

# Winning Space Race with Data Science

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# Outline











**Executive** Summary

Introduction

Methodology

Results

Conclusion

### **Executive Summary**

- Summary of methodologies
  - Data collection
    - API, Web scraping
  - Data Wrangling
  - Exploratory data analysis (EDA)
    - SQL, Data visualization (matplotlib, pandas)
  - Interactive visual analytics
    - Folium, Dashboard
  - Predictive analysis (classification)
    - Logistic regression, SVM, Classification tree, KNN

- Summary of results
  - EDA: Launch success improves over time, relationship[s between launch sites, orbit types, payload, flight number
  - Visualisation of where the launch sites are located
  - Predictive analytics shows similar results for different classification models

### Introduction

- Project Background and Context
- The commercial space age is here, making space travel affordable for everyone.
- Companies like Virgin Galactic, Rocket Lab, Blue Origin, and SpaceX are leading the charge.
- SpaceX Accomplishments:
  - Sending spacecraft to the International Space Station.
  - Starlink satellite internet constellation.
  - Manned missions to space.
  - Cost-effective launches with reusable rockets.
- Problems You Want to Find Answers
- Key Question: Will the first stage of SpaceX's Falcon 9 rocket land successfully?
- Goal: Determine the cost of each rocket launch (which depends on whether the first stage will land)
- Approach:
  - Gather information about SpaceX's launches.
  - Create dashboards for analysis.
  - Use machine learning to predict the reuse of the first stage.



# Methodology

#### **Executive Summary**

- Data collection methodology:
  - Data was collected using web scraping and API
- Perform data wrangling
  - Changing categorical features (success or failure specifically) to numbers using one hot encoding.
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
  - Four different machine learning models were used for classification: logistic regression, decision tree, svm and knn. For each, the best parameters to fit the model were found using grid search.

#### **Data Collection**

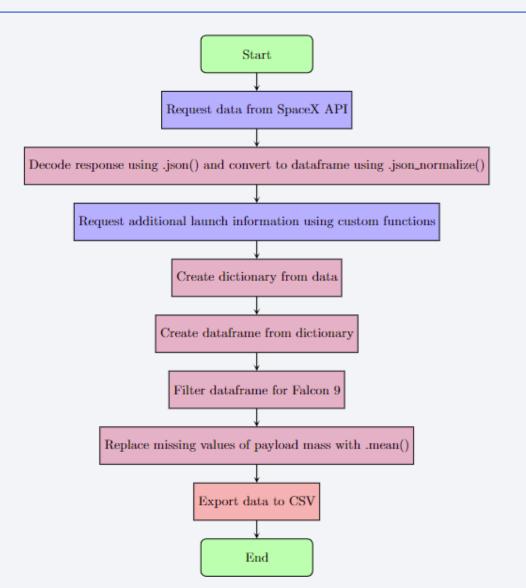
- The data was collected using 2 different methods: API and web scraping
- Get request to the SpaceX API.
- Using .json() function decode the response and read it as a pandas dataframe using .json\_normalize().
- Moreover, web scraping from Wikipedia was performed for Falcon 9 launch records with BeautifulSoup.
- Data was cleaned and null values removed for further analysis

# Data Collection – SpaceX API

 Data collection with SpaceX REST API

 The code can be found at the GitHub URL: <a href="https://github.com/federicazanca/d">https://github.com/federicazanca/d</a> <a href="atasc/blob/main/Data%20science">atasc/blob/main/Data%20science</a> <a href="#www.20science">%20capstone/jupyter-labs-spacex-</a>

data-collection-api.ipynb

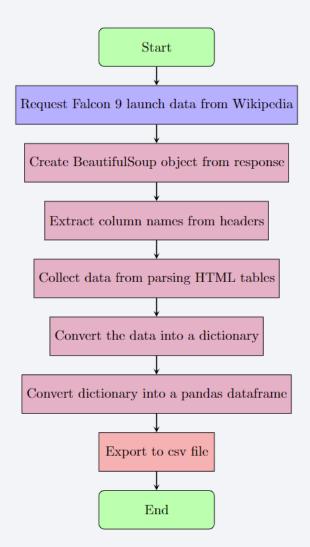


# **Data Collection - Scraping**

 Webscraping Falcon 9 launch records with BeautifulSoup

 The code can be found at the GitHub URL:

https://github.com/federicaza nca/datasc/blob/main/Data% 20science%20capstone/jupy ter-labs-webscraping.ipynb

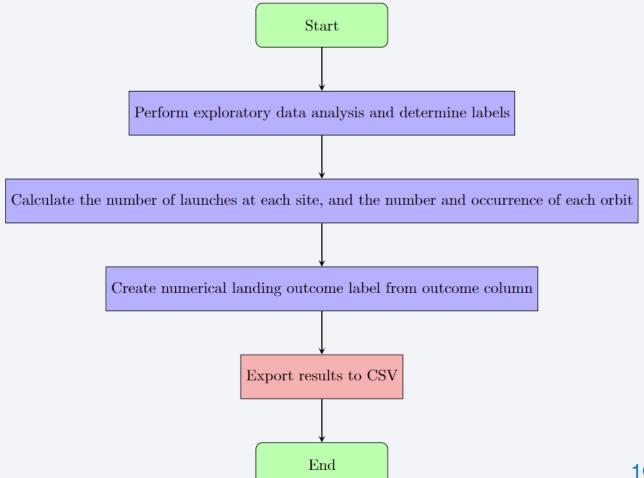


### **Data Wrangling**

 Data wrangling: EDA and converting categorical features to numerical ones.

 The code can be found at the GitHub URL:

https://github.com/federicaza nca/datasc/blob/main/Data% 20science%20capstone/labs -jupyter-spacex-Data%20wrangling.ipynb



#### **EDA** with Data Visualization

#### • GitHub URL:

https://github.com/federicazanca/datasc/blob/main/Data%20science%20caps tone/edadataviz.ipynb

#### Presented plots (in results section):

- Flight Number vs. Payload
- Flight Number vs. Launch Site
- Payload Mass (kg) vs. Launch Site
- Payload Mass (kg) vs. Orbit Type

#### They are in the form of

Scatter Plots: Explore relationships between variables.

Bar Charts: Compare discrete categories, illustrate relationships among categories and measured values.

### **EDA** with SQL

GitHub URL: <a href="https://github.com/federicazanca/datasc/blob/main/Data%20science%20capstone/jupyter-labs-eda-sql-coursera\_sqllite.ipynb">https://github.com/federicazanca/datasc/blob/main/Data%20science%20capstone/jupyter-labs-eda-sql-coursera\_sqllite.ipynb</a>

#### SQL queries to show:

- Names of the unique launch sites in the space mission
- 5 records where launch sites begin with the string 'CCA'
- Total payload mass carried by boosters launched by NASA (CRS)
- Average payload mass carried by booster version F9 v1.1
- · Date when the first succesful landing outcome in ground pad was acheived.
- Names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000
- Total number of successful and failure mission outcomes
- Names of the booster\_versions which have carried the maximum payload mass. Use a subquery
- Month names, failure landing\_outcomes in drone ship ,booster versions, launch\_site for the months in year 2015.
- How many landing outcomes (such as Failure (drone ship) or Success (ground pad)) are between the date 2010-06-04 and 2017-03-20, in descending order.

# Build an Interactive Map with Folium

#### Comprehensive Launch Sites and Outcomes Visualization

#### Markers Indicating Launch Sites

- Added blue circle at NASA Johnson Space Center's coordinate with a popup label showing its name using its latitude and longitude coordinates.
- Added red circles at all other launch sites coordinates with popup labels showing their names using their latitude and longitude coordinates.

#### Coloured Markers of Launch Outcomes

- Added coloured markers of successful and unsuccessful launches at each launch site to show which launch sites have high success rates.
- Assigned launch outcomes to class 0 for failure and class 1 for success to visually differentiate them on the map.

#### Distances Between a Launch Site to Proximities

- Added coloured lines to show distances between launch site CCAFS SLC-40 and its proximity to the nearest coastline, railway, highway, and city.
- Calculated distances to determine whether launch sites are near railways, highways, and coastlines, and if they maintain a certain distance from cities.

#### Map with Folium

- Combined the above elements into a comprehensive visualization using Folium, providing a detailed overview of launch site locations, their success rates, and their proximities to important geographical features.

### Build a Dashboard with Plotly Dash

GitHub: <a href="https://github.com/federicazanca/datasc/blob/main/Data%20science%20capstone/spacex\_dash\_app.py">https://github.com/federicazanca/datasc/blob/main/Data%20science%20capstone/spacex\_dash\_app.py</a>

#### **Dropdown List with Launch Sites**

Allow users to select all launch sites or a specific launch site for detailed analysis.

#### Slider of Payload Mass Range

Allow users to select a payload mass range to filter the data displayed.

#### Pie Chart Showing Successful Launches

- Provide a pie chart to display successful and unsuccessful launches as a percentage of the total launches.
- Allow users to view total launches by specific sites through interactive pie charts.

#### Scatter Chart Showing Payload Mass vs. Success Rate by Booster Version

- Provide a scatter chart to show the correlation between payload mass and launch success.
- Allow users to see the relationship between payload mass (Kg) and outcome for different booster versions.

#### Dashboard with Plotly Dash

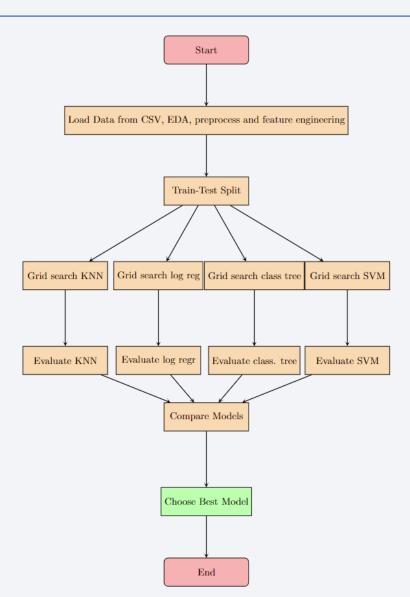
• Built an interactive dashboard using Plotly Dash to integrate these features, enabling users to dynamically explore and analyze the launch data.

# Predictive Analysis (Classification)

#### GitHub:

https://github.com/federicazanca/datasc/blob/main/Data%2 Oscience%20capstone/SpaceX\_Machine%20Learning%20P rediction\_Part\_5.ipynb

We found the best hyperparameters for 4 classification models and trained them to get the best predictions



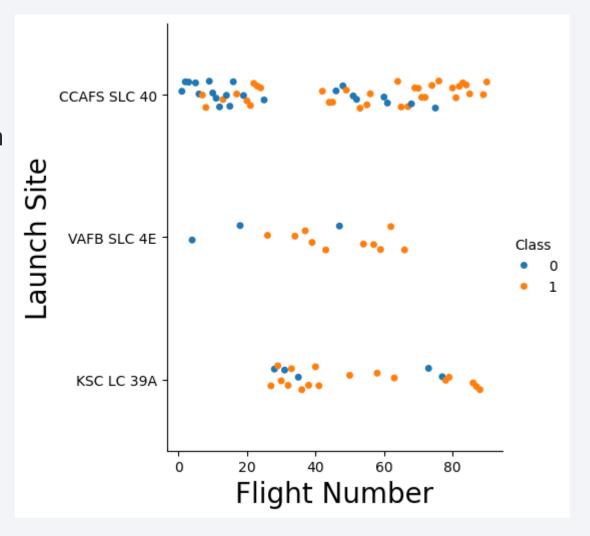
### Results

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



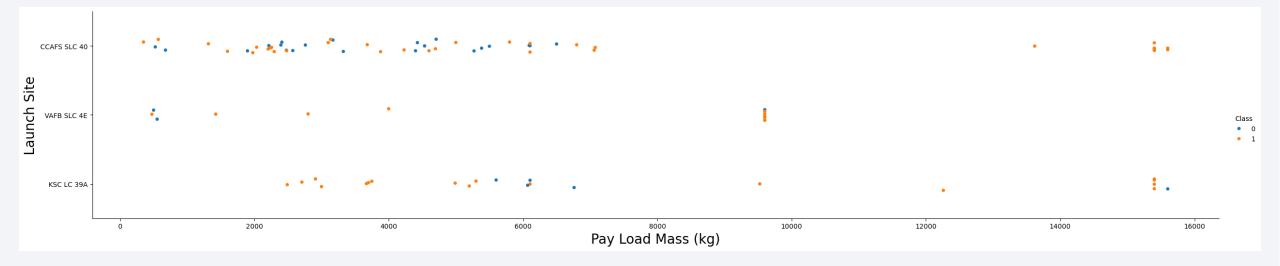
# Flight Number vs. Launch Site

- Flight Number vs. Launch Site
- We find that the more flights at a launch site, the greater the success rate at a launch site.



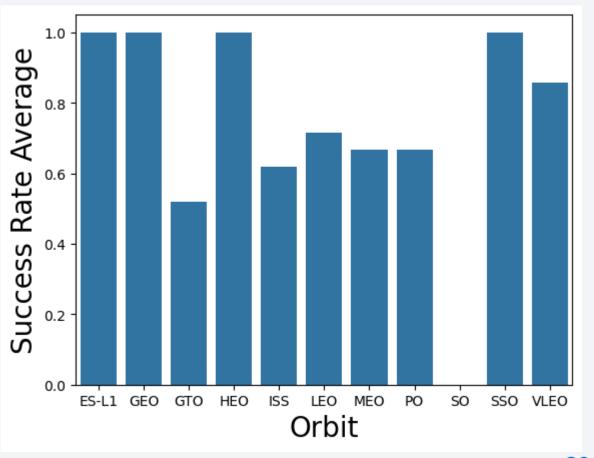
# Payload vs. Launch Site

• A big payload mass seems correlated to success



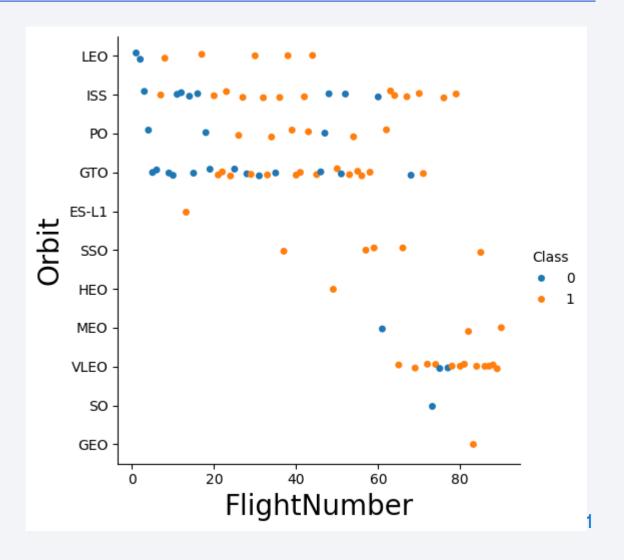
# Success Rate vs. Orbit Type

GTO seems to be the orbit with less success rate while SSO, HEO, GEO, ES-L1 perform very well



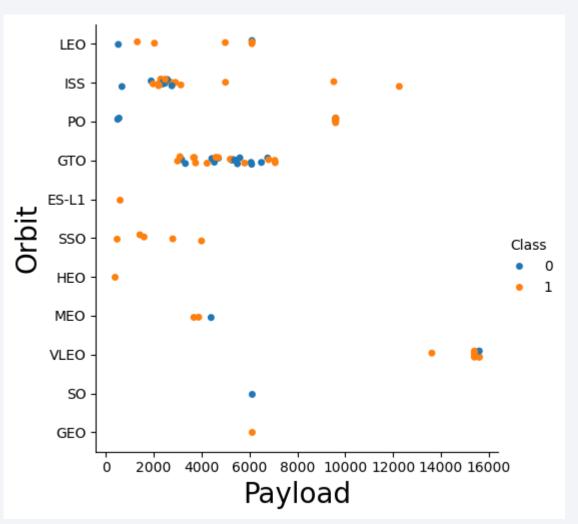
# Flight Number vs. Orbit Type

• In some orbits (eg LEO), success is related to the number of flights whereas in others (like GTO), there is no relationship between flight number and the orbit.



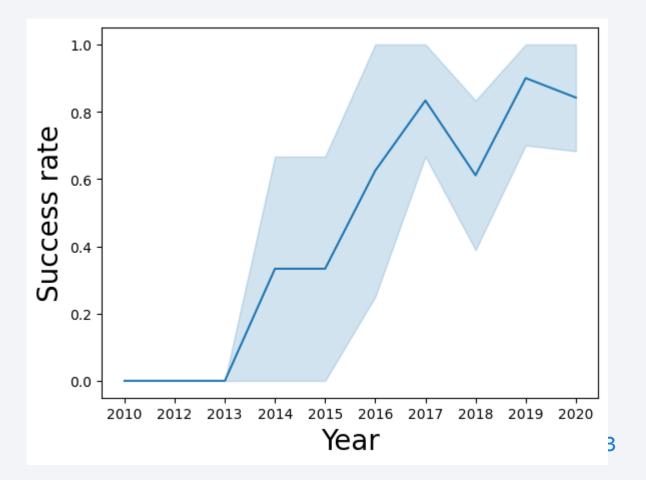
# Payload vs. Orbit Type

 With heavy payloads, PO, LEO and ISS orbits have more successful landings.



# Launch Success Yearly Trend

 Success rate increases throughout the years



### All Launch Site Names

 We use SQL and sqlite in jupyter to query the database

The launch site names are queried using select

```
%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'

Find 5 records where launch sites begin with `CCA`

• We use the keyword like to define that the launch site should contain CCA (it should actually be CCA% if we want it to begin with CCA but it is the same in this case)

• We use limit to get 5 results

* %s	al select	* from SPACEXTB								
* sqlite:///my_data1.db Done.										
Date	(UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS_I	KG_	Orbit	Customer	Mission_Outcome	Landing_Ou
2010- 06-04	18:45:00	F9 v1.0 B0003	CCAFS LC- 40	Dragon Spacecraft Qualification Unit		0	LEO	SpaceX	Success	Failure (para
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 (par
2012- 05-22	7:44:00	F9 v1.0 B0005	CCAFS LC- 40	Dragon demo flight C2		525	LEO (ISS)	NASA (COTS)	Success	No a
2012- 10-08	0:35:00	F9 v1.0 B0006	CCAFS LC- 40	SpaceX CRS-1	:	500	LEO (ISS)	NASA (CRS)	Success	No a
2013- 03-01	15:10:00	F9 v1.0 B0007	CCAFS LC- 40	SpaceX CRS-2		677	LEO (ISS)	NASA (CRS)	Success	No a

# **Total Payload Mass**

- Calculate the total payload carried by boosters from NASA
- Sum keyword used to calculate the sum of some values

```
%sql select sum(PAYLOAD_MASS__KG_) from SPACEXTBL where Customer is "NASA (CRS)"

* sqlite://my_data1.db
Done.
sum(PAYLOAD_MASS__KG_)

45596
```

# Average Payload Mass by F9 v1.1

- Calculate the average payload mass carried by booster version F9 v1.1
- Avg keyword used to calculate the average of some values

```
%sql select avg(PAYLOAD_MASS__KG_) from SPACEXTBL where Booster_Version is "F9 v1.1"

* sqlite://my_data1.db
Done.
avg(PAYLOAD_MASS__KG_)

2928.4
```

# First Successful Ground Landing Date

- Find the dates of the first successful landing outcome on ground pad
- Using min to find the first successful landing

```
%sql select min(Date),Landing_Outcome from SPACEXTBL where Landing_Outcome is "Success (ground pad)"
```

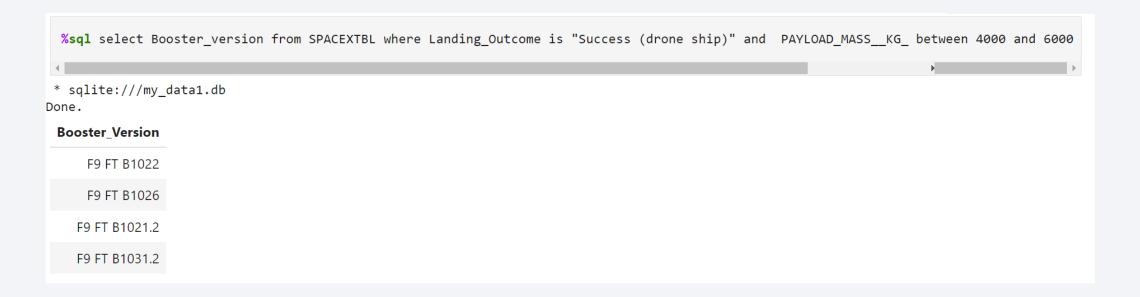
```
* sqlite://my_data1.db
Done.
```

#### min(Date) Landing\_Outcome

2015-12-22 Success (ground pad)

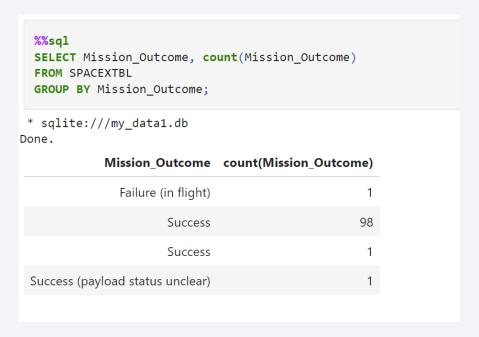
#### Successful Drone Ship Landing with Payload between 4000 and 6000

- List the names of boosters which have successfully landed on drone ship and had payload mass greater than 4000 but less than 6000
- Using keyword between to define a range for a selection



#### Total Number of Successful and Failure Mission Outcomes

- Calculate the total number of successful and failure mission outcomes
- Keyword group by is used to group results with the same mission outcome



# **Boosters Carried Maximum Payload**

- List the names of the booster which have carried the maximum payload mass
- Using a subquery to select specifically boosters with maximum payload mass

```
%%sql
  select Booster_version, PAYLOAD_MASS__KG_
  from SPACEXTBL
  where PAYLOAD_MASS__KG_ in
  (select max(PAYLOAD MASS KG ) from SPACEXTBL)
* sqlite:///my data1.db
Done.
 Booster Version PAYLOAD MASS KG
   F9 B5 B1048.4
                                15600
   F9 B5 B1049.4
                                15600
   F9 B5 B1051.3
                                15600
   F9 B5 B1056.4
                                15600
   F9 B5 B1048.5
                                15600
   F9 B5 B1051.4
                                15600
```

### 2015 Launch Records

- List the failed landing\_outcomes in drone ship, their booster versions, and launch site names for in year 2015
- Here we use substring for the dates as SQLLite does not support monthnames

```
%%sql
select substr(Date, 6,2) as Month, Landing_Outcome, Booster_Version, Launch_Site
from SPACEXTBL
where substr(Date,0,5)='2015'
and Landing_Outcome is "Failure (drone ship)"

* sqlite://my_data1.db
Done.

Month Landing_Outcome Booster_Version Launch_Site

01 Failure (drone ship) F9 v1.1 B1012 CCAFS LC-40

04 Failure (drone ship) F9 v1.1 B1015 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

%%sql

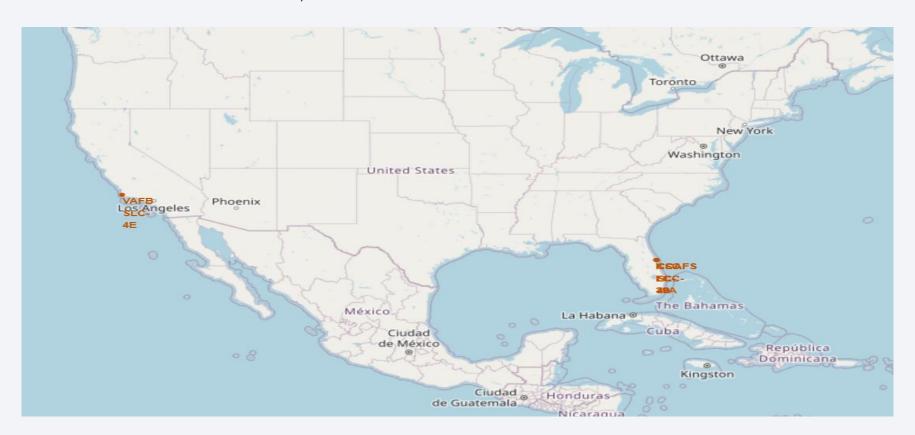
descending order

```
select Landing_Outcome, count(Landing_Outcome)
 from SPACEXTBL
 where date between '2010-06-04' and '2017-03-20'
 group by Landing Outcome
 order by count(Landing Outcome) desc
* sqlite:///my data1.db
Done.
   Landing_Outcome count(Landing_Outcome)
                                           10
          No attempt
  Success (drone ship)
   Failure (drone ship)
 Success (ground pad)
    Controlled (ocean)
                                            3
  Uncontrolled (ocean)
                                            2
```



### All launch sites

• Launch sites are in the US, in Florida and California



# Markers indicating success and failure

- The red markers indicate the failure of a launch and the green one success.
- The number on the launch sites zoomed out represents the total number of launches





#### Distances between launch sites and coast

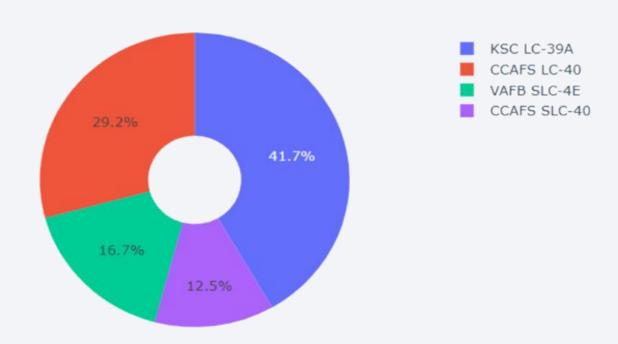
- Folium can also be used to calculate distances between parts of the map. The figure shows the distance between one of the sites and the coast.
- We calculated that launch sites are in close proximity to the coastline and cities, but not to highways and railways





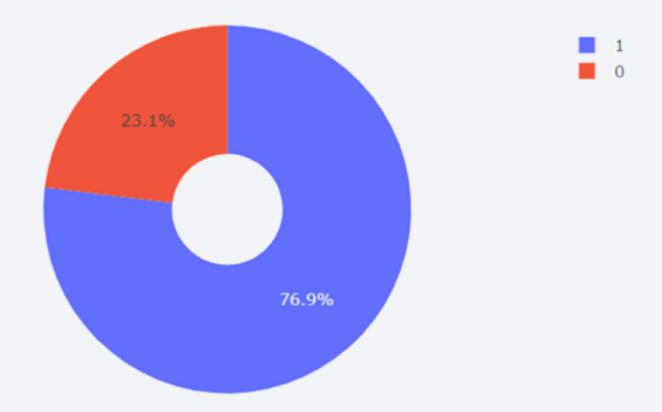
### Pie chart of success count for al sites

 The pie chart shows that KSC LC39A has more successful launches than the others



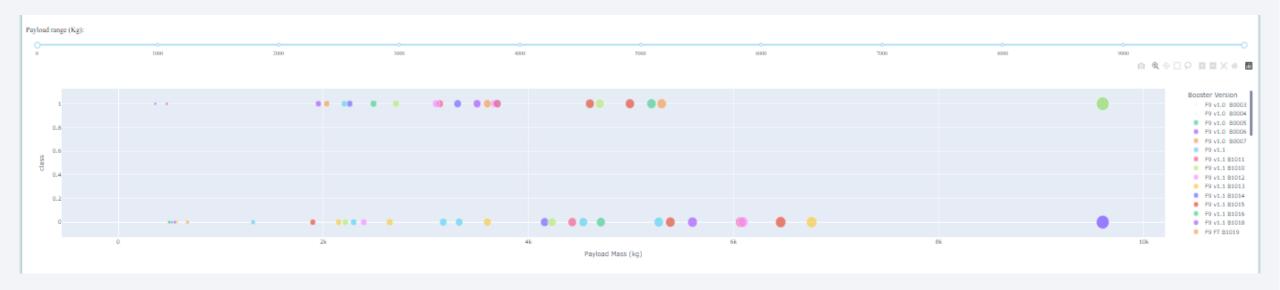
### Pie chart for KSC LC39A

• The site KSC LC39A has 76.9 % of success and 23.1 of failure for its launches



### Scatter plot of Payload vs Launch Outcome for all sites

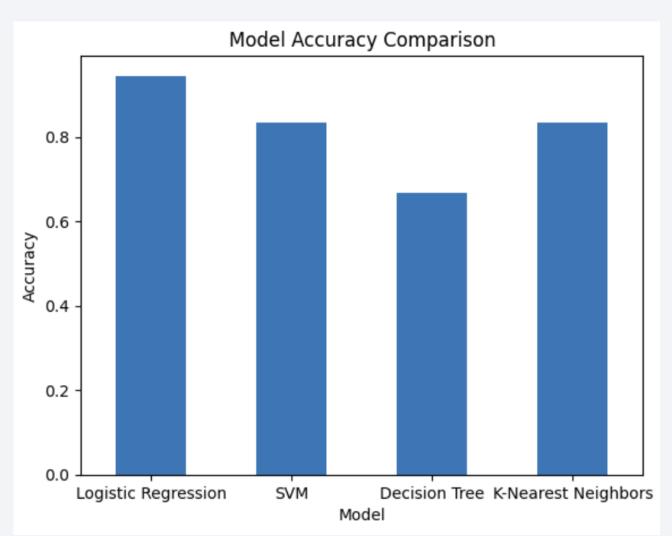
The dashboard visualiser allows to use the slider to visualise success rate of different booster versions in different payload ranges





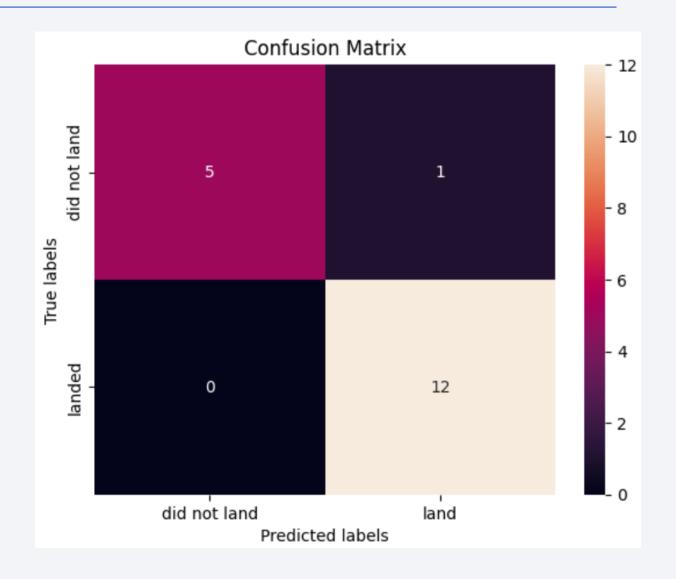
# **Classification Accuracy**

• The logistic regression model used for classification has the best accuracy in this case



### **Confusion Matrix**

• Examining the confusion matrix, we see that logistic regression can distinguish between the different classes. We see that the major problem is false positives.



### Conclusions

Launch Frequency and Success Rate: The larger the flight amount at a launch site, the greater the success rate. Launch success rate has been increasing steadily from 2013 to 2020.

Optimal Launch Sites: KSC LC-39A stands out with the highest success rate among all launch sites. Notably, it boasts a 100% success rate for launches carrying payloads less than 5,500 kg.

Geographical Advantage: Most launch sites are located near the equator and close to the coast, providing a natural boost due to the Earth's rotational speed and reducing additional fuel and booster requirements.

**Orbital Success**: Orbits such as ES-L1, GEO, HEO, SSO, and VLEO demonstrate the highest success rates.

Payload Mass Correlation: Across all launch sites, a higher payload mass (kg) is associated with a higher success rate.

Model Performance: The logistic regression classifier is identified as the best machine learning algorithm for this task, slightly outperforming other models on the test set.

