Data Science Capstone Project

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https://github.com/AlyHSaleh/IBMCapstoneProject

22/03/2024

Outline

- Executive Summary
- Introduction
- Methodology
- Results
- Conclusion

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

SpaceX Falcon 9 Rocket – The Verge

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

Methodology

- 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

Methodology

OVERVIEW OF DATA COLLECTION, WRANGLING, VISUALIZATION, DASHBOARD, AND MODEL METHODS

Data Collection Overview

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.

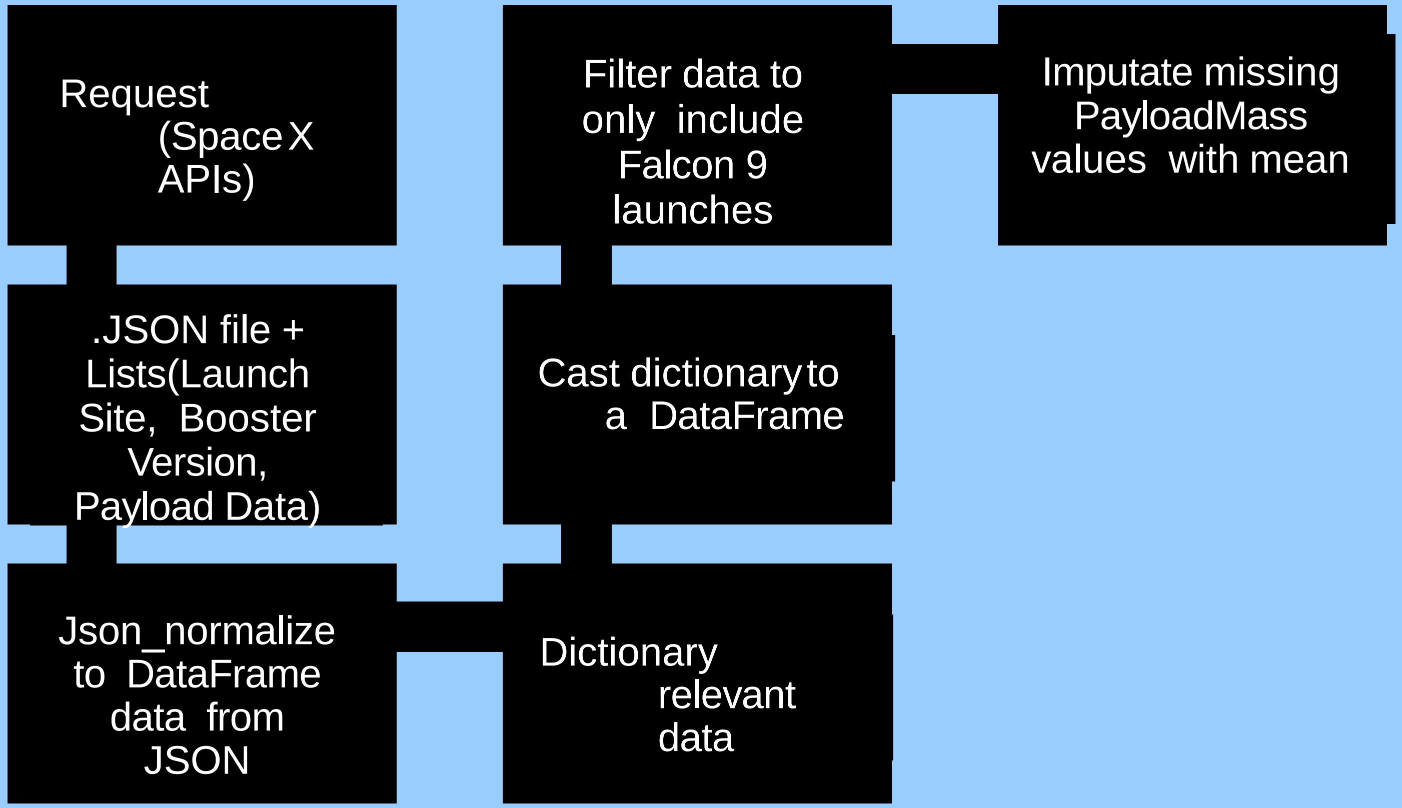
Space X API Data Columns:

FlightNumber, Date, BoosterVersion, PayloadMass, Orbit, LaunchSite, Outcome, Flights, GridFins,
Reused, Legs, LandingPad, Block, ReusedCount, Serial, Longitude, Latitude

Wikipedia Webscrape Data Columns:

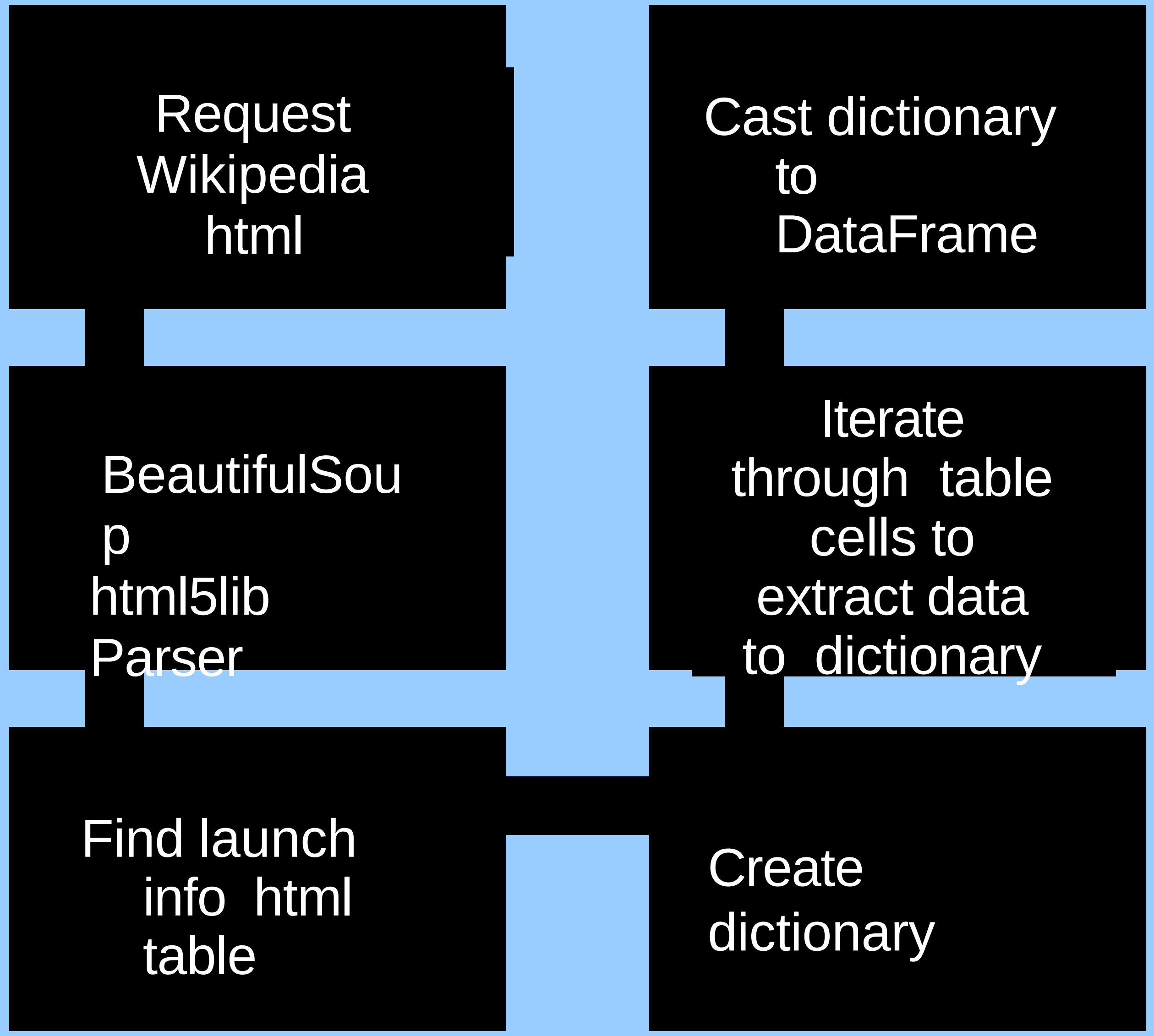
Flight No., Launch site, Payload, PayloadMass, Orbit, Customer, Launch outcome, Version Booster, Booster landing, Date, Time

Data Collection – SpaceX API



GitHub url: https://github.com/AlyHSaleh/IBMCapstoneProject/blob/main/jupyter-labs-spacex-data-collection-api%20(1).ipynb

Data Collection – Web Scraping



GitHub url: https://github.com/AlyHSaleh/IBMCapstoneProject/blob/main/jupyter-labs-webscraping.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/AlyHSaleh/IBMCapstoneProject/blob/main/labs-jupyter-spacex-Data%20wrangling.ipynb

EDA with SQL

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/AlyHSaleh/IBMCapstoneProject/blob/main/jupyter-labs-eda-sql-coursera_sqllite.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/AlyHSaleh/IBMCapstoneProject/blob/main/jupyter-labs-eda-dataviz.ipynb.jupyterlite.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/AlyHSaleh/IBMCapstoneProject/blob/main/lab_jupyter_launch_site_location.jupyterlite.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.

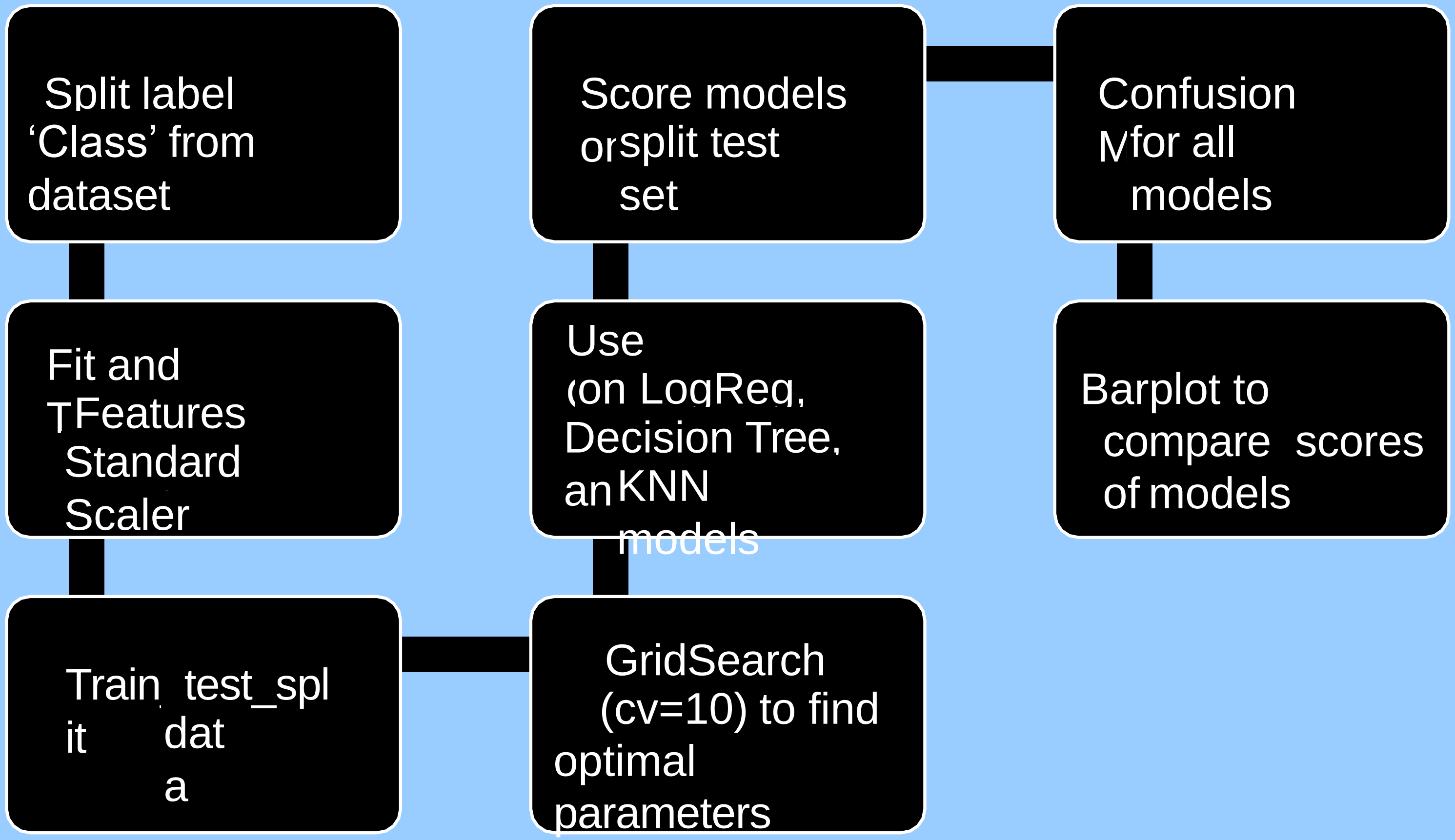
The scatter plot can help us see how success varies across launch sites, payload mass, and booster version category.

GitHub url:

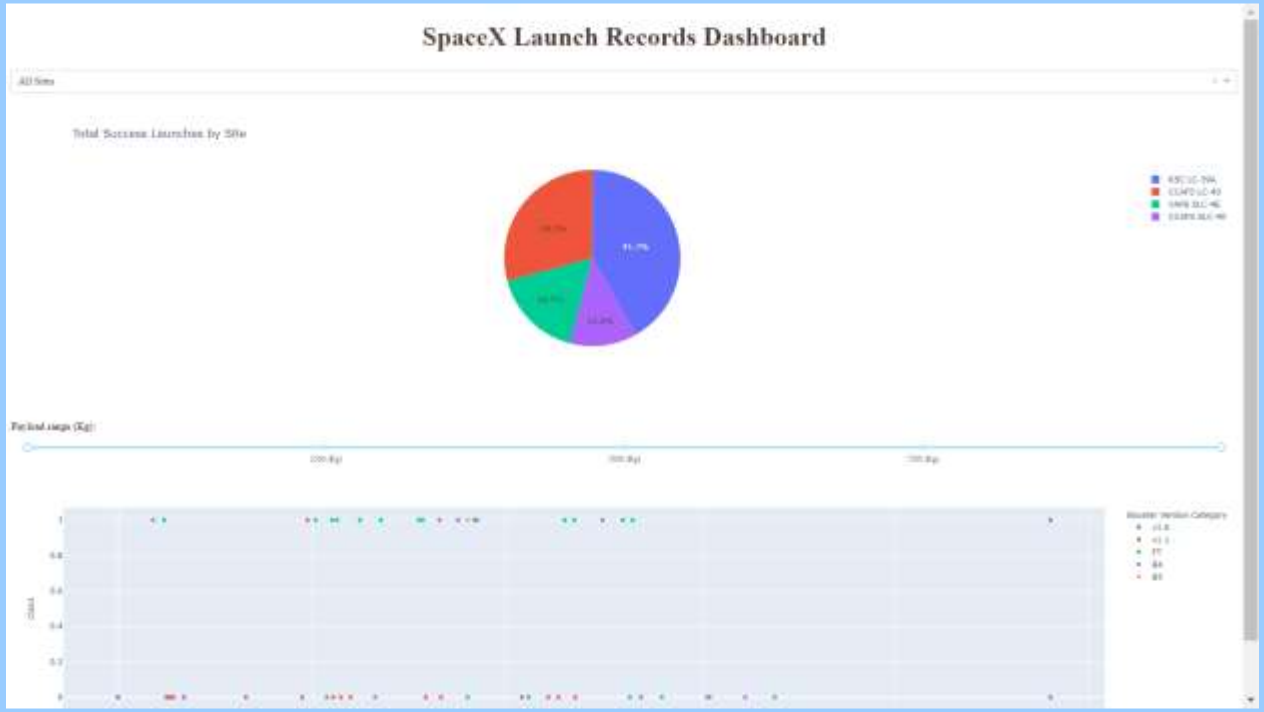
https://github.com/AlyHSaleh/IBMCapstoneProject/blob/main/spacex_dash_app.py

Predictive analysis (Classification)

GitHub url:
https://github.com/AlyHSaleh/IBMCapstoneProject/blob/main/SpaceX_Machine_Learning_Prediction_Part_5.jupyterlite.ipynb



Results

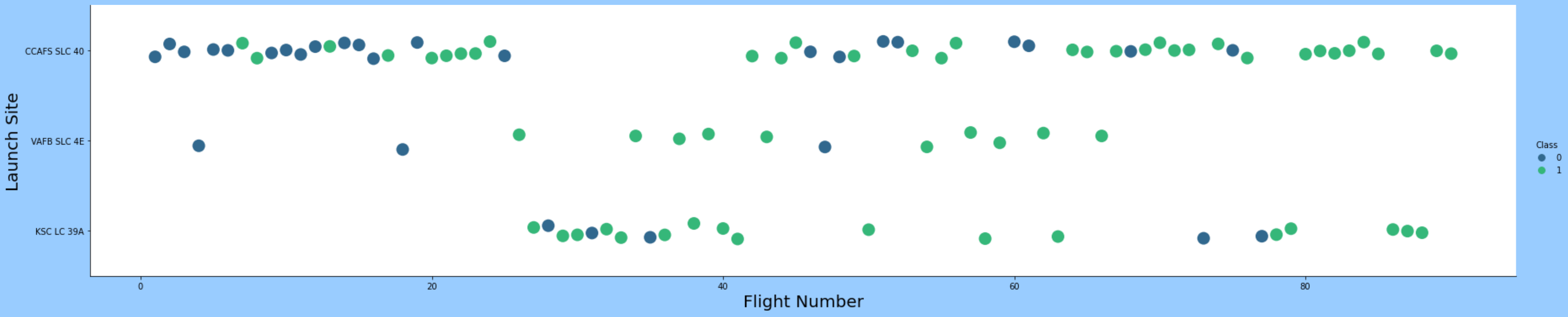


This is a preview of the Plotly dashboard. The following sides will show the results of EDA with visualization, EDA with SQL, Interactive Map with Folium, and finally the results of our model with about 83% accuracy.

EDA with Visualization

EXPLORATORY DATA ANALYSIS WITH SEABORN PLOTS

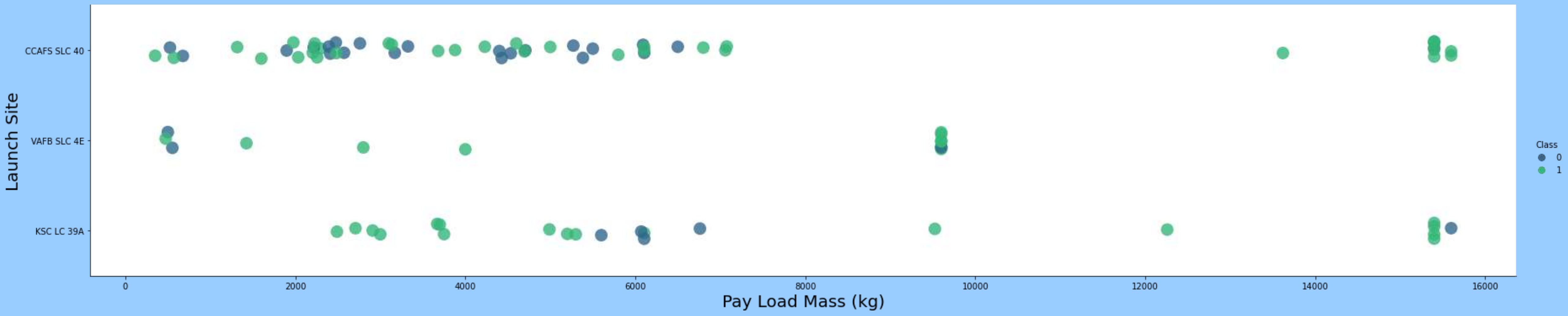
Flight Number vs. Launch Site



Green indicates successful launch; Purple indicates unsuccessful launch.

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.

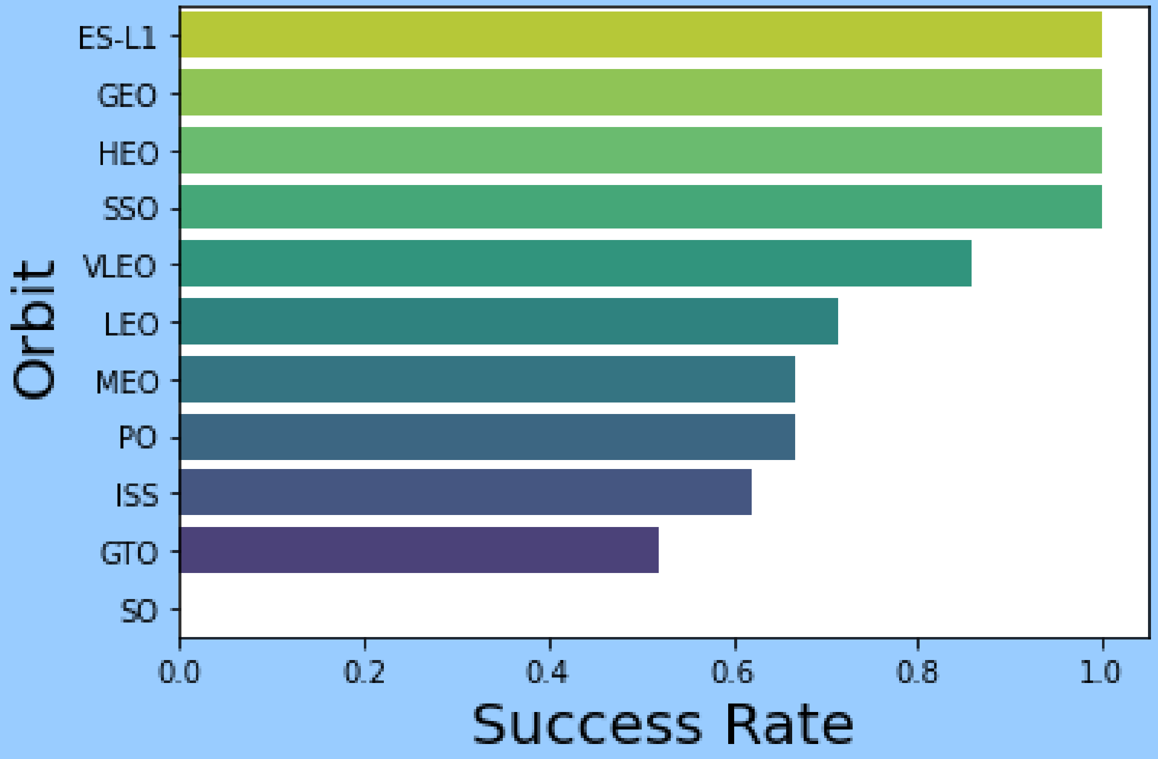
Payload vs. Launch Site



Green indicates successful launch; Purple indicates 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%

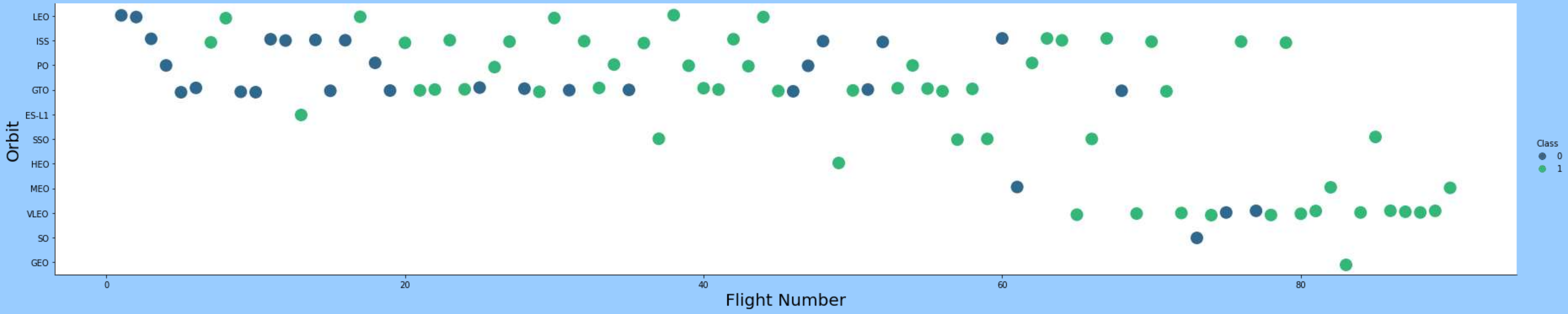
ES-L1 (1), GEO (1), HEO (1) have 100% success rate (sample sizes in parenthesis) SSO (5) has 100% success rate

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. Orbittype

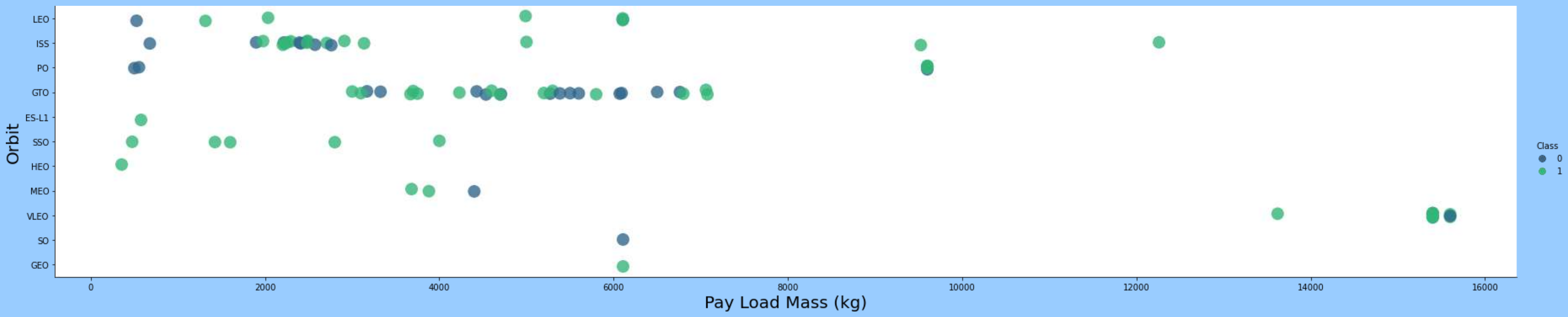


Green indicates successful launch; Purple indicates unsuccessful launch.

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



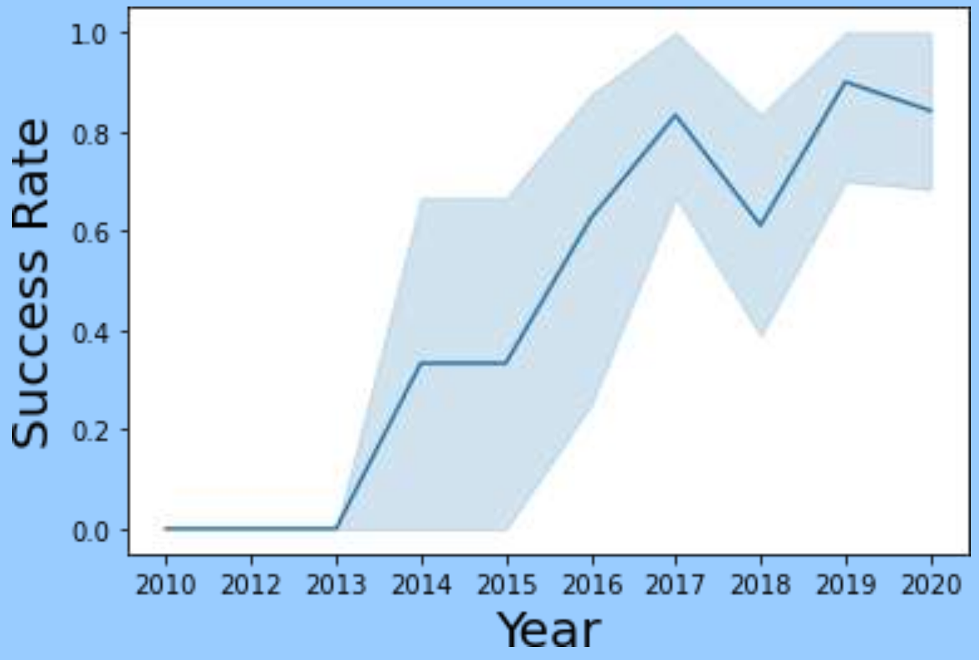
Green indicates successful launch; Purple indicates unsuccessful launch.

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%

EDA with SQL

EXPLORATORY DATA ANALYSIS WITH SQL DB2

INTEGRATED IN PYTHON WITH SQLALCHEMY

All Launch Site Names

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

```
 * sqlite:///my_data1.db
Done.
Out[10]:
```

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

Query unique launch site names from database.

Results is 4 unique launch_site

values:

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

Launch Site Names Beginning with `CCA`

In [11]:
```
%%sql
select *
from SPACEXTBL
where launch_site like 'CCA%' limit 5
```

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

Out[11]:

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	7:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	No attempt
2012-10-08	0:35:00	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

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

Total Payload Mass from NASA

```
In [12]:  %%sql
          select sum(payload_mass__kg_) as sum
          from SPACEXTBL
          where customer like 'NASA (CRS)'

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

Out[12]:

sum
45596

This query sums the total payload mass in kg where NASA was the customer.

Average Payload Mass by F9 v1.1

```
In [13]: %%sql
         select avg(payload_mass__kg_) as Average
         from SPACEXTBL
         where booster_version like 'F9 v1.1%'

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

Out[13]:

Average
2534.6666666666665

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

First Successful Ground Pad Landing Date

In [14]:
```
%%sql
select min(date) as Date
from SPACEXTBL
where mission_outcome like 'Success'
```

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

Out[14]:

Date
2010-06-04

This query returns the first successful ground pad landing date.

Successful Drone Ship Landing with Payload Between 4000 and 6000

In [16]:

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

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

Out[16]:

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 noninclusively.

2015 Failed Drone Ship Landing Records

In [27]:

```
%%sql
select Date, landing_outcome, booster_version, launch_site
from SPACEXTBL
where Date like '2015%'
AND landing_outcome like 'Failure (drone ship)'
```

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

Out[27]:

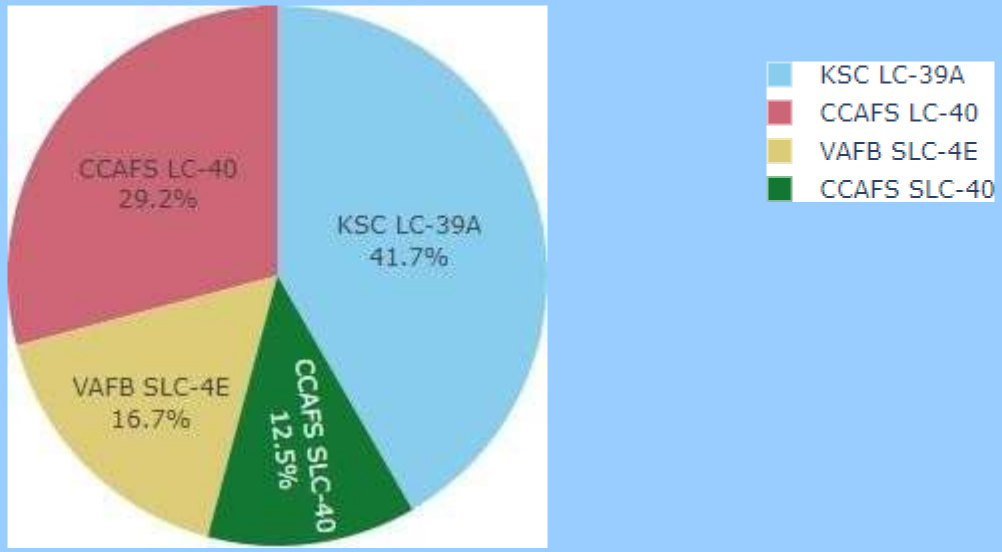
Date	Landing_Outcome	Booster_Version	Launch_Site
2015-01-10	Failure (drone ship)	F9 v1.1 B1012	CCAFS LC-40
2015-04-14	Failure (drone ship)	F9 v1.1 B1015	CCAFS LC-40

This query returns the Date, 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.

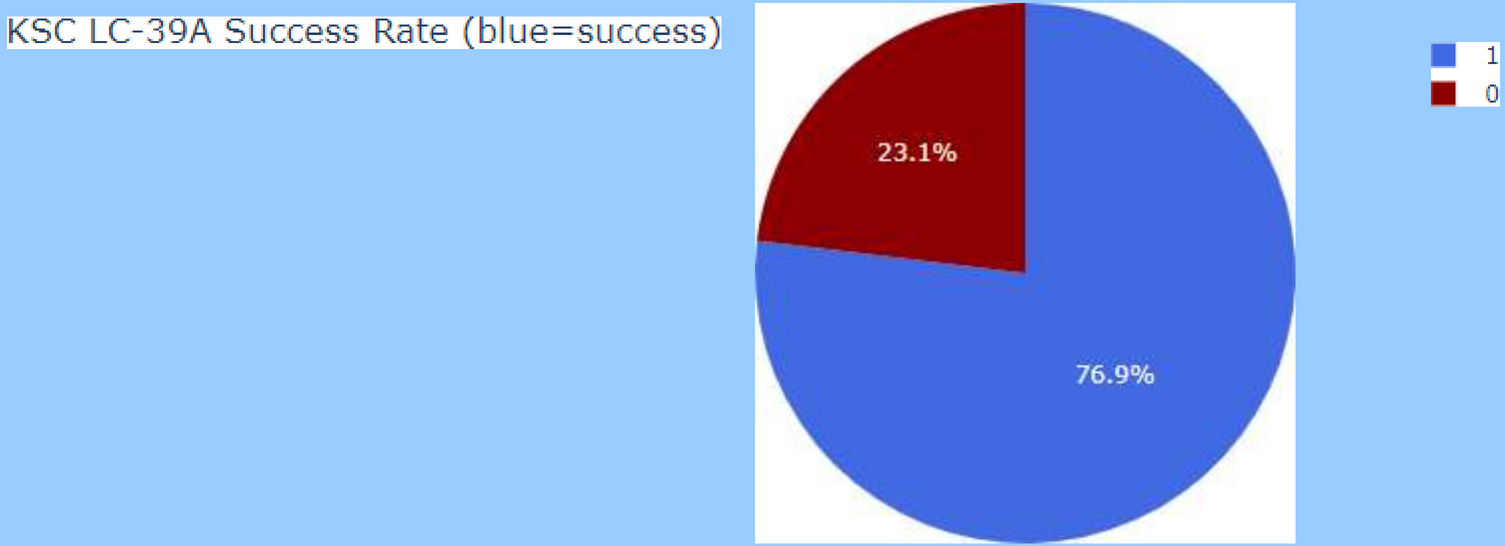
Build a Dashboard with Plotly Dash

Successful Launches Across Launch Sites



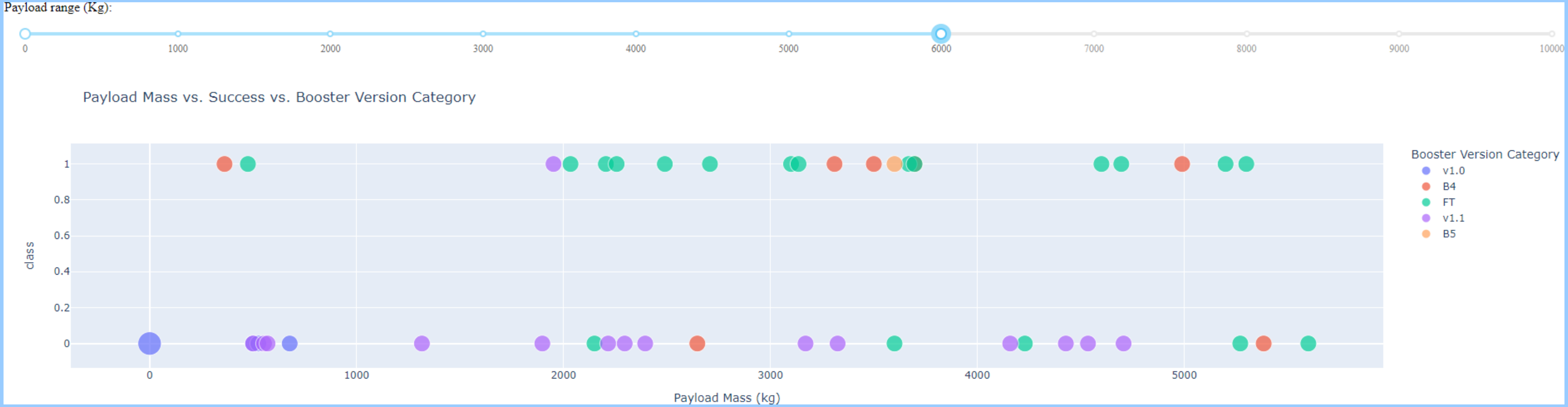
This is the distribution of successful landings across all launch sites. CCAFS LC-40 is the old name of CCAFS SLC-40 so CCAFS and KSC have the same amount of successful landings, but a majority of the successful landings where performed before the name change. VAFB has the smallest share of successful 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 has the highest success rate with 10 successful landings and 3 failed landings.

Payload Mass vs. Success vs. Booster Version Category

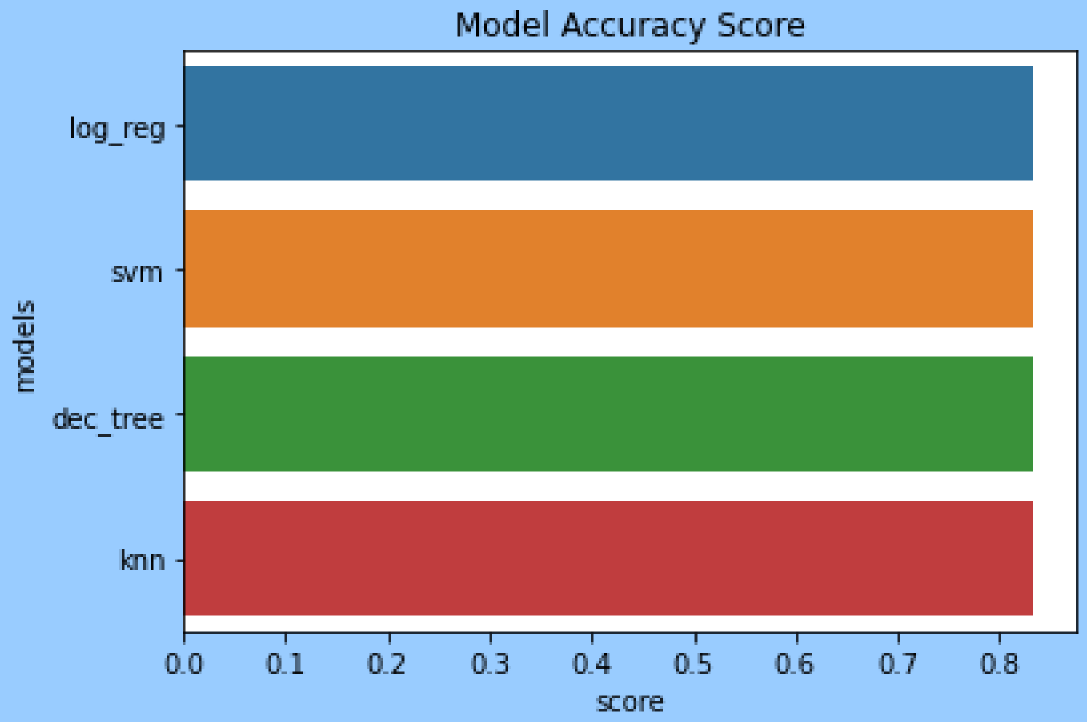


Plotly dashboard has a Payload range selector. However, this is set from 0-10000 instead of the max Payload of 15600. Class indicates 1 for successful landing and 0 for failure. Scatter plot also accounts for booster version category in color and number of launches in point size. In this particular range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

Predictive Analysis (Classification)

GRIDSEARCHCV(CV=10) ON LOGISTIC REGRESSION, SVM, DECISION TREE, AND KNN

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

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

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.

CONCLUSION

- 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
- Used data from a public SpaceX API and web scraping SpaceX Wikipedia page
- Created data labels and stored data into database
- Created a dashboard for visualization
- We created a machine learning model with an accuracy of 83%
- 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