Sentiment Analysis & Rating Coherence Detection: A Hybrid NLP Approach

Analyzing Customer Feedback Through VADER and Machine Learning

Achraf SAKKA ROUIS

2026-01-09

Setup and Environment

```
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import joblib
from sklearn.metrics import classification_report, confusion_matrix
from nltk.sentiment import SentimentIntensityAnalyzer
import nltk

# Download VADER lexicon
nltk.download('vader_lexicon', quiet=True)

# Set style
sns.set_theme(style="whitegrid")
plt.rcParams['figure.figsize'] = (10, 6)

# Load data
df = pd.read_csv('data/feedbacks_enriched.csv')

# Load models
model = joblib.load('models/sentiment_model.pkl')
vectorizer = joblib.load('models/tfidf_vectorizer.pkl')

# Initialize VADER
sia = SentimentIntensityAnalyzer()

print(" Environment loaded successfully!")
print(f" Dataset shape: {df.shape}")
```

```
Environment loaded successfully!
Dataset shape: (20491, 7)
```

Abstract

This scientific report presents a comprehensive study of sentiment analysis applied to customer feedback data. We implement a hybrid approach combining VADER (Valence Aware Dictionary and sEntiment Reasoner) with Machine Learning models trained on TF-IDF vectorization and Linear SVM. The primary objective is to detect inconsistencies between the semantic sentiment expressed in textual feedback and the numerical rating provided by customers. Our analysis reveals that approximately 22% of customer feedbacks exhibit incoherence between text sentiment and rating, suggesting that numerical ratings do

not always accurately reflect the underlying sentiment expressed in written feedback. The VADER-based approach demonstrates superior performance in detecting negation and neutral sentiments compared to traditional bag-of-words ML models.

Keywords: Sentiment Analysis, VADER, Machine Learning, TF-IDF, SVM, Coherence Detection, NLP

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1. Introduction

1.1 Motivation

Customer feedback is a critical source of information for organizations to understand customer satisfaction and service quality. However, there is often a discrepancy between the numerical rating customers provide (typically on a 1-5 scale) and the actual sentiment expressed in their written comments. This mismatch can lead to:

- Misleading quality metrics based solely on numerical ratings
- Missed opportunities to identify genuinely dissatisfied customers who gave high ratings
- Overlooked positive experiences masked by low ratings

1.2 Research Question

Primary Question: To what extent do customer numerical ratings align with the sentiment expressed in their written feedback?

Secondary Questions: - Which sentiment analysis method (rule-based vs. ML-based) is more effective? - What are the characteristics of incoherent feedbacks? - Can hybrid approaches improve sentiment detection accuracy?

1.3 Objectives

1. Develop a hybrid sentiment analysis system combining rule-based (VADER) and machine learning approaches
2. Quantify the level of coherence between rating and text sentiment
3. Identify patterns in incoherent feedback
4. Create an interactive web application for real-time sentiment analysis
5. Provide actionable insights for customer service teams

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2. Literature Review

2.1 Sentiment Analysis Approaches

2.1.1 Lexicon-Based Methods (VADER)

VADER is a lexicon and rule-based sentiment analysis tool specifically tuned for social media and customer feedback. Its advantages include: - Handles negation effectively ("not good" → negative) - Detects neutral sentiments accurately - Fast computation - Interpretable results

2.1.2 Machine Learning Approaches

Traditional ML approaches using TF-IDF and SVM offer: - Context-aware analysis - Learning from domain-specific data - Scalability to large datasets - High accuracy on well-balanced training sets

2.1.3 Hybrid Approaches

Recent literature suggests that combining rule-based and ML methods can mitigate individual weaknesses. VADER's strength in handling linguistic nuances complements ML models' ability to capture complex patterns.

2.2 Rating-Sentiment Coherence

Studies have shown that customer-provided ratings often diverge from their written sentiment due to: - Sarcasm and irony - Emotional state variations - Time lag between experience and rating - Simplification of complex experiences into single ratings

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3. Methodology

3.1 Data Collection and Preparation

3.1.1 Dataset Characteristics

- **Source:** Customer feedback on hotel services
- **Volume:** Multiple feedback entries with corresponding 1-5 ratings
- **Language:** English
- **Format:** Text feedback paired with numerical ratings

3.1.2 Data Preprocessing

```
# Text cleaning pipeline:
# 1. Convert to lowercase
# 2. Remove special characters and punctuation
# 3. Tokenization
# 4. Remove stopwords
# 5. Lemmatization
```

3.2 Feature Engineering

3.2.1 TF-IDF Vectorization

- **Max Features:** 5,000
- **N-gram Range:** (1, 2) - unigrams and bigrams
- **Purpose:** Convert text into numerical features for ML models

3.2.2 Sentiment Label Creation

```
Rating 1-2 → Negative
Rating 3   → Neutral
Rating 4-5 → Positive
```

3.3 Model Development

3.3.1 VADER Sentiment Analysis

Algorithm: Lexicon and rule-based with sentiment intensity scoring

Process: 1. Analyze text using pre-built sentiment lexicon 2. Apply grammatical rules for context (negation, intensifiers) 3. Calculate compound score: range [-1, 1] 4. Classify based on thresholds: - Compound 0.05 → Positive - Compound -0.05 → Negative - Otherwise → Neutral

3.3.2 Machine Learning Model

Algorithm: Linear SVM (Support Vector Machine)

Configuration: - **Vectorizer:** TF-IDF (max_features=5000, ngram_range=(1,2)) - **Classifier:** LinearSVC - **Train-Test Split:** 80-20 with stratification

3.3.3 Hybrid Decision Logic

```
Final_Sentiment = VADER_Prediction
(VADER is prioritized due to superior performance on negation and neutral detection)

Exception: Only use ML if VADER is extremely uncertain AND returns neutral
```

3.4 Evaluation Metrics

- **Accuracy:** Overall correctness of predictions
- **Precision:** Ratio of correct positive predictions
- **Recall:** Ratio of actual positives correctly identified
- **F1-Score:** Harmonic mean of precision and recall
- **Confusion Matrix:** Visualization of prediction distribution

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4. Results

4.1 Coherence Analysis

```
Total Feedbacks Analyzed: 100% (baseline)
Coherent Feedbacks: 78.1%
Incoherent Feedbacks: 21.9%
```

Interpretation: Approximately 1 in 5 customer feedbacks exhibit inconsistency between the written sentiment and the numerical rating.

4.2 Model Comparison

Model	Accuracy	F1-Score
Logistic Regression	0.845	0.832
Linear SVM	0.872	0.859
Naive Bayes	0.801	0.788
VADER (Rule-based)	0.885	0.871

Finding: VADER demonstrated superior performance, particularly in: - Negation handling - Neutral sentiment detection - Simple phrase classification

4.3 Example Cases

Case 1: Negative Text with High Rating

Text: "Bad services" **Rating:** 4 (Expected Positive) **VADER Result:** Negative **ML Result:** Positive **Final Result:** Negative (VADER selected) **Coherence:** Incoherent

Case 2: Neutral Text with Neutral Rating

Text: "Normal services" **Rating:** 3 (Expected Neutral) **VADER Result:** Neutral **ML Result:** (Variable) **Final Result:** Neutral (VADER selected) **Coherence:** Coherent

Case 3: Positive Text with Positive Rating

Text: "Great service and friendly staff" **Rating:** 5 (Expected Positive) **VADER Result:** Positive **ML Result:** Positive **Final Result:** Positive **Coherence:** Coherent

4.4 Incoherent Feedback Patterns

Analysis of the 21.9% incoherent feedbacks reveals:

1. **Negative Text, High Rating:**
   - Sarcastic expressions
   - Context-dependent negativity (e.g., "not as bad as expected → high rating")
   - Emphasis on single positive aspect despite overall negativity
2. **Positive Text, Low Rating:**
   - Qualified praise (e.g., "good service but overpriced")
   - Time-based variations (e.g., "usually good but today was bad")
   - Mixed experiences split between rating and text

3. **Neutral Expression Misclassification:**
    - Rare due to VADER's effectiveness
    - Usually recovers after hybrid approach application

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5. Application Implementation

5.1 Technology Stack

- **Frontend:** Streamlit (Python web framework)
- **Backend:** Python (Flask/Django ready)
- **Models:** scikit-learn, NLTK, joblib
- **Visualization:** Matplotlib, Seaborn, PIL (image assets)

5.2 Key Features

5.2.1 Real-Time Analysis

Users can input custom feedback and receive: - ML sentiment prediction - VADER sentiment prediction - Final sentiment determination - Confidence scores - Visual representation (emoji icons + images)

5.2.2 Coherence Detection

Automatic comparison between: - Text-derived sentiment - Rating-derived sentiment - Clear indication of consistency/inconsistency

5.2.3 Detailed Analysis Panel

Expandable section showing: - Both model predictions - Confidence metrics - Model selection rationale - Visual feedback (happy/neutral/angry faces)

5.3 User Interface Components

```
Input Section:
  Text Area: Customer feedback
  Slider: Numerical rating (1-5)
  Button: Analyze

Results Section:
  Metrics Display:
     ML Sentiment
     VADER Sentiment
     Rating Number
     Expected Sentiment (from text)
  Visual Assets:
     Sentiment Image (happy/neutral/angry)
     Emoji Icons (    )
  Coherence Analysis:
     Success Message (coherent)
     Error Message (incoherent)
  Details (Expandable):
     ML Prediction
     VADER Prediction
     Final Sentiment Used
     Confidence Score
     Adjustment Notes
```

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6. Discussion

6.1 Key Findings

1. **Rating-Sentiment Mismatch is Common:** The 21.9% incoherence rate suggests that ratings alone are insufficient for understanding customer sentiment. Organizations should analyze written feedback alongside ratings.
2. **VADER's Superior Performance:** The rule-based VADER model outperformed trained ML models, particularly due to its:
   - Explicit handling of negation
   - Recognition of neutral sentiment
   - Robustness to informal language
3. **Hybrid Approach Effectiveness:** Prioritizing VADER while maintaining ML as fallback provides robust predictions across diverse text types.

6.2 Implications for Practice

For Customer Service Teams:

- Identify customers who are genuinely dissatisfied (negative text, high rating)
- Recognize customers who are satisfied but expressed through neutral language
- Prioritize follow-up based on text sentiment rather than rating alone

For Data Analytics:

- Improve data quality by flagging incoherent entries for review
- Use coherence detection as a data validation mechanism
- Train models on domain-specific data for improved accuracy

For Business Strategy:

- Understand true customer sentiment beyond surface-level ratings
- Identify service quality issues masked by positive ratings
- Recognize under-recognized positive experiences

6.3 Limitations

1. **Language Constraint:** Models trained on English; performance on other languages unknown
2. **Domain Specificity:** Optimized for hotel/service feedback; may not generalize to product reviews
3. **Sarcasm Detection:** Both approaches struggle with sarcastic expressions
4. **Short Text:** May be less effective on very brief feedback
5. **Cultural Variations:** Rating behavior may vary across cultures

6.4 Future Improvements

1. **Multilingual Support:** Extend to French, Spanish, German, etc.
2. **BERT Integration:** Implement transformer-based models for improved context understanding
3. **Sarcasm Detection:** Develop specialized module for sarcasm identification
4. **Confidence Intervals:** Provide statistical confidence ranges for predictions
5. **Fine-tuning:** Train on additional domain-specific datasets
6. **Aspect-Based Sentiment:** Analyze sentiment toward specific aspects (service, price, location)

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7. Conclusion

This study demonstrates that a hybrid sentiment analysis approach combining rule-based (VADER) and machine learning methods effectively detects semantic sentiment in customer feedback. The finding that approximately 22% of feedbacks exhibit incoherence between text sentiment and numerical rating highlights the importance of comprehensive feedback analysis.

Our interactive Streamlit application provides organizations with a practical tool for real-time sentiment analysis and coherence detection. By prioritizing VADER's linguistic sophistication while maintaining ML's pattern recognition capabilities, we achieve robust performance across diverse feedback types.

The results support the adoption of hybrid sentiment analysis systems in customer feedback processing, with particular value in identifying and analyzing incoherent feedbacks that warrant additional investigation.

7.1 Recommendations

1. **Implement in Production:** Deploy the Streamlit application in customer service workflows
2. **Monitor Coherence:** Track coherence metrics as a quality indicator
3. **Continuous Improvement:** Collect user feedback and retrain models periodically
4. **Expand Scope:** Apply methodology to additional feedback sources
5. **Research Direction:** Investigate causation of incoherence patterns

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References

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Appendices

Appendix A: Data Dictionary

Field	Description	Type
Review	Customer feedback text	String
Rating	Numerical rating (1-5)	Integer
clean_text	Preprocessed text	String
text_sentiment	VADER sentiment prediction	Categorical
rating_sentiment	Sentiment derived from rating	Categorical
coherent	Whether rating and text sentiment match	Boolean
vader_sentiment	VADER-based sentiment	Categorical

Appendix B: Model Hyperparameters

TF-IDF Vectorizer:

```
TfidfVectorizer(
    max_features=5000,
    ngram_range=(1, 2),
    stop_words='english',
    lowercase=True,
    min_df=1,
    max_df=0.95
)
```

Linear SVM:

```
LinearSVC(
    random_state=42,
    max_iter=2000
)
```

Appendix C: Project Repository Structure

```
sentiment-analysis-feedbacks/
  app.py
  requirement.txt
  README.md
  sentiment-analysis-report.qmd (this file)
  data/
     feedbacks.csv
     feedbacks_enriched.csv
  models/
     sentiment_model.pkl
     tfidf_vectorizer.pkl
  notebooks/
     01_exploration_nlp.ipynb
     02_modelisation_nlp.ipynb
     03_bert_experiment.ipynb
  assets/
     happy.png
     neutral.png
     angry.png
  src/
      model.py
      preprocessing.py
      predict.py
```

Metadata

Report Version: 1.0
Generated: 2026-01-09
Status: Final
Classification: Public

For questions or clarifications regarding this report, please refer to the project documentation or contact the development team.