Winning Space Race With Data Science

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SKILLS NETWORK

OUTLINE

- Executive Summary
- Introduction
- Methodology
- Results
  - Visualization – Charts
  - Dashboard
- Discussion
  - Findings & Implications
- 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**

  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, we can determine the cost of a launch. This information can be used if an alternate company wants to bid against SpaceX 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.

METHODOLOGY

- 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, deploy and evaluate classification models

DATA COLLECTION

- **Data collection using API:**
  - Collected data using get request to the SpaceX API.
  - Decoded the response content as a Json using .json() function call and turn it into a pandas dataframe using .json_normalize().
  - Cleansed the data, checked for missing values and fill in missing values where necessary.
- **Data collection with web scrapping:**
  - 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 the pandas data frame for further analysis.

Data collection–SpaceX API

- Used the get request to the SpaceX API to collect data and performed basic data cleaning.
- Link to the notebook: https://github.com/jankee31/Applied-Data-Science/blob/main/Data%20Collection/jupyter-labs-spacex-data-collection-api.ipynb

Now let's start requesting rocket launch data from SpaceX API with the following URL:

```
spacex_url="https://api.spacexdata.com/v4/launches/past"
```

```
response = requests.get(spacex_url)
```

```
static_json_url='https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/datasets/API_call_spacex_api.json'
```

We should see that the request was successfull with the 200 status response code

```
response.status_code
```

```
200
```

Now we decode the response content as a Json using `.json()` and turn it into a Pandas dataframe using `.json_normalize()`

```
# Use json_normalize meethod to convert the json result into a dataframe
data = pd.json_normalize(response.json())
```

```
# Calculate the mean value of PayloadMass column
Mean_PayloadMass = data_falcon9.PayloadMass.mean()
# Replace the np.nan values with its mean value
data_falcon9['PayloadMass'] = data_falcon9['PayloadMass'].replace(np.nan, Mean_PayloadMass)
```

Data Collection-Web Scrapping

- Applied web scrapping to Falcon 9 launch records using BeautifulSoup.
- Parsed the HTML table, stored it into the dictionary and converted it into a pandas dataframe.
- Link to the notebook: https://github.com/jankee31/Applied-Data-Science/blob/main/Data%20Collection/jupyter-labs-webscraping.ipynb

First, let's perform an HTTP GET method to request the Falcon9 Launch HTML page, as an HTTP response.

In [28]:
```
# use requests.get() method with the provided static_url
# assign the response to a object
data=requests.get(static_url).text
```

Create a `BeautifulSoup` object from the HTML `response`

In [29]:
```
# Use BeautifulSoup() to create a BeautifulSoup object from a response text content
soup=BeautifulSoup(data, 'html5lib')
```

Print the page title to verify if the `BeautifulSoup` object was created properly

In [30]:
```
# Use soup.title attribute
tag_title=soup.title
tag_string_tag_title=tag_title.string
tag_string_tag_title
```

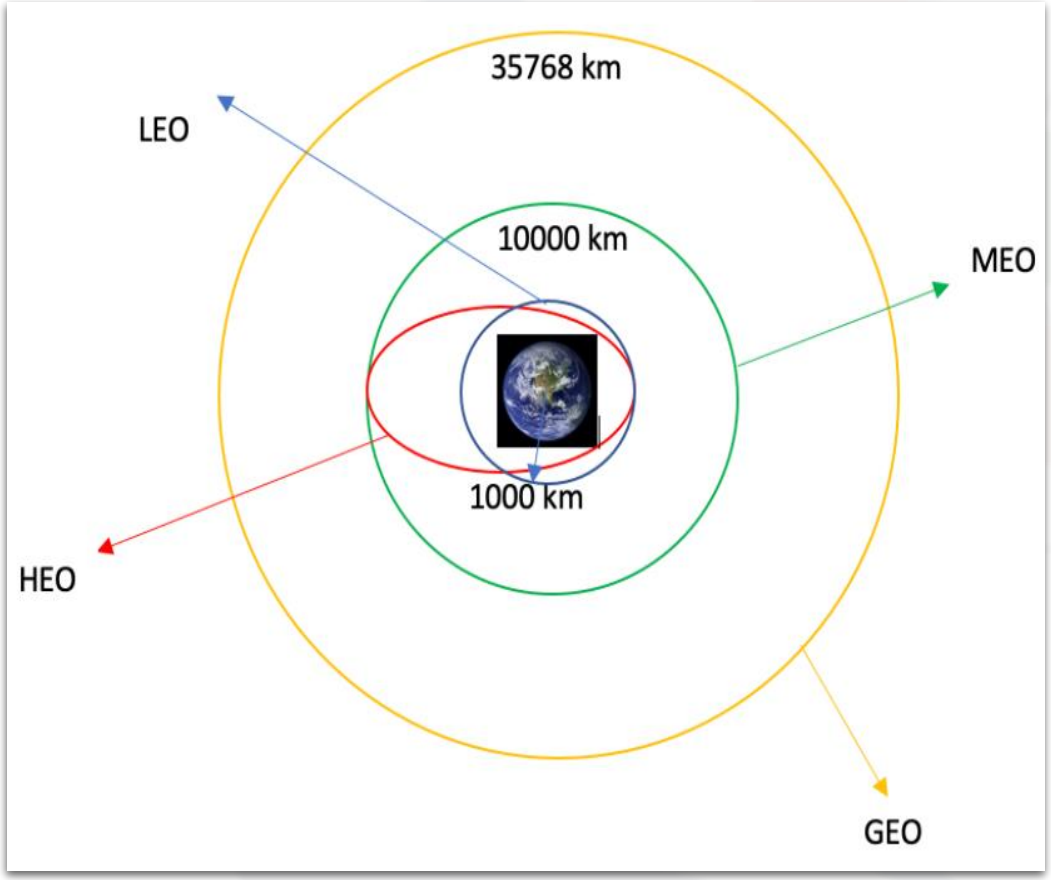
Out[30]:
```
'List of Falcon 9 and Falcon Heavy launches - Wikipedia'
```

After you have fill in the parsed launch record values into `launch_dict`, you can create a dataframe from it.

In [37]:
```
df=pd.DataFrame(launch_dict)
```

In [38]:
```
df.head()
```

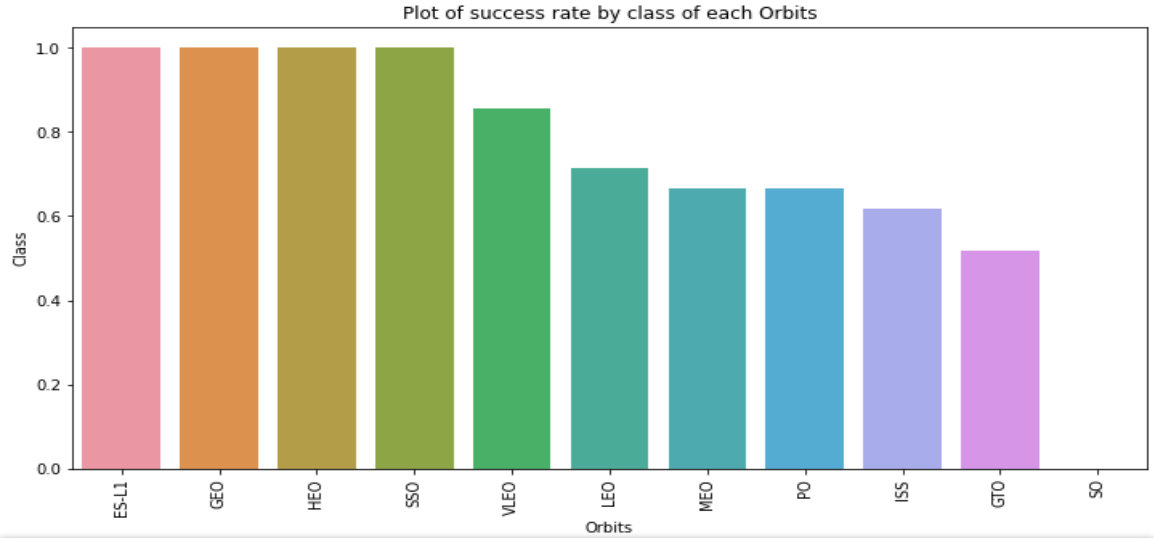
Data Wrangling

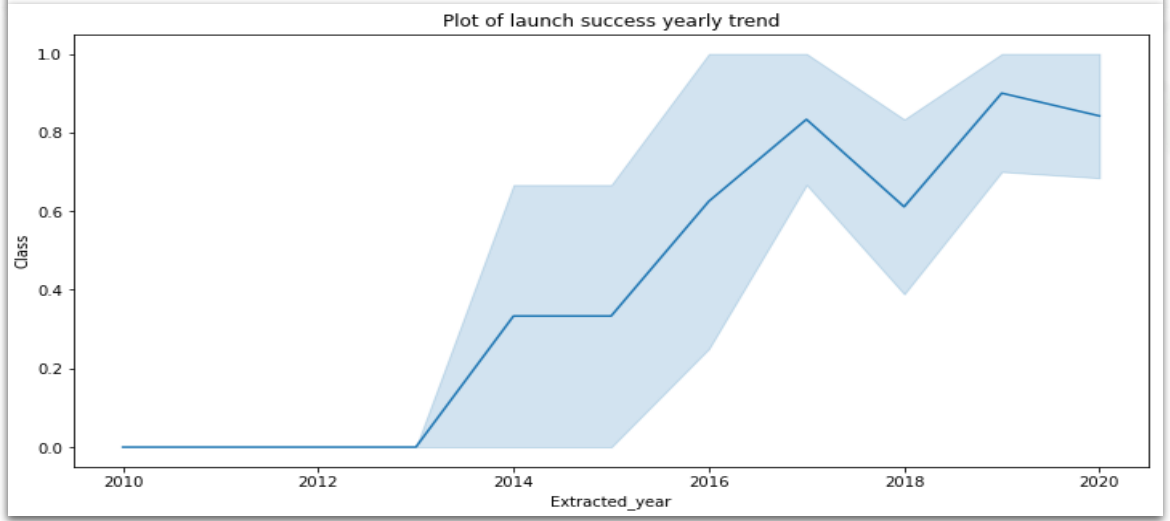


- Performed exploratory data analysis and determined the training labels.
- Calculated the number of launches at each site and occurrence of each orbits.
- Created landing outcome label from outcome column and exported the results to csv.
- Link to the notebook:

https://github.com/jankee31/Applied-Data-Science/blob/main/Data%20Wrangling/labs-jupyter-spacex-Data%20wrangling.ipynb

EDA with Data Visualization





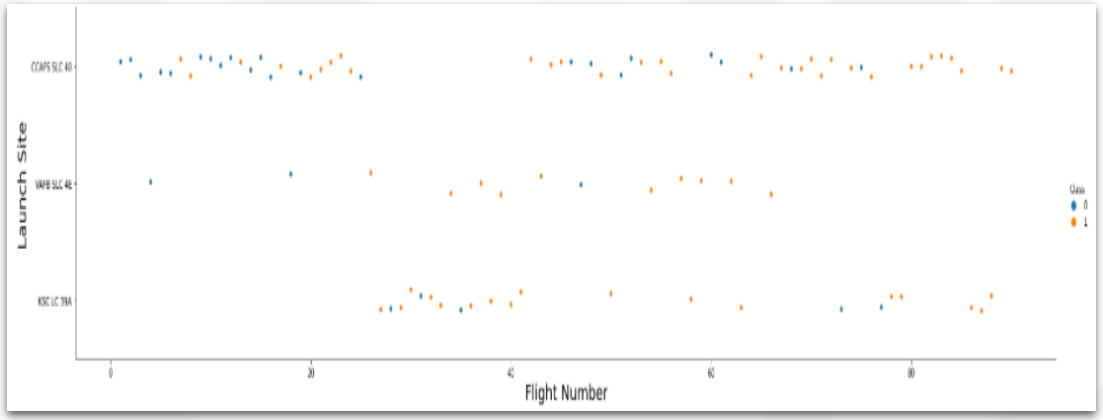
- Performed exploratory data analysis to the data by visualizing the relationship between flight number and launch Site, payload and launch site, success rate of each orbit type, flight number and orbit type with feature engineering and plotted the launch success yearly trend.
- Link to the notebook:

https://github.com/jankee31/Applied-Data-Science/blob/main/Exploratory%20Data%20Analysis/jupyter-labs-eda-dataviz.ipynb

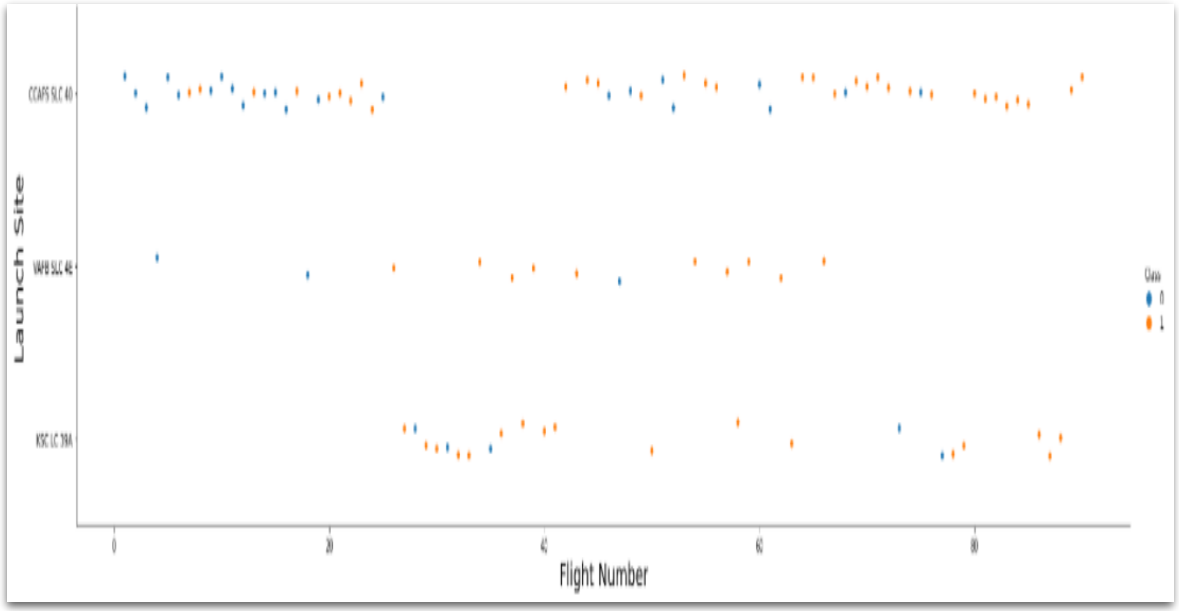
Insights from EDA (Contd..)

- Flight No vs Launch Site:

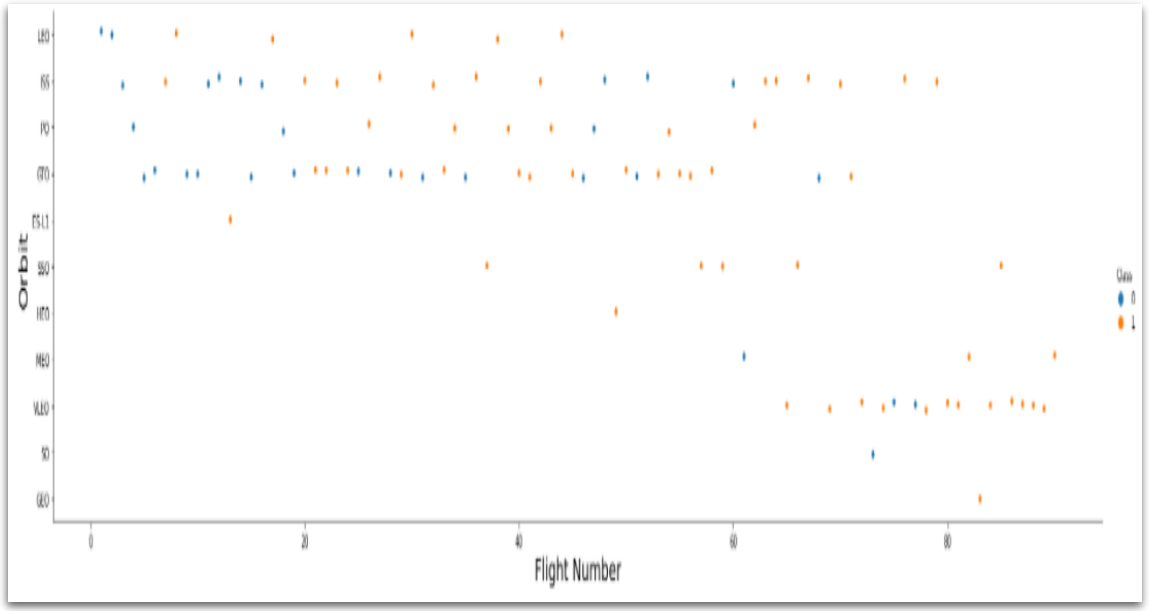
From the plot, we can identify that the larger the flight amount at a launch site, the greater the success rate at a launch site.



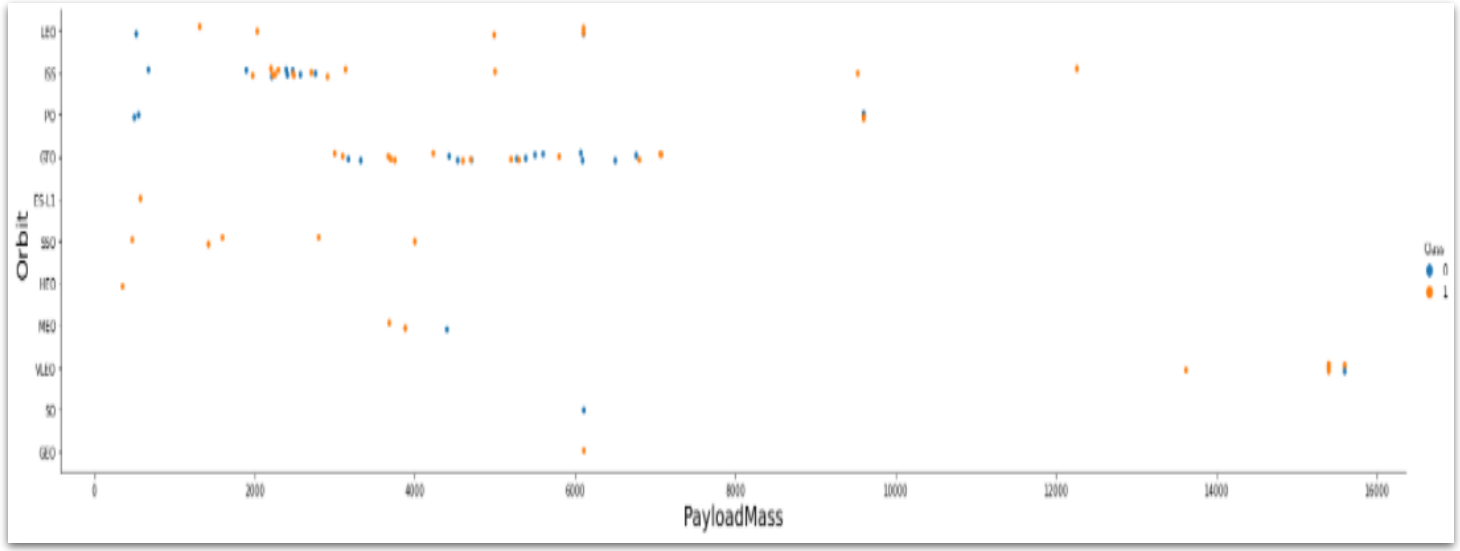
Payload vs. Launch Site



Flight Number vs. Orbit Type

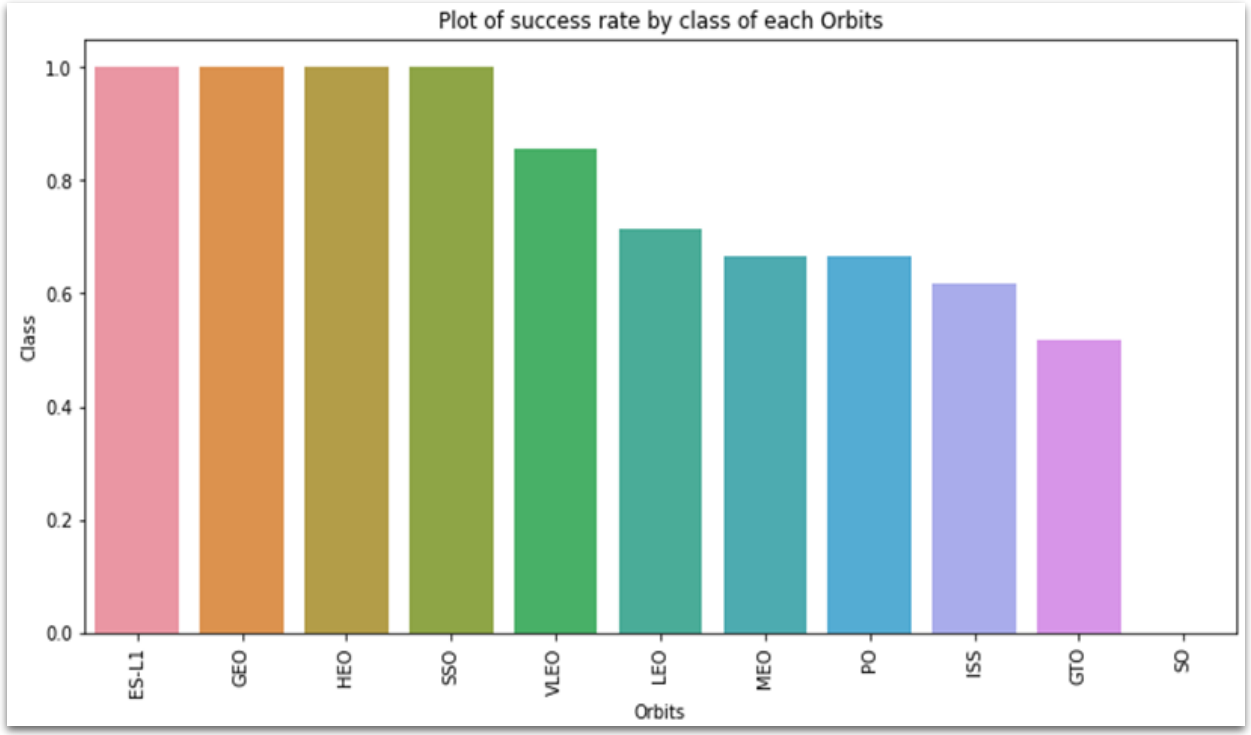


Payload vs. Orbit Type



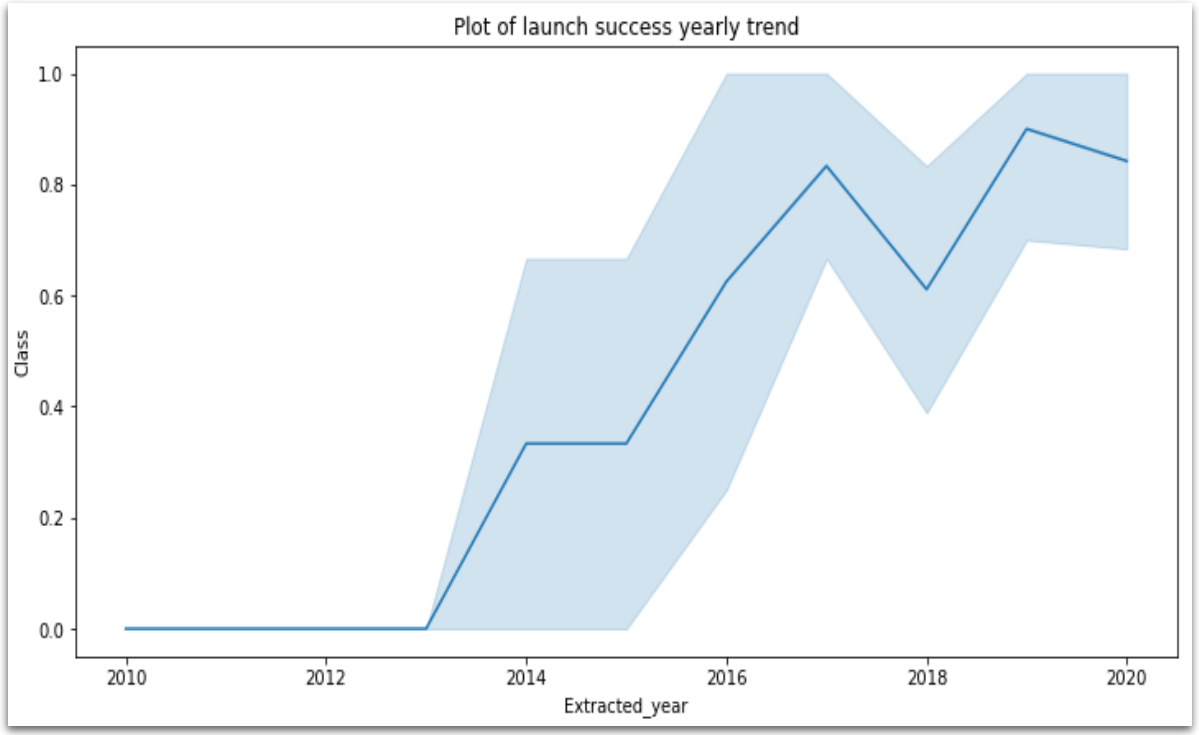
We can observe that with heavy payloads, the successful landing are more for PO, LEO and ISS orbits.

Success Rate vs. Orbit Type



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

Launch Success Yearly Trend



From the plot, we can observe that success rate since 2013 kept on increasing till 2020.

EDA with SQL

- Applied EDA with SQL to get insight from the data for below aspects: (Explored separately using PostgreSQL)
  - 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.

All Launch Site Names and launch sites begin with CCA

```
task_1 = '''
        SELECT DISTINCT LaunchSite
        FROM SpaceX
'''
create_pandas_df(task_1, database=conn)
```

	launchsite
0	KSC LC-39A
1	CCAFS LC-40
2	CCAFS SLC-40
3	VAFB SLC-4E

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

	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 & Average Payload Mass

Total payload carried by boosters from NASA as 45596:

```
task_3 = '''
        SELECT SUM(PayloadMassKG) AS Total_PayloadMass
        FROM SpaceX
        WHERE Customer LIKE 'NASA (CRS)'
        '''
create_pandas_df(task_3, database=conn)
```

	total_payloadmass
0	45596

Calculated the average payload mass carried by booster version F9 v1.1 as 2928.4

```
task_4 = '''
        SELECT AVG(PayloadMassKG) AS Avg_PayloadMass
        FROM SpaceX
        WHERE BoosterVersion = 'F9 v1.1'
        '''
create_pandas_df(task_4, database=conn)
```

	avg_payloadmass
0	2928.4

First Successful Ground Landing Date

```
task_5 = '''
        SELECT MIN(Date) AS FirstSuccessfull_landing_date
        FROM SpaceX
        WHERE LandingOutcome LIKE 'Success (ground pad)'
        '''
create_pandas_df(task_5, database=conn)
```

	firstsuccessfull_landing_date
0	2015-12-22

Successful Drone Ship Landing with Payload between 4000 and 6000

```
task_6 = '''
        SELECT BoosterVersion
        FROM SpaceX
        WHERE LandingOutcome = 'Success (drone ship)'
            AND PayloadMassKG > 4000
            AND PayloadMassKG < 6000
        '''
create_pandas_df(task_6, database=conn)
```

	boosterversion
0	F9 FT B1022
1	F9 FT B1026
2	F9 FT B1021.2
3	F9 FT B1031.2

first successful landing outcome on ground pad was 22nd December 2015

Total Number of Successful and Failure Mission Outcomes

```
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:
```

	failureoutcome
0	1

Maximum Payload carried out by booster

```
task_8 = '''
         SELECT BoosterVersion, PayloadMassKG
         FROM SpaceX
         WHERE PayloadMassKG = (
                                SELECT MAX(PayloadMassKG)
                                FROM SpaceX
                                )
         ORDER BY BoosterVersion
         '''
create_pandas_df(task_8, database=conn)
```

	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

```
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)
```

	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

```
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)
```

	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

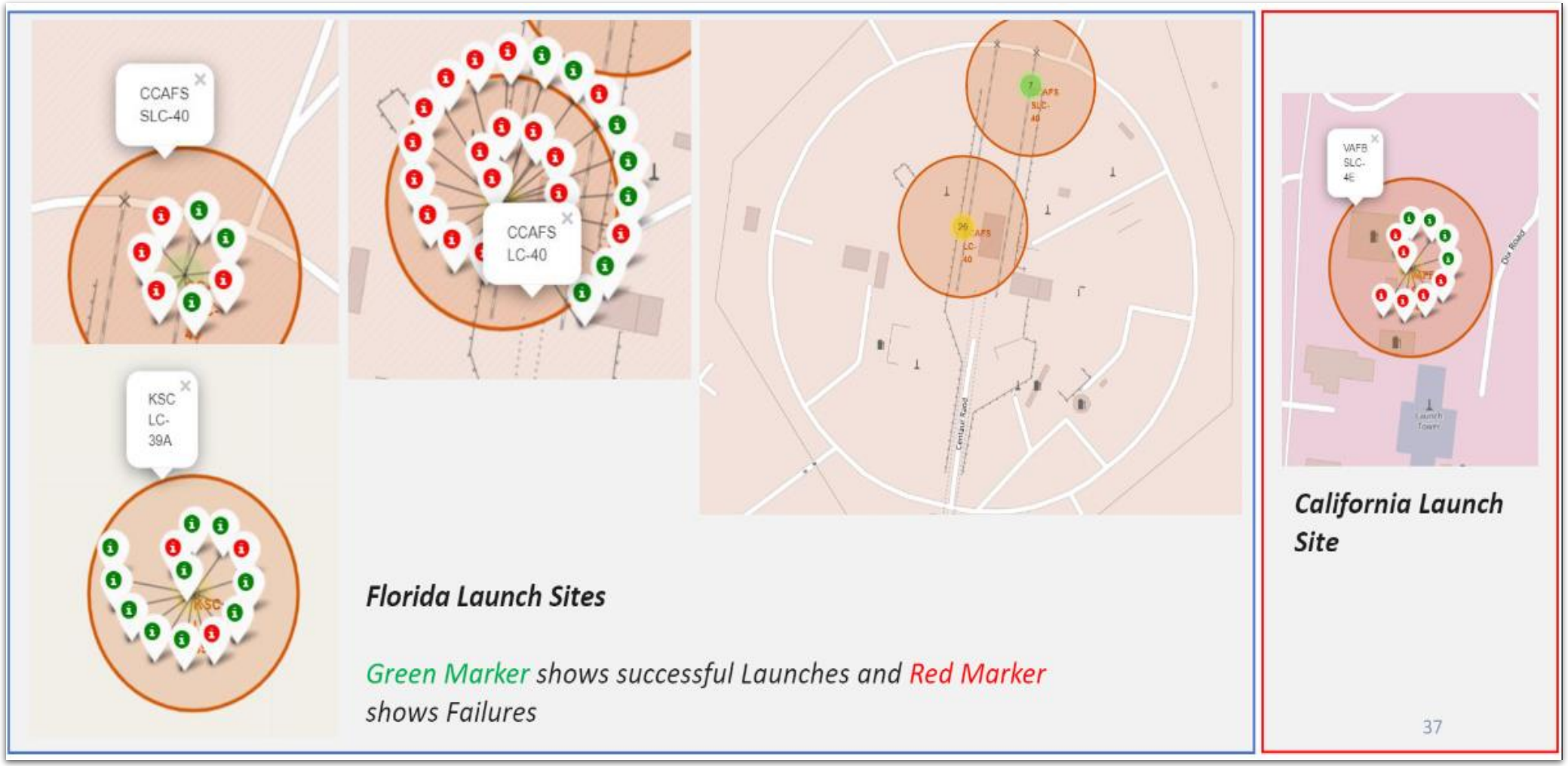
Interactive Visual Analytics With Folium

- 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.
- Assigned the feature launch failure or success outcomes to class 0 and 1 (0 for failure, and 1 for success).
- Using the color-labeled marker clusters, identified which launch sites have relatively high success rate.
- Calculated the distances between a launch site to its proximities.

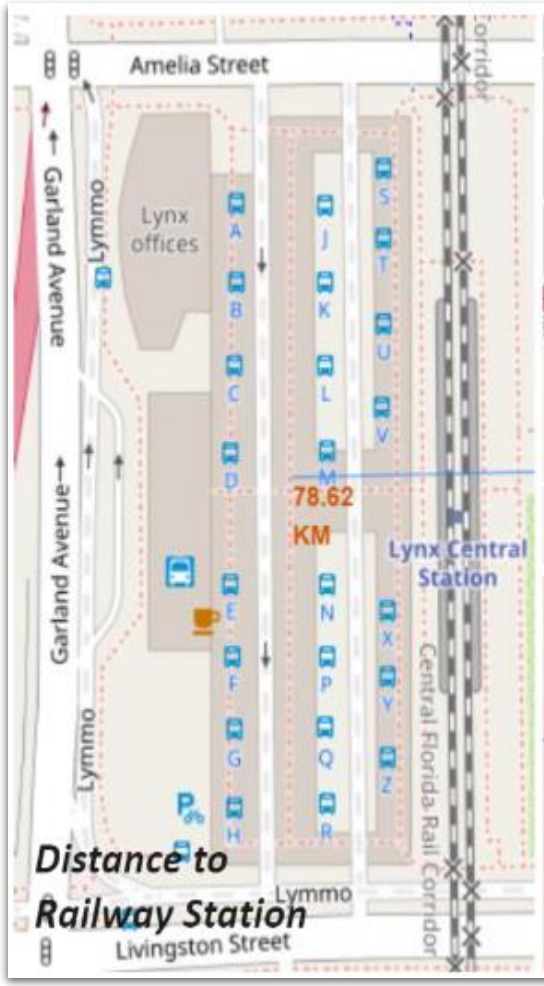
Launch Sites proximities analysis (contd..)

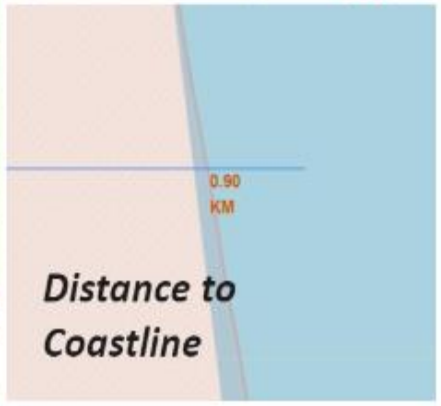
All launch sites global map markers

Markers showing launch sites with color labels



Launch Site distance to landmarks



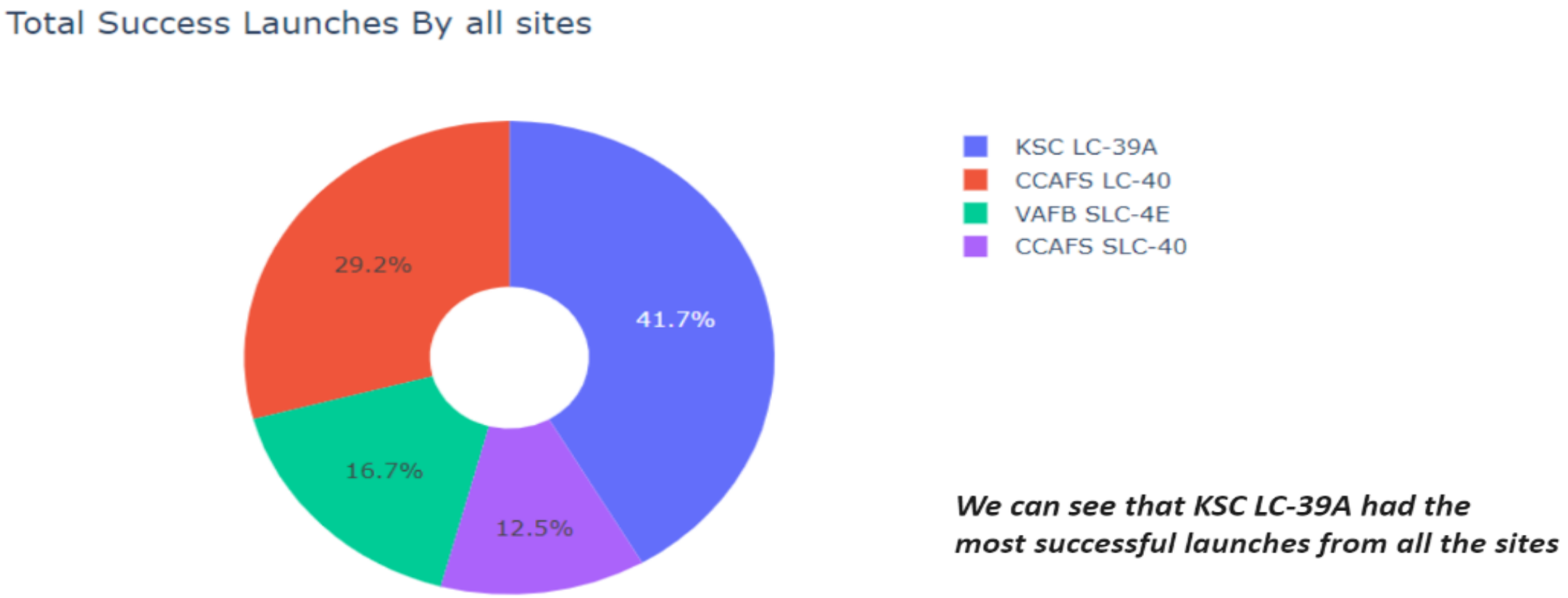


- Are launch sites in close proximity to railways? No
- Are launch sites in close proximity to highways? No
- Are launch sites in close proximity to coastline? Yes
- Do launch sites keep certain distance away from cities? Yes

Interactive Dashboard With Plotly

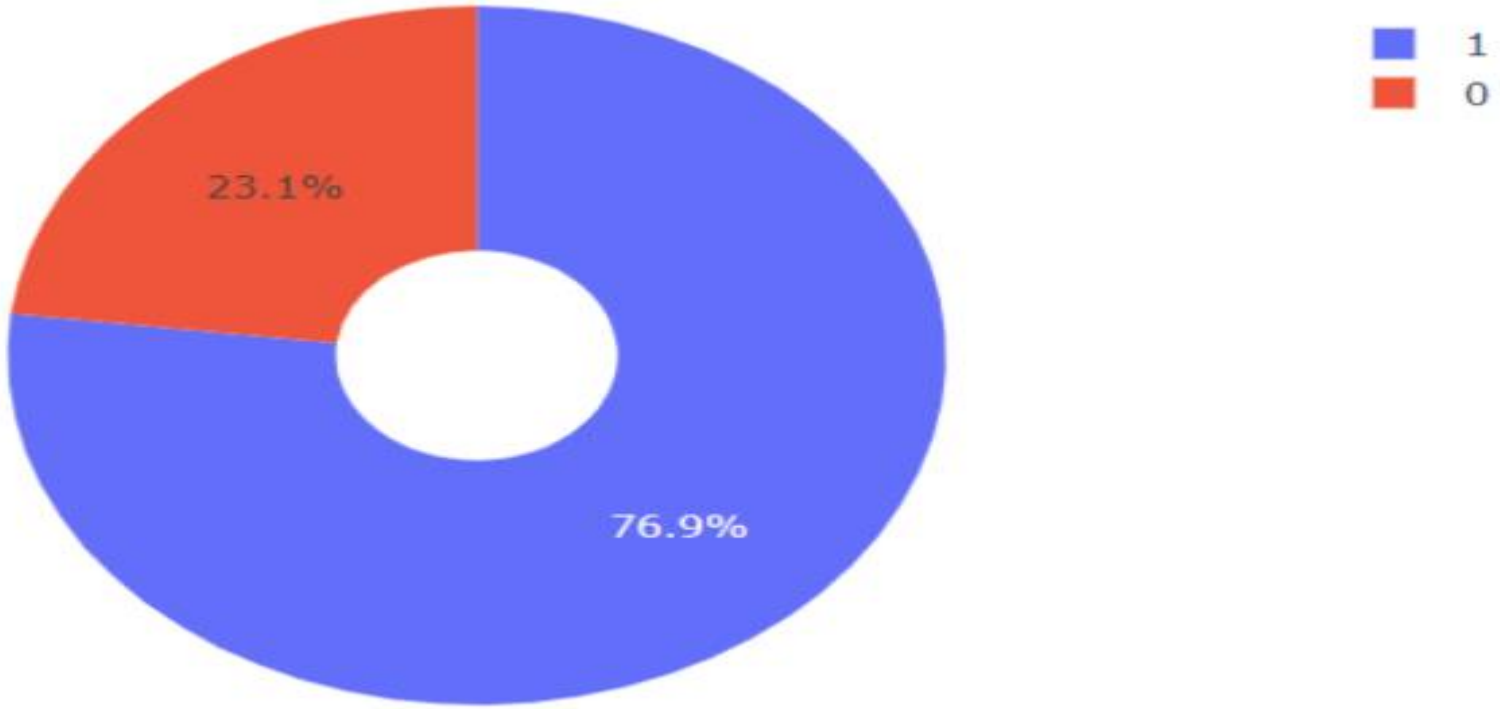
- Built an interactive dashboard with Plotly dash.
- Plotted pie charts showing the total launches by a certain sites.
- Plotted scatter graph showing the relationship with Outcome and Payload Mass (Kg) for the different booster version.
- Link to the dash app https://github.com/jankee31/Applied-Data-Science/blob/main/Interactive%20Visual%20Analytics/DashApp.py

Pie chart showing the success percentage achieved by each launch site



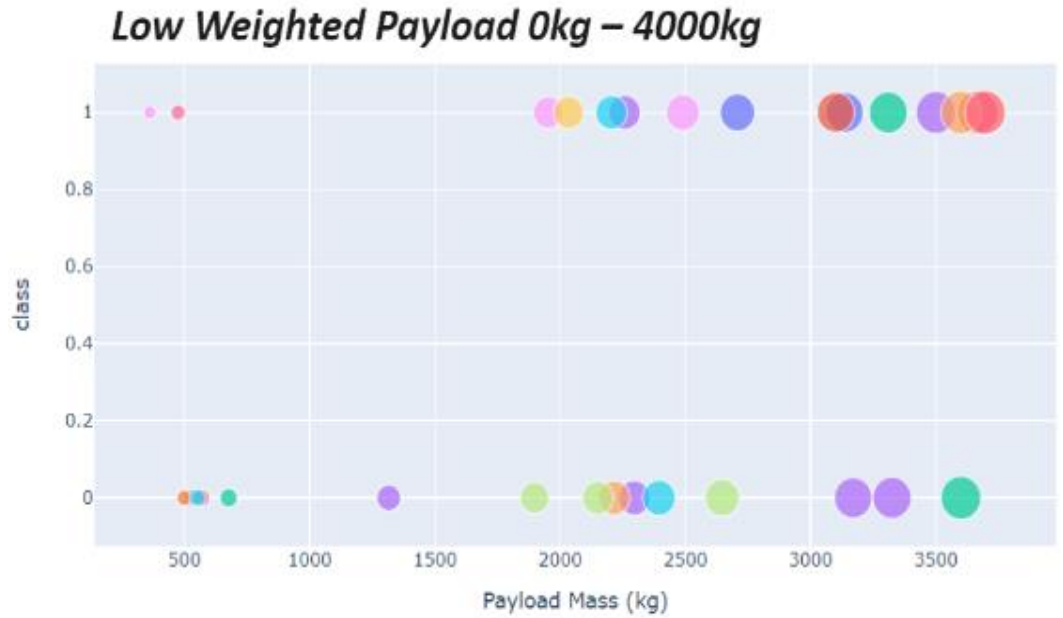
We can see that KSC LC-39A had the most successful launches from all the sites

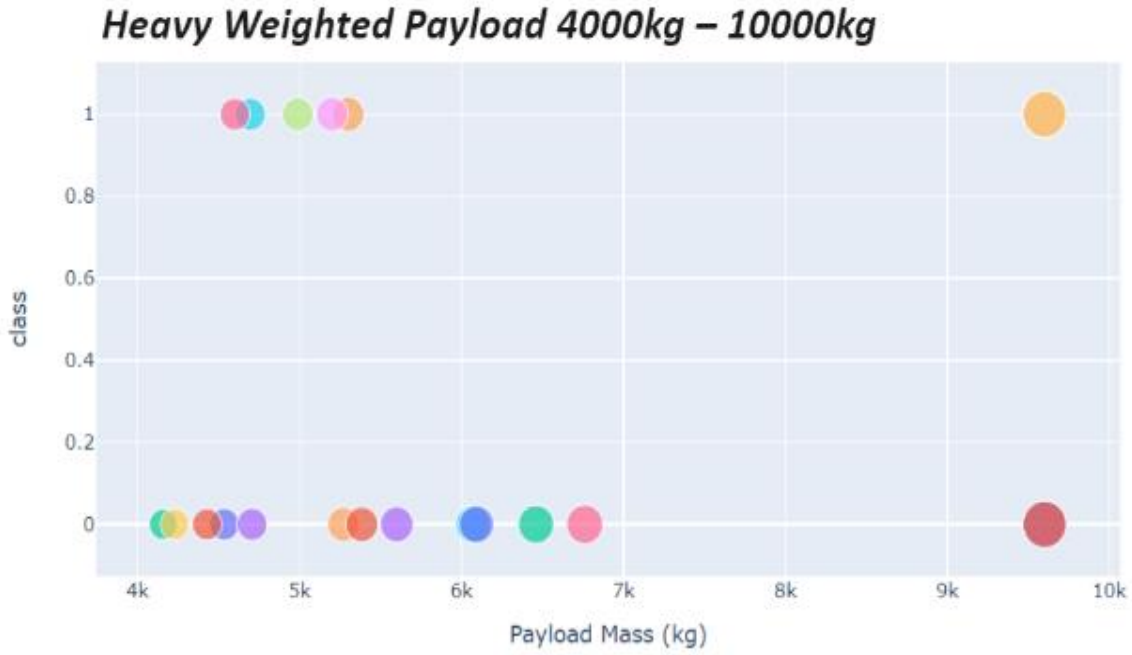
Pie chart showing the Launch site with the highest launch success ratio



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

Predictive Analysis-Classification

- **Classification Accuracy:**

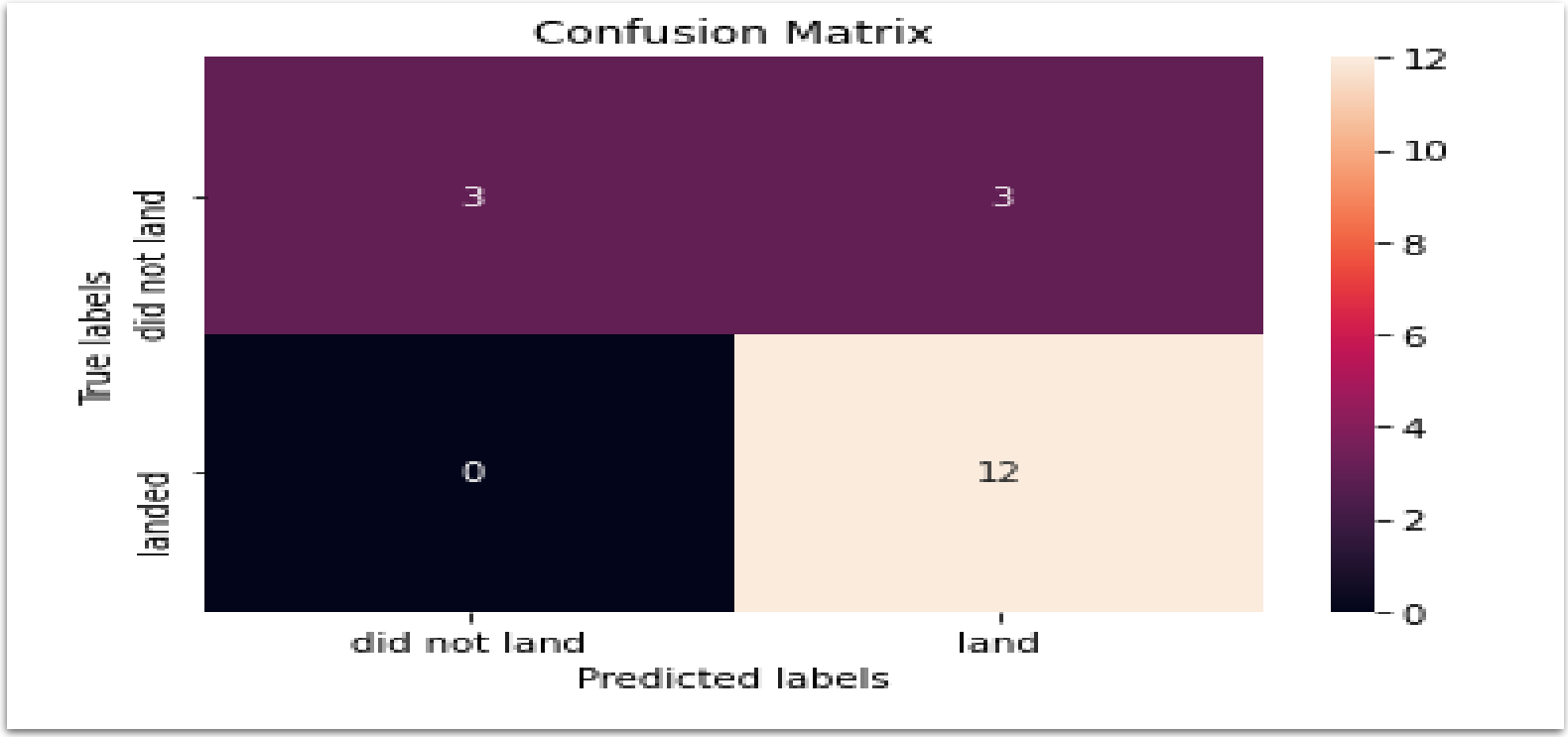
✓The decision tree classifier is the model with the highest classification accuracy

```
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.

CONCLUSION

- 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!

IBM Developer

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