Project Name - Productionization of ML Systems

Project Type - MLOps

Contribution - Individual

Team Member 1 - Sudip Bairagi

Project Summary -

In the realm of travel and tourism, the intersection of data analytics and machine learning presents an opportunity to revolutionize the way travel experiences are curated and delivered. This capstone project revolves around a trio of datasets - users, flights, and hotels - each providing a unique perspective on travel patterns and preferences. The goal is to leverage these datasets to build and deploy sophisticated machine learning models, serving a dual purpose: enhancing predictive capabilities in travel-related decision-making and mastering the art of MLOps through hands-on application.

GitHub Link -

https://github.com/bairagis/prodmlsys

Problem Statement

**1. Regression Model Development:

Build a regression model to predict the price of a flight using the flights.csv dataset. Focus on feature selection, model training, and validation to ensure accuracy and reliability.

2. REST API for Regression Model:

Develop a REST API using Flask to serve the flight price prediction model, enabling real-time price predictions.

3. Containerization:

Package and deploy the flight price prediction model using Docker, ensuring portability and ease of deployment.

4. Kubernetes for Scalability:

Deploy the model using Kubernetes to manage scalability and handle varying loads efficiently.

5. Automated Workflows with Apache Airflow:

Design and implement automated workflows for managing the travel data, specifically for the regression models. Develop Directed Acyclic Graphs (DAGs) to orchestrate complex workflows in an efficient and manageable way.

6. CI/CD Pipeline with Jenkins:

Implement a Continuous Integration/Continuous Deployment (CI/CD) pipeline using Jenkins for consistent and reliable deployment of the travel price prediction model..**

Let's Begin !

1. Know Your Data

Import Libraries

```
# Import Libraries
import pandas as pd
```

Dataset Loading

```
# Load Dataset
# load flights.csv
flights = pd.read_csv('flights.csv')
# load hotels.csv
hotels = pd.read_csv('hotels.csv')
# load users.csv
users = pd.read_csv('users.csv')
```

Dataset First View

```
# Dataset First Look
flights.head()
```

	travelCode	userCode	from	to	flightType	price	time	distance	agency	date
0	0	0	Recife (PE)	Florianopolis (SC)	firstClass	1434.38	1.76	676.53	FlyingDrops	09/26/2019
1	0	0	Florianopolis (SC)	Recife (PE)	firstClass	1292.29	1.76	676.53	FlyingDrops	09/30/2019
2	1	0	Brasilia (DF)	Florianopolis (SC)	firstClass	1487.52	1.66	637.56	CloudFy	10/03/2019
3	1	0	Florianopolis (SC)	Brasilia (DF)	firstClass	1127.36	1.66	637.56	CloudFy	10/04/2019
4	2	0	Aracaju (SE)	Salvador (BH)	firstClass	1684.05	2.16	830.86	CloudFy	10/10/2019

```
hotels.head()
```

	travelCode	userCode	name	place	days	price	total	date
0	0	0	Hotel A	Florianopolis (SC)	4	313.02	1252.08	09/26/2019
1	2	0	Hotel K	Salvador (BH)	2	263.41	526.82	10/10/2019
2	7	0	Hotel K	Salvador (BH)	3	263.41	790.23	11/14/2019
3	11	0	Hotel K	Salvador (BH)	4	263.41	1053.64	12/12/2019
4	13	0	Hotel A	Florianopolis (SC)	1	313.02	313.02	12/26/2019

Next steps: Generate code with hotels | View recommended plots | New interactive sheet

```
users.head()
```

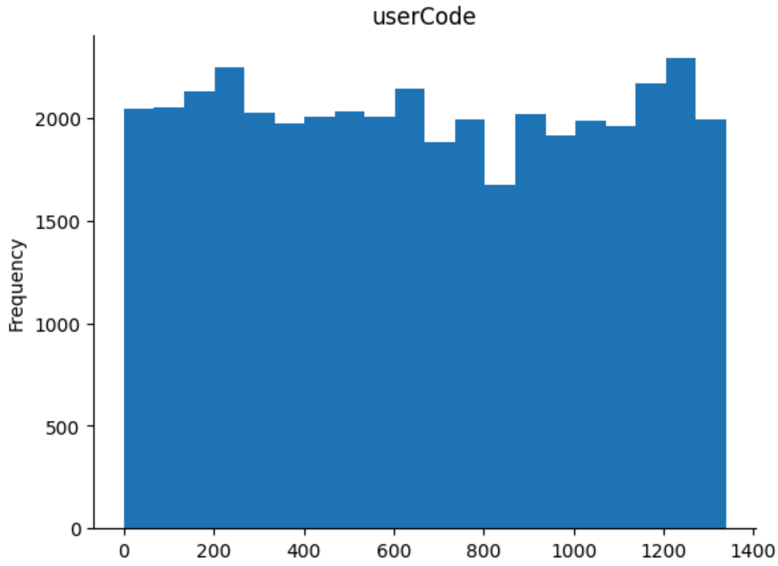
	code	company	name	gender	age
0	0	4You	Roy Braun	male	21
1	1	4You	Joseph Holsten	male	37
2	2	4You	Wilma Mcinnis	female	48
3	3	4You	Paula Daniel	female	23
4	4	4You	Patricia Carson	female	44

Next steps: Generate code with users | View recommended plots | New interactive sheet

Data Analysis

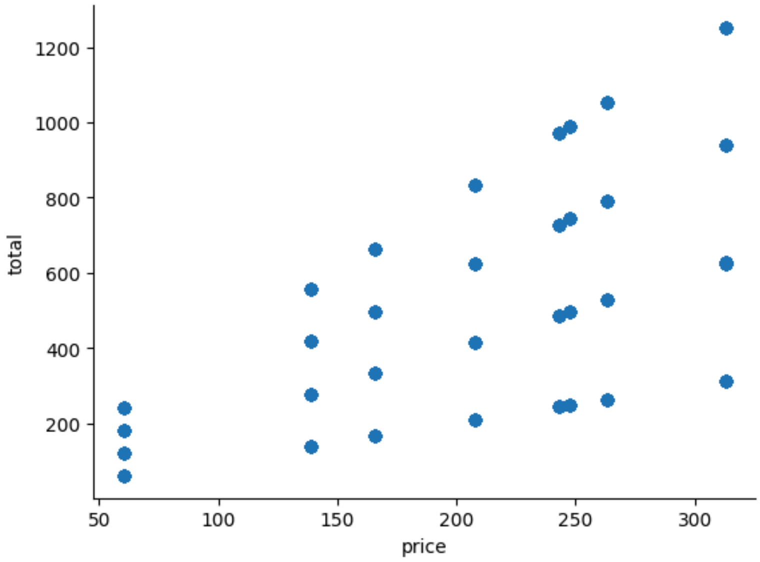
userCode

```
# @title userCode

from matplotlib import pyplot as plt
hotels['userCode'].plot(kind='hist', bins=20, title='userCode')
plt.gca().spines[['top', 'right',]].set_visible(False)
```



price vs total

```
# @title price vs total

from matplotlib import pyplot as plt
hotels.plot(kind='scatter', x='price', y='total', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```



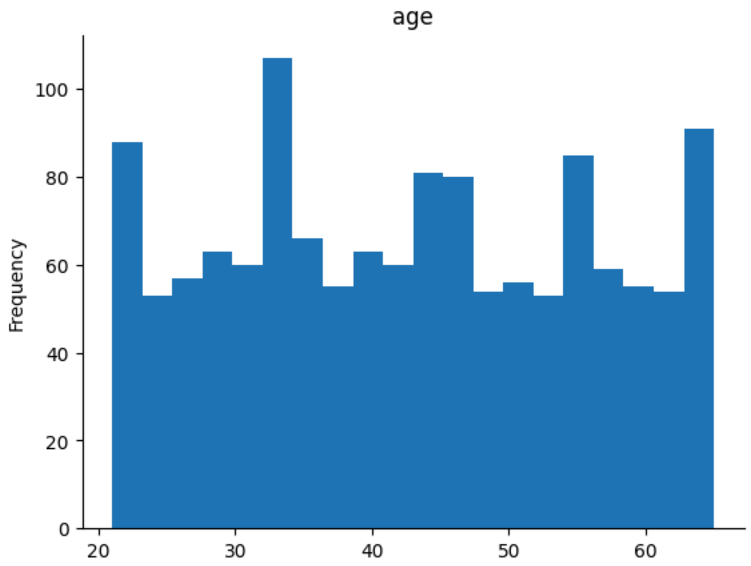

```
users.head()
```

	code	company	name	gender	age
0	0	4You	Roy Braun	male	21
1	1	4You	Joseph Holsten	male	37
2	2	4You	Wilma Mcinnis	female	48
3	3	4You	Paula Daniel	female	23
4	4	4You	Patricia Carson	female	44

Next steps: Generate code with users | View recommended plots | New interactive sheet

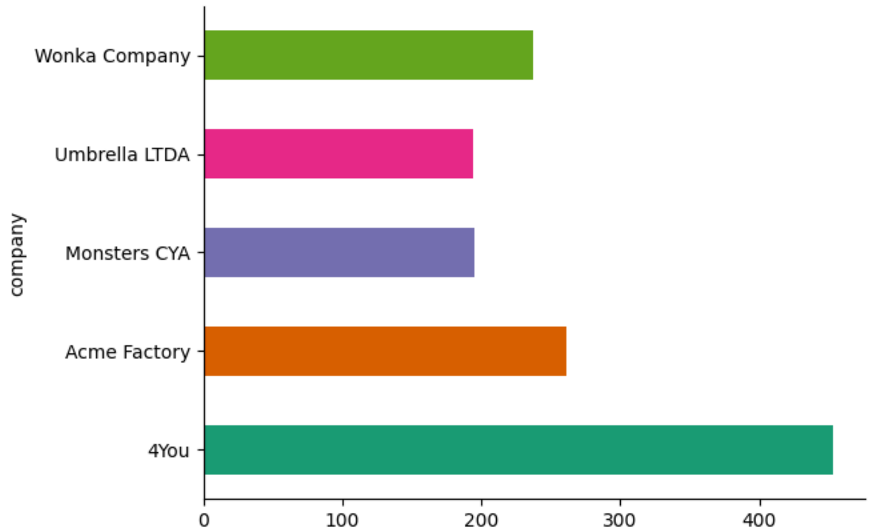
age

```
# @title age

from matplotlib import pyplot as plt
users['age'].plot(kind='hist', bins=20, title='age')
plt.gca().spines[['top', 'right',]].set_visible(False)
```



company

```
# @title company

from matplotlib import pyplot as plt
import seaborn as sns
users.groupby('company').size().plot(kind='barh', color=sns.palettes.mpl_palette('Dark2'))
plt.gca().spines[['top', 'right',]].set_visible(False)
```



Duplicate Values

```
# Dataset Duplicate Value Count for flights
flights.duplicated().sum()
# Dataset Duplicate Value Count for hotels
hotels.duplicated().sum()
# Dataset Duplicate Value Count for users
users.duplicated().sum()
```

```
np.int64(0)
```

Missing Values/Null Values

```
# Missing Values/Null Values Count hotels
hotels.isnull().sum()
# Missing Values/Null Values Count users
```

```
users.isnull().sum()
# Missing Values/Null Values Count flights
flights.isnull().sum()
```

	0
travelCode	0
userCode	0
from	0
to	0
flightType	0
price	0
time	0
distance	0
agency	0
date	0

dtype: int64

What did you know about your dataset?

Answer Here

2. Understanding Your Variables

```
# Dataset Columns description
print(flights.describe(include='all'))
print(hotels.describe(include='all'))
print(users.describe(include='all'))
```

```
freq        116418          NaN          NaN          NaN   116752
mean           NaN    957.37503     1.421147   546.955535      NaN
std            NaN    362.31189     0.542541   208.851288      NaN
min            NaN    301.51000     0.440000   168.220000      NaN
25%            NaN    672.66000     1.040000   401.660000      NaN
50%            NaN    904.00000     1.460000   562.140000      NaN
75%            NaN   1222.24000     1.760000   676.530000      NaN
max            NaN   1754.17000     2.440000   937.770000      NaN

              date
count       271888
unique         999
top     09/26/2019
freq          1335
mean           NaN
std            NaN
min            NaN
25%            NaN
50%            NaN
75%            NaN
max            NaN
          travelCode     userCode     name          place         days  \
count   40552.000000 40552.000000    40552          40552 40552.000000
unique           NaN          NaN        9              9          NaN
top              NaN          NaN  Hotel K  Salvador (BH)          NaN
freq             NaN          NaN     5094           5094          NaN
mean    67911.794461   666.963726      NaN            NaN     2.499679
std     39408.199333   391.136794      NaN            NaN     1.119326
min         0.000000     0.000000      NaN            NaN     1.000000
```

code company name gender age

```
              code company                name gender          age
count  1340.000000    1340                1340   1340  1340.000000
unique         NaN       5                1338      3          NaN
top            NaN    4You  Charlotte Johnson   male          NaN
freq           NaN     453                   2    452          NaN
mean    669.500000     NaN                 NaN    NaN    42.742537
std     386.968991     NaN                 NaN    NaN    12.869779
min       0.000000     NaN                 NaN    NaN    21.000000
25%     334.750000     NaN                 NaN    NaN    32.000000
50%     669.500000     NaN                 NaN    NaN    42.000000
75%    1004.250000     NaN                 NaN    NaN    54.000000
max    1339.000000     NaN                 NaN    NaN    65.000000
```

3. ***Data Wrangling***

```
# Merge datasets on userCode
import pandas as pd
combined_df = pd.merge(
    flights,
    pd.merge(hotels, users, left_on='userCode', right_on='code'),
    on='travelCode'
)
combined_df.head()
```

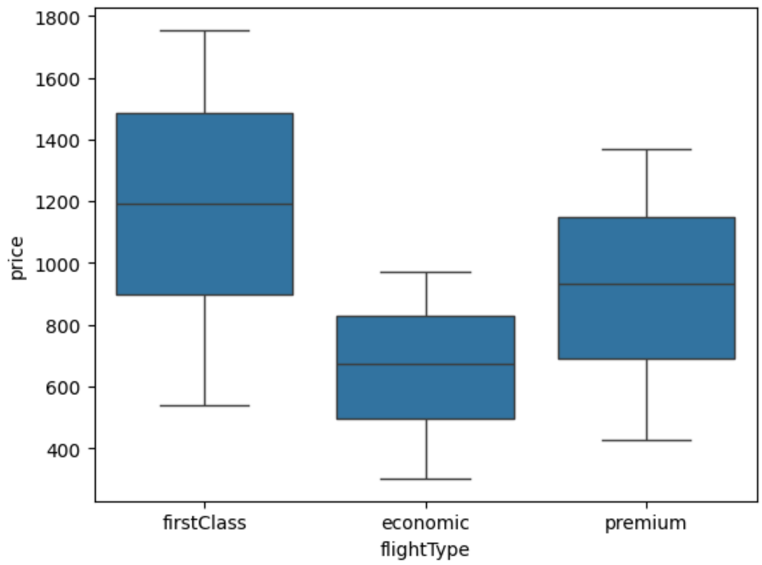
	travelCode	userCode_x	from	to	flightType	price_x	time	distance	agency	date_x	...	place
0	0	0	Recife (PE)	Florianopolis (SC)	firstClass	1434.38	1.76	676.53	FlyingDrops	09/26/2019	...	Florianopolis (SC)
1	0	0	Florianopolis (SC)	Recife (PE)	firstClass	1292.29	1.76	676.53	FlyingDrops	09/30/2019	...	Florianopolis (SC)
2	2	0	Aracaju (SE)	Salvador (BH)	firstClass	1684.05	2.16	830.86	CloudFy	10/10/2019	...	Salvador (BH)
3	2	0	Salvador (BH)	Aracaju (SE)	firstClass	1531.92	2.16	830.86	CloudFy	10/12/2019	...	Salvador (BH)
4	7	0	Aracaju (SE)	Salvador (BH)	economic	964.83	2.16	830.86	CloudFy	11/14/2019	...	Salvador (BH)

5 rows × 22 columns

Data Visualization

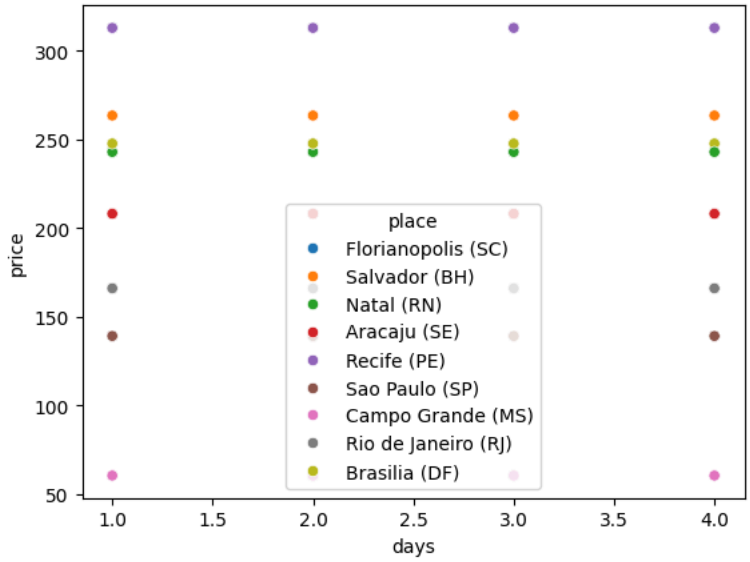
```
import seaborn as sns
sns.boxplot(x='flightType', y='price', data=flights)
```

```
<Axes: xlabel='flightType', ylabel='price'>
```



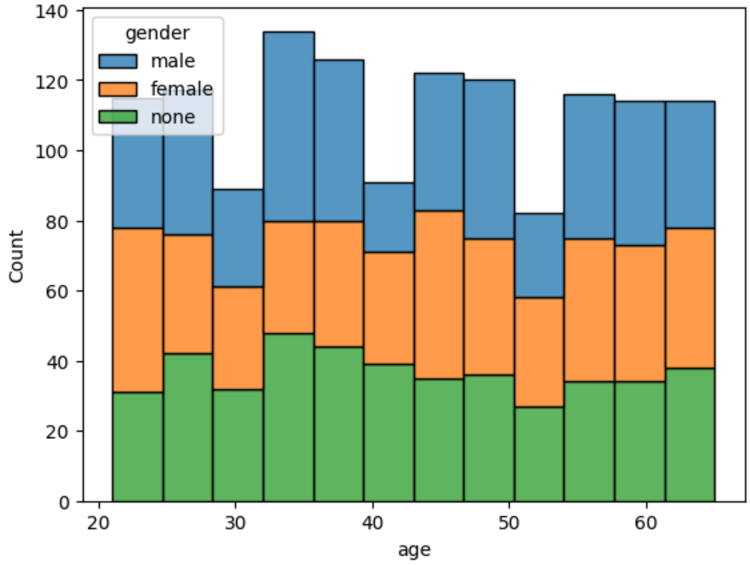

```
sns.scatterplot(x='days', y='price', hue='place', data=hotels)
```

```
<Axes: xlabel='days', ylabel='price'>
/usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151: UserWarning: Creating legend with loc="best" can
  fig.canvas.print_figure(bytes_io, **kw)
```



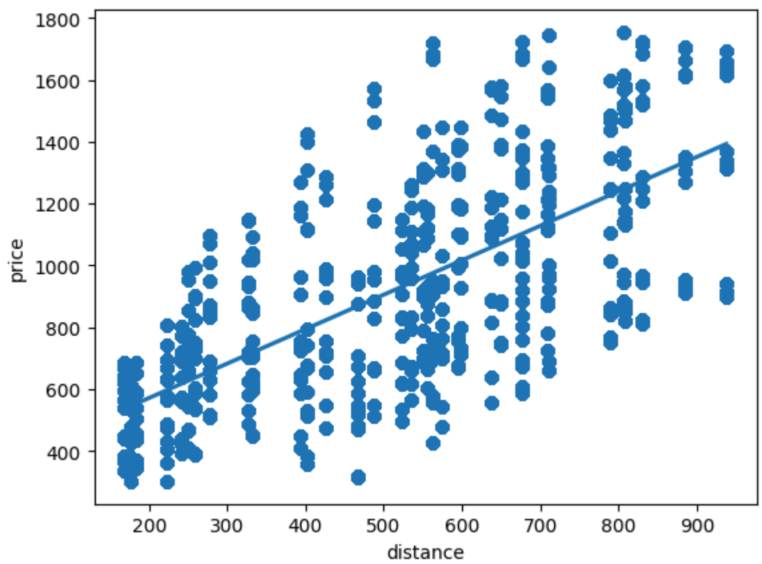

```
sns.histplot(x='age', hue='gender', data=users, multiple='stack')
```

```
<Axes: xlabel='age', ylabel='Count'>
```




```
sns.regplot(x='distance', y='price', data=flights)
```

```
<Axes: xlabel='distance', ylabel='price'>
```



6. Feature Engineering & Data Pre-processing

```
# Encode categorical features
from sklearn.preprocessing import LabelEncoder
encoder = LabelEncoder()
combined_df['flightType_encoded'] = encoder.fit_transform(combined_df['flightType'])
```

Answer Here.

2. Handling Outliers

```
# Handling Outliers & Outlier treatments for flights data
from scipy import stats
flight_price_mean = stats.trim_mean(flights['price'], proportiontocut=0.05)
hotel_price_mean= stats.trim_mean(hotels['price'], proportiontocut=0.05)
users_age_mean = stats.trim_mean(users['age'], proportiontocut=0.05)

flights['price'] = flights['price'].apply(lambda x: x if x <= 1000 else flight_price_mean)
# Handling Outliers & Outlier treatments for hotels data
hotels['price'] = hotels['price'].apply(lambda x: x if x <= 500 else hotel_price_mean)
# Handling Outliers & Outlier treatments for users data
users['age'] = users['age'].apply(lambda x: x if x <= 100 else users_age_mean)
# Handling Missing Values
```

Feature Selection

```
# Encode your categorical columns
flights.head()
flights_data = flights[['flightType', 'price', 'distance', 'time','agency']]
flights_data.head()

# shuffle the data
flights_data = flights_data.sample(frac=1, random_state=42).reset_index(drop=True)

# find unique values in flightType
unique_flight_types = flights_data['flightType'].unique()
unique_flight_types
# unique flightType counts
flight_type_counts = flights_data['flightType'].value_counts()
flight_type_counts

X = flights_data.drop('price', axis=1)
Y= flights_data['price']
```

2. Train Test Split

```
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.1, random_state=42)

# unique values of flightType in X_train and X_test
unique_flight_types_train = X_train['flightType'].unique()
unique_flight_types_test = X_test['flightType'].unique()
print("Unique flightType in X_train:", unique_flight_types_train)
print("Unique flightType in X_test:", unique_flight_types_test)
```

```
Unique flightType in X_train: ['premium' 'economic' 'firstClass']
Unique flightType in X_test: ['firstClass' 'premium' 'economic']
```

5. Data Transformation

```
# Encode categorical features
from sklearn.preprocessing import LabelEncoder

flightType_encoder = LabelEncoder()
```

```
agency_encoder = LabelEncoder()

X_train['flightType_encoded'] = flightType_encoder.fit_transform(X_train['flightType'])
X_train['agency_encoded'] = agency_encoder.fit_transform(X_train['agency'])

X_test['flightType_encoded'] = flightType_encoder.transform(X_test['flightType'])
X_test['agency_encoded'] = agency_encoder.transform(X_test['agency'])

# Drop original categorical columns
X_train = X_train.drop(['flightType', 'agency'], axis=1)
X_test = X_test.drop(['flightType', 'agency'], axis=1)
```

6. Data Scaling

```
X_train.describe(include='all')
```

	distance	time	flightType_encoded	agency_encoded
count	244699.000000	244699.000000	244699.000000	244699.000000
mean	546.901414	1.421007	1.002158	1.001083
std	208.818852	0.542458	0.755981	0.925929
min	168.220000	0.440000	0.000000	0.000000
25%	401.660000	1.040000	0.000000	0.000000
50%	562.140000	1.460000	1.000000	1.000000
75%	676.530000	1.760000	2.000000	2.000000
max	937.770000	2.440000	2.000000	2.000000

```
Y_train.describe()
```

	price
count	244699.000000
mean	802.925291
std	185.196501
min	301.510000
25%	672.660000
50%	904.000000
75%	950.643347
max	998.180000

dtype: float64

7. ML Model Implementation

ML Model - 1 : Random Forest Flight Price predictor model

```
# implement a random forest regressor
from sklearn.ensemble import RandomForestRegressor
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, Y_train)
```

```
▾ RandomForestRegressor
RandomForestRegressor(random_state=42)
```

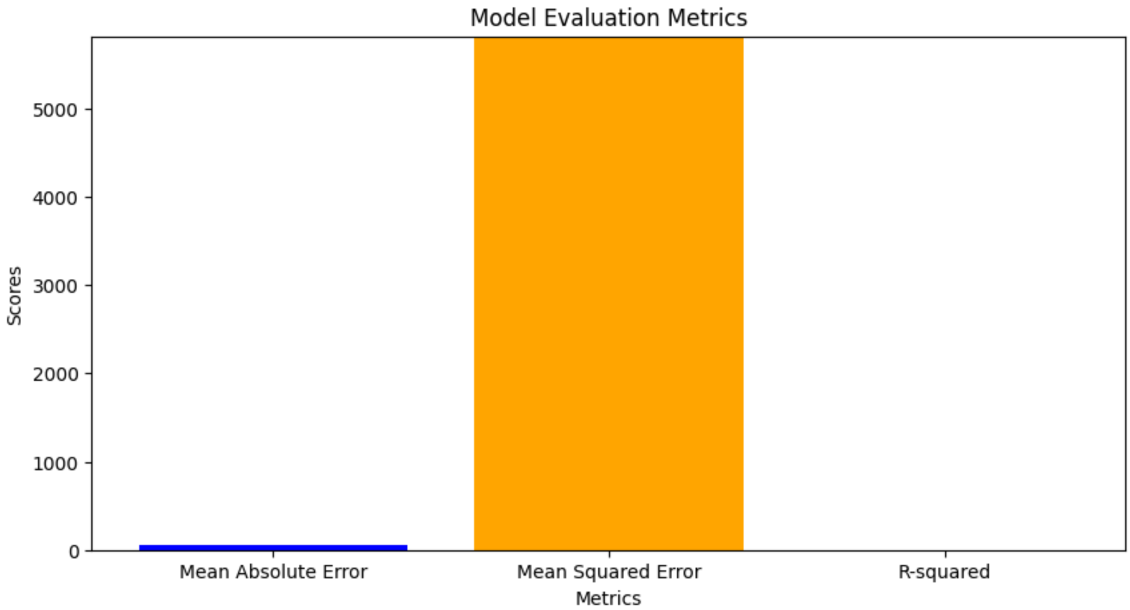
1. Explain the ML Model used and it's performance using Evaluation metric Score Chart.

```
# Evaluate the model
from sklearn.metrics import mean_squared_error, r2_score
Y_pred = rf_model.predict(X_test)
mse = mean_squared_error(Y_test, Y_pred)
r2 = r2_score(Y_test, Y_pred)
```

```
print("Mean Squared Error:", mse)
print("R-squared:", r2)
```

```
Mean Squared Error: 5816.577944613706
R-squared: 0.8297810843101414
```

```
# Visualizing evaluation Metric Score chart the model performance
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import matplotlib.pyplot as plt
y_pred = rf_model.predict(X_test)
mae = mean_absolute_error(Y_test, y_pred)
mse = mean_squared_error(Y_test, y_pred)
r2 = r2_score(Y_test, y_pred)

# Plotting the evaluation metrics
metrics = ['Mean Absolute Error', 'Mean Squared Error', 'R-squared']
scores = [mae, mse, r2]
plt.figure(figsize=(10, 5))
plt.bar(metrics, scores, color=['blue', 'orange', 'green'])
plt.title('Model Evaluation Metrics')
plt.xlabel('Metrics')
plt.ylabel('Scores')
plt.ylim(0, max(scores) + 1)
plt.show()
```



2. Cross- Validation & Hyperparameter Tuning

```
# ML Model - 1 Implementation with hyperparameter optimization techniques (i.e., GridSearch CV, RandomSearch CV, Bayesian Op
from sklearn.model_selection import GridSearchCV
param_grid = {
    'n_estimators': [10, 15],
    'max_depth': [10, 20],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2],
    'max_features': ['auto', 'log2']
}
grid_search = GridSearchCV(estimator=rf_model, param_grid=param_grid, cv=3, n_jobs=-1, verbose=2)
grid_search.fit(X_train, Y_train)
# Best parameters from GridSearchCV
best_params = grid_search.best_params_
print("Best parameters from GridSearchCV:", best_params)
# Fit the model with best parameters
rf_model_best = RandomForestRegressor(**best_params, random_state=42)
rf_model_best.fit(X_train, Y_train)
```

```
Fitting 3 folds for each of 32 candidates, totalling 96 fits
/usr/local/lib/python3.11/dist-packages/sklearn/model_selection/_validation.py:528: FitFailedWarning:
48 fits failed out of a total of 96.
The score on these train-test partitions for these parameters will be set to nan.
If these failures are not expected, you can try to debug them by setting error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
14 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.11/dist-packages/sklearn/model_selection/_validation.py", line 866, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.11/dist-packages/sklearn/base.py", line 1382, in wrapper
    estimator._validate_params()
  File "/usr/local/lib/python3.11/dist-packages/sklearn/base.py", line 436, in _validate_params
    validate_parameter_constraints(
  File "/usr/local/lib/python3.11/dist-packages/sklearn/utils/_param_validation.py", line 98, in validate_parameter_cons
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'max_features' parameter of RandomForestRegressor must be an

--------------------------------------------------------------------------------
34 fits failed with the following error:
Traceback (most recent call last):
  File "/usr/local/lib/python3.11/dist-packages/sklearn/model_selection/_validation.py", line 866, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "/usr/local/lib/python3.11/dist-packages/sklearn/base.py", line 1382, in wrapper
    estimator._validate_params()
  File "/usr/local/lib/python3.11/dist-packages/sklearn/base.py", line 436, in _validate_params
    validate_parameter_constraints(
  File "/usr/local/lib/python3.11/dist-packages/sklearn/utils/_param_validation.py", line 98, in validate_parameter_cons
    raise InvalidParameterError(
sklearn.utils._param_validation.InvalidParameterError: The 'max_features' parameter of RandomForestRegressor must be an

  warnings.warn(some_fits_failed_message, FitFailedWarning)
/usr/local/lib/python3.11/dist-packages/sklearn/model_selection/_search.py:1108: UserWarning: One or more of the test sc
        nan        nan 0.82936488 0.82939006 0.82936488 0.82939006
 0.82936488 0.82939006 0.82936488 0.82939006        nan        nan
        nan        nan        nan        nan        nan        nan
 0.82942794 0.82943177 0.82942794 0.82943177 0.82942794 0.82943177
 0.82942794 0.82943177]
  warnings.warn(
Best parameters from GridSearchCV: {'max_depth': 20, 'max_features': 'log2', 'min_samples_leaf': 1, 'min_samples_split':
```

RandomForestRegressor

```
RandomForestRegressor(max_depth=20, max_features='log2', n_estimators=15,
```

```
# Predict on the model
Y_pred_best = rf_model_best.predict(X_test)
# Evaluate the model with best parameters
mse_best = mean_squared_error(Y_test, Y_pred_best)
r2_best = r2_score(Y_test, Y_pred_best)
print("Mean Squared Error with best parameters:", mse_best)
print("R-squared with best parameters:", r2_best)
```

```
Mean Squared Error with best parameters: 5816.48842178441
R-squared with best parameters: 0.8297837041459069
```

8. *Save the RegressorModel *

Start coding or generate with AI.

1. Save the best performing ml model in a pickle file or joblib file format for deployment process.

```
# Save the File
import joblib

# get the fitted ecoder and model
joblib.dump(flightType_encoder, 'flightType_encoder.pkl')
print("FlightType encoder saved as flightType_encoder.pkl")
joblib.dump(agency_encoder, 'agency_encoder.pkl')
print("Agency encoder saved as agency_encoder.pkl")
joblib.dump(rf_model_best, 'rf_model_best.pkl')
print("Model saved as rf_model_best.pkl")
```

```
FlightType encoder saved as flightType_encoder.pkl
Agency encoder saved as agency_encoder.pkl
Model saved as rf_model_best.pkl
```

2. Again Load the saved model file and try to predict unseen data for a sanity check.

```
# Load the File and predict unseen data.

loaded_model = joblib.load('rf_model_best.pkl')
# Predict on new data
new_data = X_test.sample(5)  # Sample 5 rows from the test set
predictions = loaded_model.predict(new_data)
print("Predictions on new data:", predictions)
print("Actual values:", Y_test.loc[new_data.index].values)
print("New data features:\n", new_data)
```

```
Predictions on new data: [950.64334696 565.34749047 974.55780841 950.64334696 912.67207638]
Actual values: [950.64334696 591.19       950.64334696 950.64334696 991.22      ]
New data features:
         distance  time  flightType_encoded  agency_encoded
271281    650.10  1.69                   1               1
242039    183.37  0.48                   1               1
129114    595.03  1.55                   2               0
50417     709.37  1.84                   2               0
190727    535.40  1.39                   2               2
```

```
# load encoders and model
flightType_encoder = joblib.load('flightType_encoder.pkl')
agency_encoder = joblib.load('agency_encoder.pkl')
rf_model_best = joblib.load('rf_model_best.pkl')

# test with a new data point from flights dataset
# Use valid values from your training data
new_flight_data = pd.DataFrame({
    'distance': [1000],
    'time': [2],
    'flightType': ['premium'],  # valid: 'premium', 'firstClass', 'economic'
    'agency': ['Rainbow']       # valid: 'Rainbow', 'CloudFy', 'FlyingDrops'
})

# predict the price for the new data point
new_flight_data['flightType_encoded'] = flightType_encoder.transform(new_flight_data['flightType'])
new_flight_data['agency_encoded'] = agency_encoder.transform(new_flight_data['agency'])
new_flight_data = new_flight_data.drop(['flightType', 'agency'], axis=1)
predicted_price = rf_model_best.predict(new_flight_data)
print("Predicted price for the new flight data:", predicted_price[0])
```

```
Predicted price for the new flight data: 950.6433469553932
```

Flask API to call the regressor

```
# Define a function for Flask app that take flightType, agency, distance, time as input and return the predicted price
def predict_flight_price(flightType, agency, distance, time):
    # Create a DataFrame for the input data
    input_data = pd.DataFrame({
        'flightType': [flightType],
        'agency': [agency],
        'distance': [distance],
        'time': [time]
    })


    # load encoders and model
    flightType_encoder = joblib.load('flightType_encoder.pkl')
    agency_encoder = joblib.load('agency_encoder.pkl')
    rf_model_best = joblib.load('rf_model_best.pkl')

    # Encode the categorical features
    input_data['flightType_encoded'] = flightType_encoder.transform(input_data['flightType'])
    input_data['agency_encoded'] = agency_encoder.transform(input_data['agency'])

    # Drop the original categorical columns
    input_data = input_data.drop(['flightType', 'agency'], axis=1)

    # Predict the price using the loaded model
    predicted_price = rf_model_best.predict(input_data)

    return predicted_price[0]  # Return the predicted price


# implement a simple Flask app to serve the model
from flask import Flask, request, jsonify
app = Flask(__name__)
```

```
@app.route('/predict', methods=['POST'])
def predict():
    data = request.get_json()
    flightType = data['flightType']
    agency = data['agency']
    distance = data['distance']
    time = data['time']

    # Call the prediction function
    predicted_price = predict_flight_price(flightType, agency, distance, time)

    return jsonify({'predicted_price': predicted_price})


# call the Flask Rest API
if __name__ == '__main__':
    app.run(debug=True, host='localhost', port=5002)
```

```
 * Serving Flask app '__main__'
 * Debug mode: on
INFO:werkzeug:WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI ser
 * Running on http://localhost:5002
INFO:werkzeug:Press CTRL+C to quit
INFO:werkzeug: * Restarting with stat
```