IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

Elia Broggio

07 October 2023

Outline

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- Results
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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
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Introduction

SpaceX has revolutionized the space industry by offering Falcon 9 rocket launches for as low as $62 million, a fraction of the competition's $165 million cost. Their innovative approach of reusing the first stage of the rocket significantly contributes to these savings. As a data scientist at a rival startup, our goal is to create a machine learning pipeline to predict first-stage landing outcomes for future missions, crucial for competitive bidding against SpaceX. Key challenges encompass:

- Identifying all factors influencing the landing outcome.
- Analyzing the relationships among variables and their impact on the outcome.
- Determining the ideal conditions to enhance the likelihood of a successful landing.

Section
1

Methodology

Methodology

Executive Summary

- Data collection methodology:
  - Data was collected using SpaceX REST API and web scraping 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

- Data collection involves gathering and measuring information on specific variables within an established system, enabling us to address pertinent questions and assess outcomes. In this context, the dataset was obtained through REST API requests and web scraping from Wikipedia.
- For REST API data collection, we initiated the process with a GET request. Subsequently, we decoded the response content as JSON and converted it into a Pandas dataframe using json_normalize(). Following this, data cleaning was performed, addressing missing values as required.
- In the case of web scraping, we employed BeautifulSoup to extract launch records in the form of an HTML table. We then parsed and converted this table into a Pandas dataframe, facilitating further analysis.

Data Collection – SpaceX API

Get request for rocket launch data using API

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

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

Use json_normalize method to convert json result to dataframe

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

Performed data cleaning and filling the missing value

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

# We will remove rows with multiple cores because those are falcon rockets with 2 extra
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 single value in
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 extracting the d
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)]
```

From:
https://github.com/Eliab96/Applied-Data-Science-Capstone-SpaceX/blob/main/jupyter-labs-spacex-data-collection-api.ipynb

Data Collection - Scraping

Request the Falcon9 Launch Wiki page from url

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

Create a BeautifulSoup from the HTML response

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

Extract all column/variable names from the HTML header

```
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)
```

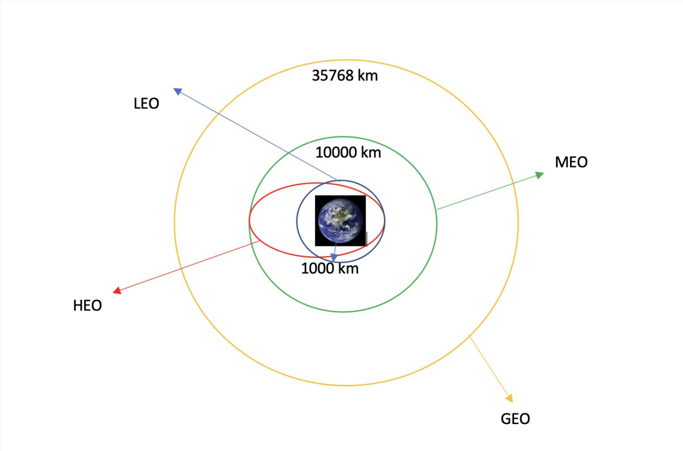
From:
https://github.com/Eliab96/Applied-Data-Science-Capstone-SpaceX/blob/main/jupyter-labs-webscraping.ipynb

Data Wrangling

Data Wrangling is the process of cleaning and unifying messy and complex data sets for easy access and Exploratory Data Analysis (EDA).

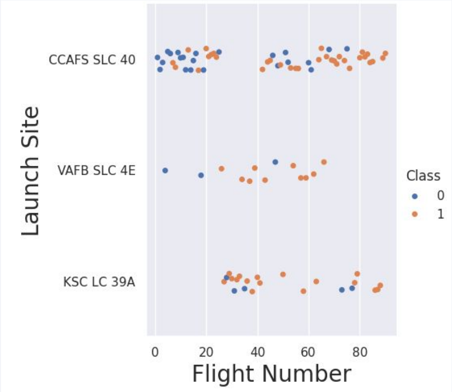
We will first calculate the number of launches on each site, then calculate the number and occurrence of mission outcome per orbit type.

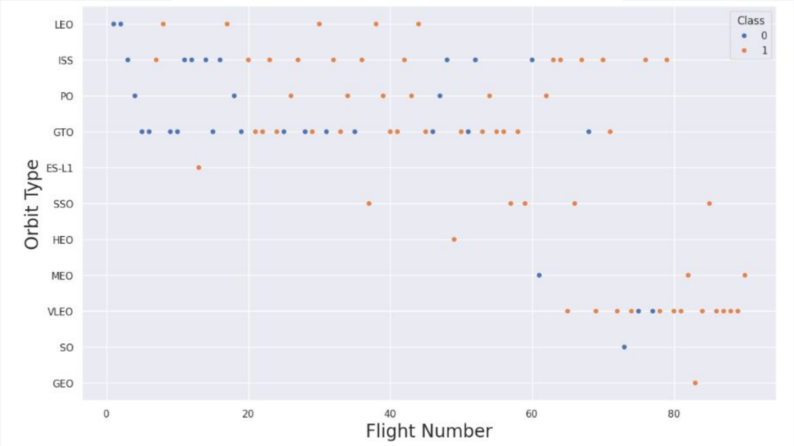
We then create a landing outcome label from the outcome column. This will make it easier for further analysis, visualization, and ML. Lastly, we will export the result to a CSV.



From:
https://github.com/Eliab96/Applied-Data-Science-Capstone-SpaceX/blob/main/1_L3_labs-jupyter-spacex-data_wrangling_jupyterlite.jupyterlite.ipynb

EDA with Data Visualization





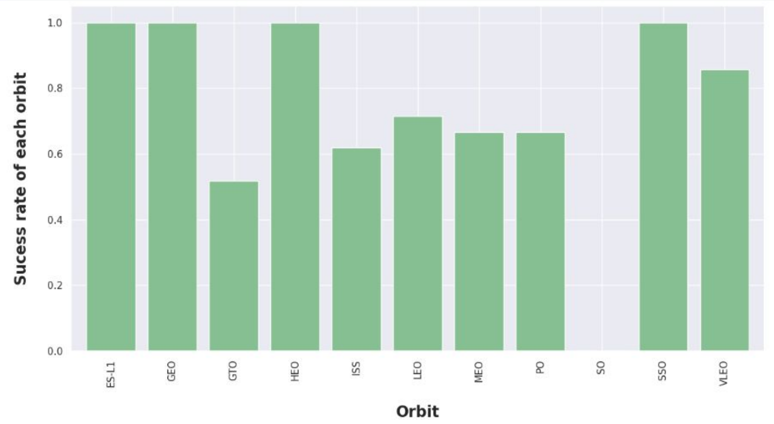
We first started by using scatter graph to find the relationship between the attributes such as between:

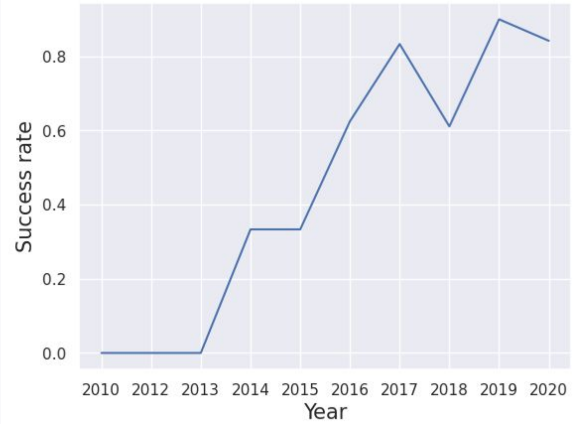
- Payload and Flight Number.
- Flight Number and Launch Site.
- Payload and Launch Site.
- Flight Number and Orbit Type.
- Payload and Orbit Type.

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.

https://github.com/Eliab96/Applied-Data-Science-Capstone-SpaceX/blob/main/2_jupyter-labs-eda-dataviz.ipynb.jupyterlite.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.

https://github.com/Eliab96/Applied-Data-Science-Capstone-SpaceX/blob/main/2_jupyter-labs-eda-dataviz.ipynb.jupyterlite.ipynb

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.

https://github.com/Eliab96/Applied-Data-Science-Capstone-SpaceX/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 calculate 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?

https://github.com/Eliab96/Applied-Data-Science-Capstone-SpaceX/blob/main/3_lab_jupyter_launch_site_location.jupyterlite.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.

https://github.com/Eliab96/Applied-Data-Science-Capstone-SpaceX/blob/main/spacex_dash_app.py

Predictive Analysis (Classification)

Build	Evaluate	Improve	Choose
• 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.	• Check the accuracy for each model • Get tuned hyperparameters for each type of algorithm • plot the confusion matrix.	• Use Feature Engineering and Algorithm Tuning	• The model with the best accuracy score will be the best performing model.

https://github.com/Eliab96/Applied-Data-Science-Capstone-SpaceX/blob/main/spacex_dash_app.py

Results

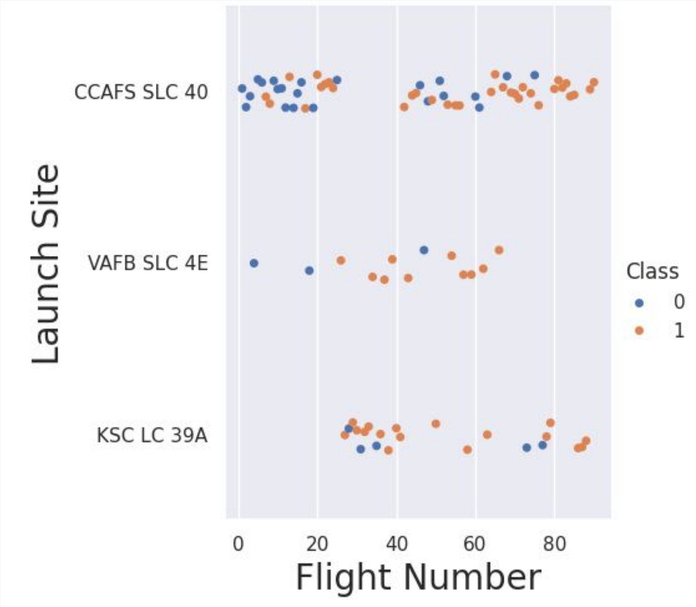
The results will be categorized to 3 main results which are:

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

Section 2

Insights drawn from EDA

Flight Number vs. Launch Site

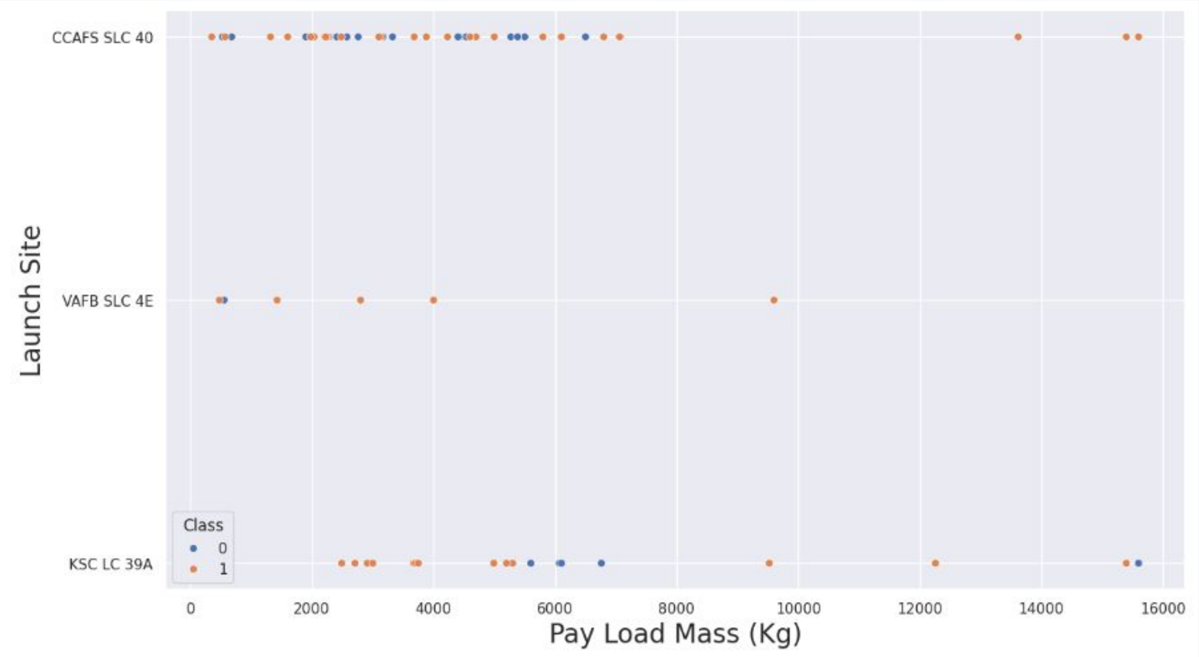


This scatter plot shows that the larger the flights amount of the launch site, the greater the the success rate will be. However, site CCAFS SLC40 shows the least pattern of this.

Payload vs. Launch Site

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

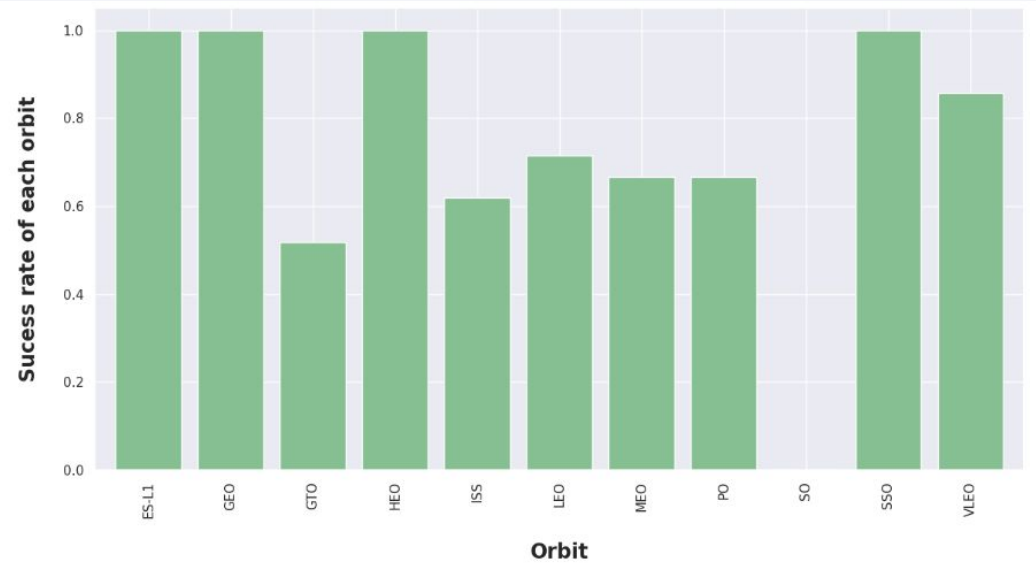
However, there is no clear pattern to say the launch site is dependent to the payload mass for the success rate.



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.

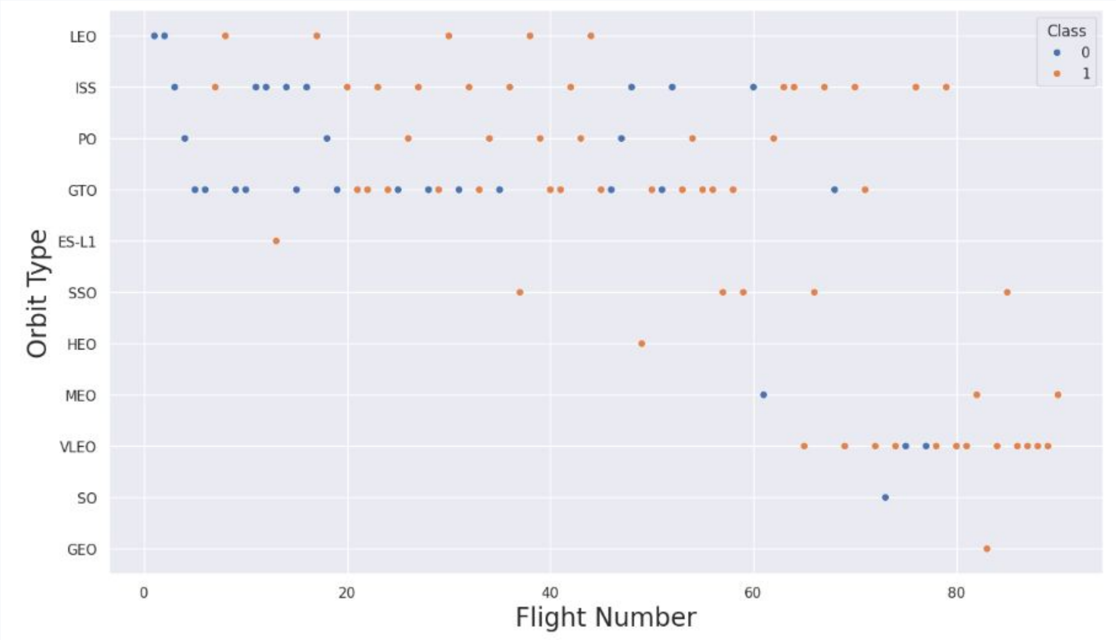
However, deeper analysis show that some of this orbits has only 1 occurrence such as GEO, SO, HEO and ES-L1 which mean this data need more dataset to see pattern or trend before we draw any conclusion.



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.

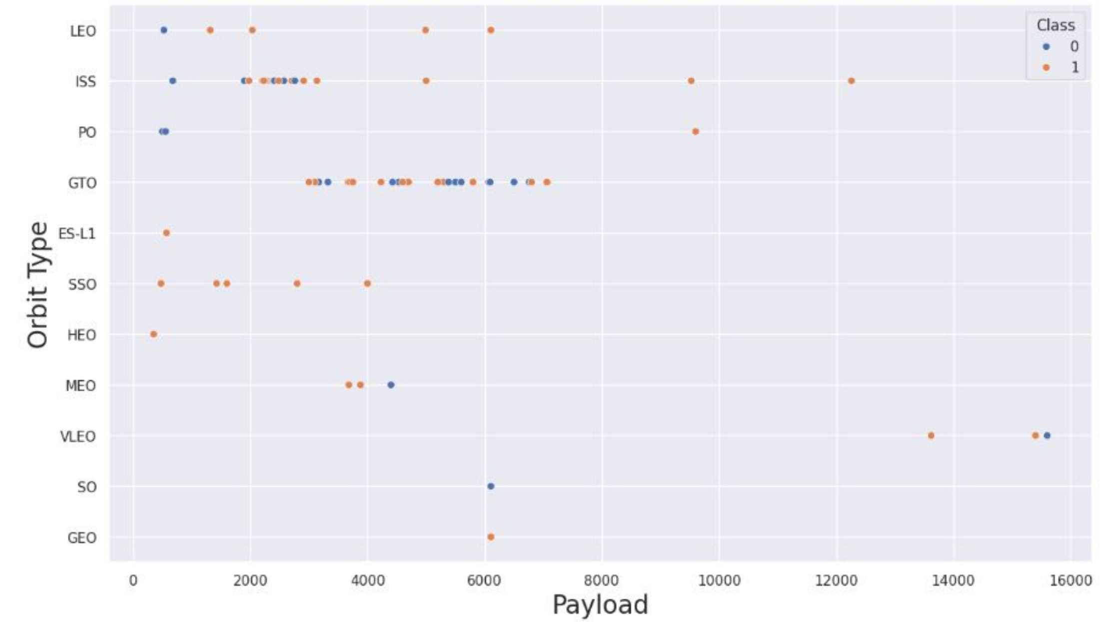


Payload vs. Orbit Type

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.

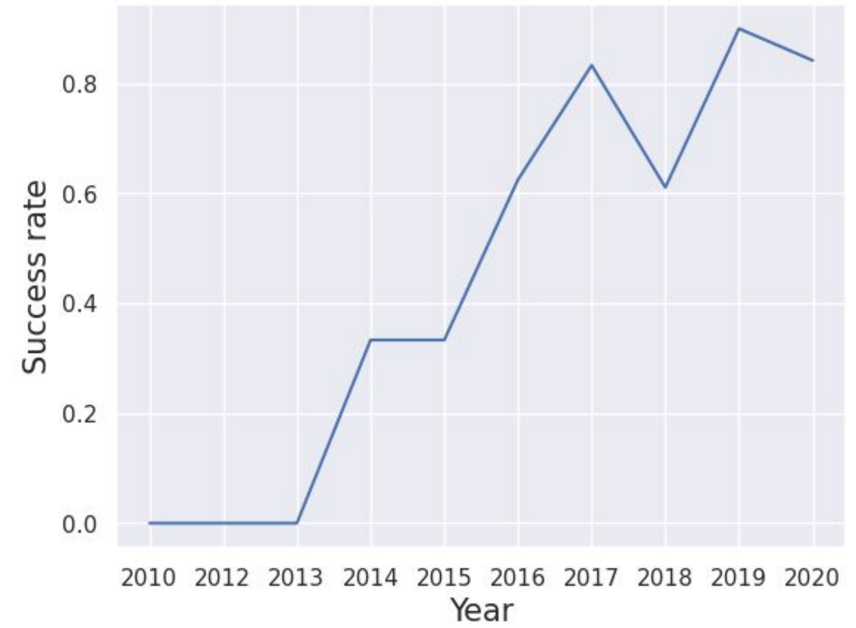
Meanwhile, again, SO, GEO and HEO orbit need more dataset to see any pattern or trend.



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 keyword DISTINCT to show only unique launch sites from the SpaceX data.

```
%sql SELECT DISTINCT LAUNCH_SITE as "Launch_Sites" FROM SPACEXTBL;
```

```
 * sqlite:///my_data1.db
Done.
```

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

Launch Site Names Begin with 'CCA'

We used the query above to display 5 records where launch sites begin with `CCA`

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

```
 * sqlite:///my_data1.db
Done.
```

Launch_Site
CCAFS LC-40
CCAFS LC-40
CCAFS LC-40
CCAFS LC-40
CCAFS LC-40

Total Payload Mass

We calculated the total payload carried by boosters from NASA as 45596 using the query below

```
%sql SELECT SUM (PAYLOAD_MASS__kg_) FROM SPACEXTBL WHERE CUSTOMER = 'NASA (CRS)';
```

```
 * sqlite:///my_data1.db
Done.
```

SUM (PAYLOAD_MASS__kg_)
45596

Average Payload Mass by F9 v1.1

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

```
%sql SELECT AVG (PAYLOAD_MASS__KG_) FROM SPACEXTBL WHERE BOOSTER_VERSION = 'F9 v1.1';
```

```
 * sqlite:///my_data1.db
Done.
```

AVG (PAYLOAD_MASS__KG_)
2928.4

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 Successful Landing" FROM SPACEXTBL WHERE LANDING_OUTCOME = 'Success (ground pad)';
```

```
 * sqlite:///my_data1.db
Done.
```

First Successful Landing
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 SPACEXTBL WHERE LANDING_OUTCOME = 'Success (drone ship)' AND PAYLOAD_MASS__KG_ > 4000 AND 
```

```
 * sqlite:///my_data1.db
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

We used wildcard like ‘%’ to filter for WHERE MissionOutcome was a success or a failure.

```
%sql SELECT sum(case when MISSION_OUTCOME LIKE '%Success%' then 1 else 0 end) AS "Successful Mission", \
    sum(case when MISSION_OUTCOME LIKE '%Failure%' then 1 else 0 end) AS "Failure Mission" \
FROM SPACEXTBL;
```

```
 * sqlite:///my_data1.db
Done.
```

Successful Mission	Failure Mission
100	1

Boosters Carried Maximum Payload

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

```
 * sqlite:///my_data1.db
Done.
```

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

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.clogj3sd0tgtu0lqde00.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

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.

```
%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.cloud: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 applied the GROUP BY clause to group the landing outcomes and the ORDER BY clause to order the grouped landing outcome in descending order.

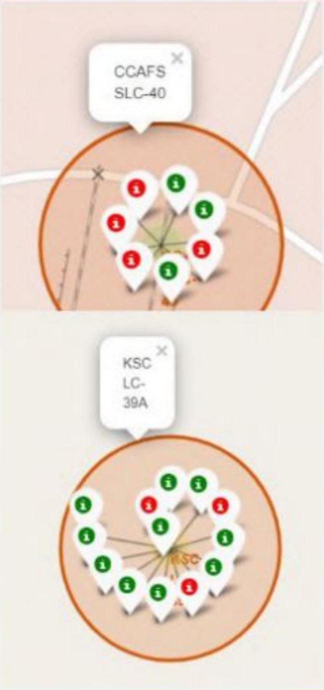
Section
3

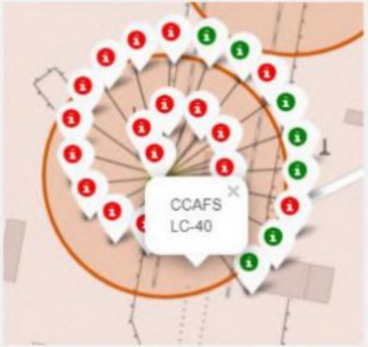
Launch Sites Proximities Analysis

Location of all the Launch Sites

We can see that all the SpaceX launch sites are located inside the US

Markers showing launch sites with color labels





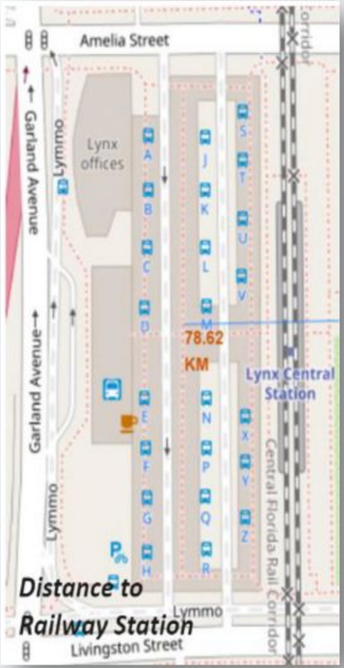
Florida Launch Sites

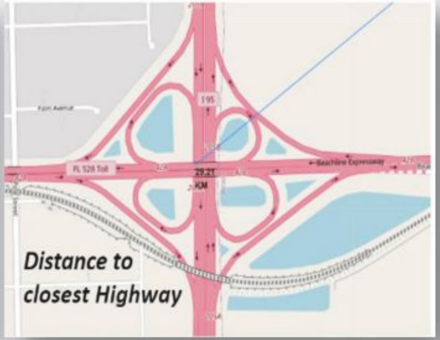
Green Marker shows successful Launches and Red Marker shows Failures

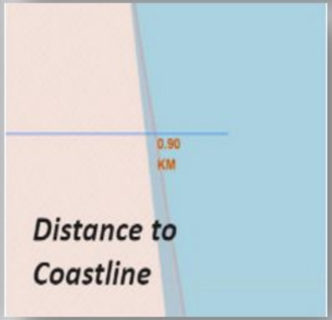
California Launch Site

37

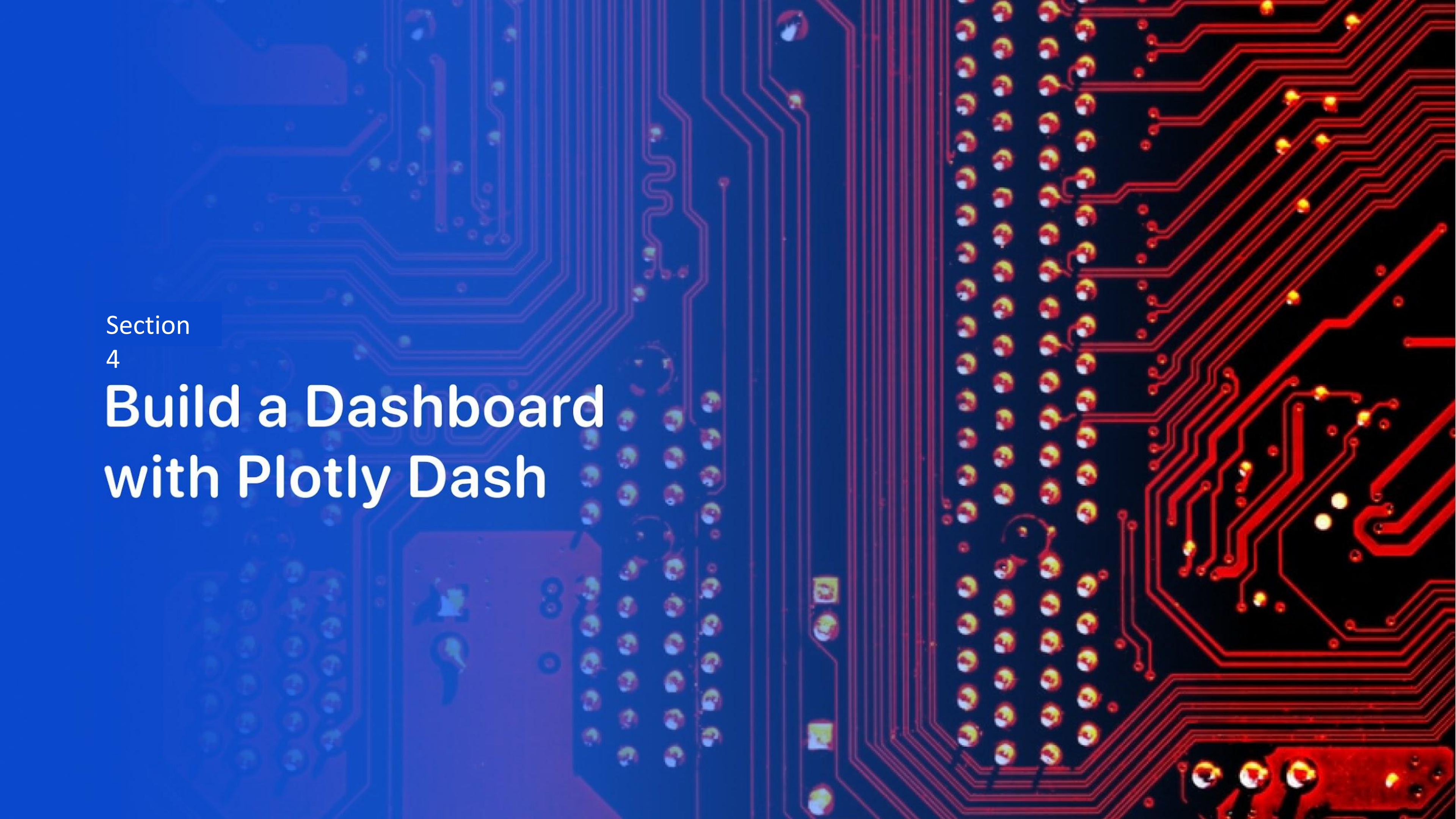
Launch Sites Distance to Landmarks







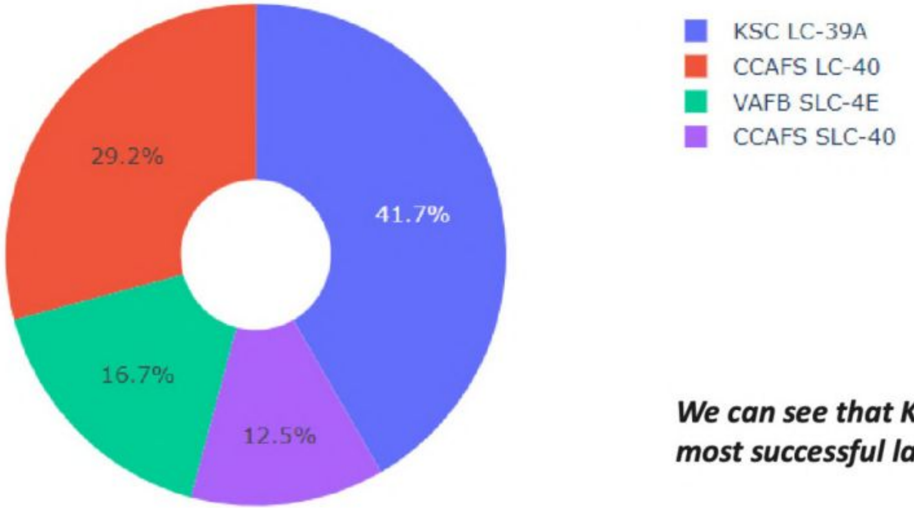
- Are launch sites in close proximity to railways? No
- Are launch sites in close proximity to highways? No
- Are launch sites in close proximity to coastline? Yes
- Do launch sites keep certain distance away from cities? Yes



Section
4

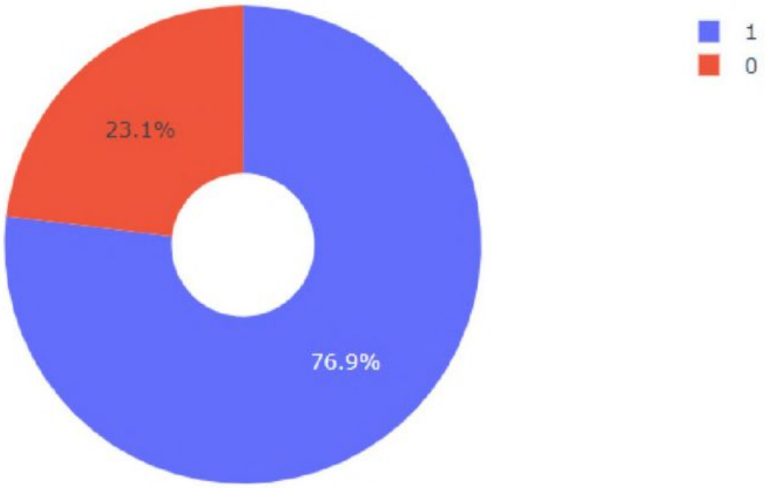
Build a Dashboard with Plotly Dash

The success percentage by each sites.



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

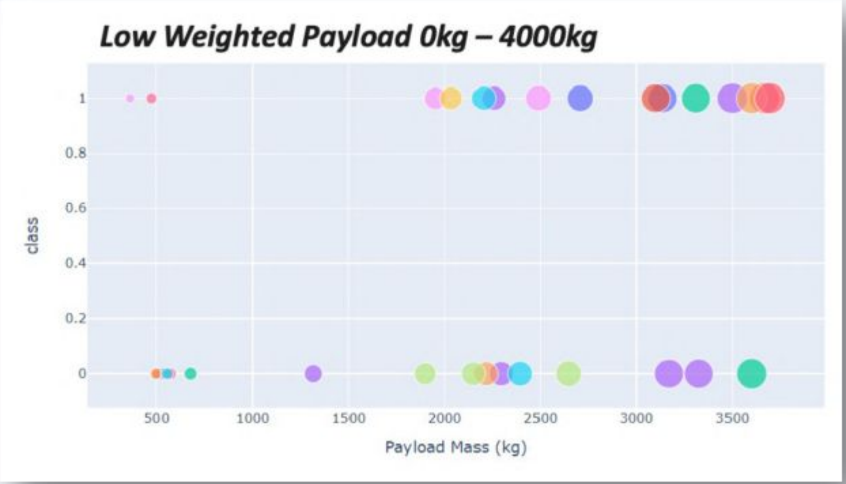
The highest launch-success ratio: KSC LC-39A

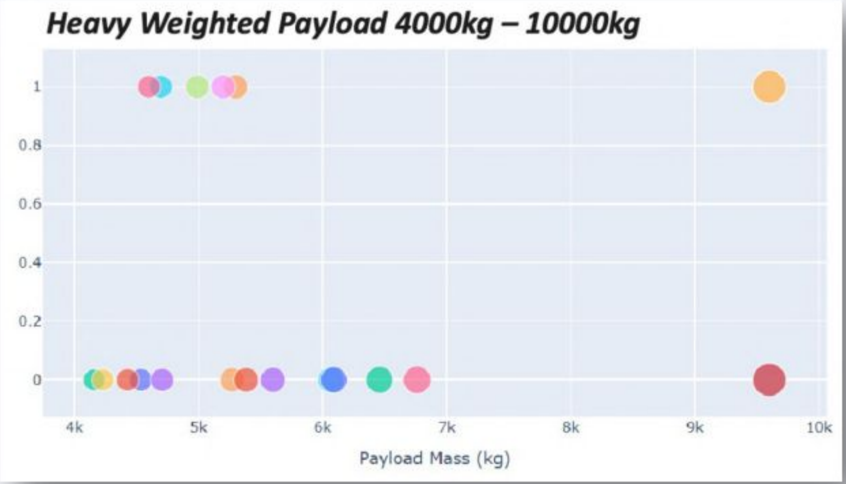


KSC LC-39A achieved a 76.9% success rate while getting a 23.1% failure rate

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

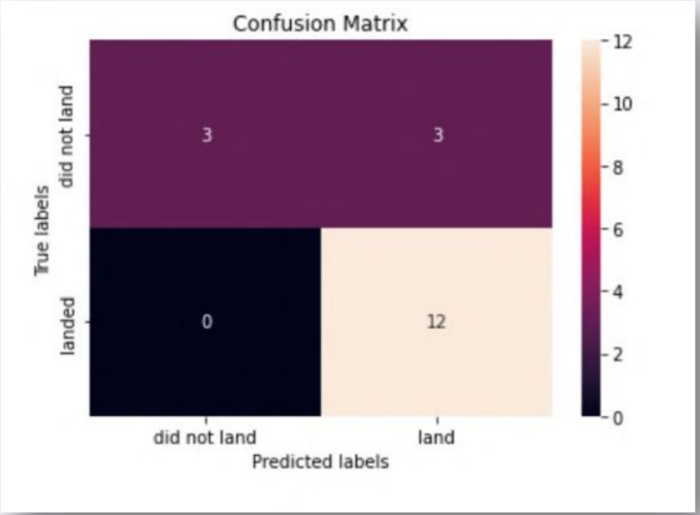
As we can see, by using the code as below: we could identify that the best algorithm to be the Tree Algorithm which have the highest classification accuracy

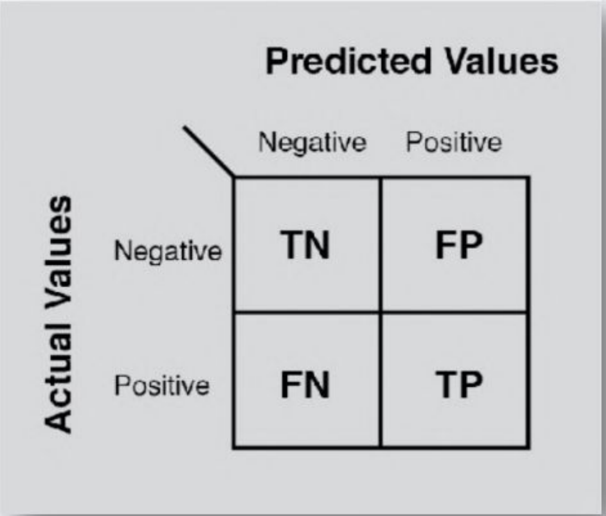
```
algorithms = {'KNN':knn_cv.best_score_,'Tree':tree_cv.best_score_,'LogisticRegression':logreg_cv.best_score_}
bestalgorithm = max(algorithms, key=algorithms.get)
print('Best Algorithm is',bestalgorithm,'with a score of',algorithms[bestalgorithm])
if bestalgorithm == 'Tree':
    print('Best Params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

```
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_sampl
es_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!