis-precondition idiom. Opportunity, motive and credibility are examples of legal preconditions.

instantiations of the uncertainty node in the evidence-uncertainty idiom. For example, Fig. 15 shows a forensic instantiation of the evidence-uncertainty idiom with uncertain factor RECOVERY.

Lagnado et al. [7] state that "in the limiting cases with a fully reliable measurement process, the status of the hypothesis guarantees the status of the evidence report and vice-versa." (p. 52). We believe this statement holds in a legal context, when the evidence is usually based on testimonies about the true state of the hypothesis rather than the true state of the evidence. As such, in legal context, ACTUAL EVIDENCE in the evidence-uncertainty idiom can be replaced by HYPOTHESIS. However, in forensic activity level evaluations, forensic reports do not include a statement about the true state of an hypothesis, but include a statement about the probability to observe the evidence given the hypotheses. As such, forensic evidence may be reliable, but the evidence does not guarantee the state of the hypothesis.

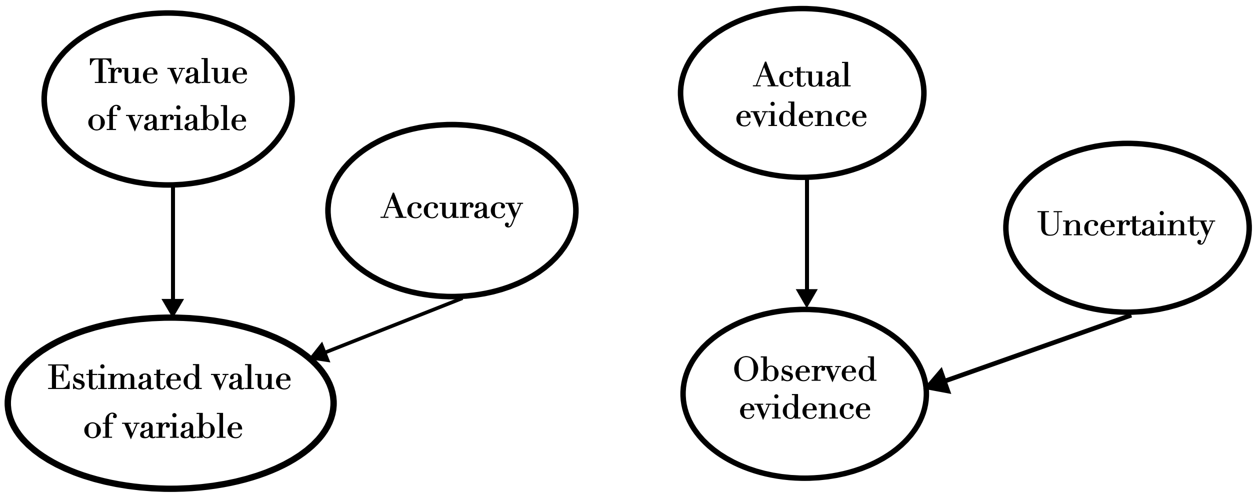
Substitution with ACCURACY, CREDIBILITY or RELIABILITY results in three idioms that have frequently been used in BNs for modeling legal arguments: the *evidence-accuracy idiom* [22], the *evidence-reliability idiom* [6,7,21], and the *evidence-credibility idiom* [21].[4] The evidence-accuracy and the evidence-reliability idiom model the extent to which the evidence is an accurate and reliable reflection of the true state of the hypothesis [7]. The evidence-credibility idiom relates to the credibility of the source, rather than the evidence itself. For example, the credibility of a(n) (expert) witness testimony. The uncertain factors can be decomposed into components defining the factor, which results in a definitional idiom. For example, accuracy may be divided into veracity, objectivity and sensitivity [7].

Please note that uncertain factors can be modeled as a parent node of variables outside the forensic discipline too, see for example [8,11]. However, as we focus on forensic activity level evaluations, we restrict ourselves to evidence-uncertainty relations.

3.6.1. Summary and applications

- The evidence-conditioning idioms, for example the evidence-uncertainty idiom, model uncertainties in the evaluation of evidence or strict preconditions for the evidence to be taken into account.
- The evidence-accuracy idiom, the evidence-reliability idiom, and the evidence-credibility idiom are examples of legal evidence-conditioning idioms.
- Item relevance, recovery of trace material and other uncertainties regarding the evidence are frequently modeled in forensic activity level evaluations, see for example [3,36,48,54,58,60,68,75].

[4] The evidence-accuracy idiom is sometimes referred to as evidence-credibility idiom or evidence-reliability idiom and vice-versa. Although the literature is inconsistent about the definition of the variables in the uncertainty node, the modeling aim of all three idioms remains.



E.G1: The measurement idiom

E.F1: The evidence-uncertainty idiom

Fig. 14. The generic measurement idiom and the forensic evidence-uncertainty idiom.

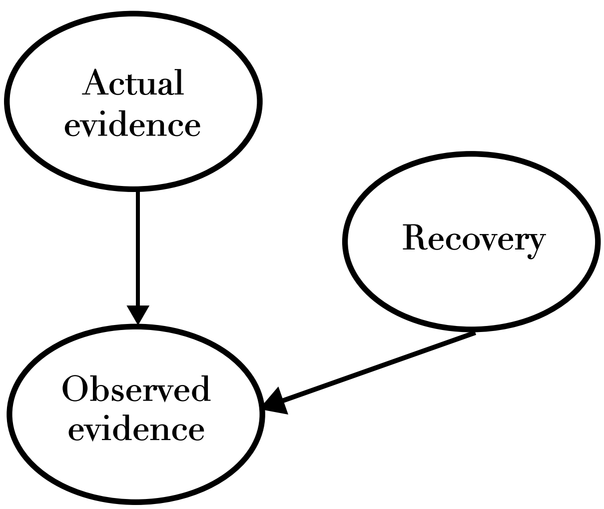


Fig. 15. Instantiation of the evidence-uncertainty idiom with RECOVERY as one of the common uncertainties in forensic evidence evaluation at activity level.

4. Final remarks

Our research advocates the idiom-based approach to modeling activity level evaluations in forensic science. We reviewed existing idioms within and outside of the forensic discipline and organized them into five categories: *cause-consequence idioms*, *narrative idioms*, *synthesis idioms*, *hypothesis-conditioning idioms*, and *evidence-conditioning idioms*. We elaborated on generic idioms and emphasized forensic instantiations that are useful for modeling activity level evaluations using BNs. The collection is by no means exhaustive; for example, we omitted the induction idiom and the reconciliation idiom from Neil et al. [5]. Nevertheless, we think that our collection of idioms is a good starting point for constructing "basic" case models. In fact, we illustrated the idiom-based approach by combining some of the idioms in category A, B and C to develop a larger template model. The template model is a generalization of Taylor's template model in Ref. [58] and includes Kokshoorn et al.'s [9] ideas concerning the dispute over the actor or activity.

Although idioms are based on generic reasoning and can be applied to multiple modeling problems, case models still reflect the expert's perspective of a case. Therefore, an idiom-based approach alone is not sufficient to ensure consistency among BNs created by different experts. Moreover, we focused on the qualitative design of a BN as the idiom-based approach largely focuses on identifying the structure of a BN. Practical methods for forensic experts to identify the relevant variables or to elicit the conditional probabilities from experts are underdeveloped in the forensic literature, and so, much work remains to be done.

CrediT

M. Vink: conceptualization, methodology, investigation, writing - original draft, writing - review & editing.

M.J Sjerps: conceptualization, methodology, supervision, writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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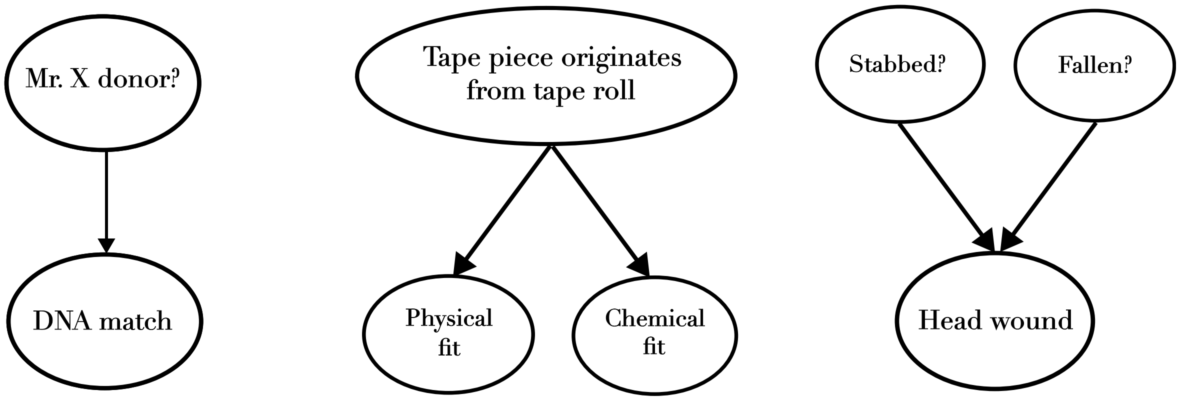
Appendices.

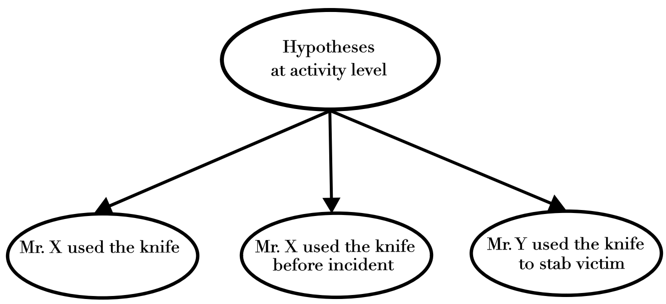
A. Concrete examples of the forensic idioms and their use in casework

This appendix provides concrete examples of the use of the forensic idioms presented in the paper. We only provide examples for the idioms where the variations lie in the node names (and not in the states, as in the case of the extended-likelihood ratio idiom).

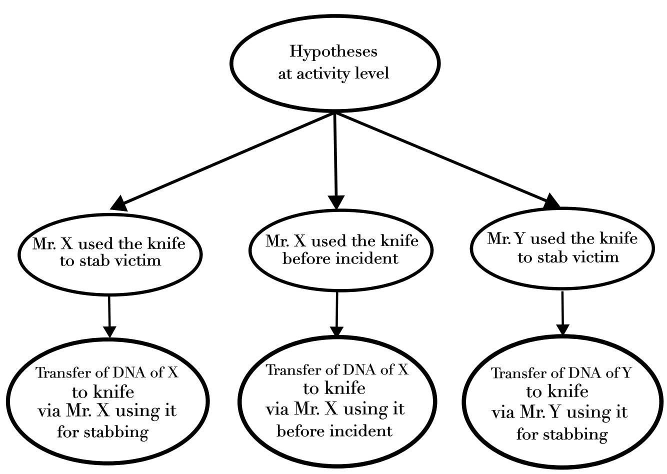


A.F1 **A.F2** **A.F3**

Fig. 16. Examples of the hypothesis-evidence idiom (left), the common cause idiom (middle) and the common effect idiom (right).

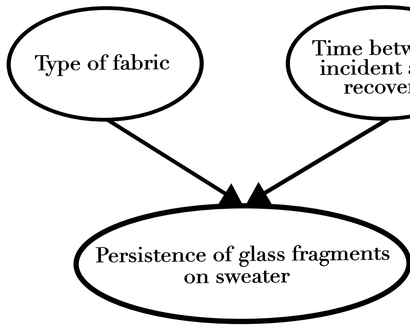


B.F1

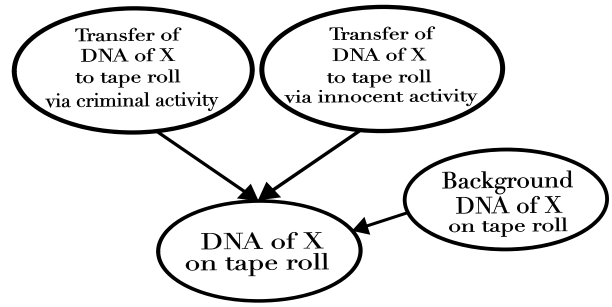


B.F2

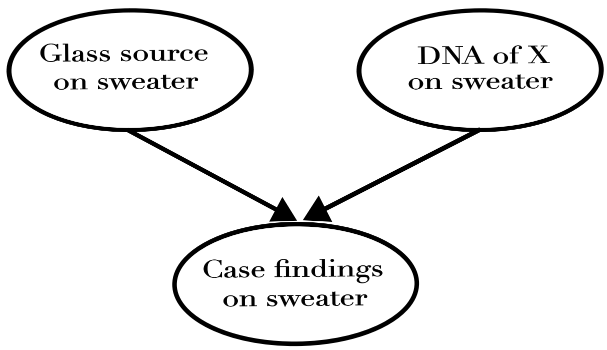
Fig. 17. Examples of the forensic hypothesis-to-activity idiom (above) and the hypothesis-to-transfer idiom (below).



C.F2



C.F3



C.F4

Fig. 18. Examples of the influential-factors idiom (upper left), the trace-accumulation idiom (upper right) and the case-findings idiom (bottom).

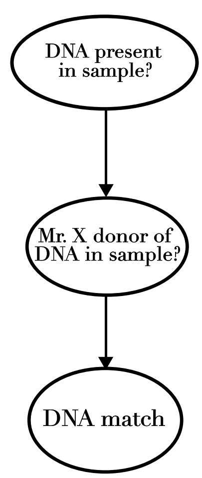


Fig. 19. Example of **D.F3**, the hypothesis-precondition idiom.

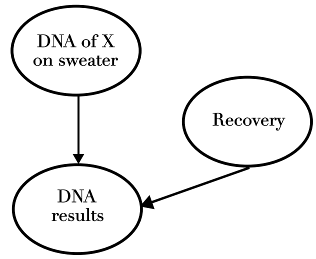


Fig. 20. Example of **E.F1**, the evidence-uncertainty idiom.

References

[1] R. Cook, I.W. Evett, G. Jackson, P. Jones, J. Lambert, A hierarchy of propositions: deciding which level to address in casework, Sci. Justice 38 (4) (1998) 231–239.
[2] C. Aitken, A. Gammerman, Probabilistic reasoning in evidential assessment, J. Forensic Sci. Soc. 29 (1989) 303–316.
[3] P. Garbolino, F. Taroni, Evaluation of scientific evidence using bayesian networks, Forensic Sci. Int. 125 (2002) 149–155.
[4] N. Fenton, M. Neil, Risk Assessment and Decision Analysis with Bayesian Networks, Crc Press, 2018.
[5] M. Neil, N. Fenton, L. Nielson, Building large-scale bayesian networks, Knowl. Eng. Rev. 15 (2000) 257–284.
[6] D.A. Lagnado, Explaining the Evidence: How the Mind Investigates the World, Cambridge University Press, 2021.
[7] D.A. Lagnado, N. Fenton, M. Neil, Legal idioms: a framework for evidential reasoning, Argument Comput. 4 (2013) 46–63.
[8] E. Kyrimi, M.R. Neves, S. McLachlan, M. Neil, W. Marsh, N. Fenton, Medical idioms for clinical bayesian network development, J. Biomed. Inf. 108 (2020), 103495.
[9] B. Kokshoorn, B.J. Blankers, J. de Zoete, C.E. Berger, Activity level dna evidence evaluation: on propositions addressing the actor or the activity, Forensic Sci. Int. 278 (2017) 115–124.
[10] N. Fenton, M. Neil, Avoiding probabilistic reasoning fallacies in legal practice using bayesian networks, Australasian J. Legal Philos. (36) (2011) 114–150.
[11] C. Hobbs, M. Lloyd, The application of bayesian belief networks to assurance case preparation, Achiev. Syst. Safety (2012) 159–176.
[12] F. Taroni, A. Biedermann, P. Garbolino, C.G. Aitken, A general approach to bayesian networks for the interpretation of evidence, Forensic Sci. Int. 139 (2004) 5–16.
[13] F. Taroni, A. Biedermann, Inadequacies of posterior probabilities for the assessment of scientific evidence, Law, Probabil. Risk 4 (2005) 89–114.
[14] J.S. Buckleton, C.M. Triggs, C. Champod, An extended likelihood ratio framework for interpreting evidence, Sci. Justice - J. Forensic Sci. Soc. 46 (2006) 69–78.
[15] A. Biedermann, R. Voisard, F. Taroni, Learning about bayesian networks for forensic interpretation: an example based on 'the problem of multiple propositions', Sci. Justice 52 (2012) 191–198.
[16] N. Fenton, M. Neil, D.A. Lagnado, A general structure for legal arguments about evidence using bayesian networks, Cognit. Sci. 37 (2013) 61–102.
[17] C. Vlek, H. Prakken, S. Renooij, B. Verheij, Modeling crime scenarios in a bayesian network, Proceed. Int. Conf. Artif. Intell. Law (2013) 150–159.
[18] C.S. Vlek, H. Prakken, S. Renooij, B. Verheij, Building bayesian networks for legal evidence with narratives: a case study evaluation, Artif. Intell. Law 22 (2014) 375–421.
[19] N. Fenton, D. Berger, D. Lagnado, M. Neil, A. Hsu, When 'neutral' evidence still has probative value (with implications from the barry george case), Sci. Justice 54 (2014) 274–287.
[20] A.Y. Tawfik, E.M. Neufeld, Temporal reasoning and bayesian networks, Comput. Intell. 16 (2000) 349–377.
[21] S.C. Desai, S. Reimers, D.A. Lagnado, Consistency and credibility in legal reasoning: a bayesian network approach, Proceed. 38th Annual Meet. Cognit. Sci. Soc. 1 (2016) 626–631.
[22] N. Fenton, M. Neil, B. Yet, D. Lagnado, Analyzing the simonshaven case using bayesian networks, Topics Cognit. Sci. (2019) 1–23.
[23] P. Juchli, A. Biedermann, F. Taroni, Graphical probabilistic analysis of the combination of items of evidence, Law, Probabil. Risk 11 (2012) 51–84.
[24] F. Taroni, S. Bozza, A. Biedermann, Two items of evidence, no putative source: an inference problem in forensic intelligence, J. Forensic Sci. 51 (6) (2006) 1350–1361.
[25] G. Wieten, F. Bex, H. Prakken, S. Renooij, Exploiting causality in constructing bayesian network graphs from legal arguments, Legal Knowledge Info. Syst. 313 (2018) 151–160.
[26] A. Biedermann, F. Taroni, O. Delemont, C. Semadeni, A.C. Davison, The evaluation of evidence in the forensic investigation of fire incidents (part I): an approach using bayesian networks, Forensic Sci. Int. 147 (2005) 49–57.
[27] A. Biedermann, F. Taroni, Bayesian networks and probabilistic reasoning about scientific evidence when there is a lack of data, Forensic Sci. Int. 157 (2006) 163–167.
[28] A.B. Hepler, A.P. Dawid, V. Leucari, Object-oriented graphical representations of complex patterns of evidence, Law, Probabil. Risk 6 (2007) 275–293.
[29] M.P. Wellman, Fundamental concepts of qualitative probabilistic networks, Artif. Intell. 44 (1990) 257–303.
[30] N. Fenton, M. Neil, D. Lagnado, W. Marsh, B. Yet, A. Constantinou, How to model mutually exclusive events based on independent causal pathways in bayesian network models, Knowl. Base Syst. 113 (2016) 39–50.
[31] C.S. Vlek, H. Prakken, S. Renooij, B. Verheij, A method for explaining bayesian networks for legal evidence with scenarios, Artif. Intell. Law 24 (2016) 285–324.
[32] S.T. Timmer, J.J.C. Meyer, H. Prakken, S. Renooij, B. Verheij, A two-phase method for extracting explanatory arguments from bayesian networks, Int. J. Approx. Reason. 80 (2017) 475–494.
[33] R. Meester, K. Slooten, Probability and Forensic Evidence: Theory, Philosophy, and Applications, Cambridge University Press, 2021.
[34] C.S. Vlek, H. Prakken, S. Renooij, B. Verheij, Representing and Evaluating Legal Narratives with Subscenarios in a Bayesian Network, 2013.
[35] M. Neil, N. Fenton, D. Lagnado, R.D. Gill, Modelling competing legal arguments using bayesian model comparison and averaging, Artif. Intell. Law 27 (2019) 403–430.
[36] C.D. van Dijk, A. van Someren, R. Visser, M. Sjerps, Evidential value of duct tape comparison using loopbreaking patterns, Forensic Sci. Int. 332 (2022), 111178.
[37] N. Fenton, M. Neil, The "jury fallacy" and the use of bayesian networks to present probabilistic legal arguments, Math. Today 37 (1) (2000) 61–102.
[38] C. Aitken, F. Taroni, P. Garbolino, A graphical model for the evaluation of cross-transfer evidence in dna profiles, Theor. Popul. Biol. 63 (2003) 179–190.
[39] A. Biedermann, F. Taroni, O. Delemont, C. Semadeni, A.C. Davison, The evaluation of evidence in the forensic investigation of fire incidents. part II. practical examples of the use of bayesian networks, Forensic Sci. Int. 147 (2005) 59–69.
[40] A. Biedermann, F. Taroni, A probabilistic approach to the joint evaluation of firearm evidence and gunshot residues, Forensic Sci. Int. 163 (2006) 18–33.
[41] R. Lee, S.-D. Lang, K. Stenger, From digital forensic report to bayesian network representation, in: 2009 IEEE International Conference on Intelligence and Security Informatics, IEEE, 2009, pp. 303–306.
[42] A. Biedermann, S. Bozza, F. Taroni, Probabilistic evidential assessment of gunshot residue particle evidence (part I): likelihood ratio calculation and case pre-assessment using bayesian networks, Forensic Sci. Int. 191 (2009) 24–35.
[43] A. Biedermann, S. Gittelson, F. Taroni, Recent misconceptions about the 'database search problem': a probabilistic analysis using bayesian networks, Forensic Sci. Int. 212 (2011) 51–60.
[44] S. Gittelson, A. Biedermann, S. Bozza, F. Taroni, Bayesian networks and the value of the evidence for the forensic two-trace transfer problem, J. Forensic Sci. 57 (2012) 1199–1216.
[45] A. Biedermann, S. Bozza, P. Garbolino, F. Taroni, Decision-theoretic analysis of forensic sampling criteria using bayesian decision networks, Forensic Sci. Int. 223 (2012) 217–227.
[46] R. Haraksim, D. Meuwly, G. Doekhie, P. Vergeer, M. Sjerps, Assignment of the evidential value of a fingermark general pattern using a bayesian network, in: 2013 International Conference of the BIOSIG Special Interest Group (BIOSIG), IEEE, 2013, pp. 1–11.
[47] N. Fenton, M. Neil, A. Hsu, Calculating and understanding the value of any type of match evidence when there are potential testing errors, Artif. Intell. Law 22 (2014) 1–28.
[48] R. Wieten, J.D. Zoete, B. Blankers, B. Kokshoorn, The interpretation of traces found on adhesive tapes, Law, Probabil. Risk 14 (2015) 305–322.
[49] D. Taylor, T. Hicks, C. Champod, Using sensitivity analyses in bayesian networks to highlight the impact of data paucity and direct future analyses: a contribution to the debate on measuring and reporting the precision of likelihood ratios, Sci. Justice 56 (2016) 402–410.
[50] D. Taylor, D. Abarno, T. Hicks, C. Champod, Evaluating forensic biology results given source level propositions, Forensic Sci. Int.: Genetics 21 (2016) 54–67.
[51] I.D. March, E. Sironi, F. Taroni, Probabilistic evaluation of n traces with no putative source: a likelihood ratio based approach in an investigative framework, Forensic Sci. Int. 266 (2016) 527–533.
[52] E. Sironi, V. Pinchi, F. Taroni, Probabilistic age classification with bayesian networks: a study on the ossification status of the medial clavicular epiphysis, Forensic Sci. Int. 258 (2016) 81–87.

[53] J. de Zoete, M. Sjerps, R. Meester, Evaluating evidence in linked crimes with multiple offenders, Sci. Justice 57 (2017) 228–238.
[54] D. Taylor, A. Biedermann, L. Samie, K.M. Pun, T. Hicks, C. Champod, Helping to distinguish primary from secondary transfer events for trace dna, Forensic Sci. Int.: Genetics 28 (2017) 155–177.
[55] L. Gaborini, A. Biedermann, F. Taroni, Towards a bayesian evaluation of features in questioned handwritten signatures, Sci. Justice 57 (2017) 209–220.
[56] A.E. Fonneløp, M. Ramse, T. Egeland, P. Gill, The implications of shedder status and background dna on direct and secondary transfer in an attack scenario, Forensic Sci. Int.: Genetics 29 (2017) 48–60.
[57] E. Sironi, V. Pinchi, F. Pradella, M. Focardi, S. Bozza, F. Taroni, Bayesian networks of age estimation and classification based on dental evidence: a study on the third molar mineralization, J. Forensic Legal Med. 55 (2018) 23–32.
[58] D. Taylor, A. Biedermann, T. Hicks, C. Champod, A template for constructing bayesian networks in forensic biology cases when considering activity level propositions, Forensic Sci. Int.: Genetics 33 (2018) 136–146.
[59] L. Wang, M. Jia, C. Peng, S. Ni, S. Shen, Scenario-entity analysis based on an entity-relationship model: revisiting crime reconstruction, Forensic Sci. Int. 302 (2019), 109923.
[60] D. Taylor, L. Samie, C. Champod, Using bayesian networks to track dna movement through complex transfer scenarios, Forensic Sci. Int.: Genetics 42 (2019) 69–80.
[61] L. Wang, M. Jia, Y. Shi, F. Chen, S. Ni, S. Shen, A knowledge-based reasoning model for crime reconstruction and investigation, Expert Syst. Appl. 159 (2020), 113611.
[62] F. Taroni, P. Garbolino, C. Aitken, A generalised bayes' factor formula for evidence evaluation under activity level propositions: variations around a fibres scenario, Forensic Sci. Int. 322 (2021), 110750.
[63] L. Samie, C. Champod, S. Delémont, P. Basset, T. Hicks, V. Castella, Use of bayesian networks for the investigation of the nature of biological material in casework, Forensic Sci. Int. 331 (2022), 111174.
[64] I.W. Evett, P.D. Gill, G. Jackson, J. Whitaker, C. Champod, Interpreting small quantities of dna: the hierarchy of propositions and the use of bayesian networks, J. Forensic Sci. 47 (2002) 520–530.
[65] M. Kwan, K.-P. Chow, F. Law, P. Lai, Reasoning about evidence using bayesian networks, in: Advances in Digital Forensics IV 4, Springer, 2008, pp. 275–289.
[66] J. Drábek, Activity level in the hierarchy of propositions in case of the people of the state of California v. orenthal james simpson analyzed using bayesian network, Forensic Sci. Int.: Genetic. Supplement Series 5 (2015) e67–e68.
[67] N.M. Smit, D.A. Lagnado, R.M. Morgan, N.E. Fenton, Using bayesian networks to guide the assessment of new evidence in an appeal case, Crime Sci. 5 (2016).
[68] B. Szkuta, K.N. Ballantyne, B. Kokshoorn, R.A. van Oorschot, Transfer and persistence of non-self dna on hands over time: using empirical data to evaluate dna evidence given activity level propositions, Forensic Sci. Int.: Genetics 33 (2018) 84–97.
[69] A. de Ronde, B. Kokshoorn, C.J. de Poot, M. de Puit, The evaluation of fingermarks given activity level propositions, Forensic Sci. Int. 302 (9) (2019).
[70] J. de Zoete, N. Fenton, T. Noguchi, D. Lagnado, Resolving the so-called "probabilistic paradoxes in legal reasoning" with bayesian networks, Sci. Justice 59 (2019) 367–379.
[71] L. Mayuoni-Kirshenbaum, O. Waiskopf, N. Finkelstein, Z. Pasternak, How did the dna of a suspect get to the crime scene? a practical study in dna transfer during lock-picking, Aust. J. Forensic Sci. 00 (2020) 1–11.
[72] A. de Ronde, B. Kokshoorn, M. de Puit, C.J. de Poot, Using case specific experiments to evaluate fingermarks on knives given activity level propositions, Forensic Sci. Int. 320 (2021), 110710.
[73] A.E. Fonneløp, S. Faria, G. Shanthan, P. Gill, Who packed the drugs? application of bayesian networks to address questions of dna transfer, persistence, and recovery from plastic bags and tape, Genes 13 (2021) 18.
[74] D. Taylor, L. Volgin, B. Kokshoorn, C. Champod, The importance of considering common sources of unknown dna when evaluating findings given activity level propositions, Forensic Sci. Int.: Genetics 53 (2021), 102518.
[75] S. Uitdehaag, T. Donders, I. Kuiper, F. Wagner-Cremer, M. Sjerps, Use of bayesian networks in forensic soil casework, Sci. Justice 62 (2022) 229–238.
[76] M. Onofri, C. Altomare, S. Severini, F. Tommolini, M. Lancia, L. Carlini, C. Gambelunghe, E. Carnevali, Direct and secondary transfer of touch dna on a credit card: evidence evaluation given activity level propositions and application of bayesian networks, Genes 14 (5) (2023) 996.
[77] P. Gill, Ø. Bleka, A. Roseth, A.E. Fonneløp, An lr framework incorporating sensitivity analysis to model multiple direct and secondary transfer events on skin surface, Forensic Sci. Int.: Genetics 53 (7) (2021).
[78] L. Volgin, The importance of evaluating findings given activity level propositions in order to avoid misleading evidence, Aust. J. Forensic Sci. 51 (S1) (2019). S10–S13.
[79] J.J. Lucena-Molina, M. Gascon-Abellan, V. Pardo-Iranzo, Technical support for a judge when assessing a priori odds, Law, Probabil. Risk 14 (2015) 147–168.
[80] A.C. Constantinou, M. Freestone, W. Marsh, J. Coid, Causal inference for violence risk management and decision support in forensic psychiatry, Decis. Support Syst. 80 (2015) 42–55.
[81] A.C. Constantinou, N. Fenton, W. Marsh, L. Radlinski, From complex questionnaire and interviewing data to intelligent bayesian network models for medical decision support, Artif. Intell. Med. 67 (2016) 75–93.
[82] T. Lefèvre, A. Lepresle, P. Chariot, Detangling complex relationships in forensic data: principles and use of causal networks and their application to clinical forensic science, Int. J. Leg. Med. 129 (2015) 1163–1172.
[83] J.A. de Koeijer, M.J. Sjerps, P. Vergeer, C.E. Berger, Combining evidence in complex cases - a practical approach to interdisciplinary casework, Sci. Justice 60 (2020) 20–29.
[84] A. Biedermann, S. Bozza, K. Konis, F. Taroni, Inference about the number of contributors to a dna mixture: comparative analyses of a bayesian network approach and the maximum allele count method, Forensic Sci. Int.: Genetics 6 (2012) 689–696.
[85] S. Gittelson, A. Biedermann, S. Bozza, F. Taroni, Modeling the forensic two-trace problem with bayesian networks, Artif. Intell. Law 21 (2013) 221–252.