IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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Outline

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

Executive Summary

- Collected data from public SpaceX API and SpaceX Wikipedia page. Created labels column 'class' which classifies successful landings. Explored data using SQL, visualization, folium maps, and dashboards. Gathered relevant columns to be used as features. Changed all categorical variables to binary using one hot encoding. Standardized data and used GridSearchCV to find best parameters for machine learning models. Visualize accuracy score of all models.

- Four machine learning models were produced: Logistic Regression, Support Vector Machine, Decision Tree Classifier, and K Nearest Neighbors. All produced similar results with accuracy rate of about 83.33%. All models over predicted successful landings. More data is needed for better model determination and accuracy.

Introduction

Background

- Commercial Space Age is Here
- Space X has best pricing ($62 million vs. $165 million USD)
- Largely due to ability to recover part of rocket (Stage 1)
- Space Y wants to compete with Space X

Problem

- Space Y tasks us to train a machine learning model to predict successful Stage 1 recovery

Section 1

Methodology

Methodology

Executive Summary

- Data collection methodology:
  - Combined data from SpaceX public API and SpaceX Wikipedia page
- Perform data wrangling
  - Classifying true landings as successful and unsuccessful otherwise
- 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 webscraping.
- <u>Space X API Data Columns:</u>
- FlightNumber, Date, BoosterVersion, PayloadMass, Orbit, LaunchSite, Outcome, Flights, GridFins,
- Reused, Legs, LandingPad, Block, ReusedCount, Serial, Longitude, Latitude
- <u>Wikipedia Webscrape Data Columns:</u>
- Flight No., Launch site, Payload, PayloadMass, Orbit, Customer, Launch outcome, Version Booster, Booster landing, Date, Time

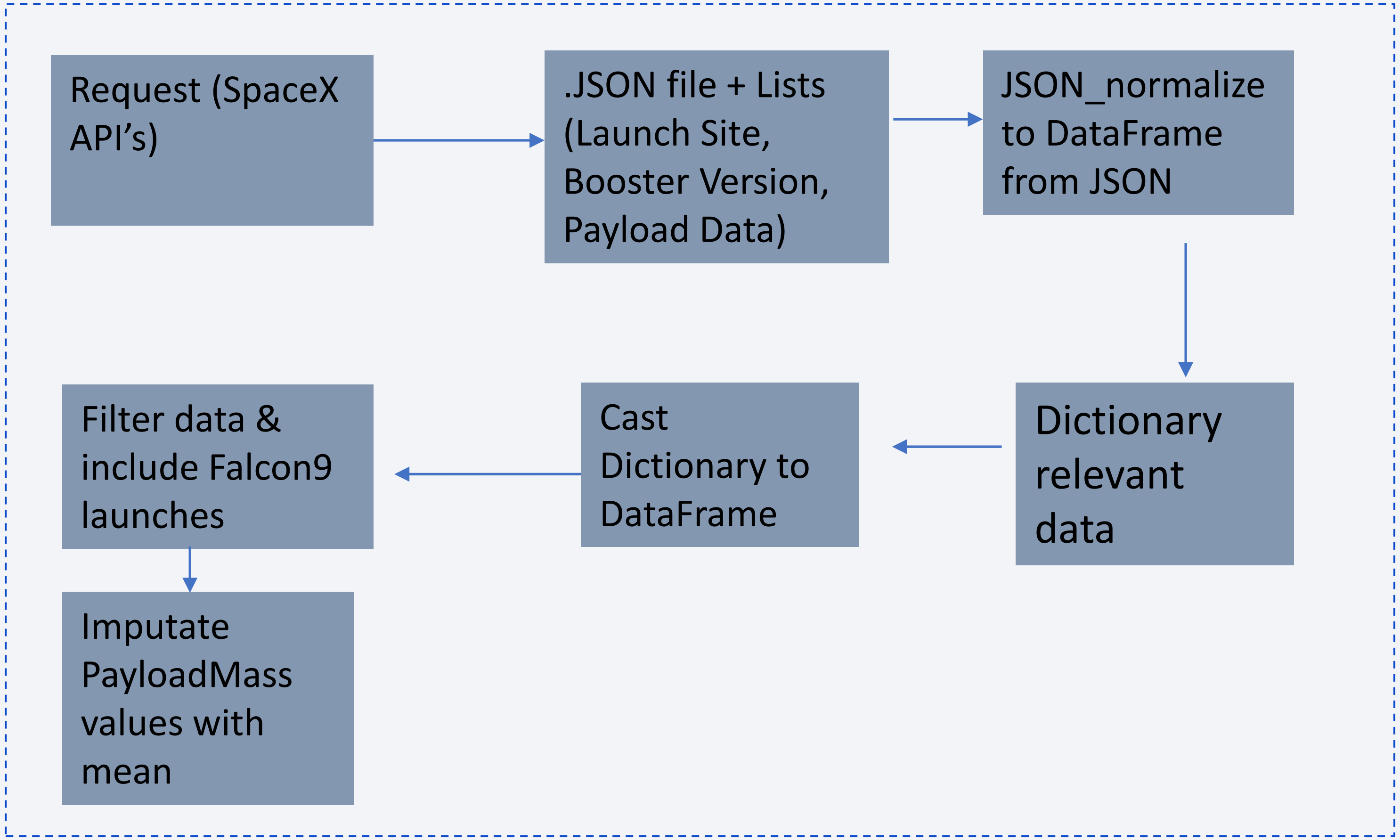
Data Collection – SpaceX API

Data Collection-

SpaceX API

GitHub URL:

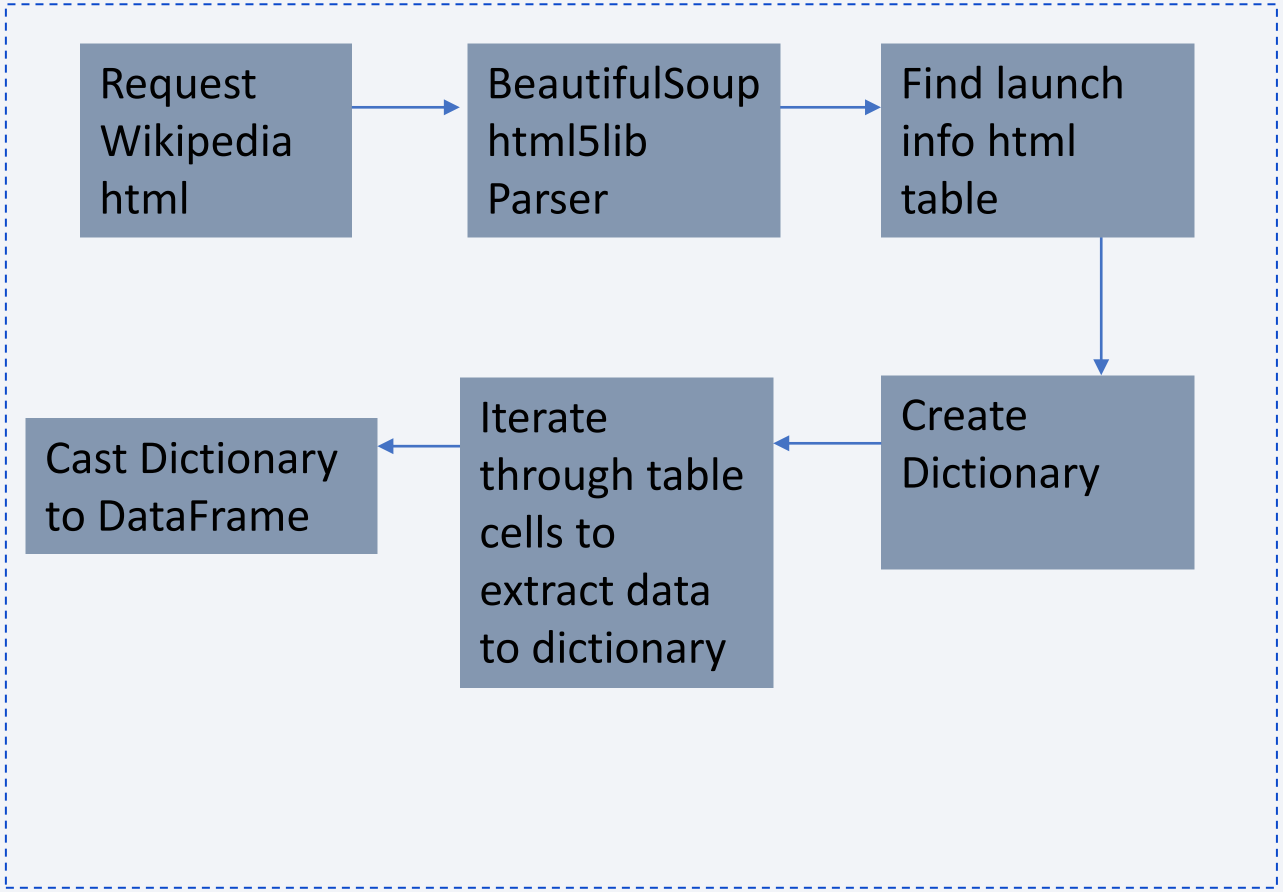
https://github.com/ronlicaj/IBM-Data-Science-Professional-Certificate/blob/main/WEEK1/Data%20Collection%20Api%20.ipynb



Data Collection - Scraping

Data Collection –

Web Scraping



GitHub url:

https://github.com/ronlicaj/IBM-Data-Science-Professional-Certificate/blob/main/WEEK1/Data%20Collection%20with%20Web%20Scraping.ipynb

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

Github url:

https://github.com/ronlicaj/IBM-Data-Science-Professional
Certificate/blob/main/WEEK1/Data%20Wrangling.ipynb

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

Github url:

https://github.com/ronlicaj/IBM-Data-Science-Professional-Certificate/blob/main/WEEK2/Eda%20with%20Data%20Visualization.ipynb

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.

Github url:

https://github.com/ronlicaj/IBM-Data-Science-Professional-Certificate/blob/main/WEEK2/EDA%20with%20SQL.ipynb

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.

Github url:

https://github.com/ronlicaj/IBM-Data-Science-Professional-Certificate/blob/main/WEEK3/Interactive%20Visual%20Analytics%20with%20Folium.ipynb

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.

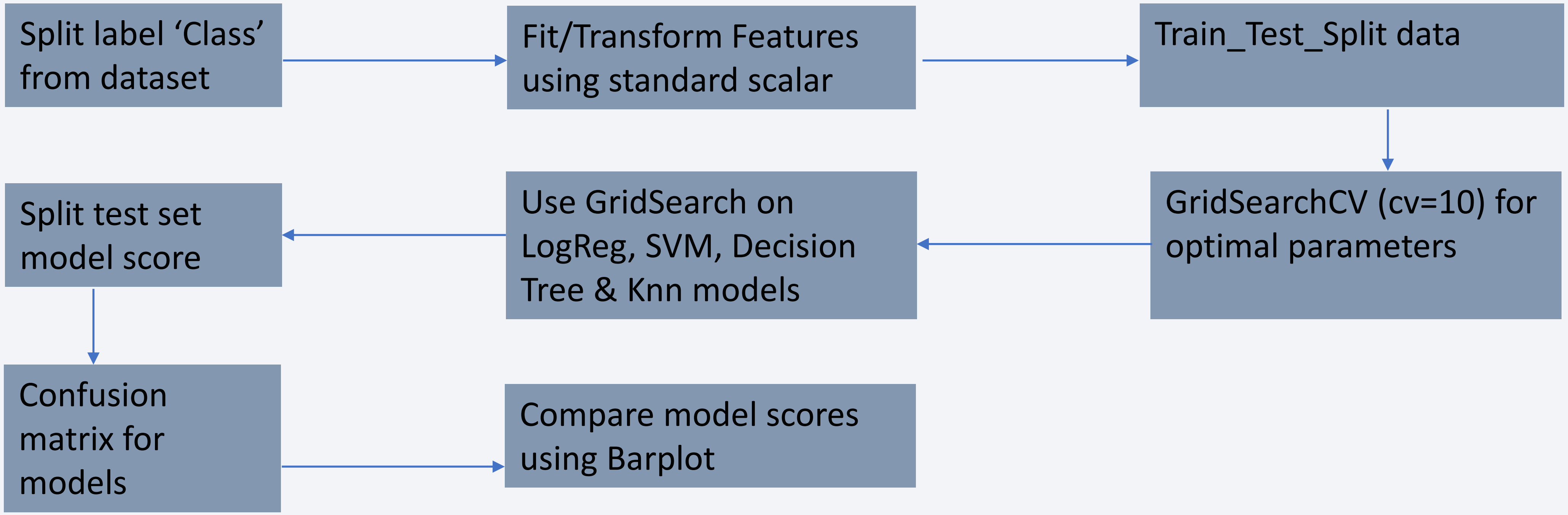
Github url:

https://github.com/ronlicaj/IBM-Data-Science-Professional-Certificate/blob/main/WEEK3/spacex_dash_app.py

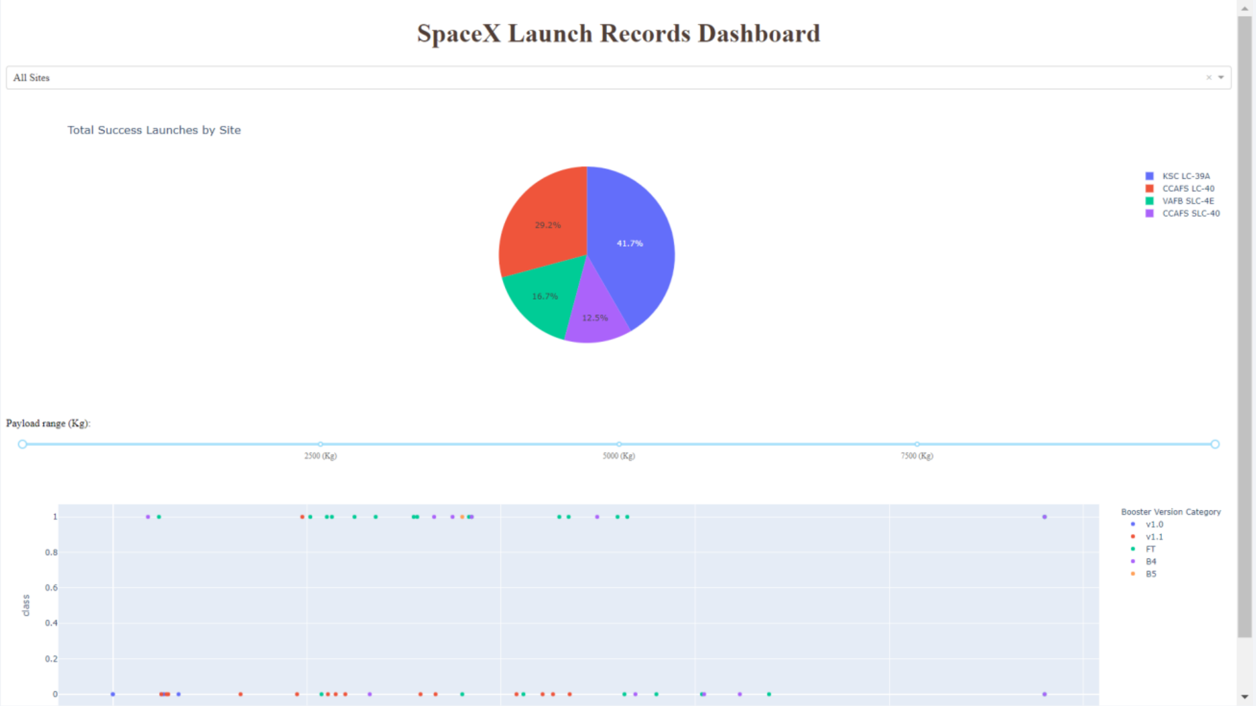
Predictive Analysis (Classification)

Github url:

https://github.com/ronlicaj/IBM-Data-Science-Professional-Certificate/blob/main/WEEK4/Machine%20Learning%20Prediction.ipynb



Results

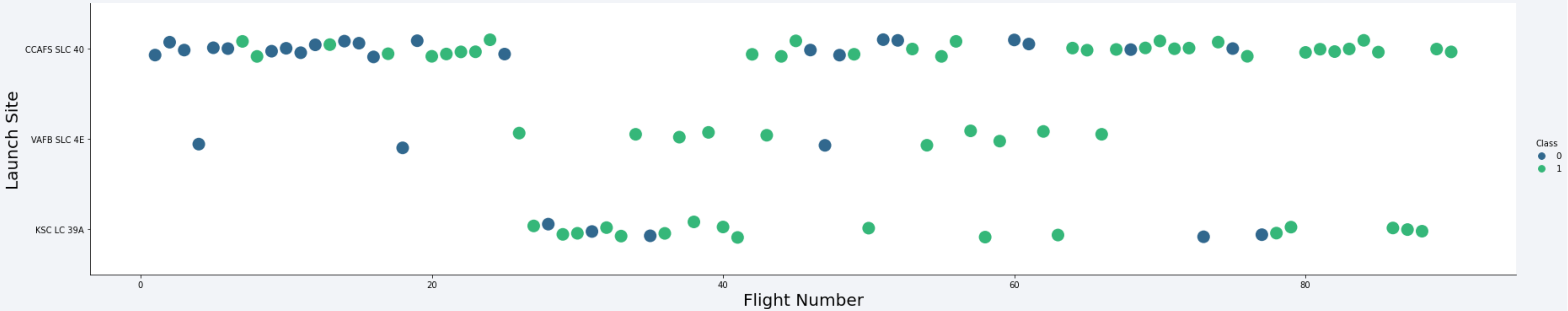


Preview of the Plotly dashboard. The following sides will show the results of EDA with visualization, EDA with SQL, Interactive Map with Folium, and the results of our model with around 83% accuracy.

Section 2

Insights drawn from EDA

Flight Number vs. Launch Site



Green: successful launch Blue: unsuccessful launch

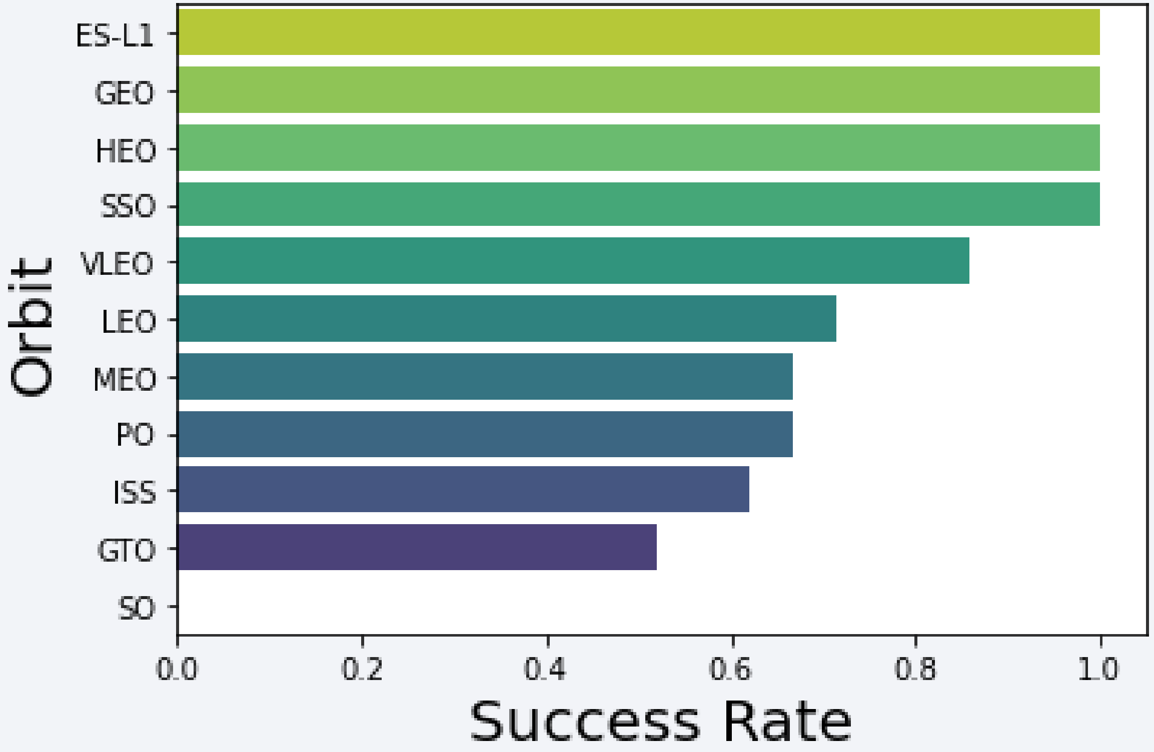
The graph suggests an increase in success rate over time (indicated in Flight Number). Likely a big breakthrough around flight 20 which significantly increased success rate. CCAFS appears to be the main launch site as it has the most volume.

Payload vs. Launch Site

Green: successful launch   Purple: unsuccessful launch

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



Success Rate Scale with
0 as 0%
0.6 as 60%
1 as 100%

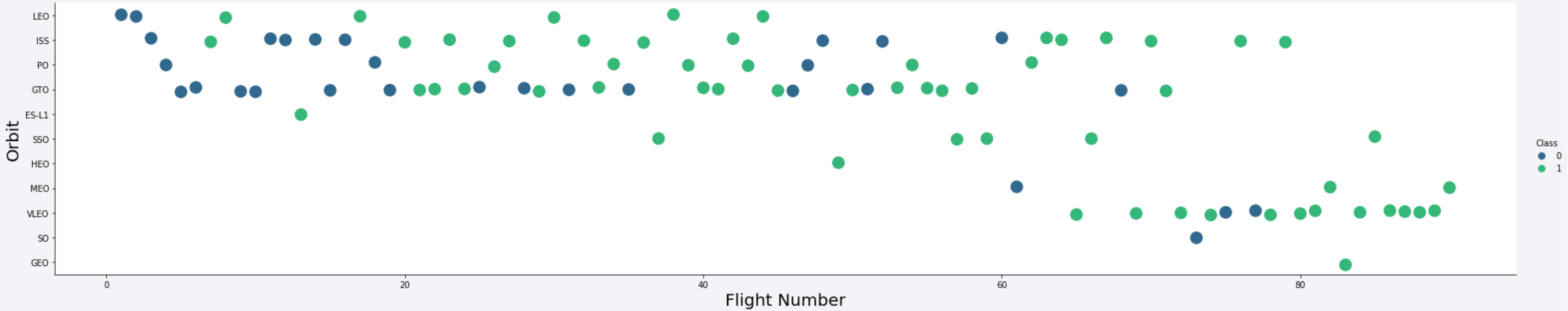
ES-L1 (1), GEO (1), HEO (1) have 100% success rate (sample sizes in parenthesis) SSO (5) has 100% success rate

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



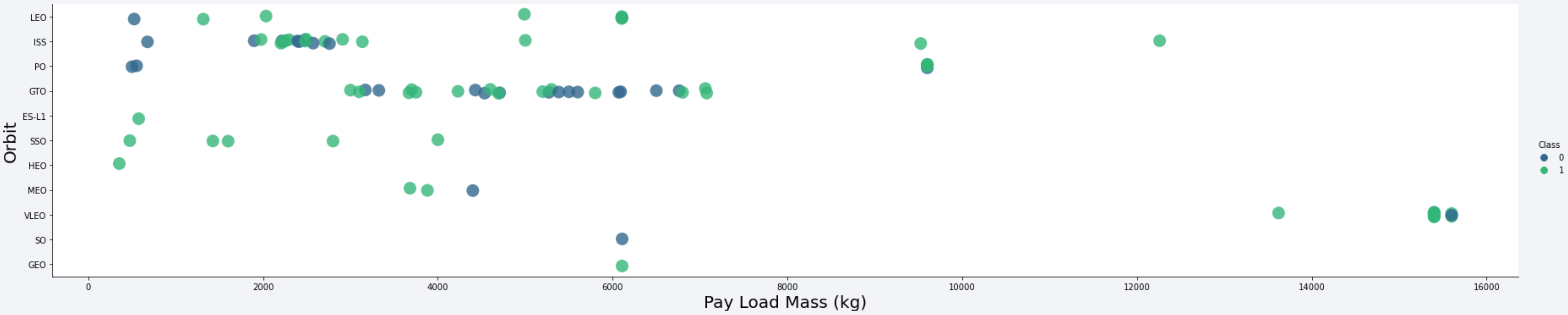
Green: successful launch Blue: unsuccessful launch

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



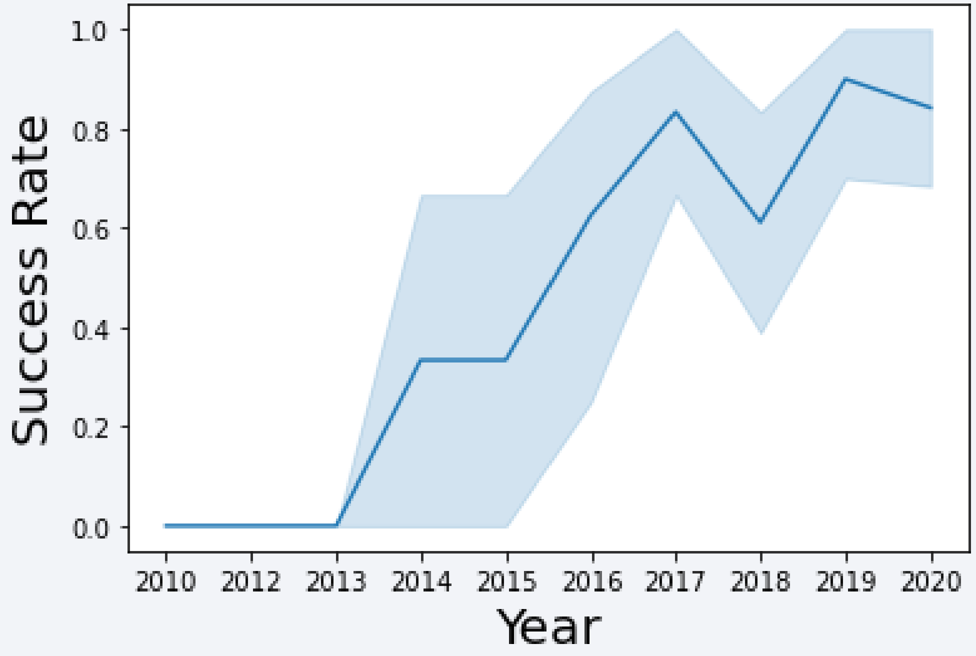
Green: successful launch   Purple: unsuccessful launch

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



95% confidence interval
(light blue shading)

Success generally increases over time since 2013 with a slight dip in 2018

Success in recent years at around 80%

All Launch Site Names

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

```
%sql select DISTINCT LAUNCH_SITE from SPACEXTBL
```

```
 * ibm_db_sa://gqk30869:***@21fecfd8-47b7-4937-840d-d791d0218660.bs2io90l08kqb1od8lcg.databases
Done.
```

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

Displaying unique values with the distinct function

Launch Site Names Begin with 'CCA'

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

```
%sql select * from SPACEXTBL where launch_site like 'CCA%' limit 5
```

```
 * ibm_db_sa://gqk30869:***@21fecfd8-47b7-4937-840d-d791d0218660.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:31864/bludb
Done.
```

DATE	time__utc_	booster_version	launch_site	payload	payload_mass__kg_	orbit	customer	mission_outcom
2010-06-04	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Succe
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	Succe
2012-05-22	07:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Succe
2012-10-08	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Succe
2013-03-01	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Succe

The like function allows us to specify the launch site while the limit displays only 5 results

Total Payload Mass

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

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

```
 * ibm_db_sa://gqk30869:***@21fecfd8-47b7-4937-840d-d791d0218660.bs2io90l08kqb1od8lcg.databases.appd
Done.
```

SUM
45596

Selecting the sum of payload mass where only ‘NASA’ (CRS) with the like function

Average Payload Mass by F9 v1.1

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

```
%sql select avg(payload_mass__kg_) as Average from SPACEXTBL where booster_version like 'F9 v1.1%'
```

```
 * ibm_db_sa://gqk30869:***@21fecfd8-47b7-4937-840d-d791d0218660.bs2io90l08kqb1od8lcg.databases.appdo
Done.
```

average
2534

Selecting the average with avg function and restricting the query to show only where version is ‘F9 v1.1%’

First Successful Ground Landing Date

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

Hint:Use min function

```
%sql select min(date) as Date from SPACEXTBL where mission_outcome like 'Success'
```

```
 * ibm_db_sa://gqk30869:***@21fecfd8-47b7-4937-840d-d791d0218660.bs2io90l08kqb1od8lcg.databases.appd
Done.
```

DATE
2010-06-04

Using min function for the earliest date where mission was noted as success

Successful Drone Ship Landing with Payload between 4000 and 6000

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

```
%sql select booster_version from SPACEXTBL where (mission_outcome like 'Success') AND (payload_mass__kg_ BETWEEN 4000 AND 6000) AND (landing__outcome
```

```
 * ibm_db_sa://gqk30869:***@21fecfd8-47b7-4937-840d-d791d0218660.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:31864/bludb
Done.
```

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

Selecting the booster version noted as success, with payload mass between 4-6000 and landing outcome is successful.

Total Number of Successful and Failure Mission Outcomes

List the total number of successful and failure mission outcomes

```
%sql SELECT mission_outcome, count(*) as Count FROM SPACEXTBL GROUP by mission_outcome ORDER BY mission_outcome
```

```
 * ibm_db_sa://gqk30869:***@21fecfd8-47b7-4937-840d-d791d0218660.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:31864/bludb
Done.
```

mission_outcome	COUNT
Failure (in flight)	1
Success	99
Success (payload status unclear)	1

We are counting all mission outcomes and then we are grouping and ordering by mission outcome to see the successful and unsuccessful mission

Boosters Carried Maximum Payload

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

```
maxm = %sql select max(payload_mass__kg_) from SPACEXTBL
maxv = maxm[0][0]
%sql select booster_version from SPACEXTBL where payload_mass__kg_=(select max(payload_mass__kg_) from SPACEXTBL)
```

```
 * ibm_db_sa://gqk30869:***@21fecfd8-47b7-4937-840d-d791d0218660.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:31864/
Done.
 * ibm_db_sa://gqk30869:***@21fecfd8-47b7-4937-840d-d791d0218660.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:31864/
Done.
```

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

The subquery is giving the max payload kg from the table and that is used in the main query to display the booster version where the value is extracted by the subquery

2015 Launch Records

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

```
%sql select MONTHNAME(DATE) as Month, landing__outcome, booster_version, launch_site from SPACEXTBL where DATE like '2015%' AND
```

```
 * ibm_db_sa://gqk30869:***@21fecfd8-47b7-4937-840d-d791d0218660.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:31864/bludb
Done.
```

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

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

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

```
%sql select landing__outcome, count(*) as count from SPACEXTBL where Date >= '2010-06-04' AND Date <= '2017-03-20' GROUP by landing__outcome ORDE
```

```
 * ibm_db_sa://gqk30869:***@21fecfd8-47b7-4937-840d-d791d0218660.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:31864/bludb
Done.
```

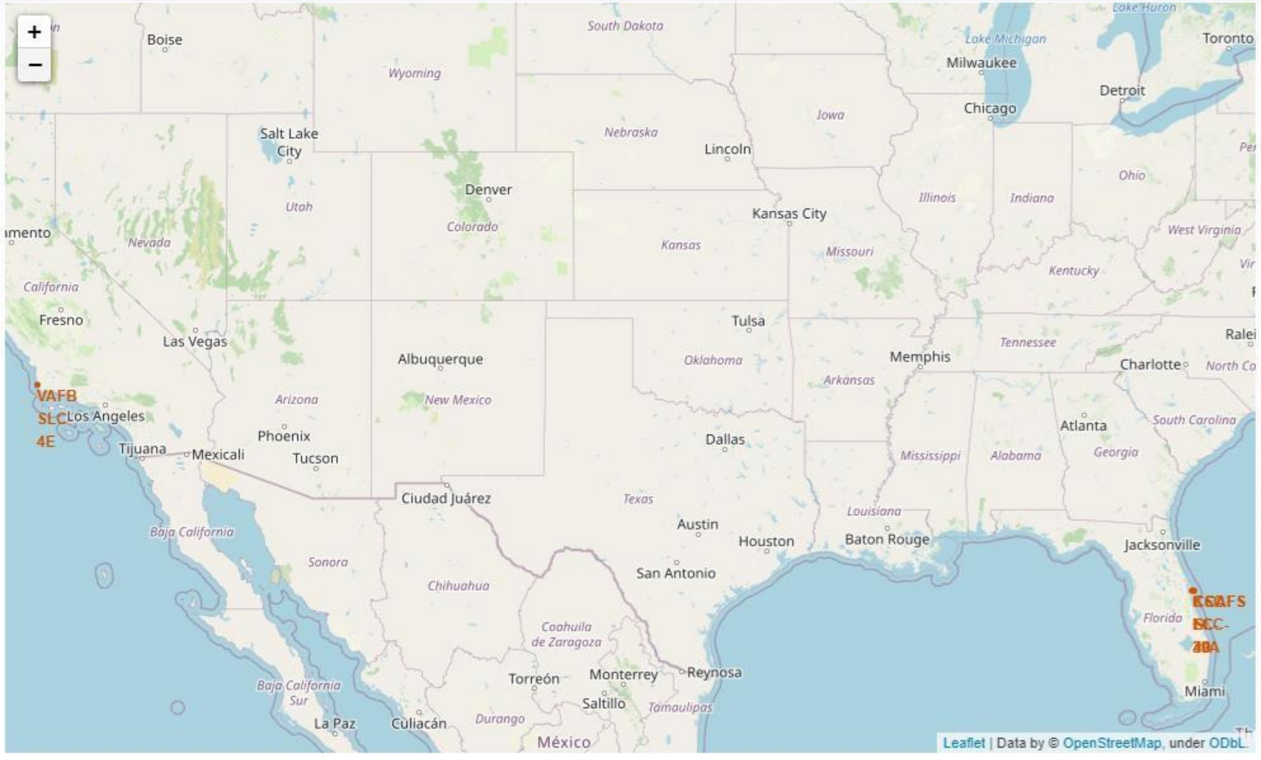
landing__outcome	COUNT
No attempt	10
Failure (drone ship)	5
Success (drone ship)	5
Controlled (ocean)	3
Success (ground pad)	3
Failure (parachute)	2
Uncontrolled (ocean)	2
Precluded (drone ship)	1

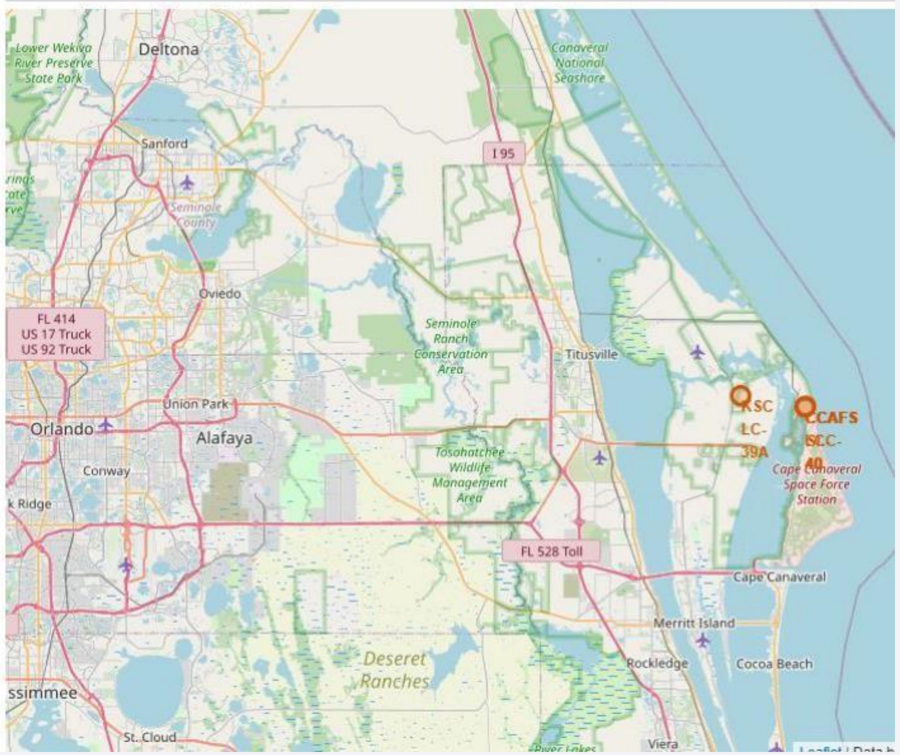
The query successfully displays in desc order the landing outcomes by specifying with the where function the date grouping by landing outcome

Section 3

Launch Sites Proximities Analysis

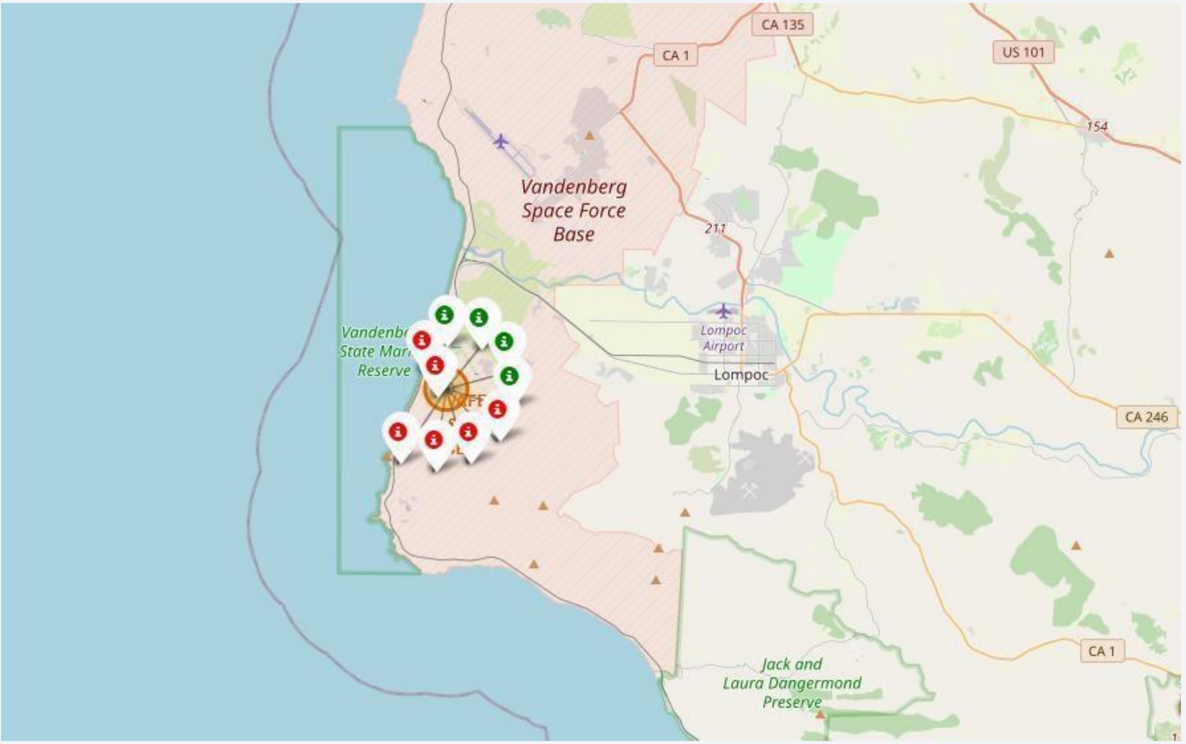
Launch Site Locations





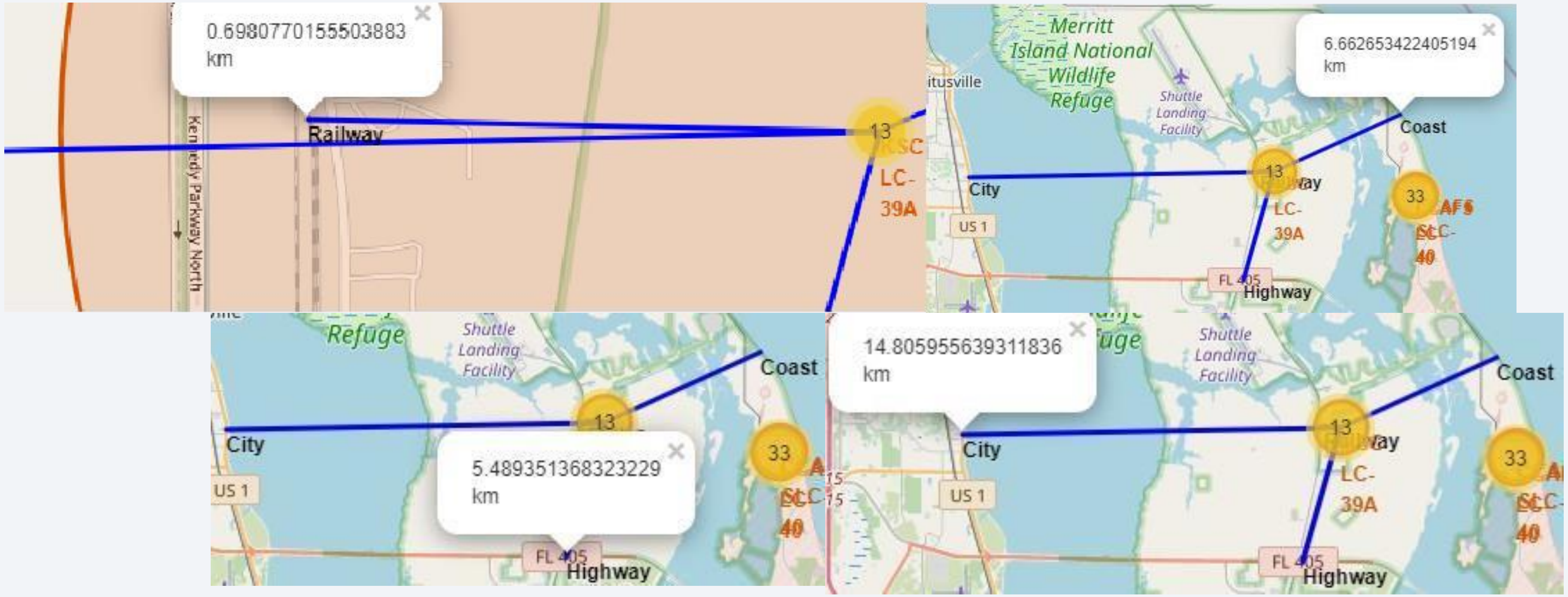
The left map shows all launch sites relative US map. The right map shows the two Florida launch sites since they are very close to each other. All launch sites are near the ocean

Color-Coded Launch Markers



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>

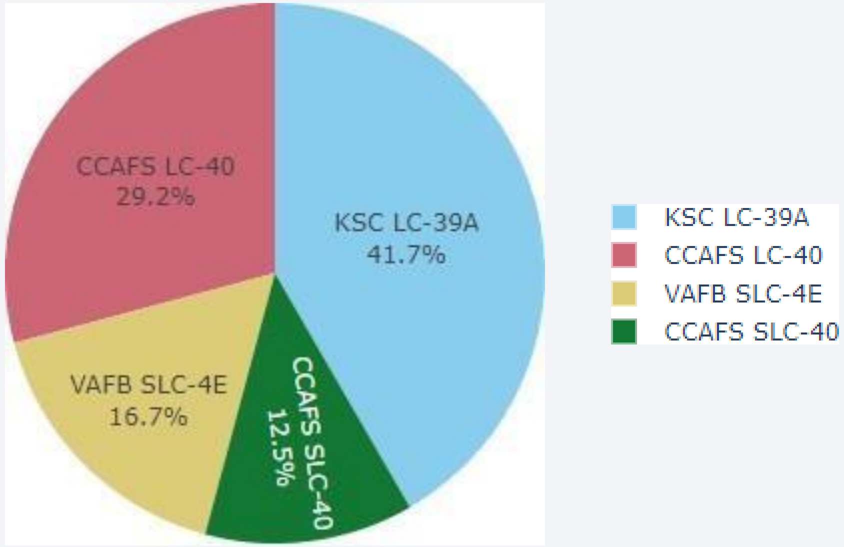


Using KSC LC-39A as an example, launch sites are very close to railways for large part and supply transportation. Launch sites are close to highways for human and supply transport. Launch sites are also close to coasts and relatively far from cities so that launch failures can land in the sea to avoid rockets falling on densely populated areas.

Section 4

Build a Dashboard with Plotly Dash

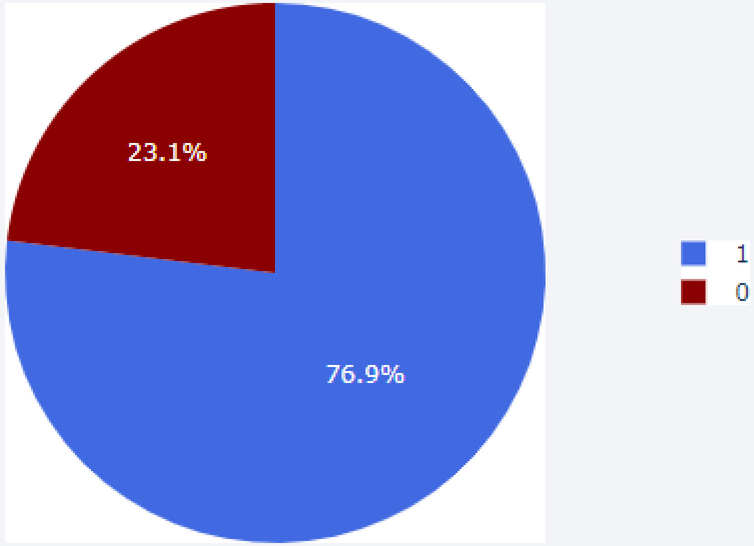
Successful Launches Across Launch Sites



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.

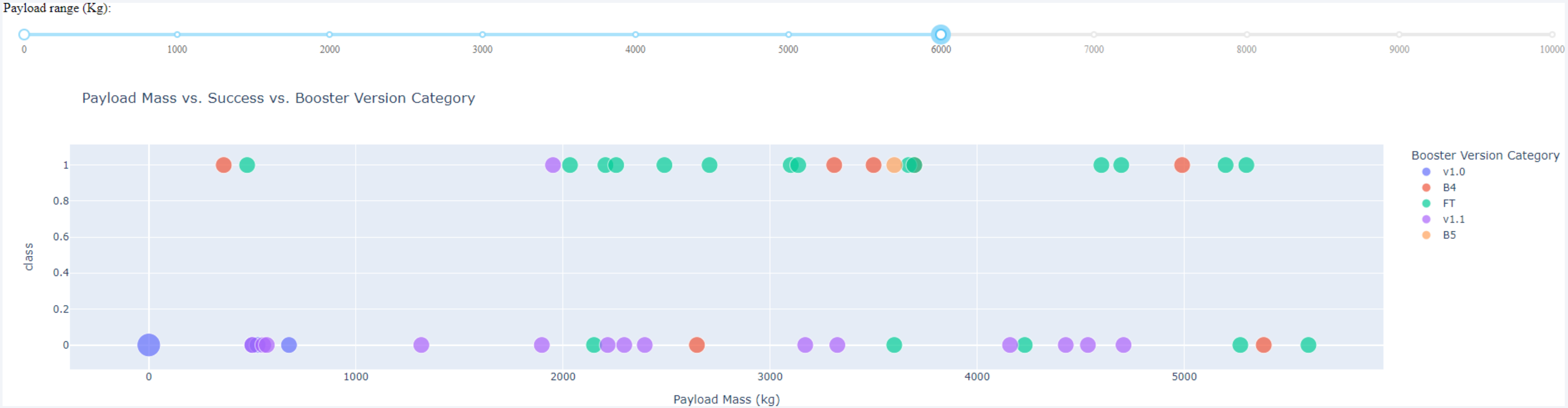
Highest Success Rate Launch Site

KSC LC-39A Success Rate (blue=success)



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

<Dashboard Screenshot 3>

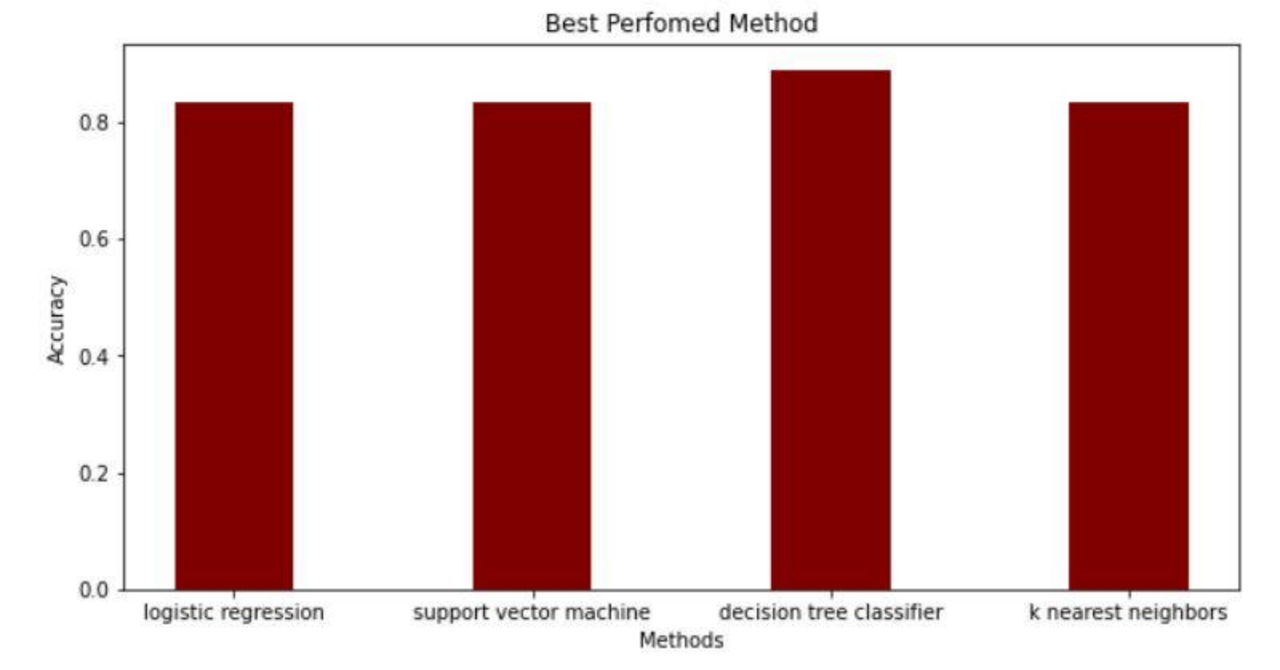


Plotly dashboard has a Payload range selector. However, this is set from 0-10000 instead of the max Payload of 15600. Class indicates 1 for successful landing and 0 for failure. Scatter plot also accounts for booster version category in color and number of launches in point size. In this particular range 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., with the exception of decision tree model.

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

Correct predictions are on a diagonal from top left to bottom right.

Since all models performed almost 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

- Our task: to develop a machine learning model for Space Y who wants to bid against SpaceX
- The goal of model is to predict when Stage 1 will successfully land to save ~$100 million USD
- Used data from a public SpaceX API and web scraping SpaceX Wikipedia page
- Created data labels and stored data into a DB2 SQL database
- Created a dashboard for visualization
- We created a machine learning model with an accuracy around of 88%
- Allon Mask of SpaceY can use this model to predict with relatively high accuracy whether a launch will have a successful Stage 1 landing before launch to determine whether the launch should be made or not
- If possible more data should be collected to better determine the best machine learning model and improve accuracy

Appendix

GitHub repository url:

https://github.com/ronlicaj/IBM-Data-Science-Professional-Certificate

Instructors:

Instructors: Rav Ahuja, Alex Aklson, Aije Egwaikhide, Svetlana Levitan, Romeo Kienzler, Polong Lin, Joseph Santarcangelo, Azim Hirjani, Hima Vasudevan, Saishruthi Swaminathan, Saeed Aghabozorgi, Yan Luo

Special Thanks to:

https://www.coursera.org/professional-certificates/ibm-data-science?#instructors

Thank you!