IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

Juha Lappalainen
8th of March, 2022

Outline

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

Executive Summary

- Summary of methodologies
  - Data Collection through API
  - Data Collection with Web Scraping
  - Data Wrangling
  - Exploratory Data Analysis with SQL
  - Exploratory Data Analysis with Data Visualization
  - Interactive Visual Analytics with Folium
  - Machine Learning Prediction
- Summary of all results
  - Exploratory Data Analysis result
  - Interactive analytics in screenshots
  - Predictive Analytics result

Introduction

- Project background and context
    - Space X advertises Falcon 9 rocket launches on its website with a cost of 62 million dollars. Other providers cost upward of 165 million dollars each, much of the savings is because Space X can reuse the first stage. Thus, 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. The goal of this 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 the 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 different methods.
- Data collection was done using the *get request* to the SpaceX API
- Then we decoded the response content as a Json using json() function call and turn it into a pandas dataframe using json_normalize.
- Then we cleaned the data, checked for missing values and fill in missing values where necessary.
- Additionally, we performed web scraping from Wikipedia for Falcon 9 launch records with BeautifulSoup.
- The objective was to extract the launch records as HTML table, parse the table and convert it to a pandas dataframe for future analysis.

Data Collection – SpaceX API

- We used the get request to the SpaceX API to collect data, clean the requested data and did some basic data wrangling and formatting.
- The link to the notebook is: https://github.com/jutala/applied_data_science_capstone/blob/4e2aafbba9761926c98a118b510bb0c60d236f70/1%20-%20Data%20Collection%20API%20Lab.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 applied web scraping to webscrap Falcon 9 launch records with BeautifulSoup. We parsed the table and converted it into a pandas dataframe.

- GitHub URL: https://github.com/jutala/applied_data_science_capstone/blob/4e2aafbba9761926c98a118b510bb0c60d236f70/2%20-%20Data%20Collection%20with%20Web%20Scraping%20Lab.ipynb

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

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

In [5]:
```python
# 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]:
```python
# 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]:
```python
# Use soup.title attribute
soup.title
```

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

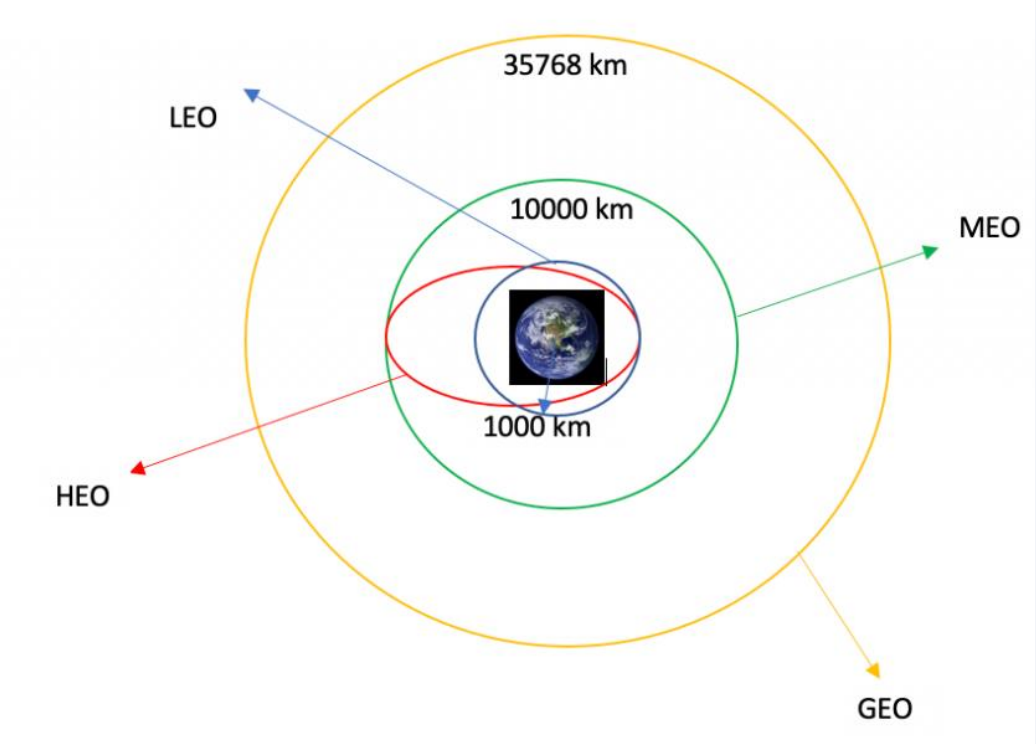
3. Extract all column names from the HTML table header

In [10]:
```python
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

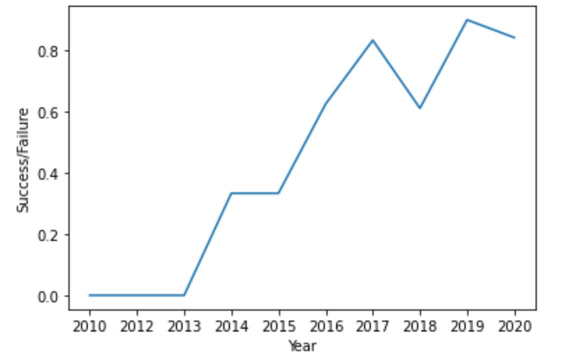
Data Wrangling

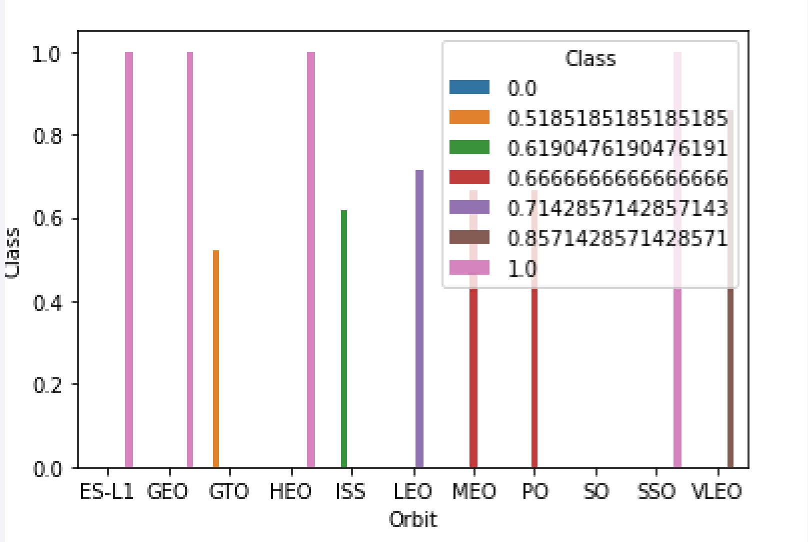
- We performed exploratory data analysis and determined the training labels. We calculated the number of launches at each site, and the number and occurrence of each orbits. We created landing outcome label from the outcome column and exported the results to csv.
- GitHub URL: https://github.com/jutala/applied_data_science_capstone/blob/4e2aafbba9761926c98a118b510bb0c60d236f70/3%20-%20Data%20Wrangling%20EDA%20lab.ipynb



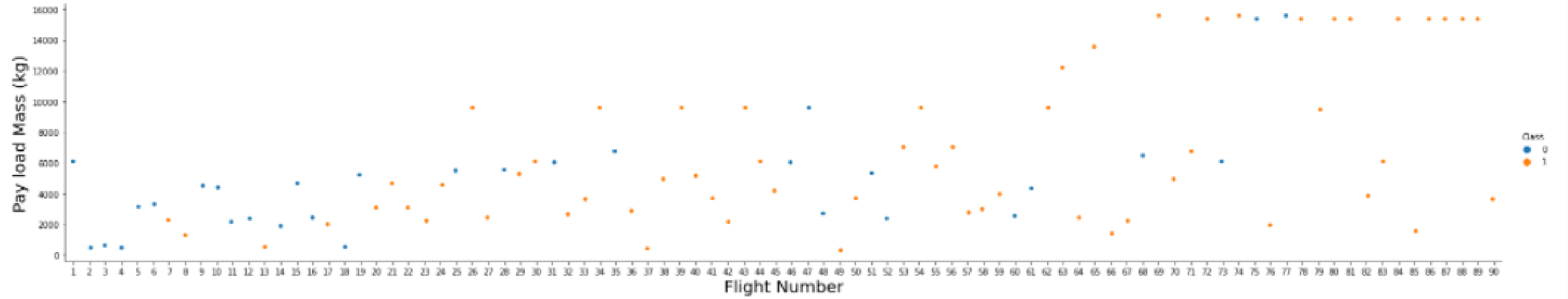
EDA with Data Visualization

- We explored the data by visualizing the relationship between things such as flight number and launch Site, payload and launch site, success rate of each orbit type, flight number and orbit type, and the launch success yearly trend.





- GitHub URL: [https://github.com/jutala/applied_da e2aafbba9761926c98a118b510bb %20EDA%20with%20Visualization](https://github.com/jutala/applied_da)



EDA with SQL

- We loaded the SpaceX dataset into a PostgreSQL database without leaving the jupyter notebook. We applied EDA with SQL to get insight from the data.
- We wrote queries to find out:
  - The names of the unique launch sites in the space mission.
  - The total payload mass carried by the boosters launched by NASA (CRS)
  - The average payload mass carried by the booster version F9 v1.1
  - The total number of successful and failure mission outcomes
  - The failed landing outcomes in the drone ship, their booster version and launch site names.
- GitHub URL: https://github.com/jutala/applied_data_science_capstone/blob/4e2aafbba9761926c98a118b510bb0c60d236f70/4%20-%20EDA%20with%20SQL%20lab.ipynb

Build an Interactive Map with Folium

- We marked all launch sites, and added map objects like markers, circles, lines to mark the success or failure of launches for each site on the map.
- We assigned the feature launch outcomes (failure or success) to class 0 and 1. 0 for failure, and 1 for success.
- Using the color labeled marker clusters, we identified which launch sites have relatively high success rate.
- We calculated the distances between a launch site to its proximities.
- We added these objects to answer questions like:
  - Are launch sites near railways, highways and coastlines?
  - Do launch sites keep certain distance away from cities?
- GitHub URL: https://github.com/jutala/applied_data_science_capstone/blob/4e2aafbba9761926c98a118b510bb0c60d236f70/6%20-%20Interactive%20Visual%20Analytics%20with%20Folium%20lab.ipynb

Build a Dashboard with Plotly Dash

- We built an interactive dashboard with the Plotly dash.
- We plotted pie charts showing the total launches of specific sites.
- We plotted scatter graph showing the relationship with the Outcome and the Payload and Mass (Kg) for the different booster version.

Predictive Analysis (Classification)

- We loaded the data using numpy and pandas, transformed the data, split our data into training and testing samples.
- We built different machine learning models and tuned different hyperparameters using GridSearchCV.
- We used accuracy as the metric for our model, improved the model using feature engineering and algorithm tuning.
- Finally, we found the best performing classification model.
- GitHub URL: https://github.com/jutala/applied_data_science_capstone/blob/4e2aafbba9761926c98a118b510bb0c60d236f70/7%20-%20Machine%20Learning%20Prediction%20lab.ipynb

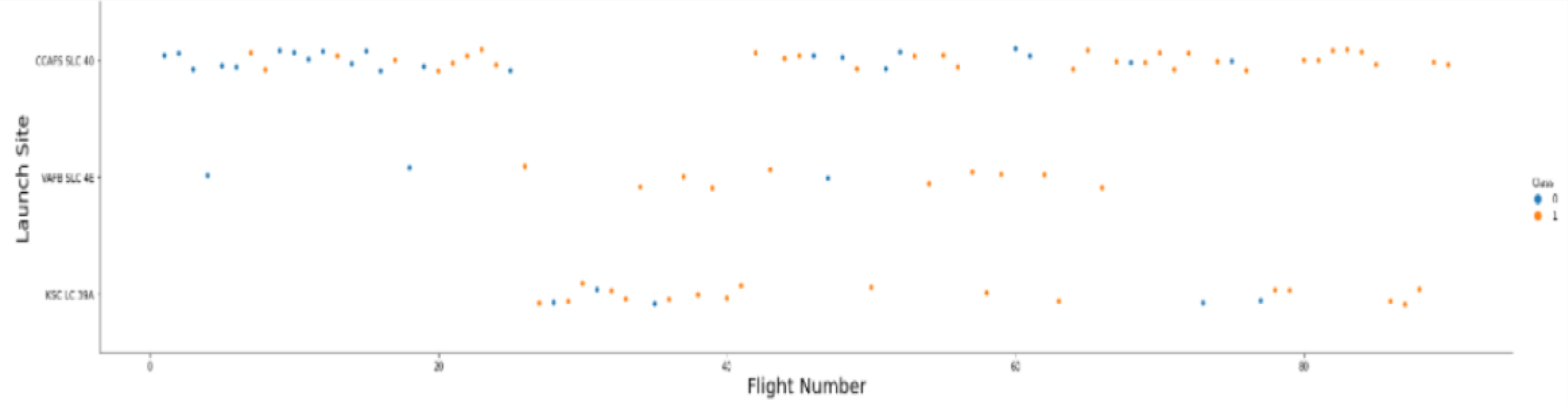
Results

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

Section 2

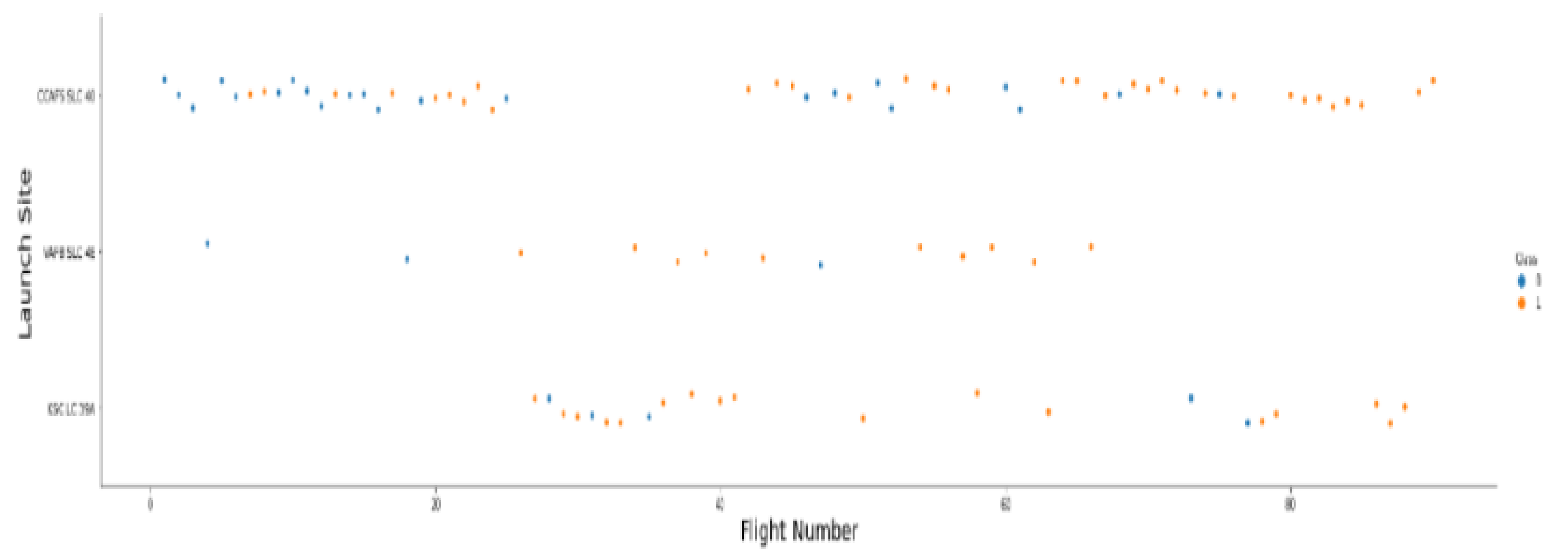
Insights drawn from EDA

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.

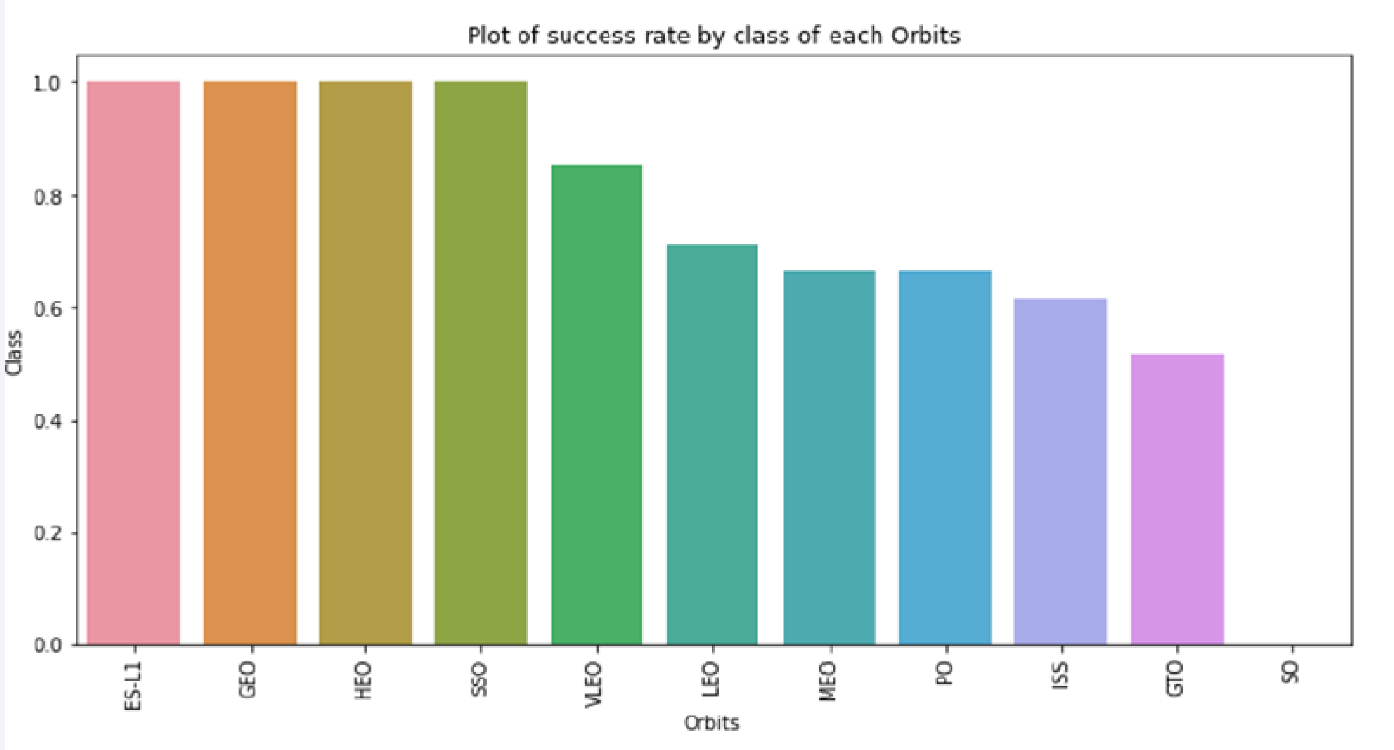
Payload vs. Launch Site



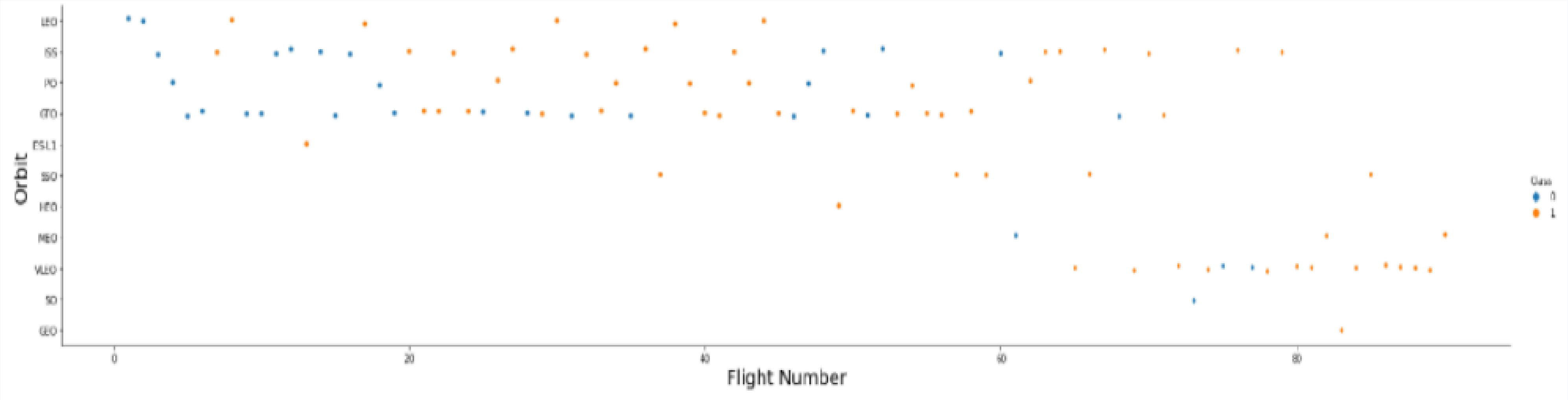
- Looking at the scatter plot we found out that the greater the payload mass for launch site CCAFS SLC 40 the higher the success rate for the rocket.

Success Rate vs. Orbit Type

- From the bar chart, we can see that ES L1, GEO, HEO, SSO, VLEO had the highest success rates.

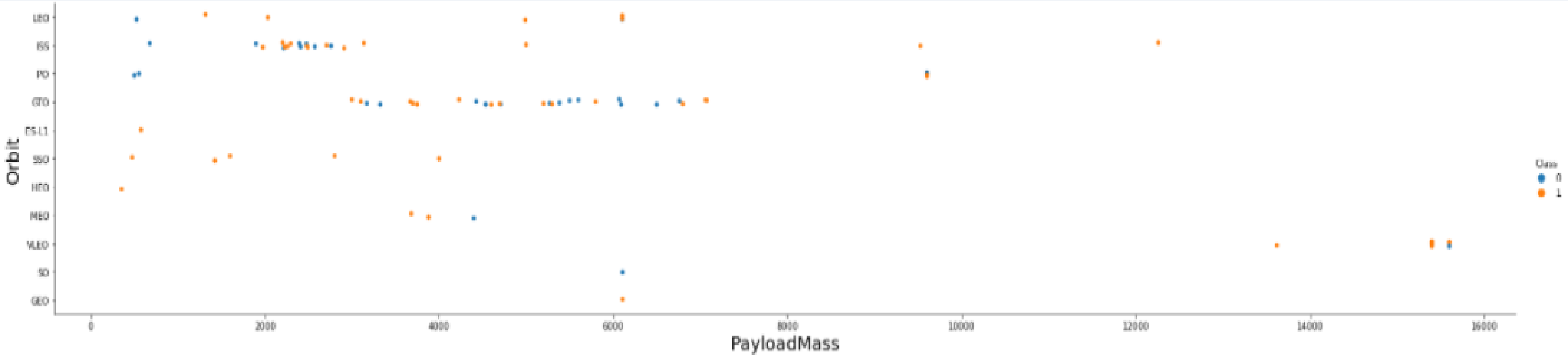


Flight Number vs. Orbit Type



- The scatter plot shows the Flight Number vs. Orbit type. We can 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.

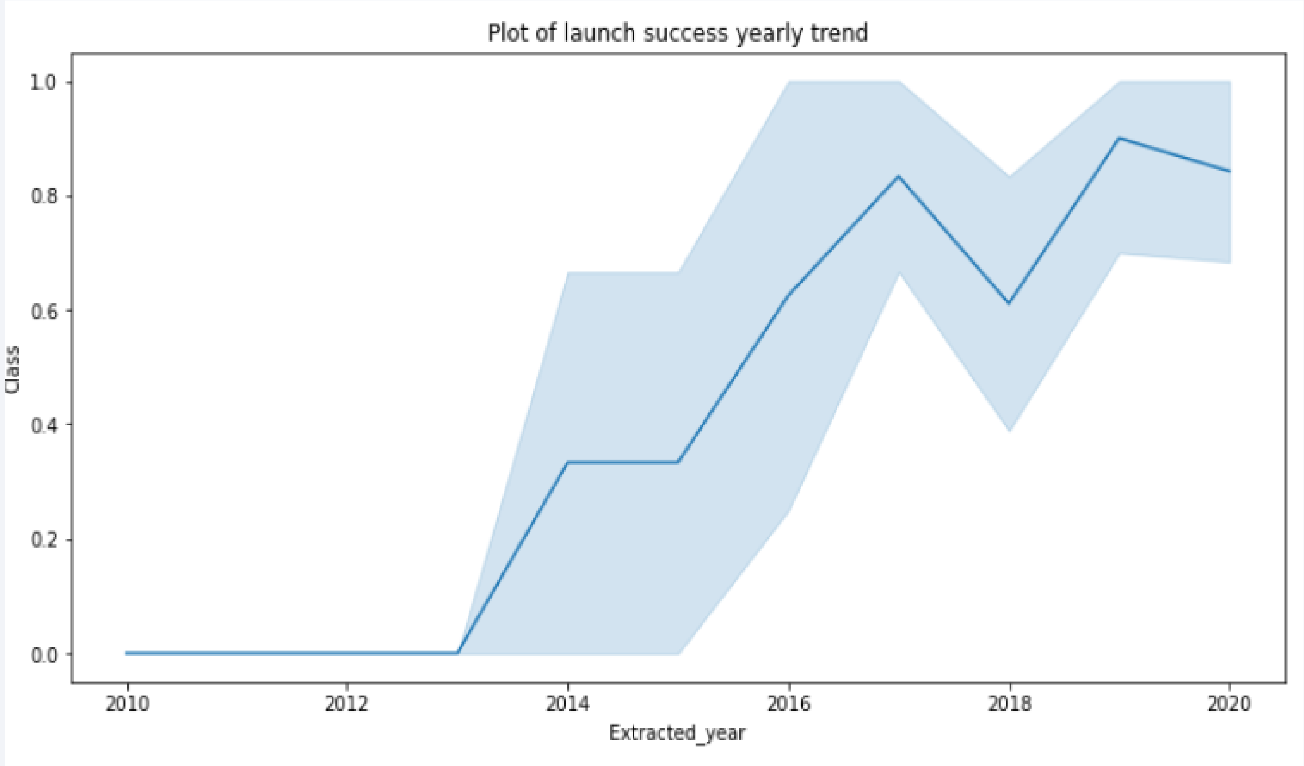
Payload vs. Orbit Type



- Looking at the scatter plot we can observe that with heavy payloads, the successful landing occurs more frequently for PO, LEO and ISS orbits.

Launch Success Yearly Trend

- From the line chart, we can see 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'

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 used this query to display 5 records where launch sites begin with “CCA”

Total Payload Mass

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

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 using the query below.

```
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 22 nd December 2015. We used this query to find the answer:

```
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. See the "Out[15]" result for the list:

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 the wildcard like ‘%’ to filter for WHERE MissionOutcome was a success or a failure.

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.

```
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.

```
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 sort the grouped landing outcome in descending order.

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]:

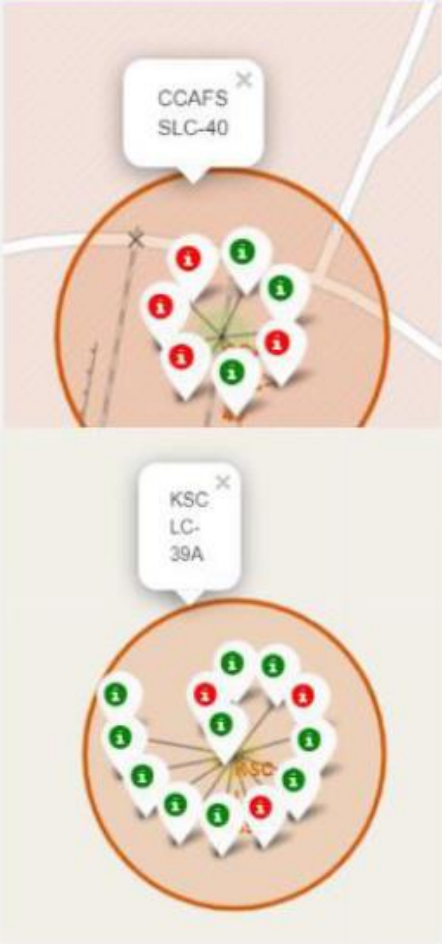
	landingoutcome	count
0	No attempt	10
1	Success (drone ship)	6
2	Failure (drone ship)	5
3	Success (ground pad)	5
4	Controlled (ocean)	3
5	Uncontrolled (ocean)	2
6	Precluded (drone ship)	1
7	Failure (parachute)	1

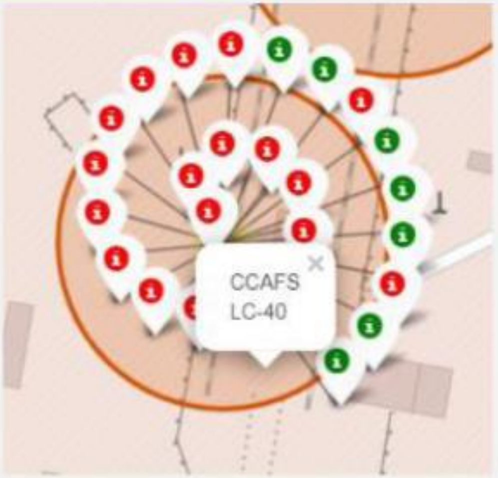
Section 3

Launch Sites Proximities Analysis

All launch sites global map markers

Markers showing launch sites with color labels





Florida Launch Sites

Green Marker shows successful Launches and Red Marker shows Failures

California Launch Site

37

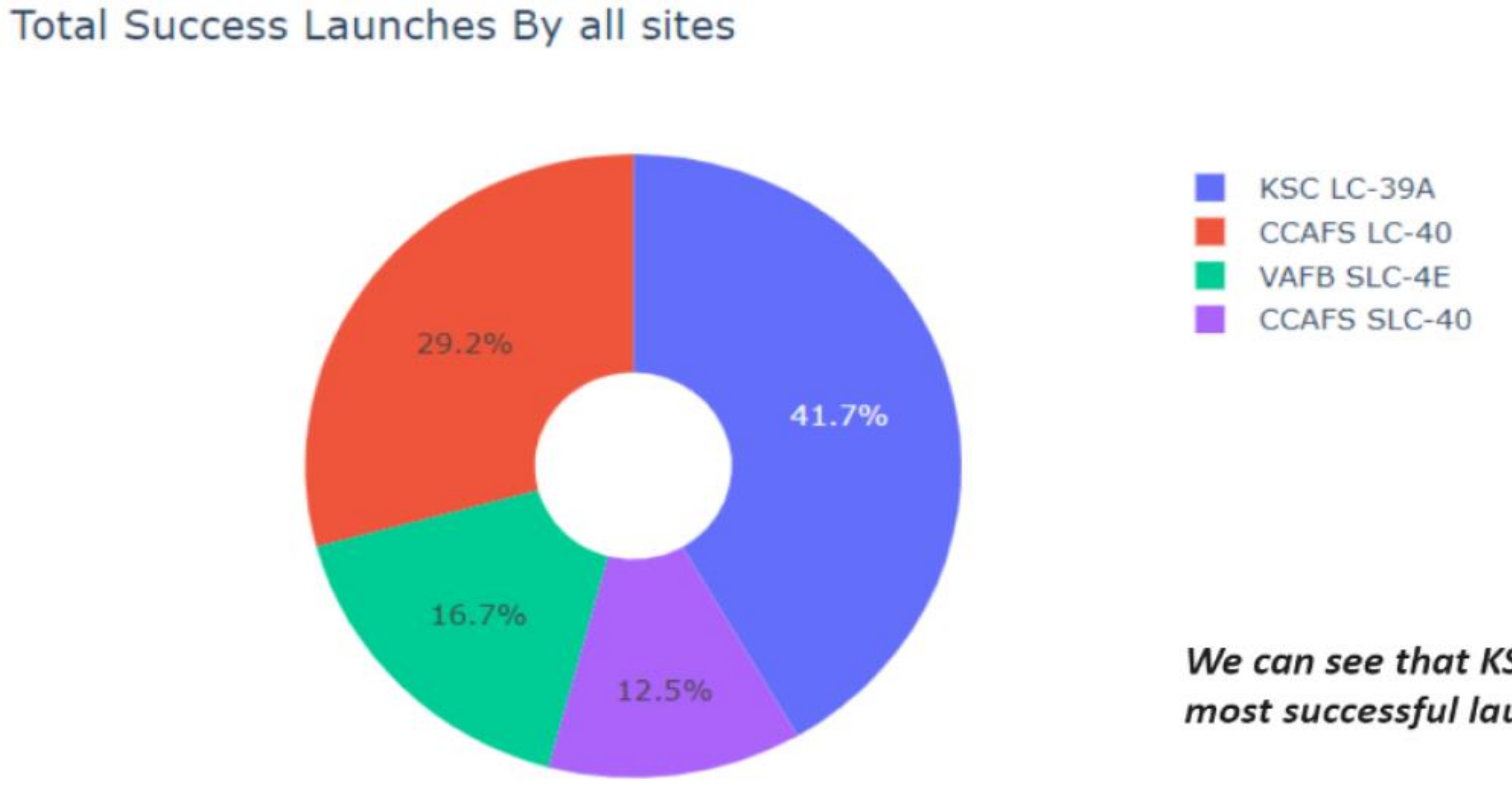
Launch Site distance to landmarks

- 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 4

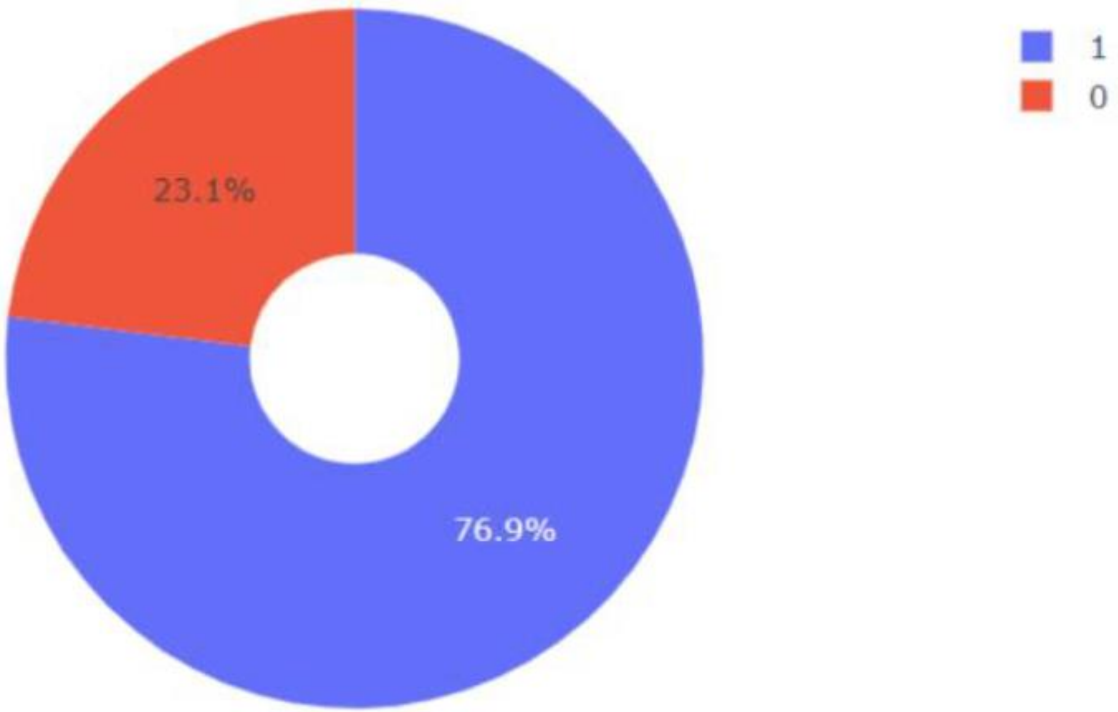
Build a Dashboard with Plotly Dash

Chart showing the success percentage achieved by each launch site



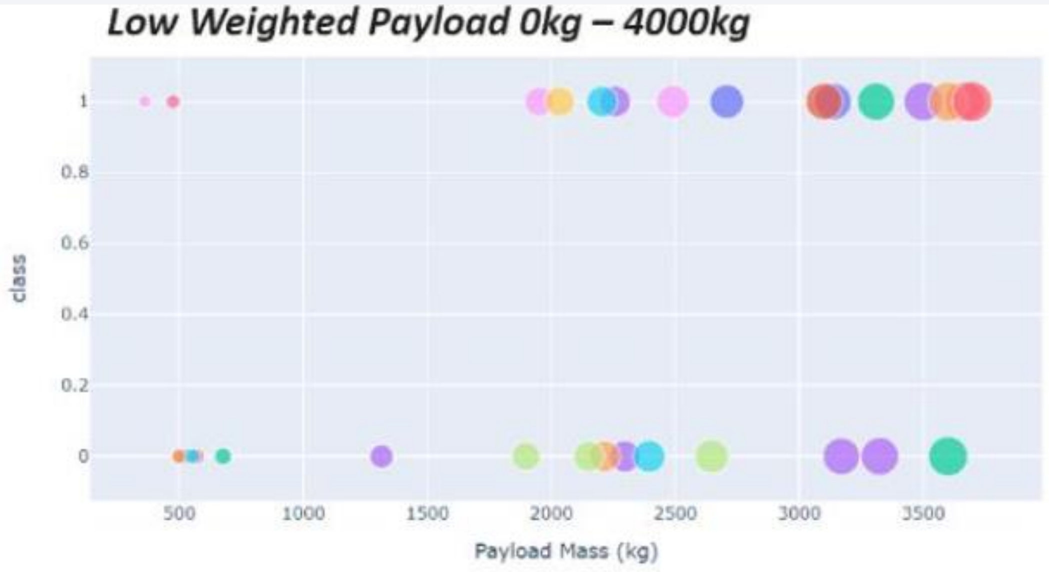
We can see that KSC LC-39A had the most successful launches from all the sites

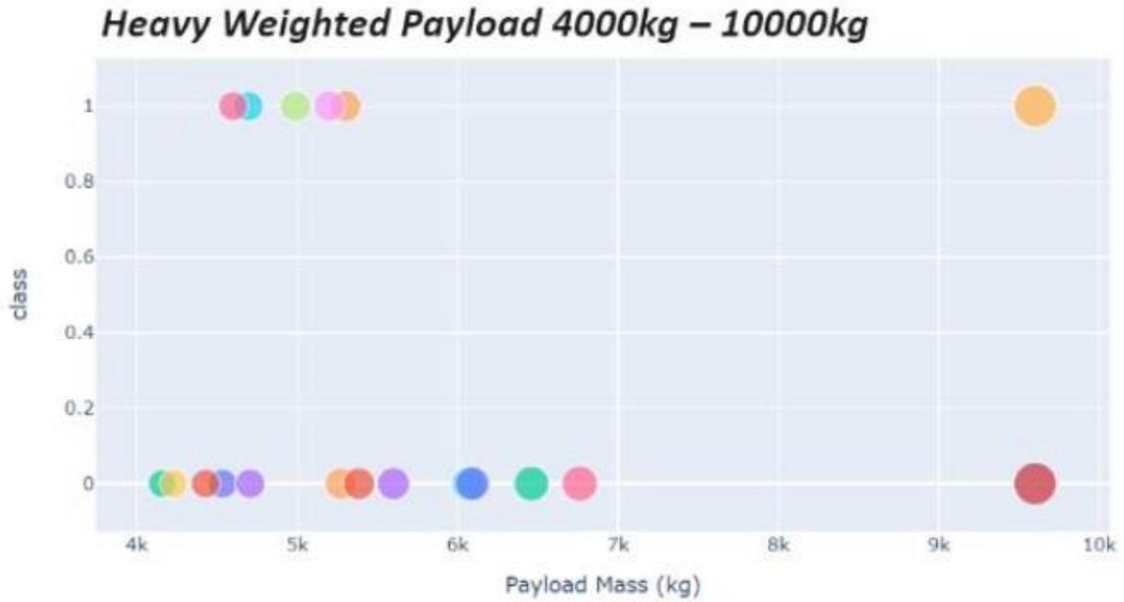
Chart showing the Launch site with the highest launch success ratio



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

Scatter plots 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)

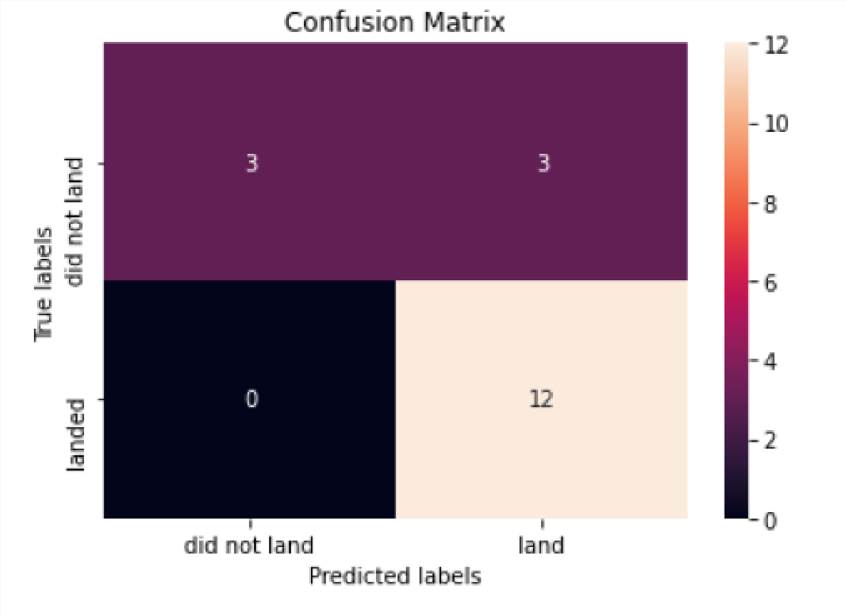
Classification Accuracy

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

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

bestalgorithm = max(models, key=models.get)
print('Best model is', bestalgorithm,'with a score of', models[bestalgorithm])
if bestalgorithm == 'DecisionTree':
    print('Best params is :', tree_cv.best_params_)
if bestalgorithm == 'KNeighbors':
    print('Best params is :', knn_cv.best_params_)
if bestalgorithm == 'LogisticRegression':
    print('Best params is :', logreg_cv.best_params_)
if bestalgorithm == 'SupportVector':
    print('Best params is :', svm_cv.best_params_)
```

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

Confusion Matrix



- The confusion matrix for the decision tree classifier shows that the classifier can distinguish between the different classes. The major problem is the false positives .i.e., unsuccessful landing marked as successful landing by the classifier.

Conclusions

- We can conclude the following:
  - The larger the flight amount at a launch site, the greater the success rate at the launch site.
  - Launch success rate started to increase in 2013 until 2020.
  - Orbits ES L1, GEO, HEO, SSO, VLEO had the most success rate.
  - KSC LC 39A had the largest number of successful launches of any of the sites.
  - The Decision tree classifier is the best machine learning algorithm for this task.

Thank you!