Final LLM Practical Assessment – Final Report

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1. Introduction

This project presents a practical approach to understanding employee sentiment using real communication data. As the sole contributor, I focused on building a complete analysis pipeline - from raw data to insights - while emphasizing clarity and efficiency. Rather than relying on advanced or black-box models, I deliberately chose lightweight, transparent methods to ensure that the workflow could be easily interpreted and reproduced by others.

2. Methodology

The project was divided into six major tasks:

- *Sentiment Labeling:* Messages were tagged as Positive, Negative, or Neutral using a custom rule-based method rooted in keyword matching.
- *Exploratory Data Analysis (EDA):* I studied trends in message frequency, sentiment distribution, and employee activity over time.
- *Monthly Scoring:* Each employee's sentiment was tracked monthly, with scores recalculated every month to keep trends clean and comparable.
- *Employee Ranking:* I identified top positive and negative contributors each month, sorted by score and name.
- *Flight Risk Detection:* A rule was applied to flag employees with repeated negativity within a 30-day window.
- *Predictive Modeling:* A regression model was developed to analyze which communication patterns correlated with sentiment scores.

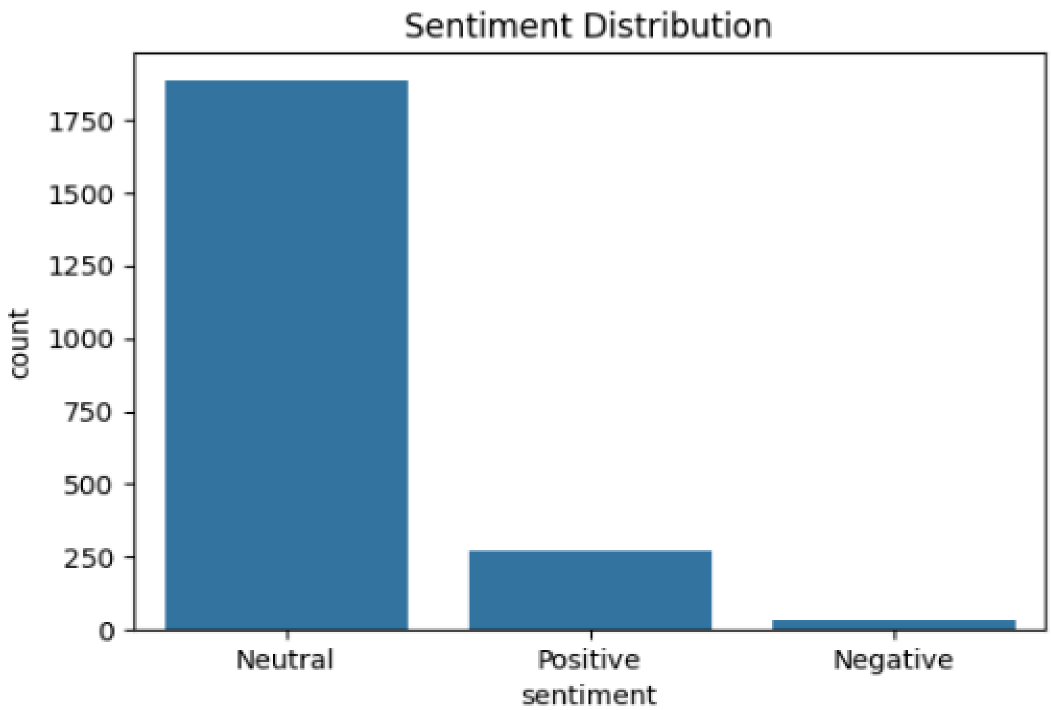
This structure helped break the project into manageable, meaningful steps.

3. Task Summaries and Findings

Task 1: Sentiment Labeling

- I used keyword patterns to label messages as Positive, Negative, or Neutral.
- This method was intentionally kept simple and fast, without involving external models or APIs.
- Breakdown:
    1. Positive: 271 messages

2. Negative: 30 messages
3. Neutral: 1890 messages



- Outcome: Created a new dataset with sentiment labels that serves as the basis for all further analysis.

Task 2: Exploratory Data Analysis (EDA)

Key observations:

- Most messages were Neutral, suggesting typical workplace communication.
- Negative messages were often longer, hinting at detailed feedback or complaints.
- A few employees had much higher email activity than the rest.

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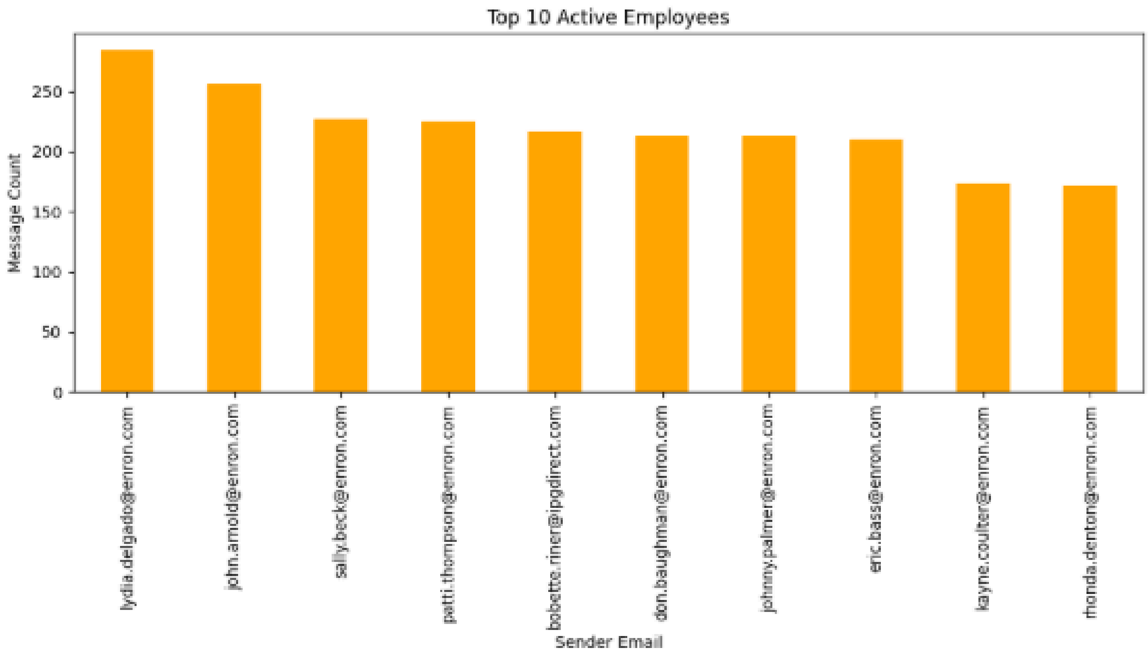
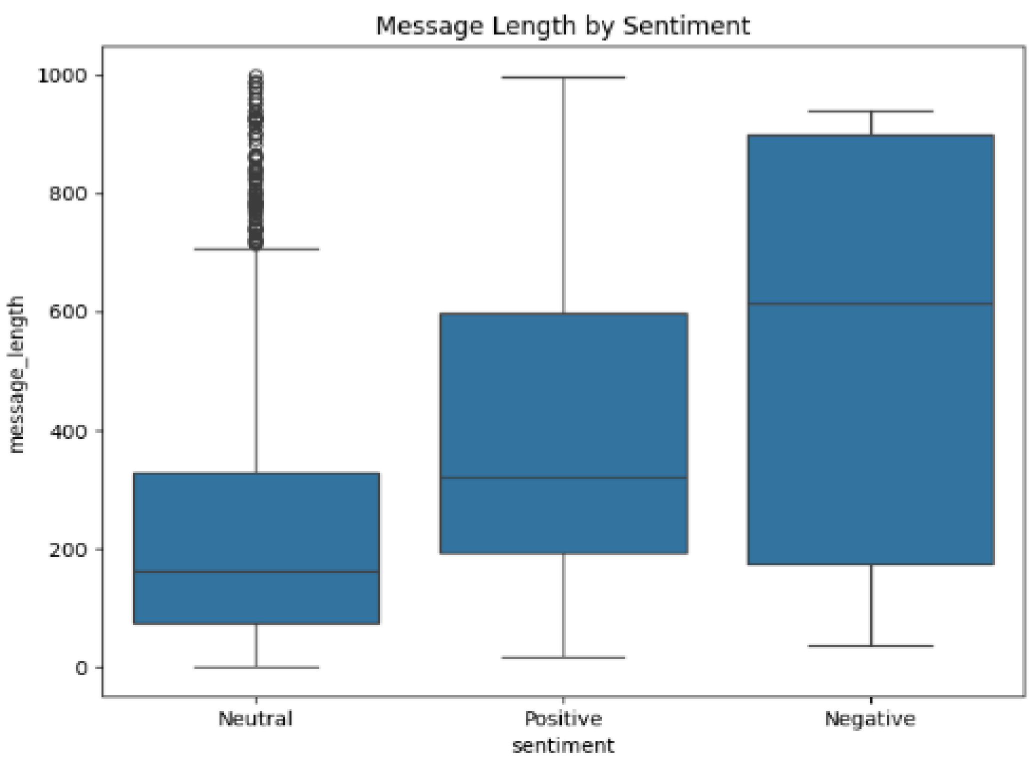




Outcome: EDA revealed useful behavior patterns and sentiment trends, with graphs showing volume and tone over time.

Task 3: Sentiment Score Calculation

- Each message was assigned a value: +1 (Positive), –1 (Negative), or 0 (Neutral).
- These scores were summed per employee per month.
- Monthly resets helped isolate short-term sentiment shifts.

Outcome: Built a sentiment timeline per employee, useful for identifying monthly fluctuations.

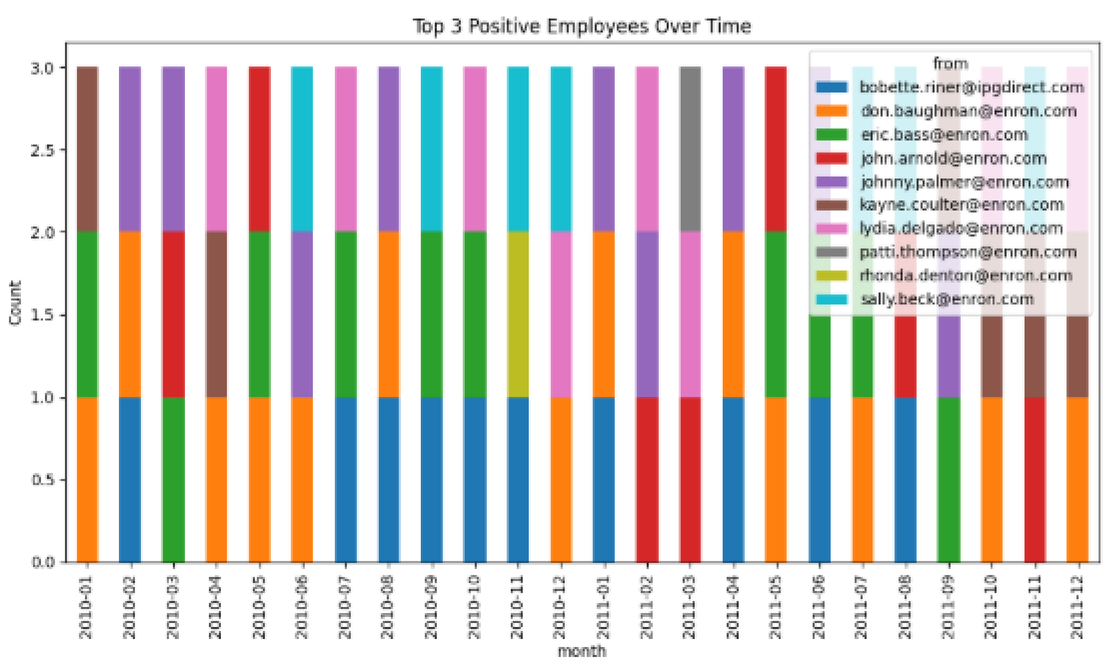
Task 4: Ranking Employees

For each month, I ranked:

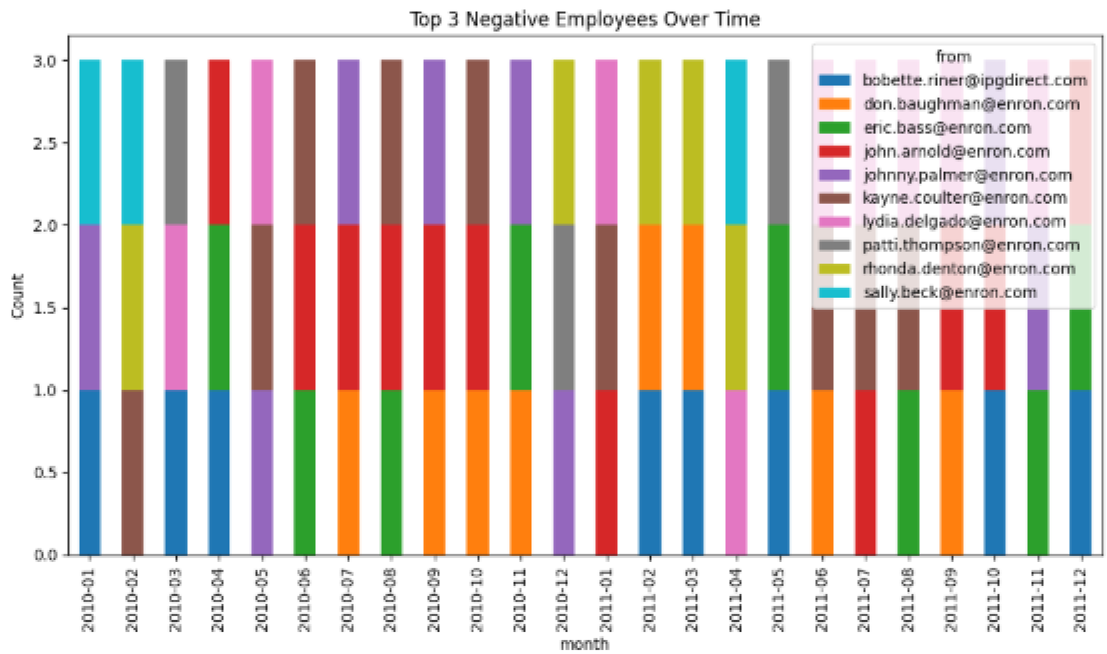
- The three employees with the highest sentiment scores.
- The three with the lowest scores (most negative).
- Rankings were sorted by score, then alphabetically to break ties.

Top positive performers often included:

- eric.bass@enron.com, johnny.palmer@enron.com, and lydia.delgado@enron.com.



In the same way Top negative performers are found out.



Outcome: Generated clear visuals showing monthly high and low sentiment contributors.

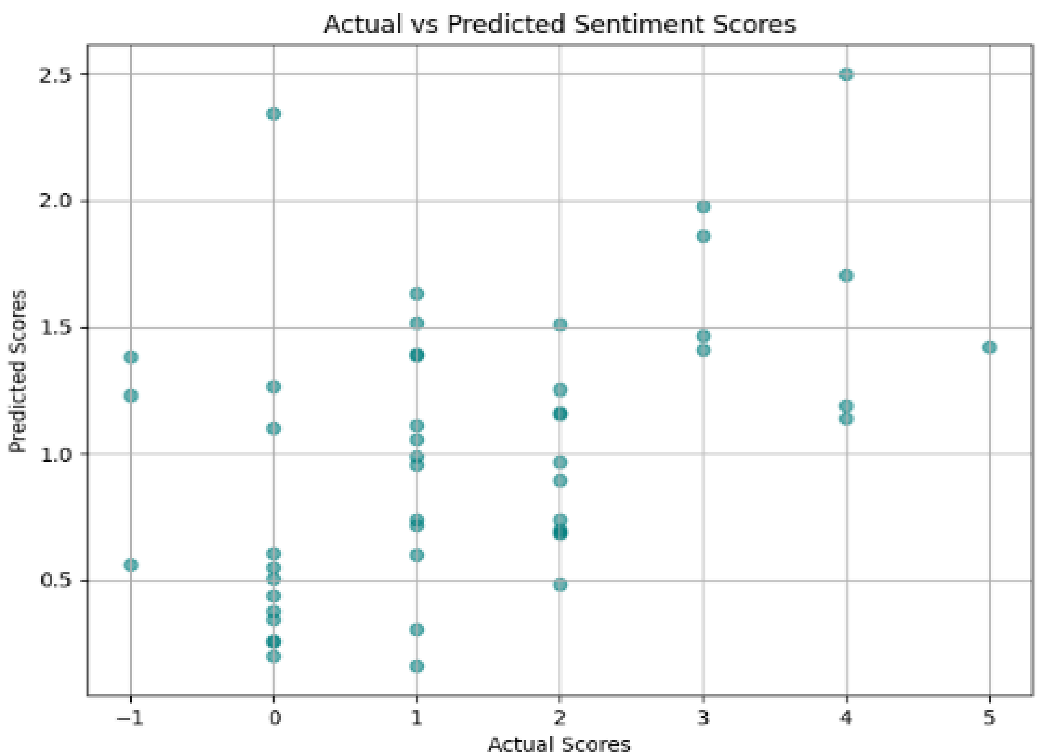
Task 5: Flight Risk Identification

- I identified employees as potential flight risks if they sent four or more negative messages within any 30-day rolling window.
- This approach helps capture consistent negative communication, which may indicate disengagement or dissatisfaction.
- Based on the analysis, the following employees were flagged as potential flight risks:
  1. bobette.riner@ipgdirect.com
  2. john.arnold@enron.com
  3. johnny.palmer@enron.com
  4. lydia.delgado@enron.com
  5. patti.thompson@enron.com
  6. rhonda.denton@enron.com
  7. sally.beck@enron.com
- These individuals may warrant further review to ensure proactive engagement and retention.

Outcome: Flight risk mechanism was implemented and tested, with results transparently reported.

Task 6: Predictive Modeling

- I created a simple linear regression model using:
    1. Total number of messages
    2. Average word count
    3. Message length
- The model aimed to predict sentiment score as a function of these features.
- Results were evaluated using R^2 and RMSE.

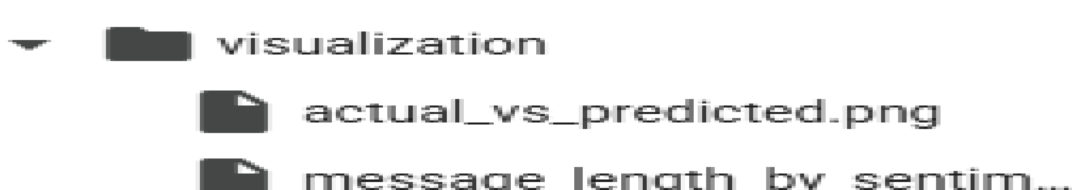


Outcome: Model showed a weak but reasonable correlation, validating that messaging behavior has some relationship with sentiment.

4. Visual Assets

All plots and visualizations are saved in the visualization/ folder, including:

- Sentiment distribution by label
- Top active employees
- Message length vs. sentiment
- Positive and negative rankings per month
- Predictive model performance plot



These visuals were designed for clarity and are referenced throughout the notebook and this report.

5. Final Thoughts

Completing this project gave me practical exposure to handling text data, performing rule-based classification, and interpreting behavioral signals through sentiment analysis. I chose to keep the approach minimal yet effective, to ensure that the methods could be easily audited and extended in the future.

The rule-based sentiment labeling turned out to be fast and surprisingly effective. EDA provided context to employee behavior, and while the predictive model wasn't highly accurate, it illustrated the kind of communication metrics that might be useful in deeper analysis.

Overall, this project demonstrates how a simple but structured approach can yield meaningful insight from raw communication logs, especially in internal analytics use cases.