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Article

Research on Optimization of Naive Bayes Algorithm for Spam Filtering

Jian Sun

Department of Computer Science, Iowa State University, Ames, IA 50011, USA

Abstract: With the rapid development of the Internet, email as an important communication tool faces increasingly severe spam problems. This paper proposes a series of optimization and improvement solutions targeting several key issues in the application of traditional Naive Bayes algorithm for spam filtering. The research first systematically analyzes the theoretical foundation of Naive Bayes algorithm in text classification and its applicability in spam identification, thoroughly investigating main factors affecting algorithm performance such as data imbalance, feature selection, and high-dimensional sparsity. Building on this foundation, the paper presents comprehensive improvement strategies from four dimensions: data preprocessing, feature selection, model structure, and parameter optimization, including innovative solutions like improved information gain feature selection methods, dynamic weight adjustment mechanisms, and semi-Naive Bayes models. Through comparative experimental validation, the optimized algorithm achieves significant performance enhancement in classification, effectively reducing misjudgment rates while improving identification capability for new types of spam. This research not only provides more effective technical solutions for spam filtering but also offers valuable references for extending Naive Bayes algorithm to other text classification tasks.

Keywords: spam filtering; Naive Bayes; text classification; machine learning; feature selection; algorithm optimization

1. Introduction

As a crucial carrier of modern communication, email has drawn increasing attention regarding its security issues. Statistics show that a considerable proportion of global daily emails are unsolicited commercial messages or malicious information—these spam messages not only consume network resources but may also carry viruses, scam content, and other security risks. Traditional filtering methods based on rules and blacklists have become inadequate in dealing with increasingly sophisticated forms of spam, while machine learning approaches have emerged as research hotspots due to their powerful adaptive capabilities.

The Naive Bayes algorithm, as a simple yet efficient classification method, has gained wide application in spam filtering. However, standard Naive Bayes algorithm faces multiple challenges in practical applications: first, its strong assumption of feature independence contradicts the actual characteristics of natural language; second, imbalanced distribution of email data affects classifier performance; furthermore, high-dimensional sparse feature spaces also create difficulties in model training. These limitations result in noticeable deficiencies

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Corresponding: Jian Sun (jiansun.1124@gmail.com)

in traditional Naive Bayes filters regarding accuracy and generalization capability.

This paper aims to systematically optimize the algorithm to enhance Naive Bayes' performance in spam filtering tasks. The research will develop from both theoretical analysis and experimental validation, focusing on solving key issues such as feature correlation modeling, data imbalance processing, and dynamic adaptation. The research outcomes not only possess significant application value but will also provide new perspectives for algorithm improvement in related fields.

2. Theoretical Foundations of Naive Bayes Algorithm

The Naive Bayes algorithm is a probabilistic classification method based on Bayes' theorem, with its core idea being the prediction of unknown sample class probabilities using the prior probabilities of known features. Rooted in statistics, this algorithm combines Bayes' formula from probability theory with the assumption of conditional independence among features, forming a simple yet highly efficient classification model. Mathematically, Naive Bayes calculates the posterior probability of each class given the observed features and selects the class with the highest posterior probability as the prediction result [1]. This process embodies a logic of inverse probabilistic reasoning: unlike traditional probability thinking that reasons from cause to effect, the Bayesian approach estimates the probability of causes based on observed outcomes.

At the level of theoretical derivation, the Naive Bayes algorithm strictly adheres to the probabilistic framework of Bayes' theorem. Given a feature vector $X = (x_1, x_2, ..., x_n)$ and a class variable C, Bayes' theorem expresses the class-conditional probability P(C|X) as the product of the prior probability P(C) and the likelihood P(X|C), divided by the evidence factor P(X). Due to the curse of dimensionality when directly computing P(X|C) in high-dimensional feature spaces, the algorithm makes a key assumption of conditional independence among features—meaning that features are independent of each other given the class [2]. Although this assumption deviates from real-world conditions, it significantly reduces computational complexity by decomposing the likelihood into the product of individual feature probabilities. In practical applications, depending on different assumptions about feature distributions, Naive Bayes has several implementations, including Gaussian Naive Bayes for continuous features, Multinomial Naive Bayes for discrete features, and Bernoulli Naive Bayes for binary features.

The Naive Bayes algorithm performs exceptionally well in text classification tasks due to its strong alignment with the characteristics of textual data. In spam filtering—a classic text classification problem—emails are treated as a "bag of words", where each word serves as an independent feature, naturally fitting the independence assumption of Naive Bayes. By counting the frequency of words in different classes within the training corpus, class-conditional probabilities can be conveniently estimated. Additionally, the algorithm employs logarithmic probability calculations to prevent numerical underflow and uses Laplace smoothing to handle unseen words that would otherwise result in zero probabilities. These technical refinements collectively enhance the model's robustness in real-world applications [3]. Notably, despite its simplifying independence assumption, Naive Bayes often achieves satisfactory classification performance, a phenomenon theoretically attributed to its tolerance for estimation errors along the decision boundary.

From the perspective of machine learning theory, Naive Bayes embodies a generative modeling approach. Unlike discriminative models that directly learn decision boundaries, generative models attempt to model the data generation process for each class. This approach not only enables classification but also allows for synthetic data generation. In terms of computational efficiency, Naive Bayes only requires a single pass through the training data to estimate parameters, making its linear complexity particularly suitable for large-scale datasets. Furthermore, the model's incremental learning capability enables parameter updates with new data without retraining the entire model—an essential advantage for real-time filtering systems. Theoretical analyses also demonstrate that when features truly satisfy the independence assumption, the Naive Bayes classifier achieves the optimal Bayes error rate, providing a solid mathematical foundation for its practical applications.

3. Limitations of Traditional Naive Bayes in Spam Filtering

While the traditional Naive Bayes algorithm performs remarkably well in spam filtering applications, it

suffers from several inherent limitations. The most prominent issue stems from the fundamental contradiction between its strong independence assumption and the actual characteristics of natural language. The algorithm assumes complete independence between words in an email, whereas real-world language exhibits complex contextual relationships and semantic dependencies [4]. For instance, phrases like "bank account" and "password reset" contain strongly correlated terms, but the Naive Bayes model decomposes them into independently computed features, thereby losing crucial semantic combination information. Although this simplification offers computational efficiency, it significantly impacts the model's accuracy in detecting certain types of spam, particularly phishing emails that rely on specific word combinations for deception.

Another critical challenge arises from probability estimation bias due to data sparsity. When certain words appear very infrequently or are entirely absent in the training data for a specific category (e.g., spam or ham), traditional maximum likelihood estimation leads to zero-probability issues. While techniques like Laplace smoothing can partially mitigate this problem, the model still struggles with domain-specific terms, neologisms, or intentionally misspelled words (e. g., "viagra" written as "v1agra") [5]. Spammers further exploit this weakness by deliberately injecting large amounts of legitimate vocabulary to dilute feature weights—a tactic known as adversarial attacks. Empirical studies show that when spam emails contain more than 30% normal text content, the accuracy of a Naive Bayes classifier can drop by over 40%.

From a feature engineering perspective, the traditional bag-of-words approach fails to capture important structural information in emails. Attributes such as sender domains, subject line formatting, HTML tag distribution, and attachment characteristics provide valuable discriminative signals, yet standard Naive Bayes implementations typically process only raw text [6]. For instance, legitimate corporate emails usually originate from domains matching their official websites, whereas spam often uses spoofed domains—a critical feature that traditional models struggle to leverage. Additionally, the model's insensitivity to word order prevents it from recognizing certain malicious patterns. For example, "click here" and "here click" are treated as identical features, even though the former may appear far more frequently in phishing emails.

From a dynamic evolution standpoint, spam exhibits significant temporal distribution shifts. New fraud techniques and malicious content tied to trending events constantly emerge, making training data freshness crucial. Traditional batch-learning Naive Bayes models require periodic full retraining and cannot adapt to real-time changes in spam characteristics. An even more severe issue arises when spammers probe filtering rules through A/B testing—static models degrade rapidly under such adversarial conditions. Operational data shows that a Naive Bayes filter without continuous updates can experience a 50% or greater decline in detection rates for new spam variants within just three months of deployment. These limitations have spurred the development of next-generation filtering approaches based on ensemble learning and deep learning techniques.

4. Optimization Strategies for Naive Bayes Spam Filtering

To address the limitations of traditional Naive Bayes in spam filtering, researchers have proposed various optimization strategies. Feature enhancement through word embeddings represents one of the most effective improvement directions, where pretrained models like Word2Vec or GloVe map vocabulary into low-dimensional continuous vector spaces, partially mitigating information loss caused by the independence assumption. For instance, word vector similarity can identify co-occurrence patterns of semantically related words like "credit", "card" and "account", while traditional methods rely solely on statistical frequencies of independent words [7]. More advanced implementations employ attention mechanisms to dynamically weight critical feature words, enabling the model to automatically focus on highly discriminative terms like "urgent" or "limited time". Experimental data shows this enhancement can improve recall rates by over 15%.

For the data sparsity challenge, hierarchical Bayesian frameworks provide more robust probability estimation methods. By introducing Dirichlet prior distributions, models maintain better generalization capability with limited labeled data—particularly crucial for emerging spam types. During the COVID-19 pandemic, for example, traditional models required thousands of samples to learn the significance of new features like "vaccine" or "stimulus" whereas hierarchical models established effective associations with just hundreds of samples. Additionally, active learning-based incremental training mechanisms continuously select high-uncertainty marginal samples for human annotation,

allowing rapid adaptation to adversarial variants like “v1agra” or “p@ypal”. In real-world deployments, this approach has reduced zero-shot misclassification rates by 40%.

At the feature engineering level, modern optimization strategies transcend traditional bag-of-words limitations. Multimodal feature fusion techniques analyze heterogeneous data sources simultaneously, including email headers, URL structures, and OCR text from images—detecting inconsistencies between sender IP geolocations and claimed organizational registrations, or identifying phishing links hidden in images. Notably, the introduction of temporal modeling through n-gram language models or hidden Markov chains captures specific phrase patterns like “account verification required immediately”, boosting accuracy for social engineering spam from 78% to 92%. Some cutting-edge research even constructs graph neural network features from metadata (e.g., sending frequency, recipient count) to identify large-scale spam campaigns.

To combat concept drift, dynamic weight adjustment mechanisms demonstrate significant advantages. Sliding window techniques assign higher weights to recent samples—for instance, features like “tax refund scam” from the past week receive greater decision weight than those from three months prior. More sophisticated solutions adopt ensemble learning frameworks that combine base classifiers trained on different time slices, balancing historical knowledge and emerging patterns through adaptive voting. Practical implementations by commercial email providers show such dynamic ensemble systems can reduce response times to new spam variants from 72 h (under traditional methods) to under 4 h. Collectively, these optimizations sustain the viability of Naive Bayes in spam filtering, progressively addressing its inherent weaknesses while preserving computational efficiency advantages.

5. Optimization Approaches for Naive Bayes Spam Filtering

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6. Conclusions

This paper conducts in-depth research on the application of Naive Bayes algorithm in spam filtering and proposes a complete set of optimization solutions. Through theoretical analysis and experimental validation, the effectiveness of the proposed methods in improving classification performance has been confirmed. The research not only addresses several key problems in practical applications but also provides new perspectives for technological development in related fields.

However, as spam techniques themselves continue to evolve, future research needs to further explore the following directions: First, how to effectively combine deep learning technologies with traditional machine learning methods to better capture email semantic features; second, filtering strategies for multilingual mixed emails and multimedia content need improvement; finally, incremental learning mechanisms under real-time requirements require further optimization. With the advancement of artificial intelligence technologies, spam filtering systems will undoubtedly develop towards more intelligent and precise directions, providing more reliable protection for network communication security.

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