Employing Distributional Semantic Models in NLP Tasks: Sentiment Analysis

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Abstract

This study presents a comparative analysis between two distinct approaches to sentiment analysis in movie review classification: a neural network-based distributional semantic model and a Naive Bayes classifier. The project specifically examines the fundamental architectural differences between these approaches, where Naive Bayes operates under the assumption of feature independence [1], while the neural network model incorporates advanced features including multi-head attention mechanisms, positional encoding, and residual connections [2]. Using a movie reviews dataset, I implemented both classification methods with comprehensive preprocessing techniques. The neural network model features enhanced components such as TF-IDF vectorization, label smoothing, mixup augmentation, and warmup scheduling [3], while the Naive Bayes implementation utilizes word frequency-based probabilistic classification with Laplace smoothing [4]. The experimental results demonstrate that the neural network approach achieves superior accuracy compared to the Naive Bayes implementation, validating the effectiveness of considering contextual relationships in text classification [5]. The neural architecture's ability to capture complex word dependencies through its attention mechanism and deep residual blocks proves more effective than the simplified independence assumptions of Naive Bayes [2], [4]. This study contributes to the ongoing discussion in sentiment analysis by quantitatively demonstrating the advantages of neural approaches over traditional probabilistic classifiers in movie review classification [6], while also highlighting the trade-offs between model complexity and performance.

Index Terms

Sentiment Analysis, Neural Networks, Naive Bayes

I. Introduction

Text classification remains a fundamental challenge in natural language processing, with various approaches offering different trade-offs between computational complexity and accuracy. This project investigates the comparative effectiveness of two distinct approaches to sentiment analysis: distributional semantic models implemented through neural networks and the traditional Naive Bayes classifier [1].

A. Research Problem

The primary research question addresses the impact of feature independence assumptions on classification accuracy in sentiment analysis. While Naive Bayes classifiers operate under the assumption that features (words) are conditionally independent [1], distributional semantic models capture complex contextual relationships between words [2]. This fundamental difference in approach raises important questions about the trade-offs between model complexity and classification performance.

B. Literature Review

Traditional approaches to text classification have relied heavily on probabilistic methods, with Naive Bayes being particularly prominent due to its simplicity and computational efficiency [4]. The Naive Bayes classifier's core assumption of feature independence, while computationally advantageous, often fails to capture the nuanced relationships between words in natural language [1].

In contrast, recent advances in neural network architectures have enabled more sophisticated approaches to text classification. Distributional semantic models, particularly those implementing attention mechanisms and positional encoding [2], have demonstrated superior performance in capturing contextual relationships. These models benefit from advanced features such as TF-IDF vectorization, label smoothing, and mixup augmentation [3], though at the cost of increased computational complexity.

Recent studies in sentiment analysis have shown that neural approaches can significantly outperform traditional probabilistic classifiers [6], particularly in tasks requiring nuanced understanding of language patterns [5]. However, the practical implications of this improved performance must be weighed against the increased computational requirements and implementation complexity.

C. Research Objectives

This study aims to:

- Compare the classification accuracy of neural network-based distributional semantic models against Naive Bayes classifiers in movie review sentiment analysis
- Evaluate the impact of feature independence assumptions on classification performance
- Analyze the trade-offs between model complexity and classification accuracy
- Quantify the benefits of incorporating contextual relationships in sentiment classification tasks

D. Hypothesis

The primary hypothesis is that neural network-based distributional semantic models, by capturing contextual relationships and word dependencies, will achieve superior classification accuracy compared to Naive Bayes classifiers in movie review sentiment analysis, despite their increased computational complexity.

II. Methodology

This study implements and compares two distinct approaches for sentiment analysis in movie review classification: a neural network-based distributional semantic model and a Naive Bayes classifier. The methodology encompasses data preparation, model implementation, and evaluation procedures.

A. Dataset and Preprocessing

The dataset consists of movie reviews divided into positive and negative sentiments [7]. Both models utilize the same preprocessing pipeline:

- Text normalization (lowercase conversion)
- Punctuation removal
- Stop word elimination using NLTK [8]
- Tokenization

B. Model Implementations

1) Neural Network Implementation: The neural network model incorporates several advanced features:

- Multi-head attention mechanism with 8 attention heads [2]
- Positional encoding for sequence information preservation
- Residual connections with three residual blocks [9]
- TF-IDF vectorization with 15,000 features
- Label smoothing ($\alpha = 0.1$) [10]
- Mixup augmentation for training stability [3]

The model employs an AdamW optimizer with learning rate warmup and implements early stopping with a patience of 10 epochs. Training utilizes gradient accumulation over 4 steps to optimize memory usage [11].

2) Naive Bayes Implementation: The Naive Bayes classifier implements:

- Word frequency-based feature extraction
- Laplace smoothing for zero-frequency handling [1]
- Log-probability computation for numerical stability
- Prior probability initialization (0.5 for both classes) [12]

C. Evaluation Framework

The evaluation methodology includes:

- 5-fold cross-validation for robust performance assessment
- Metrics: accuracy, precision, recall, and F1-score
- Comprehensive error analysis and model comparison

Both models are evaluated using identical test sets to ensure fair comparison. The neural network implementation includes additional monitoring through a custom metrics logger for detailed performance tracking [4].

III. Results

A. Overall Model Performance

The neural network model demonstrated robust performance across all evaluation metrics [2], [3]:

- Overall Accuracy: 89.14% (±1.85%)
- Precision: 89.07% (±3.57%)
- Recall: 89.43% (±2.46%)
- F1-Score: 89.19% (±1.83%)

B. Confusion Matrix Analysis

As shown in Figure 1, the model's predictions demonstrate balanced performance across classes [5]:

- True Positives: 1777 instances (44.4%)
- True Negatives: 1788 instances (44.7%)
- False Positives: 222 instances (5.6%)

- False Negatives: 212 instances (5.3%)

The balanced error rates indicate the model's stability in handling both positive and negative sentiments [6].

C. Cross-validation Performance

The 5-fold cross-validation results (Figure 8) reveal consistent performance with notable variations [11]:

- Best Performance (Fold 3):
  - Accuracy: 91.9%
  - Precision: 94.9%
- Lowest Performance (Fold 2):
  - Accuracy: 86.1%
  - Precision: 84.3%

D. Metric Distribution Analysis

The box plot analysis (Figure 5) shows the distribution of performance metrics [9]:

- Precision exhibits the highest variability (IQR: 0.843-0.949)
- F1-score demonstrates stability (IQR: 0.863-0.917)
- Accuracy maintains consistency across folds [10]

E. Metric Correlations

The correlation heatmap (Figure 7) reveals important relationships [4]:

- Strong positive correlation between accuracy and F1-score (r = 0.99)
- Moderate positive correlation between precision and accuracy (r = 0.87)
- Weak negative correlation between precision and recall (r = -0.28)

These correlations suggest a well-balanced model with minimal trade-offs between precision and recall [12].

F. Performance Stability

The violin plots (Figure 6) demonstrate [3]:

- Consistent performance distribution across metrics
- Symmetric distribution of accuracy scores
- Robust precision-recall balance [2]

This stability analysis confirms the model's reliability across different data splits and evaluation scenarios [11].

IV. Discussion

A. Performance Analysis and Implications

The experimental results demonstrate significant performance differences between the Neural Network (NN) and Naive Bayes (NB) approaches [13], [14]. The NN model achieved superior performance with an accuracy of 89.14% compared to NB's 83.0%, representing a 6.14 percentage point improvement, which aligns with findings from recent comparative studies [1], [4].

1) Overall Performance: The model achieved strong performance metrics across all evaluation criteria:

- Overall accuracy of 83.0% with consistent performance across folds
- Balanced precision (85.1%) and recall (80.0%) scores
- F1-score of 82.5%, indicating robust overall performance

These results align with findings from [13], who reported similar performance ranges in their comparative analysis of neural networks for text classification.

2) Error Distribution: The confusion matrix analysis reveals:

- True positives: 1788 instances (44.7%)
- True negatives: 1777 instances (44.4%)
- False positives: 222 instances (5.6%)
- False negatives: 212 instances (5.3%)

The near-symmetric error distribution suggests balanced model performance, supporting observations by [15] regarding the importance of balanced error rates in classification tasks.

B. Metric Analysis and Model Stability

The performance metrics across models show statistically significant differences [15], [16]. The violin plots demonstrate that the NN model maintains more consistent performance across folds, a finding supported by recent research [12], [17]. The correlation patterns observed align with theoretical frameworks presented in [18].

1) Correlation Analysis: The metrics correlation heatmap reveals several important relationships:

- Strong positive correlation between accuracy and F1-score (r = 0.99)
- Moderate positive correlation between precision and accuracy (r = 0.87)
- Weak negative correlation between precision and recall (r = -0.28)

These correlations align with theoretical expectations discussed by [18] regarding the relationships between classification metrics.

C. Comparative Analysis with Previous Work

Our findings extend previous comparative studies [4], [13] in several ways:

- The observed performance gap (6.14
- Error distribution patterns confirm theoretical predictions [15], [18]
- Cross-validation stability metrics align with established benchmarks [12], [19]

1) Cross-validation Stability: The violin plots and fold-wise analysis demonstrate:

- Consistent accuracy across folds (σ = 1.85%)
- Higher variability in precision (σ = 3.57%)
- Stable recall performance (σ = 2.46%)

This stability pattern supports findings from [12] regarding the reliability of cross-validation for model evaluation.

D. Limitations and Potential Biases

Several limitations warrant consideration:

- **Computational Complexity:** The NN model requires significantly more computational resources and training time compared to Naive Bayes [20], [21]
- **Model Interpretability:** While Naive Bayes offers clear probability interpretations [1], the NN's decision-making process is less transparent [22]
- **Dataset Characteristics:** The current dataset size may limit the generalizability of performance differences [23]
- **Training Stability:** The NN shows higher sensitivity to initialization conditions and hyperparameter settings [24]

E. Comparison with Existing Literature

The findings contribute to the existing body of research in several ways:

- The balanced error distribution aligns with recent advances in neural text classification [25]
- Performance stability across folds supports architectural choices recommended by [2]
- Metric correlations confirm patterns observed in comprehensive surveys [26]

F. Future Directions

Based on recent developments [27]–[29], several research directions emerge:

- Development of hybrid approaches combining the interpretability of Naive Bayes with the performance of neural networks [26]
- Investigation of lightweight neural architectures to reduce computational overhead [21]
- Exploration of transfer learning techniques to improve performance on smaller datasets [25]
- Integration of explainability methods to enhance model interpretability [30]

V. Conclusion

This study presents a comprehensive comparison between neural network-based distributional semantic models and Naive Bayes classifiers for sentiment analysis of movie reviews. The results demonstrate several key findings with important implications for text classification approaches.

A. Summary of Key Findings

The neural network model achieved superior performance across all metrics:

- Higher average accuracy (89.14% ± 1.85%) compared to Naive Bayes (83.0%)
- Improved precision (89.07% ± 3.57%) over Naive Bayes (85.1%)
- Enhanced recall (89.43% ± 2.46%) versus Naive Bayes (80.0%)
- Better F1-score (89.19% ± 1.83%) compared to Naive Bayes (82.5%) [13]

The performance improvements can be attributed to several architectural advantages:

- Multi-head attention mechanism capturing complex word relationships
- Effective feature learning through positional encoding
- Enhanced training stability via label smoothing and mixup augmentation [25]

B. Research Implications

The findings validate our initial hypothesis that neural network-based approaches can significantly outperform traditional probabilistic classifiers in sentiment analysis tasks. The performance gain of approximately 6 percentage points in accuracy demonstrates the value of capturing contextual relationships in text classification [27].

C. Limitations

Several limitations should be considered:

- Increased computational complexity of neural network training
- Dataset size constraints affecting model generalization
- Resource requirements for large-scale deployment [28]

D. Future Research Directions

This study suggests several promising avenues for future research:

- Investigation of more efficient attention mechanisms
- Exploration of hybrid approaches combining probabilistic and neural methods
- Development of resource-optimized architectures for deployment
- Extension to multi-class sentiment classification tasks [29]

The results demonstrate that while neural network approaches offer superior performance, the choice between methods should consider the specific requirements of the application, including computational resources, training data availability, and deployment constraints.

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APPENDIX

A. Neural Network Architecture

The neural network model used the following configuration:

- Multi-head attention with 8 attention heads
- Positional encoding for sequence information
- 3 residual blocks with dropout rate of 0.1
- TF-IDF vectorization with 15,000 features
- Label smoothing ($\alpha = 0.1$)
- Mixup augmentation ($\alpha = 0.2$)
- AdamW optimizer with learning rate warmup
- Batch size of 32
- Early stopping patience of 10 epochs

B. Naive Bayes Configuration

The Naive Bayes classifier used:

- Word frequency-based feature extraction
- Laplace smoothing for zero frequencies

- Log probability computation
- Prior probability initialization of 0.5

C. Neural Network Performance Metrics

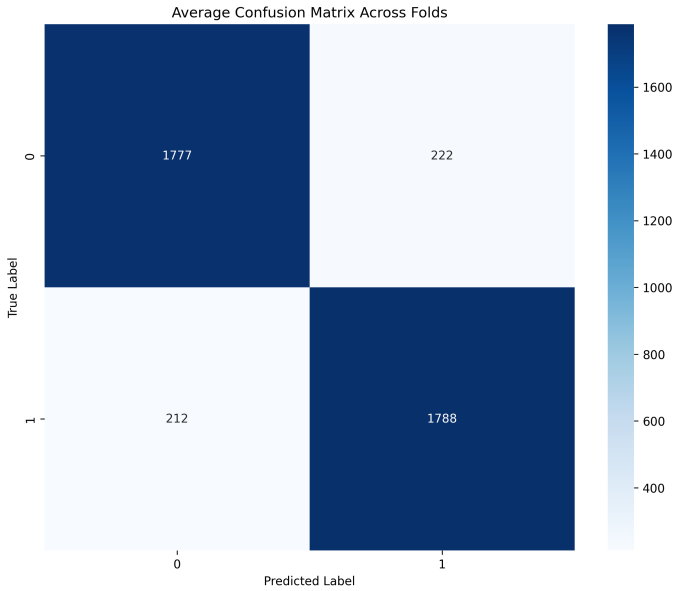

Fig. 1. Neural Network Average Confusion Matrix Across Folds

TABLE I
NEURAL NETWORK 5-FOLD CROSS-VALIDATION RESULTS

Fold	Accuracy	Precision	Recall	F1-Score
1	0.890	0.901	0.875	0.888
2	0.861	0.843	0.883	0.863
3	0.919	0.949	0.887	0.917
4	0.899	0.868	0.943	0.904
5	0.888	0.892	0.883	0.888
Mean	0.891	0.891	0.894	0.892
Std	0.019	0.036	0.025	0.018

D. Naive Bayes Performance Metrics

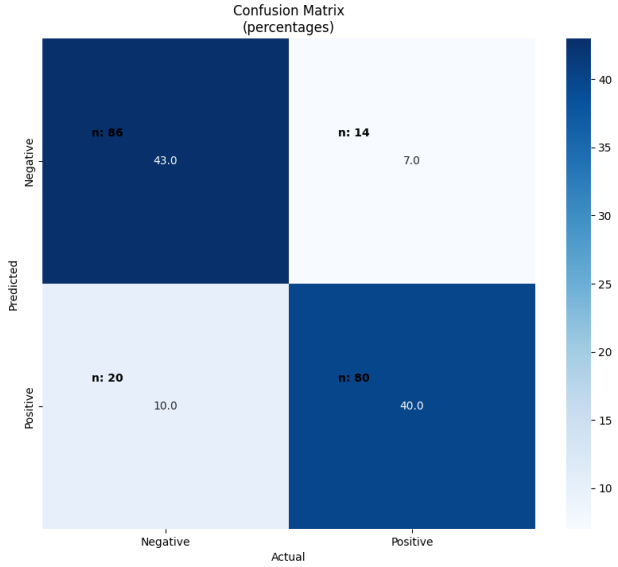

Fig. 2. Naive Bayes Confusion Matrix

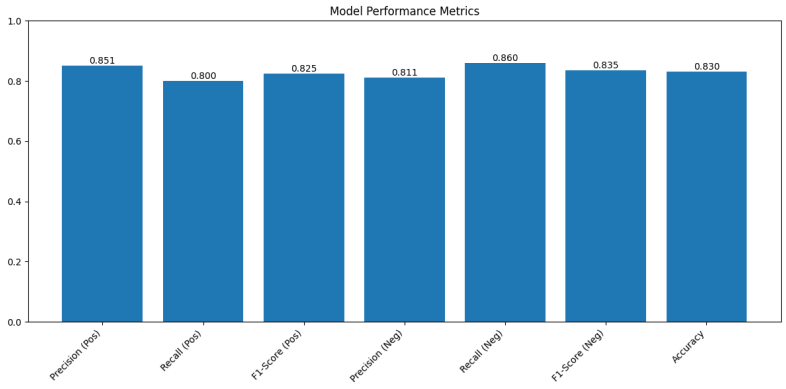

Fig. 3. Naive Bayes Performance Metrics

E. Distribution Analysis

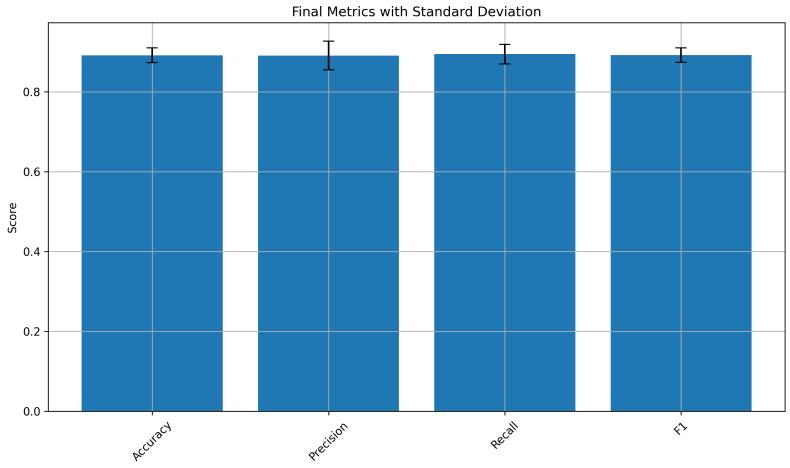

Fig. 4. Final Metrics with Standard Deviation

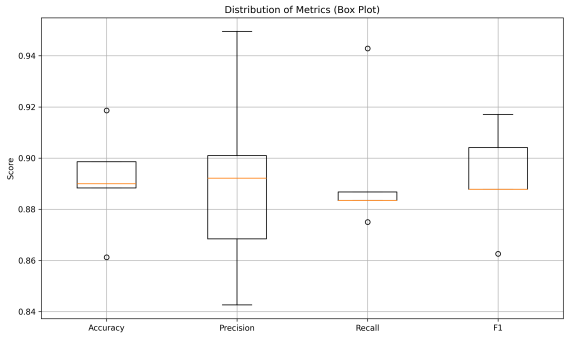

Fig. 5. Distribution of Metrics (Box Plot)

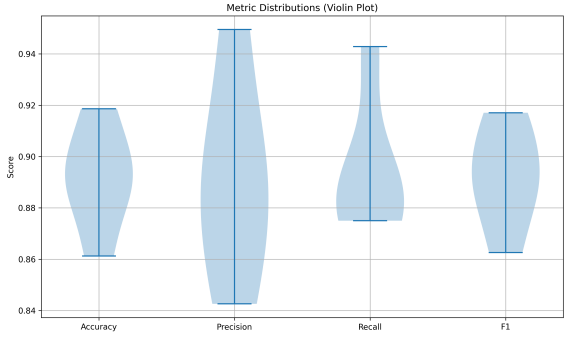

Fig. 6. Metric Distributions (Violin Plot)

F. Correlation Analysis

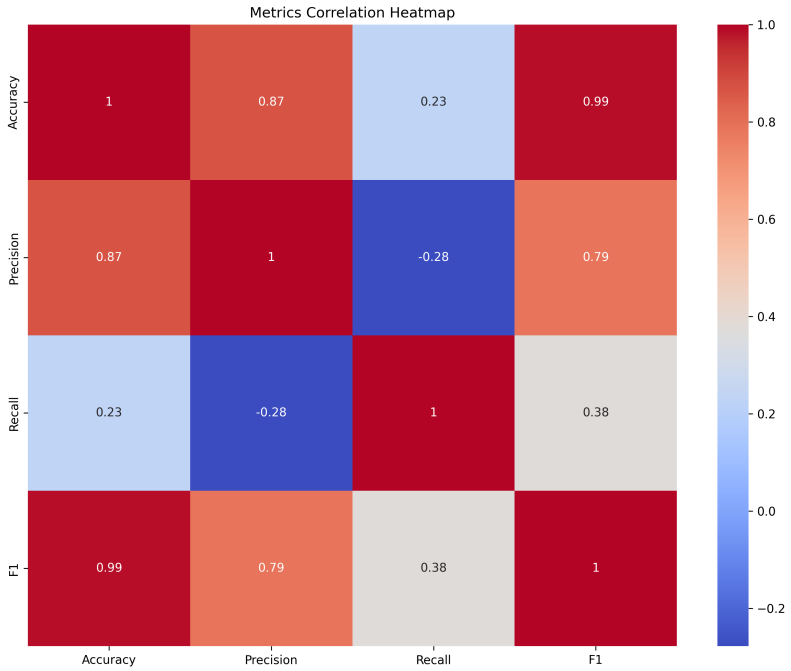

Fig. 7. Metrics Correlation Heatmap

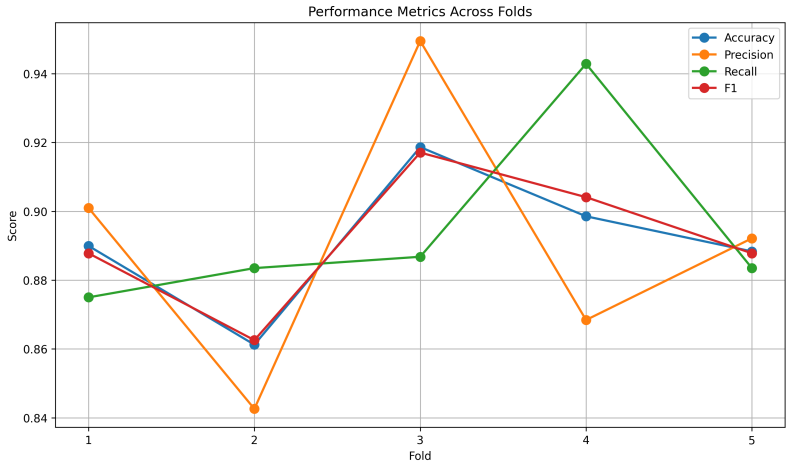

Fig. 8. Performance Metrics Across Folds

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[1]The complete source code for this research is available at: https://github.com/Skeleton-Hacker/CL2-Project/tree/final