IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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5th September 2024

Outline

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

Executive Summary

Summary of methodologies

- Gathering Data via API
- Gathering Data through Web Scraping
- Data Cleaning and Preparation
- Exploratory Data Analysis using SQL
- Exploratory Data Analysis using Data Visualizations
- Interactive Visual Analysis using Folium
- Machine Learning Forecasting
- Overview of All Findings

Summary of all results

- Results from Exploratory Data Analysis
- Screenshots of Interactive Analytics
- Results of Predictive Analytics

Introduction

- Project background and context
  - SpaceX promotes its Falcon 9 rocket launches on its website at a price of $62 million, while competitors charge at least $165 million each. A significant portion of the cost savings comes from SpaceX's ability to reuse the first stage of the rocket. By predicting whether the first stage will land successfully, we can estimate the launch cost. This insight can be beneficial for other companies looking to compete with SpaceX for rocket launch contracts. The project's objective is to develop a machine learning pipeline to forecast the successful landing of the first stage.
- Problems you want to find answers

  Factors Influencing Successful Rocket Landings

  - Key Determinants: Various features interact to influence the likelihood of a successful landing.
  - Operating Conditions: Specific operating conditions must be met to ensure the effectiveness of the landing program.

Section 1

Methodology

Methodology

Executive Summary

- Data collection methodology:
  - Data was collected using SpaceX API and web scraping from Wikipedia
- Perform data wrangling
  - One-hot encoding has been utilized for the categorical variables.
- 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 carried out by making GET requests to the SpaceX API. Subsequently, we decoded the response content as JSON using the .json() function and transformed it into a pandas DataFrame using .json_normalize(). We then cleaned the data, checked for any missing values, and filled in those missing values as needed. Additionally, we conducted web scraping from Wikipedia to gather Falcon 9 launch records using BeautifulSoup. The goal was to extract the launch records from an HTML table, parse the table, and convert it into a pandas DataFrame for further analysis.

- You need to present your data collection process use key phrases and flowcharts

Data Collection – SpaceX API

- https://github.com/AnnijaR88/IBM-Data-Science-Capstone-SpaceX-/blob/afe74ecf692ca16f7001f0f305e50e70249e4d44/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

- We utilized web scraping techniques with BeautifulSoup to gather Falcon 9 launch records. After extracting the data, we parsed the table and converted it into a pandas DataFrame.
- https://github.com/AnnijaR88/IBM-Data-Science-Capstone-SpaceX-/blob/9d4251cad020bdac5c33cf58b14a79f6d8cbc6f6/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

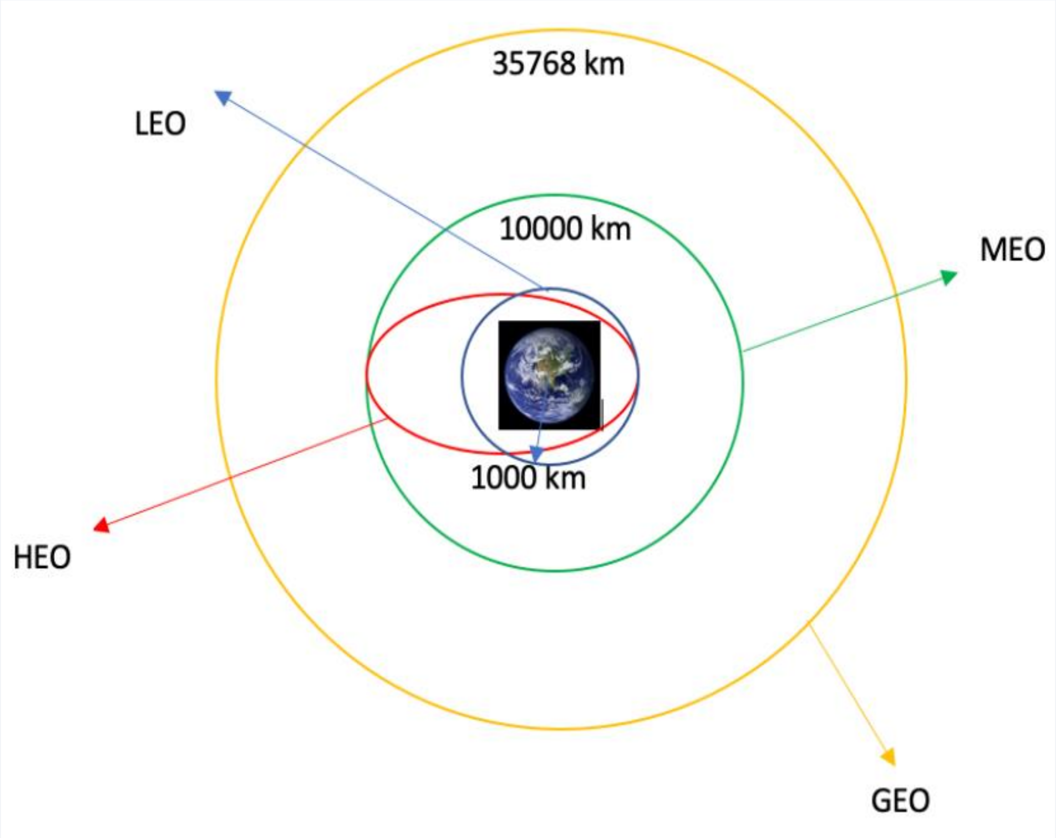
```
In [10]: column_names = []

         # 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

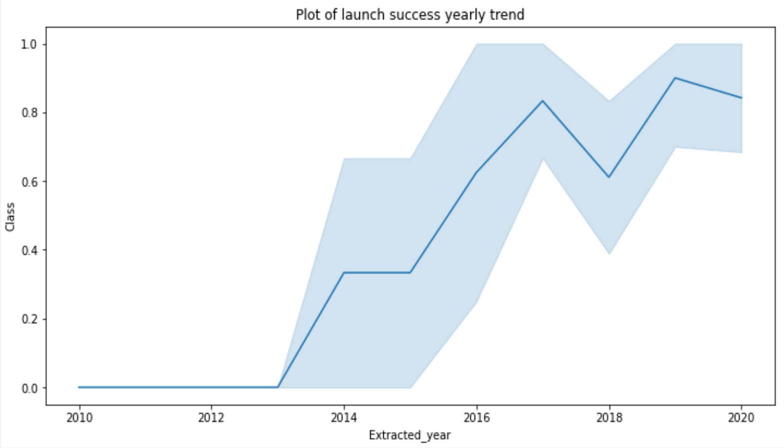
- We conducted exploratory data analysis to identify the training labels. We counted the total number of launches at each site as well as the frequency of each orbit. Additionally, we generated a landing outcome label from the outcome column and exported the results to a CSV file.

- https://github.com/AnnijaR88/IBM-Data-Science-Capstone-SpaceX-/blob/b7d0f3adbc4955ec96036eb959ece45d7dd3539c/Data%20Wrangling.ipynb

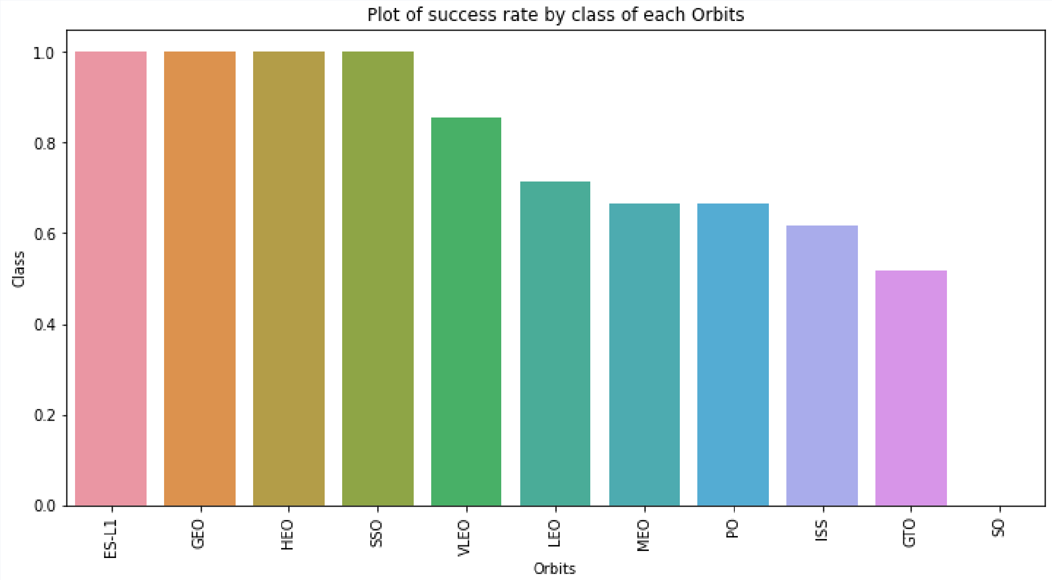


EDA with Data Visualization

- We examined the data by visualizing various relationships, including the correlation between flight number and launch site, payload versus launch site, success rates for each type of orbit, flight number in relation to orbit type, and the annual trends in launch success.



https://github.com/AnnijaR88/IBM-Data-Science-Capstone-SpaceX-/blob/0c3f4f5229ac690b580b38964fc9afa4458bd9ed/EDA%20with%20Data%20Visualization.ipynb



EDA with SQL

- We imported the SpaceX dataset into a PostgreSQL database directly from the Jupyter Notebook.
- We conducted exploratory data analysis (EDA) using SQL to glean insights from the data. We formulated queries to determine, for example:
  - The names of distinct launch sites involved in the space missions.
  - The total payload mass transported by NASA-launched boosters (CRS).
  - The average payload mass carried by the F9 v1.1 booster version.
  - The overall count of successful and failed mission outcomes.
  - The details of failed landing outcomes on the drone ship, including the corresponding booster versions and launch site names.

- https://github.com/AnnijaR88/IBM-Data-Science-Capstone-SpaceX-/blob/d0218583a899a8fe7b4cd0ee5f70da926db89f47/EDA%20with%20SQL.ipynb

Build an Interactive Map with Folium

- We marked all launch sites on the Folium map and incorporated map objects such as markers, circles, and lines to denote the success or failure of launches at each site. We categorized the launch outcomes, assigning class 0 for failure and class 1 for success. By using color-coded marker clusters, we identified launch sites with relatively high success rates. Additionally, we calculated the distances from each launch site to nearby landmarks and addressed questions such as:
  - Are launch sites located near railways, highways, and coastlines?
  - Do launch sites maintain a certain distance from urban areas?

- https://github.com/AnnijaR88/IBM-Data-Science-Capstone-SpaceX-/blob/33657f62d187ec6b8eec363653b5691cb219f8c0/Interactive%20Visual%20Analytics%20with%20Folium.ipynb

Build a Dashboard with Plotly Dash

- We developed an interactive dashboard using Plotly Dash. Within this dashboard, we displayed pie charts illustrating the total number of launches by specific sites. Additionally, we created scatter plots to visualize the relationship between launch outcomes and payload mass (in kilograms) for various booster versions.

- https://github.com/AnnijaR88/IBM-Data-Science-Capstone-SpaceX-/blob/33657f62d187ec6b8eec363653b5691cb219f8c0/app.py

Predictive Analysis (Classification)

- We imported the data using NumPy and pandas, transformed the dataset, and divided it into training and testing sets. We developed various machine learning models and optimized their hyperparameters using GridSearchCV. Using accuracy as the evaluation metric, we enhanced the model through feature engineering and algorithm tuning. Ultimately, we identified the best-performing classification model.
- https://github.com/AnnijaR88/IBM-Data-Science-Capstone-SpaceX-/blob/4a7e986953b099f9fd544fc96688ceba91231a06/Machine%20Learning%20Prediction.ipynb

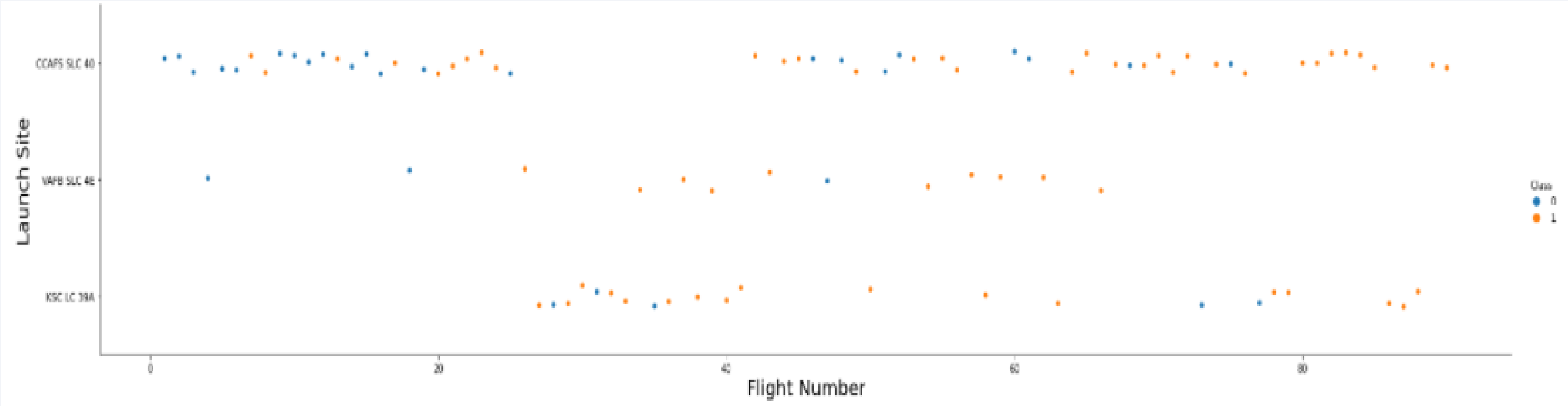
Results

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

Section 2

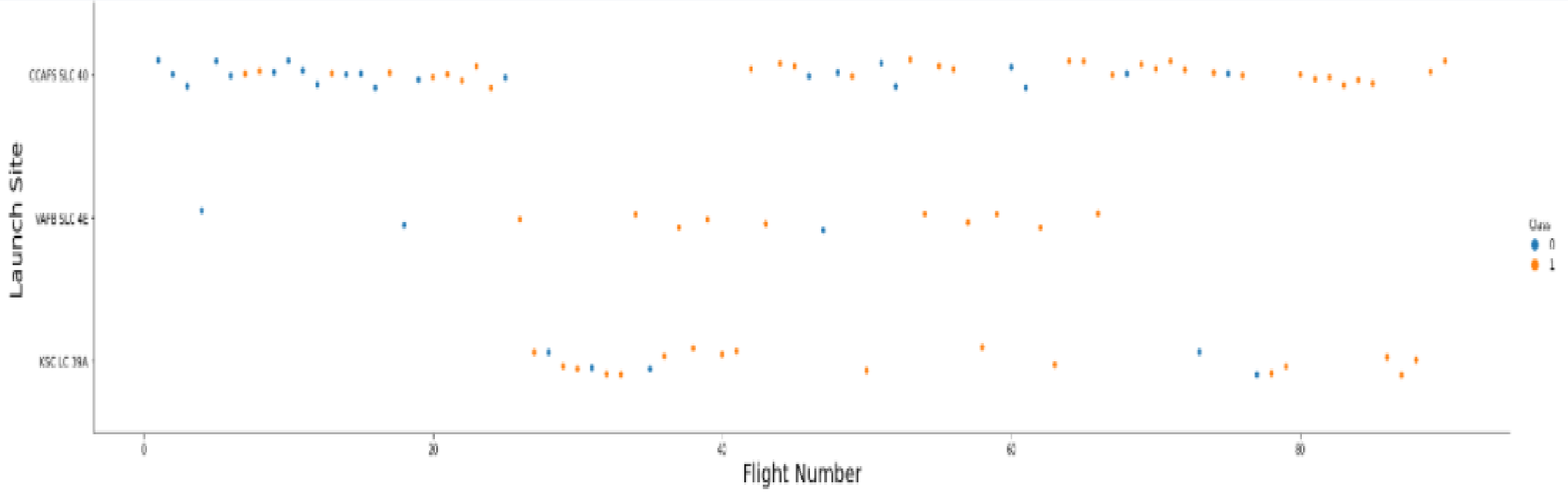
Insights drawn from EDA

Flight Number vs. Launch Site



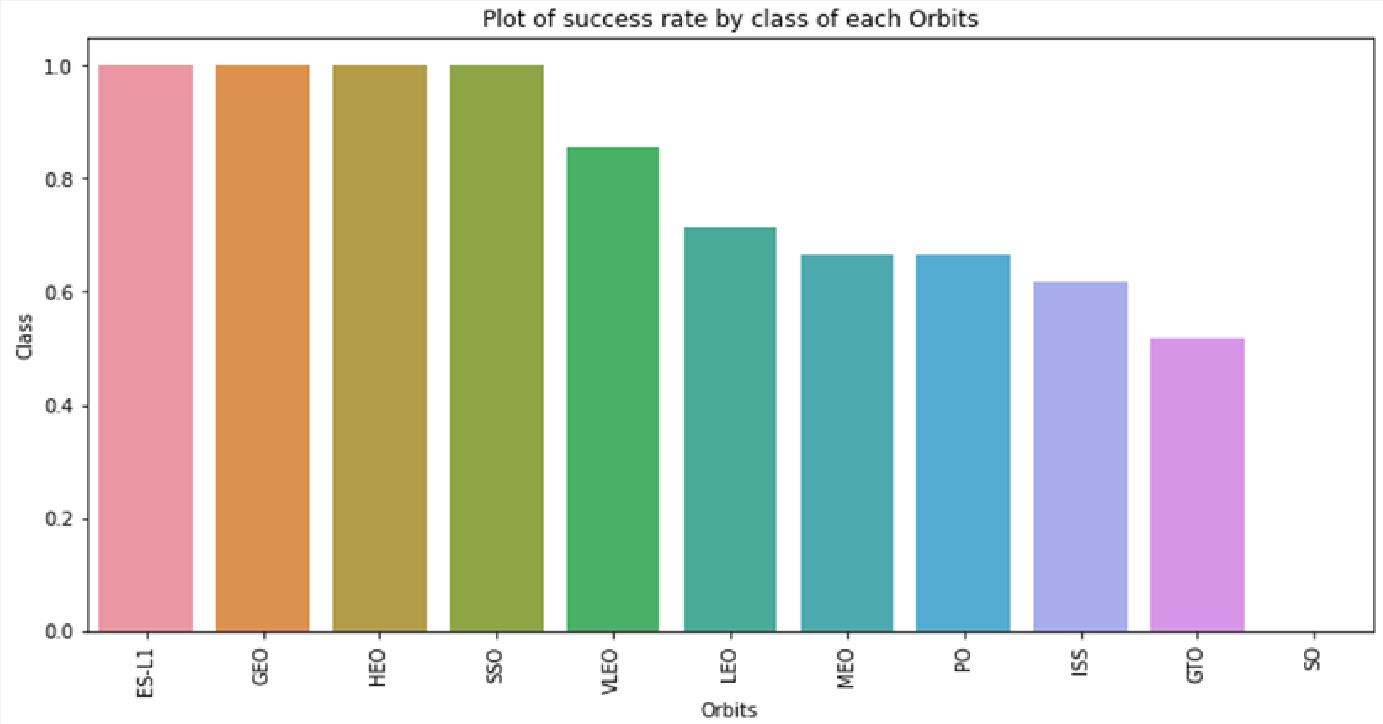
From the plot, we observed that an increase in the number of flights at a launch site correlates with a higher success rate for that site.

Payload vs. Launch Site



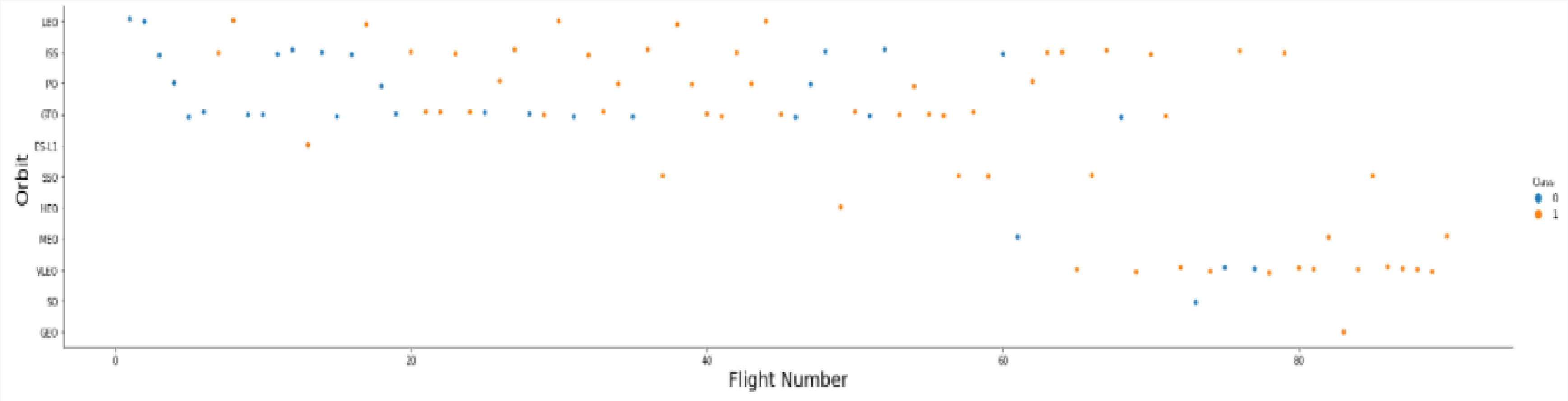
The greater the payload the higher the success rate.

Success Rate vs. Orbit Type



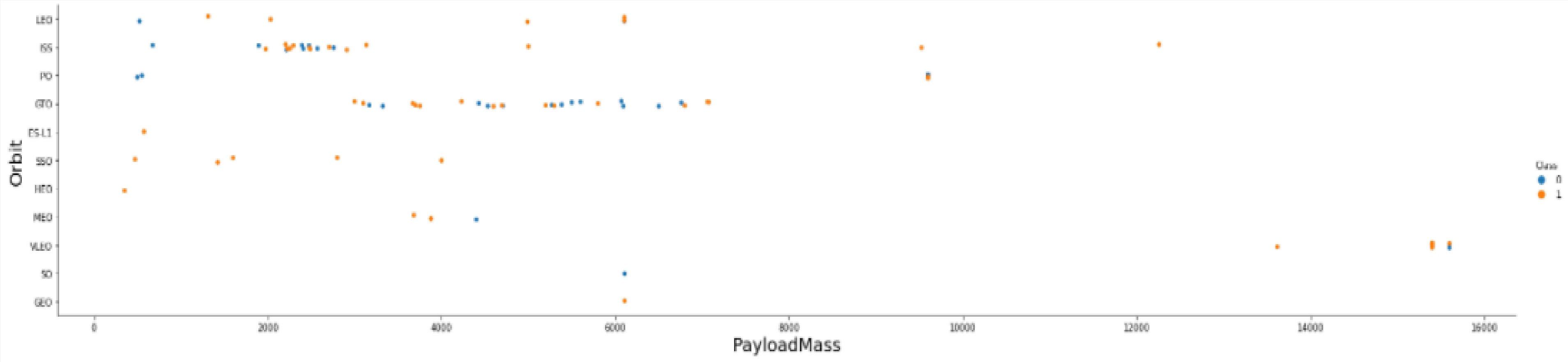
- ES-L1, GEO, HEO, SSO and VLEO had the most success rate

Flight Number vs. Orbit Type



- The plot below illustrates the relationship between Flight Number and Orbit type. We note that in the LEO orbit, the success rate appears to be connected to the number of flights, while in the GTO orbit, there is no evident relationship between the flight number and the orbit.

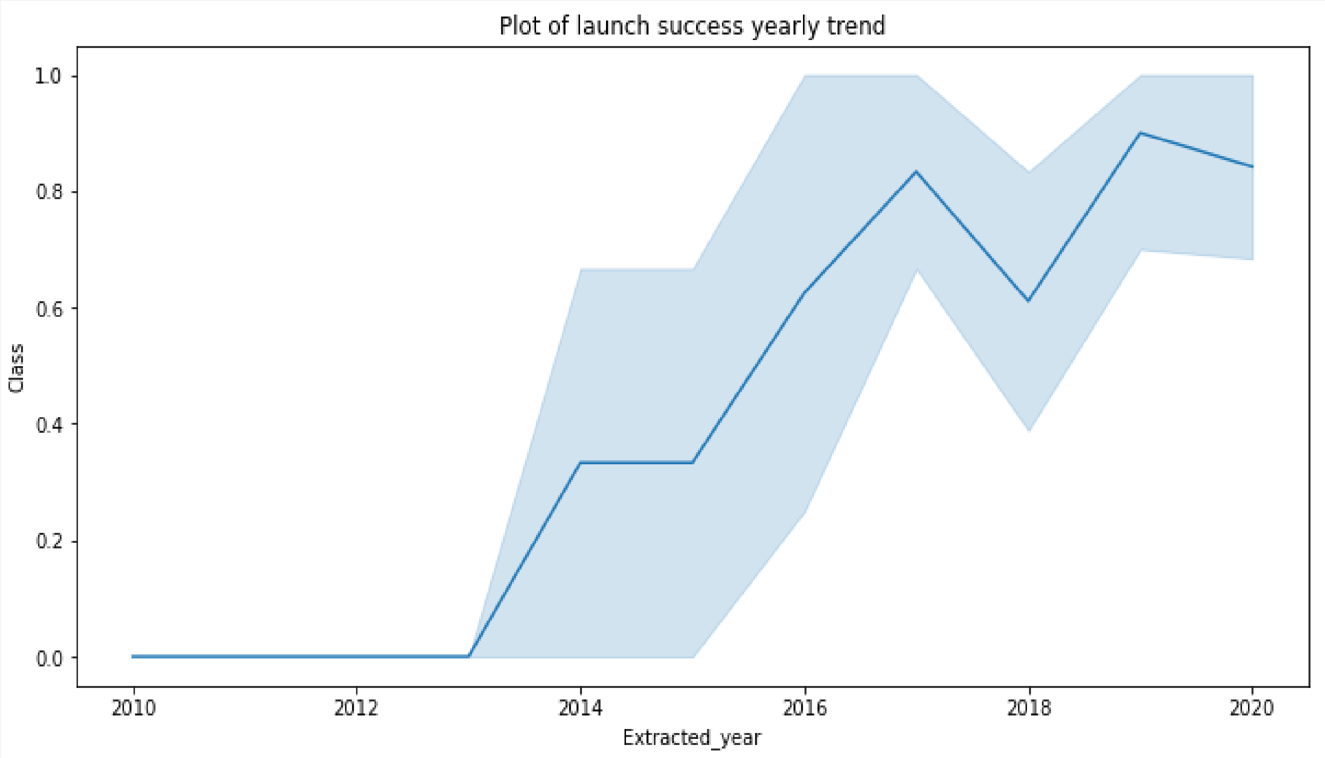
Payload vs. Orbit Type



We can see that successful landings are more frequent for heavy payloads in the PO, LEO, and ISS orbits.

Launch Success Yearly Trend

- Success rate increased from 2013 till 2020



All Launch Site Names

KEYWORD - DISTINCT

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'

- Query using launch site beginning 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

Total Payload Mass

We determined that the total payload carried by NASA boosters is 45,596, using the query provided 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 found that the average payload mass carried by the booster version F9 v1.1 is 2,928.4.

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 noted that the date of the first successful landing outcome on the ground pad was December 22, 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 utilized the WHERE clause to filter for boosters that successfully landed on the drone ship, applying an AND condition to specify a payload mass greater 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

We employed the wildcard '%' in the WHERE clause to filter for records where the MissionOutcome was either a success or a failure.

Boosters Carried Maximum Payload

We identified the booster that transported the maximum payload by using a subquery in the WHERE clause along with 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 employed a combination of the WHERE clause, LIKE, AND, and BETWEEN conditions to filter for failed landing outcomes on the drone ship, along with their corresponding booster versions and launch site names for the 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

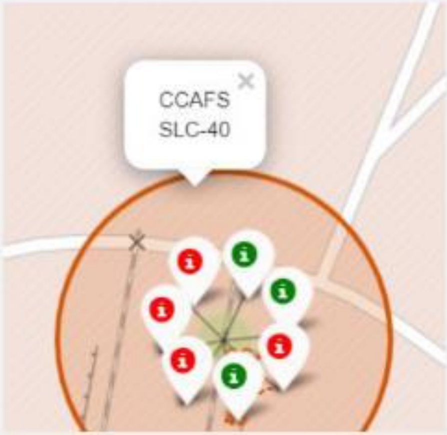
We selected landing outcomes and the count of those outcomes from the dataset, using the WHERE clause to filter for landing outcomes between June 4, 2010, and March 20, 2010. We then applied the GROUP BY clause to group the landing outcomes and used the ORDER BY clause to sort the grouped landing outcomes in descending order.

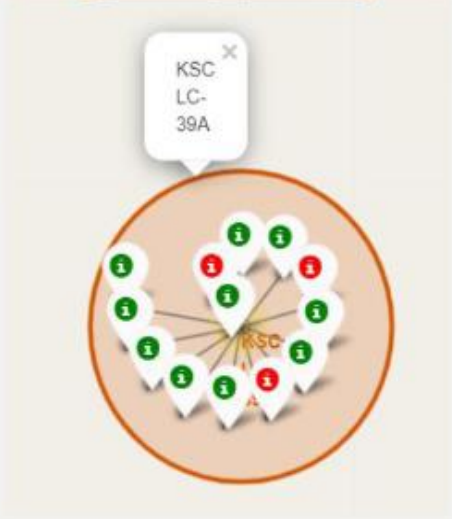
Section 3

Launch Sites Proximities Analysis

All launch sites global map markers

Markers showing launch sites with color labels



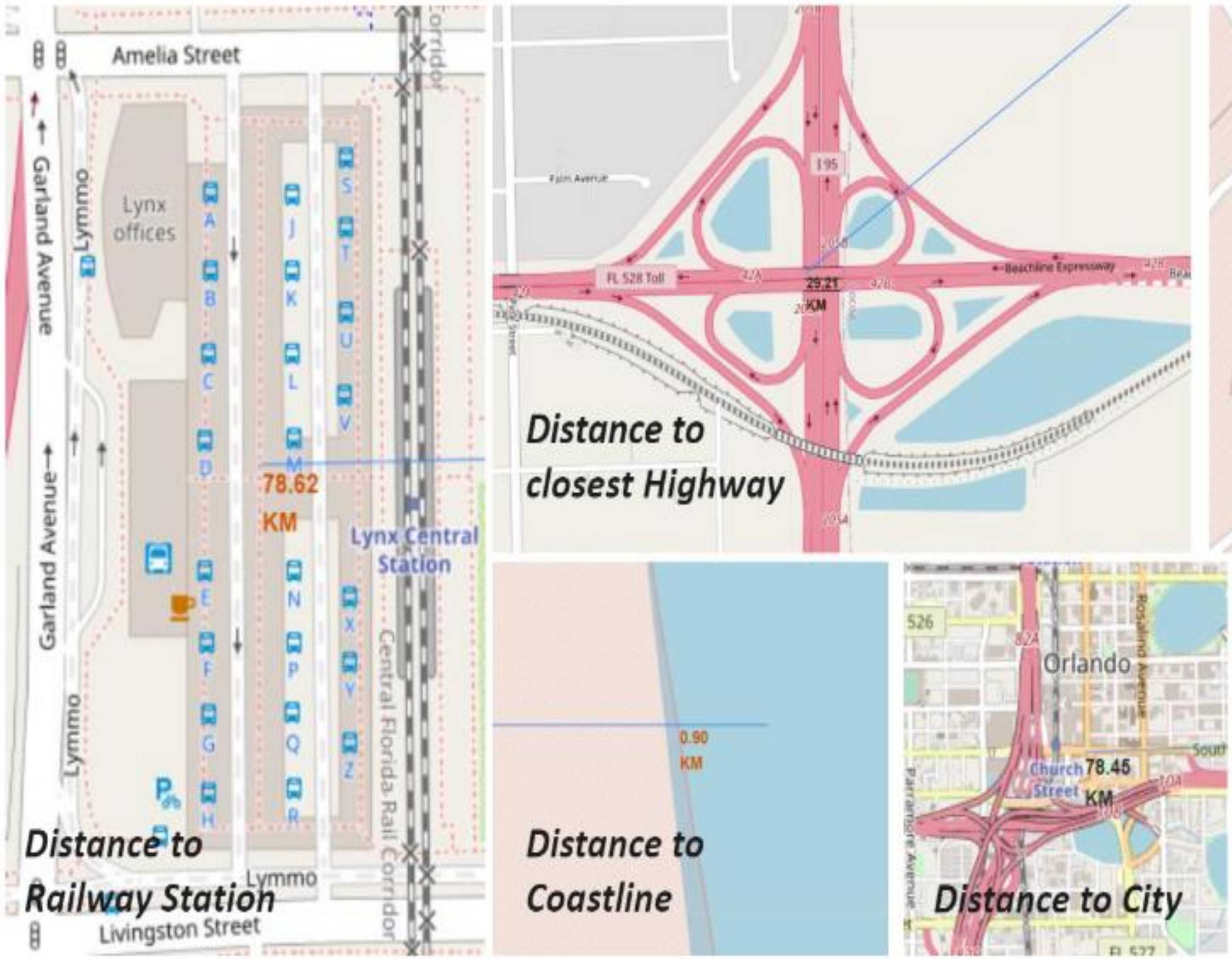


Florida Launch Sites

Green Marker shows successful Launches and Red Marker shows Failures

California Launch Site

Launch Site distance to landmarks

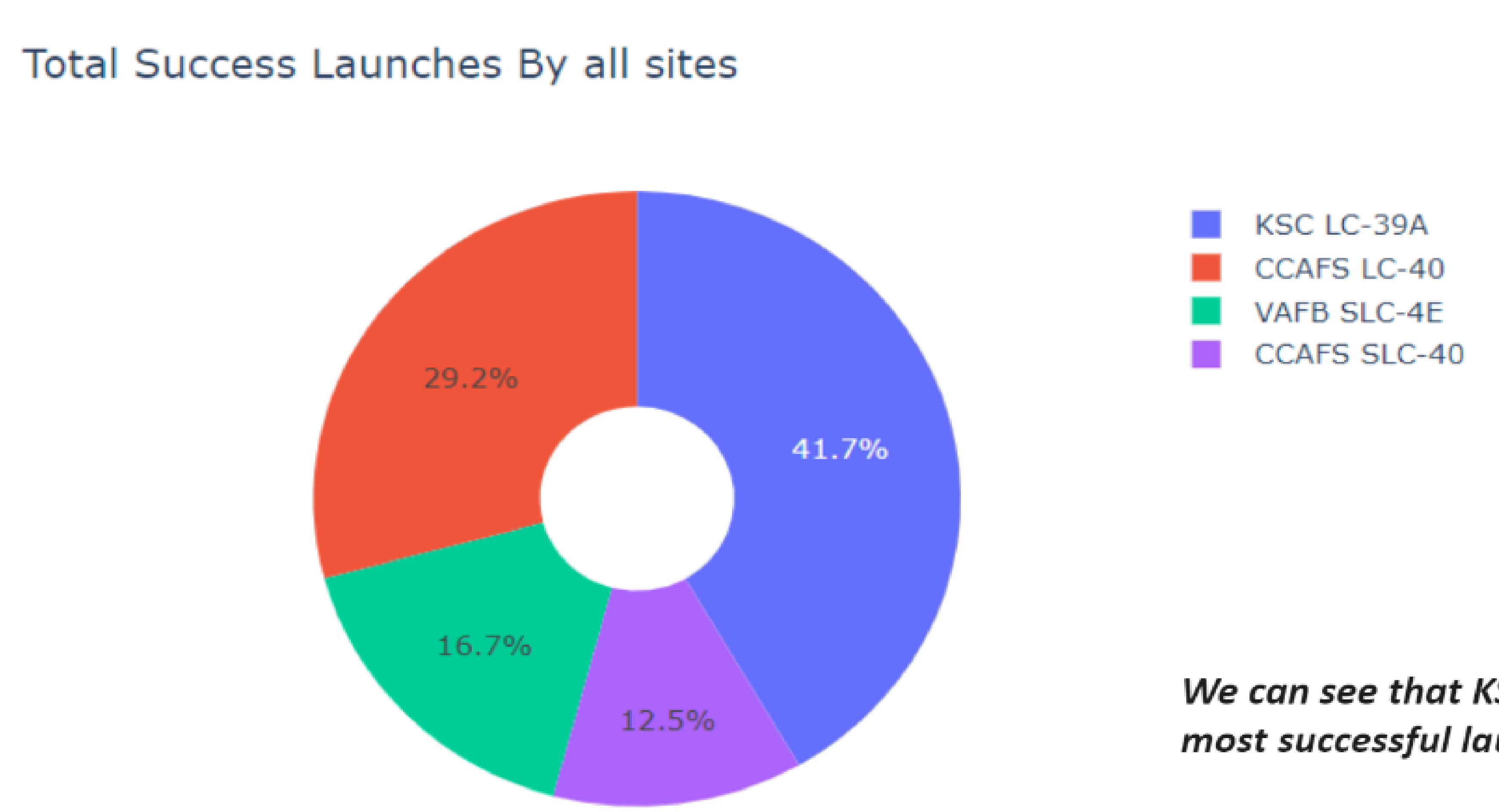


- Are launch sites in close proximity to railways? No
- Are launch sites in close proximity to highways? No
- Are launch sites in close proximity to coastline? Yes
- Do launch sites keep certain distance away from cities? Yes

Section 4

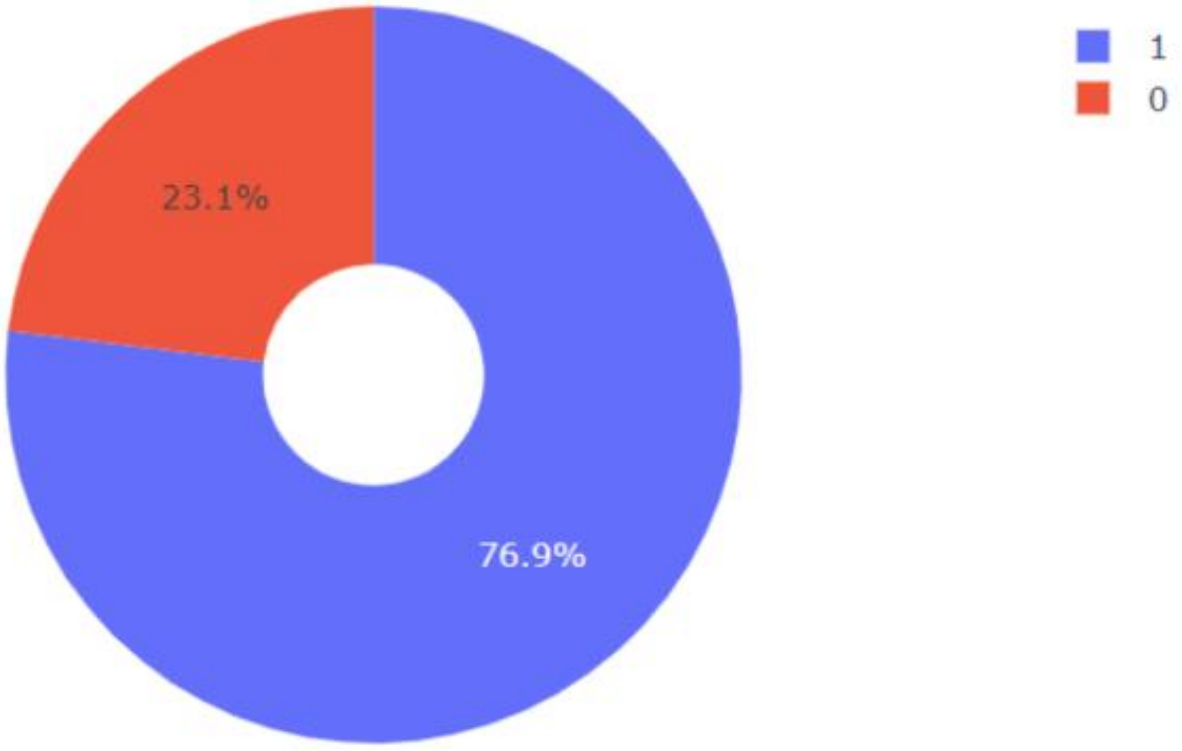
Build a Dashboard with Plotly Dash

Pie chart showing the success percentage achieved by each launch site



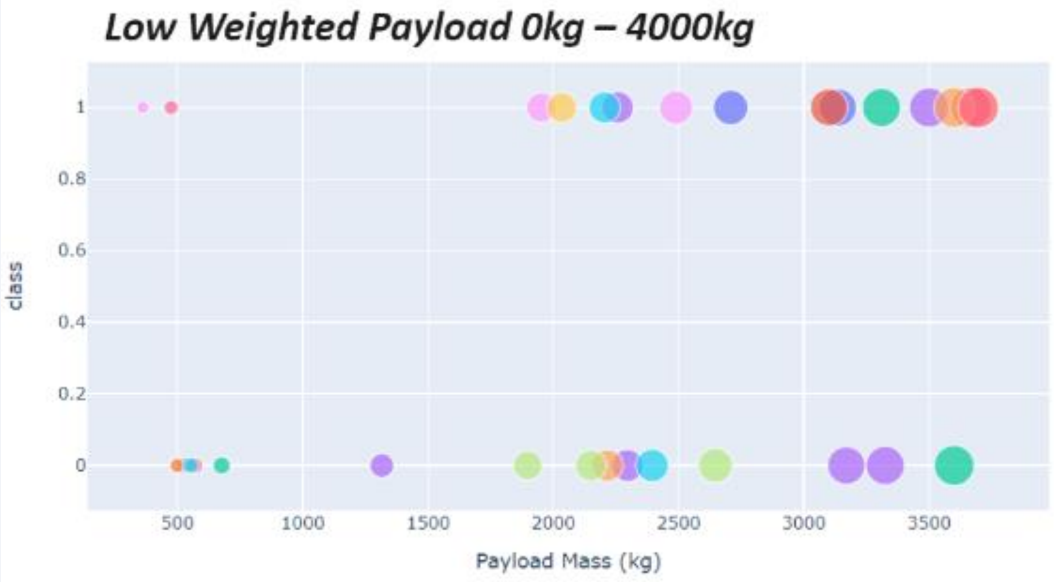
We can see that KSC LC-39A had the most successful launches from all the sites

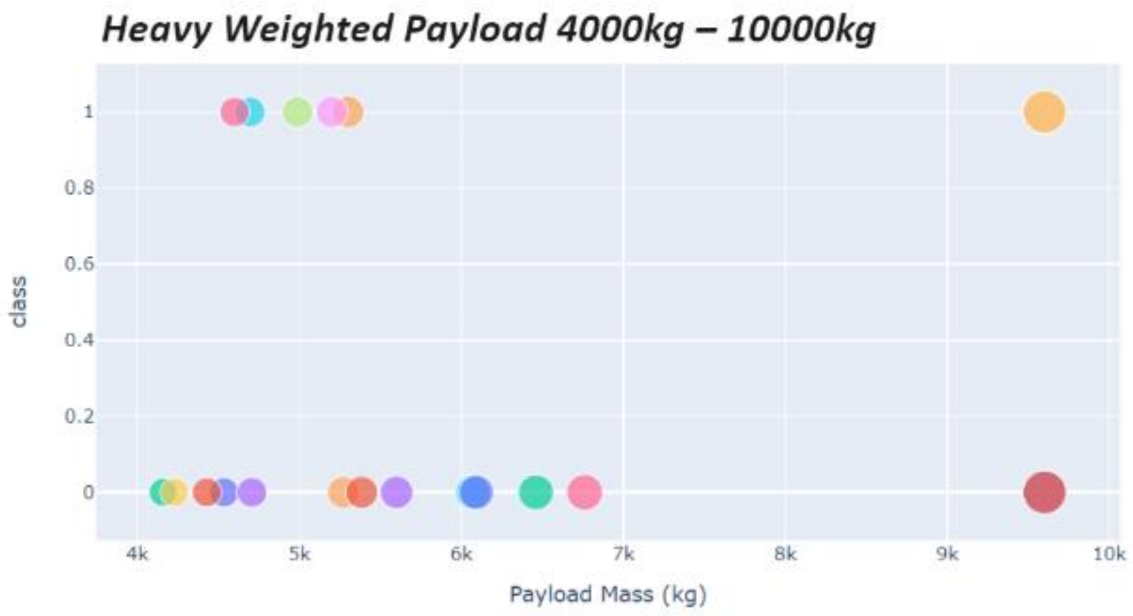
Pie chart showing the Launch site with the highest launch success ratio



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

A scatter plot illustrating the relationship between Payload and Launch Outcome for all sites, featuring a range slider to select different payload values





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

Section 5

Predictive Analysis (Classification)

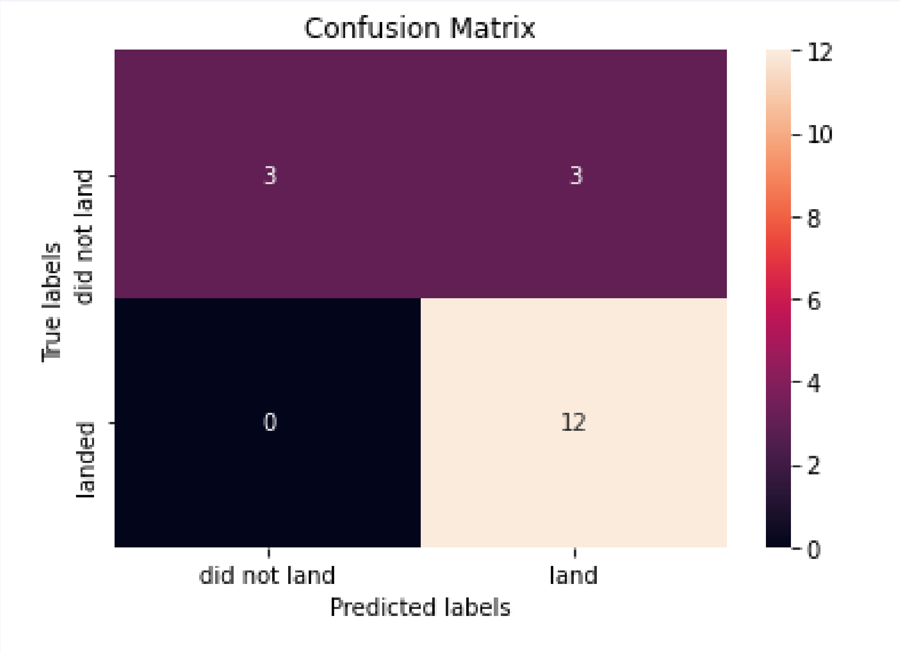
Classification Accuracy

```
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 indicates that the model is capable of differentiating between the various classes. However, a significant issue is the occurrence of false positives, where unsuccessful landings are incorrectly classified as successful landings by the classifier.



Conclusions

- We can conclude that:
  - A higher number of flights at a launch site correlates with a greater success rate.
  - The launch success rate began to rise from 2013 and continued to increase until 2020.
  - The orbits ES-L1, GEO, HEO, SSO, and VLEO achieved the highest success rates.
  - KSC LC-39A recorded the most successful launches among all sites.
  - The decision tree classifier is the most effective machine learning algorithm for this specific task.

Thank you!