IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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- Methodology
- Results
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Executive Summary

- Summary of methodologies
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- Data Collection With Web Scraping
- Data Wrangling
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- Interaction Visual Analytics with Folium
- Machine Learning Prediction
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- Interaction Analytics in screenshots
- Predictive Analytics result

Introduction

- ## Project background and context

  SpaceX advertises Falcon 9 rocket launches on its website with a cost of 62 million dollars other providers cost upward of 165 million dollars each, much of the savings is because 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 need 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
  - How to build, tune, evaluate classification models

Data Collection

- The data was collected using various methods
  - 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 turned it into pandas dataframe using json_normalize().
    - We then cleaned the data, checked for missing values, and filled 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 an HTML table, parse the table and convert it to a pandas dataframe for future analysis.

Data Collection – SpaceX API

- We used the get request to the SpaceX API to collect data, clean the requested data and do some basic data wrangling and formatting.
- The link to the notebook is:
- https://github.com/khaledaladib/IBM-Data-Science-Capstone-SpaceX/blob/main/jupyter-labs-spacex-data-collection-api.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 applied web scrapping to webscrap Falcon 9 launch records with BeautifulSoup
- We parsed the table and converted it into a pandas dataframe.

[IBM-Data-Science-Capstone-SpaceX/jupyter-labs-webscraping.ipynb at main · khaledaladib/IBM-Data-Science-Capstone-SpaceX (github.com)]

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

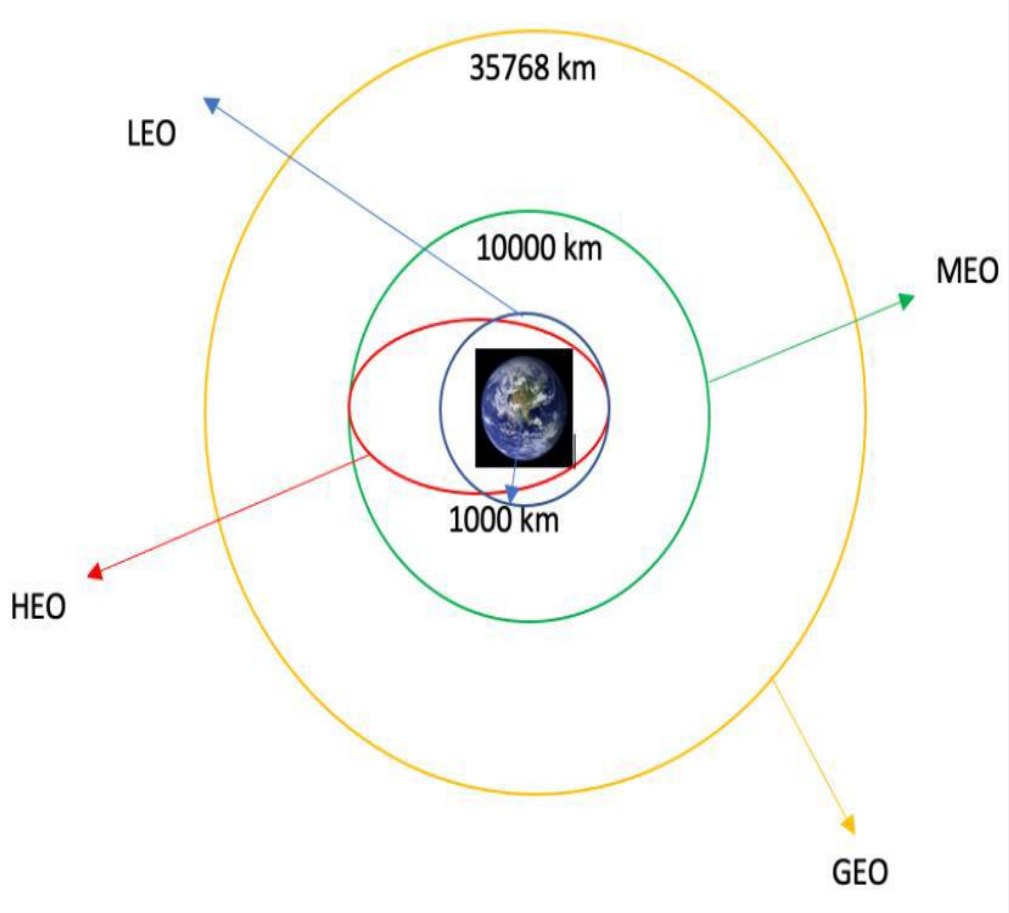
```
In [10]: column_names = []

# 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

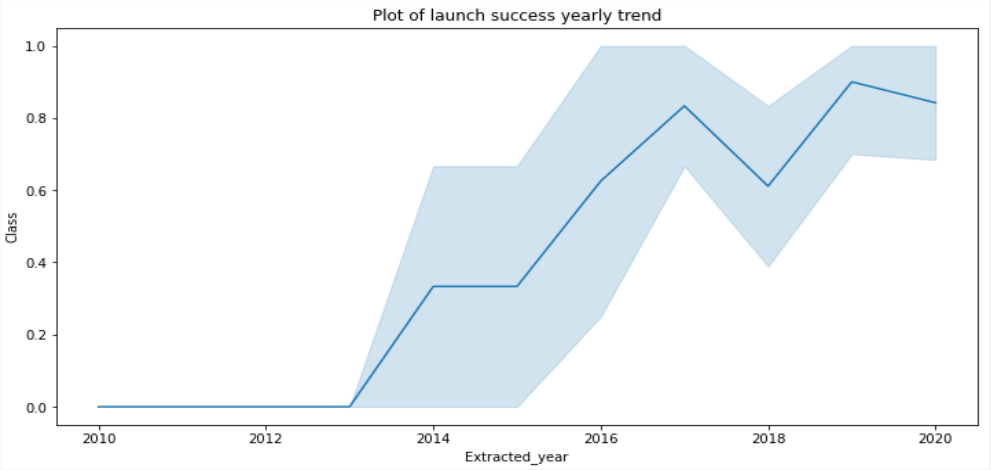
- We performed exploratory data analysis and determined the training labels.
- We calculated the number of launches at each site, and the number and occurrence of each orbits
- We created landing outcome label from outcome column and exported the results to csv.

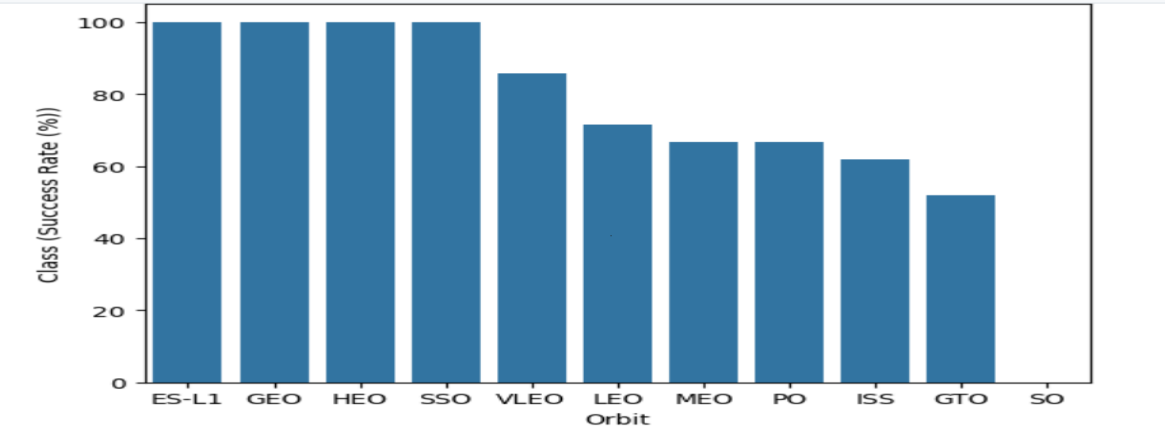
- https://github.com/khaledaladib/IBM-Data-Science-Capstone-SpaceX/blob/950c27b11b4a08435a45032a1a4f46bc58d01d9d/labs-jupyter-spacex-Data%20wrangling.ipynb



EDA with Data Visualization

- We explored the data by visualizing the relationship between flight number and launch Site, payload and launch site, the success rate of each orbit type, flight number, and orbit type, and the launch success yearly trend.
- https://github.com/khaledaladib/IBM-Data-Science-Capstone-SpaceX/blob/950c27b11b4a08435a45032a1a4f46bc58d01d9d/jupyter-labs-eda-dataviz.ipynb.jupyterlite.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.
- https://github.com/khaledaladib/IBM-Data-Science-Capstone-SpaceX/blob/950c27b11b4a08435a45032a1a4f46bc58d01d9d/jupyter-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.

- https://github.com/khaledaladib/IBM-Data-Science-Capstone-SpaceX/blob/950c27b11b4a08435a45032a1a4f46bc58d01d9d/spacex_dash_app.py

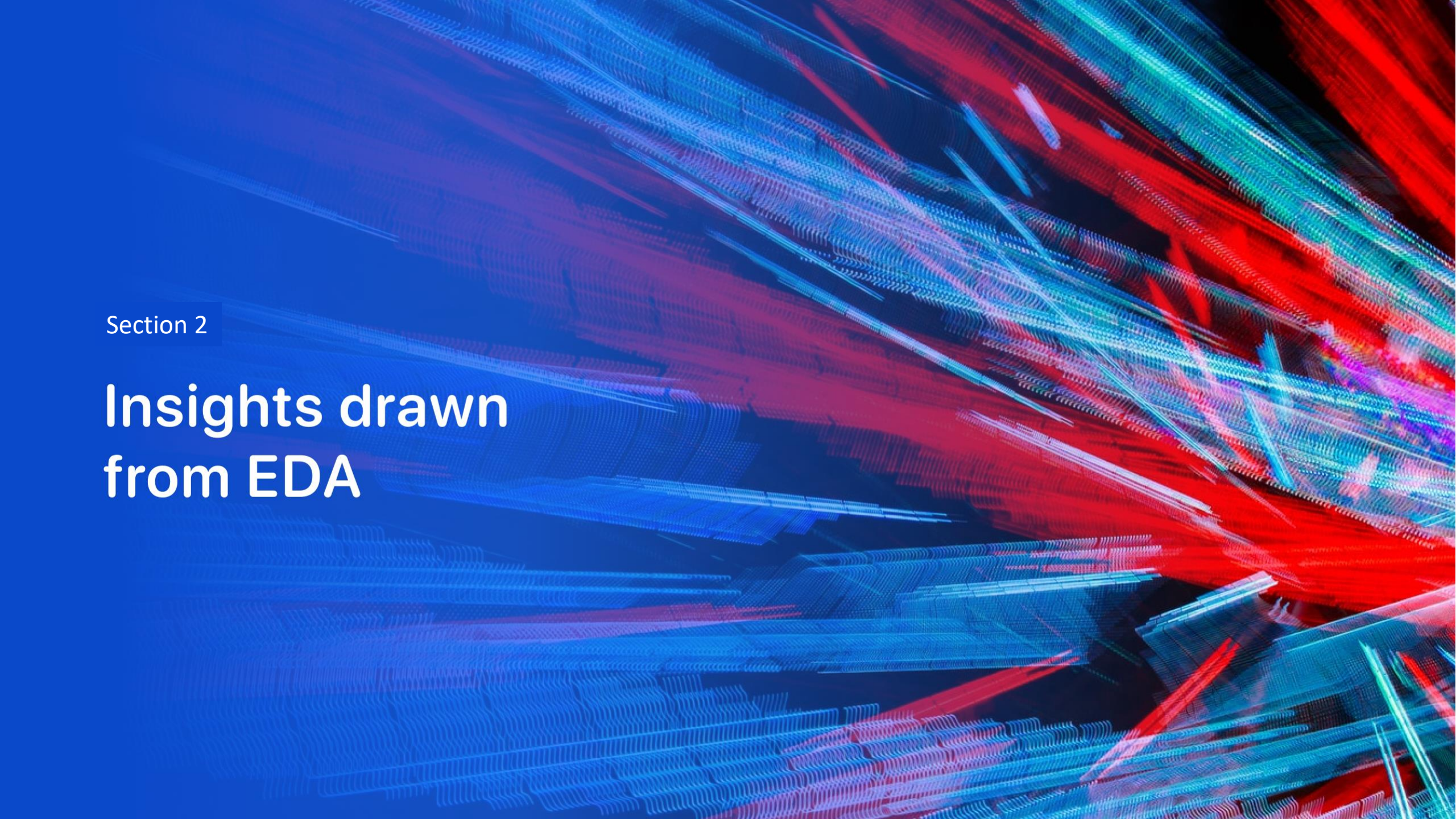
Predictive Analysis (Classification)

- We loaded the data using NumPy and pandas, transformed the data, and 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 improved the model using feature engineering and algorithm tuning.
- We found the best-performing classification model.

- https://github.com/khaledaladib/IBM-Data-Science-Capstone-SpaceX/blob/950c27b11b4a08435a45032a1a4f46bc58d01d9d/SpaceX_Machine_Learning_Prediction_Part_5.jupyterlite.ipynb

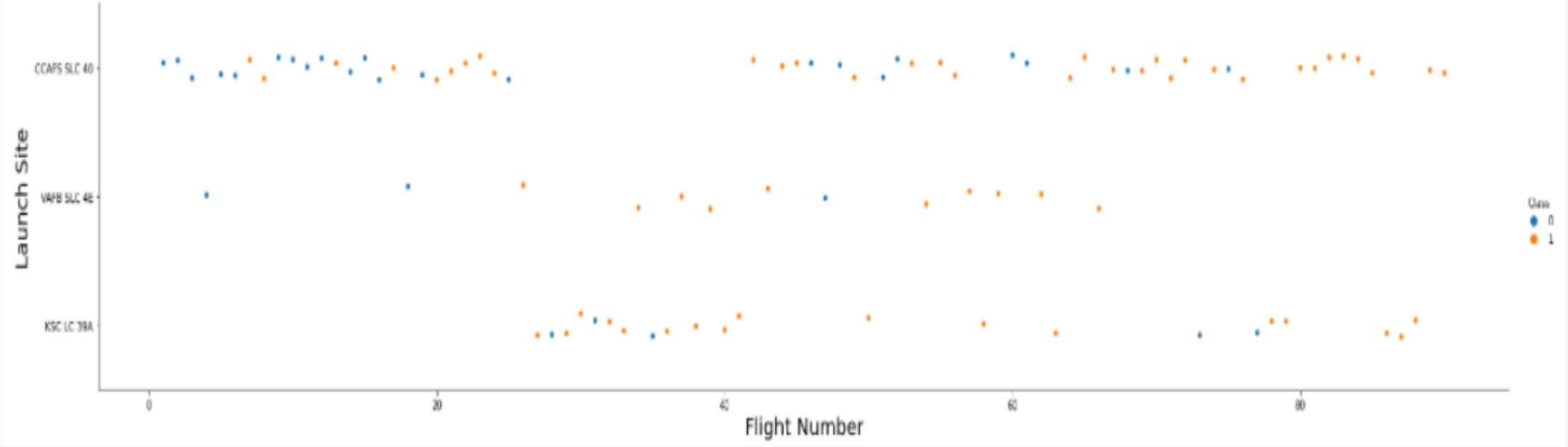
Results

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


Section 2
Insights drawn from EDA

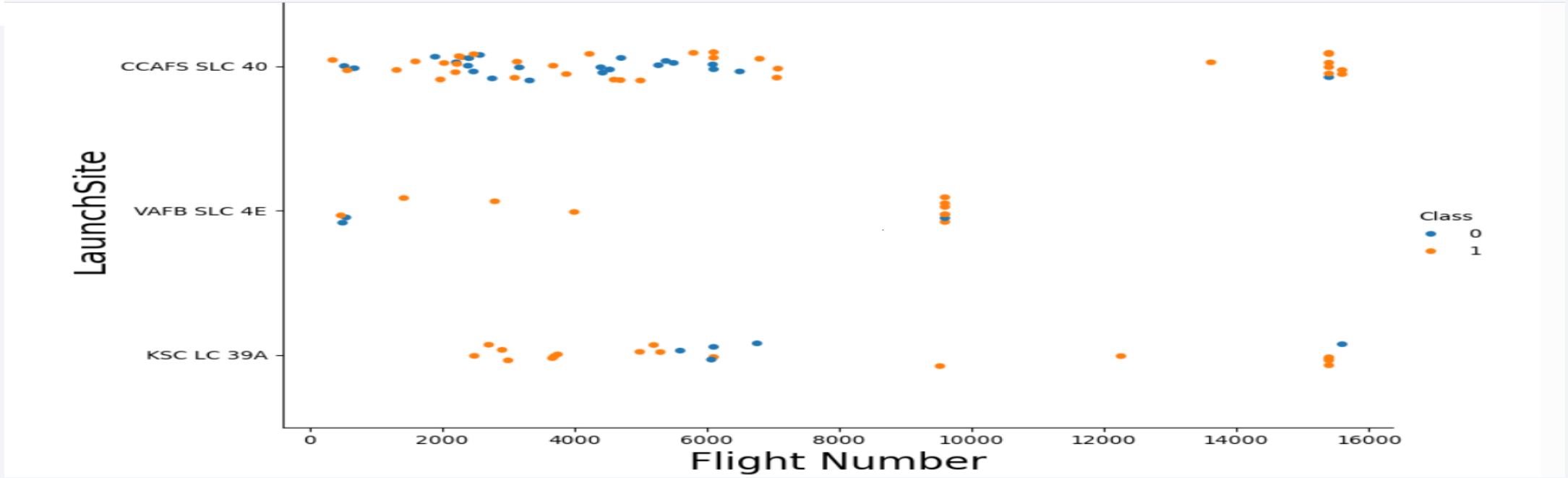
Flight Number vs. Launch Site

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



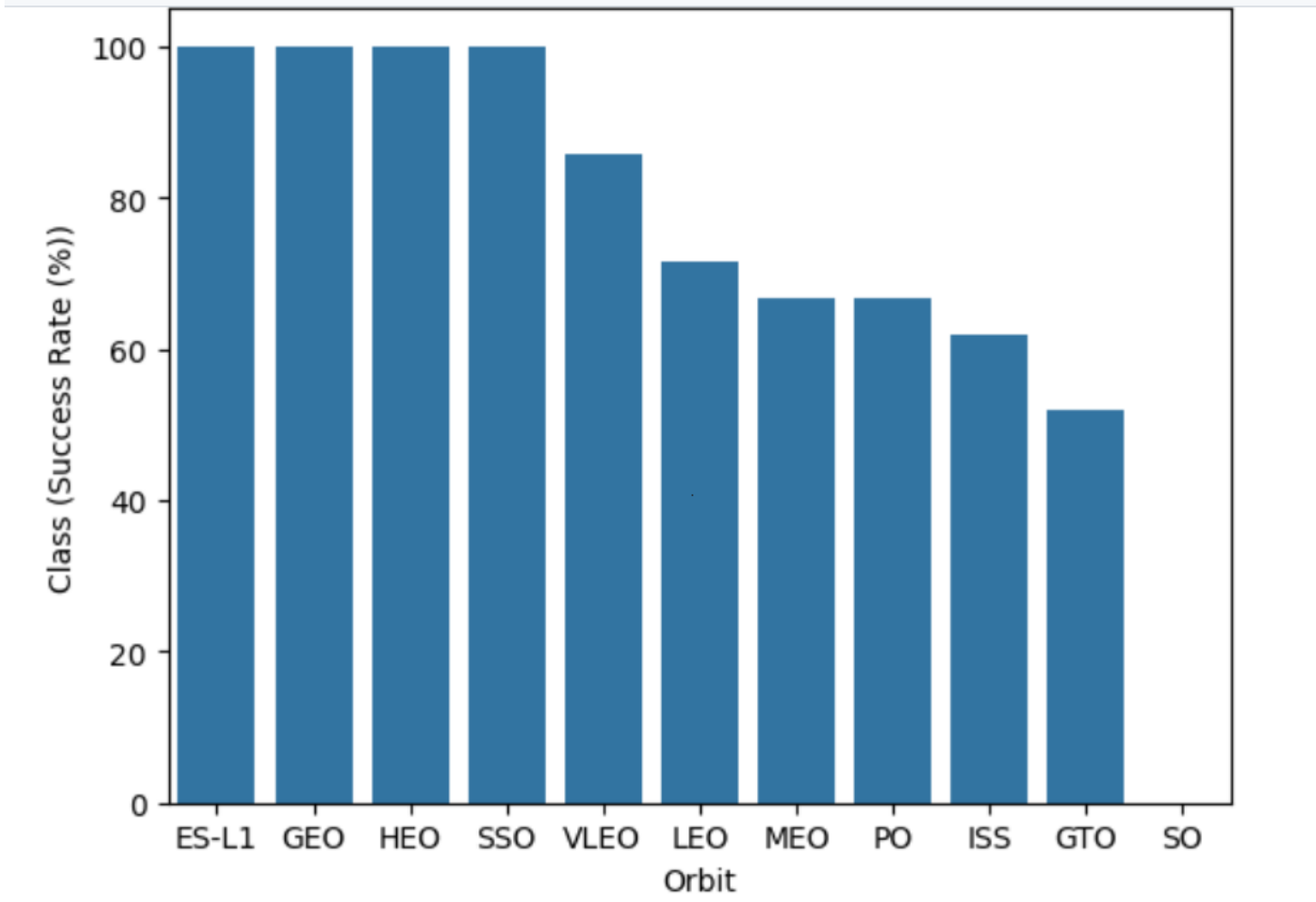
Payload vs. Launch Site

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



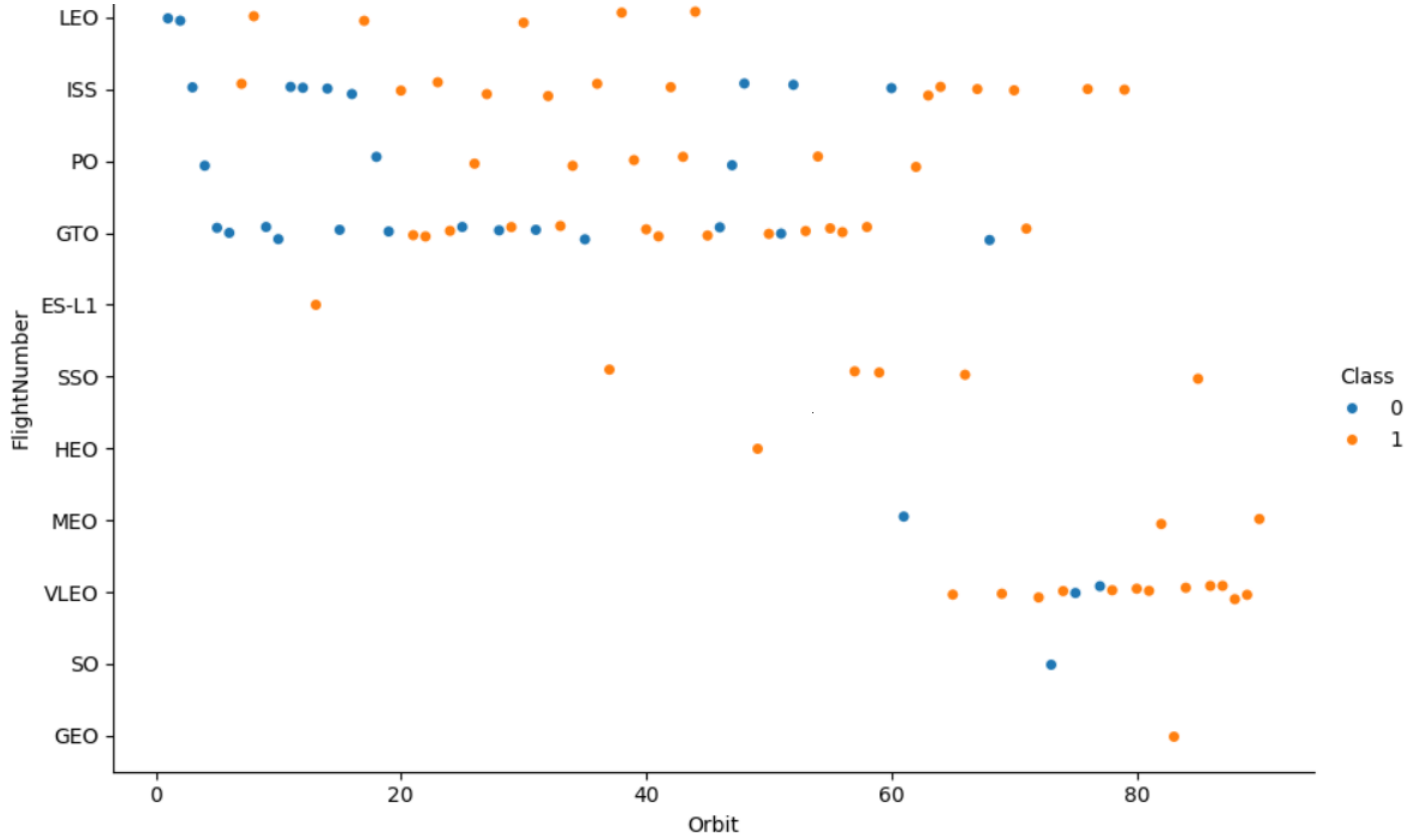
Success Rate vs. Orbit Type

- From the plot, we can see:
- that ES-L1, GEO, HEO, SSO, VLEO had the most success rate 20.



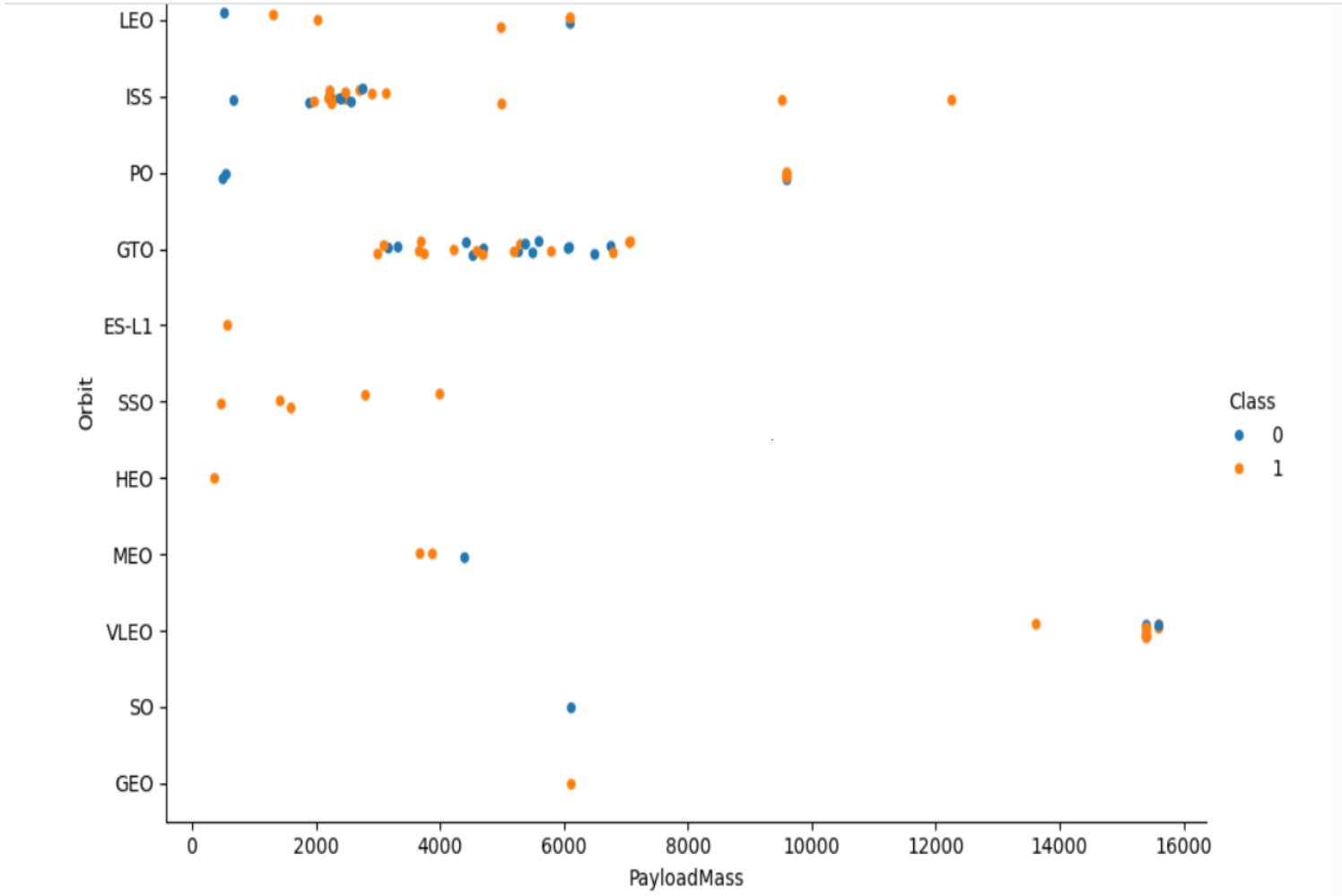
Flight Number vs. Orbit Type

- The plot below shows the 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.



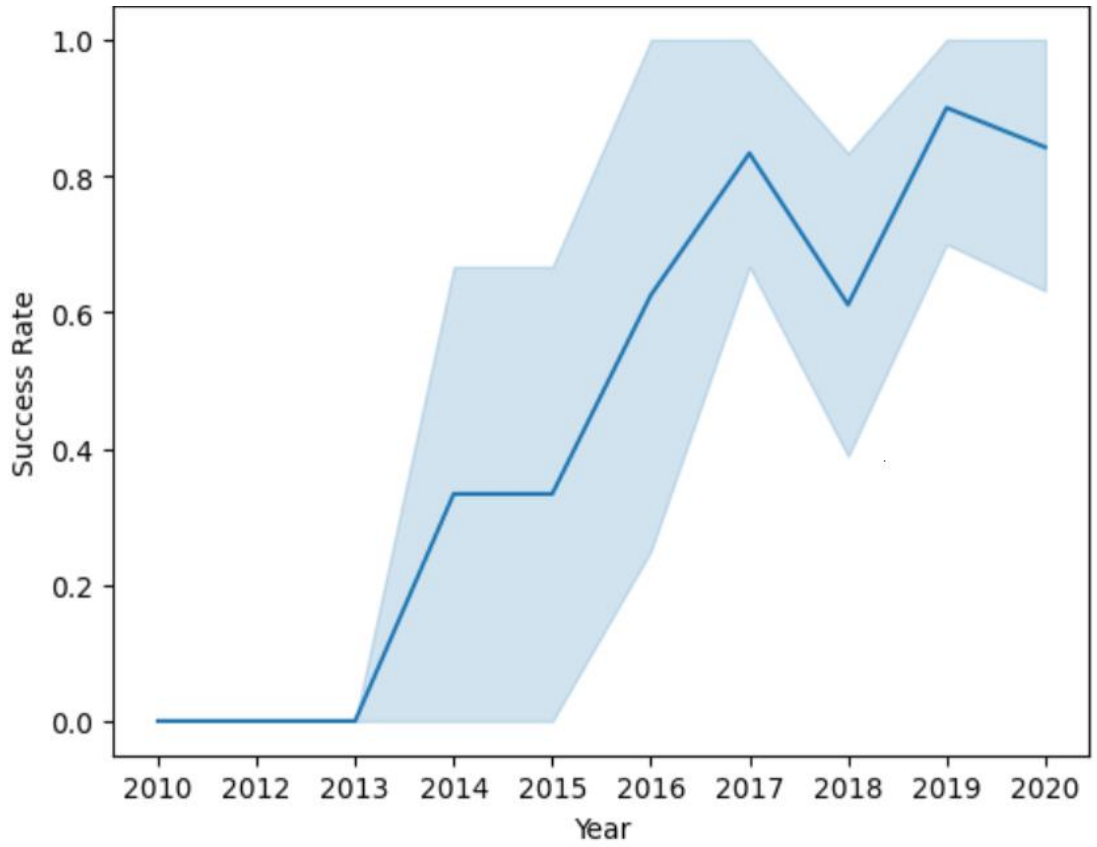
Payload vs. Orbit Type

- 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 DISTINCTto show only unique launch sites from the SpaceX data.

In [14]:
```
%sql select distinct Launch_Site from SPACEXTABLE;
```

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

Out[14]:

Launch_Site
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`

```
In [19]: %sql select * from SPACEXTABLE where Launch_Site like 'CCA%' limit 5
 * sqlite:///my_data1.db
Done.
```

Out[19]:

Date	Time (UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS__KG_	Orbit	Customer	Mission_Outcome	La
2010-06-04	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Fa
2010-12-08	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	Fa
2012-05-22	7:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	

Total Payload Mass

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

In [23]:
```
%sql select SUM(PAYLOAD_MASS__KG_) from SPACEXTABLE \
where customer = 'NASA (CRS)'
```

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

Out[23]:

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

In [24]:
```
%sql select AVG(PAYLOAD_MASS__KG_) from SPACEXTABLE \
where Booster_Version = 'F9 v1.1'
```

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

Out[24]:

AVG(PAYLOAD_MASS__KG_)
2928.4

First Successful Ground Landing Date

- We observed that the dates of the first successful landing outcome on ground pad was 22ndDecember 2015

In [26]:

```
%sql select min(Date) From SPACEXTABLE \
where Landing_Outcome = 'Success (ground pad)'
```

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

Out[26]:

min(Date)
2015-12-22

Successful Drone Ship Landing with Payload between 4000 and 6000

- We used the WHERE clause to filter for boosters that have successfully landed on the drone ship and applied the condition to determine successful landing with payload mass greater than 4000 but less than 6000.

In [37]:
```
%sql select * From SPACEXTABLE where (Landing_Outcome = 'Success (drone ship)') \
and (PAYLOAD_MASS__KG_ between 4000 and 6000)
```

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

Out[37]:

Date	Time (UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS__KG_	Orbit	Customer	Mission_Outcome	Landir
2016-05-06	5:21:00	F9 FT B1022	CCAFS LC-40	JCSAT-14	4696	GTO	SKY Perfect JSAT Group	Success	Su
2016-08-14	5:26:00	F9 FT B1026	CCAFS LC-40	JCSAT-16	4600	GTO	SKY Perfect JSAT Group	Success	Su
2017-03-30	22:27:00	F9 FT B1021.2	KSC LC-39A	SES-10	5300	GTO	SES	Success	Su
2017-10-11	22:53:00	F9 FT B1031.2	KSC LC-39A	SES-11 / EchoStar 105	5200	GTO	SES EchoStar	Success	Su

Total Number of Successful and Failure Mission Outcomes

- We used a filter for WHERE Mission Outcome was a success or a failure.

In [47]:
```
%sql select Mission_Outcome, count(*) from SPACEXTABLE \
GROUP BY Mission_Outcome
```

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

Out[47]:

Mission_Outcome	count(*)
Failure (in flight)	1
Success	98
Success	1
Success (payload status unclear)	1

Boosters Carried Maximum Payload

```
54]: %sql select Booster_Version, PAYLOAD_MASS__KG_ from SPACEXTABLE \
     where PAYLOAD_MASS__KG_ = (select max(PAYLOAD_MASS__KG_) from SPACEXTABLE)

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

54]:

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

- We determined the booster that has carried the maximum payload using a subquery in the WHERE clause and the MAX() function.

2015 Launch Records

- We used a combination of the WHERE clause, LIKE, AND, and BETWEEN conditions to filter for failed outcomes in drone ship, their booster versions, and launch site names for the year 2015

In [68]:

```
%sql select substr(Date,6,2) as month, Booster_Version, Launch_Site,Landing_Outcome \
from SPACEXTABLE \
where (Landing_Outcome = 'Failure (drone ship)') and (substr(Date,0,5)='2015')
```

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

Out[68]:

month	Booster_Version	Launch_Site	Landing_Outcome
01	F9 v1.1 B1012	CCAFS LC-40	Failure (drone ship)
04	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 BETWEEN2010-06-04 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 outcomes in descending order.

In [81]:
```
%sql select Landing_Outcome, count(Landing_Outcome) from SPACEXTABLE\
WHERE Date BETWEEN '2010-06-04' AND '2017-03-20' \
group by Landing_Outcome
```

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

Out[81]:

Landing_Outcome	count(Landing_Outcome)
Controlled (ocean)	3
Failure (drone ship)	5
Failure (parachute)	2
No attempt	10
Precluded (drone ship)	1
Success (drone ship)	5
Success (ground pad)	3
Uncontrolled (ocean)	2

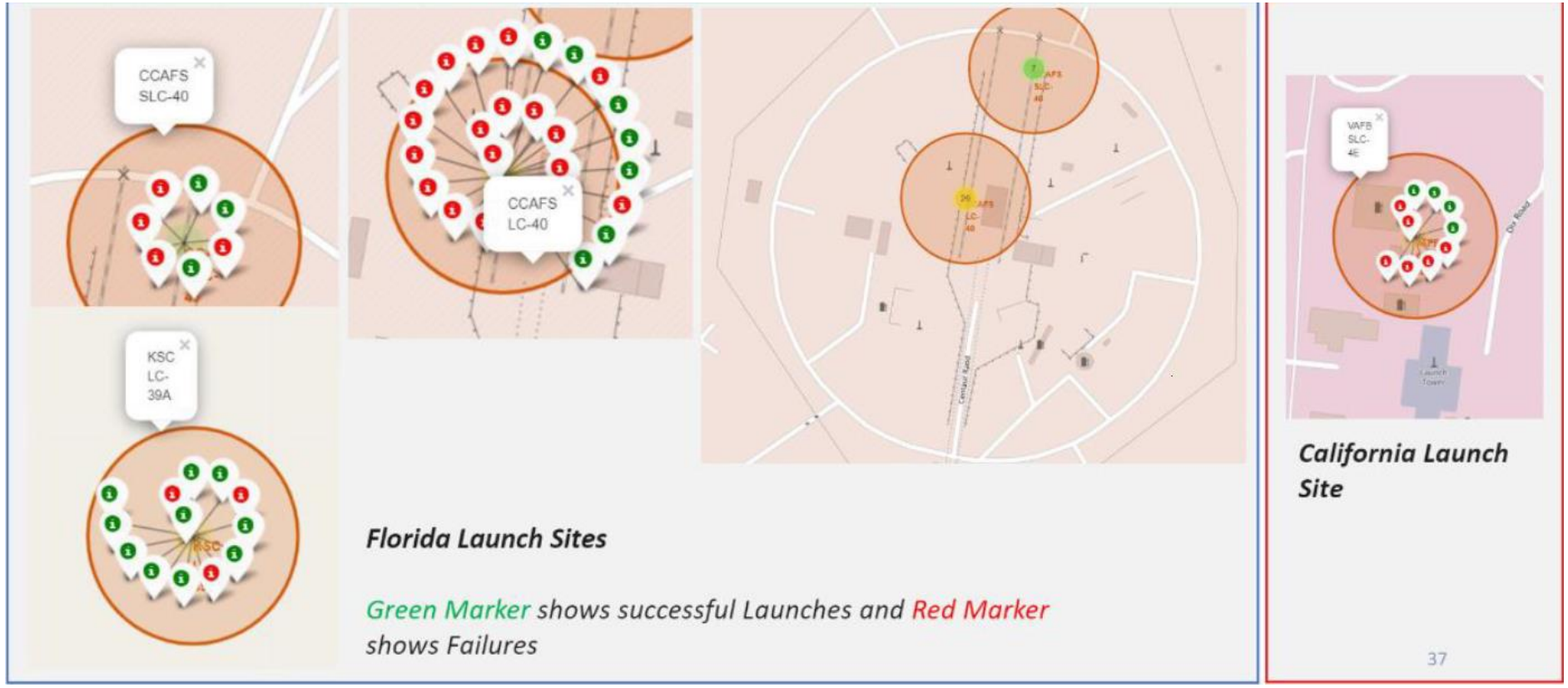
Section 3

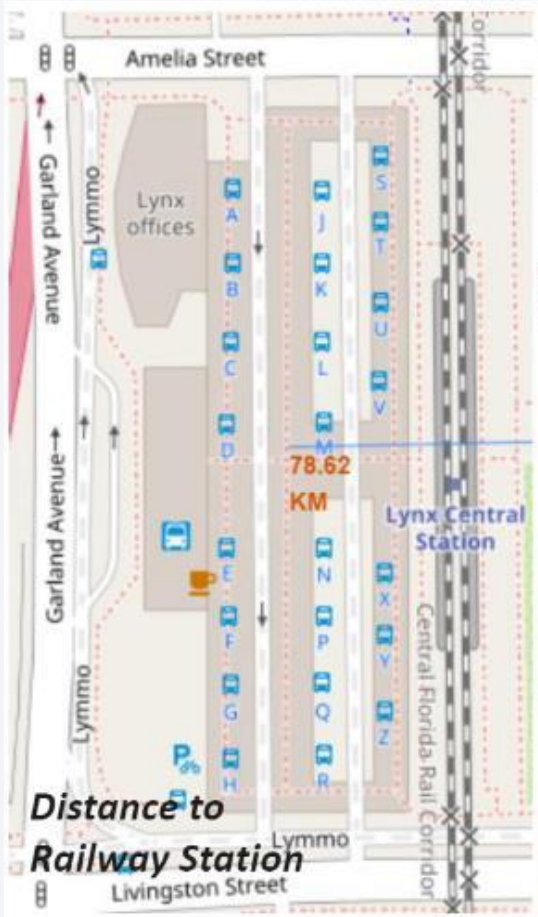
Launch Sites Proximities Analysis

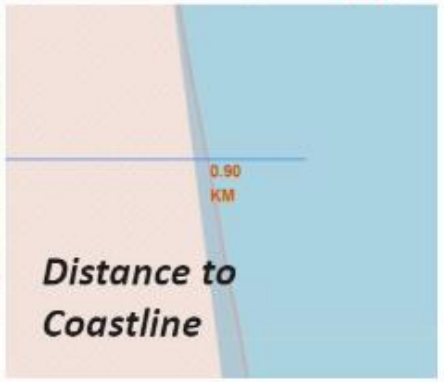
All launch sites global map markers

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

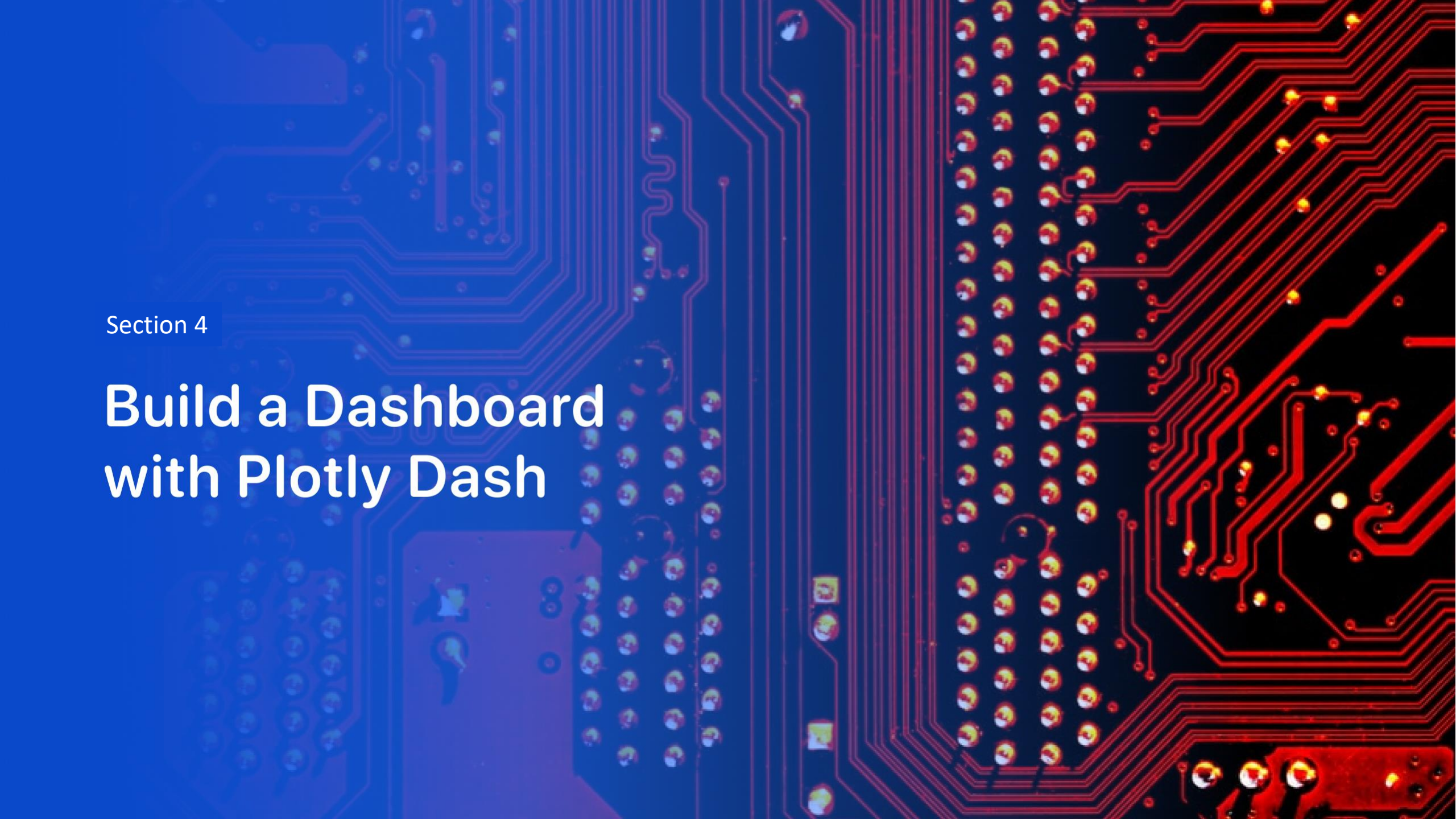
Markers showing launch sites with color labels



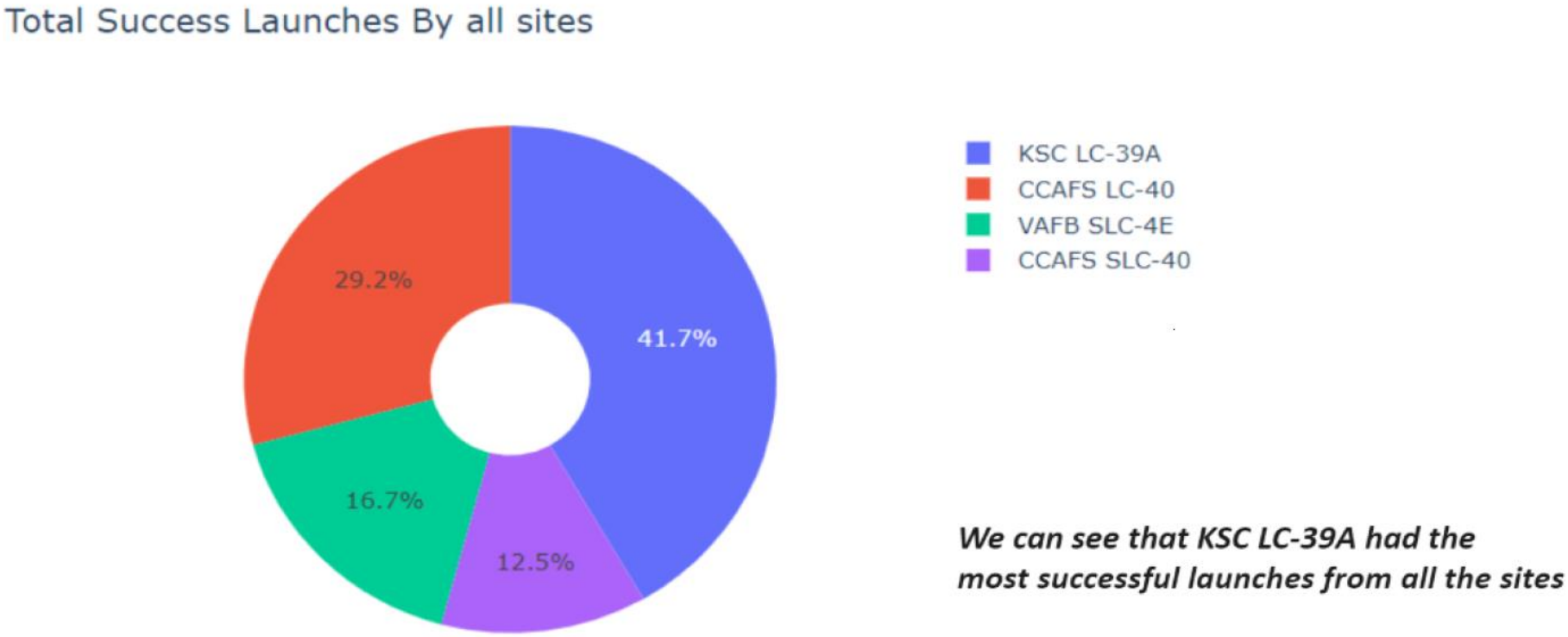




- Are launch sites in close proximity to railways? No
- Are launch sites in close proximity to highways? No
- Are launch sites in close proximity to coastline? Yes
- Do launch sites keep certain distance away from cities? Yes

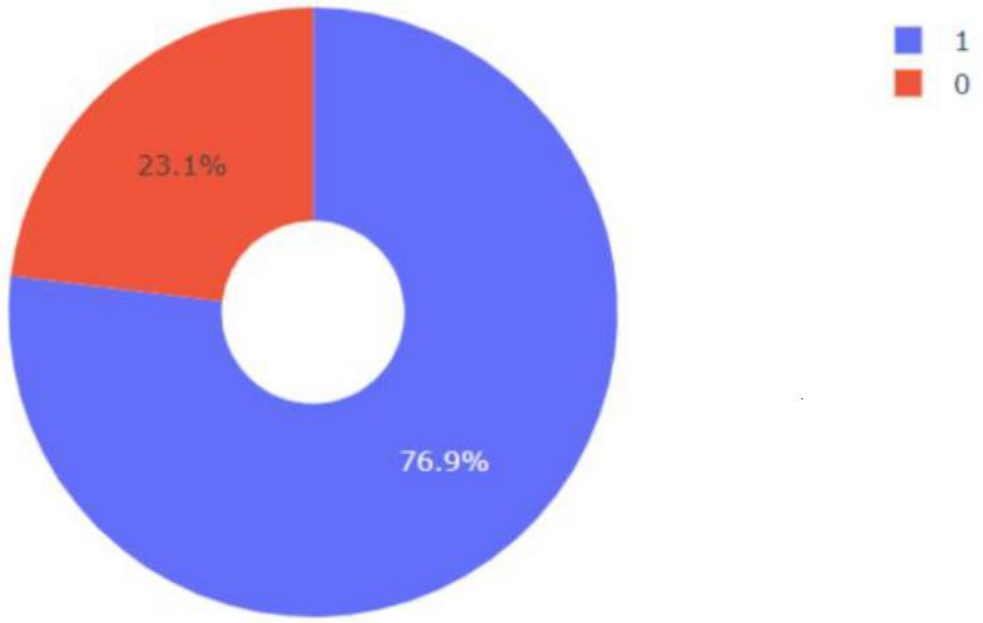

Section 4
Build a Dashboard with Plotly Dash

Pie chart showing the success percentage achieved by each launch site



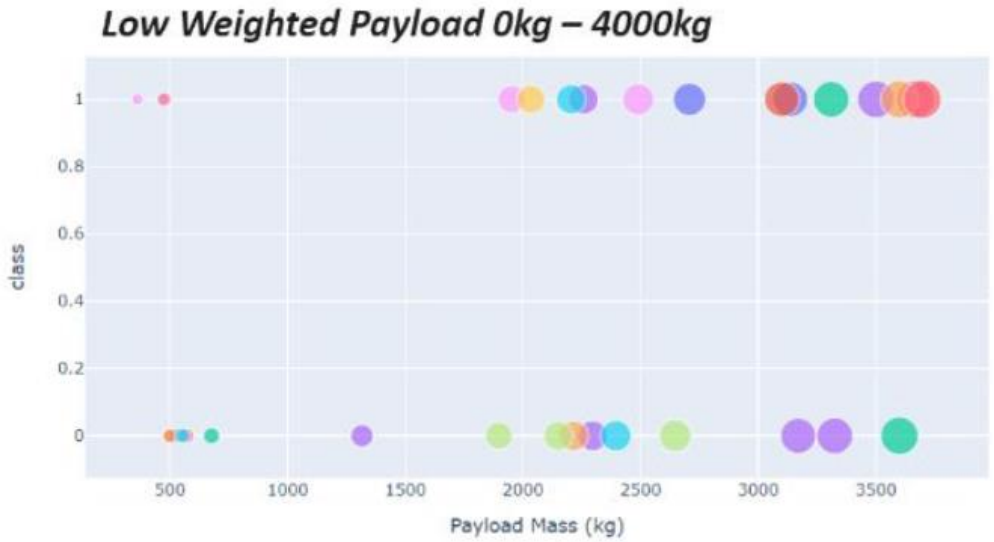
We can see that KSC LC-39A had the most successful launches from all the sites

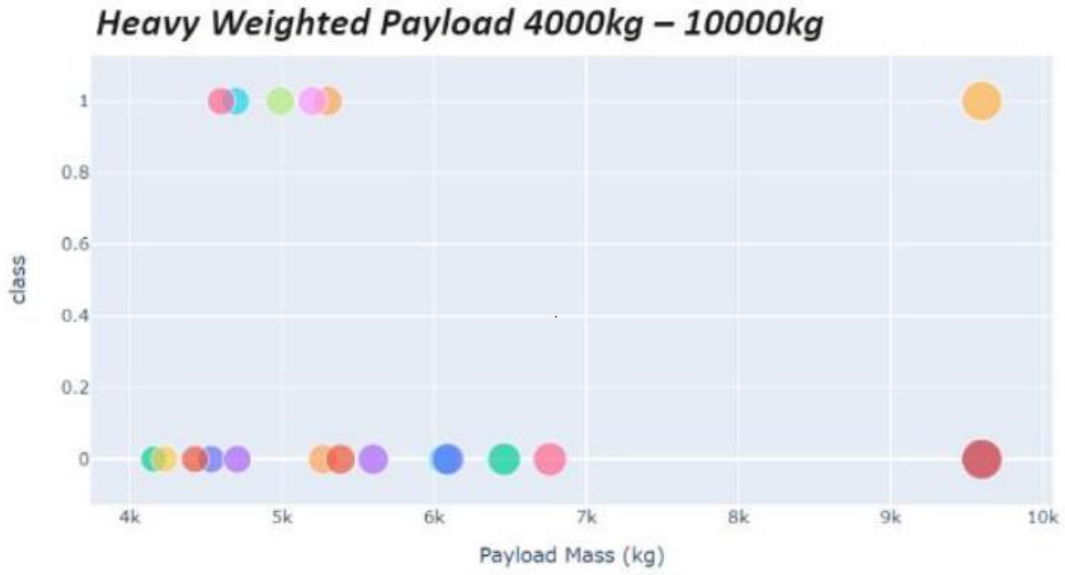
Pie chart showing the Launch site with the highest launch success ratio



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 decision tree classifier is the model with the highest classification accuracy

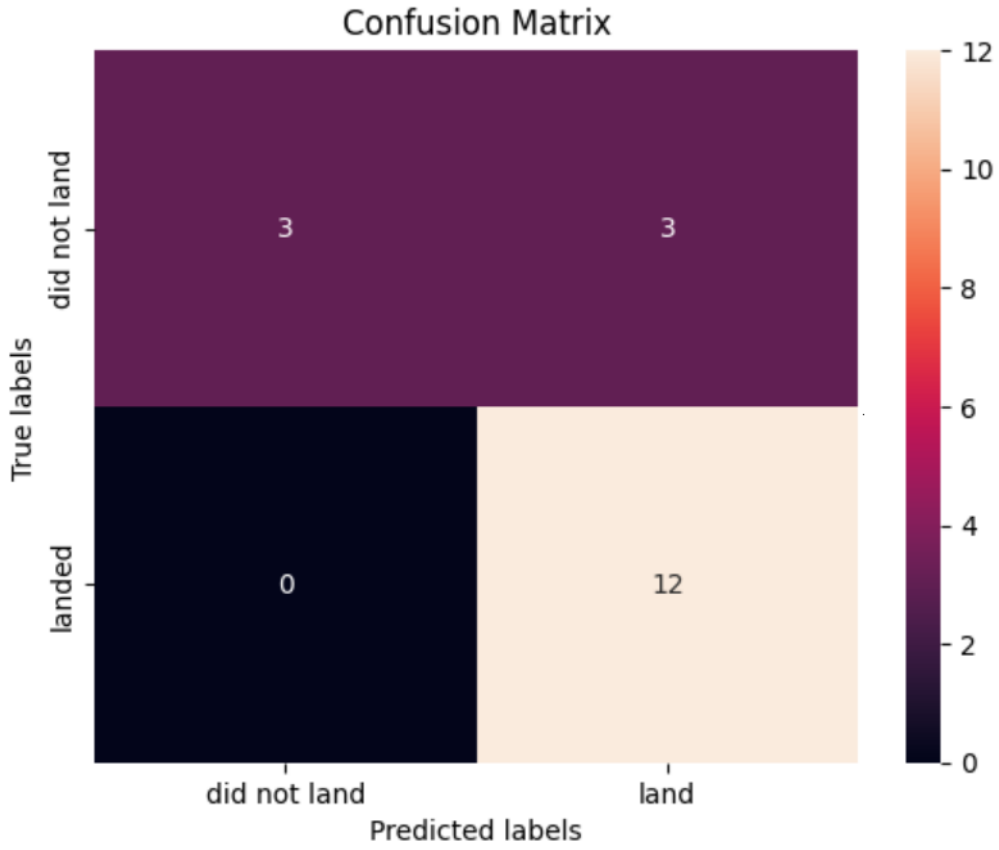
In [37]:

```
models = {'KNeighbors':knn_cv.best_score_,
              'DecisionTree':tree_cv.best_score_,
              'LogisticRegression':logreg_cv.best_score_,
              'SupportVector': svm_cv.best_score_}

bestalgorithm = max(models, key=models.get)
print('Best model is', bestalgorithm,'with a score of', models[bestalgorithm])
if bestalgorithm == 'DecisionTree':
    print('Best params is :', tree_cv.best_params_)
if bestalgorithm == 'KNeighbors':
    print('Best params is :', knn_cv.best_params_)
if bestalgorithm == 'LogisticRegression':
    print('Best params is :', logreg_cv.best_params_)
if bestalgorithm == 'SupportVector':
    print('Best params is :', svm_cv.best_params_)
```

```
Best model is DecisionTree with a score of 0.8892857142857145
Best params is : {'criterion': 'gini', 'max_depth': 18, 'max_features': 'auto', 'min_samples_leaf': 1, 'min_sam
ples_split': 5, 'splitter': 'random'}
```

Confusion Matrix

- The confusion matrix for the decision tree classifier shows that the classifier can distinguish between the different classes. The major problem is the false positives .i.e., unsuccessful landing marked as successful landing by the classifier.



Conclusions

- 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 site.
- The Decision tree classifier is the best machine learning algorithm for this task.

Appendix

- Include any relevant assets like Python code snippets, SQL queries, charts, Notebook outputs, or data sets that you may have created during this project

Thank you!