Zero-day Malicious Email Investigation and Detection Using Features with Deep-learning Approach

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Abstract: Cyber hackers use email as a tool to trick, inject or drop malicious software into the recipient’s device. Everyday users have to face off against, phishing or malicious emails and it would be a huge problem for whole organizations even if only one user clicked on a single link from this malicious email. The difficult issue is how to classify and detect those malicious emails from ordinary, especially spear phishing emails, which are designed for a particular target, or zero-day malicious emails that no one has ever found until now. In this paper, we introduce a way to classify and detect zero-day malicious emails by using deep-learning with data investigated from the email header and body itself, combined with dynamic analysis information as a group of features. Four different language email datasets can be used to train and test the system to simulate real-world diversity and zero-day malicious email attack situations. We succeeded in obtaining a satisfactory accuracy rate for detection results for both zero-day malicious email types and normal spam.

Keywords: zero-day malicious spam, spam detection, deep-learning, features extraction

1. Introduction

Nowadays, people are easily accessing the internet compared to the past. Among the thousands of types of internet services, email is still the most popular choice. We are all using emails for work, to contact people, and email is a basic requirement for system registration to apply for services on the internet. On the other hand, international cybersecurity reports such as the Cisco 2018 annual cybersecurity report\cite{1} said that the most common initial hacker attack method is by using malicious emails and APT \textit{Advanced Persistent Threat} attacks. Moreover, there is confirmation from other cybersecurity organizations, such as the Center for Internet Security report\cite{2}, that the number of cyberattack incidents increased in recent years, and doubled in 2017. The report showed that malicious spam (malspam) infection vector continues to stay the primary entry vector, from December 2017, increasing 8% in January 2018. The ISTR report from Symantec\cite{3} also confirmed that the percentage of emails which contain spam is 53%, 53% and 55% from 2015, 2016 and 2017 respectively. This means about 14.5 billion malicious spams are sent every single day in the first quarter of 2018 with spear phishing being the number one infection vector employed by 71% of organized groups in 2017. Spam mail is defined as the type of electronic spam where unsolicited messages are sent by email. Many spam emails are merely advertisements for products or services but some of them also contain disguised links that appear to be phishing websites or sites that host malware as scripts or other executable file attachments. These days, spam emails can also directly contain various malicious files such as Microsoft Office documents, pdf, JavaScript or PE files. Therefore, we call this type of email malicious spam (malspam). Consequently, a zero-day malspam is an email that contains a cyber-attack exploiting a vulnerability that has not been disclosed publicly. Machine learning is popular for automatically detecting both known and unknown threat types of infections. The technology can learn to identify unusual malspam in large numbers and automatically detect new malspam in the future. Above the popular well-known algorithms NB, SVN, or K-Nearest Neighbor (KNN), running the MPL neural network algorithm on test data seems to be the best way to detect spam in terms of efficiency. To detect malspam, email messages, headers, URL links, hash values and other features have been used to train the machine. However, for zero-day malspam, new APT threats or spear phishing, which is particularly designed to fool users and systems, is not easy for AI system to detect by training from those main features above. In this case, zero-day malspam still requires cybersecurity experts to investigate and analyze them manually. The question is, what is the difference between the information that we give to train the AI system and the information that experts use for classifying malspam? To verify this, more than 200 malspams have been manually investigated and analyzed\cite{4}, and we developed techniques to detect malware infection on the workstation\cite{5}, [6] in our earlier works. We have found the difference between malspam information and legitimate email from both header and body. Malspam usually has suspicious email header information, such as misconfigured time format, the unrelated relationship between domain time zone and language used, an unclear title that might have been taken from machine translation, etc. So, in this research, we...
design approaches to obtain more informational features similar to how cybersecurity experts do when investigating suspicious emails. We then use a deep-learning approach to increase detection accuracy and aim for an automatic system of zero-day malspam detection.

2. Related Research

Much research has already been done on spam and phishing email filtering by using machine learning with basic message information. In addition, Support Vector Machine (SVM), Naive Bayes (NB), K-Nearest Neighbor (K-NN) and Deep-Learning with Artificial Natural Network (NN) are the most common ways to classify email threats and the current accuracy of those classification results are already quite satisfactory. In 2017, Ajaz et al. [12] proposed a sophisticated and robust e-mail abstraction scheme based on Bayesian with a new scheme and efficiently captured the near duplicate of the spams as well as achieved efficient similarity matching and reduced data storage. Al-Jarrah et al. [7] identified potentially useful email header features for email spam filtering and used them as input to several machine learning-based classifiers and compared their performance in filtering email spam. More than 10 features from email header, such as the number of hops, spam time, domain address and legality, etc., were used and their results showed that Random Forest classifier has the best performance with an average accuracy, precision, recall, F-Measure, ROC area of 98.5%, 98.4%, 98.5%, and 98.5%, respectively. Wang et al. [16] also proposed the similar spam classification technique by using features of the sender and receiver address (To, CC, BCC), mail user agent and message-ID to train the system. Similar research by Hu et al. [17], Wu et al. [14], Ye et al. [15] and Sheu [13] also classified spam email by using different features information such as the size of an email, time, length of sender-destination field, sender IP or email subject and others with machine learning.

Shi and Xie [20] propose a reputation-based collaborative anti-spam approach to adopt fingerprinting techniques and for evaluating if a reporter is genuine by using MIME features of emails. By dividing each incoming email into five subparts: email header, text/plain content, text/html content, embedded resources and attachments, then generate a weighing fingerprint for different MIME subparts, they can achieve better performance and robustness than other methods.

Similarly, our research is also using email features information with deep-learning to classify and detect malicious email but we extract and collect more features information from both the email header and body and a relationship between them by using static and dynamic analysis. Moreover, these days zero-day malspam usually first release in one language and then be translated into other languages to spread into world-wide. So, we extract a new method to collect email subjects and titles in different languages to detect another version of malspam by using machine translation which was used by recent year zero-day ransomware attacks. While the related research above do not guarantee to detect zero-day malspam, we do aim to achieve this goal.

Not only bad email classification, but phishing webpage classification is also a popular research applied with machine learning. Mao et al. [8] proposed a learning-based aggregation analysis mechanism to determine the similarity of page layouts and detect phishing pages. Their approach automatically trains classifiers to determine web page similarity from CSS layout features, without requiring a human expert. By using SVM and Decision Tree (DT), the method achieved 93% and more than 95% accuracy results. Moghimi et al. [9] proposed two feature sets to improve a detecting phishing attack performance and preventing data loss in internet banking webpages. By using relevant features plus page resource identity feature set and page resource access protocol feature set with SVM, they got 99.14% true positive with 0.86 false positive alerts. Sonowal et al. [10] proposed a phishing detection model with a multi-filter approach. The result from their experiment shows that the model is capable to detect phishing sites with an accuracy of 92.72%. Basnet et al. [11] evaluated two common feature selection techniques, correlation based and wrapper-based techniques, for phishing detection. They compared the features selection techniques by using two feature space searching techniques, then conducted the experiments and evaluated results on a real world dataset with more than 16,000 phishing webpages and more than 32,000 non-phishing webpages. In our research, because the phishing spams usually contained a link or internal file attachment, we use API to upload and check suspicious links and files with free online dynamic analysis service and collect the results. Feature information such as Link status, File scan result, SHA-256, and others are extracted from the dynamic analysis results and given for the AI system process.

3. Method

Recently, neural networks and deep learning provides the best solutions to many problems in image recognition, speech recognition, and natural language processing. In this paper also we design to use neural network and deep learning by aiming to archive the best result of zero-day malspam detection. However, the result will also depend on which features we give to the system.

Features in machine learning is a piece of information included in the representation of the data they are given. It is well-known that a performance of machine learning algorithms depends on the representation of the data they are given. Most of the popular research on spam classification uses a set of features that come from the email header and body themselves directly, such as domain name, IP address, email title and body, or other features from text words analysis. Similar to what the security experts do, we collect and extract features from the email header analyzed information and email body dynamic analysis information that could be a clue to indicate suspicious email and judge them whether or not to be malspam or even unknown (zero-day) malspam. From analyzing more than 500,000 emails, we have discovered that a relationship between those headers and body features information is very important. For example, more than 99 percent of work emails are sent only within the working time period (8AM–8PM) which corresponds with the sender’s domain time-zone and language used (in case the language is not English). In case of Japanese email datasets, the result shows that Japanese people commonly use Japanese languages to communicate with the receiver during working time by using local email
domain service. On the other hand, malspam can be any language, sent in random time and might use domain service from a different geolocation. This means, the common Japanese email characteristic should be Japanese language title, correctly configured Japanese time zone, sent during the working time period from domain located in Japan time zone, while malspam can be any language title, misconfigured time zone, sent in any time from any domain outside Japan. Of course, there is a chance that malspam also has all common characteristics in the email header, that is why features from the email body is also important. Generally, the URL-based approach, content-based approach and the combination of those two are popularly used to generate features to detect phishing websites or phishing emails. So, from well-known features such as email title, body message, URL link, IP address, time stamp, etc., in this research, we analyze more information such as the domain location, domain time zone, language detected, machine translated detected, uncommon time format, sent time after normal work hours as well as relationship between each feature are also included. Consequently, the dynamic analysis for links, pictures, and attachment files from the email body includes link status, file scan result, file type, SHA-256, other file names, file size, last scan time, etc. Figure 1 shows the overall features of extraction flow from both the email header and body.

3.1 Email Header Extraction

In the email header extraction part, Fig. 2 shows the flow chart of this method. From the email dataset we first extract 3 main features: source address, timestamp and subject/title from email header directly. Then from the source address, we discover and extract domain location and domain time zone by using Whois API. At the same time, from timestamp we detect the time structure, time zone, time sent and create time related features. From the subject/title, we detect language and extract a language time zone feature. We also match subject/title with a bag of subject database to detect machine translated and risk words detected features.

Define an email as the symbol \( e = \{e_h, e_b\} \). Then from the email header and body part \( e_h \) and \( e_b \) extract into subfeatures \( e_h = \{e_h^1, e_h^2, \ldots, e_h^i\} \) and \( e_b = \{e_b^1, e_b^2, \ldots, e_b^i\} \).

3.2 Bag of Subject Database

Bag of subject is a concept similar to bag of words or bag of features which is popularly used in image processing. Because these days the attackers usually translate malspam into many different languages to expand an attack to many targeted countries world-wide, inside the database, we collect all types of email subject/title including both normal and abnormal language and aim to collect several language based email datasets other than English. By using language detection API, we can identify the email subject language and record the original subject/title into the database. Moreover, we use Yandex-translate API to translate the subject/title from the original form into other languages and record them into the database. In this research, we collect 4 languages (English, Chinese, Japanese and Lao) for experiments. However, as we randomly check the translation result from Yandex-API, the translation accuracy is still low compared to a well-known commercial Google translation API. We suggest adding more translation languages and a better accuracy translation result in the future for more efficiency. Finally, in case that subject/title is an abnormal language such as symbolic, digit numbers, emoticon or blank, these none-language subjects are directly sent to the database without translation. Figure 3 shows a Bag of subject database flows chart.

3.3 Email Body Extraction

From the email body, Fig. 4 shows how we extract features from the email body. First, we detect and extract 4 features included a story, URL link, picture and attachment file. For the email story, it has the same process as a subject/title feature, which is a detected language, classify words and store in the database. URL link, picture and attachment file will be uploaded into free online dynamic analysis service via Virustotal API. We then extract features from dynamic analysis result obtained from Virustotal API report include link status, link scan result, URL link, link last analyze date, web category, file type, file size, file name, file scan result, file SHA-256, file type detected, file last analyze date and other file names.

Table 1 shows all 27 features with their descriptions that we extracted from emails which used in deep-learning neural network model to classify and detect zero-day malspam.

Figure 5 displays the overall of the proposed method which
Table 1 Features list extracted from the email header and body.

| Feature Name       | From      | Description                                                                 |
|--------------------|-----------|-----------------------------------------------------------------------------|
| Sender address     | Header    | Email address of the sender                                                  |
| D location         | Header    | Location of the domain that sender use                                      |
| D time zone        | Header    | Time zone of the domain location                                             |
| Time structure     | Header    | Email time format                                                           |
| Email time zone    | Header    | Time zone set in email                                                       |
| Email time sent    | Header    | Time that email was sent                                                     |
| L detected         | Header    | Language detected from email subject                                         |
| L time zone        | Header    | Time zone of the language used in subject                                   |
| Subject/title      | Header    | Email subject/title                                                         |
| M detected         | Header    | Machine translated detected result                                           |
| W detected         | Header    | Risk words matching result                                                   |
| N detected         | Header    | None language detected from subject                                          |
| Link status        | Body      | Current status of targeted website                                           |
| Link scan result   | Body      | Result of link scan from dynamic analysis                                    |
| L last analyze     | Body      | Link’s last analyzed date                                                    |
| Url                | Body      | Link url                                                                    |
| Web category       | Body      | Targeted website category                                                    |
| F detected         | Body      | Detected a file attach in email                                             |
| F detected         | Body      | Detected a picture of logo in email                                         |
| F SHA-256          | Body      | SHA-256 of the attach file                                                  |
| F name             | Body      | File’s name                                                                 |
| F type             | Body      | File’s type                                                                 |
| F type detected    | Body      | File’s type detected from scan result                                        |
| F size             | Body      | File’s size                                                                 |
| F last analyze     | Body      | File’s last analyzed date                                                    |
| F scan result      | Body      | Result of file scan from dynamic analysis                                    |
| O file name        | Body      | Other file’s name information                                               |

Fig. 4 Features extraction from the email body’s flows.

4. Experiments

This section our experimentation grouped into 3 subsections: Environment and hardware implementation, Experiments and Evaluation methods.

4.1 Environment and Hardware Implementation

For training on deep-learning, we use Kyushu university’s supercomputer ITO-subsystem B [19] which satisfied the resource requirements for the experiment. TensorFlow, CUDA, and Python based APIs are used in software training. Table 2 shows email dataset that we currently own and use to extract features. Most of the datasets are downloaded from untroubled.org (spam), Enron email dataset (legitimate) and from the Kyushu university zero-day malicious email investigation and analysis lab which contain spam, legitimate, and malicious/phishing spam emails from 2012 to a recent time. We also use our private email dataset (TM) which contain in English, Japanese, Chinese, Lao and other language based subject/title emails. Thus, We keep searching for more email datasets of legitimate email and malicious spam in other language than English to increase capacity and diversity of the database.

4.2 Experiments

After extracting all 27 features from the email dataset, we train and test the system with different email datasets. We have done 4 separate experiments in different number of features in order to check the efficiency of the feature group. First, we used only plain-text words feature which is very popularly used for spam email classification. Second, we used 9 features from header parts including Sender email address, Domain location, Domain time zone, time structure, time zone, time sent, subject/title, language detect and language time zone. Next, we increase the number of features to be 12 which are all features obtained from email header part, Machine translated detect features, risk words detect features, normal and abnormal language detected features are included from the previous experiment case. Finally, we use all 27 features extracted from both the email header and body part which are also included in the features extracted from dynamic analysis results.

In this research, a Multi Layer Perceptron (MLP) artificial neuron network (ANN) algorithm [24] was applied to the extract features. We also use the concept of mutual information [25] to determine the root features in the detection process. The features vector can be defined as a group of features that are used in classification. Here, the mutual information score of each feature F and the candidate features in the training dataset are identified as follows:

\[ MI(F) = \sum_{F \subseteq [0,1], C \subseteq [0,1]} P(F = f, C = c) \log \frac{P(F = f, C = c)}{P(F = f)(C = c)} \]  

(1)

where \( C \) denotes the class (malspam or normal), \( P(F = f, C = c) \) is the probability that the features \( F \) occurs (\( F = 1 \)) or not (\( F = 0 \)) in malspam (\( C = \text{malspam} \)) or normal (\( C = \text{normal} \) emails,
\( P(F = f) \) is the probability that the feature \( F \) occurs \( (F = 1) \) or not \( (F = 0) \) in all emails, and \( P(C = c) \) is the probability that an email is malspam \( (C = \text{malspam}) \) or normal \( (C = \text{normal}) \).

A number of features with the highest mutual information scores were selected and we refer to this number as the feature vector size. The highest valued features are most probably the features occurring frequently in one class of normal emails and not so much in the malspam. The algorithms were executed with different feature vector sizes. After the feature vector size and the root features that form the feature vector are identified, it is necessary to determine the range of values that each element of the vector can take. Each vector element corresponds to an input node in the ANN and the value of that element corresponds to the value of the node.

### 4.3 Evaluation Results

This subsection explains how we calculate Precision, Recall and Accuracy in each part as follows:

\[
\text{Precision} = \frac{TP}{TP + FP} \quad (2)
\]

\[
\text{Recall} = \frac{TP}{TP + FN} \quad (3)
\]

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)
\]

While \( FP \) and \( TN \) are important values for detection results, \( FP \) has a strong relation with Precision and \( TN \) with Recall. Next section will show the experiment result with Precision, Recall and Accuracy rate using ANN models.

### 5. Result and Discussion

In our experiment, to verify an accuracy rate of our method of zero-day malspam detection, we use the extracted 27 features and use the testing datasets different from the training datasets with TensorFlow. Table 3 shows that the results of both spam and normal email type detection are very similar with 61.71%, 67.06%, 77.11% and 78.12% accuracy in order from 1, 9, 12 and 27 features experiments even using the dataset that have never been trained to the system before.

Currently our experiment cannot show which one is the most effective features to detect zero-day malspam because all features are related to each other and we need to give a set of features to the system. For example, we cannot adjudge that all emails which sent from African’s IP address are malspam. What we should do is to check the relationship of the set of features include domain location, domain time zone, email time sent, language detect, language time zone, M-W-N detected features before adjudge. So we believe that the most effective way to detect zero-day malspam is to use a set of features which contain some information from several features that related to each other.

From the result, the accuracy rate is significantly increased by increasing a number of features. However, in case of the 27 features, the result only increases 1% from the 12 features experiment. The reason is that the spam email dataset we used contains only normal spam, not malicious or phishing spam. Because normal spam email does not contain malicious file or link, so the system cannot receive any information from the dynamic analysis from email body, and this explains why 14 features from email body are not so efficient. We believe that if the trained dataset also contains enough malspam, the result from 27 features experiment will be improved. We also found that, to extract some features, such as machine translated detection and risk words detection features, the email title database is required to have as much translated text words in as many languages as possible. In addition, the effectiveness of the translation tool is also important. Currently, we are using free Yandex-translation API because of budget issues. The database we offer only supports 4 languages included English, Japanese, Chinese and Lao using Yandex-Translate API. By randomly checking the translation results, we found that some subject/titles are still not translated correctly, compared to the popular commercial translation service such as Google translator, so it is also possible that this issue could be affecting the overall result.

There are some miss-detection cases of normal email that adjudge to be a malspam. Those email are the email that have emotion or some special symbol in title that our system cannot extract feature information correctly. Those group of email that contain an archived a file locked with a password are also get the result depends on only features from the email header part. Our proposed method still cannot detect some zero-day malspam especially in spear phishing email. Normally a zero-day malspam is generated from virus infected victim’s devices or created by updating its previous version, or both. This means that combinations of these versions might be changed but at least it is still using some part from previous version such as it uses a same story but change a sender address and malicious file type. In some patterns, zero-day malspam change email story, sender address, file name/type but the hash value of the attach file still be the same and already discovered or can be detected by using dynamic analysis. However, the system cannot detect zero-day malspam in case of spear phishing technique which is good design for both the information from email header part and also new composition (a new malicious file or new phishing URL link) that cannot detect by using dynamic analysis.

In Table 4 we compare our result with some related research.

### Table 2  Email dataset collection and sources.

| Dataset          | Amount     | Type     | Description & Reference |
|------------------|------------|----------|-------------------------|
| Spam             | 4,567,714  | spam     | Spam emails (2012-June 2018) http://untroubled.org/spam/ |
| Zmal             | 281        | Malspam  | Malicious & phishing spam (2017-2018) Okamura Lab. Kyushu university. [19] |
| Enron            | 517,401    | legitimate | May 7, 2015 version of dataset https://www.cs.cmu.edu/~enron/ |
| TM               | 4,251      | legitimate | Email dataset (2012-2018) |

### Table 3  Zero-day malspam detection results.

| Features Used | Data type | Precision | Recall | TP   | FP   | FP accuracy |
|---------------|-----------|-----------|--------|------|------|-------------|
|               | Spam      | Normal    |         |      |      |             |
| 1             | 0.6152    | 0.6254    | 0.6254 | 0.3746 | 0.3911 | 0.6711     |
| 9             | 0.6648    | 0.6881    | 0.6881 | 0.3118 | 0.6530 | 0.6706     |
| 12            | 0.7785    | 0.7758    | 0.7758 | 0.2242 | 0.7711 |            |
| 27            | 0.7782    | 0.7866    | 0.7866 | 0.2133 | 0.7812 |             |
The spam filter results by using a same source of training and testing dataset. Our approach resulted in 92.86% accuracy while others such as Al-Jarrah et al., He et al. and Sheu resulted in a higher accuracy rate. However, those approaches are not confirmed in cases of a testing dataset that are different from training. While our approach got the best accuracy rate at 78.12%, we can say that we have successfully improved a method to detect a zero-day malspam. Thus, we believe that our method still has a lot of things to improve and evaluate to get better results in the future.

6. Conclusion

In this paper we propose a method by using new features extracted from email and deep-learning approach to detect zero-day malspam. We have successfully extracted 27 features from email’s header and body part, included machine translation detected, risk words detected and other features by using several APIs. We also use 4 different languages email dataset for more diversity and realistic purpose to build a words database and create features. Our experiment results show the accuracy rate of a zero-day malspam detection is about 78% and 92.8% for normal spam. Thus, we believe that the system still can be improved by adding more malicious spam datasets to train the system, as well as using a translation API having better accuracy.

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Appendix

A.1 Risk Words List

A.1.1 List of Risk Words in English

Here is the risk word list (English version) contains 455 key words. For more 3 other languages (Japanese, Chinese and Lao version please download from our dataset [26].

The risk words are: [100% #1 $$$ 100% free 100% Satisfied 4U 50% off Accept credit cards Acceptance Access Accordingly Act Now Action Ad Additional income Addresses on CD A

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