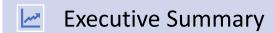


Winning Space Race with Data Science

Jaime Solis June 28th, 2022



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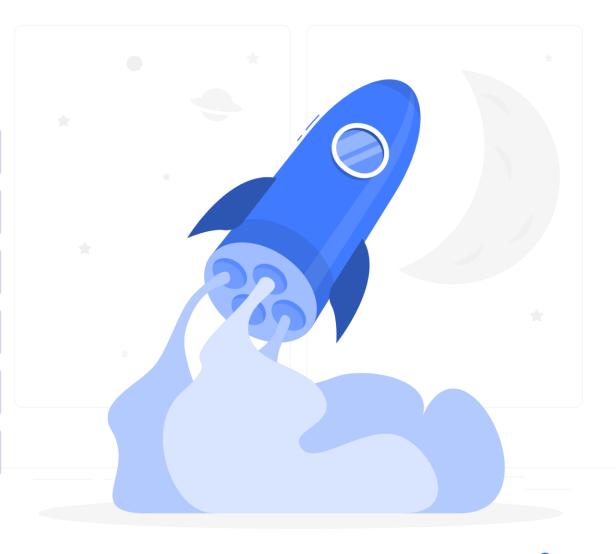
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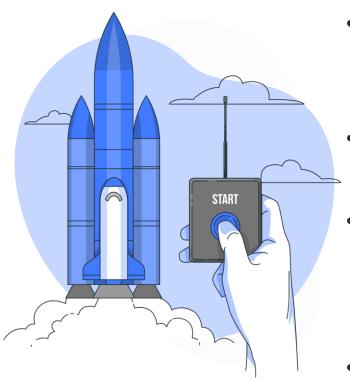
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Executive Summary

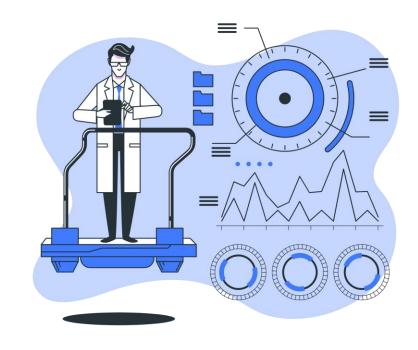


- SpaceY, a new rocket launch company, wants to compete with SpaceX.
- SpaceX advertises Falcon 9 rocket launches on its website with a cost of **62 million dollars**; other providers cost upwards of 165 million dollars each, much of the savings is because <u>SpaceX can reuse the first stage</u>.
- If it can be determined if the first stage will land, it can be determined the cost of a launch.
- After collecting and analyzing data some models were trained to predict if the first-stage rocket booster will land successfully after a launch with an accuracy level of 83.33%, given some parameters like payload mass and desired orbit.
- As a result, SpaceY will be able to make more informed bids against SpaceX by using 1st stage landing prediction as a proxy for launch costs.



Introduction — Backgound

- This report has been prepared as the final deliverable for the <u>Applied Data Science Capstone</u> course, part of IBM Data Science Professional Certification.
- In this project, the Data Science methodology has been followed, involving data collection, data wrangling, exploratory data analysis, data visualization, model development, model evaluation, and reporting results.
- Using data science findings and models, the data science team of the fictional company SpaceY, will be able to make more informed bids against SpaceX for a rocket launch.





Introduction — Business Problem



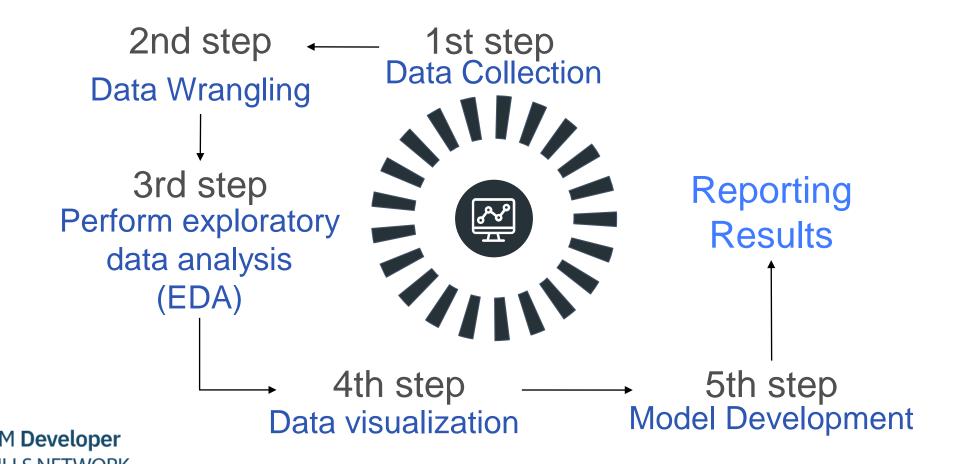
- SpaceX advertises Falcon 9 rocket launches on its website, with a cost of 62 million dollars; other providers cost upward of 165 million dollars each, much of the savings is because SpaceX can reuse the first stage.
- Therefore, this report aims to accurately <u>predict the likelihood of the first</u>
 <u>stage rocket landing successfully</u> as a proxy to determine the cost of a
 launch, using parameters like payload mass, desired orbit, and launch site,
 among others.





Methodology

For this report, the data science methodology followed can be outlined as such:



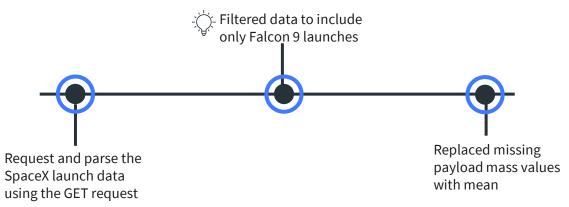
Data Collection



Falcon 9 launch dataset was limited to launches before December 2020 per instructions

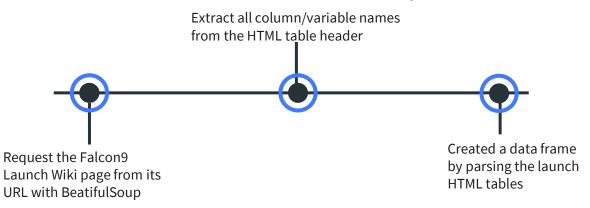


1) API Historical launch data from SpaceX REST API



2) Web Scraping

Historical launch data from a Wikipedia page called "List of Falcon 9 and Falcin Heavy Launches[



Data Wrangling

- Explored data to determine the label for training supervised models
 - Calculated the number of launches on each site
 - Calculated the number and occurrence of each orbit
 - Calculated the number and occurrence of mission outcome per orbit type
- Created a landing outcome label 'Class' from Outcome column

True ASDS 41 \$\times\$
None None 19 \$\times\$
True RTLS 14 \$\times\$
False ASDS 6 \$\times\$
True Ocean 5 \$\times\$
False Ocean 2 \$\times\$
None ASDS 2 \$\times\$
False RTLS 1

First stage booster did not land successfully
Class = 0

None None: not attempted
None ASDS: unable to be attempted
due to launch failure

False ASDS: drone ship landing failed False Ocean: ocean landing failed False RTLS: ground pad landing failed

First stage booster landed successfully
Class = 1

True ASDS: drone ship landing succeeded True RTLS: ground pad landing succeeded True Ocean: ocean landing succeeded



Exploratory Data Analysis

a) with SQL



Ran SQL queries to display information about

- Launch sites
- Payload masses
- Booster versions
- Mission outcomes
- Booster landings

b) with visualization

Used Matplotlib and Seaborn libraries to plot



- Flight Number x Payload Mass
- Flight Number x LaunchSite
- Payload x LaunchSite
- Orbit type x Success rate
- Flight Number x Orbit type
- Payload x Orbit type
- Year x Success rate





Data Visualization

Launch Sites Location Analysis

- Used Folium, an interactive mapping library for Python
- Marked all launch sites on map
- Marked the successful/failed launches for each site
- Calculated distances between a launch site and its proximities

Launch Records Dashboards

- Used Plotly Dash, an interactive dashboarding library for Python
- Added pie chart showing success rate by site
- Added scatter chart showing payload mass vs landing outcome
- Added drop-down menu to choose between all sites and individual launch site
- Added range slider for limiting payload amount





Predictive Analysis (Classification)

Created a column for training label 'Class'

Created during data wrangling

Split data into train and test sets

Used cross-validated grid-search with hyperparameter to select the best ones GridSearchCV



















Imported libraries and load data frame

Pandas
Numpy
Matplotlib
Seaborn
Scikit-learn

Standardized the data

Fit training data
to models
Logistic Regression
SVM
Decision Tree
KNN

Evaluated accuracy of each model using test data to select the best model

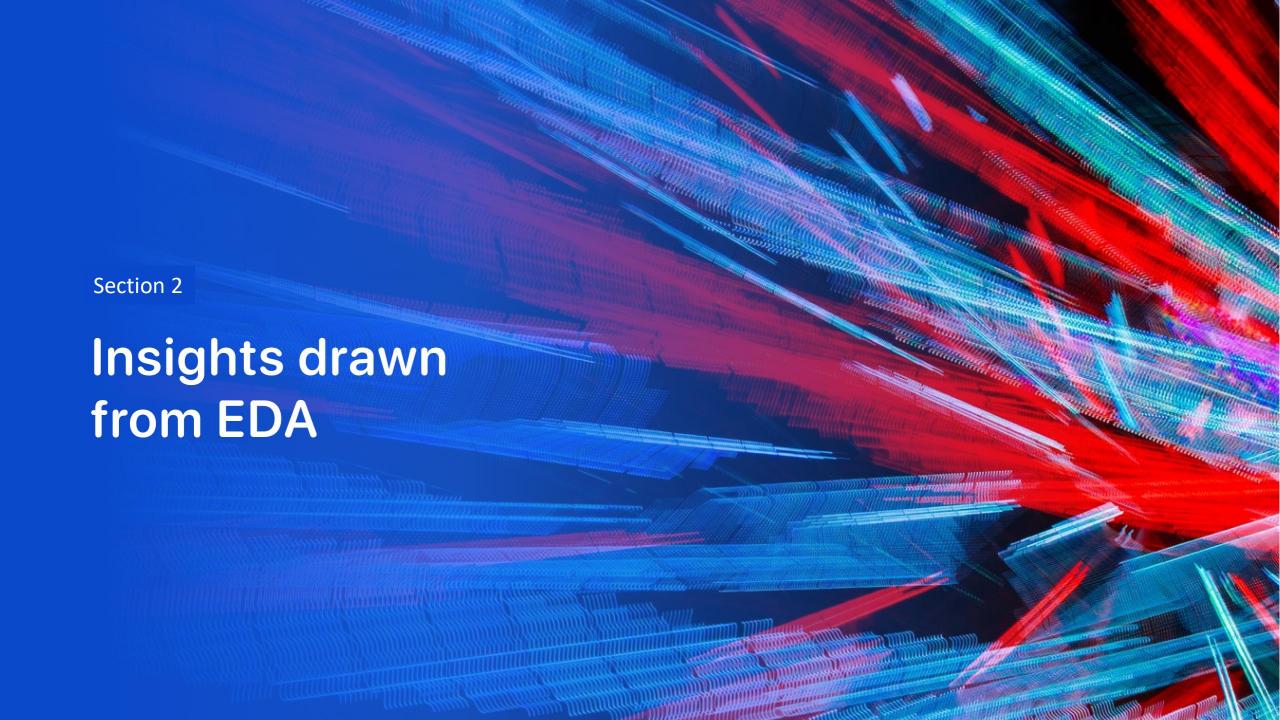


Results

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







EDA with SQL

Names of the launch sites

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

- Records where launch sites begin with `CCA`
 Last launch from CCAFS LC-40 was 2016-08-14
 First launch from CCAFS SLC-40 was 2017-12-15
- Total payload carried by boosters from NASA 45,596 KG.
- Average payload mass carried by booster version F9 v1.1 2,534 KG
- The dates of the first successful landing outcome on ground pad 01-05-2017



EDA with SQL

 Names of boosters that have successfully landed on a drone ship and had payload mass greater than 4000 but less than 6000

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

The total number of successful and failed mission outcomes

```
Failure (in flight) 1
Success 99
Success (payload status unclear) 1
```

 Names of the booster which have carried the maximum payload mass B1048.4, B1049.4, B1051.3, B1056.4, B1048.5, B1051.4, B1049.5, B1060.2, B1058.3, B1051.6, B1060.3, B1049.7

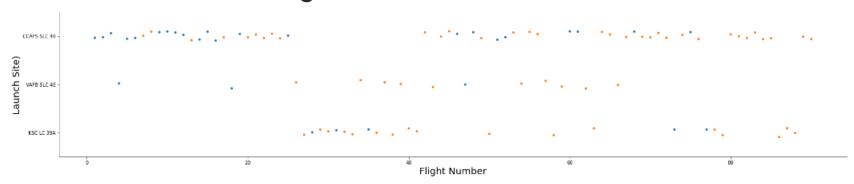
 Failed landing_outcomes in drone ship, their booster versions, and launch site names for in year 2015

```
January F9 v1.1 B1012 CCAFS LC-40 Failure (drone ship)
April F9 v1.1 B1015 CCAFS LC-40 Failure (drone ship)
```



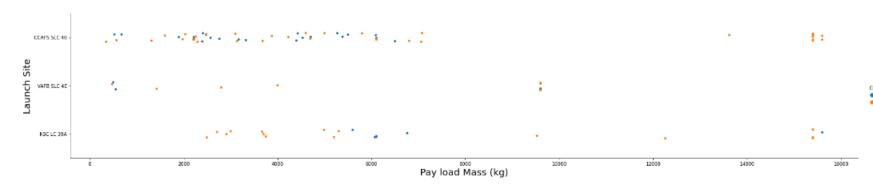
EDA with Visualization

Launch Site vs Flight Number



CCAFS SLC 40 has more flights than the other launch sites combined and the first third of them were mostly failures but as the flight number increases, the first stage is more likely to land successfully.

Launch Site vs Payload Mass

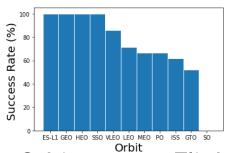


VAFB-SLC launch site there are no rockets launched for heavy payload mass(greater than 10000).



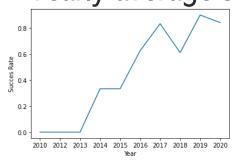
EDA with Visualization

• Success rate of each orbit type



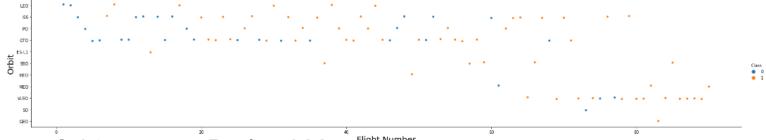
All orbit types have had successful landings except "SO"

Yearly average success rate

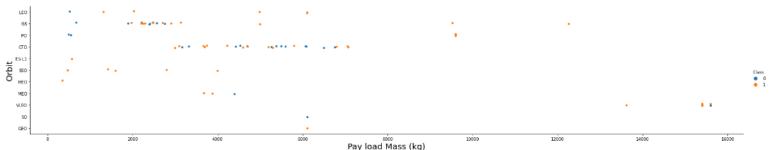


The success rate since 2013 kept increasing till 2020

• Orbit type vs Flight number



Orbit type vs Payload Mass



In the LEO orbit the Success appears related to the number of flights; on the other hand, there seems to be no relationship between flight number when in GTO orbit

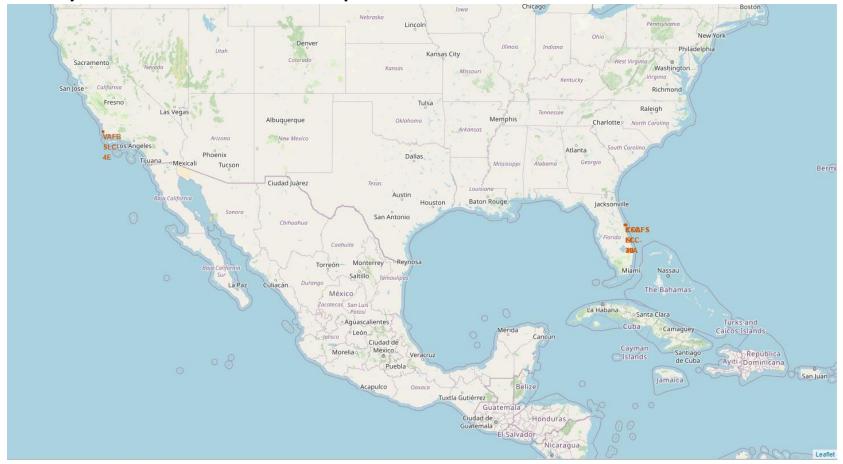
With heavy payloads the successful landing or positive landing rate are more for Polar, LEO and ISS. However, for GTO it cannot be distinguished this well as both positive landing rate and negative landing (unsuccessful mission) are both there here.





All Launch Sites

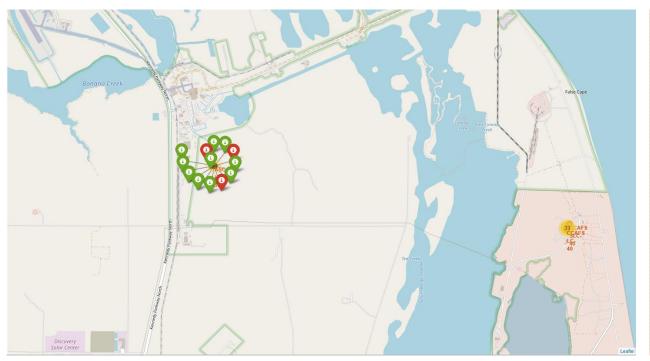
Visualizing all the launch sites on a map help to highlight the importance of launch site proximity to coasts and the equator.





Success/failed launches for each site

Visualizing landing outcomes for each launch site highlights which launch sites have relatively high success rates.





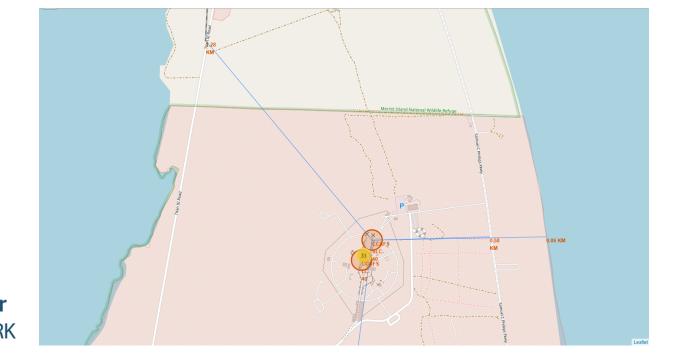


Distances between a launch site to its proximities

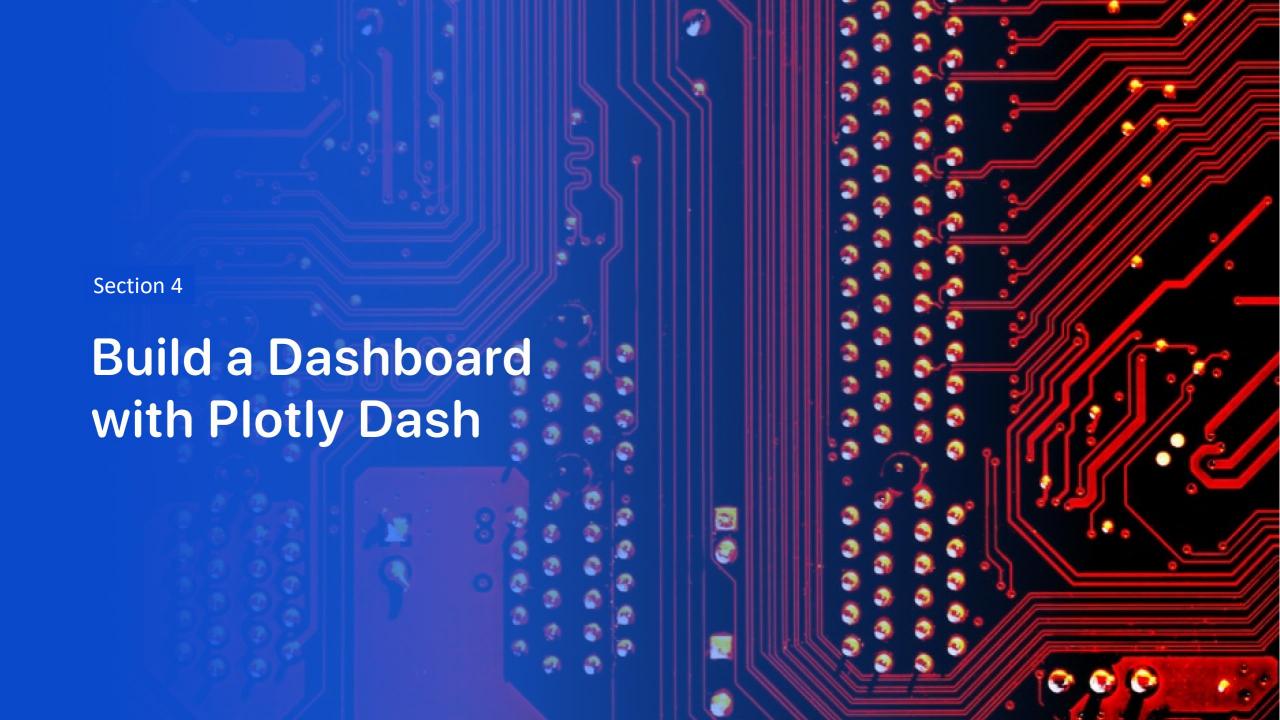
Visualizing proximities with railways, highways, coastlines and cities allows to conclude that launch sites are **near railways** (the transport for heavy cargo), **highways**(for easily transport required people and equipment), and **coastlines** (so they can fly over the ocean during launch if a launch abort is required and attempt a water landing to minimize risk for people and property from falling debris).

Launch sites are not in close proximity to cities, which minimizes danger to population-dense

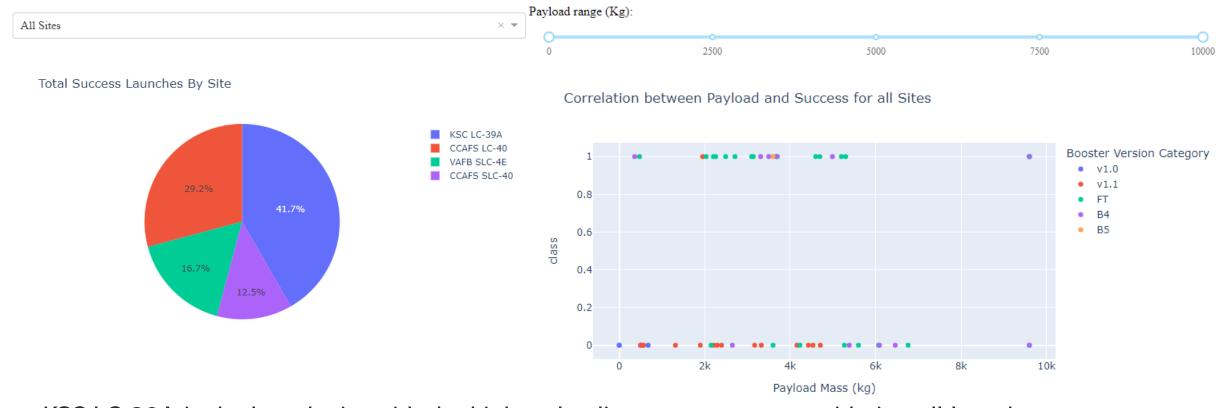
areas.







SpaceX Launch Records Dashboard



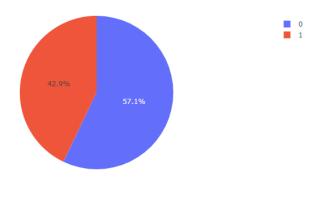
- KSC LC-39A is the launch site with the highest landing success rate considering all launches
- The heavier the payload is, the more likely failure landing is
- VAFB SLC-4E has the heaviest succesful landing.

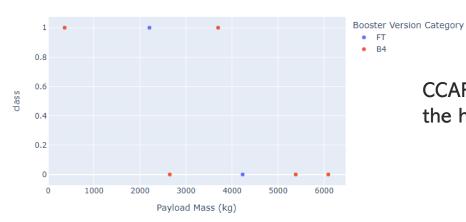


Observations





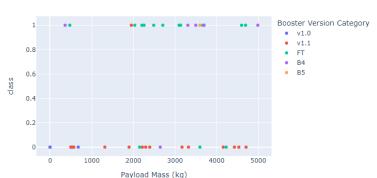




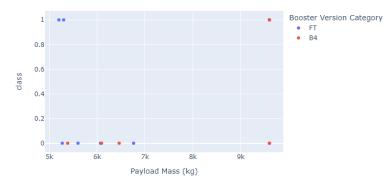
CCAFS SLC-40 is the launch site with the highest success rate of 42.9%.



Correlation between Payload and Success for all Sites



Correlation between Payload and Success for all Sites

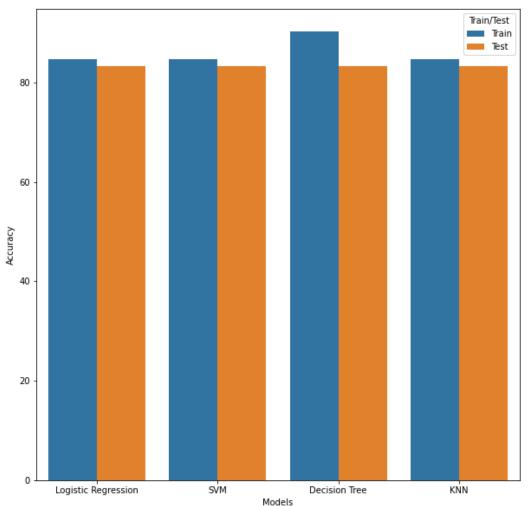


Payloads < 5000 kg have higher booster landing success.





Classification Accuracy

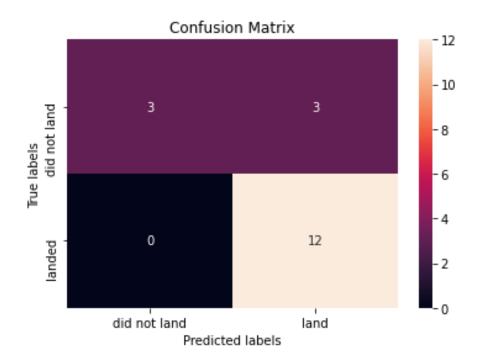


- All models performed practically the same, except for the Decision Tree Model which fitted better on train data but worse on test data.
- Each of the four models retrieved the same accuracy score of 83.33%



Confusion Matrix

- The confusion matrices for all four models are the same.
- The main issue with the models is false positives as they incorrectly predicted 3 failure landings as successful ones out of 18 samples in the test set.





Conclusions

- Using the models from this report SpaceY can predict when SpaceX will successfully land the 1st stage booster with 83.3% accuracy
- This will enable SpaceY to make more informed bids against SpaceX, since they will have a good idea of when to expect the SpaceX bid to include the cost of sacrificed 1st stage booster
- Biggest opportunities going forward to make even more informed bids:
 - Retrain the models with the whole dataset using the same hyperparameters previously defined
 - Incorporate additional launch data to the dataset and model as it becomes available



Appendix

- Notebook files to recreate this same project can be found on this github repository: https://github.com/JaimeSolisS/IBM-Applied-Data-Science-Capstone
 - Collect data:
 https://github.com/JaimeSolisS/IBM-Applied-Data-Science-Capstone/blob/main/O1-Collecting_the_Data/O1-spacex-data-collection-api.ipynb
 https://github.com/JaimeSolisS/IBM-Applied-Data-Science-Capstone/blob/main/O1-Collecting_the_Data/O2-webscraping.ipynb
 - Data Wrangling
 https://github.com/JaimeSolisS/IBM-Applied-Data-Science-Capstone/blob/main/02-Data_Wrangling/01-spacex-Data%20wrangling.ipynb
 - Exploratory Analysis

 https://github.com/JaimeSolisS/IBM-Applied-Data-Science-Capstone/blob/main/03-Exploratory Analysis/01-eda-sql sqllite.ipynb
 https://github.com/JaimeSolisS/IBM-Applied-Data-Science-Capstone/blob/main/03-Exploratory Analysis/02-eda-dataviz.ipynb
 - Data Visualization

 https://github.com/JaimeSolisS/IBM-Applied-Data-Science-Capstone/blob/main/04-Interactive Visual Analytics and Dashboard/01-launch visual analytics folium.ipynb
 https://github.com/JaimeSolisS/IBM-Applied-Data-Science-Capstone/blob/main/04-Interactive Visual Analytics and Dashboard/02-spacex dash app.py
 - Predictive Analysis
 https://github.com/JaimeSolisS/IBM-Applied-Data-Science-Capstone/blob/main/05-Predictive_Analysis_Classification/01-spacex_machine%20_learning_prediction.ipynb
- Illustrations from <u>storyset.com</u>
- Icons from <u>slidesgo.com</u>



