IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

Ganesh Subramanian
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Outline

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- Introduction
- Methodology
- Results
- Conclusion
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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
- Summary of all results
  - Exploratory Data Analysis result
  - Interactive analytics in screenshots
  - 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. 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.

Section 1

Methodology

Methodology

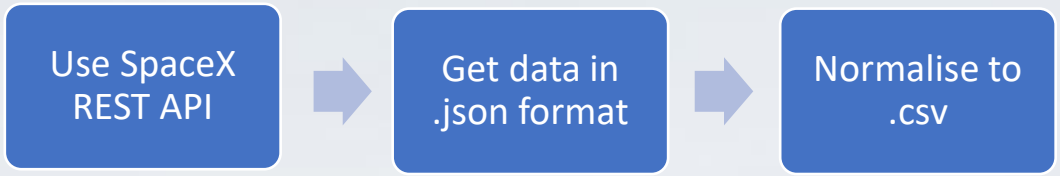
Executive Summary

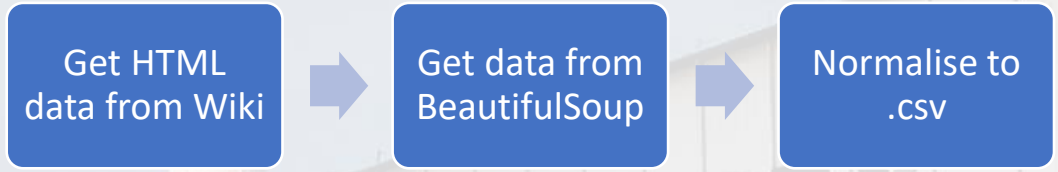
- Data collection methodology:
  - Data was collected using SpaceX API and web scraping from Wikipedia.
- Perform data wrangling
  - One-hot encoding was applied to categorical features.
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using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

Data Collection

- 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 fill 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 using API





Data collection using Webscraping

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.

[Data_collection_from_API-Github_link]

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 applied web scrapping to webscrap Falcon 9 launch records with BeautifulSoup
- We parsed the table and converted it into a pandas dataframe.

[Webscraping-Github_link]

1. Apply HTTP Get method to request the Falcon 9 rocket launch page

```
In [4]: static_url = "https://en.wikipedia.org/w/index.php?title=List_of_Falcon_9_and_Falcon_Heavy_launches&oldid=1027686922"
```

```
In [5]: # use requests.get() method with the provided static_url
        # assign the response to a object
        html_data = requests.get(static_url)
        html_data.status_code
Out[5]: 200
```

2. Create a BeautifulSoup object from the HTML response

```
In [6]: # Use BeautifulSoup() to create a BeautifulSoup object from a response text content
        soup = BeautifulSoup(html_data.text, 'html.parser')
```

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

```
In [7]: # Use soup.title attribute
        soup.title
Out[7]: <title>List of Falcon 9 and Falcon Heavy launches - Wikipedia</title>
```

3. Extract all column names from the HTML table header

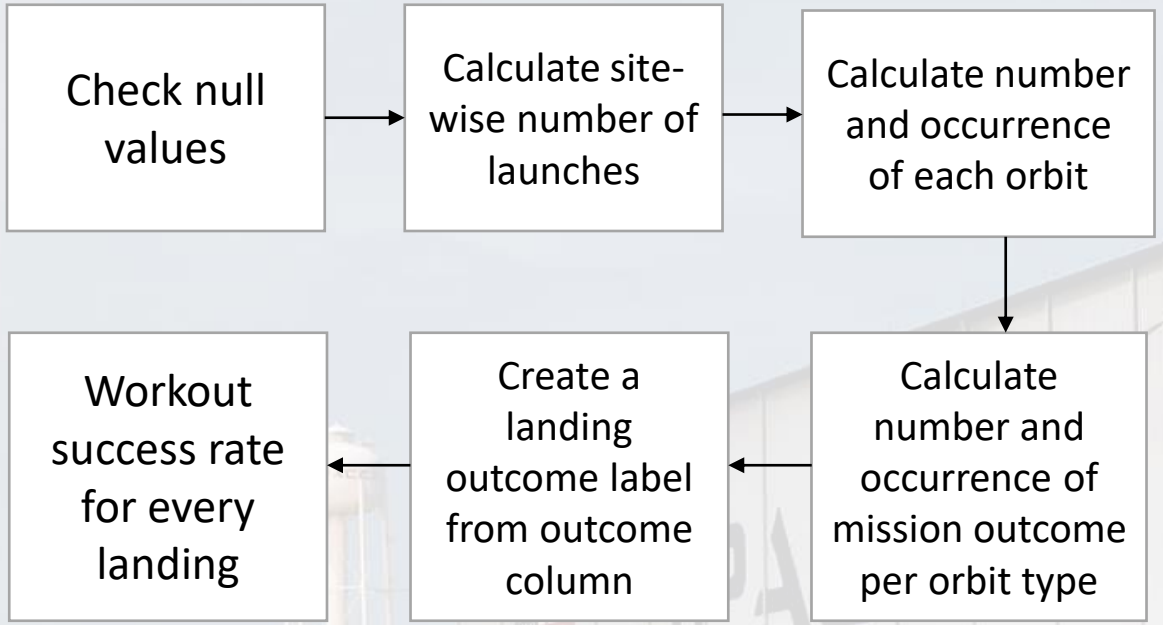
```
In [10]: column_names = []

# Apply find_all() function with `th` element on first_launch_table
# Iterate each th element and apply the provided extract_column_from_header() to get a column name
# Append the Non-empty column name (`if name is not None and len(name) > 0`) into a list called column_names

element = soup.find_all('th')
for row in range(len(element)):
    try:
        name = extract_column_from_header(element[row])
        if (name is not None and len(name) > 0):
            column_names.append(name)
    except:
        pass
```

4. Create a dataframe by parsing the launch HTML tables
5. Export data to csv

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.

- Data_wrangling-Github_link



EDA with Data Visualization

We visualized the relationship between

- flight number and launch site - scatterplot
- payload and launch site - scatterplot
- success rate of each orbit type – bar plot
- flight number and orbit type - scatterplot
- the launch success yearly trend – line chart

Scatterplots show the correlation between two variables, while bar plots can be used to compare categories of data with a discrete variable and with line charts it is easy to view the trend of a variable over a period of time.

EDA Data Visualization-Github link

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.

EDA SQL-Github link

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.

Analysis with folium-Github link

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 so that we can display relative proportions of multiple classes of data.
- We plotted scatter graph showing the relationship with Outcome and Payload Mass (Kg) for the different booster version because in addition to showing relationship between two variables it shows a non-linear pattern and the range can be determined.

Plotly_Dash_py-Github_link

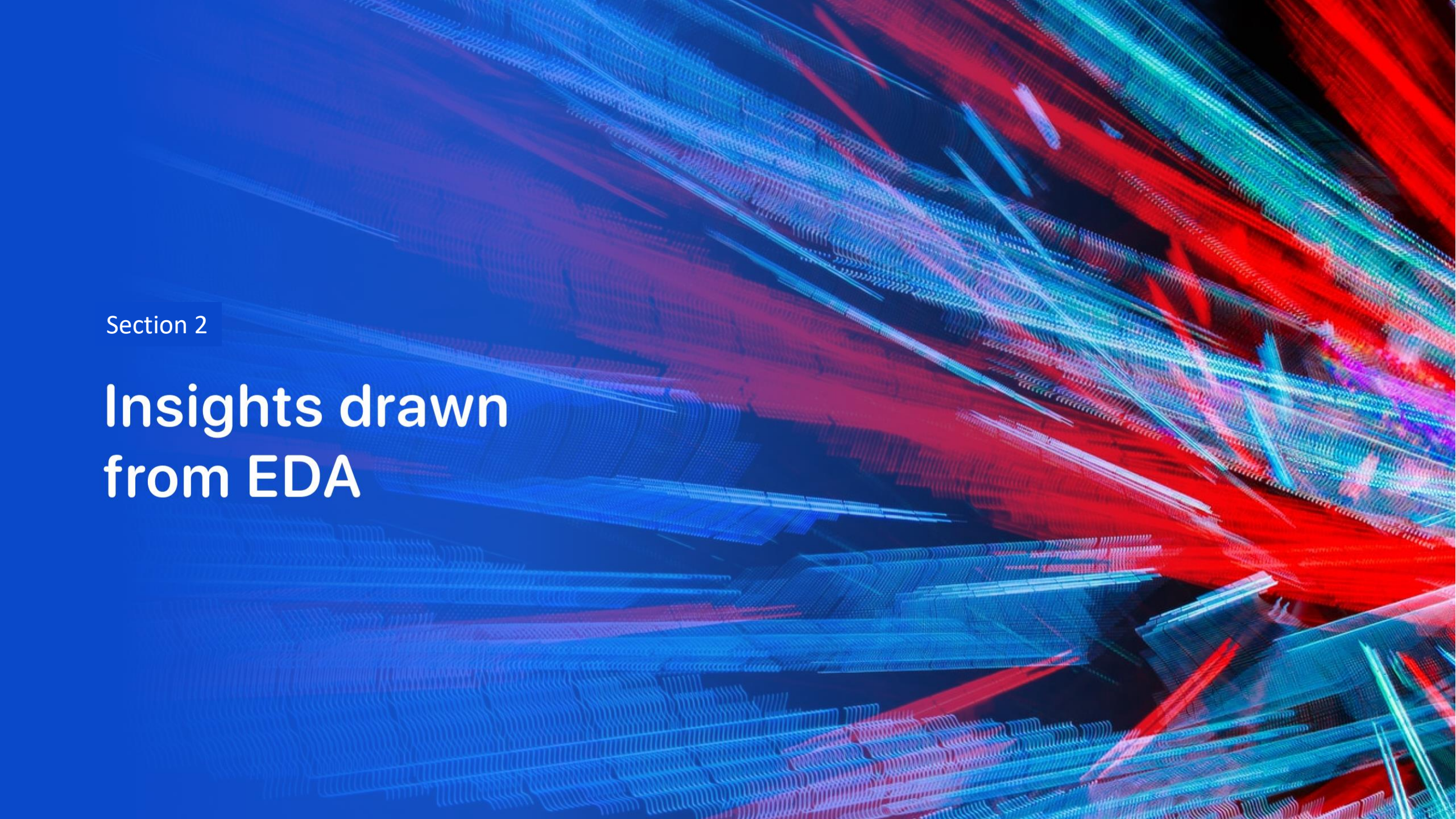
Predictive Analysis (Classification)

- 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 tuned different hyperparameters using GridSearchCV.
- We used accuracy as the metric for our model and plotted confusion matrix, improved the model using feature engineering and algorithm tuning.
- We found the best performing classification model.

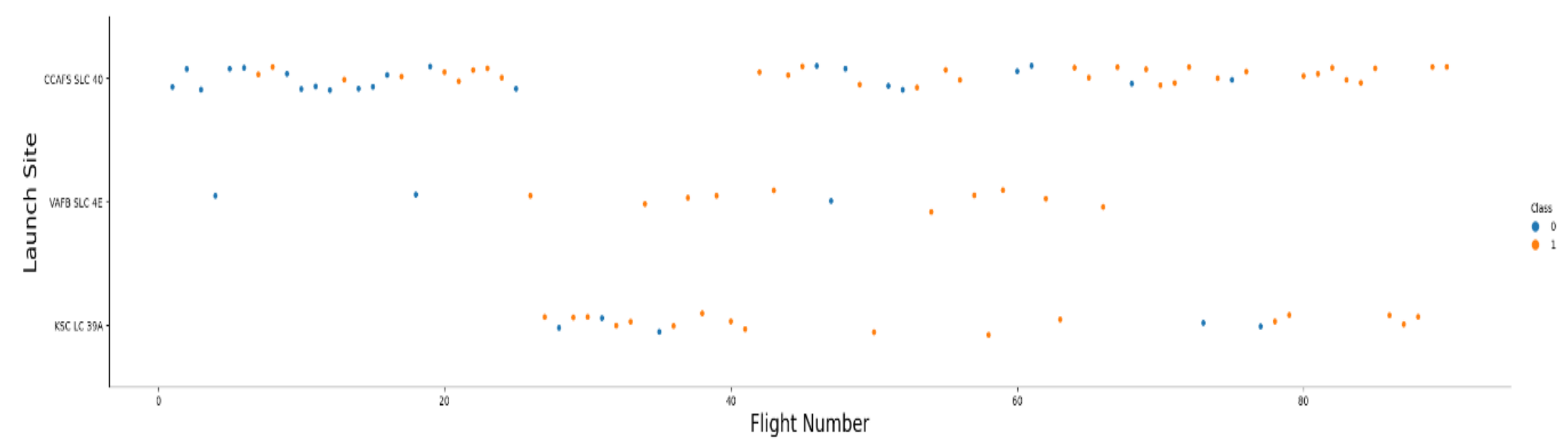
Machine_learning_prediction-Github_link

Results

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

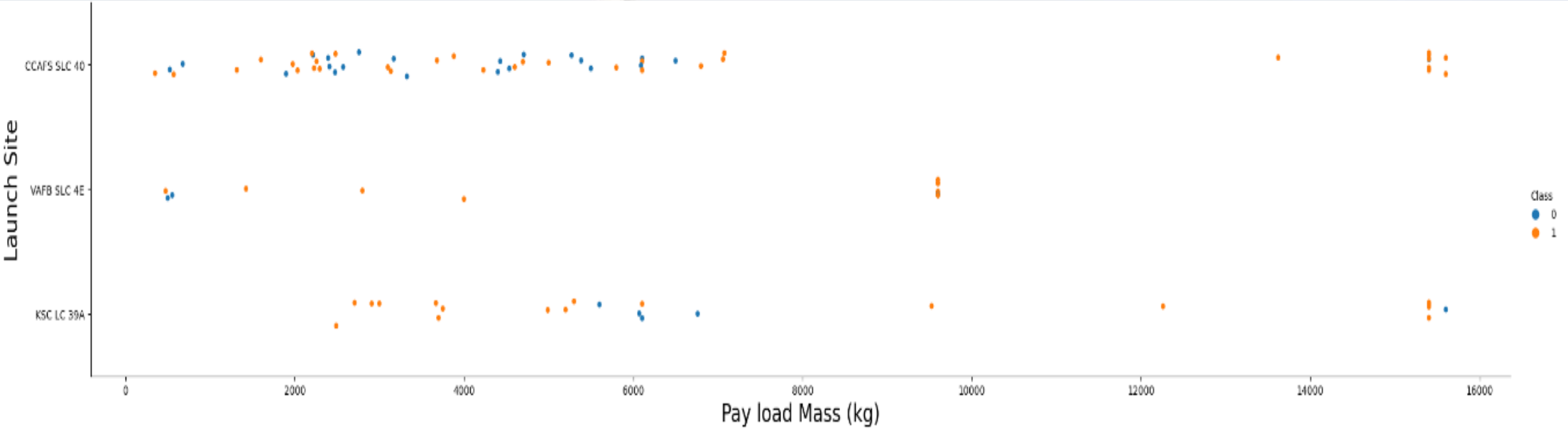

Section 2
Insights drawn from EDA

Flight Number vs. Launch Site



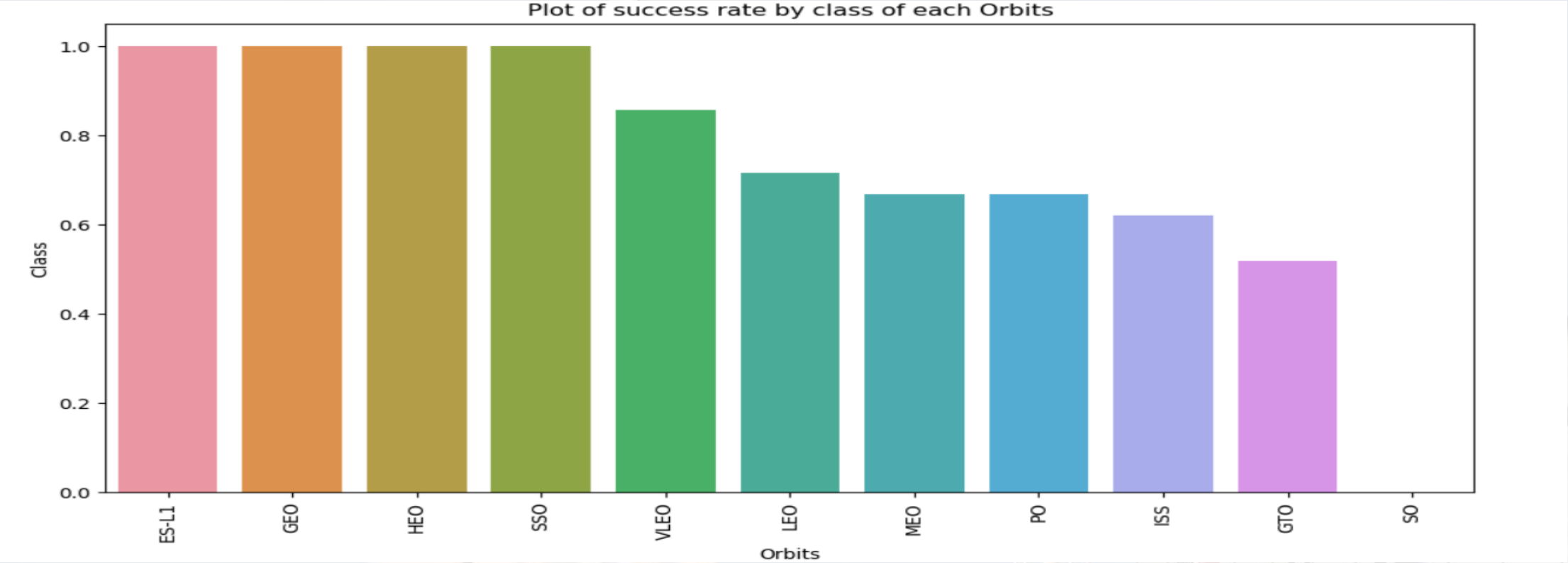
From the plot, we found that the larger the flight amount at a launch site, the greater the success rate at a launch site.

Payload vs. Launch Site



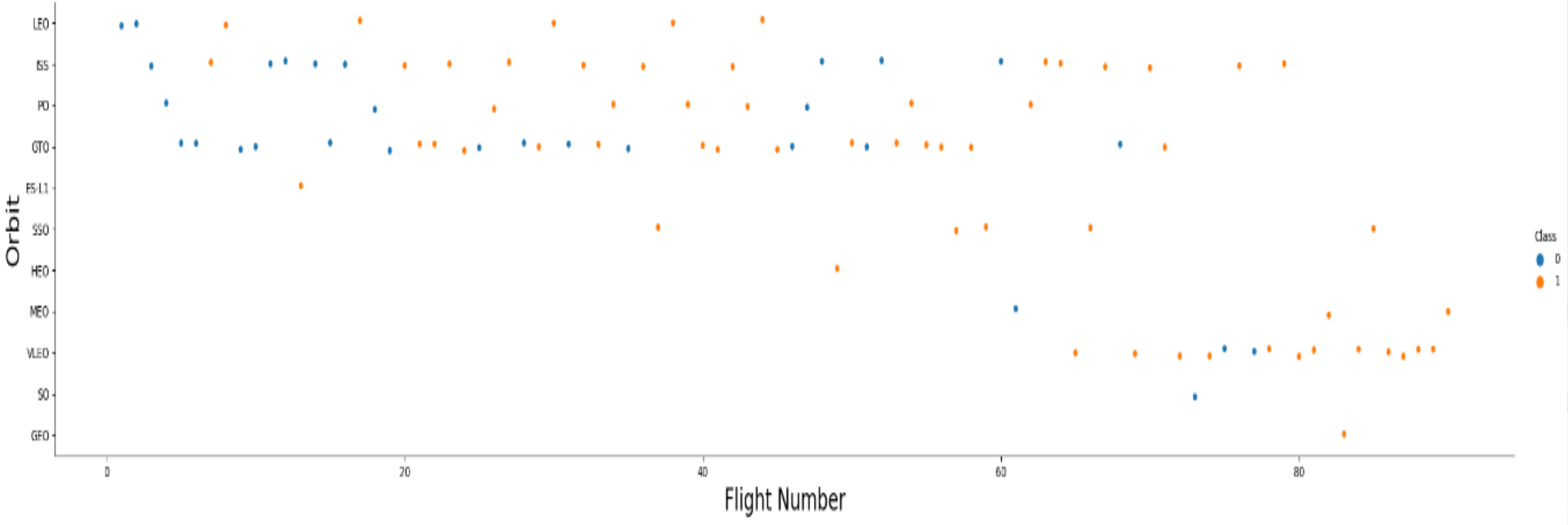
The greater the payload mass for launch site CCAFS SLC 40 the higher is the success rate

Success Rate vs. Orbit Type



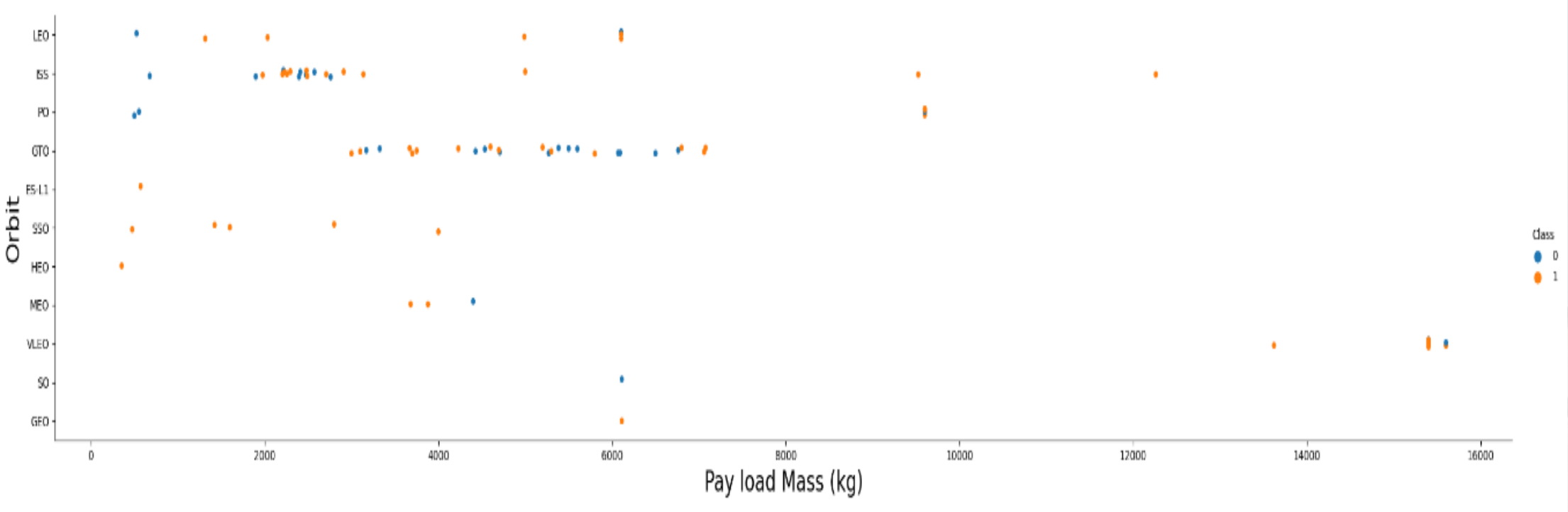
From the plot, we can see that ES-L1, GEO, HEO, SSO, VLEO had the most success rate.

Flight Number vs. Orbit Type



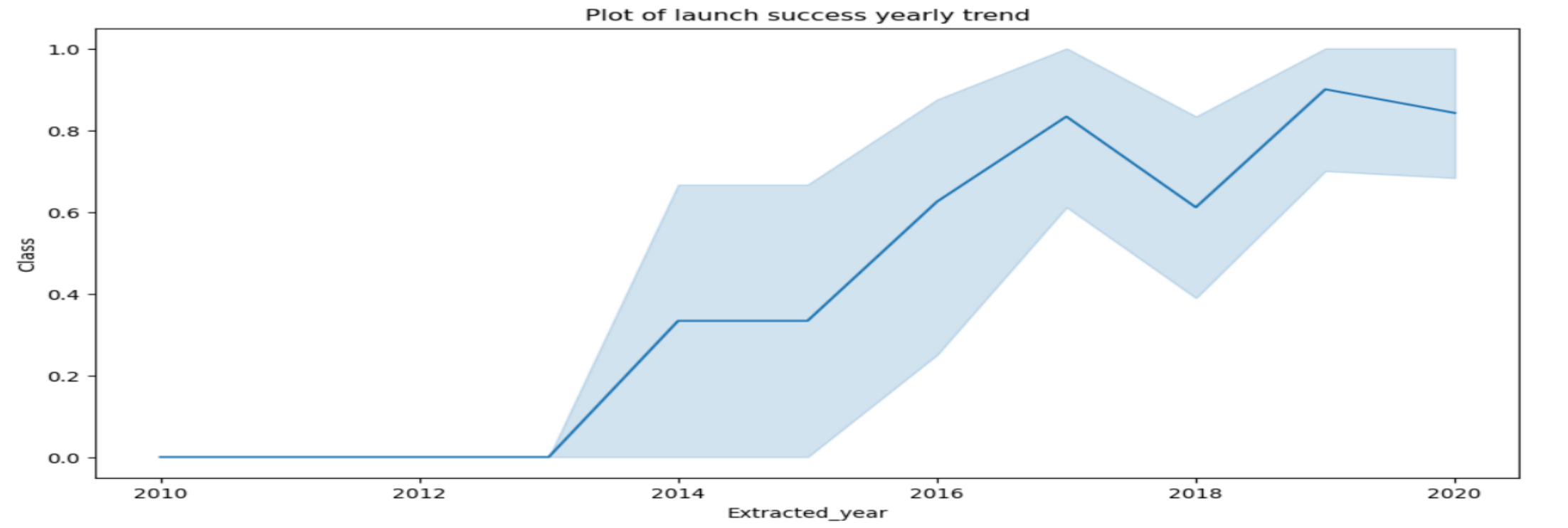
We observe that in the LEO orbit, success is related to the number of flights whereas in the GTO orbit, there is no relationship between flight number and the orbit.

Payload vs. Orbit Type



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

Launch Success Yearly Trend



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

All Launch Site Names

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

```
%sql select distinct(launch_site) from SPACEXTBL
```

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

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

Launch Site Names Begin with 'CCA'

We used the below query with like parameter and limit to display 5 records with site names beginning with ‘CCA’

```
%sql select * from SPACEXTBL where launch_site like 'CCA%' limit 5
```

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

Date	Time (UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS__KG_	Orbit	Customer	Mission_Outcome	Landing _Outcome
04-06-2010	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
08-12-2010	15:43:00	F9 v1.0 B0004	CCAFS LC-40	Dragon demo flight C1, two CubeSats, barrel of Brouere cheese	0	LEO (ISS)	NASA (COTS) NRO	Success	Failure (parachute)
22-05-2012	07:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	No attempt
08-10-2012	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
01-03-2013	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 with the query below using sum function

```
%sql select sum(payload_mass__kg_) as total from SPACEXTBL where customer = 'NASA (CRS)'
```

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

total
45596

Average Payload Mass by F9 v1.1

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

```
%sql select avg(payload_mass__kg_) as avg from SPACEXTBL where booster_version = 'F9 v1.1'
```

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

avg
2928.4

First Successful Ground Landing Date

We observed that the date of the first successful landing outcome on ground pad was 22nd December 2015 using the min function

```
%sql select min(date) from SPACEXTBL where `landing _outcome` = 'Success (ground pad)'
```

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

min(date)
22-12-2015

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 payload_mass__kg_ < 6000
```

```
 * 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 COUNT(mission_outcome) AS SuccessOutcome
        FROM SPACEXTBL
        WHERE mission_outcome LIKE 'Success%';
```

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

SuccessOutcome
100

```
%%sql SELECT COUNT(mission_outcome) AS FailureOutcome
        FROM SPACEXTBL
        WHERE mission_outcome LIKE 'Failure%'
```

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

FailureOutcome
1

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.

```
%%sql SELECT booster_version, payload_mass__kg_
        FROM SPACEXTBL
        WHERE payload_mass__kg_ = (
                                   SELECT MAX(payload_mass__kg_)
                                   FROM SPACEXTBL
                                   )
        ORDER BY booster_version
```

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

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

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

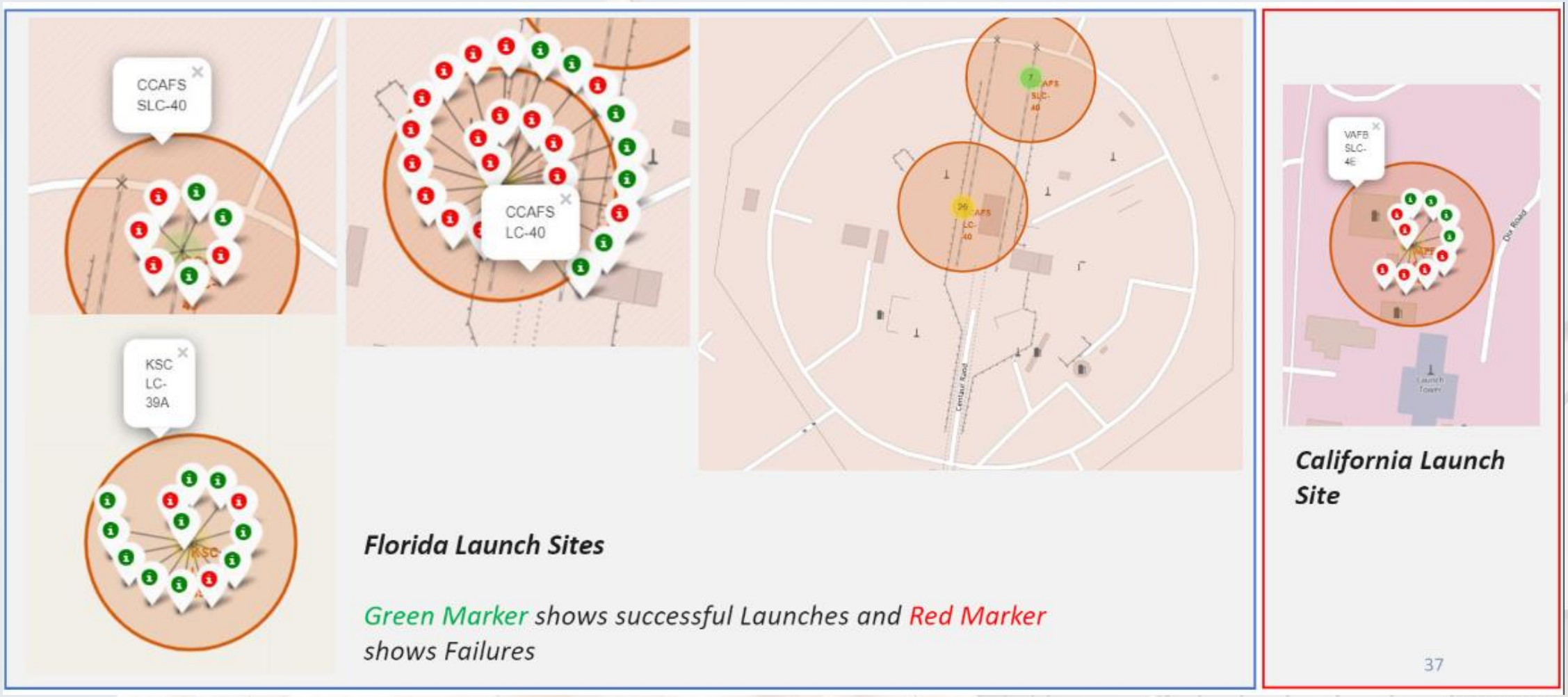
Section 3

Launch Sites Proximities Analysis

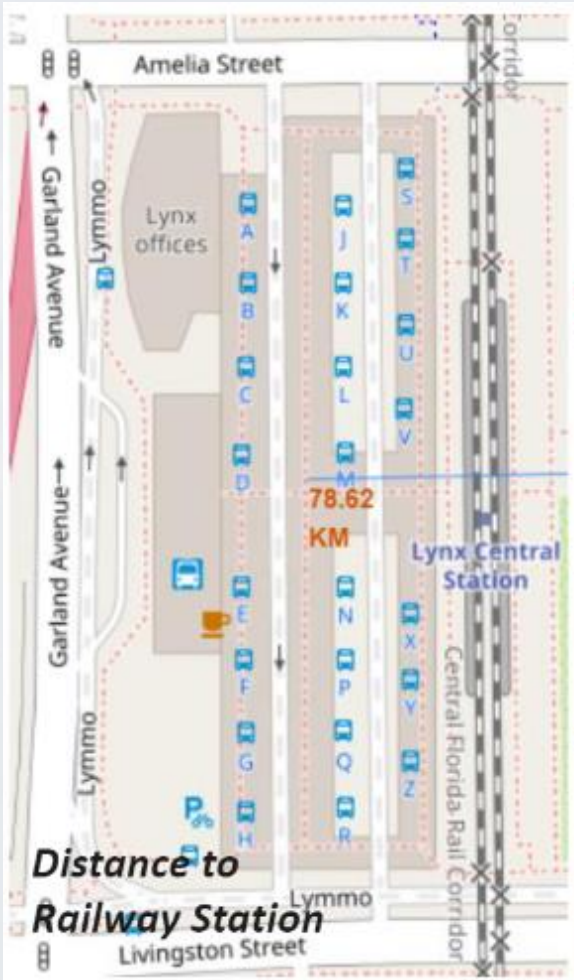
SpaceX launch sites on Global Map

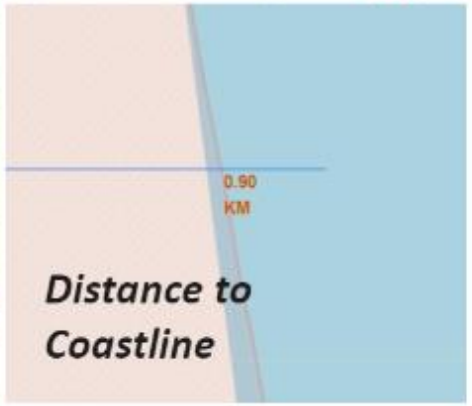
We can see that the SpaceX launch sites are in the United States of America coasts. Florida and California

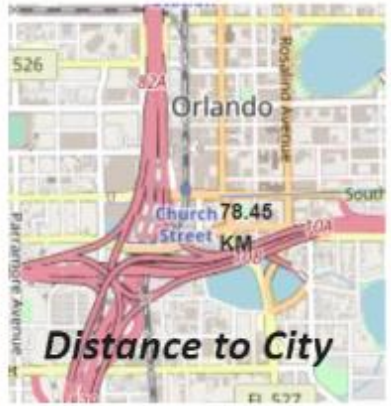
Colored markers at launch sites



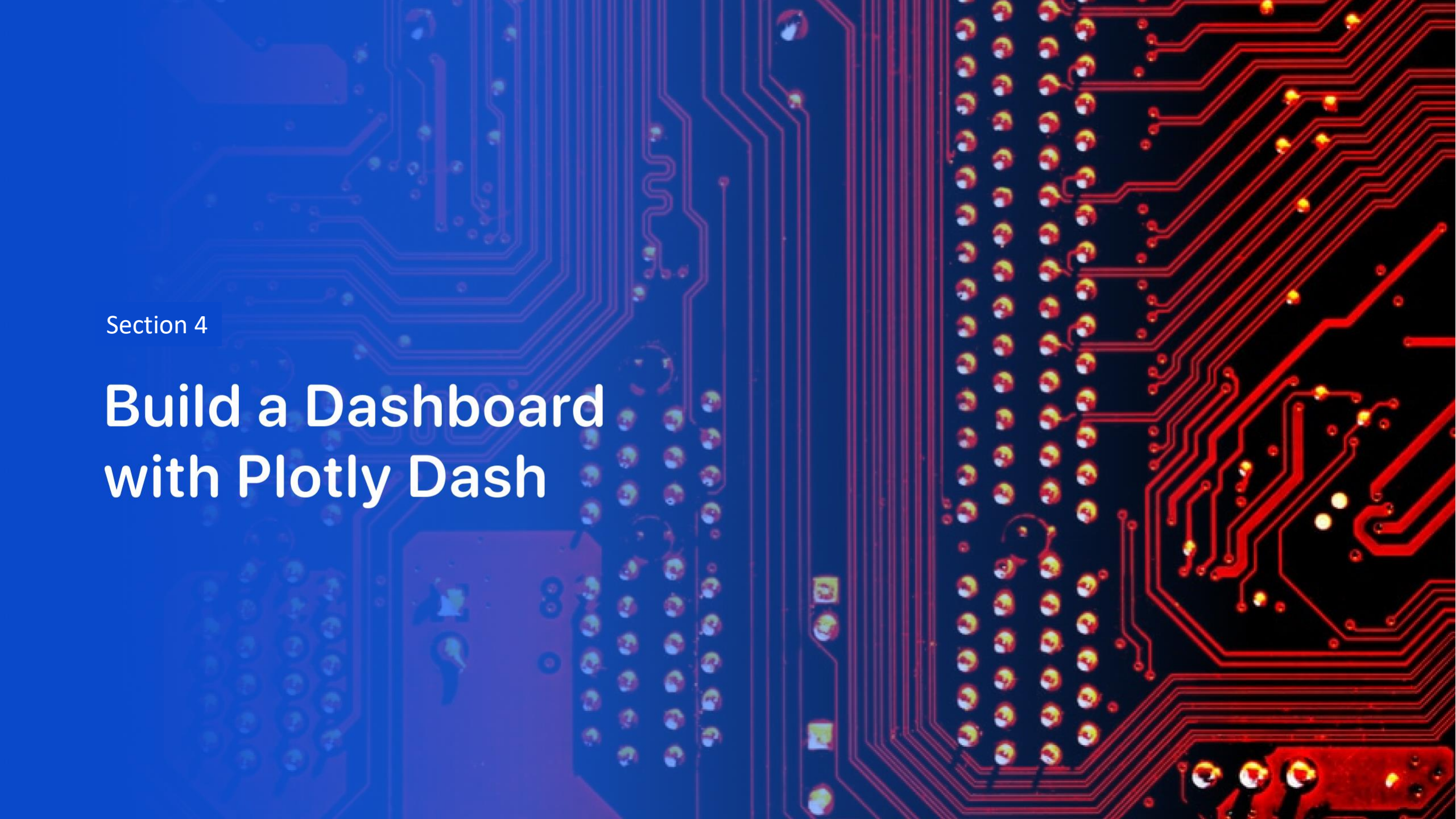
Launch site distance from nearest landmarks



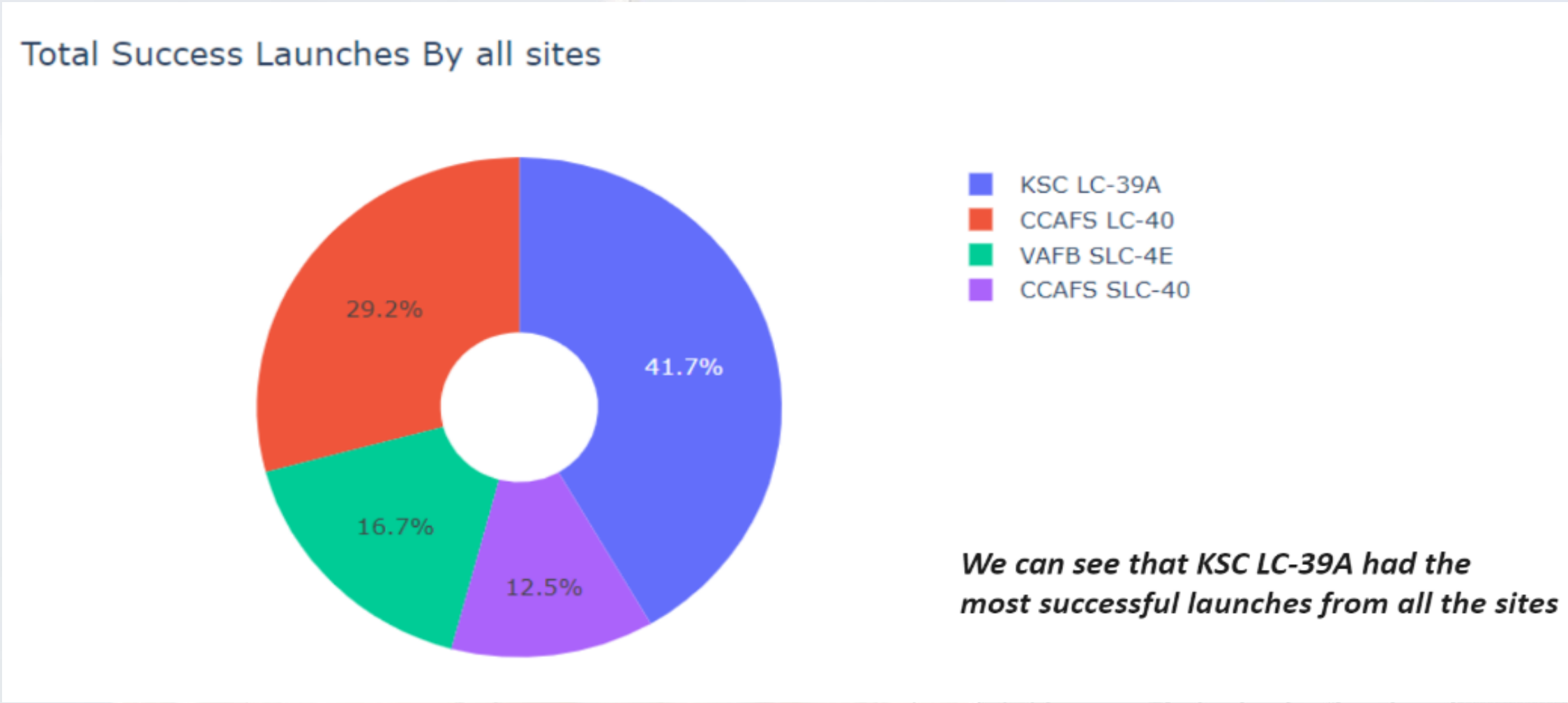




- Are launch sites in close proximity to railways? No
- Are launch sites in close proximity to highways? No
- Are launch sites in close proximity to coastline? Yes
- Do launch sites keep certain distance away from cities? Yes

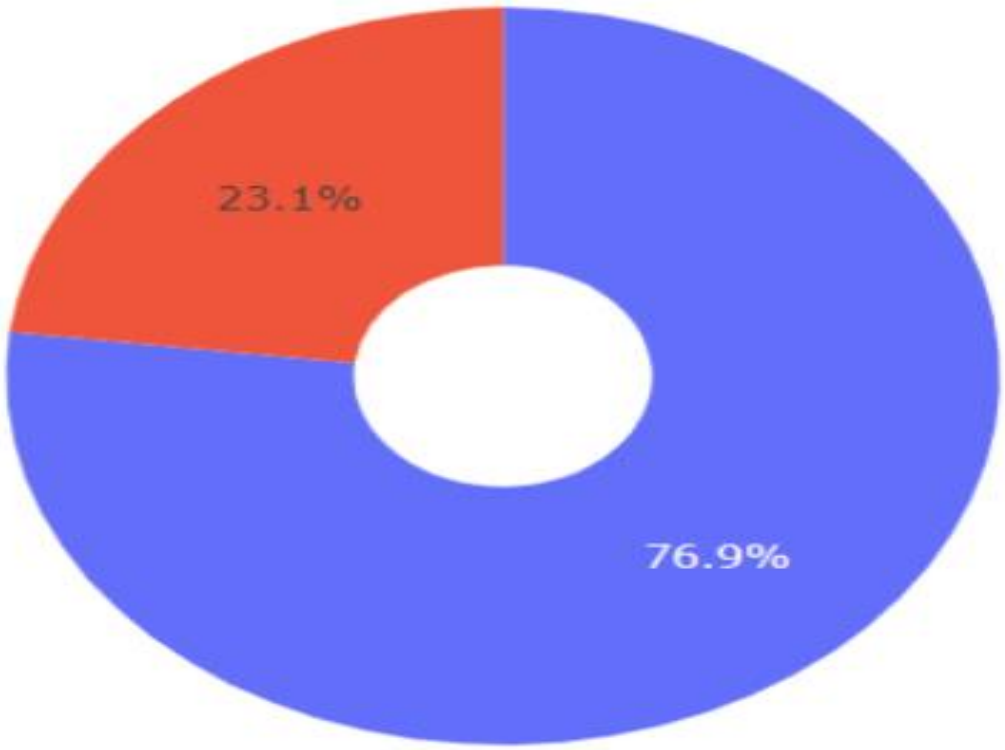

Section 4
Build a Dashboard with Plotly Dash

Launch site success percentage



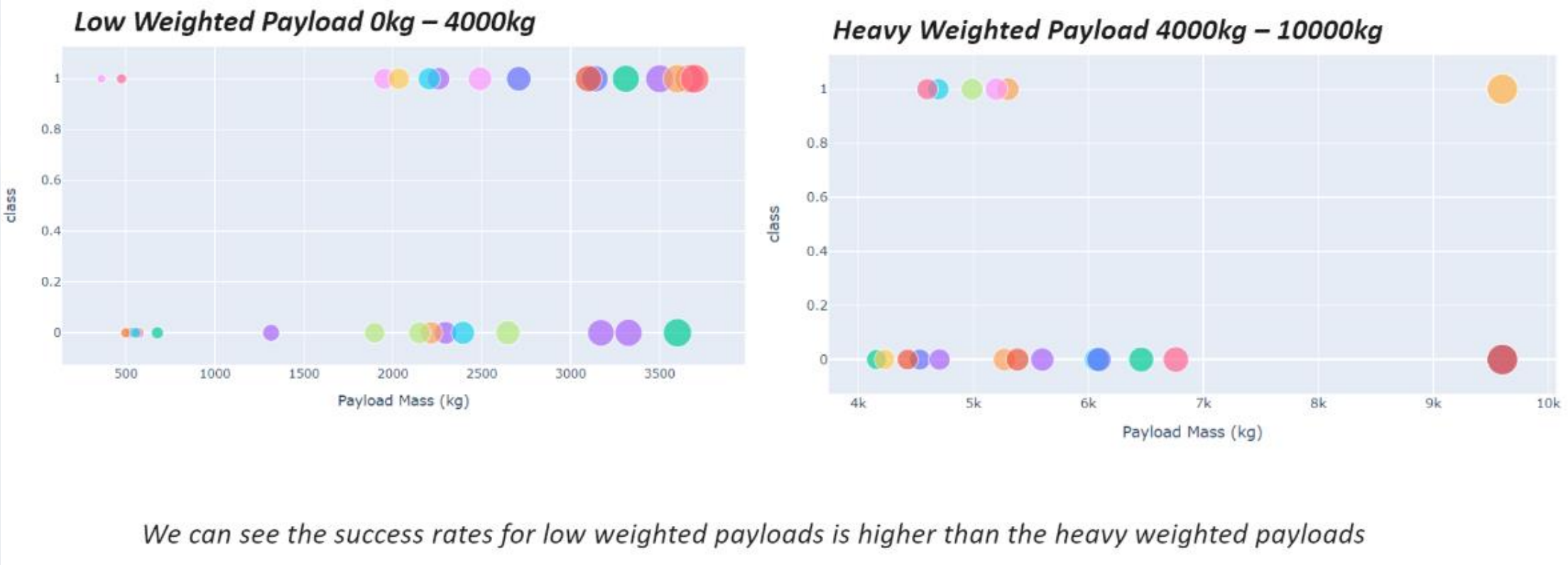
We can see that KSC LC-39A had the most successful launches from all the sites

Highest launch success ratio



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

Payload Vs Launch outcome of all sites



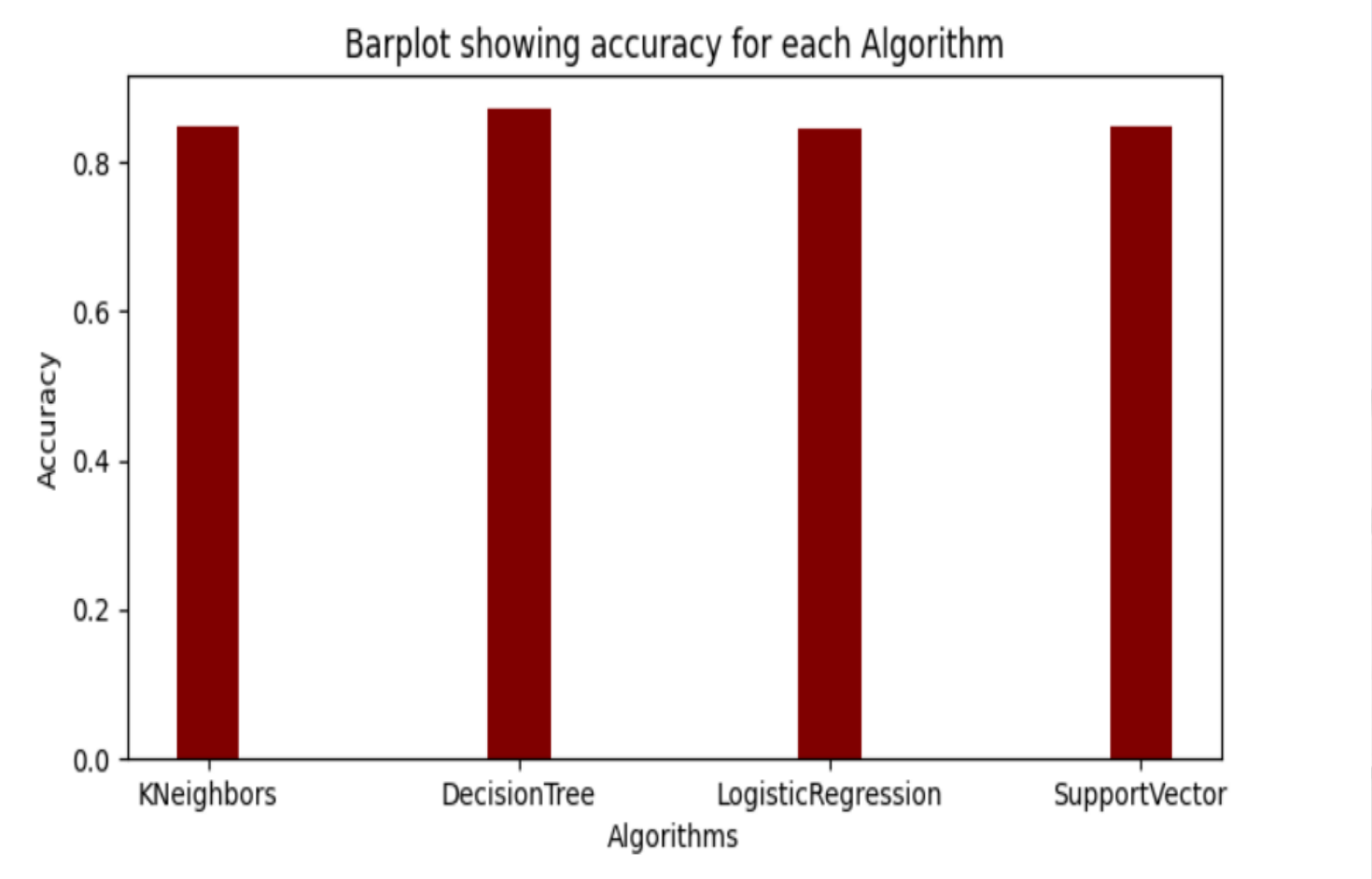
We can see the success rates for low weighted payloads is higher than the heavy weighted payloads

Section 5

Predictive Analysis (Classification)

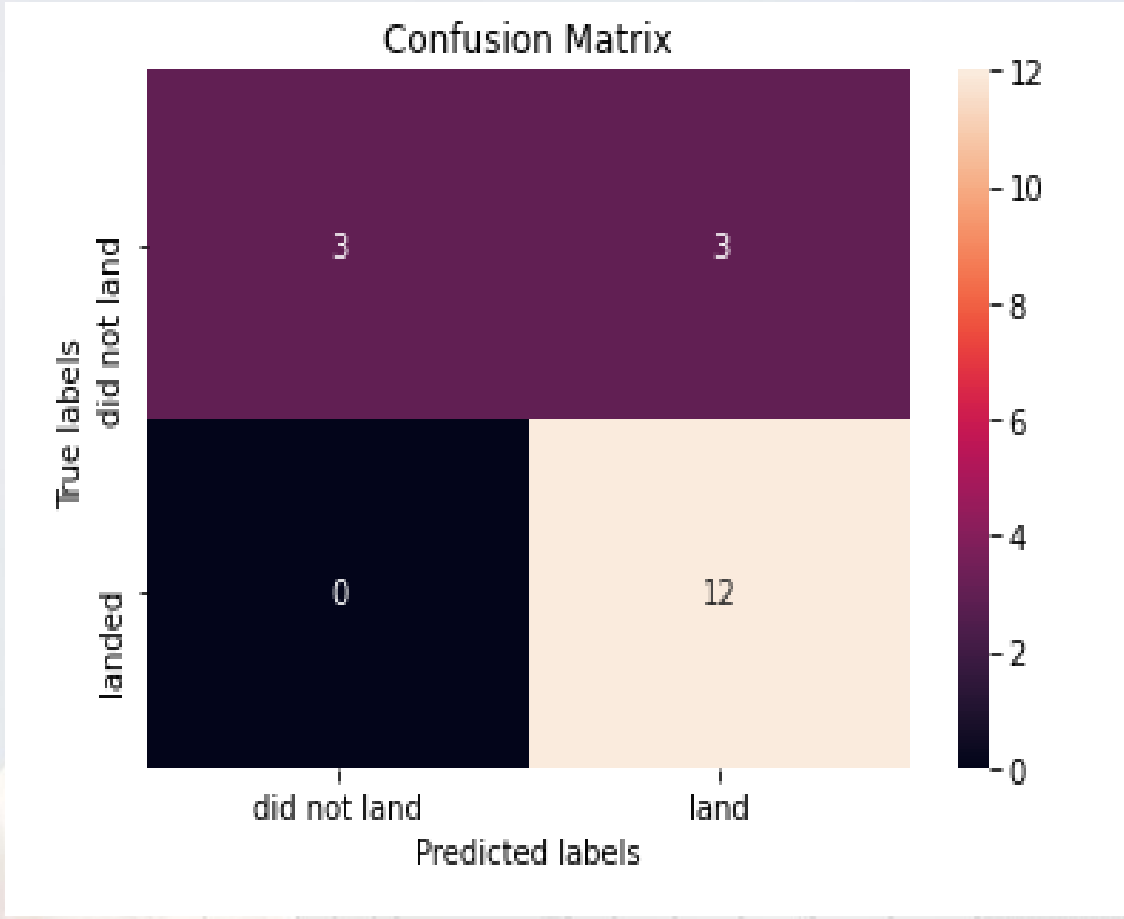
Classification Accuracy

From the bar chart visualization, we can conclude that the decision tree classifier is the model with the highest classification accuracy



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.

Thank you!