Capstone Introduction and Understanding the Datasets

Outline

- Interactive visual analytics and Dashboard
- Wrangling the data
- Predictive Analysis (Classification)
- Data-Driven Insights

- Summary of methodologies
  - Data Collection through API
  - Data Collection with Web Scraping
  - Data Wrangling
  - Exploratory Data Analysis with SQL
  - Exploratory Data Analysis with Data Visualization
  - Interactive Visual Analytics with Folium
  - Machine Learning Prediction
- Summary of all results
  - Exploratory Data Analysis result
  - Interactive analytics in screenshots
  - Predictive Analytics result

Outline

Introduction

- Project background and context

  Space X 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 Space X can reuse the first stage. 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 space X for a rocket launch. This goal of the project is to create a machine learning pipeline to predict if the first stage will land successfully.

- Problems you want to find answers

  - What factors determine if the rocket will land successfully?
  - The interaction amongst various features that determine the success rate of a successful landing.
  - What operating conditions needs to be in place to ensure a successful landing program.

Section 1

Methodology

Methodology

Summary

- Data collection methodology:
  - Data was collected using SpaceX API and web scraping from Wikipedia.
- Perform data wrangling
  - One-hot encoding was applied to categorical features
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
  - How to build, tune, evaluate classification models

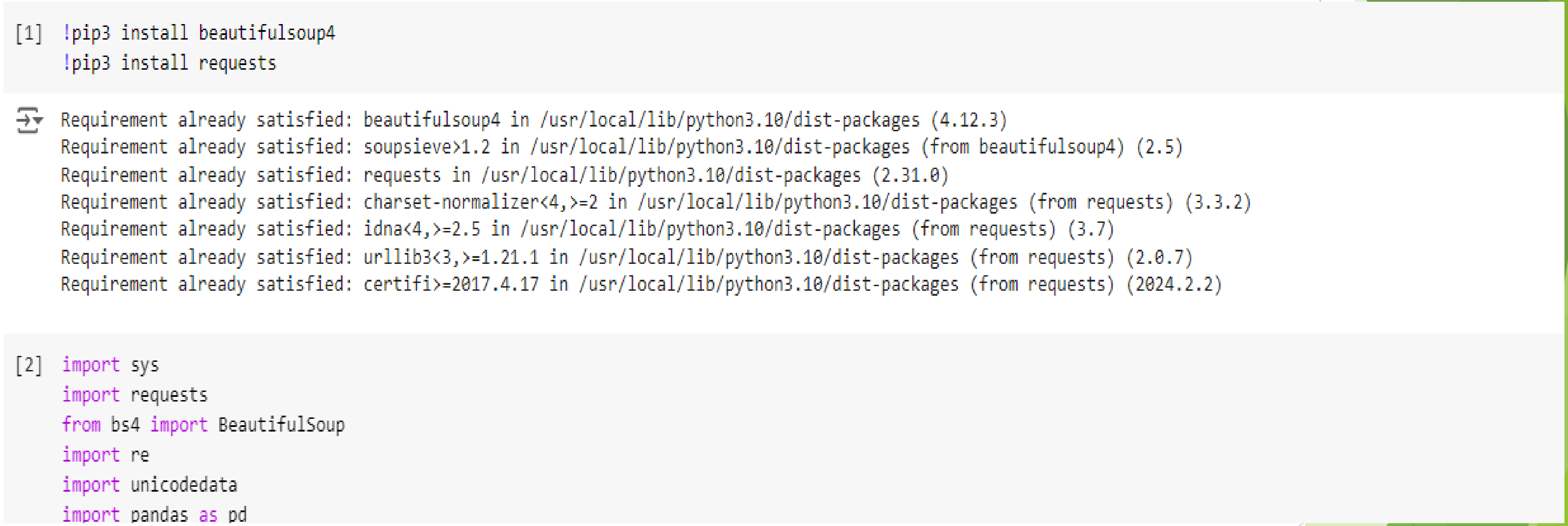
Data Collection

- The data was collected using various methods
  - Data collection was done using get request to the SpaceX API.
  - Next, we decoded the response content as a Json using .json() function call and turn it into a pandas dataframe using .json_normalize().
  - We then cleaned the data, checked for missing values and fill in missing values where necessary.
  - In addition, we performed web scraping from Wikipedia for Falcon 9 launch records with BeautifulSoup.
  - The objective was to extract the launch records as HTML table, parse the table and convert it to a pandas dataframe for future analysis.

Data Collection – SpaceX API

- We used the get request to the SpaceX API to collect data, clean the requested data and did some basic data wrangling and formatting.
- The link to the notebook is
- https://github.com/devipriyak/CapStone-ML-Project/blob/main/DataWrangling.ipynb

Importing Libraries

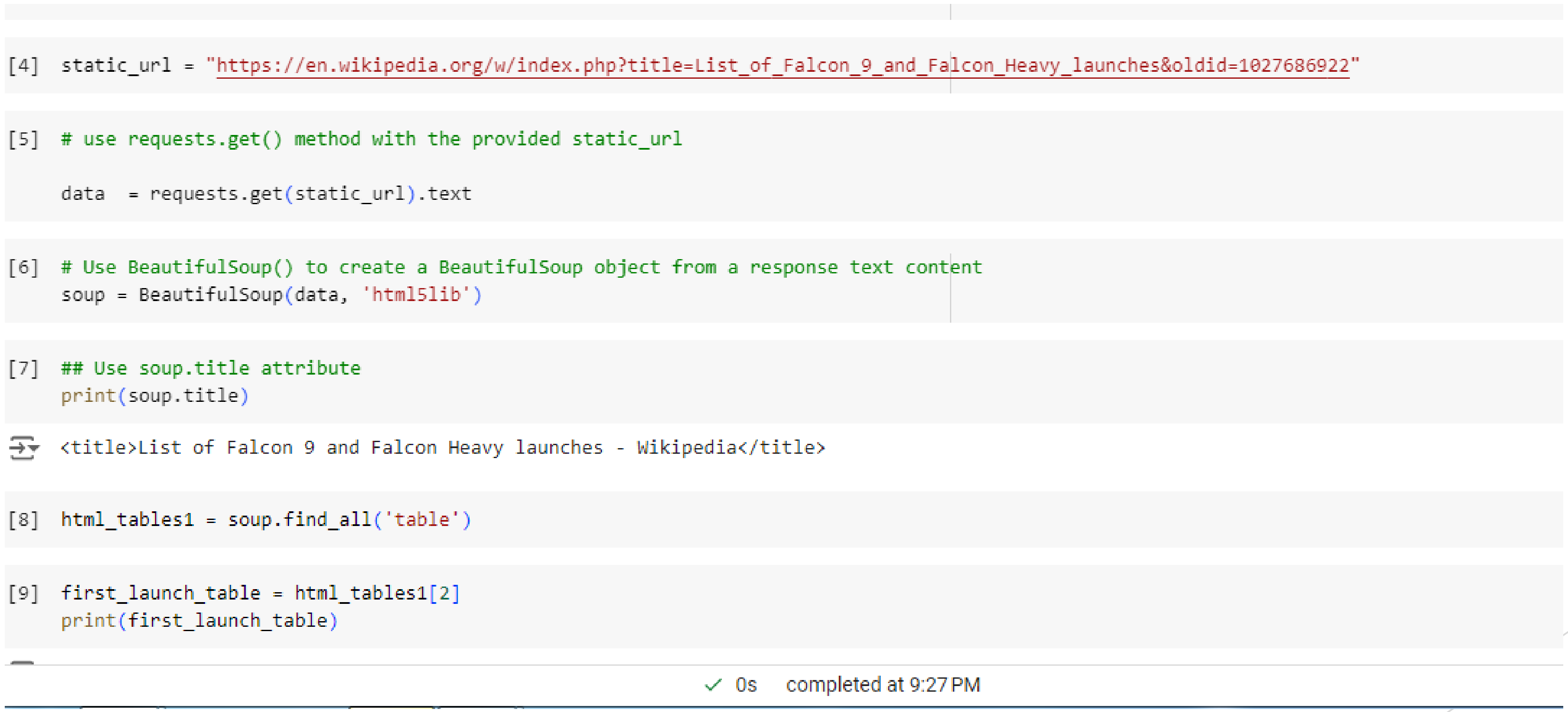


```
[1]  !pip3 install beautifulsoup4
     !pip3 install requests
```

```
Requirement already satisfied: beautifulsoup4 in /usr/local/lib/python3.10/dist-packages (4.12.3)
Requirement already satisfied: soupsieve>1.2 in /usr/local/lib/python3.10/dist-packages (from beautifulsoup4) (2.5)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (2.31.0)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests) (3.7)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests) (2024.2.2)
```

```
[2]  import sys
     import requests
     from bs4 import BeautifulSoup
     import re
     import unicodedata
     import pandas as pd
```

Accessing data



```
[4]  static_url = "https://en.wikipedia.org/w/index.php?title=List_of_Falcon_9_and_Falcon_Heavy_launches&oldid=1027686922"
```

```
[5]  # use requests.get() method with the provided static_url

     data  = requests.get(static_url).text
```

```
[6]  # Use BeautifulSoup() to create a BeautifulSoup object from a response text content
     soup = BeautifulSoup(data, 'html5lib')
```

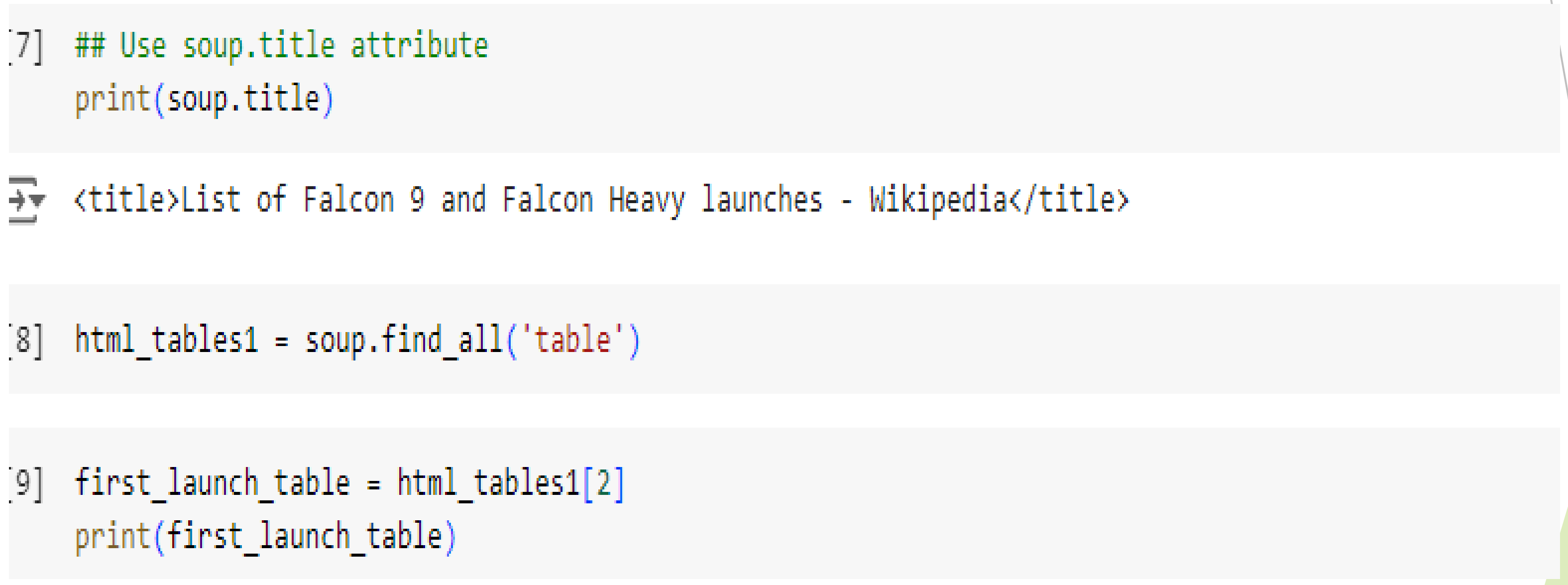
```
[7]  ## Use soup.title attribute
     print(soup.title)

     <title>List of Falcon 9 and Falcon Heavy launches - Wikipedia</title>
```

```
[8]  html_tables1 = soup.find_all('table')
```

```
[9]  first_launch_table = html_tables1[2]
     print(first_launch_table)
```

✓ 0s   completed at 9:27 PM

Printing Details



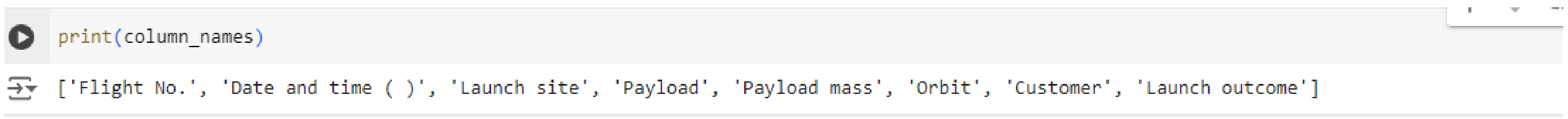
```
7]  ## Use soup.title attribute
    print(soup.title)
```

```
<title>List of Falcon 9 and Falcon Heavy launches - Wikipedia</title>
```

```
8]  html_tables1 = soup.find_all('table')
```

```
9]  first_launch_table = html_tables1[2]
    print(first_launch_table)
```

Print Feature Details



```
print(column_names)
```

```
['Flight No.', 'Date and time ( )', 'Launch site', 'Payload', 'Payload mass', 'Orbit', 'Customer', 'Launch outcome']
```

Code in Git Hub

- https://github.com/devipriyak/CapStone-ML-Project/blob/main/webscrap.ipynb

Data Wrangling

- Identify duplicate values in the dataset.
- Remove duplicate values from the dataset.
- Identify missing values in the dataset.
- Impute the missing values in the dataset.
- Normalize data in the dataset.

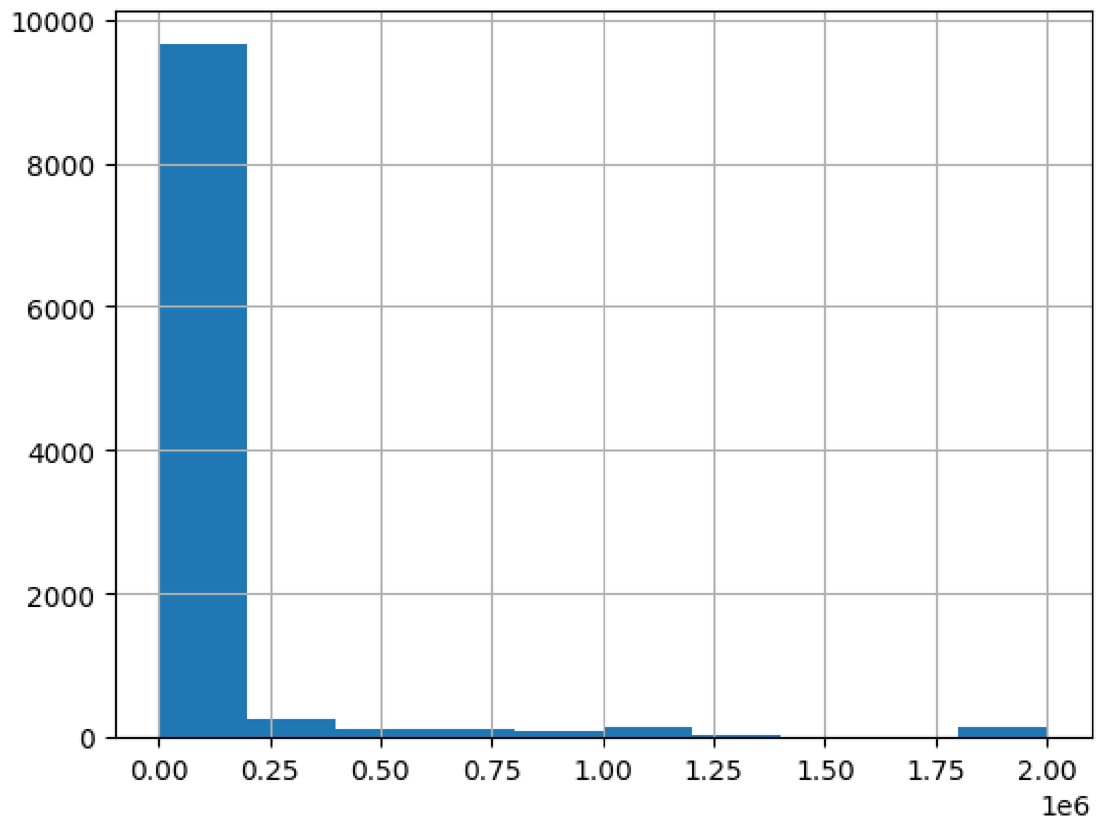
Github Id

- https://github.com/devipriyak/CapStone-ML-Project/blob/main/DataWrangling.ipynb

Module 2 - Exploratory Data Analysis (EDA)

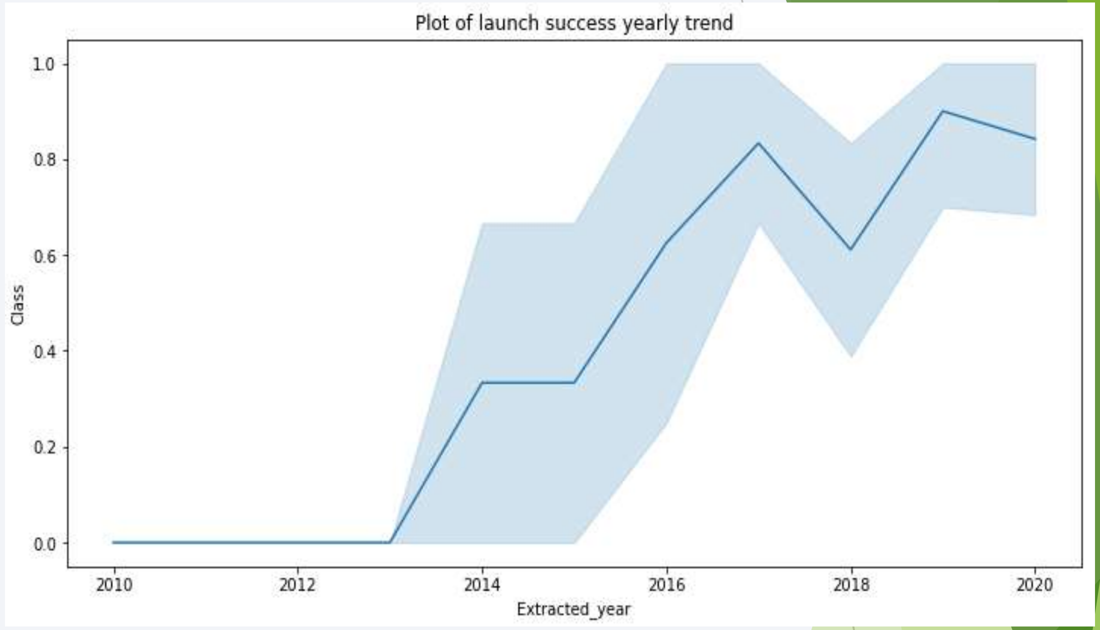
- In this module, you will collect data on the Falcon 9 first-stage landings. You will use a RESTful API and web scraping. You will also convert the data into a dataframe and then perform some data wrangling.
- **Learning Objectives**
- Load a dataset into a database.
- Write and execute SQL queries to select and sort data.
- Write Python code to conduct exploratory data analysis by manipulating data in a Pandas data frame.
- Visualize the data and extract meaningful patterns to guide the modeling process.
- Create scatter plots and bar charts to analyze data in a Pandas data frame.

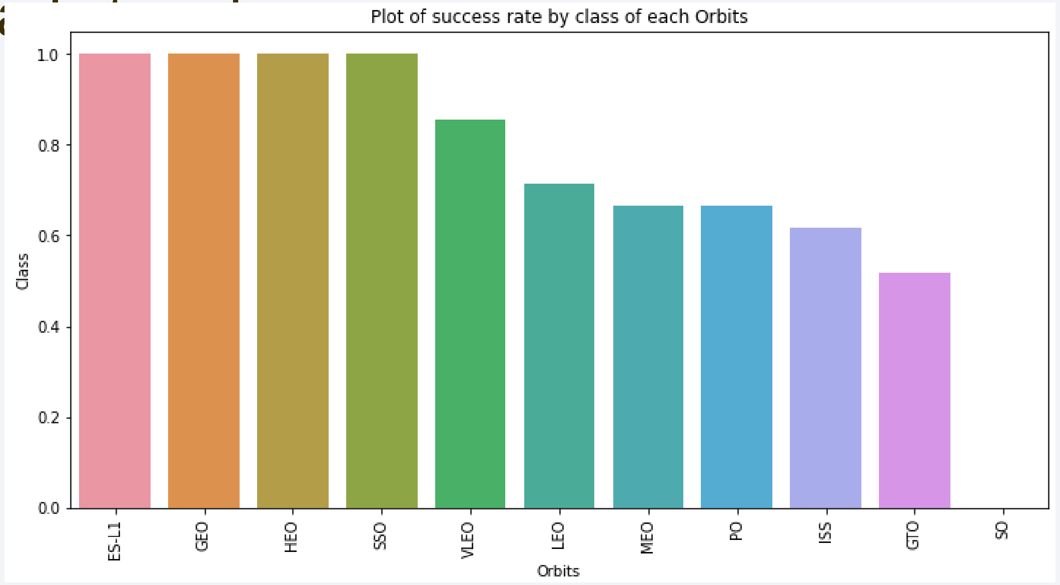
Visualizing data



EDA with Data Visualization https://github.com/devipriyak/CapStone-ML-Project/blob/main/Data_Explo.ipynb

- We explored the data by visualizing the relationship between flight number and launch Site, payload and launch site, success rate of each orbit type, flight number and orbit type, the launch success yea





https://github.com/devipriyak/CapStone-ML-Project/blob/main/Data_Explo.ipynb

EDA with SQL

- We loaded the SpaceX dataset into a PostgreSQL database without leaving the jupyter notebook.
- We applied EDA with SQL to get insight from the data. We wrote queries to find out for instance:
  - The names of unique launch sites in the space mission.
  - The total payload mass carried by boosters launched by NASA (CRS)
  - The average payload mass carried by booster version F9 v1.1
  - The total number of successful and failure mission outcomes
  - The failed landing outcomes in drone ship, their booster version and launch site names.
- The link to the notebook
- https://github.com/devipriyak/CapStone-ML-Project/blob/main/Data_Explo.ipynb

Build an Interactive Map with Folium

- We marked all launch sites, and added map objects such as markers, circles, lines to mark the success or failure of launches for each site on the folium map.
- We assigned the feature launch outcomes (failure or success) to class 0 and 1.i.e., 0 for failure, and 1 for success.
- Using the color-labeled marker clusters, we identified which launch sites have relatively high success rate.
- We calculated the distances between a launch site to its proximities. We answered some question for instance:
  - Are launch sites near railways, highways and coastlines.
  - Do launch sites keep certain distance away from cities.
  - https://github.com/devipriyak/CapStone-ML-Project/blob/main/Interactive_Visual_Analytics_with_Folium.ipynb

Build a Dashboard with Plotly Dash

- We built an interactive dashboard with Plotly dash
- We plotted pie charts showing the total launches by a certain sites
- We plotted scatter graph showing the relationship with Outcome and Payload Mass (Kg) for the different booster version.
- The link to the notebook is https://github.com/devipriyak/CapStone-ML-Project/

Predictive Analysis (Classification)

- We loaded the data using numpy and pandas, transformed the data, split our data into training and testing.
- We built different machine learning models and tune different hyperparameters using GridSearchCV.
- We used accuracy as the metric for our model, improved the model using feature engineering and algorithm tuning.
- We found the best performing classification model.
- The link to the notebook https://github.com/devipriyak/CapStone-ML-Project/blob/main/Machine_Learning_Prediction.ipynb

Results

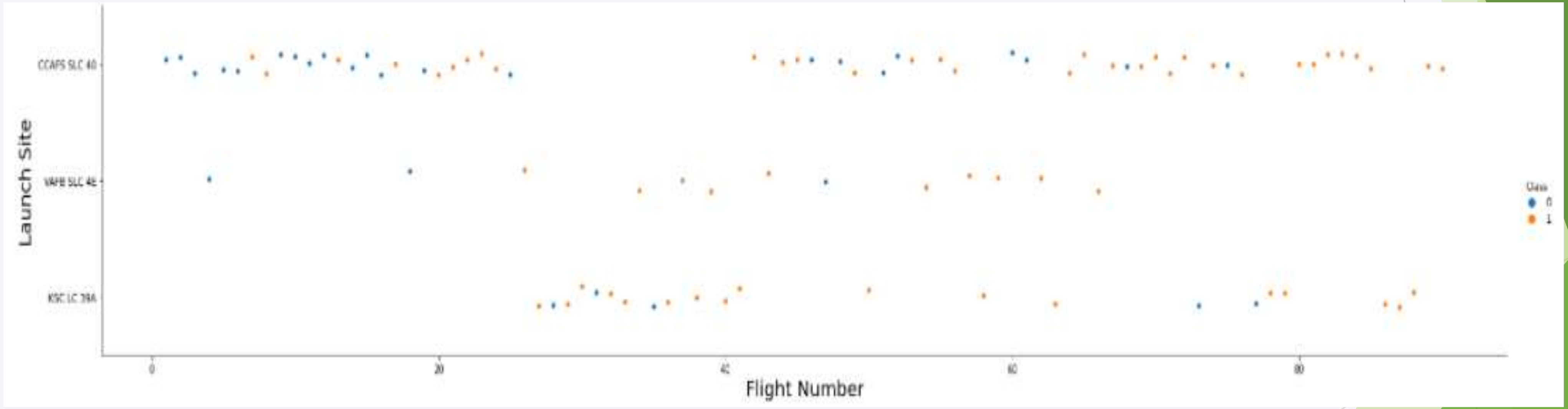
- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results

Section 2

Insights drawn from EDA

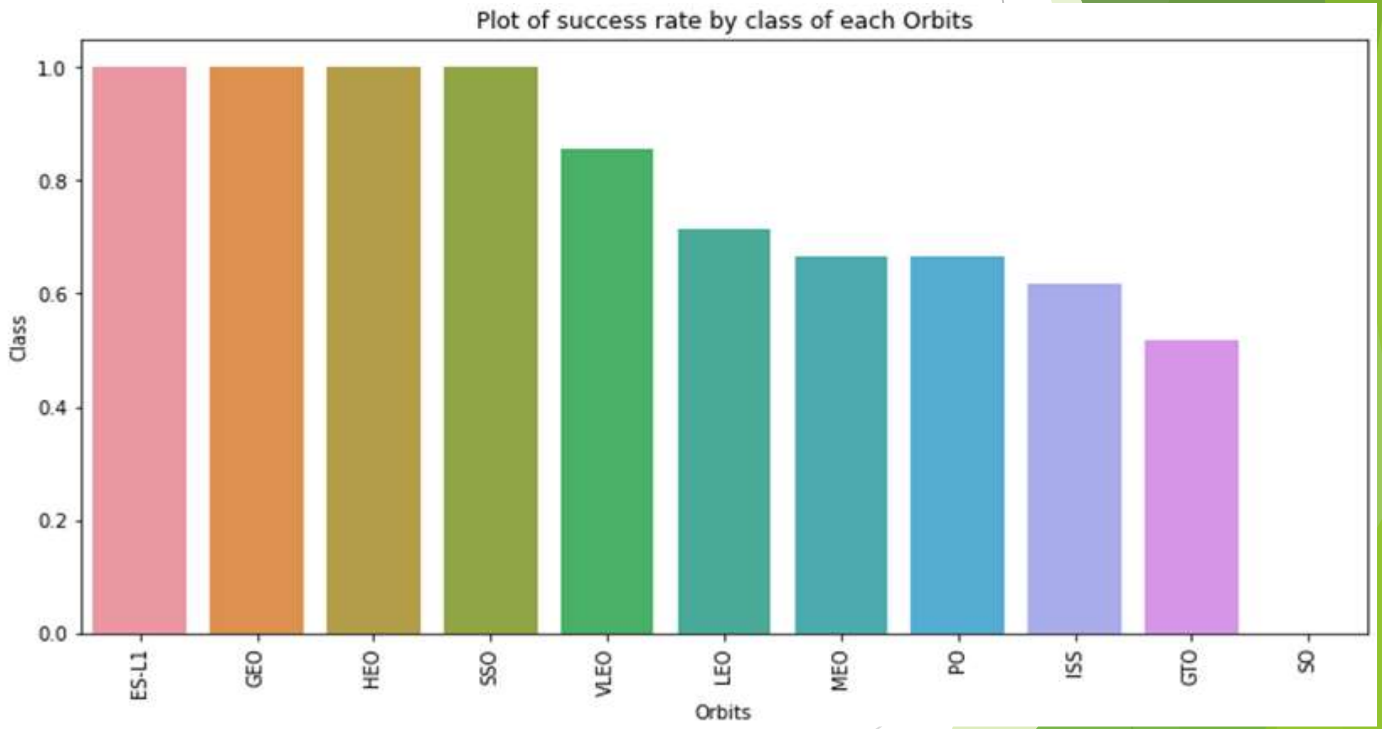
Flight Number vs. Launch Site

- From the plot, we found that the larger the flight amount at a launch site, the greater the success rate at a launch site.



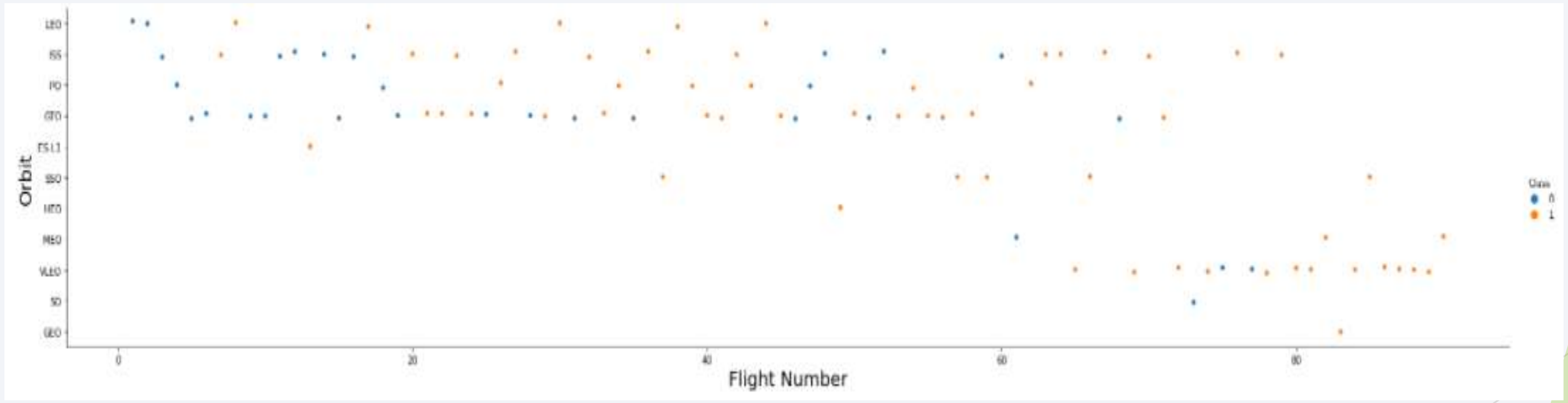
Success Rate vs. Orbit Type

- From the plot, we can see that ES-L1, GEO, HEO, SSO, VLEO had the most success rate.



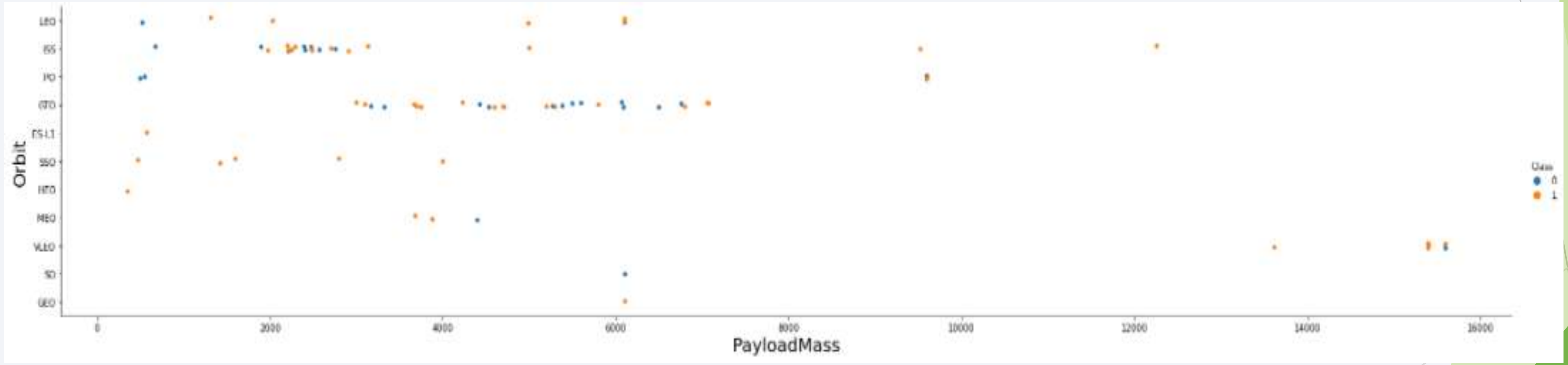
Flight Number vs. Orbit Type

- The plot below shows the Flight Number vs. Orbit type. We observe that in the LEO orbit, success is related to the number of flights whereas in the GTO orbit, there is no relationship between flight number and the orbit.



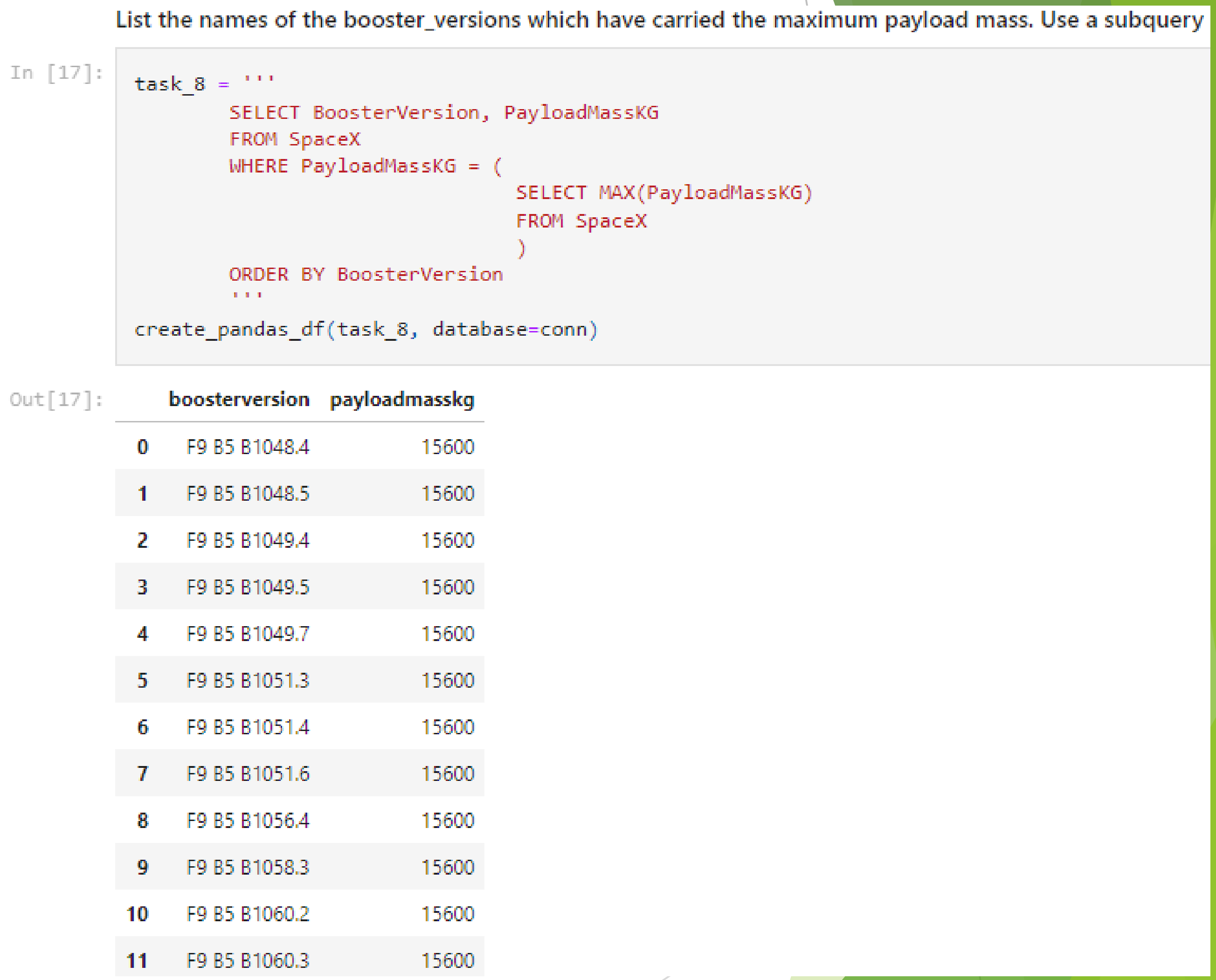
Payload vs. Orbit Type

- We can observe that with heavy payloads, the successful landing are more for PO, LEO and ISS orbits.



Boosters Carried Maximum Payload

- We determined the booster that have carried the maximum payload using a subquery in the **WHERE** clause and the **MAX()** function.


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

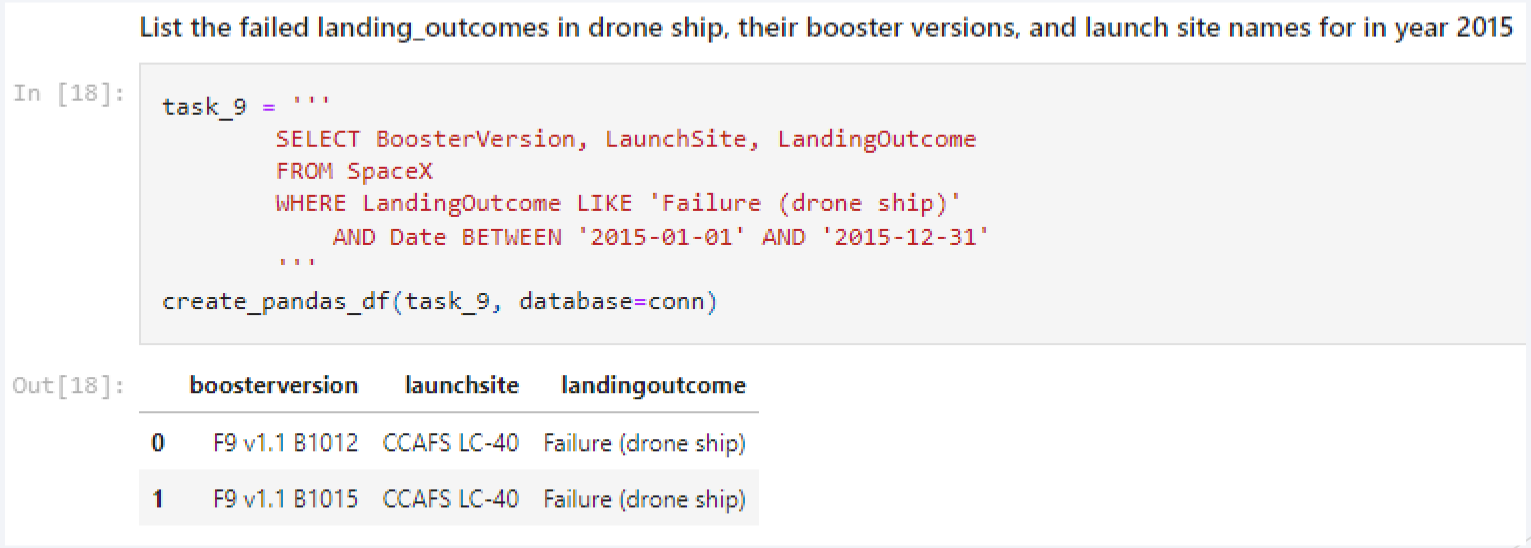
```
In [17]:  task_8 = '''
                  SELECT BoosterVersion, PayloadMassKG
                  FROM SpaceX
                  WHERE PayloadMassKG = (
                                          SELECT MAX(PayloadMassKG)
                                          FROM SpaceX
                                          )
                  ORDER BY BoosterVersion
                  '''
          create_pandas_df(task_8, database=conn)
```

Out[17]:

	boosterversion	payloadmasskg
0	F9 B5 B1048.4	15600
1	F9 B5 B1048.5	15600
2	F9 B5 B1049.4	15600
3	F9 B5 B1049.5	15600
4	F9 B5 B1049.7	15600
5	F9 B5 B1051.3	15600
6	F9 B5 B1051.4	15600
7	F9 B5 B1051.6	15600
8	F9 B5 B1056.4	15600
9	F9 B5 B1058.3	15600
10	F9 B5 B1060.2	15600
11	F9 B5 B1060.3	15600

2015 Launch Records

- We used a combinations of the **WHERE** clause, **LIKE**, **AND**, and **BETWEEN** conditions to filter for failed landing outcomes in drone ship, their booster versions, and launch site names for year 2015



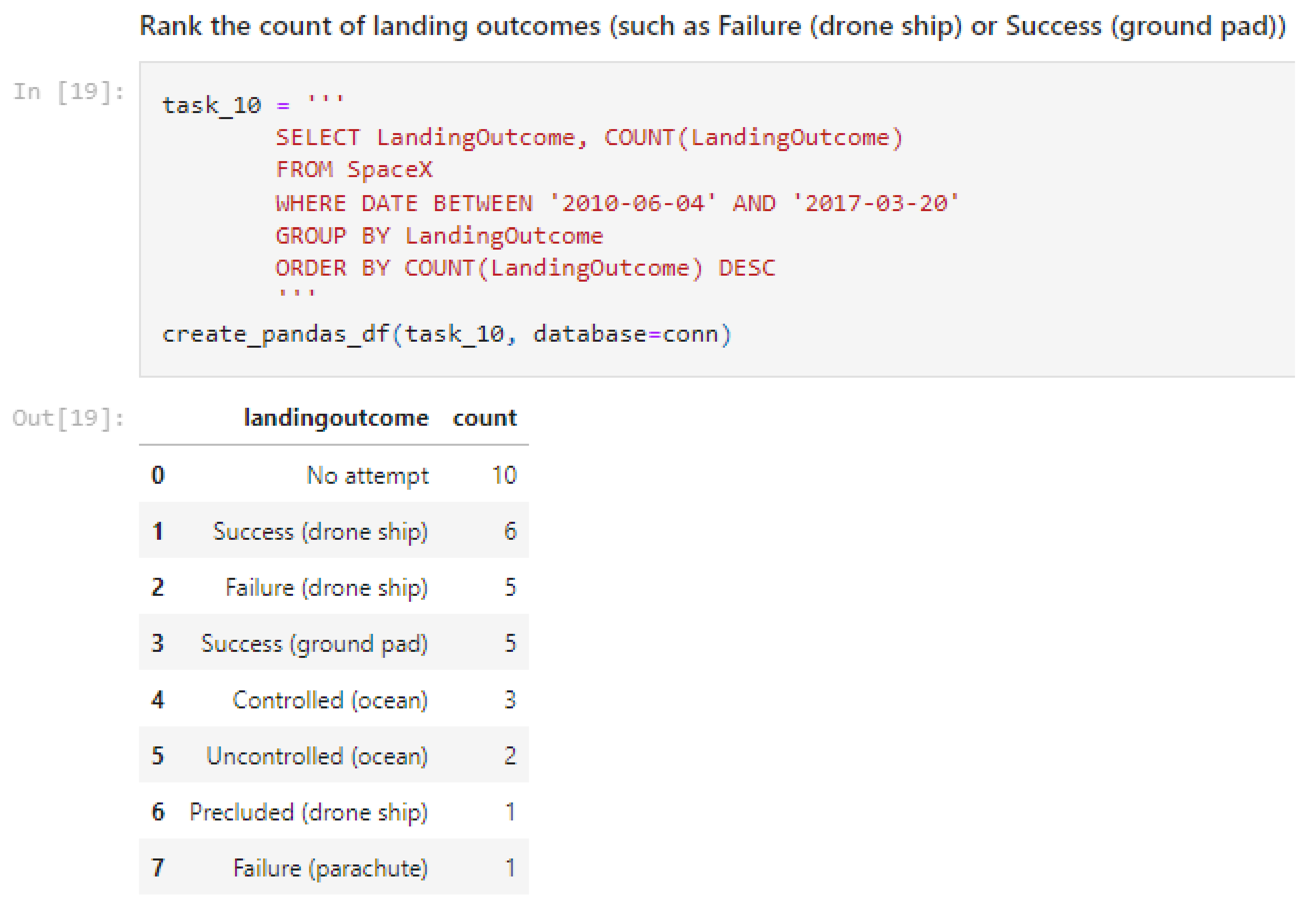
List the failed landing_outcomes in drone ship, their booster versions, and launch site names for in year 2015

```
In [18]:
task_9 = '''
        SELECT BoosterVersion, LaunchSite, LandingOutcome
        FROM SpaceX
        WHERE LandingOutcome LIKE 'Failure (drone ship)'
            AND Date BETWEEN '2015-01-01' AND '2015-12-31'
        '''
create_pandas_df(task_9, database=conn)
```

Out[18]:

	boosterversion	launchsite	landingoutcome
0	F9 v1.1 B1012	CCAFS LC-40	Failure (drone ship)
1	F9 v1.1 B1015	CCAFS LC-40	Failure (drone ship)

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



Rank the count of landing outcomes (such as Failure (drone ship) or Success (ground pad))

```
In [19]:  task_10 = '''
                  SELECT LandingOutcome, COUNT(LandingOutcome)
                  FROM SpaceX
                  WHERE DATE BETWEEN '2010-06-04' AND '2017-03-20'
                  GROUP BY LandingOutcome
                  ORDER BY COUNT(LandingOutcome) DESC
                  '''
          create_pandas_df(task_10, database=conn)
```

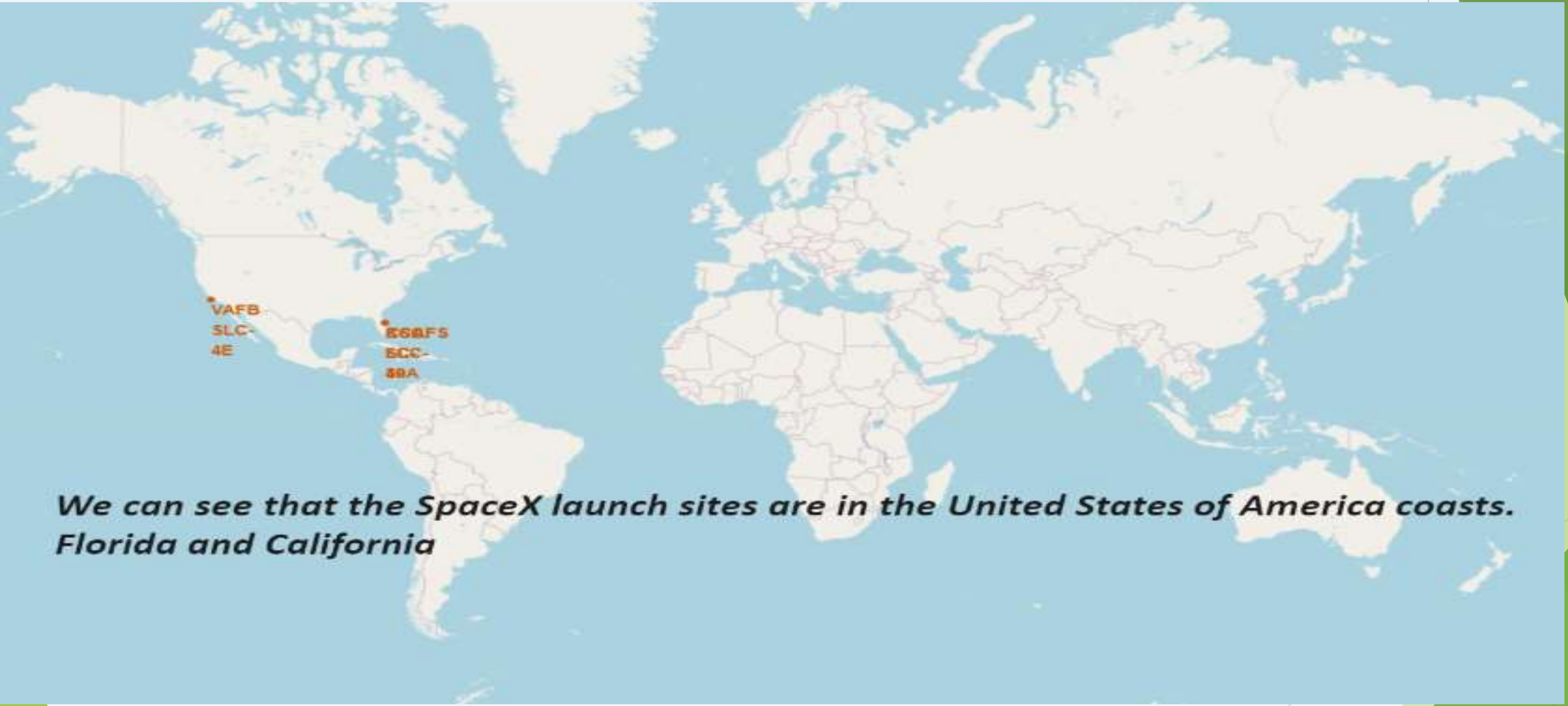
```
Out[19]:
      landingoutcome          count
   0  No attempt                 10
   1  Success (drone ship)        6
   2  Failure (drone ship)        5
   3  Success (ground pad)        5
   4  Controlled (ocean)          3
   5  Uncontrolled (ocean)        2
   6  Precluded (drone ship)      1
   7  Failure (parachute)         1
```

- We selected Landing outcomes and the **COUNT** of landing outcomes from the data and used the **WHERE** clause to filter for landing outcomes **BETWEEN** 2010-06-04 to 2010-03-20.
- We applied the **GROUP BY** clause to group the landing outcomes and the **ORDER BY** clause to order the grouped landing outcome in descending order.

Section 4

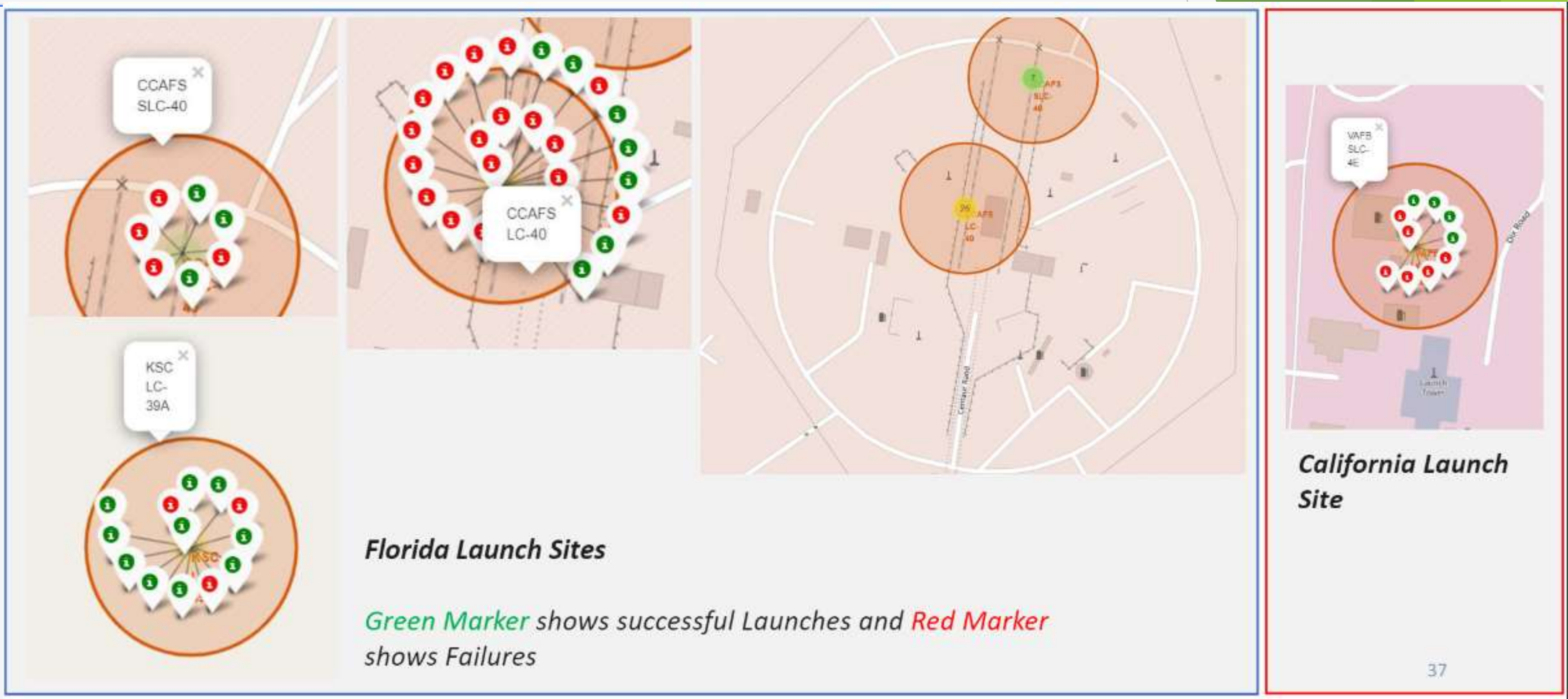
Launch Sites Proximities Analysis

All launch sites global map markers



We can see that the SpaceX launch sites are in the United States of America coasts. Florida and California

Markers showing launch sites with color labels



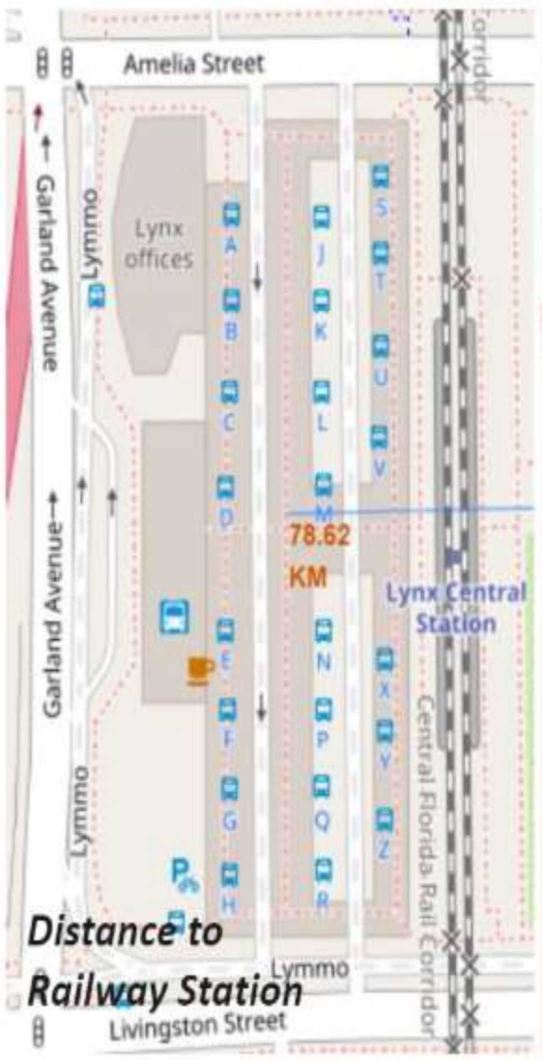
Florida Launch Sites

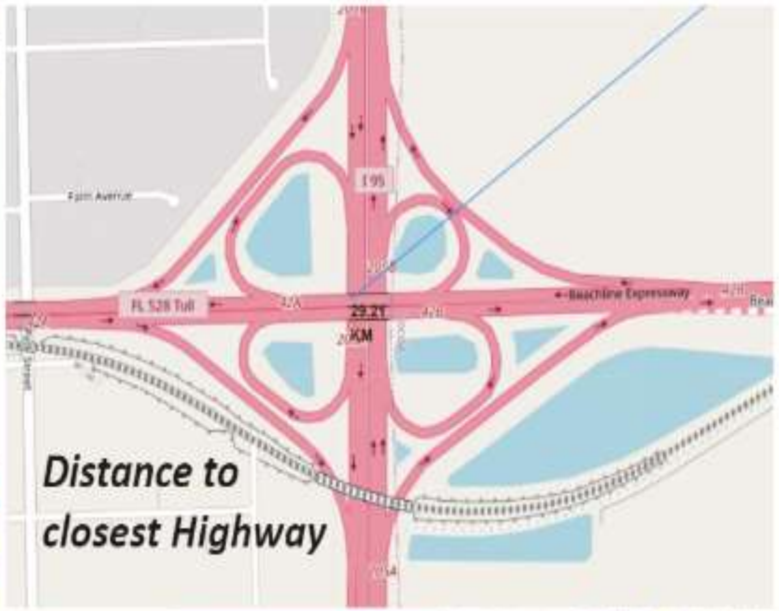
Green Marker shows successful Launches and Red Marker shows Failures

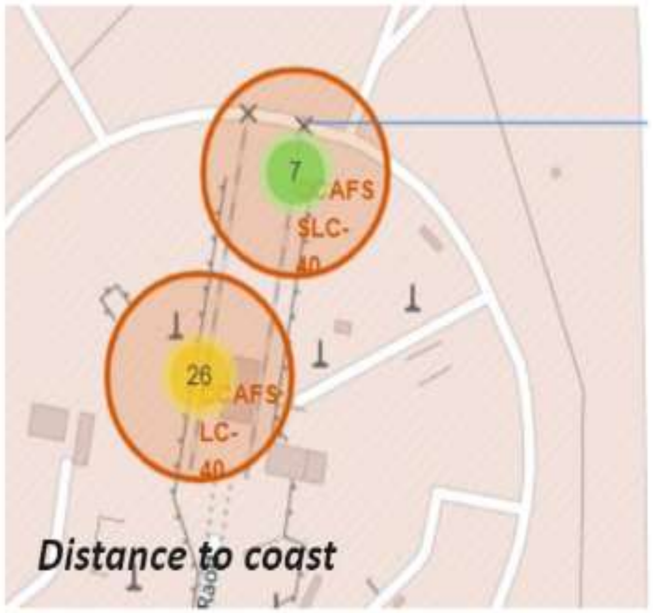
California Launch Site

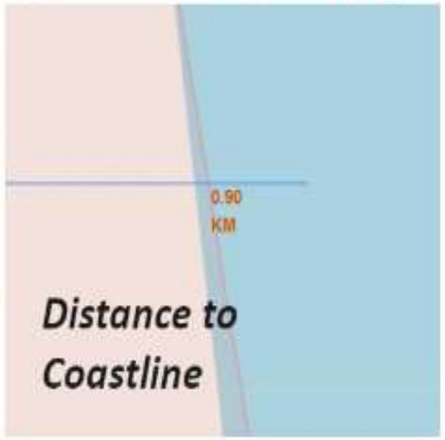
37

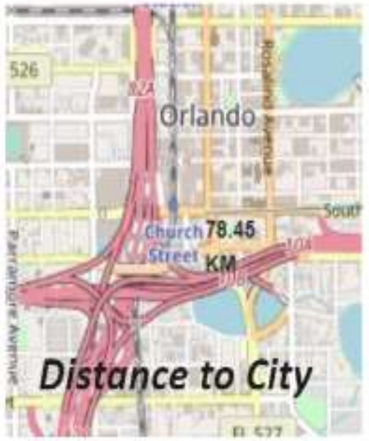
Launch Site distance to landmarks









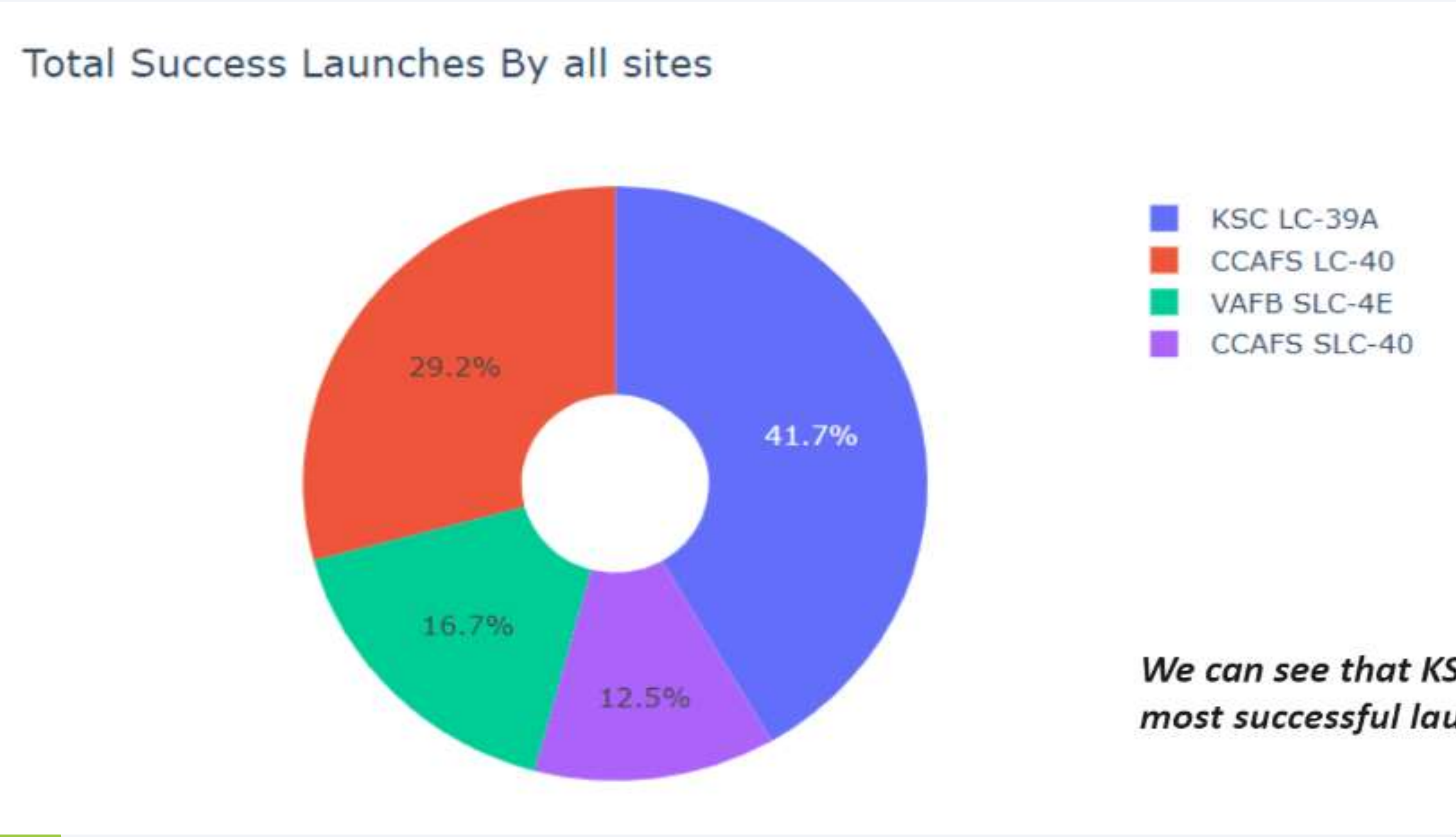


- Are launch sites in close proximity to railways? No
- Are launch sites in close proximity to highways? No
- Are launch sites in close proximity to coastline? Yes
- Do launch sites keep certain distance away from cities? Yes

Section 5

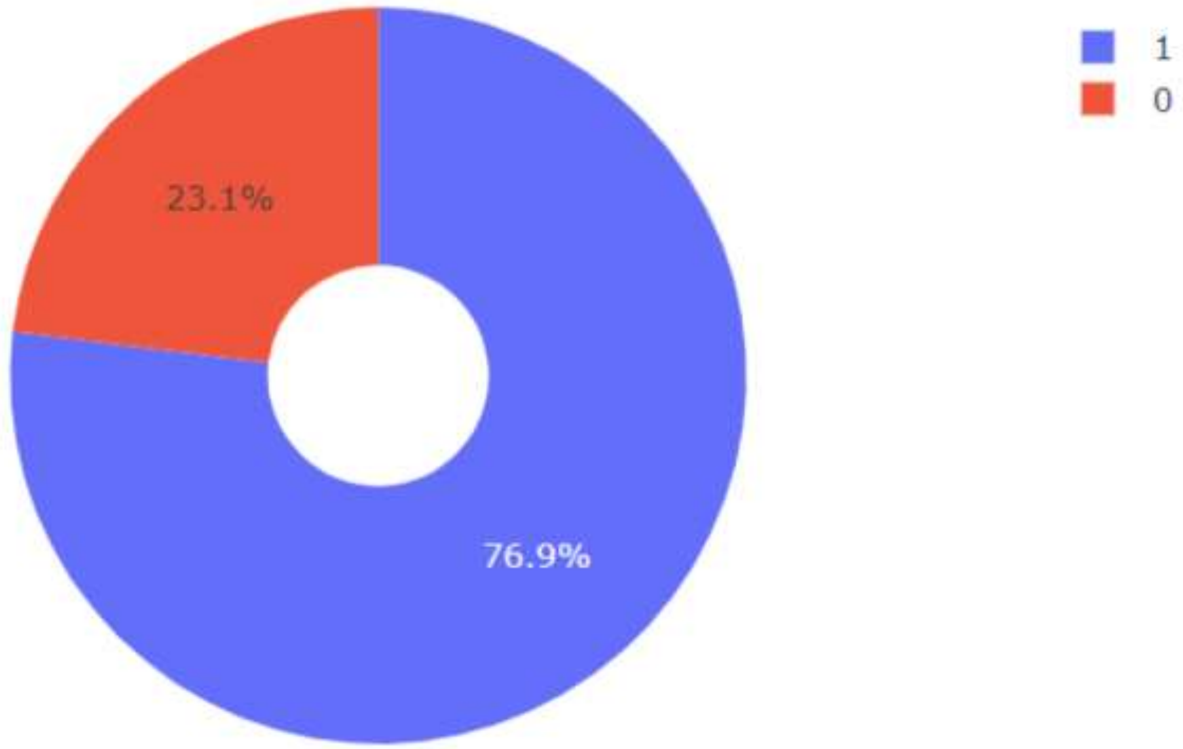
Build a Dashboard with Plotly Dash

Pie chart showing the success percentage achieved by each launch site



We can see that KSC LC-39A had the most successful launches from all the sites

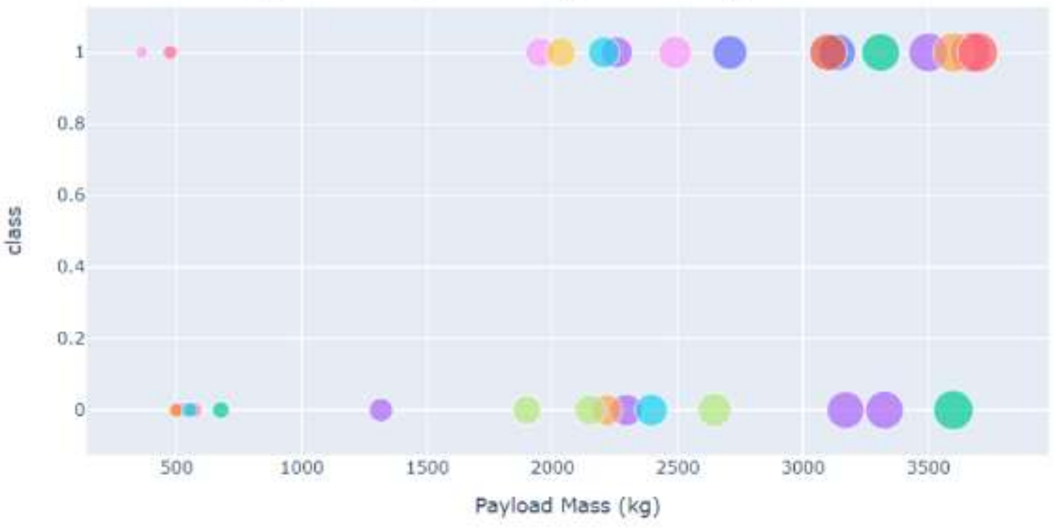
Pie chart showing the Launch site with the highest launch success ratio



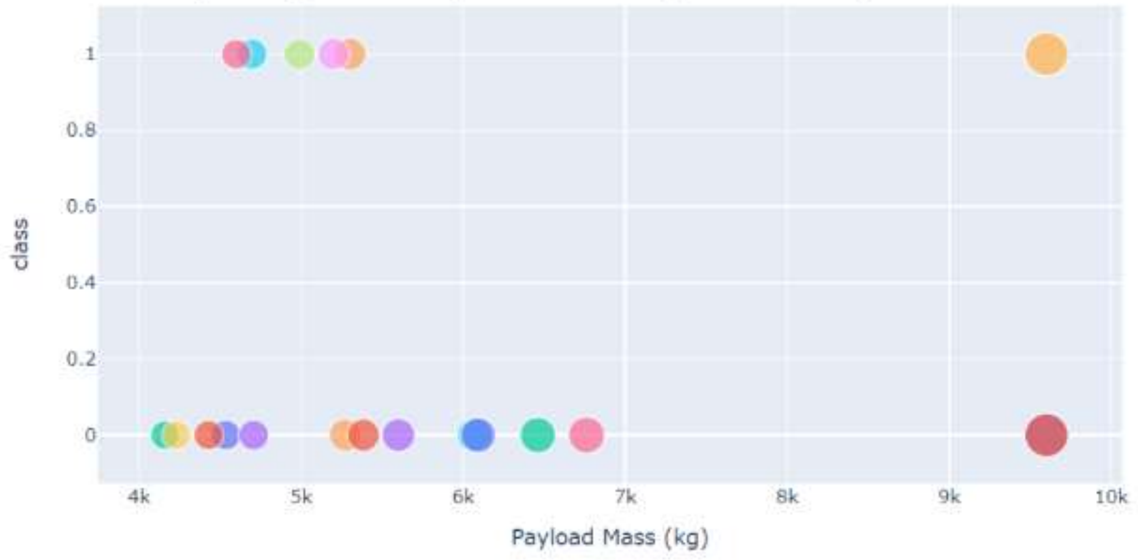
KSC LC-39A achieved a 76.9% success rate while getting a 23.1% failure rate

Scatter plot of Payload vs Launch Outcome for all sites, with different payload selected in the range slider

Low Weighted Payload 0kg – 4000kg



Heavy Weighted Payload 4000kg – 10000kg



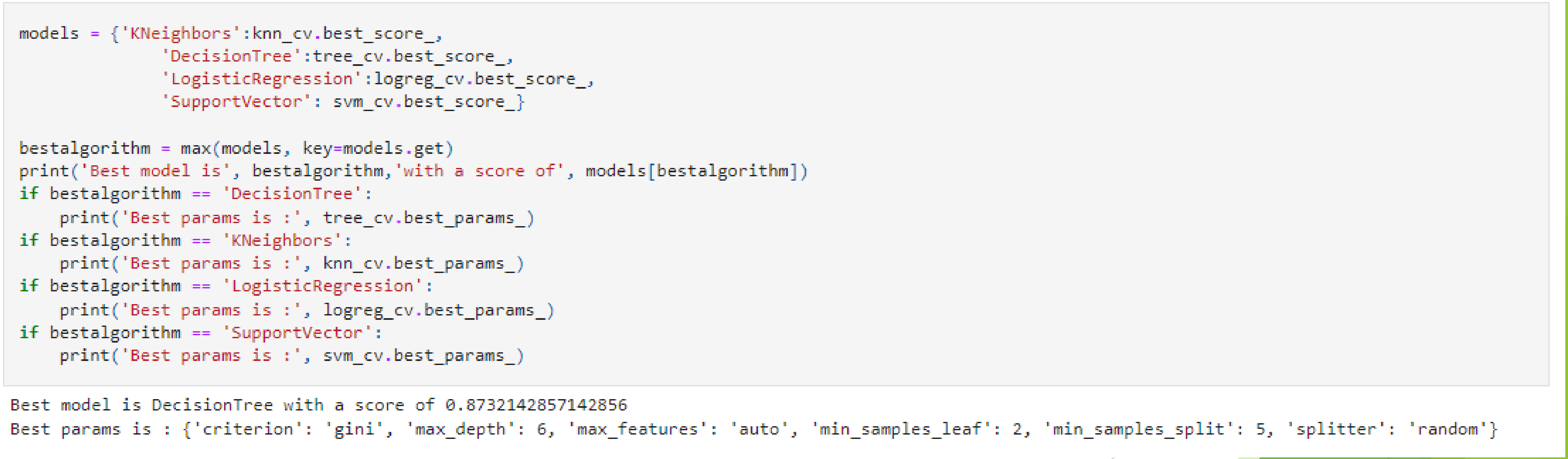
We can see the success rates for low weighted payloads is higher than the heavy weighted payloads

Section 6

Predictive Analysis (Classification)

Classification Accuracy

- The decision tree classifier is the model with the highest classification accuracy

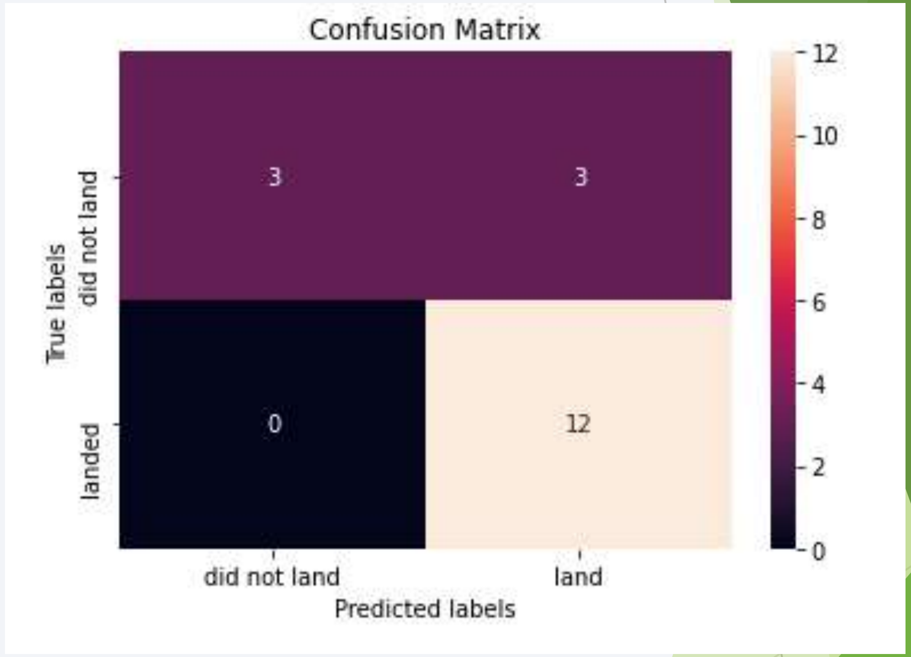


```
models = {'KNeighbors':knn_cv.best_score_,
              'DecisionTree':tree_cv.best_score_,
              'LogisticRegression':logreg_cv.best_score_,
              'SupportVector': svm_cv.best_score_}

bestalgorithm = max(models, key=models.get)
print('Best model is', bestalgorithm,'with a score of', models[bestalgorithm])
if bestalgorithm == 'DecisionTree':
    print('Best params is :', tree_cv.best_params_)
if bestalgorithm == 'KNeighbors':
    print('Best params is :', knn_cv.best_params_)
if bestalgorithm == 'LogisticRegression':
    print('Best params is :', logreg_cv.best_params_)
if bestalgorithm == 'SupportVector':
    print('Best params is :', svm_cv.best_params_)
```

```
Best model is DecisionTree with a score of 0.8732142857142856
Best params is : {'criterion': 'gini', 'max_depth': 6, 'max_features': 'auto', 'min_samples_leaf': 2, 'min_samples_split': 5, 'splitter': 'random'}
```

Confusion Matrix

- The confusion matrix for the decision tree classifier shows that the classifier can distinguish between the different classes. The major problem is the false positives .i.e., unsuccessful landing marked as successful landing by the classifier.



Conclusions

We can conclude that:

- The larger the flight amount at a launch site, the greater the success rate at a launch site.
- Launch success rate started to increase in 2013 till 2020.
- Orbits ES-L1, GEO, HEO, SSO, VLEO had the most success rate.
- KSC LC-39A had the most successful launches of any sites.
- The Decision tree classifier is the best machine learning algorithm for this task.

Thank you!