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Project Objective

Flight delays are a modern-day problem. Passengers, airlines, and airports all suffer from these delays, which are inconvenient and costly. This project analyzes flight delay data in order to gain a better understanding of how commercial aviation operates and to anticipate when delays are likely.

CRISM-DM PROCESS

Importing the packages

In [1]:
```
# Importing the necessary libraries :
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.neighbors import KNeighborsClassifier
```

Importing the Datasets

In [2]:
```
# loading the data :
df = pd.read_csv('flights 2.csv')
airlines_data = pd.read_csv('airlines.csv')
airport_data = pd.read_csv('airports.csv')
```

```
/Users/sanjana/opt/anaconda3/lib/python3.8/site-packages/IPython/core/interactiveshell.py:3165: DtypeWarning: C
olumns (7,8) have mixed types.Specify dtype option on import or set low_memory=False.
  has_raised = await self.run_ast_nodes(code_ast.body, cell_name,
```

We need to identify the charecteristics of our dataset .For this we use three methods:-
info()-Used for identifying the different features and data types in a dataset.
shape()-We used this method to get an idea of the rows and columns in a dataframe.
head()-We used this method to examine the first few rows of the dataset
describe()-We used this method to identify the summary statistic's of all the features of the dataset.

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5819079 entries, 0 to 5819078
Data columns (total 31 columns):
 #   Column               Dtype
---  ------               -----
 0   YEAR                 int64
 1   MONTH                int64
 2   DAY                  int64
 3   DAY_OF_WEEK          int64
 4   AIRLINE              object
 5   FLIGHT_NUMBER        int64
 6   TAIL_NUMBER          object
 7   ORIGIN_AIRPORT       object
 8   DESTINATION_AIRPORT  object
 9   SCHEDULED_DEPARTURE  int64
 10  DEPARTURE_TIME       float64
 11  DEPARTURE_DELAY      float64
 12  TAXI_OUT             float64
 13  WHEELS_OFF           float64
 14  SCHEDULED_TIME       float64
 15  ELAPSED_TIME         float64
 16  AIR_TIME             float64
 17  DISTANCE             int64
 18  WHEELS_ON            float64
 19  TAXI_IN              float64
 20  SCHEDULED_ARRIVAL    int64
 21  ARRIVAL_TIME         float64
 22  ARRIVAL_DELAY        float64
 23  DIVERTED             int64
 24  CANCELLED            int64
 25  CANCELLATION_REASON  object
 26  AIR_SYSTEM_DELAY     float64
 27  SECURITY_DELAY       float64
 28  AIRLINE_DELAY        float64
 29  LATE_AIRCRAFT_DELAY  float64
 30  WEATHER_DELAY        float64
dtypes: float64(16), int64(10), object(5)
memory usage: 1.3+ GB
```

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

Out[4]:

	YEAR	MONTH	DAY	DAY_OF_WEEK	AIRLINE	FLIGHT_NUMBER	TAIL_NUMBER	ORIGIN_AIRPORT	DESTINATION_AIRPORT	SCHEDU
0	2015	1	1	4	AS	98	N407AS	ANC	SEA	
1	2015	1	1	4	AA	2336	N3KUAA	LAX	PBI	
2	2015	1	1	4	US	840	N171US	SFO	CLT	
3	2015	1	1	4	AA	258	N3HYAA	LAX	MIA	
4	2015	1	1	4	AS	135	N527AS	SEA	ANC	

5 rows × 31 columns

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

Out[5]:

	YEAR	MONTH	DAY	DAY_OF_WEEK	FLIGHT_NUMBER	SCHEDULED_DEPARTURE	DEPARTURE_TIME	DEPAR
count	5819079.0	5.819079e+06	5.819079e+06	5.819079e+06	5.819079e+06	5.819079e+06	5.732926e+06	
mean	2015.0	6.524085e+00	1.570459e+01	3.926941e+00	2.173093e+03	1.329602e+03	1.335204e+03	
std	0.0	3.405137e+00	8.783425e+00	1.988845e+00	1.757064e+03	4.837518e+02	4.964233e+02	
min	2015.0	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	
25%	2015.0	4.000000e+00	8.000000e+00	2.000000e+00	7.300000e+02	9.170000e+02	9.210000e+02	
50%	2015.0	7.000000e+00	1.600000e+01	4.000000e+00	1.690000e+03	1.325000e+03	1.330000e+03	
75%	2015.0	9.000000e+00	2.300000e+01	6.000000e+00	3.230000e+03	1.730000e+03	1.740000e+03	
max	2015.0	1.200000e+01	3.100000e+01	7.000000e+00	9.855000e+03	2.359000e+03	2.400000e+03	

8 rows × 26 columns

In [6]:
```
df.isnull().sum()
```

Out[6]:
```
YEAR                         0
MONTH                        0
DAY                          0
DAY_OF_WEEK                  0
AIRLINE                      0
FLIGHT_NUMBER                0
TAIL_NUMBER              14721
ORIGIN_AIRPORT               0
DESTINATION_AIRPORT          0
SCHEDULED_DEPARTURE          0
DEPARTURE_TIME           86153
DEPARTURE_DELAY          86153
TAXI_OUT                 89047
WHEELS_OFF               89047
SCHEDULED_TIME               6
ELAPSED_TIME            105071
AIR_TIME                105071
DISTANCE                     0
WHEELS_ON                92513
TAXI_IN                  92513
SCHEDULED_ARRIVAL            0
ARRIVAL_TIME             92513
ARRIVAL_DELAY           105071
DIVERTED                     0
CANCELLED                    0
CANCELLATION_REASON    5729195
AIR_SYSTEM_DELAY       4755640
SECURITY_DELAY         4755640
AIRLINE_DELAY          4755640
LATE_AIRCRAFT_DELAY    4755640
WEATHER_DELAY          4755640
dtype: int64
```

In [7]:
```
airlines_data.describe()
```

Out[7]:

	IATA_CODE	AIRLINE
count	14	14
unique	14	14
top	OO	American Airlines Inc.
freq	1	1

In [8]:
```
airport_data.describe()
```

Out[8]:

	LATITUDE	LONGITUDE
count	319.000000	319.000000
mean	38.981244	-98.378964
std	8.616736	21.523492
min	13.483450	-176.646030
25%	33.652040	-110.839385
50%	39.297610	-93.403070
75%	43.154675	-82.722995
max	71.285450	-64.798560

In [9]:
```
airport_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 322 entries, 0 to 321
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   IATA_CODE  322 non-null    object
 1   AIRPORT    322 non-null    object
 2   CITY       322 non-null    object
 3   STATE      322 non-null    object
 4   COUNTRY    322 non-null    object
 5   LATITUDE   319 non-null    float64
 6   LONGITUDE  319 non-null    float64
dtypes: float64(2), object(5)
memory usage: 17.7+ KB
```

In [10]:
```
airport_data.head(30)
```

Out[10]:

	IATA_CODE	AIRPORT	CITY	STATE	COUNTRY	LATITUDE	LONGITUDE
0	ABE	Lehigh Valley International Airport	Allentown	PA	USA	40.65236	-75.44040
1	ABI	Abilene Regional Airport	Abilene	TX	USA	32.41132	-99.68190
2	ABQ	Albuquerque International Sunport	Albuquerque	NM	USA	35.04022	-106.60919
3	ABR	Aberdeen Regional Airport	Aberdeen	SD	USA	45.44906	-98.42183
4	ABY	Southwest Georgia Regional Airport	Albany	GA	USA	31.53552	-84.19447
5	ACK	Nantucket Memorial Airport	Nantucket	MA	USA	41.25305	-70.06018
6	ACT	Waco Regional Airport	Waco	TX	USA	31.61129	-97.23052
7	ACV	Arcata Airport	Arcata/Eureka	CA	USA	40.97812	-124.10862
8	ACY	Atlantic City International Airport	Atlantic City	NJ	USA	39.45758	-74.57717
9	ADK	Adak Airport	Adak	AK	USA	51.87796	-176.64603
10	ADQ	Kodiak Airport	Kodiak	AK	USA	57.74997	-152.49386
11	AEX	Alexandria International Airport	Alexandria	LA	USA	31.32737	-92.54856
12	AGS	Augusta Regional Airport (Bush Field)	Augusta	GA	USA	33.36996	-81.96450
13	AKN	King Salmon Airport	King Salmon	AK	USA	58.67680	-156.64922
14	ALB	Albany International Airport	Albany	NY	USA	42.74812	-73.80298
15	ALO	Waterloo Regional Airport	Waterloo	IA	USA	42.55708	-92.40034
16	AMA	Rick Husband Amarillo International Airport	Amarillo	TX	USA	35.21937	-101.70593
17	ANC	Ted Stevens Anchorage International Airport	Anchorage	AK	USA	61.17432	-149.99619
18	APN	Alpena County Regional Airport	Alpena	MI	USA	45.07807	-83.56029
19	ASE	Aspen-Pitkin County Airport	Aspen	CO	USA	39.22316	-106.86885
20	ATL	Hartsfield-Jackson Atlanta International Airport	Atlanta	GA	USA	33.64044	-84.42694
21	ATW	Appleton International Airport	Appleton	WI	USA	44.25741	-88.51948
22	AUS	Austin-Bergstrom International Airport	Austin	TX	USA	30.19453	-97.66987
23	AVL	Asheville Regional Airport	Asheville	NC	USA	35.43619	-82.54181
24	AVP	Wilkes-Barre/Scranton International Airport	Wilkes-Barre/Scranton	PA	USA	41.33815	-75.72427
25	AZO	Kalamazoo/Battle Creek International Airport	Kalamazoo	MI	USA	42.23488	-85.55206
26	BDL	Bradley International Airport	Windsor Locks	CT	USA	41.93887	-72.68323
27	BET	Bethel Airport	Bethel	AK	USA	60.77978	-161.83800
28	BFL	Meadows Field	Bakersfield	CA	USA	35.43360	-119.05677
29	BGM	Greater Binghamton Airport	Binghamton	NY	USA	42.20848	-75.97961

In [11]:
```
df.isnull().sum()
```

Out[11]:
```
YEAR                         0
MONTH                        0
DAY                          0
DAY_OF_WEEK                  0
AIRLINE                      0
FLIGHT_NUMBER                0
TAIL_NUMBER              14721
ORIGIN_AIRPORT               0
DESTINATION_AIRPORT          0
SCHEDULED_DEPARTURE          0
DEPARTURE_TIME           86153
DEPARTURE_DELAY          86153
TAXI_OUT                 89047
WHEELS_OFF               89047
SCHEDULED_TIME               6
ELAPSED_TIME            105071
AIR_TIME                105071
DISTANCE                     0
WHEELS_ON                92513
TAXI_IN                  92513
SCHEDULED_ARRIVAL            0
ARRIVAL_TIME             92513
ARRIVAL_DELAY           105071
DIVERTED                     0
CANCELLED                    0
CANCELLATION_REASON    5729195
AIR_SYSTEM_DELAY       4755640
SECURITY_DELAY         4755640
AIRLINE_DELAY          4755640
LATE_AIRCRAFT_DELAY    4755640
WEATHER_DELAY          4755640
dtype: int64
```

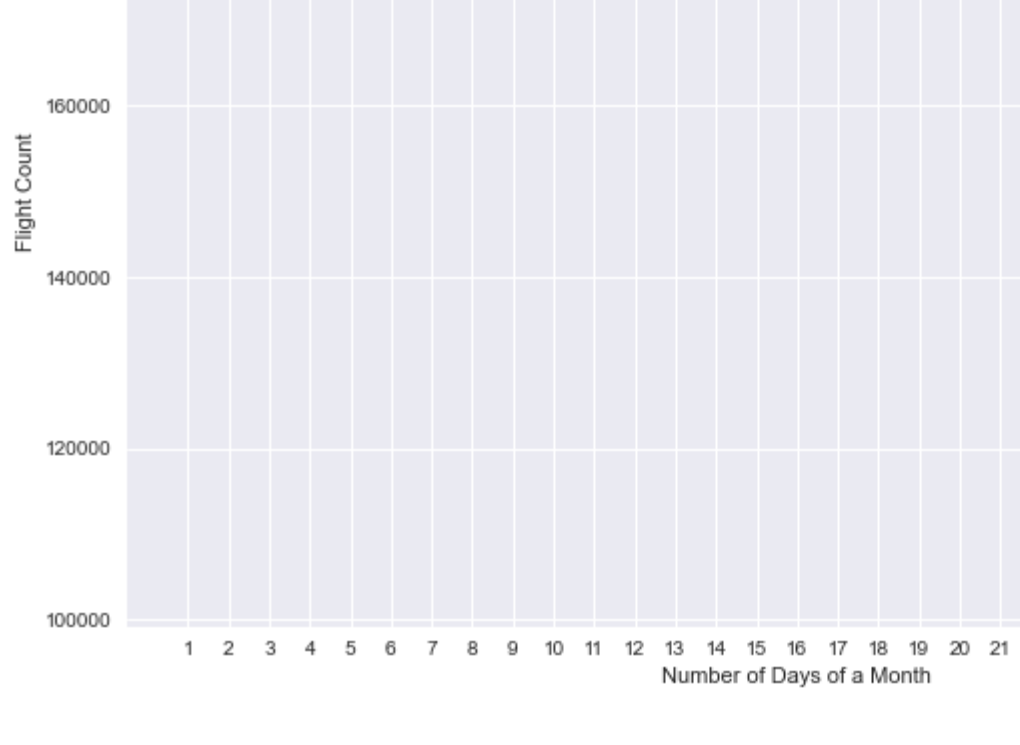
Based on the above df.isnull().sum(), Cancellation reason, air system delay, security delay, airline delay, late aircraft delay and weather delay have the highest number of null values, hence we drop them.

In [12]:
```
# Dropping the columns with highest number of null values:
cols_to_drop = ['CANCELLATION_REASON', 'AIR_SYSTEM_DELAY', 'SECURITY_DELAY', 'AIRLINE_DELAY', 'LATE_AIRCRAFT_D
df.drop(cols_to_drop, axis=1, inplace=True)
```

In [13]:
```
df.info()
```

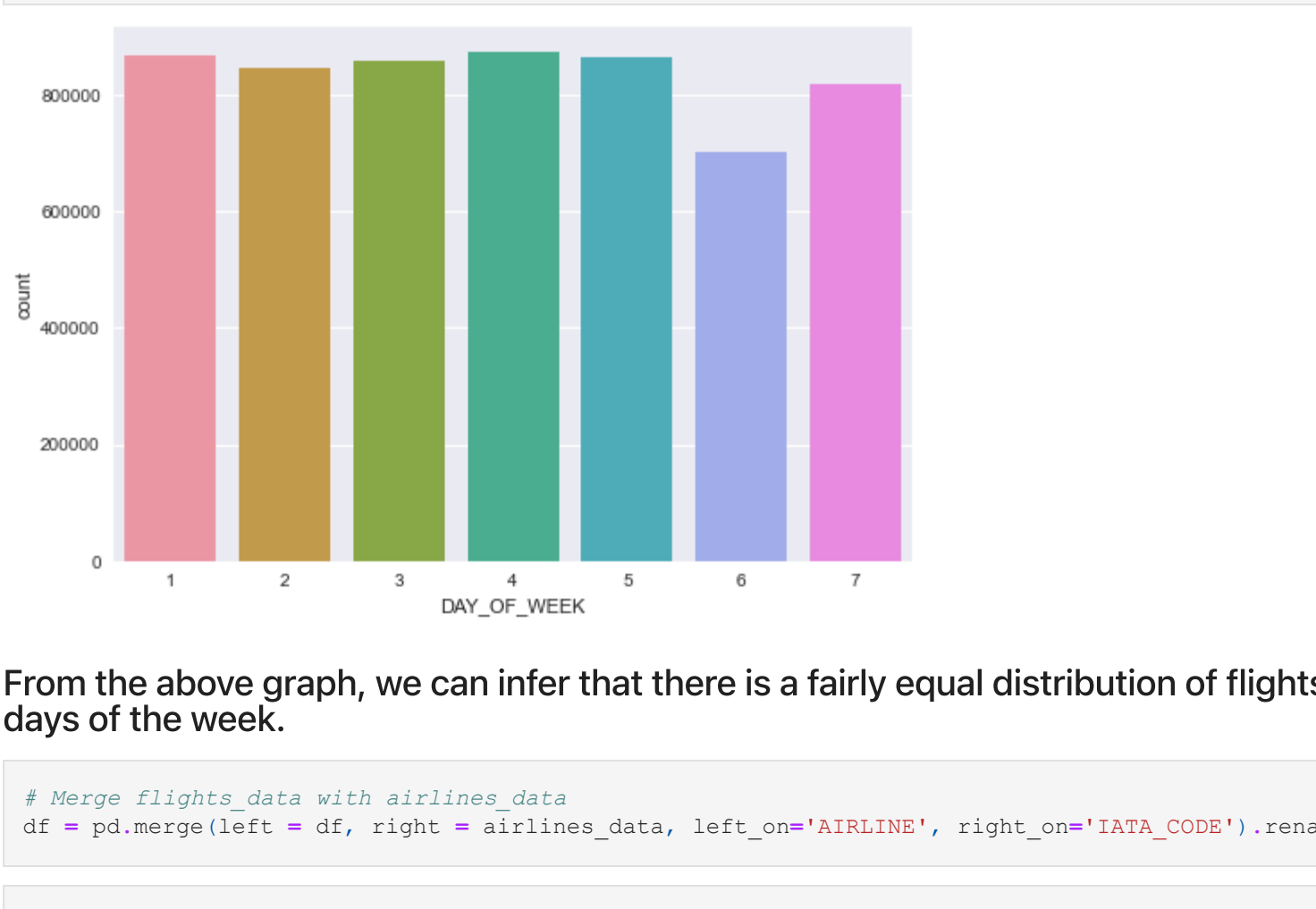
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5819079 entries, 0 to 5819078
Data columns (total 25 columns):
 #   Column               Dtype
---  ------               -----
 0   YEAR                 int64
 1   MONTH                int64
 2   DAY                  int64
 3   DAY_OF_WEEK          int64
 4   AIRLINE              object
 5   FLIGHT_NUMBER        int64
 6   TAIL_NUMBER          object
 7   ORIGIN_AIRPORT       object
 8   DESTINATION_AIRPORT  object
 9   SCHEDULED_DEPARTURE  int64
 10  DEPARTURE_TIME       float64
 11  DEPARTURE_DELAY      float64
 12  TAXI_OUT             float64
 13  WHEELS_OFF           float64
 14  SCHEDULED_TIME       float64
 15  ELAPSED_TIME         float64
 16  AIR_TIME             float64
 17  DISTANCE             int64
 18  WHEELS_ON            float64
 19  TAXI_IN              float64
 20  SCHEDULED_ARRIVAL    int64
 21  ARRIVAL_TIME         float64
 22  ARRIVAL_DELAY        float64
 23  DIVERTED             int64
 24  CANCELLED            int64
dtypes: float64(11), int64(10), object(4)
memory usage: 1.1+ GB
```

In [14]:
```
# plot the monthly data
plt.style.use('seaborn')
labels = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec']
df.groupby('MONTH').count()['FLIGHT_NUMBER'].plot(kind="bar")
plt.xlabel("Months")
plt.xticks(labels=labels, ticks=np.arange(0,12,1))
plt.ylabel("Flight Count")
plt.title("Monthly Flight Count for the year 2019")
plt.show()
```



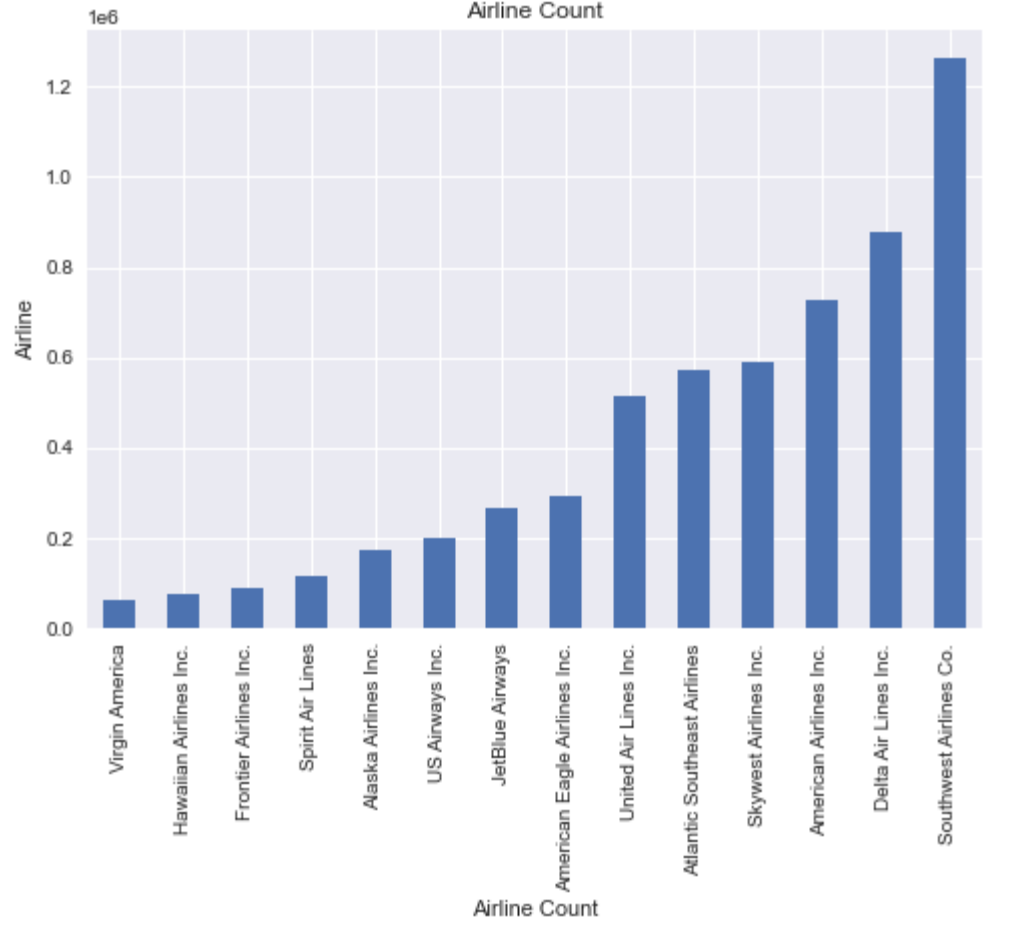
Monthly flight count for the year 2019 was fairly equal

In [15]:
```
# Plot the daily flight data for the year 2015
df.groupby('DAY').count()['AIRLINE'].plot(figsize=(12,8))
plt.xlabel("Day of the Month")
plt.xticks(np.arange(1, 32, 1))
plt.ylabel("Flight Count")
plt.title("Daily Flight count for the year 2019")
plt.show()
```



As Day 31 is not present in all the months, we can see that daily flight count for that day is the least and in the other days it is fairly distributed.

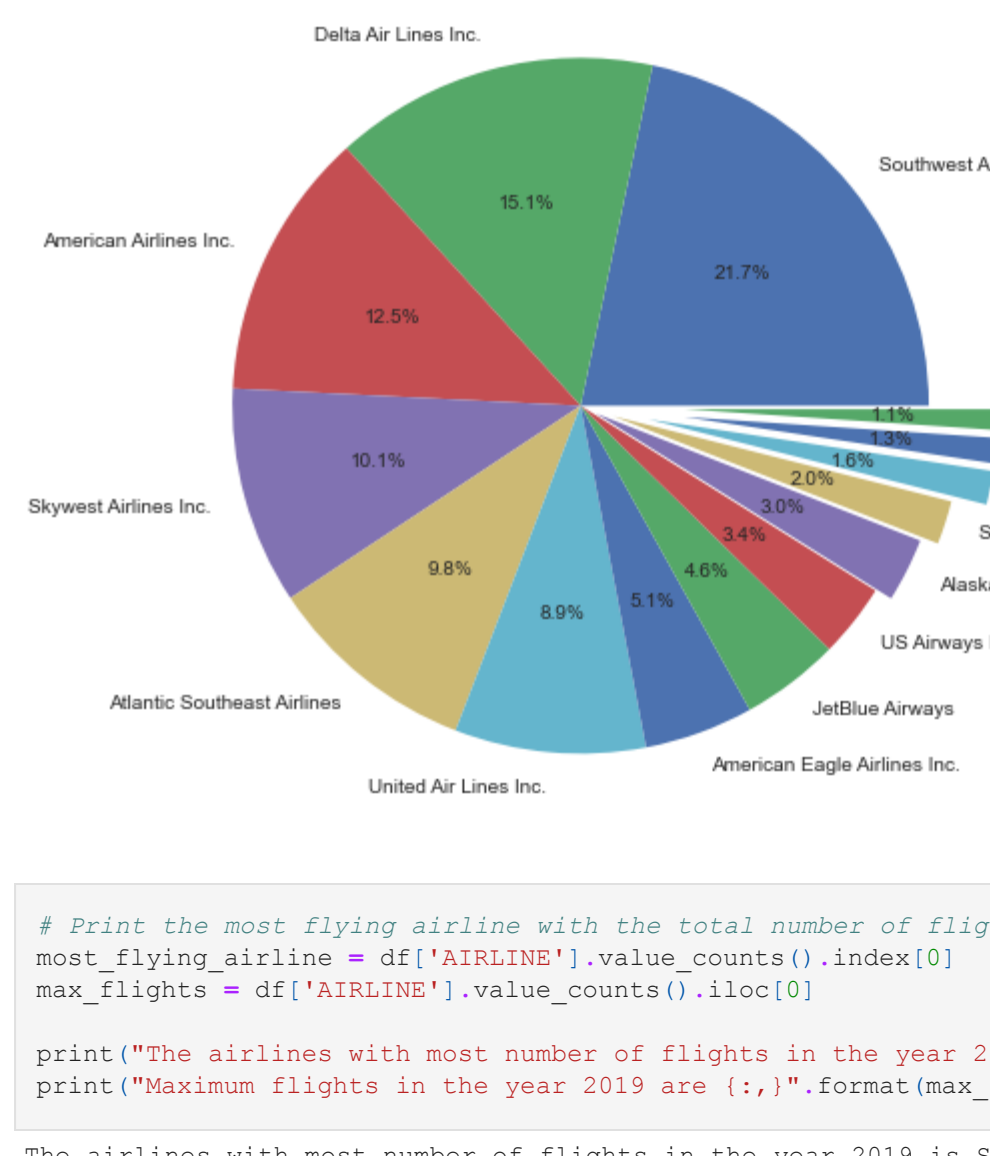
In [16]:
```
# plot the distribution of flights across DAY_OF_WEEK
sns.countplot(data=df, x='DAY_OF_WEEK')
plt.show()
```



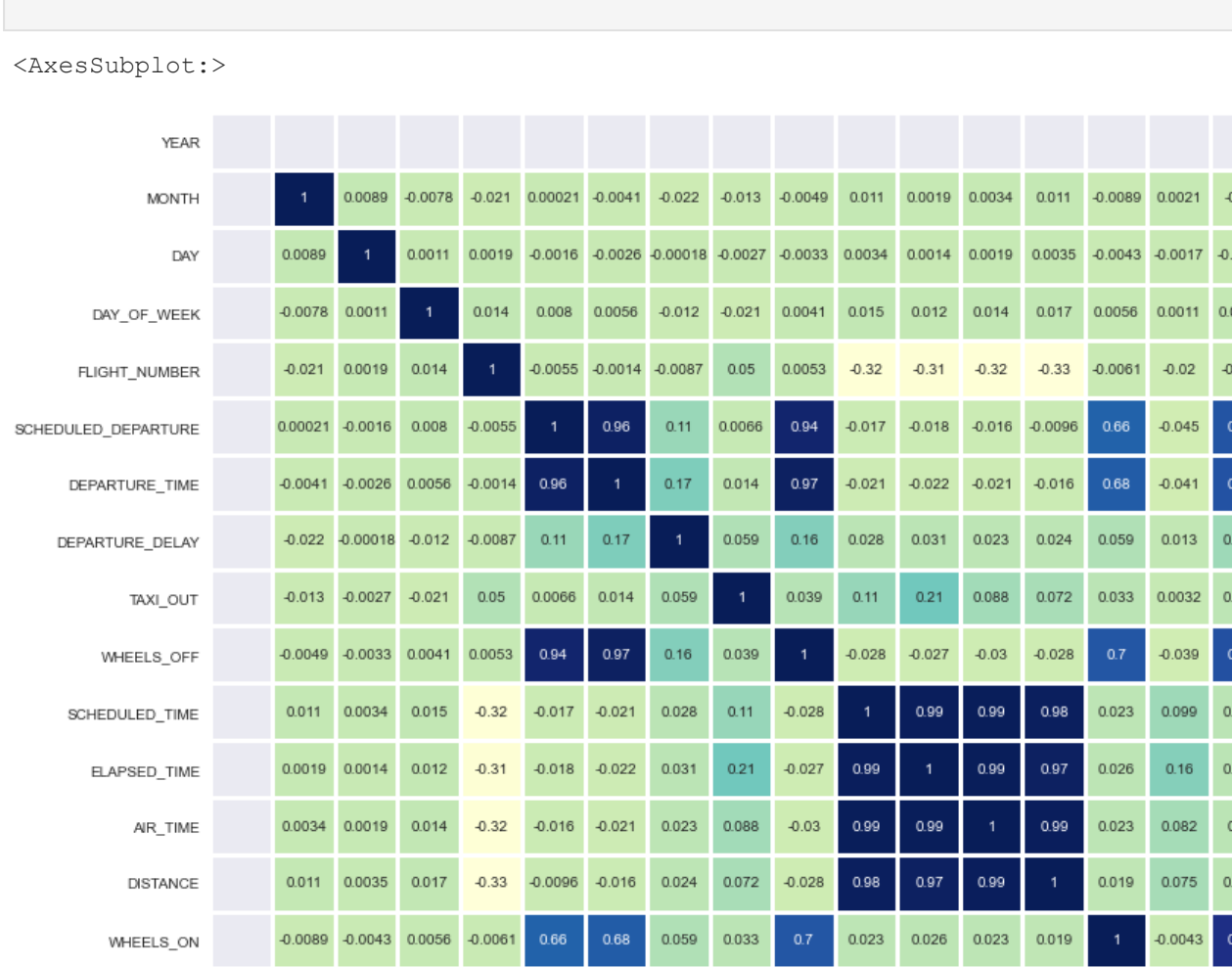
From the above graph, we can infer that there is a fairly equal distribution of flights across all days of the week.

In [17]:
```
# Merge flights_data with airlines_data
df = pd.merge(left = df, right = airlines_data, left_on='AIRLINE', right_on='IATA_CODE').rename(columns={'AIRLI
```

In [18]:
```
# Plot the AIRLINE count distribution
df['AIRLINE'].value_counts().sort_values().plot(kind='bar')
plt.ylabel("Airline")
plt.xlabel("Airline Count")
plt.title("Airline Count")
plt.show()
```



In [19]:
```
airlines_labels = list(df['AIRLINE'].value_counts().index)
plt.figure(figsize=(15,8))
plt.pie(df['AIRLINE'].value_counts(), autopct = '%1.1f%%', labels = airlines_labels, explode = (0,0,0,0,0,0,0,(
plt.title("Airline Count")
plt.show()
```

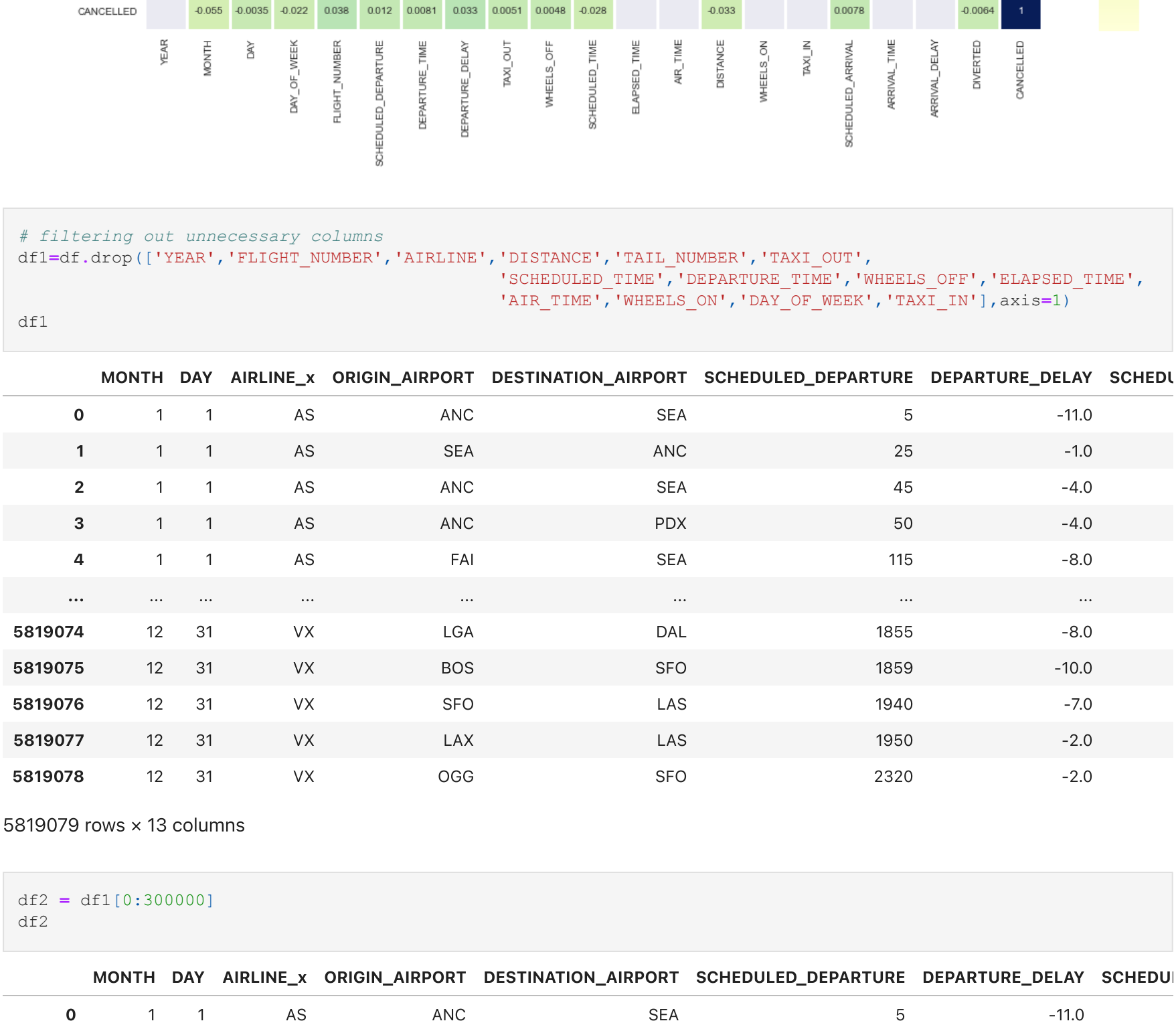


In [20]:
```
# Print the most flying airline with the total number of fligths in the year 2015
most_flying_airline = df['AIRLINE'].value_counts().index[0]
max_flights = df['AIRLINE'].value_counts().iloc[0]

print("The airlines with most number of flights in the year 2019 is {}".format(most_flying_airline))
print("Maximum flights in the year 2019 are {:,}".format(max_flights))
```

```
The airlines with most number of flights in the year 2019 is Southwest Airlines Co.
Maximum flights in the year 2019 are 1,261,855
```

In [21]:
```
plt.figure(figsize=(20,15))
sns.heatmap(df.corr(), annot=True, linewidth=2, cmap='YlGnBu')
```

Out[21]: <AxesSubplot:>



In [22]:
```
# filtering out unnecessary columns
df1=df.drop(['YEAR','FLIGHT_NUMBER','AIRLINE','DISTANCE','TAIL_NUMBER','TAXI_OUT',
             'SCHEDULED_TIME','DEPARTURE_TIME','WHEELS_OFF','ELAPSED_TIME',
             'AIR_TIME','WHEELS_ON','DAY_OF_WEEK','TAXI_IN'],axis=1)
df1
```

Out[22]:

	MONTH	DAY	AIRLINE_x	ORIGIN_AIRPORT	DESTINATION_AIRPORT	SCHEDULED_DEPARTURE	DEPARTURE_DELAY	SCHEDU
0	1	1	AS	ANC	SEA	5	-11.0	
1	1	1	AS	SEA	ANC	25	-1.0	
2	1	1	AS	ANC	SEA	45	-4.0	
3	1	1	AS	ANC	PDX	50	-4.0	
4	1	1	AS	FAI	SEA	115	-8.0	
...	...	...	...	...	...	...	...	
5819074	12	31	VX	LGA	DAL	1855	-8.0	
5819075	12	31	VX	BOS	SFO	1859	-10.0	
5819076	12	31	VX	SFO	LAS	1940	-7.0	
5819077	12	31	VX	LAX	LAS	1950	-2.0	
5819078	12	31	VX	OGG	SFO	2320	-2.0	

5819079 rows × 13 columns

In [23]:
```
df2 = df1[0:300000]
df2
```

Out[23]:

	MONTH	DAY	AIRLINE_x	ORIGIN_AIRPORT	DESTINATION_AIRPORT	SCHEDULED_DEPARTURE	DEPARTURE_DELAY	SCHEDU
0	1	1	AS	ANC	SEA	5	-11.0	
1	1	1	AS	SEA	ANC	25	-1.0	
2	1	1	AS	ANC	SEA	45	-4.0	
3	1	1	AS	ANC	PDX	50	-4.0	
4	1	1	AS	FAI	SEA	115	-8.0	
...	...	...	...	...	...	...	...	
299995	3	30	AA	FLL	DFW	1200	-3.0	
299996	3	30	AA	DFW	MSY	1203	-2.0	
299997	3	30	AA	PBI	DFW	1205	8.0	
299998	3	30	AA	DFW	MIA	1205	22.0	
299999	3	30	AA	DFW	TUS	1205	-3.0	

300000 rows × 13 columns

In [24]:
```
df2=df2.fillna(df2.mean())
```

In [25]:
```
result=[]
```

In [26]:
```
for row in df2['ARRIVAL_DELAY']:
    if row > 15:
        result.append(1)
    else:
        result.append(0)
```

In [27]:
```
df2['result'] = result
```

In [28]:
```
df2.value_counts('result')
```

Out[28]:
```
result
0    252928
1     47072
dtype: int64
```

In [29]:
```
# removing some more columns
df2=df2.drop(['ORIGIN_AIRPORT', 'DESTINATION_AIRPORT', 'ARRIVAL_TIME', 'ARRIVAL_DELAY', 'AIRLINE_x', 'IATA_CODE
df2
```

Out[29]:

	MONTH	DAY	SCHEDULED_DEPARTURE	DEPARTURE_DELAY	SCHEDULED_ARRIVAL	DIVERTED	CANCELLED	result
0	1	1	5	-11.0	430	0	0	0
1	1	1	25	-1.0	320	0	0	0
2	1	1	45	-4.0	509	0	0	0
3	1	1	50	-4.0	525	0	0	0
4	1	1	115	-8.0	548	0	0	0
...	...	...	...	...	...	...	...	...
299995	3	30	1200	-3.0	1421	0	0	0
299996	3	30	1203	-2.0	1338	0	0	0
299997	3	30	1205	8.0	1420	0	0	0
299998	3	30	1205	22.0	1600	0	0	0
299999	3	30	1205	-3.0	1236	0	0	0

300000 rows × 8 columns

Modeling

In [30]:
```
data = df2.values
X, y = data[:,:-1], data[:,-1]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state=2021)  # splitting in th
```

In [31]:
```
scaled_features = StandardScaler().fit_transform(X_train, X_test)
```

Logistic Regression

Logistic Regression is used to predict the probability of a target variable.

R-Squared value This value ranges from 0 to 1. Value '1' indicates predictor perfectly accounts for all the variations in Y. Value '0' indicates that predictor 'x' accounts for no variation in 'y'.

In [32]:
```
model_lr = LogisticRegression()
result = model_lr.fit(X_train, y_train)
```

In [33]:
```
from sklearn import metrics
prediction_test1 = model_lr.predict(X_test)
# Printing the prediction accuracy from training on logistic regression
print ('The accuracy of the Logistic Regression  is',metrics.accuracy_score(y_test, prediction_test1))
```

```
The accuracy of the Logistic Regression  is 0.9308111111111111
```

Decision Tree

Decision Tree algorithm is used to create a model that predicts the value of a target variable, for which the decision tree uses the tree representation to solve the problem in which the leaf node corresponds to a class label and attributes are represented on the internal node of the tree.

In [34]:
```
#DecisionTree
model_dt = DecisionTreeClassifier()
model_dt.fit(X_train,y_train)
preds=model_dt.predict(X_test)
print('The accuracy of the Decision Tree is',metrics.accuracy_score(y_test,preds))
```

```
The accuracy of the Decision Tree is 0.8868111111111111
```

Random forest

Random Forest algorithm builds multiple decision trees and merges them together to get a more accurate and stable prediction.

In [35]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=101)
model_rf = RandomForestClassifier(n_estimators=1000 , oob_score = True, n_jobs = -1,random_state =50, max_featu
model_rf.fit(X_train, y_train)

#accuracy given by Random forest and printing the accuracy given by the random forest algorithm
preds = model_rf.predict(X_test)
print ('The accuracy of the Random forest is',metrics.accuracy_score(y_test, preds))
```

```
The accuracy of the Random forest is 0.9331333333333334
```

Naive Bayes

Naive Bayes is a simple learning algorithm that utilizes Bayes rule together with a strong assumption that the attributes are conditionally independent, given the class.

In [36]:
```
#NaiveBayes
model_gnb = GaussianNB(priors=None)
model_gnb.fit(X_train, y_train)
preds = model_gnb.predict(X_test)
metrics.accuracy_score(y_test, preds)
```

Out[36]: 0.8195666666666667

Evaluation

In [37]:
```
import plotly.offline as py #Model Performance
py.init_notebook_mode(connected=True)
import plotly.figure_factory as ff
from sklearn.metrics import f1_score
from sklearn.metrics import cohen_kappa_score
from sklearn.metrics import confusion_matrix,accuracy_score,classification_report
from sklearn.metrics import roc_auc_score,roc_curve
import statsmodels.api as sm
from sklearn.metrics import precision_score,recall_score
```

In [38]:
```
def model_report(model,X_train, X_test, y_train, y_test,name) :
        predictions  = model.predict(X_test)
        accuracy     = accuracy_score(y_test,predictions)
        recallscore  = recall_score(y_test,predictions)
        precision    = precision_score(y_test,predictions)
        roc_auc      = roc_auc_score(y_test,predictions)
        f1score      = f1_score(y_test,predictions)
        kappa_metric = cohen_kappa_score(y_test,predictions)

        df3 = pd.DataFrame({"Model"           : [name],
                            "Accuracy score"  : [accuracy],
                            "Recall score"    : [recallscore],
                            "Precision"       : [precision],
                            "F1 score"        : [f1score],
                            "Area under curve": [roc_auc],
                            "Kappa metric"    : [kappa_metric],
                           })
        return df3

#outputs for every model
model1 = model_report(model_lr,X_train, X_test, y_train, y_test, "Logistic Regression")
model2 = model_report(model_dt,X_train, X_test, y_train, y_test,"Decision Tree")
model3 = model_report(model_rf,X_train, X_test, y_train, y_test,"RF Classifier")
model4 = model_report(model_gnb, X_train, X_test, y_train, y_test,"Naive Bayes")

model_performances = pd.concat([model1,model2,model3,model4],axis = 0).reset_index()

model_performances = model_performances.drop(columns = "index",axis =1)

table  = ff.create_table(np.round(model_performances,4))

py.iplot(table)
```

Model	Accuracy score	Recall score	Precision	F1 score	Area under curve	Kappa metric
Logistic Regression	0.9313	0.6435	0.8828	0.7444	0.8139	0.7058
Decision Tree	0.8875	0.669	0.6305	0.6492	0.7984	0.5823
RF Classifier	0.9331	0.6721	0.8682	0.7577	0.8267	0.7196
Naive Bayes	0.8196	0.8147	0.4553	0.5841	0.8176	0.4804

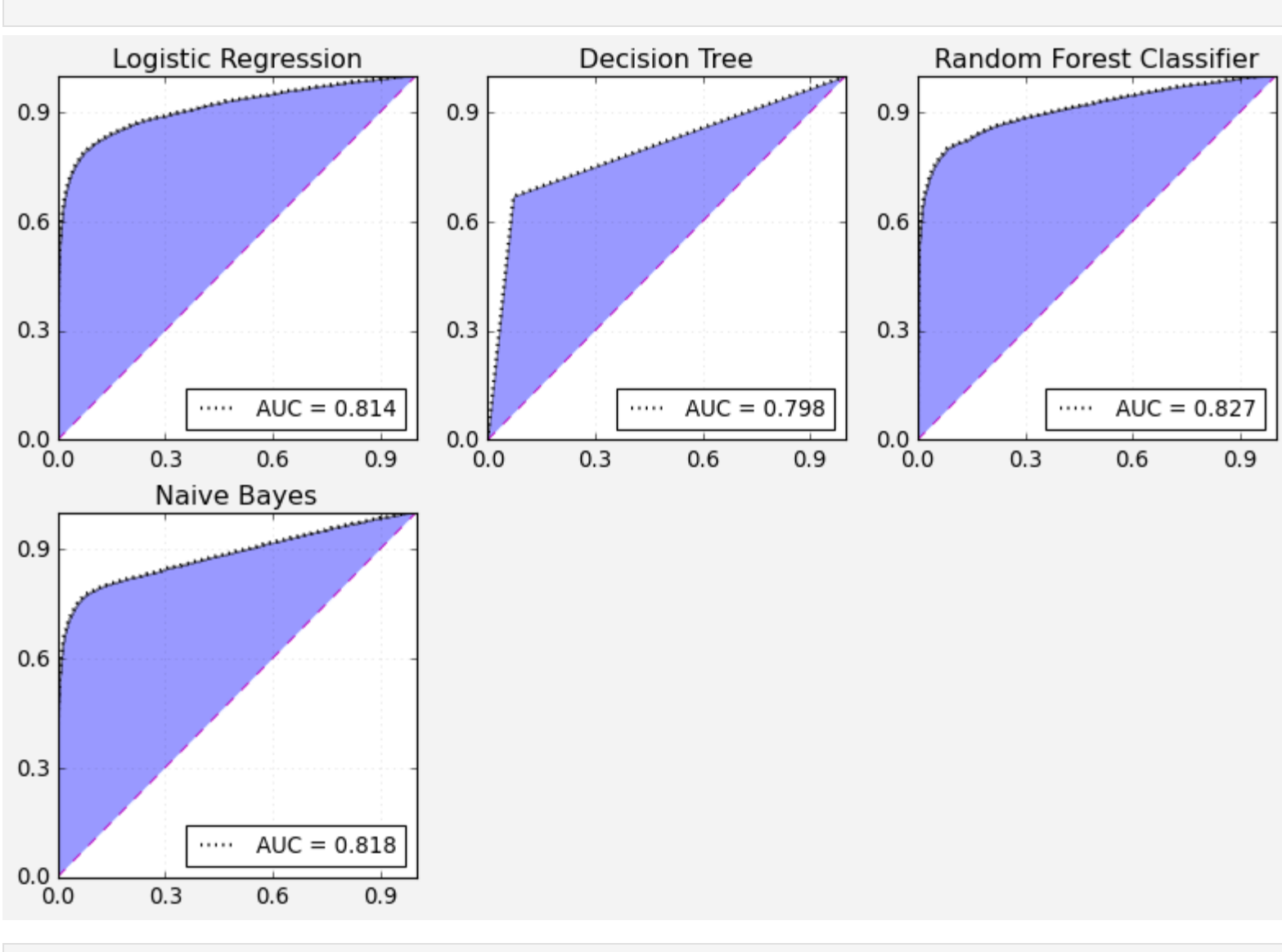
In [39]:

```python
import itertools
import seaborn as sns;
lst    = [model_lr,model_dt,model_rf, model_gnb]

length = len(lst)

mods   = ['Logistic Regression',
          'Decision Tree','Random Forest Classifier', 'Naive Bayes']

fig = plt.figure(figsize=(13,15))
fig.set_facecolor("#F3F3F3")
for i,j,k in itertools.zip_longest(lst,range(length),mods) :
    plt.subplot(5,3,j+1)
    predictions = i.predict(X_test)
    conf_matrix = confusion_matrix(predictions,y_test)
    ax = sns.heatmap(conf_matrix,annot = True,fmt = "d",square =True,
                xticklabels=["not churn","churn"],
                yticklabels=["not churn","churn"],
                linewidths = 0.5, linecolor = "w",cmap = "Set1")
    ax.set_ylim(0 ,2)
    plt.title(k,color = "b")
    plt.subplots_adjust( wspace = .3,hspace = .5)
```

Plottting Area Under Curve

In [40]:

```python
plt.style.use("classic")
fig = plt.figure(figsize=(12,16))
fig.set_facecolor("#F3F3F3")
for i,j,k in itertools.zip_longest(lst,range(length),mods):
    qx = plt.subplot(4,3,j+1)
    probabilities = i.predict_proba(X_test)
    predictions   = i.predict(X_test)
    fpr,tpr,thresholds = roc_curve(y_test,probabilities[:,1])
    plt.plot(fpr,tpr,linestyle = "dotted",
             color = "k",linewidth = 2,
             label = "AUC = " + str(np.around(roc_auc_score(y_test,predictions),3)))
    plt.plot([0,1],[0,1],linestyle = "dashed",
             color = "m",linewidth = 0.8)
    plt.fill_between(fpr,tpr,alpha = .4)
    plt.fill_between([0,1],[0,1],color = "w")
    plt.legend(loc = "lower right",
               prop = {"size" : 12})
    qx.set_facecolor("w")
    plt.grid(True,alpha = .15)
    plt.title(k,color = "k")
    plt.xticks(np.arange(0,1,.3))
    plt.yticks(np.arange(0,1,.3))
```



In [ ]: