

Exploring the Current State of Machine Learning in Spam Filters

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Abstract: This paper systematically analyzes the development of spam detection technology. Spam poses a significant threat to network security, personal privacy, and enterprise productivity. Traditional filtering methods, such as rule-based filtering and Bayesian classification, have difficulty adapting and coping with evolving spam strategies. This paper focuses on machine learning and evaluates its adaptability, feature extraction capabilities, and algorithmic effectiveness in enhancing spam detection. By analyzing algorithms such as Naive Bayes, Random Forest, and LSTM, this study highlights the improvements in adaptability and accuracy brought by machine learning. However, existing challenges include dependence on labelled datasets and computing resources. This study provides theoretical and practical insights for building adaptive spam detection systems. This study not only provides theoretical support for the development of spam filtering technology but also provides practical references for enterprises and individuals to build efficient and intelligent spam defense systems in practical applications, which helps to improve email security, which is crucial to maintaining trust in the digital economy.


1 INTRODUCTION

Email has always been a core communication tool, and its security is directly related to personal privacy, corporate assets, and even national network security. However, with the advent of the digital age of artificial intelligence, spam has seriously troubled the majority of users and has become more stubborn and complex. While most spam is just some companies advertising their products, some other spam acts as a carrier for phishing attacks, scams and malware. Its harm is not limited to harassing users, but also leads to a series of serious consequences such as phishing attacks, identity theft, and loss of corporate productivity. Spam can lead to information breaches, fraud, and loss of business productivity, so efficient spam detection is critical to cybersecurity in the digital age. Exploring efficient spam filtering technology is not only a technical need, but also an inevitable choice to maintain the healthy development of the Internet economy.

Traditional spam filtering technologies, such as rule-based filtering and Bayesian classification, have played an important role in mitigating the threat of spam (Wang & Peng, 2010). However, these methods have difficulty keeping up with the evolving strategies

adopted by spammers. The rise of AI-generated spam, dynamic IP blocking and sophisticated phishing techniques requires more advanced detection mechanisms. Academia and industry have long been committed to optimizing spam detection technology. Early research focused on rule filtering and Bayesian classification. However, these traditional methods have gradually revealed their limitations because static rules are easily bypassed and cannot cope with dynamic attack strategies. In recent years, machine learning technology has become a research hotspot. For example, (Kumar, 2020) demonstrated the advantage of machine learning in accuracy; further pointed out that deep learning models can capture text contextual relationships and significantly improve the recognition rate of complex spam. Despite this, existing research focuses on a single algorithm (Mao, 2024), and the defense mechanism against dynamic adversarial attacks remains to be explored in depth.

This paper aims to analyze the evolution of spam detection methods, evaluate the limitations of traditional filtering techniques, and introduce some filtering methods based on machine learning. The following sections will discuss the types and threats of spam, review the weaknesses of traditional filtering

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methods, and explore how machine learning can enhance spam classification. This paper attempts to provide a theoretical basis and practical reference for building an efficient and adaptive spam defense system.

2 THE HARM OF SPAM

Spam has become a common phenomenon in modern life, bringing with it a variety of potential threats, including serious risks to network security and personal privacy. Many spam emails look harmless, but there are often great risks and threats hidden behind them. And when people find themselves suffering from these losses, it is usually too late.

First of all, one of the main threats of spam is phishing attacks. Criminals can use some deceptive emails to obtain sensitive information from recipients. They will make the email look like an official email. These emails will pretend to be legitimate information from relatives, well-known companies, social media platforms, banks, or national institutions. The user clicks on the malicious link in the email and enters a phishing website disguised as an official page. When they click on the link, they need to enter sensitive or private information, such as important account passwords, credit card details or passport and ID numbers. This whole process is monitored by criminals. Once the user enters the information, criminals can use this information to make money. Many victims don't even know that they have been deceived afterwards. Some victims only go to modify the password when their property has been damaged.

In addition, the unnecessary consumption of productivity and financial losses of enterprises and institutions when dealing with spam are also one of the hazards. In order to deal with the threats brought by spam software, institutions and organizations need to spend a lot of resources to filter and manage spam. The financial loss caused by this is far greater than the cost of spam. Many IT teams of enterprises need to spend a lot of energy to deploy security measures to prevent the risks brought by spam. Many employees will waste precious time doing repetitive and meaningless things. Finally, this will lead to a decrease in productivity.

Spam will reduce people's trust in online communications and the Internet economy, causing economic losses in the long run. When people are attacked by too many spam emails, many people will have a sense of distrust in things on the Internet. This will lead to a decrease in people's willingness to

choose the digital economy. For example, users may become more cautious and reluctant to click on links in emails or participate in online transactions to avoid potential security risks. Even many people are reluctant to click on emails from legitimate companies or governments because they are afraid that it is a scam. Or sometimes legitimate emails are hidden in spam, causing people to ignore the emails they need to check. These will have a negative impact on the development of many industries that have a positive impact on the economy, such as e-commerce, online financial services and other Internet industries, and ultimately have a negative impact on overall economic growth.

Spam is not only a nuisance and economic loss to individuals and businesses, but also a challenge and threat to the entire Internet ecosystem. Its impact covers consumers, businesses, government agencies, advertisers and even the entire digital economy. In the long run, the proliferation of spam will undermine people's trust in online communications and thus affect the development of the global Internet economy.

3 COMMON TYPES OF SPAM CURRENTLY

Spam has become more diverse over time. Each form has different characteristics and purposes (Ma, 2024). Understanding the different types of spam can help us recognize and avoid spam. More importantly, it can help us design effective detection systems.

3.1 Advertising Spam

Advertising spam is the most common type of spam. These spam messages usually send advertisements to users. These advertisements include products, services, and various websites. Even though most advertising spam messages are legitimate, these messages are essentially sent without the consent of the recipient. Advertising spam is characterized by its large number. Especially when the recipient's mail address is leaked, advertising spam will swarm in. Some companies or organizations obtain email addresses of potential users through unethical means, which makes it difficult for users to control the influx of spam. Due to its large number and legal fringe, this behavior is usually difficult to punish.

3.2 Phishing Emails

The purpose of phishing emails is to obtain information from the victim through clever disguises.

These emails usually appear to come from trusted organizations, such as banks, government agencies, or e-commerce platforms. They remind users to update their account details, reset passwords, or claim that the user's information needs to be checked. Phishing attacks can have serious consequences. Most of the time, victims suffer financial losses. Sometimes victims also suffer identity theft. For companies and institutions, phishing can lead to data breaches.

3.3 Second Section

Scam emails prey on simple human emotions to deceive the recipient. These emotions are usually greed, urgency, fear, or lust. They will tell the recipient that they have won a lottery or a competition. Even if the person did not buy or enter any lottery or competition. After the victim pays a fee, they will disappear. Sometimes, the fraudster will say that the recipient has inherited a fortune from a distant relative. Again, a fee must be paid upfront. They will tell investors about non-existent investment opportunities. These investment opportunities appear to be high-return projects, but in fact, the money will be used for fraudulent business activities. Although scam emails have been around for decades, they are still evolving and becoming more and more difficult to identify. There are even many AI-driven scams emerging, where attackers use automated systems to create more convincing messages, thereby increasing the effectiveness of these fraudulent activities.

4 DISADVANTAGES OF TRADITIONAL FILTRATION METHODS

The current traditional spam filtering methods mainly include Rule-based filtering, Bayesian filtering and IP-based blacklists, but these methods have many limitations and are difficult to effectively deal with modern spam strategies. These filters help people identify and lock spam, so people can reduce losses. However, while traditional spam filters are useful, they have significant limitations. Especially with the increasing popularity of artificial intelligence, it hinders their effectiveness in detecting modern spam strategies.

4.1 Rule-Based Filtering

Rule-based filtering is an earlier detection method. It classifies emails according to some rules, usually including pre-defined ones. The system automatically

detects keywords such as "free", "lottery", "product", etc. contained in the email. In this way, it analyzes whether the email is spam. In addition, some rules analyze the format and attachments of the email.

However, spammers can easily circumvent the rules. They can replace keywords with words that the system cannot detect. For example, "lott3ry" instead of "lottery". In addition, due to the rise of artificial intelligence, spam has become more and more elusive. The forms and types of spam are changing all the time. But the rules need to be constantly updated and maintained. This is very inefficient and time-consuming. And the accuracy rate is not high.

4.2 Bayesian Filtering

Bayesian Filtering analyzes the frequency of words in an email and calculates the probability of spam. In this process, Bayesian Filtering uses a statistical theorem, namely "Bayes' rule", to calculate and identify spam (Han, 2023).

Bayesian filtering is a spam classification method based on statistical probability. It analyzes the frequency of words in an email and calculates the probability that the email is spam or normal (Lu & Yin, 2008). This method is considered to be more accurate than rule-based filtering because it can gradually learn email features as users use it and improve detection accuracy (Chakraborty, 2012).

However, Bayesian filtering also has its limitations. Spammers can also use many methods to avoid Bayesian Filtering detection. Spammers can choose to add some normal words or words that are unlikely to appear in spam to confuse Bayesian Filtering. This phenomenon is called "Bayes poisoning". For example, spammers can choose to add scientific and technological words, political current affairs words, or the names of legitimate large companies to evade detection. Also, Bayesian Filtering lacks the test of spam with artificial intelligence.

4.3 IP-based Blacklists

Internet Protocol addresses are addresses used to identify devices in a computer network. An IP address is a unique identifier for a device on a computer network and is used to enable communication between devices. IP blacklists are a common spam filtering strategy. When people find known spammers, they can record the IP addresses in a blacklist. That is, all emails from these IP addresses will be considered spam. This method has a certain effect on blocking spam from known malicious servers.

The effectiveness of IP blacklists is subject to many challenges. Spammers can use dynamic IP addresses. That is, senders can frequently change IPs through cloud servers. This means that IP-based blacklists are difficult to track the sender's new address. And the update speed of the blacklist often cannot keep up with the speed at which spammers change IPs. Ultimately, a large number of new spam can bypass the interception mechanism.

In addition, some spammers use shared IPs. This will cause shared IPs to be mistaken as spam sources, resulting in normal emails being intercepted.

5 ADVANTAGES OF MACHINE LEARNING IN SPAM CLASSIFICATION

Machine learning is a branch of artificial intelligence. Machine learning enables computers to learn from data and make predictions or decisions based on learned patterns. This process does not require humans to explicitly program rules. The core idea of this process is to let the machine discover patterns in the data, analyze the data and use these discovered patterns to classify the data.

Machine learning has revolutionized spam detection with its intelligent and efficient classification technology. Compared to traditional methods, machine learning models continue to learn from evolving spam strategies and provide higher accuracy.

5.1 Adaptability

Machine learning has shown great adaptability in the process of spam detection. When spam has been updated at a very fast speed, machine learning is also adapting to new environments at a rapid speed. Adapting to new spam patterns is the most important advantage of machine learning over traditional methods. Traditional spam filters rely on static rules. This means that these rules need to be constantly updated manually to maintain accuracy. Machine learning achieves the effect of dynamic defense by analyzing large data sets. This significantly reduces costs and improves accuracy.

5.2 Feature Extraction

Feature extraction can extract the most representative information from raw data. Because the content of emails is complex and diverse, it is difficult and

inefficient for computers to process this raw information directly. The purpose of feature extraction is to simplify this complex text information into simple and understandable data, so that computer models can process it more efficiently. This technology can significantly enhance the efficiency of spam classification.

5.3 Machine Learning Algorithms

Currently, common spam filtering machine learning algorithms include Naïve Bayes, Random Forests, and Long Short-Term Memory (LSTM).

Naive Bayes is an algorithm based on Bayes' theorem. Naive Bayes calculates the probability of a word in a spam email given the category of spam or normal email. Each word is relatively independent in the calculation process. Naive Bayes is simple to calculate and efficient, especially for small data sets. However, if there is a correlation between the words in spam email, it may affect the result (Agarwal & Kumar, 2018).

Random forests consist of multiple independently trained decision trees, which we call trees. Each tree randomly extracts a subset of the original data during training and calculates the best answer. This randomness makes each tree somewhat different, which improves accuracy. Random forests combine the predictions of all trees. Finally, the most reasonable or most selected result is followed. It is like a team, each person makes an independent judgment and finally decides the category of the email by voting. This method is more accurate than a single person's judgment because different opinions in the team can complement each other and reduce errors. The disadvantage of random forests is that training multiple trees requires more memory and processing power, and predictions on large data sets may be slower than simple models such as naive Bayes.

Deep learning uses multi-layer neural networks to automatically extract data features and can identify more complex spam patterns (Yu, 2023). Traditional machine learning methods usually rely on manually designed features and are difficult to adapt to changing spam strategies (Zhang, 2024).

LSTM (Long Short-Term Memory) is a Recurrent Neural Network that is specifically designed to process sequence data, especially data that needs to capture contextual relationships, such as text, time series, and speech recognition (Hans, 2020). LSTM has a unique memory mechanism. It can remember important information in an email and help us determine whether the email is spam or normal. This

memory mechanism helps us overcome the gradient vanishing problem of traditional RNN when processing long sequences, and thus significantly improves the accuracy in spam classification, especially in long data sets.

6 CONCLUSION

This article systematically analyzes the development of spam filtering technology from the perspective of technological evolution. The limitations and shortcomings of traditional methods are analyzed and evaluated. The core value of machine learning in modern spam defense is demonstrated. The harm of spam is multidimensional. In addition to harassment, its derivative risks include phishing attacks, productivity loss, and long-term erosion of trust in the digital economy. Traditional methods are ineffective. Although rule-based filtering, Bayesian classification, and IP blacklists are effective in the early stages, they are difficult to combat modern spam because they rely on static rules. Spammers use loopholes such as obfuscation techniques, Bayesian poisoning, and dynamic IP blocking to bypass traditional filters.

Machine learning models dynamically learn from evolving spam patterns, thereby achieving a constantly adapting filtering system. Algorithms such as Naive Bayes, Random Forest, and LSTM networks can improve detection accuracy by analyzing contextual relationships and complex patterns in email content. Despite the many advantages of machine learning models, they require large labeled data sets, computing resources, and continuous retraining to remain effective.

As spam strategies continue to evolve, deep learning is essential to enhancing email security. Future research should focus on developing real-time, computational efficiency. Lightweight spam detection models can provide a good balance between accuracy and computational efficiency. Deep learning frameworks with low computational costs should be developed to adapt to enterprise-level real-time filtering needs. In addition, integrating AI-based collaborative filtering across multiple platforms can help build a stronger defense against spam threats. The federated filtering system allows spam filters to learn from user data from multiple email providers without compromising privacy. This decentralized approach enhances detection capabilities while keeping users safe.

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