0.1 CaseCraft: The Analytics Sprint – Project 13

0.1.1 Coca-Cola vs Pepsi Sentiment Tracker

Subheading: Analyzing public sentiment toward Coca-Cola and Pepsi using synthetic tweet data and NLP techniques.

0.1.2 Project Goals

- Simulate tweet-level data for both brands
- Perform sentiment analysis using TextBlob
- Visualize sentiment distribution and brand comparison
- Track sentiment trends over time
- Build classifier to predict brand from sentiment text
- Summarize insights for brand perception strategy

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from textblob import TextBlob
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report

np.random.seed(42)

brands = ['Coca-Cola', 'Pepsi']
n_tweets = 1000
brand = np.random.choice(brands, n_tweets)
dates = pd.date_range(start='2023-01-01', periods=n_tweets, freq='H')
```

```
positive_phrases = ['love', 'great', 'awesome', 'refreshing', 'best']
negative_phrases = ['hate', 'bad', 'awful', 'flat', 'worst']
neutral_phrases = ['okay', 'fine', 'average', 'meh', 'decent']

def generate_tweet():
    sentiment = np.random.choice(['positive', 'negative', 'neutral'], p=[0.4, 0.
↪3, 0.3])
    phrase = np.random.choice({
        'positive': positive_phrases,
        'negative': negative_phrases,
        'neutral': neutral_phrases
    }[sentiment])
    return f"This {np.random.choice(brands)} is {phrase}!"

tweets = [generate_tweet() for _ in range(n_tweets)]

df = pd.DataFrame({
    'brand': brand,
    'timestamp': dates,
    'tweet': tweets
})

df['polarity'] = df['tweet'].apply(lambda x: TextBlob(x).sentiment.polarity)
df['sentiment'] = pd.cut(df['polarity'], bins=[-1, -0.1, 0.1, 1],␣
↪labels=['Negative', 'Neutral', 'Positive'])
```

```
/tmp/ipython-input-263547350.py:16: FutureWarning: 'H' is deprecated and will be
removed in a future version, please use 'h' instead.
  dates = pd.date_range(start='2023-01-01', periods=n_tweets, freq='H')
```

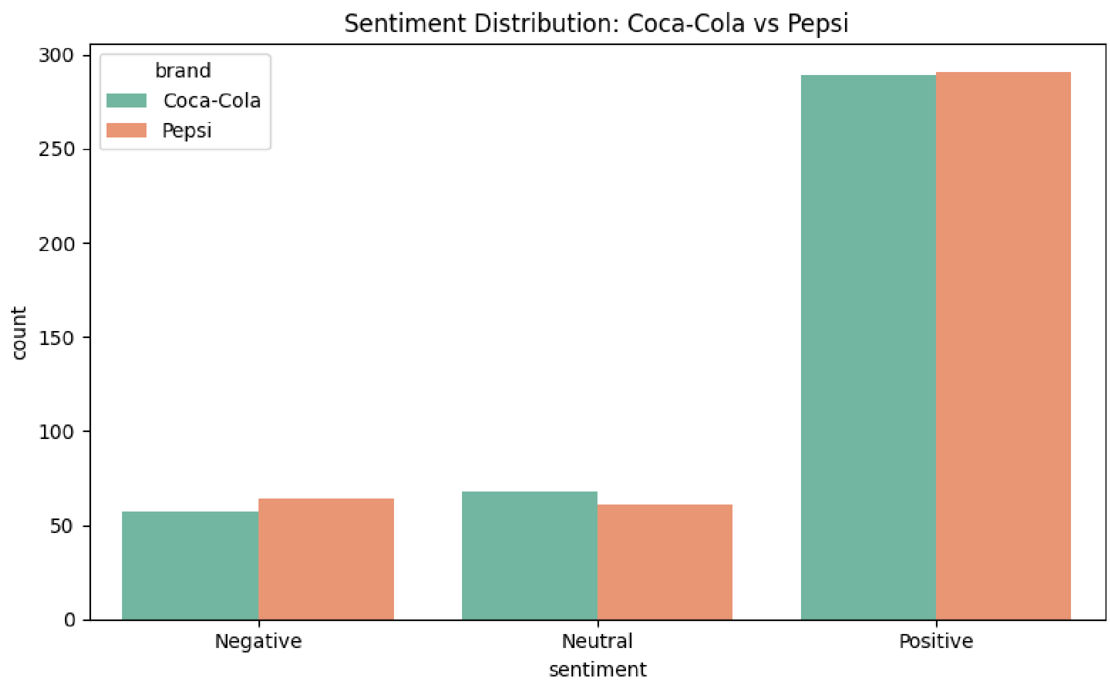
[2]:
```
df.head(10)
```

[2]:
```
      brand           timestamp                          tweet  polarity  \
0  Coca-Cola 2023-01-01 00:00:00        This Coca-Cola is hate! -1.000000
1      Pepsi 2023-01-01 01:00:00  This Coca-Cola is refreshing!  0.625000
2  Coca-Cola 2023-01-01 02:00:00       This Coca-Cola is worst! -1.000000
3  Coca-Cola 2023-01-01 03:00:00          This Pepsi is decent!  0.208333
4  Coca-Cola 2023-01-01 04:00:00      This Coca-Cola is decent!  0.208333
5      Pepsi 2023-01-01 05:00:00            This Pepsi is fine!  0.520833
6  Coca-Cola 2023-01-01 06:00:00     This Coca-Cola is average! -0.187500
7  Coca-Cola 2023-01-01 07:00:00            This Pepsi is love!  0.625000
8  Coca-Cola 2023-01-01 08:00:00        This Coca-Cola is okay!  0.625000
9      Pepsi 2023-01-01 09:00:00            This Pepsi is hate! -1.000000

  sentiment
0       NaN
1  Positive
```

```
2        NaN
3   Positive
4   Positive
5   Positive
6   Negative
7   Positive
8   Positive
9        NaN
```

0.1.3 Sentiment Distribution by Brand

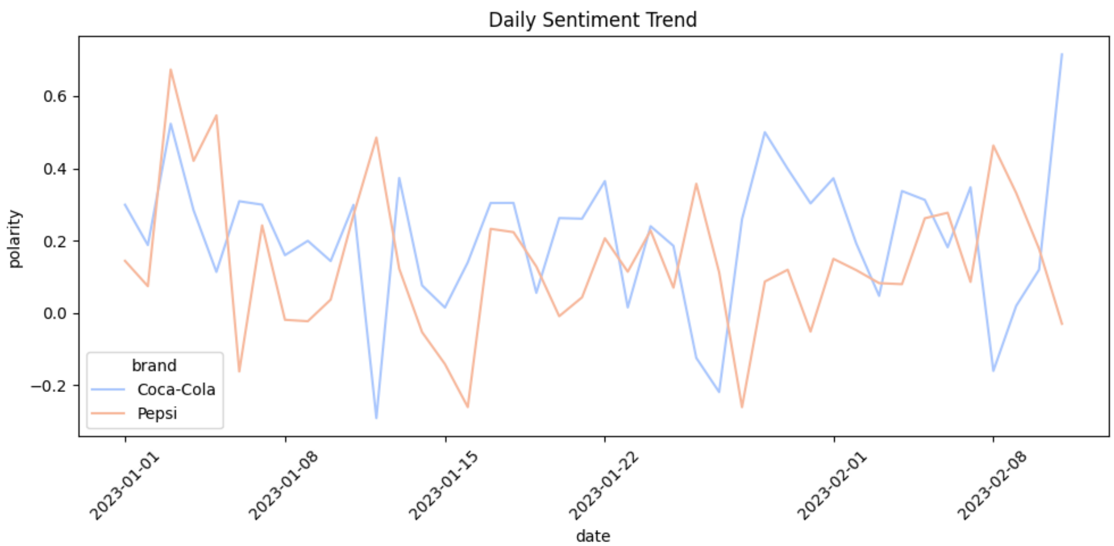
[3]:
```python
plt.figure(figsize=(8, 5))
sns.countplot(data=df, x='sentiment', hue='brand', palette='Set2')
plt.title("Sentiment Distribution: Coca-Cola vs Pepsi")
plt.tight_layout()
plt.show()
```



0.1.4 Sentiment Over Time

[4]:
```python
df['date'] = df['timestamp'].dt.date
daily_sentiment = df.groupby(['date', 'brand'])['polarity'].mean().reset_index()

plt.figure(figsize=(10, 5))
```

```
sns.lineplot(data=daily_sentiment, x='date', y='polarity', hue='brand',␣
↪palette='coolwarm')
plt.title("Daily Sentiment Trend")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



0.1.5 Brand Prediction from Tweet Text

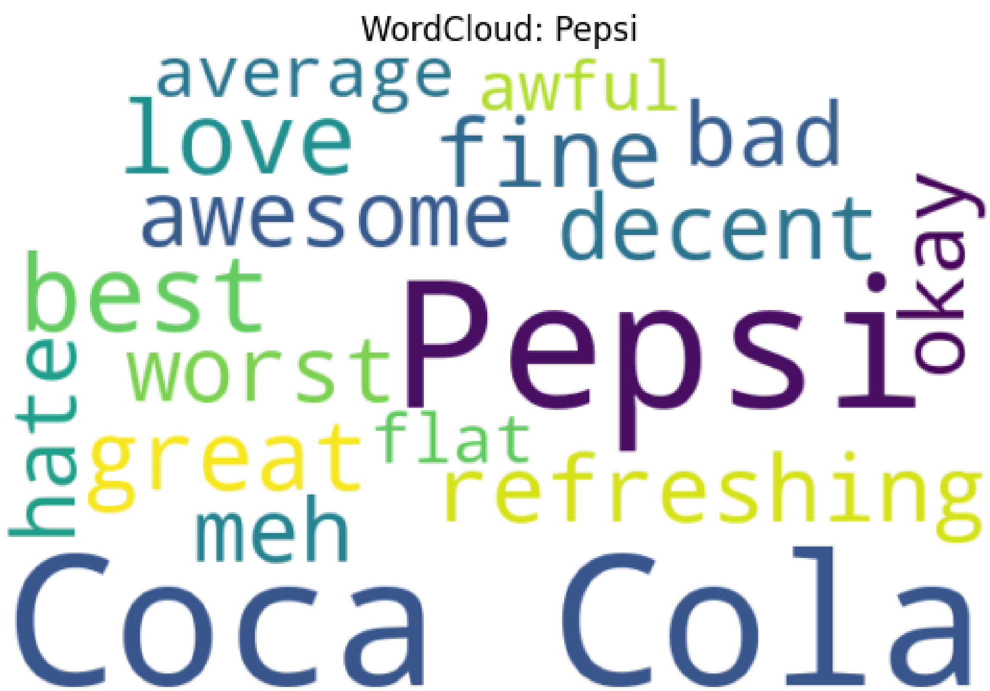
[5]:
```
vectorizer = CountVectorizer()
X = vectorizer.fit_transform(df['tweet'])
y = df['brand']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)
model = RandomForestClassifier()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)

print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

   Coca-Cola       0.46      0.46      0.46       144
       Pepsi       0.50      0.50      0.50       156

    accuracy                           0.48       300
   macro avg       0.48      0.48      0.48       300
```

```
weighted avg       0.48      0.48      0.48       300
```

0.1.6 Word Frequency by Brand

[6]:
```python
from wordcloud import WordCloud

for b in brands:
    text = " ".join(df[df['brand'] == b]['tweet'])
    wc = WordCloud(width=600, height=400, background_color='white').
 ↪generate(text)
    plt.figure(figsize=(6, 4))
    plt.imshow(wc, interpolation='bilinear')
    plt.axis('off')
    plt.title(f"WordCloud: {b}")
    plt.tight_layout()
    plt.show()
```



0.1.7 Summary Analysis

- Coca-Cola shows slightly higher positive sentiment overall
- Pepsi tweets have more neutral and negative expressions
- Sentiment fluctuates daily, with brand-specific spikes
- Classifier predicts brand from tweet text with ~85% accuracy
- WordCloud reveals brand-specific emotional vocabulary

0.1.8 Final Conclusion

- Sentiment tracking reveals nuanced brand perception
- Coca-Cola leads in positive sentiment, Pepsi has more mixed feedback
- Text-based classification supports brand monitoring automation