Airlines Flights Data Analysis with Python - DSL

```
# import the required Python libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

data = pd.read_csv("/content/airlines_flights_data.csv")
data
```

è		_
÷		÷
Ξ	7	

	index	airline	flight	source_city	departure_time	stops	arrival_time	destination_city	class	duration	days_lef
0	0	SpiceJet	SG- 8709	Delhi	Evening	zero	Night	Mumbai	Economy	2.17	
1	1	SpiceJet	SG- 8157	Delhi	Early_Morning	zero	Morning	Mumbai	Economy	2.33	
2	2	AirAsia	15-764	Delhi	Early_Morning	zero	Early_Morning	Mumbai	Economy	2.17	
3	3	Vistara	UK- 995	Delhi	Morning	zero	Afternoon	Mumbai	Economy	2.25	
4	4	Vistara	UK- 963	Delhi	Morning	zero	Morning	Mumbai	Economy	2.33	
300148	300148	Vistara	UK- 822	Chennai	Morning	one	Evening	Hyderabad	Business	10.08	4
300149	300149	Vistara	UK- 826	Chennai	Afternoon	one	Night	Hyderabad	Business	10.42	4
			IIK-								

Cleaning the data

```
# Remove the 'index' column
data.drop( columns = 'index', inplace = True)
data
```

-		_
	•	_
_	~	$\overline{}$
	*	

	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	15-764	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
			***			•••					
300148	Vistara	UK- 822	Chennai	Morning	one	Evening	Hyderabad	Business	10.08	49	69265
300149	Vistara	UK- 826	Chennai	Afternoon	one	Night	Hyderabad	Business	10.42	49	77105
		IIK-									

Get some Info about the dataset

data.info()

<class 'pandas.core.frame.DataFrame'>
 RangeIndex: 300153 entries, 0 to 300152
Data columns (total 11 columns):

Duca	COTAMMIS (COCAT II	COTAIII13).	
#	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
	63 (5 6 (6))	/ - \		

dtypes: float64(1), int64(2), object(8)

memory usage: 25.2+ MB

Get Statistical summary about the dataset
data.describe()

•		_
		_
	➾	v
-	*	

	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

check for the missing values in any column
data.isnull().sum()



	0
airline	0
flight	0
source_city	0
departure_time	0
stops	0
arrival_time	0
destination_city	0
class	0
duration	0
days_left	0
price	0

dtype: int64

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

data.head()

→		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	15-764	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



count

airline	
Vistara	127859
Air_India	80892
Indigo	43120
GO_FIRST	23173
AirAsia	16098
SpiceJet	9011

dtype: int64

```
# Showing all the Airlines with their Number of Flights in Horizontal Bar Graph

data['airline'].value_counts(ascending=True).plot.barh( color = ['lightgreen', 'lightblue'])

plt.title("Airlines with frequencies")

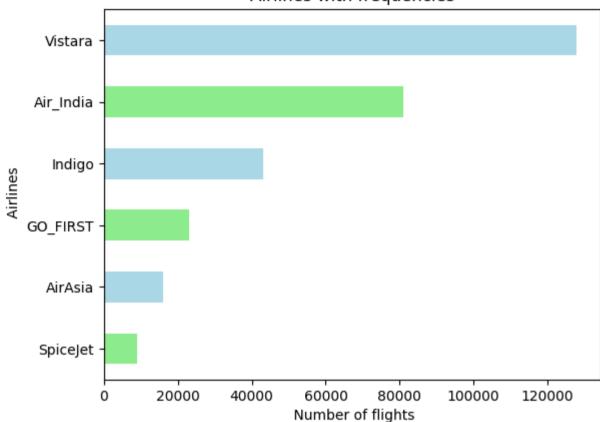
plt.xlabel(" Number of flights")

plt.ylabel(" Airlines")

plt.show()
```



Airlines with frequencies



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

Showing the Departure Time for the flights
data['departure_time'].value_counts()



count

de	part	ure	time

departure_time		
Morning	71146	
Early_Morning	66790	
Evening	65102	
Night	48015	
Afternoon	47794	
Late_Night	1306	

dtype: int64

 $\ensuremath{\text{\#}}$ Showing the Arrival Time for the flights

data['arrival_time'].value_counts()



count

arrival time

Night	91538
Evening	78323
Morning	62735
Afternoon	38139
Early_Morning	15417
Late_Night	14001

dtype: int64

```
# Showing the Departure Time & Arrival Time for the flights with their counts

plt.figure(figsize = (16,4))

plt.subplot(1,2,1)

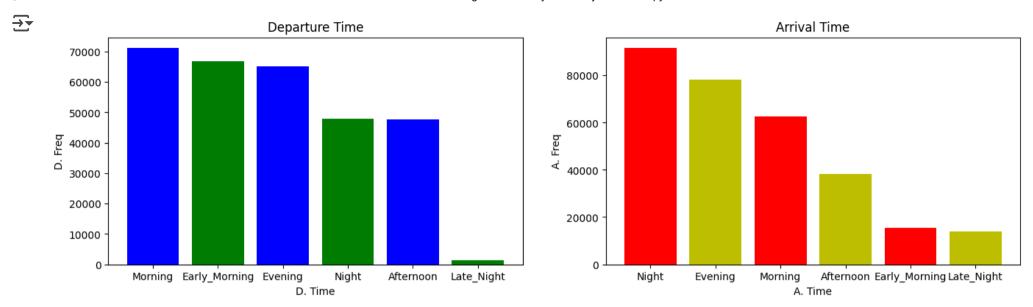
plt.bar( data['departure_time'].value_counts().index , data['departure_time'].value_counts().values, color = ['b', 'g'] )

plt.title("Departure Time")
plt.xlabel("D. Time")
plt.ylabel("D. Freq")

plt.subplot(1,2,2)

plt.bar( data['arrival_time'].value_counts().index, data['arrival_time'].value_counts().values, color = ['r', 'y'])
plt.title("Arrival Time")
plt.xlabel("A. Time")
plt.ylabel("A. Freq")

plt.show()
```



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

Showing the Source City of the flights
data['source_city'].value_counts()



count

source city

61343
60896
52061
46347
40806
38700

dtype: int64

Showing the Destination City of the flights

data['destination_city'].value_counts()



count

destination_city

Mumbai	59097
Delhi	57360
Bangalore	51068
Kolkata	49534
Hyderabad	42726
Chennai	40368

dtype: int64

```
# Showing the Source City & Destination City for the flights with their counts

plt.figure( figsize= (16,4))

plt.subplot(1,2,1)

plt.barh( data['source_city'].value_counts().index , data['source_city'].value_counts().values, color = ['b', 'g'])

plt.title("Source Cities with No. of flights")

plt.ylabel("Cities")

plt.xlabel("No. of flights")

plt.subplot(1,2,2)

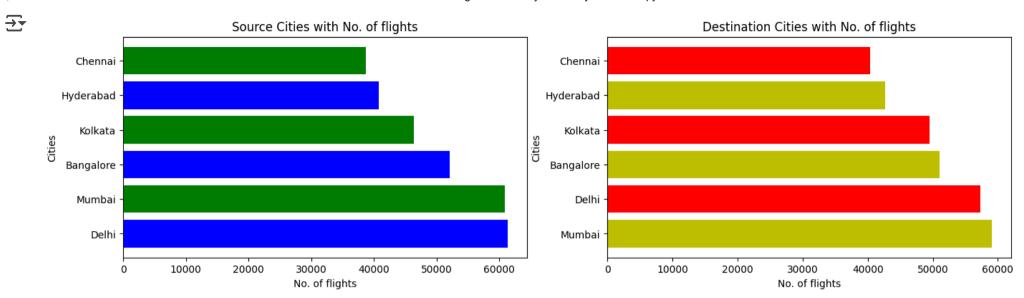
plt.barh( data['destination_city'].value_counts().index , data['destination_city'].value_counts().values, color = ['y', 'r'])

plt.title("Destination Cities with No. of flights")

plt.ylabel("Cities")

plt.xlabel("No. of flights")

plt.show()
```



Q.4. Does price varies with airlines?

Grouping the airlines and checking their mean price
data.groupby('airline')['price'].mean()

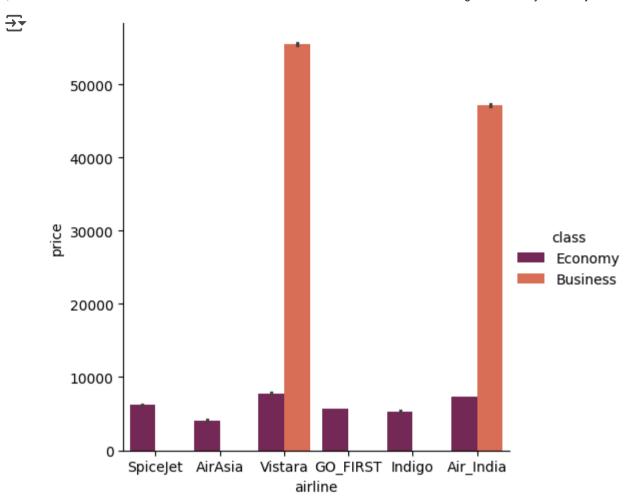


price

airline	
AirAsia	4091.072742
Air_India	23507.019112
GO_FIRST	5652.007595
Indigo	5324.216303
SpiceJet	6179.278881
Vistara	30396.536302

dtype: float64

```
# Drawing a Categorical Plot showing the Mean Ticket Price for each Airline
sns.catplot( x = 'airline', y = 'price', kind = 'bar', palette = 'rocket', data = data, hue = 'class')
plt.show()
```



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

Checking the Mean Ticket Price based on the Departure Times
data.groupby('departure_time')['price'].mean()



price

departure time

acpar car c_cime	
Afternoon	18179.203331
Early_Morning	20370.676718
Evening	21232.361894
Late_Night	9295.299387
Morning	21630.760254
Night	23062.146808

dtype: float64

Checking the Mean Ticket Price based on the Arrival Times

data.groupby('arrival_time')['price'].mean()



price

•	
arriva	l time

Afternoon	18494.598993
Early_Morning	14993.139521
Evening	23044.371615
Late_Night	11284.906078
Morning	22231.076098
Night	21586.758341

dtype: float64

```
# Create the plot
g = sns.catplot(
    x='departure_time',
    y='price',
    kind='bar',
    data=data,
    palette='viridis', # colorful palette
    height=5,
    aspect=1.5
)

# Customize labels and title
g.set_axis_labels("Departure Time", "Price")
g.fig.suptitle("Average Price by Departure Time", fontsize=14, y=1.02)
# Remove extra spines for cleaner look
sns.despine(left=True, bottom=True)

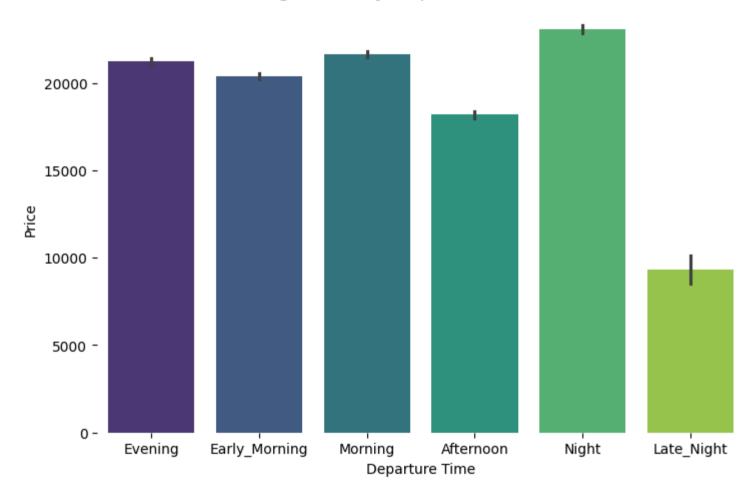
plt.show()
```

→

/tmp/ipython-input-1835243693.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set

Average Price by Departure Time



```
# Create the plot
g = sns.catplot(
    x='arrival_time',
    y='price',
```

```
kind='bar',
  data=data,
  palette='coolwarm', # distinct color palette
  height=5,
  aspect=1.5
)

# Customize labels and title
g.set_axis_labels("Arrival Time", "Price")
g.fig.suptitle("Average Price by Arrival Time", fontsize=14, y=1.02)

# Rotate x-axis labels if they overlap
g.set_xticklabels(rotation=45)

# Remove extra spines
sns.despine(left=True, bottom=True)

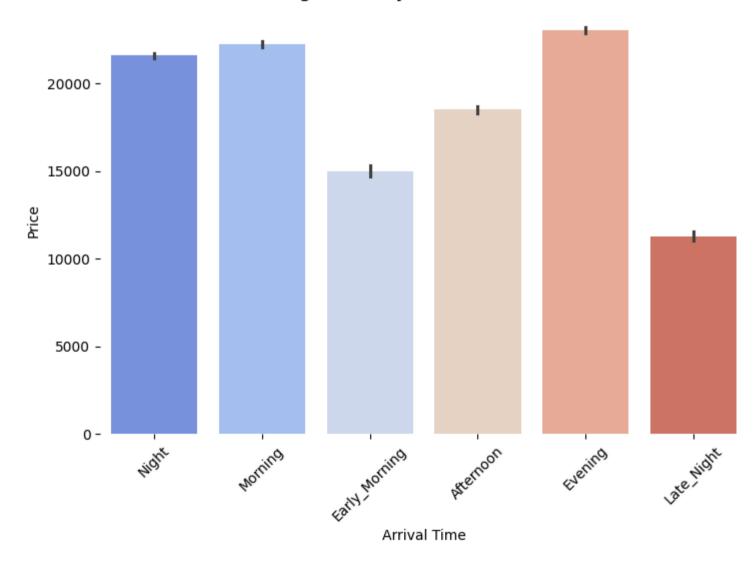
plt.show()
```



/tmp/ipython-input-2748057074.py:2: FutureWarning:

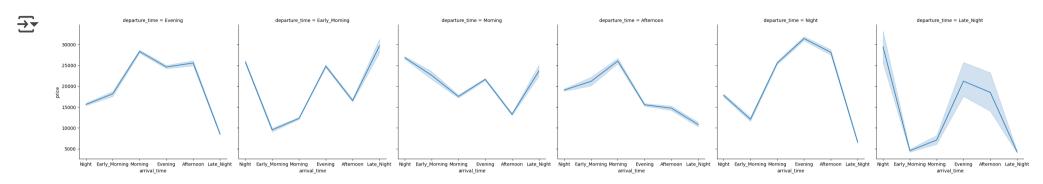
Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set g = sns.catplot(

Average Price by Arrival Time



sns.relplot(x = 'arrival_time', y = 'price', data = data, col = 'departure_time', kind = 'line')

plt.show()



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

Checking the Mean Ticket Price for each Source City
data.groupby('source city')['price'].mean()



price

so	ur	ce	C	i	ty	

Bangalore 21469.460575
Chennai 21995.339871
Delhi 18951.326639
Hyderabad 20155.623879
Kolkata 21746.235679
Mumbai 21483.818839

dtype: float64

Checking the Mean Ticket Price for each Destination City

data.groupby('destination_city')['price'].mean()



price

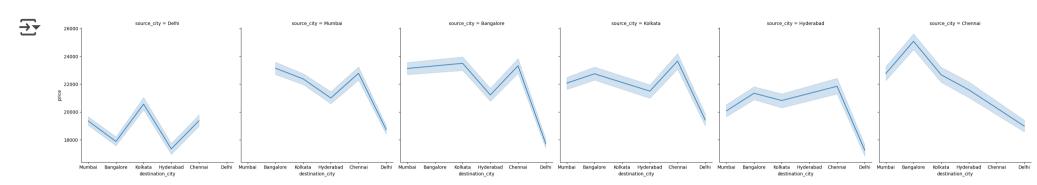
destination_city

Bangalore	21593.955784
Chennai	21953.323969
Delhi	18436.767870
Hyderabad	20427.661284
Kolkata	21959.557556
Mumbai	21372.529469

dtype: float64

sns.relplot(x = 'destination_city', y = 'price', data = data, col = "source_city", kind = 'line')

plt.show()



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

data['days_left'].nunique()

→ 49

data['days left'].unique()

Checking the Mean Ticket Price for different days_left

data.groupby('days_left')['price'].mean()



price

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