DATA ANALYSIS

COURSE PRESENTER
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Sentiment140 dataset with 1.6 million tweets

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INTRODUCTION

The **Sentiment140 dataset** is a widely used resource for sentiment analysis, comprising 1.6 million tweets. It was created to facilitate research and development in natural language processing (NLP) and machine learning, particularly in sentiment classification.

The tweets were collected using Twitter's API and pre-processed to remove irrelevant information, ensuring a clean and rich dataset for analysis.

OBJECTIVE

perform sentiment analysis on the Sentiment140 dataset to classify the sentiment expressed in tweets as positive, negative, or neutral.

DATA EXPLORATION

In this step we are focusing on understanding the structure of the data by:

Displaying Data Information
df.columns: Prints the names of all columns in the DataFrame.
df.describe().T: Provides descriptive statistics (like count, mean, standard deviation, etc.) for numerical columns, transposed for easier reading.
df.info(): Displays a concise summary of the DataFrame, including the number of non-null entries and data types for each column.
df.head(): Shows the first five rows of the DataFrame, giving a quick look at the data.

Renaming Columns
renames the columns to more meaningful names. This improves readability and makes it easier to understand the data:

- The first column is renamed to "target".
- The second column is renamed to "id".
- The date column is renamed to "date."
- A flag column is renamed to "flag".
- A user column is renamed to "user".

The sixth column (the exact name isn't specified) is renamed to "text" for the textual data

Checking for Missing Values
There are no missing values

Selecting Columns for Analysis
Select 'target', 'user', 'flag', 'id', 'date', 'text' columns this ensures that the upcoming operations focus only on these specific columns

Counting Unique Values in Each Column
It uses value_counts() to display the frequency of unique values in that column, which helps in understanding the distribution of data.

VISUALIZATION

```
import matplotlib.pyplot as plt
from wordcloud import WordCloud
# النصوص الإيجابية
positive_text = ' '.join(df[df['target'] == 4]['text'])  # تأكد من استخدام القيمة الصحيحة للإيجابية

# إنشاء سحابة الكلمات للنصوص الإيجابية
positive_wordcloud = WordCloud(width=800, height=400, background_color='white').generate(positive_text)

# عرض سحابة الكلمات للنصوص الإيجابية
plt.figure(figsize=(10, 5))
plt.imshow(positive_wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('wordcloudTekst Positif')  # عنوان السحابة
plt.show()
```

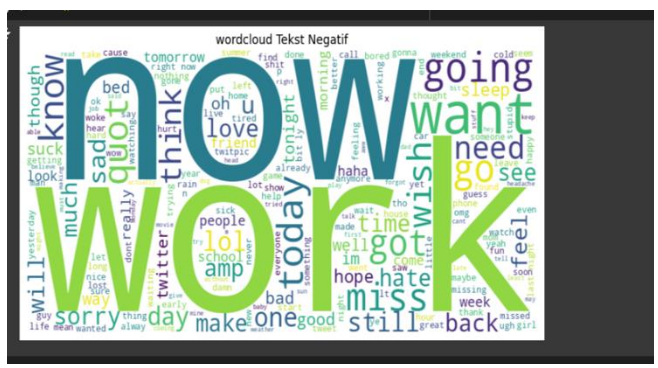
```
import matplotlib.pyplot as plt
from wordcloud import WordCloud
# النصوص السلبية
negative_text = ' '.join(df[df['target'] == 0]['text'])  # تأكد من استخدام القيمة الصحيحة للسلبية

# إنشاء سحابة الكلمات للنصوص السلبية
negative_wordcloud = WordCloud(width=800, height=400, background_color='white').generate(negative_text)

# عرض سحابة الكلمات للنصوص السلبية
plt.figure(figsize=(10, 5))
plt.imshow(negative_wordcloud, interpolation='bilinear')
plt.axis('off')
plt.title('wordcloud Tekst Negatif')  # عنوان السحابة
plt.show()
```

The overall function of this code is to create a visual representation of the most common words found in a collection of positive texts from a Data Frame. The words that appear most frequently are displayed in larger font sizes, making it easy to identify key themes or sentiments in the text data.

Also used the same code for the negative words, but change the target to 0 (negative).



we can see the difference between the negative word cloud and the positive word cloud, the words like love, thank, and ha-ha…are the most frequent in positive texts and the words like now, work, and sorry are the most frequent in negative texts.

TEXT PREPROCESSING

```python
# 1. تنظيف عمود النص
if 'text' in df.columns:
    df['text'] = df['text'].str.replace(r'http\S+|www\S+|https\S+', '', case=False)  # وابط
    df['text'] = df['text'].str.replace(r'\@\w+|\#', '', regex=True)  # ذف الأسماء والعلامات
    df['text'] = df['text'].str.replace(r'\W', ' ', regex=True)  # حذف الرموز
    df['text'] = df['text'].str.lower()  # تحويل النصوص إلى أحرف صغيرة
    df['text'] = df['text'].str.strip()  # إزالة المسافات الزائدة
else:
    print("العمود 'text' غير موجود في DataFrame.")
```

```python
# 2. تنظيف عمود التاريخ
if 'date' in df.columns:
    df['date'] = pd.to_datetime(df['date'], format='%a %b %d %H:%M:%S %Z %Y', errors='coerce'

# 3. تنظيف عمود الهدف (target)
if 'target' in df.columns:
    df['target'] = df['target'].astype('category')  # تحويل إلى نوع فئة

# 4. تنظيف عمود المستخدم (user)
if 'user' in df.columns:
    df['user'] = df['user'].str.strip()  # إزالة المسافات الزائدة

# 5. تنظيف عمود الاستعلام (flag)
if 'flag' in df.columns:
    df['flag'] = df['flag'].str.strip()  # إزالة المسافات الزائدة

# 6. تنظيف عمود المعرف (id)
if 'id' in df.columns:
    df['id'] = df['id'].astype(str)  # تحويل معرف التغريدة إلى سلسلة نصية
# عرض البيانات بعد التنظيف
print("عرض البيانات بعد التنظيف:", df.head())
```

Cleaning the Text Column

- Check for 'text' Column
- Remove URLs
- Remove Usernames and Hashtags
- Remove Special Characters
- Convert to Lowercase
- Error handling

Cleaning the Date Column

- Check for 'date' Column
- Convert to Datetime

Cleaning the Target Column

- Check for 'target' Column
- Convert to Categorical

Cleaning the Flag Column

- Check for 'flag' Column
- Strip Extra Spaces

Cleaning the ID Column

- Check for 'id' Column

Display Cleaned Data: After all the cleaning steps, the first few rows of the cleaned Data Frame are displayed using print, allowing for a quick review of the results.

```python
import nltk
from nltk.corpus import stopwords

# تحميل قائمة كلمات التوقف
nltk.download('stopwords')
stop_words = set(stopwords.words('english'))

# دالة لإزالة كلمات التوقف
def remove_stopwords(text):
    return ' '.join([word for word in text.split() if word.lower(

# حصر الأعمدة النصية
text_columns = ['text','flag','user']

# تطبيق إزالة كلمات التوقف على الأعمدة النصية
for column in text_columns:
    df[column] = df[column].apply(remove_stopwords)

# عرض البيانات بعد إزالة كلمات التوقف
print(df.head())
```

This code snippet is focused on removing stop words from specific text columns in a pandas Data Frame. Stop words are commonly used words (like "and," "the," "is," etc.) that are often filtered out in natural language processing (NLP) because they carry little meaningful information.

```python
import nltk
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer

# تأكد من تحميل المكتبات المطلوبة
nltk.download('punkt')
nltk.download('wordnet')
nltk.download('omw-1.4')

# إنشاء كائن من WordNetLemmatizer
lemmatizer = WordNetLemmatizer()

# دالة لتطبيق Tokenization وLemmatization
def tokenize_and_lemmatize(text):
    # Tokenization
    tokens = word_tokenize(text)
    # Lemmatization
    lemmatized_tokens = [lemmatizer.lemmatize(token) for token in tokens]
    return lemmatized_tokens

# تطبيق الدالة على عمود 'text'
df['processed_text'] = df['text'].apply(tokenize_and_lemmatize)

# عرض البيانات بعد المعالجة
print(df[['text', 'processed_text']].head())
```

this code is aimed at preparing text data for further analysis by breaking it down into its basic components (tokens) and reducing those components to their root forms (lemmatization). This preprocessing step is essential for many natural language processing tasks, as it helps for standardizing the text and removing

BUILD NAÏVE BAYES MODEL

```python
import pandas as pd
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import classification_report

# تقسيم البيانات إلى الميزات (X) والأهداف (y)
X = df['text']  # النصوص
y = df['target']  # المشاعر الفعلية (0 للسلبية و 4 للإيجابية)

# تقسيم البيانات إلى بيانات تدريب وبيانات اختبار
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# تحويل النصوص إلى تمثيل TF-IDF
vectorizer = TfidfVectorizer(ngram_range=(1, 2))
X_train_tfidf = vectorizer.fit_transform(X_train)
X_test_tfidf = vectorizer.transform(X_test)

model = MultinomialNB()
model.fit(X_train_tfidf, y_train)

# التنبؤ بالمشاعر على مجموعة الاختبار
y_pred = model.predict(X_test_tfidf)

# عرض التقرير التصنيفي للمشاعر المتوقعة
print(classification_report(y_test, y_pred))

# حفظ التنبؤات في DataFrame الأصلي
df['predicted_sentiment'] = model.predict(vectorizer.transform(df['text']))

# عرض بعض النتائج
print(df[['text', 'predicted_sentiment']].head())
```

Preparing the Data:

- It defines the text data and the corresponding sentiment labels from the dataset. The labels indicate whether the sentiment is negative or positive.

Splitting the Data:

- The dataset is divided into training and testing sets, with 80% of the data used for training the model and 20%for testing.

Transforming Text Data:

- The text data is converted into a numerical format using a technique called TF-IDF. This representation captures both individual words and pairs of words (bigrams), making it suitable for the model.

Training the Model:

- A Naive Bayes classifier is created and trained on the transformed training data.

Making Predictions:

- The trained model is used to predict sentiments for the test set.

Evaluating the Model:

- The model's performance is assessed using metrics like precision, recall, and F1-score, which provide insights into how well it classifies the sentiments.

Making Predictions for the Entire Dataset:

- The model is then used to predict sentiments for the entire dataset, adding a new column to indicate these predicted sentiments.

Displaying Results:

- the script displays a few examples from the dataset, showing the original text along with its predicted sentiment.

BUILD LOGISTIC REGRESSION MODEL

```
+ Code  + Text

from sklearn.linear_model import LogisticRegression  # استخدام Logistic Regression

# تقسيم البيانات إلى الميزات (X) والأهداف (y)
X = df['text']  # النصوص
y = df['target']  # المشاعر الفعلية (0 للسلبية و 4 للإيجابية)

# تقسيم البيانات إلى بيانات تدريب وبيانات اختبار
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# تحويل النصوص إلى تمثيل TF-IDF
vectorizer = TfidfVectorizer(ngram_range=(1, 2))  # يمكنك استخدام unigram و bigram
X_train_tfidf = vectorizer.fit_transform(X_train)
X_test_tfidf = vectorizer.transform(X_test)

# بناء نموذج Logistic Regression
model = LogisticRegression(max_iter=1000)  # زيادة max_iter إذا واجه النموذج مشاكل في التقارب
model.fit(X_train_tfidf, y_train)

# التنبؤ بالمشاعر على مجموعة الاختبار
y_pred = model.predict(X_test_tfidf)

# عرض التقرير التصنيفي للمشاعر المتوقعة
print(classification_report(y_test, y_pred))

# حفظ التنبؤات في DataFrame الأصلي
df['predicted_sentiment'] = model.predict(vectorizer.transform(df['text']))

# عرض بعض النتائج
print(df[['text', 'predicted_sentiment']].head())
```

Prepare Data:
- X gets the text data from the Data Frame, and y gets the sentiment labels (0 for negative, 4 for positive).

Split Data:
- The dataset is divided into training and testing sets, with 20% for testing.

Text Processing:
- It uses TfidfVectorizer to convert the text into numerical format, considering both single words (unigrams) and pairs of words (bigrams).

Train Model:
- A logistic regression model is created and trained on the processed training data.

Make Predictions:
- The model predicts sentiments for the test set.

Evaluate Model:
- It prints a classification report to show how well the model performed.

Store Predictions:
- Predictions for all texts are added to the original Data Frame.

Display Results:
- The script shows a few examples from the DataFrame, displaying the original text and the model's predicted sentiment.

LOGISTIC REGRESSION

```
              precision    recall  f1-score   support

           0       0.80      0.78      0.79    159494
           4       0.79      0.80      0.79    160506

    accuracy                           0.79    320000
   macro avg       0.79      0.79      0.79    320000
weighted avg       0.79      0.79      0.79    320000

                                              text  predicted_sentiment
0  upset update facebook texting might cry result...                    0
1  dived many times ball managed save 50 rest go ...                    4
2                    whole body feels itchy like fire                    0
3                                    behaving mad see                    0
4                                          whole crew                    4
```

The overall accuracy of the model is **0.79**, meaning it correctly classified **79%** of the instances across both classes.

NAÏVE BAYES (multinomial)

```
              precision    recall  f1-score   support

           0       0.77      0.80      0.78    159494
           4       0.79      0.76      0.78    160506

    accuracy                           0.78    320000
   macro avg       0.78      0.78      0.78    320000
weighted avg       0.78      0.78      0.78    320000

                                              text  predicted_sentiment
0  upset update facebook texting might cry result...                    0
1  dived many times ball managed save 50 rest go ...                    0
2                    whole body feels itchy like fire                    0
3                                    behaving mad see                    0
4                                          whole crew                    4
```

The overall accuracy of the model is **0.78**, indicating it correctly classified **78%** of the total instances across both classes.