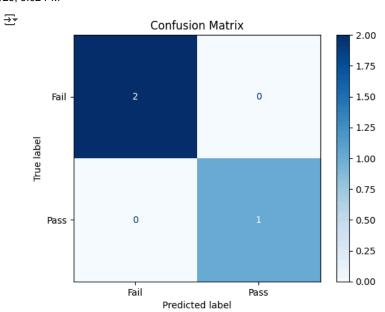
Task 1: Student Pass/Fail Prediction

```
# Step 1: Install and Import Required Libraries
{\tt import\ pandas\ as\ pd}
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from \ sklearn.linear\_model \ import \ LogisticRegression
from \ sklearn.model\_selection \ import \ train\_test\_split
from \ sklearn.metrics \ import \ accuracy\_score, \ confusion\_matrix, \ ConfusionMatrix Display
# Step 2: Create Sample Dataset
data = {
    'Study Hours': [2, 3, 4, 5, 1, 6, 7, 2.5, 3.5, 8, 4.5, 1.5, 9, 6.5, 2],
    'Attendance': [60, 65, 70, 80, 50, 90, 95, 55, 75, 96, 85, 40, 98, 93, 52],
                   [0, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0]
df = pd.DataFrame(data)
# Step 3: Data Exploration
print("\nDataset Preview:")
print(df.head())
\label{lem:print("nChecking for missing values:")} \\
print(df.isnull().sum())
# Visualizing Study Hours vs Attendance
plt.figure(figsize=(8, 5))
\verb|sns.scatterplot(x='Study Hours', y='Attendance', hue='Pass', data=df, palette='Set1')| \\
plt.title('Study Hours vs Attendance (Pass/Fail)')
<del>_</del>
     Dataset Preview:
        Study Hours Attendance
                                  Pass
                                     0
                2.0
                              60
                                     0
                3.0
                              65
                                     0
                4.0
                              70
                5.0
                                     1
                1.0
     Checking for missing values:
     Study Hours
     Attendance
                     0
     Pass
     dtype: int64
                                   Study Hours vs Attendance (Pass/Fail)
         100
                 Pass
                    0
                 • 1
          90
          80
      Attendance
          70
          60
          50
          40
                                                       5
                                                                 6
                                                   Study Hours
# Step 4: Split Data
X = df[['Study Hours', 'Attendance']]
y = df['Pass']
 X\_train, \ X\_test, \ y\_train, \ y\_test = train\_test\_split(X, \ y, \ test\_size=0.2, \ random\_state=42) 
# Step 5: Train Logistic Regression Model
model = LogisticRegression()
model.fit(X_train, y_train)
      ▼ LogisticRegression ① ?
     LogisticRegression()
# Step 6: Predictions
y\_pred = model.predict(X\_test)
# Step 7: Model Evaluation
accuracy = accuracy_score(y_test, y_pred)
cm = confusion_matrix(y_test, y_pred)
print(f"\nAccuracy: {accuracy:.2f}")
₹
     Accuracy: 1.00
# Display Confusion Matrix
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=["Fail", "Pass"])
disp.plot(cmap='Blues')
plt.title('Confusion Matrix')
plt.show()
```



```
# Step 8: Insights

print("\nModel Coefficients (Impact of features):")

coefficients = pd.DataFrame(model.coef_[0], index=X.columns, columns=["Coefficient"])

print(coefficients)

print("\nInsight: Higher study hours and attendance are strongly associated with passing.")
```

Model Coefficients (Impact of features):
Coefficient
Study Hours -0.059434
Attendance 0.738628

Insight: Higher study hours and attendance are strongly associated with passing.

Start coding or generate with AI.

Task 2: Sentiment Analysis with Natural Language Processing

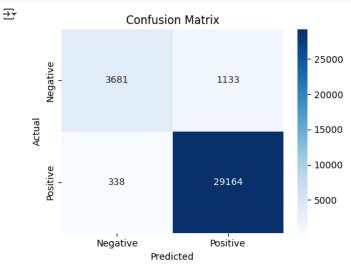
```
# Install
!pip install -q spacy
!python \verb|-m spacy download en_core_web_sm|\\
# Import required libraries
import pandas as pd
\verb"import numpy as np"
{\tt import\ matplotlib.pyplot\ as\ plt}
import seaborn as sns
import re
import spacy
from \ sklearn.model\_selection \ import \ train\_test\_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
from sklearn.metrics import (
    {\tt accuracy\_score, precision\_score, recall\_score,}
    f1_score, confusion_matrix, classification_report
# Load spaCy English model
nlp = spacy.load("en_core_web_sm")
# Upload the file if running in Colab
from google.colab import files
uploaded = files.upload()
# Load the dataset
df = pd.read_csv('reviews.csv')
print(df.head())
     Choose Files No file chosen
                                        Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.
     Saving reviews.csv to reviews (1).csv
                                              product_name product_price Rate \
     0 Candes 12 L Room/Personal Air Cooler??????(Whi...
       Candes 12 L Room/Personal Air Cooler??????(Whi...
     2 Candes 12 L Room/Personal Air Cooler??????(Whi...
                                                                     3999
                                                                             3
       Candes 12 L Room/Personal Air Cooler??????(Whi...
                                                                     3999
     4 Candes 12 L Room/Personal Air Cooler??????(Whi...
                                                                     3999
                                                                     Summary \
                 Review
                 super! great cooler excellent air flow and for this p...
     0
                                     best budget 2 fit cooler nice cooling
                awesome
                   fair the quality is good but the power of air is de...
        useless product
                                          very bad product its a only a fan
                                                               ok ok product
       Sentiment
     0 positive
       positive
     2 positive
       negative
        neutral
# Clean column names (remove spaces)
df.columns = df.columns.str.strip()
# Check available columns
print("Available columns:", df.columns.tolist())
Available columns: ['product_name', 'product_price', 'Rate', 'Review', 'Summary', 'Sentiment']
# Automatically identify 'review' and 'sentiment' columns
review_col = None
sentiment_col = None
for col in df.columns:
   if 'review' in col.lower():
        review_col = col
    if 'sentiment' in col.lower():
        sentiment\_col = col
print(f"Review column: {review_col}")
print(f"Sentiment column: {sentiment_col}")
Review column: Review
     Sentiment column: Sentiment
# Function to clean and lemmatize text
def preprocess(text):
    text = text.lower()
    text = re.sub(r'[^\w\s]', '', text)
    text = re.sub(r'\d+', '', text)
    doc = nlp(text)
    tokens = [token.lemma_ for token in doc if not token.is_stop and token.is_alpha]
    return ' '.join(tokens)
# Apply preprocessing
df = df[[review col, sentiment col]].dropna().reset index(drop=True) # Add reset index(drop=True) here
df['Cleaned_Review'] = df[review_col].astype(str).apply(preprocess)
# Preview cleaned data
df[[review_col, 'Cleaned_Review', sentiment_col]].head()
<del>_</del>
                Review Cleaned_Review Sentiment
      0
                                           positive
                 super!
                                  super
      1
              awesome
                              awesome
                                           positive
      2
                   fair
                                    fair
                                           positive
      3 useless product
                         useless product
                                           negative
                                    fair
                                            neutral
                   fair
# Drop rows with missing values in Review or Sentiment
df.dropna(subset=['Review', 'Sentiment'], inplace=True)
# Now map sentiment to 0/1
\label{eq:dfsentiment'} $$ df['Sentiment'].map(\{'positive': 1, 'negative': 0\}) $$
\ensuremath{\mathtt{\#}} Optional: drop rows where sentiment was neither positive nor negative
df.dropna(subset=['Sentiment'], inplace=True)
```

weighted avg

0.96

0.96

```
X = tfidf.fit_transform(df['Cleaned_Review']).toarray()
y = df['Sentiment']
\mbox{\tt\#} Convert text to TF-IDF vectors
tfidf = TfidfVectorizer()
X = tfidf.fit_transform(df['Cleaned_Review'])
# Convert sentiment to binary
y = df[sentiment_col]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
model = LogisticRegression()
{\tt model.fit(X\_train,\ y\_train)}
      ▼ LogisticRegression ① ?
     LogisticRegression()
\mbox{\tt\#} Clean the test set: remove rows where \mbox{\tt y\_test} is \mbox{\tt NaN}
mask = \sim pd.isnull(y_test)
valid_indices = np.where(mask)[0]
X_test_clean = X_test[valid_indices]
y_test_clean = y_test.iloc[valid_indices] # use .iloc if y_test is a Series
y_pred = model.predict(X_test_clean)
# Evaluate
print("Accuracy:", accuracy_score(y_test_clean, y_pred))
print("Precision:", precision_score(y_test_clean, y_pred, pos_label=1.0)) # or pos_label=1
print("Recall:", recall_score(y_test_clean, y_pred, pos_label=1.0))
print("F1 Score:", f1_score(y_test_clean, y_pred, pos_label=1.0))
# Detailed classification report (auto-detects labels)
print("\nClassification Report:\n", classification_report(y_test_clean, y_pred))
Accuracy: 0.9571336985662665
     Precision: 0.9626035581080635
     Recall: 0.9885431496169751
     F1 Score: 0.9754009264368969
     Classification Report:
                                  recall f1-score
                                                    support
                    precision
              0.0
                         0.92
                                   0.76
                                             0.83
                                                        4814
              1.0
                         0.96
                                   0.99
                                             0.98
                                                      29502
                                             0.96
                                                      34316
         accuracy
                         0.94
                                   0.88
                                             0.90
                                                      34316
        macro avg
```



Correctly classified negative reviews:

did not meet expectations

horrible

unsatisfactory

27724

73221 7181 34316

0.96

```
test_results = pd.DataFrame({
    'Review Text': df.loc[y_test_clean.index][review_col], # Use y_test_clean.index and review_col
    'Sentiment': y_test_clean.values, # Use y_test_clean.values
    'Predicted': y_pred
})
# Correctly classified samples
print("Correctly classified positive reviews:")
print(test\_results[(test\_results['Sentiment'] == 1) \& (test\_results['Predicted'] == 1)]. \\ head(3)['Review Text'])
print("\nCorrectly classified negative reviews:")
print(test_results[(test_results['Sentiment'] == 0) & (test_results['Predicted'] == 0)].head(3)['Review Text'])
# Misclassified samples
print("\nIncorrectly classified as positive:")
print(test_results[(test_results['Sentiment'] == 0) & (test_results['Predicted'] == 1)].head(3)['Review Text'])
print("\nIncorrectly classified as negative:")
print(test\_results[(test\_results['Sentiment'] == 1) \& (test\_results['Predicted'] == 0)]. \\ head(3)['Review Text'])
→ Correctly classified positive reviews:
     133769
                  great product
     39685
                 perfect product!
              best in the market!
     160332
     Name: Review Text, dtype: object
```

```
Name: Review Text, dtype: object
Incorrectly classified as positive:  \\
15257
                   nice
         decent product
174594
94895
                   fair
Name: Review Text, dtype: object
Incorrectly classified as negative:
               could be way better
16297
          expected a better product
109404
                          very poor
Name: Review Text, dtype: object
```

```
# Top positive and negative words
feature_names = np.array(tfidf.get_feature_names_out())
coefficients = model.coef_[0]
top_pos_idx = np.argsort(coefficients)[-10:]
top_neg_idx = np.argsort(coefficients)[:10]
print("Top Positive Sentiment Words:\n", feature_names[top_pos_idx])
print("\nTop Negative Sentiment Words:\n", feature_names[top_neg_idx])
Top Positive Sentiment Words:
      ['super' 'awesome' 'brilliant' 'wow' 'buy' 'worth' 'fabulous' 'terrific' 'market' 'highly']
     Top Negative Sentiment Words:
['terrible' 'useless' 'bad' 'expect' 'waste' 'hate' 'worthless'
       'recommend' 'poor' 'unsatisfactory']
# Extract top positive and negative word coefficients
feature_names = np.array(tfidf.get_feature_names_out())
coefficients = model.coef_[0]
# Sort features
top_n = 10
```

reature_names = np.array(tridf.get_reature_names_out())
coefficients = model.coef_[0]

Sort features
top_n = 10
top_pos_idx = np.argsort(coefficients)[-top_n:]
top_neg_idx = np.argsort(coefficients)[:top_n]

top_features = np.concatenate([top_neg_idx, top_pos_idx])
top_words = feature_names[top_features]

top_coeffs = coefficients[top_features]

Create bar plot
plt.figure(figsize=(12, 6))
colors = ['red'] * top_n + ['green'] * top_n
plt.barh(top_words, top_coeffs, color=colors)
plt.axvline(0, color='black')
plt.title("Top Influential Words for Sentiment Classification")
plt.xlabel("Logistic Regression Coefficient")
plt.ylabel("Words")
plt.tight_layout()
plt.show()



