IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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Outline

Executive Summary

The objective of this project report is to predict SpaceX future rocket first-stage landing outcomes using machine learning models. The results will support identifying competitive pricing to compete with SpaceX.

- Summary of methodologies
  - Data collection using API and Web Scraping
  - Data Wrangling
  - Exploratory Data Analysis (EDA) with SQL and Data Visualization
  - Interactive Visual Analytics with Folium
  - Machine Learning Prediction
- Summary of all results
  - Exploratory Data Analysis (EDA) Results
  - Interactive Analytics
  - Predictive Analytics Results

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.

- Problems you want to find answers
  - Identifying factors that influence the landing outcome
  - Establish the relationship between each variables and how it is affecting the outcome
  - The best condition needed to increase the probability of successful landing

Section 1

Methodology

Methodology

Executive Summary

- Data collection methodology:
  - SpaceX REST API and web scrapping from Wikipedia
- Data wrangling
  - One-hot encoding for categorical features
- Exploratory data analysis (EDA)
  - SQL and data visualization
- Interactive visual analytics
  - Folium and Plotly Dash
- Predictive analysis
  - Logistic Regression, Support Vector Machine, Decision Tree, K-Nearest Neighbor.

Data Collection – SpaceX API

```python
spacex_url="https://api.spacexdata.com/v4/launches/past"
```

```python
response = requests.get(spacex_url)
```

```python
# Use json_normalize meethod to convert the json result into a dataframe
data = pd.json_normalize(response.json())
```

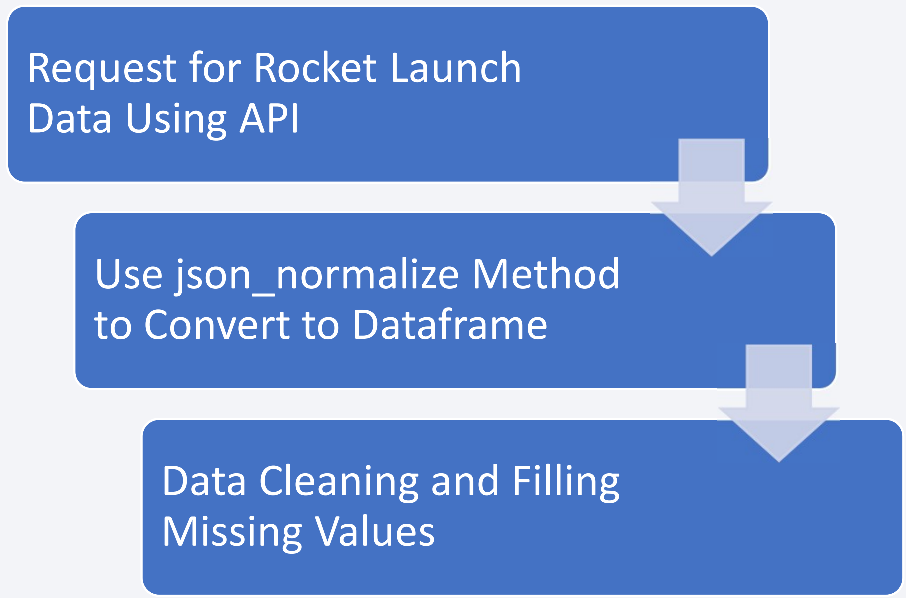
```python
# Lets take a subset of our dataframe keeping only the features we want and the flight number, and date_utc.
data = data[['rocket', 'payloads', 'launchpad', 'cores', 'flight_number', 'date_utc']]

# 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)]
```



https://github.com/bstorino/IBM-Data-Science-Final-Presentation/blob/main/jupyter-labs-spacex-data-collection-api.ipynb

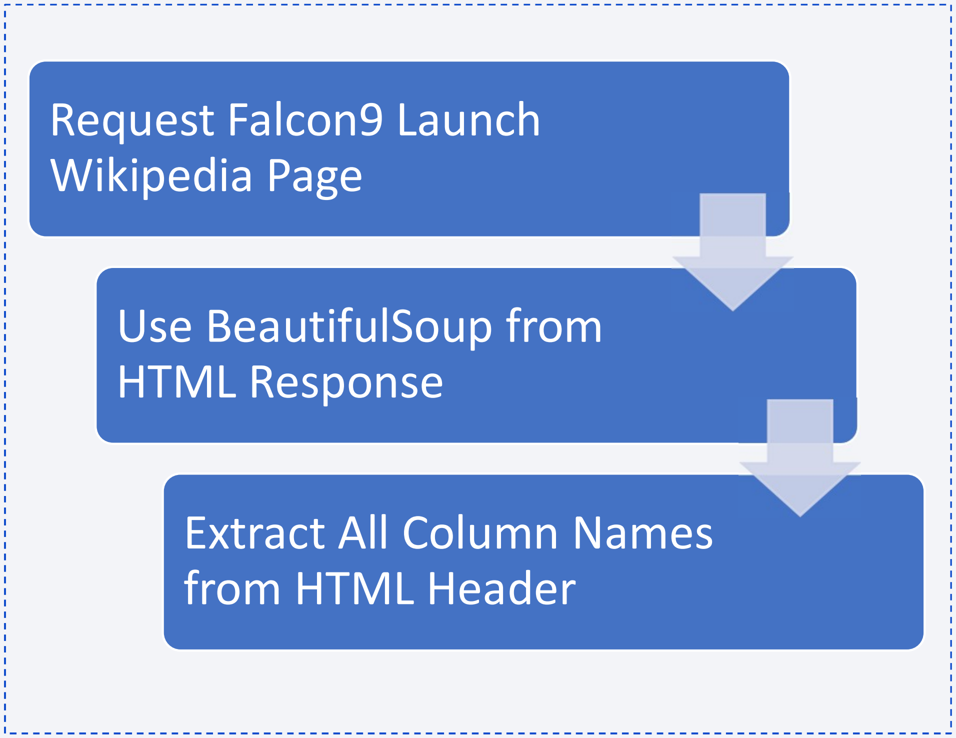
Data Collection - Scraping

```python
# use requests.get() method with the provided static_url
# assign the response to a object
r = requests.get(static_url)
data = r.text
```

```python
# Use BeautifulSoup() to create a BeautifulSoup object from a response text content
soup = BeautifulSoup(data,"html.parser")
```

```python
extracted_row = 0
#Extract each table
for table_number,table in enumerate(soup.find_all('table',"wikitable plainrowheaders collapsible")):
   # get table row
    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:
            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
            # TODO: Append the flight_number into launch_dict with key `Flight No.`
            #print(flight_number)
            datatimelist=date_time(row[0])

            # Date value
            # TODO: Append the date into launch_dict with key `Date`
            date = datatimelist[0].strip(',')
            #print(date)
```



https://github.com/bstorino/IBM-Data-Science-Final-Presentation/blob/main/jupyter-labs-webscraping.ipynb

Data Wrangling

```
# Apply value_counts() on column LaunchSite
df['LaunchSite'].value_counts()
```

```
# landing_outcomes = values on Outcome column
landing_outcomes = df['Outcome'].value_counts()
landing_outcomes
```

```
# landing_class = 0 if bad_outcome
# landing_class = 1 otherwise
landing_class = [0 if x in bad_outcomes else 1 for x in df['Outcome']]
# landing_class
df['Class']=landing_class
print(df[['Class']].head(8))
print(df["Class"].mean())  # probability of positive outcome 2/3
print(df.head(5))
```

```
df.to_csv("dataset_part_2.csv", index=False)
```

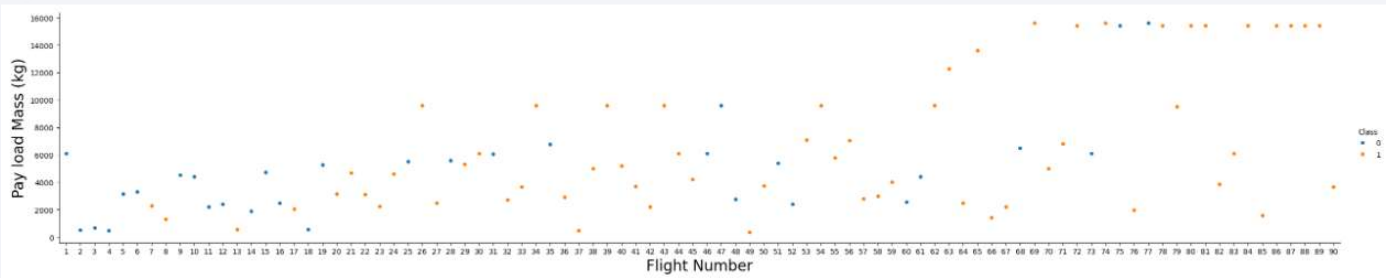
https://github.com/bstorino/IBM-Data-Science-Final-Presentation/blob/main/labs-jupyter-spacex-Data%20wrangling.ipynb

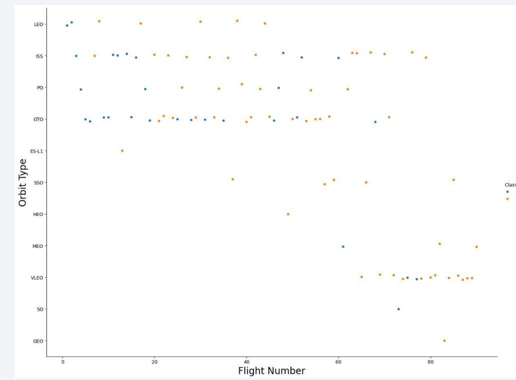
Calculate Number of Launches on Each Site

Calculate the Number and of Mission Outcomes per Orbit Type

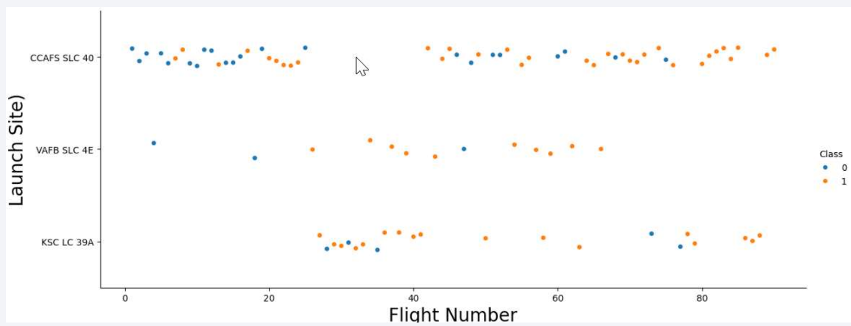
Create Label for Landing Outcome and Export Results to a CSV file

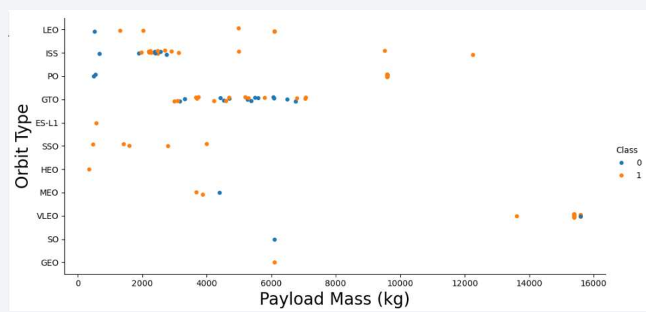
EDA with Data Visualization – Scatter Plots





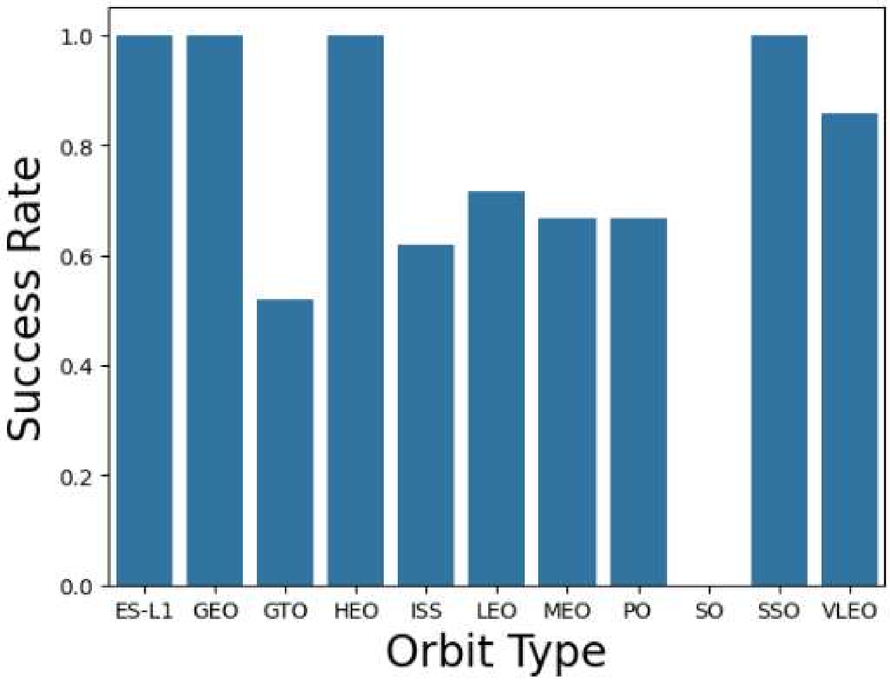
- Scatter Plots:
  - Payload vs. Flight Number
  - Flight Number vs. Launch Site
  - Flight Number vs. Orbit Type
  - Payload vs. Orbit Type

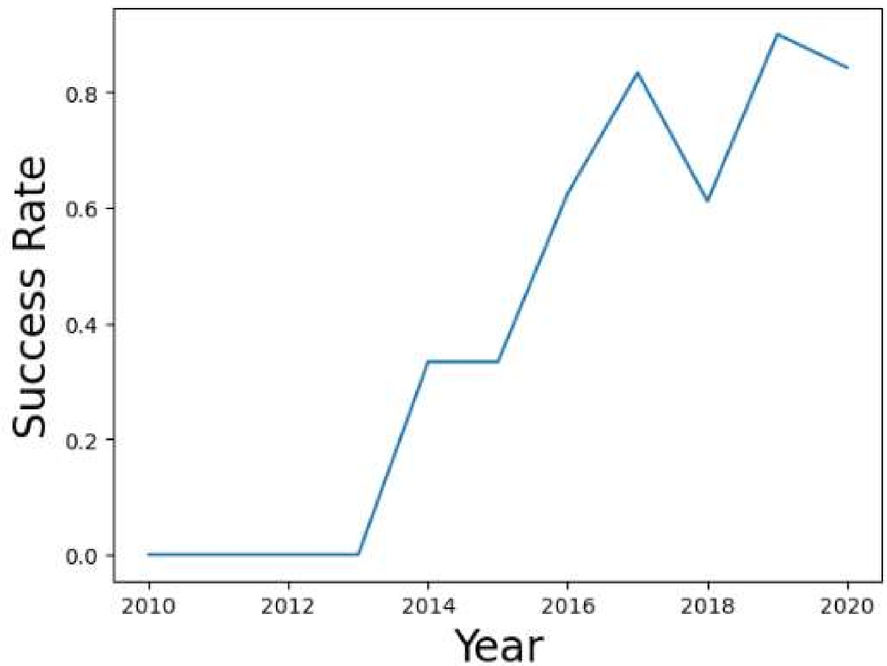




- https://github.com/bstorino/IBM-Data-Science-Final-Presentation/blob/main/edadataviz.ipynb

EDA with Data Visualization – Success Rate





- https://github.com/bstorino/IBM-Data-Science-Final-Presentation/blob/main/edadataviz.ipynb

EDA with SQL

- Performed Querries:
  - Names of launch sites
  - Top 5 records for launch sites beginning with ‘CCA’ string
  - Total payload carried by booster launched by NASA (CRS)
  - Average payload carried by booster version F9
  - Date when first successful landing outcome was achieved
  - List of boosters with successful outcomes landing on drone ships with payload greater than 4,000 but less than 6,000
  - Number of successful and failure mission outcomes
  - List of booster versions that have carried the maximum payload
  - List of failed landing outcomes on drone ships, their booster versions, and launch sites in 2015
  - Rank with the count of landing outcomes or success between 6/4/2010 and 3/20/2017
- https://github.com/bstorino/IBM-Data-Science-Final-Presentation/blob/main/jupyter-labs-eda-sql-coursera_sqllite.ipynb

Build an Interactive Map with Folium

- To visualize the launch data into an interactive map. We took the latitude and longitude coordinates at each launch site and added a circle marker around each launch site with a label of the name of the launch site.
- We then assigned the dataframe launch_outcomes (failure,success) to classes 0 and 1 with Red and Green markers on the map in MarkerCluster().
- We then used the Haversine's formula to calculated the distance of the launch sites to various landmark to find answer to the questions of:
  - How close the launch sites with railways, highways and coastlines?
  - How close the launch sites with nearby cities?

- https://github.com/bstorino/IBM-Data-Science-Final-Presentation/blob/main/lab_jupyter_launch_site_location.ipynb

Build a Dashboard with Plotly Dash

- Interactive Dashboards:
  - Pie chart with total launches by sites.
  - Scatter plot with relationship between payloads and outcomes for different booster versions
- Explain why you added those plots and interactions
- Add the GitHub URL of your completed Plotly Dash lab, as an external reference and peer-review purpose

Predictive Analysis (Classification)

Build the Model	Evaluate the Model	Improving the Model	Select Best Model
• Load Data into Numpy and Pandas • Transform data • Split data into training and test datasets	• Check each model accuracy • Get tuned hyperparameters • Plot confusion matrices	• Feature engineering • Algorithm tuning	• Evaluate accuracy scores • Best accuracy score will be the best performing model

- https://github.com/bstorino/IBM-Data-Science-Final-Presentation/blob/main/SpaceX_Machine%20Learning%20Prediction_Part_5.ipynb

Results

Overall project results in three categories:

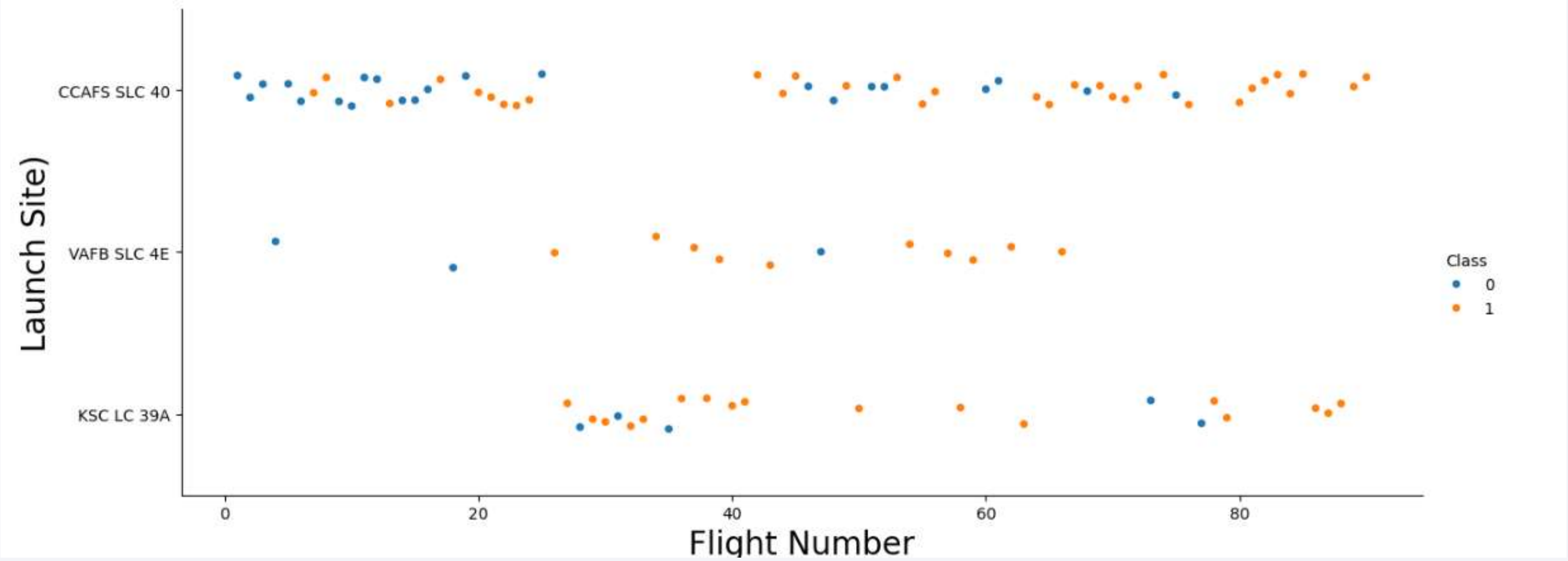
- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results

Section 2

Insights drawn from EDA

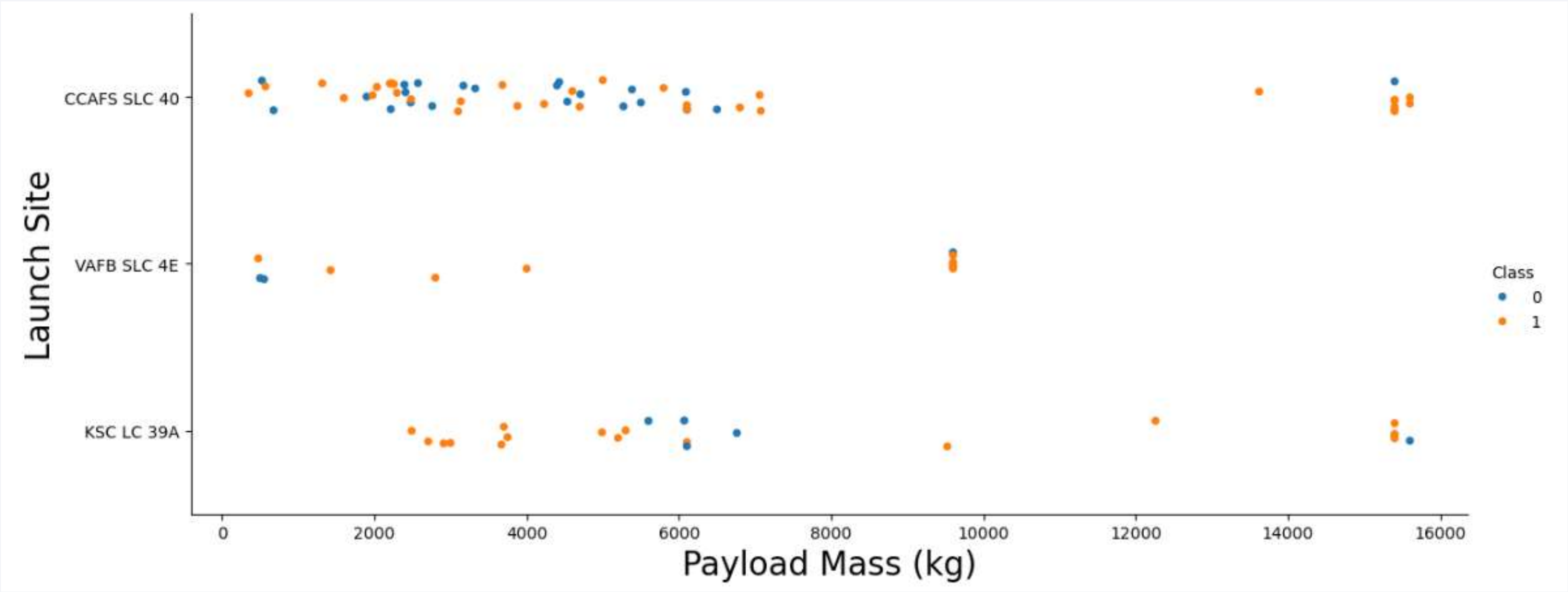
Flight Number vs. Launch Site

- Most initial launches were failures.
- The larger the number of launches, the greater success rate.



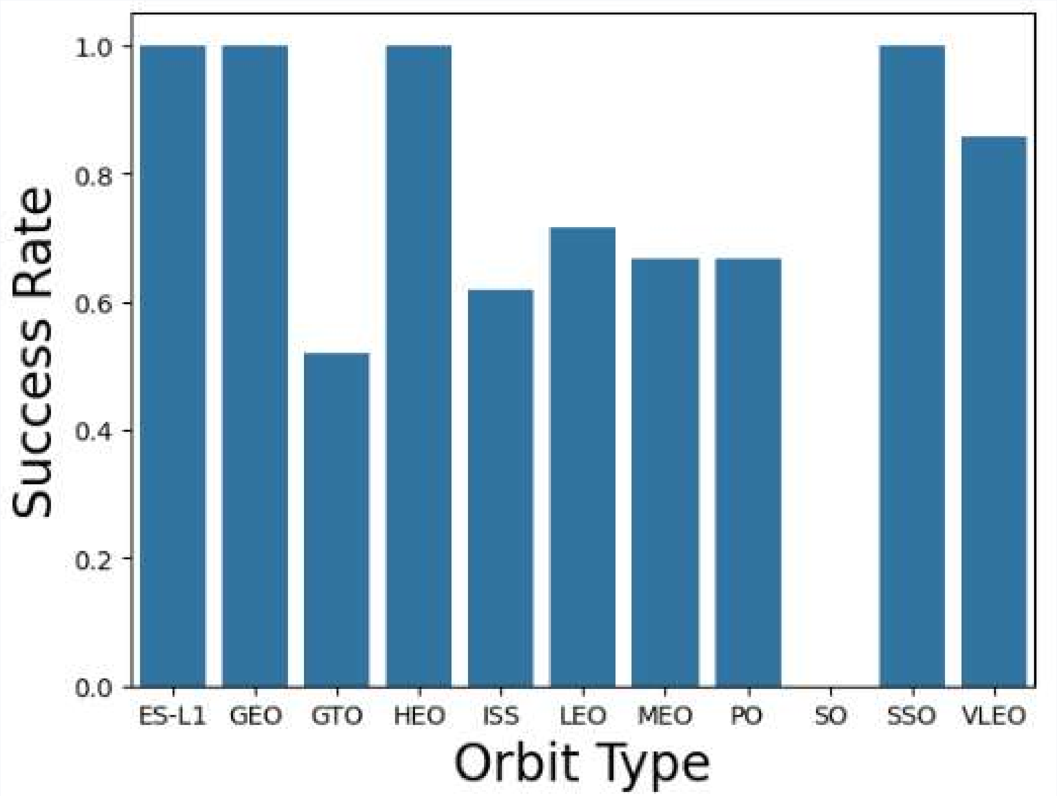
Payload vs. Launch Site

- Payloads greater than 7,000 kg present greater probability of success.
- No clear relationship between launch sites and payload.



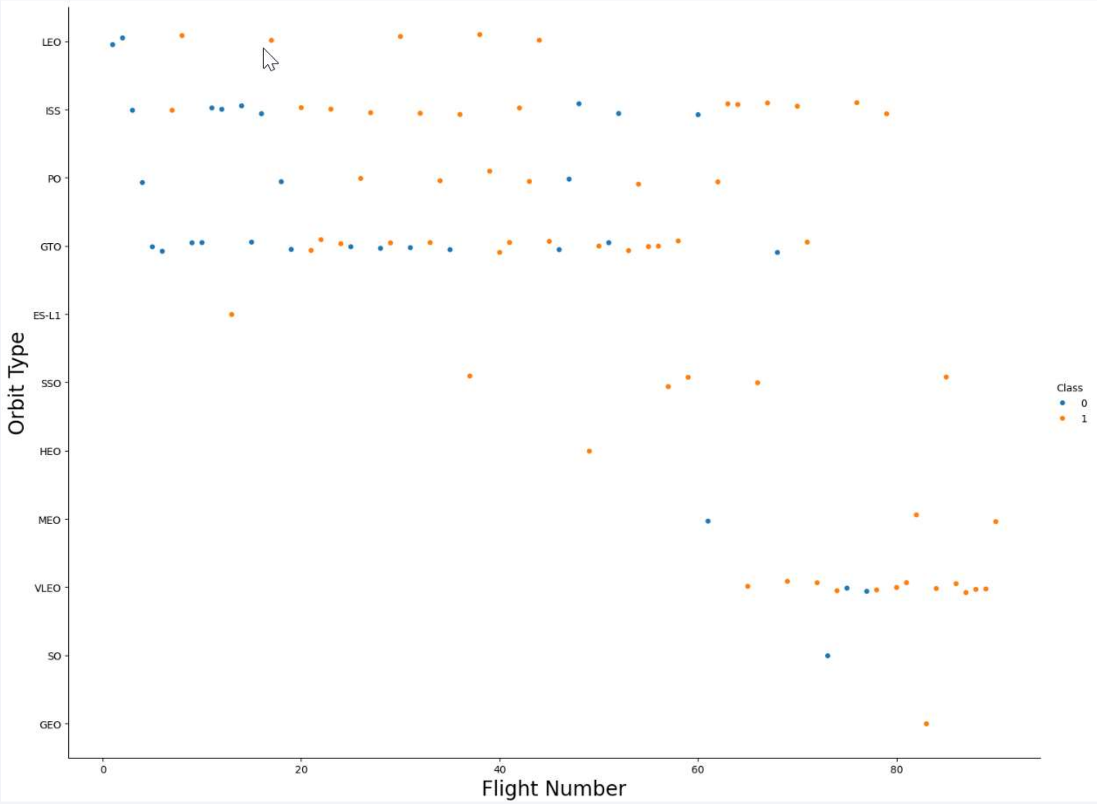
Success Rate vs. Orbit Type

- Success Rate is greater for ES-L1, GEO, HEO, and SSO orbit types



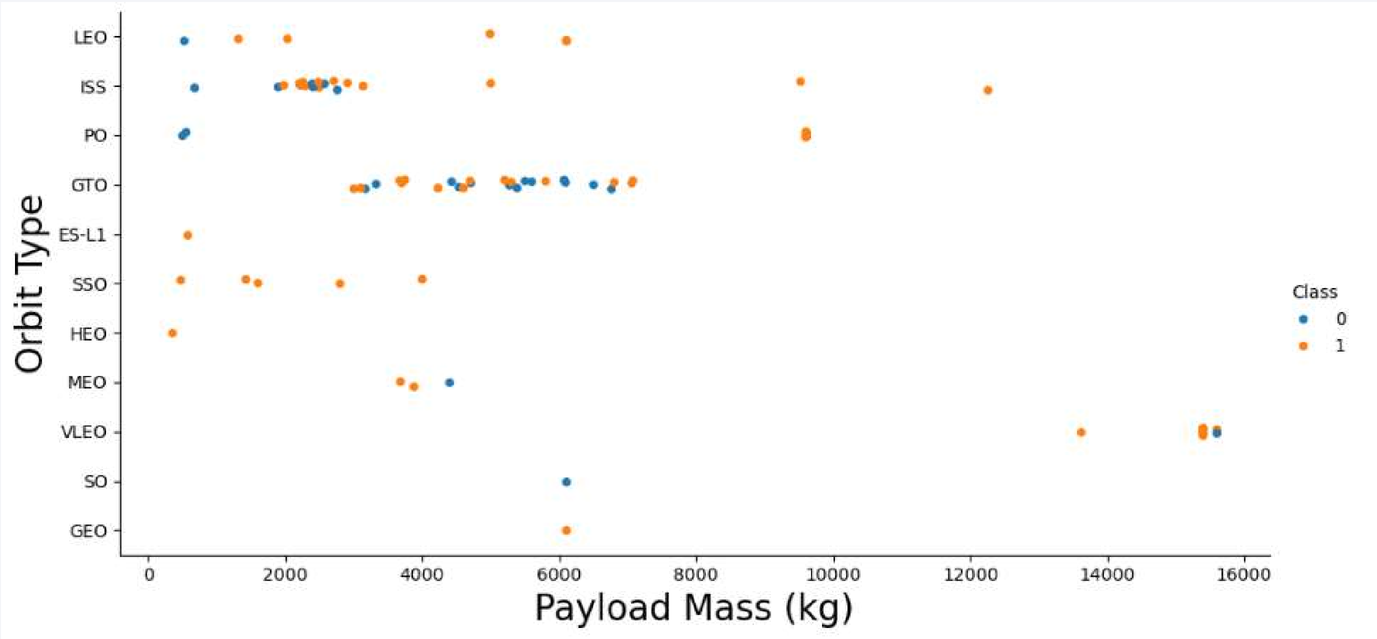
Flight Number vs. Orbit Type

- LEO orbit success rate appears related to the number of flights; on the other hand, there seems to be no relationship between flight number when in GTO orbit.



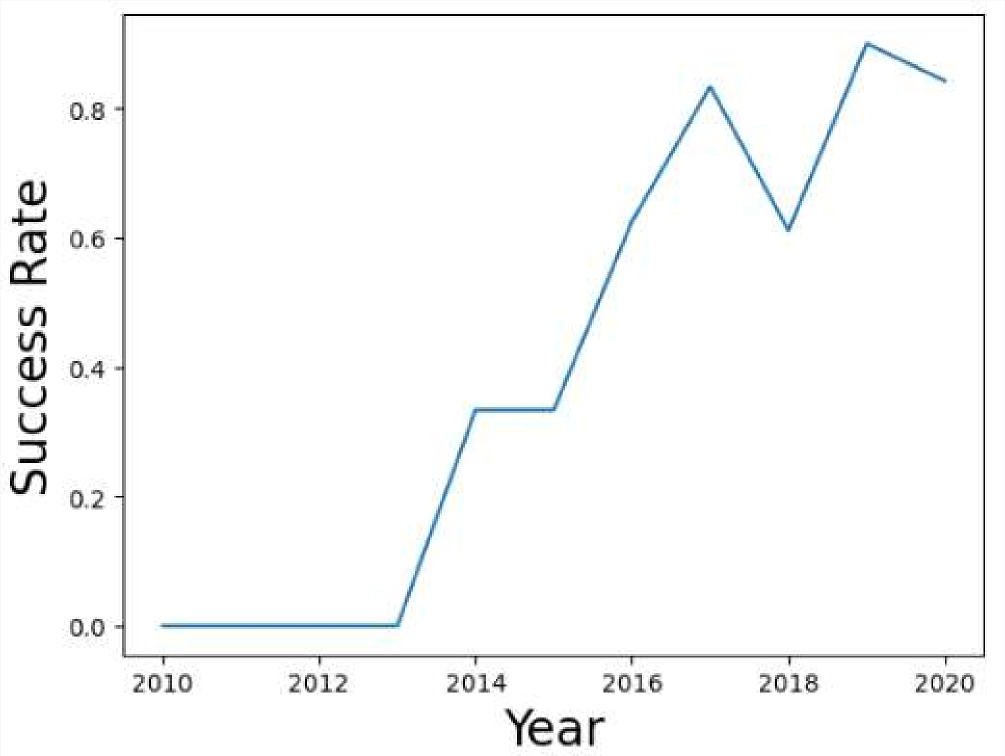
Payload vs. Orbit Type

- With heavy payloads the successful landing or positive landing rate are more for Polar,LEO and ISS.
- For GTO we cannot distinguish this relationship as both positive and negative results are present for heavier payloads.



Launch Success Yearly Trend

- Increasing success rates since 2013.



All Launch Site Names

- Names of the unique launch sites

```
q = pd.read_sql('select distinct Launch_Site from spacexdata', conn)
q
```

	Launch_Site
0	CCAFS LC-40
1	VAFB SLC-4E
2	KSC LC-39A
3	CCAFS SLC-40

Launch Site Names Begin with 'CCA'

- Five records where launch sites begin with `CCA`

```
q = pd.read_sql("select * from spacexdata where Launch_Site like 'CCA%' limit 5", conn)
q
```

	index	Date	Time_(UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS__KG_	Orbit	Customer	Mission_Outcome	Landing_Outcome
0	0	None	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
1	1	None	15:43:00	F9 v1.0 B0004	CCAFS LC-40	Dragon demo flight C1, two CubeSats, barrel of...	0	LEO (ISS)	NASA (COTS) NRO	Success	Failure (parachute)
2	2	None	7:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	No attempt
3	3	None	0:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
4	4	None	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

Total Payload Mass

- Total payload carried by boosters from NASA

```
q = pd.read_sql("select sum(PAYLOAD_MASS__KG_) from spacexdata where Customer='NASA (CRS)'", conn)
q
```

	sum(PAYLOAD_MASS__KG_)
0	45596

Average Payload Mass by F9 v1.1

- Average payload mass carried by booster version F9 v1.1

```
q = pd.read_sql("select avg(PAYLOAD_MASS__KG_) from spacexdata where Booster_Version='F9 v1.1'", conn)
q
```

	avg(PAYLOAD_MASS__KG_)
0	2928.4

First Successful Ground Landing Date

- Dates of the first successful landing outcome on ground pad

Successful Drone Ship Landing with Payload between 4000 and 6000

- List the names of boosters which have successfully landed on drone ship and had payload mass greater than 4000 but less than 6000

```
q = pd.read_sql("select distinct Booster_Version from spacexdata where Landing_Outcome='Success (drone ship)' and PAYLOAD_MASS__KG_ between 4000 and 6000", conn)
q
```

	Booster_Version
0	F9 FT B1022
1	F9 FT B1026
2	F9 FT B1021.2
3	F9 FT B1031.2

Total Number of Successful and Failure Mission Outcomes

- Total number of successful and failure mission outcomes

```
q = pd.read_sql("select substr(Mission_Outcome,1,7) as Mission_Outcome, count(*) from spacexdata  group by 1", conn)
q
```

	Mission_Outcome	count(*)
0	Failure	1
1	Success	100

Boosters Carried Maximum Payload

- List the names of the booster which have carried the maximum payload mass

```
q = pd.read_sql("select distinct Booster_Version from spacexdata where PAYLOAD_MASS__KG_ = (select max(PAYLOAD_MASS__KG_) from spacexdata)", conn)
q
```

	Booster_Version
0	F9 B5 B1048.4
1	F9 B5 B1049.4
2	F9 B5 B1051.3
3	F9 B5 B1056.4
4	F9 B5 B1048.5
5	F9 B5 B1051.4
6	F9 B5 B1049.5
7	F9 B5 B1060.2
8	F9 B5 B1058.3
9	F9 B5 B1051.6
10	F9 B5 B1060.3
11	F9 B5 B1049.7

2015 Launch Records

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

```
q = pd.read_sql("select distinct Landing_Outcome, Booster_Version, Launch_Site from spacexdata where Landing_Outcome='Failure (drone ship)'", conn)
q
```

	Landing_Outcome	Booster_Version	Launch_Site
0	Failure (drone ship)	F9 v1.1 B1012	CCAFS LC-40
1	Failure (drone ship)	F9 v1.1 B1015	CCAFS LC-40
2	Failure (drone ship)	F9 v1.1 B1017	VAFB SLC-4E
3	Failure (drone ship)	F9 FT B1020	CCAFS LC-40
4	Failure (drone ship)	F9 FT B1024	CCAFS LC-40

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

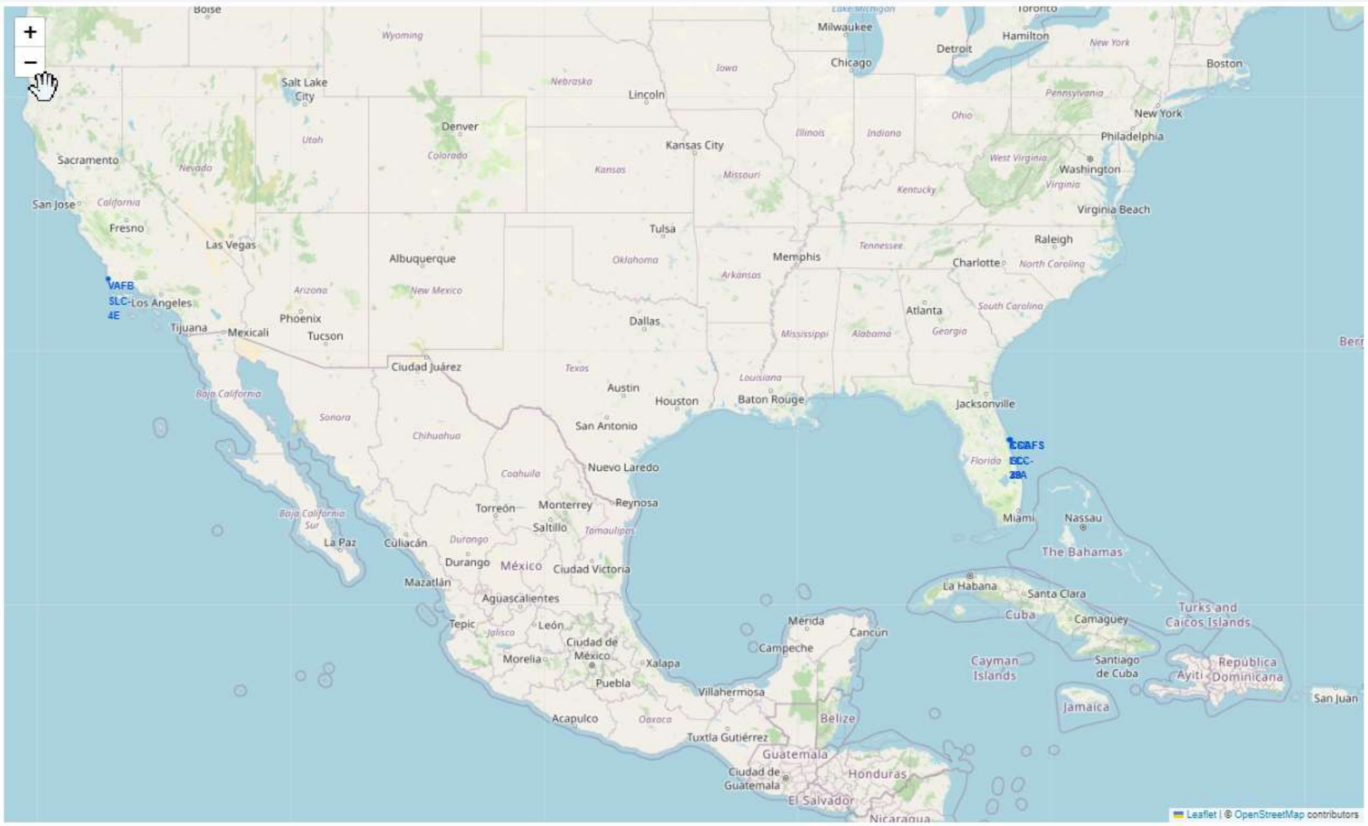
- Rank the count of landing outcomes (such as Failure (drone ship) or Success (ground pad)) between the date 2010-06-04 and 2017-03-20, in descending order

Section 3

Launch Sites Proximities Analysis

Launch Sites Location Map

- Launch sites are located on the east and west coasts of the United States.



Detailed Launch Site Maps

- Launch sites with markers indicating successful and failure outcomes

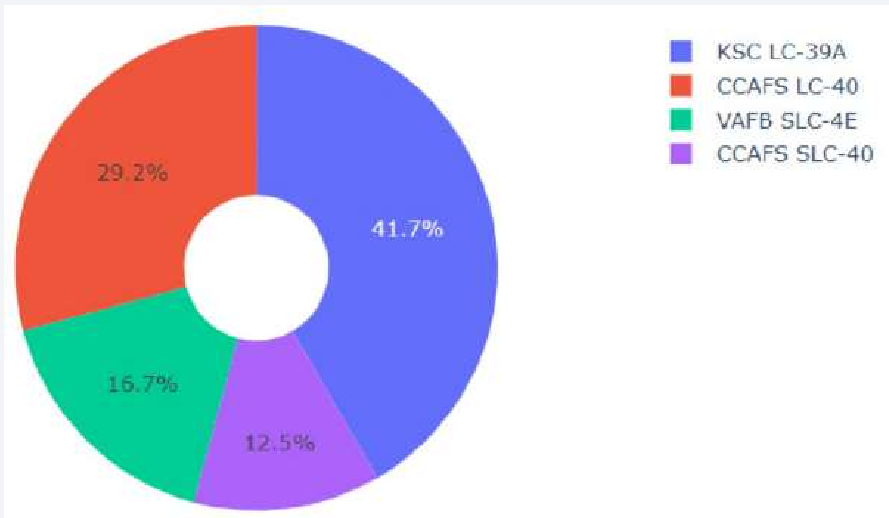
Distance from Launch Site to Coastline

Section 4

Build a Dashboard with Plotly Dash

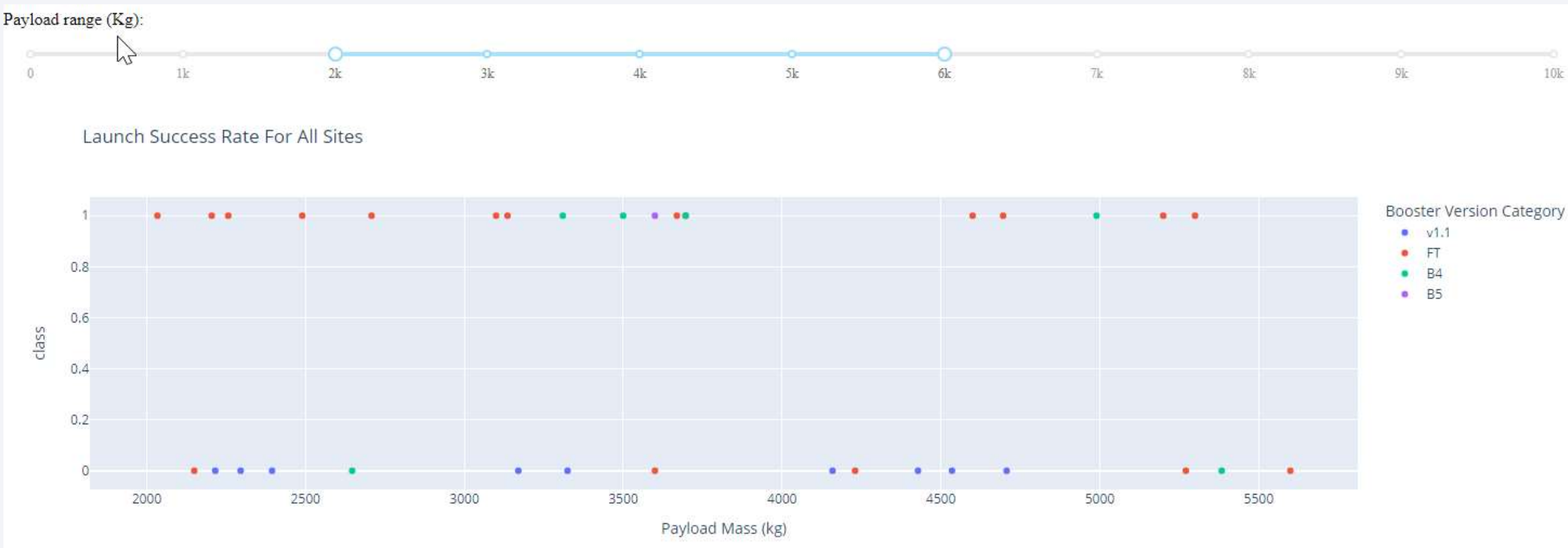
Launch Sites and Success Percentage

- KSC LC-39A has the highest rate of successful launches



Launch Outcome vs Payload

- Outcomes for different payload levels and ranges



Section 5

Predictive Analysis (Classification)

Classification Accuracy

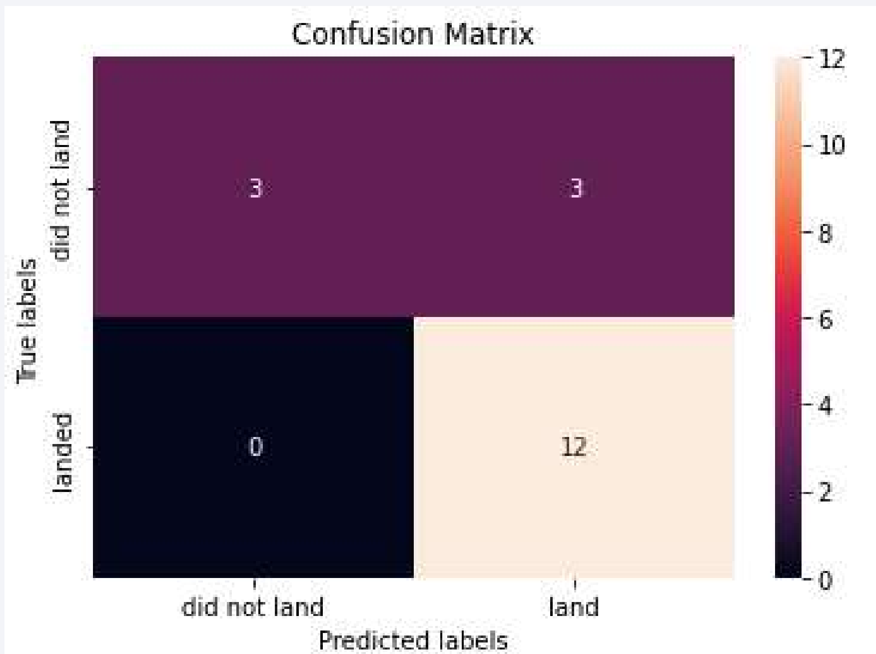
- Find which model has the highest classification accuracy

```
algorithms = {'KNN':knn_cv.best_score_,'Tree':tree_cv.best_score_,'LogisticRegression':logreg_cv.best_score_}
bestalgorithm = max(algorithms, key=algorithms.get)
print('Best Algorithm is',bestalgorithm,'with a score of',algorithms[bestalgorithm])
if bestalgorithm == 'Tree':
    print('Best Params is :',tree_cv.best_params_)
if bestalgorithm == 'KNN':
    print('Best Params is :',knn_cv.best_params_)
if bestalgorithm == 'LogisticRegression':
    print('Best Params is :',logreg_cv.best_params_)
```

```
Best Algorithm is Tree with a score of 0.9017857142857142
Best Params is : {'criterion': 'entropy', 'max_depth': 10, 'max_features': 'auto', 'min_samples_leaf': 2, 'min_samples_spli
t': 10, 'splitter': 'random'}
```

Confusion Matrix

- The best performing model is the decision tree classifier.
- The confusion matrix shows the major problem is predicting unsuccessful landings as successful (false positives).



Conclusions

- The best classifier methodology for this dataset is Machine Learning approach.
- The heavy weighted payloads (>4,000kg) performed worse than the low weighted payloads.
- The success rate for SpaceX launches increased starting from 2013, showing progress that will eventually perfect the launches in the future.
- KSC LC-39A have the most successful launches of any sites; 76.9%
- SSO orbit have the most success rate; 100% and more than 1 occurrence.

Thank you!