

Machine Learning Based Sentiment Analysis of Financial Texts

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December 14, 2024



**Note: The order of authors' names follows the alphabetical order of their last names.*

Problem Statement

Background:

- Massive volumes of financial text (news, reports, social media) influence investment decisions.
- Traditional analysis often overlooks subtle emotional cues embedded in textual data.
- Objective: Integrate sentiment analysis into financial decision-making to enhance rationality and predictive accuracy.

Objectives:

- Challenge: Limited high-quality, annotated Chinese financial sentiment corpora.
- Need: A robust methodology to generate and leverage domain-specific labeled datasets.
- Goal: Improve Chinese financial sentiment classification via data augmentation and Transformer-based models.

Dataset Description

Dataset Overview:

- Extended Chinese financial news articles from *Various Sources*.
- Sentiment Labels: Positive, Neutral, Negative.
- Size: 54749 labeled articles.

Data Preprocessing:

- Extension: Translated high-quality labeled English financial sentiment corpora into Chinese.
- Prelabel: Used a Chinese financial sentiment lexicon for non-labeled data.
- Tokenization: Jieba Chinese tokenizer.

Dataset Visualization

Sentiment Distribution:

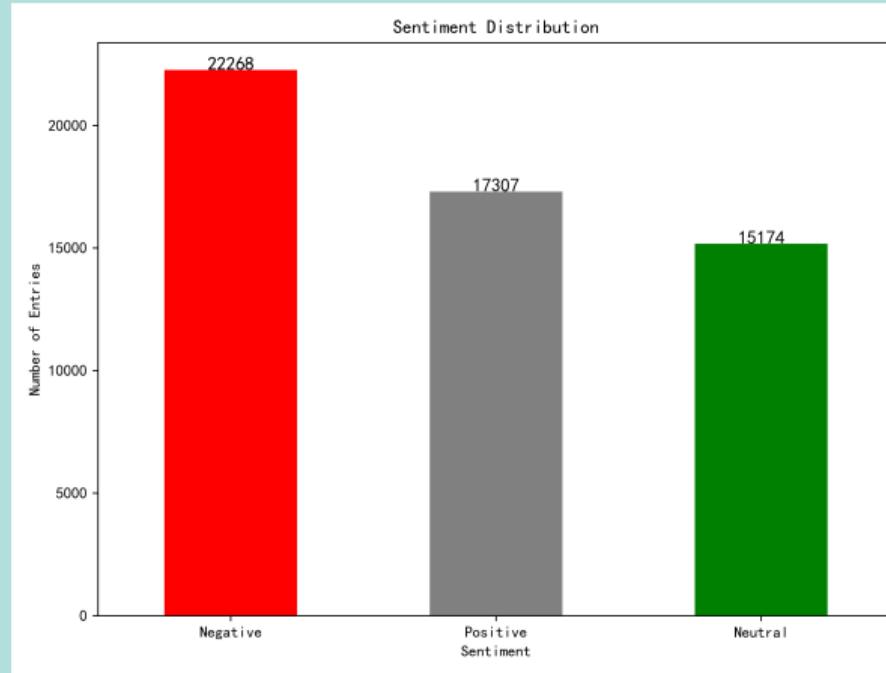


Figure: Distribution of Sentiments

Dataset Visualization (Continue)

Word Clouds:



Figure: Neutral Sentiment



Figure: Positive Sentiment



Figure: Negative Sentiment

1. Data Preparation and Augmentation:

- Translate high-quality English financial sentiment corpora into Chinese using a Transformer-based NMT model (TNMT).
- Result: Enlarged Chinese corpus for sentiment analysis.

2. Lexicon-Based Annotation:

- Use a Chinese financial sentiment lexicon for labeling, inspired by Jiang et al. (2019)¹.
- Assign sentiments (positive, neutral, negative) via domain-specific terms.
- Outputs: Automatically annotated Chinese dataset.

3. Model Training: BERT Fine-Tuning:

- Fine-tune a pre-trained Chinese BERT model with the annotated dataset.
- BERT captures contextual nuances, surpassing traditional methods.

¹Jiang et al., *J. Fin. Econ.*, 132(1), 126-149.

Results: Transformer-based NMT model (TNMT)

Transformer Model Results:

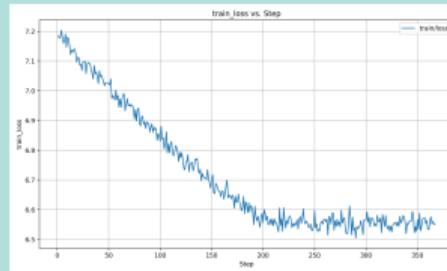


Figure: Training Loss: 200 steps stable

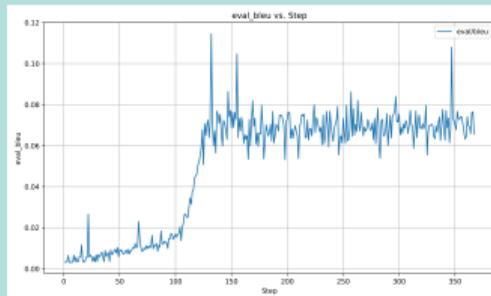


Figure: Evaluation BLEU Score: 130 steps stable

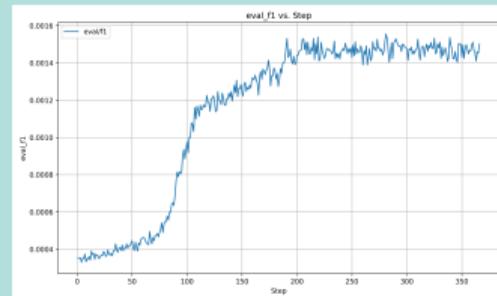


Figure: Evaluation F1 Score: 200 steps stable

Results: BERT Training

BERT Model Training Results:

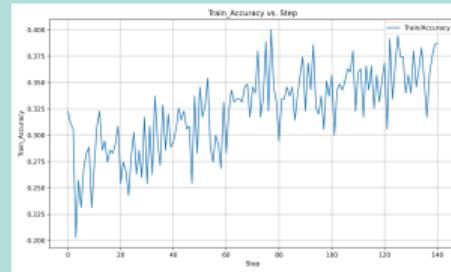


Figure: Training Accuracy: Increasing

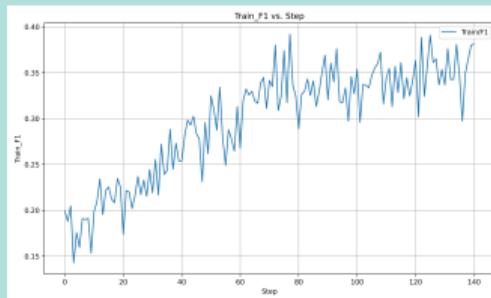


Figure: Training F1 Score: 60 steps stable

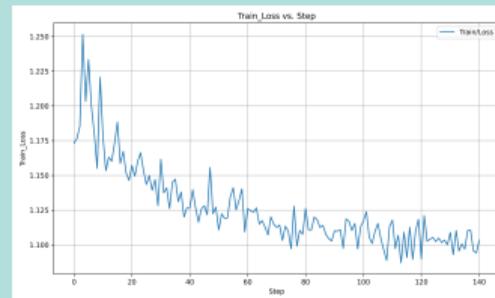


Figure: Training Loss: 120 steps stable

Results - Domain Adaptation

- Effectively adapted English-origin sentiment cues to Chinese texts.
- Enhanced model robustness in dynamic financial contexts.
- Demonstrated scalable approach to other languages/domains.

Conclusions (1/2)

- Leveraged NMT to generate Chinese financial sentiment data from English corpora.
- Applied lexicon-based annotation to expand labeled datasets.
- Fine-tuned BERT to achieve improved classification performance.

Conclusions (2/2) - Resources

- **Video Presentation:** <https://example.com/video-demo>
- **Code Repository:** <https://github.com/username/fin-sentiment-analysis>