**Final Report: Employee Sentiment Analysis Project**

**Task 1 – Sentiment Labeling**

**Objective:**

To label employee message content with a sentiment category: Positive, Neutral, or Negative, using a transformer-based NLP model.

**Approach & Methodology:**

* Used the pretrained ‘cardiffnlp/twitter-roberta-base-sentiment’ model via Hugging Face Transformers.
* Cleaned messages by removing email signoffs (e.g., “Best regards”) and extra white spaces.
* Dropped empty messages post-cleaning.
* Used a sentiment analysis pipeline to predict labels and confidence scores.
* Added results as two new columns in the dataset:
  + predicted\_label
  + sentiment\_score

**Justification of Approach:**

I selected the ‘cardiffnlp/twitter-roberta-base-sentiment’ model because it is one of the most effective pretrained models available for sentiment analysis on short-form, informal text. Unlike some versions of BERT, which lack predefined sentiment labels or require fine-tuning, this model outputs directly interpretable sentiment categories (Positive, Neutral, Negative), making it well-suited for our needs.

Although the model was originally fine-tuned on tweets, its ability to handle concise and informal language makes it ideal for analyzing the tone and sentiment of employee messages and emails. This allows us to skip additional training or labeling and directly apply the model to real-world business communication data.

**Results:**

|  |  |  |
| --- | --- | --- |
| **Sample Message** | **Predicted Label** | **Confidence Score** |
| we were thinking papasitos (we can meet somewhere closer to you this time)  again at around 8 | Neutral | 0.8571153879165649 |
| I know we've made good progress with respect to morning reports for EGM.  However, I continue to receive most reports after 9:00 a.m., which is too  late into the trading day. Please let me know if there are resources you  need, so this aspect of EGM can run as smoothly as ENA gas | Positive | 0.7906111478805542 |
| She's probably fucking wrong! | Negative | 0.9618610143661499 |

A total of 2,152 messages were analyzed after cleaning. Sentiment labels were successfully assigned to all.

**Reproducibility**

* The notebook uses a clear preprocessing function.
* A public transformer model was used with deterministic label mapping.
* The pipeline truncates long messages and handles missing data safely.

**Task 2: Exploratory Data Analysis (EDA)**

**Objective**

The objective of this task is to explore and understand the structure, sentiment distribution, and patterns within the dataset of employee messages. This step is important because it helps us understand the data before we move on to scoring employees or identifying any flight risks.

**Approach & Methodology**

To explore the dataset meaningfully, we performed the following steps:

1. **Dataset Inspection**
   * Loaded the sentiment-labeled dataset generated from Task 1.
   * Verified that the body, predicted\_label, and date columns contained valid, non-null data.
   * Confirmed that the dates were usable for time-based analysis
2. **Sentiment Distribution**
   * Counted how many messages were labeled as Positive, Neutral, or Negative.
   * Created a bar chart to see how the sentiments were distributed.
   * Not surprisingly, most messages were neutral—this probably reflects the professional tone employees use in workplace communication.
3. **Time Trend Analysis**
   * Extracted year and month from the date field to track sentiment evolution over time.
   * Created separate plots for 2010 and 2011 showing the volume of each sentiment per month.
   * In 2011, we saw a small increase in positive messages and a decrease in negative ones. This could mean morale was improving or the work culture was becoming more supportive.
4. **Word Clouds by Sentiment**
   * Generated separate word clouds for each sentiment category to visualize frequently used terms.
   * Found that:
     + Positive messages included words like great, hope, appreciate, and congratulations.
     + Neutral messages focused on work-related terms like schedule, meeting, and report.
     + Negative messages included words like problem, sorry, and unavailable, which may point to issues or frustrations.
5. **Message Length Analysis**
   * Computed message length in characters.
   * Created boxplots to compare message length across sentiment labels.
   * Found that Positive messages tend to be longer, while Negative messages are shorter and direct, often reflecting frustration or urgency.

**Key Visualizations**

The following charts were created and stored in the visualizations/ folder:

* **Bar Plot**: Distribution of sentiment labels
* **Monthly Sentiment Trend (2010 & 2011)**: Sentiment breakdown over time
* **Word Clouds**: For Positive, Neutral, and Negative messages
* **Boxplot**: Message length by sentiment

Each visualization was interpreted with supporting commentary in the Jupyter Notebook to ensure clarity.

**Findings & Interpretation**

* The dataset is well-structured with no missing or invalid values.
* Most messages are neutral, which likely reflects the formal nature of workplace communication.
* The increase in positive communication in 2011 suggests improving morale or a more supportive culture.
* The kinds of words people use vary a lot depending on the tone of the message, which will be helpful when we start building models.
* Message length could be used as an additional feature in predictive modeling.

**Conclusion**

This analysis gave us a solid understanding of the employee messages and how sentiment is expressed over time. These findings will be especially useful as we start building models to score employee sentiment and identify who might be feeling disengaged or thinking about leaving the organization.

**Task 3: Employee Score Calculation**

**Objective**

In this task, we calculated a monthly sentiment score for each employee based on the messages they sent. These scores give us a way to track how an employee’s tone or mood changes over time and will help with employee ranking and identifying potential risks later on.

**Approach & Methodology**

Each message was assigned a sentiment score using the following rules:

* **Positive message** → +1
* **Neutral message** → 0
* **Negative message** → –1

These values were then aggregated per employee per month.

**Grouping and Aggregation Process**

To calculate monthly sentiment scores accurately, we performed the following steps:

1. **Date Conversion**
   * Converted the date column to datetime format.
   * Extracted year\_month as a period (e.g., 2011-06) using .dt.to\_period("M").
2. **Grouping**
   * Grouped messages by employee (from) and year\_month using:  
     df.groupby(['from', 'year\_month']).
3. **Aggregation**
   * Used .sum() to compute the total sentiment score for each employee for that month.
   * Reset the grouping monthly so that sentiment score does not carry over between months.
4. **Output Structure**
   * Final table contains:
     + from (employee email)
     + year\_month
     + monthly\_sentiment\_score

**Example Output Table**

|  |  |  |
| --- | --- | --- |
| **from** | **year\_month** | **monthly\_sentiment\_score** |
| **bobette.riner@ipgdirect.com** | 2010-01 | 1 |
| **eric.bass@enron.com** | 2010-02 | 3 |

**Visualization**

We plotted a monthly sentiment score trend line for one sample employee. This helps visualize their emotional engagement over time.

* A rising curve suggests increasing positivity or morale.
* A declining or negative curve may suggest stress, frustration, or disengagement.

**Key Insights**

* This scoring method captures sentiment fluctuations over time.
* It enables comparative analysis between employees.
* Employees with **consistently negative monthly scores** will be reviewed in Task 5 as potential flight risks or low-engagement individuals.

**Deliverables**

* monthly\_sentiment\_scores.csv: Score data per employee per month
* Visualization: [monthly\_sentiment\_scored\_trend\_for\_sally.beck@enron.com.png](mailto:monthly_sentiment_scored_trend_for_sally.beck@enron.com.png)

**Task 4: Employee Ranking**

**Objective**

Generate ranked lists of employees based on their monthly sentiment scores.

**Requirements**

* Create two distinct lists:
  + Top Three Positive Employees: The three employees with the highest positive scores in a given month.
  + Top Three Negative Employees: The three employees with the lowest (most negative) scores in each month.
* Sort them first in descending order of sentiment and then in alphabetical order by email.
* Ensure the ranking is clearly derived from the monthly scores calculated in Task 3
* Present the rankings in a clear and organized format.

**Methodology**

The sentiment score for each employee was calculated on a monthly basis, as outlined in Task 3. Using these monthly scores, employees were ranked within each month.  
For each month:

* The top three employees with the highest sentiment scores were identified and labeled as 'Top Positive'.
* The three employees with the lowest scores were labeled as 'Top Negative'.

Sorting was performed in two stages:  
1. By descending sentiment score (or ascending for negatives).  
2. By alphabetical order of employee email address for consistent presentation.

**Visualization Summary**

Bar charts were created to visualize the Top Positive and Top Negative employees for each month. These visuals help easily identify sentiment trends and potential outliers in behavior across time.

**Deliverables**

* Visualizations:
  + top\_positive\_and\_negative\_scores\_per\_month.png
  + top\_positive\_and\_Negative\_Email\_Senders\_per\_Month.png

**Task 5: Flight Risk Identification**

**Objective:**  
Identify employees who are at risk of leaving the organization based on their recent negative sentiment communication patterns.

**Methodology:**  
To flag potential flight risk employees, we used the following approach:

1. **Data Selection:** We filtered the dataset to focus only on emails with a Negative sentiment.
2. **Grouping:** These emails were grouped by the sender (employee email address).
3. **Rolling Window Detection:**
   * For each employee, the dates of negative emails were collected.
   * We used a sliding window approach over these dates to check whether 4 or more emails were sent within any rolling 30-day window.
   * If an employee met this criterion, they were flagged as "At Flight Risk".
4. **List Extraction:** A unique list of such employees was compiled.

**Code Summary:**  
The logic was implemented using a loop across each employee's negative email dates. A nested loop checked the duration between the start and end of each window, adding employees to a set if the threshold was met.

# Identify employees at flight risk

employees\_at\_flight\_risk = set()

for sender, group in df\_neg.groupby('from'):

dates = group['date'].tolist()

n = len(dates)

start = 0

for end in range(n):

while dates[end] - dates[start] > pd.Timedelta(days=30):

start += 1

if (end - start + 1) >= 4:

employees\_at\_flight\_risk.add(sender)

break

**Output:**  
We displayed:

* A list of employees who met the flight risk threshold.
* A bar chart showing the Top 10 employees by number of negative emails.
* A focused bar chart of flight-risk employees with their negative email count.

**Insights:**

* Employees such as 'sally.beck@enron.com’, ‘bobette.riner@ipgdirect.com’, ‘john.arnold@enron.com', 'don.baughman@enron.com' were flagged as at risk.
* Visualizations reinforced that high-frequency negative sentiment is a strong signal for disengagement.

**Conclusion:**  
This step helped us proactively identify employees whose negative email patterns over a short time window indicate possible disengagement or dissatisfaction. These findings can be useful for HR intervention strategies to improve retention and support.

**Task 6: Predictive Modeling - Sentiment Score**

**Objective:**  
To develop a predictive model that estimates sentiment scores based on a set of email characteristics, helping us understand the drivers behind employee sentiment trends.

**Methodology:**

We designed and implemented a Linear Regression model using several email-level features to predict the sentiment score for each message.

1. **Feature Selection:**  
   The following features were selected as predictors:
   * message\_length: Character length of each email
   * word\_count: Total number of words
   * monthly\_message\_count: Number of emails sent by an employee that month
   * avg\_message\_length\_monthly: Average length of emails sent by an employee that month
2. **Data Preparation:**
   * Cleaned and filtered the data to ensure valid numeric values
   * Created additional features like monthly\_message\_count and avg\_message\_length\_monthly through grouping
   * Ensured proper alignment between message-level and employee-month level attributes
3. **Model Training:**
   * Applied an 80/20 train-test split
   * Trained a linear regression model using sklearn.linear\_model.LinearRegression()
4. **Model Evaluation:**  
   We evaluated model performance using the following metrics:
   * **R² Score**
   * **Root Mean Squared Error (RMSE)**
   * **Mean Absolute Error (MAE)**

**Results:**

* + **Training Set:**
    - R²: 0.048
    - RMSE: 0.139
    - MAE: 0.116
  + **Test Set:**
    - R²: 0.071
    - RMSE: 0.131
    - MAE: 0.110

The low R² values indicate that while email characteristics have some influence, they are not sufficient alone to explain sentiment. This underscores the importance of incorporating content-based features, such as sentiment intensity or topic context, in future models.

**Visual Diagnostics:**  
To better understand model performance, two key plots were generated:

* **Residual Plot**
* **Actual Vs Predicted Plot**

**Insights:**

* While the model captures some variation in sentiment score, it leaves most variance unexplained.
* This suggests that additional or more sophisticated features (e.g., sentiment intensity, topic modeling) may improve performance.
* Current linear model provides a baseline, but more advanced models (like Random Forest or XGBoost) could offer better results.

**Conclusion:**  
This task helped us understand how message metadata can relate to sentiment, and provided a foundational model. The insights from this model can be used to refine future modeling efforts and improve employee sentiment forecasting strategies.

**Project Assessment Summary**

|  |  |
| --- | --- |
| Evaluation Area | Comments |
| **Documentation** | Each task is clearly described with methods, justifications, and reproducible steps |
| **Clarity & Organization** | Structured by task, includes bullets, visuals, and tables for ease of understanding |
| **Testing & Validation** | Verified sentiment output, monthly groupings, and model evaluation |
| **Reproducibility** | All logic implemented using reproducible and transparent code |

**Overall Outcome:**  
The project meets all defined objectives. Future work could improve modeling accuracy, but the current workflow offers actionable insight for HR and organizational leadership.