E-Mail Worm Detection Using Data Mining

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ABSTRACT

This work applies data mining techniques to detect e-mail worms. E-mail messages contain a number of different features such as the total number of words in message body/subject, presence/absence of binary attachments, type of attachments, and so on. The goal is to obtain an efficient classification model based on these features. The solution consists of several steps. First, the number of features is reduced using two different approaches: feature-selection and dimension-reduction. This step is necessary to reduce noise and redundancy from the data. The feature-selection technique is called Two-phase Selection (TPS), which is a novel combination of decision tree and greedy selection algorithm. The dimension-reduction is performed by Principal Component Analysis. Second, the reduced data is used to train a classifier. Different classification techniques have been used, such as Support Vector Machine (SVM), Naïve Bayes, and their combination. Finally, the trained classifiers are tested on a dataset containing both known and unknown types of worms. These results have been compared with published results. It is found that the proposed TPS selection along with SVM classification achieves the best accuracy in detecting both known and unknown types of worms.

Keywords: e-mail worm; feature selection; Naïve Bayes; principal component analysis; support vector machine

INTRODUCTION

E-mail worm spreads through infected e-mail messages. The worm may be carried by attachment, or the e-mail may contain links to an infected Web site. When the user opens the attachment, or clicks the link, the host gets infected immediately. The worm exploits the vulnerable e-mail software in the host machine to send infected e-mails to addresses stored in address book. Thus, new machines get infected. Worms bring damage to computer and people in various ways. They may clog the network traffic, cause damage to the system, and make the system unstable or even unusable.

The traditional way of worm detection is signature based. A signature is a unique pattern in the worm body that can identify it as a particular type of worm. Thus, a worm can be
detected from its signature. But the problem with this approach is that it involves significant amount of human intervention and may take a long time (from days to weeks) to discover the signature. Thus, this approach is not useful against “zero-day” attacks of computer worm. Besides, signature matching is not effective against polymorphism.

Thus, there is a growing need for a fast and effective detection mechanism that requires no manual intervention. Our work is directed towards automatic and efficient detection of e-mail worms. We apply a feature-based approach for this purpose. A number of features of e-mail messages have been identified in Martin, Sewani, Nelson, Chen, and Joseph (2005a) and discussed in the Feature Reduction and Classification section. The total number of features is large, some of which may be redundant or noisy. So we apply two different feature-reduction techniques: a dimension-reduction technique called Principal Component Analysis (PCA) and our novel feature-selection technique called Two-phase Selection (TPS) that applies decision tree and greedy elimination. These features are used to train a classifier to obtain a classification model. We use three different classifiers for this task: Support Vector Machine (SVM), Naïve Bayes (NB), and a combination of SVM and NB, mentioned henceforth as the Series classifier. The Series approach was first proposed by Martin, Sewani, Nelson, Chen, and Joseph (2005b).

We use the dataset of (Martin et al., 2005a) for evaluation purposes. The original data distribution was unbalanced, so we balance it by rearranging. We divide the dataset into two disjoint subsets: the known worms set or K-Set and the novel worms set or N-Set. The K-Set contains some clean e-mails and e-mails infected by five different types of worms. The K-Set contains e-mails infected by a sixth type worm, but no clean e-mails. We run a three-fold cross validation on K-Set and the average accuracy of novel worm detection on N-Set.

Our contributions to this research work are as follows: First, we apply two special feature-reduction techniques to remove redundancy and noise from data. One technique is PCA, and the other is our novel TPS algorithm. PCA is commonly used to extract patterns from high dimensional data, especially when the data are noisy. Besides, it is a simple and nonparametric method. TPS applies decision tree C4.5 (Quinlan, 1993) for initial selection, and thereafter, it applies the greedy elimination technique (see the Two-phase Feature Selection section). Second, we create a balanced dataset as explained above. Finally, we compare the individual performances among NB, SVM, and Series and show empirically that the Series approach proposed by Martin et al. (2005b) performs worse than either NB or SVM.

The rest of this article is organized as follows: The Related Work section describes related work in automatic e-mail worm detection; the Feature Reduction and Classification Techniques section describes the feature-selection, dimension-reduction, and classification techniques; the Dataset section describes the distribution of the dataset; the Experimental Setup section describes the experimental setup such as hardware, software, and system parameters; the Results section discusses the results; and the Conclusion section offers future guidelines for research.

RELATED WORK

There are different approaches to automate the detection of worms. These approaches are mainly of two types: behavioral and content-based. Behavioral approaches analyze the behavior of messages like source-destination addresses, attachment types, message frequency. Content-based approaches look into the content of the message and try to detect signature automatically. There are also combined methods that take advantage of both techniques.

An example of behavioral detection is social network analysis (Golbeck & Hendler, 2004; Newman, Forrest, & Balthrop, 2002).
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