Machine Learning Approaches to Email Spam Detection

Spam emails continue to pose a significant challenge, filling inboxes with unwanted messages and potential cyber threats. Traditional filtering methods have struggled to keep up with evolving spam tactics, making machine learning a preferred approach. Various techniques, including Naïve Bayes Classifier, Support Vector Machines (SVM), Decision Trees, Random Forests, and Deep Learning, have been widely explored in research.

Early machine learning models relied on statistical approaches, focusing on word frequency and character-based patterns to classify emails. For instance, Tekerek and Bay [1] employed Bayesian Classification, Random Tree, and SVM, achieving 99.93% accuracy with the Random Tree model. However, such models lack deep semantic comprehension and can be bypassed by sophisticated spam emails that mimic legitimate patterns.

Supervised learning models, including SVM and Naïve Bayes, have demonstrated effectiveness in distinguishing spam from legitimate emails. These models require high-quality, labeled datasets to maintain accuracy [2]. Decision trees and random forests further improve spam detection by analyzing email attributes such as sender domain, keyword usage, and link frequency [3]. Despite their high accuracy, these approaches struggle with evolving spam techniques and concept drift.

Hybrid models combining traditional machine learning with deep learning have gained attention. An improved deep learning model has been proposed for spam detection in social networks, showcasing its potential for email filtering [4]. Similarly, research on Naïve Bayes classifiers with feature subset selection has shown enhanced spam filtering efficiency compared to traditional models [5].

Transformer-based architecture, particularly BERT and encoder-decoder models built on the "Attention is All Need" framework [6], present promising advancements. These models excel at capturing contextual relationships and

semantic meaning, addressing the limitations of traditional feature extraction techniques. Their self-attention mechanisms enable a deeper understanding of deceptive content that may otherwise appear statistically normal.

The evolution of spam detection methods also highlights the impact of Bayesian filtering, which remains foundational in spam research [7]. Moreover, surveys on spam filtering techniques emphasize the importance of adaptive and ensemble learning strategies to counter evolving spam tactics [8].

While machine learning has significantly improved spam detection, challenges persist, including dataset quality, adversarial attacks, and computational efficiency. Future research suggests further integration of deep learning and hybrid models to enhance adaptability and accuracy in email spam detection systems.

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