

Outline

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Executive Summary

- In this capstone project, we will predict if the SpaceX Falcon 9 first stage will land successfully using several machine learning classification algorithms.
- The main steps in this project include:
 - · Data collection, wrangling, and formatting
 - Exploratory data analysis
 - Interactive data visualization
 - Machine learning prediction
- Our graphs show that some features of the rocket launches have a correlation with the outcome of the launches, i.e., success or failure.
- It is also concluded that decision tree may be the best machine learning algorithm to predict if the Falcon 9 first stage will land successfully.

Introduction

- In this capstone, we will predict if the Falcon 9 first stage will land successfully. SpaceX advertises Falcon 9 rocket launches on its website with a cost of 62 million dollars; other providers cost upward of 165 million dollars each, much of the savings is because SpaceX can reuse the first stage. Therefore if we can determine if the first stage will land, we can determine the cost of a launch. This information can be used if an alternate company wants to bid against SpaceX for a rocket launch.
- Most unsuccessful landings are planned. Sometimes, SpaceX will perform a controlled landing in the ocean.
- The main question that we are trying to answer is, for a given set of features about a Falcon 9 rocket launch which include its payload mass, orbit type, launch site, and so on, will the first stage of the rocket land successfully?

Methodology

- The overall methodology includes:
 - 1. Data collection, wrangling, and formatting, using:
 - SpaceX API
 - Web scraping
 - 2. Exploratory data analysis (EDA), using:
 - Pandas and NumPy
 - SQL
 - 3. Data visualization, using:
 - Matplotlib and Seaborn
 - Folium
 - Dash
 - 4. Machine learning prediction, using
 - Logistic regression
 - Support vector machine (SVM)
 - Decision tree
 - K-nearest neighbors (KNN)

Data Collection

1. API Request and read response into DF

2. Declare global variables

Call helper functions with API calls to populate global vars

4. Construct data using dictionary

5. Convert Dict to Dataframe, filter for Falcon9 launches, covert to CSV

 Create API GET request, normalize data and read in to a Dataframe:

```
spacex_url="https://api.spacexdata.com/v4/launches/past"
response = requests.get(spacex_url)
# Use json_normalize meethod to convert the json
data = pd.json_normalize(response.json())
```

 Declare global variable lists that will store data returned by helper functions with additional API calls to get relevant data #GLobal variables

```
#GLobal variables
BoosterVersion = []
PayloadMass = []
Orbit = []
LaunchSite = []
Outcome = []
Flights = []
GridFins = []
Reused = []
Legs = []
LandingPad = []
Block = []
ReusedCount = []
Serial = []
Longitude = []
Latitude = []
```

- Call helper functions to get relevant data where columns have IDs (e.g., rocket column is an identification number)
 - getBoosterVersion(data)
 - getLaunchSite(data)
 - getPayloadData(data)
 - getCoreData(data)
- Construct dataset from received data & combine columns into a dictionary:

```
launch_dict = {'FlightNumber': list(data['flight_number']),
'Date': list(data['date']),
'BoosterVersion':BoosterVersion,
'PayloadMass':PayloadMass,
'Orbit':Orbit,
'LaunchSite':LaunchSite.
'Outcome':Outcome,
'Flights':Flights,
'GridFins':GridFins,
'Reused':Reused,
'Legs':Legs,
'LandingPad':LandingPad,
'Block':Block,
'ReusedCount':ReusedCount,
'Serial':Serial,
'Longitude': Longitude,
'Latitude': Latitude}
```

4. Create Dataframe from dictionary and filter to keep only the Falcon9 launches:

Create a data from Launch dict

```
df_launch = pd.DataFrame(launch_dict)

# Hint data['BoosterVersion']!='Falcon 1'
data_falcon9 = df_launch[df_launch['BoosterVersion']!= 'falcon 1']

data_falcon9.to_csv('dataset_part\ 1.csv', index=False)
```

GitHub 8

Data Collection - Scraping

1. Perform HTTP GET to request HTML page 2. Create Beautiful Soap object

3. Extract column names from HTML table header 4. Create Dictionary with keys from extracted column names

Call helper functions to fill up dict with launch records 6. Convert Dictionary to Dataframe

 Create API GET method to request Falcon9 launch HTML page

```
static_url = "https://en.wikipedia.org/w/index.php?title-list_of_Falcon_9_and_Falcon_Heavy_launcheskoldid=1827885992"

html_data = requests.get(static_url).text
```

2. Create Beautiful Soap object
soup = Beautiful Soup(html_data, "html.parser")

 Find all the tables on the Wiki page and extract relevant column names from the HTML table header

```
html_tables = soup.find_all ('table')
column_names = []

# Apply find_all() function with `th` element on firs
# Iterate each th element and apply the provided extr
# Append the Non-empty column name ('if name is not N
colnames = soup.find_all('th')
for x in range (len(colnames)):
    name2 = extract_column_from_header(colnames[x])
    if (name2 is not None and len(name2) > 3):
        column_names.append(name2)
```

 Create an empty Dictionary with keys from extracted column names:

```
launch_dict= dict.fromkeys(column_names)
# Remove an irrelvant column
del launch dict['Date and time ( )']
# Let's initial the launch dict with each vc
launch dict['Flight No.'] = []
launch_dict['Launch site'] = []
launch_dict['Payload'] = []
launch dict['Payload mass'] = []
launch dict['Orbit'] = []
launch dict['Customer'] = []
launch_dict['Launch outcome'] = []
# Added some new columns
launch dict['Version Booster']=[]
launch_dict['Booster landing']=[]
launch dict['Date']=[]
launch dict['Time']=[]
```

- Fill up the launch_dict with launch records extracted from table rows.
 - Utilize following helper functions to help parse HTML data

```
def date_time(table_cells):
    def booster_version(table_cells):
    def landing_status(table_cells):
    def get_mass(table_cells):
```

6. Convert launch dict to Dataframe:

```
df=pd.DataFrame(launch dict)
```

Data Wrangling

- The data is later processed so that there are no missing entries and categorical features are encoded using one-hot encoding.
- An extra column called 'Class' is also added to the data frame. The column 'Class' contains 0 if a given launch is failed and 1 if it is successful.
- In the end, we end up with 90 rows or instances and 83 columns or features.

EDA with Data Visualization





- Pandas and NumPy
 - Functions from the Pandas and NumPy libraries are used to derive basic information about the data collected, which includes:
 - The number of launches on each launch site
 - The number of occurrence of each orbit
 - The number and occurrence of each mission outcome





- The data is queried using SQL to answer several questions about the data such as:
 - The names of the unique launch sites in the space mission
 - The total payload mass carried by boosters launched by NASA (CRS)
 - The average payload mass carried by booster version F9 v1.1

• The names of the unique launch sites in the space mission

Launch_Sites
CCAFS LC-40
CCAFS SLC-40
KSC LC-39A
VAFB SLC-4E

• 5 records where launch sites begin with 'CCA'

DATE	timeutc_	booster_version	launch_site	payload	payload_masskg_	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	07:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	No attempt
2012-10-08	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
2013-03-01	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

The total payload mass carried by boosters launched by NASA (CRS)

Total payload mass by NASA (CRS) 45596

• The average payload mass carried by booster version F9 v1.1

Average payload mass by Booster Version F9 v1.1 2928

• The date when the first successful landing outcome in ground pad was achieved

Date of first successful landing outcome in ground pad 2015-12-22

• The names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000



• The total number of successful and failure mission outcomes

```
number_of_success_outcomes number_of_failure_outcomes

100 1
```

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

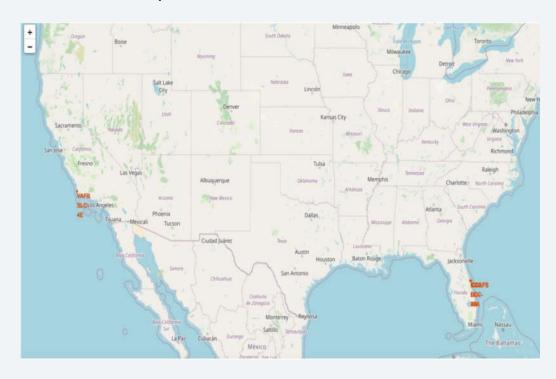


 The count of landing outcomes between the date 2010-06-04 and 2017-03-20, in descending order

landing_outcome	landing_count
No attempt	10
Failure (drone ship)	5
Success (drone ship)	5
Controlled (ocean)	3
Success (ground pad)	3
Failure (parachute)	2
Uncontrolled (ocean)	2
Precluded (drone ship)	1

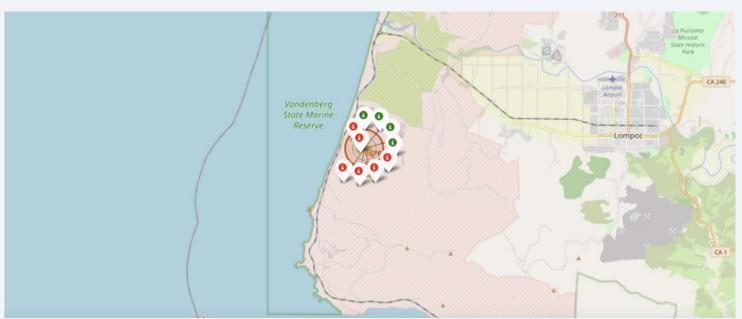
Build an Interactive Map with Folium

All launch sites on map



Build an Interactive Map with Folium

- The succeeded launches and failed launches for each site on map
 - If we zoom in on one of the launch site, we can see green and red tags. Each green tag represents a successful launch while each red tag represents a failed launch



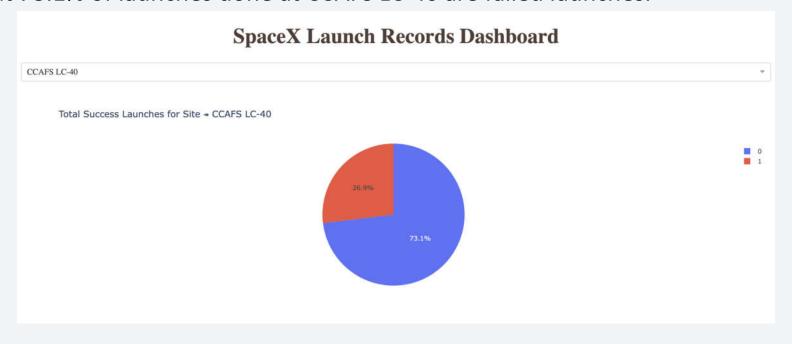
Build an Interactive Map with Folium

- The distances between a launch site to its proximities such as the nearest city, railway, or highway
 - The picture below shows the distance between the VAFB SLC-4E launch site and the nearest coastline



Build a Dashboard with Plotly Dash

- The picture below shows a pie chart when launch site CCAFS LC-40 is chosen.
- 0 represents failed launches while 1 represents successful launches. We can see that 73.1% of launches done at CCAFS LC-40 are failed launches.



Build a Dashboard with Plotly Dash

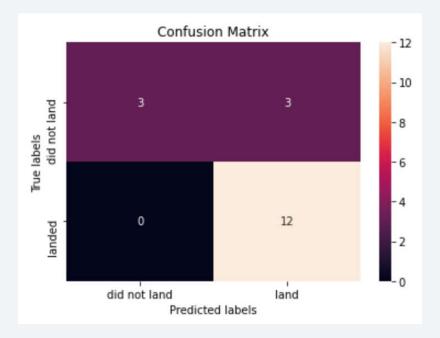
- The picture below shows a scatterplot when the payload mass range is set to be from 2000kg to 8000kg.
- Class 0 represents failed launches while class 1 represents successful launches.



Predictive Analysis (Classification)

- Logistic regression
 - GridSearchCV best score: 0.8464285714285713

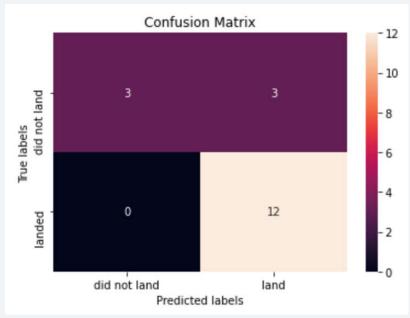
 - Confusion matrix:



Predictive Analysis (Classification)

- Decision tree
 - GridSearchCV best score: 0.8892857142857142

 - Confusion matrix:



Predictive Analysis (Classification)

- K nearest neighbors (KNN)
 - GridSearchCV best score: 0.8482142857142858

 - Confusion matrix:

