IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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Outline

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

- We analyse SpaceX data to better understand space transportation industry.
- This report uses various Python libraries to make sense of the data.
- We observe 67% successful landings

Introduction

- 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, 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
- Given this, we would like to know important factors that contributes to a successful landing

Section 1

Methodology

Methodology

Executive Summary

Data collection methodology:

- Data collected from SpaceX API

Perform data wrangling

- We generate variables that capture landing outcomes

Perform exploratory data analysis (EDA) using visualization and SQL

- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
- We use machine learning techniques to predict landing outcome based on the most accurate model we have

Data Collection

We import data using SpaceX API from this URL: https://api.spacexdata.com/v4/launches/past

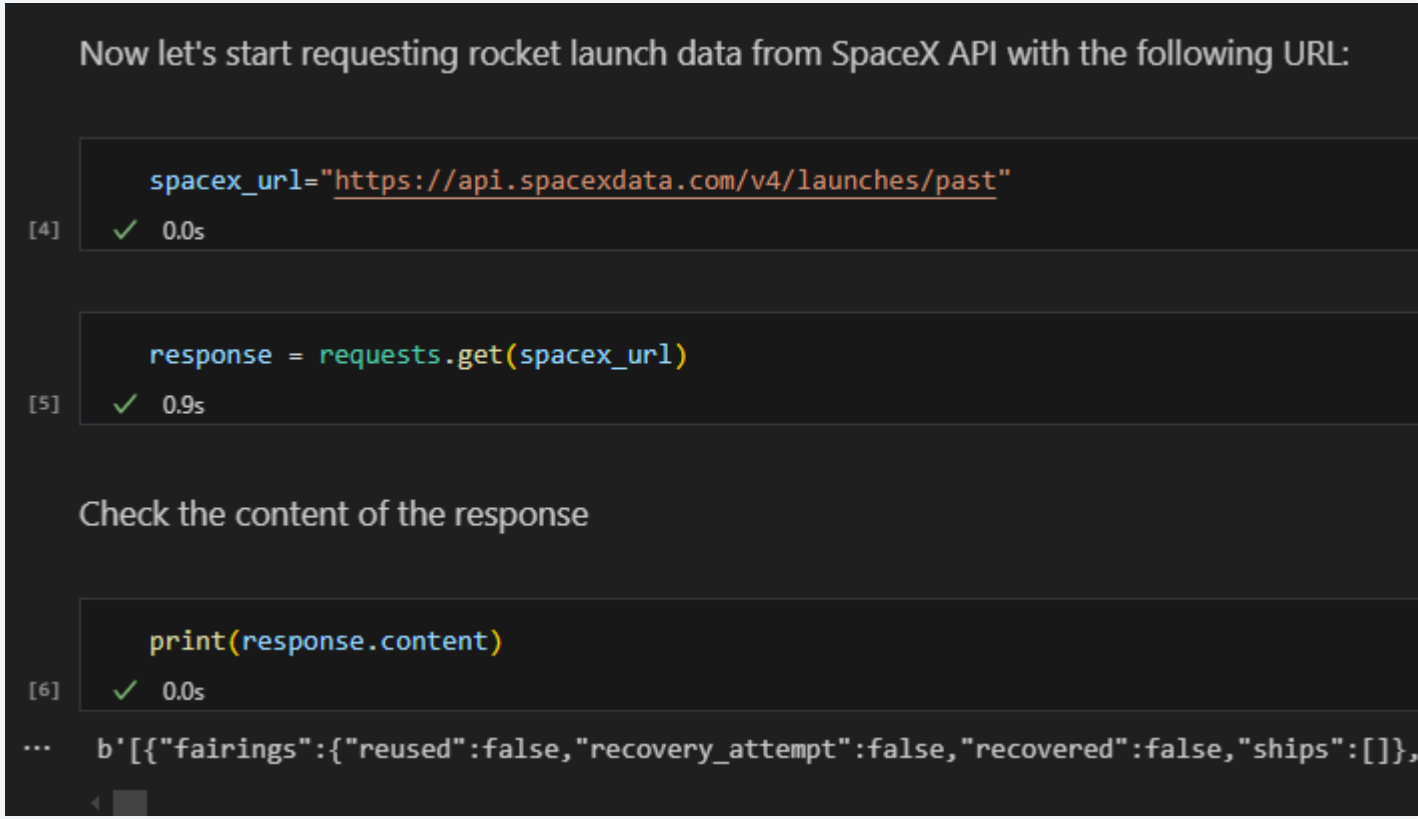
The imported data is normalized and turn it to dataframe using Pandas

From the loaded data we can get various information such as booster versions and landing outcome

Data Collection – SpaceX API

- We utilize get request

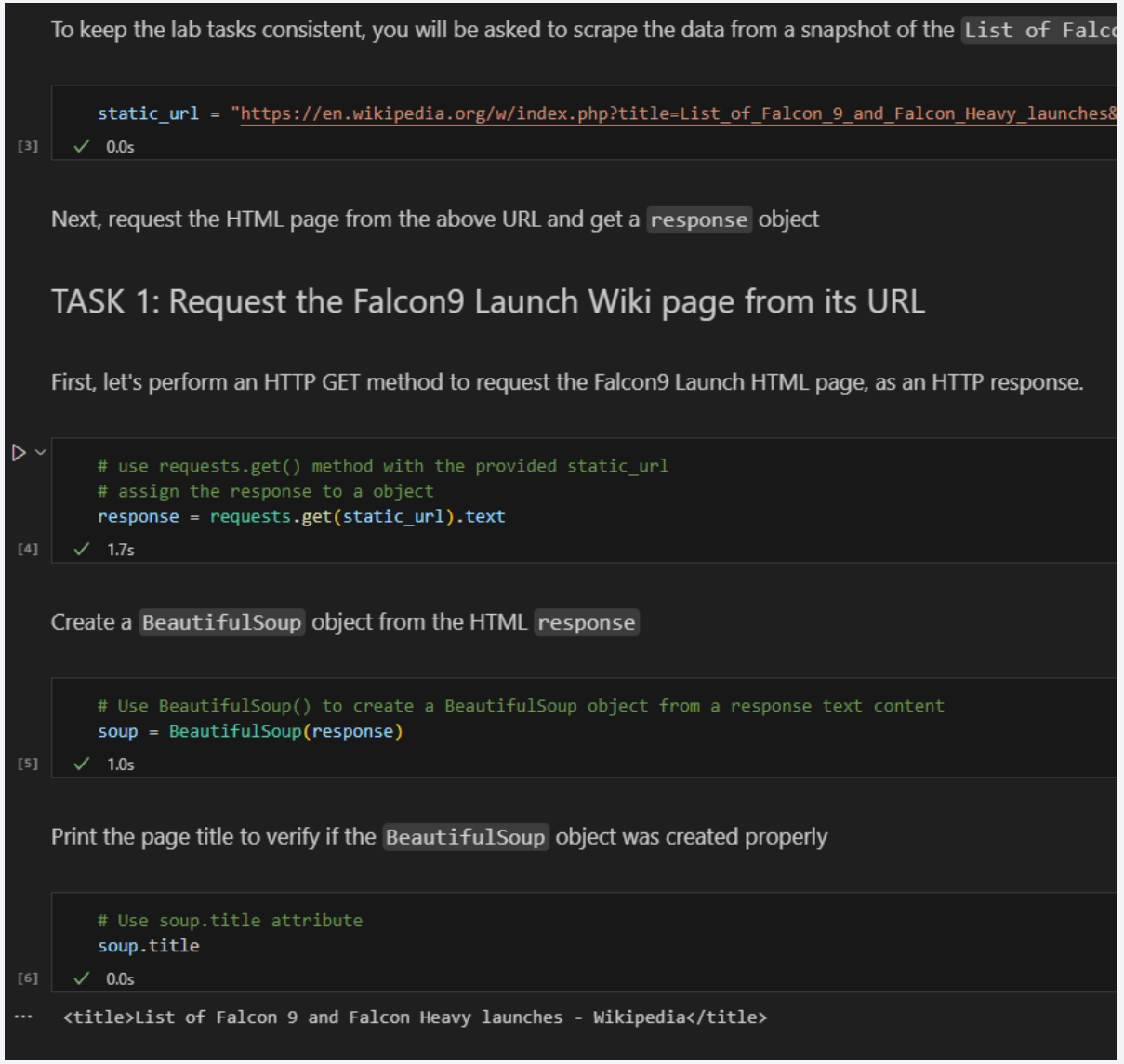
- The GitHub URL of the completed SpaceX API calls notebook is: https://github.com/mryansanjaya/capstone-spacex/blob/main/jupyter-labs-spacex-data-collection-api-v2.ipynb



Data Collection - Scraping

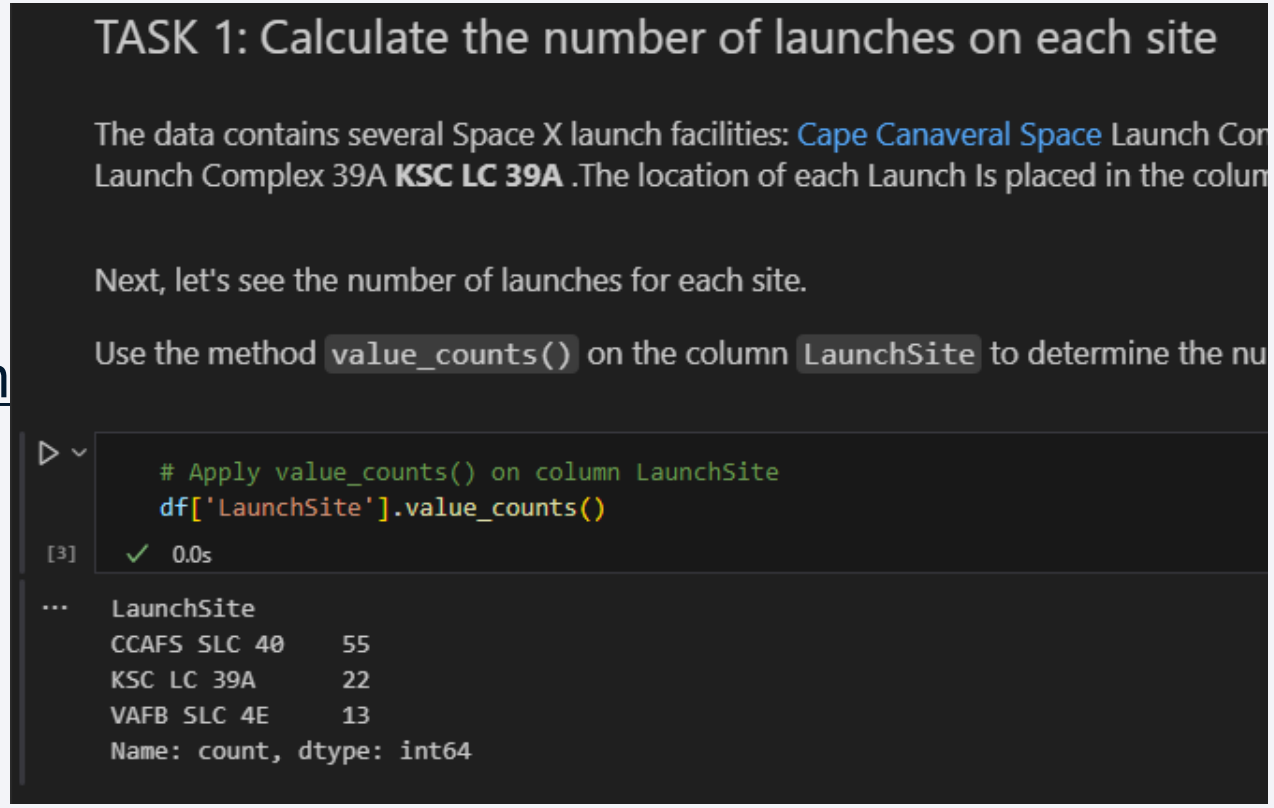
- Again we use get request to obtain Falcon 9 HTML Wiki page and create BeautifulSoup object

- The GitHub URL of the completed web scraping notebook is: https://github.com/mryansanjaya/capstone-spacex/blob/main/jupyter-labs-webscraping.ipynb



Data Wrangling

The data were processed using Pandas and Numpy libraries
We can get, for example, the number of launches on each site
The GitHub URL of data wrangling related notebook is: https://github.com/mryansanjaya/capstone-spacex/blob/main/labs-jupyter-spacex-Data%20wrangling-v2.ipynb

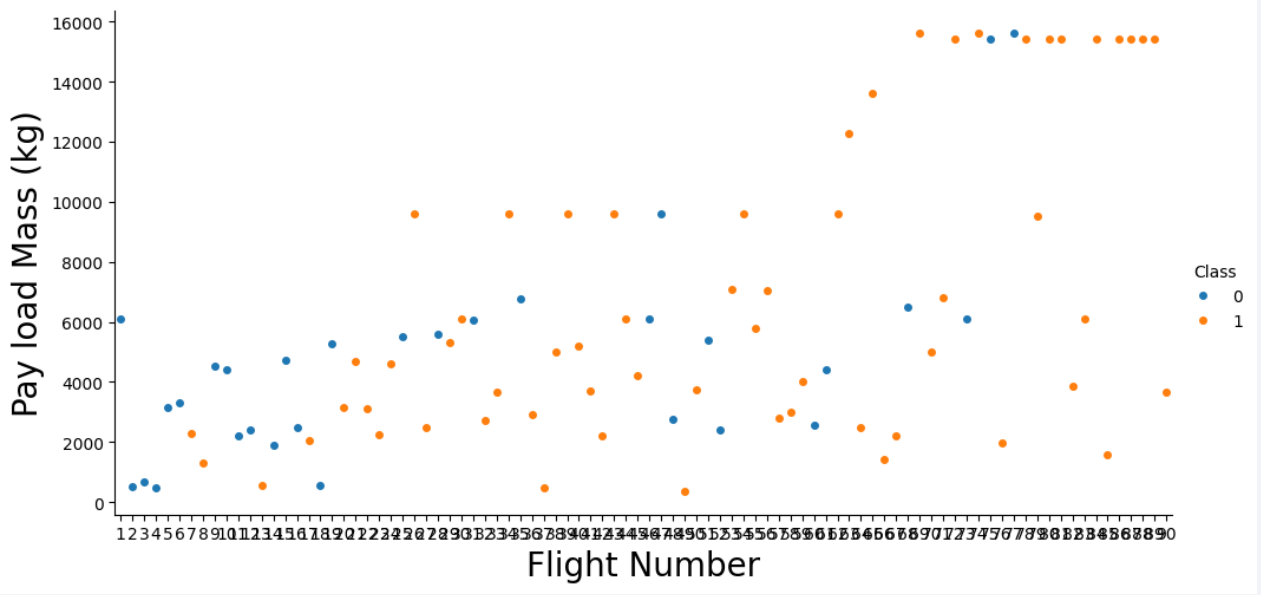


EDA with Data Visualization

We use scatter plot of flight number and payload mass to make it easier to visualize the relationship between these variables

We find a positive relationship

The GitHub URL of EDA with data visualization notebook is: https://github.com/mryansanjaya/capstone-spacex/blob/main/jupyter-labs-eda-dataviz-v2.ipynb



EDA with SQL

SQL queries we did are:

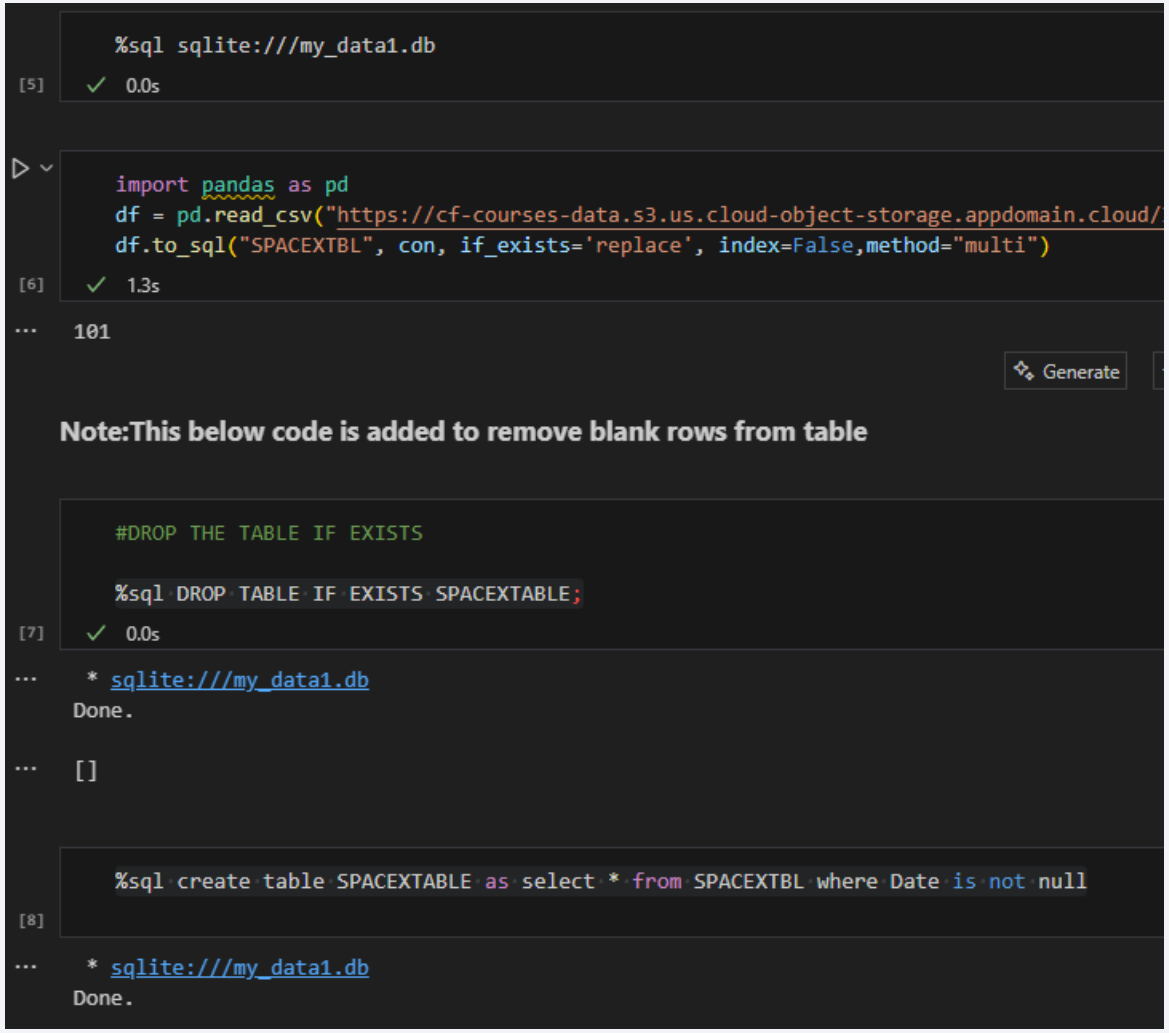
```
%sql DROP TABLE IF EXISTS SPACEXTABLE;

%sql create table SPACEXTABLE as select *
from SPACEXTBL where Date is not null

%sql SELECT * FROM SPACEXTBL LIMIT 20
```

And so on

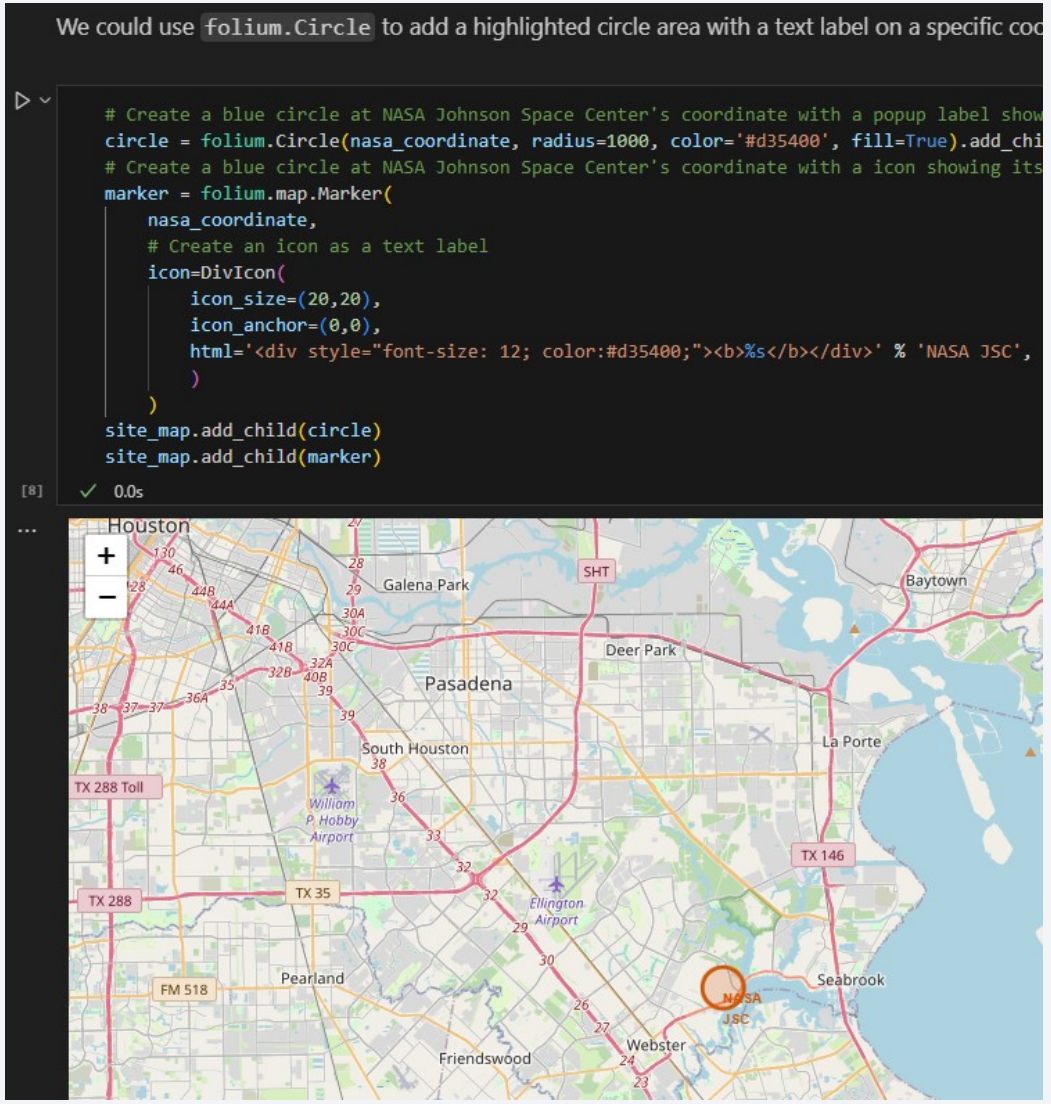
The GitHub URL of EDA with SQL notebook is: https://github.com/mryansanjaya/capstone-spacex/blob/main/jupyter-labs-eda-sql-coursera_sqllite.ipynb



Build an Interactive Map with Folium

We use markers such as circle as map objects which is helpful to point out the important location

The GitHub URL of interactive map with Folium map is: https://github.com/mryansanjaya/capstone-spacex/blob/main/lab-jupyter-launch-site-location-v2.ipynb



Build a Dashboard with Plotly Dash

Summarize what plots/graphs and interactions you have added to a dashboard

Explain why you added those plots and interactions

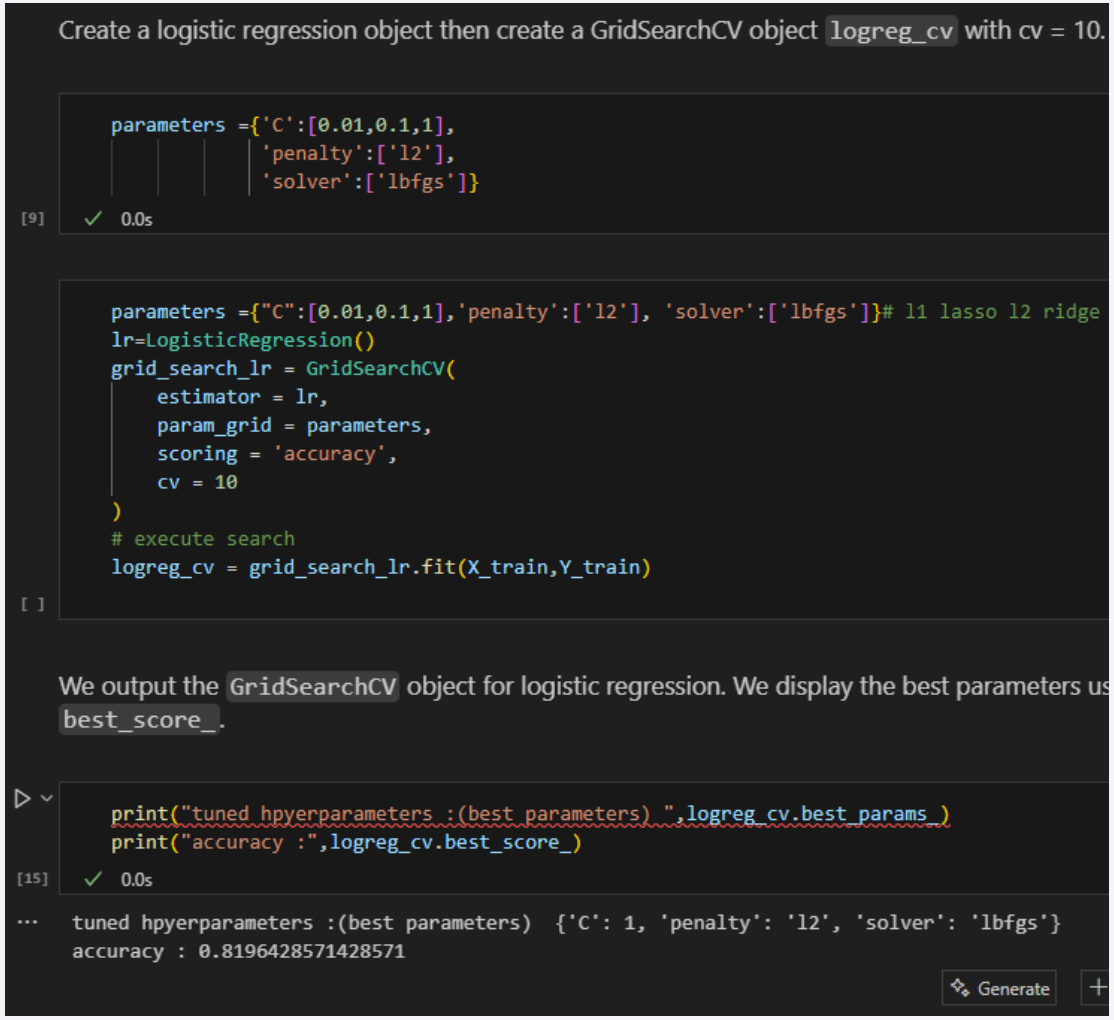
Add the GitHub URL of your completed Plotly Dash lab, as an external reference and peer-review purpose

Predictive Analysis (Classification)

We built predictive models by first splitting data to train set and test set, then we use logistic regression and create the parameters dictionary

Best model is judged by using Grid Search technique

The GitHub URL of predictive analysis lab is: https://github.com/mryansanjaya/capstone-spacex/blob/main/SpaceX-Machine-Learning-Prediction-Part-5-v1.ipynb



Results

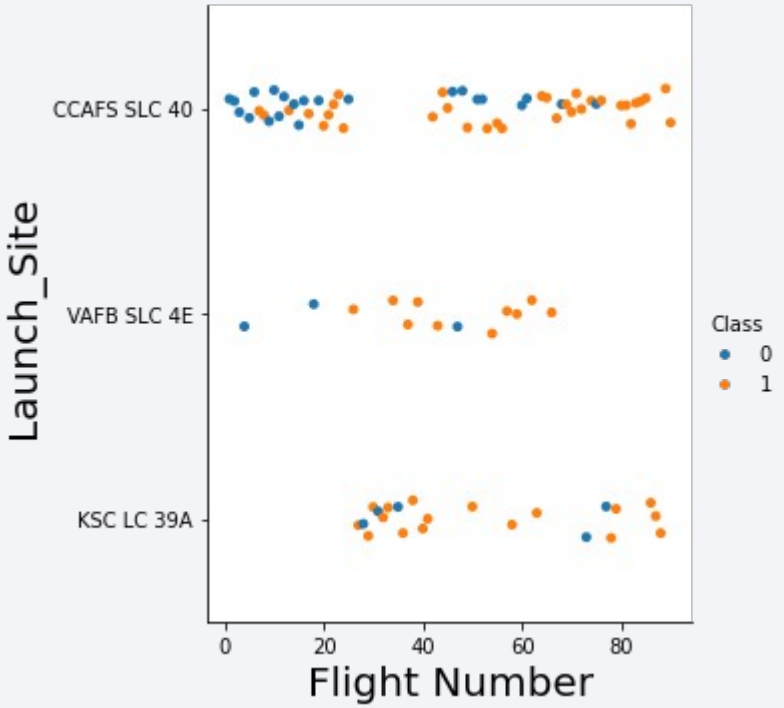
- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results

Section 2

Insights drawn from EDA

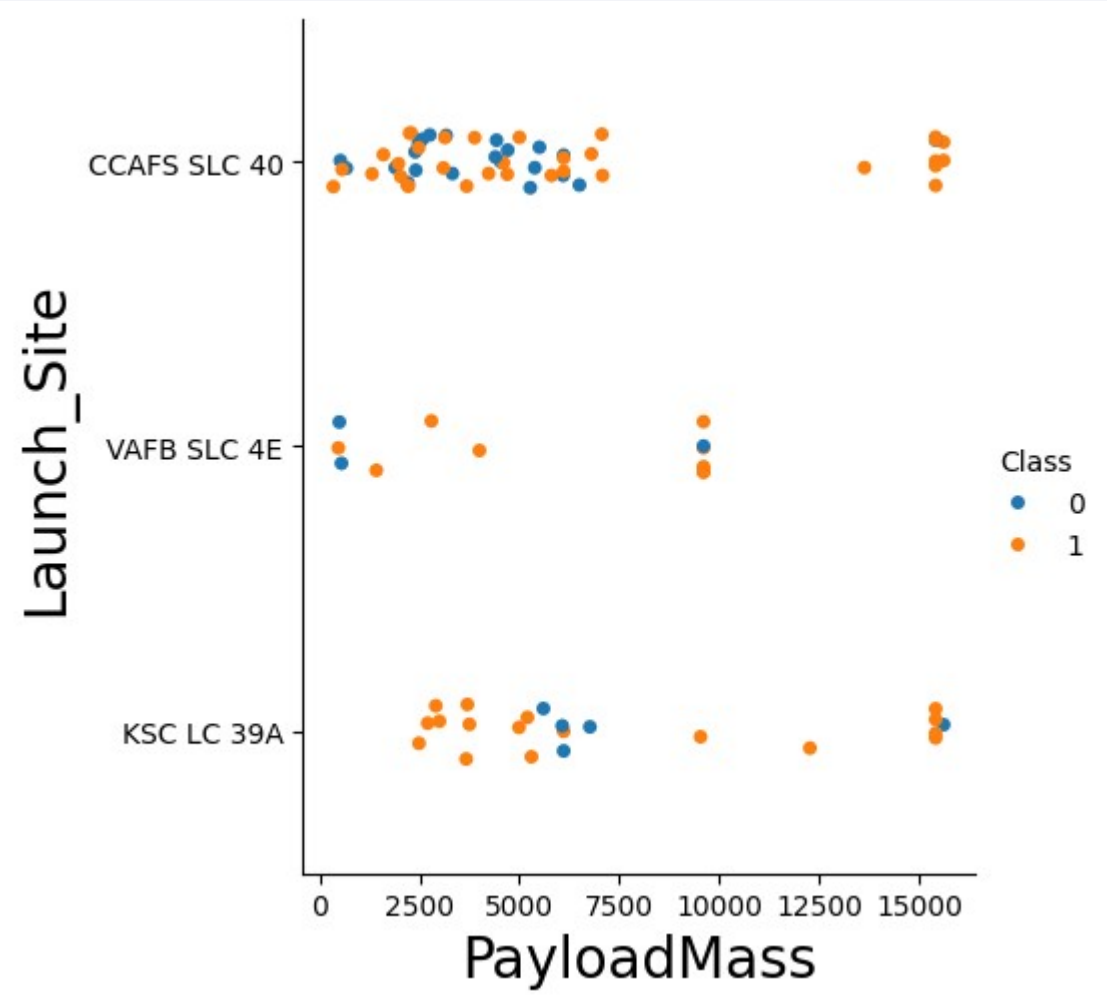
Flight Number vs. Launch Site

- We use scatter plot of flight number and launch site to make it easier to visualize the relationship between these variables
- We find a positive relationship: in any launch site, most recent flights tend to be much more successful than early flights



Payload vs. Launch Site

- Show a scatter plot of Payload vs. Launch Site
- Large payload mass is more successful in recent flights



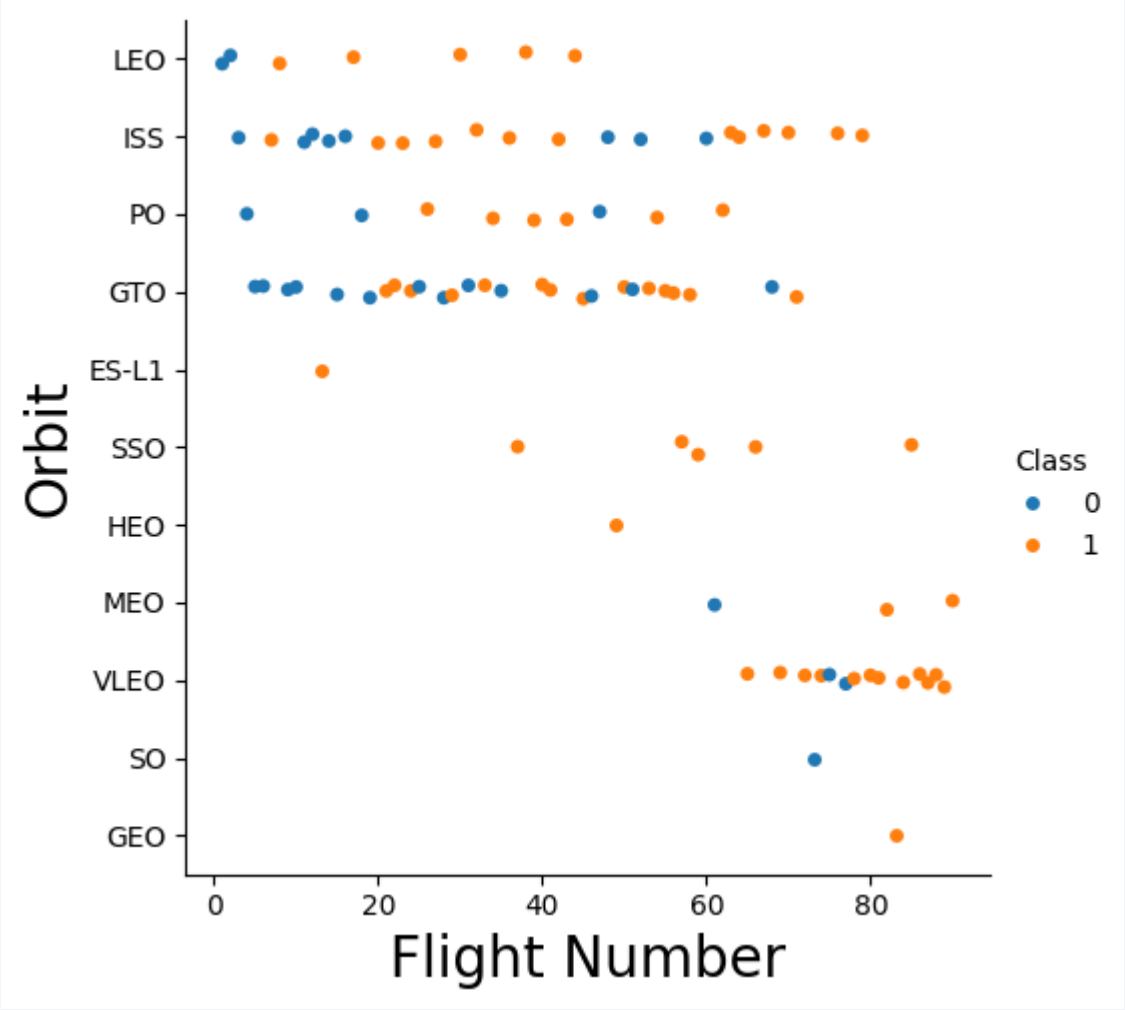
Success Rate vs. Orbit Type

- Show a bar chart for the success rate of each orbit type

- Show the screenshot of the scatter plot with explanations

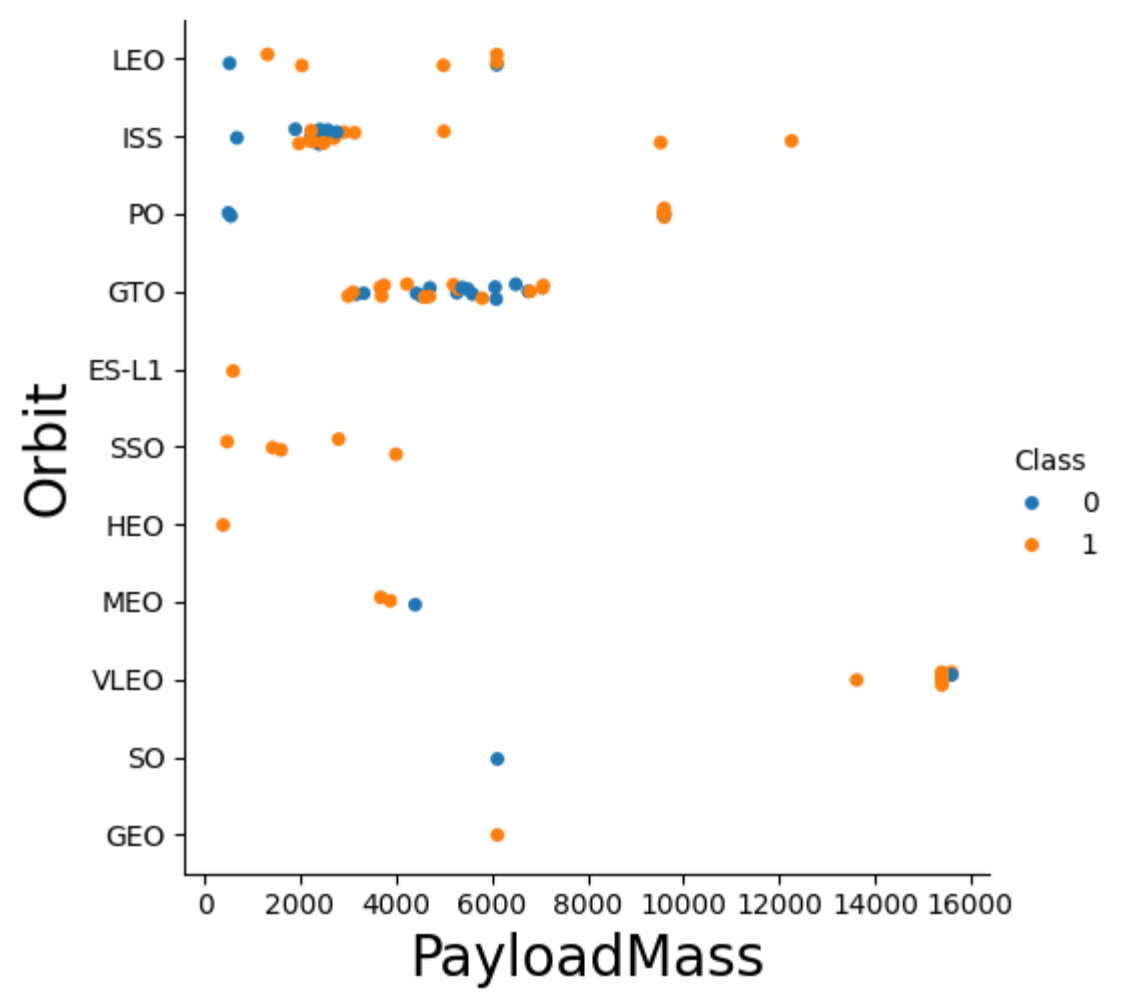
Flight Number vs. Orbit Type

- Show a scatter point of Flight number vs. Orbit type
- In all orbit type, recent flights are more successful
- ES-L1, SSO, HEO, and GEO has the highest success rate but maybe because they only have few observations



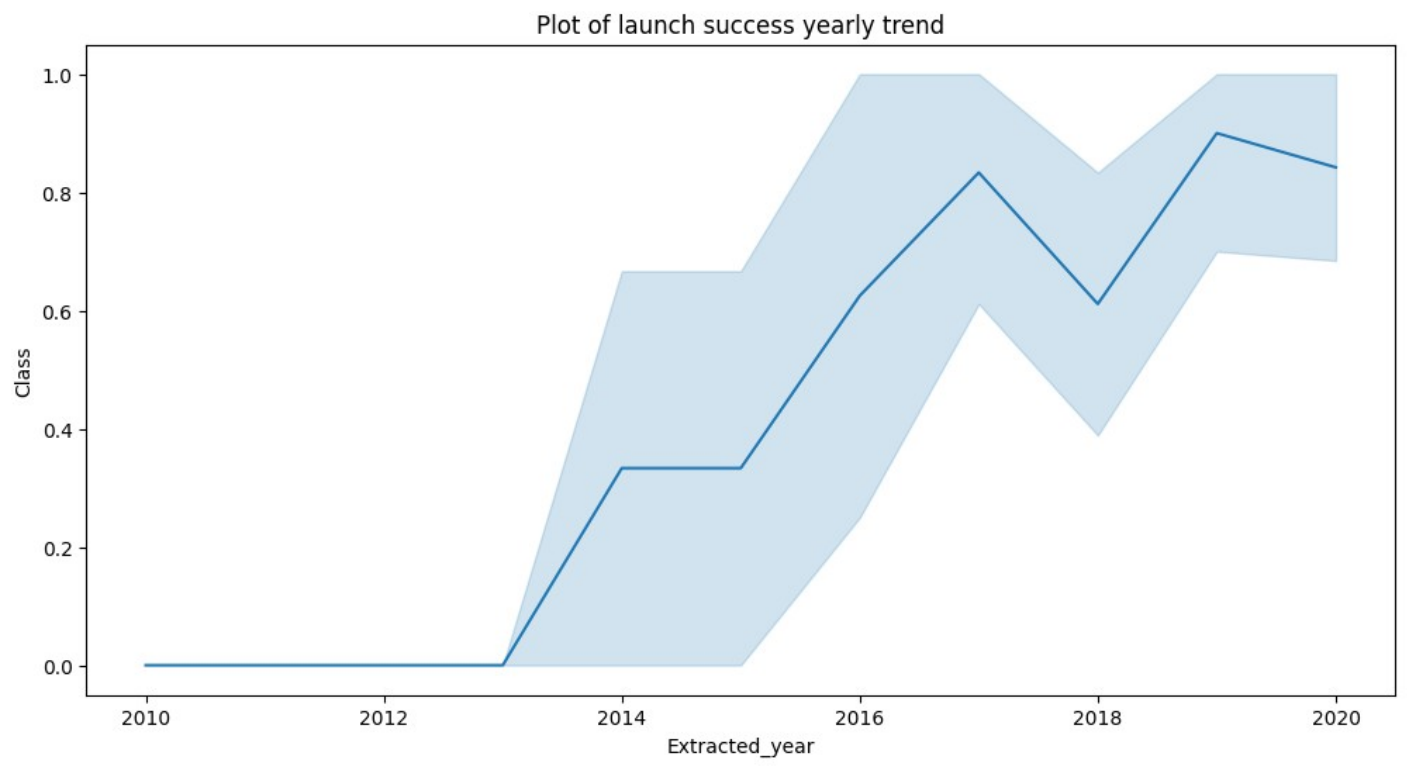
Payload vs. Orbit Type

- Show a scatter point of payload vs. orbit type
- There’s unclear relationship



Launch Success Yearly Trend

- Show a line chart of yearly average success rate
- Success rate increases almost in every year



All Launch Site Names

Find the names of the unique launch sites:

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

We use: SELECT DISTINCT Launch_Site FROM SPACEXTBL

Launch Site Names Begin with 'CCA'

We use this command:

SELECT * FROM SPACEXTBL WHERE Launch_Site LIKE 'CCA%' LIMIT 5

```
%sql SELECT * FROM SPACEXTBL WHERE Launch_Site LIKE 'CCA%' LIMIT 5
```

[9] ✓ 0.0s

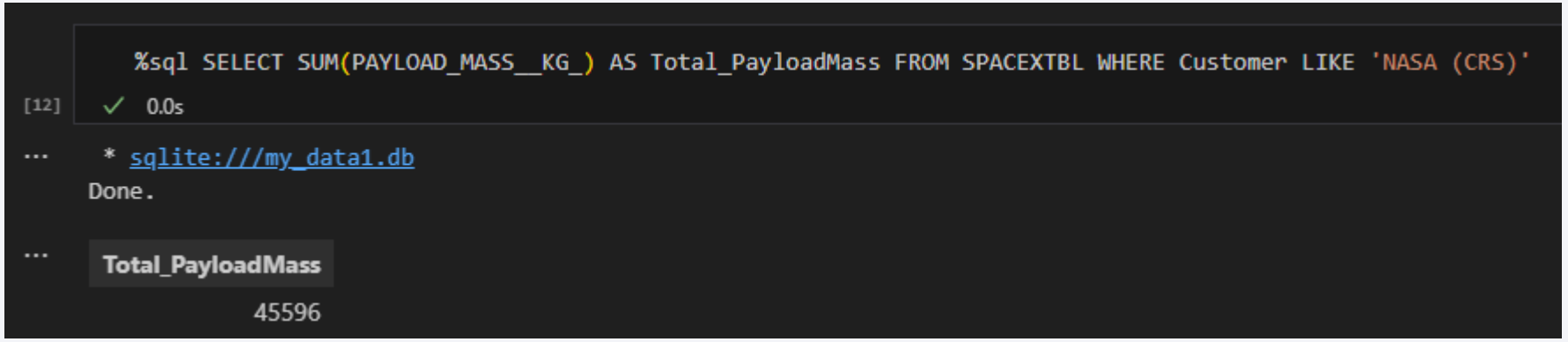
```
 * sqlite:///my_data1.db
Done.
```

Date	Time (UTC)	Booster_Version	Launch_Site	Payload
2010-06-04	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit
2010-12-08	15:43:00	F9 v1.0 B0004	CCAFS LC-40	Dragon demo flight C1, two CubeSats, barrel of Brouere cheese
2012-05-22	7:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2
2012-10-08	0:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1
2013-03-01	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2

Total Payload Mass

We use this code:

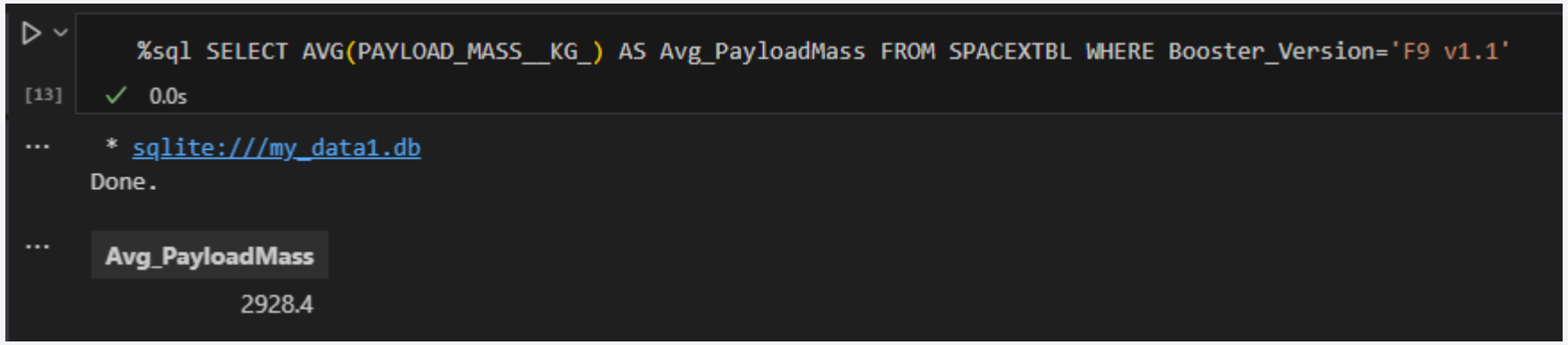
SELECT SUM(PAYLOAD_MASS__KG_) AS Total_PayloadMass FROM SPACEXTBL WHERE Customer LIKE 'NASA (CRS)'



Average Payload Mass by F9 v1.1

We use this code:

SELECT AVG(PAYLOAD_MASS__KG_) AS Avg_PayloadMass FROM SPACEXTBL WHERE Booster_Version='F9 v1.1'



First Successful Ground Landing Date

The code is:

SELECT MIN(Date) AS First_Success FROM SPACEXTBL WHERE Landing_Outcome='Success (ground pad)'

```
%sql SELECT MIN(Date) AS First_Success FROM SPACEXTBL WHERE Landing_Outcome='Success (ground pad)'
[18] ✓ 0.0s
... * sqlite:///my_data1.db
Done.
...
First_Success
2015-12-22
```

Successful Drone Ship Landing with Payload between 4000 and 6000

The code is:

SELECT Booster_Version FROM SPACEXTBL WHERE Landing_Outcome = 'Success (drone ship)' AND PAYLOAD_MASS__KG_ > 4000 AND PAYLOAD_MASS__KG_ < 6000

```
%sql SELECT Booster_Version FROM SPACEXTBL WHERE Landing_Outcome = 'Success (drone ship)' AND PAYLOAD_MASS__KG_ > 4000 AND PAYLOAD_MASS__KG_ < 6000
[20] ✓ 0.0s
 * sqlite:///my_data1.db
Done.
```

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

Total Number of Successful and Failure Mission Outcomes

```
%sql SELECT COUNT(Mission_Outcome) AS Outcome_Success FROM SPACEXTBL WHERE Mission_Outcome LIKE 'Success%'
```

[21] ✓ 0.0s

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

Outcome_Success
100

```
%sql SELECT COUNT(Mission_Outcome) AS Outcome_Failure FROM SPACEXTBL WHERE Mission_Outcome LIKE 'Failure%'
```

[22] ✓ 0.0s

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

Outcome_Failure
1

Boosters Carried Maximum Payload

List the names of the booster which have carried the maximum payload mass:

- F9 B5 B1048.4
- F9 B5 B1048.5
- F9 B5 B1049.4
- F9 B5 B1049.5
- F9 B5 B1049.7
- F9 B5 B1051.3
- F9 B5 B1051.4
- F9 B5 B1051.6
- F9 B5 B1056.4
- F9 B5 B1058.3
- F9 B5 B1060.2
- F9 B5 B1060.3

2015 Launch Records

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

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

Both failures happen in CCAFS LC-40 launch site.

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

This table shows the count of landing outcome from 2010-06-04 to 2017-03-20.

“No attempt” occurred most often.

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

Section 3

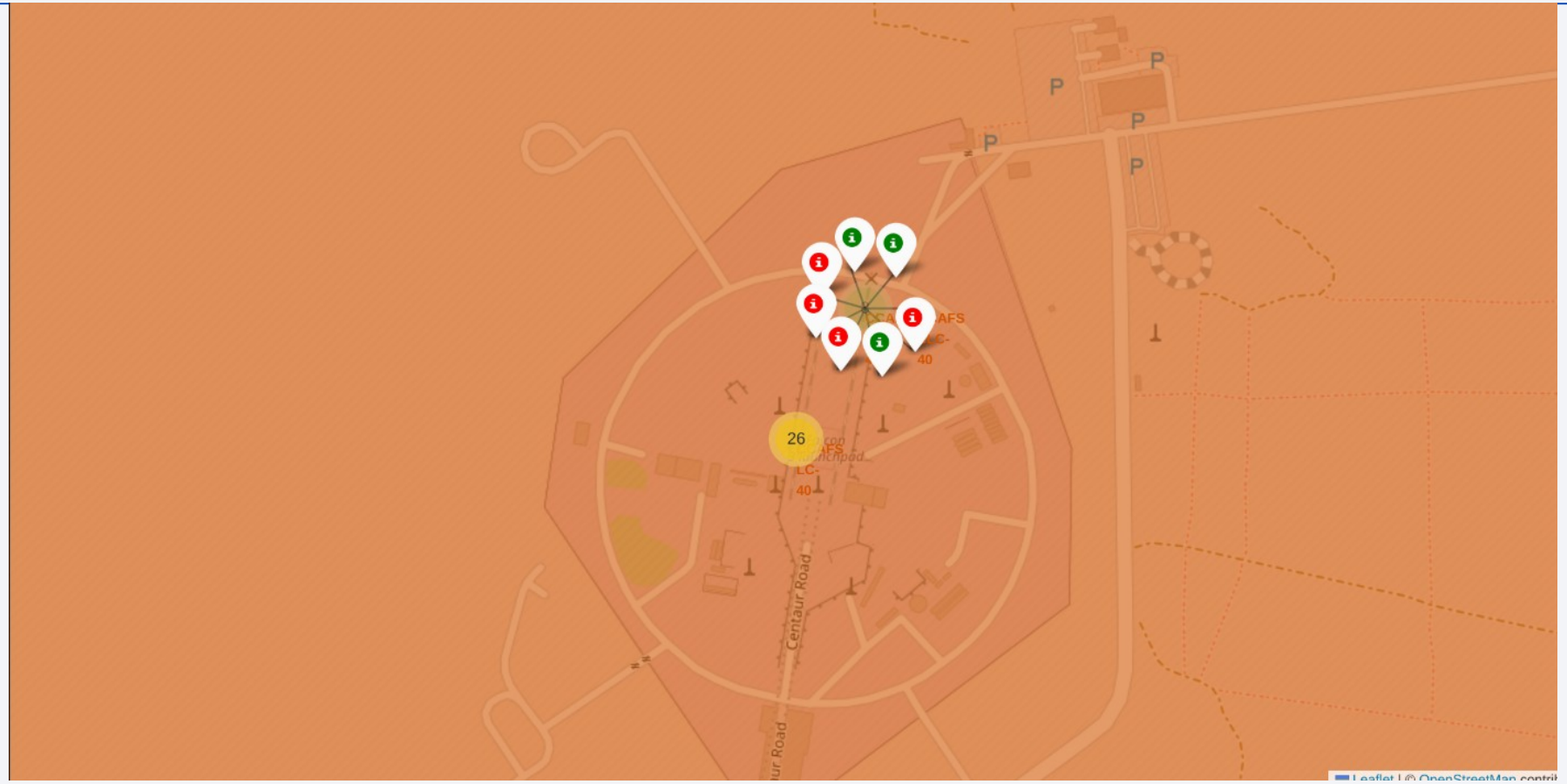
Launch Sites Proximities Analysis

Launch Site Locations

There are four launch sites, three in the East Coast and one in the West Coast.

They are also located as close as possible to the equator line.

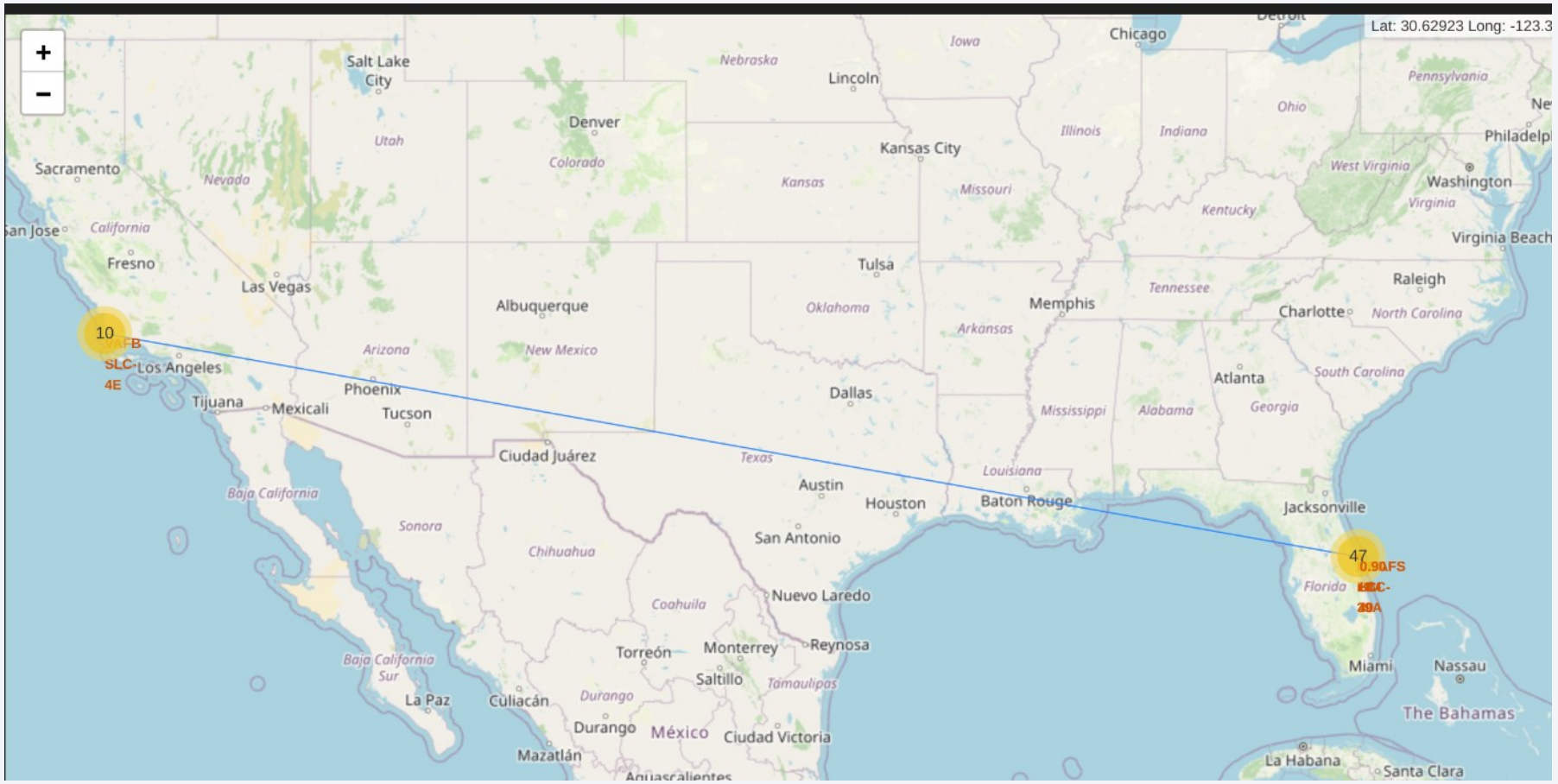
Launch Sites and Outcomes



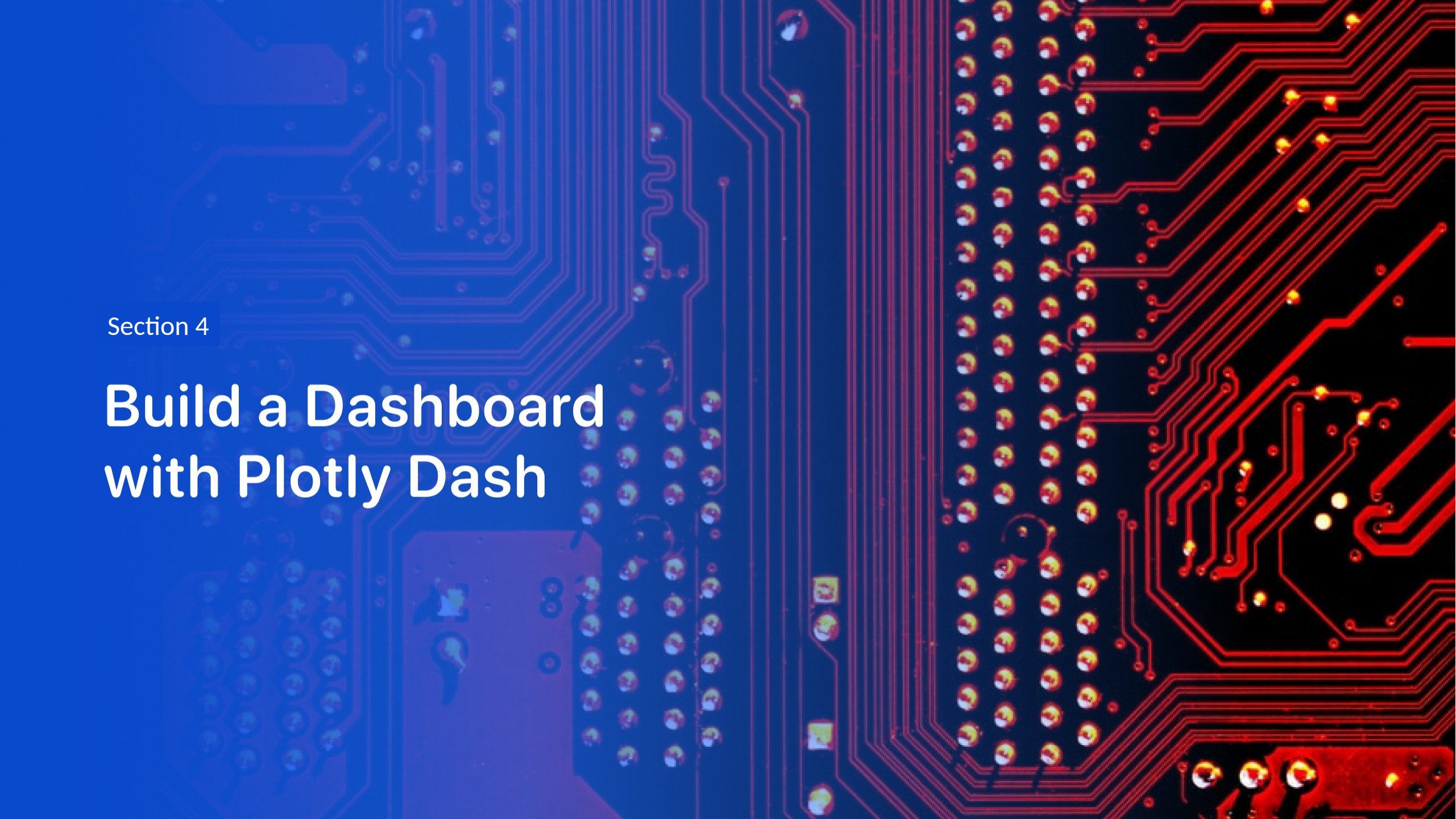
This is the launch outcomes from two locations in the East Coast.

Green means success, red means failure

<Folium Map Screenshot 3>



The distance between the two sites are quite far!


Section 4
Build a Dashboard with Plotly Dash

<Dashboard Screenshot 1>

Replace <Dashboard screenshot 1> title with an appropriate title

Show the screenshot of launch success count for all sites, in a piechart

Explain the important elements and findings on the screenshot

<Dashboard Screenshot 2>

Replace <Dashboard screenshot 2> title with an appropriate title

Show the screenshot of the piechart for the launch site with highest launch success ratio

Explain the important elements and findings on the screenshot

<Dashboard Screenshot 3>

Replace <Dashboard screenshot 3> title with an appropriate title

Show screenshots of Payload vs. Launch Outcome scatter plot for all sites, with different payload selected in the range slider

Explain the important elements and findings on the screenshot, such as which payload range or booster version have the largest success rate, etc.

Section 5

Predictive Analysis (Classification)

Classification Accuracy

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

[11] ✓ 7.2s

Outputs are collapsed ···

We output the `GridSearchCV` object for logistic regression. We display the best parameters using the data attr
the validation data using the data attribute `best_score_`.

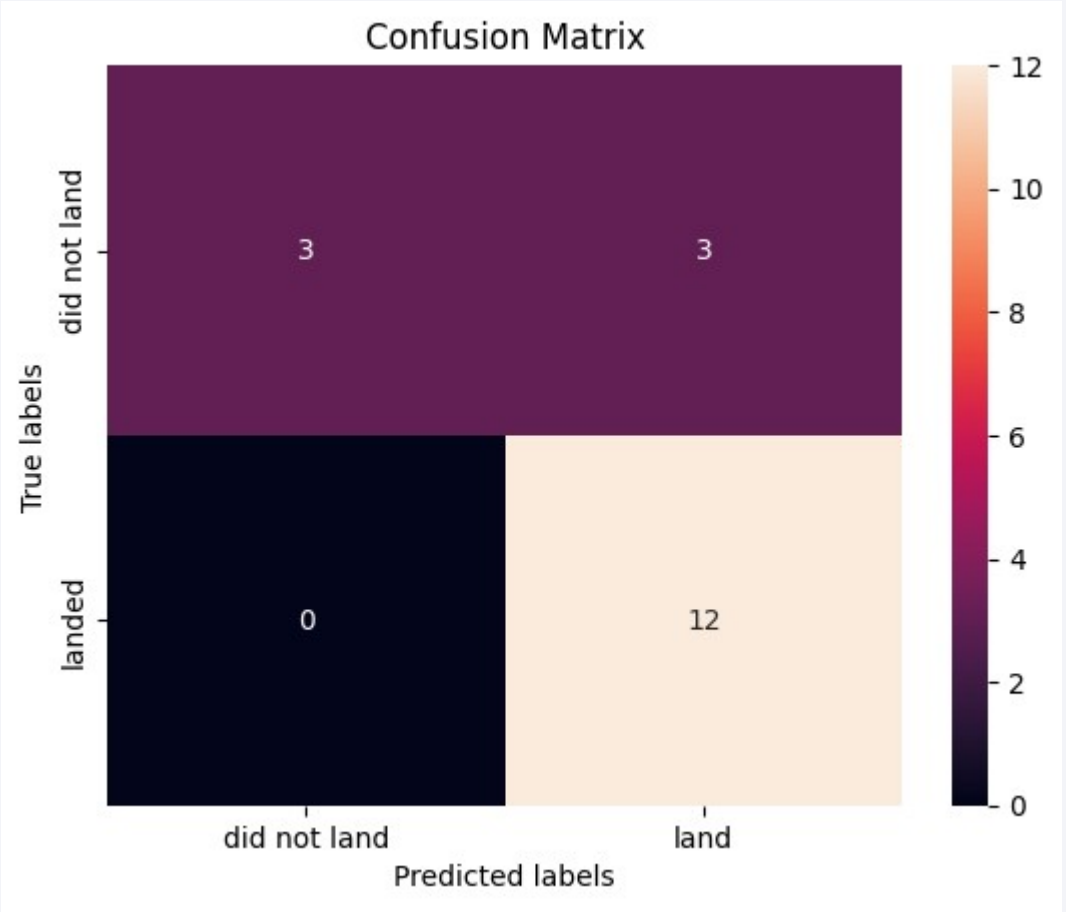
```
print("tuned hpyerparameters :(best parameters) ",logreg_cv.best_params_)
print("accuracy :",logreg_cv.best_score_)
```

[12] ✓ 0.0s

```
tuned hpyerparameters :(best parameters)  {'C': 1, 'penalty': 'l2', 'solver': 'lbfgs'}
accuracy : 0.8196428571428571
```

Confusion Matrix

- We saw some misclassification, where there are 3 launches that failed to land but were predicted to land



Conclusions

- We find a positive relationship: in any launch site, most recent flights tend to be much more successful than early flights
- ES-L1, SSO, HEO, and GEO has the highest success rate but maybe because they only have few observations
- Success rate increases almost in every year
- We saw some misclassification in the predictive model, where there are 3 launches that failed to land but were predicted to land

Thank you!