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LINKING EXPLOITS FROM THE DARK WEB TO KNOWN VULNERABILITIES FOR PROACTIVE CYBER THREAT INTELLIGENCE: AN ATTENTION-BASED DEEP STRUCTURED SEMANTIC MODEL[1]

Sagar Samtani
Department of Operations and Decision Technologies, Indiana University,
Bloomington, IN, U.S.A. {ssamtani@iu.edu}

Yidong Chai
School of Management, Hefei University of Technology,
Hefei, Anhui, CHINA {cahiyd@hfut.edu.cn}

Hsinchun Chen
Department of Management Information Systems, University of Arizona,
Tucson, AZ, U.S.A. {hsinchun@arizona.edu}

Black hat hackers use malicious exploits to circumvent security controls and take advantage of system vulnerabilities worldwide, costing the global economy over $450 billion annually. While many organizations are increasingly turning to cyber threat intelligence (CTI) to help prioritize their vulnerabilities, extant CTI processes are often criticized as being reactive to known exploits. One promising data source that can help develop proactive CTI is the vast and ever-evolving Dark Web. In this study, we adopted the computational design science paradigm to design a novel deep learning (DL)-based exploit-vulnerability attention deep structured semantic model (EVA-DSSM) that includes bidirectional processing and attention mechanisms to automatically link exploits from the Dark Web to vulnerabilities. We also devised a novel device vulnerability severity metric (DVSM) that incorporates the exploit post date and vulnerability severity to help cybersecurity professionals with their device prioritization and risk management efforts. We rigorously evaluated the EVA-DSSM against state-of-the-art non-DL and DL-based methods for short text matching on 52,590 exploit-vulnerability linkages across four testbeds: web application, remote, local, and denial of service. Results of these evaluations indicate that the proposed EVA-DSSM achieves precision at 1 scores 20% - 41% higher than non-DL approaches and 4% - 10% higher than DL-based approaches. We demonstrated the EVA-DSSM's and DVSM's practical utility with two CTI case studies: openly accessible systems in the top eight U.S. hospitals and over 20,000 Supervisory Control and Data Acquisition (SCADA) systems worldwide. A complementary user evaluation of the case study results indicated that 45 cybersecurity professionals found the EVA-DSSM and DVSM results more useful for exploit-vulnerability linking and risk prioritization activities than those produced by prevailing approaches. Given the rising cost of cyberattacks, the EVA-DSSM and DVSM have important implications for analysts in security operations centers, incident response teams, and cybersecurity vendors.

Keywords: hacker forums, design science, dark web, online hacker community, cybersecurity analytics, cybersecurity

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Introduction

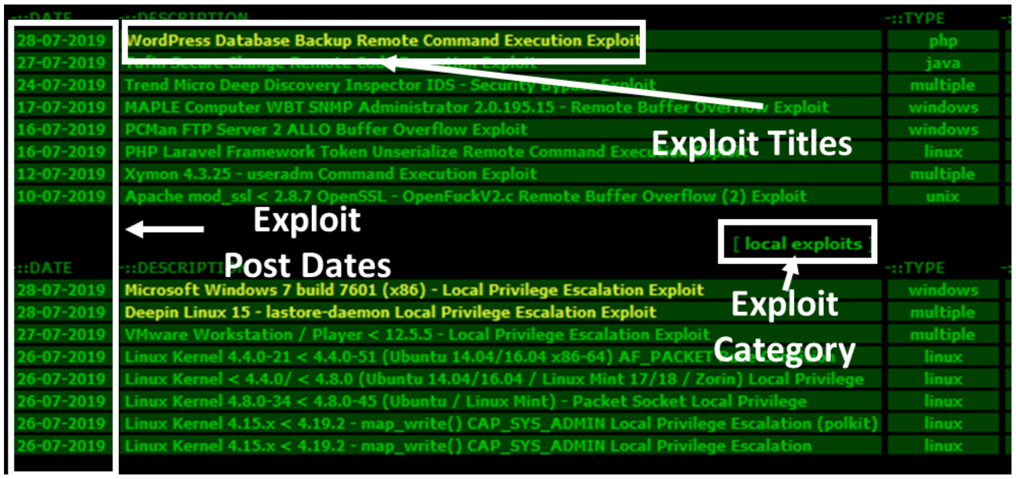
The rapid proliferation of computing technologies has afforded modern society with unprecedented benefits. Industry, government, and academia use databases, communication networks, and other information systems (IS) to execute day-to-day operations with unparalleled efficiency and effectiveness. Unfortunately, black hat hackers often use malicious exploits to circumvent security controls and take advantage of system vulnerabilities for cyberwarfare, hacktivism, espionage, or financial purposes. These cyberattacks cost the global economy over $450 billion annually (Graham, 2017). To combat this societal issue, many organizations are increasingly developing cyber threat intelligence (CTI) to manage knowledge about hackers and emerging threats (Samtani et al., 2020a). A common step within the CTI process is vulnerability assessment, where organizations assess their systems' flaws using automated tools such as Nessus. Vulnerability assessment results help analysts collect relevant data from log files located in databases, firewalls, and servers. Analytics such as malware analysis, event correlation, and forensics derive intelligence for CTI professionals to prioritize vulnerable devices for subsequent remediation and mitigation.

Despite the maturity of CTI procedures, experts note that the reliance on past events (e.g., log files) creates reactive intelligence (Bromiley, 2016). Major industry firms such as Ernst & Young have long expressed that "organizations need to take a more proactive approach to cybersecurity" (EY, 2014). Similarly, the internationally recognized SANS Institute has consistently urged organizations to use "external threat intelligence sources to help alert the organization of threats it was not previously aware of" (Bromiley, 2016). One promising and emerging data source that can help CTI professionals proactively identify exploits is the online hacker community or "Dark Web" (Benjamin et al., 2019). The Dark Web is an appealing data source for CTI as it contains millions of hacking tools from hackers in the US, Russia, the Middle East, and China. The Dark Web comprises four major platforms (Benjamin et al., 2019): forums, Internet-Relay-Chat (IRC), DarkNet Markets (DNMs), and carding shops. While each platform offers CTI value, forums are the largest (often tens of millions of posts in a forum) and allow hackers to freely share exploits (Samtani et al., 2017). We illustrate example exploits with their metadata (e.g., titles, dates, categories) from a hacker forum on the Dark Web in Figure 1.

Researchers and practitioners have found thousands of SQL injections, rootkits, crypters, and other malicious exploits within large, international, and evolving hacker forums (Samtani et al., 2017). Such exploits have helped hackers execute highly publicized attacks resulting in organizations losing tens of millions of dollars and significant reputation (e.g., BlackPOS for Target breach) (Kitten, 2014). These significant ramifications underscore the importance for organizations to identify the hacker exploits relevant to their vulnerabilities to improve their cybersecurity posture (Shackleford, 2016). Although many exploit and vulnerability names share similar semantics (e.g., "Telnet Cracker" exploit and "Unencrypted Telnet Server" vulnerability), automatically creating links in a scalable and accurate manner is a nontrivial task due to significant non-natural language content (e.g., system and technology names) and volume of hacker forums and vulnerability assessment data. These data characteristics limit the direct application of standard CTI and text mining methods and necessitate novel computational algorithms rooted in artificial intelligence (AI) (Benjamin et al., 2019; Samtani et al., 2020a).

While IS scholars are uniquely equipped to tackle these challenges, existing IS cybersecurity research has focused on behavioral compliance (Wang et al., 2010; Wang et al., 2015; Vance et al., 2015; Chen & Zahedi, 2016), risk management (Spears & Barki, 2010), security investments (Li et al., 2012; Ransbotham et al., 2012; Kwon & Johnson, 2014), and market effects of cybersecurity (Gupta & Zhdanov, 2012; Kim & Kim, 2014). Studies in each area use behavioral or economic methods to make excellent contributions to our understanding of cybersecurity. The unique characteristics of hacker forum and vulnerability assessment data combined with CTI's emphasis on the rapid development of novel systems and algorithms necessitates novel computational information technology (IT) artifacts (Rai, 2017; Mahmood et al., 2010; Samtani et al., 2020a). Motivated by the ever-increasing attention on developing proactive CTI from the online hacker community and by the lack of IS and cybersecurity analytics studies, we adopted the computational design science paradigm to develop a CTI framework with two contributions:

1. **Exploit vulnerability attention deep structured semantic model (EVA-DSSM).** We designed a novel Deep Learning (DL)-based EVA-DSSM that automatically links exploits from hacker forums to vulnerabilities detected by prevailing vulnerability assessment tools. EVA-DSSM incorporates principles from emerging methods such as the deep structured semantic model (DSSM) from neural information retrieval and attention mechanisms from interpretable DL to automatically extract and weight the sequential dependencies and global relationships present in exploit and vulnerability names to create exploit-vulnerability linkages.



```
::DATE       ::DESCRIPTION                                                                          ::TYPE
28-07-2019   WordPress Database Backup Remote Command Execution Exploit                             php
27-07-2019   [illegible]                                                                            java
24-07-2019   Trend Micro Deep Discovery Inspector IDS - Security [illegible] Exploit                multiple
17-07-2019   MAPLE Computer WBT SNMP Administrator 2.0.195.15 - Remote Buffer [illegible] Exploit   windows
16-07-2019   PCMan FTP Server 2 ALLO Buffer Overflow Exploit                                        windows
16-07-2019   PHP Laravel Framework Token Unserialize Remote Command Execu[illegible]                linux
12-07-2019   Xymon 4.3.25 - useradm Command Execution Exploit                                       multiple
10-07-2019   Apache mod_ssl < 2.8.7 OpenSSL - OpenFuckV2.c Remote Buffer Overflow (2) Exploit       unix

                                                                            [ local exploits ]
::DATE       ::DESCRIPTI[illegible]                                                                 ::TYPE
28-07-2019   Microsoft Windows 7 build 7601 (x86) - Local Privilege Escalation Exploit              windows
28-07-2019   Deepin Linux 15 - lastore-daemon Local Privilege Escalation Exploit                    multiple
27-07-2019   VMware Workstation / Player < 12.5.5 - Local Privilege Escalation Exploit              multiple
26-07-2019   Linux Kernel 4.4.0-21 < 4.4.0-51 (Ubuntu 14.04/16.04 x86-64) AF_PACKET[illegible]      linux
26-07-2019   Linux Kernel < 4.4.0/ < 4.8.0 (Ubuntu 14.04/16.04 / Linux Mint 17/18 / Zorin) Local Privilege   linux
26-07-2019   Linux Kernel 4.8.0-34 < 4.8.0-45 (Ubuntu / Linux Mint) - Packet Socket Local Privilege linux
26-07-2019   Linux Kernel 4.15.x < 4.19.2 - map_write() CAP_SYS_ADMIN Local Privilege Escalation (polkit)   linux
26-07-2019   Linux Kernel 4.15.x < 4.19.2 - map_write() CAP_SYS_ADMIN Local Privilege Escalation    linux
```

Figure 1. Sample Hacker Forum Posts with Exploits

2. **Device vulnerability severity metric (DVSM).** Based on the exploit-vulnerability linkages generated from the EVA-DSSM, we devised a new DVSM that incorporates exploit and vulnerability metadata such as exploit post date and vulnerability severity into a single score. DVSM aims to provide a holistic metric to help cybersecurity professionals execute their device prioritization, vulnerability remediation, and risk management efforts.

Consistent with the computational design science paradigm (Rai, 2017), we rigorously evaluated the EVA-DSSM against state-of-the-art non-DL and DL-based short text matching methods with a series of technical benchmark experiments on four large-scale testbeds of exploits: web application, remote, local, and denial of service (DoS). We demonstrated the EVA-DSSM's and DVSM's practical utility with two CTI case studies: openly accessible systems in major U.S. hospitals and supervisory control and data acquisition (SCADA) systems. Finally, we conducted a complementary user evaluation with 45 cybersecurity professionals that examined the usefulness of the EVA-DSSM and DVSM results against those generated by prevailing benchmark approaches for the hospital and SCADA case studies. Taken together, the EVA-DSSM and DVSM have implications for analysts in security operations centers (SOCs), incident response (IR) teams, and cybersecurity vendors.

Related Work

We review four streams of literature to ground and guide our work: (1) hacker community (Dark Web) research to provide an overview of major platforms and identify how past studies have examined exploits within hacker forums, (2) vulnerability assessment principles to understand the prevailing approaches for discovering, assessing, and ranking vulnerabilities, (3) the DSSM to understand how the prevailing DL-based approach for short text matching operates, and (4) attention mechanisms identify how they can be incorporated into the DSSM to improve exploit-vulnerability linking performance.

Hacker Community (Dark Web) Research

As indicated in the introduction, hackers from the US, Russia, China, and the Middle East often congregate on hacker forums, DarkNet Markets, IRC, and carding shops to exchange malicious tools, knowledge, and other content (Du et al., 2018; Benjamin et al., 2019). We further describe each platform, its CTI value, and analytical challenges in Table 1.

Hacker forums contain thousands of freely available exploits, have rich metadata (e.g., post dates), and focus on major themes (e.g., carding, exploits only). DNMs often contain considerable non-cybersecurity-related content (e.g., porn, drugs) and lack valuable CTI metadata (e.g., date) (Ebrahimi et al., 2020). Moreover, products must be purchased (a significant risk for researchers) to gain additional details. IRC and carding shops allow plain-text conversations or the posting of stolen credit cards, respectively, but prevent hackers from posting exploits (Benjamin et al., 2016; Li et al., 2016). Given the analytical challenges that DNMs, IRC, and carding shops present, hacker forums are often preferred by cybersecurity researchers aiming to examine exploit-related content for CTI (Benjamin et al., 2019). We present selected recent studies that examine exploits in online hacker forums in Table 2. We summarize each study's CTI task(s), method(s) employed, identified exploits, and whether any exploit-vulnerability linking was conducted.

Table 1. Summary of Major Hacker Community (Dark Web) Platforms

Platform	Description	CTI value	Analytical challenges
Hacker Forums	Discussion boards allowing hackers to freely share, access, and discuss malicious tools	• Only platform providing freely accessible tools • Richest metadata (post dates, hacker names) for identifying key hacker and emerging threats	• Significant natural, multilingual and non-natural text content • Large quantities of data precludes conventional CTI analytics or manual analysis
DarkNet Markets	Online marketplaces that sell malicious content, illicit goods, and illegal products	• Discover breached/stolen content • Serve as early indicator for breached companies • Pinpoint key sellers	• Lacks key metadata (e.g., post date) • Purchase content before access • Mostly content unrelated to cybersecurity (e.g., drugs, porn)
Internet-Relay-Chat	Online channels that allow clear-text, real-time chat	• Commonly used by hacktivist groups	• No mechanism to share exploits • Significant text content
Carding Shops	Platforms selling stolen credit/debit card information	• Detect breached individuals, organizations, and entities	• Lacks CTI-relevant metadata (e.g., post date) • Limited mechanisms for exploit-sharing

Table 2. Selected Recent Studies Examining Exploits in Online Hacker Forums

Year	Author	CTI task(s)	Method(s)	Identified exploits	Vulnerability linking?
2020	Ampel et al.	Categorizing and labeling hacker exploits	Deep transfer learning	Web applications, DoS, Remote, Local, SQLi, XSS, File inclusion, Overflow	No
2020c	Samtani et al.	Detecting emerging hacker exploits	Diachronic linguistics	DoS, Crypters	No
2019	Schäfer et al.	Forum exploration	SNA	DDoS, botnets, DoS	No
2018	Deliu et al.	Exploit categorization	SVM, LDA	Botnet, crypter, DDoS, rootkit	No
2018	Williams et al.	Incremental collection	LSTM	Database, network, mobile	No
2017	Deliu et al.	Exploit categorization	SVM	Spamming, crypters, SQLi	No
2017	Sapienza et al.	Emerging trends	Keywords	Botnets, DDoS, DoS	No
2017	Samtani et al.	Exploit categorization, key hacker ID, CTI system	SVM, LDA, SNA	Bots, crypters, keyloggers, SQLi, XSS	No
2017	Grisham et al.	Detecting key hackers for mobile malware	RNN, SNA	Mobile malware	No
2016	Samtani and Chen	Identifying key hackers	SNA	Keyloggers	No
2016	Li et al.	Exploring hacker exploits	sLDA	Malware, phishing, botnets	No
2016	Nunes et al.	Exploring hacker exploits	SVM	Botnets, keyloggers, 0-days	No
2015	Samtani et al.	Exploring hacker exploits	SVM, LDA	Bots, crypters, web exploits	No

Note: DDoS = distributed denial of service; DoS = denial of service; DTL= deep transfer learning; LDA = latent Dirichlet allocation; LSTM = long-short term memory; OLS = ordinary least squares; RNN = recurrent neural network; sLDA = supervised latent Dirichlet allocation; SNA = social network analysis; SQLi = structured query language injection; SVM = support vector machine; XSS = cross-site scripting.

Most studies have used algorithms such as SVM, RNN, LSTM, and LDA to identify and categorize bot nets, email hacks, keyloggers, web exploits, and other exploits (Samtani et al., 2015; Nunes et al., 2016; Li et al., 2016; Deliu et al., 2017; Deliu et al., 2018; Williams et al., 2018; Schäfer et al., 2019; Ampel et al., 2020). Some studies have made efforts to study phenomena related to exploits, including identifying key hackers sharing exploits (Samtani et al., 2016; Grisham et al., 2017) and emerging threats (Sapienza et al., 2017; Samtani et al., 2020c). While each study provides valuable knowledge about exploits in Dark Web forums, we are unaware of any studies identifying how exploits link to an organization's vulnerabilities. Designing a forum-based approach to link tens of thousands of exploits and vulnerabilities automatically requires a principled, data-driven methodology. Therefore, we summarize metadata available in hacker forums that provide exploits in Table 3. We categorize metadata into three groups: (1) *description*, which pertains to key descriptors associated with the exploit; (2) *operation*, which details how the exploit operates; and (3) *content*, which is the raw text content from the exploit.

Each exploit has metadata such as the post date, author name, description, category (e.g., web, remote, etc.), and targeted platforms. All fields are fully populated except for "verified exploit" and "common vulnerabilities and exposure" (CVE). Additionally, data may vary in quality and volume. For example, the exploit description and exploit content often contain significant noise and are therefore not reliable data sources for automated exploit-vulnerability linking (Ampel et al., 2020; Samtani et al., 2017). Each exploit name is created by a hacker and therefore often includes information about the targeted system, version, technology, and functions (typically in that order) clearly and unambiguously. These data characteristics can be leveraged to link to an organization's vulnerabilities. However, this requires understanding approaches to discover and categorize vulnerabilities and their data characteristics.

Vulnerability Assessment Principles

A vulnerability is "a flaw within a system, application or service which allows an attacker to circumvent security controls and manipulate systems in ways the developer never intended" (Kennedy et al., 2011). Organizations often use assessment tools to automatically identify, categorize, and prioritize tens of thousands of vulnerabilities, including web application issues, unpatched technology, and default logins (Sectools, 2018). We illustrate a sample vulnerability listing from Nessus, a prevailing vulnerability assessment tool in Table 4. We also categorize and describe key metadata available in the listing.

Each vulnerability in prevailing scanners provides description-based metadata such as name, synopsis, description, class (family) name, CVE, published and updated dates, and a list of vulnerable system versions. Additionally, each vulnerability includes risk details such as CVSS score and risk factor. The vulnerability name is the only fully populated attribute (appears in all records). Cybersecurity professionals construct each name to summarize its key aspects (e.g., susceptible system, version, operations). With respect to risk details, CVSS is essential for vulnerability prioritization and risk management. Designed by Carnegie Mellon University's Computer Emergency Response Team (CERT) and the National Institute of Standards and Technology (NIST), CVSS standardizes vulnerability information by considering various base, environmental, and temporal factors such as vulnerability type, age, and the severity of the consequences if the vulnerability is exploited (Mell et al., 2007). CVSS scores range from 0.0 to 10.0, and are segmented as "informational," "low," "medium," "high," and "critical" levels. We summarize CVSS severity (risk) ranks, CVSS ranges, and examples of vulnerabilities in Table 5.

CVSS provides security practitioners (analysts in SOCs, IR teams) a mechanism for prioritizing and managing the risk of their vulnerable devices (Farris et al., 2018; Samtani et al., 2018). Despite the extensive usage of vulnerability scanners and CVSS, we are unaware of any study that leverages the content within vulnerability names (e.g., system names, technology names, etc.) to identify the most relevant exploit name (also fully populated) from online hacker forums in the Dark Web. Fusing both data sources can help facilitate the development of novel device prioritization metrics that incorporate key metadata from hacker exploits (e.g., post dates) and vulnerability descriptions (e.g., CVSS) (Allodi & Massacci, 2014).

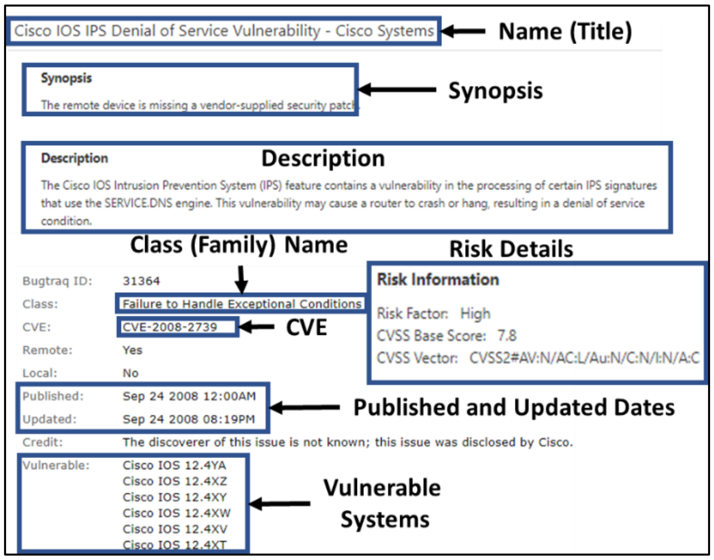
Deep Structured Semantic Model (DSSM)

Our review of the data characteristics of exploits from hacker forums indicates that exploit names are short texts created by hackers that sequentially detail the vulnerability and system(s) they are designed for. Similarly, vulnerability names are short texts produced by cybersecurity professionals that often sequentially summarize the system, version, and method of exploitation. Both attributes are fully populated in exploit and vulnerability data sources and often have relevant and overlapping contents (e.g., system names). Therefore, automatically linking exploits to vulnerabilities using their names only is a scalable, practical, and low-risk approach (no vulnerability recreation or exploit dropping is required).

Table 3. Summary of Metadata in Hacker Forums that Provide Exploits

Category	Metadata	Description
Description	Exploit name	Exploit name that defines its function and target
	Author name	Name of hacker who posted
	Post date	Date when exploit was posted
	Exploit category	Major category an exploit belongs to
Operation	Targeted platform	Specific platform and exploit targets
	Common vulnerabilities and exposure (CVE)	Standardized representation of a vulnerability
	Verified exploit	Verified by community that the exploit is operational
Content	Exploit description	Natural language explanation of the exploit
	Exploit discussion	Discussions between forum members
	Exploit content	Raw exploit source code

Table 4. Illustration and Summary of Vulnerability Assessment Metadata


Cisco IOS IPS Denial of Service Vulnerability - Cisco Systems

Synopsis

The remote device is missing a vendor-supplied security patch

Description

The Cisco IOS Intrusion Prevention System (IPS) feature contains a vulnerability in the processing of certain IPS signatures that use the SERVICE.DNS engine. This vulnerability may cause a router to crash or hang, resulting in a denial of service condition.

Bugtraq ID:	31364
Class:	Failure to Handle Exceptional Conditions
CVE:	CVE-2008-2739
Remote:	Yes
Local:	No
Published:	Sep 24 2008 12:00AM
Updated:	Sep 24 2008 08:19PM
Credit:	The discoverer of this issue is not known; this issue was disclosed by Cisco.
Vulnerable:	Cisco IOS 12.4YA Cisco IOS 12.4XZ Cisco IOS 12.4XY Cisco IOS 12.4XW Cisco IOS 12.4XV Cisco IOS 12.4XT

Risk Information

Risk Factor: High

CVSS Base Score: 7.8

CVSS Vector: CVSS2#AV:N/AC:L/Au:N/C:N/I:N/A:C

Category	Metadata	Description
Description	Name (Title)	Short, descriptive name of vulnerability
	Synopsis	Short description of vulnerability
	Description	Text description about vulnerability
	Class (family) name	Family of the vulnerability
	CVE	Vulnerability number
	Published and updated dates	Date vulnerability was publicly published
	Vulnerable systems	List of systems susceptible to vulnerability
Risk details	CVSS score*	0.0-10.0 vulnerability severity value
	Risk factor	Categorical rating of risk (High, Low)

Note: *CVSS = common vulnerability scoring system.

Table 5. CVSS Score Severity (Risk) Rankings, Ranges, and Examples

Severity (risk) ranking	CVSS range	Examples of vulnerabilities
Critical	9.0 – 10.0	Unsupported* operating system, hypertext preprocessor (PHP) unsupported version detection, open secure sockets layer (OpenSSL) unsupported
High	7.0 – 8.9	SQL injections, OpenSSH vulnerabilities, buffer overflows, Linux chunk handling
Medium	4.0 – 6.9	Cross-site scripting (XSS), browsable web directories, OpenPAM DoS, unencrypted telnet server, Dropbear secure socketshell (SSH) vulnerabilities
Low	0.1 – 3.9	Cleartext submission of credentials, authentication without HTTPS

Note: *Unsupported means that the vendor of the system is no longer providing patches and updates for the system. A viable solution to solve this issue is to upgrade to the latest system version.

Prevailing short-text matching algorithms such as cosine similarity, latent semantic analysis (LSA), best matching 25 (BM25), and term-frequency inverse document frequency (TF-IDF) originate from information retrieval literature (Chen et al., 2012). Despite their widespread usage, these conventional algorithms often suffer in performance when analyzing user- or machine-generated text corpora that contain misspellings, variations, and non-natural language, especially for cybersecurity applications (Nunes et al., 2018). These limitations have ushered in DL-based short text similarity methods from neural information retrieval literature. DL uses multiple layers of neural networks with nonlinear activation functions to automatically learn feature representations from data (Goodfellow et al., 2016; LeCun et al., 2015). DL has achieved unprecedented performance in malware analysis, DNM language translation, and other cybersecurity applications (Samtani et al., 2020a). The prevailing DL-based short text matching algorithm is the DSSM (Huang et al., 2013; Mitra & Crasswell, 2018). We depict the DSSM operating in a short text matching task (retrieving a document title based on a query) in Figure 2.

A DSSM has three major components (excluding preprocessing):

1. **Word hashing:** DSSM extracts letter trigrams from input texts before proceeding to neural network processing. For example, "*buffer overflow*" is hashed to "*#bu, buf, uff, ffe, fer, er#, #ov, ove, ver, rfl, flo, low, ow#.*" This increases robustness to noise (e.g., word variations, misspellings, etc.) and captures fine-grained linguistic cues such as roots and morphs.

2. **Deep neural network (DNN) processing:** Each hashed phrase is inputted as a bag of trigrams into a fully connected (i.e., dense) feed-forward DNN layer for conversion into a low-dimensional embedding. Multiple layers can be stacked to reduce dimensionality (e.g., layer 1 → 30K dimensions to 300, layer 2 → 300 to 128 dimensions) and identify semantics missed by non-DL approaches.

3. **Computing embedding similarity:** Cosine similarity calculates the distance between embeddings. A softmax function calculates the conditional probability (i.e., P(D|Q)) for a document (D) – query (Q) pair. The document title with the highest conditional probability with the query is the most relevant. During training, this probability is compared with the ground truth. The residual error is backpropagated to update the weights of the DNN.

Past studies have adjusted DSSM by substituting the feed-forward network with a convolutional neural network (CNN) to capture word co-occurrences from input text (Mitra et al., 2016; Pang et al., 2016b; Shen et al., 2014b). In situations where word orders or sequential dependencies exist in the input text, scholars have replaced the first dense layer with a long-short term memory (LSTM) layer (Wan et al., 2016; Wang & Jiang, 2017). DSSM-based models have been used for searching news articles (Guo et al., 2016; Pang et al., 2016a), retrieving social media posts (Jaech et al., 2017; Song et al., 2016), ranking web pages (Shen et al., 2014a), digital assistant systems (Sarikaya, 2017), community question answering (Zhou et al., 2016), and recommender systems (Zhang et al., 2019).

Despite its widespread usage, DSSM processes input texts separately until the final embedding comparison. As a result, DSSM cannot capture global relationships across input texts during the training process to improve overall matching performance. However, exploit and vulnerability names often have overlapping contents (e.g., system names) and similar semantics; processing them separately cannot weigh and prioritize their overlapping input text features to improve exploit-vulnerability linking performance. An emerging and promising approach that can capture relationships across input texts and feature importance during DL training is the use of attention mechanisms (Du et al., 2019), which we review next.

Attention Mechanisms

Attention mechanisms belong to an emerging branch of machine learning known as interpretable deep learning (IDL). Two major categories of IDL exist: post hoc and intrinsic (Du et al., 2019). Post hoc approaches use a second method to examine major model components and/or individual parameters *after* training (after model convergence) to identify how they contribute to the final output. Intrinsic approaches integrate self-explanatory models into a DL architecture and operate *during* training (e.g., feed-forward, backpropagate, and weight updates). Two major categories of intrinsic approaches exist: (1) *global*, which includes mechanisms such as capsule networks (Sabour et al., 2017) and wide and deep networks (Cheng et al., 2016); and (2) *local*, which primarily comprises attention mechanisms. The selection of an IDL approach is dependent on the task, data, and requirements of a particular study (Du et al., 2019; Samtani et al., 2020b). Attention mechanisms are often preferred when aiming to assign trainable weights to individual features within a data input, using feature weights to improve model performance, and/or identifying how input data features affect end model performance (Du et al., 2019). We further examine attention mechanisms since exploit and vulnerability names often contain overlapping features (global relationships) that could be leveraged to improve exploit-vulnerability linking performance.

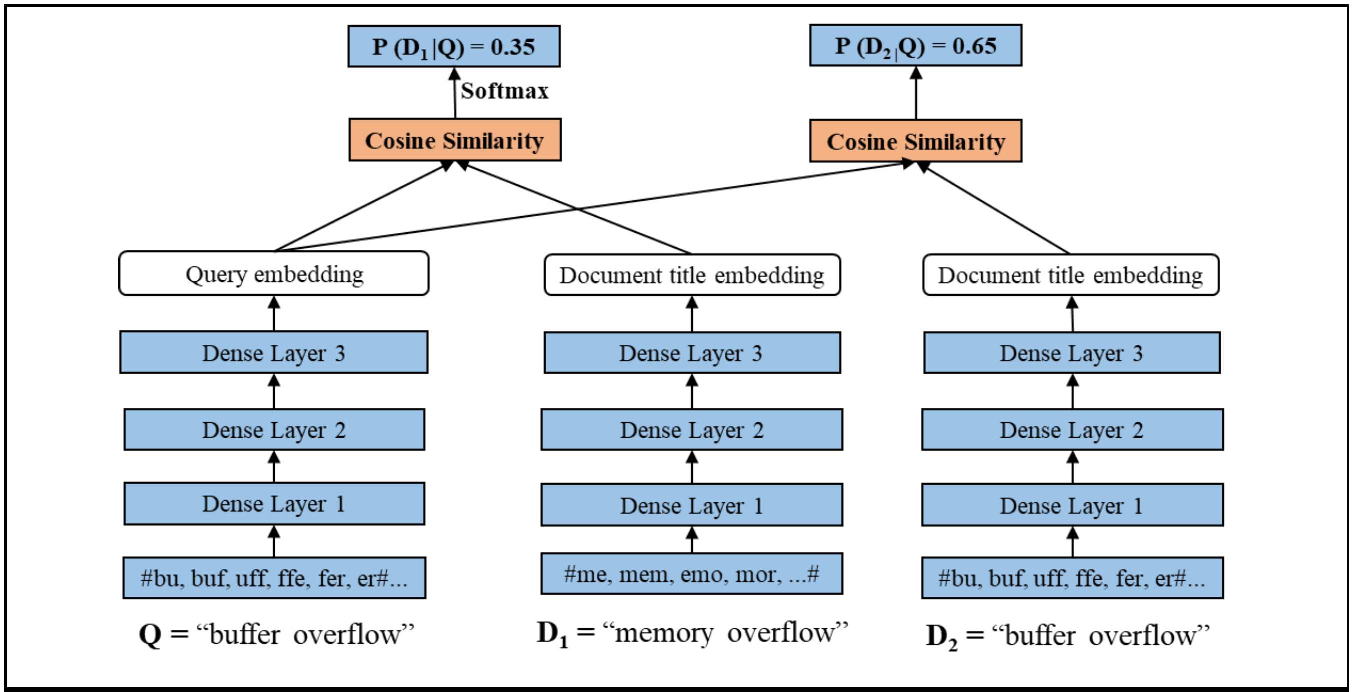


Figure 2. Deep Structured Semantic Model (DSSM) (adapted from Huang et al., 2013)

Attention mechanisms are implemented as carefully formulated layers within a neural network architecture (Du et al., 2019). Formally, an attention mechanism is denoted by a query Q and a key-value pair (K, V). The attention is computed as the weighted sum of value V and the weight assigned for each value is determined by the scoring function which measures the similarity between the query Q and the key K. For instance, in the sequence-to-sequence model for language translation, at each step, the query Q is the hidden state of the last timestep in the decoder while the hidden states from the encoder act as both Q and K. Based on the similarity distance computed by the scoring function, the weights for the inputted features are updated and indexed with a softmax function. Features are iteratively reweighted during training until model convergence. Attention mechanisms can be customized to focus on entire input sequences or portions, depending on the data characteristics and/or network architecture. To date, attention mechanisms have improved the performance of conventional DL architectures (e.g., DNN, recurrent neural network, convolutional neural network, variational autoencoders) for neural machine translation (Luong et al., 2015), sentiment analysis (Letarte et al., 2018), image classification (Schlemper et al., 2019), adverse event detection (Ahmad et al., 2020), and other applications. Evaluation is typically executed by comparing the extended model against the original on a gold-standard (i.e., ground-truth) dataset (Du et al., 2019). Despite its increasing usage, we are unaware of any attention mechanisms designed for DSSMs to support exploit-vulnerability linking.

Research Gaps and Questions

We identified several key research gaps from the literature review. First, most hacker forum studies have focused only on exploring hacker exploits. We are unaware of any integrated hacker forum-data driven approach linking exploits to vulnerabilities. Since organizations have limited security budgets and must prioritize exploits based on their vulnerabilities, simply exploring exploits has minimal CTI value. Second, while automated tools exist for conducting vulnerability assessments, there lacks literature examining vulnerability text to create exploit-vulnerability links. This prevents a holistic perspective of what exploits can target vulnerabilities and precludes the development of advanced vulnerability severity metrics for enhanced device prioritization or risk management. Third, DSSM processes input texts separately until embedding comparison and therefore cannot capture and prioritize overlapping input text features (e.g., system names) and semantics between exploit and vulnerability names to improve linking performance. Attention mechanisms can be a viable approach for addressing these issues and can enhance DSSM's performance in creating exploit-vulnerability linkages. However, we are unaware of any design artifacts that integrate attention mechanisms into DSSMs for exploit-vulnerability tasks. Taking these gaps together, we pose the following research questions for study:

- What vulnerabilities do hacker exploits from hacker forums target?
- How can device-level severity scores be calculated that incorporate vulnerability and hacker exploit metadata to facilitate CTI?
- How can attention mechanisms be incorporated into the DSSM to capture and prioritize overlapping features within exploit and vulnerability names to create exploit-vulnerability links?

Proposed Exploit-Vulnerability Linking Framework

The research gaps described above are underscored by the lack of a technical framework within academia or industry that can automatically link thousands of hacker exploits to vulnerabilities (Samtani et al., 2020d). Therefore, we propose an exploit-vulnerability linking framework for CTI with four major components: (1) data collection, (2) exploit-vulnerability linking and prioritization, (3) technical benchmark experiments, and (4) case studies and expert evaluation. We present the proposed framework in Figure 3. Each major framework component is described in the following subsections.

Data Collection

We aimed to collect a large set of hacker exploits and vulnerabilities to facilitate the proposed analysis. For the hacker exploit collection, we identified a large and long-standing exploit-specific hacker forum well-known in the hacker community for containing a variety of malicious tools. This forum (anonymized to protect us) has contributors from the Middle East, the U.S., Russia, and other regions. Many exploits are 0-days used in well-publicized attacks. A web crawler routed through Tor collected and parsed all exploit-category, post-date, author-name, platforms-targeted, and exploit-description data into a relational database. This resulted in nearly 21,000 exploits. We filtered out exploits that did not include the targeted platform or category, as they prevented our proposed analysis. A summary of each exploit category and the number of authors and platforms targeted is presented in Table 6.

In total, our collection and filtering processes resulted in 18,052 exploits across four categories: web applications (10,368 exploits), local (2,399 exploits), remote (2,602 exploits), and DoS (2,683 exploits). All exploits were non-overlapping; no exploit appeared in more than one dataset. In total, these exploits targeted 31 operating systems, web applications, and programming languages. In addition to collecting hacker forum exploits, we also compiled a comprehensive list of vulnerability names, their descriptions, and severity scores from Securityfocus.com, a trusted INFOSEC resource providing vulnerability information for tools such as Nessus, Qualys, and Burp Suite (Mell et al., 2007). The overall collection is summarized in Table 7.

The vulnerability collection contained 87,109 “critical,” “high,” “medium,” “low,” and “informational” listings. We note that two categories of vulnerabilities are not amenable to the proposed text analytics. The first pertains to social engineering (e.g., usernames/passwords). These lack “technical” exploits. Rather than posting credentials on forums as exploits, hackers directly consult the user manuals for default login credentials (Samtani et al., 2016). Second, none of the “informational” vulnerabilities were not suitable for linking as they simply provide system information and do not associate a vulnerability severity (thus preventing their inclusion into severity metrics). When accounting for these two situations, 64,104 / 87,019 (73.67%) of vulnerabilities were suitable for linking.

Exploit Vulnerability Linking and Prioritization: Exploit-Vulnerability Attention Deep Structured Semantic Model (EVA-DSSM)

Given the aforementioned issues with the conventional DSSM, we designed a novel EVA-DSSM architecture that integrates a bidirectional LSTM (Bi-LSTM) layer and two attention mechanisms (context attention and self-attention) to enhance the exploit-vulnerability linkage performance. We compare the key operational differences between the DSSM and the proposed EVA-DSSM in Figure 4. Model novelty is highlighted in red.

EVA-DSSM operates in seven steps: (1) preprocessing, (2) letter trigram word hashing, (3) Bi-LSTM processing, (4) context attention layer, (5) self-attention layer, (6) DNN processing with shared dense layer(s), and (7) computing embedding similarity. EVA-DSSM’s core novelty lies in Steps 3-5. The overall EVA-DSSM process and design rationale are described below:

Step 1 (preprocessing): Preprocessing is essential for attaining strong model performances (Chen et al., 2012; Zeng et al., 2010). Only exploit and vulnerability names are used in this study, as they are populated in all records. While additional content could be used, that is out of scope in our targeted analysis. All exploit and vulnerability names are stemmed, lowercased, and have stop words removed. Implementing these steps normalizes irregularities (e.g., capitalization) and follows common hacker forum analysis practices (Nunes et al., 2018).

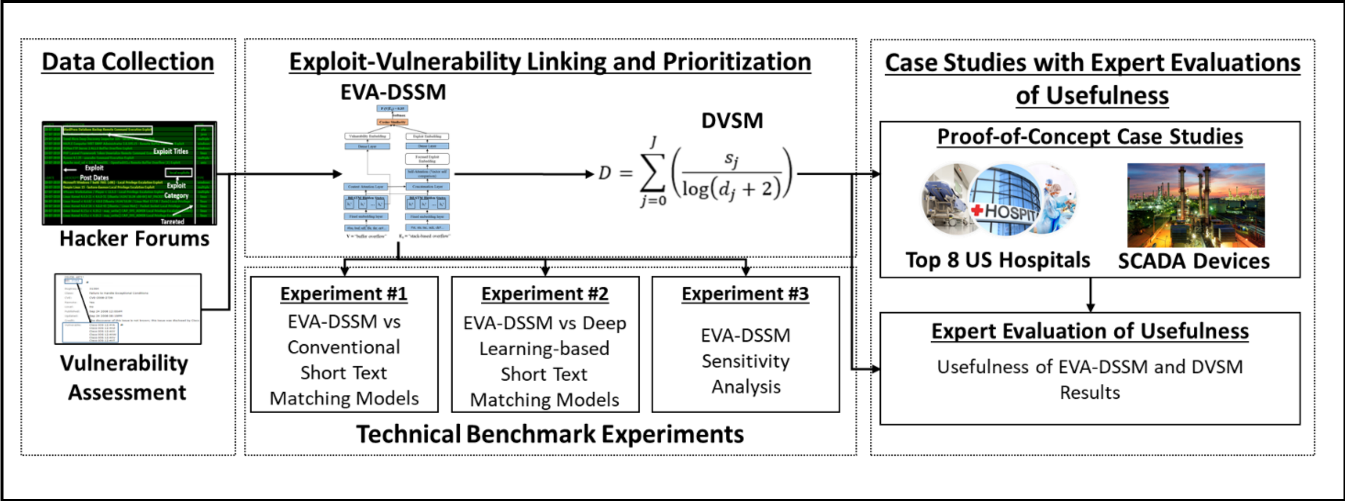

Data Collection
Exploit Titles
Exploit Post Dates
Exploit Category
Hacker Forums
Vulnerability Assessment
Exploit-Vulnerability Linking and Prioritization
EVA-DSSM
DVSM
$D = \sum_{j=0}^{J} \left(\frac{s_j}{\log(d_j + 2)} \right)$
Experiment #1
EVA-DSSM vs Conventional Short Text Matching Models
Experiment #2
EVA-DSSM vs Deep Learning-based Short Text Matching Models
Experiment #3
EVA-DSSM Sensitivity Analysis
Technical Benchmark Experiments
Case Studies with Expert Evaluations of Usefulness
Proof-of-Concept Case Studies
Top 8 US Hospitals
SCADA Devices
Expert Evaluation of Usefulness
Usefulness of EVA-DSSM and DVSM Results

Figure 3. Proposed Exploit-Vulnerability Linking Framework for CTI

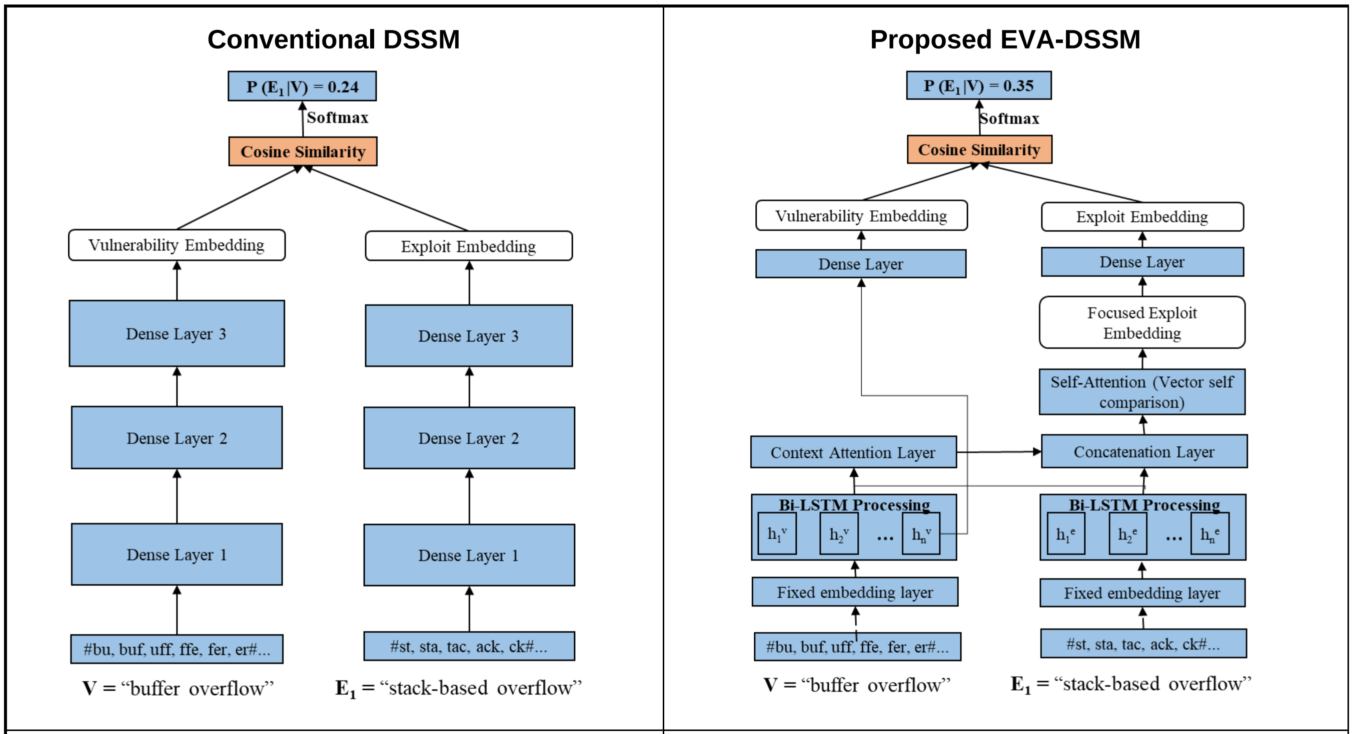
Table 6. Summary of Hacker Forum Exploit Collection

Category	Description	# of exploits	# of authors	# of platforms targeted
Web applications	Exploits targeted at web technologies	10,368	2,810	19
Local	Exploits executed on a local system	2,399	952	25
Remote	Network attack where the attacker exploits a vulnerability without local access	2,602	1,293	24
DoS	Attacks that deny service to systems	2,683	1,460	23
Totals:	**-**	**18,052**	***5,547**	***31**

Note: *Authors are overlapping (i.e., a single author can post exploits in multiple categories). The number presented is the number of unique authors. Similarly, a single exploit category can target multiple platforms, and the number presented in the unique platforms.

Table 7. Summary of Vulnerability Information Collection

Risk level	CVSS score	Number of vulnerability listings	Number amenable for text analytics
Critical	9.0 – 10.0	8,355	8,170
High	7.0 – 8.9	24,098	23,897
Medium	4.0 – 6.9	28,707	28,674
Low	0.1 – 3.9	3,163	3,163
Informational	0.0 – 0.0	22,696	0
Total:	**-**	**87,019**	**64,104**



1. **Preprocessing**
2. **Letter trigram word hashing**
3. **DNN processing with dense layer(s)**
4. **Computing embedding similarity**

EVA-DSSM Procedure (Novelty appears in red)

1. **Preprocessing**
2. **Letter trigram word hashing**
3. **Bi-LSTM processing**
4. **Context attention layer**
5. **Self-attention layer**
6. **DNN processing with shared dense layer(s)**
7. **Computing embedding similarity**

Figure 4. Conventional DSSM (left) vs. Proposed EVA-DSSM (right)

Step 2 (word hashing): A core aspect of DSSM processing is hashing inputted text. Consistent with best practices in past DSSM studies, letter trigrams are extracted from preprocessed text (Mitra & Crasswell, 2018). Extracting letter trigrams is also consistent with past literature examining non-natural language (Nunes et al., 2018). Each word hashed input is passed through a single fixed embedding layer to control embedding length size.

Step 3 (Bi-LSTM processing): The standard DSSM uses a bag-of-trigrams representation of input texts and therefore does not capture sequential dependencies within text. However, exploit and vulnerability names often possess sequential dependencies (e.g., system name appears before version type). To capture dependencies, we first replace dense (i.e., fully connected feed-forward) layer of the DSSM with a Bi-LSTM layer. Each Bi-LSTM time-step processes a letter trigram sequentially in both forward and backward directions (rather than the single direction proposed in past studies (e.g., Wan et al., 2016; Wang & Jiang, 2017)). In this fashion, the last output (i.e., after processing all previous time-steps) comprehensively captures the context of the entire letter trigrams sequence.

Step 4 (context attention layer): Rather than treating input texts separately until embedding comparison (like the standard DSSM), we aimed to examine the relationships (overlapping contents) across the inputted vulnerability and exploit names. While they cannot be directly matched due to content variations, they share similar contents (e.g., system names). Extracting and weighting vulnerability trigrams given a particular exploit can boost overall linking performance. To achieve this, we formulated a novel context attention layer that operates with five elements:

1. **Key (K):** $\boldsymbol{K}$ commonly refers to the source data in the attention mechanism. Since the Bi-LSTM is used upon the raw vulnerability input text, each Bi-LSTM hidden state corresponds to a vulnerability trigram. We denote the hidden states as $(\boldsymbol{h}_1^{\mathrm{v}}, \boldsymbol{h}_2^{\mathrm{v}}, \dots \boldsymbol{h}_n^{\mathrm{v}})$ where n is the length of the sequence and the superscript v represents vulnerability. Therefore, the key $\boldsymbol{K}$ refers to $(\boldsymbol{h}_1^{\mathrm{v}}, \boldsymbol{h}_2^{\mathrm{v}}, \dots \boldsymbol{h}_n^{\mathrm{v}})$.

2. **Query (Q):** for the i-th exploit trigram, the corresponding hidden state $\boldsymbol{h}_i^{\mathrm{e}}$ (superscript e represents exploits) from the Bi-LSTM is a query.

3. **Value (V):** Since the Bi-LSTM operates directly upon the source data, the key and the value are the same in the EVA-DSSM.

4. **Scoring function (S):** given a query $\boldsymbol{h}_i^{\mathrm{e}}$ and key $\boldsymbol{K}$, the scoring function computes the attention weights via

$$A^c(\boldsymbol{h}_i^{\mathrm{e}}, \boldsymbol{h}_j^{\mathrm{v}}) = \frac{\exp\left(\mathrm{similarity}(\boldsymbol{h}_i^{\mathrm{e}}, \boldsymbol{h}_j^{\mathrm{v}})\right)}{\sum_{j=1}^{n} \exp\left(\mathrm{similarity}(\boldsymbol{h}_i^{\mathrm{e}}, \boldsymbol{h}_j^{\mathrm{v}})\right)}, \quad \forall\, i \in [1,2 \dots, m], j \in [1,2 \dots, n], \tag{1}$$

where m is the length of the exploit text. This computation results in a set of weights identifying which aspect of the vulnerability the i-th exploit trigram is most related to. In EVA-DSSM, we adopt the multiplicative attention, a widely recognized attention mechanism by scholars (Luong et al., 2015). Formally, $\mathrm{similarity}(\boldsymbol{h}_i^{\mathrm{e}}, \boldsymbol{h}_j^{\mathrm{v}}) = (\boldsymbol{h}_i^{\mathrm{e}})^{\mathrm{T}} \boldsymbol{W}^c \boldsymbol{h}_j^{\mathrm{v}}$ where $\boldsymbol{W}^c$ is a trainable parameter.

5. **Context vector (C):** calculate weighted sum of the values for each exploit trigram,

$$\boldsymbol{c}_i = \sum_{j}^{n} A^c(\boldsymbol{h}_i^{\mathrm{e}}, \boldsymbol{h}_j^{\mathrm{v}}) \cdot \boldsymbol{h}_j^{\mathrm{v}}, \forall\, i \in [1,2 \dots, m] \tag{2}$$

Following the above process, a context vector is generated for each hidden state of the exploit trigrams. For each trigram, we concatenate the exploit trigram hidden state $\boldsymbol{h}_i^{\mathrm{e}}$ with corresponding context vector $\boldsymbol{c}_i$. We use $\boldsymbol{o}_i$ to denote the concatenated vector and the computation is given by

$$\boldsymbol{o}_i = [\boldsymbol{h}_i^{\mathrm{e}};\ \boldsymbol{c}_i] \tag{3}$$

Operating in this fashion captures the relationships across exploit and vulnerability texts (i.e., global information) with the context vector, and information within the exploit texts (i.e., local information).

Step 5 (self-attention layer): Given the concatenated vectors $[\boldsymbol{o}_1, \boldsymbol{o}_2, \dots, \boldsymbol{o}_m]$, the self-attention mechanism computes the attention weights assigned for the hidden states $[\boldsymbol{h}_1^{\mathrm{e}}, \boldsymbol{h}_2^{\mathrm{e}}, \dots, \boldsymbol{h}_m^{\mathrm{e}}]$. A focused exploit embedding $\boldsymbol{E}^{\mathrm{e}}$ is obtained as the weighted sum of the hidden states (Vashishth et al., 2019). Formally, we use A_i^{s} to denote the attention weight assigned for the i-th trigram. The computation is:

$$A_i^{\mathrm{s}} = \frac{\exp(u_i w)}{\sum_i^m \exp(u_i w)}, \tag{4}$$

$$u_i = \tanh(\boldsymbol{W}^{\mathrm{s}} \boldsymbol{o}_i + b), \tag{5}$$

where $\{w, \boldsymbol{W}^{\mathrm{s}}, b\}$ are trainable parameters. Then, the exploit embedding $\boldsymbol{E}^{\mathrm{e}}$ is given by:

$$\boldsymbol{E}^{\mathrm{e}} = \sum_i^m A_i^{\mathrm{s}} \cdot \boldsymbol{h}_i^{\mathrm{e}}\,. \tag{6}$$

In this way, the embedding $\boldsymbol{E}^{\mathrm{e}}$ summarizes the exploit texts information according to the relationships across exploit and vulnerability texts and the relationship within the exploit texts.

Step 6 (DNN processing with shared dense layer[s]): The focused exploit embedding $\boldsymbol{E}^{\mathrm{e}}$ and the last output of the Bi-LSTM assigned to the vulnerability text $\boldsymbol{h}_n^{\mathrm{v}}$ (that summarizes information of all vulnerability letter trigrams) are both embeddings that summarize the input trigram sequences. To facilitate embedding similarity calculation, we input both generated embeddings into shared dense layers to project them into the same embedding space (Step 7). Formally, $\boldsymbol{R}^{\mathrm{e}} = \mathrm{ShareDense}(\boldsymbol{E}^{\mathrm{e}}), \boldsymbol{R}^{\mathrm{v}} = \mathrm{ShareDense}(\boldsymbol{h}_n^{\mathrm{v}})$ where $\mathrm{ShareDense}(\cdot)$ refers to the projection of the same dense layers.

Step 7 (Computing Embedding Similarity): Cosine similarity computes the distance between $\boldsymbol{R}^{\mathrm{e}}$ and $\boldsymbol{R}^{\mathrm{v}}$. Consistent with Huang et al. (2013), the softmax is used to obtain the conditional probability of $P(\mathrm{E}|\mathrm{V})$ and the loss function is defined as

$$\mathcal{L} = -\log \prod_{\mathrm{E},\mathrm{V}^+} P(\mathrm{E}|\mathrm{V}^+) \tag{7}$$

where V^+ denote the relevant vulnerabilities. During the model training phase, the loss is backpropagated to update network parameters according to gradient-based methods.

EVA-DSSM was implemented with the Keras, TensorFlow, Natural Language Toolkit (NLTK), numpy, pandas, genism, and scikit-learn packages. We present the EVA-DSSM pseudocode in Algorithm 1 to help interested readers implement the core algorithm in their chosen programming language.

Algorithm 1. Pseudocode of the Proposed EVA-DSSM Algorithm

```
Inputs: $M$ exploits $\mathbf{E} = \{\mathrm{E}_i, i = 1, 2, \ldots, M\}$, $N$ vulnerabilities $\mathbf{V} = \{\mathrm{V}_j, i = 1,2, \ldots., N\}$
Outputs: EVA-DSSM parameters
procedure:
# Generate the initial trigram-hash embeddings for all vulnerabilities and exploits
triHashEmb$^{\mathrm{E}}$ = {Embedding(trigramHashing($\mathrm{E}_i$)), $i = 1, 2, \ldots, m$}
triHashEmb$^{\mathrm{V}}$ = {Embedding(trigramHashing($\mathrm{V}_j$)), $j = 1, 2, \ldots, n$}

while not convergence* do:
    for each $\mathrm{V}_j$ in $\mathbf{V}$ do:
    # Bi-LSTM processing
    Obtaining hidden states $\left[\boldsymbol{h}_1^{\mathrm{V}_j}, \boldsymbol{h}_2^{\mathrm{V}_j}, \ldots\ \boldsymbol{h}_n^{\mathrm{V}_j}\right]$ = SharedBi-LSTM(triHashEmb$_j^{\mathrm{V}}$)
    Computing final embedding of vulnerability $\boldsymbol{R}_j^{\mathrm{v}}$ = SharedDense($\boldsymbol{h}_n^{\mathrm{V}_j}$)
        for each $\mathrm{E}_i$ in $\mathbf{E}$ do:
            Obtaining hidden states $\left[\boldsymbol{h}_1^{\mathrm{E}_i}, \boldsymbol{h}_2^{\mathrm{E}_i}, \ldots\ \boldsymbol{h}_m^{\mathrm{E}_i}\right]$ = SharedBi-LSTM(triHashEmb$_i^{\mathrm{E}}$)
            # Context attention computation
            for each $k$ in $\{1, 2, \ldots, n\}$ do:
                Exploit attention weight according to Equation (1)
                Computing context vector according to Equation (2)
                Getting concatenated vector according to Equation (3)
            end for

            # Self-attention computation
            Computing self-attention weights according to Equation (4) and (5)
            Computing focused exploit embedding $\boldsymbol{E}_i^{\mathrm{e}}$ according to Equation (6)

            # DNN processing with Dense layers
            Compute final embedding of exploit $\boldsymbol{R}_i^{\mathrm{e}}$ = SharedDense($\boldsymbol{E}_i^{\mathrm{e}}$)
            Compute similarity Sim$_i = \cos\left(\boldsymbol{R}_j^{\mathrm{v}}, \boldsymbol{R}_i^{\mathrm{e}}\right)$
        end for
        Calculate the probability $P\left(\mathrm{E_i} \middle| \mathrm{V_j}\right)$ = Softmax(Sim$_i$|Sim$_1$, Sim$_2$, ..., Sim$_M$)
    end for
    Compute loss $\mathcal{L}$ according to Equation (7)
    Update weights according to gradient descent method
end while
return model parameters
```

Note: *convergence is determined by the change of $\mathcal{L}$; SharedBi-LSTM(·) refers to processing vulnerabilities and exploits using the same Bi-LSTM as suggested by Huang et al., 2013

Exploit-Vulnerability Linking and Prioritization: Device Vulnerability Severity Metric (DVSM)

The EVA-DSSM is a novel approach for automatically identifying relevant hacker exploits for a vulnerability. Coupling hacker exploit and vulnerability metadata based on EVA-DSSM's output to create specialized severity (risk) scores can further create holistic CTI and facilitate enhanced device prioritization capabilities (Allodi & Massacci, 2014; Samtani et al., 2020a). First, devices are often afflicted with multiple vulnerabilities, each with their own severity score. However, we are unaware of any approach to aggregating vulnerability severities in devices with multiple vulnerabilities. Second, each hacker exploit has a post date. Newer exploits, such as 0-days, often have significantly more CTI value than older exploits. As an exploit ages, knowledge about its operations is quickly disseminated to the cybersecurity community and therefore exponentially loses value (Mell et al., 2007). Since EVA-DSSM determines the most relevant exploit for a vulnerability, we developed a novel device vulnerability severity metric (DVSM). All DVSM features and their justification for inclusion are presented in Table 8.

Table 8. Features Incorporated into the Device Vulnerability Severity Metric (DVSM)

Feature Category	Feature	Justification for inclusion	References
Vulnerability	Vulnerability severity (CVSS, 0.0-10.0)	A higher severity score indicates more severe consequences if device is compromised.	Mell et al. 2007; Weidman 2014; Kennedy et al. 2011
	Number of device vulnerabilities	Devices with more vulnerabilities have a higher exploit susceptibility.	
Hacker exploit	# of exploits targeting vulnerabilities	More hacker exploits targeting a vulnerability increases the probability of the device's harm.	Friedman 2015; Robertson et al. 2017
	Age of hacker exploits (i.e., forum post date)	Newer exploits are more valuable for CTI since there is less time to formulate defenses.	Shackleford 2016

DVSM encompasses the number of vulnerabilities in a device, each vulnerability's severity, and the hacker exploit age for each vulnerability. Formally, the DVSM is denoted as:

$$D = \sum_{j=0}^{J} \left(\frac{s_j}{\log(d_j + 2)} \right)$$

Where *D* is the overall device severity score, *J* is the number of vulnerabilities in a system, s_j represents the severity of a specific vulnerability within the device (determined by the CVSS score for the vulnerability), d_j is the # of days since the most relevant exploit for the vulnerability s_j was posted, creating a decaying effect of the inverse log function. The most relevant exploit for a vulnerability is determined by the EVA-DSSM. A vulnerability's severity score is divided by the log of the number of days elapsed since the most relevant exploit for that vulnerability was posted (a decaying function). Severities receive a higher weighting in the metric if the vulnerability's most relevant exploit is newer. The inverse log best captures the exponential loss of value detailed in prior CTI literature (Mell et al., 2007). All vulnerability score and hacker exploit age pairs for a device are summed to create DVSM. A device's overall score is higher if it has more severe vulnerabilities or newer exploits for vulnerabilities.

Technical Benchmark Experiments

Consistent with computational design science principles (Rai, 2017) and DL fundamentals (Samtani et al., 2020b), we evaluated the proposed EVA-DSSM with three technical benchmark experiments: (1) EVA-DSSM vs. conventional short text matching algorithms, (2) EVA-DSSM vs. deep learning-based short text matching algorithms, and (3) EVA-DSSM sensitivity analysis. We describe each benchmark method included in each experiment in Table 9.

In Experiment 1, we examined EVA-DSSM's performance against conventional non-DL approaches based on direct matching (simple matching), distributional semantics (LSA), probabilistic matching (BM25), and term frequency (TF-IDF) approaches. Experiment 2 examined EVA-DSSM's performance against state-of-the-art DL-based short text matching algorithms proposed in neural IR academic literature. Each algorithm is based on DNN (aNMM, DSSM, DRMM, DUET), CNN (ARC-I, ARC-II, KNRM, Conv-KNRM), and/or LSTM (Match-LSTM, MV-LSTM) operations. We also evaluated a variation of the EVA-DSSM (EVA-DSSM-2) where the context attention operates on the exploit, and self-attention operates to create a focused vulnerability embedding.

The EVA-DSSM model used for Experiments 1 and 2 uses letter trigrams, a one-layer Bi-LSTM, two attention mechanisms (context vector and self-attention), and two dense layers. However, each EVA-DSSM model component can be varied. Therefore, Experiment 3 evaluated EVA-DSSM's sensitivity to word hashing, LSTM processing, attention mechanisms, and network depth. With regards to the word hashing and Bi-LSTM processing, the conventional DSSM uses letter trigrams and a feed-forward layer instead, respectively. However, vulnerability and hacker exploit names contain non-natural language content and sequential dependencies. Identifying word hashing and LSTM processing sensitivities can aid future DSSM research operating on non-natural language. Therefore, we evaluated EVA-DSSM's performance when using letter bigrams, letter trigrams, letter 4-grams, and word n-grams. We also evaluated EVA-DSSM's performance when EVA-DSSM uses an LSTM layer (as seen in Wan et al. (2016) and Wang and Jiang (2017)) instead of a Bi-LSTM layer. Both LSTM layer types are tested at one-layer and two-layer variations. With respect to the attention mechanisms, we examined how EVA-DSSM performs when using only one attention mechanism at a time. We also evaluated EVA-DSSM's performance when using one, two, or three dense layers. Across all variations, only one model component is varied at a time; the remainder of the model remained the same.

Table 9. Summary of Technical Benchmark Experiments

Experiment	Benchmark methods	Brief description of operations	Reference(s)
Experiment 1: EVA-DSSM vs. Conventional Short Text Matching Algorithms	BM25	Probabilistic bag-of-words retrieval function that uses term frequencies.	Robertson et al. 1995
	LSA	Calculates the semantic similarity based on distributional semantics.	Deerwester et al. 1990
	Simple matching	Directly matches two short texts by counting same appearances.	-
	TF-IDF	Short texts are weighted based on term frequency within and across the corpus.	Saltyon and Buckley 1988
Experiment 2: EVA-DSSM vs. Deep learning-based short text matching algorithms	aNMM	Matching matrix captures text interactions, and an attention mechanism weights interactions.	Yang et al. 2018
	DSSM	Standard, seminal DSSM architecture.	Huang et al. 2013
	DRMM	Builds matching histograms of interactions between query term and document. MLP and query term gates match short texts.	Guo et al. 2016
	DUET	Combines local exact matching and semantic embedding using parallel local and distributed neural models.	Mitra et al. 2017
	ARC-I	Siamese CNNs represent sentences; MLP conducts matching.	Hu et al. 2014
	ARC-II	Sentences interact by a 1D convolution. A 2D CNN represents sentences, and a MLP matches.	
	KNRM	Translation matrix models word-level similarities. Kernel-pooling extracts multi-level features. Ranking layer conducts ranking.	Xiong et al. 2017
	Conv-KNRM	A KNRM that uses convolutional and pooling layers.	Dai et al. 2018
	Match-LSTM	Represents and matches input texts using multiple LSTM layers.	Wang and Jiang 2017
	MV-LSTM	Bi-LSTMs represent input sentences, similarity k-max functions aggregate interactions, and an MLP matches representations.	Wan et al. 2016
	EVA-DSSM-2	Same as EVA-DSSM, but the left branch focuses on exploit text and the right branch on vulnerability text	-
Experiment 3: EVA-DSSM sensitivity analysis**	Letter bigrams	Letter bigram representation (e.g., *buffer* → *#b, bu, ff, fe, er, r#*)	Huang et al. 2013
	Letter trigrams	Letter trigram representation (e.g., *buffer* → *#bu, uff, ffe, fer er#*)	
	Letter 4-grams	Letter 4-gram representation (e.g., *buffer* → *#buf, uffe, ffer, fer#*)	
	Word n-grams	Word n-gram representation (e.g., *buffer overflow* → *buffer*, *overflow*)	
	Bi-LSTM layer	Swapping out a Bi-LSTM with an LSTM layer	Wan et al. 2016; Wang and Jiang 2017
	Attention mechanism	Removing either the context attention layer or the self-attention mechanism	Du et al. 2019
	Quantity of dense layers	Varying the quantity of dense layers (1, 2, or 3) after the context embedding in the EVA-DSSM	-

Note:

*aNMM = attention neural matching model; ARC-I = architecture-I; ARC-II = architecture-II; BM25 = best matching 25; CNN = convolutional neural network; DRMM = deep relevance matching model; KNRM = kernel-based neural ranking model; LSA = latent semantic analysis; LSTM = long-short term memory; MLP = multilayer perceptron; TF-IDF = term frequency inverse document frequency.

** Given that Experiment 3 is an internal evaluation (i.e., varying model components), no statistical significance was conducted. This is consistent with deep learning studies presented in recent IS literature (Zhu et al., 2020; Zhu et al., 2021) and best practices (Samtani et al., 2020b)

Executing benchmark evaluations requires a ground-truth dataset (Nunamaker et al., 1990; Hevner et al., 2004; Peffers et al., 2007). This dataset is also commonly referred to as a gold-standard dataset in past IS studies at top journals, as it comprises all correct instances that are representative of the phenomena being studied (Abbasi & Chen, 2008; Abbasi et al., 2018). To build our gold-standard dataset, we leveraged the CVE metadata available in hacker forums and vulnerability assessment data. In our datasets, 163 / 10,368 of web application exploits, 348 / 2,602 remote exploits, 230 / 2,399 local exploits, and 445 / 2,683 DoS exploits have CVEs. When linked to their CVE vulnerability counterparts, this resulted in 673 unique vulnerabilities for web application exploits, 1,806 for remote, 1,326 for local, and 1,877 for DoS. While this quantity was not high enough (<10% total) to warrant using them exclusively for creating vulnerability-exploit linkages (thus necessitating and further motivating EVA-DSSM), it was enough to develop a gold-standard dataset. Specifically, the 163-673 exploit-vulnerability combinations resulted in 1,208 unique exploit-vulnerability pairs in the web applications dataset, the 230-1,326 created 2,193 for local exploits, the 348-1,806 created 3,800 pairs in the remote exploits, and 442-1,877 created 3,445 for DoS. These unique combinations were all labeled as relevant (i.e., tagged with 1). To validate the labels, we recruited a seasoned SOC security analyst from a well-known, international healthcare organization. For this task, we presented the datasets individually to the security analyst *without* the label and asked the analyst to label the exploit-vulnerability pair as 1 for relevant or 0 for irrelevant. The analyst was presented with the exploit name, exploit category, vulnerability name, and vulnerability description to make a fully informed labeling decision. We computed the Cohen's kappa statistic between the rating provided by the analyst and the dataset generated from linking CVE's. The Cohen's kappa statistics for the web application, remote, local, and DoS datasets were 0.97, 0.96, 0.98, and 0.94, respectively. Given this near-perfect agreement between the analyst and the labels provided by the hacker exploit forum community and vulnerability assessment, we used these as the relevant labels for algorithm training, tuning, and testing.

Gold-standard datasets commonly used in DSSM literature often have 3-4 irrelevant instances (each labeled as 0) for every relevant instance (Huang et al., 2013). Therefore, the final dataset would include each exploit in a unique exploit-vulnerability pair five times—once for relevant, four for irrelevant. Unlike the relevant pairs that can be linked based on CVE, there are no clear labels provided in hacker forums about which vulnerabilities the exploits *do not* target. Therefore, we designed a custom script that examined the family name (50+, including Windows, Linux, and PHP) for the vulnerability in each relevant exploit-vulnerability pair to create four additional exploit-vulnerability pairs that were irrelevant. Once we identified the vulnerability family within the relevant pair, the script randomly selected four vulnerabilities from families outside of the one provided in the relevant pair. To ensure the quality of our script-generated labels, we recruited the same analyst from earlier, as well as a cybersecurity instructor with significant systems development experience. Each annotator was provided the irrelevant pairs without the label and asked to label them as 1 for relevant, and 0 for irrelevant. All annotations were completed separately to reduce social-desirability bias. Labeling efforts occurred over a three-week period. Both raters were presented with the exploit name, exploit category, vulnerability name, and vulnerability description without the label. Raters were instructed not to complete more than 2,000 ratings within a two-hour period.

We used Cohen's kappa to compute the level of agreement between ratings. After the first round of annotation, the Cohen's kappa between the raters resulted in 0.69, 0.72, 0.77, and 0.76 for the web application, remote, local, and DoS datasets, respectively. Both raters then met to discuss differences. After discussions, we identified the irrelevant links both raters disagreed on and altered our initial script to generate random pairs to replace these instances. The annotators were instructed to label the regenerated irrelevant pairs. In the second round of annotation, the Cohen's kappa resulted in 0.89, 0.92, 0.93, and 0.88 for the web application, remote, local, and DoS datasets, respectively. The overall testbed contained 52,590 total pairs. Adhering to best practices, each set was split using an 80%, 10%, 10% ratio across training, tuning (development), and testing subsets, respectively (Mitra & Crasswell, 2018). We summarize unique exploit and vulnerability counts, the total counts of exploit-vulnerability pairs, and the sizes of the training, development, and testing sets for each gold-standard dataset in Table 10.

Overall, the web applications dataset contained a total of 5,400 pairs (163 unique exploits and 673 unique vulnerabilities), the local dataset contained 10,965 pairs (230 unique exploits and 1,326 unique vulnerabilities), the remote dataset contained 19,000 pairs (348 unique exploits and 1,806 unique vulnerabilities), and the DoS dataset contained 17,225 pairs (442 unique exploits and 1,877 unique vulnerabilities). To illustrate examples of what was included in our gold-standard datasets, we report sample relevant and irrelevant exploit-vulnerability pairs for each dataset in Table 11.

In addition to establishing a gold-standard dataset, conducting benchmark experiments requires appropriate and well-established metrics and statistical tests to evaluate the performance of the baseline algorithms (Rai, 2017). In this research, we employed three performance metrics that are commonly used to evaluate DSSMs (Mitra & Crasswell, 2018): Normalized discounted cumulative gain (NDCG) at 1, 3, and 5; mean reciprocal rank (MRR); and mean average precision (MAP). A description and formulation for each metric is presented in Table 12.

Table 10. Summary of Gold-Standard (i.e., Ground-Truth) Datasets*

	Web applications		**Local**		**Remote**		**DoS**	
	Exploit	**Vulnerability**	**Exploit**	**Vulnerability**	**Exploit**	**Vulnerability**	**Exploit**	**Vulnerability**
Unique	163	673	230	1,326	348	1,806	442	1,877
Total Exploit-Vulnerability Pairs	1,208 Relevant Pairs 4,832 Irrelevant Pairs **Total:** 5,400		2,193 Relevant Pairs 8,772 Irrelevant Pairs **Total:** 10,965		3,800 Relevant Pairs 15,200 Irrelevant Pairs **Total:** 19,000		3,445 Relevant Pairs 13,780 Irrelevant Pairs **Total:** 17,225	
Training	4,320		8,771		15,200		13,759	
Development	540		1,097		1,900		1,733	
Testing	540		1,097		1,900		1,733	

Note: * The size of each dataset exceeds the size used in many past IS studies.

Table 11. Examples of Labeled Relevant and Irrelevant Exploit-Vulnerability Pairs in the Constructed Gold-Standard (i.e., Ground Truth) Datasets

Dataset	**Exploit name**	**Relevant vulnerability**	**Irrelevant vulnerability**
Web applications	MoinMoin 1.9.8 Cross Site Scripting Vulnerability	FreeBSD: moinmoin -- XSS vulnerabilities	Fedora 20: tcpdump-4.5.1-2.fc20 (2014-15541)
	PHPMailer 5.2.20 - Remote Code Execution Exploit	FreeBSD: phpmailer -- Remote Code Execution	CentOS 6: mysql (CESA-2017:0184)
	Trend Micro InterScan Web Security Virtual Appliance 6.5 SP2 - Multiple Vulnerabilities	Trend Micro IWSVA 6.5 < 6.5 Build 1746 Multiple Vulnerabilities	Adobe AIR for Mac & 20.0.0.204 Multiple Vulnerabilities (APSB16-01)
Local	DirtyCow Linux Kernel Race Condition Exploit	SUSE SLES12 Security Update: kernel (Dirty COW)	Cisco UCS Director Code Injection (Shellshock)
	Linux Kernel (Ubuntu / Fedora / Redhat) - “Overlayfs” Privilege Escalation Exploit	Ubuntu 12.04 LTS: linux regression (USN-2640-2)	MS16-014: Security Update for Microsoft Windows to Address Remote Code Execution
	Perl 5.20.1 Deep Recursion Stack Overflow Vulnerability	Mandriva Linux Security Advisory: perl	AIX 7.1 TL 1: libodm (IV60312)
Remote	ElasticSearch Search Groovy Sandbox Bypass Exploit	Elasticsearch Groovy Script RCE	RHEL 5 / 6: php (RHSA-2013:1824)
	JIRA Issues Collector Directory Traversal Exploit	Atlassian JIRA & 6.0.4 Arbitrary File Creation	FreeBSD telnetd Daemon Remote Buffer Overflow
	Apache Struts ClassLoader Manipulation Remote Code Execution Exploit	Apache Struts 2 class Parameter ClassLoader Manipulation	Fedora 22: fuse-2.9.4-1.fc22 (2015-8756)
DoS	Varnish Cache Server Denial of Service	Amazon Linux AMI: varnish (ALAS-2014-276)	CentOS 6: java-1.6.0-openjdk (CESA-2013:0605)
	Bind 9 DNS Server - Denial of Service Exploit	Debian DSA-3680-1: bind9 - security update	TWiki debugenableplugins Parameter RCE
	OpenSSH 7.2 - Denial of Service Exploit	Debian DLA-594-1: openssh security update	Apple TV & 9.2 Multiple Vulnerabilities

Table 12. Summary of Performance Metrics Used for Benchmark Experiments

Metric	**Metric description**	**Formulation**
Normalized discounted cumulative gain (NDCG) at 1, 3, and 5	NDCG measures ranking quality. It identifies how closely the ranked vulnerabilities match the gold-standard set. In our experiments, it identified quality at ranks 1, 3, and 5.	$NDCG = \frac{1}{M}\sum_{i=1}^{M}\left(\frac{DCG_u@p}{IDCG_u@p}\right)$
Mean reciprocal rank (MRR)	Average of the reciprocal rank (multiplicative inverse of the rank for the first correct answer) of all results for a sample of queries (in this study, exploits).	$MRR = \frac{1}{\lvert Q\rvert}\sum_{i=1}^{\lvert Q\rvert}\left(\frac{1}{rank_i}\right)$
Mean Average Precision (MAP)	MAP first calculates average precision at multiple ranks (e.g., at P@1, P@3, P@5, etc.), then the mean of all average precision scores form MAP.	$MAP = \frac{\sum_{q=1}^{Q} AveP(q)}{Q}$

Given our goal of retrieving the most relevant exploit for a vulnerability, NDCG@1 and MAP (and its constituent P@1), hold the most importance for evaluating algorithm performance. Each algorithm used the training sets for model training, the development set for model tuning, and the test set for measuring model performance. Each algorithm was run ten times for all metrics. Performances across the ten runs were averaged and reported. Paired *t*-tests were used to calculate statistically significant differences between EVA-DSSM's performance and benchmark algorithms. All experiments were conducted on a single Ubuntu Linux 16.04.3 LTS server with 132GB of random access memory (RAM), a NVIDIA GeForce GTX 1080 Ti graphical processing unit (GPU), an Intel central processing unit (CPU) E5-2640 v4 at 2.40 gigahertz (GHz), and a four terabytes of disk space.

Case Studies with Expert Evaluations of Usefulness

Case studies with expert evaluations of usefulness can demonstrate proof of concept, usability, usefulness, and the potential value of a novel technical approach (Nunamaker et al., 1990; Hevner et al., 2004). The practical value of the EVA-DSSM and DVSM (the two main contributions of this work) would ideally be illustrated on the external and internal networks within an organization. However, many firms are hesitant to disclose their vulnerabilities and the exploits against them, preferring instead to keep this knowledge classified. Therefore, we demonstrate the proof of concept of our research with case studies on publicly accessible devices from the top eight U.S. hospitals and from SCADA devices deployed worldwide. Both domains are common targets for malicious hackers. Hospitals often contain significant sensitive medical records that can net substantial revenue on DarkNet Marketplaces (Ayala, 2016). SCADA devices control modern infrastructure including power plants, sewage systems, transportation services, and more. Hackers often target such devices to severely cripple societal operations. The steps to execute each case study mimic the process a cybersecurity professional can implement in using the EVA-DSSM and DVSM in their workflow:

- **Step 1 (IP address identification):** For hospitals, we identified hacker exploits for vulnerabilities on the externally facing networks of the top eight U.S. hospitals as ranked by the 2017 *U.S. News and World Report*: (1) Mayo Clinic, (2) Cleveland Clinic, (3) Massachusetts General, (4) Johns Hopkins, (5) University of California, Los Angeles (UCLA) Medical Center, (6) New York Presbyterian, (7) University of California, San Francisco (UCSF) Medical Center, and (8) Northwestern Memorial. Shodan, a search engine that discovers publicly accessible Internet-of-Things (IoT) devices, then finds all devices available on each hospital's IP range. For the SCADA case study, we retrieved 20,641 SCADA devices and their IPs from Shodan using SCADA-specific vendor keywords (e.g., Rockwell, Siemens, and Schneider). Retrieving SCADA devices in this fashion is consistent with past vulnerability assessment literature (Samtani et al., 2016; El et al., 2017; Samtani et al., 2018).

- **Step 2 (vulnerability assessment):** Consistent with best practices, we used Nessus, a state-of-the-art vulnerability assessment tool, to discover the vulnerabilities of each device without port scanning and payload dropping. Scanning for vulnerabilities in this fashion has been noted in past literature to avoid adverse events (e.g., downtime) (Harrell et al., 2018; Williams et al., 2017; McMahon et al., 2017; McMahon et al., 2018; Lazarine et al., 2020; Ullman et al., 2020).

- **Step 3 (exploit-vulnerability linking via EVA-DSSM):** After identifying vulnerabilities, EVA-DSSM determined the most relevant hacker exploit for each vulnerability. To emulate a cybersecurity analyst's workflow (Farris et al., 2018), we only considered the top linked exploit for DVSM.

- **Step 4 (risk management via DVSM):** After creating exploit-vulnerability links, we used the metadata from the exploit (post date) and vulnerability (CVSS score) for each exploit-vulnerability pair for each device. The DVSM score for each device is computed using these data. The final outputted DVSM values are ranked in descending order to help facilitate vulnerable device prioritization.

The exploit-vulnerability linkages identified by EVA-DSSM and the DVSM scores can offer cybersecurity experts an excellent starting point for their mitigation and remediation activities. However, it is impossible to validate whether the EVA-DSSM exploit can take advantage of the detected vulnerability without executing the exploit. Such an act has significant legal and ethical ramifications. Moreover, even if vulnerabilities were susceptible to detected exploits, the usefulness and value of these linkages may vary within and between organizations due to technical capabilities, security priorities, and organizational policies. Therefore, we aimed to conduct a complementary user evaluation that aimed to ascertain how useful cybersecurity professionals find the results of our proposed EVA-DSSM and DVSM compared to results outputted from baseline approaches (e.g., DSSM and CVSS). To execute this evaluation, we sent over 60 email invitations through our university's cybersecurity centers to identify cybersecurity experts that were willing to evaluate the usefulness of our proposed approaches. In total, 45 cybersecurity experts responded to the invitation. Each expert possessed at least five years of experience in roles pertaining to security operations centers (SOCs), incident response (IR), vulnerability management, Dark Web analytics, IT audit, and/or operational cybersecurity. Each position would likely use EVA-DSSM and DVSM in their professional practice. No incentive or compensation was provided for the participant, since the time commitment was expected to be less than 15-20 minutes.

We instructed each cybersecurity expert to evaluate the perceived usefulness of the exploit-vulnerability pairs generated from the EVA-DSSM against those generated from benchmark approaches (e.g., DSSM). For each generated exploit-vulnerability pair, we also asked each expert to evaluate the usefulness of the DVSM against CVSS. Following common practice in IS literature (Abbasi et al., 2018; Chau et al., 2020), we adapted items pertaining to perceived usefulness from Davis (1989), Davis et al. (1989), and Venkatesh et al. (2003). For the exploit-vulnerability pair, the experts were asked if "the exploit-vulnerability link is useful for identifying what exploit could target this vulnerability." The experts were also asked if "the risk score is useful to prioritize exploit-vulnerability pairs more effectively" for the DVSM and CVSS scores. Adapting items in this fashion helps ensure the face validity of the items as well as correctly measure the phenomena of interest (i.e., construct validity) (Abbasi et al., 2018; Chau et al., 2020). For both items, we asked the experts to provide their responses on a scale of 1-7 (with 1 being *strongly disagree* and 7 being *strongly agree*). Exploit-vulnerability pairs with their associated severity scores were randomly interspersed and blinded (i.e., no details were provided about which algorithm or severity metric produced the results) for the hospital and SCADA case studies. The experts were not allowed to consult with each other to avoid biases. We calculated the mean for each item and used a paired *t*-test to identify if a statistically significant difference between our proposed approach and the benchmark (i.e., EVA-DSSM vs. best performing method and DVSM vs. CVSS) existed. The results of this complementary evaluation are presented in Appendix A.

Results and Discussion

Experiment 1 Results: EVA-DSSM vs. Conventional Short Text Matching Algorithms

In Experiment 1, we evaluated EVA-DSSM against four prevailing non-DL short text matching algorithms: BM25, LSA, simple matching, and TF-IDF. All models were evaluated based on MAP, MRR, and NDCG ranks of 1, 3, and 10. We present the average performances (across ten runs) for each algorithm on each dataset in Table 13. The highest scores for each dataset and metric are highlighted in bold font.

EVA-DSSM outperformed non-DL short text matching algorithms in NDCG (at all levels), MRR, and MAP. The differences in average performances between the EVA-DSSM and the next best performing algorithm BM25 ranged between 0.0509 (0.3842 for EVA-DSSM vs. 0.3333 for BM25) on the DoS dataset to 0.4214 (0.6714 for EVA-DSSM vs. 0.2500 for BM25) on the local dataset. The simple matching approach was consistently one of the poorest performing algorithms across all datasets, attaining NDCG@1 scores between 0.0314 to 0.1822. The differences between EVA-DSSM's performances and each of the benchmark methods were statistically significant at *p*-value thresholds of 0.05, 0.01, and 0.001 for each metric. These results suggest that EVA-DSSM's attention mechanisms combined with feed-forward, backpropagation, and error correction enable the model to identify finer-grained linguistic patterns within exploit and vulnerability names that benchmark methods miss. To better quantify EVA-DSSM's performance against the benchmark algorithms, we calculated the number of instances where the algorithm correctly matched a vulnerability to an exploit on the first link by multiplying each algorithm's best Precision @ 1 (P@1) score by the total number of instances in each testing dataset (denoted as n in Table 14). P@1 was calculated based on the MAP metric. We present the P@1 score as a percentage (calculated by multiplying an algorithm's P@1 score by 100) and the number of correct instances in Table 14. Top performances for each dataset are highlighted in bold.

EVA-DSSM achieved a significantly higher P@1 score over the benchmark methods in all datasets. In the web dataset, EVA-DSSM correctly identified 145 (423-278) more links (26.87% [78.40%-51.53%] increase) than the closest performing benchmark, BM25. EVA-DSSM showed similar performance gains in the local dataset (EVA-DSSM detected 459 [853-394] more instances than BM25 for a 41.83% [77.75%-35.92%] increase), remote dataset (EVA-DSSM correctly identified 694 [1,413-719] more instances than BM25 for a 36.51% [74.36%-37.85%] increase), and DoS dataset (EVA-DSSM detected 359 [1,019-660] more instances than BM25 for a 20.74% [58.84%-38.10%] increase). These differences were more pronounced for other competing algorithms (e.g., simple matching). Overall, these results indicate that EVA-DSSM's grounding in DL helps it capture linguistic cues within the exploit and vulnerability names that are missed by direct and probabilistic matching-based approaches. To better identify what EVA-DSSM detected over benchmark methods, we illustrate a sample exploit-vulnerability link in each test dataset that EVA-DSSM correctly identified but was missed by the best competing approach (BM25 for each dataset) in Table 15. We also illustrate the exploits linked by the simple word matching approach in each dataset. The exploits appearing in bold were correct (i.e., listed as relevant in the ground-truth dataset). Additional examples can be requested by contacting the lead author of this article.

Table 13. Experiment 1 Results: EVA-DSSM vs. Conventional Short Text Matching Algorithms

Algorithm	**Web applications**				
	NDCG@1	**NDCG@3**	**NDCG@5**	**MRR**	**MAP**
BM25	0.2500***	0.2573***	0.4291***	0.3747***	0.3584***
LSA	0.1156***	0.3301***	0.4308***	0.3846***	0.4037***
Simple Matching	0.1142***	0.3127***	0.4139***	0.3553***	0.3998***
TF-IDF	0.1250***	0.3394***	0.4253***	0.3659***	0.4123***
Proposed EVA-DSSM	**0.6570**	**0.7550**	**0.7944**	**0.7789**	**0.7932**
Algorithm	**Local**				
	NDCG@1	**NDCG@3**	**NDCG@5**	**MRR**	**MAP**
BM25	0.2500***	0.3034***	0.3938***	0.3764***	0.3060***
LSA	0.1275***	0.3106***	0.4314***	0.3633***	0.4141***
Simple Matching	0.1822***	0.3307***	0.4161***	0.3915***	0.4318***
TF-IDF	0.2000***	0.3472***	0.4209***	0.4036***	0.4400***
Proposed EVA-DSSM	**0.6714**	**0.6905**	**0.7322**	**0.6953**	**0.7504**
Algorithm	**Remote**				
	NDCG@1	**NDCG@3**	**NDCG@5**	**MRR**	**MAP**
BM25	0.3030***	0.3214***	0.4543***	0.3567***	0.4467***
LSA	0.0393***	0.2178***	0.3254***	0.2792***	0.3132***
Simple Matching	0.0693***	0.2215***	0.3317***	0.2839***	0.3200***
TF-IDF	0.0714***	0.2369***	0.3425***	0.2932***	0.3336***
Proposed EVA-DSSM	**0.5501**	**0.6730**	**0.6972**	**0.6852**	**0.7006**
Algorithm	**DoS**				
	NDCG@1	**NDCG@3**	**NDCG@5**	**MRR**	**MAP**
BM25	0.3333	0.3421***	0.3843***	0.4134***	0.3762***
LSA	0.0719***	0.1834***	0.2318***	0.2272***	0.2754***
Simple Matching	0.0314***	0.1363***	0.1717***	0.1788***	0.2341***
TF-IDF	0.0351***	0.1331***	0.1923***	0.1883***	0.2408***
Proposed EVA-DSSM	**0.3842**	**0.4314**	**0.4829**	**0.5394**	**0.5937**

Note: *p-value<0.05, **:p-value<0.01, ***:p-value<0.001

Table 14. Quantities and Percentages Correct at P@1 for Top Exploit-Vulnerability Link*

Algorithm	**Web applications (n=540)**		**Local (n=1,097)**		**Remote (n=1,900)**		**Dos (n=1,733)**	
	P@1 %	**# correct**	**P@1 %**	**# correct**	**P@1 %**	**# correct**	**P@1 %**	**# correct**
Bm25	51.53%	278	35.92%	394	37.85%	719	38.10%	660
Lsa	27.20%	146	25.15%	276	23.91%	454	23.85%	413
Simple matching	30.30%	163	30.20%	331	36.72%	698	18.62%	322
Tf-idf	33.86%	182	33.55%	368	36.54%	694	21.05%	364
Proposed EVA-DSSM	**78.40%**	**423**	**77.75%**	**853**	**74.36%**	**1,413**	**58.84**%	**1,019**

Note: *The # correct is calculated by multiplying the P@1 score of each algorithm by 100.

Table 15. Example Exploit-Vulnerability Link Correctly Detected by EVA-DSSM but Missed by Best Competing Non-Deep Learning Approaches

Dataset	**Selected vulnerability**	**Model**	**Top linked exploits**
Web applications	Zend Framework / zend-mail 2.4.11 - Remote Code Execution Exploit	Simple word matching	MS15-080: Vulnerabilities in Microsoft Graphics Component Could Allow Remote Code Execution (3078662)
		BM25	MS09-050: Vulnerabilities in SMBv2 Could Allow Remote Code Execution
		EVA-DSSM	**FreeBSD: phpmailer— Remote Code Execution**

Local	Systemd 228 - Privilege Escalation Vulnerability	Simple word matching	Debian DSA-2765-1: davfs2 - privilege escalation
		BM25	PHP 5.6.x < 5.6.30 Multiple DoS
		EVA-DSSM	**PHP 7.1.x < 7.1.1 Multiple Vulnerabilities**
Remote	SAP Solman 7.31 Information Disclosure Vulnerability	Simple word matching	Triangle MicroWorks SCADA Data Gateway < 3.3.729 Heartbeat Information Disclosure (Heartbleed)
		BM25	Oracle Linux 5: bind (ELSA-2015-1514)
		EVA-DSSM	**CentOS 6: squid34 (CESA-2017:0183)**
DoS	Ubuntu 11.10/12.04 - binfmt_script Stack Data Disclosure Vulnerability	Simple word matching	Ubuntu 10.04 LTS / 11.04 / 11.10 / 12.04 LTS: Firefox vulnerabilities (USN-1600-1)
		BM25	Ubuntu 16.04 LTS: linux, linux-snapdragon vulnerabilities
		EVA-DSSM	**Ubuntu 12.04 LTS: linux-lts-quantal—Linux kernel hardware enablement from Quantal regression (USN-1704-2)**

The examples listed in Table 15 indicate that the simple matching and BM25 approaches directly match contents from the exploit and vulnerability texts and result in incorrect linkages. For example, the simple word matching in each dataset incorrectly retrieved exploits that had direct overlaps with listed vulnerabilities. For the web applications dataset, this was the phrase "remote code execution"; for the local dataset, this was the phrase "privilege escalation"; for the remote dataset, this was the phrase "information disclosure"; and for the DoS dataset, this was the term "Ubuntu." The consistency of these issues across all four datasets indicates that simple matching approaches, while appearing to have some face validity for exploit-vulnerability matching because of overlapping technology names in exploit and vulnerability names, cannot capture the semantics or context of selected technology names that EVA-DSSM can. This is most pronounced on the web dataset. In the listed examples, the Zend framework in PHP and FreeBSD is commonly associated with the Linux operating system and the PHP. Our approach correctly identified these relationships, whereas the matching-based approaches match simply on the appearance of the phrase "remote code execution." Taken together, these results indicate that EVA-DSSM's use of DL processing makes it more robust to noise and word variations and in its ability to identify semantic cues (e.g., technology frameworks) missed by prevailing non-DL short text matching algorithms.

Experiment 2 Results: EVA-DSSM vs. Deep Learning-based Short Text Matching Algorithms

In Experiment 2, we evaluated the performance of EVA-DSSM against state-of-the-art DL-based short text matching algorithms. Eleven models were selected for benchmarking, including those based on feed-forward DNN, CNN, or LSTM. As in Experiment 1, all models were evaluated based on MAP, MRR, and NDCG ranks of 1, 3, and 5. All algorithm performances for each dataset are presented in Table 16. The highest performance scores for each dataset and metric are boldfaced.

EVA-DSSM attained an NDCG@1 score of 0.6570 for the web applications dataset, 0.6714 on the local dataset, 0.5501 on the remote dataset, and 0.3342 on the DoS dataset. Each of these performances was statistically significant over all benchmark algorithms across each dataset except DRMM, DUET, Conv-KNRM, and MV-LSTM in the remote dataset; however, EVA-DSSM still attained higher performances than these algorithms. Apart from the standard DSSM, the DNN-based models (aNMM, DRMM, DUET) consistently attained the lowest NDCG@1 scores on each dataset. The CNN-based models (ARC-I, ARC-II, KNRM, Conv-KNRM) and LSTM-based models (Match-LSTM, MV-LSTM) attained stronger performances over the DNN-based variations. This indicates that leveraging convolutional or long-short term dependency operations captures cues within the input texts missed by assuming a bag-of-trigrams. EVA-DSSM's outperformance of both CNN and LSTM-based methods suggests that incorporating attention mechanisms can help capture global relationships and semantics across exploit and vulnerability short texts missed by prevailing approaches. We quantified the number of instances where the algorithm correctly matched a vulnerability to an exploit on the first link by multiplying each algorithm's best P@1 score by the total number of instances in each testing dataset (denoted as n in Table 17). Top performances for each dataset are highlighted in bold.

EVA-DSSM achieved a higher P@1 score over the benchmark methods in all datasets. In the web application dataset, EVA-DSSM correctly identified 28 more instances than the original DSSM for a 5.20% increase. EVA-DSSM also demonstrated a similar performance gain in the remote dataset, where it detected 81 more links correctly than the closest benchmark, DRMM (4.24% increase).

Table 16. Experiment 2 Results: EVA-DSSM vs. Deep Learning-based Short Text Matching Algorithms

Algorithm category	Algorithm	Web applications				
		NDCG@1	**NDCG@3**	**NDCG@5**	**MRR**	**MAP**
DNN-based	aNMM	0.3125***	0.4527***	0.5114***	0.5075***	0.4704***
	DSSM	0.5968*	0.7325	0.7796	0.7468	**0.7947**
	DRMM	0.3619**	0.4874***	0.5497***	0.5156***	0.5373***
	DUET	0.0907***	0.3489***	0.4257***	0.3704***	0.3959***
CNN-based	ARC-I	0.0906***	0.3378***	0.4275***	0.3637***	0.4042***
	ARC-II	0.3250***	0.4894***	0.5410***	0.5275***	0.5405***
	KNRM	0.5312**	0.6248**	0.6728**	0.6772**	0.6786*
	Conv-KNRM	0.5531**	0.6716*	0.6973*	0.7122	0.6864*
LSTM-based	Match-LSTM	0.1063***	0.2906***	0.4187***	0.3606***	0.3839***
	MV-LSTM	0.4531***	0.6416**	0.6648**	0.6481**	0.6473**
Proposed EVA-DSSM	EVA-DSSM-2	0.6480	0.7224	0.7634	0.7561	0.7676
	EVA-DSSM	**0.6570**	**0.7550**	**0.7944**	**0.7789**	0.7932
Algorithm Category	**Algorithm**	**Local**				
		NDCG@1	**NDCG@3**	**NDCG@5**	**MRR**	**MAP**
DNN-based	aNMM	0.3525***	0.4421***	0.5099***	0.5229***	0.4897***
	DSSM	0.1700***	0.2511***	0.4242***	0.3807***	0.3606***
	DRMM	0.4850***	0.5837***	0.6311***	0.6388**	0.6188***
	DUET	0.3725***	0.4356***	0.5231***	0.5146***	0.5268***
CNN-based	ARC-I	0.3275***	0.4152***	0.4923***	0.4754***	0.4914***
	ARC-II	0.4025***	0.5010***	0.5681***	0.5646***	0.5692***
	KNRM	0.4000***	0.4603***	0.5389***	0.5478***	0.5155***
	Conv-KNRM	0.5175***	0.6455*	0.6723**	0.6696	0.6984**
LSTM-based	Match-LSTM	0.2300***	0.3459***	0.4389***	0.4053***	0.4485***
	MV-LSTM	0.5325***	0.5943***	0.6483***	0.6541*	0.6365***
Proposed EVA-DSSM	EVA-DSSM-2	0.6378*	0.6752	0.7127	0.6649	0.7441
	EVA-DSSM	**0.6714**	**0.6905**	**0.7322**	**0.6953**	**0.7504**
Algorithm Category	**Algorithm**	**Remote**				
		NDCG@1	**NDCG@3**	**NDCG@5**	**MRR**	**MAP**
DNN-based	aNMM	0.4214***	0.5453***	0.5670***	0.6009***	0.5434***
	DSSM	0.3339***	0.5019***	0.5579***	0.5391***	0.5722***
	DRMM	0.5339	0.6420	0.6830	0.6943	0.6760*
	DUET	0.5232	0.6104**	0.6601*	0.6671	0.6061***
CNN-based	ARC-I	0.2589***	0.3683***	0.4409***	0.4384***	0.4038***
	ARC-II	0.3964***	0.5450***	0.5855***	0.5999***	0.5616***
	KNRM	0.4571***	0.5521***	0.6152***	0.6433**	0.5549***
	Conv-KNRM	0.5411	0.6330*	0.6745*	**0.7053**	0.6553**
LSTM-based	Match-LSTM	0.1536***	0.3220***	0.4164***	0.3881***	0.4026***
	MV-LSTM	0.5393	0.6250**	0.6549**	0.6831	0.6420**
Proposed EVA-DSSM	EVA-DSSM-2	0.5478	**0.6742**	0.6936	0.6684	0.6992
	EVA-DSSM	**0.5501**	0.6730	**0.6972**	0.6852	**0.7006**
Algorithm Category	**Algorithm**	**DoS**				
		NDCG@1	**NDCG@3**	**NDCG@5**	**MRR**	**MAP**
DNN-based	aNMM	0.1790***	0.2691***	0.3640***	0.3969***	0.3532***
	DSSM	0.2632**	0.3625*	0.4079*	0.5011	0.4367**
	DRMM	0.2333**	0.2954***	0.3493***	0.4052**	0.3851***
	DUET	0.1561***	0.2388***	0.2917***	0.3179***	0.3368***
CNN-based	ARC-I	0.1176***	0.2111***	0.2717***	0.2828***	0.3233***
	ARC-II	0.2053***	0.2881***	0.3395***	0.3697***	0.3864***
	KNRM	0.2684**	0.3166***	0.3461***	0.3817***	0.4002***
	Conv-KNRM	0.2825**	0.3291***	0.3913**	0.4293**	0.4468**
LSTM-based	Match-LSTM	0.2986*	0.3452*	0.4102*	0.4652	0.4472**
	MV-LSTM	0.2614**	0.3397**	0.4095*	0.4524*	0.4371**
Proposed EVA-DSSM	EVA-DSSM-2	0.3801	0.4285	**0.4881**	0.5333	**0.6009**
	EVA-DSSM	**0.3842**	**0.4314**	0.4829	**0.5394**	0.5937

Note: *p-value < 0.05, **p-value < 0.01, ***p-value < 0.001

Table 17. Quantities and Percentages Correct at P@1 for Top Exploit-Vulnerability Link*

Algorithm Category	Algorithm	Web Applications (n=540)		Local (n=1,097)		Remote (n=1,900)		DoS (n=1,733)	
		P@1 %	# correct	P@1 %	# correct	P@1 %	# correct	P@1 %	# correct
DNN-based	ANMM	52.62%	284	41.82%	459	54.51%	1,036	30.52%	528
	DSSM	73.20%	395	66.91%	734	49.84%	947	46.33%	802
	DRMM	52.22%	281	39.25%	431	70.12%	1,332	40.63%	704
	DUET	33.21%	179	47.53%	521	64.65%	1,228	28.53%	494
CNN-based	ARC-I	27.73%	149	45.72%	502	40.60%	771	20.96%	363
	ARC-II	52.66%	284	51.42%	564	51.52%	979	35.86%	621
	KNRM	68.69%	370	50.89%	558	59.63%	1,133	44.87%	777
	Conv-KNRM	71.64%	386	60.69%	666	69.65%	1,323	47.60%	824
LSTM-based	Match-LSTM	37.63%	203	41.77%	458	47.21%	897	48.50%	840
	MV-LSTM	67.99%	367	61.12%	671	60.22%	1,144	45.24%	784
Proposed EVA-DSSM	EVA-DSSM-2	78.22%	422	76.14%	835	72.32%	1,374	57.98%	1,004
	EVA-DSSM	**78.40%**	**423**	**77.75%**	**853**	**74.36%**	**1,413**	**58.84**%	**1,019**

*The # correct is calculated by multiplying the P@1 score of each algorithm by 100.

EVA-DSSM showed similar improvements for both the local and DoS datasets with 10.84% and 10.34% performance gains, respectively. In Table 18, we illustrate sample exploit-vulnerability linkages in each test dataset that EVA-DSSM correctly identified but were missed by the best competing approach for each dataset (DSSM for the web application and local datasets, DRMM for the remote dataset and Match-LSTM for the DoS dataset). The exploits appearing in bold were correct (i.e., listed as relevant in the ground-truth dataset). Additional examples can be requested by contacting the lead author of this article.

The results suggest that the proposed EVA-DSSM captured the semantics of terms more effectively than benchmark approaches. In the web applications dataset, for instance, EVA-DSSM correctly identified that "FreeBSD" was associated with the "Zend Framework." Similarly, EVA-DSSM captured that "CentOS" term was more closely associated with "SAP Solman" (a technology that can run CentOS) than "Cisco Telepresence" in the remote dataset. These results indicate that EVA-DSSM's ability to capture global relationships across input texts and iterative reweighting of features via the attention mechanisms helps capture finer-grained semantic overlaps than conventional approaches. The results also suggest that EVA-DSSM captured sequences of texts more effectively in the DoS dataset than Match-LSTM (capturing "Ubuntu" at the start of the exploit and vulnerability names). This indicates that the incorporation of the BiLSTM layer captures the location of particular terms more effectively than the LSTM-based counterpart.

Experiment 3 Results: EVA-DSSM Sensitivity Analysis

In Experiment 3, we aimed to identify EVA-DSSM's sensitivity to word hashing, LSTM, the number of dense layers, and attention mechanism inclusion. As previously mentioned, standard word hashing segments input text into letter trigrams for natural language applications. However, cybersecurity text has non-natural terms such as version numbers, system names, and others. Experiment 3 examined the performance of utilizing letter bigrams, letter trigrams, letter 4-grams, and word n-gram for the EVA-DSSM. While concerns have been raised that hashing increases collisions (Huang et al., 2013) of identical letter n-grams, only the short text exploit and vulnerability names are hashed, not the underlying descriptions or discussions. Thus, the hashing collisions in our data are negligible (0.0058%) for all experiments. In addition to evaluating the performance of hashing variations, we also evaluated EVA-DSSM's sensitivity to variations in the LSTM layers (one- and two-layer LSTM and BiLSTMs), number of dense layers, and the removal of attention mechanisms. We present the results of Experiment 3 in Table 19; top performances of each variation are highlighted in bold. Across all datasets, the base EVA-DSSM model using letter trigrams, one-layer Bi-LSTM, two dense layers, and self-attention and context attention mechanisms achieved the strongest performance. When considering the word hashing sensitivity analysis, the strong performance of letter trigrams is likely attributable to its ability to capture semantics that letter bigrams and word n-grams miss.

Table 18. Example Exploit-Vulnerability Linkages Correctly Detected by EVA-DSSM but Missed by Best Competing Deep Learning Approaches

Dataset	Vulnerability	Model	Top linked exploit
Web applications	Zend Framework / zend-mail 2.4.11 - Remote Code Execution Exploit	DSSM	Oracle Linux 6: thunderbird (ELSA-2013-0821)
		EVA-DSSM	**FreeBSD: phpmailer -- Remote Code Execution**
Local	Systemd 228 - Privilege Escalation Vulnerability	DSSM	GLSA-201309-11: Subversion
		EVA-DSSM	**PHP 7.1.x < 7.1.1 Multiple Vulnerabilities**
Remote	SAP Solman 7.31 Information Disclosure Vulnerability	DRMM	Cisco TelePresence Video Communication Server Heartbeat Information Disclosure (Heartbleed)
		EVA-DSSM	**CentOS 6: squid34 (CESA-2017:0183)**
DoS	Ubuntu 11.10/12.04 - binfmt_script Stack Data Disclosure Vulnerability	Match-LSTM	RHEL 6: kernel (RHSA-2017:0316)
		EVA-DSSM	**Ubuntu 12.04 LTS: linux-lts-quantal - Linux kernel hardware enablement from Quantal regression**

Table 19. Experiment 3 Results: EVA-DSSM Sensitivity Analysis

EVA-DSSM variation		**Web applications**					**Local**				
		NDCG@1	**NDCG@3**	**NDCG@5**	**MRR**	**MAP**	**NDCG@1**	**NDCG@3**	**NDCG@5**	**MRR**	**MAP**
Input text	Letter bigrams	0.4976	0.6892	0.7022	0.6891	0.7355	0.5049	0.5844	0.6282	0.6578	0.6890
	Letter trigrams	**0.6570**	0.7550	**0.7944**	**0.7789**	**0.7932**	**0.6714**	**0.6905**	**0.7322**	0.6953	**0.7504**
	Letter 4-grams	0.6392	**0.7684**	0.7898	0.7753	0.7815	0.5663	0.6480	0.6742	**0.6959**	0.7098
	Word n-gram	0.4015	0.5310	0.5647	0.5856	0.6106	0.4837	0.5549	0.5997	0.5891	0.6240
LSTM	One Layer LSTM	0.6349	0.7258	0.7667	0.7710	0.7543	0.6125	0.6811	0.7172	0.7044	0.7340
	One Layer Bi-LSTM	0.6570	0.7550	**0.7944**	**0.7789**	0.7932	0.6714	0.6905	0.7322	0.6953	**0.7504**
	Two Layer LSTM	**0.6601**	**0.7667**	0.7890	0.7729	**0.7967**	0.6456	0.6909	0.7230	0.6948	0.7214
	Two Layer Bi-LSTM	0.6535	0.7458	0.7803	0.7414	0.7838	**0.6810**	**0.7033**	**0.7349**	**0.7057**	0.7310
Dense layer	One dense layer	0.6202	0.7135	0.7639	0.7733	0.7573	0.6489	**0.7014**	0.7280	0.7006	0.7332
	Two dense layers	0.6570	**0.7550**	**0.7944**	0.7789	**0.7932**	**0.6714**	0.6905	**0.7322**	0.6953	**0.7504**
	Three dense layers	**0.6668**	0.7424	0.7898	**0.7830**	0.7841	0.6631	0.6970	0.7185	**0.7104**	0.7459
Attention	Removing self-attention	0.6011	0.6754	0.6938	0.7042	0.7284	0.5716	0.6547	0.6834	0.6885	0.7078
	Removing context attention	0.5327	0.6372	0.6566	0.6477	0.6890	0.5580	0.6246	0.6468	0.6599	0.6823
Base EVA-DSSM Performance*		**0.6570**	**0.7550**	**0.7944**	**0.7789**	**0.7932**	**0.6714**	**0.6905**	**0.7322**	**0.6953**	**0.7504**
EVA-DSSM variation		**Remote**					**DoS**				
		NDCG@1	**NDCG@3**	**NDCG@5**	**MRR**	**MAP**	**NDCG@1**	**NDCG@3**	**NDCG@5**	**MRR**	**MAP**
Input text	Letter bigrams	0.4850	0.5927	0.6289	0.6314	0.6425	0.2711	0.3765	0.4099	0.4522	0.4492
	Letter trigrams	0.5501	**0.6730**	**0.6972**	**0.6852**	**0.7006**	0.3842	**0.4314**	**0.4829**	**0.5394**	**0.5937**
	Letter 5-grams	**0.5688**	0.6689	0.6840	0.6841	0.6833	**0.3901**	0.4149	0.4670	0.5187	0.5573
	Word n-gram	0.4201	0.5317	0.5890	0.6013	0.5893	0.3055	0.3834	0.4258	0.4780	0.5058
LSTM	One Layer LSTM	0.5077	0.6439	0.6639	0.6750	0.6574	0.3422	0.4078	0.4361	0.5005	0.5379
	One Layer Bi-LSTM	**0.5501**	**0.6730**	**0.6972**	0.6852	0.7006	**0.3842**	0.4314	**0.4829**	**0.5394**	**0.5937**
	Two Layer LSTM	0.5392	0.6644	0.6858	0.6820	0.6715	0.3535	0.4144	0.4592	0.5196	0.5768
	Two Layer Bi-LSTM	0.5569	0.6698	0.6953	**0.6872**	**0.7019**	0.3720	**0.4496**	0.4797	0.5304	0.5880
Dense layer	One dense layer	0.5305	0.6590	0.6744	0.6616	0.6658	0.3671	0.4058	0.4485	0.4870	0.5564
	Two dense layers	**0.5501**	**0.6730**	**0.6972**	**0.6852**	**0.7006**	0.3842	0.4314	**0.4829**	0.5394	**0.5937**
	Three dense layers	0.5489	0.6683	0.6948	0.6839	0.6959	**0.3864**	**0.4406**	0.4760	**0.5460**	**0.6017**
Attention	Removing self-attention	0.5244	0.6277	0.6550	0.6618	0.6647	0.3437	0.4318	0.4552	0.5065	0.5580
	Removing context attention	0.4597	0.5721	0.6014	0.6145	0.6338	0.3053	0.3822	0.4174	0.4768	0.5295
Base EVA-DSSM Performance*		**0.5501**	**0.6730**	**0.6972**	**0.6852**	**0.7006**	**0.3842**	**0.4314**	**0.4829**	**0.5394**	0.5937

Note: *The base EVA-DSSM uses letter trigrams, one layer Bi-LSTM, two dense layers, and both self-attention and context attention mechanisms. When conducting the sensitivity analysis, only one model component was varied at a time to identify the contribution of that model component to the overall EVA-DSSM. This is consistent with best practices in deep learning literature in prevailing IS journals (Zhu et al., 2020; Zhu et al., 2021).

Examining outputted results indicated that many exploit and vulnerability names contained three-letter acronyms such as *"SSH"* for *Secure Shell*, *"PHP"* for *Hypertext Preprocessor*, *"XSS"* for *Cross-Site Scripting*, and many others. These acronyms are key components of vulnerability and exploit names like *"OpenSSH Security Bypass," "SSH Cracker,"* and *"Casper PHP Trojan."* Letter bigrams create too small of a window (e.g., "*PH*" and "*HP*" for "*PHP*"), while word n-grams create windows too large (e.g., *"OpenSSH"* instead of capturing just *"SSH"*). Letter trigrams create a window large enough to capture these key three-letter acronyms. When considering the Bi-LSTM sensitivity analysis, results indicated that using only the LSTM that processes in a single direction rather than two directions resulted in performance degradation. This is likely due to the nature of how sequential dependencies appear in exploit and vulnerability names. With regard to the dense layers, the performance increased when having two layers as opposed to one, but the differences were negligible when adding a third layer. However, removing either attention mechanism from the EVA-DSSM substantially reduced the performance. This performance decrease was most pronounced when removing the context attention, which dropped by nearly 15% in some cases. This indicates that the context attention's ability to capture and weigh global relationships across input text significantly improves overall exploit-vulnerability linking.

U.S. Hospital Case Study Results

The vulnerability assessment of the top eight hospitals revealed that 344 / 1,879 (18.31%) of scanned devices have vulnerabilities, and 176 of those have multiple vulnerabilities, while the remaining 168 have only one. Vulnerabilities in the "Critical" threshold were due to outdated PHP, OpenSSL, or Unix versions. "High" and "Medium" had Apache, SQL, SSH, and XSS issues. Table 20 summarizes selected vulnerabilities in the "Critical," "High", and "Medium" levels. For each vulnerability, we list the most relevant exploit determined by EVA-DSSM.

Vulnerabilities at the "Critical" risk level pertained to unsupported PHP, OpenSSL, and Unix technologies. Their associated exploits aimed to take advantage of common issues associated with unsupported technologies such as susceptibilities to injections, memory disclosures, and backdoors. Vulnerabilities in the "High" risk level were related to Apache vulnerabilities, with the most relevant exploit related to DoS. Finally, the vulnerabilities in the "High" risk level pertained to tracing HTTP methods and weak SSH algorithms. The number of devices afflicted with vulnerabilities increased as the risk level decreased. To identify the top devices that security analysts can prioritize for remediation, we calculated the DVSM for each device. For space considerations, we list only the top-ranked device on each hospital's network in Table 21. We randomized the order in which they appear, as well as anonymized the last three octets of each hospital's IP range and selected device to protect their privacy.

Results indicate that SSH servers, web servers, Apple TV, and medical portals are vulnerable. All but one device had between two and six vulnerabilities due to web application, SSH, and outdated software issues. Hackers can potentially exploit these vulnerabilities with the linked exploits to gain a foothold into the hospital's network (Weidman, 2014). The most susceptible device was an eCare portal on the 17x.x.x.x network (DVSM 61.761) that likely provides healthcare-related services to patients. We depict the system's interface, selected vulnerabilities, most relevant exploit name for each vulnerability, the individual severity score for each exploit-vulnerability link, and the overall device vulnerability score in Figure 5.

Nessus detected 47 vulnerabilities for the device hosting the "Partners eCare Portal." After running the EVA-DSSM to create exploit-vulnerability linkages, the overall DVSM score resulted in 61.761. The large and diverse attack surface of this device increases its exploit probability. Vulnerabilities in this device include XSS, OpenSSL issues, buffer overflow, and DoS. This device also has a login form, indicating that it connects to a database. Hackers can exploit the form to access the underlying database and gain a foothold into the hospital's network to pivot to other devices. Each weak point can allow an attacker to remotely take the system offline or hijack it for their own use (Weidman, 2014).

SCADA Device Case Study Results

The case study examining SCADA devices aims to illustrate how CTI professionals can apply our framework to identify systemic vulnerabilities and their relevant hacker exploits for a specific device category rather than multiple networks with a diverse set of devices. Nessus results for the SCADA case study found that 4,009/20,461 (19.59%) devices have "critical" (182), "high" (189), "medium" (2,737), or "low" (901) risks. Most vulnerabilities pertain to unencrypted telnet servers and SSH servers. We summarize these vulnerabilities, their severities, most relevant exploit name, number of affected devices and major afflicted vendors of devices containing these vulnerabilities in Table 22.

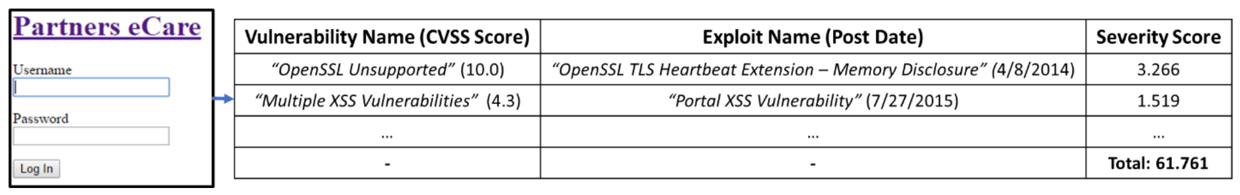
Vulnerabilities that affect SCADA devices such as programmable logic controllers (PLCs) are from major vendors including Rockwell Automation, Siemens, and Schneider Electric. PLCs are computers that automate and monitor electromechanical processes such as electrical relays, hydraulics, and motors.

Table 20. Selected Hospital Vulnerabilities and Their Most Relevant Exploits Identified by the EVA-DSSM

Risk level	Vulnerability names (severity)	Top linked exploit name and its post date	# of devices
Critical	"PHP Unsupported Version Detection" (10.0)	"phpshop 2.0 Injection Vulnerability" (1/14/2013)	11
	"OpenSSL Unsupported" (10.0)	"OpenSSL TLS Heartbeat Extension - Memory Disclosure" (4/8/2014)	7
	"Unix OS Unsupported Version Detection" (10.0)	"TCP/IP Invisible Userland Unix Backdoor with Reverse Shell" (6/30/2012)	6
High	"Multiple Apache Vulnerabilities" (8.3)	"Apache 2.4.17 - Denial of Service" (12/18/2015)	17
Medium	"HTTP TRACE / TRACK Methods Allowed" (5.0)	"traceroute Local Root Exploit" (11/15/2000)	58
	"SSH Weak Algorithms" (4.3)	"OpenSSH attack DoS" (7/4/2010)	55

Table 21. Most Susceptible Device on Each Hospital's Network

Selected devices for each hospital			Severity score information		
IP Range	**IP Address**	**Device type**	**# of Vulnerabilities**	**Vulnerabilities**	**DVSM**
12x.x.x.x	12x.x.x.x	FTP/SSH Server	3	FTP issues	4.591
19x.x.x.x	19x.x.x.x	SSH Server	3	SSH issues	4.376
17x.x.x.x	17x.x.x.x	eCare web portal	47	XSS, DoS, OpenSSL, buffer overflow	61.761
16x.x.x.x	16x.x.x.x	Medical computing portal	5	PHP and SSH issues	4.863
14x.x.x.x and 14x.x.x.x	14x.x.x.x	Web server	3	SQL Injections	7.528
	14x.x.x.x	Apple TV	2	Buffer overflow	5.381
14x.x.x.x	14x.x.x.x	SSH/Web server	4	PHP and SSH issues	3.871
6x.x.x.x	6x.x.x.x	Informational diabetes portal	3	Unix vulnerabilities	7.159
16x.x.x.x	16x.x.x.x	Web server	6	XSS	9.367



Vulnerability Name (CVSS Score)	Exploit Name (Post Date)	Severity Score
"OpenSSL Unsupported" (10.0)	*"OpenSSL TLS Heartbeat Extension – Memory Disclosure"* (4/8/2014)	3.266
"Multiple XSS Vulnerabilities" (4.3)	*"Portal XSS Vulnerability"* (7/27/2015)	1.519
...	...	...
-	-	**Total: 61.761**

Figure 5. Selected Vulnerabilities from Partners eCare Portal on the 17.x.x.x Hospital Network

Table 22. Selected SCADA Vulnerabilities and their Most Relevant Exploits as Identified by the EVA-DSSM

Vulnerability name (severity)	Exploit name (post date)	# of afflicted devices	Afflicted vendors
"Unencrypted Telnet Server" (5.8)	"Telnet-Ftp Server <= v1.218 Remote Crash" (3/19/2012)	1,407	Rockwell Automation, Siemens, Schneider, Power Measurement, Acromag, Honeywell
"Dropbear SSH Server Vulnerabilities" (5.0)	"DropBear SSHD 2015.71 - Command Injection" (3/3/2016)	524	

These components often appear in factories, industrial heating systems, and cooling units. Exploiting Telnet or SSH on these devices would allow hackers to remotely control, monitor, and alter communications to and from the system. The SSH botnet tool identified by the EVA-DSSM indicates that a skilled hacker can potentially exploit many PLCs simultaneously and turn them into bots to attack other targets. This kind of attack is not unprecedented: the Mirai malware infected hundreds of thousands of IoT devices to conduct a large-scale distributed denial of service (DDoS) against the internet's DNS servers in 2016 (Mathews, 2016). Many of the vulnerabilities detected in both case studies are addressable by following fundamental cyberhygiene. For example, Telnet is insecure by design; thus, it is recommended that users upgrade to more secure SSH clients. Outdated software issues related to PHP, Unix, and SSH can be mitigated by updating software.

Contributions and Limitations

In this paper, we carefully selected a relevant societal issue (automatic exploit-vulnerability linking) from a high-impact application environment (CTI) and searched for a solution space to identify and develop viable artifact designs (EVA-DSSM and DVSM). We conducted rigorous evaluations and proof-of-concept case study demonstrations to illustrate the validity and potential practical utility of our approaches. In the ensuing subsections, we present the contributions to the IS knowledge base, practical implications, and limitations of this work.

Contributions to the IS Knowledge Base

To date, IS scholars have extensively studied behavioral compliance, risk management, security investments, and the market effects of cybersecurity. While there is a growing body of cybersecurity analytics research, past Dark Web-based CTI efforts have almost entirely relied on one data source only (e.g., forums) (Samtani et al., 2020a). Moreover, hacker exploit and vulnerability assessment data contain significant natural and non-natural text content that sharply contrasts with data sources used in extant IS cybersecurity research. Consequently, there is a significant need for novel computational IT artifacts that can fuse multiple cybersecurity data sources (e.g., Dark Web and vulnerability assessment) to facilitate proactive CTI. In this study, we make two major contributions to the IS knowledge base: the EVA-DSSM algorithm and the DVSM score. We further describe each contribution and its related implications below.

EVA-DSSM Algorithm

Algorithms developed through the lens of the computational design science paradigm should contribute back to the methodological knowledge base from where they originated (Hevner et al., 2004; Rai, 2017). In this study, we drew upon an emerging body of DL-based short text matching algorithms to achieve our goal of automatically linking exploit and vulnerability names. Despite the promise of existing DL-based short text matching algorithms for our task, each extant algorithm relies on a single architecture (DNN, CNN, or LSTM) to represent and process input texts and often does not enhance the architecture with additional model components (e.g., attention mechanisms, highway networks, etc.) to improve model performance (Mitra & Crasswell, 2018). Against this backdrop, EVA-DSSM contributes a novel hybrid DL-based short text matching algorithm that integrates multiple architectures (Bi-LSTM and DNN) and emerging model components (attention mechanisms) to the growing body of short text matching algorithms. EVA-DSSM has three key design novelties:

- First, the first dense layer in the DSSM is replaced with a Bi-LSTM layer. As a result, the EVA-DSSM captures sequential dependencies (in both forward and backward directions) from the input exploit and vulnerability names as opposed to bag of letter trigrams.
- Second, EVA-DSSM includes a novel context attention layer to capture the global relationships across the exploit and vulnerability texts. Compared to the DSSM's approach of processing each input text separately throughout the entire matching process, this attention layer aims to identify and weigh overlapping contents prior to the final embedding matching.
- Finally, a self-attention mechanism is incorporated into the EVA-DSSM to weigh the vectors generated by the context attention layer. In contrast to DSSM not assigning weights to inputted texts or embeddings to improve exploit-vulnerability linking, the self-attention mechanism aims to iteratively re-weight embeddings to improve final matching performance.

Rigorously evaluating EVA-DSSM against prevailing short text matching approaches on web application, remote, local, and DoS exploit testbeds reveals several key insights about EVA-DSSM's design. First, the results of Experiment 1 (EVA-DSSM vs. non-DL short text matching algorithms) suggest that EVA-DSSM's basis in DL helped it capture semantics and word variations missed by algorithms with direct matching, distributional semantics, probabilistic matching, and term frequencies operations. Second, the results of Experiment 2 (EVA-DSSM vs. DL-based short text matching algorithms) suggest that EVA-DSSM's incorporation of bidirectional text processing and attention mechanisms captures sequences of text and linguistic characteristics of exploit and vulnerability names that are missed by approaches based in DNNs, LSTMs, or CNNs.

Finally, the results of the EVA-DSSM sensitivity analysis suggest that the letter trigram hashing that EVA-DSSM employs captures windows of text (e.g., three-letter technology names) that help it consistently attain stronger performances than bigram, 4-gram, or word n-gram variations. Additionally, removing either attention mechanism resulted in a precipitous decline in performance.

Since the EVA-DSSM extends the conventional DSSM for a new context (CTI), it falls into the exaptation quadrant of design science contributions (Gregor & Hevner, 2013). Although proposed for CTI, EVA-DSSM's grounding in short text matching principles suggests that it could be applied in related short text matching tasks such as query-document title matching, question-answering systems, and dialog response (e.g., automated chatbots for customer service). Each task has been noted by IS scholars as holding significant potential for addressing key tasks in important application areas (Chen et al., 2012; Samtani et al., 2020). Since differences may exist between the domains that these short text matching tasks are deployed, we identified three important design implications (through the design and evaluation of the EVA-DSSM) that IS scholars can consider when exapting EVA-DSSM or designing their short text matching algorithm:

1. **Identifying appropriate short text representations:** The results of Experiment 3 indicate that the manner in which input texts are represented (e.g., letter trigrams vs. word n-grams) affects overall matching performance. Therefore, future studies can consider capturing the semantics and structure of the input text based on the key characteristics and requirements of the domain they are studying; this could improve the performance of their DL-based algorithms for short text matching. Although letter trigrams were used in this study, other text representations that can be considered include associating named entities with each word, text graphs, and prematched grids.

2. **Integrating multiple DL architectures:** It has been well-established in short text matching literature that DL-based algorithms outperform non-DL variants (Mitra & Crasswell, 2018). The results of our study indicate that integrating multiple DL architectures (Bi-LSTM to capture sequential dependencies and DNN to generate embeddings for final exploit-vulnerability comparison) can lead to substantial improvements in performance over algorithms relying on a single DL architecture alone. Therefore, IS scholars can consider integrating multiple DL architectures (each assigned to conduct a particular processing task) for their short text matching applications.

3. **Extending base DL architectures:** EVA-DSSM's strong performance is largely attributable to extending its base Bi-LSTM and DNN architectures to operate with two attention mechanisms. When designing short text matching algorithms, scholars can consider extending their base model architecture with attention mechanisms and other emerging extensions to DL architectures (e.g., complex order embeddings, long short-range attention, and residual networks) to increase the model's capacity to learn from the input data and improve overall matching performance.

While these three considerations apply to many DL-based analytics, the results from our experiments suggest that they are especially important for attaining strong performance for our application of linking cybersecurity short texts.

DVSM Score

A key benefit of conducting multimodal analysis for cybersecurity is leveraging the metadata from heterogeneous data sources to construct specialized metrics to enhance cybersecurity decision-making (Samtani et al., 2020a). In this study, we proposed a novel DVSM score based on the exploit-vulnerability links generated by the EVA-DSSM. DVSM improves the conventional CVSS score (and therefore falls into the improvement quadrant of design science contributions) by accounting for the age of the hacker exploits linked to each vulnerability based on EVA-DSSM results. An inverse log function discounts each exploit's age to weigh newer exploits more heavily than older ones. All exploit-vulnerability severity calculations for a device are aggregated to form an overall device level score. We discovered that cybersecurity experts found the DVSM more useful than the conventional CVSS for risk prioritization in both the U.S. hospital and SCADA systems case studies through a carefully designed user evaluation. Since DVSM is flexible to numerous extensions (e.g., accounting for asset criticality) based on the context and needs of an organization and its cybersecurity team(s), it holds important implications for designing enhanced vulnerability severity scores and facilitating targeted risk management activities.

Practical Implications

The proof-of-concept case studies on U.S. hospitals and SCADA systems helped demonstrate the potential practical utility of the EVA-DSSM and DVSM. Three major groups of stakeholders can potentially benefit from the proposed approaches: analysts in SOCs, IR teams, and cybersecurity operations vendors. We further describe the implications of this study for each major stakeholder group in turn.

Analysts in SOCs. The heart of cybersecurity efforts within enterprise-level organizations often resides in SOC environments. Analysts in SOCs are typically responsible for identifying and prioritizing vulnerabilities (often based on quantity, severity, and relevant exploits) on their organization's networks. The number of devices (in the tens of thousands) and vulnerabilities (in the hundreds of thousands) that SOC analysts often manage can exceed human cognitive capacity and result in information overload. EVA-DSSM can provide a unique capability for SOC analysts to automatically sift through large quantities of Dark Web and vulnerability data to produce targeted exploit-vulnerability linkages.

IR Teams

The responsibility of remediating vulnerabilities typically belongs to IR teams. However, the scale of devices on enterprise networks often requires selecting devices for remediation. The DVSM can help IR teams prioritize devices for immediate remediation. IR teams can also adjust the base DVSM formulation to closely reflect the characteristics of their asset base. The DVSM scores for various aspects of their environment (e.g., subnets, assets, vulnerabilities, etc.) can also be included in the reports (e.g., visualizations, threat feeds, reports, etc.) that IR teams generate for their chief information security officers (CISOs) and to external information sharing and analysis organizations.

Cybersecurity Operations Vendors

Many enterprise organizations have the resources to fund dedicated cybersecurity teams with SOC analysts and IR teams. However, many small and midsize businesses cannot fund their own teams and therefore rely on third-party cybersecurity operations vendors (e.g., FireEye) for their CTI activities (e.g., vulnerability scanning, risk prioritization, mitigation). Recent studies reviewing the CTI industry have indicated that Dark Web-based analytics are included in less than 15% of CTI platforms (Samtani et al., 2020d). Recognizing this opportunity, EVA-DSSM and DVSM could potentially be included in CTI platforms to produce targeted and holistic threat intelligence.

Limitations

As with any study, our work has several limitations. First, EVA-DSSM cannot link exploits and vulnerabilities that are not yet published (i.e., publicly accessible). Second, DVSM does not explicitly account for the internal security controls that an organization may have deployed (information not available in our study). Third, we do not have access to the assets or organizational insight at any of the hospitals or SCADA networks to validate whether the detected vulnerabilities are truly susceptible to the linked hacker exploits. As a result, the expert evaluation of usefulness for the EVA-DSSM and DVSM is only a complementary evaluation (not the main evaluation) for the proposed approaches, rather than a thorough evaluation of risk likelihood and asset criticality in production environments (Agrawal et al., 2014). We note that these limitations are not limited to our study, but any study exploring vulnerabilities without organizational access (Mell et al., 2007; Farris et al., 2018).

Conclusion and Future Directions

Cybersecurity is undoubtedly one of modern society's grand challenges. CTI offers organizations the opportunity to mitigate cyberattacks. However, many organizations struggle to implement effective CTI capabilities due to their inability to automatically pinpoint relevant exploits for their vulnerabilities. Hacker forums from the Dark Web provide a novel data source that, when coupled with known vulnerabilities, can help develop proactive and holistic CTI. Although IS scholars are equipped to produce significant CTI research contributions in this regard, extant IS cybersecurity literature focuses primarily on behavioral compliance, risk management, investments in securing digital assets, and market effects of securing digital assets. Moreover, extant cybersecurity analytics literature has primarily focused on analyzing single data sources rather than multiple data sources simultaneously. Significant opportunity remains for IS scholars to develop novel computational IT artifacts that automatically link Dark Web data and vulnerability assessment data to enhance CTI capabilities.

In this study, we aimed to develop a novel approach to link hacker exploits from the Dark Web to vulnerabilities detected by vulnerability assessment tools (e.g., Nessus). To achieve this goal, we developed a novel EVA-DSSM algorithm that draws upon principles in deep learning, bidirectional text processing, and attention mechanisms. Through a series of technical benchmark experiments, we demonstrated how EVA-DSSM outperforms state-of-the-art non-DL and DL-based short text matching baseline methods across four major categories of exploits. In addition to contributing the EVA-DSSM, we also developed a novel DVSM score that incorporates vulnerability severity, quantity, and hacker exploit age to help support enhanced device prioritization. We demonstrated EVA-DSSM's and DVSM's potential practical utility with proof-of-concept case studies of openly accessible devices at the top eight U.S. hospitals and SCADA systems deployed worldwide. A complementary user evaluation indicated that 45 cybersecurity professionals (currently serving in SOC, IR, vulnerability management, and/or operational cybersecurity roles) found the EVA-DSSM and DVSM results more useful than those generated by baseline approaches for both case studies.

There are several promising directions for future research. First, researchers could apply EVA-DSSM and DVSM on foreign hacker forums (e.g., Russian, Middle Eastern) to identify the systems various geopolitical regions target. Second, behavioral IS studies could use cybercrime theories to better understand why hackers target specific vulnerabilities. Third, future work could build a user interface upon the EVA-DSSM and DVSM and deploy it into a production environment. Such a deployment could facilitate semistructured interviews with CISOs, longitudinal field studies, and case studies to help researchers understand how the approaches are adopted into practice. Finally, future computational IT artifacts could examine how to create exploit-vulnerability linkages for vulnerabilities present in emerging technologies such as GitHub, containers, dynamic virtual networks, and others. Each extension can provide much-needed cybersecurity capabilities to help secure cyberspace.

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About the Authors

Sagar Samtani is an assistant professor and Grant Thornton Scholar in the Department of Operations and Decision Technologies at the Kelley School of Business at Indiana University. Samtani graduated with his Ph.D. in management information systems from the University of Arizona's Artificial Intelligence (AI) Lab, where he served as a CyberCorps Scholarship-for-Service Fellow. Samtani's AI for cybersecurity and Dark Web analytics research initiatives have received funding from the National Science Foundation CRII, CICI, SaTC-EDU, and SFS programs. Samtani has published over 40 peer-reviewed articles in journals and conference proceedings, including *MIS Quarterly*, *Journal of MIS*, *IEEE Intelligent Systems*, *ACM*

Transactions on Privacy and Security, IEEE S&P, IEEE ICDM, IEEE ISI, and others. He is currently an associate editor at *ACM Transactions on MIS*, *ACM Digital Threats: Research and Practice*, and *Information and Management* and has served as a guest editor at *IEEE Transactions on Dependable and Secure Computing* and *ACM Transactions on MIS*. His research has received multiple awards and significant media coverage and citations from outlets such as the *Miami Herald*, *Fox News*, and *Science*. Dr. Samtani was inducted into the NSF/CISA CyberCorps SFS Hall of Fame in 2022 for his contributions to the cybersecurity community. He is a member of the IEEE, ACM, AIS, and INFORMS.

Yidong Chai is a professor at the School of Management at the Hefei University of Technology. He received his Ph.D. degree from the Department of Management Science and Engineering of Tsinghua University. His research centers around machine learning for health informatics, cyber threat intelligence, and business intelligence. His work has appeared in journals including *MIS Quarterly*, *Information Processing and Management*, *Knowledge-Based Systems* and *Applied Soft Computing*, as well as conferences and workshops including IEEE S&P, INFORMS Workshop on Data Science, Workshop on Information Technology Systems, International Conference on Smart Health, and International Conference on Information Systems.

Hsinchun Chen is Regents Professor and Thomas R. Brown Chair in Management and Technology in the Management Information Systems Department at the Eller College of Management, University of Arizona. He received his Ph.D. in Information Systems from New York University. He is the author/editor of 20 books, 300 SCI journal articles, and 200 refereed conference articles covering digital library, data/text/web mining, business analytics, security informatics, and health informatics. He founded the Artificial Intelligence Lab at The University of Arizona in 1989, which has received $50M+ research funding from the NSF, National Institutes of Health, National Library of Medicine, Department of Defense, Department of Justice, Central Intelligence Agency, Department of Homeland Security, and other agencies (100+ grants, 50+ from NSF). He has served as editor-in-chief, senior editor or AE of major ACM/IEEE (ACM TMIS, ACM TOIS, IEEE IS, IEEE SMC), MIS (MISQ, DSS) and Springer (JASIST) journals and conference/program chair of major ACM/IEEE/MIS conferences in digital library (ACM/IEEE JCDL, ICADL), information systems (ICIS), security informatics (IEEE ISI), and health informatics (ICSH). His COPLINK/i2 system for security analytics was commercialized in 2000 and acquired by IBM as its leading government analytics product in 2011. The COPLINK/i2 system is used in 5,000+ law enforcement jurisdictions and intelligence agencies in the U.S. and Europe, making a significant contribution to public safety worldwide. Dr. Chen is director of the UA AZSecure Cybersecurity Program, with $10M+ funding from NSF SFS, SaTC, and CICI programs and CAE-CD/CAE-R cybersecurity designations from NSA/DHS. He is a fellow of ACM, IEEE, and AAAS.

Appendix A

Results of the Expert Evaluation of Usefulness

In the main text, we discussed the procedure for conducting a complementary user evaluation that examined how useful cybersecurity experts found the exploit-vulnerability pairs and risk (severity) scores generated from our proposed Exploit-Vulnerability Attention Deep Structured Semantic Model (EVA-DSSM) and Device Vulnerability Severity Metric (DVSM) compared to conventional Deep Structured Semantic Model (DSSM) and Common Vulnerability Scoring System (CVSS). This complementary user evaluation was conducted for both the case studies on the top eight hospitals in the U.S. and on the over 20,000 Supervisory Control and Data Acquisition (SCADA) devices worldwide. In Table A1, we provide sample links and scores for the hospital case study that were presented to the experts.

The contents in the first and fourth rows were generated by the EVA-DSSM and DVSM. The rest were from the conventional DSSM and CVSS. Blinding and interspersing links and scores in this way helped ensure that the cybersecurity experts did not favor one approach. For each link, we asked the expert if "the exploit-vulnerability link is useful for identifying what exploit could target this vulnerability." For each score, we asked if "the risk prioritization score is useful to prioritize exploit-vulnerability pairs more effectively." Following recent studies in information systems (IS) literature (Abbasi et al., 2018; Chau et al., 2020), each item was adapted from Davis (1989), Davis et al. (1989), and Venkatesh et al. (2003). Both items were rated on a scale of 1-7, with 1 being *strongly disagree* and 7 being *strongly agree.* To control the scope of each study, we selected the 76 exploit-vulnerability links presented from the hospital case study in Table 20 and the top 50 exploit-vulnerability pairs (based on the number of devices afflicted) for the SCADA case study. Executing the usefulness evaluations with these samples simulates the kind of situations a cybersecurity analyst commonly faces when prioritizing vulnerabilities, wherein they can identify the top-rated issues for multiple types of devices across their networks (hospital case study) and/or identify the top *n* of vulnerabilities that afflict a category of their devices (SCADA case study) (Agrawal, 2014). We present the mean values of the proposed approaches, mean values of the benchmark approaches, and the p-value attained by the paired t-test for both case studies in Table A2.

Overall, the panel of 45 cybersecurity experts found the EVA-DSSM and DVSM results more useful than the results of the prevailing benchmark approaches (DSSM and CVSS). The mean averages were higher for the SCADA case study than for the hospital case study. This is likely attributable to the nature of the exploit-vulnerability links that are present in SCADA devices, many of which pertain to the remote monitoring vulnerabilities present in these devices. These types of vulnerabilities are more commonly seen by cybersecurity experts, and therefore they can more effectively ascertain their usefulness compared to the diversity of exploits in the hospital example. Taken together, these results indicate that the EVA-DSSM and the DVSM both hold promise for serving as the foundation for advanced CTI systems.

Table A1. Sample Exploit-Vulnerability Links and Severity Scores Used for the User Evaluation on the Hospital Case Study

#	Vulnerability	Exploit	Risk score
1	Web server transmits Cleartext credentials	Joomla component event manager Blind SQL injection	0.313
2	Web server transmits Cleartext credentials	Mozilla Firefox 3.6 (multitudinous looping) denial of service exploit	2.6
3	Browsable web directories	OpenOffice .slk file parsing null pointer vulnerability	5.0
4	Browsable web directories	Safari v4.0.4 Firefox v3.5.6 SeaMonkey v2.0.1 Opera v10.10 DoS exploit	0.604

Table A2. Results of the Expert Evaluations of Usefulness*

Case study	Items	EVA-DSSM + DVSM	DSSM + CVSS	P-value
		Mean	Mean	
Hospitals	The exploit-vulnerability link is useful for identifying what exploit could target this vulnerability.	6.23	5.12	$p < 0.05$

	The risk score is useful to prioritize exploit-vulnerability pairs more effectively.	6.13	4.91	$p < 0.05$
SCADA	The exploit-vulnerability link is useful for identifying what exploit could target this vulnerability.	6.54	5.45	$p < 0.05$
	The risk prioritization score is useful to prioritize exploit-vulnerability pairs more effectively.	6.47	5.17	$p < 0.05$

Note: * Following the survey, the lead author followed up with each participant to debrief them about the intent, objective, and results of the study.