Sentiment Classification Methods Using Support Vector Machines

1. Introduction

Support Vector Machines (SVMs) are powerful supervised learning algorithms widely used for classification tasks. This study focuses on evaluating and comparing two popular feature extraction techniques—Bag of Words (BoW) and Term Frequency-Inverse Document Frequency (TF-IDF)—within the context of SVM classifiers for text categorization. The primary objective is to determine which feature representation method yields superior performance and under what conditions when using SVM as the classification algorithm.

2. Methodology

2.1 Feature Extraction Methods

Two text representation methods were compared in this study:

- **Bag of Words (BoW)**: A simple representation that counts word occurrences in documents, disregarding grammar and word order but retaining multiplicity.

- **Term Frequency-Inverse Document Frequency (TF-IDF)**: A numerical statistic reflecting the importance of a word in a document relative to a corpus, combining term frequency with inverse document frequency to reduce the impact of common words.

2.2 Evaluation Metrics

Performance was evaluated using multiple metrics:

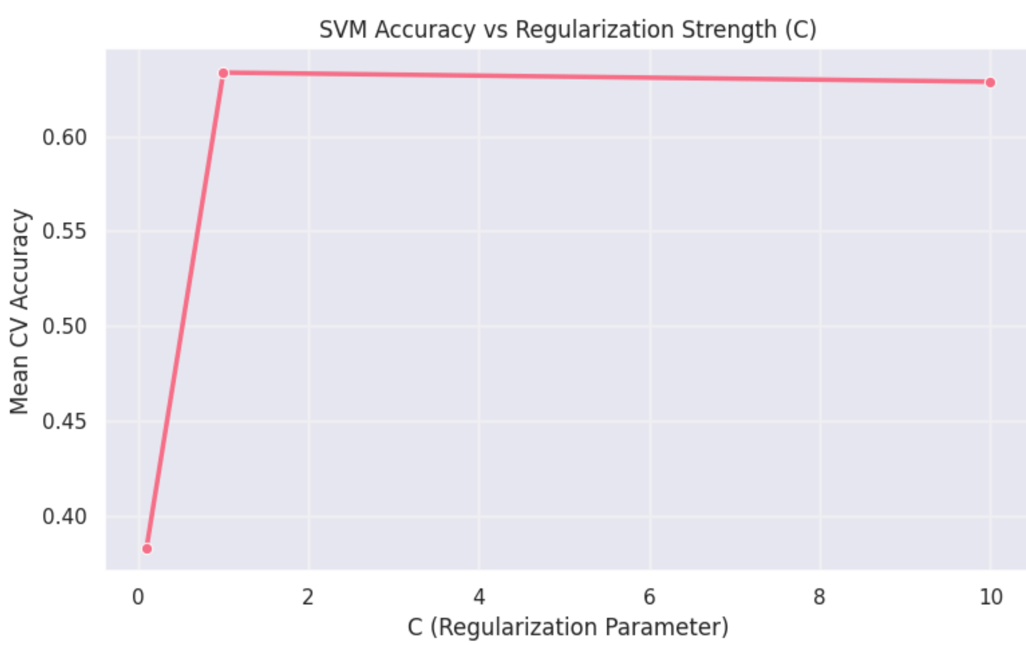
- Accuracy
- Precision
- Recall
- F1-score
- Confusion matrices

3. Results and Analysis

3.1 Effect of Regularization Strength

Regularization strength (C parameter) had a significant impact on SVM model performance. The relationship between the C parameter and model accuracy shows:

- At low C values (near 0.1), the model performed poorly with accuracy around 0.38
- A sharp increase in performance occurs between C=0.1 and C=1.0, where accuracy jumps to approximately 0.64
- Performance stabilizes for C values between 1.0 and 10.0, with a slight decrease at higher values
- Optimal performance appears to be achieved at C=1.0 with accuracy around 0.64

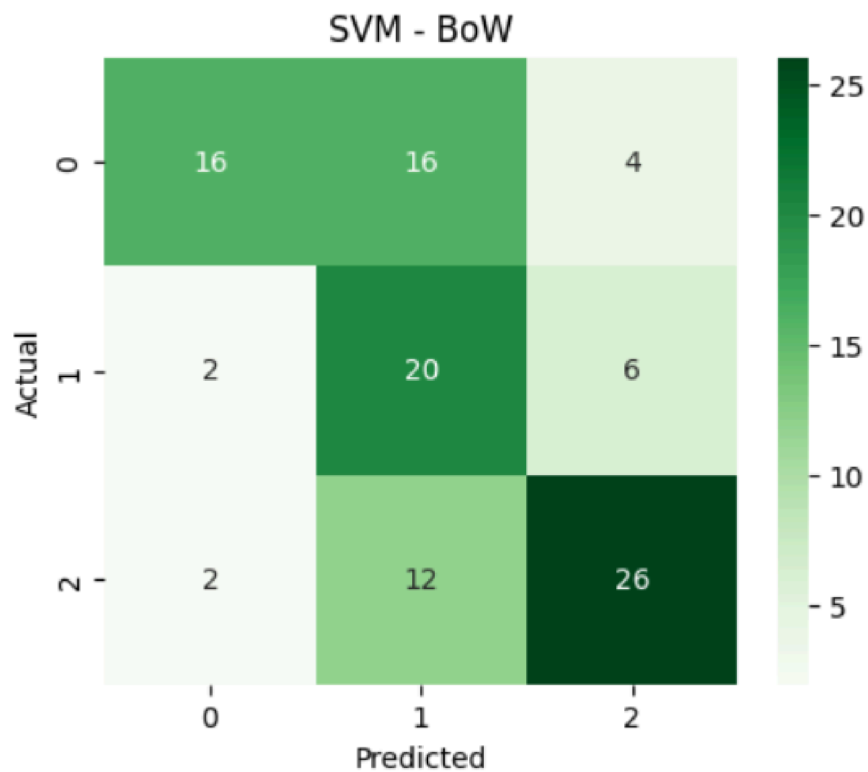


3.2 Confusion Matrix Analysis

The confusion matrices for the SVM models with both feature extraction methods reveal interesting classification patterns:

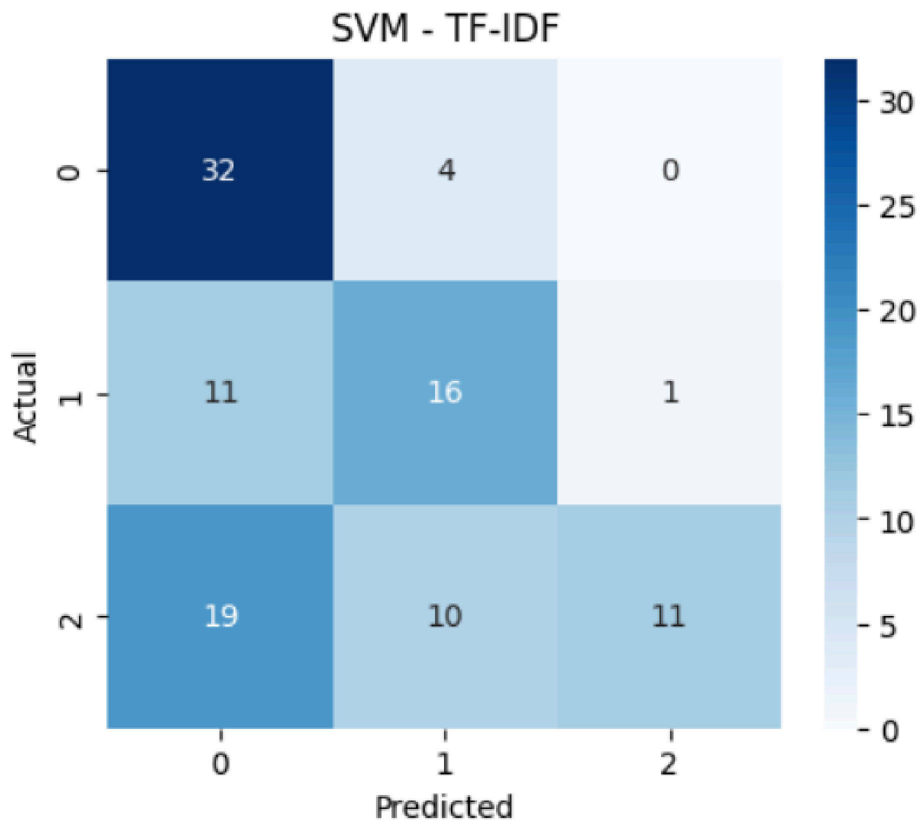
SVM with BoW (Accuracy: 0.596):

- Class 0: 16 correct predictions out of 36 samples (44.4% correct)
- Class 1: 20 correct predictions out of 28 samples (71.4% correct)
- Class 2: 26 correct predictions out of 40 samples (65.0% correct)
- Notable confusion between classes 0 and 1 (16 samples from class 0 misclassified as class 1)



SVM with TF-IDF (Accuracy: 0.567):

- Class 0: 32 correct predictions out of 36 samples (88.9% correct)
- Class 1: 16 correct predictions out of 28 samples (57.1% correct)
- Class 2: 11 correct predictions out of 40 samples (27.5% correct)
- Significant misclassification of class 2 samples as class 0 (19 instances)



3.3 Detailed Performance Metrics

SVM with TF-IDF (Accuracy: 0.567):

- Precision ranges from 0.52 to 0.92
- Recall varies significantly across classes (0.28 to 0.89)
- F1-scores range from 0.42 to 0.65
- Class 0 shows extremely high recall (0.89) but moderate precision (0.52)
- Class 2 shows very high precision (0.92) but poor recall (0.28)

SVM with BoW (Accuracy: 0.596):

- Precision ranges from 0.42 to 0.80
- Recall ranges from 0.44 to 0.71
- F1-scores range from 0.53 to 0.68
- More balanced performance across classes

- Class 1 shows the best recall (0.71)
- Class 0 shows the best precision (0.80) but poorest recall (0.44)

4. Conclusions

4.1 Feature Representation Impact

The two feature extraction methods exhibit notably different behavior with the SVM classifier:

1. **Overall Accuracy**: BoW slightly outperforms TF-IDF (0.596 vs. 0.567), but the difference is less pronounced than observed with logistic regression.

2. **Class-Specific Performance**:

   - TF-IDF excels at classifying class 0 (recall 0.89) but struggles with class 2 (recall 0.28)
   - BoW offers more balanced performance across classes, particularly for classes 1 and 2
   - The extreme precision (0.92) for class 2 with TF-IDF suggests that when the model predicts class 2, it's very reliable, but it often fails to identify class 2 instances
3. **Classification Patterns**:

   - TF-IDF shows a bias toward class 0 predictions (62 samples classified as class 0)
   - BoW distributes predictions more evenly across classes (20, 48, and 36 predictions for classes 0, 1, and 2 respectively)

4.2 Regularization Effect

The observed relationship between the C parameter and model performance aligns with SVM theory:

- Low C values prioritize a wider margin at the expense of misclassifications, leading to underfitting

- High C values prioritize minimizing misclassifications at the expense of margin width, potentially leading to overfitting
- The optimal performance at C=1.0 suggests this value provides the best balance between margin width and classification accuracy for this dataset

The relatively flat performance curve beyond C=1.0 indicates that the model is not particularly sensitive to overfitting in this range, which may be due to the inherent sparsity of text feature representations.