

Predicting whether the Falcon 9 will land successfully

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EXECUTIVE SUMMARY

The objective of this study was to investigate the factors determining the outcome of a Falcon 9 launch. Impact of factors like payload mass, launch site, orbit and booster version on the outcome of the launch was investigated.

By creating an interactive dashboard, the impact of payload mass on the outcome of the mission and the successful launches from each launch site were visualised.

Various machine learning models were trained and tested on mutually exclusive data. By doing so, we aimed to find the best model and the best parameters for predicting the outcome of a Falcon 9 launch. We concluded that a decision tree model would be the best fit.



INTRODUCTION

SpaceX advertises the cost of launching a Falcon 9 rocket as \$62 million while other competitors cost upwards of \$165 million. SpaceX saves the odd \$100 million by reusing the first stage of a Falcon 9. But, they can do so only if the launch is successful.

So, it is important to investigate which factors determine whether the first stage will land.

The knowledge gained through this study can be used by SpaceX for improving their first stage landing success rate or it can be useful for a competitor to establish a better program.



METHODOLOGY

Data collection

The data on SpaceX launches was collected through the SpaceX REST API and the Wikipedia page on SpaceX launches.

Pre-formatting data

Using the Pandas library and scikit learn library, the data was pre-formatted for the purposes of exploration and training and testing of machine learning models.

Exploratory Data Analysis

Exploratory data analysis was conducted using SQL through Jupyter Notebooks and by creating an interactive dashboard using Plotly's libraries.

Machine learning

Support vector machines, decision tree classifiers, logistic regression and K-nearest neighbors machine learning models were trained and tested on the data collected.





RESULTS

Data collection was done on two fronts:

- 1. Webscraping through the Beautiful Soup library
- 2. SpaceX REST API

Using the Pandas library, the data was pre-formatted for the purpose of exploratory data analysis. Exploratory data analysis was conducted using SQL queries and Plotly's interactive graphs.

Using GridSearchCV, the most appropriate model and its most appropriate parameters for predicting the launch outcome were selected.



Results from EDA (SQL)

Launch sites

Display the names of the unique launch sites in the space mission

```
In [7]: %sql SELECT DISTINCT Launch_site from SPACEX

* ibm_db_sa://rbk38174:***@b1bc1829-6f45-4cd4-bef4-10cf081900bf.clogj3sd0tgtu0lqde00.databases.appdomain.cloud:32304/bludb
Done.

Out[7]: launch_site

CCAFS LC-40

CCAFS SLC-40

KSC LC-39A

VAFB SLC-4E
```

Date of the first successful launch

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

Hint: Use min function

2010-06-04



Results from EDA (SQL)

Boosters used for successful drone ship landings

Launch sites and booster versions of failed drone ship landings

List the failed landing outcomes in drone ship, their booster versions, and launch site names for in year 2015





Results from EDA (SQL)

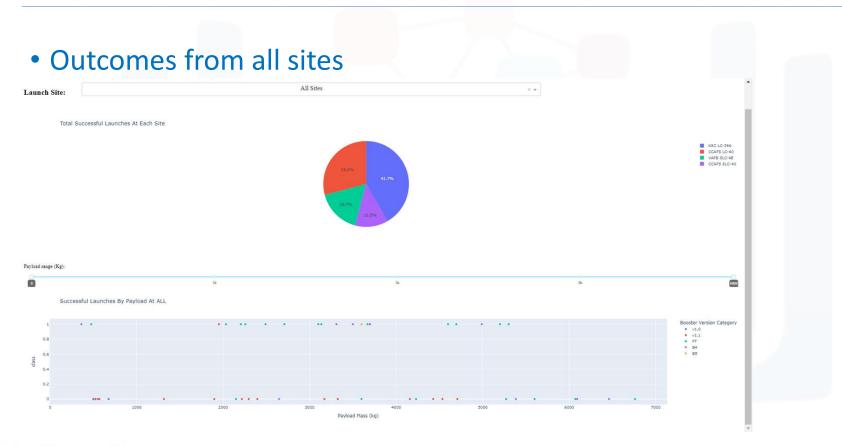
Landing outcome tally

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













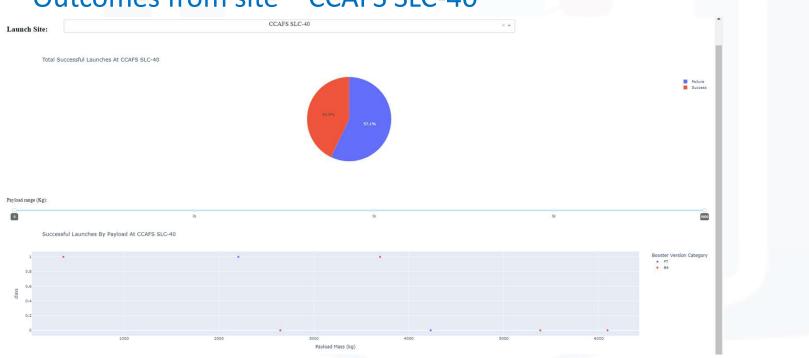
Outcomes from site – CCAFS LC-40





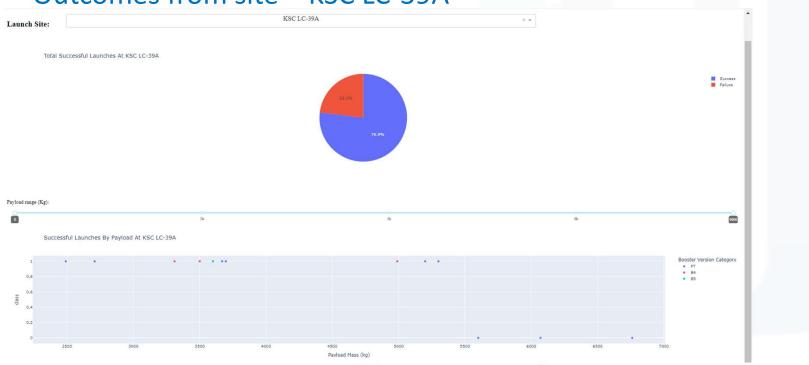


Outcomes from site – CCAFS SLC-40



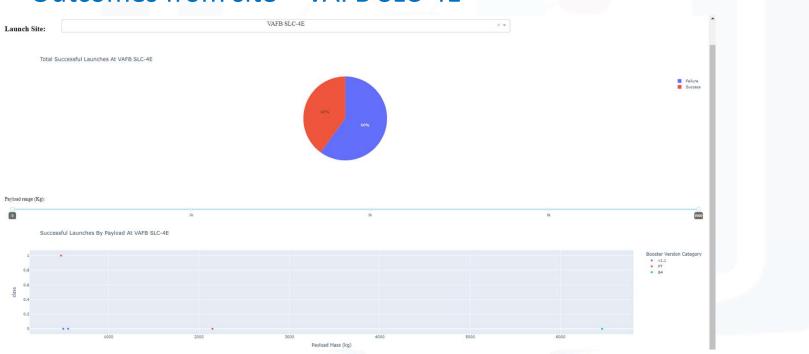


Outcomes from site – KSC LC-39A





Outcomes from site – VAFB SLC-4E

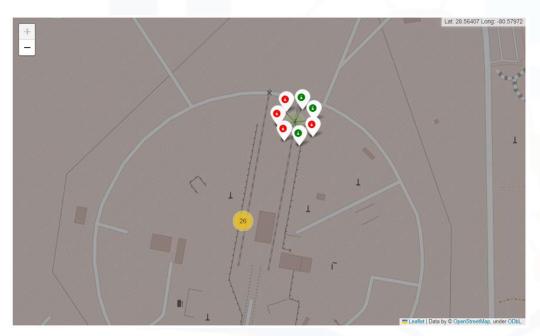




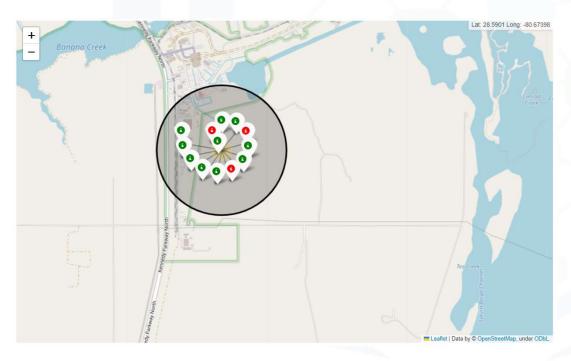
• Outcomes from site – CCAFS LC-40



• Outcomes from site – CCAFS SLC-40

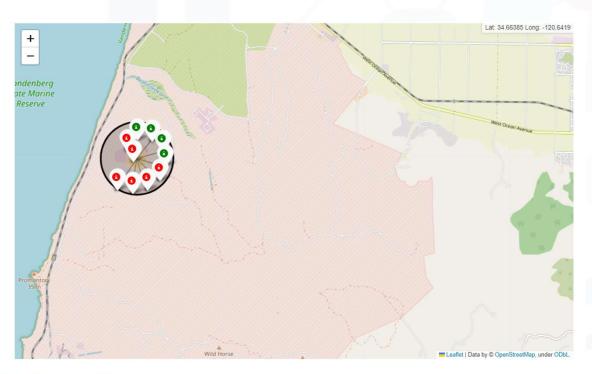


Outcomes from site – KSC LC-39A





• Outcomes from site – VAFB SLC-4E







Results from Machine Learning

Scores of machine learning models

```
In [40]: models = [['Logistic Regression', logreg cv.best score , logreg cv.score(X test, Y test)],
                   ['Support Vector Machines', svm_cv.best_score_, svm_cv.score(X_test, Y_test)],
                   ['Decision Tree', tree cv.best score , tree cv.score(X test, Y test)],
                   ['K-Nearest Neighbors', KNN_cv.best_score_, KNN_cv.score(X_test, Y_test)]]
          mt df = pd.DataFrame(models, columns=['Method', 'Training Score', 'Testing Score'])
In [41]: mt df
Out[41]:
                         Method Training Score Testing Score
                 Logistic Regression
                                      0.846429
                                                  0.833333
                                      0.848214
                                                  0.833333
          1 Support Vector Machines
                     Decision Tree
                                      0.889286
                                                  0.833333
                K-Nearest Neighbors
                                      0.848214
                                                  0.833333
In [42]: tree cv.best params
Out[42]: {'criterion': 'entropy',
            'max_depth': 14,
           'max features': 'sqrt',
           'min samples leaf': 2,
           'min samples split': 2,
           'splitter': 'best'}
```



DISCUSSION

Exploratory data analysis reveals that the highest payload mass successfully landed was 5,300 kg.

The worst performing launch sites with success rates of 26.9% and 23.1% were CCAFS LC-40 and KSC LC-39A. Other sites had a success rate of close to 40%. So, it would be better to avoid CCAFS LC-40 and KSC LC-39A and to avoid having a payload higher than 5,300 kg.



CONCLUSION

To boost the success probability, payload mass should be kept lower than 5,300 kg and launch sites CCAFS LC-40 and KSC LC-39A should be avoided.

The best machine learning model for predicting the outcome of the first stage was the decision tree classifier.

There was no difference in performance on testing data, so the model was chosen based on its fit on training data.



APPENDIX

Training data size = 80%

Testing data size = 20%

Cross-validation splitting strategy = 10

