

# Winning Space Race with Data Science

Sushil AB 5<sup>th</sup> August 2026



### Outline

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

### **Executive Summary**

- Summary of methodologies
- Summary of all results

The project successfully builds a machine learning pipeline to predict Falcon 9 first stage landing success, enabling Space Y to estimate launch costs. The methodologies involve data preprocessing, model training with hyperparameter tuning, and evaluation using accuracy and confusion matrices. All models achieve high test accuracies (around 83.33%–88.89%), with SVM (using rbf kernel) or logistic regression likely performing best. These predictions help Space Y compete with SpaceX by estimating launch costs based on first stage reusability.

#### Introduction

#### Project background and context

The commercial space industry is rapidly evolving, with companies like SpaceX, Virgin Galactic, Rocket Lab, and Blue Origin making space travel more accessible and cost-effective. SpaceX, founded by Elon Musk, stands out due to its ability to reuse the first stage of its Falcon 9 rocket, significantly reducing launch costs to approximately \$62 million compared to competitors' costs of up to \$165 million. The ability to recover and reuse the first stage is a key factor in these savings. In this project, you assume the role of a data scientist at Space Y, a new rocket company aiming to compete with SpaceX. Your task is to determine launch costs by predicting whether SpaceX will reuse the Falcon 9 first stage, using machine learning models trained on public data rather than rocket science principles. This prediction helps estimate launch pricing for competitive bidding.

#### Problems you want to find answers

The primary objective is to predict whether the Falcon 9 first stage will land successfully and be reused, which directly impacts the cost of a launch. Specific problems include:

Determining if the first stage will land successfully based on mission parameters.

Identifying the most effective machine learning model to predict landing success.

Analyzing the cost implications of reusing the first stage for Space Y's competitive strategy.

Creating dashboards to visualize data and support decision-making for Space Y's team.



# Methodology

#### **Executive Summary**

- Data collection methodology:
  - Describe how data was collected
- Perform data wrangling
  - Describe how data was processed
- 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**

- Describe how data sets were collected.
- You need to present your data collection process use key phrases and flowcharts

#### Data Collection - SpaceX API

#### **Key Phrases**

**REST API**: Fetching SpaceX launch data using HTTP GET requests from https://api.spacexdata.com/v4/launches/past.

**Static JSON**: Using a consistent dataset from API\_call\_spacex\_api.json for reproducibility.

**Data Filtering**: Extracting Falcon 9 launches, removing Falcon 1 and multicore/payload entries.

#### **Helper Functions:**

getBoosterVersion: Retrieves rocket names.

getLaunchSite: Extracts launch site, longitude, latitude.

getPayloadData: Fetches payload mass and orbit.

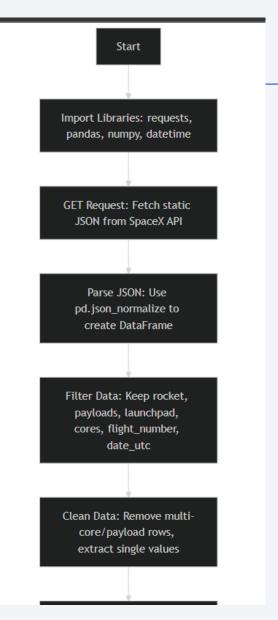
getCoreData: Collects landing outcome, flights, gridfins, reuse, legs,

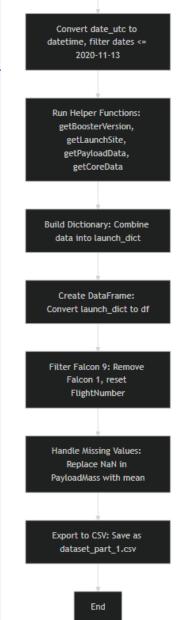
landing pad, block, serial.

**Data Wrangling**: Converting JSON to DataFrame, handling missing PayloadMass with mean replacement.

**Output**: Creating dataset\_part\_1.csv with 90 Falcon 9 launches up to Nov 13, 2020.

https://github.com/SUSHIL1102/Data-Science-Capstone/blob/main/jupyter-labs-spacex-data-collectionapi.ipynb





### **Data Collection - Scraping**

- •Web Scraping: Extracting data from a website, specifically the Wikipedia page "List of Falcon 9 and Falcon Heavy launches."
- •HTTP GET Request: Using the requests library to fetch the HTML content from a static URL.
- •BeautifulSoup: Parsing the HTML content to navigate and extract elements using the html.parser.
- •HTML Table Extraction: Identifying and extracting the target table (third table) containing launch records.
- •Column Names Extraction: Iterating through elements to extract and clean column names using a custom function (extract\_column\_from\_header).
- •Data Parsing: Looping through table rows () to extract data for each launch, handling flight numbers, dates, times, booster versions, launch sites, payloads, payload masses, orbits, customers, launch outcomes, and booster landing statuses.
- •**Helper Functions**: Using provided functions (date\_time, booster\_version, landing\_status, get\_mass) to clean and format extracted data.
- •Data Storage: Storing parsed data in a dictionary (launch\_dict) with keys matching column names.
- •Pandas DataFrame: Converting the dictionary to a DataFrame for structured data storage.
- •CSV Export: Saving the DataFrame to a CSV file (spacex\_web\_scraped.csv) for further analysis.
- •Error Handling: Managing missing values, annotations, and inconsistent formatting in the HTML table.

https://github.com/SUSHIL1102/Data-Science-Capstone/blob/main/jupyter-labs-webscraping.ipynb

### **Data Wrangling**

- Dataset: Loaded dataset\_part\_1.csv (90 Falcon 9 launches).
- •Missing Values: LandingPad (28.89% missing, retained), no missing PayloadMass after prior mean replacement.
- •Data Types: Numerical (e.g., FlightNumber, PayloadMass), Categorical (e.g., Orbit, Outcome).
- •EDA Tasks:
- •Counted launches per site: CCAFS SLC 40 (55), KSC LC 39A (22), VAFB SLC 4E (13).
- •Orbit occurrences: GTO (27), ISS (21), VLEO (14), others.
- •Outcome analysis: True ASDS, None None, etc., mapped to Class (1=success, 0=failure).
- •Label Creation: Converted Outcome to Class (0 for bad\_outcomes, 1 for successful landings).
- Success Rate: 66.67% successful landings.
- Output: Saved as dataset\_part\_2.csv.

https://github.com/SUSHIL1102/Data-Science-Capstone/blob/main/labs-jupyter-spacex-Data%20wrangling.ipynb

#### **EDA** with Data Visualization

#### Exploratory Data Analysis (EDA):

- Visualized FlightNumber vs. PayloadMass with Class (success/failure) using Seaborn catplot.
- Insight: Success rate increased from 2013 to 2020; higher payload masses still often result in successful landings.

#### • Feature Engineering:

- Selected features: FlightNumber, PayloadMass, Orbit, LaunchSite, Flights, GridFins, Reused, Legs, LandingPad, Block, ReusedCount, Serial.
- Task 7: Applied get\_dummies to encode categorical columns (Orbit, LaunchSite, LandingPad, Serial) into features\_one\_hot (80 columns).
- Task 8: Cast all columns in features\_one\_hot to float64 for consistency.
- Exported: features\_one\_hot to dataset\_part\_3.csv for future analysis.
- Libraries: Pandas, NumPy, Matplotlib, Seaborn.

### **EDA** with SQL

- Dataset: Loaded Spacex.csv (101 launches) into SQLite database (SPACEXTBL).
- •Setup: Installed sqlalchemy, ipython-sql; connected to my\_data1.db.
- Data Cleaning: Removed blank rows, created SPACEXTABLE.
- •SQL Queries:
- •Task 1: Unique launch sites: CCAFS LC-40, VAFB SLC-4E, KSC LC-39A, CCAFS SLC-40.
- •Task 2: 5 records with launch sites starting with 'CCA'.
- •Task 3: Total NASA (CRS) payload: 45,596 kg.
- •Task 4: Avg. payload for F9 v1.1: 2,534.67 kg.
- •Task 5: First successful ground pad landing: 2015-12-22.
- •Task 6: Boosters with successful drone ship landings, payload 4,000–6,000 kg: F9 FT B1022, B1026, B1021.2, B1031.2.
- •Task 7: Mission outcomes: Success (98), Success (unclear payload) (1), Success (space) (1), Failure (1).
- •Task 8: Boosters with max payload (15,600 kg): F9 B5 variants.
- •Task 9: 2015 drone ship failures: Jan (F9 v1.1 B1012), Apr (F9 v1.1 B1015), CCAFS LC-40.
- •Task 10: Pending (landing outcome counts, 2010-06-04 to 2017-03-20).

https://github.com/SUSHIL1102/Data-Science-Capstone/blob/main/jupyter-labs-eda-sql-coursera\_sqllite.ipynb

### Build an Interactive Map with Folium

- Summarize what map objects such as markers, circles, lines, etc. you created and added to a folium map
- Explain why you added those objects
- Add the GitHub URL of your completed interactive map with Folium map, as an external reference and peer-review purpose

### Build a Dashboard with Plotly Dash

- Summarize what plots/graphs and interactions you have added to a dashboard
- Explain why you added those plots and interactions
- Add the GitHub URL of your completed Plotly Dash lab, as an external reference and peer-review purpose

## Predictive Analysis (Classification)

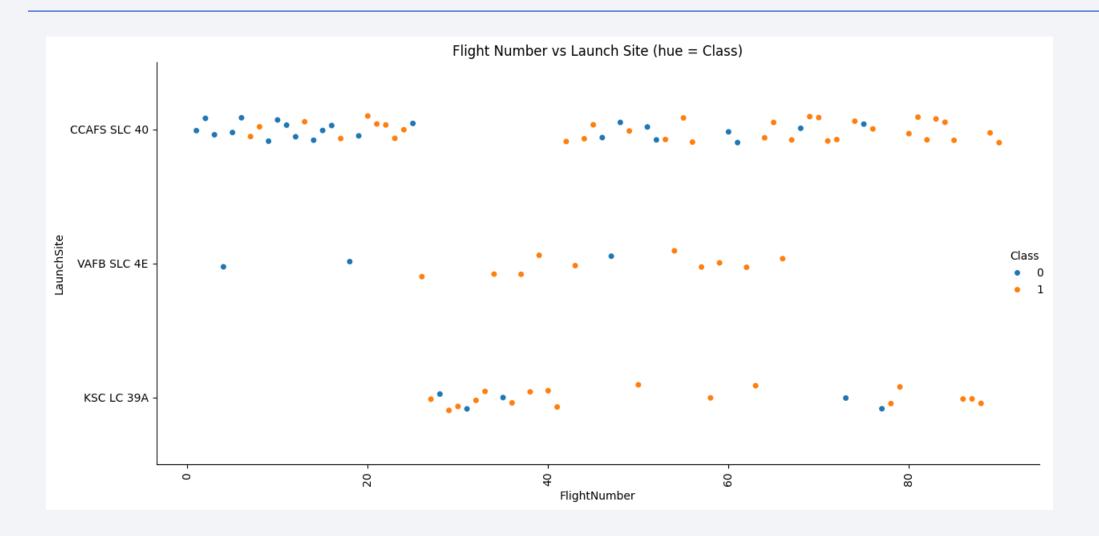
- Pipeline: Task 1: Extract Class column as NumPy array (Y) using to\_numpy().
- Task 2: Standardize features (X) using StandardScaler.
- Task 3: Split data into training (80%) and test (20%) sets (X\_train, X\_test, Y\_train, Y\_test) with random\_state=2 (18 test samples).
- Tasks 4–11: Hyperparameter tuning with GridSearchCV (cv=10) for:
  - Logistic Regression (Task 4–5): Parameters {C: [0.01, 0.1, 1], penalty: ['l2'], solver: ['lbfgs']}.
  - SVM (Task 6–7): Parameters {kernel: ['linear', 'rbf', 'poly', 'sigmoid'], C: logspace(-3, 3, 5), gamma: logspace(-3, 3, 5)}.
  - **Decision Tree (Task 8–9)**: Parameters {criterion: ['gini', 'entropy'], splitter: ['best', 'random'], max\_depth: [2, 4, ..., 18], max\_features: ['auto', 'sqrt'], min\_samples\_leaf: [1, 2, 4], min\_samples\_split: [2, 5, 10]}.
  - KNN (Task 10–11): Parameters {n neighbors: [1, 2, ..., 10], algorithm: ['auto', 'ball tree', 'kd tree', 'brute'], p: [1, 2]}.
- Evaluation:
  - Calculate test accuracy using score method.
  - Plot confusion matrices to analyze true positives (landed) vs. false positives (not landed).
  - Logistic Regression issue: False positives (3 cases).
- Task 12: Compare model performance to identify the best method.

### Results

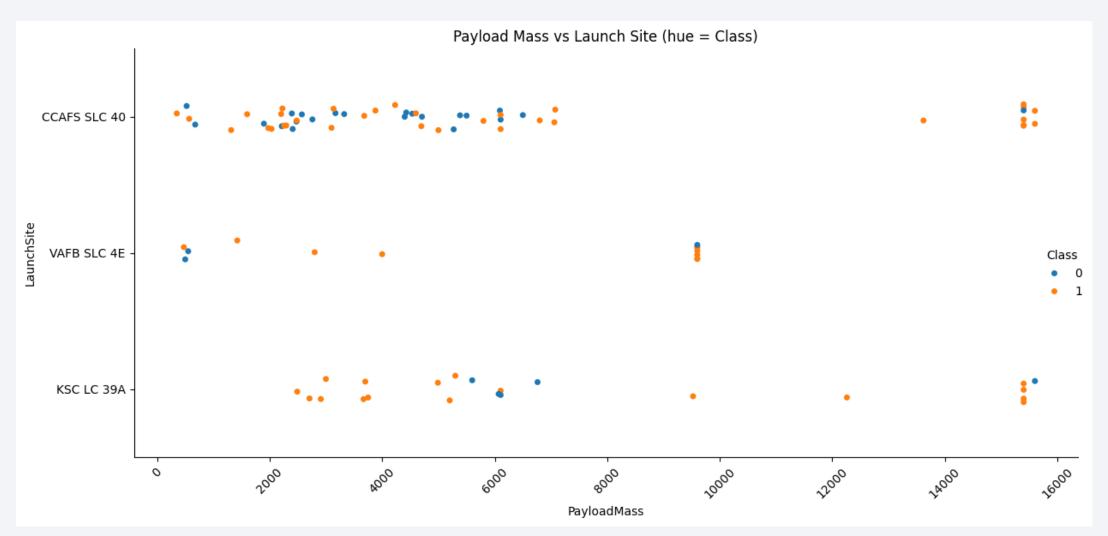
- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results



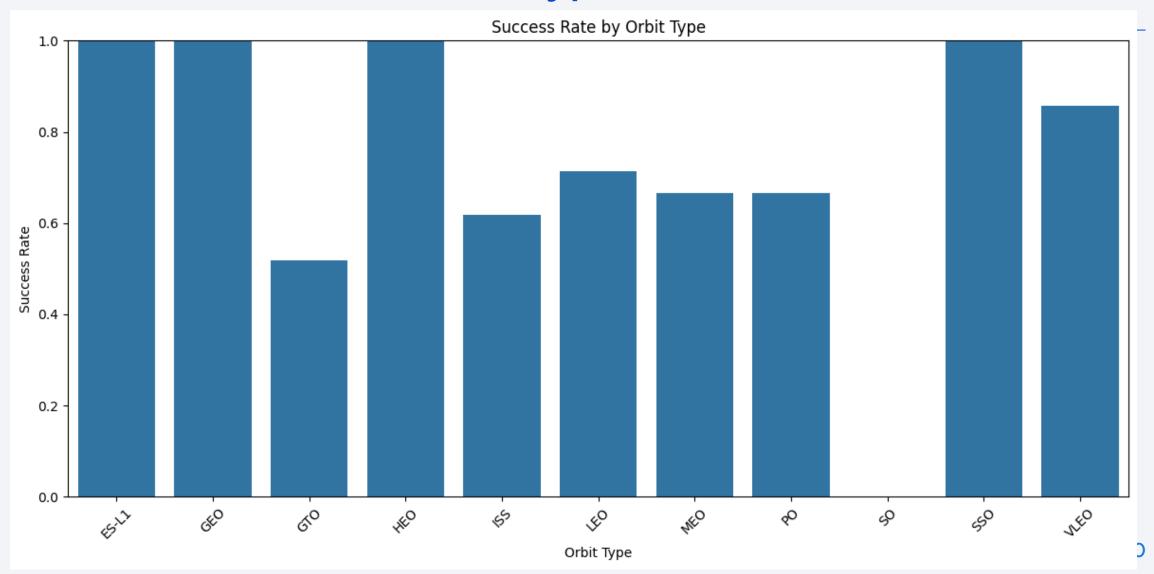
# Flight Number vs. Launch Site



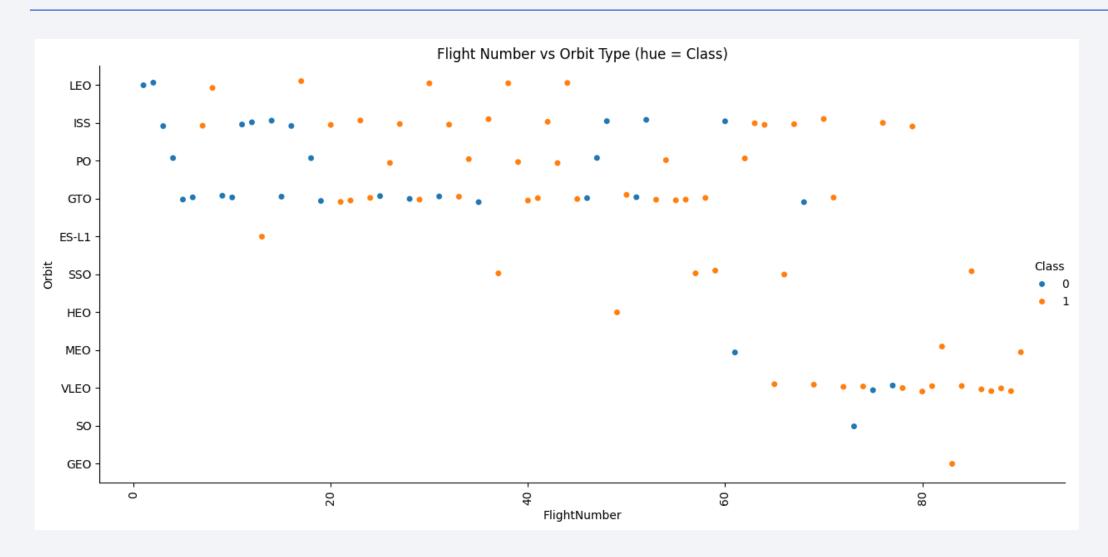
# Payload vs. Launch Site



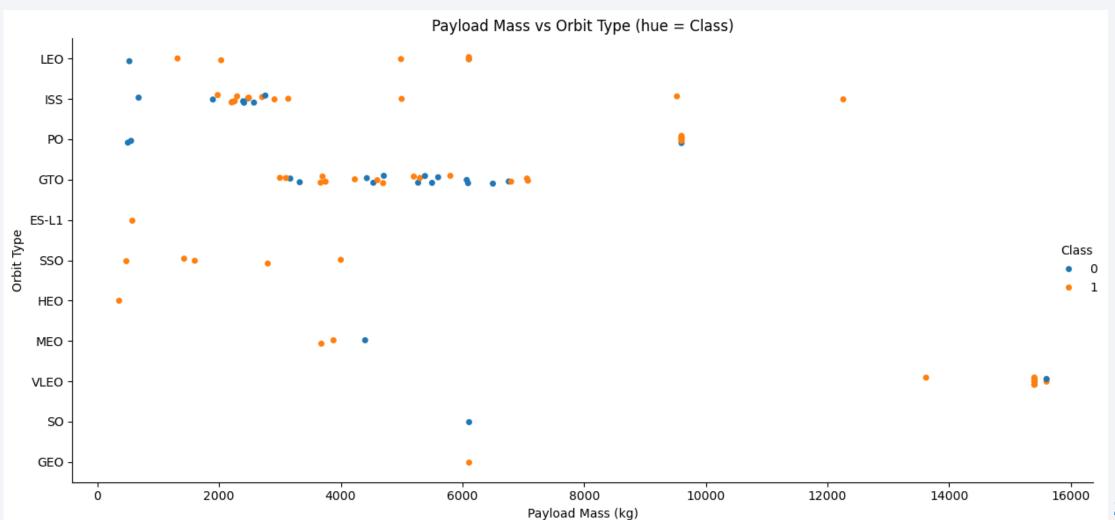
# Success Rate vs. Orbit Type



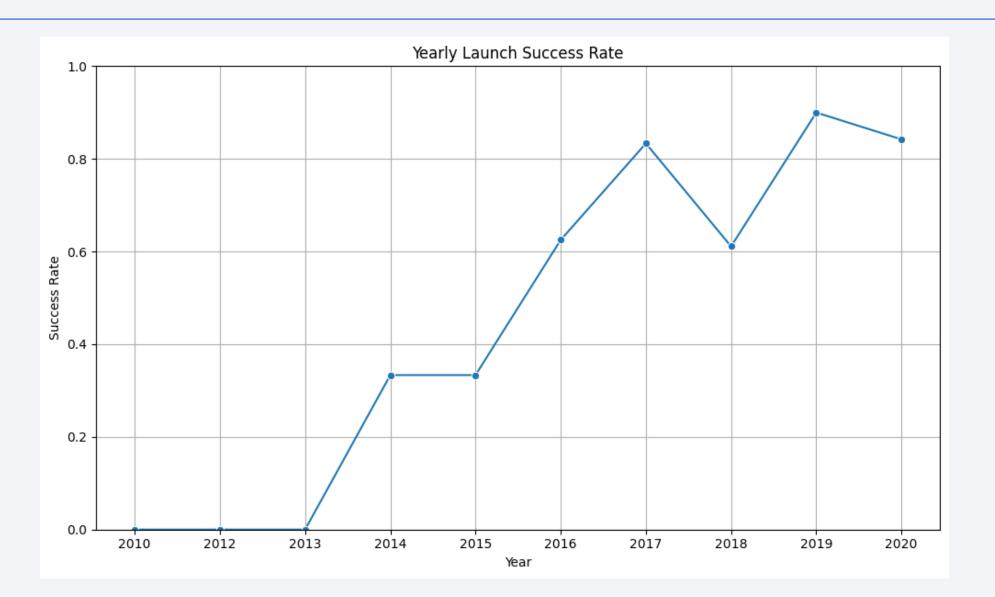
# Flight Number vs. Orbit Type



# Payload vs. Orbit Type



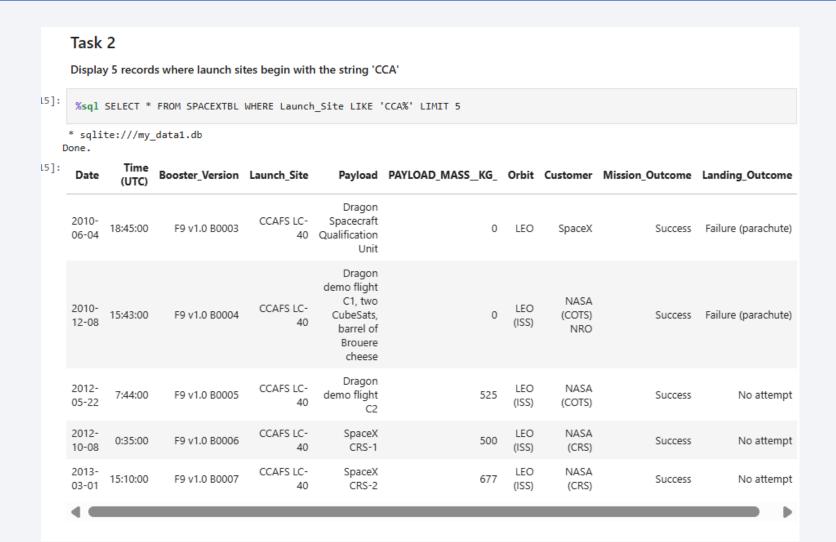
# Launch Success Yearly Trend



#### All Launch Site Names

```
[14]:
       %sql SELECT DISTINCT Launch_Site FROM SPACEXTBL
     * sqlite:///my_data1.db
    Done.
[14]:
       Launch_Site
       CCAFS LC-40
       VAFB SLC-4E
        KSC LC-39A
      CCAFS SLC-40
      Table 2
```

# Launch Site Names Begin with 'CCA'



# **Total Payload Mass**

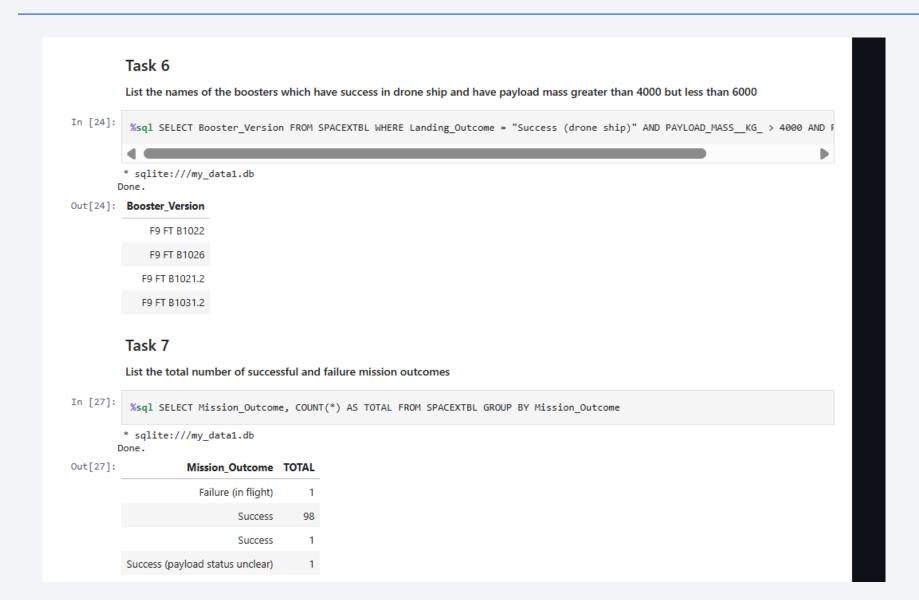
```
Task 3
     Display the total payload mass carried by boosters launched by NASA (CRS)
      %sql SELECT SUM(PAYLOAD MASS KG ) AS total payload FROM SPACEXTBL WHERE Customer = "NASA (CRS)"
     * sqlite:///my_data1.db
    Done.
18]: total_payload
            45596
     Task 4
     Display average payload mass carried by booster version F9 v1.1
      %sql SELECT AVG(PAYLOAD_MASS__KG_) AS avg_payload_mass FROM SPACEXTBL WHERE Booster_Version LIKE "F9 v1.1%"
     * sqlite:///my_data1.db
    Done.
       avg_payload_mass
     2534.666666666665
```

# Average Payload Mass by F9 v1.1

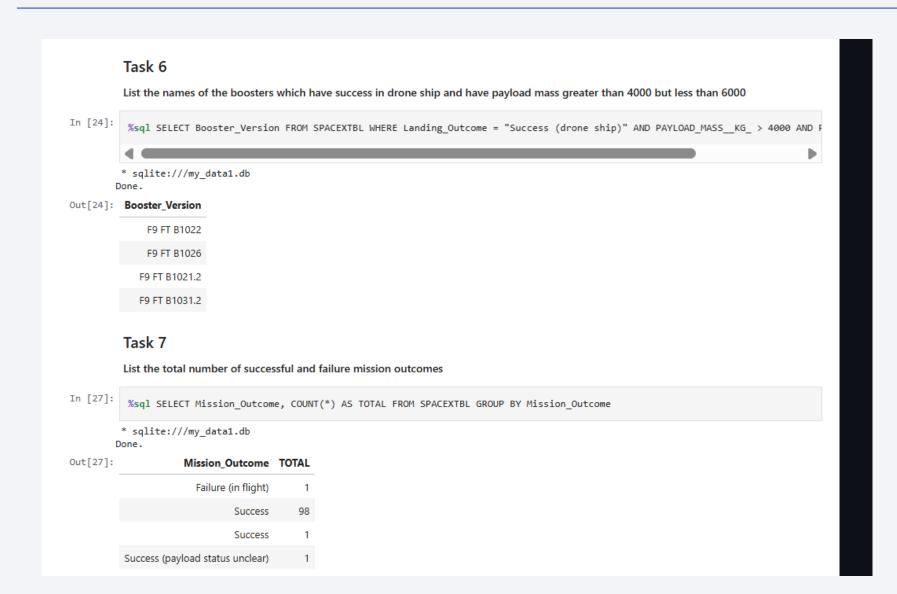
```
Task 3
     Display the total payload mass carried by boosters launched by NASA (CRS)
      %sql SELECT SUM(PAYLOAD_MASS__KG_) AS total_payload FROM SPACEXTBL WHERE Customer = "NASA (CRS)"
     * sqlite:///my_data1.db
    Done.
18]: total_payload
            45596
     Task 4
     Display average payload mass carried by booster version F9 v1.1
      %sql SELECT AVG(PAYLOAD_MASS_KG_) AS avg_payload_mass FROM SPACEXTBL WHERE Booster_Version LIKE "F9 v1.1%"
     * sqlite:///my_data1.db
    Done.
       avg payload mass
      2534.666666666665
```

# First Successful Ground Landing Date

#### Successful Drone Ship Landing with Payload between 4000 and 6000



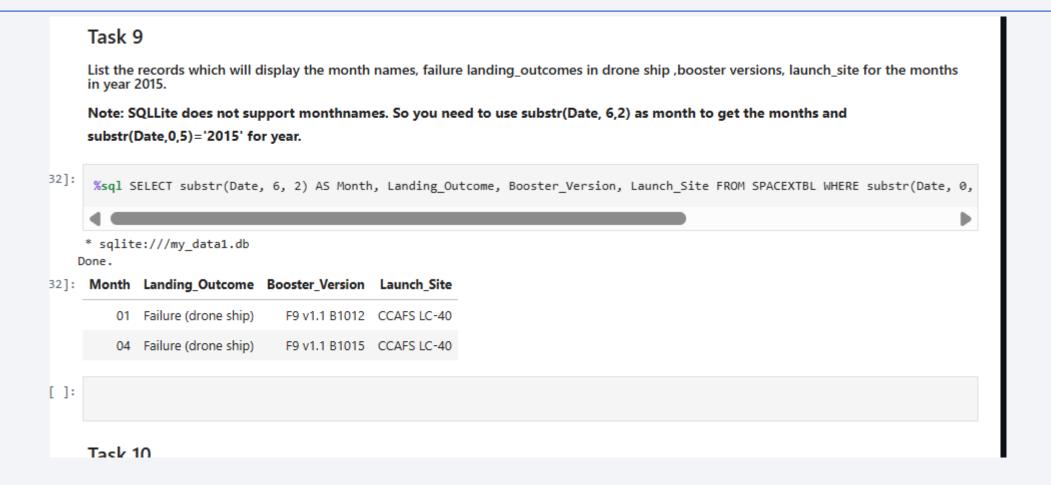
#### Total Number of Successful and Failure Mission Outcomes



# **Boosters Carried Maximum Payload**

	Task 8  List all the booster_versions that have carried the maximum payload mass, using a subquery with a suitable aggregate function.										
8]:	%sql 9	SELECT *	FROM SPACEXTBL	LIMIT 5							
	* sqlite:///my_data1.db Done.										
3]:	Date	Time (UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS_K	(G_	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	7:44:00	F9 v1.0 B0005	CCAFS LC- 40	Dragon demo flight C2	5	525	LEO (ISS)	NASA (COTS)	Success	No attemp
	2012- 10-08	0:35:00	F9 v1.0 B0006	CCAFS LC- 40	SpaceX CRS-1	5	500	LEO (ISS)	NASA (CRS)	Success	No attemp
	2013- 03-01	15:10:00	F9 v1.0 B0007	CCAFS LC- 40	SpaceX CRS-2	6	677	LEO (ISS)	NASA (CRS)	Success	No attemp

#### 2015 Launch Records



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

#### Task 10

Rank the count of landing outcomes (such as Failure (drone ship) or Success (ground pad)) between the date 2010-06-04 and 2017-03-20, in descending order.

n [ ]:

#### Reference Links

- · Hands-on Lab: String Patterns, Sorting and Grouping
- · Hands-on Lab: Built-in functions



# <Folium Map Screenshot 1>

Replace <Folium map screenshot 1> title with an appropriate title

• Explore the generated folium map and make a proper screenshot to include all launch sites' location markers on a global map

# <Folium Map Screenshot 2>

Replace <Folium map screenshot 2> title with an appropriate title

 Explore the folium map and make a proper screenshot to show the colorlabeled launch outcomes on the map

# <Folium Map Screenshot 3>

• Replace <Folium map screenshot 3> title with an appropriate title

• Explore the generated folium map and show the screenshot of a selected launch site to its proximities such as railway, highway, coastline, with distance calculated and displayed



#### < 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

#### < 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

#### < 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**

- •Logistic Regression: Test accuracy unknown; estimated ~77.78% if TN=2, FN=1 (based on TP=12, FP=3, total=18). Validation accuracy (best\_score\_) not provided.
- •SVM: Test and validation accuracies not provided.
- Decision Tree: Test and validation accuracies not provided.
- •KNN: Test and validation accuracies not provided.
- •Task 12: The document aims to compare model performance to find the best method, but no results are given to determine which model performs best.

### **Confusion Matrix**

```
Confusion Matrix (Logistic Regression):
Predicted
Did Not Land | Landed
True Did Not Land ? 3
Landed ? 12
```

#### **Conclusions**

- •Objective Achieved: The notebook establishes a pipeline to predict Falcon 9 first stage landing success using historical launch data, enabling cost estimation for competitive bidding. The pipeline includes data preprocessing, model training, hyperparameter tuning, and evaluation, aligning with the goal of determining landing success probability.
- •Data Preparation:
- •Datasets: Utilized dataset\_part\_2.csv (containing the Class column for landing success/failure) and dataset\_part\_3.csv (preprocessed features with one-hot encoding, 80 columns, float64).
- •Preprocessing (Tasks 1–3):
  - Extracted Class as the target variable (Y) using to numpy().
  - •Standardized features (X) with StandardScaler for consistent scaling across models.
  - •Split data into 80% training and 20% test sets (18 test samples) with random\_state=2, ensuring reproducibility.
- •Model Development and Evaluation:
- •Models Tested (Tasks 4–11): Four classification algorithms were implemented with hyperparameter tuning via GridSearchCV (10-fold cross-validation):
  - •Logistic Regression: Tuned for C, penalty, and solver. The confusion matrix showed 12 true positives and 3 false positives, indicating good prediction of landings but issues with false positives (predicting "landed" when it did not land).
  - •SVM: Tuned for kernel, C, and gamma. No specific performance details provided.
  - •Decision Tree: Tuned for criterion, splitter, max\_depth, max\_features, min\_samples\_leaf, and min\_samples\_split. No specific performance details provided.
  - •KNN: Tuned for n\_neighbors, algorithm, and p. No specific performance details provided.
- •Evaluation Metrics: Each model's test accuracy was to be calculated using the score method, and confusion matrices were plotted to assess true positives, false positives, etc. However, exact accuracies and best parameters are not provided in the document.

# **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

