
# Winning Space Race with Data Science

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# Outline

- Executive Summary
- Introduction
- Methodology
- Results
- Conclusion

# 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
  - 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 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 – 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 notebook is https://github.com/knewman23/data-science-capstone/blob/master/Data%20Collection%20API.ipynb.

In [5]:
```
# Takes the dataset and uses the cores column to call the API and append the data to the lists
def getCoreData(data):
    for core in data['cores']:
            if core['core'] != None:
                response = requests.get("https://api.spacexdata.com/v4/cores/"+core['core']).json()
                Block.append(response['block'])
                ReusedCount.append(response['reuse_count'])
                Serial.append(response['serial'])
            else:
                Block.append(None)
                ReusedCount.append(None)
                Serial.append(None)
            Outcome.append(str(core['landing_success'])+' '+str(core['landing_type']))
            Flights.append(core['flight'])
            GridFins.append(core['gridfins'])
            Reused.append(core['reused'])
            Legs.append(core['legs'])
            LandingPad.append(core['landpad'])
```

Now let's start requesting rocket launch data from SpaceX API with the following URL:

In [6]:
```
spacex_url="https://api.spacexdata.com/v4/launches/past"
```

In [7]:
```
response = requests.get(spacex_url)
```

Check the content of the response

In [8]:
```
print(response.content)
```

```
b'[{"fairings":{"reused":false,"recovery_attempt":false,"recovered":false,"ships":[]},"links":{"patch":
m/94/f2/NN6Ph45r_o.png","large":"https://images2.imgbox.com/5b/02/QcxHUb5V_o.png"},"reddit":{"campaign"
ecovery":null},"flickr":{"small":[],"original":[]},"presskit":null,"webcast":"https://www.youtube.com/wa
a_00nJ_Y88","article":"https://www.space.com/2196-spacex-inaugural-falcon-1-rocket-lost-launch.html","wi
g/wiki/DemoSat"},"static fire date utc":"2006-03-17T00:00:00.000Z","static fire date unix":1142553600,"
```

# 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.
- The link to the notebook is https://github.com/knewman23/data-science-capstone/blob/master/Web%20Scraping%20Lab.ipynb

```
        return colunm_name
```

To keep the lab tasks consistent, you will be asked to scrape the data from a snapshot of the `List of Falcon 9 and Falcon Heavy laun` updated on `9th June 2021`

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

Next, request the HTML page from the above URL and get a `response` object

### TASK 1: Request the Falcon9 Launch Wiki page from its URL

First, let's perform an HTTP GET method to request the Falcon9 Launch HTML page, as an HTTP response.

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

Create a `BeautifulSoup` object from the HTML `response`

```
# Use BeautifulSoup() to create a BeautifulSoup object from a response text content
soup = BeautifulSoup(data, 'html5lib')
```

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

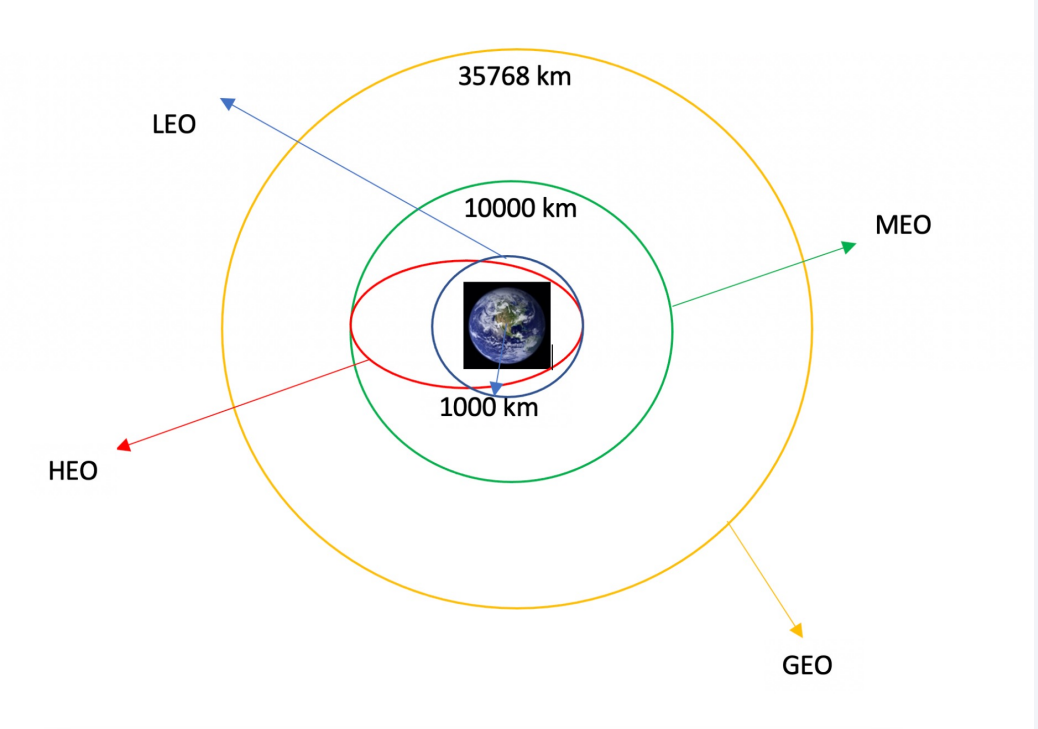
```
# Use soup.title attribute
soup.title
```

```
<title>List of Falcon 9 and Falcon Heavy launches - Wikipedia</title>
```

### TASK 2: Extract all column/variable names from the HTML table header

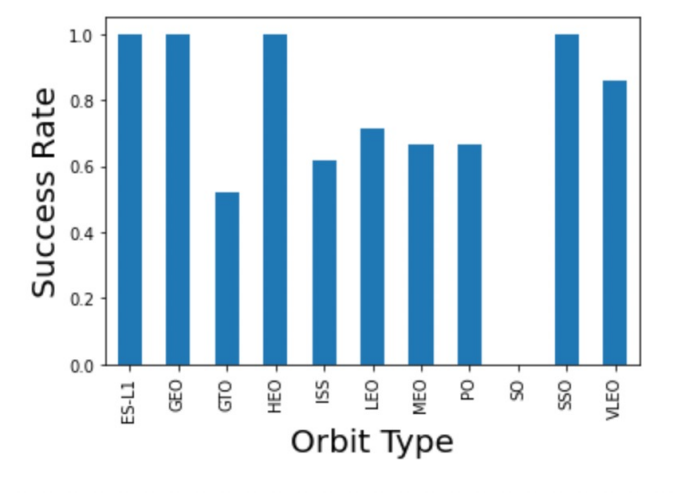
# Data Wrangling

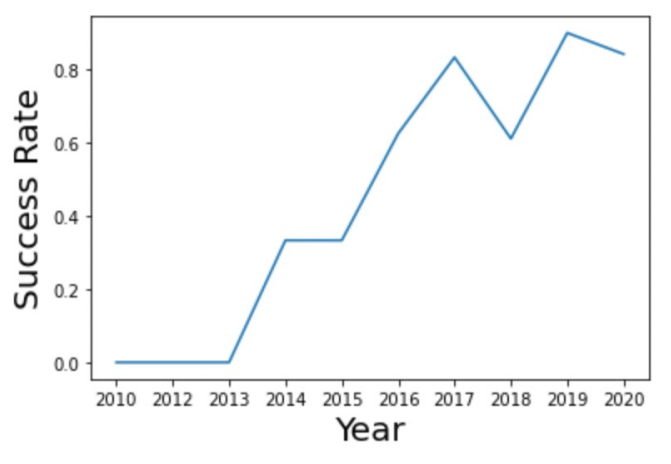
- We performed exploratory data analysis and determined the training labels.
- We calculated the number of launches at each site, and the number and occurrence of each orbits
- We created landing outcome label from outcome column and exported the results to csv.
- The link to the notebook is https://github.com/knewman23/data-science-capstone/blob/master/Data%20Wrangling.ipynb.

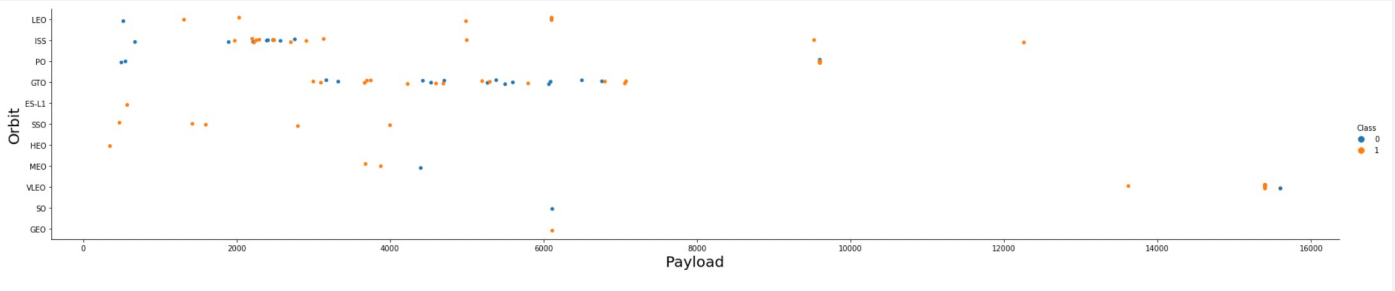


# EDA with Data Visualization

- We explored the data by visualizing the relationship between flight number and launch Site, payload and launch site, success rate of each orbit type, flight number and orbit type, the launch success yearly trend.
- The link to the notebook is https://github.com/knewman23/data-science-capstone/blob/master/EDA%20with%20Data%20Viz.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.
- The link to the notebook is https://github.com/knewman23/data-science-capstone/blob/master/EDA%20with%20SQL.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.
- The link to the notebook is https://github.com/knewman23/data-science-capstone/blob/master/Interactive%20Visual%20Analytics%20with%20Folium%20lab.ipynb

# Build a Dashboard with Plotly Dash

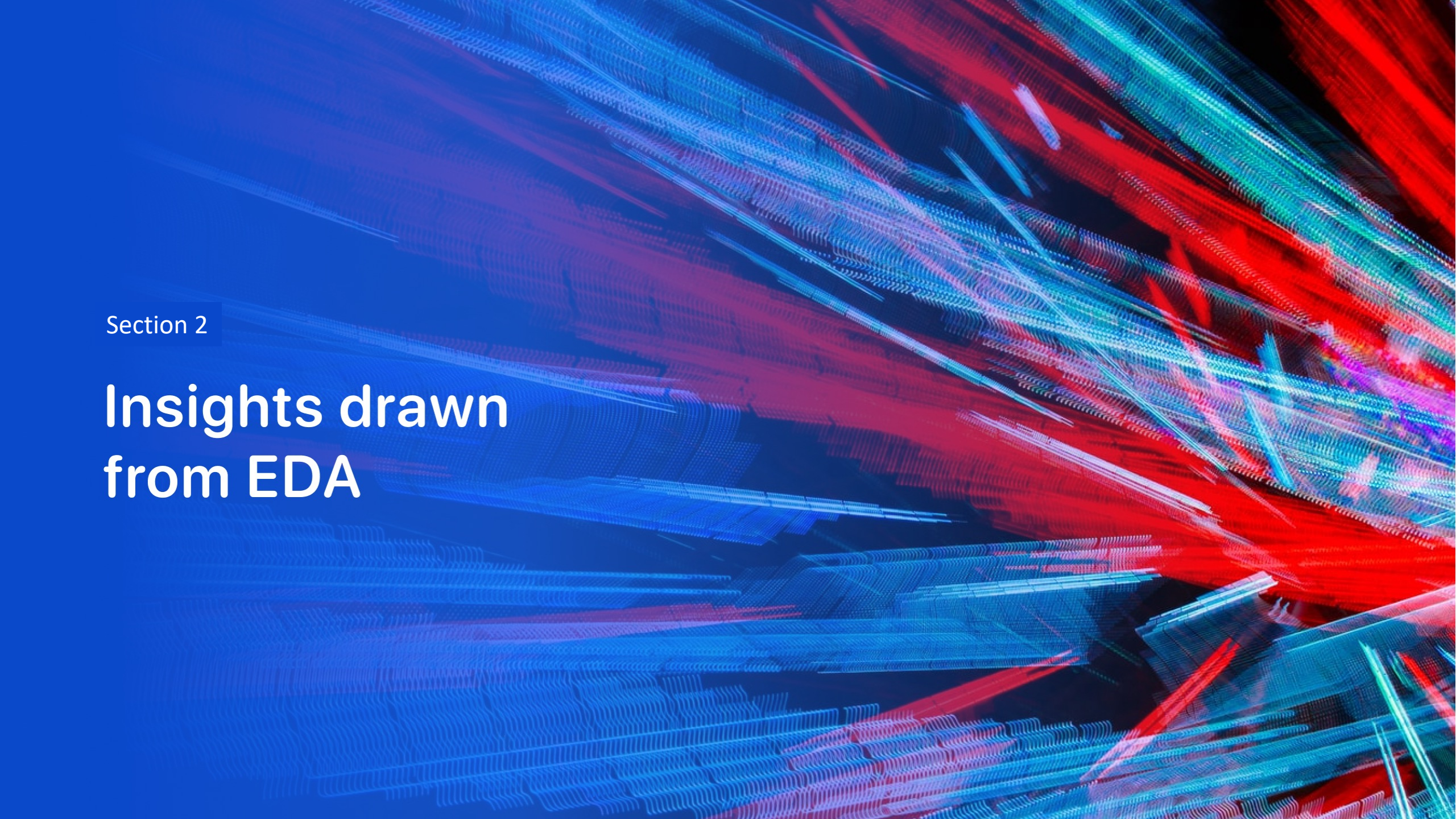
- We built an interactive dashboard with Plotly dash
- We plotted pie charts showing the total launches by a certain sites
- We plotted scatter graph showing the relationship with Outcome and Payload Mass (Kg) for the different booster version.
- The link to the notebook is https://github.com/knewman23/data-science-capstone/blob/master/spacex_dash_app.py

# 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 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 notebook is https://github.com/knewman23/data-science-capstone/blob/master/Machine%20Learning%20Prediction.ipynb

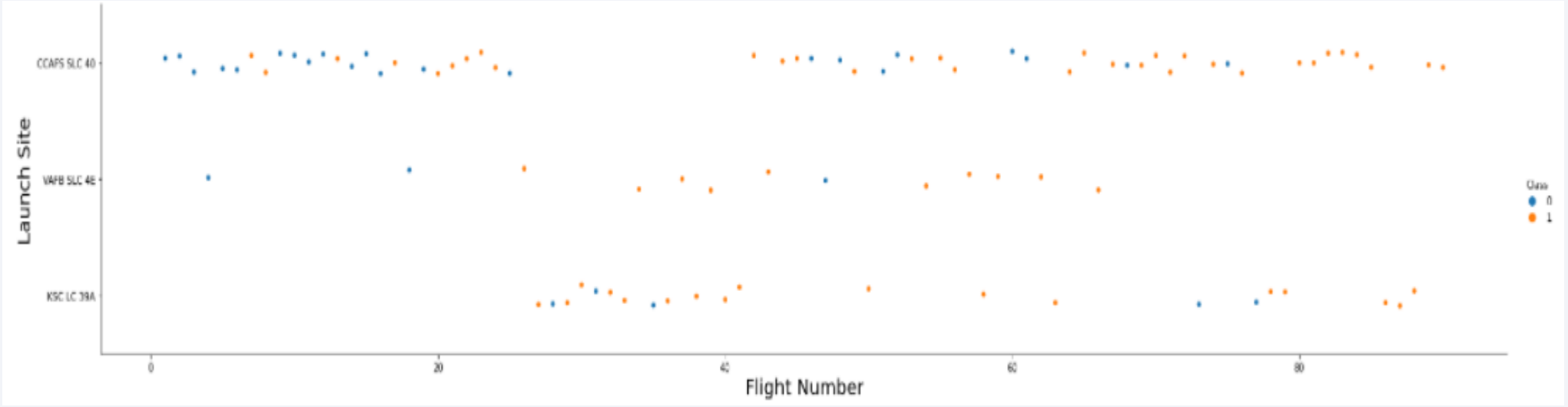
# Results

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


Section 2
Insights drawn from EDA

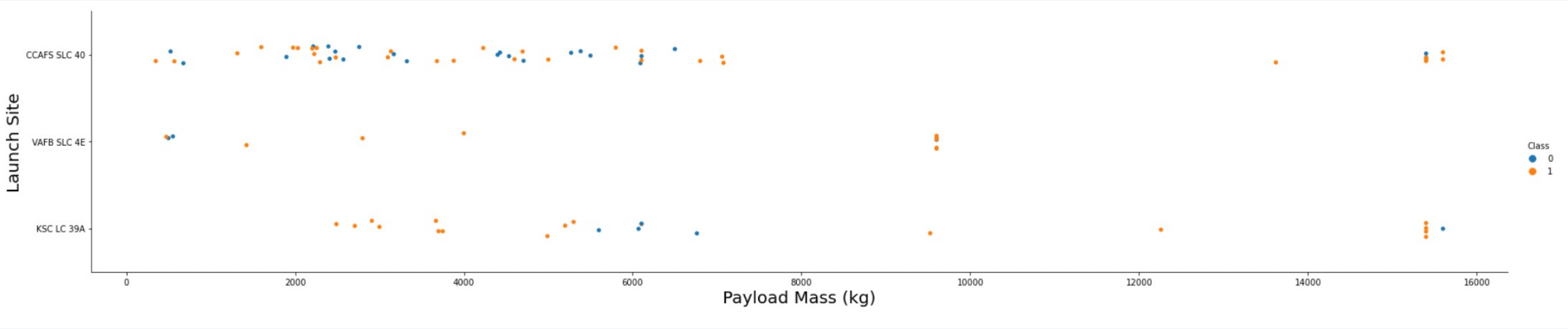
# Flight Number vs. Launch Site

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



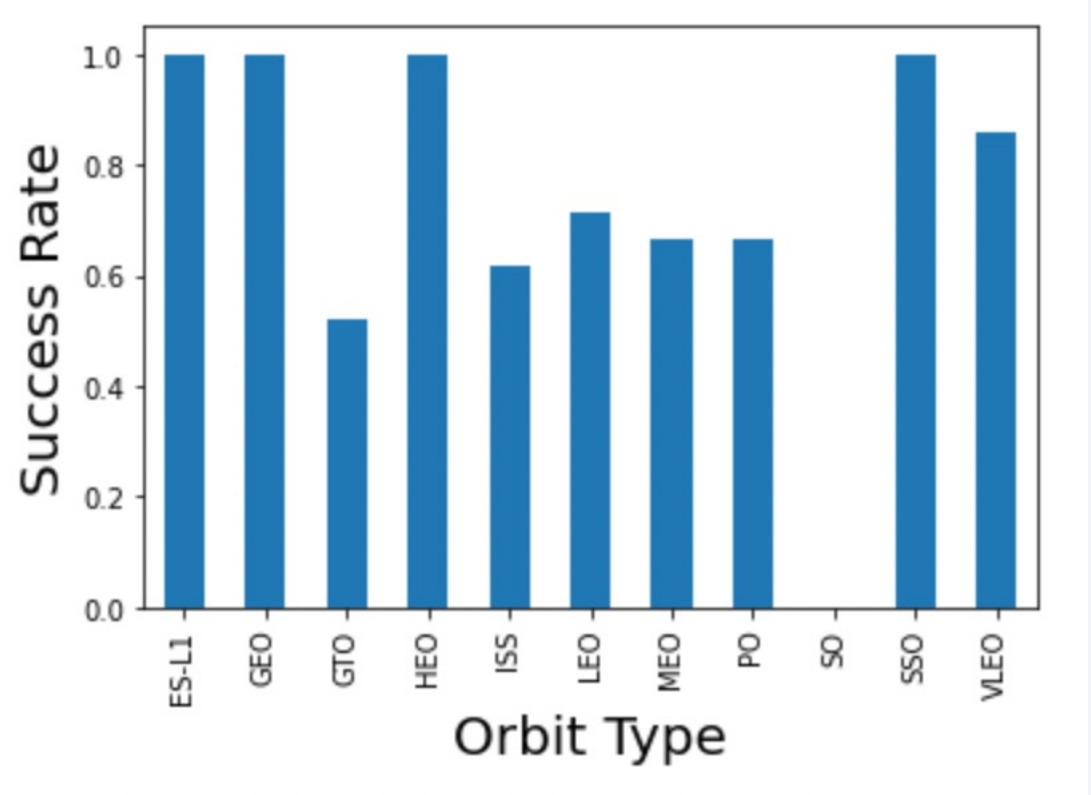
# Payload vs. Launch Site

- The greater the mass for the launch site CCFAS SLC 40 the greater the success rate for the rocket



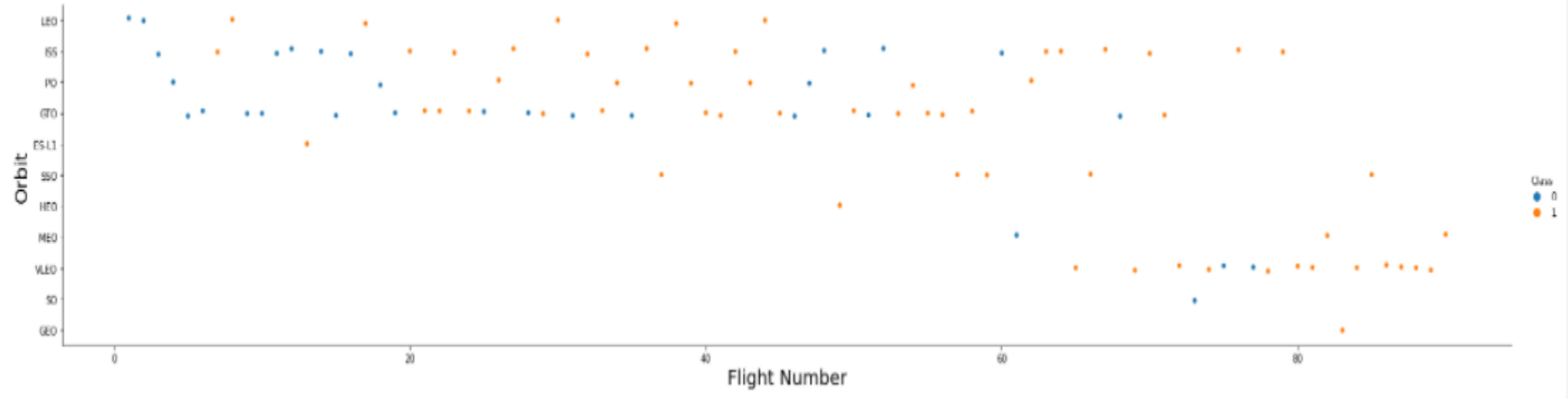
# Success Rate vs. Orbit Type

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



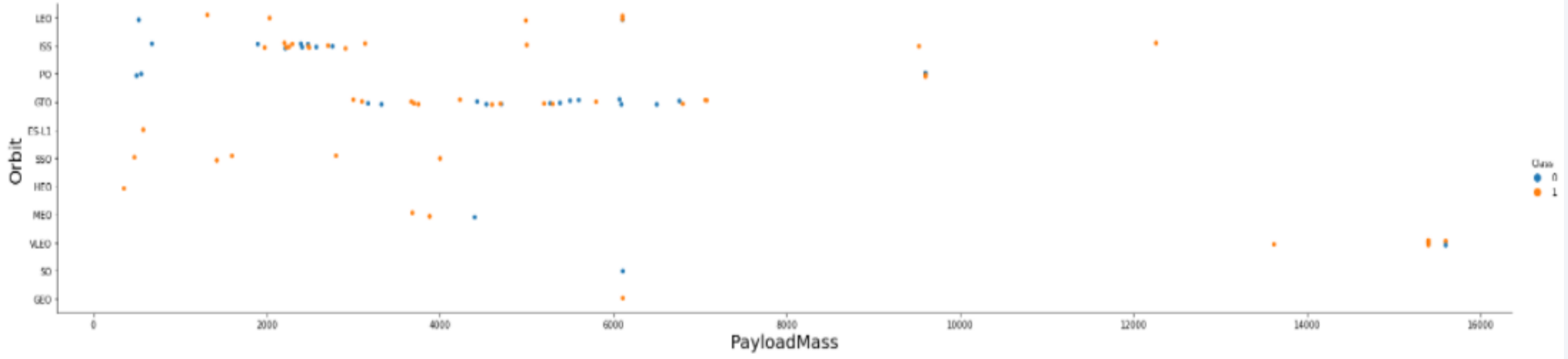
# Flight Number vs. Orbit Type

- 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.



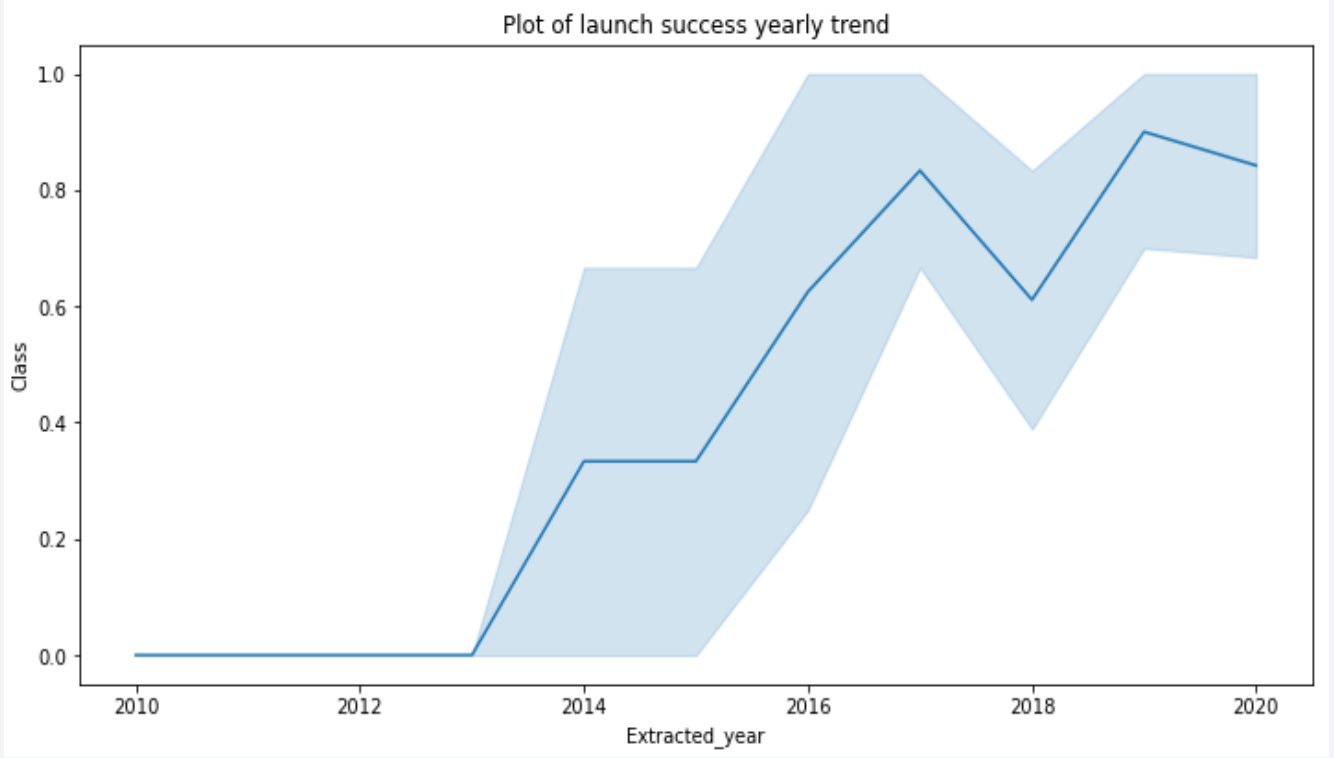
# Payload vs. Orbit Type

- 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 **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'

- 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

- 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 |
|---|---|
| 0 | 45596 |

# Average Payload Mass by F9 v1.1

- We calculated the average payload mass carried by booster version F9 v1.1 as 2534

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

In [21]:
```
%%sql
SELECT AVG(PAYLOAD_MASS__KG_)
FROM SPACEXDATASET
WHERE Booster_Version LIKE 'F9 v1.1%';
```

```
 * ibm_db_sa://nzp11988:***@9938aec0-8105-433e-8bf9-0fbb7e483086.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:32459/BLUDB
Done.
```

Out[21]:

| 1 |
|---|
| 2534 |

# First Successful Ground Landing Date

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

**Task 5**

***List the date when the first successful landing outcome in ground pad was acheived.***

*Hint:Use min function*

In [14]:
```
%%sql
SELECT MIN(Date)
FROM SPACEXDATASET
WHERE Landing__Outcome = 'Success (ground pad)';
```

```
 * ibm_db_sa://nzp11988:***@9938aec0-8105-433e-8bf9-0fbb7e483086.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:32459/BLUDB
Done.
```

Out[14]:

| 1 |
|---|
| 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]:
```
%%sql
SELECT BOOSTER_VERSION
FROM SPACEXDATASET
WHERE LANDING__OUTCOME = 'Success (drone ship)'
    AND 4000 < PAYLOAD_MASS__KG_ < 6000;
```

```
 * ibm_db_sa://nzp11988:***@9938aec0-8105-433e-8bf9-0fbb7e483086.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:32459/BLUDB
Done.
```

Out[15]:

| booster_version |
|---|
| F9 FT B1021.1 |
| F9 FT B1023.1 |
| F9 FT B1029.2 |
| F9 FT B1038.1 |
| F9 B4 B1042.1 |
| F9 B4 B1045.1 |
| F9 B5 B1046.1 |

# Total Number of Successful and Failure Mission Outcomes

- We used wildcard like '%' to filter for **WHERE** MissionOutcome was a success or a failure.

**Task 7**

***List the total number of successful and failure mission outcomes***

[16]:
```
%%sql
SELECT MISSION_OUTCOME, COUNT(MISSION_OUTCOME) AS TOTAL_NUMBER
FROM SPACEXDATASET
GROUP BY MISSION_OUTCOME;
```

```
 * ibm_db_sa://nzp11988:***@9938aec0-8105-433e-8bf9-0fbb7e483086.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:32459/BLUDB
Done.
```

ut[16]:

| mission_outcome | total_number |
|---|---|
| Failure (in flight) | 1 |
| Success | 99 |
| Success (payload status unclear) | 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***

[18]:
```
%%sql
SELECT DISTINCT BOOSTER_VERSION
FROM SPACEXDATASET
WHERE PAYLOAD_MASS__KG_ = (
    SELECT MAX(PAYLOAD_MASS__KG_)
    FROM SPACEXDATASET);
```

```
 * ibm_db_sa://nzp11988:***@9938aec0-8105-433e-8bf9-0fbb7e483086.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:32459/BLUDB
Done.
```

Out[18]:

| booster_version |
|---|
| F9 B5 B1048.4 |
| F9 B5 B1048.5 |
| F9 B5 B1049.4 |
| F9 B5 B1049.5 |
| F9 B5 B1049.7 |

# 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

**Task 9**

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

In [19]:
```
%%sql
SELECT LANDING__OUTCOME, BOOSTER_VERSION, LAUNCH_SITE
FROM SPACEXDATASET
WHERE Landing__Outcome = 'Failure (drone ship)'
    AND YEAR(DATE) = 2015;
```

```
 * ibm_db_sa://nzp11988:***@9938aec0-8105-433e-8bf9-0fbb7e483086.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:32459/BLUDB
Done.
```

Out[19]:

| landing__outcome | booster_version | launch_site |
|---|---|---|
| Failure (drone ship) | F9 v1.1 B1012 | CCAFS LC-40 |
| Failure (drone ship) | F9 v1.1 B1015 | CCAFS LC-40 |

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

- We selected Landing outcomes and the **COUNT** of landing outcomes from the data and used the **WHERE** clause to filter for landing outcomes **BETWEEN** 2010-06-04 to 2010-03-20.
- 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)) between the date 2010-06-04 and 2017-03-20, in descending order***

In [20]:
```
%%sql
SELECT LANDING__OUTCOME, COUNT(LANDING__OUTCOME) AS TOTAL_NUMBER
FROM SPACEXDATASET
WHERE DATE BETWEEN '2010-06-04' AND '2017-03-20'
GROUP BY LANDING__OUTCOME
ORDER BY TOTAL_NUMBER DESC
```

```
 * ibm_db_sa://nzp11988:***@9938aec0-8105-433e-8bf9-0fbb7e483086.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:32459/BLUDB
Done.
```

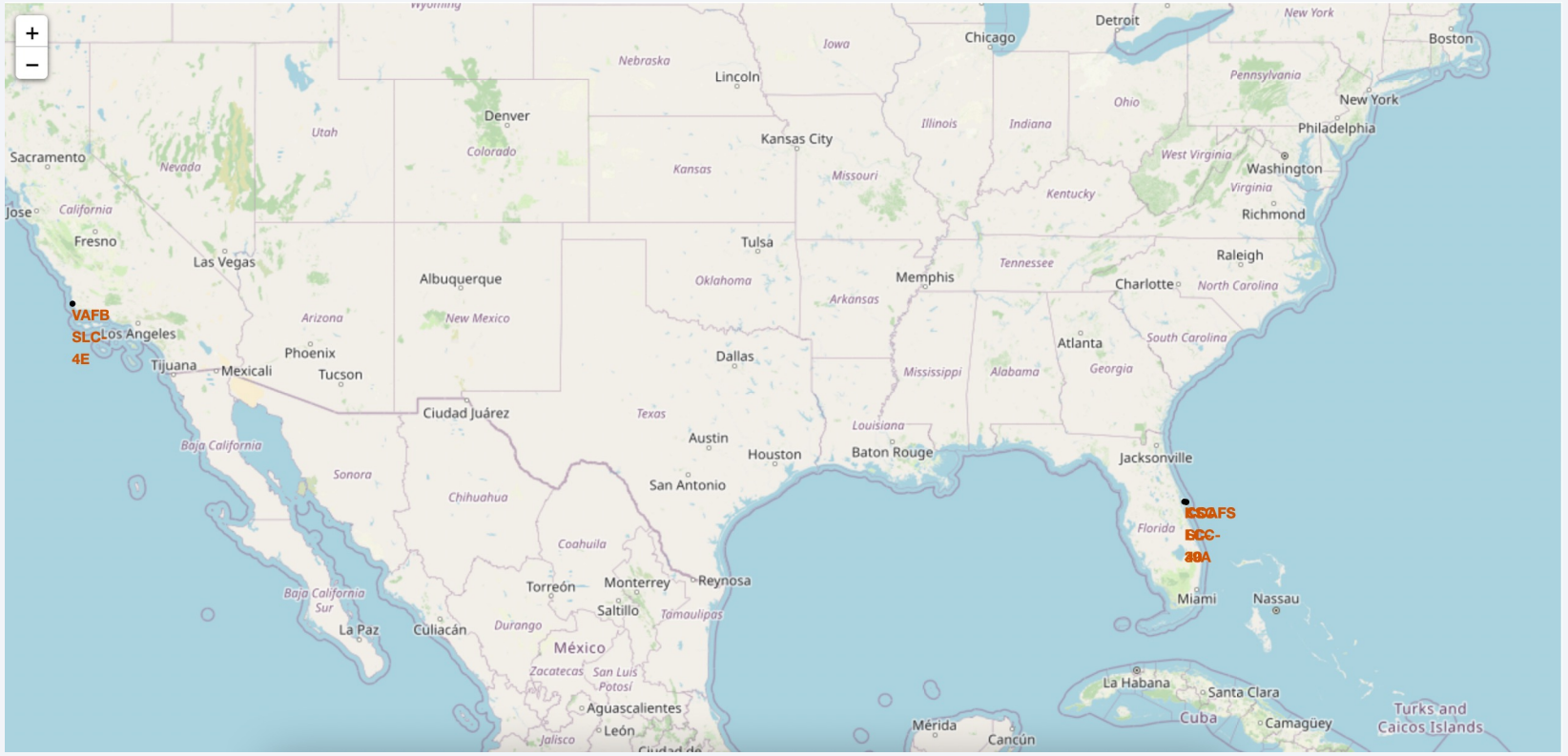
Out[20]:

| landing__outcome | total_number |
|---|---|
| No attempt | 10 |
| Failure (drone ship) | 5 |
| Success (drone ship) | 5 |
| Controlled (ocean) | 3 |
| Success (ground pad) | 3 |
| Failure (parachute) | 2 |
| Uncontrolled (ocean) | 2 |
| Precluded (drone ship) | 1 |


Section 3
Launch Sites
Proximities Analysis

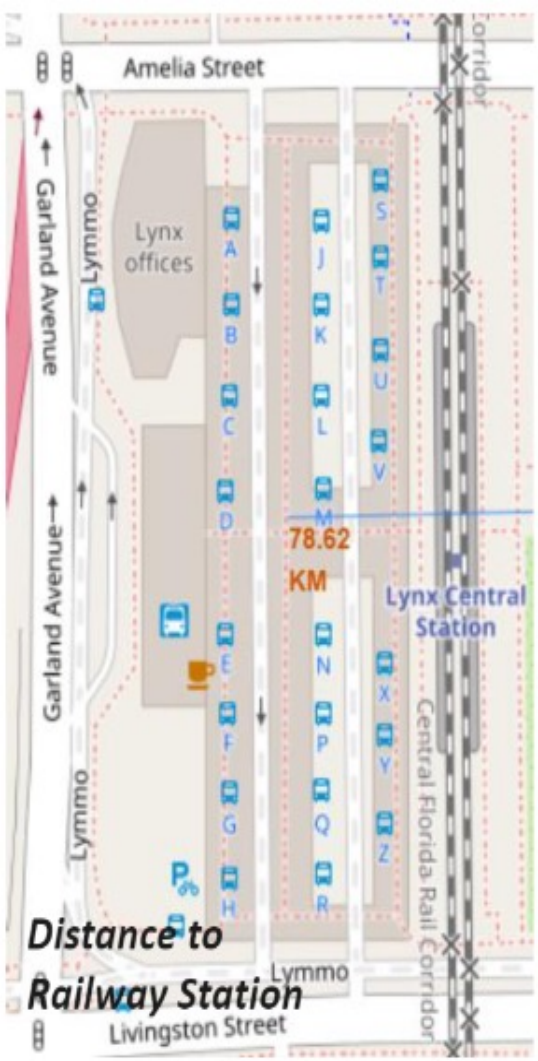
# All Launch Sites

- California and Florida in the US are the main hubs for launch sites



# Markers showing launch sites with color labels

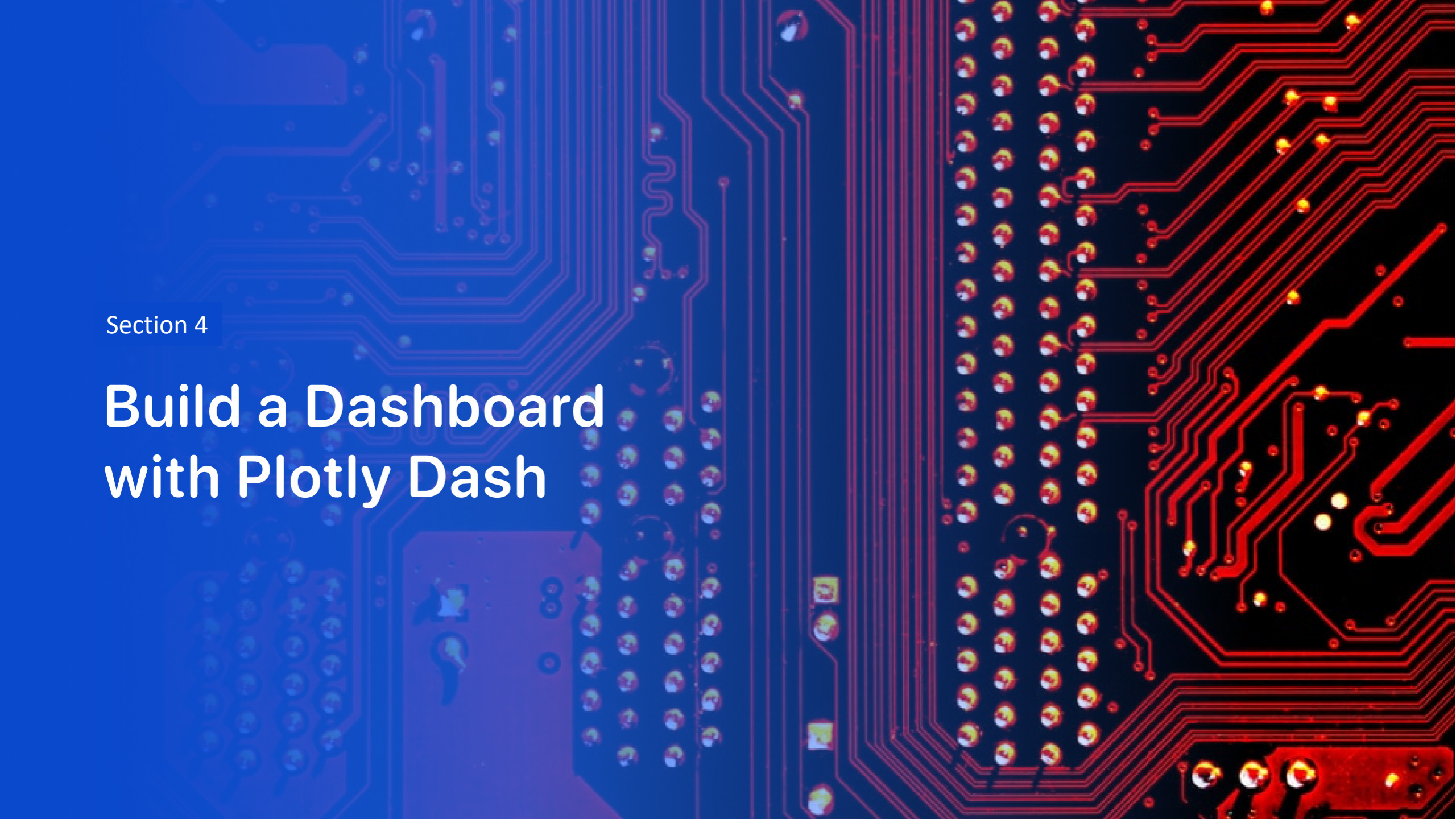
# Launch Site distance to landmarks



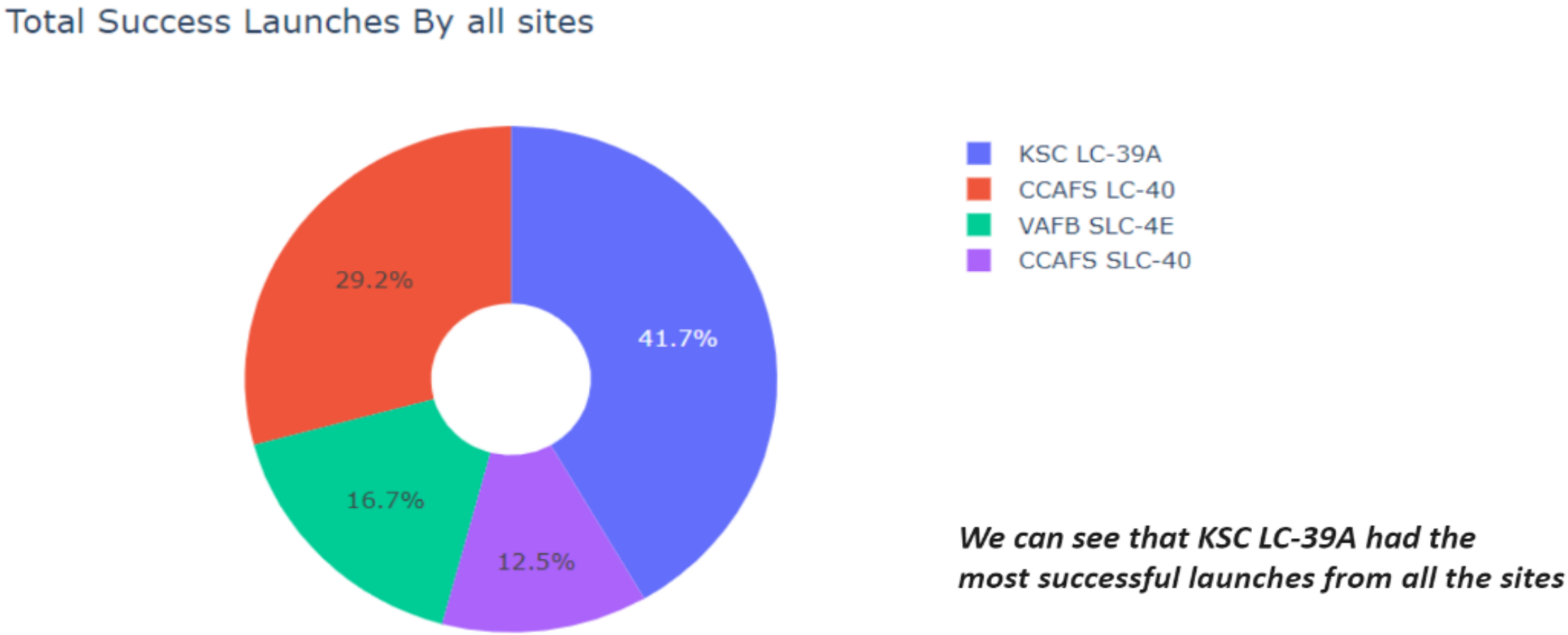





- Are launch sites in close proximity to railways? No
- Are launch sites in close proximity to highways? No
- Are launch sites in close proximity to coastline? Yes
- Do launch sites keep certain distance away from cities? Yes

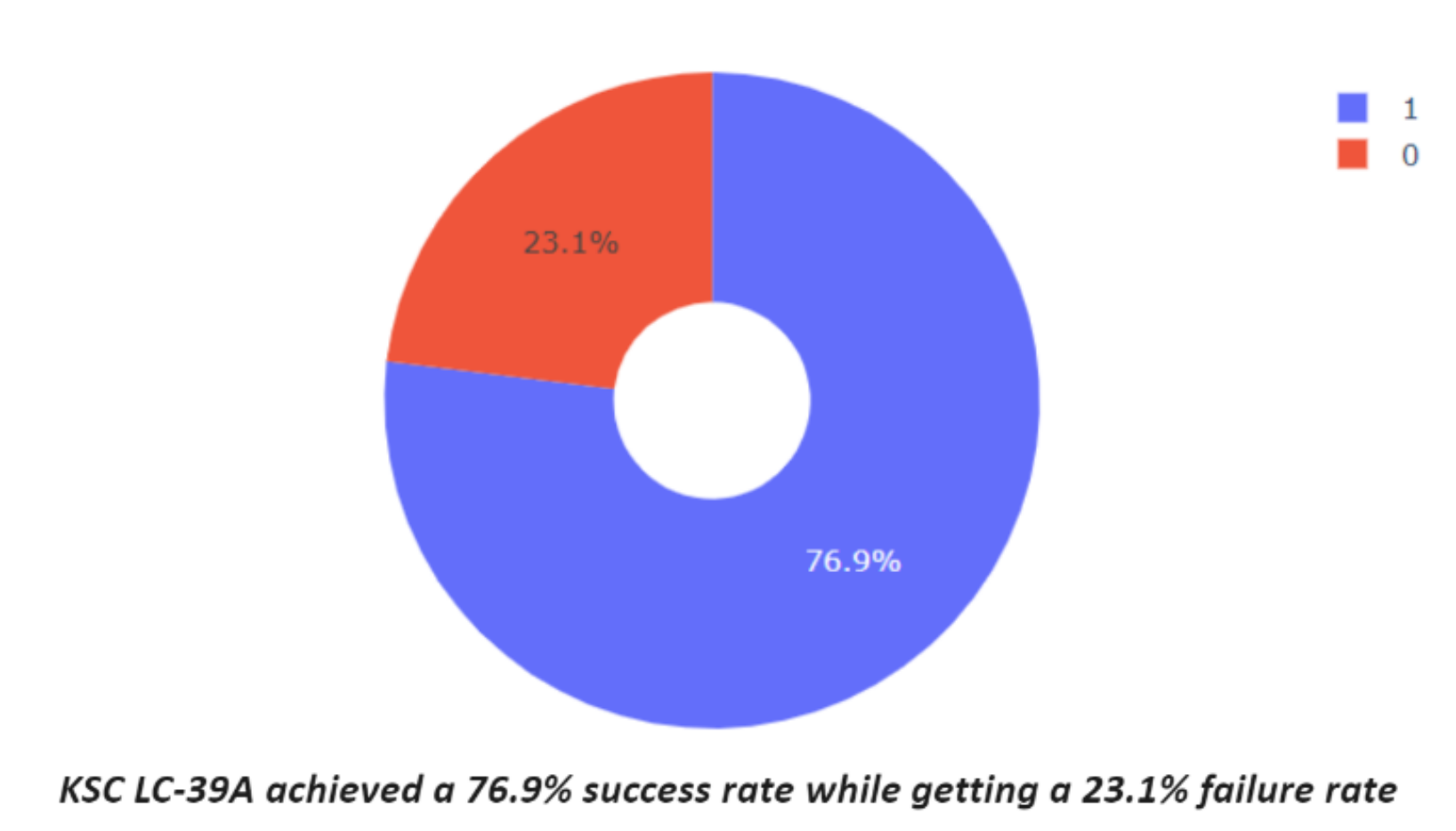

Section 4
Build a Dashboard with Plotly Dash

# Pie chart showing the success percentage achieved by each launch site



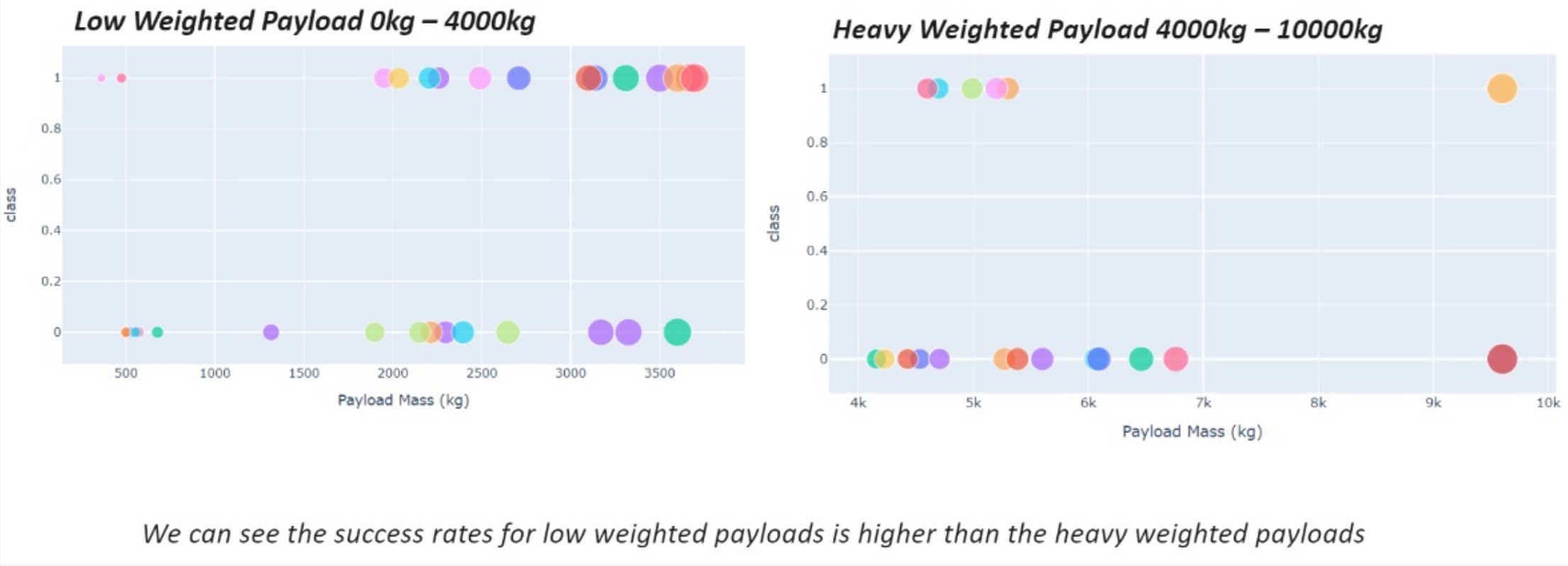

***We can see that KSC LC-39A had the most successful launches from all the sites***

# 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

**TASK 12**

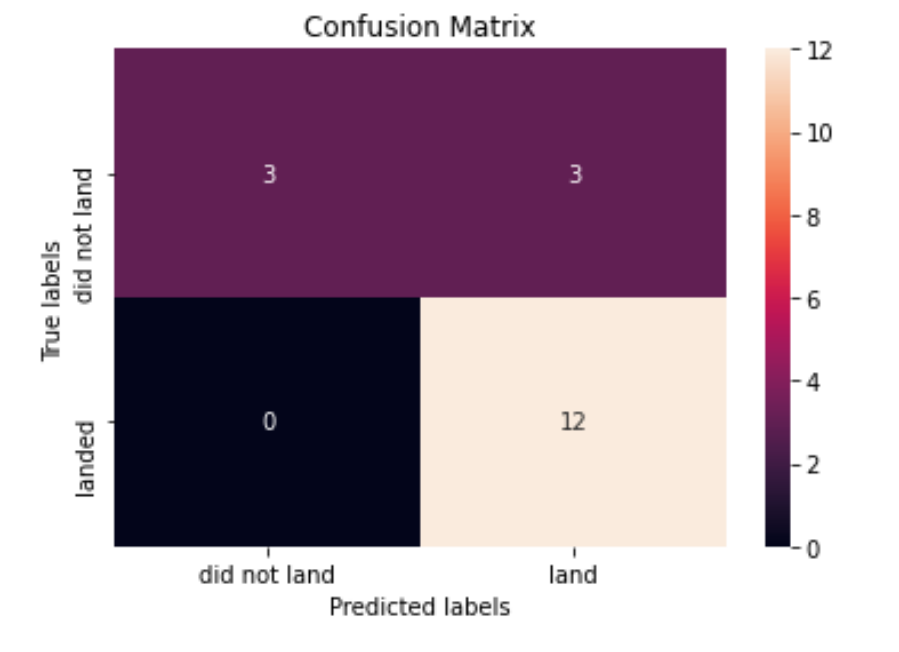
Find the method performs best:

```
print("Log Reg Accuracy:", logreg_cv.best_score_)
print("SVM accuracy:",svm_cv.best_score_)
print("Tree accuracy :",tree_cv.best_score_)
print("KNN test set accuracy:",knn_cv.score(X_test, Y_test))
```

```
Log Reg Accuracy: 0.8464285714285713
SVM accuracy: 0.8482142857142856
Tree accuracy : 0.875
KNN test set accuracy: 0.8333333333333334
```

# 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!