IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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Outline

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- Methodology
- Results
- Conclusion
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Executive Summary

- Summary of methodologies
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  - 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 publicizes Falcon 9 rocket dispatches on its site with an expense of 62 million bucks; different suppliers cost vertical of 165 million bucks every, a significant part of the investment funds is on the grounds that Space X can reuse the primary stage. In this manner, in the event that we can decide whether the primary stage will land, we can decide the expense of a send off. This data can be utilized to offer against space X for a rocket send off. This objective of the undertaking is to make an AI pipeline to foresee on the off chance that the primary stage will land effectively.

- Problems you want to find answers

  - What factors determine if the rocket will land successfully?
  - The success rate of a successful landing is determined based on the interaction among various features.
  - What operating conditions needs to be in place to ensure a successful landing program.

Section 1

Methodology

Methodology

Executive Summary

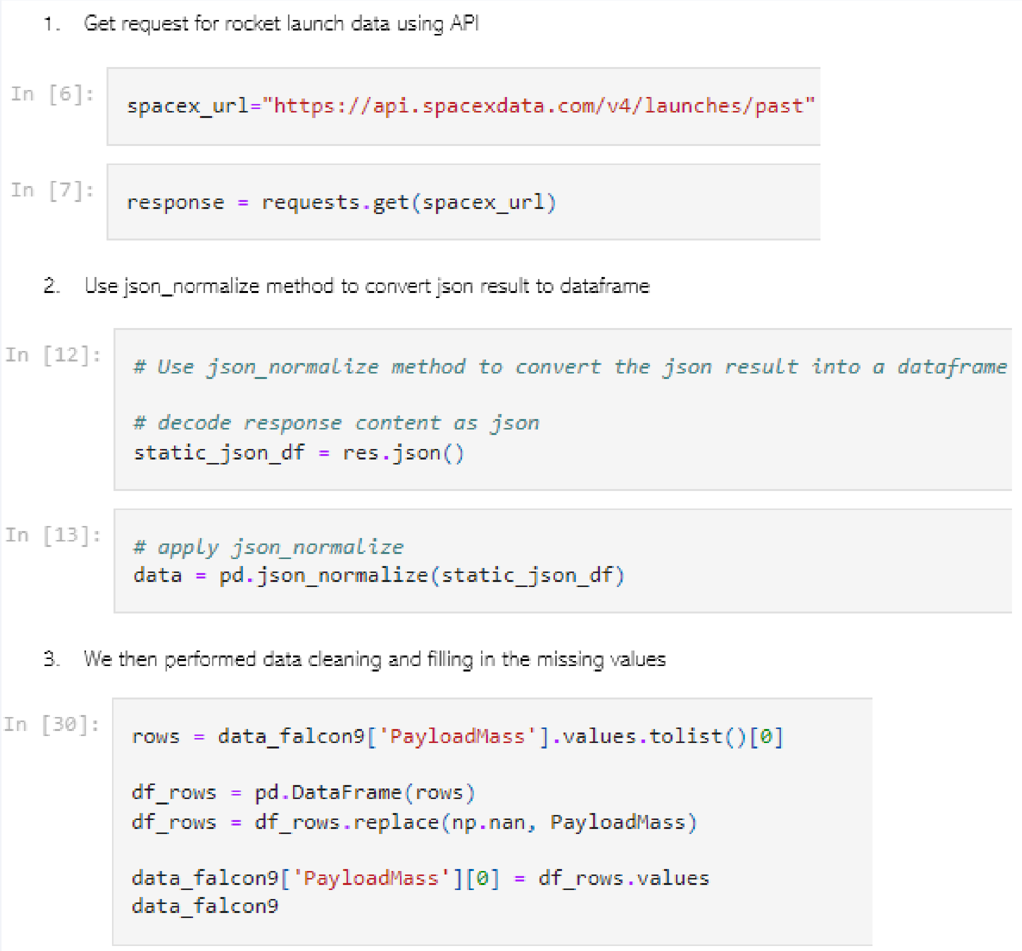
- Data collection methodology:
  - Data was collected using SpaceX API and web scraping from Wikipedia.
- Perform data wrangling
  - One-hot encoding was applied to categorical features
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using 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
  - Get request was used to collect data of the SpaceX API.
  - Next, we decoded the response content as a Json using .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 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 link to the notebook is https://github.com/neelvanani3/Neel-DS-Capstone/blob/master/jupyter-labs-webscraping.ipynb



1. Get request for rocket launch data using API

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

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

2. Use json_normalize method to convert json result to dataframe

In [12]:
```
# Use json_normalize method to convert the json result into a dataframe

# decode response content as json
static_json_df = res.json()
```

In [13]:
```
# apply json_normalize
data = pd.json_normalize(static_json_df)
```

3. We then performed data cleaning and filling in the missing values

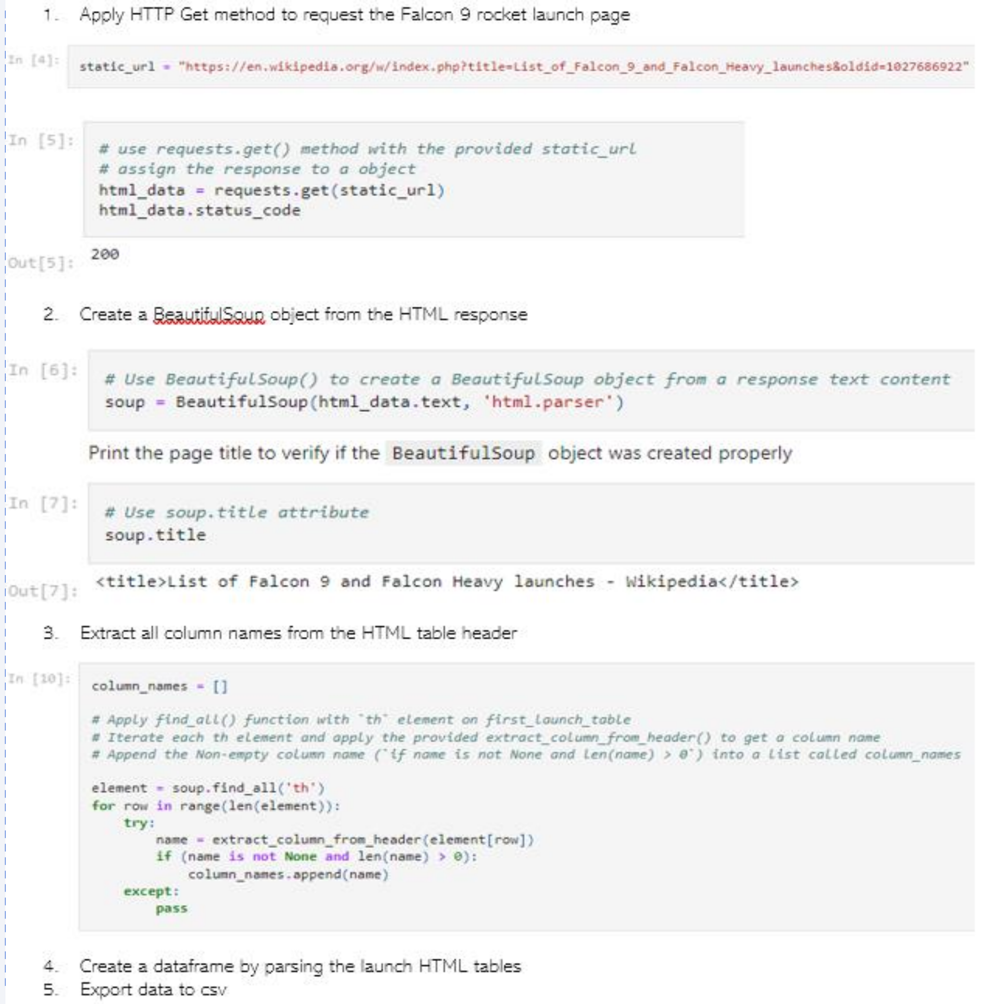
In [30]:
```
rows = data_falcon9['PayloadMass'].values.tolist()[0]

df_rows = pd.DataFrame(rows)
df_rows = df_rows.replace(np.nan, PayloadMass)

data_falcon9['PayloadMass'][0] = df_rows.values
data_falcon9
```

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/neelvanani3/Neel-DS-Capstone/blob/master/jupyter-labs-webscraping.ipynb



1. Apply HTTP Get method to request the Falcon 9 rocket launch page

```
In [4]: static_url = "https://en.wikipedia.org/w/index.php?title=List_of_Falcon_9_and_Falcon_Heavy_launches&oldid=1027686922"
```

```
In [5]: # use requests.get() method with the provided static_url
        # assign the response to a object
        html_data = requests.get(static_url)
        html_data.status_code

Out[5]: 200
```

2. Create a BeautifulSoup object from the HTML response

```
In [6]: # Use BeautifulSoup() to create a BeautifulSoup object from a response text content
        soup = BeautifulSoup(html_data.text, 'html.parser')
```

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

```
In [7]: # Use soup.title attribute
        soup.title

Out[7]: <title>List of Falcon 9 and Falcon Heavy launches - Wikipedia</title>
```

3. Extract all column names from the HTML table header

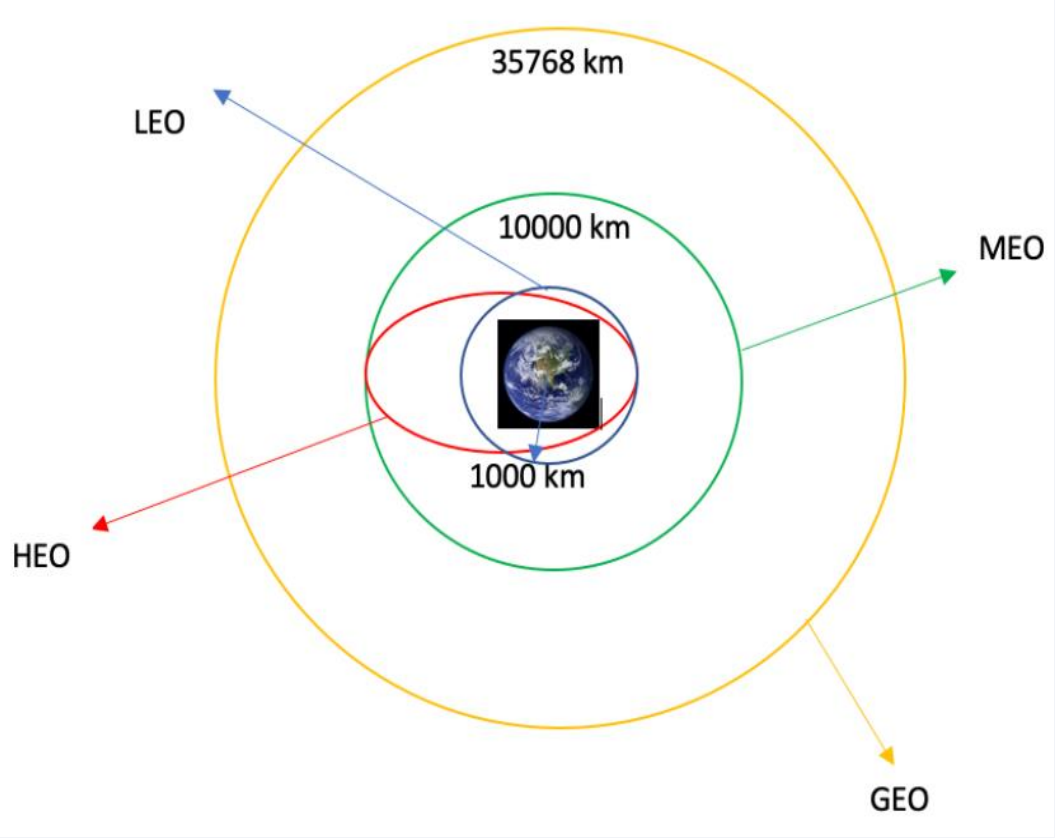
```
In [10]: column_names = []

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

         element = soup.find_all('th')
         for row in range(len(element)):
             try:
                 name = extract_column_from_header(element[row])
                 if (name is not None and len(name) > 0):
                     column_names.append(name)
             except:
                 pass
```

4. Create a dataframe by parsing the launch HTML tables
5. Export data to csv

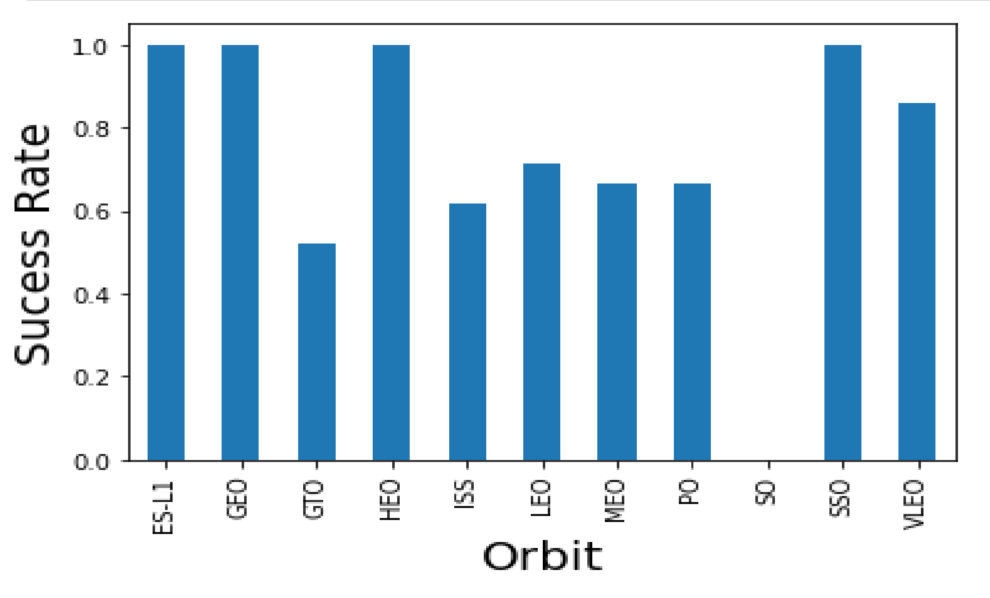
Data Wrangling

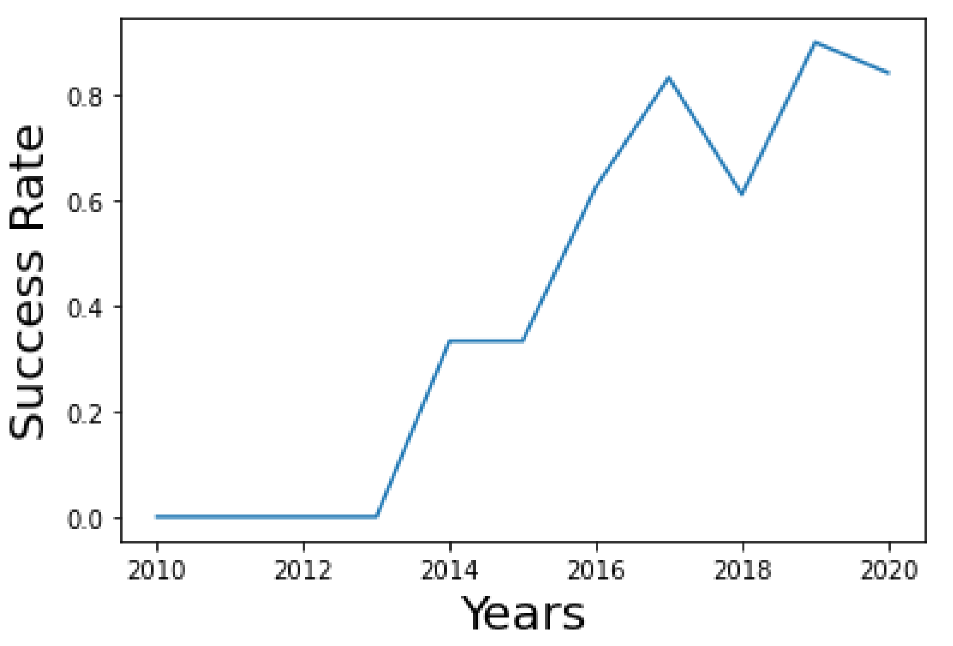


- We performed exploratory data analysis and determined the training labels.
- We calculated the number of launches at each site, and the number and occurrence of each orbits
- We created landing outcome label from outcome column and exported the results to csv.
- The link to the notebook is https://github.com/neelvanani3/Neel-DS-Capstone/blob/master/labs-jupyter-spacex-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/neelvanani3/Neel-DS-Capstone/blob/master/jupyter-labs-eda-dataviz.ipynb

EDA with SQL

- We load 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:
  - Unique launch sites names 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/neelvanani3/Neel-DS-Capstone/blob/master/jupyter-labs-eda-sql-coursera.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?

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/neelvanani3/Neel-DS-Capstone/blob/master/APP.py

Predictive Analysis (Classification)

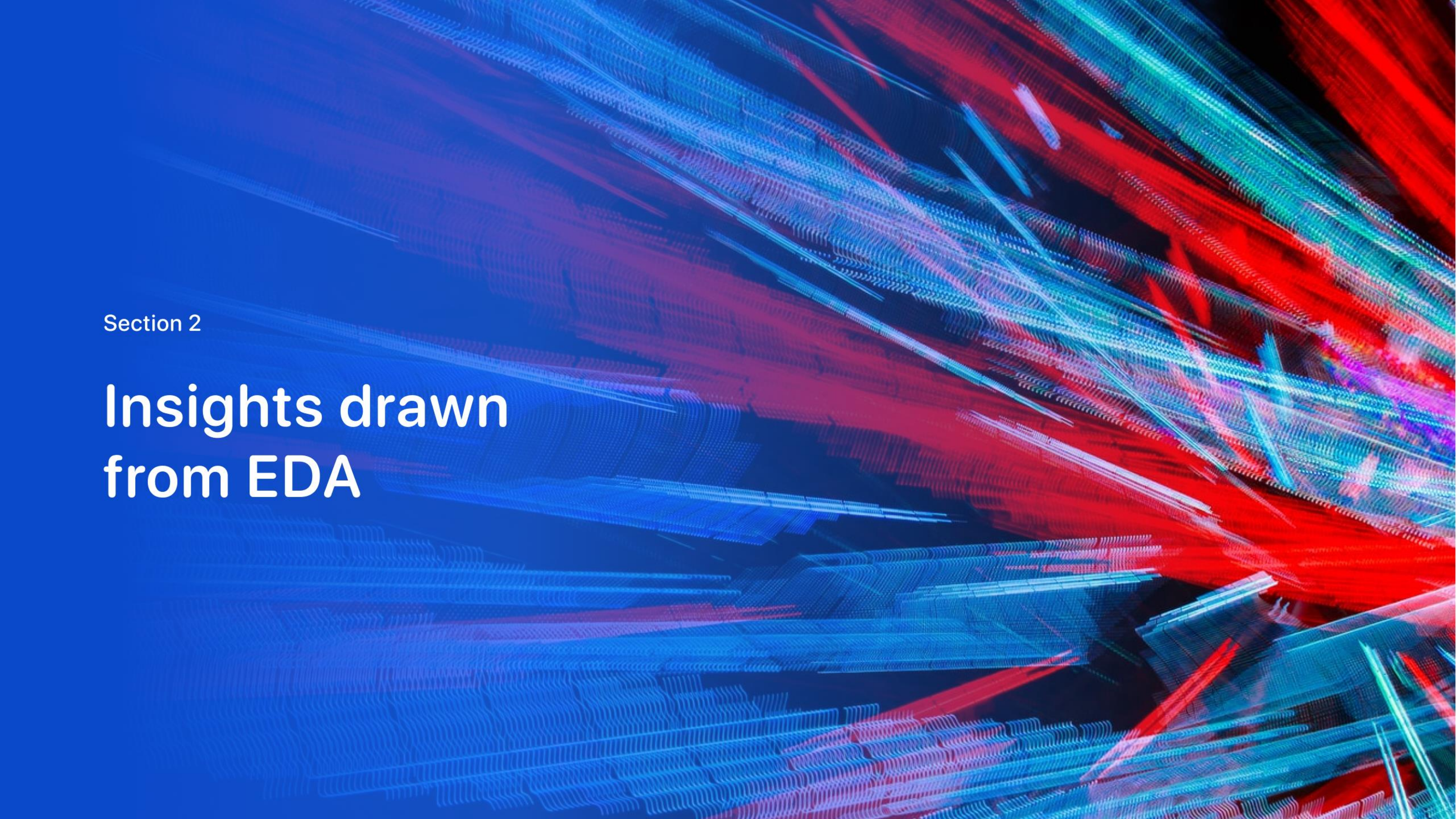
- We loaded the data using numpy and pandas, transformed the data, split our data into training and testing.
- We built different machine learning models and tune different hyperparameters using GridSearchCV.
- We used accuracy as the metric for our model, improved the model using feature engineering and algorithm tuning.
- We found the best performing classification model.
- The link to the notebook is https://github.com/neelvanani3/Neel-DS-Capstone/blob/master/SpaceX_Machine_Learning_Prediction_Part_5_(2).ipynb

Results

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

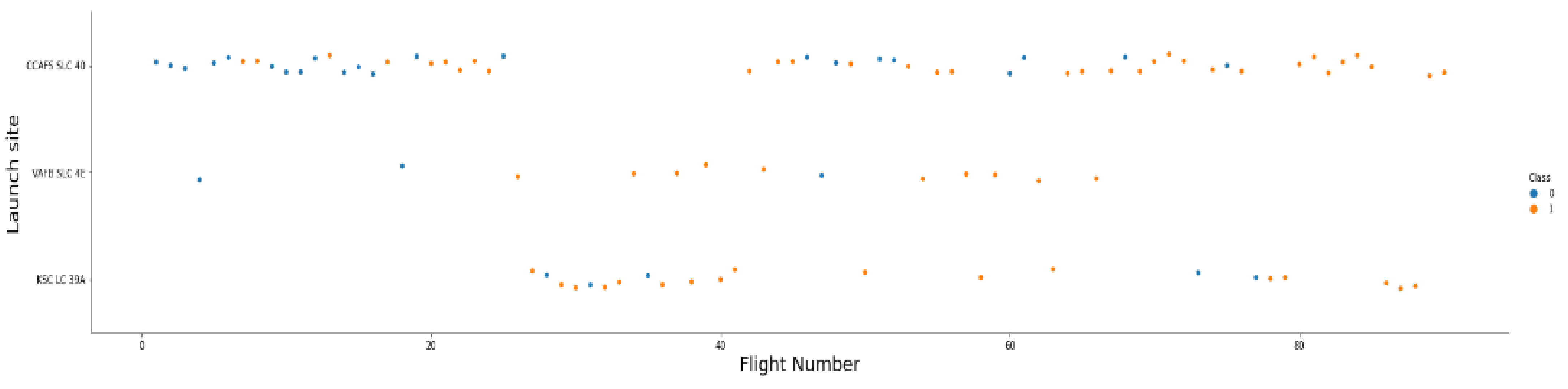
Section 2

Insights drawn from EDA

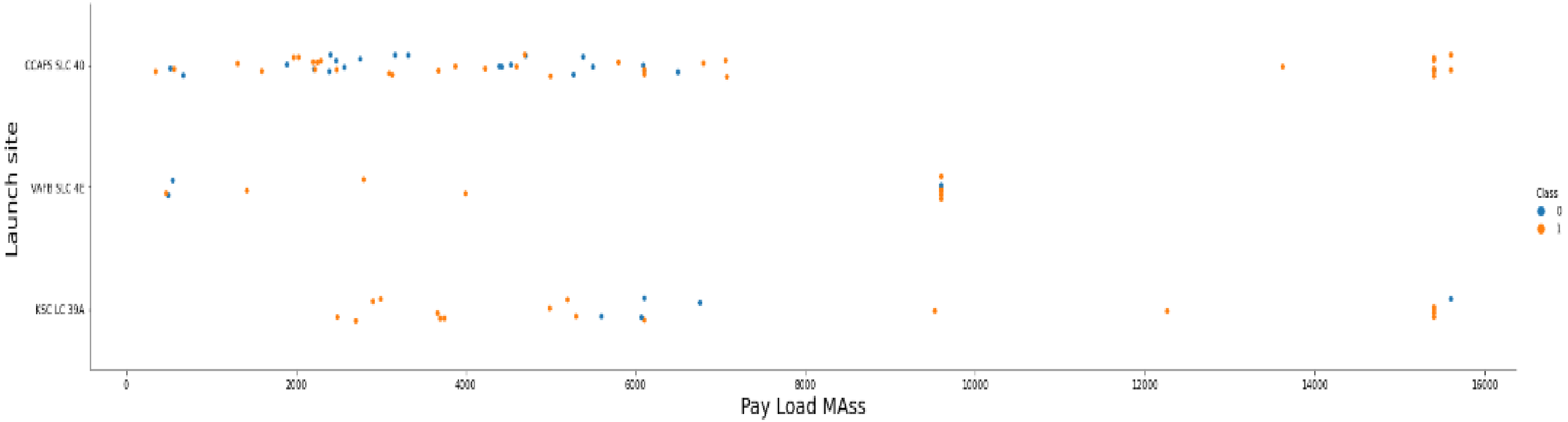


Flight Number vs. Launch Site

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

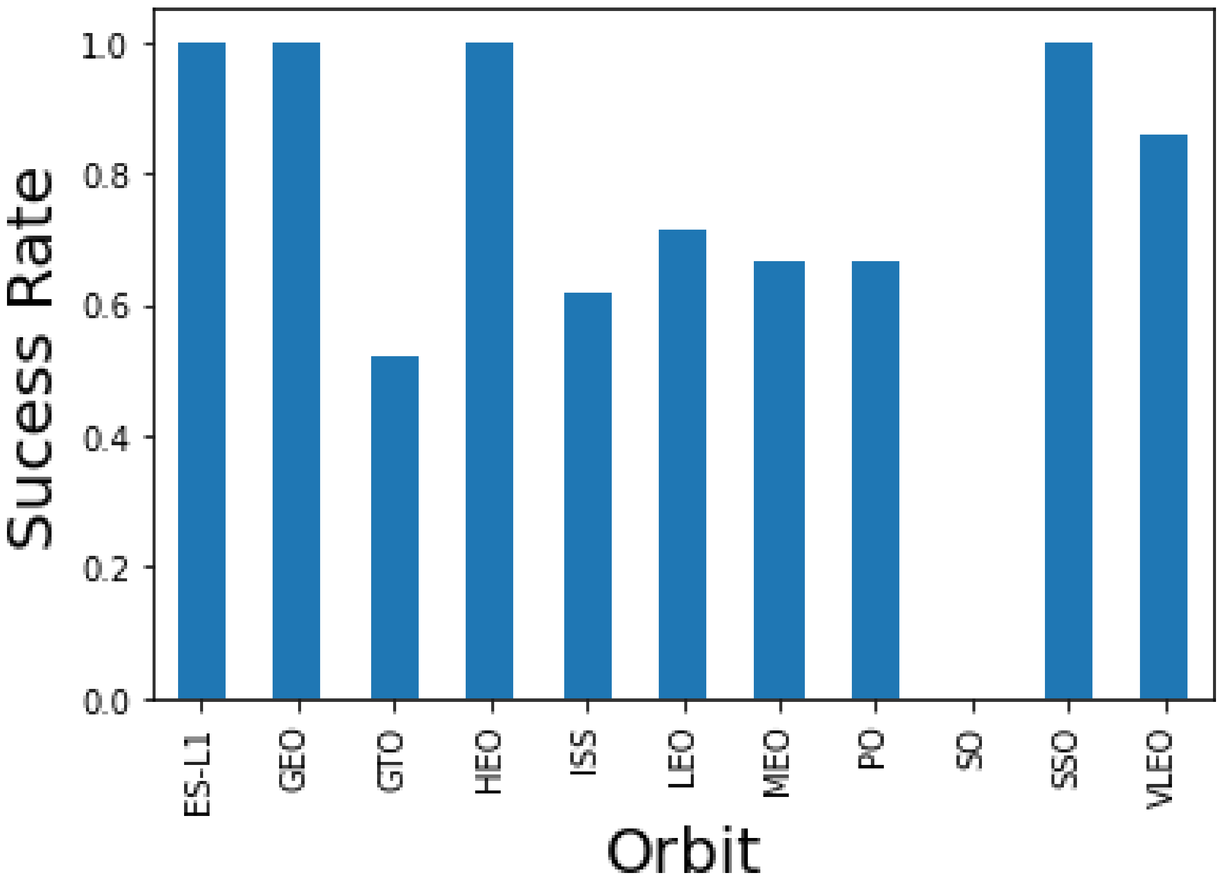


Payload vs. Launch Site



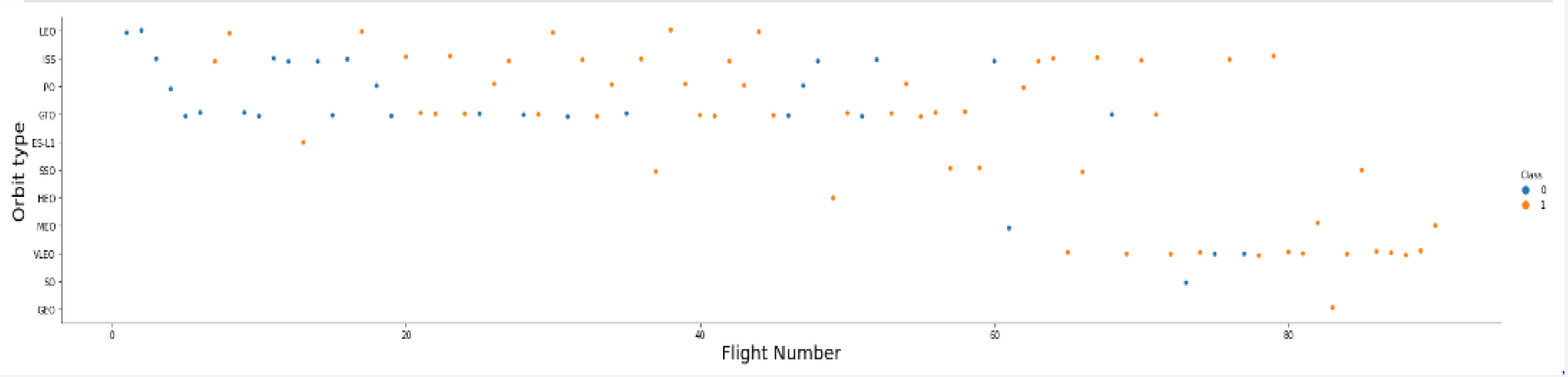
Success Rate vs. Orbit Type

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



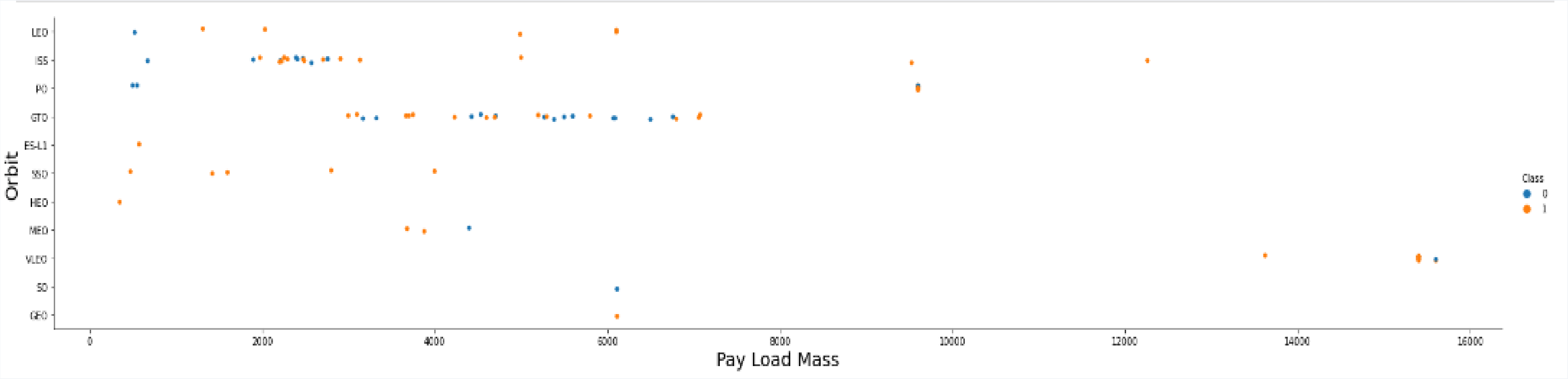
Flight Number vs. Orbit Type

- 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.



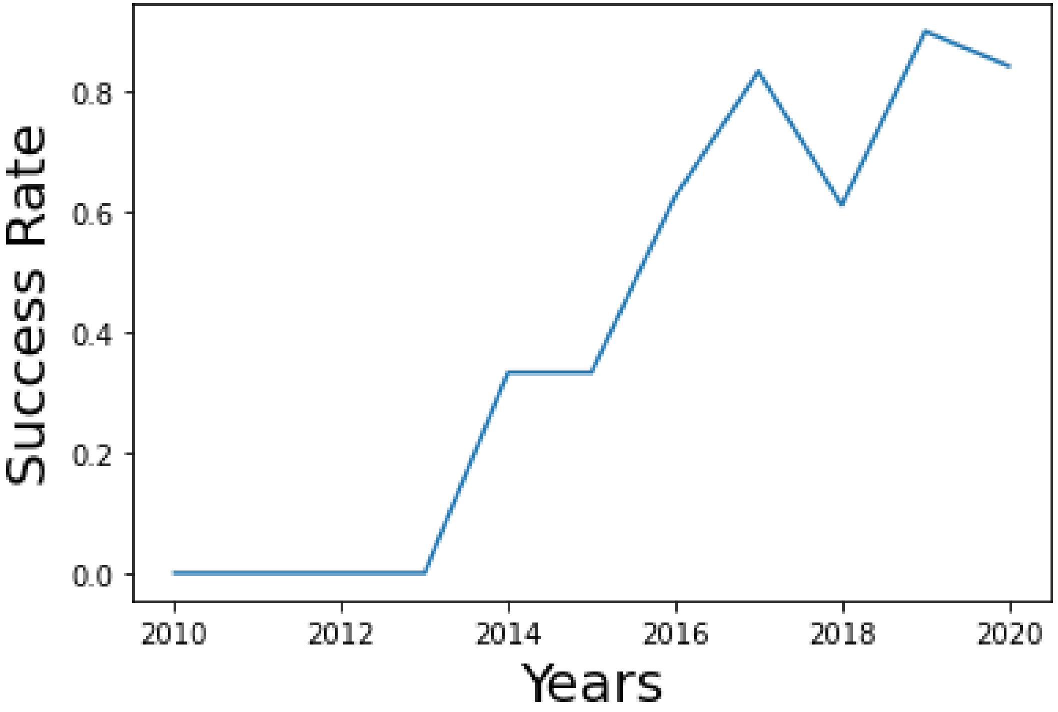
Payload vs. Orbit Type

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



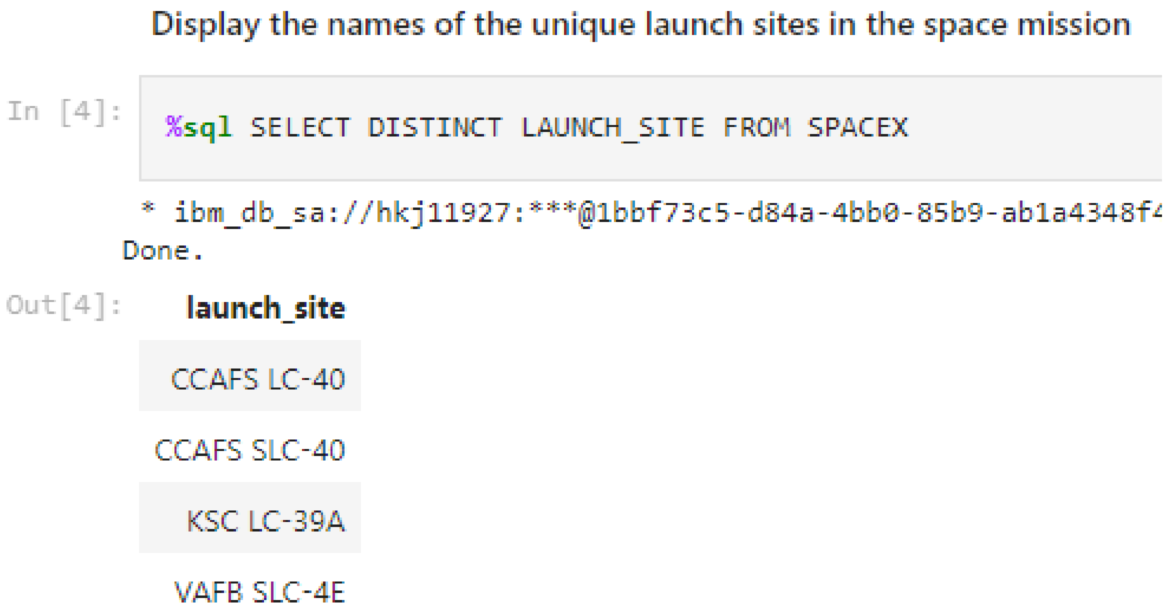
Launch Success Yearly Trend

- 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

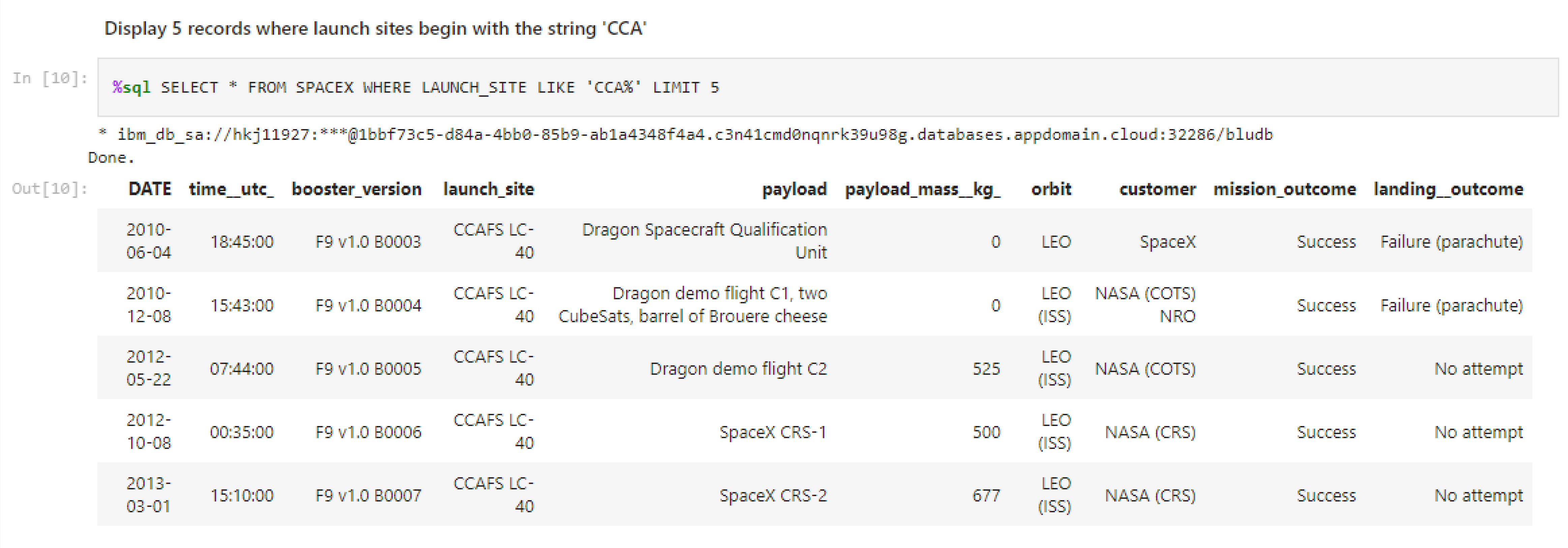
```
In [4]:  %sql SELECT DISTINCT LAUNCH_SITE FROM SPACEX
```

```
 * ibm_db_sa://hkj11927:***@1bbf73c5-d84a-4bb0-85b9-ab1a4348f4
Done.
```

Out[4]:

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

Launch Site Names Begin with 'CCA'



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

```
%sql SELECT * FROM SPACEX WHERE LAUNCH_SITE LIKE 'CCA%' LIMIT 5
```

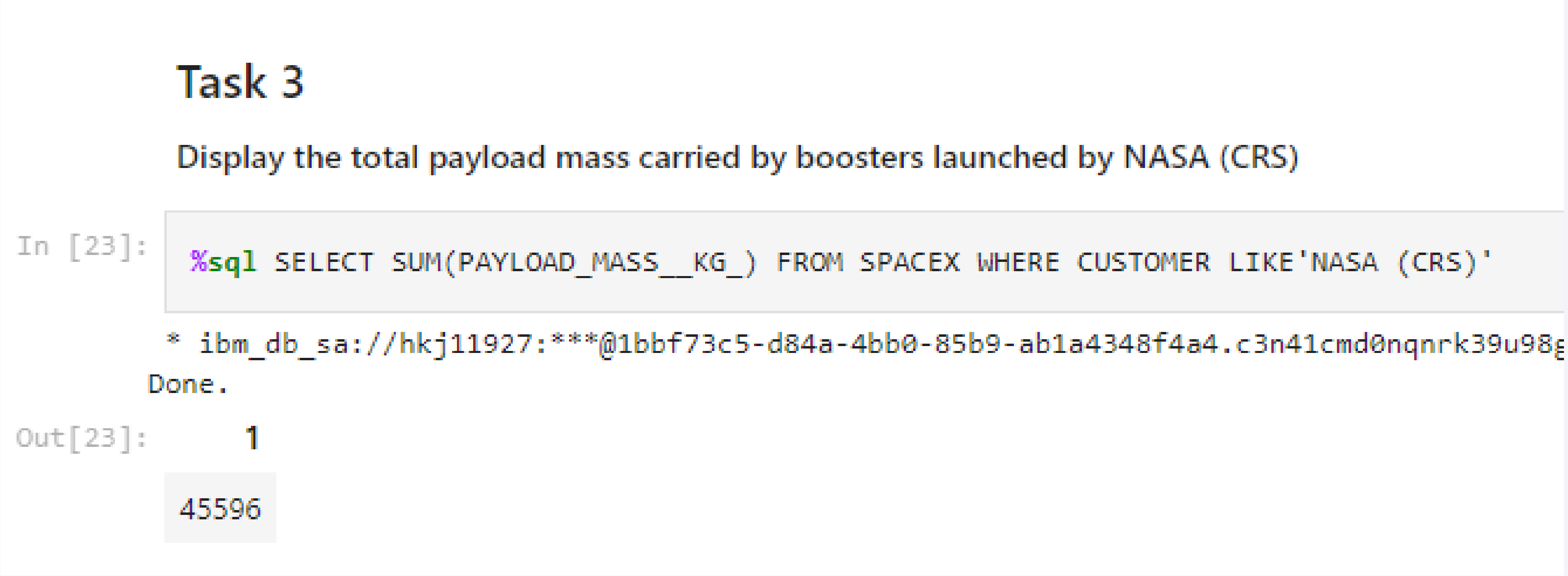
```
 * ibm_db_sa://hkj11927:***@1bbf73c5-d84a-4bb0-85b9-ab1a4348f4a4.c3n41cmd0nqnrk39u98g.databases.appdomain.cloud:32286/bludb
Done.
```

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	07:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	No attempt
2012-10-08	00:35:00	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

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

Total Payload Mass

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



Task 3

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

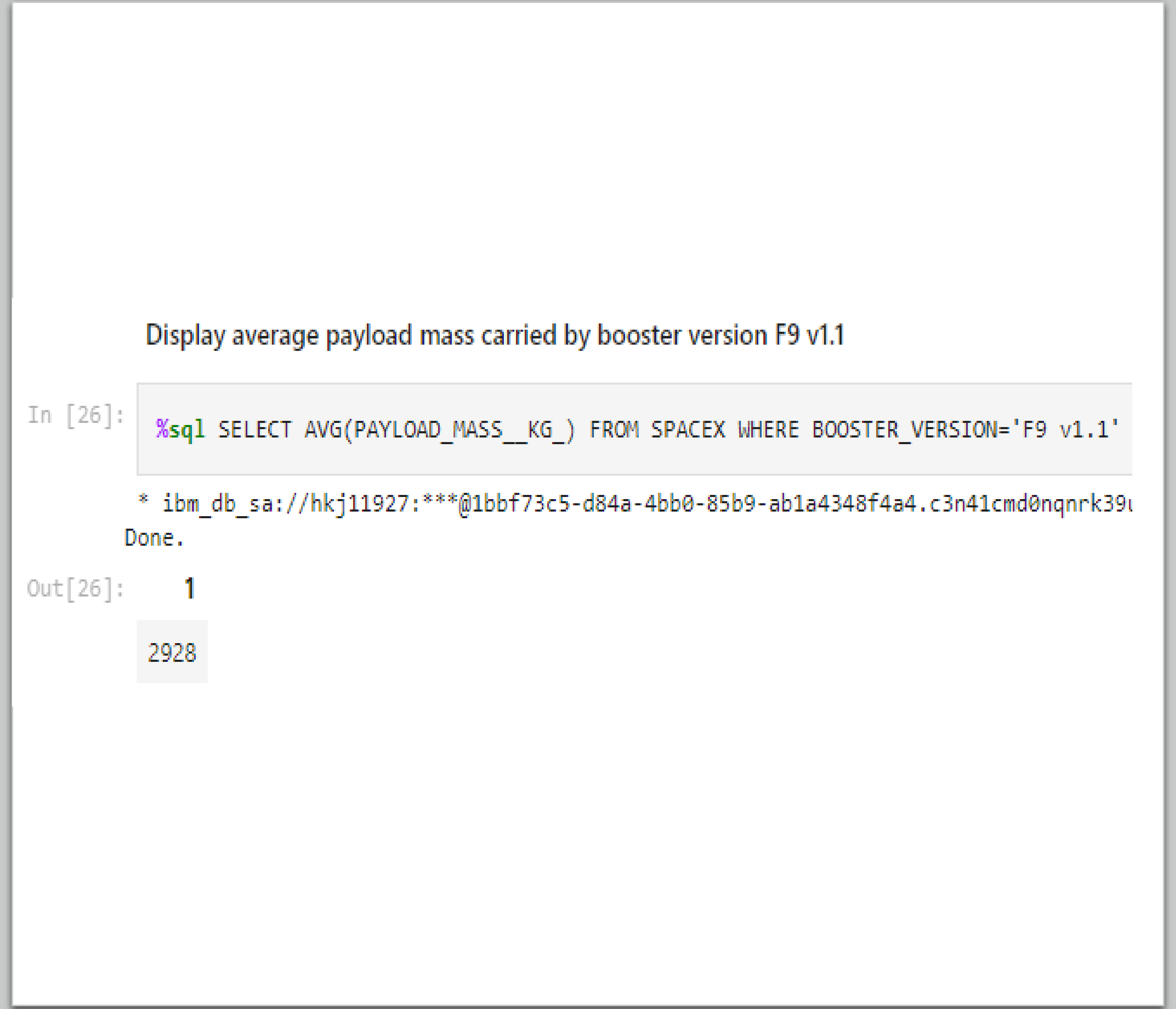
```
In [23]:  %sql SELECT SUM(PAYLOAD_MASS__KG_) FROM SPACEX WHERE CUSTOMER LIKE'NASA (CRS)'
```

```
 * ibm_db_sa://hkj11927:***@1bbf73c5-d84a-4bb0-85b9-ab1a4348f4a4.c3n41cmd0nqnrk39u98
Done.
```

```
Out[23]:      1
          45596
```

Average Payload Mass by F9 v1.1

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



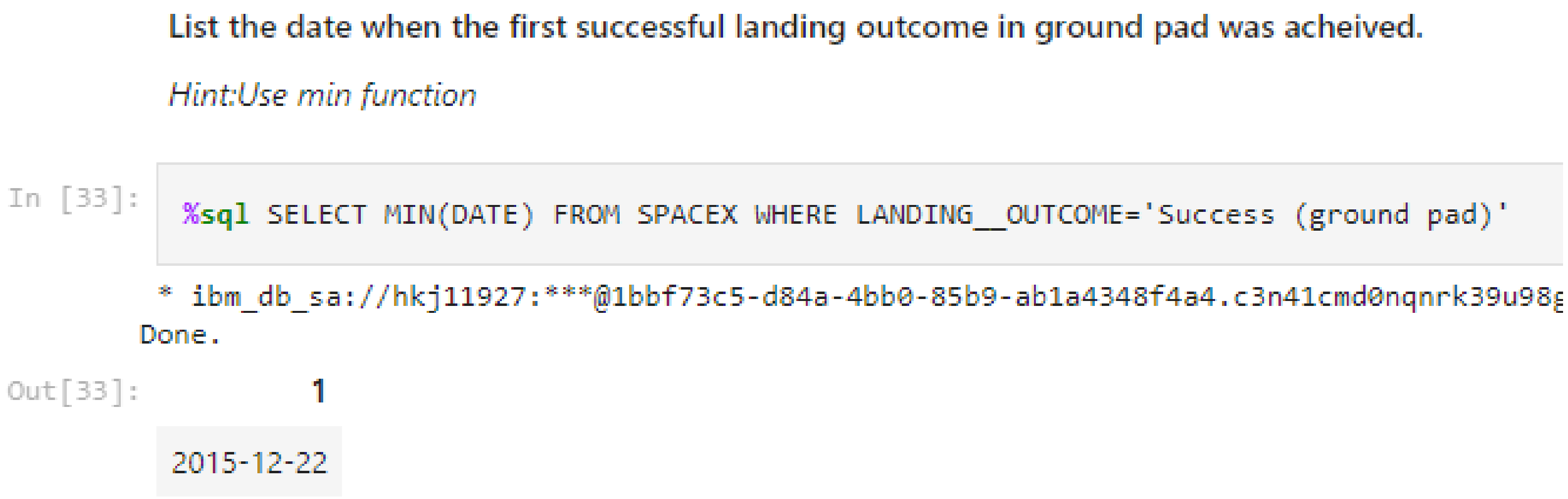
Display average payload mass carried by booster version F9 v1.1

```
In [26]:  %sql SELECT AVG(PAYLOAD_MASS__KG_) FROM SPACEX WHERE BOOSTER_VERSION='F9 v1.1'

           * ibm_db_sa://hkj11927:***@1bbf73c5-d84a-4bb0-85b9-ab1a4348f4a4.c3n41cmd0nqnrk39u
          Done.
Out[26]:     1
           2928
```

First Successful Ground Landing Date

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



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

Hint:Use min function

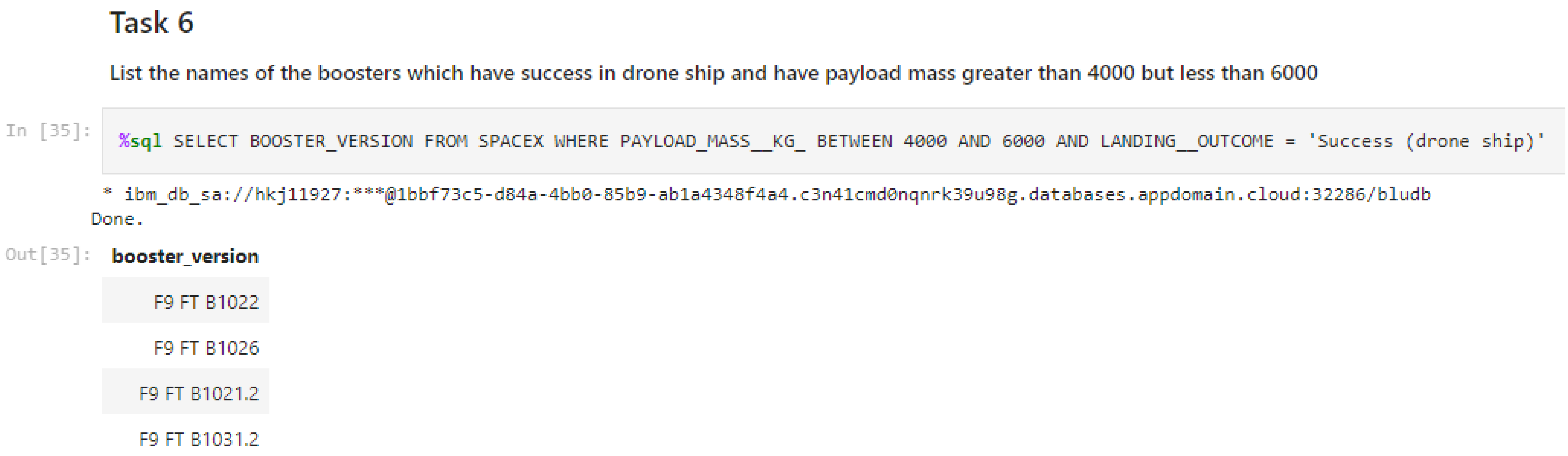
```
In [33]:  %sql SELECT MIN(DATE) FROM SPACEX WHERE LANDING__OUTCOME='Success (ground pad)'

           * ibm_db_sa://hkj11927:***@1bbf73c5-d84a-4bb0-85b9-ab1a4348f4a4.c3n41cmd0nqnrk39u98g
          Done.

Out[33]:           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



Task 6

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

```
In [35]: %sql SELECT BOOSTER_VERSION FROM SPACEX WHERE PAYLOAD_MASS__KG_ BETWEEN 4000 AND 6000 AND LANDING__OUTCOME = 'Success (drone ship)'
```

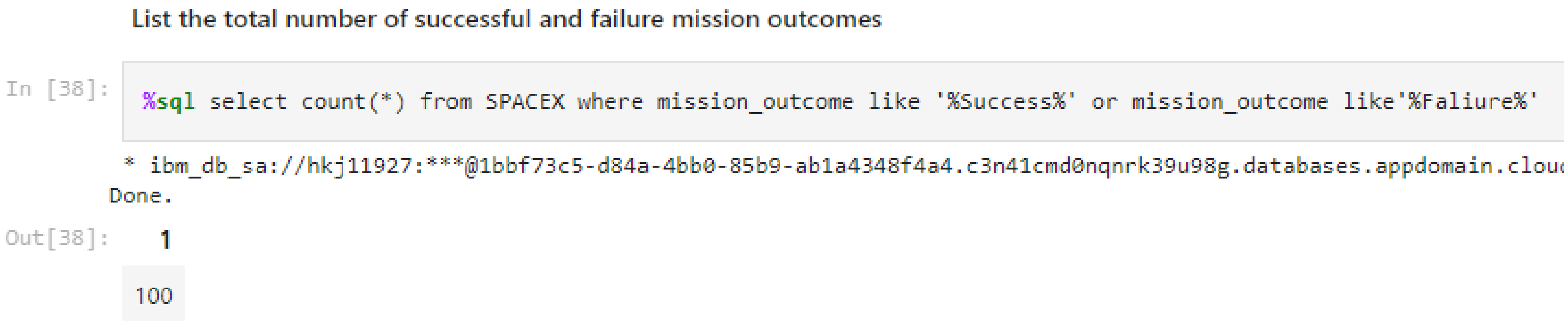
```
 * ibm_db_sa://hkj11927:***@1bbf73c5-d84a-4bb0-85b9-ab1a4348f4a4.c3n41cmd0nqnrk39u98g.databases.appdomain.cloud:32286/bludb
Done.
```

Out[35]:

booster_version
F9 FT B1022
F9 FT B1026
F9 FT B1021.2
F9 FT B1031.2

Total Number of Successful and Failure Mission Outcomes

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



List the total number of successful and failure mission outcomes

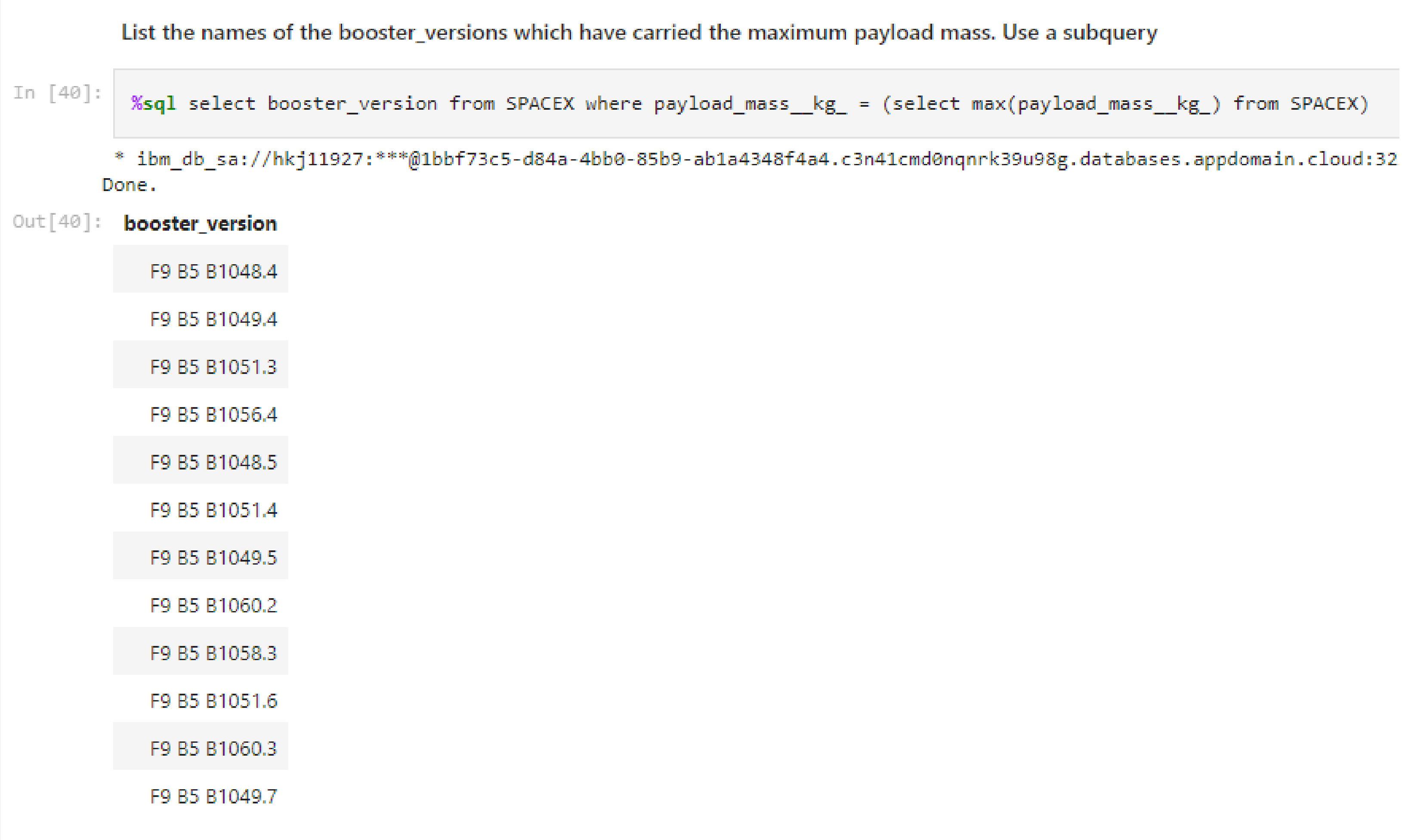
```
In [38]: %sql select count(*) from SPACEX where mission_outcome like '%Success%' or mission_outcome like'%Faliure%'
```

```
 * ibm_db_sa://hkj11927:***@1bbf73c5-d84a-4bb0-85b9-ab1a4348f4a4.c3n41cmd0nqnrk39u98g.databases.appdomain.clou
Done.
```

```
Out[38]:   1
         100
```

Boosters Carried Maximum Payload

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



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

```
In [40]: %sql select booster_version from SPACEX where payload_mass__kg_ = (select max(payload_mass__kg_) from SPACEX)
```

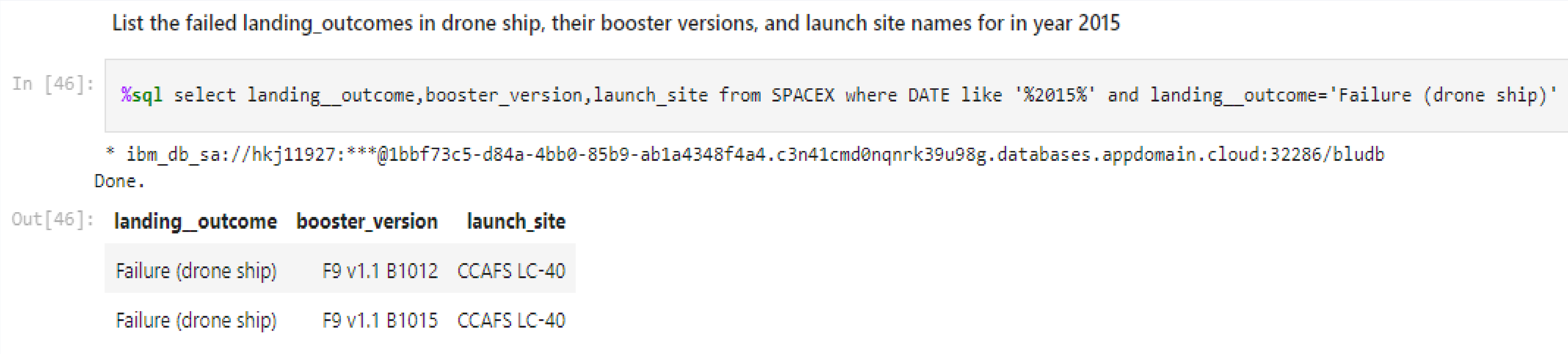
```
 * ibm_db_sa://hkj11927:***@1bbf73c5-d84a-4bb0-85b9-ab1a4348f4a4.c3n41cmd0nqnrk39u98g.databases.appdomain.cloud:32
Done.
```

Out[40]:

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

2015 Launch Records

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



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

```
In [46]:  %sql select landing__outcome,booster_version,launch_site from SPACEX where DATE like '%2015%' and landing__outcome='Failure (drone ship)'
```

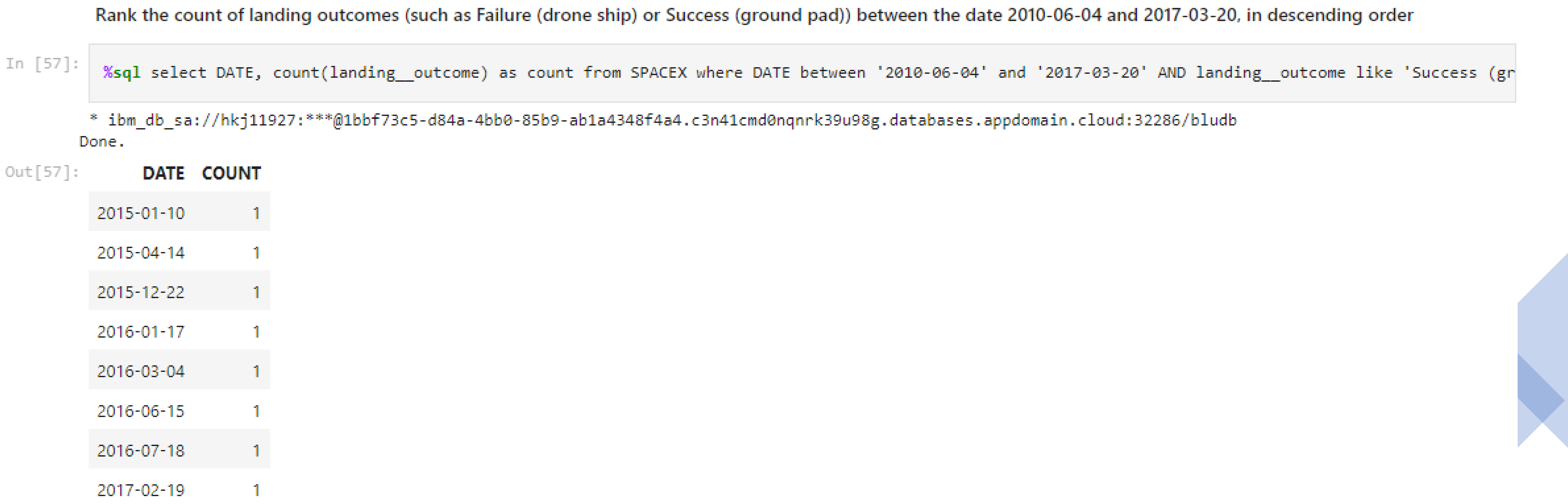
```
 * ibm_db_sa://hkj11927:***@1bbf73c5-d84a-4bb0-85b9-ab1a4348f4a4.c3n41cmd0nqnrk39u98g.databases.appdomain.cloud:32286/bludb
Done.
```

Out[46]:

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 [57]: %sql select DATE, count(landing__outcome) as count from SPACEX where DATE between '2010-06-04' and '2017-03-20' AND landing__outcome like 'Success (gr
```

```
 * ibm_db_sa://hkj11927:***@1bbf73c5-d84a-4bb0-85b9-ab1a4348f4a4.c3n41cmd0nqnrk39u98g.databases.appdomain.cloud:32286/bludb
Done.
```

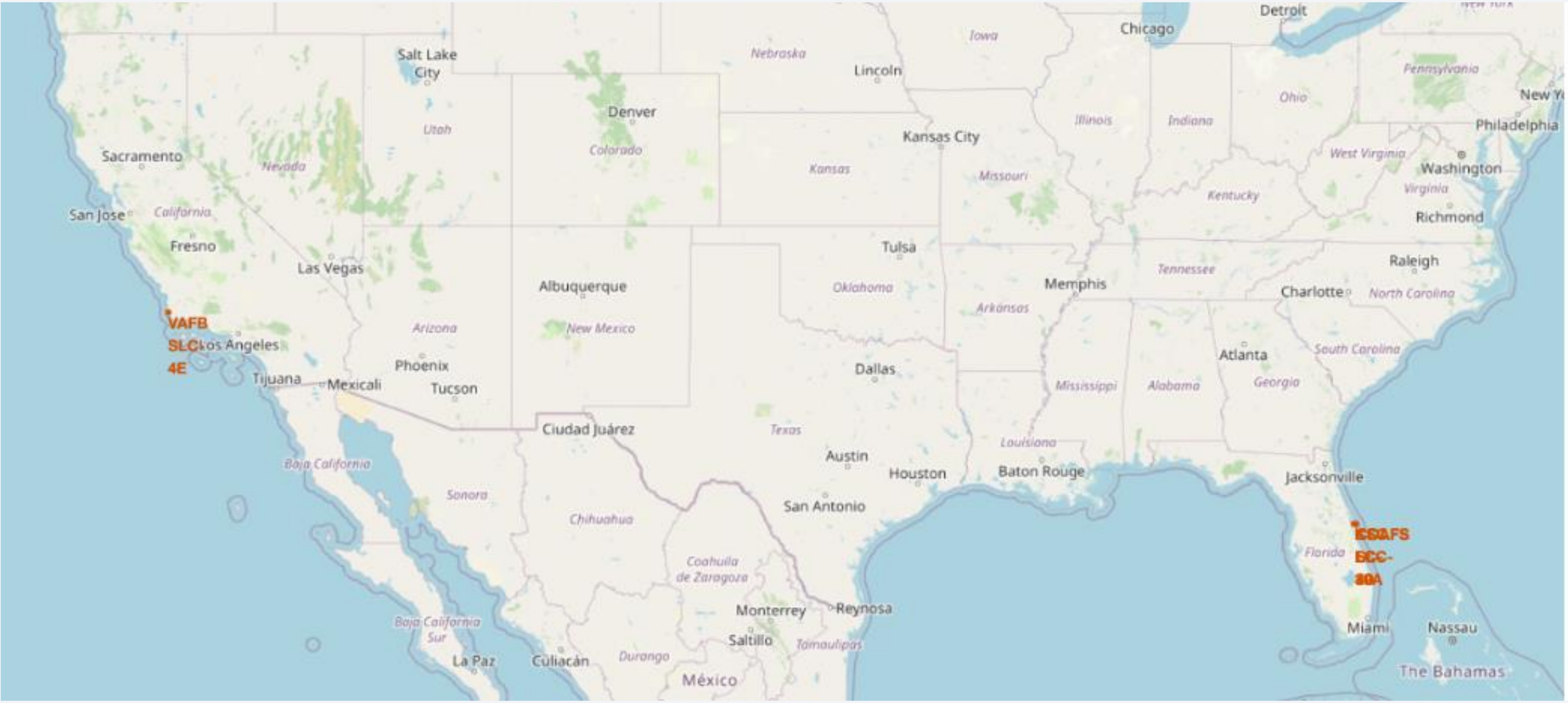
Out[57]:

DATE	COUNT
2015-01-10	1
2015-04-14	1
2015-12-22	1
2016-01-17	1
2016-03-04	1
2016-06-15	1
2016-07-18	1
2017-02-19	1

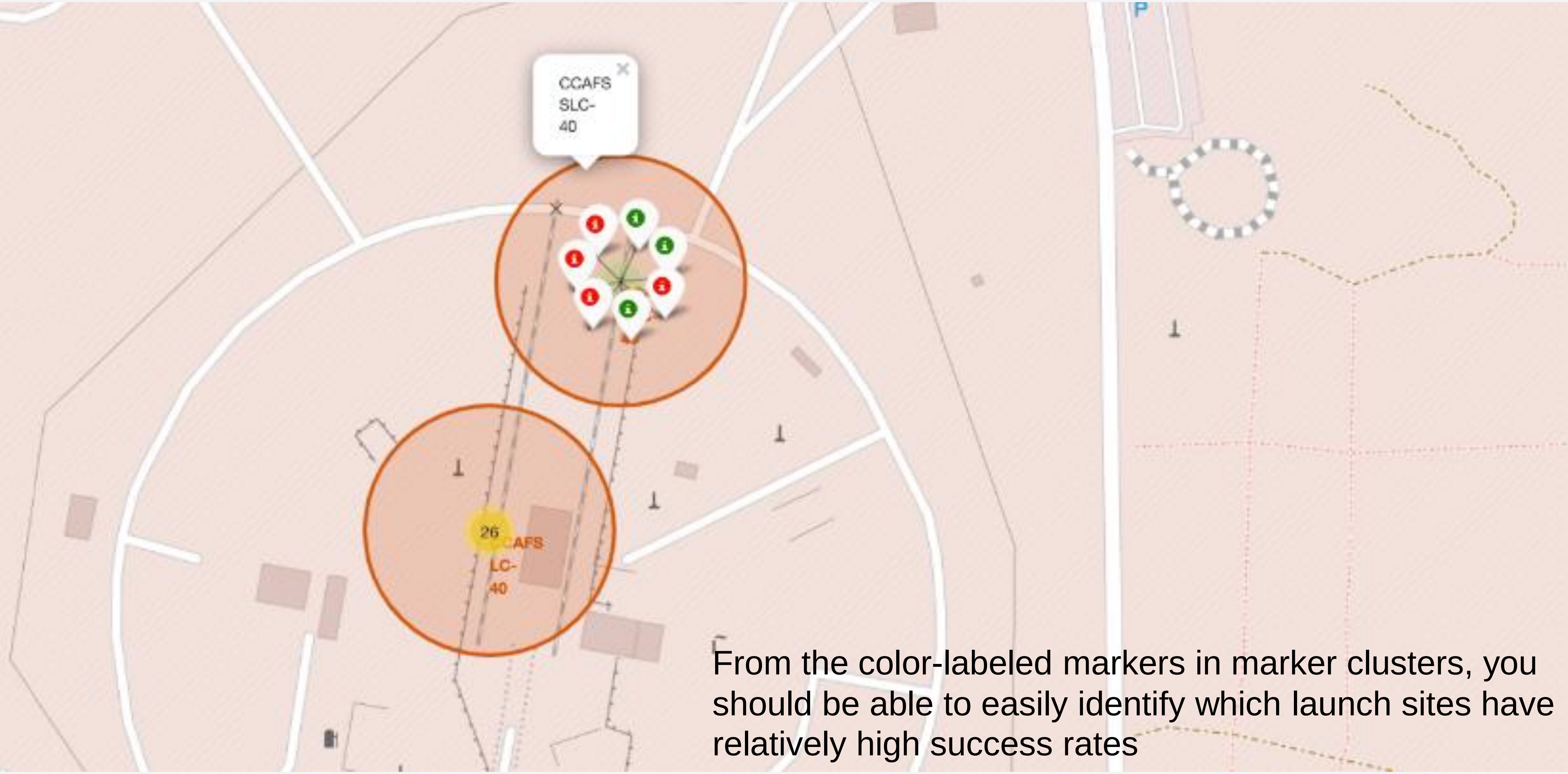
Section 4

Launch Sites Proximities Analysis

All launch sites global map markers

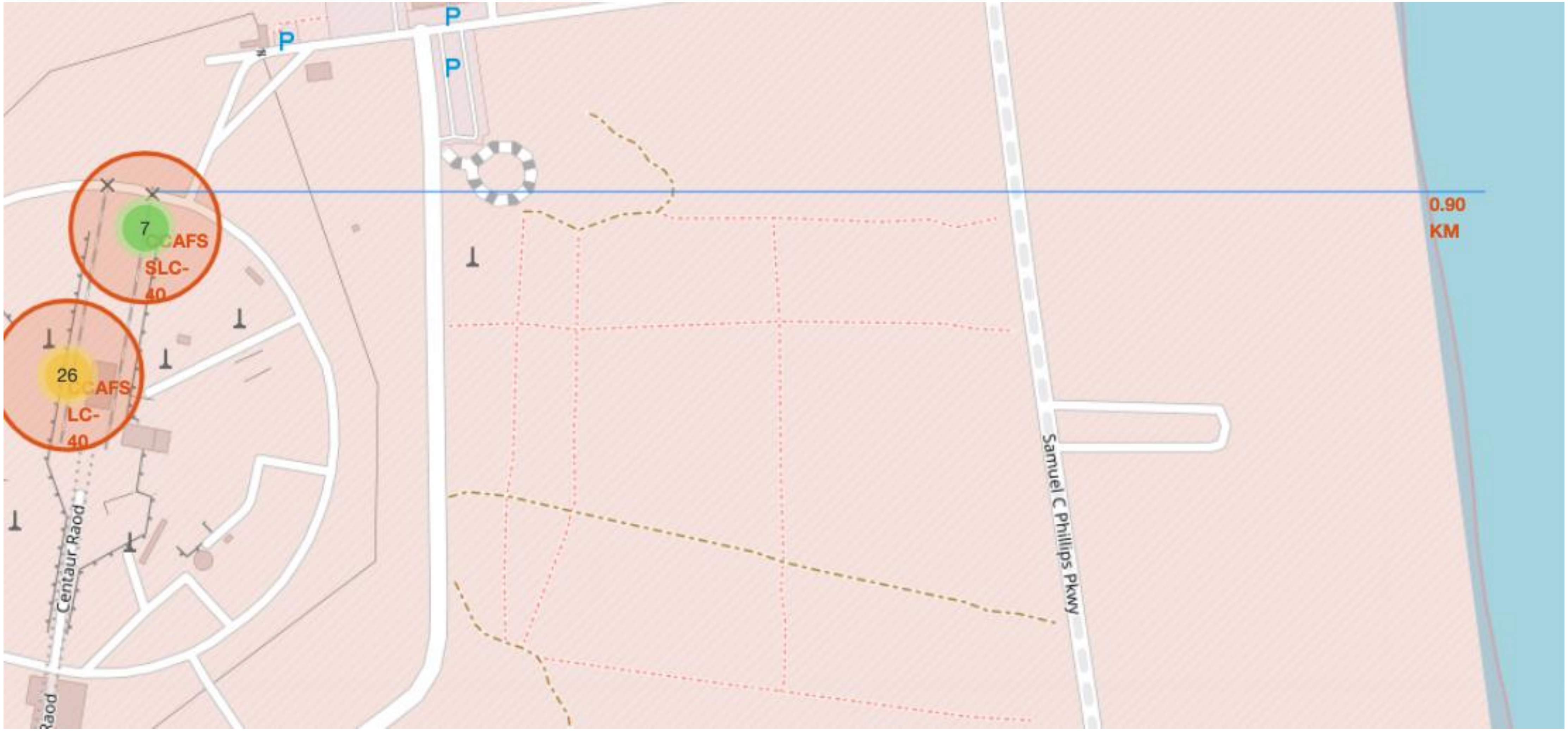


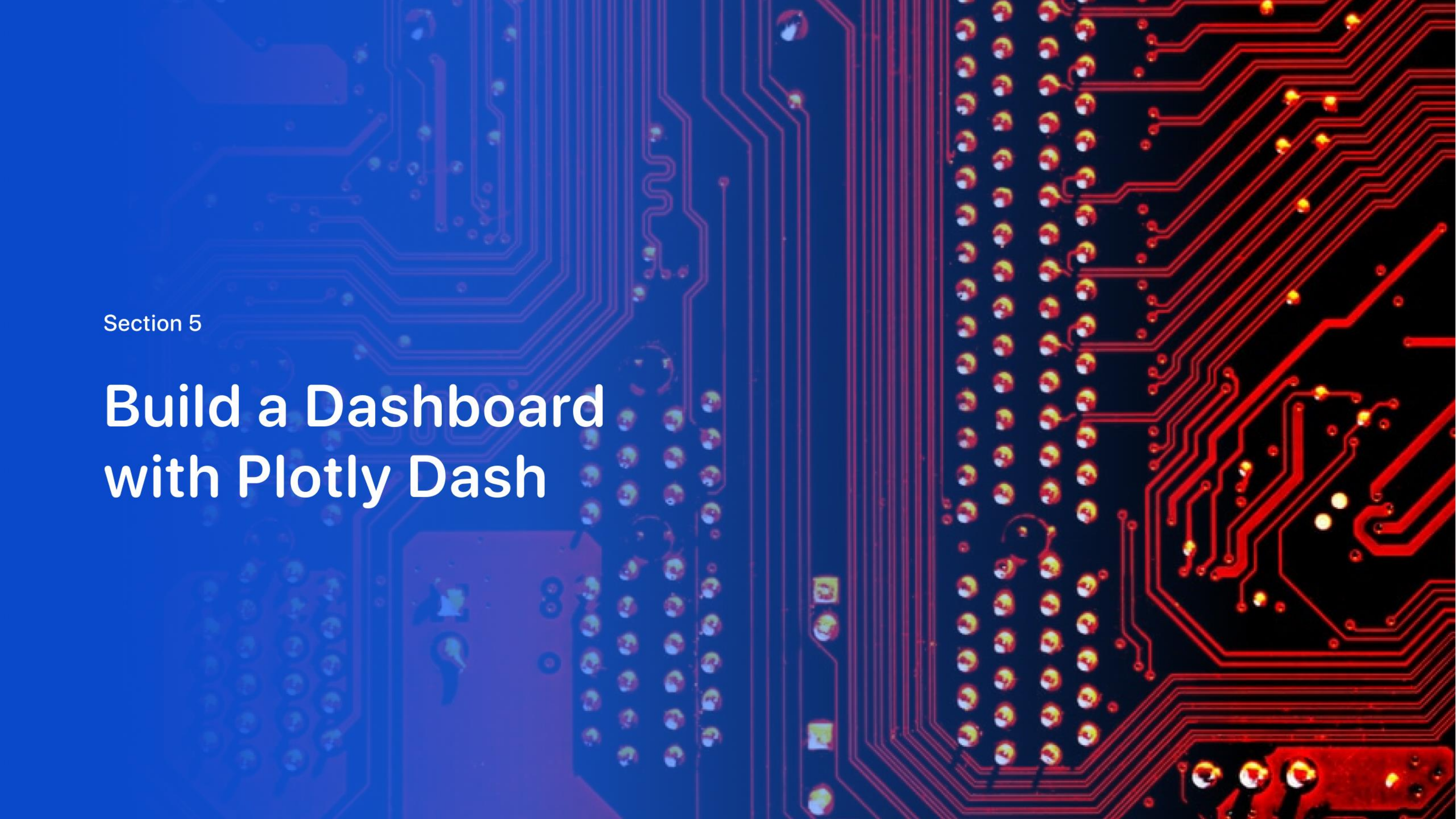
Markers showing launch sites with color labels



From the color-labeled markers in marker clusters, you should be able to easily identify which launch sites have relatively high success rates

Launch Site distance from coast

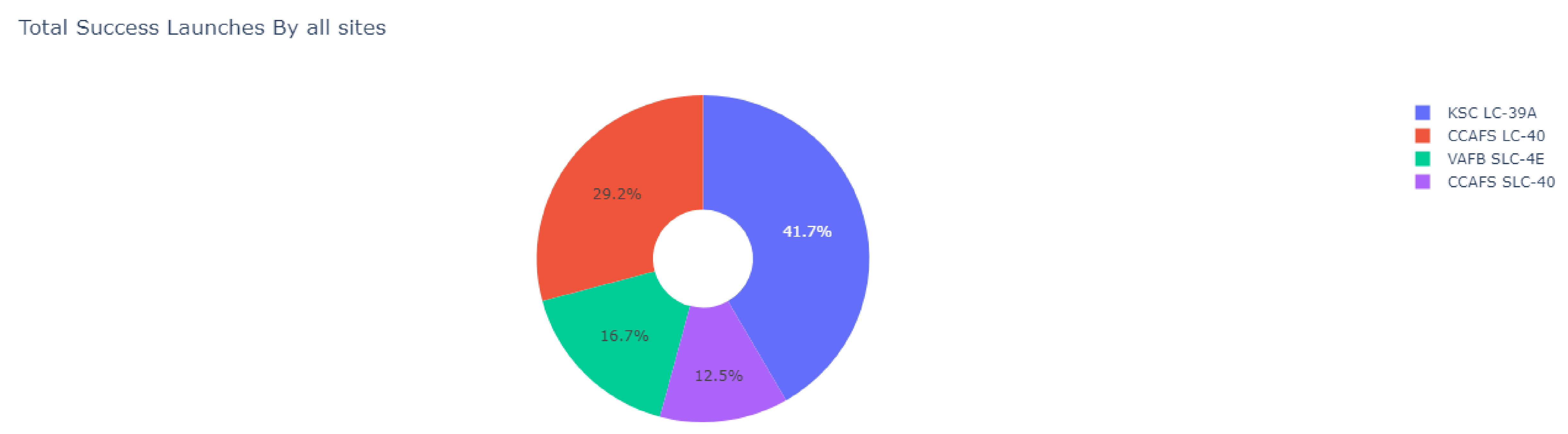




Section 5

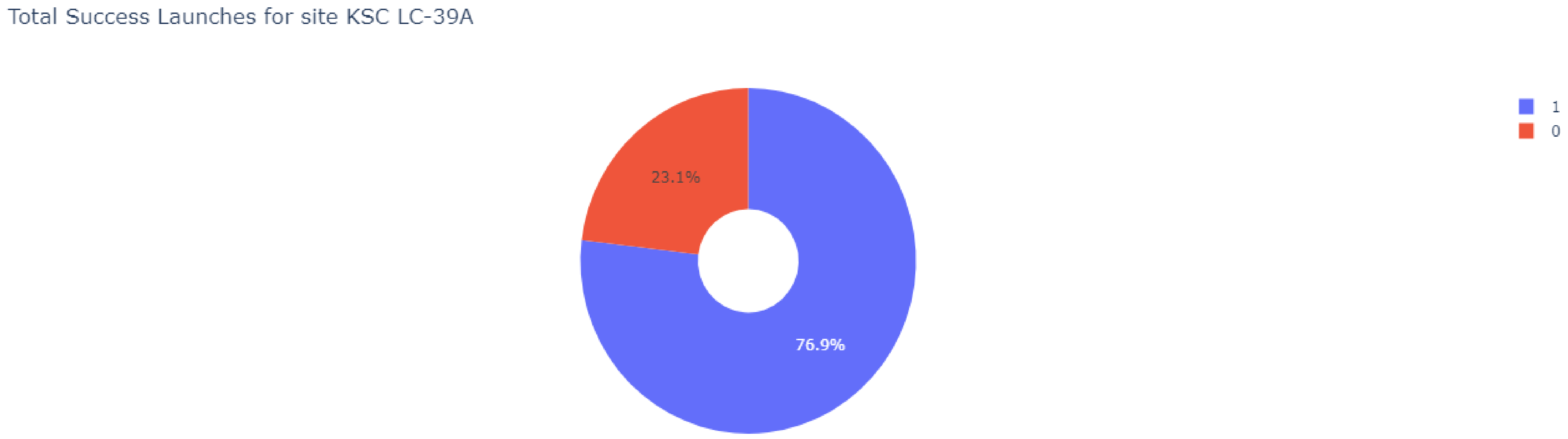
Build a Dashboard with Plotly Dash

Pie chart showing the success percentage achieved by each launch site

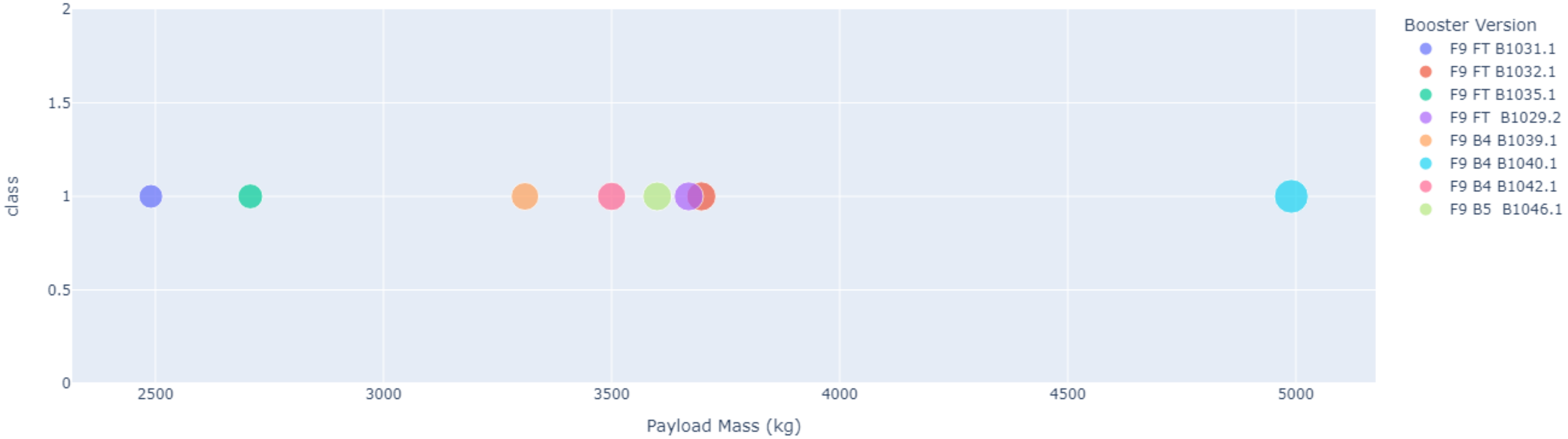


Total Success Launches By all sites

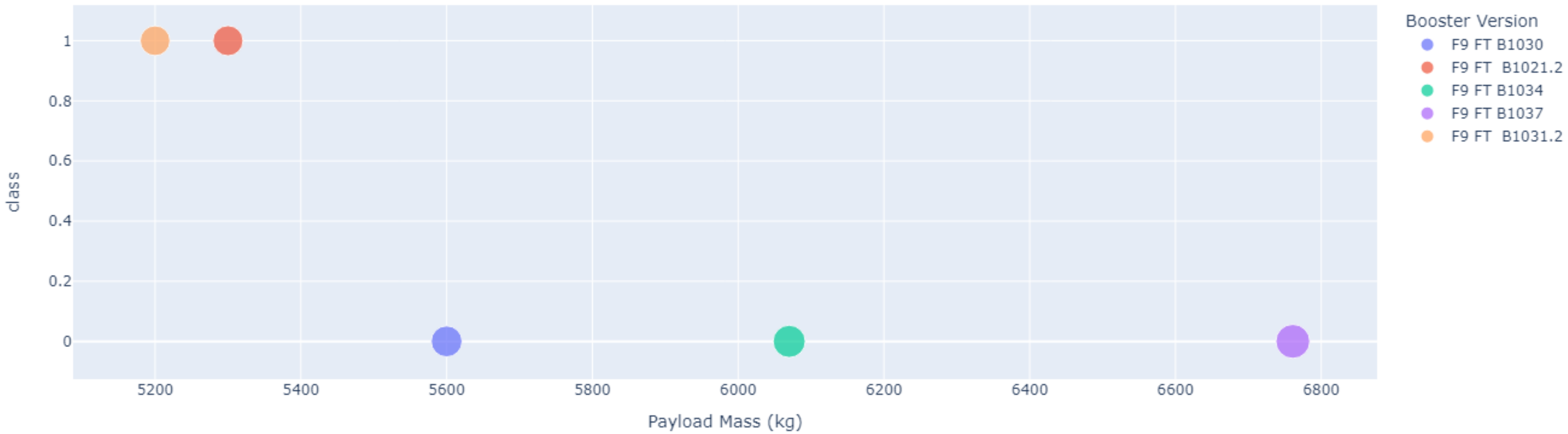
Pie chart showing the Launch site with the highest launch success ratio



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



Low payload mass 0-5000 kg



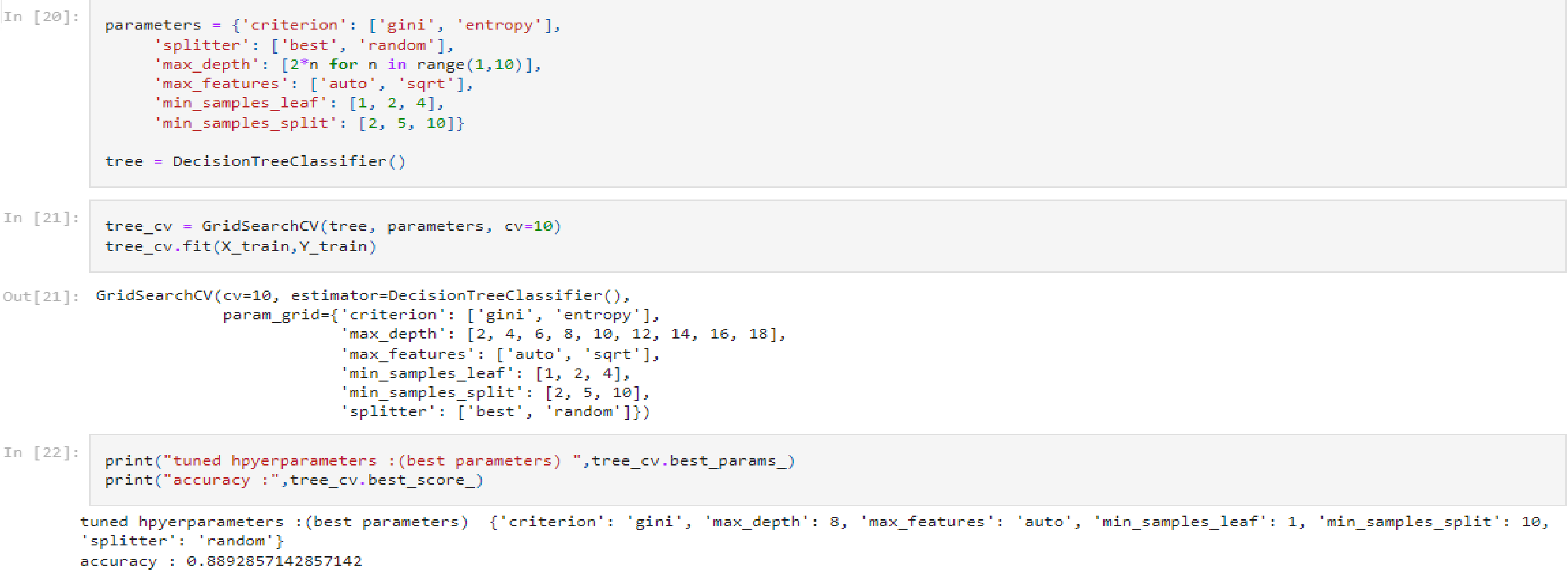
Low payload mass 5000-10000 kg

Section 6

Predictive Analysis (Classification)

Classification Model Accuracy

The decision tree classifier gives the highest accuracy.



```
In [20]:  parameters = {'criterion': ['gini', 'entropy'],
               'splitter': ['best', 'random'],
               'max_depth': [2*n for n in range(1,10)],
               'max_features': ['auto', 'sqrt'],
               'min_samples_leaf': [1, 2, 4],
               'min_samples_split': [2, 5, 10]}

          tree = DecisionTreeClassifier()
```

```
In [21]:  tree_cv = GridSearchCV(tree, parameters, cv=10)
          tree_cv.fit(X_train,Y_train)
```

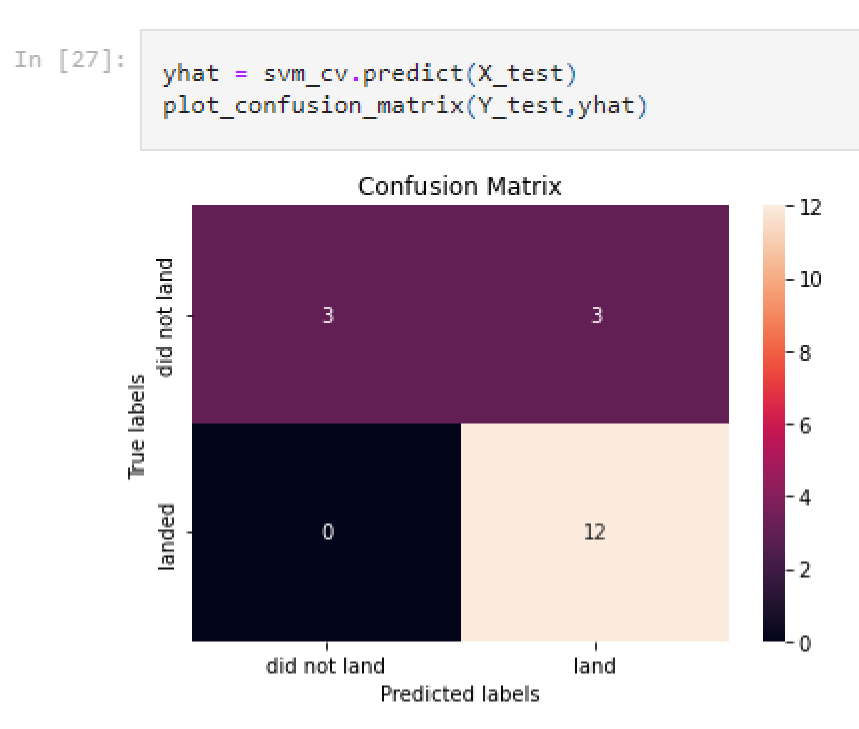
```
Out[21]: GridSearchCV(cv=10, estimator=DecisionTreeClassifier(),
                      param_grid={'criterion': ['gini', 'entropy'],
                                  'max_depth': [2, 4, 6, 8, 10, 12, 14, 16, 18],
                                  'max_features': ['auto', 'sqrt'],
                                  'min_samples_leaf': [1, 2, 4],
                                  'min_samples_split': [2, 5, 10],
                                  'splitter': ['best', 'random']})
```

```
In [22]:  print("tuned hpyerparameters :(best parameters) ",tree_cv.best_params_)
          print("accuracy :",tree_cv.best_score_)
```

```
tuned hpyerparameters :(best parameters)  {'criterion': 'gini', 'max_depth': 8, 'max_features': 'auto', 'min_samples_leaf': 1, 'min_samples_split': 10,
'splitter': 'random'}
accuracy : 0.8892857142857142
```

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.



In [27]:

```
yhat = svm_cv.predict(X_test)
plot_confusion_matrix(Y_test,yhat)
```

Conclusions

We can conclude that:

- Larger the amount of flight at a launch site, the greater the success rate.
- 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.
- The Decision tree classifier model turns out to be the best machine leaning model for this problem statement.

Thank you!