SHRI VILEPARLE KELAVANI MANDAL'S
DWARKADAS J. SANGHVI COLLEGE OF ENGINEERING
(Autonomous College Affiliated to the University of Mumbai)
NAAC ACCREDITED with "A" GRADE (CGPA : 3.18)

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEEERING

(DATA SCIENCE)

COURSE CODE: DJ19SDL306 **CLASS:** S.Y. B.Tech-B **BATCH: B3**

COURSE NAME: Programing with Python Laboratory

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Python Mini Project

AIM / OBJECTIVE: To analyze data using python that can help for Air Transport Traffic Management.

DESCRIPTION OF EXPERIMENT:

Using python dataset is being preprocessed for further analysis. We have used python libraries like matplotlib , pandas , NumPy , seaborn , folium.

Matplotlib

Matplotlib is a comprehensive library for creating static, animated, and interactive visualizations in Python. Matplotlib makes easy things easy and hard things possible.

Pandas

Pandas allows us to analyse big data and make conclusions based on statistical theories .Pandas can clean messy data sets, and make them readable and relevant. Relevant data is very important in data science.

NumPy

NumPy aims to provide an array object that is up to 50x faster than traditional Python lists.
The array object in NumPy is called ND array, it provides a lot of supporting functions that make working with ND array very easy .Arrays are very frequently used in data science, where speed and resources are very important.

Seaborn
Seaborn is a data visualization library built on top of matplotlib and closely integrated with pandas data structures in Python. Visualization is the central part of Seaborn which helps in exploration and understanding of data.

Folium
Folium is a powerful data visualization library in Python that was built primarily to help people visualize geospatial data. With Folium, one can create a map of any location in the world. Folium is actually python wrapper for leaflet.js which is a JavaScript library for plotting interactive maps.

PROBLEM STATEMENT:

One of the major challenges encountered by air traffic managers is the problem of finding good and optimal scheduling ATFM strategies that minimizes delay costs as well reducing the impact of congestion problems while satisfying the airport and en-route airspace capacity constraints. The problem statement and the expected modeling variation are presented below taking into consideration that the number of flights departing or arriving from a certain airport as well as the number of aircraft's traversing in a particular sector of the airspace are functions of several variables: the number of runways available, ATC capacity, airspace restrictions and restrictions as to which aircraft can follow an aircraft of a given class.

Project:-

1) Importing CSVs

Code:

```
airports_ex = pd.read_csv('airports-extended.csv')
routes = pd.read_csv('routes.csv')
airlines = pd.read_csv('airlines.csv')
```

2) Preprocessing airports data

Code:

airports_ex.head()

Output:

	1												
0	2	Goroka Airport	Goroka	Papua New Guinea	GKA	AYGA	-6.08168983459	145.391998291	5282	10	U	Pacific/Port_Moresby	airport	OurAirports
1	3	Madang Airport	Madang	Papua New Guinea	MAG	AYMD	-5.207080	145.789001	20	10.0	U	Pacific/Port_Moresby	airport	OurAirports
2	4	Mount Hagen Kagamuga Airport	Mount Hagen	Papua New Guinea	HGU	AYMH	-5.826790	144.296005	5388	10.0	U	Pacific/Port_Moresby	airport	OurAirports
3	5	Nadzab Airport	Nadzab	Papua New Guinea	LAE	AYNZ	-6.569803	146.725977	239	10.0	U	Pacific/Port_Moresby	airport	OurAirports
4	6	Port Moresby Jacksons International Airport	Port Moresby	Papua New Guinea	POM	AYPY	-9.443380	147.220001	146	10.0	U	Pacific/Port_Moresby	airport	OurAirports
		Wewak International Airport	Wewak	Papua New Guinea	WWK	AYWK	-3.583830	143.669006	19	10.0	U	Pacific/Port_Moresby	airport	OurAirports

Code:

airports_ex.columns = ['Airport_ID', 'Airport_Name', 'City', 'Country', 'IATA', 'ICAO', 'Latitude', 'Longitude', 'Altitude', 'Timezone', 'DST', 'Tz database time zone','Type', 'Source']

airports_ex.head()

Output:

	Airport_ID	Airport_Name	City	Country	IATA	ICAO	Latitude	Longitude	Altitude	Timezone	DST	Tz database time zone	Type	Source
0	2	Madang Airport	Madang	Papua New Guinea	MAG	AYMD	-5.207080	145.789001	20	10.0	U	Pacific/Port_Moresby	airport	OurAirports
1	3	Mount Hagen Kagamuga Airport	Mount Hagen	Papua New Guinea	HGU	AYMH	-5.826790	144.296005	5388	10.0	U	Pacific/Port_Moresby	airport	OurAirports
2	4	Nadzab Airport	Nadzab	Papua New Guinea	LAE	AYNZ	-6.569803	146.725977	239	10.0	U	Pacific/Port_Moresby	airport	OurAirports
3	5	Port Moresby Jacksons International Airport	Port Moresby	Papua New Guinea	POM	AYPY	-9.443380	147.220001	146	10.0	U	Pacific/Port_Moresby	airport	OurAirports
4	6	Wewak International Airport	Wewak	Papua New Guinea	WWK	AYWK	-3.583830	143.669006	19	10.0	U	Pacific/Port_Moresby	airport	OurAirports

+ Code + Markdown

Code:

airports_ex['Type'].value_counts()

Output:

```
airport    8263
station    1332
unknown    1320
port        101
Name: Type, dtype: int64
```

Code:

airports=airports_ex.drop(airports_ex.loc[airports_ex['Type']!= 'airport'].index)

airports['Type'].value_counts()

Output:

```
airport    8263
Name: Type, dtype: int64
```

Code:

airports.info()

Output:

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 8263 entries, 0 to 12665
Data columns (total 14 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Airport_ID            8263 non-null   int64
 1   Airport_Name          8263 non-null   object
 2   City                  8214 non-null   object
 3   Country               8263 non-null   object
 4   IATA                  6471 non-null   object
 5   ICAO                  7754 non-null   object
 6   Latitude              8263 non-null   float64
 7   Longitude             8263 non-null   float64
 8   Altitude              8263 non-null   int64
 9   Timezone              7910 non-null   float64
 10  DST                   7910 non-null   object
 11  Tz database time zone 7147 non-null   object
 12  Type                  8263 non-null   object
 13  Source                8263 non-null   object
dtypes: float64(3), int64(2), object(9)
memory usage: 968.3+ KB
```

3) VIS_1: Top 20 COuntries with most number of Airports

Code:

airports['Country'].value_counts()

Output:

```
United States    1752
Canada            459
Australia         343
Russia            271
Brazil            269
                  ...
Isle of Man         1
Jersey              1
West Bank           1
Gambia              1
Wake Island         1
Name: Country, Length: 237, dtype: int64
```

Code:

```
plot_df1 = (
   airports['Country'].value_counts()
      .head(20)
      .rename_axis('Country')
      .reset_index(name='no_of_airports')
)
plot_df1
```

Output:

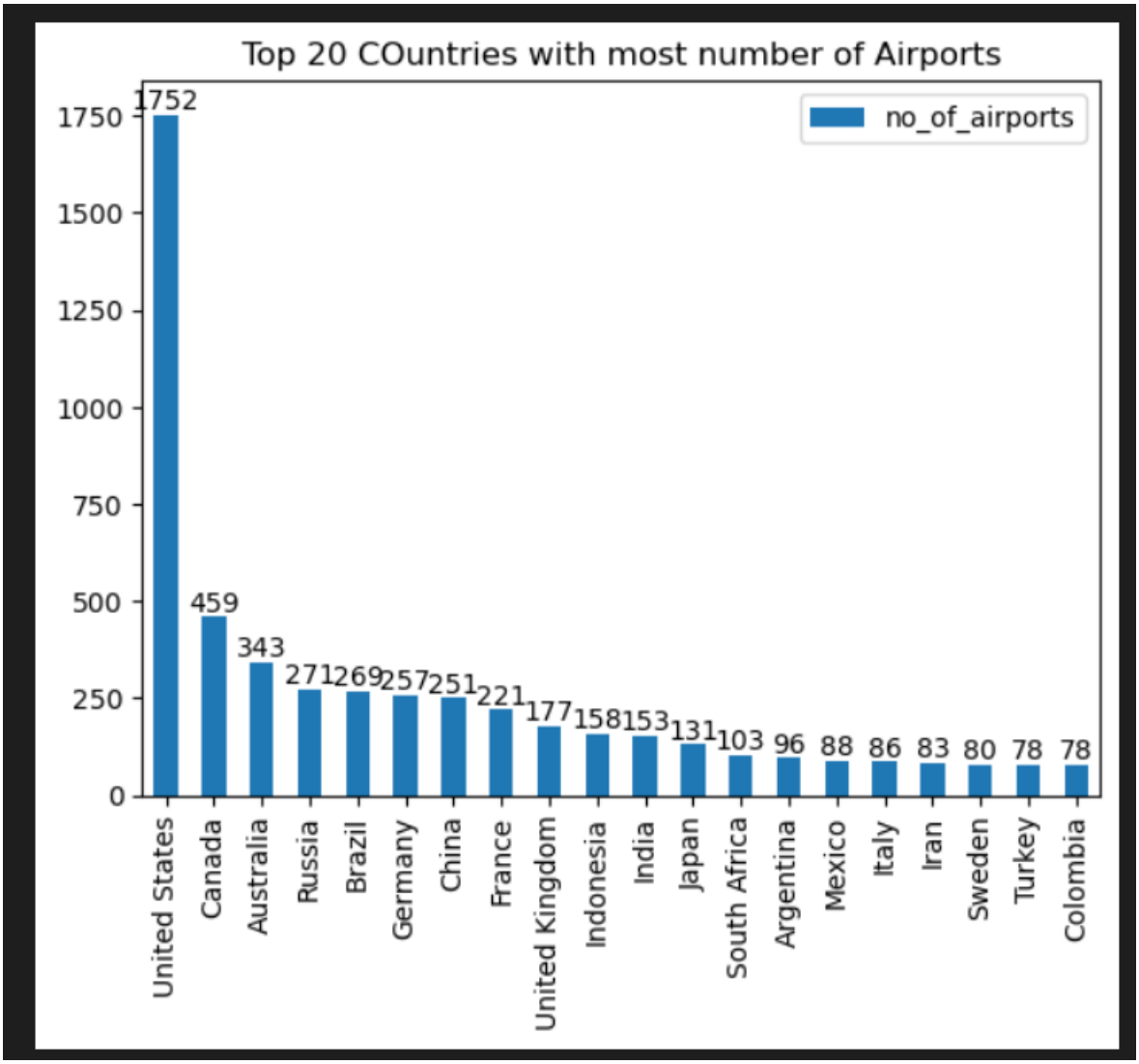
	Country	no_of_airports
0	United States	1752
1	Canada	459
2	Australia	343
3	Russia	271
4	Brazil	269
5	Germany	257
6	China	251
7	France	221
8	United Kingdom	177
9	Indonesia	158
10	India	153
11	Japan	131
12	South Africa	103
13	Argentina	96
14	Mexico	88
15	Italy	86
16	Iran	83
17	Sweden	80
18	Turkey	78
19	Colombia	78

Code:

```
x_labels = plot_df1['Country']
fig = plot_df1.plot(kind='bar')
plt.title('Top 20 COuntries with most number of Airports')
fig.set_xticklabels(x_labels)
fig.bar_label(fig.containers[0], label_type='edge')
```

Output:

```
[Text(0, 0, '1752')
 Text(0, 0, '459'),
 Text(0, 0, '343'),
 Text(0, 0, '271'),
 Text(0, 0, '269'),
 Text(0, 0, '257'),
 Text(0, 0, '251'),
 Text(0, 0, '221'),
 Text(0, 0, '177'),
 Text(0, 0, '158'),
 Text(0, 0, '153'),
 Text(0, 0, '131'),
 Text(0, 0, '103'),
 Text(0, 0, '96'),
 Text(0, 0, '88'),
 Text(0, 0, '86'),
 Text(0, 0, '83'),
 Text(0, 0, '80'),
 Text(0, 0, '78'),
 Text(0, 0, '78')]
```



Code:

```
plot_df1 = (
    airports['Country'].value_counts()
        .rename_axis('Country')
        .reset_index(name='no_of_airports')
)
plot_df1
```

Output:

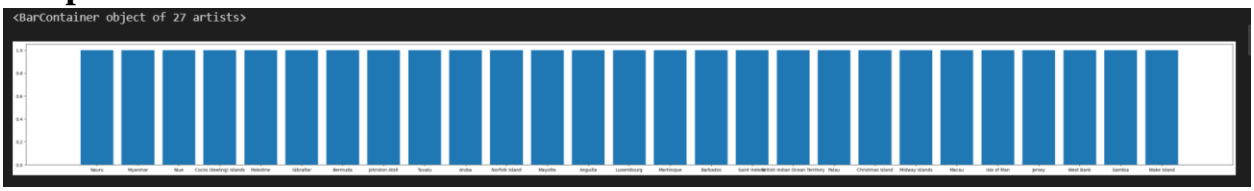
	Country	no_of_airports
0	United States	1752
1	Canada	459
2	Australia	343
3	Russia	271
4	Brazil	269
...	...	...
232	Isle of Man	1
233	Jersey	1
234	West Bank	1
235	Gambia	1
236	Wake Island	1

237 rows × 2 columns

Code:

```
plot_df2 = plot_df1[plot_df1.no_of_airports <= 1]
#np.array()plt.figure(figsize = (50,5))
plt.bar(plot_df2['Country'], plot_df2['no_of_airports'])
```

Output:



4) Preprocessing Routes data

Code:

```
routes.head()
```

Output:

	2B	410	AER	2965	KZN	2990	Unnamed: 6	0	CR2
0	2B	410	ASF	2966	KZN	2990	NaN	0	CR2
1	2B	410	ASF	2966	MRV	2962	NaN	0	CR2
2	2B	410	CEK	2968	KZN	2990	NaN	0	CR2
3	2B	410	CEK	2968	OVB	4078	NaN	0	CR2
4	2B	410	DME	4029	KZN	2990	NaN	0	CR2

Code:

routes.columns = ['Airline_IATA', 'Airline_ID', 'Source_airport', 'Source_airport_ID', 'Destination_airport', 'Destination_airport_ID', 'Codeshare', 'Stops', 'Equipment']
routes

Output:

	Airline_IATA	Airline_ID	Source_airport	Source_airport_ID	Destination_airport	Destination_airport_ID	Codeshare	Stops	Equipment
0	2B	410	ASF	2966	KZN	2990	NaN	0	CR2
1	2B	410	ASF	2966	MRV	2962	NaN	0	CR2
2	2B	410	CEK	2968	KZN	2990	NaN	0	CR2
3	2B	410	CEK	2968	OVB	4078	NaN	0	CR2
4	2B	410	DME	4029	KZN	2990	NaN	0	CR2
...	...	...	...	...	...	...	...	...	...
67657	ZL	4178	WYA	6334	ADL	3341	NaN	0	SF3
67658	ZM	19016	DME	4029	FRU	2912	NaN	0	734
67659	ZM	19016	FRU	2912	DME	4029	NaN	0	734
67660	ZM	19016	FRU	2912	OSS	2913	NaN	0	734
67661	ZM	19016	OSS	2913	FRU	2912	NaN	0	734

67662 rows × 9 columns

Code:

routes.isnull().sum()

Output:

```
Airline_IATA                0
Airline_ID                  0
Source_airport              0
Source_airport_ID           0
Destination_airport         0
Destination_airport_ID      0
Codeshare                53065
Stops                       0
Equipment                  18
dtype: int64
```

5) Preprocessing Airline data

Code:

airlines.head()

Output:

	-1	Unknown	\N	-	N/A	\N.1	\N.2	Y
0	1	Private flight	\N	-	NaN	NaN	NaN	Y
1	2	135 Airways	\N	NaN	GNL	GENERAL	United States	N
2	3	1Time Airline	\N	1T	RNX	NEXTIME	South Africa	Y
3	4	2 Sqn No 1 Elementary Flying Training School	\N	NaN	WYT	NaN	United Kingdom	N
4	5	213 Flight Unit	\N	NaN	TFU	NaN	Russia	N

Code:

airlines.columns = ['Airline_ID', 'Airline_Name', 'Airline_Alias', 'Airline_IATA', 'Airline_ICAO', 'Callsign', 'Airline_Country', 'Active']

airlines

Output:

	Airline_ID	Airline_Name	Airline_Alias	Airline_IATA	Airline_ICAO	Callsign	Airline_Country	Active
0	1	Private flight	\N	-	NaN	NaN	NaN	Y
1	2	135 Airways	\N	NaN	GNL	GENERAL	United States	N
2	3	1Time Airline	\N	1T	RNX	NEXTIME	South Africa	Y
3	4	2 Sqn No 1 Elementary Flying Training School	\N	NaN	WYT	NaN	United Kingdom	N
4	5	213 Flight Unit	\N	NaN	TFU	NaN	Russia	N
...	...	...	...	...	...	...	...	...
6156	21248	GX Airlines	NaN	NaN	CBG	SPRAY	China	Y
6157	21251	Lynx Aviation (L3/SSX)	NaN	NaN	SSX	Shasta	United States	N
6158	21268	Jetgo Australia	NaN	JG	\N	NaN	Australia	Y
6159	21270	Air Carnival	NaN	2S	\N	NaN	India	Y
6160	21317	Svyaz Rossiya	Russian Commuter	7R	SJM	RussianConnecty	Russia	Y

6161 rows × 8 columns

Code:

airlines.isnull().sum()

```
Airline_ID            0
Airline_Name          0
Airline_Alias       506
Airline_IATA       4627
Airline_ICAO         86
Callsign            808
Airline_Country      15
Active                0
dtype: int64
```

Code:

```
airlines_df = airlines[['Airline_Name', 'Airline_IATA']]
airlines_df.head()
```

Output:

	Airline_Name	Airline_IATA
0	Private flight	-
1	135 Airways	NaN
2	1Time Airline	1T
3	2 Sqn No 1 Elementary Flying Training School	NaN
4	213 Flight Unit	NaN

Code:

```
airline_routes = pd.merge(left = airlines_df,
                  right = routes,
                  how= 'right',
                  left_on='Airline_IATA',
                  right_on='Airline_IATA',
                  suffixes=('_x', '_y'))
airline_routes
```

Output:

	Airline_Name	Airline_IATA	Airline_ID	Source_airport	Source_airport_ID	Destination_airport	Destination_airport_ID	Stops	Equipment
0	Aerocondor	2B	410	ASF	2966	KZN	2990	0	CR2
1	Aerocondor	2B	410	ASF	2966	MRV	2962	0	CR2
2	Aerocondor	2B	410	CEK	2968	KZN	2990	0	CR2
3	Aerocondor	2B	410	CEK	2968	OVB	4078	0	CR2
4	Aerocondor	2B	410	DME	4029	KZN	2990	0	CR2
...	...	...	...	...	...	...	...	...	...
78215	Regional Express	ZL	4178	WYA	6334	ADL	3341	0	SF3
78216	Apache Air	ZM	19016	DME	4029	FRU	2912	0	734
78217	Apache Air	ZM	19016	FRU	2912	DME	4029	0	734
78218	Apache Air	ZM	19016	FRU	2912	OSS	2913	0	734
78219	Apache Air	ZM	19016	OSS	2913	FRU	2912	0	734

78220 rows × 9 columns

Code:

```
airline_routes.isnull().sum()
```

Output:

```
Airline_Name              852
Airline_IATA                0
Airline_ID                  0
Source_airport              0
Source_airport_ID           0
Destination_airport         0
Destination_airport_ID      0
Stops                       0
Equipment                  19
dtype: int64
```

Code:

```
airports_info =  airports[['IATA','Airport_Name', 'City', 'Country','Latitude', 'Longitude']]
airports_info.info()
```

Output:

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 8263 entries, 0 to 12665
Data columns (total 6 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   IATA          6471 non-null   object
 1   Airport_Name  8263 non-null   object
 2   City          8214 non-null   object
 3   Country       8263 non-null   object
 4   Latitude      8263 non-null   float64
 5   Longitude     8263 non-null   float64
dtypes: float64(2), object(4)
memory usage: 451.9+ KB
```

Code:

```
airline_routes1 = pd.merge(left = airports_info,
                right = airline_routes,
                how= 'right',
                left_on='IATA',
                right_on='Source_airport',
                suffixes=('_x', '_y'))
airline_routes1
```

Output:

	IATA_d	Airport_Name_d	City_d	Country_d	Latitude_d	Longitude_d	IATA_s	Airport_Name_s	City_s	Country_s	...	Longitude_s	Airline_Name	Airline_IATA	Airline_ID	Source_ai
0	KZN	Kazan International Airport	Kazan	Russia	55.606201	49.278702	ASF	Astrakhan Airport	Astrakhan	Russia	...	48.006302	Aerocondor	2B	410	
1	MRV	Mineralnyye Vody Airport	Mineralnye Vody	Russia	44.225101	43.081902	ASF	Astrakhan Airport	Astrakhan	Russia	...	48.006302	Aerocondor	2B	410	
2	KZN	Kazan International Airport	Kazan	Russia	55.606201	49.278702	CEK	Chelyabinsk Balandino Airport	Chelyabinsk	Russia	...	61.503300	Aerocondor	2B	410	
3	OVB	Tolmachevo Airport	Novosibirsk	Russia	55.012600	82.650703	CEK	Chelyabinsk Balandino Airport	Chelyabinsk	Russia	...	61.503300	Aerocondor	2B	410	
4	KZN	Kazan International Airport	Kazan	Russia	55.606201	49.278702	DME	Domodedovo International Airport	Moscow	Russia	...	37.906300	Aerocondor	2B	410	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
78215	ADL	Adelaide International Airport	Adelaide	Australia	-34.945000	138.531006	WYA	Whyalla Airport	Whyalla	Australia	...	137.514008	Regional Express	ZL	4178	
78216	FRU	Manas International Airport	Bishkek	Kyrgyzstan	43.061298	74.477600	DME	Domodedovo International Airport	Moscow	Russia	...	37.906300	Apache Air	ZM	19016	
78217	DME	Domodedovo International Airport	Moscow	Russia	55.408798	37.906300	FRU	Manas International Airport	Bishkek	Kyrgyzstan	...	74.477600	Apache Air	ZM	19016	
78218	OSS	Osh Airport	Osh	Kyrgyzstan	40.609001	72.793297	FRU	Manas International Airport	Bishkek	Kyrgyzstan	...	74.477600	Apache Air	ZM	19016	

Code:

```
final_routes.isnull().sum()
```

Output:

```
Airline_Name          852
Airline_IATA            0
Source_airport          0
Airport_Name_s        255
City_s                257
Country_s             255
Latitude_s            255
Longitude_s           255
Destination_airport     0
Airport_Name_d        263
City_d                265
Country_d             263
Latitude_d            263
Longitude_d           263
Equipment              19
dtype: int64
```

Code:

```
final_routes.to_csv('final_routes.csv')
final_routes.head()
```

Output:

	Airline_Name	Airline_IATA	Source_airport	Airport_Name_s	City_s	Country_s	Latitude_s	Longitude_s	Destination_airport	Airport_Name_d	City_d	Country_d	Latitude_d	Longitude_d
0	Aerocondor	2B	ASF	Astrakhan Airport	Astrakhan	Russia	46.283298	48.006302	KZN	Kazan International Airport	Kazan	Russia	55.606201	49.278702
1	Aerocondor	2B	ASF	Astrakhan Airport	Astrakhan	Russia	46.283298	48.006302	MRV	Mineralnyye Vody Airport	Mineralnye Vody	Russia	44.225101	43.081902
2	Aerocondor	2B	CEK	Chelyabinsk Balandino Airport	Chelyabinsk	Russia	55.305801	61.503300	KZN	Kazan International Airport	Kazan	Russia	55.606201	49.278702
3	Aerocondor	2B	CEK	Chelyabinsk Balandino Airport	Chelyabinsk	Russia	55.305801	61.503300	OVB	Tolmachevo Airport	Novosibirsk	Russia	55.012600	82.650703
4	Aerocondor	2B	DME	Domodedovo International Airport	Moscow	Russia	55.408798	37.906300	KZN	Kazan International Airport	Kazan	Russia	55.606201	49.278702

6) VIS_2: Top 10 Airlines with most routes

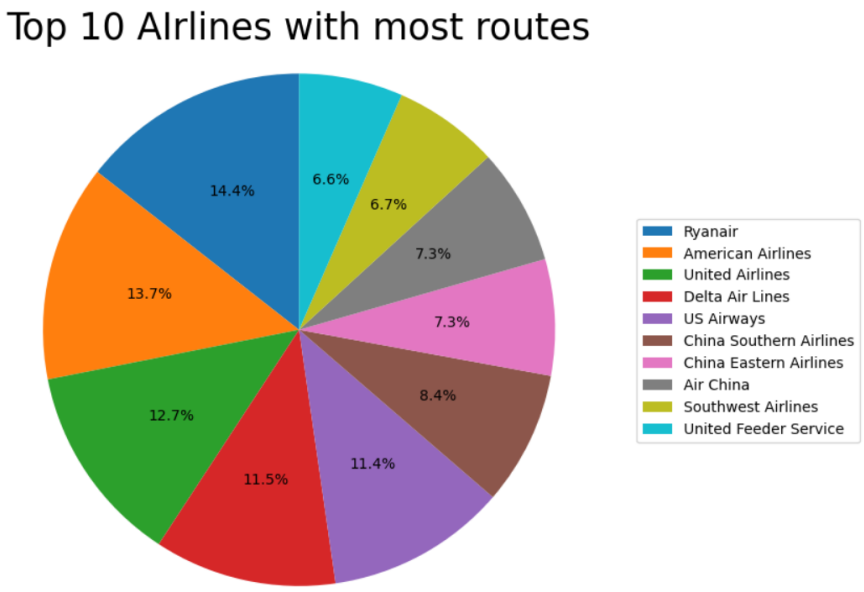
Code:

```
plot_df = (
   final_routes['Airline_Name'].value_counts()
      .head(10)
      .rename_axis('Airline_Name')
      .reset_index(name='no_of_routes')
)
plt.figure(figsize=(14,7))
y=  final_routes['Airline_Name'].value_counts().head(10)
mylabels = plot_df['Airline_Name']

plt.title('Top 10 AIrlines with most routes', fontsize=25)

pie = plt.pie(y,autopct='%1.1f%%', startangle=90)
plt.axis('equal')
plt.legend( loc = 'right', labels=mylabels)
plt.show()
```

Output:



7) VIS_2: Top 10 Airports with maximum connectivity

Code:

```
plot_df = (
    final_routes['Source_airport'].value_counts()
        .rename_axis('Airport_Name_s')
        .reset_index(name='no_of_flights_o')
)
plot_df.info()
```

Output:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3409 entries, 0 to 3408
Data columns (total 2 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   Airport_Name_s  3409 non-null   object
 1   no_of_flights_o  3409 non-null   int64 
dtypes: int64(1), object(1)
memory usage: 53.4+ KB
```

Code:

```
plot_df1 = (
   final_routes['Destination_airport'].value_counts()
      .rename_axis('Airport_Name_d')
      .reset_index(name='no_of_flights_i')
)
plot_df1.info()
```

Output:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3418 entries, 0 to 3417
Data columns (total 2 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   Airport_Name_d  3418 non-null   object
 1   no_of_flights_i  3418 non-null   int64 
dtypes: int64(1), object(1)
memory usage: 53.5+ KB
```

Code:

```
plot_df2= pd.merge(left = plot_df,
                   right = plot_df1,
                   how= 'outer',
                   left_on='Airport_Name_s',
                   right_on='Airport_Name_d',
                   suffixes=('_x', '_y'))
plot_df2 = plot_df2.head(10)
plot_df2.drop(['Airport_Name_d'], axis=1, inplace = True)
plot_df2
```

Output:

	Airport_Name_s	no_of_flights_o	no_of_flights_i
0	ATL	938.0	934.0
1	FRA	680.0	673.0
2	CDG	589.0	580.0
3	ORD	570.0	561.0
4	PEK	561.0	560.0
5	LHR	552.0	549.0
6	SIN	530.0	536.0
7	LGW	529.0	521.0
8	MUC	520.0	512.0
9	BCN	518.0	519.0

Code:

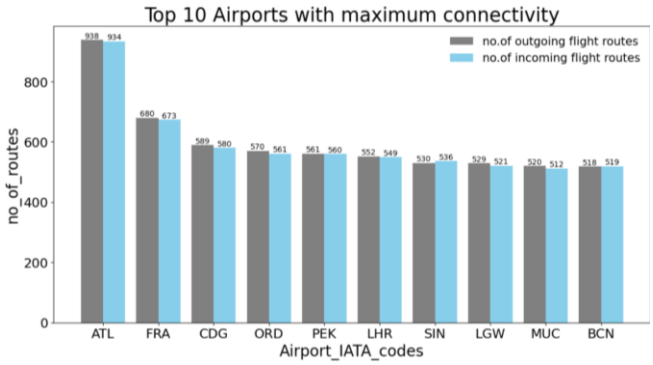
```
fig, ax = plt.subplots(figsize=(14,7))
x = np.arange(len(plot_df2))
width = 0.4
p1 = plt.bar(x-0.2, plot_df2['no_of_flights_o'],width, color='grey', label='no.of outgoing flight routes')
p2 = plt.bar(x+0.2, plot_df2['no_of_flights_i'],width, color='skyblue', label='no.of incoming flight routes')

plt.bar_label(p1, label_type='edge')
plt.bar_label(p2, label_type='edge')

plt.title('Top 10 Airports with maximum connectivity', fontsize=25)
plt.xlabel('Airport_IATA_codes', fontsize=20)
plt.xticks(plot_df2.index, plot_df2['Airport_Name_s'], fontsize=17)
plt.ylabel('no_of_routes', fontsize=20)
plt.yticks(fontsize=17)

plt.legend(frameon=False, fontsize=15)
plt.show()
```

Output:



8) VIS_3: Plotting Top 10 Airports with most connectivity

Code:

```
folium_df = pd.merge(left = plot_df2,
                     right = airports,
                     how= 'left',
                     left_on='Airport_Name_s',
                     right_on='IATA',
                     suffixes=('_l', '_r'))
import folium

map_1 = folium.Map(location=[0, 0])
folium_df.apply(lambda row:folium.Marker(location=[row["Latitude"],
row["Longitude"]]).add_to(map_1),axis=1)
map_1
```

Output:

9) VIS_4: Planes that fly the most amount of routes

Code:

final_routes['Equipment'].value_counts()

Output:

```
320                    10823
738                     7889
319                     4041
73H                     2551
737                     2491
                       ...
321 77W 333 343            1
320 773                    1
772 77W 333 773 343        1
AT7 ER4 CRJ                1
717 CR7                    1
Name: Equipment, Length: 3945, dtype: int64
```

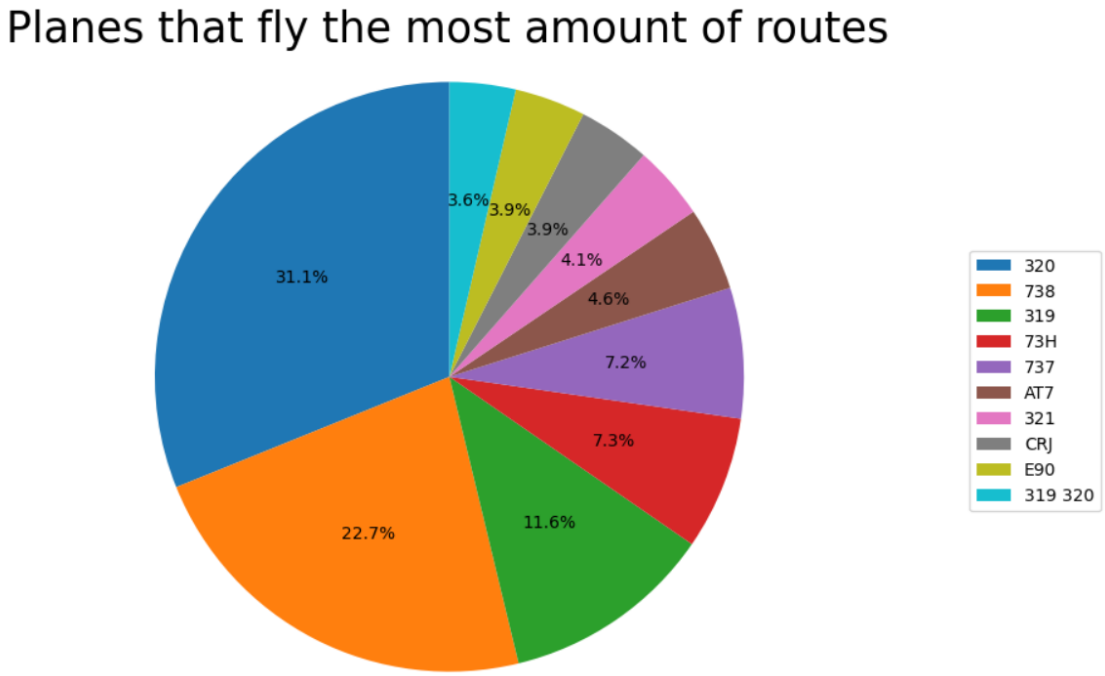
Code:

```
plot_df4 = (
   final_routes['Equipment'].value_counts()
      .head(10)
      .rename_axis('Plane')
      .reset_index(name='no_of_routes')
)
plt.figure(figsize=(14,7))
y=  final_routes['Equipment'].value_counts().head(10)
mylabels = plot_df4['Plane']

plt.title('Planes that fly the most amount of routes', fontsize=25)

pie = plt.pie(y,autopct='%1.1f%%', startangle=90)
plt.axis('equal')
plt.legend( loc = 'right', labels=mylabels)
plt.show()
```

Output:



10) Cities with most connectivity

Code:

```
plot_df5 = (
   final_routes['City_s'].value_counts()
      .rename_axis('City_Name_s')
      .reset_index(name='no_of_flights_o')
)
plot_df5.info()

plot_df6 = (
   final_routes['City_d'].value_counts()
      .rename_axis('City_Name_d')
      .reset_index(name='no_of_flights_i')
)
plot_df6.info()
```

```
plot_df7 = pd.merge(left = plot_df5,
                    right = plot_df6,
                    how= 'outer',
                    left_on='City_Name_s',
                    right_on='City_Name_d',
                    suffixes=('_x', '_y'))

plot_df7 = plot_df7.head(10)
plot_df7.drop(['City_Name_d'], axis=1, inplace = True)
plot_df7
```

Output:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3221 entries, 0 to 3220
Data columns (total 2 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   City_Name_s     3221 non-null   object
 1   no_of_flights_o  3221 non-null   int64
dtypes: int64(1), object(1)
memory usage: 50.5+ KB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3226 entries, 0 to 3225
Data columns (total 2 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   City_Name_d     3226 non-null   object
 1   no_of_flights_i  3226 non-null   int64
dtypes: int64(1), object(1)
memory usage: 50.5+ KB
```

	City_Name_s	no_of_flights_o	no_of_flights_i
0	London	1539.0	1523.0
1	Atlanta	938.0	934.0
2	Paris	847.0	840.0
3	Istanbul	723.0	726.0
4	Chicago	709.0	693.0
5	Shanghai	708.0	713.0
6	Frankfurt	680.0	673.0
7	Moscow	664.0	663.0
8	Beijing	641.0	640.0
9	New York	626.0	626.0

Code:

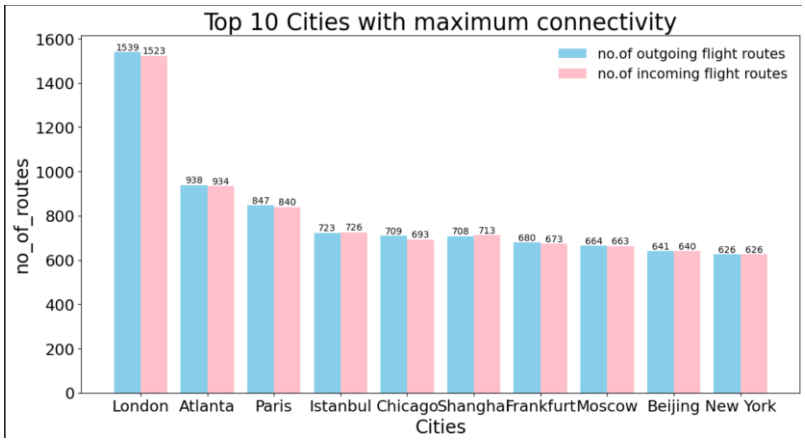
```
fig, ax = plt.subplots(figsize=(14,7))
x = np.arange(len(plot_df2))
width = 0.4
p1 = plt.bar(x-0.2, plot_df7['no_of_flights_o'],width, color='skyblue', label='no.of outgoing flight routes')
p2 = plt.bar(x+0.2, plot_df7['no_of_flights_i'],width, color='pink', label='no.of incoming flight routes')

plt.bar_label(p1, label_type='edge')
plt.bar_label(p2, label_type='edge')

plt.title('Top 10 Cities with maximum connectivity', fontsize=25)
plt.xlabel('Cities', fontsize=20)
plt.xticks(plot_df7.index, plot_df7['City_Name_s'], fontsize=17)
plt.ylabel('no_of_routes', fontsize=20)
plt.yticks(fontsize=17)

plt.legend(frameon=False, fontsize=15)
plt.show()
```

Output:



Conclusion: In this way we can use python libraries to analyse data.

Thank You.