IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

Diana Khamraeva
07/03/2024

Outline

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

Executive Summary

- The following methodologies were used to analyze data:
  - ✓ Data Collection using web scraping and SpaceX API;
  - ✓ Exploratory Data Analysis (EDA), including data wrangling, data visualization and interactive visual analytics;
  - ✓ Machine Learning Prediction.
- Summary of all results
  - ✓ It was possible to collected valuable data from public sources;
  - ✓ EDA allowed to identify which features are the best to predict success of launchings;
  - ✓ Machine Learning Prediction showed the best model to predict which characteristics are important to drive this opportunity by the best way, using all collected data

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 from Space X was obtained from 2 sources:
    - Space X API (https://api.spacexdata.com/v4/rockets/)
    - WebScraping (https://en.wikipedia.org/wiki/List_of_Falcon/_9/_and_Falcon_Heavy_launches)
- Perform data wrangling
  - Collected data was enriched by creating a landing outcome label based on outcome data after summarizing and analyzing feature
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash

Methodology

- Perform predictive analysis using classification models
  - Data that was collected until this step were normalized, divided in training and test data sets and evaluated by four different classification models, being the accuracy of each model evaluated using different combinations of parameters.

Data Collection

- Describe how data sets were collected.
  - Data collection was done using get request to the SpaceX API.
  - Next, I decoded the response content as a Json using .json() function call and turn it into a pandas dataframe using .json_normalize().
  - I then cleaned the data, checked for missing values and fill in missing values where necessary.
  - In addition, I 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 - SpaceX API

- I used the get request to the SpaceX API to collect data, clean the requested data and did some basic data wrangling and formatting.
- https://github.com/di-khamraeva/my_data_analys/blob/main/jupyter-labs-spacex-data-collection-api%20Completed.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

- I applied web scrapping to webscrape Falcon 9 launch records with BeautifulSoup
- I parsed the table and converted it into a pandas dataframe.
- https://github.com/di-khamraeva/my_data_analys/blob/main/jupyter-labs-webscraping%20Completed.ipynb

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>
```

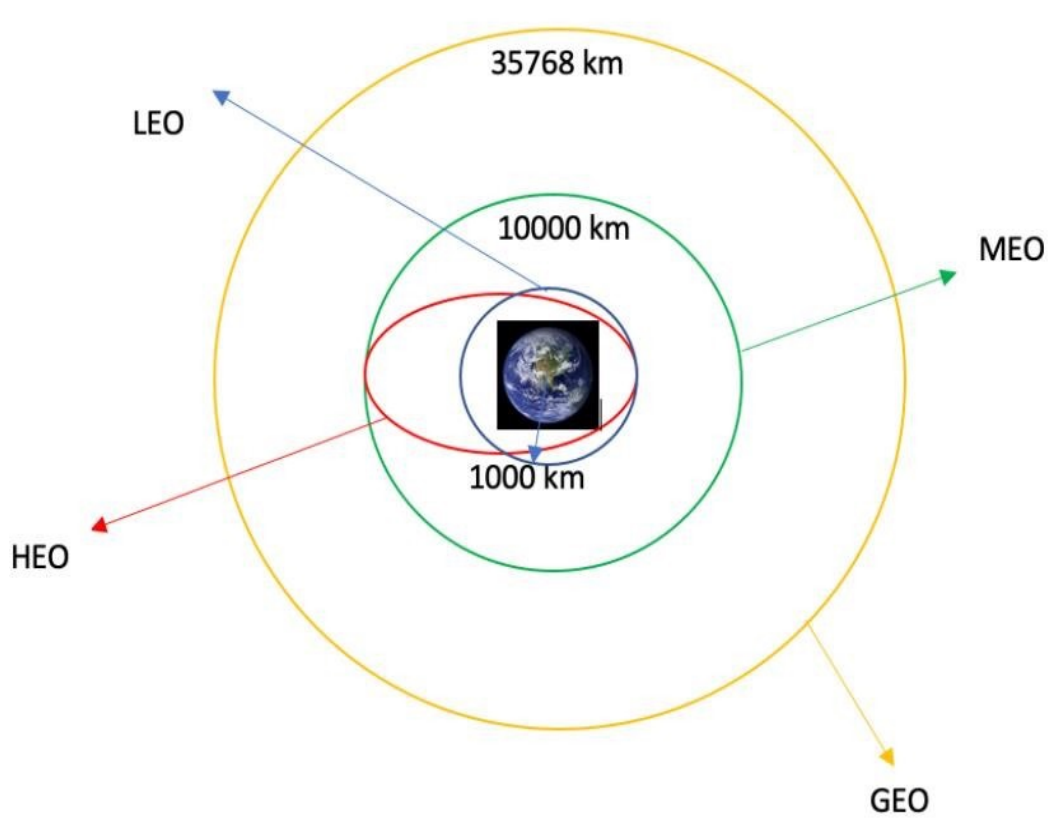
3. Extract all column names from the HTML table header

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

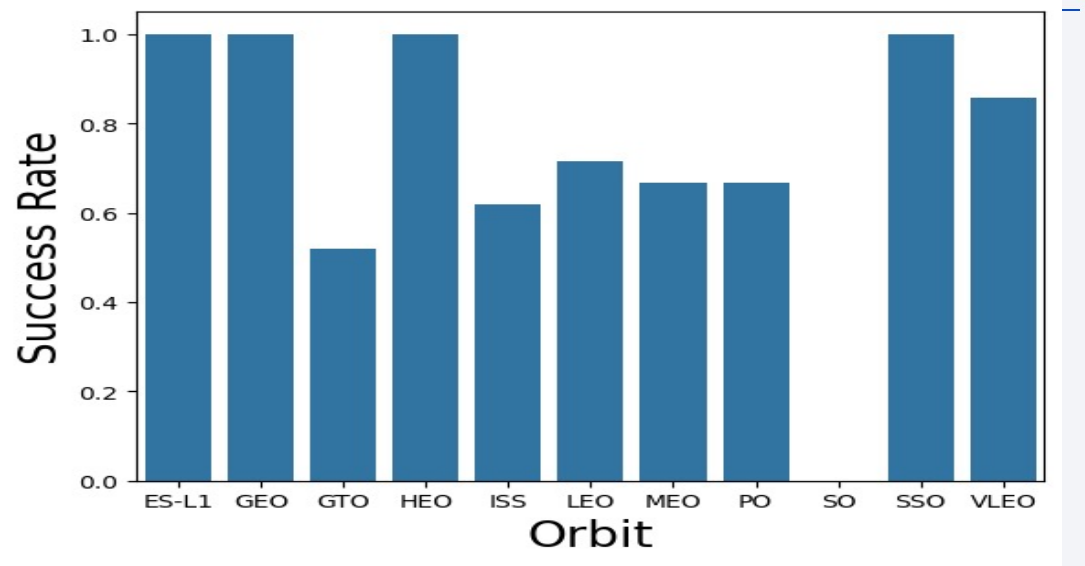
Data Wrangling

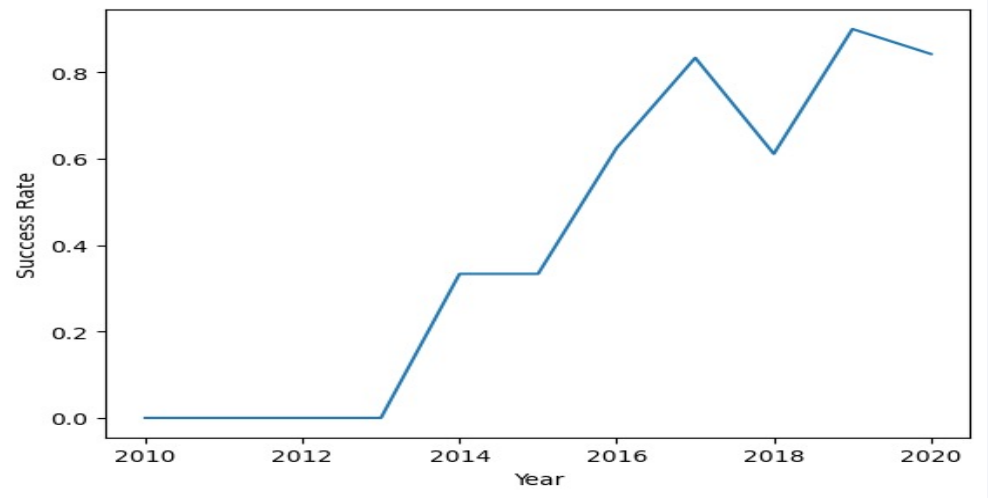
- I performed exploratory data analysis and determined the training labels.
- I calculated the number of launches at each site, and the number and occurrence of each orbits
- I created landing outcome label from outcome column and exported the results to csv.
- https://github.com/di-khamraeva/my_data_analys/blob/main/labs-jupyter-spacex-Data%20wrangling.ipynb



EDA with Data Visualization

- I explored the data by visualizing the relationship between flight number and launch Site, payload and launch site, success rate of each orbit type, flight number and orbit type, the launch success yearly trend.
- https://github.com/di-khamraeva/my_data_analys/blob/main/jupyter-labs-eda-dataviz.ipynb.jupyterlite%20Completed.ipynb





EDA with SQL

- I loaded the SpaceX dataset into a PostgreSQL database without leaving the jupyter notebook.
- I 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/di-khamraeva/my_data_analys/blob/main/jupyter-labs-eda-sql-coursera_sqllite%20Completed.ipynb

Build an Interactive Map with Folium

- Markers, circles, lines and marker clusters were used with Folium Maps
- Markers indicate points like launch sites;
- Circles indicate highlighted areas around specific coordinates, like NASA Johnson Space Center;
- Marker clusters indicates groups of events in each coordinate, like launches in a launch site; and
- Lines are used to indicate distances between two coordinates

https://github.com/di-khamraeva/my_data_analys/blob/main/Interactive%20Visual%20Analytics%20with%20Folium%20lab.ipynb

Build a Dashboard with Plotly Dash

- Summarize what plots/graphs and interactions you have added to a dashboard
- Explain why you added those plots and interactions
- Add the GitHub URL of your completed Plotly Dash lab, as an external reference and peer-review purpose
- https://github.com/di-khamraeva/my_data_analys/blob/main/Interactive%20Dashboard.py

Predictive Analysis (Classification)

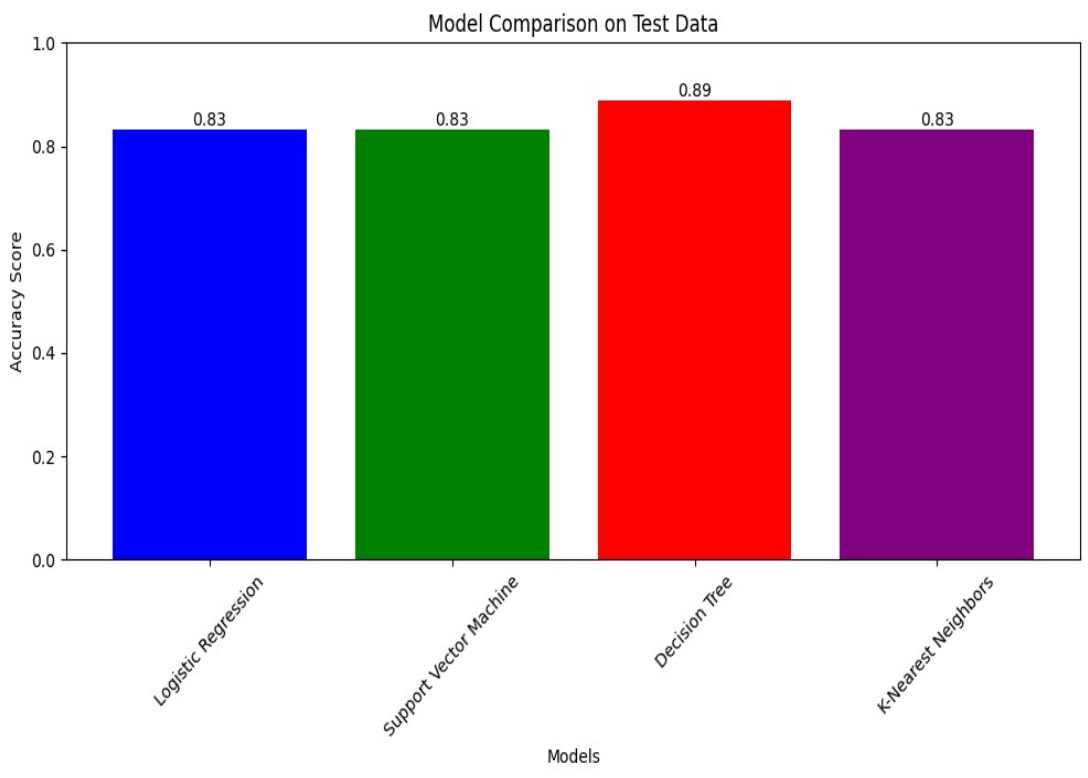
- I loaded the data using numpy and pandas, transformed the data, split our data into training and testing.
- I built different machine learning models and tune different hyperparameters using GridSearchCV.
- I used accuracy as the metric for our model, improved the model using feature engineering and algorithm tuning.
- I found the best performing classification model
- https://github.com/di-khamraeva/my_data_analys/blob/main/SpaceX_Machine_Learning_Prediction_Part_5.jupyterlite%20completed.ipynb

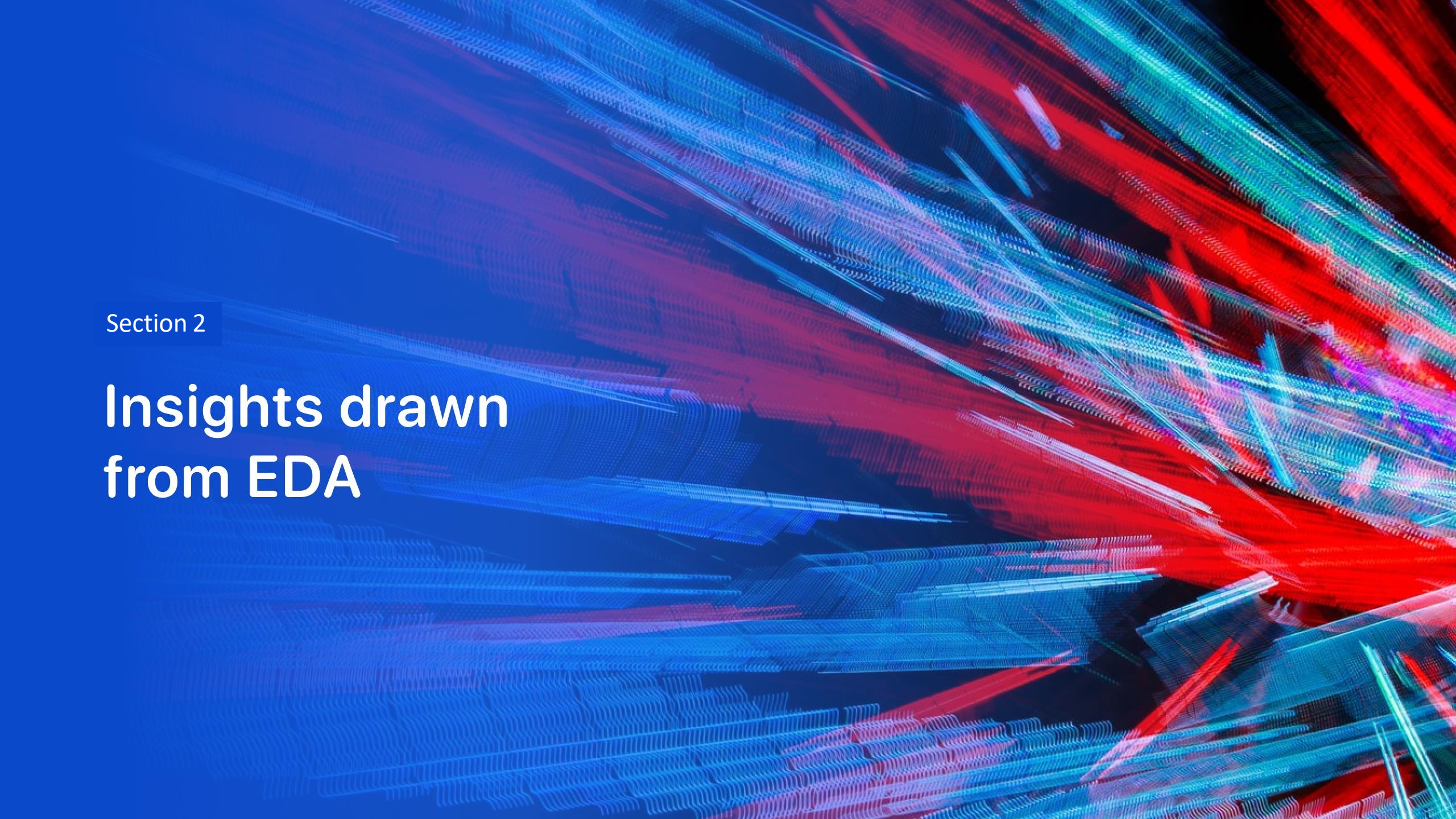
Results

- Exploratory data analysis results:
  - Space X uses 4 different launch sites;
  - The first launches were done to Space X itself and NASA;
  - The average payload of F9 v1.1 booster is 2,928 kg;
  - The first success landing outcome happened in 2015 fiver year after the first launch;
  - Many Falcon 9 booster versions were successful at landing in drone ships having payload above the average;
  - Almost 100% of mission outcomes were successful;
  - Two booster versions failed at landing in drone ships in 2015: F9 v1.1 B1012 and F9 v1.1 B1015;
  - The number of landing outcomes became as better as years passed.

Results

- Predictive Analysis showed that Decision Tree Classifier is the best model to predict successful landings, having accuracy over 89%



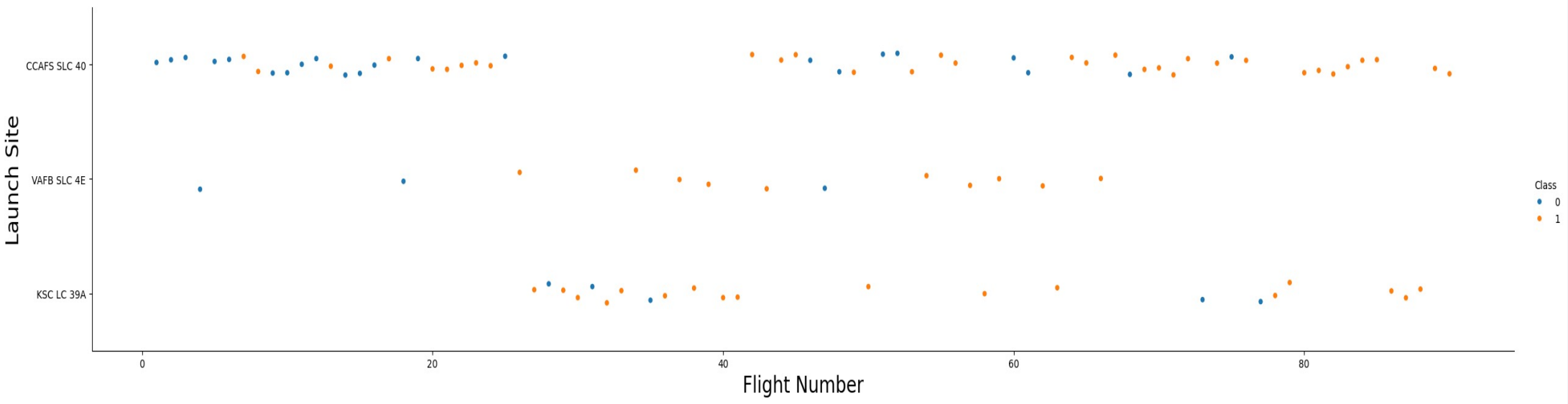

Section 2
Insights drawn from EDA

Flight Number vs. Launch Site

•According to the plot above, it's possible to verify that the best launch site nowadays is CCAF5 SLC 40, where most of recent launches were successful;

• In second place VAFB SLC 4E and third place KSC LC 39A;

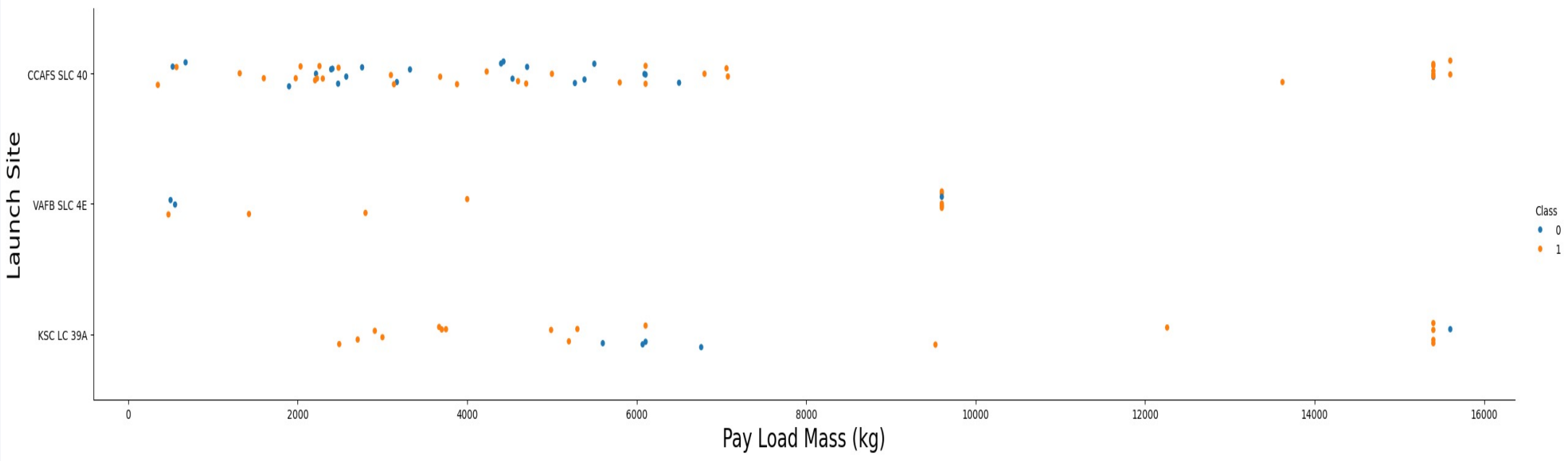
• It's also possible to see that the general success rate improved over time.



Payload vs. Launch Site

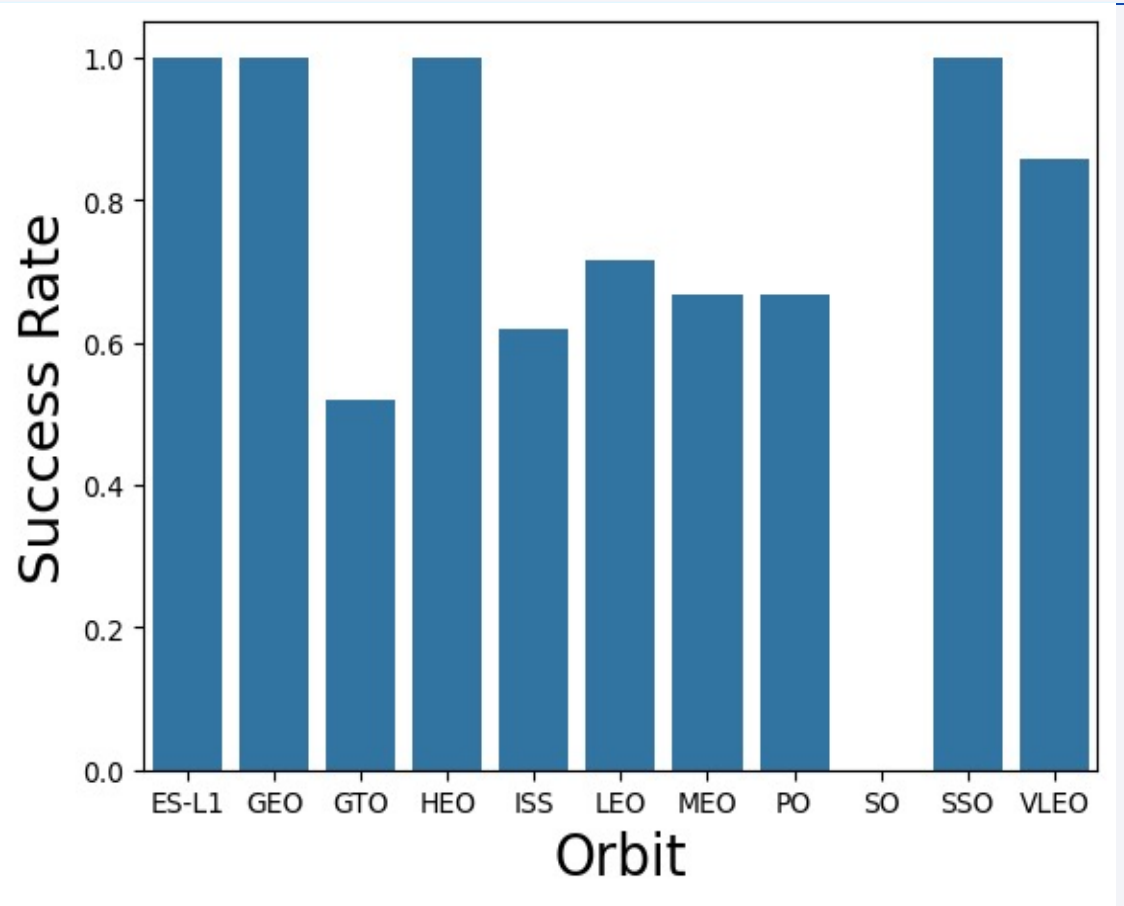
- Payloads over 9,000kg (about the weight of a school bus) have excellent success rate;

- Payloads over 12,000kg seems to be possible only on CCAFS SLC 40 and KSC LC 39A launch sites.



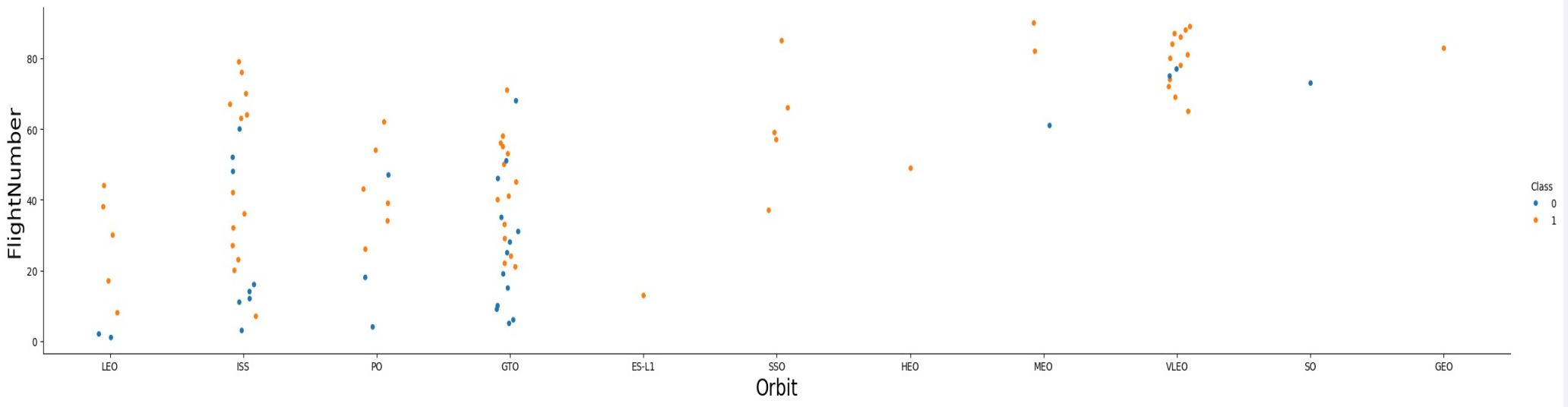
Success Rate vs. Orbit Type

- The biggest success rates happens to orbits:
  - ES-L1;
  - GEO;
  - HEO; and
  - SSO.
- Followed by:
  - VLEO (above 80%); and
  - LFO (above 70**%**).



Flight Number vs. Orbit Type

- Apparently, success rate improved over time to all orbits;
- VLEO orbit seems a new business opportunity, due to recent increase of its frequency.

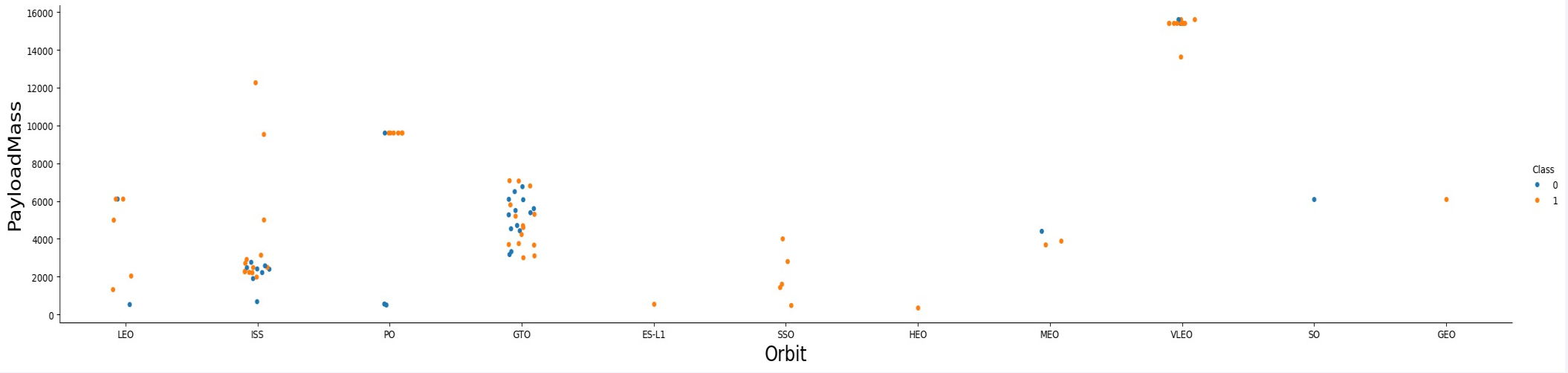


Payload vs. Orbit Type

Apparently, there is no relation between payload and success rate to orbit GTO;

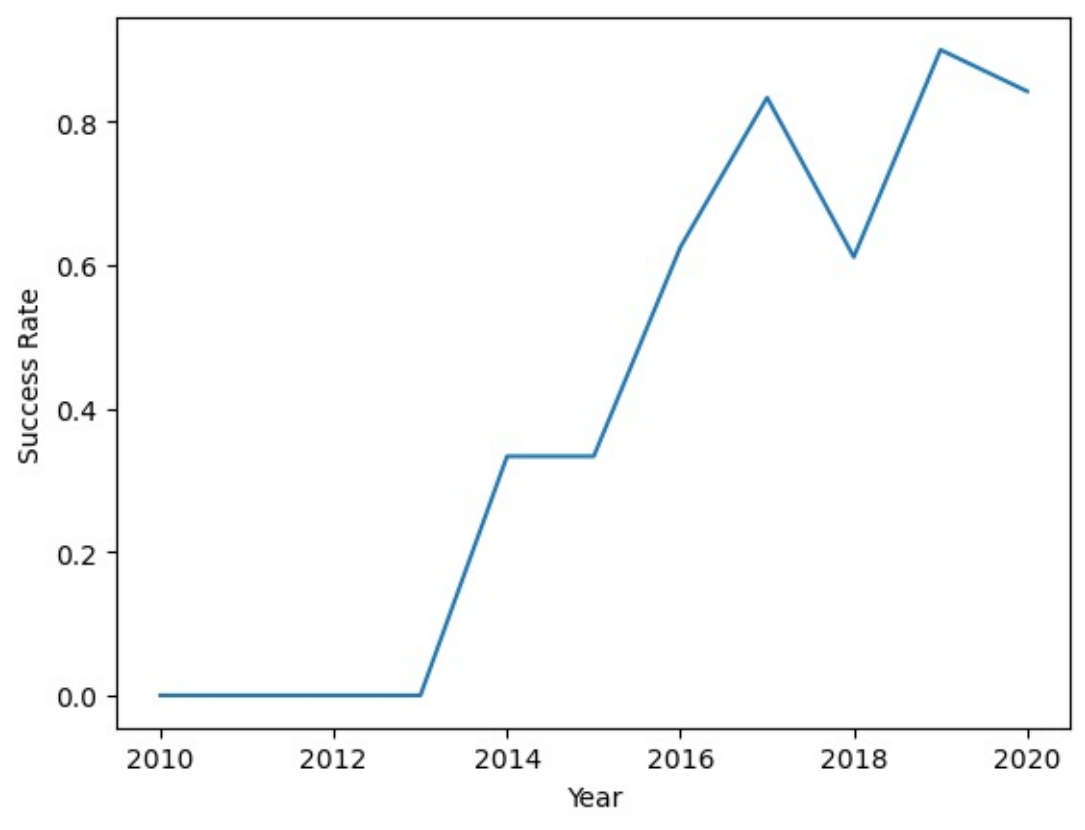
- ISS orbit has the widest range of payload and a good rate of success;

- There are few launches to the orbits SO and GEO.



Launch Success Yearly Trend

- Success rate started increasing in 2013 and kept until 2020;
- • It seems that the first three years were a period of adjusts and improvement of technology.



All Launch Site Names

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

Display the names of the unique launch sites in the space mission

In [10]:
```
task_1 = '''
        SELECT DISTINCT LaunchSite
        FROM SpaceX
'''
create_pandas_df(task_1, database=conn)
```

Out[10]:

	launchsite
0	KSC LC-39A
1	CCAFS LC-40
2	CCAFS SLC-40
3	VAFB SLC-4E

Launch Site Names Begin with 'CCA'

- I 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

- I 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)

In [12]:
```
task_3 = '''
        SELECT SUM(PayloadMassKG) AS Total_PayloadMass
        FROM SpaceX
        WHERE Customer LIKE 'NASA (CRS)'
        '''
create_pandas_df(task_3, database=conn)
```

Out[12]:

	total_payloadmass
0	45596

Average Payload Mass by F9 v1.1

- I 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

In [13]:
```
task_4 = '''
        SELECT AVG(PayloadMassKG) AS Avg_PayloadMass
        FROM SpaceX
        WHERE BoosterVersion = 'F9 v1.1'
        '''
create_pandas_df(task_4, database=conn)
```

Out[13]:

	avg_payloadmass
0	2928.4

First Successful Ground Landing Date

- I observed that the dates of the first successful landing outcome on ground pad was 22nd December 2015

In [14]:
```
task_5 = '''
        SELECT MIN(Date) AS FirstSuccessfull_landing_date
        FROM SpaceX
        WHERE LandingOutcome LIKE 'Success (ground pad)'
        '''
create_pandas_df(task_5, database=conn)
```

Out[14]:

	firstsuccessfull_landing_date
0	2015-12-22

Successful Drone Ship Landing with Payload between 4000 and 6000

- I 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

In [15]:
```
task_6 = '''
        SELECT BoosterVersion
        FROM SpaceX
        WHERE LandingOutcome = 'Success (drone ship)'
            AND PayloadMassKG > 4000
            AND PayloadMassKG < 6000
        '''
create_pandas_df(task_6, database=conn)
```

Out[15]:

	boosterversion
0	F9 FT B1022
1	F9 FT B1026
2	F9 FT B1021.2
3	F9 FT B1031.2

Total Number of Successful and Failure Mission Outcomes

- I used wildcard like '%' to filter for **WHERE** Mission Outcome was a success or a failure.

List the total number of successful and failure mission outcomes

In [16]:
```
task_7a = '''
        SELECT COUNT(MissionOutcome) AS SuccessOutcome
        FROM SpaceX
        WHERE MissionOutcome LIKE 'Success%'
        '''

task_7b = '''
        SELECT COUNT(MissionOutcome) AS FailureOutcome
        FROM SpaceX
        WHERE MissionOutcome LIKE 'Failure%'
        '''
print('The total number of successful mission outcome is:')
display(create_pandas_df(task_7a, database=conn))
print()
print('The total number of failed mission outcome is:')
create_pandas_df(task_7b, database=conn)
```

Out[16]:

The total number of successful mission outcome is:

	successoutcome
0	100

The total number of failed mission outcome is:

	failureoutcome
0	1

Boosters Carried Maximum Payload

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

List the names of the booster_versions which have carried the maximum payload mass. Use a subquery

In [17]:

```
task_8 = '''
        SELECT BoosterVersion, PayloadMassKG
        FROM SpaceX
        WHERE PayloadMassKG = (
                                SELECT MAX(PayloadMassKG)
                                FROM SpaceX
                                )
        ORDER BY BoosterVersion
        '''
create_pandas_df(task_8, database=conn)
```

Out[17]:

	boosterversion	payloadmasskg
0	F9 B5 B1048.4	15600
1	F9 B5 B1048.5	15600
2	F9 B5 B1049.4	15600
3	F9 B5 B1049.5	15600
4	F9 B5 B1049.7	15600
5	F9 B5 B1051.3	15600
6	F9 B5 B1051.4	15600
7	F9 B5 B1051.6	15600
8	F9 B5 B1056.4	15600
9	F9 B5 B1058.3	15600
10	F9 B5 B1060.2	15600
11	F9 B5 B1060.3	15600

2015 Launch Records

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

List the failed landing_outcomes in drone ship, their booster versions, and launch site names for in year 2015

In [18]:
```
task_9 = '''
        SELECT BoosterVersion, LaunchSite, LandingOutcome
        FROM SpaceX
        WHERE LandingOutcome LIKE 'Failure (drone ship)'
            AND Date BETWEEN '2015-01-01' AND '2015-12-31'
        '''
create_pandas_df(task_9, database=conn)
```

Out[18]:

	boosterversion	launchsite	landingoutcome
0	F9 v1.1 B1012	CCAFS LC-40	Failure (drone ship)
1	F9 v1.1 B1015	CCAFS LC-40	Failure (drone ship)

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

- We selected Landing outcomes and the **COUNT** of landing outcomes from the data and used the **WHERE** clause to filter for landing outcomes **BETWEEN** 2010-06-04 to 2010-03-20.
- We applied the **GROUP BY** clause to group the landing outcomes and the **ORDER BY** clause to order the grouped landing outcome in descending order.

Rank the count of landing outcomes (such as Failure (drone ship) or Success (ground pad))

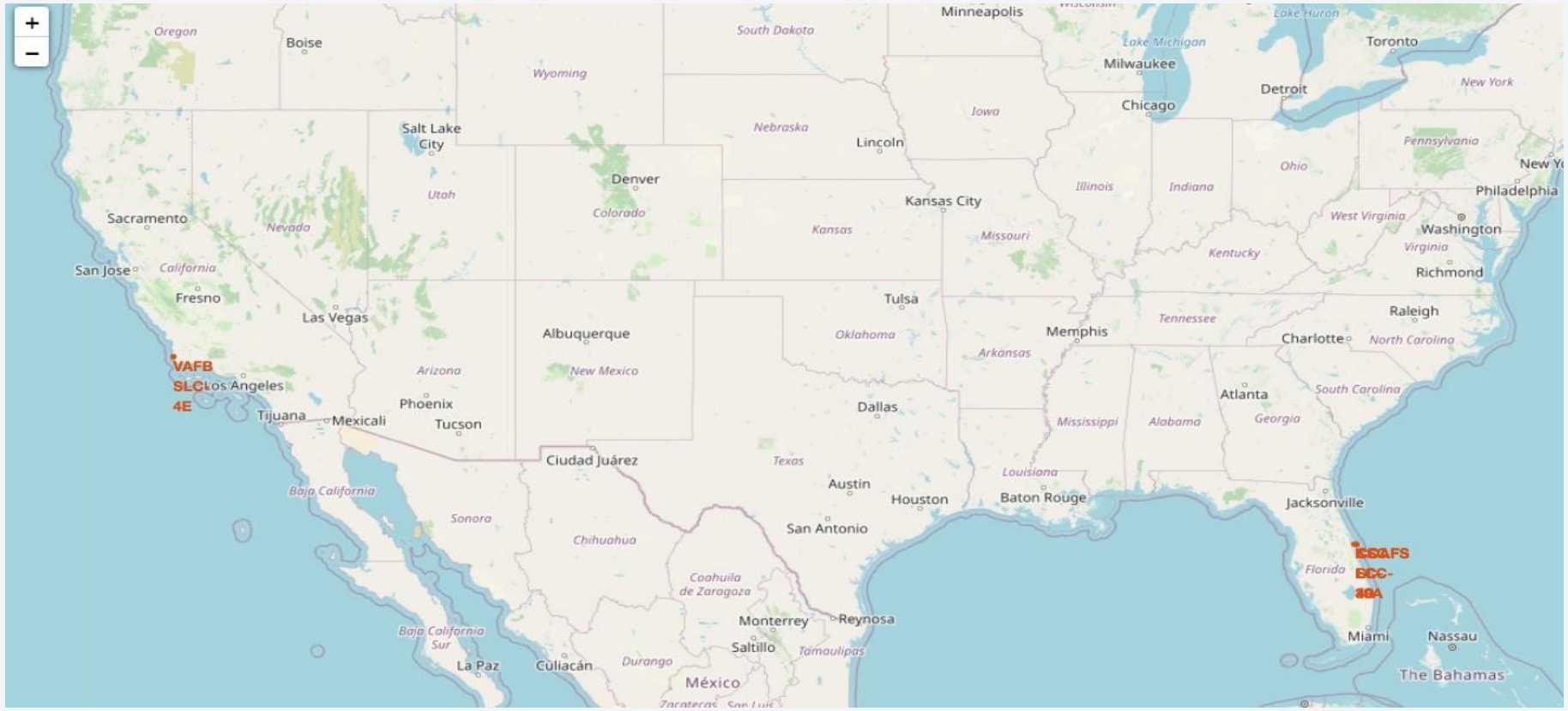
In [19]:
```
task_10 = '''
        SELECT LandingOutcome, COUNT(LandingOutcome)
        FROM SpaceX
        WHERE DATE BETWEEN '2010-06-04' AND '2017-03-20'
        GROUP BY LandingOutcome
        ORDER BY COUNT(LandingOutcome) DESC
        '''
create_pandas_df(task_10, database=conn)
```

Out[19]:

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


Section 3
Launch Sites
Proximities Analysis

All launch sites



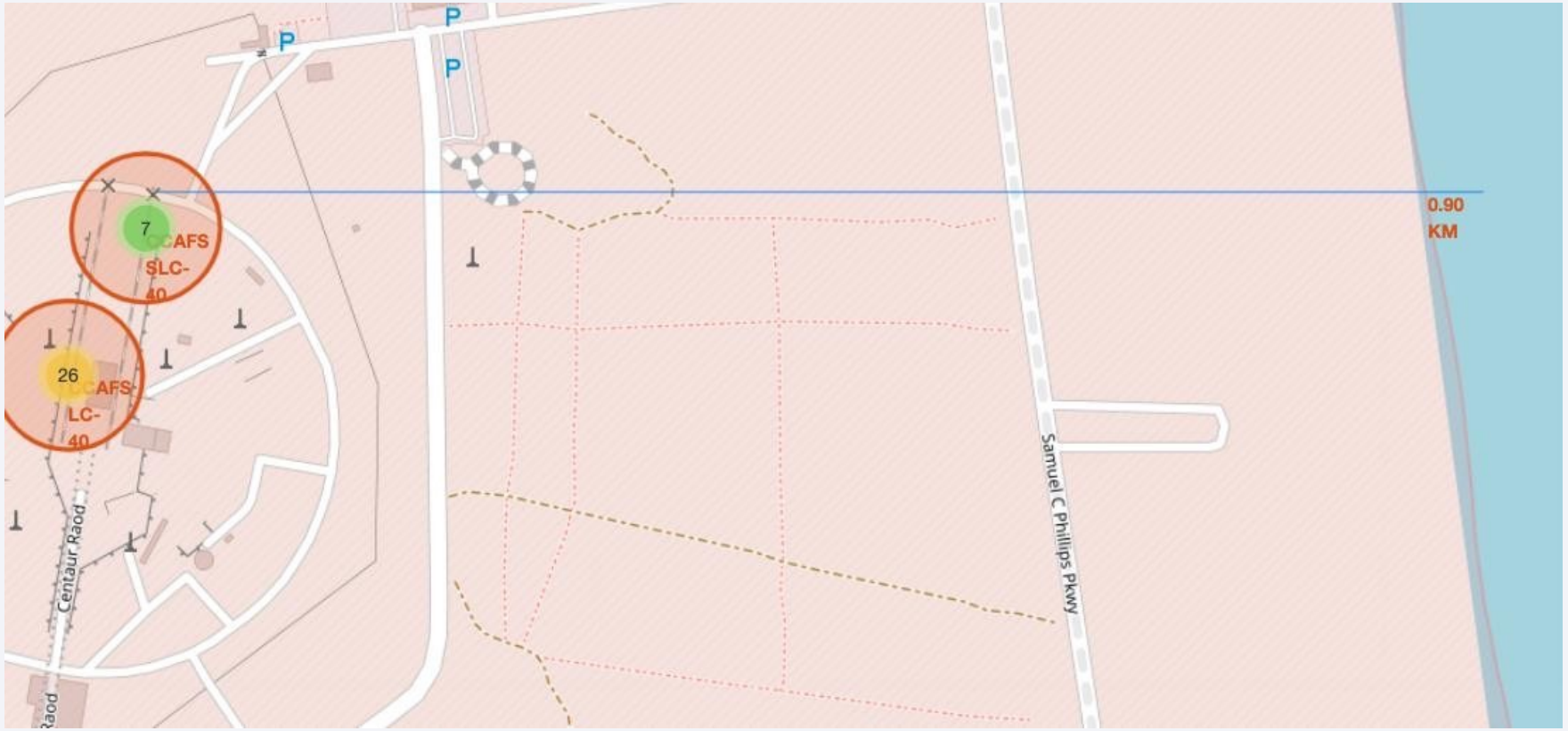
- Launch sites are near sea, probably by safety, but not too far from roads and railroads.

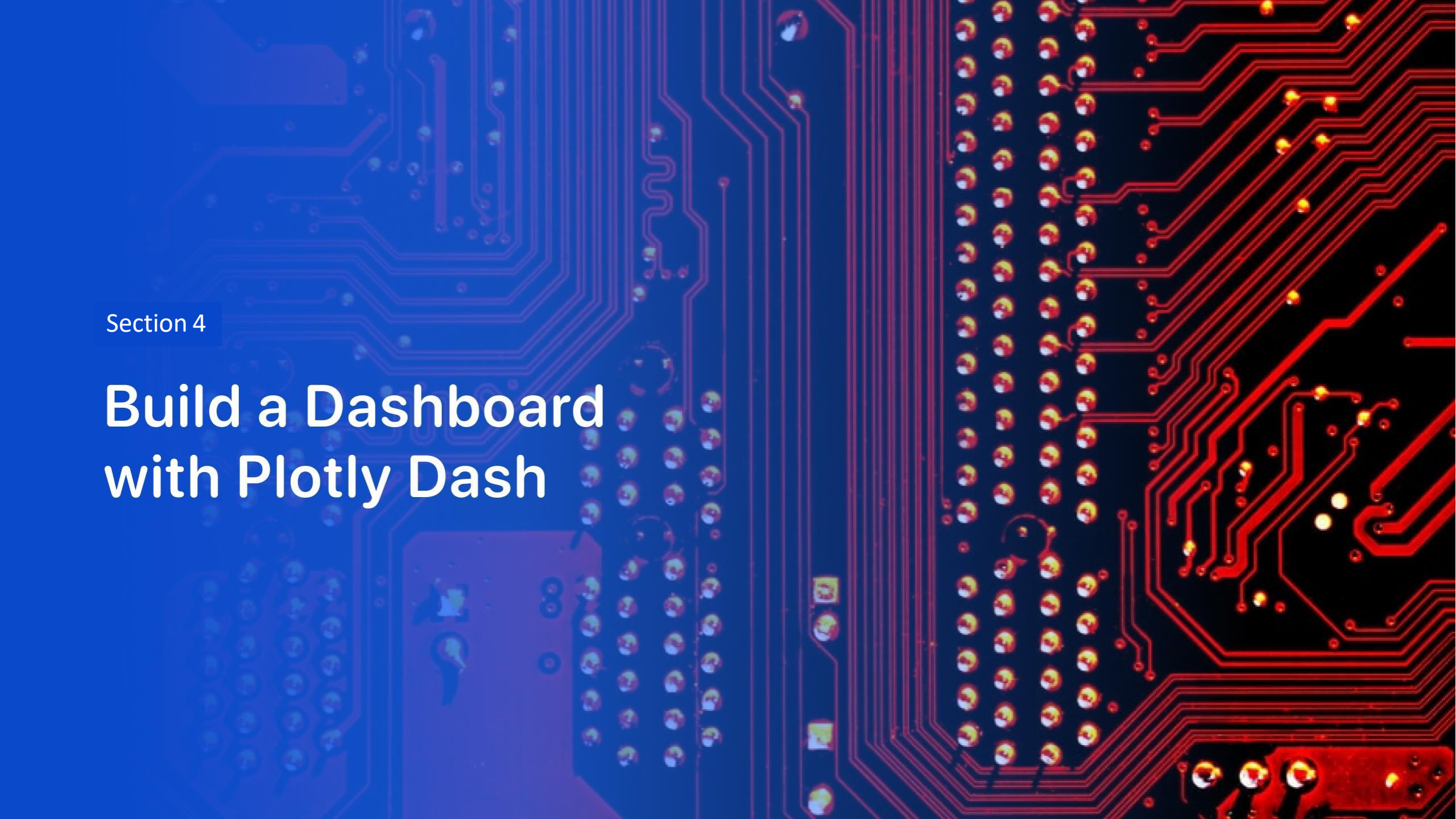
Launch Outcomes by Site

- Green markers indicate successful and red ones indicate failure

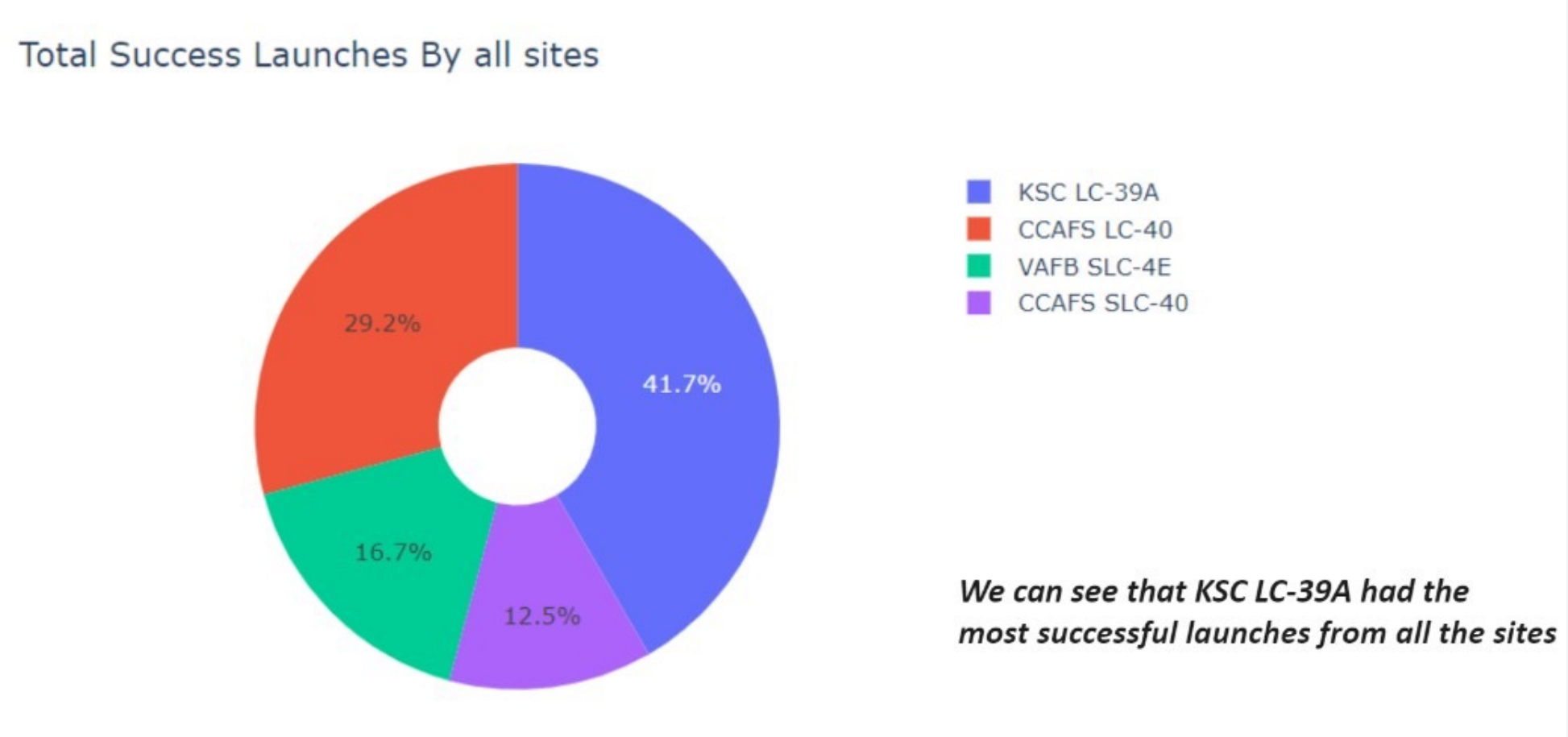
Logistics and Safety

- Launch site AFC SLC-40 has good logistics aspects, being near railroad and road and relatively far from inhabited areas.

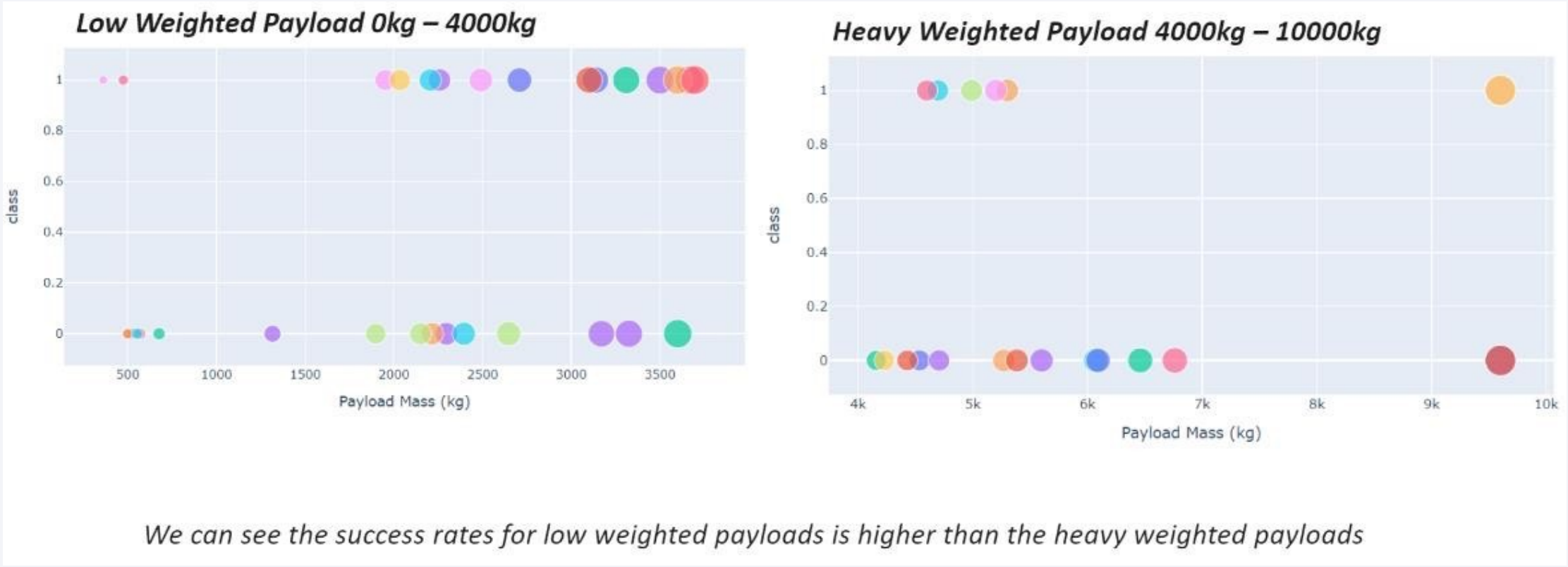



Section 4
Build a Dashboard with Plotly Dash

Successful Launches by Site

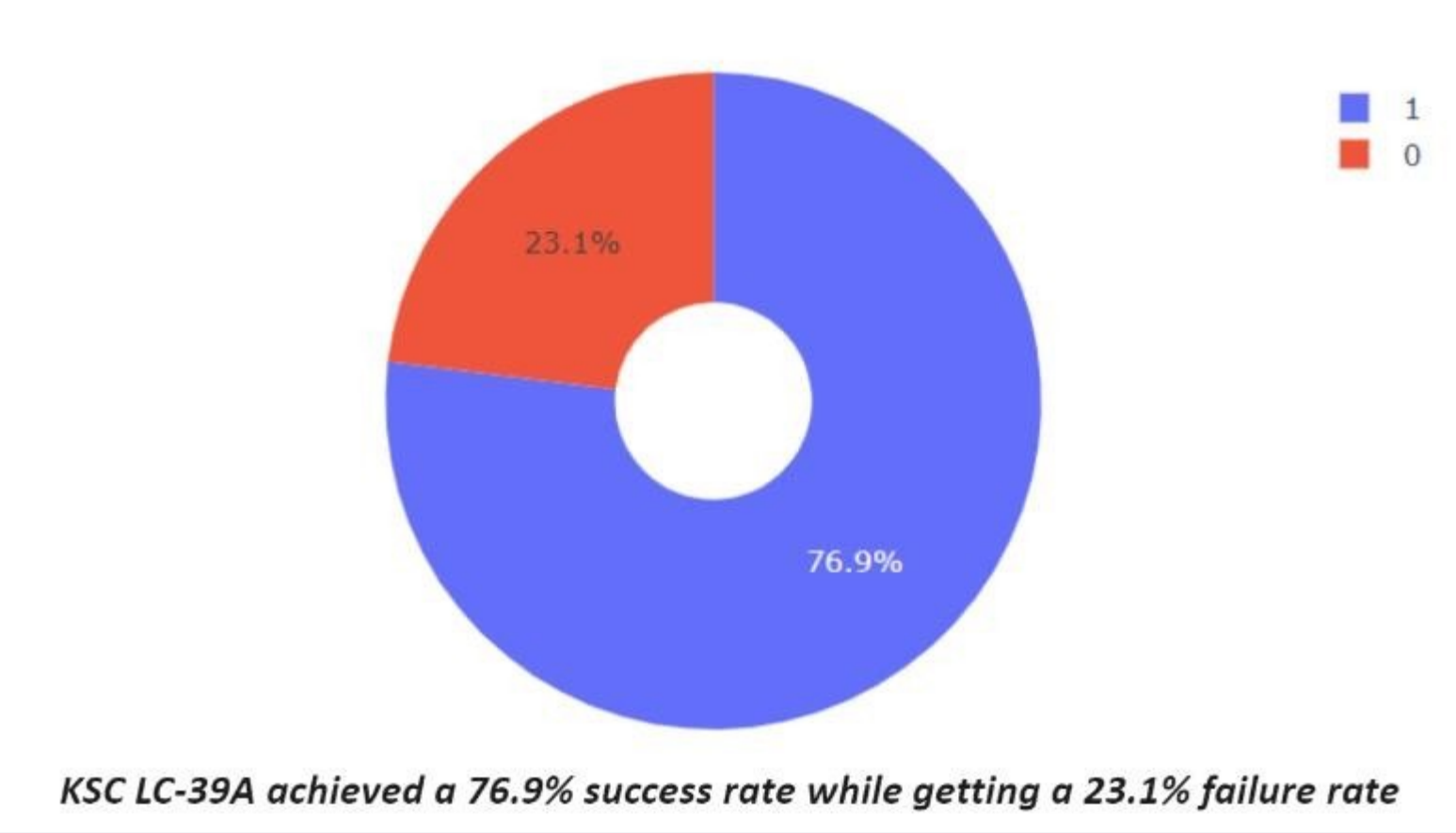


Scatter plot of Payload vs Launch Outcome for all sites, with different payload selected in the range slider



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

Launch Success Ratio for KSC LC-39A



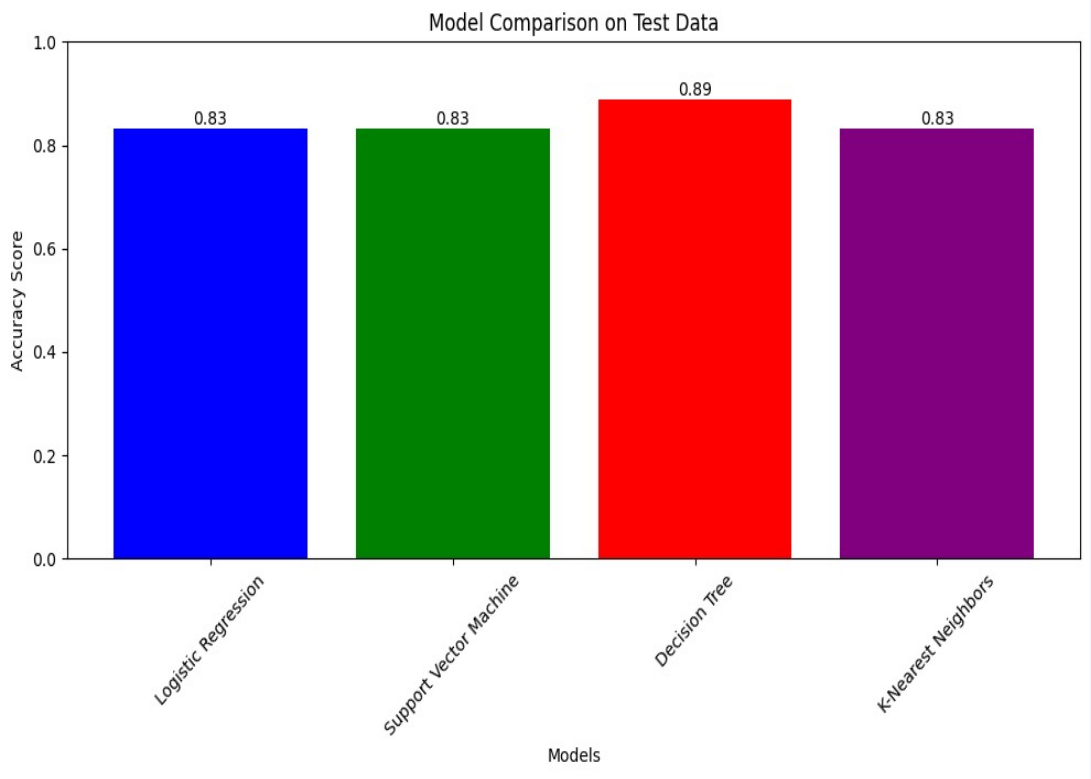
KSC LC-39A achieved a 76.9% success rate while getting a 23.1% failure rate

Section 5

Predictive Analysis (Classification)

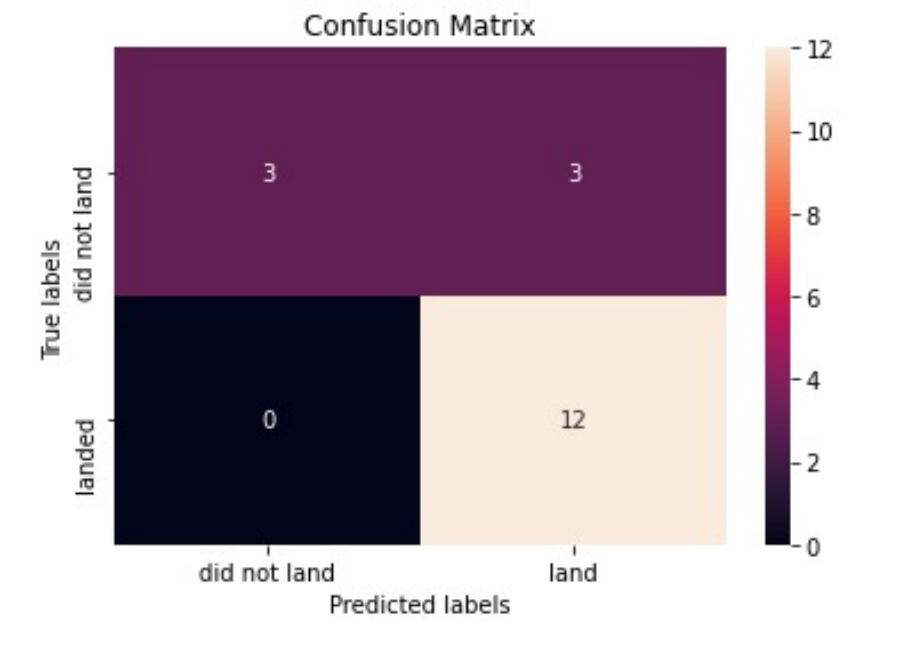
Classification Accuracy

- Four classification models were tested, and their accuracies are plotted beside;
- The model with the highest classification accuracy is Decision Tree Classifier, which has accuracies over than 89%.



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

- Different data sources were analyzed, refining conclusions along the process;
- The best launch site is KSC LC-39A;
- Launches above 7,000kg are less risky;
- Although most of mission outcomes are successful, successful landing outcomes seem to improve over time, according the evolution of processes and rockets;
- Decision Tree Classifier can be used to predict successful landings and increase profits.

Appendix

- As an improvement for model tests, it’s important to set a value to np.random.seed variable;

- Folium didn’t show maps on Github, so I took screenshots.

Thank you!