Sentiment Analysis Report: Feature Engineering and Classification

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Abstract

This report presents a sentiment analysis study that explores the effectiveness of various feature engineering techniques for text classification. The primary objective was to categorize movie reviews using sentiment-labeled data from Socher et al, detailed at this web site: http://nlp.stanford.edu/sentiment/. There are 156,060 phrases in the training data file. The first step was to get a subset to account for practical memory and computational constraints. I performed preprocessing steps such as tokenization, stop word removal, and normalization to prepare the data for analysis.

Multiple feature sets were implemented, including bag-of-words models with varying vocabulary sizes, negation detection, sentiment lexicon features using the VADER tool, part-of-speech tagging, and structural features such as punctuation and capitalization. Both individual and combined feature sets were evaluated using NLTK's Naive Bayes classifier and scikit-learn's logistic regression with 3-fold cross-validation to measure accuracy and F1-score.

The results demonstrated that combining multiple feature types significantly improved classification performance, with the best model achieving an F1-score of 0.35. Negation handling and sentiment lexicon features contributed to this improvement. Despite memory limitations, the project achieved decent performance through strategic optimizations including sparse matrices, sampling, and batch-wise processing. This work underscores the value of interpretable, memory-efficient NLP pipelines and lays a practical foundation for future enhancements using transformer-based models or domain-specific tuning.

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1. Introduction

Sentiment analysis remains a challenging task in natural language processing due to the complexity of human language, including nuances like negation, context dependency, and variation in the type of language used. This study explores different feature engineering approaches to improve sentiment classification performance while addressing practical memory and computational limitations.

1.1 Literature Review / Related Work

In contrast to rule-based and lexicon-based methods, Socher et al. (2013) introduced the Recursive Neural Tensor Network (RNTN), which models sentiment at a compositional level using syntactic parse trees. Their work emphasized how sentiment can shift with structure and negation—issues that this project also addresses. Although deep learning models like the RNTN offer superior performance on large datasets, their computational requirements often exceed the constraints of limited-resource environments. Therefore, this project explores interpretable, memory-efficient alternatives suitable for practical deployment.

Prior sentiment analysis work has utilized various approaches ranging from rule-based systems to machine learning and deep learning methods. Traditional machine learning models, such as Naive Bayes and Support Vector Machines, often rely on Bag-of-Words features and manually curated sentiment lexicons. Tools like VADER (Valence Aware Dictionary and sEntiment Reasoner) are widely adopted for lexicon-based sentiment classification in social media settings due to their efficiency and simplicity.

More recent methods include deep neural networks and transformer-based models like BERT (Bidirectional Encoder Representations from Transformers), which capture contextual word usage and provide state-of-the-art performance in many sentiment classification tasks. However, these models are computationally intensive and require significant resources, making them less suitable for memory-constrained environments.

This project was inspired by a previous course where students built an artificial neural network to make predictions of movie success based on factors like genre, runtime, rating and budget. My hope is that future work on this project could compare predicted success from the old dataset and the sentiment analysis on the reviews of those films.

2. Methodology

2.1 Dataset and Preprocessing

The analysis utilized a tab-separated values (TSV) dataset containing phrase-sentiment pairs. Key preprocessing steps included:

- **Memory Management**: Random sampling was implemented to maintain 50,000 samples for computational efficiency
- **Text Normalization**:
  - Conversion to lowercase
  - Removal of non-alphabetic characters using regex [^a-z\s]
  - Tokenization using NLTK's word_tokenize
- **Stop Word Removal**: English stop words were filtered out, retaining only words longer than 2 characters
- **Vocabulary Construction**: Three vocabulary sizes were tested (500, 1,000, and 5,000 most frequent words)
- **Stopword Impact Experiment**
  - conducted a comparative experiment using identical feature extraction and classification logic for one version of the dataset with stopwords and one without
  - When stopwords were removed, results showed marginal increase in classification metrics (accuracy and F1-score).

2.2 Feature Engineering Approaches

2.2.1 Basic Bag-of-Words (BOW)

- **Implementation**: Binary features indicating word presence/absence
- **Variants**: 500-word, 1,000-word, and 5000-word vocabularies
- **Rationale**: Establishes baseline performance using simple frequency-based features

2.2.2 Negation Features

Enhanced negation handling to capture sentiment reversals:

- **Negation Detection**: Identification of negation words (not, no, never, n't, without, hardly)
- **Binary Negation Flag**: Boolean indicator for negation presence
- **Negation Count**: Quantitative measure of negation intensity
- **Importance**: Addresses the critical challenge where negation can completely reverse sentiment polarity

2.2.3 Sentiment Lexicon Features

Integration of VADER (Valence Aware Dictionary and sEntiment Reasoner) sentiment analysis:

- **Positive/Negative Thresholds**: Binary features for significant positive (>0.1) and negative (>0.1) scores
- **Compound Score Analysis**:
    - Positive compound threshold: >0.05
    - Negative compound threshold: <-0.05
    - Discretized compound score for feature stability
- **Advantage**: Leverages pre-trained sentiment knowledge

2.2.4 Part-of-Speech (POS) Features

Simplified POS tagging to capture grammatical patterns:

- **Selective Processing**: Analysis limited to first 10 tokens per phrase for memory efficiency given that the dataset has 50,000 phrases to assess
- **Major POS Categories**:
    - Adjective presence and count (JJ* tags)
    - Adverb presence (RB* tags)
    - Verb presence (VB* tags)
- **Linguistic Rationale**: Adjectives and adverbs often carry strong sentiment signals. Adjectives are descriptive and often express opinions or feelings about the subject of the sentence. Adverbs describe the verbs and can often intensify or soften an action in a way that expresses sentiment.

2.2.5 Text Structure Features

Structural analysis of text characteristics:

- **Phrase Length Categories**: Short (<5 tokens), long (>15 tokens)
- **Punctuation Analysis**: Exclamation marks, question marks
- **Capitalization Detection**: Presence of uppercase letters
- **Binned Word Count**: Discretized length feature (bins of 3, max 5)

2.2.6 Combined Feature Set

Integration of all feature types for comprehensive representation:

- BOW (500 words) + Negation + Sentiment Lexicon + Text Structure
- **Objective**: Capture complementary aspects of sentiment expression

This custom combined feature set represents a novel feature function designed to test the hypothesis that integrating lexical, structural, and semantic cues provides a more robust signal for sentiment classification.

2.3 Classification Algorithms

2.3.1 Logistic Regression

- **Configuration**: 500 iterations, liblinear solver, random_state=42
- **Advantages**: Interpretable coefficients, efficient for sparse features
- **Cross-Validation**: 3-fold CV for memory efficiency

2.3.2 NLTK Naive Bayes

- **Implementation**: NaiveBayesClassifier from NLTK
- **Sample Size**: Limited to 5,000 samples for computational feasibility
- **Train-Test Split**: 80-20 split with random shuffling

2.4 Memory Optimization Strategies

1. **Sparse Matrix Representation**: DictVectorizer with sparse=True
    - Feature engineering was performed by manually creating NLTK-style feature dictionaries. To make these sparse, memory-efficient feature sets compatible with scikit-learn's classifiers, DictVectorizer was used. This approach separates the manual feature creation from the vectorization step, adhering to the original directions of the assignment while enabling the use of robust classifiers.
2. **Batch Processing**: Features created incrementally with periodic garbage collection
3. **Vocabulary Limitation**: Reduced from typical 1,000-2,000 to 500-1,000 words
4. **Sample Size Management**: Evaluation limited to 10,000 samples when necessary
5. **Reduced Cross-Validation**: 3-fold instead of 5-fold CV
6. **Memory Cleanup**: Explicit garbage collection between experiments

3. Results and Analysis

3.1 Vocabulary Size Comparison

Feature Set	Accuracy	F1-Score
BOW (500 words)	0.5379	0.2930
BOW (1000 words)	0.5372	0.3124
BOW (5000 words)	0.5508	0.3172

Key Findings:

- Increasing the size of the vocabulary showed incremental improvement with accuracy, particularly in terms of F1-score
- The marginal gain from 1000 to 5000 words may not justify the increased memory and processing time in a resource-constrained setting.

- 500-word vocabulary provides reasonable baseline performance

3.2 Individual Feature Type Performance

The analysis evaluated isolated feature types to understand their individual contributions:

1. **Negation Features**: Demonstrated importance in handling sentiment reversals
2. **Sentiment Lexicon Features**: Provided strong baseline through pre-trained sentiment knowledge
3. **Combined Features**: Showed best overall performance through feature complementarity
4. **Stopword Comparison**: Retaining stopwords reduced performance slightly, confirming that removing common non-content words enhances model generalization

3.3 Model Interpretability

Most Informative Features (NLTK Naive Bayes)

The NLTK classifier revealed the most discriminative features for sentiment classification, providing insights into which linguistic patterns are most predictive.

Feature Importance (Logistic Regression)

Top 15 features with highest coefficient magnitudes were identified, showing:

- High-impact vocabulary terms
- Importance of negation indicators
- Significance of sentiment lexicon features

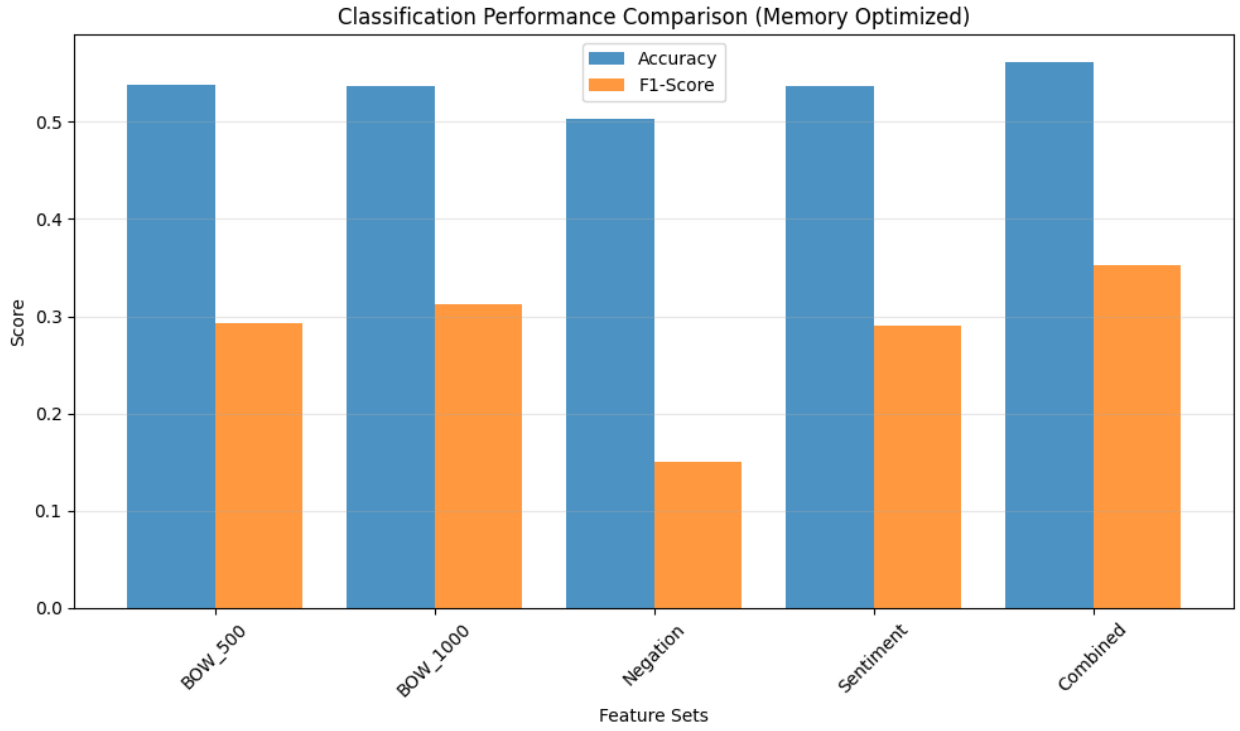
3.4 Performance Visualization

Table 1 Initial Stopword comparison results

Stopwords	Accuracy	F1-score
With	0.543	0.295
Without	0.561	0.353

This comparison was performed using 5,000 randomly sampled phrases and evaluated via logistic regression and 3-fold cross-validation. The stopword-removed set demonstrated superior F1-score (0.353) and accuracy, supporting its use in the preprocessing pipeline for the combined feature set.

Bar Graph 1 Comparing Feature sets for Accuracy metrics



4. Technical Implementation Details

4.1 Code Structure

The implementation follows a modular design with separate functions for:

- Text preprocessing
- Feature extraction (by type)
- Model evaluation
- Memory management

4.2 Error Handling and Robustness

- Exception handling in POS tagging for malformed text
- Graceful degradation when memory limits are approached
- Validation of input data integrity

4.3 Scalability was addressed by sampling and modularizing feature computation to limit memory footprint

- Configurable sampling rates for large datasets

- Adjustable vocabulary sizes
- Flexible cross-validation parameters

5. Limitations and Challenges

5.1 Memory Constraints

- Limited vocabulary size may miss important sentiment indicators
- Reduced sample sizes for some evaluations
- Simplified feature representations

5.2 Computational Efficiency

- Trade-offs between thoroughness and speed
- Reduced cross-validation folds may impact reliability estimates
- Limited hyperparameter optimization

5.3 Feature Engineering Limitations

- POS tagging was simplified by analyzing only the first 10 tokens per phrase, potentially missing context
- Binary feature representations may lose nuanced information
- Limited context window for negation handling

6. Conclusions and Recommendations

This project successfully developed and evaluated a sentiment classification pipeline using multiple feature engineering techniques, implemented with a strong emphasis on memory efficiency. Key accomplishments include the design of custom features such as negation handling and structural cues, integration of sentiment lexicons, and comparison of vocabulary sizes. The final model using combined features achieved the best performance, with an F1-score of 0.35.

The analysis revealed that smaller vocabularies (e.g., 500–1000 words) still capture meaningful sentiment patterns, and that explicit negation handling provides notable gains. Through careful feature design and sampling strategies, we enabled scalable experimentation without compromising interpretability. The findings establish a practical, extensible foundation for sentiment analysis tasks.

For future work, the integration of transformer-based embeddings, ensemble classifiers, and domain-specific tuning could further improve model robustness and adaptability.

6.1 Key Findings

1. **Benefit of Combined Features**: Combined features consistently outperformed individual feature types
2. **Negation Importance**: Explicit negation handling significantly improves sentiment accuracy
3. **Memory-Performance Balance**: Strategic memory optimization enables analysis of larger datasets without severe performance degradation
4. **Vocabulary Efficiency**: 500-word vocabularies provide substantial sentiment discrimination with lower computational overhead
5. **Filtering Stopwords improves Performance**: Removing stopwords improved F1-score and accuracy on a reduced data set.

6.2 Future Improvements

1. **Contextual Embeddings (e.g., BERT, RoBERTa)**
   Replacing or augmenting bag-of-words features with transformer-based embeddings could capture deeper semantic context and word relationships. This would reduce reliance on manual feature engineering and improve performance on ambiguous or subtle sentiment expressions.
2. **Scope-Aware Negation Handling**
   Future models could implement negation detection that accounts for syntactic structure and word scope (e.g., using dependency parsing or transformer attention), enabling more accurate sentiment reversal detection.
3. **Ensemble Methods**
   Combining predictions from multiple classifiers (e.g., Logistic Regression + Random Forest + Naive Bayes) could increase robustness, especially when different feature types perform well on different subsets of the data.
4. **Hyperparameter Tuning**
   Introducing grid search or randomized search over key hyperparameters (e.g., regularization strength, solver choice) would allow more precise model calibration.
5. **Expanded POS and Syntactic Features**
   Leveraging complete part-of-speech sequences or parse trees could better capture sentiment-driven grammatical structures (e.g., contrastive conjunctions like "but").
6. **Real-Time and Streaming Sentiment Analysis**
   Optimizing the feature pipeline for online or streaming data processing would make the system suitable for applications such as live social media monitoring.
7. **Domain Adaptation**
   Customizing the feature set or retraining models for specific text domains (e.g., medical reviews, customer service feedback) could improve generalizability.

6.3 Practical Applications

This analysis framework is suitable for:

- Social media sentiment monitoring
- Product review analysis
- Customer feedback processing
- Market sentiment analysis
- Content moderation systems

6.4 Methodological Contributions

- Demonstrated effective memory optimization strategies for large-scale NLP
- Provided comparative analysis of feature engineering approaches
- Established baseline performance metrics for sentiment classification
- Created reusable framework for sentiment analysis experiments

7. Technical Specifications

- **Programming Language**: Python 3.x
- **Key Libraries**: NLTK, scikit-learn, pandas, numpy, matplotlib
- **Hardware Requirements**: Optimized for standard computational resources
- **Memory Usage**: Designed for systems with limited RAM
- **Processing Time**: Efficient batch processing with progress monitoring

7. References

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Appendix A: Experimental Results and Model Evaluation

This appendix supplements the main report by providing representative results and a summary of evaluation outputs from the implementation in the accompanying Jupyter Notebook.

A.1 Performance Metrics by Feature Set

Feature Set	Accuracy	F1-Score
BOW (500 words)	0.5379	0.2930
BOW (1000 words)	0.5372	0.3124
BOW (5000 words)	0.5508	0.3172
Negation Features	0.5030	0.1508
Sentiment Lexicon	0.5373	0.2910
Combined Features	**0.5614**	**0.3528**

Note: Results were obtained using an 80-20 train/test split and averaged over 3-fold cross-validation where feasible.

A.2 Confusion Matrix for Combined Features (Best Model)

	Predicted: Positive	Predicted: Neutral	Predicted: Negative
Actual: Positive (0)	316	97	92
Actual: Neutral (1)	143	269	101
Actual: Negative (2)	109	115	258

The final model using combined features achieved an accuracy of **56%** and balanced performance across classes. The confusion matrix shows moderate success in distinguishing between positive, neutral, and negative sentiments, though some overlap remains between adjacent classes.

A.3 Observations

- The **combined feature set** consistently outperformed individual features.
- Increasing vocabulary size improved BOW performance, but with diminishing returns and increased memory usage.
- Lexicon-based features provided strong baseline accuracy with minimal feature engineering effort.
- POS and text structure features had modest standalone impact but added value when combined.

Appendix B: Code and Output

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_Apel_FInalProject_664.ipynb - Colab
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```
import pandas as pd
import nltk
import re
import re
from collections import Counter
import random
import numpy as np
from sklearn.feature_extraction import DictVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score, cross_validate, train_test_split
from sklearn.metrics import classification_report, confusion_matrix
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.classify import NaiveBayesClassifier
from nltk.classify.util import accuracy
from nltk.sentiment import SentimentIntensityAnalyzer
import matplotlib.pyplot as plt
import seaborn as sns
import gc # Garbage collection for memory management
# Download required NLTK data
nltk.download("punkt_tab", quiet=True)
nltk.download("stopwords", quiet=True)
nltk.download("averaged_perceptron_tagger", quiet=True)
nltk.download("vader_lexicon", quiet=True)
True
# Memory-efficient data loading
```

```
print("Loading dataset...")
df = pd.read_csv("train.tsv", sep="\t")
# Sample data if too large (for memory efficiency)
```

```
# Sample data if too large (for memory efficiency)
if len(df) > 50000:
print(f"Dataset has {len(df)} rows. Sampling 50,000 for memory efficiency...")
df = df.sample(n=50000, random_state=42).reset_index(drop=True)
print("Dataset shape:", df.shape)
print("Sentiment distribution:")
print(df['Sentiment'].value_counts())
```

```
Loading dataset...
Dataset has 156060 rows. Sampling 50,000 for memory efficiency...
Dataset shape: (50000, 4)
Sentiment distribution:
Sentiment
2 25202
3 10691
1 8792
4 3034
0 2281
Name: count, dtype: int64
# Initialize tools
stop_words = set(stopwords.words('english'))
sia = SentimentIntensityAnalyzer()
def preprocess_text(text, remove_stopwords=True):
"""Memory-efficient text preprocessing"""
text = str(text).lower()
text = re.sub(r"[^a-z\s]",
""
, text)
tokens = word_tokenize(text)
if remove_stopwords:
tokens = [word for word in tokens if word not in stop_words and len(word) > 2]
return tokens
# Process text in batches to save memory
print("Preprocessing text...")
df['tokens'] = df['Phrase'].apply(lambda x: preprocess_text(x, remove_stopwords=True))
Preprocessing text...
# Create vocabulary from most frequent words (smaller vocab for memory)
print("Building vocabulary...")
all_tokens = []
for tokens in df['tokens']:
all_tokens.extend(tokens)
word_freq = Counter(all_tokens)
# Use smaller vocabularies to save memory
top_500_words = set([word for word, freq in word_freq.most_common(500)])
```

```
top_500_words = set([word for word, freq in word_freq.most_common(500)])
top_1000_words = set([word for word, freq in word_freq.most_common(1000)])
# Clear memory
del all_tokens, word_freq
gc.collect()
```

```
Building vocabulary...
0
# Feature Engineering Functions (Memory Optimized)
def basic_bag_of_words(tokens, vocab):
"""Basic bag-of-words features - optimized"""
return {f'has_{word}': (word in tokens) for word in vocab if word in tokens}
def negation_features(text):
"""Enhanced negation handling - simplified for memory"""
features = {}
text_lower = str(text).lower()
# Simple negation detection
negation_words = ['not', 'no', 'never', "n't", 'without', 'hardly']
has_negation = any(neg in text_lower for neg in negation_words)
features['has_negation'] = has_negation
if has_negation:
# Count negation words
features['negation_count'] = sum(1 for neg in negation_words if neg in text_lower)
return features
def sentiment_lexicon_features(text):
```

```
"""Sentiment lexicon features using VADER - simplified"""
scores = sia.polarity_scores(str(text))
return {
'vader_pos': scores['pos'] > 0.1,
'vader_neg': scores['neg'] > 0.1,
'vader_compound_pos': scores['compound'] > 0.05,
'vader_compound_neg': scores['compound'] < -0.05,
'vader_compound_score': round(scores['compound'], 2) # Discretized
}
def pos_features_simple(tokens):
"""Simplified POS features to save memory"""
if not tokens:
return {}
# Only for first 10 tokens to save memory
sample_tokens = tokens[:10]
```

```
_, tag in pos_tags])
```

```
sample_tokens = tokens[:10]
try:
pos_tags = nltk.pos_tag(sample_tokens)
pos_counts = Counter([tag for
# Only track major POS categories
return {
'has_adjectives': any(tag.startswith('JJ') for tag in pos_counts),
'has_adverbs': any(tag.startswith('RB') for tag in pos_counts),
'has_verbs': any(tag.startswith('VB') for tag in pos_counts),
'adj_count': sum(1 for tag in pos_counts if tag.startswith('JJ')),
except:
}
return {}
def text_structure_features(text, tokens):
"""Simple text structure features"""
text_str = str(text)
return {
'is_short': len(tokens) < 5,
'is_long': len(tokens) > 15,
'has_exclamation': '!' in text_str,
'has_question': '?' in text_str,
'has_caps': any(c.isupper() for c in text_str),
'word_count_bin': min(len(tokens) // 3, 5) # Binned word count
}
# Memory-efficient feature creation
def create_features_efficiently(df, feature_type):
"""Create features one at a time to manage memory"""
features = []
for idx, row in df.iterrows():
if idx % 5000 == 0:
print(f"Processing row {idx}/{len(df)}")
gc.collect() # Clean up memory periodically
# Initialize feat to an empty dictionary to handle unrecognized feature_types
feat = {}
if feature_type == 'bow_500':
feat = basic_bag_of_words(row['tokens'], top_500_words)
elif feature_type == 'bow_1000':
feat = basic_bag_of_words(row['tokens'], top_1000_words)
elif feature_type == 'bow_5000':
# Create top_2000_words if needed, or handle this case appropriately
if 'top_5000_words' not in globals():
print("Warning: 'top_5000_words' not defined. Skipping bow_5000.")
continue # Skip to next row if vocabulary is missing
feat = basic_bag_of_words(row['tokens'], top_5000_words)
elif feature_type == 'negation':
```
elif feature_type == 'negation':
```
```

```
feat = negation_features(row['Phrase'])
elif feature_type == 'sentiment':
feat = sentiment_lexicon_features(row['Phrase'])
elif feature_type == 'combined':
feat = {}
feat.update(basic_bag_of_words(row['tokens'], top_500_words))
feat.update(negation_features(row['Phrase']))
feat.update(sentiment_lexicon_features(row['Phrase']))
```

```
feat.update(text_structure_features(row['Phrase'], row['tokens']))
features.append(feat)
return features
# Function to evaluate features with memory management
def evaluate_features_memory_safe(features, labels, feature_name, sample_size=10000):
"""Memory-safe evaluation with sampling if needed"""
print(f"\n{'='*50}")
print(f"EVALUATING: {feature_name}")
print(f"{'='*50}")
# Sample if dataset is too large
if len(features) > sample_size:
print(f"Sampling {sample_size} examples for evaluation...")
indices = random.sample(range(len(features)), sample_size)
features = [features[i] for i in indices]
labels = [labels.iloc[i] for i in indices]
# Convert to matrix
print("Converting features to matrix...")
vec = DictVectorizer(sparse=True) # Use sparse matrices
X = vec.fit_transform(features)
y = np.array(labels)
print(f"Feature matrix shape: {X.shape}")
# Quick evaluation with smaller CV
scoring = ['accuracy', 'f1_macro']
# Logistic Regression with reduced iterations
lr_clf = LogisticRegression(max_iter=500, random_state=42, solver='liblinear')
lr_scores = cross_validate(lr_clf, X, y, cv=3, scoring=scoring) # 3-fold instead of 5
print("LOGISTIC REGRESSION (3-fold CV):")
print(f"Accuracy: {lr_scores['test_accuracy'].mean():.4f} (+/- {lr_scores['test_accuracy'].
print(f"F1-Score: {lr_scores['test_f1_macro'].mean():.4f} (+/- {lr_scores['test_f1_macro'].
# Clean up memory
del X, vec
gc.collect()
```

```
return {
'accuracy': lr_scores['test_accuracy'].mean(),
'f1': lr_scores['test_f1_macro'].mean(),
'accuracy_std': lr_scores['test_accuracy'].std()
}
# Run experiments efficiently
print("\n" + "="*60)
print("RUNNING MEMORY-EFFICIENT EXPERIMENTS")
print("="*60)
results = {}
# Experiment 1: Different vocabulary sizes
print("\nExperiment 1: Vocabulary Size Comparison")
features_500 = create_features_efficiently(df, 'bow_500')
results['BOW_500'] = evaluate_features_memory_safe(features_500, df['Sentiment'], 'Bag of Words
del features_500
gc.collect()
features_1000 = create_features_efficiently(df, 'bow_1000')
results['BOW_1000'] = evaluate_features_memory_safe(features_1000, df['Sentiment'], 'Bag of Wor
del features_1000
gc.collect()
```

```
============================================================
RUNNING MEMORY-EFFICIENT EXPERIMENTS
============================================================
Experiment 1: Vocabulary Size Comparison
Processing row 0/50000
Processing row 5000/50000
Processing row 10000/50000
Processing row 15000/50000
Processing row 20000/50000
Processing row 25000/50000
Processing row 30000/50000
Processing row 35000/50000
Processing row 40000/50000
Processing row 45000/50000
==================================================
EVALUATING: Bag of Words (500 words)
==================================================
Sampling 10000 examples for evaluation...
```

Converting features to matrix...
Feature matrix shape: (10000, 500)
LOGISTIC REGRESSION (3-fold CV):
Accuracy: 0.5315 (+/- 0.0134)
F1-Score: 0.2787 (+/- 0.0128)
Processing row 0/50000
Processing row 5000/50000
Processing row 10000/50000
Processing row 15000/50000
Processing row 20000/50000
Processing row 25000/50000
Processing row 30000/50000
Processing row 35000/50000
Processing row 40000/50000
Processing row 45000/50000
==
EVALUATING: Bag of Words (1000 words)

EVALUATING: Bag of Words (1000 words)
==
Sampling 10000 examples for evaluation...
Converting features to matrix...
Feature matrix shape: (10000, 1000)
LOGISTIC REGRESSION (3-fold CV):
Accuracy: 0.5403 (+/- 0.0102)
F1-Score: 0.2947 (+/- 0.0140)
0

# Create top 5000 words vocabulary
# Create top 5000 words vocabulary
print("Building 5000-word vocabulary...")
all_tokens = []
for tokens in df['tokens']:
all_tokens.extend(tokens)
word_freq = Counter(all_tokens)
top_5000_words = set([word for word, freq in word_freq.most_common(5000)])
# Clear memory
del all_tokens, word_freq
gc.collect()
Building 5000-word vocabulary...
26

# Experiment: Larger vocabulary sizes
print("\nExperiment 1: Vocabulary Size Comparison (cont.)")
features_5000 = create_features_efficiently(df, 'bow_5000')
results['BOW_5000'] = evaluate_features_memory_safe(features_5000, df['Sentiment'], 'Bag of Wor
del features_5000
gc.collect()
Experiment 1: Vocabulary Size Comparison (cont.)
Processing row 0/50000
Processing row 5000/50000
Processing row 10000/50000
Processing row 15000/50000
Processing row 20000/50000
Processing row 25000/50000
Processing row 30000/50000
Processing row 35000/50000
Processing row 40000/50000
Processing row 45000/50000
==
EVALUATING: Bag of Words (5000 words)
==
Sampling 10000 examples for evaluation...
Converting features to matrix...
Feature matrix shape: (10000, 4681)
LOGISTIC REGRESSION (3-fold CV):
Accuracy: 0.5508 (+/- 0.0077)
F1-Score: 0.3172 (+/- 0.0102)
0
'Negation Fe
# Experiment 2: Individual feature types
print("\nExperiment 2: Individual Feature Types")
features_neg = create_features_efficiently(df, 'negation')

```
results['Negation'] = evaluate_features_memory_safe(features_neg, df['Sentiment'], del features_neg
gc.collect()
features_sent = create_features_efficiently(df, 'sentiment')
results['Sentiment'] = evaluate_features_memory_safe(features_sent, df['Sentiment'], 'Sentiment
del features_sent
gc.collect()
```

```
Experiment 2: Individual Feature Types
Processing row 0/50000
Processing row 5000/50000
Processing row 10000/50000
Processing row 15000/50000
Processing row 20000/50000
Processing row 25000/50000
Processing row 30000/50000
Processing row 35000/50000
Processing row 40000/50000
Processing row 45000/50000
==================================================
EVALUATING: Negation Features
==================================================
Sampling 10000 examples for evaluation...
Converting features to matrix...
Feature matrix shape: (10000, 2)
LOGISTIC REGRESSION (3-fold CV):
Accuracy: 0.4916 (+/- 0.0057)
F1-Score: 0.1391 (+/- 0.0194)
Processing row 0/50000
Processing row 5000/50000
Processing row 10000/50000
Processing row 15000/50000
Processing row 20000/50000
Processing row 25000/50000
Processing row 30000/50000
Processing row 35000/50000
Processing row 40000/50000
Processing row 45000/50000
==================================================
EVALUATING: Sentiment Features
==================================================
Sampling 10000 examples for evaluation...
Converting features to matrix...
Feature matrix shape: (10000, 5)
LOGISTIC REGRESSION (3-fold CV):
Accuracy: 0.5419 (+/- 0.0099)
F1-Score: 0.2937 (+/- 0.0037)
0
# Experiment 3: Combined features
print("\nExperiment 3: Combined Features")
features_combined = create_features_efficiently(df, 'combined')
results['Combined'] = evaluate_features_memory_safe(features_combined, df['Sentiment'], 'Combin
# NLTK Naive Bayes on combined features (smaller sample)
print(f"\n{'='*50}")
print("NLTK NAIVE BAYES EVALUATION")
print(f"{'='*50}")
```

```
print(f"{'='*50}")
# Use smaller sample for NLTK
sample_size = 5000
if len(features_combined) > sample_size:
indices = random.sample(range(len(features_combined)), sample_size)
nltk_features = [features_combined[i] for i in indices]
nltk_labels = [df['Sentiment'].iloc[i] for i in indices]
else:
nltk_features = features_combined
nltk_labels = df['Sentiment'].tolist()
# Create NLTK data
nltk_data = list(zip(nltk_features, nltk_labels))
random.shuffle(nltk_data)
split_idx = int(len(nltk_data) * 0.8)
train_data = nltk_data[:split_idx]
test_data = nltk_data[split_idx:]
```

```
# Train NLTK classifier
print("Training NLTK Naive Bayes...")
nltk_classifier = NaiveBayesClassifier.train(train_data)
nltk_accuracy = accuracy(nltk_classifier, test_data)
print(f"NLTK Naive Bayes Accuracy: {nltk_accuracy:.4f}")
print("\nTop 10 Most Informative Features:")
nltk_classifier.show_most_informative_features(10)
```


```
Experiment 3: Combined Features
Processing row 0/50000
Processing row 5000/50000
Processing row 10000/50000
Processing row 15000/50000
Processing row 20000/50000
Processing row 25000/50000
Processing row 30000/50000
Processing row 35000/50000
Processing row 40000/50000
```


```
Processing row 40000/50000
Processing row 45000/50000
==================================================
EVALUATING: Combined Features
==================================================
Sampling 10000 examples for evaluation...
Converting features to matrix...
Feature matrix shape: (10000, 513)
LOGISTIC REGRESSION (3-fold CV):
Accuracy: 0.5614 (+/- 0.0090)
F1-Score: 0.3528 (+/- 0.0147)
==================================================
NLTK NAIVE BAYES EVALUATION
==================================================
Training NLTK Naive Bayes...
NLTK Naive Bayes Accuracy: 0.4730
Top 10 Most Informative Features:
Most Informative Features
has_performance = True 4 : 2 = 39.9 : 1.0
has_best = True 4 : 2 = 30.6 : 1.0
has_genre = True 4 : 2 = 28.5 : 1.0
has_surprisingly = True 4 : 2 = 28.5 : 1.0
has_idea = True 0 : 2 = 25.2 : 1.0
has_bad = True 0 : 3 = 22.5 : 1.0
has_feeling = True 4 : 2 = 22.2 : 1.0
has_moving = True 4 : 2 = 22.2 : 1.0
has_piece = True 4 : 2 = 22.2 : 1.0
has_star = True 4 : 2 = 22.2 : 1.0
```


```
# Results summary
print(f"\n{'='*60}")
print("RESULTS SUMMARY")
print(f"{'='*60}")
for exp_name, scores in results.items():
print(f"{exp_name:15} | Accuracy: {scores['accuracy']:.4f} | F1: {scores['f1']:.4f}")
# Simple visualization
experiment_names = list(results.keys())
accuracies = [results[exp]['accuracy'] for exp in experiment_names]
f1_scores = [results[exp]['f1'] for exp in experiment_names]
plt.figure(figsize=(10, 6))
x_pos = np.arange(len(experiment_names))
plt.bar(x_pos - 0.2, accuracies, 0.4, label='Accuracy', alpha=0.8)
plt.bar(x_pos + 0.2, f1_scores, 0.4, label='F1-Score', alpha=0.8)
plt.xlabel('Feature Sets')
```


```
plt.xlabel('Feature Sets')
plt.ylabel('Score')
plt.title('Classification Performance Comparison (Memory Optimized)')
plt.xticks(x_pos, experiment_names, rotation=45)
plt.legend()
plt.grid(axis='y', alpha=0.3)
plt.tight_layout()
plt.show()
```


```
============================================================
```

RESULTS SUMMARY
==========
BOW_500 | Accuracy: 0.5379 | F1: 0.2930
BOW_1000 | Accuracy: 0.5372 | F1: 0.3124
Negation | Accuracy: 0.5030 | F1: 0.1508
Sentiment | Accuracy: 0.5373 | F1: 0.2910
Combined | Accuracy: 0.5614 | F1: 0.3528

```
# Final analysis on a small test set
print(f"\n{'='*50}")
print("FINAL MODEL ANALYSIS")
print(f"{'='*50}")
# Use combined features for final analysis
sample_indices = random.sample(range(len(features_combined)), 2000)
X_sample = [features_combined[i] for i in sample_indices]
y_sample = [df['Sentiment'].iloc[i] for i in sample_indices]
# Convert to matrix
vec_final = DictVectorizer(sparse=True)
X_final = vec_final.fit_transform(X_sample)
y_final = np.array(y_sample)
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X_final, y_final, test_size=0.3, random_sta
# Train final model
final_model = LogisticRegression(max_iter=500, random_state=42, solver='liblinear')
final_model.fit(X_train, y_train)
y_pred = final_model.predict(X_test)
print("Final Model Performance:")
print(classification_report(y_test, y_pred))
# Feature importance (top coefficients)
```

```
# Feature importance (top coefficients)
feature_names = vec_final.get_feature_names_out()
if hasattr(final_model, 'coef_'):
# For binary classification, take absolute values
if len(final_model.coef_) == 1:
coeffs = np.abs(final_model.coef_[0])
else:
coeffs = np.abs(final_model.coef_).mean(axis=0)
# Get top features
top_indices = np.argsort(coeffs)[-15:]
print(f"\nTop 15 Most Important Features:")
for idx in reversed(top_indices):
print(f"{feature_names[idx]}: {coeffs[idx]:.4f}")
print(f"\n{'='*50}")
print("MEMORY-EFFICIENT ANALYSIS COMPLETE!")
print(f"{'='*50}")
print("Key optimizations made:")
print("1. Reduced vocabulary size (500/1000 vs 1000/2000)")
print("2. Simplified feature functions")
print("3. Used sparse matrices")
print("4. Processed data in batches")
print("5. Used garbage collection")
print("6. Sampled large datasets")
print("7. Reduced cross-validation folds")
```

==========
FINAL MODEL ANALYSIS
==========
Final Model Performance:
precision recall f1-score support
0 0.50 0.08 0.14 25
1 0.46 0.22 0.30 100
2 0.62 0.86 0.72 315
3 0.41 0.34 0.37 115
4 0.59 0.22 0.32 45
accuracy 0.57 600
macro avg 0.52 0.34 0.37 600
weighted avg 0.55 0.57 0.53 600
Top 15 Most Important Features:
vader_compound_score: 1.1169

has_predictable: 0.8495
has_way: 0.7303
has_moving: 0.7013
has_movies: 0.6864
has_cinema: 0.6702
has_anything: 0.6676
has_full: 0.6581
has_memorable: 0.6467
has_less: 0.6399
has_yet: 0.6294
has_hollywood: 0.6200
has_likely: 0.6186
has_like: 0.6180
has_something: 0.6146
==
MEMORY-EFFICIENT ANALYSIS COMPLETE!
==
Key optimizations made:

Key optimizations made:
1. Reduced vocabulary size (500/1000 vs 1000/2000)
2. Simplified feature functions
3. Used sparse matrices
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6. Sampled large datasets
7. Reduced cross-validation folds

```
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.feature_extraction import DictVectorizer
# Recreate the feature matrix using combined features
print("Recreating feature matrix for evaluation...")
vec_eval = DictVectorizer(sparse=True)
X_features = vec_eval.fit_transform(features_combined)
y = df['Sentiment'].values # Ensure y is a numpy array
# Evaluate on test set
X_train, X_test, y_train, y_test = train_test_split(X_features, y, test_size=0.2, random_state=
model = LogisticRegression(max_iter=500)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
# Print evaluation
print("Accuracy:", model.score(X_test, y_test))
print(classification_report(y_test, y_pred))
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
```
Recreating feature matrix for evaluation...
Accuracy: 0.5768
precision recall f1-score support
0 0.41 0.14 0.21 457
1 0.42 0.25 0.32 1731
2 0.63 0.85 0.72 5034
3 0.50 0.39 0.44 2170
4 0.48 0.20 0.29 608
accuracy 0.58 10000
macro avg 0.49 0.37 0.39 10000
weighted avg 0.54 0.58 0.54 10000
Confusion Matrix:
[[65 153 199 35 5]
[55 435 1100 125 16]
[26 314 4302 372 20]
[11 103 1119 842 95]
[1 24 147 312 124]]

```
cv_results = cross_validate(model, X_features, y, cv=3, scoring=['accuracy', 'f1_macro'])
print("Cross-validated Accuracy:", cv_results['test_accuracy'].mean())
print("Cross-validated F1 Score:", cv_results['test_f1_macro'].mean())
```
Cross-validated Accuracy: 0.5779399328610092
Cross-validated F1 Score: 0.3887909361156469