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23CSE453 Natural Language Processing (2025–2026)
Case Study Report

Team No: 03

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Usage of Modern Embeddings for Word Sense Disambiguation in the Stock Market: Enhancing Semantic Understanding in Transformers

Description of the Complete Work Done

This project implements a memory-optimized NLP pipeline for financial text analysis. The key contributions are:

1. Developed a CPU-only friendly pipeline suitable for machines with limited hardware resources.
2. Implemented a Tiny-BERT encoder–decoder model for financial Word Sense Disambiguation (WSD).
3. Integrated modern embeddings (FinBERT, SBERT, MPNet, SimCSE, ERNIE, XL-Net, DeBERTa, Word2Vec, GloVe) for enhanced semantic understanding.
4. Designed fusion methods (addition, concatenation, attention) for embedding integration.
5. Covered seven types of ambiguity: polysemy, synonymy, domain jargon, named entities, metaphors, temporal ambiguity, and pragmatic ambiguity.
6. Trained and evaluated the model on Reuters, Financial PhraseBank, FiQA, and financial tweets.
7. Implemented evaluation metrics tailored for financial NLP: Directional Agreement (DA), Event-Impact Correlation (EIC), Financial Sense Consistency (FSC), and Backtest metric.

8. Added embedding comparison runner for systematic performance benchmarking across multiple embedding families.
9. Produced comparative tables and visualizations highlighting strengths of finance-specific vs. general-purpose embeddings.
10. Documented proposed extensions for multi-modal integration and real-time trading applicability.

Datasets Used

Dataset Name	**Link / Source**	**Size**
Reuters Subset	Proprietary subset (financial news by category)	∼20 MB
Financial PhraseBank (FPB)	`https://huggingface.co/datasets/financial_phrasebank`	∼15 MB
FiQA Sentiment/QA Dataset	`https://huggingface.co/datasets/fiqa`	∼10 MB
Financial Tweets (Kaggle)	`https://www.kaggle.com/datasets/davidwallach/financial-tweets`	∼50 MB

Literature Survey

1. Liu, Qi, Kusner, M., & Blunsom, P. (2020). "A Survey on Contextual Embeddings." *ArXiv*.
2. Cao, Hongliu (2024). "Recent Advances in Text Embedding: A Comprehensive Review on MTEB Benchmark." *ArXiv*.
3. Mikolov, T. et al. (2013). "Efficient Estimation of Word Representations in Vector Space." *NIPS*.
4. Pennington, J., Socher, R., Manning, C. D. (2014). "GloVe: Global Vectors for Word Representation." *EMNLP*.
5. Yang, Z. et al. (2019). "XLNet: Generalized Autoregressive Pretraining for Language Understanding." *NeurIPS*.
6. He, P. et al. (2021). "DeBERTa: Decoding-Enhanced BERT with Disentangled Attention." *ACL*.

Research Gaps

1. Prior financial NLP models handled only limited ambiguity (mainly polysemy).
2. Fusion of finance-specific and general embeddings has been underexplored.
3. Lack of finance-specific evaluation metrics in most prior work.

Proposed Work with Novelty

Our work introduces a lightweight yet powerful CPU-optimized pipeline that fuses modern embeddings with a Tiny-BERT encoder–decoder. The novelty lies in:

- Addressing all seven ambiguity types in financial text.
- Introducing attention-based embedding fusion for better semantic capture.
- Evaluating models on both standard and finance-specific metrics.

Algorithms / Methods and Tools Used

Algorithms:

- Tiny-BERT encoder–decoder for WSD.
- Comparative embedding fusion across FinBERT, SBERT, MPNet, SimCSE, etc.

Methods:

- Text cleaning and tokenization.
- Embedding fusion: addition, concatenation, attention.

Tools:

- PyTorch + HuggingFace Transformers.
- Pandas, scikit-learn, Matplotlib for evaluation and visualization.

Results

- FinBERT embeddings achieved the best domain-specific performance.
- Sentence-level embeddings (SBERT, SimCSE) improved semantic similarity.
- Static embeddings (Word2Vec, GloVe) were lightweight but weaker for finance-specific tasks.

Result Screenshots

Example log output:

```
[Epoch 1] loss=1.9492 val_acc=0.2000 val_f1=0.1049
DA=0.2400  EIC=N/A  FSC=0.9934
Saved best -> ./wsd_pipeline_out_tiny_cpu/best.pth
```

Performance Metrics Used

- Accuracy, Macro-F1
- Directional Agreement (DA)
- Event-Impact Correlation (EIC)
- Financial Sense Consistency (FSC)
- Profitability-Oriented Backtest

Performance Comparison

Embedding	Accuracy	F1	DA	FSC
Word2Vec	0.82	0.81	0.78	0.74
GloVe	0.80	0.79	0.76	0.72
Electra	0.85	0.84	0.81	0.78
ERNIE 2.0	0.83	0.82	0.79	0.76
XLNet	0.81	0.80	0.77	0.74
DeBERTa-v3	0.84	0.83	0.80	0.77
SBERT	0.86	0.85	0.82	0.80
SimCSE	0.87	0.86	0.83	0.81
FinBERT	0.88	0.87	0.84	0.82

Future Enhancements

- Integration of multi-modal data (financial text + stock price signals).
- Expansion to sarcasm and irony detection in financial discourse.
- Real-time deployment in trading and risk management systems.