

# Sense-making software for crime investigation: how to combine stories and arguments?

Henry Prakken

Department of Information and Computing Sciences, Utrecht University  
& Centre for Law and ICT, Faculty of Law, University of Groningen  
The Netherlands

(Joint work with Florix Bex, Susan van den Braak, Herre van Oostendorp,  
Bart Verheij & Gerard Vreeswijk)

24th January 2007

## 1 The project

Crime investigation is a difficult and laborious process, and the costs of mistakes can be high. Especially in large crime investigations, investigators are faced with a mass of unstructured evidence of which they have to make sense. They have to map out the possible hypotheses about what happened and assess the potential relevance of the available evidence to each of these hypotheses. In many cases this is a difficult and laborious task where mistakes are easily made [24]. Research has shown that often the only viable manner in which police investigators can structure the information they gathered is through scenarios [14]. Also, scenarios should be linked to the available evidence by building evidential arguments with common knowledge [3, 24, 22]. The process of generating scenarios from and testing them against evidence is prone to errors, especially in complex cases. Due to psychological factors as hindsight bias and confirmation bias [14], police investigators tend to give too much weight to some hypotheses and scenarios and too little weight to others. This may lead to a failure to identify the perpetrator of a crime or even to prosecution of the wrong suspect. Since both prosecutors and fact finders are confronted with the same problems in a later stage, miscarriages of justice may ensue.

Because of the difficulty of their task, crime investigators can greatly benefit from support tools. It has been suggested that software could offer such tools by supporting crime investigators in expressing their reasoning about a case in terms of arguments on the relevance of evidence to the various hypotheses and scenarios using common knowledge [19]. With such a programme the user could visualise his reasoning in various ways (graphs, tables, forms) and explore its consequences. Thus the programme would support investigators in seeing patterns, discovering new relationships or inconsistencies, and in identifying missing evidence. Such software would also facilitate transfer of the case files to others by increasing the transparency of the files, so that

subsequent investigators, prosecutors and fact finders could gain a quicker and better understanding of the case.

In the current practice of crime investigation and similar fact finding processes, software for managing and visualising evidence is already being used. Well-known examples are Analyst's Notebook [2] and HOLMES 2 [1]. In the Netherlands, the BRAINS system has been experimentally used in crime investigation with some success [18]. However, a limitation of such software is that it does not allow for expressing the reasons why certain evidence supports or attacks a certain hypothesis or scenario. Thus the core business of structuring evidence and assessing the relation between hypotheses, scenarios and evidence is still, in fact, wholly dependent on human reasoning, and the structures resulting from such reasoning cannot be recorded and analysed by the software.

This article reports on an ongoing research project on software that could add these 'sensemaking' capabilities to current evidence management software. Our aim is to develop software in which a human crime investigator can visualise possible scenarios about what happened and can link these scenarios through arguments with available supporting or attacking evidence. We anticipate that to make such software useful in practice, it should be combined with systems like HOLMES 2, Analyst's Notebook and Brains, so that the visualisations are linked with the documents containing the available evidence and thus make these documents more manageable. To this end, our software already supports links between components of the visualisations and pieces of text within source documents. However, a full integration with current professional document management software is outside the scope of this project.

## **2 Our approach: combining storytelling and argumentation**

To be usable in practice, our software design should be based on concepts that are actually used in evidential reasoning, while to improve the quality of crime investigations, the design should be based on a rationally founded theory of these concepts. Methods founded on probability theory (such as probabilistic networks) satisfy the second criterion but not the first since in the vast majority of legal cases reliable statistics are not available, while human experts are often unable or reluctant to provide accurate quantitative estimates. This project therefore takes its starting point in three important concepts of current legal evidence theory, viz. arguments, generalisations and scenarios (also called 'stories' or 'narratives'). The importance of these concepts has been emphasised in two recent research strands, 'New Evidence Theory' (NET, e.g.[3, 19] and 'Anchored Narratives Theory' (ANT, [24]). Both approaches stress the importance of empirical generalisations in evidential reasoning but they differ on their precise role. While NET regards generalisations as the 'glue' in evidential arguments from evidence to hypotheses, ANT regards them as the 'anchors' of evidential stories in the available evidence.

NET takes its inspiration in Wigmore's [25] charting method, in which alternative arguments from evidence to hypotheses can be graphically displayed. Schum & Tillers

take Wigmore’s method as the basis of their ideas on evidential visualisation software. As observed by [15, 4], Wigmore charts are similar to Artificial-Intelligence models of argumentation [12, 9, 23, 16], and the notion of a generalisation (or anchor) is essentially the same as AI’s notion of a default [17]. In consequence, the logical aspects of NET are now well understood. However, the relation between arguments and stories still needs to be clarified.

ANT stresses that often the only viable way in which judicial proof can proceed is by constructing alternative stories about what happened in a case, by comparing their quality as stories, and by comparing how well they are “anchored” in commonsense generalisations. A story can be anchored in two ways. The first is *internal anchoring*. Stories at least contain a sequence of events on a timeline and stories become stronger if the connections between the events it contains are not just temporal but also causal (e.g. shooting a gun causes a sound) or intentional (a man possessing a gun who is assaulted will shoot the attacker). The second type of anchoring is *external anchoring*: elements of a story can be anchored in the available evidence by sources of information, such as observation, memory or testimony. This also involves commonsense generalisations. For instance, a witness testimony supports a belief only by virtue of the common knowledge that witnesses usually tell the truth. Clearly, the general knowledge involved in anchoring stories can have exceptions and therefore anchors must be critically examined and refined when the facts indicate a possible exception. For instance, if two witnesses know each other, they may have influenced each other’s testimonies: to discard this possibility a refined anchor may be needed, such as that if two witnesses agree but did not confer, they usually tell the truth.

Our proposed software design should support the visualisation not only of arguments and counterarguments but also of stories and their internal and external anchoring. However, to properly design such innovative software, a deeper understanding is required of the relation between arguments, stories and anchors. Accordingly, our research project combines a subproject on software design with a subproject on theoretical foundations. Our main hypothesis here is that NET and ANT can be unified by regarding the anchoring of stories in evidence as argumentation.

### **3 A specific problem: causation in stories and arguments**

In the present paper we will discuss one aspect of the unification of these two approaches, namely the role of causation in evidential reasoning. Reasoning with causal information can take two forms. Using familiar AI terminology, in *prediction* one observes or assumes a certain event and tries to predict what will happen as a consequence of this event, while in *explanation* one observes an event or state of affairs and tries to explain how it could have been caused by other events. Both forms of reasoning are, of course, of prime importance in reasoning about evidence, whether story- or argument-based. Often an attempted proof that a certain crime took place is constructed by saying that an observed fact (the evidence) holds since something else (the crime) happened which caused it. Such an explanation can then be tested by predicting what else must

have been caused by the crime and by trying to find evidence concerning the predicted facts. As remarked above, the causation involved in evidential reasoning may both be physical (fire causes smoke) or mental (wanting to be rich makes one steal). Clearly, causal reasoning is defeasible in several ways: causal generalisations may have exceptions (striking a match will cause fire except if it is wet) and observed evidence may be explained by several alternatives (the grass is wet since it rained or since the sprinkler was turned on).

### 3.1 Current approaches in AI

In AI it is well-known that causal knowledge can be represented in two alternative ways, namely as causal generalisations (fire causes smoke) or as evidential generalisations (smoke means fire) (see e.g. [11, 13]). Generally, a choice is made for one of these two representation methods. For instance, the well-known MYCIN medical expert system [7] expressed empirical associations between symptoms and diseases as evidential rules (if symptoms then disease) while later, model-based approaches to medical diagnosis such as CASNET [20] represented the relevant knowledge as networks of causal rules (if disease then symptom). With evidential rules explanatory reasoning can be modus-ponens style: if the antecedent (the symptom) is known the consequent (the disease) can be inferred. Alternative explanations should then be managed with some priority mechanism between rules: MYCIN used certainty factors for this. With causal rules prediction can also be modus-ponens-style but explanation must be abductive: given the consequent (the symptom) the antecedent (the disease) is ‘inferred’ since if true it would imply the symptom by modus ponens on the causal rule. Alternative explanations must then be dealt with either by trying to find evidence concerning predicted facts or (if gathering further evidence is impossible) with some priority mechanism on abductively ‘inferred’ causes (such as a probability distribution; see [13]).

The approach with causal rules and abduction is taken in abductive AI models of diagnosis [10], while current AI models of argumentation and other nonmonotonic logics only model modus-ponens-style reasoning but allow for both causal and evidential rules. In the full version of this paper we will argue that Wigmore’s charting method in fact also takes the latter approach. Pearl [11] showed that an unprincipled combination of both types of rules in a single modus-ponens-style system may give rise to counter-intuitive consequences. For instance, if we know that the smoke machine was on and that turning the smoke machine on causes fire, we should not subsequently infer from ‘there is smoke’ and the evidential rule that smoke means fire that there is a fire.

### 3.2 Our approach

In this paper we will only be concerned with explanation and leave its combination with prediction for future occasions. As just said, in AI usually one single approach to explanatory causal reasoning is taken: either all knowledge is represented as causal rules and the reasoning is abductive, or all knowledge is represented as evidential rules and the reasoning is modus-ponens-style. However, we want to explore a combination

of both approaches. Possible scenarios about what happened are represented as networks of causal rules while the relation between the available evidence and events in the causal network is represented as evidential rules. The reason for this approach is twofold.

A practical reason is that crime investigators very often draw timelines and causal-network-like structures with the available evidence and since we want to build software for supporting crime investigators, we should respect their good habits. This explains why for our purposes a purely modus-ponens-style approach to explanatory causal reasoning is less desirable.

However, there are also theoretical reasons why a purely abductive approach is less desirable. In such an approach, the relation between a witness testimony and its content would have to be represented as causal rules. One possible cause of a witness testimony is, of course, the truth of the event to which the witness testifies. Schematically:

$$r_1: p \Rightarrow w \text{ said } "p"$$

(To be truly realistic this rule should have some auxiliary conditions like “the witness was interrogated” and so on, but for simplicity we will leave such conditions implicit.) However, there may be other possible causes of the witness testimony. for instance:

$$r_2: w \text{ has reason to lie about } p \Rightarrow w \text{ said } "p"$$

Once such reason to lie about  $p$  could be that the witness wants to protect the offender, another reason could be that by speaking the truth he would compromise himself (such as when speaking the truth would reveal a visit to the red light district).

Now if a certain testimony “ $p$ ” is given as evidence then this very simple causal network gives rise to two possible explanations for the testimony: that  $p$  is true and that the witness has reason to lie about  $p$ . Therefore, some measure of strength is needed to discriminate between them, or if further investigation is possible, further evidence should be gathered to discriminate between the two explanations. However, intuitively it seems that absent further evidence that the witness may have lied the second explanation is not even considered or taken seriously. Thagard [21] speaks in this connection of a “dual pathway model” of reasoning with testimonial evidence. He distinguishes a “default pathway” in which people almost automatically accept a testimony and a “reflective pathway” in which people build a model of the relevant knowledge and decide whether to believe the testimony by inference to the best explanation (IBE). People shift from the default to the reflective pathway when the content of the testimony is inconsistent with their current beliefs or when there is reason to doubt the credibility of the source.

The problem with a uniquely abductive approach is that it forces crime investigators to always take the reflective pathway. Clearly, this will in many cases induce unnecessary cognitive overload. More precisely, the abductive approach fails to capture that witness testimonies are usually true by mistakenly leaving the evidential default

$$r_3: w \text{ said } "p" \Rightarrow p$$

out of the problem description. Rule like this one can be regarded as compilations of deep IBE reasoning: such a rule expresses the empirical regularity that the usual cause of a testimony is the truth of its content; any other cause is an exceptional cause.

We therefore propose that while the construction of stories to explain the available evidence is modelled as abductive reasoning with causal networks, source-based

reasoning about evidence is modelled as modus-ponens-style reasoning with evidential rules. As for testimonies as sources of evidence, a shift from the default to the reflective pathway will be modelled as the construction of counterarguments based on exceptions to the evidential generalisation triggered by available evidence. The crucial difference with a purely abductive approach to reasoning with testimonies is that in the argumentation approach such counterarguments can only be constructed if there is evidence for a possible exceptional cause; in the abductive approach such an exceptional cause also counts as a possible explanation without further evidence.

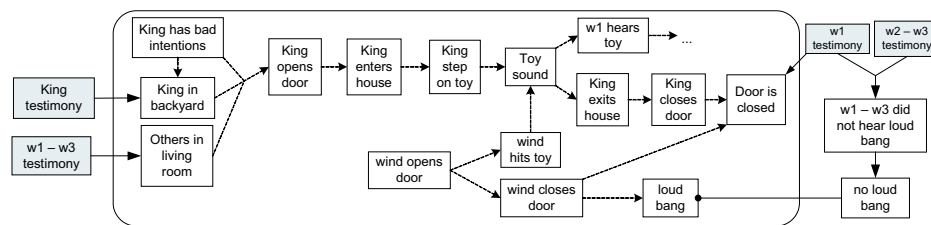
## 4 An example

Let us illustrate this approach with an example discussed in [8, pp. 460–463], a relatively simple case about an alleged burglary. (We take our analysis of the example from [5]). The prosecution presents the following story.

On the 18th of November, Andrew King climbs over the fence of the backyard of the Zomerdijk family with the intention to look if there is something interesting for him in the family’s house. Through this yard he walks to the door that offers entry into the bedroom of the 5-year-old son of the family. The door is not closed, so King opens it and enters the bedroom to see if there is anything of interest in the house. Because it is dark, King does not see the toy lying on the floor. King hits the toy, causing it to make a sound which causes the dog to give tongue. King hears the dog and runs outside, closing the door behind him. Mr. Zomerdijk hears the toy and the dog. He goes to the bedroom and sees King running away through the closed garden door. He shouts “there is a burglar, come and help me!” and runs into the garden after King. King, who wants to pretend he is lost, does not run away. In spite of this, Zomerdijk jumps on King and, aided by his brother, who is visiting the Zomerdijk family, molests King.

King has his own explanation for the fact that the toy made a sound; he claims that the wind blew open the door, hit the toy (which caused it to make a sound) and then blew the door shut again. This story predicts a loud bang as the consequence of the fact that the wind blew the door shut again. However, no witness reported such a loud bang.

The two stories can be represented together in the following causal network:



The part of the figure within the large rounded box represents the causal network combining the two stories. The four small grey boxes outside the causal network are pieces of testimonial evidence. Using the appropriate evidential generalisations, they can be used to build arguments to support nodes inside the causal network. Three of the arguments are very simple, directly supporting a node. The fourth argument in fact concludes to the negation of a network node, namely, that there was no loud bang: this can be inferred from the fact that no witness stated that they heard such a loud bang by using the generalisation ‘if a witness does not state a certain fact during interrogation, the fact is not the case’. Note that in this simple example none of the four arguments has a counterargument. In the full paper we will discuss examples where evidential arguments do have counterarguments.

In our approach the the explanation task is to explain the positive facts supported by evidential arguments while not contradicting the negative fact supported by evidential arguments. (When evidential arguments have counterarguments this is restricted to those facts that are supported by arguments that survive the competition). If we focus on minimal sets of ‘initial’ causes, then two explanations can be constructed, namely:

$$H_1 = \{King\ has\ bad\ intentions,\ others\ in\ living\ room\}$$

$$H_2 = \{wind\ opens\ door\}$$

Hypothesis  $H_1$  explains all the observations to be explained while  $H_2$  fails to explain that King was in the backyard. Also,  $H_2$  contradicts the observation that there was no loud bang. Intuitively, this clearly makes  $H_1$  the better explanation. In the full version of this paper some criteria for comparing explanations will be discussed and it will be argued that they formalise this intuition.

Concluding this example, the reader may find some of the causal or evidential generalisations weak or far-fetched. However, this is not a problem for our approach. The very idea of our sense-making system (which it shares with, for example, Wigmore’s charting method) is that it is the user of the system who is responsible for carefully testing the quality of his stories and arguments. The software should support the user in this critical process; it should not itself automatically generate sensible stories and arguments.

## 5 Our current research

From a theoretical point of view our approach is not trivial. From an AI perspective it in fact amounts to a combination of two AI approaches (abductive model-based reasoning and modus-ponens-style default reasoning) that are usually considered as irreconcilable alternatives. And from a legal-theoretical perspective it amounts to an attempt to unify the Anchored Narratives Theory and the New Evidence Theory. In the theoretical part of our project, Floris Bex is carrying out this research. First results are reported in [5]<sup>1</sup>. In the other subproject Susan van den Braak is developing a visualisation software tool in which causal networks can be combined with modus-ponens-style argumentation structures. An early version of this tool, which only supports modus-ponens-style ar-

---

<sup>1</sup>Available online at <http://www.cs.uu.nl/research/projects/evidence/publications/Jurix2006BexF.pdf>.

gumentation, is described in [6]<sup>2</sup>. A first version of the full system is currently being developed and some screenshots will be presented at the conference. At later stages of the project this tool will be empirically tested in user experiments to see whether using such a tool indeed has the benefits it is often claimed to have. Among other things, this should bring clarity on whether a combination of story-based and argument-based reasoning is indeed natural to crime investigators. At present this is just a hypothesis.

## References

- [1] HOLMES 2: Home office large major enquiry system (www page). <http://www.holmes2.com/holmes2/index.php>, 2006.
- [2] i2 Analyst's Notebook: Investigative analysis software (www page). [http://www.i2.co.uk/Products/Analysts\\_Notebook/default.asp](http://www.i2.co.uk/Products/Analysts_Notebook/default.asp), 2006.
- [3] T.J. Anderson and W. Twining. *Analysis of Evidence. How to Do Things with Facts Based on Wigmore's Science of Judicial Proof*. Little, Brown and Company, Boston, MA, 1991.
- [4] F.J. Bex, H. Prakken, C. Reed, and D.N. Walton. Towards a formal account of reasoning about evidence: argumentation schemes and generalisations. *Artificial Intelligence and Law*, 12:125–165, 2003.
- [5] F.J. Bex, H. Prakken, and B. Verheij. Anchored narratives in reasoning about evidence. In T. M. van Engers, editor, *Legal Knowledge and Information Systems. JURIX 2006: The Nineteenth Annual Conference*, pages 11–20. IOS Press, Amsterdam etc., 2006.
- [6] S.W. van den Braak and G. Vreeswijk. AVER: Argument visualization for evidential reasoning. In T. M. van Engers, editor, *Legal Knowledge and Information Systems. JURIX 2006: The Nineteenth Annual Conference*, pages 151–156. IOS Press, Amsterdam etc., 2006.
- [7] B.G. Buchanan and E.H. (eds.) Shortliffe. *Rule-Based Expert Systems: The MYCIN Experiments of the Stanford Heuristic Programming Project*. Addison-Wesley, Reading, MA, 1984.
- [8] H F M Crombag, P J van Koppen, and W A Wagenaar. *Dubieuze zaken: De psychologie van strafrechtelijk bewijs*. Uitgeverij Contact, Amsterdam, second edition, 1994.
- [9] R.P. Loui. Defeat among arguments: a system of defeasible inference. *Computational Intelligence*, 2:100–106, 1987.
- [10] P. Lucas. Symbolic diagnosis and its formalisation. *The Knowledge Engineering Review*, 12:109–146, 1997.

---

<sup>2</sup>Available online at <http://www.cs.uu.nl/people/susanb/publications/JURIX06-BraakVreeswijk.pdf>.

- [11] J. Pearl. Embracing causality in default reasoning. *Artificial Intelligence*, 35:259–271, 1988.
- [12] J.L. Pollock. *Cognitive Carpentry. A Blueprint for How to Build a Person*. MIT Press, Cambridge, MA, 1995.
- [13] D.L. Poole. Logical argumentation, abduction and Bayesian decision theory: a Bayesian approach to logical arguments and its application to legal evidential reasoning. *Cardozo Law Review*, 22:1733–1745, 2001.
- [14] C.J. Poot, R.J. Bokhorst, P.J. van Koppen, and E.R. Muller. *Rechercheportret: Over Dilemma's in de Opsporing*. Kluwer, Alphen aan den Rijn, 2004. In Dutch.
- [15] H. Prakken. Analysing reasoning about evidence with formal models of argumentation. *Law, Probability and Risk*, 3:33–50, 2004.
- [16] H. Prakken and G.A.W. Vreeswijk. Logics for defeasible argumentation. In D. Gabbay and F. Günthner, editors, *Handbook of Philosophical Logic*, volume 4, pages 219–318. Kluwer Academic Publishers, Dordrecht/Boston/London, second edition, 2002.
- [17] R. Reiter. A logic for default reasoning. *Artificial Intelligence*, 13:81–132, 1980.
- [18] J. van der Schoor. Brains voor de recherche. *Justitiële Verkenningen*, 30:96–99, 2004. In Dutch.
- [19] D. Schum and P. Tillers. Marshaling evidence for adversary litigation. *Cardozo Law Review*, 13:657–704, 1991.
- [20] Weiss S.M., Kulikowski C.A., and Amaral S. A model-based method for computer-aided medical decision-making. *Artificial Intelligence*, 11:145–172, 1978.
- [21] P. Thagard. Testimony, credibility and explanatory coherence. *Erkenntnis*, 63:295–316, 2005.
- [22] W. Twining. Necessary but dangerous? Generalisations and narrative in argumentation about “facts” in criminal process. In M. Malsch and F. Nijboer, editors, *Complex Cases. Perspectives on the Netherlands Criminal Justice System*, pages 69–98. Thela Thesis, Amsterdam, 1999.
- [23] G.A.W. Vreeswijk. Abstract argumentation systems. *Artificial Intelligence*, 90:225–279, 1997.
- [24] W.A. Wagenaar, P.J. van Koppen, and H.F.M. Crombag. *Anchored Narratives. The Psychology of Criminal Evidence*. St. Martins Press, New York, 1993.
- [25] J.H. Wigmore. *The Principles of Judicial Proof*. Little, Brown and Company, Boston, 2nd edition, 1931.