

Winning Space Race with Data Science

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Outline

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

Executive Summary

In this project, Falcon 9 launch data was collected from the SpaceX REST API and Wikipedia tables using requests, BeautifulSoup, and pandas.read_html(). The dataset was cleaned by handling missing values, normalizing site names, converting dates, and creating a binary landing success variable. Exploratory data analysis with matplotlib, seaborn, and Folium identified trends in payload, launch site, and orbit. Features were engineered through date extraction, one-hot encoding, and standardization of numeric variables. Multiple classification models—Logistic Regression, SVM, Decision Tree, and KNN—were trained and tuned via 10-fold cross-validation (GridSearchCV). The tuned Decision Tree Classifier achieved the highest test accuracy (~0.83–0.85), with launch site, payload mass, and orbit emerging as key predictors. The model provides reliable landing success probabilities, enabling more accurate cost estimates and supporting strategic mission planning.

Introduction

Space X 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 Space X can reuse the first stage. Therefore, if we can determine if the first stage will land, we can determine the cost of a launch. This information can be used if an alternate company wants to bid against space X for a rocket launch. We create a machine learning pipeline to predict if the first stage will land.



Methodology

Executive Summary

- Data collection methodology:
 - SpaceX REST API(JSON Data)
 - Wikipedia tables using webscraping
- Perform data wrangling
 - Handle missing values, normalization
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models

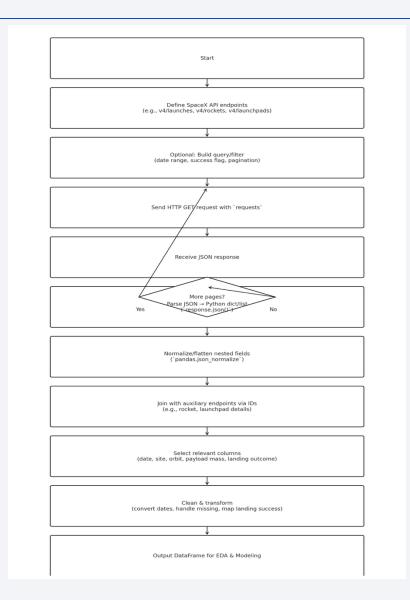
Data Collection

- Data Sets were collected using the following methods:
 - SpaceX REST APIs for launch data
 - Wikipedia mission tables (historical launches)

- Tools used:
 - Requests for API calls
 - BeautifulSoup for HTML parsing
 - Pandas.readhtml() for table extraction

Data Collection - SpaceX API

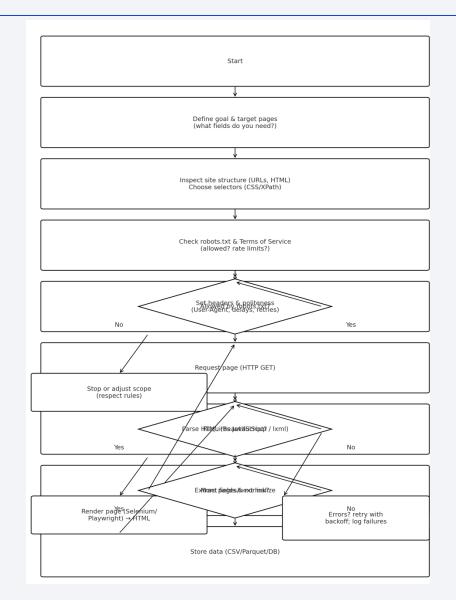
- Notebook URL:
 - https://github.com/TsuzumiTT D/ibm-DataScience-Capstone/blob/main/datacollection-api.ipynb



Data Collection - Scraping

Notebook URL:

 https://github.com/TsuzumiTT D/ibm-DataScience-Capstone/blob/main/Webscrap ing.ipynb



Data Wrangling

- Handling Missing Data: Drop rows or impute where possible.
- Standardization: Normalize site names and mission outcomes.
- Date Conversion: Convert launch dates to datetime format.
- Target Variable: Create binary LandingOutcome column (1 = success, 0 = failure).
- Notebook URL:
 - https://github.com/TsuzumiTTD/ibm-DataScience-Capstone/blob/main/Data%20Wrangling.ipynb

EDA with Data Visualization

- Used matplotlib and seaborn for trend analysis
- Folium maps for geospatial analysis to display launch sites and success rates
- Heatmaps for correlation analysis to identify relationships between features
- Notebook URL:
 - https://github.com/TsuzumiTTD/ibm-DataScience-Capstone/blob/main/EDA%20Visualization%20Lab.ipynb

EDA with SQL

- Some of the SQL used to understand the data set
 - Finding unique launch sites
 - Finding average payloads for each booster
 - Ranking the count of each boosters' landings.
- Notebook URL:
 - https://github.com/TsuzumiTTD/ibm-DataScience-Capstone/blob/main/EDA%20-%20SQL.ipynb

Build an Interactive Map with Folium

- Added markers for each launch site to find geographical patterns.
 - Are launch sites closer to railways? Highways?
 - Are they in close proximity to the city?
- Discover which geographical factor influenced landing successes.
- Notebook URL:
 - https://github.com/TsuzumiTTD/ibm-DataScience-Capstone/blob/main/Launch%20Site%20Location%20with%20Folium.ipynb

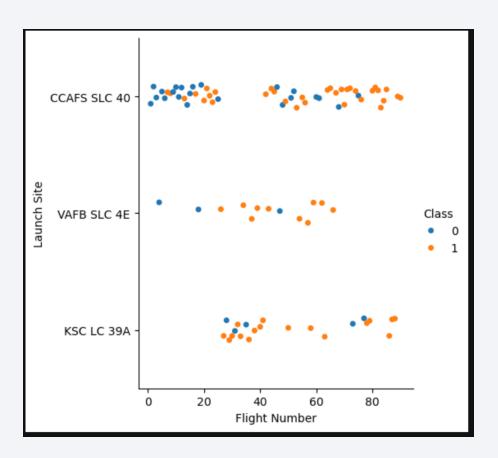
Predictive Analysis (Classification)

- Tested Logistic Regression, Support Vector Machine, Decision Tree, K-nearest neighbors
- Hyperparameter Tuning: GridSearchCV with CV = 10 for each model
- Notebook URL:
 - https://github.com/TsuzumiTTD/ibm-DataScience-Capstone/blob/main/Machine%20Learning%20Prediction.ipynb



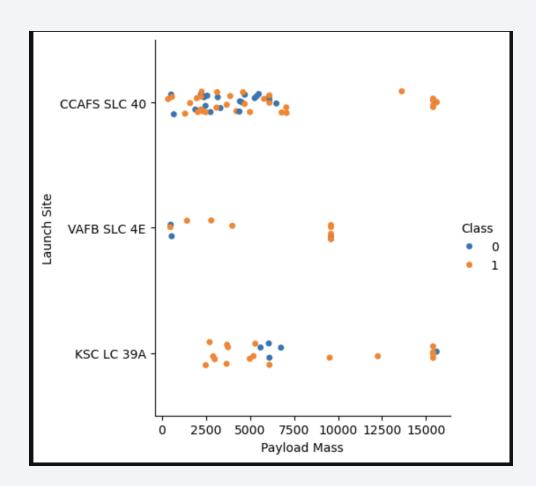
Flight Number vs. Launch Site

• We can observe that for launch site CCAFS SLC 40 and VAFB SLC 4E, the success rate increased with more flight number.



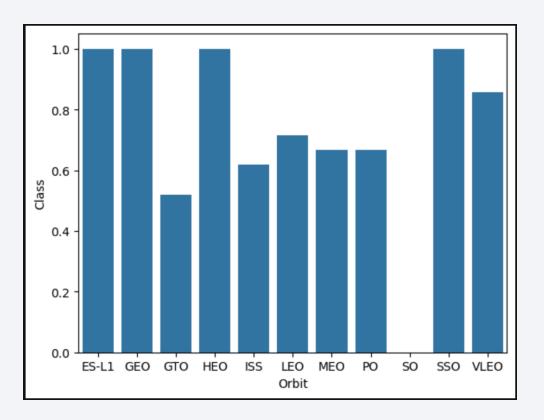
Payload vs. Launch Site

- For VAFB SLC 4E, there were no launches exceeding 10000 payload mass. Also success rate tend to be higher with heavier payloads.
- No correlation observed for the other launch sites.



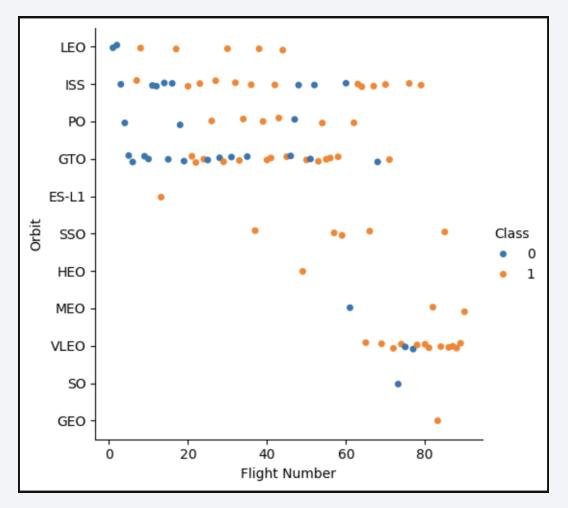
Success Rate vs. Orbit Type

• ES-L1, GEO, HEO, and SSO tend to have the highest success rates



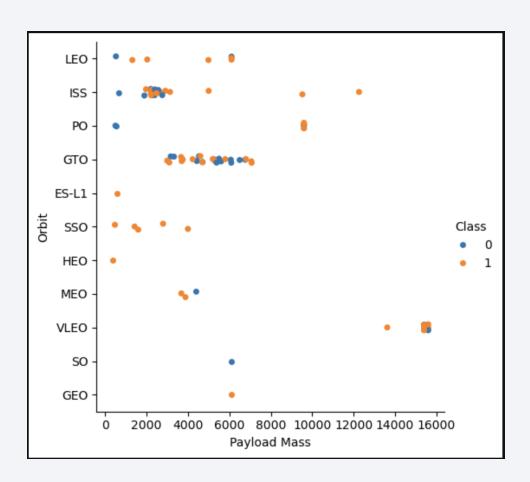
Flight Number vs. Orbit Type

 For LEO orbit, the success rate increases with flight number. Whereas for GTO and ISS, there is no correlation.



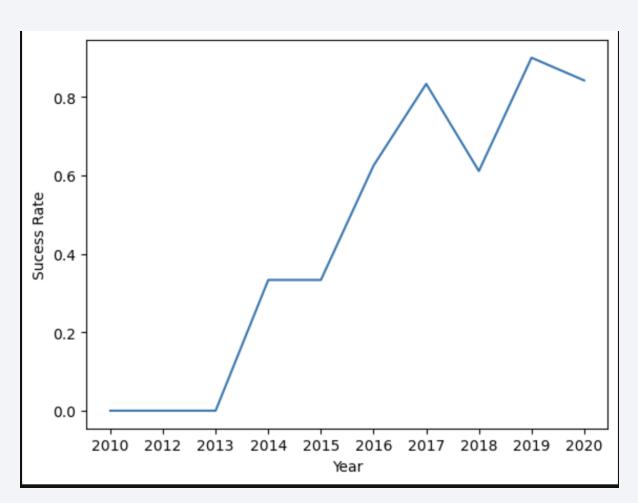
Payload vs. Orbit Type

 Heavier payloads tend to be more successful for LEO, ISS, and PO orbits. While GTO shows minimal correlation.



Launch Success Yearly Trend

• Success rates have been on the rise since 2013 with a slight drop in 2018.



All Launch Site Names

- CCAFS LC-40
- VAFB SLC-4E
- KSC LC-39A
- CCAFS SLC-4
- Query:
 - %sql SELECT DISTINCT(Launch_Site) FROM SPACEXTBL

Launch Site Names Begin with 'CCA'

• Query:

 %sql SELECT * FROM SPACEXTBL WHERE Launch_Site LIKE 'CCA%'

Dragon Spacecr aft O LEO SpaceX Success Failure (parach ute) 18:45:0 P9 v1.0 CCAFS B0003 CCAFS B0003 CCAFS LC-40 Possible Possible P9 v1.0 CCAFS CCAFS C1 two CubeSat S, barrel of Brouere cheese 2012- 07:44:0 P9 v1.0 CCAFS B0005 CCAFS C1 two CubeSat S, barrel of Brouere cheese 2012- 05-22 O B0005 CCAFS CCAFS C1 two CubeSat S, barrel of Brouere cheese 2012- 00:35:0 F9 v1.0 CCAFS CRS-1 S00 LEO (ISS) NASA (COTS) Success No attempt 2012- 10-08 O B0006 CCAFS CRS-1 S00 LEO (ISS) NASA (CRS) Success No attempt	Date	Time	Booster Version	Launch Site	Payload Descripti on	Payload Mass (kg)	Orbit	Custom er(s)	Launch Outcom e	Landing Outcom e
2010- 15:43:0					Spacecr aft Qualifica	0	LEO	SpaceX	Success	(parach
2012- 07:44:0 F9 V1.0 CCAFS demo 525 LEO (ISS) NASA (COTS) Success No attempt 2012- 00:35:0 F9 v1.0 CCAFS SpaceX 10-08 0 B0006 LC-40 CRS-1 500 LEO (ISS) NASA (CRS) Success No attempt					demo flight C1, two CubeSat s, barrel of Brouere	0	LEO (ISS)	(COTS)	Success	(parach
10-08 0 B0006 LC-40 CRS-1 500 LEO (ISS) (CRS) Success attempt					demo	525	LEO (ISS)		Success	
						500	LEO (ISS)		Success	
2013- 15:10:0 F9 v1.0 CCAFS SpaceX 677 LEO (ISS) NASA Success No attempt				CCAFS LC-40		677	LEO (ISS)		Success	

Total Payload Mass

- Total Payload Mass:
 - 45596
- Query:
 - %sql SELECT SUM(PAYLOAD_MASS__KG_) AS TotalPayloadMass FROM SPACEXTBL WHERE Customer = 'NASA (CRS)'

Average Payload Mass by F9 v1.1

- Average payload mass carried by booster version F9 v1.1:
 - 2928.4
- Query:
 - %sql SELECT AVG(PAYLOAD_MASS__KG_) AS AvgPayloadMass FROM SPACEXTBL WHERE Booster_Version = 'F9 v1.1'

First Successful Ground Landing Date

- Date of the first successful landing outcome on ground pad:
 - 2015-12-22
- Query:
 - %sql SELECT MIN(Date) AS FirstSuccesfulLanding FROM SPACEXTBL WHERE Mission_Outcome = "Success" AND Landing_Outcome LIKE "%ground pad%"

Successful Drone Ship Landing with Payload between 4000 and 6000

• List the names of boosters which have successfully landed on drone ship and had payload mass greater than 4000 but less than 6000

• Query:

• %sql SELECT Booster_Version FROM SPACEXTBL WHERE Mission_Outcome = "Success" AND PAYLOAD_MASS__KG_ > 4000 AND PAYLOAD_MASS__KG_ < 6000

Total Number of Successful and Failure Mission Outcomes

Total number of successful and failure mission outcomes:

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

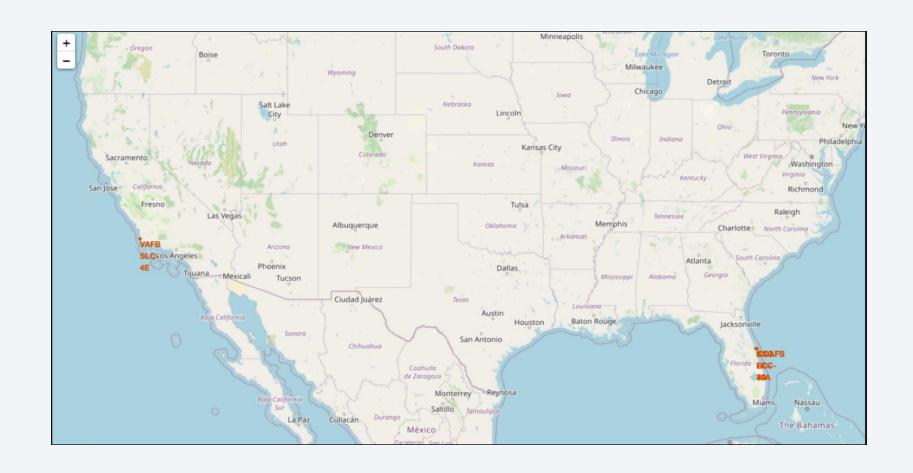
- Query:
 - %sql SELECT Mission_Outcome, COUNT(*) AS MissionCount FROM SPACEXTBL WHERE Mission_Outcome LIKE 'Failure%' OR Mission_Outcome LIKE 'Success%' GROUP BY Mission_Outcome

Boosters Carried Maximum Payload

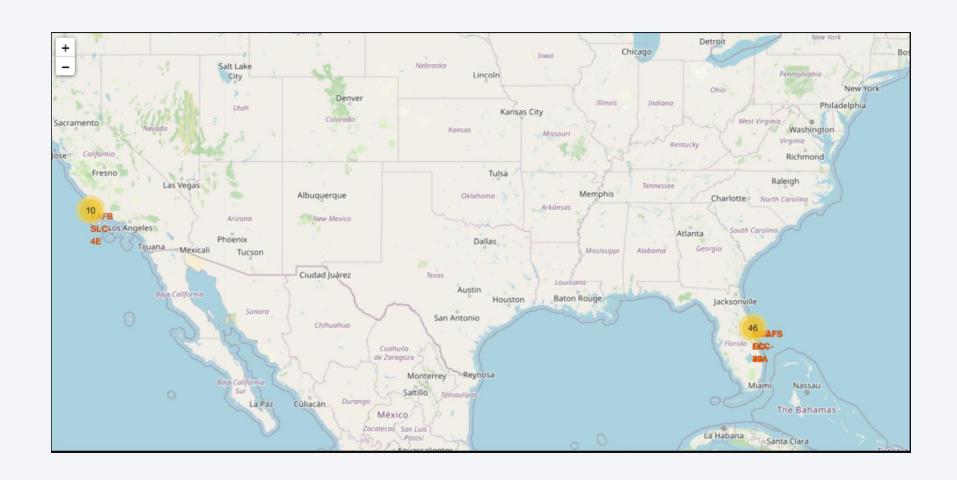
- List the names of the booster which have carried the maximum payload mass:
 - F9 B5 B1048.4, F9 B5 B1049.4, F9 B5 B1051.3, F9 B5 B1056.4, F9 B5 B1048.5, F9 B5 B1051.4, F9 B5 B1049.5, F9 B5 B1060.2, F9 B5 B1058.3, F9 B5 B1051.6, F9 B5 B1060.3, F9 B5 B1049.7
- Query:
 - %sql SELECT Booster_Version FROM SPACEXTBL WHERE PAYLOAD_MASS__KG_ = (SELECT MAX(PAYLOAD_MASS__KG_) FROM SPACEXTBL)



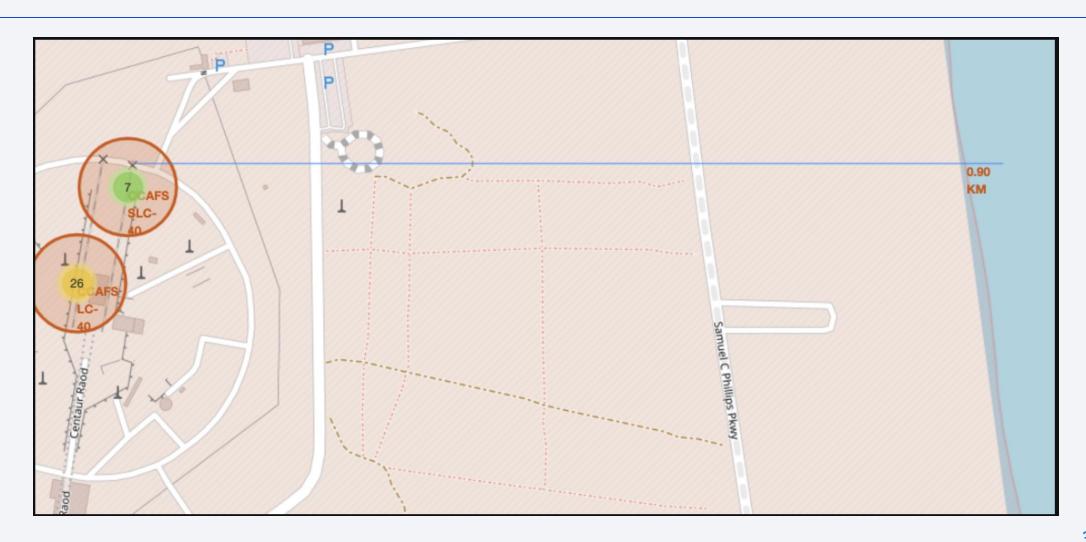
Map of All Launch Sites



All Launch Outcomes



Distance from Coast Line





< Dashboard Screenshot 1>

• Replace < Dashboard screenshot 1> title with an appropriate title

• Show the screenshot of launch success count for all sites, in a piechart

• Explain the important elements and findings on the screenshot

< Dashboard Screenshot 2>

• Replace < Dashboard screenshot 2> title with an appropriate title

• Show the screenshot of the piechart for the launch site with highest launch success ratio

• Explain the important elements and findings on the screenshot

< Dashboard Screenshot 3>

• Replace < Dashboard screenshot 3> title with an appropriate title

• Show screenshots of Payload vs. Launch Outcome scatter plot for all sites, with different payload selected in the range slider

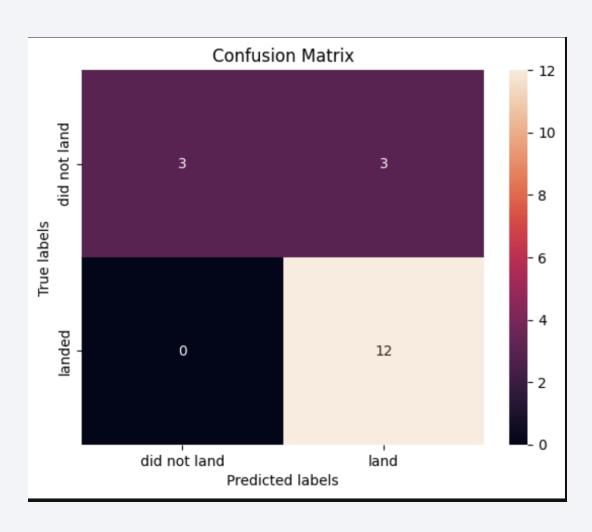
• Explain the important elements and findings on the screenshot, such as which payload range or booster version have the largest success rate, etc.



Classification Accuracy

 Decision Tree had the highest accuracy of 0.83%

Confusion Matrix



Conclusions

- Accurate Prediction: The tuned Decision Tree Classifier achieved ~83–85% test accuracy in predicting Falcon 9 first stage landing success.
- **Key Drivers Identified:** Launch site, payload mass, and orbit type were the most influential features affecting landing outcomes.
- Operational Insights: Certain sites (e.g., KSC LC-39A) consistently show higher success rates, while very heavy or very light payloads lower the probability of a successful landing.
- **Business Value:** The model can be integrated into prelaunch planning to estimate landing success, supporting cost forecasting and resource allocation.
- Scalability: The approach can be adapted for new launch data, ensuring the prediction system improves as more missions occur.
- Q Data-Driven Decision Making: Empowers stakeholders to make informed choices on mission logistics and pricing strategies based on predicted success probabilities.

Appendix

• Include any relevant assets like Python code snippets, SQL queries, charts, Notebook outputs, or data sets that you may have created during this project

