IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

Hamza Ghnaim
10th of October-2021

Outline

- Executive Summary
- Introduction
- Methodology
- Results
- Conclusion

Executive Summary

- The objective of this thesis is to give a complete explanation on how to apply a complete data-driven analytic approach.
- The report focus on collecting and preprocessing the data before building a predictive model.
- The main object of this project is fulfilled if the predictive model was successfully able to make predictions on the data used.

Introduction

In the age of commercial space travelling, SpaceX advertises Falcon 9 rocket launches on its website with a cost of 62 million dollars; other providers cost upward of 165 million dollars each, much of the savings is because SpaceX can reuse the first stage.

The aim of this data science project is to predict if the Falcon 9 first stage will land successfully, therefore if we can determine if the first stage will land, we can determine the cost of a launch. This information can be used if an alternate company wants to bid against SpaceX for a rocket launch.

Section 1

Methodology

Data Collection

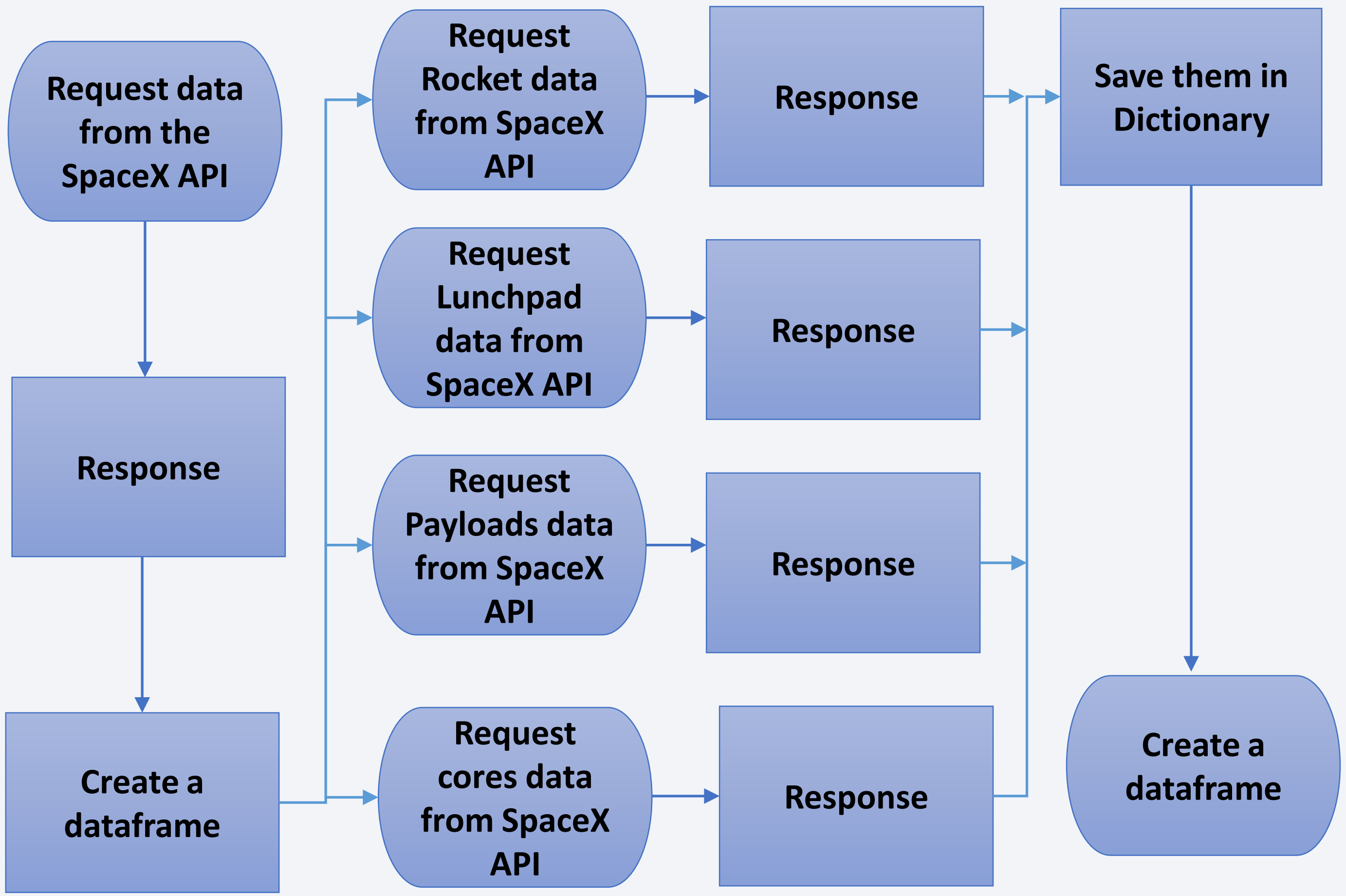
- The data set used in the project is the SpaceX Lunch data.

- The data set contains information about different flights including date, lunch site, booster version and more

- The data is collected by two main approaches:
    1. The SpaceX API
    2. Web scrapping

Data Collection – SpaceX API

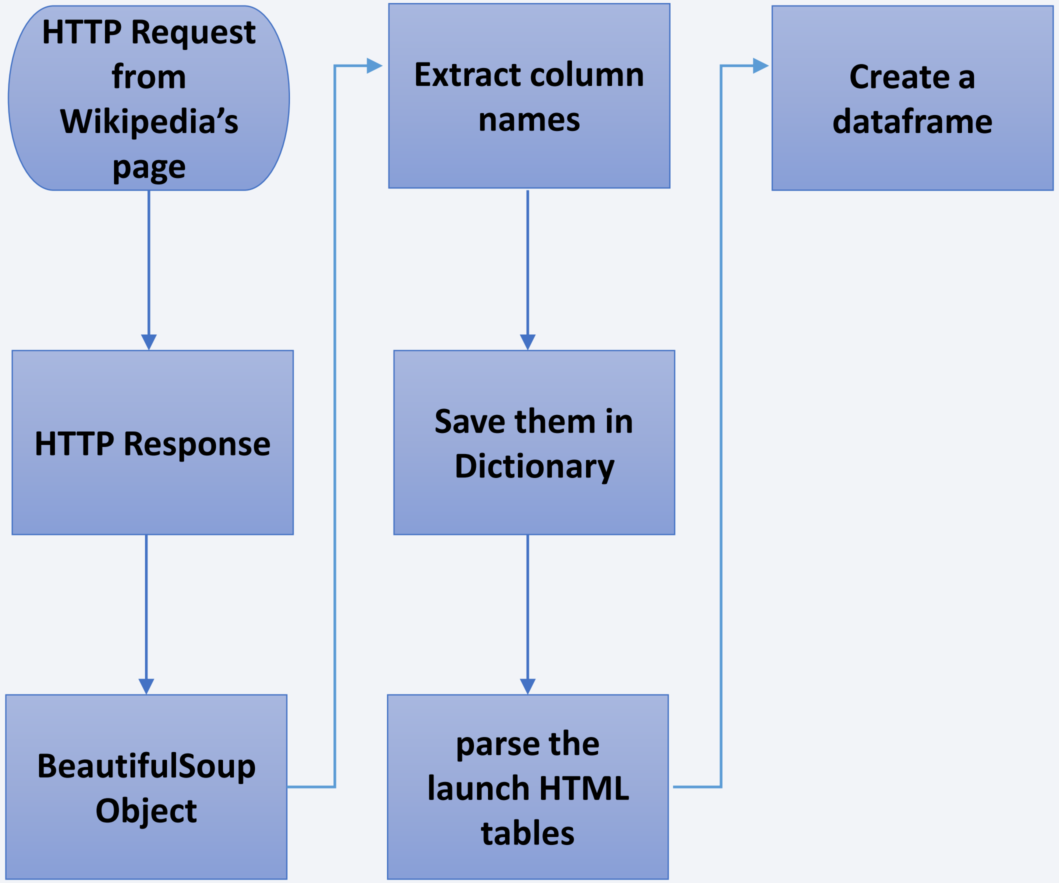
- We'll be collecting lunch data from SpaceX API, First we request lunch data from SpaceX API using the GET command (requests.get), then we create a pandas dataframe from the response, After that we make several sub requests to get more detailed and consistent information about the IDs stored in the dataframe.
- With the help of some helper functions, we save the responses into a dictionary, and then we transform it into a dataframe, which is our data set.



Data Collection - Scraping

- We'll will be performing web scraping to collect Falcon 9 historical launch records from a Wikipedia page, first we perform an HTTP GET(using requests.get command) method to request the Falcon9 Launch HTML page, as an HTTP response, then we create a BeautifulSoup object from the HTML response, we extract the column names from the object and use it as dictionary keys.

- We parse the HTML tables and fill the dictionary keys with lunch records from table rows, and finally we transform it into a dataframe.



Data Wrangling

- Exploratory data analysis is an important step while preprocessing data, it is useful to find some patterns in the data and determine what would be the label for training supervised models.

- This process was done in the following order:
  1. First thing to do is to identify the data types of the columns.
  2. Determine the number of values for each attribute.
  3. Calculate the percentage of the missing values.
  4. To determine the label, we apply zero/one hot encoding to the "Outcome" column to classify landing to either 1 (Success) of 0 (Failure)

EDA with SQL

- In order to better understand the datasets, we ran the following SQL queries:

1. *Display the names of the unique launch sites in the space mission*
2. *Display 5 records where launch sites begin with the string 'CCA'*
3. *Display the total payload mass carried by boosters launched by NASA (CRS)*
4. *Display average payload mass carried by booster version F9 v1.1*
5. *List the date when the first successful landing outcome in ground pad was achieved.*
6. *List the names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000*
7. *List the total number of successful and failure mission outcomes*
8. *List the names of the booster versions which have carried the maximum payload mass. Use a subquery*
9. *List the failed landing outcomes in drone ship, their booster versions, and launch site names for in year 2015*
10. *Rank the count of landing outcomes (such as Failure (drone ship) or Success (ground pad)) between the date 2010-06-04 and 2017-03-20, in descending order*

-

EDA with Data Visualization

- In order to understand the relations between different features, we visualize the data by plotting scatter plots, bar charts and line charts, it helps finding hidden patterns in data and gain insights about the dataset.

1. Pay load mass against the Flight number
2. Lunch site against the Flight number
3. Lunch site against the Pay load mass
4. Orbit type against Class success rate
5. Flight number against Orbit type
6. Orbit type against the Pay load mass
7. launch success yearly trend

Build an Interactive Map with Folium

- Here, we complete the interactive visual analytics using Folium.
- First we create Folium map object, with an initial center location around Nasa Johnson space center, Houston-Texas.
- We add a circle on the map for each lunch site from the dataset by creating a folium circle and folium marker, now the lunch sites are marked on the map which means we can see which one is proximate to the equator line or close to a coastline.
- In order to mark the success/failure lunches, we create a marker on the map for each lunch record from the dataset, a green marker indicates a successful lunching and a red one indicates failure,
- we need to explore and analyze the proximities of launch sites, we calculate the distance between the lunch site and its proximities and then we draw a polyline between them.

Predictive Analysis (Classification)

- Now that we finished the exploratory analysis, the next step is to determine the training labels and build a predictor using machine learning algorithms.
- after using the 'Class' column as the label, first thing to do is normalizing the data.
- We split the normalized data into test/train sets, The training data is divided into validation data, a second set used for training data.
- For the model development phase, we use the following algorithms:
    1. Logistic regression
    2. Support vector machine
    3. Decision trees
    4. K nearest neighbor
- We build a grid search object for each of the algorithms and fit it to find the best parameters of the model(hyper parameters tuning), then we choose the most accurate model.

Results

- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results

Section 2

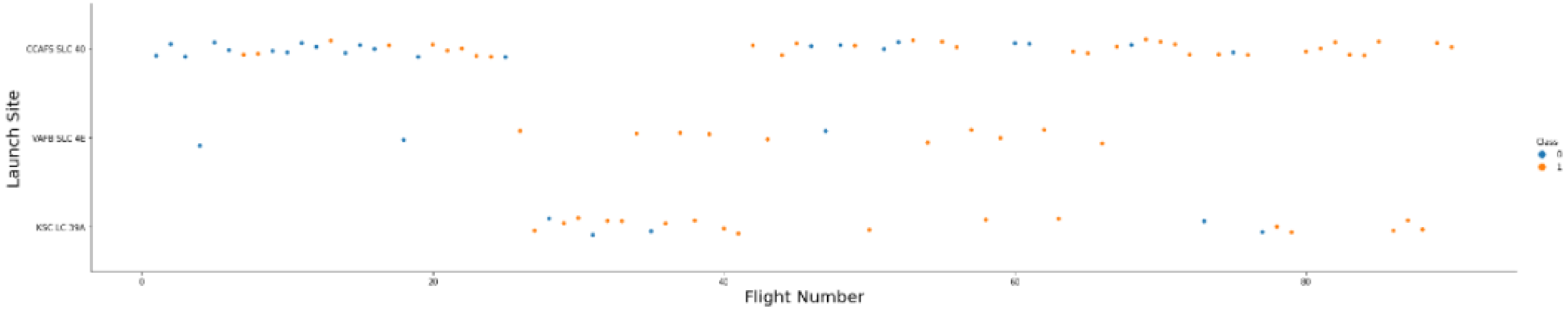
Insights drawn from EDA

Flight Number vs. Launch Site

TASK 1: Visualize the relationship between Flight Number and Launch Site

Use the function `catplot` to plot `FlightNumber` vs `LaunchSite`, set the parameter `x` parameter to `FlightNumber`,set the `y` to `Launch Site` and set the parameter `hue` to `'class'`

In [4]:
```
# Plot a scatter point chart with x axis to be Flight Number and y axis to be the launch site, and hue to be the class value
sns.catplot(y="LaunchSite", x="FlightNumber", hue="Class", data=df, aspect = 5)
plt.xlabel("Flight Number",fontsize=20)
plt.ylabel("Launch Site",fontsize=20)
plt.show()
```



Now try to explain the patterns you found in the Flight Number vs. Launch Site scatter point plots.

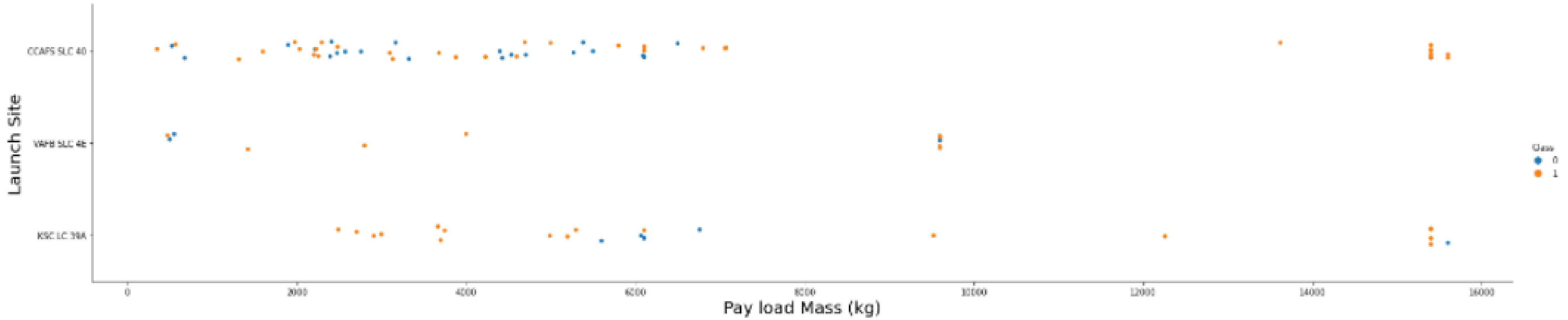
In [5]:
```
#CCAFS SLC-40 flights have higher success rate as the flight number increases
```

Payload vs. Launch Site

TASK 2: Visualize the relationship between Payload and Launch Site

We also want to observe if there is any relationship between launch sites and their payload mass.

In [6]:
```
# Plot a scatter point chart with x axis to be Pay Load Mass (kg) and y axis to be the launch site, and hue to be the class value
sns.catplot(y="LaunchSite", x="PayloadMass", hue="Class", data=df, aspect = 5)
plt.xlabel("Pay load Mass (kg)",fontsize=20)
plt.ylabel("Launch Site",fontsize=20)
plt.show()
```



Now try to explain any patterns you found in the Payload Vs. Launch Site scatter point chart.

In [7]:
```
#small pay load mass values have bad influence on CCAFS SLC-40 flights
```

Success Rate vs. Orbit Type

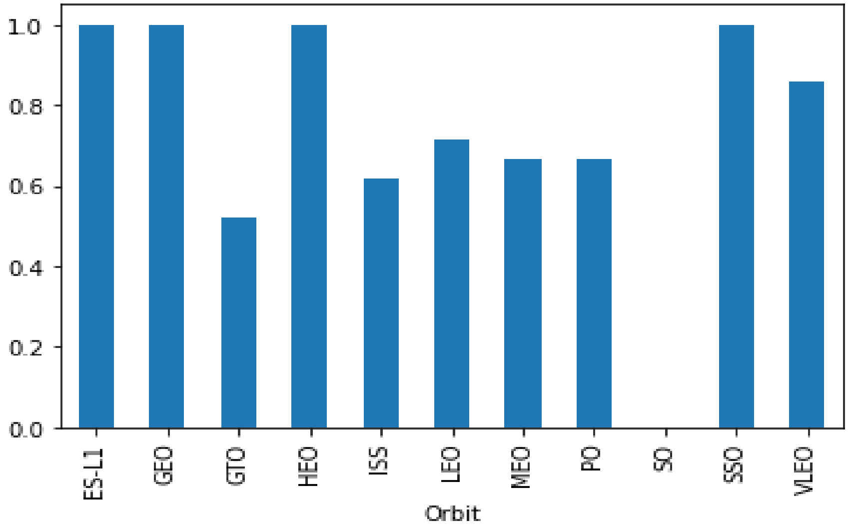
TASK 3: Visualize the relationship between success rate of each orbit type

Next, we want to visually check if there are any relationship between success rate and orbit type.

Let's create a `bar chart` for the sucess rate of each orbit

In [8]:
```
# HINT use groupby method on Orbit column and get the mean of Class column
mean = df.groupby(['Orbit'])['Class'].mean()
mean.plot(kind = 'bar')
```

Out[8]: `<AxesSubplot:xlabel='Orbit'>`

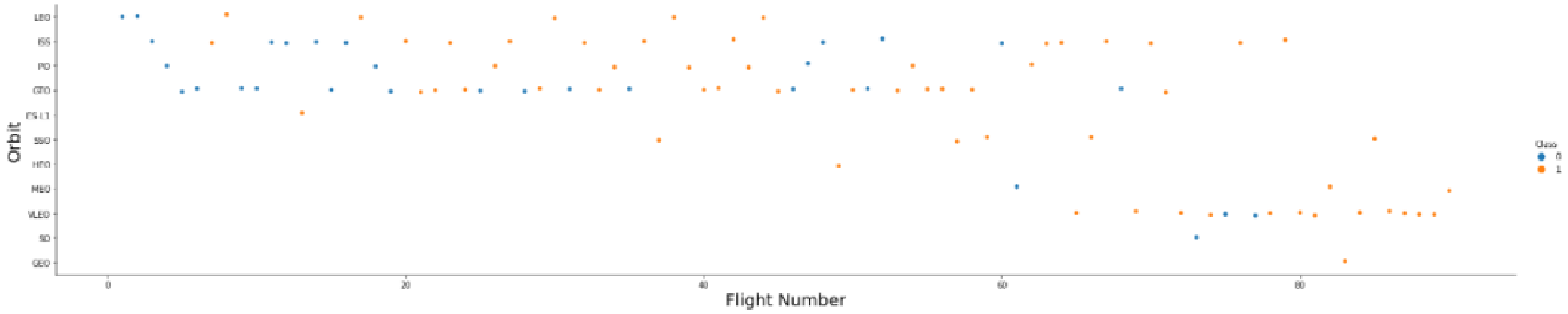


Flight Number vs. Orbit Type

TASK 4: Visualize the relationship between FlightNumber and Orbit type

For each orbit, we want to see if there is any relationship between FlightNumber and Orbit type.

In [10]:
```
# Plot a scatter point chart with x axis to be FlightNumber and y axis to be the Orbit, and hue to be the class value
sns.catplot(y="Orbit", x="FlightNumber", hue="Class", data=df, aspect = 5)
plt.xlabel("Flight Number",fontsize=20)
plt.ylabel("Orbit",fontsize=20)
plt.show()
```



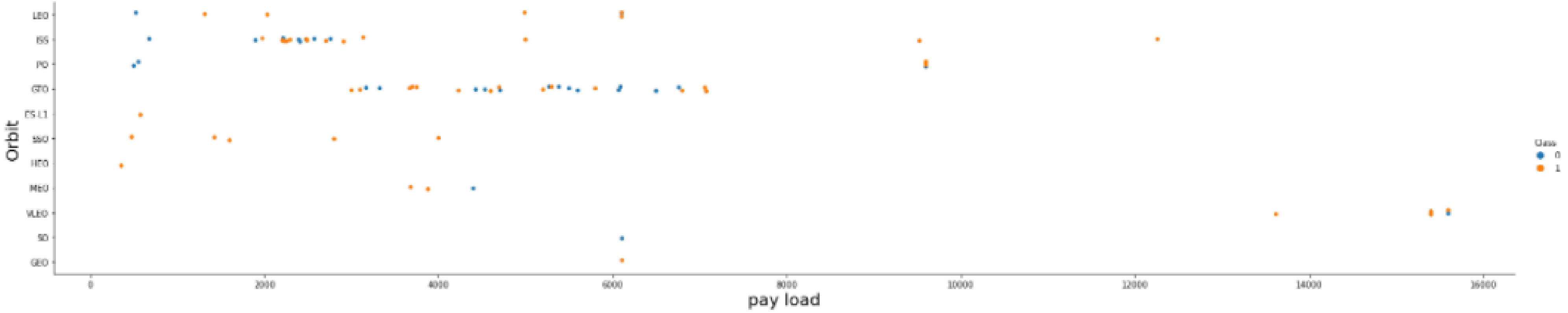
You should see that in the LEO orbit the Success appears related to the number of flights; on the other hand, there seems to be no relationship between flight number when in GTO orbit.

Payload vs. Orbit Type

TASK 5: Visualize the relationship between Payload and Orbit type

Similarly, we can plot the Payload vs. Orbit scatter point charts to reveal the relationship between Payload and Orbit type

In [21]:
```
# Plot a scatter point chart with x axis to be Payload and y axis to be the Orbit, and hue to be the class value
sns.catplot(y="Orbit", x="PayloadMass", hue="Class", data=df, aspect = 5)
plt.ylabel("Orbit",fontsize=20)
plt.xlabel("pay load",fontsize=20)
plt.show()
```



You should observe that Heavy payloads have a negative influence on GTO orbits and positive on GTO and Polar LEO (ISS) orbits.

Launch Success Yearly Trend

TASK 6: Visualize the launch success yearly trend

You can plot a line chart with x axis to be Year and y axis to be average success rate, to get the average launch success trend.

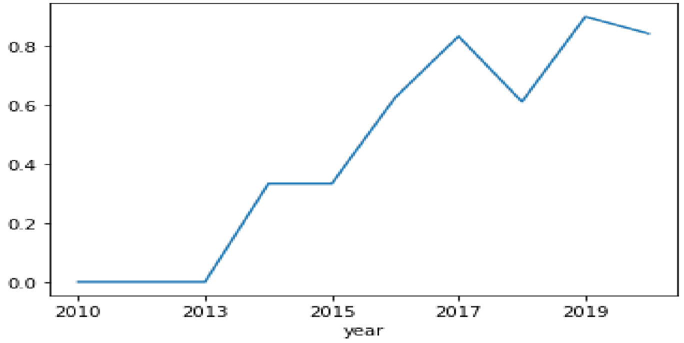
The function will help you get the year from the date:

In [12]:
```python
# A function to Extract years from the date
year=[]
def Extract_year(date):
    for i in df["Date"]:
        year.append(i.split("-")[0])
    return year
```

In [13]:
```python
Extract_year(df)
```

In [14]:
```python
Class = df['Class'].tolist()
new_df = pd.DataFrame(list(zip(year,Class)),columns = ['year','class'])
mean = new_df.groupby(['year'])['class'].mean()
mean
```

In [15]:
```python
# Plot a line chart with x axis to be the extracted year and y axis to be the success rate
line_plt = mean.plot(kind='line')
```



you can observe that the sucess rate since 2013 kept increasing till 2020

All Launch Site Names

Task 1

Display the names of the unique launch sites in the space mission

In [5]:
```
%sql SELECT DISTINCT(LAUNCH_SITE) FROM SPACX;
```

```
 * ibm_db_sa://sdw99696:***@54a2f15b-5c0f-46df-8954-7e38e612c2bd.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:32733/bludb
Done.
```

Out[5]:

launch_site
CCAFS LC-40
CCAFS SLC-40
KSC LC-39A
VAFB SLC-4E

Launch Site Names Begin with 'CCA'

Task 2

Display 5 records where launch sites begin with the string 'CCA'

In [20]:
```
%sql SELECT * from SPACX where LAUNCH_SITE like 'CCA%' LIMIT 5;
```

```
 * ibm_db_sa://sdw99696:***@54a2f15b-5c0f-46df-8954-7e38e612c2bd.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:32733/bludb
Done.
```

Out[20]:

DATE	time__utc_	booster_version	launch_site	payload	payload_mass__kg_	orbit	customer	mission_outcome	landing__outcome
2010-06-04	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
2010-12-08	15:43:00	F9 v1.0 B0004	CCAFS LC-40	Dragon demo flight C1, two CubeSats, barrel of Brouere cheese	0	LEO (ISS)	NASA (COTS) NRO	Success	Failure (parachute)
2012-05-22	07:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	No attempt
2012-10-08	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
2013-03-01	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

Total Payload Mass

Task 3

Display the total payload mass carried by boosters launched by NASA (CRS)

In [28]:
```
%sql SELECT SUM(PAYLOAD_MASS__KG_) as total_payload_mass  from SPACX where CUSTOMER = 'NASA (CRS)';
```

```
 * ibm_db_sa://sdw99696:***@54a2f15b-5c0f-46df-8954-7e38e612c2bd.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:32733/bludb
Done.
```

Out[28]:

total_payload_mass
45596

Average Payload Mass by F9 v1.1

Task 4

Display average payload mass carried by booster version F9 v1.1

In [27]:
```
%sql SELECT avg(PAYLOAD_MASS__KG_) as average_payload_mass from SPACX where BOOSTER_VERSION ='F9 v1.1';
```

```
 * ibm_db_sa://sdw99696:***@54a2f15b-5c0f-46df-8954-7e38e612c2bd.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:32733/bludb
Done.
```

Out[27]:

average_payload_mass
2928

First Successful Ground Landing Date

Task 5

List the date when the first successful landing outcome in ground pad was acheived.

Hint:Use min function

In [30]:
```
%sql select min(DATE) from SPACX where LANDING__OUTCOME = 'Success (ground pad)';
```

```
 * ibm_db_sa://sdw99696:***@54a2f15b-5c0f-46df-8954-7e38e612c2bd.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:32733/bludb
Done.
```

Out[30]:

1
2015-12-22

Successful Drone Ship Landing with Payload between 4000 and 6000

Task 6

List the names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000

In [31]:
```
%%sql
SELECT BOOSTER_VERSION FROM SPACX
WHERE LANDING__OUTCOME = 'Success (drone ship)' AND PAYLOAD_MASS__KG_ BETWEEN 4000 AND 6000;
```

```
 * ibm_db_sa://sdw99696:***@54a2f15b-5c0f-46df-8954-7e38e612c2bd.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:32733/bludb
Done.
```

Out[31]:

booster_version
F9 FT B1022
F9 FT B1026
F9 FT B1021.2
F9 FT B1031.2

Total Number of Successful and Failure Mission Outcomes

Task 7

List the total number of successful and failure mission outcomes

In [36]:
```
%sql SELECT MISSION_OUTCOME,COUNT(MISSION_OUTCOME) AS Count FROM SPACX GROUP BY MISSION_OUTCOME;
```

```
 * ibm_db_sa://sdw99696:***@54a2f15b-5c0f-46df-8954-7e38e612c2bd.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:32733/bludb
Done.
```

Out[36]:

mission_outcome	COUNT
Failure (in flight)	1
Success	99
Success (payload status unclear)	1

Boosters Carried Maximum Payload

Task 8

List the names of the booster_versions which have carried the maximum payload mass. Use a subquery

In [37]:
```
%%sql
SELECT BOOSTER_VERSION FROM SPACX WHERE PAYLOAD_MASS__KG_ =(select max(PAYLOAD_MASS__KG_) from SPACX);
```

```
 * ibm_db_sa://sdw99696:***@54a2f15b-5c0f-46df-8954-7e38e612c2bd.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:32733/bludb
Done.
```

Out[37]:

booster_version
F9 B5 B1048.4
F9 B5 B1049.4
F9 B5 B1051.3
F9 B5 B1056.4
F9 B5 B1048.5
F9 B5 B1051.4
F9 B5 B1049.5
F9 B5 B1060.2
F9 B5 B1058.3
F9 B5 B1051.6
F9 B5 B1060.3
F9 B5 B1049.7

2015 Launch Records

Task 9

List the failed landing_outcomes in drone ship, their booster versions, and launch site names for in year 2015

In [44]:
```
%%sql
SELECT LANDING__OUTCOME,BOOSTER_VERSION,LAUNCH_SITE FROM SPACX
WHERE LANDING__OUTCOME = 'Failure (drone ship)' AND DATE LIKE '%2015%';
```

```
 * ibm_db_sa://sdw99696:***@54a2f15b-5c0f-46df-8954-7e38e612c2bd.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:32733/bludb
Done.
```

Out[44]:

landing__outcome	booster_version	launch_site
Failure (drone ship)	F9 v1.1 B1012	CCAFS LC-40
Failure (drone ship)	F9 v1.1 B1015	CCAFS LC-40

Rank Landing Outcomes Between 2010-06-04 and 2017-03-20

Task 10

Rank the count of landing outcomes (such as Failure (drone ship) or Success (ground pad)) between the date 2010-06-04 and 2017-03-20, in descending order

In [51]:
```
%%sql
SELECT LANDING__OUTCOME,COUNT(LANDING__OUTCOME) AS COUNT FROM SPACX
WHERE DATE > '2010-06-04' and DATE <'2017-03-20'
GROUP BY LANDING__OUTCOME
ORDER BY COUNT DESC;
```

```
 * ibm_db_sa://sdw99696:***@54a2f15b-5c0f-46df-8954-7e38e612c2bd.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:32733/bludb
Done.
```

Out[51]:

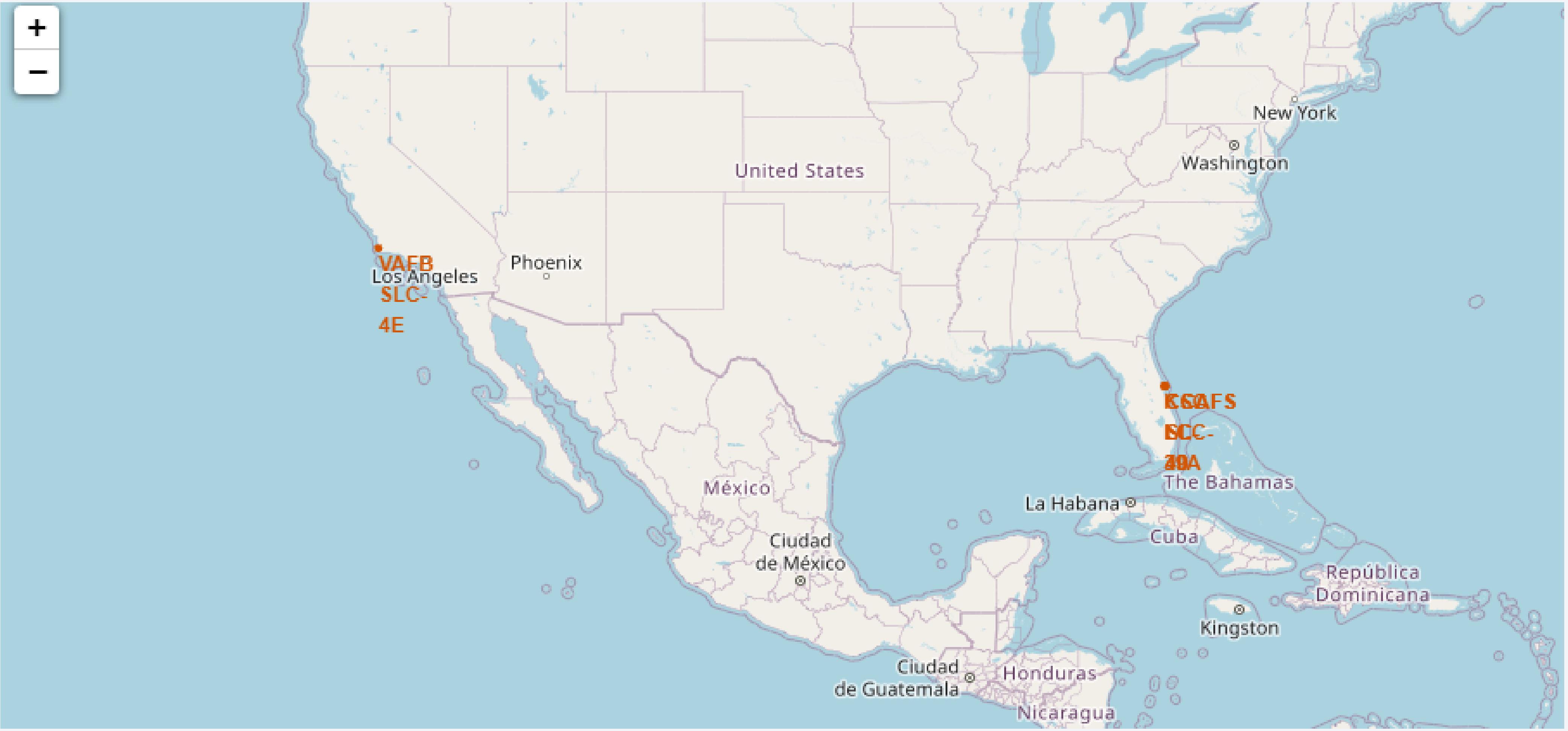
landing__outcome	COUNT
No attempt	10
Failure (drone ship)	5
Success (drone ship)	5
Controlled (ocean)	3
Success (ground pad)	3
Uncontrolled (ocean)	2
Failure (parachute)	1
Precluded (drone ship)	1

Section 4

Launch Sites Proximities Analysis

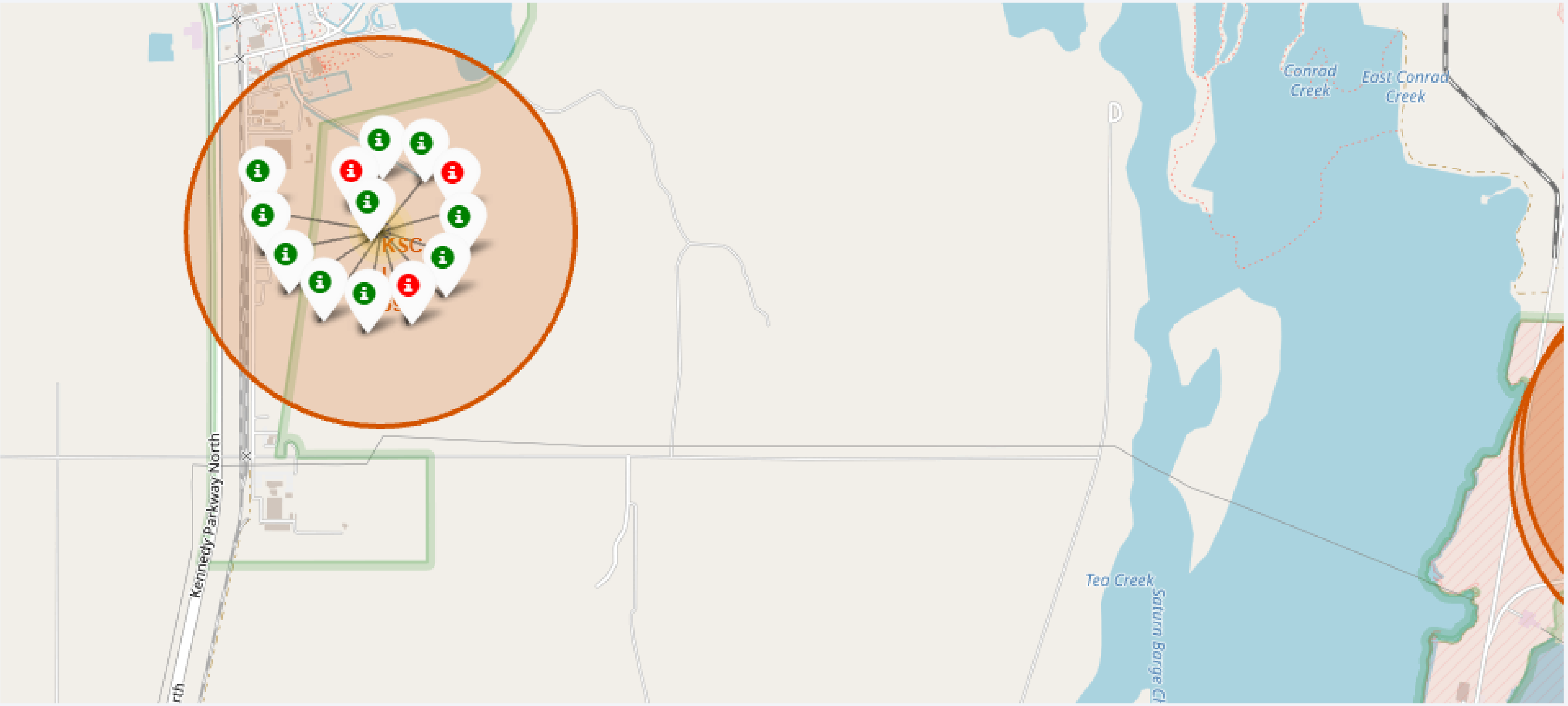
Lunch sites Marking

- The markers on this maps show the lunch site locations on the map



Mark the success/failed launches for each site on the map

- A green marker represents a successful landing outcome, while a red one represents failure



Distances between a launch site to its proximities

- The blue line represents the distance between the lunch site and the closest coastline.

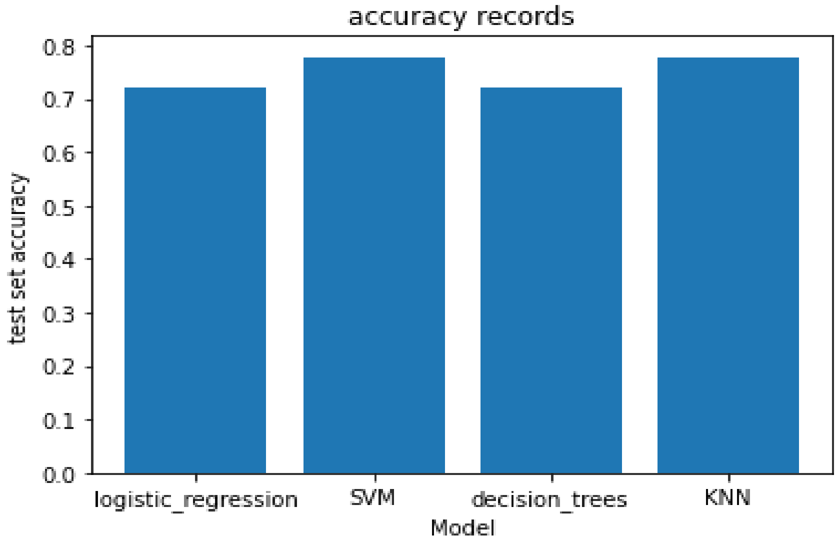
Section 5

Predictive Analysis (Classification)

Classification Accuracy

```
In [44]: x = [lr.score(X_test,Y_test),svm.score(X_test,Y_test),tree.score(X_test,Y_test),KNN.score(X_test,Y_test)]
         y = ['logistic_regression','SVM','decision_trees','KNN']
         plt.bar(y, x)
         plt.title('accuracy records')
         plt.xlabel('Model')
         plt.ylabel('test set accuracy')
         plt.show

Out[44]: <function matplotlib.pyplot.show(*args, **kw)>
```

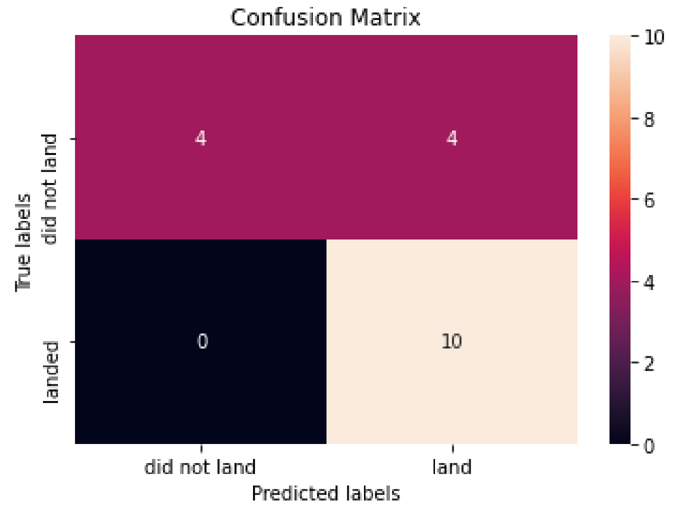



```
In [ ]: #SVM and KNN have the highest out of sample accuracy, thus they are the most accurate models.
```

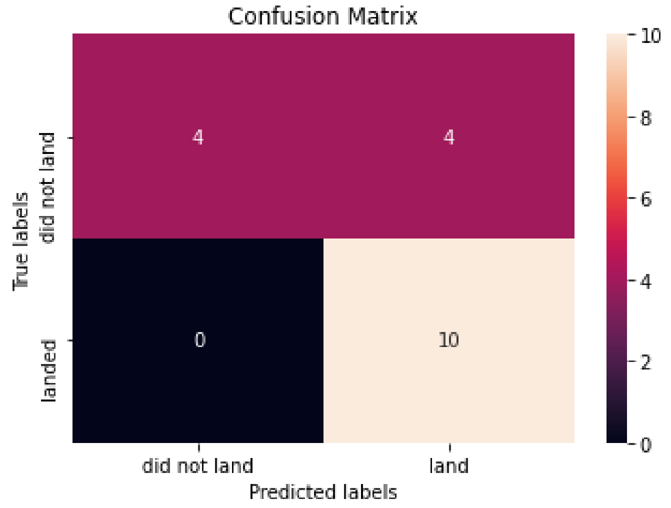
Confusion Matrix

- These two graphs represent the confusion matrix for both the SVM and KNN models
    - These confusion matrices show the largest true positive and true negative values, as well as the least false positive and false negative values.

```
In [36]: yhat = knn_cv.predict(X_test)
         plot_confusion_matrix(Y_test,yhat)
```




```
In [22]: yhat=svm_cv.predict(X_test)
         plot_confusion_matrix(Y_test,yhat)
```



Conclusions

- Not all the data is important, the collected data may contain irrelevant columns and it is normal to drop them.
- Visualizing data is a good way of determining what features have the strongest effect, in our case the lunch site and the orbit type.
- Success rate increased noticeably from 2013 and on.
- SQL queries provide wider scope to explore datasets in comparison with traditional EDA.
- SVM and KNN models are the most reliable since they have the highest out of sample accuracy and f1-score.

Thank you!