IBM Developer
SKILLS NETWORK

# Winning Space Race with Data Science

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# Outline

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

# Executive Summary

- Summary of methodologies
- Summary of all results

# Introduction

- Project background and context
- Problems you want to find answers

Section 1

# Methodology

# Methodology

## Executive Summary

- Data collection methodology:
    - Using SpaceX Rest API
    - Via web scraping Wikipedia
- Perform data wrangling
    - By hot encoding data fields and dropping the irrelevant data columns (data transformation)
- Perform exploratory data analysis (EDA) using visualization and SQL
    - Creating scatter and bar graphs to discover patterns,
- Perform interactive visual analytics using Folium and Plotly Dash
    - Using Plotly and Folium
- Perform predictive analysis using classification models
    - Building & Evaluating classification models

# Data Collection

**Data Collection – Meaning & Basic Steps**

Data collection is the process of gathering and measuring information on targeted variables in an established system, enabling one to answer relevant questions and evaluate outcomes.

- **Getting Data from API or Web Page**
- **Make a dataframe from it**
- **Filter dataframes as per requirement**
- **Export to flat file**

- GitHub Notebook

# Data Collection – SpaceX API

- **Getting Data from API or Web Page**

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

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

# Data Collection – SpaceX API

- **Make a dataframe**

```
# Use json_normalize meethod to convert the json result into a dataframe
data = pd.json_normalize(response.json())
```

# Data Collection – SpaceX API

- **Filter DF**

```
[31]:
# Hint data['BoosterVersion']!='Falcon 1'
# data_falcon9['BoosterVersion']!='Falcon 9' returns true for all rows except 'Falcon 9' and running drop, drops those rows.
data_falcon9.drop(data_falcon9[data_falcon9['BoosterVersion']!='Falcon 9'].index, inplace = True)
```

- **Work with missing values**

```
In [34]:
# Calculate the mean value of PayloadMass column
avg_payload_mass = data_falcon9["PayloadMass"].astype("float").mean(axis=0)
# Replace the np.nan values with its mean value
data_falcon9["PayloadMass"].replace(np.nan, avg_payload_mass, inplace=True)
```

You should see the number of missing values of the `PayLoadMass` change to zero.

```
In [35]:
data_falcon9.isnull().sum()
```

Out[36]:

| | FlightNumber | Date | BoosterVersion | PayloadMass | Orbit | LaunchSite | Outcome | Flights | GridFins | Reused | Legs | LandingPad | Block |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **4** | 1 | 2010-06-04 | Falcon 9 | 6123.547647 | LEO | CCSFS SLC 40 | None None | 1 | False | False | False | None | 1 |
| **5** | 2 | 2012-05-22 | Falcon 9 | 525.000000 | LEO | CCSFS SLC 40 | None None | 1 | False | False | False | None | 1 |
| **6** | 3 | 2013-03-01 | Falcon 9 | 677.000000 | ISS | CCSFS SLC 40 | None None | 1 | False | False | False | None | 1 |
| **7** | 4 | 2013-09-29 | Falcon 9 | 500.000000 | PO | VAFB SLC 4E | False Ocean | 1 | False | False | False | None | 1 |
| **8** | 5 | 2013-12-03 | Falcon 9 | 3170.000000 | GTO | CCSFS SLC 40 | None None | 1 | False | False | False | None | 1 |

# Data Collection – SpaceX API

- **Export to file**

```
data_falcon9.to_csv('dataset_part_1.csv', index=False)
```

```
[39]: data_falcon9.to_csv('csvs/dataset_part_1.csv', index=False)
```

| 1 | FlightNumber | Date | BoosterVersion | PayloadMass | Orbit | LaunchSite | Outcome | Flights | GridFins | Reused | Legs | LandingPad | Block | ReusedCount | Serial | Longitude | Latitude |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | 1 | 2010-06-04 | Falcon 9 | 6123.547647058824 | LEO | CCSFS SLC 40 | None None | 1 | False | False | False | | 1 | 0 | B0003 | -80.577366 | 28.5618571 |
| 3 | 2 | 2012-05-22 | Falcon 9 | 525.0 | LEO | CCSFS SLC 40 | None None | 1 | False | False | False | | 1 | 0 | B0005 | -80.577366 | 28.5618571 |
| 4 | 3 | 2013-03-01 | Falcon 9 | 677.0 | ISS | CCSFS SLC 40 | None None | 1 | False | False | False | | 1 | 0 | B0007 | -80.577366 | 28.5618571 |
| 5 | 4 | 2013-09-29 | Falcon 9 | 500.0 | PO | VAFB SLC 4E | False Ocean | 1 | False | False | False | | 1 | 0 | B1003 | -120.610829 | 34.632093 |
| 6 | 5 | 2013-12-03 | Falcon 9 | 3170.0 | GTO | CCSFS SLC 40 | None None | 1 | False | False | False | | 1 | 0 | B1004 | -80.577366 | 28.5618571 |
| 7 | 6 | 2014-01-06 | Falcon 9 | 3325.0 | GTO | CCSFS SLC 40 | None None | 1 | False | False | False | | 1 | 0 | B1005 | -80.577366 | 28.5618571 |
| 8 | 7 | 2014-04-18 | Falcon 9 | 2296.0 | ISS | CCSFS SLC 40 | True Ocean | 1 | False | False | True | | 1 | 0 | B1006 | -80.577366 | 28.5618571 |
| 9 | 8 | 2014-07-14 | Falcon 9 | 1316.0 | LEO | CCSFS SLC 40 | True Ocean | 1 | False | False | True | | 1 | 0 | B1007 | -80.577366 | 28.5618571 |
| 10 | 9 | 2014-08-05 | Falcon 9 | 4535.0 | GTO | CCSFS SLC 40 | None None | 1 | False | False | False | | 1 | 0 | B1008 | -80.577366 | 28.5618571 |
| 11 | 10 | 2014-09-07 | Falcon 9 | 4428.0 | GTO | CCSFS SLC 40 | None None | 1 | False | False | False | | 1 | 0 | B1011 | -80.577366 | 28.5618571 |
| 12 | 11 | 2014-09-21 | Falcon 9 | 2216.0 | ISS | CCSFS SLC 40 | False Ocean | 1 | False | False | False | | 1 | 0 | B1010 | -80.577366 | 28.5618571 |
| 13 | 12 | 2015-01-10 | Falcon 9 | 2395.0 | ISS | CCSFS SLC 40 | False ASDS | 1 | True | False | True | 5e9e3032383ecb761634e7cb | 1 | 0 | B1012 | -80.577366 | 28.5618571 |
| 14 | 13 | 2015-02-11 | Falcon 9 | 570.0 | ES-L1 | CCSFS SLC 40 | True Ocean | 1 | True | False | True | | 1 | 0 | B1013 | -80.577366 | 28.5618571 |
| 15 | 14 | 2015-04-14 | Falcon 9 | 1898.0 | ISS | CCSFS SLC 40 | False ASDS | 1 | True | False | True | 5e9e3032383ecb761634e7cb | 1 | 0 | B1015 | -80.577366 | 28.5618571 |
| 16 | 15 | 2015-04-27 | Falcon 9 | 4707.0 | GTO | CCSFS SLC 40 | None None | 1 | False | False | False | | 1 | 0 | B1016 | -80.577366 | 28.5618571 |
| 17 | 16 | 2015-06-28 | Falcon 9 | 2477.0 | ISS | CCSFS SLC 40 | None ASDS | 1 | True | False | True | 5e9e3032383ecb6bb234e7ca | 1 | 0 | B1018 | -80.577366 | 28.5618571 |
| 18 | 17 | [illegible] | Falcon 9 | 2034.0 | LEO | CCSFS SLC 40 | True RTLS | 1 | True | False | True | [illegible] | 1 | 0 | B1019 | -80.577366 | 28.5618571 |

# Data Collection - Scraping

- Web scraping was performed using BeautifulSoup
- This was then parsed and turned into a DF
- [GitHub URL]

In [8]:
```
# 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

In [10]:
```
# Use soup.title attribute
tag_title = soup.title
tag_string_tag_title = tag_title.string
tag_string_tag_title
```

After you have fill in the parsed launch record values into `launch_dict`, you can create a dataframe from it.

In [20]:
```
df=pd.DataFrame(launch_dict)
```

In [21]:
```
df.head()
```

Out[21]:

| | Flight No. | Launch site | Payload | Payload mass | Orbit | Customer | Launch outcome | Version Booster | Booster landing | Date | Time |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | CCAFS | Dragon Spacecraft Qualification Unit | 0 | LEO | SpaceX | Success\n | F9 v1.0B0003.1 | Failure | 4 June 2010 | 18:45 |
| 1 | 2 | CCAFS | Dragon | 0 | LEO | NASA | Success | F9 v1.0B0004.1 | Failure | 8 December 2010 | 15:43 |
| 2 | 3 | CCAFS | Dragon | 525 kg | LEO | NASA | Success | F9 v1.0B0005.1 | No attempt\n | 22 May 2012 | 07:44 |
| 3 | 4 | CCAFS | SpaceX CRS-1 | 4,700 kg | LEO | NASA | Success\n | F9 v1.0B0006.1 | No attempt | 8 October 2012 | 00:35 |
| 4 | 5 | CCAFS | SpaceX CRS-2 | 4,877 kg | LEO | NASA | Success\n | F9 v1.0B0007.1 | No attempt\n | 1 March 2013 | 15:10 |

In [22]:
```
df= pd.DataFrame({ key:pd.Series(value) for key, value in launch_dict.items() })
```

# Data Wrangling

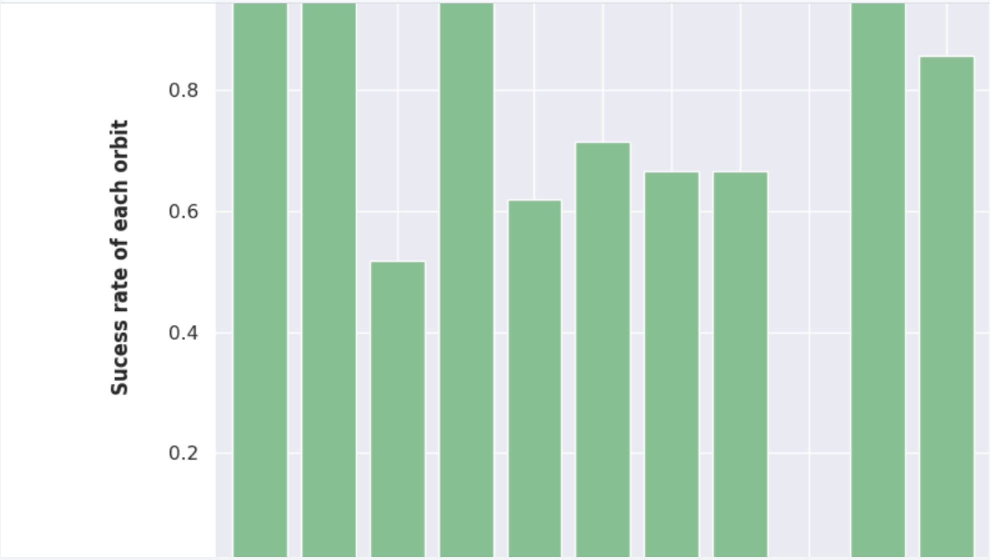
- EDA was performed and the training labels were determined.
- The number of launches for each site was calculated, and the number of occurrences of each orbit.
- A label was also created for landing outcome and this was exported to CSV.

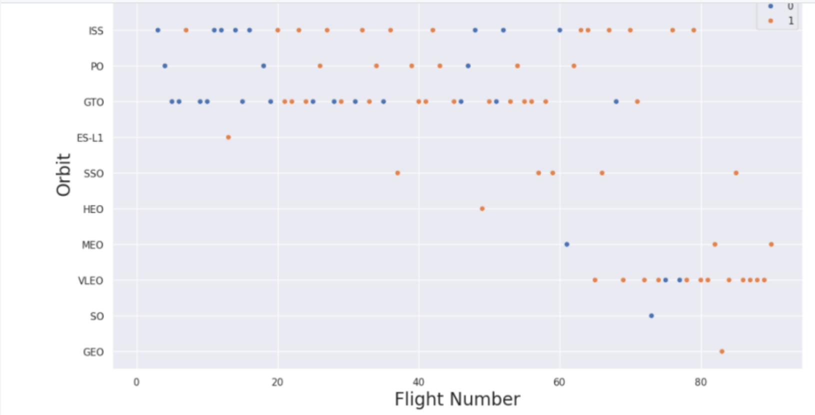
- GitHub URL

# EDA with Data Visualization

- Data Visualization performed was:
- **The relationship between flight number and launch site**
- **Payload and launch site, success rate of each orbit**
- **Flight number and orbit type**
- **Yearly trend of launch success.**

- [GitHub URL]()



# EDA with SQL

- The SpaceX dataset was loaded into a database directly inside Jupyter notebook.
- The following SQL queries were written and performed on the data:
  - **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 failed mission outcomes**
  - **The failed landing outcomes in drone ship, their booster version and launch site names**

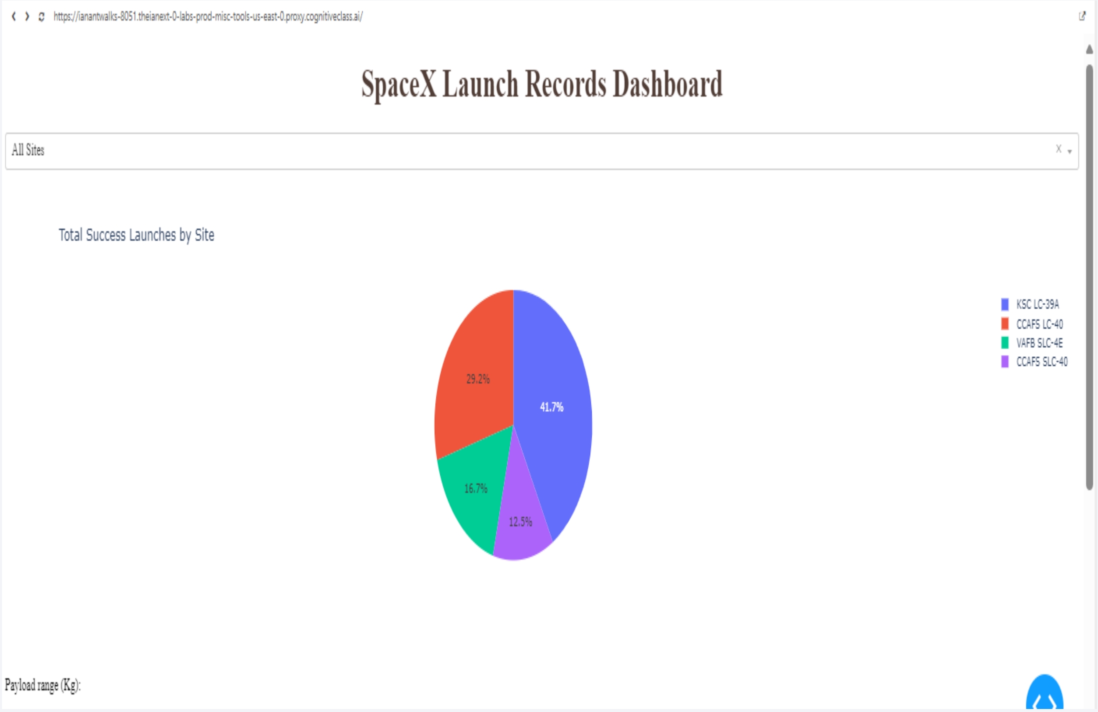
  See the notebook on GitHub for more information.

# Build an Interactive Map with Folium

- We marked all launch sites on an interactive Folium map.  This map included markers, circles and lines to measure the success or failure of each launch for each launch site.
- Classes 0 and 1 were created to signify launch outcomes (e.g. class 0 was failure and class 1 was a success).
- Colour-coded markers were also added to marked clusters to help identify which launch sites had a high rate of success.
- Distances were calculated between a launch site and area proximities such as roads and rail.  This data was then used to answer questions on the relationship between launch sites and their distance between them and cities and their overall location.
- GitHub URL

# Build a Dashboard with Plotly Dash

- An interactive dashboard was created with Plotly.
- For this, pie charts were created showing the number of launchers per site.
- Scatter graphs were also created to show relationships between Outcome and Payload Mass (Kg) for different booster version.
- [GitHub URL for .py program]



# Predictive Analysis (Classification)

- Data was loaded using NumPy and pandas. The data was then transformed and split into two sets, training and testing.
- Using GridSearchCV it allowed for building different machine learning models and for tuning of different hyperparameters.
- The metric used for the model was accuracy, this was improved using feature engineering and algorithm tuning.
- We also used this to discover which classification model performed best.

- GitHub URL

# Results

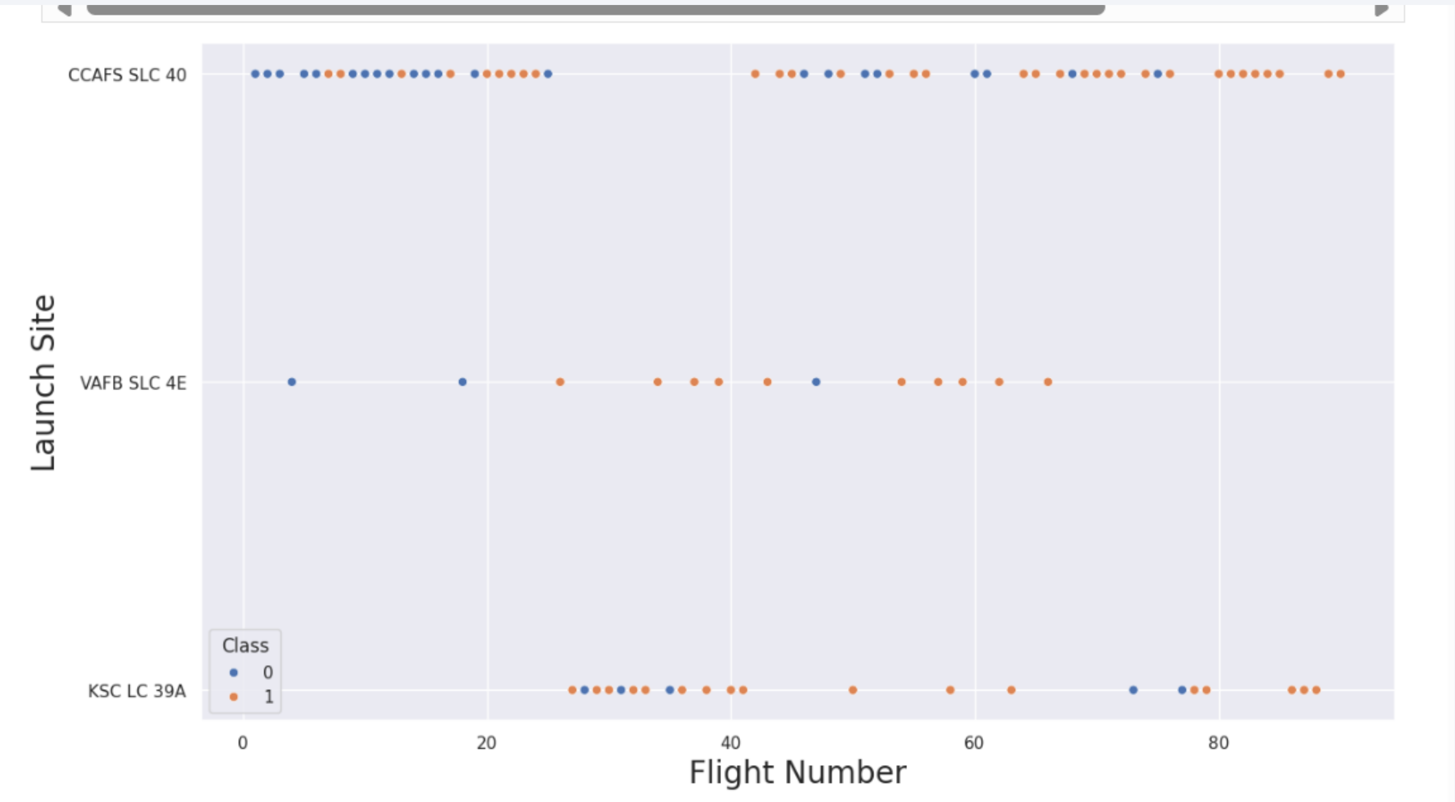
- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results

Section 2

# Insights drawn from EDA

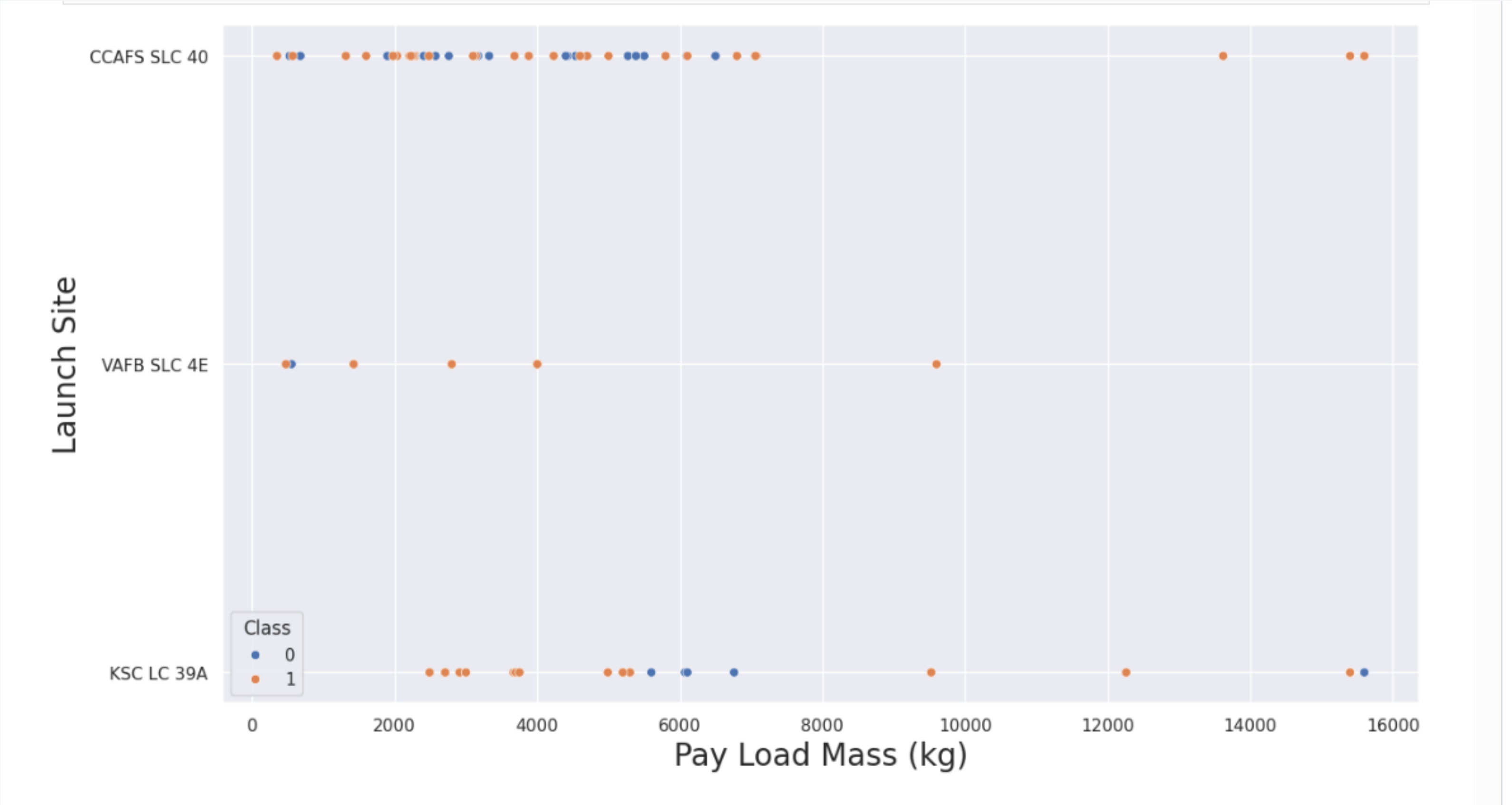
# Flight Number vs. Launch Site

- Based on the graph, it was determined that higher amount of launches a flight had at a launch site then the greater the launch success rate for that particular site.



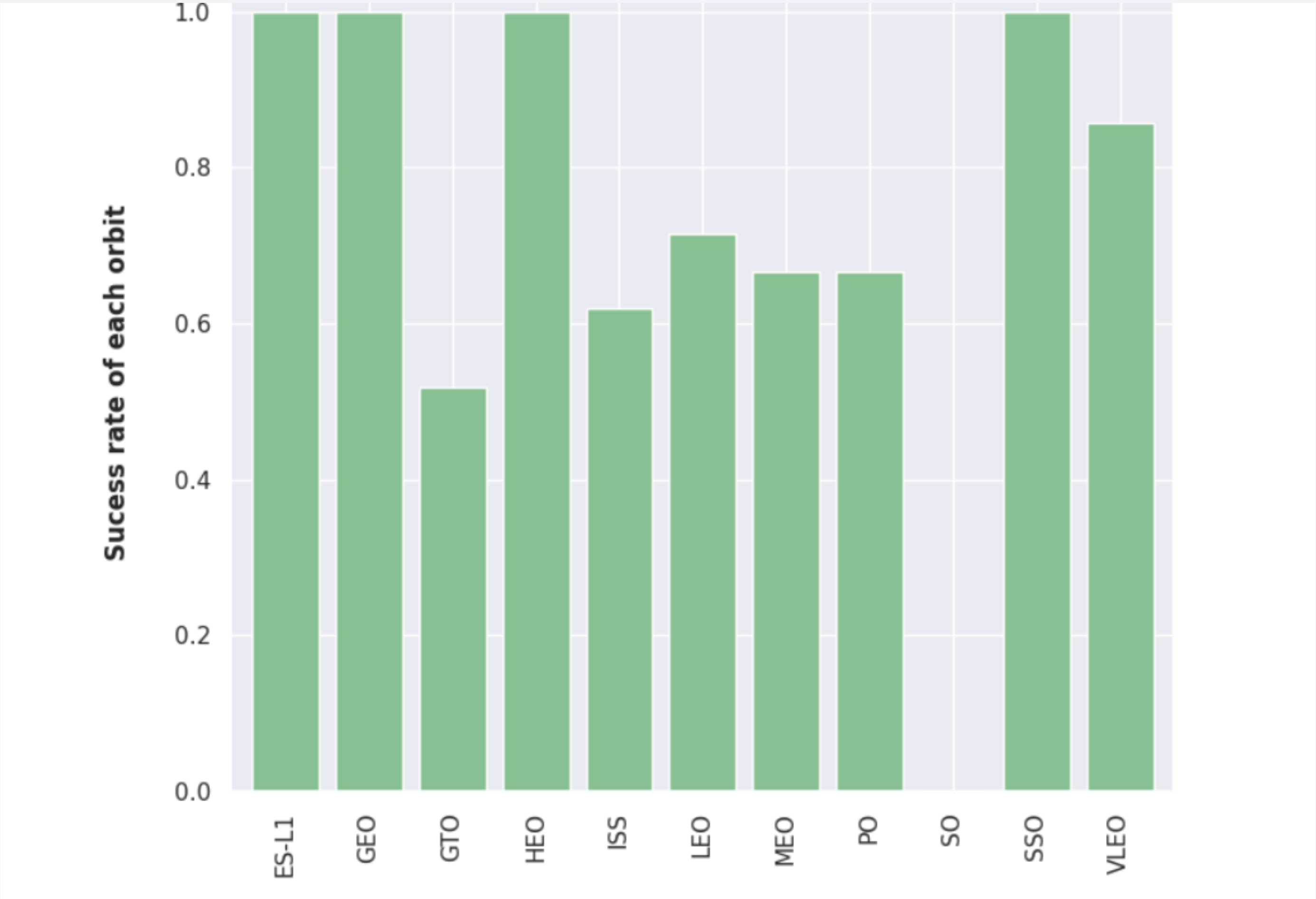
# Payload vs. Launch Site

- Based on the graph, the greater the payload mass then the higher the success rate for the rocket (e.g. CCAFS SLC 40).



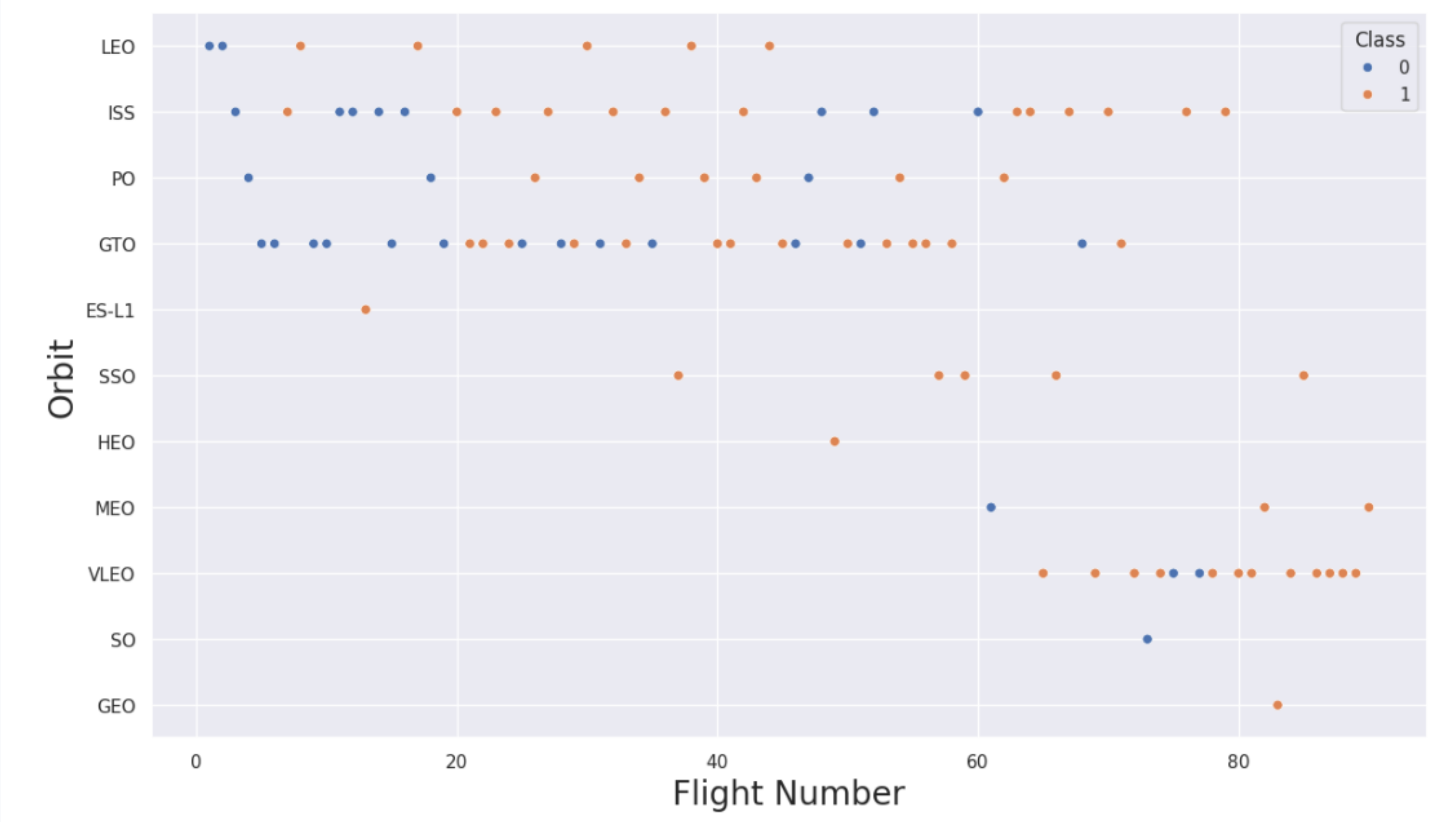
# Success Rate vs. Orbit Type

- Based on the graph, we can see that the most successful orbit types were ES-L1, GEO, HEO, SSO



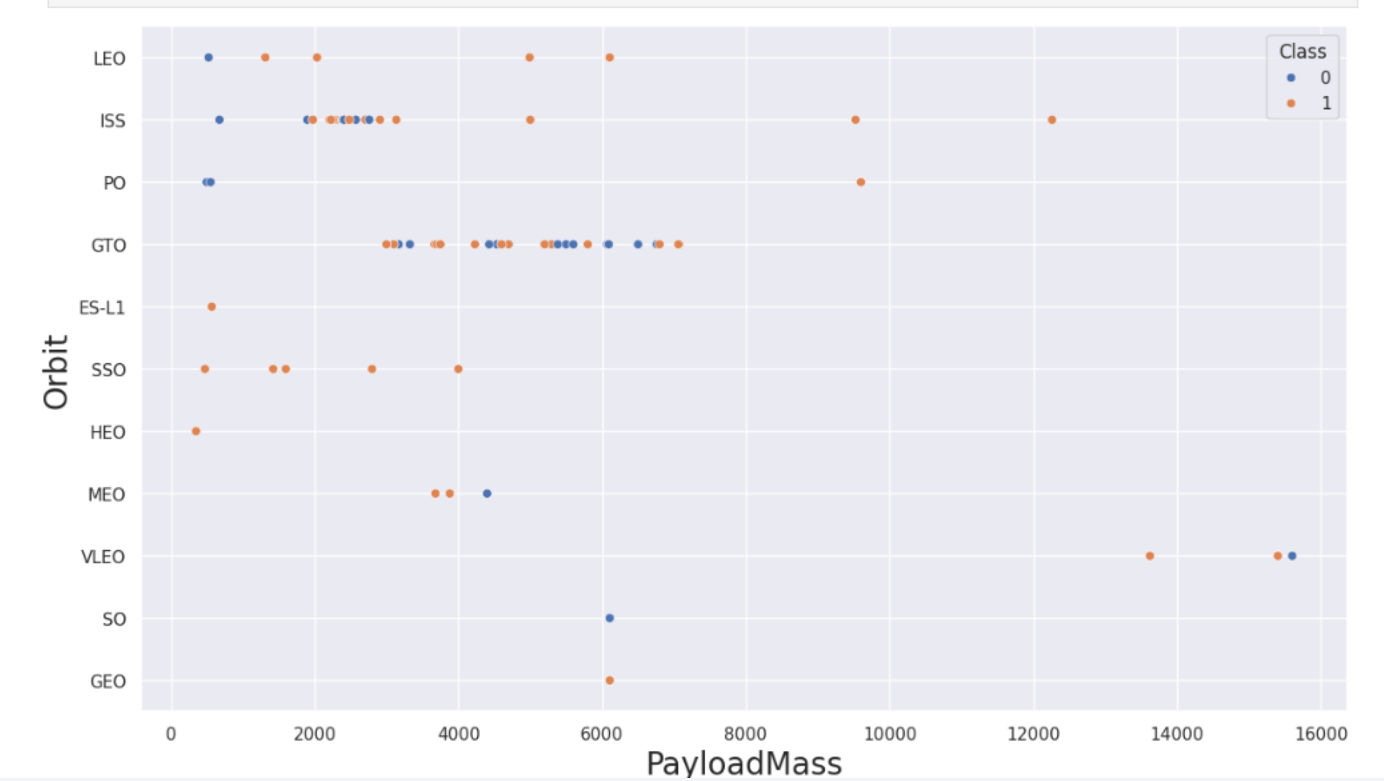
# Flight Number vs. Orbit Type

- Based on the graph, we can see that, for LEO orbit type, the success is related to the number of flights.
- For other orbit types, e.g. GTO, there is no such relationship.



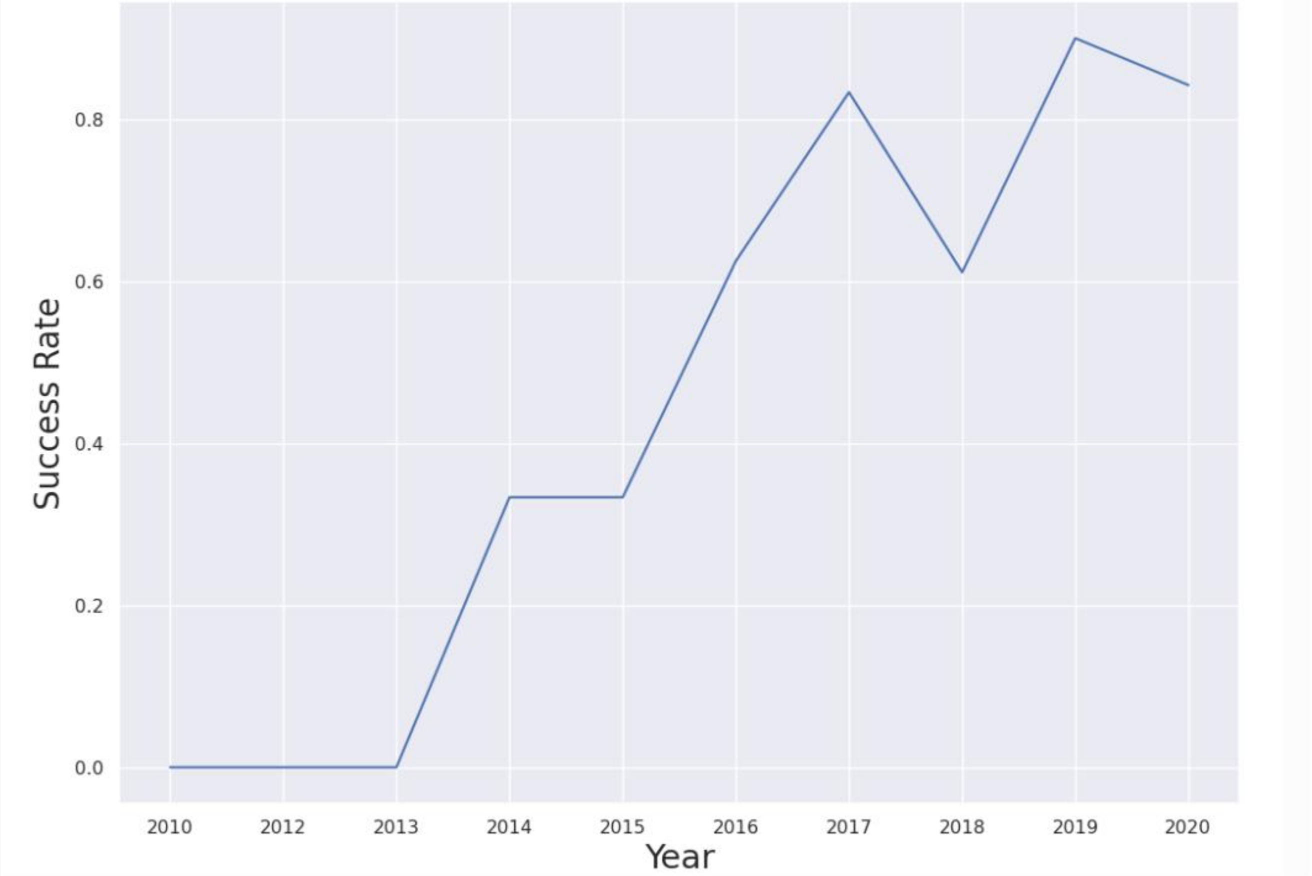
# Payload vs. Orbit Type

- From the graph we can see that when the PayloadMass (KG) is heaver then orbit types such as PO, LEO and ISS are more successful.



# Launch Success Yearly Trend

- From the graph we can see that between the years 2013 and 2020 the launch success rate continued to grow.



# All Launch Site Names

- This SQL query used DISTINCT to show only unique launch site data.

In [9]:

```
%sql SELECT DISTINCT LAUNCH_SITE as "Launch_Sites" FROM SPACEXTABLE;
```

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

Out[9]:

| Launch_Sites |
|---|
| CCAFS LC-40 |
| VAFB SLC-4E |
| KSC LC-39A |
| CCAFS SLC-40 |

# Launch Site Names Begin with 'CCA'

- The following query was used, with results shown.

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

In [10]:
```
%sql SELECT * FROM SPACEXTABLE WHERE LAUNCH_SITE LIKE 'CCA%' LIMIT 5;
```

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

Out[10]:

| Date | Time (UTC) | Booster_Version | Launch_Site | Payload | PAYLOAD_MASS__KG_ | Orbit | Customer | Mission_Outcome | Landing_Outcome |
|---|---|---|---|---|---|---|---|---|---|
| 2010-06-04 | 18:45:00 | F9 v1.0 B0003 | CCAFS LC-40 | Dragon Spacecraft Qualification Unit | 0 | LEO | SpaceX | Success | Failure (parachute) |
| 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 | Failure (parachute) |
| 2012-05-22 | 7:44:00 | F9 v1.0 B0005 | CCAFS LC-40 | Dragon demo flight C2 | 525 | LEO (ISS) | NASA (COTS) | Success | No attempt |
| 2012-10-08 | 0:35:00 | F9 v1.0 B0006 | CCAFS LC-40 | SpaceX CRS-1 | 500 | LEO (ISS) | NASA (CRS) | Success | No attempt |
| 2013-03-01 | 15:10:00 | F9 v1.0 B0007 | CCAFS LC-40 | SpaceX CRS-2 | 677 | LEO (ISS) | NASA (CRS) | Success | No attempt |

# Total Payload Mass

- The following query was used, with results shown.

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

In [11]:
```
%sql SELECT SUM(PAYLOAD_MASS__KG_) AS "Total Payload Mass by NASA (CRS)" FROM SPACEXTABLE WHERE CUSTOMER = 'NASA (CRS)';
```

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

Out[11]:

| Total Payload Mass by NASA (CRS) |
|---|
| 45596 |

# Average Payload Mass by F9 v1.1

- The following query was used, with results shown.

### Task 4

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

46]:
```
%sql SELECT AVG(PAYLOAD_MASS__KG_) AS "Average Payload Mass by Booster Version F9 v1.1" FROM SPACEXTABLE \
WHERE Booster_Version LIKE 'F9 v1.1';
```

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

46]:

| Average Payload Mass by Booster Version F9 v1.1 |
| ---: |
| 2928.4 |

# First Successful Ground Landing Date

- The following query was used, with results shown.

*** Note: Not sure about this.**

## Task 5

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

*Hint:Use min function*

In [57]:
```
%sql SELECT MIN(DATE) AS "First Succesful Landing Outcome in Ground Pad" FROM SPACEXTABLE \
WHERE 'Landing _Outcome' LIKE 'Success (ground pad)';
```

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

Out[57]:

| First Succesful Landing Outcome in Ground Pad |
| --- |
| None |

# Successful Drone Ship Landing with Payload between 4000 and 6000

- The following query was used, with results shown.

List the names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000

```
%sql SELECT BOOSTER_VERSION FROM SPACEXTABLE WHERE Landing_Outcome = 'Success (drone ship)' \
AND PAYLOAD_MASS__KG_ > 4000 AND PAYLOAD_MASS__KG_ < 6000;
```

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

| Booster_Version |
|---|
| F9 FT B1022 |
| F9 FT B1026 |
| F9 FT B1021.2 |
| F9 FT B1031.2 |

# Total Number of Successful and Failure Mission Outcomes

- The following query was used, with results shown.

## Task 7

List the total number of successful and failure mission outcomes

In [27]:
```
%sql SELECT COUNT(MISSION_OUTCOME) AS "Successful Mission" FROM SPACEXTABLE WHERE MISSION_OUTCOME LIKE 'Success%';
```

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

Out[27]:

| Successful Mission |
|---|
| 100 |

In [17]:
```
%sql SELECT COUNT(MISSION_OUTCOME) AS "Failure Mission" FROM SPACEXTABLE WHERE MISSION_OUTCOME LIKE 'Failure%';
```

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

Out[17]:

| Failure Mission |
|---|
| 1 |

# Boosters Carried Maximum Payload

- The following query was used, with results shown.

### Task 8

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

n [20]:

```
%sql SELECT DISTINCT BOOSTER_VERSION AS "Booster Versions which carried the Maximum Payload Mass" FROM SPACEXTABLE \
WHERE PAYLOAD_MASS__KG_ =(SELECT MAX(PAYLOAD_MASS__KG_) FROM SPACEXTABLE);
```

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

ut[20]:

| Booster Versions which carried the Maximum Payload Mass |
|---:|
| F9 B5 B1048.4 |
| F9 B5 B1049.4 |
| F9 B5 B1051.3 |
| F9 B5 B1056.4 |
| F9 B5 B1048.5 |
| F9 B5 B1051.4 |
| F9 B5 B1049.5 |
| F9 B5 B1060.2 |
| F9 B5 B1058.3 |
| F9 B5 B1051.6 |
| F9 B5 B1060.3 |
| F9 B5 B1049.7 |

# 2015 Launch Records

- The following query was used, with results shown.

  This used a combination of **WHERE, LIKE, AND** and **BETWEEN** to filter the required data.

Task 9

List the records which will display the month names, failure landing_outcomes in drone ship ,booster versions, launch_site for the months in year 2015.

**Note: SQLLite does not support monthnames. So you need to use substr(Date, 6,2) as month to get the months and substr(Date,0,5)='2015' for year.**

```
%sql SELECT BOOSTER_VERSION, LAUNCH_SITE FROM SPACEXTABLE WHERE DATE LIKE '2015-%' AND \
Landing_Outcome = 'Failure (drone ship)';
```

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

| Booster_Version | Launch_Site |
|---|---|
| F9 v1.1 B1012 | CCAFS LC-40 |
| F9 v1.1 B1015 | CCAFS LC-40 |

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

- The following query was used, with results shown.

  This used a combination of **COUNT** (landing outcomes), **WHERE** (to filter **BETWEEN** dates).

- A **GROUP BY** clause was applied which was had an **ORDER BY** clause added to get the landing outcome data in descending order.

### Task 10

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.

```
%sql SELECT Landing_Outcome, COUNT(*) as count \
     FROM SPACEXTABLE \
     WHERE Date BETWEEN '2010-06-04' AND '2017-03-20' \
     GROUP BY Landing_Outcome \
     ORDER BY count DESC
```

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

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

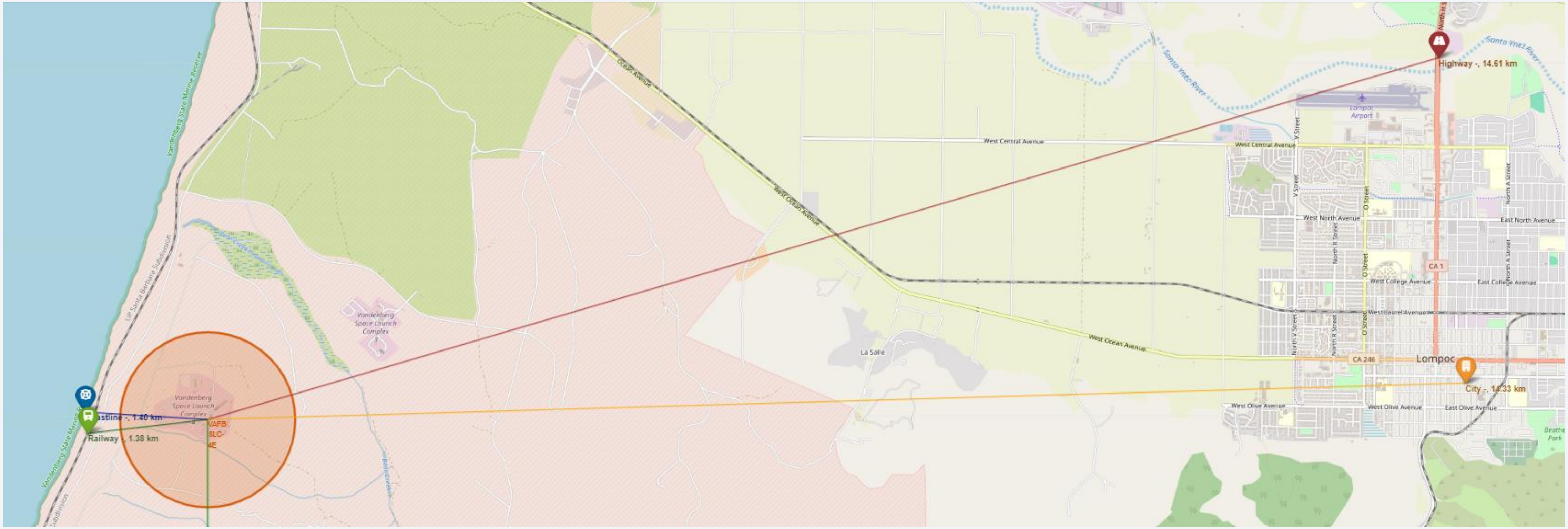
Section 3

# Launch Sites Proximities Analysis

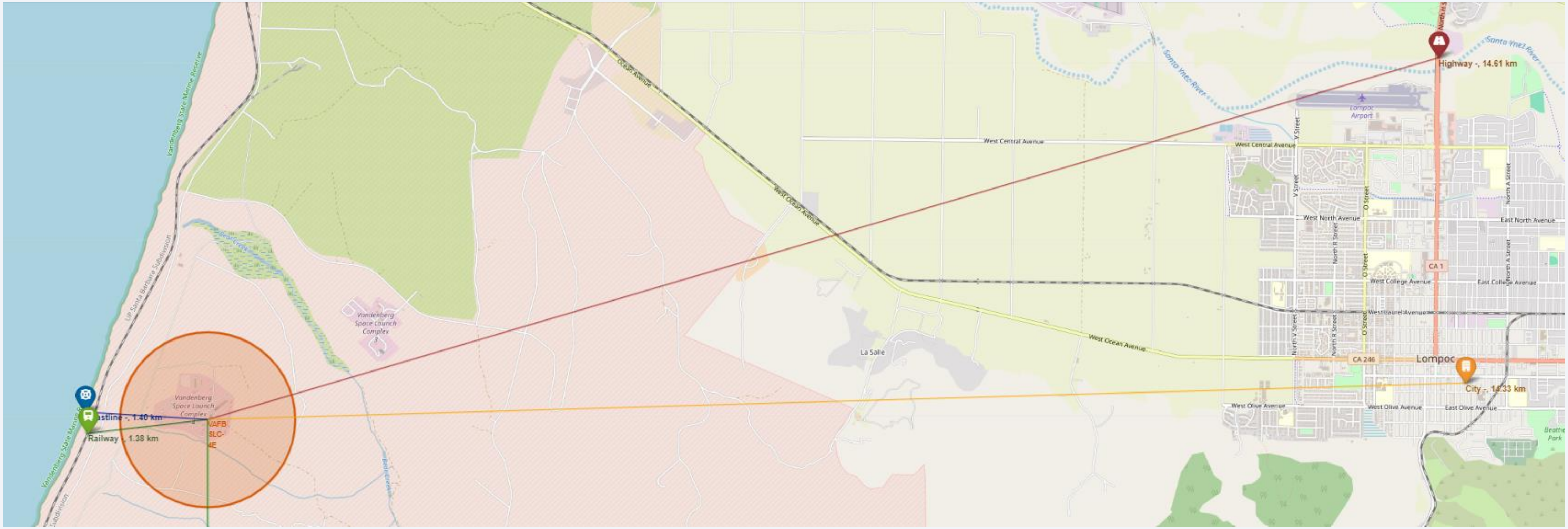
# Global markers of all launch sites in the USA

# Launch sites with colour labels

# Launch Site distance to landmarks



# Launch Site distance to landmarks

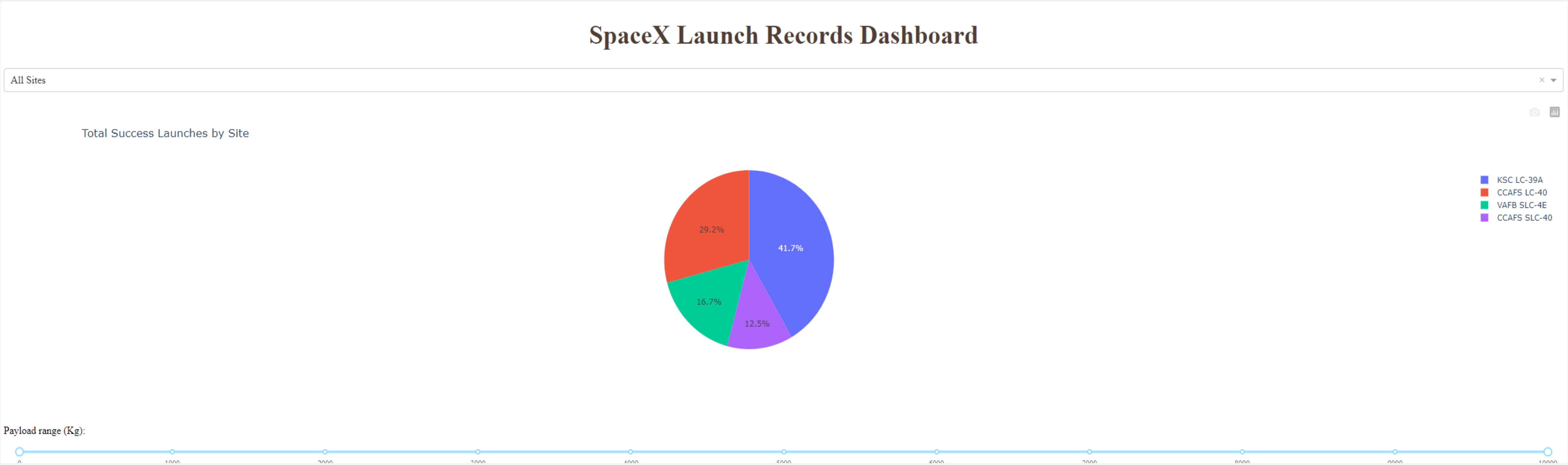


Section 4

# Build a Dashboard with Plotly Dash

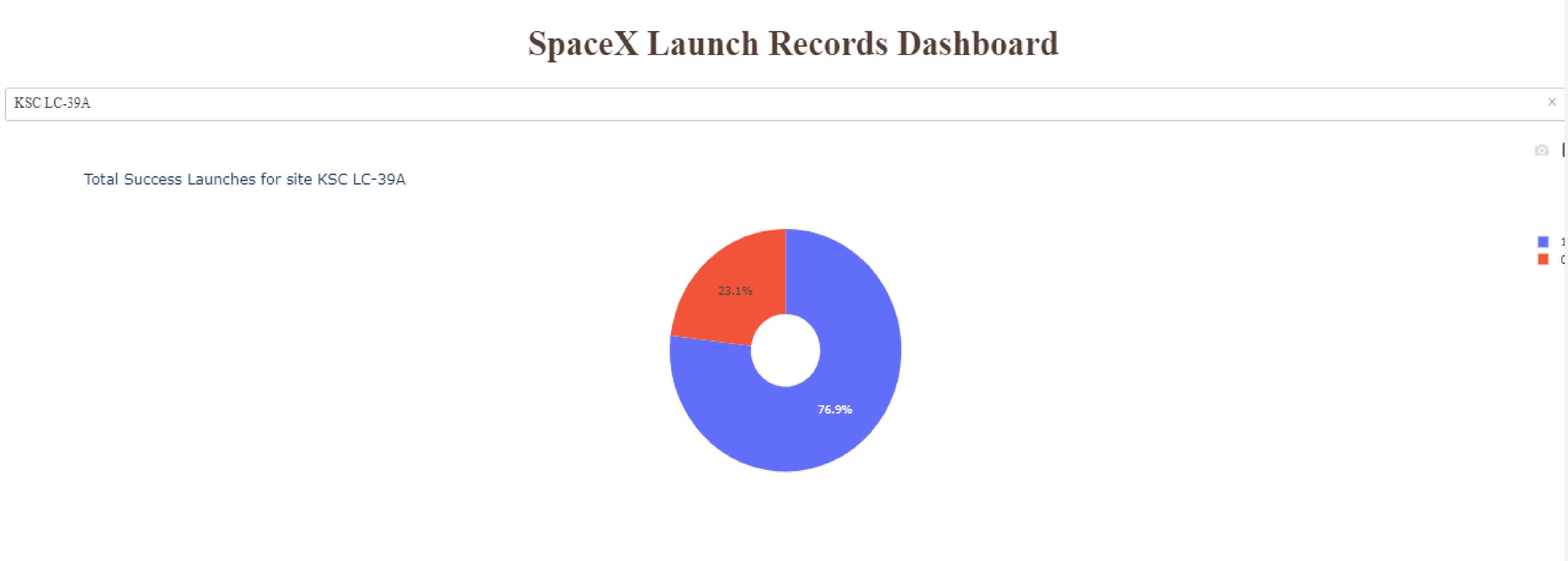
# Pie Chart showing success % per launch site

- We can see that KSC LC-39A has the most successful launches.



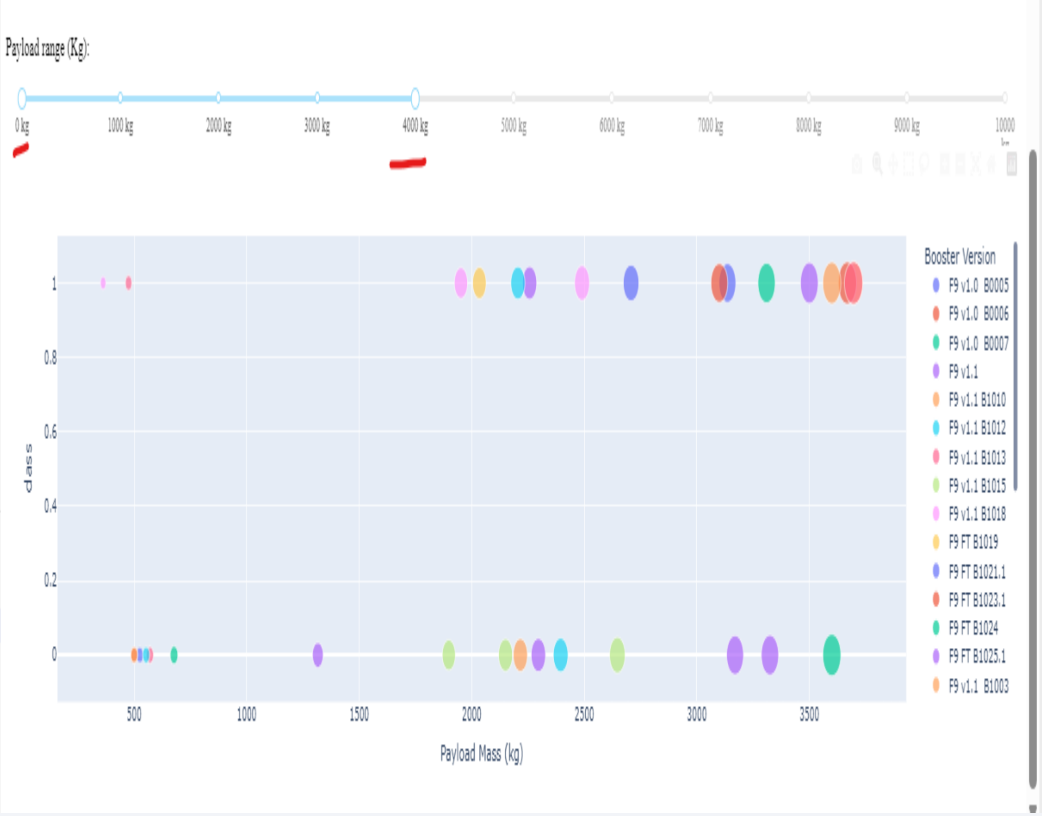
# Pie chart showing launch site with highest success ratio

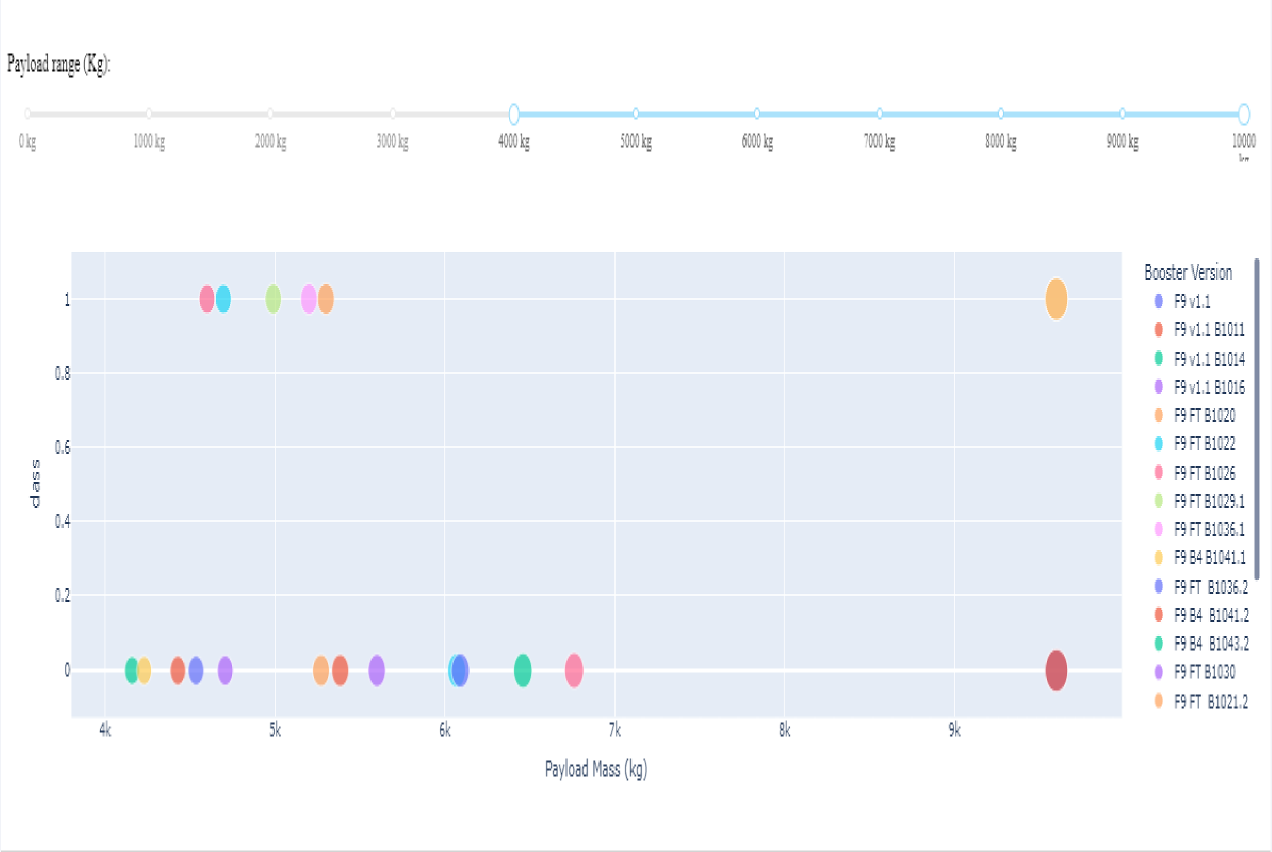
- We can see that KSC LC-39A has the highest launch success ratio (76.9%).



# Scatter plot of Payload vs Launch Outcome for All Sites

- We can see that success for low weighted payloads (0kg – 4000kg) is higher than heavy weighted payloads (4000kg – 10000kg).



Section 5

# Predictive Analysis (Classification)

# Classification Accuracy – Decision Tree is the most accurate

Find the method performs best:

In [47]:
```
algorithms = {'KNN':knn_cv.best_score_,'Decision Tree':tree_cv.best_score_,'Logistic Regression':logreg_cv.best_score_,'
best_algorithm = max(algorithms, key= lambda x: algorithms[x])

print('The method which performs best is \"',best_algorithm,'\" with a score of',algorithms[best_algorithm])
```

```
The method which performs best is " Decision Tree " with a score of 0.875
```

In [ ]:
```
Here is best performing method
```

In [48]:
```
algo_df = pd.DataFrame.from_dict(algorithms, orient='index', columns=['Accuracy'])
```

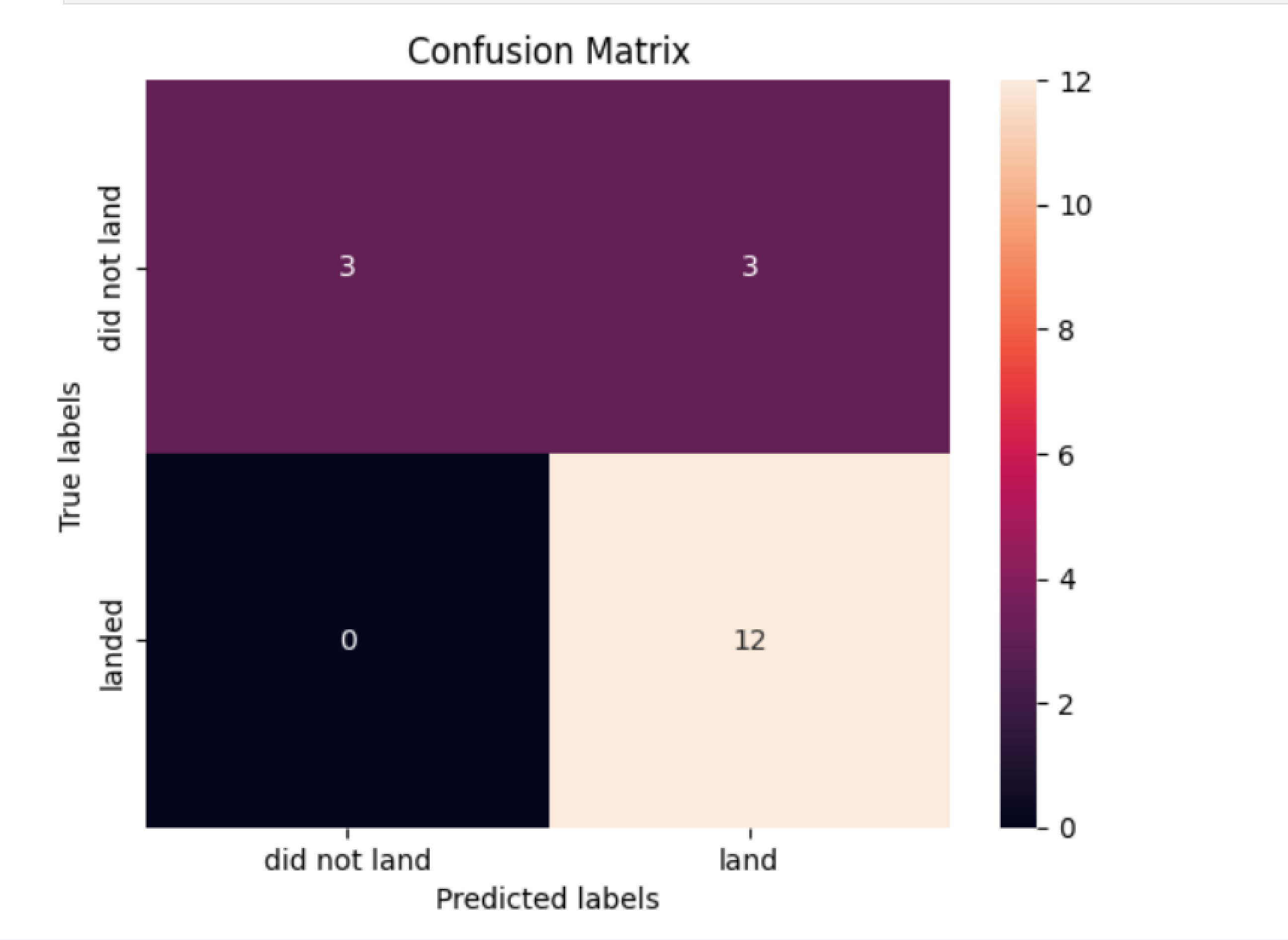
In [49]:
```
algo_df.head()
```

Out[49]:

| | Accuracy |
|---|---|
| **KNN** | 0.848214 |
| **Decision Tree** | 0.875000 |
| **Logistic Regression** | 0.846429 |
| **SVM** | 0.848214 |

# Confusion Matrix

- Based on the confusion matrix for the decision tree classifier it shows that the classifier can correctly distinguish between different classes.
- The only issue is false positives.  With some landing failures being marked as successful.



# Conclusions

From this exercise, we can conclude that:

- The larger the flight amount at a particular launch site then then the greater the rate of success.
- From 2013 to 2020 the rate of successful launch rates increased.
- The Orbits with the highest success rate were ES-L1, GEO, HEO, SSO and VLEO
- KSC-L39A was the most successful launch site overall with the most number of successful launches.
- The Decision tree classifier was the best machine learning model 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!