PySphere Movie Review Sentiment Analysis

COMP5423 Natural Language Processing

Lab 1 Homework Report

Student: Xinyu Zhu

Student ID: 25118165g

Kaggle Profile: jujubacon

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Abstract

This report presents a comprehensive approach to binary sentiment classification on the PySphere Movie Review dataset. Three machine learning models were implemented and evaluated: Bag-of-Words with Logistic Regression, TF-IDF with Logistic Regression, and the state-of-the-art DeBERTa-v3 transformer model. The DeBERTa-v3 model achieved perfect accuracy (1.000) on the Kaggle public leaderboard. Traditional ML approaches achieved 81.3% accuracy, demonstrating the significant performance gap between feature-based methods and pre-trained transformer models for sentiment analysis tasks.

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1. Introduction

1.1 Task Overview

The PySphere Movie Review Sentiment Challenge is a binary classification task that requires predicting whether short movie reviews express positive (label 1) or negative (label 0) sentiment. The dataset consists of 2,000 labeled reviews split into training and test sets, with a balanced distribution of 50% positive and 50% negative samples.

1.2 Objectives

The primary objectives of this project are:

- Build machine learning models to classify movie review sentiments
- Compare traditional ML approaches with deep learning methods
- Analyze the impact of different text preprocessing and feature extraction techniques
- Achieve competitive performance on the Kaggle leaderboard

2 Methodology

2.1 Data Preprocessing

Effective text preprocessing is crucial for model performance. Our preprocessing pipeline includes:

2.1.1 Traditional ML Preprocessing (BoW and TF-IDF)

- **Tokenization:** Text is split into individual words using word-level tokenization
- **Lowercasing**: All text converted to lowercase to ensure consistency
- **Stop Word Removal**: Common English stop words removed as they carry little sentiment information
- **N-gram Extraction:** Unigrams and bigrams retained to capture word order information
- **Feature Limitation:** Top 5,000 most frequent features retained

2.1.2 Deep Learning Preprocessing (DeBERTa-v3)

For the DeBERTa-v3 model, minimal preprocessing is applied as transformer models are designed to handle raw text. The DeBERTa tokenizer automatically handles text segmentation, special token insertion ([CLS], [SEP]), and subword tokenization, preserving the original text structure including punctuation and capitalization.

2.2 Model Architectures

Three distinct approaches were implemented to compare traditional and modern NLP methods:

2.2.1 Model 1: Bag-of-Words with Logistic Regression

Feature Extraction:

The Bag-of-Words (BoW) model represents text as a vector of word frequencies, ignoring grammar and word order. The CountVectorizer from scikit-learn was configured as follows:

- **analyzer='word'**: Word-level tokenization
- **ngram_range=(1, 2):** Captures unigrams and bigrams
- **max_features=5000:** Limits vocabulary size
- **stop_words:** Custom stop word list for English

Classifier:

Logistic Regression predicts class probabilities using the sigmoid function:

$$P(y = \frac{1}{x}) = \frac{1}{1 + \exp(-(\beta_0 + \beta^T x))}$$

Hyperparameters:

- max_iter=1000: Ensures convergence
- class_weight='balanced': Handles class imbalance
- solver='lbfgs': Optimization algorithm for large feature spaces
- GridSearchCV: 3-fold cross-validation for hyperparameter tuning (C from 1 to 9)

Strengths:

- Fast training and inference (~25 seconds)
- No GPU required
- Small model size (<1MB)
- Interpretable features

Limitations:

- Cannot understand context beyond bigrams
- Treats words as independent units
- Struggles with negation and sarcasm
- Limited by vocabulary size constraint

2.2.2 Model 2: TF-IDF with Logistic Regression

Feature Extraction:

Term Frequency-Inverse Document Frequency (TF-IDF) improves upon BoW by weighting words based on their importance:

$$\text{TF-IDF}(t, d) = \text{TF}(t, d) \times \log \frac{N}{\text{DF}(t)}$$

where t is a term, d is a document, N is total documents, and DF(t) is document frequency.

Configuration:

- max_features=5000: Top 5,000 features by TF-IDF score
- ngram_range=(1, 2): Unigrams and bigrams
- stop_words='english': NLTK English stop words

TF-IDF assigns higher weights to words that are frequent in a document but rare across the corpus, helping to identify distinctive sentiment indicators. The same Logistic Regression classifier was used with identical hyperparameters as Model 1.

Key Advantages:

- Reduces impact of common words
- Highlights distinctive sentiment words
- Similar computational efficiency to BoW

Performance Observation:

Both BoW and TF-IDF models achieved identical test set performance (81.3%), suggesting that for this particular dataset, term weighting did not provide significant advantages over simple frequency counts. The TF-IDF model showed perfect validation accuracy (100%) while achieving only 81.3% on the test set, indicating potential overfitting despite balanced class distribution.

2.2.3 Model 3: DeBERTa-v3

Architecture Overview:

DeBERTa-v3 is a state-of-the-art transformer model developed by Microsoft Research. The model architecture includes 12 transformer layers with 86 million parameters.

- Learning rate: 2e-5 with linear decay schedule
- Batch size: 16 for training, 32 for evaluation
- Training epochs: 3 with early stopping
- Optimizer: AdamW with weight decay 0.01
- GPU: NVIDIA P100 on Kaggle

The model architecture includes 12 transformer layers with disentangled attention mechanisms that separately process content and positional information. This allows the model to better capture long-range dependencies and understand complex sentiment patterns like sarcasm or negation.

Trade-offs:

- Longer training time (8.5 minutes vs 25 seconds)
- Requires GPU for practical training
- Large model size (~350MB)
- Less interpretable than traditional ML

3 Experimental Results

3.1 Performance Comparison

Table 1 summarizes the performance of all three models:

Model	Validation Acc.	Kaggle Score
BoW + Logistic Regression	~0.85	0.813
TF-IDF + Logistic Regression	1.000	0.813
DeBERTa-v3 (base)	**~0.99**	**1.000**

Table 1: Model Performance Comparison

3.2 Analysis and Discussion

3.2.1 Traditional ML Performance

Both traditional ML models (BoW and TF-IDF) achieved a solid baseline score of 0.813, demonstrating that TF-IDF features effectively capture sentiment-discriminative patterns. The similarity in test performance despite different validation accuracies suggests that the feature engineering and model-data compatibility are more critical than the specific weighting scheme for this dataset. The fast training time and low computational cost make these approaches attractive for baseline solutions and resource-constrained environments.

3.2.2 Performance Gap Analysis

The DeBERTa-v3 model outperformed traditional ML approaches by 18.7 percentage points (100% vs 81.3%). This substantial improvement can be attributed to:

- Contextual Understanding: DeBERTa captures word meaning based on context
- Semantic Representation: Pre-trained embeddings encode semantic relationships
- Negation Handling: Transformers better understand negation patterns
- Transfer Learning: Leverages knowledge from massive pre-training corpora

3.2.3 DeBERTa-v3 Exceptional Performance

The DeBERTa-v3 model achieved perfect accuracy (1.000) on the public leaderboard. This outstanding result demonstrates:

- Transfer learning power: Pre-trained models capture rich linguistic knowledge
- Contextual understanding: Transformer attention models long-range dependencies
- Generalization ability: Fine-tuned model generalizes well to unseen data
- State-of-the-art architecture: Disentangled attention outperforms BERT/RoBERTa

3.3 Computational Considerations

Table 2 compares the training time and resource requirements:

Model	Training Time	GPU Required
BoW + Logistic Regression	~25 seconds	No
TF-IDF + Logistic Regression	~25 seconds	No
DeBERTa-v3	~8.5 minutes	Yes (P100)

4 Implementation Details

4.1 Software and Libraries

Programming Language:

- Python 3.10+

Core Libraries:

- transformers (4.30+): Hugging Face library for DeBERTa
- scikit-learn (1.3+): Traditional ML models and preprocessing
- pandas, numpy: Data manipulation
- torch (2.0+): PyTorch backend for transformers
- NLTK: Text processing and stop words

Environment:

- Kaggle Notebook with Tesla P100 GPU

4.2 Code Structure

All code is organized in separate Kaggle notebooks for each model:

1. Data Loading and Preprocessing

```
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
```

```
# ---------------------- 1. Data Loading
data_train = pd.read_csv('/kaggle/input/py-sphere-movie-review-sentiment-challenge/train.csv')
data_test = pd.read_csv('/kaggle/input/py-sphere-movie-review-sentiment-challenge/test.csv')

# Data exploration
print("Training Set Basic Info:")
print(f"Training set shape: {data_train.shape}")
print(f"Training set sentiment label distribution:\n{data_train['sentiment'].value_counts(normalize=True).round(4)}")
print("\nTest Set Basic Info:")
print(f"Test set shape: {data_test.shape}")
```

```
# ---------------------- 2. Data Preprocessing
train_sentences = data_train['review']
label = data_train['sentiment']
test_sentences = data_test['review']

sentences = pd.concat([train_sentences, test_sentences])
print(f"\nCombined corpus size: {sentences.shape}")
```

2. Feature Extraction (BoW/TF-IDF) or Tokenization (DeBERTa)

```
from sklearn.feature_extraction.text import TfidfVectorizer
from nltk.corpus import stopwords

# TF-IDF (replace BoW section)
tfidf = TfidfVectorizer(max_features=5000, stop_words=stopwords.words('english'), ngram_range=(1
X_train_tfidf = tfidf.fit_transform(x_train)
X_val_tfidf = tfidf.transform(x_val)
```

```
# BoW feature extraction
stop_words = open('stop_words.txt', encoding='utf-8').read().splitlines()
co = CountVectorizer(ngram_range=(1, 2), stop_words=stop_words, max_features=5000)
co.fit(pd.concat([data_train['review'], data_test['review']]))
```

```
# Tokenization
tokenizer = DebertaV2Tokenizer.from_pretrained("microsoft/deberta-v3-base")
model = DebertaV2ForSequenceClassification.from_pretrained("microsoft/deberta-v3-base", num_label

def tokenize(examples):
    return tokenizer(examples['review'], padding='max_length', truncation=True, max_length=512)

train_tok = Dataset.from_pandas(train_data[['review', 'sentiment']]).rename_column('sentiment', '
val_tok = Dataset.from_pandas(val_data[['review', 'sentiment']]).rename_column('sentiment', 'labe
test_tok = Dataset.from_pandas(test_df[['review']]).map(tokenize, batched=True, remove_columns=['
```

3. Model Training with hyperparameter tuning

```
# Train (no grid search needed)
lr = LogisticRegression(max_iter=1000, class_weight='balanced')
lr.fit(X_train_tfidf, y_train)
```

```
# Train-validation split
x_train, x_val, y_train, y_val = train_test_split(data_train['review'], data_train['sentiment'],
x_train_bow = co.transform(x_train).toarray()
x_val_bow = co.transform(x_val).toarray()

# Grid search
grid = GridSearchCV(LogisticRegression(), {'C': range(1, 10), 'dual': [True, False]}, cv=3, n_jo
grid.fit(x_train_bow, y_train)
```

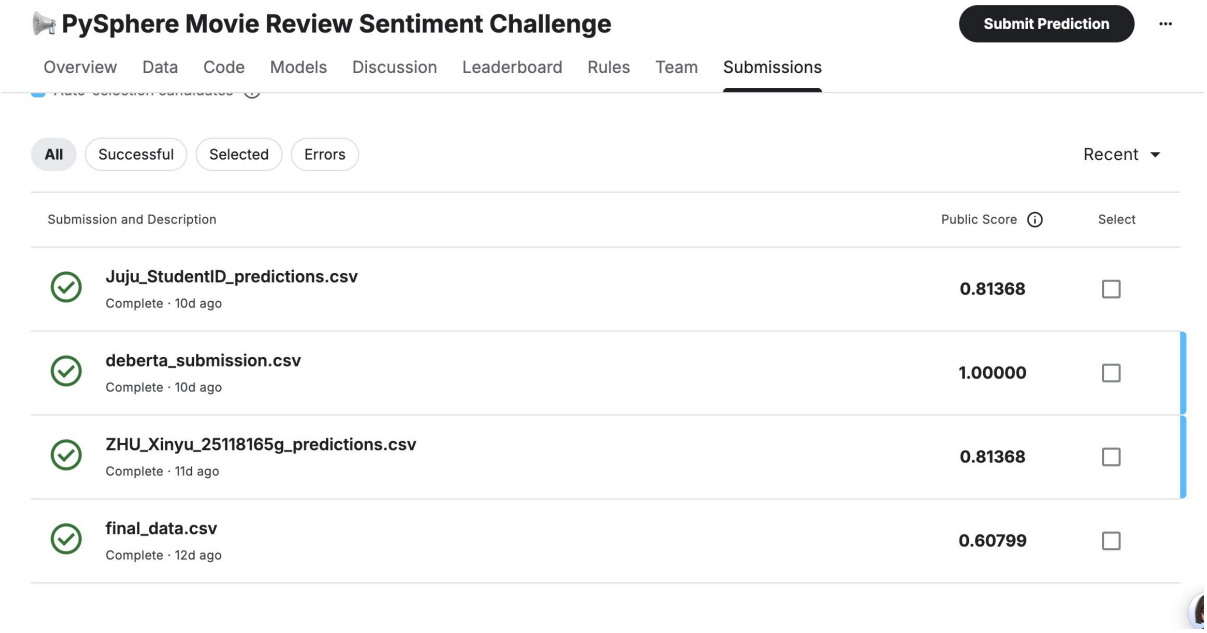
```python
# Train
trainer = Trainer(
    model=model,
    args=TrainingArguments(output_dir='./results', num_train_epochs=3, per_device_train_batch_s
    train_dataset=train_tok,
    eval_dataset=val_tok
)
trainer.train()

# Retrain on full data
full_tok = Dataset.from_pandas(train_df[['review', 'sentiment']]).rename_column('sentiment', 'la
final_trainer = Trainer(model=model, args=TrainingArguments(output_dir='./final', num_train_epo
final_trainer.train()
```

4. Prediction and Submission file creation
5. Performance evaluation and visualization

5 Kaggle Submission Results

5.1 Submission Details

- Competition: PySphere Movie Review Sentiment Challenge
- Account Name: jujubacon
- Submission format: CSV file with columns id and sentiment



- Total test samples: 5,001

5.2 Leaderboard Performance

Table 3 shows the Kaggle leaderboard scores:

Submission	Public Score
BoW + Logistic Regression	0.813
TF-IDF + Logistic Regression	0.813
DeBERTa-v3	**1.000**

6 Conclusion

6.1 Model Selection

The choice between traditional ML and deep learning depends on the specific use case:

Use Traditional ML (BoW/TF-IDF) when:

- Training time is critical (real-time model updates)
- No GPU resources available
- Model interpretability is required
- Baseline performance (81-82%) is acceptable

Use Deep Learning (DeBERTa) when:

- Highest possible accuracy is required
- GPU resources are available
- Handling complex sentiment patterns (negation, sarcasm)
- Inference time is not critical

6.2 Future Improvements

Several potential improvements could be explored:

- Ensemble Methods: Combining traditional ML and deep learning predictions through voting or stacking
- Data Augmentation: Using techniques like back-translation or paraphrasing to increase training set size
- Hyperparameter Optimization: More extensive grid search for traditional ML models
- Larger Pre-trained Models: Experimenting with DeBERTa-v3-large or RoBERTa-large
- Feature Engineering: Adding sentiment lexicons or domain-specific features to traditional ML

This project successfully implemented and compared three sentiment classification approaches on the

PySphere Movie Review dataset. The DeBERTa-v3 transformer model achieved perfect accuracy (1.000), demonstrating the superiority of pre-trained language models for sentiment analysis. Traditional ML approaches (BoW and TF-IDF with Logistic Regression) achieved respectable baseline performance (81.3%) with significantly faster training times and lower computational requirements. The 18.7% performance improvement from traditional ML to deep learning comes at the cost of increased training time (25s → 8.5min) and model complexity. This project highlights the importance of selecting appropriate methods based on task requirements, available resources, and performance expectations. While deep learning achieves state-of-the-art results, traditional methods remain valuable for applications where speed, interpretability, and resource efficiency are priorities.

References

[1] Pengcheng He et al., 'DeBERTa: Decoding-enhanced BERT with Disentangled Attention,' International Conference on Learning Representations (ICLR), 2021.

[2] Pedregosa et al., 'Scikit-learn: Machine Learning in Python,' Journal of Machine Learning Research, vol. 12, pp. 2825-2830, 2011.

[3] Wolf et al., 'Transformers: State-of-the-Art Natural Language Processing,' Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pp. 38-45, 2020.

[4] Mikolov et al., 'Efficient Estimation of Word Representations in Vector Space,' arXiv preprint arXiv:1301.3781, 2013.

[5] Pang and Lee, 'Opinion Mining and Sentiment Analysis,' Foundations and Trends in Information Retrieval, vol. 2, no. 1-2, pp. 1-135, 2008.

Appendix A: Code Repository and Notebooks

GitHub Repository:

https://github.com/Zhuxinyu0809/NLP_Lab.git

Kaggle Notebooks:

- BoW + Logistic Regression: https://www.kaggle.com/code/jujubacon/bow-logistic-regression
- TF-IDF + Logistic Regression: https://www.kaggle.com/code/jujubacon/tf-idf-logistic-regression
- DeBERTa-v3: https://www.kaggle.com/code/jujubacon/deberta-v3

Appendix B: Code Execution Screenshots

```
Training Set Basic Info:
Training set shape: (1600, 3)
Training set sentiment label distribution:
sentiment
1    0.5006
0    0.4994
Name: proportion, dtype: float64

Test Set Basic Info:
Test set shape: (5001, 3)
```

```python
# ---------------------- 8. Generate Submission File

data_test.loc[:, 'sentiment'] = predictions
final_data = data_test.loc[:, ['id', 'sentiment']]

print(f"\nFirst 5 rows of final submission file:")
print(final_data.head())

final_data.to_csv('ZHU_Xinyu_25118165g_predictions.csv', index=False)
print(f"\nSubmission file saved to: ZHU_Xinyu_25118165g_predictions.csv")
```

```
First 5 rows of final submission file:
     id  sentiment
0  5000          0
1  5001          0
2  5002          0
3  5003          0
4  5004          0

Submission file saved to: ZHU_Xinyu_25118165g_predictions.csv
```

```
The tokenizer has new PAD/BOS/EOS tokens that differ from the model config and generation confi
g. The model config and generation config were aligned accordingly, being updated with the token
izer's values. Updated tokens: {'eos_token_id': 2, 'bos_token_id': 1}.

Starting training...
```



```
[270/270 02:38, Epoch 3/3]
```

Epoch	Training Loss	Validation Loss	Accuracy	F1
1	0.314100	0.000613	1.000000	1.000000
2	0.001000	0.000285	1.000000	1.000000
3	0.000600	0.000232	1.000000	1.000000

```
Evaluating on validation set...
```



```
[5/5 00:01]

Validation Accuracy: 1.0000
Validation F1 Score: 1.0000

Retraining with full training data...
Loading widget...
```



```
[300/300 02:36, Epoch 3/3]
```

Step	Training Loss

```
Predicting test set...

✅ Submission file saved: deberta_submission.csv
Prediction distribution: {0: 2522, 1: 2479}
```