

Winning Space Race with Data Science

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Outline

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

Executive Summary

- 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

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

Executive Summary

- Data collection methodology:
 - Data was collected using SpaceX API
 - Web scraping from Wikipedia.
- Perform data wrangling
 - Filtering the data and dealing with missing values
 - 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
 - Building, tuning and evaluation of classification models to ensure the best results

Data Collection

Data collection process involved a combination of API requests from SpaceX REST API and Web Scraping data from a table in SpaceX's Wikipedia entry.

We had to use both of these data collection methods in order to get complete information about the launches for a more detailed analysis.

Data Columns are obtained by using SpaceX REST API:

- FlightNumber, Date, BoosterVersion, PayloadMass, Orbit, LaunchSite, Outcome, Flights, GridFins, Reused, Legs, LandingPad, Block, ReusedCount, Serial, Longitude, Latitude

Data Columns are obtained by using Wikipedia Web Scraping:

- Flight No., Launch site, Payload, PayloadMass, Orbit, Customer, Launch outcome, Version Booster, Booster landing, Date, Time

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/python-decorator\(ibm_data_science_capstone/blob/main/01_jupyter-labs-spacex-data-collection-api.ipynb](https://github.com/python-decorator(ibm_data_science_capstone/blob/main/01_jupyter-labs-spacex-data-collection-api.ipynb)

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

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

```
[53]: response = requests.get(spacex_url)
```

Check the content of the response

```
[ ]: print(response.content)
```

You should see the response contains massive information about SpaceX launches. Next

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

To make the requested JSON results more consistent, we will use the following static res

```
[55]: static_json_url='https://cf-courses-data.s3.us.cloud-object-storage.appdoma
```

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

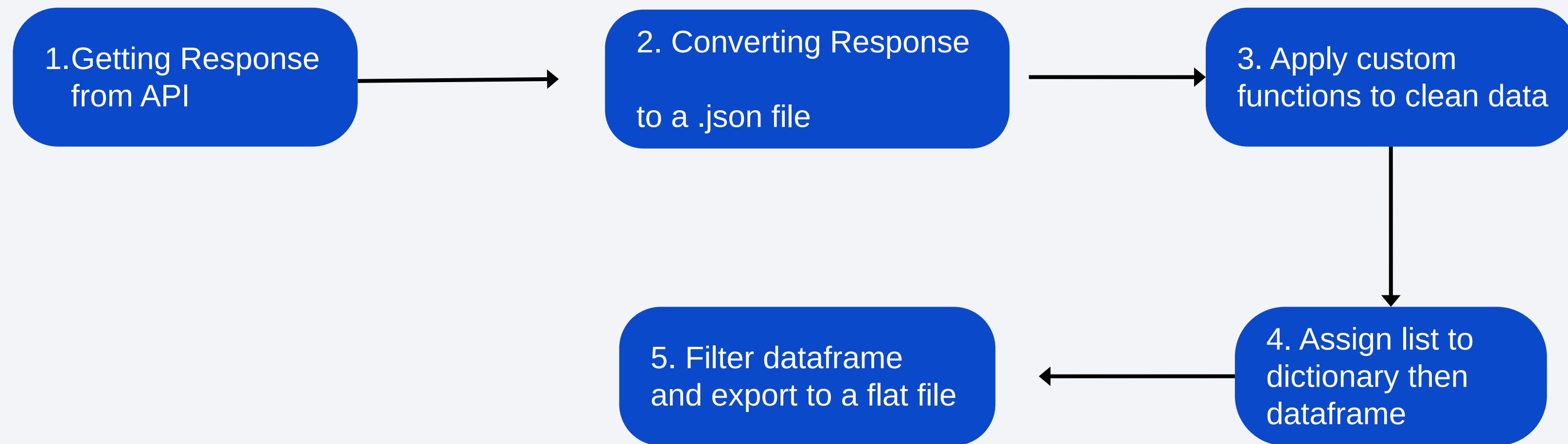
```
[56]: response.status_code
```

```
[56]: 200
```

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

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

Data Collection – SpaceX API - Flowchart



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.
- The link to the notebook is https://github.com/python-decorator/ibm_data_science_capstone/blob/main/02_jupyter-labs-webscraping.ipynb

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.

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

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

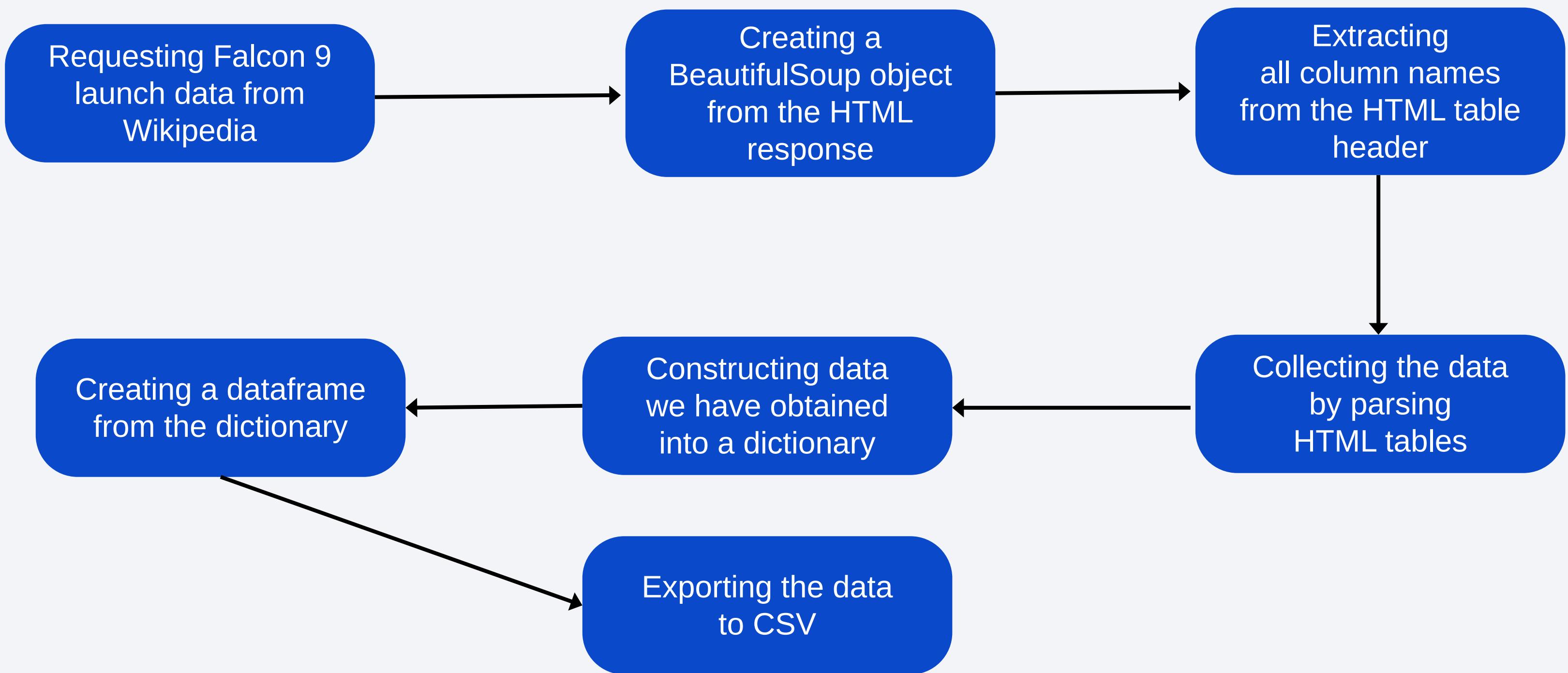
```
[16]: # Use BeautifulSoup() to create a BeautifulSoup object from a response text content  
soup = BeautifulSoup(response.content, 'html.parser')
```

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

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

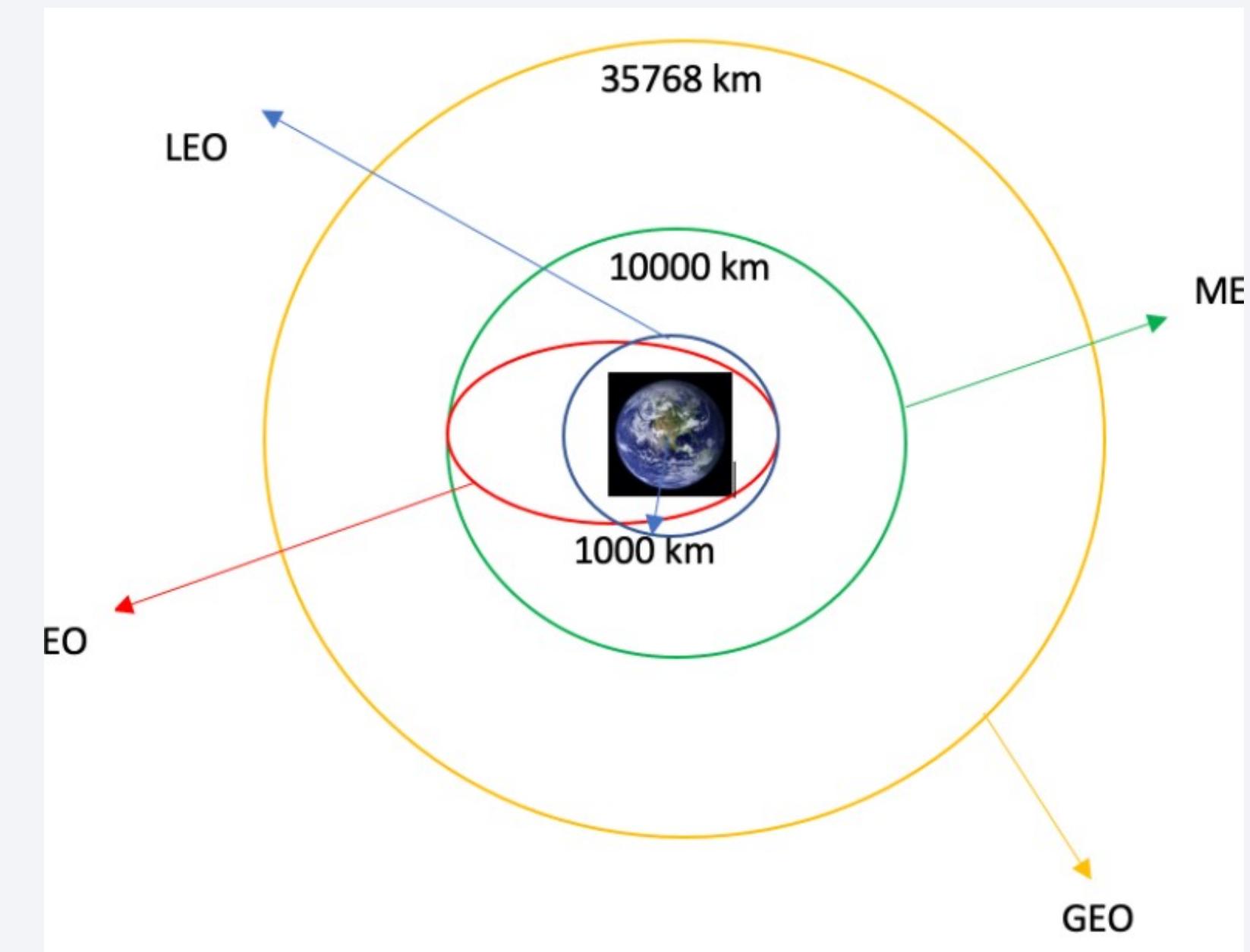
```
[90]: <title>List of Falcon 9 and Falcon Heavy launches - Wikipedia</title>
```

Data Collection - Scraping - Flowchart



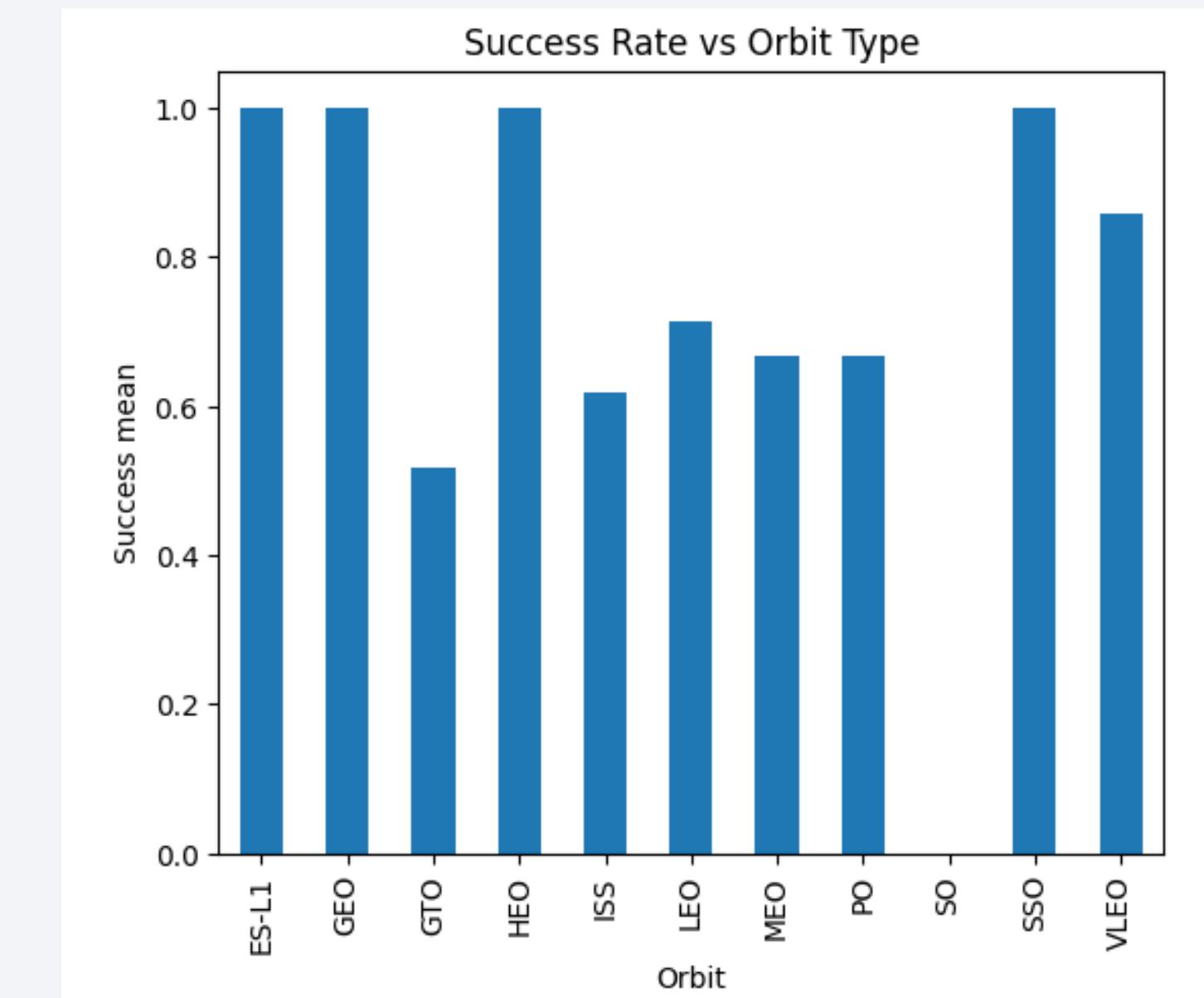
Data Wrangling

- 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.
- The link to the notebook is
https://github.com/python-decorator/ibm_data_science_capstone/blob/main/03_labs-jupyter-spacex-Data%20wrangling.ipynb



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.
- The link to the notebook is https://github.com/python-decorator/bm_data_science_capstone/blob/main/05_jupyter-labs-eda-dataviz.ipynb



EDA with SQL

- We loaded the SpaceX dataset into a SQLite 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.

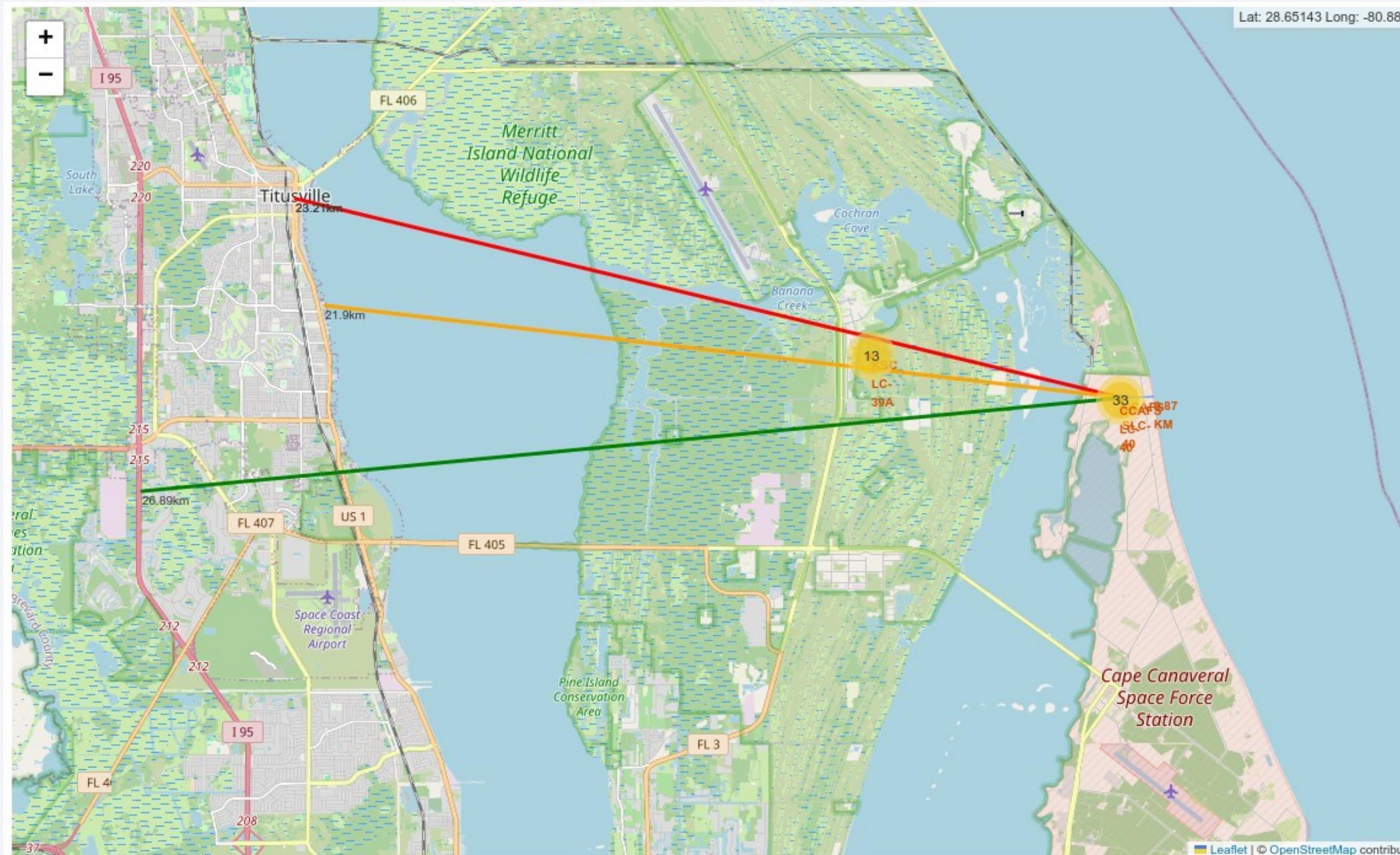
The link to the notebook is

https://github.com/python-decorator/ibm_data_science_capstone/blob/main/04_jupyter-labs-eda-sql-coursera_sqlite.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.

Build an Interactive Map with Folium



https://github.com/python-decorator/ibm_data_science_capstone/blob/main/06_lab_jupyter_launch_site_location.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/python-decorator/ibm_data_science_capstone/blob/main/08_spacex_dash_app.py

Predictive Analysis (Classification)

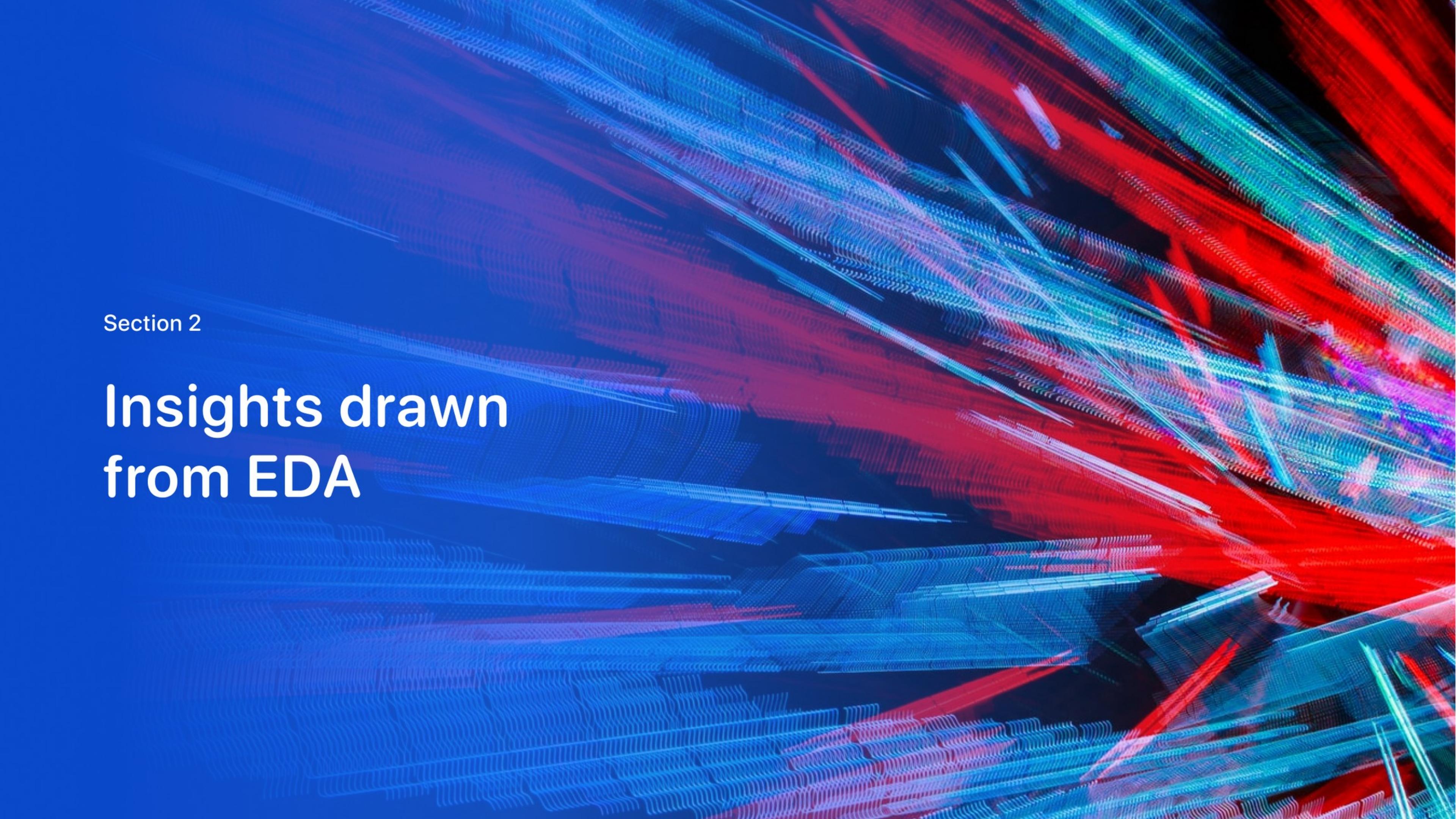
- We loaded the data using numpy and pandas, transformed the data, split our data into training and testing.
- We built different machine learning models and tune different hyperparameters using GridSearchCV.
- We used accuracy as the metric for our model, improved the model using feature engineering and algorithm tuning.
- We found the best performing classification model.

The link to the notebook is

https://github.com/python-decorator/ibm_data_science_capstone/blob/main/07_SpaceX_Machine_Learning_Prediction_Part_5.jupyterlite.ipynb

Results

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

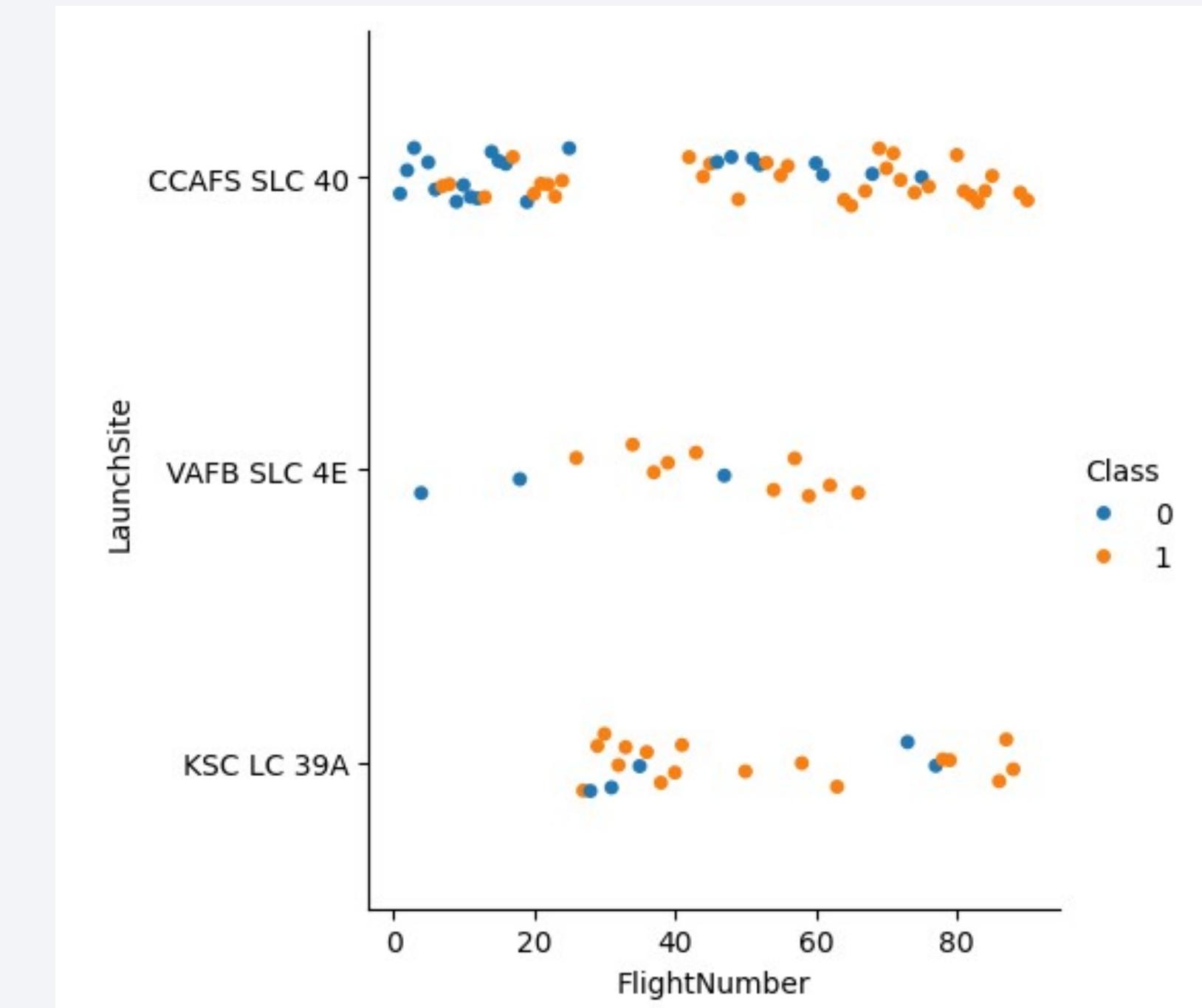
The background of the slide features a complex, abstract pattern of wavy, horizontal lines. These lines are primarily colored in shades of blue, red, and green, creating a sense of depth and motion. They are arranged in several layers, with some lines being more prominent than others. The overall effect is reminiscent of a digital or scientific visualization of data flow or signal processing.

Section 2

Insights drawn from EDA

Flight Number vs. Launch Site

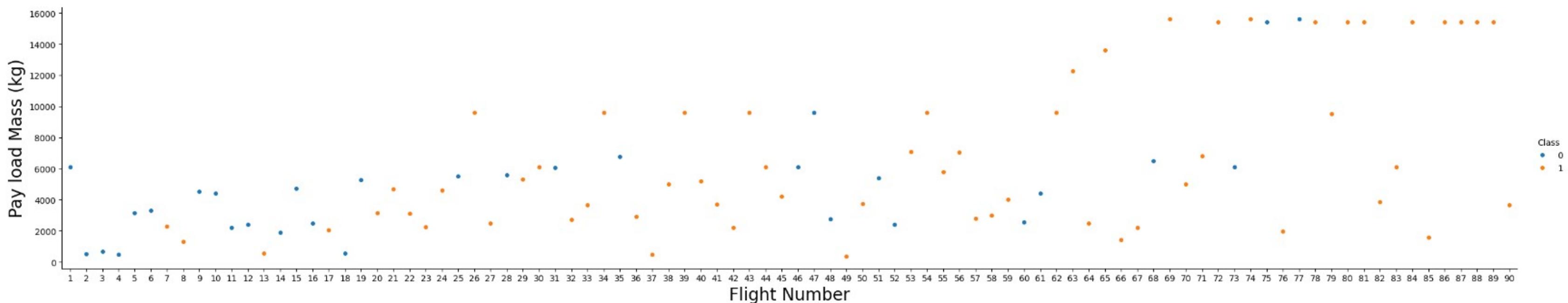
- From the plot, we found that the larger the flight amount at a launch site, the greater the success rate at a launch site.



Payload vs. Launch Site

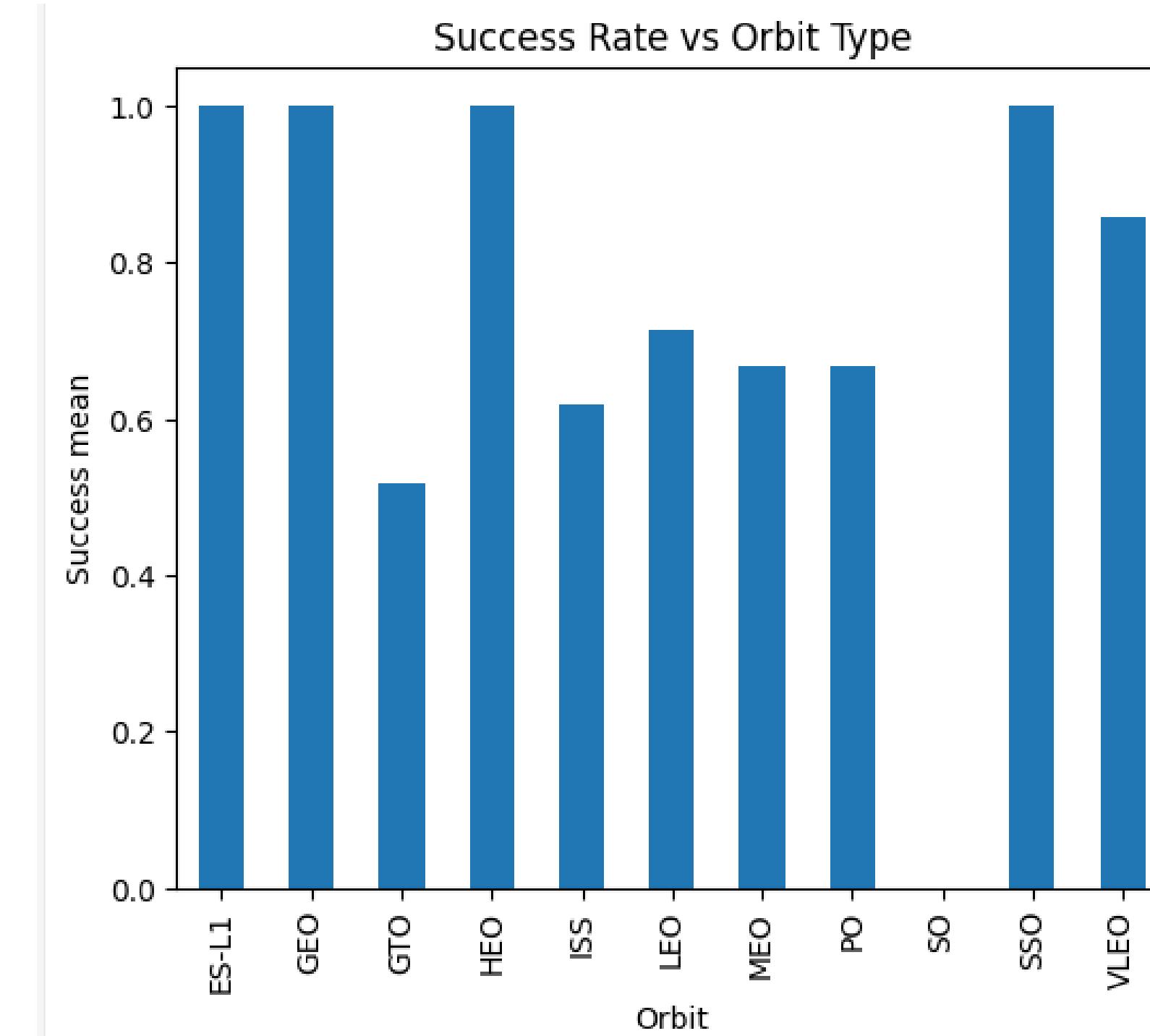


The greater the payload mass for launch site CCAFS SLC 40 the higher the success rate for the rocket.



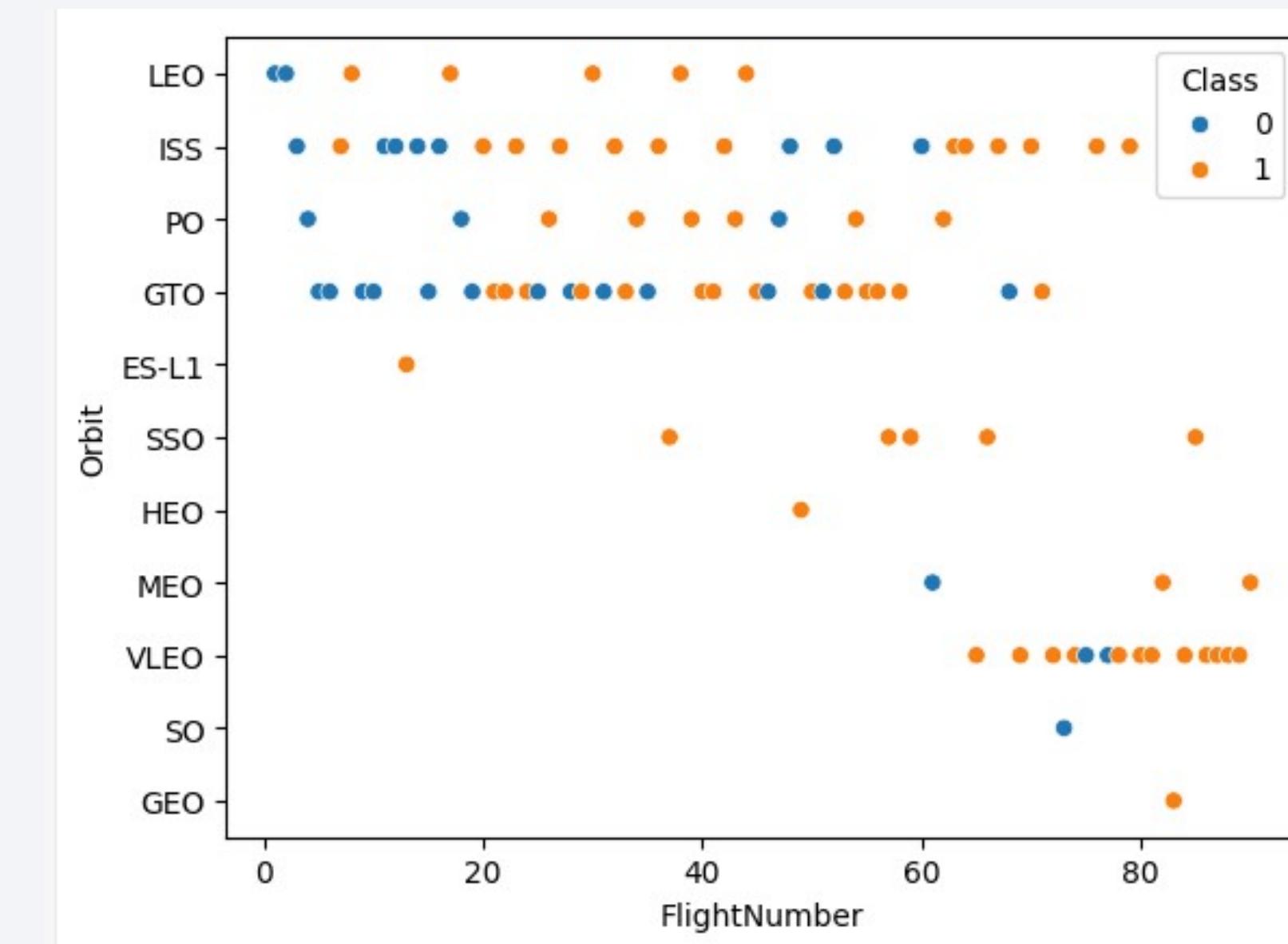
Success Rate vs. Orbit Type

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



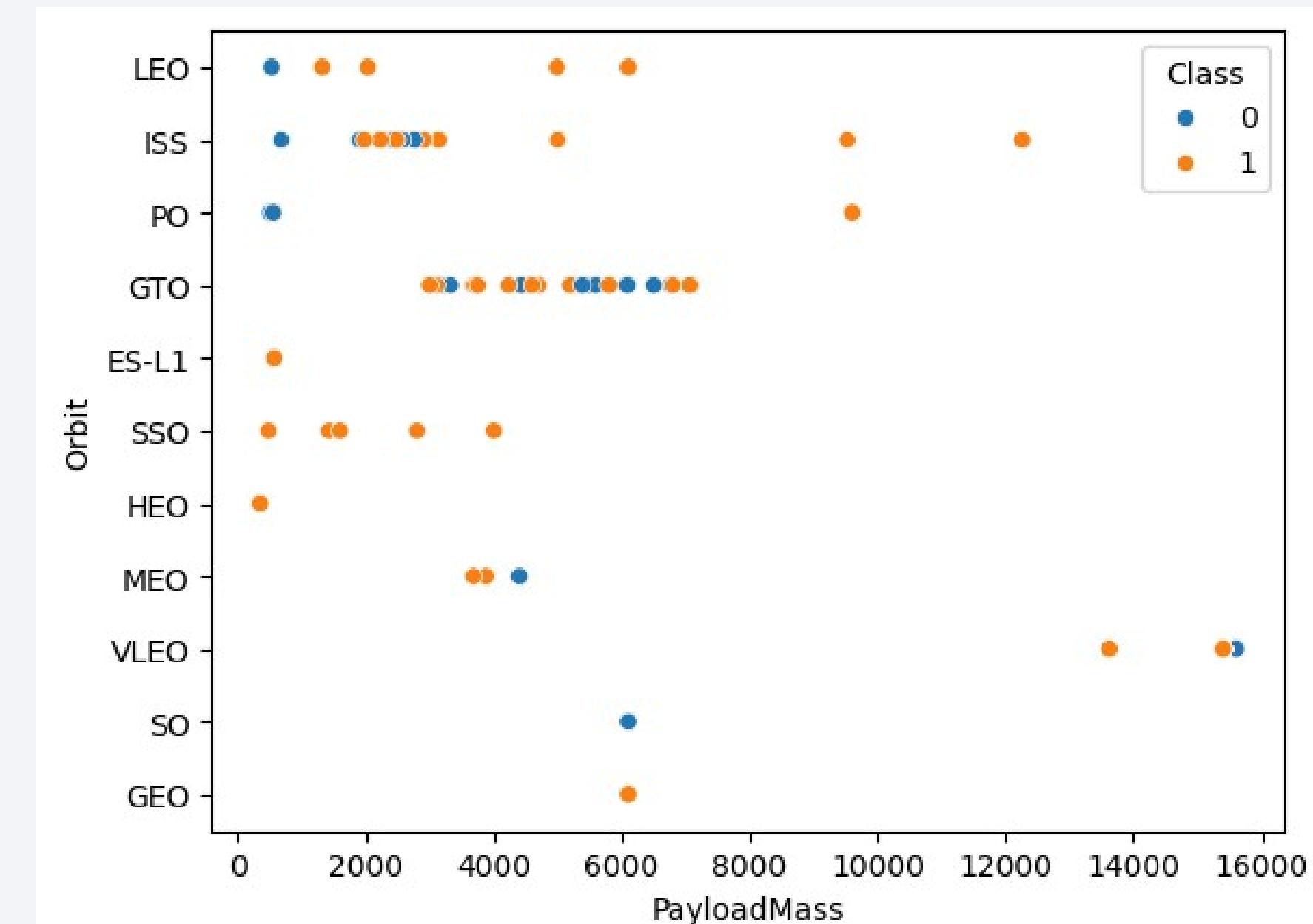
Flight Number vs. Orbit Type

- 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.



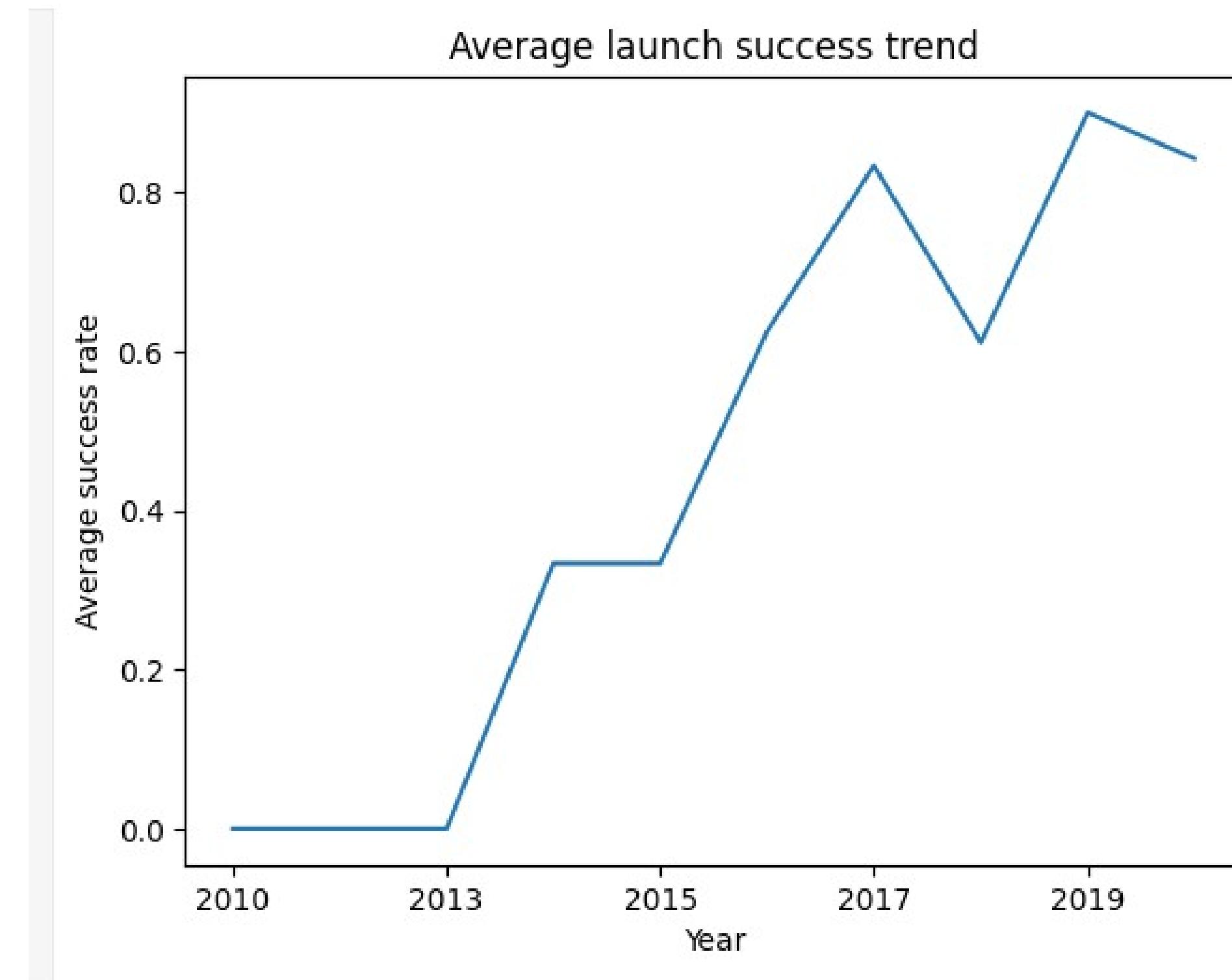
Payload vs. Orbit Type

- 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.

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

In [10]:

```
task_1 = """
    SELECT DISTINCT LaunchSite
    FROM SpaceX
"""

create_pandas_df(task_1, database=conn)
```

Out[10]:

	launchsite
0	KSC LC-39A
1	CCAFS LC-40
2	CCAFS SLC-40
3	VAFB SLC-4E

Launch Site Names Begin with 'CCA'

```
task_2 = """
    SELECT *
    FROM SpaceX
    WHERE LaunchSite LIKE 'CCA%'
    LIMIT 5
"""

create_pandas_df(task_2, database=conn)
```

Out[11]:

	date	time	boosterversion	launchsite	payload	payloadmasskg	orbit	customer	missionoutcome	landingoutcome
0	2010-04-06	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
1	2010-08-12	15:43:00	F9 v1.0 B0004	CCAFS LC-40	Dragon demo flight C1, two CubeSats, barrel of...	0	LEO (ISS)	NASA (COTS) NRO	Success	Failure (parachute)
2	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
3	2012-08-10	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt

Total Payload Mass

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

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

In [12]: task_3 = """
            SELECT SUM(PayloadMassKG) AS Total_PayloadMass
            FROM SpaceX
            WHERE Customer LIKE 'NASA (CRS)'
            """

create_pandas_df(task_3, database=conn)

Out[12]: total_payloadmass
          0      45596
```

Average Payload Mass by F9 v1.1

- We calculated the average payload mass carried by booster version F9 v1.1 as 2928.4

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

In [13]:

```
task_4 = """
    SELECT AVG(PayloadMassKG) AS Avg_PayloadMass
    FROM SpaceX
    WHERE BoosterVersion = 'F9 v1.1'
    """

create_pandas_df(task_4, database=conn)
```

Out[13]:

	avg_payloadmass
0	2928.4

First Successful Ground Landing Date

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

In [14]:

```
task_5 = """
    SELECT MIN(Date) AS FirstSuccessfull_landing_date
    FROM SpaceX
    WHERE LandingOutcome LIKE 'Success (ground pad)'
    """

create_pandas_df(task_5, database=conn)
```

Out[14]:

firstsuccessfull_landing_date

0	2015-12-22
---	------------

Successful Drone Ship Landing with Payload between 4000 and 6000

In [15]:

```
task_6 = """
    SELECT BoosterVersion
    FROM SpaceX
    WHERE LandingOutcome = 'Success (drone ship)'
        AND PayloadMassKG > 4000
        AND PayloadMassKG < 6000
    ...
create_pandas_df(task_6, database=conn)
```

Out[15]:

boosterversion

0	F9 FT B1022
1	F9 FT B1026
2	F9 FT B1021.2
3	F9 FT B1031.2

- 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

Total Number of Successful and Failure Mission Outcomes

List the total number of successful and failure mission outcomes

In [16]:

```
task_7a = '''  
    SELECT COUNT(MissionOutcome) AS SuccessOutcome  
    FROM SpaceX  
    WHERE MissionOutcome LIKE 'Success%'  
    '''  
  
task_7b = '''  
    SELECT COUNT(MissionOutcome) AS FailureOutcome  
    FROM SpaceX  
    WHERE MissionOutcome LIKE 'Failure%'  
    '''  
  
print('The total number of successful mission outcome is:')  
display(create_pandas_df(task_7a, database=conn))  
print()  
print('The total number of failed mission outcome is:')  
create_pandas_df(task_7b, database=conn)
```

The total number of successful mission outcome is:

successoutcome
0 100

The total number of failed mission outcome is:

Out[16]:

failureoutcome
0 1

- We used wildcard like '%' to filter for WHERE MissionOutcome was a success or a failure.

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

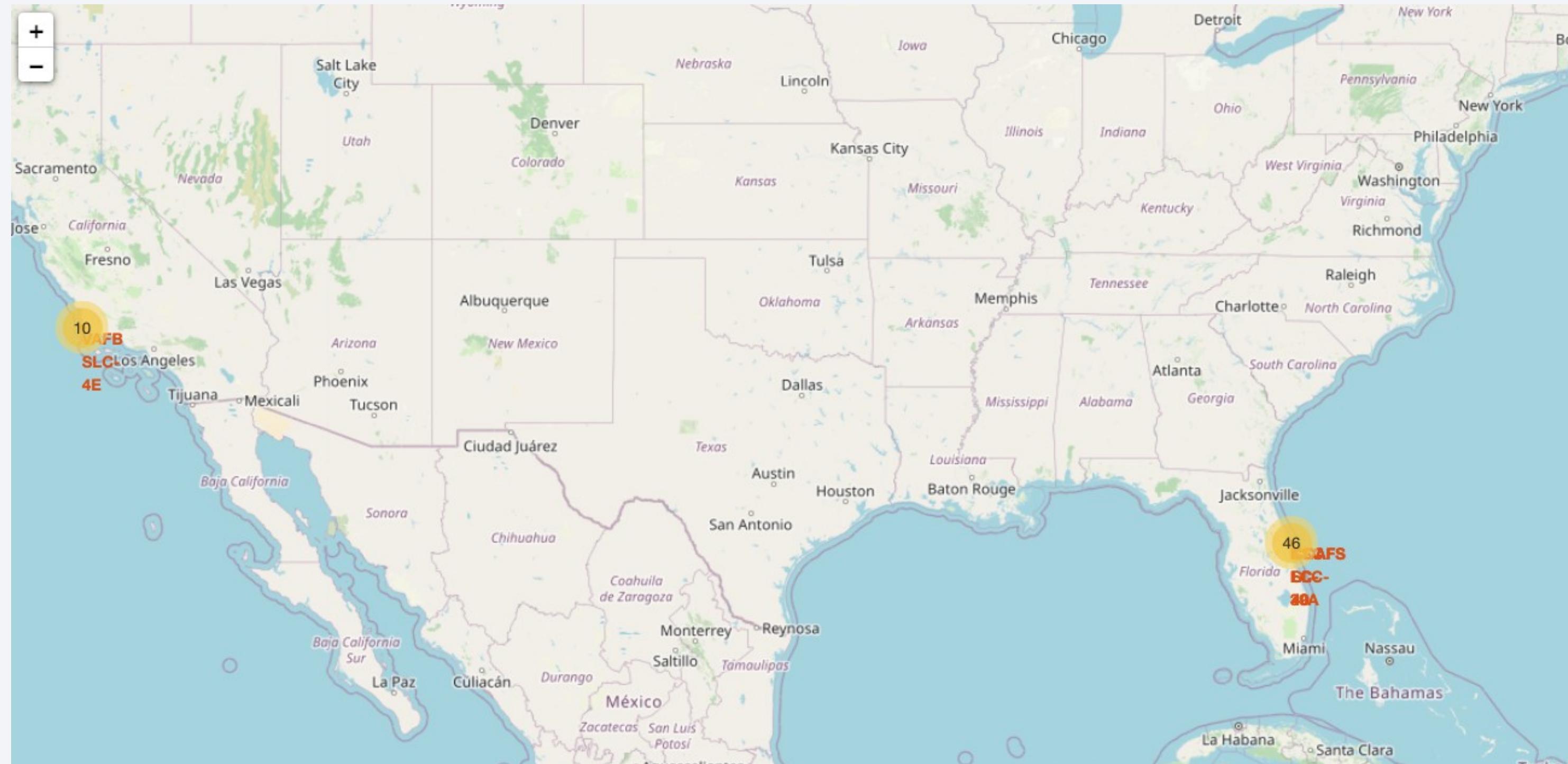
- We selected Landing outcomes and the COUNT of landing outcomes from the data and used the WHERE clause to filter for landing outcomes BETWEEN 2010-06-04 to 2010-03-20.
- We applied the GROUP BY clause to group the landing outcomes and the ORDER BY clause to order the grouped landing outcome in descending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

The background of the slide is a photograph taken from space at night. It shows the curvature of the Earth against a dark blue-black void of space. City lights are visible as numerous small yellow and white dots, primarily concentrated in coastal and urban areas. In the upper right quadrant, there is a bright, horizontal band of light, likely the Aurora Borealis or Southern Lights. The overall atmosphere is mysterious and scientific.

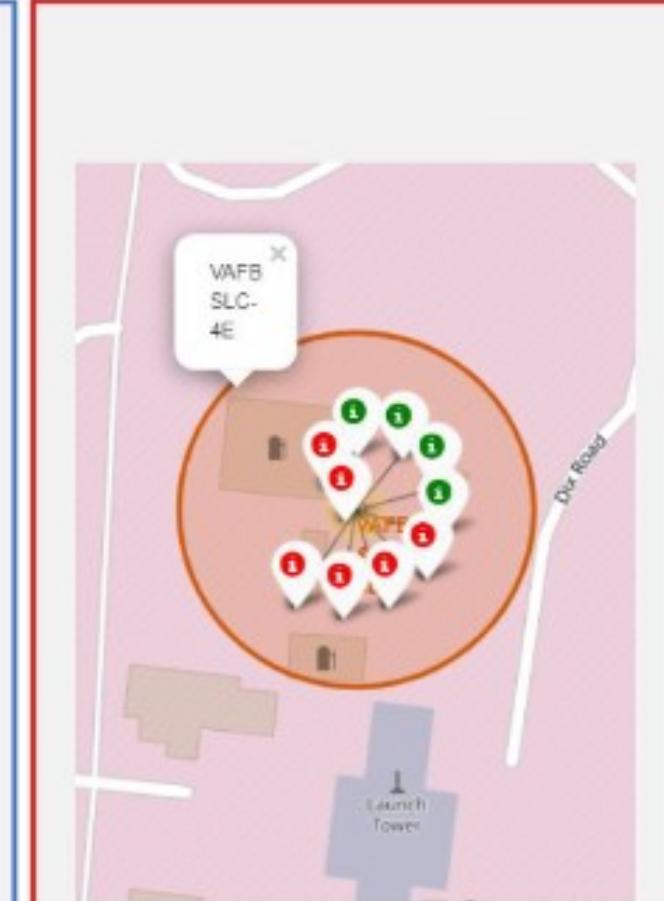
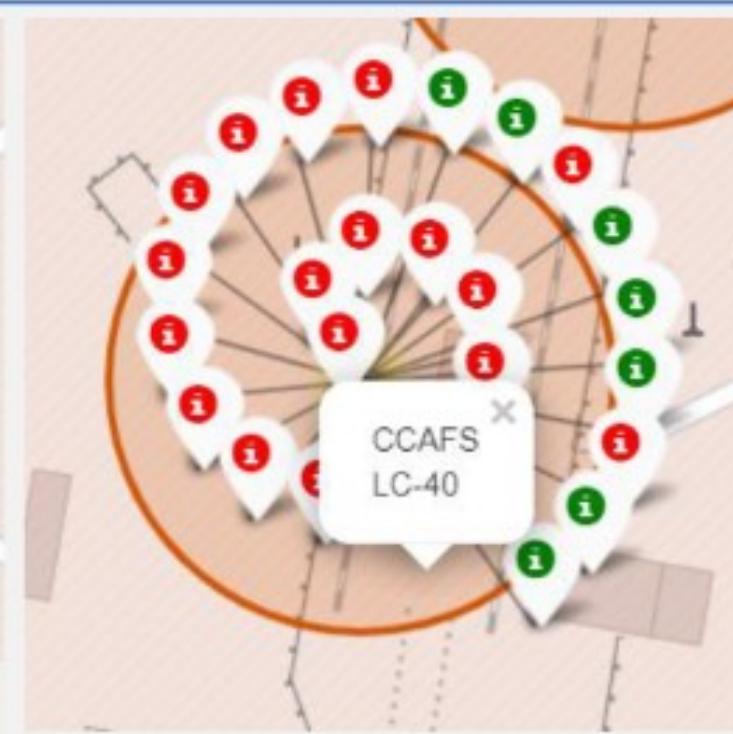
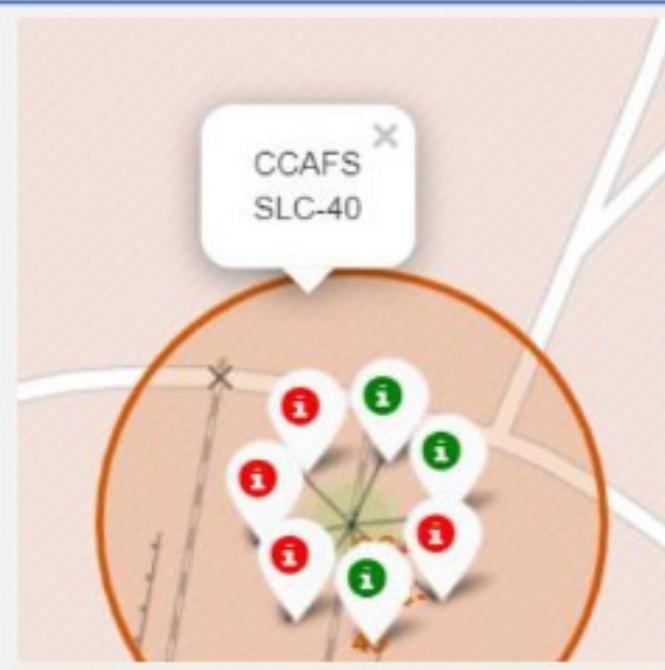
Section 4

Launch Sites Proximities Analysis

All launch sites global map markers



Markers showing launch sites with color labels



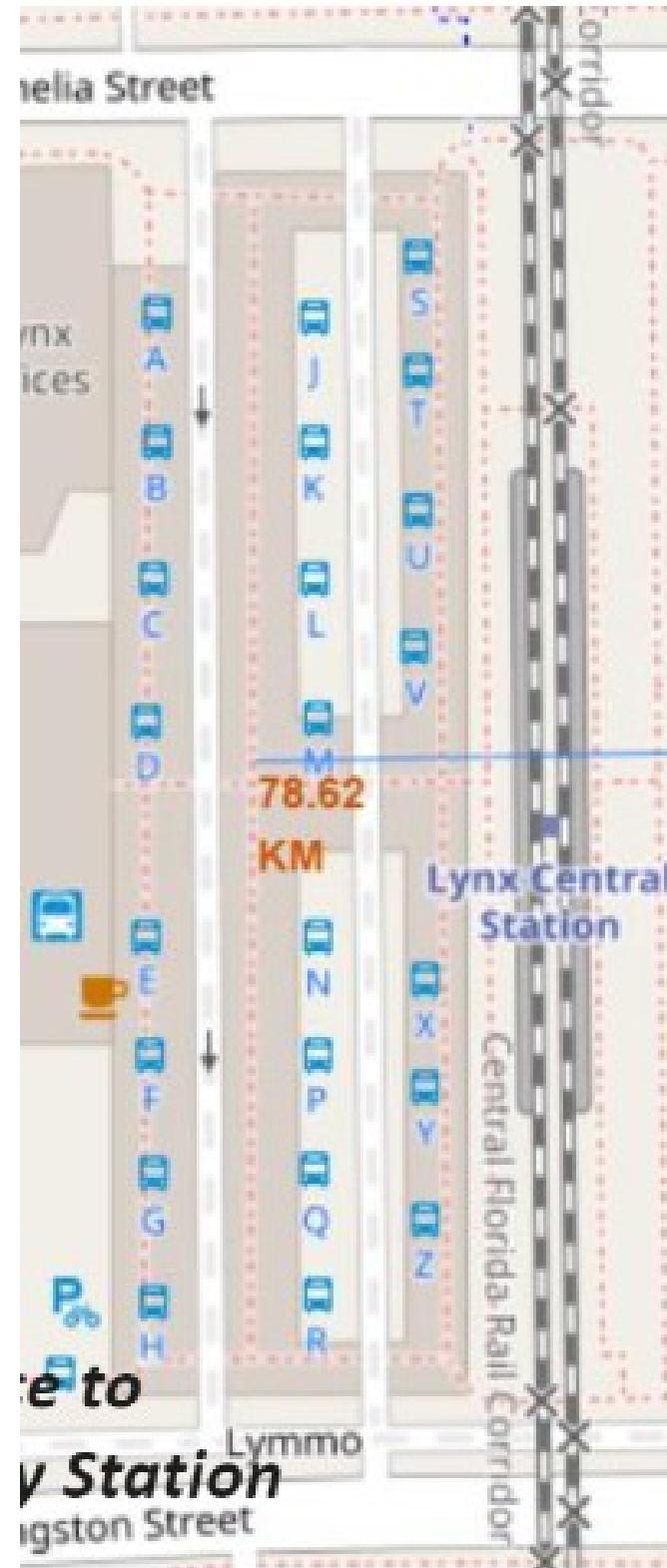
Florida Launch Sites

Green Marker shows successful Launches and *Red Marker* shows Failures

37

36

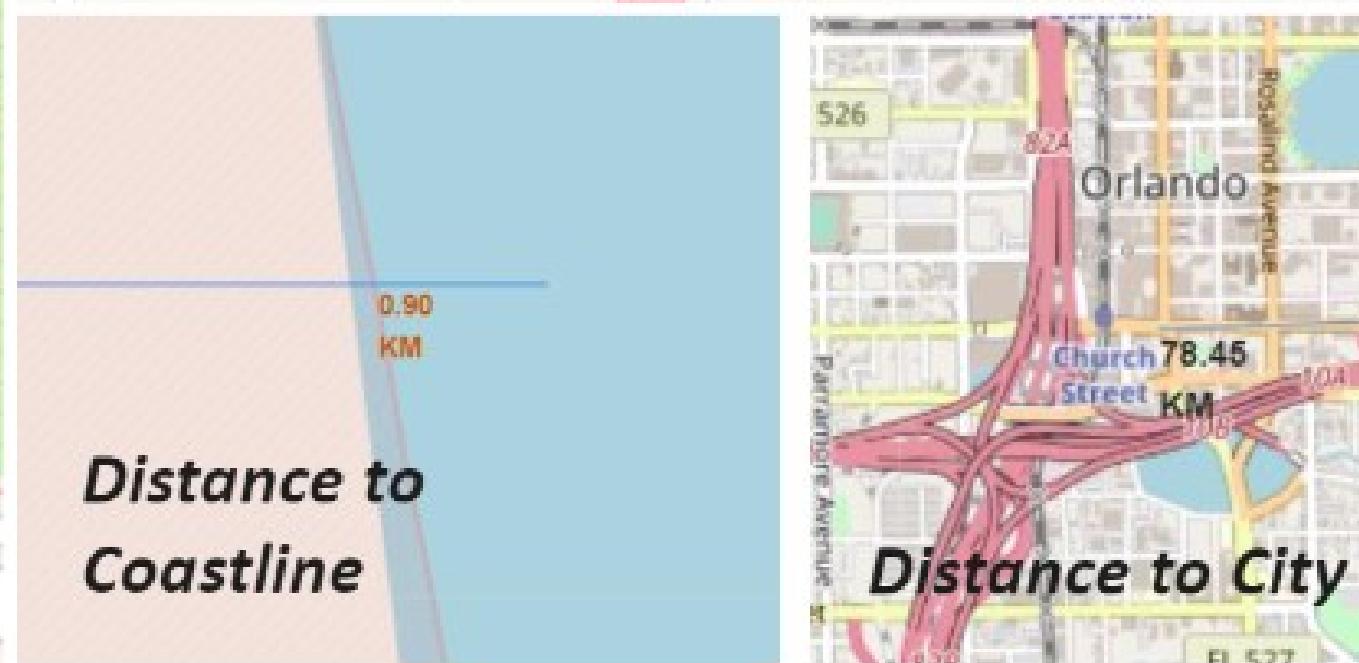
Launch Site distance to landmarks



**Distance to
closest Highway**



Distance to coast



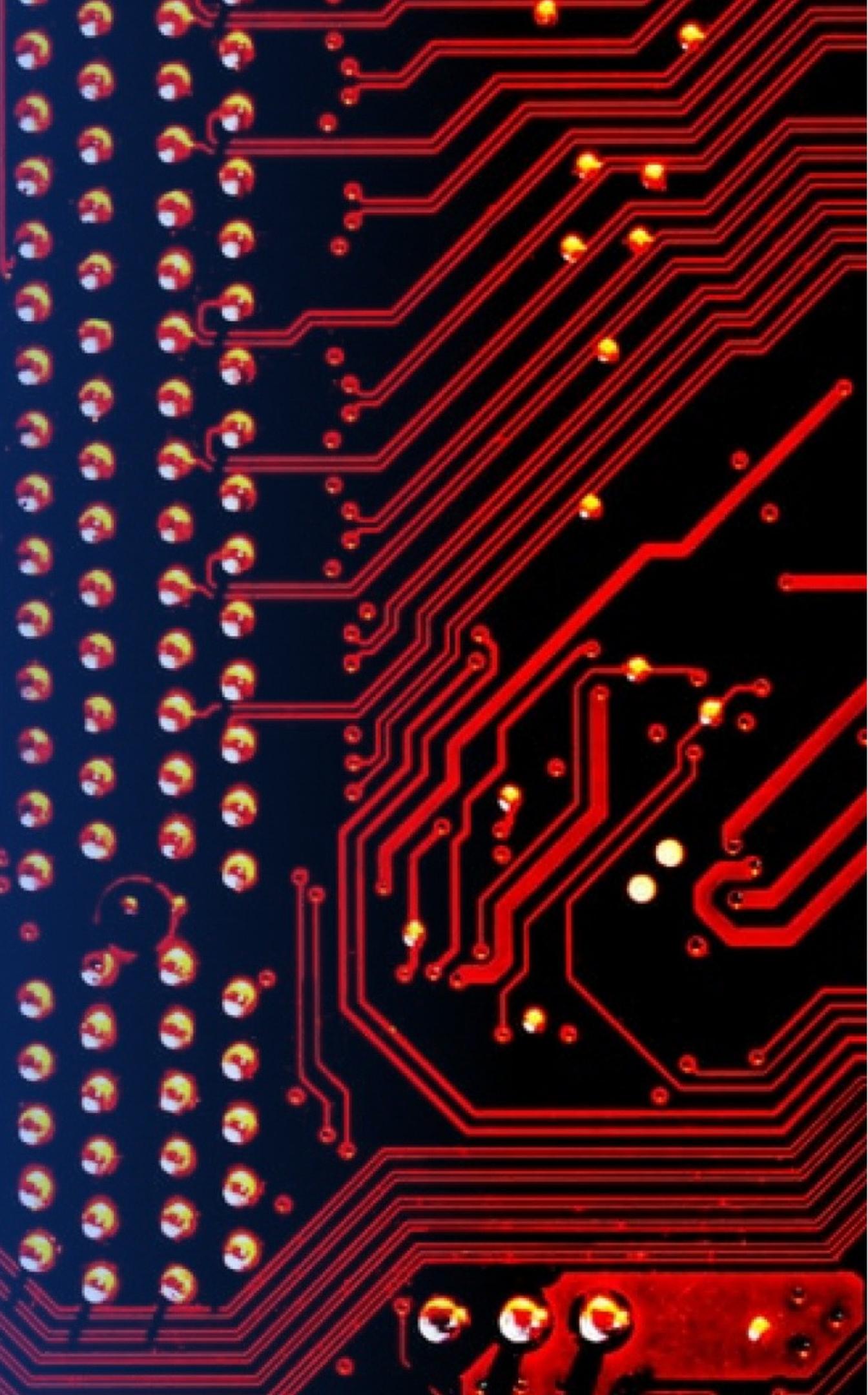
**Distance to
Coastline**

Distance to City

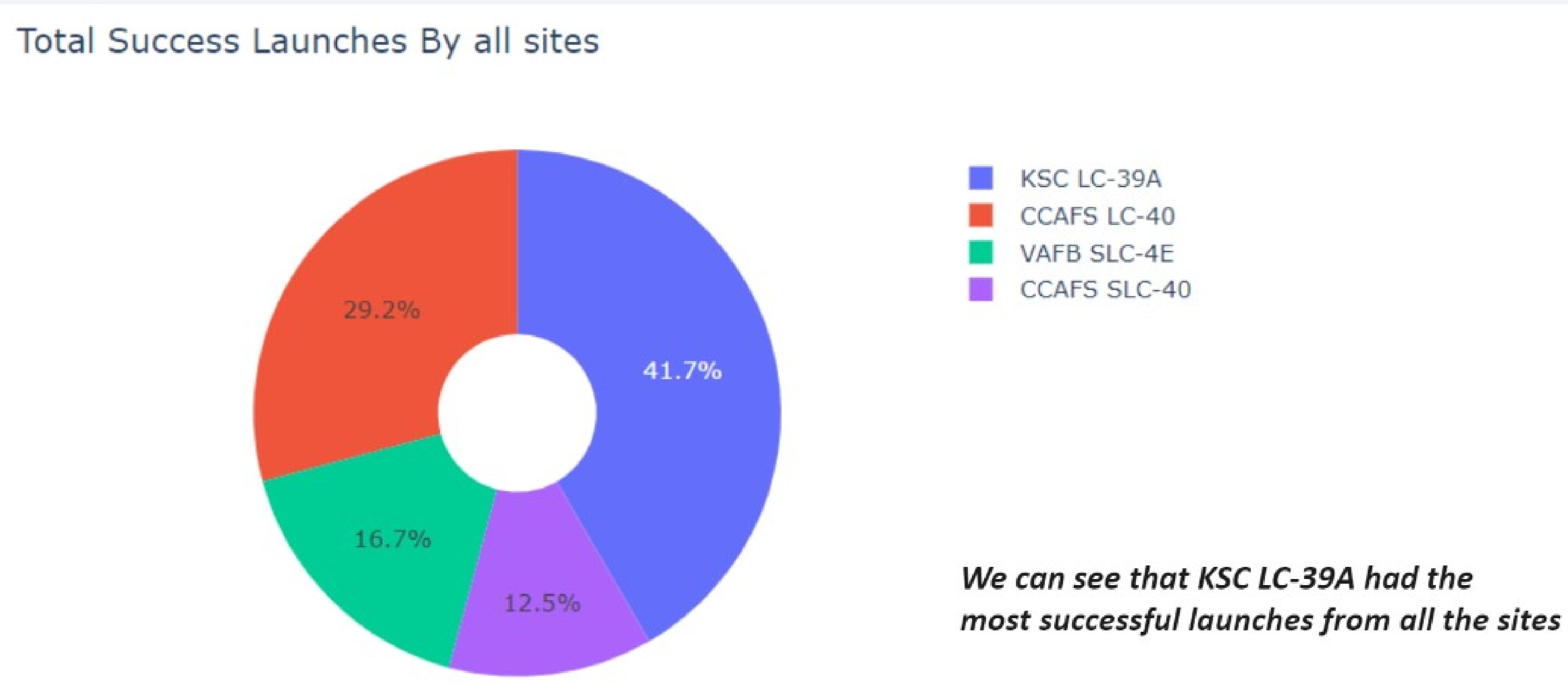
- Are launch sites in close proximity to railways? No
- Are launch sites in close proximity to highways? No
- Are launch sites in close proximity to coastline? Yes
- Do launch sites keep certain distances away from cities? Yes

Section 5

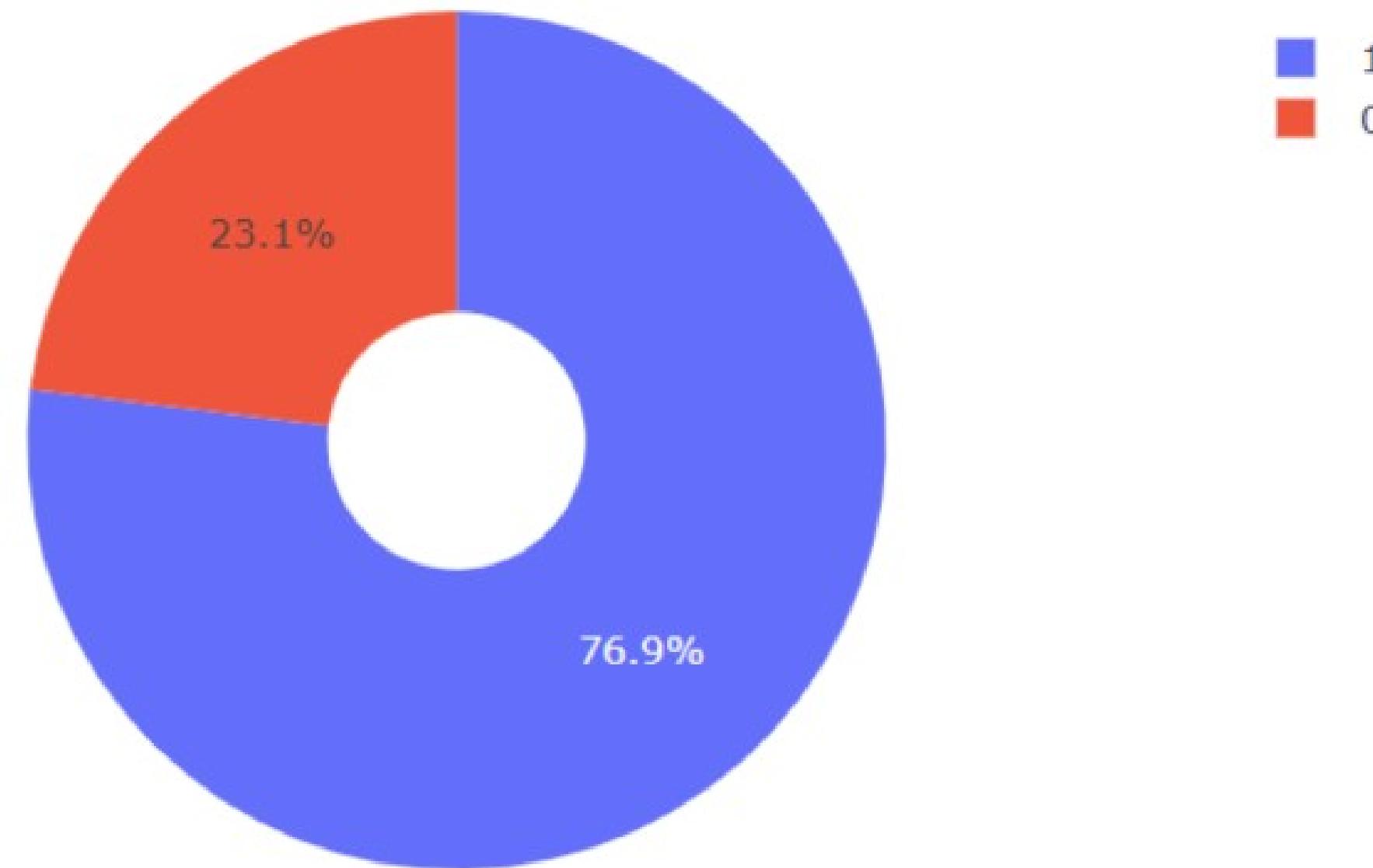
Build a Dashboard with Plotly Dash



Pie chart showing the success percentage achieved by each launch site

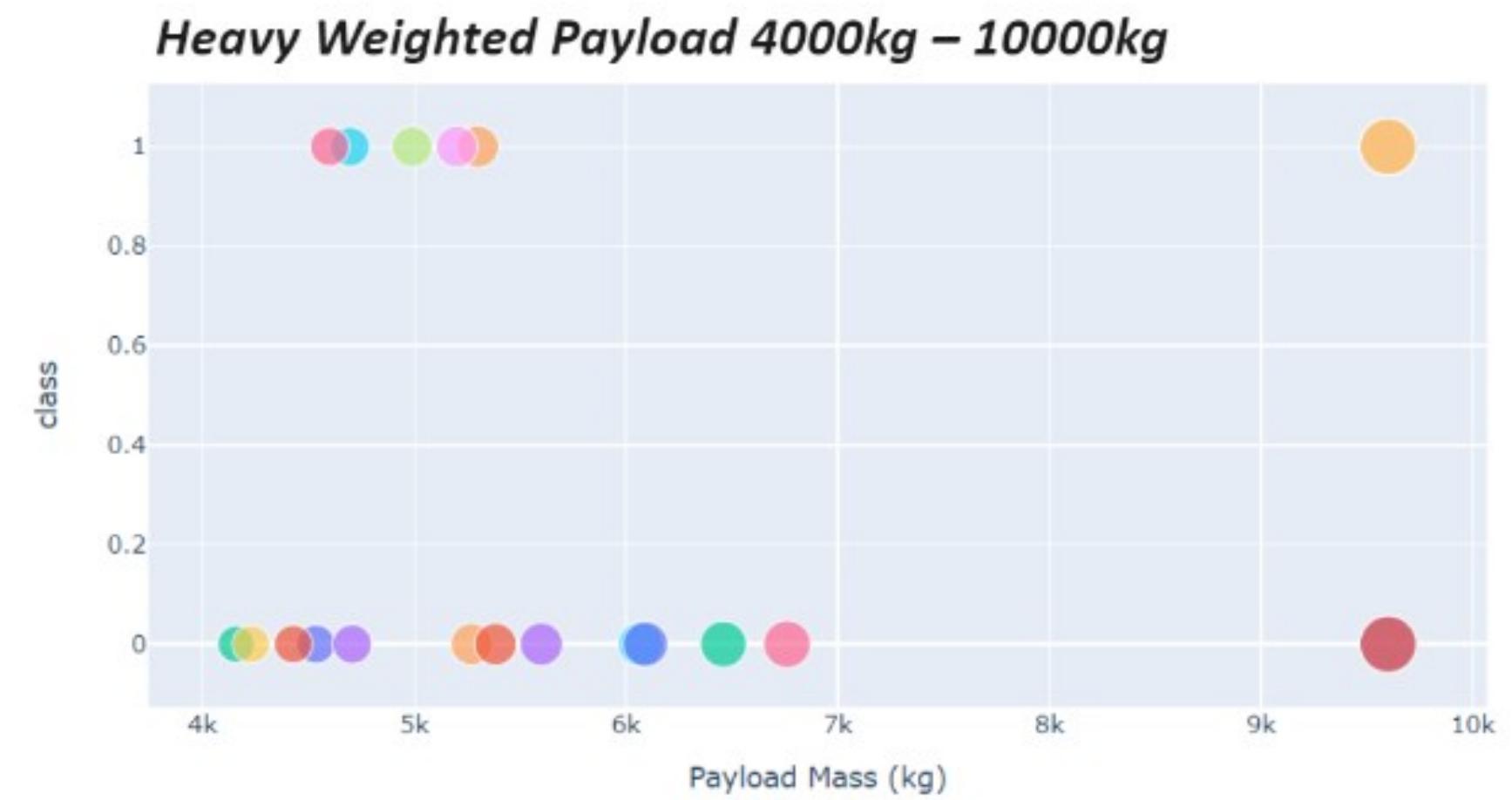
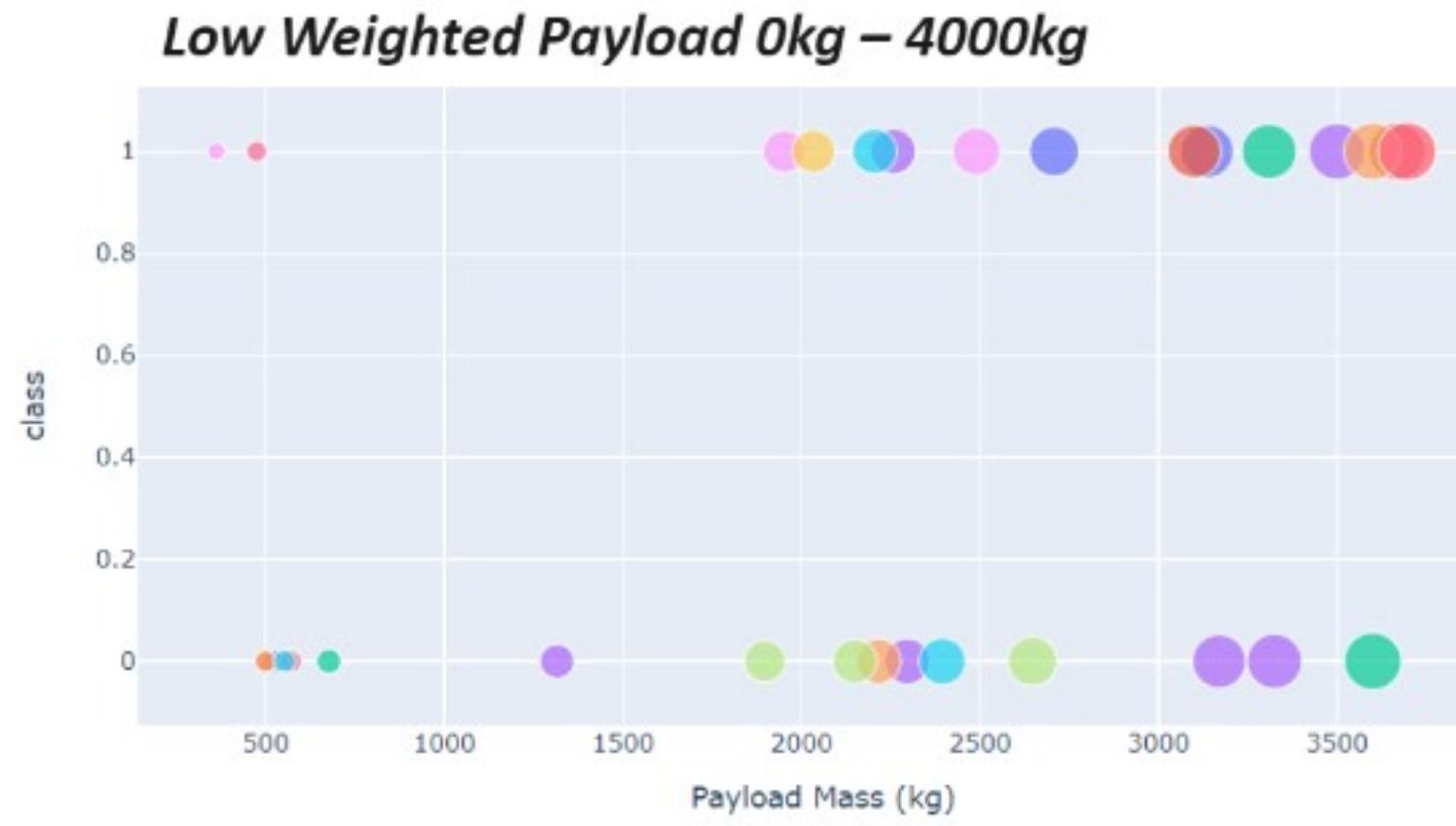


Pie chart showing the Launch site with the highest launch success ratio



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



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

Section 6

Predictive Analysis (Classification)

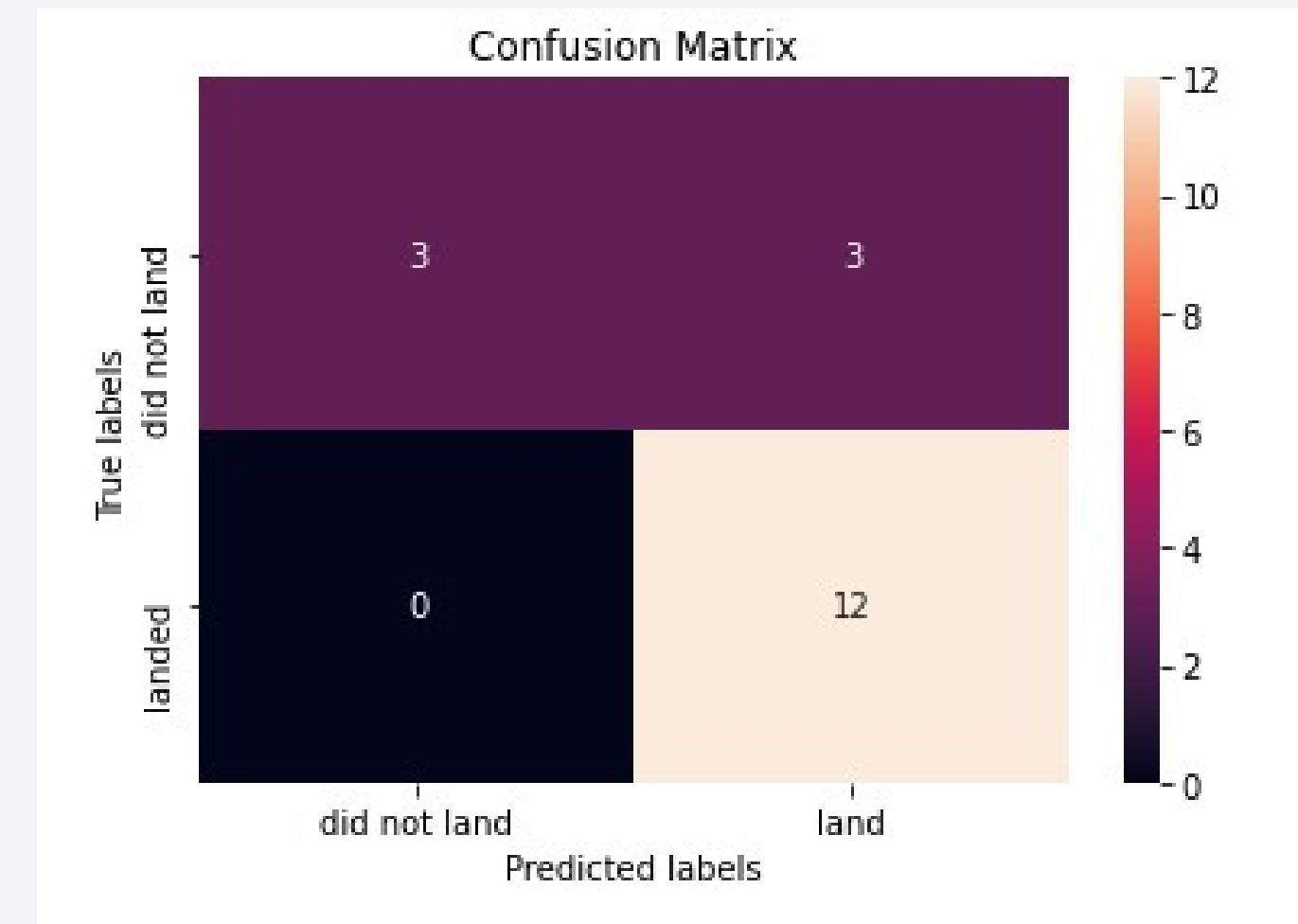
Classification Accuracy

- 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!

