IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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Outline

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Executive Summary

- Summary of methodologies
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  - Data Wrangling/ Data Cleaning
  - Exploratory Data Analysis with SQL
  - Exploratory Data Analysis with Data Visualization
  - Interactive Visual Analytics and Dashboard with Folium
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- Summary of all results
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  - 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. The 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

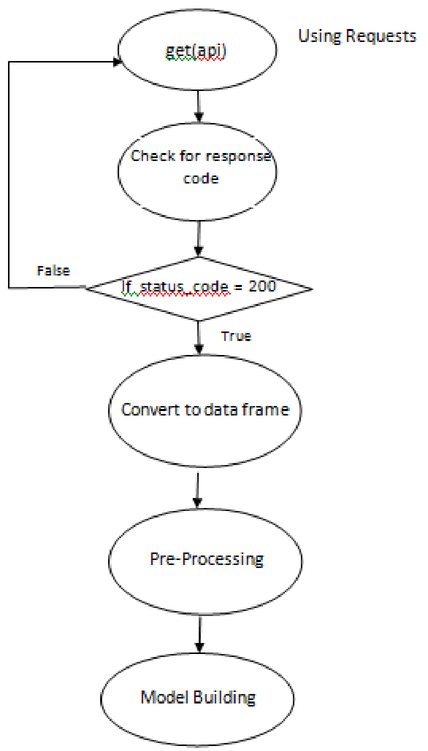
- Data collection methodology:
  - Data was collected using SpaceX API and web scraping from Wikipedia.
- Perform data wrangling
  - One-hot encoding was applied to categorical features
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
  - LR, KNN, SVM, DT models have been built and evaluated for the best classifier

Data Collection

- The data was collected using various methods
  - Data collection was done using get request to the SpaceX API.
  - Next, we decoded the response content as a Json using **.json**() function call and turn it into a pandas dataframe using **.json_normalize()**.
  - We then cleaned the data, checked for missing values and filled in missing values where necessary.
  - In addition, 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

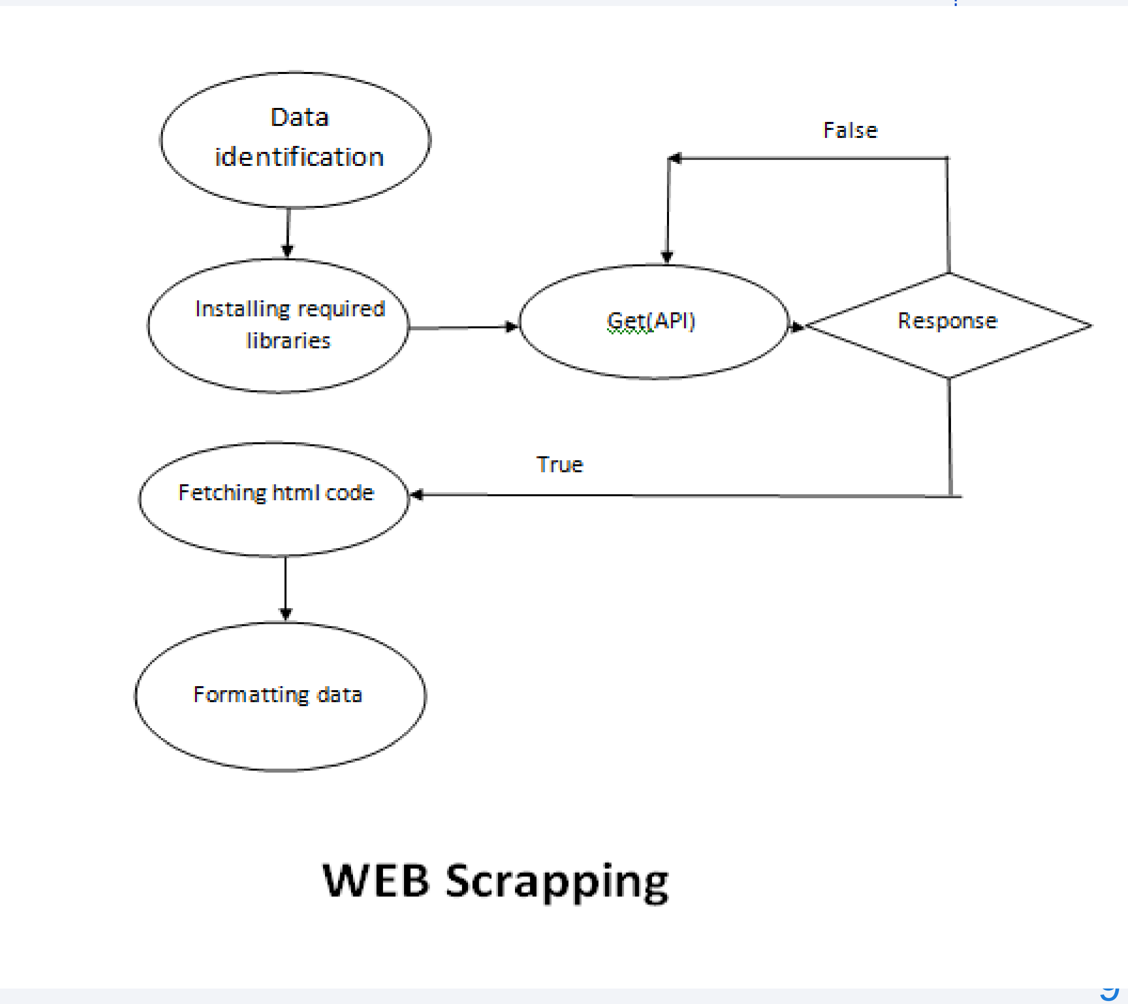
- We used the get request to the SpaceX API to collect data, clean the requested data and did some basic data wrangling and formatting.
- The link to the notebook is https://github.com/kamalnadh219/SpaceX-Falcon-9-Capstone-project/blob/main/jupyter-labs-spacex-data-collection-api.ipynb



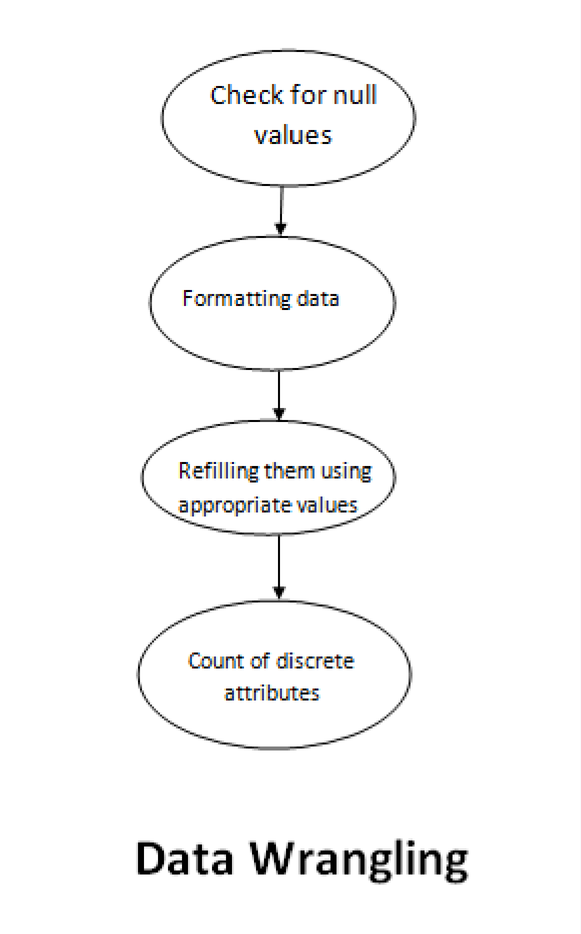
Flow chart for Collecting Data Using API

Data Collection - Scraping

- We applied web scrapping to webscrap Falcon 9 launch records with BeautifulSoup
- We parsed the table and converted it into a pandas dataframe.
- The link to the notebook is:
- https://github.com/kamalnadh219/SpaceX-Falcon-9-Capstone-project/blob/main/jupyter-labs-webscraping.ipynb



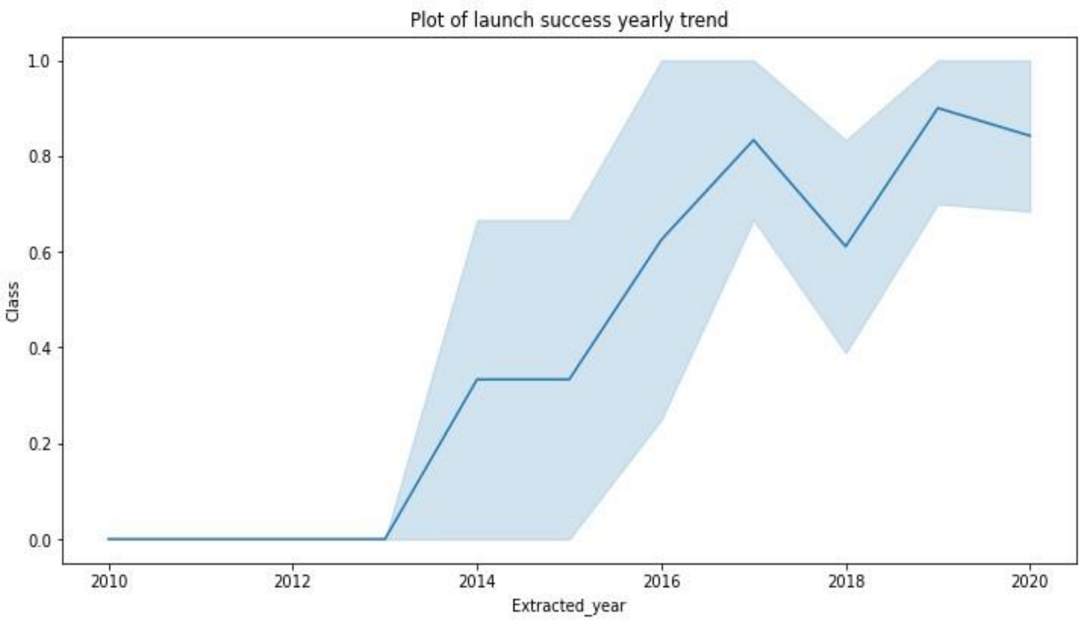
Data Wrangling

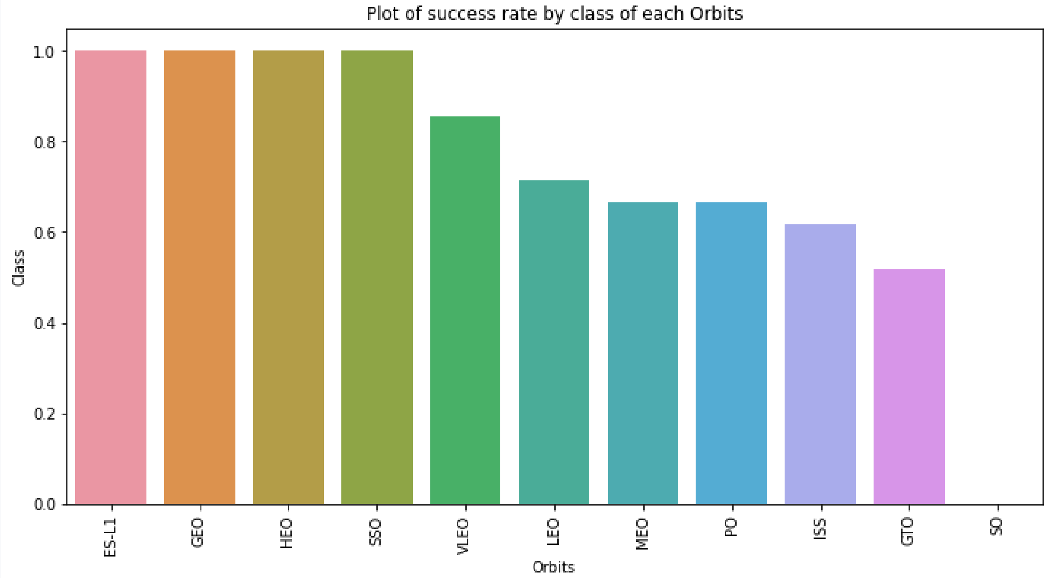


- We performed exploratory data analysis and determined the training labels.
- We calculated the number of launches at each site, and the number and occurrence of each orbits
- We created landing outcome label from outcome column and exported the results to csv.
- The link to the notebook:
  - https://github.com/kamalnadh219/SpaceX-Falcon-9-Capstone-project/blob/main/labs-jupyter-spacex-data_wrangling_jupyterlite.jupyterlite.ipynb

EDA with Data Visualization

•Used Catplot for identifying relations between variables
•Used Matplotlib.pyplot to identify patterns among thre data
•Identified correlations using group by method between variables
•Done trend analysis
•Done Time series Analysis
•Used line chart to identify Trends by Time Moving On.





- The link to the notebook is https://github.com/kamalnadh219/SpaceX-Falcon-9-Capstone-project/blob/main/jupyter-labs-eda-dataviz.ipynb.jupyterlite.ipynb

EDA with SQL

EDA Using SQL Found the below Points:

- 1. Distinct Launch Sites
- 2. Launches from Kennedy Space Center (KSC)
- 3. Total Payload Mass by NASA (CRS)
- 4. Average Payload Mass for F9 v1.1
- 5. Earliest Successful Landing Date on Drone Ship
- 6. Booster Versions for Successful Ground Pad Landings (Payload Mass 4000-6000 kg)
- 7. Count of Successful and Failed Landings
- 8. Booster Version for Maximum Payload Mass
- 9. Successful Ground Pad Landings in 2017
- 10. All Data in SPACEXTBL
- 11. Count of Landing Outcomes with Ranking

- The link to the notebook is https://github.com/kamalnadh219/SpaceX-Falcon-9-Capstone-project/blob/main/jupyter-labs-eda-sql-edx_sqllite.ipynb

Build an Interactive Map with Folium

- We've put all launch sites on the map and used markers, circles, and lines to show if launches succeeded or failed.

- We labeled success as 1 and failure as 0.

- By using colored markers, we found which sites had the most successes

- We also checked how far launch sites are from things like railways, highways, and cities.
- URL : https://github.com/kamalnadh219/SpaceX-Falcon-9-Capstone-project/blob/main/lab_jupyter_launch_site_location.jupyterlite.ipynb

Build a Dashboard with Plotly Dash

- 1. Created an interactive dashboard using Plotly Dash.
- 2. Generated pie charts illustrating the total launches per site.
- 3. Developed scatter graphs to explore the relationship between Outcome and Payload Mass (Kg) across various booster versions..
- The link to the notebook is https://github.com/kamalnadh219/SpaceX-Falcon-9-Capstone-project/tree/main

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.
- The link to the notebook is https://github.com/kamalnadh219/SpaceX-Falcon-9-Capstone-project/blob/main/SpaceX_Machine_Learning_Prediction_Part_5.jupyterlite.ipynb

Results

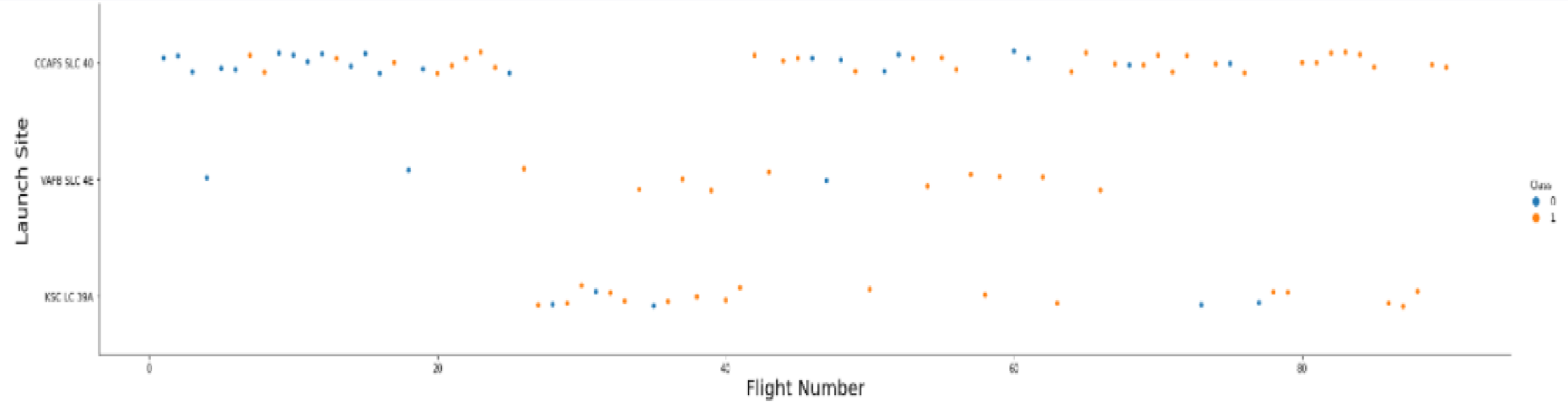
- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results

Section 2

Insights drawn from EDA

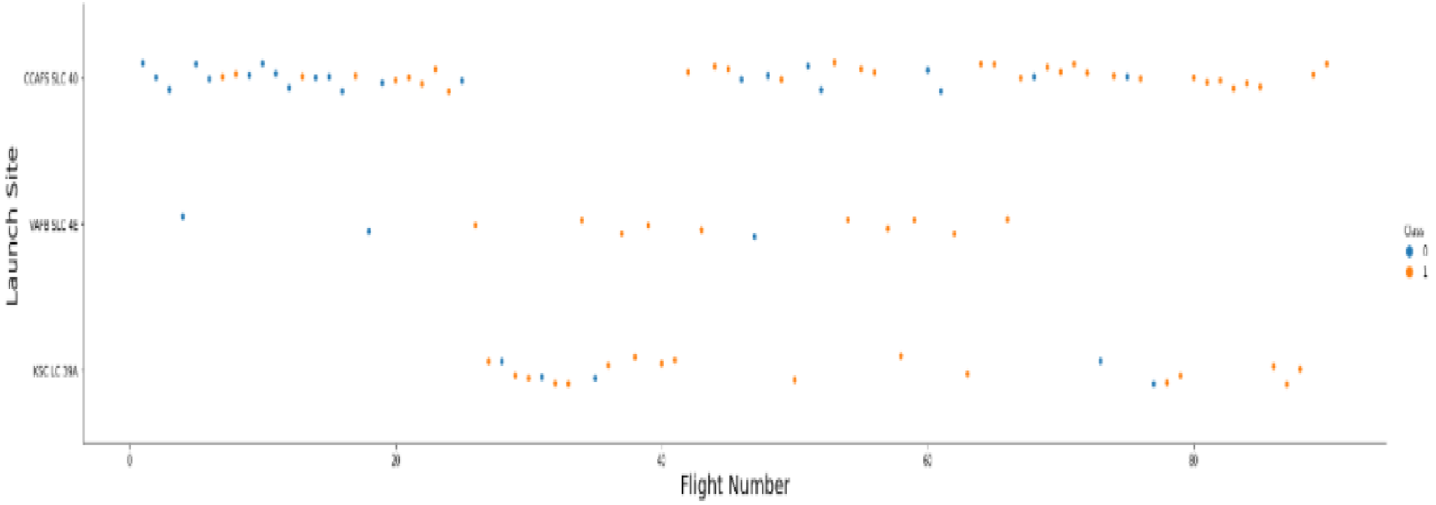
Flight Number vs. Launch Site

- We observed that as the flight number increases at a launch site, the success rate also increases.



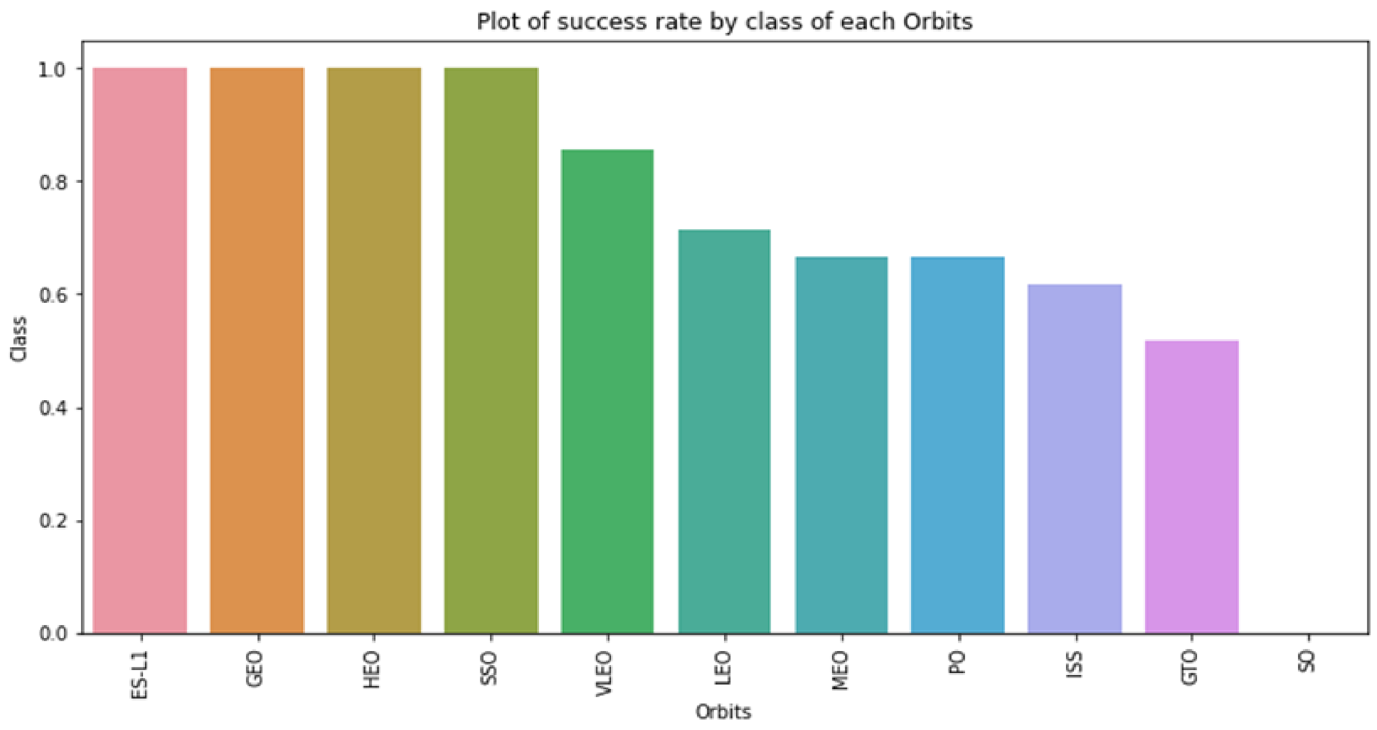
Payload vs. Launch Site

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



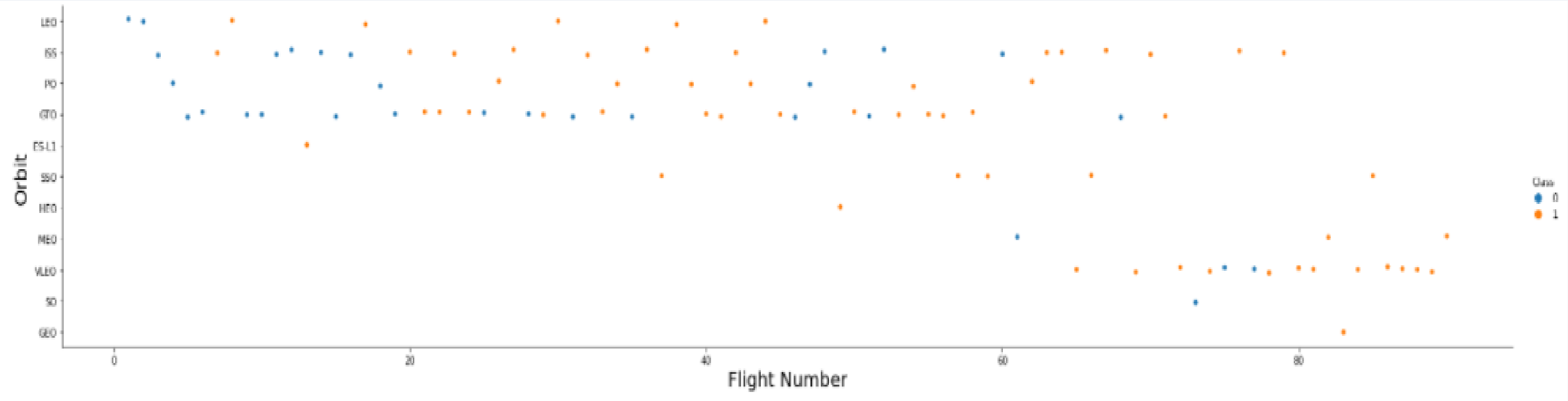
Success Rate vs Orbit Type

- The plot highlights that ES-L1, GEO, HEO, SSO, and VLEO exhibit the highest success rates.



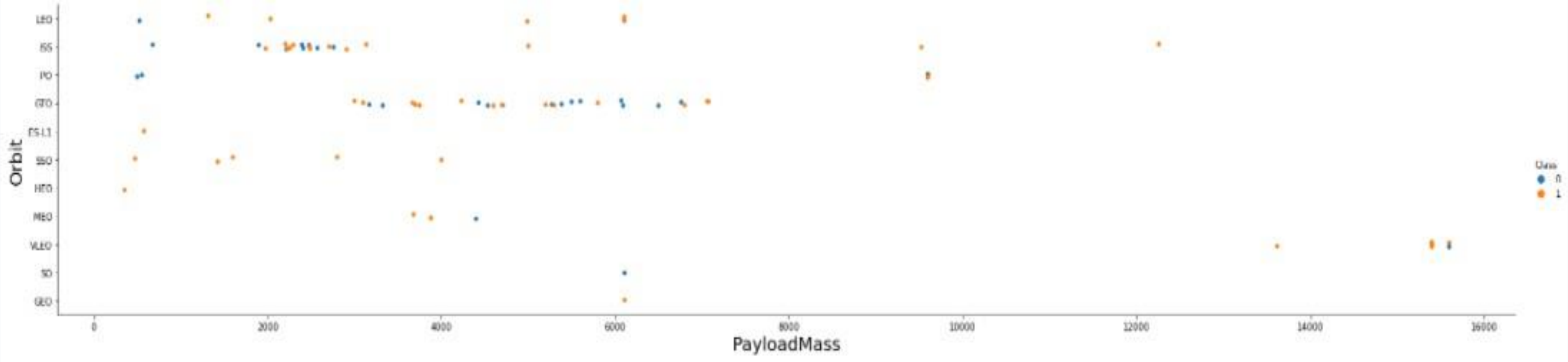
Flight Number vs. Orbit Type

- The plot illustrates Flight Number versus Orbit type. We notice that in the LEO orbit, success correlates with the number of flights, while in the GTO orbit, there is no apparent relationship between flight number and orbit.



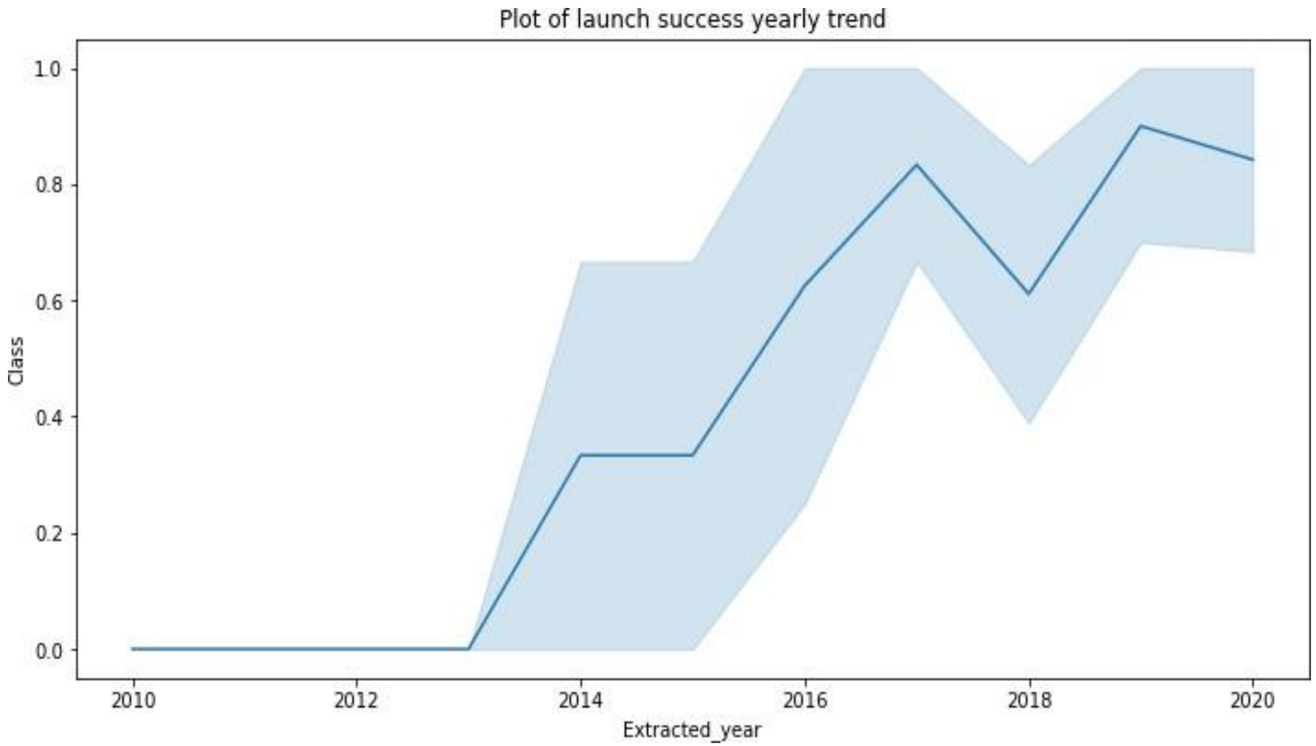
Payload vs Orbit Type

- We notice that heavier payloads tend to result in more successful landings for PO, LEO, and ISS orbits.



Launch Success Yearly Trend

- we can notice that success rate since 2013 kept on incresed till 2020.



All Launch Site Names

- We utilized the keyword DISTINCT to display 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 employed the above query to showcase 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

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 have successfully landed on a drone ship. Additionally, we applied the AND condition to identify successful landings with a 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

- We employed the wildcard '%' to filter for **WHERE** MissionOutcome where it was either a success or a failure.

Boosters Carried Maximum Payload

- We identified the booster that carried 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 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

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

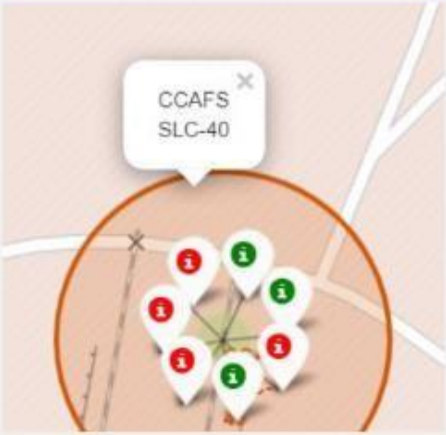
- Selected Landing outcomes and the **COUNT** of landing outcomes, filtering for landing outcomes between 2010-06-04 to 2010-03-20 using the **WHERE** clause.
- Applied the **GROUP BY** clause to group the landing outcomes and the **ORDER BY** clause to arrange the grouped landing outcome in descending order.

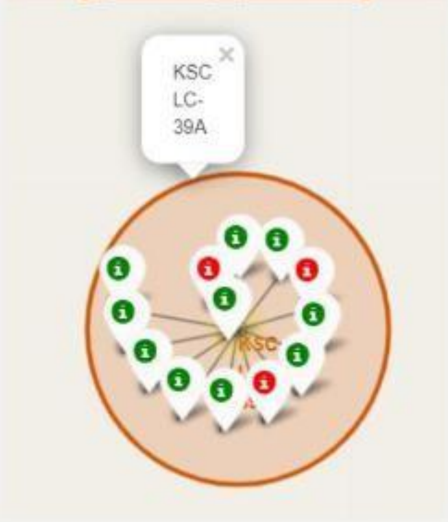
Section 4

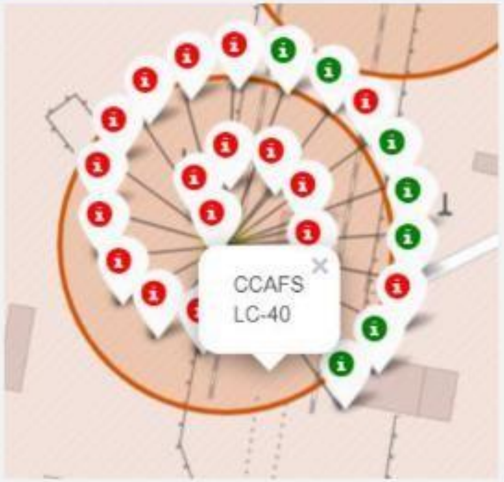
Launch Sites Proximities Analysis

All launch sites global map markers

Markers showing launch sites with color labels







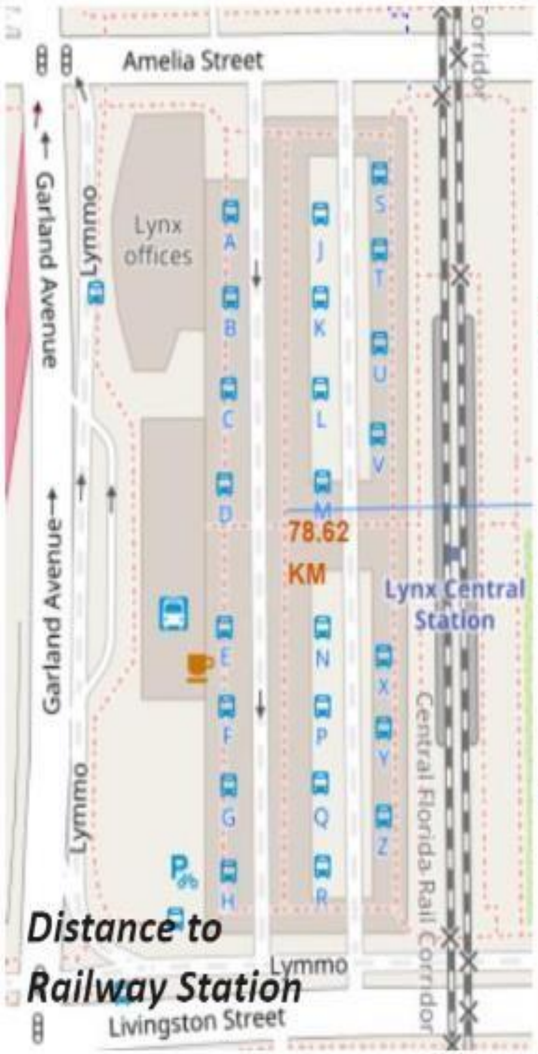
Florida Launch Sites

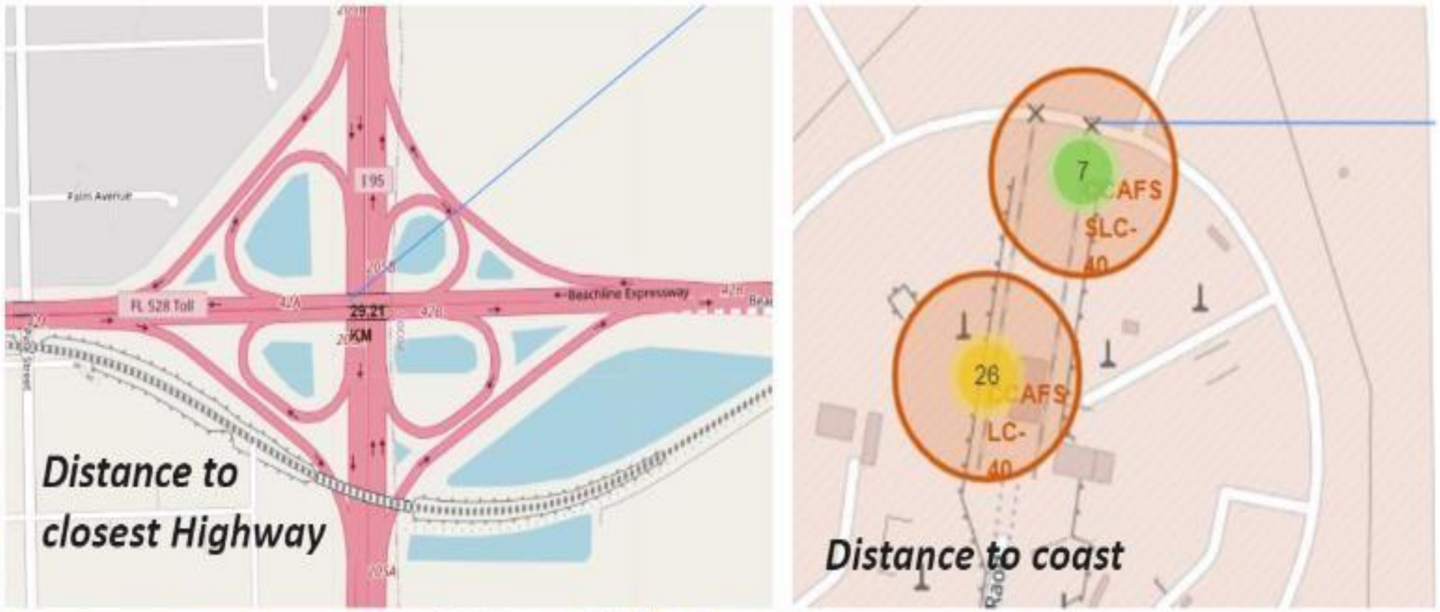
Green Marker shows successful Launches and Red Marker shows Failures

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

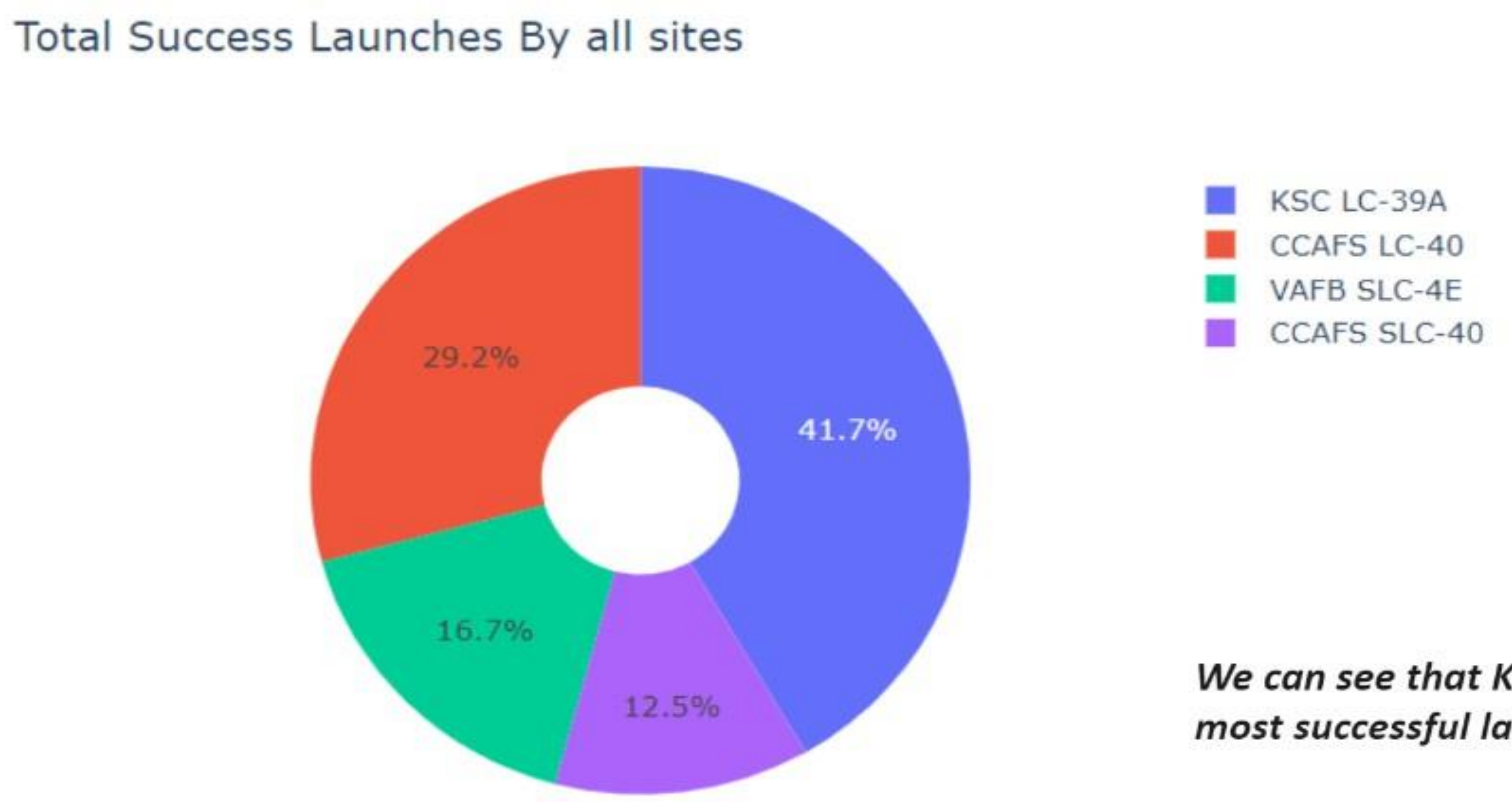
•Are launch sites in close proximity to coastline? Yes

•Do launch sites keep certain distance away from cities? Yes

Section 5

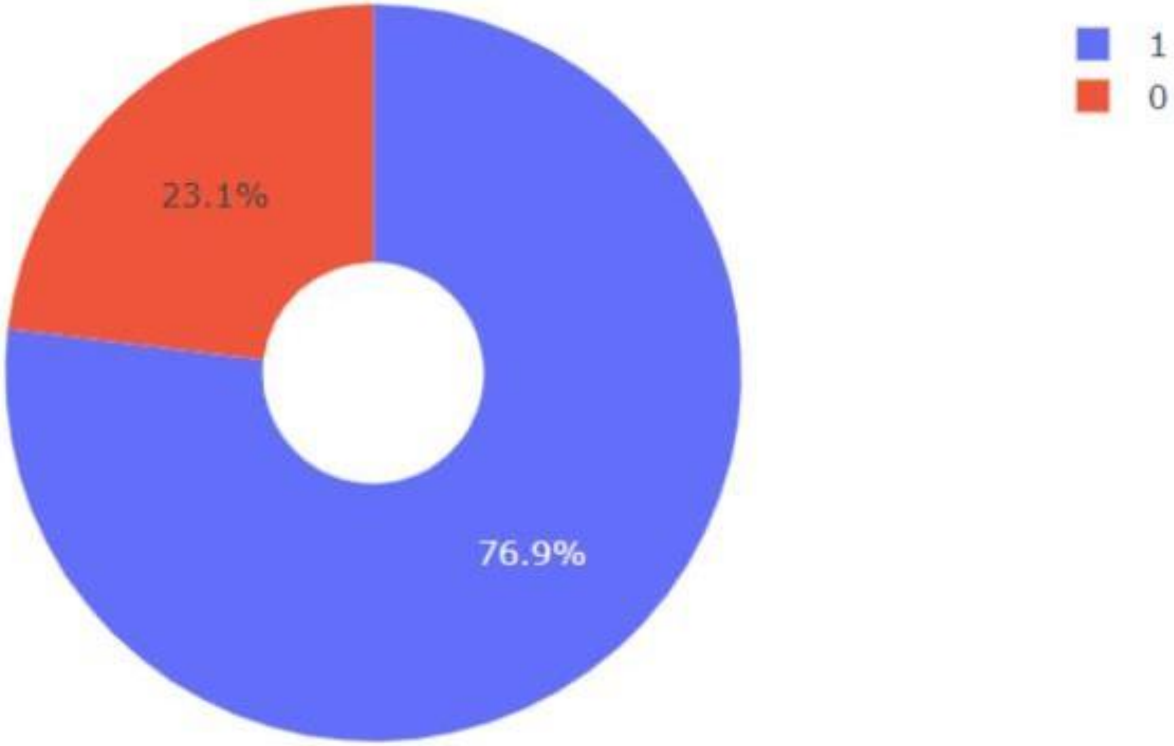
Build a Dashboard with Plotly Dash

Pie chart showing the success percentage achieved by each launch site



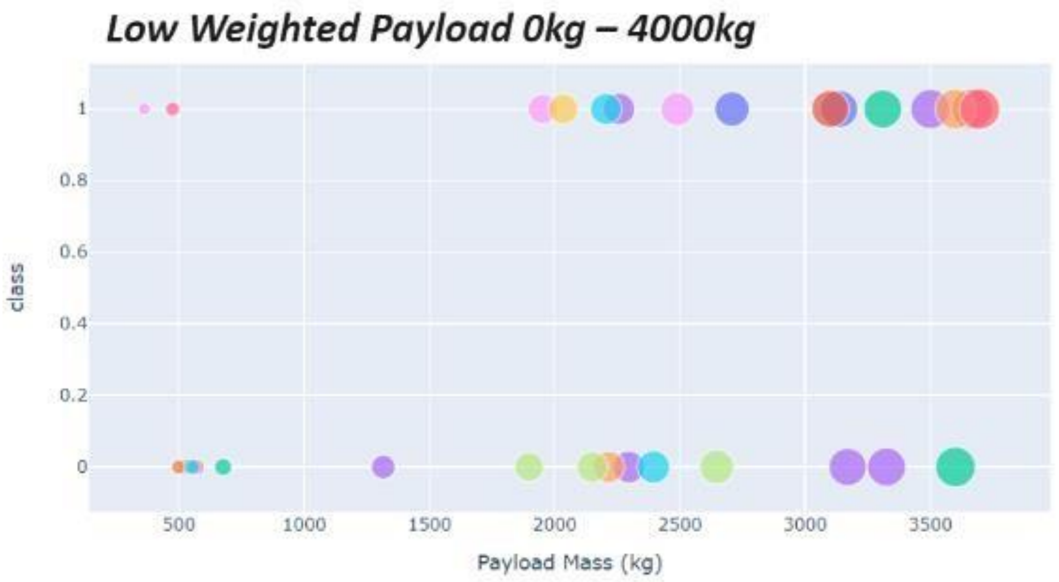
We can see that KSC LC-39A had the most successful launches from all the sites

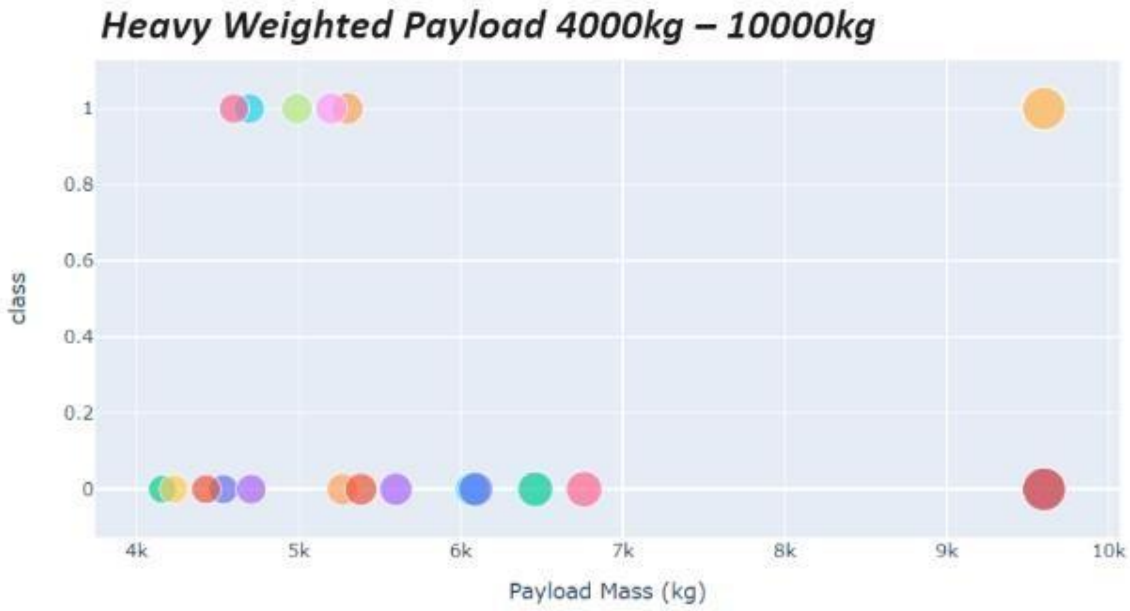
Pie chart showing the Launch site with the highest launch success ratio



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

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

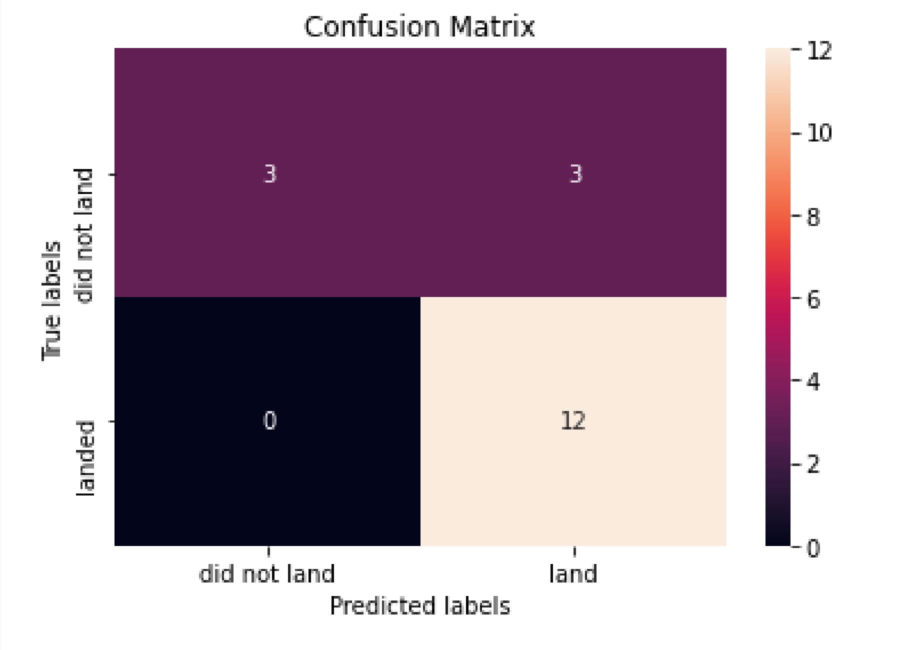
```
models = {'KNeighbors':knn_cv.best_score_,
              'DecisionTree':tree_cv.best_score_,
              'LogisticRegression':logreg_cv.best_score_,
              'SupportVector': svm_cv.best_score_}

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 decision tree classifier's confusion matrix indicates its ability to distinguish between different classes. However, the major issue lies in false positives, where unsuccessful landings are incorrectly identified as successful landings by the classifier.



Conclusions

- The success rate at a launch site tends to increase with a higher number of flights.
- From 2013 to 2020, there has been a steady rise in launch success rates.
- Orbits ES-L1, GEO, HEO, SSO, and VLEO exhibit the highest success rates.
- KSC LC-39A stands out with the highest number of successful launches among all sites.
- The Decision Tree classifier emerges as the most suitable machine learning algorithm for this task.

Thank you!