IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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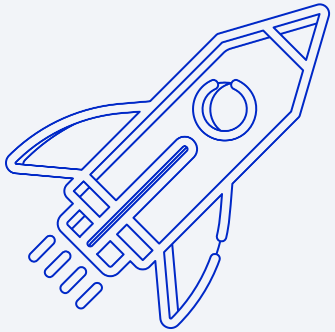
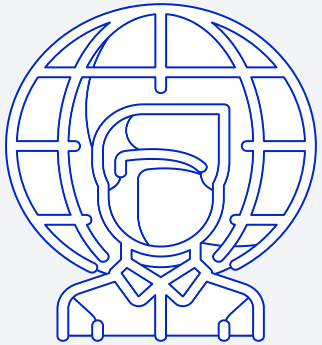
Outline

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

Executive Summary

- Methodologies: the methodologies used in this capstone were data analysis throw data wrangling, exploratory data using visualization and SQL, interactive visual and Perform predictive analysis using classification models.
- Results: with the data analyzed we realized that the experience is a big success factor in rocket launching and the classification models trend to the same result a accuracy of 83%.





Introduction

- 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, 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.

Section 1

Methodology

Methodology

Executive Summary

- Data collection methodology:
  - The data was collected using web scrapping, space X API and a JSON file provided.
- Perform data wrangling
  - The data was processed using Exploratory Data Analysis and Determine Training Labels
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models

Data Collection

- The data sets were collected using a API form space X this API will help us use the extract information using identification numbers in the launch data.
- We use request and parse the SpaceX launch data using the GET request of a JSON file.
- Also using the API to get information about the launches using the IDs given for each launch. Specifically we will be using columns rocket, payloads, launchpad, and cores.
- Finally construct our dataset using the data we have obtained. We combine the columns into a dictionary.

Data Collection – SpaceX API

- All the datra

- Here you can find the completed code cell and outcome cell in my GitHub : https://github.com/CarlosOrtiz-21/SpaceX_Data/blob/main/1.%20jupyter-labs-spacex-data-collection-api%20CO.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 use Beautiful Soup library to web scrap Falcon 9 launch records
- We parsed the table and converted it into a panda data frame
- Github:https://github.com/CarlosOrtiz-21/SpaceX_Data/blob/main/2.%20jupyter-labs-webscraping.ipynb

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

[7]:
```
# use requests.get() method with the provided static_url
data= requests.get(static_url).text
# assign the response to a object
```

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

[8]:
```
# Use BeautifulSoup() to create a BeautifulSoup object from a response text content
soup= BeautifulSoup (data, 'html5lib')
```

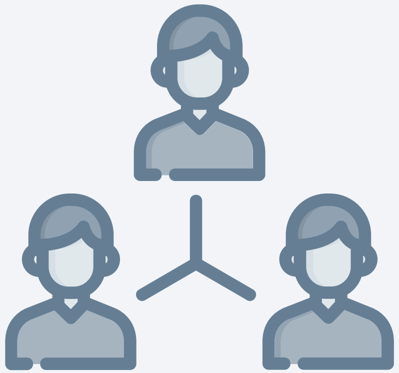
Print the page title to verify if the `BeautifulSoup` object was created properly

[9]:
```
# Use soup.title attribute
print(soup.title)
```

```
<title>List of Falcon 9 and Falcon Heavy launches - Wikipedia</title>
```

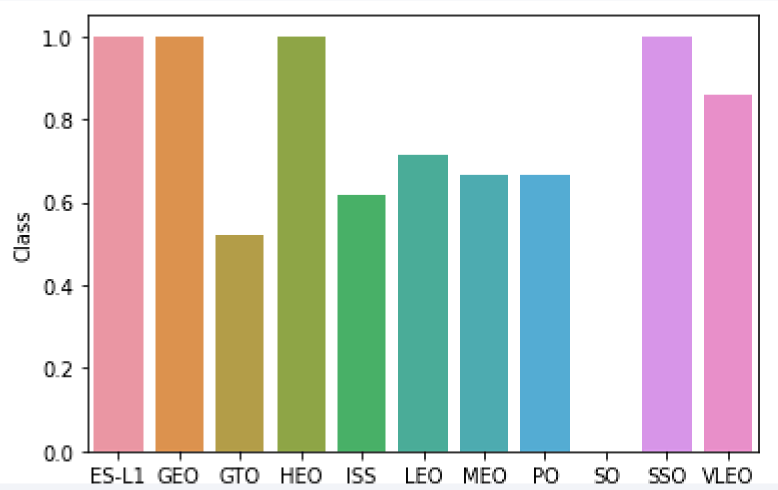
Data Wrangling

- 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.
- GitHub URL: https://github.com/CarlosOrtiz-21/SpaceX_Data/blob/main/3.%20labs-jupyter-spacex-Data%20wrangling%20.ipynb

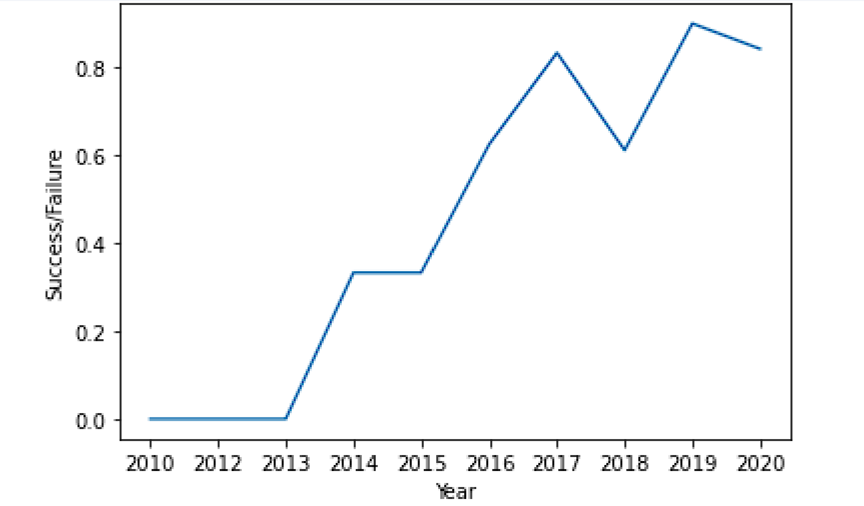


EDA with Data Visualization

- 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.



- GitHub URL: https://github.com/CarlosOrtiz-21/SpaceX_Data/blob/main/5.%20jupyter-labs-eda-dataviz%20.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.
- GitHub URL: https://github.com/CarlosOrtiz-21/SpaceX_Data/blob/main/4.%20jupyter-labs-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.
- GitHub URL : https://github.com/CarlosOrtiz-21/SpaceX_Data/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.
- GitHub URL: https://github.com/CarlosOrtiz-21/SpaceX_Data/blob/main/7.%20SpaceX_Machine%20Learning%20Prediction_Part_5.ipynb

Results

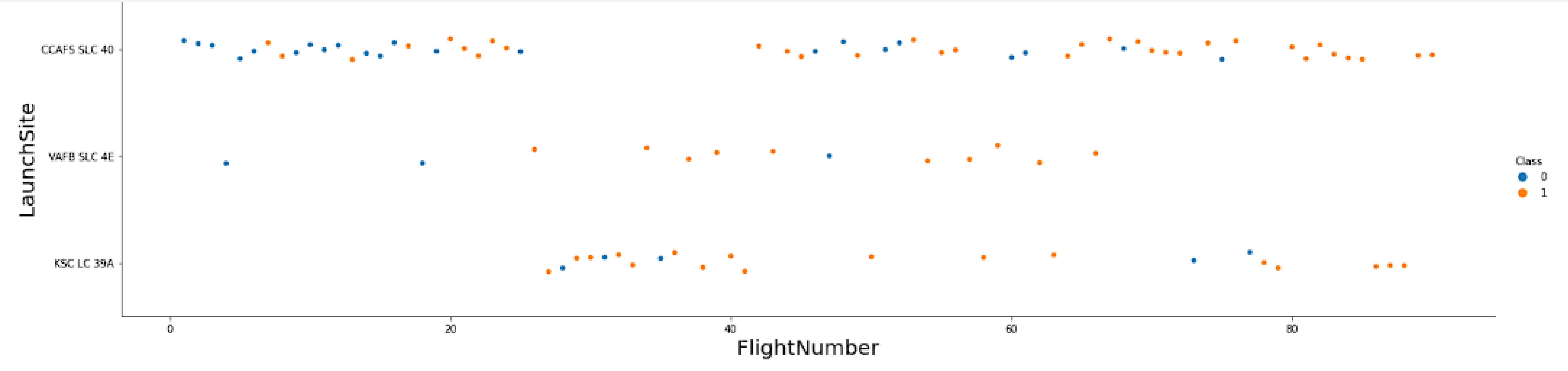
- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results

Section 2

Insights drawn from EDA

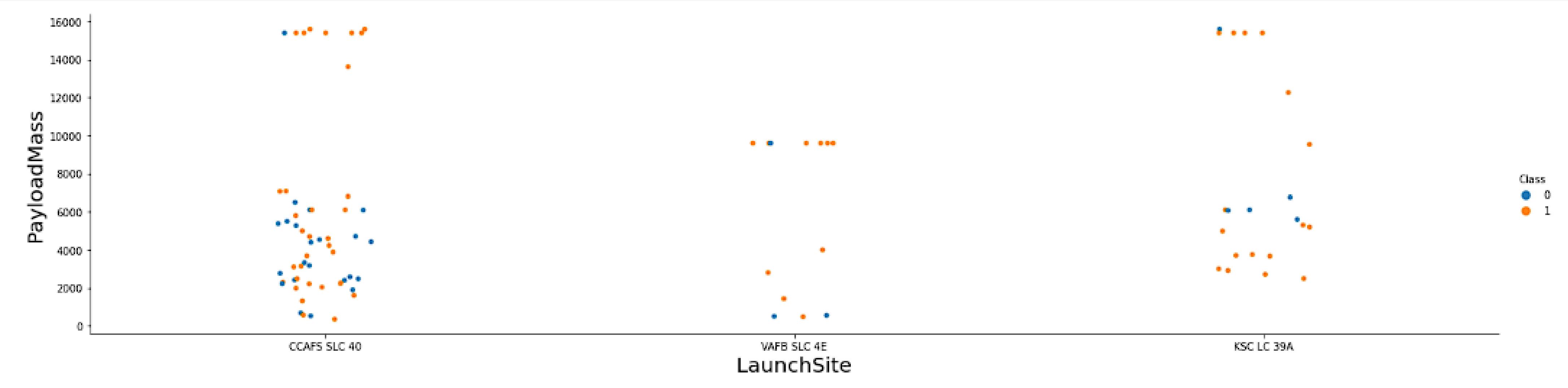
Flight Number vs. Launch Site

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



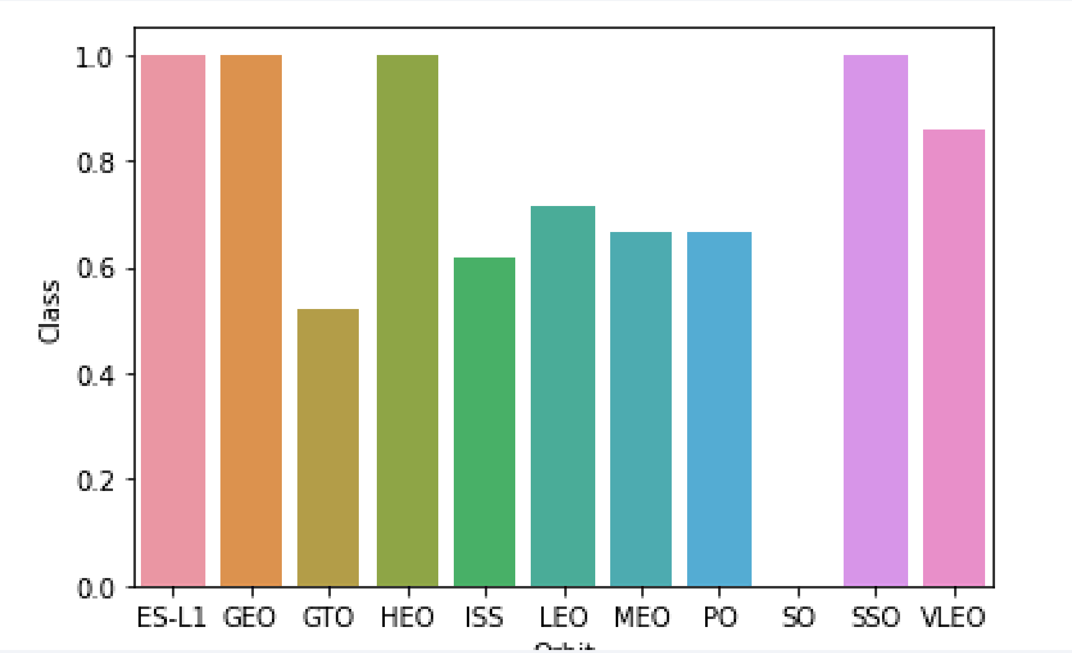
Payload vs. Launch Site

- The greater the payload mass for lauch site CCAFS SLA 40 the higher the succes rate for the lauching



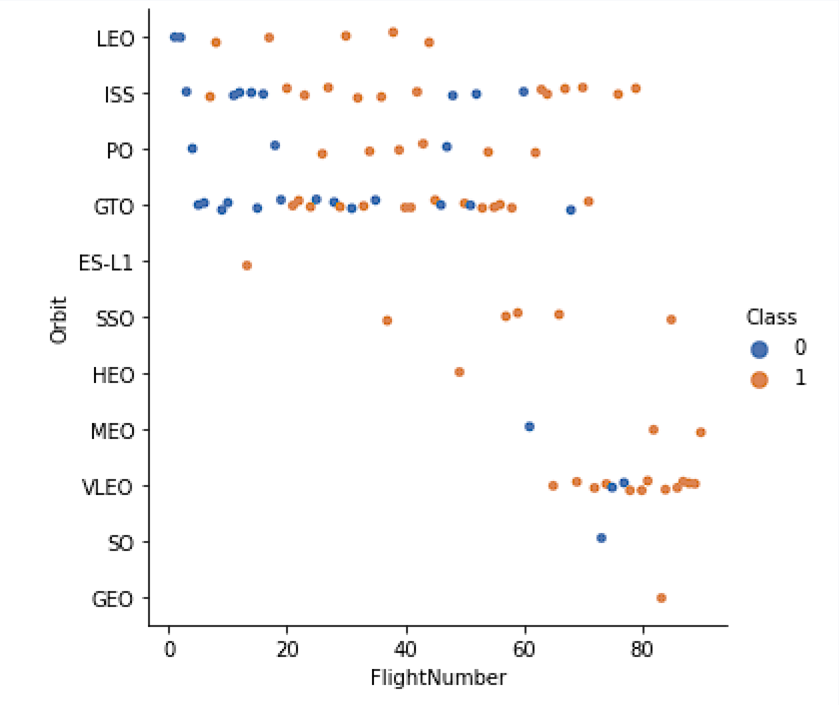
Success Rate vs. Orbit Type

- We can appreciate that the Orbit type ES-LI, GEO , HEO, SSO, VLEO have the best successful rates.



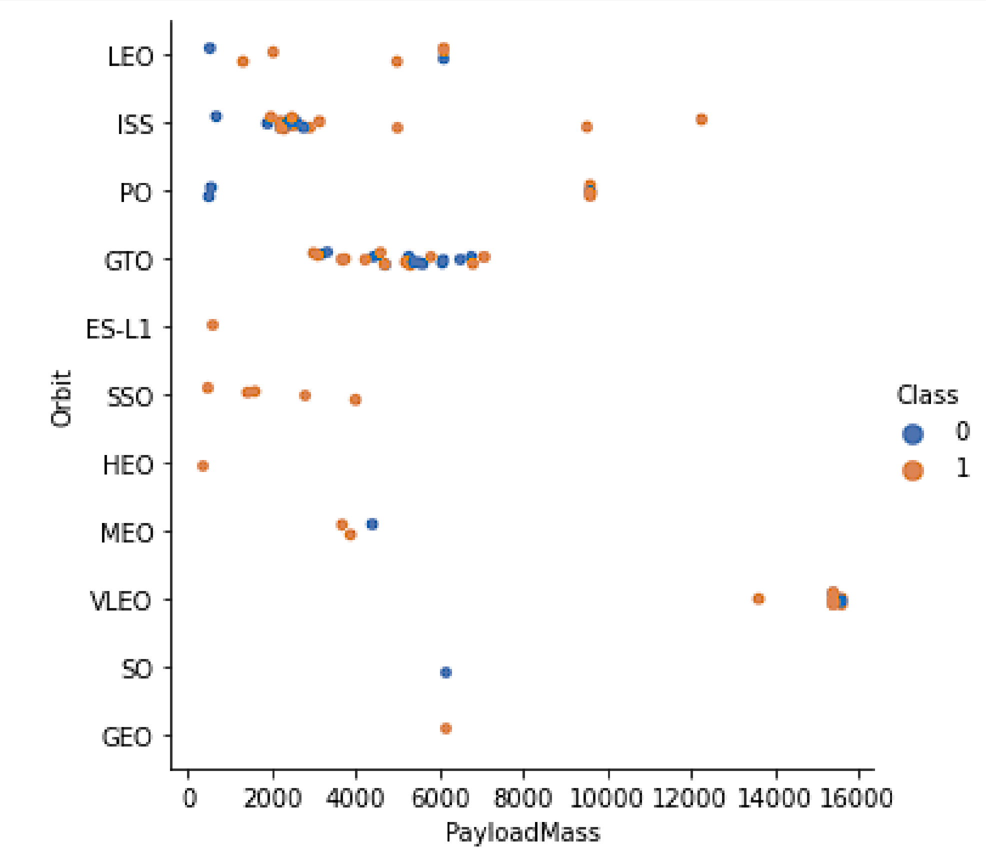
Flight Number vs. Orbit Type

- We see that in the LEO orbit the Success appears related to the number of flights; on the other hand, there seems to be no relationship between flight number when in GTO orbit.



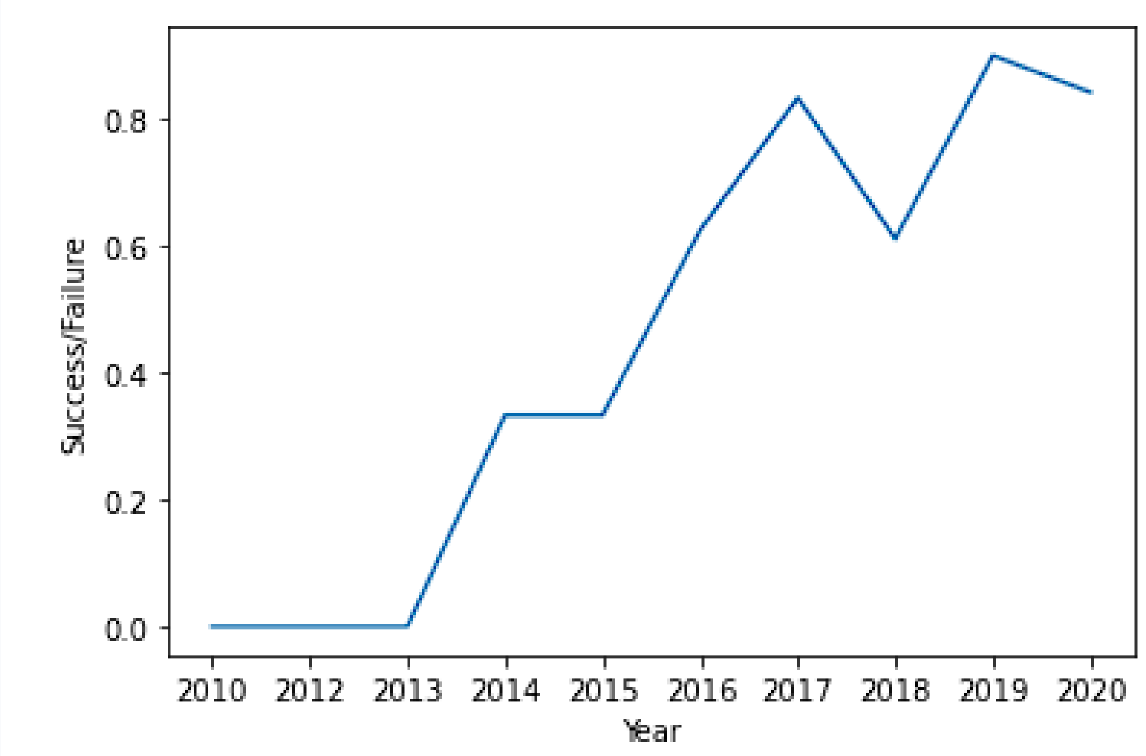
Payload vs. Orbit Type

- With heavy payloads the successful landing or positive landing rate are more for Polar,LEO and ISS.
- However for GTO we cannot distinguish this well as both positive landing rate and negative landing(unsuccessful mission) are both there here



Launch Success Yearly Trend

- We can observe that the success rate since 2013 kept increasing till 2020.
- Each launching is more experience gained in that its what we appreciate in the graph.



All Launch Site Names

- The names of the unique launch sites

```
%sql SELECT DISTINCT LAUNCH_SITE FROM NEWSPACEX
```

launch_site
CCAFS LC-40
CCAFS SLC-40
KSC LC-39A
VAFB SLC-4E

Launch Site Names Begin with 'CCA'

- 5 records where launch sites begin with `CCA`

```
%sql SELECT LAUNCH_SITE FROM NEWSPACEX WHERE LAUNCH_SITE LIKE 'CCA%' LIMIT 5
```

launch_site
CCAFS LC-40
CCAFS LC-40
CCAFS LC-40
CCAFS LC-40
CCAFS LC-40

Total Payload Mass

- We Calculate the total payload carried by boosters from NASA

sum_of_payload
45596

```
%sql SELECT SUM(PAYLOAD_MASS__KG_) AS SUM_OF_PAYLOAD FROM NEWSPACEX WHERE CUSTOMER LIKE 'NASA (CRS)'
```

Average Payload Mass by F9 v1.1

- We Calculate the average payload mass carried by booster version F9 v1.1

avg_of_f9_v1
2928

```
%sql SELECT AVG(PAYLOAD_MASS__KG_) AS AVG_OF_F9_V1 FROM NEWSPACEX WHERE BOOSTER_VERSION LIKE 'F9 v1.1'
```

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

- This is the List names of boosters which have successfully landed on drone ship and had payload mass greater than 4000 but less than 6000

```
%sql SELECT BOOSTER_VERSION, PAYLOAD_MASS__KG_ FROM NEWSPACEX WHERE LANDING__OUTCOME LIKE '%(drone ship)' AND PAYLOAD_MASS__KG_ BETWEEN 4000 AND 600
```

booster_version	payload_mass__kg_
F9 FT B1020	5271
F9 FT B1022	4696
F9 FT B1026	4600
F9 FT B1021.2	5300
F9 FT B1031.2	5200

Total Number of Successful and Failure Mission Outcomes

- Total number of successful and failure mission outcomes

mission_outcome	COUNT
Failure (in flight)	1
Success	99
Success (payload status unclear)	1

```
%sql SELECT MISSION_OUTCOME, COUNT(*) AS COUNT FROM NEWSPACEX GROUP BY MISSION_OUTCOME
```

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.

booster_version	payload_mass__kg_
F9 B5 B1048.4	15600
F9 B5 B1049.4	15600
F9 B5 B1051.3	15600
F9 B5 B1056.4	15600
F9 B5 B1048.5	15600
F9 B5 B1051.4	15600
F9 B5 B1049.5	15600
F9 B5 B1060.2	15600
F9 B5 B1058.3	15600
F9 B5 B1051.6	15600
F9 B5 B1060.3	15600
F9 B5 B1049.7	15600

```
%sql SELECT BOOSTER_VERSION, PAYLOAD_MASS__KG_ FROM NEWSPACEX WHERE PAYLOAD_MASS__KG_= (SELECT MAX (PAYLOAD_MASS__KG_) FROM NEWSPACEX)
```

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

- 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 order the grouped landing outcome in descending order.

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]:

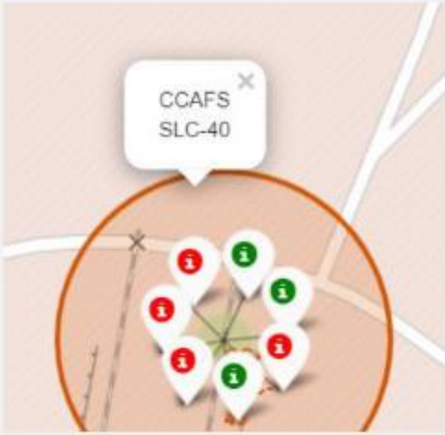
	landingoutcome	count
0	No attempt	10
1	Success (drone ship)	6
2	Failure (drone ship)	5
3	Success (ground pad)	5
4	Controlled (ocean)	3
5	Uncontrolled (ocean)	2
6	Precluded (drone ship)	1
7	Failure (parachute)	1

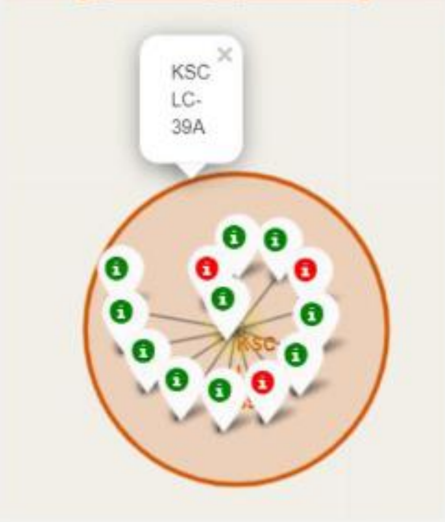
Section 3

Launch Sites Proximities Analysis

All launch sites global map markers

Markers showing launch sites with color





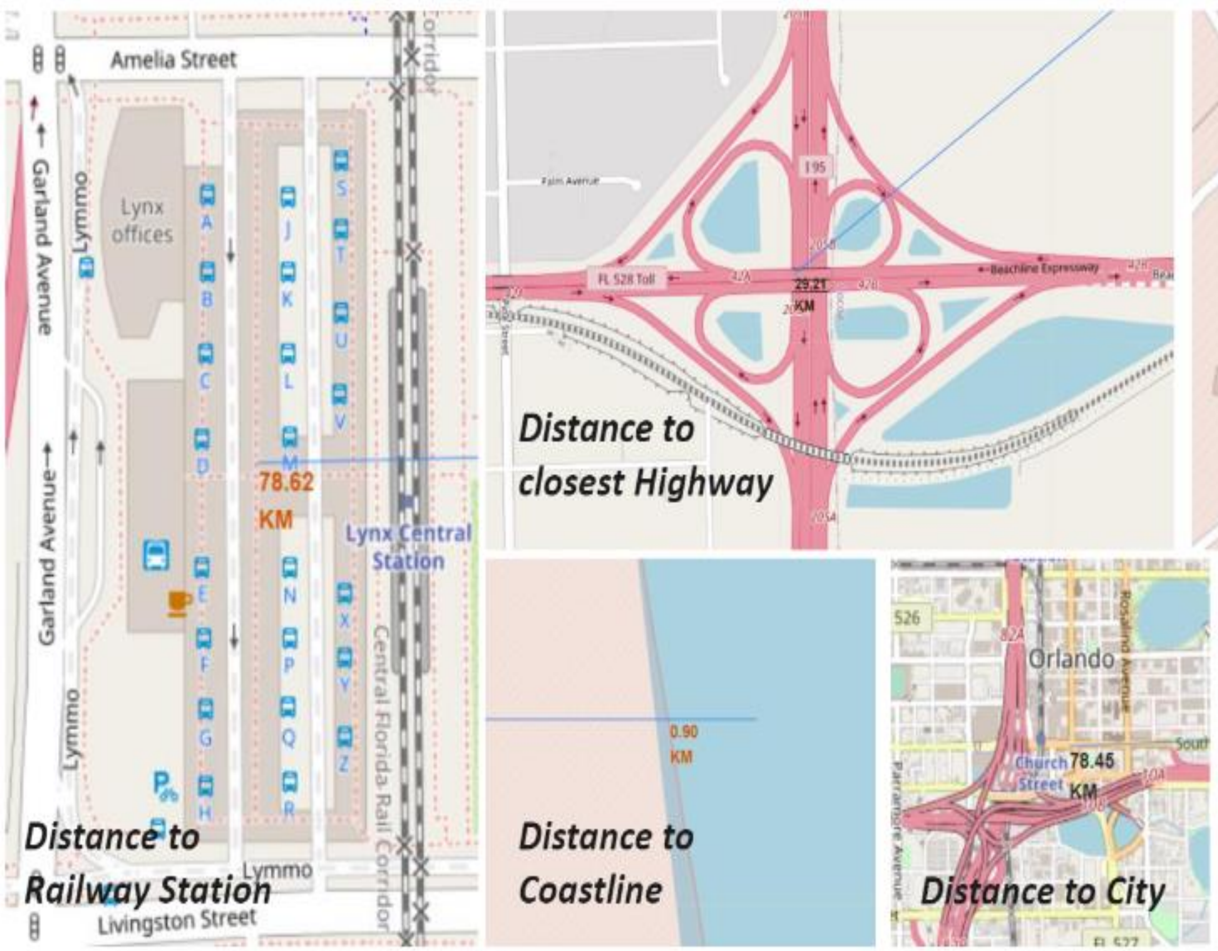
Florida Launch Sites

Green Marker shows successful Launches and Red Marker shows Failures

California Launch Site

37

Launch Site distance to landmarks

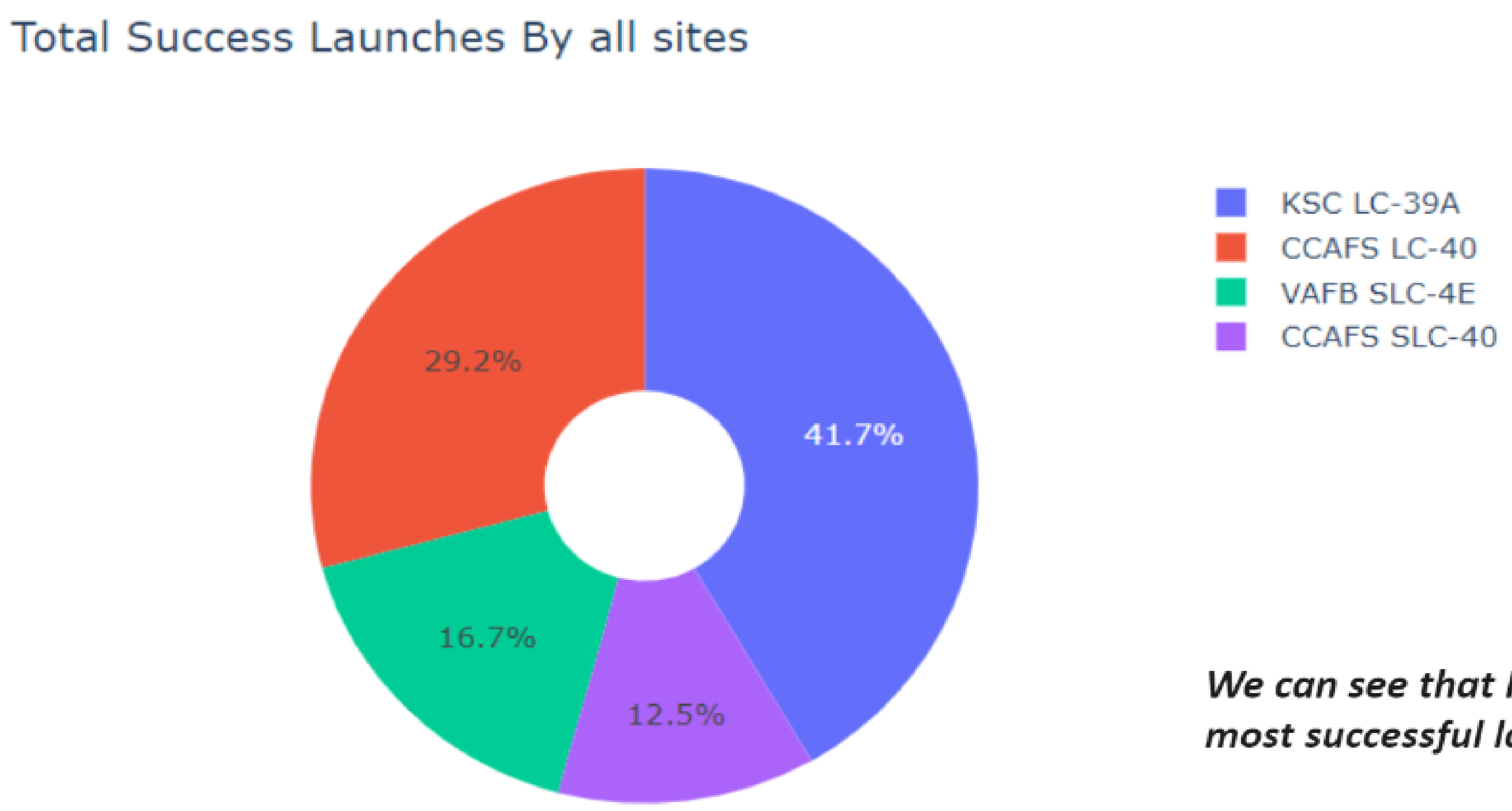


- Are launch sites in close proximity to railways? No
- Are launch sites in close proximity to highways? No
- Are launch sites in close proximity to coastline? Yes
- Do launch sites keep certain distance away from cities? Yes

Section 4

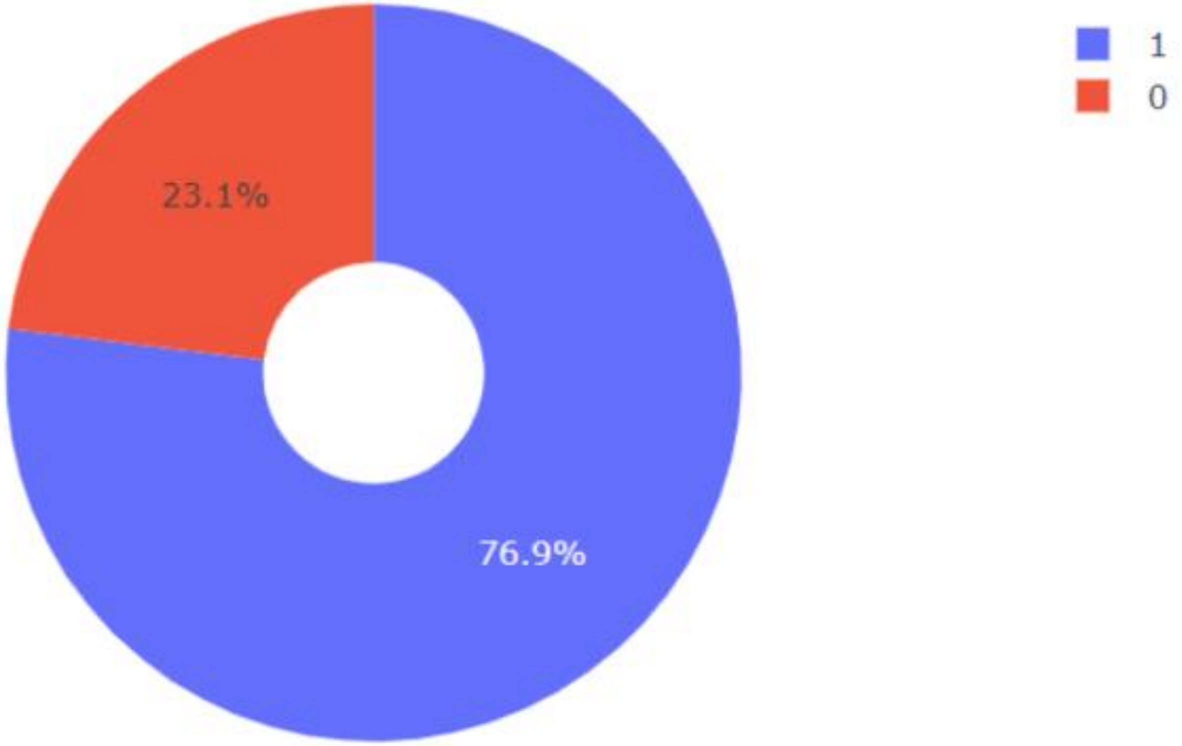
Build a Dashboard with Plotly Dash

Pie chart showing the success percentage achieved by each launch site



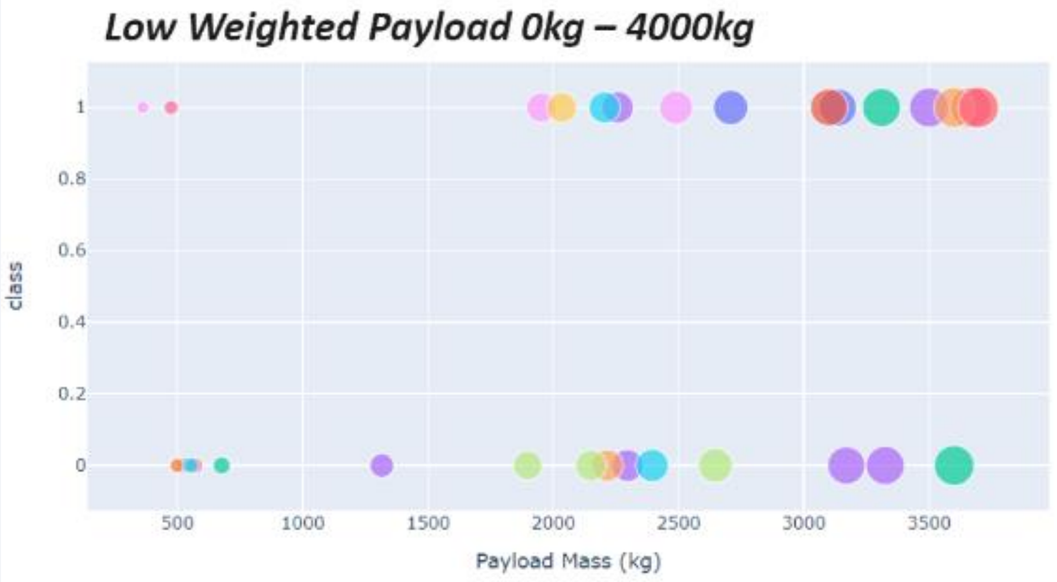
We can see that KSC LC-39A had the most successful launches from all the sites

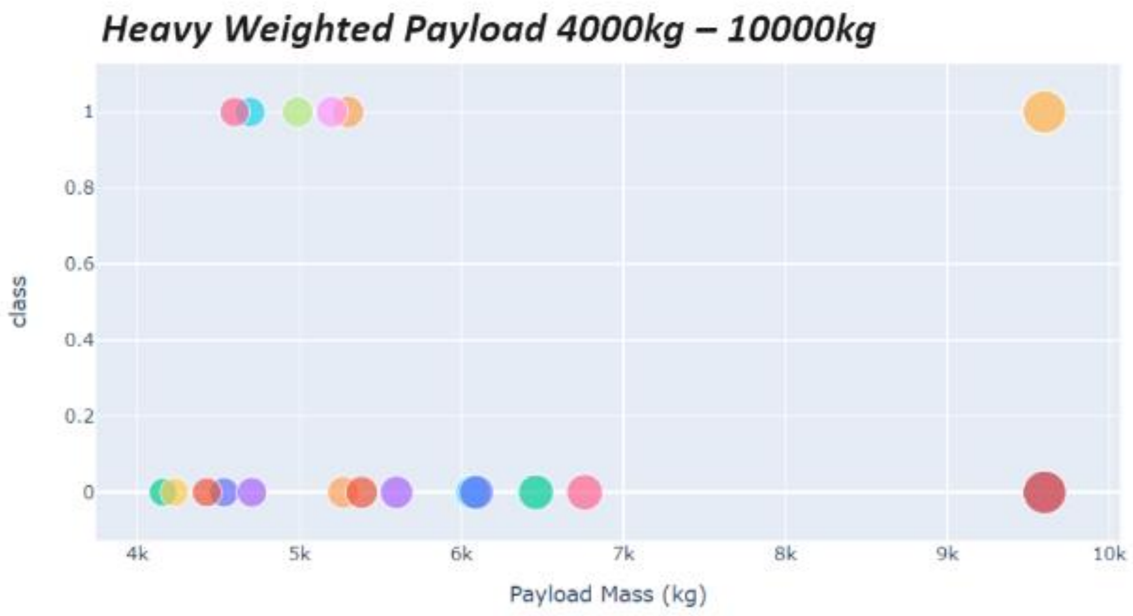
Pie chart showing the Launch site with the highest launch success ratio



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 5

Predictive Analysis (Classification)

Classification Accuracy

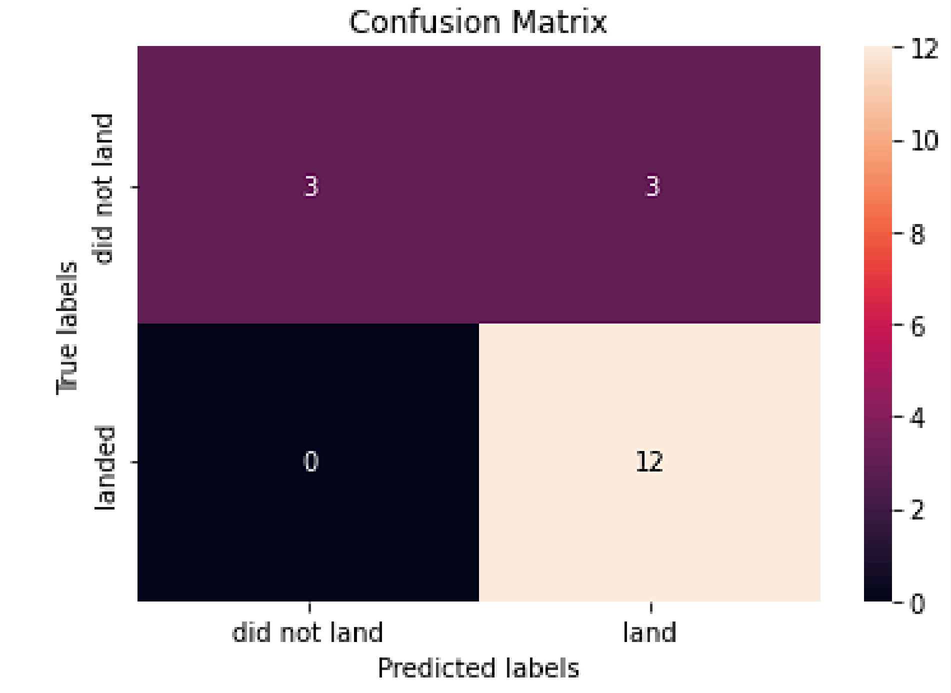
- The method performs best practically are the same.

```
print('Accuracy for Logistics Regression method:', logreg_cv.score(X_test, Y_test))
print( 'Accuracy for Support Vector Machine method:', svm_cv.score(X_test, Y_test))
print('Accuracy for Decision tree method:', tree_cv.score(X_test, Y_test))
print('Accuracy for K nearsdt neighbors method:', knn_cv.score(X_test, Y_test))
```

```
Accuracy for Logistics Regression method: 0.8333333333333334
Accuracy for Support Vector Machine method: 0.8333333333333334
Accuracy for Decision tree method: 0.8333333333333334
Accuracy for K nearsdt neighbors method: 0.8333333333333334
```

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.

Appendix

- Python
- SQL
- Jupiter Notebooks
- IBM DB2
- Space X Data set

Thank you!