IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

Johann Pineda
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Outline

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

Executive Summary

- Summary of methodologies
  - Data collection
  - Data Wrangling
  - Machine Learning
  - Data Analytics
- Summary of all results
  - Interactive Analytics
  - Predictive Analytics

Introduction

- Project background and context

  On its website, Space X promotes Falcon 9 rocket launches for 62 million dollars; other suppliers charge upwards of 165 million dollars for each launch. A large portion of the savings is due to Space X's ability to reuse the first stage. So, if we can figure out whether the first stage will land, we can figure out how much a launch will cost. If another business wishes to submit a proposal for a rocket launch against Space X, they can use this information. The project's objective is to build a pipeline for machine learning that can forecast if the initial stage will land successfully.

- Problems you want to find answers

  What are good operating conditions?

  What features make a land go well?

  What makes a rocket land with success?

Section 1

Methodology

Methodology

Executive Summary

- Data collection methodology:
    - Data was gathered through scraping Wikipedia's website and the SpaceX API.
- Perform data wrangling
    - We used one-hot encoding for 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

Utilizing a get call to the SpaceX API, data was gathered.

Next, we used the.json() function call to decode the response's content as JSON and the.json normalize function call to convert it into a pandas dataframe ().

The data was then cleansed, missing values were checked for, and filled in as appropriate.

Additionally, using BeautifulSoup, we scraped Wikipedia for information on Falcon 9 launch statistics.

The goal was to extract the launch records as an HTML table, parse the table, and then transform the table into a pandas dataframe for later analysis.

Data Collection – SpaceX API

- To gather data, sanitize the requested data, and do some simple data wrangling and formatting, we used the get request to the SpaceX API.

- The link is https://github.com/theonejohann/Peer-graded-Assignment-Peer-Review-Submit-your-Work-and-Review-your-Peers/blob/main/Data%20Collection%20API.ipynb

1. Get request for rocket launch data using API

In [6]:
```
spacex_url="https://api.spacexdata.com/v4/launches/past"
```

In [7]:
```
response = requests.get(spacex_url)
```

2. Use json_normalize method to convert json result to dataframe

In [12]:
```
# Use json_normalize method to convert the json result into a dataframe

# decode response content as json
static_json_df = res.json()
```

In [13]:
```
# apply json_normalize
data = pd.json_normalize(static_json_df)
```

3. We then performed data cleaning and filling in the missing values

In [30]:
```
rows = data_falcon9['PayloadMass'].values.tolist()[0]

df_rows = pd.DataFrame(rows)
df_rows = df_rows.replace(np.nan, PayloadMass)

data_falcon9['PayloadMass'][0] = df_rows.values
data_falcon9
```

Data Collection - Scraping

- With BeautifulSoup, we used web scraping to collect Falcon 9 launch data.
- The table was analyzed, then transformed into a pandas dataframe.

- The link is https://github.com/theonejohann/Peer-graded-Assignment-Peer-Review-Submit-your-Work-and-Review-your-Peers/blob/main/Data%20Collection%20with%20Web%20Scraping.ipynb

1. Apply HTTP Get method to request the Falcon 9 rocket launch page

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

In [5]:
```
# use requests.get() method with the provided static_url
# assign the response to a object
html_data = requests.get(static_url)
html_data.status_code
```

Out[5]:
```
200
```

2. Create a BeautifulSoup object from the HTML response

In [6]:
```
# Use BeautifulSoup() to create a BeautifulSoup object from a response text content
soup = BeautifulSoup(html_data.text, 'html.parser')
```

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

In [7]:
```
# Use soup.title attribute
soup.title
```

Out[7]:
```
<title>List of Falcon 9 and Falcon Heavy launches - Wikipedia</title>
```

3. Extract all column names from the HTML table header

In [10]:
```
column_names = []

# Apply find_all() function with `th` element on first_launch_table
# Iterate each th element and apply the provided extract_column_from_header() to get a column name
# Append the Non-empty column name (`if name is not None and len(name) > 0`) into a list called column_names

element = soup.find_all('th')
for row in range(len(element)):
    try:
        name = extract_column_from_header(element[row])
        if (name is not None and len(name) > 0):
            column_names.append(name)
    except:
        pass
```

4. Create a dataframe by parsing the launch HTML tables
5. Export data to csv

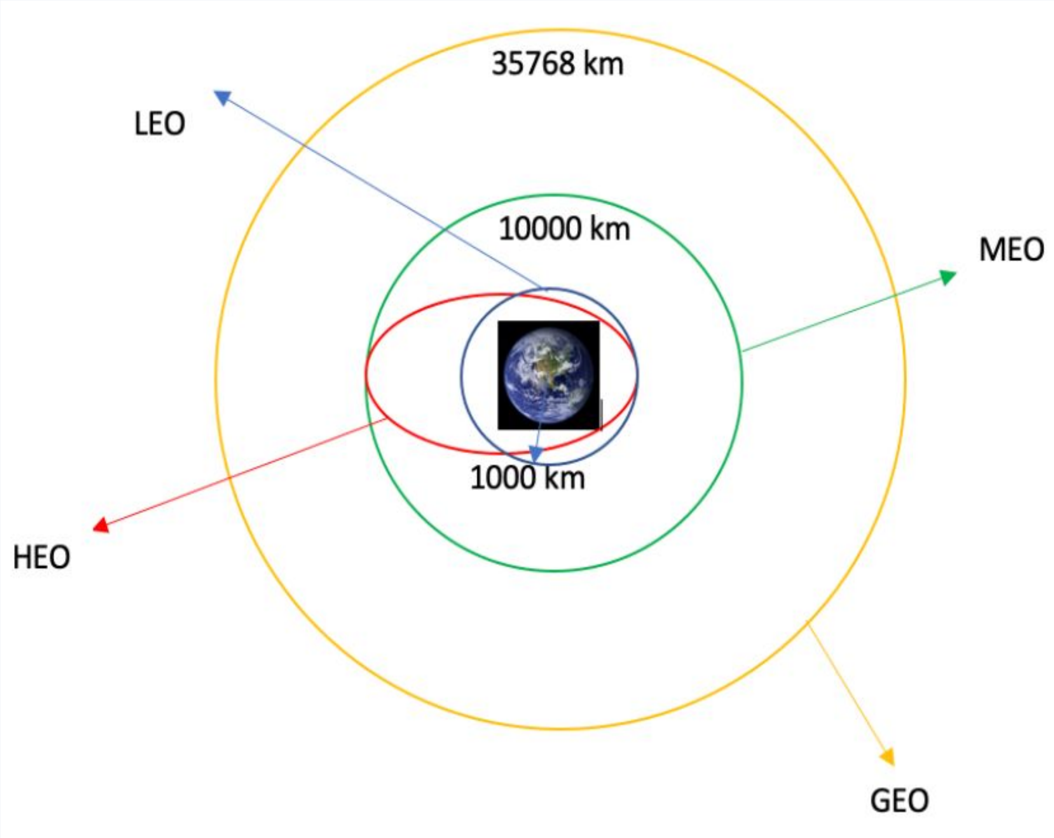
Data Wrangling

Exploratory data analysis was done to establish the training labels.

We determined the number of launches at each location as well as the frequency and number of orbits.

We used the outcome column to build the landing outcome label and saved the data to CSV.

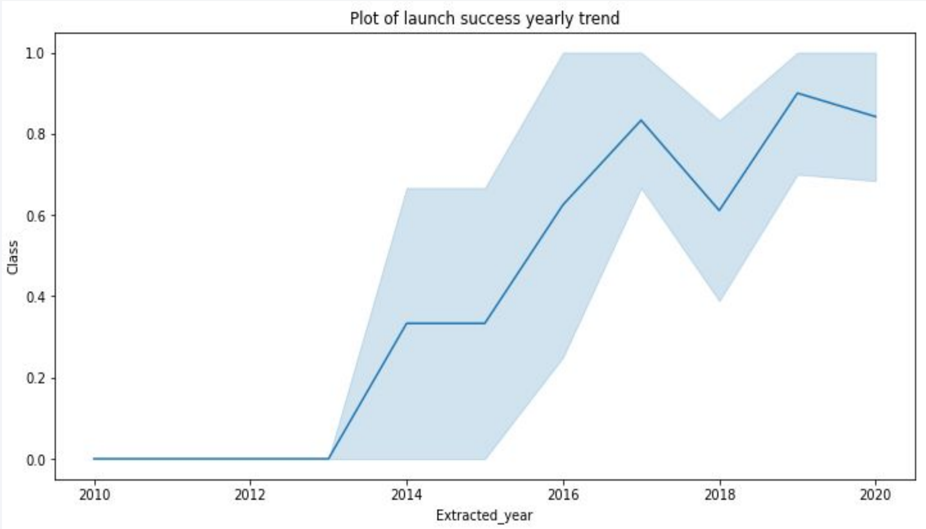
The link is https://github.com/theonejohann/Peer-graded-Assignment-Peer-Review-Submit-your-Work-and-Review-your-Peers/blob/main/Data%20Wrangling.ipynb

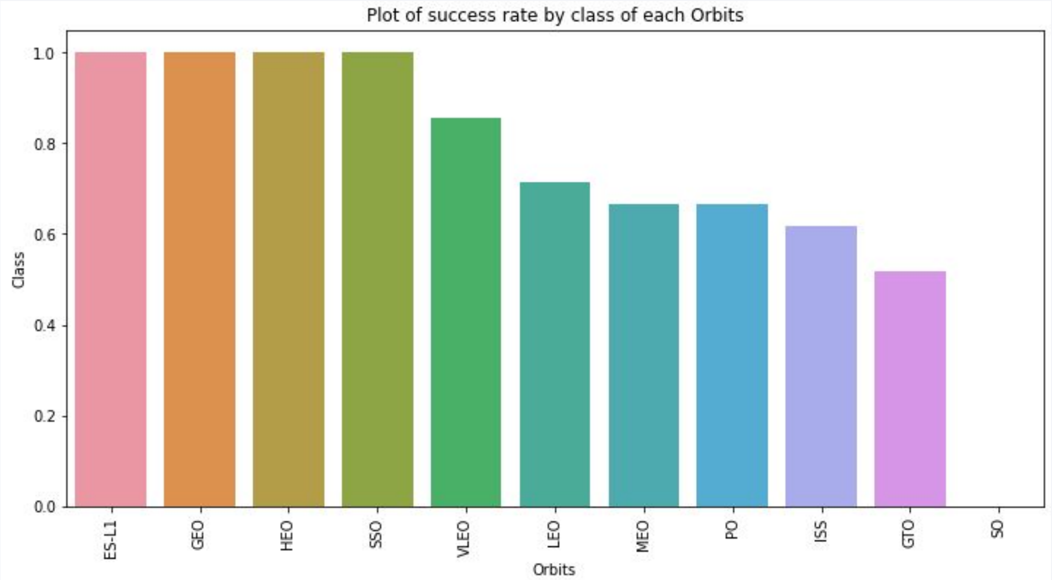


EDA with Data Visualization

By displaying the relationship between the flight number and the launch site, the payload and the launch site, the success rate of each orbit type, the flight number and the orbit type, and the yearly trend in launch success, we investigated the data.

The link is https://github.com/theonejohann/Peer-graded-Assignment-Peer-Review-Submit-your-Work-and-Review-your-Peers/blob/main/EDA%20with%20Data%20Visualization.ipynb





EDA with SQL

Without leaving the Jupyter notebook, the SpaceX dataset was loaded into a PostgreSQL database.

To gain understanding from the data, we used EDA along with SQL. We created queries to learn things like: names of distinctive launch sites used in space missions. The total weight of payloads carried by NASA-launched rockets (CRS) The typical payload mass that the booster type F9 v1.1 carries. The total number of mission successes and failures. The drone ship's booster version, launch location names, and the results of the botched landing

The LInk is https://github.com/theonejohann/Peer-graded-Assignment-Peer-Review-Submit-your-Work-and-Review-your-Peers/blob/main/EDA%20with%20SQL.ipynb

Build an Interactive Map with Folium

On the folium map, we identified every launch point and added map elements like markers, circles, and lines to indicate whether a launch was successful or unsuccessful for each location.

We categorize feature launch results (success or failure) into classes 0 and 1.

0 represents failure while 1 represents success.

The launch sites with a comparatively high success rate were determined using the color-labeled marker clusters.

We measured the separations between a launch site and its environs. We responded to various queries, such as:

Are launch points close to highways, railroads, and the ocean.

Do launch locations maintain a specific distance from cities.

Build a Dashboard with Plotly Dash

Using Plotly dash, we created an interactive dashboard.

We created pie graphs that display all of the launches made by particular sites.

For each booster version, we created a scatter graph to highlight the relationship between the outcome and the payload mass (Kg).

The notebook's link is

https://github.com/theonejohann/Peer-graded-Assignment-Peer-Review-Submit-your-Work-and-Review-your-Peers/blob/main/app.py

Predictive Analysis (Classification)

Using Numpy and Pandas, we loaded the data, transformed it, and divided it into training and testing sets.

Using GridSearchCV, we constructed various machine learning models and tuned various hyperparameters.

Our model was measured by accuracy, and it was enhanced through feature engineering and algorithm tweaking.

The most effective classification model was discovered.

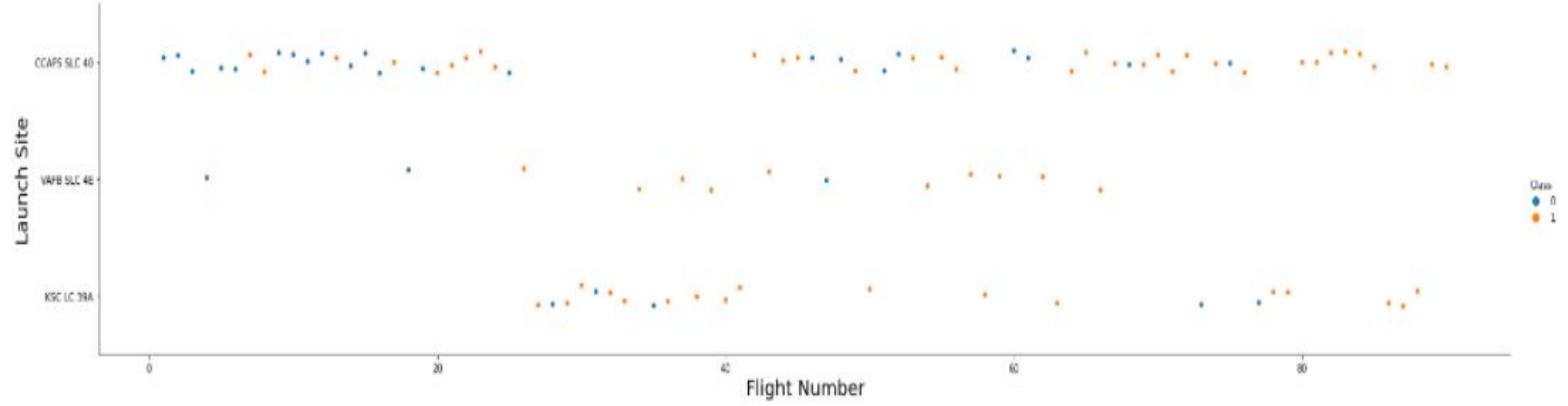
The link is https://github.com/theonejohann/Peer-graded-Assignment-Peer-Review-Submit-your-Work-and-Review-your-Peers/blob/main/Machine%20Learning%20Prediction.ipynb

Section 2

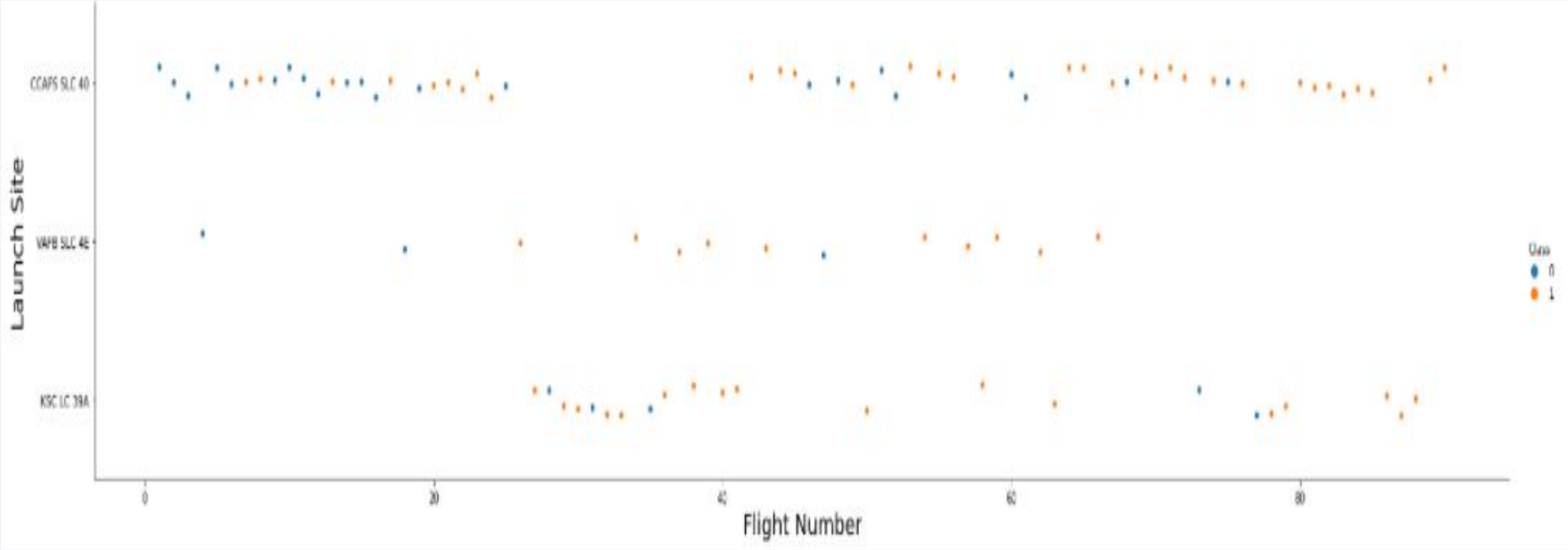
Insights drawn from EDA

Flight Number vs. Launch Site

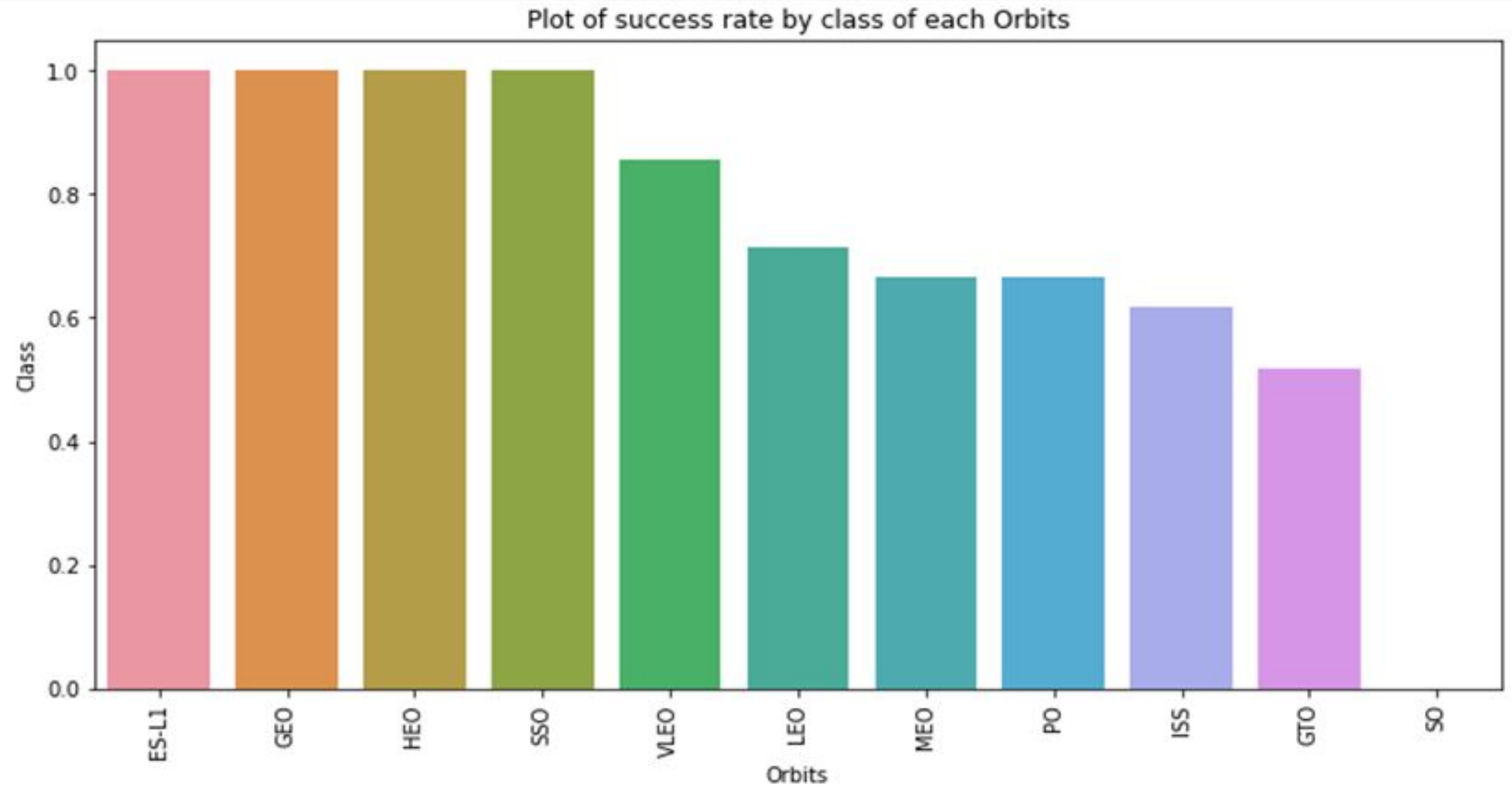
- The plot led us to the conclusion that a launch site's success rate increases with the size of the flight quantity.



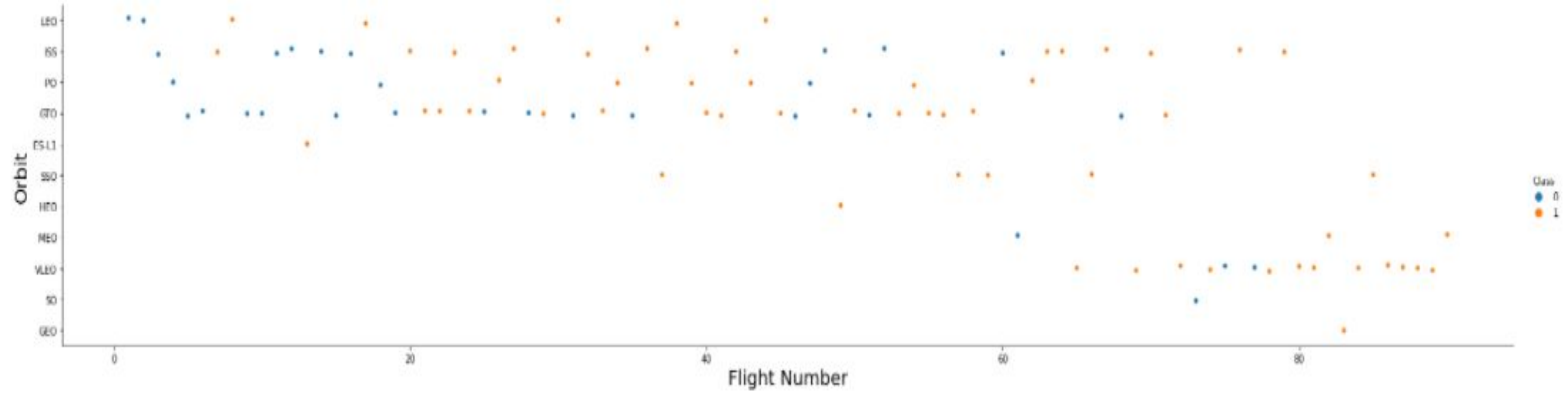
Payload vs. Launch Site



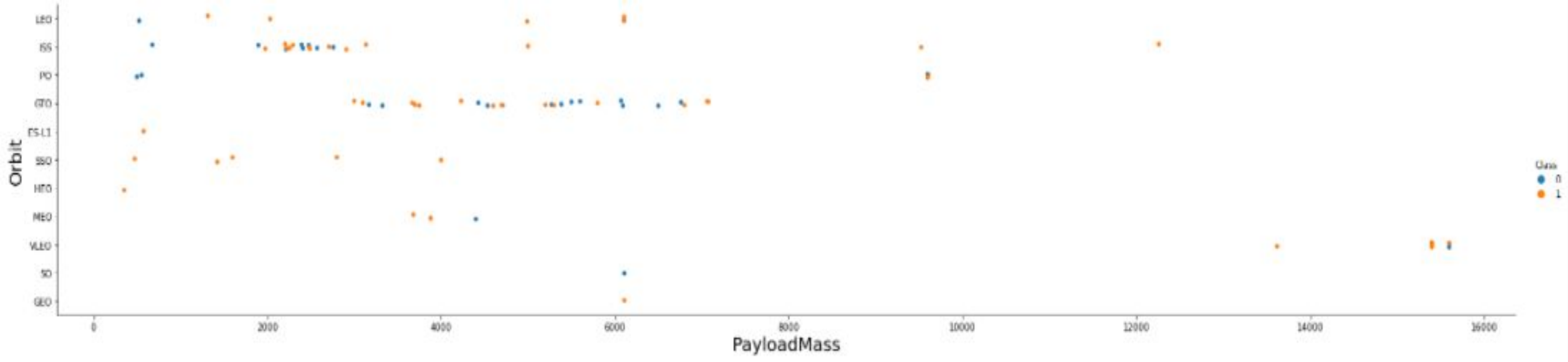
Success Rate vs. Orbit Type



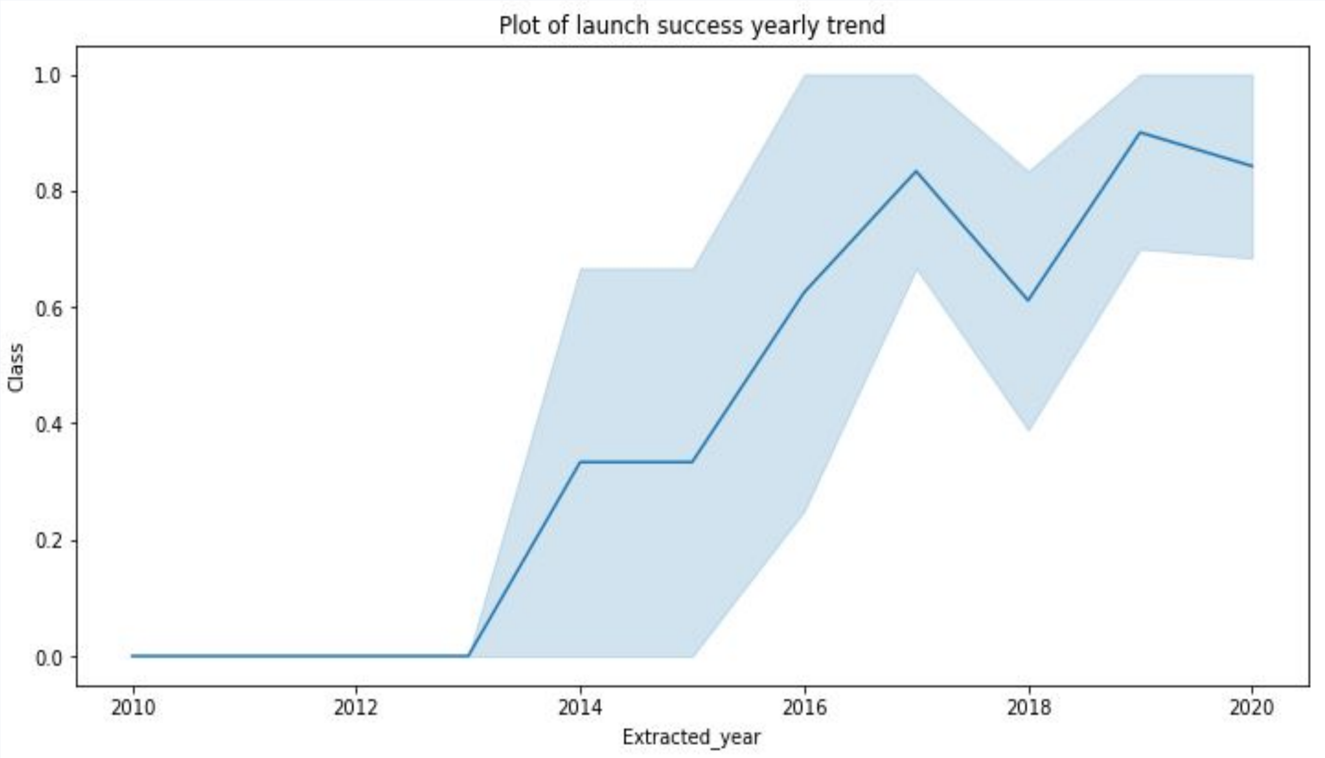
Flight Number vs. Orbit Type



Payload vs. Orbit Type



Launch Success Yearly Trend



All Launch Site Names

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'

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

In [11]:
```
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
4	2013-01-03	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

- We performed the aforementioned query to show 5 records for launch sites that start with "CCA."

Total Payload Mass

Using the following query, we determined that NASA's boosters carried a total of 45596 kilograms of payload.

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

- The average mass of the payload that booster version F9 v1.1 can carry was calculated to be 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

- In order to find boosters that have successfully landed on drone ships, we employed the WHERE clause. We then used the AND condition to identify successful landings with payload masses larger than 4,000 but less than 6,000.

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

To filter for WHERE MissionOutcome was a success or failure, we used wildcards like "%."

Boosters Carried Maximum Payload

Using a subquery in the WHERE clause and the MAX() method, we were able to identify the booster that had carried the most payload.

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

- In order to filter for failure landing outcomes in drone ship, their booster versions, and launch site names for the year 2015, we employed permutations of the WHERE clause, LIKE, AND, and BETWEEN conditions.

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

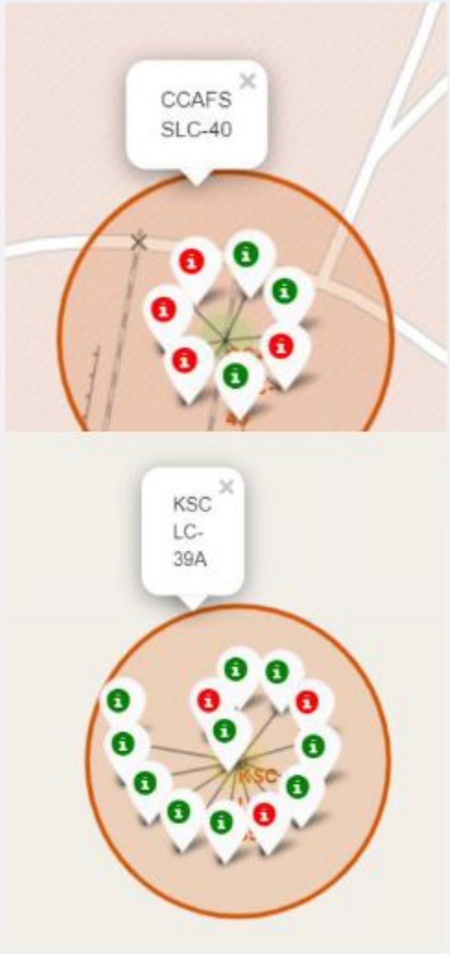
In order to filter for landing outcomes BETWEEN 2010-06-04 and 2010-03-20, we choose Landing outcomes and the COUNT of landing outcomes from the data.
The landing results were categorized using the GROUP BY clause, and they were then put in decreasing order using the ORDER BY clause.

Section 3

Launch Sites Proximities Analysis


VAFB SLC-4E
We can see that the SpaceX launch sites are in the United States of America coasts.
Florida and California

<Folium Map Screenshot 2>



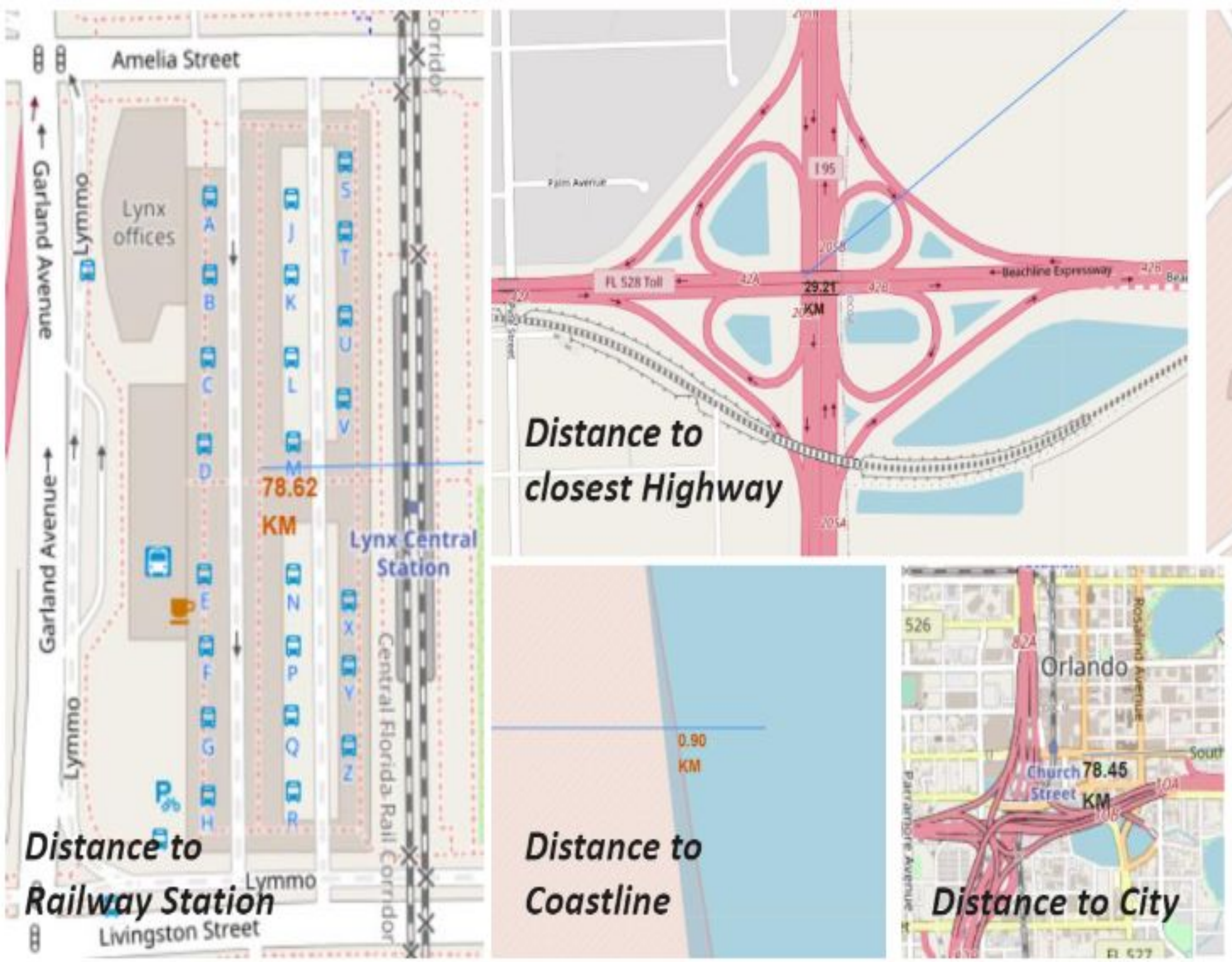
Florida Launch Sites

Green Marker shows successful Launches and Red Marker shows Failures

California Launch Site

37

<Folium Map Screenshot 3>

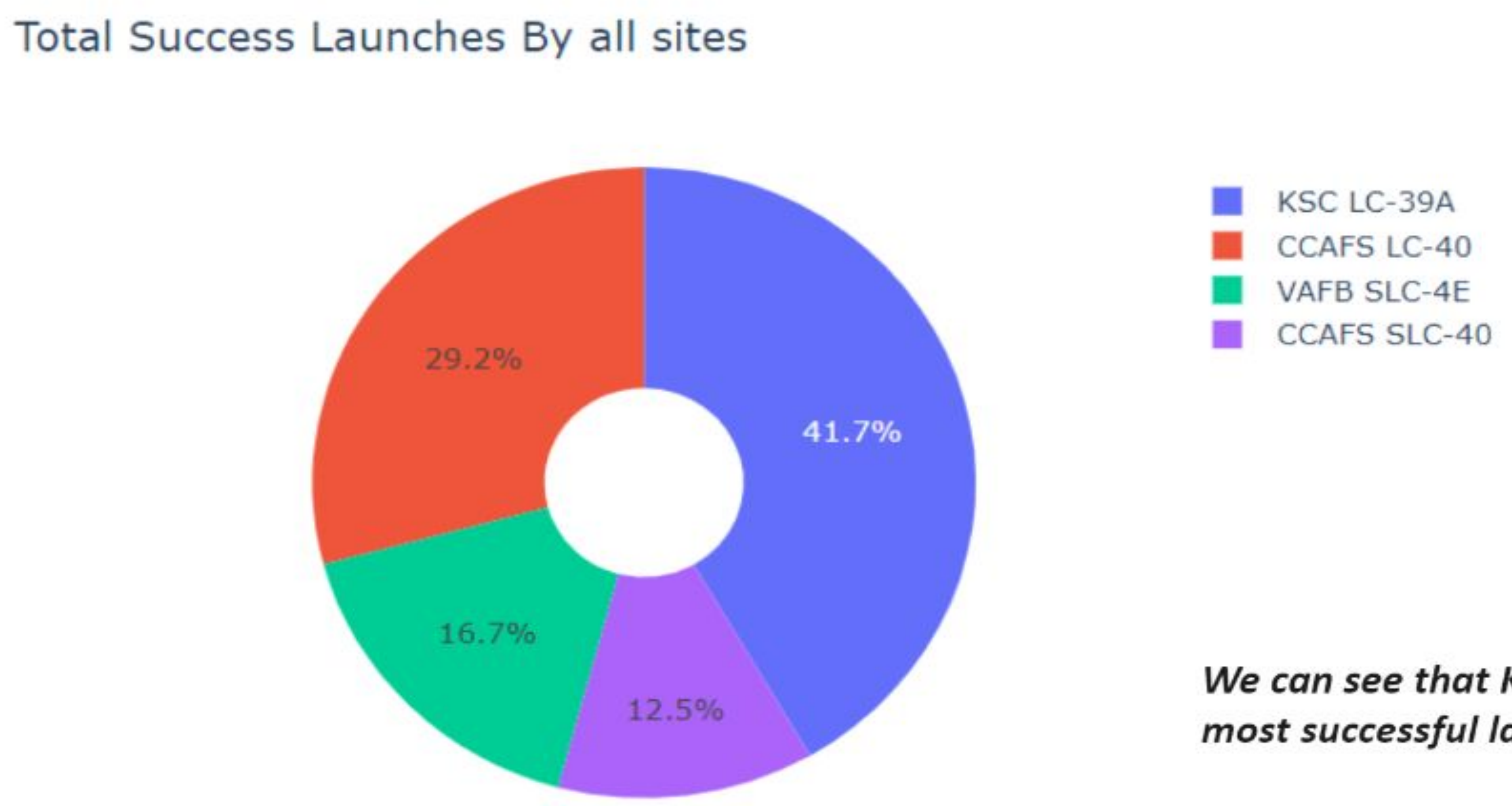


- Are launch sites in close proximity to railways? No
- Are launch sites in close proximity to highways? No
- Are launch sites in close proximity to coastline? Yes
- Do launch sites keep certain distance away from cities? Yes

Section 4

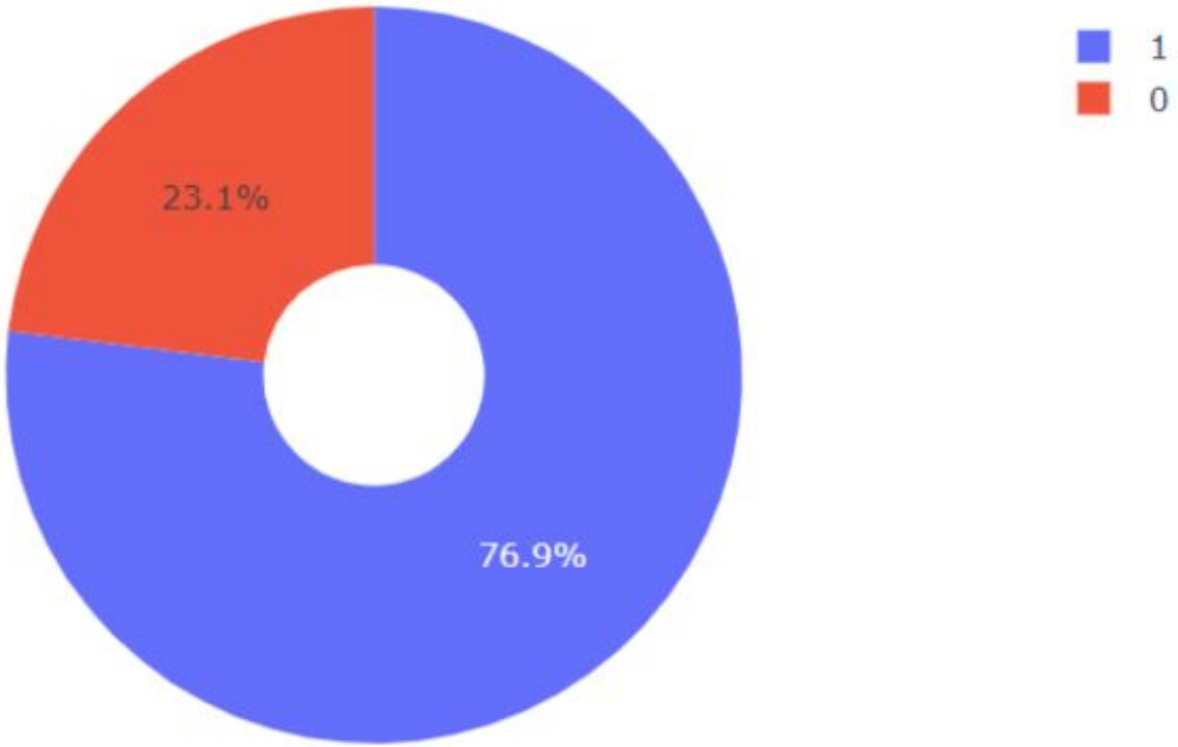
Build a Dashboard with Plotly Dash

Pie chart showing the success percentage achieved by each launch site



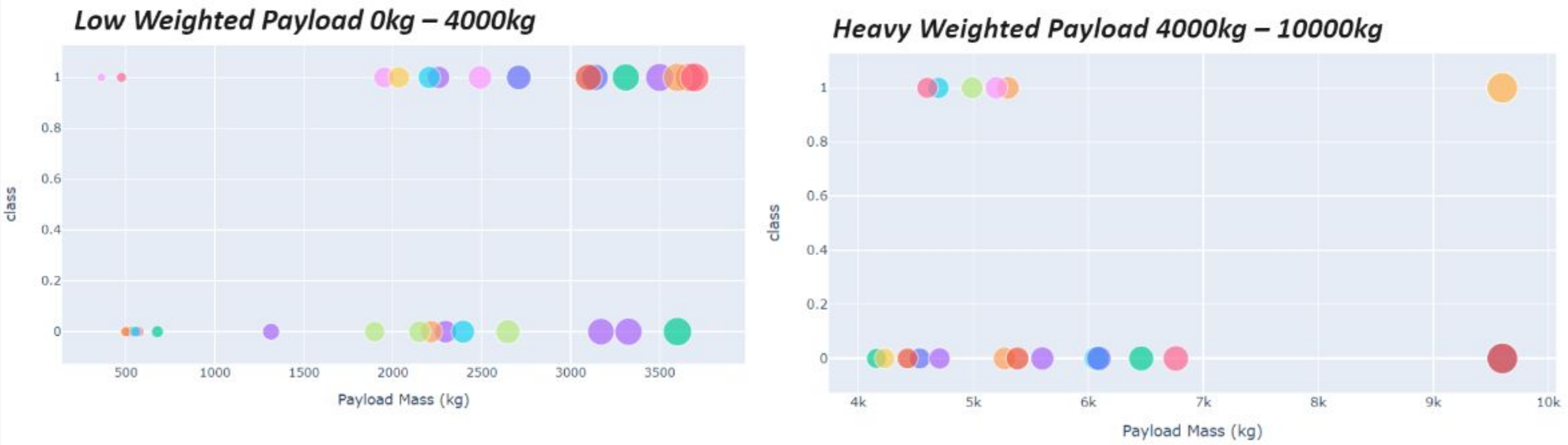
We can see that KSC LC-39A had the most successful launches from all the sites

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



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

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



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

Section 5

Predictive Analysis (Classification)

Classification Accuracy

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

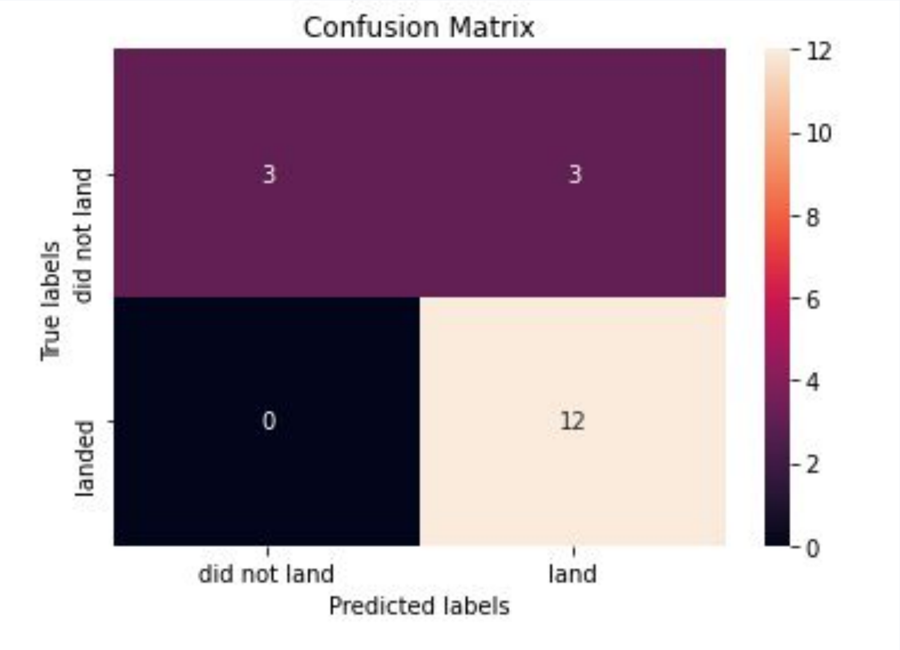
```
models = {'KNeighbors':knn_cv.best_score_,
              'DecisionTree':tree_cv.best_score_,
              'LogisticRegression':logreg_cv.best_score_,
              'SupportVector': svm_cv.best_score_}

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 decision tree classifier's confusion matrix demonstrates that it is capable of differentiating between the various classes. False positives are the main issue. In other words, the classifier misclassified a failure landing as a successful one.



Conclusions

- We can draw the following conclusion: A launch site's success rate increases with the size of the flight quantity.
- Beginning in 2013, the launch success rate will rise through 2020.
- The success rate was highest for ES-L1, GEO, HEO, SSO, and VLEO orbits.
- Of all the sites, KSC LC-39A had the most prosperous launches.
- The most effective machine learning approach for this task is the decision tree classifier.

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!