Employee Sentiment Analysis

LLM Final Assessment Report

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Overview

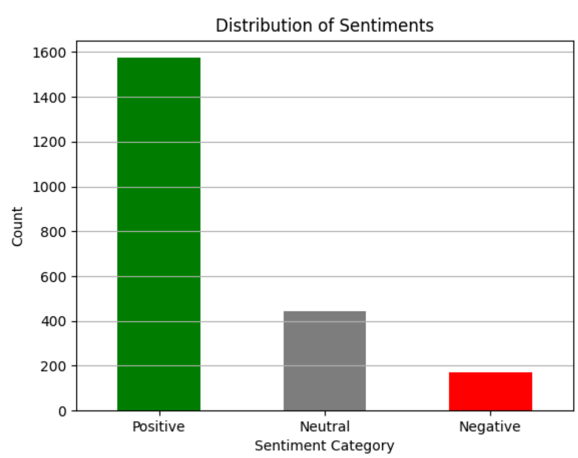
In this project a dataset of 2191 emails from ten unique employee email addresses is analyzed to determine employee sentiment. The project is broken up into six tasks: sentiment labelling, exploratory data analysis, employee score calculations, employee ranking, flight risk evaluation, and predictive modelling.

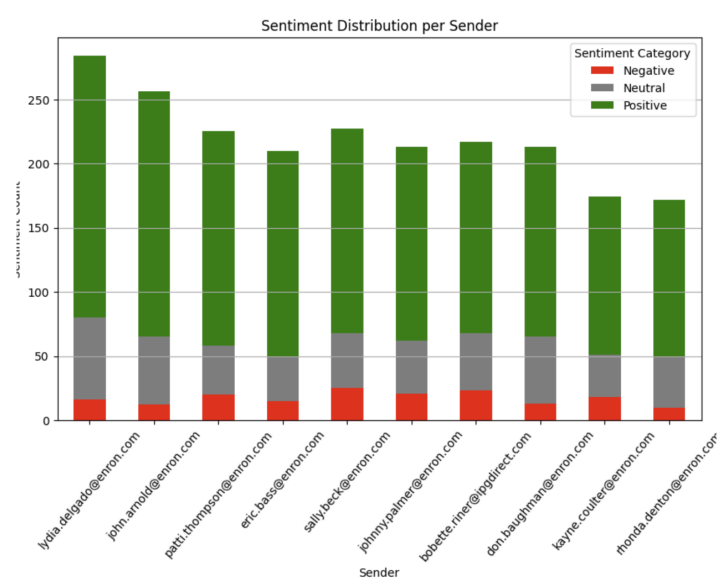
Task 1. Sentiment Labelling

For this task, I utilized Vader Sentiment's sentiment analysis feature, specifically the SentimentIntensityAnalyzer. I made a function that combines the subject and body of each email, and calculates the sentiment using Vader. Based on the result, messages were tagged as positive (if above 0.05), negative (if below -0.05), or neutral (between 0.05 and -0.05). These values were then added to the DataFrame in a new "sentiment" column.

Task 2. Exploratory Data Analysis (EDA)

From just using the describe() function, it can be seen that the most frequent sentiment is positive, and the most emails were sent on July first 2011, and lydia.delgado@enron.com sent the most emails overall. The overall distribution of sentiment shows the vast majority of emails sent had a positive sentiment, and breaking it down to look at each individual reflects this as well.

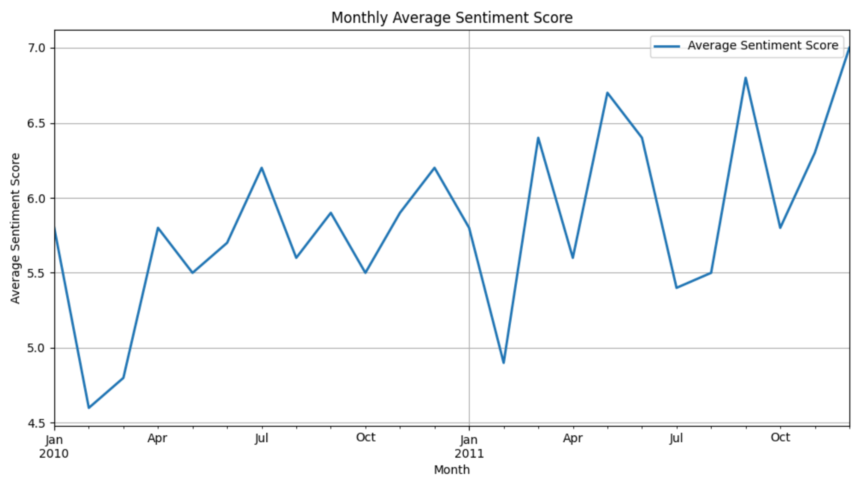




I grouped by email address and sentiment, and created a pivot table called sentiments_pivot to see a count of how many emails of each sentiment category each employee sent. Next I grouped the data by month, email address, and sentiment rating and made a pivot table called monthly_pivot. With this monthly_pivot I was able to look at trends for average and individual sentiments over time.

Task 3. Employee Score Calculation

To apply a sentiment score to each message, I developed a function to assign values of 1, 0, or -1 based on each row's corresponding sentiment label, and applied this to my DataFrame. I was then also able to apply this logic to my monthly_pivot, and calculated each employee's monthly sentiment score. The plot below shows the average monthly sentiment score over time.



Looking at the overall sentiment trends for all employees, sentiment tends to drop towards the end of each year, reaching an all time low in November 2010, and trending in the same direction at the end of 2011. Average sentiment score reached an all time high in September 2011.

Task 4. Employee Ranking

To determine the most positive and negative employees, I referred back to my sentiments_pivot, which was grouped by employee and sentiment. I created a new column showing the total sentiment score for each employee, then sorted by highest score to find the most positive employees, and the lowest score to find the most negative employees. The results for all time most positive and negative employees can be seen in the table below.

Most Positive Employees (Highest All-time Sentiment Scores)

Email Address	Sentiment Score
lydia.delgado@enron.com	188
john.arnold@enron.com	179
patti.thompson@enron.com	147

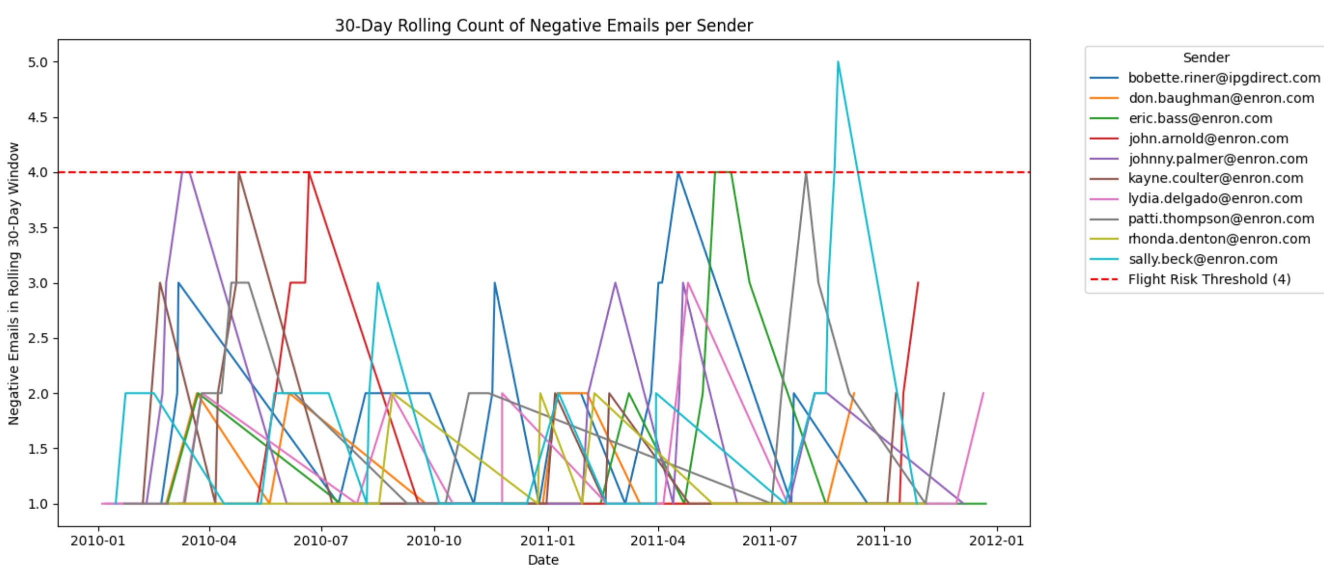
Most Negative Employees (Lowest All-time Sentiment Scores)

Email Address	Sentiment Score
kayne.coulter@enron.com	105
rhonda.denton@enron.com	112
eric.bass@enron.com	126

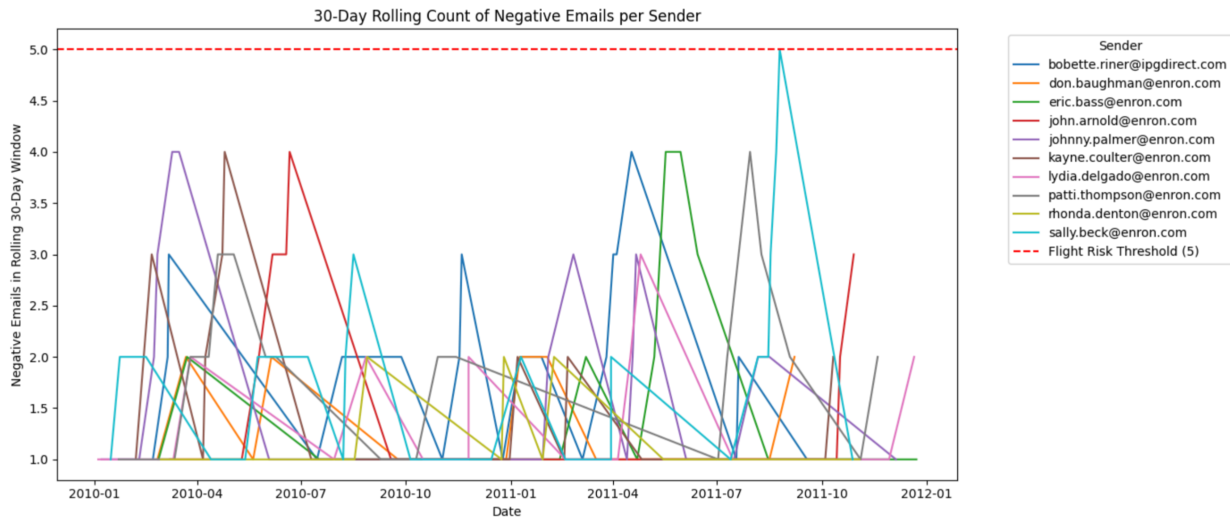
Next, I developed two functions to identify the highest and lowest sentiment scores for any given month. The first extracts data for a specified month from monthly_pivot, selects the top three senders based on the highest sentiment scores (breaking ties alphabetically), and returns a ranked DataFrame with email addresses and scores, using a dynamic column name for the selected month. The second function mirrors this process but retrieves the bottom three senders.

Task 5. Flight Risk Identification

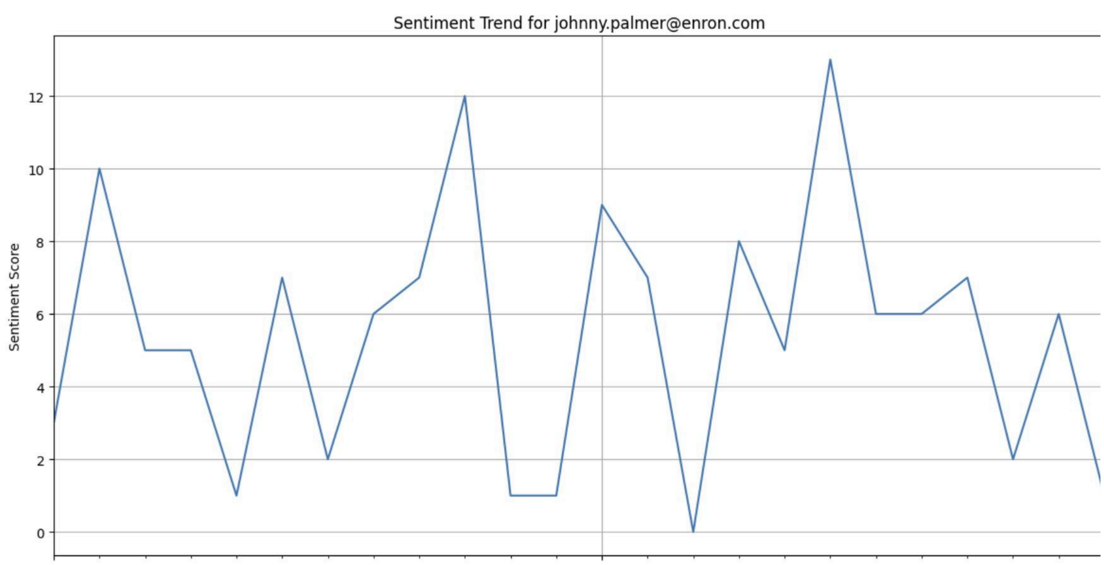
Checking for flight risk with the original criteria of anyone having four negative emails within any 30 day span was not very effective, as seven out of ten employees met that criteria. Bobette.riner@ipgdirect.com, eric.bass@enron.com, john.arnold@enron.com, johnny.palmer@enron.com, kayne.coulter@enron.com, patti.thompson@enron.com, and sally.beck@enron.com had at least four negative emails within a rolling 30 day period at some point. Only three employees were initially not ruled a flight risk using this metric.



Raising the threshold to more than five negative messages in a rolling 30 day span, only sally.beck@enron.comis is flagged.



This metric might also be flawed, as people who had a spike of negativity in the past are not necessarily all likely to leave. It might be more accurate or at least beneficial to also look at who is trending downwards in recent months. For example johnny.palmer@enron.com's monthly sentiment scores show steep decline over the last six months, yet the only time he met the original threshold was over a year prior to this decline.



Task 6. Predictive Modelling

Next I made a model predicting monthly sentiment scores, but before creating my model, I added some more features to my DataFrame. I used nltk's opinion_lexicon and word_tokenizer to find the number of positive and negative words in each email, as well as the percentage of words in each email that were positive or negative. I also added a total word count for the subject and body of each email, and a monthly count of emails for each sender. I made my date columns numeric, replacing it with a count of how many months from the start of the data, and dropped my non-numeric columns. Then I used the sklearn library for splitting my data into training and testing data, and for scaling my data. I created a LinearRegression model, trained it on my X_train_scaled, and used my X_test_scaled to make predictions.

The resulting model ended up with a mean squared error of 3.5, and an R^2 score of 0.8, meaning the model is able to explain about 80% of the sentiment variation. Plotted below is the predicted vs actual monthly sentiment scores. The model still has room for improvement, and perhaps another deep learning model could bring stronger results. This model is generally able to predict the linear progression of monthly sentiment as it relates to the other features in the data set at a high level.