

# Object-Oriented Graphical Representations of Complex Patterns of Evidence

Amanda B. Hepler<sup>1</sup>, A. Philip Dawid<sup>1</sup> and Valentina Leucari<sup>2</sup>

<sup>1</sup>Department of Statistical Science, University College London, London, UK

<sup>2</sup>NUNATAC s.r.l., Via Crocefisso 5, 20122 Milano, Italy

## Abstract

We reconsider two graphical aids to handling complex mixed masses of evidence in a legal case: Wigmore charts and Bayesian networks. Our aim is to forge a synthesis of their best features, and to develop this further to overcome remaining limitations.

One important consideration is the multi-layered nature of a complex case, which can involve direct evidence, ancillary evidence, evidence about ancillary evidence... all of a number of different kinds. If all these features are represented in one diagram, the result can be messy and hard to interpret. In addition there are often recurrent features and patterns of evidence and evidential relations, *e.g.* credibility processes or match identification (DNA, eyewitness evidence,...) that may appear, in identical or similar form, at many different places within the same network, or within several different networks, and it is wasteful to model these all individually.

The recently introduced technology of “object-oriented Bayesian networks” suggests a way of dealing with these problems. Any network can itself contain instances of other networks, the details of which can be hidden from view until information on their detailed structure is desired. Moreover, generic networks to represent recurrent patterns of evidence can be constructed once and for all, and copied or edited for re-use as needed. We describe the potential of this mode of description to simplify the construction and display of complex legal cases.

To facilitate our narrative the celebrated Sacco and Vanzetti murder case is used to illustrate the various methods discussed.

**Key words:** Bayesian network; evidence analysis; graphical representation; object-oriented; Sacco and Vanzetti; Wigmore chart

## 1 Introduction

Complex structure and ambiguity are typical features of the evidence in a legal case. A major forensic task is the interpretation of patterns of evidence involving many variables and combining different varieties of evidence within a complex framework. A logical approach to the marshalling and evaluation of such evidence is thus required as an essential foundation for legal reasoning, whether for constructing arguments about questions of fact or for making decisions.

A number of tools have been crafted to aid in this enterprise. In this paper we focus on two graphical methods for the structuring, display and manipulation of complex inter-relationships between items of evidence in a legal case: *Wigmore Charts* and *Bayesian Networks*.

The “chart method” of Wigmore 1913 (see also Anderson, Schum, and Twining 2005) assists one in describing and organising the available evidence in a case, and in following reasoning processes through sequential steps. Bayesian Networks (Cowell, Dawid, Lauritzen, and Spiegelhalter 1999) are a general statistical tool, which can be applied in the legal context to model the relationships between different sources of evidence, weigh the available evidence, and draw inferences from it (Taroni, Aitken, Garbolino, and Biedermann 2006). Wigmore charts and Bayesian networks have many similarities but also many differences, especially in the way in which the flow of information is represented. Therefore, we are interested in pointing out strengths and weaknesses of such tools and exploring possible interactions between them. The

ultimate objective would be the development of a formal method to handle multiple sources of evidence in legal cases by jointly exploiting the specific strengths of both Wigmore charts and Bayesian networks. This synthesis is largely at its very early stages and the model presented here is a first attempt at combining the two methods.

Both Wigmorean analysis and Bayesian network construction are best considered as describing an individual's viewpoint, rather than objective reality. Following the advice of Anderson, Schum, and Twining (2005), we therefore first clarify our own standpoint, according to the following questionnaire:

**Who are we?** We are statisticians with an interest in developing methods for analyzing complex masses of evidence.

**At what stage in what process are we?** The process in which we are involved is the research of methods for the representation and analysis of inference networks based on masses of evidence whose items have a variety of subtle and interesting relationships. The stage of this process varies among the authors; Professor Dawid is at an advanced stage of this enquiry, whereas Drs. Leucari and Hepler are novices to this area of research.

**What materials are available for analysis?** We use the Sacco and Vanzetti case for illustration. There are libraries full of accounts of this case, but we largely restrict attention to the description and analysis given by Kadane and Schum (1996).

**What are our objectives?** We aim to demonstrate to those interested in legal reasoning how a synthesis of Wigmorean and Bayesian network ideas can assist in the interpretation of evidence; and in particular to show that object-oriented networks are well-suited to handling large masses of evidence with complicated dependency relations exist. Finally, we intend to show that a combination of insights and techniques taken from Wigmorean

analysis and Bayesian network methodology can result in a more coherent analysis of a mass of evidence.

## 2 The Sacco and Vanzetti Case

The following is a description of the Sacco and Vanzetti case, relying on accounts taken from Kadane and Schum (1996) and Cheung (2005). A more detailed narrative of the case, as told by a member of the defense team, can be found in Ehrmann (1969).

On the afternoon of 15 April 1920, two payroll guards, Alessandro Berardelli and Frederick Parmenter, were transporting \$15,000 from one factory of the Slater and Morris shoe factory to a second factory in South Braintree, Massachusetts. During their journey, they were attacked by two men from behind and were both robbed and murdered. After the incident, the two culprits escaped in a black car with three other men who had picked them up at the scene of the crime. On 5 May, Nicola Sacco and Bartolomeo Vanzetti, both Italian immigrants with ties to the anarchist movement, were arrested after they had gone with two others to a garage to claim a car which local police had connected with the crime. Their trial commenced on 31 May 1921, and ended on 13 July 1921 with a first degree murder conviction for both men. Following an arduous six year battle of legal motions, petitions and appeals, Sacco and Vanzetti were put to death by electrocution. Up until their deaths on 23 August 1927, they both firmly denied any involvement in the South Braintree crime.

There are several reasons for selecting this particular case to illustrate our main objectives in this narrative. First, the case has been carefully examined by Kadane and Schum (1996), which includes both an in-depth probabilistic analysis of the evidence in the case, and a comprehensive Wigmorean analysis. Another advantage for our present purposes is the realistic complexity of

the case: the Wigmorean analysis presented in Kadane and Schum (1996) required over 25 charts involving 400 pieces of evidence.

### 3 Graphical Approaches to Analysis of Evidence

Several graphic and visual representations of evidence in legal settings exist, as illustrated elsewhere in this volume. Rather than summarize each here, we will simply describe the two methods addressed in this work: Wigmore charts and Bayesian networks. For a comparison of these with other methods see Bex, Prakken, Reed, and Walton (2003).

#### 3.1 Wigmorean analysis

The “chart method” (Wigmore 1913) was introduced by the American jurist John Henry Wigmore (1863-1943) as an aid to lawyers. Renewed interest in this method has followed on the work of evidence scholars William Twining, Terence Anderson and David Schum (see Kadane and Schum 1996; Anderson, Schum, and Twining 2005; Schum 2005).

The Wigmore chart is a diagram consisting of various symbols and arrows. Each symbol represents a different type of proposition, and these are connected by means of arrows indicating the flow and degree of inference. The end goal is a coherent presentation of a large mass of evidence, facilitating the reasoning processes required to confirm or rebut various hypotheses presented in court. Wigmore referred to these legal hypotheses as probanda, defining one ultimate probandum and a collection of penultimate probanda, each a necessary condition for proving the ultimate probandum. Legal scenarios are uniquely suited for this type of analysis, due to what Schum (2005) refers to as the *materiality* criteria: Once the ultimate probandum has been specified, substantive law dictates what specific elements [penultimate probanda] one must prove

in order to prove the ultimate probandum.

To illustrate, consider the indictment charge against Nicola Sacco: “Sacco was one of the two men who fired shots into the bodies of Parmenter and Berardelli, during a robbery of the payroll Parmenter and Berardelli were carrying. . .” (Kadane and Schum 1996). For simplicity, we have abbreviated the charge to that against Sacco only. Following Kadane and Schum (1996), this charge can be restated as the following *ultimate probandum*:

*U*: Sacco was guilty of first-degree murder in the slaying of Alessandro Berardelli during the robbery that took place in South Braintree, MA, on 15 April 1920.

In the light of the details of the charge and the relevant legal definition of first-degree murder, this proposition can be decomposed into three *penultimate probanda*:

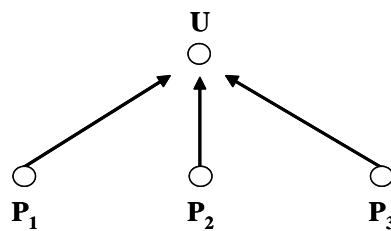
*P*<sub>1</sub>: Berardelli died of gunshot wounds he received on 15 April 1920.

*P*<sub>2</sub>: At the time he was shot, Berardelli, along with Parmenter, was in possession of payroll.

*P*<sub>3</sub>: It was Sacco who intentionally fired shots that took the life of Alessandro Berardelli during the robbery of payroll he and Parmenter were carrying.

Once the ultimate and penultimate probanda are defined, they become the first symbols in the Wigmore chart, as seen in Figure 1.

Figure 1: Wigmore chart of the ultimate and penultimate probanda



To determine the rest of the diagram structure, one must first parse all available facts about a case into a ‘Key List’ of the relevant details (or ‘Trifles’). A trifle is relevant and thus becomes evidence if it is linked, directly or indirectly, to one of the penultimate probanda. See Table 1 for a Key List from the Sacco and Vanzetti case pertaining to eyewitness identification evidence placing Sacco at the scene of the crime (thus relevant to  $P_3$ ). The list is an abbreviated version (not including post-trial evidence from Young and Kaiser 1985; Starrs 1986a; Starrs 1986b) of that shown on p. 290 of Kadane and Schum (1996).

Once the trifles are defined and assigned to the various probanda, one must then enter them into the diagram, representing any inferential linkages by arrows. In Anderson, Schum, and Twining (2005), the extensive array of symbols used by Wigmore (1937) is reduced to eight. Schum (2005) makes do with just five symbols: white dots (directly relevant propositions), black dots (directly relevant evidential facts), white squares (ancillary propositions), black squares (ancillary evidential facts), and arrows (flow of inference). An illustration of these symbols assigned to the items shown in Table 1 appears as a completed Wigmore chart (a modified version of Chart 4, Appendix A in Kadane and Schum 1996) in Figure 2. The entire Wigmorean representation of the Sacco and Vanzetti case is not shown here as it consists of 25 charts similar in size to Figure 2. The reader is referred to Appendix A of Kadane and Schum (1996).

### **3.2 Bayesian networks**

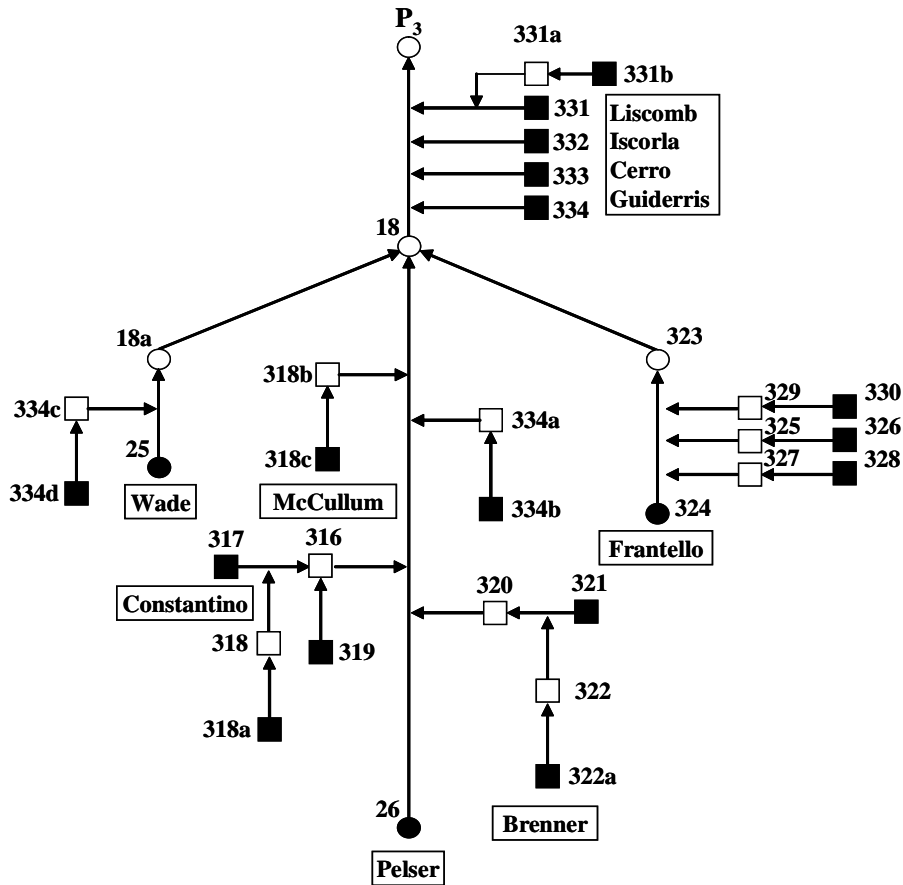
A Bayesian network (BN) is a graphical and numerical representation which enables us to reason about uncertainty. For the moment we set aside the numerical or quantitative side of Bayesian networks, as our principal intent here is to explore the qualitative features making BNs an appropriate graphical tool for marshaling masses of evidence.

The graphical component of a BN includes nodes representing relevant hypotheses, items

Table 1: Key list for eyewitness evidence relating to probandum  $P_3$

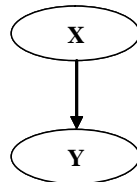
| Item     | Description                                                                                                                                   |
|----------|-----------------------------------------------------------------------------------------------------------------------------------------------|
| 18.      | Sacco was at the scene of the crimes when they occurred.                                                                                      |
| 18a.     | One of the men at the scene of the crime looked like Sacco.                                                                                   |
| 25.      | Wade testimony to 18a.                                                                                                                        |
| 26.      | Pelser testimony to 18.                                                                                                                       |
| 316.     | Pelser was under a bench when the shooting started.                                                                                           |
| 317.     | Constantino testimony to 316.                                                                                                                 |
| 318.     | Constantino doubt about where Pelser was.                                                                                                     |
| 318a.    | Constantino testimony on cross-examination.                                                                                                   |
| 318b.    | Pelser could not have seen what he testified.                                                                                                 |
| 318c.    | McCullum equivocal testimony to 318b.                                                                                                         |
| 319.     | Pelser testimony to 316 on cross-examination                                                                                                  |
| 320.     | Pelser was not near the window.                                                                                                               |
| 321.     | Brenner testimony to 320.                                                                                                                     |
| 322.     | Brenner had doubts about where Pelser was during the shooting.                                                                                |
| 322a.    | Brenner admission on cross-examination.                                                                                                       |
| 323.     | Sacco was not one of the men leaning on the pipe-rail fence when, before the crime, Frantello passed the two men on his way to Hampton House. |
| 324.     | Frantello testimony to 323.                                                                                                                   |
| 325.     | The man on the fence was speaking “American”                                                                                                  |
| 326.     | Frantello testimony to 325.                                                                                                                   |
| 327.     | Sacco speaks broken English                                                                                                                   |
| 328.     | Observable by fact finders                                                                                                                    |
| 329.     | Frantello’s powers of observation are weak; he incorrectly identified characteristics of the jurors he had been asked to view.                |
| 330.     | Cross-examination of Frantello                                                                                                                |
| 331-334. | Liscomb, Iscorla, Cerro, and Guiderris testimony that Sacco was not one of the gunmen.                                                        |
| 331a.    | Liscomb was inconsistent about the details of her observation.                                                                                |
| 331b.    | Cross-examination of Liscomb.                                                                                                                 |
| 334a.    | Pelser had earlier told the defense that he did not see the actual shooting.                                                                  |
| 334b.    | Pelser admission on cross-examination by defense.                                                                                             |
| 334c.    | Wade would not say that Sacco was the man who shot Berardelli.                                                                                |
| 334d.    | Wade testimony on cross-examination by McAnarny.                                                                                              |

Figure 2: Wigmore chart of the eyewitness evidence



of evidence and unobserved variables. Arrows connecting these nodes represent probabilistic dependence. For example, consider the simple diagram in Figure 3.

Figure 3: Simple Bayesian network

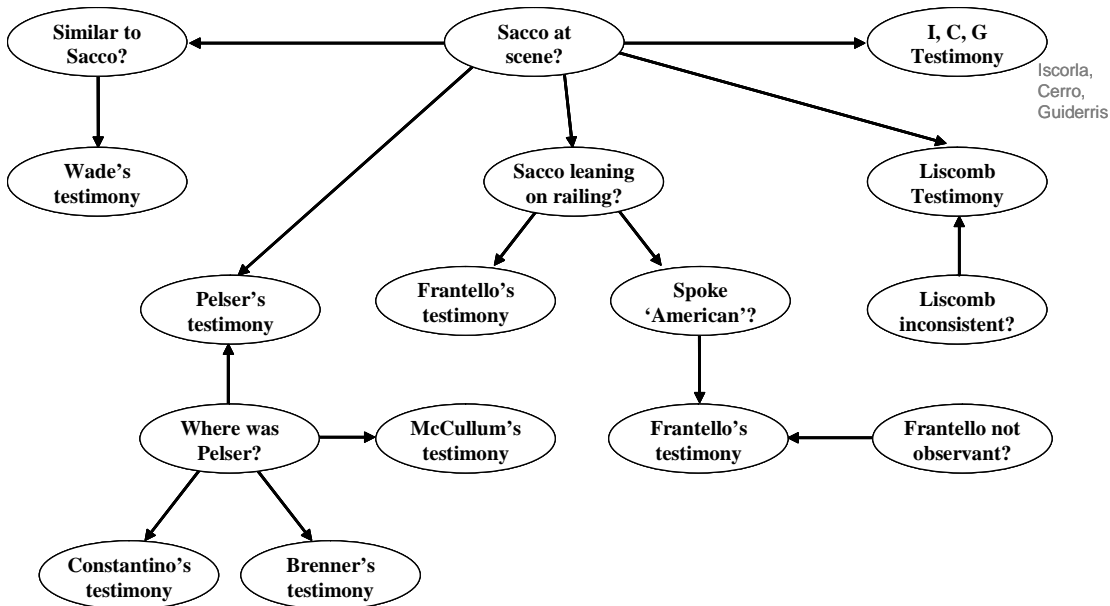


The node  $X$  is termed the ‘parent’ of the ‘child’ node  $Y$ , and the probability with which  $Y$  takes on a particular value depends on the value of  $X$ , as indicated by the arrow from  $X$  to  $Y$ . A node can have several parents (or none), their joint values determining the probabilities

for the various states of  $Y$ .

Consider again the eyewitness evidence from Figure 2. The Bayesian network appearing in Figure 4 also describes this evidence and illustrates dependencies among some of the Key List items in Table 1.

Figure 4: Bayesian Network for the eyewitness evidence



### 3.3 A brief comparison

Wigmore charts and Bayesian networks can both be used to graphically represent complex masses of evidence. The rigorous decomposition of a case required by a Wigmorean chart is a burdensome but necessary task when attempting to graphically represent legal scenarios appropriately. No such schematic approach to dissecting the evidence is generally specified for Bayesian network analyses: it would be advantageous for BN creators to adopt this practice.

The functionality of a Wigmore chart is limited in that probabilistic calculations require additional analysis, whereas such calculations can be automated in a BN. In a legal case this can be quite a limitation, as it can be useful to weigh various evidential facts based on their

probative force (Kadane and Schum 1996). Another limitation of Wigmore charts is that only binary propositions are charted, the nodes taking values *true* or *false*. In a BN, a node can take on a number of states, which can be helpful in many scenarios. For example, consider the confusion surrounding Pelser’s testimony in the above example. A more concise representation was possible in the BN of Figure 4 because of the node **Where was Pelser?**, which took on several states (*under the table* as Constantino claimed, *near the window* as Pelser claimed and Brenner denied, or *elsewhere*).

A common criticism of BNs is that they “blur the distinction between directly relevant and ancillary evidence” (Bex et al. 2003). This is apparent in the representation of Pelser’s testimony, as ancillary evidence pertaining to his testimony was provided by Constantino, Brenner and McCullum. In Section 4 we will see that it is relatively simple, by a reorganizing and relabeling of nodes, to emphasize this distinction.

Another common criticism of BNs is that they require specification of (potentially) hundreds of conditional probabilities. In legal scenarios, reliable probabilities are often hard to obtain and indeed even hard to define at times (see Dawid 2005, Section 2 for a detailed discussion of the philosophical issues clouding probabilities and their use in courts). However it is not the case that precise numerical values are always required for a Bayesian network to be meaningful. In the Appendix we present an elaboration of the basic BN which allows one to specify the uncertainty attached to any probability values in the network, together with the sources of that uncertainty.

In any case our main aim here is to show how a BN can be useful for the purely qualitative analysis of masses of evidence, its graphical representation supplying a helpful way of understanding the relationships between hypotheses and evidence. An added advantage is that there exists a rigorous formal syntax and semantics to go along with this representation, supporting the manipulation and discovery of relevance relationships between all the variables (Lauritzen, Dawid,

Larsen, and Leimer 1990; Dawid 2001).

Perhaps the most prohibitive disadvantage of both Wigmore charts and Bayesian networks is that, when applied to complex and realistic cases, their graphical structures rapidly become too unwieldy to be useful. We have already seen that the representations of just the eyewitness evidence in the Sacco and Vanzetti case are large and difficult to interpret. Combining these with similar representations for the remaining evidence leads to large and potentially unmanageable representations for the case as a whole.

In many applications, not just law, the size of the problems that it is desired to analyze using BNs has grown, and researchers are looking for ways to avoid modeling chaos. The paradigm of *object-oriented programming* has recently been applied to Bayesian network design (Laskey and Mahoney 1997, Koller and Pfeffer 1997, Levitt and Laskey 2001). We adopt this paradigm here to help model the entire Sacco and Vanzetti case. Our approach combines the benefits of a rigorous handling of evidence as prescribed by Wigmorean analysis with the quantitative and qualitative benefits afforded by Bayesian networks, the whole enhanced by the clarity and simplicity of an object-oriented approach.

## 4 Object-Oriented Bayesian Networks

Object-oriented Bayesian networks (OOBNs) facilitate hierarchical construction, utilizing small modular networks (or network fragments) as building blocks. Thus instead of building a network for the Sacco and Vanzetti case all at once, one can consider each collection of evidence in turn, creating a module for each (e.g. the network in Figure 4 could be one such building block). Once each module is created and approved, the modules are placed into a top-level network, significantly simplifying the modeling process. Alternatively, this architecture facilitates a “top-

down” approach, in which the details of lower-level modules do not have to be specified at the very beginning.

There is an additional advantage to an object-oriented design that makes it particularly suited for evidence analysis: multiple instantiation of a module or fragment. It is common to find certain patterns of evidence used repeatedly, both within a single case and across different cases. For example, eyewitness testimony commonly arises in criminal casework. OOBNs allow a user to model eyewitness testimony as a general basic network, and then reuse this module (perhaps with some modifications) throughout the main network, and/or reuse it in further networks.

In the following we describe our OOBN representation of the Sacco and Vanzetti case. Rather than presenting the entire body of evidence (as can be found in Kadane and Schum 1996), we first consider the overall structure of the network, and then analyze in more detail some of the evidence pertaining to penultimate probandum  $P_3$ .

#### 4.1 The Sacco and Vanzetti case

To prove an ultimate probandum of “felony first degree murder,” three penultimate probanda must all be proved: Was a murder committed? Was a felony being committed? Is the accused the culprit? These hypotheses serve as top-level nodes for a generic OOBN representation of a felony murder case, as shown in Figure 5.

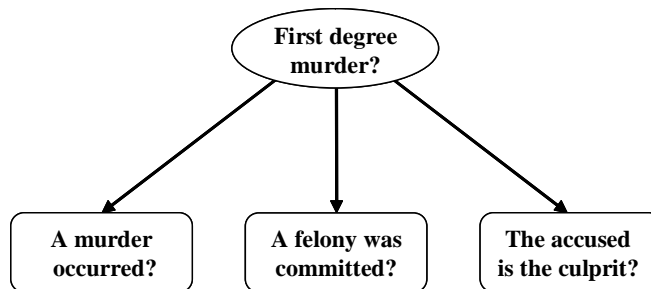
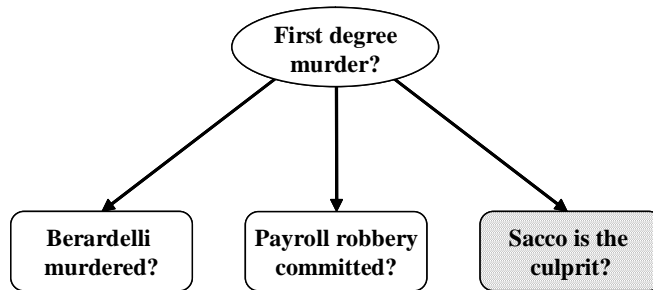


Figure 5: Generic top-level network representing a felony first degree murder case

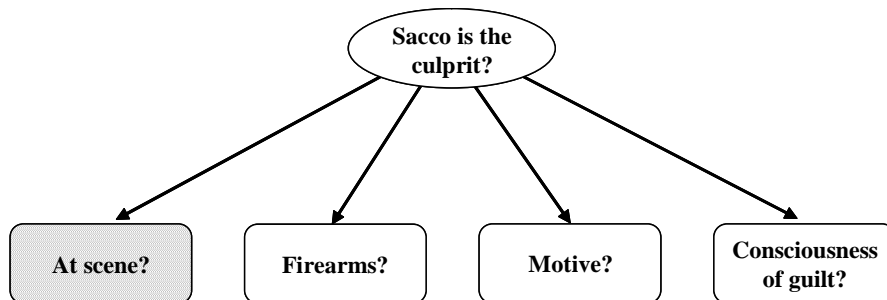
The node labeled **First degree murder?** is a simple variable (shown as an oval), whereas the nodes **A murder occurred?**, **A felony was committed?**, and **The accused is the culprit?** are modules (shown as curved rectangles). Each module may contain an assortment of variables and other modules within it, but at this level all one sees is the module name. Thus, it is quite straightforward to glance at the network and quickly determine its principal elements. While the general layout of Figure 5 applies to all felony murder cases, in any specific case it will be appropriate to specify the relevant aspects more fully, as in Figure 6.

Figure 6: Specific top-level network representing first degree murder charge against Sacco



To further analyze the case, each penultimate probandum can be considered in turn, to determine the type and weight of evidence provided for and against it. For the sake of brevity we only consider some of the evidence relating to  $P_3$ : module **Sacco is the murderer?**. Thus, we traverse through this module to this next level of our OOBN, shown in Figure 7. A quick glance

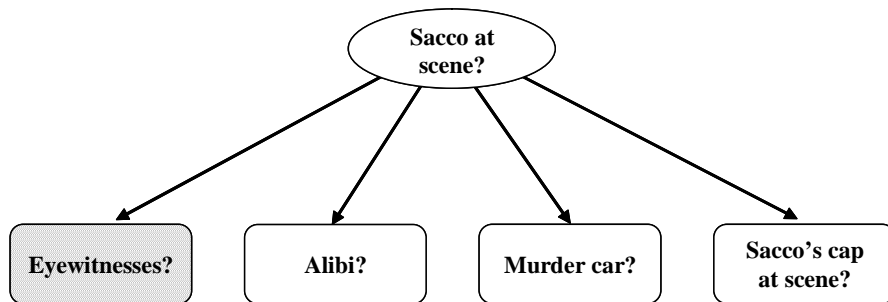
Figure 7: Expansion of **Sacco is the culprit?** module from Figure 6



shows that four classes of evidence were used to determine whether or not Sacco was indeed the guilty party: **Scene?**, **Firearms?**, **Motive?**, and **Consciousness of guilt**. Again, each of these is a module, itself housing other variables and modules.

We now zero in on the evidence provided to determine whether or not Sacco was at the scene of the crime. This leads us to the next level (contained within the **At scene?** node of Figure 7), as shown in Figure 8.

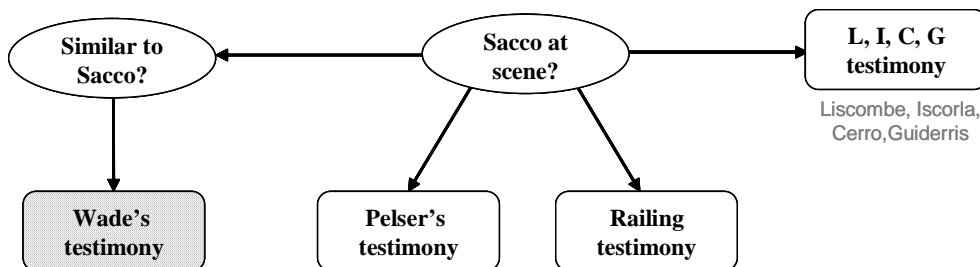
Figure 8: Expansion of **At scene?** module from Figure 7



Again, a quick glance tells us that evidence relating to **Eyewitnesses?**, **Alibi?**, **Murder car?**, and **Sacco's cap at scene?** was presented to try and place Sacco at the scene of the crime.

We now focus on the eyewitness evidence, previously discussed in Sections 3.1 and 3.2. The object-oriented depiction appears in Figure 9. The simplification brought about by transforming

Figure 9: Expansion of **Eyewitness?** module from Figure 8

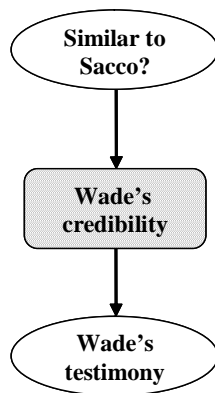


the Bayesian network of Figure 4 to an object-oriented network is striking. It is now much easier

to see what evidence was presented, and how it relates to the question of whether or not Sacco was at the scene.

However, at this level we do not see the ancillary evidence provided by many of the other witnesses. This is deliberate. To see this extra detail we must ‘zoom in’ on each of the testimony modules. This is illustrated below for the case of Pelser’s evidence. But first we take a closer look at Wade’s testimony, as depicted in Figure 10.

Figure 10: Expansion of **Wade’s testimony** module from Figure 9

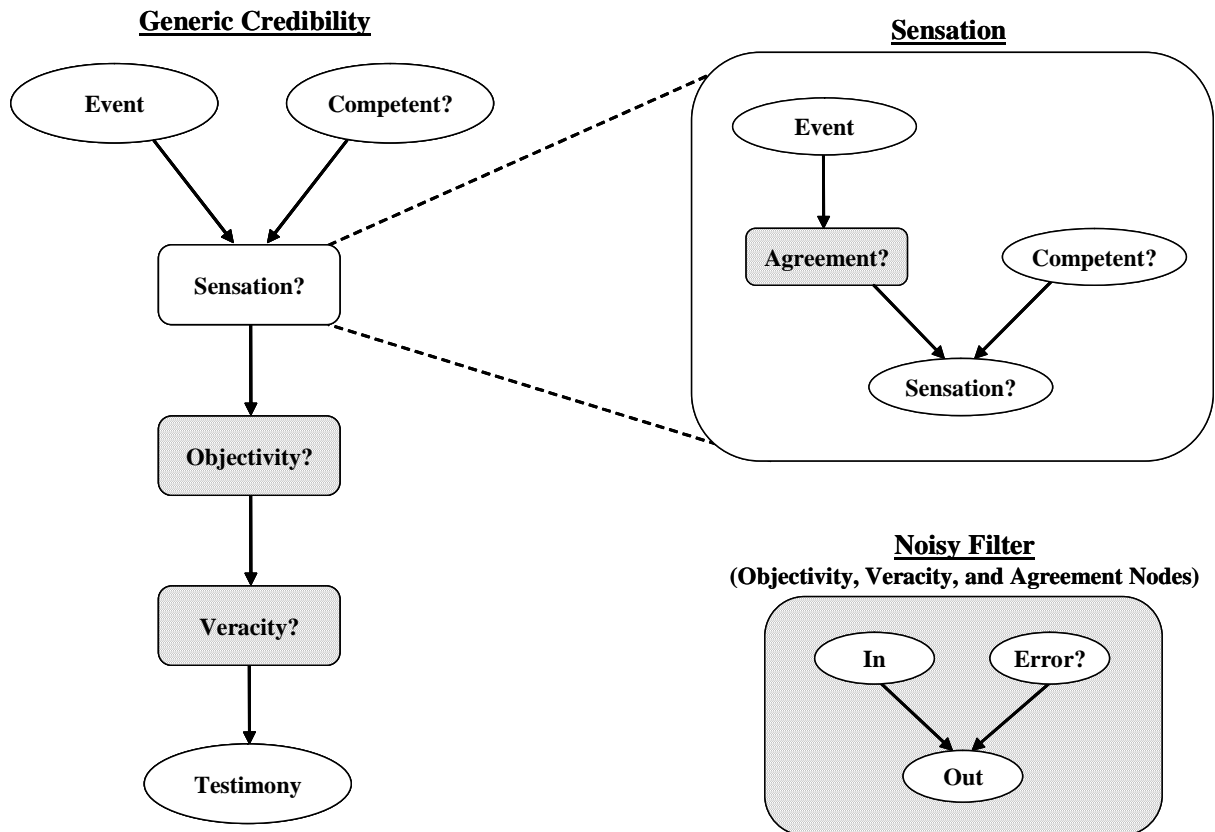


Wade testified that he saw someone who was similar-looking to Sacco, but would not confirm that the individual that he saw was in fact Sacco. This is a simple case with no ancillary evidence regarding Wade’s testimony. The impact of this testimony is thus crucially dependent on its *credibility*. Credibility of evidence is an extremely important generic attribute that needs to be explicitly modeled. This is done in Figure 11, which depicts what is inside the **Wade’s credibility** module.

Those familiar with David Schum’s work in the area of credibility assessment will recognize what he refers to as the three attributes of credibility. For a more detailed discussion of these attributes, the reader is referred to Schum and Morris (2008).

The first attribute we label **Sensation?** (Schum typically refers to this attribute as “obser-

Figure 11: Successive expansions of Wade’s credibility module from Figure 10



vational sensitivity” (Anderson, Schum, and Twining 2005). This involves assessing the witness’s sensory systems and general physical condition. At the same time it is affected by whether or not the witness was **Competent?** to observe the event: that is, what were the conditions under which the observations were made? — *e.g.*, as in an earlier example, was the witness in fact under a table at the time of the incident?

The second attribute is **Objectivity?**: did the witness testify based on an objective understanding of her sensation, or did she form it on the basis of what she either expected or wanted to occur?

The third and final attribute is **Veracity?**: did the witness truthfully report what she believed?

To model the uncertainty that exists at each level of the chain of credibility assessment, we pass the information through a series of “noisy filters”, with a possibility of error at each stage. A generic module for this is shown in Figure 11: this is used for each of the modules **Objectivity?**, **Veracity?** and **Agreement?** (this last itself being a component of the module for **Sensation?**).

An important feature of the credibility module in Figure 11 is that it is generic enough to be used throughout the OOBN, yet it can also be tailored as needed to fit into a particular circumstance. We will see in Section 5 that several other evidence types can be made into modules and reused as needed for modeling legal scenarios.

Wade testified that a man he had seen at the scene of the robbery and shooting resembled Sacco. His testimony will be correct if 1) there was no error associated with each of the credibility attributes and 2) he was competent at the time the observation took place.

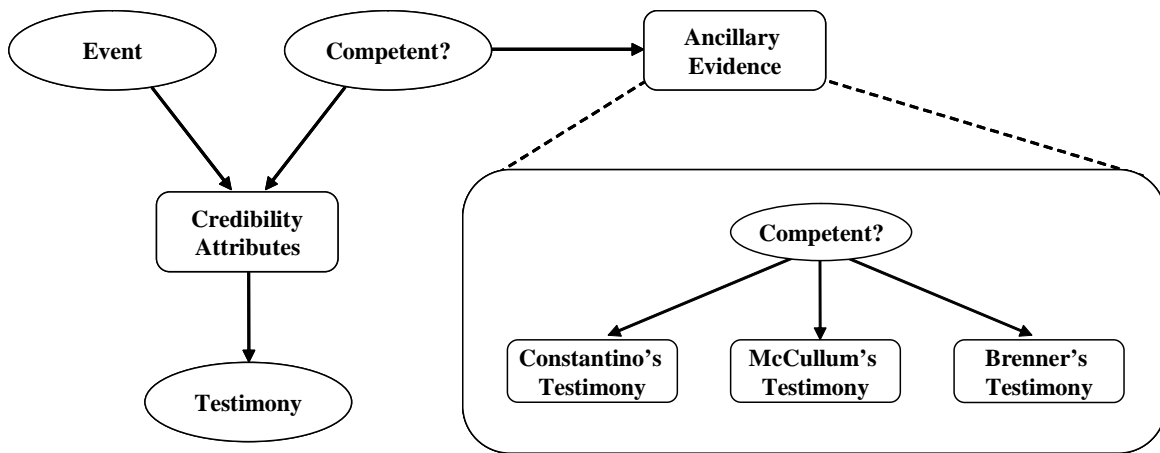
The **Noisy filter** module incorporates an error rate as part of its underlying quantitative specification. We can allow this to vary according to the attribute considered and the individual providing testimony; and we could further elaborate this module to allow the error-rate to depend on the true state of affairs. But over and above generic aspects incorporated into the **Noisy filter** module, it will frequently happen that we have additional or ancillary evidence pertaining to the credibility of specific testimony.

This was the case for the testimony given by Pelsler, one of the prosecution’s star witnesses. He testified that, from the window of the Rice & Hutchins factory, he saw Sacco at the scene of the robbery and shootings. Several challenges were made by the defense to Pelsler’s competence to make this observation. Constantino stated that Pelsler was under a table and thus could not see the events unfold. Brenner also stated that he could not have seen the events, as Pelsler was not actually near the window at the time. Yet another witness provided testimony to the

fact that Pelsler was not able to see the crime. These three testimonies speak directly to the (in)competence of Pelsler with respect to this specific piece of testimony.

Figure 12 shows how, with the aid of an object-oriented approach and some useful labels, such ancillary evidence can be made represented in a Bayesian network. In its collapsed state

Figure 12: Modified version of Figure 11 specific to Pelsler’s testimony, incorporating ancillary evidence



as the module **Pelsler’s testimony** in Figure 9, the details of the ancillary evidence, relating to Pelsler’s credibility in this specific case, are buried deep inside and hidden from view. But as shown in Figure 12 we can open it up, to various different levels, to reveal relevant ancillary evidence and describe its effect.

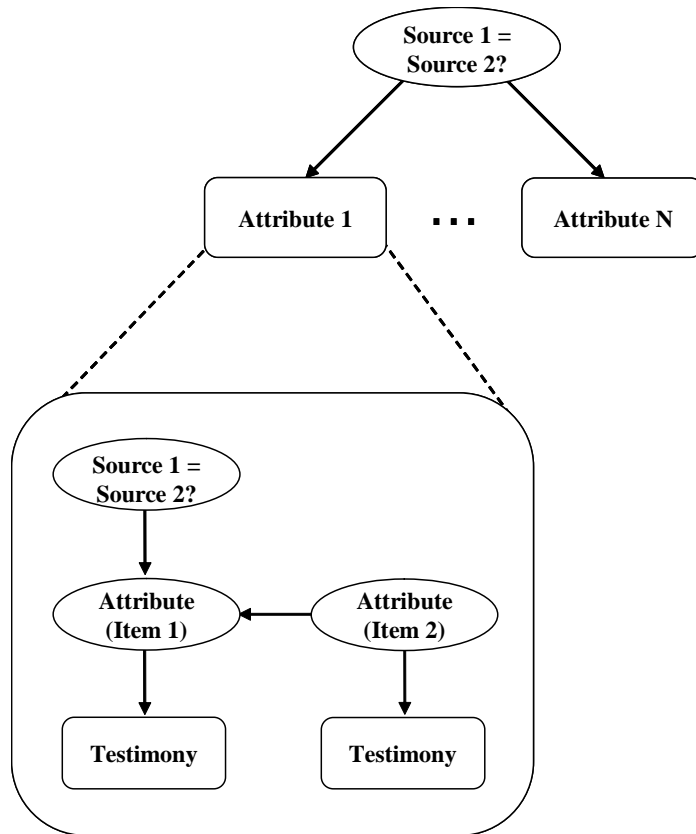
## 5 Recurrent Patterns of Evidence

We now present some further useful generic modules, together with illustrations of their use. Although we rely heavily on legal examples, these modules may also be applicable in other fields of enquiry where careful analysis of evidence is required.

**Identification** The first recurrent structure we consider is used to handle identification evidence. By this we mean that there exist two descriptions of items, and doubt arises as to whether or not they pertain to the same item. For example, is [the suspect] [the source of item found at the crime scene]? Is [the source of DNA recovered from the crime scene] the same as [the source of DNA taken from the suspect]? There are many circumstances, legal and otherwise, where issues of identification are fundamental to the interpretation of evidence: Dawid, Mortera, and Vicard (2007) describe the use of OOBNs to solve a variety of complex DNA identification problems.

A BN depiction of a generic identification module appears in Figure 13. It is helpful to

Figure 13: Generic identification module



have an example in mind to facilitate discussion of the module, and we return to the Sacco and Vanzetti case briefly. During Sacco’s trial the prosecution introduced into evidence a cap, re-

portedly recovered from the crime scene, which it claimed belonged to Sacco, providing witnesses testifying to this fact. During the trial, the defense requested that Sacco try on the cap and, much to the prosecution’s dismay, it did not fit. In this example, there are actually three distinct (though related) identification issues. Was [the cap found at the scene] the same as [the cap presented at trial]? Was [the owner of the cap at the scene] actually [Sacco]? Was [the owner of the cap presented at trial] actually [Sacco]? We will focus on the last, so that node **Source 1** represents the owner of the cap presented at trial, and **Source 2** represents Sacco.

Attributes of the items can be observed, or ascertained or inferred, to help determine whether or not the two items are from the same source. One such attribute in our example could be size of the cap. It was observable to the jury that the trial cap did not fit Sacco, from which it might be inferred that Sacco was not the owner of that cap. Another attribute presented was a torn lining; the trial cap had a torn lining, and there was testimony that Sacco typically hung his cap on a hook at work: identity of the two caps could thus be an explanation of the torn lining.

**Contradiction/Corroboration** The next module represents a situation where two sources give either contradictory or corroborating evidence about the same event (see Schum 2001 for a more detailed description). The network has the same representation for both types of evidence and is shown in Figure 14. Corroborating evidence occurs when both sources claim that the identical state of the **Event** node occurred. For example, recall the testimony of Liscomb and Iscorla (Key List items 331 and 332 from Table 1). They were both claiming that the **Event** node **Sacco at scene?** was false. If they were testifying to mutually contradictory events (“Sacco at scene” and “Sacco not at scene”) the model would remain the same, but the states entered as evidence at the testimony nodes change. Note that since contradictory evidence involves events

that cannot happen at the same time, the relative credibility of the sources becomes crucial.

**Conflict/Convergence** Conflicting or convergent testimony arises when two sources testify to two different events that can occur jointly. Conflict occurs when the two events testified to favor different conclusions about a hypothesis of interest. Convergence occurs when the two events support the same conclusion about the hypothesis. The module is shown in Figure 15.

Figure 14: Generic contradiction/corroboration module

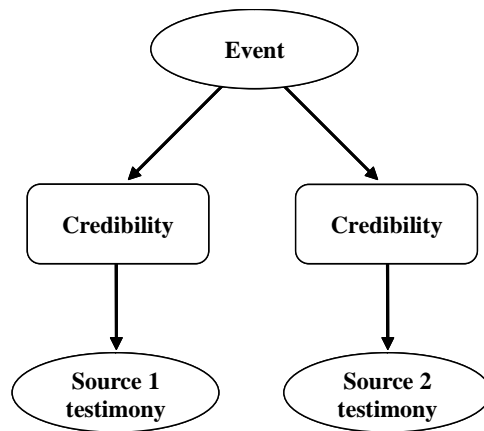
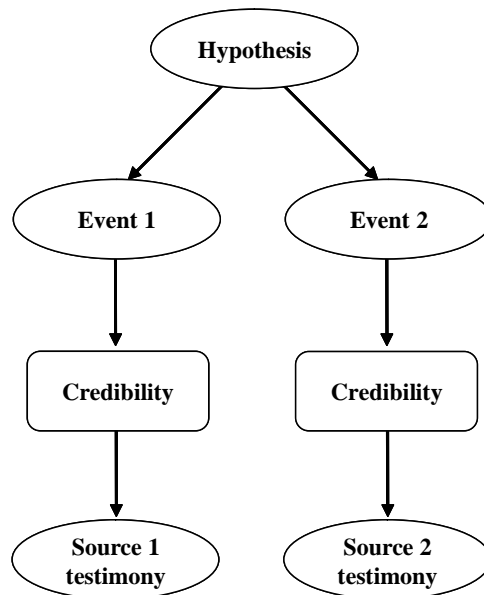


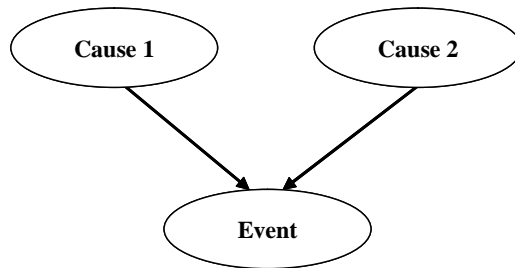
Figure 15: Generic conflict/convergence module



**Explaining away** When there are two possible causes of the same observed event, discovering that one of them is true will lower the probability of the other one. For example Lagnado and Harvey (2007) suppose **Cause 1** represents the event that a suspect committed a crime; **Cause 2** is the event that the interrogating official has coerced the suspect; and **Event** represents whether or not the suspect has confessed to the crime. If we are only told the suspect confessed, the probability that the suspect is guilty could be quite high. However, if we are also informed, or have other reasons to believe, that the official coerced the suspect, our revised assessment of the probability of guilt would be much lower: knowledge of coercion “explains away” the suspect’s confession.

An arrangement of nodes with the desired property is shown in Figure 16. More detailed

Figure 16: Explaining away



descriptions and additional examples can be found in Wellman and Henrion (1993), Pearl (2000), and Taroni, Aitken, Garbolino, and Biedermann (2006)

## 6 Discussion and Future Work

A Wigmorean approach to the analysis of evidence is appealing for many reasons, yet has severe limitations. The same is true for traditional Bayesian network representations of large masses of evidence. Of primary concern is the arduous modeling task and the sheer size and complexity

of the finished product. We have argued that an object-oriented approach can aid both in the creation of the model (by reusing purpose-built or off-the-shelf modules) and in its presentation and application (by the ability to view or hide details as desired). Although we have illustrated object-oriented methods in the context of Bayesian networks, there is no reason why similar methods could not be applied to Wigmore charts.

Any realistic application of object-oriented methods will require the availability of suitable software. There does exist a number of software applications for building and manipulating OOBNS *via* a graphical interface<sup>1</sup>, but these are primarily aimed at numerical computation and do not currently implement the range of graphical display and manipulation features desirable for our purposes.

Along with the need for software enhancement, considerable additional theoretical development is needed. Currently we are developing and refining modules to represent a number of common recurrent types of evidence. Several types of testimonies are being examined: alibis, expert witnesses, witnesses biased due to manipulation or financial gain, *etc.* We also plan to further refine the credibility module, incorporating the various questions used to assess credibility in the MACE software program (Schum and Morris 2008). Another line of investigation is the potential of qualitative probabilistic networks (Wellman and Henrion 1993; Biedermann and Taroni 2006) to manipulate directional relevance and strength of evidence without the need to assign numerical probabilities.

## 7 Acknowledgements

This research was supported by the Leverhulme Trust. We are deeply indebted to David Schum for his suggestions and insights.

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<sup>1</sup>We have made extensive use of HUGIN version 6 (see [www.hugin.com](http://www.hugin.com))

## Appendix: Demystifying the numbers

An important aspect of Bayesian networks that has been largely ignored thus far is the numerical specification of conditional probabilities to accompany the graphical representation. For every node  $Y$  in the network, we need to supply probabilities for its possible values, conditional on each combination of values for all its parent nodes.

In Figure 3, variable  $Y$  has a single parent variable  $X$ . If both nodes are binary, we need to specify two conditional probabilities: the *hit rate*,  $\Pr(Y = \text{true} | X = \text{true})$  and the *false positive rate*,  $\Pr(Y = \text{true} | X = \text{false})$ . The full specification of the parent-child conditional probabilities is then given by Table 7, with  $h$  denoting the hit rate and  $f$  the false positive rate.

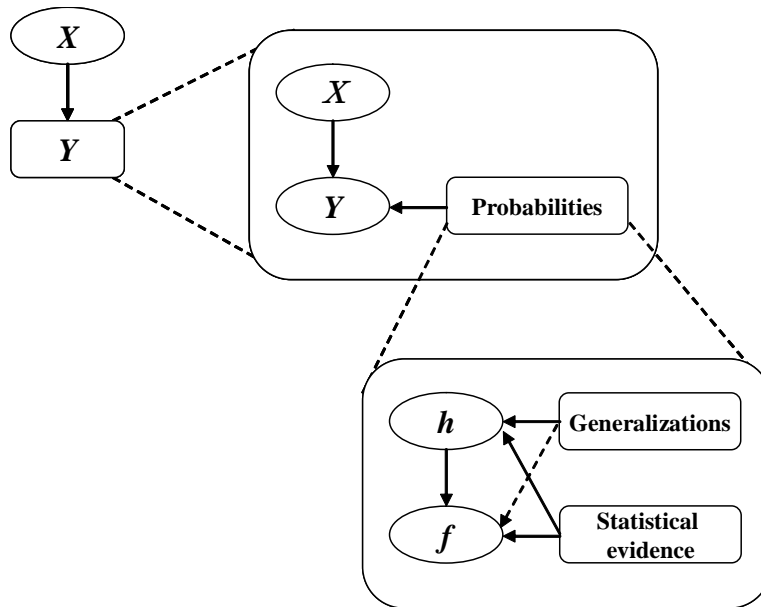
|     |       | $X$     |         |
|-----|-------|---------|---------|
|     |       | True    | False   |
| $Y$ | True  | $h$     | $f$     |
|     | False | $1 - h$ | $1 - f$ |

Table 2: Conditional probability table for  $Y$  dependent on  $X$

In applications there will rarely be uniquely agreed and defensible values for such conditional probabilities: they too are uncertain, just like everything else represented in the network. We can elaborate our representation to make this explicit.

Figure 17 shows our extended representation of the above parent-child relationship. At the top level  $Y$  is now a module, rather than a simple variable. This module consists of  $Y$  itself together with  $Y$ 's parent node  $X$  and a further module labeled **Probabilities**. This probability module in turn contains variables representing the hit rate  $h$  and false positive rate  $f$ , making it explicit that these quantities are themselves variables about which there can be uncertainty. It can also explicitly display the sources and determinants of that uncertainty: for example, accepted generalizations and/or statistical studies. These could be used to set ranges of plausible

Figure 17: Transparent representation of probability specification in Bayesian networks



values for  $h$  and  $f$ , which could then be varied in these ranges to allow sensitivity analysis (along the lines of the MACE system). Alternatively, and in many ways more satisfactory, background generalizations might be used to set prior distributions (generally rather vague) for  $h$  and  $f$ , which might then be updated to more precise posterior distributions in the light of statistical or other data (with a suitable software system, this updating would look after itself).

All the above considerations focus on the values of the parent-child probabilities in an initial network specification, and must not be confused with the impact of evidence specific to the case at hand, which has to be input into the network after it has been initialized. Thus we might have ancillary evidence, such as that disputing Pelser's competence in Figure 12; or a situation of "explaining away". After the case network has been built, incorporating the above extensions to account for uncertain input probabilities, we can then enter the case-specific evidence, and use standard numerical computational methods to analyse its impact on the hypotheses of interest.

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