

Winning Space Race with Data Science

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Outline

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

Executive Summary

Summary of methodologies:

Data Collection

Web Scraping

Data Wrangling

Exploratory Data Analysis using SQL

Exploratory Data Analysis and Feature Engineering using Pandas and Matplotlib

Launch Sites Locations Analysis with Folium

Building an Interactive Dashboard with Plotly Dash

Machine Learning Prediction

Executive Summary

- Summary of all results
- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results

Introduction

Project background and context

The commercial space age is here, companies are making space travel affordable for everyone, examples of companies involved with space travel in one way or the other are: Virgin Galactic, Rocket Lab, Blue Origin, and Space X. Perhaps the most successful is SpaceX. SpaceX advertises Falcon 9 rocket launches on its website with a cost of 62 million dollars; other providers cost upwards of 165 million dollars each, much of the savings is because SpaceX can reuse the first stage. Therefore, if we can determine if the first stage will land, we can determine the cost of a launch. There are two stages involved in a rocket launch, the first stage and the second stage. The first stage stage is quite large and expensive. Unlike other rocket providers, SpaceX's Falcon 9 Can recover the first stage.

Introduction

Problems I want to find answers

In this project, I am taking on the role of a data scientist working for a new rocket company. Space Y that would like to compete with SpaceX founded by Billionaire industrialist Allon Mask. Your job is to determine the price of each launch. I will do this by gathering information about Space X and creating dashboards for your team. I will also determine if SpaceX will reuse the first stage. Instead of using rocket science to determine if the first stage will land successfully, I will train a machine learning model and use public information to predict if SpaceX will reuse the first stage.



Methodology

Executive Summary

- Data collection methodology:
 - Describe how data was collected
- Perform data wrangling
 - Describe how data was processed
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
 - How to build, tune, evaluate classification models

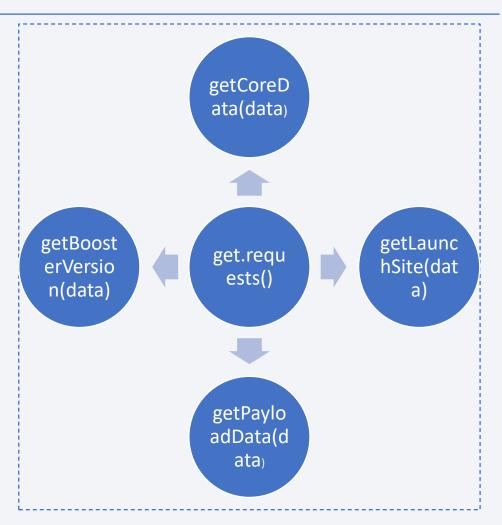
Data Collection

The data was collected by using the get.requests() method on the API URL of the data, and also using webscraping using BeautifulSoup()

Data Collection – SpaceX API

- As we can see from the flowchart to the right, the get.requests() method is the building block in this process of obtaining data. It is used in the four other functions, which are later used to get the data from the API
- This is the link of the SpaceX API calls notebook:

https://github.com/Jesutimilehin-Onayemi/Capstone-Project/blob/main/jupyter-labs-spacex-data collection-api%20(Solved).ipynb



Data Collection - Scraping

 The BeautifulSoup object is used here in scraping data from the web as well the find_all function with the respective elements

 This is the link of the Webscraping notebook: https://github.com/Jesutimilehin-Onayemi/Capstone-Project/blob/main/jupyterlabs-webscraping%20(Solved).ipynb use requests.get() method with the provided static_url

Use BeautifulSoup() to create a
BeautifulSoup object from a
response text content

Use the find_all function in the BeautifulSoup object, with element type `table to find the required table

Create a list of columns and extract the column names using find_all with the element 'th' on the required table

Create a dataframe and a function to append values to the column of the dataframe

Update your dataframe and export it to the required format e.g csv

Data Wrangling

- Description of how data were processed
- The data is loaded into a pandas dataframe, and checked for null values
- The datatypes function is used to check for all the data types.
- I determined the number of launches on each launchesite
- I determined the number and occurrence of each orbit in the column Orbit.
- I determined the number of landing outcomes, then assigned it to a variable.
- Created a landing outcome label from the Outcome column

This is the link of the Data wrangling notebook:

https://github.com/Jesutimilehin-Onayemi/Capstone-Project/blob/main/labs-jupyter-spacex-Data%20wrangling%20(Solved).ipynb

EDA with Data Visualization

- 1. The first chart here was a categorical plot. It was plotted to see how the FlightNumber (indicating the continuous launch attempts.) and Payload variables would affect the launch outcome.
- 2. The second chart here was a categorical plot (catplot). To visualize the relationship between Flight Number and Launch Site, with the hue set to 'class'. In order to know the successful and unsuccessful launch attempts associated with each Launch Site.
- 3. The third chart was a categorical plot. To visualize the relationship between PayloadMass(in kg) and Launch Site, with the hue set to 'class'. The Launch Site is a categorical variable, hence the use of a categorical plot.

EDA with Data Visualization

- 4. The fourth chart was a barplot, which was constructed in order to visualize the relationship between success rate of each orbit type.
- 5. In the fifth, I had a categorical plot to visualize the relationship between FlightNumber and Orbit type, Orbit type here, is a categorical data.
- 6. For the sixth chart, it was also a categorical plot, but in this case, it was constructed to visualize the relationship between Payload and Orbit type.
- 7. The last chart under the Exploratory Data analysis with Data Visualization section, was a line chart which was plotted to visualize how the success rate of the launches changed from year to year.

EDA with Data Visualization

Below is the GitHub link of the completed Exploratory Data analysis with data visualization notebook:

https://github.com/Jesutimilehin-Onayemi/Capstone-Project/blob/main/jupyter_labs_eda_dataviz(Solved).ipynb

EDA with SQL

In this section we use SQL magic in python to query from the SPACEXTABLE after establishing a connection with a database.

- 1. I displayed the names of the unique launch sites in the space mission using sql query.
- 2. I displayed five records where launch sites begin with the string 'CCA'.
- 3. I displayed the total payload mass carried by boosters launched by NASA (CRS).
- 4. I displayed the average payload mass carried by booster version F9 v1.1
- 5. I listed the date when the first successful landing outcome in ground pad was achieved.

EDA with SQL

- 6. I listed the names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000.
- 7. I listed the total number of successful and failure mission outcomes
- 8. I listed the names of the booster versions which have carried the maximum payload mass using a subquery.
- 9. I listed the records which will display the month names, failure landing outcomes in drone ship ,booster versions, launch sites for the months in year 2015.
- 10. I ranked 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.

EDA with SQL

Below is the GitHub link of the completed Exploratory Data analysis with data visualization notebook:

https://github.com/Jesutimilehin-Onayemi/Capstone-Project/blob/main/jupyter_labs_eda_sql_coursera_sqllite(Solved).ipynb

Build an Interactive Map with Folium

I created and added map objects such as markers, circles, markercluster, and lines on the folium map.

- folium.Circle was used to add a highlighted circle area with a text label on a specific coordinate
- folium.Marker() object was used to plot markers on the map
- Marker clusters were used to simplify a map containing many markers having the same coordinate.

Lines were drawn on the map to indicate a straight line distance from a launch site to its closest city, railway, and highway.

Build an Interactive Map with Folium

Below is the GitHub link of the completed Interactive map with Folium map notebook:

https://github.com/Jesutimilehin-Onayemi/Capstone-Project/blob/main/lab_jupyter_launch_site_location.ipynb

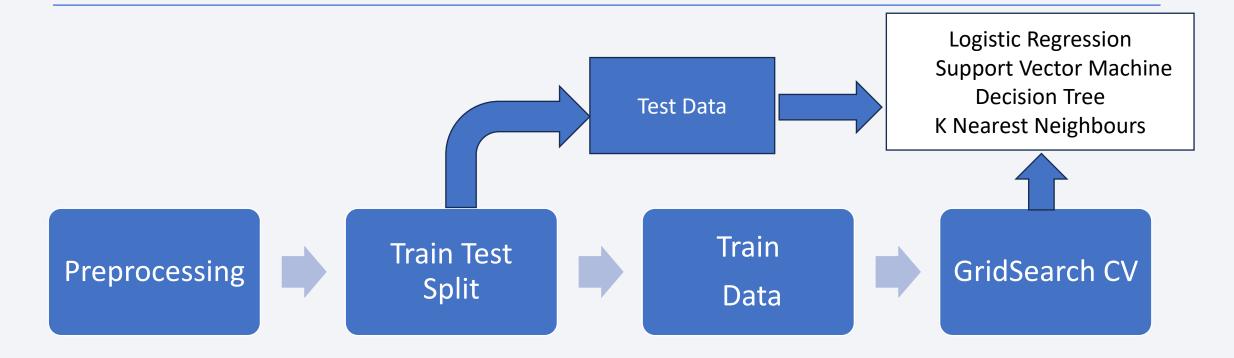
Build a Dashboard with Plotly Dash

- I built a dashboard containing a pie chart and scatterplot, that could change depending on the values or options selected, in terms of Launch Site, or the payload mass.
- I added the pie chart in order to be able to view the percentage of successful launches per location. The scatter plot however, was added to view the successful and failed launches per range of payload mass.

To view the raw python file, with the complete code for creating the dashboard, go to the URL address below:

https://github.com/Jesutimilehin-Onayemi/Capstone-Project/blob/main/Dash.py

Predictive Analysis (Classification)



Predictive Analysis (Classification)

As represented in the flowchart in the previous page, this is the process by which we found the best performing model:

- 1. The data was first preprocessed using StandardScaler()
- 2. Then the data was split into train and test data.
- Created GridSearch objects using the four different classification models as indicated in the flowchart.
- 4. Fit the GridSearch object on the train data.
- 5. Find the best performing parameters and score on the train data for all the models
- 6. Find the score on the test data for all the models and hence, find the best performing model.

Predictive Analysis (Classification)

To view the predictive analysis notebook, go to the URL address below:

 https://github.com/Jesutimilehin-Onayemi/Capstone-Project/blob/main/SpaceX_Machine_Learning_Prediction_Part_5_(solved).ipynb

Results

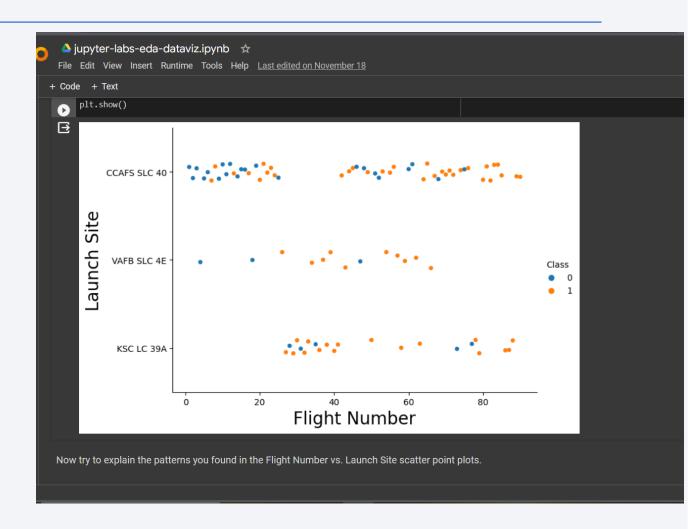
- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results



Flight Number vs. Launch Site

The screenshot to the right is a plot of Launch Site against Flight Number. It shows the different Launch Sites with the respective Flight numbers. The Class O, which are the blue points on the graph are the failures, while Class 1, which are the orange-colored points on the plot, are the successes.

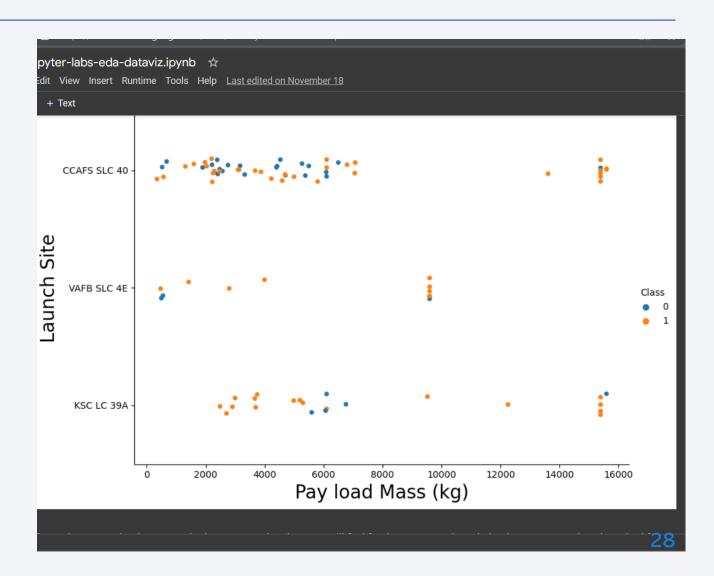
From the screenshot therefore, we can infer that with the increase in Flight Number, the percentage of successful outcomes increases with each Launch site.



Payload vs. Launch Site

The screenshot to the right is a plot of Launch Site against Payload Mass (kg). It shows the different Launches belonging to different Launch sites with the respective Payload Mass associated with them. The Class O, which are the blue points on the graph are the failures, while Class 1, which are the orange-colored points on the plot, are the successes.

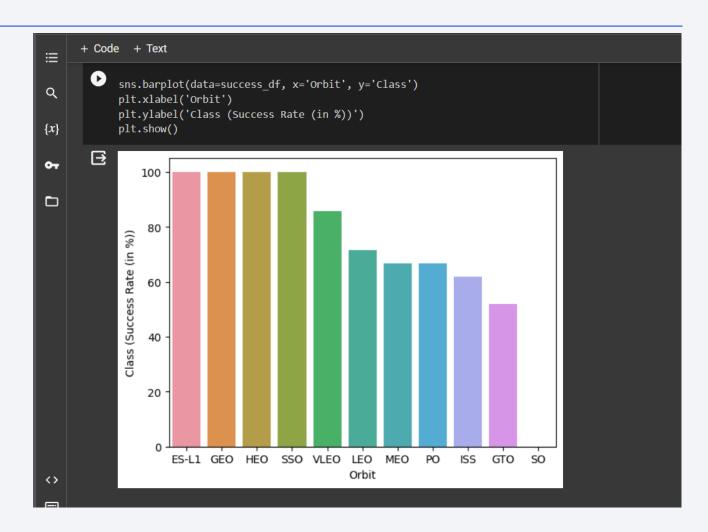
Also, in this case, the closer the payload Mass to 10000kg, the more the tendency for a successful outcome.



Success Rate vs. Orbit Type

The screenshot to the right is a barplot of Success Rate against Orbit type. It shows the different Orbit types with their respective Success Rates. In the graph, we can see that certain orbit types have a higher success rate than others, some even have success rates as high as 100%.

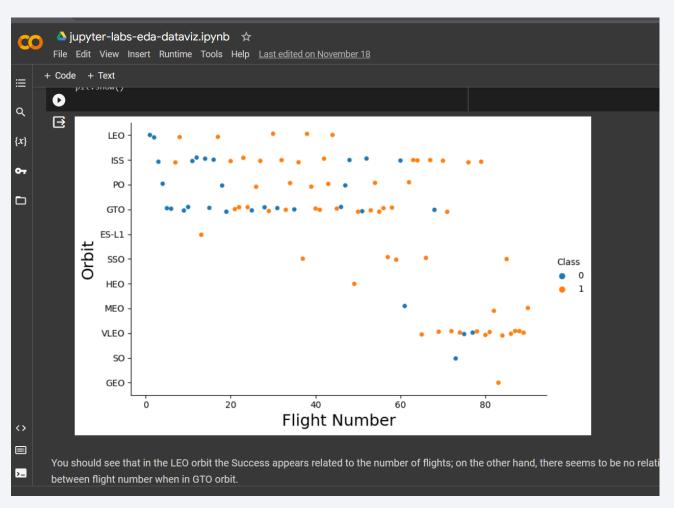
But this measurement can be misleading, and the reason why is that some orbit types may not be used as frequently as others thereby leading to the possibility of higher rates.



Flight Number vs. Orbit Type

The screenshot to the right is a categorical plot of Orbit type against Flight Number. It shows the different Launches, with their orbit types and their respective Flight numbers. The Class O, which are the blue points on the graph are the failures, while Class 1, which are the orange-colored points on the plot, are the successes.

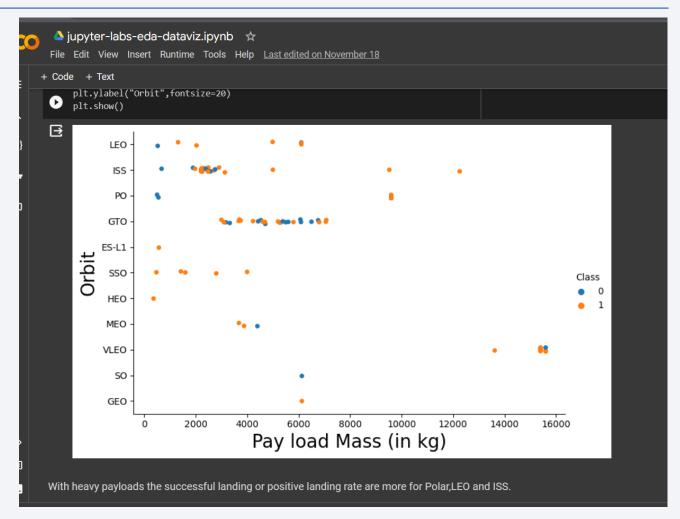
The graph in this picture consolidates the point I made in the previous slide. In the graph, we can see that Orbit type 'ES-L1' was only used once in the space mission and it's outcome was positive, leading to a success rate of 100%



Payload vs. Orbit Type

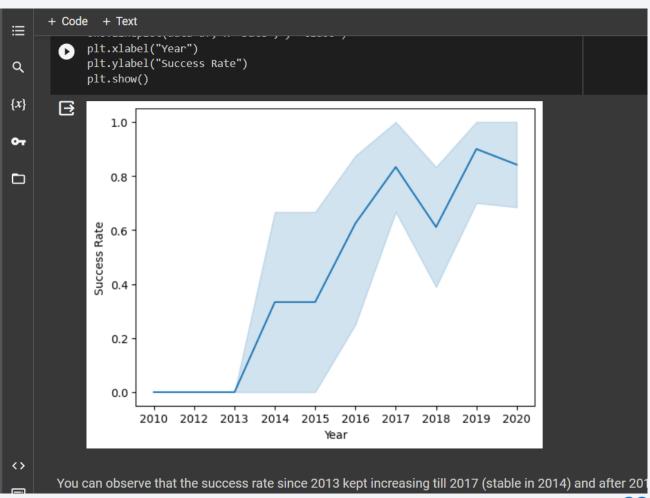
The screenshot to the right is a categorical plot of Orbit type against Payload Mass (kg). It shows the different Launches belonging to different Orbit types with the respective Payload Mass.

The Class O, which are the blue points on the graph are the launches that failed, while Class 1, which are the orange-colored points on the plot, are the successful launches.



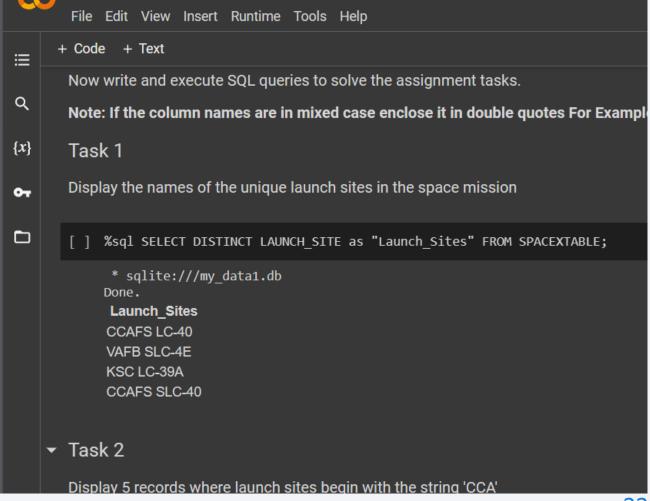
Launch Success Yearly Trend

The screenshot to the right is a line plot of the Launch Success Rate per year. It shows the trend of the average success rate of the Launches for the respective years. This line plot in general suggests an improvement in the success rate with time, and this good sense, because with breakthroughs in research and technology year on year, there is supposed to be a proportionate improvement in success rate.



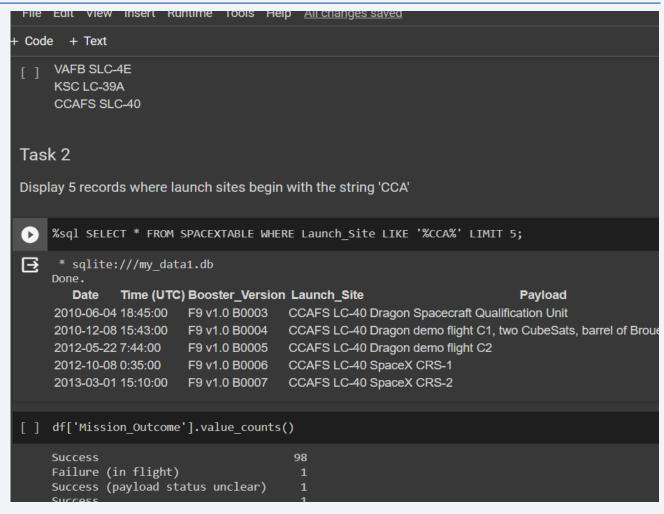
All Launch Site Names

The picture located to the right of this text shows the unique Launch sites in the mission, and this is achieved using sql magic, writing an sql query in python.



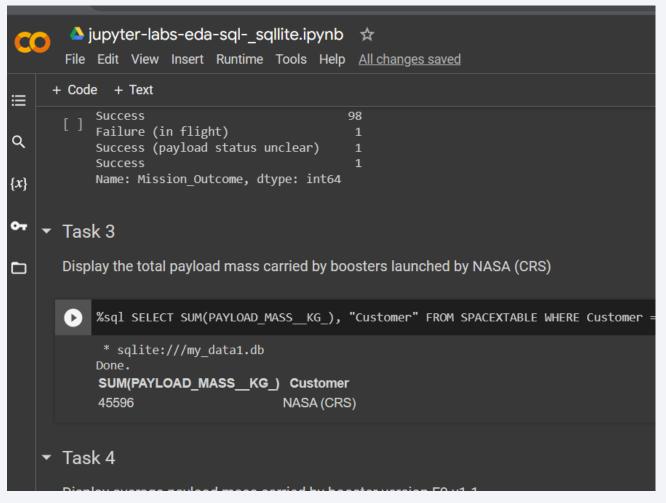
Launch Site Names Begin with 'CCA'

The picture located to the right of this text shows five records with Launch Site names beginning with 'CCA', and this is achieved using sql magic, writing an sql query in python.



Total Payload Mass

The picture located to the right of this text shows the total payload mass carried by boosters launched by NASA (CRS). This is achieved using sql magic, writing an sql query in python.



Average Payload Mass by F9 v1.1

The picture located to the right of this text shows the average payload mass carried by booster version F9 v1.1. This is achieved using sql magic, writing an sql query in python.

```
🄰 jupyter-labs-eda-sgl- sgllite.ipynb 🛚 🖈
   Edit View Insert Runtime Tools Help All changes saved
ode + Text
   Done.
   SUM(PAYLOAD MASS KG ) Customer
   45596
                              NASA (CRS)
ask 4
splay average payload mass carried by booster version F9 v1.1
   %sql SELECT AVG(PAYLOAD MASS KG ), Booster Version FROM SPACEXTABLE WHERE Booster Versi
    * sqlite:///my data1.db
   AVG(PAYLOAD MASS KG ) Booster Version
   2534.6666666666665
                             F9 v1.1 B1003
ask 5
st the date when the first succesful landing outcome in ground pad was acheived.
nt:lice min function
```

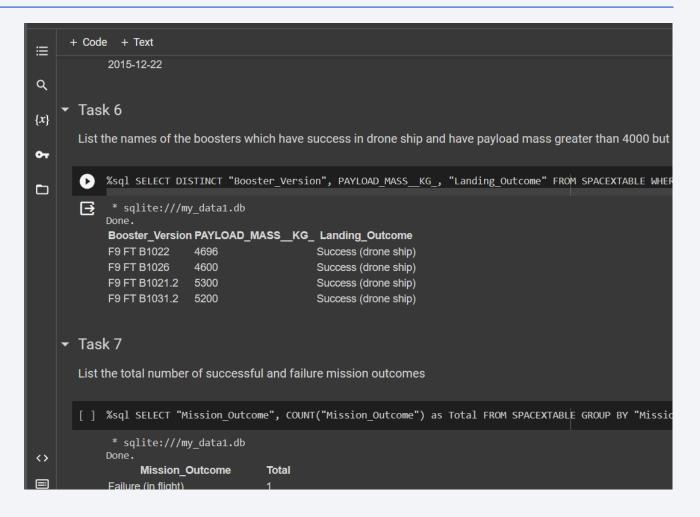
First Successful Ground Landing Date

The picture located to the right of this text shows the date of the first successful ground pad landing. This is achieved using sql magic, writing an sql query in python.



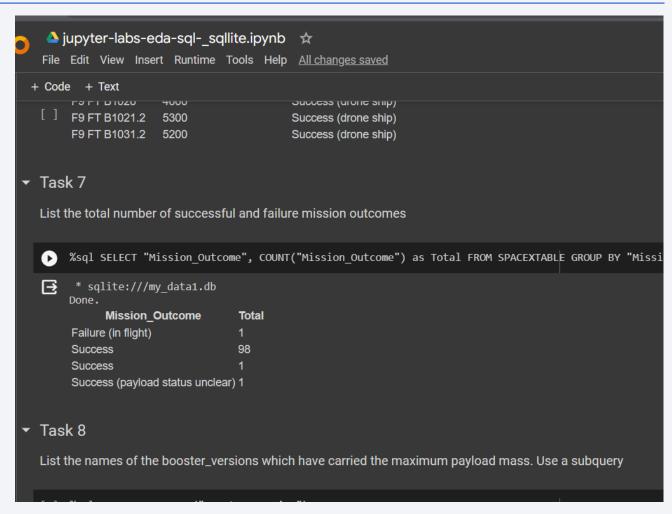
Successful Drone Ship Landing with Payload between 4000 and 6000

The picture located to the right of this text shows the names of boosters which have successfully landed on drone ship, and also had a paload mass greater than 4000kg but less than 6000kg. This is achieved using sql magic, writing an sql query in python.



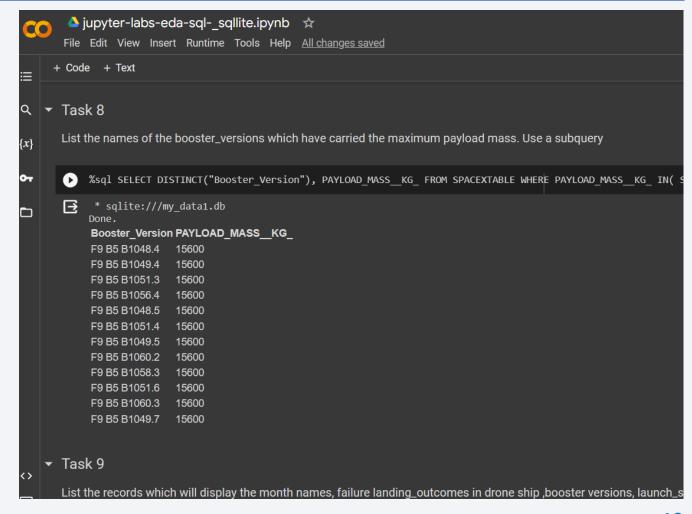
Total Number of Successful and Failure Mission Outcomes

The picture to the right displays the total number of successful and failed mission outcomes.



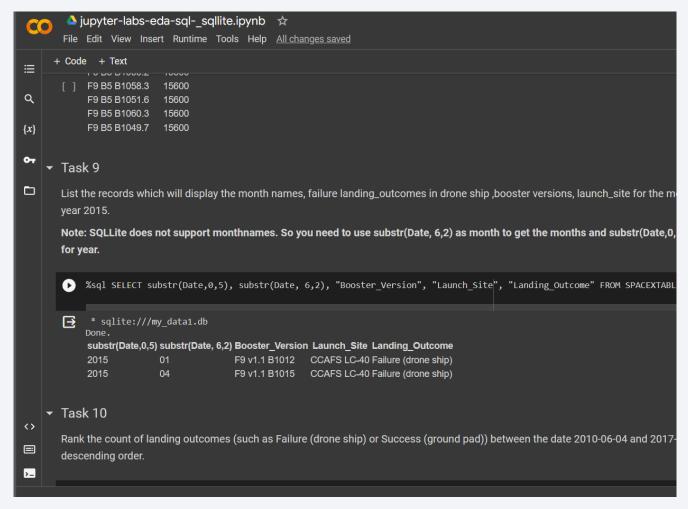
Boosters Carried Maximum Payload

The picture to the right displays the names of booster versions that have carried the maximum payload mass. To see the full code used in achieving this, follow the GitHub URL on page 18 to go the code page.



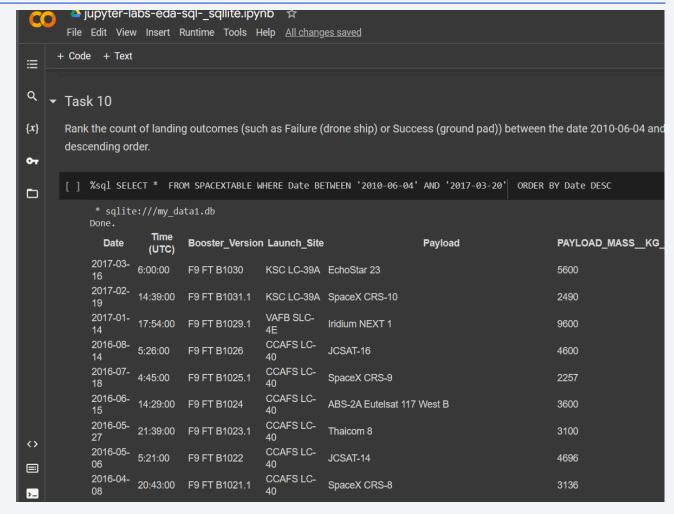
2015 Launch Records

The picture to the right of this text, displays the failed landing_outcomes in drone ship, their booster versions, and launch site names for the year 2015.



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

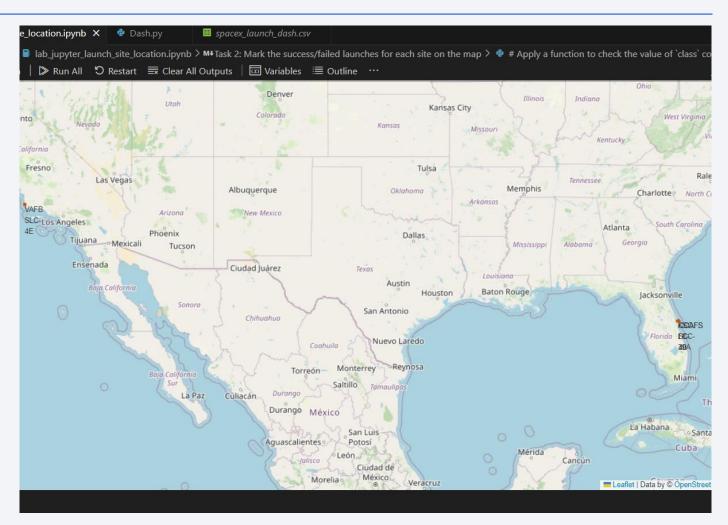
The picture on this page displays the Landing Outcomes between 2010-06-04 and 2017-03-20, to see the full list of output, go to the GitHub URL on page 18.





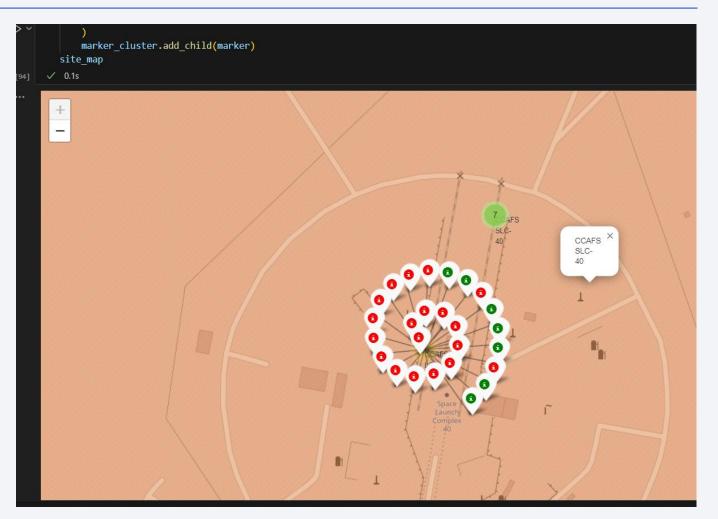
Marked all the Launch Sites on the Map with Folium

The generated map to the right shows the location markers of all the launch sites with a red dot indication. From the map we can see that all the launch sites are situated in USA, and are all close to the coast.



Marked the successful/failed launches for each site

The picture in this slide shows the color-labeled launch outcomes on the map. The red labeled markers indicate the failed launches while the green labeled marked indicate the successful ones.

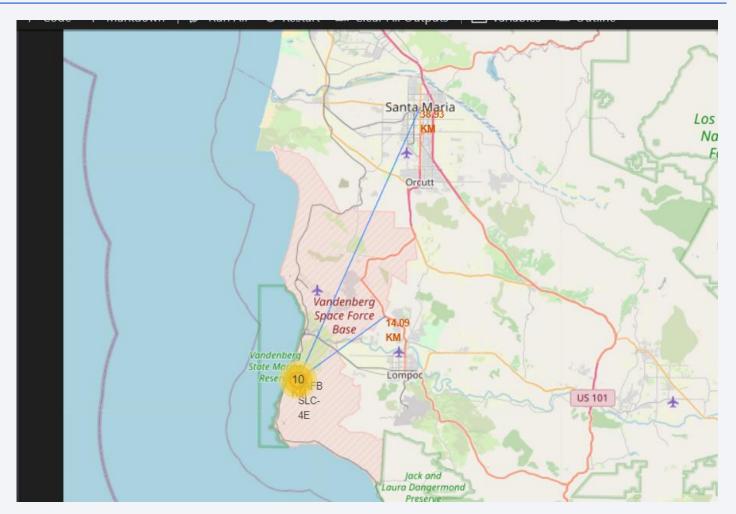


Calculated the distance between a Launchsite and specific structures

There are three distances that were calculated, the shortest distance is to the closest railway line. This is visible in the screenshot to the right of this text. This is because the distance is small, it can only be seen when the map has been zoomed in.

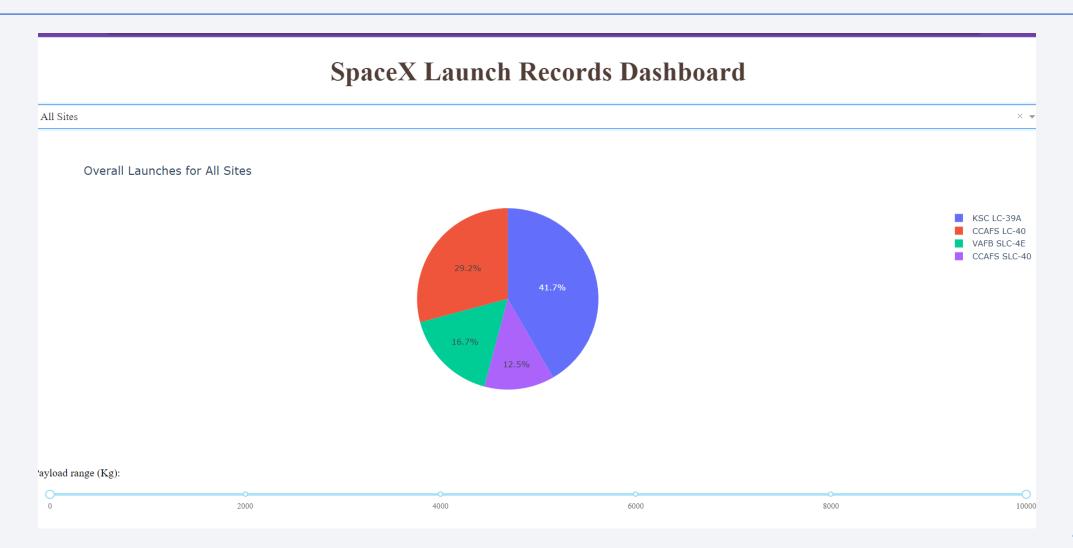
From this map, we can see that the launch site is situated far away from the highway, and even farther away from the city.

Follow the URL on page 20 to view the raw python file that was used to create these folium maps.





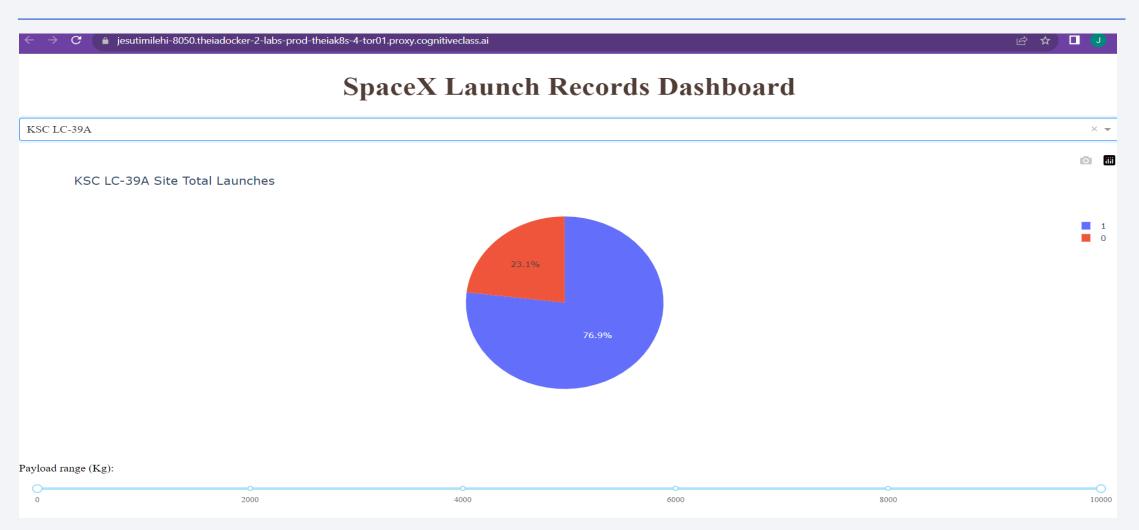
Pie chart for the launch success count for all sites.



Pie chart for the launch success count for all sites.

The picture in the previous slide shows the Launch success count for the various Launch sites in the Space X space mission. From the picture we see that launch site 'KSC LC-39A' has the highest proportion of successful launches out of all the launch sites.

Piechart for the launchsite with the highest launch success ratio



Piechart for the Launchsite with the highest launch success ratio

The picture in the previous slide shows the pie chart indicating the success/failure percentage of the launch site with the highest launch success ratio. This is 'KSC LC-39A'.







The three preceding pictures are screenshots of the dashboard showing a scatterplot of Payload vs Launch Outcome for the space mission.

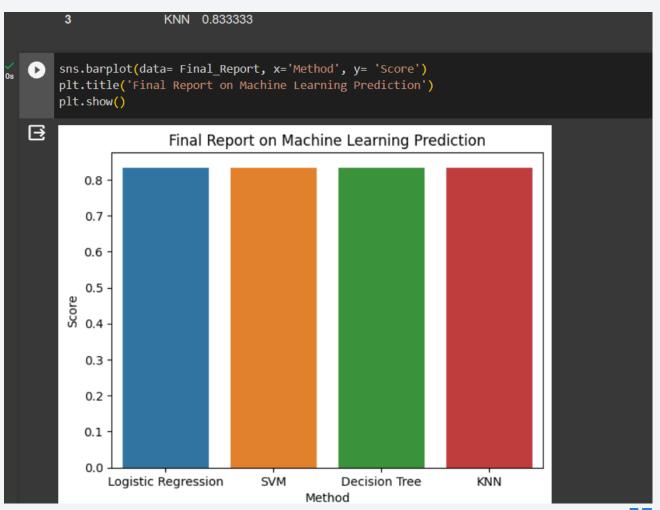
The Payload Range that has the highest success rate is 8000-10000kg with 50% success rate.

The booster version with the largest success rate is FT.



Classification Accuracy

All the four models used had the same accuracy score on the test data, which is 0.833 or 83.33%. So technically, there is no 'best performing model'.

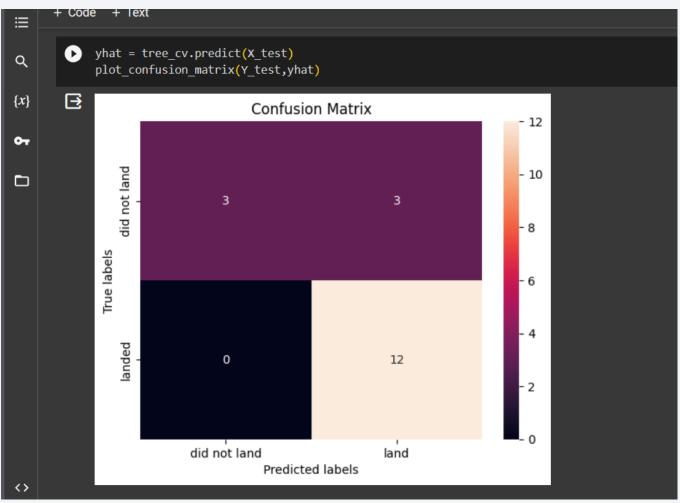


Confusion Matrix

All the four models used had the same accuracy score on the test data, so there is technically no 'best performing model'. But I have chosen the confusion matrix of the Decision tree model here because, out of all the models, it had the best training score.

The URL address to the complete code is this:

https://github.com/Jesutimilehin-Onayemi/Capstone-Project/blob/main/SpaceX_Machin e_Learning_Prediction_Part_5_(so lved).ipynb



Conclusions

- 1. From the insights drawn from the analysis on page 33, we can see that Rocket Launching should get cheaper in terms of cost, because with time, the success rate of first stage landing has gone up. T Hence, the possibility of re-using the first stage is higher.
- 2. SSO is the most successful orbit type, so the more this is used, the more likely, that the company will re-use the first stage.
- 3. KSC LC-39A is the most successful Launches, a further in depth research can be done to find out the reason for this, maybe it's the nature of the wind speed in that location, a research will help unfold this.
- 4. The most successful booster version, is 'FT'.

Conclusions

In this project, the aim was to determine if SpaceX will reuse the first stage, I have however used Machine Learning prediction to predict this, and the link to the code for creating the model is available on page 58.

So, from the findings in this project, we see that with time, Space X is expected to reuse more of its launches' first stage, they are also more likely to reuse the first stage if; Sun Synchronous Orbit or SSO is used as the orbit type, the launches are carried out are at KSC LC-39A launch site, and if FT is used as the Booster Version.

Appendix

To see the complete code to each of the sections in this presentation, follow the respective URLs to the code page.

