IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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17/11/2022

Outline

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

Executive Summary

- **Summary of methodologies**
- Data Collection via API, SQL and Web Scraping
- Data Wrangling and Analysis
- Interactive Maps with Folium
- Predictive Analysis for each classification model
- **Summary of all results**
- Data Analysis along with Interactive Visualizations
- Best model for Predictive Analysis

Introduction

- Project background and context
- Here we will predict if the Falcon 9 first stage will land successfully. SpaceX 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 SpaceX can reuse the first stage. Therefore, if we can determine if the first stage will land successfully. This information can be used if an alternate company wants to bid against SpaceX for a rocket launch.
- Problems you want to find answers
- With what factors, the rocket will land successfully?
- The effect of each relationship of rocket variables on outcome.
- Conditions which will aid SpaceX have to achieve the best results

Section 1

Methodology

Methodology

Executive Summary

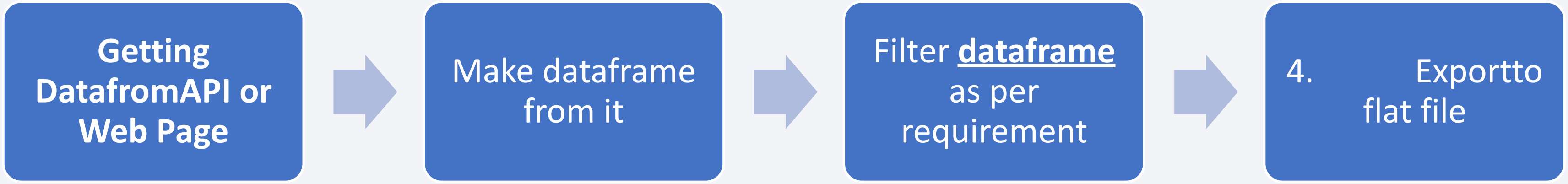
- Data collection methodology:
  - Via SpaceX Rest API
  - Web Scrapping from Wikipedia
- Perform data wrangling
  - One hot encoding data fields for machine learning and dropping irrelevant columns (Transforming data for Machine Learning)
- Perform exploratory data analysis (EDA) using visualization and SQL
  - Scatter and bar graphs to show patterns between data
- Perform interactive visual analytics using Folium and Plotly Dash
  - Using Folium and Plotly Dash Visualizations
- Perform analysis using classification models
  - Build and evaluate classification models

Data Collection

- **What is Data Collection**?

Data collection is the process of gathering and measuring information on targeted variables in an established system, which then enables one to answer relevant questions and evaluate outcomes.

- **Data Collection Process-**



Data Collection – SpaceX API

Getting response from API

- spacex_url="https://api.spacexdata.com/v4/launches/past”
- response= requests.get(spacex_url)

Converting response to a json file

- jlist requests.get(static_json_url).json()
- df = pd.json_normalize(jlist)
- df.head()

Apply custom functions to clean data

- getBoosterVersion(data)
- getLaunchSite(data)
- **getPayloadData(data)**
- getCoreData(data)

Assign to dictonary then create a dataframe

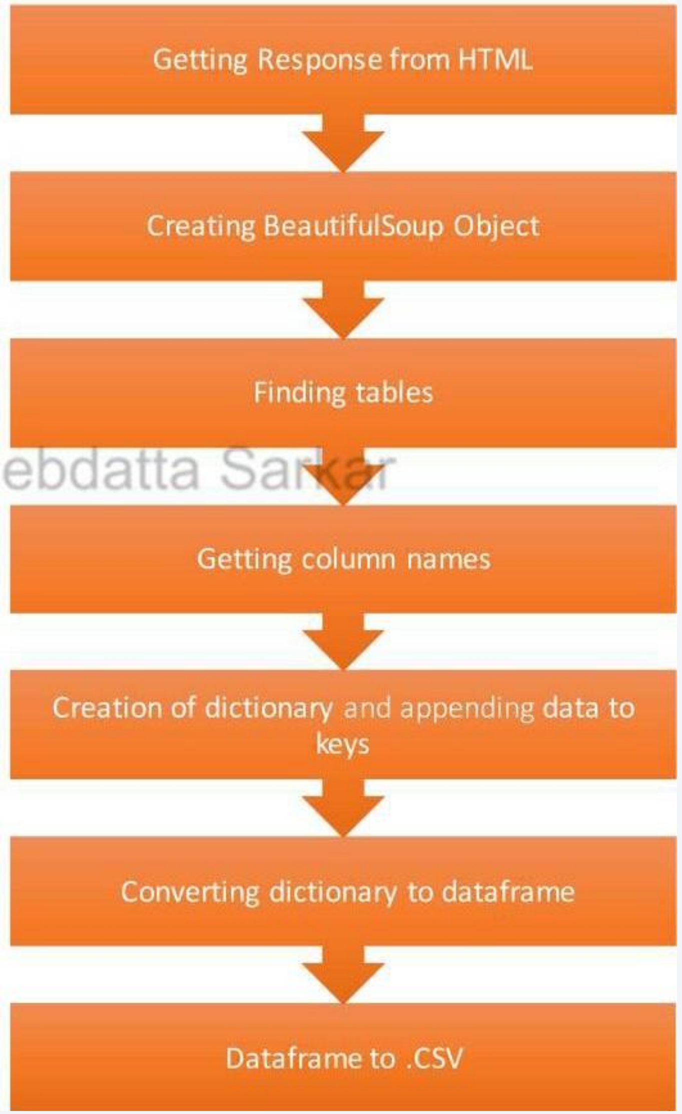
- : list(data['flight_number'J),
- 'Date': list(data['date'J),
- 'BoosterVersion':BoosterVersion, launch_dict = {'FlightNumber'

Export dataframe to a flat file

- data_falcon9.drop(data_falcon9[data_falcon9('BoosterVersion'Jl•'Falcon 9').index, data_falcon9.loc(:, 'FlightNumber' J **s** list(range(l, data_falcon9.shape[OJ+l)) data_falcon9 inplace **a True**)I
- data_falcon9.to_csv('dataset_part_l.csv', **index=False)**

GIT hub URL- https://github.com/asmanaaz132/SpaceX/blob/main/jupyter-labs-spacex-data-collection-api.ipynb

Data Collection - Scraping




```
static_url • "https: //en.wikiped.ia. org/w/ index.
php?title•I,ist_of_Falcon_9_and_Falcon_Heavy_launches&oldid•l
027686922"
data     •requests.get(static_url).text
soup= BeautifulSoup(data, 'html5lib');
html_tables=soup.find_all("table") first_launch_table =
html_tables[2J
ths = first_launch_table.find_all('th')
for th in ths:
name• extract_column_from_header(th)
if name is not None and len(name•) > 0:
column_names.append(name)
launch_dict= dict.fromkeys(column_names)
```

GIT hub URL-
https://github.com/asmanaaz132/SpaceX/blob/main/jupyter-labs-webscraping.ipynb

Data Wrangling

Data wrangling is the process of cleaning and unifying messy and complex data sets for easy access and analysis.

Here we mainly convert those outcomes into Training Labels with 1 means the booster successfully landed O means it was unsuccessful.

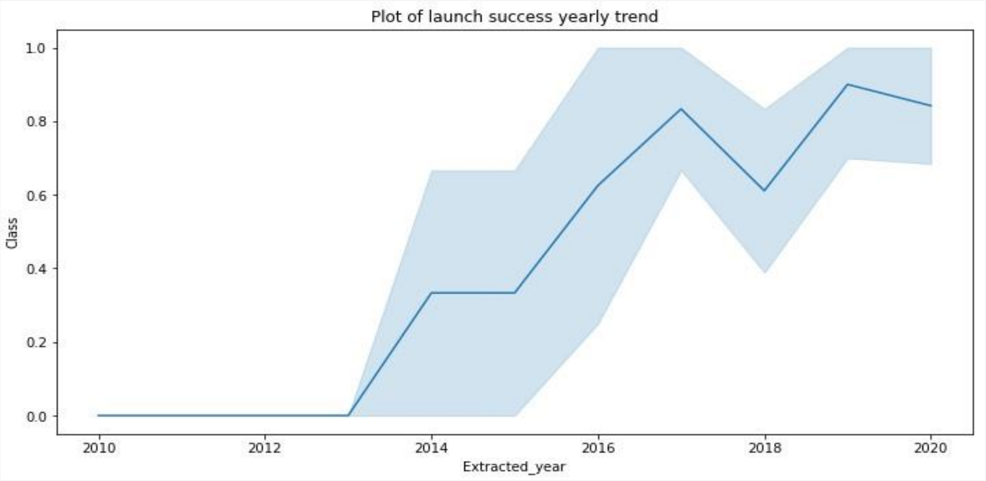
```
df['Class') = df('Outcome').apply(lambda landing_class: 0 if landing_class in
bad_outcomes else 1)
```

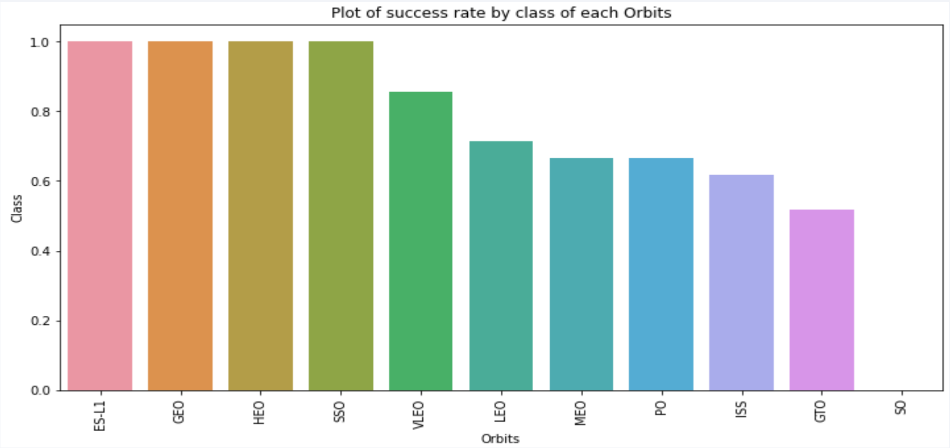
Calculate number of occurrence of each sites → Calculate number of occurrence of each orbit → Calculate number of occurrence of mission outcoe per orbit type → Calculate landing outcome lable from landing outcome column → Export to flat file - CSV

GIT hub URL- https://github.com/asmanaaz132/SpaceX/blob/main/module_1_L3_labs-jupyter-spacex-data_wrangling_jupyterlite.jupyterlite.ipynb

EDA with Data Visualization

We explored the data by visualizing 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.





GIT Hub:- https://github.com/asmanaaz132/SpaceX/blob/main/module_2_jupyter-labs-eda-dataviz.ipynb.jupyterlite.ipynb

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 for instance:

- 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.

- GIT Hub URL- https://github.com/asmanaaz132/SpaceX/blob/main/eda-sql-coursera_sqllite.ipynb

Build an Interactive Map with Folium

- We marked all launch sites, and added map objects such as markers, circles, lines to
- mark the success or failure of launches for each site on the folium map.
- We 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, we identified which launch sites have relatively high success rate.
- We calculated the distances between a launch site to its proximities. We answered some question for instance:
  - Are launch sites near railways, highways and coastlines.
  - Do launch sites keep certain distance away from cities.

Build a Dashboard with Plotly Dash

- We built an interactive dashboard with Plotly dash
- We plotted pie charts showing the total launches by a certain sites
- We plotted scatter graph showing the relationship with Outcome and Payload Mass (Kg) for the different booster version.
- GIT Hub URL- https://github.com/asmanaaz132/SpaceX/blob/main/spacex_dash_app.py

Predictive Analysis (Classification)

- We loaded the data using numpy and pandas, transformed the data, split our data into training and testing.
- We built different machine learning models and tune different hyperparameters using GridSearchCV.
- We used accuracy as the metric for our model, improved the model using feature engineering and algorithm tuning.
- We found the best performing classification model.
- GIT Hub URL- https://github.com/asmanaaz132/SpaceX/blob/main/IBM-DS0321EN-SkillsNetwork_labs_module_4_SpaceX_Machine_Learning_Prediction_Part_5.jupyterlite.ipynb

Results

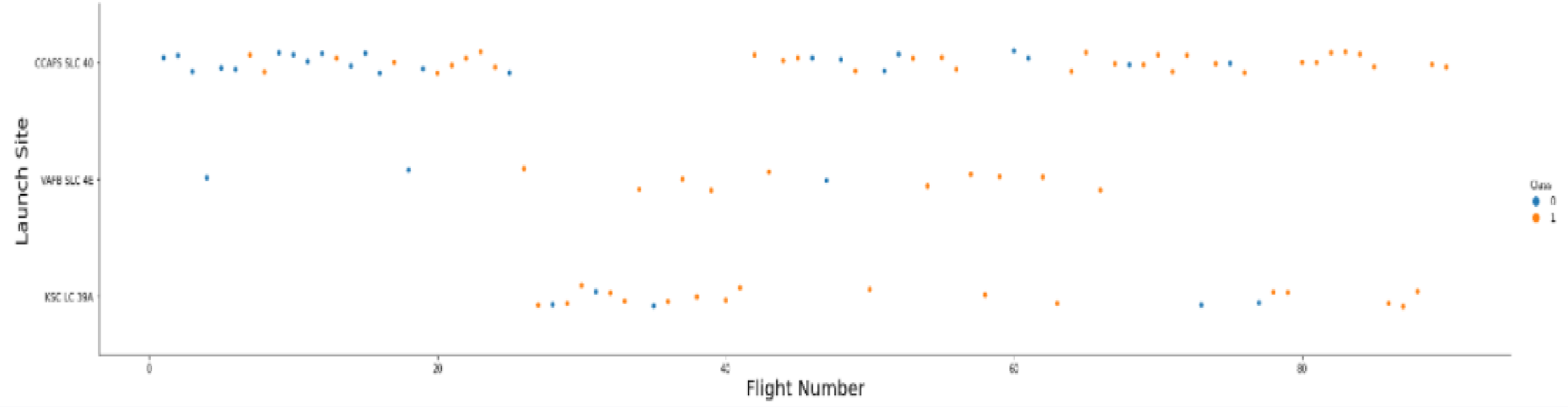
- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results

Section 2

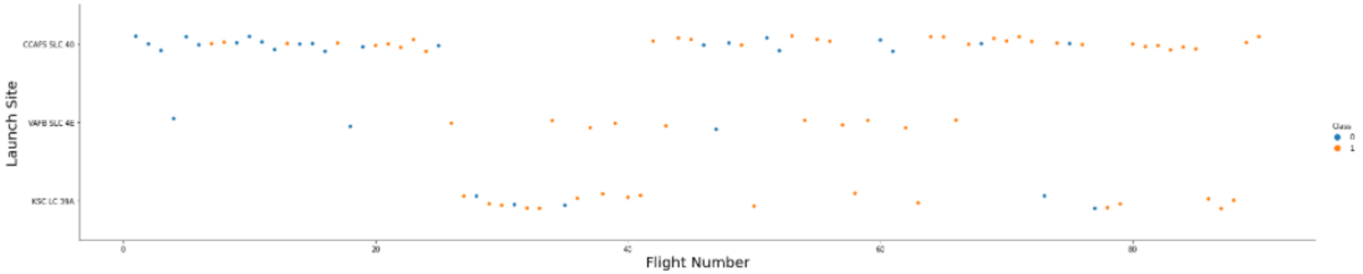
Insights drawn from EDA

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.



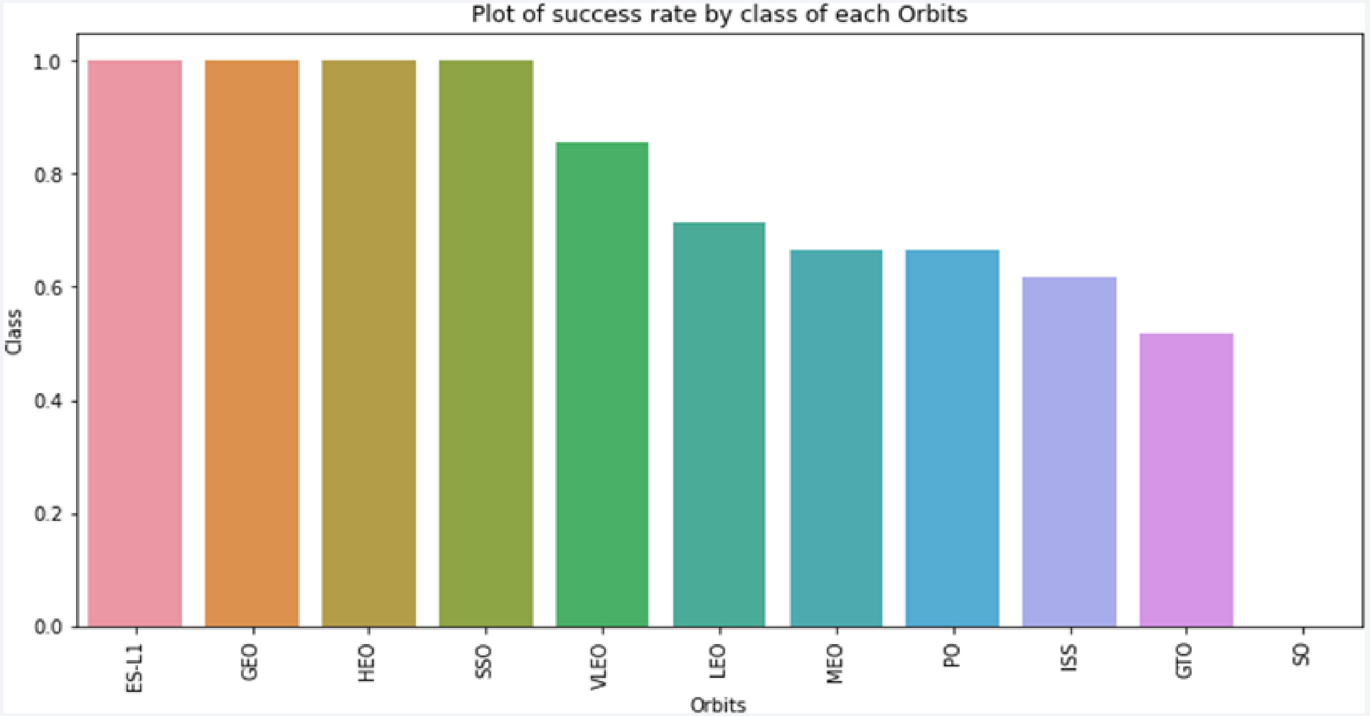
Payload vs. Launch Site



The greater the payload mass for launch site CCAFS SLC 40 the higher the success rate for the rocket.

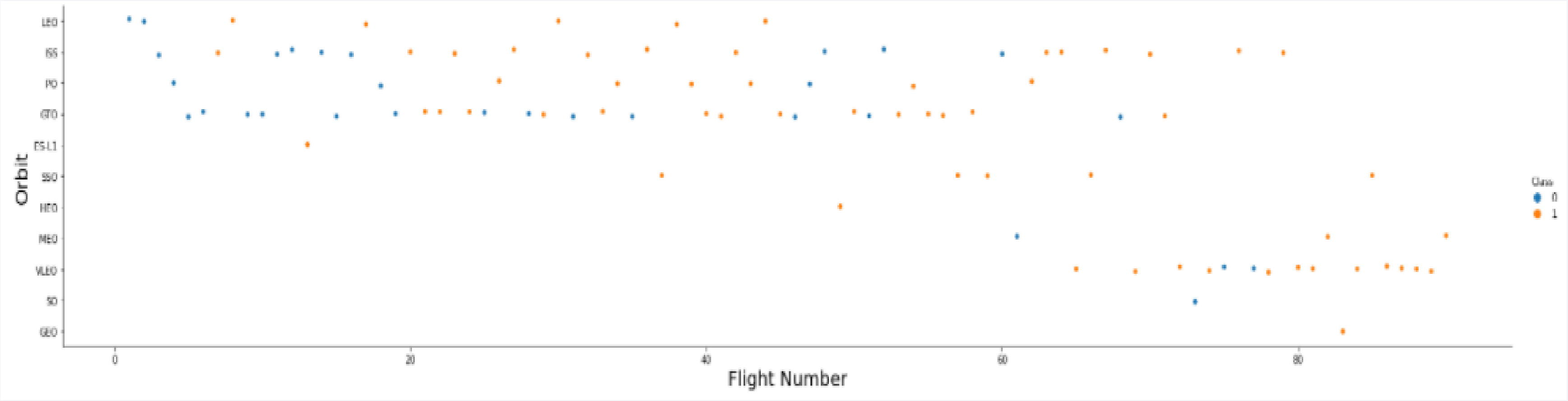
Success Rate vs. Orbit Type

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



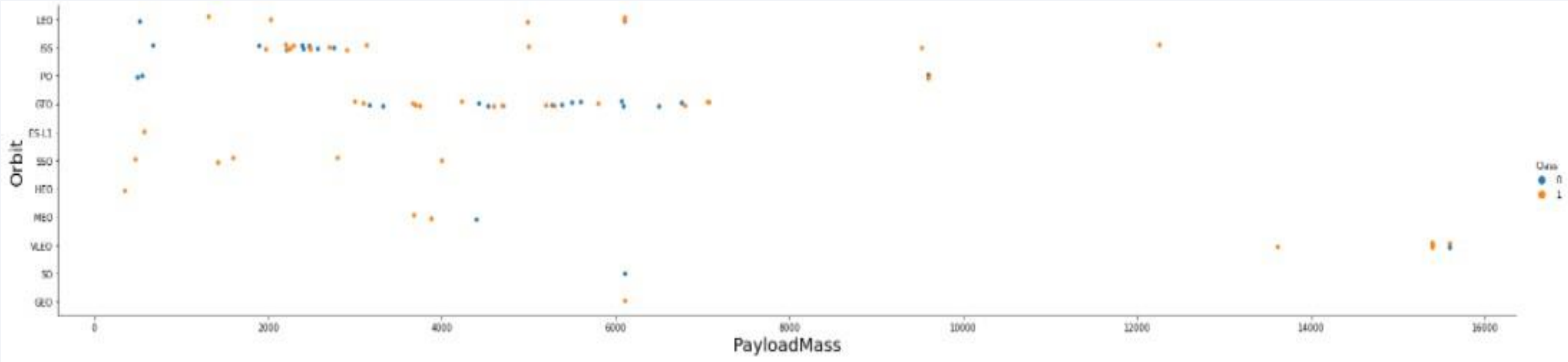
Flight Number vs. Orbit Type

- 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.



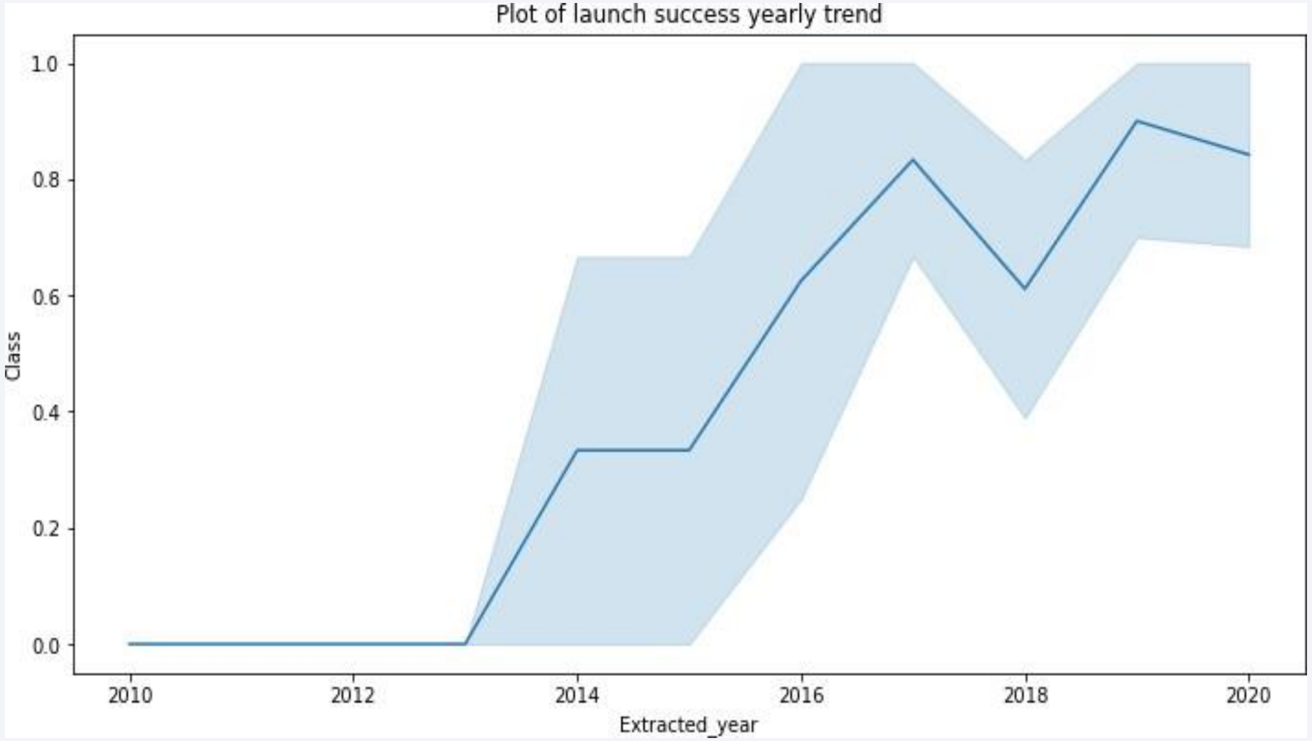
Payload vs. Orbit Type

- 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'

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

In [11]:
```
task_2 = '''
        SELECT *
        FROM SpaceX
        WHERE LaunchSite LIKE 'CCA%'
        LIMIT 5
        '''
create_pandas_df(task_2, database=conn)
```

Out[11]:

	date	time	boosterversion	launchsite	payload	payloadmasskg	orbit	customer	missionoutcome	landingoutcome
0	2010-04-06	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
1	2010-08-12	15:43:00	F9 v1.0 B0004	CCAFS LC-40	Dragon demo flight C1, two CubeSats, barrel of...	0	LEO (ISS)	NASA (COTS) NRO	Success	Failure (parachute)
2	2012-05-22	07:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	No attempt
3	2012-08-10	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
4	2013-01-03	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

- We used the query above 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 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

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 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 maxin

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

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

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

```
[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)
```

t[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

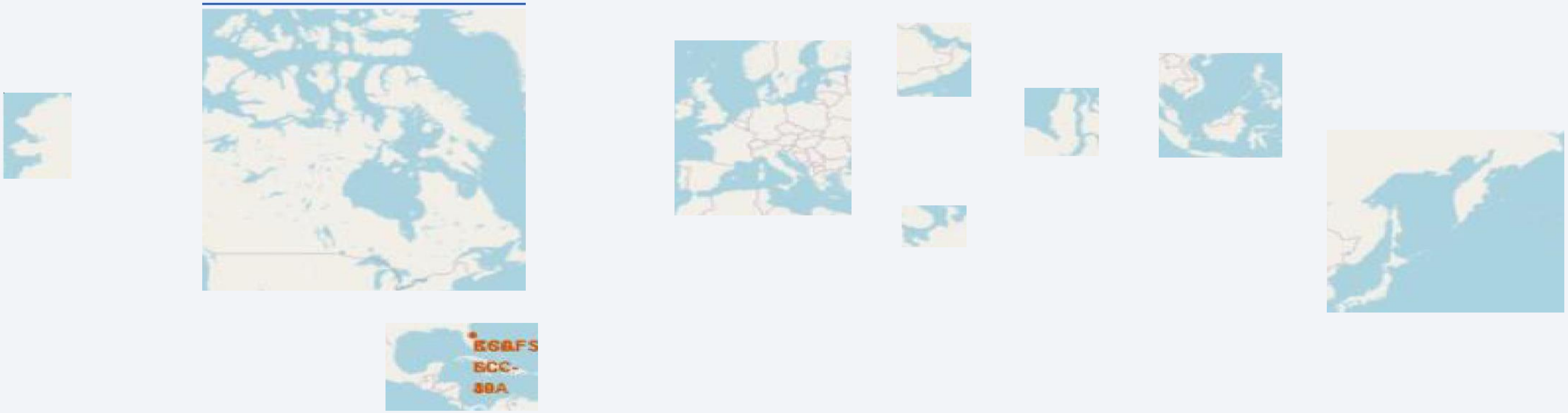
- We applied the **GROUP BY** and used the **WHERE** clause to filter for landing outcomes **BETWEEN** 2010-06-04 clause We selected Landing outcomes and the **COUNT** of landing outcomes from the data to 2010-03-20.

- to group the landing outcomes and the **ORDER BY** clause to order the grouped landing outcome in descending order.

Section 3

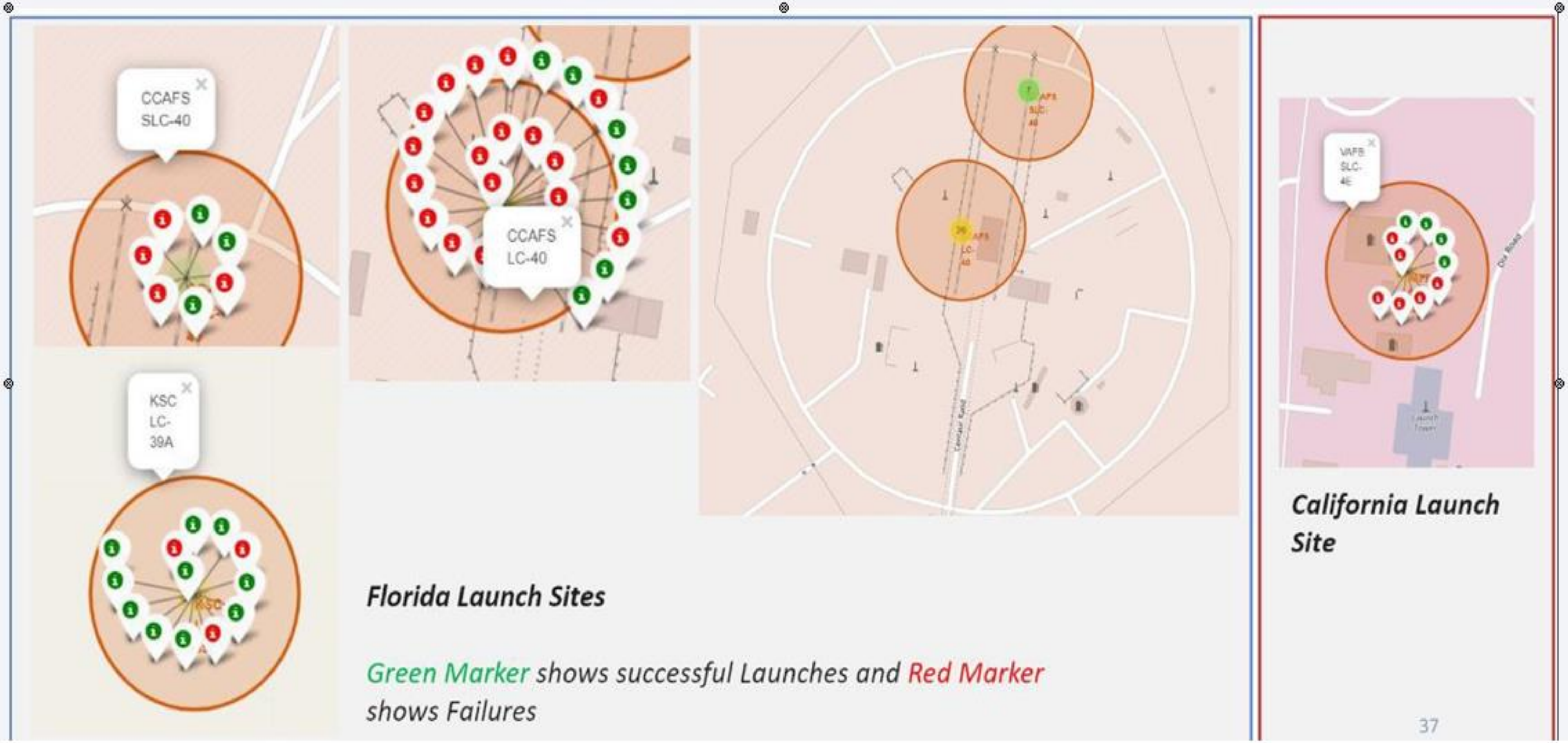
Launch Sites Proximities Analysis

All launch sites global map markers

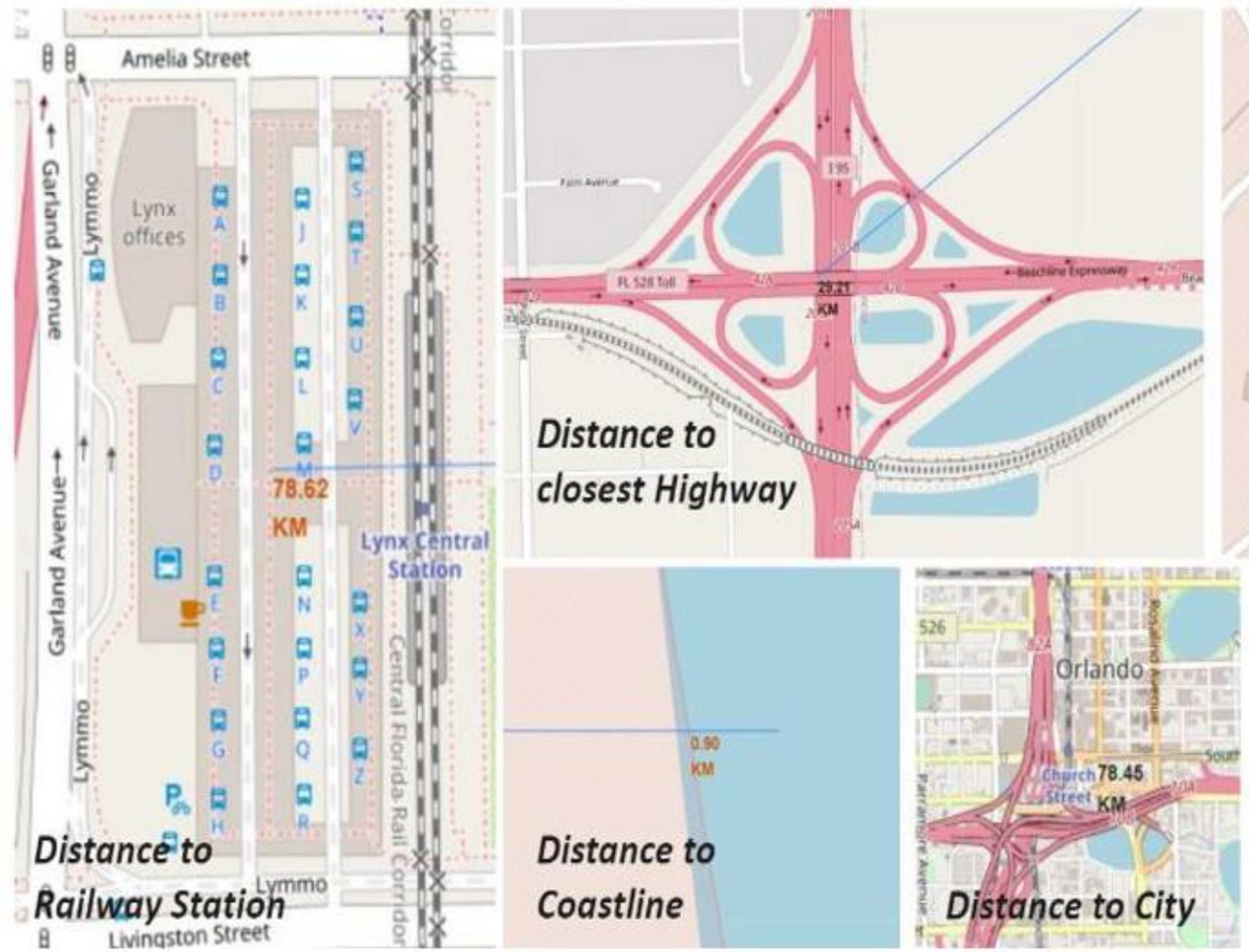


we, can see that the SpaceX launch sites are in the United States of America coasts. Florida and Californ'ia

Markers showing launch sides with color lables



Launch site distance to landmarks

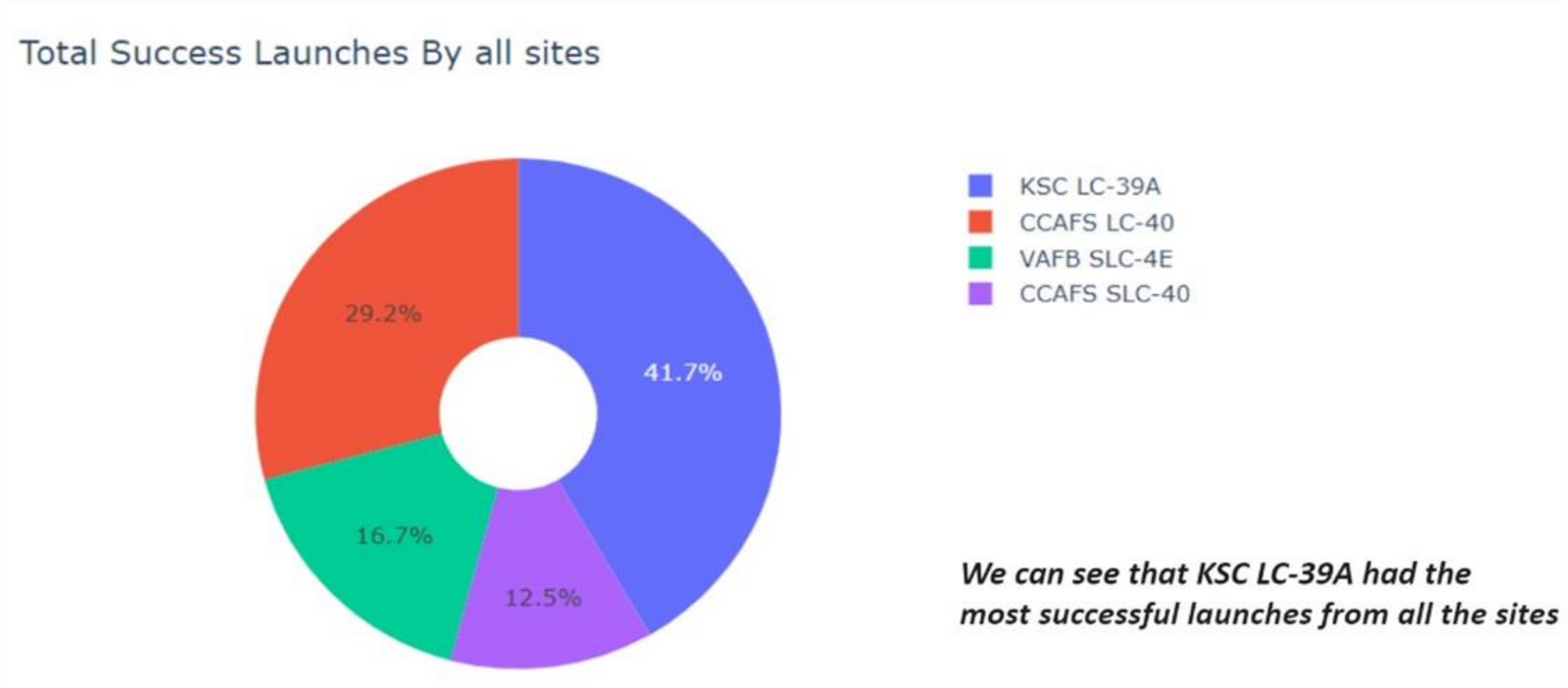


- Are launch sites in close proximity to railways? No
- Are launch sites in close proximity to highways? No
- Are launch sites in close proximity to coastline? Yes
- Do launch sites keep certain distance away from cities? Yes

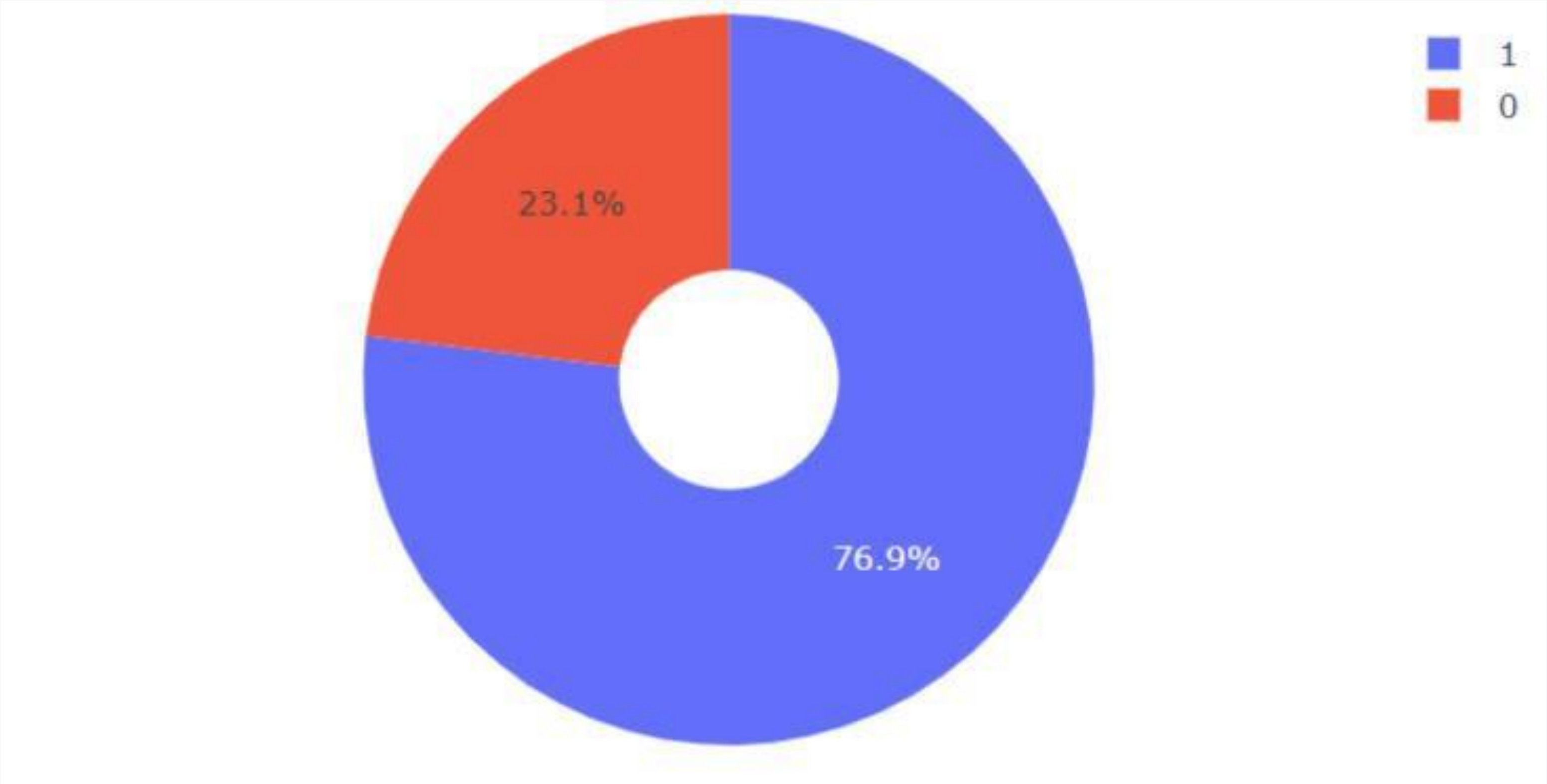
Section 4

Build a Dashboard with Plotly Dash

Pie chart showing success percentage achieved by each launch site

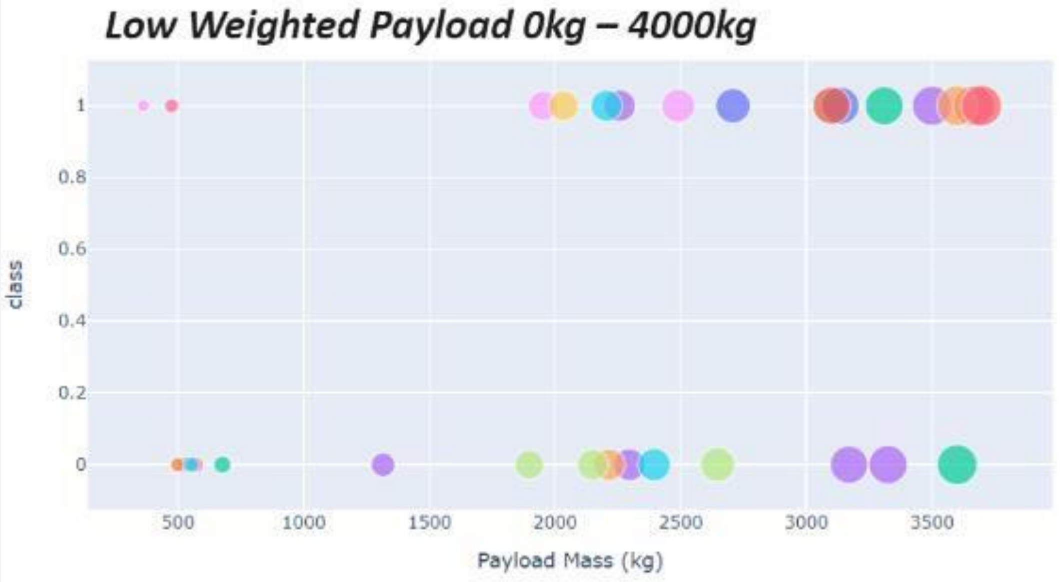


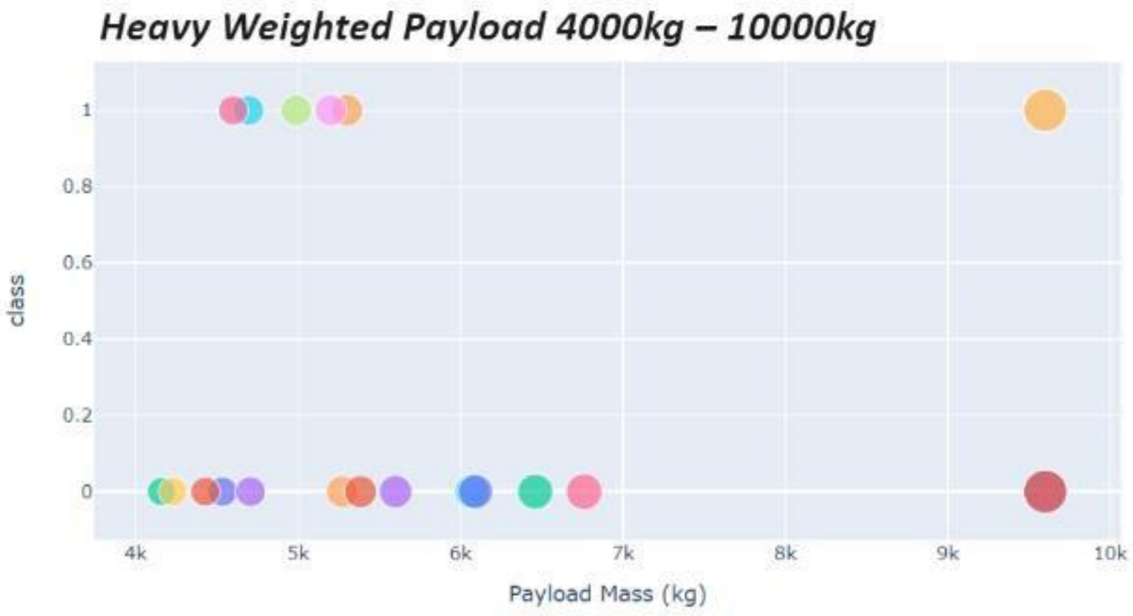
Pie chart showing the launch site with the highest success ratio



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

Scatter plot of payload vs launch outcome for all sites, with different payload selected in the range slider





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

Section 5

Predictive Analysis (Classification)

Classification Accuracy

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

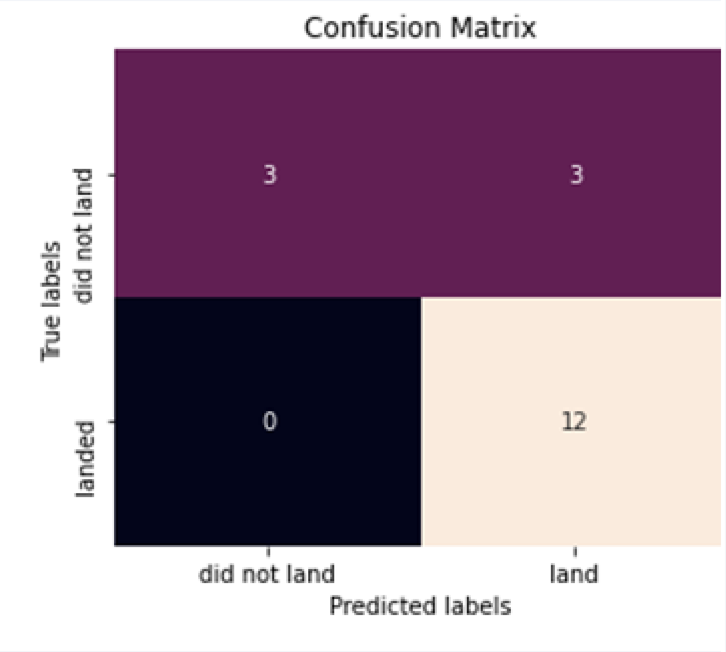
```
models = {'KNeighbors':knn_cv.best_score_,
              'DecisionTree':tree_cv.best_score_,
              'LogisticRegression':logreg_cv.best_score_,
              'SupportVector': svm_cv.best_score_}

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 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!