Measuring Network Security Using Dynamic Bayesian Network

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ABSTRACT
Given the increasing dependence of our societies on networked information systems, the overall security of these systems should be measured and improved. Existing security metrics have generally focused on measuring individual vulnerabilities without considering their combined effects. Our previous work tackle this issue by exploring the causal relationships between vulnerabilities encoded in an attack graph. However, the evolving nature of vulnerabilities and networks has largely been ignored. In this paper, we propose a Dynamic Bayesian Networks (DBNs)-based model to incorporate temporal factors, such as the availability of exploit codes or patches. Starting from the model, we study two concrete cases to demonstrate the potential applications. This novel model provides a theoretical foundation and a practical framework for continuously measuring network security in a dynamic environment.

Categories and Subject Descriptors
D.4.6 [Security and Protection]: Invasive software (e.g., viruses, worms, Trojan horses); K.6.5 [Security and Protection]: Unauthorized access (e.g., hacking, phreaking)

General Terms
Security

1. INTRODUCTION
Our society has become increasingly dependant on the reliability and proper functioning of a vast number of interconnected information systems. To improve the security of these systems, it is necessary to measure the amount of security provided by different configurations since you cannot improve what you cannot measure [12]. The aim of our research is to develop coherent, logical and applicable security metrics for computer networks.

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There exist considerable research and standard techniques for measuring individual vulnerabilities, such as the Common Vulnerability Scoring System (CVSS) [7]. However, by considering vulnerabilities on an individual basis, a network security administrator could be misled in a situation where individual vulnerabilities scores are low but these vulnerabilities can be combined to compromise a critical resource. Our previous research explores the causal relationships between vulnerabilities encoded in an attack graph to model the overall security of a network, which includes a general framework [26], a real-valued metric [28], a probabilistic metric [24], and a Bayesian Network (BN)-based approach [8].

Problem Statement and Success Criteria.
The main problem solved in this paper is the following. The evolving nature of vulnerabilities has largely been ignored in most existing work on network security metrics. The main hypothesis is that the threat posed by a vulnerability may change over time in today’s dynamic network environment. When more technical details of a vulnerability become available, its exploitability or severity may need to be adjusted; when patches are released by vendors to counter an exploit, the vulnerability may become less severe; on the other hand, when exploit codes become more widely spread, the severity of a vulnerability may increase. Therefore, it is insufficient to rate vulnerabilities with fixed scores.

In our understanding, a successful solution to network security metrics should meet following criteria. First, it should model various temporal aspects of a vulnerability. The temporal scores in CVSS [7] provide a partial solution. Second, the solution should combine the temporal scores of individual vulnerabilities into a global rating of security of the whole network at any given time. CVSS lacks such a capability as it does not take into consideration the interplay of vulnerabilities in a given network. Third, it is also desirable that temporal trends and patterns can be discovered and used for reasoning about future security scores based on past incidents or observations.

In this paper, we propose a Dynamic Bayesian Network (DBN)-based model to incorporate relevant temporal factors, such as the availability of exploit codes or patches, into attack graph-based security metrics. As we shall show, our model meets all aforementioned success criteria of a network security metric. More specifically, we first show how to interpret an attack graph as a special DBN; then we combine individual base scores of CVSS using their causal relationships; finally, we integrate the effect of temporal factors into an overall network security score.
scores of CVSS to derive the final measurement of security. To demonstrate potential applications of our model, we discuss two concrete cases where either the exploitability or the temporal score of a vulnerability is unobservable and can be derived through reasoning with the proposed model.

The main contribution of the paper is two fold. First, by modeling attack graphs as special DBNs, we devise a sound theoretic foundation for the development and application of security metrics in a dynamic environment. Second, by binding our model to the CVSS standard, we provide a practical way for deriving actionable knowledge about the overall security of a network. The rest of the paper is organized as follows. Section 2 reviews relevant concepts of attack graph and DBN. Section 3 describes the proposed model and discusses two concrete cases. Section 4 studies two cases of applying the model. Section 5 reviews related work. Section 6 discusses future work and concludes the paper.

2. PRELIMINARIES

To be self-contained, this section reviews relevant concepts of the attack graph model and DBN.

2.1 Attack Graph Model

Attack graphs model the knowledge about how multiple vulnerabilities may be combined for an attack. The model represents system states using security-related conditions, such as the existence of vulnerabilities on a host or the connectivity between hosts, and state transitions using exploits of vulnerabilities. For our purposes, an attack graph is a directed graph with conditions and exploits as vertices, and their relationships as edges [1]. Figure 1 shows a toy example of network configuration on the left-hand side and the corresponding attack graph on the right-hand side.

![Figure 1: Network Configuration and Attack Graph](image)

This section introduces the proposed models in three steps. We first describe the value assignment for individual exploits based on CVSS scores; we then describe the model for static domain; finally, we discuss the models for dynamic domain in two cases.

3. THE MODEL

3.1 CVSS-Based Individual Value Assignment

There are two inputs to our model, namely, attack graph and CVSS scores. First, we assume the attack graph of a given network can be obtained using existing tools, such as the Topological Vulnerability Analysis (TVA) system, which can generate attack graphs model the knowledge about how multiple vulnerabilities may be combined for an attack.
graphs for more than 37,000 vulnerabilities taken from 24 information sources including X-Force, Bugtraq, CVE, CERT, Nessus, and Snort [11]. Second, we assume the CVSS scores of vulnerabilities in the given attack graph can be obtained from existing vulnerability databases, such as the National Vulnerability Database (NVD) [18]. To facilitate further discussions, we review relevant CVSS concepts in the following.

- The Base Score (BS) for each vulnerability quantifies its intrinsic and fundamental properties that are supposed to be constant over time and independent of user environments. The value of BS ranges from 0 to 10.

- The Temporal Metric Values quantify a vulnerability when considering properties of the vulnerability that may change over time. The three temporal metric values used in CVSS are Exploitability (E), Remediation Level (RL), and Report Confidence (RC). In particular, the Exploitability (E) can take one of the four annotated values: 0.85 (U), 0.9 (PoC), 0.95 (F), and 1.00 (H).

- For convenience, we name the product \( TGS = (E \times RL \times RC) \) as the Temporal Group Score (TGS). Based on the possible values of E, RL and RC [7], the value of TGS ranges from 0.67 to 1.0.

- The Temporal Score (TS) is the product of BS and TGS:

\[
TS = \text{round}_\text{to}_1_{\text{decimal}}(BS \times TGS)
\]  

TS ranges from 0 to 10.

We convert CVSS scores of a vulnerability to probabilities as follows. First, we convert the score BS (or TS in the dynamic case) to a probability using a simple approach of diving it by the domain size 10. We then associate this probability to all the exploits that has this vulnerability (recall that an exploit is a vulnerability bound to specific source and destination hosts). Second, CVSS scores are proposed for quantifying individual vulnerabilities only. Those scores ignore the causal relationships between exploits in the context of a given network, which is modeled in attack graphs. Therefore, we define the probability converted from a score as the conditional probability of an exploit when all of its preconditions in the attack graph are already satisfied (by other exploits that imply the attack graph are already satisfied). Those scores ignore the causal relationships between exploits in the context of a given network, which is modeled in attack graphs.

For example, Figure 2 shows a BN with three exploits A, B, and C in which an attacker can achieve the goal state by following one of either two paths (for simplicity, we shall omit conditions from now on). The probabilities are converted from BS scores (by dividing them by 10). Using Equation 2, we can construct the CPDs for each vertex as shown on the right-hand side of Figure 2. From the CPD tables, we can observe that C is true as long as at least one of A and B is true. This indicates a disjunctive relationship between A and B with respect to C.

\[
P(e = T | \forall c \in R_e (e) \ c = T) = BS/10
\]  

For example, in Figure 1, we have \( P(\text{rsh}(0, 1) = T | \text{trust}(0, 1) = T) = BS_{\text{rsh}(0,1)}/10 \). Since the condition \( \text{trust}(0, 1) \) can only be satisfied by one exploit \( ftp_{\text{rhosts}}(0,1) \), we can relate probabilities of the two exploits as \( P(\text{rsh}(0, 1) = T | \text{trust}(0, 1) = T) = P(\text{rsh}(0, 1) = T | ftp_{\text{rhosts}}(0,1) = T) = BS_{\text{rsh}(0,1)}/10 \).

### 3.2 Static Domain

We are now ready to use Bayesian network (BN) to represent attack graph-based probabilistic metrics in the static case. The vertices of the BN represent exploits derived from the attack graph. Each vertex is annotated with a probability assigned according to Equation 2. The CPD tables can then be developed to encode the probability values for each vertex and its conditional dependencies. Such a BN-based model allows propagating probabilities of an attacker reaching each condition. In particular, we are interested in the goal state (the final conditions), which can be used as an indicator about the overall security of the network.

More formally, given an attack graph \( G(E \cup C, R_e \cup R_c) \), we represent the attack graph using a Bayesian network which is a pair \( B = (G, Q) \) where \( G \) is the directed graph corresponding to the attack graph but with a different semantics, that is, the vertices represent the binary variables of the system and the edges represent the conditional relationships among the variables. \( Q \) is the set of parameters that quantify the BN such as the conditional distribution values for each variable (vertex). The joint distribution for a Bayesian network is represented in the standard way as (the notations are self-explanatory): \( P(X_1, ..., X_n) = \prod_{i=1}^{n} P(X_i | \text{parents}(X_i)) \).

The unique aspect of this BN representation is the following. In an attack graph, the causal relationships between exploits can be disjunctive or conjunctive based on how they are related through conditions [8]. Such relationships are represented in our BN representation using conditional probabilities of 0 or 1. More specifically,

- We say a disjunctive relationship exists between any exploits \( e_1, e_2, ..., e_n \) with respect to \( e_{n+1} \) when \( e_j R e_{n+1} \) holds for all \( j = 1, 2, ..., n \) and some condition \( e_{n+1} \) is true. In such a case, the probability assignment based on Equation 2 will satisfy \( P(e_{n+1} = T | X) = 1 \) for all \( X \) that has \( e_j = T \) hold for at least one \( j \in [1, n] \).

- We say a conjunctive relationship exists between exploits \( e_1, e_2, ..., e_n \) with respect to \( e_{n+1} \) when \( e_j R e_{n+1} \) and \( e_j R e_{n+1} \) both hold for all \( j = 1, 2, ..., n \) and some conditions \( e_j \)’s. In such a case, we have \( P(e_{n+1} = T | X) = 0 \) whenever \( X \) has \( e_j = F \) hold for at least one \( j \in [1, n] \).

For example, Figure 2 shows a BN with three exploits A, B, and C in which an attacker can achieve the goal state by following one of either two paths (for simplicity, we shall omit conditions from now on). The probabilities are converted from BS scores (by dividing them by 10). Using Equation 2, we can construct the CPDs for each vertex as shown on the right-hand side of Figure 2. From the CPD tables, we can observe that C is true as long as at least one of A and B is true. This indicates a disjunctive relationship between A and B with respect to C.

\[
\text{Figure 2: Representing Attack Graphs as BNs}
\]
we are interested in the probability that $C = T$ (that is, vulnerability $C$ has been successfully exploited). This can be calculated as $P(C = T) = \sum_{A, B} P(C = T | A, B) = 0.204$. As an example application, this calculation can be applied to different network configurations in order to compare their relative security.

### 3.3 Dynamic Domain

As described in Section 3.1, CVSS provides several temporal scores in addition to base scores in order to model the time variant factors in determining the severity of a vulnerability. Such scores are, however, still intended for individual vulnerabilities instead of the overall security of a network. Our objective is to evolve the aforementioned BN-based model to DBNs such that we can model the security of dynamically changing networks. The temporal links between time slices of the DBN will be established between the unobservable variables of the model. Those links will then enable the inference of unknown values based on the previous slice of the DBN.

We introduce two additional sets of vertices into the previous BN model. The first is the collection of BS vertices that correspond to the base score of vulnerabilities. The second is the collection of TGS vertices that correspond to the temporal group scores as defined in Section 3.1. The existing exploit vertices will then carry the final metric score $TS$ (instead of the BS in the static case), which has a similar role as the calculated scores in the case of static domain (as described in Section 3.2). However, in the dynamic domain, the final score of each exploit will depend on four factors: The base score, the temporal score, the causal relationship between exploits and others, and the previous time slice (this will become clearer later when we discuss the two concrete cases).

Formally, given an attack graph $G$ as a directed graph $G(E \cup C, R, \cup R_t)$, we define $E_{BS}$ and $E_{TGS}$ with the same cardinality as $E$ to represent the set of BS and TGS nodes. We then obtain an enriched set of nodes as $E' = E \cup E_{BS} \cup E_{TGS}$. Let $G'$ be the directed graph corresponding to $E'$ in which the relations $R_t$ and $R$ remain the same. Then we can have the one slice BN as a pair $(G', Q)$ where $Q$ represents the conditional probabilities assigned as before. We then define a DBN as a pair $(B_0, B_1)$, where $B_0$ defines the prior $P(X_i)$, and $B_1$ is a two-slice temporal Bayes net(2TBN) that defines $P(X_i | X_{i-1})$ by means of a DAG: $P(X_i | X_{i-1}) = \prod_{s \in S} P(X_s | parents(X_s))$.

For $B_0$, conditional probabilities are assigned in a similar way as in the static case except that now we use the TS scores instead of the BS scores. More specifically, the TS scores are derived as the product of BS and TGS using Equation 1. The derived TS scores are then assigned as conditional probabilities based on Equation 2. For $B_1$, the assignment of interslice conditional probabilities will depend on specific needs of applications, since different variables in a time slice may be regarded as unobservable, and the effect of a previous slice will depend on the semantics of the variables in question. To make our discussions more concrete, we shall discuss two cases to illustrate the potential of our model.

First, the TS score of each vulnerability is of interest (for example, to security administrators of a network) and needs to be derived from the base scores, temporal scores, and interslice dependency. More formally, our DBN $(B_0, B_1)$ will be a two-slice temporal Bayes net(2TBN) that defines a DAG including only arcs between nodes in $E$. In this case, we assign conditional probabilities as follows. When a vulnerability has been successfully exploited in one time slice, then its probability of being exploited in the next time slice is equal to “1”, otherwise the probability assigned to the exploit vertex is the same as in the case of $B_0$ (that is, the previous slice has no effect). This simple choice reflects the intuition that a successful exploit will lead to more exploits of the same vulnerability (more realistic ways for assigning such probabilities certainly exist).

Second, the temporal score of a vulnerability is of interest (for example, to security vendors who maintain those scores) and needs to be derived from base scores and the observed TS scores (estimated from the amount of reported security incidents involving that vulnerability). More formally, in this case, our DBN $(B_0, B_1)$ will be a two-slice temporal Bayes net(2TBN) that defines a DAG including only arcs between nodes in $TGS$ (or its components). For this case, the conditional probabilities can be assigned to reflect the temporal trends in those scores. In next section, we shall rely on a simple choice that if the $E$ (Exploitability) score is confirmed to be one of the four discrete levels (U=0.85, PoC=0.9, F=0.95, or H=1.0 [7]), then its calculated value will be rounded to the same level in the next slice. For example, if without considering interslice conditional probabilities we can calculate $E$ as 0.94, then the conditional probability that $E$ is rounded to PoC (instead of F) given $E$=PoC in the preceding slice will be assigned as 1 (again, this is only an illustrative example and other temporal trends can certainly be used here).

### 4. CASE STUDY

This section studies two examples of applying the proposed model.

#### 4.1 Case 1: Exploit Scores Are Unobservable

To security administrators, the final score of each exploit is usually unobservable, whereas the BS and TGS vertices are observable. The observable values for the BS vertices can be obtained from NVD and the observable values for the TGS vertices can be calculated using CVSS equations described in Section 3.1. To model the temporal dependency between time slices, arcs linking the time slices are introduced between the exploit vertices since they are unobservable. Our objective is to infer their values and eventually calculate the likelihood of attackers in reaching the goal state.

Figure 3 shows our DBN model in this case through a toy example of two exploits. In our model, we define the exploit vertices (“addusrphp” and “sunvect”) in this example) to be conditionally dependent on their respective BS and TGS vertex values as represented graphically in Figure 3. In the example, the value of exploit “sunvect” is conditionally dependent on the value of exploit vertex “addusrphp”. This causal relationship implies that vulnerability “addusrphp” must be exploited first in order for vulnerability “sunvect” to be exploited. In this example, the goal state is the successful exploitation of vulnerability “sunvect”.

To model the temporal dependency, arcs linking the time slices are introduced between “addusrphp” and “sunvect”. To complete the model, we need to develop the CPDs for the intraslice relationships (within the same time slice) and the interslice relationships (from one time slice to the next). Suppose our objective is to calculate the probability value of an attacker successfully exploiting “sunvect” for any time slice. From NVD we obtain the BS for each vulnerability as follows: $BS(addusrphp) = 7.5$ and $BS(sunvect) = 10.0$. For simplicity, we will consider only the E temporal metric and will assume initially the E metric is Unproven (U). We compute $TGS = 0.85 \times 1.0 \times 1.0$. We can then derive the probability for “addusrphp” as 0.64 and that for “sunvect” as 0.85. Figure 4 illustrates the intraslice CPDs. We can then compute that $P(sunvect = T) = 0.54$ for the first slice. Figure 5 illustrates how the interslice CPD can be calculated for later slices (in this
particular example the values do not change in the 2nd slice so we omit the table).

<table>
<thead>
<tr>
<th>addusrphp</th>
<th>T</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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<table>
<thead>
<tr>
<th>sunvect</th>
<th>T</th>
<th>T</th>
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</thead>
<tbody>
<tr>
<td></td>
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</table>

4.2 Case 2: Temporal Scores Are Unobservable

To vendors that create and maintain the CVSS databases, temporal scores are unobservable and must be estimated based on base scores and reported security incidents. We now consider the case where the exploitability (E) temporal metric vertex for each vulnerability is unobservable. In the previous case, we were able to observe the E metric value and then compute the TGS value. In this case, we have the reverse situation. The goal in this case is to update the E Temporal Metric values for maintaining the CVSS databases based on the DBN model.

Figure 6 illustrates the DBN model for this case where only the unobservable E metric vertices are linked from one time slice to the next. The interpretation is that the value of the E metric in the previous time slice will have an impact on determining the likelihood of which state the E metric vertex will be in during the subsequent time slices. Figure 7 shows the intraslice CPDs while Figure 8 shows the interslice CPDs (we only show the results since the calculation is similar to the previous case).

We now discuss an example analysis using the model. Suppose reported security incidents show that the likelihood that “addusrphp” will be exploited in “Time 0” is 0.66 and that the likelihood of “sunvect” being exploited is 0.94. We can calculate the TGS vertex scores for each exploit as $0.66 / 0.75 = 0.88$ and $0.94 / 1 = 0.94$, respectively. We then need to map these calculated scores to one of the four discrete levels given by CVSS (U=0.85, POC=0.9, F=0.95 and H=1.0). The DBN model will allow us to base such a mapping on the previous slice, since a previously confirmed level will support mapping the calculated value to the same level.

5. RELATED WORK
The idea of using BNs to model network vulnerabilities and determine a quantitative value representing the security of a network has been explored by Liu and Man [13]. A BN is used to model all potential atomic attack steps in a network. Each vertex represents a single security property violation state and each edge corresponds to an exploitation of one or more exhibited vulnerabilities. They assign edge weights to represent the probability of successful execution of an exploit and then demonstrate how the use of DBNs can be used to determine network security. The work on minimum-cost network hardening represents an early effort toward the quantitative study of network security. This paper has pointed out the lack of consideration for temporal factors in previous work on measuring network security. This paper then proposes a novel DBN-based model for capturing the evolving nature of vulnerabilities in a computer network. We show that DBN can be derived from attack graphs and standard metric values and the derived model can be used for analyzing the constantly changing security aspects of a network. We develop our model in close association with the standard CVSS scores in order to ensure the model can lead to actionable knowledge.

As future work, we are implementing a practical tool for measuring network security by integrating attack graphs generated by the TVA system [11] with CVSS scores provided by NVD. Based on such a tool, we plan to conduct real-world experiments to evaluate our methods. We will continue to refine our approach using DBNs to encompass more properties of the temporal metrics established in the CVSS in order to develop a more accurate model. We will examine how the model can be refined to take into consideration the environmental factors of CVSS. We will also study the application of the proposed model for hardening a vulnerable network with the least cost. In our model, we made the assumption that the Markovian Property applies. It would be interesting to explore the relevance of this assumption in real-world scenarios.

### Figure 7: Intraslice CPDs

| E_{i-1} | TGS_{\theta} | P(E_i=column value|TGS_{\theta}) |
|---------|-------------|-------------------------------|
| U       | 0.85        | 1.0                           |
|         | 0.9         | 0.7                           |
|         | 0.95        | 0.3                           |
|         | 1.0         | 0.0                           |
| POC     | 0.85        | 1.0                           |
|         | 0.9         | 0.1                           |
|         | 0.95        | 0.0                           |
|         | 1.0         | 0.0                           |
| F       | 0.85        | 1.0                           |
|         | 0.9         | 0.1                           |
|         | 0.95        | 0.0                           |
|         | 1.0         | 0.0                           |
| H       | 0.85        | 1.0                           |
|         | 0.9         | 0.1                           |
|         | 0.95        | 0.0                           |
|         | 1.0         | 0.0                           |

### Figure 8: Interslice CPDs

| E_{i-1} | TGS_{\theta} | P(E_i=column value|E_{i-1}) |
|---------|-------------|-------------------------------|
| U       | 0.85        | 1.0                           |
|         | 0.9         | 0.7                           |
|         | 0.95        | 0.3                           |
|         | 1.0         | 0.0                           |
| POC     | 0.85        | 1.0                           |
|         | 0.9         | 0.1                           |
|         | 0.95        | 0.0                           |
|         | 1.0         | 0.0                           |
| F       | 0.85        | 1.0                           |
|         | 0.9         | 0.1                           |
|         | 0.95        | 0.0                           |
|         | 1.0         | 0.0                           |
| H       | 0.85        | 1.0                           |
|         | 0.9         | 0.1                           |
|         | 0.95        | 0.0                           |
|         | 1.0         | 0.0                           |

### 6. CONCLUSION AND FUTURE WORK

This paper has pointed out the lack of consideration for temporal factors in previous work on measuring network security. This paper then proposes a novel DBN-based model for capturing the evolving nature of vulnerabilities in a computer network. We show that DBN can be derived from attack graphs and standard metric values and the derived model can be used for analyzing the constantly changing security aspects of a network. We develop our model in close association with the standard CVSS scores in order to ensure the model can lead to actionable knowledge.
usefulness of a model where this is not necessarily the case.

Acknowledgements

The authors thank the anonymous reviewers and the shepherd Fabio Massacci for their valuable comments. This material is based upon work supported by National Institute of Standards and Technology Computer Security Division; by Homeland Security Advanced Research Projects Agency under the contract FA8750-05-C-0212 administered by the Air Force Research Laboratory/Rome; by Army Research Office under grant W911NF-05-1-0374, by Federal Aviation Administration under the contract DTFWA-04-P-00278/0001, by the National Science Foundation under grants CT-0627493, IIS-0242237 and IIS-0430402, by Natural Sciences and Engineering Research Council of Canada under Discovery Grant N01035, and by Fonds de recherche sur la nature et les technologies. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the sponsoring organizations.

7. REFERENCES


