In [1]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import warnings
import shap
from sklearn.preprocessing import OneHotEncoder
from category_encoders import TargetEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from xgboost import XGBRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split, RandomizedSearchCV, cross_val_score, KFold
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

warnings.filterwarnings('ignore')
```

In [2]:

```
df = pd.read_csv("/kaggle/input/airlines-flights-data/airlines_flights_data.csv")
df.head()
```

Out[2]:

	index	airline	flight	source_city	departure_time	stops	arrival_time	destination_city	class	duration	days_left	price
0	0	SpiceJet	SG-8709	Delhi	Evening	zero	Night	Mumbai	Economy	2.17	1	5953
1	1	SpiceJet	SG-8157	Delhi	Early_Morning	zero	Morning	Mumbai	Economy	2.33	1	5953
2	2	AirAsia	I5-764	Delhi	Early_Morning	zero	Early_Morning	Mumbai	Economy	2.17	1	5956
3	3	Vistara	UK-995	Delhi	Morning	zero	Afternoon	Mumbai	Economy	2.25	1	5955
4	4	Vistara	UK-963	Delhi	Morning	zero	Morning	Mumbai	Economy	2.33	1	5955

In [3]:

```
df.drop(columns=['index'], inplace=True)
```

EXPLORATORY DATA ANALYSIS

In [4]:
```
df.head()
```

Out[4]:

	airline	flight	source_city	departure_time	stops	arrival_time	destination_city	class	duration	days_left	price
0	SpiceJet	SG-8709	Delhi	Evening	zero	Night	Mumbai	Economy	2.17	1	5953
1	SpiceJet	SG-8157	Delhi	Early_Morning	zero	Morning	Mumbai	Economy	2.33	1	5953
2	AirAsia	I5-764	Delhi	Early_Morning	zero	Early_Morning	Mumbai	Economy	2.17	1	5956
3	Vistara	UK-995	Delhi	Morning	zero	Afternoon	Mumbai	Economy	2.25	1	5955
4	Vistara	UK-963	Delhi	Morning	zero	Morning	Mumbai	Economy	2.33	1	5955

In [5]:
```
df.describe()
```

Out[5]:

	duration	days_left	price
count	300153.000000	300153.000000	300153.000000
mean	12.221021	26.004751	20889.660523
std	7.191997	13.561004	22697.767366
min	0.830000	1.000000	1105.000000
25%	6.830000	15.000000	4783.000000
50%	11.250000	26.000000	7425.000000
75%	16.170000	38.000000	42521.000000
max	49.830000	49.000000	123071.000000

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 300153 entries, 0 to 300152
Data columns (total 11 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   airline           300153 non-null  object 
 1   flight            300153 non-null  object 
 2   source_city       300153 non-null  object 
 3   departure_time    300153 non-null  object 
 4   stops             300153 non-null  object 
 5   arrival_time      300153 non-null  object 
 6   destination_city  300153 non-null  object 
 7   class             300153 non-null  object 
 8   duration          300153 non-null  float64
 9   days_left         300153 non-null  int64  
 10  price             300153 non-null  int64  
dtypes: float64(1), int64(2), object(8)
memory usage: 25.2+ MB
```

In [7]:
```
df[df['duration'] == df['duration'].max()]
```

Out[7]:

	airline	flight	source_city	departure_time	stops	arrival_time	destination_city	class	duration	days_left	price
193889	Air_India	AI-672	Chennai	Evening	two_or_more	Evening	Bangalore	Economy	49.83	2	23891
194359	Air_India	AI-672	Chennai	Evening	one	Evening	Bangalore	Economy	49.83	9	17538

In [8]:
```
df[df['duration'] == df['duration'].min()]
```

Out[8]:

	airline	flight	source_city	departure_time	stops	arrival_time	destination_city	class	duration	days_left	price
115869	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	6	3498
115943	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	7	3498
116010	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	8	3498
116081	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	9	3498
116163	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	10	3498
116236	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	11	3498
116322	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	12	3498
116411	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	13	3498
116496	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	14	3498
116656	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	16	1924
116835	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	18	1924
116924	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	19	1924
117019	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	20	1924
117101	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	21	1924
117190	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	22	1924
117274	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	23	1924
117366	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	24	1924
117461	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	25	1924
117547	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	26	1924
117643	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	27	1924
117728	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	28	1924
117817	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	29	1924

	airline	flight	source_city	departure_time	stops	arrival_time	destination_city	class	duration	days_left	price
117900	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	30	1924
117995	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	31	1604
118086	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	32	1604
118173	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	33	1604
118269	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	34	1604
118355	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	35	1604
118445	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	36	1604
118528	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	37	1604
118622	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	38	1604
118712	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	39	1604
118799	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	40	1604
118896	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	41	1604
118982	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	42	1604
119072	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	43	1604
119155	Indigo	6E-357	Bangalore	Night	zero	Night	Chennai	Economy	0.83	44	1604
197354	Indigo	6E-987	Chennai	Early_Morning	zero	Early_Morning	Bangalore	Economy	0.83	45	1443
197355	Indigo	6E-477	Chennai	Early_Morning	zero	Morning	Bangalore	Economy	0.83	45	1443
197356	Indigo	6E-6137	Chennai	Morning	zero	Morning	Bangalore	Economy	0.83	45	1443
197445	Indigo	6E-987	Chennai	Early_Morning	zero	Early_Morning	Bangalore	Economy	0.83	46	1443
197446	Indigo	6E-477	Chennai	Early_Morning	zero	Morning	Bangalore	Economy	0.83	46	1443
197447	Indigo	6E-6137	Chennai	Morning	zero	Morning	Bangalore	Economy	0.83	46	1443
197537	Indigo	6E-987	Chennai	Early_Morning	zero	Early_Morning	Bangalore	Economy	0.83	47	1443

	airline	flight	source_city	departure_time	stops	arrival_time	destination_city	class	duration	days_left	price
197538	Indigo	6E-477	Chennai	Early_Morning	zero	Morning	Bangalore	Economy	0.83	47	1443
197539	Indigo	6E-6137	Chennai	Morning	zero	Morning	Bangalore	Economy	0.83	47	1443
197626	Indigo	6E-987	Chennai	Early_Morning	zero	Early_Morning	Bangalore	Economy	0.83	48	1443
197627	Indigo	6E-477	Chennai	Early_Morning	zero	Morning	Bangalore	Economy	0.83	48	1443
197628	Indigo	6E-6137	Chennai	Morning	zero	Morning	Bangalore	Economy	0.83	48	1443
197712	Indigo	6E-987	Chennai	Early_Morning	zero	Early_Morning	Bangalore	Economy	0.83	49	1443
197713	Indigo	6E-477	Chennai	Early_Morning	zero	Morning	Bangalore	Economy	0.83	49	1443
197724	Indigo	6E-6137	Chennai	Morning	zero	Morning	Bangalore	Economy	0.83	49	1549

In [9]:
```
df[df['price'] == df['price'].max()]
```

Out[9]:

	airline	flight	source_city	departure_time	stops	arrival_time	destination_city	class	duration	days_left	price
261377	Vistara	UK-772	Kolkata	Morning	one	Night	Delhi	Business	13.5	3	123071

In [10]:
```
df[df['price'] == df['price'].min()]
```

Out[10]:

	airline	flight	source_city	departure_time	stops	arrival_time	destination_city	class	duration	days_left	price
203807	AirAsia	I5-517	Chennai	Morning	zero	Morning	Hyderabad	Economy	1.17	16	1105
203808	GO_FIRST	G8-505	Chennai	Evening	zero	Evening	Hyderabad	Economy	1.25	16	1105
203908	AirAsia	I5-517	Chennai	Morning	zero	Morning	Hyderabad	Economy	1.17	17	1105
203909	GO_FIRST	G8-505	Chennai	Evening	zero	Evening	Hyderabad	Economy	1.25	17	1105
204003	AirAsia	I5-517	Chennai	Morning	zero	Morning	Hyderabad	Economy	1.17	18	1105
...	...	...	...	...	...	...	...	...	...	...	...
206601	Indigo	6E-7261	Chennai	Morning	one	Evening	Hyderabad	Economy	7.92	49	1105
206602	Indigo	6E-611	Chennai	Evening	one	Late_Night	Hyderabad	Economy	8.25	49	1105
206603	Indigo	6E-581	Chennai	Morning	one	Evening	Hyderabad	Economy	9.17	49	1105
206604	Indigo	6E-7127	Chennai	Afternoon	one	Night	Hyderabad	Economy	9.50	49	1105
206605	Indigo	6E-7261	Chennai	Morning	one	Night	Hyderabad	Economy	10.08	49	1105

300 rows × 11 columns

In [11]:
```
df.groupby('airline')['price'].max()
```

Out[11]:
```
airline
AirAsia       31917
Air_India     90970
GO_FIRST      32803
Indigo        31952
SpiceJet      34158
Vistara      123071
Name: price, dtype: int64
```

In [12]:
```
df.groupby('airline')['price'].min()
```

Out[12]:
```
airline
AirAsia      1105
Air_India    1526
GO_FIRST     1105
Indigo       1105
SpiceJet     1106
Vistara      1714
Name: price, dtype: int64
```

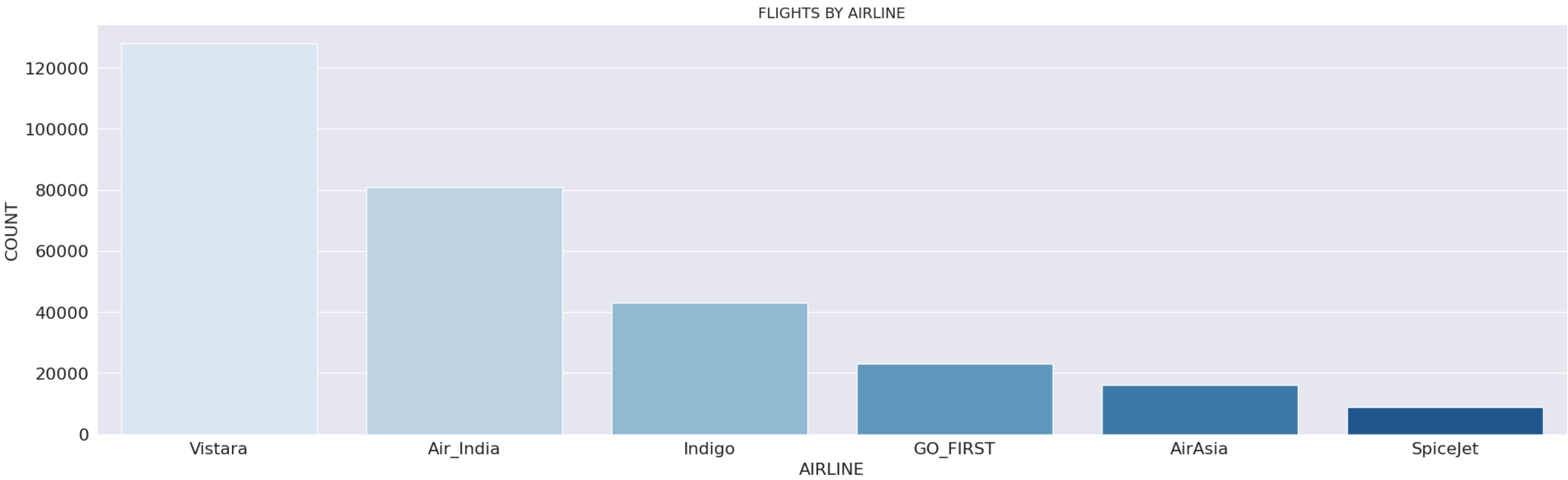
CASE STUDY

1.What are the airlines in the dataset, accompanied by their frequencies?

In [13]:
```
df['airline'].value_counts()
```

Out[13]:
```
airline
Vistara      127859
Air_India     80892
Indigo        43120
GO_FIRST      23173
AirAsia       16098
SpiceJet       9011
Name: count, dtype: int64
```

In [69]:
```
airline_counts = df['airline'].value_counts()
sns.set_style('darkgrid')
plt.figure(figsize=(25,7))
sns.barplot(x=airline_counts.index, y=airline_counts.values, palette='Blues')
plt.xlabel('AIRLINE', fontsize=16)
plt.ylabel('COUNT',fontsize=16)
plt.title('FLIGHTS BY AIRLINE', fontsize=14)
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.show()
```



2.Show Bar Graphs representing the Departure Time & Arrival Time.

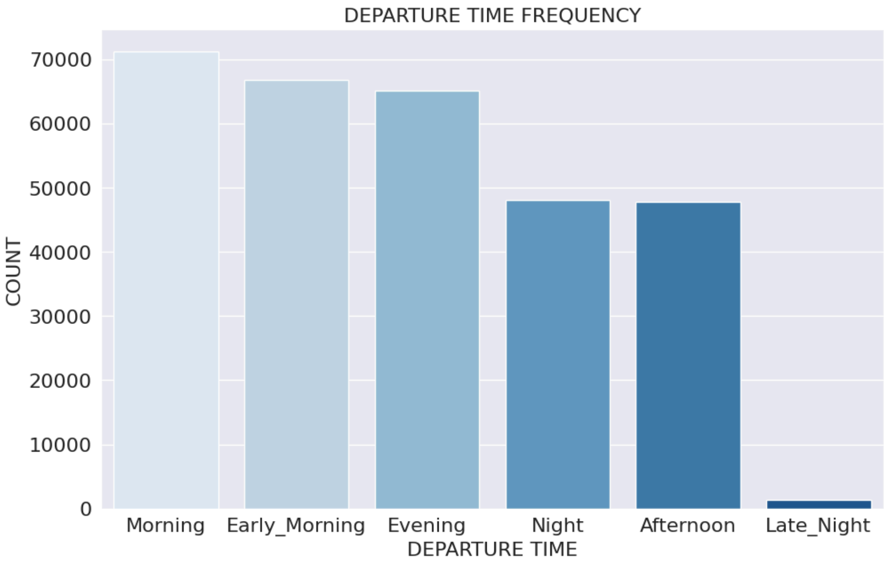
In [15]:
```
df['departure_time'].value_counts()
```

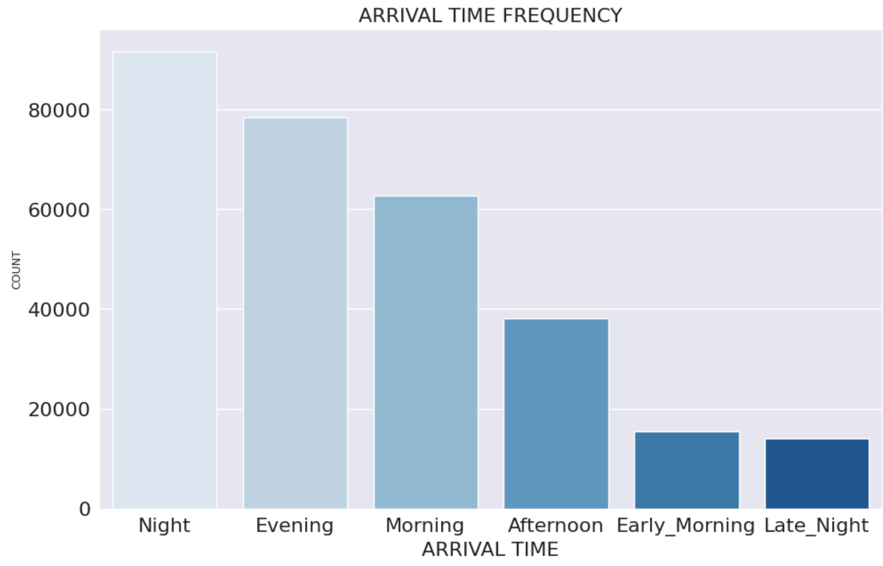
Out[15]:
```
departure_time
Morning          71146
Early_Morning    66790
Evening          65102
Night            48015
Afternoon        47794
Late_Night        1306
Name: count, dtype: int64
```

In [16]:
```
df['arrival_time'].value_counts()
```

Out[16]:
```
arrival_time
Night            91538
Evening          78323
Morning          62735
Afternoon        38139
Early_Morning    15417
Late_Night       14001
Name: count, dtype: int64
```

In [70]:
```
departure_time = df['departure_time'].value_counts()
arrival_time = df['arrival_time'].value_counts()

sns.set_style('darkgrid')

plt.figure(figsize=(25,7))
plt.subplot(1,2,1)
sns.barplot(x=departure_time.index, y=departure_time.values, palette='Blues')
plt.xlabel('DEPARTURE TIME', fontsize=16)
plt.ylabel('COUNT',fontsize=16)
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.subplot(1,2,1)
plt.title('DEPARTURE TIME FREQUENCY', fontsize=16)

plt.subplot(1,2,2)
sns.barplot(x=arrival_time.index, y=arrival_time.values, palette='Blues')
plt.xlabel('ARRIVAL TIME', fontsize=16)
plt.ylabel('COUNT',fontsize=9)
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.subplot(1,2,2)
plt.title('ARRIVAL TIME FREQUENCY', fontsize=16)
plt.show()
```





3.Show Bar Graphs representing the Source City & Destination City

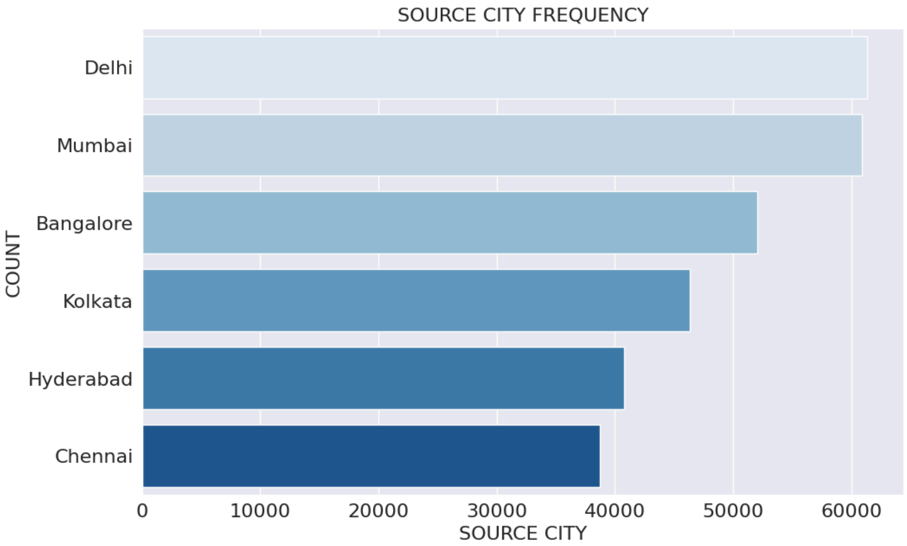
In [18]:
```
df['source_city'].value_counts()
```

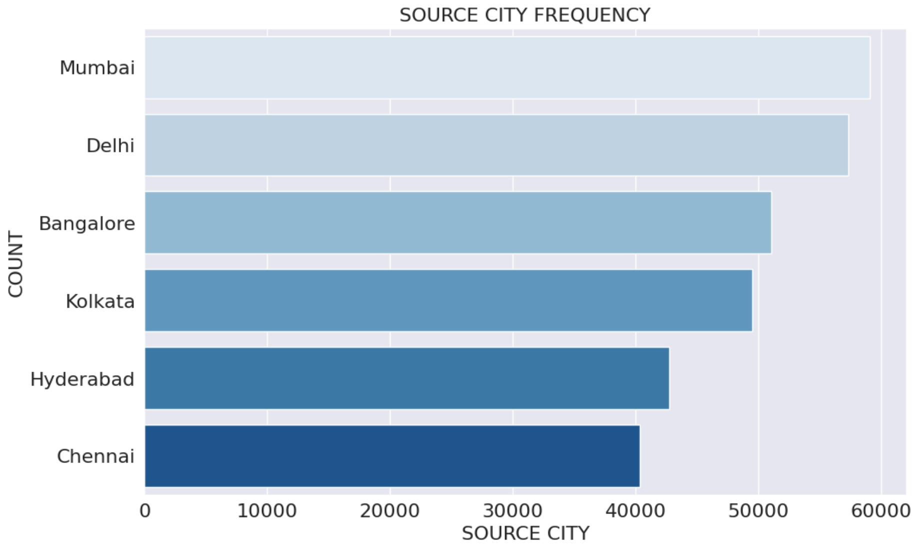
Out[18]:
```
source_city
Delhi        61343
Mumbai       60896
Bangalore    52061
Kolkata      46347
Hyderabad    40806
Chennai      38700
Name: count, dtype: int64
```

In [19]:
```
df['destination_city'].value_counts()
```

Out[19]:
```
destination_city
Mumbai       59097
Delhi        57360
Bangalore    51068
Kolkata      49534
Hyderabad    42726
Chennai      40368
Name: count, dtype: int64
```

In [72]:
```
source_city = df['source_city'].value_counts()
destination_city = df['destination_city'].value_counts()

plt.figure(figsize=(25,7))
plt.subplot(1,2,1)
sns.barplot(x=source_city.values, y=source_city.index, palette='Blues')
plt.xlabel('SOURCE CITY', fontsize=16)
plt.ylabel('COUNT', fontsize=16)
plt.title('SOURCE CITY FREQUENCY', fontsize=16)
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)

plt.subplot(1,2,2)
sns.barplot(x=destination_city.values, y=destination_city.index, palette='Blues')
plt.xlabel('SOURCE CITY', fontsize=16)
plt.ylabel('COUNT', fontsize=16)
plt.title('SOURCE CITY FREQUENCY', fontsize=16)
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)

plt.show()
```



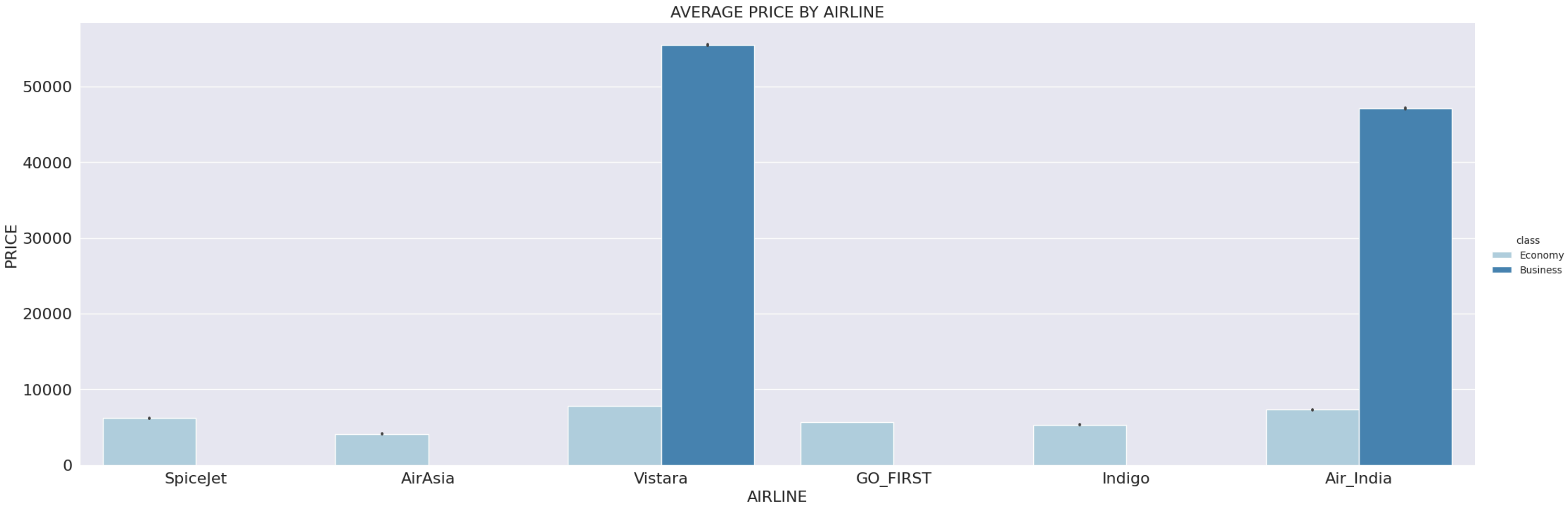


4.Does price varies with airlines?

In [21]:
```
df.groupby('airline')['price'].mean()
```

Out[21]:
```
airline
AirAsia       4091.072742
Air_India    23507.019112
GO_FIRST      5652.007595
Indigo        5324.216303
SpiceJet      6179.278881
Vistara      30396.536302
Name: price, dtype: float64
```

In [84]:
```
sns.catplot(x='airline', y='price', kind='bar', palette='Blues', data=df, hue='class', height=7, aspect=3)
plt.xlabel('AIRLINE', fontsize=16)
plt.ylabel('PRICE', fontsize=16)
plt.title('AVERAGE PRICE BY AIRLINE',fontsize=16)
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.show()
```



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

In [23]:

```
df.groupby('departure_time')['price'].mean()
```

Out[23]:

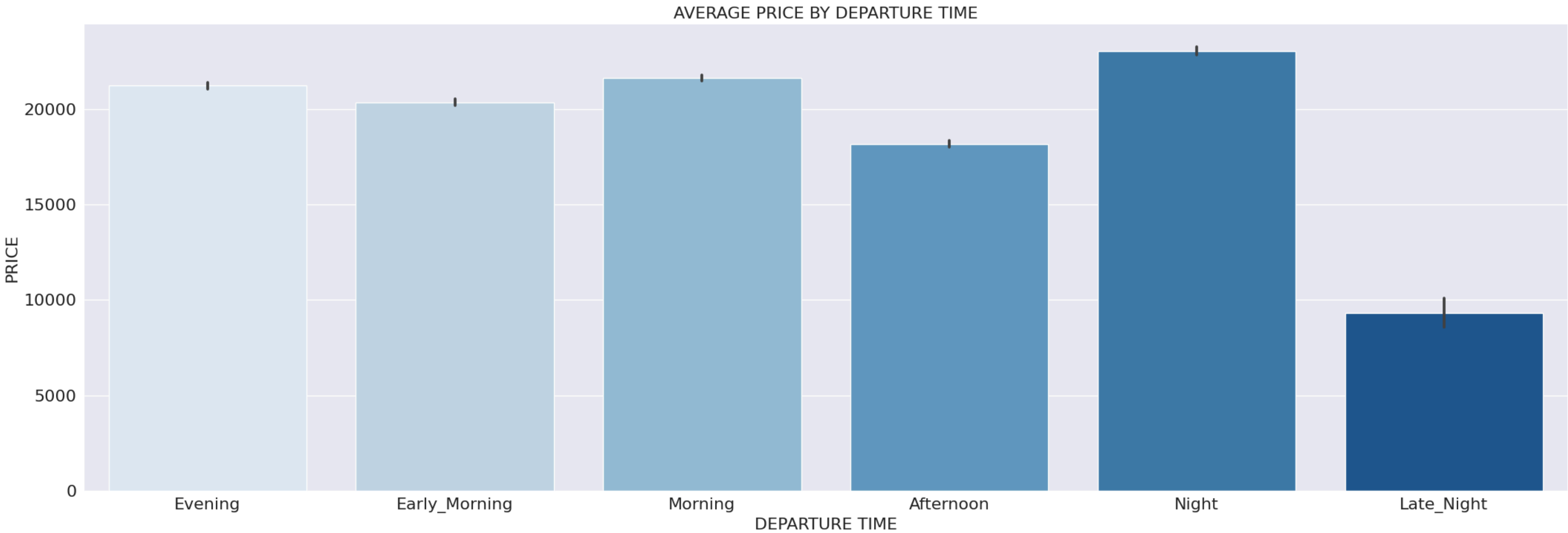
```
departure_time
Afternoon        18179.203331
Early_Morning    20370.676718
Evening          21232.361894
Late_Night        9295.299387
Morning          21630.760254
Night            23062.146808
Name: price, dtype: float64
```

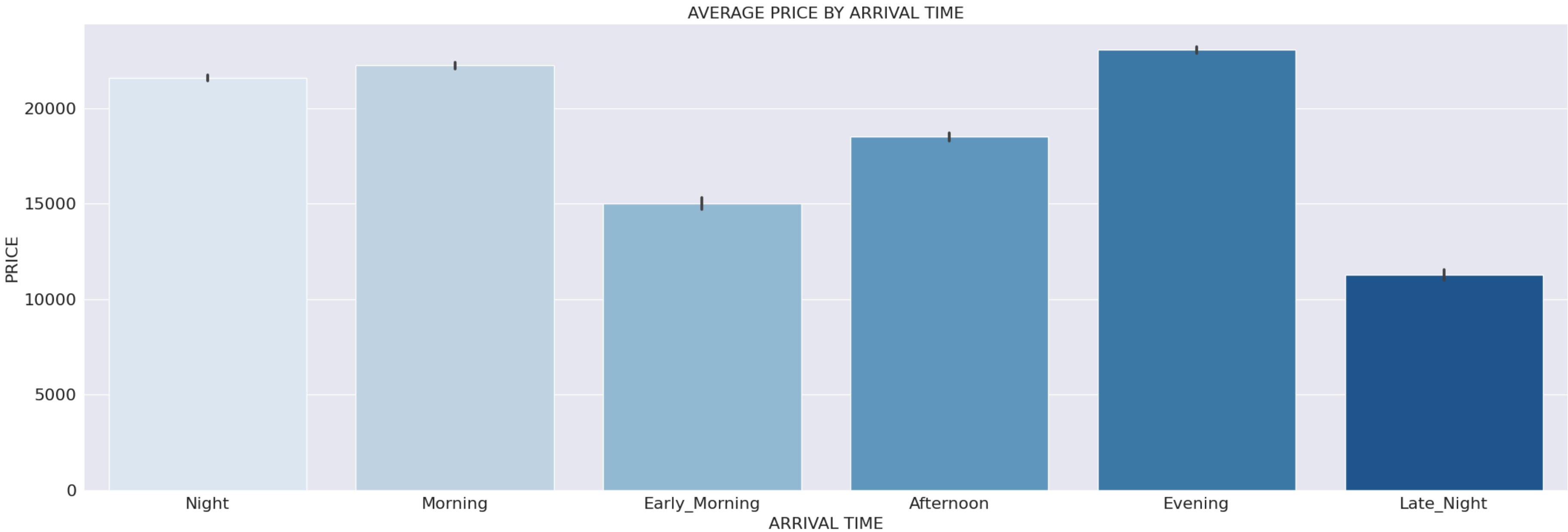
In [24]:

```
df.groupby('arrival_time')['price'].mean()
```

Out[24]:
```
arrival_time
Afternoon        18494.598993
Early_Morning    14993.139521
Evening          23044.371615
Late_Night       11284.906078
Morning          22231.076098
Night            21586.758341
Name: price, dtype: float64
```

In [75]:
```
sns.catplot(x='departure_time', y='price', kind='bar', data=df, palette='Blues', height=7, aspect=3)
plt.xlabel('DEPARTURE TIME', fontsize=16)
plt.ylabel('PRICE',fontsize=16)
plt.title('AVERAGE PRICE BY DEPARTURE TIME', fontsize=16)
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)

sns.catplot(x='arrival_time', y='price', kind='bar', data=df, palette='Blues', height=7, aspect=3)
plt.xlabel('ARRIVAL TIME', fontsize=16)
plt.ylabel('PRICE',fontsize=16)
plt.title('AVERAGE PRICE BY ARRIVAL TIME', fontsize=16)
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.show()


plt.show()
```





6.How the price changes with change in Source and Destination?

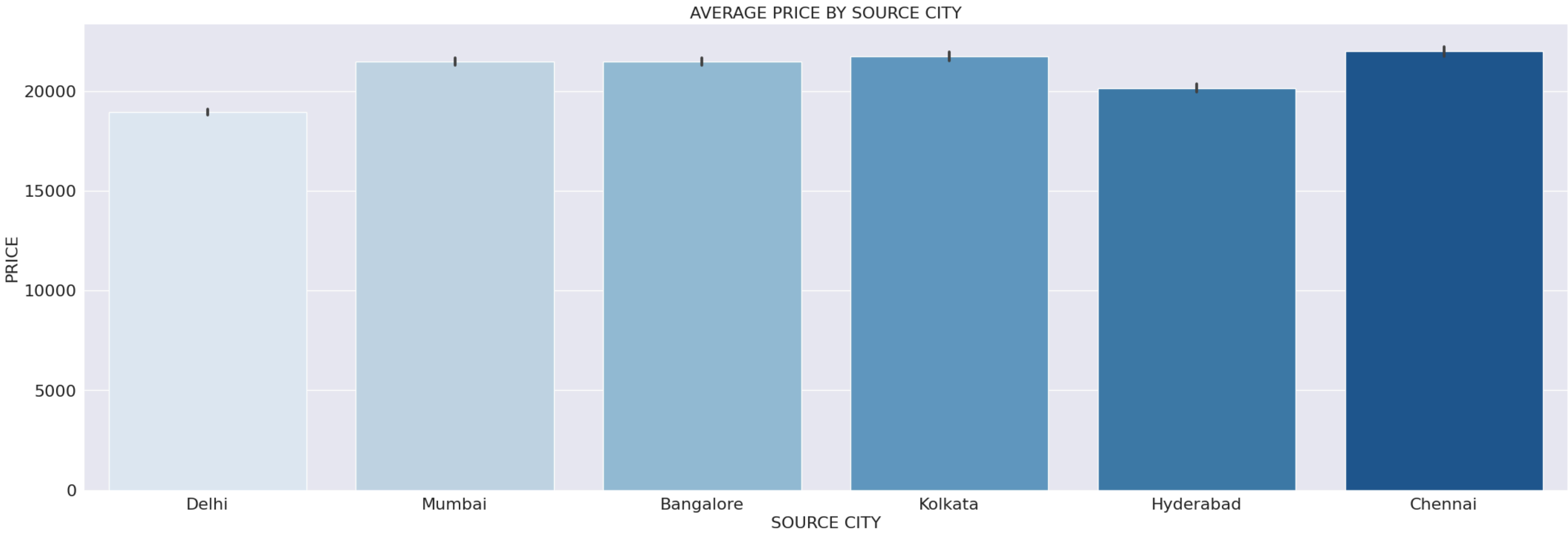
In [26]:
```
df.groupby('source_city')['price'].mean()
```

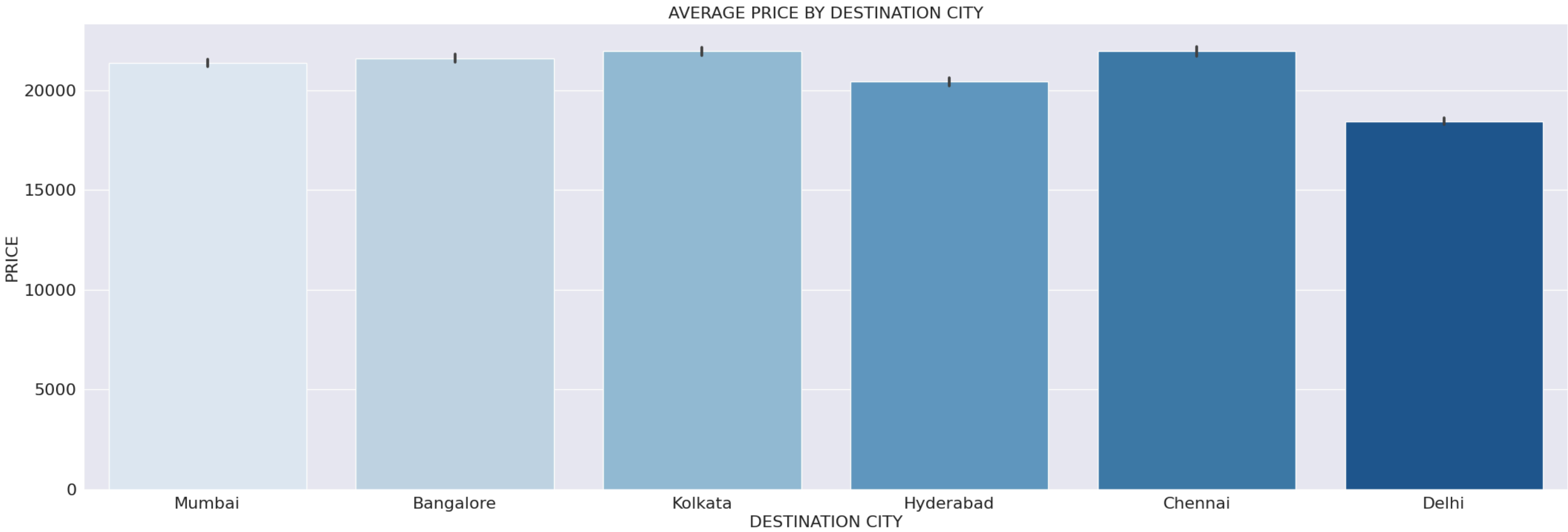
Out[26]:
```
source_city
Bangalore    21469.460575
Chennai      21995.339871
Delhi        18951.326639
Hyderabad    20155.623879
Kolkata      21746.235679
Mumbai       21483.818839
Name: price, dtype: float64
```

In [27]:
```
df.groupby('destination_city')['price'].mean()
```

Out[27]:
```
destination_city
Bangalore    21593.955784
Chennai      21953.323969
Delhi        18436.767870
Hyderabad    20427.661284
Kolkata      21959.557556
Mumbai       21372.529469
Name: price, dtype: float64
```

In [76]:
```
sns.catplot(x='source_city', y='price', kind='bar', data=df, palette='Blues', height=7, aspect=3)
plt.xlabel('SOURCE CITY', fontsize=16)
plt.ylabel('PRICE',fontsize=16)
plt.title('AVERAGE PRICE BY SOURCE CITY', fontsize=16)
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)

sns.catplot(x='destination_city', y='price', kind='bar', data=df, palette='Blues', height=7, aspect=3)
plt.xlabel('DESTINATION CITY', fontsize=16)
plt.ylabel('PRICE',fontsize=16)
plt.title('AVERAGE PRICE BY DESTINATION CITY', fontsize=16)
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.show()
```



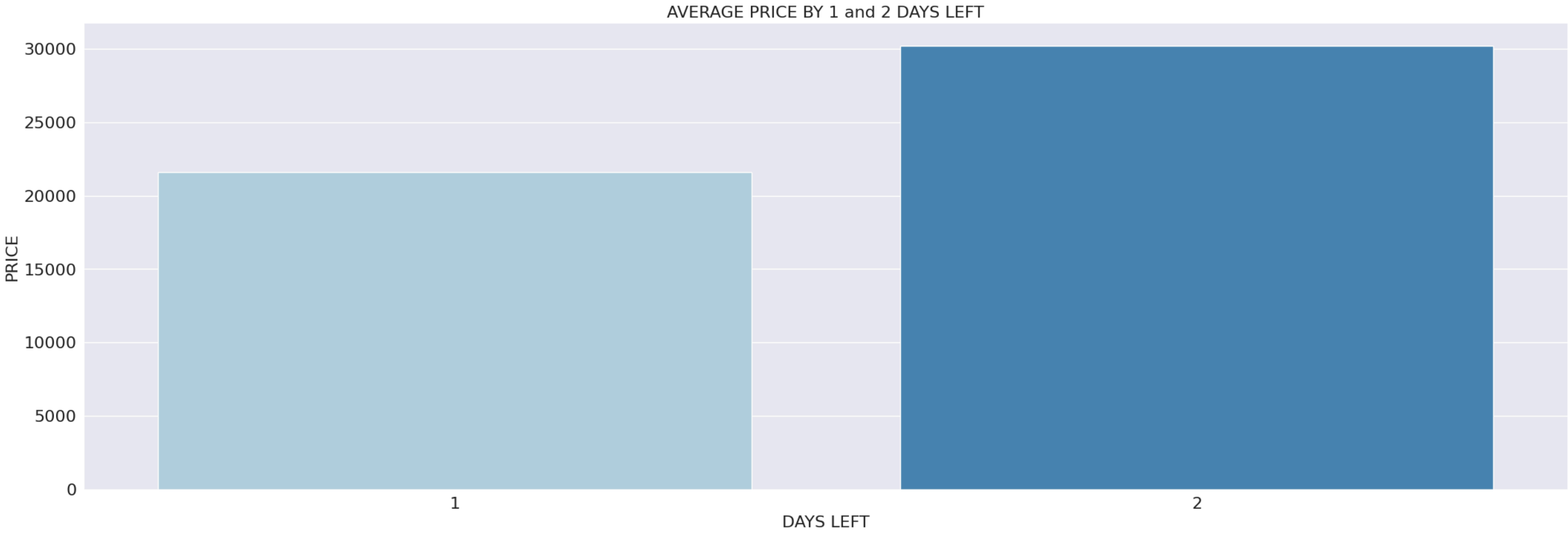


7.How is the price affected when tickets are bought in just 1 or 2 days before departure?

In [29]:
```
media_por_dia = df[df['days_left'].isin([1, 2])].groupby('days_left')['price'].mean().reset_index()
print(media_por_dia)
```

```
   days_left         price
0          1  21591.867151
1          2  30211.299801
```

In [77]:
```
sns.catplot(x='days_left', y='price', kind='bar', data=media_por_dia, palette='Blues', height=7, aspect=3)
plt.xlabel('DAYS LEFT', fontsize=16)
plt.ylabel('PRICE', fontsize=16)
plt.title('AVERAGE PRICE BY 1 and 2 DAYS LEFT', fontsize=16)
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.show()
```



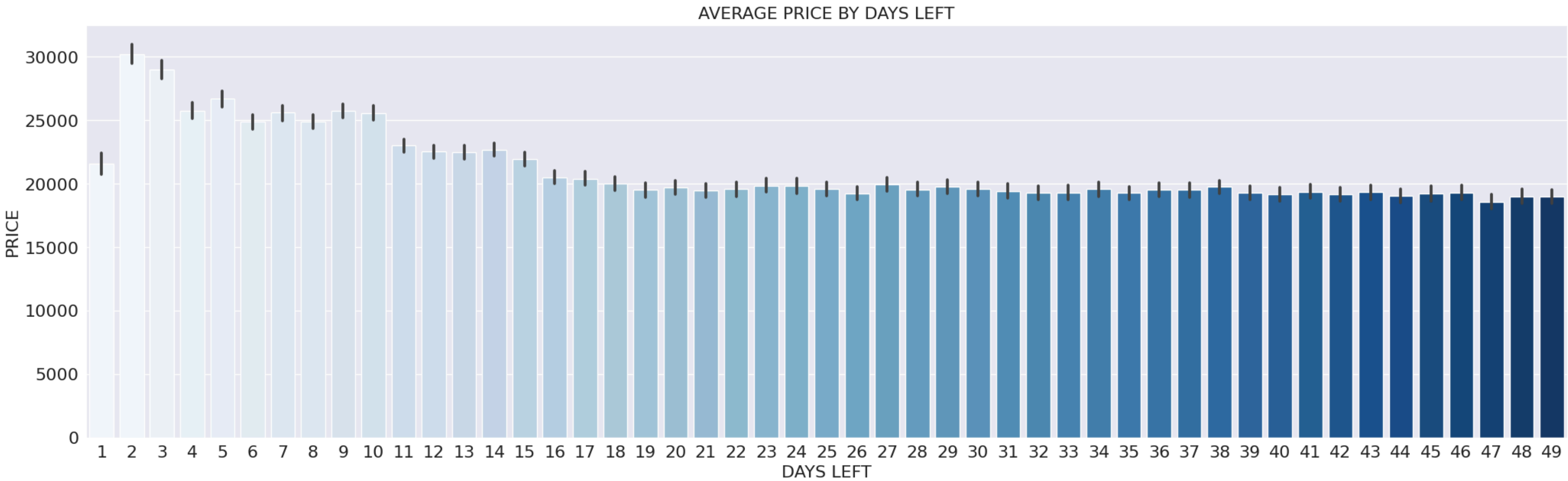
In [31]:
```
df.groupby('days_left')['price'].mean()
```

```
Out[31]: days_left
1     21591.867151
2     30211.299801
3     28976.083569
4     25730.905653
5     26679.773368
6     24856.493902
7     25588.367351
8     24895.883995
9     25726.246072
10    25572.819134
11    22990.656070
12    22505.803322
13    22498.885384
14    22678.002363
15    21952.540852
16    20503.546237
17    20386.353949
18    19987.445168
19    19507.677375
20    19699.983390
21    19430.494058
22    19590.667385
23    19840.913451
24    19803.908896
25    19571.641791
26    19238.290278
27    19950.866195
28    19534.986047
29    19744.653119
30    19567.580834
31    19392.706612
32    19258.135308
33    19306.271739
34    19562.008266
35    19255.652996
36    19517.688444
37    19506.306516
38    19734.912316
39    19262.095556
```

```
40    19144.972439
41    19347.440460
42    19154.261659
43    19340.528894
44    19049.080174
45    19199.876307
46    19305.351623
47    18553.272038
48    18998.126851
49    18992.971888
Name: price, dtype: float64
```

In [78]:

```
plt.figure(figsize=(25,7))
sns.barplot(x='days_left', y= 'price', data=df, palette='Blues')
plt.xlabel('DAYS LEFT', fontsize=16)
plt.ylabel('PRICE', fontsize=16)
plt.title('AVERAGE PRICE BY DAYS LEFT', fontsize=16)
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.show()
```

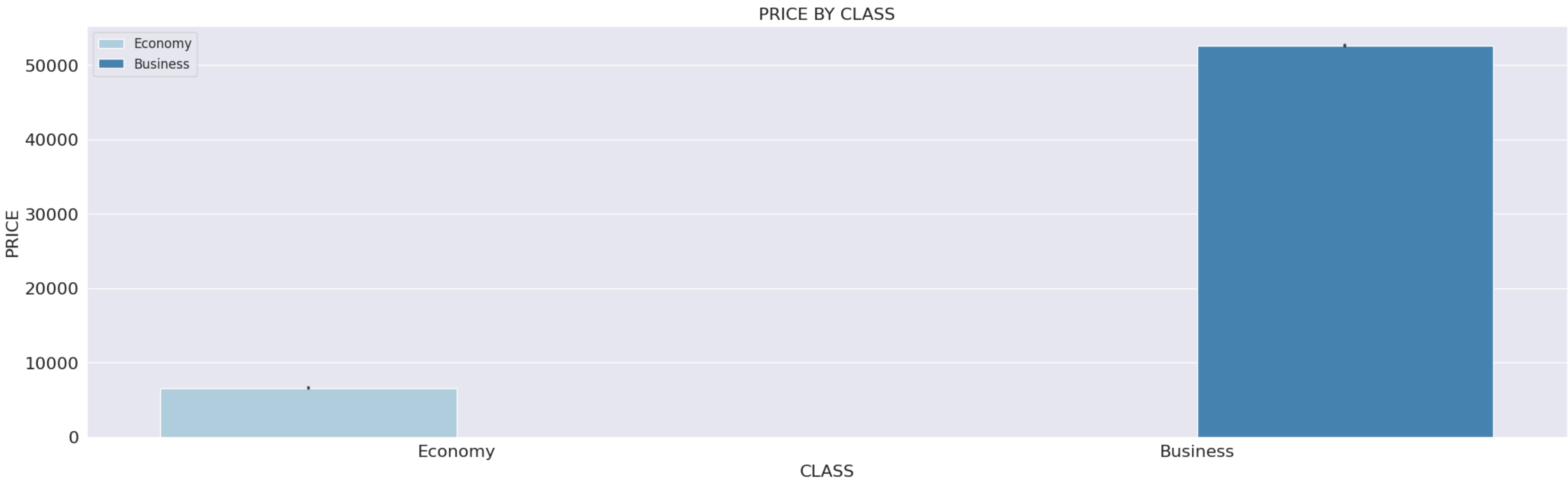


8.How does the ticket price vary between Economy and Business class?

```
In [33]: df.groupby('class')['price'].mean()
```

```
Out[33]: class
Business    52540.081124
Economy      6572.342383
Name: price, dtype: float64
```

```
In [80]: plt.figure(figsize=(25,7))
sns.barplot(x='class', y='price', data=df, palette='Blues', hue='class')
plt.xlabel('CLASS', fontsize=16)
plt.ylabel('PRICE', fontsize=16)
plt.title('PRICE BY CLASS', fontsize=16)
plt.xticks(fontsize=16)
plt.yticks(fontsize=16)
plt.legend(fontsize=12)
plt.show()
```



9.What will be the Average Price of Vistara airline for a flight from Delhi to Hyderabad in Business Class?

In [35]:
```
question9_df = df [(df['airline'] == 'Vistara') & (df['source_city'] == 'Delhi') & (df['destination_city'] == 'Hyderabad') & (
question9_df
```

Out[35]:

	airline	flight	source_city	departure_time	stops	arrival_time	destination_city	class	duration	days_left	price
219123	Vistara	UK-871	Delhi	Night	zero	Night	Hyderabad	Business	2.33	1	30630
219124	Vistara	UK-879	Delhi	Evening	zero	Evening	Hyderabad	Business	2.25	1	38470
219129	Vistara	UK-955	Delhi	Evening	one	Night	Hyderabad	Business	27.17	1	63513
219130	Vistara	UK-955	Delhi	Evening	one	Afternoon	Hyderabad	Business	18.50	1	65764
219131	Vistara	UK-985	Delhi	Evening	one	Night	Hyderabad	Business	25.08	1	69113
...	...	...	...	...	...	...	...	...	...	...	...
221863	Vistara	UK-963	Delhi	Morning	one	Early_Morning	Hyderabad	Business	23.00	49	53937
221864	Vistara	UK-985	Delhi	Evening	one	Early_Morning	Hyderabad	Business	12.00	49	59537
221865	Vistara	UK-985	Delhi	Evening	one	Afternoon	Hyderabad	Business	16.42	49	59537
221866	Vistara	UK-955	Delhi	Evening	one	Early_Morning	Hyderabad	Business	14.08	49	61889
221867	Vistara	UK-955	Delhi	Evening	one	Afternoon	Hyderabad	Business	18.50	49	61889

1660 rows × 11 columns

In [36]:
```
price = round(question9_df['price'].mean(), 0)
print ('The Average Price of Vistara airline for a flight from Delhi to Hyderabad in Business Class is:', price)
```

```
The Average Price of Vistara airline for a flight from Delhi to Hyderabad in Business Class is: 47940.0
```

FEATURES ENGINEERING

In [37]:
```
df.head()
```

Out[37]:

	airline	flight	source_city	departure_time	stops	arrival_time	destination_city	class	duration	days_left	price
0	SpiceJet	SG-8709	Delhi	Evening	zero	Night	Mumbai	Economy	2.17	1	5953
1	SpiceJet	SG-8157	Delhi	Early_Morning	zero	Morning	Mumbai	Economy	2.33	1	5953
2	AirAsia	I5-764	Delhi	Early_Morning	zero	Early_Morning	Mumbai	Economy	2.17	1	5956
3	Vistara	UK-995	Delhi	Morning	zero	Afternoon	Mumbai	Economy	2.25	1	5955
4	Vistara	UK-963	Delhi	Morning	zero	Morning	Mumbai	Economy	2.33	1	5955

In [38]:

```
df_new = df.copy()
```

In [39]:

```
df_new.drop(columns= 'flight', inplace=True)
```

In [40]:

```
df_new['stops'].value_counts()
```

Out[40]:

```
stops
one            250863
zero            36004
two_or_more     13286
Name: count, dtype: int64
```

In [41]:

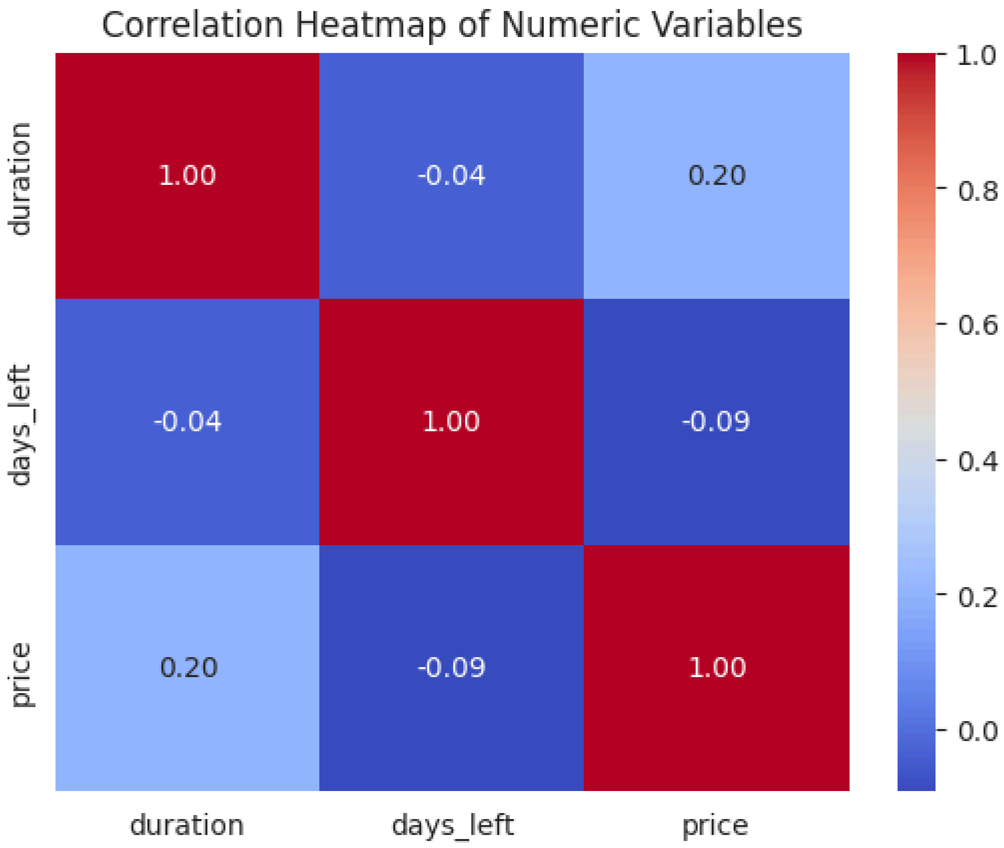
```
df_new['departure_time'].value_counts()
```

Out[41]:

```
departure_time
Morning          71146
Early_Morning    66790
Evening          65102
Night            48015
Afternoon        47794
Late_Night        1306
Name: count, dtype: int64
```

In [42]:

```
corr = df_new.select_dtypes(include=[np.number]).corr()
sns.heatmap(corr, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Heatmap of Numeric Variables')
plt.show()
```



In [43]:

```python
# Diccionario de mapeo
franjas = {
    "Late_Night":    "02:00:00",
    "Early_Morning": "05:00:00",
    "Morning":       "09:00:00",
    "Afternoon":     "15:00:00",
    "Evening":       "19:00:00",
    "Night":         "22:00:00"
}

# Reemplazar con la hora correspondiente
df_new["departure_time"] = df_new["departure_time"].map(franjas)
```

```
# Convertir a tipo time
df_new["departure_time"] = pd.to_datetime(df_new["departure_time"], format="%H:%M:%S").dt.time
```

In [44]:
```
# Reemplazar con la hora correspondiente
df_new["arrival_time"] = df_new["arrival_time"].map(franjas)

# Convertir a tipo time
df_new["arrival_time"] = pd.to_datetime(df_new["arrival_time"], format="%H:%M:%S").dt.time
```

In [45]:
```
# Encoding cíclico para las franjas horarias
def encode_time(df_new, col):
    seconds = df_new[col].apply(lambda t: t.hour*3600 + t.minute*60 + t.second)
    df_new[col+"_sin"] = np.sin(2 * np.pi * seconds / 86400)
    df_new[col+"_cos"] = np.cos(2 * np.pi * seconds / 86400)
    return df_new

df_new = encode_time(df_new, "departure_time")
df_new = encode_time(df_new, "arrival_time")
```

In [46]:
```
# Definimos las variables con más y menos clases para el codificador
low_card = ["airline", "stops", "class"] # pocas clases → OHE
high_card = ["source_city", "destination_city"] # muchas clases → Target Encoding

preprocessor = ColumnTransformer(
    transformers=[
        ("low_card_ohe", OneHotEncoder(handle_unknown="ignore"), low_card),
        ("high_card_target", TargetEncoder(), high_card)
    ],
    remainder="passthrough"  # deja el resto de columnas tal cual
)

pipeline = Pipeline(steps=[
    ("preprocessor", preprocessor),
    ("model", RandomForestRegressor())  # pon aquí tu modelo
])
```

In [47]:
```
df_new.drop(columns='departure_time', inplace=True)
```

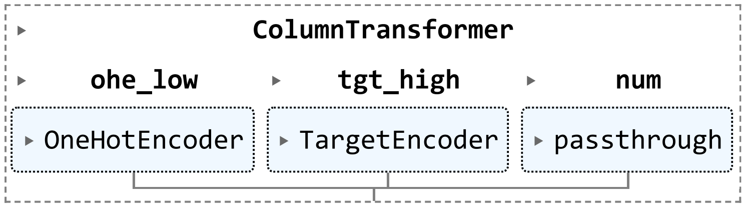
In [48]:
```python
df_new.drop(columns='arrival_time', inplace=True)
```

In [49]:
```python
# numéricas/passthrough (ajusta si tienes más)
num_cols = [c for c in df_new.columns
            if c not in low_card + high_card + ["price"]]   # quita la y si está en X
```

In [50]:
```python
# 2) Crea los transformadores
ohe = OneHotEncoder(handle_unknown="ignore", sparse_output=False)  # nombres expandibles
tgt = TargetEncoder()

preprocessor = ColumnTransformer(
    transformers=[
        ("ohe_low", ohe, low_card),
        ("tgt_high", tgt, high_card),
        ("num", "passthrough", num_cols)
    ],
    verbose_feature_names_out=False
)
```

In [51]:
```python
# 3) Haz que devuelva un **DataFrame** (no una matriz)
preprocessor.set_output(transform="pandas")
```

Out[51]:



In [52]:
```python
# 4) Separa X, y y transforma
y = df_new["price"]
X = df_new.drop(columns=["price"])

X_enc = preprocessor.fit_transform(X, y)   # ← TargetEncoder necesita y
```

In [53]:
```python
# 5) Revisa resultado
print(X_enc.columns.tolist()[:25])  # ver primeros nombres
X_enc.head()
```

['airline_AirAsia', 'airline_Air_India', 'airline_GO_FIRST', 'airline_Indigo', 'airline_SpiceJet', 'airline_Vistara', 'stops_one', 'stops_two_or_more', 'stops_zero', 'class_Business', 'class_Economy', 'source_city', 'destination_city', 'duration', 'days_left', 'departure_time_sin', 'departure_time_cos', 'arrival_time_sin', 'arrival_time_cos']

Out[53]:

	airline_AirAsia	airline_Air_India	airline_GO_FIRST	airline_Indigo	airline_SpiceJet	airline_Vistara	stops_one	stops_two_or_more	stops_z
0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	
2	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	

ML MODELS AND EVALUATION

In [54]:

```
# Train test split
X_train, X_test, y_train, y_test = train_test_split(X_enc, y, test_size=0.2, random_state=42)

# Entrenamos RandomForestRegressor
model = RandomForestRegressor(random_state=42)
model.fit(X_train, y_train)

# Predicción
preds = model.predict(X_test)
rmse = np.sqrt(mean_squared_error(y_test, preds))
# MAE (Mean Absolute Error)
mae = mean_absolute_error(y_test, preds)

# R² (Coeficiente de determinación)
r2 = r2_score(y_test, preds)

print(f"RMSE: {rmse:,.2f}")
print(f"MAE:  {mae:,.2f}")
print(f"R²:   {r2:.4f}")
```

```
RMSE: 2,774.16
MAE:  1,075.83
R²:   0.9851
```

In [55]:

```python
# Modelo base
xgb = XGBRegressor(random_state=42, n_jobs=-1)

# Espacio de búsqueda
param_dist = {
    "n_estimators": [200, 400, 600, 800],
    "learning_rate": [0.01, 0.05, 0.1, 0.2],
    "max_depth": [3, 5, 6, 8, 10],
    "subsample": [0.6, 0.8, 1.0],
    "colsample_bytree": [0.6, 0.8, 1.0],
    "gamma": [0, 1, 5]
}

# Búsqueda aleatoria
random_search = RandomizedSearchCV(
    estimator=xgb,
    param_distributions=param_dist,
    n_iter=20,               # número de combinaciones a probar
    scoring="neg_mean_squared_error",
    cv=3,
    verbose=1,
    random_state=42,
    n_jobs=-1
)

random_search.fit(X_train, y_train)

# Mejor modelo
best_xgb = random_search.best_estimator_
print("Mejores parámetros:", random_search.best_params_)

# Predicciones
preds = best_xgb.predict(X_test)

# Métricas
rmse = np.sqrt(mean_squared_error(y_test, preds))
mae = mean_absolute_error(y_test, preds)
```

```
r2 = r2_score(y_test, preds)

print(f"RMSE: {rmse:,.2f}")
print(f"MAE:  {mae:,.2f}")
print(f"R²:   {r2:.4f}")
```

```
Fitting 3 folds for each of 20 candidates, totalling 60 fits
Mejores parámetros: {'subsample': 1.0, 'n_estimators': 600, 'max_depth': 8, 'learning_rate': 0.2, 'gamma': 1, 'colsample_bytre
e': 0.8}
RMSE: 2,458.58
MAE:  1,258.63
R²:   0.9883
```

In [56]:

```
# XGBoost Cross Validation
kf = KFold(n_splits=5, shuffle=True, random_state=42)

rmse_scores = []
mae_scores = []
r2_scores = []

for train_idx, test_idx in kf.split(X_enc):
    X_train, X_test = X_enc.iloc[train_idx], X_enc.iloc[test_idx]
    y_train, y_test = y.iloc[train_idx], y.iloc[test_idx]

    # Entrenar
    best_xgb.fit(X_train, y_train)

    # Predecir
    preds = best_xgb.predict(X_test)

    # Métricas
    rmse_scores.append(np.sqrt(mean_squared_error(y_test, preds)))
    mae_scores.append(mean_absolute_error(y_test, preds))
    r2_scores.append(r2_score(y_test, preds))

# Resultados
print("📊 XGBoost")
print("RMSE por fold:", rmse_scores)
print("MAE por fold:", mae_scores)
print("R² por fold:", r2_scores)
```

```python
print("\nPromedios:")
print(f"RMSE medio: {np.mean(rmse_scores):,.2f} ± {np.std(rmse_scores):.2f}")
print(f"MAE medio:  {np.mean(mae_scores):,.2f} ± {np.std(mae_scores):.2f}")
print(f"R² medio:   {np.mean(r2_scores):.4f} ± {np.std(r2_scores):.4f}")
```

```
📊 XGBoost
RMSE por fold: [2458.581620710177, 2430.2753569624438, 2455.7461470454214, 2473.094920448661, 2429.885715398126]
MAE por fold: [1258.631701793551, 1251.4457718248566, 1274.2230557450307, 1257.2291140699792, 1257.9916161314281]
R² por fold: [0.9882738478205182, 0.9885573174488035, 0.9882888347373722, 0.9881418013929509, 0.9885031376654303]

Promedios:
RMSE medio: 2,449.52 ± 16.93
MAE medio:  1,259.90 ± 7.60
R² medio:   0.9884 ± 0.0002
```

In [57]:
```python
# RandomForestRegressor Cross Validation
rf_model = RandomForestRegressor(
    n_estimators=500,
    max_depth=None,
    random_state=42,
    n_jobs=-1
)

# Cross Validation (5 folds)
kf = KFold(n_splits=5, shuffle=True, random_state=42)

rmse_scores = []
mae_scores = []
r2_scores = []

for train_idx, test_idx in kf.split(X_enc):
    X_train, X_test = X_enc.iloc[train_idx], X_enc.iloc[test_idx]
    y_train, y_test = y.iloc[train_idx], y.iloc[test_idx]

    rf_model.fit(X_train, y_train)
    preds = rf_model.predict(X_test)

    rmse_scores.append(np.sqrt(mean_squared_error(y_test, preds)))
    mae_scores.append(mean_absolute_error(y_test, preds))
    r2_scores.append(r2_score(y_test, preds))
```

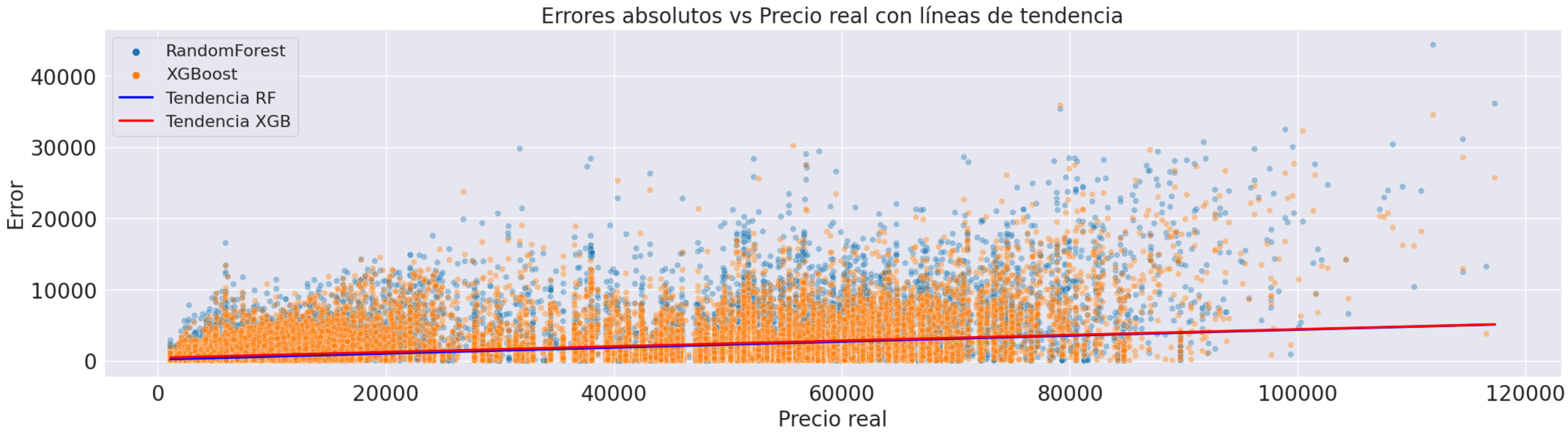
```python
print("📊 RandomForest")
print("RMSE por fold:", rmse_scores)
print("MAE por fold:", mae_scores)
print("R² por fold:", r2_scores)

print("\nPromedios:")
print(f"RMSE medio: {np.mean(rmse_scores):,.2f} ± {np.std(rmse_scores):.2f}")
print(f"MAE medio:  {np.mean(mae_scores):,.2f} ± {np.std(mae_scores):.2f}")
print(f"R² medio:   {np.mean(r2_scores):.4f} ± {np.std(r2_scores):.4f}")
```

```
📊 RandomForest
RMSE por fold: [2764.2436860423827, 2730.88367323717, 2710.4547542572122, 2717.4439348411806, 2679.97774849615]
MAE por fold: [1071.0650716570694, 1061.0252021783094, 1076.4131363122488, 1060.455053690341, 1054.8170366800414]
R² por fold: [0.9851769041388689, 0.9855514825974288, 0.9857334983524717, 0.9856827920038108, 0.986014757172144]

Promedios:
RMSE medio: 2,720.60 ± 27.47
MAE medio:  1,064.76 ± 7.83
R² medio:   0.9856 ± 0.0003
```

In [106…

```python
# MAE vs Precio Real
rf_model.fit(X_train, y_train)
rf_preds = rf_model.predict(X_test)

best_xgb.fit(X_train, y_train)
xgb_preds = best_xgb.predict(X_test)

# Errores absolutos
rf_errors = np.abs(rf_preds - y_test)
xgb_errors = np.abs(xgb_preds - y_test)

# DataFrame para seaborn
import pandas as pd
df_plot = pd.DataFrame({
    "Precio_real": y_test,
    "Error": rf_errors,
    "Modelo": "RandomForest"
})
df_plot = pd.concat([
    df_plot,
    pd.DataFrame({
```

```python
        "Precio_real": y_test,
        "Error": xgb_errors,
        "Modelo": "XGBoost"
    })
])

# --- Gráfico ---
plt.figure(figsize=(25,6))
sns.scatterplot(data=df_plot, x="Precio_real", y="Error", hue="Modelo", alpha=0.4)
sns.regplot(data=df_plot[df_plot["Modelo"]=="RandomForest"],
            x="Precio_real", y="Error", scatter=False, color="blue", label="Tendencia RF")
sns.regplot(data=df_plot[df_plot["Modelo"]=="XGBoost"],
            x="Precio_real", y="Error", scatter=False, color="red", label="Tendencia XGB")

plt.title("Errores absolutos vs Precio real con líneas de tendencia",fontsize=20)
plt.xlabel("Precio real", fontsize=20)
plt.ylabel("Error", fontsize=20)
plt.xticks(fontsize=20)
plt.yticks(fontsize=20)
plt.legend(fontsize=16)
plt.show()
```

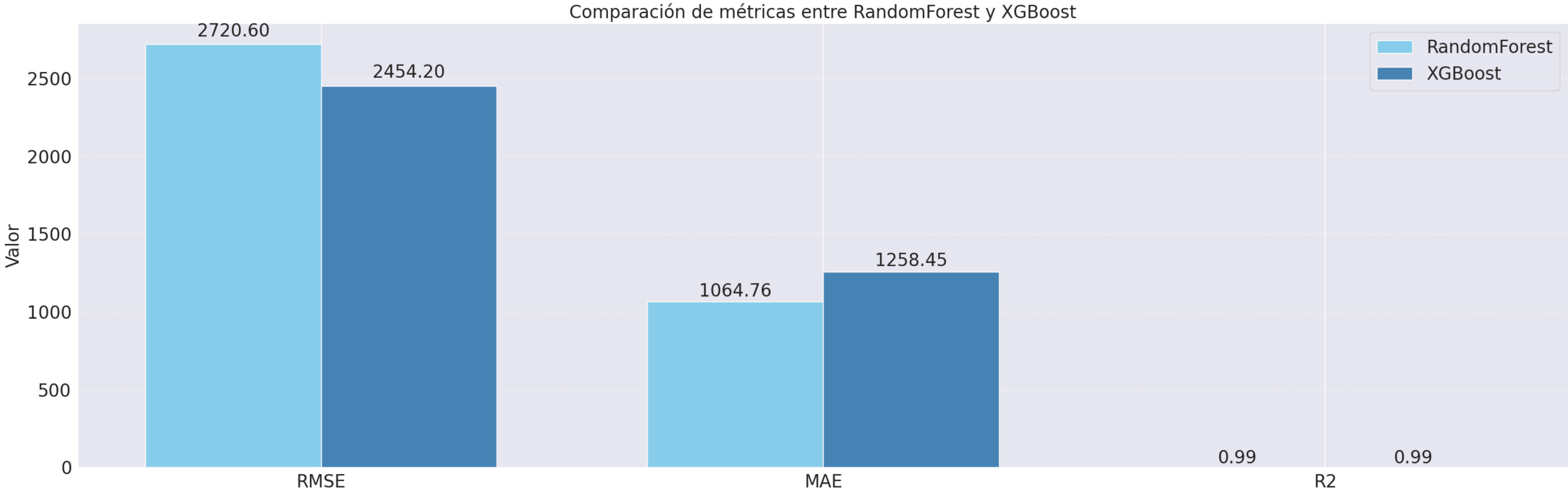


In [105…

```python
# Datos de resultados promedio
resultados = {
    "RandomForest": {
```

```python
        "RMSE": 2720.60,
        "MAE": 1064.76,
        "R2": 0.9856
    },
    "XGBoost": {
        "RMSE": 2454.20,
        "MAE": 1258.45,
        "R2": 0.9883
    }
}

# Configuración
metricas = ["RMSE", "MAE", "R2"]
x = np.arange(len(metricas))  # posiciones
ancho = 0.35  # ancho de las barras

fig, ax = plt.subplots(figsize=(25, 8))

# Barras para RF y XGB
rf_vals = [resultados["RandomForest"][m] for m in metricas]
xgb_vals = [resultados["XGBoost"][m] for m in metricas]

ax.bar(x - ancho/2, rf_vals, ancho, label="RandomForest", color="skyblue")
ax.bar(x + ancho/2, xgb_vals, ancho, label="XGBoost", color="steelblue")

# Etiquetas y formato
ax.set_ylabel("Valor", fontsize=20)
ax.set_title("Comparación de métricas entre RandomForest y XGBoost", fontsize=20)

# Ticks del eje X
ax.set_xticks(x)
ax.set_xticklabels(metricas, fontsize=20)
ax.tick_params(axis='y', labelsize=20)

ax.legend(fontsize=20)
ax.grid(axis='y', linestyle='--', alpha=0.6)

# Mostrar valores sobre las barras
for i, v in enumerate(rf_vals):
    ax.text(i - ancho/2, v + max(0.01*v, 0.005), f"{v:.2f}", ha='center', va='bottom', fontsize=20)
```

```
for i, v in enumerate(xgb_vals):
    ax.text(i + ancho/2, v + max(0.01*v, 0.005), f"{v:.2f}", ha='center', va='bottom', fontsize=20)

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

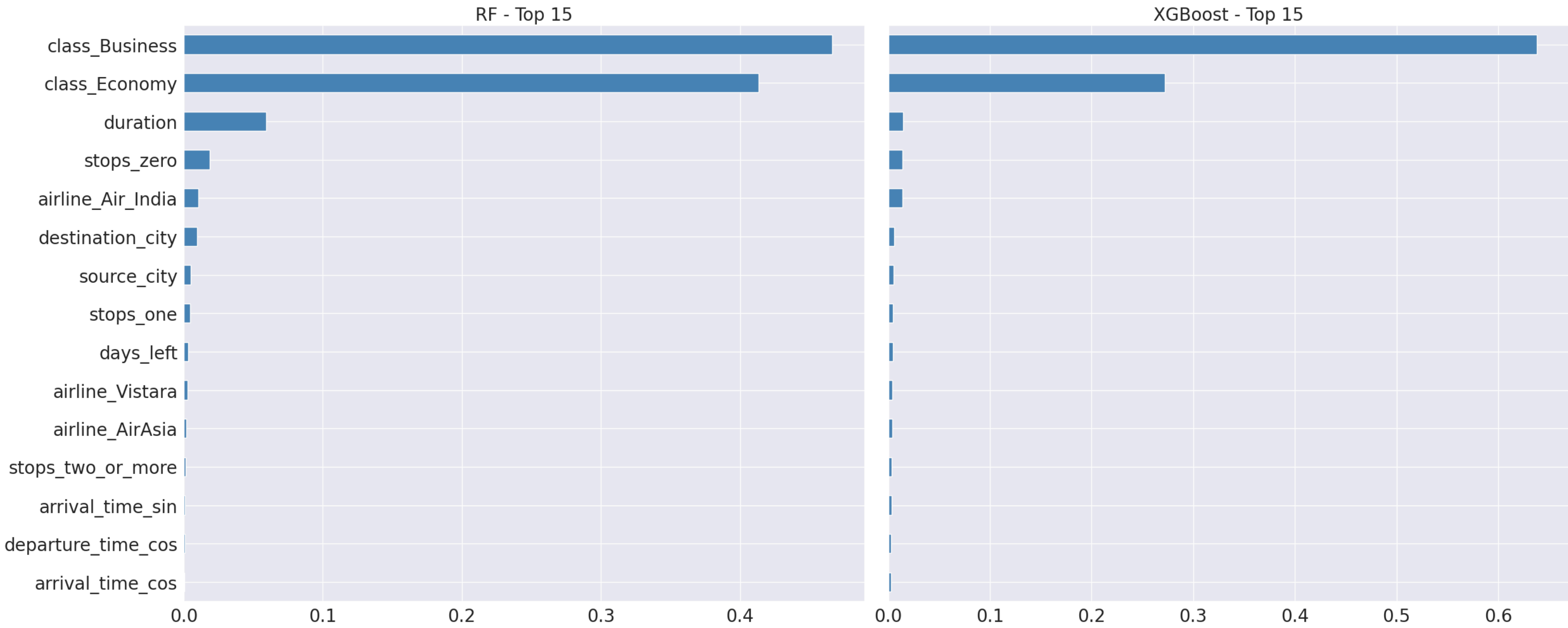


FEATURE IMPORTANCES

In [107…

```
# Feature importances series ordenadas
rf_imp  = pd.Series(rf_model.feature_importances_, index=X_enc.columns).sort_values(ascending=False)
xgb_imp = pd.Series(best_xgb.feature_importances_, index=X_enc.columns).sort_values(ascending=False)

top_k = 15
fig, axs = plt.subplots(1, 2, figsize=(25, 10), sharey=True)

rf_imp.head(top_k).iloc[::-1].plot(kind="barh", ax=axs[0], title="RF - Top 15", fontsize=20, color='steelblue')
xgb_imp.head(top_k).iloc[::-1].plot(kind="barh", ax=axs[1], title="XGBoost - Top 15", fontsize=20, color='steelblue')

plt.xticks(fontsize=20)
plt.yticks(fontsize=20)
plt.tight_layout()
```

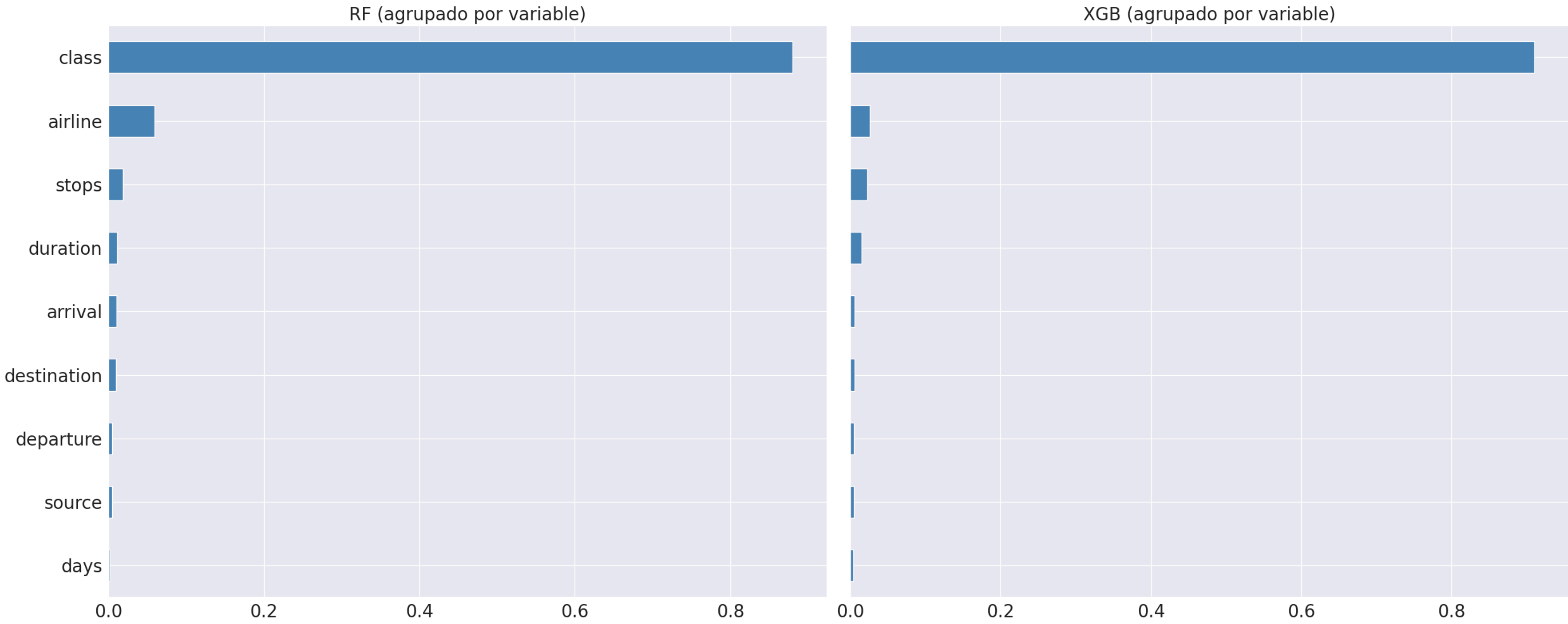
```python
axs[0].set_title("RF - Top 15", fontsize=20)
axs[1].set_title("XGBoost - Top 15", fontsize=20)

plt.show()
```



In [108…

```python
# Feature importances (variables iniciales)
def group_importances(imp_series):
    grp = {}
    for col, val in imp_series.items():
        key = col.split("_")[0]  # prefijo antes del primer "_"
        grp[key] = grp.get(key, 0.0) + val
    return pd.Series(grp).sort_values(ascending=False)

rf_grp  = group_importances(rf_imp)
xgb_grp = group_importances(xgb_imp)

fig, axs = plt.subplots(1, 2, figsize=(25, 10), sharey=True)
```

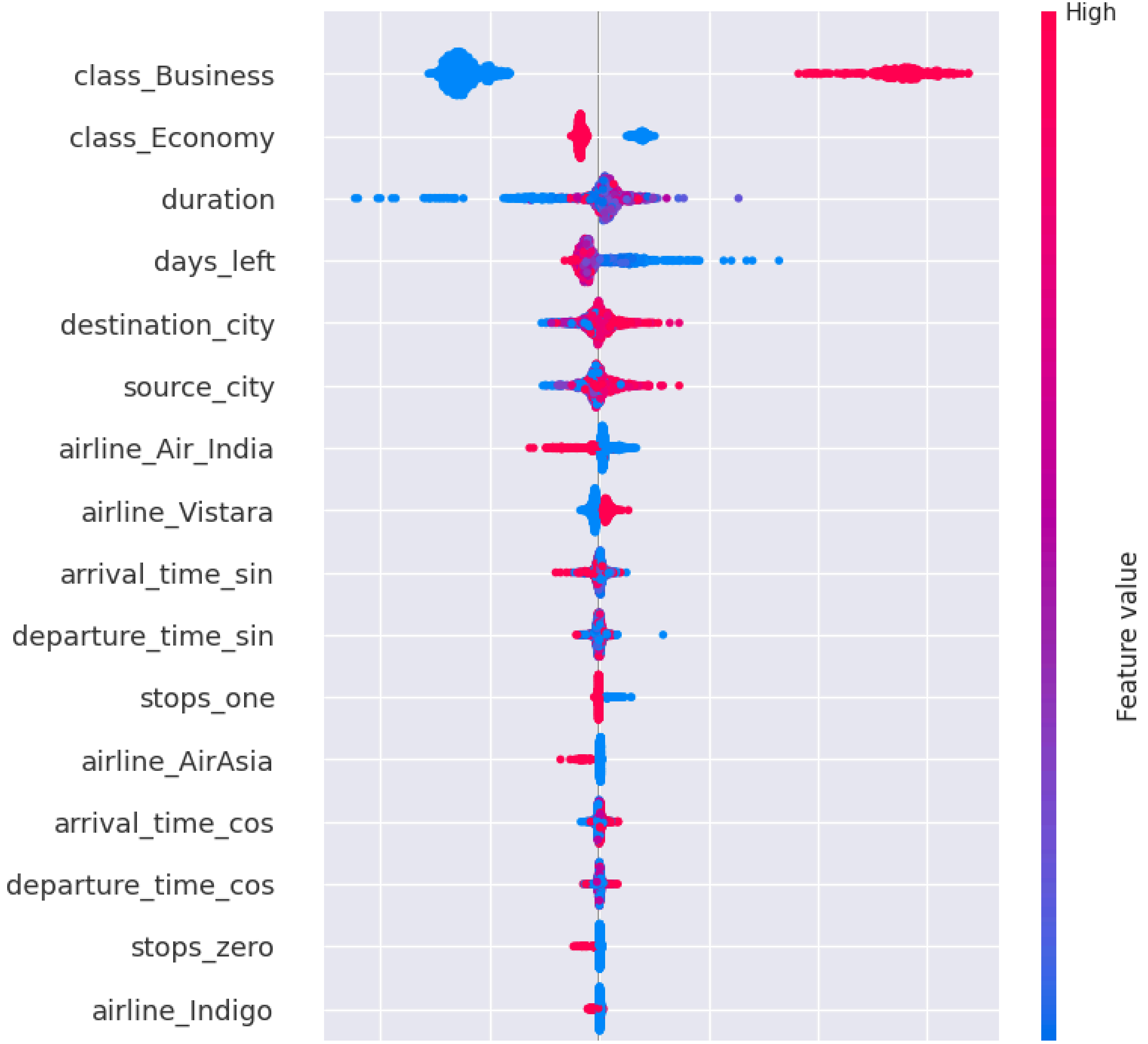
```
rf_grp.head(10).iloc[::-1].plot(kind="barh", ax=axs[0], title="RF (agrupado por variable)", fontsize=20, color='steelblue')
xgb_grp.head(10).iloc[::-1].plot(kind="barh", ax=axs[1], title="XGB (agrupado por variable)", fontsize=20, color='steelblue')

plt.xticks(fontsize=20)
plt.yticks(fontsize=20)
plt.tight_layout()

axs[0].set_title("RF (agrupado por variable)", fontsize=20)
axs[1].set_title("XGB (agrupado por variable)", fontsize=20)

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

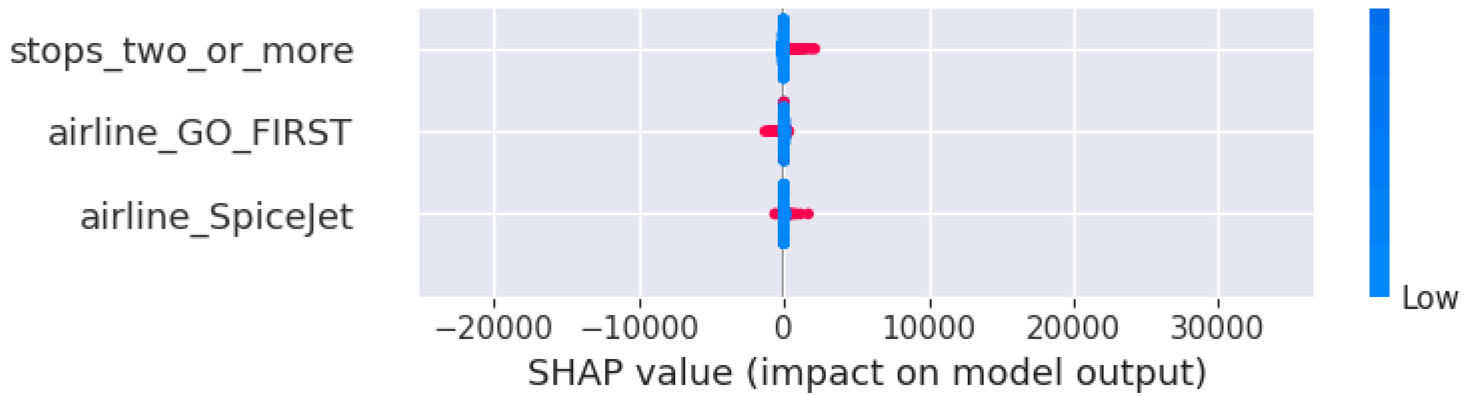


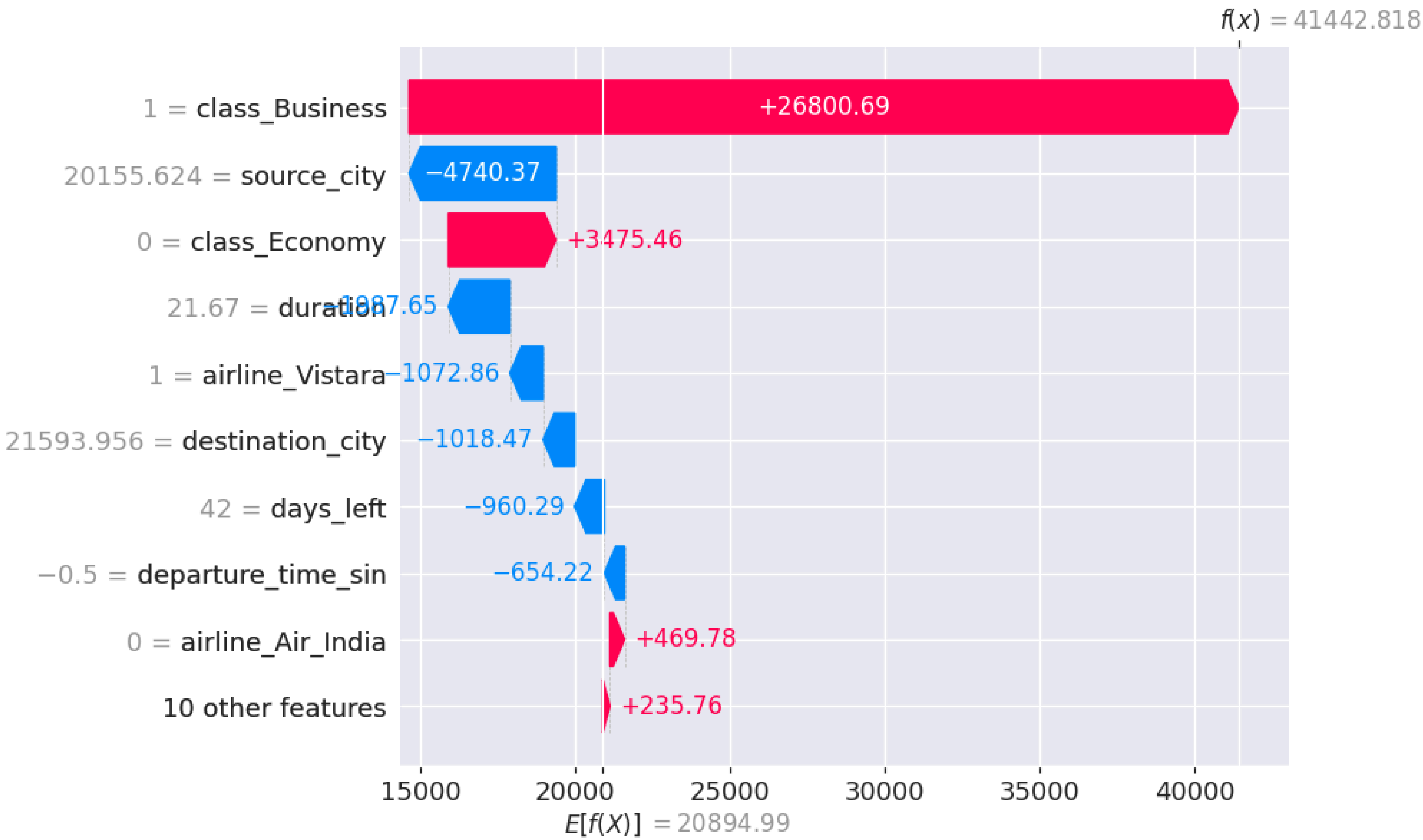
SHAP

In [62]:

```
X_shap = X_enc.sample(1000, random_state=42)  # sube a 2000 si puedes

explainer = shap.TreeExplainer(best_xgb)  # sin approximate
shap_vals = explainer.shap_values(X_shap, check_additivity=True)

# Global
shap.summary_plot(shap_vals, X_shap)

# Local
i = 10
shap.waterfall_plot(
    shap.Explanation(values=shap_vals[i],
                     base_values=explainer.expected_value,
                     data=X_shap.iloc[i,:],
                     feature_names=X_shap.columns.tolist())
)
```


class_Business
class_Economy
duration
days_left
destination_city
source_city
airline_Air_India
airline_Vistara
arrival_time_sin
departure_time_sin
stops_one
airline_AirAsia
arrival_time_cos
departure_time_cos
stops_zero
airline_Indigo
High
Feature value


stops_two_or_more
airline_GO_FIRST
airline_SpiceJet
−20000
−10000
0
10000
20000
30000
SHAP value (impact on model output)
Low



INSIGHTS

1. Distribution and Trends

- The dataset shows a wide variability in prices, with extreme cases on both ends (very cheap and very expensive flights).
- The `class` variable has a clear impact: **Business** flights have significantly higher prices than **Economy**.
- `days_left` (days remaining until the flight) follows the expected trend: the fewer the days left, the higher the price, with sharp increases in the last days before departure.
- **Flight duration** shows an inverse relationship with price for short and direct routes, but for longer routes the relationship is not always linear, likely due to combinations of stops and cities.

---

2. Model Results

RandomForest:

- RMSE ≈ **2,720**
- MAE ≈ **1,065**
- R^2 ≈ **0.9856**
- Strong overall performance, low errors, and high explanatory power, though it tends to make bigger mistakes for high-priced flights.

XGBoost:

- RMSE ≈ **2,454**
- MAE ≈ **1,258**
- R^2 ≈ **0.9883**
- Slight improvement in RMSE and R^2 compared to RF, with a small increase in MAE.
- Cross-validation confirms model stability and generalization.

---

3. Feature Importance

In both models, the most influential variables globally are:

1. **class**
2. **days_left**

3. **duration**
4. **stops**
5. Time-related features (`departure_time_sin` , `arrival_time_cos`)
6. Origin/destination cities (moderate importance)

Airline-related features have lower but still relevant impact.

---

4. Explainability

Using **SHAP**:

- Not being Business class strongly reduces the predicted price.
- Booking with very few days left significantly increases the price.
- Shorter flight duration tends to lower the price.
- Airline and departure time effects are secondary but still present.

Both models tend to have higher prediction errors for expensive flights, suggesting that extreme values in the dataset are harder to model.

---

5. Conclusions and Opportunities

- Both models are robust, but **XGBoost provides a slight edge** in overall accuracy.
- Performance for high-priced flights could be improved by:
  - Balancing the dataset in those price ranges.
  - Using hybrid models or transforming the target variable (e.g., `log(price)`).
- SHAP interpretability adds value in understanding the drivers of price and could be leveraged for dynamic pricing or user recommendations.

PLEASE UP VOTE AND SUPPORT MY WORK AS STUDENT!! :) Thanks for reading!

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ADRIÁN ZAMBRANA | Aug 2025