SpaceX Falcon 9 first stage Landing Prediction

Mohamed Gamal Fahmy

Issued: 5 March, 2023

OUTLINE

- Executive Summary
- Introduction
- Methodology
- Results
  - Visualization – Charts
  - Dashboard
- Discussion
  - Findings & Implications
- Conclusion
- Appendix

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, and 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 must be in place to ensure a successful landing program?

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, and evaluate classification models

Data Collection

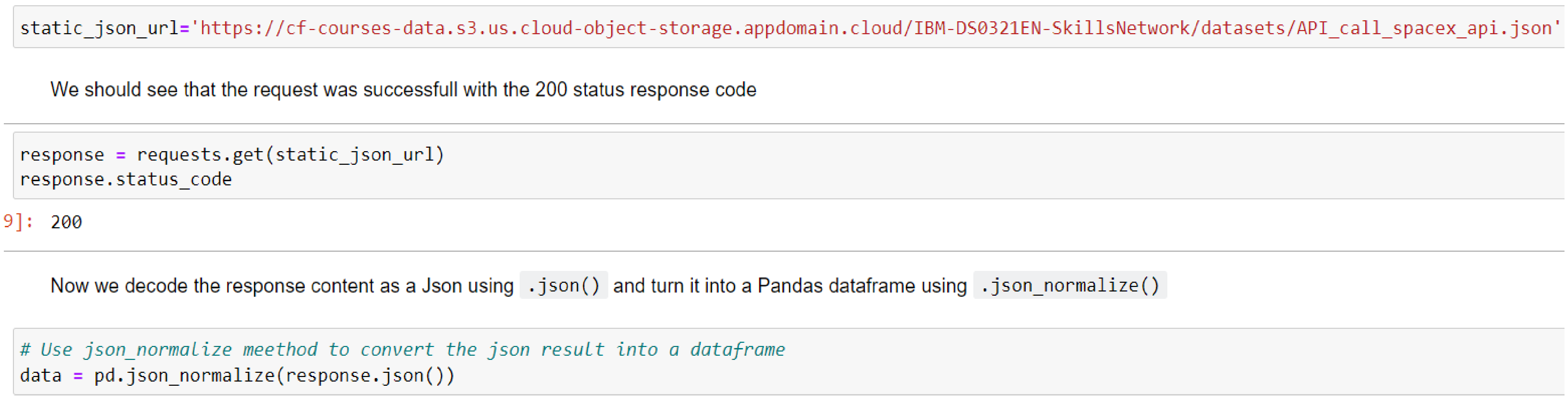
The data was collected using various methods

- Data collection was done using get request to the SpaceX API.
- Next, we decoded the response content as a JSON using the .json() function call and turn it into a pandas data frame 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 an HTML table, parse the table and convert it to a pandas data frame 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 Reference notebook https://github.com/MohammedGamall/SpaceX-Falcon-9-first-stage-Landing-Prediction/blob/main/Data%20Collection.ipynb



```
static_json_url='https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/datasets/API_call_spacex_api.json'
```

We should see that the request was successfull with the 200 status response code

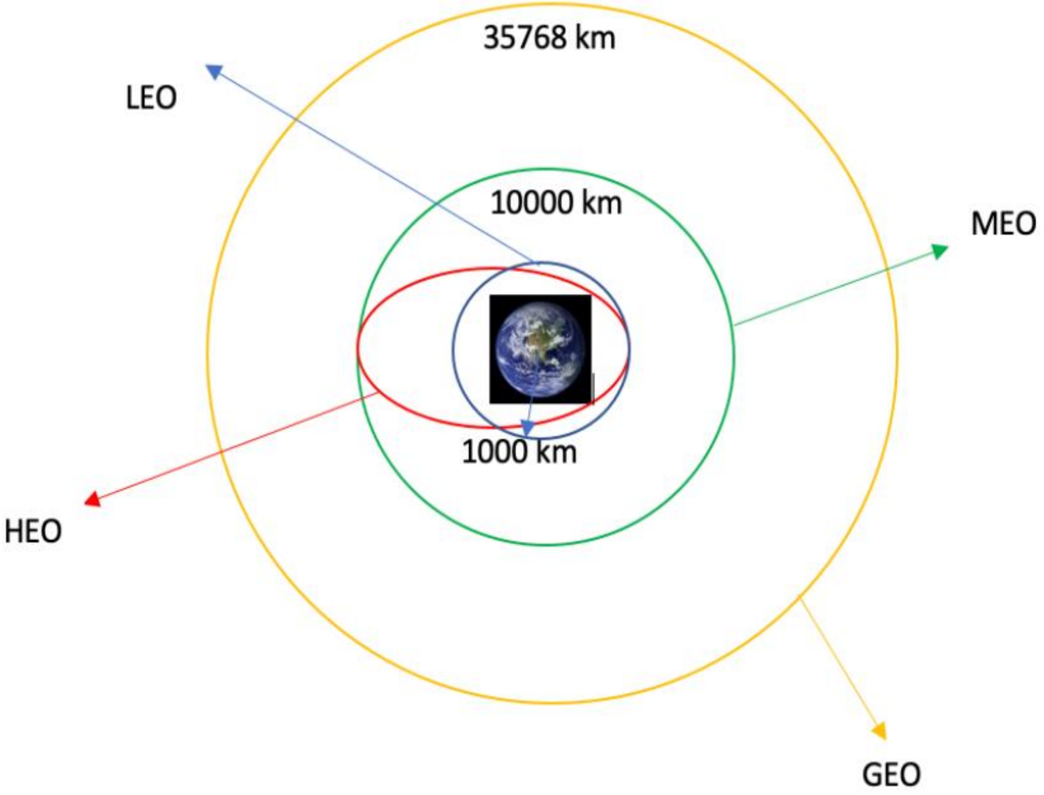
```
response = requests.get(static_json_url)
response.status_code
```

```
9]:  200
```

Now we decode the response content as a Json using `.json()` and turn it into a Pandas dataframe using `.json_normalize()`

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

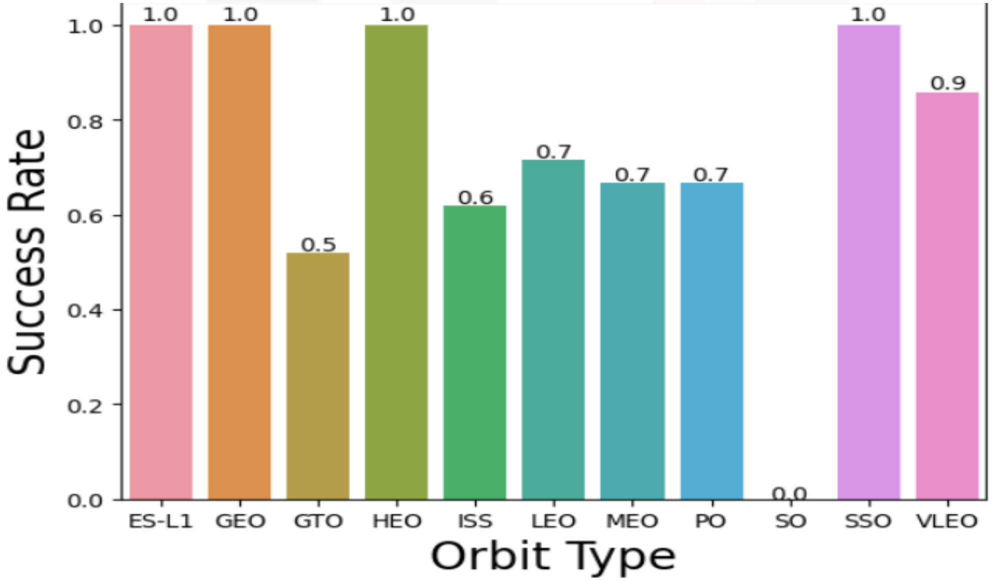
Data Wrangling

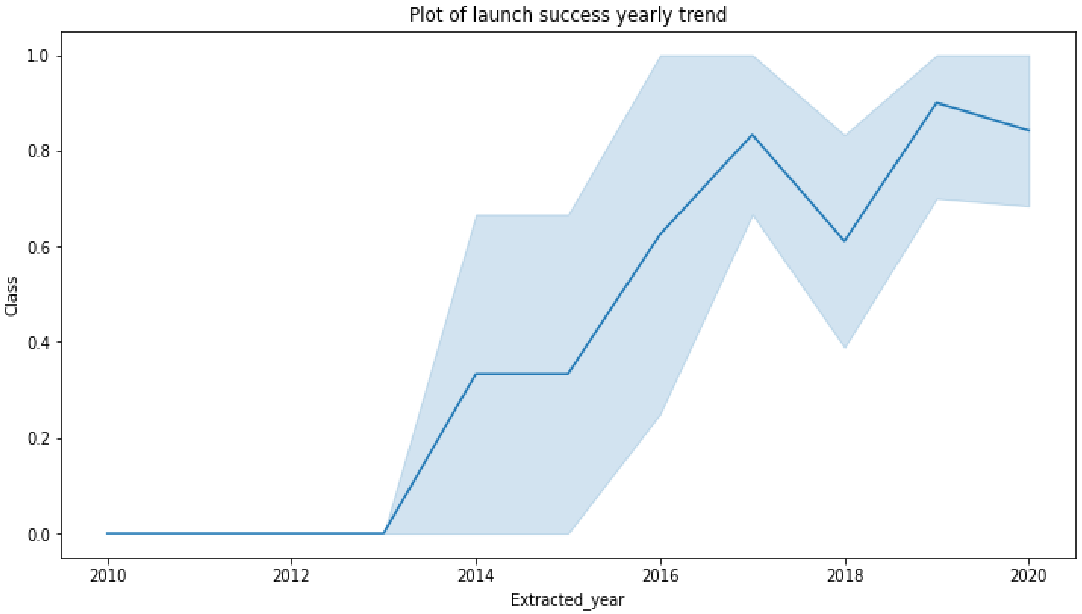


- We performed exploratory data analysis and determined the training labels.
- We calculated the number of launches at each site, and the number and occurrence of each orbit
- We created a landing outcome label from the outcome column and exported the results to CSV.
- The Reference notebook https://github.com/MohammedGamall/SpaceX-Falcon-9-first-stage-Landing-Prediction/blob/main/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 Reference notebook https://github.com/MohammedGamall/SpaceX-Falcon-9-first-stage-Landing-Prediction/blob/master/Exploratory%20Analysis%20Using%20Pandas%20and%20Matplotlib.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 failed mission outcomes
  - The failed landing outcomes in drone ship, their booster version, and launch site names.
- The Reference notebook
- https://github.com/MohammedGamall/SpaceX-Falcon-9-first-stage-Landing-Prediction/blob/master/Exploratory%20Analysis%20Using%20SQL.ipynb

Build an Interactive Map with Folium

- We marked all launch sites and added map objects such as markers, circles, and 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 classes 0 and 1. i.e., 0 for failure, and 1 for success.
- Using the color-labeled marker clusters, we identified which launch sites have a relatively high success rate.
- We calculated the distances between a launch site to its proximities. We answered some questions for instance:
  - Are launch sites near railways, highways, and coastlines?
  - Do launch sites keep a certain distance away from cities?

Build a Dashboard with Plotly Dash

- We built an interactive dashboard with Plotly dash
- We plotted pie charts showing the total launches by certain sites
- We plotted a scatter graph showing the relationship between Outcome and Payload Mass (Kg) for the different booster versions.
- The Reference notebook
- https://github.com/MohammedGamall/SpaceX-Falcon-9-first-stage-Landing-Prediction/blob/master/spacex_dash_app.py

Predictive Analysis (Classification)

- We loaded the data using numpy and pandas, transformed the data, and 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 and improved the model using feature engineering and algorithm tuning.
- We found the best-performing classification model.
- The Reference notebook
- https://github.com/MohammedGamall/SpaceX-Falcon-9-first-stage-Landing-Prediction/blob/master/SpaceX_Machine%20Learning%20Prediction_Part_5.ipynb

Results

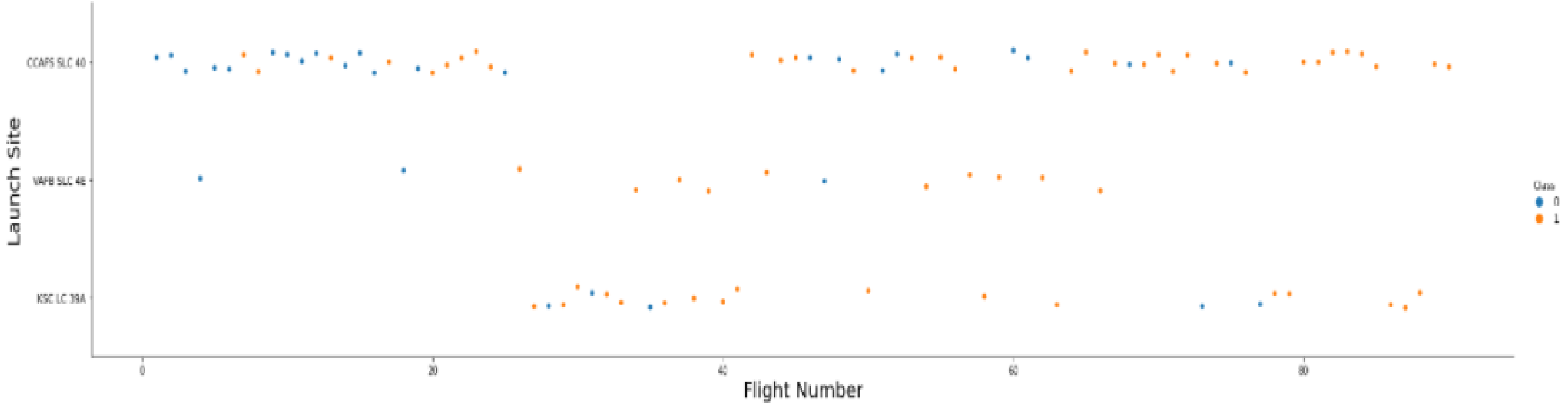
- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results

Section 2

Insights drawn from EDA

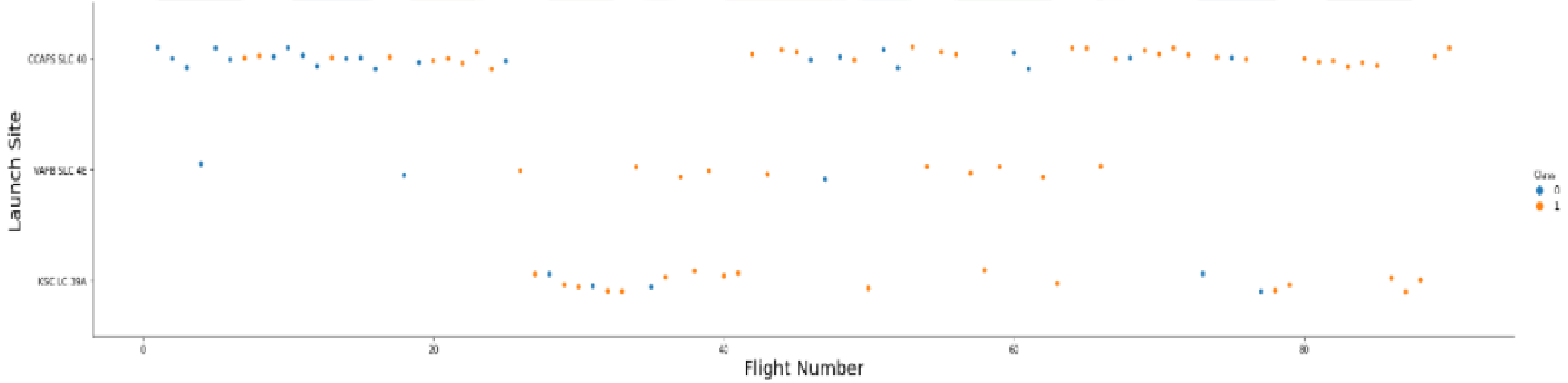
Flight Number vs. Launch Site

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



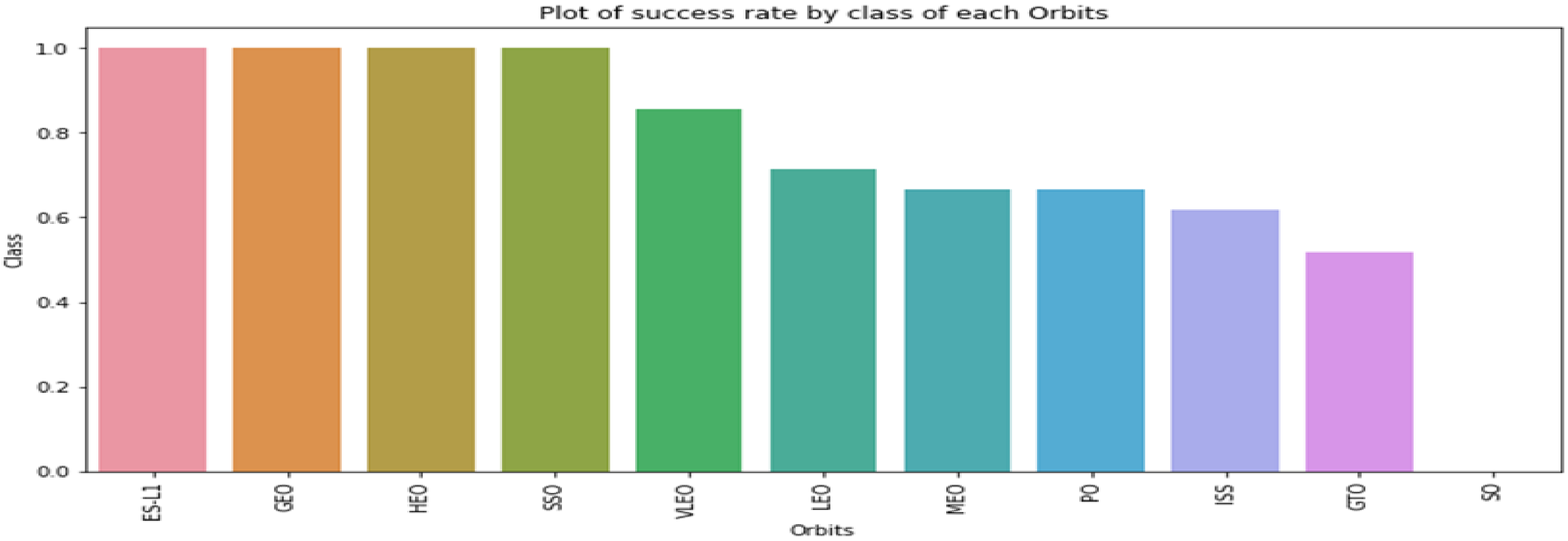
Payload vs. Launch Site

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



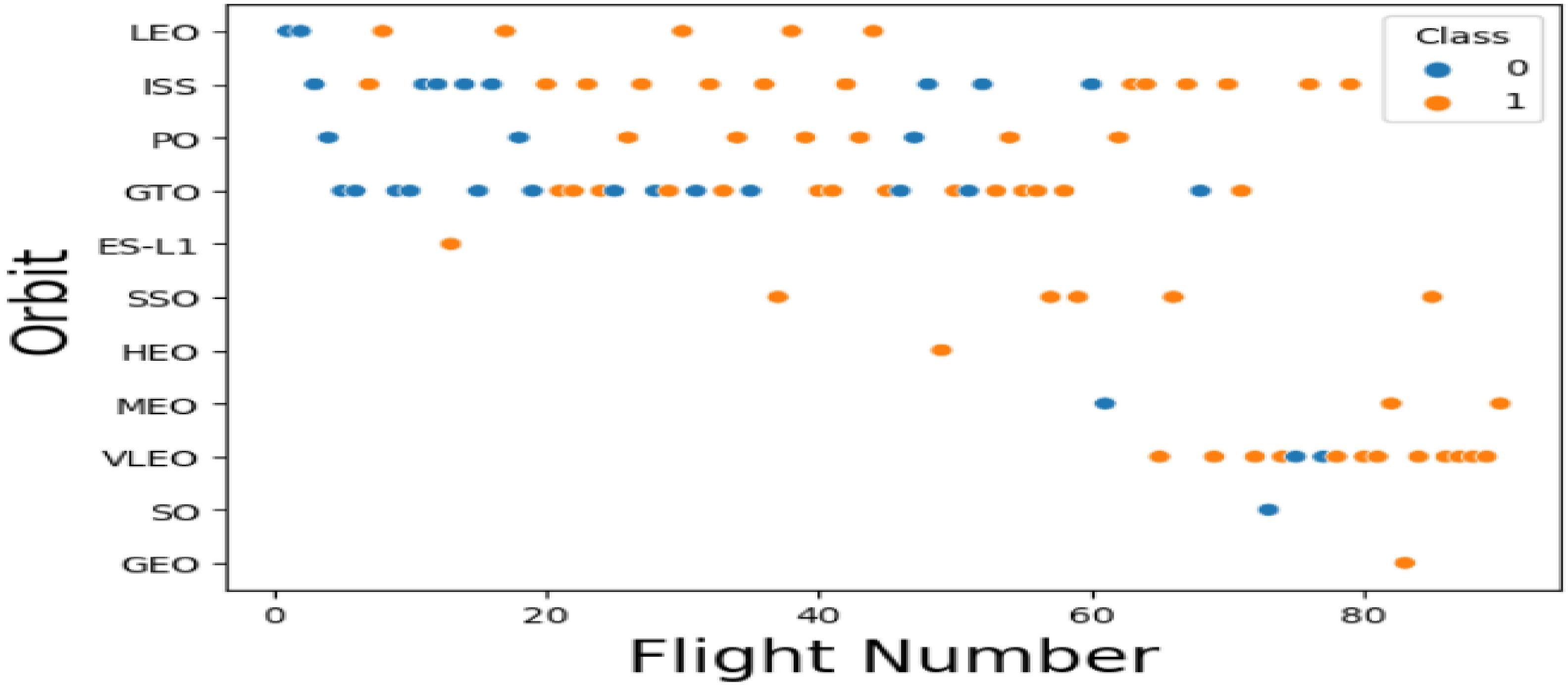
Success Rate vs. Orbit Type

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



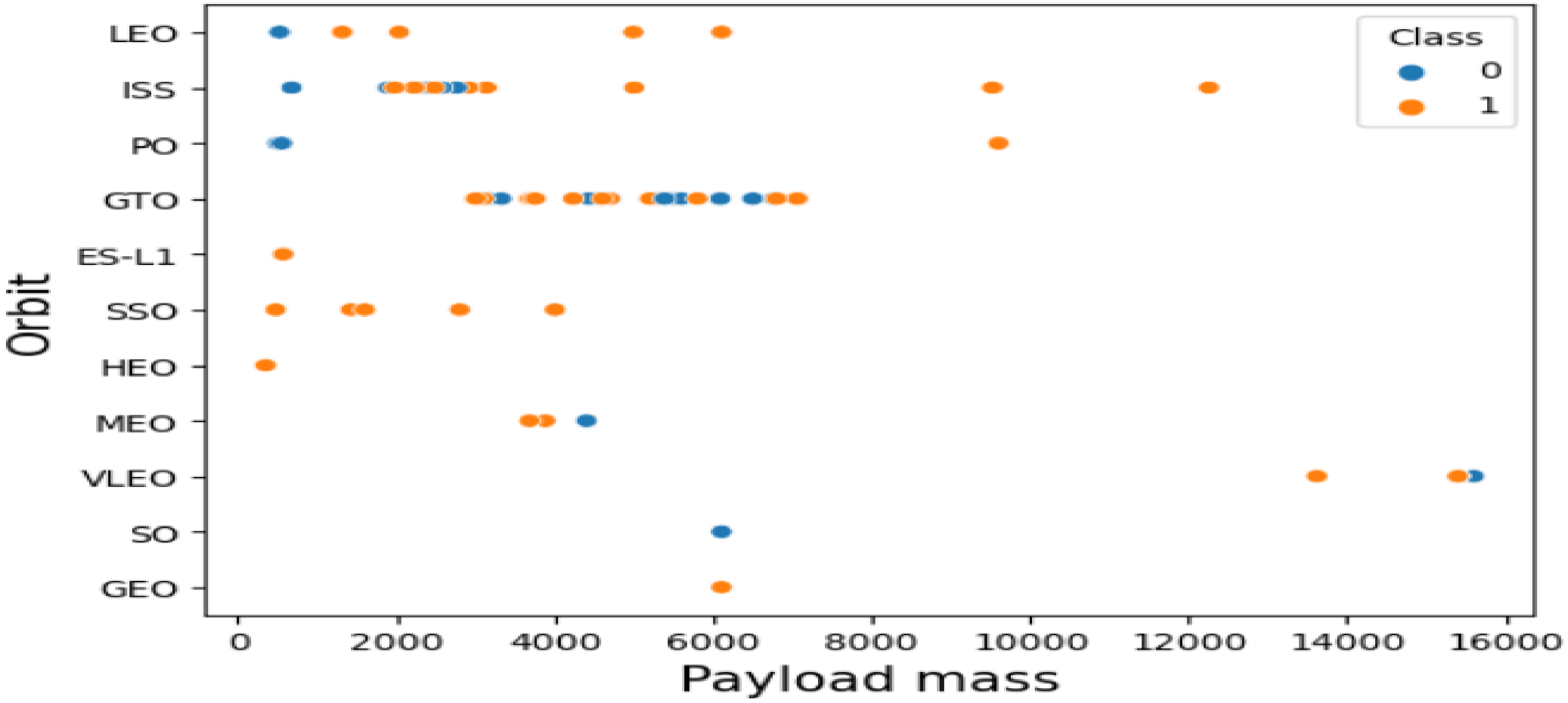
Flight Number vs. Orbit Type

- 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.



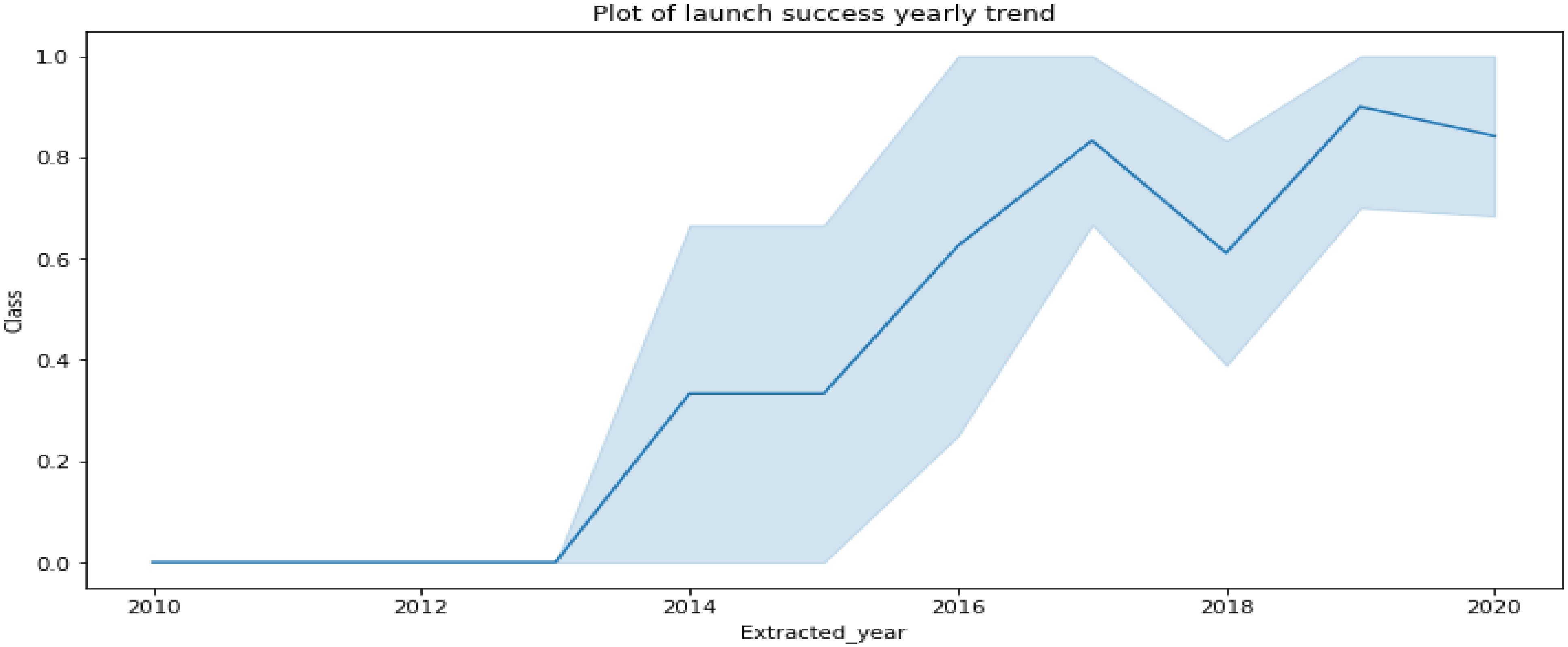
Payload vs. Orbit Type

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



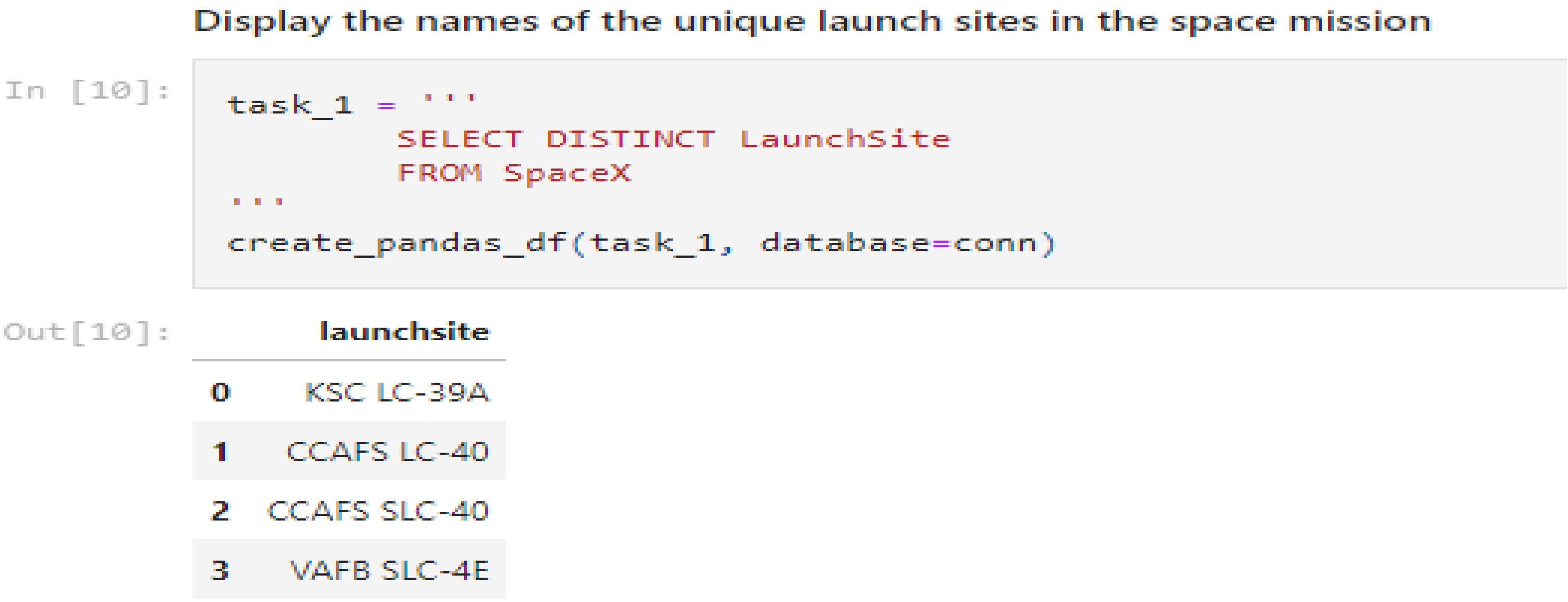
Launch Success Yearly Trend

- From the plot, we can observe that the 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]:

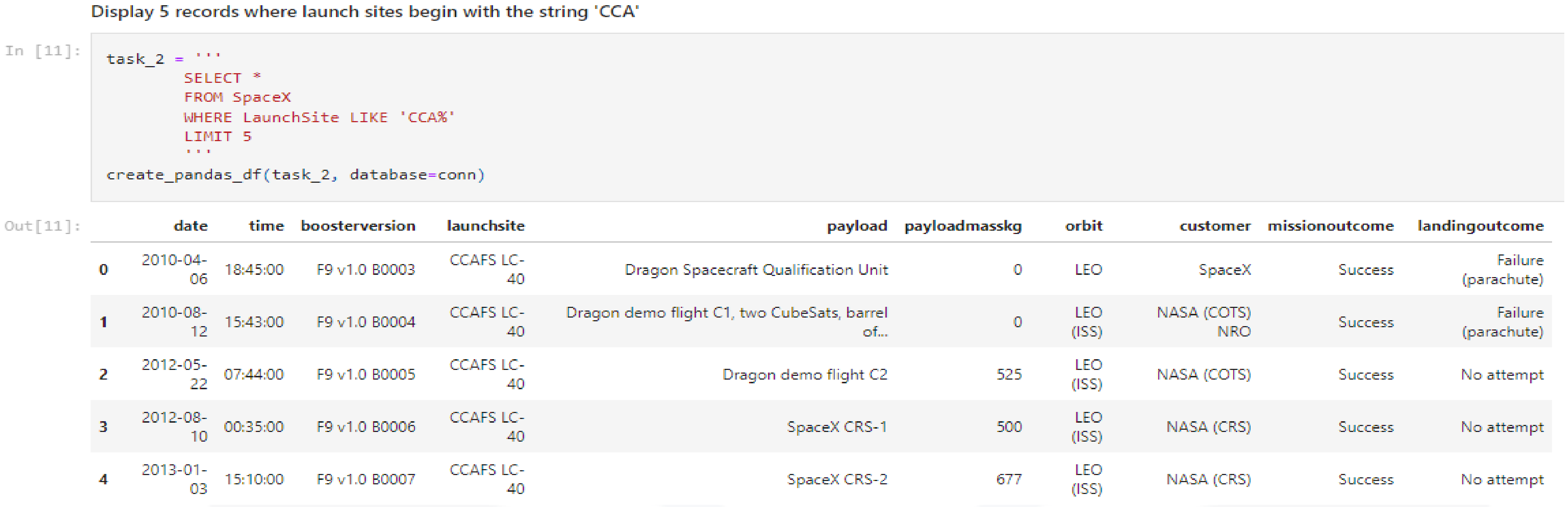
```
task_1 = '''
        SELECT DISTINCT LaunchSite
        FROM SpaceX
'''
create_pandas_df(task_1, database=conn)
```

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]:

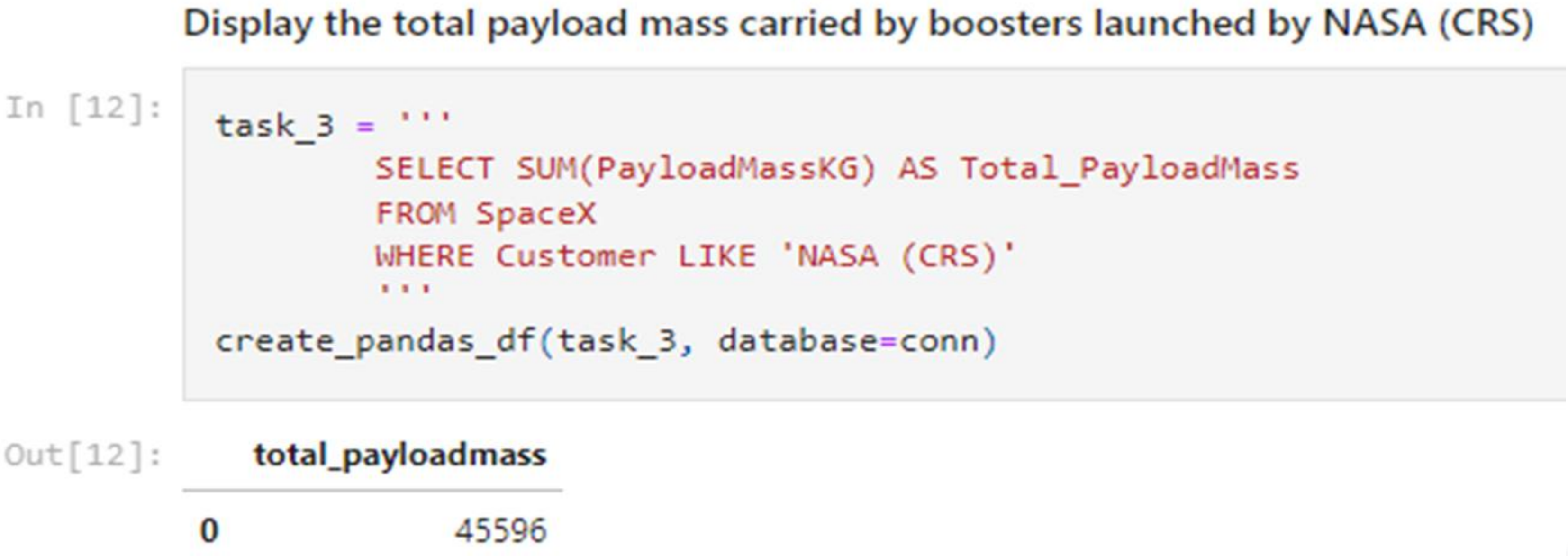
```
task_2 = '''
        SELECT *
        FROM SpaceX
        WHERE LaunchSite LIKE 'CCA%'
        LIMIT 5
        '''
create_pandas_df(task_2, database=conn)
```

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]:

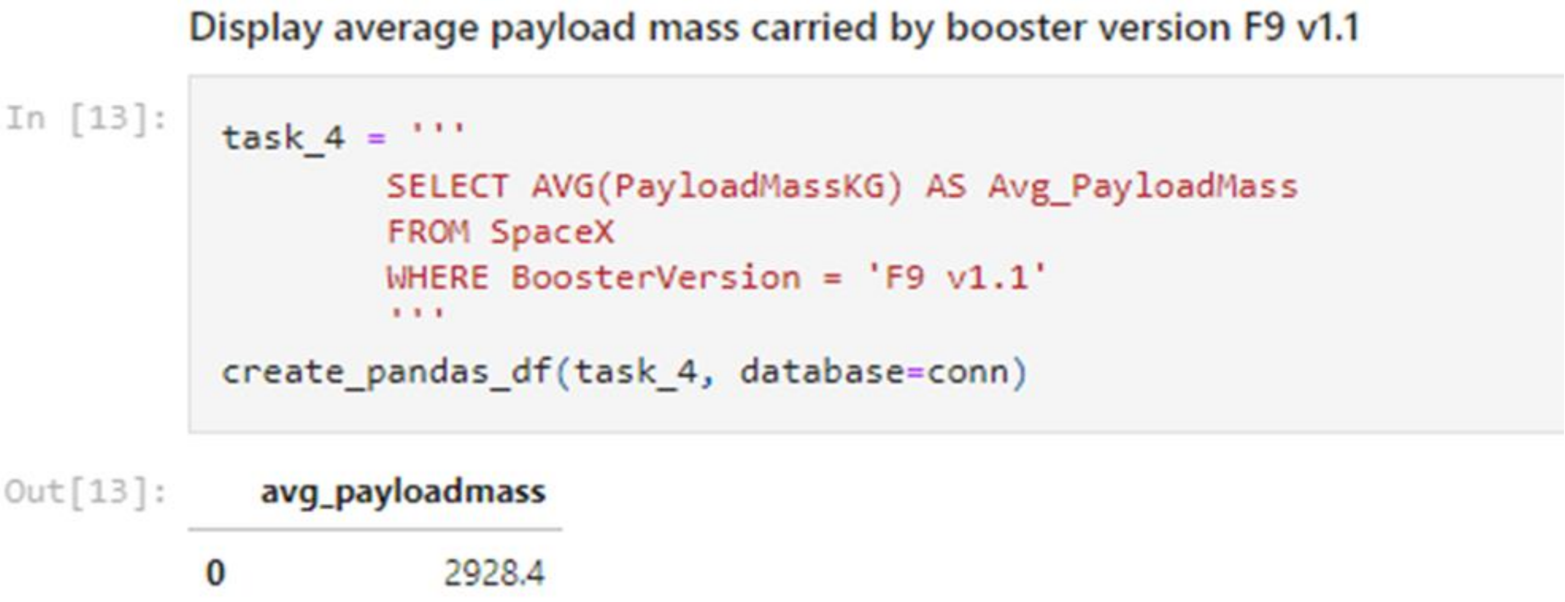
```
task_3 = '''
        SELECT SUM(PayloadMassKG) AS Total_PayloadMass
        FROM SpaceX
        WHERE Customer LIKE 'NASA (CRS)'
        '''
create_pandas_df(task_3, database=conn)
```

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 2928.4



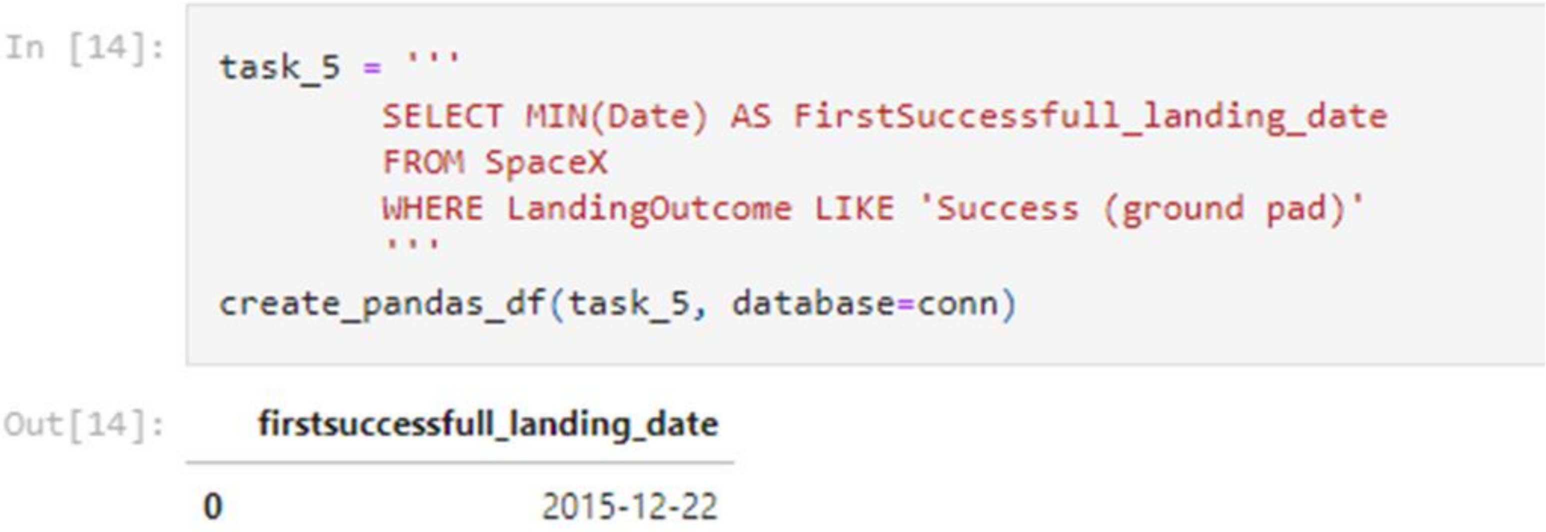
Display average payload mass carried by booster version F9 v1.1

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

```
Out[13]:     avg_payloadmass
          0           2928.4
```

First Successful Ground Landing Date

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

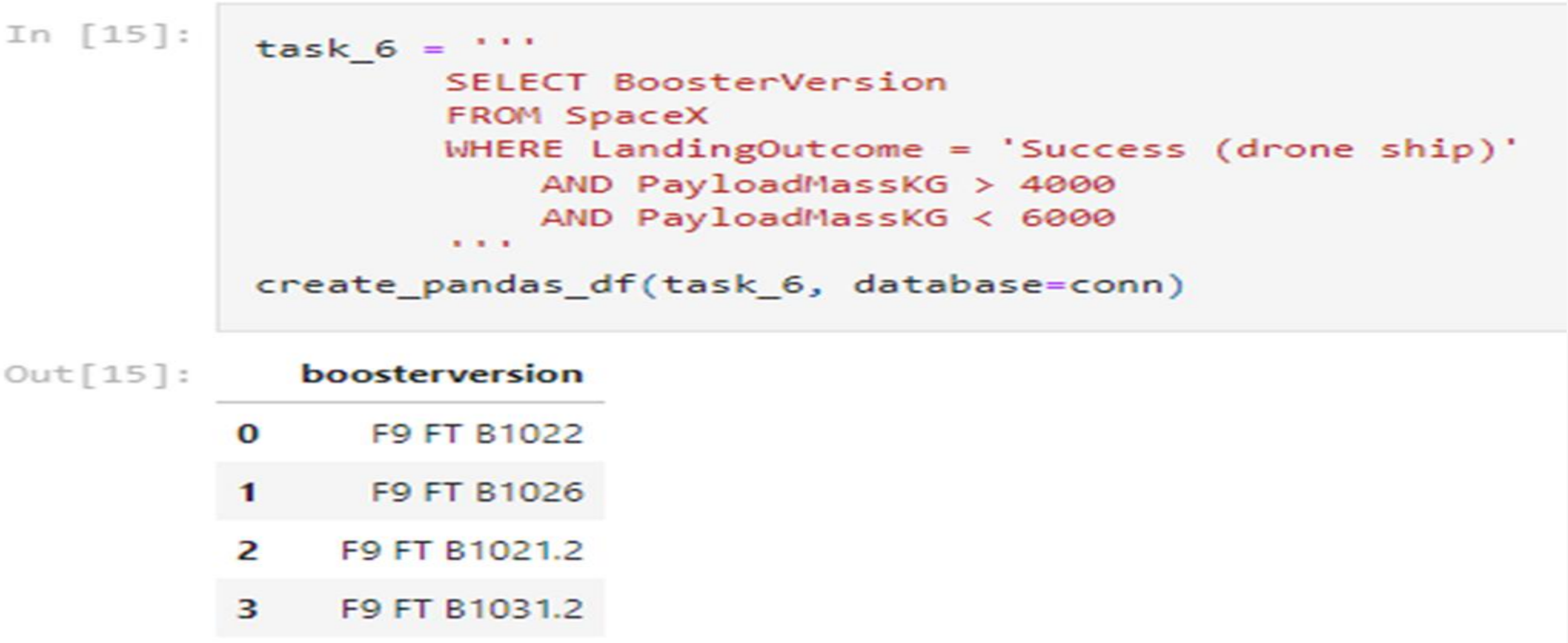


```
In [14]:  task_5 = '''
                  SELECT MIN(Date) AS FirstSuccessfull_landing_date
                  FROM SpaceX
                  WHERE LandingOutcome LIKE 'Success (ground pad)'
                  '''
          create_pandas_df(task_5, database=conn)
```

```
Out[14]:     firstsuccessfull_landing_date
          0                     2015-12-22
```

Successful Drone Ship Landing with Payload between 4000 and 6000

- We used the WHERE clause to filter for boosters that have successfully landed on the drone ship and applied the AND condition to determine successful landing with payload mass greater than 4000 but less than 6000



In [15]:

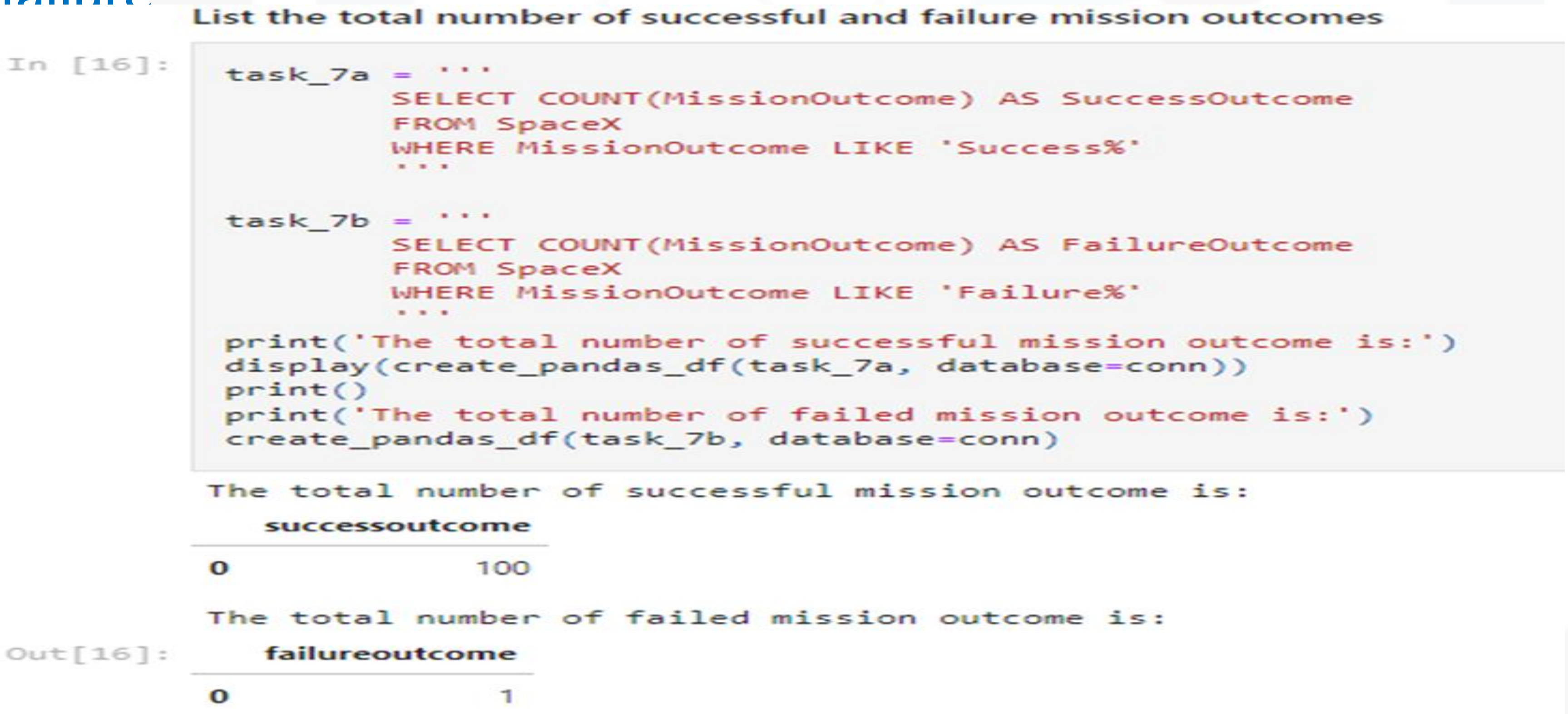
```
task_6 = '''
        SELECT BoosterVersion
        FROM SpaceX
        WHERE LandingOutcome = 'Success (drone ship)'
            AND PayloadMassKG > 4000
            AND PayloadMassKG < 6000
        '''
create_pandas_df(task_6, database=conn)
```

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 wildcards 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

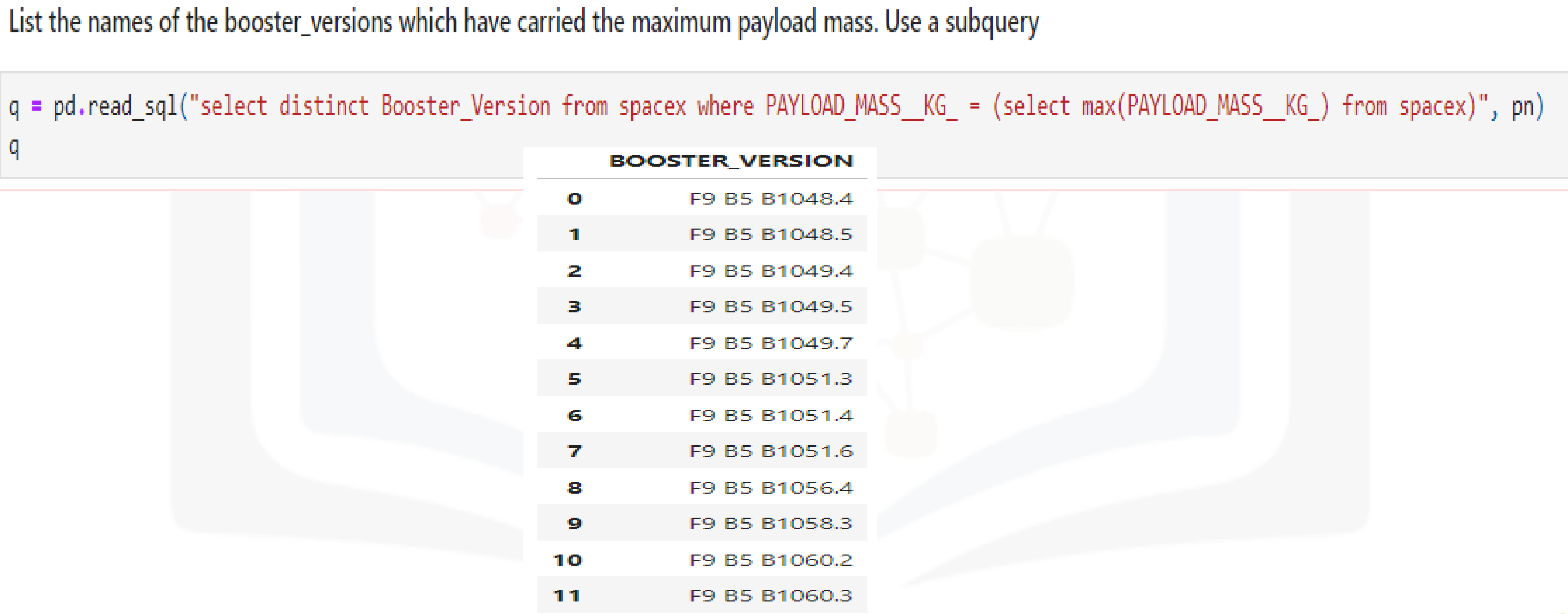
```
The total number of failed mission outcome is:
```

Out[16]:

	failureoutcome
0	1

Boosters Carried Maximum Payload

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



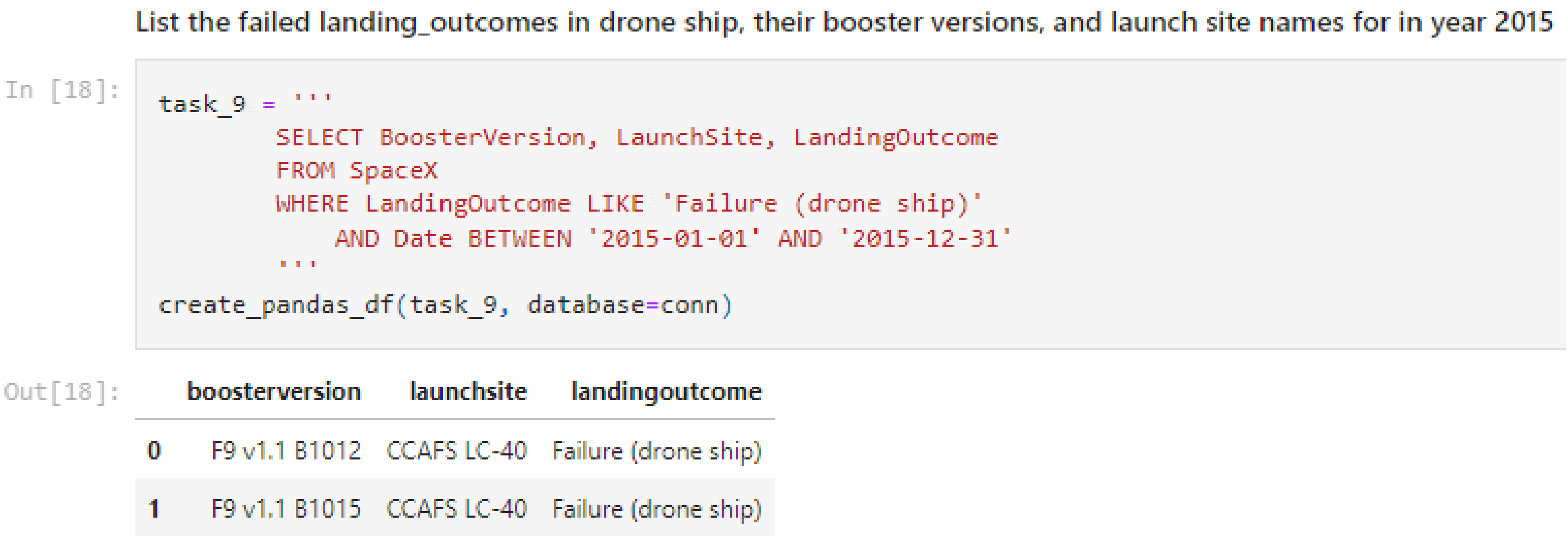
List the names of the booster_versions which have carried the maximum payload mass. Use a subquery

```
q = pd.read_sql("select distinct Booster_Version from spacex where PAYLOAD_MASS__KG_ = (select max(PAYLOAD_MASS__KG_) from spacex)", pn)
q
```

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

2015 Launch Records

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



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

In [18]:

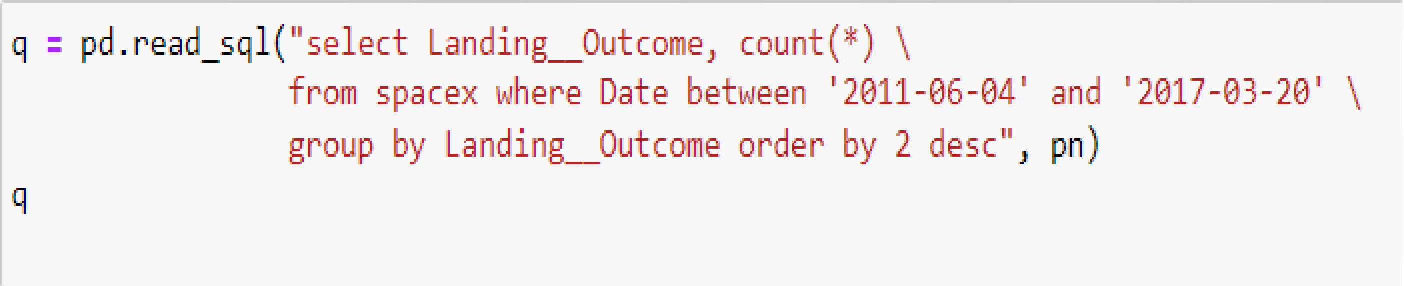
```
task_9 = '''
        SELECT BoosterVersion, LaunchSite, LandingOutcome
        FROM SpaceX
        WHERE LandingOutcome LIKE 'Failure (drone ship)'
            AND Date BETWEEN '2015-01-01' AND '2015-12-31'
        '''
create_pandas_df(task_9, database=conn)
```

Out[18]:

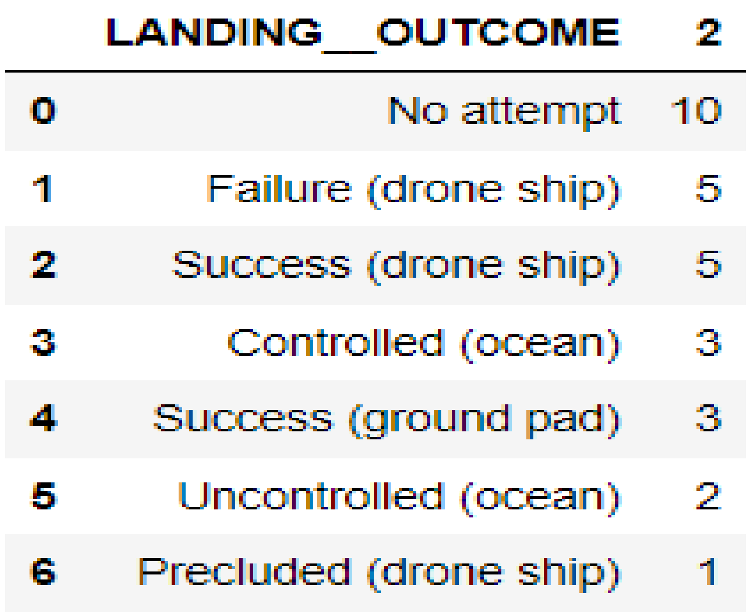
	boosterversion	launchsite	landingoutcome
0	F9 v1.1 B1012	CCAFS LC-40	Failure (drone ship)
1	F9 v1.1 B1015	CCAFS LC-40	Failure (drone ship)

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

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



```
q = pd.read_sql("select Landing__Outcome, count(*) \
                from spacex where Date between '2011-06-04' and '2017-03-20' \
                group by Landing__Outcome order by 2 desc", pn)
q
```

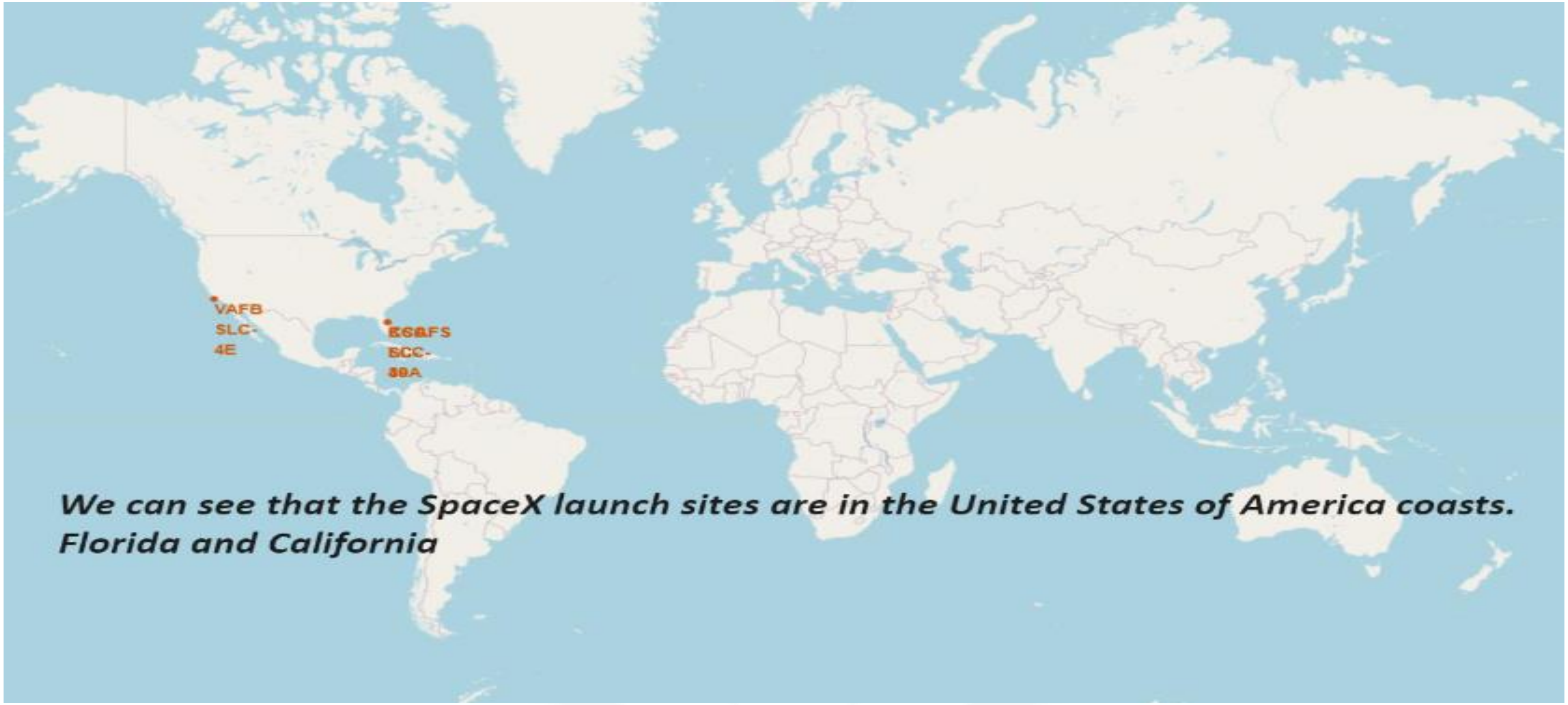


	LANDING__OUTCOME	2
0	No attempt	10
1	Failure (drone ship)	5
2	Success (drone ship)	5
3	Controlled (ocean)	3
4	Success (ground pad)	3
5	Uncontrolled (ocean)	2
6	Precluded (drone ship)	1

Section 4

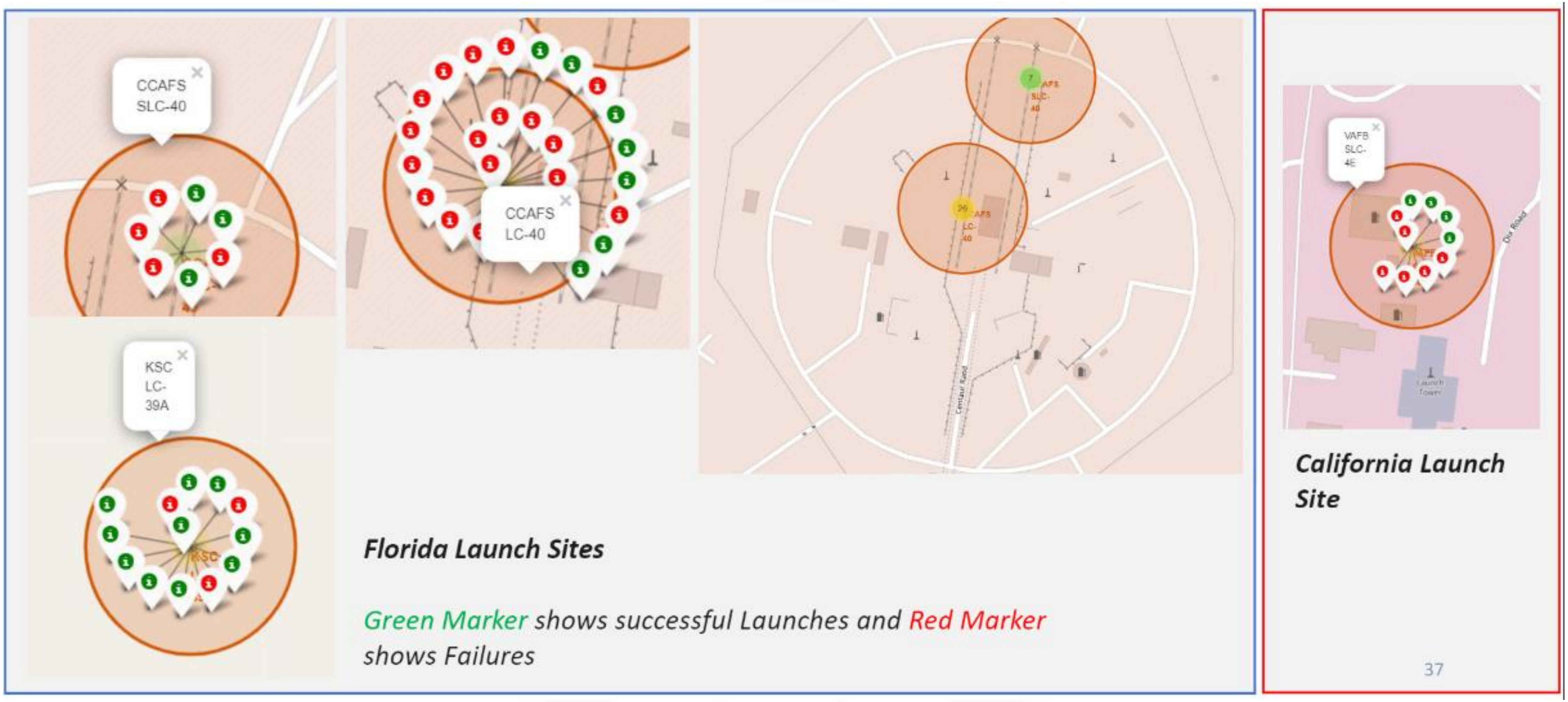
Launch Sites Proximities Analysis

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



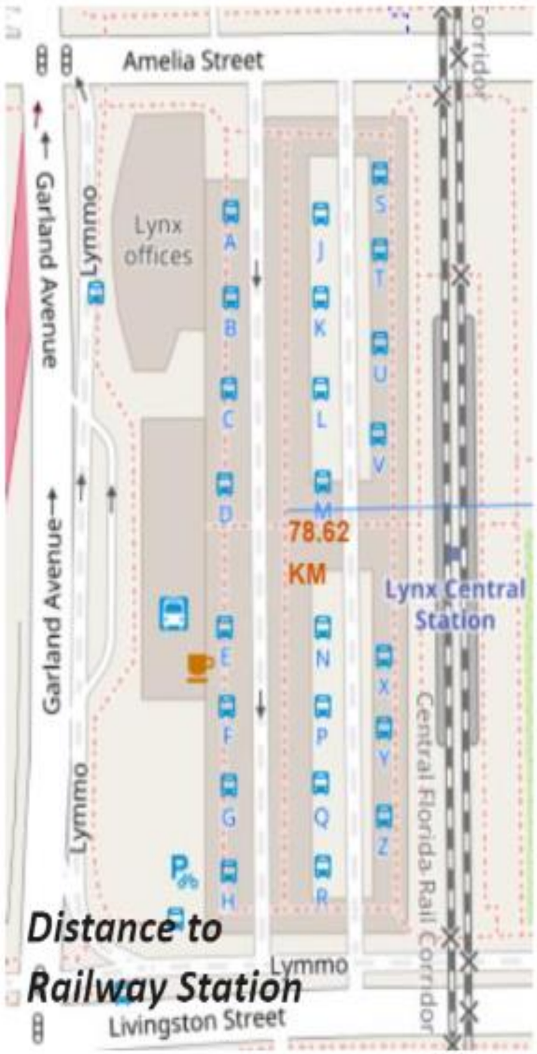
Florida Launch Sites

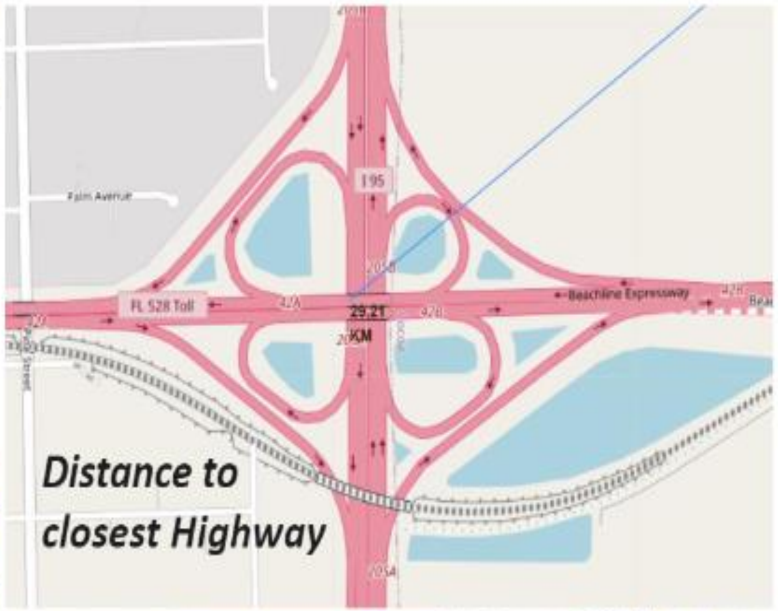
Green Marker shows successful Launches and Red Marker shows Failures

California Launch Site

37

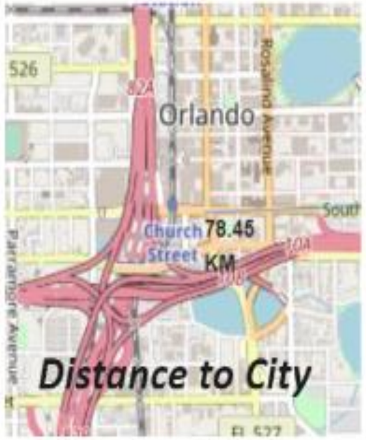
Launch Site distance to landmarks





7
CCAFS SLC-40
26
CCAFS LC-40
Distance to coast

0.90 KM
Distance to Coastline

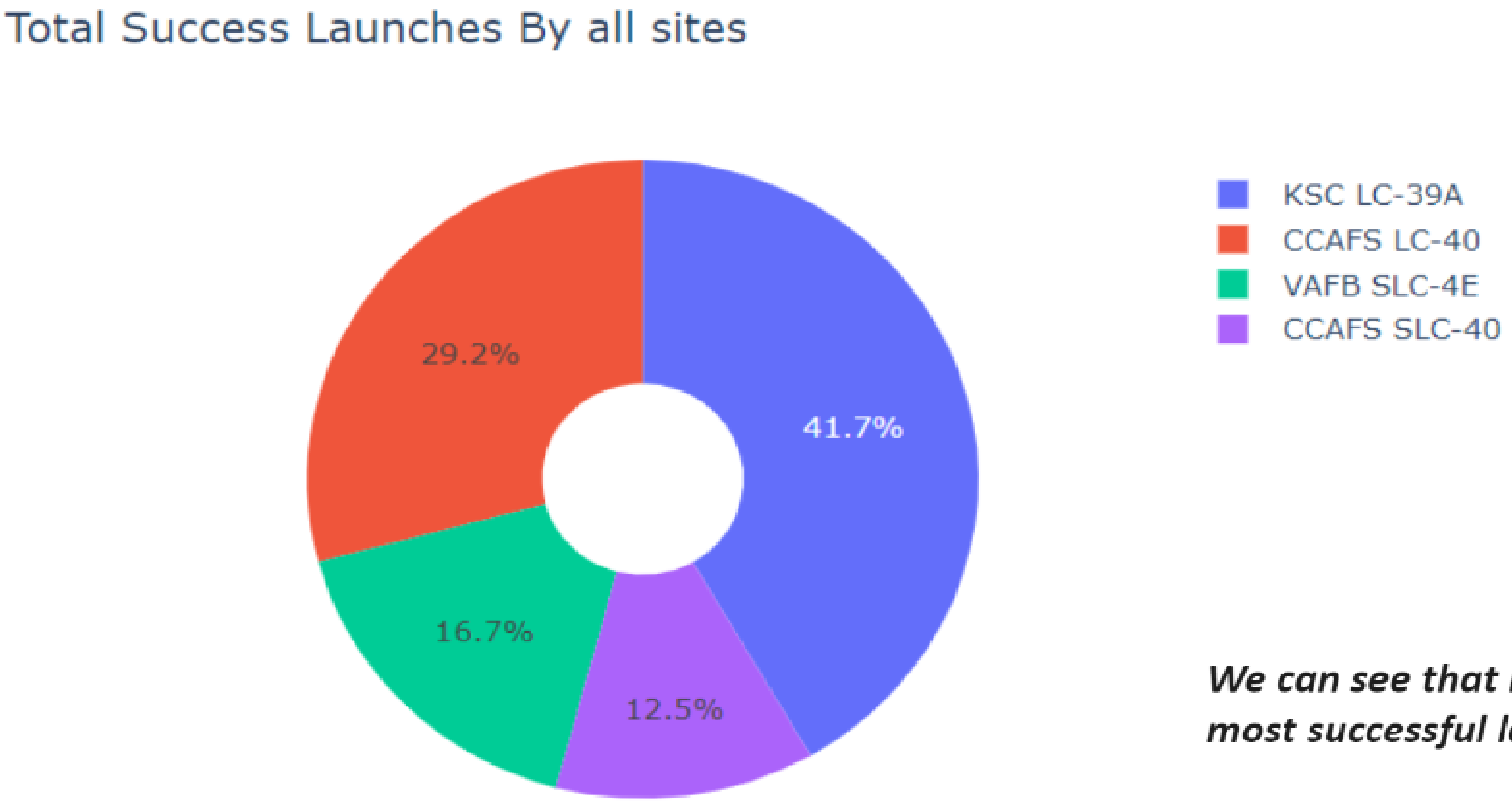


- •Are launch sites in close proximity to railways? No
- •Are launch sites in close proximity to highways? No
- •Are launch sites in close proximity to coastline? Yes
- •Do launch sites keep certain distance away from cities? Yes

Section 5

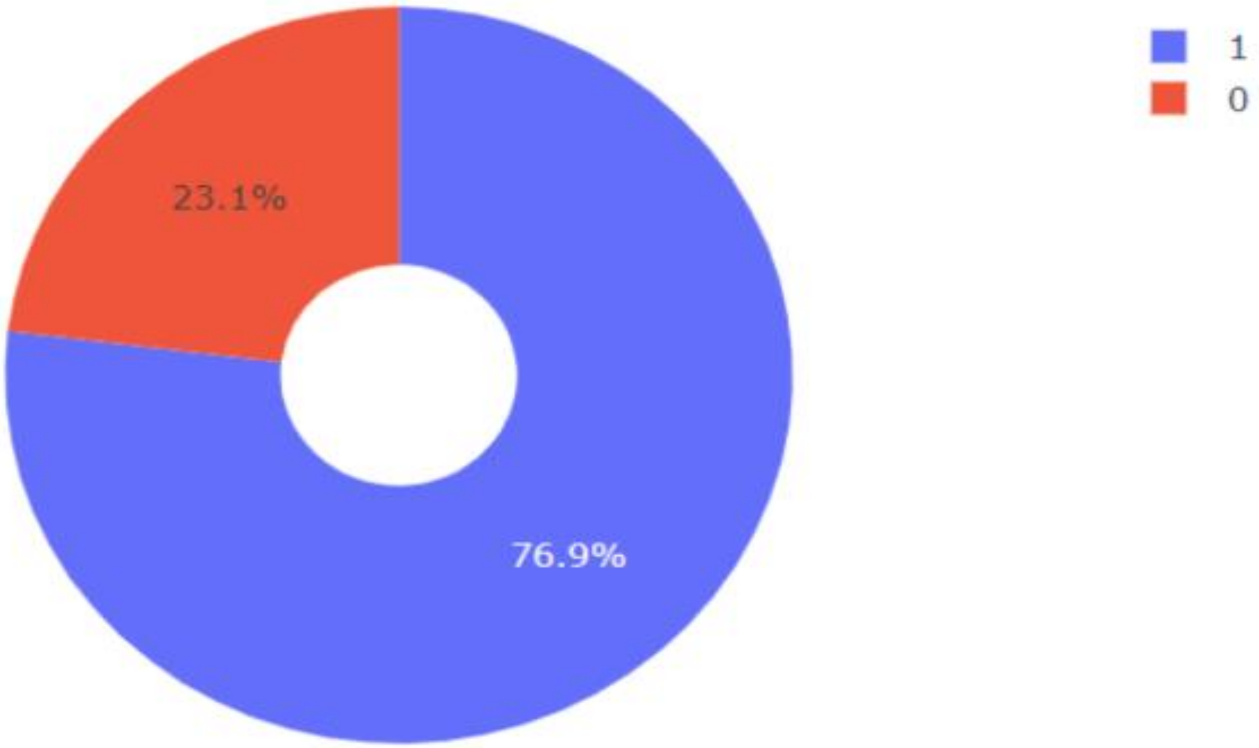
Build a Dashboard with Plotly Dash

Pie chart showing the success percentage achieved by each launch site



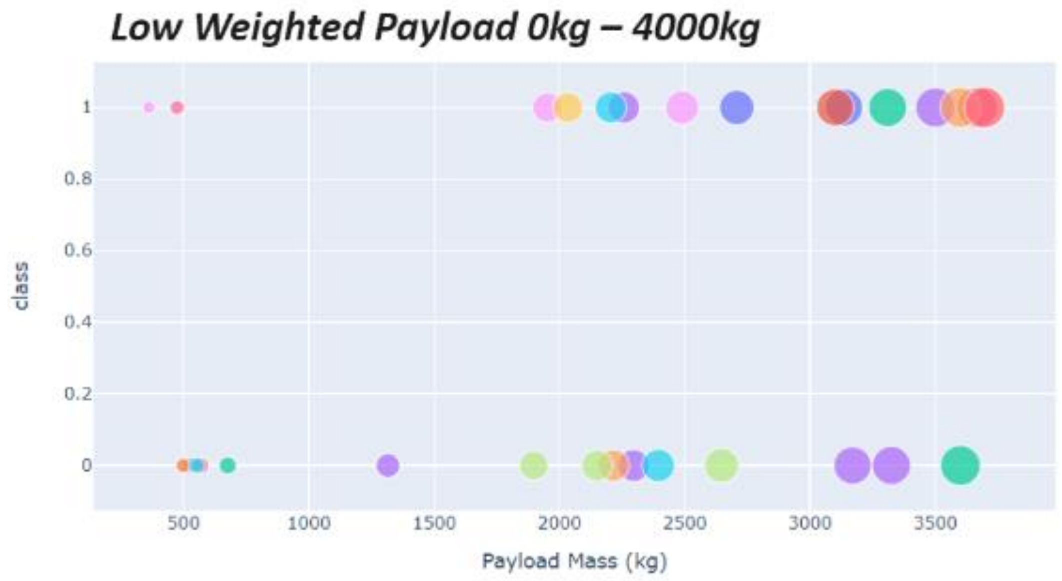
We can see that KSC LC-39A had the most successful launches from all the sites

Pie chart showing the Launch site with the highest launch success ratio

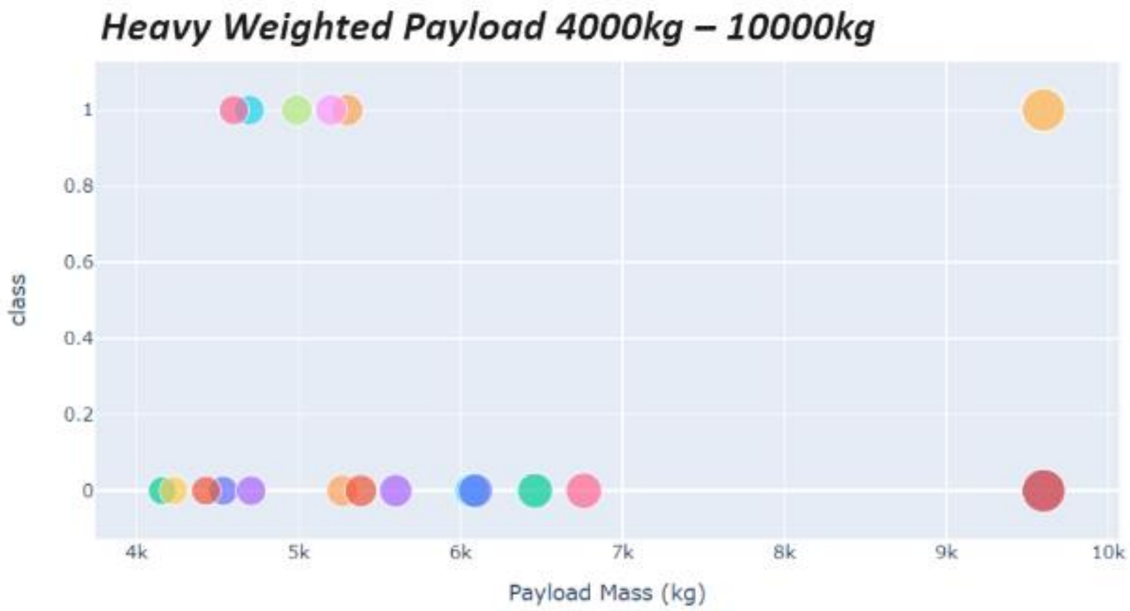


KSC LC-39A achieved a 76.9% success rate while getting a 23.1% failure rate

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

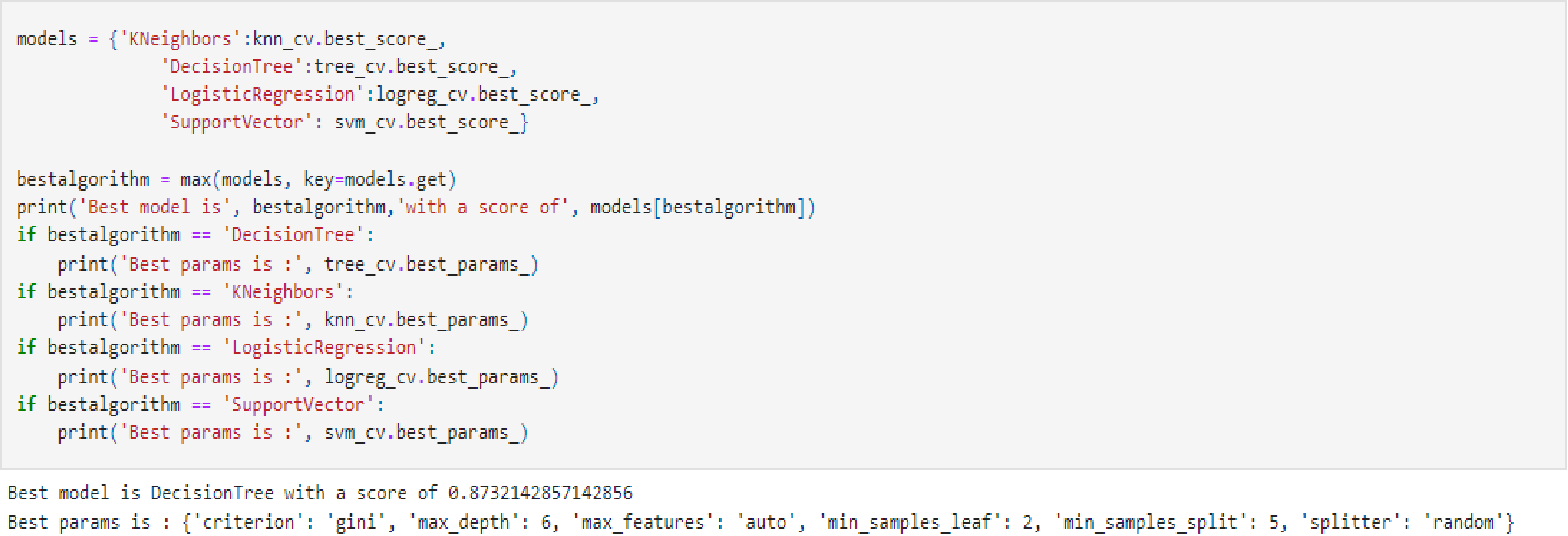
We can see the success rates for low weighted payloads is higher than the heavy weighted payloads

Section 6

Predictive Analysis (Classification)

Classification Accuracy

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



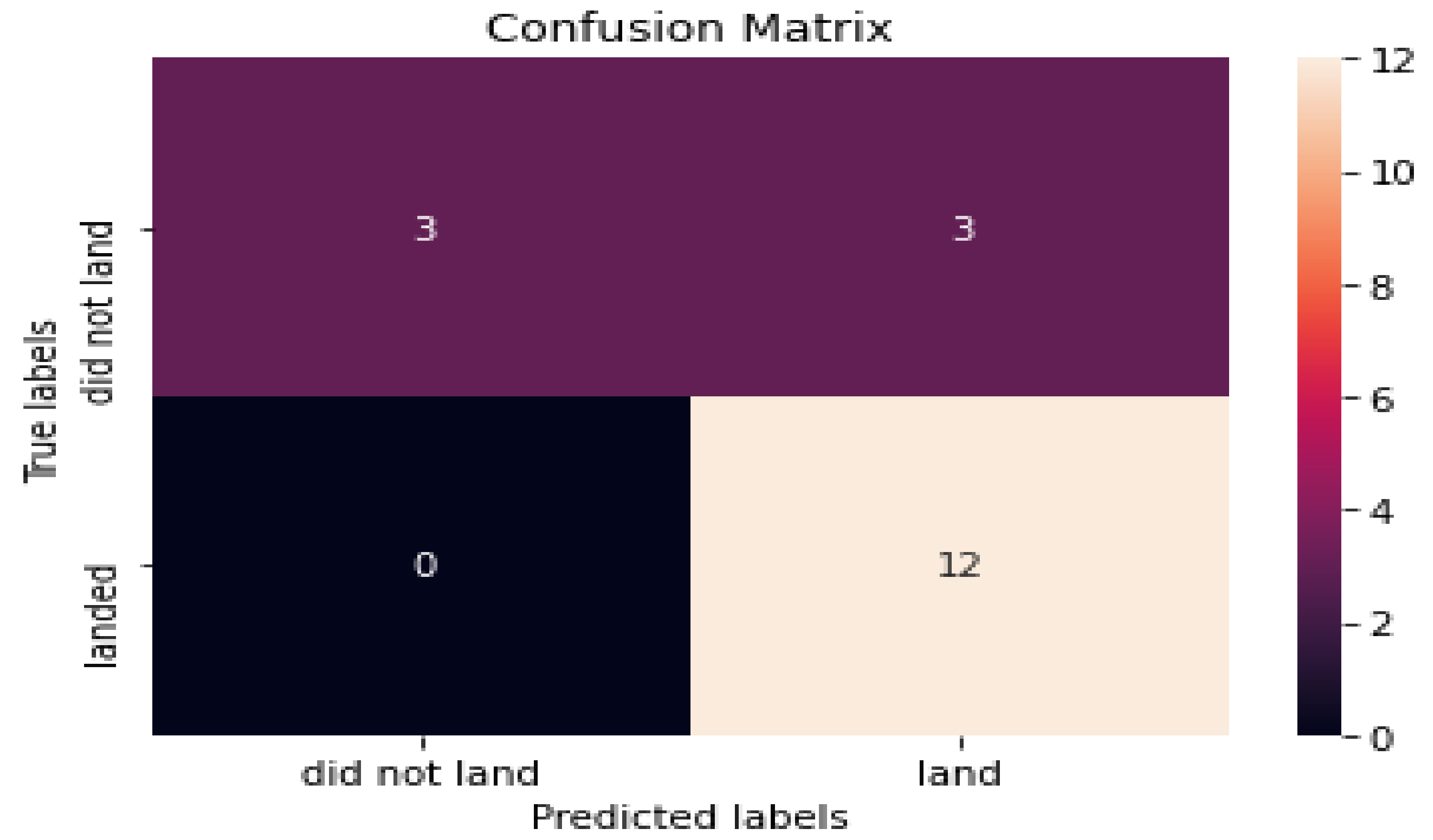
```
models = {'KNeighbors':knn_cv.best_score_,
              'DecisionTree':tree_cv.best_score_,
              'LogisticRegression':logreg_cv.best_score_,
              'SupportVector': svm_cv.best_score_}

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., an unsuccessful landing is marked as a successful landing by the classifie



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.