Airline Data Analysis

Overview and goals

With the COVID-19 pandemic hitting the airline industry hard with significant losses in 2020 and 2021, the airline industry is now getting back on track in 2023 and 2024. In this data analysis, an airline database will be analyzed to identify ways to help further increase the profit of an airline company. The main goal of the analysis is to show through data how the airline can increase their profits by improving flight occupancy rates, prioritizing certain types of aircraft, and prioritizing certain types of aircraft seating on certain aircraft.

Python and SQL will be leveraged to conduct the analysis. The personal goals for the project are to demonstrate proficiency in data analysis, data cleaning, data visualization, Python (pandas, matplotlib, and seaborn packages), and SQL queries (SELECT, JOINs, GROUP BYs), utilizing all throughout the project. We will conduct an exploratory data analysis and answer the analysis questions below.

Analysis Questions

1. How can the profit of the airline be increased?
2. Can increasing occupancy rate on all aircrafts increase revenue?
3. Are there certain aircraft types we can use more to generate a higher profit?
4. Are there certain aircraft seating types we can prioritize to generate more earnings?

Database

The airlines database obtained from Kaggle contains eight tables: aircraft data, airport data, boarding pass, bookings data, flights, seats, ticket flights, and tickets.

Connecting to database

In [ ]:
```
import sqlite3
import pandas as pd
import matplotlib.pyplot as plt
import json
import seaborn as sns
import numpy as np
```

In [ ]:
```
db_path = r'C:\Users\malop\Documents\airline-analysis\travel.sqlite'
connection = sqlite3.connect(db_path)
cursor = connection.cursor()
```

In [ ]:
```
# Print names of 8 tables in the database

cursor.execute("""SELECT name FROM sqlite_master WHERE type = 'table';""")
table_list = [table[0] for table in cursor.fetchall()]
table_list
```

Out[ ]:
```
['aircrafts_data',
 'airports_data',
 'boarding_passes',
 'bookings',
 'flights',
 'seats',
 'ticket_flights',
 'tickets']
```

Exploratory data analysis

In the exploratory data analysis, we will print each data table provided to us and examine at the data provided. For each table we will look at the data types provided, if there are any null values in the data, and max/min values of numerical values. We will calculate basic statistics such as mean, median, mode, etc. of each numeric field. Additionally, we will create basic visualizations of the data.

aircrafts_data table

We observe that we are given model in English and Russian in a json format, we will later modify the table to keep just the English model name.

In [ ]:
```
aircrafts_data = pd.read_sql_query("SELECT * FROM aircrafts_data", connection)
aircrafts_data
```

Out[ ]:

	aircraft_code	model	range
0	773	{"en": "Boeing 777-300", "ru": "Боинг 777-300"}	11100
1	763	{"en": "Boeing 767-300", "ru": "Боинг 767-300"}	7900
2	SU9	{"en": "Sukhoi Superjet-100", "ru": "Сухой Суп...	3000
3	320	{"en": "Airbus A320-200", "ru": "Аэробус A320-...	5700
4	321	{"en": "Airbus A321-200", "ru": "Аэробус A321-...	5600
5	319	{"en": "Airbus A319-100", "ru": "Аэробус A319-...	6700
6	733	{"en": "Boeing 737-300", "ru": "Боинг 737-300"}	4200
7	CN1	{"en": "Cessna 208 Caravan", "ru": "Сессна 208...	1200
8	CR2	{"en": "Bombardier CRJ-200", "ru": "Бомбардье ...	2700

airports_data table

Again, we are given airport_name and city in both Russian and English and will modify later to keep just the English name.

In [ ]:
```
airports_data = pd.read_sql_query("SELECT * FROM airports_data", connection)
airports_data
```

Out[ ]:

	airport_code	airport_name	city	coordinat
0	YKS	{"en": "Yakutsk Airport", "ru": "Якутск"}	{"en": "Yakutsk", "ru": "Якутск"}	(129.77099609375,62.093299865722656
1	MJZ	{"en": "Mirny Airport", "ru": "Мирный"}	{"en": "Mirnyj", "ru": "Мирный"}	(114.03900146484375,62.53469848632812
2	KHV	{"en": "Khabarovsk-Novy Airport", "ru": "Хабар...	{"en": "Khabarovsk", "ru": "Хабаровск"}	(135.18800354004,48.527999877930000
3	PKC	{"en": "Yelizovo Airport", "ru": "Елизово"}	{"en": "Petropavlovsk", "ru": "Петропавловск-К...	(158.453994750976562,53.167900085449218
4	UUS	{"en": "Yuzhno-Sakhalinsk Airport", "ru": "Хом...	{"en": "Yuzhno-Sakhalinsk", "ru": "Южно-Сахали...	(142.718002319335938,46.888698577880859
...	...	...	...	
99	MMK	{"en": "Murmansk Airport", "ru": "Мурманск"}	{"en": "Murmansk", "ru": "Мурманск"}	(32.7508010864257812,68.781700134277343
100	ABA	{"en": "Abakan Airport", "ru": "Абакан"}	{"en": "Abakan", "ru": "Абакан"}	(91.3850021362304688,53.740001678466796
101	BAX	{"en": "Barnaul Airport", "ru": "Барнаул"}	{"en": "Barnaul", "ru": "Барнаул"}	(83.5384979248046875,53.36380004882812
102	AAQ	{"en": "Anapa Vityazevo Airport", "ru": "Витяз...	{"en": "Anapa", "ru": "Анапа"}	(37.3473014831539984,45.00210189819299
103	CNN	{"en": "Chulman Airport", "ru": "Чульман"}	{"en": "Neryungri", "ru": "Нерюнгри"}	(124.914001464839998,56.913898468017997

104 rows × 5 columns

boarding_passes table

In [ ]:
```
boarding_passes = pd.read_sql_query("SELECT * FROM boarding_passes", connection)
boarding_passes
```

Out[ ]:

	ticket_no	flight_id	boarding_no	seat_no
0	0005435212351	30625	1	2D
1	0005435212386	30625	2	3G
2	0005435212381	30625	3	4H
3	0005432211370	30625	4	5D
4	0005435212357	30625	5	11A
...	...	...	...	...
579681	0005434302871	19945	85	20F
579682	0005432892791	19945	86	21C
579683	0005434302869	19945	87	20E
579684	0005432802476	19945	88	21F
579685	0005432802482	19945	89	21E

579686 rows × 4 columns

bookings table

total_amount is likely in Russian rubles. 1 Russian ruble is equal to 0.011 USD.

In [ ]:
```
bookings = pd.read_sql_query("SELECT * FROM bookings", connection)
bookings
```

Out[ ]:

	book_ref	book_date	total_amount
0	00000F	2017-07-05 03:12:00+03	265700
1	000012	2017-07-14 09:02:00+03	37900
2	000068	2017-08-15 14:27:00+03	18100
3	000181	2017-08-10 13:28:00+03	131800
4	0002D8	2017-08-07 21:40:00+03	23600
...	...	...	...
262783	FFFEF3	2017-07-17 07:23:00+03	56000
262784	FFFF2C	2017-08-08 05:55:00+03	10800
262785	FFFF43	2017-07-20 20:42:00+03	78500
262786	FFFFA8	2017-08-08 04:45:00+03	28800
262787	FFFFF7	2017-07-01 22:12:00+03	73600

262788 rows × 3 columns

flights table

In [ ]:

```
flights = pd.read_sql_query("SELECT * FROM flights", connection)
flights
```

Out[ ]:

	flight_id	flight_no	scheduled_departure	scheduled_arrival	departure_airport	arriv
0	1185	PG0134	2017-09-10 09:50:00+03	2017-09-10 14:55:00+03	DME	
1	3979	PG0052	2017-08-25 14:50:00+03	2017-08-25 17:35:00+03	VKO	
2	4739	PG0561	2017-09-05 12:30:00+03	2017-09-05 14:15:00+03	VKO	
3	5502	PG0529	2017-09-12 09:50:00+03	2017-09-12 11:20:00+03	SVO	
4	6938	PG0461	2017-09-04 12:25:00+03	2017-09-04 13:20:00+03	SVO	
...	...	...	...	...	...	
33116	33117	PG0063	2017-08-02 19:25:00+03	2017-08-02 20:10:00+03	SKX	
33117	33118	PG0063	2017-07-28 19:25:00+03	2017-07-28 20:10:00+03	SKX	
33118	33119	PG0063	2017-09-08 19:25:00+03	2017-09-08 20:10:00+03	SKX	
33119	33120	PG0063	2017-08-01 19:25:00+03	2017-08-01 20:10:00+03	SKX	
33120	33121	PG0063	2017-08-26 19:25:00+03	2017-08-26 20:10:00+03	SKX	

33121 rows × 10 columns

seats table

In [ ]:

```
seats = pd.read_sql_query("SELECT * FROM seats", connection)
seats
```

Out[ ]:

	aircraft_code	seat_no	fare_conditions
0	319	2A	Business
1	319	2C	Business
2	319	2D	Business
3	319	2F	Business
4	319	3A	Business
...	...	...	...
1334	773	48H	Economy
1335	773	48K	Economy
1336	773	49A	Economy
1337	773	49C	Economy
1338	773	49D	Economy

1339 rows × 3 columns

ticket_flights table

In [ ]:

```
ticket_flights = pd.read_sql_query("SELECT * FROM ticket_flights", connection)
ticket_flights
```

Out[ ]:

	ticket_no	flight_id	fare_conditions	amount
0	0005432159776	30625	Business	42100
1	0005435212351	30625	Business	42100
2	0005435212386	30625	Business	42100
3	0005435212381	30625	Business	42100
4	0005432211370	30625	Business	42100
...	...	...	...	...
1045721	0005435097522	32094	Economy	5200
1045722	0005435097521	32094	Economy	5200
1045723	0005435104384	32094	Economy	5200
1045724	0005435104352	32094	Economy	5200
1045725	0005435104389	32094	Economy	5200

1045726 rows × 4 columns

tickets table

In [ ]:
```
tickets = pd.read_sql_query("SELECT * FROM tickets", connection)
tickets
```

Out[ ]:

	ticket_no	book_ref	passenger_id
0	0005432000987	06B046	8149 604011
1	0005432000988	06B046	8499 420203
2	0005432000989	E170C3	1011 752484
3	0005432000990	E170C3	4849 400049
4	0005432000991	F313DD	6615 976589
...	...	...	...
366728	0005435999869	D730BA	0474 690760
366729	0005435999870	D730BA	6535 751108
366730	0005435999871	A1AD46	1596 156448
366731	0005435999872	7B6A53	9374 822707
366732	0005435999873	7B6A53	7380 075822

366733 rows × 3 columns

Check for null values in each table

In [ ]:
```
for table in table_list:
    query = f"SELECT * FROM {table}"
    data = pd.read_sql_query(query, connection)

    # Check for null values in each column
    null_values = data.isnull().sum()

    # Print the table name and corresponding null values
    print(f"Null values in table '{table}':\n{null_values}\n")
```

```
Null values in table 'aircrafts_data':
aircraft_code    0
model            0
range            0
dtype: int64

Null values in table 'airports_data':
airport_code    0
airport_name    0
city            0
coordinates     0
timezone        0
dtype: int64

Null values in table 'boarding_passes':
ticket_no      0
flight_id      0
boarding_no    0
seat_no        0
dtype: int64

Null values in table 'bookings':
book_ref        0
book_date       0
total_amount    0
dtype: int64

Null values in table 'flights':
flight_id              0
flight_no              0
scheduled_departure    0
scheduled_arrival      0
departure_airport      0
arrival_airport        0
status                 0
aircraft_code          0
actual_departure       0
actual_arrival         0
dtype: int64

Null values in table 'seats':
aircraft_code      0
seat_no            0
fare_conditions    0
dtype: int64

Null values in table 'ticket_flights':
ticket_no          0
flight_id          0
fare_conditions    0
amount             0
dtype: int64

Null values in table 'tickets':
ticket_no       0
book_ref        0
```

```
passenger_id    0
dtype: int64
```

Check data types contained in each table

In [ ]:

```
# Iterate through each table and check the data types of each column
for table in table_list:
    query = f"PRAGMA table_info({table})"
    table_info = pd.read_sql_query(query, connection)

    # Extract column names and data types
    column_data_types = table_info[['name', 'type']]

    # Print the table name and corresponding column data types
    print(f"Data types in table '{table}':\n{column_data_types}\n")
```

```
Data types in table 'aircrafts_data':
            name          type
0  aircraft_code  character(3)
1          model         jsonb
2          range       INTEGER

Data types in table 'airports_data':
           name          type
0  airport_code  character(3)
1  airport_name         jsonb
2          city         jsonb
3   coordinates         point
4      timezone          TEXT

Data types in table 'boarding_passes':
          name                  type
0    ticket_no         character(13)
1    flight_id               INTEGER
2  boarding_no               INTEGER
3      seat_no  character varying(4)

Data types in table 'bookings':
           name                      type
0      book_ref              character(6)
1     book_date  timestamp with time zone
2  total_amount             numeric(10,2)

Data types in table 'flights':
                  name                      type
0            flight_id                   INTEGER
1            flight_no              character(6)
2  scheduled_departure  timestamp with time zone
3    scheduled_arrival  timestamp with time zone
4    departure_airport              character(3)
5      arrival_airport              character(3)
6               status     character varying(20)
7        aircraft_code              character(3)
8     actual_departure  timestamp with time zone
9       actual_arrival  timestamp with time zone

Data types in table 'seats':
              name                   type
0    aircraft_code           character(3)
1          seat_no   character varying(4)
2  fare_conditions  character varying(10)

Data types in table 'ticket_flights':
              name                   type
0        ticket_no          character(13)
1        flight_id                INTEGER
2  fare_conditions  character varying(10)
3           amount          numeric(10,2)

Data types in table 'tickets':
           name                  type
0     ticket_no         character(13)
```

```
1      book_ref           character(6)
2  passenger_id  character varying(20)
```

Calculating statistics for relevant numerical variables in table

Statistics of aircraft ranges

In [ ]:
```
range_column = pd.read_sql_query("SELECT range FROM aircrafts_data", connection)['r

# Set display options to show values without scientific notation
pd.set_option('display.float_format', lambda x: '%.2f' % x)

# Display basic statistics for the 'range' column
statistics_summary = range_column.describe()

# Calculate range and variance separately
range_value = range_column.max() - range_column.min()
variance_value = range_column.var()

# Add range, standard deviation, and variance to the summary DataFrame
statistics_summary['range'] = range_value
statistics_summary['variance'] = variance_value

# Display the summary statistics
print(statistics_summary)
```

```
count           9.00
mean         5344.44
std          3013.76
min          1200.00
25%          3000.00
50%          5600.00
75%          6700.00
max         11100.00
range        9900.00
variance  9082777.78
Name: range, dtype: float64
```

From the statistics summary we calculate that the average plane has a range of 5344.44 with a minimum of 1200 and maximum of 11100.

Statistics of total amount of money spent for each booking

In [ ]:
```
range_column = pd.read_sql_query("SELECT total_amount FROM bookings", connection)['

# Set display options to show values without scientific notation
pd.set_option('display.float_format', lambda x: '%.2f' % x)

# Display basic statistics for the 'range' column
statistics_summary = range_column.describe()
```

```
# Calculate range and variance separately
range_value = range_column.max() - range_column.min()
variance_value = range_column.var()

# Add range, standard deviation, and variance to the summary DataFrame
statistics_summary['range'] = range_value
statistics_summary['variance'] = variance_value

# Display the summary statistics
print(statistics_summary)
```

```
count          262788.00
mean            79025.61
std             77621.92
min              3400.00
25%             29000.00
50%             55900.00
75%             99200.00
max           1204500.00
range         1201100.00
variance   6025162887.25
Name: total_amount, dtype: float64
```

From the statistics summary, we find that an average of 79,025.61 is spent on each booking. The lowest amount (min) from the bookings was 3400 and the maximum was 1,204,500.

Cost of each individual ticket statistics

In [ ]:
```
range_column = pd.read_sql_query("SELECT amount FROM ticket_flights", connection)['

# Set display options to show values without scientific notation
pd.set_option('display.float_format', lambda x: '%.2f' % x)

# Display basic statistics for the 'range' column
statistics_summary = range_column.describe()

# Calculate range and variance separately
range_value = range_column.max() - range_column.min()
variance_value = range_column.var()

# Add range, standard deviation, and variance to the summary DataFrame
statistics_summary['range'] = range_value
statistics_summary['variance'] = variance_value

# Display the summary statistics
print(statistics_summary)
```

```
count        1045726.00
mean           19858.91
std            22612.39
min             3000.00
25%             7200.00
50%            13400.00
75%            23100.00
max           203300.00
range         200300.00
variance   511320068.85
Name: amount, dtype: float64
```

From the summary statistics, we find that the average ticket costs 19,858.91. The lowest cost of a ticket was 3,000 and the highest cost was 203,300.

Statistics of cost of business class tickets

In [ ]:
```
query = "SELECT amount FROM ticket_flights WHERE fare_conditions = 'Business'"
amount_business = pd.read_sql_query(query, connection)['amount']

# Set display options to show values without scientific notation
pd.set_option('display.float_format', lambda x: '%.2f' % x)

# Display basic statistics for the 'amount' column in Business class
statistics_summary_business = amount_business.describe()

# Calculate range and variance separately for Business class
range_value_business = amount_business.max() - amount_business.min()
variance_value_business = amount_business.var()

# Add range, standard deviation, and variance to the summary DataFrame
statistics_summary_business['range'] = range_value_business
statistics_summary_business['variance'] = variance_value_business

# Display the summary statistics for Business class
print(statistics_summary_business)
```

```
count          107642.00
mean            51143.42
std             46924.00
min              9100.00
25%             20000.00
50%             35000.00
75%             57200.00
max            203300.00
range          194200.00
variance   2201861758.24
Name: amount, dtype: float64
```

Business class tickets cost on average 51,143.42 from the airline.

Statistics of cost of economy class tickets

In [ ]:
```
query = "SELECT amount FROM ticket_flights WHERE fare_conditions = 'Economy'"
amount_economy = pd.read_sql_query(query, connection)['amount']

# Set display options to show values without scientific notation
pd.set_option('display.float_format', lambda x: '%.2f' % x)

# Display basic statistics for the 'amount' column in economy
statistics_summary_economy = amount_economy.describe()

# Calculate range and variance separately for economy
range_value_economy = amount_economy.max() - amount_economy.min()
variance_value_economy = amount_economy.var()

# Add range, standard deviation, and variance to the summary DataFrame
statistics_summary_economy['range'] = range_value_economy
statistics_summary_economy['variance'] = variance_value_economy

# Display the summary statistics for economy
print(statistics_summary_economy)
```

```
count         920793.00
mean           15959.81
std            13703.85
min             3000.00
25%             6800.00
50%            12100.00
75%            17600.00
max            74500.00
range          71500.00
variance   187795395.89
Name: amount, dtype: float64
```

Economy class tickets cost on average 15,959.81 from the airline.

Statistics of cost of comfort class tickets

In [ ]:
```
query = "SELECT amount FROM ticket_flights WHERE fare_conditions = 'Comfort'"
amount_comfort = pd.read_sql_query(query, connection)['amount']

# Set display options to show values without scientific notation
pd.set_option('display.float_format', lambda x: '%.2f' % x)

# Display basic statistics for the 'amount' column in comfort
statistics_summary_comfort = amount_comfort.describe()

# Calculate range and variance separately for comfort
range_value_comfort = amount_comfort.max() - amount_comfort.min()
variance_value_comfort = amount_comfort.var()

# Add range, standard deviation, and variance to the summary DataFrame
statistics_summary_comfort['range'] = range_value_comfort
statistics_summary_comfort['variance'] = variance_value_comfort
```

```
# Display the summary statistics for Comfort class
print(statistics_summary_comfort)
```

```
count          17291.00
mean           32740.55
std            12143.54
min            19900.00
25%            23900.00
50%            24400.00
75%            47400.00
max            47600.00
range          27700.00
variance   147465581.51
Name: amount, dtype: float64
```

Comfort class tickets cost on average 32,740.55.

From the summary statistics we conclude that a business seat costs on average 51,143.42, a comfort seat costs 32,740.55 on average, and an economy seat costs 15,959.81 on average. This makes logical sense as well since economy is typically the lowest cost, comfort economy is the middle option, and a business seat would be most expensive.

Data cleaning & Visualization

We notice that some of the data points are in a json format with a name in either English or Russian. For those data points, we will be selecting the English option. Additionally, in this module we will be visualizing data from the table after cleaning it.

In [ ]:
```
aircrafts_data['model'] = aircrafts_data['model'].apply(lambda x: json.loads(x)['en
aircrafts_data
```

Out[ ]:

	aircraft_code	model	range
0	773	Boeing 777-300	11100
1	763	Boeing 767-300	7900
2	SU9	Sukhoi Superjet-100	3000
3	320	Airbus A320-200	5700
4	321	Airbus A321-200	5600
5	319	Airbus A319-100	6700
6	733	Boeing 737-300	4200
7	CN1	Cessna 208 Caravan	1200
8	CR2	Bombardier CRJ-200	2700

In [ ]:
```
airports_data['airport_name'] = airports_data['airport_name'].apply(lambda x: json.
airports_data['city'] = airports_data['city'].apply(lambda x: json.loads(x)['en'])
```

```
airports_data
```

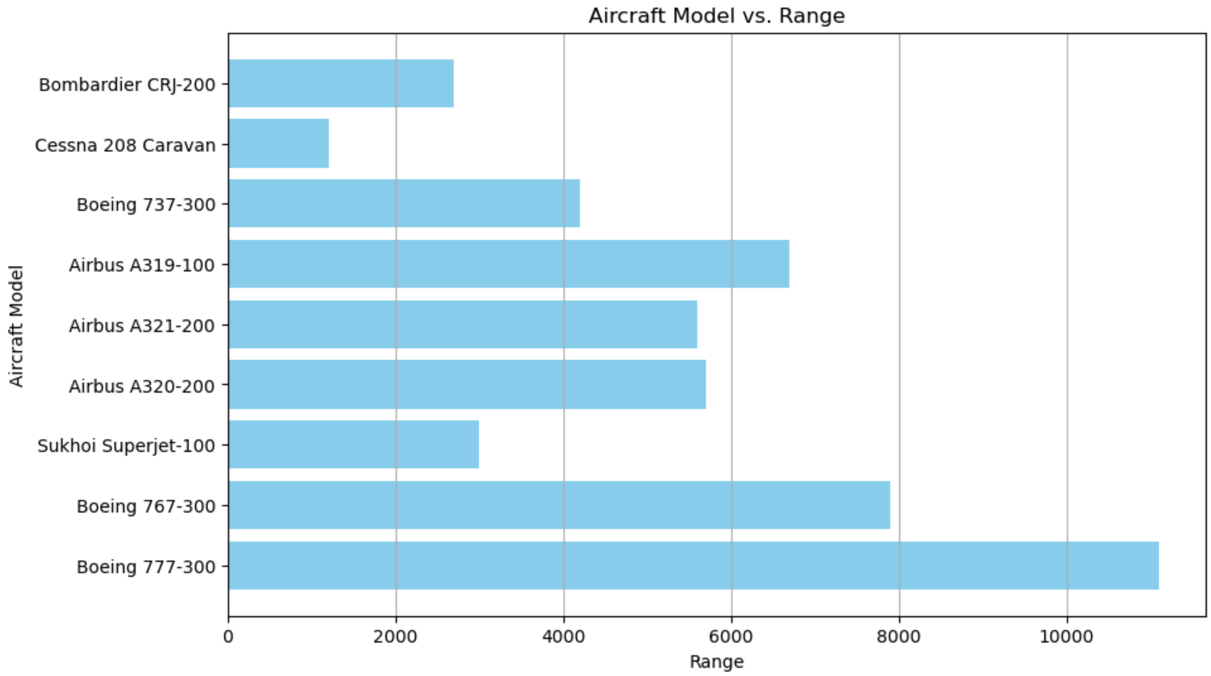
Out[ ]:

	airport_code	airport_name	city	coordinates
0	YKS	Yakutsk Airport	Yakutsk	(129.77099609375,62.0932998657226562)
1	MJZ	Mirny Airport	Mirnyj	(114.03900146484375,62.534698486328125)
2	KHV	Khabarovsk-Novy Airport	Khabarovsk	(135.18800354004,48.5279998779300001)
3	PKC	Yelizovo Airport	Petropavlovsk	(158.453994750976562,53.1679000854492188)
4	UUS	Yuzhno-Sakhalinsk Airport	Yuzhno-Sakhalinsk	(142.718002319335938,46.8886985778808594)
...	...	...	...	...
99	MMK	Murmansk Airport	Murmansk	(32.7508010864257812,68.7817001342773438)
100	ABA	Abakan Airport	Abakan	(91.3850021362304688,53.7400016784667969)
101	BAX	Barnaul Airport	Barnaul	(83.5384979248046875,53.363800048828125)
102	AAQ	Anapa Vityazevo Airport	Anapa	(37.3473014831539984,45.002101898192997)
103	CNN	Chulman Airport	Neryungri	(124.914001464839998,56.9138984680179973)

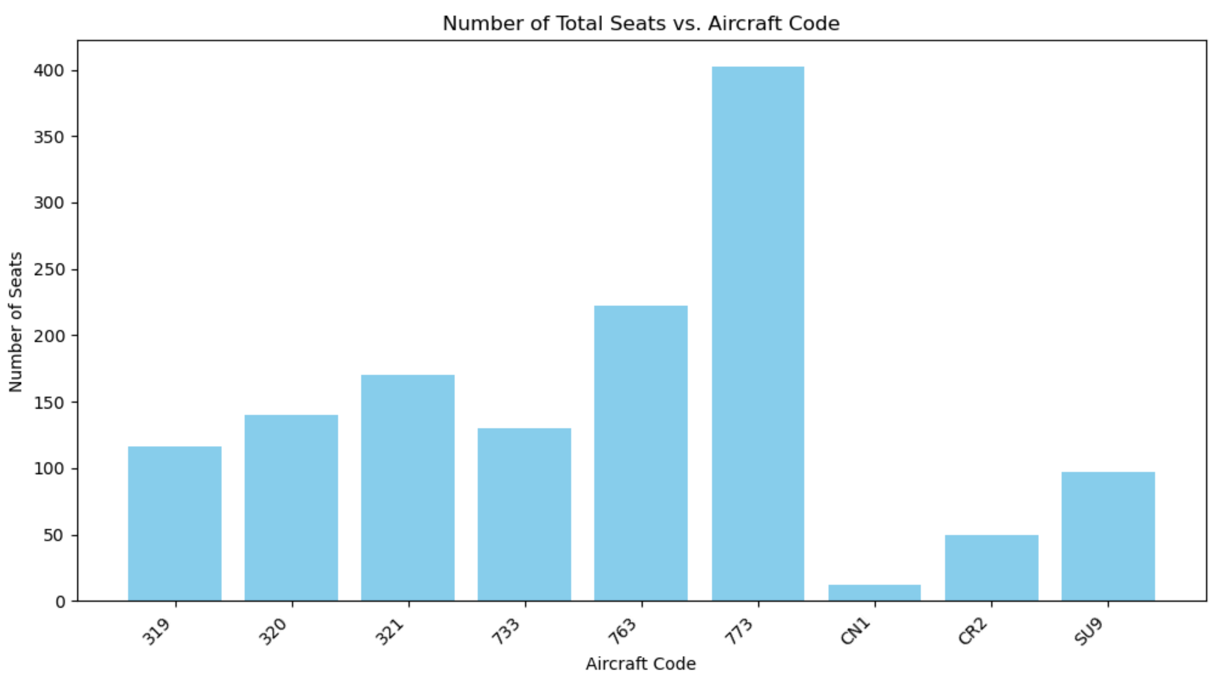
104 rows × 5 columns

In [ ]:

```
plt.figure(figsize=(10, 6))
plt.barh(aircrafts_data['model'], aircrafts_data['range'], color='skyblue')
plt.xlabel('Range')
plt.ylabel('Aircraft Model')
plt.title('Aircraft Model vs. Range')
plt.grid(axis='x')
plt.show()
```

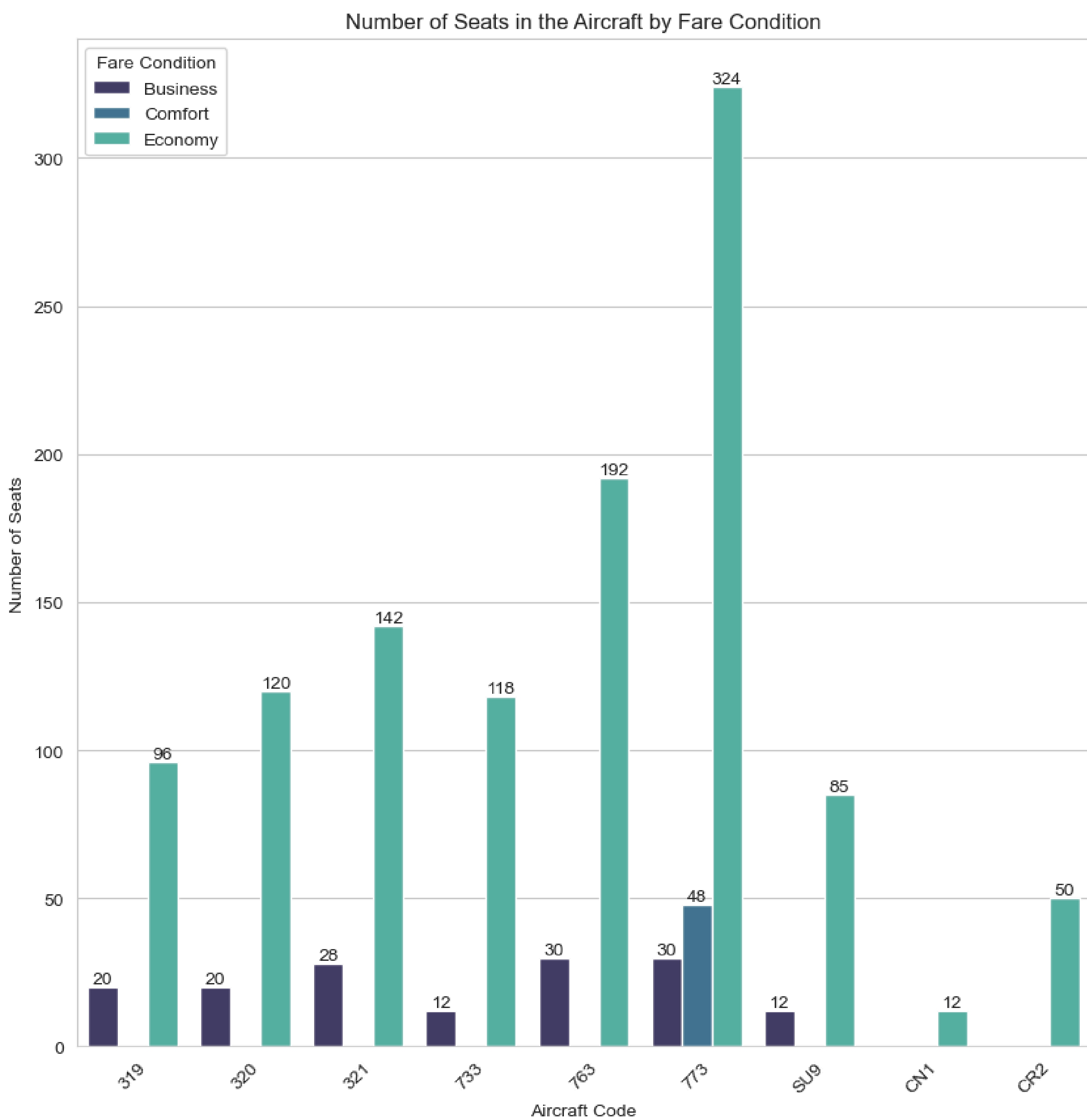


In [ ]:
```
seats_per_aircraft = seats.groupby('aircraft_code')['seat_no'].count().reset_index(

plt.figure(figsize=(12, 6))
plt.bar(seats_per_aircraft['aircraft_code'], seats_per_aircraft['seat_no'], color='
plt.xlabel('Aircraft Code')
plt.ylabel('Number of Seats')
plt.title('Number of Total Seats vs. Aircraft Code')
plt.xticks(rotation=45, ha='right')
plt.show()
```



In [ ]:
```
# Group seats by fare_conditions and aircraft_code, and count the number of seats
seats_per_fare_per_aircraft = seats.groupby(['fare_conditions', 'aircraft_code']).s

# Convert 'seat_count' column to numeric type
```

```
seats_per_fare_per_aircraft = seats_per_fare_per_aircraft.apply(pd.to_numeric, erro

# Plot the number of seats for each fare condition and aircraft code using seaborn
sns.set_style('whitegrid')
fig, axes = plt.subplots(figsize=(10, 10))
ax = sns.barplot(x='aircraft_code', y='seat_count', hue='fare_conditions', data=sea
ax.set(xlabel='Aircraft Code', ylabel='Number of Seats')
ax.legend(title='Fare Condition')
for container in ax.containers:
    ax.bar_label(container)
plt.title('Number of Seats in the Aircraft by Fare Condition')
plt.xticks(rotation=45)
plt.show()

seats_per_fare_per_aircraft
```



Out[ ]:

	fare_conditions	aircraft_code	seat_count
0	Business	319	20
1	Business	320	20
2	Business	321	28
3	Business	733	12
4	Business	763	30
5	Business	773	30
6	Business	SU9	12
7	Comfort	773	48
8	Economy	319	96
9	Economy	320	120
10	Economy	321	142
11	Economy	733	118
12	Economy	763	192
13	Economy	773	324
14	Economy	CN1	12
15	Economy	CR2	50
16	Economy	SU9	85

In [ ]:

```
# cleaning to create a better tickets table, adjusting the dates

tickets = pd.read_sql_query("""select * from tickets inner join bookings
                    on tickets.book_ref = bookings.book_ref""", connection)
tickets['book_date'] = pd.to_datetime(tickets['book_date'])
tickets['date'] = tickets['book_date'].dt.date

tickets
```

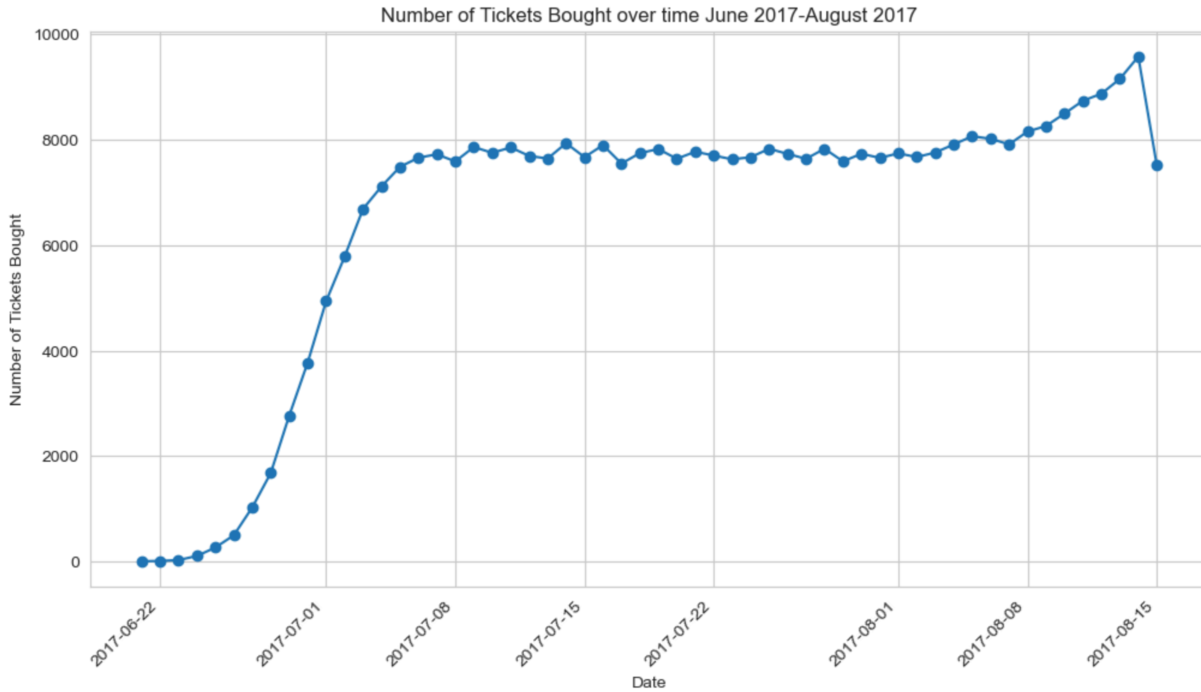
Out[ ]:

	ticket_no	book_ref	passenger_id	book_ref	book_date	total_amount	c
0	0005432000987	06B046	8149 604011	06B046	2017-07-05 20:19:00+03:00	12400	2(07
1	0005432000988	06B046	8499 420203	06B046	2017-07-05 20:19:00+03:00	12400	2(07
2	0005432000989	E170C3	1011 752484	E170C3	2017-06-29 01:55:00+03:00	24700	2(06
3	0005432000990	E170C3	4849 400049	E170C3	2017-06-29 01:55:00+03:00	24700	2(06
4	0005432000991	F313DD	6615 976589	F313DD	2017-07-03 04:37:00+03:00	30900	2(07
...	...	...	...	...	...	...	
366728	0005435999869	D730BA	0474 690760	D730BA	2017-08-14 11:50:00+03:00	210600	2(08
366729	0005435999870	D730BA	6535 751108	D730BA	2017-08-14 11:50:00+03:00	210600	2(08
366730	0005435999871	A1AD46	1596 156448	A1AD46	2017-08-13 03:49:00+03:00	45900	2(08
366731	0005435999872	7B6A53	9374 822707	7B6A53	2017-08-15 15:54:00+03:00	219400	2(08
366732	0005435999873	7B6A53	7380 075822	7B6A53	2017-08-15 15:54:00+03:00	219400	2(08

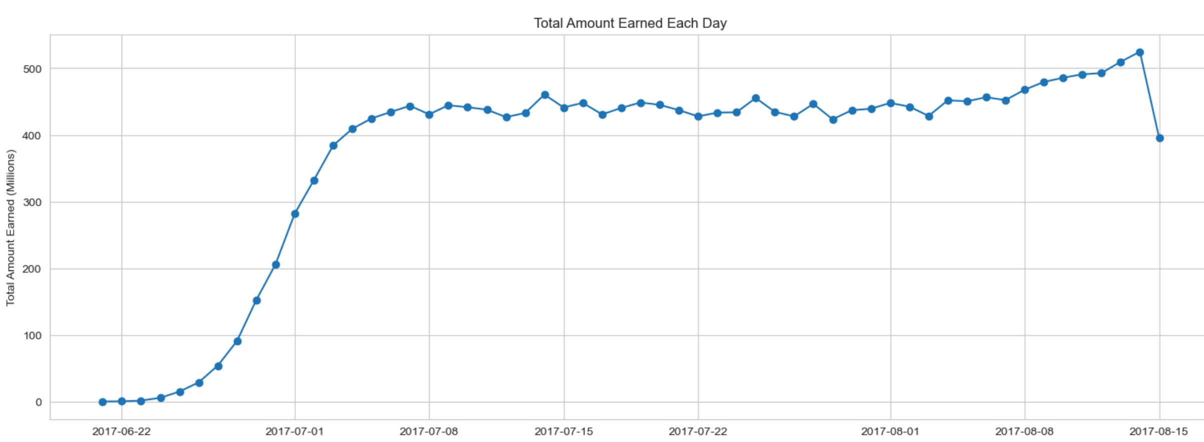
366733 rows × 7 columns

In [ ]:

```python
# Group by date and calculate the number of tickets for each date
tickets_by_date = tickets.groupby('date')['ticket_no'].count().reset_index()

# Plot the number of tickets bought vs. date
plt.figure(figsize=(12, 6))
plt.plot(tickets_by_date['date'], tickets_by_date['ticket_no'], marker='o', linesty
plt.xlabel('Date')
plt.ylabel('Number of Tickets Bought')
plt.title('Number of Tickets Bought over time June 2017-August 2017')
plt.xticks(rotation=45, ha='right')
plt.grid(True)
plt.show()
```

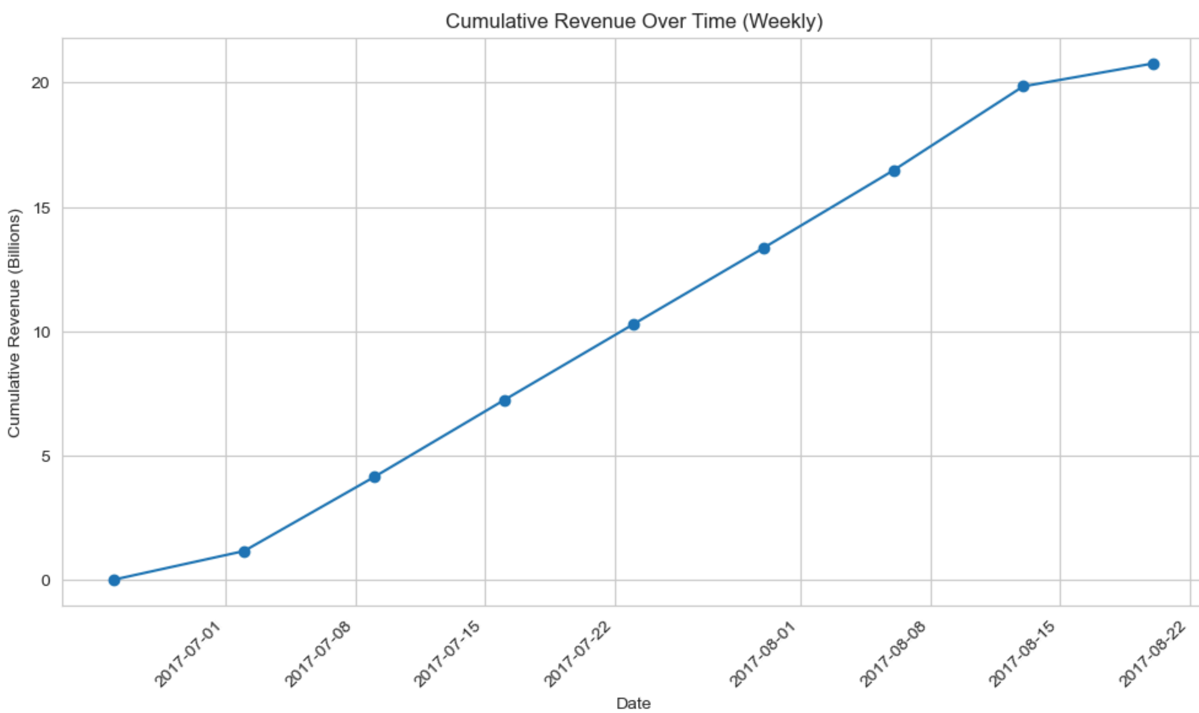


In [ ]:
```
# Read data from the SQL query
bookings = pd.read_sql_query("SELECT * FROM bookings", connection)
# Convert to datetime format
bookings['book_date'] = pd.to_datetime(bookings['book_date'])
# Take only the date for the graph
bookings['date'] = bookings['book_date'].dt.date
# Group the bookings by date
booking_amount = bookings.groupby('date')[['total_amount']].sum()
# Convert total amount to millions
booking_amount['total_amount_millions'] = booking_amount['total_amount'] / 1e6

plt.figure(figsize=(18, 6))
plt.plot(booking_amount.index, booking_amount['total_amount_millions'], marker='o',
plt.title('Total Amount Earned Each Day')
plt.xlabel('Date')
plt.ylabel('Total Amount Earned (Millions)')
plt.grid(True)
plt.show()
```



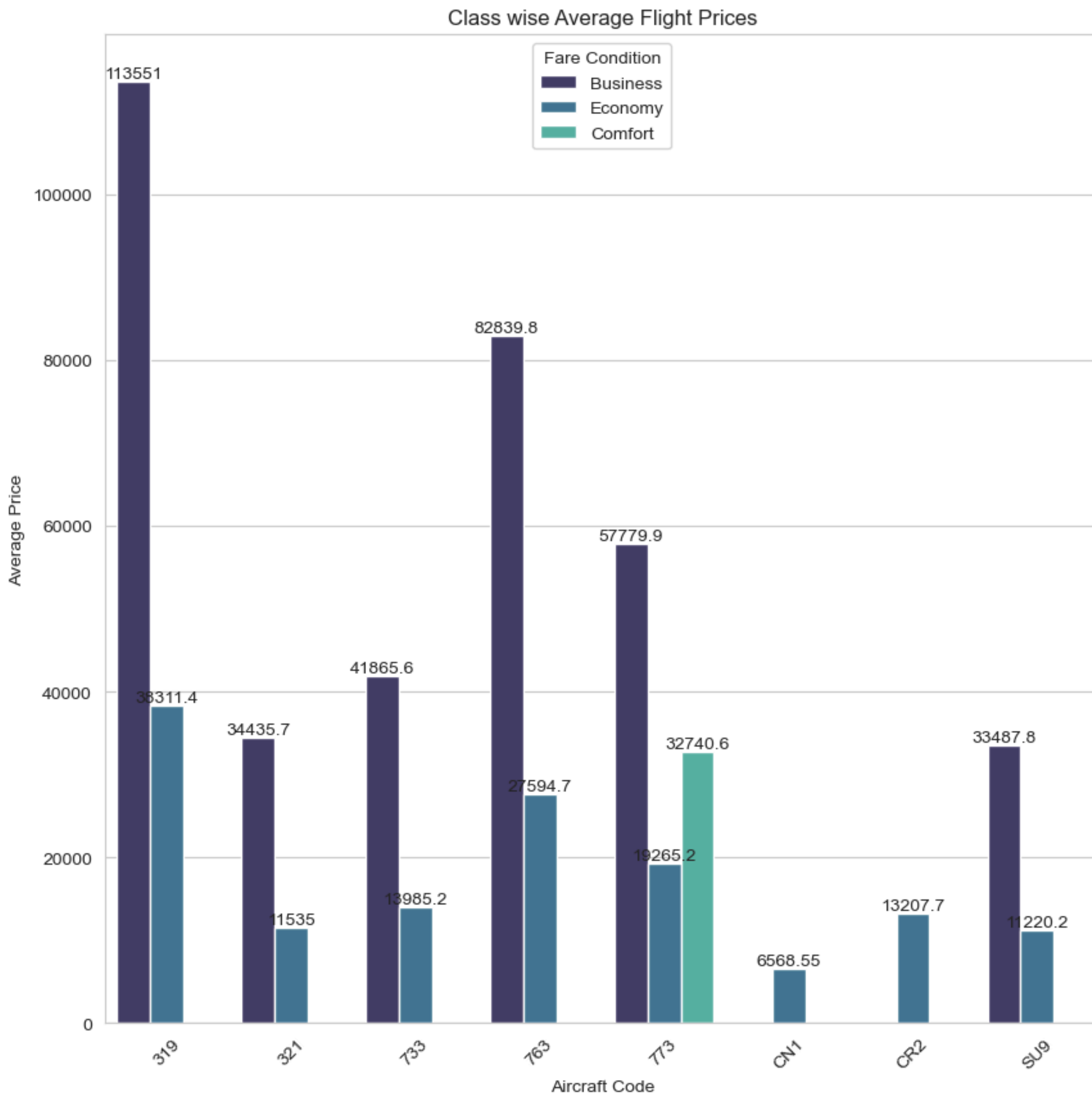
We notice a strong increase in total amount earned per day and number of tickets purchased around the first week of July, this could signal peak summer travel season.

In [ ]:
```
# Read data from the SQL query
bookings = pd.read_sql_query("SELECT * FROM bookings", connection)

# Convert to datetime format
bookings['book_date'] = pd.to_datetime(bookings['book_date'])
# Group by weekly frequency and calculate cumulative sum
cumulative_revenue_by_date = bookings.groupby(pd.Grouper(key='book_date', freq='W')

# Convert total amount to billions
cumulative_revenue_by_date['total_amount_billions'] = cumulative_revenue_by_date['t

plt.figure(figsize=(12, 6))
plt.plot(cumulative_revenue_by_date['book_date'], cumulative_revenue_by_date['total
plt.xlabel('Date')
plt.ylabel('Cumulative Revenue (Billions)')
plt.title('Cumulative Revenue Over Time (Weekly)')
plt.xticks(rotation=45, ha='right')
plt.grid(True)
plt.show()
```



In [ ]:
```
class_wise_avg_prices = pd.read_sql_query("""select fare_conditions, aircraft_code,
                        from ticket_flights join flights
                        on ticket_flights.flight_id = flights.flight_id
                        group by aircraft_code, fare_conditions""", connection)
sns.set_style('whitegrid')
fig,axes = plt.subplots(figsize=(10,10))
ax = sns.barplot(x='aircraft_code',y='avg_price',hue='fare_conditions', data=class_
ax.set(xlabel='Aircraft Code', ylabel='Average Price')
ax.legend(title='Fare Condition')
for container in ax.containers:
```

```
    ax.bar_label(container)
plt.title('Class wise Average Flight Prices')
plt.xticks(rotation=45)
plt.show()

class_wise_avg_prices
```



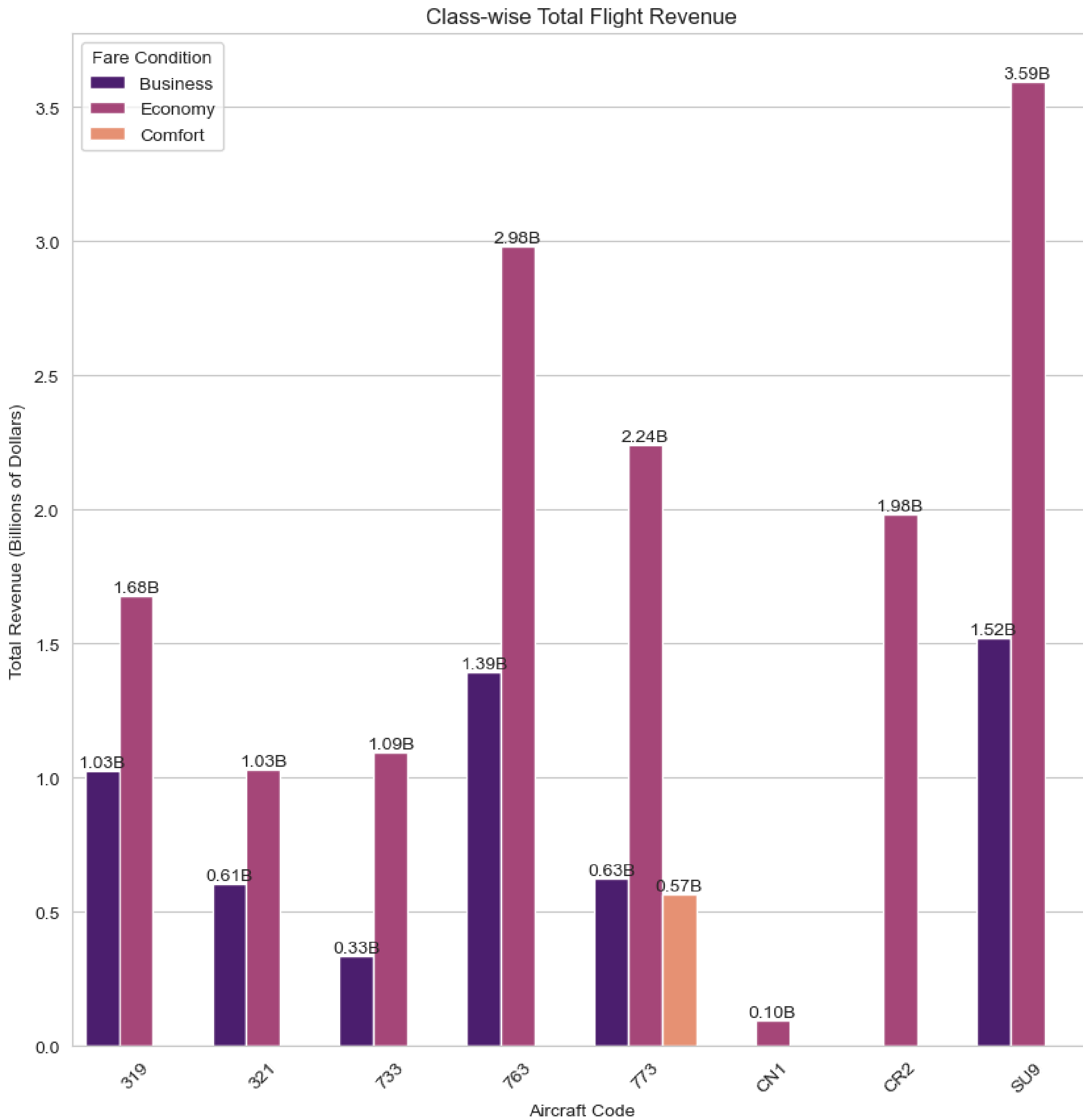
Out[ ]:

	fare_conditions	aircraft_code	avg_price
0	Business	319	113550.56
1	Economy	319	38311.40
2	Business	321	34435.66
3	Economy	321	11534.97
4	Business	733	41865.63
5	Economy	733	13985.15
6	Business	763	82839.84
7	Economy	763	27594.72
8	Business	773	57779.91
9	Comfort	773	32740.55
10	Economy	773	19265.23
11	Economy	CN1	6568.55
12	Economy	CR2	13207.66
13	Business	SU9	33487.85
14	Economy	SU9	11220.18

In [ ]:

```
# Calculate total flight revenue per fare_condition and aircraft_code
query = """
SELECT
    fare_conditions,
    aircraft_code,
    SUM(amount) AS total_amount
FROM ticket_flights
JOIN flights ON ticket_flights.flight_id = flights.flight_id
GROUP BY aircraft_code, fare_conditions
"""

# Read data from the SQL query
df_total_revenue = pd.read_sql_query(query, connection)

# Convert total amount to billions of dollars
df_total_revenue['total_amount_billions'] = df_total_revenue['total_amount'] / 1e9

# Plotting
sns.set_style('whitegrid')
fig, axes = plt.subplots(figsize=(10, 10))
ax = sns.barplot(x='aircraft_code', y='total_amount_billions', hue='fare_conditions
ax.set(xlabel='Aircraft Code', ylabel='Total Revenue (Billions of Dollars)')
ax.legend(title='Fare Condition')
for container in ax.containers:
    ax.bar_label(container, fmt='%.2fB')  # Format labels in billions
plt.title('Class-wise Total Flight Revenue')
```

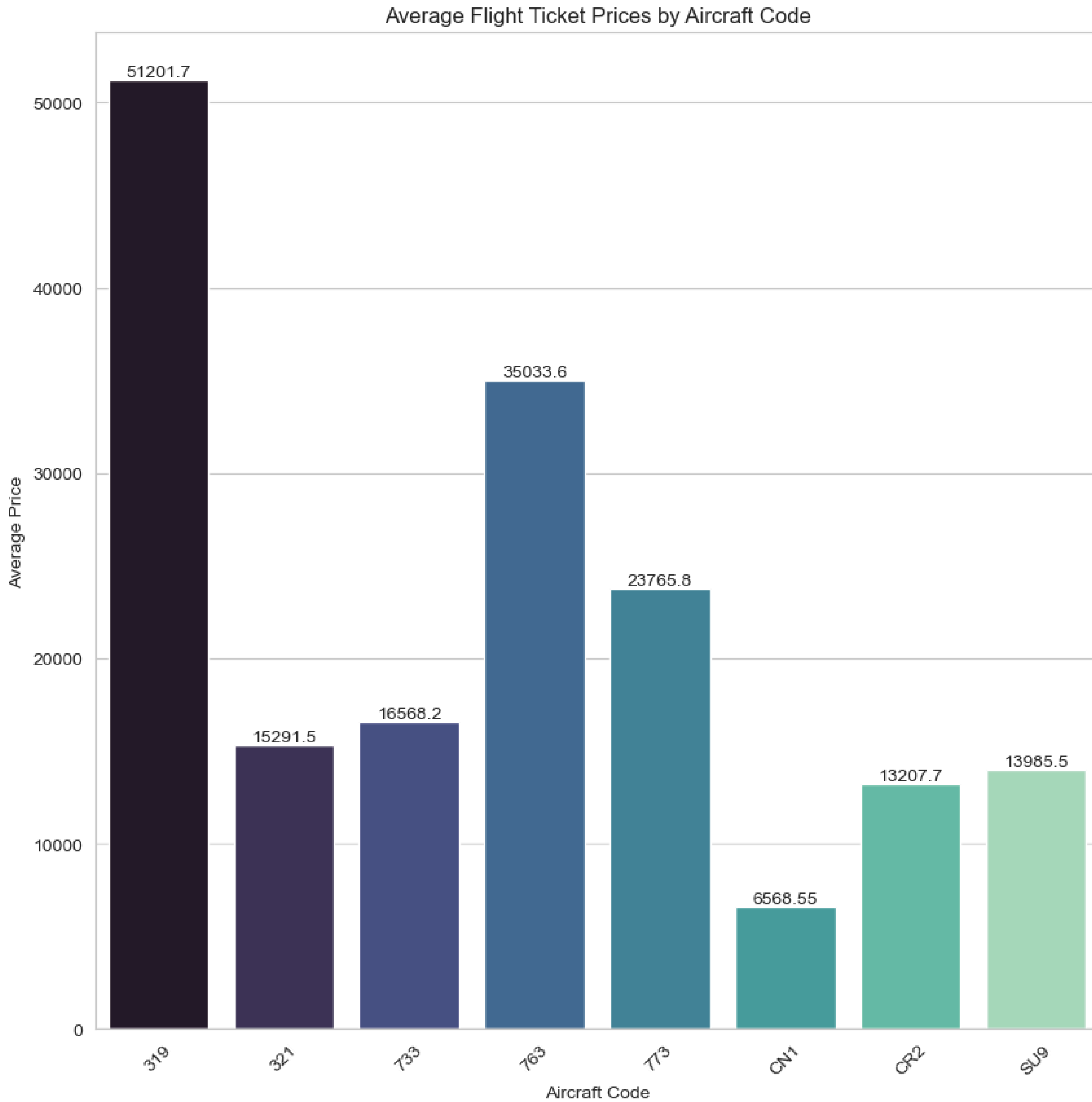
```
plt.xticks(rotation=45)
plt.show()
```



In [ ]:

```
query = """
SELECT aircraft_code, AVG(amount) AS avg_price
FROM ticket_flights
JOIN flights ON ticket_flights.flight_id = flights.flight_id
GROUP BY aircraft_code
"""

# Read data from the SQL query into a DataFrame
avg_prices_by_aircraft = pd.read_sql_query(query, connection)

# Plotting
sns.set_style('whitegrid')
fig, axes = plt.subplots(figsize=(10, 10))
ax = sns.barplot(x='aircraft_code', y='avg_price', data=avg_prices_by_aircraft, pal
ax.set(xlabel='Aircraft Code', ylabel='Average Price')
```

```
ax.set_title('Average Flight Ticket Prices by Aircraft Code')
for container in ax.containers:
    ax.bar_label(container)
plt.xticks(rotation=45)
plt.show()

avg_prices_by_aircraft
```

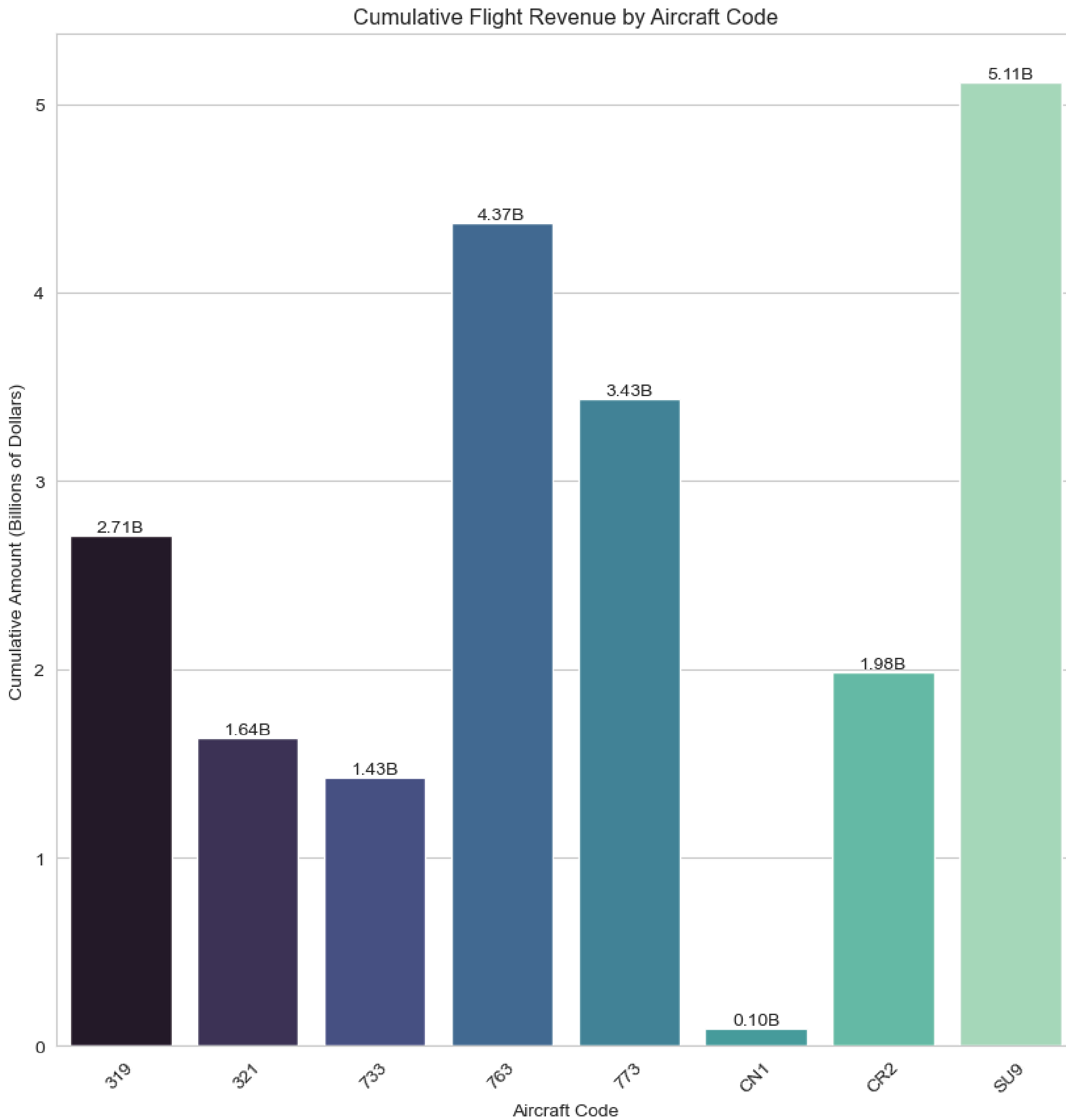


Out[ ]:

	aircraft_code	avg_price
0	319	51201.69
1	321	15291.51
2	733	16568.16
3	763	35033.56
4	773	23765.76
5	CN1	6568.55
6	CR2	13207.66
7	SU9	13985.54

In [ ]:

```
query = """
SELECT aircraft_code, SUM(amount) AS cumulative_amount
FROM ticket_flights
JOIN flights ON ticket_flights.flight_id = flights.flight_id
GROUP BY aircraft_code
"""

# Read data from the SQL query into a DataFrame
df = pd.read_sql_query(query, connection)

# Convert cumulative amount to billions of dollars
df['cumulative_amount_billions'] = df['cumulative_amount'] / 1e9

# Plotting
sns.set_style('whitegrid')
fig, axes = plt.subplots(figsize=(10, 10))
ax = sns.barplot(x='aircraft_code', y='cumulative_amount_billions', data=df, palett
ax.set(xlabel='Aircraft Code', ylabel='Cumulative Amount (Billions of Dollars)')
ax.set_title('Cumulative Flight Revenue by Aircraft Code')
for container in ax.containers:
    ax.bar_label(container, fmt='%.2fB')  # Format labels in billions
plt.xticks(rotation=45)
plt.show()
```



Business data analysis

What is the total revenue generated by airline from bookings?

In [ ]:
```
total_revenue = bookings['total_amount'].sum()

print(f'Total Revenue from Bookings: {total_revenue}')
```

```
Total Revenue from Bookings: 20766980900
```

What is the average occupancy rate for each aircraft?

Using the boarding_passes table and the flights table, as well as our previously created seats_per_aircraft table, we want to return a table containing the average booked seats, average seats per aircraft, and occupancy rate for each aircraft.

Our strategy will be to first inner join the boarding_passes and flights tables on flight_id and then calculate the total amount of seats booked for each aircraft_code and divide that number by the unique number of flight_ids for each aircraft_code to find the average number of booked seats.

Once we calculate average_booked_seats, then we can divide that by the number of seats on each aircraft from our seats_per_aircraft_table to find an average occupancy rate.

In [ ]:

```
query = """
SELECT
    flights.aircraft_code,
    COUNT(boarding_passes.seat_no) / COUNT(DISTINCT flights.flight_id) AS average_b
FROM boarding_passes INNER JOIN flights ON boarding_passes.flight_id = flights.flig
GROUP BY flights.aircraft_code
"""

# Read data from the SQL query into a DataFrame
average_booked_seats = pd.read_sql_query(query, connection)

occupancy_rate = pd.merge(average_booked_seats, seats_per_aircraft, on='aircraft_co

# Calculate occupancy rate and add a new column
occupancy_rate['occupancy_rate'] = (occupancy_rate['average_booked_seats'] / occupa

occupancy_rate
```

Out[ ]:

	aircraft_code	average_booked_seats	seat_no	occupancy_rate
0	319	53	116	45.69
1	321	88	170	51.76
2	733	80	130	61.54
3	763	113	222	50.90
4	773	264	402	65.67
5	CN1	6	12	50.00
6	CR2	21	50	42.00
7	SU9	56	97	57.73

Calculate potential increased revenue from increased occupancy rate

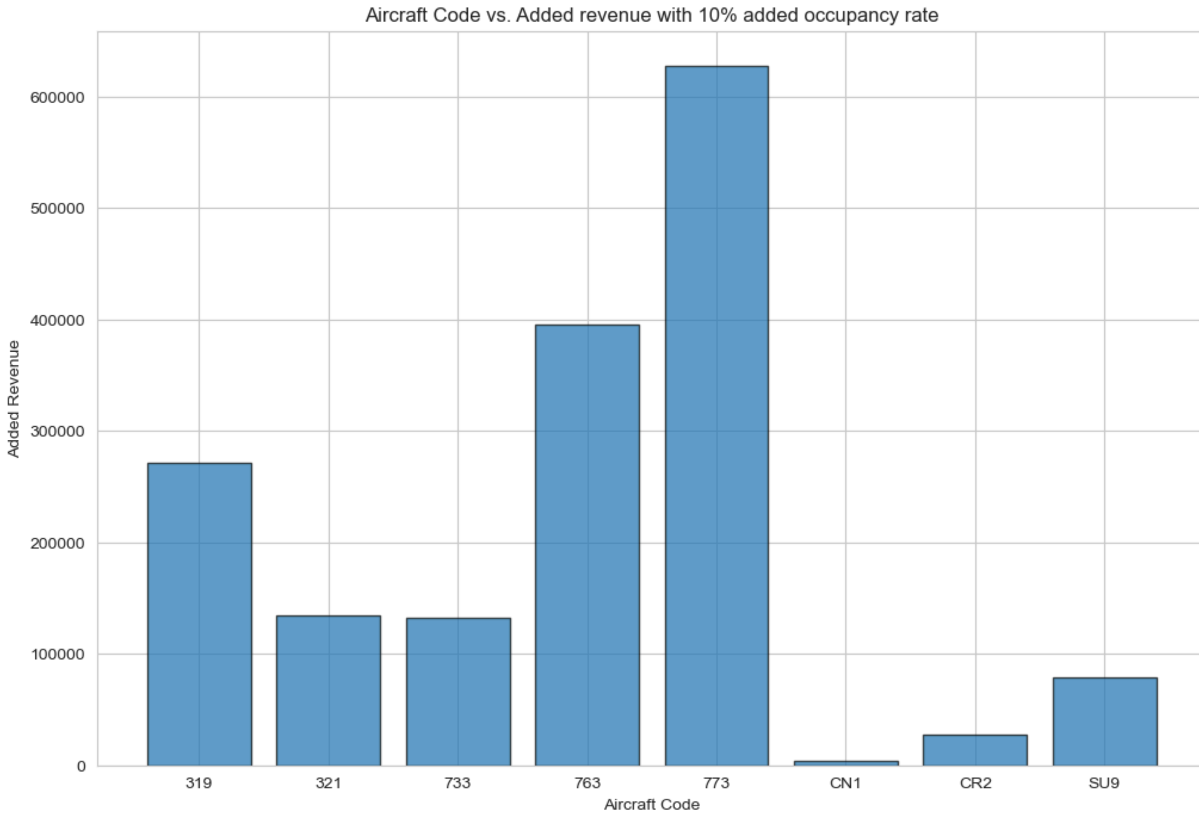
Occupancy rate increase by 10% per aircraft

In [ ]:
```
# Create a column showing a 10% increase in occupancy rate of each aircraft

occupancy_rate['10pct_occupancy_rate'] = (occupancy_rate['occupancy_rate'] * 0.10)

# Create a column showing the additional average seats (tickets) booked

occupancy_rate['10pct_add_seats'] = (occupancy_rate['seat_no'] * (0.01 * occupancy_

# Create column showing the additional revenue created by increasing occupancy rate

occupancy_rate['10pct_add_revenue'] = (occupancy_rate['10pct_add_seats'] * avg_pric


occupancy_rate
```

Out[ ]:

	aircraft_code	average_booked_seats	seat_no	occupancy_rate	10pct_occupancy_rate	10p
0	319	53	116	45.69	50.26	
1	321	88	170	51.76	56.94	
2	733	80	130	61.54	67.69	
3	763	113	222	50.90	55.99	
4	773	264	402	65.67	72.24	
5	CN1	6	12	50.00	55.00	
6	CR2	21	50	42.00	46.20	
7	SU9	56	97	57.73	63.51	

In [ ]:
```
plt.figure(figsize=(12, 8))

# Creating a bar graph
plt.bar(occupancy_rate['aircraft_code'], occupancy_rate['10pct_add_revenue'], alpha

plt.title('Aircraft Code vs. Added revenue with 10% added occupancy rate')
plt.xlabel('Aircraft Code')
plt.ylabel('Added Revenue')

plt.show()
```



Occupancy rate increase by 20% per aircraft

In [ ]:
```
# Create a column showing a 20% increase in occupancy rate of each aircraft

occupancy_rate['20pct_occupancy_rate'] = (occupancy_rate['occupancy_rate'] * 0.20)

# Create a column showing the additional average seats (tickets) booked

occupancy_rate['20pct_add_seats'] = (occupancy_rate['seat_no'] * (0.01 * occupancy_

# Create column showing the additional revenue created by increasing occupancy rate

occupancy_rate['20pct_add_revenue'] = (occupancy_rate['20pct_add_seats'] * avg_pric


occupancy_rate
```

Out[ ]:

	aircraft_code	average_booked_seats	seat_no	occupancy_rate	10pct_occupancy_rate	10
0	319	53	116	45.69	50.26	
1	321	88	170	51.76	56.94	
2	733	80	130	61.54	67.69	
3	763	113	222	50.90	55.99	
4	773	264	402	65.67	72.24	
5	CN1	6	12	50.00	55.00	
6	CR2	21	50	42.00	46.20	
7	SU9	56	97	57.73	63.51	

Takeaways from occupancy rate analysis

From our calculations of the impacts of a 10 percent or 20 percent increase in occupancy rate, we see that aircraft such as the 773 have the most to gain from an increased occupancy rate. In the 20 percent occupancy increase, we saw that the 773 gained 1,254,832.18 in added revenue. The 763 came in second with 791,758.40 in added revenue. Meanwhile, aircraft like the CN1 provide nearly no gain for the airline (7882.26). The SU9 is the aircraft that generates the most cumulative revenue likely due to its low ticket prices, however increasing the occupancy rate doesn't show us that it would give us the best gains because these aircraft are small.

The 773 and 763 gain the most revenue most likely because they have more economy seating and seating in general, allowing more tickets to be sold. By filling these open seats, the airline company can stand to improve profit. The airline can possibly look at decreasing ticket prices to sell more tickets, or improve advertising. These approaches come with a potential loss and require statistical calculations to ensure the company doesn't lose money.

What is the average occupancy rate for each aircraft by fare conditions?

In addition to which aircrafts can help the airline generate more revenue, we want to examine which fare conditions on these airlines will generate more revenue.

10 percent increase of occupancy rate by aircraft code and fare conditions

In [ ]:

```
query = """
SELECT
    flights.aircraft_code,
```

```
    ticket_flights.fare_conditions,
    COUNT(ticket_flights.ticket_no) / COUNT(DISTINCT flights.flight_id) AS average_
FROM
    ticket_flights
    INNER JOIN flights ON ticket_flights.flight_id = flights.flight_id
GROUP BY
    flights.aircraft_code,
    ticket_flights.fare_conditions
"""

# Read data from the SQL query into a DataFrame
average_booked_seats_by_fare = pd.read_sql_query(query, connection)

average_booked_seats_by_fare = pd.merge(average_booked_seats_by_fare, seats_per_far

average_booked_seats_by_fare['occupancy_rate'] = (average_booked_seats_by_fare['ave

average_booked_seats_by_fare

# Create a column showing a 10% increase in occupancy rate of each aircraft

average_booked_seats_by_fare['10pct_occupancy_rate'] = (average_booked_seats_by_far

# Create a column showing the additional average seats (tickets) booked

average_booked_seats_by_fare['10pct_add_seats'] = (average_booked_seats_by_fare['se

# Create column showing the additional revenue created by increasing occupancy rate

average_booked_seats_by_fare['10pct_add_revenue'] = (average_booked_seats_by_fare['

average_booked_seats_by_fare
```

Out[ ]:

	aircraft_code	fare_conditions	average_booked_seats	seat_count	occupancy_rate	10pct
0	319	Business	8	20	40.00	
1	319	Economy	41	96	42.71	
2	321	Business	14	28	50.00	
3	321	Economy	69	142	48.59	
4	733	Business	7	12	58.33	
5	733	Economy	67	118	56.78	
6	763	Business	14	30	46.67	
7	763	Economy	90	192	46.88	
8	773	Business	18	30	60.00	
9	773	Comfort	28	48	58.33	
10	773	Economy	191	324	58.95	
11	CN1	Economy	5	12	41.67	
12	CR2	Economy	20	50	40.00	
13	SU9	Business	6	12	50.00	
14	SU9	Economy	46	85	54.12	

From the table, we see that the most additional revenue gained by increasing the occupancy rate by 10% is from the 773 economy class (367,965.81), 763 economy class (248,352.50), and 319 economy class (157,076.75). The 763 business class and 773 business class also have revenue increase of over 100,000.

Conclusion

From our data analysis, we have picked out specific aircraft such as the 773, 763, and 319 planes that the airline can prioritize. We also picked specific classes such as the 773 economy, 763 economy, and 319 economy that the airline can look at increasing the occupancy rate of.

Possible ways to accomplish increasing the occupancy rate could be to make a push with marketing and advertising or to lower ticket prices or to add some deals that will attract more customers and help the company in the long-run. In order to find if these strategies are profitable, companies will need to do further statistical analysis and balance their revenue with their potential expenses from these strategies.