IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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Executive Summary

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  - Data Wrangling
  - Exploratory Data Analysis with SQL
  - Exploratory Data Analysis with Data Visualization
  - Interactive Visual Analytics with Folium
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Introduction

SpaceX has revolutionized the space industry by offering rocket launches, specifically with the Falcon 9, at prices as low as $62 million. In contrast, other providers charge upwards of $165 million per launch. This significant cost reduction is largely due to SpaceX's innovative approach of reusing the first stage of their rockets by landing them back on Earth for future missions. This reuse strategy not only lowers costs but also has the potential to reduce prices even further with repeated use.

The goal of this project is to develop a machine learning pipeline to predict the landing outcomes of the first stage in future missions. This project is essential for determining the optimal price to bid against SpaceX for rocket launches.

The key challenges include:

- Identifying all factors that influence the landing outcome.
- Understanding the relationships between these variables and their impact on the outcome.
- Determining the best conditions to increase the probability of a successful landing.

Section 1

Methodology

Methodology

Executive Summary

- Data collection methodology:
  - Data was collected using SpaceX REST API and web scrapping from Wikipedia
- Perform data wrangling
  - Data was processed using one-hot encoding for 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

Executive Summary

- Data collection involves gathering and measuring information on specific variables within a system to answer questions and evaluate outcomes. In this case, the dataset was collected using REST API and web scraping from Wikipedia.
- For the REST API, We started with a GET request. The response content was decoded as JSON and converted into a pandas DataFrame using json_normalize(). The data was then cleaned, missing values were checked, and necessary adjustments were made.
- For web scraping, We used BeautifulSoup to extract launch records from an HTML table on Wikipedia. The table was parsed and converted into a pandas DataFrame for further analysis.

Data Collection – SpaceX API

Get request for rocket launch data using API

Use json_normalize method to convert json result to dataframe

Performed data cleaning and filling the missing value

From : https://github.com/shrutinidhi/Applied-Data-Science-Capstone-Winning-Space-Race/blob/main/jupyter-labs-spacex-data-collection-api.ipynb

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

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

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

```
# Lets take a subset of our dataframe keeping only the features we want a
nd the flight number, and date_utc.
data = data[['rocket', 'payloads', 'launchpad', 'cores', 'flight_number',
'date_utc']]

# We will remove rows with multiple cores because those are falcon rocket
s with 2 extra rocket boosters and rows that have multiple payloads in a
single rocket.
data = data[data['cores'].map(len)==1]
data = data[data['payloads'].map(len)==1]

# Since payloads and cores are lists of size 1 we will also extract the s
ingle value in the list and replace the feature.
data['cores'] = data['cores'].map(lambda x : x[0])
data['payloads'] = data['payloads'].map(lambda x : x[0])

# We also want to convert the date_utc to a datetime datatype and then ex
tracting the date leaving the time
data['date'] = pd.to_datetime(data['date_utc']).dt.date

# Using the date we will restrict the dates of the launches
data = data[data['date'] <= datetime.date(2020, 11, 13)]
```

Data Collection - Scraping

Request the Falcon9 Launch Wiki page from url

Create a BeautifulSoup from the HTML response

Extract all column/variable names from the HTML header

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

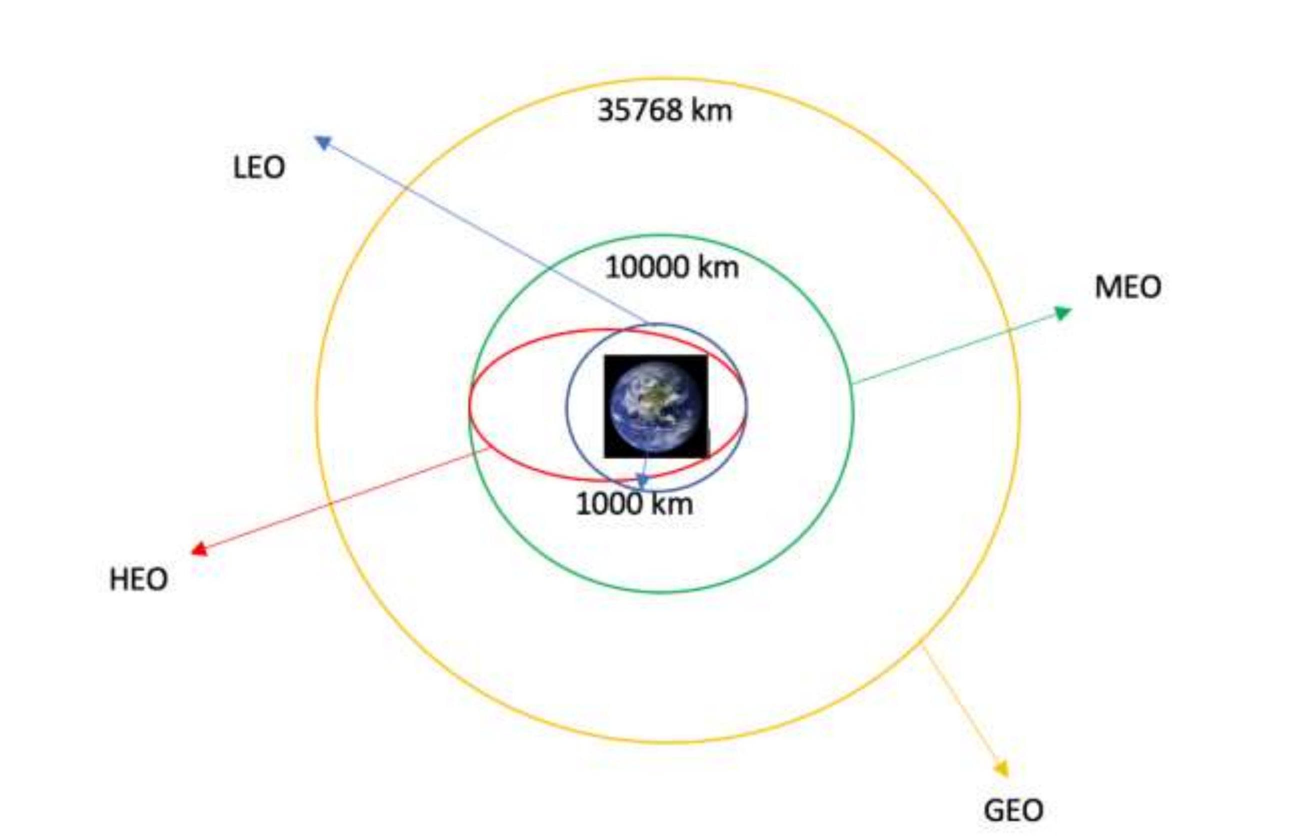
```
# Use BeautifulSoup() to create a BeautifulSoup object from a response text content
soup = BeautifulSoup(data,'html.parser')
```

```
extracted_row = 0
#Extract each table
for table_number,table in enumerate(soup.find_all('table',"wikitable plainrowheaders collapsible")):
    # get table row
    for rows in table.find_all("tr"):
        #check to see if first table heading is as number corresponding to launch a number
        if rows.th:
            if rows.th.string:
                flight_number=rows.th.string.strip()
                flag=flight_number.isdigit()
        else:
            flag=False
        #get table element
        row=rows.find_all('td')
        #if it is number save cells in a dictonary
        if flag:
            extracted_row += 1
            # Flight Number value
            launch_dict['Flight No.'].append(flight_number)
            # TODO: Append the flight_number into launch_dict with key `Flight No.`
            #print(flight_number)
            print(flight_number)
            datatimelist=date_time(row[0])

            # Date value
            # TODO: Append the date into launch_dict with key `Date`
            date = datatimelist[0].strip(',')
```

From : https://github.com/shrutinidhi/Applied-Data-Science-Capstone-Winning-Space-Race/blob/main/jupyter-labs-webscraping.ipynb

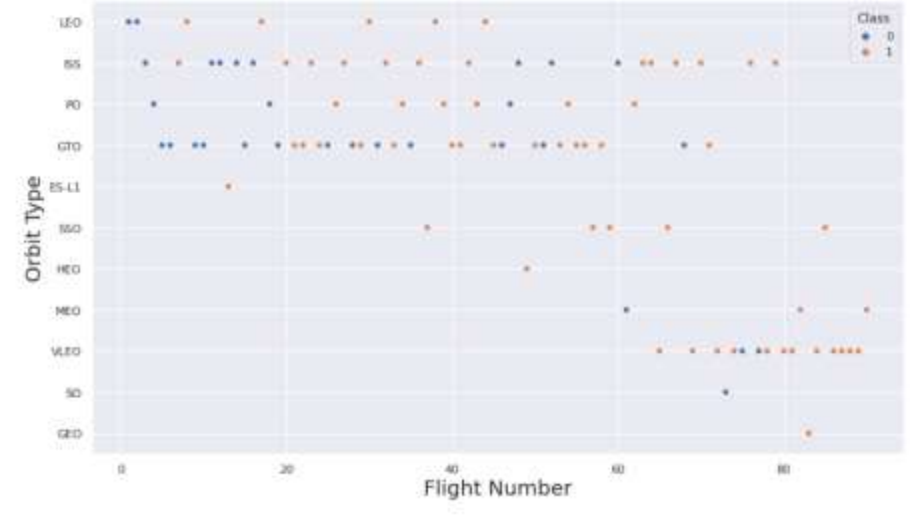
Data Collection - Wrangling

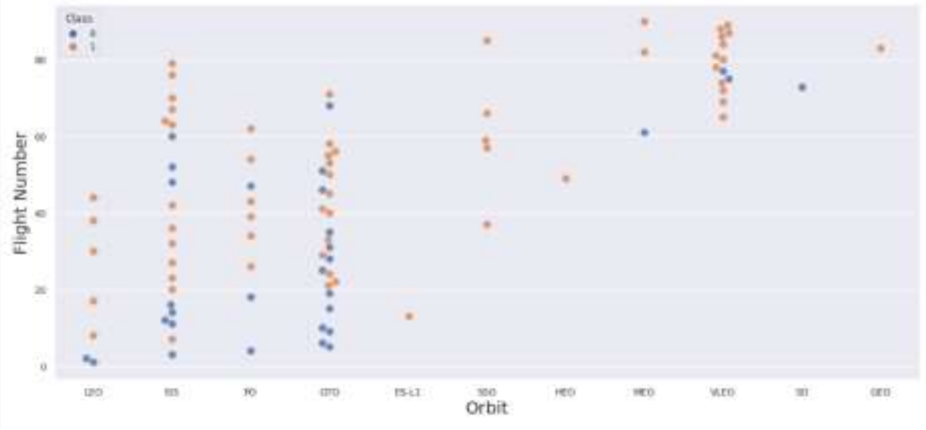


From : https://github.com/shrutinidhi/Applied-Data-Science-Capstone-Winning-Space-Race/blob/main/labs-jupyter-spacex-Data%20wrangling.ipynb

- Data Wrangling is the process of cleaning and unifying messy and complex data sets for easy access and Exploratory Data Analysis (EDA)
- We will first calculate the number of launches on each site, then calculate the number and occurrence of mission outcome per orbit type.
- We then create a landing outcome label from the outcome column. This will make it easier for further analysis, visualization, and ML. Lastly, we will export the result to a CSV.

EDA with Data Visualization





We first started by using scatter graph to find the relationship
between the attributes such as between:

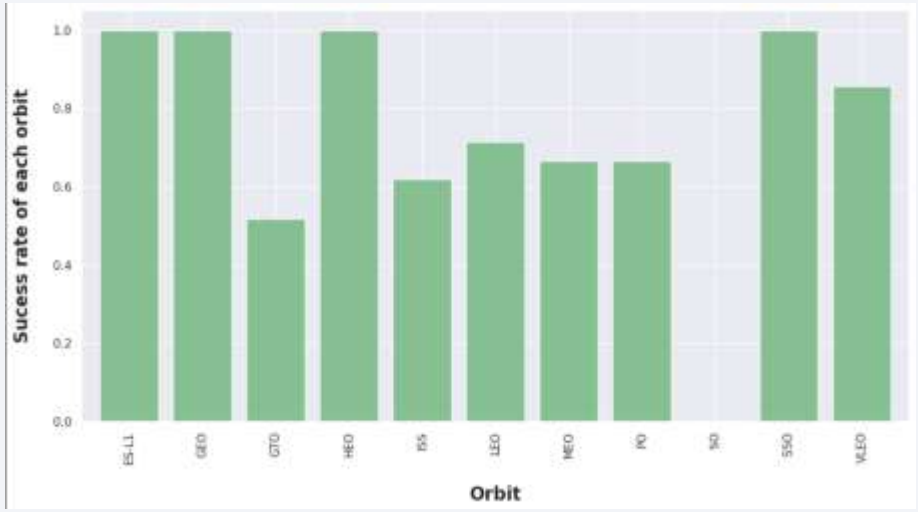
- Payload and Flight Number.
- Flight Number and Launch Site.
- Payload and Launch Site.
- Flight Number and Orbit Type.
- Payload and Orbit Type.

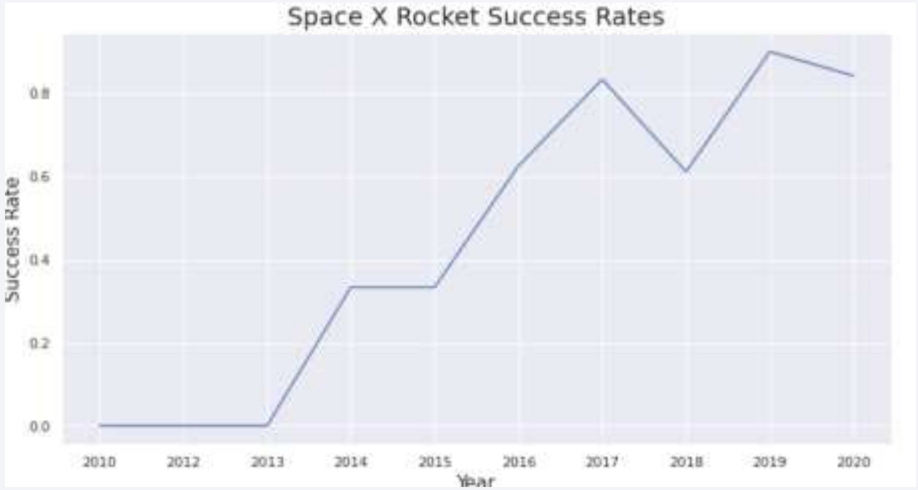
Scatter plots show dependency of attributes on each other.

Once a pattern is determined from the graphs. It’s very easy to see which factors affecting the most to the success of the landing outcomes

From : https://github.com/shrutinidhi/Applied-Data-Science-Capstone-Winning-Space-Race/blob/main/labs-jupyter-data-visualization.ipynb

EDA with Data Visualization





Once we get a hint of the relationships using scatter plot. We will then use further visualization tools such as bar graph and line plots graph for further analysis.

Bar graphs is one of the easiest way to interpret the relationship between the attributes. In this case, we will use the bar graph to determine which orbits have the highest probability of success.

We then use the line graph to show a trends or pattern of the attribute over time which in this case, is used for see the launch success yearly trend.

We then use Feature Engineering to be used in success prediction in the future module by created the dummy variables to categorical columns.

EDA with SQL

Using SQL, we had performed many queries to get better understanding of the dataset, Ex:

- Displaying the names of the launch sites.
- Displaying 5 records where launch sites begin with the string 'CCA'.
- Displaying the total payload mass carried by booster launched by NASA (CRS).
- Displaying the average payload mass carried by booster version F9 v1.1.
- Listing the date when the first successful landing outcome in ground pad was achieved.
- Listing the names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000.
- Listing the total number of successful and failure mission outcomes.
- Listing the names of the booster_versions which have carried the maximum payload mass.
- Listing the failed landing_outcomes in drone ship, their booster versions, and launch sites names for in year 2015.
- -Rank the count of landing outcomes or success between the date 2010-06-04 and 2017-03-20, in descending order.

From : https://github.com/shrutinidhi/Applied-Data-Science-Capstone-Winning-Space-Race/blob/main/jupyter-labs-eda-sql-coursera_sqllite.ipynb

Build an Interactive Map with Folium

- To visualize the launch data into an interactive map. We took the latitude and longitude coordinates at each launch site and added a circle marker around each launch site with a label of the name of the launch site.
- We then assigned the dataframe launch_outcomes(failure,success) to classes 0 and 1 with Red and Green markers on the map in MarkerCluster().
- We then used the Haversine's formula to calculated the distance of the launch sites to various landmark to find answer to the questions of:
- How close the launch sites with railways, highways and coastlines?
- How close the launch sites with nearby cities?

From : https://github.com/shrutinidhi/Applied-Data-Science-Capstone-Winning-Space-Race/blob/main/jupyter_Interactive_Visual_Analytics_with_Folium.ipynb

Build a Dashboard with Plotly Dash

- We built an interactive dashboard with Plotly dash which allowing the user to play around with the data as they need.
- We plotted pie charts showing the total launches by a certain sites.
- We then plotted scatter graph showing the relationship with Outcome and Payload Mass (Kg) for the different booster version.

From : https://github.com/shrutinidhi/Applied-Data-Science-Capstone-Winning-Space-Race/blob/main/spacex_dash_app.py

Predictive Analysis (Classification)

Building the Model

- Load the dataset into NumPy and Pandas
- Transform the data and then split into training and test datasets
- Decide which type of ML to use
- set the parameters and algorithms to GridSearchCV and fit it to dataset.

Evaluating the Model

- Check the accuracy for each model
- Get tuned hyperparameters for each type of algorithms.
- plot the confusion matrix.

Improving the Model

- Use Feature Engineering and Algorithm Tuning

Find the Best Model

- The model with the best accuracy score will be the best performing model.

From : https://github.com/shrutinidhi/Applied-Data-Science-Capstone-Winning-Space-Race/blob/main/spacex_dash_app.py

Results

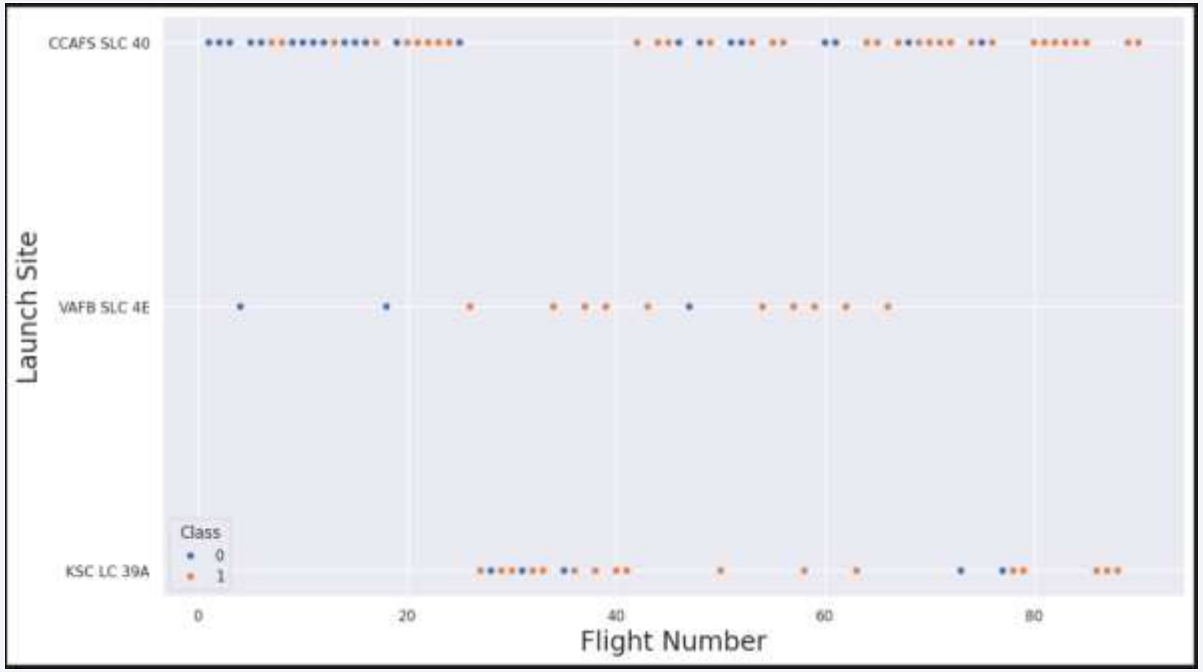
The results will be categorized to 3 main results which is:

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

Section 2

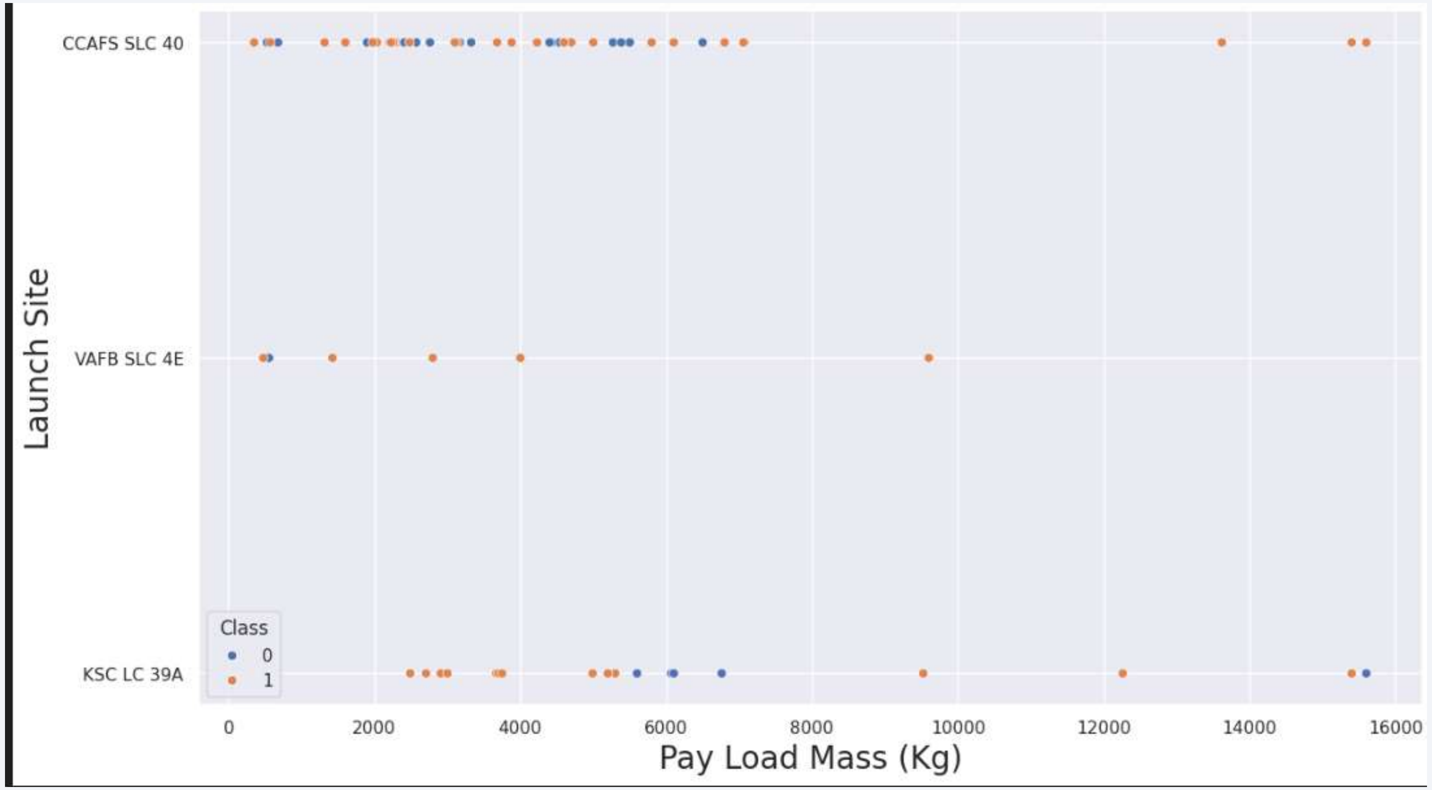
Insights drawn from EDA

Flight Number vs. Launch Site



This scatter plot shows that the larger the flights amount of the launch site, the greater the the success rate will be.
However, site CCAFS SLC40 shows the least pattern of this.

Payload vs. Launch Site



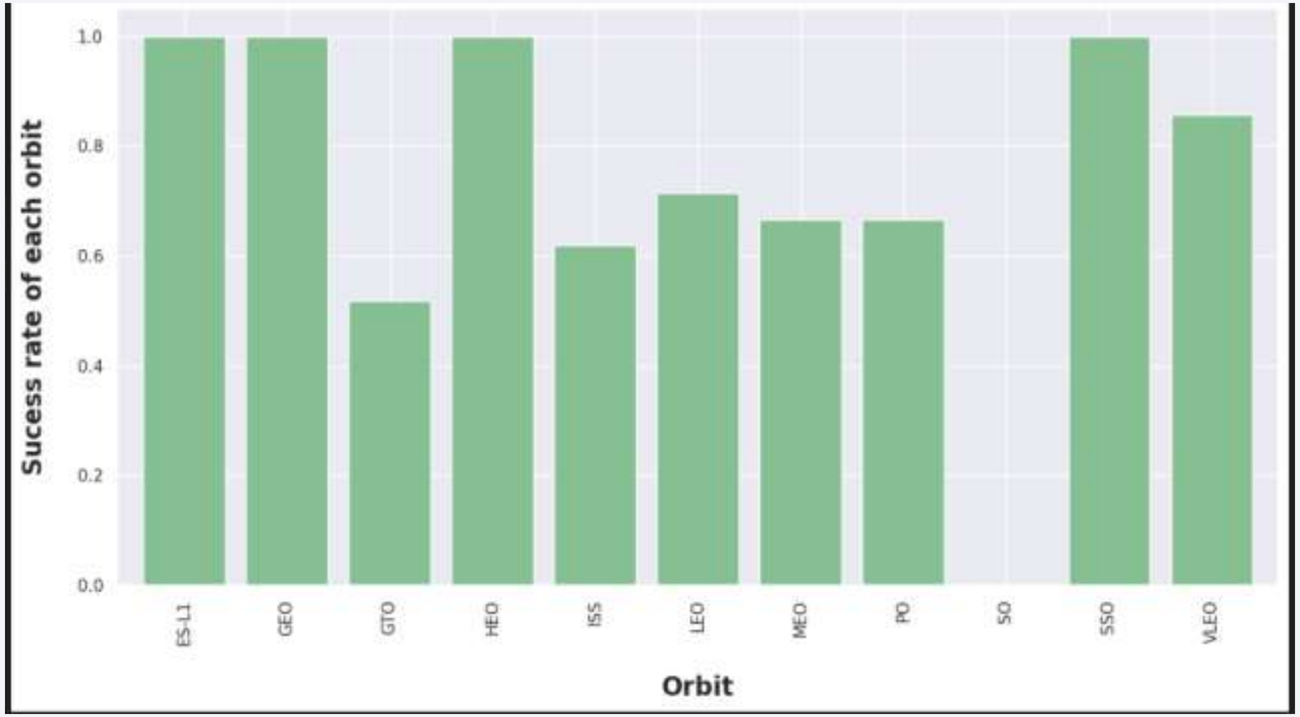
This scatter plot shows once the pay load mass is greater than 7000kg, the probability of the success rate will be highly increased.

However, there is no clear pattern to say the launch site is dependent to the pay load mass for the success rate.

Success Rate vs. Orbit Type

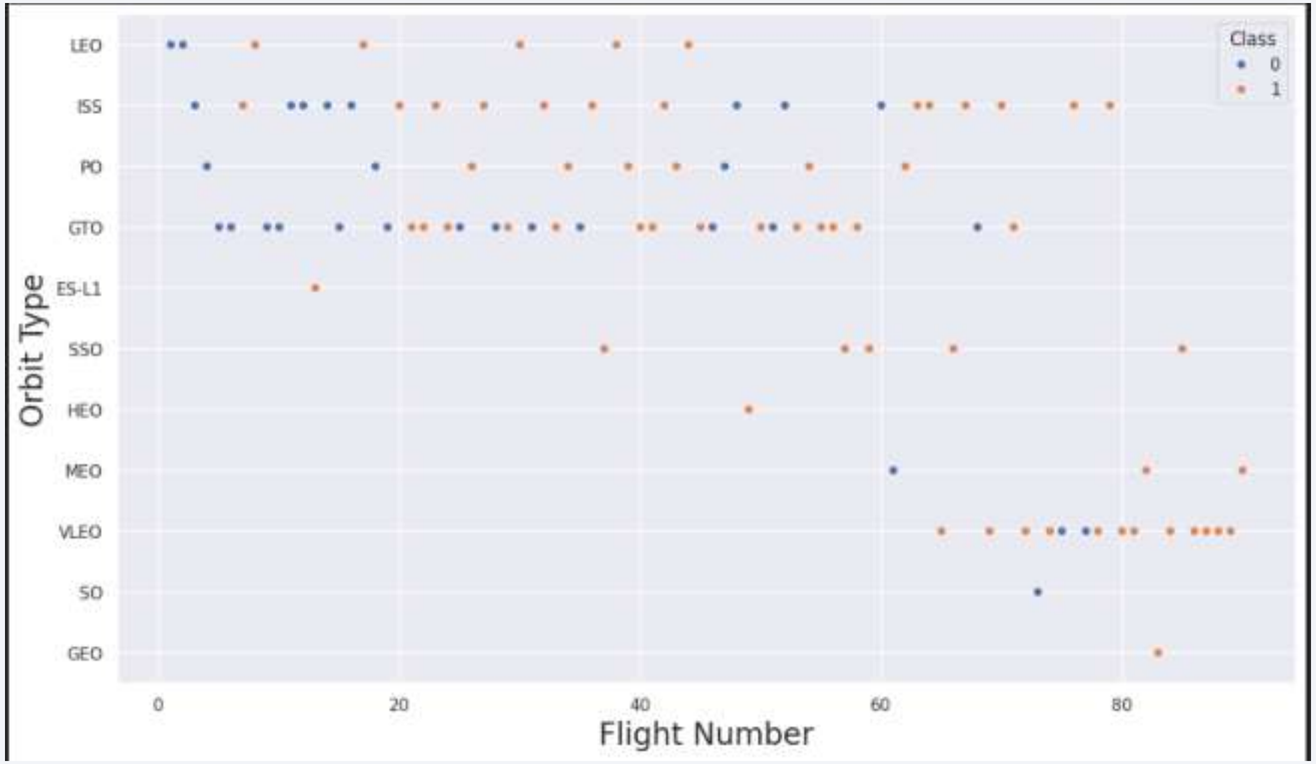
This figure depicted the possibility of the orbits to influences the landing outcomes as some orbits has 100% success rate such as SSO, HEO, GEO AND ES-L1 while SO orbit produced 0% rate of success.

However, deeper analysis show that some of this orbits has only 1 occurrence such as GEO, SO, HEO and ES-L1 which mean this data need more dataset to see pattern or trend before we draw any conclusion.



Flight Number vs. Orbit Type

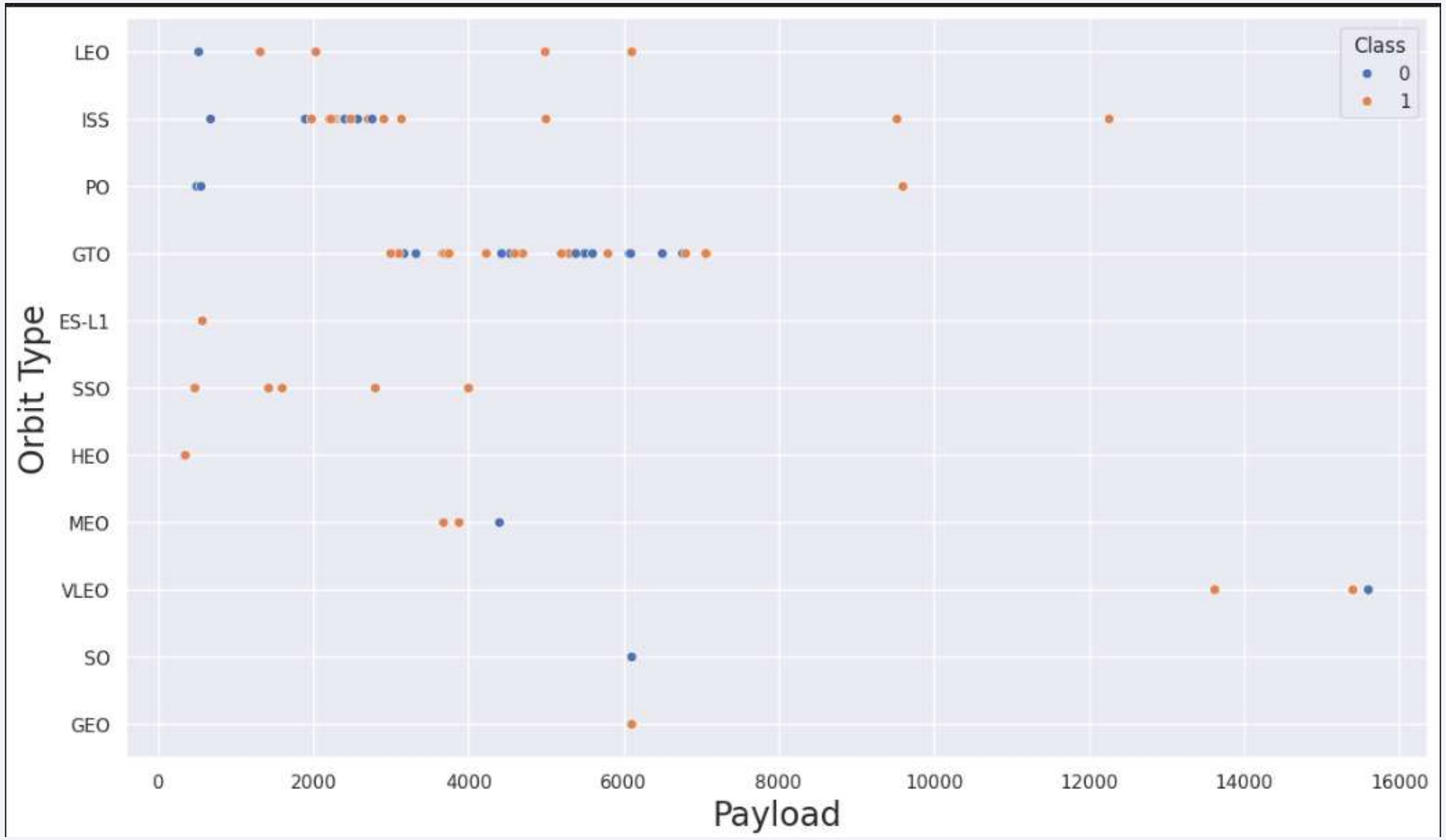
This scatter plot shows that generally, the larger the flight number on each orbits, the greater the success rate (especially LEO orbit) except for GTO orbit which depicts no relationship between both attributes.
Orbit that only has 1 occurrence should also be excluded from above statement as it's needed more dataset.



Payload vs. Orbit Type

Heavier payload has positive impact on LEO, ISS and P0 orbit. However, it has negative impact on MEO and VLEO orbit.

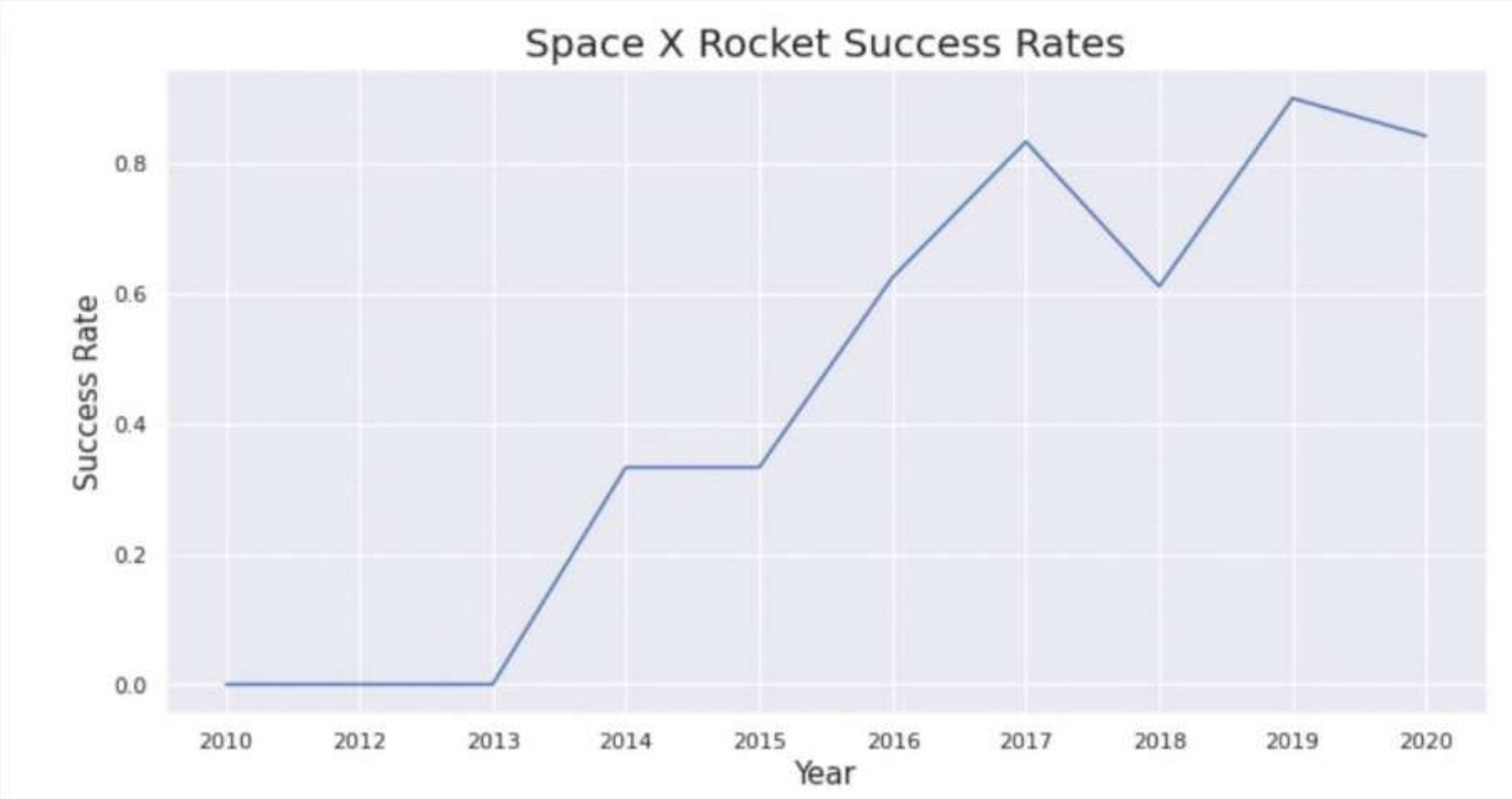
GTO orbit seem to depict no relation between the attributes. Meanwhile, again, SO, GEO and HEO orbit need more dataset to see any pattern or trend.



Launch Success Yearly Trend

This figures clearly depicted and increasing trend from the year 2013 until 2020.

If this trend continue for the next year onward. The success rate will steadily increase until reaching 1/100% success rate.



All Launch Site Names

- We used the key word DISTINCT to show only unique launch sites from the SpaceX data.

In [5]:
```
%sql SELECT DISTINCT LAUNCH_SITE as "Launch_Sites" FROM SPACEX;
```

```
 * ibm_db_sa://zpw86771:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.c1ogj3
sd0tgtu0lqde00.databases.appdomain.cloud:32731/bludb
Done.
```

Out[5]:

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

Launch Site Names Begin with 'CCA'

- We used the query above to display 5 records where launch sites 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

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)

```
%sql SELECT SUM(PAYLOAD_MASS__KG_) AS "Total Payload Mass by NASA (CRS)
```

```
 * ibm_db_sa://zpw86771:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.clogj3
sd0tgtu0lqde00.databases.appdomain.cloud:32731/bludb
Done.
```

Total Payload Mass by NASA (CRS)
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

```
%sql SELECT AVG(PAYLOAD_MASS__KG_) AS "Average Payload Mass by Booster
WHERE BOOSTER_VERSION = 'F9 v1.1';
```

```
 * ibm_db_sa://zpw86771:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.c1ogj3
sd0tgtu0lqde00.databases.appdomain.cloud:32731/bludb
Done.
```

Average Payload Mass by Booster Version F9 v1.1
2928

First Successful Ground Landing Date

- We use the min() function to find the result
- We observed that the dates of the first successful landing outcome on ground pad was 22nd December 2015

```
%sql SELECT MIN(DATE) AS "First Succesful Landing Outcome in Ground Pad
WHERE LANDING__OUTCOME = 'Success (ground pad)';
```

```
 * ibm_db_sa://zpw86771:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.clogj3
sd0tgtu0lqde00.databases.appdomain.cloud:32731/bludb
Done.
```

First Succesful Landing Outcome in Ground Pad
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

```
%sql SELECT BOOSTER_VERSION FROM SPACEX WHERE LANDING__OUTCOME = 'Success (drone ship)' \
AND PAYLOAD_MASS__KG_ > 4000 AND PAYLOAD_MASS__KG_ < 6000;
```

```
 * ibm_db_sa://zpw86771:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.c1ogj3sd0tgtu0lqde00.datab
ases.appdomain.cloud:32731/bludb
Done.
```

booster_version
F9 FT B1022
F9 FT B1026
F9 FT B1021.2
F9 FT B1031.2

Total Number of Successful and Failure Mission Outcomes

List the total number of successful and failure mission outcomes

```
%sql SELECT COUNT(MISSION_OUTCOME) AS "Successful Mission" FROM SPACEX WHERE MISSION_OUTCOME LIKE 'Success%';
```

```
 * ibm_db_sa://zpw86771:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:32731/bludb
Done.
```

Successful Mission
100

```
%sql SELECT COUNT(MISSION_OUTCOME) AS "Failure Mission" FROM SPACEX WHERE MISSION_OUTCOME LIKE 'Failure%';
```

```
 * ibm_db_sa://zpw86771:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.c1ogj3sd0tgtu0lqde00.databases.appdomain.clou
d:32731/bludb
Done.
```

Failure Mission
1

Boosters Carried Maximum Payload

```
%sql SELECT DISTINCT BOOSTER_VERSION AS "Booster Versions which carried the Maximum Payload Mass" FROM SPACEX
WHERE PAYLOAD_MASS__KG_ =(SELECT MAX(PAYLOAD_MASS__KG_) FROM SPACEX);
```

```
 * ibm_db_sa://zpw86771:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.clogj3sd0tgtu0lqde00.databases.appdomain.clou
d:32731/bludb
Done.
```

Booster Versions which carried the Maximum Payload Mass
F9 B5 B1048.4
F9 B5 B1048.5
F9 B5 B1049.4
F9 B5 B1049.5
F9 B5 B1049.7
F9 B5 B1051.3
F9 B5 B1051.4
F9 B5 B1051.6
F9 B5 B1056.4
F9 B5 B1058.3
F9 B5 B1060.2
F9 B5 B1060.3

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

```
%sql SELECT BOOSTER_VERSION, LAUNCH_SITE FROM SPACEX WHERE DATE LIKE '2015-%' AND \
LANDING__OUTCOME = 'Failure (drone ship)';
```

```
 * ibm_db_sa://zpw86771:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.c1ogj3sd0tgtu0lqde00.
databases.appdomain.cloud:32731/bludb
Done.
```

booster_version	launch_site
F9 v1.1 B1012	CCAFS LC-40
F9 v1.1 B1015	CCAFS LC-40

Rank Landing Outcomes Between 2010-06-04 and 2017-03-20

```
%sql SELECT LANDING__OUTCOME as "Landing Outcome", COUNT(LANDING__OUTCOME) AS "Total Count" FROM SPACEX \
WHERE DATE BETWEEN '2010-06-04' AND '2017-03-20' \
GROUP BY  LANDING__OUTCOME \
ORDER BY COUNT(LANDING__OUTCOME) DESC ;
```

```
 * ibm_db_sa://zpw86771:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.clogj3sd0tgtu0lqde00.databases.appdomain.c
loud:32731/bludb
Done.
```

Landing Outcome	Total Count
No attempt	10
Failure (drone ship)	5
Success (drone ship)	5
Controlled (ocean)	3
Success (ground pad)	3
Failure (parachute)	2
Uncontrolled (ocean)	2
Precluded (drone ship)	1

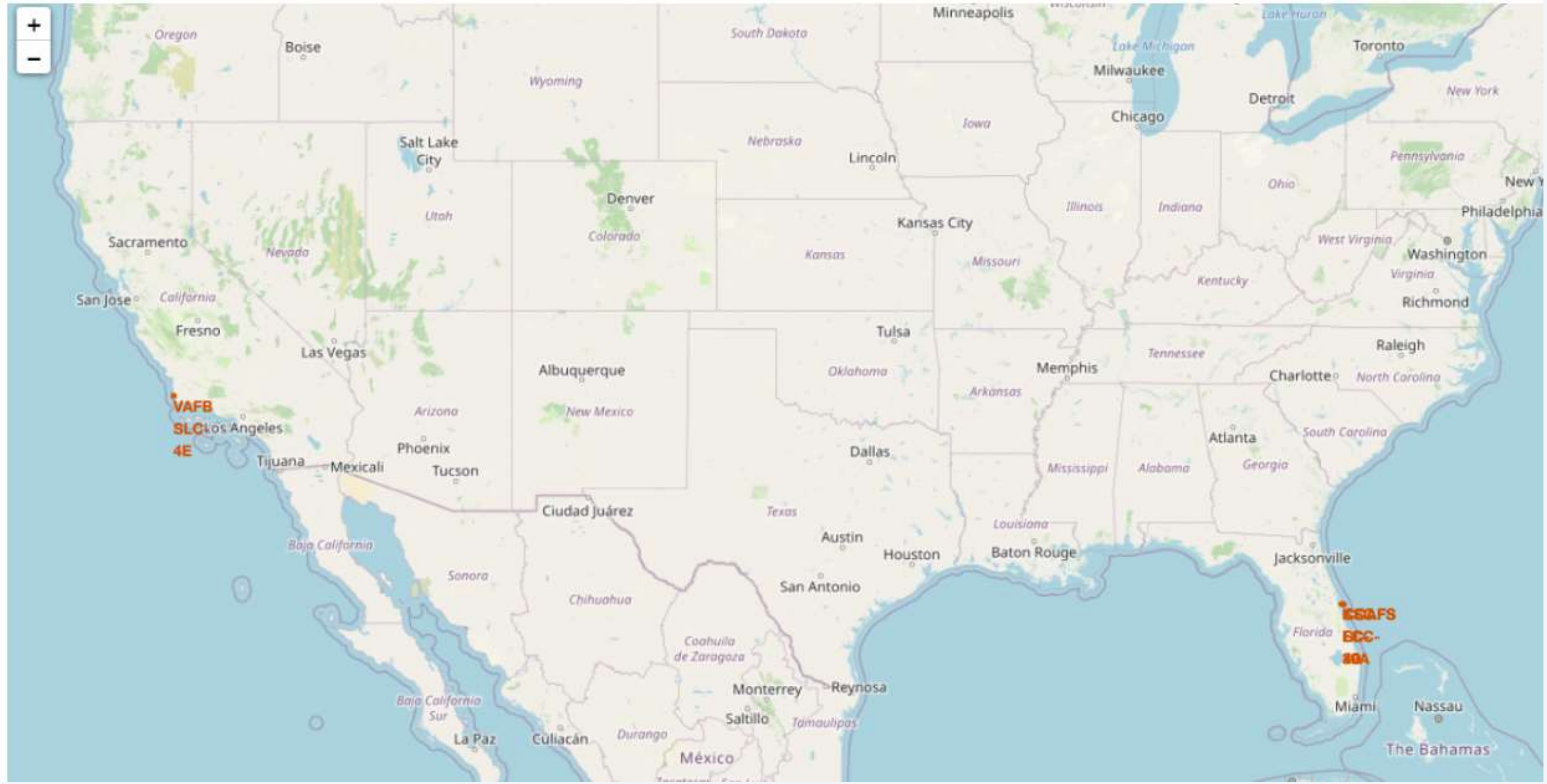
We selected Landing outcomes and the COUNT of landing outcomes from the data and used the WHERE clause to filter for landing outcomes BETWEEN 2010-06-04 to 2010-03-20.

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.

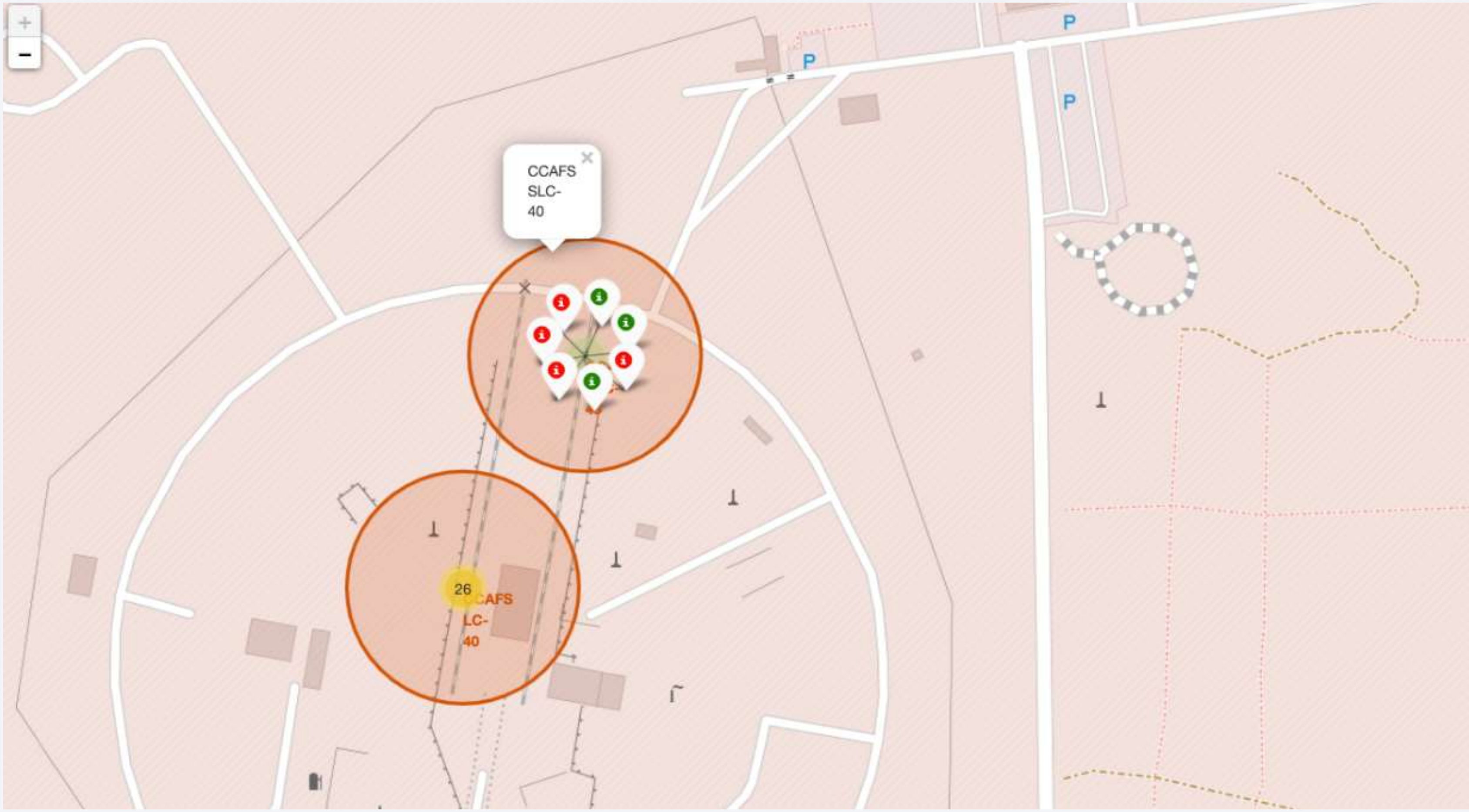
Section 3

Launch Sites Proximities Analysis

Location of all the Launch Sites



Markers showing launch sites with color labels



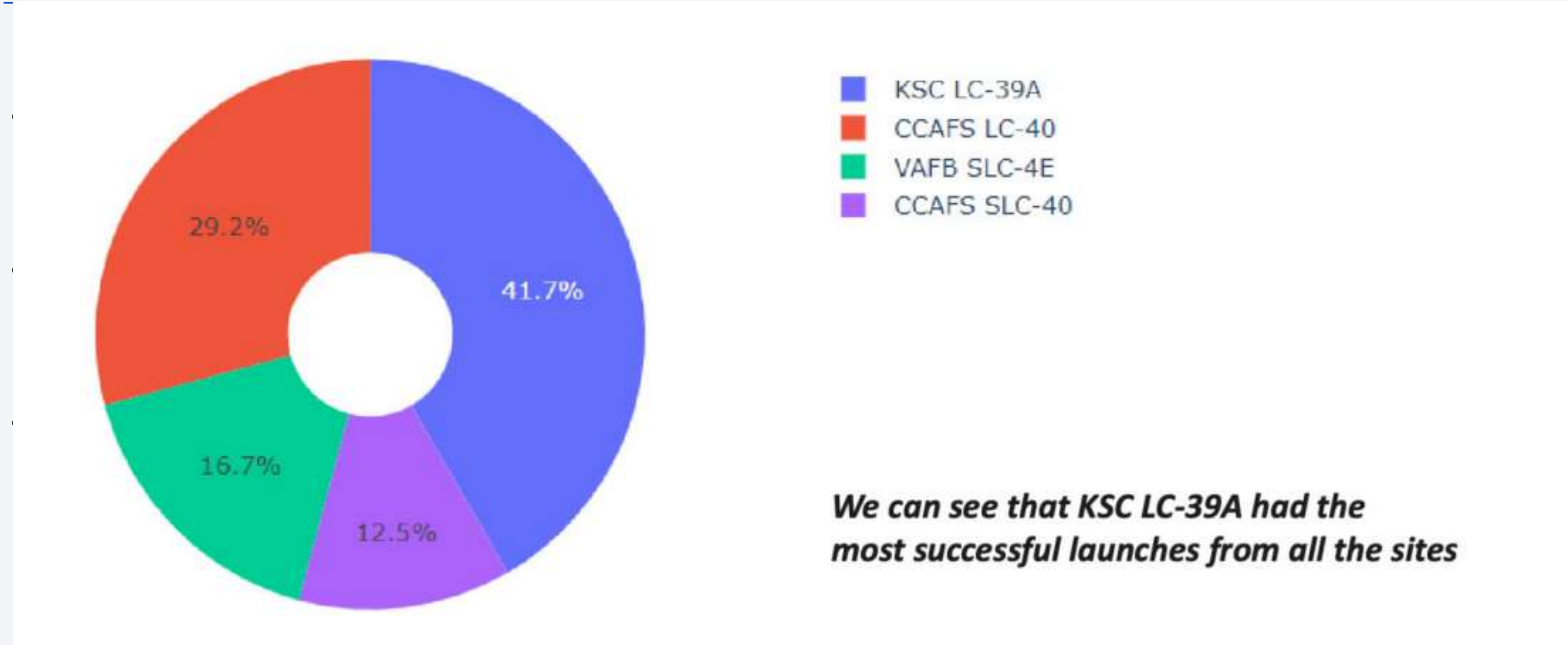
Launch Sites Distance to Landmarks

General

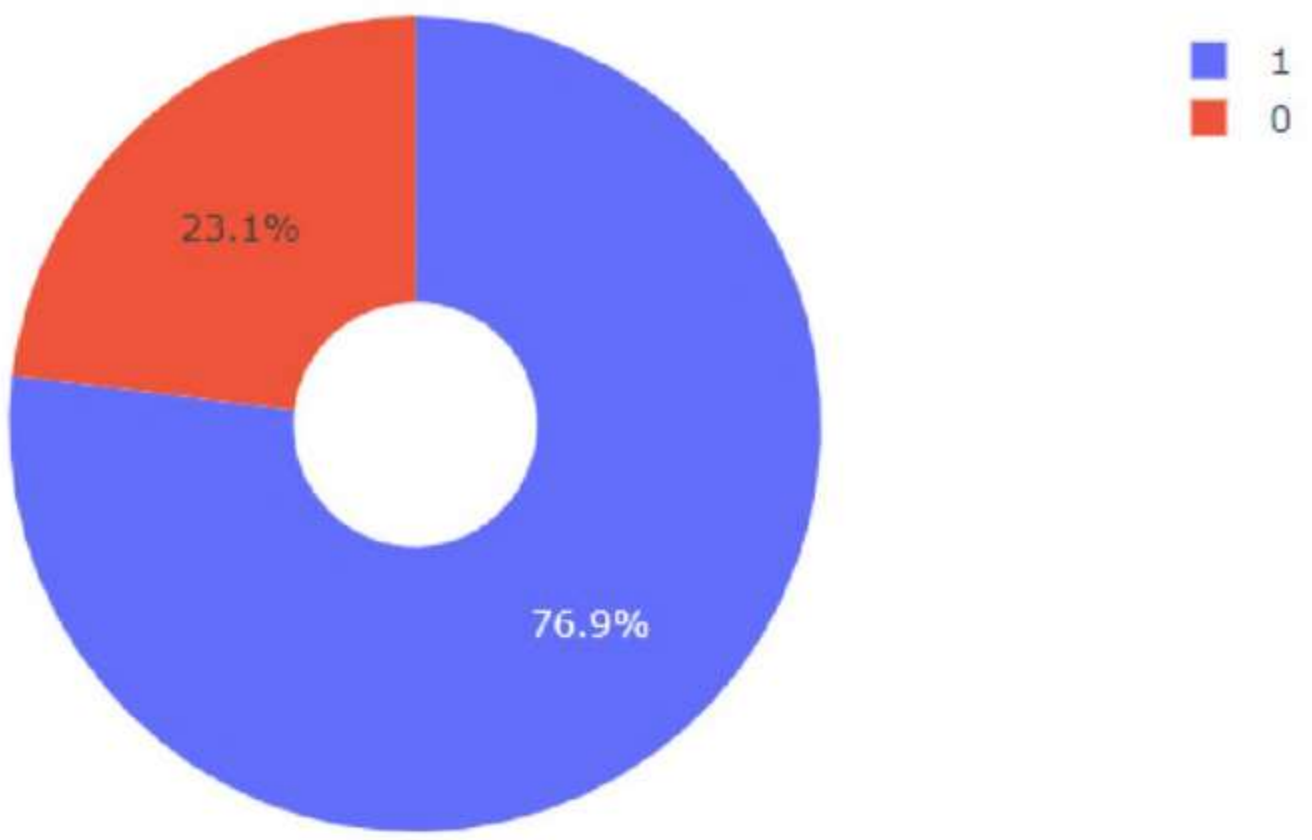
Section 4

Build a Dashboard with Plotly Dash

The success percentage by each sites

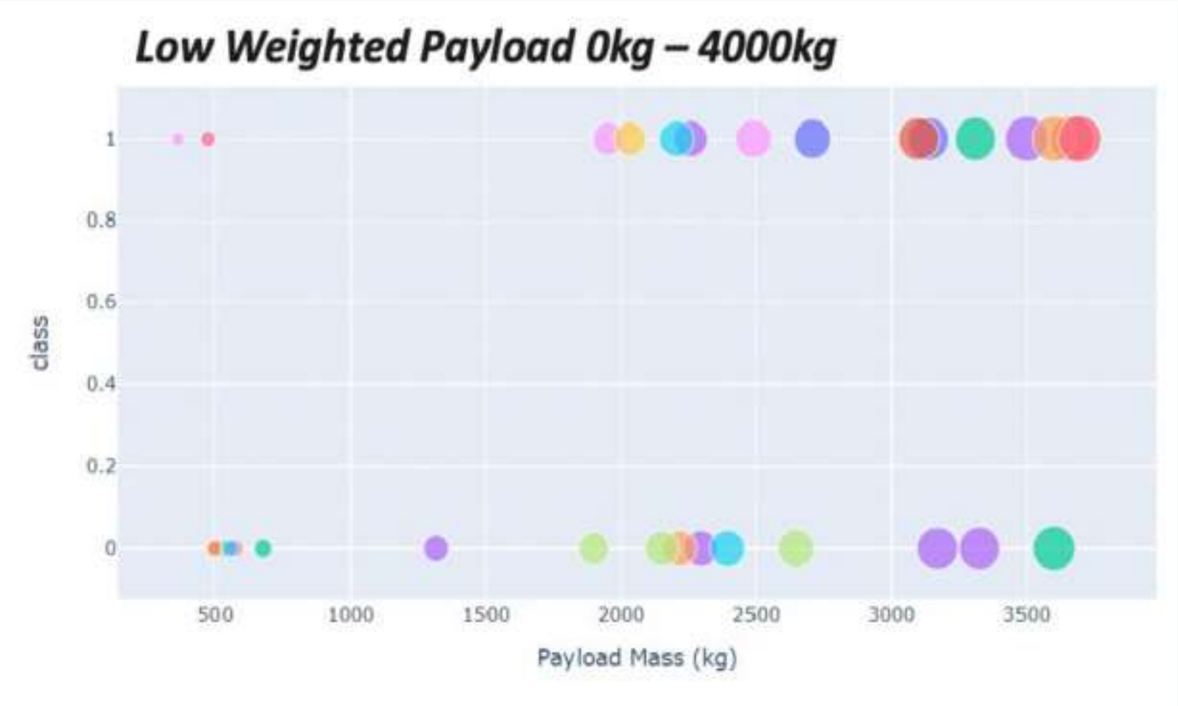


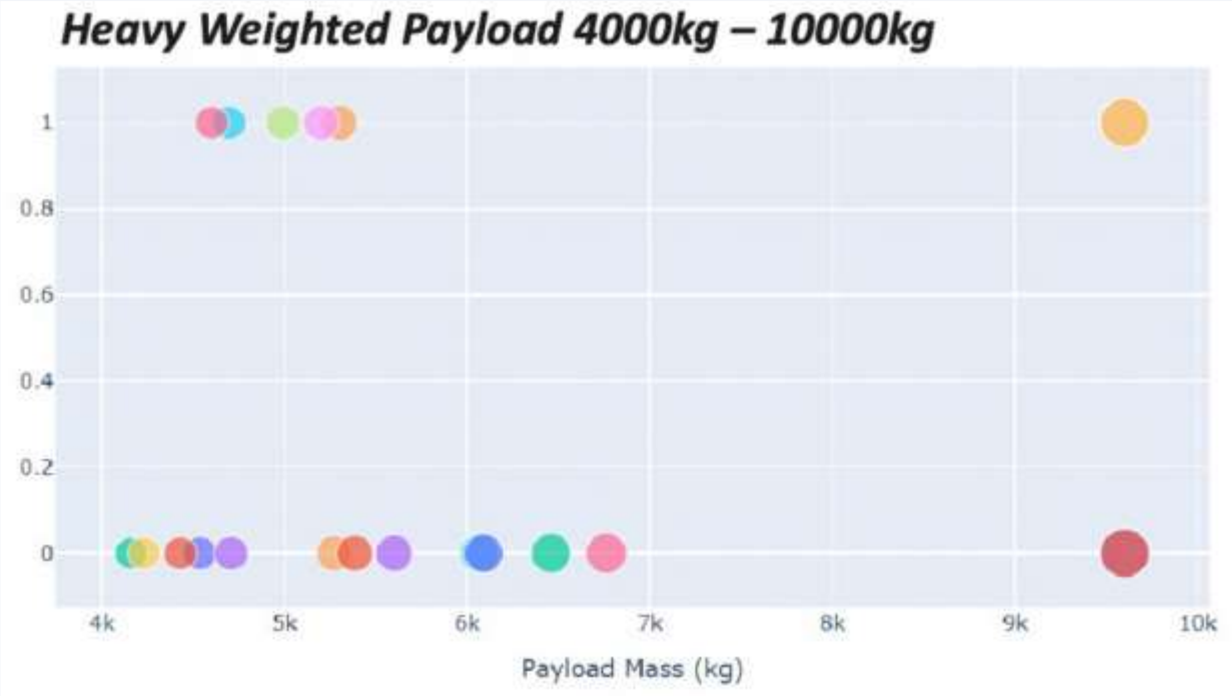
The highest launch-success ratio: KSC LC-39A



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

Payload vs Launch Outcome Scatter Plot





We can see that all the success rate for low weighted payload is higher than heavy weighted payload

Section 5

Predictive Analysis (Classification)

Classification Accuracy

- As we can see, by using the code as below: we could identify that the best algorithm to be the Tree Algorithm which have the highest classification accuracy

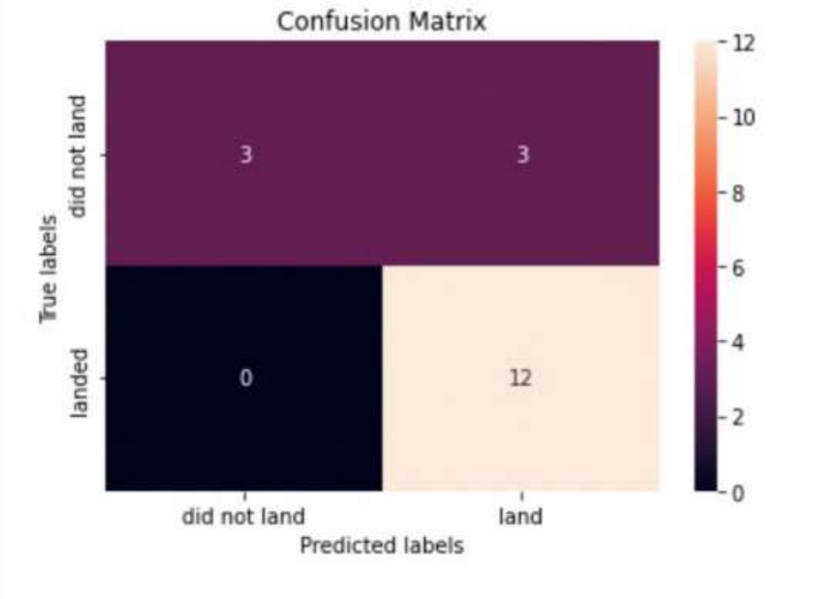
```python
algorithms = {'KNN':knn_cv.best_score_,'Tree':tree_cv.best_score_,'LogisticRegression':logreg_cv.best_score_}
bestalgorithm = max(algorithms, key=algorithms.get)
print('Best Algorithm is',bestalgorithm,'with a score of',algorithms[bestalgorithm])
if bestalgorithm == 'Tree':
    print('Best Params is :',tree_cv.best_params_)
if bestalgorithm == 'KNN':
    print('Best Params is :',knn_cv.best_params_)
if bestalgorithm == 'LogisticRegression':
    print('Best Params is :',logreg_cv.best_params_)
```

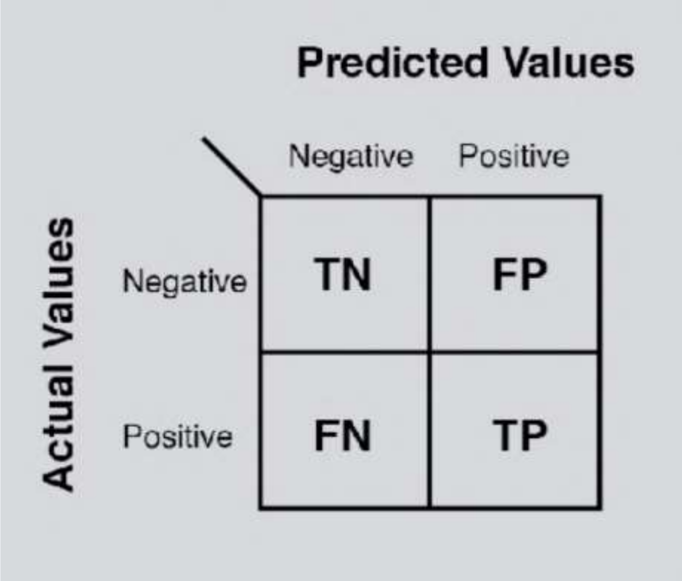
Pytho

```
Best Algorithm is Tree with a score of 0.9017857142857142
Best Params is : {'criterion': 'entropy', 'max_depth': 10, 'max_features': 'auto', 'min_samples_leaf': 2, 'min_samples_split': 10, '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 Tree Classifier Algorithm is the best Machine Learning approach for this dataset.
- The low weighted payloads (which define as 4000kg and below) performed better than the heavy weighted payloads.
- Starting from the year 2013, the success rate for SpaceX launches is increased, directly proportional time in years to 2020, which it will eventually perfect the launches in the future.
- KSC LC-39A have the most successful launches of any sites; 76.9%
- SSO orbit have the most success rate; 100% and more than 1 occurrence.

Thank you!