

Winning Space Race with Data Science

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Executive Summary

- Summary of methodologies
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Introduction

- Project background and context

Space X 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 Space X 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 space X for a rocket launch. This goal of the project is to create a machine learning pipeline to predict if the first stage will land successfully.

- Problems you want to find answers

- What factors determine if the rocket will land successfully?
- The interaction amongst various features that determine the success rate of a successful landing.
- What operating conditions needs to be in place to ensure a successful landing program.

Section 1

Methodology

Methodology

Executive Summary

- Data collection methodology:
 - Data was collected using SpaceX API and web scraping from Wikipedia.
- Perform data wrangling
 - One-hot encoding was applied to categorical features
- 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

- The data was collected using various methods
 - Data collection was done using get request to the SpaceX API.
 - Next, we decoded the response content as a Json using `.json()` function call and turn it into a pandas dataframe using `.json_normalize()`.
 - We then cleaned the data, checked for missing values and fill in missing values where necessary.
 - In addition, we performed web scraping from Wikipedia for Falcon 9 launch records with BeautifulSoup.
 - The objective was to extract the launch records as HTML table, parse the table and convert it to a pandas dataframe for future analysis.

Data Collection – SpaceX API

- We used the get request to the SpaceX API to collect data, clean the requested data and did some basic data wrangling and formatting.
- The link to the notebook is <https://github.com/chuksoo/IBM-Data-Science-Capstone-SpaceX/blob/main/Data%20Collection%20API.ipynb>.

Task 1: Request and parse the SpaceX launch data using the GET request

To make the requested JSON results more consistent, we will use the following static response object for this project:

```
static_json_url='https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/datasets/API_call_spacex_api.json'
```

We should see that the request was successful with the 200 status response code

```
response.status_code
```

200

Now we decode the response content as a json using `.json()` and turn it into a Pandas dataframe using `.json_normalize()`

```
# Use json_normalize method to convert the json result into a dataframe
jlist = requests.get(static_json_url).json()
df2 = pd.json_normalize(jlist)
df2.head()
```


Task 2: Filter the dataframe to only include Falcon 9 launches

Finally we will remove the Falcon 1 launches keeping only the Falcon 9 launches. Filter the data dataframe using the `BoosterVersion` column to only keep the Falcon 9 launches. Save the filtered data to a new dataframe called `data_falcon9`.

```
# Hint data['BoosterVersion']!='Falcon 1'  
data_falcon9.drop(data_falcon9[data_falcon9['BoosterVersion']!='Falcon 9'].index, inplace = True)
```

Now that we have removed some values we should reset the `FlightNumber` column

```
data_falcon9.loc[:, 'FlightNumber'] = list(range(1, data_falcon9.shape[0]+1))  
data_falcon9
```

Data Collection - Scraping

- We applied web scrapping to webscrap Falcon 9 launch records with BeautifulSoup
- We parsed the table and converted it into a pandas dataframe.
- The link to the notebook is <https://github.com/chuksoo/IBM-Data-Science-Capstone-SpaceX/blob/main/Data%20Collection%20with%20Web%20Scraping.ipynb>.

```
1. Apply HTTP Get method to request the Falcon 9 rocket launch page

In [4]: static_url = "https://en.wikipedia.org/w/index.php?title=List_of_Falcon_9_and_Falcon_Heavy_launches&oldid=1027686922"

In [5]: # use requests.get() method with the provided static_url
        # assign the response to a object
        html_data = requests.get(static_url)
        html_data.status_code

Out[5]: 200

2. Create a BeautifulSoup object from the HTML response

In [6]: # Use BeautifulSoup() to create a BeautifulSoup object from a response text content
        soup = BeautifulSoup(html_data.text, 'html.parser')

        Print the page title to verify if the BeautifulSoup object was created properly

In [7]: # Use soup.title attribute
        soup.title

Out[7]: <title>List of Falcon 9 and Falcon Heavy launches - Wikipedia</title>

3. Extract all column names from the HTML table header

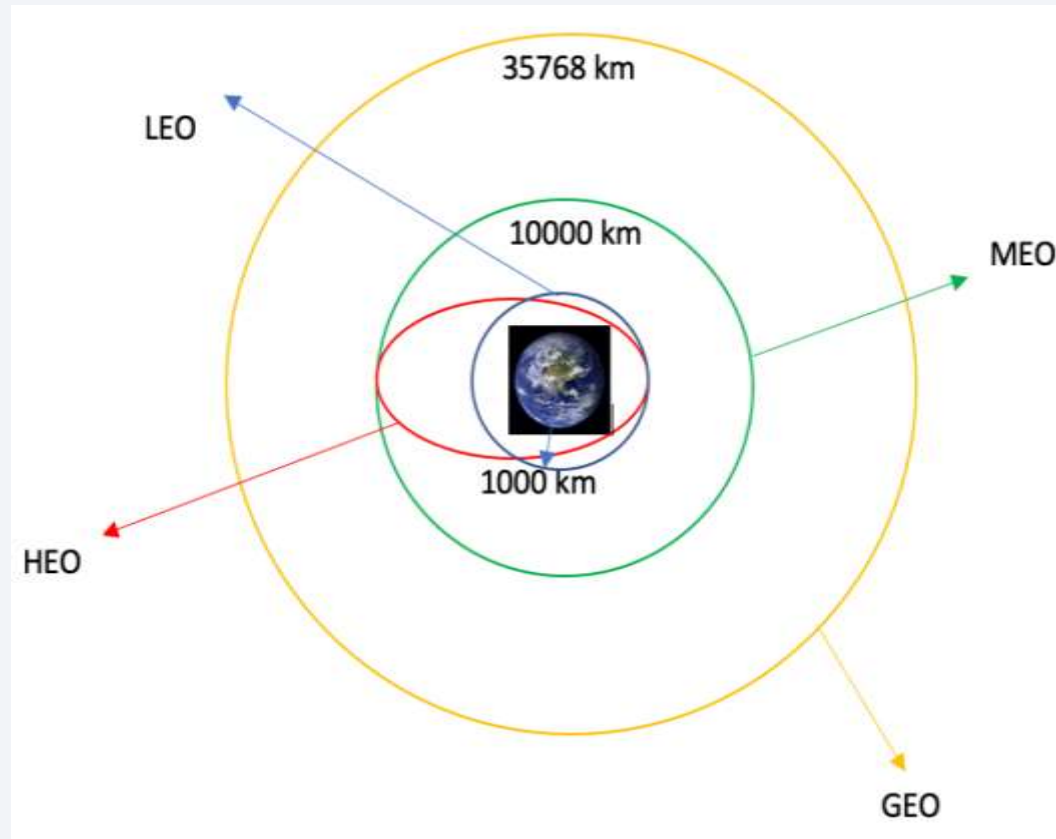
In [10]: column_names = []

        # 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

        element = soup.find_all('th')
        for row in range(len(element)):
            try:
                name = extract_column_from_header(element[row])
                if (name is not None and len(name) > 0):
                    column_names.append(name)
            except:
                pass

4. Create a dataframe by parsing the launch HTML tables
5. Export data to csv
```

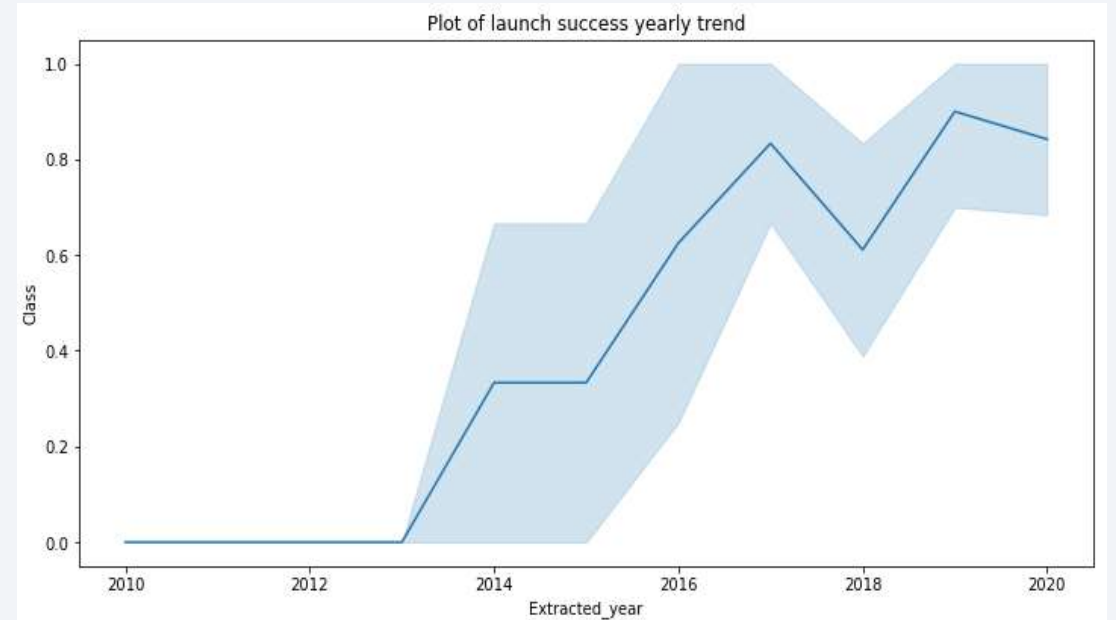
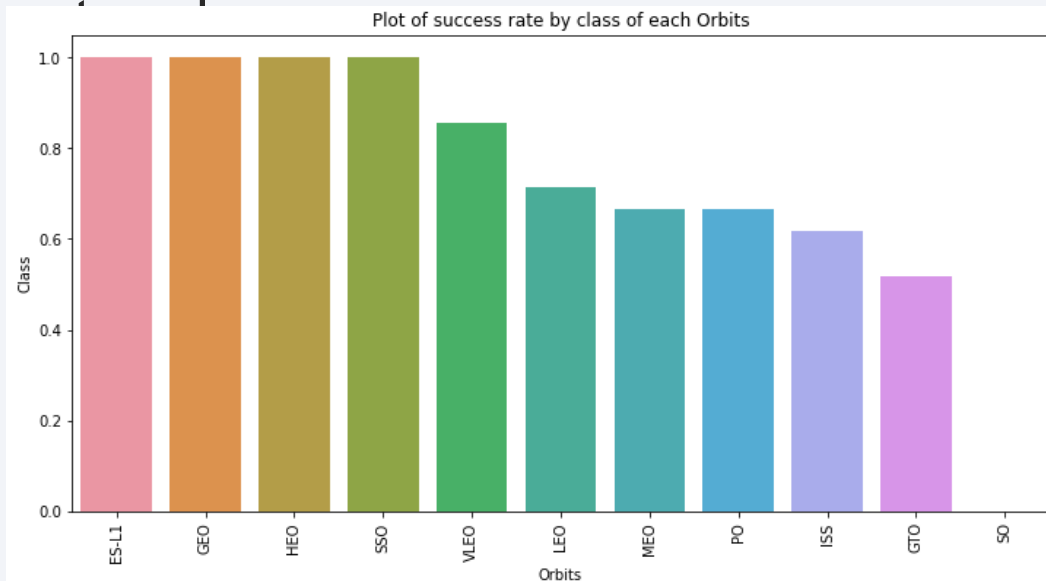
Data Wrangling



- We performed exploratory data analysis and determined the training labels.
- We calculated the number of launches at each site, and the number and occurrence of each orbits
- We created landing outcome label from outcome column and exported the results to csv.
- The link to the notebook is <https://github.com/chuksoo/IBM-Data-Science-Capstone-SpaceX/blob/main/Data%20Wrangling.ipynb>.

EDA with Data Visualization

- We explored the data by visualizing the relationship between flight number and launch Site, payload and launch site, success rate of each orbit type, flight number and orbit type, the launch success yearly



- The link to the notebook is <https://github.com/chuksoo/IBM-Data-Science-Capstone-SpaceX/blob/main/EDA%20with%20Data%20Visualization.ipynb>

EDA with SQL

- We loaded the SpaceX dataset into a PostgreSQL database without leaving the jupyter notebook.
- We applied EDA with SQL to get insight from the data. We wrote queries to find out for instance:
 - The names of 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 total number of successful and failure mission outcomes
 - The failed landing outcomes in drone ship, their booster version and launch site names.
- The link to the notebook is <https://github.com/chuksoo/IBM-Data-Science-Capstone-SpaceX/blob/main/EDA%20with%20SQL.ipynb>

Build an Interactive Map with Folium

- We marked all launch sites, and added map objects such as markers, circles, lines to mark the success or failure of launches for each site on the folium map.
- We assigned the feature launch outcomes (failure or success) to class 0 and 1.i.e., 0 for failure, and 1 for success.
- Using the color-labeled marker clusters, we identified which launch sites have relatively high success rate.
- We calculated the distances between a launch site to its proximities. We answered some question for instance:
 - Are launch sites near railways, highways and coastlines.
 - Do launch sites keep certain distance away from cities.

Predictive Analysis (Classification)

- We loaded the data using numpy and pandas, transformed the data, split our data into training and testing.
- We built different machine learning models and tune different hyperparameters using GridSearchCV.
- We used accuracy as the metric for our model, improved the model using feature engineering and algorithm tuning.
- We found the best performing classification model.
- The link to the notebook is <https://github.com/chuksoo/IBM-Data-Science-Capstone-SpaceX/blob/main/Machine%20Learning%20Prediction.ipynb>

Results

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

The background of the slide is an abstract composition. It features a solid blue area on the left side, which transitions into a dynamic pattern of diagonal streaks in shades of blue, red, and cyan on the right. These streaks have a textured, almost woven appearance, suggesting a digital or data-driven theme. The overall effect is one of movement and complexity.

Section 2

Insights drawn from EDA

Flight Number vs. Launch Site

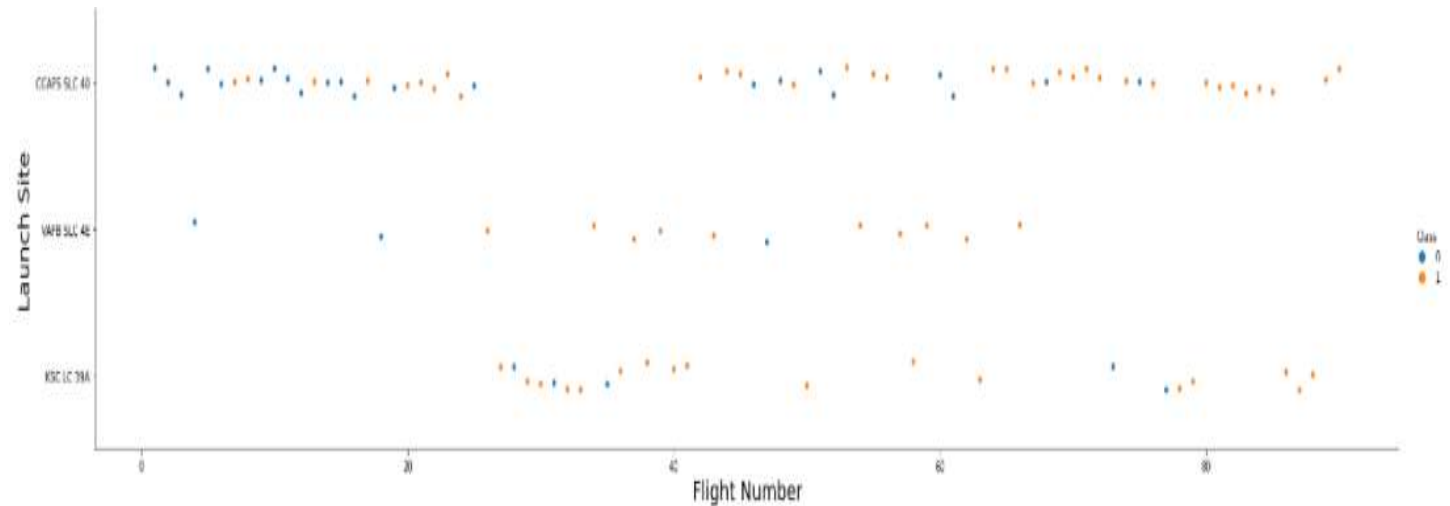
- From the plot, we found that the larger the flight amount at a launch site, the greater the success rate at a launch site.



Payload vs. Launch Site

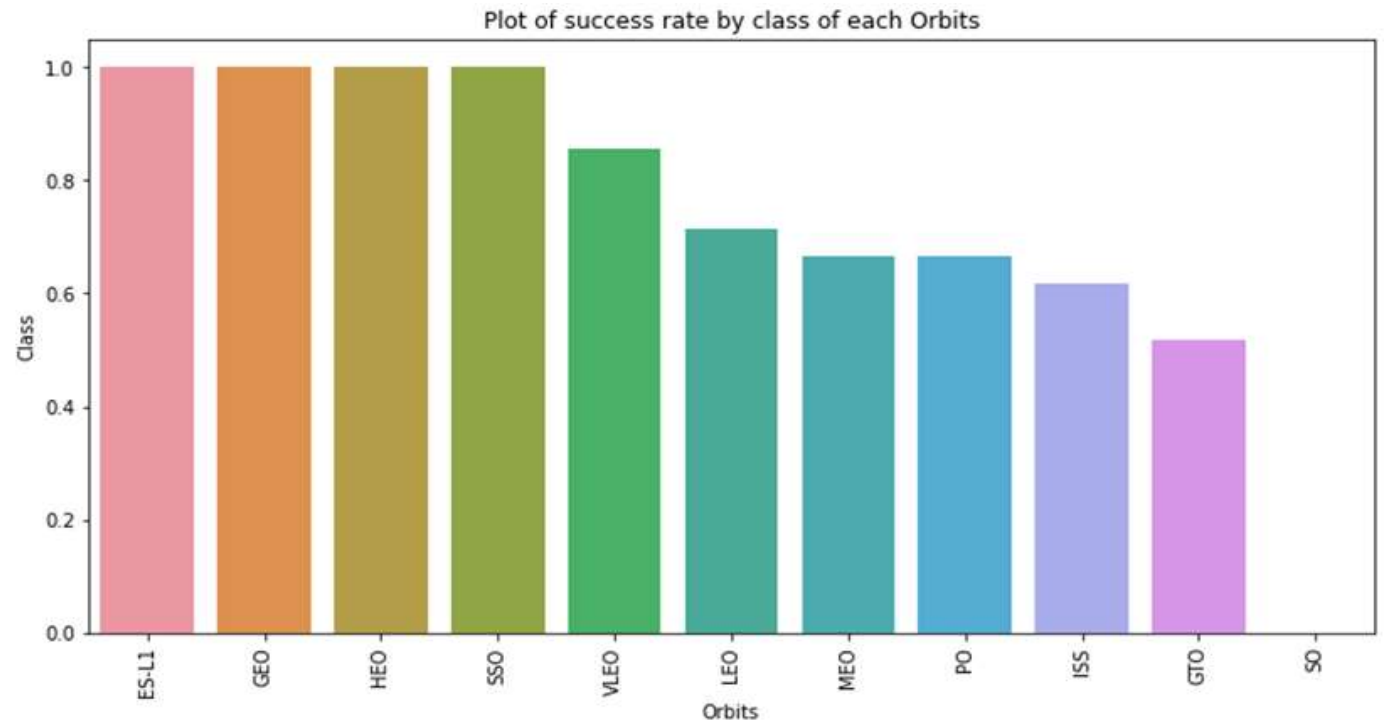


The greater the payload mass for launch site CCAFS SLC 40 the higher the success rate for the rocket.



Success Rate vs. Orbit Type

- From the plot, we can see that ES-L1, GEO, HEO, SSO, VLEO had the most success rate.



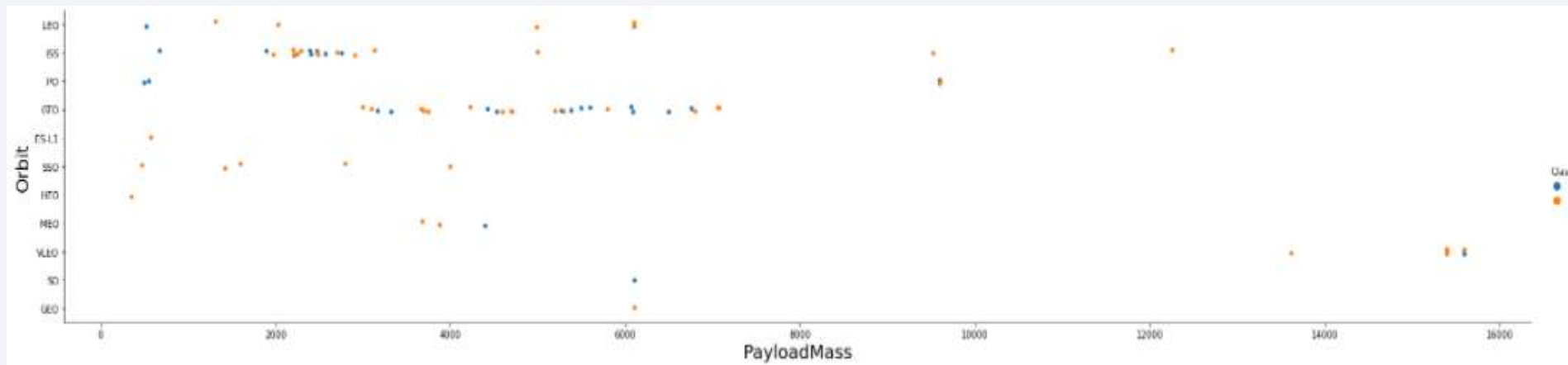
Flight Number vs. Orbit Type

- The plot below shows the Flight Number vs. Orbit type. We observe that in the LEO orbit, success is related to the number of flights whereas in the GTO orbit, there is no relationship between flight number and the orbit.



Payload vs. Orbit Type

- We can observe that with heavy payloads, the successful landing are more for PO, LEO and ISS orbits.



Launch Success Yearly Trend

- From the plot, we can observe that success rate since 2013 kept on increasing till 2020.



All Launch Site Names

- We used the key word **DISTINCT** to show only unique launch sites from the SpaceX data.

Task 1

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

```
%sql SELECT DISTINCT Launch_Site FROM SPACEXTBL
```

```
* sqlite:///my_data1.db  
Done.
```

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

Launch Site Names Begin with 'CCA'

Task 2

Display 5 records where launch sites begin with the string 'CCA'

```
%sql SELECT *FROM SPACEXTBL WHERE Launch_Site LIKE 'CCA%' LIMIT 5
```

```
* sqlite:///my_data1.db  
Done.
```

Date	Time (UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS_KG_	Orbit	Customer	Mission_Outcome	Landing_Outcome
04-06-2010	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
08-12-2010	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)
22-05-2012	07:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	No attempt
08-10-2012	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
01-03-2013	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

- We used the query above to display 5 records where launch sites begin with 'CCA'

Total Payload Mass

- We calculated the total payload carried by boosters from NASA as 45596 using the query below

Task 3

Display the total payload mass carried by boosters launched by NASA (CRS)

```
%sql SELECT SUM(PAYLOAD_MASS_KG_) AS Total_PayloadMass FROM SPACEXTBL WHERE Customer LIKE 'NASA (CRS)'
```

```
* sqlite:///my_data1.db
```

```
Done.
```

```
: Total_PayloadMass
```

```
45596
```


Average Payload Mass by F9 v1.1

- We calculated the average payload mass carried by booster version F9 v1.1 as 2928.4

Task 4

Display average payload mass carried by booster version F9 v1.1

```
%sql SELECT AVG(PAYLOAD_MASS_KG_) AS Avg_PayloadMass FROM SPACEXTBL WHERE Booster_Version = 'F9 v1.1'
```

```
* sqlite:///my_data1.db
```

```
Done.
```

Avg_PayloadMass

2928.4

Total Number of Successful and Failure Mission Outcomes

- We used wildcard like '%' to filter for **WHERE** MissionOutcome was a success or a failure.

Task 7

List the total number of successful and failure mission outcomes

```
%sql SELECT COUNT(Mission_Outcome) AS "Successful Mission" FROM SPACEXTBL WHERE Mission_Outcome LIKE 'Success%';
```

```
* sqlite:///my_data1.db
```

```
Done.
```

```
Successful Mission
```

```
100
```

```
%sql SELECT COUNT(Mission_Outcome) AS "Failure Mission" FROM SPACEXTBL WHERE Mission_Outcome LIKE 'Failure%';
```

```
* sqlite:///my_data1.db
```

```
Done.
```

```
Failure Mission
```

Boosters Carried Maximum Payload

- We determined the booster that have carried the maximum payload using a subquery in the **WHERE** clause and the **MAX()** function.

Task 8

List the names of the booster_versions which have carried the maximum payload mass. Use a subquery

```
%sql SELECT DISTINCT Booster_Version AS "Booster Versions which carried the Maximum Payload Mass" FROM SPACEXTBL \
WHERE PAYLOAD_MASS__KG_ =(SELECT MAX(PAYLOAD_MASS__KG_) FROM SPACEXTBL);
```

```
* sqlite:///my_data1.db
```

Done.

Booster Versions which carried the Maximum Payload Mass

F9 B5 B1048.4
F9 B5 B1049.4
F9 B5 B1051.3
F9 B5 B1056.4
F9 B5 B1048.5
F9 B5 B1051.4
F9 B5 B1049.5
F9 B5 B1060.2
F9 B5 B1058.3
F9 B5 B1051.6
F9 B5 B1060.3
F9 B5 B1049.7

A satellite view of Earth from space, showing the curvature of the planet and city lights at night. The image is a composite of a solid blue background on the left and a satellite photograph of Earth on the right. The Earth's surface is dark, with numerous bright yellow and orange lights representing cities and urban areas. The horizon line of the Earth is visible, separating the dark surface from the deep blue of the sky.

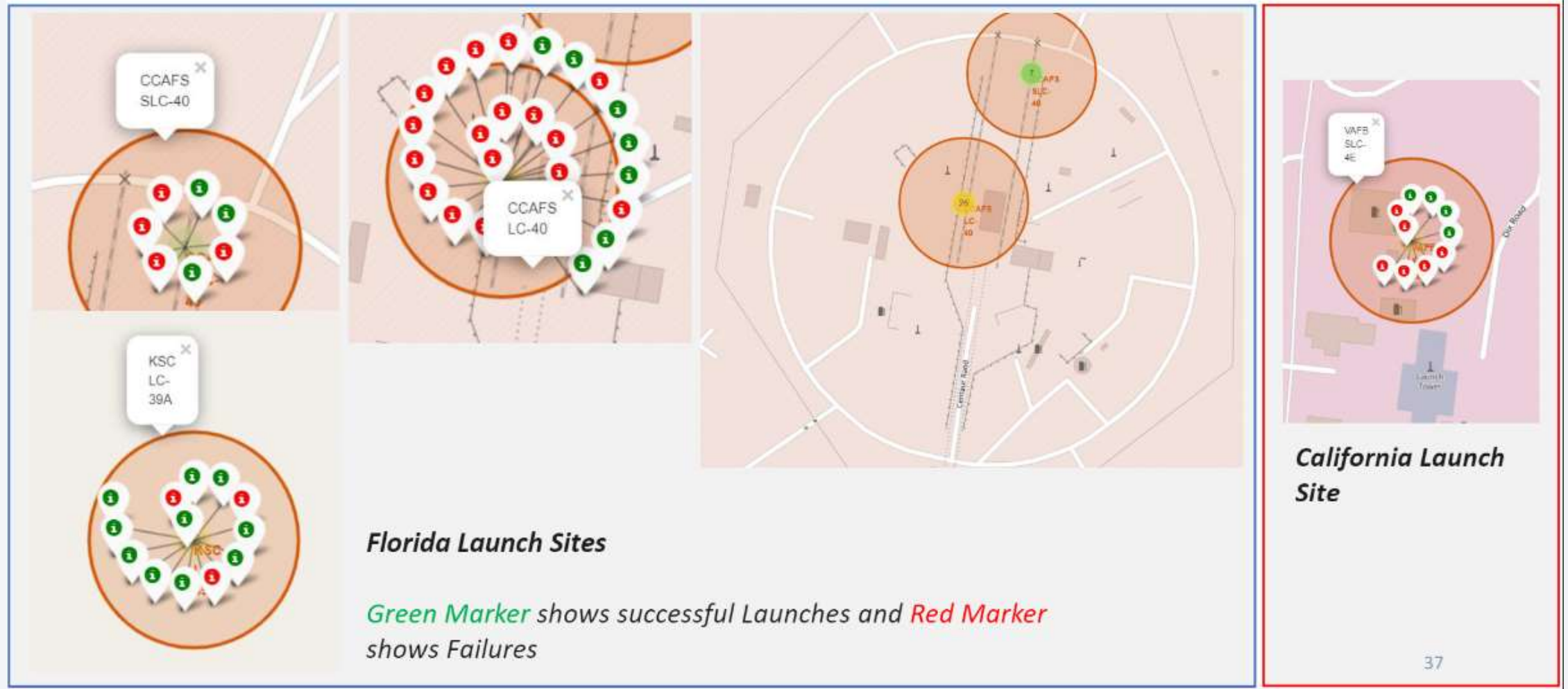
Section 4

Launch Sites Proximities Analysis

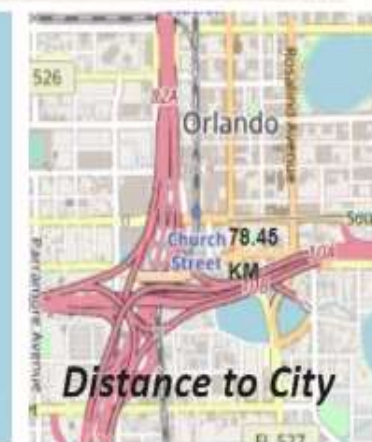
All launch sites global map markers



Markers showing launch sites with color labels



Launch Site distance to landmarks



- Are launch sites in close proximity to railways? No
- Are launch sites in close proximity to highways? No
- Are launch sites in close proximity to coastline? Yes
- Do launch sites keep certain distance away from cities? Yes



Section 6

Predictive Analysis (Classification)

Classification Accuracy

- The decision tree classifier is the model with the highest classification accuracy

```
models = {'KNeighbors': knn_cv.best_score_,
          'DecisionTree': tree_cv.best_score_,
          'LogisticRegression': logreg_cv.best_score_,
          'SupportVector': svm_cv.best_score_}

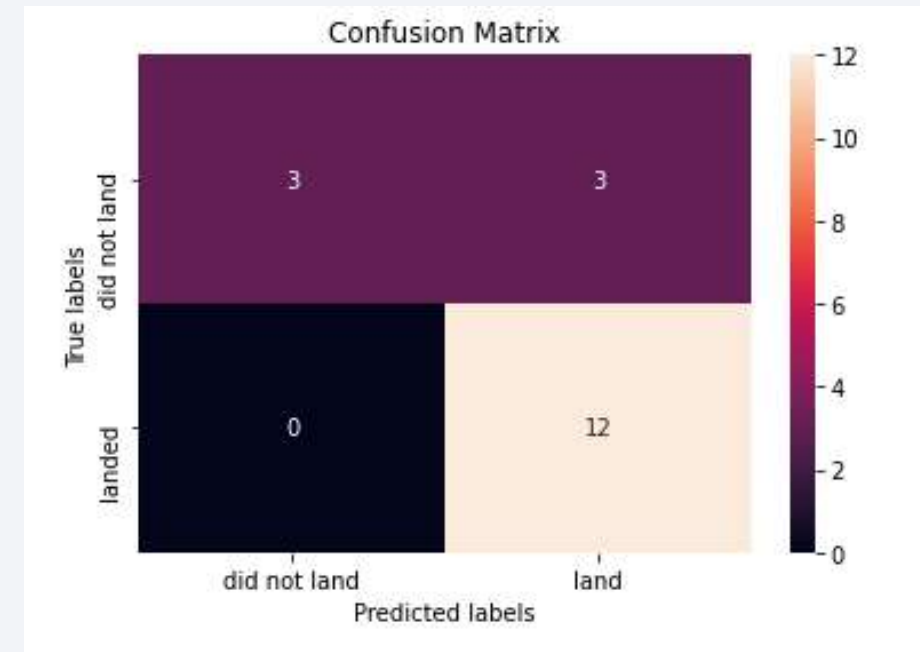
bestalgorithm = max(models, key=models.get)
print('Best model is', bestalgorithm, 'with a score of', models[bestalgorithm])
if bestalgorithm == 'DecisionTree':
    print('Best params is :', tree_cv.best_params_)
if bestalgorithm == 'KNeighbors':
    print('Best params is :', knn_cv.best_params_)
if bestalgorithm == 'LogisticRegression':
    print('Best params is :', logreg_cv.best_params_)
if bestalgorithm == 'SupportVector':
    print('Best params is :', svm_cv.best_params_)
```

Best model is DecisionTree with a score of 0.8732142857142856

Best params is : {'criterion': 'gini', 'max_depth': 6, 'max_features': 'auto', 'min_samples_leaf': 2, 'min_samples_split': 5, 'splitter': 'random'}

Confusion Matrix

- The confusion matrix for the decision tree classifier shows that the classifier can distinguish between the different classes. The major problem is the false positives .i.e., unsuccessful landing marked as successful landing by the classifier.



Conclusions

We can conclude that:

- The larger the flight amount at a launch site, the greater the success rate at a launch site.
- Launch success rate started to increase in 2013 till 2020.
- Orbits ES-L1, GEO, HEO, SSO, VLEO had the most success rate.
- KSC LC-39A had the most successful launches of any sites.
- The Decision tree classifier is the best machine learning algorithm for this task.

Thank you!

