IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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Executive Summary

- Summary of methodologies
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    - Predictive Analytics result

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. The goal of the project is to create a machine learning pipeline to predict whether the first stage will land successfully.

- Problems you want to find answers

  What factors determine whether the rocket will land successfully?

  The interaction between various characteristics that determine the success rate of a landing?

  What operational conditions must be in place to ensure a successful landing programme?

Section 1

Methodology

Methodology

Executive Summary

- Data collection methodology:
  - The data was collected using the SpaceX API and Wikipedia web scraping.
- Perform data wrangling
  - One-hot encoding was applied to categorical features to improve the prediction of machine learning algorithms.
- 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 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 have used the SpaceX API get request to collect data, clean the requested data and perform some basic data manipulation and formatting operations.

- Link to the notebook

We start requesting rocket launch data from SpaceX API with the following URL:

```python
spacex_url="https://api.spacexdata.com/v4/launches/past"
response = requests.get(spacex_url)
```

Python

We decode the response content as a Json using .json() and turn it into a Pandas dataframe using .json_normalize()

```python
data = pd.json_normalize(response.json())
```

Python

We will remove the Falcon 1 launches keeping only the Falcon 9 launches. Filter the data dataframe using the BoosterVersion column to only keep the Falcon 9 launches. Save the filtered data to a new dataframe called data_falcon9

```python
data_falcon9 = df[df['BoosterVersion']!='Falcon 1']
data_falcon9.loc[:,'FlightNumber'] = list(range(1, data_falcon9.shape[0]+1))
```

Python

Fill in the missing values by calculating below the mean for the PayloadMass using the .mean(). Then use the mean and the .replace() function to replace np.nan values in the data with the mean you calculated.

```python
payloadmassavg = data_falcon9['PayloadMass'].mean()
data_falcon9['PayloadMass'].replace(np.nan, payloadmassavg, inplace=True)
```

Python

Data Collection - Scraping

- We applied web scrapping to webscrap Falcon 9 launch records with BeautifulSoup
- We parsed the table and converted it into a pandas dataframe.
- [Link to the notebook]

We perform an HTTP GET method to request the Falcon9 Launch HTML page, as an HTTP response. Using requests.get() method with the provided static_url and assigning the response to a object, we create a BeautifulSoup object from the HTML response.

```python
static_url = "https://en.wikipedia.org/w/index.php?title=List_of_Falcon_9_and_Falcon_Heavy_launches&oldid=1027686922"
data  = requests.get(static_url).text
soup = BeautifulSoup(data, "html.parser")
```

Python

We print the page title to verify if the BeautifulSoup object was created properly and then, we will extract all column/variable names from the HTML table header to create an empty dictionary with the names as keys.

+ Código + Markdown

We use the find_all function in the BeautifulSoup object, with element type `table` and we assign the result to a list called `html_tables`. Next, we just need to iterate through the elements and apply the provided extract_column_from_header() to extract column name one by one

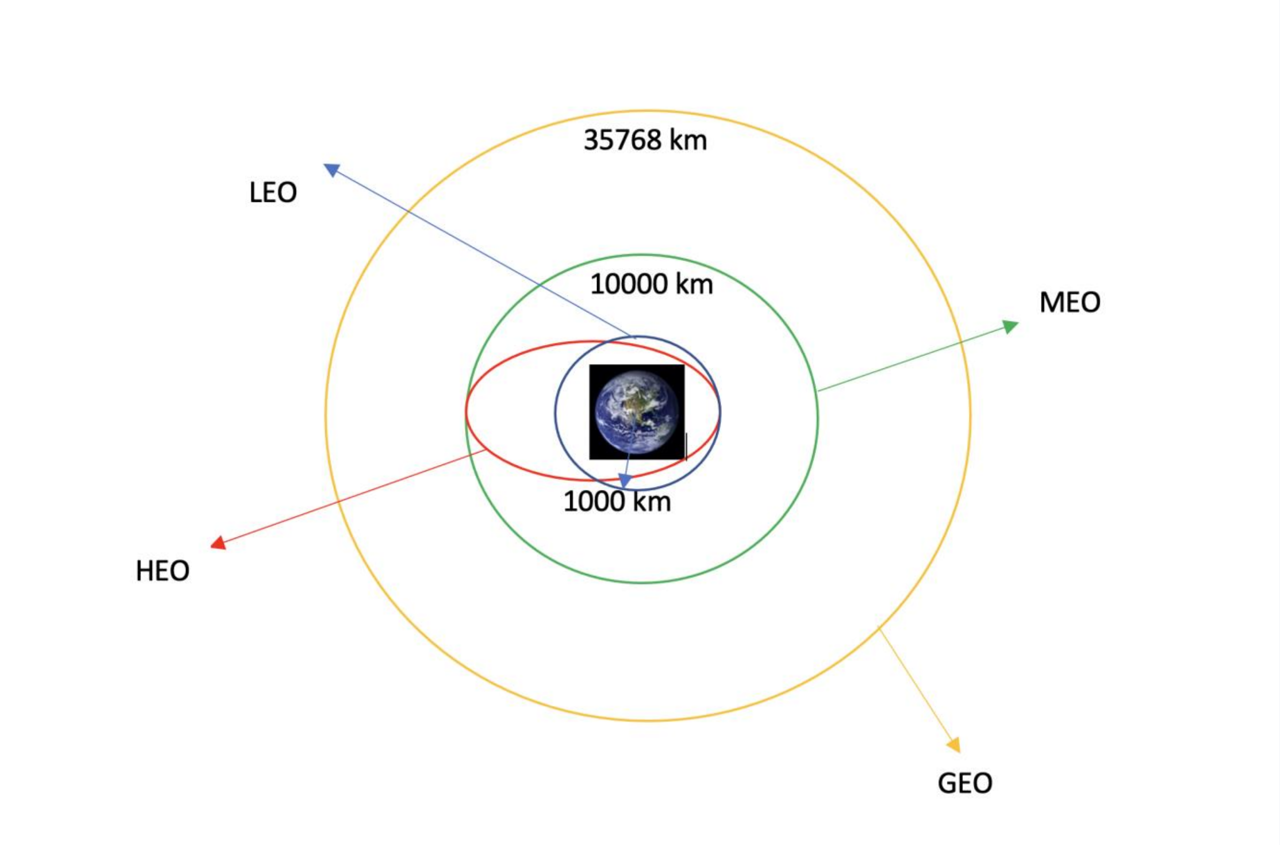
```python
html_tables = soup.find_all('table')
column_names = []
for row in first_launch_table.find_all('th'):
    name = extract_column_from_header(row)
    if (name != None and len(name) > 0):
        column_names.append(name)
```

Python

Finally, we just need to fill up the launch_dict with launch records extracted from table rows and export data to csv.

Data Wrangling

- We performed exploratory data analysis and determined the training labels.
- We calculated the number of launches at each site, and the number and occurrence of each orbits
- We created landing outcome label from outcome column and exported the results to csv.



- [Link to the notebook]

EDA with Data Visualization

- 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 yearly trend.
- Scatter diagrams were used to visualise the relationship between some numerical variables, bar charts to visualise the relationship between a numerical variable and a categorical variable, and line diagrams to study trends over the years.

- [Link to the notebook]()

EDA with SQL

- We load the SQL extension and establish a connection with the database.
- 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.

- Link to the notebook

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.

- Link to the notebook

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.

- Link to the notebook

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.

- Link to the notebook

Results

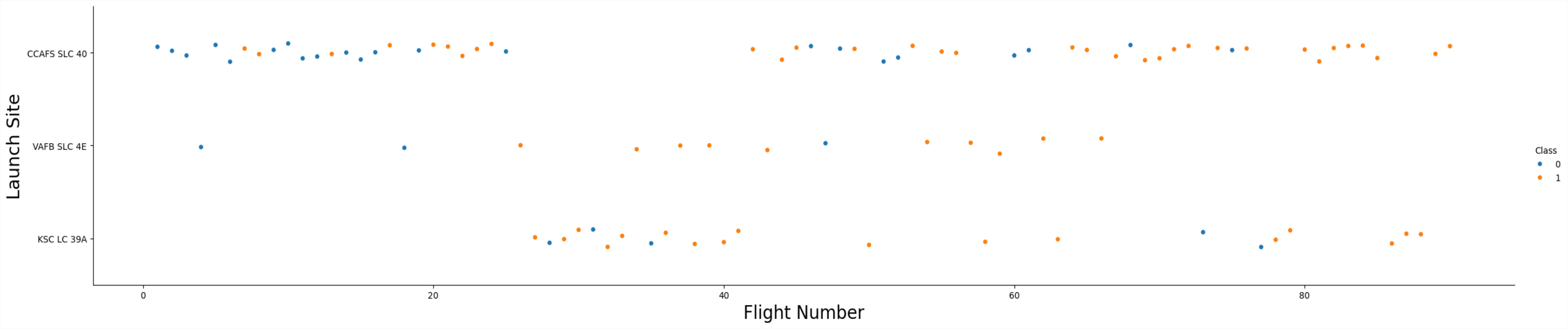
- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results

Section 2

Insights drawn from EDA

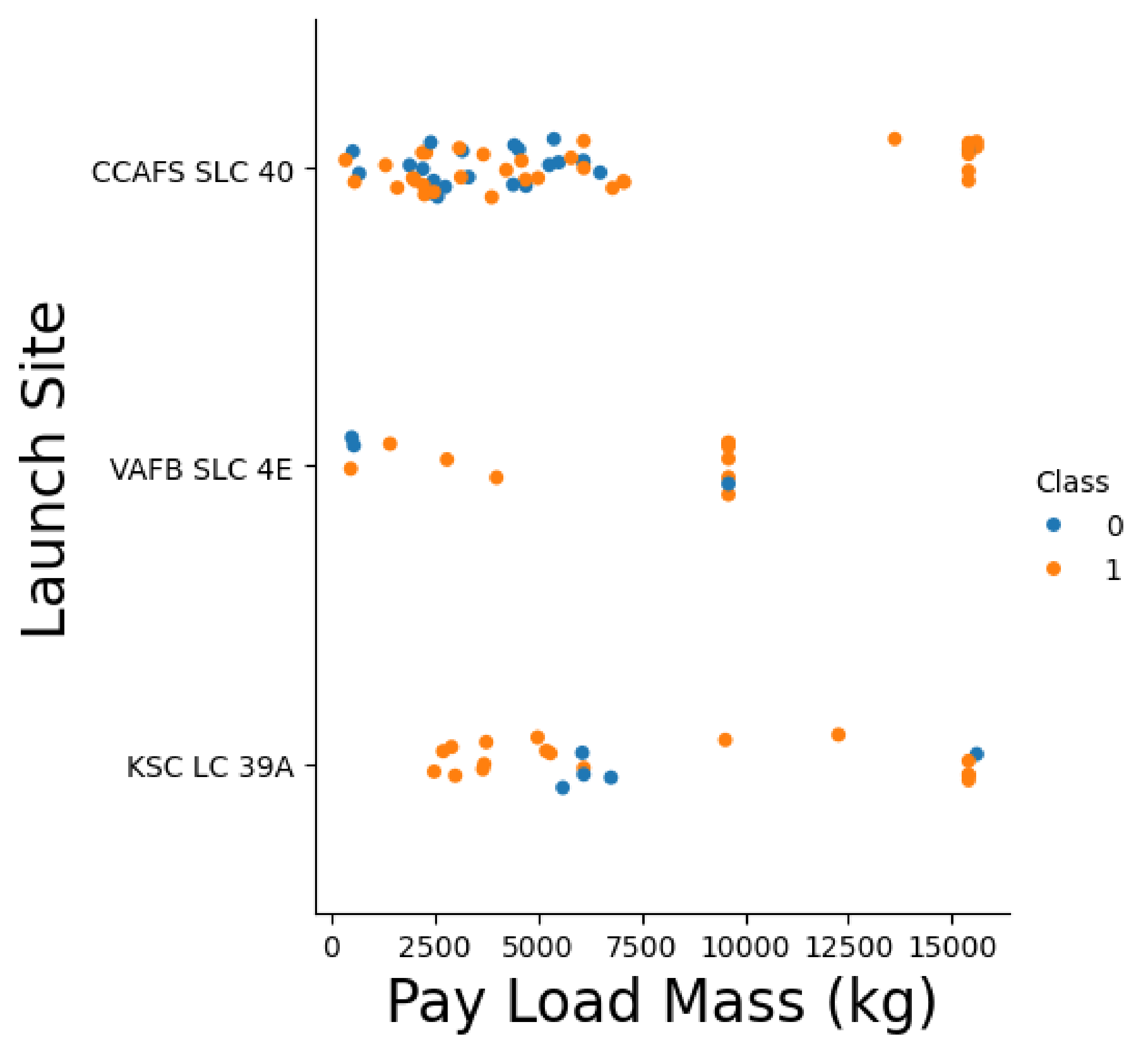
Flight Number vs. Launch Site

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



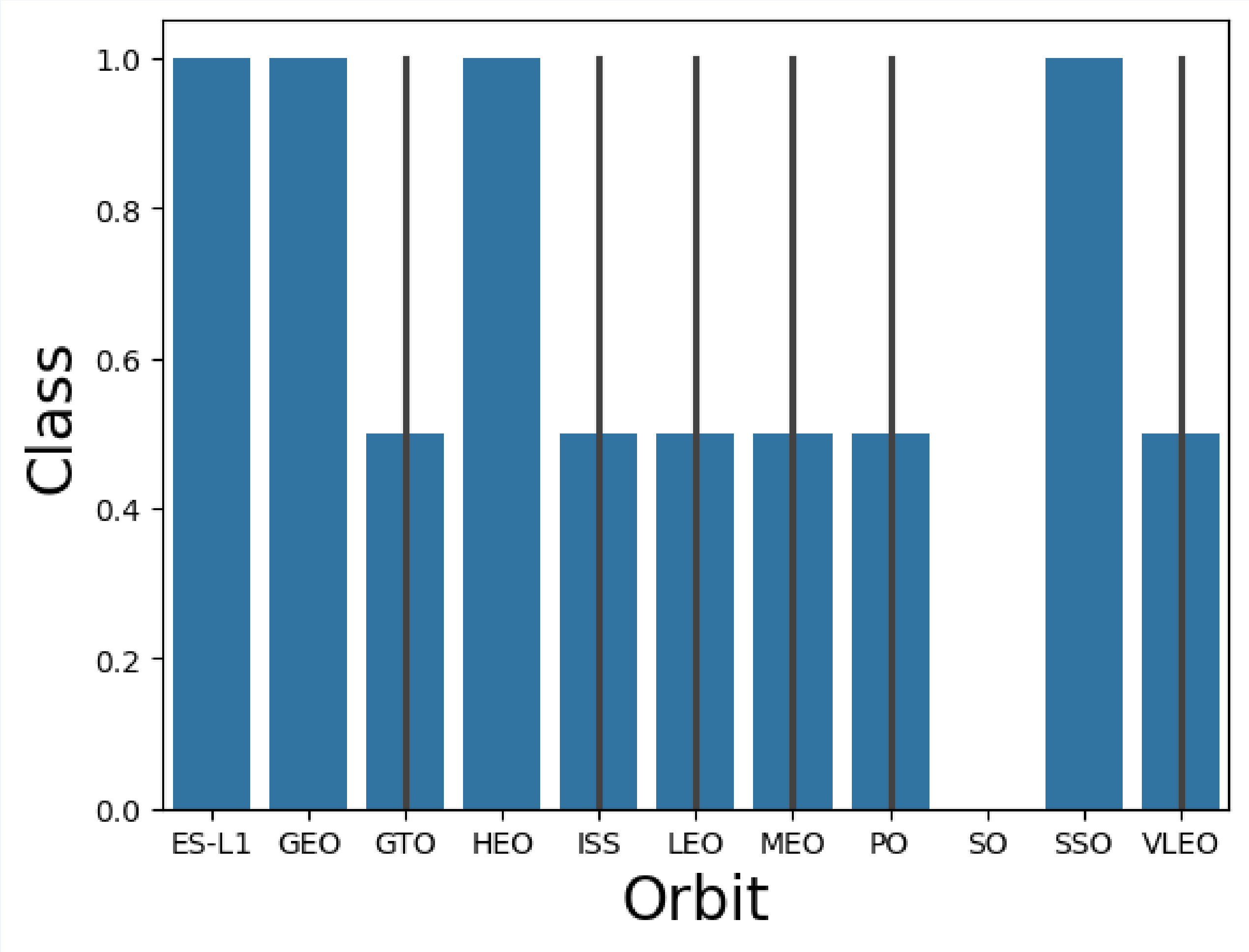
Payload vs. Launch Site

- The greater the playload mass for launch site CCAFS SLC 40
- The higher the success rate for the rocket.



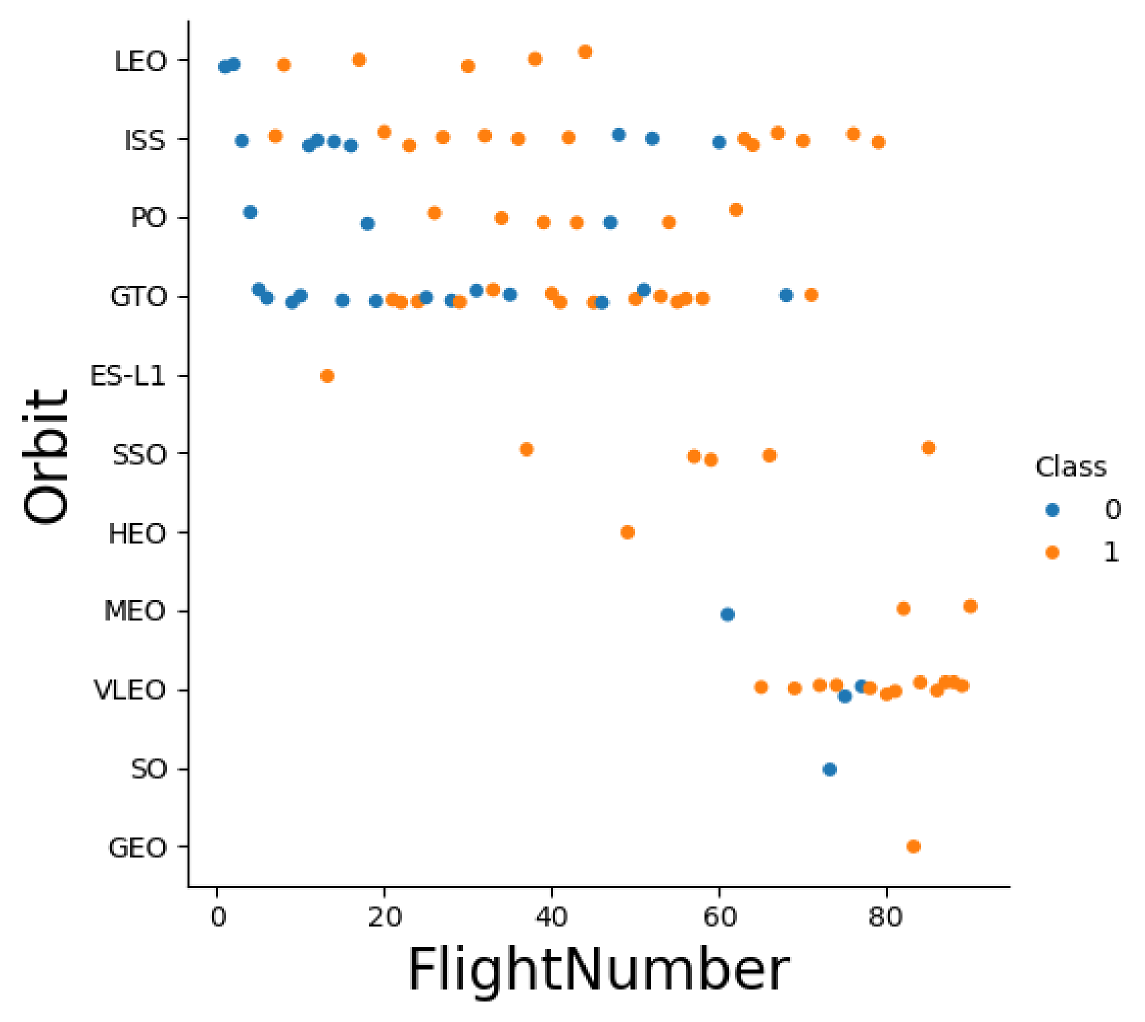
Success Rate vs. Orbit Type

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



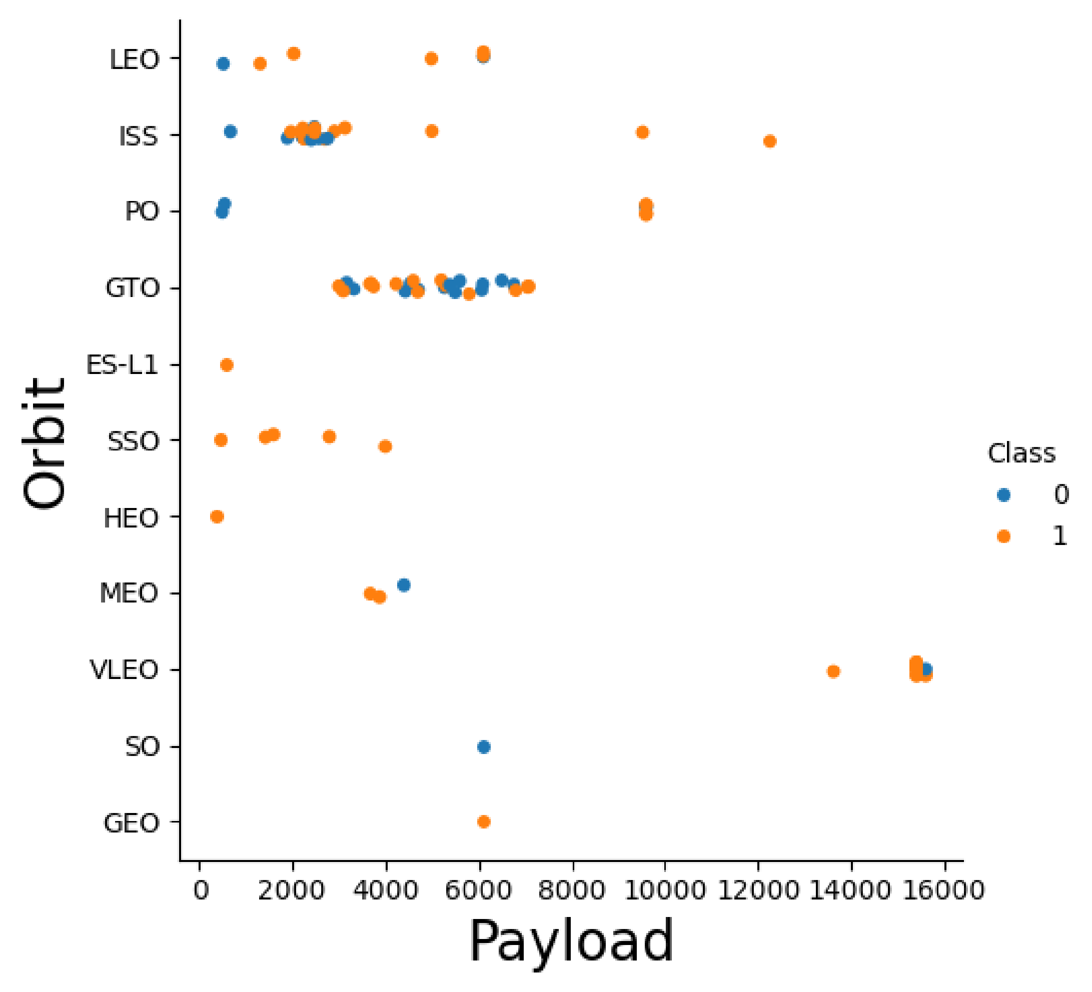
Flight Number vs. Orbit Type

- 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.



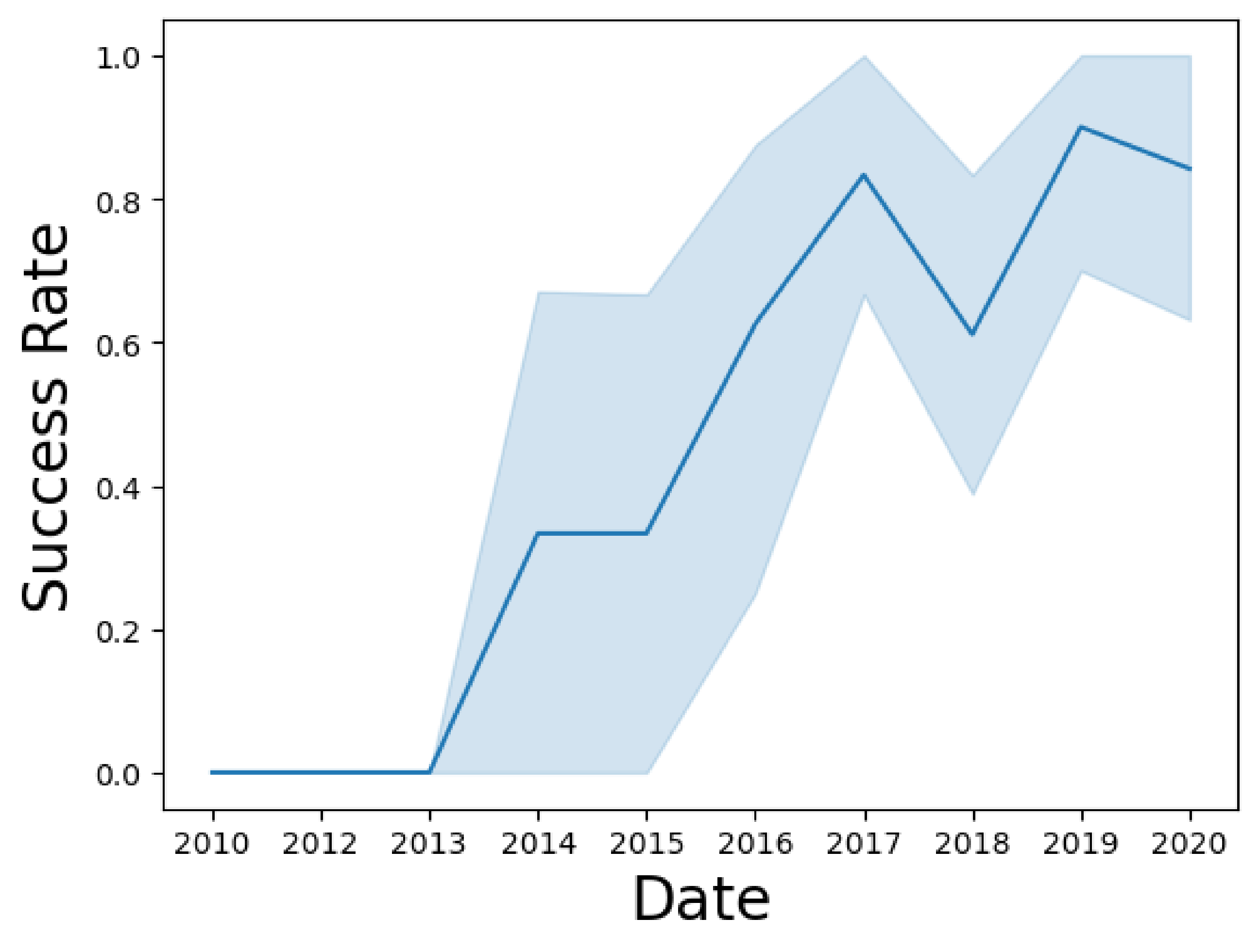
Payload vs. Orbit Type

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



Launch Success Yearly Trend

- From the plot, we can observe that success rate since 2013 kept on increasing till 2020.



All Launch Site Names

- We used the key word **DISTINCT** to show only unique launch sites from the SpaceX data.

```
%%sql
SELECT DISTINCT LAUNCH_SITE
FROM SPACEXTBL;
```

```
 * sqlite:///my_data1.db
Done.
```

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

Launch Site Names Begin with 'CCA'

- We used the query above to display 5 records where launch sites begin with `CCA`

```
%%sql
SELECT LAUNCH_SITE
FROM SPACEXTBL
WHERE LAUNCH_SITE LIKE 'CCA%'
LIMIT 5;
```

```
* sqlite:///my_data1.db
Done.
```

Launch_Site
CCAFS LC-40
CCAFS LC-40
CCAFS LC-40
CCAFS LC-40
CCAFS LC-40

Total Payload Mass

- We calculated the total payload carried by boosters from NASA as 45596 using the query below

```
%%sql
SELECT SUM(PAYLOAD_MASS__KG_)
FROM SPACEXTBL
WHERE Customer = 'NASA (CRS)';
```

```
 * sqlite:///my_data1.db
Done.
```

SUM(PAYLOAD_MASS__KG_)
45596

Average Payload Mass by F9 v1.1

- We observed that the dates of the first successful landing outcome on ground pad was 22nd December 2015

```
%%sql
SELECT AVG(PAYLOAD_MASS__KG_)
FROM SPACEXTBL
WHERE Booster_Version LIKE 'F9 v1.0%';
```

```
 * sqlite:///my_data1.db
Done.
```

AVG(PAYLOAD_MASS__KG_)
340.4

First Successful Ground Landing Date

- We observed that the dates of the first successful landing outcome on ground pad was 22nd December 2015

```
%%sql
SELECT MIN(Date)
FROM SPACEXTBL
WHERE Landing_Outcome = 'Success (ground pad)';
```

```
 * sqlite:///my_data1.db
Done.
```

MIN(Date)
2015-12-22

Successful Drone Ship Landing with Payload between 4000 and 6000

- We used the **WHERE** clause to filter for boosters which have successfully landed on drone ship and applied the **AND** condition to determine successful landing with payload mass greater than 4000 but less than 6000

```
%%sql
SELECT BOOSTER_VERSION
FROM SPACEXTBL
WHERE LANDING_OUTCOME = 'Success (drone ship)'
    AND 4000 < PAYLOAD_MASS__KG_ < 6000;
```

```
 * sqlite:///my_data1.db
Done.
```

Booster_Version
F9 FT B1021.1
F9 FT B1022
F9 FT B1023.1
F9 FT B1026
F9 FT B1029.1
F9 FT B1021.2
F9 FT B1029.2
F9 FT B1036.1
F9 FT B1038.1
F9 B4 B1041.1
F9 FT B1031.2
F9 B4 B1042.1
F9 B4 B1045.1
F9 B5 B1046.1

Total Number of Successful and Failure Mission Outcomes

- We selected Mission_outcome and the **COUNT** of Mission_outcome from the data
- We applied the **GROUP BY** clause to group the Mission_outcome.

```
%%sql
SELECT MISSION_OUTCOME, COUNT(MISSION_OUTCOME) AS TOTAL_NUMBER
FROM SPACEXTBL
GROUP BY MISSION_OUTCOME;
```

```
 * sqlite:///my_data1.db
Done.
```

Mission_Outcome	TOTAL_NUMBER
Failure (in flight)	1
Success	98
Success	1
Success (payload status unclear)	1

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.

```
%%sql
SELECT DISTINCT BOOSTER_VERSION
FROM SPACEXTBL
WHERE PAYLOAD_MASS__KG_ = (
    SELECT MAX(PAYLOAD_MASS__KG_)
    FROM SPACEXTBL);
```

```
 * sqlite:///my_data1.db
Done.
```

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

- We selected Landing outcomes, Booster_version, Launch_site and the number of the month from the date column subtracting it with the command subtr from the data and used the **WHERE** clause to filter for landing outcomes='Failure (drone ship)' and for year=2015 in the column Date

```
%%sql SELECT BOOSTER_VERSION, LAUNCH_SITE, LANDING_OUTCOME, substr(Date,6,2) as month
    FROM SPACEXTBL
    WHERE LANDING_OUTCOME = 'Failure (drone ship)' and substr(Date,0,5)='2015';
```

```
 * sqlite:///my_data1.db
Done.
```

Booster_Version	Launch_Site	Landing_Outcome	month
F9 v1.1 B1012	CCAFS LC-40	Failure (drone ship)	01
F9 v1.1 B1015	CCAFS LC-40	Failure (drone ship)	04

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

- 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.

```
%%sql
SELECT LANDING_OUTCOME, COUNT(LANDING_OUTCOME) AS TOTAL_NUMBER
FROM SPACEXTBL
WHERE DATE BETWEEN '2010-06-04' AND '2017-03-20'
GROUP BY LANDING_OUTCOME
ORDER BY TOTAL_NUMBER DESC
```

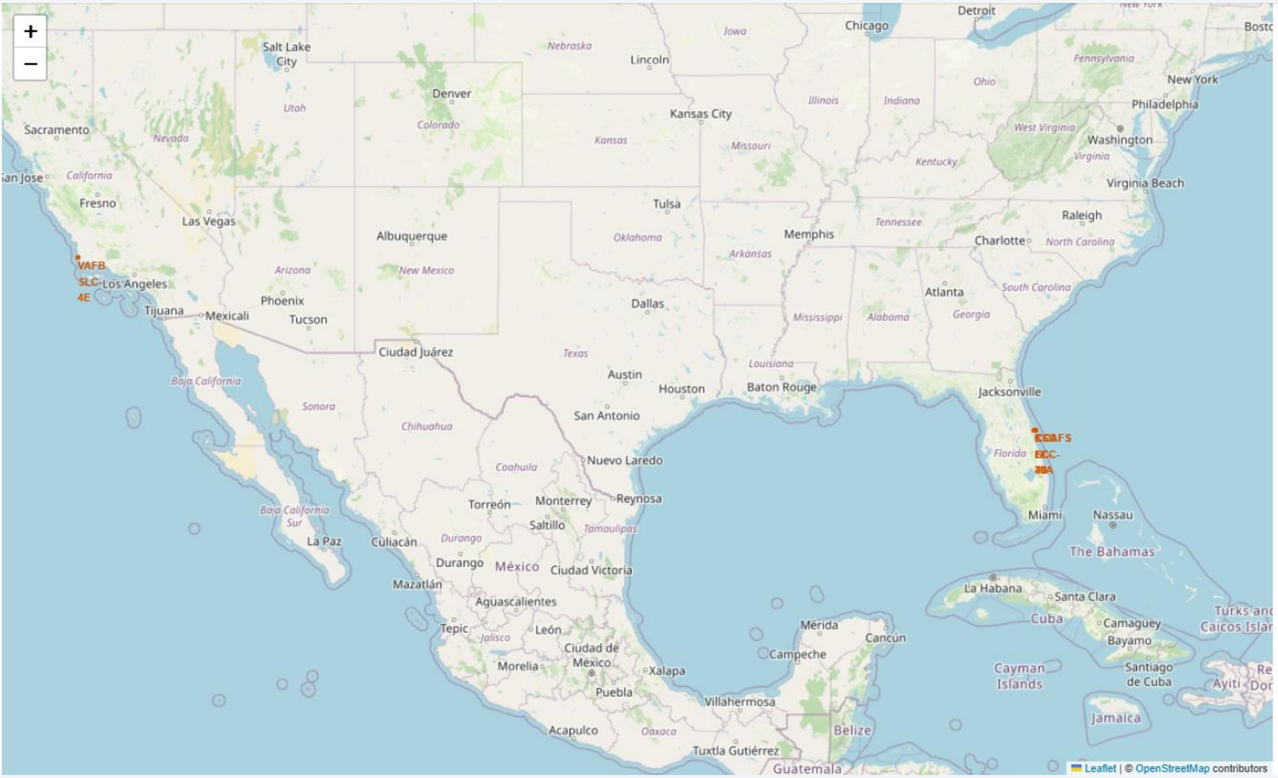
```
 * sqlite:///my_data1.db
Done.
```

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

Section 3

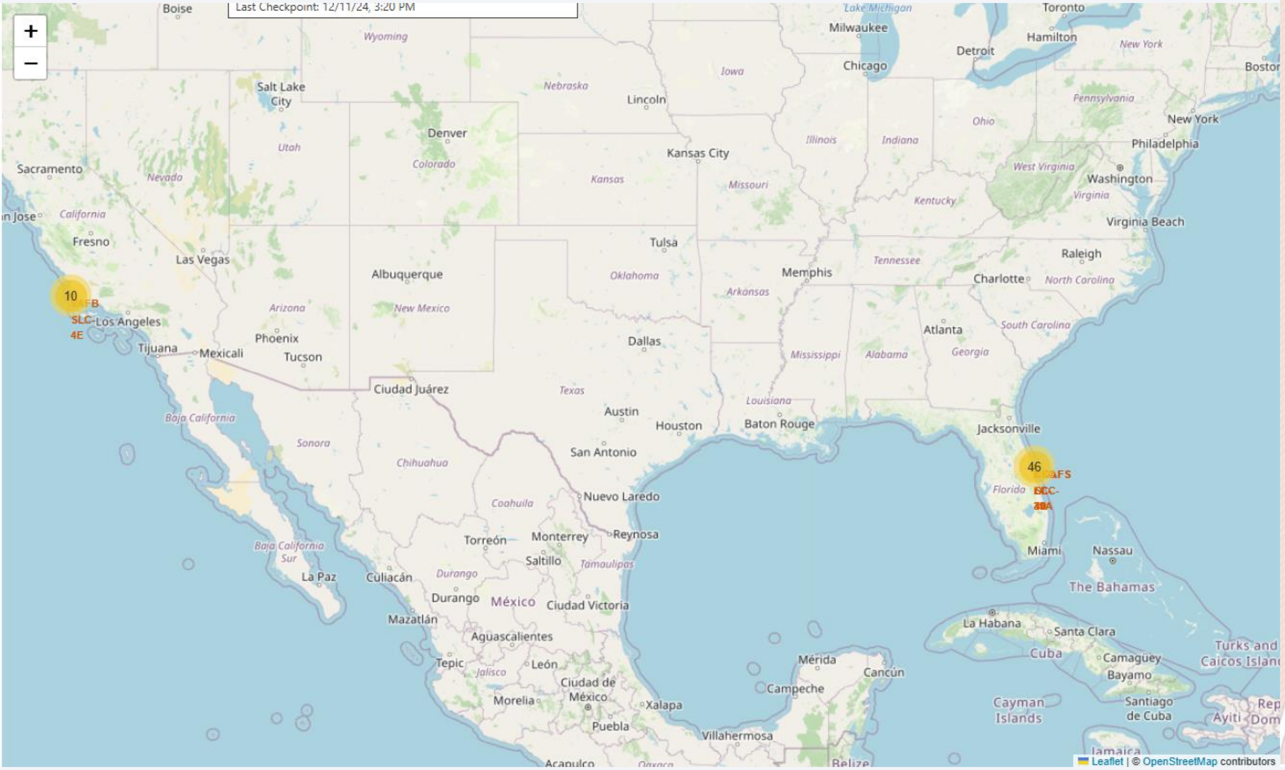
Launch Sites Proximities Analysis

All launch sites global map markers



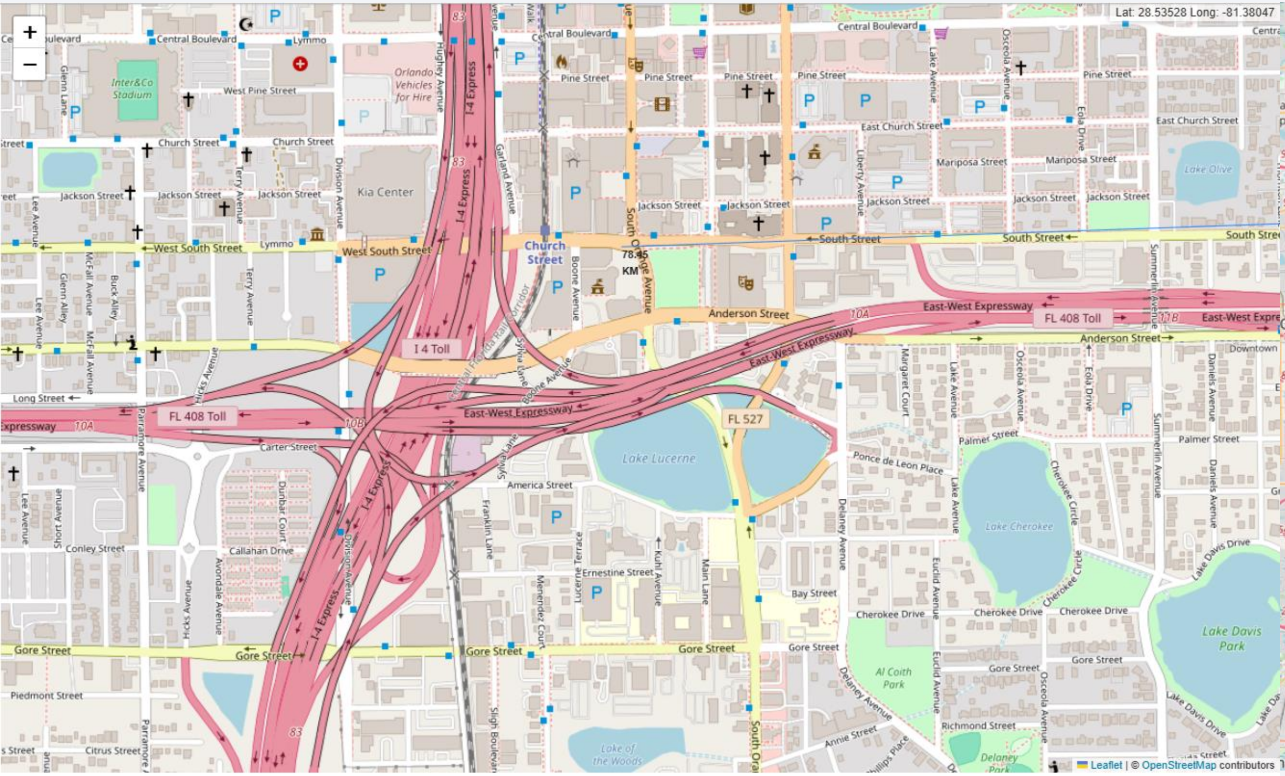
- The SpaceX launch sites are un the USA coast. In Florida and California.

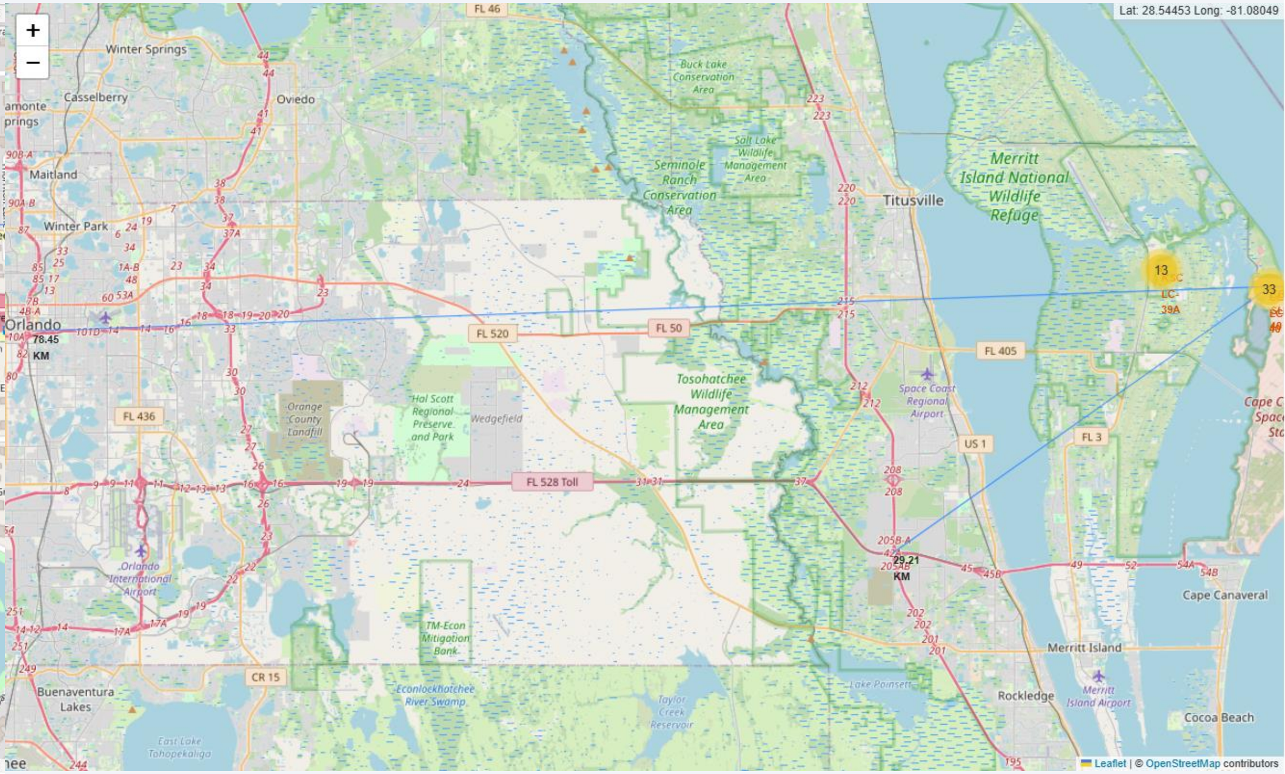
Markers showing launch sites with color labels



- Green marker shows successful Launches an Red marker shows failures

Launch Site distance to landmarks





Are launch sites in close proximity to railways? No

Are launch sites in close proximity to highways? No

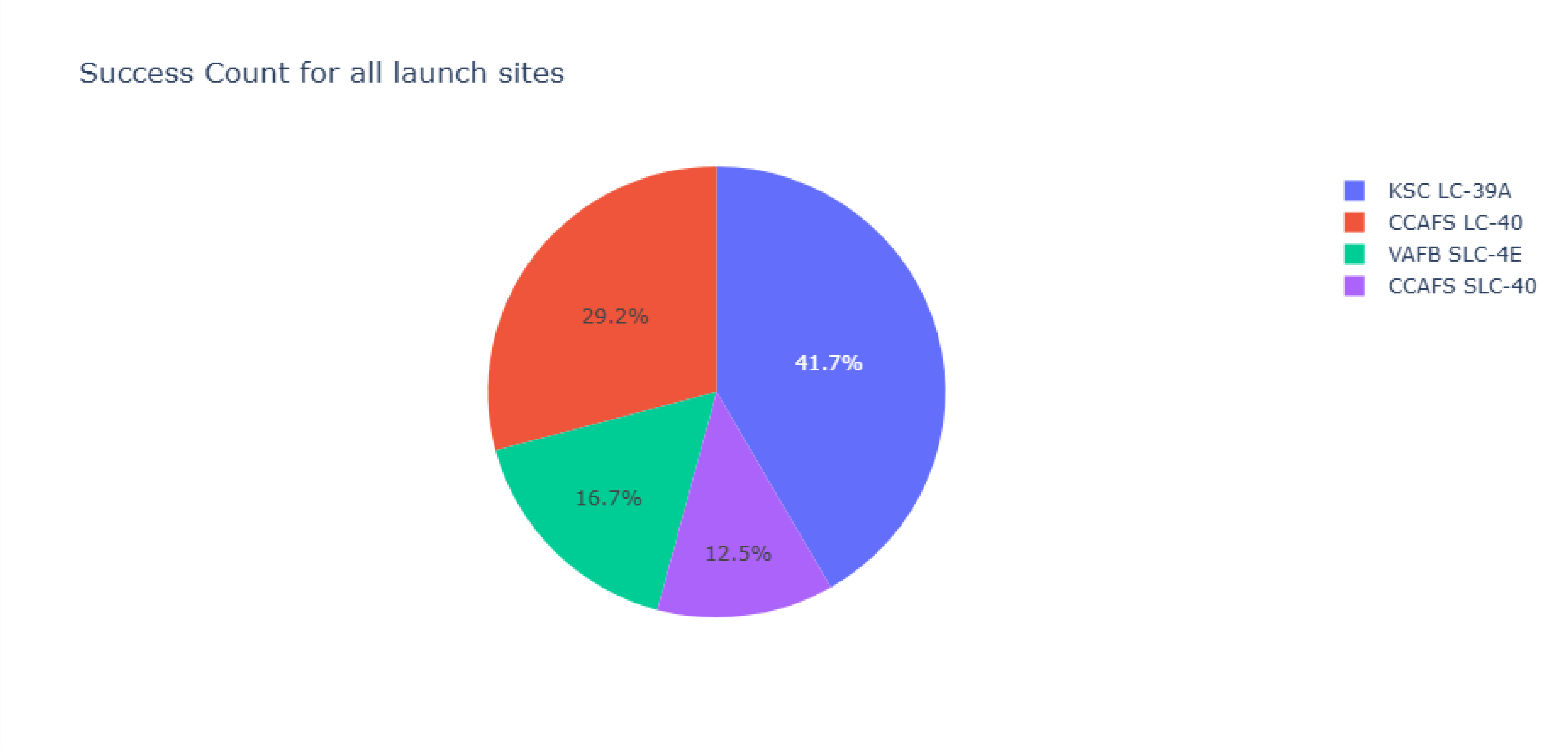
Are launch sites in close proximity to coastline? Yes

Do launch sites keep certain distance away from cities? Yes

Section 4

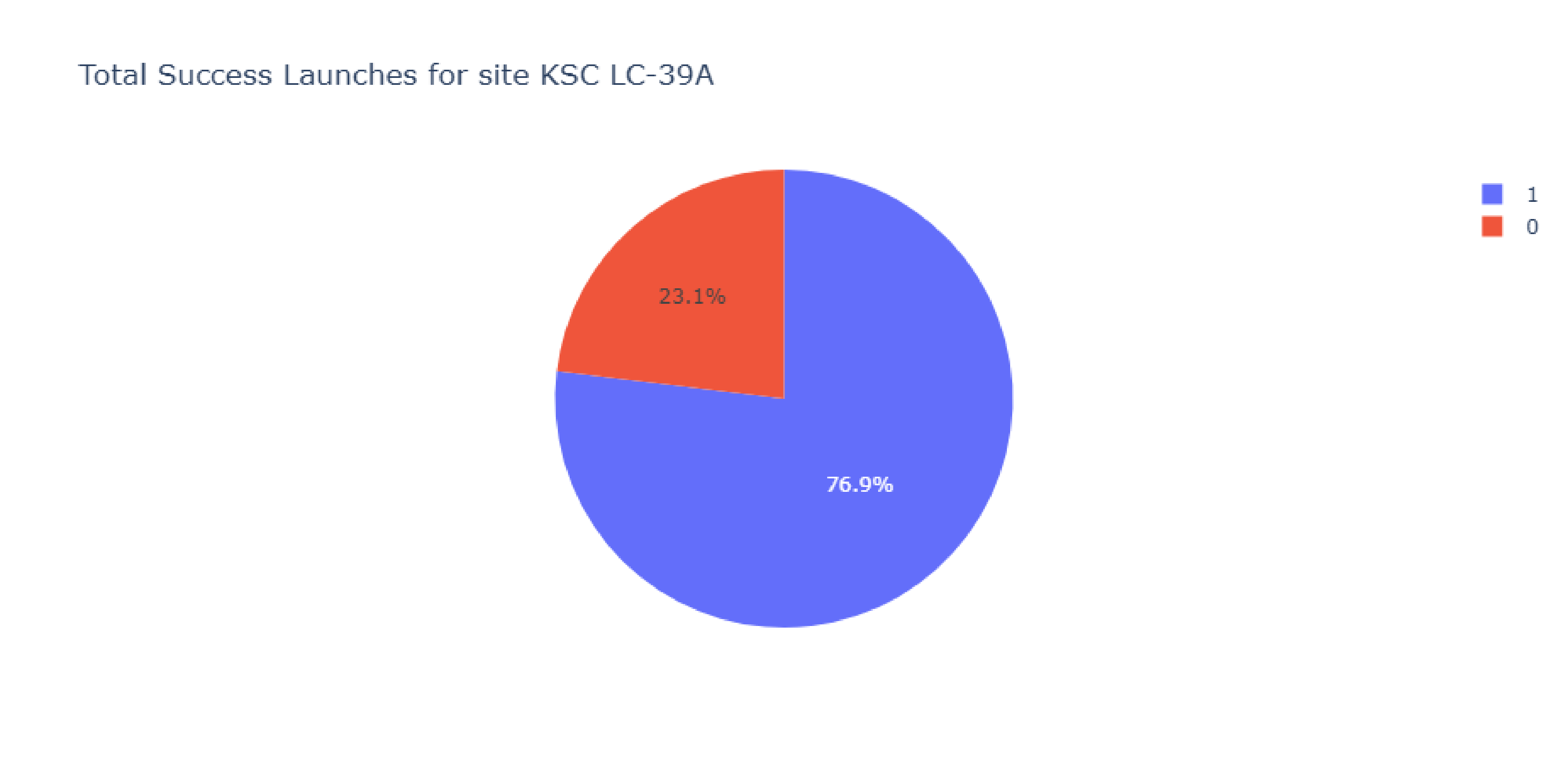
Build a Dashboard with Plotly Dash

Pie chart showing the success percentage achieved by each launch site



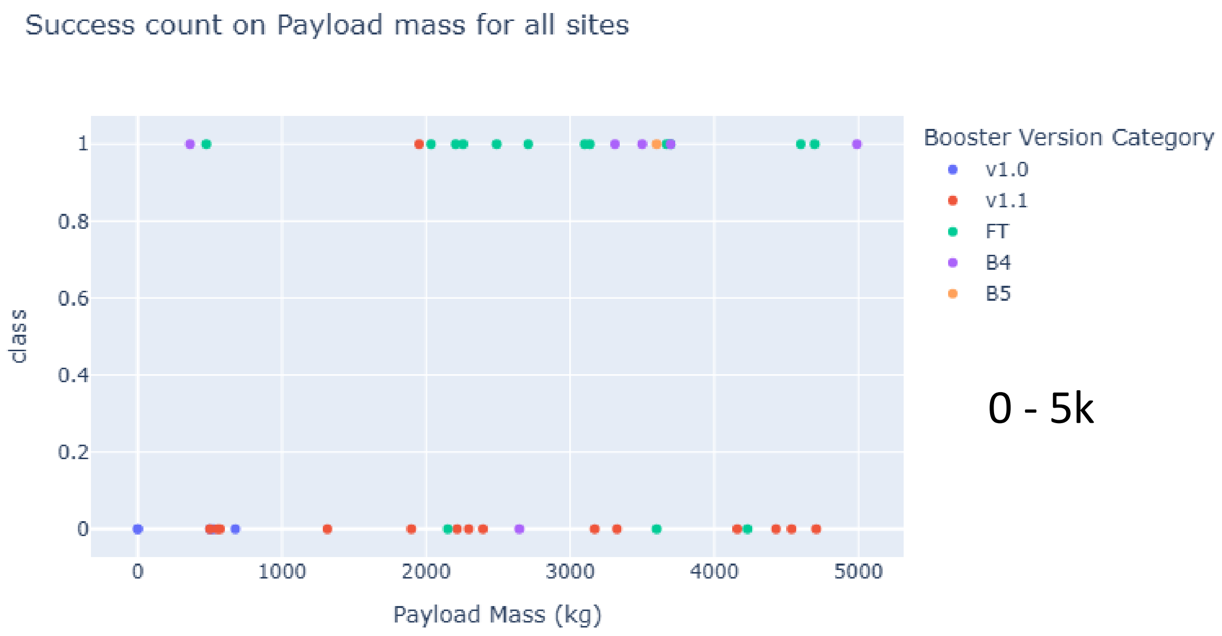
- KSC LC-39A had the most successful launches from all the sites

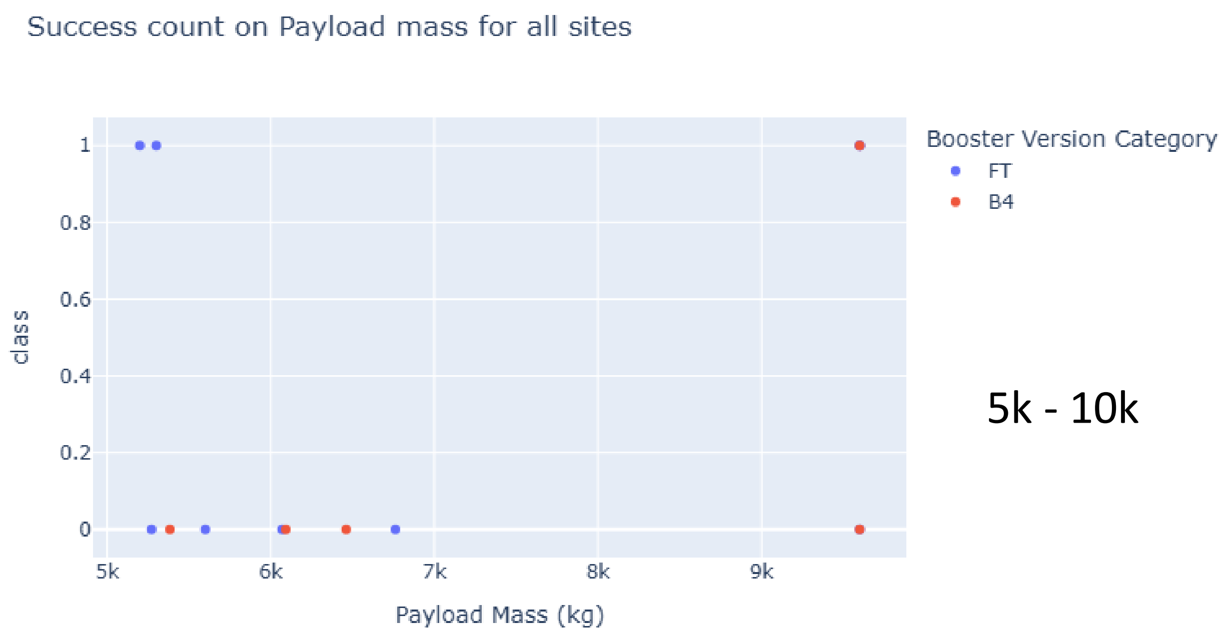
Pie chart showing the Launch site with the highest launch success ratio



- 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





- The success rate for 0-5k weighted payloads is higher than the success rate for 5k - 10k weighted payloads

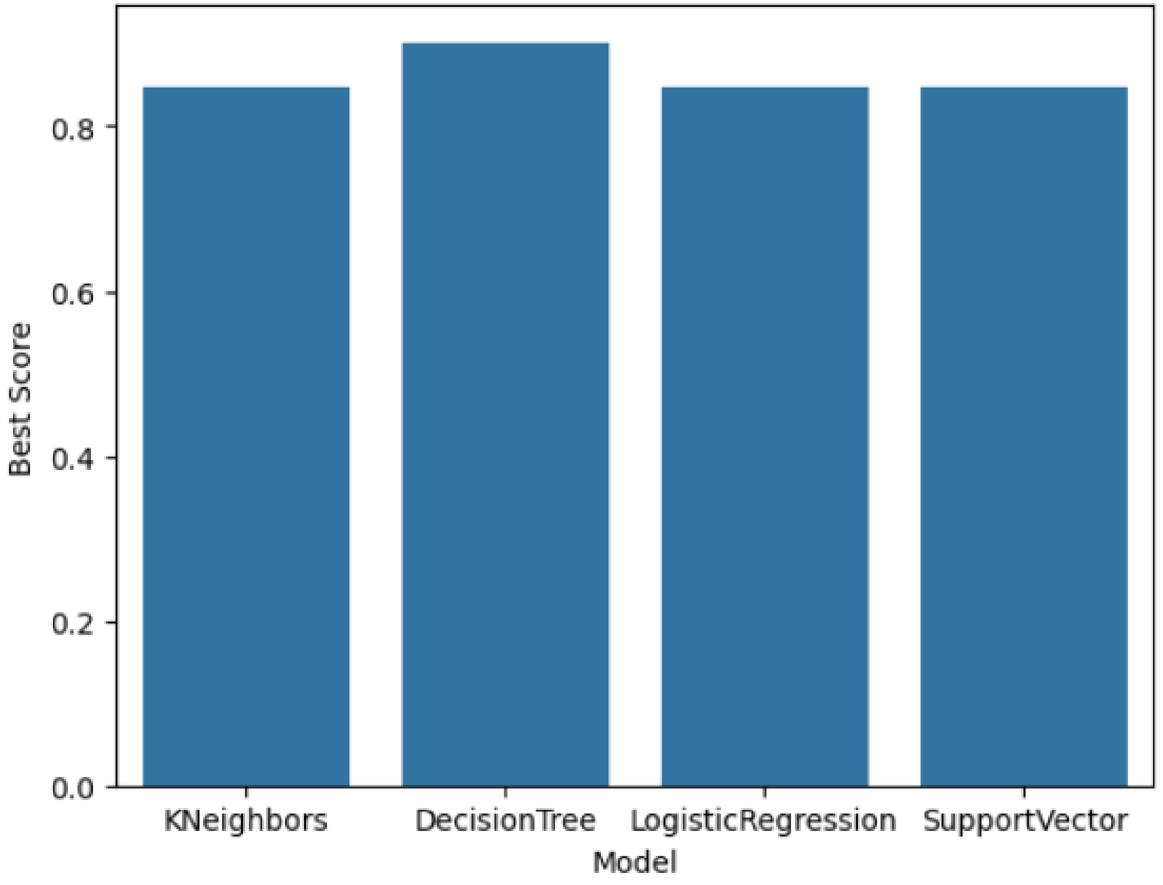
Section 5

Predictive Analysis (Classification)

Classification Accuracy

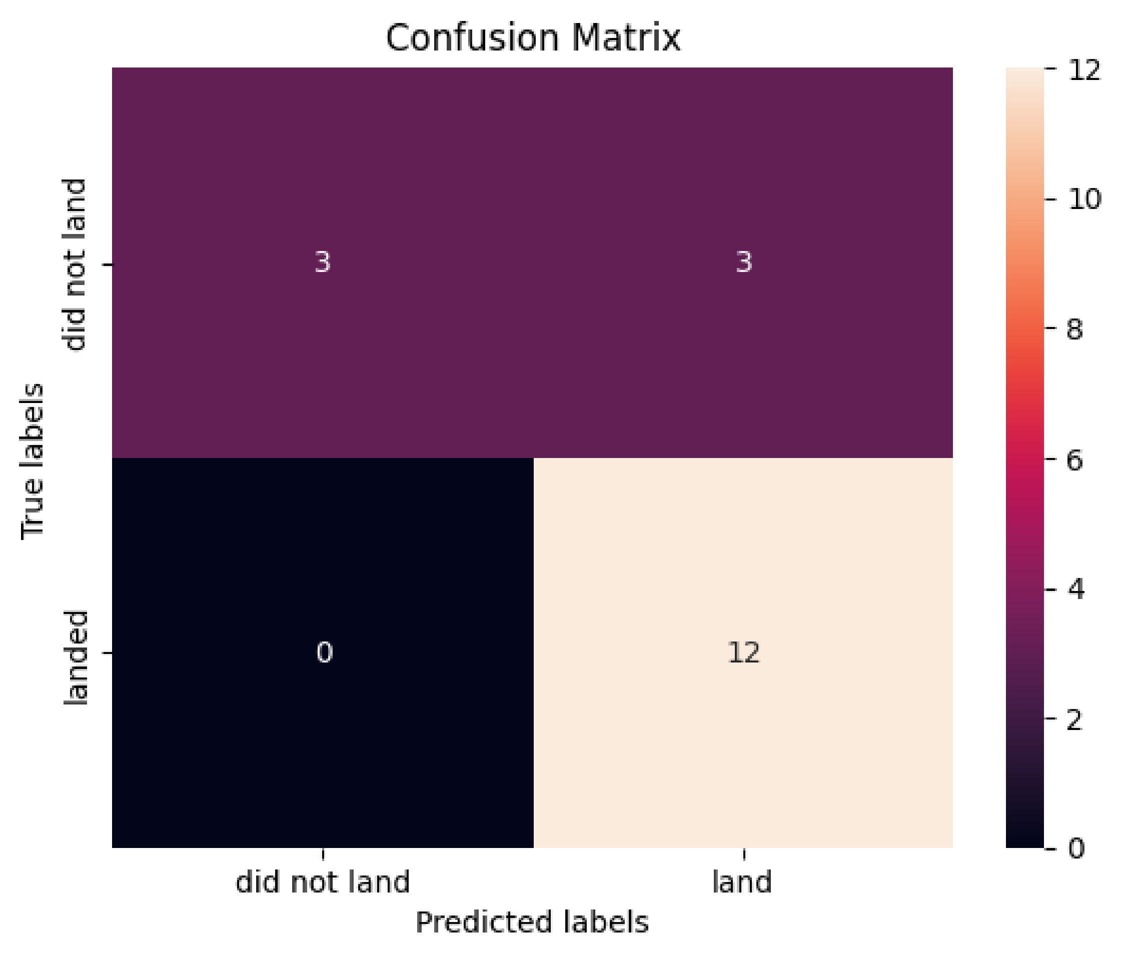
- The decision tree classifier is the model with the highest classification accuracy

```
Best model is DecisionTree with a score of 0.9017857142857144
Best params is : {'criterion': 'entropy', 'max_depth': 16, 'max_features': 'sqrt',
'min_samples_leaf': 2, 'min_samples_split': 10, '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

- The higher the number of flights at a launch point, the higher the success rate at a launch point.
- The launch success rate started to increase in 2013 until 2020.
- The ES-L1, GEO, HEO, SSO, VLEO orbits had the highest success rate.
- KSC LC-39A had the highest number of successful launches.
- The decision tree classifier is the best machine learning algorithm for this task.

Thank you!