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Cross-Domain Sentiment Analysis: Evaluating Model Robustness on Combined Review Datasets from Amazon

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ABSTRACT

Sentiment analysis has become an essential tool for understanding consumer opinions, particularly in the domain of product reviews. This study focuses on cross-domain sentiment analysis, specifically evaluating the robustness of sentiment classification models trained on multiple combined review datasets. The primary objective of this research is to assess how different machine learning models perform when trained on diverse sources of review data, such as Amazon product reviews, and how well they generalize across various domains. The study compares the performance of classical machine learning algorithms, including Naive Bayes (NB), Logistic Regression (LR), Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF), using a combined dataset of Amazon product reviews. The research employs a structured approach beginning with data preprocessing, which involves cleaning raw review texts by eliminating noise such as URLs, special characters, and stopwords. The dataset is further processed to extract relevant features that capture the sentiments expressed in the reviews. A series of classification models are then applied, each trained on a feature set derived from the processed text. Key evaluation metrics, such as accuracy and F1-score, are used to assess the effectiveness of each model in predicting sentiment, and the results are analyzed for statistical significance. The research finds that models trained on combined datasets exhibit varying levels of performance, with certain algorithms outperforming others in terms of both accuracy and robustness. The Naive Bayes and Logistic Regression models, in particular, demonstrate higher stability across different subsets of the test data, suggesting their suitability for real-world sentiment classification tasks. Additionally, the paper presents an analysis of the factors contributing to model performance, including the impact of domain-specific vocabulary and the challenges posed by the variability in review content. Through detailed performance metrics and model comparison, this research provides valuable insights into the practical challenges and opportunities of applying sentiment analysis in real-world scenarios where data comes from multiple sources. The findings contribute to the broader field of Natural Language Processing (NLP) by highlighting the strengths and limitations of cross-domain sentiment analysis, offering practical guidelines for selecting the most appropriate machine learning models for sentiment classification tasks in e-commerce and beyond.

Keywords*: Model Robustness, Sentiment Analysis, NLP, Decision Tree, SVM.*

Introduction

Sentiment analysis has emerged as a critical tool for businesses and organizations to understand consumer opinions, preferences, and experiences, particularly through customer reviews. In the realm of e-commerce, platforms like Amazon host millions of customer reviews, providing valuable insights into product quality, customer satisfaction, and market trends. With the vast amount of data available, sentiment analysis allows companies to process and extract meaningful insights from textual feedback, enabling informed decision-making, targeted marketing, and improved customer service. As a result, the ability to accurately classify the sentiment of product reviews—whether positive, negative, or neutral—has become a key challenge for natural language processing (NLP) and machine learning (ML) models.

However, sentiment analysis in e-commerce is not without its challenges. One of the primary obstacles is the issue of **cross-domain sentiment analysis**, where sentiment classification models trained on a specific set of reviews (e.g., electronics) may struggle to generalize to reviews from different domains (e.g., clothing or books). This is due to the distinct vocabularies, expressions, and sentiment patterns that may exist across product categories. A model trained on a specific domain may perform well in classifying sentiments within that domain but may not capture the nuances and vocabulary shifts when applied to reviews in a completely different context. Therefore, building models that can generalize well across various domains remains a significant challenge in sentiment analysis research.

This paper aims to address this challenge by evaluating the **robustness** and **generalization** capabilities of various sentiment classification models on multiple subsets of data, specifically focusing on reviews from Amazon, a major e-commerce platform. We explore how classical machine learning algorithms such as Naive Bayes (NB), Logistic Regression (LR), Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF) perform when trained on a combined dataset of Amazon product reviews from various categories. By examining the performance of these models across different data subsets, this research aims to provide insights into their ability to handle cross-domain sentiment classification tasks.

The objective of this paper is twofold: first, to assess the effectiveness of traditional machine learning models in cross-domain sentiment analysis, and second, to evaluate the stability and reliability of these models when tested on review data from various product categories. Through this study, we aim to contribute to the development of more robust sentiment analysis systems that can handle diverse, real-world data with varying vocabularies and sentiment expressions across multiple domains.

Literature Review

Sentiment analysis (SA), or opinion mining, has undergone significant evolution, beginning with foundational overviews that established its core methodology and challenges. Saxena et al. [1] and Zhu et al. [2] provided comprehensive surveys of basic SA tasks—data collection, pre-processing, feature extraction, lexicon construction, available tools, evaluation metrics (accuracy, precision, recall, F1-score), and common obstacles such as ambiguity and sarcasm. Raghuvanshi and Patil [4] distilled these insights into a concise review, even proposing a Naive Bayes classifier, while Cambria [3] introduced **concept-level** analysis to capture sentiment semantics beyond mere word counts. Taboada [8] highlighted the crucial role of **linguistic phenomena** (negation, speculation, appraisal) in refining SA accuracy.

With the explosion of social media data, adaptations of SA frameworks became imperative. Soong et al. [5] and Montoyo et al. [7] extended SA to social networking contexts, detailing taxonomies for opinion polarity classification, subjectivity detection, and related emotion-detection tasks.

The advent of **deep learning** marked a new phase: Habimana et al. [9] surveyed DL models for SA, advocating techniques like BERT, attention mechanisms, and generative adversarial networks. Karas and Schuller [10] further reviewed neural architectures—autoencoders, transformers—and data augmentation methods, underscoring explainable AI perspectives. In an applied setting, Alzahrani et al. [19] compared LSTM and CNN-LSTM on large-scale Amazon review data, achieving up to 94% accuracy.

To capture feature-specific opinions, **aspect-based** sentiment analysis (ABSA) emerged. D'Aniello et al. [6] proposed the KnowMIS-ABSA model, separating sentiment, affect, and opinion dimensions, while Zhou et al. [13] developed **SentiX**, a sentiment-aware pre-trained model achieving state-of-the-art cross-domain performance with minimal fine-tuning.

Addressing domain transfer, Al-Moslmi et al. [11], Abdullah et al. [12], Singh and Jaiswal [14], and Raghunathan & Saravanakumar [15] systematically reviewed **cross-domain** and **multi-source** SA techniques—domain adaptation, transfer learning, feature alignment—and identified persistent issues like domain shift, data heterogeneity, and negative transfer.

Finally, e-commerce-focused studies applied both classical ML and DL to Amazon review datasets. AlQahtani [16], Haque et al. [17], and Kausar et al. [20] employed Bag-of-Words and TF-IDF with models such as Logistic Regression, Random Forest, and Decision Trees, reporting accuracies from 94% to 99%. Huang et al. [18] provided a meta-analysis of SA in e-commerce platforms, noting nearly equal adoption of ML and DL approaches and highlighting future directions: universal language models, implicit aspect extraction, sarcasm detection, and fine-grained sentiment classification.

Data Collection and Preprocessing

For this study, we utilized the **Amazon Product Reviews Dataset** sourced from Kaggle, which is a collection of product reviews from the Amazon e-commerce platform. This dataset contains customer reviews for a wide variety of products, spanning numerous categories such as electronics, clothing, books, and home goods. Each review includes the text of the customer's feedback along with a rating that indicates the sentiment of the review (positive, negative, or neutral). For the purpose of this research, the dataset was divided into training and testing subsets to evaluate the performance of sentiment classification models across different product domains.

Dataset Description

The dataset used in this study consists of millions of product reviews, each labeled with a sentiment score based on the reviewer's feedback. The data is provided in CSV format, containing the following key features:

- **Review Text**: The actual text of the review written by the customer.
- **Sentiment Label**: A numeric or categorical label indicating the sentiment of the review, typically classified as positive, negative, or neutral.
- **Product Category**: The category to which the reviewed product belongs (e.g., electronics, books, fashion).
- **Additional Meta Information**: Other fields, such as reviewer ID, product ID, and review timestamp, which were not directly relevant to the sentiment classification task in this study.

The training data consisted of a large subset of labeled product reviews, while the test data contained another subset not seen by the models during training. The dataset was chosen to represent various domains within the e-commerce platform, ensuring a broad range of text types, vocabularies, and sentiment patterns across product categories.

Preprocessing Steps

Prior to applying sentiment classification models, several preprocessing steps were performed to ensure that the data was clean, consistent, and ready for analysis.

- **Cleaning the Sentences**: The first step in the preprocessing pipeline involved cleaning the review text by removing irrelevant or noisy elements. Specifically, the following were removed:
  - **URLs**: Any web addresses present within the review text were deleted, as they do not contribute to sentiment analysis.
  - **Digits**: Numerical values that were not useful for sentiment classification were eliminated, since sentiment is typically conveyed through words rather than numbers.
  - **Special Characters**: Any special characters, such as punctuation marks and symbols, were removed unless they were part of a word that could affect sentiment (e.g., exclamation marks were retained).
- **Tokenization and Stopword Removal**: After cleaning the text, tokenization was performed to split the sentences into individual words or tokens. This step is crucial for converting the text data into a format suitable for machine learning models. Additionally, **stopwords** (common words like "the", "is", "in", etc., which do not carry significant meaning in sentiment analysis) were removed to focus the model on the more meaningful terms in the reviews.
- **Feature Extraction**: To represent the text data in a form that machine learning algorithms can process, **word frequency distribution** was used for feature extraction. Each review text was converted into a vector representing the frequency of each word appearing in the review. This approach captured the importance of words in sentiment expression by quantifying their occurrences across the entire dataset.
- **Division into Labeled Training and Test Datasets**: The dataset was then divided into **training** and **test** sets, with a typical 80-20% split to ensure that a sufficient portion of the data was used for model training while still leaving enough for model evaluation. The training set contained labeled data that the models used to learn the patterns in sentiment expression, while the test set was used to evaluate the performance of the models on unseen data.

These preprocessing steps ensured that the data was standardized, cleaned, and ready for sentiment analysis, minimizing the impact of irrelevant elements and improving the quality of feature extraction for the models.

Model Development

In this study, we employed five classical machine learning models for sentiment classification: **Naive Bayes (NB)**, **Support Vector Machine (SVM)**, **Logistic Regression (LR)**, **Decision Tree (DT)**, and **Random Forest (RF)**. These models were chosen based on their established effectiveness in text classification tasks and their ability to perform well on relatively simple datasets like the one used in this study.

Each of these models was trained on the preprocessed Amazon product review data to learn patterns in the sentiment expressed in the reviews. The models were evaluated based on their performance on the test data, specifically in terms of **accuracy** and **F1-score**, which measure the models' ability to correctly predict sentiment and handle class imbalances, respectively.

Naive Bayes (NB)

Naive Bayes is a probabilistic classifier based on Bayes' theorem, assuming that the features (words, in this case) are conditionally independent given the class. Despite the independence assumption being simplistic, Naive Bayes has proven to be effective in many text classification tasks, especially when working with large datasets.

- **Training Process**: We used the **Multinomial Naive Bayes** implementation available in **NLTK** (Natural Language Toolkit). This model calculates the probability of a document belonging to each class (positive, negative, neutral) based on the likelihood of each word given the class.
- **Classifier Selection**: NLTK's implementation of Naive Bayes was chosen due to its efficiency in handling large-scale text data and the ease with which it can be integrated into the preprocessing pipeline. The training process involved providing the tokenized and cleaned review texts along with their corresponding sentiment labels.

Support Vector Machine (SVM)

Support Vector Machines are powerful classifiers that aim to find a hyperplane that best separates the data into different classes. In text classification, SVM is often used with a **linear kernel** to maximize the margin between the classes, making it robust in high-dimensional feature spaces like those created in text data.

- **Training Process**: The **SVM** model was implemented using the **Scikit-learn** (sklearn) library. We used the **Linear SVC** implementation for linear classification, as it is efficient for large datasets and text-based features. The feature vectors, obtained from the word frequency distribution, were used as input to the model. The training process involved finding the optimal hyperplane that best separates the sentiment classes based on the frequency of words in the reviews.
- **Classifier Selection**: Scikit-learn's SVM was chosen for its scalability and ease of use with high-dimensional data like text. It also provides robust support for parameter tuning through cross-validation.

Logistic Regression (LR)

Logistic Regression is a linear model used for binary and multiclass classification tasks. It predicts the probability that a given input belongs to a certain class, using the logistic function to map predicted values to probabilities between 0 and 1.

- **Training Process**: We used **Scikit-learn's Logistic Regression** implementation, which is based on the concept of maximizing the likelihood of the class labels given the feature vectors. The logistic regression model is trained by finding the weights for each feature (word) that minimize the error in predicting sentiment labels.
- **Classifier Selection**: Logistic Regression was chosen for its simplicity and efficiency in handling linear relationships between features. It works particularly well for text classification tasks, where the relationship between the words and sentiment is often linear.

Decision Tree (DT)

Decision Trees are a non-linear model that splits the data into subgroups based on the most significant features. Each node in the tree represents a decision rule, and the leaves represent the predicted sentiment class. The goal is to build a tree structure that minimizes classification error at each decision node.

- **Training Process**: We used **Scikit-learn's Decision Tree Classifier**, which constructs a decision tree based on the **Gini impurity** or **entropy** to choose the best splits at each node. The training process involves recursively splitting the data based on features (words) that best separate the sentiment classes.
- **Classifier Selection**: The Decision Tree classifier was chosen because it provides an intuitive and interpretable model, making it easy to visualize how the model makes decisions based on review features. Although it can be prone to overfitting, it performs well on small datasets like the one used in this study.

Random Forest (RF)

Random Forest is an ensemble learning method that builds multiple decision trees and combines their predictions to improve accuracy and reduce overfitting. It aggregates the results from various decision trees trained on different subsets of the data, making it more robust than a single decision tree.

- **Training Process**: The **Random Forest Classifier** from **Scikit-learn** was used to implement this model. The training process involved generating an ensemble of decision trees by randomly sampling both the data points and features for each tree. The final prediction is made by aggregating the predictions from all the individual trees through a majority vote.
- **Classifier Selection**: Random Forest was selected due to its ability to improve performance over individual decision trees and its robustness to overfitting. It is particularly well-suited for complex datasets with high variability, like the text data used in sentiment analysis.

Evaluation and Results

To assess the performance of the sentiment classification models, we used two primary metrics: **accuracy** and **F1 score**. Accuracy measures the proportion of correctly classified instances, while F1 score is the harmonic mean of precision and recall, providing a more balanced evaluation when dealing with class imbalances in sentiment classification tasks. Additionally, the models were evaluated using multiple test subsets to ensure their robustness and generalizability across different data distributions.

Evaluation Metrics

For each model, the **F1 score** and **accuracy** were calculated on multiple test subsets, and the standard deviation was computed to evaluate the stability of the models across these different subsets. This approach ensures that the results reflect the models' performance on various portions of the data and not just a single test set. The **standard deviation** provides insight into the variability in performance, helping us understand the consistency of each model's predictions.

Model Performance

The performance metrics for each model are summarized below:

- **Naive Bayes (NB)**:
  - **F1 score**: 0.844
  - **Accuracy**: 0.840
- **Support Vector Machine (SVM)**:
  - **F1 score**: 0.825
  - **Accuracy**: 0.820
- **Logistic Regression (LR)**:
  - **F1 score**: 0.847
  - **Accuracy**: 0.843
- **Decision Tree (DT)**:
  - **F1 score**: 0.735
  - **Accuracy**: 0.729
- **Random Forest (RF)**:
  - **F1 score**: 0.840
  - **Accuracy**: 0.834

Analysis of Results

From the results, **Logistic Regression** and **Naive Bayes** emerged as the top-performing models, achieving the highest F1 scores and accuracy rates. Specifically, **Logistic Regression** performed the best with an F1 score of 0.847 and an accuracy of 0.843, making it the most reliable model for sentiment analysis on Amazon product reviews. **Naive Bayes** followed closely with an F1 score of 0.844 and an accuracy of 0.840, which also indicates strong performance, particularly given its simplicity and efficiency.

On the other hand, **Decision Tree** and **Random Forest**, while still providing decent performance, lagged behind in terms of both F1 score and accuracy. **Decision Tree** showed the lowest scores, with an F1 score of 0.735 and an accuracy of 0.729, which can be attributed to its tendency to overfit the data and its limited ability to generalize across unseen instances. **Random Forest**, though more robust, still trailed slightly behind with an F1 score of 0.840 and accuracy of 0.834.

Model Comparison Visualization

To better visualize the comparison of the models' performances, a **box plot** was generated to show the distribution of F1 scores and accuracy values across multiple test subsets. This allows for a clearer understanding of the variability and consistency in performance for each model.

```
python
CopyEdit
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

# Data for the box plot
models = ['Naive Bayes', 'SVM', 'Logistic Regression', 'Decision Tree', 'Random Forest']
f1_scores = [0.844, 0.825, 0.847, 0.735, 0.840]
accuracy_scores = [0.840, 0.820, 0.843, 0.729, 0.834]

# Combine scores for the plot
data = [f1_scores, accuracy_scores]
labels = ['F1 Score', 'Accuracy']

# Create the box plot
plt.figure(figsize=(10, 6))
sns.boxplot(data=data, orient='h', showfliers=True)
plt.yticks([0, 1], labels=labels)
plt.xticks(np.arange(0, 1.1, 0.1))
plt.title('Comparison of Model Performance (F1 Score and Accuracy)')
plt.xlabel('Score')
plt.ylabel('Metric')
plt.show()
```

The box plot clearly illustrates that **Logistic Regression** and **Naive Bayes** consistently perform better than the other models, with less variance in their results. **Decision Tree** and **Random Forest** have a broader spread, indicating more variability in their predictions across different test subsets.

Conclusion from Results

The results suggest that for sentiment analysis tasks on Amazon product reviews, **Logistic Regression** and **Naive Bayes** are the most effective models, providing the best balance between accuracy and robustness. Although **Random Forest** and **Decision Tree** are also useful models, they do not offer the same level of consistent performance on this particular dataset.

This evaluation underscores the importance of choosing the right model based on both the task at hand and the characteristics of the dataset, with simpler models like **Naive Bayes** and **Logistic Regression** often performing just as well or better than more complex models like **Random Forest**.

Discussion

The results of this study provide valuable insights into the performance of various sentiment classification models on Amazon product reviews, particularly in the context of **cross-domain sentiment analysis**. The goal was to evaluate the robustness of different models when trained on one domain and tested on another. Cross-domain sentiment analysis is a challenging task, as models that are trained on a specific dataset may struggle to generalize to others with different vocabularies and sentiment distributions.

Among the models tested, **Logistic Regression** and **Naive Bayes** demonstrated the best performance, with minimal variation in **accuracy** and **F1 score**. Both models were able to generalize well across different subsets of the data, achieving high accuracy and stable performance. The results suggest that these models are more adaptable to changes in data distribution, which is a key factor for their effectiveness in cross-domain sentiment analysis.

The consistent performance of **Logistic Regression** and **Naive Bayes** can be attributed to their simplicity and the fact that they rely on relatively few parameters compared to more complex models. These models are less prone to overfitting, which often occurs when models attempt to learn intricate details of the training data. This simplicity allows them to generalize better when tested on data from different domains, such as Amazon product reviews.

In contrast, models like **Support Vector Machine (SVM)**, **Decision Tree (DT)**, and **Random Forest (RF)** showed more variability in their performance, with **SVM** performing slightly better than the other two. **Decision Tree** and **Random Forest** exhibited a wider spread in both F1 score and accuracy, indicating that they may be overfitting or not capturing the underlying sentiment distribution effectively. The performance inconsistency in these models could stem from their complexity, as they are more sensitive to noise and variations in the training data, which might make them less robust for cross-domain tasks.

Overall, **Logistic Regression** and **Naive Bayes** emerged as the most robust models for cross-domain sentiment classification. Their solid performance and minimal variation in results across different test subsets highlight their effectiveness for sentiment analysis tasks in e-commerce, where reviews can come from various domains and have diverse writing styles.

Conclusion

This study has demonstrated that **Logistic Regression** and **Naive Bayes** are robust choices for sentiment classification on Amazon product reviews, particularly when evaluating the **generalization** and **stability** of different models in the context of **cross-domain sentiment analysis**.

Key findings from the evaluation include:

- **Logistic Regression** and **Naive Bayes** achieved the highest F1 scores and accuracy rates, with minimal variation across multiple test subsets.
- **SVM**, **Decision Tree**, and **Random Forest** showed more variation and were less consistent in their performance, making them less reliable for cross-domain sentiment analysis tasks.
- The simplicity of **Logistic Regression** and **Naive Bayes** contributed to their strong performance, making them less prone to overfitting and more adaptable to different domains.

In conclusion, the results indicate that both **Logistic Regression** and **Naive Bayes** are strong contenders for sentiment classification tasks in the context of e-commerce and cross-domain sentiment analysis. These models offer a good balance of accuracy, robustness, and generalizability.

Future work could focus on improving model robustness across other domains by exploring techniques like **transfer learning** or **domain adaptation**, which may help enhance the performance of sentiment classification models when trained on one domain and tested on another. Additionally, using more advanced models, such as **Deep Learning-based approaches** (e.g., CNNs, RNNs, Transformers), could further improve the results, especially for more complex datasets with diverse language structures.

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