

Winning Space Race with Data Science

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Outline

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- Conclusion
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Executive Summary

Summary of methodologies

• Data was collected from SpaceX API and SpaceX Wikipedia; a new column name label, Class, was created to classify successful landings; data was explored by using SQL, visualisations, folium maps and dashboards; gathered several relevant columns as features; modified all categorical variables to binary using one-hot encoding; normalised data and utilised GridSearchCV to find the best parameters for machine learning models; and visualised the accuracy score of all models.

Summary of all results

• All results in this project were produced with four machine learning models: Logistic Regression, Support Vector Machine, Decision Tree Classifier and K Nearest Neighbours. These results have the similar accuracy score on the test data: 83.33%. This depicts that all models have predicted more successful landings. Hence, more data is required for calculating the best accuracy and performance of the methods.

Introduction

Project background

• Space X is one of the most successful companies that makes space travel affordable for the majority in this commercial space age. Space X had several achievements: sending spacecraft to the International Space Station; utilizing Starlink, a satellite internet constellation that provides the satellite internet access; and sending manned missions to Space. The main reason behind these achievements is due to inexpensive Falcon 9 rocket launches with \$62 million, while other suppliers cost about \$165 million. Thus, this can be determined whether the first stage will land and the cost of a launch. However, a new rocket company, Space Y, wants to compete with Space X.

Problems you want to find answers

• As a data scientist in Space Y, gathering information and creating dashboards for data analysis will be required as the first step. Then, a machine learning model will be trained to predict the first stage of successful recovery.



Methodology

Executive Summary

- Data collection methodology:
 - Data was collected from SpaceX API and SpaceX Wikipedia
- Perform data wrangling
 - Data was processed by classifying whether the booster has landed successfully or not.
- 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

Data collection involves the Space X Public API using GET requests, web scraping data from an HTML table on Space X's Wikipedia page, and basic data wrangling and formatting. The list will store the retrieved data and create into a new dataframe. The below depicts the column names of Space X API and Space X's Wikipedia Web Scraping respectively.

Space X API Column Names:

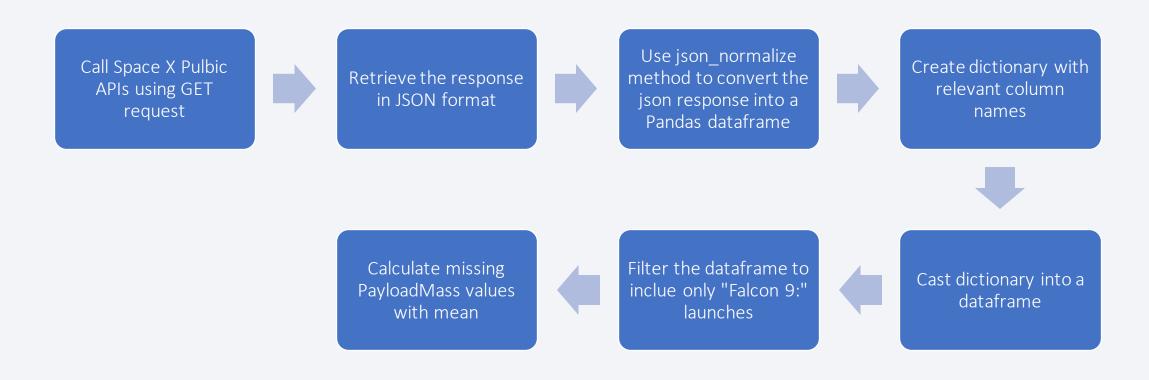
FlightNumber, Date, BoosterVersion, PayloadMass, Orbit, LaunchSite, Outcome, Flight s, GridFins, Reused, Legs, LandingPad, Block, ReusedCount, Serial, Longitude, Latitude

Wikipedia Webscrape Column Names:

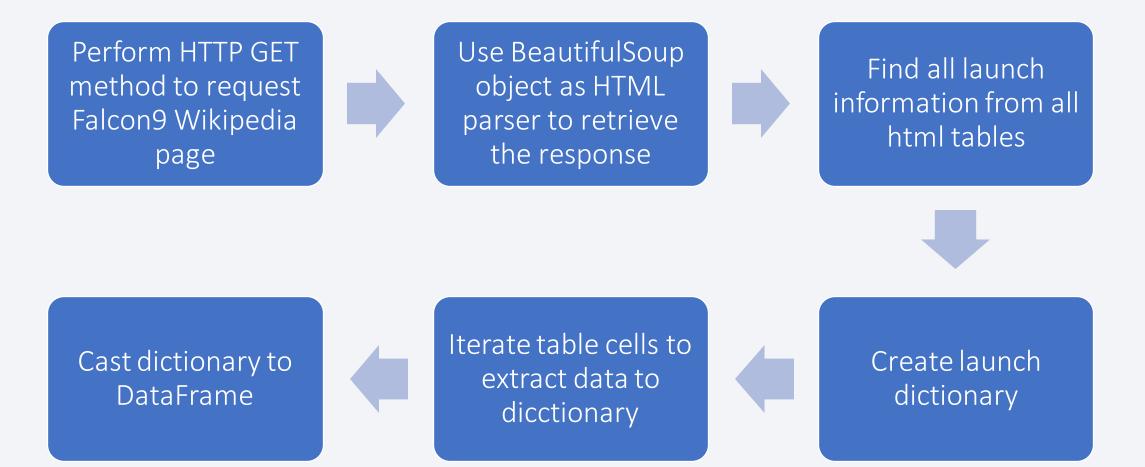
FlightNumber, Launch site, Payload, PayloadMass, Orbit, Customer, Launch out come, Version Booster, Booster landing, Date, Time

The flowcharts will be presented in Slides 8 and 9.

Data Collection – SpaceX API



Data Collection - Scraping



Gitlab URL: https://github.com/jaketee93/capstone_project/blob/develop/wk%201/jupyter-labs-webscraping.ipynb

Data Wrangling

The landing outcomes convert into training labels with 1 – booster landed successfully, and 0 – booster landed unsuccessfully. Both landing outcome and mission outcome labels will be created from the Outcome column. The new training label column, Class, is the classification variable that represents the outcome of each launch. The first stage did not land successfully if the value is 0. Otherwise, the first stage landed successfully if the value is 1. The table below depicts the mapping of the outcome.

Value	Outcome
0	False Ocean, False RTLS, None ASDS. None None
1	True Ocean, True RTLS, True ASDS

EDA with Data Visualization

Both Pandas and Matplotlib perform Exploratory Data Analysis (EDA) and Feature Engineering. The following variables are used to perform EDA: Flight Number, Payload Mass, Launch Site, Orbit, Class and Year. With that, the following relationships were visualised on its detailed launch records.

Plots	Relationships				
Catplot	Flight Number vs Launch Site; Payload vs Launch Site; Flgiht Number vs Orbit Type; Payload vs Orbit Type				
Line chart	Success yearly trend				
Bar chart	Orbit vs Success rate of each orbit type				

The above table depicts the plots use on these relationships. Should these relationships exist, they could be used for training machine learning model.

EDA with SQL

- SQL queries performed
 - Load dataset into IBM DB2 Database
 - Used SQL Python Integration for SQL queries. The database connection must be established with our own Service Credentials beforehand.
 - Learnt basic SQL commands such as 'SELECT', 'FROM', 'WHERE', 'ORDER BY' and more.
 - Retrieved information such as launch site names, mission outcomes, payload mass carried by booster version F9 v1.1, landing outcomes and the names of boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000.

Build an Interactive Map with Folium

Folium maps are utilised to label launch sites, successful and unsuccessful landings, and a proximity example to key locations such as Railway, Highway, Coast, and City. Hence, this enables us to comprehend the approximate locations of the launch sites and visualise all successful landings that are relative to their location.

Build a Dashboard with Plotly Dash

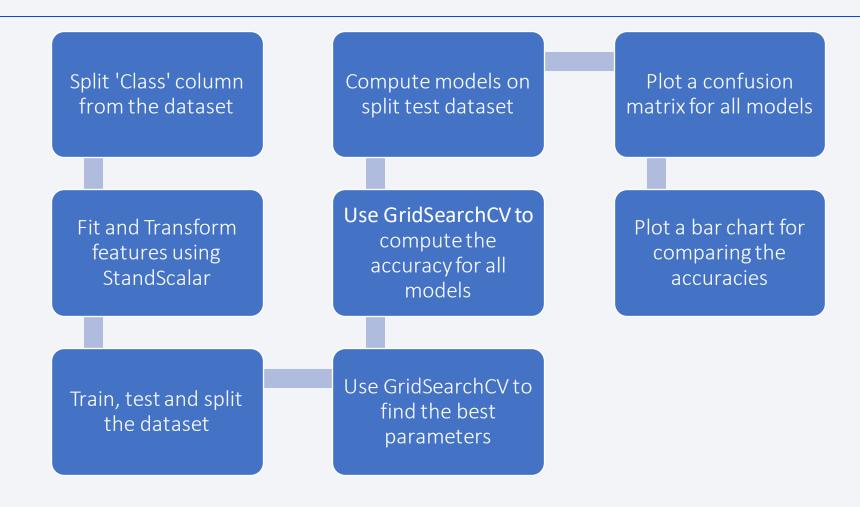
SpaceX Launch Records Dashboard contains both pie and scatter charts for all launch sites. The infographic will be displayed in these charts depending on all launch sites or any individual launch sites. The pie chart displays the distribution of successful landings across these sites' success rates with its visualisation while the scatter plot displays the success that varies across launch sites, payload mass and booster version category with these two inputs: All sites or any individual site; and payload mass on the HTML slider between 0 and 10000kg.

Predictive Analysis (Classification)

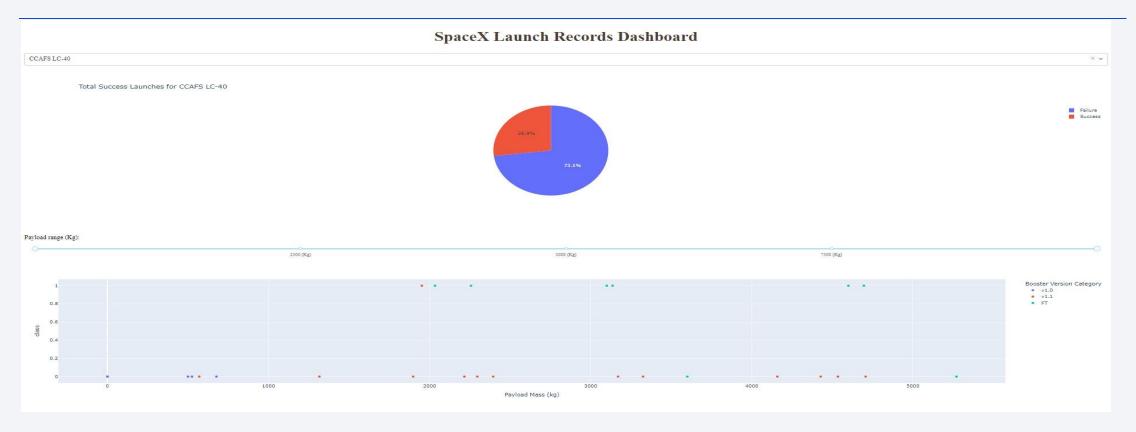
First, the 'Class' column will be split from the dataframe to a NumPy array as variable Y using the method to_numpy(). Next, StandardScaler() will be used for fitting and transforming the features from the dataframe as variable X. Once the fit and transform process completes, tran_test_split function starts to split the data X and Y into training and test datasets. Thus, the number of samples will be available in both training and test datasets. Furthermore, GridSearchCV object looks for the best parameters and best accuracy. This method applies to Logistic Regression, support vector machine (SVM), decision tree classifier and K-Nearest Neighbour models. Once computing the accuracy scores of all models completes, the test dataset is used for plotting a confusion matrix. Finally, these accuracy scores will be analysed to see which method has the same performance.

The flow chart is presented in <u>slide 16</u>.

Predictive Analysis (Classification)



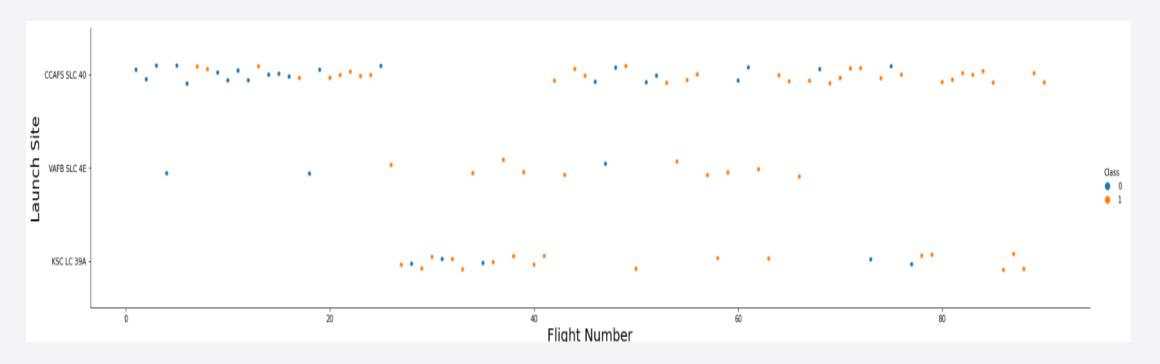
Results



The above diagram depicts the Plotly dashboard. The results of EDA with Visualisation, EDA with SQL, Interactive Map with Folium and accuracy score of all models are displayed in the next section.

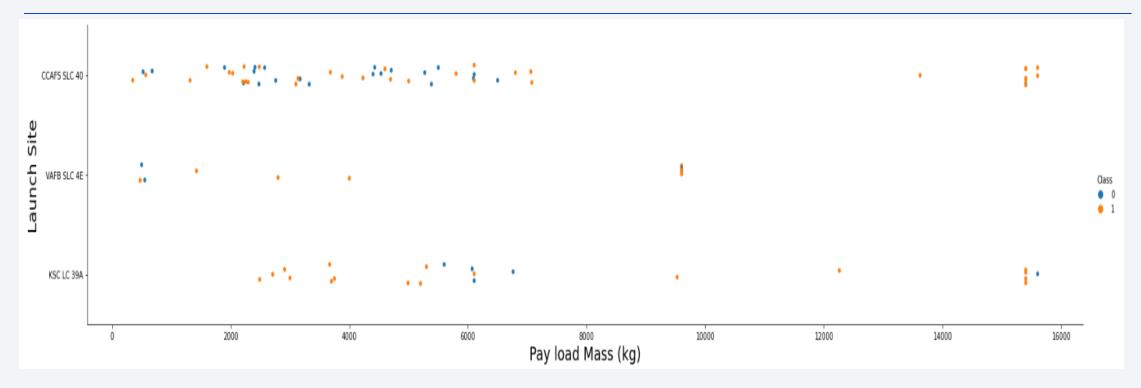


Flight Number vs. Launch Site



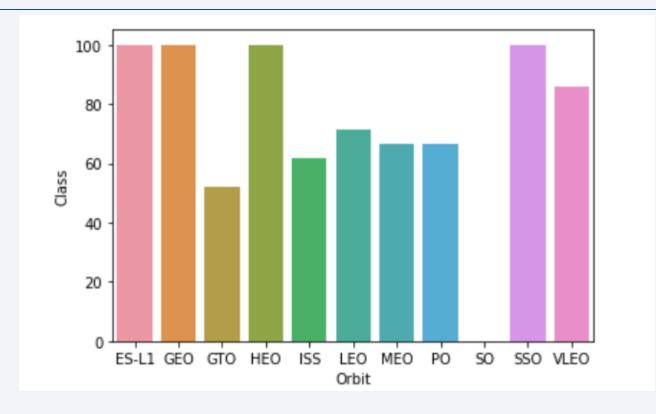
In the above infographic, orange indicates a successful launch, and blue indicates an unsuccessful launch. This infographic depicts that the success rate has increased significantly after the <u>20th flight</u>. <u>CCAFS SLC 40</u> is most likely the main launch due to the higher number of flights.

Payload vs. Launch Site



In the above infographic, orange indicates a successful launch, and blue indicates an unsuccessful launch. This infographic depicts that the payload is not massive as the first stage returns between <u>O and 6000kg</u>. Different launch sites are using different payload mass.

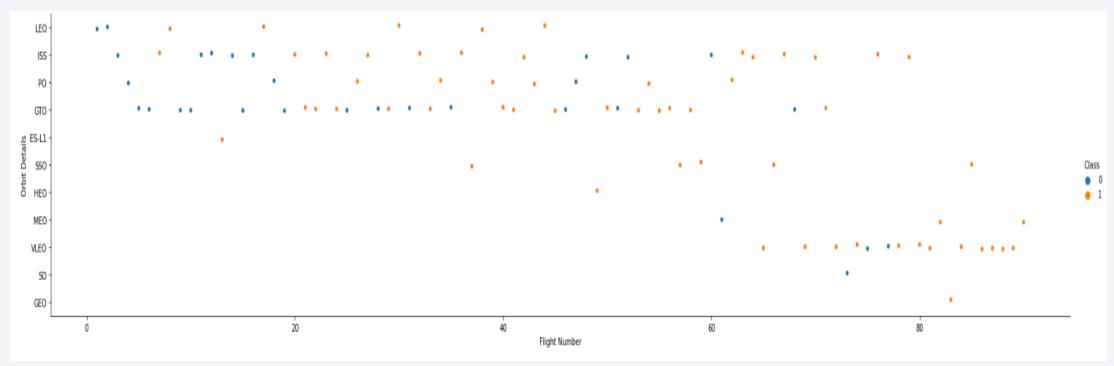
Success Rate vs. Orbit Type



The success rate is labelled as Class.

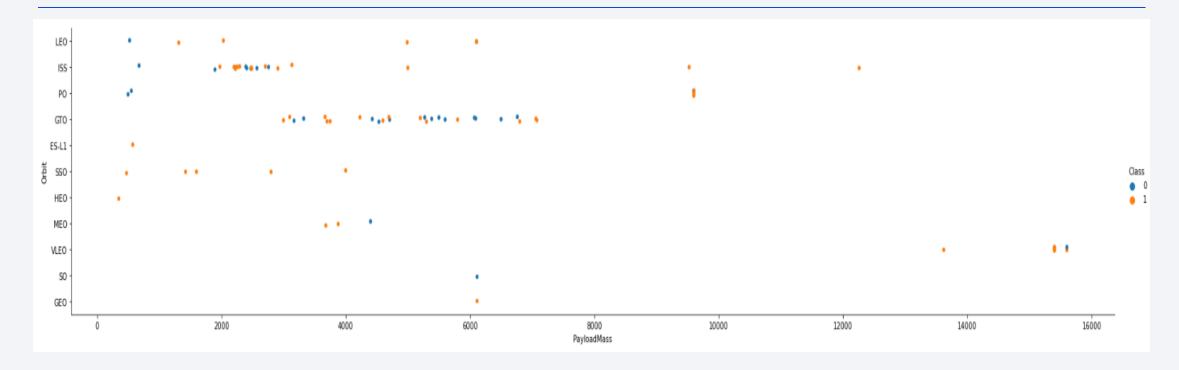
The above chart depicts that <u>ES-L1</u>, <u>GEO</u>, <u>HEO</u> and <u>SSO</u> have the highest success rate which is <u>100%</u>; <u>VLEO</u> has <u>80% success rate</u>; and <u>SO</u> has <u>0% success rate</u>.

Flight Number vs. Orbit Type



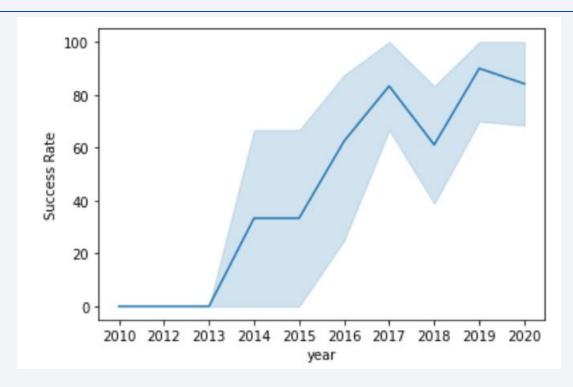
In the above infographic, orange indicates a successful launch, and blue indicates an unsuccessful launch. This infographic depicts that the launches of the orbit types change over flight numbers. Launch outcome is correlated with this preference. Therefore, SpaceX started launching LEO orbits with moderate success and then returned to VLEO in the recent launches. Thus, this shows that SpaceX can perform better in lower orbits.

Payload vs. Orbit Type



In the above infographic, orange indicates a successful launch, and blue indicates an unsuccessful launch. This infographic depicts that Orbits <u>LEO, ES-L1, SSO and HEO</u> have the lowest Payload Mass with <u>below 2000kg</u>. On the other hand, <u>VELO</u> has the <u>highest Payload Mass nearer to 16000kg</u>.

Launch Success Yearly Trend



The above line chart displays that the success rate has increased rapidly to 80% from 2010 to 2017. Despite the slight decline to 60% success rate in 2018, it has surged to 80% success rate approximately in 2020. Light blue shaded area indicates that 95% confidence interval is used in this line chart.

All Launch Site Names

```
%sql select Unique(LAUNCH_SITE) from SPACEXTBL;
 * ibm_db_sa://rvb93661:***@8e359033-a1c9-4643-81
Done.
 launch site
 CCAFS LC-40
CCAFS SLC-40
 KSC LC-39A
 VAFB SLC-4E
```

The query in the above image <u>retrieves all unique names</u> of the launch sites. All launch site names: CCAFS LC-40, CCAFS SLC-40, KSC LC-39A, VAFB SLC-4E.

Launch Site Names Begin with 'CCA'

* ibm_ Done.	15m_d5_5d.7/17055661. (@5555565) d165 4045 6261 6d6661516765.052165616B.dd1d3655.dppd6md111.c16dd.56126761dd5												
DATE	timeutc_	booster_version	launch_site	payload	payload_masskg_	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	07:44:00	F9 v1.0 B0005	CCAFS LC- 40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	No attempt				
2012- 10-08	00:35:00	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				

The query in the above image <u>retrieves the first five entries</u> with the launch site names that start with 'CCA' in the database.

Total Payload Mass

```
%sql select sum(PAYLOAD_MASS__KG_) AS PAYLOAD_MASS from SPACEXTBL where customer like 'NASA (CRS)';

* ibm_db_sa://rvb93661:***@8e359033-a1c9-4643-82ef-8ac06f5107eb.bs2io90108kqb1od8lcg.databases.appdcDone.
payload_mass
45596
```

The query in the above image calculates the <u>total payload mass</u> carried by boosters launched by <u>NASA (CRS)</u>.

Average Payload Mass by F9 v1.1

The query in the above image calculates the <u>average payload mass</u> carried by boosters version F9 v1.1.

First Successful Ground Landing Date

The query in the above image queries the <u>first successful ground landing date</u> on 22 December 2015.

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

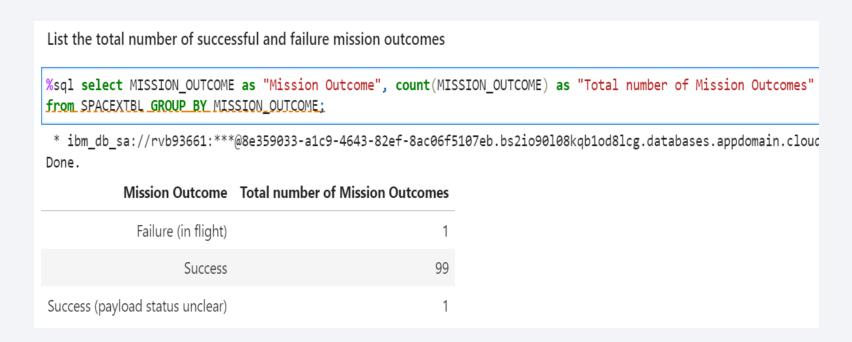
**sql select BOOSTER_VERSION AS "Name of the boosters"
from_SPACEXTBL_where_(LANDING_OUTCOME='Success_(drone_ship)') and (PAYLOAD_MASS__KG__BETWEEN_4000 and 6000);

* ibm_db_sa://rvb93661:***@8e359033-a1c9-4643-82ef-8ac06f5107eb.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:Done.

**Name of the boosters
F9 FT B1022
F9 FT B1021.2
F9 FT B1031.2
```

The query in the above image queries the <u>list of boosters names that have</u> success in drone ship and payload mass between 4000 to 6000kg.

Total Number of Successful and Failure Mission Outcomes



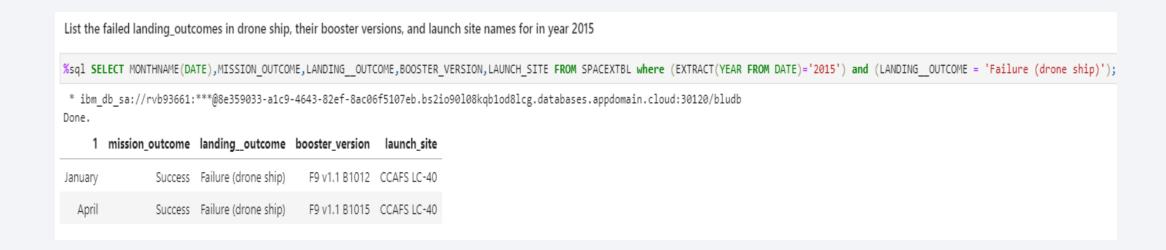
The query in the above image queries the <u>total number of successful and failure</u> mission outcomes.

Boosters Carried Maximum Payload



The query in the above image queries the <u>names of the booster version</u> that carry the <u>maximum payload mass</u>.

2015 Launch Records



The query in the above image queries the <u>names of the booster version</u> that carry the <u>maximum payload mass</u>.

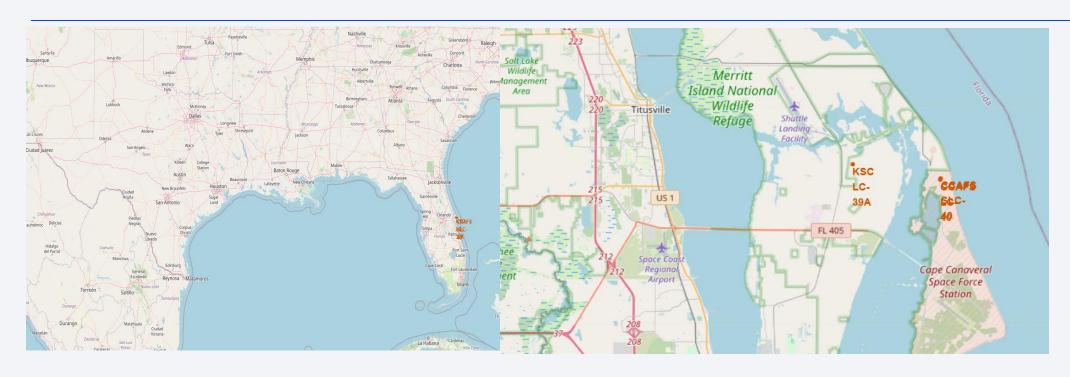
Rank Landing Outcomes Between 2010-06-04 and 2017-03-20



The query in the above image queries the <u>number of landing outcome</u>, such as Failure (drone ship), between <u>4 June 2010</u> and <u>20 March 2017</u> in <u>descending</u> order.

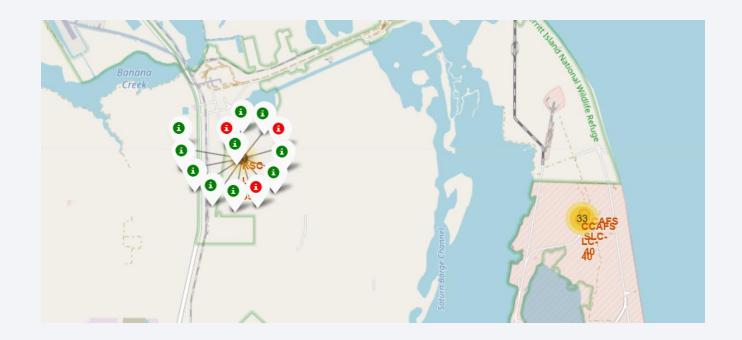


Folium Map Screenshot 1: Launch Site Locations



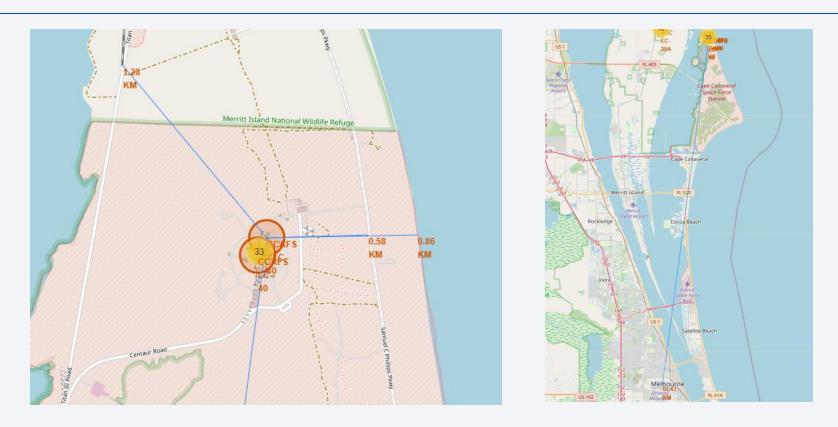
The map on the left shows all launch sites in US, while the other map shows all launch sites in Florida are nearer to one another. These launch sites are nearer to the ocean

Folium Map Screenshot 2: Launch Site Markers with Colour Code



Each cluster shows the total number of launches from their launch sites. If one cluster is selected in the map, it will display each successful landing location (green) and failed landing location (red). For example, KSC LC-39A has 10 successful landings and 3 failed landings.

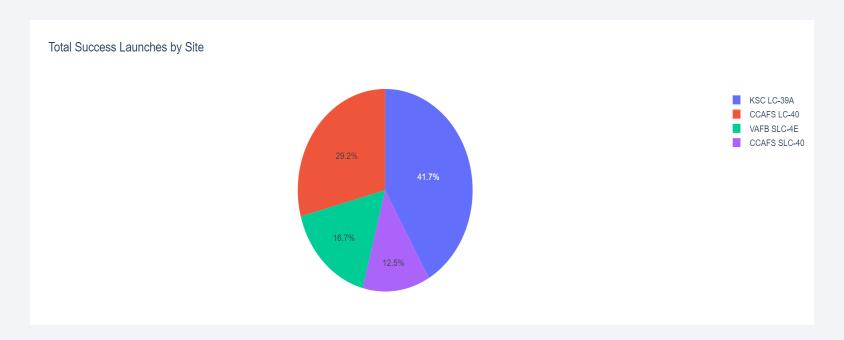
Folium Map Screenshot 3: Key Location Proximities



CCAFS SLC-40 will be used as an example in this section. This shows that CCAFS SLC-40 is nearer to several landmarks such as the road (0.58km), Samuel C Phillips Parkway, coastlines (0.86km) and railroad (1.28km). The farthest landmark is Olando Melbourne International Airport (51.43km).

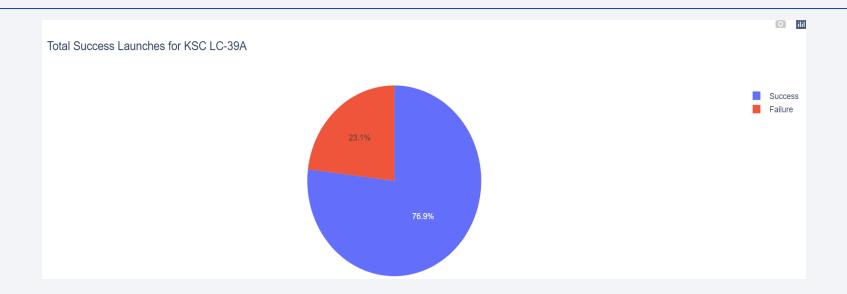


Dashboard Screenshot 1: Successful Launches Across All Launch Sites



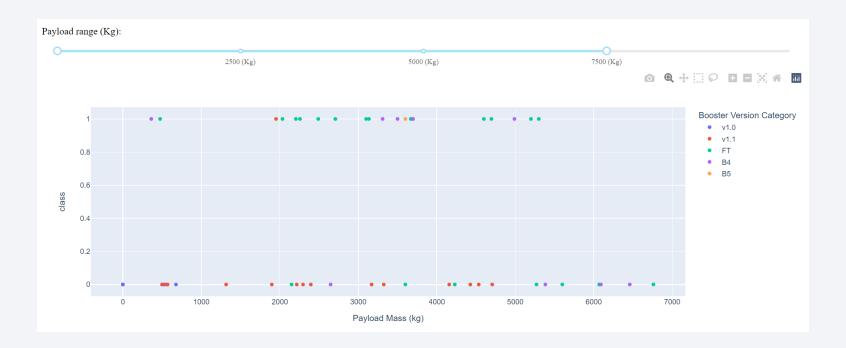
The pie chart displays the distribution of <u>successful landings across all launch sites</u>. CCAFS LC-40 is an old name of CCAFS SLC-40, so both <u>CCAFS</u> and <u>KSC</u> sites have the same <u>highest weightage</u> of <u>successful launches</u> (41.7%). On the other hand, <u>VAFB</u> has the <u>lowest weightage</u> of the successful launches due to the smaller sample and higher difficulty of launching in the west coast.

Dashboard Screenshot 2: Highest Launch Success Ratio



KSC LC-39A has the <u>highest launch success ratio</u> with 10 successful landings and 3 failed landings.

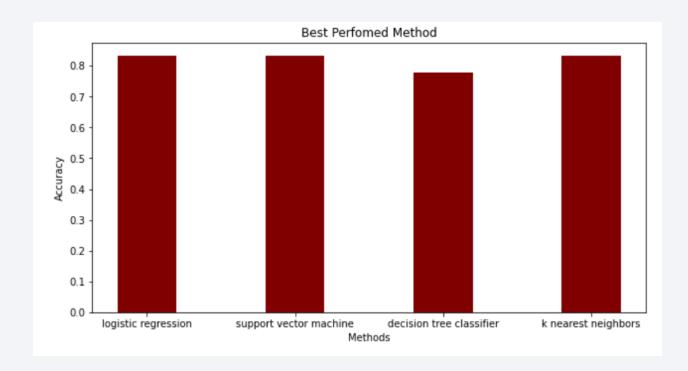
Dashboard Screenshot 3: Payload vs Launch Outcome



Plotly Dashboard has a Payload Mass range slider with the range of 0-10000. The above scatter plot shows an example of the payload mass range from 0 to 7500kg. Class 1 indicates successful landings whil Class 0 indicates unsuccessful landings. Interestingly, the scatter plot shows that there are numerous unsuccessful landings as indicated in Class 0 as compared to Class 1.

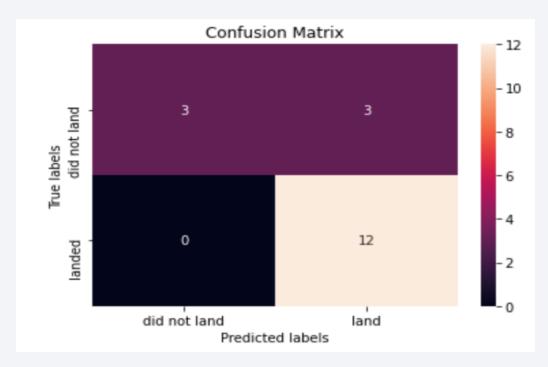


Classification Accuracy



All methods have the <u>same accuracy</u> (80%) on the test set with the <u>test size = 0.2</u> and <u>random state = 2</u>. Since the test size is smaller, we only have <u>18 test samples</u> altogether. This would cause large variance in accuracy, such as Logistic Regression and Decision Tree Classifier, in the repeated runs. Hence, we require more data, test size and random state to determine the best training model in terms of accuracy.

Confusion Matrix



Since all training models have the same results as shown in slide 44, the confusion matrix is the same across all of them. As shown in the above confusion matrix, the models have predicted that there are 12 successful landings when the true label was successful landing (<u>True Negative</u>); and no unsuccessful landings when the true label was unsuccessful landing (<u>False Negative</u>). On the other hand, the models have predicted that there are 3 unsuccessful landings when the true label was unsuccessful landing (<u>True Positive</u>); and there are 3 successful landings when the true label was unsuccessful landings (<u>False Positive</u>).

Conclusions

- SpaceY wants to compete with SpaceX.
- As a data scientist in Space Y, the objective is to develop a machine learning model by predicting the first stage of successful recovery to save USD \$100 million approximately.
- Collected data from SpaceX API using GET request and used web scraping in SpaceX Wikipedia page.
- Created dashboards for visualisations.
- Executed SQL queries in IBM DB2 SQL database.
- Created a machine learning model with 80% accuracy.
- Will be better to collect more data for determining the best machine learning model and enhance its accuracy.

Appendix

GitHub repository for IBM Data Science Capstone Project:

https://github.com/jaketee93/capstone_project

Special Thanks To All IBM Instructors:

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

