IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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Outline

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Executive Summary

Problem: Commercial spaceflight is a rapidly growing industry with major competitors such as SpaceX and Blue Origin. As a newcomer, we must be willing to review and analyze our competitor's current and past methods, practices and results. The analysis of this data will hopefully allow us to gain insight into which features and conditions correlate with successful missions. Our goal is to discover ways to decrease the pre-launch and operational cost for each flight thereby making us viable competition in this market.

Method: Because it is a behemoth in the spaceflight industry, Space X was chosen by our team as the company to investigate. Space X recycles parts of its spacecraft based on its landing success. This is how it keeps its prices low. We started by reviewing its launch history and collecting this data. Data collection was performed through web scraping and by using application programming interfaces to retrieve the data. We then processed the data and used it to develop machine learning models to predict the landing outcome of Space X future flights. Statistical analysis and graphic visualization allowed us to detect specific relationships and patterns between launch features and landing outcomes. A dashboard was also assembled that shows various graphs comparing the success rate of each launch site to one another and comparing the success rate based on payload mass.

Results: As a result of this project, we have developed four machine learning models, all with similar accuracy, to predict landing outcomes. We have also been able to correlate payload mass, launch site, number of flights and type of orbit with successful launches. A higher payload, for instance, generally correlates with higher success rates as does a higher number of previous flights. By accessing this information in relation to upcoming flights, we can determine whether the spacecraft parts will be recovered and predict the overall launching expenditure for that particular flight. This allows us to set our market price accordingly.

Introduction

The commercial spaceflight industry has grown rapidly in recent years. It is expected to grow to 29.6 billion by 2027 with regular commercial space travel becoming a reality by 2045. Currently, a typical commercial spaceflight is priced at or around $165 million per flight. However, Space X, a leader in commercial spaceflight, has found a way cut this cost by 60%. It does this through reusable rocket technology.

Now for a little rocket anatomy review. The picture to the right shows the parts of the Falcon 9 rocket. In general, the stage 2 sits atop stage one (the largest stage). This is then topped by the fairings which contain the payload. A payload can be anything from a satellite to a human crew.

Space X recycles stage one of the spacecraft but can only do so if the landing is successful. This innovation allows Space X to charge $62 million dollars (as opposed to $165 mil) and has enabled it to become the world's leading space launch provider.

How do we, as a newcomer to this industry, compete with an industry giant? If we are able to predict which launches will have successful landings, it may give us an advantage and allow us to discern how much a flight will cost on Space X. The idea is to be able to provide a comparable and competitive price for the same flight.

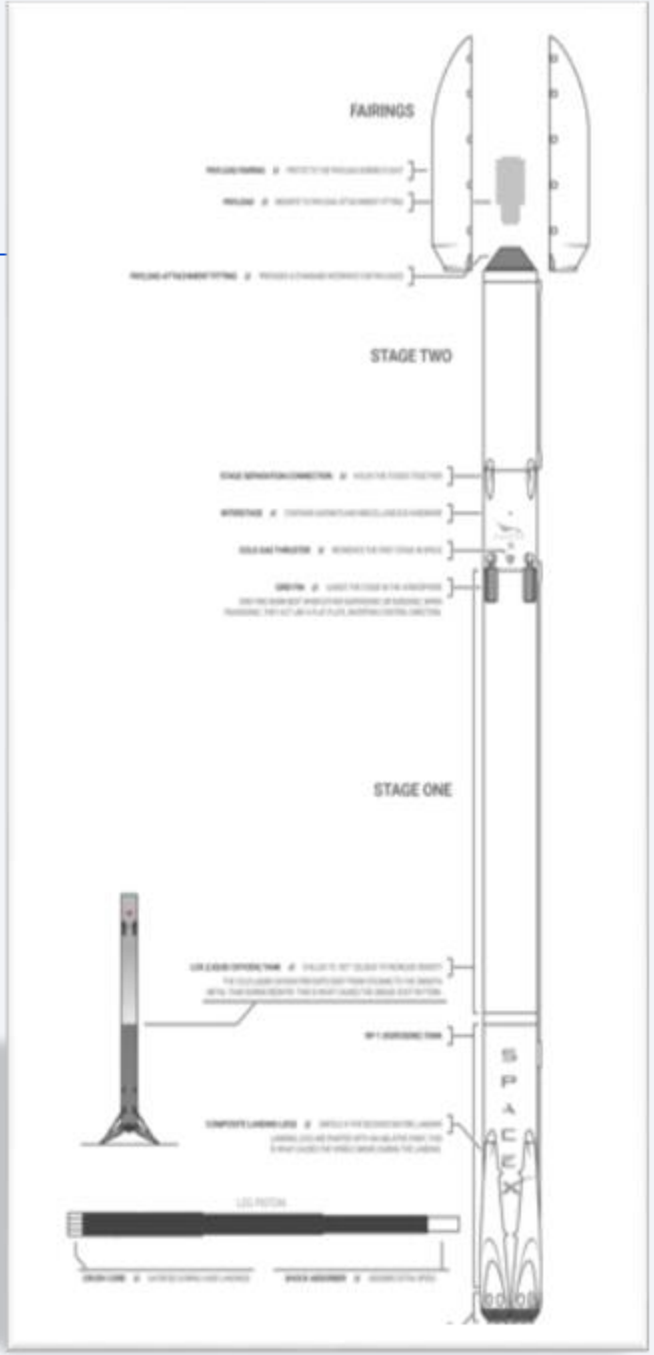


Image borrowed from Forest Kach @ zlsadesign.com

Section 1

Methodology

Methodology

Data collection methodology:

- Data collection was performed through web-scraping and using application programming interfaces to retrieve data from a Space X database.

- Perform data wrangling
  - Data was processed by replacing missing values. Datasets filled with ID numbers were replaced with actual data via API's. One-hot-encoding method was applied to change categorial values to numerical values. Data was also normalized before exploratory analysis, visualization and model fitting.
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
  - The data was split into training and testing groups. Training group was used to develop the model and the testing group was used to test the model. The test results were compared to the actual results and the accuracy was calculated. Confusion matrices were also used to assess accuracy. Four models were tested including the logistic regression model, support vector machine model, decision tree machine model, and k-nearest neighbor model.

Data Collection

- Data collection was performed through web scraping a wikipage chart of Space X launch records.

- Space X launch records were also available and retrieved through Space X application programming interface or API.

Data Collection – SpaceX API

- Space X launch data was requested through a Space X API. The .json file that was received was converted to a data frame.
- Most of the Space X data from the main API contained ID numbers in lieu of actual descriptions. Namely the rocket booster version, the payload mass, the launchpad, and the core were all recorded as ID numbers.
- As such, the API was called several times to extract the actual descriptions that matched the ID numbers. This was done by specifying different endpoints.
- Lastly, the data frame was reconstructed with the actual descriptions. More data wrangling was performed before exploratory data analysis and visualization
- https://github.com/labrownmd/Coursera_Capstone/blob/c1813f2ee877b037ecb9c221dd137b54d75e8ac1/jupyter-labs-spacex-data-collection-api.ipynb

MAIN API
https://api.spacexdata.com/v4/launches/past

API FOR ROCKET INFO
https://api.spacexdata.com/v4/rockets/

API FOR CORE INFO
https://api.spacexdata.com/v4/cores/

API FOR LAUNCHPAD INFO
https://api.spacexdata.com/v4/launchpads/

API FOR PAYLOAD INFO
https://api.spacexdata.com/v4/payloads/

RECONSTRUCTED DATA FRAME

	FlightNumber	Date	BoosterVersion	PayloadMass	Orbit	LaunchSite	Outcome	Flights	GridFins	Reused	Legs	LandingPa
0	1	2006-03-24	Falcon 1	20.0	LEO	Kwajalein Atoll	None None	1	False	False	False	Non
1	2	2007-03-21	Falcon 1	NaN	LEO	Kwajalein Atoll	None None	1	False	False	False	Non
2	4	2008-09-28	Falcon 1	165.0	LEO	Kwajalein Atoll	None None	1	False	False	False	Non

Data Collection - Scraping

- A chart comprised of Falcon 9 Space X launch records was extracted from a wikipage.
- Parsing of the data contained in the chart was performed using the python BeautifulSoup library.
- The data was collected into a data dictionary from which a new data frame was constructed. The new data frame contained only information that was pertinent to our study.
- https://github.com/labrownmd/Coursera_Capstone/blob/cadd371386867cbe93e9a8723cc36478542f5451/jupyter-labs-webscraping.ipynb

	Flight No.	Launch site	Payload	Payload mass	Orbit	Customer	Launch outcome	Version Booster	Booster landing	Date	Time
0	1	CCAFS	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success\n	F9 v1.07B0003.18	Failure	4 June 2010	18:45
1	2	CCAFS	Dragon	0	LEO	NASA	Success	F9 v1.07B0004.18	Failure	8 December 2010	15:43
2	3	CCAFS	Dragon	525 kg	LEO	NASA	Success	F9 v1.07B0005.18	No attempt\n	22 May 2012	07:44
3	4	CCAFS	SpaceX CRS-1	4,700 kg	LEO	NASA	Success\n	F9 v1.07B0006.18	No attempt	8 October 2012	00:35
4	5	CCAFS	SpaceX CRS-2	4,877 kg	LEO	NASA	Success\n	F9 v1.07B0007.18	No attempt\n	1 March 2013	15:10

Data Wrangling

- Data from API was filtered to only include Falcon 9 as this the only rocket that is used by Space X for commercial flights.
- Dataset also contained missing values for the payload mass. Those values were replaced with the average payload based on the mean of that category in the data frame.
- One-hot-encoding method was applied to change categorial values to numerical values.
- Data was also normalized before exploratory analysis, visualization and model fitting.
- Total launches per launch site and the most common orbits that were taken amongst all launches were determined.
- A successful landing vs an unsuccessful landing: There were eight outcome classifications. Four of which were deemed 'bad outcomes' and four that were 'good outcomes'. 'Good outcomes' mean that the first stage landed.
- Based on these parameters, the dataframe was filtered and labeled. All launches that fell into the 'bad outcomes' received a "0" landing class and the 'good outcomes' received a "1" for their landing class. A new column was added to the dataframe labeled 'Class' which would be used to classify a landing as successful or unsuccessful. The 'Class' was also used to calculate the launch success rate.
- https://github.com/labrownmd/Coursera_Capstone/blob/c1813f2ee877b037ecb9c221dd137b54d75e8ac1/labs-jupyter-spacex-Data%20wrangling.ipynb
- https://github.com/labrownmd/Coursera_Capstone/blob/cadd371386867cbe93e9a8723cc36478542f5451/jupyter-labs-spacex-data-collection-api.ipynb

EDA with Data Visualization

- The visualization charts helped to recognize patterns and correlations in the data. It was determined that higher payloads and more previous flights lead to higher landing success rates.
- The orbit correlates with landing success with highly elliptical orbits and geosynchronous orbits are amongst the orbits with the highest success rates.
- Certain orbits are also better with heavier payloads such as the Polar and low earth orbits.
- The average success rate has steadily improved since the year 2013.
- https://github.com/labrownmd/Coursera_Capstone/blob/c1813f2ee877b037ecb9c221dd137b54d75e8ac1/edadataviz.ipynb

EDA with SQL – Searches Performed:

- Searched by unique launch site to list all of the launch sites.
- Selected a table of flights with only Cape Canaveral launch sites.
- Found the average payload mass for launches from NASA launch sites.
- Calculated the average payload for the booster rocket Falcon 9.
- Determined the date of the first successful ground landing.
- Determined which booster version of the Falcon 9 has success in drone ship landing.
- Determined which booster versions can carry the maximum payload.
- Determined the total successful mission outcomes vs the total failed mission outcomes. Mission outcomes are different from landing outcomes. A launch can be a successful mission but fail at landing.
- Looked at the months in 2015 where the drone ship landings were failures. After 2 failures in 2015 the first ground pad landing took place at the end of that year.
- Also ranked the landing outcomes by frequency or total count.
- https://github.com/labrownmd/Coursera_Capstone/blob/c1813f2ee877b037ecb9c221dd137b54d75e8ac1/jupyter-labs-eda-sql-coursera_sqllite.ipynb

Build an Interactive Map with Folium

- Started by mapping and marking all of the launch sites.
- Marked each launch site with cluster markers to denote the successful and failed launches at each site. This allowed a quick general assessment of the total number of launches and the success rate.
- Created distance markers and polylines to show the proximity of a launch site to major structures or places around it such as highways, railroads, major cities and coastlines
- This was done to gather insight into whether launch sites have similarities regarding their proximity to major structures. It was determined that launch sites appear to be close to coastlines and a good distance is kept from highways and major cities. The proximity to railroads seemed random.
- https://github.com/labrownmd/Coursera_Capstone/blob/c1813f2ee877b037ecb9c221dd137b54d75e8ac1/lab_jupyter_launch_site_location.ipynb

Build a Dashboard with Plotly Dash

- Created a dashboard to allow visualization of and interaction with the graphs. The dashboard shows a pie chart that compares each sites success rate to each other.
- The site with the best success rate, Kennedy Space Center, was determined by the pie chart for this site.
- A scatterplot is incorporated into the dashboard that compares the payload mass to the success rate while showing the rocket booster version that wasd used in each flight.
- As it is interactive, the user is allowed to select a specific site or all sites. They can also select a payload range to for the scatterplot which will zoom in on a particular part of the graph and make other observations.
- https://github.com/labrownmd/Coursera_Capstone/blob/c1813f2ee877b037ecb9c221dd137b54d75e8ac1/spacex_dash_app.py

Predictive Analysis (Classification)

- The data was normalized and transformed through the Skilearn preprocessing library. The data was then split into training and testing groups. Both groups have actual results. The actual results from the training group are used to train the model. The actual results from the testing group are used to measure the model's predictive accuracy.
- Four classification models were used: logistic regression, support vector machine, decision trees, and k nearest neighbor. Each model was trained using the training data and the best hyperparameters were found via GridSearchCV in python.
- With these hyperparameters in place, the models were tested with the testing data. The results predicted by the models were compared to the actual results from the testing group and the accuracy of each was calculated.
- This accuracy score along with the confusion matrix for each model allowed for assessment and determination of the best performing classification model.
- All of the methods had the same accuracy score and confusion matrix results. Therefore, there was no superior model. This may be due to the small sample size of the testing data.
- https://github.com/labrownmd/Coursera_Capstone/blob/c1813f2ee877b037ecb9c221dd137b54d75e8ac1/SpaceX_Machine%20Learning%20Prediction_Part_5.ipynb

Results

Exploratory Data Analysis Results (Graphs and SQL queries)

Observation/Result
Higher the previous flight number and higher payloads lead to higher success rates
The best orbits are ESL1, GEO, HEO and SSO across all payloads.
An increase in flight number improved flights from CCAFS and VAFB
The LEO orbit also improved with more flights
GTO orbit appeared to not be influenced by flight number.
For payloads greater than 8K kg, ISS and Polar orbits had a success rate of 100%. The VLEO orbit had a 75% success rate at this payload and also had twice as many flights as the two aforementioned orbits.
SQL query revealed that the max payload was over 15K Kg and carried by B5 booster however that database used with the dashboard analytics had a maximum payload of 10K kg.

Predictive Analysis Results

Yielded four models with equal accuracy, 83% and confusion matrices that were exactly the same.

Interactive Dashboard Analytics *

Observation	Site/BV/Payload	Success Rate
Best launch site	Kennedy Space Center	77%
Worst launch site	Cape Canaveral Launch Center	27%
Best Booster	B5 (only one flight recorded) Falcon 9 FT	100% 63%
Worst Booster	Falcon 9 v1.0	0%
Best Payload Mass	2K – 4K kg	60%
Worst Payload Mass	6K – 8K kg	0%

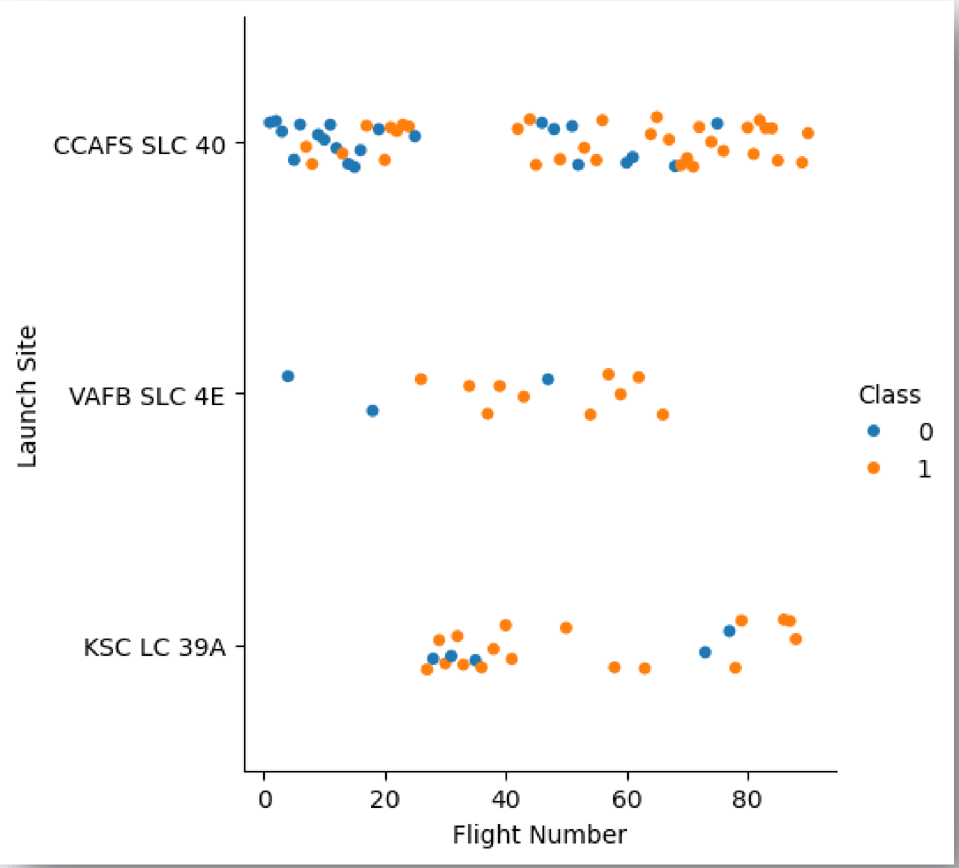
*Payloads between 0K and 10K kg only – max payload not included

Section 2

Insights drawn from EDA

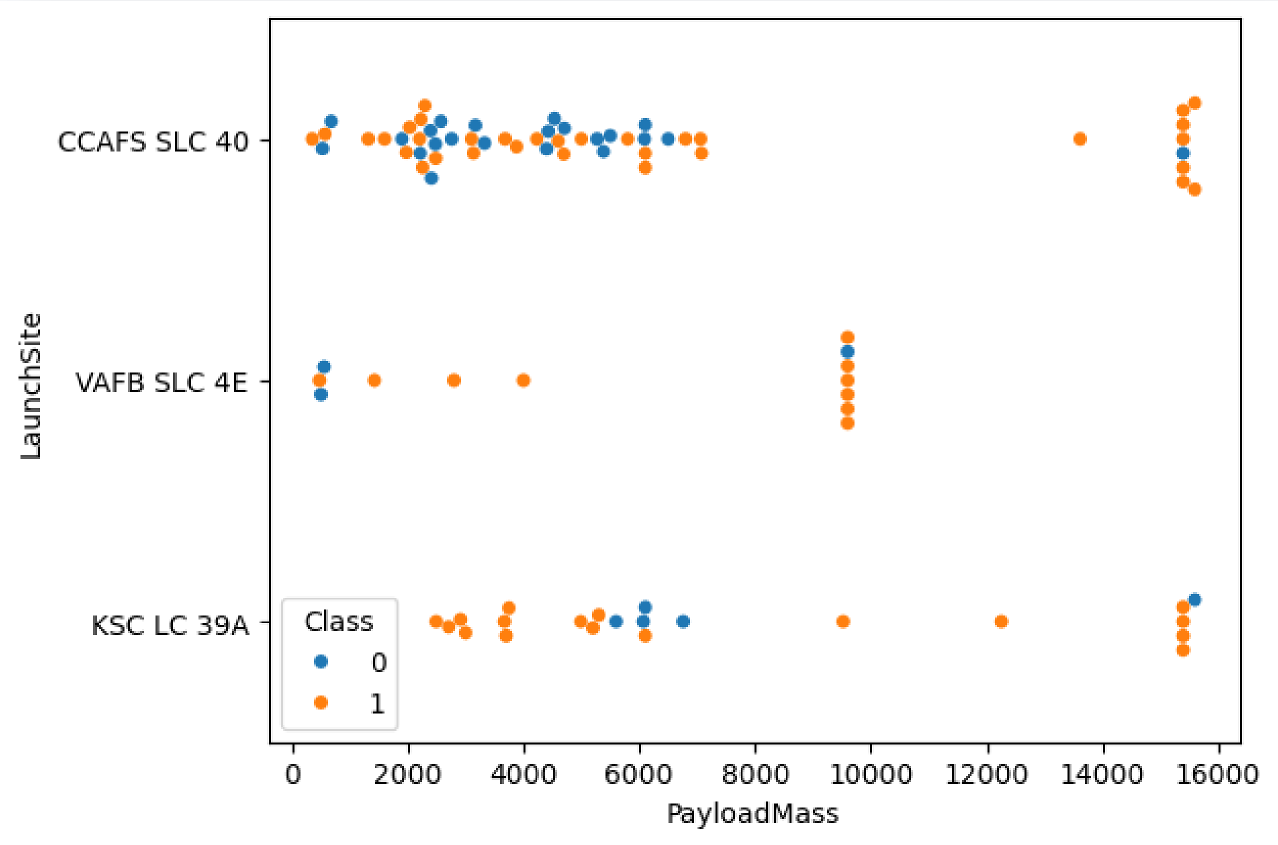
Flight Number vs. Launch Site

- This graph shows the relationship between the number of previous flights and the success rate at each launch site
- Cape Canaveral's success rate improved as the flight number increased.
- VAFB was quickly successful with a low number of flights.



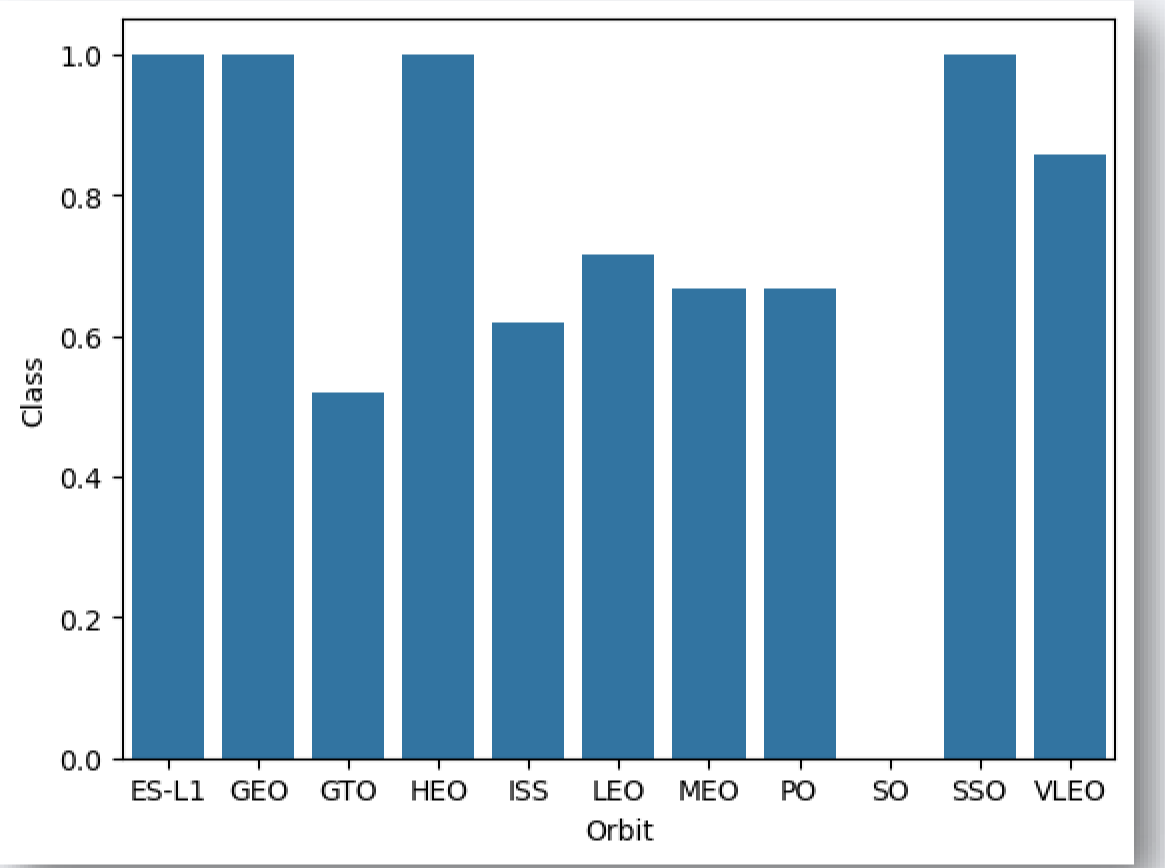
Payload vs. Launch Site

- This graph shows the relationship between payload mass and success rate at each launch site.
- VAFB has a lot successful flights but maintains a payload less than 10,000 kg.
- The other two sites show marked improvement in their success rates at higher payloads of around 15,000 kg.



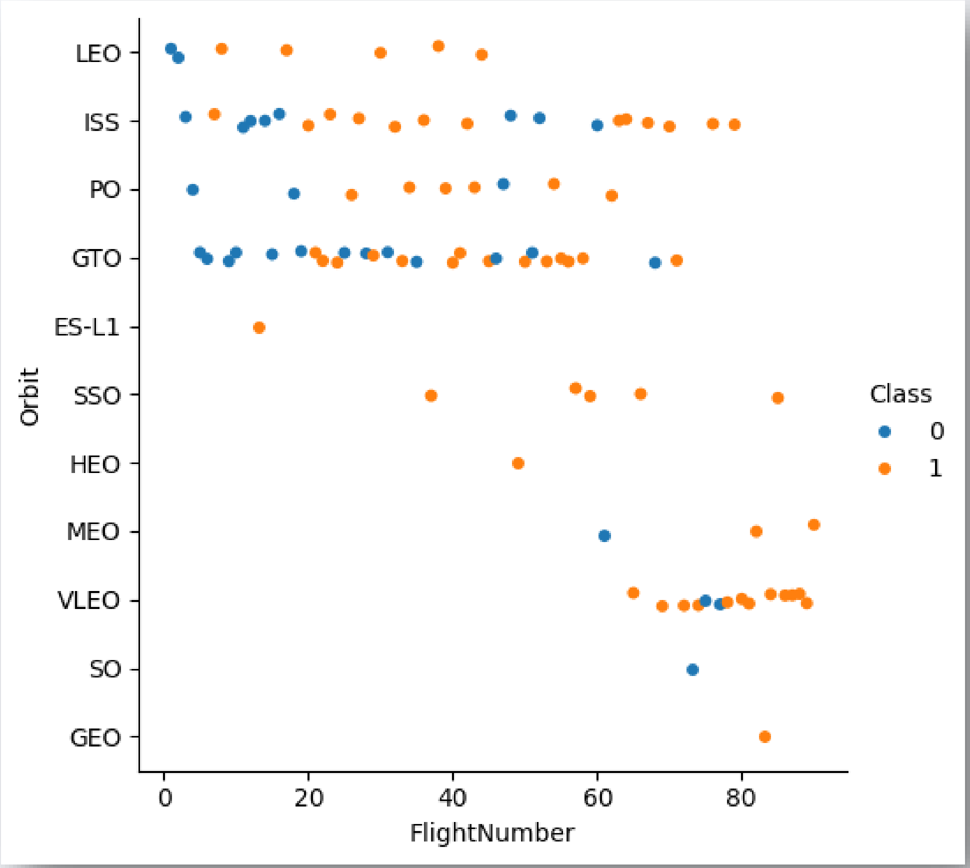
Success Rate vs. Orbit Type

- This bar chart shows the the success rate for each orbit type.
- Highly elliptical orbits, geosynchronous orbits, ES – L1 orbit and the sun synchronous orbit have the highest average success rate.



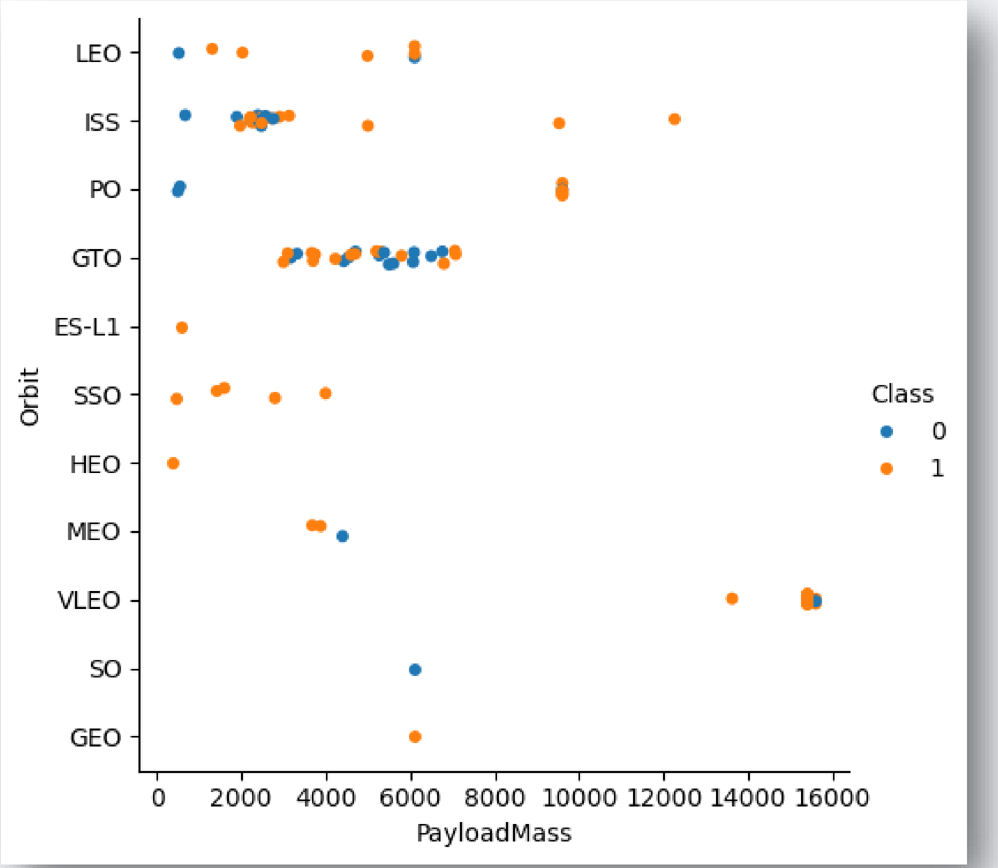
Flight Number vs. Orbit Type

- This a scatter plot comparing the flight number with the orbit type and determining the success rate.
- The low eart orbit improves with an increase in flight number.
- The geosynchoronous GTO orbit does not exhibit a relationship between flight number and success rate. Changes in its success rate appears to be random



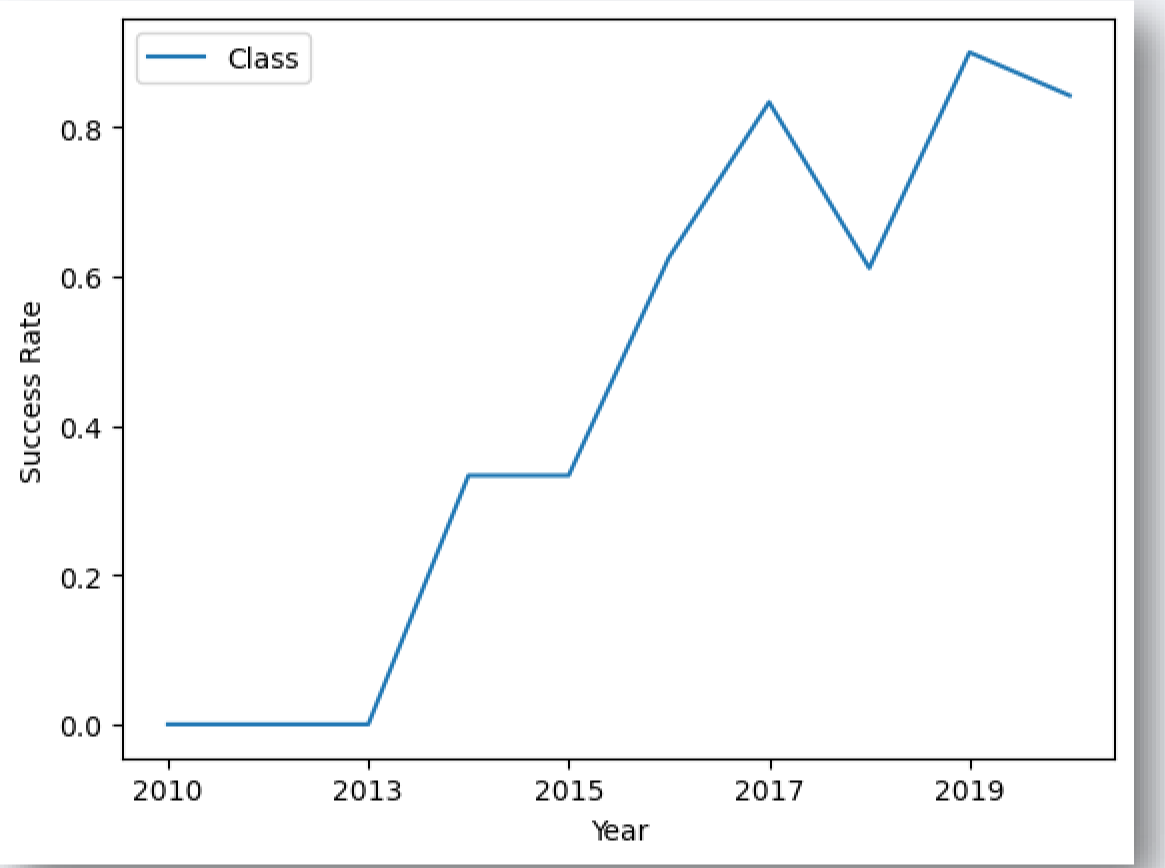
Payload vs. Orbit Type

- This is a scatter plot of showing the payload and orbit type and comparing it to the success rate.
- An increase in payload mass with the Polar orbit, the low earth orbit, international space station orbit all improve their success rate with an increase in payload on the spacecraft.



Launch Success Yearly Trend

- This graph is a line chart of the yearly average launch success rate
- It shows that the success rate has steadily improved since 2013 with just one dip in performance in 2018.



All Launch Site Names

```
%sql select DISTINCT Launch_Site from SPACEXTABLE
```

- Performed an SQL search to reveal the names of all launch sites in the database.

- There are four: Cape Canaveral Space Launch Complex, Cape Canaveral Launch Complex, Vandenberg Airforce Base Space Launch Complex 4, and Kennedy Space Center Launch Complex.

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

Launch Site Names Begin with 'CCA'

```
%sql SELECT * FROM SPACEXTABLE WHERE Launch_Site like 'CCA%' limit 5
```

- Performed an SQL search for the first 5 records where the launch sites names begin with `CCA`
- This search revealed 5 launches that took place at a Cape Canaveral Launch SIte, specifically CCAFS LC-40.

Date	Time (UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS__KG_	Orbit	Customer	Mission_Outcome	Landing_
2010-06-04	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (p
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 (p
2012-05-22	7:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	N
2012-10-08	0:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	N
2013-03-01	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	N

Total Payload Mass

```
%sql SELECT SUM(PAYLOAD_MASS__KG_) from SPACEXTABLE WHERE "Customer" = 'NASA (CRS)'
```

- Performed an SQL query to calculate the total payload carried by boosters from NASA
- The total payload mass carried by NASA spacecraft alone was over 50 tons.

SUM(PAYLOAD_MASS__KG_)
45596

Average Payload Mass by F9 v1.1

```
%sql SELECT AVG(PAYLOAD_MASS__KG_) from SPACEXTABLE WHERE "Booster_Version" like 'F9 v1.1%'
```

- Performed an SQL query to calculate the average payload mass carried by booster version F9 v1.1
- The average payload mass carried by a Falcon 9 spacecraft is less than 3 tons.

AVG(PAYLOAD_MASS__KG_)
2534.6666666666665

First Successful Ground Landing Date

```
%sql SELECT MIN(Date) as 'FIRST SUCCESSFUL GROUND PAD LANDING' from SPACEXTABLE \
WHERE "Landing_Outcome" = 'Success (ground pad)'
```

- Performed an SQL search to find the dates of the first successful landing outcome on ground pad
- The first successful ground pad landing took place after 2 unsuccessful drone ship landings earlier that year.

FIRST SUCCESSFUL GROUND PAD LANDING
2015-12-22

Successful Drone Ship Landing with Payload between 4000 and 6000

```
%sql SELECT  DISTINCT "Booster_Version" from SPACEXTABLE where "Landing_Outcome" = 'Success (drone ship)' and \
PAYLOAD_MASS__KG_ BETWEEN 4000 AND 6000
```

- Performed an SQL query to list the names of boosters which have successfully landed on drone ships and had payload mass greater than 4000 kg but less than 6000 kg.

- There were four rocket boosters that fit this description. All were versions of the F9 FT booster.

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 Mission_Outcome, COUNT(Mission_Outcome) AS Total FROM SPACEXTBL GROUP BY Mission_Outcome
```

- Performed an SQL query to calculate the total number of successful and failure mission outcomes.
- Mission outcomes are different from landing outcomes. Landing outcomes refer to stage one landing successfully.

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

Boosters Carried Maximum Payload

```
%sql SELECT DISTINCT Booster_Version FROM SPACEXTBL WHERE PAYLOAD_MASS__KG_ = (SELECT MAX(PAYLOAD_MASS__KG_)\
FROM SPACEXTBL) ORDER BY Booster_Version
```

- Performed an SQL query to list the names of the boosters that have carried the maximum payload mass.
- Results are shown.

Booster_Version
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

```
%sql SELECT substr(Date,6,2) as 'Month in 2015', Landing_Outcome, Booster_Version, Launch_Site from SPACEXTABLE \
where Landing_Outcome = 'Failure (drone ship)' and substr(Date,0,5) = '2015'
```

- Performed an SQL query to list the failed landing outcomes in a drone ship, their booster versions, and launch site names for the year 2015.
- These were the landing failures that took place before the first successful ground pad landing in December of the same year.

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

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

```
%sql SELECT Landing_Outcome as 'Landing Outcome', COUNT(Landing_Outcome) as Total from SPACEXTABLE WHERE Date between \
'2010-06-04' and '2017-03-20' GROUP BY Landing_Outcome ORDER BY COUNT(Landing_Outcome) DESC
```

- Performed an SQL query to rank the total 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.
- The success rate of drone ship landing is about 50% overall.

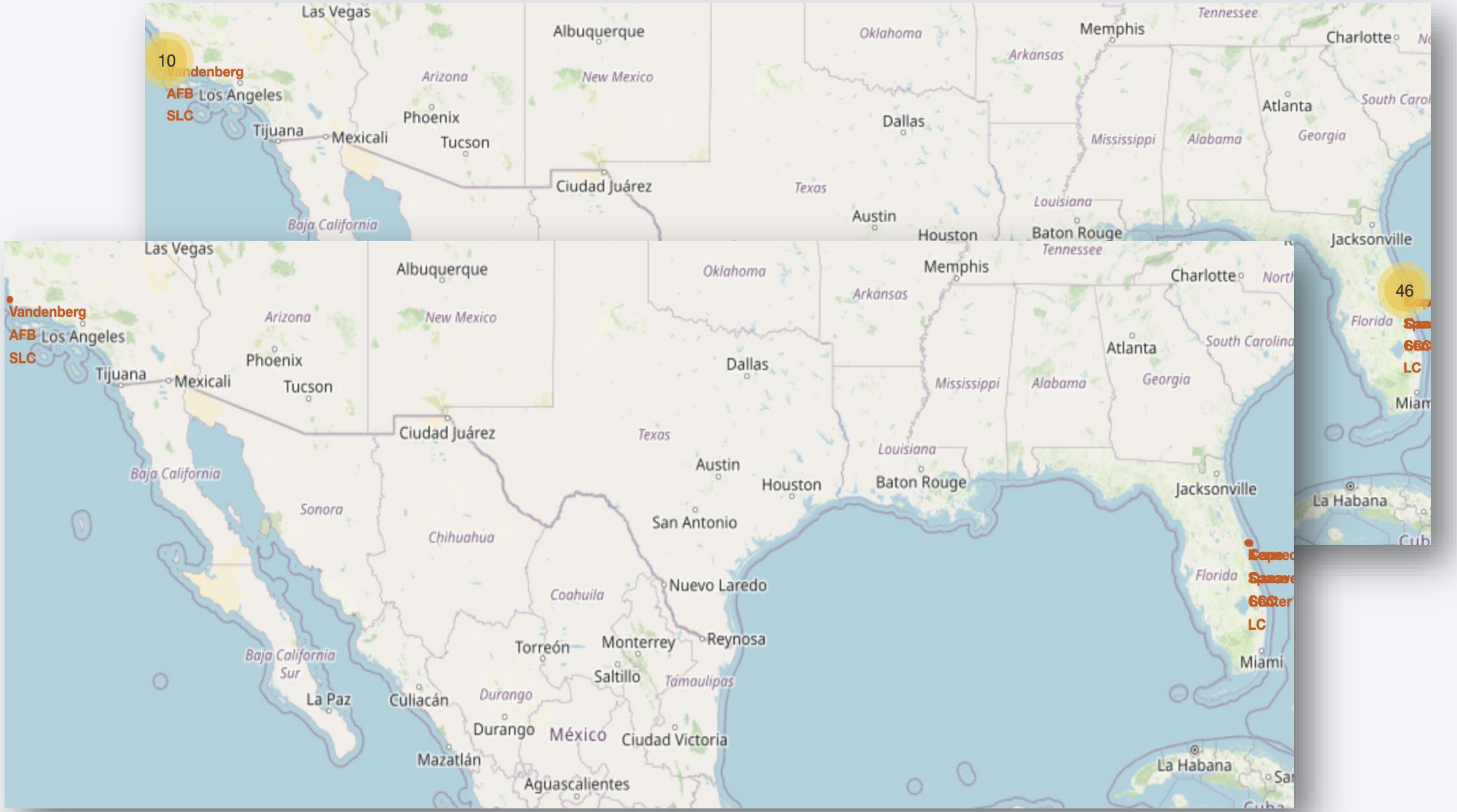
Landing Outcome	Total
No attempt	10
Success (drone ship)	5
Failure (drone ship)	5
Success (ground pad)	3
Controlled (ocean)	3
Uncontrolled (ocean)	2
Failure (parachute)	2
Precluded (drone ship)	1

Section 3

Launch Sites Proximities Analysis

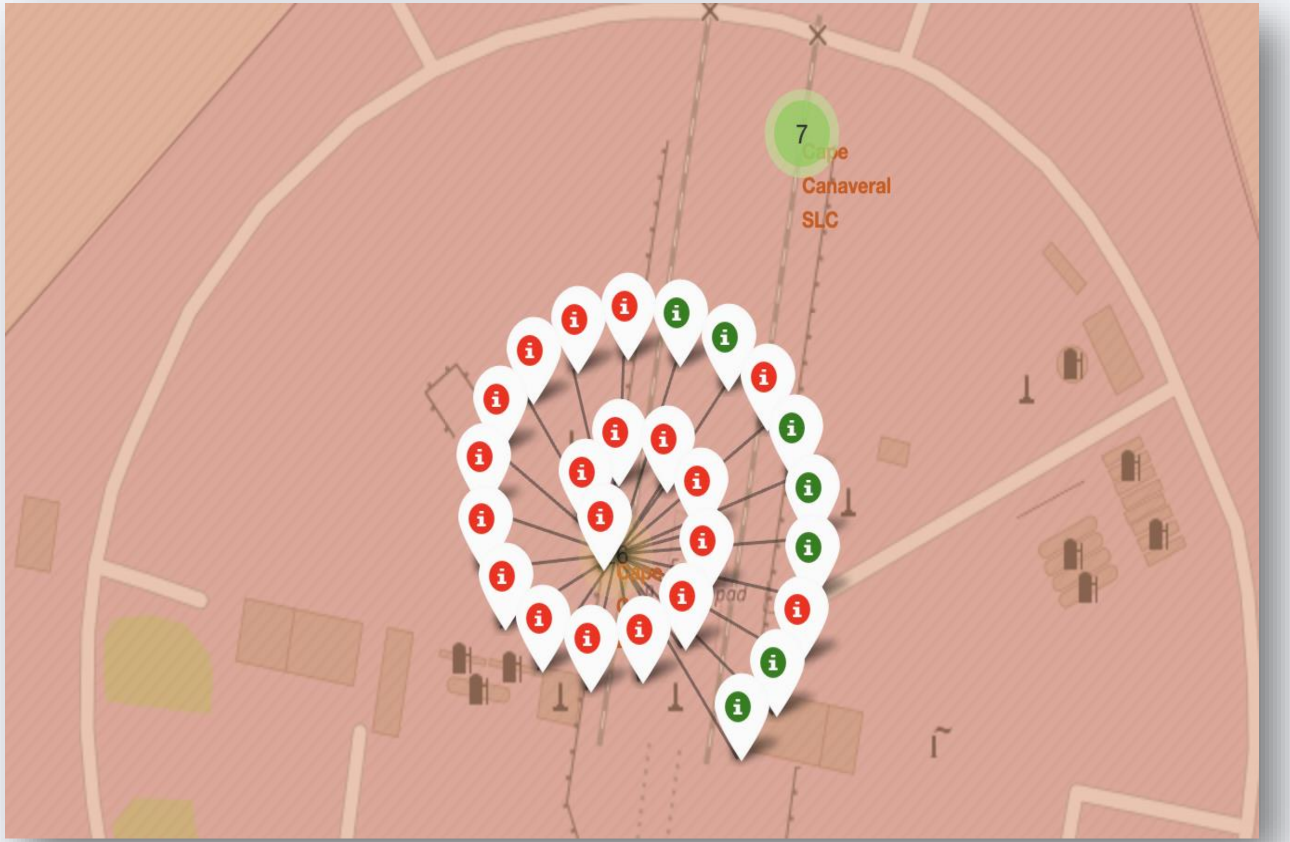
Folium Map with Launch Site Location Markers

The placement of launch site location markers on a global map using Folium in Python allows the visualization of the geographic location and proximity of all of the launch sites to each other and to major landmarks and structures.



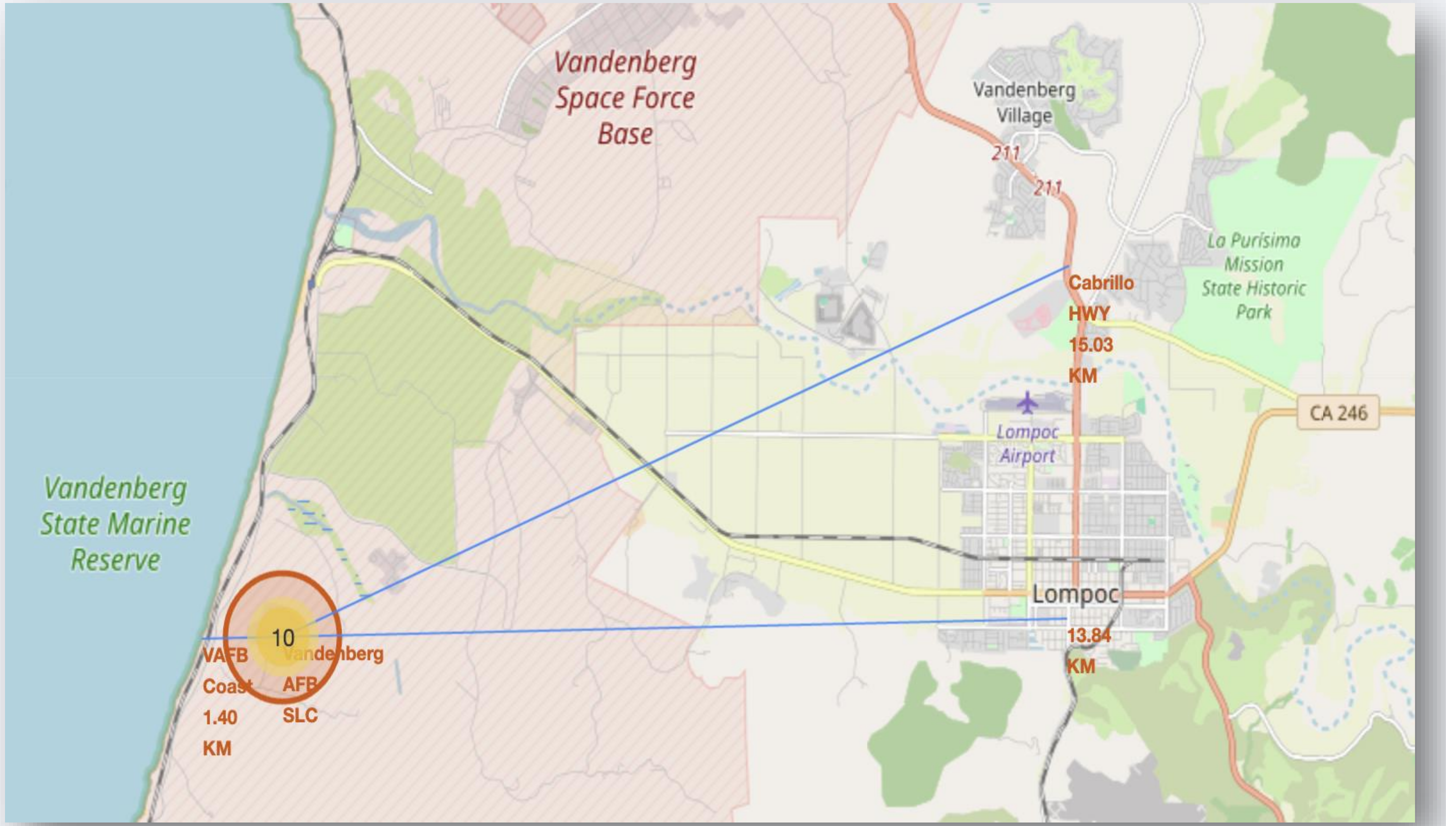
Folium Map With Cluster Markers

Marking each launch site with cluster markers helps to denote the successful and failed launches at each site. This allows a quick general assessment of the total number of launches and the success rate.



Folium Map showing Launch Site Proximity to Surrounding Structures

- After distances were calculated, distance markers and lines were created and displayed to show the proximity of a launch site to major structures or places around it such as highways, railroads, major cities and coastlines
- This allowed insight into whether launch sites have similarities regarding their proximity to major structures. It was determined that launch sites appear to be close to coastlines and a good distance away from highways and major cities. The proximity to railroads seemed random.

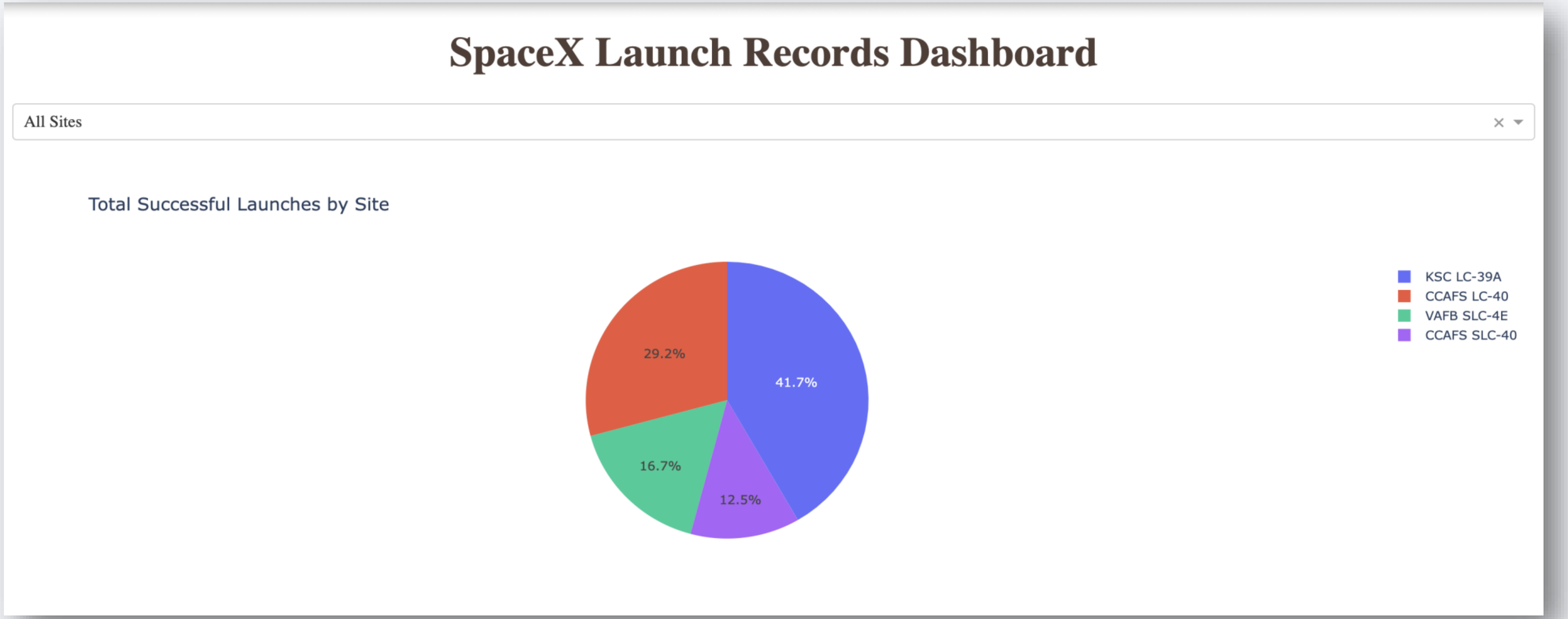


Section 4

Build a Dashboard with Plotly Dash

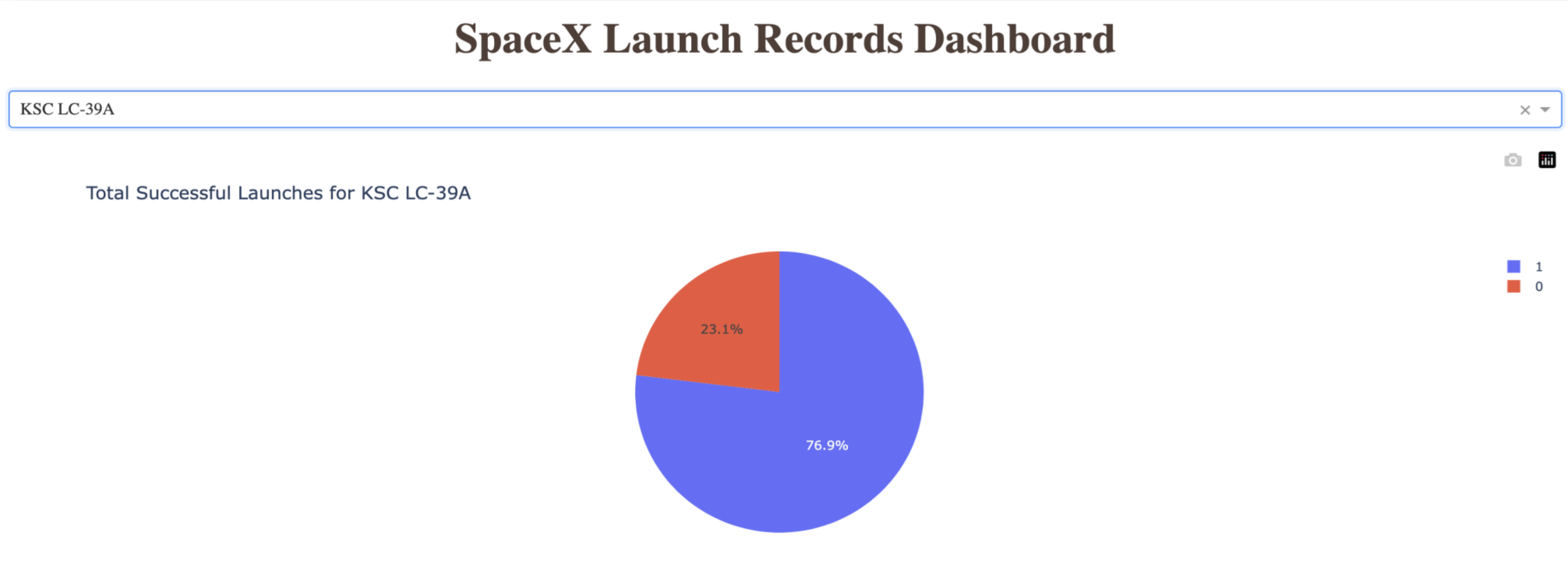
Dashboard Pie Chart

- Created a dashboard to allow the visualization of and interaction with graphs. The dashboard shows a pie chart that compares each sites success rate to each other.
- The site with the best success rate, Kennedy Space Center, was determined by the pie chart.



Dashboard Pie Chart - Launch Site with Highest Success Rate

- The dashboard allows for user interaction which allows the user to select a pie chart showing the success rate for each launch site.
- The user-selected pie chart below shows the success rate , 76.9%, for the launch site with highest launch success ratio, Kennedy Space Center.



Dashboard Scatterplot with Payload Selector

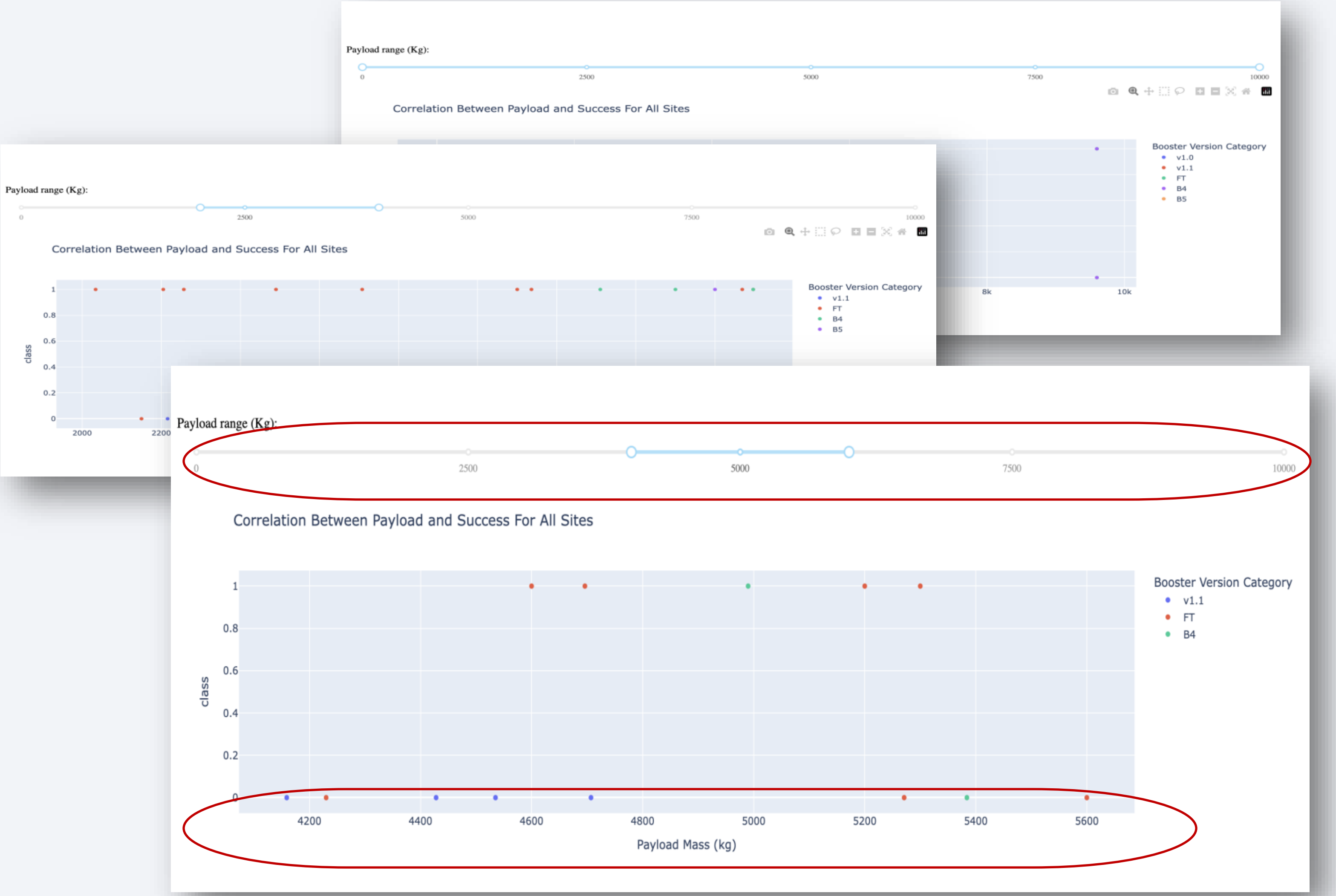
- A scatterplot is incorporated into the dashboard that compares the payload mass to the success rate while showing the rocket booster version that was used in each flight.

- As it is interactive, the user is allowed to select a specific site or all sites. They can also select a payload range for the scatterplot which will zoom in on a selected payload range part of the graph and allow the user to make other observations.

- The scatterplot shows that the B4 booster version had a 50% success rate with payloads close to 10,000 kg.

- The FT booster had a 70% success rate with payloads between 2,000 kg and 6,000 kg. While the B4 had a success rate of 66% in this payload range

- B5 booster data was limited due to the 10K kg payload limitation.

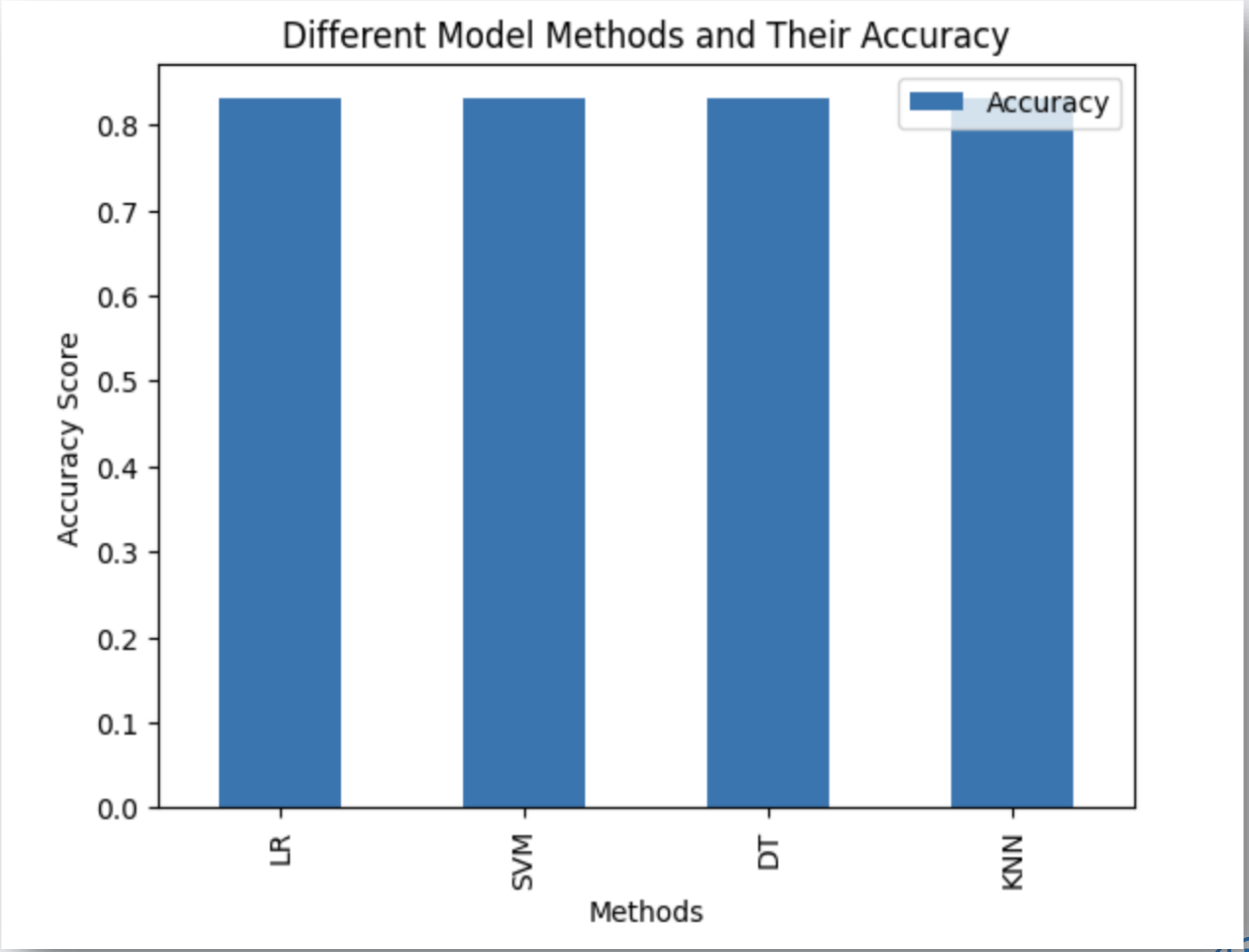


Section 5

Predictive Analysis (Classification)

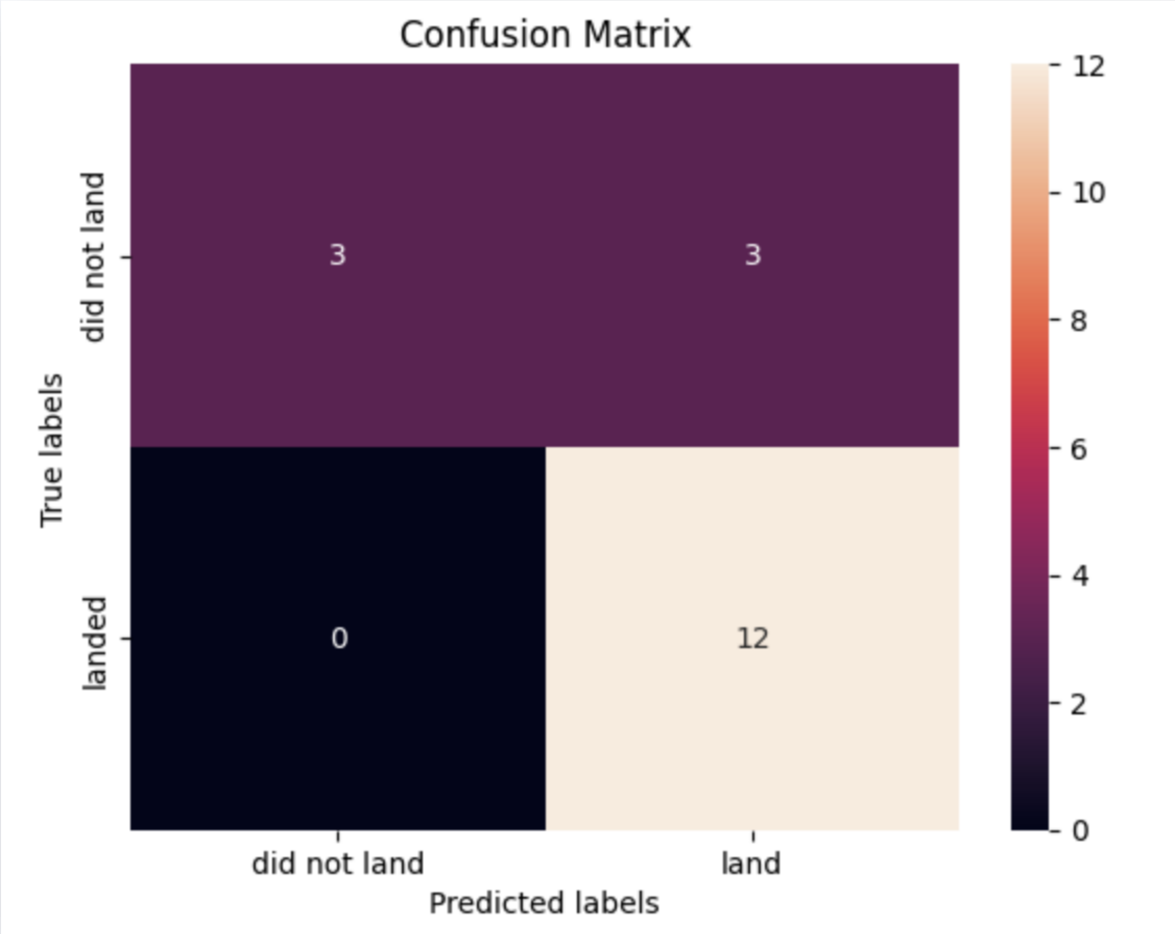
Classification Accuracy

- The built model accuracy for all built classification models was visualized in a bar chart.
- This chart shows that all of the classification models have the same classification accuracy. No one model was superior to the others. This may be due to the small sample size of the test group.



Confusion Matrix

- All of the classification models had the same confusion matrix that is shown to the right.
- This correlates with the accuracy scores that are also identical as shown in the previous slide.



Conclusions

- Many features appear to relate to landing outcomes. The previous number of flights, the orbit, the version of the booster being used , the payload mass and the launch site can all be used to predict whether a Space X landing will be successful.
- The interactive dashboard allowed for many comparisons however, the limitation of the dashboard dataset to 10k kg prevented the evaluation of the B5 booster as it was identified in the SQL as the booster most frequently transporting the maximum payload of 15,600kg. This limitation yielded only one flight record for this booster.
- By processing and analyzing SpaceX launch records and results, we have been able formulate four models that can predict with 83% accuracy whether or not a launch will be successful. A successful launch and landing will allow SpaceX to recycle it's parts and keep their pricing low. Being able to predict this outcome will allow us to determine the flights for which we can offer competitive pricing and bidding.
- Although 83% accuracy may be adequate, more testing with a larger testing sample size is needed to improve the fit and accuracy of the models. This will hopefully lead to finding the superior model that can be used with the data and will predict, with more accuracy, the success or failure of future Space X flights.

Appendix

- **Python Code Dashboard**
  https://github.com/labrownmd/Coursera_Capstone/blob/cadd371386867cbe93e9a8723cc36478542f5451/spacex_dash_app.py
- **Dashboard Scatterplot for All Launch Sites Payload 0kg – 10K kg**
  https://github.com/labrownmd/Coursera_Capstone/blob/10cb29ee733951abcd3ffd46d79a0b21c331a8f5/Payload%20vs%20Success%20All%200k-10k.png
- **Dashboard Scatterplot for KSC Payload 0kg – 10K kg**
  https://github.com/labrownmd/Coursera_Capstone/blob/66046bb19b58834b9fa0aa117cc426ef8a51941c/Dashboard%20SP%20for%20KSC%200k%20-10k.png
- **Dashboard Scatterplot for KSC Payload 2500kg – 5K kg**
  https://github.com/labrownmd/Coursera_Capstone/blob/66046bb19b58834b9fa0aa117cc426ef8a51941c/Dashboard%20SP%20for%20KSC%202500%20-%205%20kg.png

Thank you!