Final Report: Employee Sentiment Analysis

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Executive Summary

This comprehensive analysis of employee sentiment was conducted on a dataset of 2,191 internal employee messages sent by 226 unique employees. Leveraging modern natural language processing (NLP) techniques, we implemented an end-to-end system for sentiment labeling, exploratory data analysis (EDA), employee sentiment scoring, engagement ranking, flight risk detection, and predictive modeling.

Key Findings:
• Three employees showed consistent, positive engagement patterns across months.
• A small group of employees were flagged as potential flight risks due to persistent negative sentiment.
• The predictive model achieved an R^2 score of 0.63 in forecasting monthly sentiment scores.
• Clear temporal sentiment trends were observed, aligning with potential business cycles.

1. Project Overview and Objectives

This project aimed to analyze internal employee communications to uncover engagement patterns, detect signs of dissatisfaction, and model future sentiment trends. The solution integrates NLP, data aggregation, statistical feature engineering, and machine learning.

Primary Objectives:

1. Automatically classify each message as Positive, Negative, or Neutral.
2. Analyze communication trends and patterns using EDA.
3. Score each employee's monthly sentiment and monitor changes over time.
4. Identify top and bottom performing employees per month.

5. Flag flight risk candidates using a 30-day rolling window heuristic.
6. Develop a regression model to predict sentiment scores using message-based features.

2. Dataset Overview and Characteristics

• Messages: 2,191
• Unique Employees: 226
• Data Quality: No missing fields for employee ID, message content, or date.

• Message Structure: Professional internal messages (email-like), combining subject and body.

Preprocessing Steps: Cleaned text, parsed timestamps, merged subject and body, removed duplicates, and flagged outliers.

3. Sentiment Labeling Methodology

We used HuggingFace's `cardiffnlp/twitter-roberta-base-sentiment` model to label messages. This transformer-based model, trained on tweet-level sentiment, generalizes well to short formal communications.

Each message (subject + body) was passed to the transformer pipeline with GPU acceleration. Labels were mapped as:
• LABEL_0 → Negative
• LABEL_1 → Neutral
• LABEL_2 → Positive

Manual review and comparison with VADER sentiment analyzer were performed for validation. Some misclassifications were noted with domain-specific phrases (e.g., "no excuses" marked as neutral).

4. Exploratory Data Analysis (EDA)

Key observations:
• Neutral messages dominate the corpus (68.7%).
• Positive messages constitute 24.6% of the dataset.
• Negative messages make up just 6.7%, clustered among a few employees.
• Peak activity seen during weekdays; temporal sentiment variation aligns with work cycles.
• Longer messages tend to be neutral; positive messages are slightly shorter on average.

5. Monthly Sentiment Score Calculation

Messages were scored: +1 (Positive), 0 (Neutral), -1 (Negative). These were aggregated per employee per month to compute `message_score` and `message_count`. The resulting scores reflect each employee's monthly engagement tone.

6. Employee Ranking System

For each month:
• Top 3 Positive: Highest message_score
• Top 3 Negative: Lowest message_score

Tie-breaker: Employee ID (alphabetical). Monthly leaderboards help identify highly engaged contributors and those at risk of disengagement.

7. Flight Risk Identification

An employee is considered a flight risk if they send 4 or more negative messages within any 30-day rolling window. This rule-based method was implemented using date arithmetic over sorted messages per employee. The resulting flags provide high-confidence early warnings.

8. Predictive Modeling

We used linear regression to predict monthly sentiment scores using these features:
• message_count
• avg_message_length
• avg_word_count
• positive_ratio
• negative_ratio

The model achieved $R^2 = 0.63$ and MSE ≈ 0.92, showing that sentiment trends can be partially predicted using basic behavioral features.

9. Key Findings and Insights

• Neutral tone dominates, as expected in corporate settings.
• Small subset of employees exhibit repeated negativity.
• Flight risk rule successfully flags long-term disengagement.
• Sentiment ratios are strong predictors in forecasting engagement levels.

10. Recommendations

• Conduct monthly sentiment audits to proactively monitor engagement.
• Fine-tune sentiment models on internal communication for better accuracy.
• Highlight and reward consistently positive communicators.
• Follow up with flagged flight-risk employees for early intervention.

11. Attachments and Deliverables

• sentiment_labeled_data.csv
• monthly_employee_scores.csv
• visualizations/*.png
• flight_risk_employees.csv
• model_predictions.csv
• employee_sentiment_analysis.ipynb
• README.md