IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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Outline

Executive Summary

- Summary of methodologies
- Summary of all results

Introduction

Background

- **SpaceX** is a private Space Exploration company. It designs, manufactures, and launches advanced rockets and spacecraft into various earth orbits. It competes with other companies in launching rockets/spacecrafts into orbits. The competitive advantage of SpaceX over its competitors is its ability to reuse the first stage of its Falcon 9 booster rockets, As such, based on this, SpaceX is in a position to quote lower launch price than its competitors, if they can reuse the captured booster from the launch.

Problem Statement

The business problems emanating from the above are as follows:

- First SpaceX is interested in assessing and predicting the probability of capturing the first stage of Falcon 9 booster rocket following a launch into orbit.

- Second, given the four launch sites they can launch from, they are interested in determining/identifying the launch site which is most likely to ensure a successful recapture of the booster rocket.

Section 1

Methodology

Methodology

Executive Summary

- Data collection methodology:
  - Describe how data was collected
- Perform data wrangling
  - Describe how data was processed
- 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

- Describe how data sets were collected.
  - Data was collected from sites on the internet using web scrapping applications
- You need to present your data collection process use key phrases and flowcharts

Data Collection – SpaceX API

Github Link:

#1:

https://github.com/iabiola1979/Course-10----Applied-Data-Science-Capstone/blob/main/Course10_iaa.py

#2:

jupyter-labs-spacex-data-collection-api-v2_iaa.ipynb

Import Python Libraries:

Requests

Pandas

numpy

4 Helper Files to get the following:

BoosterVersion, LaunchSites

PayloadData; and CoreData

TASK #1

- Using request library
  - → Get SpaceX past launch data from url
  - → Response is Jason data
- The Jason data is turned to pandas dataframe by applying pd.jason_normalise()
- Apply the 4 helper functions to extract BoosterVersion, LaunchSite, PayloadMass, FlightNumber, Date, oRbit, Longitude,latititude, and etc.

TASK #2

- Filter the data above by removing recods withFalcon1 Booster Version
- The flightNumber is then reset into their location in the list +1
- The last step test for records with missing values

TASK #3

- Compute the mean value of payload mass from dataframe from Task #2
- Then replace missing value of payload mass with calculated mean value.
- The dataframe from this task is then saved to a “dataset_part1.csv” file.

Data Collection - Scraping

- #1
- https://github.com/iabiola1979/Course-10----Applied-Data-Science-Capstone/blob/main/Course10-Webscrapping.py

- #2
- https://github.com/iabiola1979/Course-10----Applied-Data-Science-Capstone/blob/main/jupyter-labs-webscraping_vscode.ipynb

mport Python Libraries:

Sys, requests,

BeautifulSoup from bs4,

Re, unicodedata, and pandas

5 Helper Files to get the following:

date_time, booster_version, landing_status

get_mass, and extract_column_from_header

TASK #1

- Using request library
  - → Get Falcon 9 wiki page data from url
  - → Response is HTML encoded data
- Beautifulsoup is applied to parse the html encodings
- The title of html data is read from data as "<title>List of Falcon 9 and Falcon Heavy launches - Wikipedia</title>"

TASK #2

- By applying the helper functions to the 'table' we extract the data columns BoosterVersionPayloadMass, FlightNumber, Date, oRbit, Longitude,latititude, and etc.

TASK #3

- Extract individual fields e.g., where data and time are combined as a list
- Save the extracted data as a csv file.

Data Wrangling

Import Python Libraries:

1, Numpy

2. Pandas

- https://github.com/iabiola1979/Course-10---Applied-Data-Science-Capstone/blob/main/labs-jupyter-spa
v2.ipynb

Step #1

- Using Pandas, we load the data from data from previous step.
- To ensure we loaded the appropriate data we printed out the first five observations. Following , we check each field for percent of missing observations. All fields had 0% missing except "landind pad with 28% missing. Next, we check each colum ns. Most fields are numeric float64, others such as 'BoosterVersion', "LaunchSite', 'Outcome' are of object and there were three Boolean type fields as well ('reused', 'legs' and 'gridfins')

Step #2

- We further analyzed the counts by launchsites, the number of orbit types
- We analyzed the outcome of launches from this we made the determination whether it failed (0) or it was successful (1) . The last step was used to determine Y, the dependent variable. The success rate wass 66.67%

EDA with Data Visualization

- Summarize what charts were plotted and why you used those charts
- Visualize the relationship between the following variables in the dataset: between Flight Number and Launch Site; between Payload and Launch Site; between success rate of each orbit type; between FlightNumber and Orbit type; between Payload and Orbit type; and rate the launch success yearly trend
- https://github.com/iabiola1979/Course-10----Applied-Data-Science-Capstone/blob/main/jupyter-labs-eda-dataviz-v2.ipynb

EDA with SQL

- Display the names of the unique launch sites in the space mission
    - CCAFS LC-40 26
    - CCAFS SLC-40 34
    - KSC LC-39A 25
    - VAFB SLC-4E 16
- Display the total payload mass carried by boosters launched by NASA (CRS)
    - (619967,)
- Display average payload mass carried by booster version F9 v1.1
    - 6138.29
- List the date when the first succesful landing outcome in ground pad was acheived.
    - '2015-12-22'
- https://github.com/iabiola1979/Course-10----Applied-Data-Science-Capstone/blob/main/jupyter-labs-eda-sql-coursera_sqllite.ipynb

Build an Interactive Map with Folium

- Mark all launch sites on the MAP of USA– Florida and California
- Mark location with success/failure flags
- Mark the launch site by closeness to the coastline, nearest railine and the closest city/town

- https://github.com/iabiola1979/Course-10----Applied-Data-Science-Capstone/blob/main/lab-jupyter-launch-site-location-v2.ipynb

Build a Dashboard with Plotly Dash

- Plotted a pie chart that shows the distribution of launches by launch sites
- The second graph plots the relationship between the success rate and payload by the booster version

The pie chart is helpful is showing that the KSC LC 39A launch site produces the most successful launches.

- https://github.com/iabiola1979/Course-10----Applied-Data-Science-Capstone/blob/main/Module10-DashboardExam.py

Predictive Analysis (Classification)

- https://github.com/iabiola1979/Course-10----Applied-Data-Science-Capstone/blob/main/SpaceX-Machine-Learning-Prediction-Part-5-v1.ipynb

Import Python Libraries:

1, Numpy

2. Pandas

3.seaborn and

4 scikit-learn

Helper function leveraged

Plot_confusion_Matric()

Step #1

- Using Pandas, we load the data from data from previous step.
- To ensure we loaded the appropriate data we printed out the first five observations. Following , we check each field for percent of missing observations.
- We then assign the fields into X, the independent variables ; and Y the dependent variable with 1/0 value. The X variable was scaled using Standard Scaler to normalize the input variables. Following, we then apply sklearn.train a-test_split to assign records into 80% training group and 20% test group

Step #2

- We further analyzed the above data by running binary logistic regression , Support Vector classifier (SVC) model, decision tree model, and K-Nearest Neighbor model on the data. We used 10-fold cross to evaluate each of this model by evaluating their accuracy and confusion metrics.
- Logistic REgression perform best with 10-fold cross valition score 87.5%

Results

Exploratory data analysis results

- The plots indicate a significant relationship between payload mass a laund success with the most success from KSC LC -39A launchsite.

Interactive analytics demo in screenshots

Predictive analysis results

- The binary logistic regression model is the most predictive. The cross validation score on test sample is 87.5%. Next are and the Support vector classification and KNN models each with 83.3% and the last is the tree model with score of 72.2% in test sample.
- The confusion matrix however show that the binary logistic, SVM and KNN model have the same performance based on the confusion matrix.

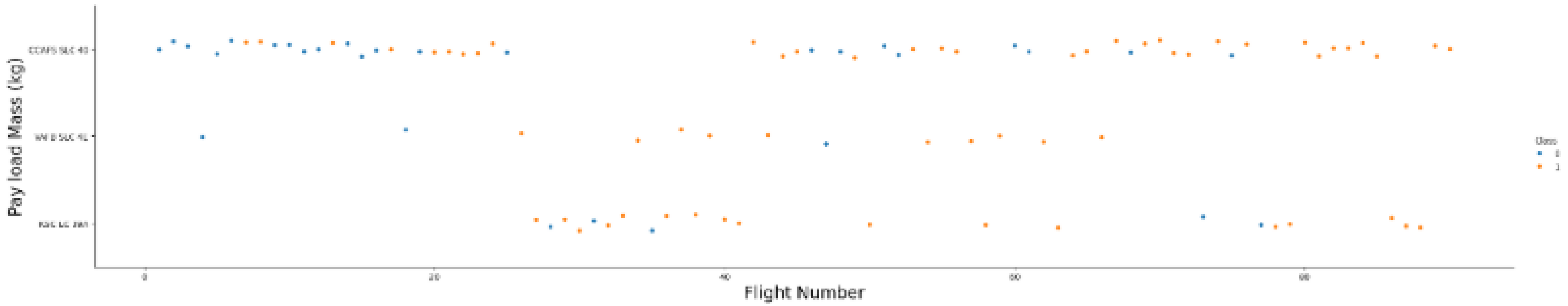
Section 2

Insights drawn from EDA

Flight Number vs. Launch Site

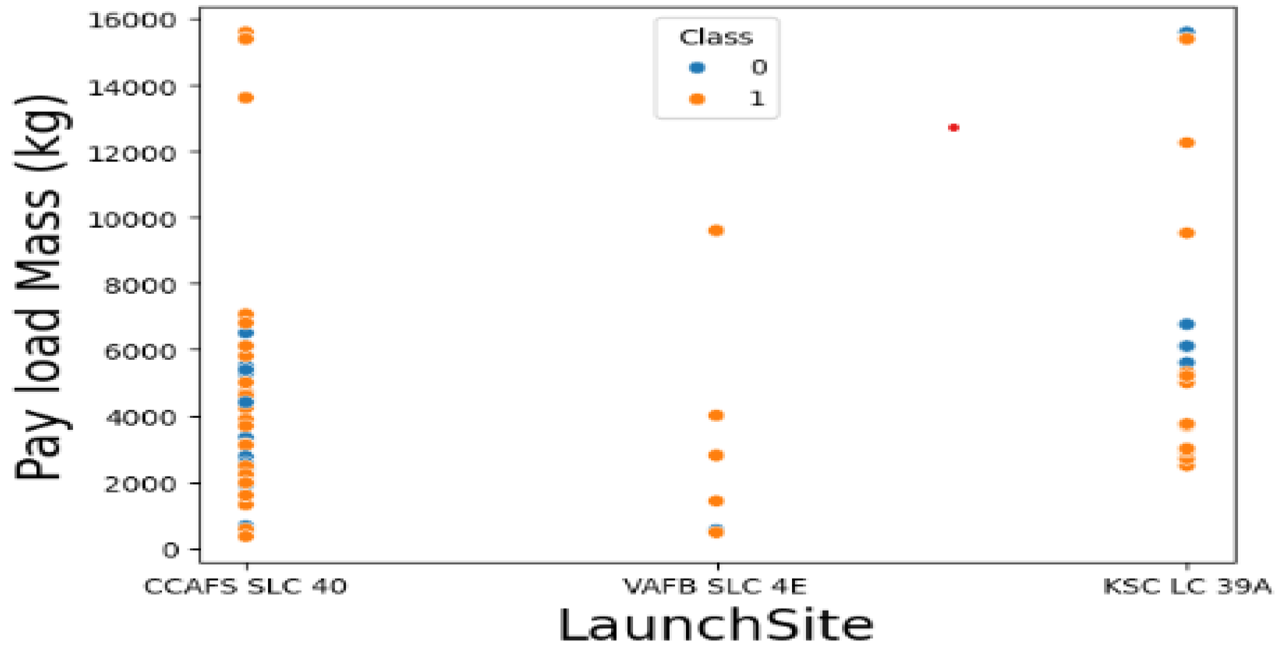
[6]:

```python
# 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 va
sns.catplot(y="LaunchSite", x="FlightNumber", hue="Class", data=df, aspect = 5)
plt.xlabel("Flight Number",fontsize=20)
plt.ylabel("Pay load Mass (kg)",fontsize=20)
plt.show()
```



Payload vs. Launch Site

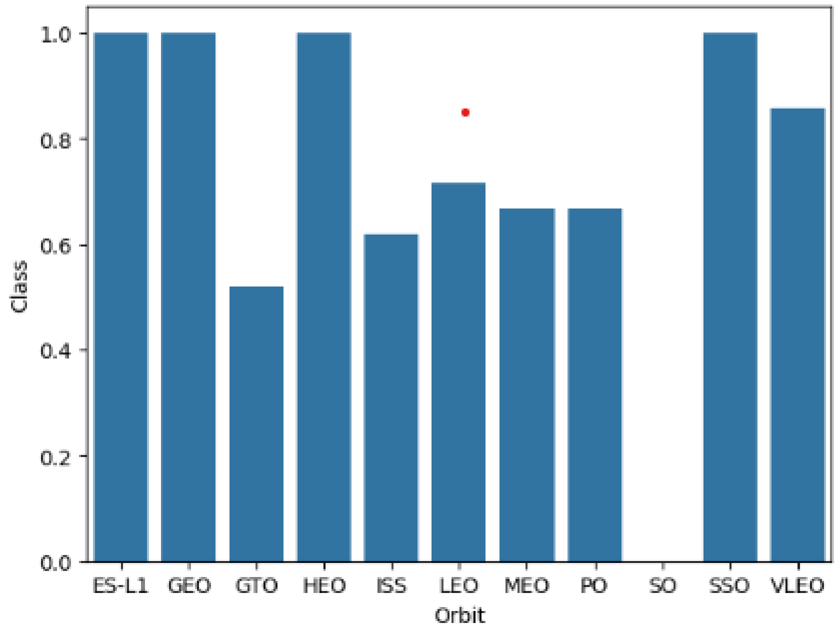
```
# Plot a scatter point chart with x axis to be Pay Load Mass (kg) and y axis to be the launch site, and
sns.scatterplot(y="PayloadMass", x="LaunchSite", hue="Class", data=df)
plt.xlabel("LaunchSite",fontsize=20)
plt.ylabel("Pay load Mass (kg)",fontsize=20)
plt.show()
```



Success Rate vs. Orbit Type

```
[15]: # HINT use groupby method on Orbit column and get the mean of Class column
      aa = df.groupby('Orbit')['Class'].mean().reset_index()
      sns.barplot(data=aa, x='Orbit', y='Class')
```

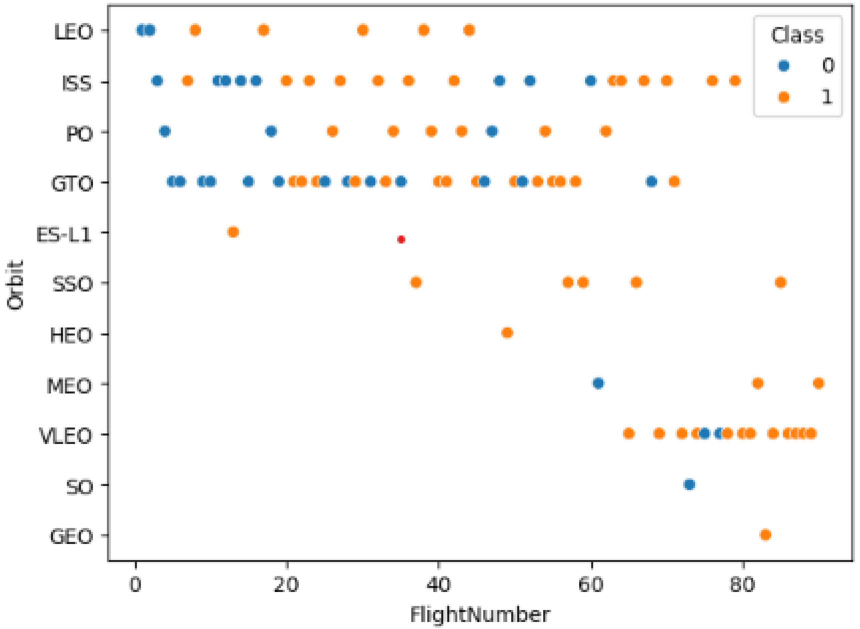
```
[15]: <Axes: xlabel='Orbit', ylabel='Class'>
```



Flight Number vs. Orbit Type

```
# 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.scatterplot(data=df, x='FlightNumber', y='Orbit', hue='Class')
```

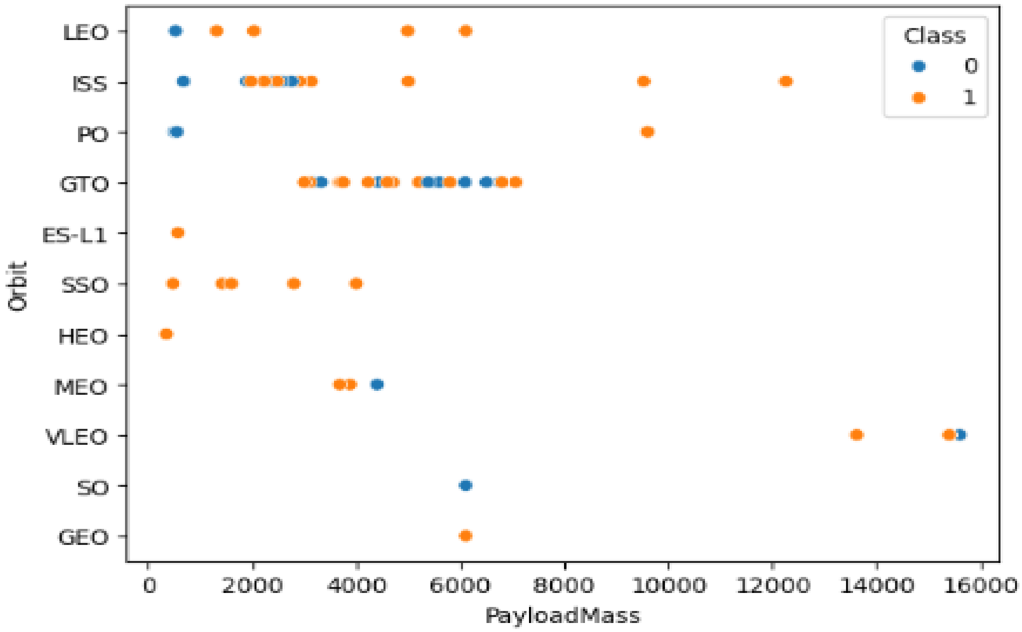
```
<Axes: xlabel='FlightNumber', ylabel='Orbit'>
```



Payload vs. Orbit Type

```
0]:  # 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.scatterplot(data=df, x='PayloadMass', y='Orbit',hue='Class')

0]:  <Axes: xlabel='PayloadMass', ylabel='Orbit'>
```

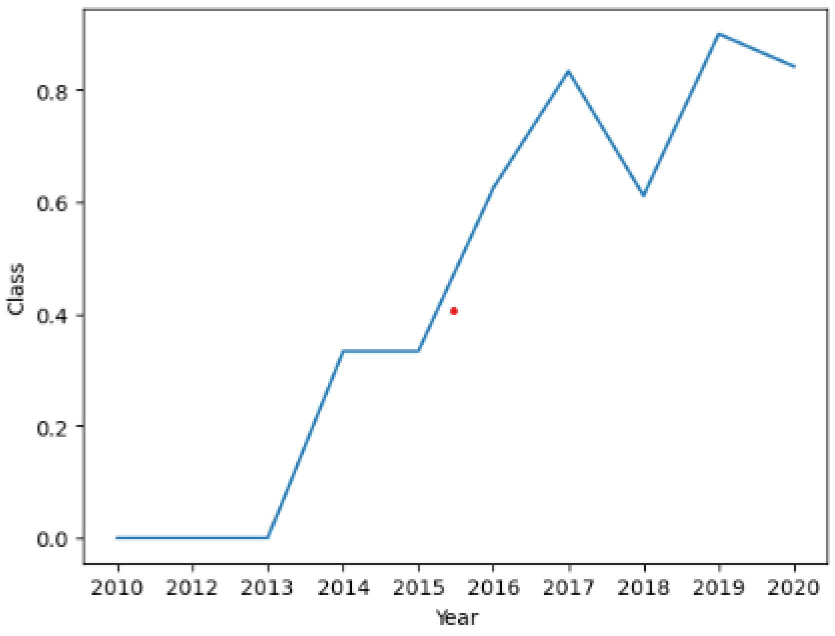


Launch Success Yearly Trend

```
# Plot a line chart with x axis to be the extracted year and y axis to be the success rate
xx = list(df.Date)
df['Year'] =[str(xx[i])[0:4] for i in range(len(xx))]

xdf = df.groupby('Year')['Class'].mean().reset_index()
xdf
sns.lineplot(data=xdf, x='Year', y='Class', errorbar= ('ci', 95))
```

```
<Axes: xlabel='Year', ylabel='Class'>
```



All Launch Site Names

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

```
cursor = conn.cursor()
cursor.execute("SELECT Launch_Site, COUNT(Launch_Site) as LS FROM spacex_table GROUP BY Launch_Site" )
result = cursor.fetchall()

for   k, v in result:

    print(k, v)
```

```
CCAFS LC-40 26
CCAFS SLC-40 34
KSC LC-39A 25
VAFB SLC-4E 16
```

Launch Site Names Begin with 'CCA'

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

```
cursor = conn.cursor()
cursor.execute("SELECT * FROM spacex_table WHERE  Launch_Site LIKE ?  LIMIT 5", ('%CCA%',) )
result = cursor.fetchall()

for   k in result:
     print(k)
```

```
('2010-06-04', '18:45:00', 'F9 v1.0  B0003', 'CCAFS LC-40', 'Dragon Spacecraft Qualification Unit', 0, 'LEO', 'SpaceX', 'Success', 'Failure (parachut
e)')
('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 (COT
S) NRO', 'Success', 'Failure (parachute)')
('2012-05-22', '7:44:00', 'F9 v1.0  B0005', 'CCAFS LC-40', 'Dragon demo flight C2', 525, 'LEO (ISS)', 'NASA (COTS)', 'Success', 'No attempt')
('2012-10-08', '0:35:00', '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

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

```
cursor = conn.cursor()
cursor.execute("SELECT sum(PAYLOAD_MASS__KG_) FROM spacex_table" )
result = cursor.fetchall()

for   k in result:
    print(k)
```

```
(619967,)
```

Average Payload Mass by F9 v1.1

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

```
cursor = conn.cursor()
cursor.execute("SELECT avg(PAYLOAD_MASS__KG_) FROM spacex_table" )
result = cursor.fetchall()

for   k in result:
     print(k)
```

```
(6138.287128712871,)
```

First Successful Ground Landing Date

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

Hint:Use min function

```
4]: cursor = conn.cursor()
cursor.execute("SELECT MIN(DATE) FROM spacex_table Where (Mission_Outcome =='Success') & (Landing_Outcome=='Success (ground pad)')" )
result = cursor.fetchall()

for   k in result:
    print(k)
```

```
('2015-12-22',)
```

Successful Drone Ship Landing with Payload between 4000 and 6000

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

```
cursor = conn.cursor()
cursor.execute("SELECT Booster_Version FROM spacex_table Where ((4000 < PAYLOAD_MASS__KG_) and (PAYLOAD_MASS__KG_ < 6000) ) & (Landing_Outcome=='Success
result = cursor.fetchall()

for   k in result:
    print(k)
```

```
('F9 FT B1022',)
('F9 FT B1026',)
('F9 FT  B1021.2',)
('F9 FT  B1031.2',)
```

Total Number of Successful and Failure Mission Outcomes

List the total number of successful and failure mission outcomes

```
cursor = conn.cursor()
cursor.execute("SELECT Mission_Outcome, count(Mission_Outcome) FROM spacex_table GROUP BY Mission_Outcome" )
result = cursor.fetchall()

for   k, v in result:
    print(k, v)
```

```
Failure (in flight) 1
Success 98
Success  1
Success (payload status unclear) 1
```

Boosters Carried Maximum Payload

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

```
cursor = conn.cursor()
cursor.execute("SELECT Booster_Version FROM spacex_table Where  PAYLOAD_MASS__KG_= (SELECT Max(PAYLOAD_MASS__KG_) FROM spacex_table)" )
result = cursor.fetchall()

for   k in result:
     print(k)
```

```
('F9 B5 B1048.4',) •••
```

2015 Launch Records

List the records which will display the month names, failure landing_outcomes in drone ship ,booster versions, launch_site for the months in year 2015.

Note: SQLLite does not support monthnames. So you need to use substr(Date, 6,2) as month to get the months and substr(Date,0,5)='2015' for year.

```
xmonth = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec']
monthdict={}

for i in   range(len(xmonth)):
     if i+1 < 10:
         monthdict['0'+str(i+1)] = xmonth[i]
     else:
        monthdict[str(i+1)] = xmonth[i]



cursor = conn.cursor()
cursor.execute("SELECT  substr(Date, 6,2), substr(Date,0,5), Booster_Version, Launch_Site, Landing_Outcome  FROM spacex_table  Where (Landing_Outcome ==
result = cursor.fetchall()

print('Month','Year','Booster_Version', 'Launch_Site', 'Landing_Outcome')
for i, j, k, l, m in result:
    print(monthdict[i],j,k,l,m)
```

```
Month Year Booster_Version Launch_Site Landing_Outcome
Jan 2015 F9 v1.1 B1012 CCAFS LC-40 Failure (drone ship)
Apr 2015 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)) between the date 2010-06-04 and 2017-03-20, in descending order.

```
cursor = conn.cursor()
cursor.execute("SELECT  Landing_Outcome, count(Landing_Outcome) as counter  FROM spacex_table  \
                      where ('2010-06-04' <= Date) & (Date <='2017-03-20') \
                      Group by Landing_Outcome" )
result = cursor.fetchall()

print('Landing_Outcome', 'Counter')
for i,j in result:
    print(i,j)
```

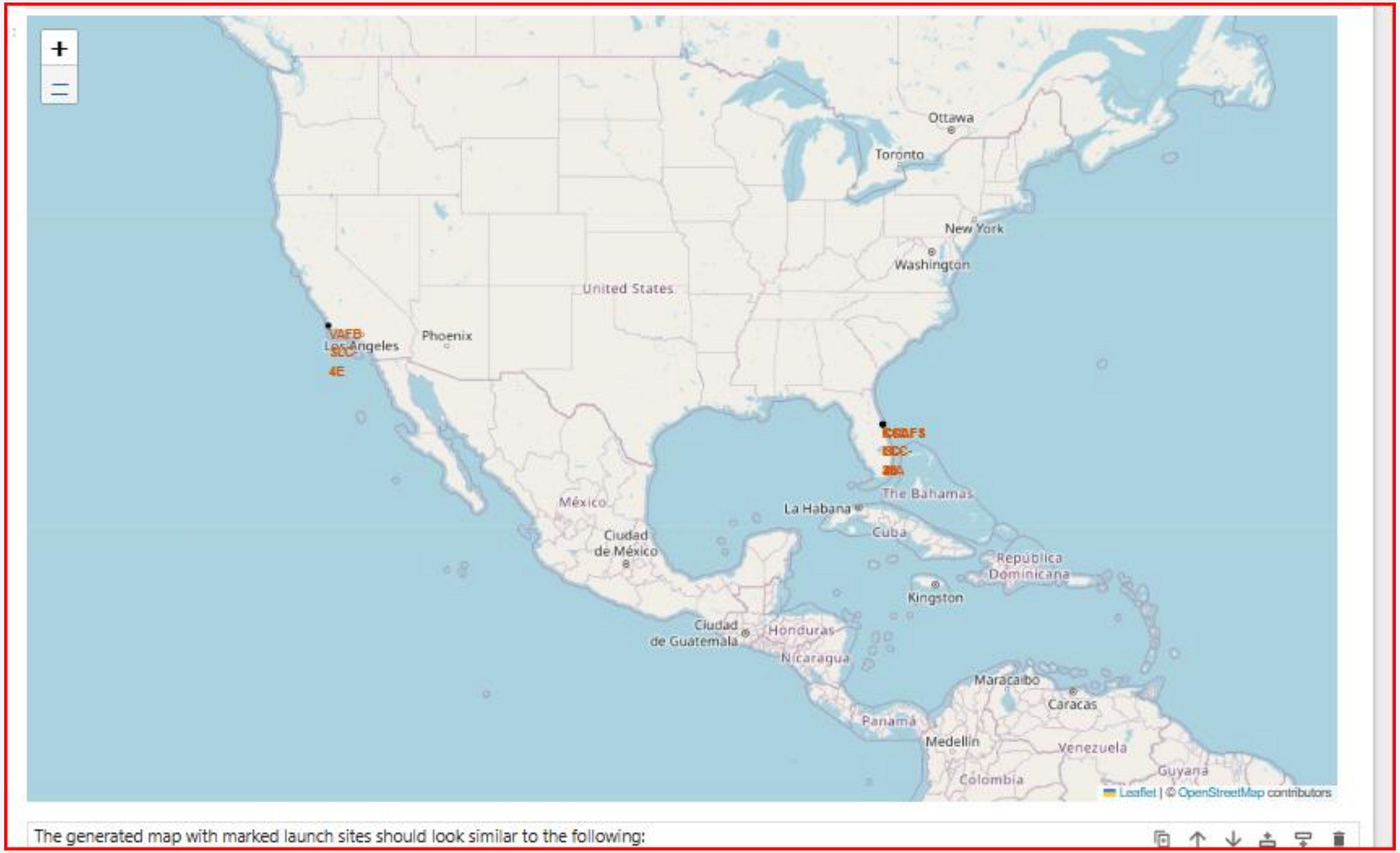
```
Landing_Outcome Counter
Controlled (ocean) 3
Failure (drone ship) 5
Failure (parachute) 2
No attempt 10
Precluded (drone ship) 1
Success (drone ship) 5
Success (ground pad) 3
Uncontrolled (ocean) 2
```

Section 3

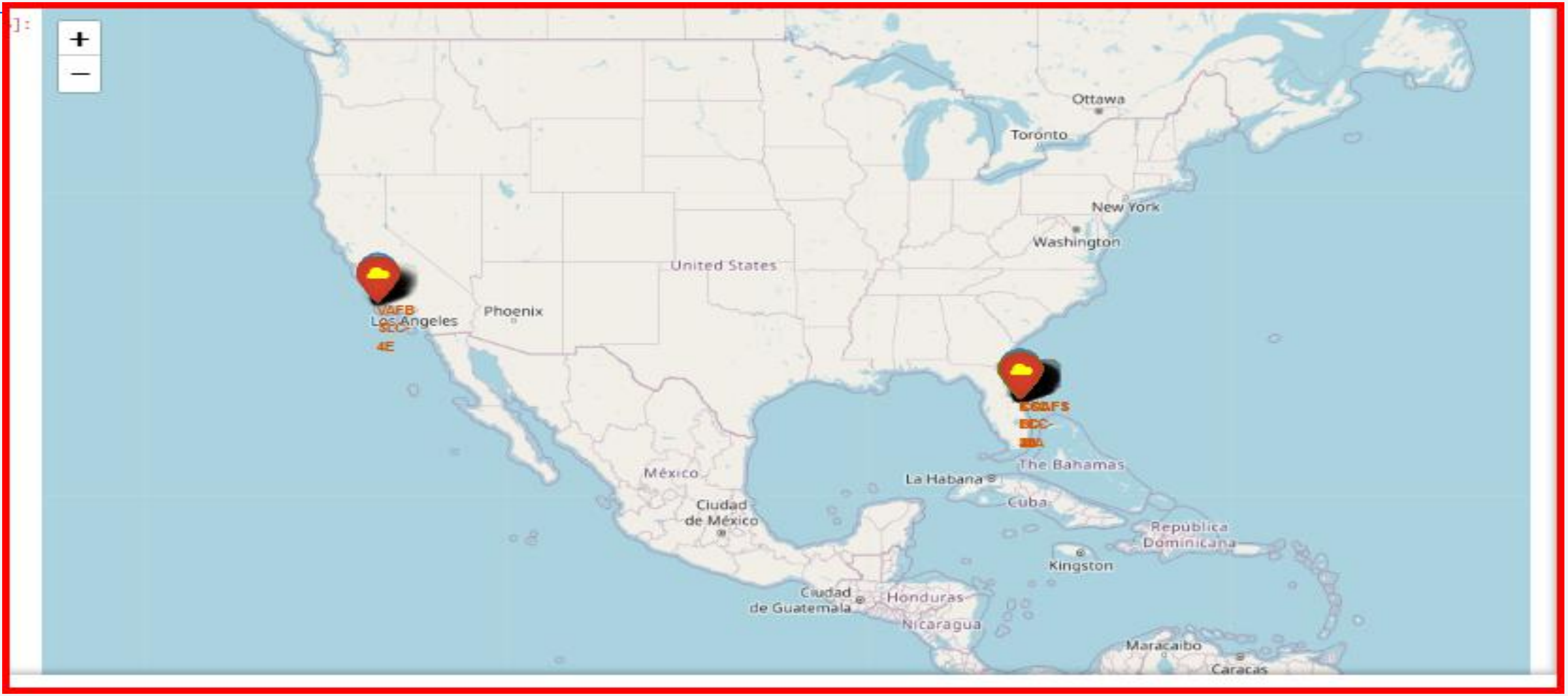
Launch Sites Proximities Analysis

Falcon 9 Rockets Launch Sites

- The four locations where Falcon 9 rockets are launched in California and Florida



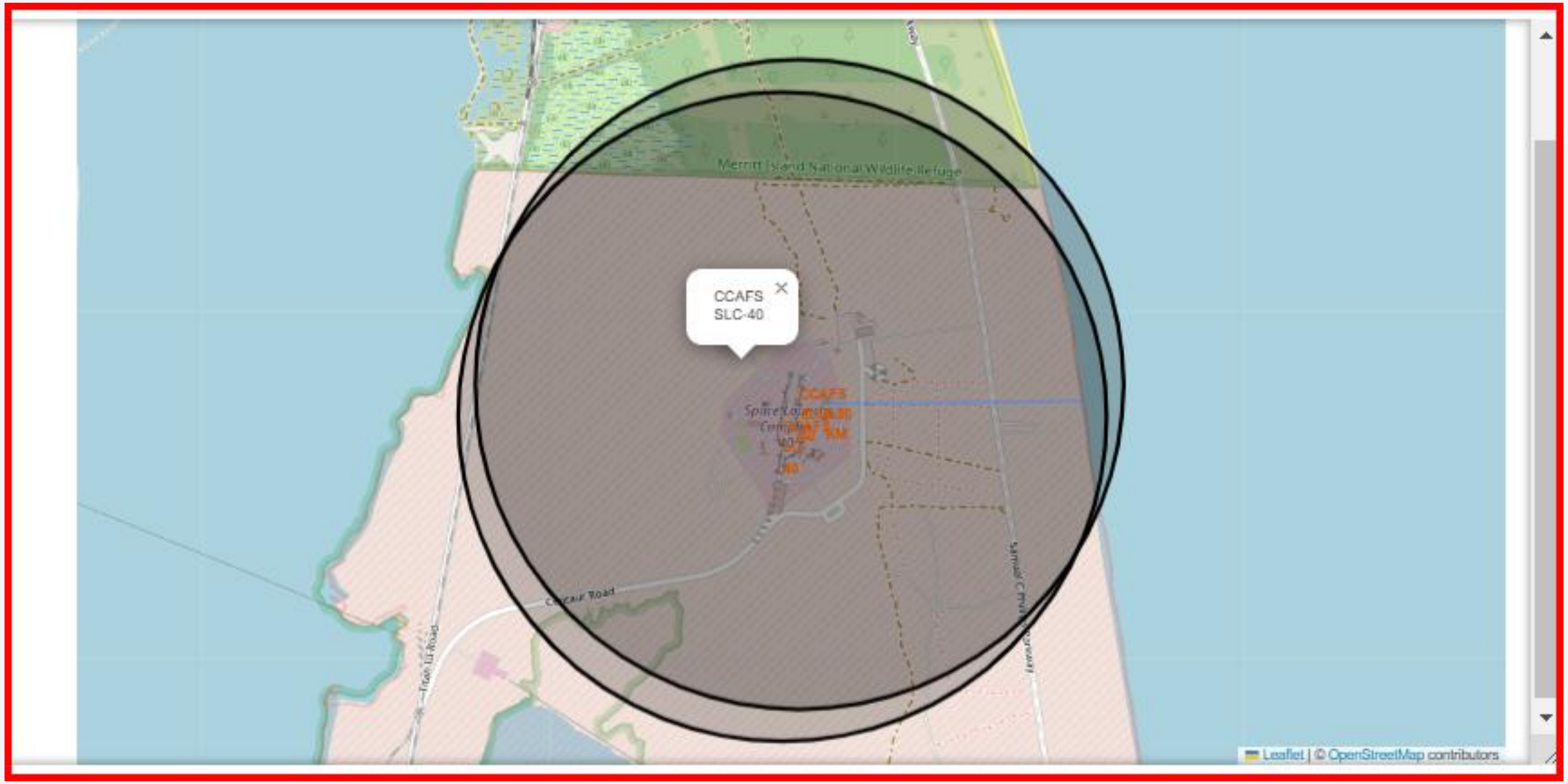
Launch Sites Marked with Success/Failures



Launch Site Closeness to Facilities—Beach, Rail and Cities

- Launch site proximities t0 railway, highway, coastline, with distance calculated and displayed

- Launch site is about 9 miles to the beach and there is no city nearby.



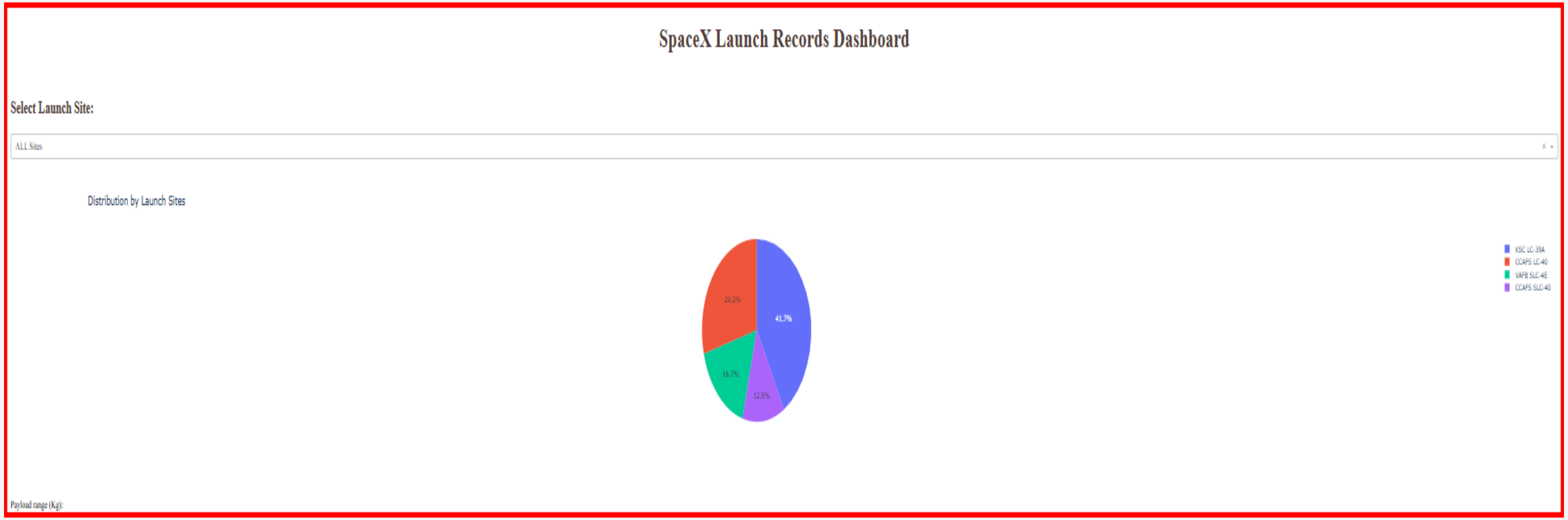
Section 4

Build a Dashboard with Plotly Dash

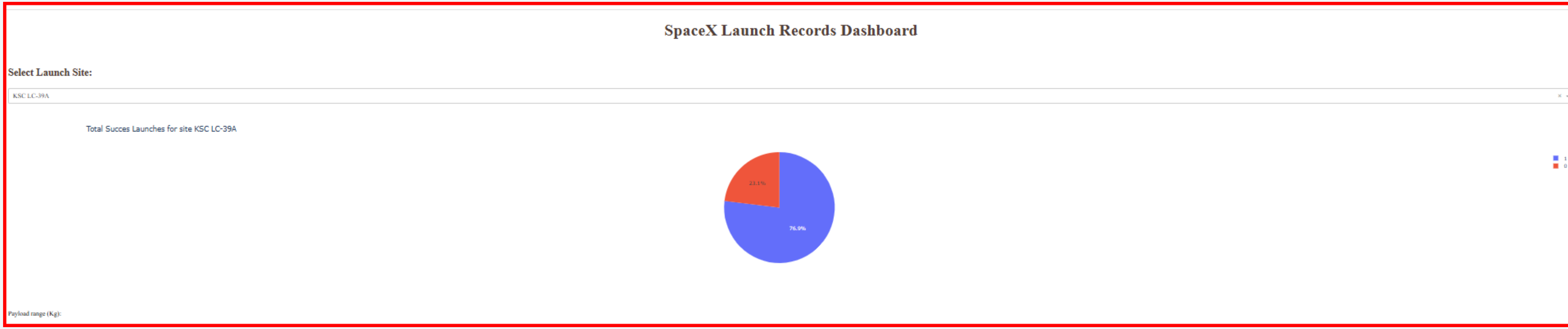
Launch Site Success Rate Distrinution

- Show the screenshot of launch success count for all sites, in a piechart

- KSC LC 39A is the best site for successful launch of all the available launch sites.



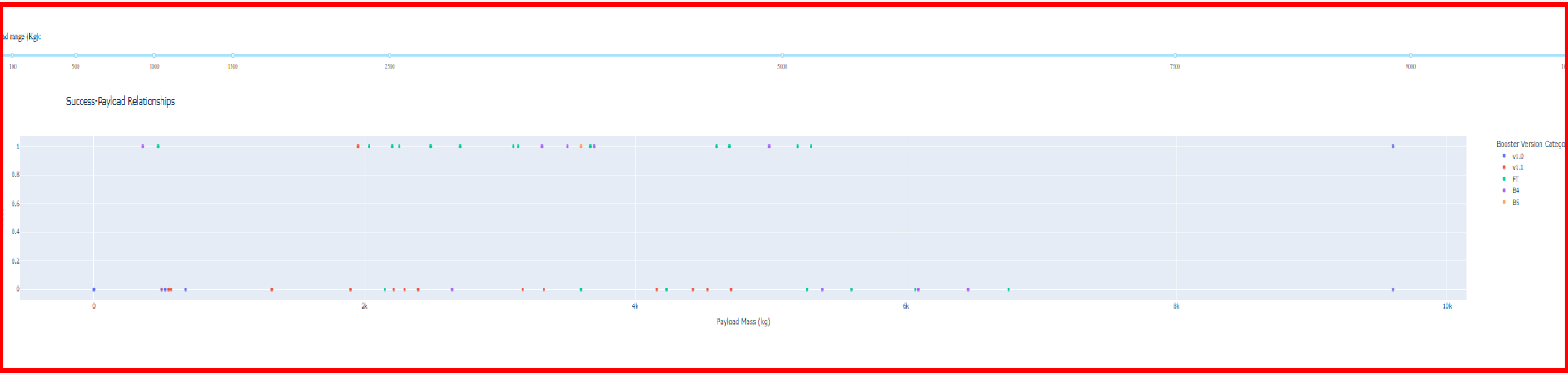
KSC LC -39A Launch Site Success Rate



- Show the screenshot of the piechart for the launch site with highest launch success ratio

- The site have a successful launch rate of 76.9%

Successful Luanch – Payload Relationship by Rocket Type



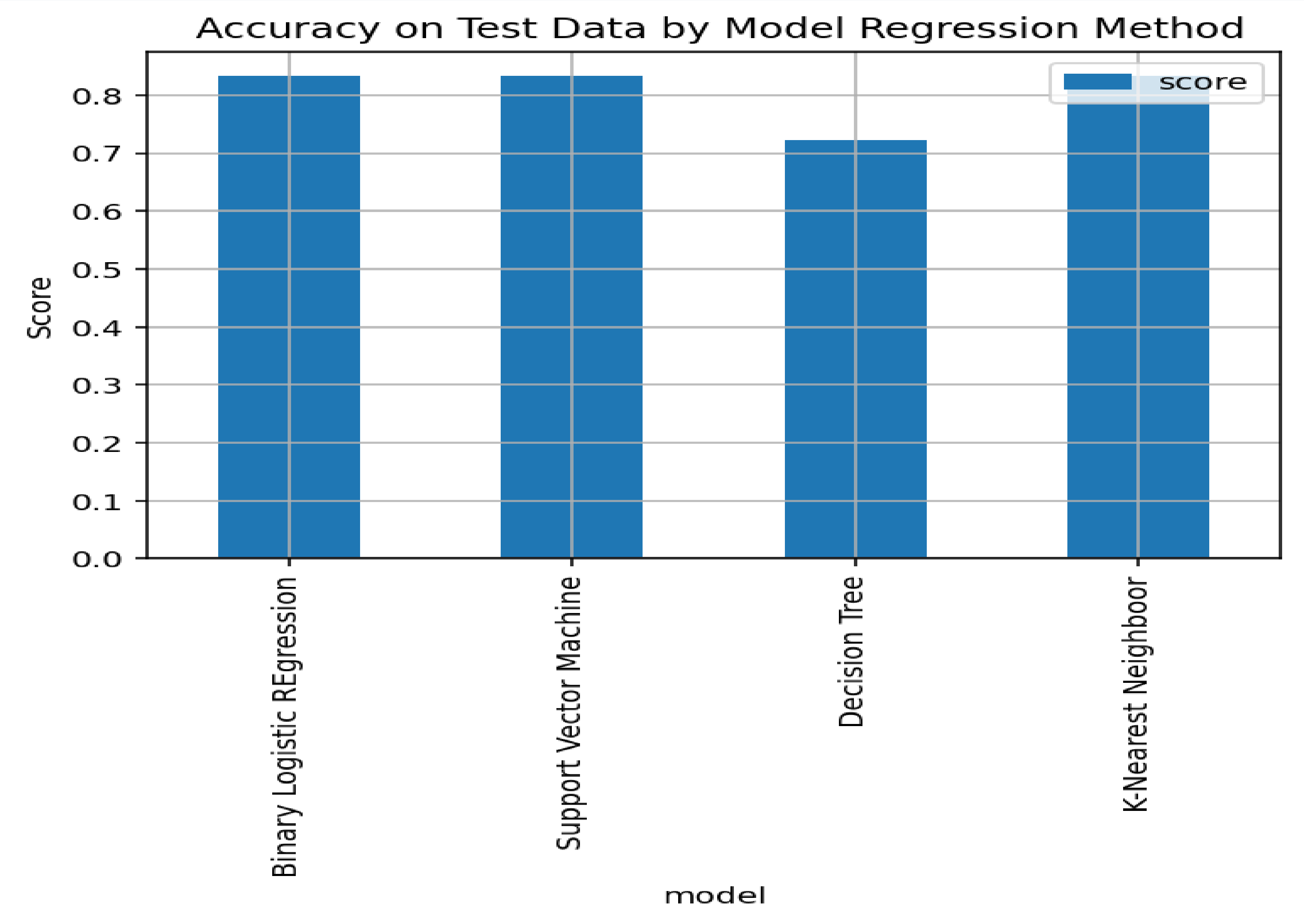
- The FT booster is the most successful given that most of the launches in reach orbit

Section 5

Predictive Analysis (Classification)

Classification Accuracy

- Binary Logistic, Support Vector Machines and KNN Regression have the best accuracy. They are the tallest and the score value is the same at 83.3%.



Confusion Matrix

- The confusion matrix of logistic regression , SVM and KNN are similar. They also have the same score on the test sample.

Conclusions

- The predictive accuracy as measured by the score, of the binary logisic regression, the support vector machine, and the K-Nearest Neighbor model on the test data are the same. Thus none is preferred over the other in this study.
- The confusion matrix of the three models are also the same which further reinforces the fact that the models performs similarly.
- The tree model though easy to interprete and explain is not the preferred choice here because its performance in the test sample is not as good as the other models.
- …

Appendix

- Include any relevant assets like Python code snippets, SQL queries, charts, Notebook outputs, or data sets that you may have created during this project

Thank you!