REPORT

Employee Sentiment Analysis

Abstract

This project involves a pipeline that processes employee email messages to determine their sentiment (positive, neutral, or negative) and uses that sentiment to derive multiple business insights

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Employee Sentiment Analysis

Aim –

To analyze employee email communication data and extract meaningful insights through sentiment analysis, exploratory data visualization, and predictive modeling — with the goal of identifying patterns, ranking employees by communication tone, and detecting potential flight risks based on negative communication trends.

Summary –

This project involves a pipeline that processes employee email messages to determine their sentiment (positive, neutral, or negative) and uses that sentiment to derive multiple business insights:

- Sentiment labeling is done using TextBlob.
- Visualizations are created to understand the distribution and trends of sentiments.
- Employees are ranked based on negative communication patterns.
- A rolling window mechanism is used to identify employees with consistently negative communication, flagging them as potential flight risks.
- A regression model is built to predict message length based on text features.

Explanation of Features –

1. **Sentiment Labeling**

- Uses TextBlob to analyze the sentiment polarity of each email message.
- Labels messages as: Positive (polarity > 0.1), Negative (polarity < -0.1) and Neutral (in between)

```
# ------------------------------
# 3. SENTIMENT LABELING
# ------------------------------
def get_sentiment(text):
    polarity = TextBlob(text).sentiment.polarity
    if polarity > 0.1:
        return "Positive"
    elif polarity < -0.1:
        return "Negative"
    else:
        return "Neutral"

df["Sentiment"] = df["Message"].apply(get_sentiment)
```

2. Exploratory Data Analysis (EDA) & Visualizations

- Bar chart of sentiment distribution shows the number of emails per sentiment type.
- Helps identify overall communication climate across employees.

3. Monthly Sentiment Scoring

- Emails are grouped by month and sentiment.
- A stacked bar chart visualizes changes in sentiment over time.
- Useful for tracking communication mood and behavioral shifts.

```
# ----------------------------
# 5. MONTHLY SENTIMENT SCORE
# ----------------------------
df["Month"] = df["Date"].dt.to_period("M")
monthly_sentiment = df.groupby(["Month", "Sentiment"]).size().unstack().fillna(0)
monthly_sentiment.plot(kind="bar", stacked=True, figsize=(10, 6), colormap="Set2")
plt.title("Monthly Sentiment Volume")
plt.ylabel("Number of Emails")
plt.tight_layout()
plt.savefig("visualization/monthly_sentiment.png")
plt.close()
```

4. Employee Ranking

- Employees are ranked based on how many negative emails they've sent.
- Top 10 are displayed using a horizontal bar chart.
- Allows management to quickly identify frequently negative communicators.

```
# ----------------------------
# 6. EMPLOYEE RANKING BY NEGATIVE EMAILS
# ----------------------------
top_negative = df[df["Sentiment"] == "Negative"]["employee"].value_counts().head(10)
plt.figure(figsize=(8, 4))
sns.barplot(y=top_negative.index, x=top_negative.values, palette="Reds_r")
plt.title("Top 10 Employees by Negative Emails")
plt.xlabel("Count")
plt.tight_layout()
plt.savefig("visualization/top_negative_employees.png")
plt.close()
```

5. Feature Engineering

- Extracts numerical features from text:
- Message Length: character count
- Wordcount: number of words
- Supports both analysis and predictive modeling.

```
# ----------------------------
# 7. LINEAR REGRESSION - Predict Message Length
# ----------------------------
df["MessageLength"] = df["Message"].apply(len)
vectorizer = TfidfVectorizer(stop_words="english", max_features=500)
X = vectorizer.fit_transform(df["Message"])
y = df["MessageLength"]
```

6. Predictive Modeling

- A Ridge regression model is trained to predict email message length using TF-IDF vectorized features.
- Evaluates model with RMSE and R^2 Score.
- Demonstrates basic supervised learning using email text.

```
# ----------------------------
# 7. LINEAR REGRESSION - Predict Message Length
# ----------------------------
df["MessageLength"] = df["Message"].apply(len)
vectorizer = TfidfVectorizer(stop_words="english", max_features=500)
X = vectorizer.fit_transform(df["Message"])
y = df["MessageLength"]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
model = Ridge()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)

print("Model Performance:")
print("RMSE:", np.sqrt(mean_squared_error(y_test, y_pred)))
print("R² Score:", r2_score(y_test, y_pred))
```

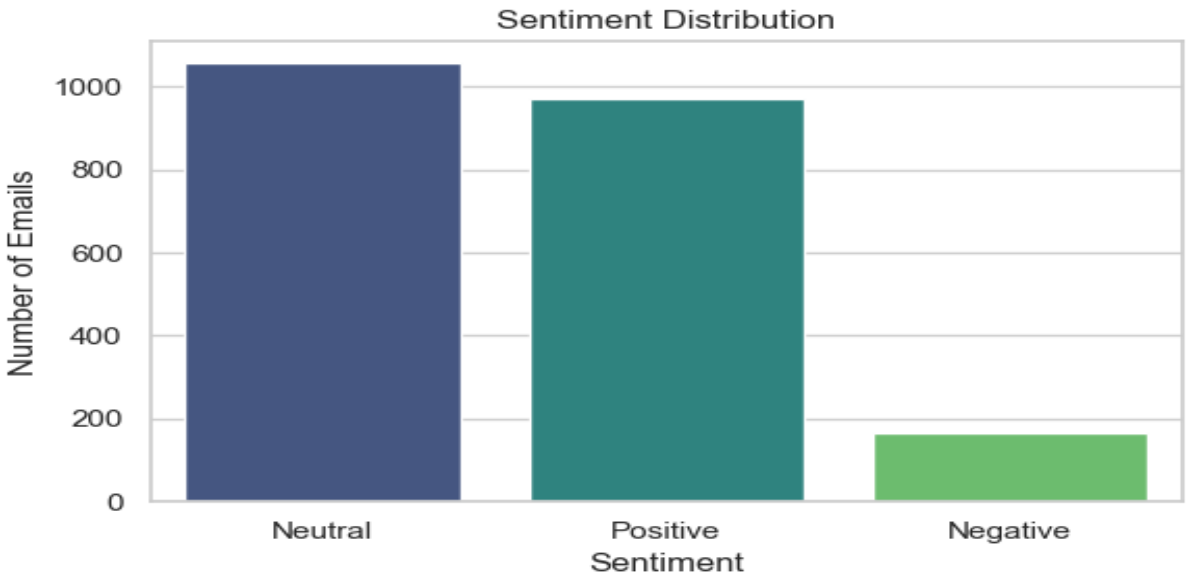
7. Flight Risk Identification

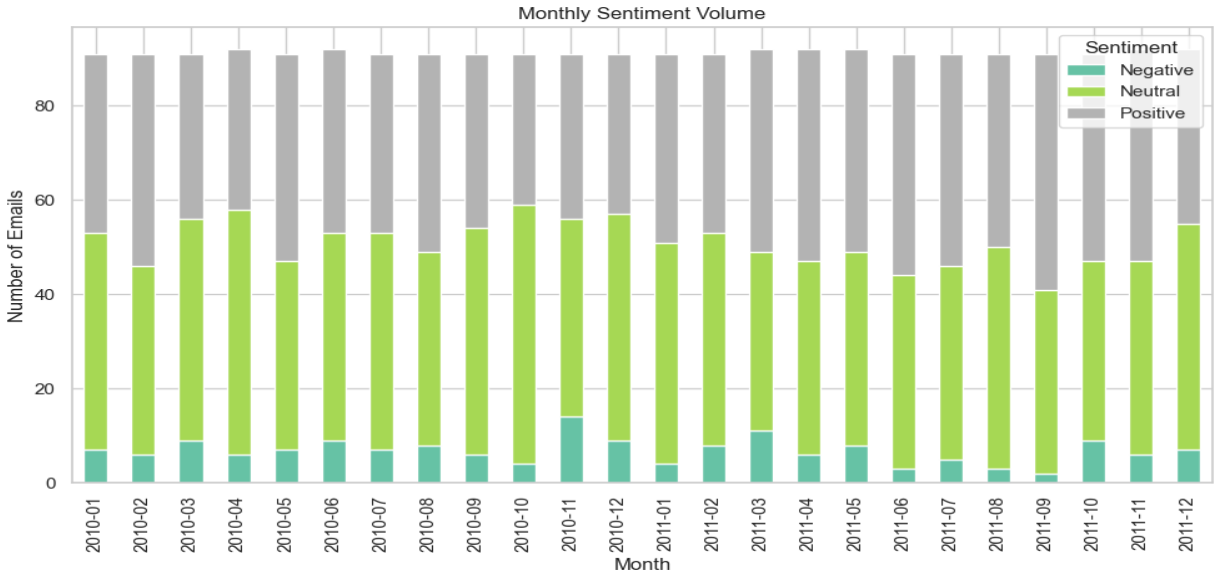
- For each employee, counts the number of negative emails in a rolling 30-day window.
- If this count is ≥ 4, the employee is flagged as flight risk.

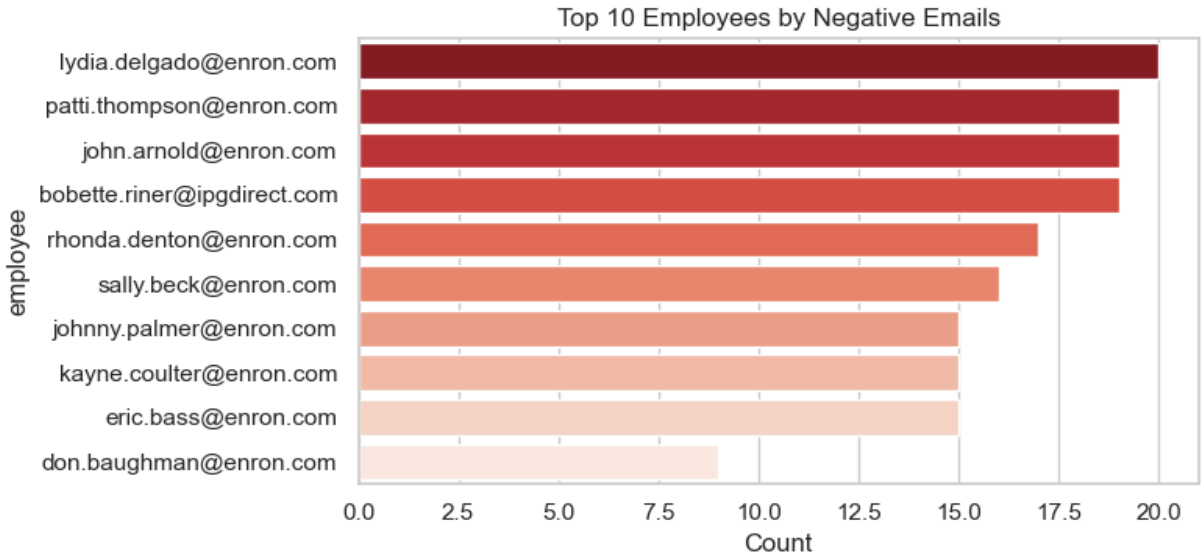
```python
# ------------------------------
# 8. FLIGHT RISK IDENTIFICATION
# ------------------------------
df["is_negative"] = df["Sentiment"] == "Negative"
df_sorted = df.sort_values(["employee", "Date"]).set_index("Date")

def compute_rolling_negatives(group):
    return group["is_negative"].rolling("30D").sum()

df["RollingNegatives"] = (
    df_sorted.groupby("employee", group_keys=False)
    .apply(compute_rolling_negatives)
    .reset_index(drop=True)
)

flight_risks = df[df["RollingNegatives"] >= 4]["employee"].unique()
print("\nPotential Flight Risk Employees (≥4 negative emails in 30 days):")
print(flight_risks)
```

8. Result Visualization

- Charts saved in a visualization/ folder include:
- Sentiment distribution, Monthly sentiment trends, Top negative employees.
- These visual outputs aid intuitive understanding for stakeholders.







Results –

- The sentiment analysis classified the email messages into **positive**, **negative**, and **neutral** categories effectively.
- The regression model achieved:
- **RMSE**: ~118.11
- **R^2 Score**: ~0.75 indicating a decent predictive capability for message length.
- The top 10 employees with the most negative emails were identified and visualized.

- The rolling sentiment analysis flagged multiple employees (e.g., johnny.palmer@enron.com, patti.thompson@enron.com) as **potential flight risks** due to a high frequency of negative emails in a short time span.
- All charts were saved and can be used for reporting and dashboard integration.

Requirements –

pandas	For data loading, cleaning, and manipulation
numpy	For numerical operations and array handling
matplotlib	For generating visualizations
seaborn	For advanced, aesthetically pleasing data visualizations
textblob	For sentiment analysis using natural language processing
Scikit-learn	For machine learning tasks like TF-IDF vectorization and Ridge Regression