Space X Falcon 9 Landing Analysis

IBM Data Science Capstone Project

OUTLINE

Executive Summary

Introduction

Methodology

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Conclusion

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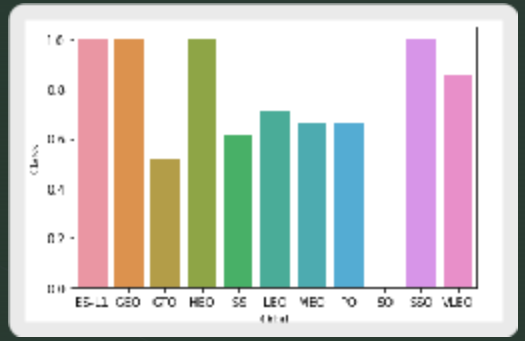
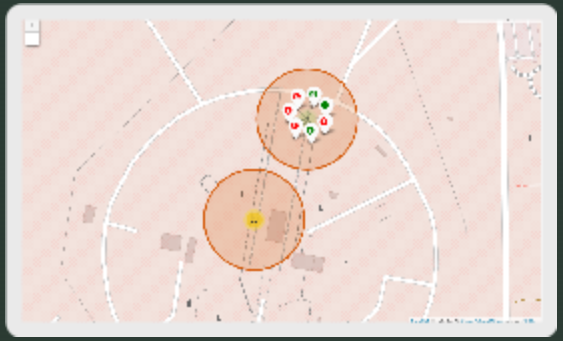
Summary of Methodologies:

This project follows these steps:

- Data Collection
- Data Wrangling
- Exploratory Data Analysis
- Interactive Visual Analytics
- Predictive Analysis (Classification)

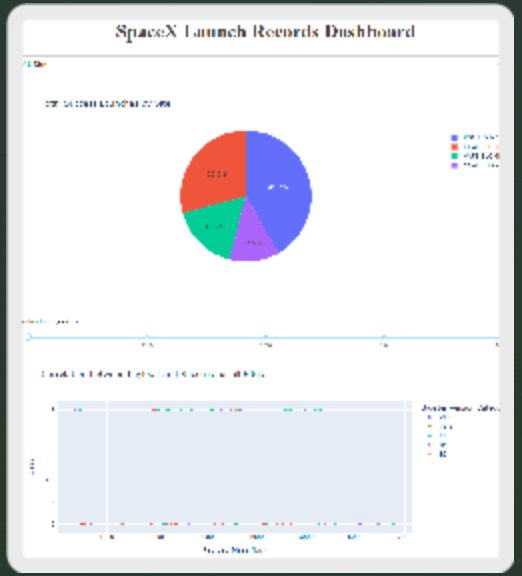


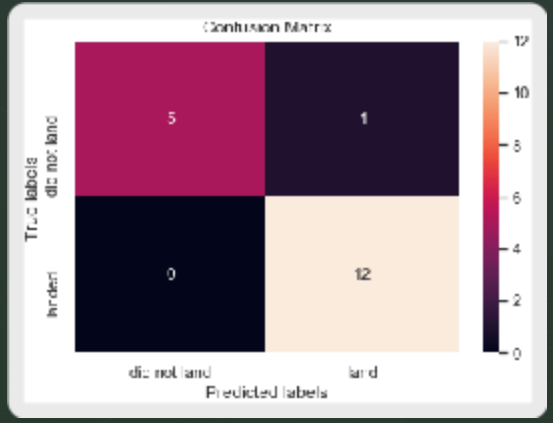


Summary of Results:

This project produced the following outputs and visualizations:

1. Exploratory Data Analysis (EDA) results
2. Geospatial analytics
3. Interactive dashboard
4. Predictive analysis of classification models





Introduction

- SpaceX launches Falcon 9 rockets at a cost of around $62m. This is considerably cheaper than other providers (which usually cost upwards of $165m), and much of the savings are because SpaceX can land, and then re-use the first stage of the rocket.
- If we can make predictions on whether the first stage will land, we can determine the cost of a launch, and use this information to assess whether or not an alternate company should bid and SpaceX for a rocket launch.
- This project will ultimately predict if the Space X Falcon 9 first stage will land successfully.

Methodology summary

1. Data Collection
   - Making GET requests to the SpaceX REST API
   - Web Scraping
2. Data Wrangling
   - Using the `.fillna()` method to remove NaN values
   - Using the `.value_counts()` method to determine the following:
     - Number of launches on each site
     - Number and occurrence of each orbit
     - Number and occurrence of mission outcome per orbit type
   - Creating a landing outcome label that shows the following:
     - 0 when the booster did not land successfully
     - 1 when the booster did land successfully
3. Exploratory Data Analysis
   - Using SQL queries to manipulate and evaluate the SpaceX dataset
   - Using Pandas and Matplotlib to visualize relationships between variables, and determine patterns
4. Interactive Visual Analytics
   - Geospatial analytics using Folium
   - Creating an interactive dashboard using Plotly Dash
5. Data Modelling and Evaluation
   - Using Scikit-Learn to:
     - Pre-process (standardize) the data
     - Split the data into training and testing data using `train_test_split`
     - Train different classification models
     - Find hyperparameters using `GridSearchCV`
   - Plotting confusion matrices for each classification model
   - Assessing the accuracy of each classification model

DATA COLLECTION – space x REST api

Using the SpaceX API to retrieve data about launches, including information about the rocket used, payload delivered, launch specifications, landing specifications, and landing outcome.

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

response = requests.get(spacex_url)

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

1
- Make a GET response to the SpaceX REST API
- Convert the response to a .json file then to a Pandas DataFrame

2
- Use custom logic to clean the data (see Appendix)
- Define lists for data to be stored in
- Call custom functions (see Appendix) to retrieve data and fill the lists
- Use these lists as values in a dictionary and construct the dataset

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

```
# Call getBoosterVersion
getBoosterVersion(data)

# Call getLaunchSite
getLaunchSite(data)

# Call getPayloadData
getPayloadData(data)

# Call getCoreData
getCoreData(data)
```

```
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}
```

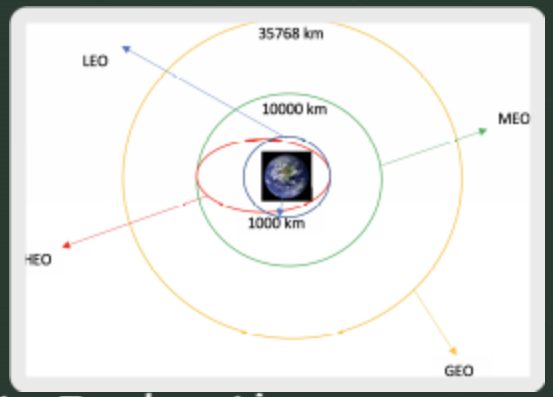
3
- Create a Pandas DataFrame from the constructed dictionary dataset

4
- Filter the DataFrame to only include Falcon 9 launches
- Reset the FlightNumber column
- Replace missing values of PayloadMass with the mean PayloadMass value

Data Manipulation

Context:

- The SpaceX dataset contains several Space X launch facilities, and each location is in the `LaunchSite` column.
- Each launch aims to a dedicated orbit, and some of the common orbit types are shown in the figure below. The orbit type is in the `Orbit` column.



Initial Data Exploration:

- Using the `.value_counts()` method to determine the following:
  1. Number of launches on each site
  2. Number and occurrence of each orbit
  3. Number and occurrence of landing outcome per orbit type

DATA MANIPULATION/WRANGLING – PANDAS

Context:

- The landing outcome is shown in the `Outcome` column:
  - `True Ocean` – the mission outcome was successfully landed to a specific region of the ocean
  - `False Ocean` – the mission outcome was unsuccessfully landed to a specific region of the ocean.
  - `True RTLS` – the mission outcome was successfully landed to a ground pad
  - `False RTLS` – the mission outcome was unsuccessfully landed to a ground pad.
  - `True ASDS` – the mission outcome was successfully landed to a drone ship
  - `False ASDS` – the mission outcome was unsuccessfully landed to a drone ship.
  - `None ASDS` and `None None` – these represent a failure to land.

Data Wrangling:

- To determine whether a booster will successfully land, it is best to have a binary column, i.e., where the value is 1 or 0, representing the success of the landing.
- This is done by:
  1. Defining a set of unsuccessful (bad) outcomes, `bad_outcome`
  2. Creating a list, `landing_class`, where the element is 0 if the corresponding row in `Outcome` is in the set `bad_outcome`, otherwise, it's 1.
  3. Create a `Class` column that contains the values from the list `landing_class`
  4. Export the DataFrame as a .csv file.

```
bad_outcomes=set(landing_outcomes.keys()[1,3,5,6,7])
bad_outcomes
```

```
{'False ASDS', 'False Ocean', 'False RTLS', 'None ASDS', 'None None'}
```

```
# landing_class = 0 if bad_outcome
# landing_class = 1 otherwise

landing_class = []

for outcome in df['Outcome']:
    if outcome in bad_outcomes:
        landing_class.append(0)
    else:
        landing_class.append(1)
```

```
df.to_csv("dataset_part\_2.csv", index=False)
```

Exploratory data analysis (eda) – SQL

To gather some information about the dataset, some SQL queries were performed.

The SQL queries performed on the data set were used to:

1. Display the names of the unique launch sites in the space mission
2. Display 5 records where launch sites begin with the string 'CCA'
3. Display the total payload mass carried by boosters launched by NASA (CRS)
4. Display the average payload mass carried by booster version F9 v1.1
5. List the date when the first successful landing outcome on a ground pad was achieved
6. List the names of the boosters which had success on a drone ship and a payload mass between 4000 and 6000 kg
7. List the total number of successful and failed mission outcomes
8. List the names of the booster versions which have carried the maximum payload mass
9. List the failed landing outcomes on drone ships, their booster versions, and launch site names for 2015
10. 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

Geospatial analysis – folium

The following steps were taken to visualize the launch data on an interactive map:

1. Mark all launch sites on a map
   - Initialise the map using a Folium `Map` object
   - Add a `folium.Circle` and `folium.Marker` for each launch site on the launch map

2. Mark the success/failed launches for each site on a map
   - As many launches have the same coordinates, it makes sense to cluster them together.
   - Before clustering them, assign a marker colour of successful (class = 1) as green, and failed (class = 0) as red.
   - To put the launches into clusters, for each launch, add a `folium.Marker` to the `MarkerCluster()` object.
   - Create an icon as a text label, assigning the `icon_color` as the `marker_colour` determined previously.

3. Calculate the distances between a launch site to its proximities
   - To explore the proximities of launch sites, calculations of distances between points can be made using the `Lat` and `Long` values.
   - After marking a point using the `Lat` and `Long` values, create a `folium.Marker` object to show the distance.
   - To display the distance line between two points, draw a `folium.PolyLine` and add this to the map.

Interactive dashboard – plotly dash

The following plots were added to a Plotly Dash dashboard to have an interactive visualisation of the data:

1. Pie chart (`px.pie()`) showing the total successful launches per site
   - This makes it clear to see which sites are most successful
   - The chart could also be filtered (using a `dcc.Dropdown()` object) to see the success/failure ratio for an individual site

2. Scatter graph (`px.scatter()`) to show the correlation between outcome (success or not) and payload mass (kg)
   - This could be filtered (using a `RangeSlider()` object) by ranges of payload masses
   - It could also be filtered by booster version

Predictive Analysis - Classification

Model Development

- To prepare the dataset for model development:
  - Load dataset
  - Perform necessary data transformations (standardise and pre-process)
  - Split data into training and test data sets, using `train_test_split()`
  - Decide which type of machine learning algorithms are most appropriate
- For each chosen algorithm:
  - Create a `GridSearchCV` object and a dictionary of parameters
  - Fit the object to the parameters
  - Use the training data set to train the model

Model Evaluation

- For each chosen algorithm:
  - Using the output GridSearchCV object:
    - Check the tuned hyperparameters (`best_params_`)
    - Check the accuracy (`score` and `best_score_`)
  - Plot and examine the Confusion Matrix

1

- Review the accuracy scores for all chosen algorithms
- The model with the highest accuracy score is determined as the best performing model

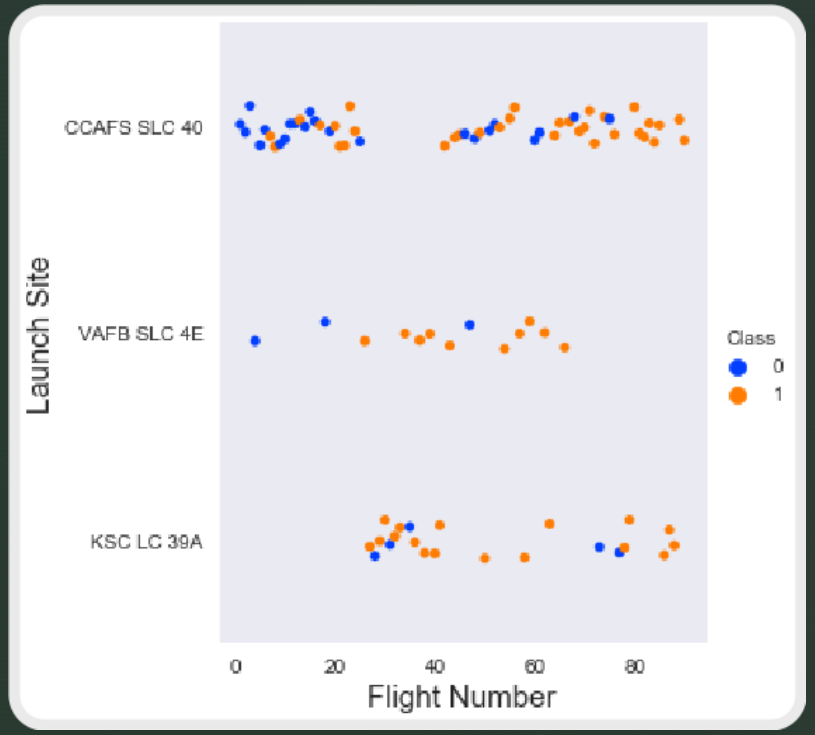
results

- Exploratory Data Analysis
- Interactive Analytics
- Predictive Analysis

Launch Site VS. FLIGHT NUMBER

The scatter plot of Launch Site vs. Flight Number shows that:

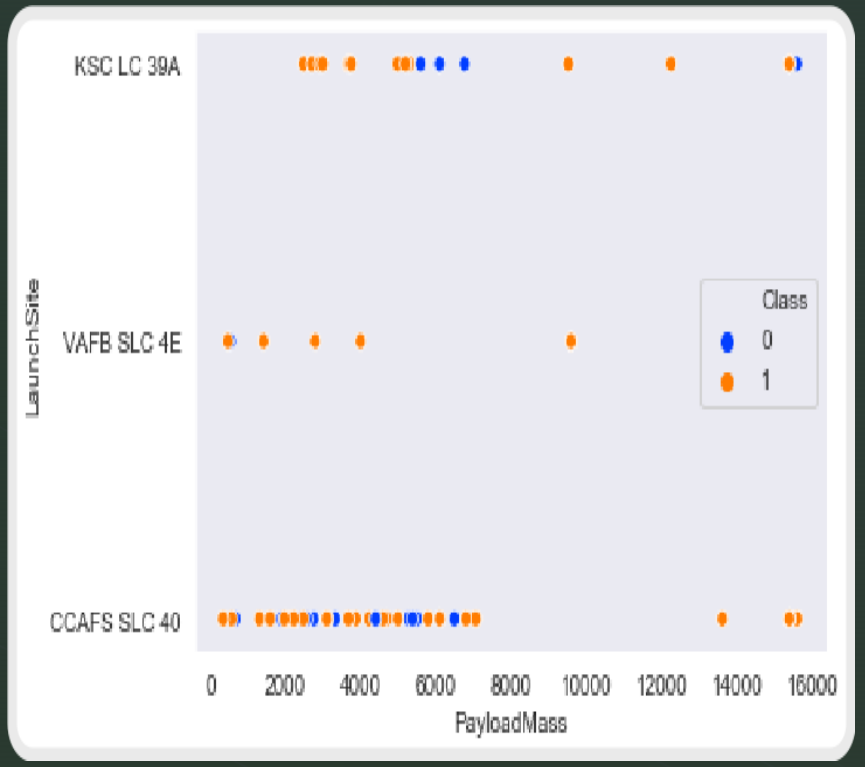
- As the number of flights increases, the rate of success at a launch site increases.
- Most of the early flights (flight numbers < 30) were launched from CCAFS SLC 40, and were generally unsuccessful.
- The flights from VAFB SLC 4E also show this trend, that earlier flights were less successful.
- No early flights were launched from KSC LC 39A, so the launches from this site are more successful.
- Above a flight number of around 30, there are significantly more successful landings (Class = 1).



LAUNCH SITE vs. PAYLOAD MASS

The scatter plot of Launch Site vs. Payload Mass shows that:

- Above a payload mass of around 7000 kg, there are very few unsuccessful landings, but there is also far less data for these heavier launches.
- There is no clear correlation between payload mass and success rate for a given launch site.
- All sites launched a variety of payload masses, with most of the launches from CCAFS SLC 40 being comparatively lighter payloads (with some outliers).



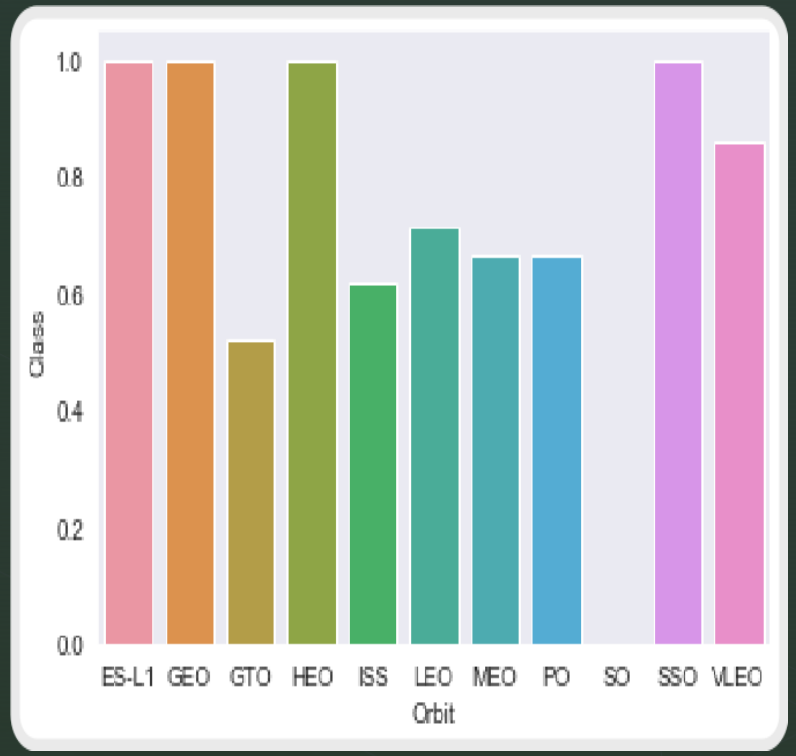
Success Rate vs. Orbit Type

The bar chart of Success Rate vs. Orbit Type shows that the following orbits have the highest (100%) success rate:

- ES-L1 (Earth-Sun First Lagrangian Point)
- GEO (Geostationary Orbit)
- HEO (High Earth Orbit)
- SSO (Sun-synchronous Orbit)

The orbit with the lowest (0%) success rate is:

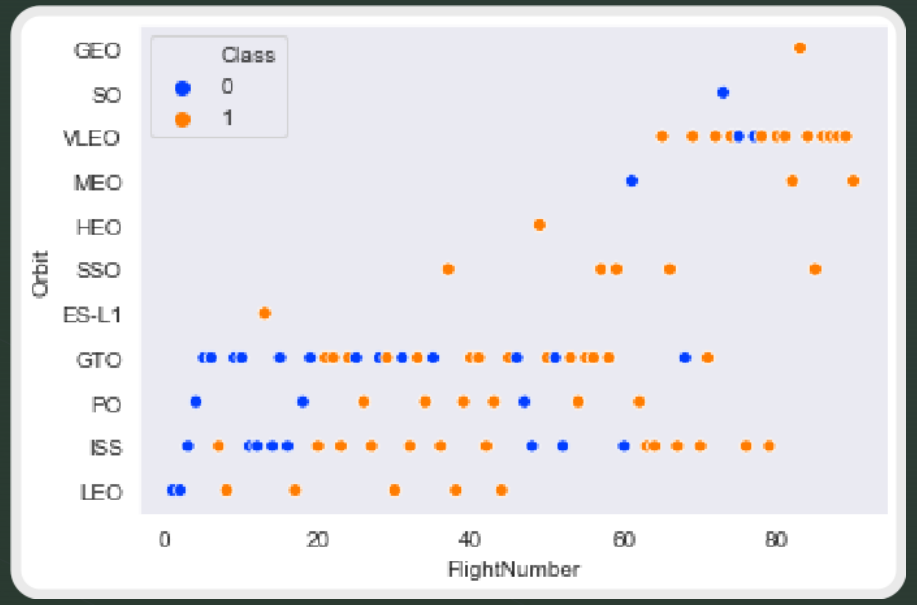
- SO (Heliocentric Orbit)



Orbit Type vs. flight number

This scatter plot of Orbit Type vs. Flight number shows a few useful things that the previous plots did not, such as:

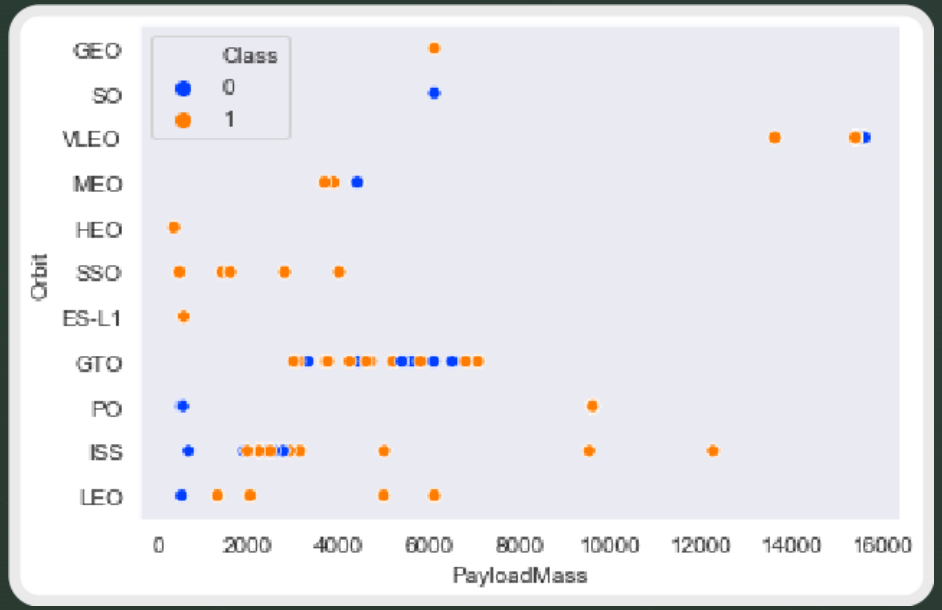
- The 100% success rate of GEO, HEO, and ES-L1 orbits can be explained by only having 1 flight into the respective orbits.
- The 100% success rate in SSO is more impressive, with 5 successful flights.
- There is little relationship between Flight Number and Success Rate for GTO.
- Generally, as Flight Number increases, the success rate increases. This is most extreme for LEO, where unsuccessful landings only occurred for the low flight numbers (early launches).



ORBIT TYPE VS. PAYLOAD MASS

This scatter plot of Orbit Type vs. Payload Mass shows that:

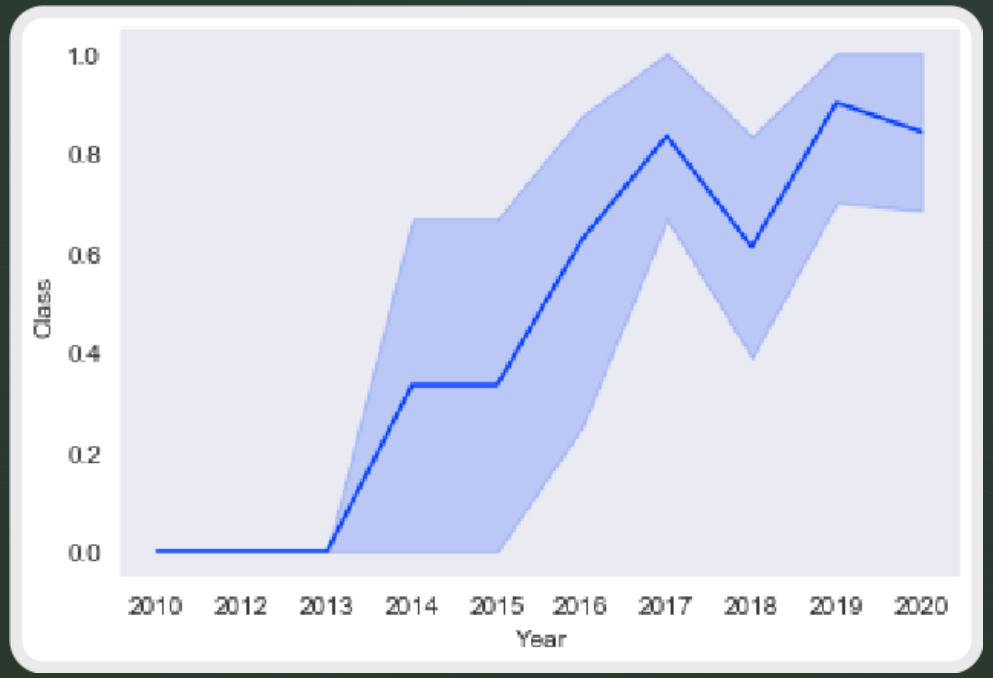
- The following orbit types have more success with heavy payloads:
  - PO (although the number of data points is small)
  - ISS
  - LEO
- For GTO, the relationship between payload mass and success rate is unclear.
- VLEO (Very Low Earth Orbit) launches are associated with heavier payloads, which makes intuitive sense.



Launch Success Yearly Trend

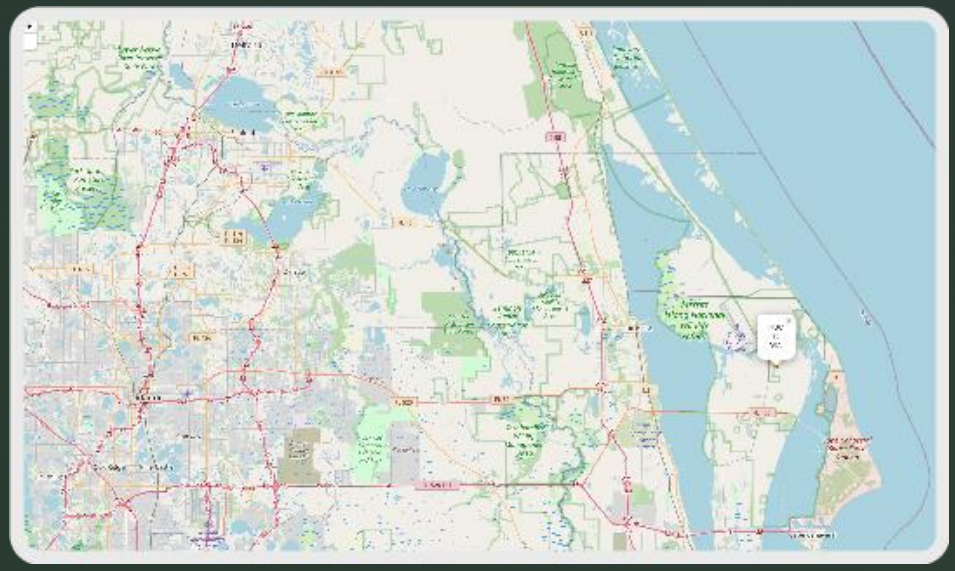
The line chart of yearly average success rate shows that:

- Between 2010 and 2013, all landings were unsuccessful (as the success rate is 0).
- After 2013, the success rate generally increased, despite small dips in 2018 and 2020.
- After 2016, there was always a greater than 50% chance of success.



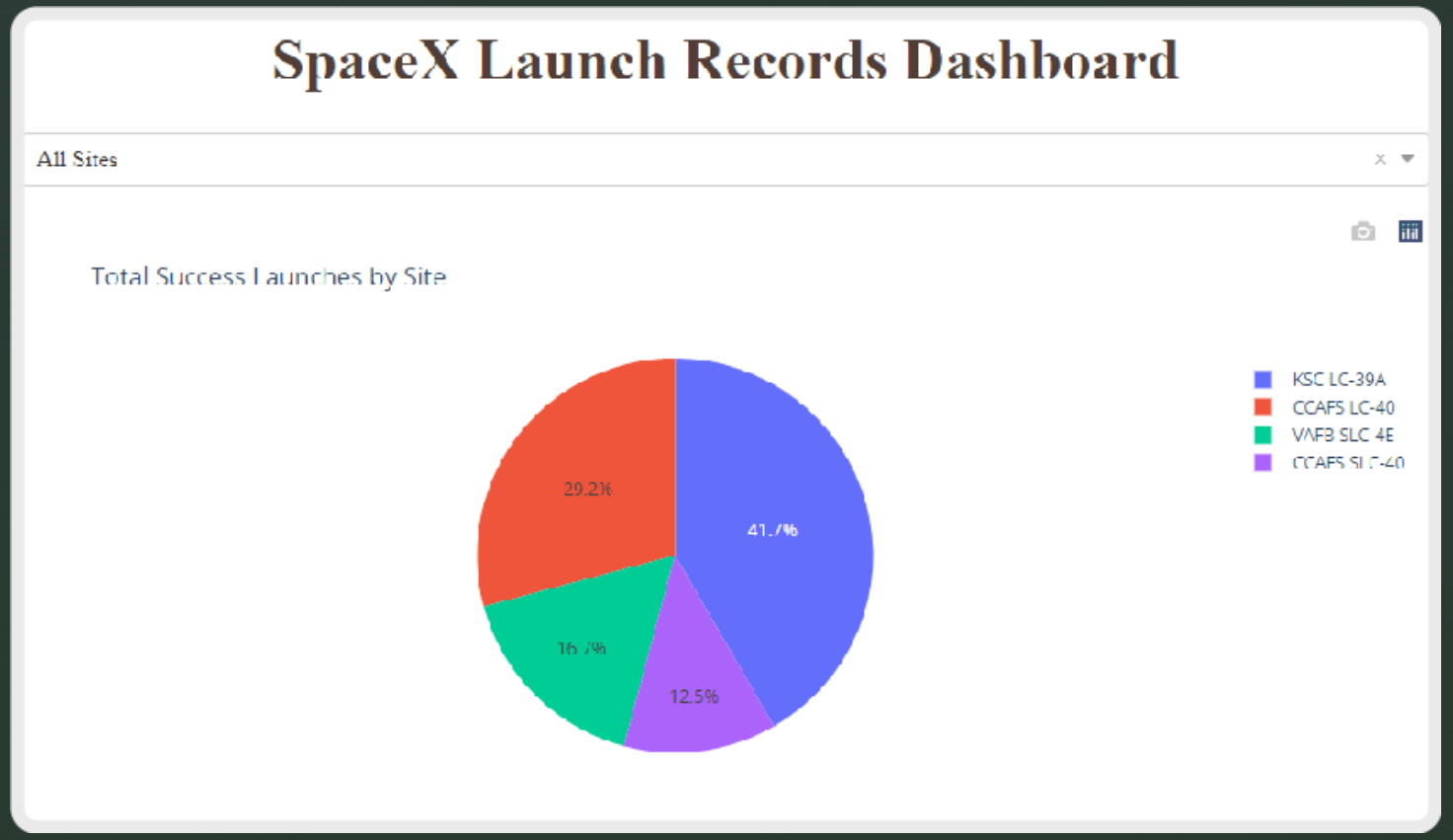
- LAUNCH SITES PROXIMITY ANALYSIS – FOLIUM INTERACTIVE MAP

ALL LAUNCH SITES ON A MAP



- interactive dashboard - Plotly Dash

launch success count for all sites



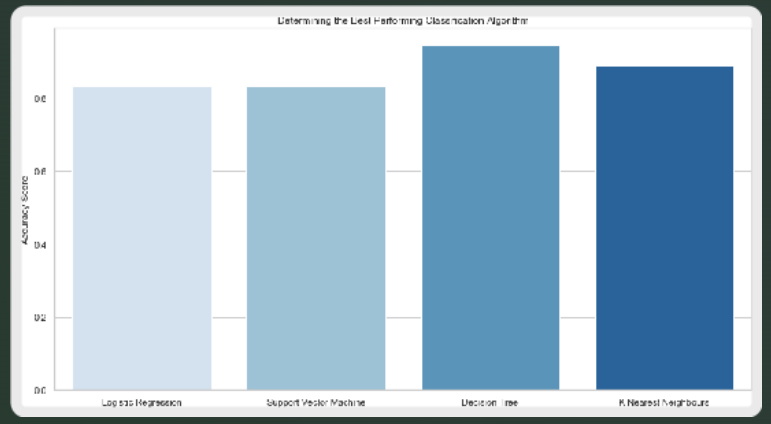
The launch site KSC LC-39 A had the most successful launches, with 41.7% of the total successful launches.

- PREDICTIVE ANALYSIS - CLASSIFICATION

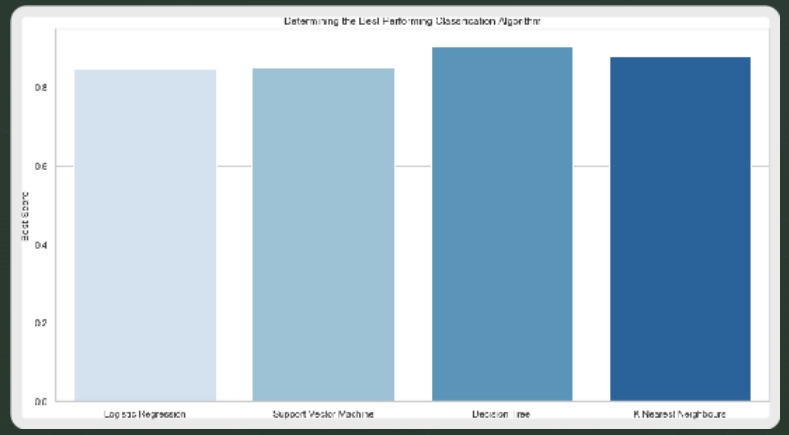
CLASSIFICATION ACCURACY

Plotting the Accuracy Score and Best Score for each classification algorithm produces the following result:

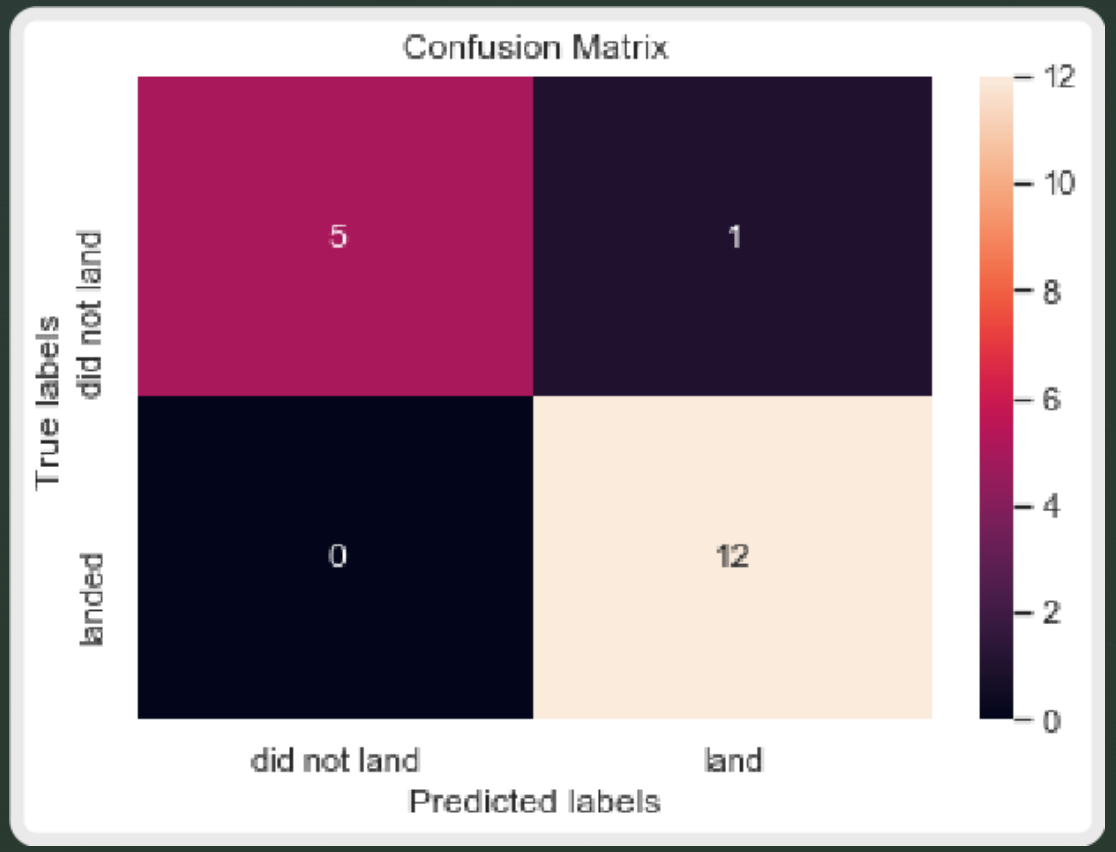
- The Decision Tree model has the highest classification accuracy
  - The Accuracy Score is 94.44%
  - The Best Score is 90.36%



Algorithm	Accuracy Score	Best Score
Logistic Regression	0.833333	0.846429
Support Vector Machine	0.833333	0.848214
Decision Tree	0.944444	0.903571
K Nearest Neighbours	0.888889	0.876786



Confusion Matrix



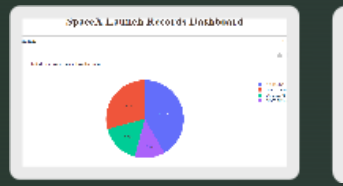
- As shown previously, best performing classification model is the Decision Tree model, with an accuracy of 94.44%.
- This is explained by the confusion matrix, which shows only 1 out of 18 total results classified incorrectly (a false positive, shown in the top-right corner).
- The other 17 results are correctly classified (5 did not land, 12 did land).

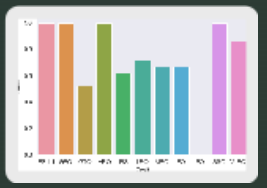
- CONCLUSIONS

CONCLUSIONS

- As the number of flights increases, the rate of success at a launch site increases, with most early flights being unsuccessful. I.e. with more experience, the success rate increases.
  - Between 2010 and 2013, all landings were unsuccessful (as the success rate is 0).
  - After 2013, the success rate generally increased, despite small dips in 2018 and 2020.
  - After 2016, there was always a greater than 50% chance of success.

- Orbit types ES-L1, GEO, HEO, and SSO, have the highest (100%) success rate.
  - The 100% success rate of GEO, HEO, and ES-L1 orbits can be explained by only having 1 flight into the respective orbits.
  - The 100% success rate in SSO is more impressive, with 5 successful flights.
  - The orbit types PO, ISS, and LEO, have more success with heavy payloads:
  - VLEO (Very Low Earth Orbit) launches are associated with heavier payloads, which makes intuitive sense.





- The launch site KSC LC-39 A had the most successful launches, with 41.7% of the total successful launches, and also the highest rate of successful launches, with a 76.9% success rate.

- The success for massive payloads (over 4000kg) is lower than that for low payloads.

- The best performing classification model is the Decision Tree model, with an accuracy of 94.44%.