IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

Luki Prasetyo

March 13, 2024

Outline

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

Executive Summary

Summary of Methodologies

The research attempts to identify the factors for a successful rocket landing. To make this determination, the following methodologies where used:

- **Collect** data using SpaceX REST API and web scraping techniques
- **Wrangle** data to create success/fail outcome variable
- **Explore** data with data visualization techniques, considering the following factors: payload, launch site, flight number and yearly trend
- **Analyze** the data with SQL, calculating the following statistics: total payload, payload range for successful launches, and total # of successful and failed outcomes
- **Explore** launch site success rates and proximity to geographical markers
- **Visualize** the launch sites with the most success and successful payload ranges
- **Build Models** to predict landing outcomes using logistic regression, support vector machine (SVM), decision tree and K-nearest neighbor (KNN)

Introduction

Background

SpaceX, a leader in the space industry, strives to make space travel affordable for everyone. Its accomplishments include sending spacecraft to the international space station, launching a satellite constellation that provides internet access and sending manned missions to space. SpaceX can do this because the rocket launches are relatively inexpensive ($62 million per launch) due to its novel reuse of the first stage of its Falcon 9 rocket. Other providers, which are not able to reuse the first stage, cost upwards of $165 million each. By determining if the first stage will land, we can determine the price of the launch. To do this, we can use public data and machine learning models to predict whether SpaceX – or a competing company – can reuse the first stage.

Explore

- How payload mass, launch site, number of flights, and orbits affect first-stage landing success
- Rate of successful landings over time
- Best predictive model for successful landing (binary classification)

Section 1

Methodology

Methodology

Executive Summary

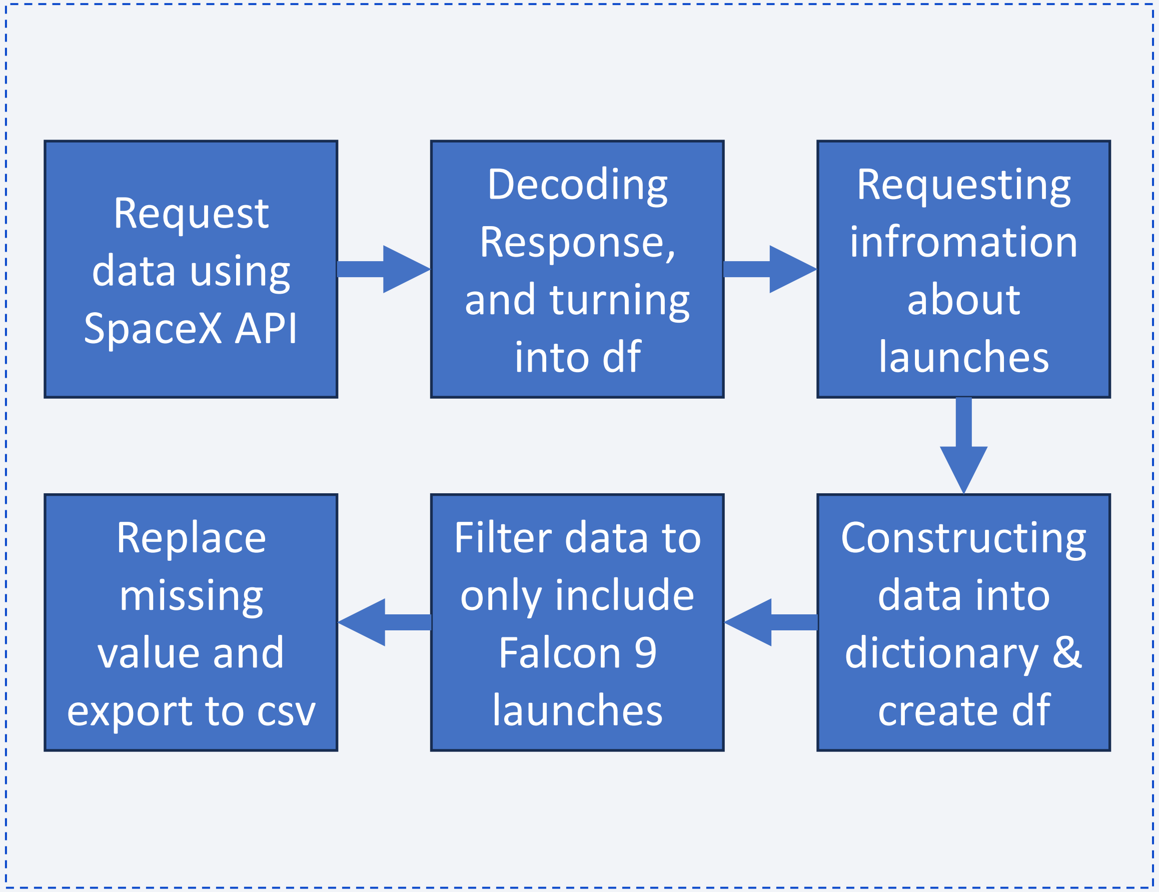
- Data collection methodology:
  - Request data from SpaceX API, Decode response using and convert to a dataframe.
- Perform data wrangling
  - One-hot encoding was applied to categorical features
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
  - Creating chart, standardize the data, split the data, create hyperparameter tuning, apply GridSearchCV, Calculating Score, Identify the best model

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.

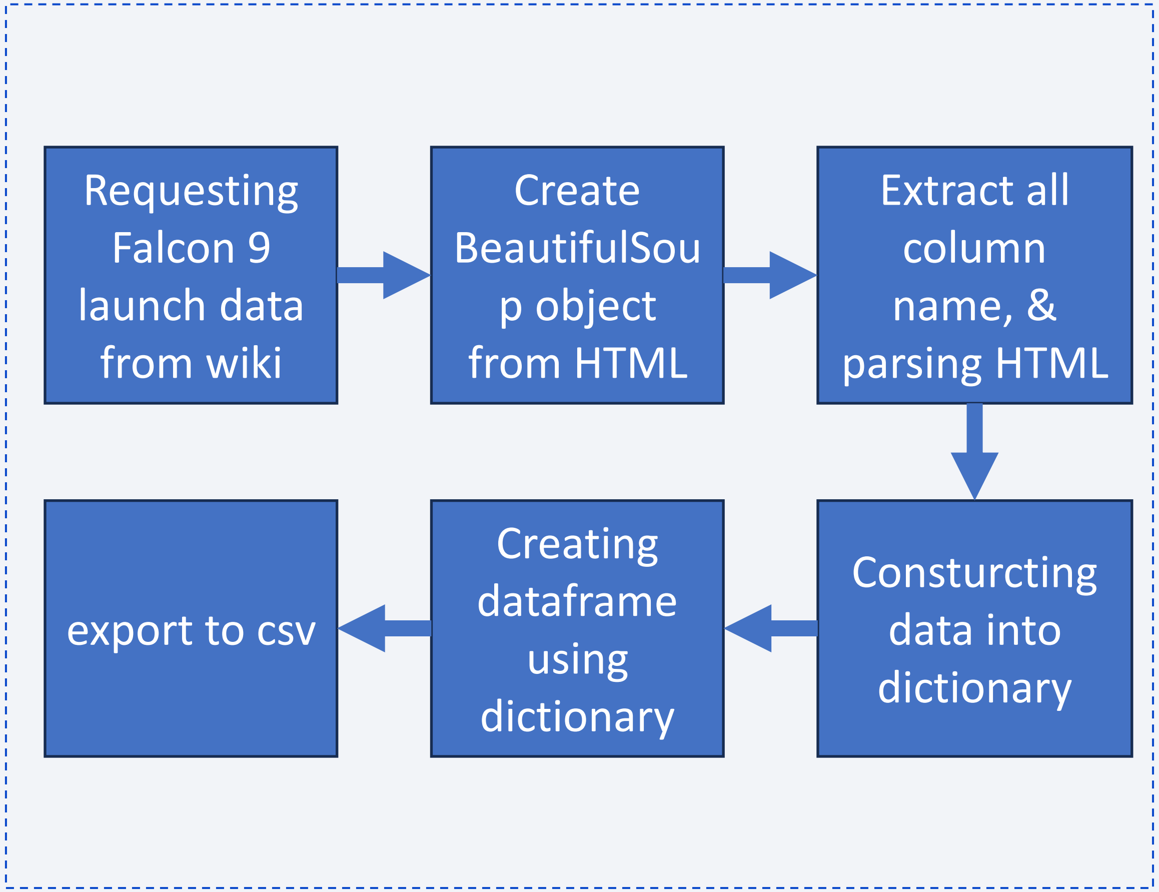
Data Collection – SpaceX API

- 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/lukpras/ibm-data-science-capstone/blob/main/01-spacex-data-collection-api.ipynb


Request data using SpaceX API
Decoding Response, and turning into df
Requesting infromation about launches
Constructing data into dictionary & create df
Filter data to only include Falcon 9 launches
Replace missing value and export to csv

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/lukpras/ibm-data-science-capstone/blob/main/02-spacex-webscraping.ipynb



Requesting Falcon 9 launch data from wiki

Create BeautifulSoup object from HTML

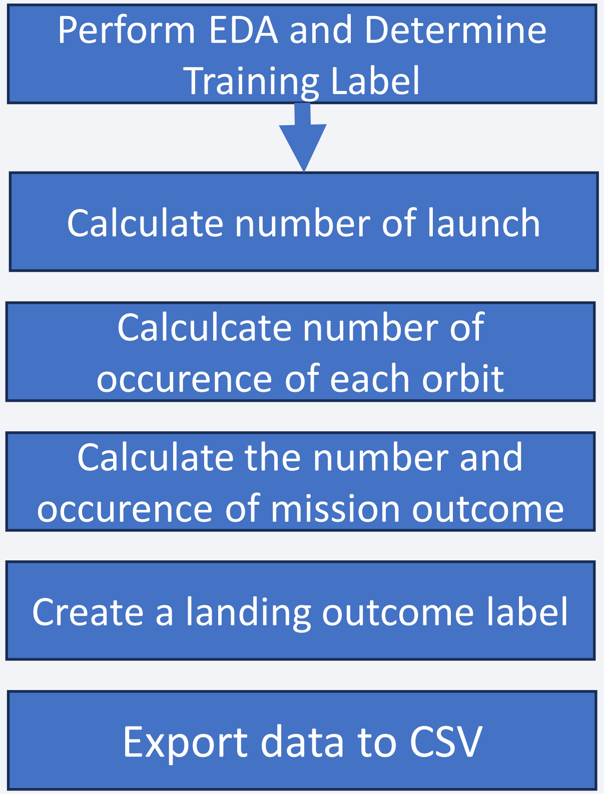
Extract all column name, & parsing HTML

Consturcting data into dictionary

Creating dataframe using dictionary

export to csv

Data Wrangling



Perform EDA and Determine Training Label

Calculate number of launch

Calculcate number of occurence of each orbit

Calculate the number and occurence of mission outcome

Create a landing outcome label

Export data to CSV

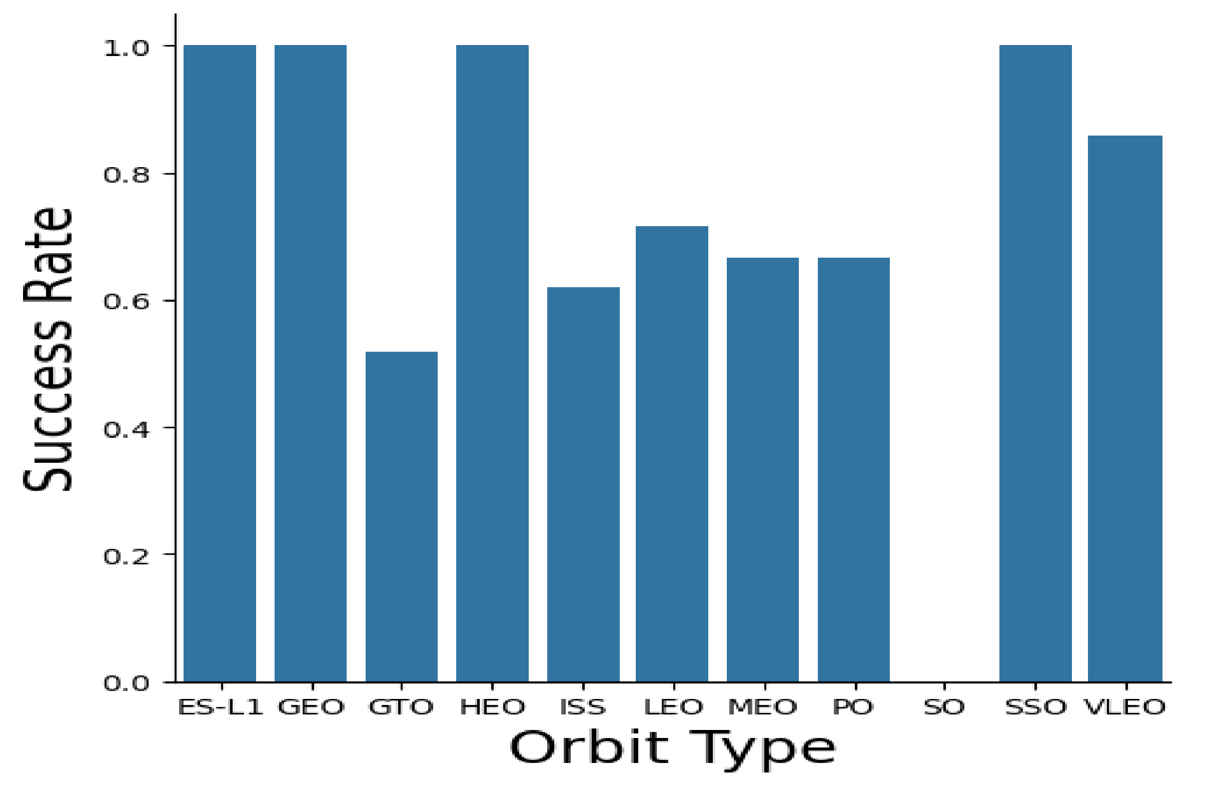
In the data set, there are several different cases where the booster did not land successfully. Sometimes a landing was attempted but failed due to an accident; for example, True Ocean means the mission outcome was successfully landed to a specific region of the ocean while False Ocean means the mission outcome was unsuccessfully landed to a specific region of the ocean. True RTLS means the mission outcome was successfully landed to a ground pad False RTLS means the mission outcome was unsuccessfully landed to a ground pad. True ASDS means the mission outcome was successfully landed on a drone ship False ASDS means the mission outcome was unsuccessfully landed on a drone ship. We mainly convert those outcomes into Training Labels with “1” means the booster successfully landed, “0” means it was unsuccessful.

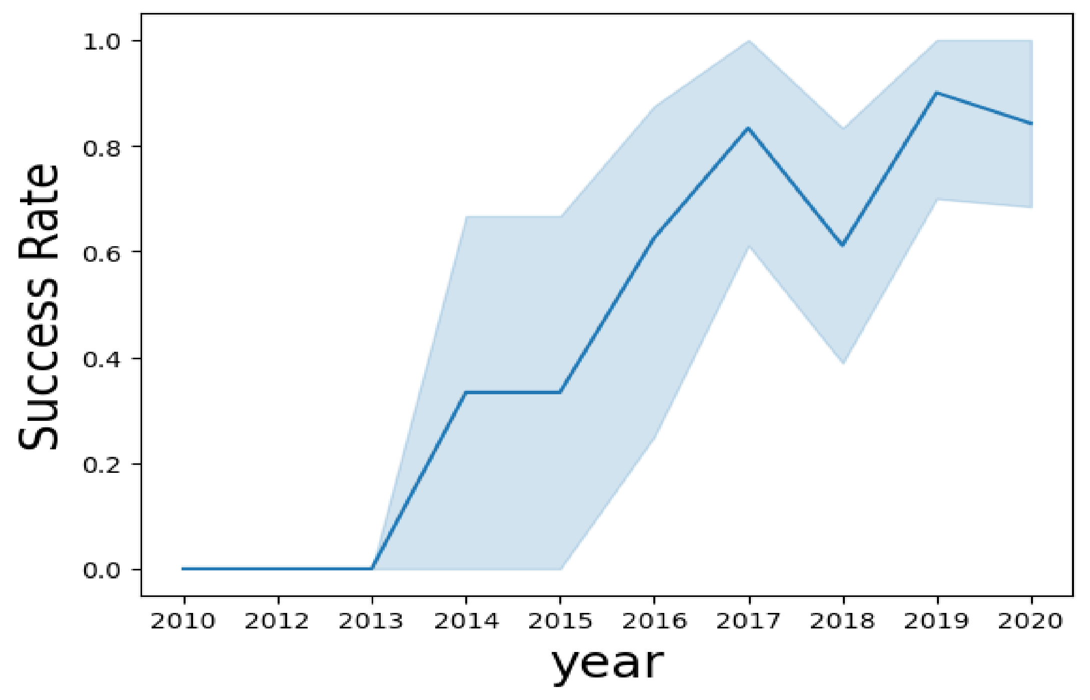
The link to the notebook is:

https://github.com/lukpras/ibm-data-science-capstone/blob/main/03-spacex-data-wrangling.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/lukpras/ibm-data-science-capstone/blob/main/05-spacex-eda-dataviz.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/lukpras/ibm-data-science-capstone/blob/main/04-spacex-eda-sql-sqllite.ipynb

Build an Interactive Map with Folium

- We marked all launch sites, and added map objects such as markers, circles, lines to mark the success or failure of launches for each site on the folium map.
- We assigned the feature launch outcomes (failure or success) to class 0 and 1.i.e., 0 for failure, and 1 for success.
- Using the color-labeled marker clusters, we identified which launch sites have relatively high success rate.
- We calculated the distances between a launch site to its proximities. We answered some question for instance:
  - Are launch sites near railways, highways and coastlines.
  - Do launch sites keep certain distance away from cities.
- The link to the notebook is https://github.com/lukpras/ibm-data-science-capstone/blob/main/06-spacex-interactive-viz-folium.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/lukpras/ibm-data-science-capstone/blob/main/07-spacex-interactive-viz-plotly.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/lukpras/ibm-data-science-capstone/blob/main/08-spacex-predictive-analytics.ipynb

Results

Exploratory Data Analysis

- Launch success has improved over time
- KSC LC-39A has the highest success rate among landing sites
- Orbits ES-L1, GEO, HEO and SSO have a 100% success rate

Visual Analytics

- Most launch sites are near the equator, and all are close to the coast
- Launch sites are far enough away from anything a failed launch can damage (city, highway, railway), while still close enough to bring people and material to support launch activities

Predictive Analytics

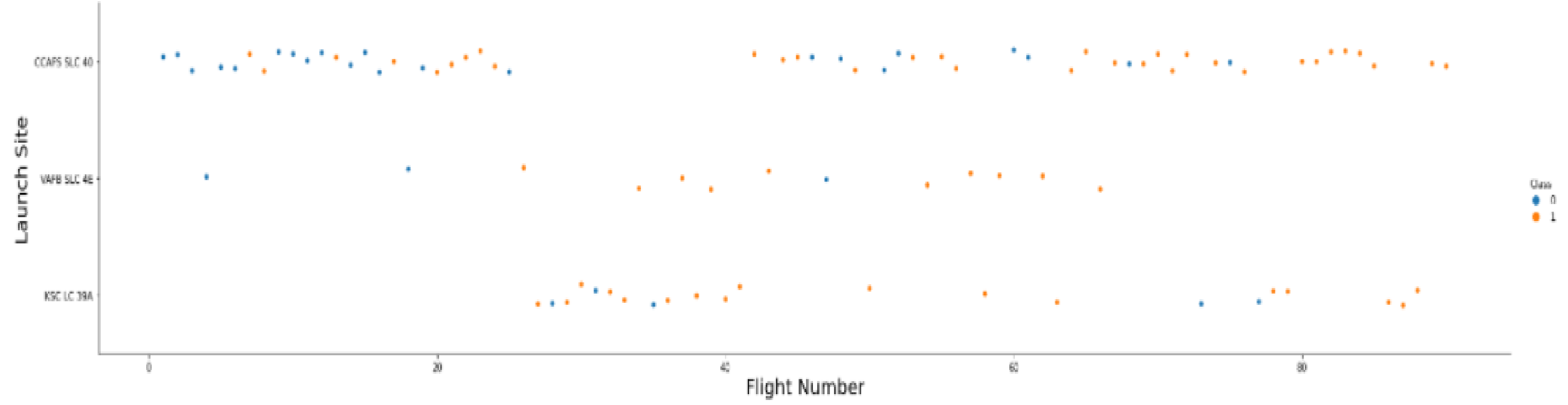
- Decision Tree model is the best predictive model for the dataset

Section 2

Insights drawn from EDA

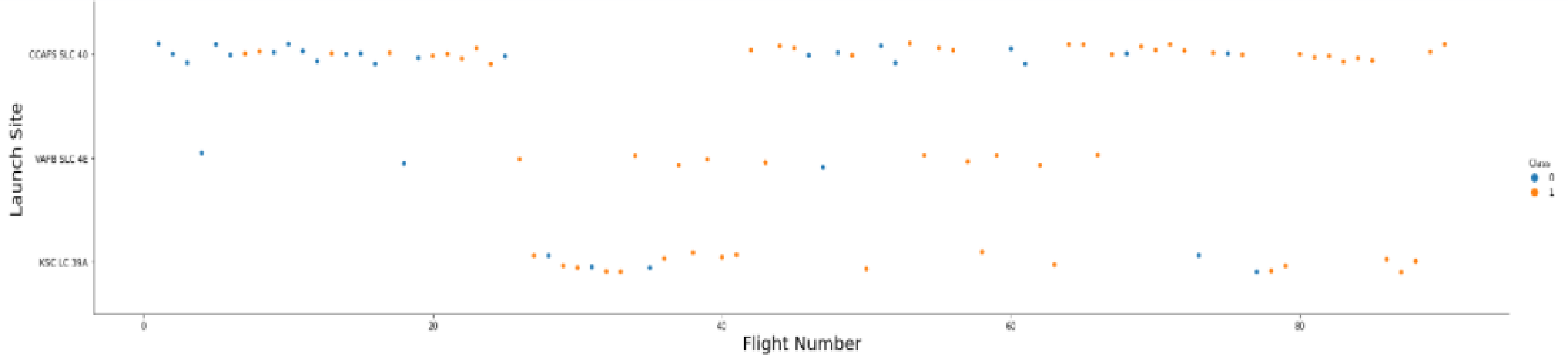
Flight Number vs. Launch Site

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



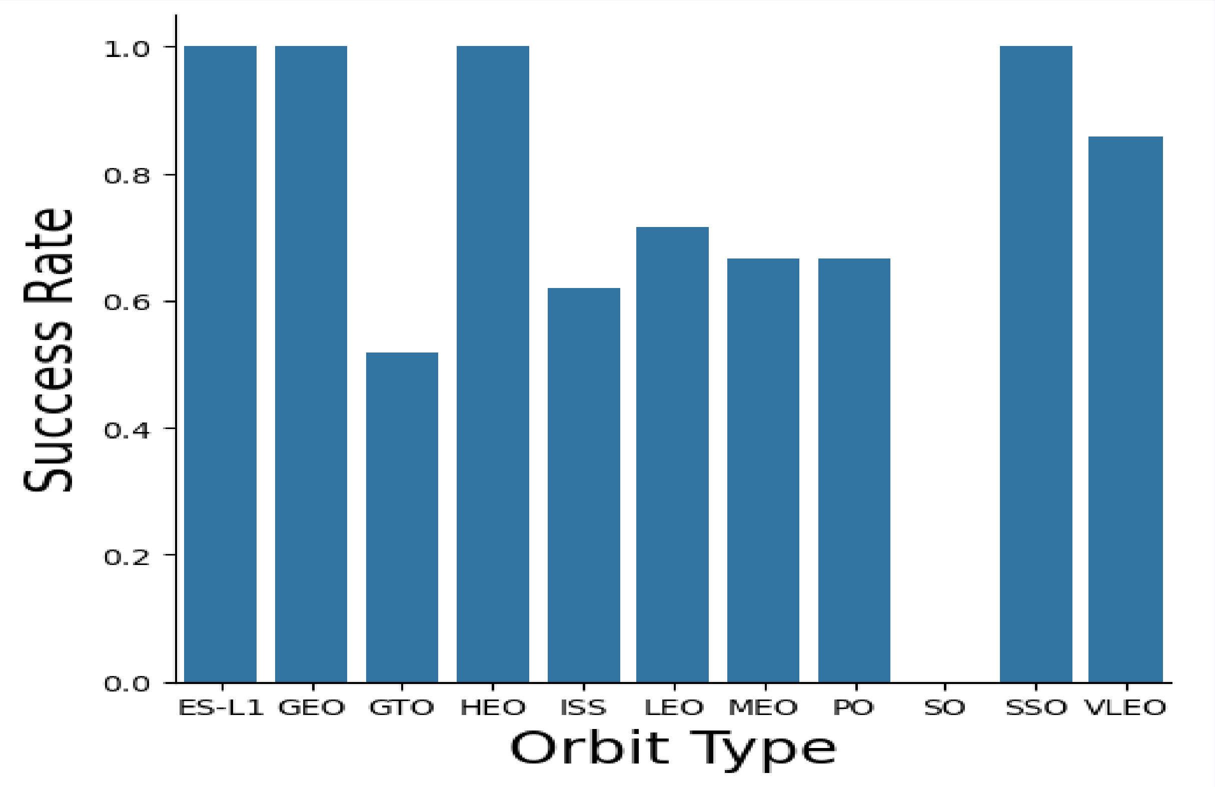
Payload vs. Launch Site

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



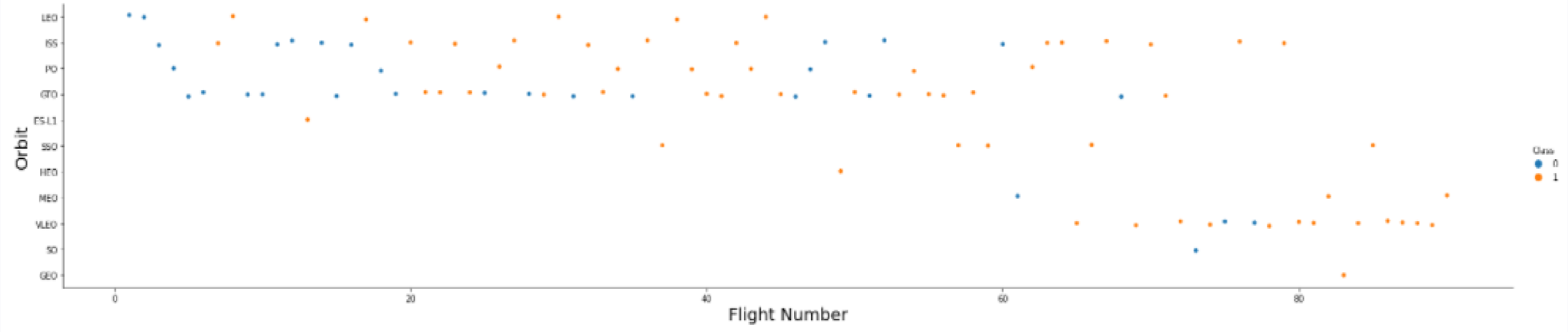
Success Rate vs. Orbit Type

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



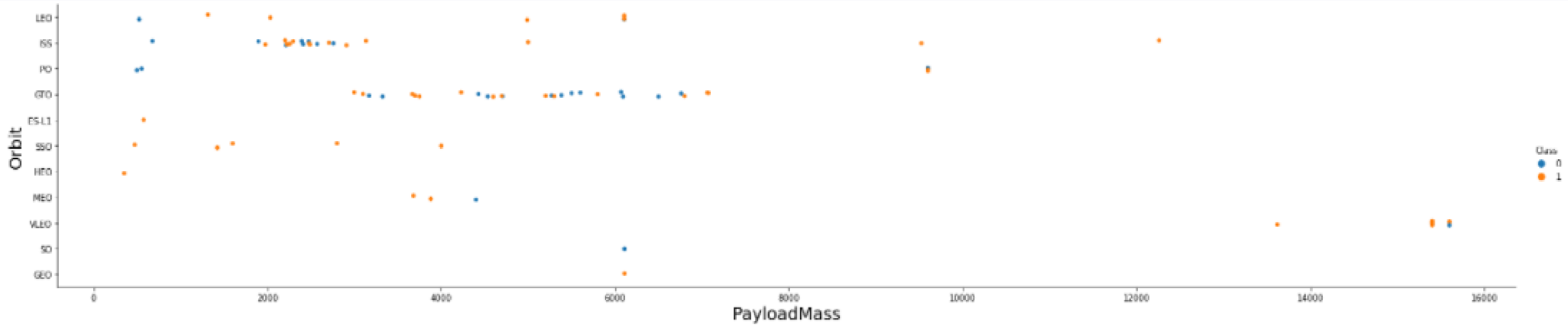
Flight Number vs. Orbit Type

- 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.



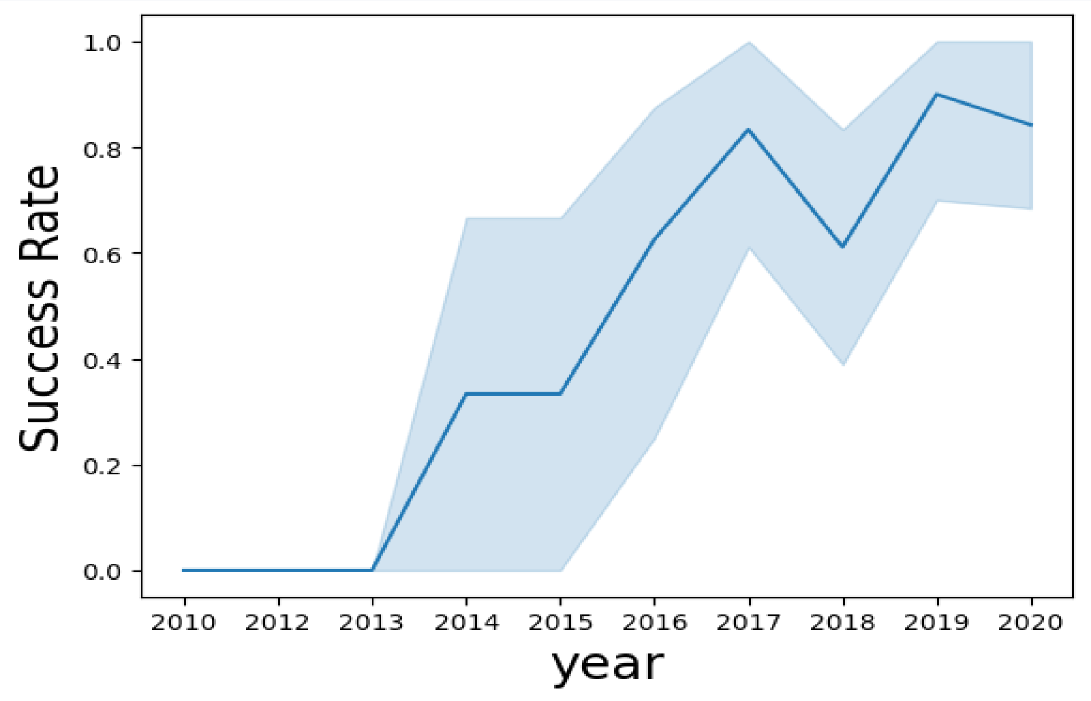
Payload vs. Orbit Type

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



Launch Success Yearly Trend

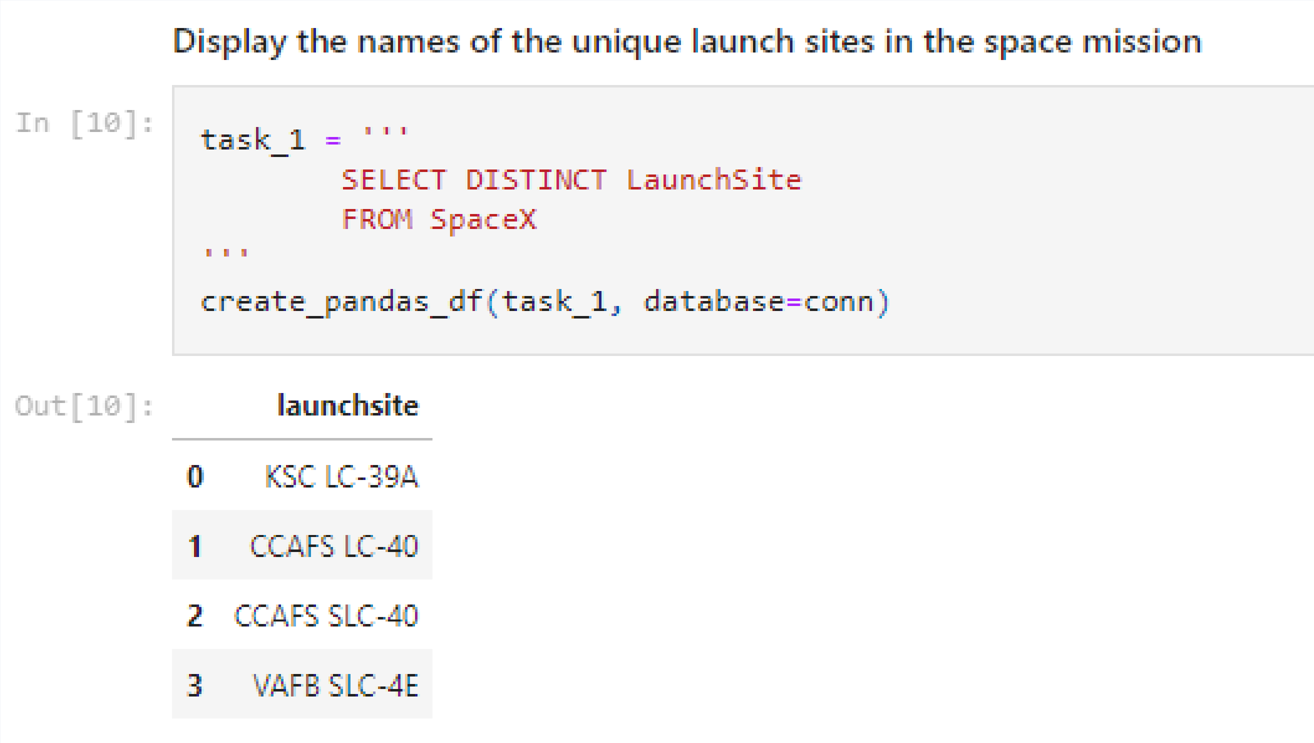
- From the plot, we can observe that success rate since 2013 kept on increasing till 2020.



All Launch Site Names

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

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



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

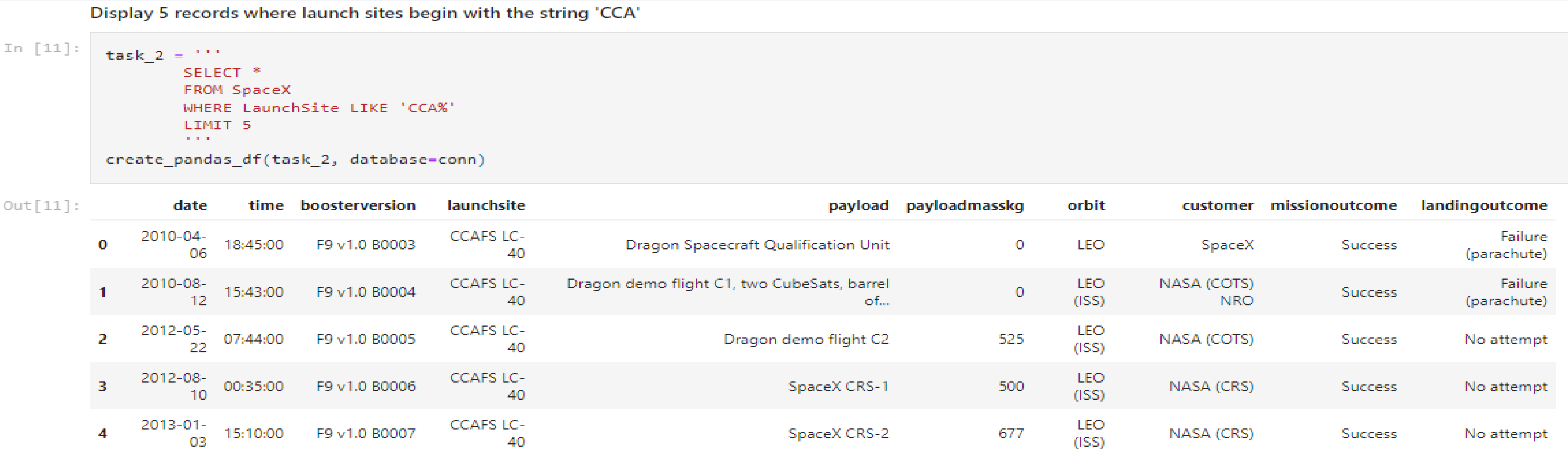
```
In [10]:
task_1 = '''
        SELECT DISTINCT LaunchSite
        FROM SpaceX
'''
create_pandas_df(task_1, database=conn)
```

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 below to display 5 records where launch sites begin with `CCA`



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

In [11]:

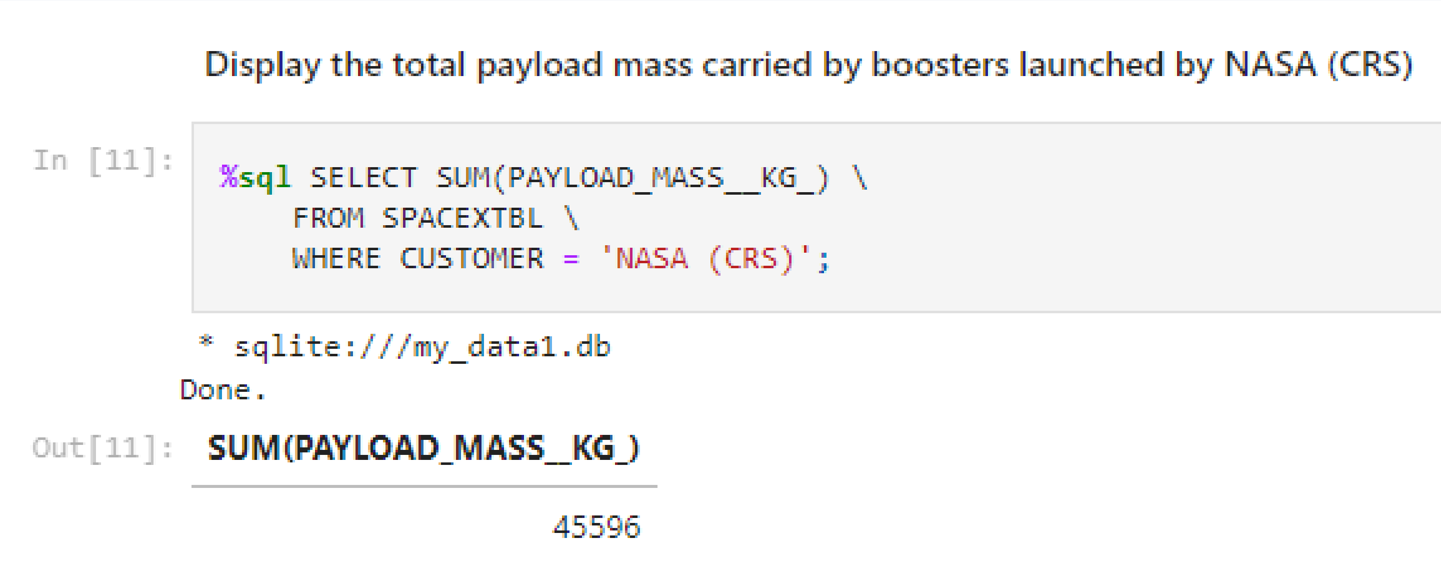
```
task_2 = '''
        SELECT *
        FROM SpaceX
        WHERE LaunchSite LIKE 'CCA%'
        LIMIT 5
        '''
create_pandas_df(task_2, database=conn)
```

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)

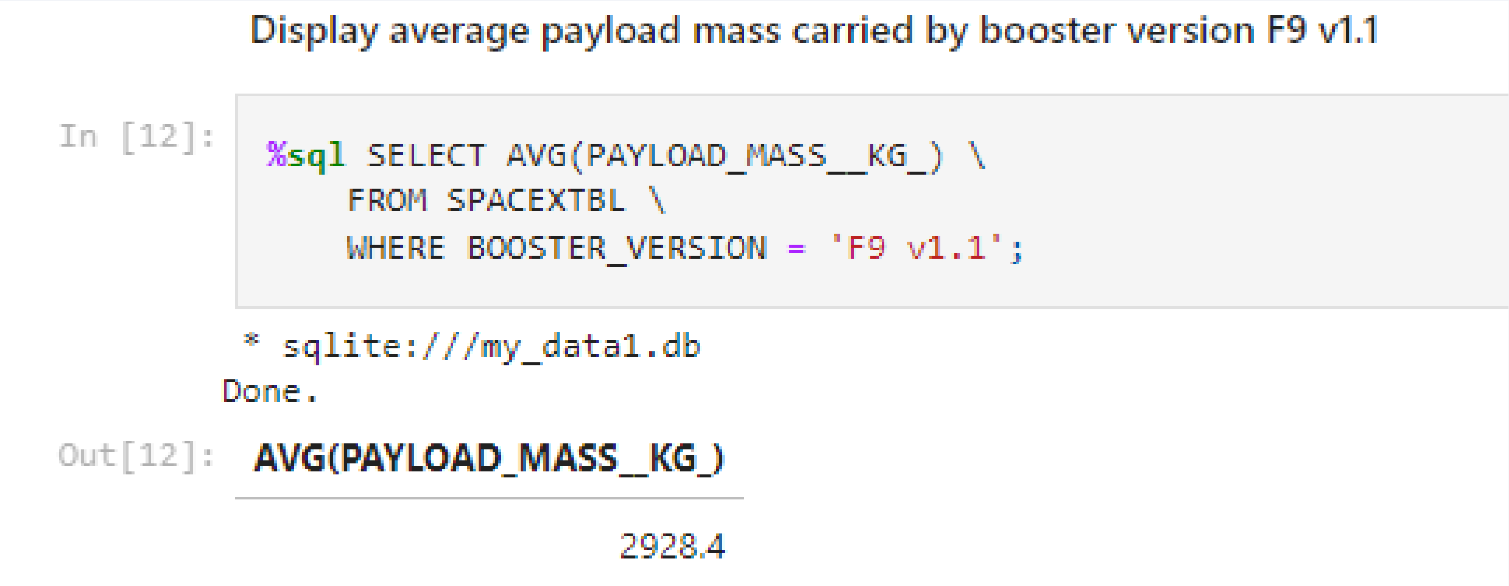
```
In [11]:  %sql SELECT SUM(PAYLOAD_MASS__KG_) \
              FROM SPACEXTBL \
              WHERE CUSTOMER = 'NASA (CRS)';
```

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

```
Out[11]: SUM(PAYLOAD_MASS__KG_)
                          45596
```

Average Payload Mass by F9 v1.1

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

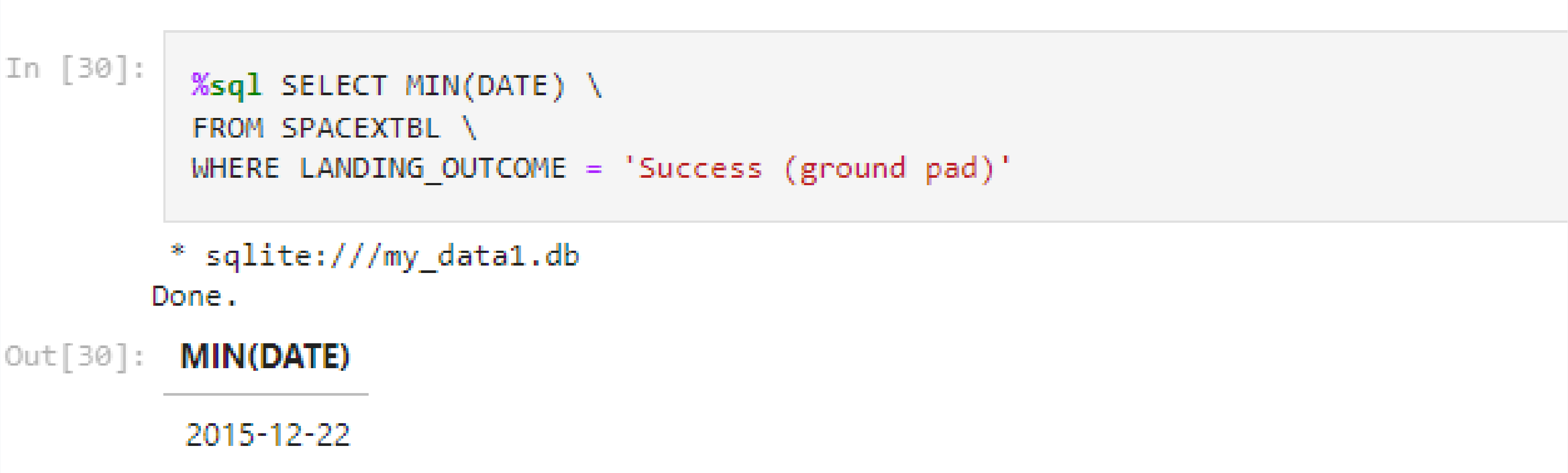


Display average payload mass carried by booster version F9 v1.1

```
In [12]:  %sql SELECT AVG(PAYLOAD_MASS__KG_) \
              FROM SPACEXTBL \
              WHERE BOOSTER_VERSION = 'F9 v1.1';

 * sqlite:///my_data1.db
Done.

Out[12]:  AVG(PAYLOAD_MASS__KG_)
                          2928.4
```

First Successful Ground Landing Date

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



In [30]:

```
%sql SELECT MIN(DATE) \
FROM SPACEXTBL \
WHERE LANDING_OUTCOME = 'Success (ground pad)'
```

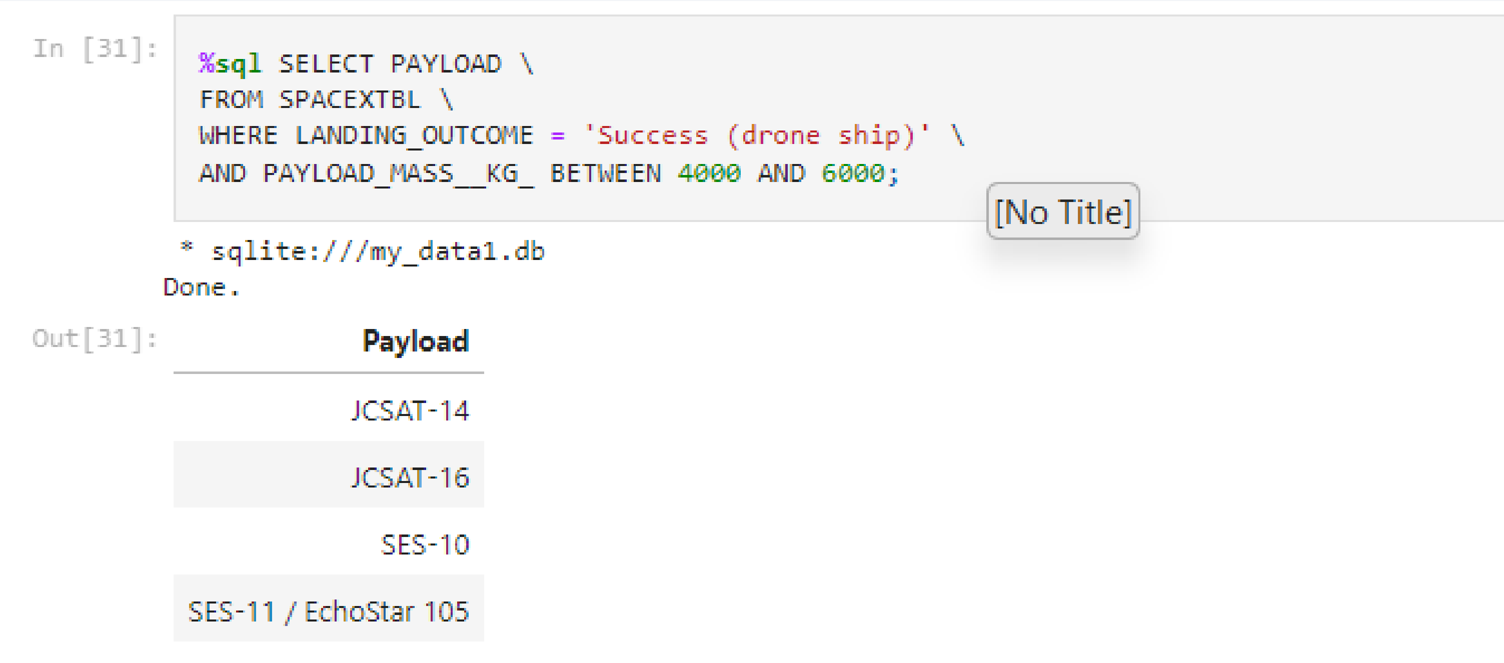
```
 * sqlite:///my_data1.db
Done.
```

Out[30]:

MIN(DATE)
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



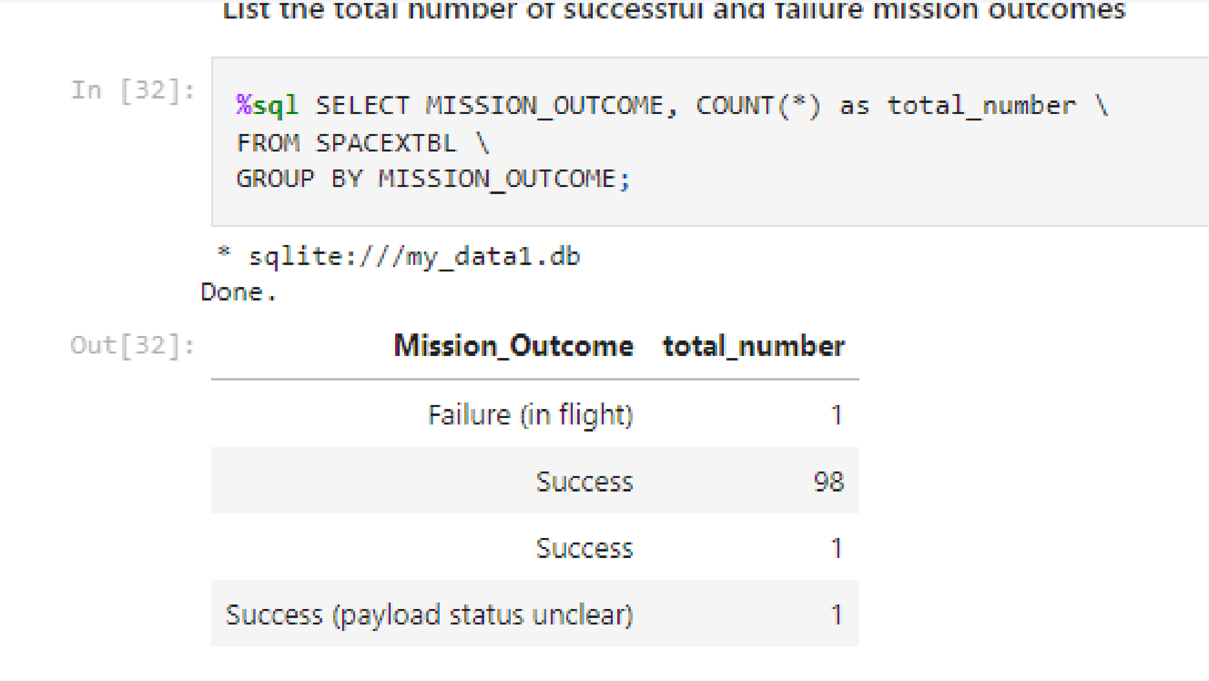
```
In [31]: %sql SELECT PAYLOAD \
         FROM SPACEXTBL \
         WHERE LANDING_OUTCOME = 'Success (drone ship)' \
         AND PAYLOAD_MASS__KG_ BETWEEN 4000 AND 6000;

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

Out[31]:

Payload
JCSAT-14
JCSAT-16
SES-10
SES-11 / EchoStar 105

Total Number of Successful and Failure Mission Outcomes

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



List the total number of successful and failure mission outcomes

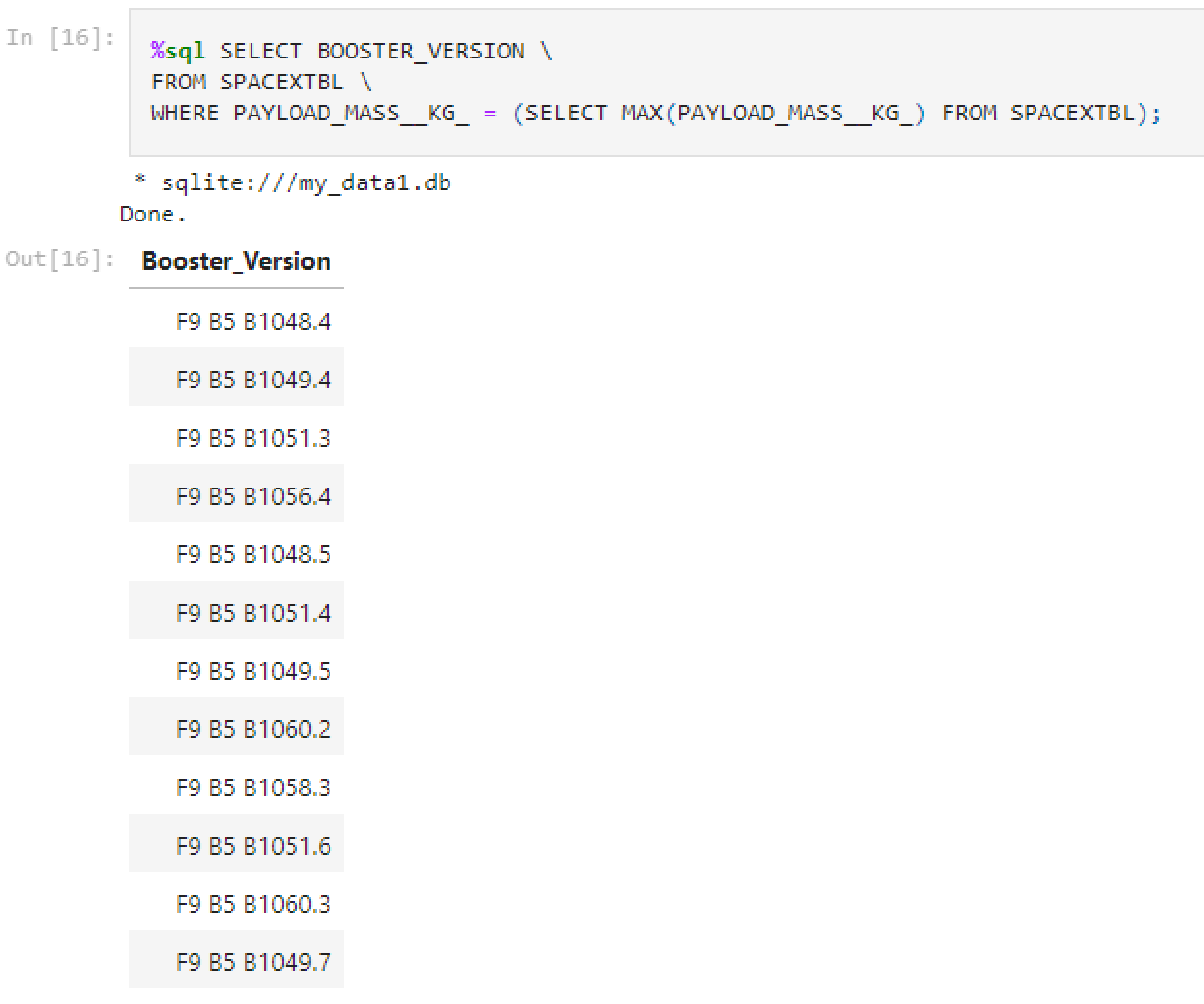
```
In [32]:  %sql SELECT MISSION_OUTCOME, COUNT(*) as total_number \
          FROM SPACEXTBL \
          GROUP BY MISSION_OUTCOME;
```

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

Out[32]:

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

Boosters Carried Maximum Payload



```
In [16]: %sql SELECT BOOSTER_VERSION \
         FROM SPACEXTBL \
         WHERE PAYLOAD_MASS__KG_ = (SELECT MAX(PAYLOAD_MASS__KG_) FROM SPACEXTBL);

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

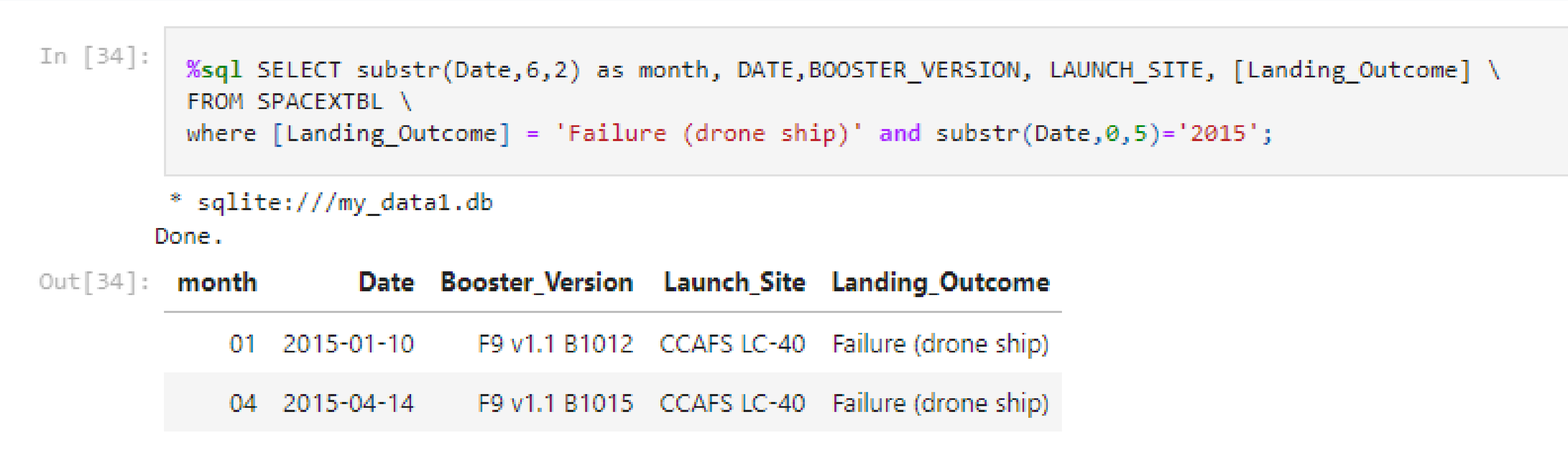
Out[16]:

Booster_Version
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

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

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



In [34]:

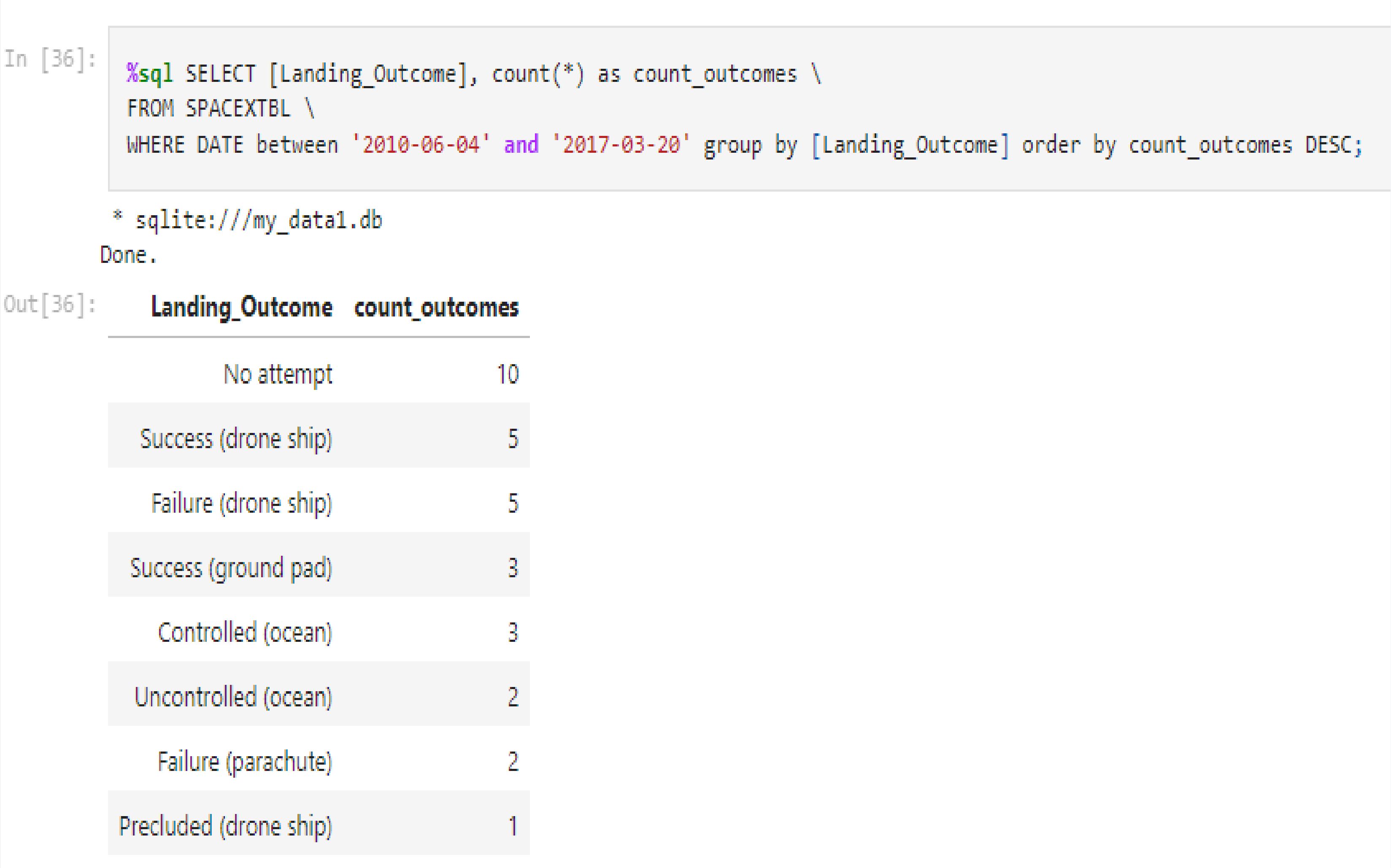
```
%sql SELECT substr(Date,6,2) as month, DATE,BOOSTER_VERSION, LAUNCH_SITE, [Landing_Outcome] \
FROM SPACEXTBL \
where [Landing_Outcome] = 'Failure (drone ship)' and substr(Date,0,5)='2015';
```

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

Out[34]:

month	Date	Booster_Version	Launch_Site	Landing_Outcome
01	2015-01-10	F9 v1.1 B1012	CCAFS LC-40	Failure (drone ship)
04	2015-04-14	F9 v1.1 B1015	CCAFS LC-40	Failure (drone ship)

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



In [36]:

```
%sql SELECT [Landing_Outcome], count(*) as count_outcomes \
FROM SPACEXTBL \
WHERE DATE between '2010-06-04' and '2017-03-20' group by [Landing_Outcome] order by count_outcomes DESC;
```

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

Out[36]:

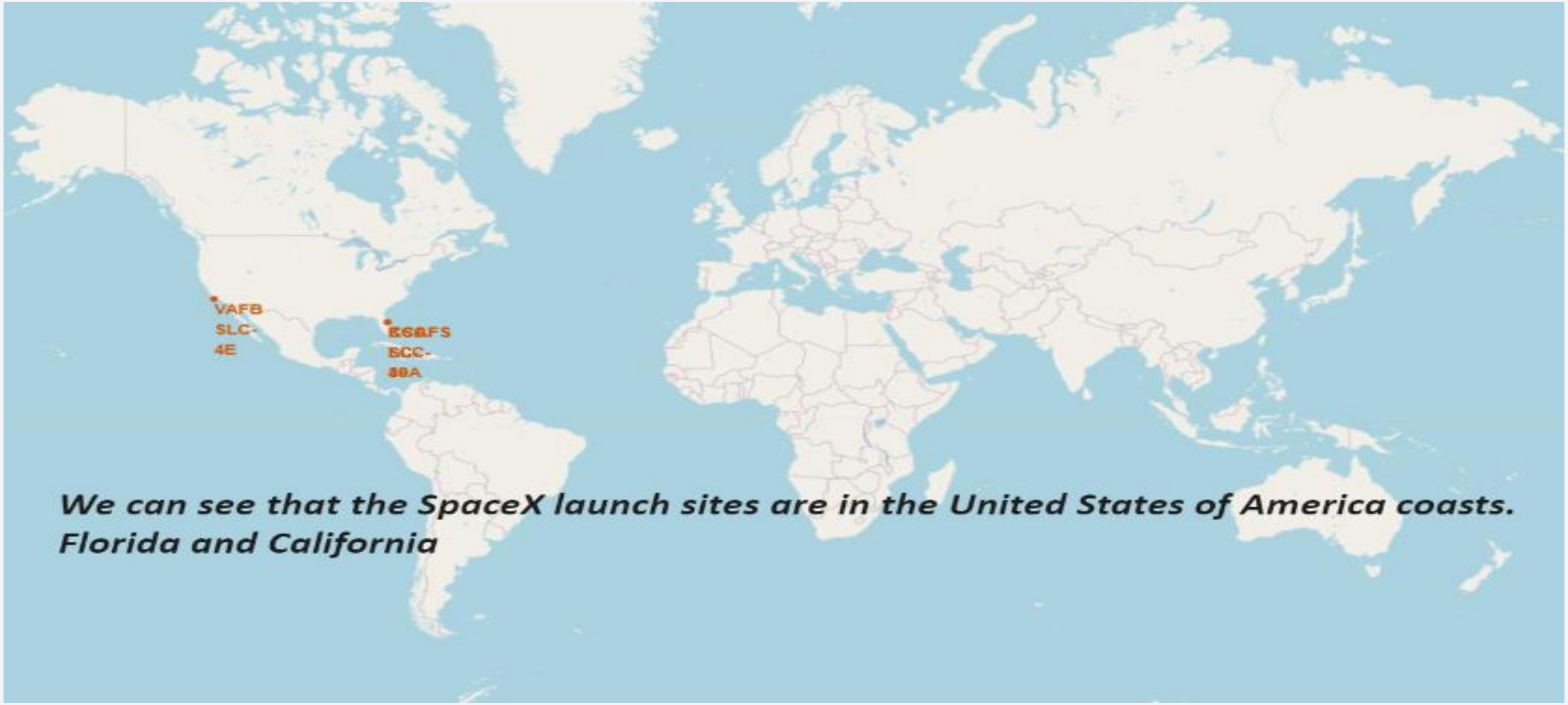
Landing_Outcome	count_outcomes
No attempt	10
Success (drone ship)	5
Failure (drone ship)	5
Success (ground pad)	3
Controlled (ocean)	3
Uncontrolled (ocean)	2
Failure (parachute)	2
Precluded (drone ship)	1

- 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.

Section 3

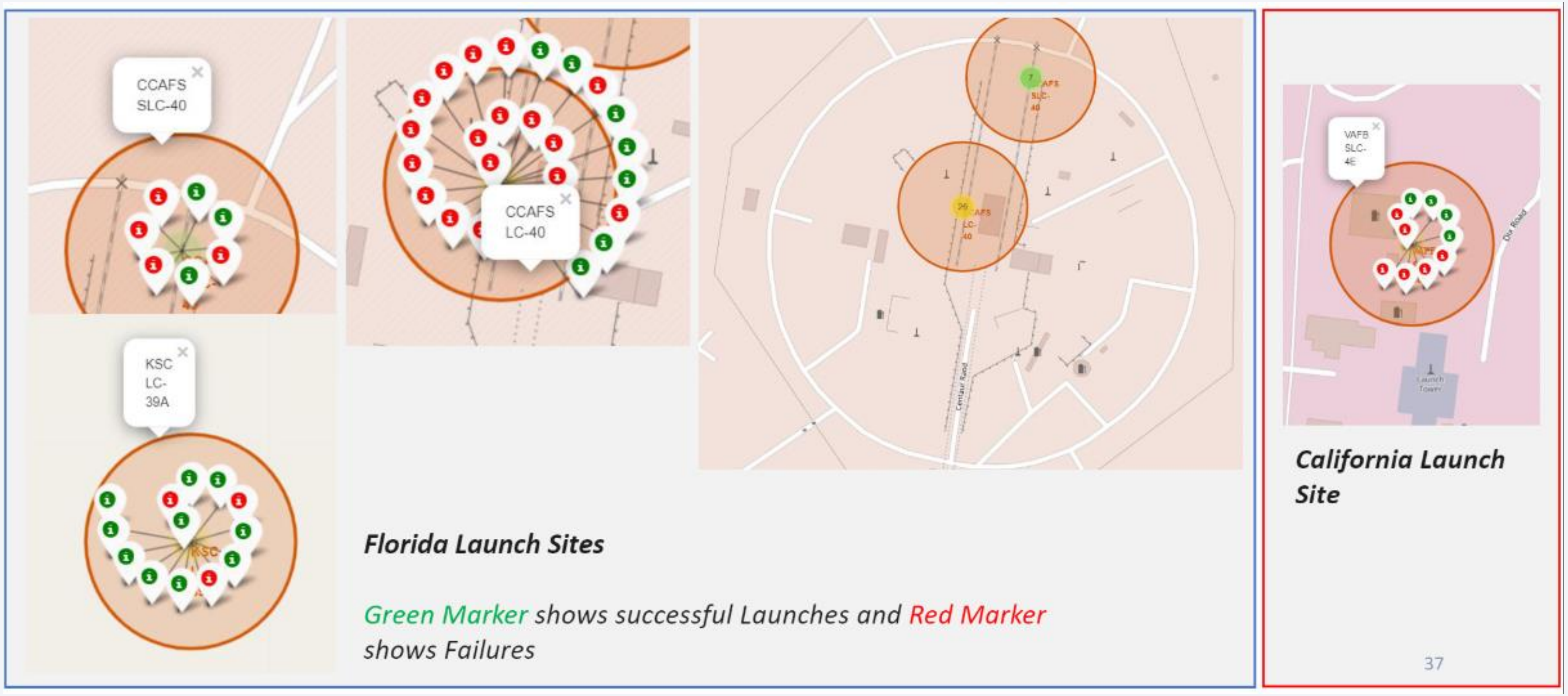
Launch Sites Proximities Analysis

All launch sites global map markers



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

Markers showing launch sites with color labels



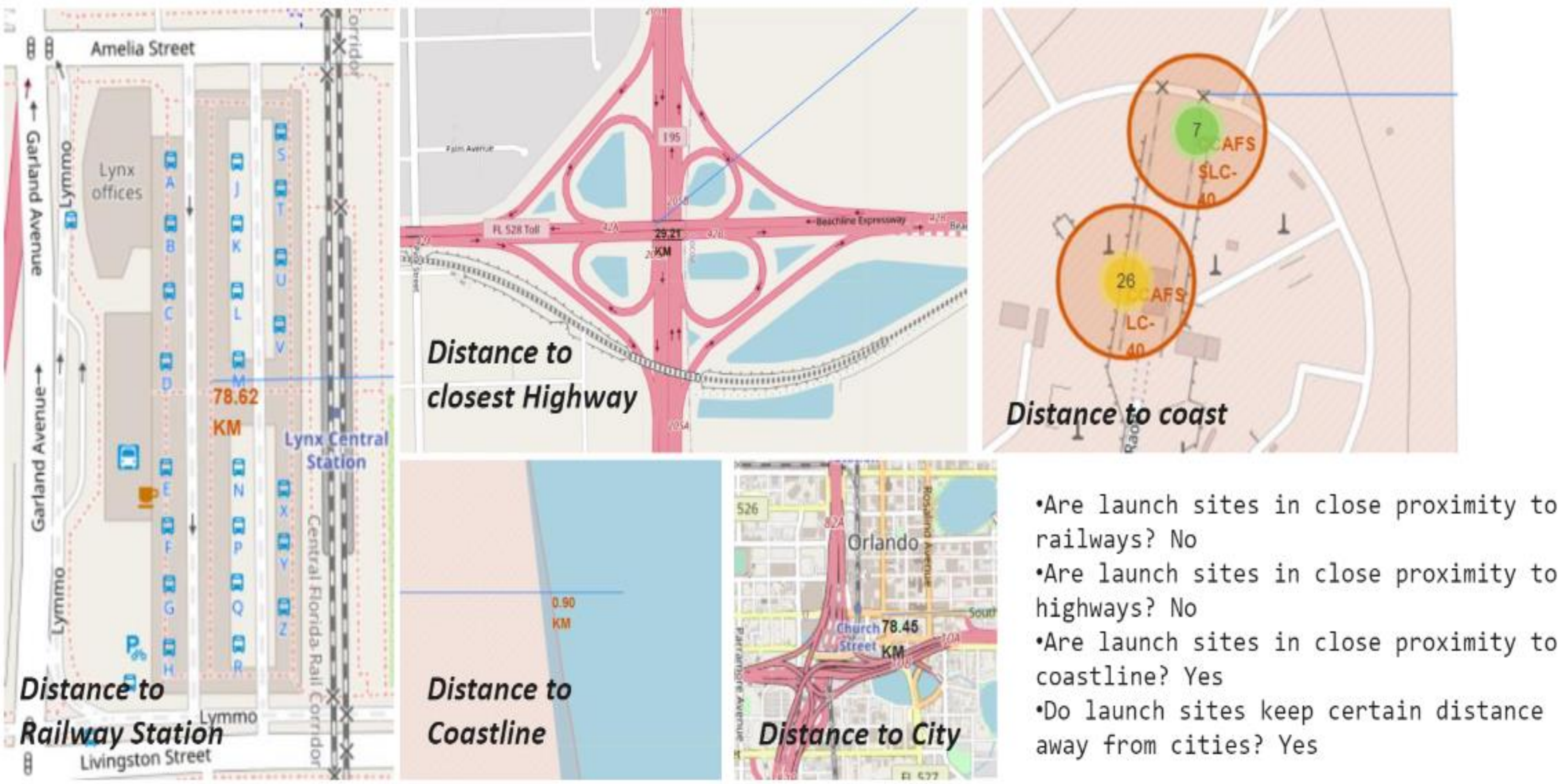
Florida Launch Sites

Green Marker shows successful Launches and Red Marker shows Failures

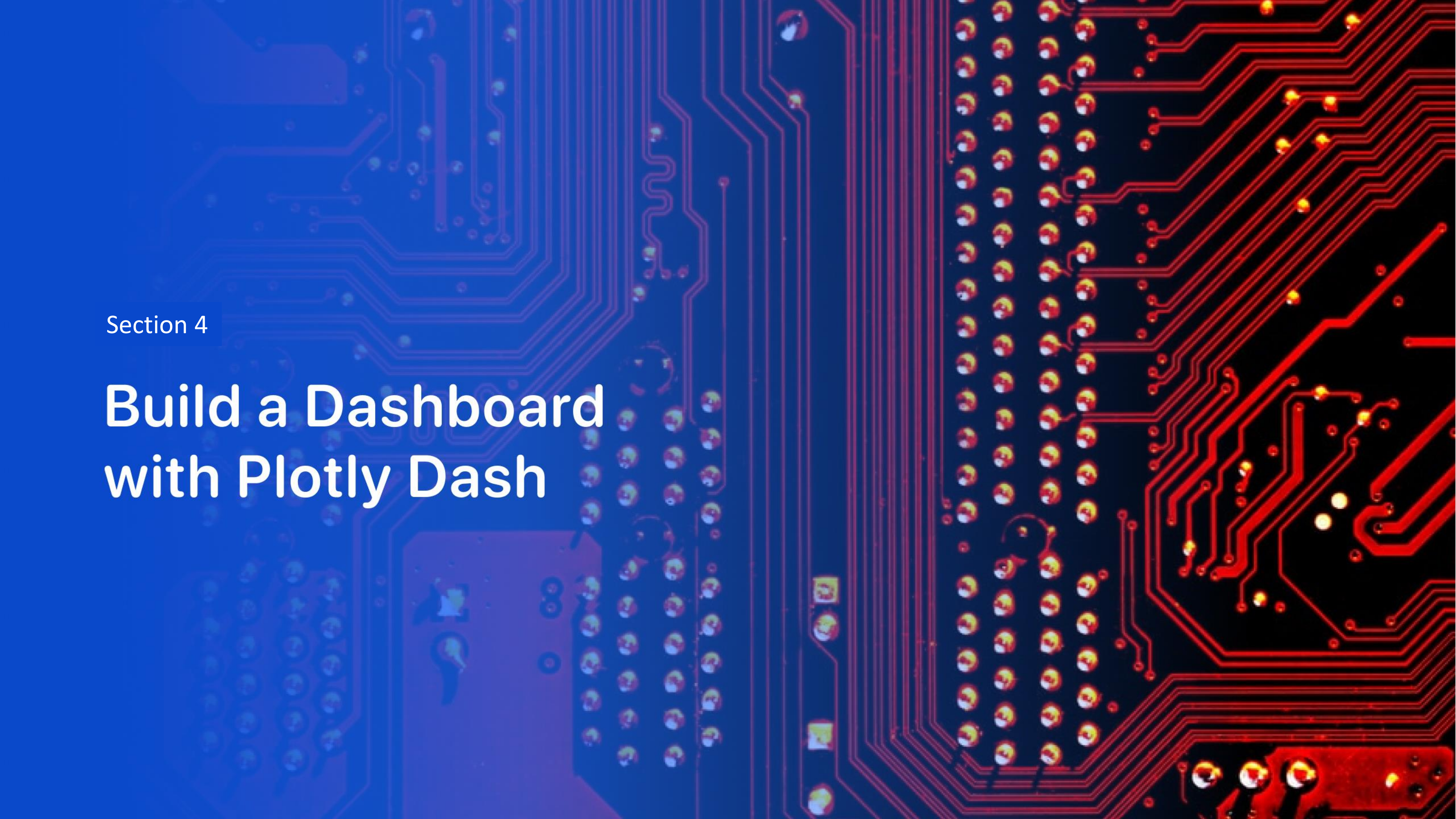
California Launch Site

37

Launch Site distance to landmarks



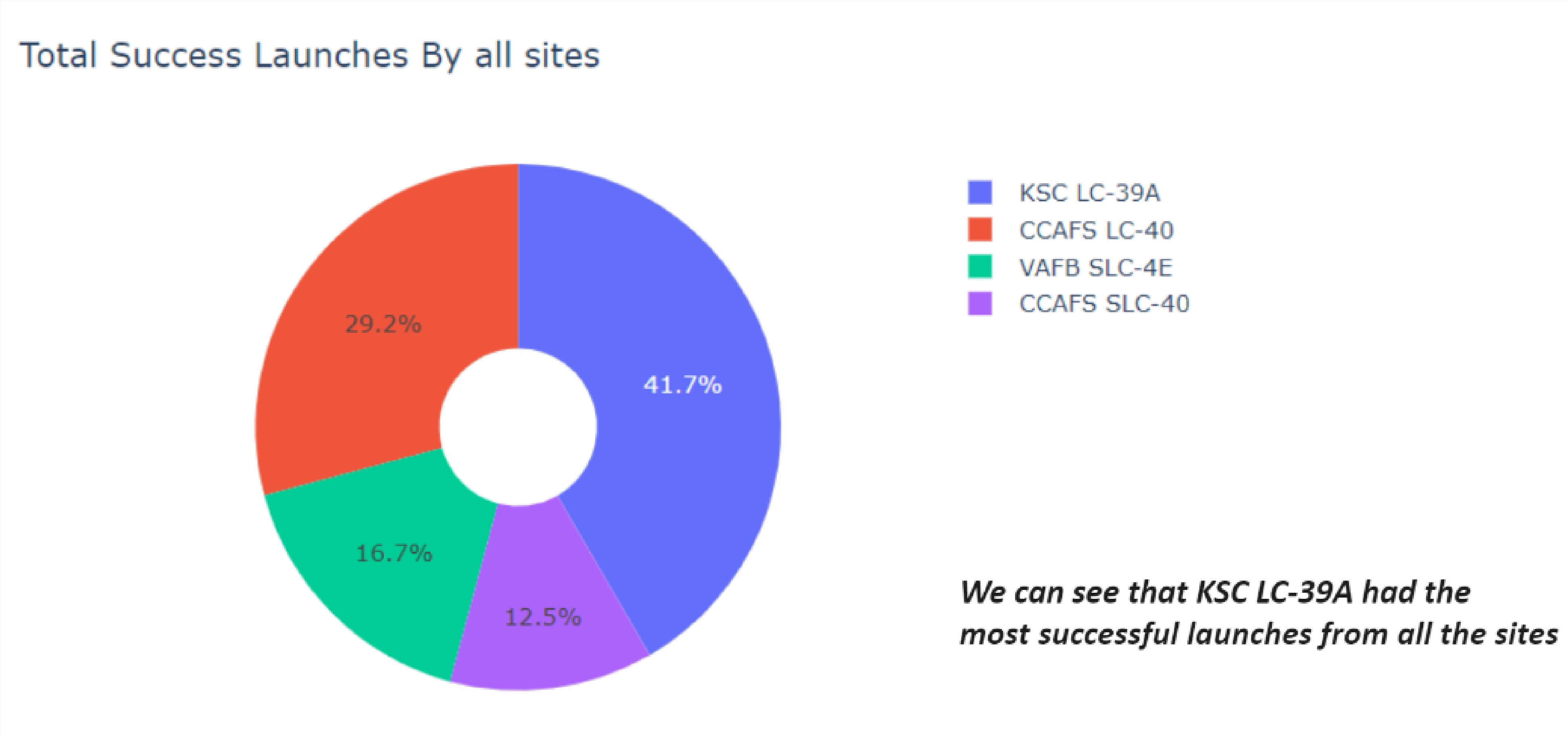
- Are launch sites in close proximity to railways? No
- Are launch sites in close proximity to highways? No
- Are launch sites in close proximity to coastline? Yes
- Do launch sites keep certain distance away from cities? Yes



Section 4

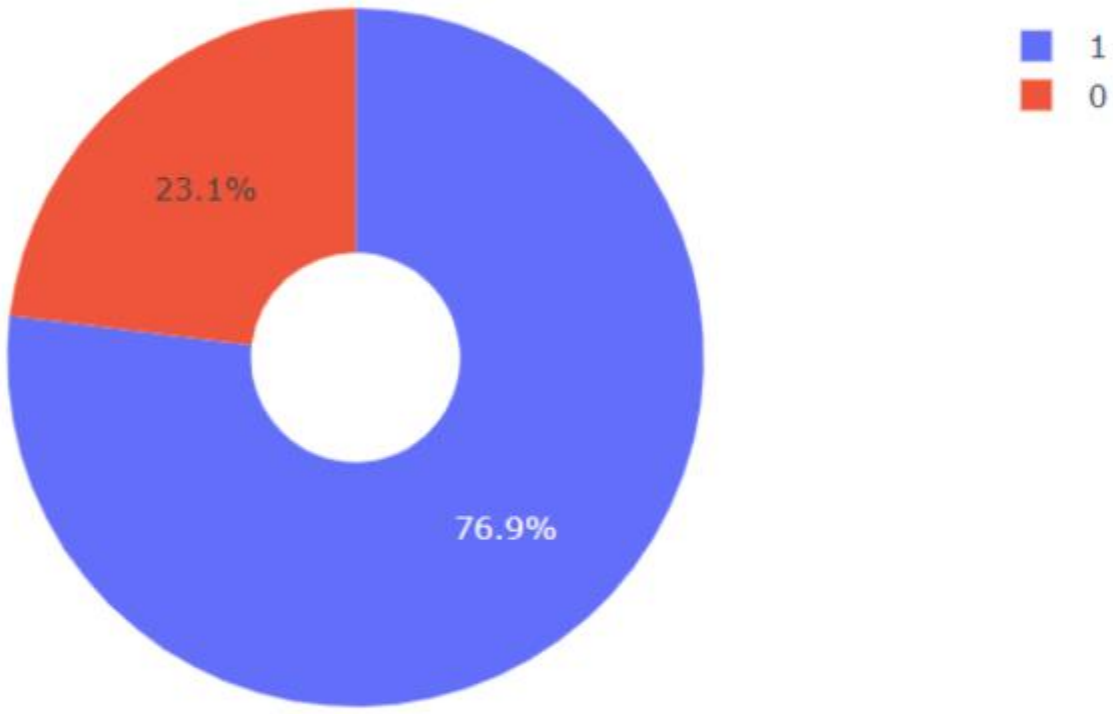
Build a Dashboard with Plotly Dash

Pie chart showing the success percentage achieved by each launch site



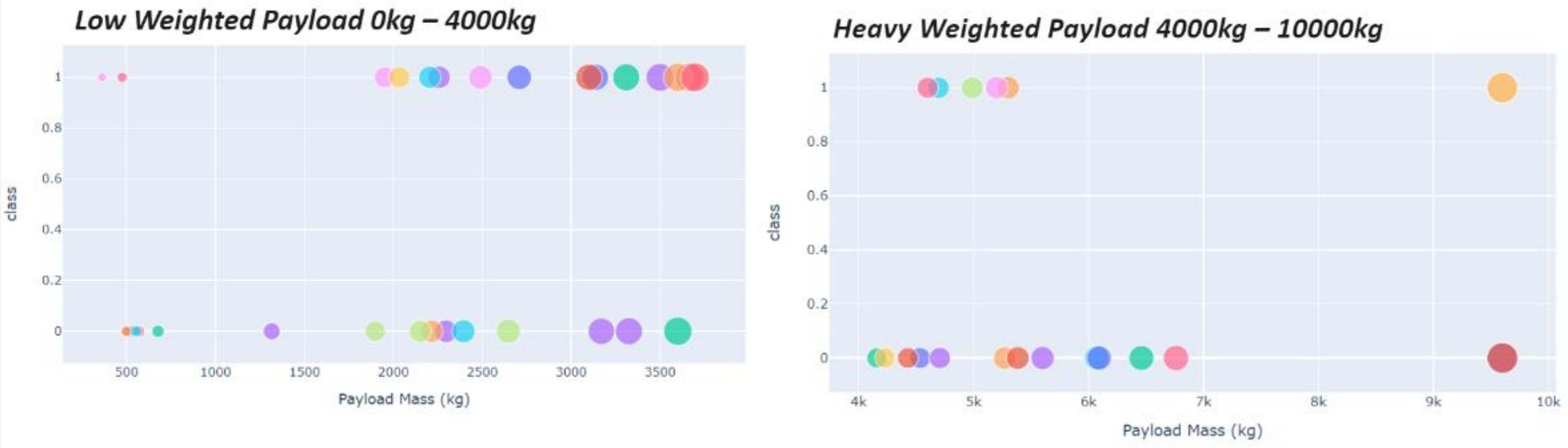
We can see that KSC LC-39A had the most successful launches from all the sites

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



Low Weighted Payload 0kg – 4000kg

Heavy Weighted Payload 4000kg – 10000kg

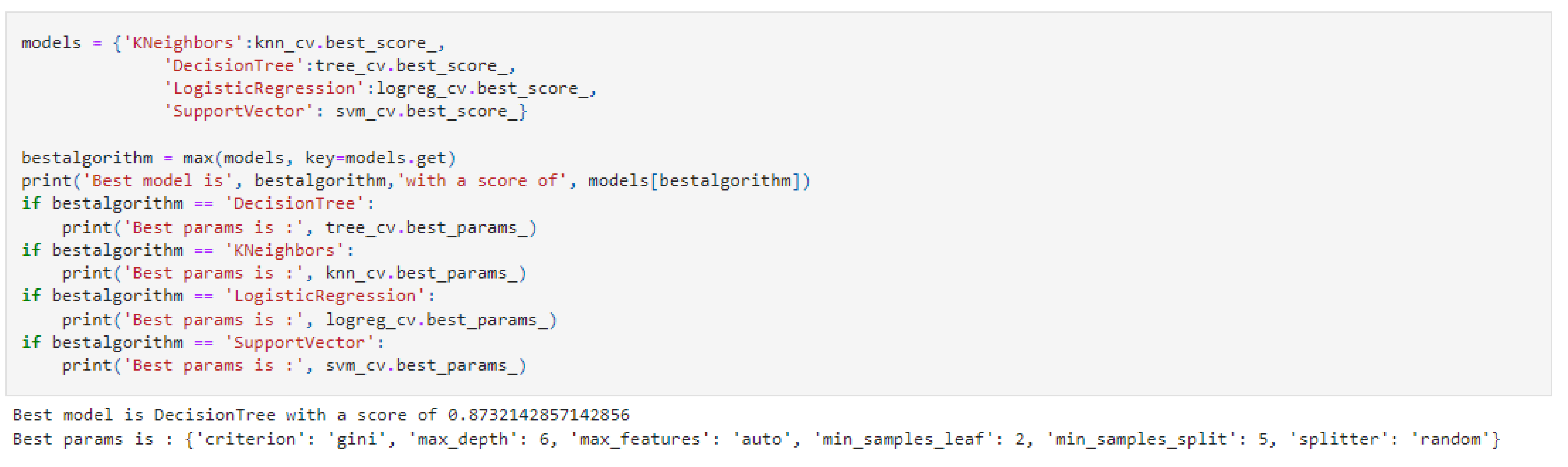
We can see the success rates for low weighted payloads is higher than the heavy weighted payloads

Section 5

Predictive Analysis (Classification)

Classification Accuracy

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

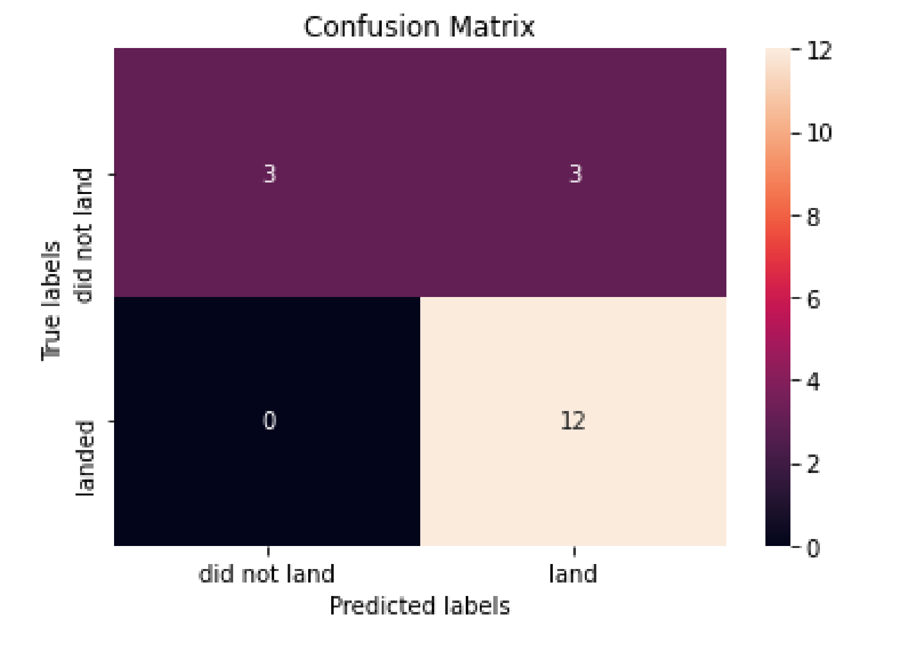


```
models = {'KNeighbors':knn_cv.best_score_,
              'DecisionTree':tree_cv.best_score_,
              'LogisticRegression':logreg_cv.best_score_,
              'SupportVector': svm_cv.best_score_}

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.



Conclusions

We can conclude that:

- **Model Performance**: The models performed similarly on the test set with the decision tree model slightly outperforming
- **Equator**: Most of the launch sites are near the equator for an additional natural boost - due to the rotational speed of earth - which helps save the cost of putting in extra fuel and boosters
- **Coast**: All the launch sites are close to the coast
- **Launch Success**: Increases over time • KSC LC-39A: Has the highest success rate among launch sites. Has a 100% success rate for launches less than 5,500 kg • Orbits: ES-L1, GEO, HEO, and SSO have a 100% success rate
- **Payload Mass**: Across all launch sites, the higher the payload mass (kg), the higher the success rate

Thank you!