

Winning Space Race with Data Science

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Executive Summary

- Summary of methodologies
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 - Data Collection with Web Scraping
 - Data Wrangling
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 - Interactive Visual Analytics with Folium
 - Machine Learning Prediction
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 - Interactive analytics in screenshots
 - Predictive Analytics result

Introduction

Project background and context

SpaceX offers Falcon 9 rocket launches for \$62 million, while other providers charge over \$165 million. The main reason for SpaceX's lower cost is that it can reuse the first stage of the rocket. If we can predict whether the first stage will land successfully, we can estimate launch costs. This information could help other companies compete with SpaceX for rocket launch contracts. The goal of this project is to build a machine learning model to predict first-stage landings.

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.



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.
 - We then 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.

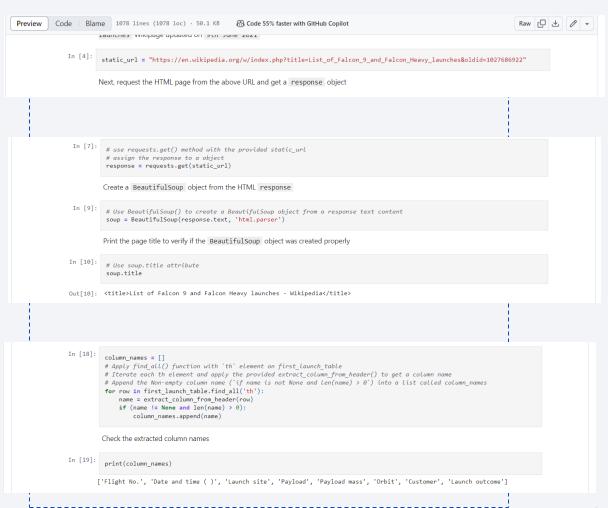
Data Collection - SpaceX API

- 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/PaulineLikoso/
 /IBMDS/blob/main/capstone folder
 /jupyter-labs-spacex-data collection-api%20(1).ipynb

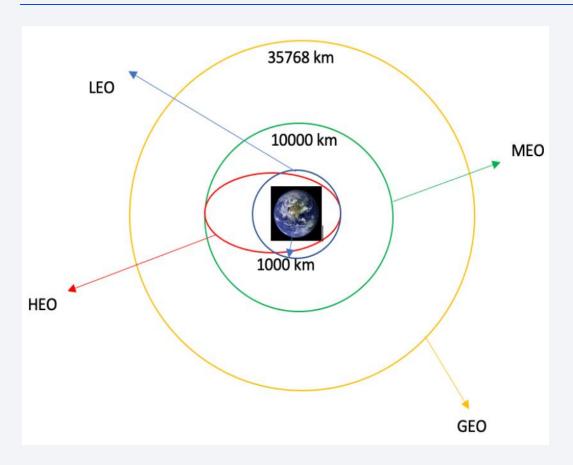
```
Now let's start requesting rocket launch data from SpaceX API with the following URL:
In [7]:
 spacex_url="https://api.spacexdata.com/v4/launches/past"
In [8]:
 response = requests.get(spacex_url)
In [22]:
 response=requests.get(static_json_url)
In [23]:
 response.status code
Out[23]:
 Now we decode the response content as a Json using .json() and turn it into a Pandas dataframe
 using .json normalize()
In [24]:
 # Use json normalize meethod to convert the json result into a dataframe
 data = pd.json_normalize(response.json())
In [25]:
 # Lets take a subset of our dataframe keeping only the features we want and the flight number
 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 rocl
 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
 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 I
 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)]</pre>
 data.head()
```

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 <u>https://github.com/PaulineLikoso/l</u> <u>BMDS/blob/main/capstone_folder/j</u> <u>upyter-labs-webscraping.ipynb</u>



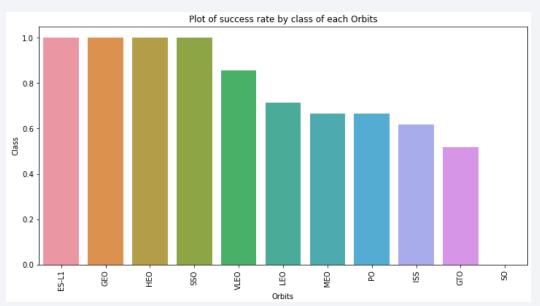
Data Wrangling

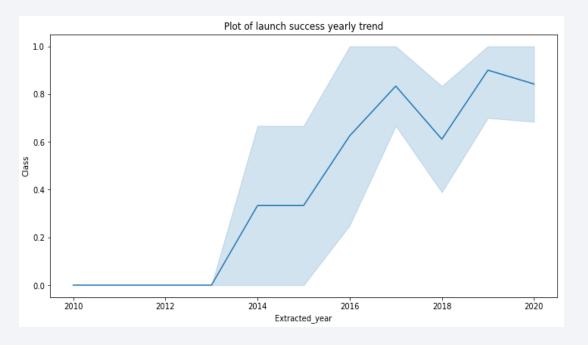


- We performed exploratory data analysis and determined the training labels.
- We calculated the number of launches at each site, and the number and occurrence of each orbits
- We created landing outcome label from outcome column and exported the results to csv.
- The link to the notebook is https://github.com/PaulineLikoso/IBMDS/
 blob/main/capstone folder/labs-jupyter-spacex-Data%20wrangling.ipynb">blob/main/capstone folder/labs-jupyter-spacex-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 trend.





 The link to the notebook is <u>https://github.com/PaulineLikoso/IBMD</u> <u>S/blob/main/capstone_folder/edadatavi</u> <u>z.ipynb</u>

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/PaulineLikoso/IBMDS/blob/main/capstone-folder/jupyter-labs-eda-sql-coursera-sqllite.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.

Build a Dashboard with Plotly Dash

- We built an interactive dashboard with Plotly dash
- We plotted pie charts showing the total launches by a certain sites
- We plotted scatter graph showing the relationship with Outcome and Payload Mass (Kg) for the different booster version.
- The link to the notebook is unavailable.

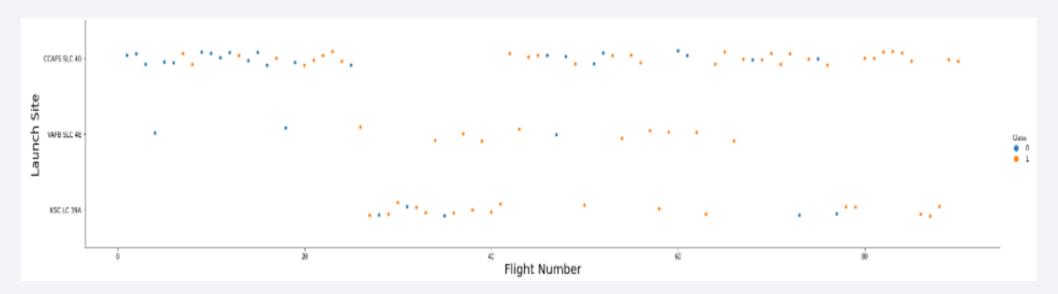
Predictive Analysis (Classification)

- 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/PaulineLikoso/IBMDS/blob/main/capstone-folder/SpaceX-Machine%20Learning%20Prediction-Part-5.ipynb



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

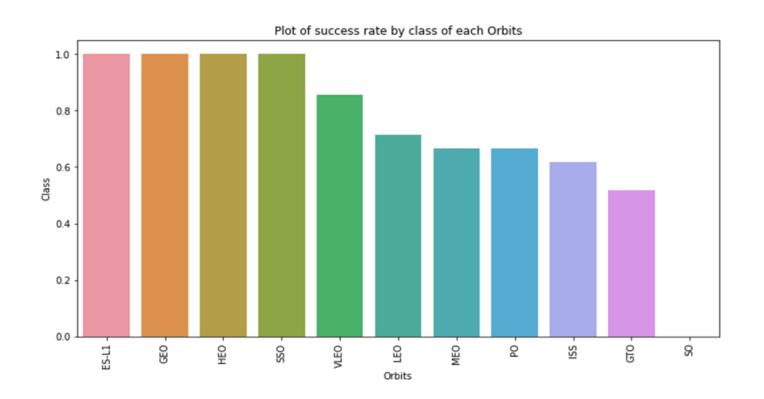


The greater the payload mass for launch site CCAFS SLC 40 the higher the success rate for the rocket.



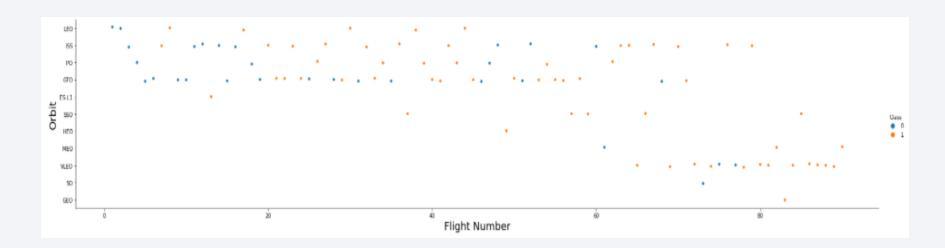
Success Rate vs. Orbit Type

• 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.



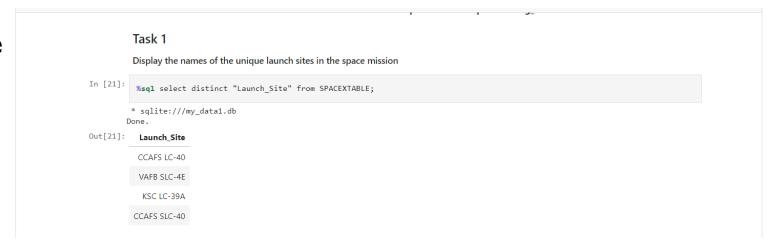
Launch Success Yearly Trend

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

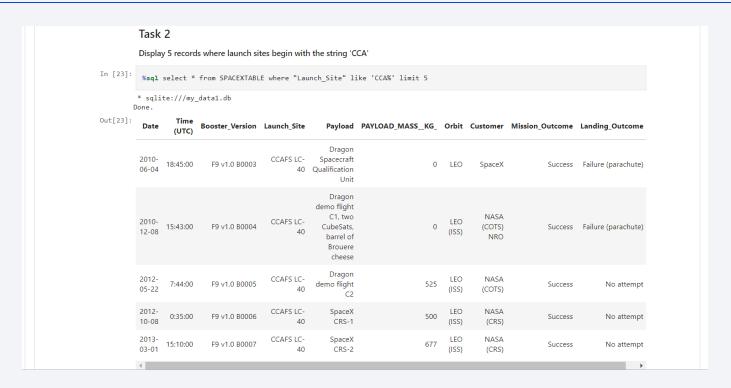


All Launch Site Names

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



Launch Site Names Begin with 'CCA'



 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)

In [32]: 

**sql select sum("PAYLOAD_MASS__KG_") as "TOTAL_PLM_LAUNCHED_NASA(CRS)" from SPACEXTABLE where Customer = 'NASA (CRS)'

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

Out[32]: 

**TOTAL_PLM_LAUNCHED_NASA(CRS)

45596
```

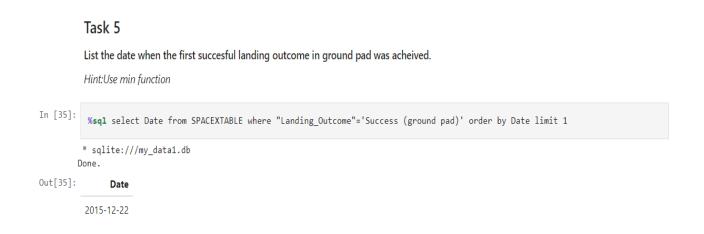
Average Payload Mass by F9 v1.1

 We calculated the average payload mass carried by booster version F9 v1.1 as 2534.67

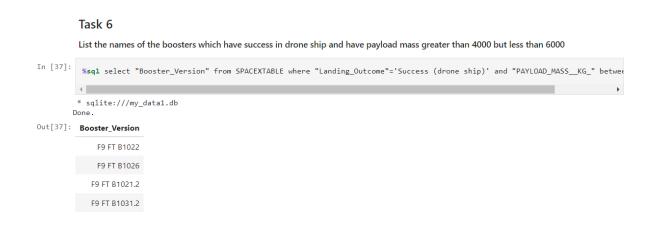
Task 4 Display average payload mass carried by booster version F9 v1.1 In [31]: **sql select avg("PAYLOAD_MASS__KG_") as "AVG_PLM_CARRIED_BY_F9V1.1" from SPACEXTABLE where "Booster_Version" like "F9 v1.1%" * sqlite://my_data1.db Done. Out[31]: AVG_PLM_CARRIED_BY_F9V1.1 2534.666666666665

First Successful Ground Landing Date

 We observed that the dates of the first successful landing outcome on ground pad was 22nd December 2015



Successful Drone Ship Landing with Payload between 4000 and 6000



 We used the WHERE clause to filter for boosters which have successfully landed on drone ship and applied the AND condition to determine successful landing with payload mass greater than 4000 but less than 6000

Total Number of Successful and Failure Mission Outcomes

Task 7 List the total number of successful and failure mission outcomes In [42]: %%sql SELECT WHEN "Mission_Outcome" LIKE 'Success%' THEN 'Success' WHEN "Mission Outcome" LIKE 'Failure%' THEN 'Failure' END AS Outcome. COUNT(*) AS Total Count FROM SPACEXTABLE WHERE "Mission_Outcome" LIKE 'Success%' OR "Mission_Outcome" LIKE 'Failure%' GROUP BY Outcome; * sqlite:///my_data1.db Done. Out[42]: Outcome Total_Count Failure Success

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

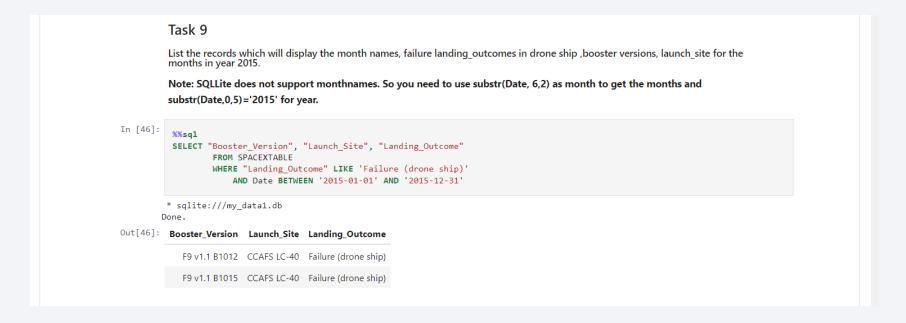
Boosters Carried Maximum Payload

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

```
SELECT "Booster_Version"
                  FROM SPACEXTABLE
                  WHERE "PAYLOAD MASS KG " = (
                                           SELECT MAX("PAYLOAD_MASS__KG_")
                                           FROM SPACEXTABLE
                  ORDER BY "Booster_Version";
         * sqlite:///my_data1.db
Out[45]: Booster_Version
            F9 B5 B1048.4
            F9 B5 B1048.5
            F9 B5 B1049.4
            F9 B5 B1049.5
            F9 B5 B1049.7
            F9 B5 B1051.3
            F9 B5 B1051.4
            F9 B5 B1051.6
            F9 B5 B1056.4
            F9 B5 B1058.3
            F9 B5 B1060.2
            F9 B5 B1060.3
```

2015 Launch Records

• We used a combinations of the WHERE clause, LIKE, AND, and BETWEEN conditions to filter for failed landing outcomes in drone ship, their booster versions, and launch site names for year 2015



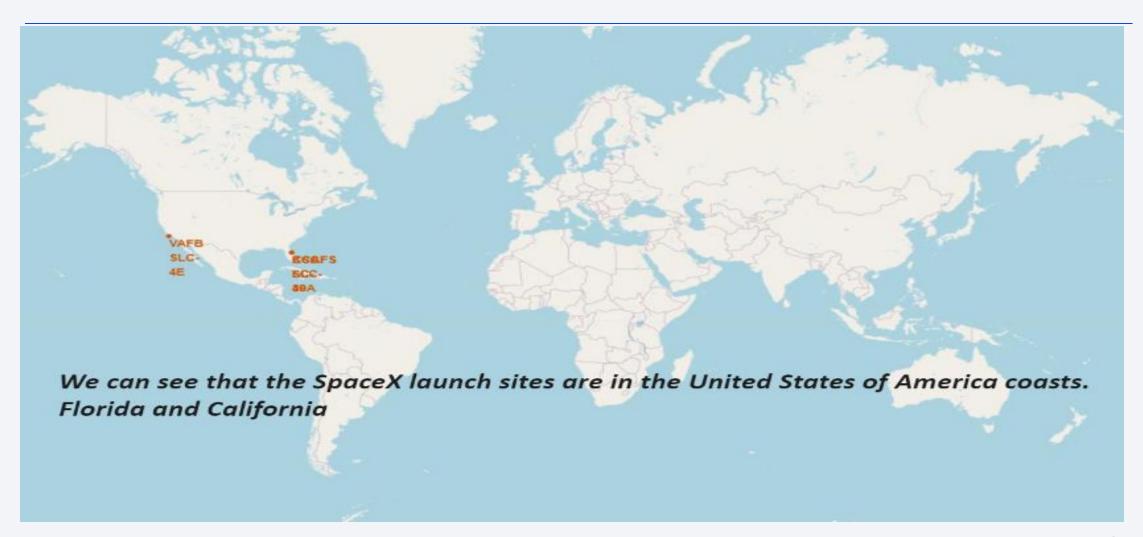
Rank Landing Outcomes Between 2010-06-04 and 2017-03-20

Task 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. In [47]: SELECT "Landing_Outcome", COUNT("Landing_Outcome") FROM SPACEXTABLE WHERE Date BETWEEN '2010-06-04' AND '2017-03-20 GROUP BY "Landing Outcome" ORDER BY COUNT("Landing_Outcome") DESC * sqlite:///my_data1.db Landing_Outcome COUNT("Landing_Outcome") No attempt Success (drone ship) Failure (drone ship) Success (ground pad) Controlled (ocean) Uncontrolled (ocean) Failure (parachute) Precluded (drone ship)

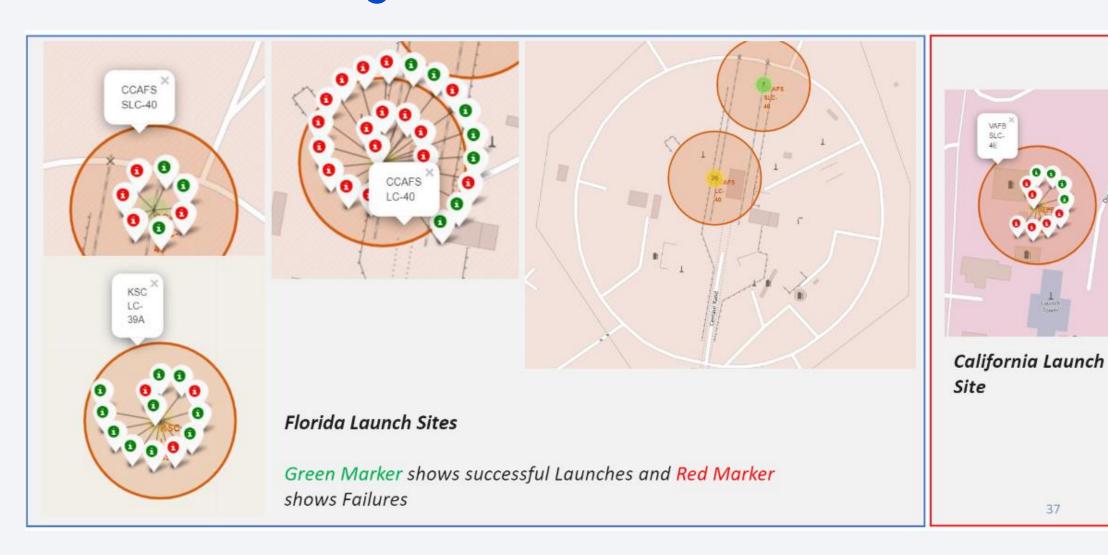
- We selected Landing outcomes and the COUNT of landing outcomes from the data and used the WHERE clause to filter for landing outcomes BETWEEN 2010-06-04 to 2010-03-20.
- We applied the GROUP BY clause to group the landing outcomes and the ORDER BY clause to order the grouped landing outcome in descending order.



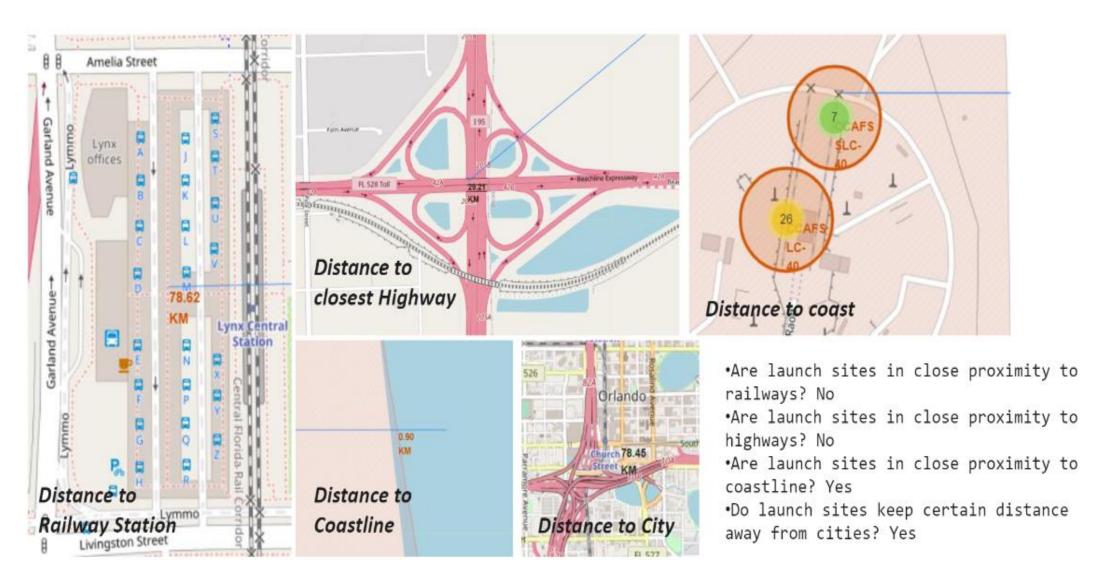
All launch sites global map markers



Markers showing launch sites with color labels



Launch Site distance to landmarks

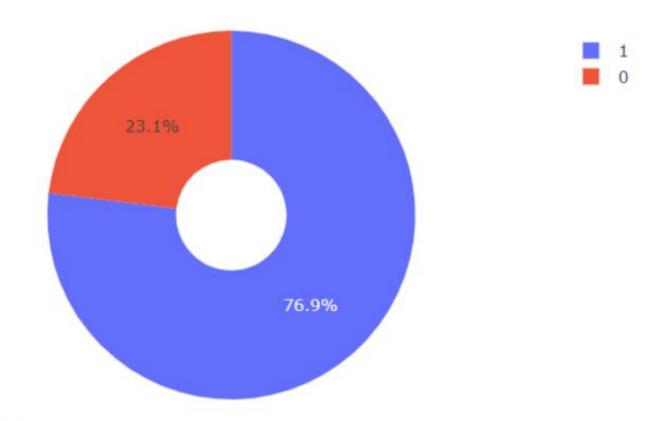




Pie chart showing the success percentage achieved by each launch site



Pie chart showing the Launch site with the highest launch success ratio



KSC LC-39A achieved a 76.9% success rate while getting a 23.1% failure rate

Scatter plot of Payload vs Launch Outcome for all sites, with different payload selected in the range slider



We can see the success rates for low weighted payloads is higher than the heavy weighted payloads



Classification Accuracy

• The SVM classifier is the model with the highest classification accuracy

TASK 12

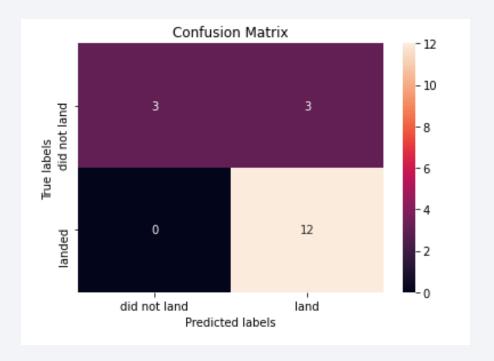
Find the method performs best:

```
In [62]:
  best_model = max((svm_score, "SVM"), (tree_score, "Decision Tree"), (knn_score, "KNN"))
  print("Best performing model:", best_model[1])
```

Best performing model: SVM

Confusion Matrix

 The confusion matrix for the SVM 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:

- Launch sites with more flights tend to have higher success rates.
- Success rates improved steadily from 2013 to 2020.
- The most successful orbits were ES-L1, GEO, HEO, SSO, and VLEO.
- KSC LC-39A had the highest number of successful launches.
- The SVM classifier was the best machine learning model for this task.

