Flight Price Prediction with XGBoost

August 25, 2024

1 Business Understanding

Dataset contains information about flight booking options from the website Easemytrip for flight travel between India's top 6 metro cities. There are 300261 datapoints and 11 features in the cleaned dataset. Our goals is to (1) answer the business questions proposed and (2) to build a machine learning model to predict flight prices.

1.1 Business questions

- Does price vary with Airlines?
- How is the price affected when tickets are bought in just 1 or 2 days before departure?
- Does ticket price change based on the departure time and arrival time?
- How the price changes with change in Source and Destination?
- How does the ticket price vary between Economy and Business class?

2 Data Understanding

2.1 Libraries import and loading the data

[ ]:
```
# Data manipulation
import pandas as pd
import numpy as np

# EDA
import matplotlib.pyplot as plt
import seaborn as sns

# Machine Learning
from xgboost import XGBRegressor

# Pre-prccessing
import optuna
from sklearn import metrics
from sklearn.model_selection import train_test_split, KFold, cross_val_score
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import FunctionTransformer
from sklearn.compose import ColumnTransformer
```

```python
from sklearn.impute import SimpleImputer
from category_encoders import TargetEncoder

# Notebook config
import warnings
warnings.filterwarnings('ignore')
plt.style.use('ggplot')
palette = ["#1F4E79", "#4F81BD", "#A9CCE3", "#D9EAD3", "#BFBFBF", "#595959",␣
 ↪"#D0E0EB", "#8FA3BF"]
sns.set_palette(palette)
pd.set_option('display.max_rows', 50)
pd.set_option('display.max_columns', None)
```

[ ]:
```python
data = pd.read_csv("../data/raw/Clean_Dataset.csv")
```

2.2 Data check-up

[ ]:
```python
print(f"The dataset has {data.shape[0]} rows and {data.shape[1]} columns.")
```

```
The dataset has 300153 rows and 12 columns.
```

[ ]:
```python
print(f"The dataset has: {len(data.select_dtypes(include = 'object').columns.
 ↪to_list())} categorical columns.")
print(f"The dataset has: {len(data.select_dtypes(include = 'number').columns.
 ↪to_list())} numeric columns.")
```

```
The dataset has: 8 categorical columns.
The dataset has: 4 numeric columns.
```

[ ]:
```python
data.nunique().sort_values()
```

[ ]:
```
class                    2
stops                    3
airline                  6
source_city              6
departure_time           6
arrival_time             6
destination_city         6
days_left               49
duration               476
flight                1561
price                12157
Unnamed: 0          300153
dtype: int64
```

We've got to deleted this Unnamed: 0 column (probably the index)

[ ]:
```python
data.isnull().mean()
```

[ ]:
```
Unnamed: 0          0.0
airline             0.0
flight              0.0
source_city         0.0
departure_time      0.0
stops               0.0
arrival_time        0.0
destination_city    0.0
class               0.0
duration            0.0
days_left           0.0
price               0.0
dtype: float64
```

We've got no null data.

[ ]:
```
data.dtypes
```

[ ]:
```
Unnamed: 0            int64
airline              object
flight               object
source_city          object
departure_time       object
stops                object
arrival_time         object
destination_city     object
class                object
duration            float64
days_left             int64
price                 int64
dtype: object
```

[ ]:
```
data.head()
```

[ ]:
```
   Unnamed: 0   airline   flight source_city departure_time stops  \
0           0  SpiceJet  SG-8709       Delhi        Evening  zero
1           1  SpiceJet  SG-8157       Delhi  Early_Morning  zero
2           2   AirAsia   I5-764       Delhi  Early_Morning  zero
3           3   Vistara   UK-995       Delhi        Morning  zero
4           4   Vistara   UK-963       Delhi        Morning  zero

    arrival_time destination_city    class  duration  days_left  price
0          Night           Mumbai  Economy      2.17          1   5953
1        Morning           Mumbai  Economy      2.33          1   5953
2  Early_Morning           Mumbai  Economy      2.17          1   5956
3      Afternoon           Mumbai  Economy      2.25          1   5955
4        Morning           Mumbai  Economy      2.33          1   5955
```

We don't need further data manipulation besides excluding the columns `Unnamed: 0` and `flight`

[ ]:
```
df = data.drop(columns = ['Unnamed: 0', 'flight'], axis = 1).copy()
df.head()
```

[ ]:
```
    airline source_city departure_time stops   arrival_time destination_city  \
0  SpiceJet       Delhi        Evening  zero          Night           Mumbai
1  SpiceJet       Delhi  Early_Morning  zero        Morning           Mumbai
2   AirAsia       Delhi  Early_Morning  zero  Early_Morning           Mumbai
3   Vistara       Delhi        Morning  zero      Afternoon           Mumbai
4   Vistara       Delhi        Morning  zero        Morning           Mumbai

     class  duration  days_left  price
0  Economy      2.17          1   5953
1  Economy      2.33          1   5953
2  Economy      2.17          1   5956
3  Economy      2.25          1   5955
4  Economy      2.33          1   5955
```

2.3 EDA

[ ]:
```
df.select_dtypes(include = 'object').describe().T
```

[ ]:
```
                   count unique      top    freq
airline           300153      6  Vistara  127859
source_city       300153      6    Delhi   61343
departure_time    300153      6  Morning   71146
stops             300153      3      one  250863
arrival_time      300153      6    Night   91538
destination_city  300153      6   Mumbai   59097
class             300153      2  Economy  206666
```

[ ]:
```
df.describe().round(2).T
```

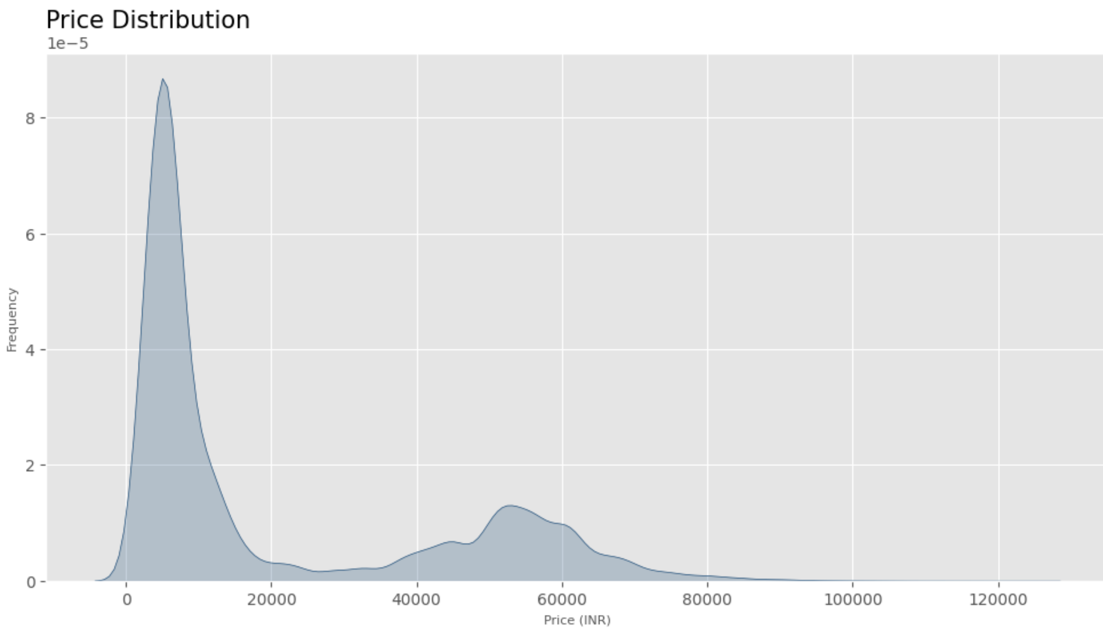
[ ]:
```
              count      mean       std      min      25%      50%       75%  \
duration   300153.0     12.22      7.19     0.83     6.83    11.25     16.17
days_left  300153.0     26.00     13.56     1.00    15.00    26.00     38.00
price      300153.0  20889.66  22697.77  1105.00  4783.00  7425.00  42521.00

                 max
duration       49.83
days_left      49.00
price      123071.00
```

[ ]:
```
print(f"Target Skewness and Kurtosis")
print("=" * 30)
print(f"Price Skewness: {df['price'].skew():.4f}")
print(f"Price Kurtosis: {df['price'].kurt():.4f}")
```

```
Target Skewness and Kurtosis
```

```
==============================
Price Skewness: 1.0614
Price Kurtosis: -0.3963
```

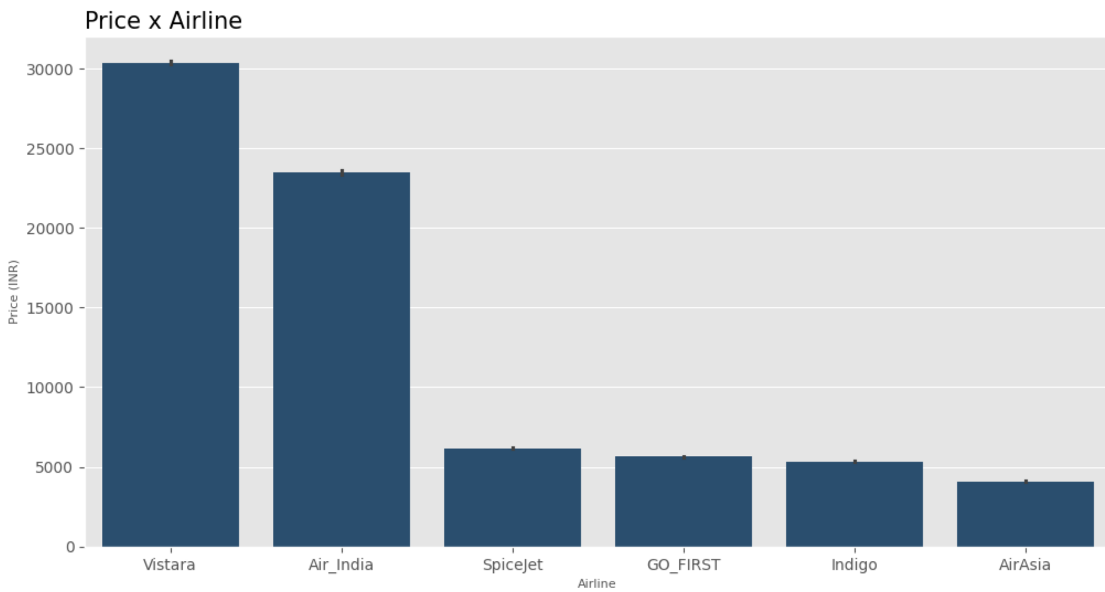
[ ]:
```
fig, ax = plt.subplots(figsize = (12, 6))
sns.kdeplot(df.price, fill = True)

ax.set_title("Price Distribution", fontsize = 15, pad = 5, loc = 'left')
ax.set_xlabel("Price (INR)", fontsize = 8)
ax.set_ylabel("Frequency", fontsize = 8)
plt.show()
```



Our target is right-skewed, which may be caused by the price difference between the flight classes.

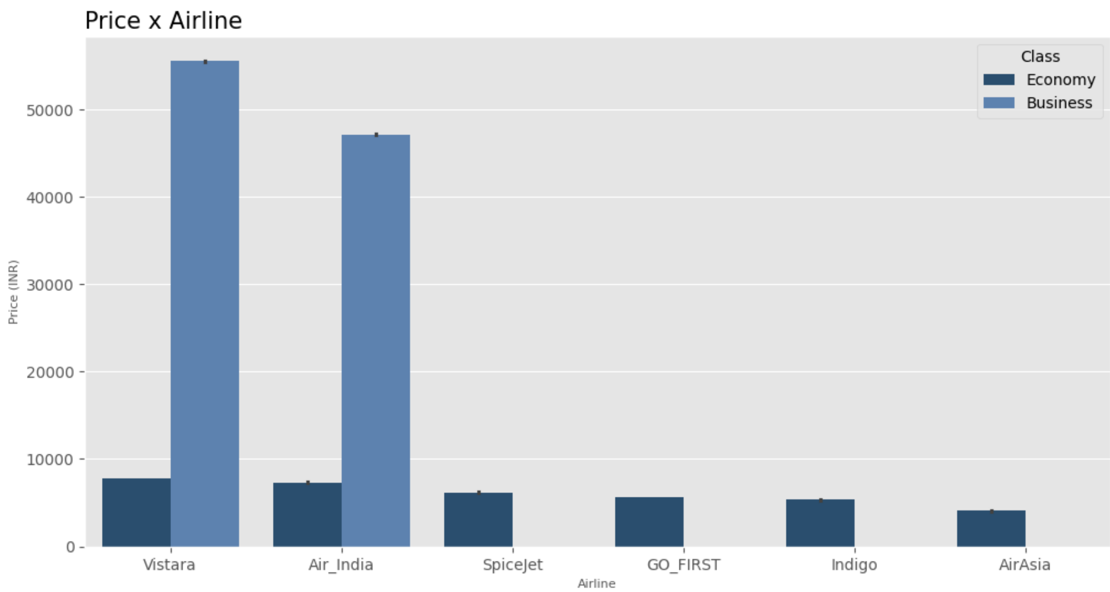
2.3.1 Does price vary with Airlines?

[ ]:
```
fig, ax = plt.subplots(figsize = (12, 6))

sns.barplot(x = df.airline, y = df.price, color = '#1F4E79', order = df.
 ↪groupby('airline')['price'].mean().sort_values(ascending=False).index)
ax.set_title("Price x Airline", fontsize = 15, pad = 5, loc = 'left')
ax.set_xlabel("Airline", fontsize = 8)
ax.set_ylabel("Price (INR)", fontsize = 8)
plt.show()
```



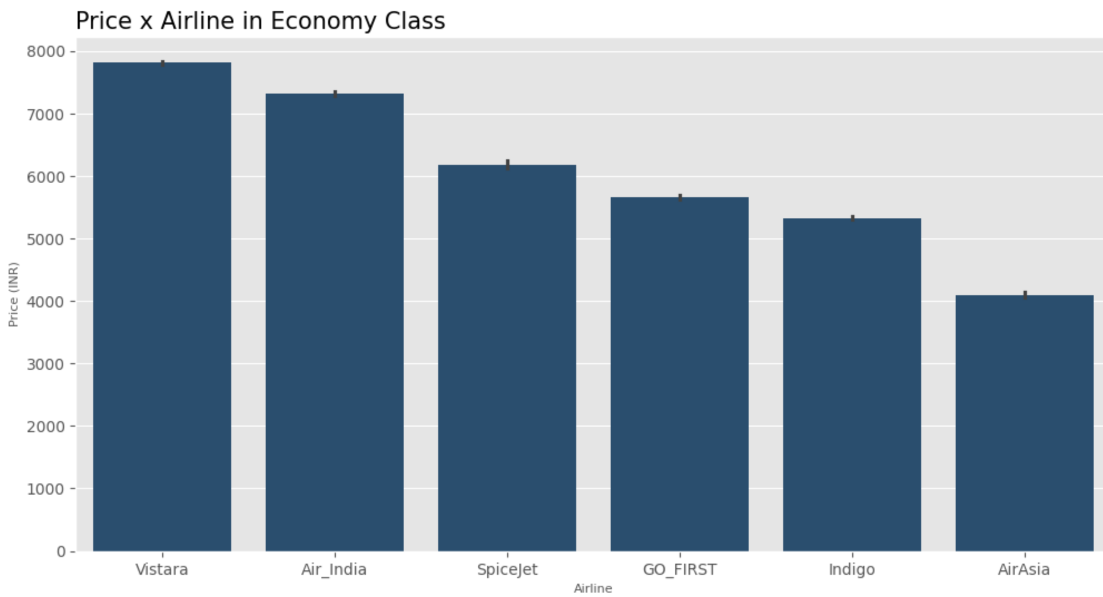
2.3.2 Does price vary with class?

[ ]:
```
fig, ax = plt.subplots(figsize = (12, 6))

sns.barplot(x = df.airline, y = df.price, hue = df['class'],order = df.
 ↪groupby('airline')['price'].mean().sort_values(ascending=False).index)
ax.set_title("Price x Airline", fontsize = 15, pad = 5, loc = 'left')
ax.set_xlabel("Airline", fontsize = 8)
ax.set_ylabel("Price (INR)", fontsize = 8)
ax.legend(title = 'Class')
plt.show()
```



Vistara and Air India have higher prices, but does it remain this way when looking only at economy class flights?

[ ]:
```
econ = df[df['class'] == 'Economy']

fig, ax = plt.subplots(figsize = (12, 6))
sns.barplot(x = econ.airline, y = econ.price, color = '#1F4E79', order = econ.
  ↪groupby('airline')['price'].mean().sort_values(ascending=False).index)
ax.set_title("Price x Airline in Economy Class", fontsize = 15, pad = 5, loc =␣
  ↪'left')
ax.set_xlabel("Airline", fontsize = 8)
ax.set_ylabel("Price (INR)", fontsize = 8)
plt.show()
```



Vistara and Air India still have the higher prices.

2.3.3 How is the price affected when tickets are bought in just 1 or 2 days before departure?

[ ]:
```
def days(i):
    if i > 2:
        return 'Over 2 days'
    else:
        return 'Under 2 days'
```

[ ]:
```
df_days = df.copy()
df_days['days'] = df['days_left'].apply(days)
```

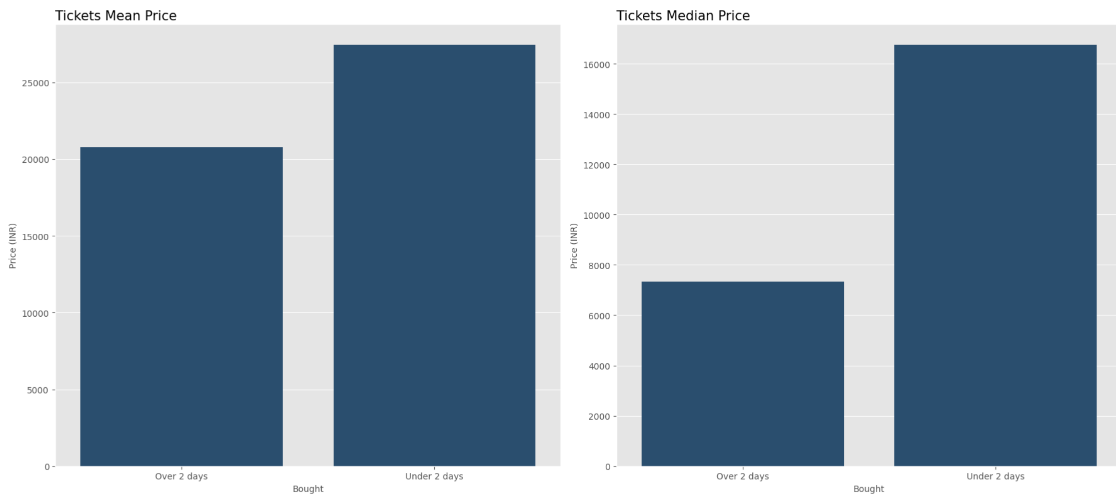
[ ]:
```
days = df_days.groupby("days").agg(price_mean = ('price', 'mean'), price_median␣
 ↪= ('price', 'median')).reset_index()
days
```

[ ]:

	days	price_mean	price_median
0	Over 2 days	20757.498484	7347.0
1	Under 2 days	27421.169326	16739.0

[ ]:
```
fig, axes = plt.subplots(1, 2, figsize = (18, 8))

sns.barplot(ax = axes[0], x = days.days, y = days.price_mean)
axes[0].set_title("Tickets Mean Price", fontsize = 15, pad = 5, loc = 'left')
axes[0].set_xlabel("Bought", fontsize = 10)
axes[0].set_ylabel("Price (INR)", fontsize = 10)
```

```
sns.barplot(ax = axes[1], x = days.days, y = days.price_median)
axes[1].set_title("Tickets Median Price", fontsize = 15, pad = 5, loc = 'left')
axes[1].set_xlabel("Bought", fontsize = 10)
axes[1].set_ylabel("Price (INR)", fontsize = 10)

plt.tight_layout()
plt.show()
```



The price of airline tickets tends to be higher the closer you are to the flight date.

2.3.4 Does ticket price change based on the departure time and arrival time?

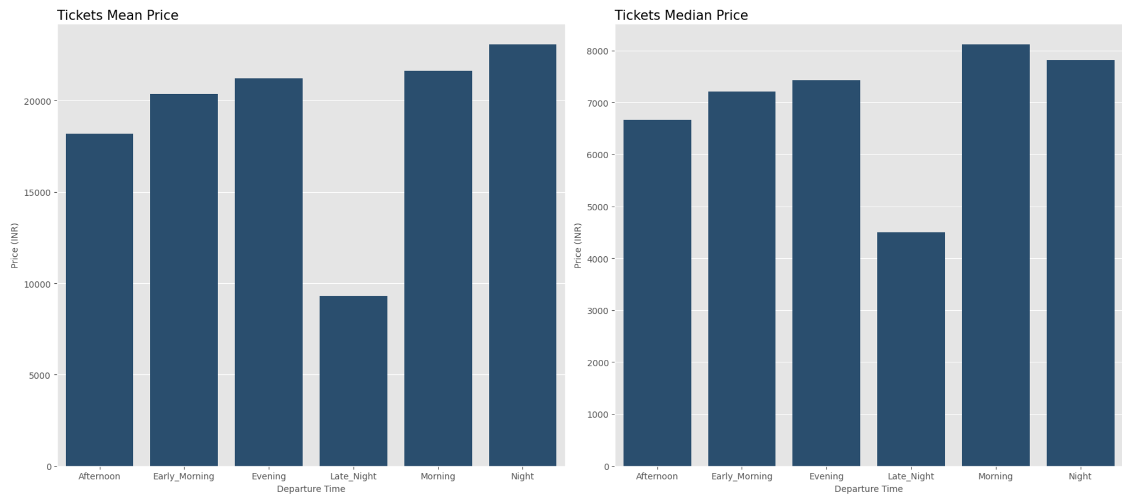
[ ]:
```
departure = df.groupby(["departure_time"]).agg(price_mean = ('price', 'mean'),␣
↪price_median = ('price', 'median')).reset_index()
departure
```

[ ]:

	departure_time	price_mean	price_median
0	Afternoon	18179.203331	6663.0
1	Early_Morning	20370.676718	7212.0
2	Evening	21232.361894	7425.0
3	Late_Night	9295.299387	4499.0
4	Morning	21630.760254	8112.0
5	Night	23062.146808	7813.0

[ ]:
```
fig, axes = plt.subplots(1, 2, figsize = (18, 8))

sns.barplot(ax = axes[0], x = departure.departure_time, y = departure.
↪price_mean, color = '#1F4E79', order = departure.departure_time)
axes[0].set_title("Tickets Mean Price", fontsize = 15, pad = 5, loc = 'left')
```

```
axes[0].set_xlabel("Departure Time", fontsize = 10)
axes[0].set_ylabel("Price (INR)", fontsize = 10)

sns.barplot(ax = axes[1], x = departure.departure_time, y = departure.
 ↪price_median, color = '#1F4E79', order = departure.departure_time)
axes[1].set_title("Tickets Median Price", fontsize = 15, pad = 5, loc = 'left')
axes[1].set_xlabel("Departure Time", fontsize = 10)
axes[1].set_ylabel("Price (INR)", fontsize = 10)

plt.tight_layout()
plt.show()
```



Morning and night have the highest prices in departure time.

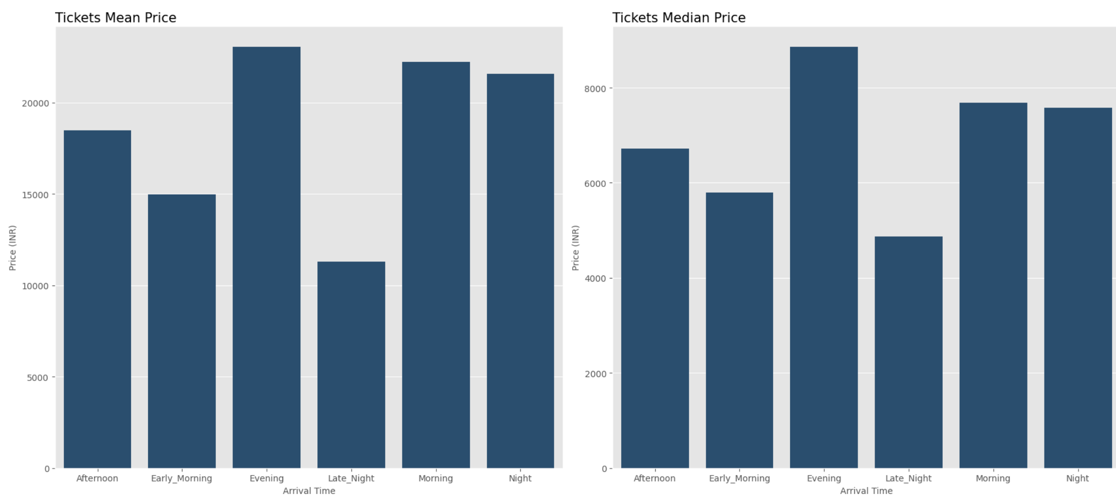
[ ]:
```
arrival = df.groupby(["arrival_time"]).agg(price_mean = ('price', 'mean'),␣
 ↪price_median = ('price', 'median')).reset_index()
arrival
```

[ ]:

	arrival_time	price_mean	price_median
0	Afternoon	18494.598993	6714.0
1	Early_Morning	14993.139521	5800.0
2	Evening	23044.371615	8854.0
3	Late_Night	11284.906078	4867.0
4	Morning	22231.076098	7687.0
5	Night	21586.758341	7584.0

[ ]:
```
fig, axes = plt.subplots(1, 2, figsize = (18, 8))

sns.barplot(ax = axes[0], x = arrival.arrival_time, y = arrival.price_mean,␣
 ↪color = '#1F4E79', order = arrival.arrival_time)
```

```
axes[0].set_title("Tickets Mean Price", fontsize = 15, pad = 5, loc = 'left')
axes[0].set_xlabel("Arrival Time", fontsize = 10)
axes[0].set_ylabel("Price (INR)", fontsize = 10)

sns.barplot(ax = axes[1], x = arrival.arrival_time, y = arrival.price_median,␣
 ↪color = '#1F4E79', order = arrival.arrival_time)
axes[1].set_title("Tickets Median Price", fontsize = 15, pad = 5, loc = 'left')
axes[1].set_xlabel("Arrival Time", fontsize = 10)
axes[1].set_ylabel("Price (INR)", fontsize = 10)

plt.tight_layout()
plt.show()
```



Evening and morning have the highest prices in arrival time.

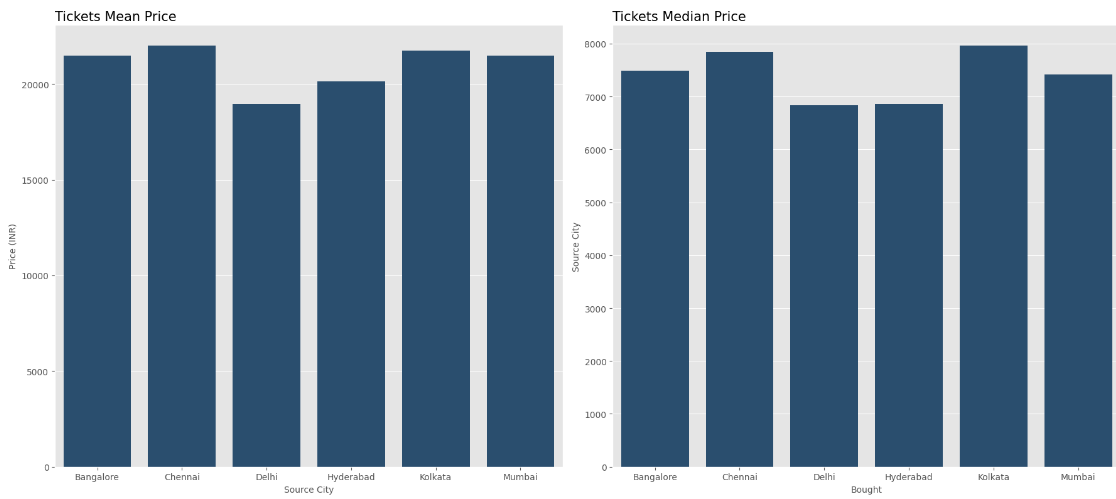
2.3.5 How the price changes with change in Source and Destination?

[ ]:
```
source = df.groupby("source_city").agg(price_mean = ('price', 'mean'),␣
 ↪price_median = ('price', 'median')).reset_index()
source
```

[ ]:

	source_city	price_mean	price_median
0	Bangalore	21469.460575	7488.0
1	Chennai	21995.339871	7846.0
2	Delhi	18951.326639	6840.0
3	Hyderabad	20155.623879	6855.0
4	Kolkata	21746.235679	7958.0
5	Mumbai	21483.818839	7413.0

```
[ ]: fig, axes = plt.subplots(1, 2, figsize = (18, 8))

sns.barplot(ax = axes[0], x = source.source_city, y = source.price_mean, color = '#1F4E79', order = source.source_city)
axes[0].set_title("Tickets Mean Price", fontsize = 15, pad = 5, loc = 'left')
axes[0].set_xlabel("Source City", fontsize = 10)
axes[0].set_ylabel("Price (INR)", fontsize = 10)

sns.barplot(ax = axes[1], x = source.source_city, y = source.price_median, color = '#1F4E79', order = source.source_city)
axes[1].set_title("Tickets Median Price", fontsize = 15, pad = 5, loc = 'left')
axes[1].set_xlabel("Bought", fontsize = 10)
axes[1].set_ylabel("Source City", fontsize = 10)

plt.tight_layout()
plt.show()
```

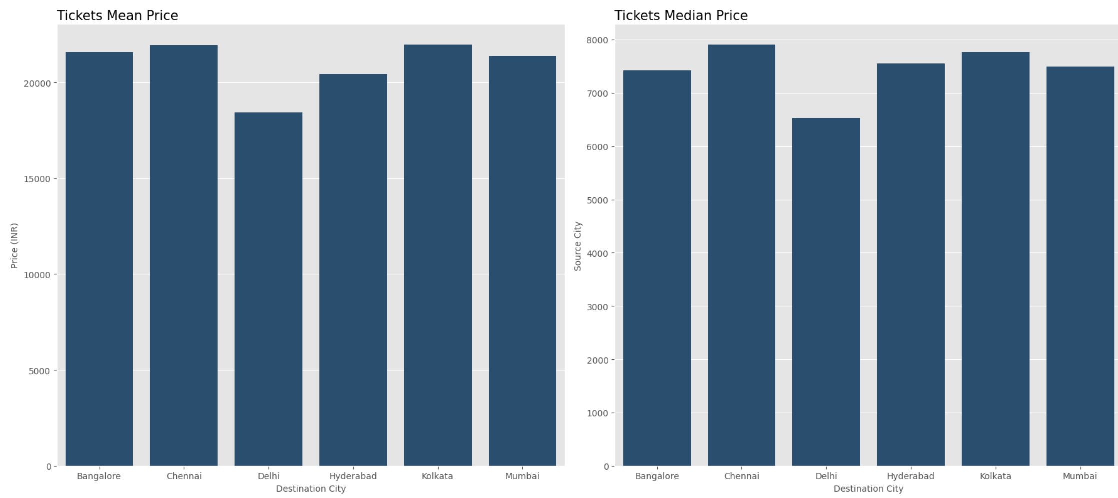



```
[ ]: destination = df.groupby("destination_city").agg(price_mean = ('price', 'mean'), price_median = ('price', 'median')).reset_index()
destination
```

[ ]:

	destination_city	price_mean	price_median
0	Bangalore	21593.955784	7425.0
1	Chennai	21953.323969	7900.0
2	Delhi	18436.767870	6521.0
3	Hyderabad	20427.661284	7548.0
4	Kolkata	21959.557556	7767.0
5	Mumbai	21372.529469	7496.0

```
[ ]: fig, axes = plt.subplots(1, 2, figsize = (18, 8))

sns.barplot(ax = axes[0], x = destination.destination_city, y = destination.
 ↪price_mean, color = '#1F4E79', order = destination.destination_city)
axes[0].set_title("Tickets Mean Price", fontsize = 15, pad = 5, loc = 'left')
axes[0].set_xlabel("Destination City", fontsize = 10)
axes[0].set_ylabel("Price (INR)", fontsize = 10)

sns.barplot(ax = axes[1], x = destination.destination_city, y = destination.
 ↪price_median, color = '#1F4E79', order = destination.destination_city)
axes[1].set_title("Tickets Median Price", fontsize = 15, pad = 5, loc = 'left')
axes[1].set_xlabel("Destination City", fontsize = 10)
axes[1].set_ylabel("Source City", fontsize = 10)

plt.tight_layout()
plt.show()
```



Kolkata and Chennai have the most expensive tickets.

2.3.6 Correlation Matrix

```
[ ]: dummies = pd.get_dummies(df, prefix = ['airline',
 'source_city',
 'departure_time',
 'stops',
 'arrival_time',
 'destination_city',
 'class'], dtype = int)
corr = dummies.corr()
```

[ ]:
```python
corr.loc['price'].sort_values(ascending = False)
```

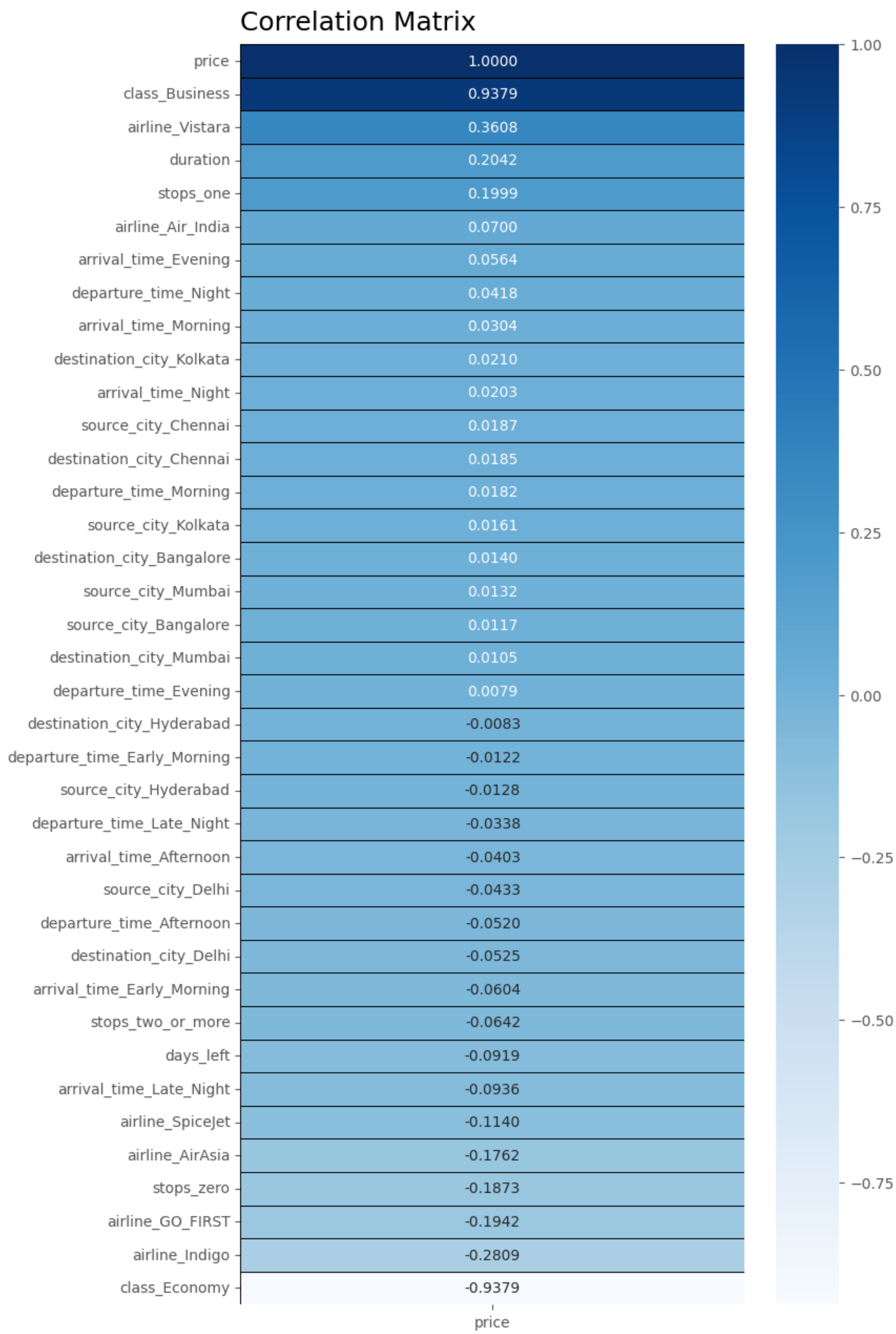
[ ]:
```
price                          1.000000
class_Business                 0.937860
airline_Vistara                0.360816
duration                       0.204222
stops_one                      0.199913
airline_Air_India              0.070041
arrival_time_Evening           0.056408
departure_time_Night           0.041768
arrival_time_Morning           0.030379
destination_city_Kolkata       0.020956
arrival_time_Night             0.020344
source_city_Chennai            0.018742
destination_city_Chennai       0.018473
departure_time_Morning         0.018199
source_city_Kolkata            0.016127
destination_city_Bangalore     0.014050
source_city_Mumbai             0.013206
source_city_Bangalore          0.011702
destination_city_Mumbai        0.010533
departure_time_Evening         0.007946
destination_city_Hyderabad    -0.008292
departure_time_Early_Morning  -0.012232
source_city_Hyderabad         -0.012828
departure_time_Late_Night     -0.033768
arrival_time_Afternoon        -0.040258
source_city_Delhi             -0.043282
departure_time_Afternoon      -0.051968
destination_city_Delhi        -0.052527
arrival_time_Early_Morning    -0.060449
stops_two_or_more             -0.064248
days_left                     -0.091949
arrival_time_Late_Night       -0.093602
airline_SpiceJet              -0.114019
airline_AirAsia               -0.176188
stops_zero                    -0.187277
airline_GO_FIRST              -0.194179
airline_Indigo                -0.280882
class_Economy                 -0.937860
Name: price, dtype: float64
```

The highlights:

- Business class has a quite high correlation with price.
- Vistara has the highest positive correlation with price, which is the highest among the airlines.
- Duration and single stop also have significant correlations.

Why not visualize this?

[ ]:
```
fig = plt.figure(figsize = (6, 12))
ax = fig.add_axes([0, 0, 1, 1])
sns.heatmap(corr[['price']].sort_values(by = 'price', ascending = False), annot␣
  ↪= True, fmt = '.4f', cmap = 'Blues', linecolor='black', linewidths=0.5)
ax.set_title("Correlation Matrix", fontsize = 18, pad = 10, loc = 'left')
plt.show()
```


Correlation Matrix
price 1.0000
class_Business 0.9379
airline_Vistara 0.3608
duration 0.2042
stops_one 0.1999
airline_Air_India 0.0700
arrival_time_Evening 0.0564
departure_time_Night 0.0418
arrival_time_Morning 0.0304
destination_city_Kolkata 0.0210
arrival_time_Night 0.0203
source_city_Chennai 0.0187
destination_city_Chennai 0.0185
departure_time_Morning 0.0182
source_city_Kolkata 0.0161
destination_city_Bangalore 0.0140
source_city_Mumbai 0.0132
source_city_Bangalore 0.0117
destination_city_Mumbai 0.0105
departure_time_Evening 0.0079
destination_city_Hyderabad -0.0083
departure_time_Early_Morning -0.0122
source_city_Hyderabad -0.0128
departure_time_Late_Night -0.0338
arrival_time_Afternoon -0.0403
source_city_Delhi -0.0433
departure_time_Afternoon -0.0520
destination_city_Delhi -0.0525
arrival_time_Early_Morning -0.0604
stops_two_or_more -0.0642
days_left -0.0919
arrival_time_Late_Night -0.0936
airline_SpiceJet -0.1140
airline_AirAsia -0.1762
stops_zero -0.1873
airline_GO_FIRST -0.1942
airline_Indigo -0.2809
class_Economy -0.9379
price
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75

3 Data Preparation

[ ]:
```
features = df.drop(columns = ['price'], axis = 1).columns.to_list()
target = 'price'

X = df[features]
y = df[target]
```

[ ]:
```
X_temp, X_test, y_temp, y_test = train_test_split(X, y, test_size=0.20,␣
↪random_state=21)

X_train, X_val, y_train, y_val = train_test_split(X_temp, y_temp, test_size = 0.
↪25, random_state=21)
```

[ ]:
```
cat_features = X_train.select_dtypes(exclude = 'number').columns.to_list()
num_features = X_train.select_dtypes(include = 'number').columns.to_list()
```

[ ]:
```
cat_transformer = Pipeline([
    ('imput', SimpleImputer(strategy = "most_frequent")),
    ('enconder', TargetEncoder())
])

num_transformer = Pipeline([
    ('imput', SimpleImputer(strategy = 'median')),
])

preprocessor = ColumnTransformer(
    transformers = [
        ('cat', cat_transformer, cat_features),
        ('num', num_transformer, num_features)
    ])
```

4 Modeling

4.1 The base model

[ ]:
```
model = XGBRegressor(objective='reg:squarederror', random_state = 21)

reg = Pipeline([
    ('preprocessor', preprocessor),
    ('regressor', model)
])

reg.fit(X_train, y_train)
```

```
[ ]: Pipeline(steps=[('preprocessor',
                     ColumnTransformer(transformers=[('cat',
                                                      Pipeline(steps=[('imput',
SimpleImputer(strategy='most_frequent')),
                                                                      ('enconder',
TargetEncoder())]),
                                                      ['airline', 'source_city',
                                                       'departure_time', 'stops',
                                                       'arrival_time',
                                                       'destination_city',
                                                       'class']),
                                                     ('num',
                                                      Pipeline(steps=[('imput',
SimpleImputer(strategy='median'))]),
                                                      ['duration', 'days_le…
                              feature_types=None, gamma=None, grow_policy=None,
                              importance_type=None,
                              interaction_constraints=None, learning_rate=None,
                              max_bin=None, max_cat_threshold=None,
                              max_cat_to_onehot=None, max_delta_step=None,
                              max_depth=None, max_leaves=None,
                              min_child_weight=None, missing=nan,
                              monotone_constraints=None, multi_strategy=None,
                              n_estimators=None, n_jobs=None,
                              num_parallel_tree=None, random_state=21, …))])
```

```
[ ]: y_pred = reg.predict(X_val)
```

```
[ ]: print(f"Validation Set")
     print("=" * 30)
     print(f"MSE: {metrics.mean_squared_error(y_val, y_pred):.4f}")
     print(f"RMSE: {metrics.mean_squared_error(y_val, y_pred, squared = False):.4f}")
     print(f"MAE: {metrics.mean_absolute_error(y_val, y_pred):.4f}")
     print(f"MAPE: {metrics.mean_absolute_percentage_error(y_val, y_pred):.4f}")
     print(f"R2 Score: {metrics.r2_score(y_val, y_pred):.4f}")
```

```
Validation Set
==============================
MSE: 12790568.0237
RMSE: 3576.3904
MAE: 2048.7408
MAPE: 0.1504
R2 Score: 0.9751
```

These are the base model results let's work it better with hyperparamer optimization.

4.2 Optimized model

[ ]:
```python
def objective(trial):
    model = Pipeline([
    ('preprocessor', preprocessor),
    ('regressor', XGBRegressor(
        objective = 'reg:squarederror',
        n_estimators = trial.suggest_int("n_estimators", 100, 1000),
        learning_rate = trial.suggest_float("learning_rate", 1e-3, 0.1,␣
 ↪log=True),
        max_depth = trial.suggest_int("max_depth", 1, 10),
        subsample = trial.suggest_float("subsample", 0.05, 1.0),
        colsample_bytree = trial.suggest_float("colsample_bytree", 0.05, 1.0),
        min_child_weight = trial.suggest_int("min_child_weight", 1, 20),
        random_state = 21
    ))
    ])

    model.fit(X_train, y_train)
    predictions = model.predict(X_val)
    rmse = metrics.mean_squared_error(y_val, predictions, squared=False)
    return rmse
```

[ ]:
```python
study = optuna.create_study(direction='minimize')
study.optimize(objective, n_trials=30)
```

```
[I 2024-08-25 18:59:56,491] A new study created in memory with name: no-
name-77cb1f25-546f-450e-b906-570e0a907ace
[I 2024-08-25 19:00:02,407] Trial 0 finished with value: 8862.57658862416 and
parameters: {'n_estimators': 229, 'learning_rate': 0.024492389628324486,
'max_depth': 6, 'subsample': 0.2550588484785341, 'colsample_bytree':
0.23487901404061928, 'min_child_weight': 9}. Best is trial 0 with value:
8862.57658862416.
[I 2024-08-25 19:00:12,848] Trial 1 finished with value: 13377.321509158486 and
parameters: {'n_estimators': 833, 'learning_rate': 0.0011862800787346272,
'max_depth': 2, 'subsample': 0.287177984250061, 'colsample_bytree':
0.597102663039611, 'min_child_weight': 19}. Best is trial 0 with value:
8862.57658862416.
[I 2024-08-25 19:00:17,781] Trial 2 finished with value: 10143.12062061122 and
parameters: {'n_estimators': 363, 'learning_rate': 0.005012523465267334,
'max_depth': 1, 'subsample': 0.9066574973209431, 'colsample_bytree':
0.5745271035798778, 'min_child_weight': 6}. Best is trial 0 with value:
8862.57658862416.
[I 2024-08-25 19:00:25,659] Trial 3 finished with value: 5220.244817019831 and
parameters: {'n_estimators': 578, 'learning_rate': 0.013331414719213857,
'max_depth': 3, 'subsample': 0.7338248812020122, 'colsample_bytree':
0.5528055750913233, 'min_child_weight': 17}. Best is trial 3 with value:
5220.244817019831.
```

```
[I 2024-08-25 19:00:40,638] Trial 4 finished with value: 3430.148895520396 and
parameters: {'n_estimators': 835, 'learning_rate': 0.034093230314878084,
'max_depth': 7, 'subsample': 0.8425699635909832, 'colsample_bytree':
0.7639393898246126, 'min_child_weight': 1}. Best is trial 4 with value:
3430.148895520396.
[I 2024-08-25 19:00:46,678] Trial 5 finished with value: 4345.345818433851 and
parameters: {'n_estimators': 362, 'learning_rate': 0.03420095978797079,
'max_depth': 5, 'subsample': 0.3027445461141159, 'colsample_bytree':
0.7972863298661383, 'min_child_weight': 2}. Best is trial 4 with value:
3430.148895520396.
[I 2024-08-25 19:01:06,309] Trial 6 finished with value: 4098.152181211634 and
parameters: {'n_estimators': 723, 'learning_rate': 0.004478972337335129,
'max_depth': 10, 'subsample': 0.9377742222228224, 'colsample_bytree':
0.7835008738456918, 'min_child_weight': 15}. Best is trial 4 with value:
3430.148895520396.
[I 2024-08-25 19:01:16,206] Trial 7 finished with value: 3900.9973631500907 and
parameters: {'n_estimators': 496, 'learning_rate': 0.018072673176409943,
'max_depth': 7, 'subsample': 0.19289290264290615, 'colsample_bytree':
0.8938799879780247, 'min_child_weight': 4}. Best is trial 4 with value:
3430.148895520396.
[I 2024-08-25 19:01:21,297] Trial 8 finished with value: 18818.848514541034 and
parameters: {'n_estimators': 186, 'learning_rate': 0.003870787437535607,
'max_depth': 7, 'subsample': 0.9370731995203976, 'colsample_bytree':
0.3177843378411038, 'min_child_weight': 20}. Best is trial 4 with value:
3430.148895520396.
[I 2024-08-25 19:01:27,635] Trial 9 finished with value: 18099.112077715938 and
parameters: {'n_estimators': 428, 'learning_rate': 0.001346066777203931,
'max_depth': 3, 'subsample': 0.16951403572568063, 'colsample_bytree':
0.33594353062755317, 'min_child_weight': 13}. Best is trial 4 with value:
3430.148895520396.
[I 2024-08-25 19:01:59,920] Trial 10 finished with value: 2643.9141673555478 and
parameters: {'n_estimators': 1000, 'learning_rate': 0.09966133771268752,
'max_depth': 10, 'subsample': 0.5688373909283602, 'colsample_bytree':
0.9316787148859975, 'min_child_weight': 9}. Best is trial 10 with value:
2643.9141673555478.
[I 2024-08-25 19:02:26,792] Trial 11 finished with value: 2622.1551841132173 and
parameters: {'n_estimators': 956, 'learning_rate': 0.08885057738863303,
'max_depth': 10, 'subsample': 0.560743995211729, 'colsample_bytree':
0.9985920323190209, 'min_child_weight': 9}. Best is trial 11 with value:
2622.1551841132173.
[I 2024-08-25 19:02:56,855] Trial 12 finished with value: 2641.5514477161096 and
parameters: {'n_estimators': 982, 'learning_rate': 0.09640189438514946,
'max_depth': 10, 'subsample': 0.554626170108951, 'colsample_bytree':
0.9697152090965963, 'min_child_weight': 10}. Best is trial 11 with value:
2622.1551841132173.
[I 2024-08-25 19:03:19,096] Trial 13 finished with value: 2714.4756414577146 and
parameters: {'n_estimators': 965, 'learning_rate': 0.082850949744856,
'max_depth': 9, 'subsample': 0.4668061915390079, 'colsample_bytree':
```

```
0.9930249947994891, 'min_child_weight': 12}. Best is trial 11 with value:
2622.1551841132173.
[I 2024-08-25 19:03:27,477] Trial 14 finished with value: 6632.783312487924 and
parameters: {'n_estimators': 670, 'learning_rate': 0.05417508190052682,
'max_depth': 9, 'subsample': 0.5511198035324097, 'colsample_bytree':
0.10550187167886843, 'min_child_weight': 7}. Best is trial 11 with value:
2622.1551841132173.
[I 2024-08-25 19:03:45,165] Trial 15 finished with value: 2790.9313417747553 and
parameters: {'n_estimators': 870, 'learning_rate': 0.05247343772861899,
'max_depth': 9, 'subsample': 0.6958264863288773, 'colsample_bytree':
0.6780883799235097, 'min_child_weight': 11}. Best is trial 11 with value:
2622.1551841132173.
[I 2024-08-25 19:04:00,367] Trial 16 finished with value: 3852.8169513821376 and
parameters: {'n_estimators': 720, 'learning_rate': 0.008591745322137117,
'max_depth': 8, 'subsample': 0.4434147021134358, 'colsample_bytree':
0.8924115303253563, 'min_child_weight': 14}. Best is trial 11 with value:
2622.1551841132173.
[I 2024-08-25 19:04:13,996] Trial 17 finished with value: 3735.6769928667954 and
parameters: {'n_estimators': 903, 'learning_rate': 0.06092789943867181,
'max_depth': 5, 'subsample': 0.6527694236750965, 'colsample_bytree':
0.9801787225334296, 'min_child_weight': 8}. Best is trial 11 with value:
2622.1551841132173.
[I 2024-08-25 19:04:36,304] Trial 18 finished with value: 3184.1916607492976 and
parameters: {'n_estimators': 777, 'learning_rate': 0.03225538748462477,
'max_depth': 10, 'subsample': 0.07067098169689312, 'colsample_bytree':
0.6752219938856643, 'min_child_weight': 5}. Best is trial 11 with value:
2622.1551841132173.
[I 2024-08-25 19:04:52,092] Trial 19 finished with value: 4767.629480219714 and
parameters: {'n_estimators': 609, 'learning_rate': 0.009562616898461822,
'max_depth': 8, 'subsample': 0.38756963664584776, 'colsample_bytree':
0.45425041049110376, 'min_child_weight': 10}. Best is trial 11 with value:
2622.1551841132173.
[I 2024-08-25 19:05:14,242] Trial 20 finished with value: 2717.2916679968557 and
parameters: {'n_estimators': 978, 'learning_rate': 0.09451574613160346,
'max_depth': 8, 'subsample': 0.8083091583103925, 'colsample_bytree':
0.833392984731383, 'min_child_weight': 16}. Best is trial 11 with value:
2622.1551841132173.
[I 2024-08-25 19:05:53,105] Trial 21 finished with value: 2634.378721971906 and
parameters: {'n_estimators': 990, 'learning_rate': 0.09583541671831836,
'max_depth': 10, 'subsample': 0.5969909240808767, 'colsample_bytree':
0.9184009108796035, 'min_child_weight': 10}. Best is trial 11 with value:
2622.1551841132173.
[I 2024-08-25 19:06:25,054] Trial 22 finished with value: 2635.969874375013 and
parameters: {'n_estimators': 909, 'learning_rate': 0.06044884059919022,
'max_depth': 10, 'subsample': 0.6212571409729032, 'colsample_bytree':
0.9958393871003632, 'min_child_weight': 11}. Best is trial 11 with value:
2622.1551841132173.
[I 2024-08-25 19:06:50,515] Trial 23 finished with value: 2742.4568220592378 and
```

```
parameters: {'n_estimators': 864, 'learning_rate': 0.05955187642511468,
'max_depth': 9, 'subsample': 0.6213721417231871, 'colsample_bytree':
0.8606082660923033, 'min_child_weight': 12}. Best is trial 11 with value:
2622.1551841132173.
[I 2024-08-25 19:07:19,748] Trial 24 finished with value: 2663.65379376364 and
parameters: {'n_estimators': 915, 'learning_rate': 0.043579686126519926,
'max_depth': 10, 'subsample': 0.7550692310656586, 'colsample_bytree':
0.7210719048107044, 'min_child_weight': 7}. Best is trial 11 with value:
2622.1551841132173.
[I 2024-08-25 19:07:38,849] Trial 25 finished with value: 3084.2276678095877 and
parameters: {'n_estimators': 778, 'learning_rate': 0.022136167906717383,
'max_depth': 9, 'subsample': 0.46755345479520605, 'colsample_bytree':
0.9049239772672324, 'min_child_weight': 11}. Best is trial 11 with value:
2622.1551841132173.
[I 2024-08-25 19:07:56,193] Trial 26 finished with value: 2863.4264035442498 and
parameters: {'n_estimators': 783, 'learning_rate': 0.06757966034251568,
'max_depth': 8, 'subsample': 0.622856073631866, 'colsample_bytree':
0.9952279668630203, 'min_child_weight': 13}. Best is trial 11 with value:
2622.1551841132173.
[I 2024-08-25 19:08:12,012] Trial 27 finished with value: 3545.18621684338 and
parameters: {'n_estimators': 916, 'learning_rate': 0.044795768275337454,
'max_depth': 6, 'subsample': 0.39328505913497, 'colsample_bytree':
0.8193048186197822, 'min_child_weight': 8}. Best is trial 11 with value:
2622.1551841132173.
[I 2024-08-25 19:08:38,832] Trial 28 finished with value: 5420.144191965624 and
parameters: {'n_estimators': 925, 'learning_rate': 0.002147573427269228,
'max_depth': 10, 'subsample': 0.6792164479192159, 'colsample_bytree':
0.9340497790264902, 'min_child_weight': 4}. Best is trial 11 with value:
2622.1551841132173.
[I 2024-08-25 19:08:48,815] Trial 29 finished with value: 4650.7264288550905 and
parameters: {'n_estimators': 662, 'learning_rate': 0.02858470121364258,
'max_depth': 4, 'subsample': 0.5024618000666115, 'colsample_bytree':
0.4560553241436307, 'min_child_weight': 9}. Best is trial 11 with value:
2622.1551841132173.
```

[ ]:
```python
print('Best hyperparameters:', study.best_params)
print('Best RMSE:', study.best_value)
```

```
Best hyperparameters: {'n_estimators': 956, 'learning_rate':
0.08885057738863303, 'max_depth': 10, 'subsample': 0.560743995211729,
'colsample_bytree': 0.9985920323190209, 'min_child_weight': 9}
Best RMSE: 2622.1551841132173
```

[ ]:
```python
reg_optuna = Pipeline([
    ('preprocessor', preprocessor),
    ('regressor', XGBRegressor(**study.best_params, random_state = 21))
])
```

```
reg_optuna.fit(X_train, y_train)
```

```
[ ]: Pipeline(steps=[('preprocessor',
                  ColumnTransformer(transformers=[('cat',
                                                   Pipeline(steps=[('imput',
SimpleImputer(strategy='most_frequent')),
                                                                   ('enconder',
TargetEncoder())]),
                                                   ['airline', 'source_city',
                                                    'departure_time', 'stops',
                                                    'arrival_time',
                                                    'destination_city',
                                                    'class']),
                                                  ('num',
                                                   Pipeline(steps=[('imput',
SimpleImputer(strategy='median'))]),
                                                   ['duration', 'days_le…
                              feature_types=None, gamma=None, grow_policy=None,
                              importance_type=None,
                              interaction_constraints=None,
                              learning_rate=0.08885057738863303, max_bin=None,
                              max_cat_threshold=None, max_cat_to_onehot=None,
                              max_delta_step=None, max_depth=10,
                              max_leaves=None, min_child_weight=9, missing=nan,
                              monotone_constraints=None, multi_strategy=None,
                              n_estimators=956, n_jobs=None,
                              num_parallel_tree=None, random_state=21, …))])
```

```
[ ]: y_pred_optuna = reg_optuna.predict(X_val)
```

```
[ ]: print("Validation Set - Optimized")
print("=" * 30)
print(f"MSE: {metrics.mean_squared_error(y_val, y_pred_optuna):.4f}")
print(f"RMSE: {metrics.mean_squared_error(y_val, y_pred_optuna, squared =
  ↪False):.4f}")
print(f"MAE: {metrics.mean_absolute_error(y_val, y_pred_optuna):.4f}")
print(f"MAPE: {metrics.mean_absolute_percentage_error(y_val, y_pred_optuna):.
  ↪4f}")
print(f"R2 Score: {metrics.r2_score(y_val, y_pred_optuna):.4f}")
```

```
Validation Set - Optimized
==============================
MSE: 6875697.8096
RMSE: 2622.1552
MAE: 1333.2493
MAPE: 0.0971
R2 Score: 0.9866
```

Our final model got good metrics in the validation set. The Mean Absolute Percentage Error is arround 9% which shows a good performance, time to evaluate using the test set.

5 Evaluation

5.1 The metrics

[ ]:
```
y_pred_test = reg_optuna.predict(X_test)
```

[ ]:
```
print("Test Set")
print("=" * 30)
print(f"MSE: {metrics.mean_squared_error(y_test, y_pred_test):.4f}")
print(f"RMSE: {metrics.mean_squared_error(y_test, y_pred_test, squared = False):
  ↪.4f}")
print(f"MAE: {metrics.mean_absolute_error(y_test, y_pred_test):.4f}")
print(f"MAPE: {metrics.mean_absolute_percentage_error(y_test, y_pred_test):.
  ↪4f}")
print(f"R2 Score: {metrics.r2_score(y_test, y_pred_test):.4f}")
```

```
Test Set
==============================
MSE: 6855205.6699
RMSE: 2618.2448
MAE: 1328.5562
MAPE: 0.0962
R2 Score: 0.9868
```

The model showed good metrics, a high R2 score, and good RMSE and MAE.

5.2 Cross-validation

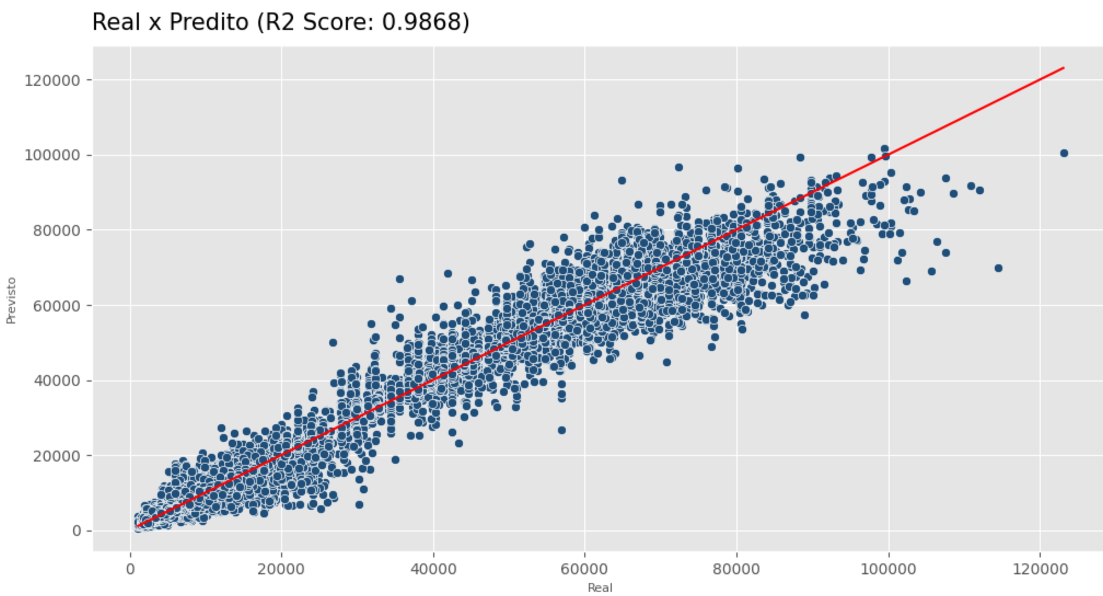
[ ]:
```
scoring = metrics.make_scorer(metrics.mean_absolute_error)
cv = KFold(n_splits = 5, shuffle=True, random_state=21)

scores = cross_val_score(reg_optuna, X_train, y_train, cv = cv, scoring =␣
  ↪scoring)
print(f'Mean MAE: {scores}')
print(f'General Mean MAE: {scores.mean()}')
print(f'MAE Standard Deviation: {scores.std()}')
```

```
Mean MAE: [1393.91755665 1378.22671365 1368.95018009 1383.35412869 1363.1419011
]
General Mean MAE: 1377.5180960373127
MAE Standard Deviation: 10.803590968524654
```

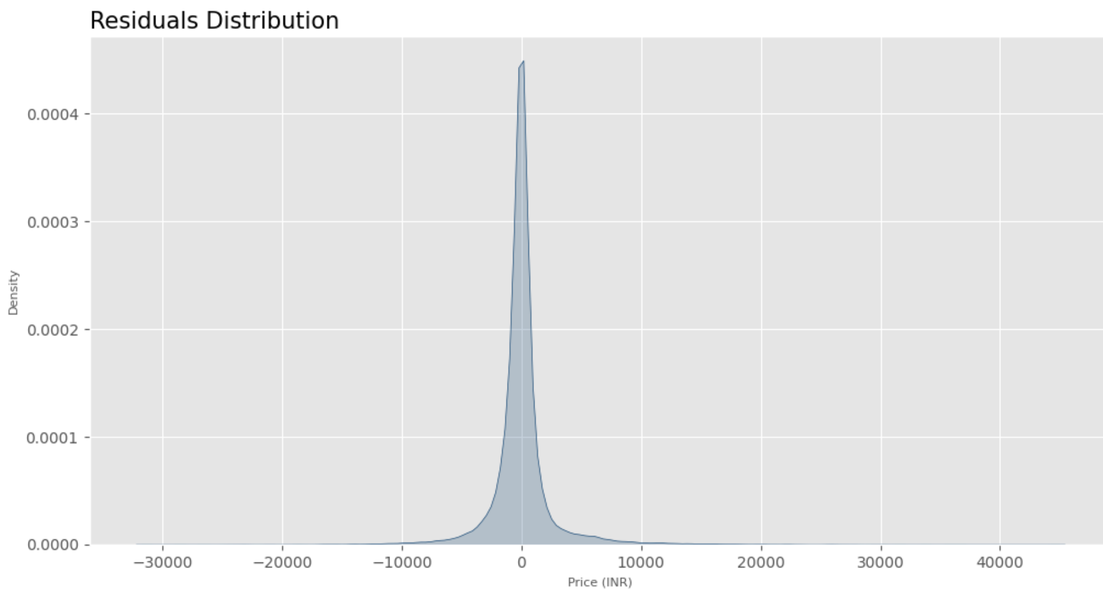
We can also see that the model demonstrated good generalization, with no signs of overfitting.

5.3 Visualization

[ ]:
```python
fig, ax = plt.subplots(figsize = (12, 6))

sns.scatterplot(x = y_test, y = y_pred_test)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color = 'red')
ax.set_title(f"Real x Predito (R2 Score: {metrics.r2_score(y_test, y_pred_test):
  ↪.4f})", fontsize = 15, pad = 10, loc = 'left')
ax.set_xlabel("Real", fontsize = 8)
ax.set_ylabel("Previsto", fontsize = 8)
plt.show()
```



[ ]:
```python
residuals = y_test - y_pred_test

fig, ax = plt.subplots(figsize = (12, 6))
sns.kdeplot(residuals, fill = True)
ax.set_title("Residuals Distribution", fontsize = 15, pad = 5, loc = 'left')
ax.set_xlabel("Price (INR)", fontsize = 8)
ax.set_ylabel("Density", fontsize = 8)
plt.show()
```



6 Conclusions

That's my first time trying to work with the CRISP-DM framework, and it was a good experience throughout this project. Regarding the business questions, we can say that:

- Price varies with class and airline, especially with class. In the case of airlines, there is a significant difference when we consider Vistara and Air India;
- Kolkata and Chennai are the most expensive destinations;
- For arrival time, evening and morning have the highest prices, and for departure, morning and night do;
- Buying tickets in advance is the best way to get good prices.

For the model we got good generalization and results, for more of my work you can find me on: - LinkedIn - Github