IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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Outline

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- Conclusion
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Executive Summary

- Summary of methodologies
  - Data collection and data wrangling
  - EDA and interactive visual analytics
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  - interactive map with Folium results
  - Plotly Dash dashboard
  - Predictive analysis
- 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 and web scraping from Wikipedia.
- 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

- The data was collected using various methods
  - Collect data through a get request to the SpaceX API.
  - Decode the response content into Json format using the .json() function and convert it into a pandas dataframe using .json_normalize().
  - Clean the data, check for missing values, and fill in missing values where necessary.
  - Perform web scraping from Wikipedia for Falcon 9 launch records using BeautifulSoup to extract the launch records as an HTML table, parse it, and convert it into a pandas dataframe for future analysis.

Data Collection – SpaceX API

- To gather the data, we utilized the get request to the SpaceX API. Following that, we performed basic data wrangling and formatting, including data cleaning, to prepare it for further analysis.
- The link to the notebook is https://github.com/moustafa126/IBM-Data-Science-Capstone-SpaceX/blob/main/Data_Collection_Via_SpaceX_API.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

- To obtain Falcon 9 launch records, we utilized web scraping with BeautifulSoup. We then parsed the resulting table and transformed it into a pandas dataframe.
- The link to the notebook is https://github.com/moustafa126/IBM-Data-Science-Capstone-SpaceX/blob/main/Data_Collection_with_Web_Scraping.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>
```

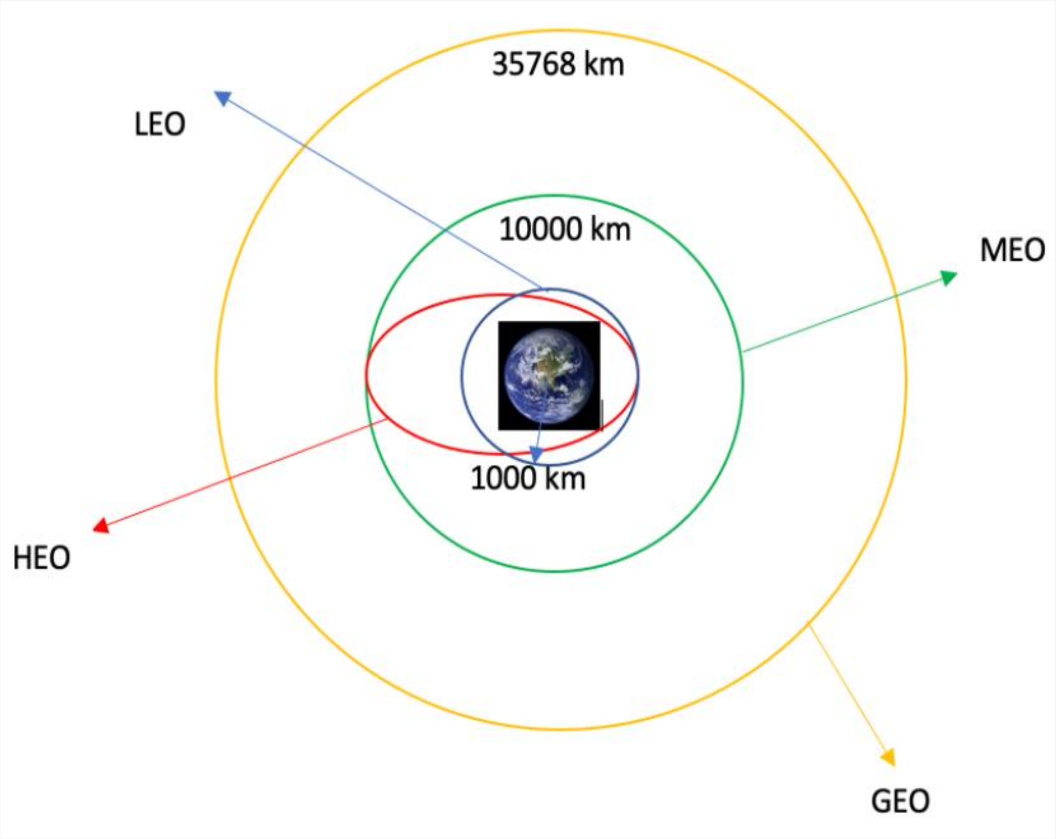
3. Extract all column names from the HTML table header

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

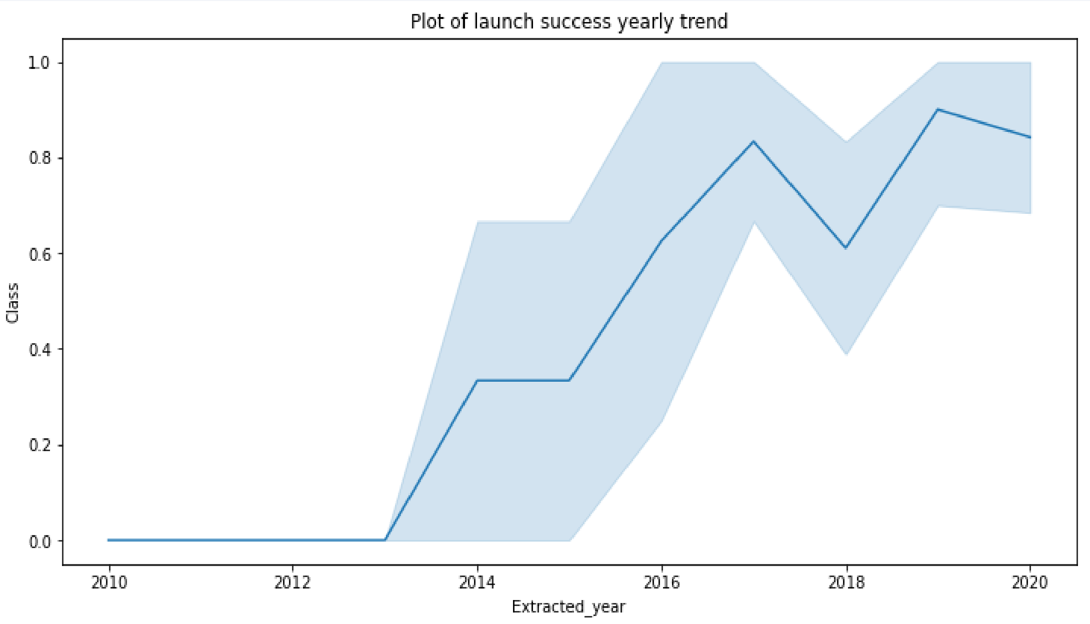
Data Wrangling

- Perform exploratory data analysis to determine the training labels.
- Calculate the number of launches at each site and the frequency and occurrence of each orbit.
- Generate a landing outcome label using data from the outcome column.
- Export the results to a csv file.
- The link to the notebook is https://github.com/moustafa126/IBM-Data-Science-Capstone-SpaceX/blob/main/Data_Wrangling.ipynb



EDA with Data Visualization

- We analyzed the data by creating visual representations of various relationships. These included the relationship between flight number and launch site, payload and launch site, success rate of each orbit type, flight number and orbit type, and the yearly trend in launch success.
- The link to the notebook is https://github.com/moustafa126/IBM-Data-Science-Capstone-SpaceX/blob/main/EDA_with_Visualization.ipynb



EDA with SQL

- Load the SpaceX dataset into a PostgreSQL database directly from the Jupyter Notebook.
- Use SQL to conduct exploratory data analysis and gain insight from the data.
- Write queries to answer various questions, such as identifying the unique launch sites in the space mission, determining the total payload mass carried by boosters launched by NASA (CRS), calculating the average payload mass carried by booster version F9 v1.1, and determining the total number of successful and failed mission outcomes.
- Use SQL to identify the booster version and launch site names for failed landing outcomes in drone ships.
- The link to the notebook is: https://github.com/moustafa126/IBM-Data-Science-Capstone-SpaceX/blob/main/EDA_with_SQL.ipynb

Build an Interactive Map with Folium

- Add various map objects, such as markers, circles, and lines, to a folium map to indicate the success or failure of launches at each launch site.
- Assign launch outcomes to class 0 (failure) or 1 (success).
- Use color-labeled marker clusters to identify launch sites with relatively high success rates.
- Calculate distances between launch sites and their proximities to answer questions such as whether launch sites were located near railways, highways, and coastlines, or whether they maintained a certain distance from nearby cities.
- The link to the notebook is: https://github.com/moustafa126/IBM-Data-Science-Capstone-SpaceX/blob/main/Interactive_Visual_Analytics_with_Folium.ipynb

Build a Dashboard with Plotly Dash

- Build an interactive dashboard using Plotly Dash.
- Plot pie charts displaying the total number of launches at each site.
- Plot scatter plots showing the relationship between the outcome and payload mass (in kg) for different booster versions.
- The link to the notebook is https://github.com/moustafa126/IBM-Data-Science-Capstone-SpaceX/blob/main/Plotly%20Dash.py

Predictive Analysis (Classification)

- Load the data using NumPy and Pandas libraries, transform it, and split it into a training set and a testing set.
- Build different machine learning models and tune various hyperparameters using GridSearchCV.
- Evaluate the models using accuracy as the performance metric.
- Improve the models using feature engineering and algorithm tuning.
- Identify the best performing classification model among the various models tested.
- The link to the notebook is https://github.com/moustafa126/IBM-Data-Science-Capstone-SpaceX/blob/main/Machine_Learning_Prediction.ipynb

Results

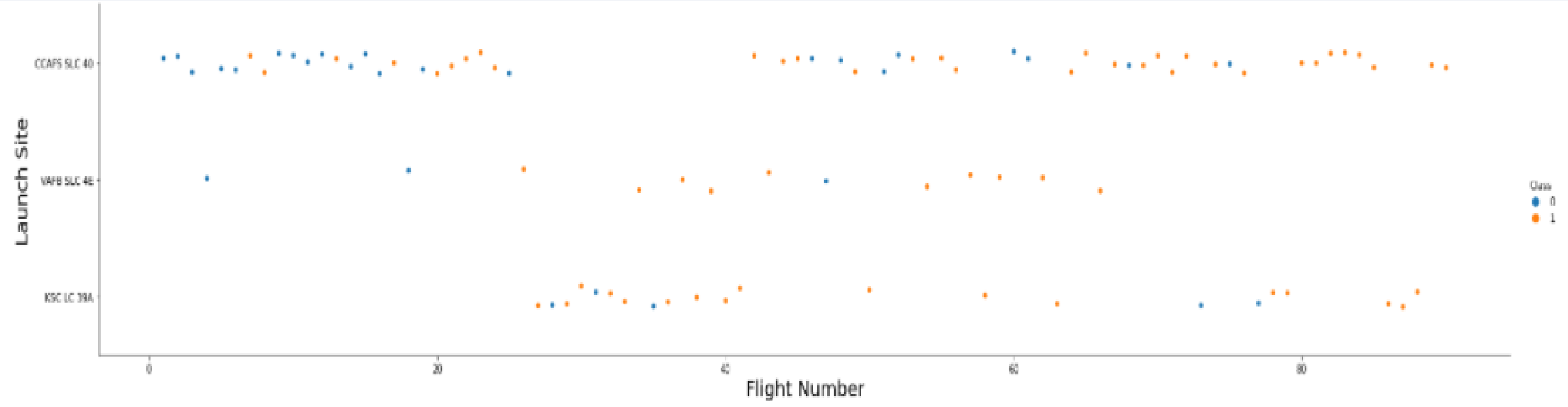
- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results

Section 2

Insights drawn from EDA

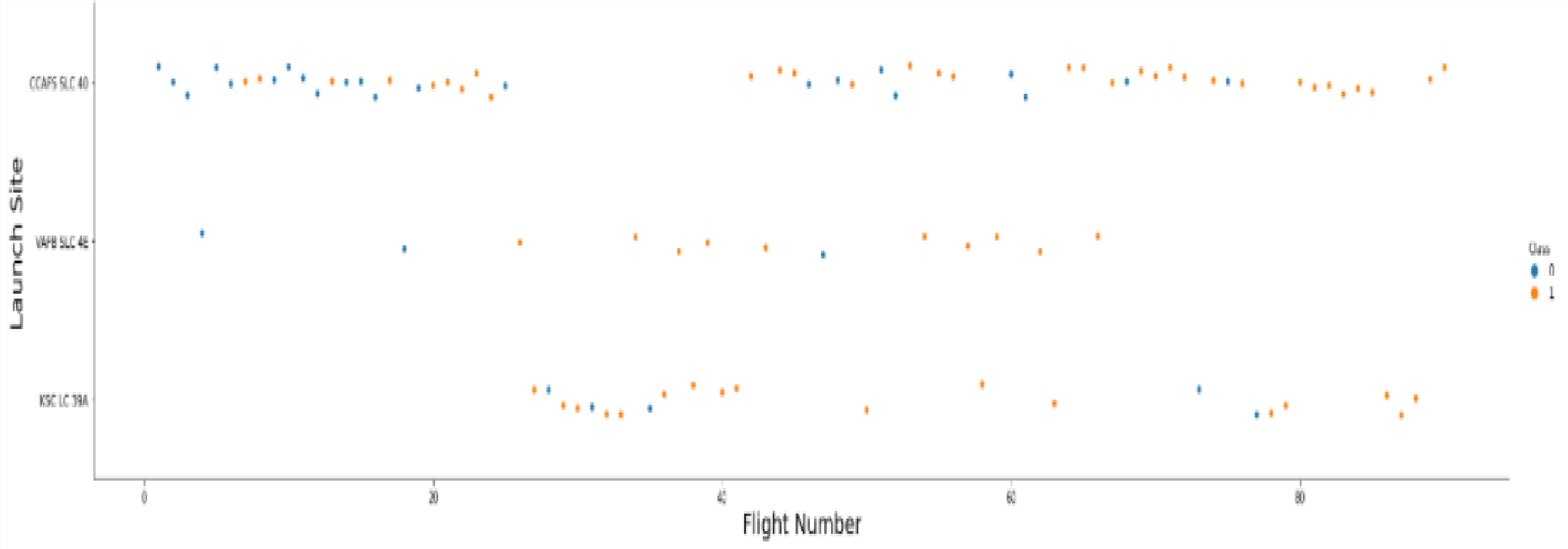
Flight Number vs. Launch Site

- From the plot, we 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.

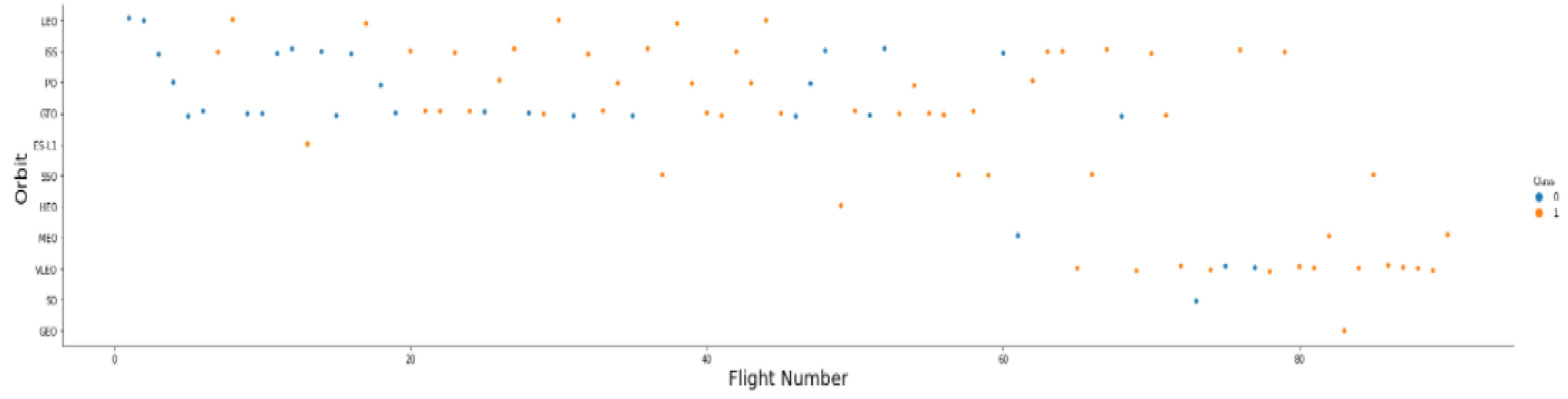


Success Rate vs. Orbit Type

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

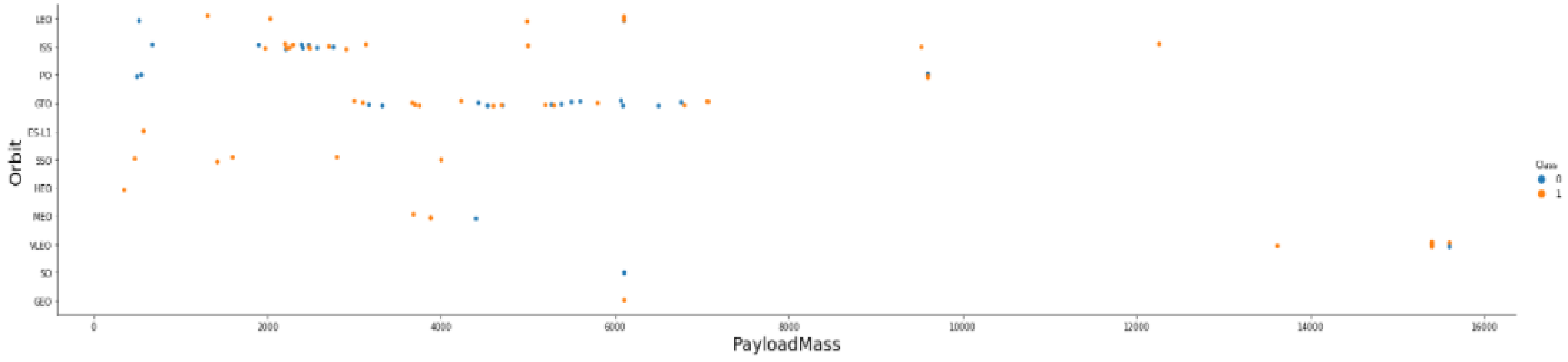
Flight Number vs. Orbit Type

- 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.



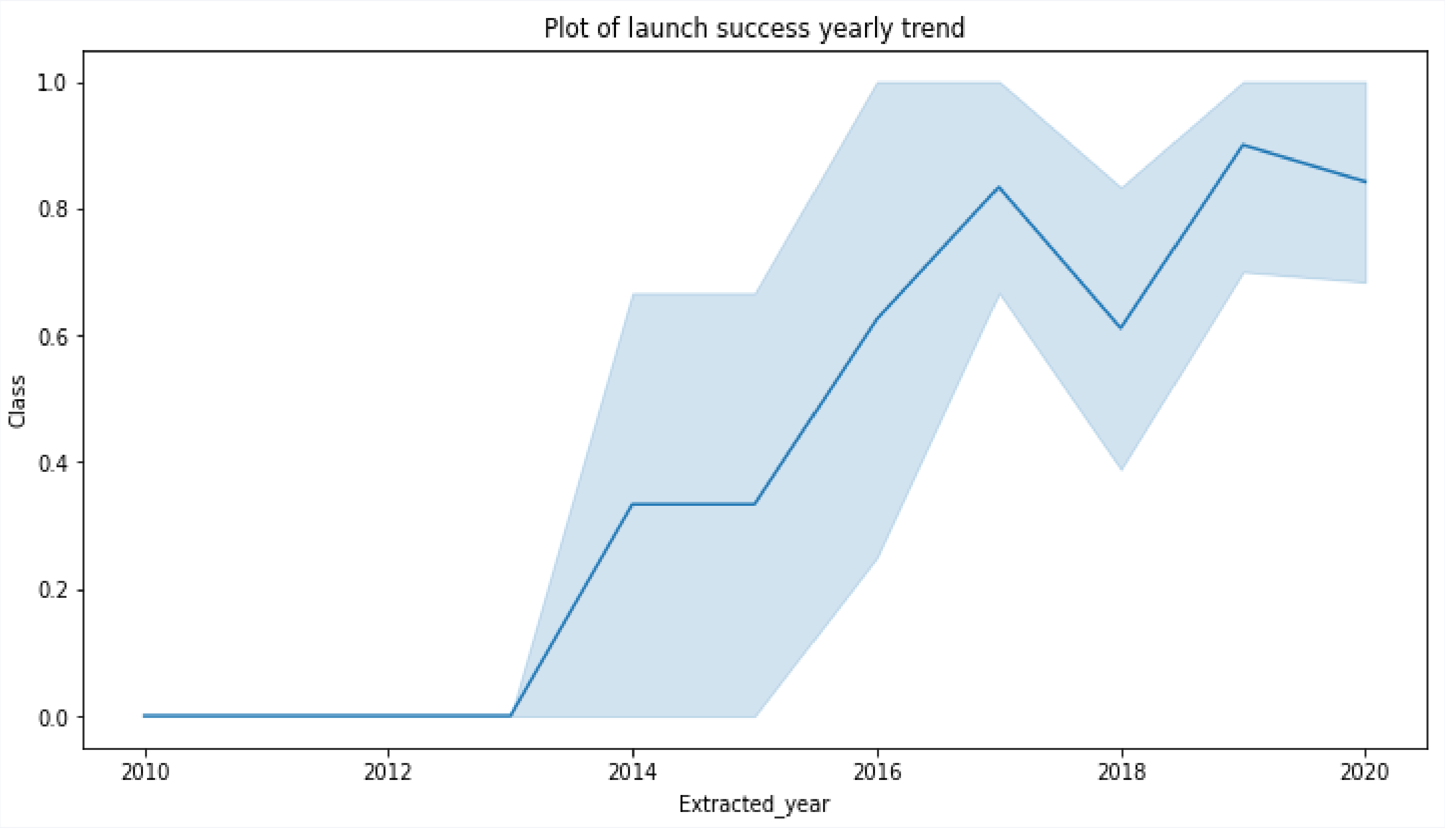
Payload vs. Orbit Type

- 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'

- We used the query above to display 5 records where launch sites 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

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

- 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

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

Total Number of Successful and Failure Mission Outcomes

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

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

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

- 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.

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

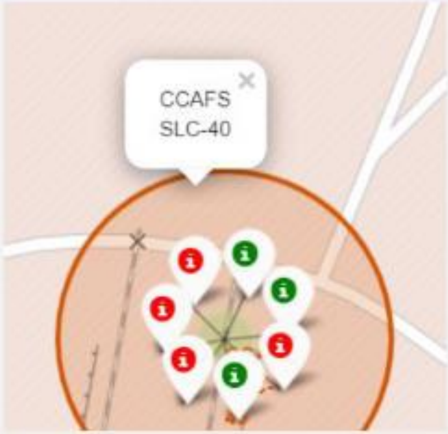
Section 3

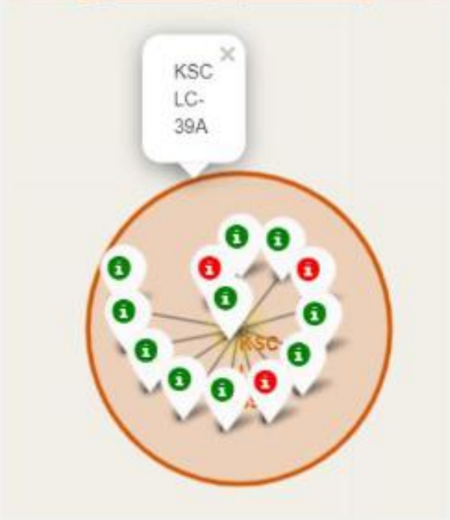
Launch Sites Proximities Analysis

All launch sites global map markers

We can see that the SpaceX launch sites are in the United States
Florida and California

Markers showing launch sites with color labels



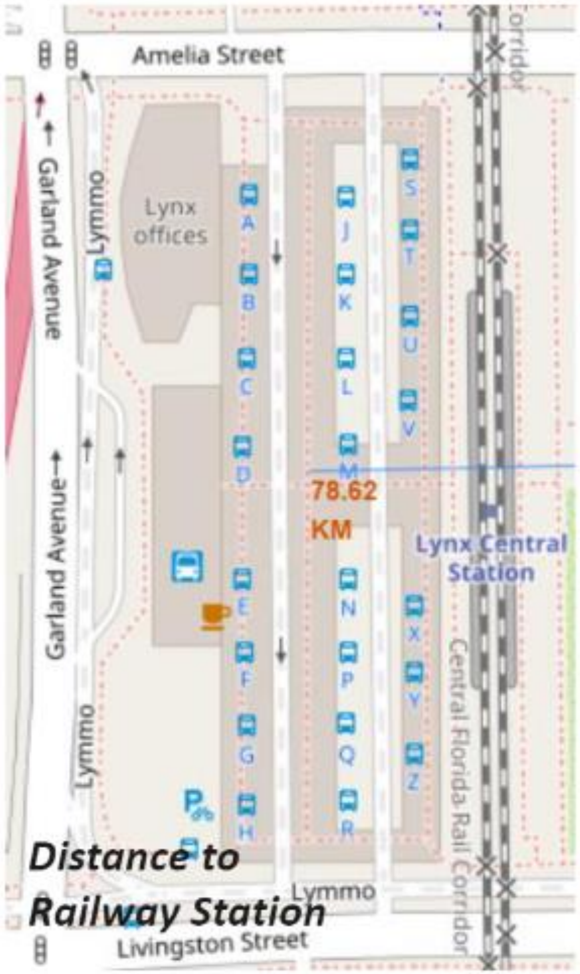


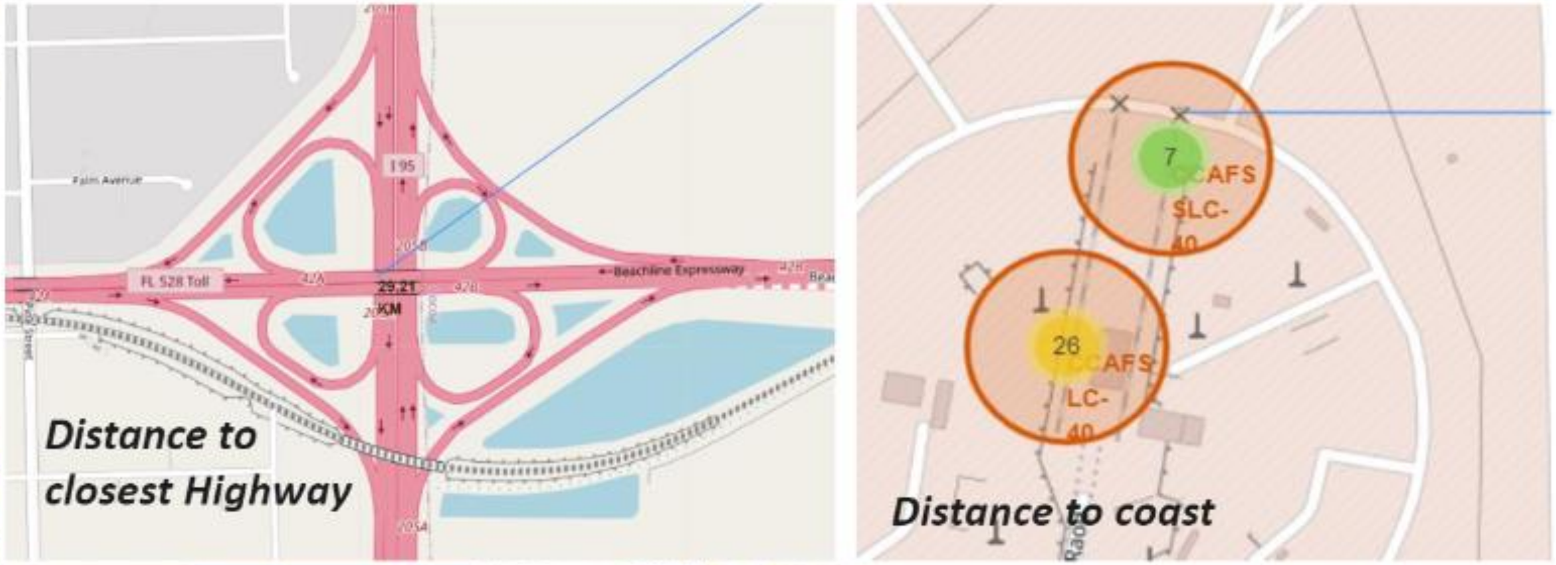
Florida Launch Sites

Green Marker shows successful Launches and Red Marker shows Failures

California Launch Site

Launch Site distance to landmarks



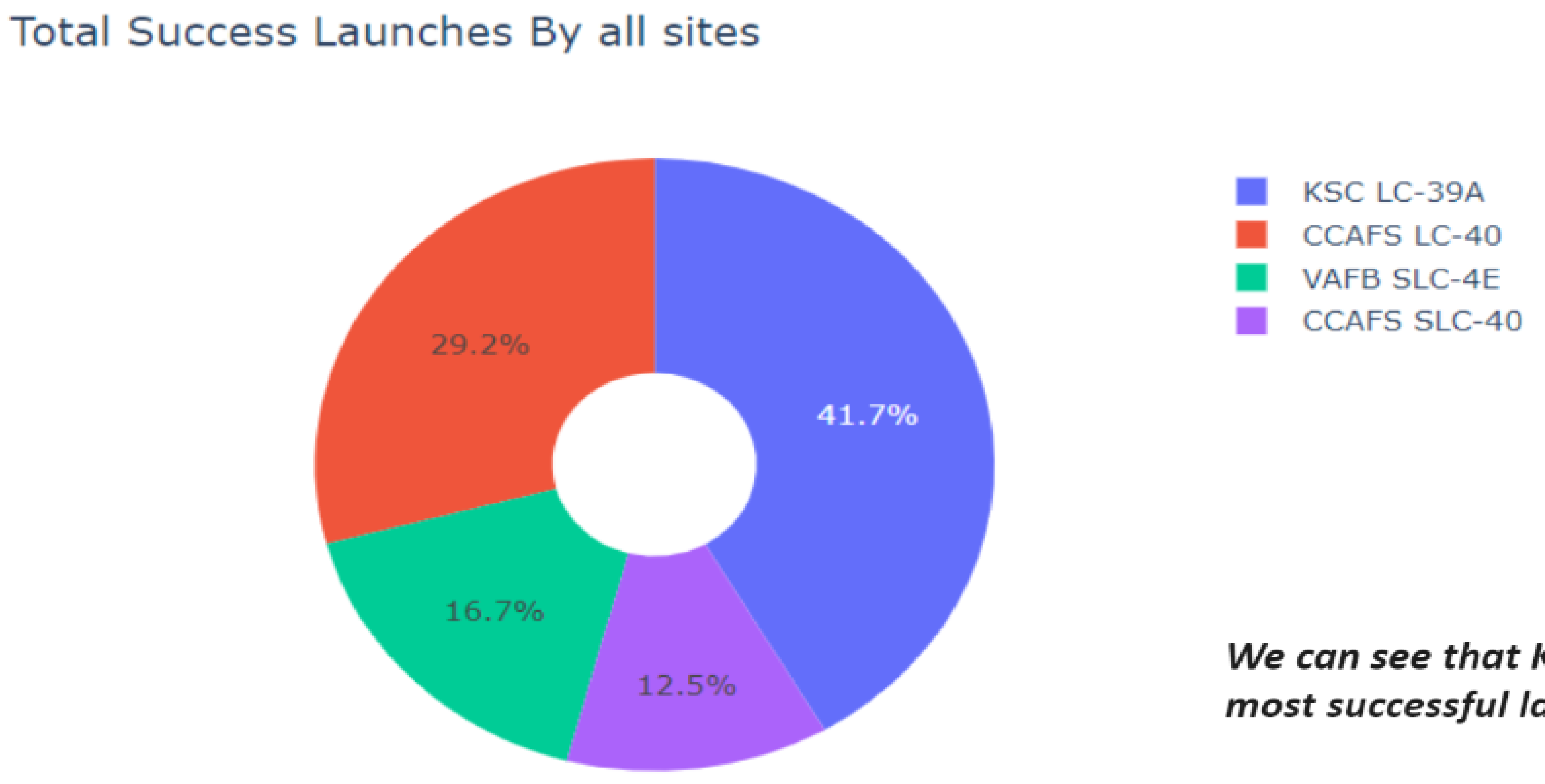


- Are launch sites in close proximity to railways? No
- Are launch sites in close proximity to highways? No
- Are launch sites in close proximity to coastline? Yes
- Do launch sites keep certain distance away from cities? Yes

Section 4

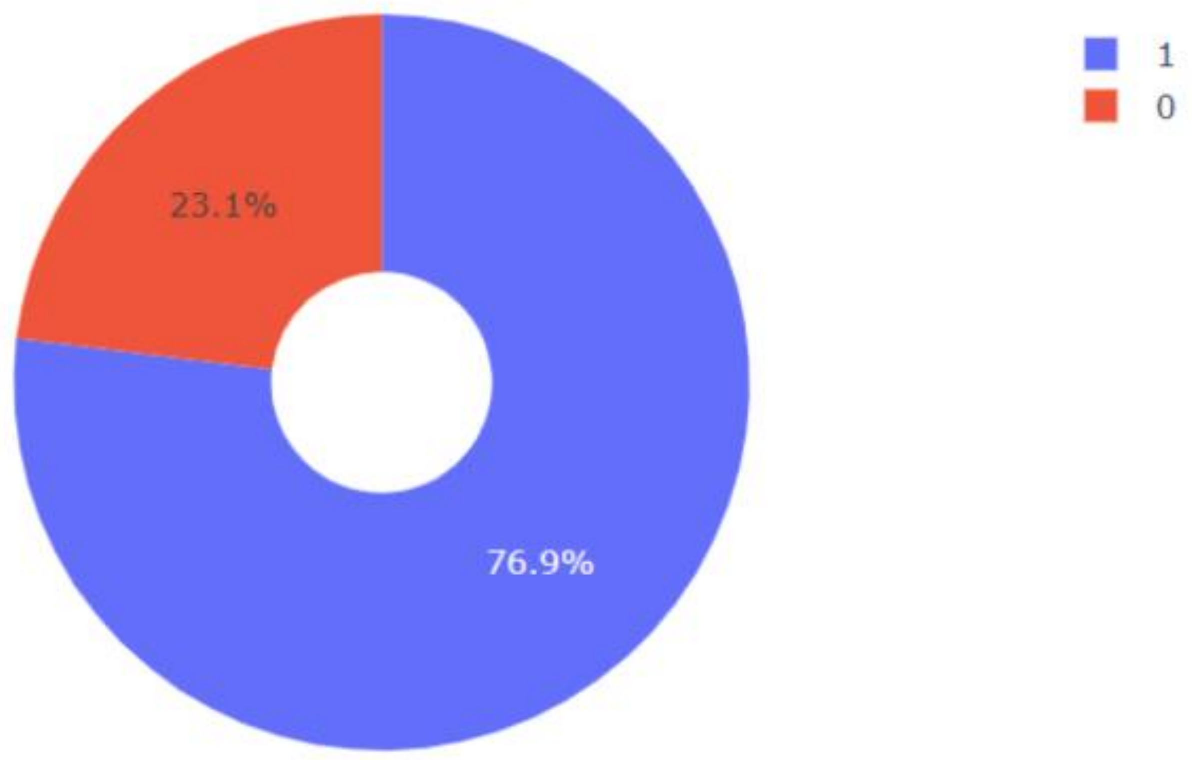
Build a Dashboard with Plotly Dash

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

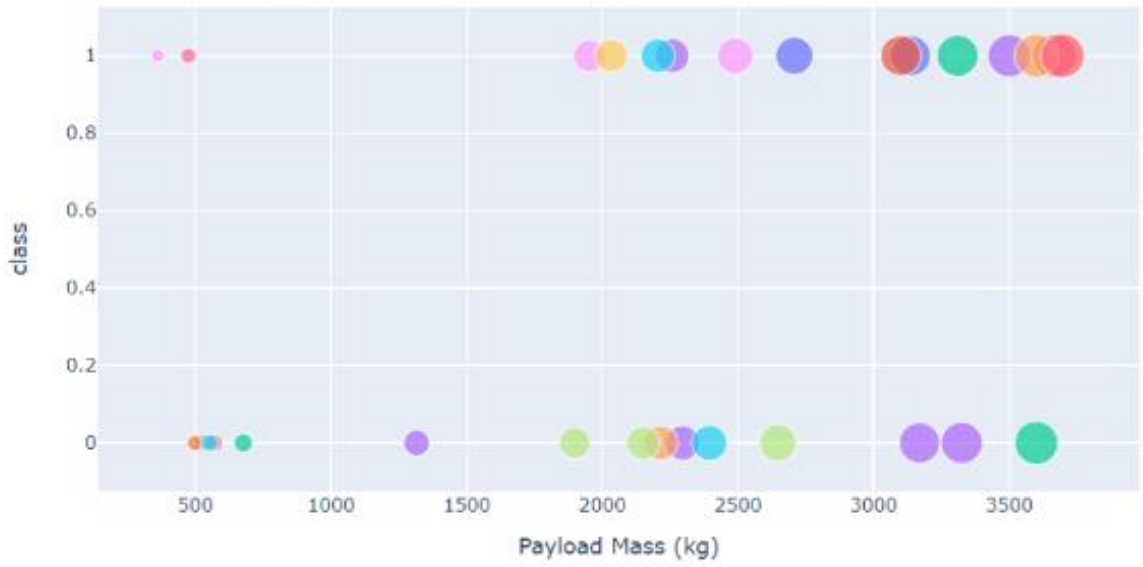
Pie chart showing the Launch site with the highest launch success ratio



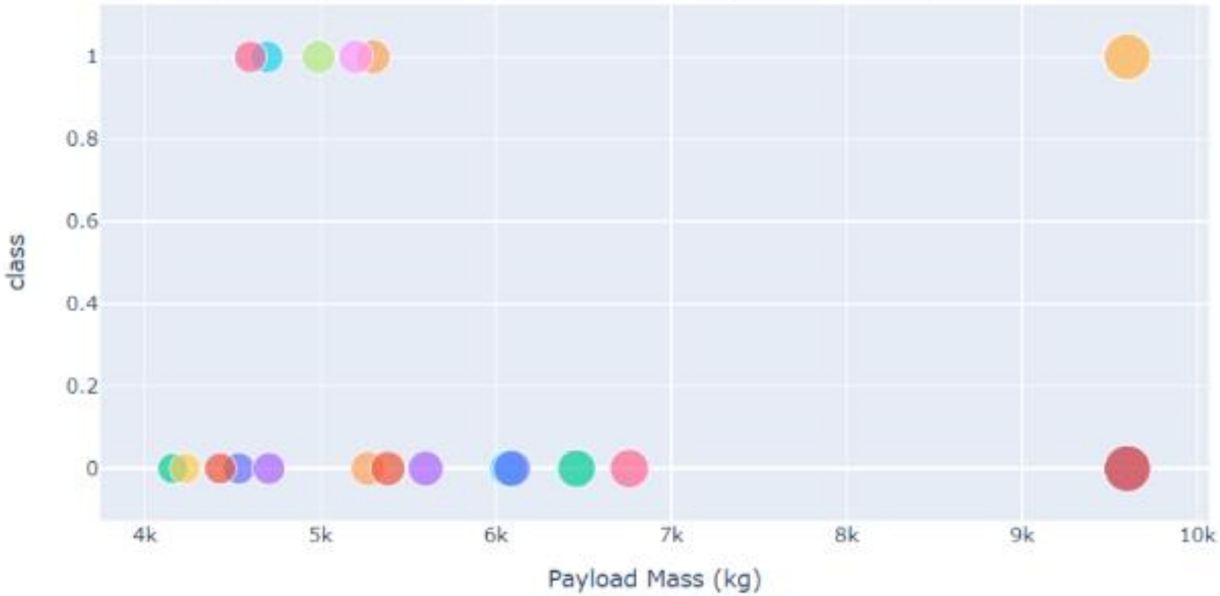
KSC LC-39A achieved a 76.9% success rate while getting a 23.1% failure rate

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

Low Weighted Payload 0kg – 4000kg



Heavy Weighted Payload 4000kg – 10000kg



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

Section 5

Predictive Analysis (Classification)

Classification Accuracy

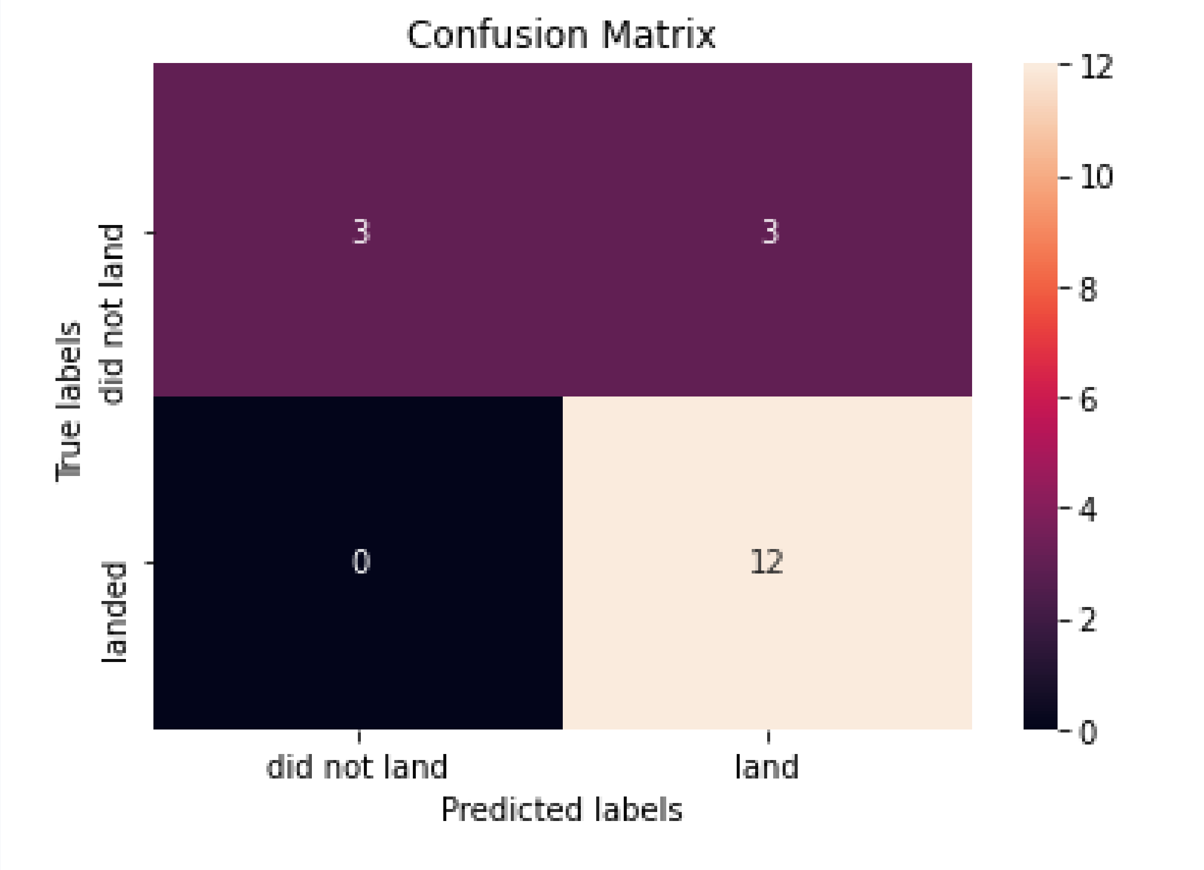
- The decision tree classifier is the model with the highest classification accuracy

```
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

- Conclude that the success rate at a launch site increases with the number of flights at that site.
- Observe that the launch success rate has been increasing since 2013 and has continued until 2020.
- Note that the orbits ES-L1, GEO, HEO, SSO, and VLEO had the highest success rates.
- Identify KSC LC-39A as the launch site with the most successful launches.
- Determine that the Decision tree classifier is the best machine learning algorithm for this particular task.

Thank you!