

Winning Space Race with Data Science

Andrey Kobelev January 2025



Outline

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

Executive Summary

Summary of methodologies

- Data Collection with API
- Data Collection with Web Scraping
- Data Wrangling
- Exploratory Data Analysis with SQL
- Exploratory Data Analysis with Data Visualization
- Interactive Visual Analytics with Folium
- Machine Learning Prediction

Summary of all results

- Exploratory Data Analysis result
- Interactive analytics in screenshots
- Predictive Analytics result

Introduction

Project background and context

Falcon 9 launch costs of about \$62 millions, while other providers cost exceeding \$165 million. The Faclon 9 cost advantage stemmed from the reuse of the first stage. Singling out the factors of a successful landing of the first stage, one can save millions by making more launches successful in landing the first stage and re-use it.

This goal of the project is to built a machine learning, modelling the first stage landing successfully.

- Problems you want to find answers
 - Factors impact the rocket successfully landing
 - How to increase successful landing rate?
 - Operating conditions to ensure a successful landing program



Methodology

Executive Summary

- Data collection methodology:
 - Data was collected from the SpaceX REST API and by scraping wiki pages
- Perform data wrangling
 - Raw data had JSON object and HTML tables formats. To perform the visualization and analysis the data was transformed into pandas dataframe.
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
 - Machine Learning model was build to determine the conditions for the first stage of Falcon 9 to land successfully

Data Collection

Two methods for Data collection were used:

get request to the SpaceX API

followed with decoding the response content as a Json using .json() function call and converting it into a pandas dataframe with .json_normalize(). The ata was cleaned, checked for missing values and filled in missing values as necessary

web scraping from Wikipedia with BeautifulSoup

followed with extracting the launch records as HTML table, parsing the table and converting the data into a pandas dataframe for future analysis.

Data Collection - SpaceX API

 Get request was used to collect the data. The data was cleaned and formatted.

GitHub link:

https://github.com/AndreyKobelev /IBM-Data-Science-Capstone-SpaceX/blob/main/1.jupyter-labsspacex-data-collection-api.ipynb

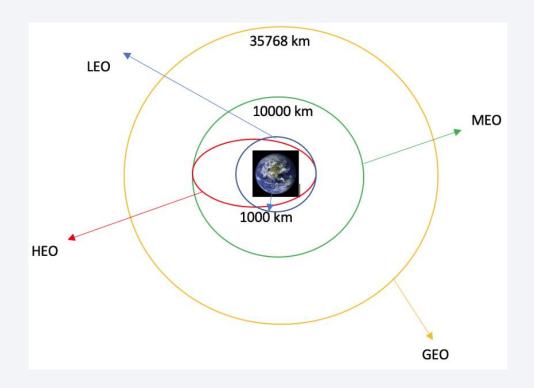


Data Collection - Scraping

- To scrape the Falcon 9 launch records from wiki, we used BeatifulSoup.
- We parsed the response and converted into the dataframe for the analysis and visualization.
- GitHub URL:
 https://github.com/AndreyKo
 belev/IBM-Data-Science Capstone SpaceX/blob/main/2.%20jup
 yter-labs-webscraping.ipynb

```
static url = "https://en.wikipedia.org/w/index.php?title=List of Falcon 9 and Falcon Heavy launches&oldid=1027686922"
Next, request the HTML page from the above URL and get a response object
TASK 1: Request the Falcon9 Launch Wiki page from its URL
First, let's perform an HTTP GET method to request the Falcon9 Launch HTML page, as an HTTP response.
 # use requests.get() method with the provided static url
 # assign the response to a object
 response = requests.get(static_url).text
Create a BeautifulSoup object from the HTML response
 # Use BeautifulSoup() to create a BeautifulSoup object from a response text content
 soup= BeautifulSoup(response, 'html.parser')
```

Data Wrangling

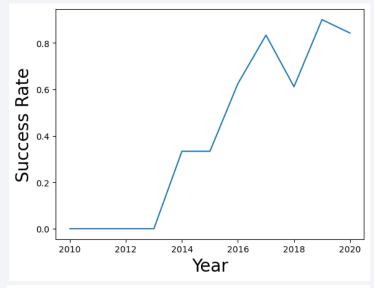


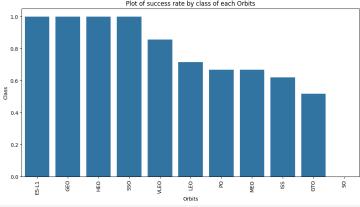
- Exploratory Data Analysis (EDA) was performed to determine the training labels.
- The number of launches at each site and occurrence of each orbits were calculated
- GitHub URL:

https://github.com/AndreyKobelev/IBM-Data-Science-Capstone-SpaceX/blob/main/3.%20labs-jupyter-spacex-Data%20wrangling.ipynb

EDA with Data Visualization

- To perform EDA we visualized the relations among flight numbers and launch sites, payload and launch sites, success rate for each orbit type, flight number and orbit type, the launch success yearly trend
- GitHub URL: https://github.com/AndreyKobelev/IBM-Data-Science-Capstone-SpaceX/blob/main/5.%20edadataviz.ipynb





EDA with **SQL**

- SpaceX dataset was loaded into a SQLite database. The sql queries were made to extract:
 - The names of unique launch sites
 - The total payload mass
 - The average payload mas
 - The total number of successful and failure outcomes
 - The failed landing outcomes
- GitHub URL: https://github.com/AndreyKobelev/IBM-Data-Science-Capstone-SpaceX/blob/main/4.%20jupyter-labs-eda-sql-coursera_sqllite.ipynb

Build an Interactive Map with Folium

- Marked launch sites and added map objects (markers, circles, lines etc) for each site on the folium map
- the feature launch outcomes were assigned as 0 (failure) and 1 (success)
- with the color-labeled marker clusters, we identified the launch sites with high success rates
- the distances between a launch site to its proximities were calculated. The proximity of the launch sites to cities, railways, highways and coastlines was evaluated.
- GitHub URL: https://github.com/AndreyKobelev/IBM-Data-Science-Capstone-SpaceX/blob/main/6.%20lab_jupyter_launch_site_location.ipynb

Build a Dashboard with Plotly Dash

- Interactive dashboard was built using Plotly Dash
 - pie charts with the total launches by each site
 - scatter graph for the relationship between Outcome and Payload Mass for different booster version
- GitHub URL: https://github.com/AndreyKobelev/IBM-Data-Science-Capstone-SpaceX/blob/main/7.%20spacex_dash_app.py

Predictive Analysis (Classification)

- The data was loaded using numpy and pandas, transformed the data, and split the data into training and testing subsets.
- Different machine learning models were used with hyperparameters optimized using GridSearchCV.
- Accuracy of the model was assessed. Feature improvement and algorithm fine tuning were used to refine the models.
- We found the best performing classification model.
- GitHub URL: https://github.com/AndreyKobelev/IBM-Data-Science-Capstone-SpaceX/blob/main/8.%20SpaceX_Machine%20Learning%20Prediction_Part_5.ipyn

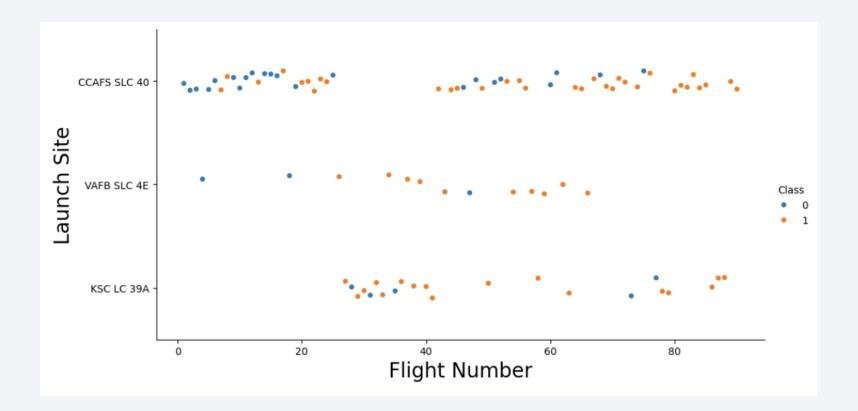
Results

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



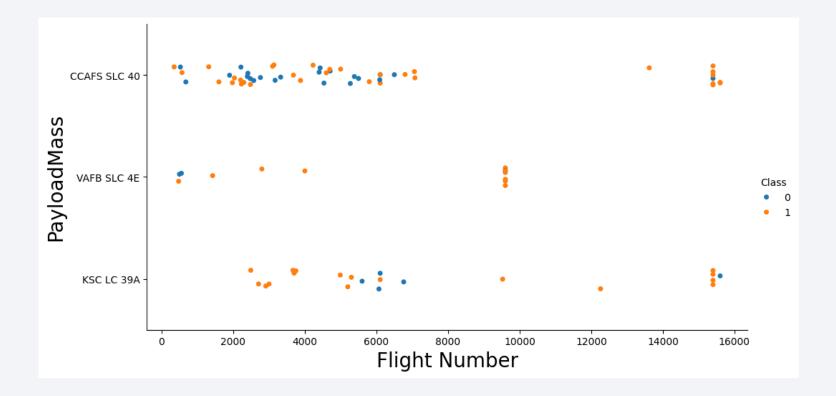
Flight Number vs. Launch Site

 Success rate follows the experience: the more number of landing attempt, the higher the success rate



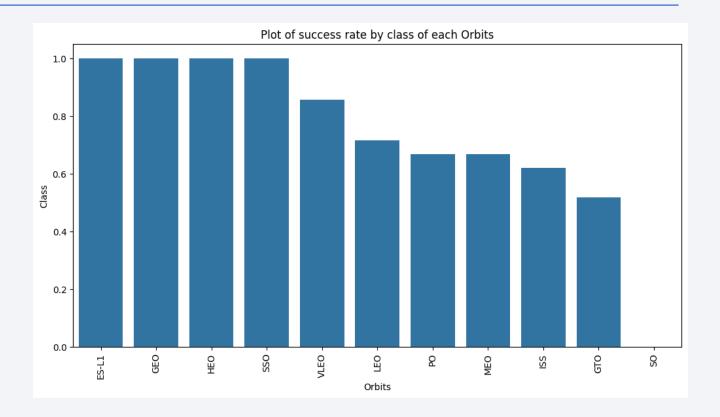
Payload vs. Launch Site

 Heavier payloads rockets are being tested in deeper details: the heavier payload, the higher the success rate. However, heavier payloads might be an indication of a specific types of orbits that are "easier" for the 1st stage landing.



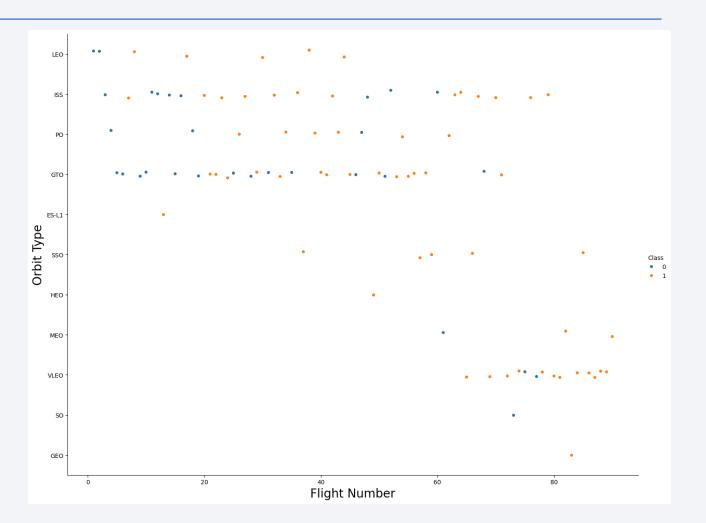
Success Rate vs. Orbit Type

- High altitude orbits and stationary ones have success stage 1 landing rate close to 100%.
- Lower altitude orbits or ones with more complex trajectory have 30-40% less success rate in landing of the first stage.



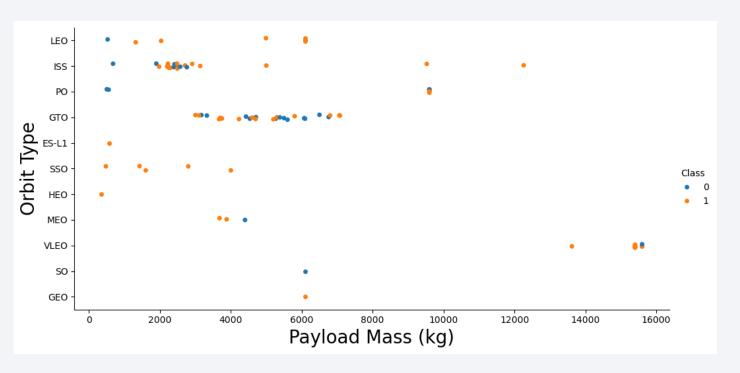
Flight Number vs. Orbit Type

Learning curve does
 exist: the more flight
 number, the higher the
 success landing rate for
 any orbit



Payload vs. Orbit Type

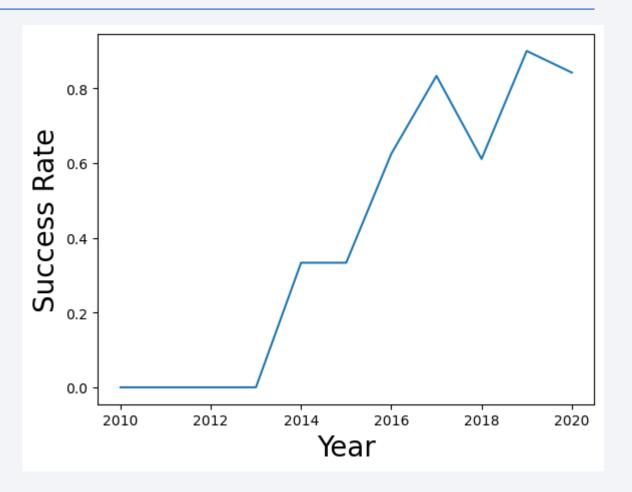
- GTO is the most difficult for landing stage 1. Regardless of the payload, success rate does not converge to a pattern
- For LEO and ISS payload affects positively on the success rate of the tage 1 landing. Mechanism is yet unknown, perhaps higher scrutiny in pre-launch testing
- For the others, the orbit type seems to be more important than the payload. However, for many orbits there is not yet enough statistics.



22

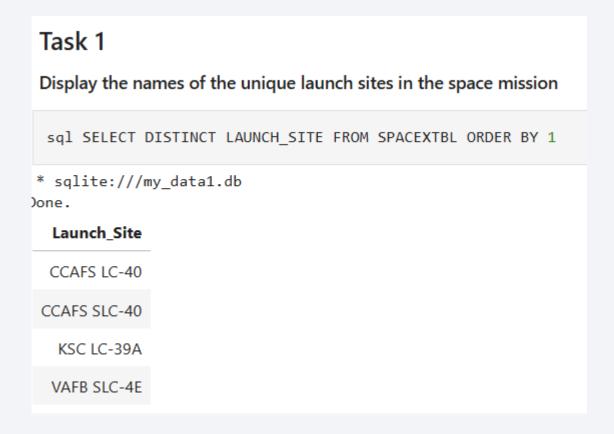
Launch Success Yearly Trend

 Obviously, over the years the engineers have been steadily improving the technologies leading to higher success rate for the first stage landing.



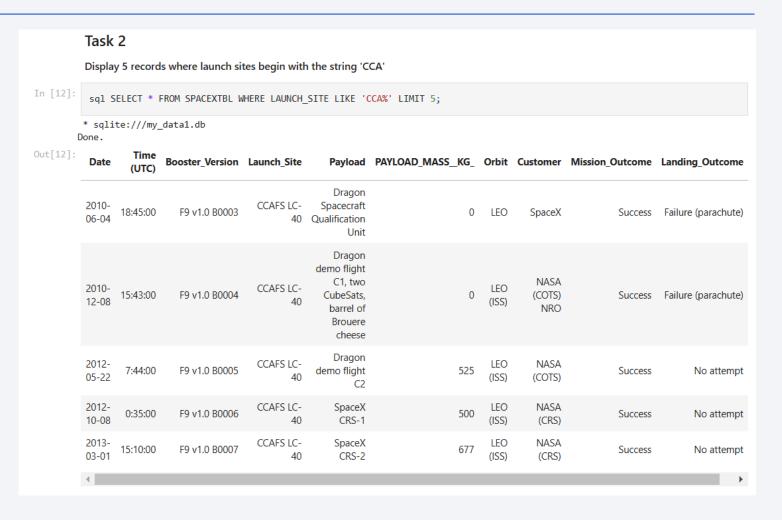
All Launch Site Names

 SELECT **DISTINCT** query was used to extract unique names of the launch sites



Launch Site Names Begin with 'CCA'

 LIMIT query was used to get exactly 5 data points on the launch sites 'CCA'.



Total Payload Mass

- SUM() function was used to extract the total payload mass directly from the DB without transforming the table to dataframe.
- Total payload mass is: 111 268 kg

```
Task 3

Display the total payload mass carried by boosters launched by NASA (CRS)

In [13]: sql SELECT SUM(PAYLOAD_MASS__KG_) AS TOTAL_PAYLOAD FROM SPACEXTBL WHERE PAYLOAD LIKE '%CRS%';

* sqlite:///my_data1.db
Done.

Out[13]: TOTAL_PAYLOAD

111268
```

Average Payload Mass by F9 v1.1

- As previously we used AVG() SQL function to extract average value directly from the DB without need of using data frames and further processing in python.
- Average payload mass carried by booster version F9 v1.1 is 3 metric tons

```
Task 4

Display average payload mass carried by booster version F9 v1.1

In [14]: sql SELECT AVG(PAYLOAD_MASS__KG_) AS AVG_PAYLOAD FROM SPACEXTBL WHERE BOOSTER_VERSION = 'F9 v1.1';

* sqlite:///my_data1.db
Done.

Out[14]: AVG_PAYLOAD

2928.4
```

First Successful Ground Landing Date

- To extract the first successful ground Landing Date we used MIN() function
- The first successful landing on the ground happened on Dec 22, 2015

```
Task 5

List the date when the first successful landing outcome in ground pad was acheived.

Hint:Use min function

In [16]: sql SELECT MIN(DATE) AS FIRST_SUCCESS_GP FROM SPACEXTBL WHERE LANDING_OUTCOME = 'Success (ground pad)';

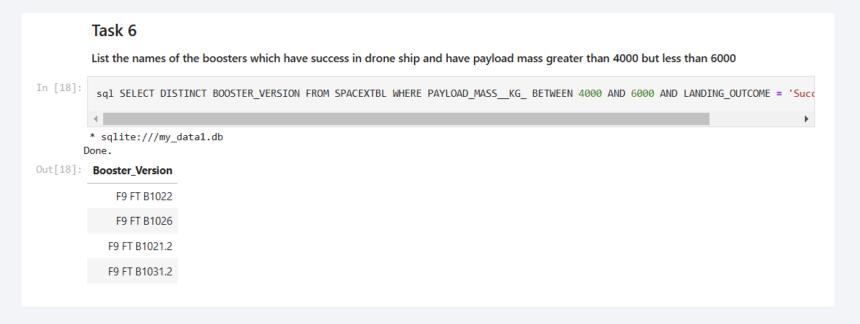
* sqlite:///my_datal.db
Done.

Out[16]: FIRST_SUCCESS_GP

2015-12-22
```

Successful Drone Ship Landing with Payload between 4000 and 6000

 To list the names of boosters that have successfully landed on drone ship and had payload mass greater than 4000 but less than 6000 we used:



Total Number of Successful and Failure Mission Outcomes

To calculate the total number of successful and failure mission outcomes:



Boosters Carried Maximum Payload

 To list the names the booster that have carried the maximum payload, a subquery in the WHERE clause and the MAX() function were used



2015 Launch Records

- To show the month names we had to create detailed code, since SQLLite does not support monthnames()
- WHERE, LIKE, AND and BETWEEN to filter the information were used

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

Date Month_Name Landing_Outcome Booster_Version Launch_Site

2015-01-10 January Failure (drone ship) F9 v1.1 B1012 CCAFS LC-40

2015-04-14 April Failure (drone ship) F9 v1.1 B1015 CCAFS LC-40
```

%%sql SELECT Date, CASE

WHEN SUBSTR(Date, 6, 2) = '01' THEN 'January' WHEN SUBSTR(Date, 6, 2) = '02' THEN 'February' WHEN SUBSTR(Date, 6, 2) = '03' THEN 'March' WHEN SUBSTR(Date, 6, 2) = '04' THEN 'April' WHEN SUBSTR(Date, 6, 2) = '05' THEN 'May' WHEN SUBSTR(Date, 6, 2) = '06' THEN 'June' WHEN SUBSTR(Date, 6, 2) = '07' THEN 'July' WHEN SUBSTR(Date, 6, 2) = '08' THEN 'August' WHEN SUBSTR(Date, 6, 2) = '09' THEN 'September' WHEN SUBSTR(Date, 6, 2) = '10' THEN 'October' WHEN SUBSTR(Date, 6, 2) = '11' THEN 'November' WHEN SUBSTR(Date, 6, 2) = '12' THEN 'December' END AS Month Name,

Landing_Outcome, Booster_Version, Launch_Site FROM SpaceXTBL WHERE Landing_Outcome LIKE 'Failure (drone ship)' AND SUBSTR(Date, 1, 4) = '2015';

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

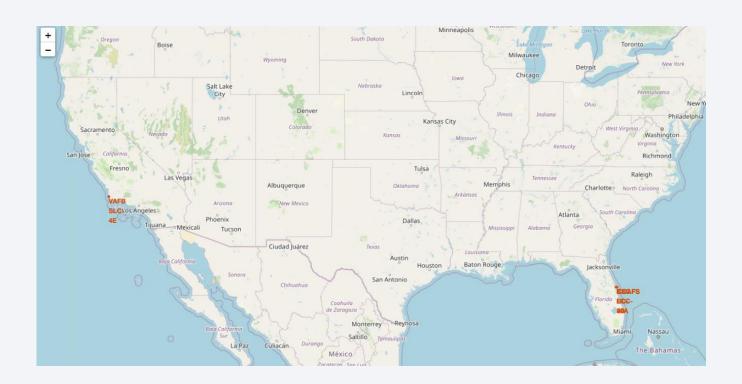
- COUNT, WHERE and BETWEEN were used to filter the required information
- Further, GROUP BY and ORDER BY clauses were applied to order grouped landing outcomes.





SpaceX Launch Sites

 All SpaceX Launch sites are in a very close proximity to the coast line and close to equator to partially balance the gravity and to cut fuel costs



Launch Sites with color-coded labels

• Green marker shows Success, while red label show Failures.



Launch Sites distance to landmarks

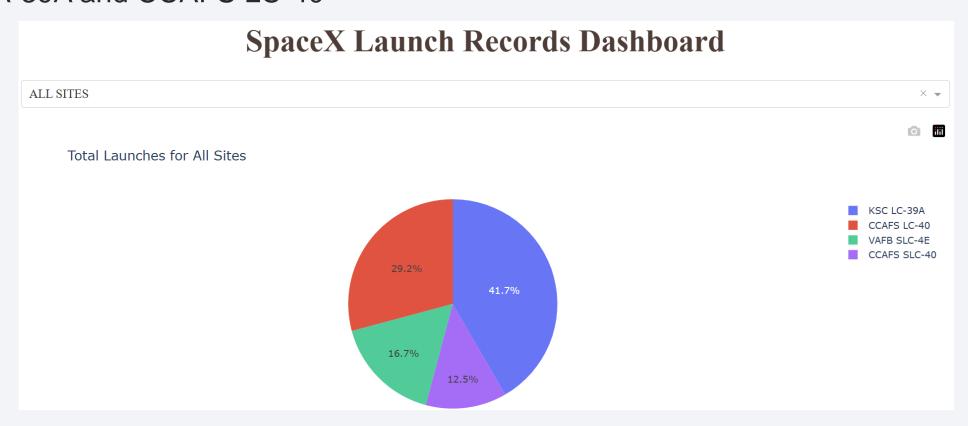
 Launch sites generally keep certain distance from cities but very close to the coastlines, None of the Launch sites are in close proximity to highways or railways





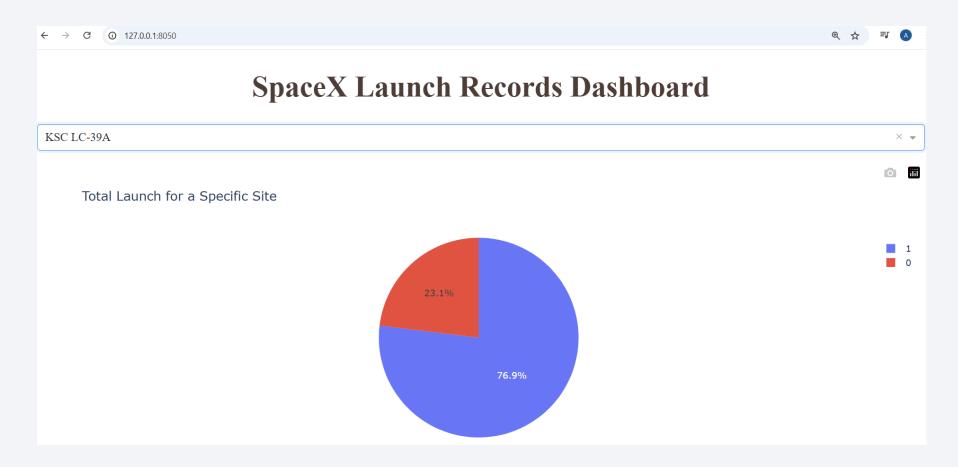
Success rate by the Launch sites

 More of 70% of all successful landings are happened on two sites: KSC LA-39A and CCAFS LC-40



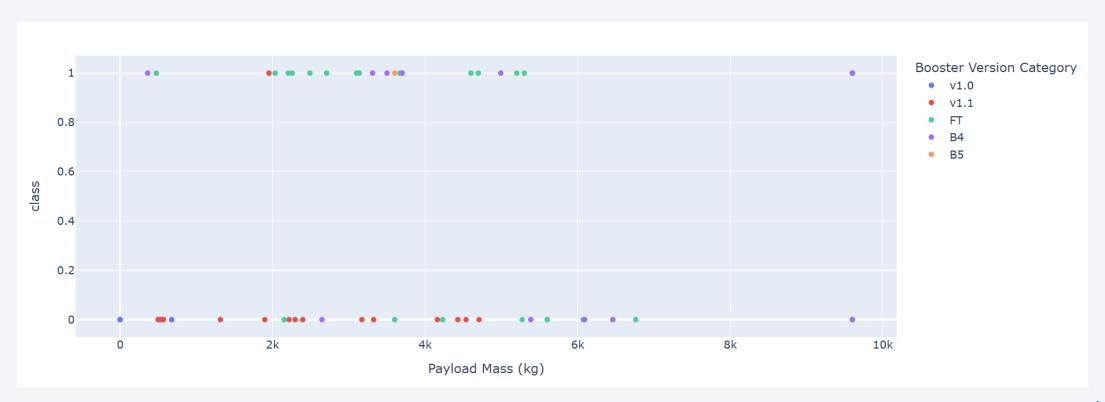
KSC LC-39A 3 landings out of 4 successful!

• KSC LC-39A has the highest success rate of landing the first stage, representing about 77%. Blue color shows success, while red shows failure to land the first stage



All sites cumulative Payload vs. Launch Outcome

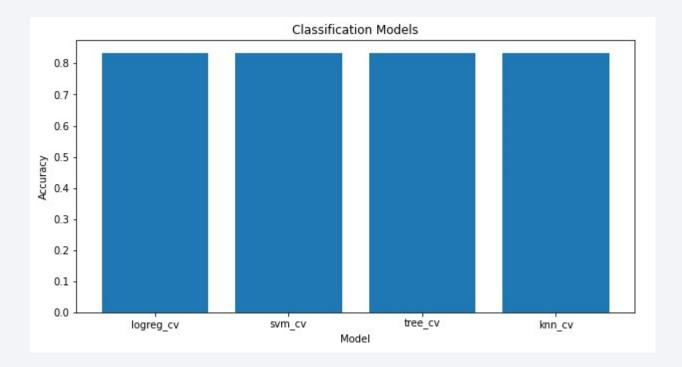
For different Booster Version Category the success rate vary





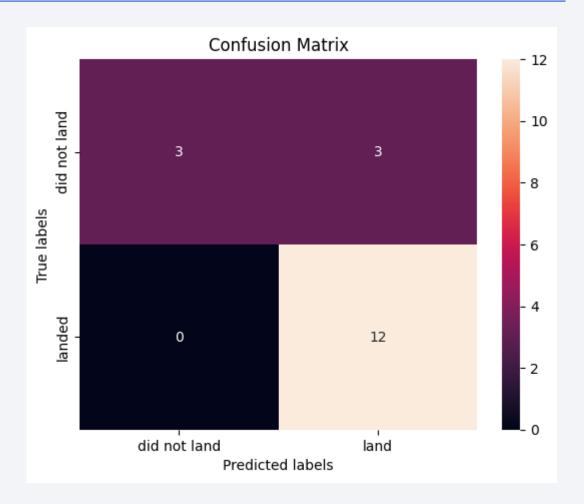
Classification Accuracy

• The accuracy is the same for all models and is equal to 0.8(3)



Confusion Matrix

 The confusion matrix is the same across all the models. The major problem is the false positives, meaning failure to land as success by the model.



Conclusions

- Learning curve does exist:
 - Success rate has been increasing since 2013
 - The more the number of attempt to land at a certain site, the greater the success rate at this site
- High altitude and/or stable orbits have almost 100% success rate in landing the 1st stage
- KSC LC-39A has the most successful landing among all the sites
- ML algorithms are having the same accuracy
- ML was quite instrumental in our objective to predict if the first stage landing of our competitor will land and as such to evaluate the launch cost

Appendix

Extra materials, including datasets, code, and others are available at GitHub Repository

