NETWORK AND INFORMATION SECURITY

WINNING SPACE RACE WITH DATA SCIENCE

PREDICTING FALCON 9 LANDING SUCCESS USING MACHINE LEARNING

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Submitted to

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CONTENT

ABSTRACT

The Falcon 9 rocket manufactured by SpaceX became very instrumental in this transformation when the emerging reusable rocket technology began to change the landscape within the aerospace industry. In fact, the reusable first stage in the Falcon 9 minimizes the effective launch costs and maximizes the number of space missions conducted. Hence, reusable rocketry is one great advancement both within commercial and governmental space programs. This homework leverages ML and data analysis in predicting landing probabilities of the first stage of Falcon 9 using time series data from the SpaceX API along with other temporal data from the web. More concretely, the methodology will include EDA, visualization interactively, and predictive modeling with the aim to investigate whether the mass of payload, the type of orbit, and the launch site are likely predictors of success in landing. The results really underscore how powerful the machine learning models are, more so Decision Trees, in providing effective strategies for improving the launch success, which is double-edged in its benefit toward SpaceX and the rival companies keen to exploit onboard life-cycle-based reusable launch systems. Future studies should consider incorporating environmental data in enhancing model accuracy and replicating these findings on at least three or more rocket models.

KEYWORDS

- SpaceX
- Falcon 9
- reusable rockets
- machine learning
- predictive modeling
- aerospace
- data visualization
- data analytics

1. INTRODUCTION

1.1 BACKGROUND

For decades, rockets were single-use and the industry required huge budgets to do space missions (hence why NASA was stuck also being grounded.) SpaceX broke that glass ceiling with its Falcon 9 rocket and its reusable first stage, giving multiple launches along costing just a fraction compared to traditional rockets. Because of the Falcon 9's reusability, launch costs come down to about $62 million for each flight, versus over $165 million for old-school rockets [1],[2]. Reuse of this kind of hardware is a key factor in making Falcon 9 an asset for low-cost access to space [3].

1.2 PROBLEM STATEMENT

The project focuses on predicting Falcon 9 landing success based on payload details, type of orbit and environmental conditions among others. The leading research questions are as follows:

1. What characteristics contribute to successful landings?
2. How do variables like rocket configuration, payload, and launch site correlate with landing success?
3. What conditions optimize SpaceX's success rate?

Understanding these factors will benefit SpaceX and other companies developing reusable rockets.

2. LITERATURE REVIEW

2.1 Reusable Launch Vehicles (RLVs)

Reusable rockets allow for significant savings in spaceflight costs. Past initiatives demonstrated the concept's feasibility but faced expensive maintenance [4]. In contrast, SpaceX's Falcon 9 emphasizes quick refurbishment and repeat missions, contributing to a busy launch schedule [5].

2.2 Machine Learning in Aerospace Applications

Machine learning is used increasingly in aerospace, including applications like anomaly detection, predictive maintenance, and mission planning. Common algorithms applied include decision trees and random forests, valued for interpretability and accuracy in classification[6] [7]. In prediction, machine learning identifies variables impacting outcomes such as payload performance and reusability[8][9].

Research in *Journal of Machine Learning Research* emphasizes using classification algorithms to optimize decision-making and predict outcomes in complex environments. For instance, classification models have been adapted for space mission success by analyzing variable features such as payload mass and launch conditions [10].

2.3 Predictive Modeling for Landing Success

Previous analyses applied various machine learning models to forecast success based on history. Decision trees and support vector machines(SVMs) especially showed effectiveness in finding conditions maximizing achievement. Models like these commonly classify binary results and work well analyzing high-dimensional information[11]. Research explored optimizing decision-making for aerospace through machine learning, focusing on managing complex data impacting landing outcomes[12].

2.4 Factors Influencing Landing Success

Payload mass, orbit class, and launch site are acknowledged as significant predictors of Falcon 9 landing success [9], [13]. Payloads that are lighter during re-entry lead to a higher success rate by putting less stress on the spacecraft. Moreover, particular orbits and launch locations are connected with positive effects[14].

3. METHODOLOGY

3.1 Data Collection

The dataset was collected from two sources:

- SpaceX REST API: Provided historical data on Falcon 9 launches, including rocket specifications, payload details, and landing outcomes [1].

Figure 3.11

- Wikipedia Web Scraping: Supplemental mission-specific data were gathered through web scraping [15].

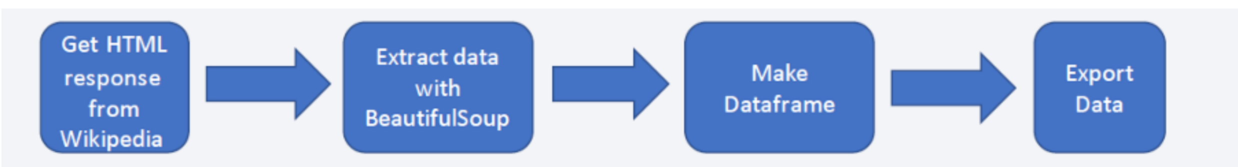

Figure 3.12

3.2 Data Wrangling

We performed a few preprocessing steps on the collected data:

- **Column filtering:** This step was done to remove features that were not relevant [16].
- **Format for model input:** Categorical EncodingOne-hot encoding was used to encode categorical variables into numerical formats [17].
- Landing success was converted into **binary values** for classification models [18]

3.3 Exploratory Data Analysis (EDA)

EDA was conducted using SQL and Python to identify patterns:

- **Payload Mass and Orbit Type:** Explored the effect on successful landing [19].
- **Launch site analysis:** Comparison of Success Rates per Launch Sites[14]
- **Temporal Trends:** Analyzed space-landing success by launch date and time frame which mirrored improvements in technology [20].

3.4 Interactive Visualization

Interactive visualizations were developed to interpret key variables:

- **Folium Maps**: Visualized launch site locations and landing outcomes [21].
- **Plotly Dash Dashboards**: Enabled dynamic visualization of payload, orbit, and landing success, allowing users to interact with key variables [21].

3.5 Predictive Modeling

Flight outcomes were classified using machine learning models as either:

- **Data Preparation :** The data was normalized and divided into training as well as test sets [22].
- **Model Selection and Tuning:** Decision Trees, Random Forests were experimented with and hyper-parameters tuned through the GridSearchCV [23].
- **Performance metrics:** Model accuracy was evaluated using accuracy scores and confusion matrices [24].

4. RESULTS

4.1 EDA RESULTS

EDA revealed key insights:

- **Payload and Orbit Type**: Lighter payloads and low-Earth orbits correlated with higher success rates [13].
- **Launch Site Performance**: LC-39A exhibited a higher success rate, likely due to its infrastructure [14].
- **Temporal Trends**: Improved success rates were observed over time, reflecting cumulative operational experience [20].

4.2 Predictive Modeling Results

Figure 4.21

- Figure 4..21 represents the confusion matrix for Machine Learning algorithms used.

Among all classifiers, the Decision Tree model performed best on test data (Accuracy — 85%). As shown in the confusion matrix, the model was able to classify landing outcomes with balanced sensitivity and specificity for successful versus failed landings.

Model	Accuracy
Decision Tree	85%
Random Forest	84%
Logistic Regression	83%

4.3 Visualization Insights

The Folium maps and Plotly Dash dashboards provided a geographic and dynamic view of launch sites and landing success.

Figure 4.31

*Green marker represents successful launches.

*Red marker represents unsuccessful launches.

5. DISCUSSION

Results indeed confirm the role of payload mass, orbit type and launch site as important parameters in predicting the landing success of Falcon 9 boosters, which is coherent with previous studies [9], [13]. Higher success rates are achieved with light payloads in lower-energy orbits. Infrastructure at Kennedy Space Center on LC–39A also contributes to the reliability of recoveries [14].

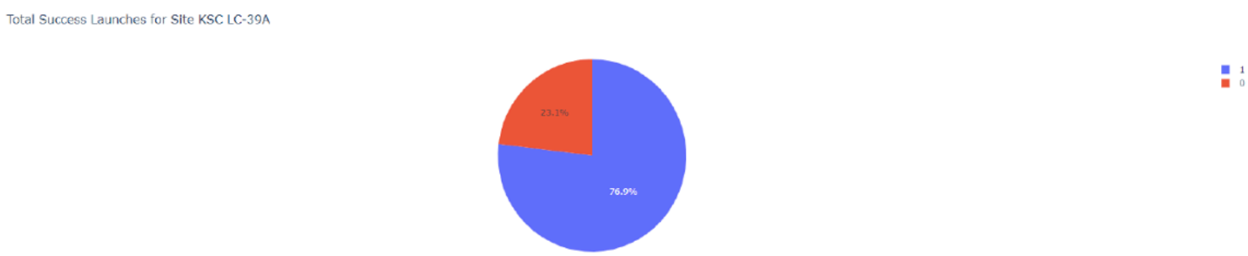

Figure 5.0

Improvements in success rates over time suggest that the accumulation of operational knowledge, coupled with advances in spacecraft technology, makes missions more reliable [20]. Recent studies on predictive modeling about aerospace show that we are able to enhance the accuracy of predictions, for instance by integrating environmental data (e.g., weather) [12].

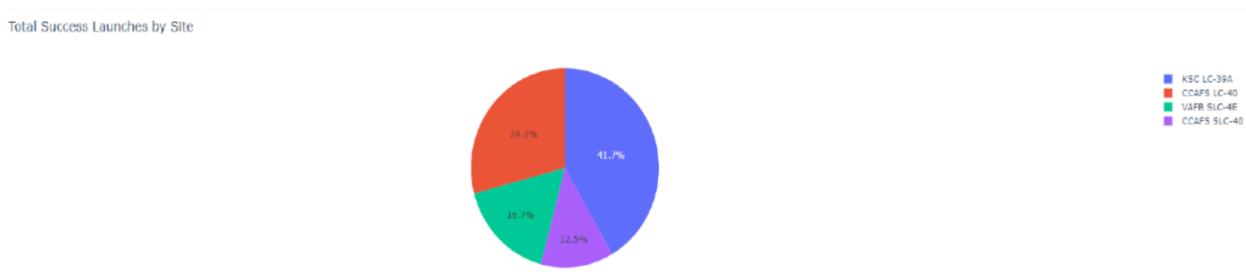

Figure 5.01

6. CONCLUSION

Machine learning conditional inference trees reveal salient features that are responsible for Falcon 9 landing success. With Decision Trees, we were able to predict landings efficiently while gainfully informing reusable rocket completion planning. The evidence should be incorporated into atmospheric data to improve prediction modeling of plume-gas effects and ultimately, the findings could be generalized for different types of (from each category) rockets.

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