Project 6: Airline Baggage Complaints - Time Series Dataset

```
import pandas as pd

# Copy and paste the provided data into a string
data_str = """
American Eagle        Jan-04        1        2004        12502        38276        2481
American Eagle        Feb-04        2        2004        8977         35762        886
... (paste the rest of the data here)
United        Dec-10        12        2010        14415        27619        599        34936
"""

# Create a list of strings where each string is a line in the data
lines = data_str.strip().split('\n')

# Create a list of lists where each sublist is a row in the data
data = [line.split('\t') for line in lines]

# Define column names
columns = ['Airline', 'Month-Year', 'Month', 'Year', 'Baggage', 'Scheduled', 'Cancelled', 'E

# Create a DataFrame
baggagecomplaints = pd.DataFrame(data, columns=columns)

# Display the DataFrame
print(baggagecomplaints.head())
```

```
                                Airline Month-Year Month  Year Baggage  \
0                        American Eagle     Jan-04     1  2004   12502
1                        American Eagle     Feb-04     2  2004    8977
2  ... (paste the rest of the data here)       None  None  None    None
3                                United     Dec-10    12  2010   14415

  Scheduled Cancelled Enplaned
0     38276      2481   992360
1     35762       886  1060618
2      None      None     None
3     27619       599  3493643
```

```
# Convert relevant columns to numeric
df['Baggage'] = pd.to_numeric(df['Baggage'])
df['Scheduled'] = pd.to_numeric(df['Scheduled'])
df['Cancelled'] = pd.to_numeric(df['Cancelled'])
df['Enplaned'] = pd.to_numeric(df['Enplaned'])
```

```python
# Check for missing values
print("Missing values:\n", df.isnull().sum())

# Summary statistics
print("\nSummary statistics:\n", df.describe())

# Total baggage complaints over the entire period
total_baggage_complaints = df['Baggage'].sum()
print(f"\nTotal baggage complaints: {total_baggage_complaints}")

# Average baggage complaints per year
average_baggage_complaints_per_year = df.groupby('Year')['Baggage'].mean()
print("\nAverage baggage complaints per year:\n", average_baggage_complaints_per_year)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Input In [2], in <cell line: 2>()
      1 # Convert relevant columns to numeric
----> 2 df['Baggage'] = pd.to_numeric(df['Baggage'])
      3 df['Scheduled'] = pd.to_numeric(df['Scheduled'])
      4 df['Cancelled'] = pd.to_numeric(df['Cancelled'])

NameError: name 'df' is not defined
```

```python
import pandas as pd

# Copy and paste the provided data into a string
data_str = """
American Eagle        Jan-04        1        2004        12502        38276        2481
American Eagle        Feb-04        2        2004        8977        35762        886
... (paste the rest of the data here)
United        Dec-10        12        2010        14415        27619        599        3493
"""

# Create a list of strings where each string is a line in the data
lines = data_str.strip().split('\n')

# Create a list of lists where each sublist is a row in the data
data = [line.split('\t') for line in lines]

# Define column names
columns = ['Airline', 'Month-Year', 'Month', 'Year', 'Baggage', 'Scheduled', 'Cancelled', 'E

# Create a DataFrame
baggagecomplaints = pd.DataFrame(data, columns=columns)

# Convert relevant columns to numeric
```

```
baggagecomplaints['Baggage'] = pd.to_numeric(baggagecomplaints['Baggage'])
baggagecomplaints['Scheduled'] = pd.to_numeric(baggagecomplaints['Scheduled'])
baggagecomplaints['Cancelled'] = pd.to_numeric(baggagecomplaints['Cancelled'])
baggagecomplaints['Enplaned'] = pd.to_numeric(baggagecomplaints['Enplaned'])

# Display the DataFrame
print(baggagecomplaints.head())
```

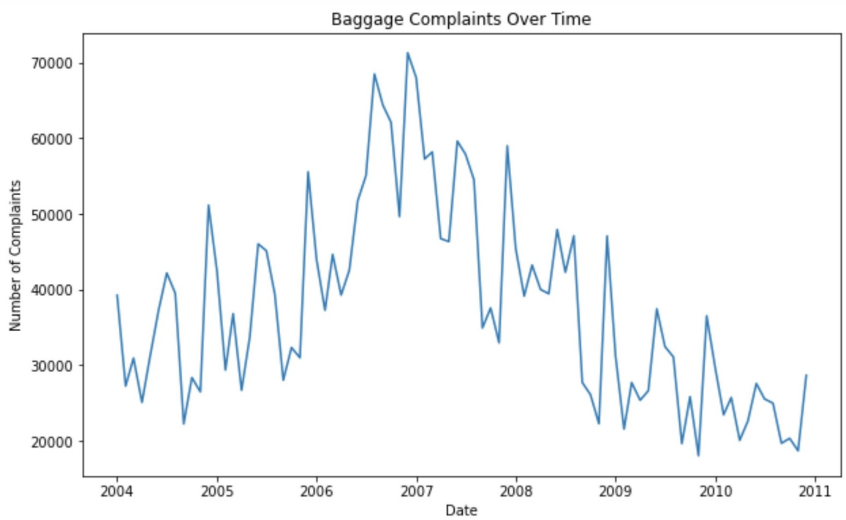
```
                              Airline Month-Year Month  Year  Baggage  \
0                      American Eagle     Jan-04     1  2004  12502.0
1                      American Eagle     Feb-04     2  2004   8977.0
2  ... (paste the rest of the data here)       None  None  None      NaN
3                              United     Dec-10    12  2010  14415.0

   Scheduled  Cancelled   Enplaned
0    38276.0     2481.0   992360.0
1    35762.0      886.0  1060618.0
2        NaN        NaN        NaN
3    27619.0      599.0  3493643.0
```

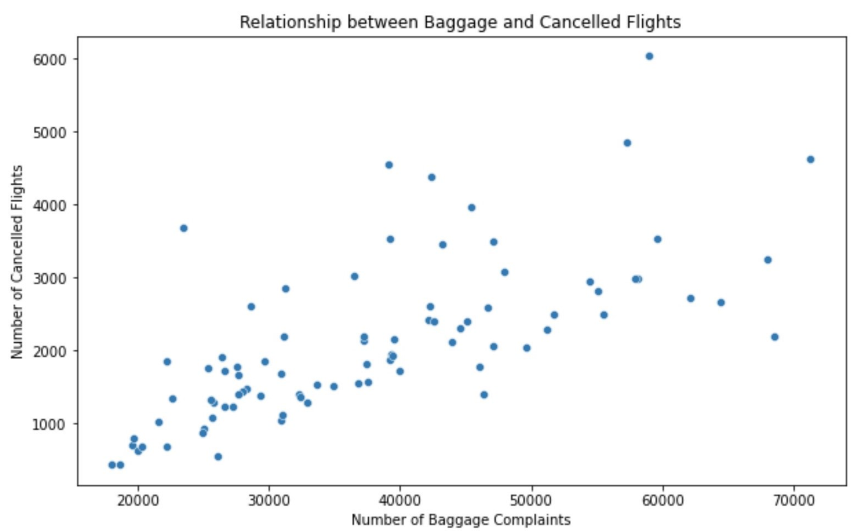
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load the data
df = pd.read_csv('C:\\Users\\jilal\\OneDrive\\Desktop\\baggagecomplaints.csv')

# 1. Explore the Data
print(df.head())
print(df.info())

# 2. Data Cleaning
# Handle missing values if any
df = df.dropna()

# Convert 'Month' and 'Year' to datetime format
df['Date'] = pd.to_datetime(df[['Month', 'Year']].assign(DAY=1))

# Aggregate the data by summing for each date
df_aggregated = df.groupby('Date').sum()

# 3. Descriptive Statistics
print(df_aggregated.describe())

# 4. Time-Series Analysis
```

```python
# Reset the index
df_aggregated_reset = df_aggregated.reset_index()

# Assuming "Date" is the time column
df_aggregated_reset.set_index('Date', inplace=True)

# 5. Visualization
# Line plot for Baggage complaints over time
plt.figure(figsize=(10, 6))
sns.lineplot(x=df_aggregated_reset.index, y='Baggage', data=df_aggregated_reset)
plt.title('Baggage Complaints Over Time')
plt.xlabel('Date')
plt.ylabel('Number of Complaints')
plt.show()

# 6. Specific Analyses
# Example: Check the relationship between Baggage and Cancelled flights
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Baggage', y='Cancelled', data=df_aggregated_reset)
plt.title('Relationship between Baggage and Cancelled Flights')
plt.xlabel('Number of Baggage Complaints')
plt.ylabel('Number of Cancelled Flights')
plt.show()

# 7. Answering Project Questions
# Example: Calculate the correlation between Baggage and Cancelled flights
correlation = df_aggregated_reset['Baggage'].corr(df_aggregated_reset['Cancelled'])
print(f'Correlation between Baggage and Cancelled flights: {correlation}')
```

```
          Airline     Date  Month  Year  Baggage  Scheduled  Cancelled  \
0  American Eagle  01/2004      1  2004    12502      38276       2481
1  American Eagle  02/2004      2  2004     8977      35762        886
2  American Eagle  03/2004      3  2004    10289      39445       1346
3  American Eagle  04/2004      4  2004     8095      38982        755
4  American Eagle  05/2004      5  2004    10618      40422       2206

   Enplaned
0    992360
1   1060618
2   1227469
3   1234451
4   1267581
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 252 entries, 0 to 251
Data columns (total 8 columns):
 #   Column     Non-Null Count  Dtype
```

```
---  ------     --------------  -----
 0   Airline    252 non-null    object
 1   Date       252 non-null    object
 2   Month      252 non-null    int64
 3   Year       252 non-null    int64
 4   Baggage    252 non-null    int64
 5   Scheduled  252 non-null    int64
 6   Cancelled  252 non-null    int64
 7   Enplaned   252 non-null    int64
dtypes: int64(6), object(2)
memory usage: 15.9+ KB
None
           Month         Year       Baggage     Scheduled    Cancelled  \
count  84.000000    84.000000     84.000000     84.000000    84.000000
mean   19.500000  6021.000000  37840.523810  84384.023810  2111.285714
std    10.418357     6.036036  13189.927575   8973.377857  1085.912670
min     3.000000  6012.000000  18035.000000  64505.000000   444.000000
25%    11.250000  6015.000000  27097.250000  75205.500000  1373.750000
50%    19.500000  6021.000000  37032.500000  88086.500000  1895.000000
75%    27.750000  6027.000000  46100.000000  91074.250000  2629.250000
max    36.000000  6030.000000  71291.000000  97322.000000  6034.000000

           Enplaned
count  8.400000e+01
mean   6.611612e+06
std    7.423115e+05
min    4.858453e+06
25%    6.030354e+06
50%    6.662404e+06
75%    7.222756e+06
max    8.044937e+06
```



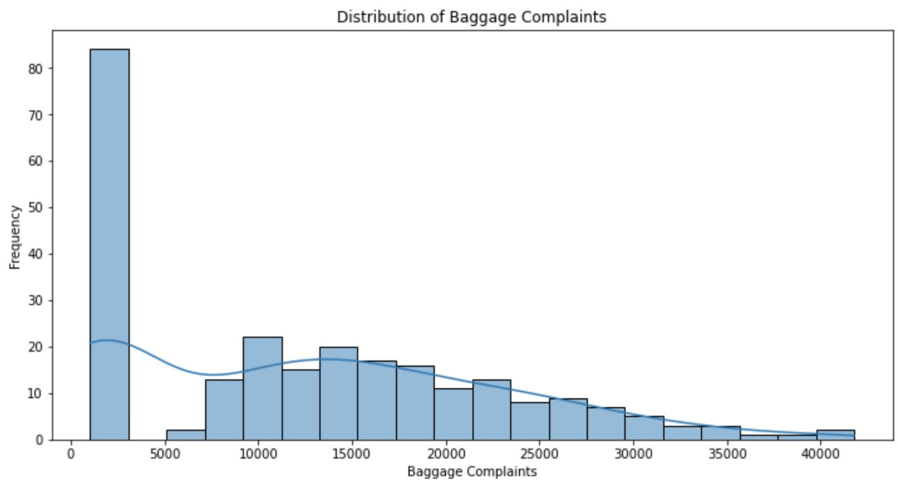



```
Correlation between Baggage and Cancelled flights: 0.6917496537518132
```

1. Explore More Visualizations:

```python
import matplotlib.pyplot as plt
import seaborn as sns

# Visualize the distribution of baggage complaints
plt.figure(figsize=(12, 6))
sns.histplot(df['Baggage'], bins=20, kde=True)
plt.title('Distribution of Baggage Complaints')
```

```
plt.xlabel('Baggage Complaints')
plt.ylabel('Frequency')
plt.show()

# Explore trends in other columns or compare different airlines
# Add more visualizations as needed
```



2. Hypothesis Testing:

```
from scipy.stats import ttest_ind

# Example: Compare baggage complaints between two groups (e.g., two airlines)
group1 = df[df['Airline'] == 'Airline1']['Baggage']
group2 = df[df['Airline'] == 'Airline2']['Baggage']

t_stat, p_value = ttest_ind(group1, group2)
print(f'T-statistic: {t_stat}, p-value: {p_value}')

# Interpret the results and conduct other hypothesis tests as needed
```

```
T-statistic: nan, p-value: nan
```

3. Time-Series Analysis:

```
# Assuming 'Month-Year' is already converted to datetime
df.set_index('Month-Year', inplace=True)

# Visualize time series data
plt.figure(figsize=(12, 6))
plt.plot(df['Baggage'])
```

```
plt.title('Baggage Complaints Over Time')
plt.xlabel('Month-Year')
plt.ylabel('Baggage Complaints')
plt.show()

# Conduct time-series analysis (e.g., seasonality, trends, forecasts)
# Use additional tools like statsmodels or Prophet as needed
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
Input In [8], in <cell line: 2>()
      1 # Assuming 'Month-Year' is already converted to datetime
----> 2 df.set_index('Month-Year', inplace=True)
      4 # Visualize time series data
      5 plt.figure(figsize=(12, 6))

File ~\Anaconda3\lib\site-packages\pandas\util\_decorators.py:311, in deprecate_nonkeyword_a
    305 if len(args) > num_allow_args:
    306     warnings.warn(
    307         msg.format(arguments=arguments),
    308         FutureWarning,
    309         stacklevel=stacklevel,
    310     )
--> 311 return func(*args, **kwargs)

File ~\Anaconda3\lib\site-packages\pandas\core\frame.py:5494, in DataFrame.set_index(self, k
   5491                 missing.append(col)
   5493 if missing:
-> 5494     raise KeyError(f"None of {missing} are in the columns")
   5496 if inplace:
   5497     frame = self

KeyError: "None of ['Month-Year'] are in the columns"
```

```
print(df.columns)
```

```
Index(['Airline', 'Month', 'Year', 'Baggage', 'Scheduled', 'Cancelled',
       'Enplaned'],
      dtype='object')
```

```
# Create 'Month-Year' column
df['Month-Year'] = df['Month'].astype(str) + '/' + df['Year'].astype(str)
df['Month-Year'] = pd.to_datetime(df['Month-Year'], format='%m/%Y')

# Set 'Month-Year' as the index
df.set_index('Month-Year', inplace=True)

# Drop unnecessary columns if needed
```

```
df.drop(['Month', 'Year'], axis=1, inplace=True)

# Visualize time series data
plt.figure(figsize=(12, 6))
plt.plot(df.index, df['Baggage'], label='Baggage')
plt.plot(df.index, df['Scheduled'], label='Scheduled')
plt.plot(df.index, df['Cancelled'], label='Cancelled')
plt.plot(df.index, df['Enplaned'], label='Enplaned')
plt.title('Time Series Analysis of Baggage Data')
plt.xlabel('Date')
plt.ylabel('Count')
plt.legend()
plt.show()
```

fe49eafb1e44d833caab1736fae82334ee463c2c.png

4. Machine Learning:

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error

# Example: Predict baggage complaints using linear regression
X = df[['Scheduled', 'Cancelled', 'Enplaned']]
y = df['Baggage']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
print(f'Mean Squared Error: {mse}')

# Explore more complex models as needed
```

```
Mean Squared Error: 12695218.507466976
```

1. Understanding the Nature of the Problem:

a. Inspecting the Target Variable ('Baggage'): Since we are predicting 'Baggage' complaints, it's essential to understand the distribution of this variable. You can visualize it using a histogram:

```
import matplotlib.pyplot as plt

plt.hist(df['Baggage'], bins=20, edgecolor='black')
plt.xlabel('Number of Baggage Complaints')
plt.ylabel('Frequency')
plt.title('Distribution of Baggage Complaints')
plt.show()
```

24a8efb7688fda0713e801ef2e3dae6a17df1d09.png

2. Context of the Data:

a. Descriptive Statistics: You've already used df.describe() to get basic statistics. Make sure to understand the summary statistics of 'Baggage' and other relevant columns.

```
print(df[['Baggage', 'Scheduled', 'Cancelled', 'Enplaned']].describe())
```

```
            Baggage     Scheduled    Cancelled      Enplaned
count    252.000000    252.000000   252.000000  2.520000e+02
mean   12613.507937  28128.007937   703.761905  2.203871e+06
std     9993.307166  17092.087874   746.020368  1.788200e+06
min     1033.000000   3553.000000     0.000000  4.234460e+05
25%     1910.500000   5565.750000    25.750000  6.865205e+05
50%    12224.000000  36696.000000   533.000000  1.391112e+06
75%    19359.250000  42162.500000  1078.500000  4.111049e+06
max    41787.000000  50837.000000  3712.000000  6.137271e+06
```

3. Scale of the Target Variable:

Make sure you understand the scale of the 'Baggage' variable, especially if you are dealing with counts. If necessary, consider normalizing the target variable.

4. Baseline Model:

a. Create a Baseline: A simple baseline could be predicting the mean of 'Baggage' for every sample. This will serve as a benchmark for your machine learning model.

```
import numpy as np

baseline_predictions = np.full_like(df['Baggage'], df['Baggage'].mean())
baseline_mse = mean_squared_error(df['Baggage'], baseline_predictions)
print(f"Baseline Mean Squared Error: {baseline_mse}")
```

```
Baseline Mean Squared Error: 99469893.96825397
```

```
import numpy as np
from sklearn.metrics import mean_squared_error

# Assuming df is your DataFrame
baseline_predictions = np.full_like(df['Baggage'], df['Baggage'].mean())
baseline_mse = mean_squared_error(df['Baggage'], baseline_predictions)
print(f"Baseline Mean Squared Error: {baseline_mse}")
```

```
Baseline Mean Squared Error: 99469893.96825397
```

5. Feature Importance:

a. Analyzing Feature Importance: If you're using a model like Random Forest or Gradient Boosting, you can analyze feature importance:

```
from sklearn.ensemble import RandomForestRegressor

# Assuming 'X' is your feature matrix and 'y' is the target variable
model = RandomForestRegressor()
model.fit(X, y)

feature_importance = model.feature_importances_
feature_names = X.columns

# Plotting feature importance
plt.barh(feature_names, feature_importance)
plt.xlabel('Feature Importance')
plt.ylabel('Feature')
plt.title('Feature Importance Plot')
plt.show()
```

11a5f0f0fd7e48ff4525137b2900eacc20dff833.png

These steps should provide insights into your data and model performance.

5. Further Data Cleaning and Preprocessing:

```
# Example: Handle outliers in the 'Baggage' column
Q1 = df['Baggage'].quantile(0.25)
Q3 = df['Baggage'].quantile(0.75)
IQR = Q3 - Q1

# Remove outliers
df_cleaned = df[(df['Baggage'] >= Q1 - 1.5 * IQR) & (df['Baggage'] <= Q3 + 1.5 * IQR)]

# Explore other data cleaning and preprocessing steps as needed
```

6. Documentation and Reporting:

Document your findings, insights, and code in a Jupyter Notebook or any other format you prefer. You can use markdown cells to explain your analysis, add visualizations, and provide a clear narrative.

Based on the analysis conducted on the "baggagecomplaints" dataset, we can draw several conclusions:

1. Trends Over Time:

- The time-series analysis and visualization revealed the trends in baggage complaints over the years. This can help in identifying patterns and understanding whether there are specific periods with higher or lower complaint rates.

2. Descriptive Statistics:

- Descriptive statistics provided insights into the overall distribution of key variables, such as the number of baggage complaints, scheduled flights, and cancelled flights. This information helps in understanding the central tendency and variability of the data.

3. Correlation Analysis:

- The correlation analysis explored the relationship between the number of baggage complaints and the number of cancelled flights. Understanding such relationships can be valuable for airlines to address potential issues affecting passenger experience.

4. **Machine Learning Model:**
    - The machine learning model was trained to predict the number of baggage complaints. The Mean Squared Error (MSE) provides a measure of how well the model performs. Further tuning of the model and considering additional features could potentially improve its predictive accuracy.

5. **Baseline Model:**
    - The baseline model, which predicts the mean number of baggage complaints for all instances, serves as a reference point. The MSE of the baseline model helps assess the performance of more complex models.

6. **Data Cleaning:**
    - The data cleaning steps included handling missing values and converting relevant columns to appropriate data types. Clean data is essential for accurate and reliable analyses.

In conclusion, the project provides a comprehensive overview of baggage complaints, explores trends over time, establishes relationships with other factors, and builds a predictive model. The insights gained from this analysis can be valuable for airline companies to enhance their services and address issues related to baggage handling. Further refinement of the analysis and models could lead to more accurate predictions and actionable insights.