Winning Space Race with Data Science

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Outline

- Executive Summary
- Introduction
- Methodology
- Results
- Conclusion
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Executive Summary

- Summary of methodologies

✓ Data Collection

✓ Data Wrangling

✓ Exploratory Data Analysis with SQL

✓ Exploratory Data Analysis with Visualization

✓ Exploratory Data Analysis with Folium

✓ Machine Learning Prediction

- Summary of all results

✓ Exploratory Data Analysis Result

✓ Interactive Analysis with Folium Result

✓ Prediction Result

Introduction

- Project background and context:

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. 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.

- Problems you want to find answers:

✓ Predicting if the Falcon 9 first stage will land successfully.

✓ Factors that affect successful landing.

✓ Interactions between various features that determine its success.

✓ Operating conditions to be set in place for a successful outcome.

Section 1

Methodology

Methodology

Executive Summary

- Data collection methodology:

  Data was collected by webscraping through the Spacex API.

- 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

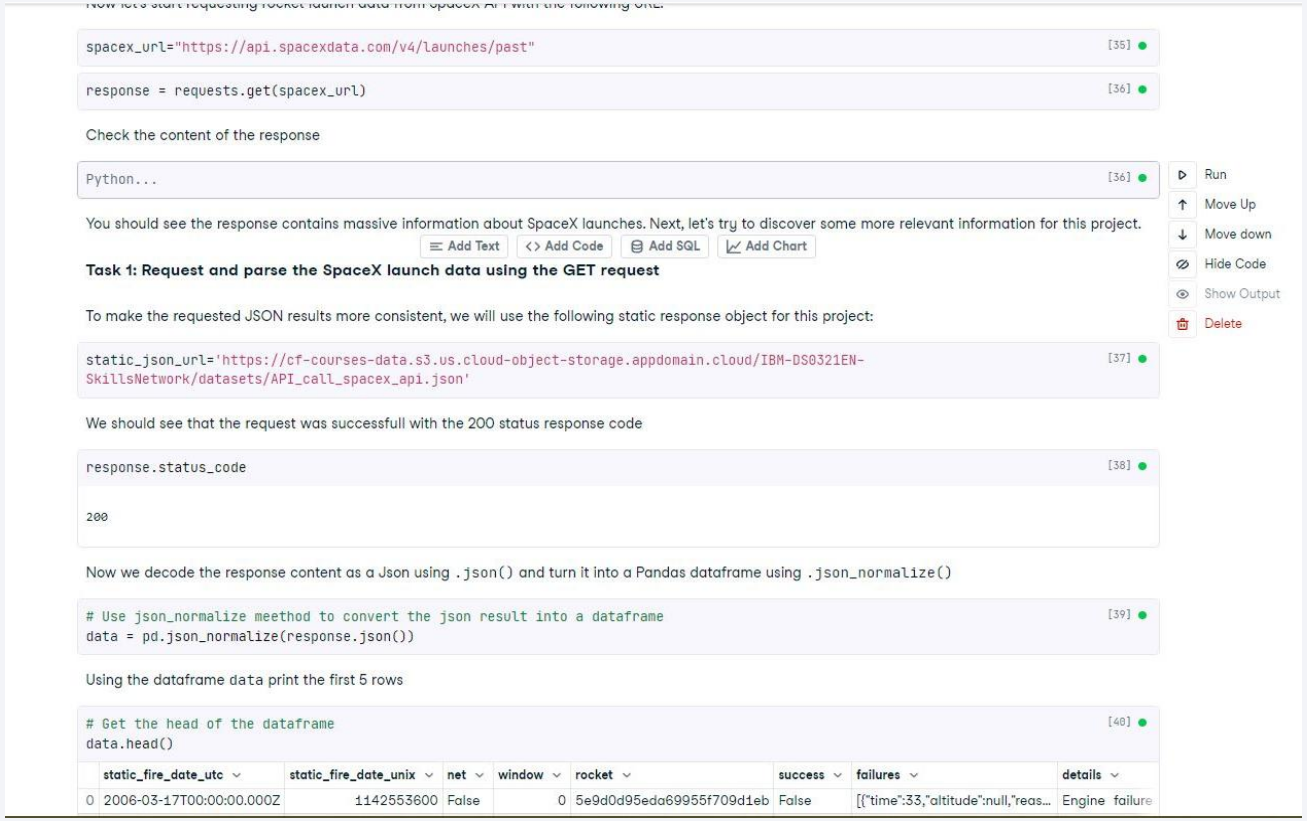
- Describe how data sets were collected.

  - We defined a series of helper functions that will help us use the API to extract information using identification numbers in the launch data.
    - We used the get requests to collect the data from the SpaceX API.
    - We used a static response object to make the JSON result more consistent.
    - We converted the JSON result into a pandas dataframe using .json_normalize().
    - We filtered the dataframe to keep only falcon9 launches.
    - We checked for missing values and filled them up with its mean.

Data Collection – SpaceX API

- The get requests was used to collect data from the SpaceX API. The data was then cleaned and formatted as necessary, including some data wrangling.

- The link to access the notebook is: [Data Collection notebook]



Now let's start requesting rocket launch data from SpaceX API with the following URL:

```
spacex_url="https://api.spacexdata.com/v4/launches/past"
```
[35]

```
response = requests.get(spacex_url)
```
[36]

Check the content of the response

```
Python...
```
[36]

Run
Move Up
Move down
Hide Code
Show Output
Delete

You should see the response contains massive information about SpaceX launches. Next, let's try to discover some more relevant information for this project.

Add Text | Add Code | Add SQL | Add Chart

Task 1: Request and parse the SpaceX launch data using the GET request

To make the requested JSON results more consistent, we will use the following static response object for this project:

```
static_json_url='https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/datasets/API_call_spacex_api.json'
```
[37]

We should see that the request was successfull with the 200 status response code

```
response.status_code
```
[38]

```
200
```

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

```
# Use json_normalize meethod to convert the json result into a dataframe
data = pd.json_normalize(response.json())
```
[39]

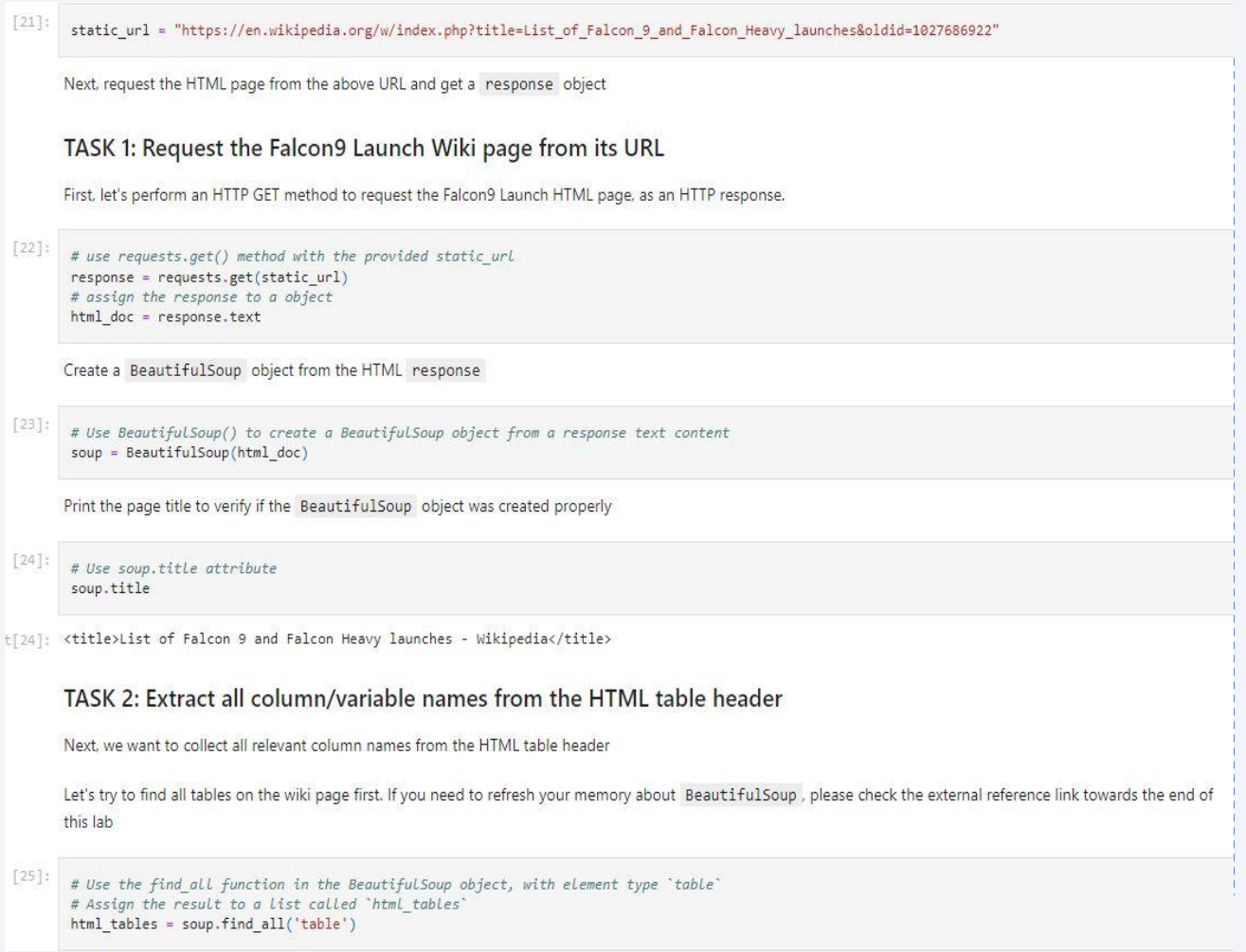
Using the dataframe `data` print the first 5 rows

```
# Get the head of the dataframe
data.head()
```
[40]

	static_fire_date_utc	static_fire_date_unix	net	window	rocket	success	failures	details
0	2006-03-17T00:00:00.000Z	1142553600	False	0	5e9d0d95eda69955f709d1eb	False	[{"time":33,"altitude":null,"reas...	Engine failure

Data Collection - Scraping

- We used an HTTP GET method to request the Falcon9 Launch HTML page, as an HTTP response.
- A BeautifulSoup object was then created from the HTML response.
- The table was then parsed and converted into a pandas dataframe.
- Add the GitHub URL of the completed web scraping notebook, as an external reference and peer-review purpose.
- The link to the notebook is: [Web Scraping]



[21]:
```
static_url = "https://en.wikipedia.org/w/index.php?title=List_of_Falcon_9_and_Falcon_Heavy_launches&oldid=1027686922"
```

Next, request the HTML page from the above URL and get a `response` object

TASK 1: Request the Falcon9 Launch Wiki page from its URL

First, let's perform an HTTP GET method to request the Falcon9 Launch HTML page, as an HTTP response.

[22]:
```
# use requests.get() method with the provided static_url
response = requests.get(static_url)
# assign the response to a object
html_doc = response.text
```

Create a `BeautifulSoup` object from the HTML `response`

[23]:
```
# Use BeautifulSoup() to create a BeautifulSoup object from a response text content
soup = BeautifulSoup(html_doc)
```

Print the page title to verify if the `BeautifulSoup` object was created properly

[24]:
```
# Use soup.title attribute
soup.title
```

t[24]:
```
<title>List of Falcon 9 and Falcon Heavy launches - Wikipedia</title>
```

TASK 2: Extract all column/variable names from the HTML table header

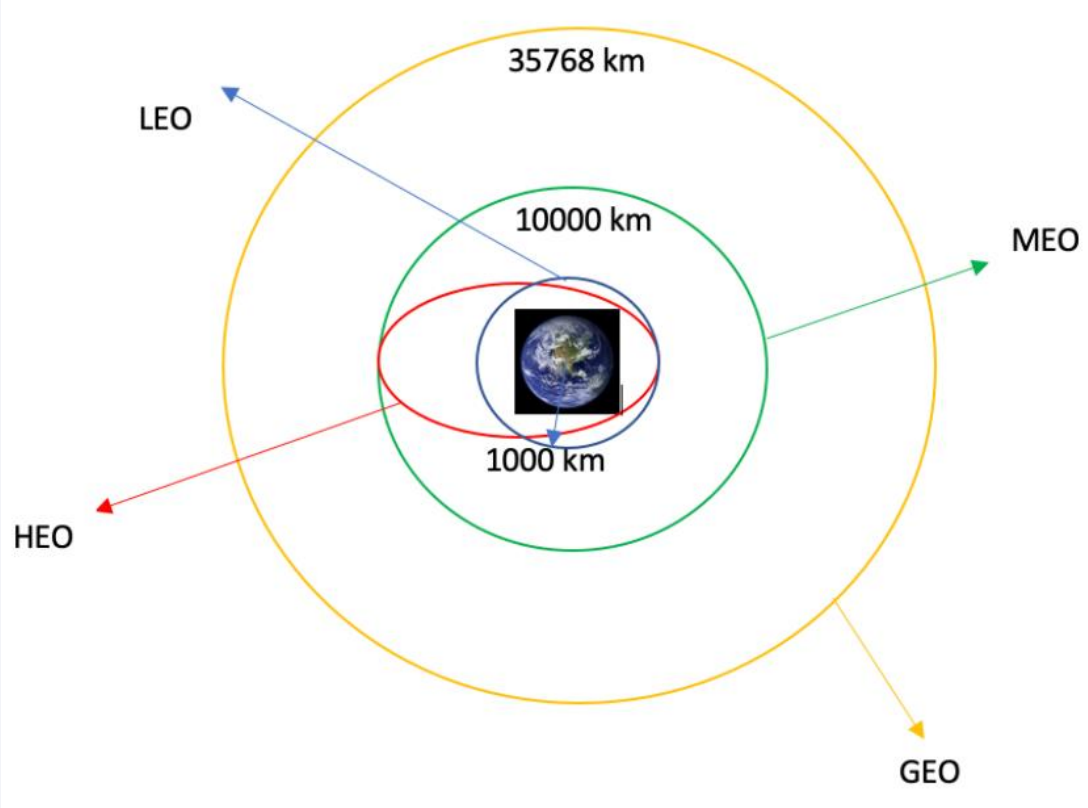
Next, we want to collect all relevant column names from the HTML table header

Let's try to find all tables on the wiki page first. If you need to refresh your memory about `BeautifulSoup`, please check the external reference link towards the end of this lab

[25]:
```
# Use the find_all function in the BeautifulSoup object, with element type `table`
# Assign the result to a list called `html_tables`
html_tables = soup.find_all('table')
```

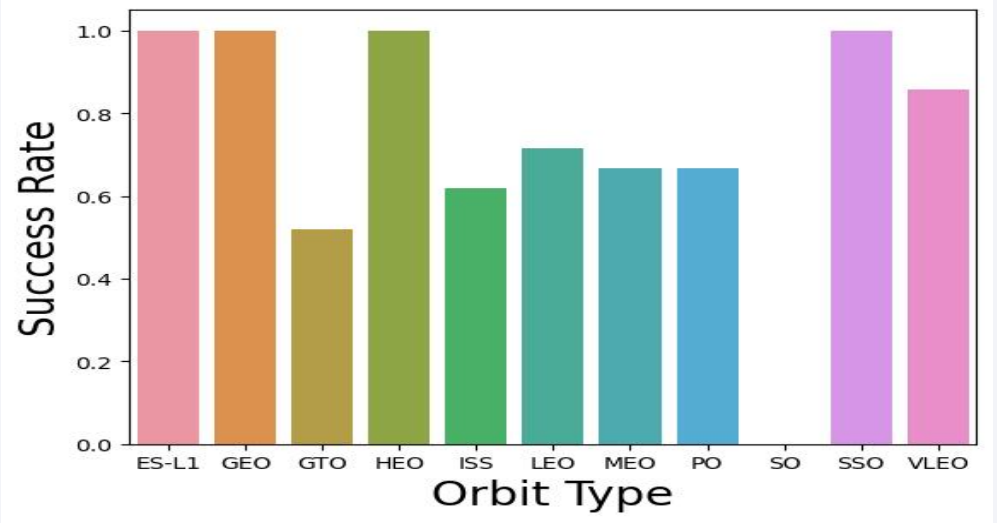
Data Wrangling

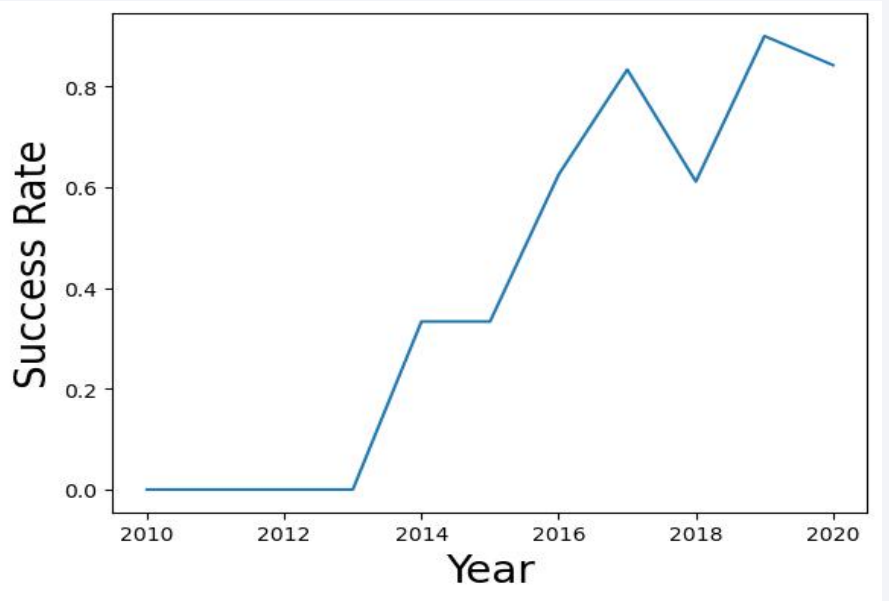
- We performed some Exploratory Data Analysis (EDA) to find some patterns in the data
- We also determined the label for training supervised models.
- We calculated the number of launches on each site.
- We also calculated the number and occurence of mission outcome per orbit type.
- We created a landing outcome label from the Outcome column.
- The github link to the notebook is: Data Wrangling



EDA with Data Visualization

- We observed the relationship between several factors.
- We observed if there is any relationship between the success rate and the type of orbit it reached.
- We also observed the launch success rate over the years to determine if there has been an improvement or decline.
- The github link to the notebook is: [Data Visualization]





EDA with SQL

- We connected to the MySql database to access our data.
- 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 github link to the notebook is: EDA with SQL

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 rate.
- We calculated the distances between a launch site to its proximities. We answered some questions for instance:

  - Are launchsite in close proximity to railways, highways and coastline?

  - Do launchsite keep certain distance from cities?

- The github link to the notebook is: Data visualization with folium

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 github link to the notebook is: Interactive design with Plotly

Predictive Analysis (Classification)

- We imported all the necessary libraries needed for the analysis and then loaded the data.
- We created a numpy array, standardized the data and then split the dataset into train and test data.
- We built different machine learning models and tuned into different parameters using GridSearchCV.
- We calculated the accuracy and confusion matrix of each model used.
- The github link to the notebook is: Prediction Analysis

Results

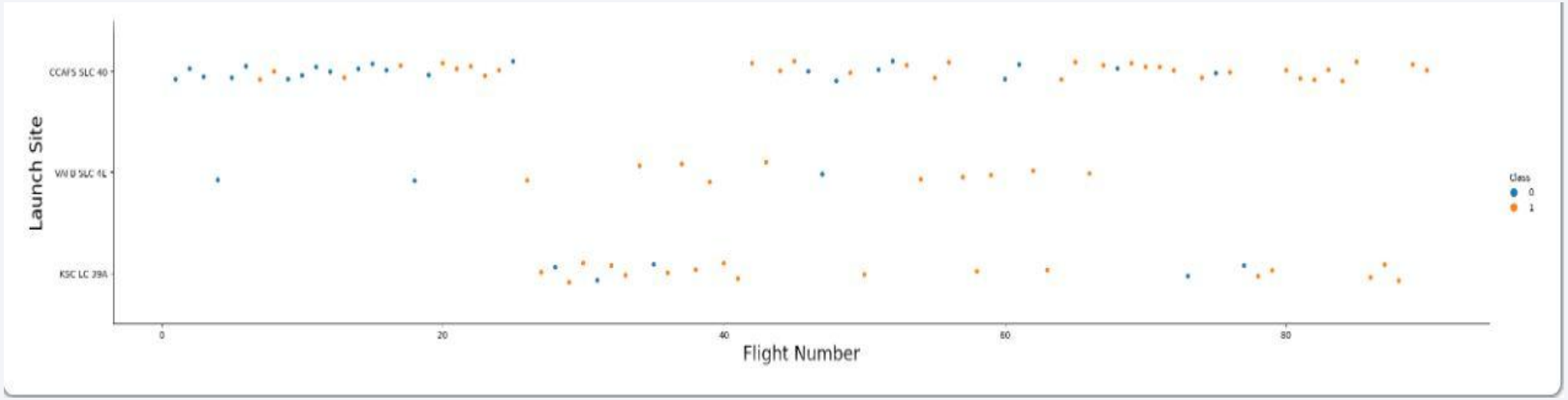
- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results

Section 2

Insights drawn from EDA

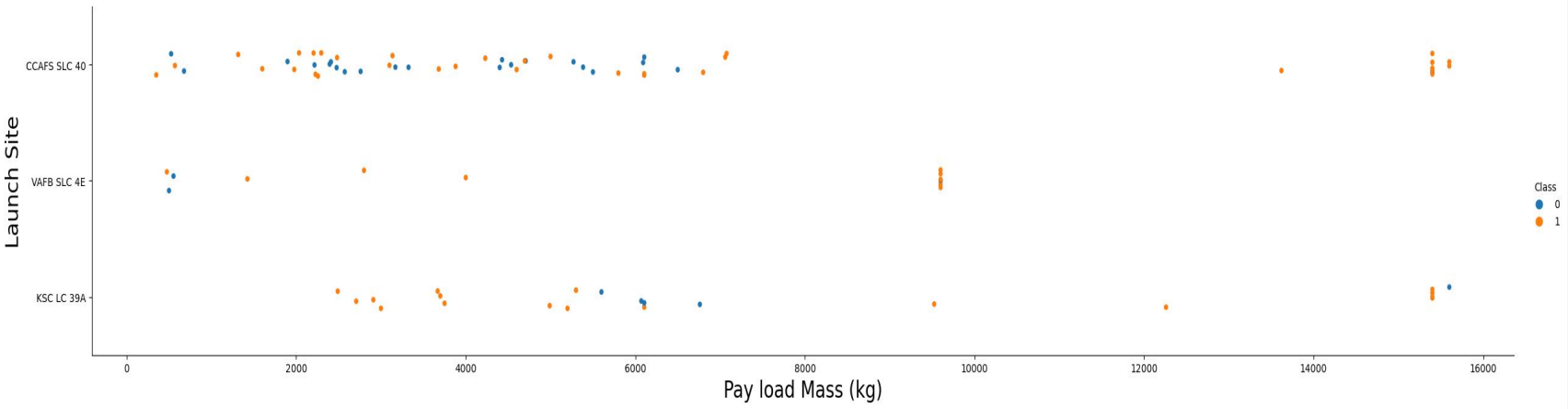
Flight Number vs. Launch Site

- From the scatter plot below, we noted that the higher/ larger the amount of flight at a launch site, the higher the number of successul launches or the greater the success rate.

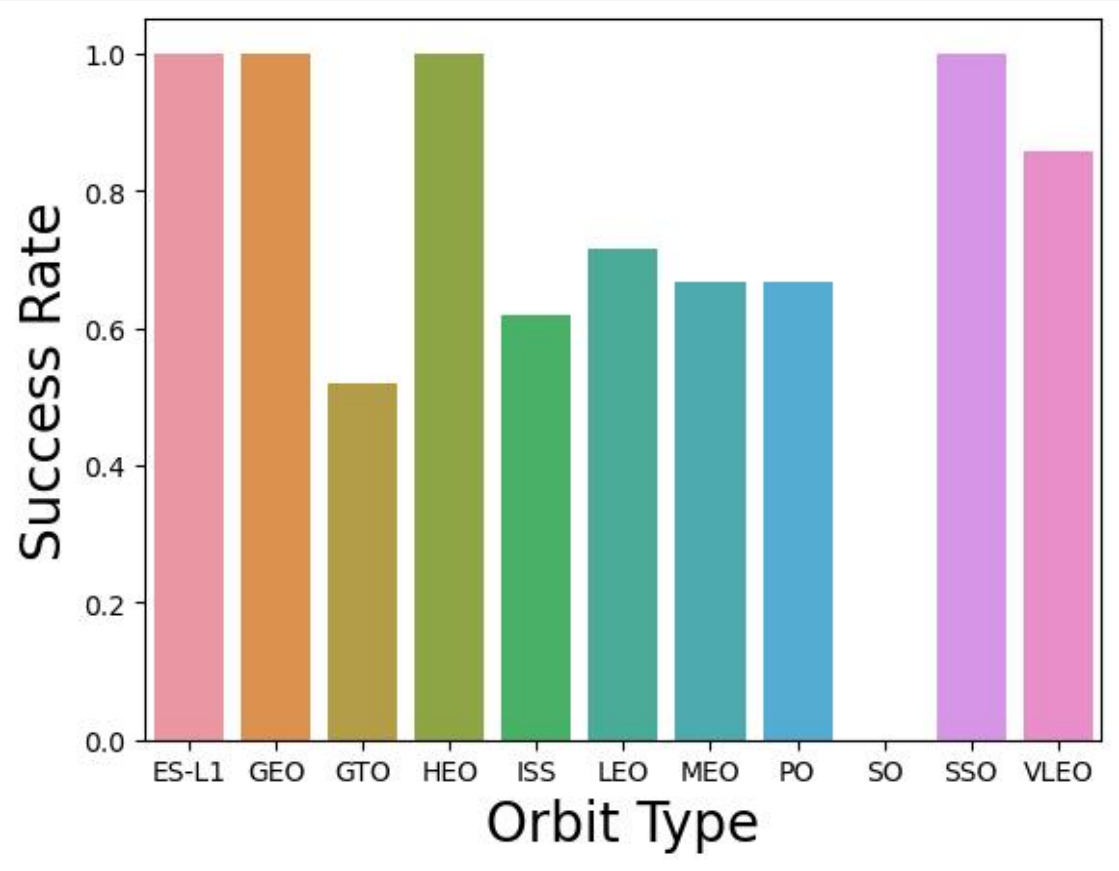


Payload vs. Launch Site

- From the plot below, we can note that the lower the payload mass at launchsite KSC LC-39A, the higher the number of successful launches.



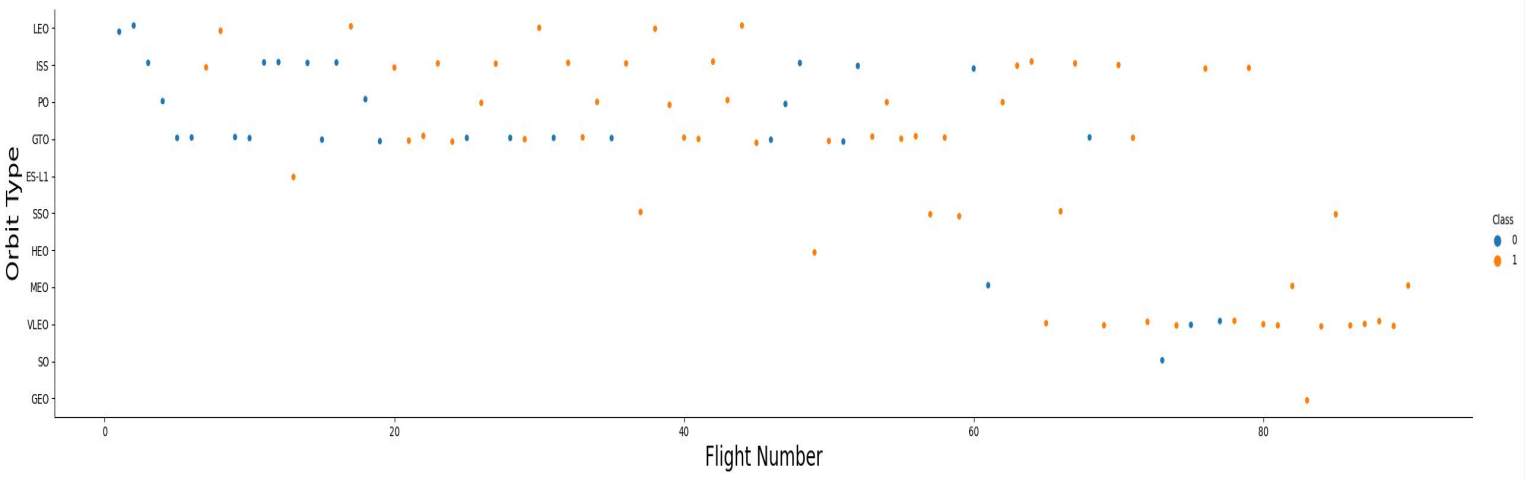
Success Rate vs. Orbit Type



- From the chart, we can note that orbit type : ES-L1, GEO, HEO and SSO had the highest success rate.

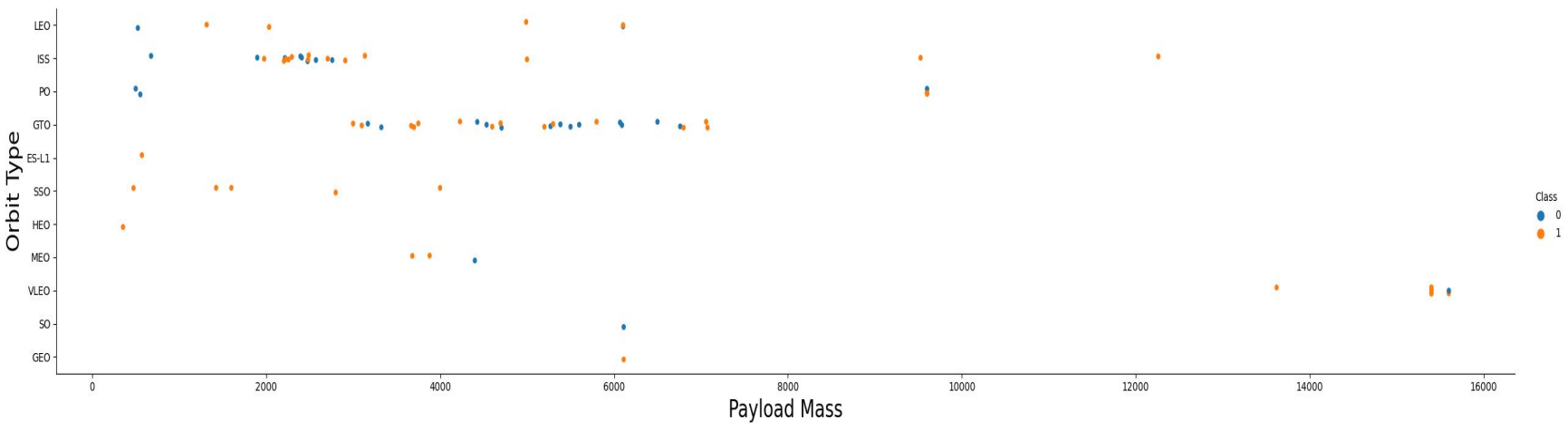
Flight Number vs. Orbit Type

- We can observe from the chart below, we observed that in the LEO and ISS orbit, success rate is relative to the number of flight taken. But for the GTO orbit, there is no observable relationship between the orbit type and number of flight.



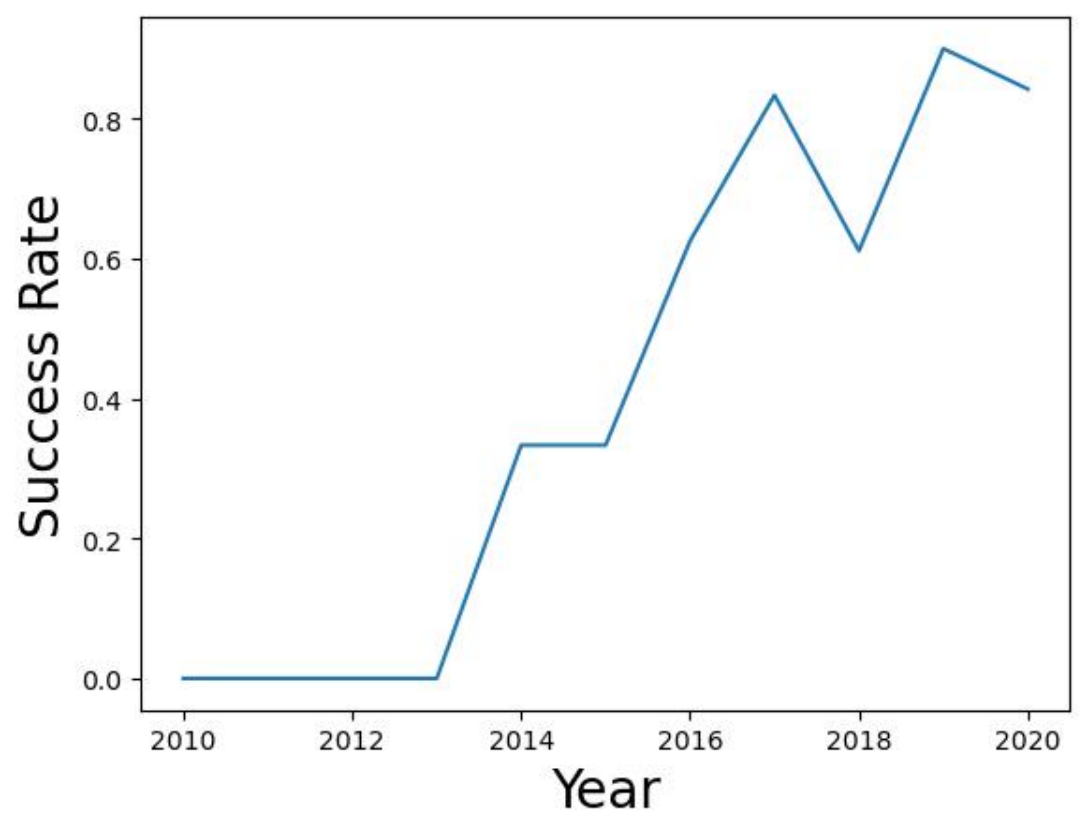
Payload vs. Orbit Type

- From the chart below, we can observe a noticable relationship between payloadmass and orbit type in the orbits LEO, ISS. While there is no noticable relationship in the orbit GTO.



Launch Success Yearly Trend

- We can observe that there was an impressive increase in success rate from 2013 to 2020.



All Launch Site Names

Out[11]:

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

- We applied the SELECT DISTINCT query to access all launch site names.

Launch Site Names Begin with 'CCA'

Out[13]:

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

- We used the LIKE query function to get launch site names that begins with CAA

Total Payload Mass

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

Out[19]:

total_payloadmass
45596

Average Payload Mass by F9 v1.1

- We used the sql query below to find the average payload mass of booster version F9.

In [33]:
```
%%sql SELECT AVG(Payload_mass__kg_) AS Avg_PayloadMass
        FROM SpaceX
        WHERE Booster_version = 'F9 v1.1'
```

```
 * ibm_db_sa://ggy48494:***@ea286ace-86c7-4d5b-8580-3fbfa46b1c66.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:31505/bludb
Done.
```

Out[33]:

avg_payloadmass
2928

First Successful Ground Landing Date

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

```
In [39]: %%sql SELECT MIN(Date) AS FirstSuccessfull_landing_date
         FROM SpaceX
         WHERE Landing__outcome LIKE 'Success (ground pad)'

 * ibm_db_sa://ggy48494:***@ea286ace-86c7-4d5b-8580-3fbfa46b1c66.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:31505/bludb
Done.

Out[39]: firstsuccessfull_landing_date
         2015-12-22
```

Successful Drone Ship Landing with Payload between 4000 and 6000

In [40]:
```
%%sql SELECT booster_version AS Succsess_booster
      FROM SPACEX
      WHERE Landing__outcome LIKE 'Success (drone ship)'
          AND Payload_mass__kg_ > 4000
          AND Payload_mass__kg_ < 6000 ;
```

```
 * ibm_db_sa://ggy48494:***@ea286ace-86c7-4d5b-8580-3fbfa46b1c66.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:31505/bludb
Done.
```

Out[40]:

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

- These are the successful drone ship landing with a payload between the range of 4000 and 6000.

Total Number of Successful and Failure Mission Outcomes

In [45]:
```
%%sql SELECT COUNT(mission_outcome) AS Success_outcome
      FROM SPACEX
      WHERE mission_outcome LIKE 'Success%'
```

```
 * ibm_db_sa://ggy48494:***@ea286ace-86c7-4d5b-8580-3fbfa46b1c66.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:31505/bludb
Done.
```

Out[45]:

success_outcome
100

In [46]:
```
%%sql  SELECT COUNT(mission_outcome) AS Failure_outcome
      FROM SPACEX
      WHERE mission_outcome LIKE 'Failure%';
```

```
 * ibm_db_sa://ggy48494:***@ea286ace-86c7-4d5b-8580-3fbfa46b1c66.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:31505/bludb
Done.
```

Out[46]:

failure_outcome
1

- We used wildcard like '%' to filter for **WHERE** MissionOutcome was a success or a failure
- The total number of successful mission outcome is 100.
- The total number of failed mission outcome is 1.

Boosters Carried Maximum Payload

In [47]:
```
%%sql SELECT Booster_version, Payload_mass__kg_
        FROM SPACEX
        WHERE Payload_mass__kg_ = (
                                   SELECT MAX(Payload_mass__kg_)
                                   FROM SPACEX
                                   )
        ORDER BY Booster_version
```

```
 * ibm_db_sa://ggy48494:***@ea286ace-86c7-4d5b-8580-3fbfa46b1c66.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:31505/bludb
Done.
```

Out[47]:

booster_version	payload_mass__kg_
F9 B5 B1048.4	15600
F9 B5 B1048.5	15600
F9 B5 B1049.4	15600
F9 B5 B1049.5	15600
F9 B5 B1049.7	15600
F9 B5 B1051.3	15600
F9 B5 B1051.4	15600
F9 B5 B1051.6	15600
F9 B5 B1056.4	15600
F9 B5 B1058.3	15600
F9 B5 B1060.2	15600
F9 B5 B1060.3	15600

- Using a subquery, we got the list of boosters that carried the maximum payload.

2015 Launch Records

In [52]:
```
%%sql SELECT booster_version, launch_site, landing__outcome
      FROM SPACEX
      WHERE landing__outcome LIKE 'Failure (drone ship)'
         AND DATE BETWEEN '2015-01-01' AND '2015-12-31';
```

```
 * ibm_db_sa://ggy48494:***@ea286ace-86c7-4d5b-8580-3fbfa46b1c66.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:31505/bludb
Done.
```

Out[52]:

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

- 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.

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

In [55]:
```
%%sql SELECT Landing__outcome, COUNT(Landing__outcome)
        FROM SPACEX
        WHERE DATE BETWEEN '2010-06-04' AND '2017-03-20'
        GROUP BY Landing__outcome
        ORDER BY COUNT(Landing__outcome) DESC ;
```

```
 * ibm_db_sa://ggy48494:***@ea286ace-86c7-4d5b-8580-3fbfa46b1c66.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:31505/bludb
Done.
```

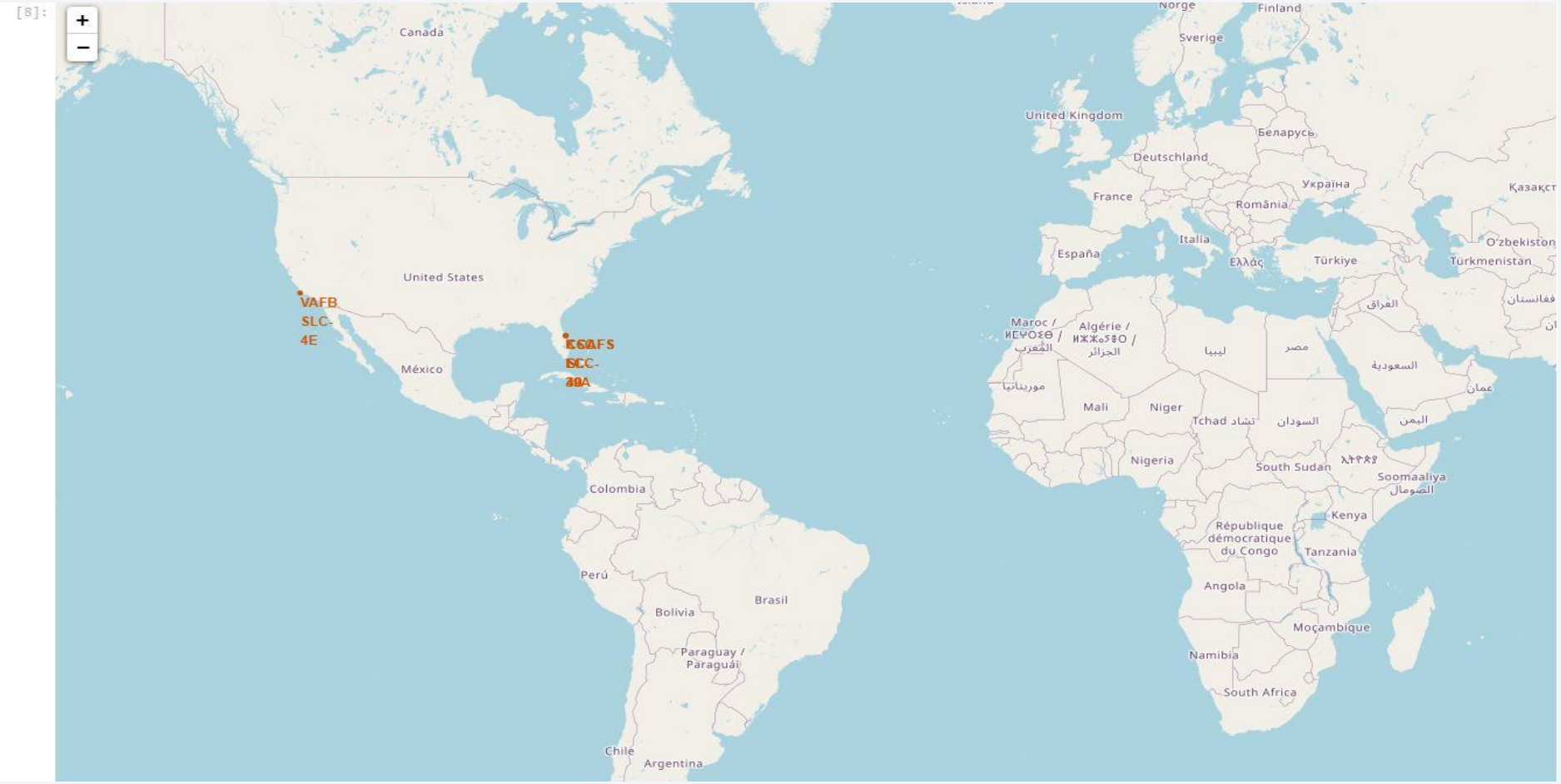
Out[55]:

landing__outcome	2
No attempt	10
Failure (drone ship)	5
Success (drone ship)	5
Controlled (ocean)	3
Success (ground pad)	3
Failure (parachute)	2
Uncontrolled (ocean)	2
Precluded (drone ship)	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 2017-03-20.
- 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.

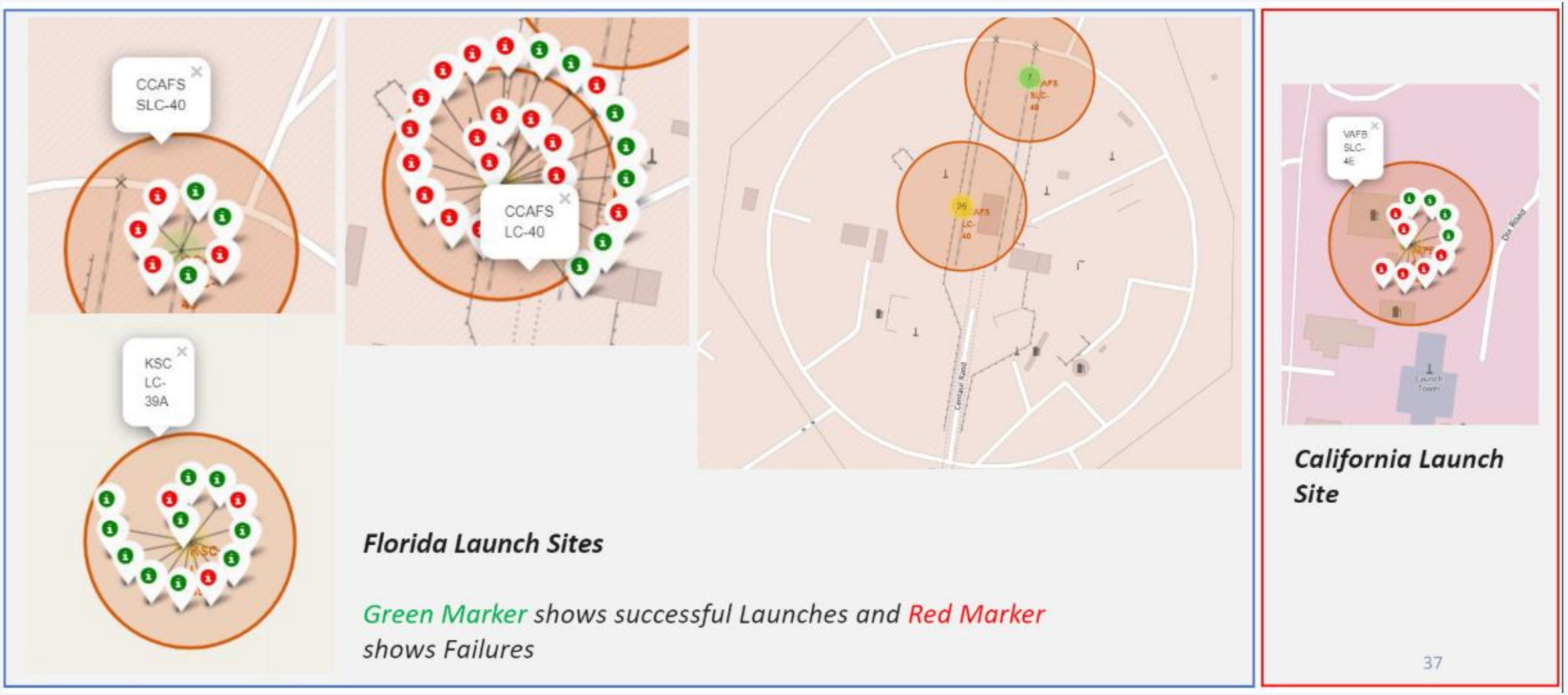

Section 3
Launch Sites
Proximities Analysis

All launch sites global map markers

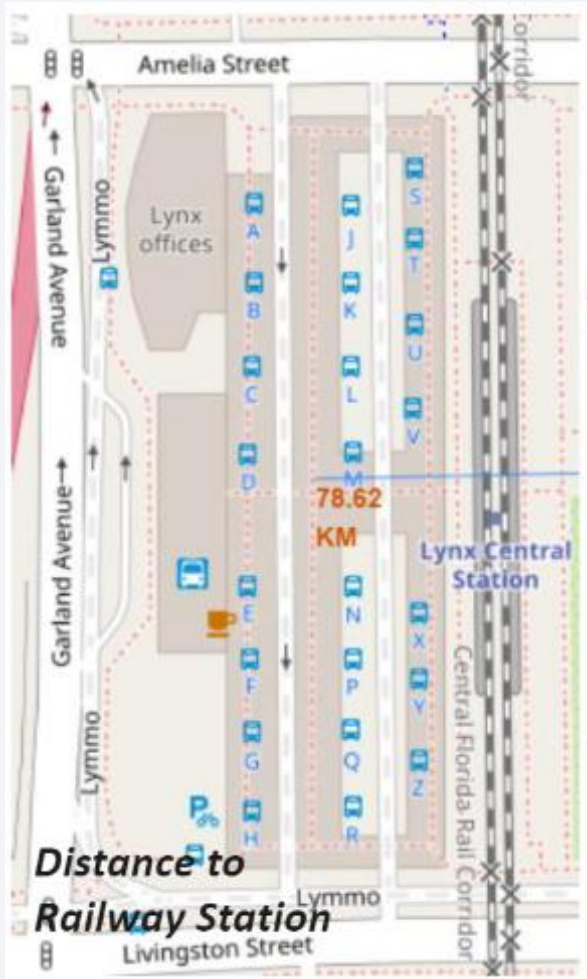


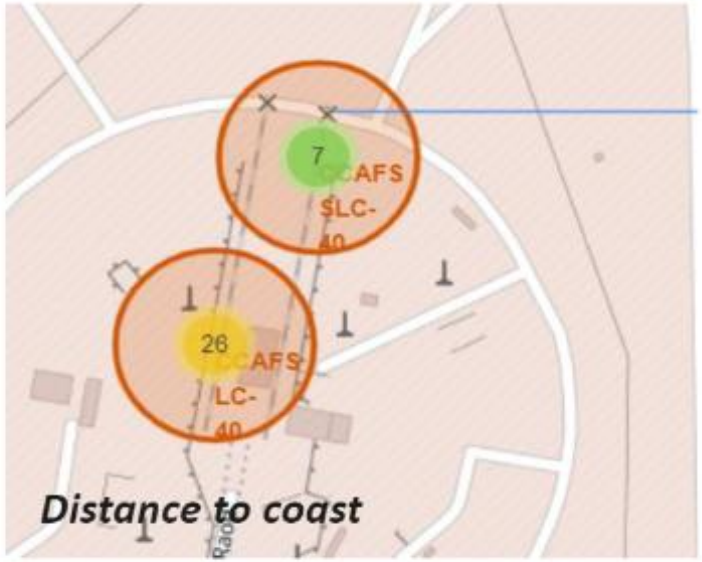
- We can see that the Spacex launch sites are on the US coasts, Florida and California.

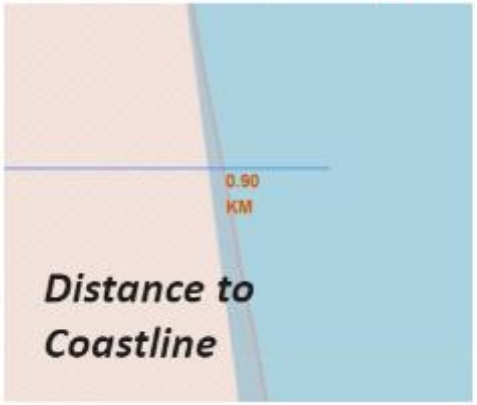
Markers showing launch sites with color labels



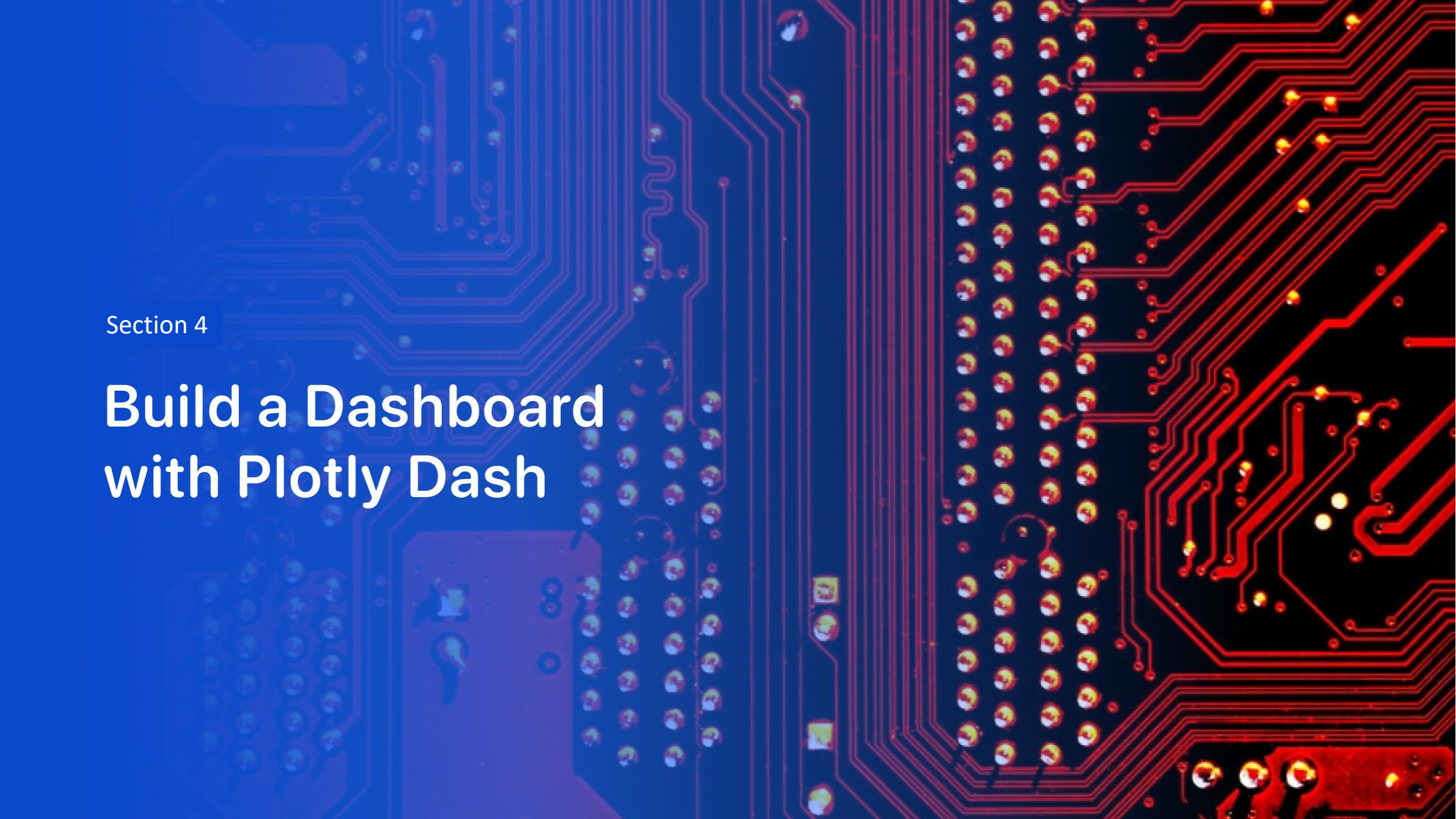
Launch site distance to landmarks



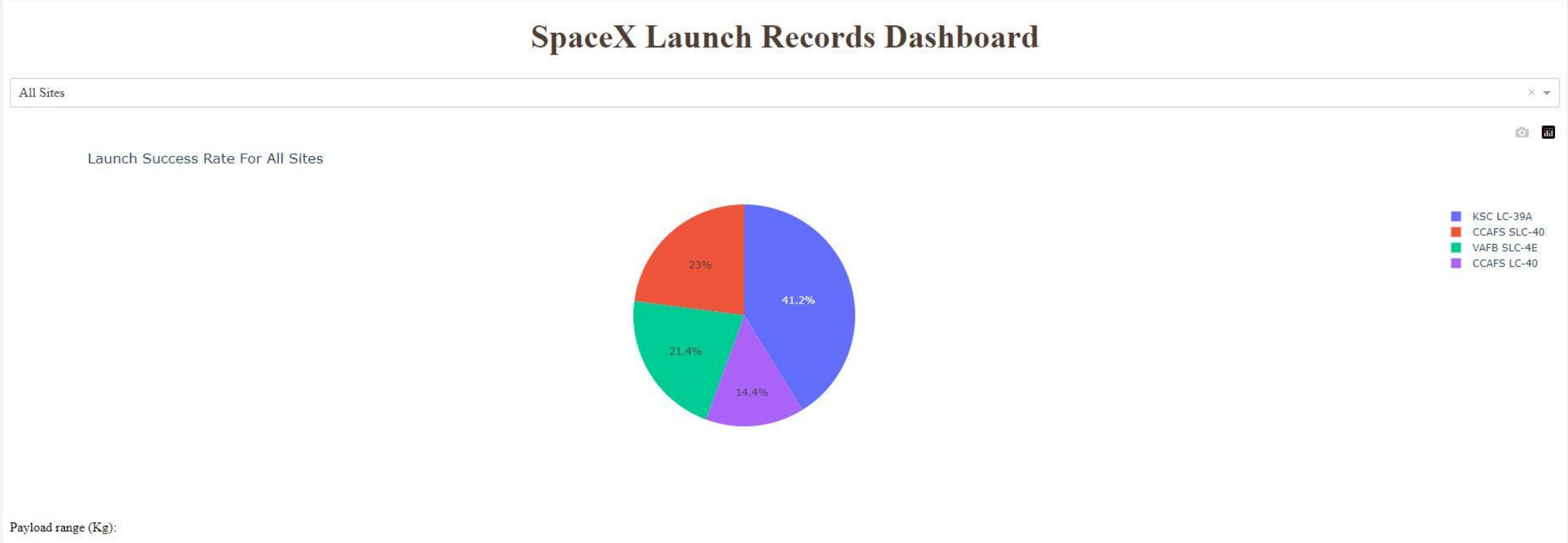




- Are launch sites in close proximity to railways? No
- Are launch sites in close proximity to highways? No
- Are launch sites in close proximity to coastline? Yes
- Do launch sites keep certain distance away from cities? Yes

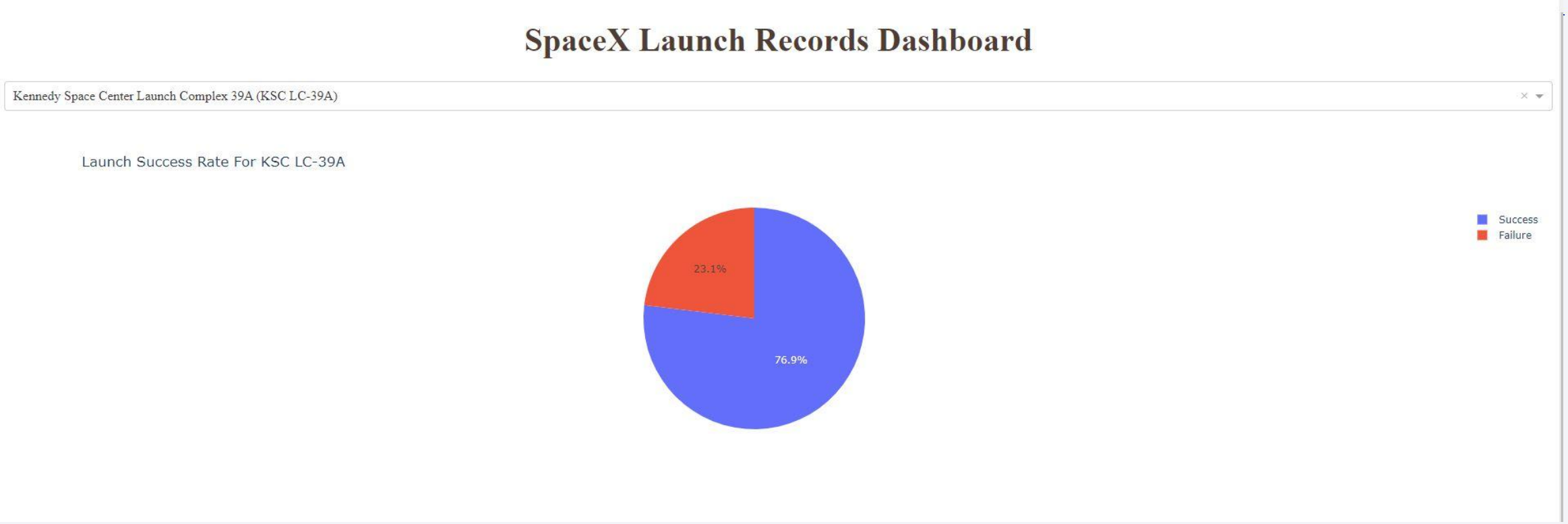

Section 4
Build a Dashboard with Plotly Dash

Launch Success For All Sites



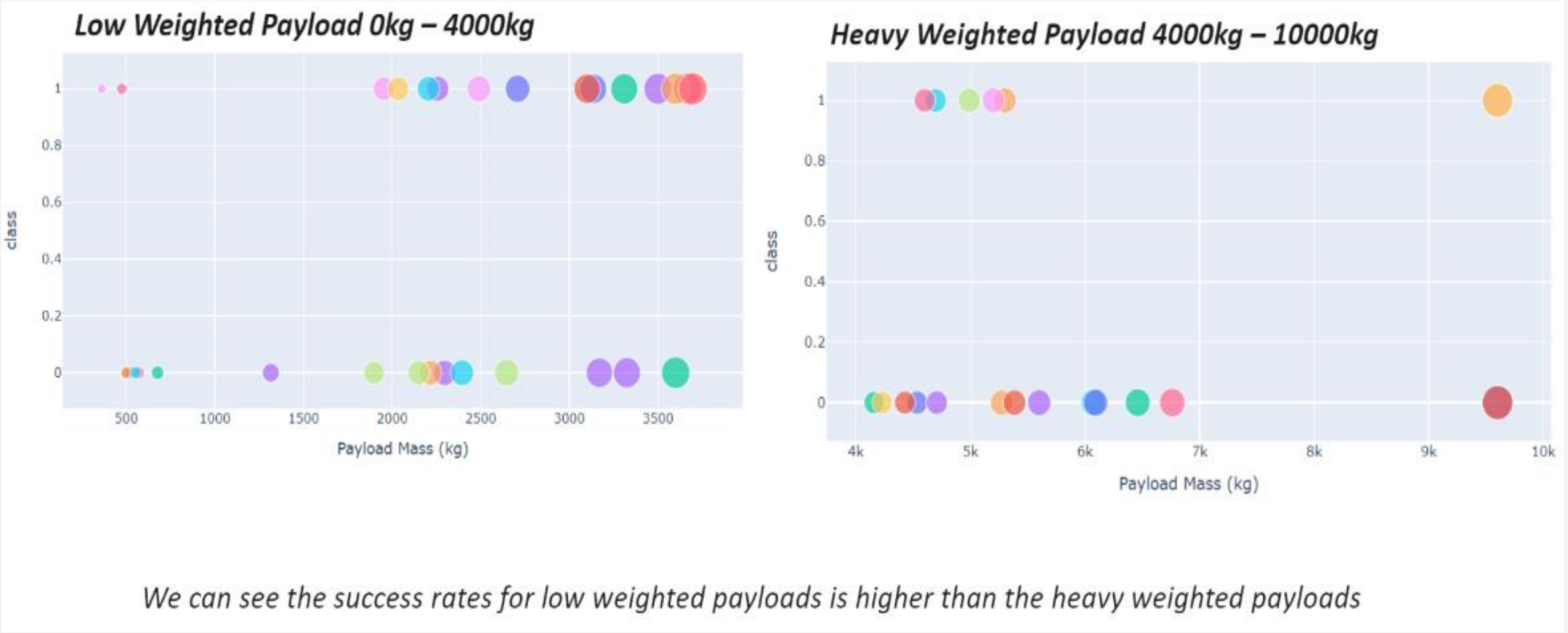
- This shows the launch success rate for all the sites.
- We can note that KSC LC-39A has the highest success rate

Launch Site with highest launch success ratio



- KSC LC-39A has the highest launch success rate with 76.9%

Payload vs Launch outcome for all sites with different payload selection in range slider



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

Section 5

Predictive Analysis (Classification)

Classification Accuracy

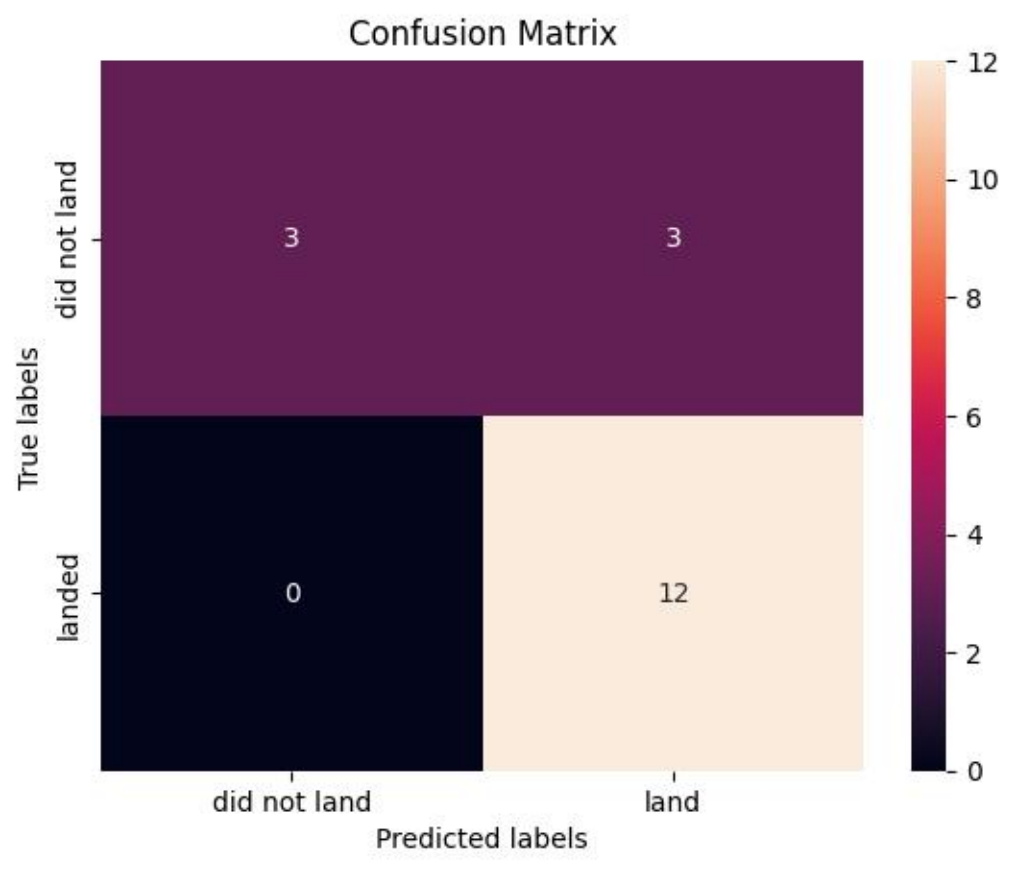
In [32]:

```
print('Accuracy for Logistics Regression method:', logreg_cv.score(X_test, Y_test))
print( 'Accuracy for Support Vector Machine method:', svm_cv.score(X_test, Y_test))
print('Accuracy for Decision tree method:', tree_cv.score(X_test, Y_test))
print('Accuracy for K nearsdt neighbors method:', knn_cv.score(X_test, Y_test))
```

```
Accuracy for Logistics Regression method: 0.8333333333333334
Accuracy for Support Vector Machine method: 0.8333333333333334
Accuracy for Decision tree method: 0.6111111111111112
Accuracy for K nearsdt neighbors method: 0.8333333333333334
```

- Due to the small size of our test data, our different models would give similar accuracy score.
- Only the Decision Tree method gave a different accuracy score.

Confusion Matrix



- Due to the small size of the test data, almost all the models had the same accuracy score and confusion matrix.
- The major problem is the false positives .i.e., unsuccessful landing marked as successful landing by the classifier.

Conclusions

From all the analysis done so far, we can conclude that:

- The higher/ larger the amount of flight at a launch site, the higher the number of successul launches or the greater the success rate.
- Launchsite KSC LC-39A has the highest the number of successful launches.
- Orbit types : ES-L1, GEO, HEO and SSO had the highest success rate.
- There was an increase in success rate from 2013 to 2020.
- The total number of successful outcome is 100.

Thank you!