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Project: Fine-tuned Sentiment Analysis with DistilBERT

Sentiment Analysis Project Report

1. Model Selection

Chosen Model: DistilBERT Base Uncased

Rationale:

- Efficiency: DistilBERT is 60% faster than BERT while retaining 97% of its language understanding capabilities
- Size: Reduced model size (66M parameters vs 110M in BERT) enables faster inference and lower resource requirements
- Performance: Proven effectiveness on sentiment analysis tasks with excellent accuracy
- Deployment: Smaller footprint makes it ideal for production deployment on standard hardware

Alternative Models Considered:

- BERT Base: Rejected due to larger size and slower inference
- RoBERTa: Rejected due to increased computational requirements
- LSTM-based models: Rejected due to inferior performance on context understanding

2. Fine-tuning Process

Dataset

- Source: IMDB Movie Reviews Dataset (50,000 reviews)
- Split: 25,000 training samples, 25,000 test samples
- Classes: Binary classification (Positive/Negative)

Training Configuration

Base Model: distilbert-base-uncased
Learning Rate: 2e-5
Batch Size: 16
Epochs: 3
Optimizer: AdamW
Max Sequence Length: 512 tokens

Training Phases

Phase 1: Standard Fine-tuning

- Trained on IMDB dataset
- Model path: `models/sentiment-distilbert-imdb-final`
- Training time: ~45 minutes on CPU

Phase 2: Modern Language Enhancement

- Additional fine-tuning on modern slang and casual language
- Enhanced dataset with contemporary expressions
- Model path: `models/sentiment-distilbert-imdb-modern`
- Improved handling of informal text and social media language

Training Metrics

- Training Loss: Steadily decreased across epochs
- Validation Accuracy: Achieved >90% on test set
- Convergence: Model converged successfully within 3 epochs

3. Deployment

Architecture

Project Structure:

```
├── models/                    # Trained model weights
├── deployment/
│   ├── streamlit_app.py       # Web interface
│   └── requirements.txt       # Dependencies
├── train_model_colab.ipynb    # Training script
└── tests/                     # Test suite
```

Deployment Steps

1. Environment Setup

```
python -m venv venv
source venv/bin/activate
pip install -r requirements.txt
```

2. Model Training

```
python train_model.py
```

3. Web Application Launch

```
cd deployment
streamlit run streamlit_app.py
```

Deployment Features

- Web Interface: Streamlit-based UI for easy interaction
- Real-time Inference: Instant sentiment prediction
- Confidence Scores: Probability distributions for predictions
- User-friendly: Example inputs and clear result visualization

Technical Stack

- Framework: Transformers (Hugging Face)
- Web Framework: Streamlit
- Deep Learning: PyTorch
- Language: Python 3.12

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4. Test Results and Observations

Functional Testing

Test Case 1: Simple Greetings

Input: "Hi"
Result: POSITIVE (99.24% confidence)
Observation: Correctly identifies friendly greetings

Test Case 2: Positive Review

Input: "This movie was absolutely amazing!"
Result: POSITIVE (99.87% confidence)
Observation: Strong confidence on clear positive sentiment

Test Case 3: Negative Review

Input: "Terrible waste of time."
Result: NEGATIVE (98.45% confidence)
Observation: Accurately detects negative sentiment

Test Case 4: Modern Slang

Input: "This is fire!"
Result: POSITIVE (96.32% confidence)
Observation: Enhanced model handles contemporary expressions

Performance Metrics

Inference Speed:

- CPU: ~100-150ms per prediction
- Suitable for real-time applications

Model Size:

- Final model: ~268MB (safetensors format)
- Tokenizer files: ~711KB
- Total deployment size: <300MB

Accuracy Observations:

- High confidence (>95%) on clear sentiment statements
- Robust performance on informal language
- Handles context effectively for medium-length text

5. Conclusion

The fine-tuned DistilBERT model achieves high accuracy in sentiment analysis while utilizing resources efficiently. The deployment pipeline provides a user-friendly interface suitable for both

testing and production use. The model demonstrates robust performance across various text types, including modern informal language, making it ideal for real-world applications.

Github Repository: https://github.com/desshah/Huggingface