

Configuration Manual

MSc Research Project
MSCDAD_B

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I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project.

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Configuration Report

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This report outlines the required software tools, libraries, and settings necessary to successfully replicate the experimental environment used in the sentiment analysis and trend forecasting project.

1 Operating System

The experiments were conducted on a system compatible with Python and PyTorch environments.

Recommended OS:

- Windows 10/11 (64-bit)
- Ubuntu 20.04+ or any Linux distribution with Python support
- macOS (for development, not recommended for GPU training with CUDA)

2 Hardware Requirements

- **CPU:** Intel i5/i7 or AMD equivalent
- **RAM:** Minimum 8 GB (16 GB recommended)
- **GPU:** NVIDIA GPU with CUDA support (e.g., GTX 1650, RTX 2060 or higher)
- **Storage:** At least 5 GB free space for datasets and model checkpoints

3 Programming Language

Python Version: 3.8 or higher (tested with Python 3.9)

4 Dataset Configuration

The dataset file must be named **Review_Dataset.csv** and placed in the working directory.

Required columns:

- asins – Product identifier
- reviews.text – Review text
- reviews.rating – Numerical rating (1-5)
- reviews.doRecommend – Boolean recommendation field
- reviews.date – Review date for time-series analysis

5 Required Python Libraries

Install all dependencies via pip:

```
pip install pandas numpy matplotlib seaborn scikit-learn nltk wordcloud statsmodels torch  
torchvision transformers
```

List of Required Libraries

Library	Version	Usage in Project
pandas	1.5.3	Data manipulation, cleaning, and handling datasets
matplotlib	3.7.1	Visualization of results and time series plots
seaborn	0.12.2	Enhanced statistical data visualization
scikit-learn (sklearn)	1.3.0	Model training (Logistic Regression), feature extraction (TF-IDF), evaluation metrics, label encoding, train-test splitting
nltk	3.8.1	Natural Language Processing tasks like tokenization, stemming, lemmatization, stopwords removal
re (regex)	Built-in (Python 3.10)	Text cleaning and preprocessing (removing special characters, URLs, etc.)
numpy	1.24.3	Numerical computations, array operations, and ROC/AUC calculations
transformers (HuggingFace)	4.30.0	BERT Tokenization, loading BERT model, fine-tuning for sentiment classification
torch (PyTorch)	2.0.1	Building, training, and optimizing neural network models
wordcloud	1.9.2	Generating visual word clouds from review text
statsmodels	0.14.0	Time series analysis, ARIMA/SARIMA modeling, and statistical testing (ADF test)
time	Built-in (Python 3.10)	Measuring execution/training time

6 NLTK Resource Downloads

The following NLTK resources must be downloaded before running the script:

```
import nltk
nltk.download('stopwords')
nltk.download('wordnet')
```

7 Model Configurations

7.1 Traditional ML Models

- Vectorization: TF-IDF with max_features=5000
- Logistic Regression:
 - max_iter=1000
 - Evaluation metrics: Accuracy, Precision, Recall, F1-score, Cohen's Kappa

7.2 Deep Learning Model (BERT + GRU)

- Tokenizer: bert-base-uncased (from HuggingFace Transformers)
- GRU Hidden Dimension: 128
- Dropout: 0.3
- Batch Size: 16
- Optimizer: AdamW with lr=2e-5

- Loss Function: CrossEntropy with class weights
- Epochs: 3
- Fine-tuning: Two variants were trained (Frozen BERT vs. Fine-tuned BERT)

8 Time Series Forecasting Configuration

Models Used: ARIMA, SARIMAX

Orders Tested:

- ARIMA: (1,0,1), (1,0,2), (2,0,1), (2,0,2), (2,1,1), (2,1,2), (3,0,1), (3,1,2) and (4,0,1)
- SARIMAX: (1,1,1), (2,1,1), (2,1,2), (3,1,2), (1,0,1), (2,0,2), (4,1,2), (4,1,3) and (4,1,4)

Exogenous Variables for SARIMAX: recommend_rate and sentiment_score

9 Visualization Settings

- Dark background theme applied to all plots.
- Custom color palette for sentiment distribution:
 - Positive: Red (#FF0000)
 - Neutral: Green (#00FF00)
 - Negative: White (#FFFFFF)
- All generated plots (e.g., confusion matrices, word clouds, ARIMA/SARIMAX forecasts) are saved as .png files in the working directory.

10 Additional Notes

- Ensure CUDA is enabled for faster training if using a GPU.
- If running on CPU, expect slower BERT training times.
- Ensure all random seeds (`random_state=42`) are set to maintain reproducibility.

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