

Winning Space Race with Data Science

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Outline

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

- The goal of this project is to predict the success of Space X Falcon 9 first-stage landings to build a business case for reusable first-stage rockets. According to available data, he ability to reuse the first-stage reduces the price of a lauch from roughly \$165 millions dollars to around \$62 million dollars which is a substantial savings.
- The approach is:
 - Collect data from publicly available databases and websites
 - Explore and wrangle data to analyze and summarize datasets to understand their main characteristics and uncover patterns.
 - Build and compare machine learning modules to predict the success of first-stage landings
- The tools used are Python, Dash, Folium, SQL, Scikit-learn and multiple other data science libraries
- From multiple models, the decision tree shows the most promise with a prediction accuracy on the testing data of 88% (the decision tree parameters where adjusted due to an issue with the auto criterion in max_features parameter).

Introduction

Background

- SpaceX launches are significantly cheaper due to reusability.
- Predicting landing success helps understand launch economics.
- Project explores this using real launch data from various sources.

Problem Statement

- Can we accurately predict whether a Falcon 9 first-stage will land successfully?
- Binary classification problem: O = Failure, 1 = Success.
- Focus on identifying key features affecting landing outcome.



Methodology

Executive Summary

- Data collection methodology:
 - Data collection was done using APIs and Web Scraping
- Perform data wrangling
 - Data was explored to identify missing values, identify characteristics of the data, etc...
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
 - After the data was cleaned and understood (characteristics), it was standardized, split into training and testing sets, and used to build and compare Logistic Regression, Support Vector Machine (SVM), Classification tree and K nearest neighbor (KNN) models.

Data Collection

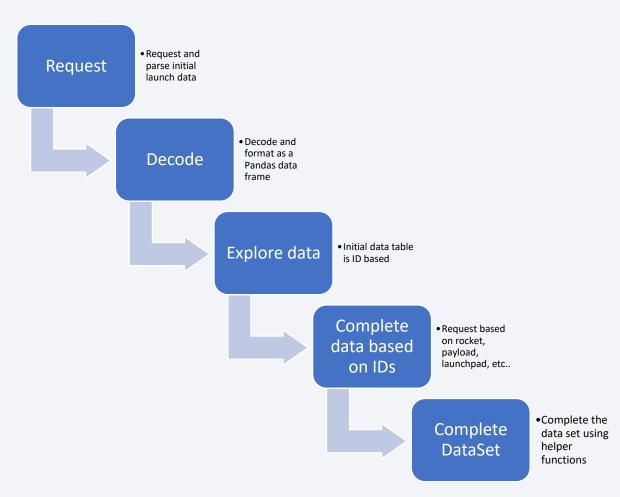
- Data Sources Overview
 - SpaceX REST API launch data.
 - Wikipedia rocket details and historical launches.
 - External JSON/CSV datasets.
 - Data integrated and cleaned into a unified pandas DataFrame for modeling.

Data Collection – SpaceX API

- Collected historical launch data using SpaceX REST API.
- Data includes launch site, payload mass, orbit, and landing outcome.
- Sample API response parsed from JSON to DataFrame.
- Challenges: handling inconsistent or missing fields.
- Code available at (may have to download it to visualize it)

https://github.com/Andre-Roussel/IBM-Skills-Build-DataScience-Capstone/blob/6fb62b72c62eeebb5b8f185cafbf1

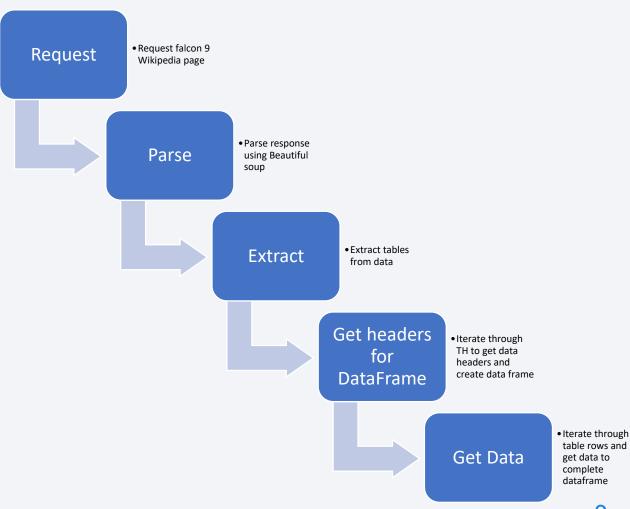
<u>Capstone/blob/6fb62b72c62eeebb5b8f185cafbf1</u> <u>7010d40c84f/jupyter-labs-spacex-data-collection-api-v2.ipynb</u>



Data Collection - Scraping

- Supplemented API data with Wikipedia scraping for rocket specs.
- Used BeautifulSoup to extract tabular data on Falcon 9 launches.
- Data merged and deduplicated based on flight number and date.
- Code available at (may need to be downloaded):

https://github.com/Andre-Roussel/IBM-Skills-Build-DataScience-Capstone/blob/6fb62b72c62eeebb5b8f1 85cafbf17010d40c84f/jupyter-labswebscraping.ipynb



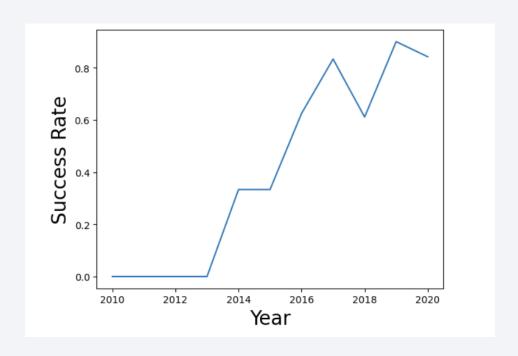
Data Wrangling

- Merged datasets from API and web sources.
- Dropped nulls and redundant columns.
- Created new features: booster version, landing pad, etc.
- Filtered for Falcon 9 missions only.

EDA with Data Visualization

- Used Seaborn and Matplotlib for visual analysis.
- Key charts: payload vs. success, launch site success rate, orbit type trends.
- Detected correlations and candidate features for modeling.
- Code available at (may need to be downloaded):

https://github.com/Andre-Roussel/IBM-Skills-Build-DataScience-Capstone/blob/main/jupyter-labseda-dataviz-v2.ipynb



EDA with SQL

- Queried launch site names, payload distributions, and mission outcomes.
- Example: total payload mass from NASA launches.
 - %sql select sum(PAYLOAD_MASS__KG_) as Total_Payload_Mass from SPACEXTABLE where Customer = 'NASA (CRS)'
- Used SQLite to interact with structured dataset and confirm patterns.
- Code available at (may need to be downloaded):

https://github.com/Andre-Roussel/IBM-Skills-Build-DataScience-Capstone/blob/main/jupyter-labs-eda-sql-coursera_sqllite.ipynb

Build an Interactive Map with Folium

- Mapped launch sites using Folium.
- Markers show site names, success/failure, and coordinates.
- Used Circle and PolyLine to highlight proximity to coastlines, highways.
- Code available at (may need to be downloaded):

https://github.com/Andre-Roussel/IBM-Skills-Build-DataScience-Capstone/blob/main/lab-jupyter-launchsite-location-v2.ipynb



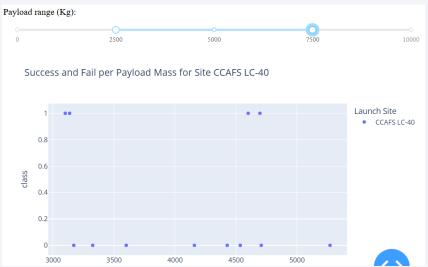
Build a Dashboard with Plotly Dash

- Pie chart shows success count per site or for all sites combined.
 - Highlights which sites have higher reliability.
- Scatter plot visualizes relationship between payload mass and landing outcome.
 - Interactive payload slider allows dynamic filtering.
 - Insights: mid-range payloads often show higher success.
- Code available at (may need to be downloaded):

https://github.com/Andre-Roussel/IBM-Skills-Build-DataScience-Capstone/blob/main/spacex_dash_app.py

Note: This was coded to run on my RaspberryPi at home which was actually kinda fun...

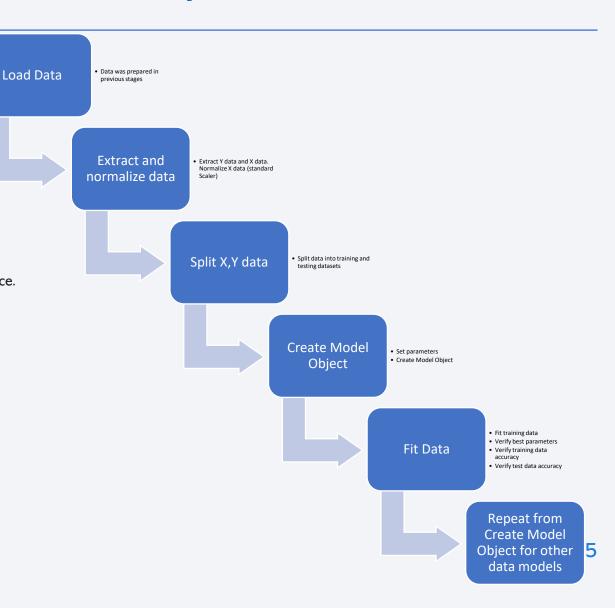




Predictive Analysis (Classification)

Overview

- Objective: classify if a launch will be successful.
- Features: payload, orbit, booster version, launch site, etc.
- Target: landing success (1) or failure (0).
- Models tested: Logistic Regression, Decision Tree, SVM, KNN
- · Model building and Preprocessing
 - · Preprocessing steps: encoding categorical variables, feature scaling.
 - Train-test split: 80/20 ratio with stratification to preserve class balance.
 - StandardScaler used for numerical features like payload mass.
 - OneHotEncoder used for orbit, launch site, and booster version.
- Model Evaluation Metrics
 - Used Accuracy, Precision, Recall, and F1-Score.
 - Confusion Matrix used to analyze false positives and false negatives.
 - · Cross-validation applied to improve reliability of scores.
- Code available at (may need to be downloaded):



Results

The next section, the following topics are going to be explored

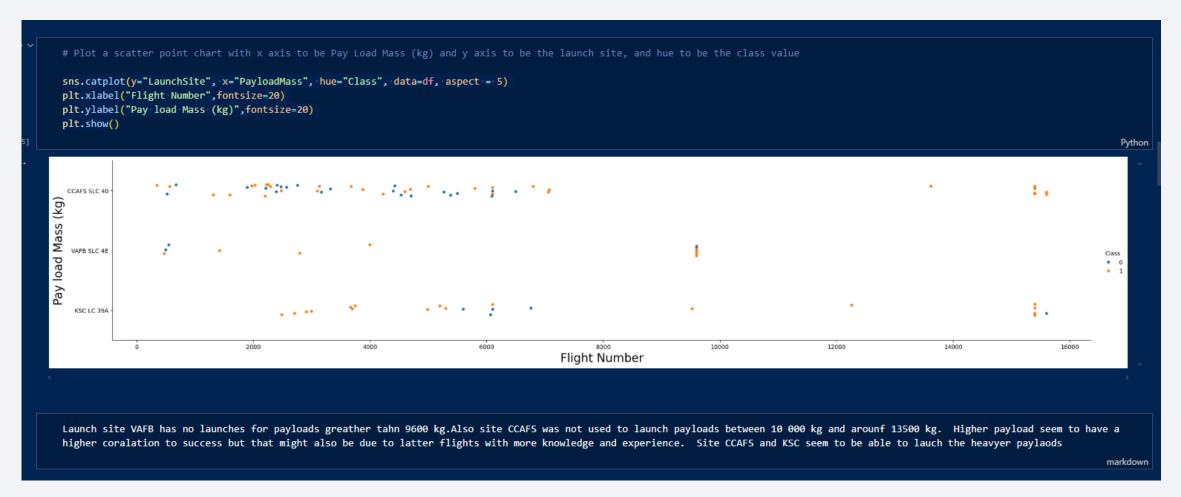
- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results



Flight Number vs. Launch Site



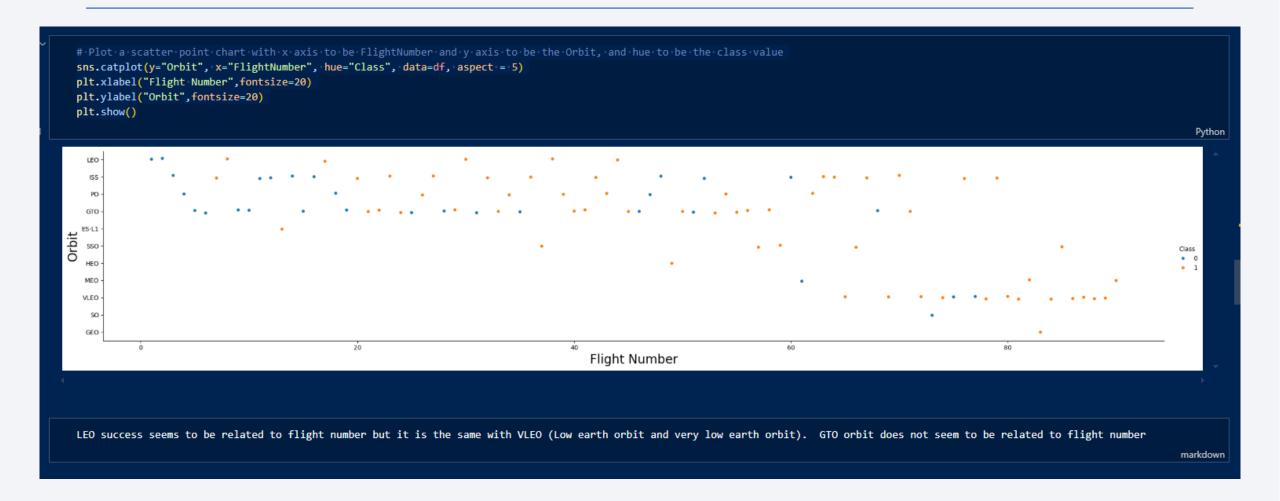
Payload vs. Launch Site



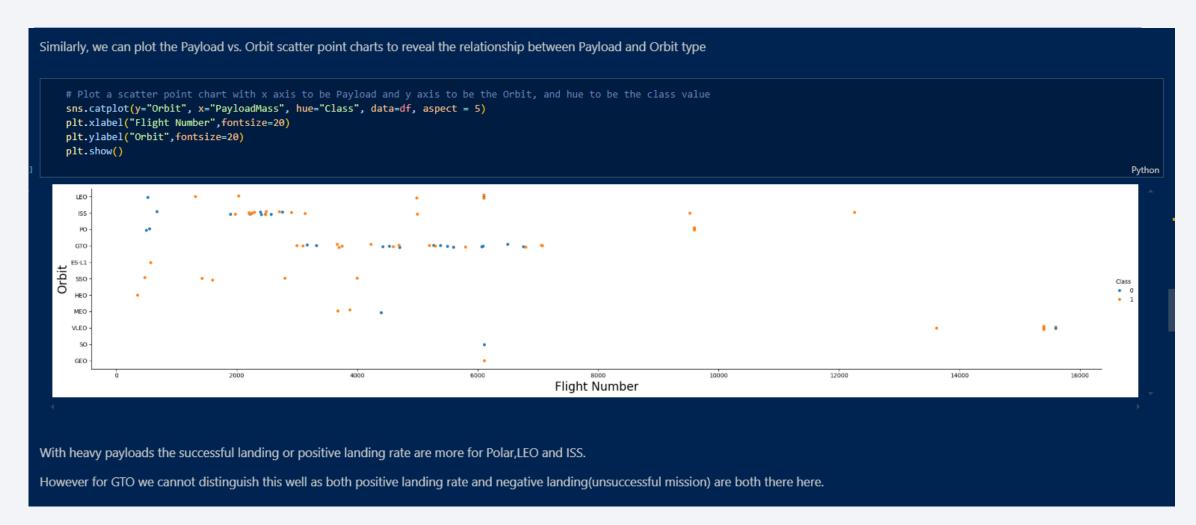
Success Rate vs. Orbit Type



Flight Number vs. Orbit Type



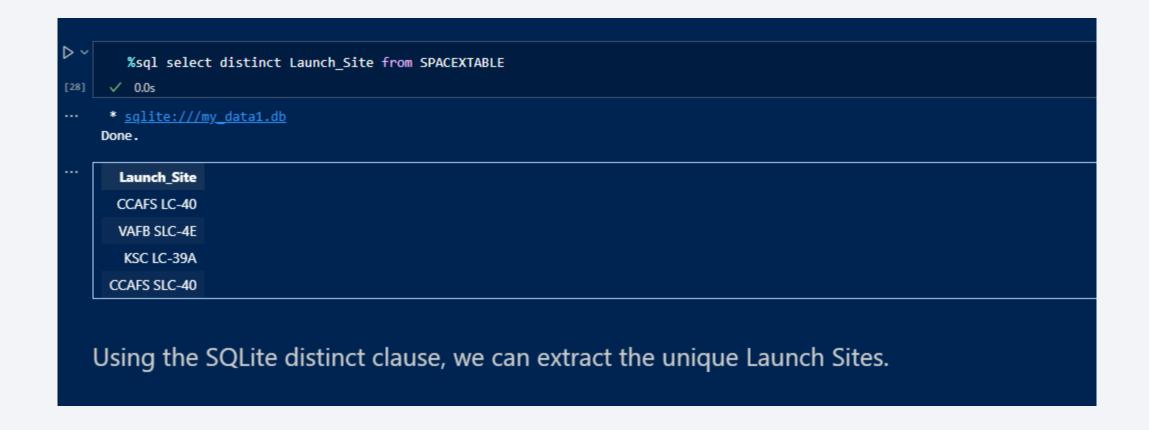
Payload vs. Orbit Type



Launch Success Yearly Trend

```
year = Extract_year(df["Date"])
    df["Year"] = year
    df["Year"] = pd.to_numeric(df["Year"])
    success_rate = df.groupby("Year")["Class"].mean()
    success_rate.plot()
    plt.xlabel("Year",fontsize=20)
    plt.ylabel("Success Rate",fontsize=20)
    plt.show()
       0.8
   Rate
   Success
        0.0
            2010
                        2012
                                    2014
                                                2016
                                                            2018
                                                                       2020
                                         Year
You can observe that the success rate since 2013 kept increasing till 2017 (stable in 2014) and after 2015 it started increasing.
```

All Launch Site Names



Launch Site Names Begin with 'CCA'

#%sql select * from SPACEXTABLE where Booster Version like '%F9 v1.1%' %sql select * from SPACEXTABLE where Launch Site like '%CCA%' Limit 5 √ 0.0s * sqlite:///my_data1.db Done. Date Time (UTC) Booster Version Launch Site Payload PAYLOAD MASS KG Orbit Customer Mission Outcome Landing Outcome 2010-06-04 18:45:00 F9 v1.0 B0003 CCAFS LC-40 Dragon Spacecraft Qualification Unit LEO Failure (parachute) SpaceX 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) F9 v1.0 B0005 CCAFS LC-40 Dragon demo flight C2 2012-05-22 7:44:00 525 LEO (ISS) NASA (COTS) Success No attempt 2012-10-08 0:35:00 F9 v1.0 B0006 CCAFS LC-40 SpaceX CRS-1 500 LEO (ISS) NASA (CRS) Success No attempt 2013-03-01 F9 v1.0 B0007 CCAFS LC-40 SpaceX CRS-2 677 LEO (ISS) NASA (CRS) No attempt 15:10:00 Success The like clause enable lookup of fields containing a specific string. The Limit clause limits the number of output rows

Total Payload Mass

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

**sql select sum(PAYLOAD_MASS__KG_) as Total_Payload_Mass from SPACEXTABLE where Customer = 'NASA (CRS)'

* sqlite://my_datal.db
Done.

Total_Payload_Mass

45596

The sum clause enable the sum of all records meeting the where clause 'NASA (CRS)'

Average Payload Mass by F9 v1.1

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

**sql select avg(PAYLOAD_MASS_KG_) as AVG_Payload_Mass from SPACEXTABLE where Booster_Version = 'F9 v1.1'

** o.0s

** sqlite://my_data1.db
Done.

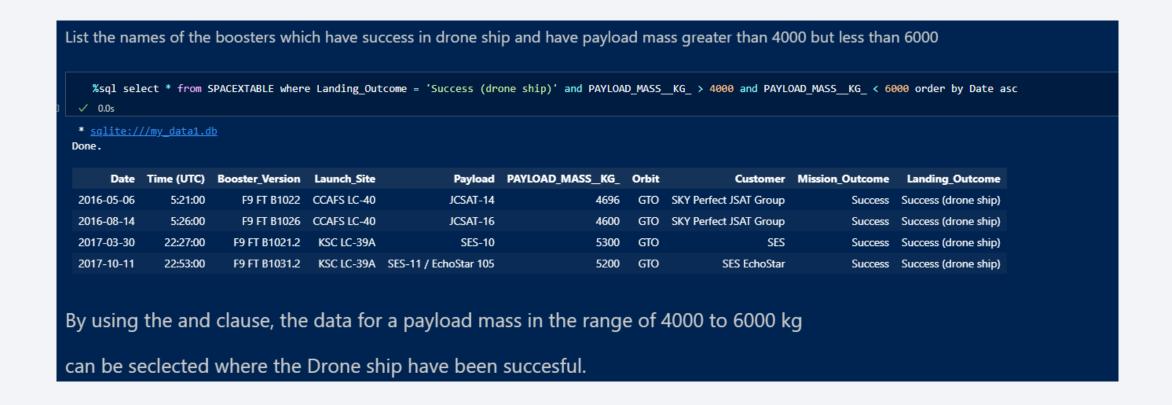
**AVG_Payload_Mass
2928.4

The avg clause averages the rows of the result set where the Booster Version is 'F0 v1.1'

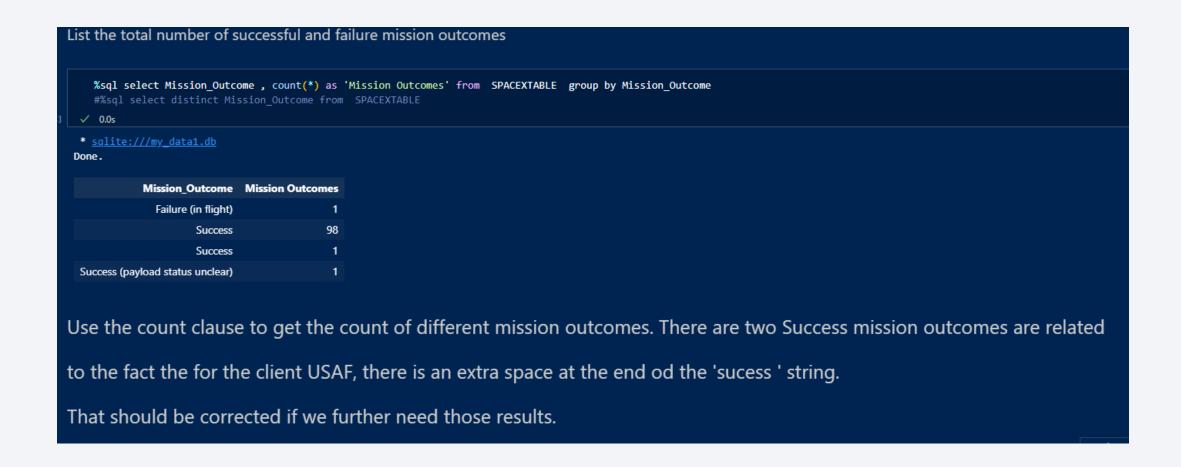
First Successful Ground Landing Date



Successful Drone Ship Landing with Payload between 4000 and 6000



Total Number of Successful and Failure Mission Outcomes



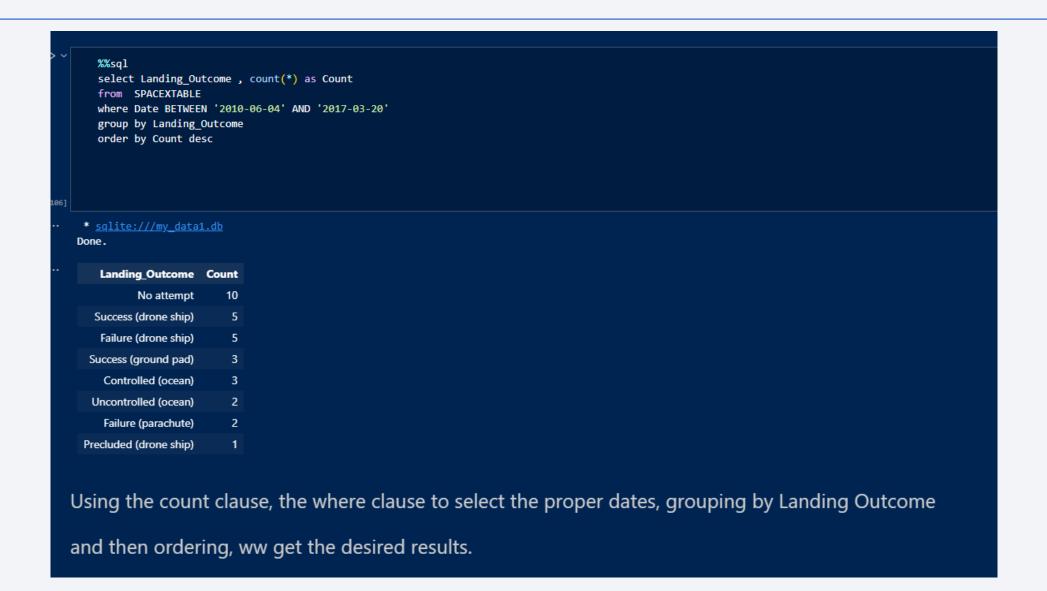
Boosters Carried Maximum Payload



2015 Launch Records

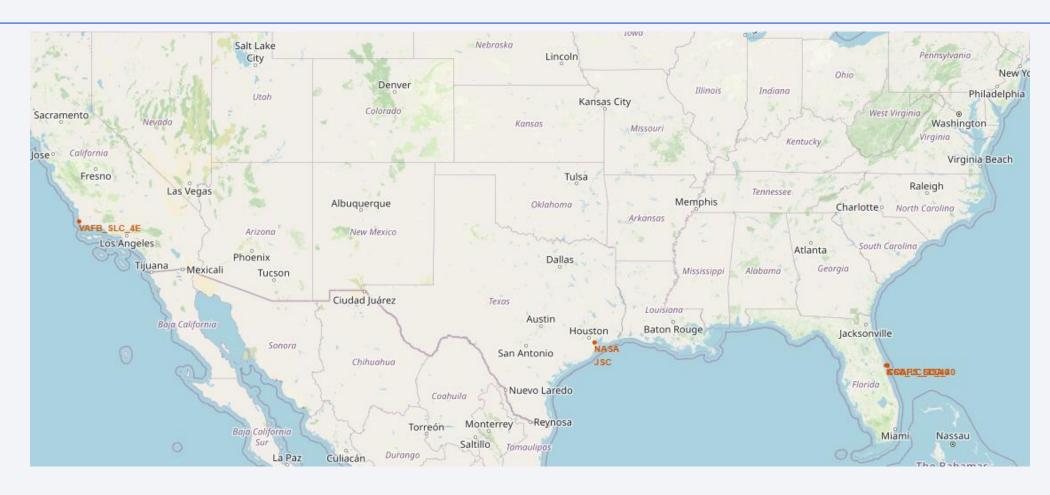
List the records which will display the month names, failure landing_outcomes in drone ship ,booster versions, launch_site for the months in year 2015. Note: SQLLite does not support monthnames. So you need to use substr(Date, 6,2) as month to get the months and substr(Date,0,5)='2015' for year. %%sql select substr(Date,6,2) as MonthName,* from spacextable where substr(Date,0,5) = '2015' and landing outcome = 'Failure (drone ship)' * sqlite:///my_data1.db Done. MonthName Date Time (UTC) Booster_Version Launch_Site Payload PAYLOAD MASS KG Orbit Customer Mission Outcome Landing Outcome 01 2015-01-10 F9 v1.1 B1012 CCAFS LC-40 SpaceX CRS-5 9:47:00 2395 LEO (ISS) NASA (CRS) Success Failure (drone ship) 04 2015-04-14 20:10:00 F9 v1.1 B1015 CCAFS LC-40 SpaceX CRS-6 1898 LEO (ISS) NASA (CRS) Success Failure (drone ship) Using the substr function, we can extract the proper month and date with the desired landing outcome 'Failure (drone ship)'

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





Map of Launch Sites including Huston NASA site



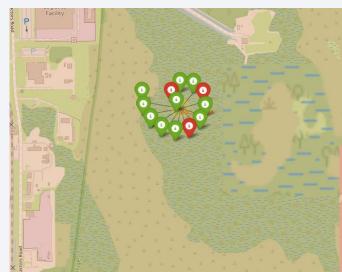
The first thing that we notice is that the launch sites are as south as possible in the US, very flat areas, close to the sea and with low population and traffic.

Color coded launch outcomes of all 4 sites.

Cap Canaveral Sites

Vandenberg Site

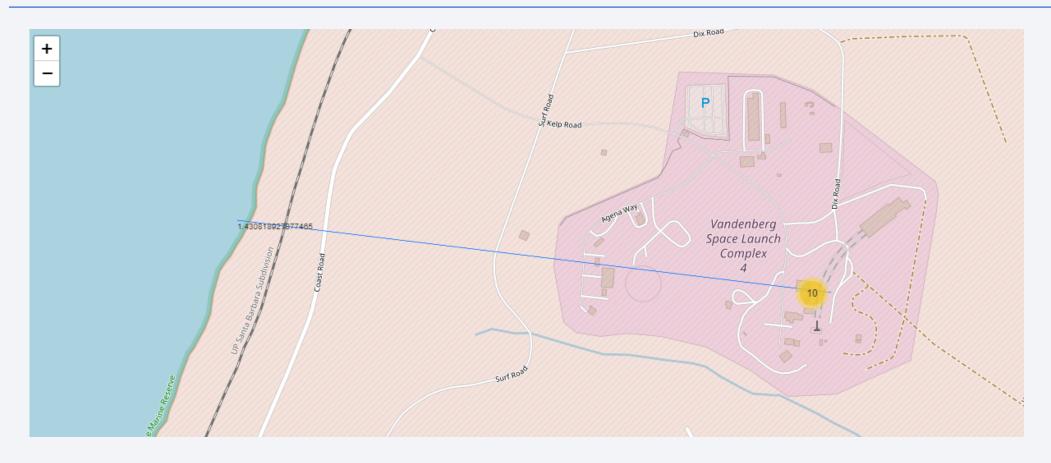






 The most used site it Cap Canaveral. It also has the most successful launch outcomes

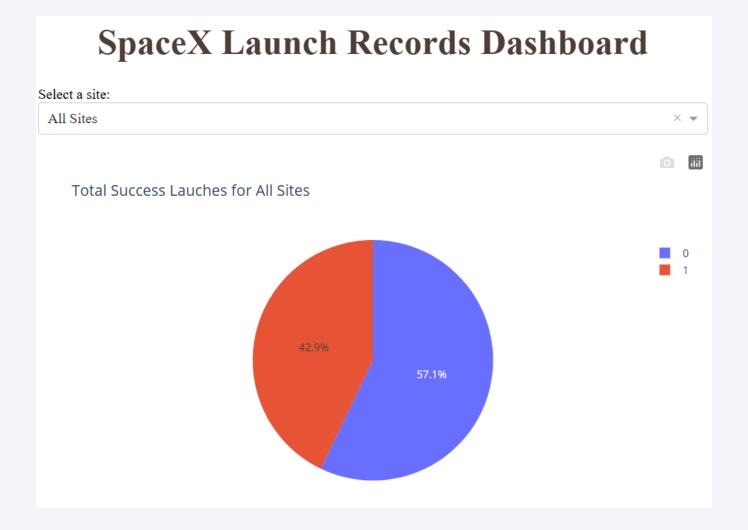
Distance from Vandenberg Launch Site to Sea



Can be used to calculate distance to point of interest for informational, environmental or safety pruposes.

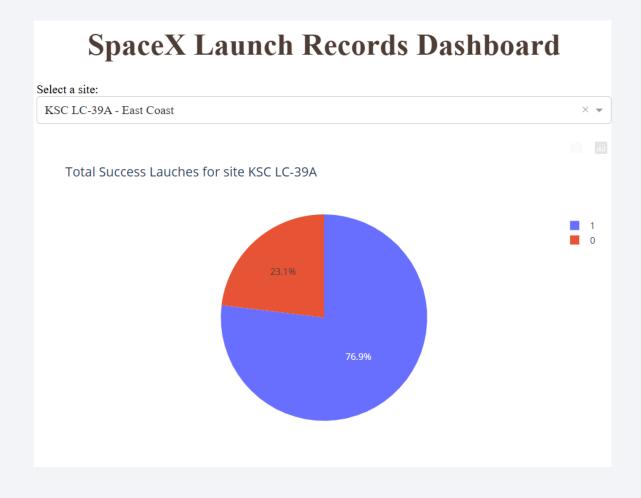


Succes and Failure for All Sites



 The conclusion from this is that it is a very expensive undertaking as only 57.1% of the outcomes are succesful

Site with the best outcome



• The launch site with the best outcome is KSC LC-39A.

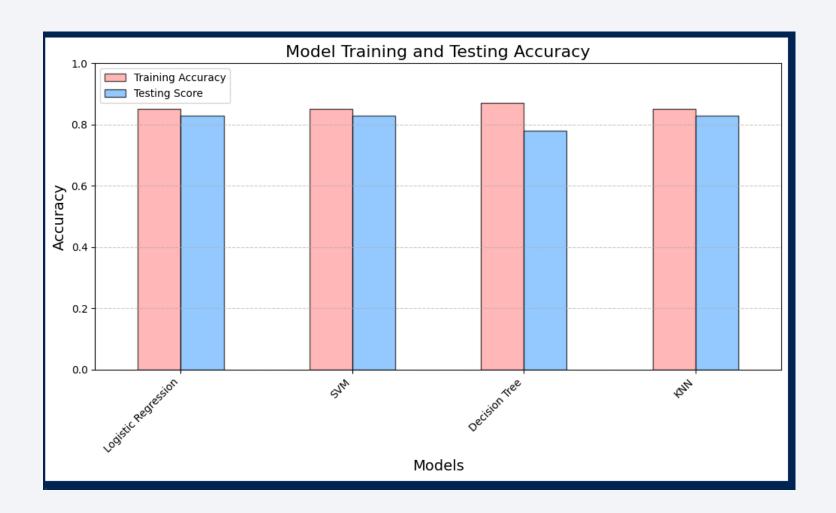
Outcomes for all site for selected payload.



 Outcomes for all sites for Payloads between 2500 and 7500 kg. Not very successful is it?

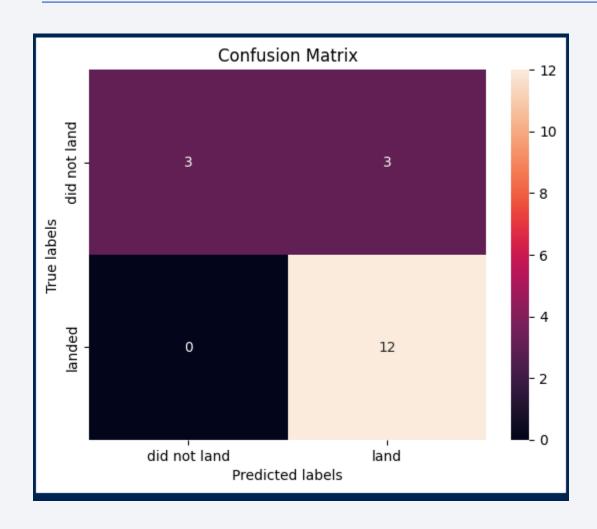


Classification Accuracy



The decision tree with the Log2, sqrt and none has the highest training accuracy but the lowest score on the test data. All other models have the same score for the test data.

Confusion Matrix



The Logistic Regression, SVM and KNN models essentially perform all the same on the testing data by correctly predicting the non successful launches and by mis predicting 3 successful landing when the where actually no successful.

Conclusions

Overall Project Results

- Achieved 83% score on testing data for LogReg, SVM and KNN model and only 77% on Tree classifier model.
- Identified payload mass and site as top predictors.
- Interactive dashboards and geospatial analysis enriched insights.

Business Implications

- Predictive models help forecast cost and risk.
- Can be used by competitors or partners to benchmark performance.
- Supports data-driven decision-making in aerospace logistics.

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Recommendations

- Incorporate live API data for real-time prediction updates.
- Expand dataset with additional providers for broader comparison.
- Deploy the model in a monitoring dashboard for internal use.

Appendix

• All notebooks are available at https://github.com/Andre-Roussel/IBM-Skills-Build-DataScience-Capstone

