



# Winning Space Race with Data Science

Kyle Jerome N. Santos

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# Outline

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

# Executive Summary

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- **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

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- **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. The project aims 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.

The background on the left side of the slide features a complex, abstract geometric pattern composed of numerous white, light gray, and dark gray 3D-like polygons. These shapes overlap and interlock to create a sense of depth and texture.

# Section 1

# Methodology

# Methodology

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- 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

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- 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 turn it into a 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 data frame for future analysis.

# 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.
- ❖ The link to the notebooks is [SolarStellaris/Data-Science-Capstone: Data Science Capstone \(SpaceX\) \(github.com\)](#)

```
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
```

# Web Scraping

- ❖ We applied web scrapping to web scrap Falcon 9 launch records with BeautifulSoup
- ❖ We parsed the table and converted it into a pandas dataframe.
- ❖ The link to the notebooks is [SolarStellaris/DataScience-Capstone: 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 = []

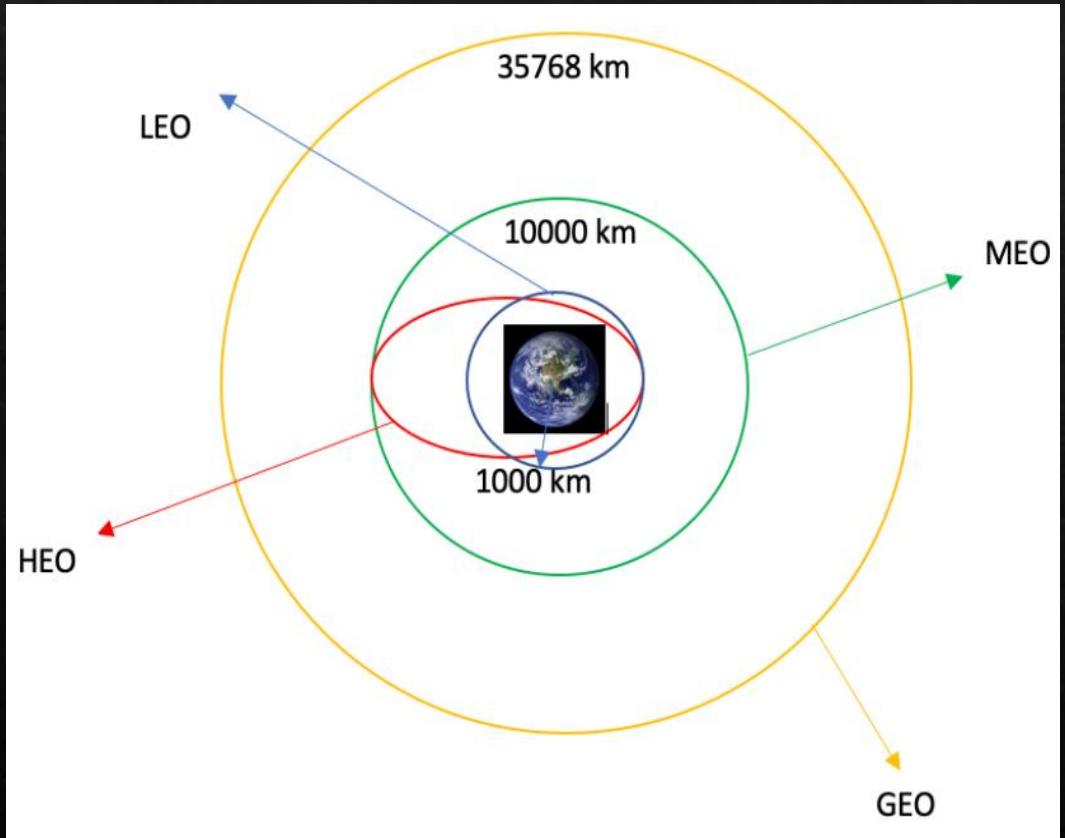
# Apply find_all() function with 'th' element on first_launch_table
# Iterate each th element and apply the provided extract_column_from_header() to get a column name
# Append the Non-empty column name ('if name is not None and len(name) > 0') into a list called column_names

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

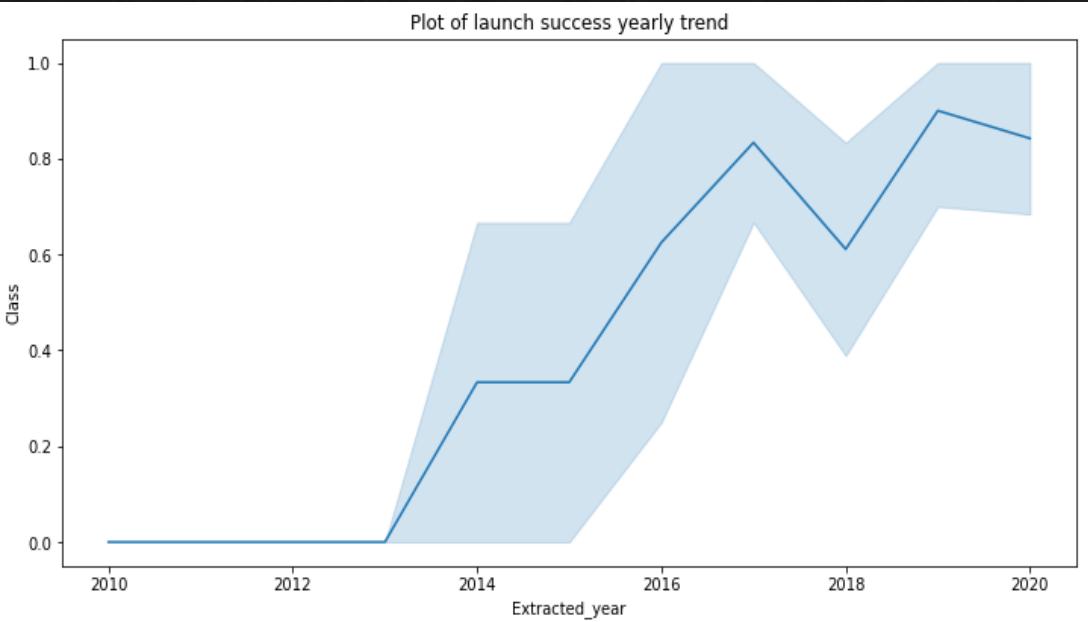
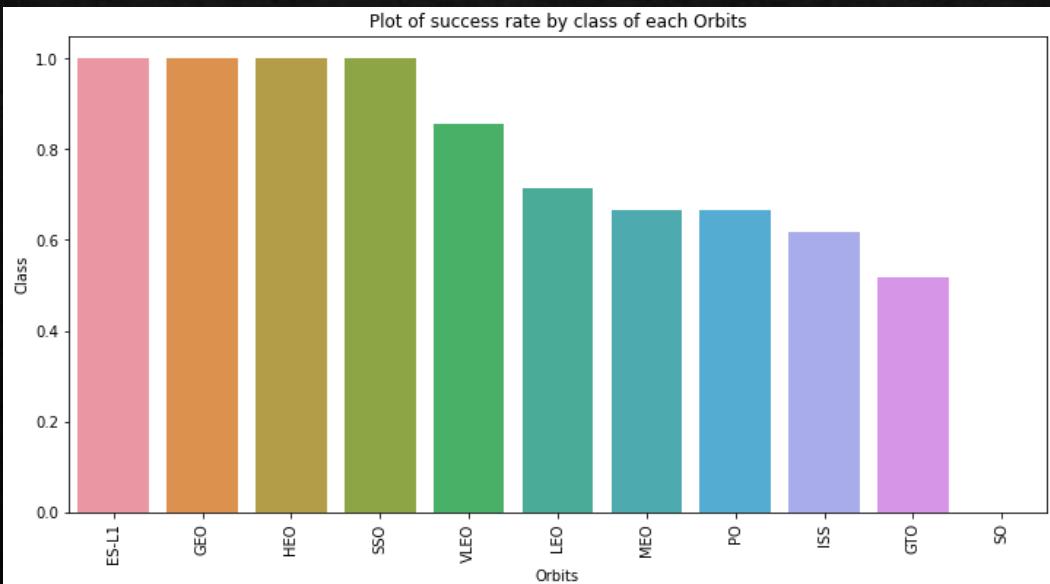
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- ❖ We performed exploratory data analysis and determined the training labels.
- ❖ We calculated the number of launches at each site, and the number and occurrence of each orbits
- ❖ We created landing outcome label from outcome column and exported the results to csv.
- ❖ The link to the notebooks is [SolarStellaris/Data-Science-Capstone: Data Science Capstone \(SpaceX\) \(github.com\)](https://github.com/SolarStellaris/Data-Science-Capstone)

# EDA with Data Visualization

- ❖ We 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.



- The link to the notebooks is [SolarStellaris/Data-Science-Capstone: Data Science Capstone \(SpaceX\) \(github.com\)](https://SolarStellaris/Data-Science-Capstone: Data Science Capstone (SpaceX) (github.com))

# EDA with SQL

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- ❖ 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.
- ❖ The link to the notebooks is [SolarStellaris/Data-Science-Capstone: Data Science Capstone \(SpaceX\) \(github.com\)](https://github.com/SolarStellaris/Data-Science-Capstone)

# Interactive Map with Folium

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- ❖ 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.

# Dashboard with Plotly Dash

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- ❖ 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.

# Predictive Analysis

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- ❖ 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 tune different hyperparameters using GridSearchCV.
- ❖ We used accuracy as the metric for our model, improved the model using feature engineering and algorithm tuning.
- ❖ We found the best performing classification model.
- ❖ The link to the notebooks is [SolarStellaris/Data-Science-Capstone: Data Science Capstone \(SpaceX\) \(github.com\)](https://github.com/SolarStellaris/Data-Science-Capstone)

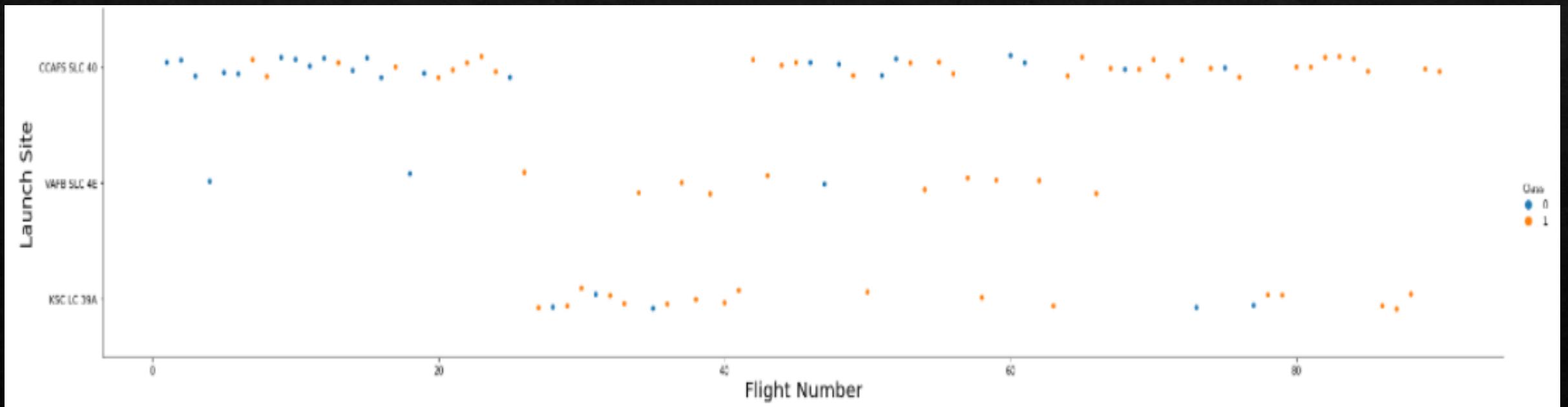
The background on the left side of the slide features a complex, abstract geometric pattern composed of numerous white and light gray 3D-like polygons. These shapes overlap and interlock to create a sense of depth and volume, resembling a stylized landscape or a microscopic view of a material's crystalline structure.

## Section 2

# EDA Insights

# Flight Number vs. Launch Site

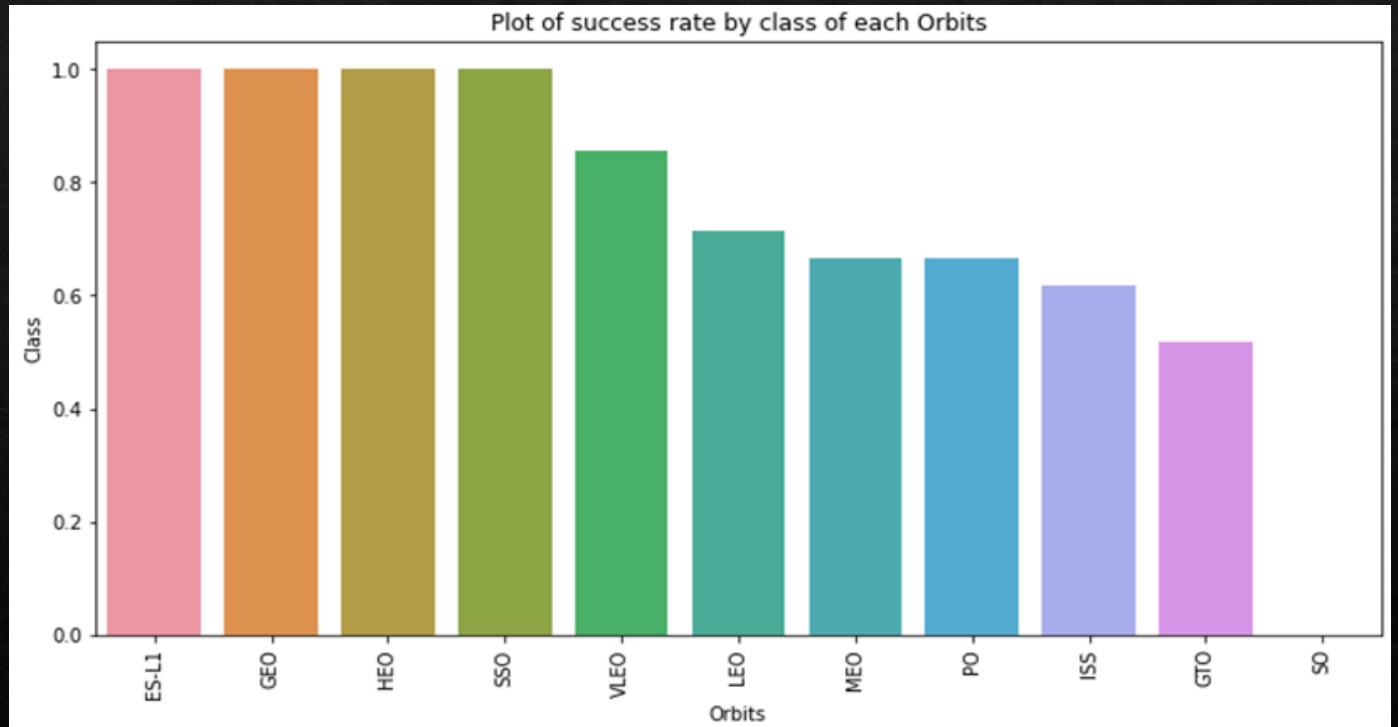
- ❖ From the plot, we found that the larger the flight amount at a launch site, the greater the success rate at a launch site.
- ❖ The greater the payload mass for launch site CCAFS SLC 40, the higher the success rate for the rocket.



# Success Rate vs. Orbit Type

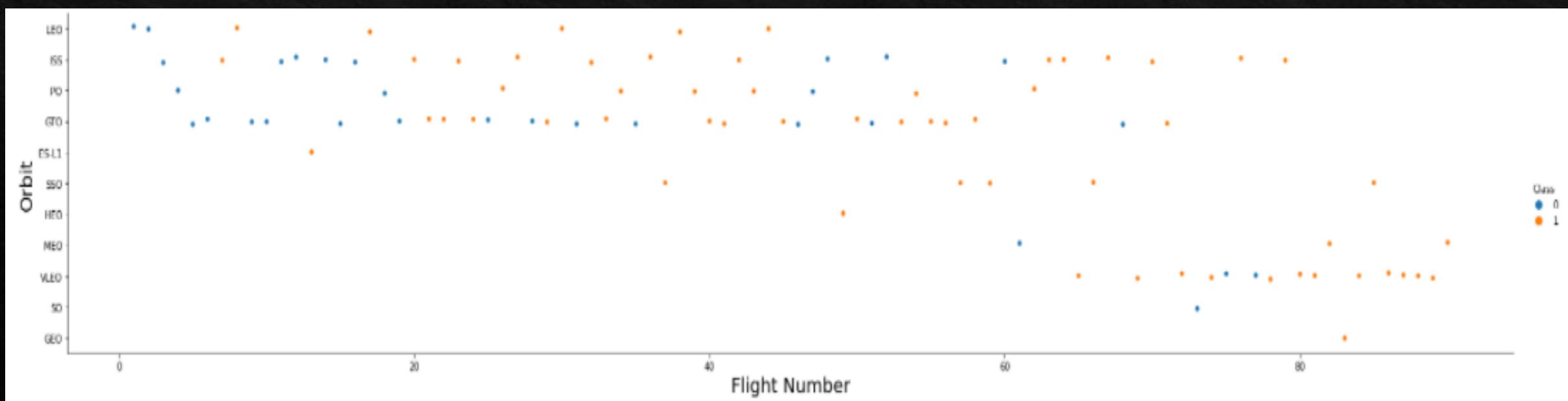
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- ❖ From the plot, we can see that ES-L1, GEO, HEO, SSO, VLEO had the most success rate.



# Flight Number vs. Orbit Type

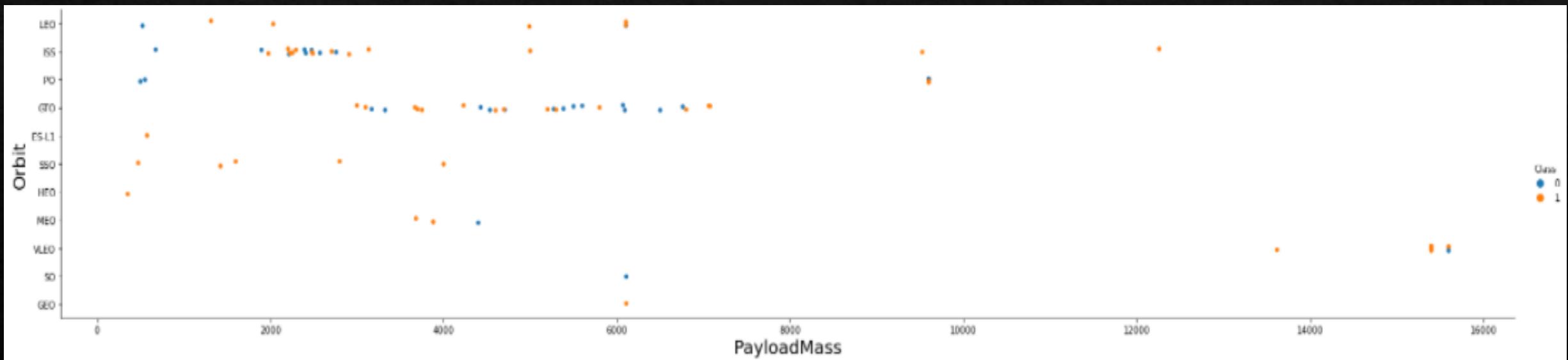
- ◊ The plot below shows the Flight Number vs. Orbit type. We observe that in the LEO orbit, success is related to the number of flights whereas in the GTO orbit, there is no relationship between flight number and the orbit.



# Payload vs. Orbit Type

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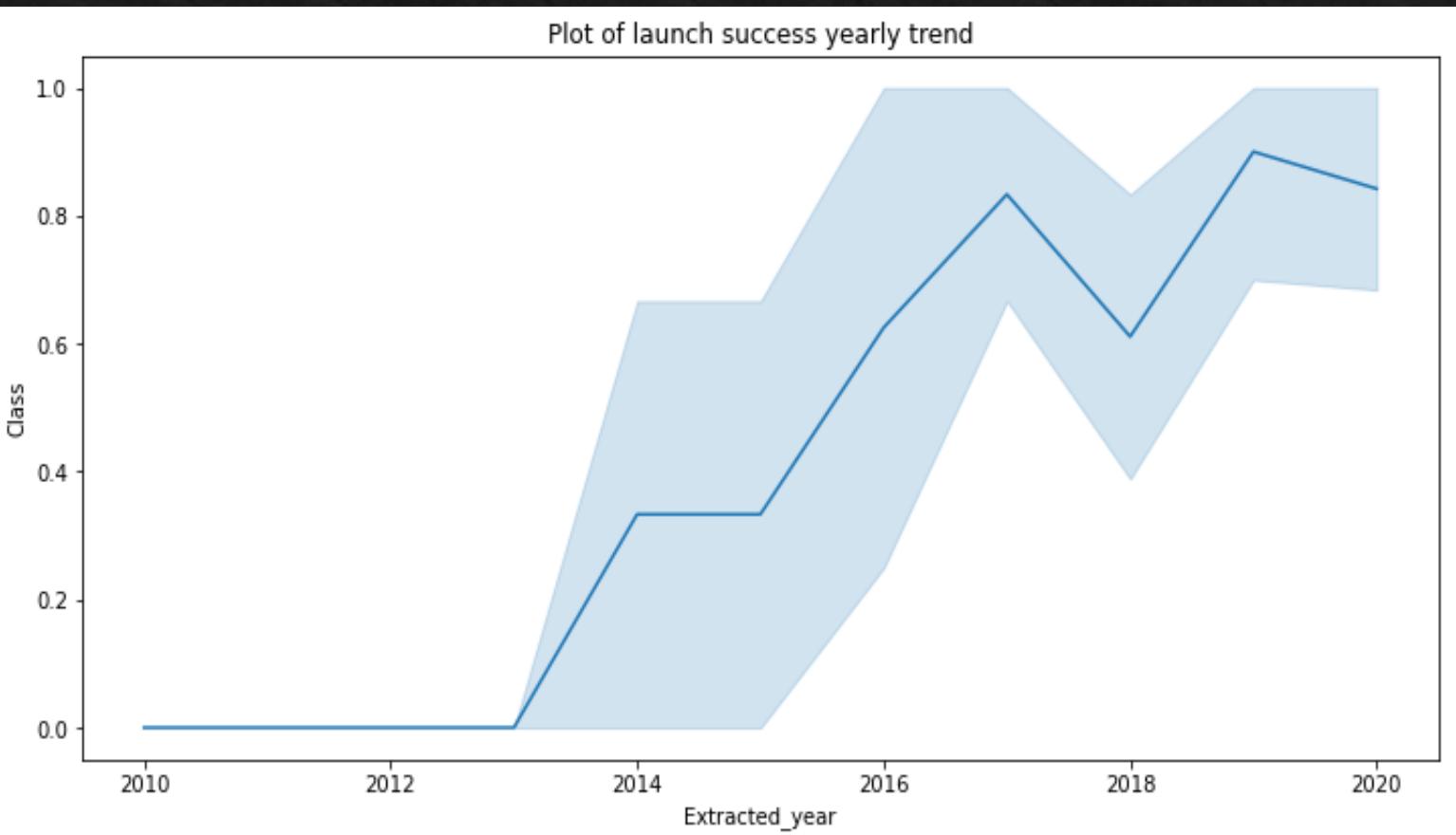
- ◊ We can observe that with heavy payloads, the successful landing are more for PO, LEO and ISS orbits.



# Launch Success Yearly Trend

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



# Launch Site Names (CCA)

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

Display 5 records where launch sites begin with the string 'CCA'

In [11]:

```
task_2 = """
    SELECT *
    FROM SpaceX
    WHERE LaunchSite LIKE 'CCA%'
    LIMIT 5
"""

create_pandas_df(task_2, database=conn)
```

Out[11]:

	date	time	boosterversion	launchsite	payload	payloadmasskg	orbit	customer	missionoutcome	landingoutcome
0	2010-04-06	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
1	2010-08-12	15:43:00	F9 v1.0 B0004	CCAFS LC-40	Dragon demo flight C1, two CubeSats, barrel of...	0	LEO (ISS)	NASA (COTS) NRO	Success	Failure (parachute)
2	2012-05-22	07:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	No attempt
3	2012-08-10	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
4	2013-01-03	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

# Total Payload Mass

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

Display the total payload mass carried by boosters launched by NASA (CRS)

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

	total_payloadmass
0	45596

# Average Payload Mass (F9 v1.1)

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

Display average payload mass carried by booster version F9 v1.1

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

	avg_payloadmass
0	2928.4

# First Successful Ground Landing Date

- ◊ We observed that the dates of the first successful landing outcome on ground pad was 22<sup>nd</sup> 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

---

- ❖ 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

```
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

---

- ❖ We 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)
```

The total number of successful mission outcome is:

successoutcome
0
100

The total number of failed mission outcome is:

Out[16]:

failureoutcome
0
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.

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

---

- ◆ 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 (2010-06-04 - 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)
```

	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

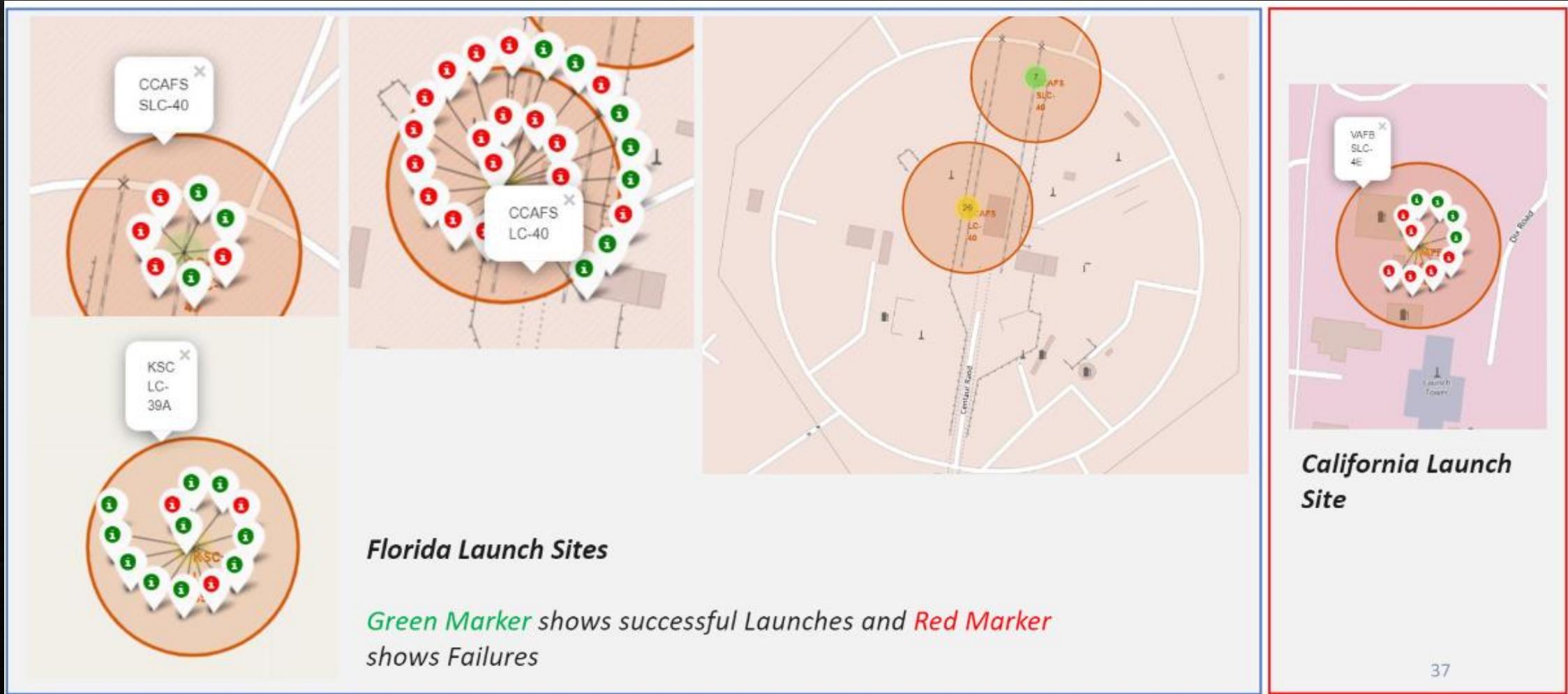
# Analysis

# Launch Sites Global Map Markers

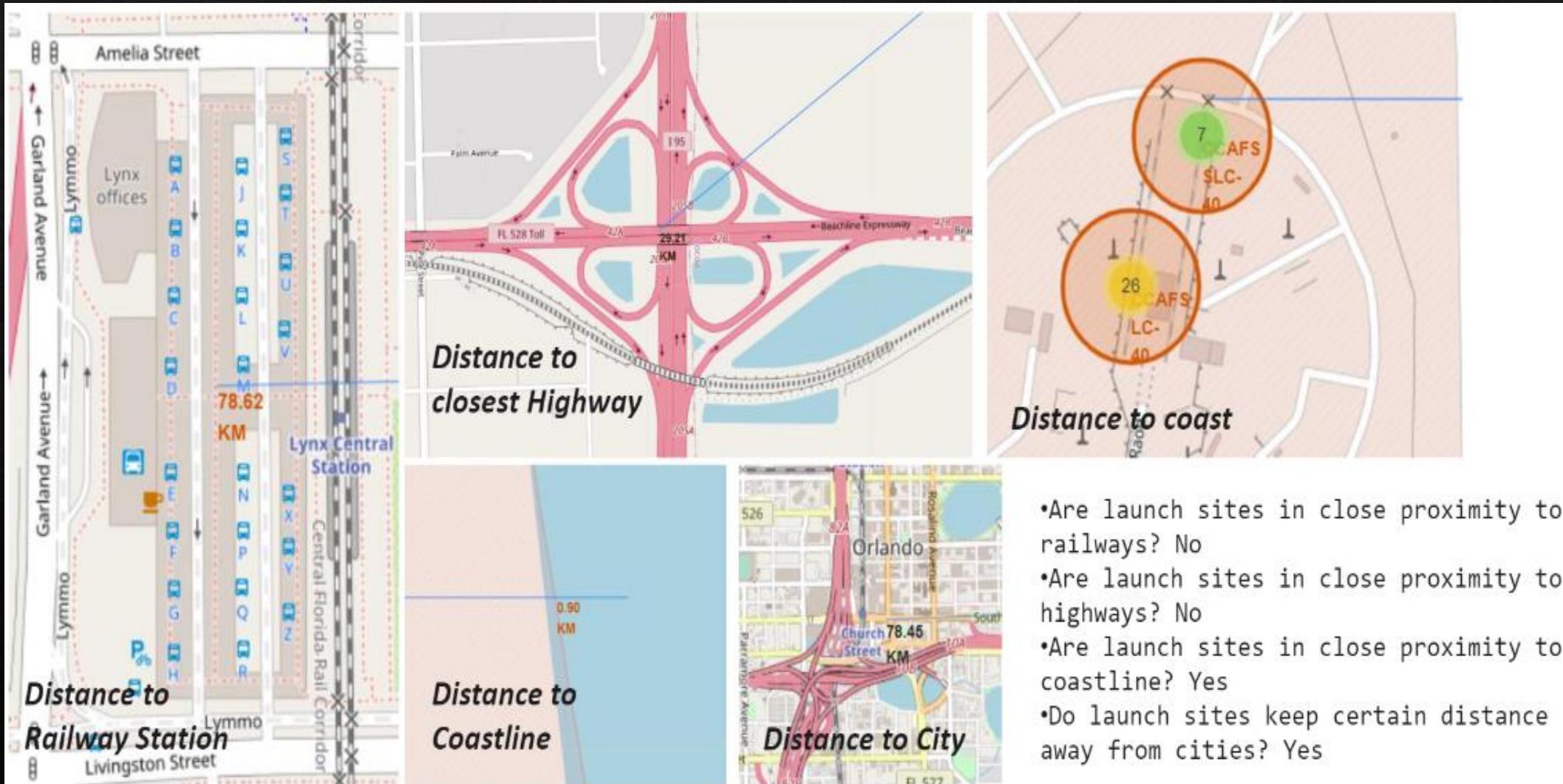
---



# Launch Sites with Color Labels



# Launch Sites distance to Landmarks





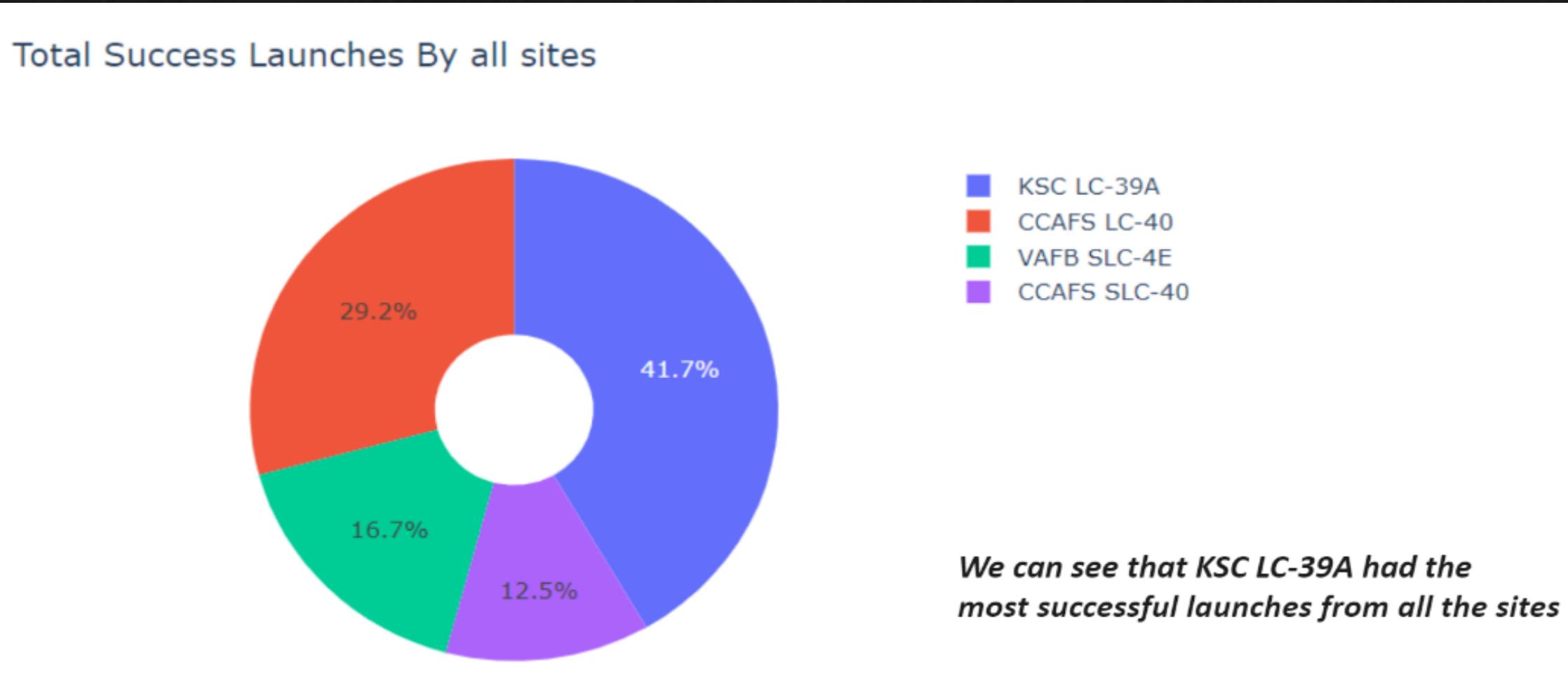
# Section 4

# Dashboard

# with Plotly

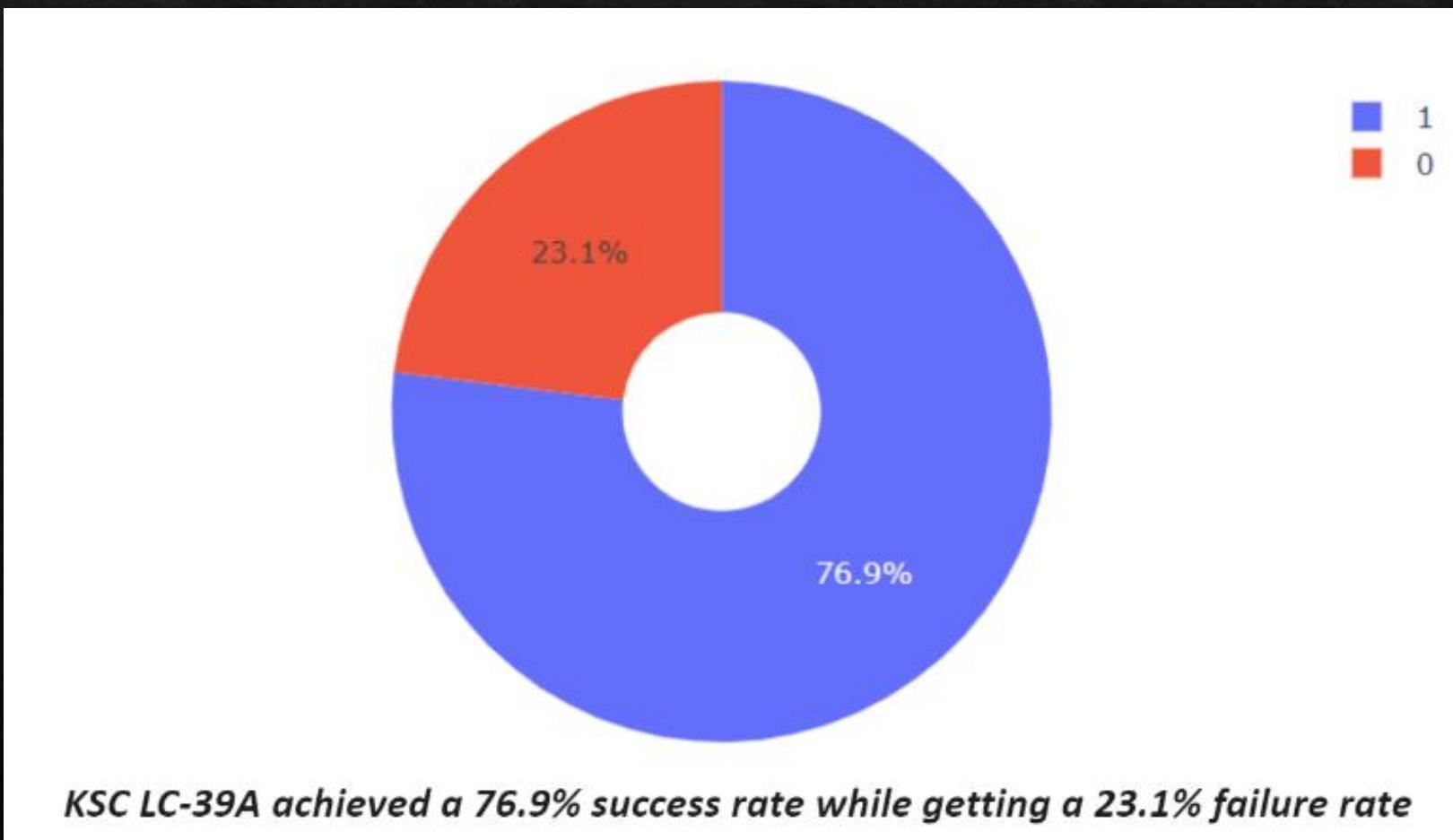
# Dash

# Success Percentage Achieved by each Launch Site

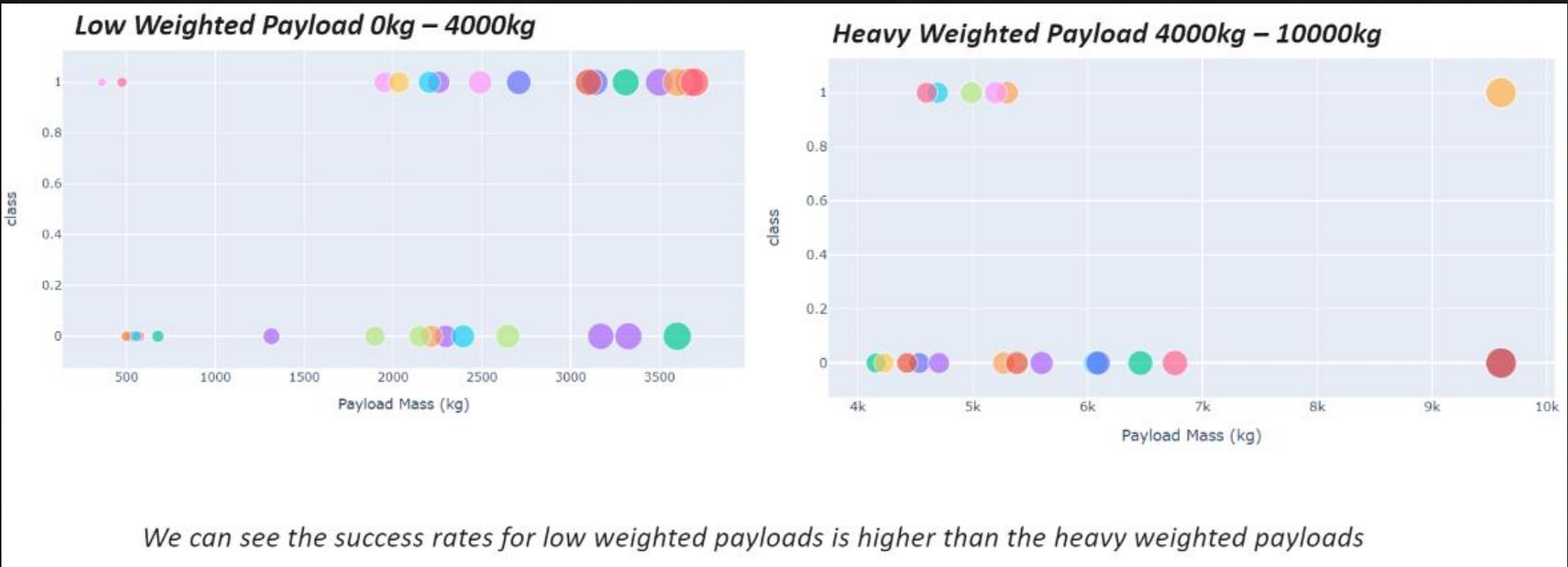


# Launch Site with the Highest Launch Success Ratio

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



The background on the left side of the slide features a complex, abstract geometric pattern composed of numerous white and light gray 3D-like polygons. These shapes overlap and interlock to create a sense of depth and complexity.

# Section 5

# Predictive

# Analysis

# Classification Accuracy

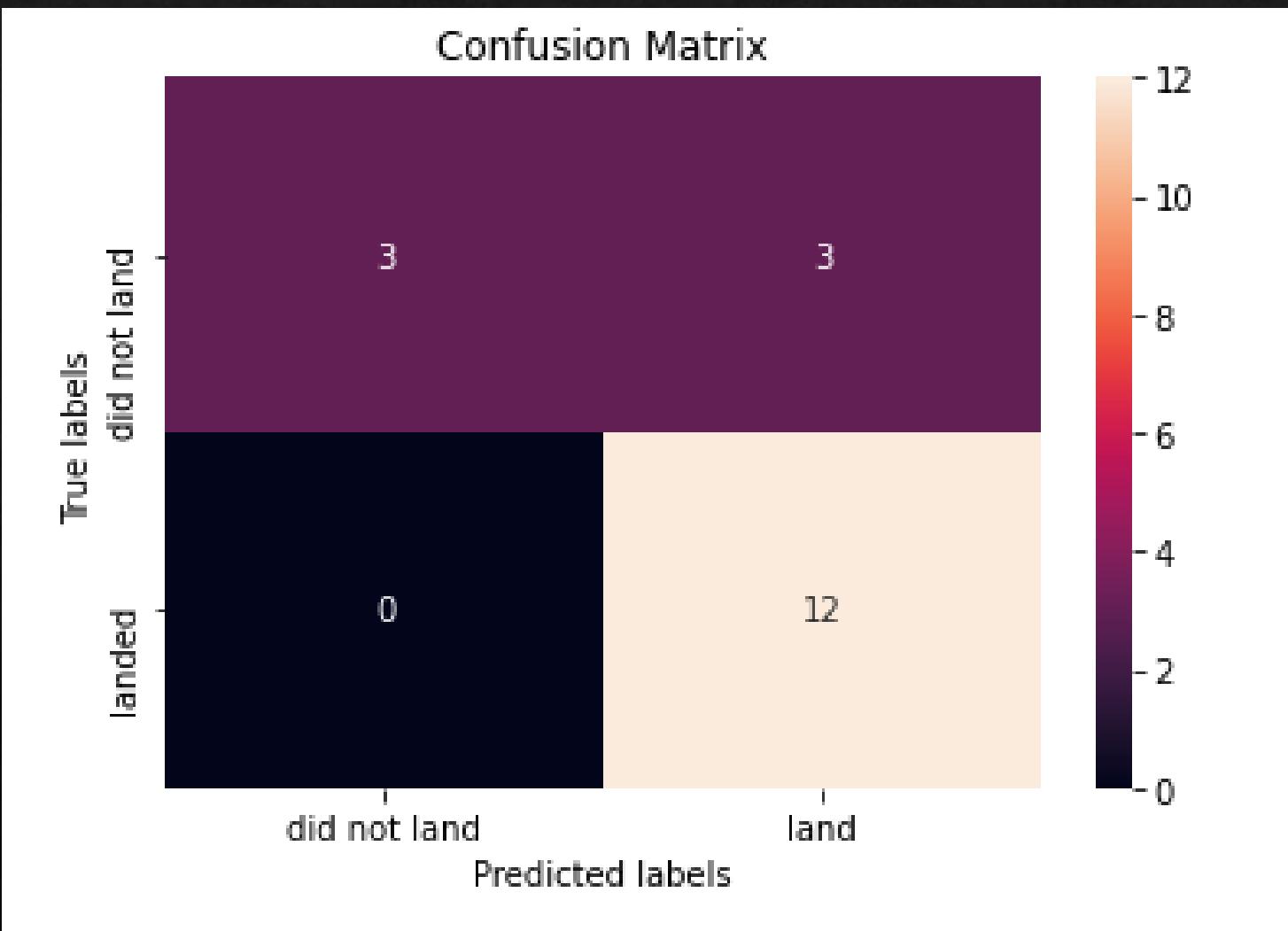
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- ❖ The decision tree classifier is the model with the highest classification accuracy

```
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 0.8732142857142856  
Best params is : {'criterion': 'gini', 'max_depth': 6, 'max_features': 'auto', 'min_samples_leaf': 2, 'min_samples_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.



# Conclusion

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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.



A large, semi-transparent black rectangular overlay covers the right side of the image. Inside this overlay, the words "Thank You!" are written in a bold, white, sans-serif font.

Thank You!