IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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Outline

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

Executive Summary

- Data Collection – Space X API & SPACE X WIKI
- Four ML Model are used -
  - Logistic Regression
  - SVM
  - Decision Tree Classifier
  - KNN
- Exported Data from SQL
- Project uses Folium Maps and Visualizations Methods
- The Accuracy Rate of Successful Landings – 83.33%

Introduction

- Aim – SPACE Y is about to compete with SPPACE X
- Service – Commercial Space Carrier
- Problem – To tackle the landings failure using Data Science
- Solution -
  - Study and Analyze SPACE X DATA
  - Calculate the findings and Deploy the Solutions at SPACE Y.

Section 1

Methodology

Methodology

Executive Summary

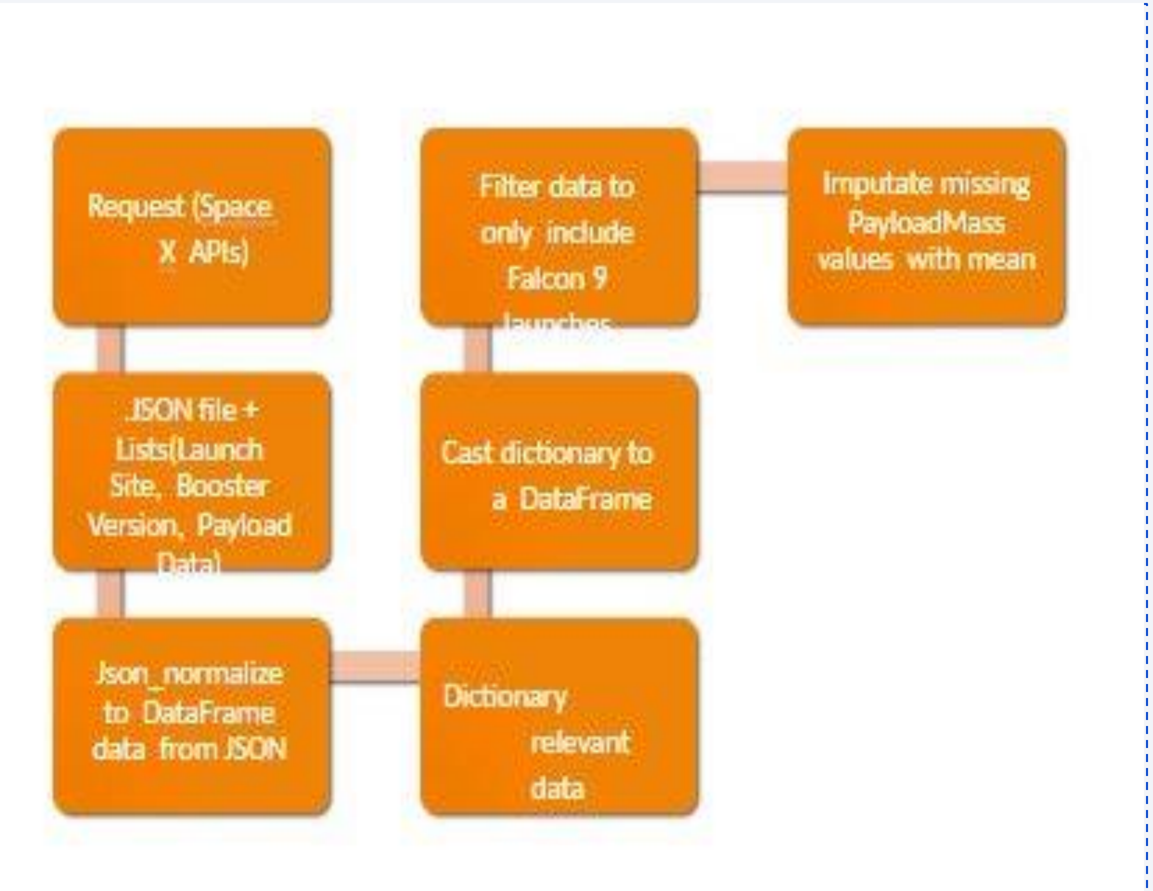
- Data collection methodology:
  - Data collected by using SPACE X API and Web Scraping
- Perform data wrangling
  - By classifying successful landings and unsuccessful landings
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
  - Tuned Models using GridSearchCV

Data Collection

- Data collection process involved a combination of API requests from Space X public API and web scraping data from a table in Space X's Wikipedia entry.
- The next slide will show the flowchart of data collection from API and the one after will show the flowchart of data collection from web scraping.
- Space X API Data Columns:
- FlightNumber, Date, BoosterVersion, PayloadMass, Orbit, LaunchSite, Outcome, Flights, GridFins,
- Reused, Legs, LandingPad, Block, ReusedCount, Serial, Longitude, Latitude
- Wikipedia Webscrape Data Columns:
- Flight No., Launch site, Payload, PayloadMass, Orbit, Customer, Launch outcome, Version Booster, Booster landing, Date, Time

Data Collection – SpaceX API

SPACE X DATA COLLECTION



Request (Space X APIs)

JSON file + Lists(Launch Site, Booster Version, Payload Data)

Json_normalize to DataFrame data from JSON

Dictionary relevant data

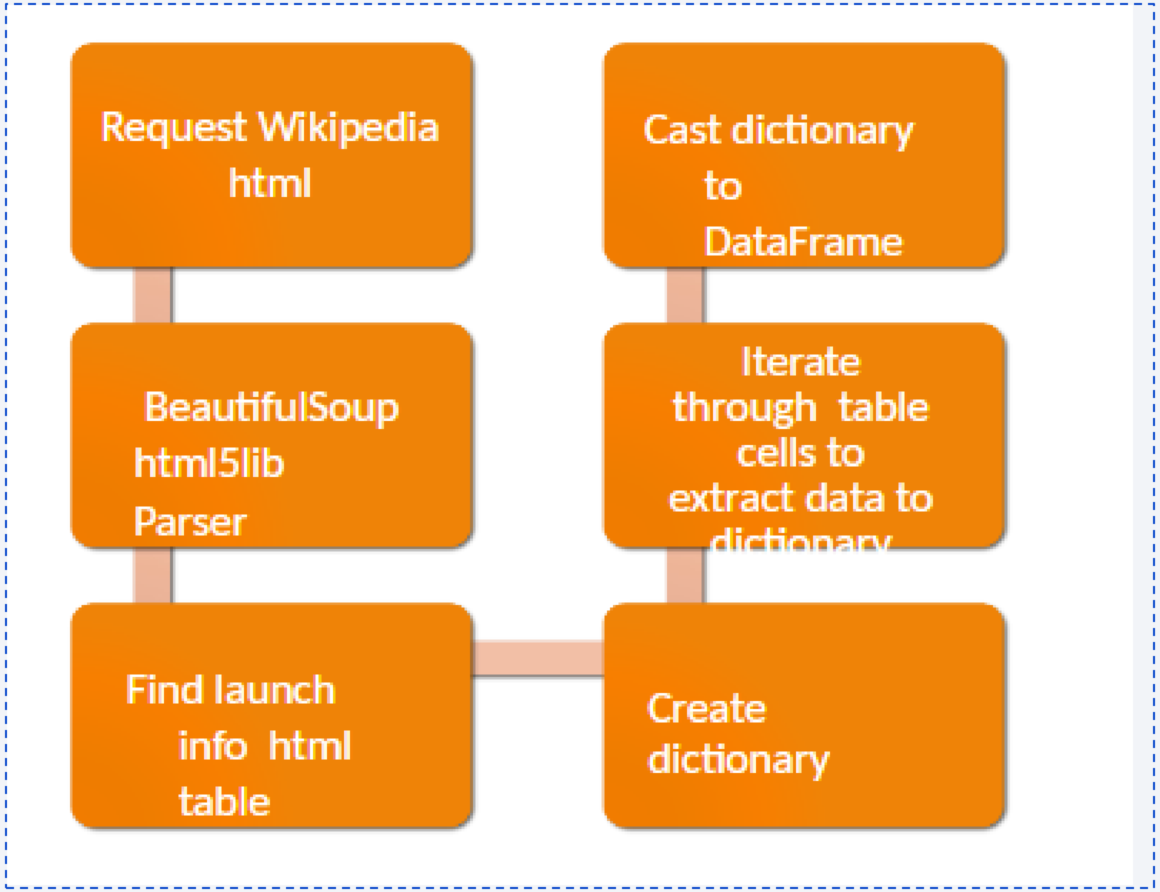
Cast dictionary to a DataFrame

Filter data to only include Falcon 9 launches

Imputate missing PayloadMass values with mean

Data Collection - Scraping

- SPACE X DATA WEB SCRAPING



Request Wikipedia html

BeautifulSoup html5lib Parser

Find launch info html table

Create dictionary

Iterate through table cells to extract data to dictionary

Cast dictionary to DataFrame

Data Wrangling

- Create a training label with landing outcomes where successful = 1 & failure = 0.
- Outcome column has two components: ‘Mission Outcome’ ‘Landing Location’
- New training label column ‘class’ with a value of 1 if ‘Mission Outcome’ is True and 0 otherwise. Value Mapping:
- True ASDS, True RTLS, & True Ocean – set to -> 1
- None None, False ASDS, None ASDS, False Ocean, False RTLS – set to -> 0

DATA WRANGLING

EDA with Data Visualization

- Exploratory Data Analysis performed on variables Flight Number, Payload Mass, Launch Site, Orbit, Class and Year.
- Plots Used:
- Flight Number vs. Payload Mass, Flight Number vs. Launch Site, Payload Mass vs. Launch Site, Orbit vs. Success Rate, Flight Number vs. Orbit, Payload vs Orbit, and Success Yearly Trend
- Scatter plots, line charts, and bar plots were used to compare relationships between variables to
- decide if a relationship exists so that they could be used in training the machine learning model
- EDA DATA VISUALIZATION

EDA with SQL

- Loaded data set into IBM DB2 Database.
- Queried using SQL Python integration.
- Queries were made to get a better understanding of the dataset.
- Queried information about launch site names, mission outcomes, various pay load sizes of customers and booster versions, and landing outcomes

EDA WITH SQL

Build an Interactive Map with Folium

- Folium maps mark Launch Sites, successful and unsuccessful landings, and a proximity example to key locations: Railway, Highway, Coast, and City.
- This allows us to understand why launch sites may be located where they are. Also visualizes successful landings relative to location.

- FOLLIUM MAPS

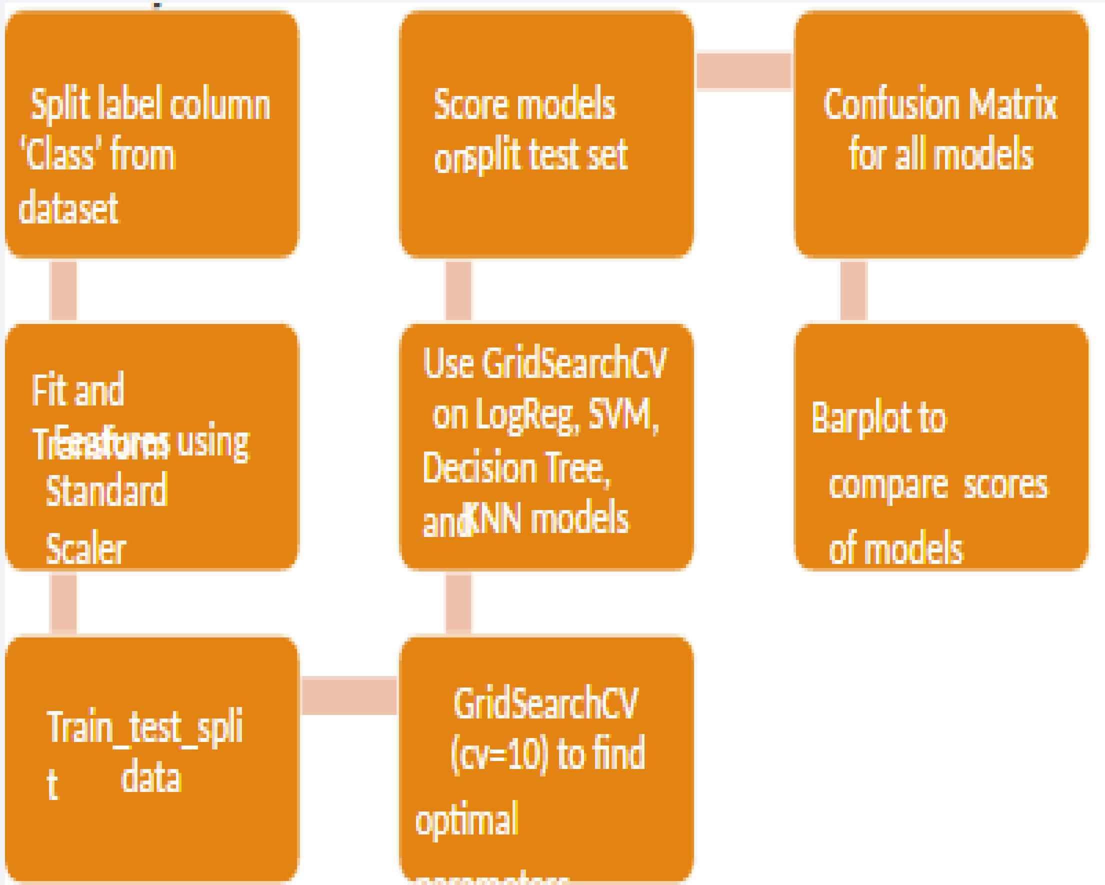
Build a Dashboard with Plotly Dash

- Dashboard includes a pie chart and a scatter plot.
- Pie chart can be selected to show distribution of successful landings across all launch sites and can be selected to show individual launch site success rates.
- Scatter plot takes two inputs: All sites or individual site and payload mass on a slider between 0 and 10000 kg.
- The pie chart is used to visualize launch site success rate.
- The scatter plot can help us see how success varies across launch sites, payload mass, and
- booster version category.

- PLOTLY AND DASH - DASHBOARD

Predictive Analysis (Classification)

ML CLASSIFICATION AND PREDICTION



Split label column 'Class' from dataset

Fit and Transform Features using Standard Scaler

Train_test_split data

GridSearchCV (cv=10) to find optimal parameters

Use GridSearchCV on LogReg, SVM, Decision Tree, and KNN models

Score models on split test set

Confusion Matrix for all models

Barplot to compare scores of models

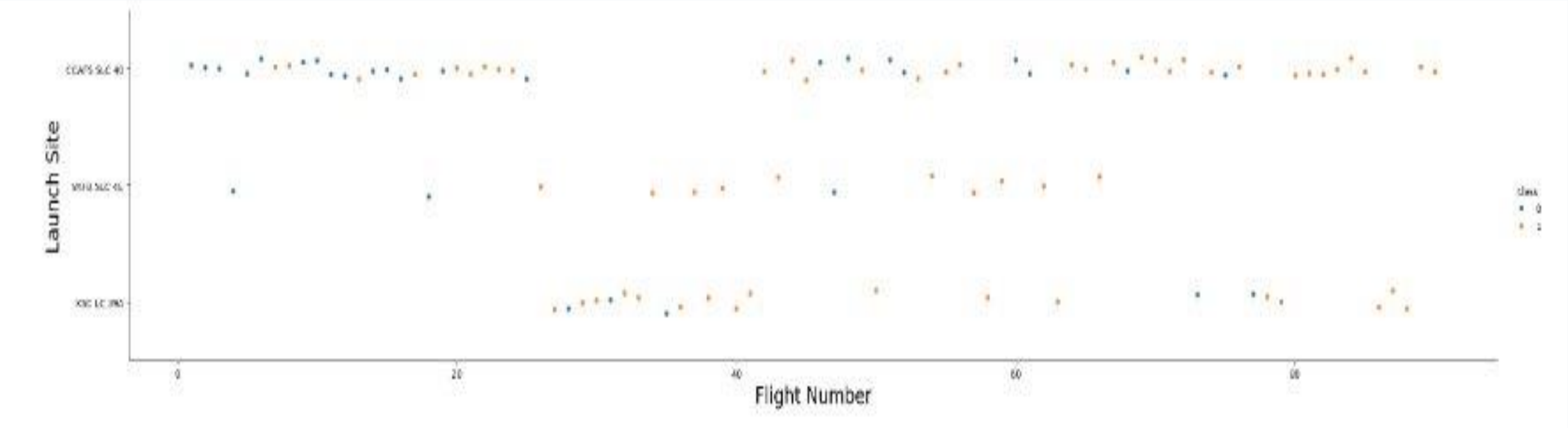
Results

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

Section 2

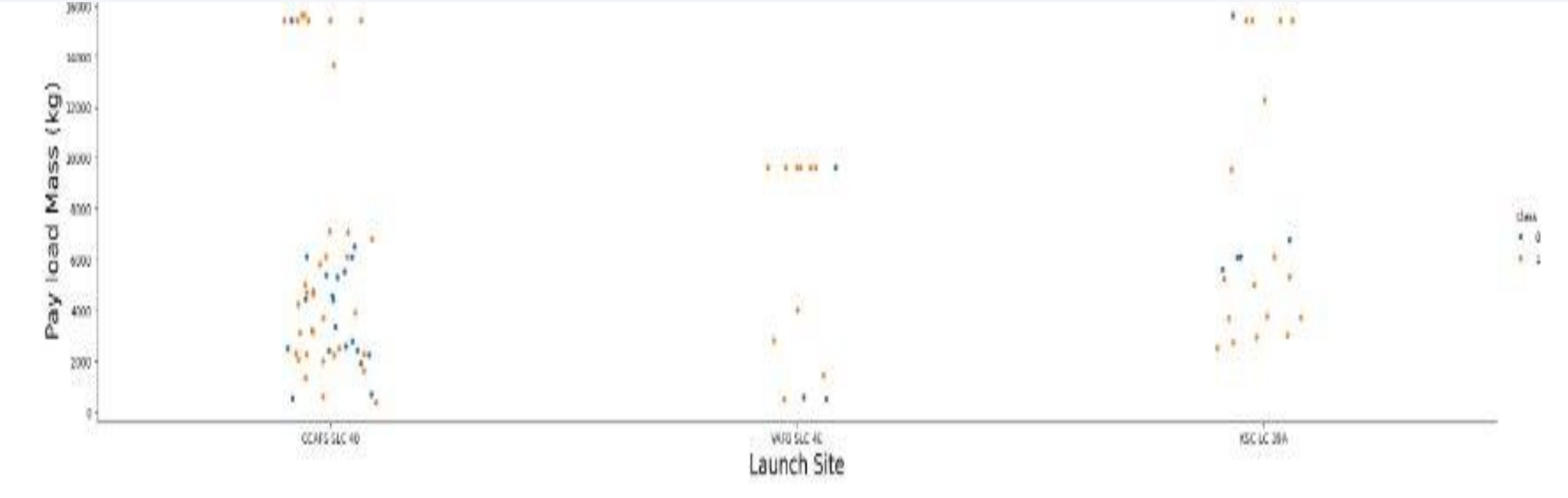
Insights drawn from EDA

Flight Number vs. Launch Site



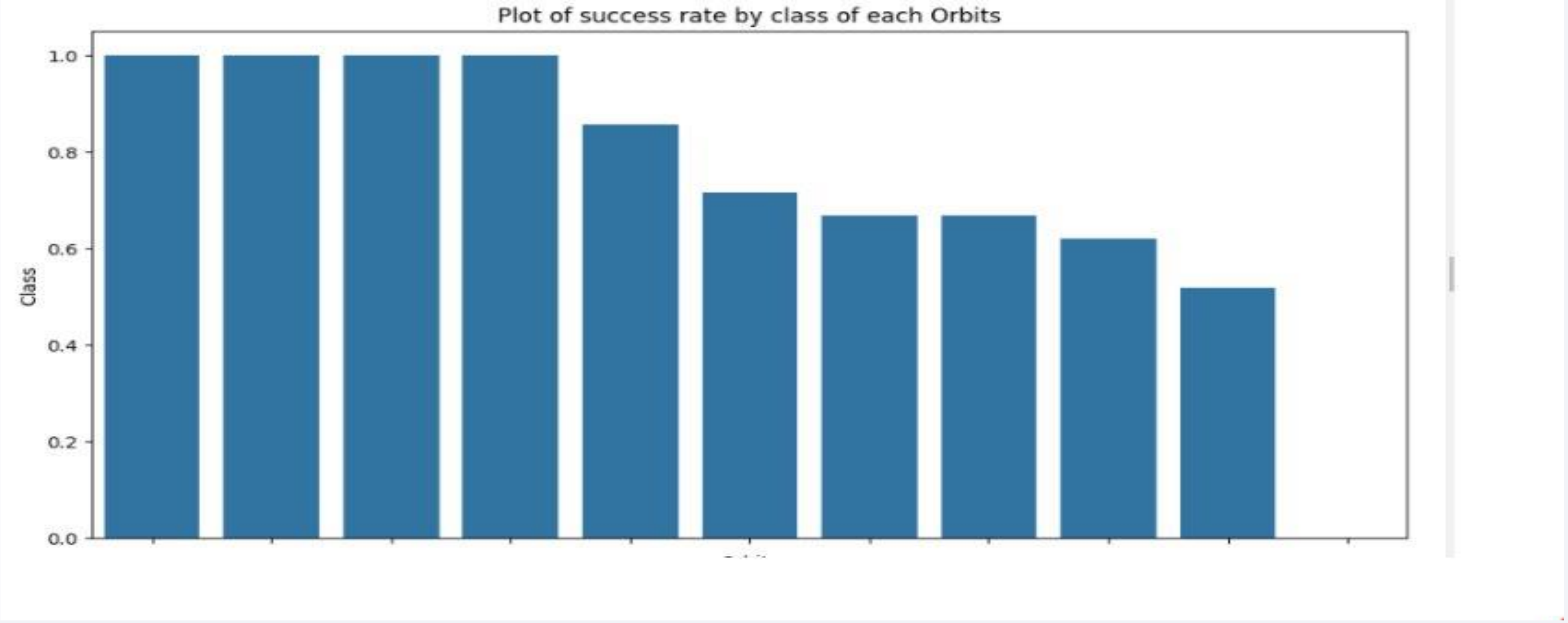
Graphic suggests an increase in success rate over time (indicated in Flight Number). Likely a big breakthrough around flight 20 which significantly increased success rate. CCAFS appears to be the main launch site as it has the most volume.

Payload vs. Launch Site



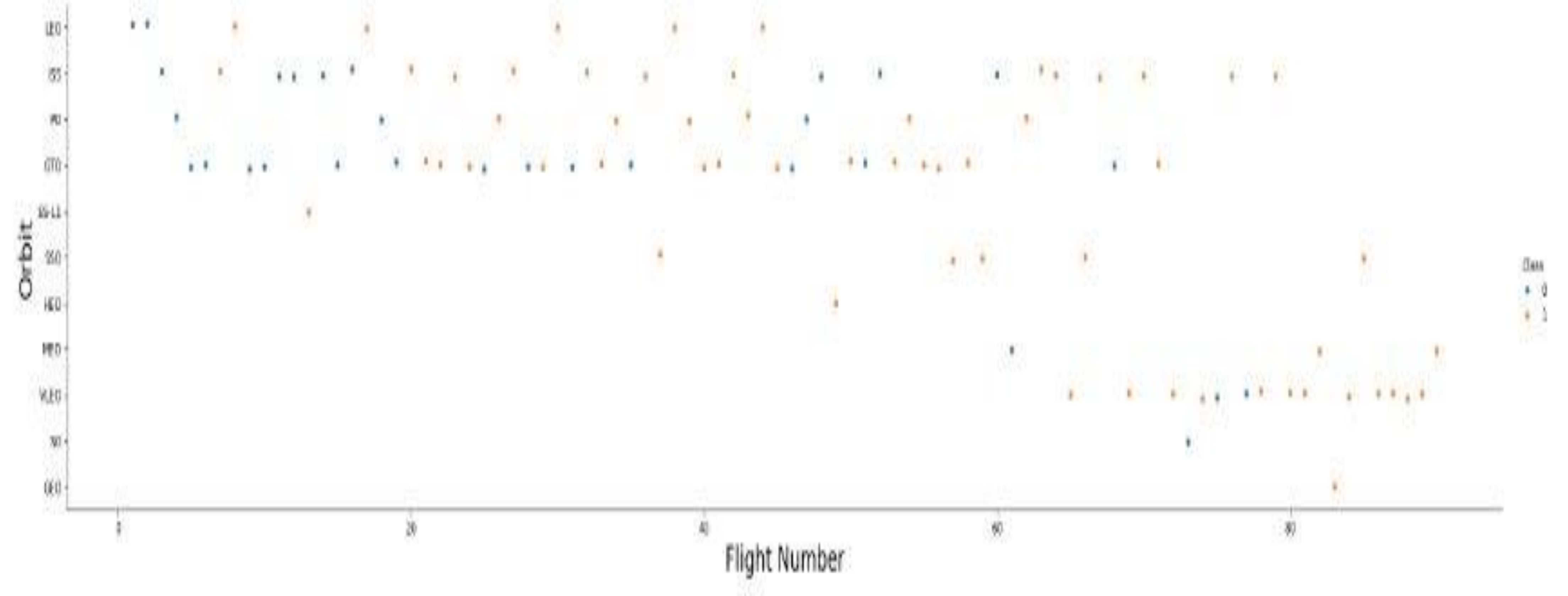
Payload mass appears to fall mostly between 0-6000 kg. Different launch sites also seem to use different payload mass.

Success Rate vs. Orbit Type



ES-L1 (1), GEO (1), HEO (1) have 100% success rate (sample sizes in parenthesis) SSO (5) has 100% success rate
VLEO (14) has decent success rate and attempts
SO (1) has 0% success rate
GTO (27) has the around 50% success rate but largest sample

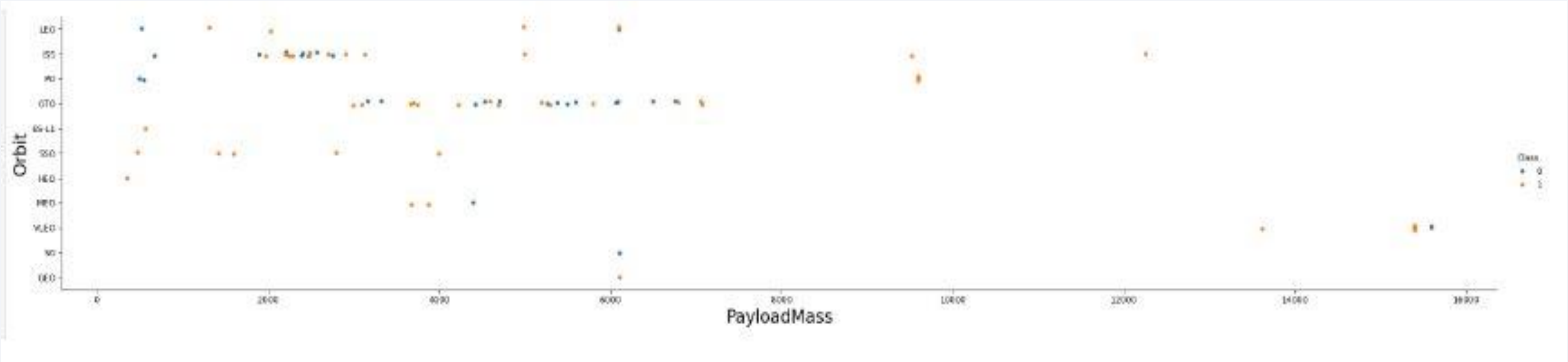
Flight Number vs. Orbit Type



Launch Orbit preferences changed over Flight Number. Launch Outcome seems to correlate with this preference.

SpaceX started with LEO orbits which saw moderate success LEO and returned to VLEO in recent launches SpaceX appears to perform better in lower orbits or Sun-synchronous orbits

Payload vs. Orbit Type

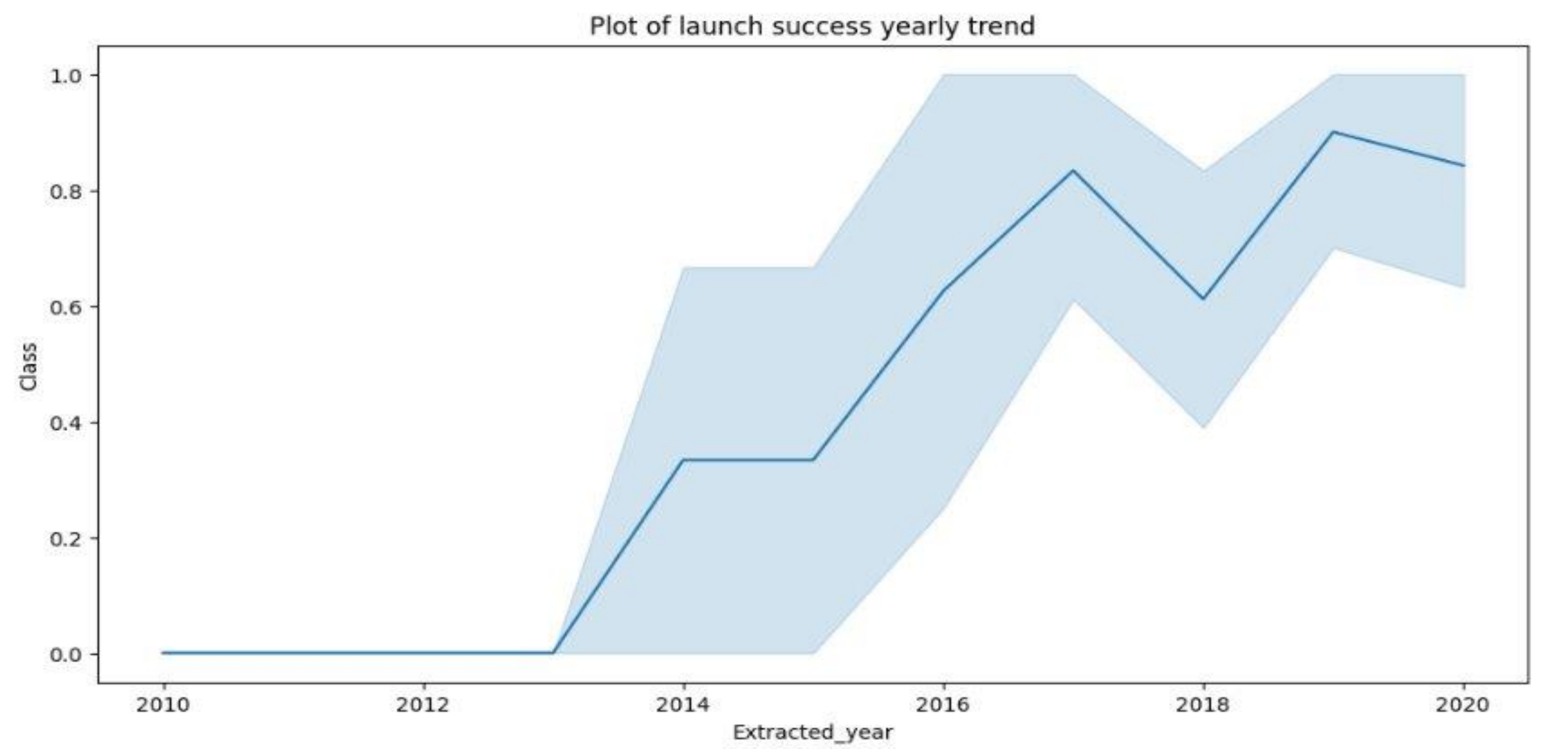


Payload mass seems to correlate with orbit

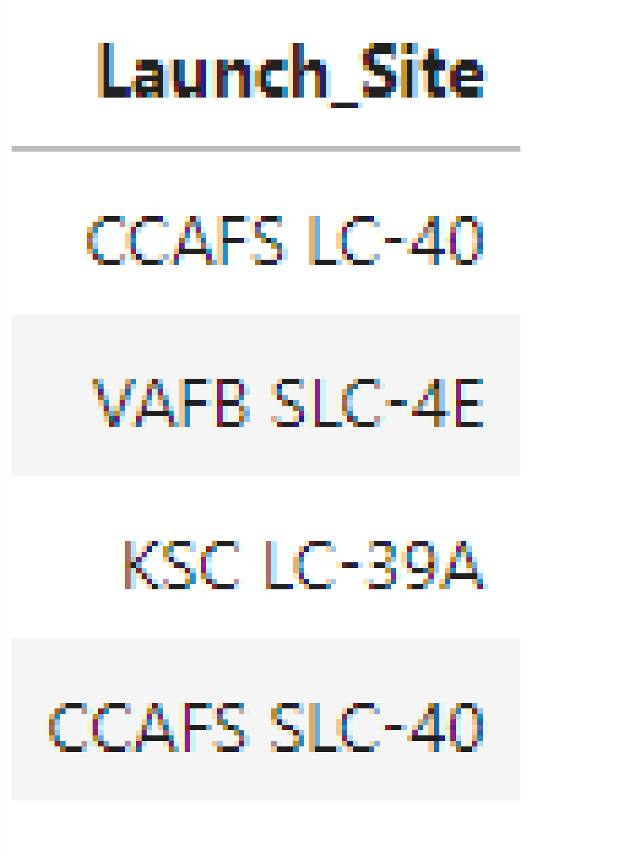
LEO and SSO seem to have relatively low payload mass

The other most successful orbit VLEO only has payload mass values in the higher end of the range

Launch Success Yearly Trend



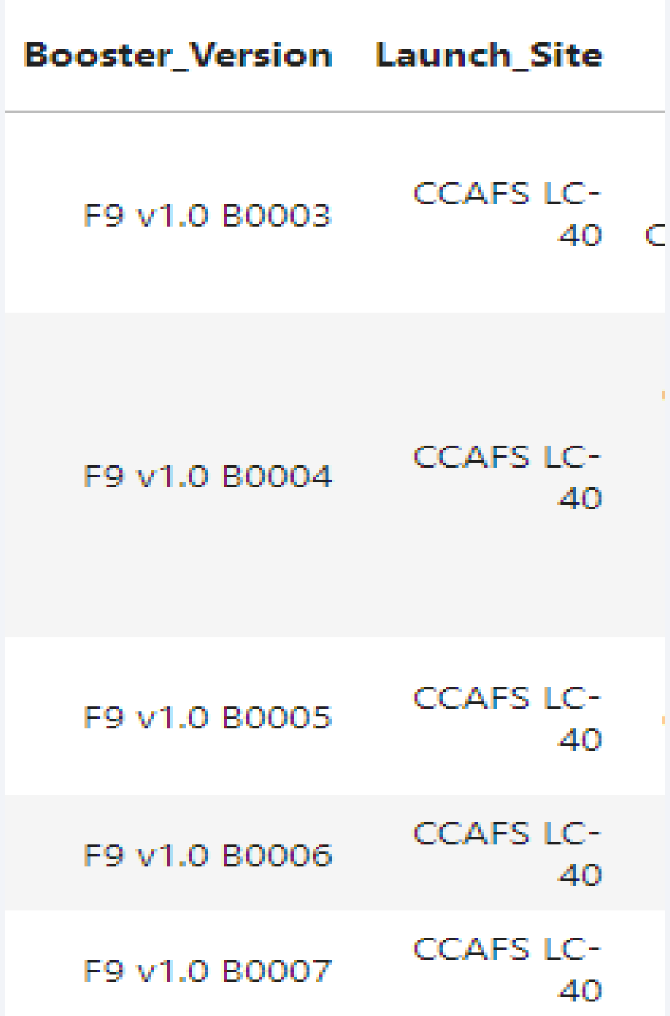
All Launch Site Names



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

- There are four launch sites .

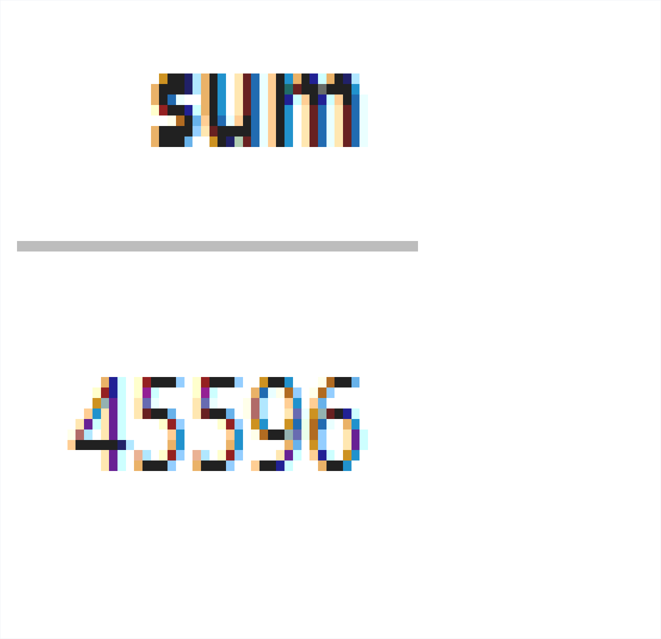
Launch Site Names Begin with 'CCA'



Booster_Version	Launch_Site
F9 v1.0 B0003	CCAFS LC-40
F9 v1.0 B0004	CCAFS LC-40
F9 v1.0 B0005	CCAFS LC-40
F9 v1.0 B0006	CCAFS LC-40
F9 v1.0 B0007	CCAFS LC-40

First five entries in database with Launch Site name beginning with CCA.

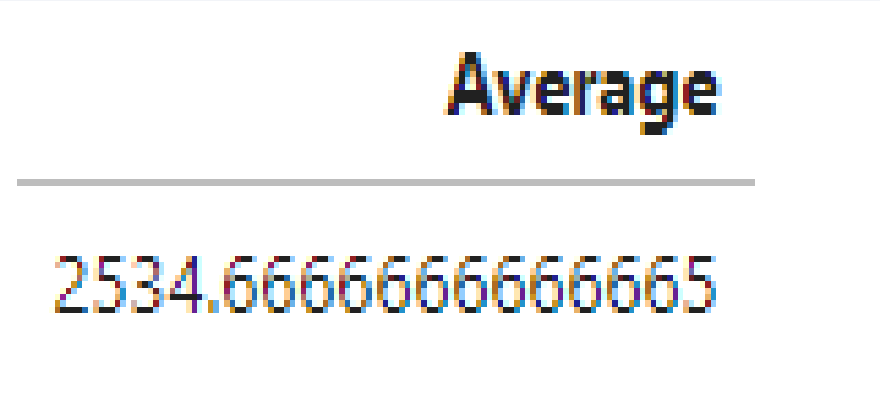
Total Payload Mass



sum
45596

This query sums the total payload mass in kg where NASA was the customer.
CRS stands for Commercial Resupply Services which indicates that these payloads were sent to the International Space Station (ISS).

Average Payload Mass by F9 v1.1

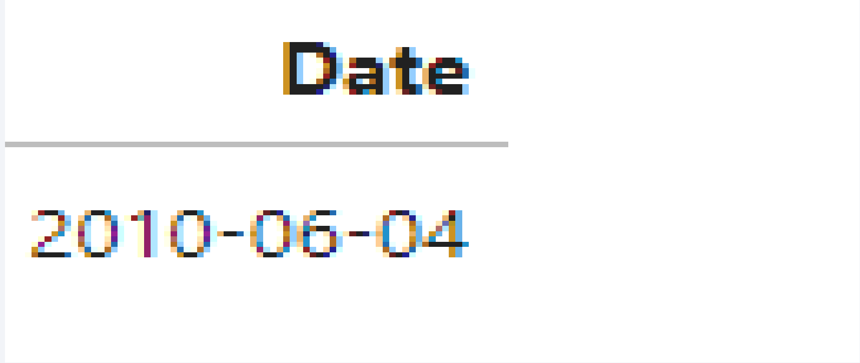


Average
2534.6666666666665

This query calculates the average payload mass or launches which used booster version F9 v1.1

Average payload mass of F9 1.1 is on the low end of our payload mass range

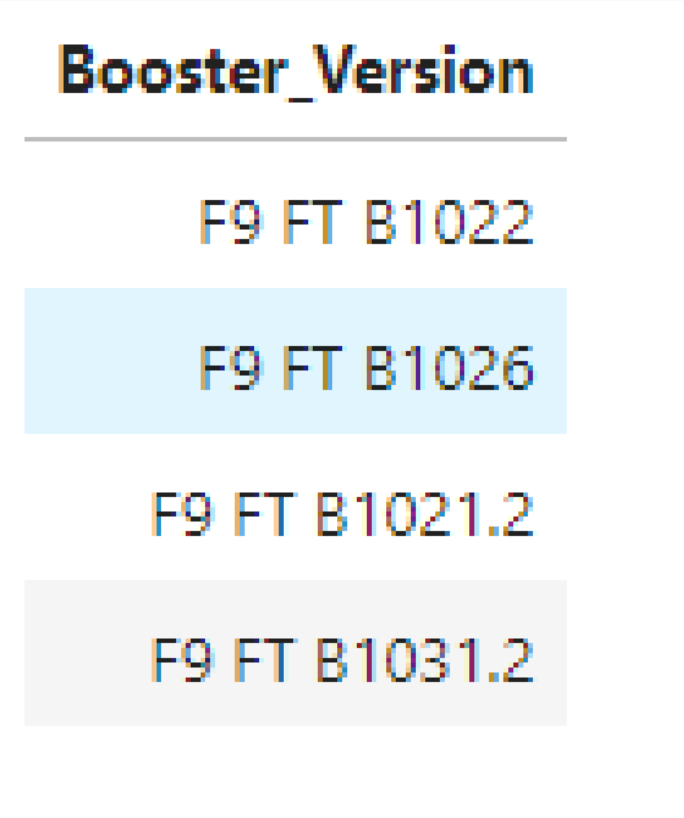
First Successful Ground Landing Date



Date
2010-06-04

This query returns the first successful ground pad landing date.

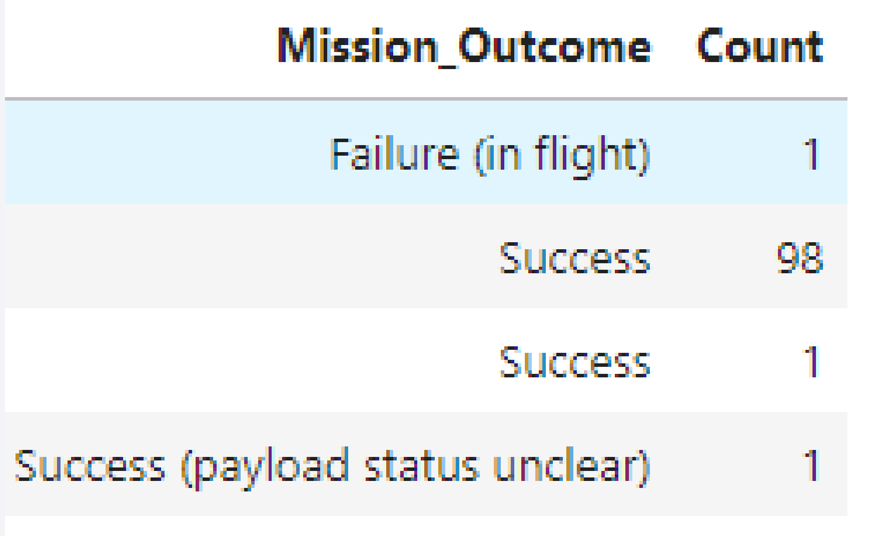
Successful Drone Ship Landing with Payload between 4000 and 6000



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

This query returns the four booster versions that had successful drone ship landings and a payload mass between 4000 and 6000 non-inclusively.

Total Number of Successful and Failure Mission Outcomes

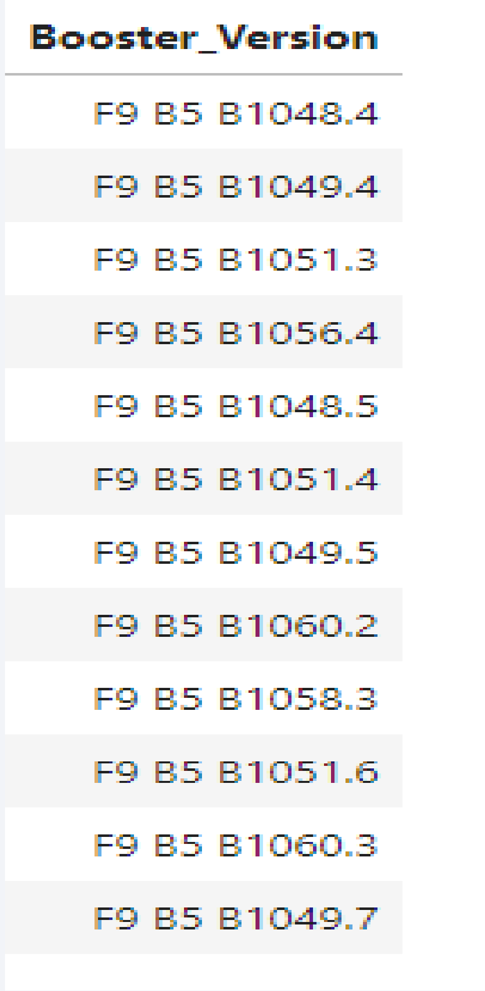


Mission_Outcome	Count
Failure (in flight)	1
Success	98
Success	1
Success (payload status unclear)	1

This query returns a count of each mission outcome.

SpaceX appears to achieve its mission outcome nearly 98% of the time.

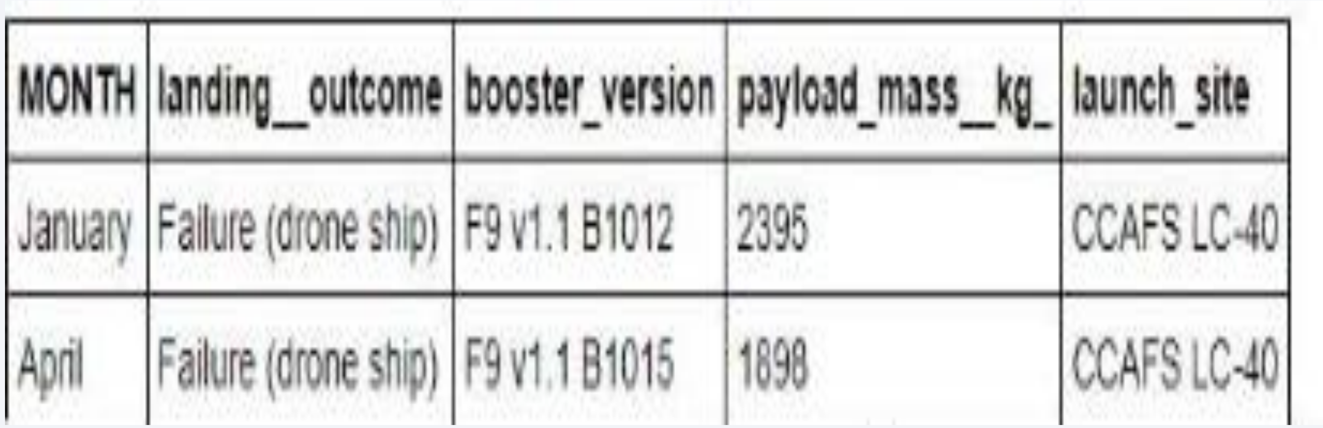
Boosters Carried Maximum Payload



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

This likely indicates payload mass correlates with the booster version that is used.

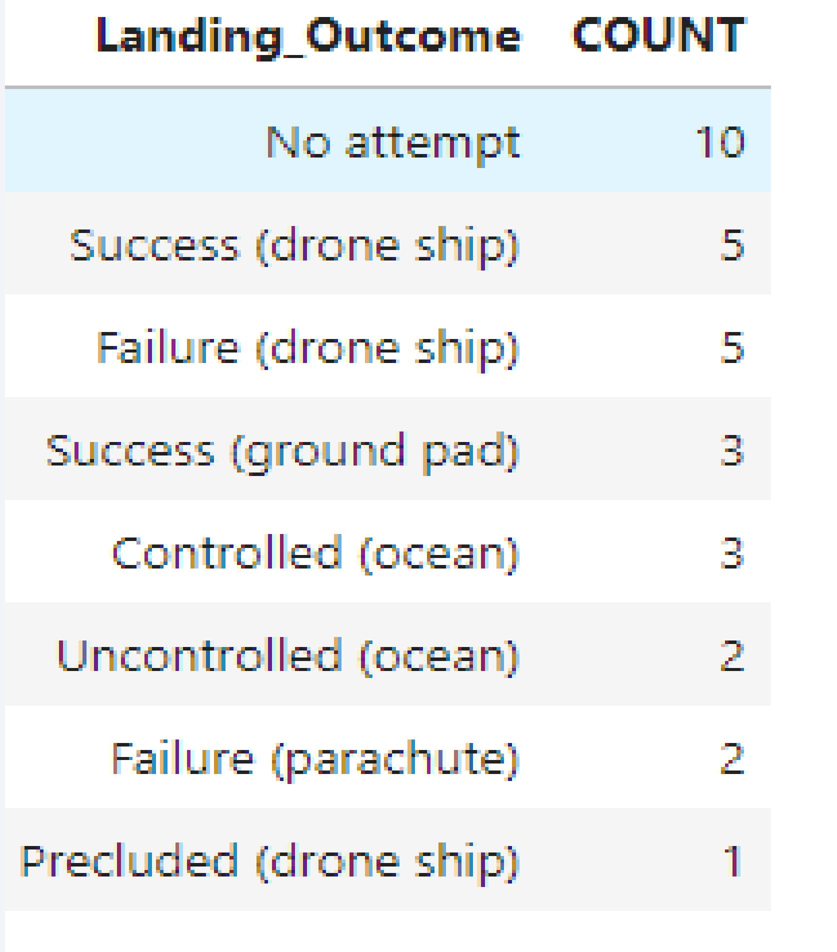
2015 Launch Records



MONTH	landing__outcome	booster_version	payload_mass__kg_	launch_site
January	Failure (drone ship)	F9 v1.1 B1012	2395	CCAFS LC-40
April	Failure (drone ship)	F9 v1.1 B1015	1898	CCAFS LC-40

This query returns the Month, Landing Outcome, Booster Version, Payload Mass (kg), and Launch site of 2015 launches where stage 1 failed to land on a drone ship. There were two such occurrences.

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



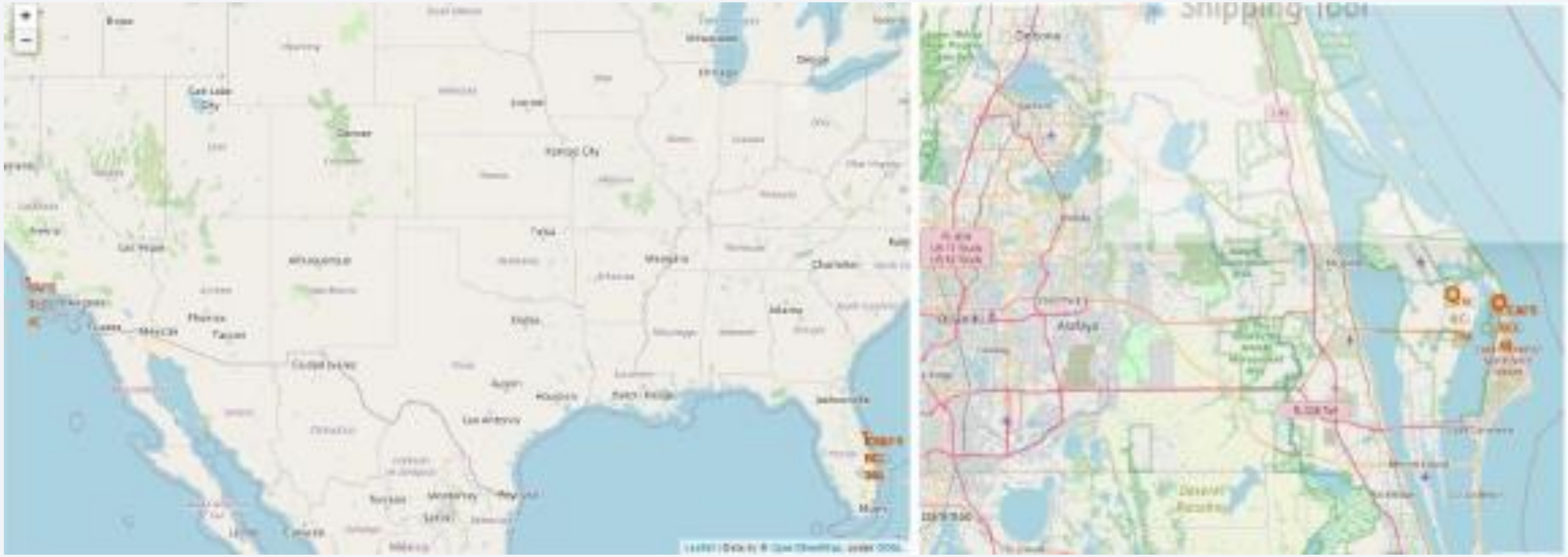
Landing_Outcome	COUNT
No attempt	10
Success (drone ship)	5
Failure (drone ship)	5
Success (ground pad)	3
Controlled (ocean)	3
Uncontrolled (ocean)	2
Failure (parachute)	2
Precluded (drone ship)	1

- This query returns a list of successful landings and between 2010-06-04 and 2017-03-20 inclusively.
- There are 10 no attempts.
- Total success is about 10 rank.

Section 3

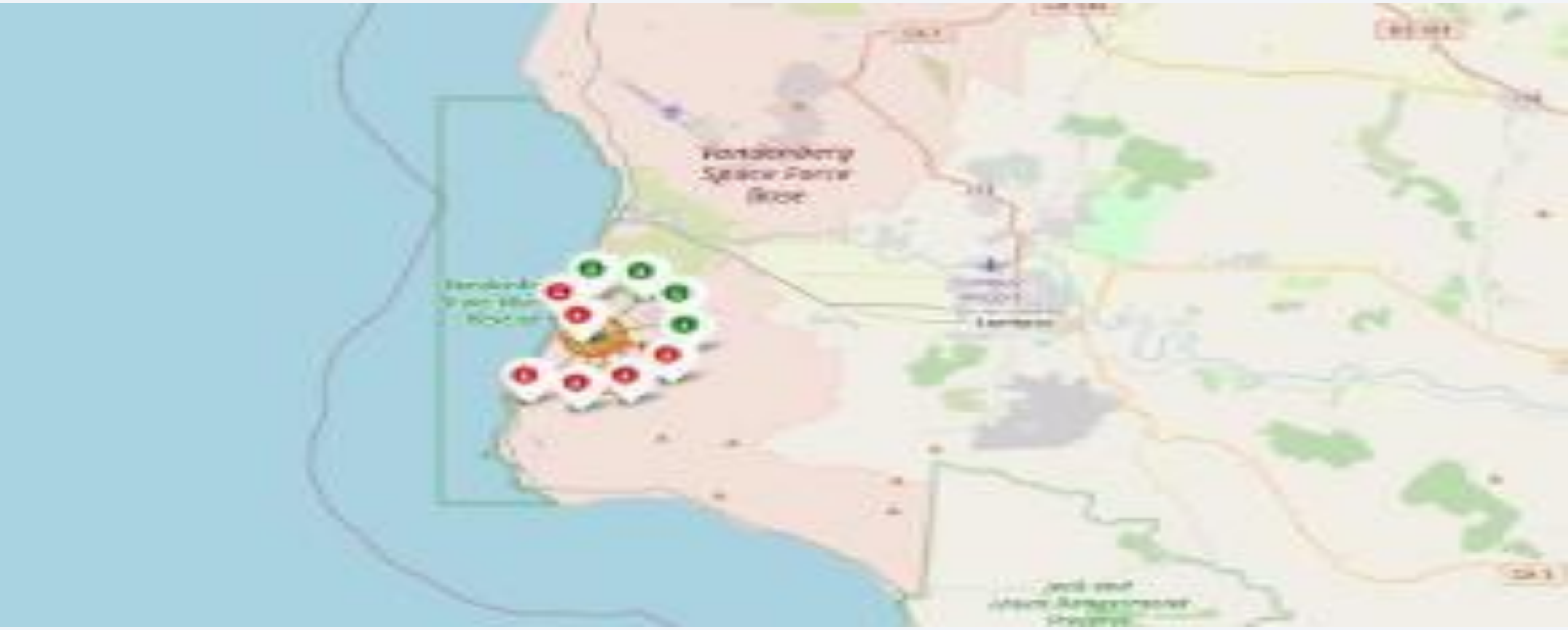
Launch Sites Proximities Analysis

<Folium Map Screenshot 1>



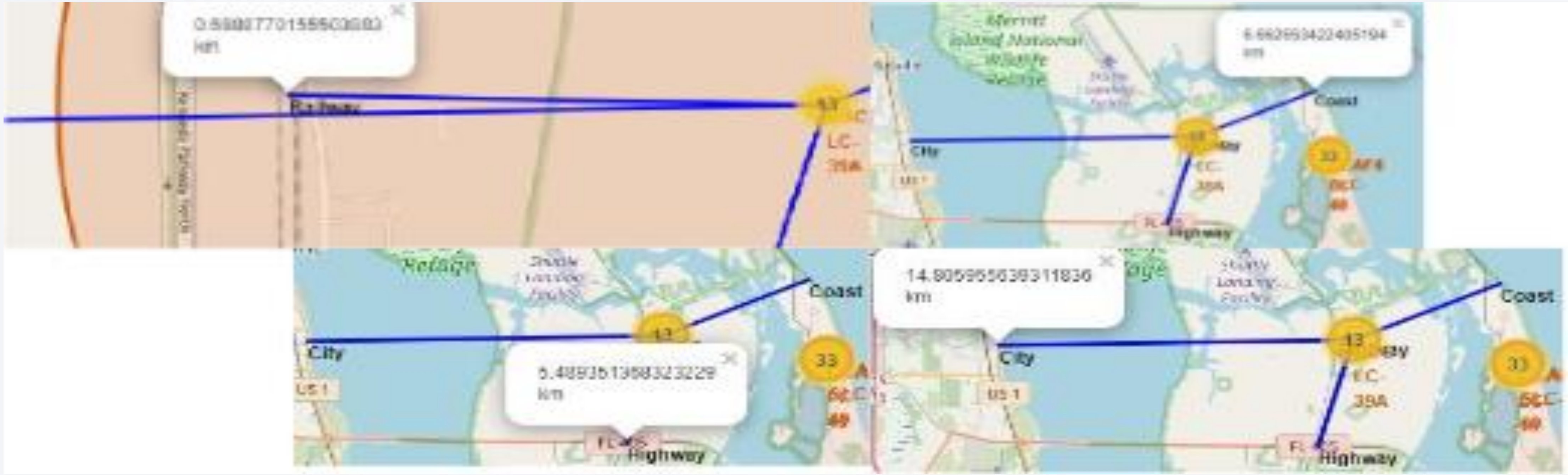
The left map shows all launch sites relative US map. The right map shows the two Florida launch sites since they are very close to each other. All launch sites are near the ocean.

<Folium Map Screenshot 2>

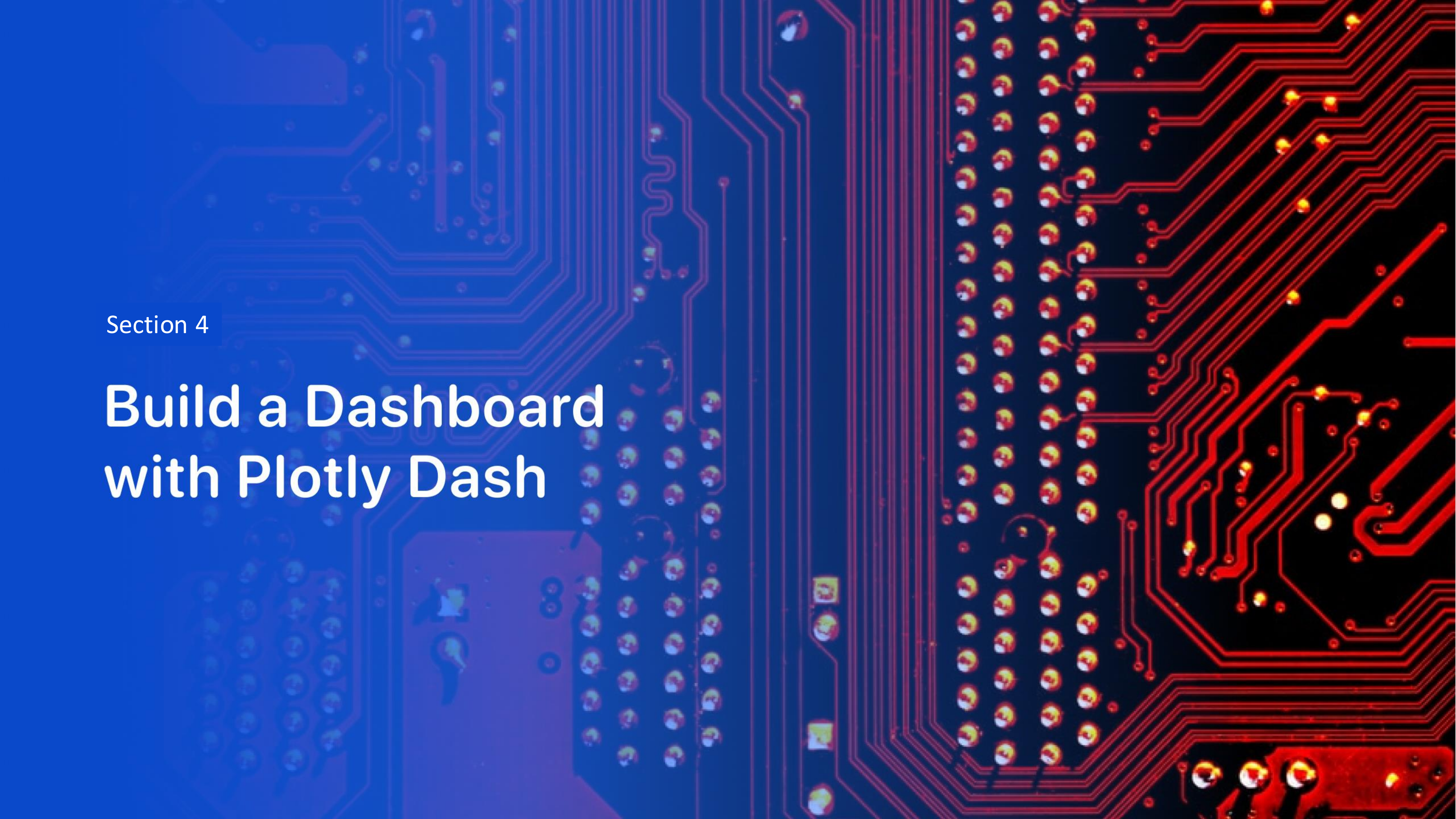


Clusters on Folium map can be clicked on to display each successful landing (green icon) and failed
landing (red icon). In this example VAFB SLC-4E shows 4 successful landings and 6 failed landings.

<Folium Map Screenshot 3>



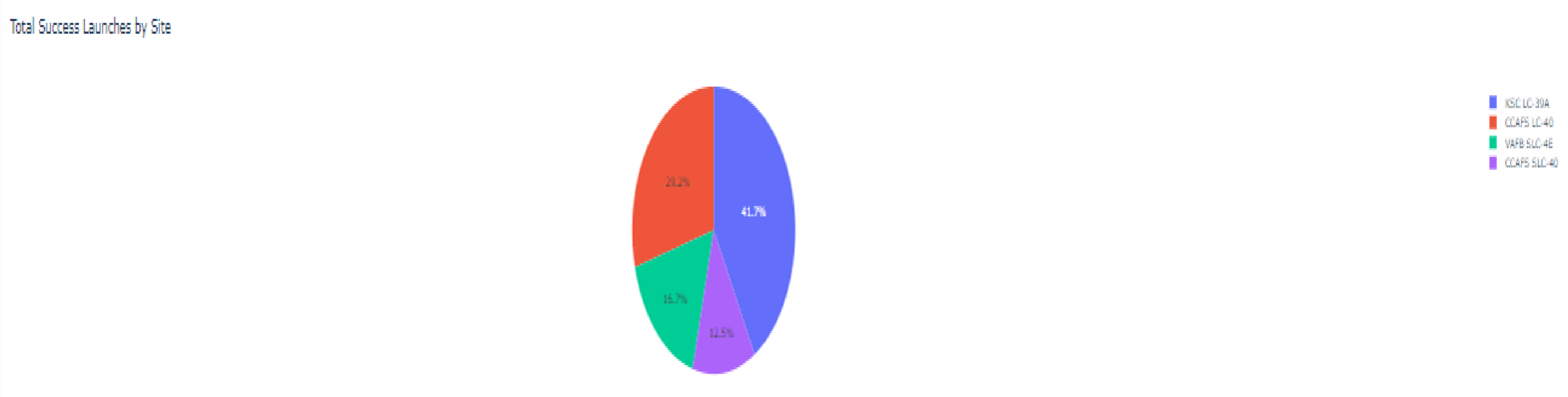
Launch sites are very close to railways for large part and supply transportation. Launch sites are close to highways for human and supply transport. Launch sites are also close to coasts and relatively far from cities so that launch failures can land in the sea to avoid rockets falling on densely populated areas.



Section 4

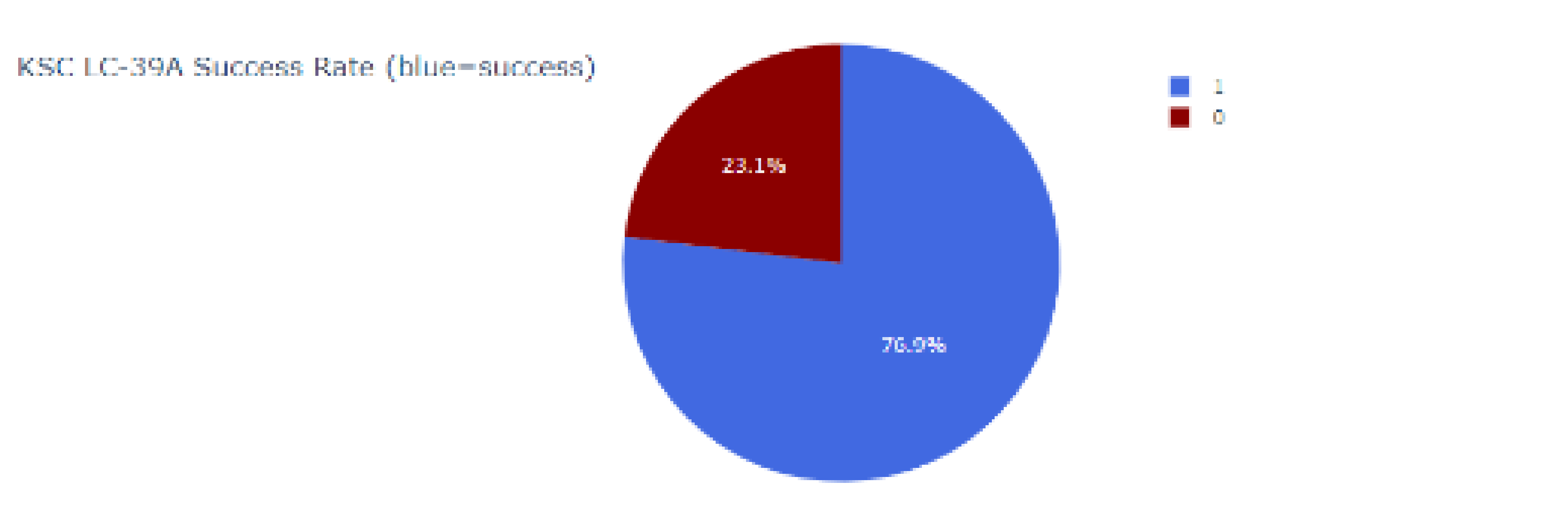
Build a Dashboard with Plotly Dash

<Dashboard Screenshot 1>



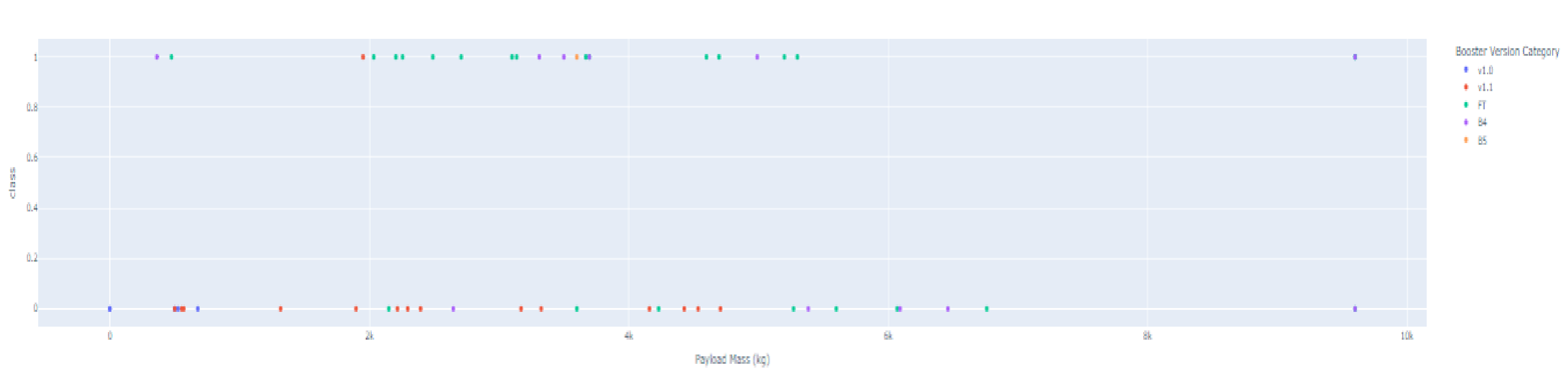
This is the distribution of successful landings across all launch sites. CCAFS LC-40 is the old name of CCAFS SLC-40 so CCAFS and KSC have the same amount of successful landings, but a majority of the successful landings where performed before the name change. VAFB has the smallest share of successful landings. This may be due to smaller sample and increase in difficulty of launching in the west coast.

<Dashboard Screenshot 2>



KSC LC-39A has the highest success rate with 10 successful landings and 3 failed landings.

<Dashboard Screenshot 3>

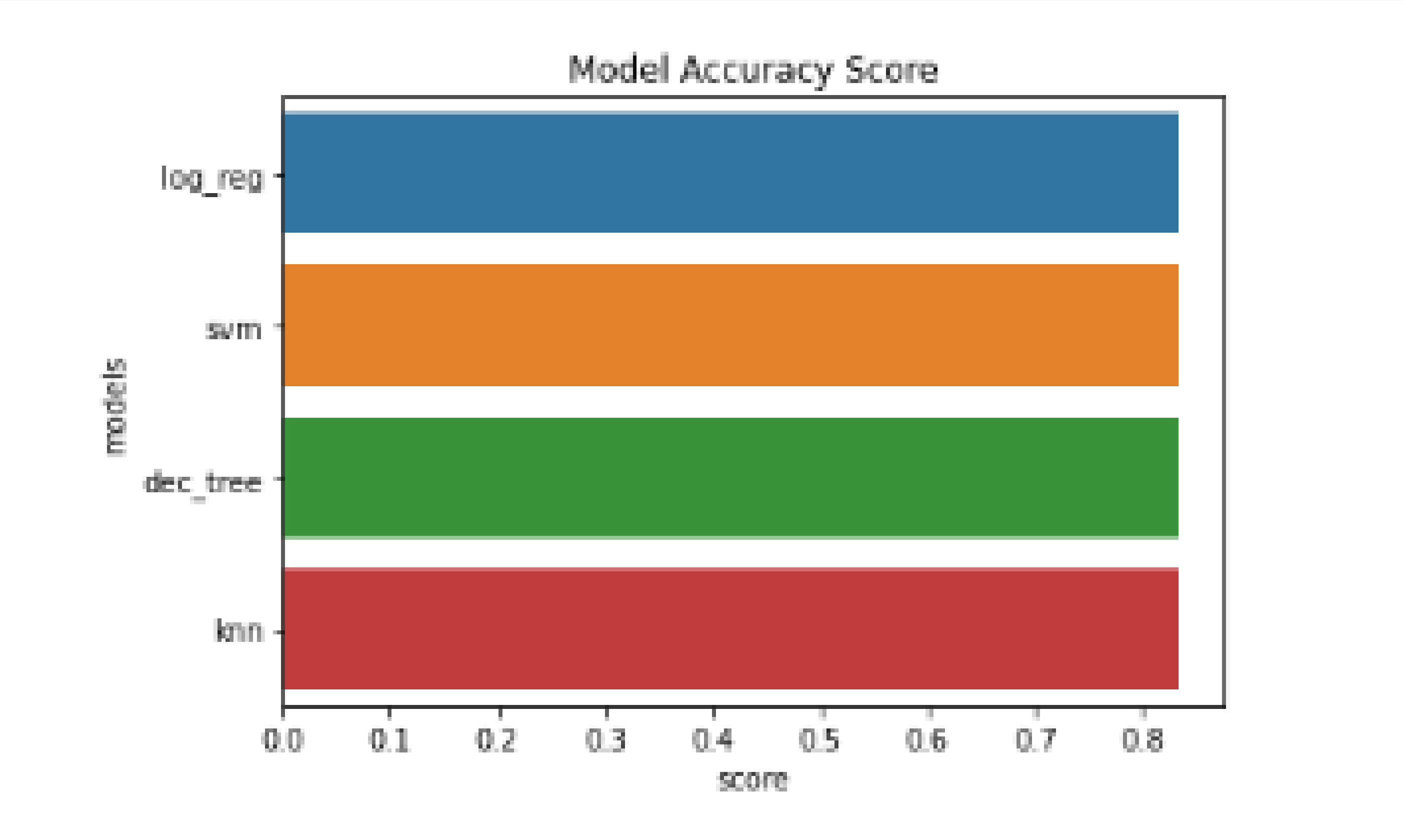


Plotly dashboard has a Payload range selector. However, this is set from 0-10000 instead of the max Payload of 15600. Class indicates 1 for successful landing and 0 for failure. Scatter plot also accounts for booster version category in color and number of launches in point size. In this particular range of 0-6000, interestingly there are two failed landings with payloads of zero kg.

Section 5

Predictive Analysis (Classification)

Classification Accuracy

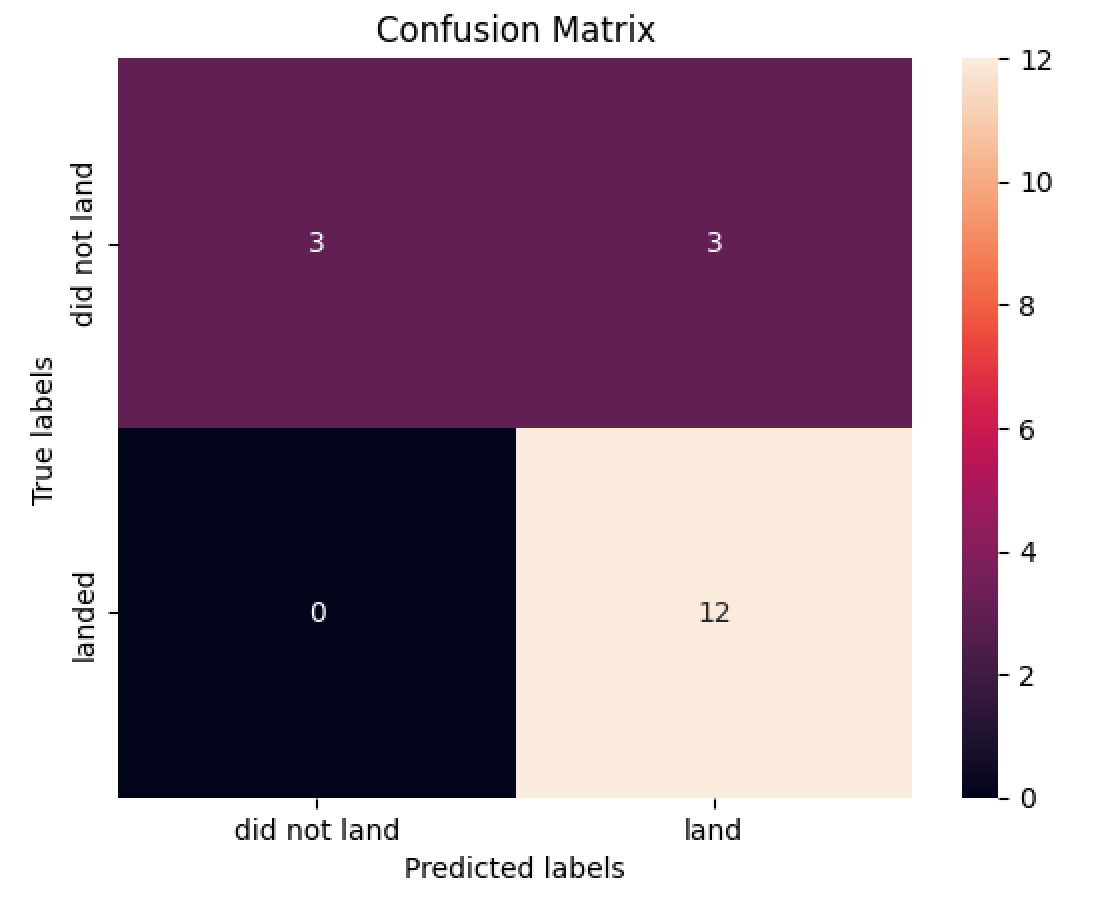


All models had virtually the same accuracy on the test set at 83.33% accuracy. It should be noted that test size is small at only sample size of 18.

This can cause large variance in accuracy results, such as those in Decision Tree Classifier model in repeated runs.

We likely need more data to determine the best model.

Confusion Matrix



Since all models performed the same for the test set, the confusion matrix is the same across all models. The models predicted 12 successful landings when the true label was successful landing.

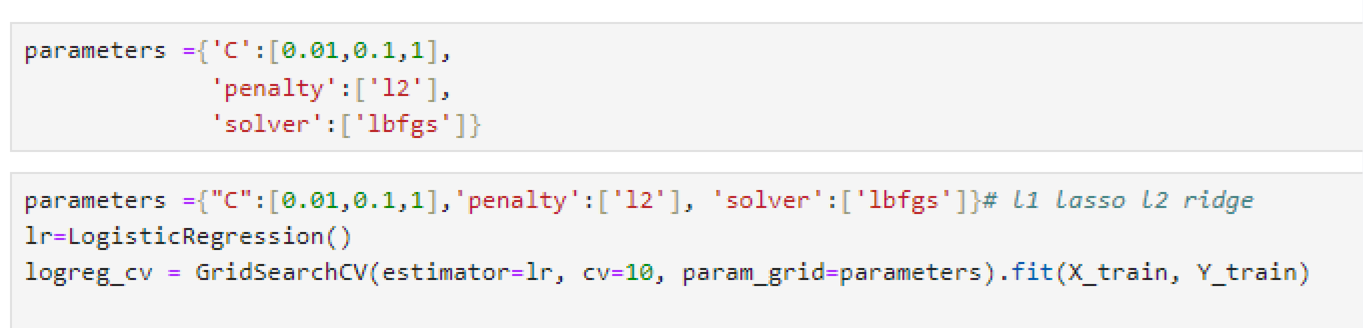
The models predicted 3 unsuccessful landings when the true label was unsuccessful landing.

The models predicted 3 successful landings when the true label was unsuccessful landings (false positives). Our models over predict successful landings.

Conclusions

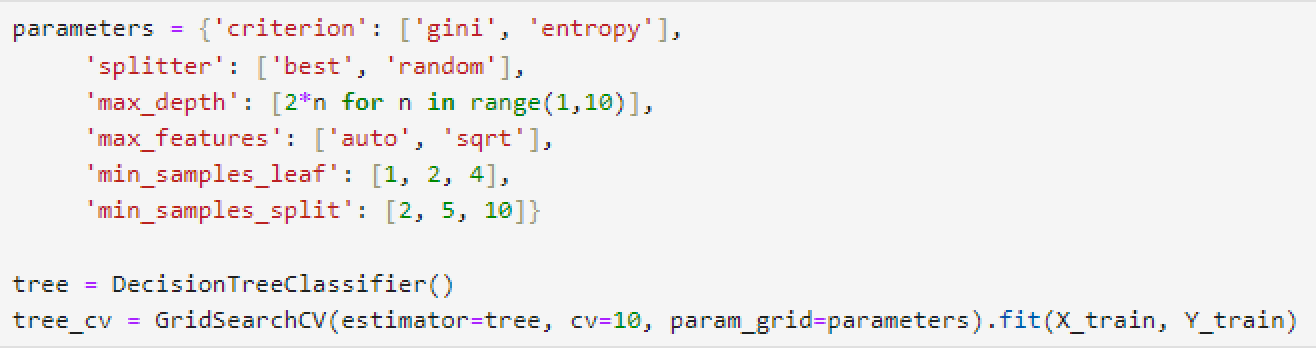
- Allon Mask can save 100 million USD.
- He can use this model for better accuracy.
- We can improve accuracy with more data.
- All the data is collected by using SPACE X API AND Web scraping

Appendix



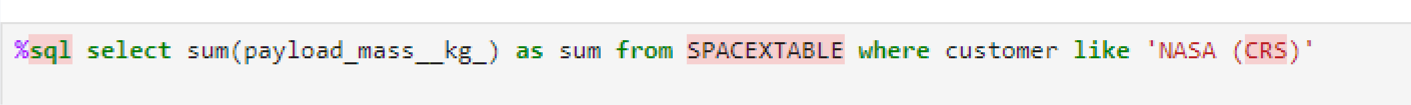
```
parameters ={'C':[0.01,0.1,1],
             'penalty':['l2'],
             'solver':['lbfgs']}
```

```
parameters ={"C":[0.01,0.1,1],'penalty':['l2'], 'solver':['lbfgs']}# l1 lasso l2 ridge
lr=LogisticRegression()
logreg_cv = GridSearchCV(estimator=lr, cv=10, param_grid=parameters).fit(X_train, Y_train)
```



```
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()
tree_cv = GridSearchCV(estimator=tree, cv=10, param_grid=parameters).fit(X_train, Y_train)
```



```
%sql select sum(payload_mass__kg_) as sum from SPACEXTABLE where customer like 'NASA (CRS)'
```

Thank you!