

Outline

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



Executive Summary

1

Results suggestion launches have a correlation with the outcome of the launches

2.

Decision Tree is the best machine learning algorithm to predict if the Falcon 9 first stage will land successfully.

3.Srd Executive Summary Element

Introduction



Project Overview

Analyze SpaceX Falcon 9 rocket landing success patterns using machine learning techniques.



Business Problem

Predict first stage landing success to determine launch costs and competitive bidding strategies against SpaceX.



The Challenge

SpaceX Falcon 9: \$62M per launch

Other providers: \$165M+ per launch

Cost advantage from first stage reusability

Need to predict landing success for competitive analysis



Project Goal

Develop a machine learning model to predict whether the Falcon 9 first stage will land successfully, enabling accurate cost estimation for competitive bidding.



Success Criteria

Create accurate predictive models using data science methodology including data collection, wrangling, exploratory analysis, visualization, and machine learning model development.



Methodology

Data Collection

API Access and Web Scraping

Data Wrangling

Cleaning and Processing

Exploratory Data Analysis

Exploration

Visualization

• Infographics Interactive Dashboards

Modeling

Algorithm Development

Evaluation

Results and Insights

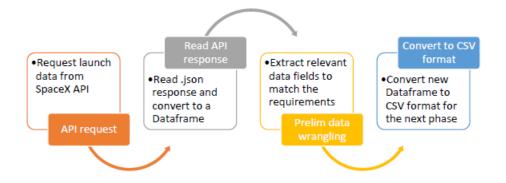
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Data Collection

SpaceX REST API

Historical launch data (2010-2020)
Rocket specifications & configurations
Mission details & outcomes
Landing success/failure records
Launch site information

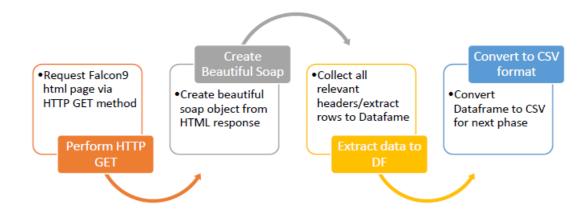
SpaceX API



Web Scraping (Wikipedia)

Falcon 9 launch history tables
Mission payload information
Orbit type classifications
Launch site details
Additional mission context

Web scraping data from Wiki



Data Collection Using SpaceX API

```
# 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

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 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 flightlumber Date BoosterVersion PayloadMass Orbit LaunchSite Outcome Flights GridFins Reused Legs

data['date'] = pd.to_datetime(data['date_utc']).dt.date
```

Notebook

data.head()

Output Dataset



Calculate the mean value of PayloadMass column

		05-01				40	None					
7	4	2013- 09-29	Falcon 9	500.0	РО	VAFB SLC 4E	False Ocean	1	False	False	False	
8	5	2013- 12-03	Falcon 9	3170.0	GTO	CCSFS SLC 40	None None	1	False	False	False	
		•••										
89	86	2020- 09-03	Falcon 9	15600.0	VLEO	KSC LC 39A	True ASDS	2	True	True	True	5e9
90	87	2020- 10-06	Falcon 9	15600.0	VLEO	KSC LC 39A	True ASDS	3	True	True	True	5e9
91	88	2020- 10-18	Falcon 9	15600.0	VLEO	KSC LC 39A	True ASDS	6	True	True	True	5e9
92	89	2020- 10-24	Falcon 9	15600.0	VLEO	CCSFS SLC 40	True ASDS	3	True	True	True	5e9
				1611	43.1		100					

Cleaning Things Up!

Using the date we will restrict the dates of the launches
data = data[data['date'] <= datetime.date(2020, 11, 13)]</pre>



```
payload_mean = data_falcon9['PayloadMass'].mean()

# Replace NaN values with the mean
data_falcon9.loc[:, 'PayloadMass'] = data_falcon9['PayloadMass'].replace(np.nan, payload_mean)
```

Web Scraping

```
column_names = []

# Apply find_all() function with `th` element on first_launch_table
# Iterate each th element and apply the provided extract_column_from_header() to get a column name
# Append the Non-empty column name (`if name is not None and len(name) > 0`) into a list called column_names
th_elements = first_launch_table.find_all('th')
for th in th_elements:
    name = extract_column_from_header(th)
    if name is not None and len(name) > 0:
        column_names.append(name)
```

```
# Orbit
if row[5].a:
   orbit = row[5].a.string
else:
   orbit = row[5].get text(strip=True)
launch dict['Orbit'].append(orbit)
# Customer
if row[6].a:
   customer = row[6].a.string
   customer = row[6].get_text(strip=True)
launch_dict['Customer'].append(customer)
# Launch outcome
launch_outcome = list(row[7].strings)[0]
launch dict['Launch outcome'].append(launch outcome)
# Booster Landing
booster landing = landing status(row[8])
launch dict['Booster landing'].append(booster landing)
```

Parsing

Notebook

Output Dataset

```
extracted_row = 0
for table_number,table in enumerate(soup.find_all('table',"wikitable plainrowheaders collapsible")):
   for rows in table.find_all("tr"):
       #check to see if first table heading is as number corresponding to launch a number
            if rows.th.string:
               flight number=rows.th.string.strip()
                flag=flight_number.isdigit()
       else:
            flag=False
       #get table element
       row=rows.find_all('td')
       #if it is number save cells in a dictonary
       if flag:
           extracted_row += 1
           # Flight Number value
            launch dict['Flight No.'].append(flight number)
            datatimelist=date time(row[0])
            # Date value
            date = datatimelist[0].strip(',')
            launch dict['Date'].append(date)
```

The Good Stuff!

Data Wrangling

Notebook

Output Dataset



Analyzed SpaceX Falcon 9 dataset with 90+ launch records, identifying that only LandingPad had missing values (28.9% missing data)

Launch Site Analysis

Discovered CCAFS SLC 40 had the most launches (55), followed by KSC LC 39A (22) and VAFB SLC 4E (13), with GTO being the most common orbit type (27 missions)

Binary Classification Labels

Created training labels by converting mission outcomes into binary format - successful landings (True Ocean, True RTLS, True ASDS) = 1, unsuccessful landings (False outcomes and None outcomes) = 0

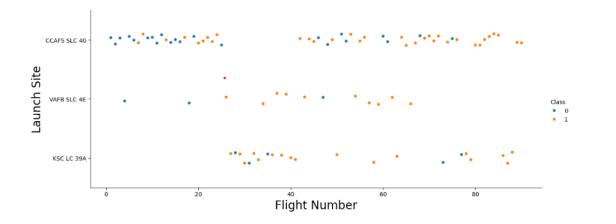
Success Rate Calculation

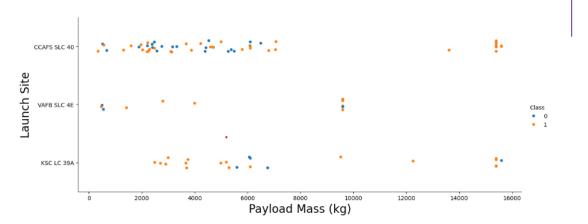
Determined overall landing success rate of 66.7% across all missions, providing baseline performance metric for predictive modeling

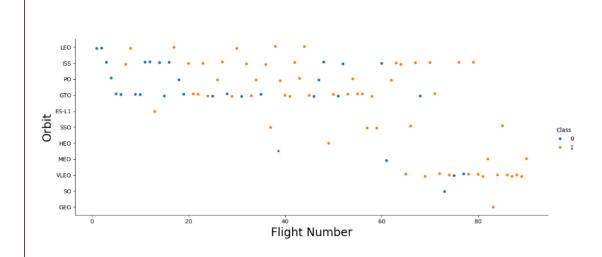
Dataset Preparation

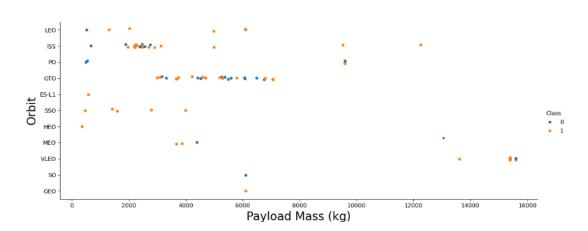
Exported cleaned and labeled dataset for machine learning model development, with all features properly categorized as numerical or categorical variables

Visualization





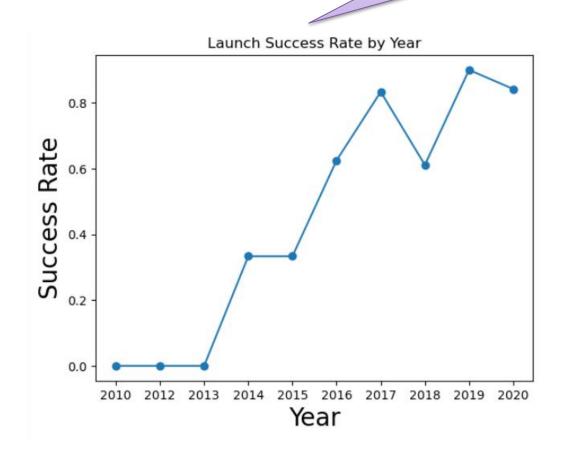




Visualization

Notebook

Output Dataset



Notebook

Database

%%sql
SELECT DISTINCT "Launch_Site"
FROM SPACEXTABLE;

Unique launch site

```
%%sql
SELECT *
FROM SPACEXTABLE
WHERE "Launch_Site" LIKE 'CCA%'
LIMIT 5;
```

Launch sites with 'CCA"

```
%%sql
SELECT AVG("PAYLOAD_MASS__KG_") AS "Average_Payload_Mass"
FROM SPACEXTABLE
WHERE "Booster_Version" = 'F9 v1.1';
```

Average payload mass carried by booster version F9 v1.1

```
%%sql
SELECT "Booster_Version"
FROM SPACEXTABLE
WHERE "Landing_Outcome" = 'Success (drone ship)'
AND "PAYLOAD_MASS__KG_" > 4000
AND "PAYLOAD_MASS__KG_" < 6000;</pre>
```

Names of boosters between 4 and 6K

```
%%sql
SELECT SUM("PAYLOAD_MASS__KG_") AS "Total_Payload_Mass"
FROM SPACEXTABLE
WHERE "Customer" LIKE '%CRS%';
```

Total payload mass carried by boosters launched by NASA (CRS)

```
%%sql
SELECT MIN("Date") AS "First_Successful_Ground_Landing"
FROM SPACEXTABLE
WHERE "Landing_Outcome" = 'Success (ground pad)'
```

Date when the first successful landing outcome

```
%%sql
SELECT "Mission_Outcome", COUNT(*) AS "Count"
FROM SPACEXTABLE
GROUP BY "Mission_Outcome";
```

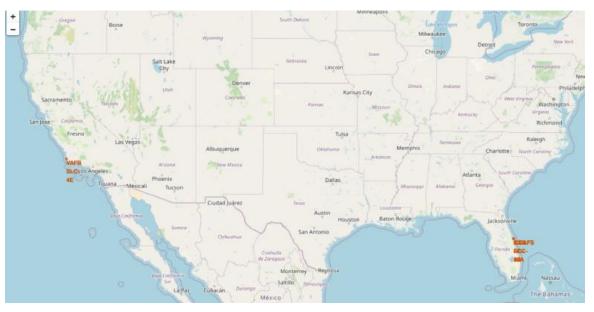
Mission success

```
%%sql
SELECT
   SUBSTR("Date", 6, 2) AS "Month",
   "Landing_Outcome",
   "Booster_Version",
   "Launch_Site"
FROM SPACEXTABLE
WHERE SUBSTR("Date", 0, 5) = '2015'
AND "Landing_Outcome" = 'Failure (drone ship)';
```

```
%%sql
SELECT "Booster_Version"
FROM SPACEXTABLE
WHERE "PAYLOAD_MASS__KG_" = (
    SELECT MAX("PAYLOAD_MASS__KG_")
    FROM SPACEXTABLE
);
```

Booster version







Site Location Mapping

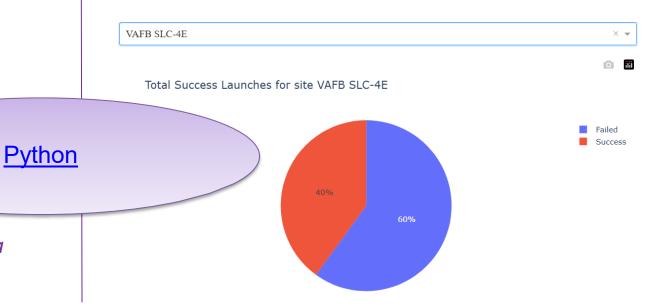
Proximaty Analysis Lat: 34.63164 Long: -120.61005 + Marine Lat: 28.51278 Long: -80.52422 Lat: 34.63164 Long: -120.61005 + FL 405 ape Canaveral Space Force Station Port Saint John **Notebook** Leaflet **Cluster Markers Measuring Distances**

Dynamic success analysis

Launch site comparison



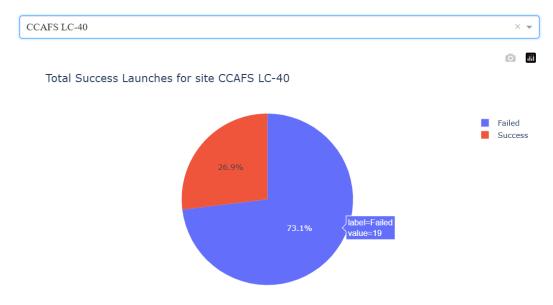
- Kennedy Space Center (KSC) Florida
- Cape Canaveral Air Force Station (CCAFS) Florida
- Vandenberg Air Force Base (VAFB) California

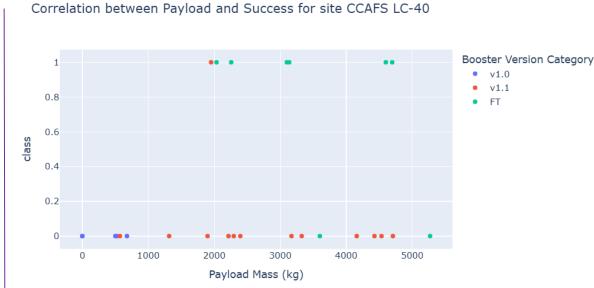


VAFB SLC-4E

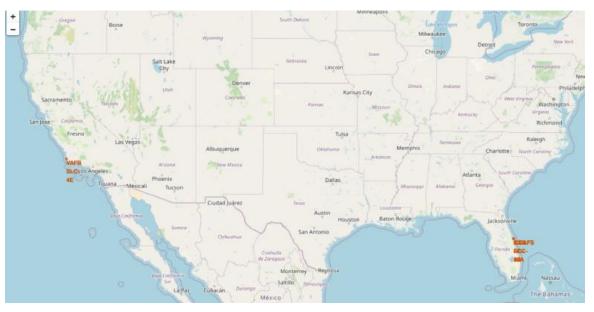
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Results Dashboard





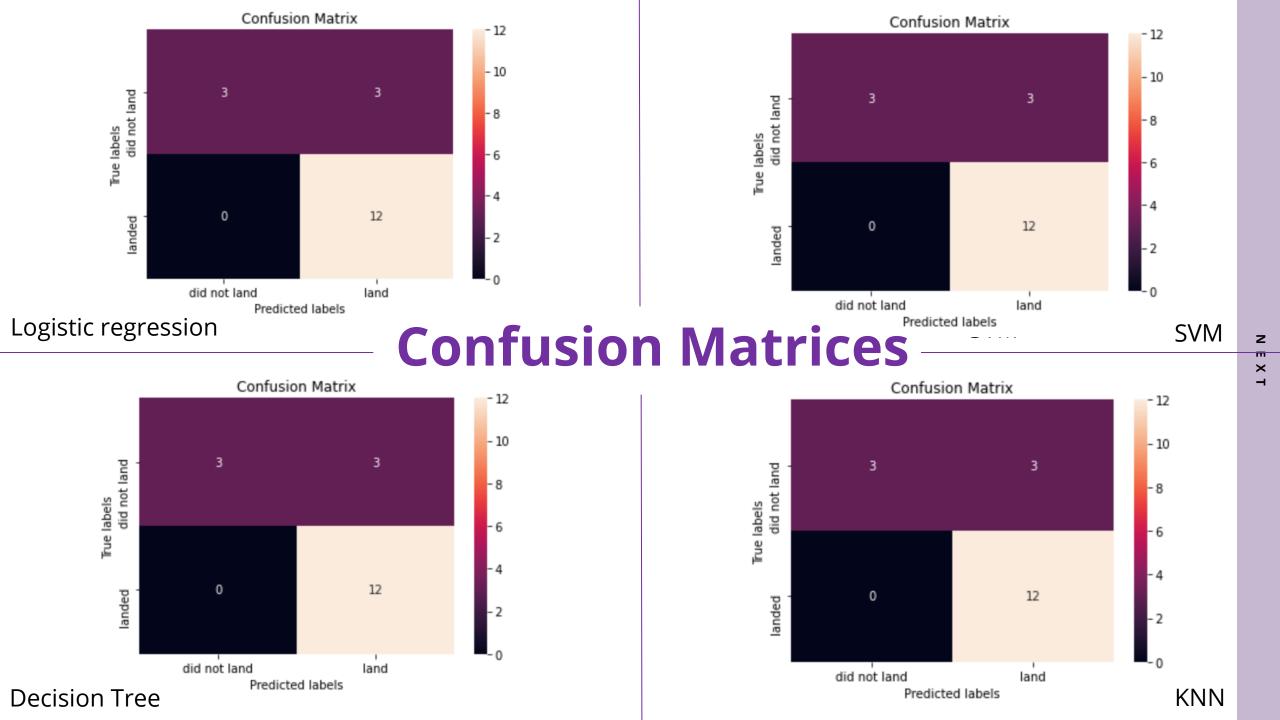
Correlation: Payload and Success—CCAFS LC-40





Site Location Mapping

Proximaty Analysis Lat: 34.63164 Long: -120.61005 + Marine Lat: 28.51278 Long: -80.52422 Lat: 34.63164 Long: -120.61005 + FL 405 ape Canaveral Space Force Station Port Saint John **Notebook** Leaflet **Cluster Markers Measuring Distances**



Predictive Analysis



Models Used

- Logistic Regression
- Support Vector Machine (SVM)
- Decision Tree Classifier
- K-Nearest Neighbors (KNN)



Input Features

- Flight Number (experience proxy)
- Payload Mass (kg)
- Orbit Type (LEO, GTO, etc.)
- Launch Site (encoded)
- Grid Fins, Legs, Landing Pad



Training Process

- Data Split: 80% training, 20% testing
- Preprocessing: StandardScaler for feature normalization
- Optimization: GridSearchCV with 5-fold cross-validation
- Evaluation: Accuracy, Precision, Recall, F1-Score, AUC-ROC

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Model Performance Results

Notebook

83.3%

Decision Tree Accuracy

83.3%

SVM Accuracy

80.0%

Logistic Regression

66.7%

KNN Accuracy



- Decision Tree & SVM tied at 83.3%
- ▶ Excellent precision and recall balance
- ► Consistent cross-validation performance
- Low overfitting risk



- ▶ Precision: ~85%
- ► Recall: ~80%
- ► F1-Score: ~82%
- ► AUC-ROC: ~0.85

o Model Selection Rationale

Decision Tree was selected as the final model due to its interpretability and robust performance. The 83.3% accuracy provides reliable predictions for business decision-making while maintaining model transparency.

Key Insights



Success Factors Identified

- Experience matters: Success improves with flight number
- Heavy payloads correlate with higher success rates
- KSC LC-39A shows superior performance
- LEO missions have different patterns than GTO



Temporal

- Dramatic improvement from 2015-2020
- Clear organizational learning curve
- Recent missions achieve 80%+ success
- Technology advancement visible in data

Project Achievements

- Developed predictive models with 83% accuracy
- Identified critical success factors
- Created actionable business intelligence
- Demonstrated complete data science methodology

Technical Accomplishments

- Comprehensive data collection & processing
- Interactive visualizations & dashboards
- Multiple ML model evaluation & optimization
- Geospatial analysis with mapping



Appendix

- Data Collection (SpaceX API)
 - <u>Notebook</u>
 - Output Dataset
- Web Scraping (Wikipedia)
 - <u>Notebook</u>
 - Output Dataset
- Data Wrangling
 - <u>Notebook</u>
 - Output Dataset
- Visualization
 - <u>Notebook</u>
 - Output Dataset
- SQL
 - Notebook
 - Database



- Proximity Analysis
 - <u>Notebook</u>
- Results Dashboard (Plotly Dash)
 - <u>Python</u>
- Predictive Modeling
 - Notebool