IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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Outline

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

Github Repository - https://github.com/imran-basha-s/Applied-Data-Science-Capstone-Project

Executive Summary

- Summary of methodologies
  - Data Collection through API
  - Data Collection by Web Scraping
  - Data Wrangling
  - Exploratory Data Analysis using SQL
  - Exploratory Data Analysis & Data Visualization using Pandas & Matplotlib
  - Interactive Visual Analytics with Folium
  - Dashboard Application using Plotly Dash
  - Machine Learning Prediction
- Summary of all results
  - Exploratory Data Analysis result
  - Interactive Data Visualization & Dash Application results
  - Predictive Analytics result

Introduction

- Project background and context

  Its commercial space age and companies are focusing on affordable space travel. Space X, using its Falcon 9 rocket is able to achieve missions at 62 million dollars; while the other companies cost up to more than 165 million dollars.

  Space X is able to achieve this because it is able to reuse its first stage. Thus, the aim of this project is to determine the factors which can ensure landing of the first stage of the rocket. So that, any company can compete with Space X.

- Problems you want to find answers

  - The relationship between various features that determine the success rate of a successful landing of first stage.
  - Can the first stage be reused?
  - Can the space missions be achieved more economically?

Section 1

Methodology

Methodology

Executive Summary

- Data collection methodology:
  - SpaceX API was used for Data Collection and web scraping from Wikipedia.
- Perform data wrangling
  - Missing Data was gathered using other API's from SpaceX
  - Filtering and Sampling of Data was done to remove Falcon 1 Launches
  - 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
  - Various classification models and evaluations were done to find the optimum model

Data Collection

- The data was collected using various methods
  - SpaceX API was used for data collection through a get request.
  - .json() function call was used to decode and convert it into a pandas dataframe using .json_normalize().
  - Data was cleaned, missing data was obtained using other API's from SpaceX, data was sampled/filtered to remove Falcon 1 Launches, Null values were replaced with mean values
  - Web scraping of Data from Wikipedia for Falcon 9 launch records using BeautifulSoup.
  - The objective was to extract the launch records as HTML table, parse the table and convert it to a pandas dataframe for further analysis.

Data Collection - SpaceX API

- SpaceX API was used to collect data.
- Data cleaning and wrangling was done.
- Missing data was obtained.
- Data was sampled and filtered to remove Falcon 1 launch records.
- One hot encoding was used.

- The link to the notebook is https://github.com/imran-basha-s/Applied-Data-Science-Capstone-Project/blob/main/jupyter-labs-spacex-data-collection-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

- BeautifulSoup was used to web scrape the data of Falcon 9 Launches from Wikipedia
- HTML tables were parsed and converted into a pandas dataframe.
- The link to the notebook is https://github.com/imran-basha-s/Applied-Data-Science-Capstone-Project/blob/main/jupyter-labs-webscraping.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

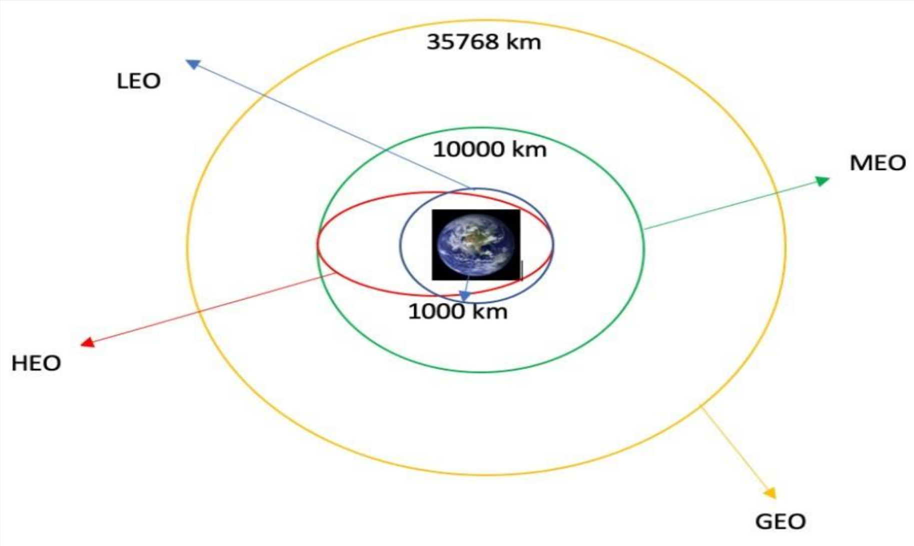
In [10]:
```
column_names = []

# 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

- Data wrangling was done to determine patterns in the data.
- Training labels were identified.
- Number of launches at each site were calculated.
- Number and occurrence of each orbit was also calculated.
- Landing Outcome was determined.
- Exported the results to a CSV file.
- The link to the note book is

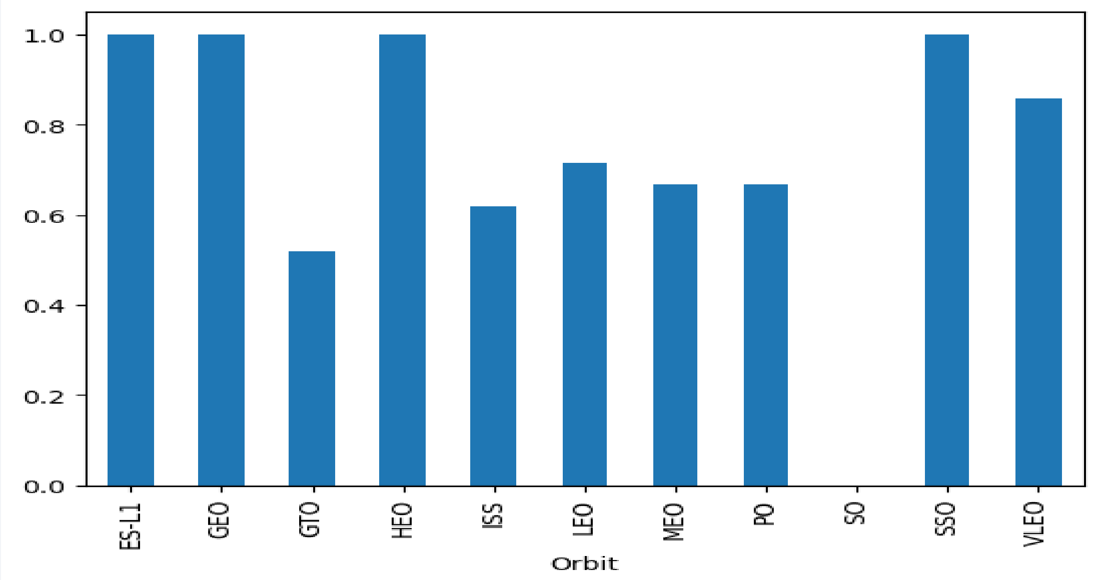
https://github.com/imran-basha-s/Applied-Data-Science-Capstone-Project/blob/main/labs-jupyter-spacex-data_wrangling_jupyterlite.jupyterlite.ipynb

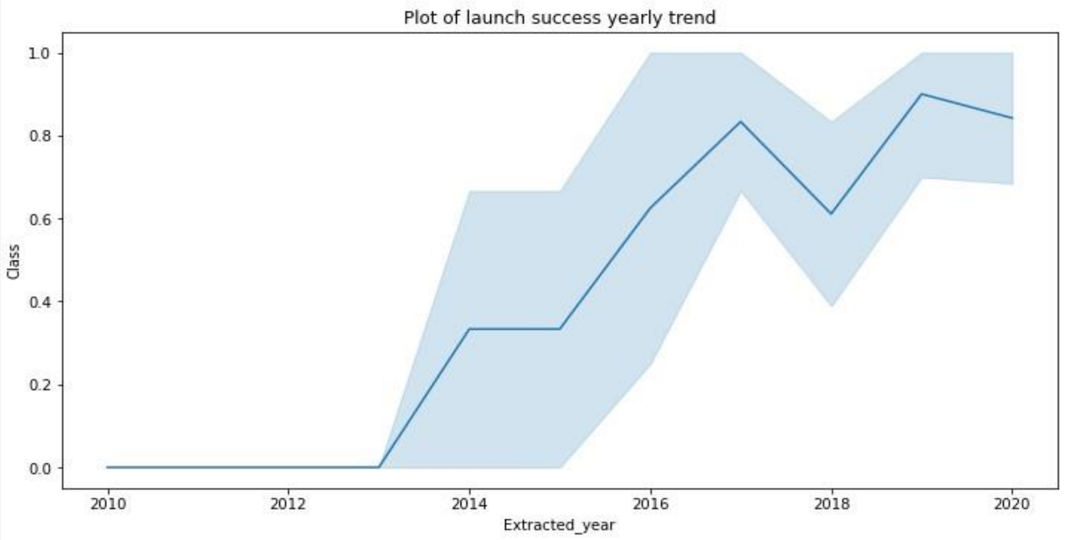


EDA with Data Visualization

- Data was Explored by visualization
- Feature Engineering was done to identify features for further Prediction.
- 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 were visually analyzed

- The link to the notebook is https://github.com/imran-basha-s/Applied-Data-Science-Capstone-Project/blob/main/jupyter-labs-eda-dataviz.ipynb.jupyterlite.ipynb





EDA with SQL

- SpaceX dataset was downloaded and then loaded in a sqlite database.
- EDA was performed with SQL queries. Summary of the queries are as follows:
  - 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/imran-basha-s/Applied-Data-Science-Capstone-Project/blob/main/jupyter-labs-eda-sql-coursera_sqllite.ipynb

Build an Interactive Map with Folium

- All launch sites were marked, and added map objects such as markers, circles, lines to mark the success or failure of launches for each site on the folium map.
- 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, the launch sites having relatively high success rate were identified.
- Calculated the distances between a launch site to its proximities. Some of the questions were answered, for example:
  - Are launch sites near railways, highways and coastlines.
  - Do launch sites keep certain distance away from cities.
- The link to the notebook is

https://github.com/imran-basha-s/Applied-Data-Science-Capstone-Project/blob/main/lab_jupyter_launch_site_location.jupyterlite.ipynb

Build a Dashboard with Plotly Dash

- An interactive dashboard was built using Plotly Dash
- Pie charts were plotted showing the total launches by certain sites
- Scatter graph showing the relationship with Outcome and Payload Mass (Kg) for the different booster version were plotted.
- The link to the notebook/python file is

https://github.com/imran-basha-s/Applied-Data-Science-Capstone-Project/blob/main/spacex_dash_app.py

Predictive Analysis (Classification)

- Data was loaded using numpy and pandas, transformed the data, split the data into training and testing.
- Built different machine learning models and tuned them with different hyperparameters using GridSearchCV.
- Accuracy was used as the metric for the ML models, improved the model using feature engineering and algorithm tuning.
- Best performing classification model was finally developed.
- The link to the notebook is

https://github.com/imran-basha-s/Applied-Data-Science-Capstone-Project/blob/main/SpaceX_Machine%20Learning%20Prediction_Part_5.ipynb

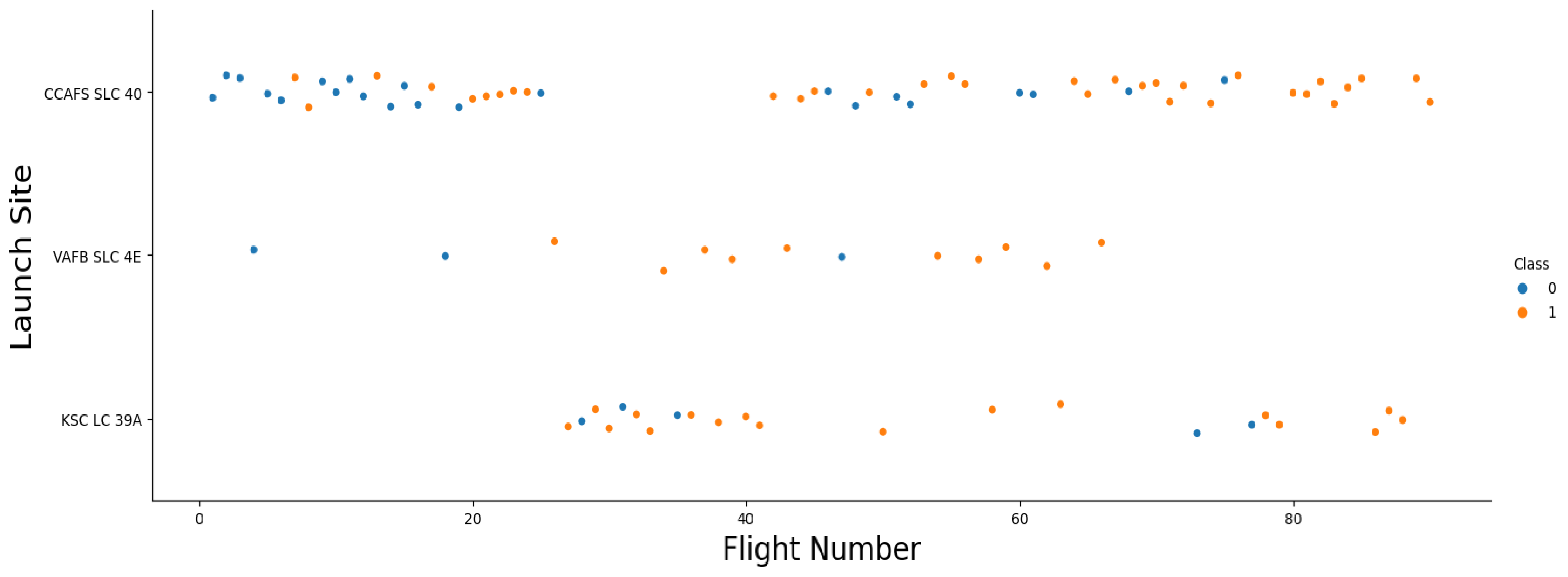
Results

- Exploratory data analysis was conducted using SQL, Pandas & Matplotlib.
- Data was manipulated, analyzed in a Pandas Data frame as well as using SQL queries.
- Data visualization was done using Matplotlib to derive meaningful patterns and to further aid in Model building process.
- Interactive Visualization Plots were developed using Folium.
- And also, an Dashboard application was built using Plotly Dash.
- A predictive Machine learning classification model was built and optimized.
- The details of the results can be seen briefly in the slides below.

Section 2

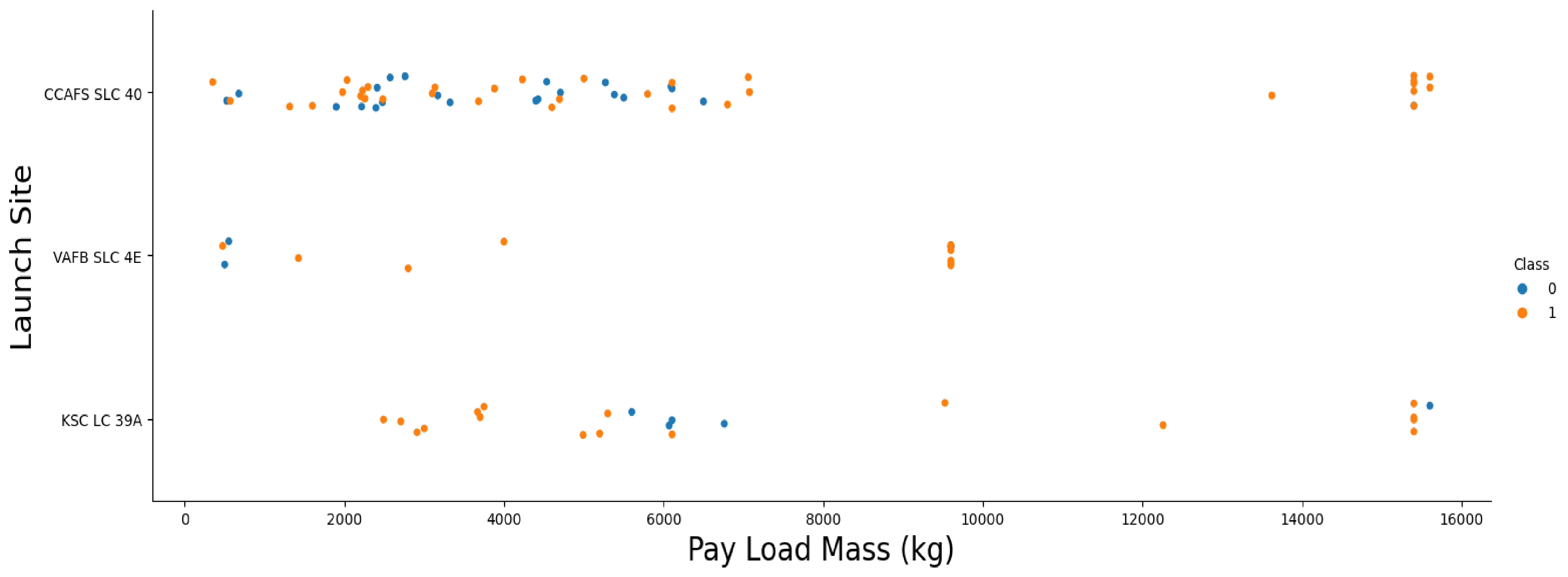
Insights drawn from EDA

Flight Number vs. Launch Site



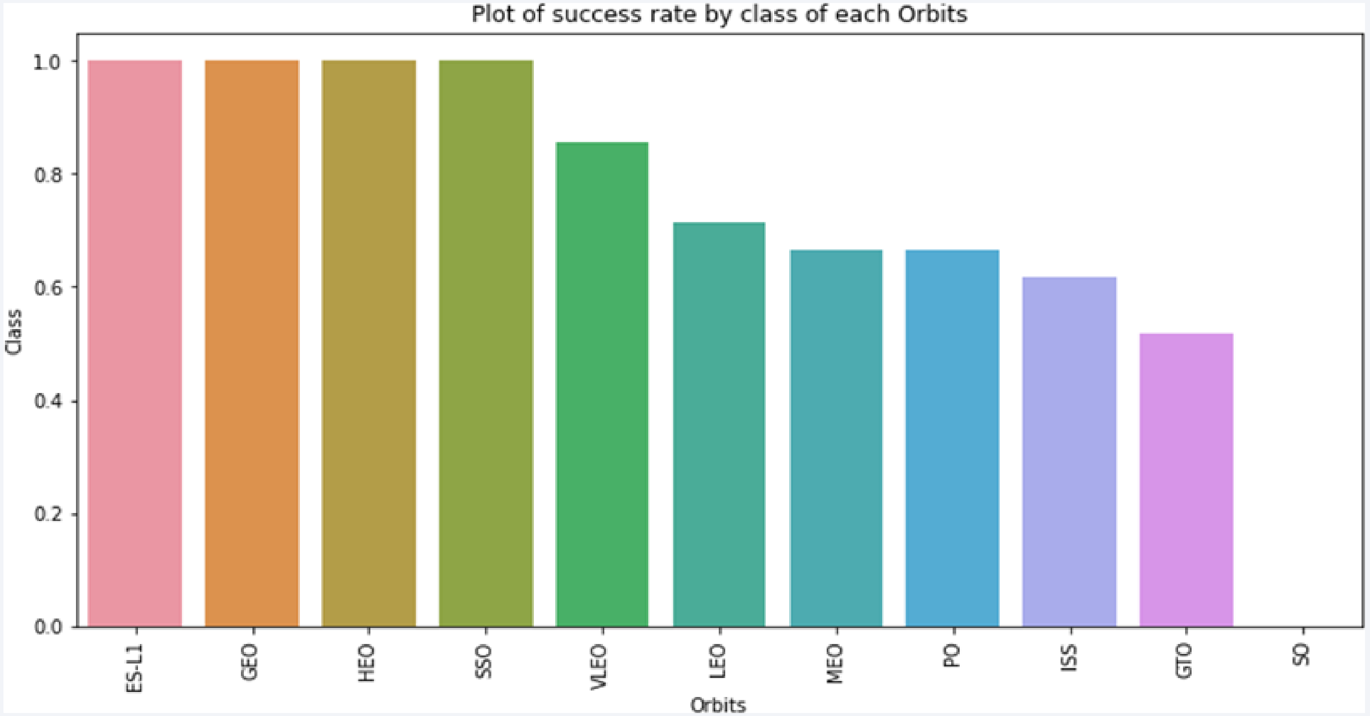
- We see that the larger the flight amount at a launch site, the greater the success rate at a launch site.

Payload vs. Launch Site



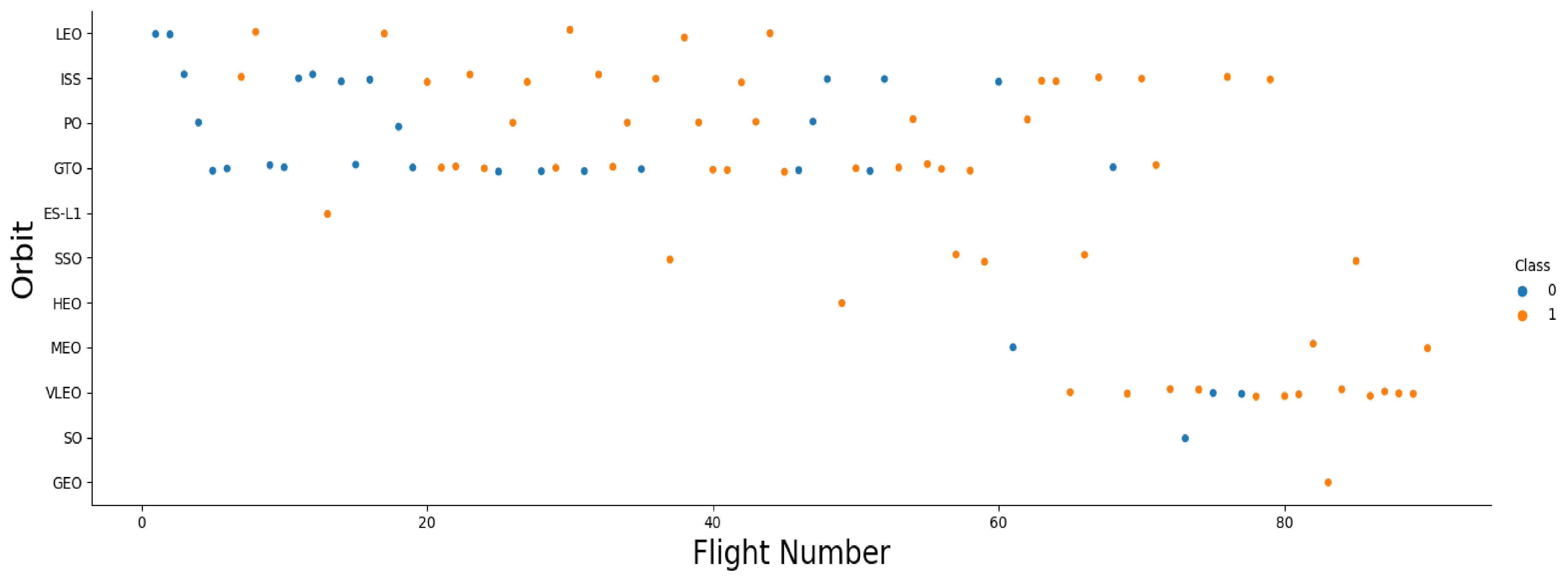
- The greater the payload mass for the launch site CCAFS SLC 40, the higher the success rate of landing

Success Rate vs. Orbit Type



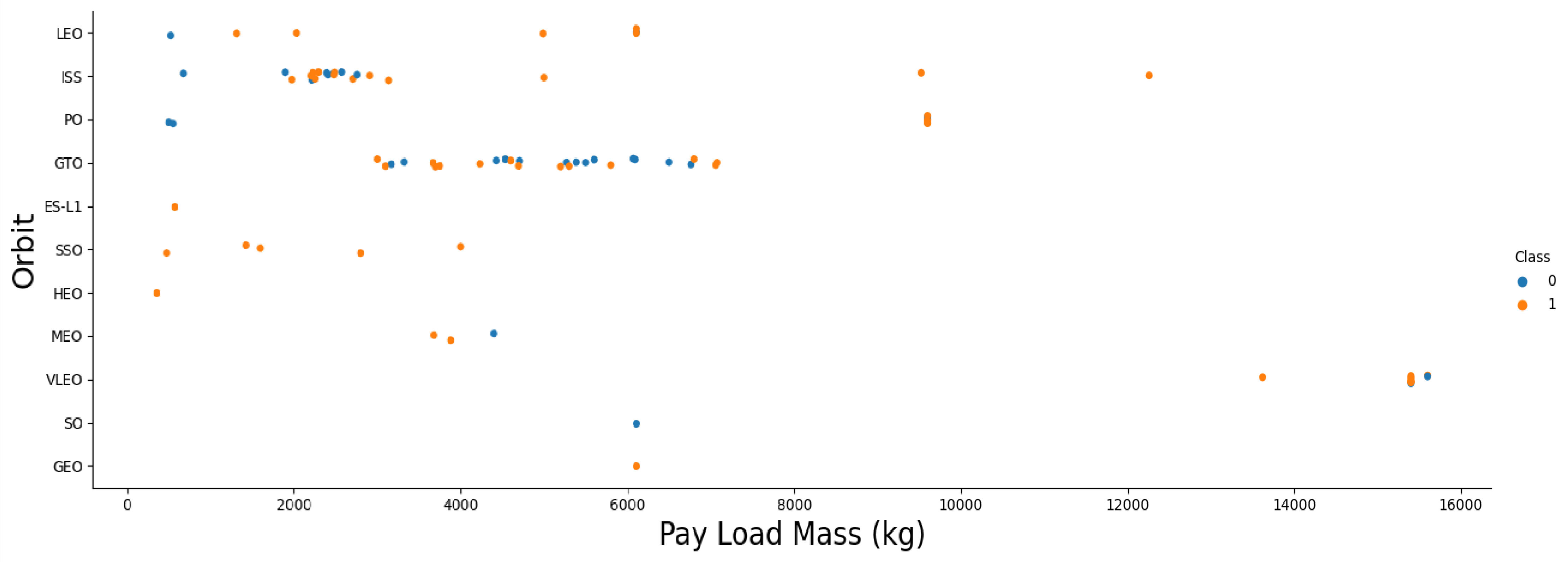
- From the plot, we can see that ES-L1, GEO, HEO, SSO, VLEO had the most success rate.

Flight Number vs. Orbit Type



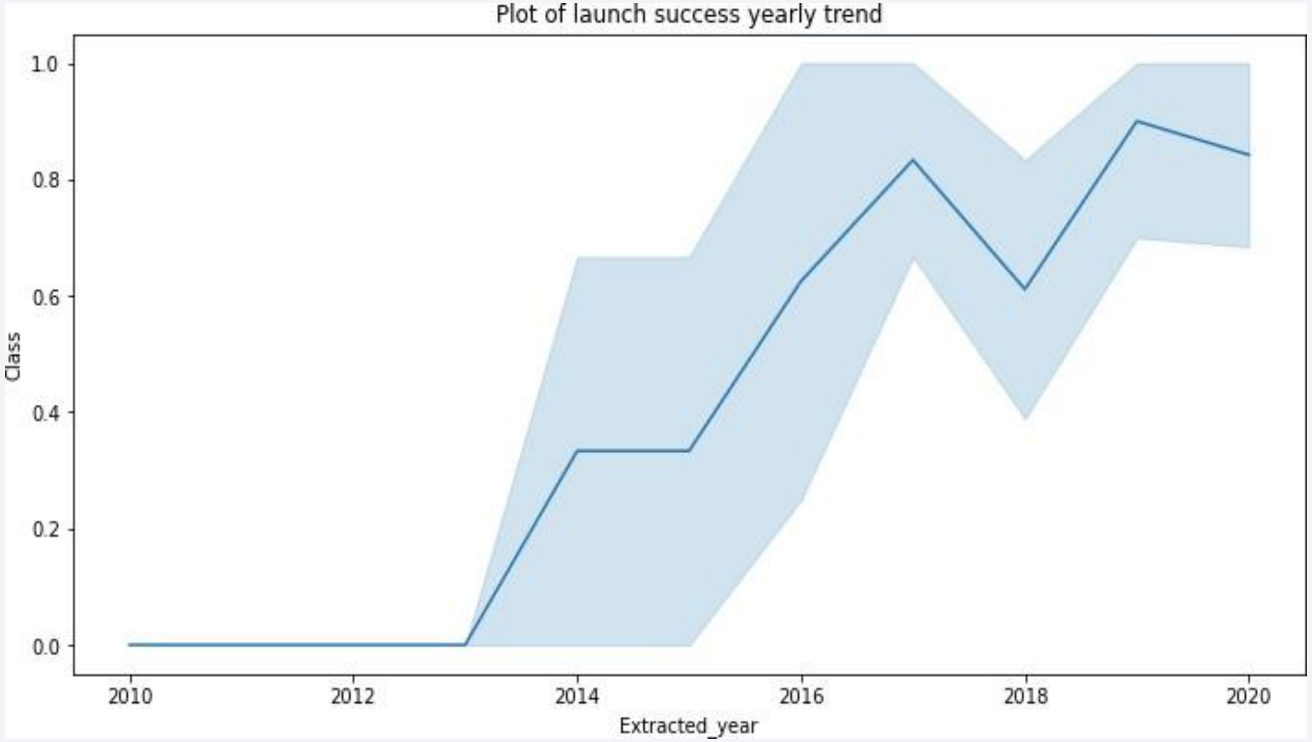
- Observe that in the LEO orbit, success is related to the number of flights whereas in the GTO orbit, there is no relationship between flight number and the orbit.

Payload vs. Orbit Type



- We can observe from the scatter plat that ; With Heavy payloads, 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

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

- The key word **DISTINCT** to show only unique launch sites from the SpaceX data.

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

- WHERE clause along with LIKe and LIMIT was used to display 5 records where launch sites begin with `CCA`

Total Payload Mass

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

- Calculated the total payload carried by boosters from NASA as 45596 using SUM and AS option with LIKE

Average Payload Mass by F9 v1.1

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

- The average payload mass carried by booster version F9 v1.1 was 2928.4

First Successful Ground Landing Date

```
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

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

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

- 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

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

Boosters Carried Maximum 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

- Determined the booster that have carried the maximum payload using a subquery in the **WHERE** clause and the **MAX()** function.

2015 Launch Records

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)

- A combinations of the **WHERE** clause, **LIKE**, **AND**, and **BETWEEN** conditions to filter for failed landing outcomes in drone ship, their booster versions, and launch site names for year 2015

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

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

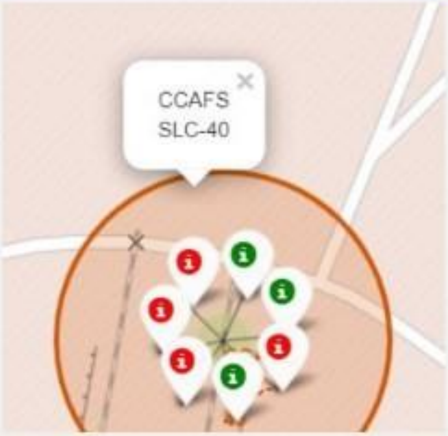
- Selected Landing outcomes and the **COUNT** of landing outcomes from the data and used the **WHERE** clause to filter for landing outcomes **BETWEEN** 2010-06-04 to 2010-03-20.
- Applied the **GROUP BY** clause to group the landing outcomes and the **ORDER BY** clause to order the grouped landing outcome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

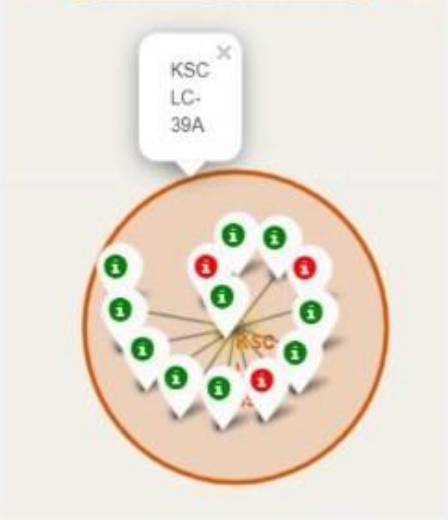
Section 4

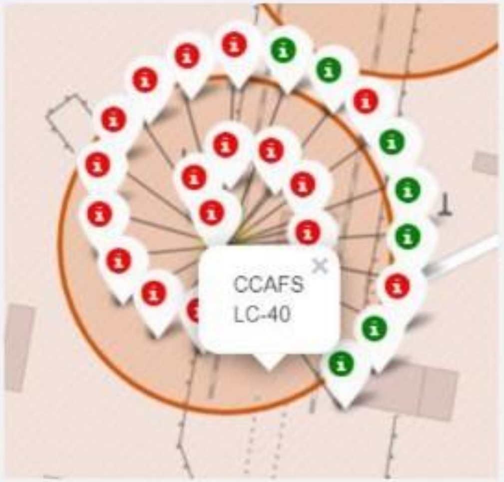
Launch Sites Proximities Analysis

All launch sites global map markers

Markers showing launch sites with color labels







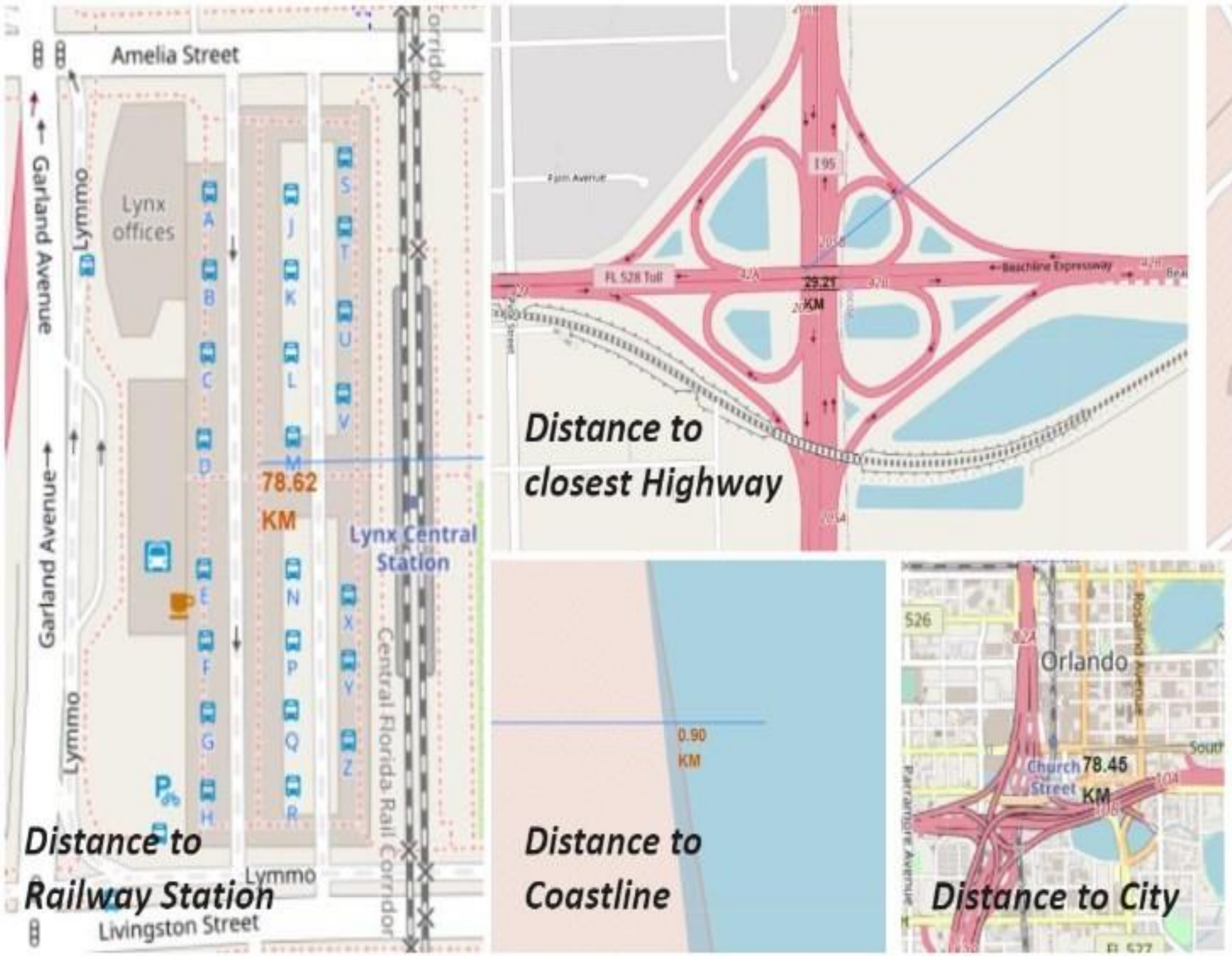
Florida Launch Sites

Green Marker shows successful Launches and Red Marker shows Failures

California Launch Site

37

Launch Site distance to landmarks

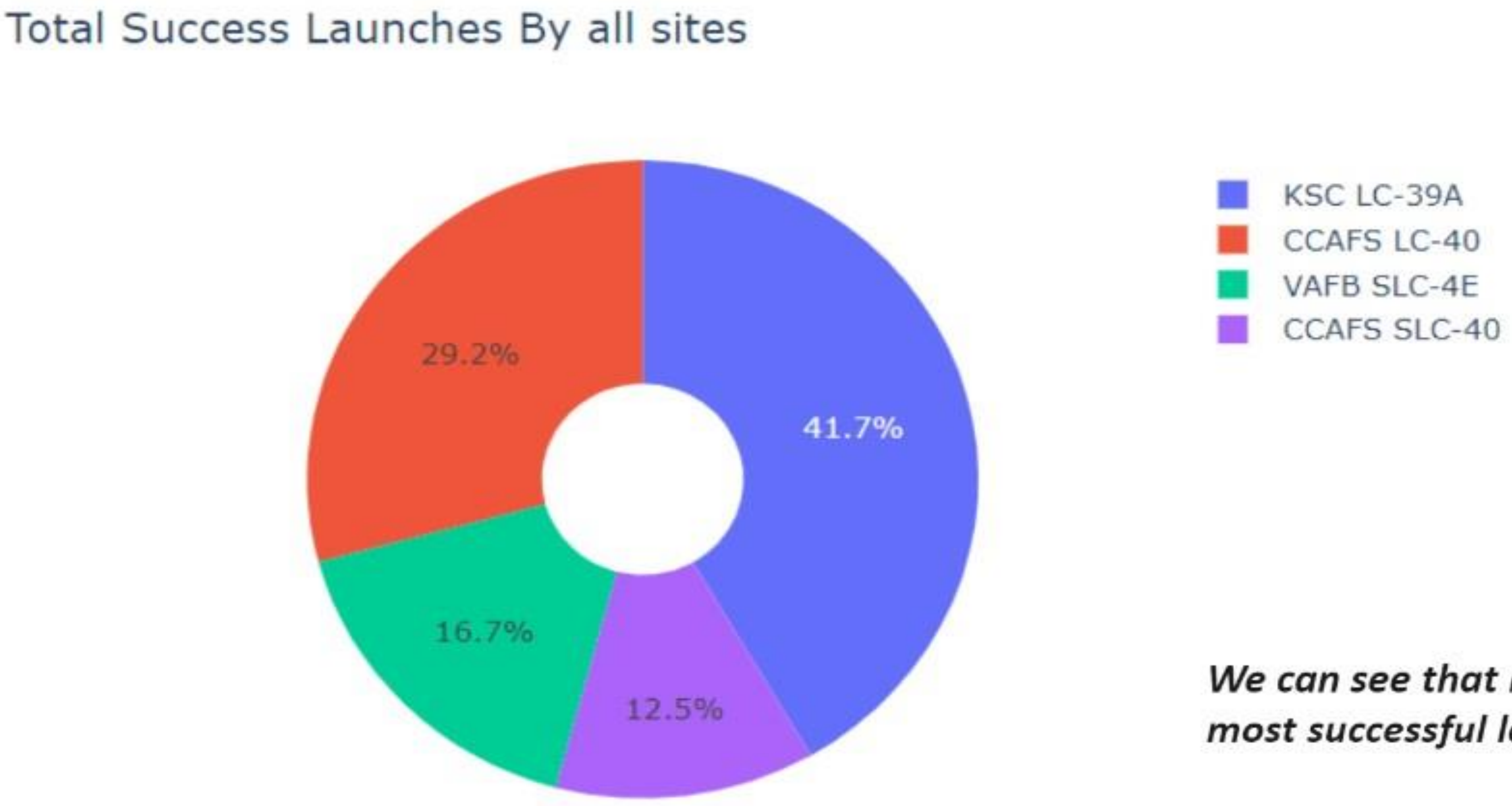


- Are launch sites in close proximity to railways? No
- Are launch sites in close proximity to highways? No
- Are launch sites in close proximity to coastline? Yes
- Do launch sites keep certain distance away from cities? Yes

Section 5

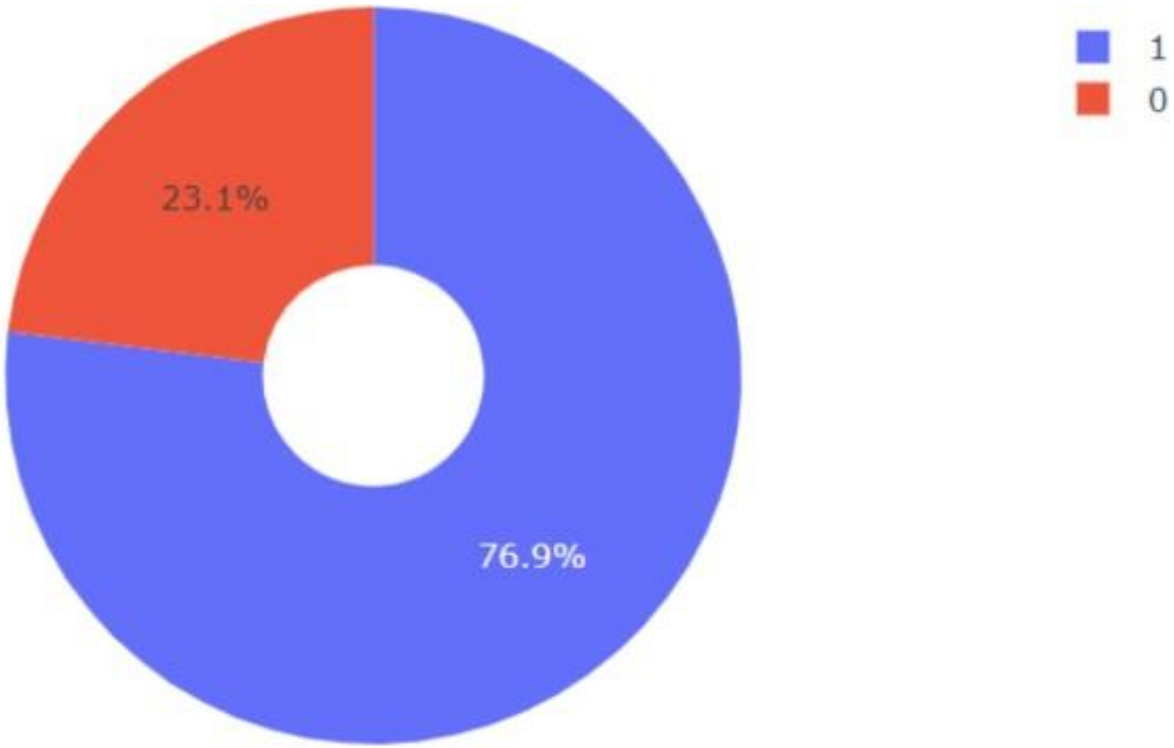
Build a Dashboard with Plotly Dash

Pie chart showing the success percentage achieved by each launch site



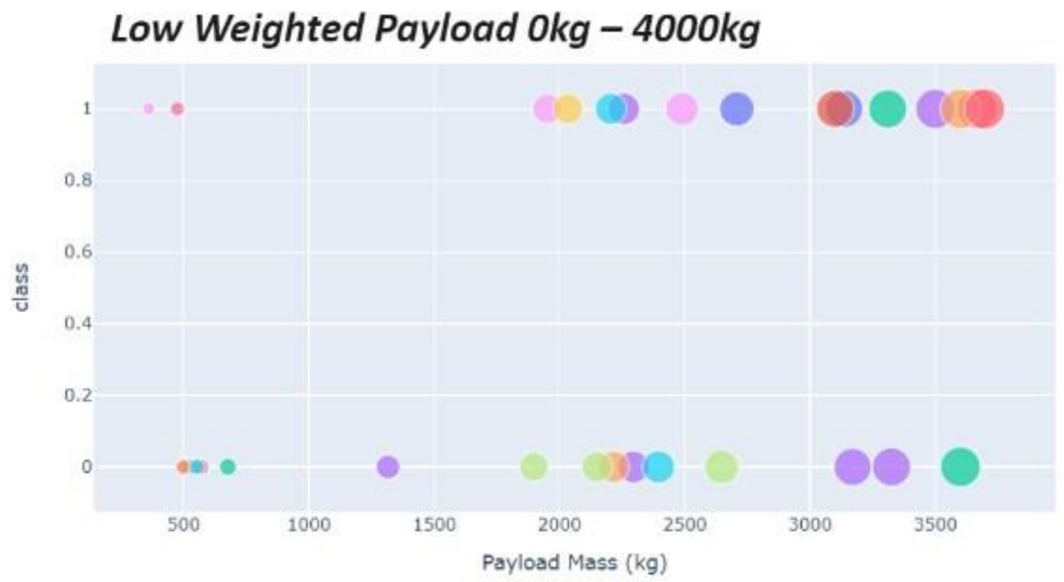
We can see that KSC LC-39A had the most successful launches from all the sites

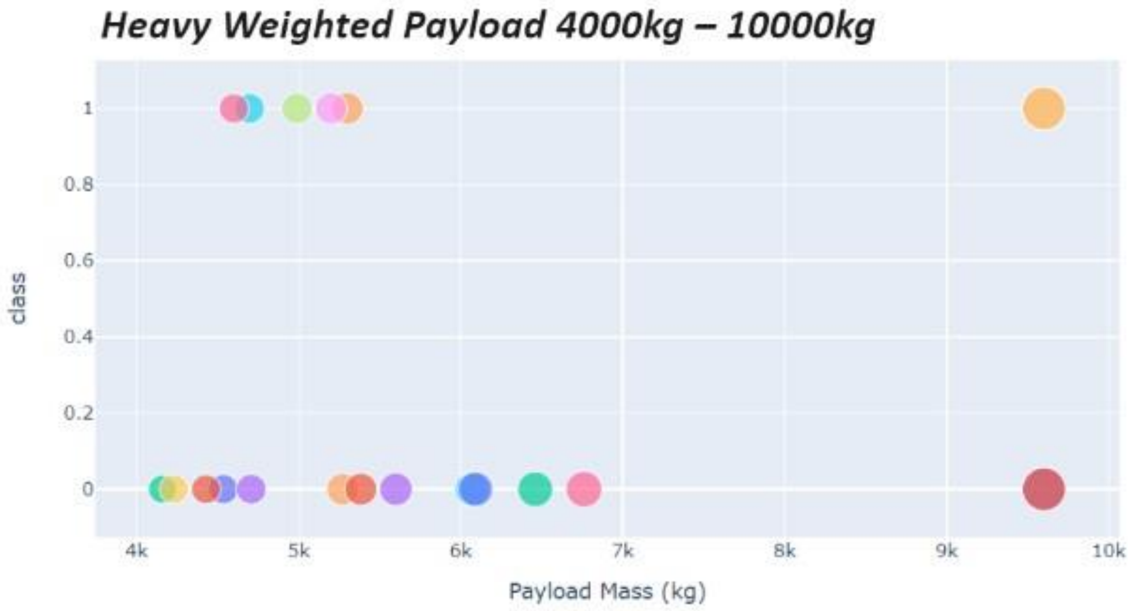
Pie chart showing the Launch site with the highest launch success ratio



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 6

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_)
```

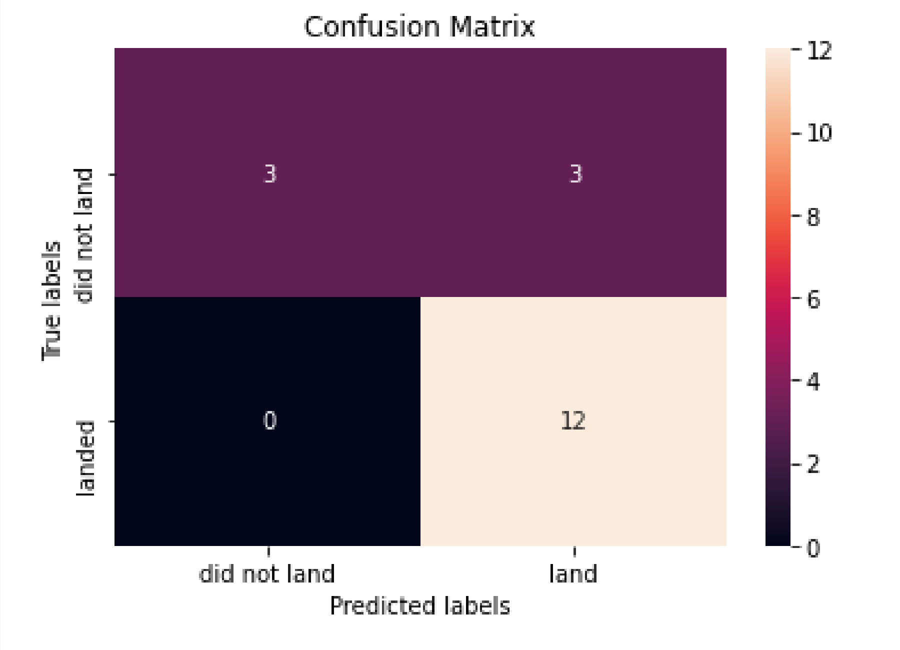
```
Best model is DecisionTree with a score of 0.8732142857142856
Best params is : {'criterion': 'gini', 'max_depth': 6, 'max_features': 'auto', 'min_samples_leaf': 2, 'min_samples_split': 5, 'splitter': 'random'}
```

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

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!