

# Movie Reviews Sentiment Analysis

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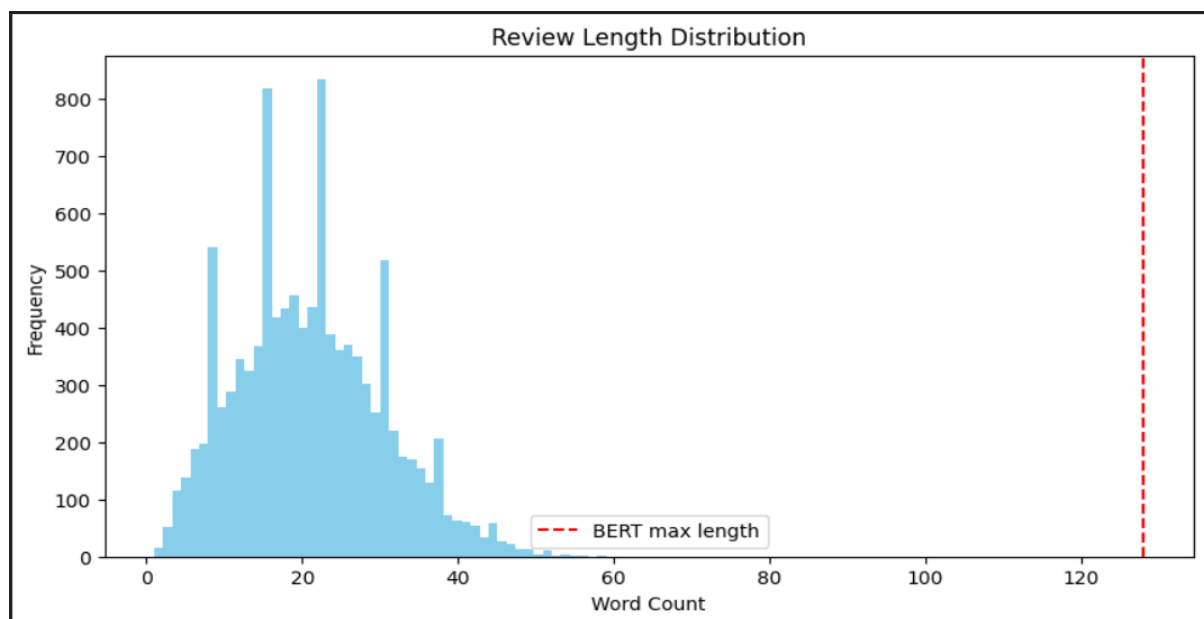
# Overview

This project implements sentiment analysis on movie reviews using both traditional Machine Learning and BERT-based approaches. The goal is to classify movie reviews as either positive or negative.

## Data

- **Source:** Movie reviews dataset from `rt_polarity` stored in ``all_reviews.csv``
- **Structure:**
  - Size: **10,662** reviews
  - Features:
    - review: The movie review text
    - label: Sentiment label (1 for positive, 0 for negative)
- **Data Overview:**
  - No missing (null) values in the dataset
  - Some duplicate entries present (removed during preprocessing)
  - Balanced classes: 5,331 positive and 5,331 negative reviews
- **Text Characteristics:**
  - Review lengths are well within BERT's 128-token limit
  - Maximum review length: 59 tokens
  - Average review length: 21 tokens

## Review Length Distribution



# Data Preprocessing

## Text Preprocessing Pipeline

### 1. Clean Text

- ❖ Remove URLs
- ❖ Remove special characters and numbers
- ❖ Remove extra whitespace

### 2. Character Normalization

- ❖ Normalize repeated characters (e.g., "gooooood" → "good")

### 3. N-gram Deduplication

- ❖ Remove duplicate n-grams for n=1,2,3
- ❖ Process contiguous sequences

### 4. Stop Words Removal

- ❖ Using NLTK stopwords
- ❖ Preserving sentiment words:
  - not, no, never, very, really, too, so, much, many, few, little, hardly, barely, scarcely

### 5. Word Normalization

- ❖ Primary approach: Lemmatization using NLTK's WordNetLemmatizer
- ❖ Alternative tested: Stemming was also evaluated using NLTK's PorterStemmer
- ❖ Comparison results showed no significant performance difference between stemming and lemmatization
- ❖ Chose lemmatization for final implementation as it produces more readable words

## Models

### Machine Learning Approach

- **Vectorization:** TF-IDF with unigrams and bigrams
- **Models Used:**
  - Logistic Regression
  - Linear SVM
  - Random Forest (n\_estimators=100)
- **Data Split:** 80% training, 20% testing

## Classification Reports

Random Forest Classification Report:					
	precision	recall	f1-score	support	
Negative	0.66	0.82	0.73	1062	
Positive	0.77	0.58	0.66	1071	
accuracy			0.70	2133	
macro avg	0.71	0.70	0.70	2133	
weighted avg	0.71	0.70	0.70	2133	

Logistic Regression Classification Report:					
	precision	recall	f1-score	support	
Negative	0.72	0.76	0.74	1062	
Positive	0.75	0.71	0.73	1071	
accuracy			0.73	2133	
macro avg	0.74	0.73	0.73	2133	
weighted avg	0.74	0.73	0.73	2133	

Linear SVC Classification Report:					
	precision	recall	f1-score	support	
Negative	0.74	0.77	0.76	1062	
Positive	0.76	0.74	0.75	1071	
accuracy			0.75	2133	
macro avg	0.75	0.75	0.75	2133	
weighted avg	0.75	0.75	0.75	2133	

## BERT Model

- **Base Model:** textattack/bert-base-uncased-SST-2
- **Device:** CUDA/CPU auto-detection

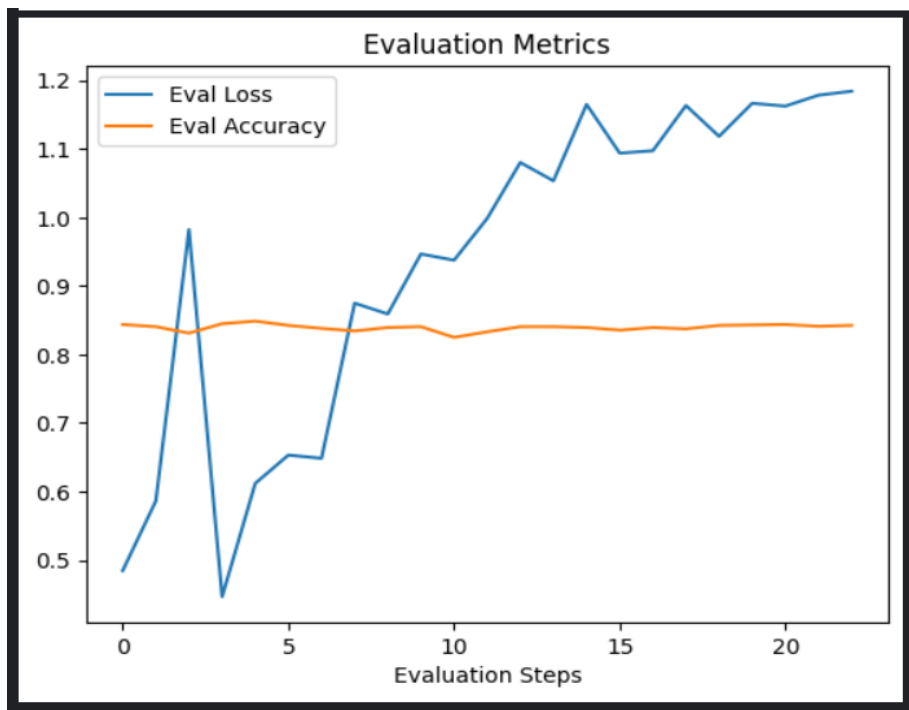
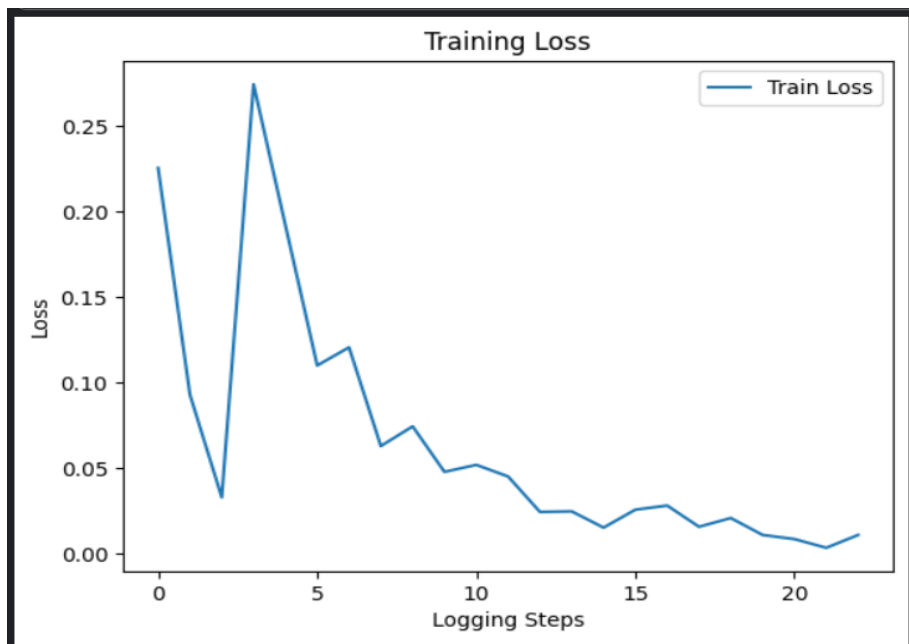
## Parameters

- BATCH\_SIZE = 16
- MAX\_LENGTH = 128
- LEARNING\_RATE = 2e-5
- NUM\_EPOCHS = 10
- PATIENCE = 2
- LOGGING\_STEPS = 50

## Training Configuration

- AdamW optimizer
- CrossEntropyLoss
- Data split:
  - 70% training
  - 15% validation
  - 15% test
- Training arguments:
  - warmup\_steps = 200
  - weight\_decay = 0.01
  - gradient\_accumulation\_steps = 2

## Training Progress

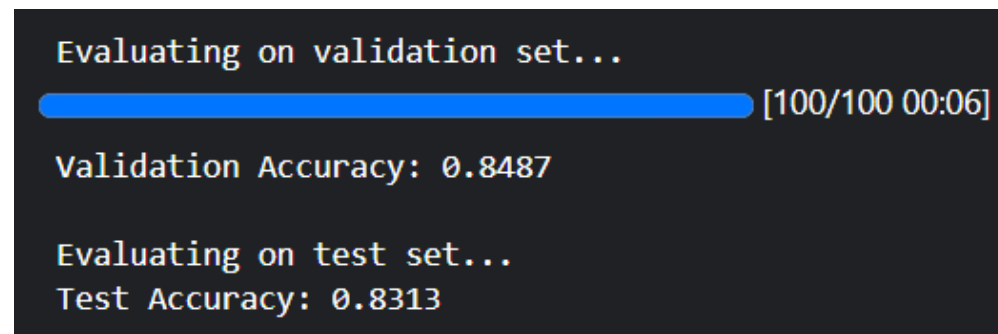


# Results and Evaluation

## Machine Learning Models Performance

- Evaluated using:
  - Accuracy
  - Precision
  - Recall
  - F1 Score

## BERT Model Performance



- Validation Accuracy: 84%
- Test Accuracy: 83%