

# Winning Space Race with Data Science

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## **Outline**

- Executive Summary
- Introduction
- Methodology
- Results
- Conclusion
- Appendix

# **Executive Summary**

- Summary of methodologies
  - Data Collection from API
  - Data collection via webscraping
  - Data wrangling
  - EDA (Exploratory Data Analysis) with SQL and data visualization
  - Interactive visual analytics using Folium
  - Machine Learning Prediction
- Summary of all results
  - EDA result
  - Interactive analysis (screenshots)
  - ML Predictive Analytics results

## Introduction

- Project background and context
  - SpaceX advertises Falcon 9 rocket launches on its website with a cost of \$62 million, while other providers charge upwards of \$165 million per launch. Much of the savings come from SpaceX's ability to reuse the first stage of the rocket. Therefore, by predicting whether the first stage will land successfully, we can estimate the cost of a launch. This information can be valuable for alternate companies looking to compete with SpaceX for rocket launch contracts. The goal of this project is to create a machine learning pipeline to predict the successful landing of the first stage.
- Problems you want to find answers
  - What factors determine a successful rocket landing?
  - How are the features that determine the success rate of landing related?
  - Are any operating conditions needed to determine if a landing will be successful?



# Methodology

#### **Executive Summary**

- Data collection methodology:
  - Using SpaceX Rest API
  - Via web scraping Wikipedia
- Perform data wrangling
  - By hot encoding data fields and dropping the irrelevant data columns (data transformation)
- Perform exploratory data analysis (EDA) using visualization and SQL
  - Creating scatter and bar graphs to discover patterns,
- Perform interactive visual analytics using Folium and Plotly Dash
  - Using Plotly and Folium
- Perform predictive analysis using classification models
  - · Building & Evaluating classification models

## **Data Collection**

#### **Data Collection – Meaning & Basic Steps**

Data collection is the process of gathering and measuring information on targeted variables in an established system, enabling one to answer relevant questions and evaluate outcomes.

- Getting Data from API or Web Page
- Make a dataframe from it
- Filter dataframes as per requirement
- Export to flat file

GitHub Notebook

Getting Data from API or Web Page

```
In [6]: spacex_url="https://api.spacexdata.com/v4/launches/past"
In [7]: response = requests.get(spacex_url)
```

#### Make a dataframe

```
# Use json_normalize meethod to convert the json result into a dataframe

data = pd.json_normalize(response.json())
```

#### Filter DF

```
# Hint data['BoosterVersion']!='Falcon 1'
# data_falcon9['BoosterVersion']!='Falcon 9' returns true for all rows except 'Falcon 9' and running drop, drops those rows.

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

#### Work with missing values

```
In [34]: # Calculate the mean value of PayLoadMass column
avg_payload_mass = data_falcon9["PayloadMass"].astype("float").mean(axis=0)
# Replace the np.nan values with its mean value
data_falcon9["PayloadMass"].replace(np.nan, avg_payload_mass, inplace=True)

You should see the number of missing values of the PayLoadMass change to zero.

In [35]: data_falcon9.isnull().sum()
```

Out[36]:		FlightNumber	Date	BoosterVersion	PayloadMass	Orbit	LaunchSite	Outcome	Flights	GridFins	Reused	Legs	LandingPad	Block
	4	1	2010- 06-04	Falcon 9	6123.547647	LEO	CCSFS SLC 40	None None	1	False	False	False	None	1
	5	2	2012- 05-22	Falcon 9	525.000000	LEO	CCSFS SLC 40	None None	1	False	False	False	None	1
	6	3	2013- 03-01	Falcon 9	677.000000	ISS	CCSFS SLC 40	None None	1	False	False	False	None	1
	7	4	2013- 09-29	Falcon 9	500.000000	РО	VAFB SLC 4E	False Ocean	1	False	False	False	None	1
	8	5	2013- 12-03	Falcon 9	3170.000000	GTO	CCSFS SLC 40	None None	1	False	False	False	None	1

#### Export to file

```
data_falcon9.to_csv('dataset_part_1.csv', index=False)

data_falcon9.to_csv('csvs/dataset_part_1.csv', index=False)
```

1	FlightNumber	Date	BoosterVersion	PayloadMass	Orbit	LaunchSite	Outcome	Flights	GridFins	Reused	Legs	LandingPad	Block	ReusedCount	Serial	Longitude	Latitude
2	1	2010-06-04	Falcon 9	6123.547647058824	LEO	CCSFS SLC 40	None None	1	False	False	False		1	0	B0003	-80.577366	28.5618571
3	2	2012-05-22	Falcon 9	525.0	LEO	CCSFS SLC 40	None None	1	False	False	False		1	0	B0005	-80.577366	28.5618571
4	3	2013-03-01	Falcon 9	677.0	ISS	CCSFS SLC 40	None None	1	False	False	False		1	0	B0007	-80.577366	28.5618571
5	4	2013-09-29	Falcon 9	500.0	PO	VAFB SLC 4E	False Ocean	1	False	False	False		1	0	B1003	-120.610829	34.632093
6	5	2013-12-03	Falcon 9	3170.0	GTO	CCSFS SLC 40	None None	1	False	False	False		1	0	B1004	-80.577366	28.5618571
7	6	2014-01-06	Falcon 9	3325.0	GTO	CCSFS SLC 40	None None	1	False	False	False		1	0	B1005	-80.577366	28.5618571
8	7	2014-04-18	Falcon 9	2296.0	ISS	CCSFS SLC 40	True Ocean	1	False	False	True		1	0	B1006	-80.577366	28.5618571
9	8	2014-07-14	Falcon 9	1316.0	LEO	CCSFS SLC 40	True Ocean	1	False	False	True		1	0	B1007	-80.577366	28.5618571
10	9	2014-08-05	Falcon 9	4535.0	GTO	CCSFS SLC 40	None None	1	False	False	False		1	0	B1008	-80.577366	28.5618571
11	10	2014-09-07	Falcon 9	4428.0	GTO	CCSFS SLC 40	None None	1	False	False	False		1	0	B1011	-80.577366	28.5618571
12	11	2014-09-21	Falcon 9	2216.0	ISS	CCSFS SLC 40	False Ocean	1	False	False	False		1	0	B1010	-80.577366	28.5618571
13	12	2015-01-10	Falcon 9	2395.0	ISS	CCSFS SLC 40	False ASDS	1	True	False	True	5e9e3032383ecb761634e7cb	1	0	B1012	-80.577366	28.5618571
14	13	2015-02-11	Falcon 9	570.0	ES-L1	CCSFS SLC 40	True Ocean	1	True	False	True		1	0	B1013	-80.577366	28.5618571
15	14	2015-04-14	Falcon 9	1898.0	ISS	CCSFS SLC 40	False ASDS	1	True	False	True	5e9e3032383ecb761634e7cb	1	0	B1015	-80.577366	28.5618571
16	15	2015-04-27	Falcon 9	4707.0	GTO	CCSFS SLC 40	None None	1	False	False	False		1	0	B1016	-80.577366	28.5618571
17	16	2015-06-28	Falcon 9	2477.0	ISS	CCSFS SLC 40	None ASDS	1	True	False	True	5e9e3032383ecb6bb234e7ca	1	0	B1018	-80.577366	28.5618571
18	17	2015-12-22	F-1 0	2034.0	LEO	CCSES SIC AD	T RTIS	1	T	Falso	Т	520230323832, 1,267,3427, 7	1	0	R1010	-80 577366	28 5618571

# **Data Collection - Scraping**

- Web scraping was performed using BeautifulSoup
- This was then parsed and turned into a DF
- GitHub URL

```
In [8]: # Use BeautifulSoup() to create a BeautifulSoup object from a response text content
soup = BeautifulSoup(data, 'html5lib')

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

In [10]: # Use soup.title attribute
tag_title = soup.title
tag_string_tag_title = tag_title.string
tag_string_tag_title
```

:	df=pd.DataFrame(launch_dict)											
	df.h	nead()										
		Flight No.	Launch site	Payload	Payload mass	Orbit	Customer	Launch outcome	Version Booster	Booster landing	Date	Time
	0	1	CCAFS	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success\n	F9 v1.0B0003.1	Failure	4 June 2010	18:45
	1	2	CCAFS	Dragon	0	LEO	NASA	Success	F9 v1.0B0004.1	Failure	8 December 2010	15:43
	2	3	CCAFS	Dragon	525 kg	LEO	NASA	Success	F9 v1.0B0005.1	No attempt\n	22 May 2012	07:44
	3	4	CCAFS	SpaceX CRS-1	4,700 kg	LEO	NASA	Success\n	F9 v1.0B0006.1	No attempt	8 October 2012	00:35
	4	5	CCAFS	SpaceX CRS-2	4,877 kg	LEO	NASA	Success\n	F9 v1.0B0007.1	No attempt\n	1 March 2013	15:10
	df=	pd.Dat	aFrame({ k	ey:pd.Series(value)	for key,	value	in launch d	ict.items()	})			

# **Data Wrangling**

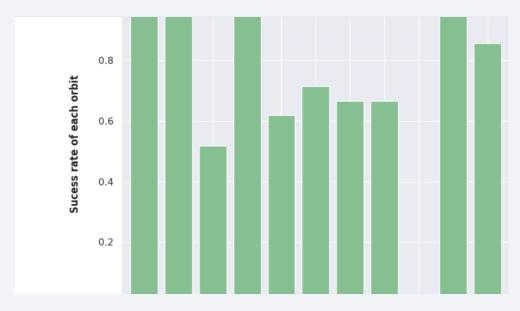
- EDA was performed and the training labels were determined.
- The number of launches for each site was calculated, and the number of occurrences of each orbit.
- A label was also created for landing outcome and this was exported to CSV.

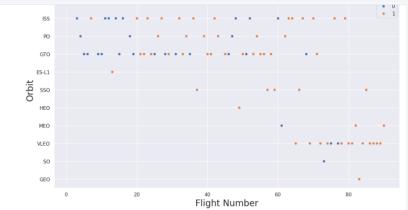
GitHub URL

## **EDA** with Data Visualization

- Data Visualization performed was:
- The relationship between flight number and launch site
- Payload and launch site, success rate of each orbit
- Flight number and orbit type
- Yearly trend of launch success.

GitHub URL





# **EDA** with SQL

- The SpaceX dataset was loaded into a database directly inside Jupyter notebook.
- The following SQL queries were written and performed on the data:
  - 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 failed mission outcomes
  - The failed landing outcomes in drone ship, their booster version and launch site names

See the notebook on GitHub for more information.

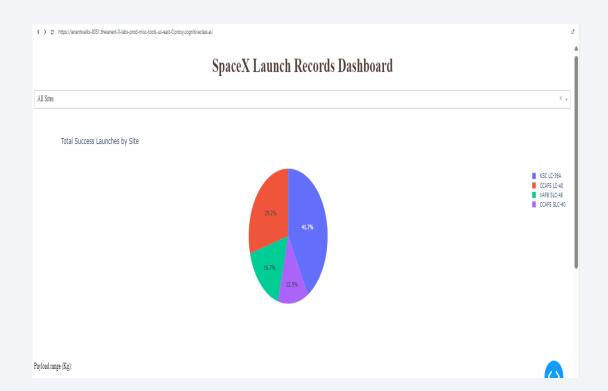
# Build an Interactive Map with Folium

- We marked all launch sites on an interactive Folium map. This map included markers, circles and lines to measure the success or failure of each launch for each launch site.
- Classes O and 1 were created to signify launch outcomes (e.g. class O was failure and class 1 was a success).
- Colour-coded markers were also added to marked clusters to help identify which launch sites had a high rate of success.
- Distances were calculated between a launch site and area proximities such as roads and rail. This data was then used to answer questions on the relationship between launch sites and their distance between them and cities and their overall location.
- GitHub URL

# Build a Dashboard with Plotly Dash

- An interactive dashboard was created with Plotly.
- For this, pie charts were created showing the number of launchers per site.
- Scatter graphs were also created to show relationships between Outcome and Payload Mass (Kg) for different booster version.

GitHub URL for .py program



# Predictive Analysis (Classification)

- Data was loaded using NumPy and pandas. The data was then transformed and split into two sets, training and testing.
- Using GridSearchCV it allowed for building different machine learning models and for tuning of different hyperparameters.
- The metric used for the model was accuracy, this was improved using feature engineering and algorithm tuning.
- We also used this to discover which classification model performed best.

GitHub URL

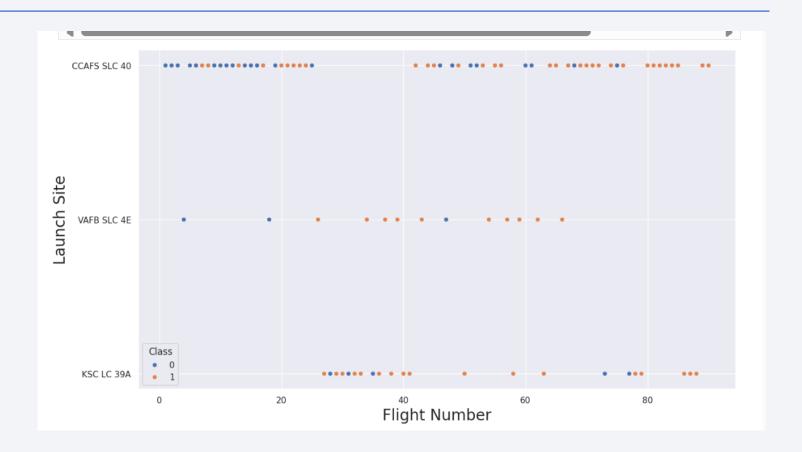
## Results

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



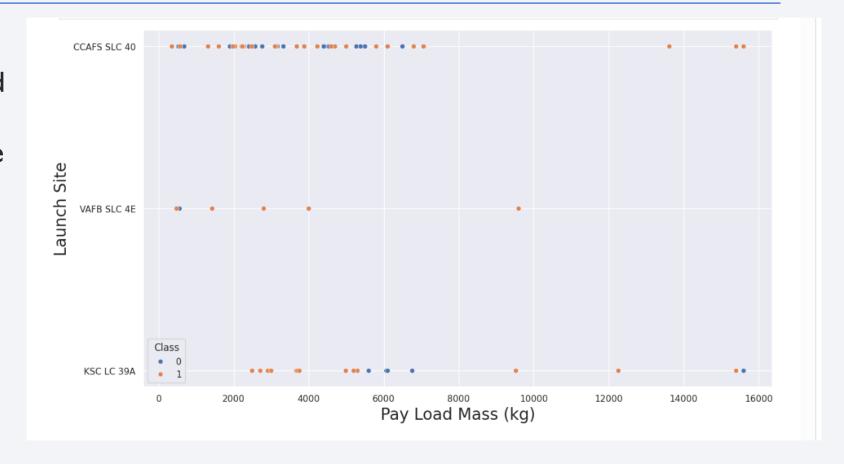
# Flight Number vs. Launch Site

Based on the graph, it
 was determined that
 higher amount of
 launches a flight had at
 a launch site then the
 greater the launch
 success rate for that
 particular site.



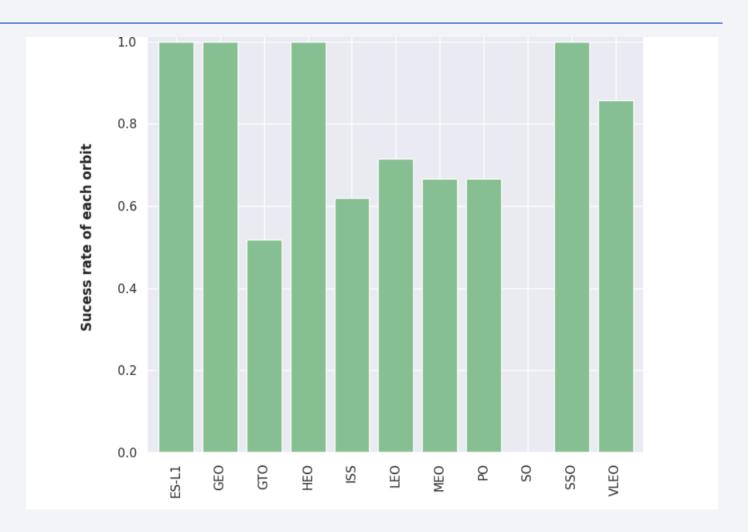
# Payload vs. Launch Site

 Based on the graph, the greater the payload mass then the higher the success rate for the rocket (e.g. CCAFS SLC 40).



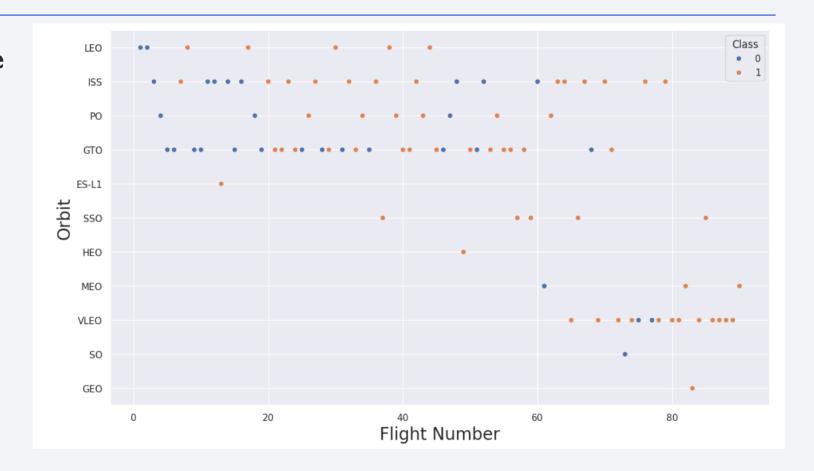
# Success Rate vs. Orbit Type

 Based on the graph, we can see that the most successful orbit types were ES-L1, GEO, HEO, SSO



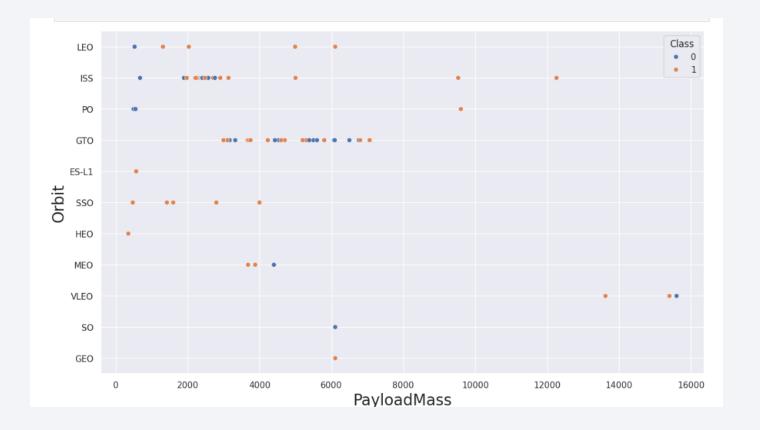
# Flight Number vs. Orbit Type

- Based on the graph, we can see that, for LEO orbit type, the success is related to the number of flights.
- For other orbit types,
   e.g. GTO, there is no such relationship.



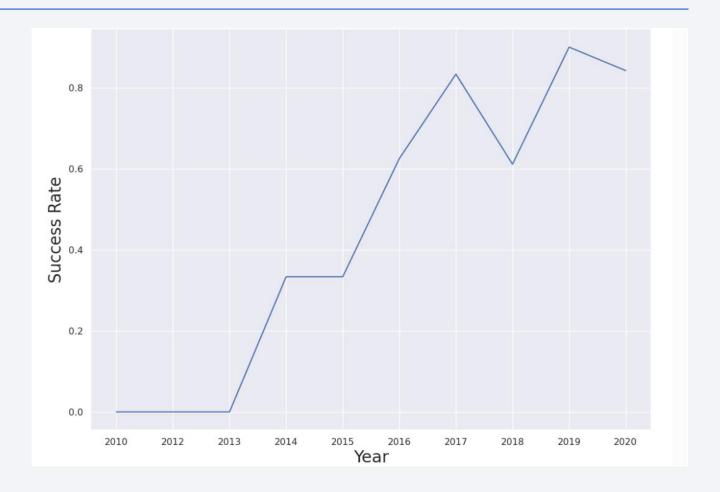
# Payload vs. Orbit Type

 From the graph we can see that when the PayloadMass (KG) is heaver then orbit types such as PO, LEO and ISS are more successful.



# Launch Success Yearly Trend

• From the graph we can see that between the years 2013 and 2020 the launch success rate continued to grow.



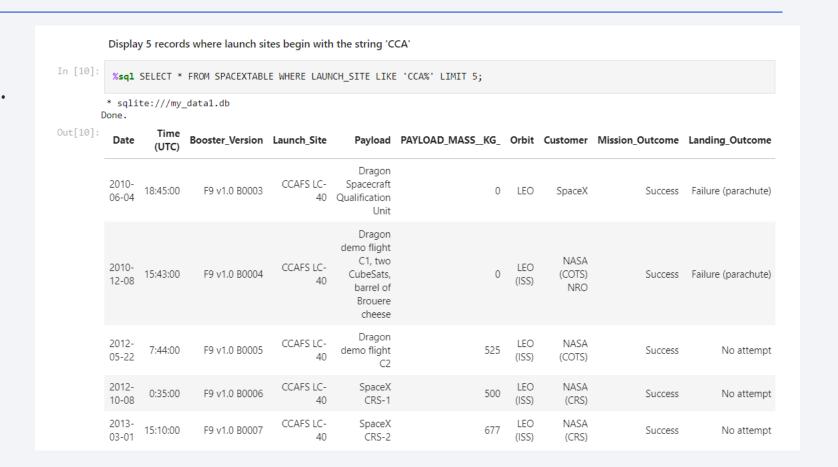
## All Launch Site Names

• This SQL query used DISTINCT to show only unique launch site data.

```
In [9]:
         %sql SELECT DISTINCT LAUNCH_SITE as "Launch_Sites" FROM SPACEXTABLE;
        * sqlite:///my_data1.db
       Done.
Out[9]:
         Launch_Sites
         CCAFS LC-40
          VAFB SLC-4E
          KSC LC-39A
        CCAFS SLC-40
```

# Launch Site Names Begin with 'CCA'

• The following query was used, with results shown.



# **Total Payload Mass**

• The following query was used, with results shown.

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

**sql SELECT SUM(PAYLOAD_MASS__KG_) AS "Total Payload Mass by NASA (CRS)" FROM SPACEXTABLE WHERE CUSTOMER = 'NASA (CRS)';

**sqlite:///my_datal.db
Done.

#t[11]: Total Payload Mass by NASA (CRS)

45596
```

# Average Payload Mass by F9 v1.1

 The following query was used, with results shown.

#### Task 4

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

```
# sqlite://my_data1.db
Done.
# Select Avg(PayLoad_Mass by Booster Version F9 v1.1" FROM SPACEXTABLE \
# sqlite://my_data1.db
Done.

# 2928.4
```

# First Successful Ground Landing Date

• The following query was used, with results shown.

\* Note: Not sure about this.

```
Task 5

List the date when the first succesful landing outcome in ground pad was acheived.

Hint:Use min function

In [57]: 
*sql SELECT MIN(DATE) AS "First Succesful Landing Outcome in Ground Pad" FROM SPACEXTABLE \
WHERE 'Landing _Outcome' LIKE 'Success (ground pad)';

* sqlite:///my_datal.db
Done.

Out[57]: 
First Succesful Landing Outcome in Ground Pad

None
```

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

 The following query was used, with results shown.

List the names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000

\*\*sql SELECT BOOSTER\_VERSION FROM SPACEXTABLE WHERE Landing\_Outcome = 'Success (drone ship)' \
AND PAYLOAD\_MASS\_\_KG\_ > 4000 AND PAYLOAD\_MASS\_\_KG\_ < 6000;

\* sqlite:///my\_data1.db
Done.

\*\*Booster\_Version

F9 FT B1022

F9 FT B1021.2

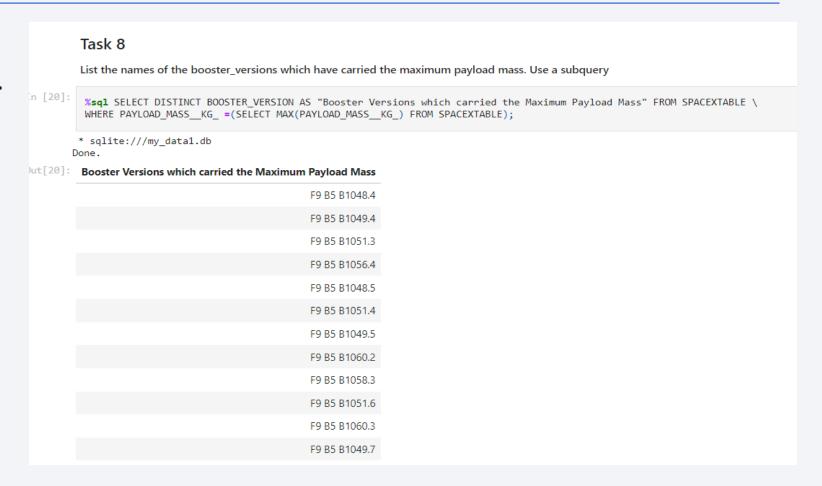
F9 FT B1021.2

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

 The following query was used, with results shown.

# **Boosters Carried Maximum Payload**

• The following query was used, with results shown.



## 2015 Launch Records

• The following query was used, with results shown.

This used a combination of WHERE, LIKE, AND and BETWEEN to filter the required data.

#### Task 9

List the records which will display the month names, failure landing\_outcomes in drone ship ,booster versions, launch\_site for the months in year 2015.

Note: SQLLite does not support monthnames. So you need to use substr(Date, 6,2) as month to get the months and substr(Date, 0,5)='2015' for year.

```
%sql SELECT BOOSTER_VERSION, LAUNCH_SITE FROM SPACEXTABLE WHERE DATE LIKE '2015-%' AND \
Landing_Outcome = 'Failure (drone ship)';

* sqlite://my_data1.db
Done.

Booster_Version Launch_Site

F9 v1.1 B1012 CCAFS LC-40

F9 v1.1 B1015 CCAFS LC-40
```

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

• The following query was used, with results shown.

This used a combination of COUNT (landing outcomes), WHERE (to filter BETWEEN dates).

 A GROUP BY clause was applied which was had an ORDER BY clause added to get the landing outcome data in descending order.

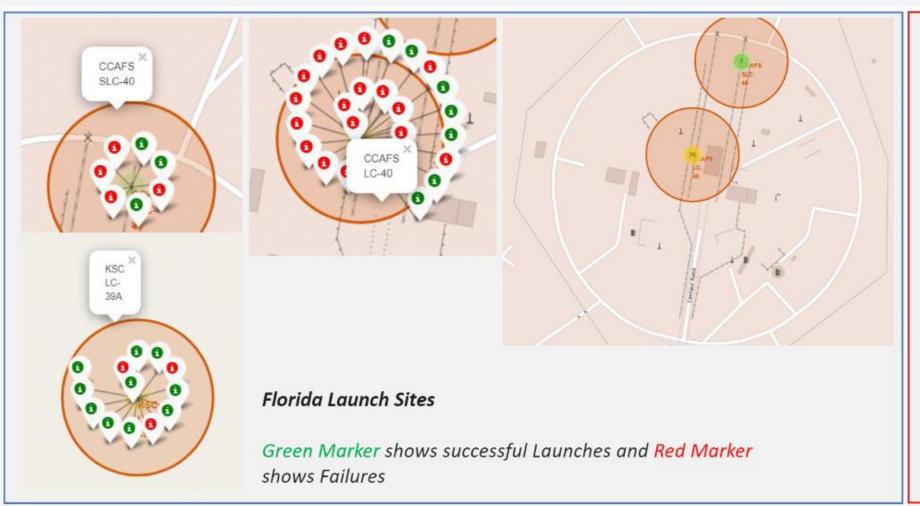




## Global markers of all launch sites in the USA

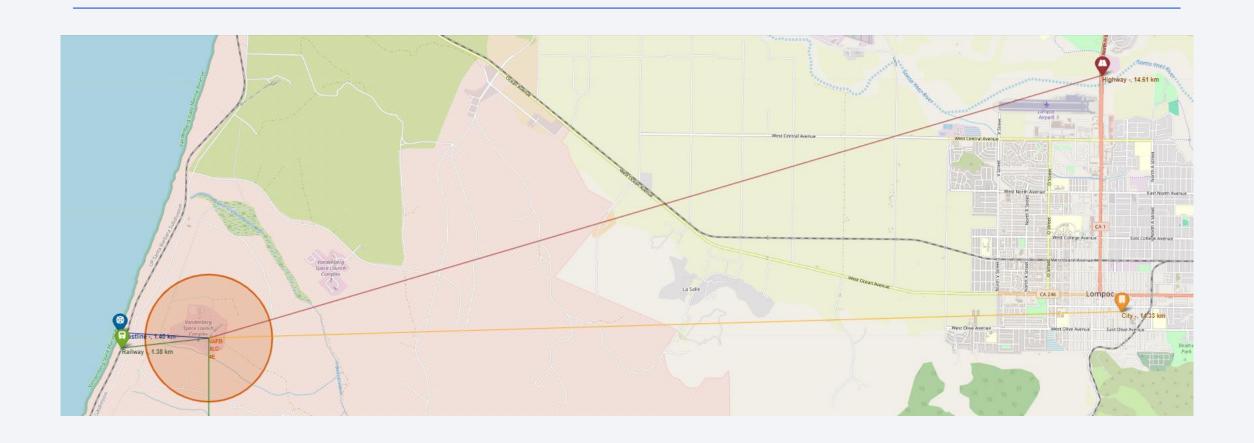


## Launch sites with colour labels

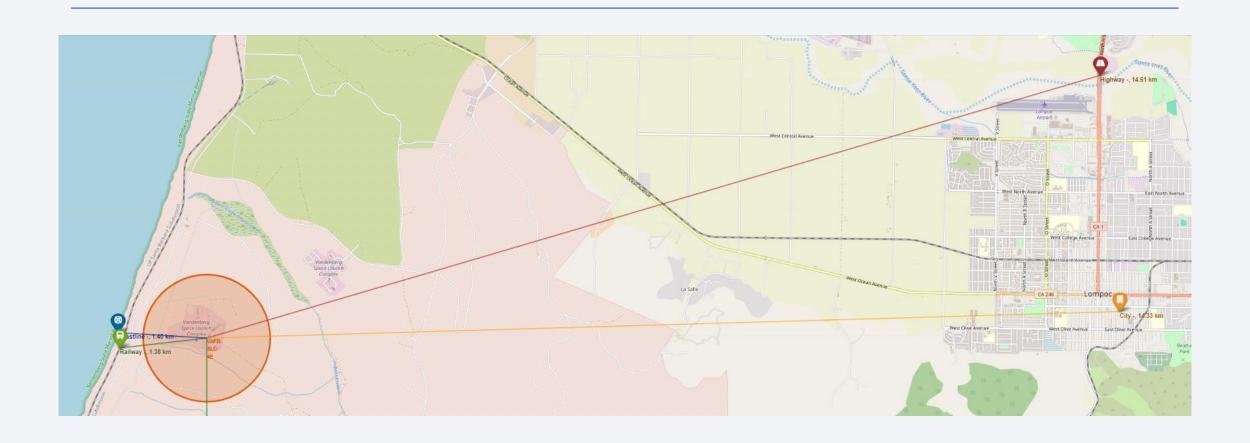




# Launch Site distance to landmarks



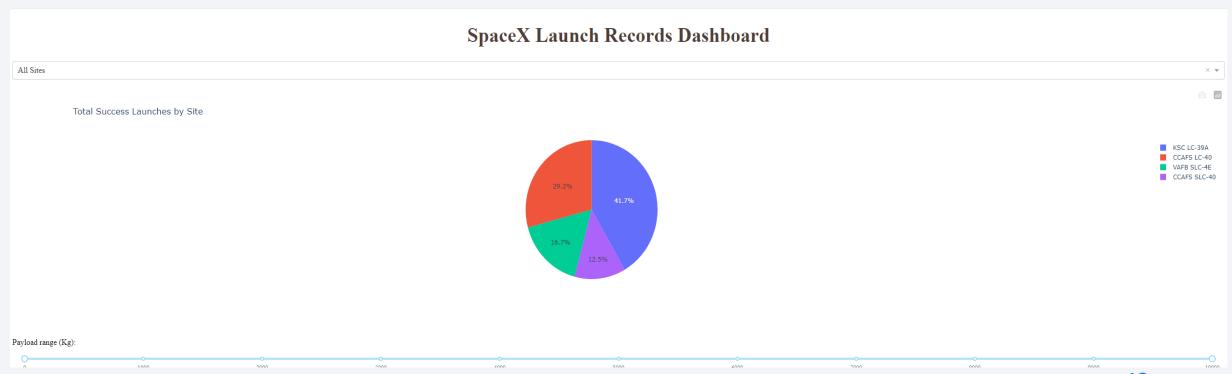
# Launch Site distance to landmarks





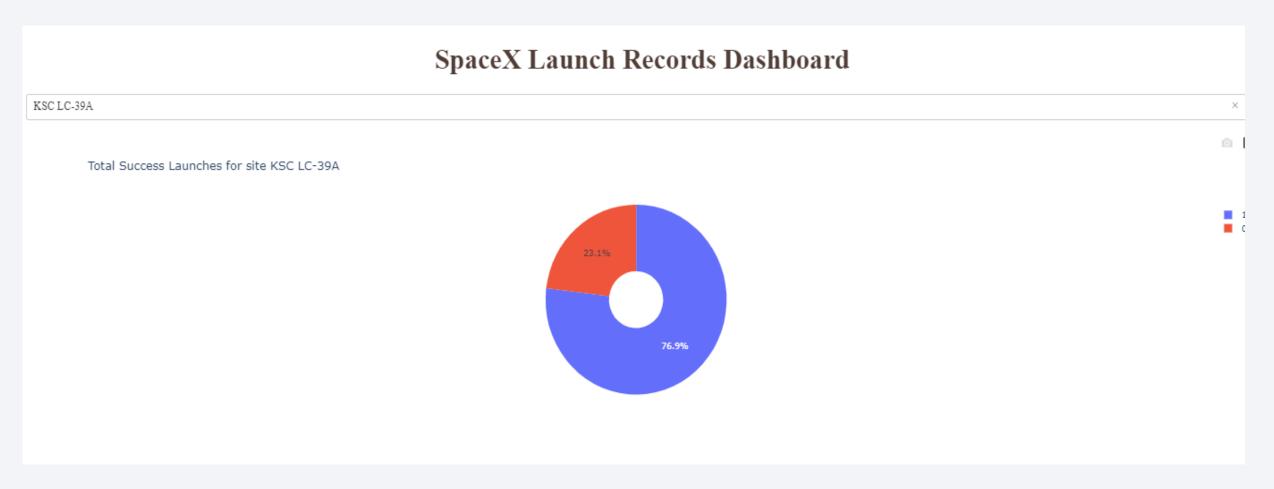
# Pie Chart showing success % per launch site

We can see that KSC LC-39A has the most successful launches.



## Pie chart showing launch site with highest success ratio

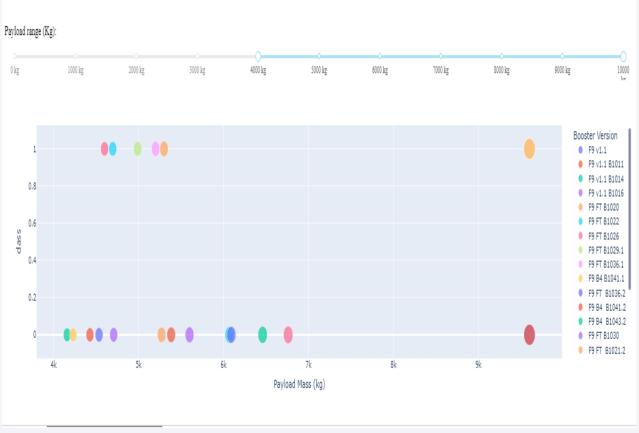
• We can see that KSC LC-39A has the highest launch success ratio (76.9%).



### Scatter plot of Payload vs Launch Outcome for All Sites

 We can see that success for low weighted payloads (Okg – 4000kg) is higher than heavy weighted payloads (4000kg – 10000kg).





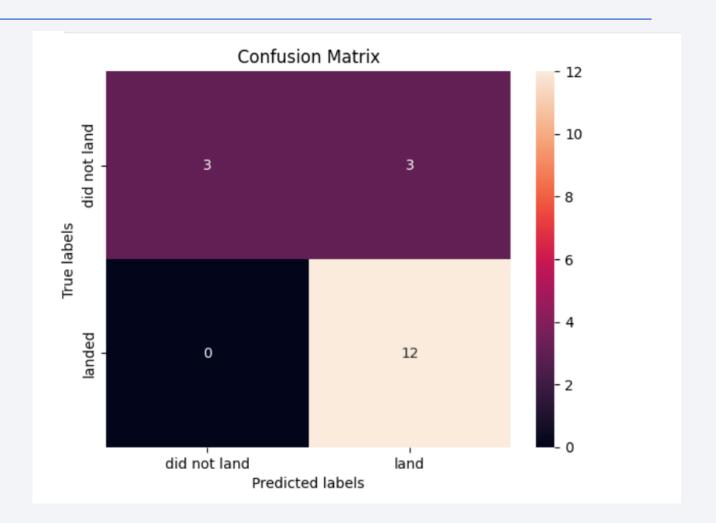


### Classification Accuracy – Decision Tree is the most accurate

```
Find the method performs best:
In [47]:
          algorithms = {'KNN':knn cv.best score ,'Decision Tree':tree cv.best score ,'Logistic Regression':logreg cv.best score ,
          best algorithm = max(algorithms, key= lambda x: algorithms[x])
          print('The method which performs best is \"',best algorithm,'\" with a score of',algorithms[best algorithm])
        The method which performs best is "Decision Tree " with a score of 0.875
 In [ ]:
          Here is best performing method
In [48]:
          algo df = pd.DataFrame.from dict(algorithms, orient='index', columns=['Accuracy'])
In [49]:
          algo df.head()
Out[49]:
                            Accuracy
                      KNN 0.848214
               Decision Tree 0.875000
          Logistic Regression 0.846429
                      SVM 0.848214
```

### **Confusion Matrix**

- Based on the confusion matrix for the decision tree classifier it shows that the classifier can correctly distinguish between different classes.
- The only issue is false positives. With some landing failures being marked as successful.



#### **Conclusions**

From this exercise, we can conclude that:

- The larger the flight amount at a particular launch site then then the greater the rate of success.
- From 2013 to 2020 the rate of successful launch rates increased.
- The Orbits with the highest success rate were ES-L1, GEO, HEO, SSO and VLEO
- KSC-L39A was the most successful launch site overall with the most number of successful launches.
- The Decision tree classifier was the best machine learning model for this task.

# **Appendix**

• Include any relevant assets like Python code snippets, SQL queries, charts, Notebook outputs, or data sets that you may have created during this project

