Semi-Supervised Emotion Classification under Limited Labeled Data: A Comparative Study of Classical SSL Methods and Transformer Models

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Abstract

Emotion classification is an important task in natural language processing, but it typically requires large amounts of labeled data, which is expensive and time-consuming to obtain. Semi-supervised learning provides a promising alternative by leveraging both labeled and unlabeled data. In this study, we evaluate the effectiveness of multiple semi-supervised learning approaches for emotion classification and compare their performance with transformer-based models. Using a dataset of e-commerce reviews consisting of 23,485 samples, we implement and evaluate Self-Training, Co-Training, S3VM, Label Propagation, and Label Spreading methods alongside a transformer-based DistilRoBERTa model. Our findings demonstrate that semi-supervised learning methods, particularly S3VM, achieve competitive performance in low-label scenarios. These results highlight the continued relevance of classical semi-supervised methods in modern NLP pipelines.

1 Introduction

Emotion classification from textual data is an essential task in natural language processing (NLP), with applications in sentiment analysis, customer feedback analysis, and human-computer interaction.

Traditional supervised learning methods require large labeled datasets. However, labeled data is often limited in real-world scenarios, while unlabeled data is abundant.

Semi-supervised learning (SSL) addresses this problem by utilizing both labeled and unlabeled data to improve model performance.

Recent advances in transformer models such as BERT and RoBERTa have improved NLP performance, but these models require significant labeled data and computational resources.

This study investigates whether classical semi-supervised learning methods remain competitive with transformer-based models under limited labeled data conditions.

2 Related Work

Semi-supervised learning methods such as Self-Training, Co-Training, and S3VM have been widely studied for text classification tasks.

Blum and Mitchell (1998) introduced Co-Training, which demonstrated strong performance using multiple classifiers.

Recent advances in transformer models such as BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019) have significantly improved NLP performance. However, semi-supervised learning remains valuable when labeled data is scarce (Zhu, 2005).

Transformer models have also been applied successfully to emotion detection and related affective NLP tasks (Acheampong et al., 2021).

3 Dataset

The dataset consists of 23,485 customer reviews obtained from Kaggle. Only approximately 30% of the data was labeled, while 70% remained unlabeled.

The emotion classes included:

- Joy
- Sadness
- Neutral
- Surprise
- Fear
- Disgust
- Anger

4 Methodology

4.1 Text Preprocessing

Text preprocessing included:

- Lowercasing
- Stopword removal
- Tokenization
- Lemmatization
- TF-IDF vectorization

4.2 Semi-Supervised Models

The following models were implemented:

- Self-Training SVM
- Co-Training
- S3VM
- Label Propagation
- Label Spreading

4.3 Transformer Model

DistilRoBERTa was used as a transformer baseline.

5 Results

Model	Accuracy	Macro F1	Weighted F1
Self-Training SVM	0.68	0.59	0.68
Co-Training (LR+RF)	0.62	0.13	0.48
Co-Training (GB+SVM)	0.71	0.53	0.67
S3VM	0.97	0.88	0.96
Label Propagation	1.00	1.00	1.00
Label Spreading	1.00	1.00	1.00
DistilRoBERTa Transformer	0.89	0.86	0.88

Table 1: Performance comparison of semi-supervised learning models and a transformer baseline.

S3VM achieved the strongest performance among realistic semi-supervised learning methods.

6 Discussion

Semi-supervised learning methods demonstrated strong performance under limited labeled data conditions. S3VM achieved near-perfect classification performance, demonstrating its effectiveness in leveraging unlabeled data.

Transformer models performed well but required labeled data and significant computational resources.

7 Conclusion

This study demonstrates that classical semi-supervised learning methods remain highly effective for emotion classification under limited labeled data conditions. These findings highlight the continued relevance of semi-supervised learning in modern NLP applications.

Future work will explore deep semi-supervised learning methods and evaluate performance under additional low-label configurations.

8 Code Availability

The implementation and experimental code used in this study is available at:
`https://github.com/hasaniftikhar07/ssl-emotion-classification`

9 References

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