

Winning Space Race with Data Science

Michael Korn January 15, 2024



Outline

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

Executive Summary

- Summary of methodologies
 - Collection, wrangling, explored, visualized, predicted
- Summary of all results
 - We were able to predict landing outcomes with a 94% success rate

Introduction

A SpaceX Falcon 9 rocket launches with a cost of \$62m compared to \$165m for other providers. Reusable rockets allow SpaceX launches to be over 60% cheaper. The goal of this research is to predict whether a particular launch will be successful. By predicting successful launches, we can ideally improve success rate to decrease launch cost. In addition, a party bidding on a launch can be informed when making a bid.



Methodology

Executive Summary

- Data collection methodology:
 - API, Scraping
- 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

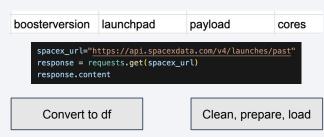
Data Collection

Methodologies

- API <u>Github Link</u>
- Webscraping <u>Github Link</u>

Data Collection – SpaceX API

 Data collection with SpaceX REST calls



```
static_json_url='https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/datasets/API_call_spacex_api.json'
response = requests.get(static_json_url)
response.status_code
response = response.json()
# Lets take a subset of our dataframe keeping only the features we want and the flight number, and date_utc.
data = data[['rocket', 'payloads', 'launchpad', 'cores', 'flight_number', 'date_utc']]
# We will remove rows with multiple cores because those are falcon rockets with 2 extra rocket boosters and rows that have multiple payloads in a single rocket.
data = data[data['cores'].map(len)==1]
data = data[data['payloads'].map(len)==1]
# Since payloads and cores are lists of size 1 we will also extract the single value in the list and replace the feature.
data['cores'] = data['cores'].map(lambda x : x[0])
data['payloads'] = data['payloads'].map(lambda x : x[0])
# We also want to convert the date_utc to a datetime datatype and then extracting the date leaving the time
data['date'] = pd.to_datetime(data['date_utc']).dt.date
# Using the date we will restrict the dates of the launches
data = data[data['date'] <= datetime.date(2020, 11, 13)]</pre>
```

Data Collection - Scraping

Web scraping process

Ping Wikipedia URI

Extract Column Headers

Extract Row Contents

Format into Dataframe

Data Wrangling

- Data massaging was continuously necessary during collection
- After table creation, wrangling is necessary to prepare data for analysis. This includes creating policies for handling missing data.
- Elements:
 - Labels column
 - Replacing Nan with mean

Data Wrangling - Creating Labels Column

```
for i,outcome in enumerate(landing_outcomes.keys()):
       print(i,outcome)
 √ 0.0s
0 True ASDS
1 None None
2 True RTLS
3 False ASDS
4 True Ocean
5 False Ocean
6 None ASDS
7 False RTLS
   bad outcomes=set(landing outcomes.keys()[[1,3,5,6,7]])
   bad outcomes
 ✓ 0.0s
{'False ASDS', 'False Ocean', 'False RTLS', 'None ASDS', 'None None'}
   # landing_class = 0 if bad_outcome
   # landing class = 1 otherwise
   landing_class=[]
    for row in df.Outcome:
       if row in bad outcomes:
            landing_class.append(0)
       else:
            landing class.append(1)
   df['Class']=landing_class
 ✓ 0.0s
```

Data Wrangling – Replacing Nan with Mean

```
# Calculate the mean value of PayloadMass column
   df9_mean = data_falcon9.PayloadMass.mean()
   # Replace the np.nan values with its mean value
   data_falcon9.PayloadMass.replace(np.nan, df9_mean)
       6123.547647
        525,000000
        677.000000
        500.000000
8
       3170.000000
          . . .
89
      15600,000000
90
      15600,000000
      15600,000000
91
92
      15600.000000
93
       3681.000000
Name: PayloadMass, Length: 90, dtype: float64
```

EDA with Data Visualization

- Flight Number vs Payload Mass
- Flight Number vs Launch Site
- Payload Mass vs Launch Site
- Success Rate vs Orbit Type
- Flight Number vs Orbit Type
- Payload Mass vs Orbit Type
- Launch Success vs Yearly Trend
- Features Engineering

EDA with SQL

- Distinct launch sites
- Total payload mass carried by NASA boosters
- Average payload mass carried by booster version F9 v1.1
- Date when first successful landing outcome in ground pad was achieved
- Names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000
- Total number of successful and failure mission outcomes
- Names of the booster_versions which have carried the maximum payload mass
- Records which will display the month names, failure landing_outcomes in drone ship ,booster versions, launch_site for the months in year 2015
- Ranked count of landing outcomes (such as Failure (drone ship) or Success (ground pad)) between the date 2010-06-04 and 2017-03-20.)

Build an Interactive Map with Folium

- The launch success rate may depend on many factors such as payload mass, orbit type, and so on. It may also depend on the location and proximities of a launch site, i.e., the initial position of rocket trajectories. Finding an optimal location for building a launch site certainly involves many factors and hopefully we could discover some of the factors by analyzing the existing launch site locations.
 - Maps of launch sites
 - Distance between launch sites and POI.

Build a Dashboard with Plotly Dash

- Success rates by launch site
 - Launch site is a low-hanging fruit in terms of outcome relationship. A launch site contains a large number of variables that may be unaccounted for in the dataset: from staff to weather conditions.
- Launches, outcomes by payload mass and booster version
 - As the goal is to send massive payloads to Mars, understanding success rates as payload increases and as boosters upgrade is essential.
- Success rate by booster version

Predictive Analysis (Classification)

- Tested multiple classification models
 - Logistic regression
 - Support vector machine
 - Decision tree
 - KNN
 - Method:
 - Chose parameters
 - Choose a model
 - Hyperparameter tuning
 - Fitting/tuning
 - Evaluating by viewing scores and confusion matrix
- You need present your model development process using key phrases and flowchart

Results

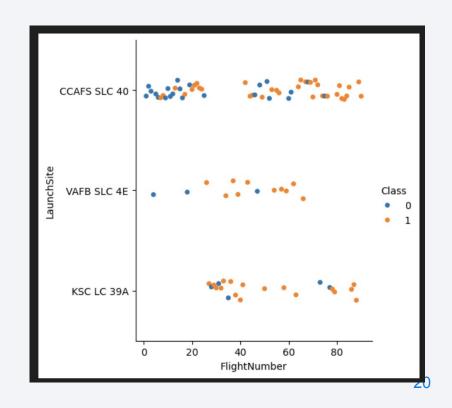
- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results



Flight Number vs. Launch Site

Flight Number vs. Launch Site

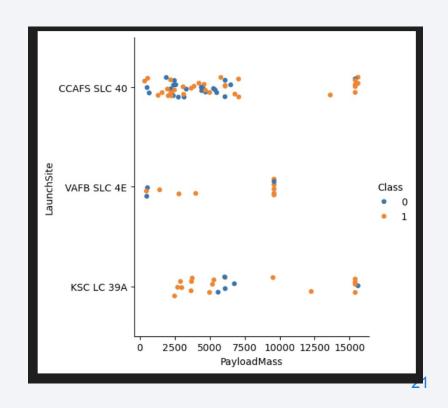
- CCAFS SLC 40 appears to have the highest volum of launches.
- VAFB seems to have slowed
- KSC seems to be a newer site



Payload vs. Launch Site

Payload vs. Launch Site

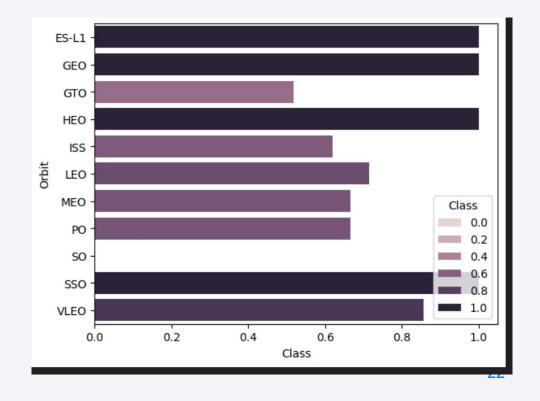
- Largest payloads are with CCAFS and KSC
- A cluster of failures appear between 5,000 and 7,500 kg payloads at KSC
- Early low payload launches at CCAFS had mixed success



Success Rate vs. Orbit Type

Success rate of each orbit type

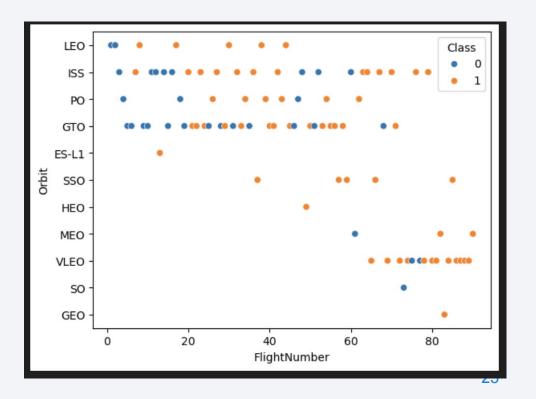
- Darker hues have higher success rates
 - ES-L1
 - o GEO
 - HEO
 - o SSO



Flight Number vs. Orbit Type

Flight number vs. Orbit type

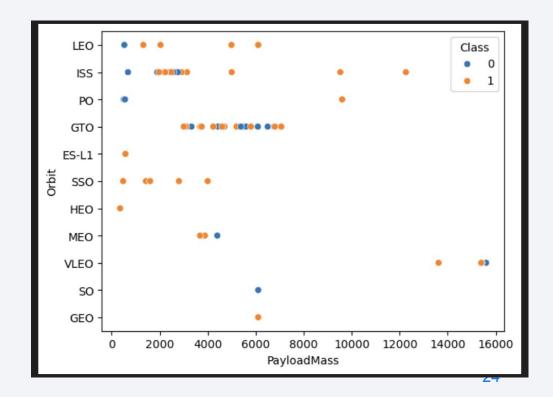
 VLEO and ISS seem to have the latest success



Payload vs. Orbit Type

Payload vs. orbit type

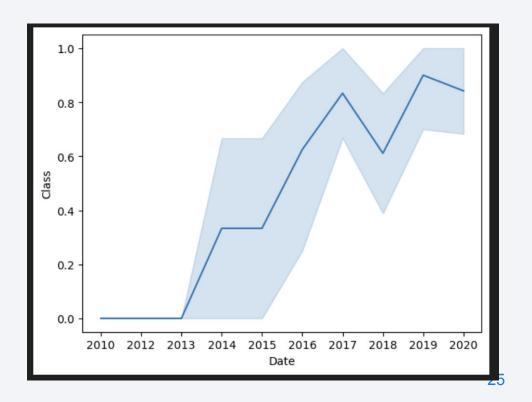
- ISS, PO, VLEO are the only orbits with successful high payload mass launches
- GTO is hard to distinguish



Launch Success Yearly Trend

Yearly average success rate

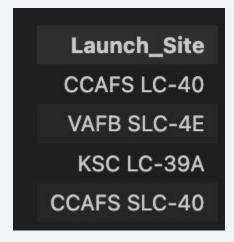
 The success rate has clearly improved



All Launch Site Names

```
%sql select distinct launch_site from spacextable

✓ 0.0s
```



Launch Site Names Begin with 'CCA'

```
%sql select * from spacextable where launch_site like 'CCA%' limit 5
 ✓ 0.0s
* sqlite:///my_data1.db
Done.
                  Time
                          Booster_Version
      Date
                                            Launch_Site
                                                                                                    Payload
                  (UTC)
                                             CCAFS LC-
  2010-06-
               18:45:00
                            F9 v1.0 B0003
                                                                           Dragon Spacecraft Qualification Unit
        04
                                                     40
   2010-12-
                                             CCAFS LC-
                                                          Dragon demo flight C1, two CubeSats, barrel of Brouere
               15:43:00
                            F9 v1.0 B0004
        08
                                                     40
                                                                                                     cheese
                                             CCAFS LC-
  2012-05-
                7:44:00
                            F9 v1.0 B0005
                                                                                       Dragon demo flight C2
        22
                                                     40
  2012-10-
                                             CCAFS LC-
                0:35:00
                            F9 v1.0 B0006
                                                                                              SpaceX CRS-1
        08
                                                     40
  2013-03-
                                             CCAFS LC-
                15:10:00
                            F9 v1.0 B0007
                                                                                              SpaceX CRS-2
                                                     40
```

Total Payload Mass

```
%sql select sum(PAYLOAD_MASS__KG_) from spacextable where customer = 'NASA (CRS)'

* sqlite:///my_data1.db
Done.

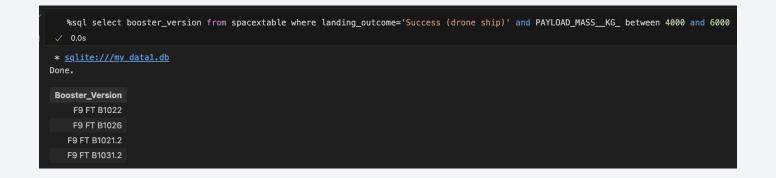
sum(PAYLOAD_MASS__KG_)

45596
```

Average Payload Mass by F9 v1.1

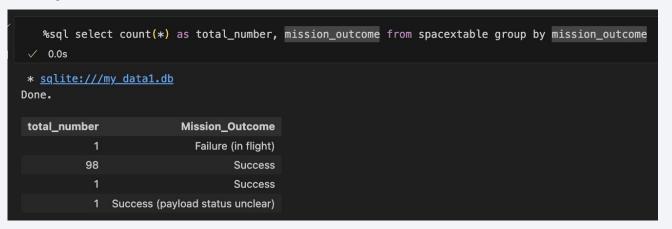
First Successful Ground Landing Date

Successful Drone Ship Landing with Payload between 4000 and 6000



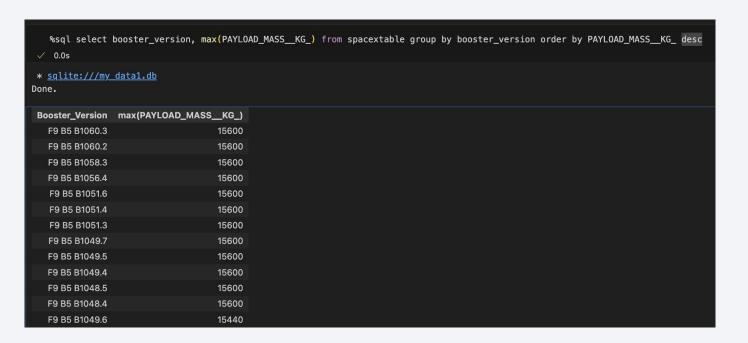
Total Number of Successful and Failure Mission Outcomes

• The vast majority of missions were successful even though many did not successfully land.



Boosters Carried Maximum Payload

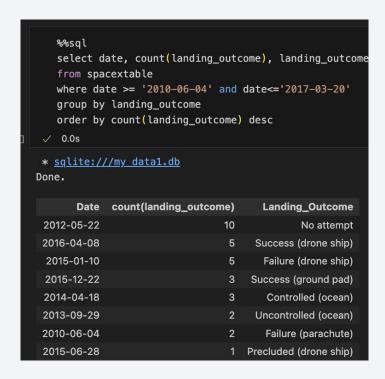
Several booster versions have carried the maximum payload



2015 Launch Records

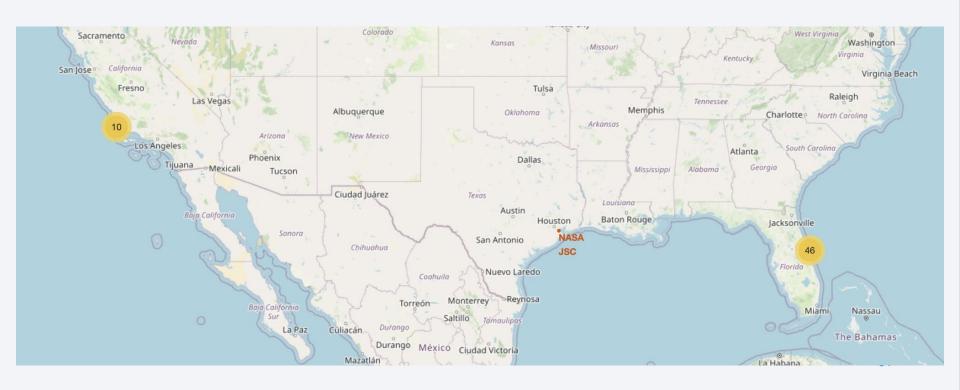
```
%sql
   select
       CASE strftime('%m', date)
           WHEN '01' THEN 'January'
           WHEN '02' THEN 'February'
           WHEN '03' THEN 'March'
           WHEN '04' THEN 'April'
           WHEN '05' THEN 'May'
           WHEN '06' THEN 'June'
           WHEN '07' THEN 'July'
           WHEN '08' THEN 'August'
           WHEN '09' THEN 'September'
           WHEN '10' THEN 'October'
           WHEN '11' THEN 'November'
           WHEN '12' THEN 'December'
       END AS month_name
       , Landing Outcome
       , booster_version
       , launch_site
       , substr(Date,0,5) as year
   from spacextable where landing outcome = 'Failure (drone ship)' and substr(Date,0,5)='2015'
 ✓ 0.0s
* sqlite:///my data1.db
Done.
month_name Landing_Outcome Booster_Version Launch_Site year
     January Failure (drone ship)
                                  F9 v1.1 B1012 CCAFS LC-40 2015
        April Failure (drone ship)
                                  F9 v1.1 B1015 CCAFS LC-40 2015
```

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

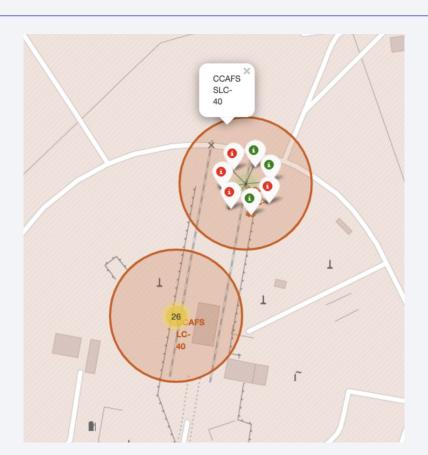




Map of Launch Sites



Color Coded Success Rate of Launch Sites

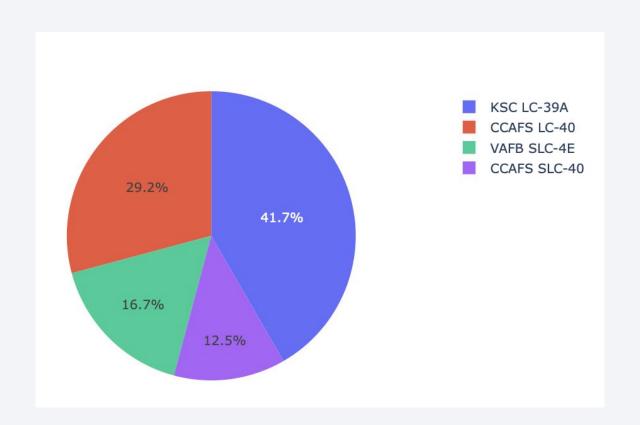


Launch Site Distance from POI



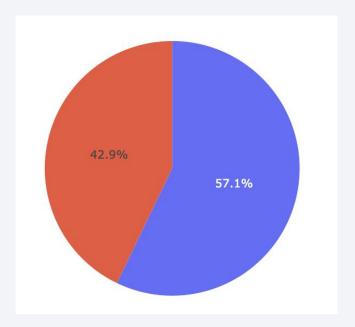


Success Rate for All Launch Sites

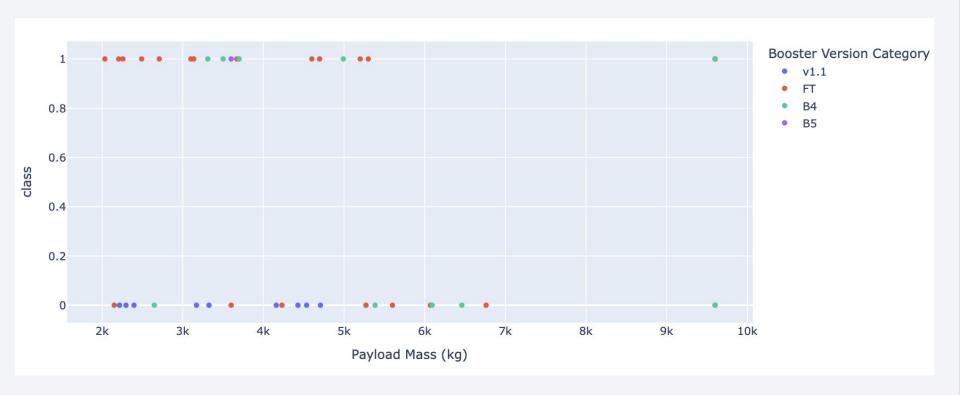


Highest Success Rate

• CCAFS SLC-40 @ 42.9% Success



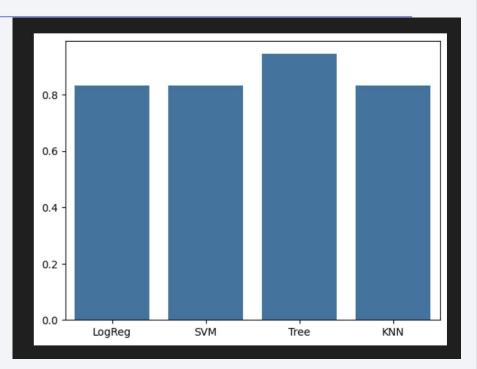
Payload Mass vs Outcomes





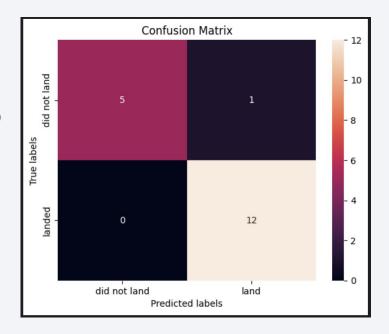
Classification Accuracy

The Decision Tree Classifier had the highest score, scoring .94 compared to .83.



Confusion Matrix

- The decision tree classifier correctly predicted 12 launches to land and 5 launches to not land.
- The model incorrectly predicted 1 launch to land that ultimately did not land.
- These results are fairly optimistic, but would like to see performance as more data becomes available.



Conclusions

 Many variables contribute to a successful launch and landing. The best predictions were able to predict 94% of landing outcomes successfully. This information is practical in pricing and bidding, designing successful launch/landing conditions, and improving unsuccessful launch/landing conditions.

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

