Computer Forensics using Bayesian Network: A Case Study

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Abstract

Like the traditional forensics, computer forensics involves formulation of hypotheses grounding on the available evidence or facts. Though digital evidence has been statutory witnesses for a span of time, it is a controversial issue that conclusions drawn from revealed digital evidence are subjective views without scientific justifications. There is an escalating perception that computer forensics is just the subjective conclusion of computer professionals.

The purpose of this paper is to present a reasoning model based on the probability distribution in a Bayesian Network. By setting out probability distributions over hypotheses for computer forensics analyses, we hope to quantify the evidential strengths of such hypotheses, and thereby enhance the reliability and traceability on the analytical results of computer forensics examinations. To study the validity of the proposed model, a real court case about BT technology has been fitted to the calculations. In order to detach the subjective views, a survey was carried out to collect the expertise of 31 experienced law enforcement agencies. Their responses were aggregated to generate some more objective assignments to the prior probabilities to be used. The outcome demonstrates a high propagated probability of 92.7%, which is in accordance with the actual court verdict of guilty. That presents computer forensics a real scientific science with quantifiable analyses.

Keywords: Bayesian Network, digital evidence, prior probability

I. INTRODUCTION

The proliferation of computer crimes has driven the need for the analysis of digital evidence. As forensic science has long been used to resolve legal disputes regarding different branches of science, computer forensics is developed naturally in the aspects of computer crimes or misbehaviours.

Similar to other forensics taxonomies, computer forensics involves the formulation of hypotheses that are based on available evidence or facts and the assessment of their likelihood that support or refute the hypotheses. Although there are principles and guidelines established on how to retrieve digital evidence [14,15,16], there seems lack of researches on the evaluation of the accuracy of the established hypotheses. To reach persuasive forensics conclusions, computer forensics analyses require reliable, accurate and scientific methodologies to justify their hypotheses.

Without reliable and scientific analytical models, computer forensics analysts are facing the challenges of unjustified forensic conclusions or that the findings are speculations without concrete scientific support. It also renders forensic results varies from analyst to analyst. These contrasting interpretations will bring different analysts resulting in contradictory conclusions even given the same set of digital evidence.

Today, this shortage has drawn impacts on the reliability of the forensics findings as well as the credibility of the analyst. Speculations or subjective views of forensic analyst under the name of expert opinion are no longer sufficient for legal arguments [1].

The purpose of this paper is to present a reasoning model based on the probability distribution in a Bayesian Network. The model is expected to provide scientific justifications for the conclusions or findings of computer forensics examinations. This model is developed to facilitate other computer forensics practitioners to trace and to assess events or parameters of the examinations such that the reasoning for the conclusions can be evaluated.

II. LITERATURE REVIEW

Forensics is the process of analysis and interpretation of evidence so as to determine the "likelihood" of a crime. Many researchers revealed that this process should cover the formulation of hypotheses from evidence and the evaluation of the hypotheses' likelihood for the sake of legal arguments in court proceedings [2, 3, 4, 5, 6]

Aitken and Taroni [7] viewed that likelihood is indeed an exercise in hypothetical reasoning. It denotes the degree of belief on the truthfulness of the hypothesis. In the scientific community, likelihood is expressed in terms of probability. As probability is the logic of chance, hence probability theories are able to deduce the likelihood of hypotheses from assumptions.

Although probabilistic methods seem to be viable measures to prove or refute the hypotheses of a crime, it is viewed by Jones et al [8] that simply obtaining all possible probability distributions on the entailing evidence of a crime are not practical. Given that the volume of evidence of a crime is usually large, the effort to obtain the joint probability distributions for all possible evidential variables is therefore very large and expensive. Moreover, since simple probabilistic methods cannot reflect any of the conditional dependencies between the evidence, these methods are considered impractical from an analytical point of view [9]. From researches, it was concluded that a more structural probabilistic model should be used in order to provide a more efficient and representation of the conditional dependencies of evidence [9,10,11].

Indeed, crime investigation should be considered as an abductive diagnosis problem [10]. However, it is difficult to design a model that can deterministically describe all the assumptions of a crime. Poole [12] therefore proposed a model that can describe crime scenarios non-deterministically using symbolic logic and probabilistic Bayesian methods. However, the profound model proposed by Poole [12] is considered too abstract to be applied in real scenario.

Furthermore, digital events are discrete computer events that are deterministic and in temporal causal sequence. Therefore, it is a prevailing practice that computer forensic analysts will establish their abductive reasoning based on the existence or validity of the causation events that entailing the hypotheses. However, it is difficult to have consistent models to determine the supporting events for hypotheses. Different analyst may attach different events for the same hypothesis. Even if the same set of events is determined, analysts may assign different probabilistic values to the events. This is referred as the subjective probability.

Moreover, analysts are facing the challenge of uncertainty in forming their reasoning when certain evidential events of the hypotheses are found missing or uncertain. This uncertainty also causes difficulties for computer forensics analysts to evaluate the remaining events. On one hand, these remaining events cannot prove complete truthfulness of the hypotheses, whilst on the other, these events indicate a certain extent of likelihood of the hypotheses.

In this paper, we propose the usage of the Bayesian Network model to evaluate digital evidence and to handle evidential uncertainties in reasoning formulation. Furthermore, in order to obtain a more objective prior probability or measurement of belief for events that are believed to be caused by the hypotheses, statistical data on the probabilistic values of a number of digital forensics scenarios are gathered from computer crime investigators and computer forensics examiners through questionnaires.

III. OVERVIEW OF BAYESIAN NETWORK

Before we explore the Bayesian network, it is worthwhile to emphasis that digital evidence is indeed “past” event that was caused by the hypothetical event. For example, the suspect had downloaded some child-pornographic materials from a pornographic web site and the URL of the web site was then recorded on the Internet history file.

A Bayesian Network is a graphical model that applies probability theory and graph theory to construct probabilistic inference and reasoning models. The nodes represent variables, events or evidence, whilst the arc between two nodes represents conditional dependences between the nodes.

A Bayesian Network is defined as a Directed Acyclic Graph (DAG) in which the arcs are unidirectional and feedback loops are not allowed in the graph. Because of this feature, it is easy to identify the parent-child relationship or the probability dependency between two nodes.

A Bayesian Network operates on conditional probability. For example, if the occurrence of evidence E depends on a hypothesis H, then the probability for both E and H happened can be expressed as Figure 1.

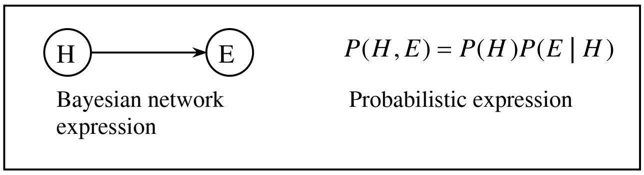


Figure 1

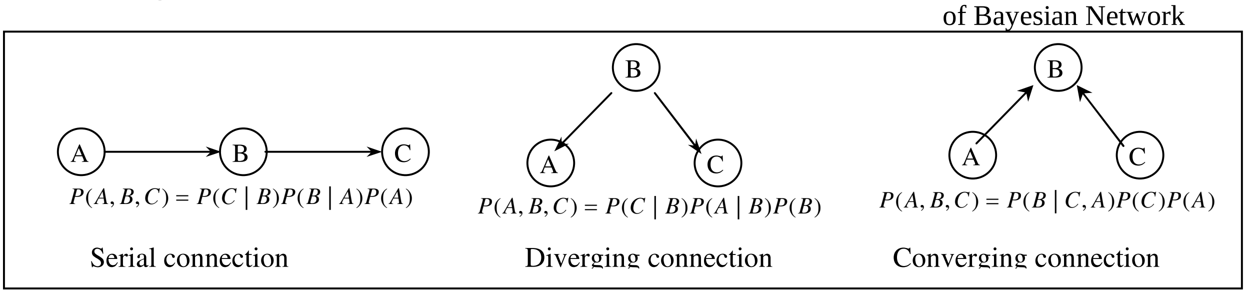
According to multiplication law of probability, which denotes the commutative feature, i.e. if A is relevant for E, then E must also relevant for A. The joint probability expression therefore becomes: $P(H,E) = P(H)P(E \mid H) = P(E)P(H \mid E)$, hence $P(E \mid H) = \frac{P(E)P(H|E)}{P(H)}$

The above is called the Bayes' Theorem. It forms the basis of the probability distributions between the nodes. From a statistical point of view, $P(E|H)$ denotes the conditional probability of evidence *E* caused by the hypothesis *H*. This is also referred as the likelihood ratio of *H* given *E*. It denotes the situation when hypothesis *H* is true the degree of belief that evidence *E* will be occurred.

$P(H \mid E)$ is the posterior probability. It means the probability value such that when evidence *E* is detected the degree of belief that the hypothesis *H* has actually occurred. $P(H)$ denotes the prior probability of the hypothesis H at a stage where evidence is not yet presented. $P(E)$ is the prior probability of evidence *E*, which is sometimes referred as a normalizing constant. Therefore, the above expression can be interpreted as : $likelihood\ ratio = \frac{posterior\ probability \times normalizing\ constant}{hypothesis\ prior\ probability}$, or $likelihood\ ratio\ \alpha\ posterior\ probability$. Since the likelihood ratio is proportional to posterior probability, hence larger the posterior probability denotes a higher likelihood ratio. In the perspective of evidence, it also means more the evidence supporting the hypothesis, more likely that the hypothesis is true.

Apart from the Bayes' Theorem, a Bayesian Network is also constructed from three elementary connections that represent three different categories of probability distributions amongst its nodes. Figure 2 illustrates these three connections.

Figure 2 : Elementary connections of Bayesian Network



$P(A,B,C)=P(C \mid B)P(B \mid A)P(A)$

Serial connection

$P(A,B,C)=P(C \mid B)P(A \mid B)P(B)$

Diverging connection

$P(A,B,C)=P(B \mid C,A)P(C)P(A)$

Converging connection

In a serial connection, it is noted that if B is unknown, A and C are dependent on each other. In other words, there are evidential influence between A and C if the evidential state of B is unknown. However, if B's state is known then A and C are independence to each other. Therefore, A and C are conditionally independent to each other given B. In a diverging connection, the same conditional independency is also observed between A and C. That is, if B's state is known then A and C are independent to each other. In a converging connection, the probabilistic relationships revealed that if B's state is unknown then A and C are independent to each other. In other words, unless the state of B is known, then A and C can evidentially influence each other.

Algorithms exist that allow probabilities to be propagated efficiently in a Bayesian Network [21] and will not be repeated here. Moreover, software tools have been developed to process a Bayesian network.

IV. THE PROPOSED MODEL

To demonstrate how the model works, a real case concerning online distribution of pirated movie using the Peer-to-Peer protocol "BitTorrent" is used for illustration. The digital evidence mentioned in this paper are presented evidence in the court during the criminal trial.

Background of the case

Defendant of the case was alleged using his own computer to distribute pirated movie to others through the Internet using the BitTorrent program [20]. Judgment of the case revealed that the defendant was in possession of optical disc of the movie. To achieve the distribution act, the defendant copied the movie from the optical disc onto his computer. He then used the BitTorrent program to create a torrent file from the movie file. Torrent file contains meta-date of the source file (i.e. the movie file) and the URL of the Tracker server. It can facilitate other Internet users to join the Peer-to-Peer network.

To make it available for other users, the defendant sent the torrent file to various newsgroup forums. He thereafter activated the created torrent file on his computer, which rendered his computer connected to the Tracker server. When connected, the Tracker server would query the computer with regard to the meta contents of the torrent file. The Tracker server would then return a peer list showing existing IP addresses on the network and the percentage of the target file existed on each peer machine.

Since the defendant's computer had a complete copy of the movie, hence the Tracker server would label it as seeder computer. Finally, the defendant maintained the connection between the Tracker server and his computer so that other peers could download the movie from his computer.

Building the model

Constructing a Bayesian model for computer forensics analysis begins with the set up of the top-most hypothesis. Usually, this hypothesis represents the main argument that the analyst wants to determine. For the purpose of prove the alleged illicit act, the hypothesis to be used is :

Hypothesis *H* : "*The seized computer was used as the initial seeder to share infringing file on a BitTorrent networ*k"

Then we have to express the hypothesis's possible states, which indeed denote the possible findings of the hypothesis. In the case, the possible states of the hypothesis are : "*Yes, No, Uncertain*". It is also required to assign the probability values to these three states. These values are also known as *prior probability* of the hypothesis.

The hypothesis *H* is the root node without any parent nodes. Indeed, node *H* is an ancestor of every other node in the Bayesian Network, hence its states' probabilities are unconditional. Until the states of the child nodes of *H* are certain, the probabilities of *H* should be evenly distributed amongst its states. Therefore the probability of *H* is *P(H)* = (0.333, 0.333, 0.333)

Root node of
Bayesian network

Node Name	*H*		
State	Yes	No	Uncertain
Prior probability *P(H)*	0.333	0.333	0.333

Table 1

Having established the root node, we then move to explore evidence or events that are causally dependent on *H*. These evidence or events are usually observable variables. However, it is noted that sub-hypotheses may also added under the root node of a Bayesian network. Although these sub-hypotheses are not having observable states, they are useful because they can refine the resultant model to a more structural and clearer graph. To support the hypothesis, that is "The seized computer was used as the initial seeder to share infringing file on a BitTorrent network", the following five sub-hypotheses are created:

(1) H_1: The pirated file was copied from the seized optical disc, which was found at the scene of crime, to the seized computer (states : "*Yes, No, Uncertain*");

(2) H_2: A torrent file was created from the copied file (states : "*Yes, No, Uncertain*");

(3) H_3: The torrent file was sent to newsgroup forum for publishing (states : "*Yes, No, Uncertain*");

(4) H_4: The torrent file was activated, which rendered the seized computer connected to the Tracker server (states : "*Yes, No, Uncertain*"); and

(5) H_5: The connection between the seized computer and the Tracker server was maintained (states : "*Yes, No, Uncertain*").

At this point, since the sub-hypotheses are dependent on *H*, we need to assign conditional probability values to these sub-hypotheses.

Table 2

Node Name	H_1		
State	Yes	No	Uncertain
H = Yes	0.6	0.35	0.05
H = No	0.35	0.6	0.05
H = Uncertain	0.05	0.05	0.9

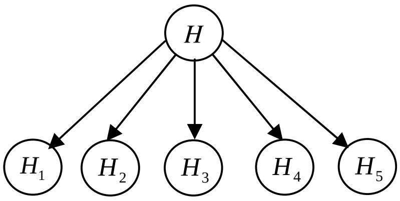


Table 2 illustrates the conditional probability values of hypothesis H_1 given the state of hypothesis *H*. Initial or prior probabilistic values are assigned to the possible states of H_1 for different states of *H*. Take the third row of the table as an example, We assign an initial values of 0.6 for the situation when H and H_1 are both "*Yes*". That means when the seized computer has been used as an initial seeder, the chance that the infringing movie file found on the computer had been copied from the seized optical disc found at scene is 60%.

H = Yes	0.6	0.35	0.05

However, there may be chances that although the seized computer was the initial seeder, the infringing movie was not copied from optical disc but downloaded from the Internet or copied from another computer in a local network, hence we assign a probabilistic value of 0.35 0r 35% to represent such situations.

Lastly, there may be chances that even though the seized computer was the initial seeder, we may not be able to confirm a "Yes" or "No" state of hypothesis H_1 from evidence observations. Therefore, there may be chances that the seized computer was the initial seeder, but we are uncertain to confirm the source from which the infringing movie was copied.

Tables 3 to 6 provide the conditional probabilities of hypotheses H_2 to H_5 given the state of hypothesis *H.*

Node Name	H_2		
State	Yes	No	Uncertain
H = Yes	0.6	0.35	0.05
H = No	0.35	0.6	0.05
H = Uncertain	0.05	0.05	0.9

Table 3

Node Name	H_3		
State	Yes	No	Uncertain
H = Yes	0.6	0.35	0.05
H = No	0.35	0.6	0.05
H = Uncertain	0.05	0.05	0.9

Table 4

Node Name	H_4		
State	Yes	No	Uncertain
H = Yes	0.6	0.35	0.05
H = No	0.35	0.6	0.05
H = Uncertain	0.05	0.05	0.9

Table 5

Node Name	H_5		
State	Yes	No	Uncertain
H = Yes	0.6	0.35	0.05
H = No	0.35	0.6	0.05
H = Uncertain	0.05	0.05	0.9

Table 6

Following the assignment of conditional probabilities to the sub-hypotheses, we then try to develop the entailing casual events or evidence for those sub-hypotheses. Indeed, it is the aim of a Bayesian network to perform probability propagation on linked hypotheses through the observation on the states of events or evidence.

In this case, the hypothesis *H* and the five sub-hypotheses are in a diverging connection. According to the probabilistic rules of a Bayesian network, nodes in a diverging connection will influence each other provided their parent node's state is still unknown. Therefore, it is envisaged that the five sub-hypotheses are having probabilistic relationship with each other. Their probabilities are affected by the observation of all the child events or evidence under these five sub-hypotheses.

For the purpose of this paper, hypothesis H_1 (i.e. The pirated file was copied from the seized optical disc, which was found at the scene of crime, to the seized computer) will be discussed in detail to demonstrate how the Bayesian network model applies.

V. PRIOR PROBABILITY – SUBJECTIVE PERSONAL BELIEF

Before we go further to analysis hypothesis H_1, it is worthwhile to mention that retrieved digital evidence are indeed past digital events (or posterior evidence) that can support or refute the occurrence of the 5 sub-hypotheses, which in turn support the hypothesis *H*. One of the main challenges in the application of Bayesian Network model on evidence evaluation is the assignment of probabilistic values to posterior evidences. Such assignments are usually based on subjective personal beliefs. Although the personal belief of a digital forensic analyst is assumed to be sourced from professional knowledge and experience, there is no means to determine whether a particular digital forensic examiner's belief can truly represent the general and acceptable view in the digital forensic discipline, not to mention the extent or appropriateness of the assigned probabilistic values to posterior evidences.

With a view to escalating the reliability and accuracy of the probability assignment to posterior evidence, we used questionnaires to collect information from digital crime investigators and digital forensic examiners of two law enforcement agencies in Hong Kong, namely the Technical Crime Bureau of Hong Kong Police and the Computer Forensic Laboratory of Hong Kong Customs. Indeed, this is the first study on the collection of probabilistic values on digital evidence.

The questionnaire[1] consists of 9 pages. It includes (a) background of the respondent in terms of digital investigation and digital forensic training and experience, (b) the degree of belief on the digital evidence resulted from general computer operations, and (c) the degree of belief on the digital evidence relating to the operation of the BitTorrent protocol.

There are a total of 31 questionnaires received. To analysis the collected data, we used the weighted average approach to find the probability values. For example, item 7 of the questionnaire requires respondents to gauge the probability ranges on the likelihood that visited web sites' Uniform Resource Locators (URL) and the access time would be stored in the file named "index.dat" at the folder "History.IE5". The overall result is 1 for 20-40%, 1 for 40-60%, 6 for 60-80%, 22 for 80-100%, and 1 for uncertain. The weighted average for the state that the URL and access time would be stored at the mentioned file and location is : (1x0.3) + (1x0.5) + (6x0.7) + (22x0.9) = 24.8, hence the probability for the state "*Yes*" is 24.8/31 = 0.8. In regard to the uncertain selection, the probability for "*Uncertain*" state is 1/31 = 0.03. Therefore, applying the law of total probability, the probabilistic value for state "*No*", that is the URL and the access time would not be stored at the mentioned file and location is : 1 – 0.8 – 0.03 = 0.17.

[1] The full version of the questionnaire is available at http://www.cs.hku.hk/kylai/qr.pdf

VI. ANALYSIS HYPOTHESIS H_1

The arguments describe events or evidence that would be caused by copying a file from optical disc to hard disk drive locally are : (1) E_1: "modify" time of the destination file equals to that of the sourced file (states : "*Yes, No, Uncertain*"), (2) E_2: "Creation" time of the destination file lag behind its own "modify" time (states : "*Yes, No, Uncertain*) and (3) E_3: Hash value of the destination file matches that of the sourced file (states : "*Yes, No, Uncertain*");

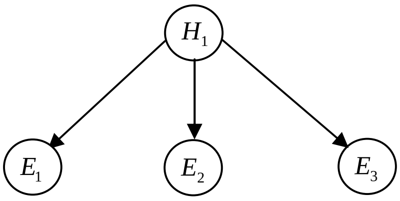


Figure 3

Once the evidence for the hypothesis is defined, the next task is to assign conditional probability values to these evidence. Tables 7 to 9 show the conditional probability values of evidence E_1, E_2 and E_3, given the state of hypothesis H_1.

Table 7

Node Name	E_1		
State	Yes	No	Uncertain (U)
H_1 = *Yes*	0.85	0.15	0
H_1 = *No*	0.15	0.85	0
H_1 = *Uncertain*	0	0	1

Table 8

Node Name	E_2		
State	Yes	No	U
H_1 = *Yes*	0.85	0.15	0
H_1 = *No*	0.15	0.85	0
H_1 = *Uncertain*	0	0	1

Table 9

Node Name	E_3		
State	Yes	No	U
H_1 = *Yes*	0.85	0.12	0.03
H_1 = *No*	0.12	0.85	0.03
H_1 = *Uncertain*	0.03	0.03	0.94

After assigning the conditional probability to the entailing evidence, next step is to obtain the statistical results of probability propagations within the network, that is, to calculate the certainty of H_1 based on the observed probability values of evidence E_1, E_2 and E_3. Since it is not the focus of this paper to address calculation details of a Bayesian network, the software "MSBNX" is used to handle the probability propagation within the network [13].

Before any observation conducted on the evidence, the probability values for nodes in this network are illustrated in Figure 4 and Figure 5.

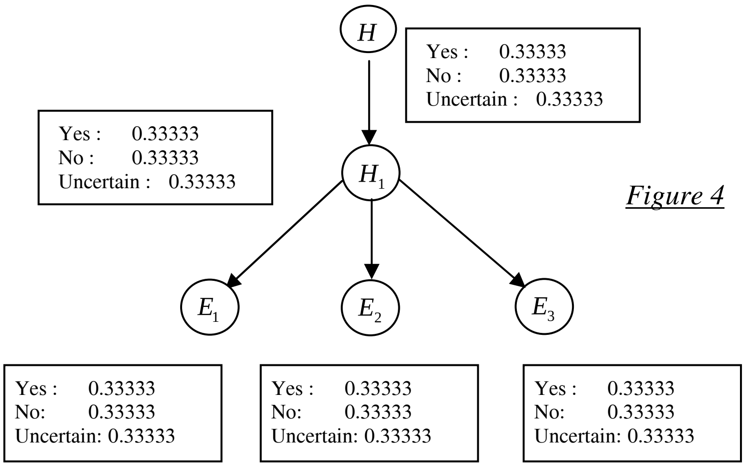


Figure 4

The above probability propagation diagram reveals the initial probability distributions in the network without any observed evidence. Now, let us assume evidence E_1 becomes "*Yes*" state while E_2 and E_3 still unobservable.

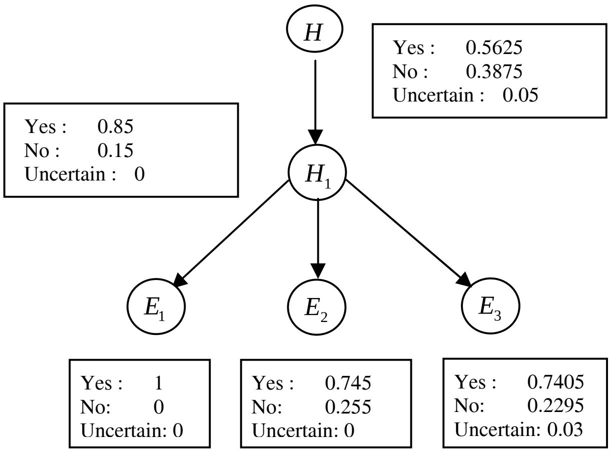


Figure 5

Because H_1 is in a diverging connection with E_1, E_2 and E_3, hence, provided the state of H_1 is still unobserved, change in E_1 will also change the probability values of nodes H_1. When H_1 changes, the likelihood ratio of E_2 and E_3 will change also. Similarly, since *H*, H_1 and E_1 are in serial connection, hence change in E_1 will also propagate the variation to *H* if H_1 remains unobservable. Indeed, it is obvious that there are two more serial connections existed in the network and they are :

$H \longrightarrow H_1 \longrightarrow E_2$ and $H \longrightarrow H_1 \longrightarrow E_3$

Therefore, any change in the states of E_2 and E_3 will also affect the probabilities of hypotheses *H* and H_1. Suppose we now examine the state of another posterior evidence E_2 and found it is "*Yes*". The propagated probabilities amongst the network become :

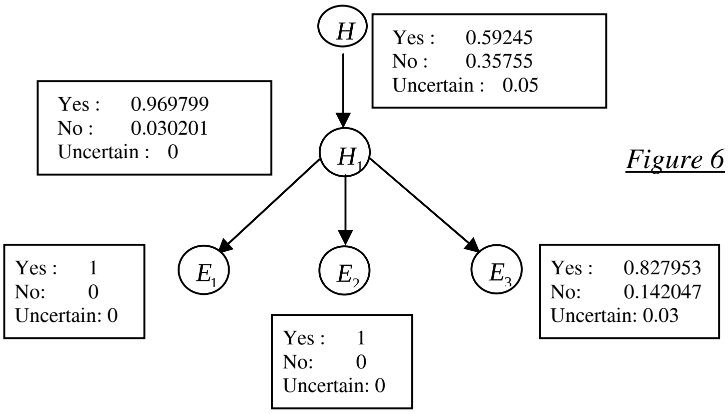


Figure 6

Suppose the final posterior evidence E_3 is also observed to be "*Yes*", the resultant probabilities are :

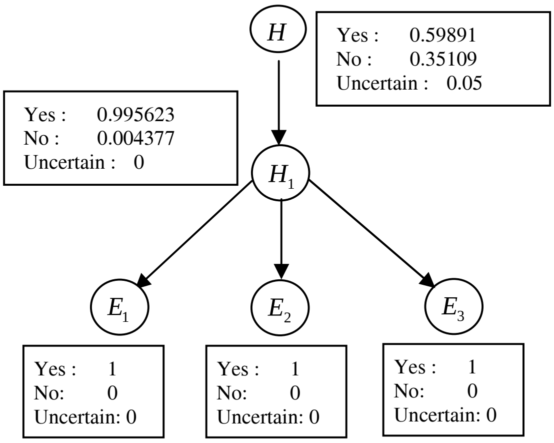


Figure 7

From Figure 7, we can see that when all the evidence states are "*Yes*", the propagated probability values for H_1 = "*Yes*" would be 99.6% and for H = "*Yes*", it would be 59.9%. In other words, if evidence E_1, E_2 and E_3 are observed to be "*Yes*", then the computer forensic analyst can confirm that there is a probability of 99.6% that the hypothesis H_1 (the pirated movie file was copied from the optical disc, which was found at the scene of crime, onto the seized computer) was true. Furthermore, judging on the 99.6% statistical result of H_1, the forensic practitioner can also conclude that the chance that *H* (the seized computer is the initial seeder) is true is 59.9%.

On the contrary, if all the evidence are in "*No*" states, then the resulting probabilities become :

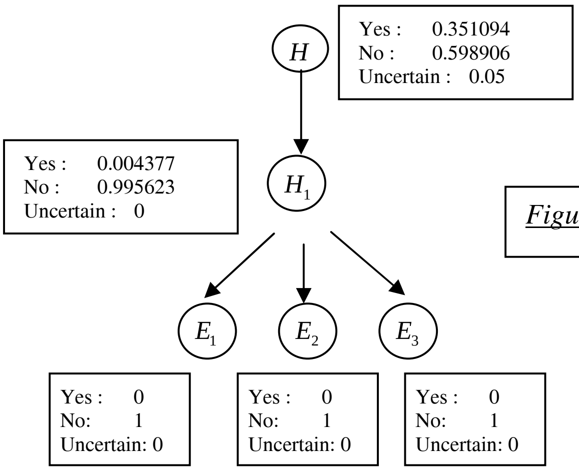


Figure 8

Now, the probability that H_1 is true is dropped to 0.4% and there is a probability of 99.6% that H_1 is false, i.e. the pirated movie was not copied from the optical disc that was found at the scene of crime. Unless there is posterior event or evidence existed, otherwise the probability that H = *"Yes"*, i.e. the seized is the initial seeder, is trimmed down to 35.1%; and that H = *"No"*, i.e. the seized computer is not the initial seeder, is escalated to 59.9%.

VII. ANALYSIS OF THE CASE

A complete case analysis using the Bayesian network approach is conducted. The overall network diagram is demonstrated at Appendix. From the probability calculations based on the Bayesian Network, we found that when there is no observation made to any evidence, the initial probabilities of the hypotheses are:

Table 10

Hypothesis	Description	Probability (%)
H	Seized computer is the initial seeder	Yes: 33.33 No: 33.33 Uncertain: 33.33
H_1	Pirated file was copied from optical disc found at the scene of crime	Yes: 33.33 No: 33.33 Uncertain: 33.33
H_2	Torrent file was created by the seized computer	Yes: 33.33 No: 33.33 Uncertain: 33.33
H_3	Torrent file was sent to newsgroup forums	Yes: 33.33 No: 33.33 Uncertain: 33.33
H_4	Torrent file was activated and the seized computer connected with Tracker server	Yes: 33.33 No: 33.33 Uncertain: 33.33
H_5	Connection between the seized computer and the Tracker server was maintained	Yes: 33.33 No: 33.33 Uncertain: 33.33

If we now switch all the entailing evidence to state "*Yes*" the propagated probability values for the hypotheses are:

Hypothesis	"*Yes*" (%)	"*No*" (%)	"*Uncertain*" (%)
H	92.54	7.45	0.01
H_1	99.71	0.29	0
H_2	99.98	0.0015	0.0185
H_3	99.98	0.02	0
H_4	99.93	0.07	0
H_5	89.31	10.47	0.22

Table 11

According to the trial verdict reports, there was no indication that the created torrent file was found existed in the seized computer. Moreover, there was no mention about the existent of cookies in the judgment regarding the publishing of the torrent file at newsgroup forums. Therefore we should amend corresponding observations on the existence of the created Torrent file (node "E_8" at Appendix) and cookies of newsgroup forum (node "E_{14}" at Appendix) from "*Yes*" to "*No*" in order to reveal their impact to the hypotheses.

It is worth to mention that the "Torrent File" node is a common node for hypotheses H_2, H_3 and H_4. In other words, there is a converging connection to the "Torrent Node" node from hypothesis nodes H_2, H_3 and H_4, as shown in Figure 9.

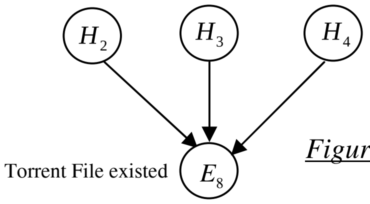


Figure 9

According to the rules of probability propagation for converging connection in Bayesian network, when the state of "Torrent File" node is known the probabilities of H_2, H_3 and H_4 will influence each other. Therefore, change in the state of "Torrent File" node will change the probability of these three hypotheses. Further, since H_1, H_2, H_3, H_4, H_5 are in divergent connection with parent hypothesis *H*, hence changes in H_2, H_3 and H_4 will also influence the probabilities of H_1 and H_5. After we changed the states of the nodes E_8 and E_{14} from "*Yes*" to "*No*", the resulting probabilities values are shown at Table 12.

Hypothesis	*"Yes"* (%)	*"No"* (%)	*"Uncertain"* (%)
H	92.27	7.72	0.01
H_1	99.70	0.30	0
H_2	99.92	0.07	0.01
H_3	97.80	2.20	0
H_4	99.51	0.49	0
H_5	89.45	10.33	0.22

Table 12

Table 12 illustrates that the propagated probability for the hypothesis *H* from the available evidence is 92.27%. In other words, from the observed evidence, there is a chance of 92.27% that the seized had been used as the initial seeder to distribute infringing movie on a BitTorrent network. In regard to the sufficiency of this probabilistic outcome in supporting the hypothesis *H*, it should be decided by the court and not the computer forensics analyst.

It is the jury or judge who should exercise inductive steps by taking into account all the presented evidence and to come up with a verdict for the case. That evidence includes not only digital evidence, but also physical evidence, such as confession made by the defendant, finger-print, etc. The duty of digital forensic analyst is to present digital forensic findings that have been evaluated accurately and scientifically.

In the current Internet piracy case, there exists some other digital evidence that are also related to the hypothesis. For example email exchanges, in-depth comparison of the torrent file metadata to the computer trails, time-line analysis, etc. However, as this paper aims to demonstrate the significance of Bayesian network to digital forensics analysis, hence only paramount digital evidence are selected for illustration.

VIII. CONCLUSIONS

In this paper, a real Internet piracy case is evaluated by using the Bayesian network model. In the model, hypotheses and their encompassing evidence are clearly set out. Most importantly, the established model also displays clearly the probabilistic values and the causal relationships between hypotheses and evidence.

Through the evaluation on prior evidence and the probabilistic analysis on posterior evidence, the Bayesian network model is able to help computer forensics analyst to assess possible states of each piece of evidence. In addition, the model can determine the evidence that will have the most effect on the forensics findings. It can also illustrate how digital evidence affects each other and the relating hypotheses. Thus, the Bayesian model is not only an analytical tool used in evidence evaluation, but also a tracking tool to enable other forensics practitioners to review and to re-examine the original forensics findings.

Perhaps the most significant contribution of the model is that it can offer a way to handle evidence that are of uncertainty or unobserved status. Most of time, it is difficult to retrieve all possible evidence of a case, or that the collected evidence are contradictory to the hypotheses. Sometimes, forensic analyst may tend to ignore evidence that are uncertain or contradict to the formulated hypotheses, in particular when large amount of digital evidence is involved.

Even if the analyst is cautious and wants to evaluate the impact of uncertain or contradictory evidence, it is difficult for him to project such influences by simply using his personal intuition. Furthermore, the analyst is also difficult to crystallize the interactive influences between each piece of evidence and the relating hypotheses. Obviously, the Bayesian network model is an optimum solution to solve the problems.

In order to minimize the impact of subjectivity when assigning prior probabilities to the posterior evidence involved in the BitTorrent case, we have gathered data on probability values through survey research by administering questionnaires to law enforcement officers who are involving in computer crime investigation or computer forensic examination. However, the subjectivity constraints on the sub-hypotheses still prevail. The limitation focuses on the prior probability assignments to the constructed sub-hypotheses that give rise to the root hypothesis. Since sub-hypotheses are causal events to digital evidence, hence they are based on the propagation of probability values of the evidence. It is therefore difficult to ask respondents to evaluate the posterior probabilistic values of sub-hypotheses unless the posterior beliefs on finite digital evidence can be established in the first place. Therefore, it is the view of this paper that such limitation deserves further research and verification by methodology like sensitive analysis such that the reliability, accuracy, and precision of the Bayesian Network model can be evaluated.

In fact, a Bayesian network model is not focused to give strict answers. The model aims to develop a traceable and scientific infrastructure that can project the likelihood of a hypothesis. In order to increase the accuracy of the projection or to simplify the Bayesian construction cycle, there are various approaches and methodologies developed. For example, the Markov property is developed to handle the computational problem when there are large common nodes or large joint probability propagation occurred in a Bayesian network. By Learning methods, such as structural learning, parametric learning, adaptation learning, etc., we can use experience gained from these models to construct an accurate Bayesian network and to assign sensible probability values to evidence.

This paper has demonstrated the potentials of applying the Bayesian Network model in computer forensics analyses. Since computer forensics science is still in its developing stage, a Bayesian Network model analysis can offer scientific grounds for a computer forensics practitioner to evaluate and to justify his forensics findings. Moreover, further research and analysis are needed to enhance the inference capability and accuracy of the Bayesian Network model before it can widely be adopted in the computer forensics discipline.

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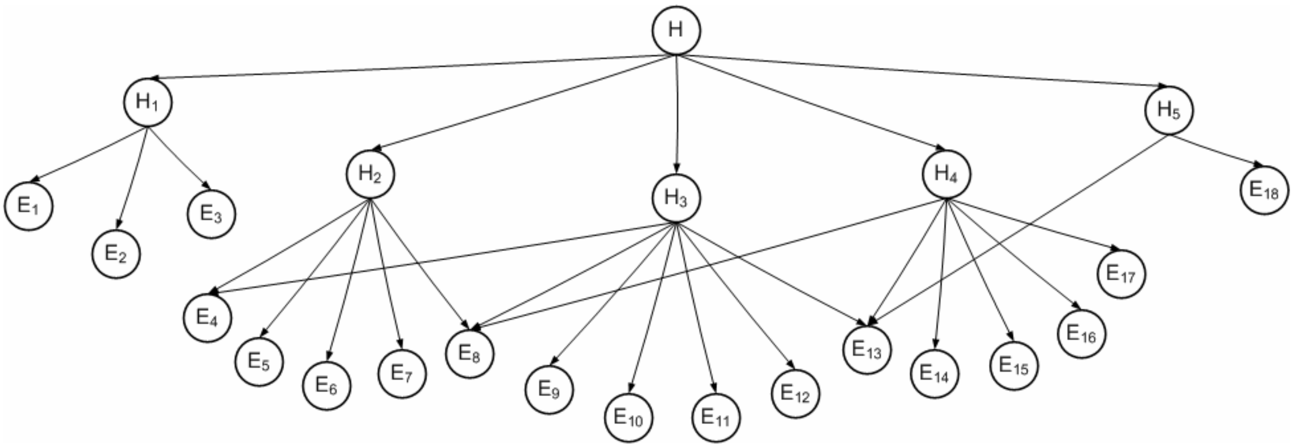
Appendix

Overall Bayesian network diagram:



HYPOTHESES:

H - Has the seized computer been used as the initial seeder to share infringing file on a BitTorrent network?
H_1 - Has the pirated file copied from optical disc to computer?
H_2 - Has a BT torrent file been created from the copied file?
H_3 - Has the torrent file been sent to newsgroup forum for publishing?
H_4 - Has the torrent file been activated and made the computer connected to the Tracker server?
H_5 - Has the connection between the computer and the Tracker server been maintained?

EVIDENCE:

E_1 - "Modify" time of the destination file equals to that of the sourced file
E_2 - "Creation" time of the destination file lags behind its own "modify" time
E_3 - Hash value of the destination file matches that of the sourced file
E_4 - BitTorrent client software is installed on the computer
E_5 - File link for the shared file created
E_6 - File being shared exists in the hard disk
E_7 - Torrent file creation record is found
E_8 - Torrent file exists in the hard disk
E_9 - Peer connection information is found
E_{10} - Tracker server log-in record is found
E_{11} - Torrent file activation time reflected from MAC time of Torrent file and its link file
E_{12} - Internet history record on publishing website is found
E_{13} - Internet connection is available
E_{14} - Cookie of the publishing website is found
E_{15} - URL of the publishing website is stored in the web browser
E_{16} - Web browser software is available
E_{17} - Internet cache record on publishing of Torrent file is found
E_{18} - Internet history record on Tracker server connection is found