### Outline

- Executive Summary
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- Methodology
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### **Executive Summary**

- We have explored data available about Space X's launches to build machine learning models that predict if Space X plan to reuse the First Stage on the next launches.
- Predicting Space X plans is key to Space Y, as the reuse of the First Stage allows a launch at a cost of USD 62 million, whilst not reusing it the cost remains around USD 165 million.
- Data indicates that:
  - Success rate on landing Falcon 9 first stage has significantly increased over the years
  - Most of the successful landing and reuse of FS have occurred on KSC 39A site
  - About 75% of CCAFS LC40 launches did not end with FS being landed
  - Booster version v 1.1 in general did not land to be reused
- Logistic Regression, Decision Tree, SVM and KNN methods had a similar performance with an accuracy of 83.3%

#### Introduction

- Space Y wishes to enter on the Space Race that is dominated by Space X.
- One of the main Space X's competitive advantages is their capacity to land and reuse the First Stage
  of their rockets. This technology allows Space X to operate at a USD 62 million cost per launch as
  compared to USD 165 million all other companies' cost.
- For different reasons, Space X not always reuse their Falcon 9 First Stage and we wish to be able to predict when this will happen, using data available about the several Space X launches.
- The proposed approach is to build machine learning models, based on public information, that predicts when Space X will not reuse the First Stage allowing Space Y to define its pricing strategy for the next bids.
- On this project we tested KNN, Decision Tree, SVM and Logistic Regression models.
- This presentation summarizes the methodology, results and insights obtained from an exploration of data provided by Space X and the support provided by IBM Coursera team.

# Methodology

### **Executive Summary**

- Data collection methodology:
- Perform data wrangling
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models

#### **Data Collection**

- SpaceX launch data is available at url= <a href="https://api.spacexdata.com/v4/launches/past">https://api.spacexdata.com/v4/launches/past</a>
- Data was obtained through SpaceX REST API, using the Python's requests library:

```
response = requests.get(url)
```

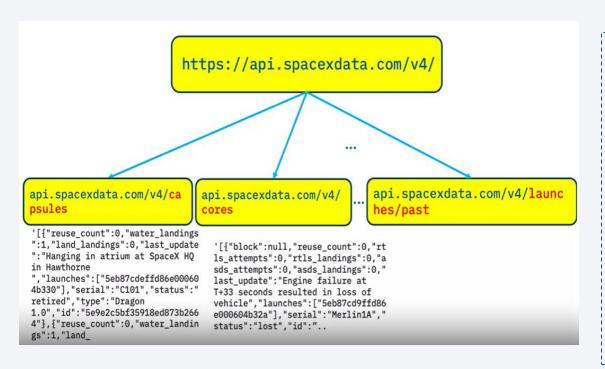
• The SpaceX REST API returned JSON objects that were converted into tables using:

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

- Additional info was collected by web scraping related Wiki pages, using the BeautifulSoup package
- The complex work was done by IBM Data Science team that compiled launches' data containing rocket used, payload delivered, launch specifications, landing specifications, and landing outcome and saved on a Lab Test directory.

# Data Collection - SpaceX API

#### Space X files were organized as below:



To have a consolidated table the following steps were observed:

- 1. Booster name obtained from Rocket column
- 2. Launch site, long. and lat. obtained from Launchpad
- 3. Payload mass and orbit obtained from Payload
- 4. Outcome, Type of landing number of flights obtained from Cores
- 5. For the course all the info above was saved on a static objects and in: 'https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/datasets/API\_call\_spacex\_api.json'

IBM-Data-Science-Capstone-Project/jupyter-labs-spacex-data-collection-api.ipynb\_at\_main · hsgeral/IBM-Data-Science-Capstone-Project (github.com)

# **Data Collection - Scraping**

To extract the info from the Falcon 9 Wiki page, the following steps were observed:

- 1. Used requests.get(url).text, to store the content of the webpage into a text object ('data')
- 2. With BeautifulSoup parsed the text from 'data' into a structured BeautifulSoup object ('soup')
- 3. With html identifiers in soup, found the tables and in the tables the columns names and respective contents
- 4. Columns contents were first stored in a dictionary type and then converted into a pandas dataframe type.
- 5. The dataframe could be then saved as a .csv file
- 6. For the course all the html page was sourced from a static object in "https://en.wikipedia.org/w/index.php?title=List\_of\_Falcon\_9\_and\_Falcon\_Heavy\_launches&oldid =1027686922"

IBM-Data-Science-Capstone-Project/jupyter-labs-webscraping.ipynb at main · hsgeral/IBM-Data-Science-Capstone-Project (github.com)

# **Data Wrangling**

Data were processed from: <a href="https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/datasets/dataset\_part\_1.csv">https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/datasets/dataset\_part\_1.csv</a>

The discovery and preparation of the data observed the following steps:

- 1. Identify and calculate the percentage of the missing values in each attribute using: df.isnull().sum()/len(df)\*100
- 2. Identify which columns are numerical and categorical, using: df.dtypes
- 3. Calculate the number of launches on each site, using: df.value\_counts('LaunchSite')
- 4. Calculate the number and occurrence of each orbit, using: df.value\_counts('Orbit')
- 5. Determine the number of landing\_outcomes: using df.value\_counts('Outcome')
- 6. Create a list with (0) if the landing outcome was failed or (1) if the landing outcome was successful, using: ~df['Outcome'].isin(bad\_outcomes)

### EDA with SQL

The following queries were made on the file: <a href="https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/labs/module\_2/data/Spacex.csv">https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/labs/module\_2/data/Spacex.csv</a>:

- 1. Names of the unique launch sites in the space mission
- 2. 5 records where launch sites begin with the string 'CCA'
- 3. The total payload mass carried by boosters launched by NASA
- 4. Average payload mass carried by booster version F9 v1.1
- Date when the first successful landing outcome in ground pad was achieved ]
- 6. The names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000

### EDA with SQL (cont.)

- 7. List the total number of successful and failure mission outcomes
- 8. Names of the booster versions which have carried the maximum payload mass.
- 9. List the records with month names, failure landing outcomes in drone ship, booster versions, launch site for the months in year 2015.
- 10. Rank of the count of landing outcomes (such as Failure (drone ship) or Success (ground pad)) between the date 2010-06-04 and 2017-03-20)

IBM-Data-Science-Capstone-Project/jupyter-labs-eda-sql-coursera\_sqllite.ipynb at main · hsgeral/IBM-Data-Science-Capstone-Project (github.com)

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

#### Charts generated at this phase:

- 1. Scatter with FlightNumber x Payload
- 2. FlightNumber vs LaunchSite
- 3. launch sites and their payload mass
- 4. relationship between success rate and orbit type.
- 5. relationship between FlightNumber and Orbit type
- 6. relationship between Payload and Orbit type
- 7. to get the average launch success trend.

This phase aimed to obtain some preliminary insights about how each important variable would affect the success rate,

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### Build an Interactive Map with Folium

- Map objects added to a folium map with coordinates close to the launch sites:
  - Markers, Circles, Lines, Text, Pop up text, markers clusters
- Those objects were added using the following commands:
  - circle = folium.Circle(long\_lat\_coord, radius=1000, color='#d35400', fill=True).add\_child(folium.Popup(row['Launch Site']))
  - marker = folium.map.Marker(Coordinates, icon=DivIcon(icon\_size=(20,20),icon\_anchor=(0,0),
  - html='<div style="'])</li>
    - icon=folium.lcon(color='white', icon\_color=row['marker\_color']
  - lines=folium.PolyLine(locations=coordinates, weight=1)
  - map.add\_child(circle)
  - map.add\_child(marker)
  - map.add child(lines)

IBM-Data-Science-Capstone-Project/lab\_jupyter\_launch\_site\_location (1).ipynb at main · hsgeral/IBM-Data-Science-Capstone-Project (github.com)

### Build a Dashboard with Plotly Dash

- Pie Charts and Scatter plots about success rate on first stage landing were added to a dashboard.
- Options were provided to look for the overall launches on all launch sites or to select the details of launches in each one of the sites.
- Plots were added to seek for more details on whether first stage successful landings could be different with payload and booster version

IBM-Data-Science-Capstone-Project/spacex\_dash\_app (3).py at main · hsgeral/IBM-Data-Science-Capstone-Project (github.com)

# Predictive Analysis (Classification)

- Data was extracted from: <u>https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/datasets/dataset\_part\_3.csv</u>, normalized and transformed (X = preprocessing.StandardScaler().fit(X).transform(X))
- Data was split betwee train and test sets.
- models were trained and hyperparameters were selected using GridSearchCV, to find the best estimator parameters
- The accuracy on the test data was calculated using the method score
- Results were visualized with confusion matrix

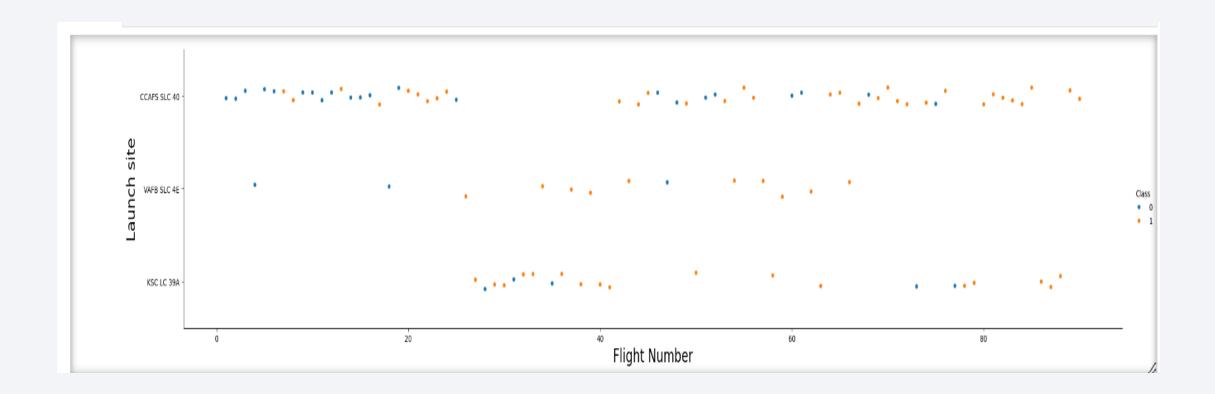
IBM-Data-Science-Capstone-Project/SpaceX Machine Learning Prediction Part 5.ipynbat main hsgeral/IBM-Data-Science-Capstone-Project (github.com)

#### Results

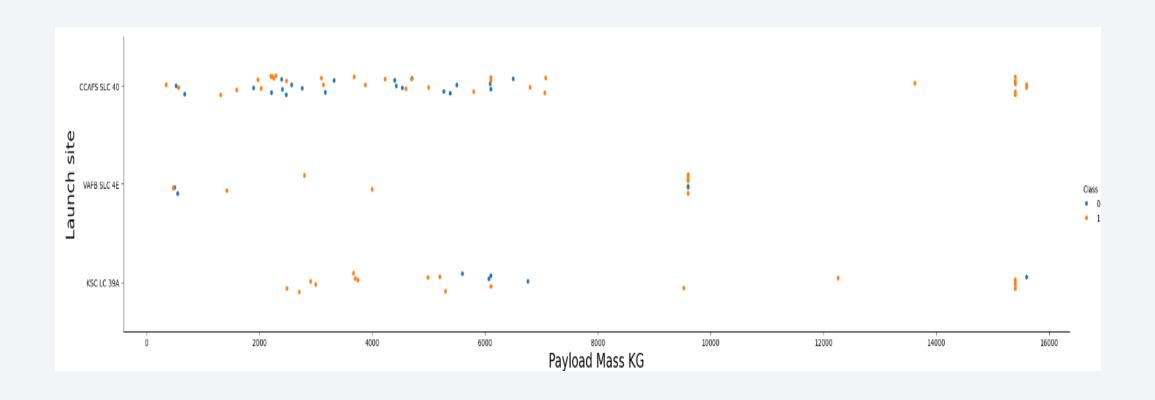
In exploring the dataset, we noticed some interesting points:

- Success rate on landing Falcon 9 first stage has significantly increased over the years
- Different launch sites have different success rates:
  - Most of the successful landing and reuse of FS have occurred on KSC 39A site
  - About 75% of CCAFS LC40 launches did not end with FS being landed
- Booster version v 1.1 in general did not land to be reused
- Majority of payloads seems to be in the range of 1000 to 8000KG
- O Most common Orbits (GTO, ISS, LEO, PO) have a success landing rate <100% others have a 100% rate
- As there are several parameters, using a machine learning capable of processing all data seems much more effective than trying to analyzing them manually.

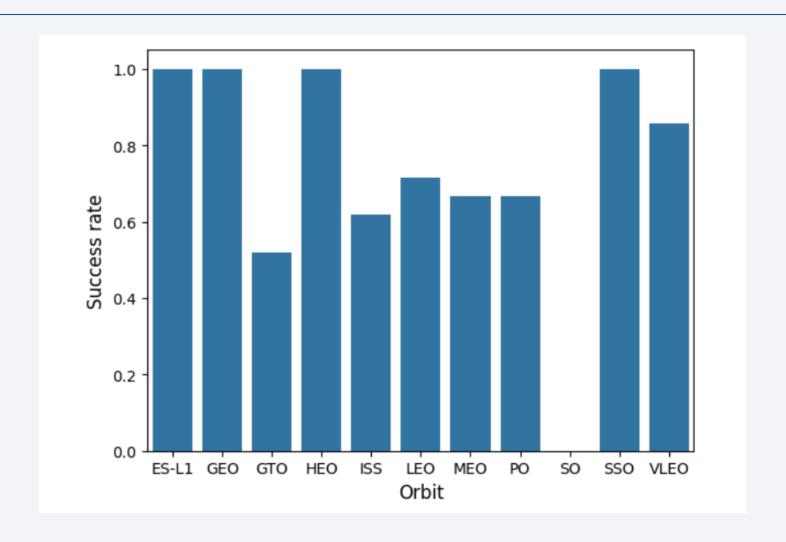
# Flight Number vs. Launch Site



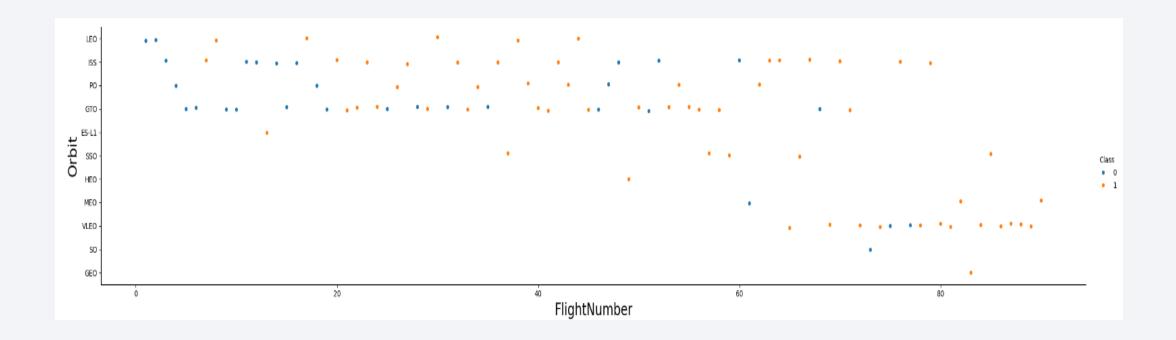
# Payload vs. Launch Site



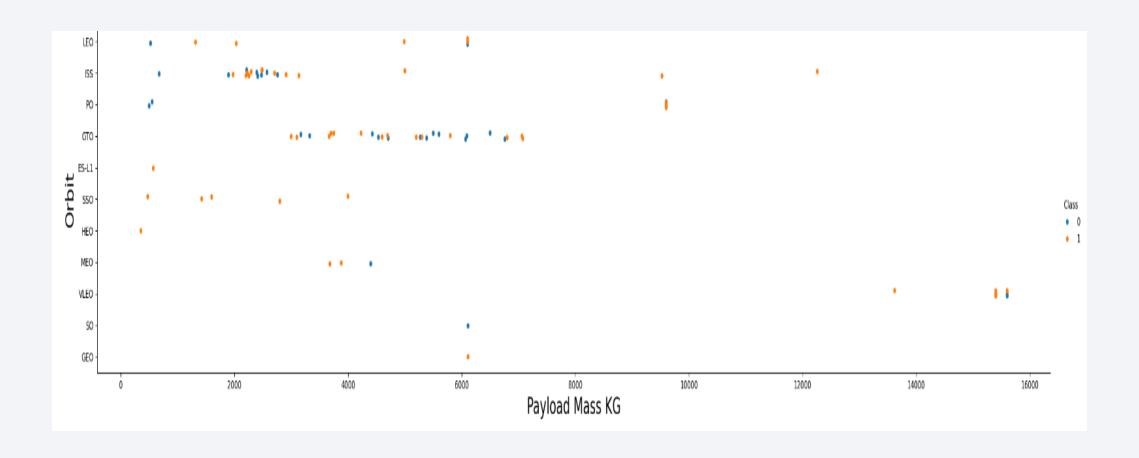
# Success Rate vs. Orbit Type



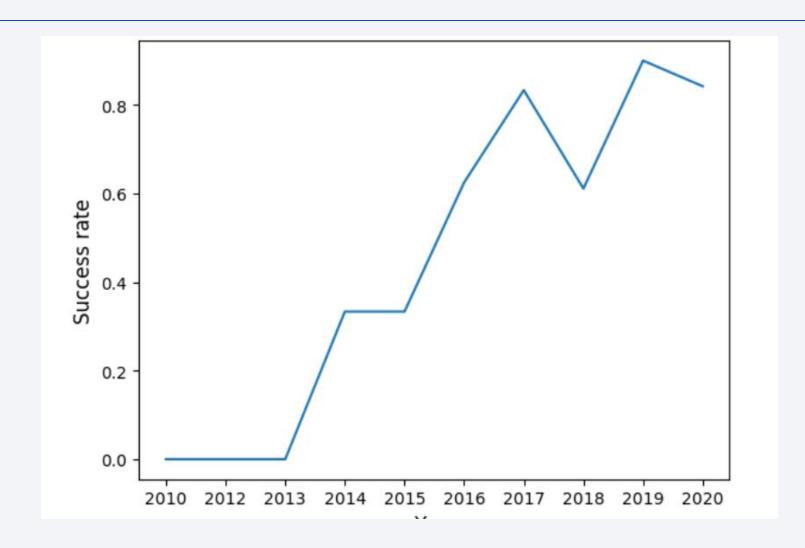
# Flight Number vs. Orbit Type



# Payload vs. Orbit Type



# Launch Success Yearly Trend



### All Launch Site Names

```
[19]: %sql Select Distinct "Launch_Site" from SPACEXTABLE
    * sqlite://my_data1.db
Done.
[19]: Launch_Site
    CCAFS LC-40
    VAFB SLC-4E
    KSC LC-39A
    CCAFS SLC-40
```

# Launch Site Names Begin with 'CCA'

23]:	Date	Time (UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS_KG_	Orbit	Customer	Mission_Outcome	Landing_Outcome
	2010- 06-04	18:45:00	F9 v1.0 B0003	CCAFS LC- 40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
	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 (parachute)
	2012- 05-22	7:44:00	F9 v1.0 B0005	CCAFS LC- 40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	No attempt
	2012- 10-08	0:35:00	F9 v1.0 B0006	CCAFS LC- 40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
	2013- 03-01	15:10:00	F9 v1.0 B0007	CCAFS LC- 40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

# **Total Payload Mass**

```
Task 3 ¶

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

[24]: %sql select SUM("PAYLOAD_MASS__KG_") from SPACEXTABLE WHERE "Customer" LIKE '%NASA (CRS)%'

* sqlite://my_data1.db
Done.

[24]: SUM("PAYLOAD_MASS__KG_")

48213
```

# Average Payload Mass by F9 v1.1

```
[25]: %sql SELECT AVG("PAYLOAD_MASS__KG_") from SPACEXTABLE WHERE "Booster_Version" LIKE '%F9 v1.1%'

* sqlite://my_data1.db
Done.

[25]: AVG("PAYLOAD_MASS__KG_")

2534.66666666666665
```

# First Successful Ground Landing Date

```
Task 5

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

Hint:Use min function

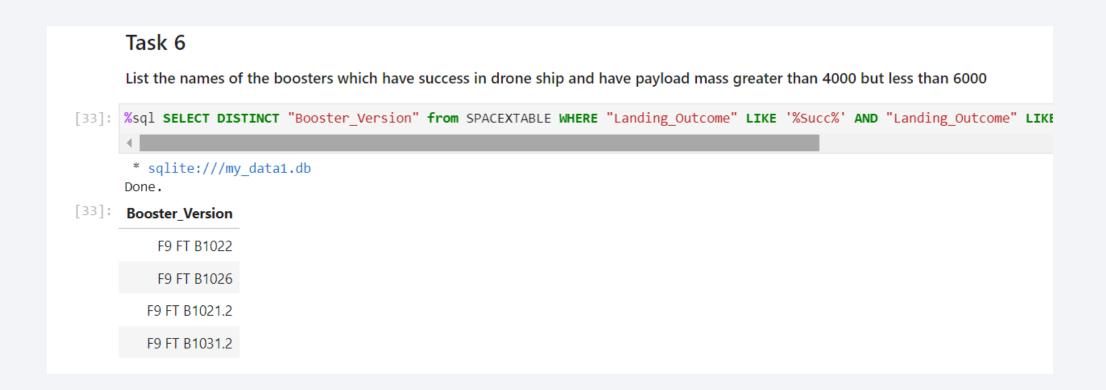
[27]: %sql SELECT MIN("Date") from SPACEXTABLE WHERE "Landing_Outcome" LIKE '%Succ%'

* sqlite:///my_datal.db
Done.

[27]: MIN("Date")

2015-12-22
```

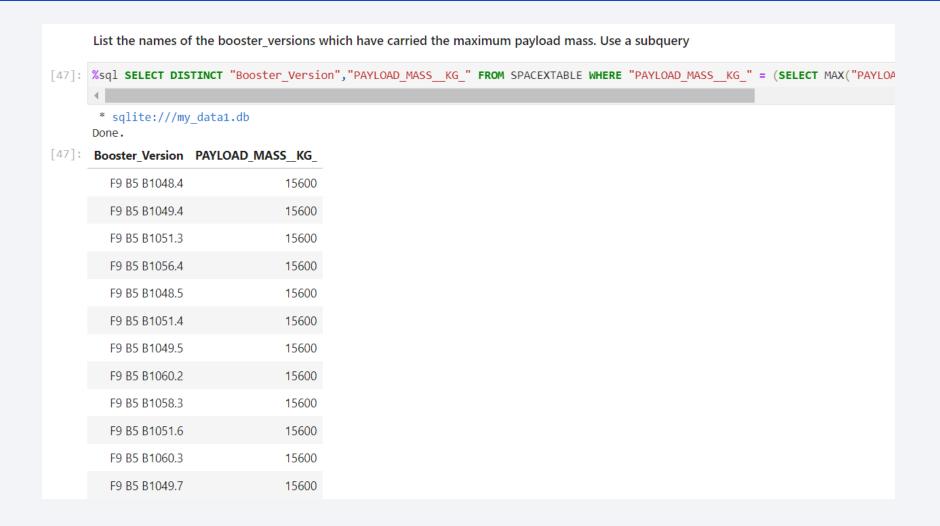
#### Successful Drone Ship Landing with Payload between 4000 and 6000



### Total Number of Successful and Failure Mission Outcomes

	List the total number of successful and failure mission outcomes							
[42]:	%sql SELECT "Mission_Outcome", COUNT("Mission_Outcome") from SPACEXTABLE GROUP BY "Mission_Outcome"							
	<pre>* sqlite:///my_data1.db Done.</pre>							
[42]:	Mission_Outcome	COUNT("Mission_Outcome")						
	Failure (in flight)	1						
	Success	98						
	Success	1						
	Success (payload status unclear)	1						

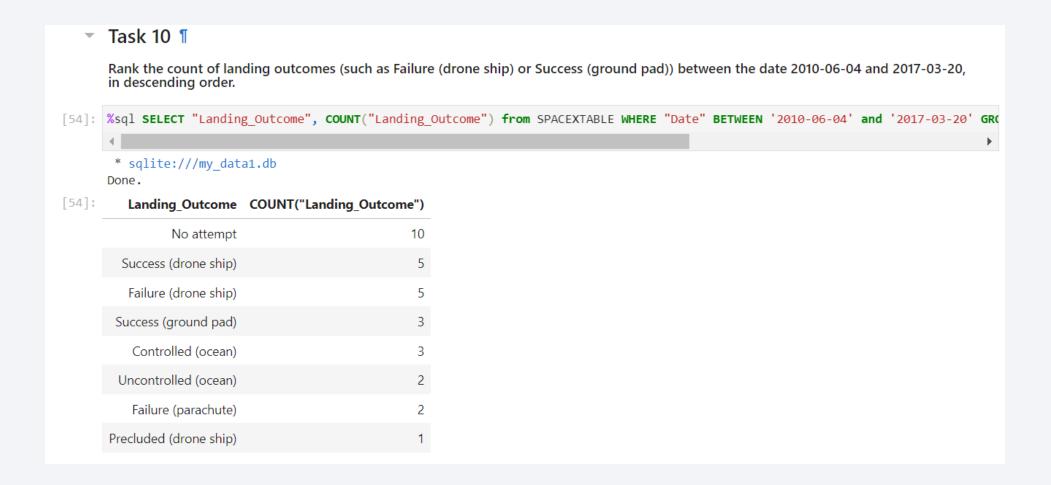
# **Boosters Carried Maximum Payload**



#### 2015 Launch Records

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. [52]: %sql SELECT substr(Date, 6,2), substr(Date,0,5), "Landing\_Outcome", "Booster\_Version", "Launch\_Site" FROM SPACEXTABLE WHERI \* sqlite:///my\_data1.db Done. substr(Date, 6,2) substr(Date,0,5) Landing\_Outcome Booster\_Version Launch\_Site 01 2015 Failure (drone ship) F9 v1.1 B1012 CCAFS LC-40 04 2015 Failure (drone ship) F9 v1.1 B1015 CCAFS LC-40

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

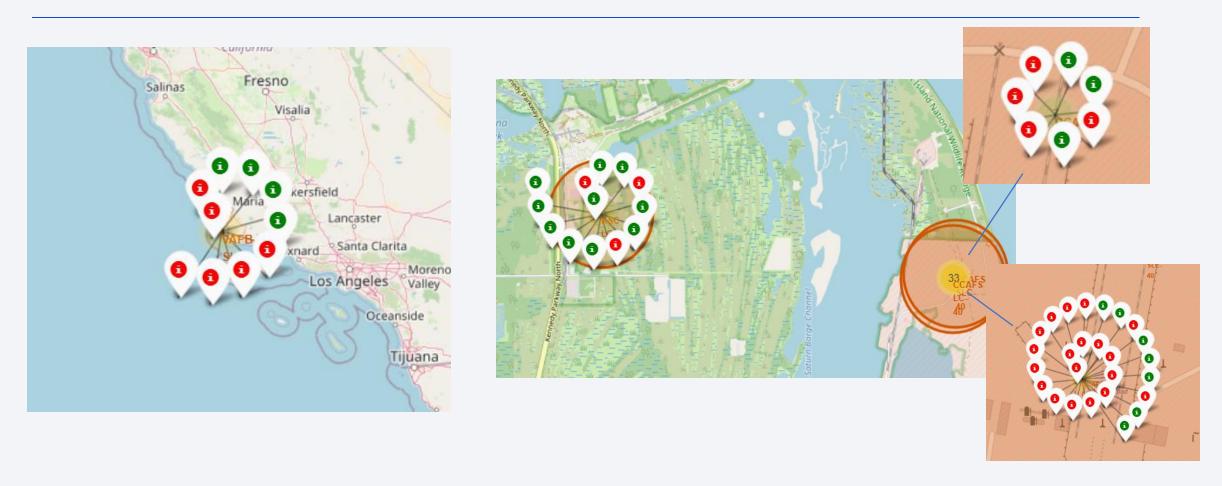


# Locations of launching sites



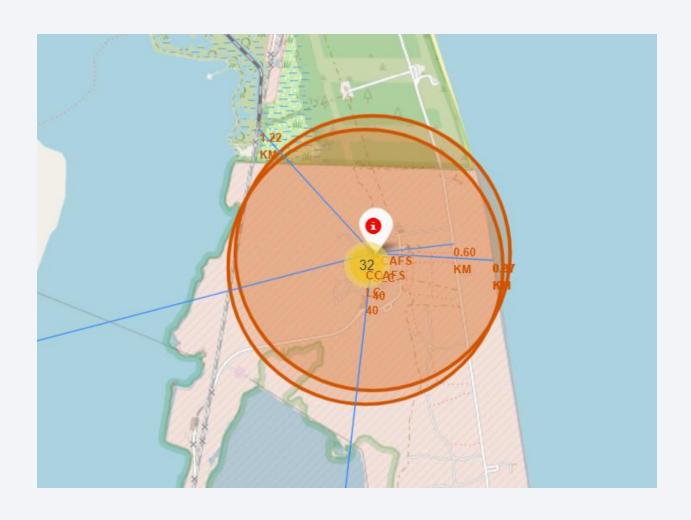
• Launch sites are usually close to ocean, and distant from cities. They are also close to Equator line

# Landing Outcome of Launch sites



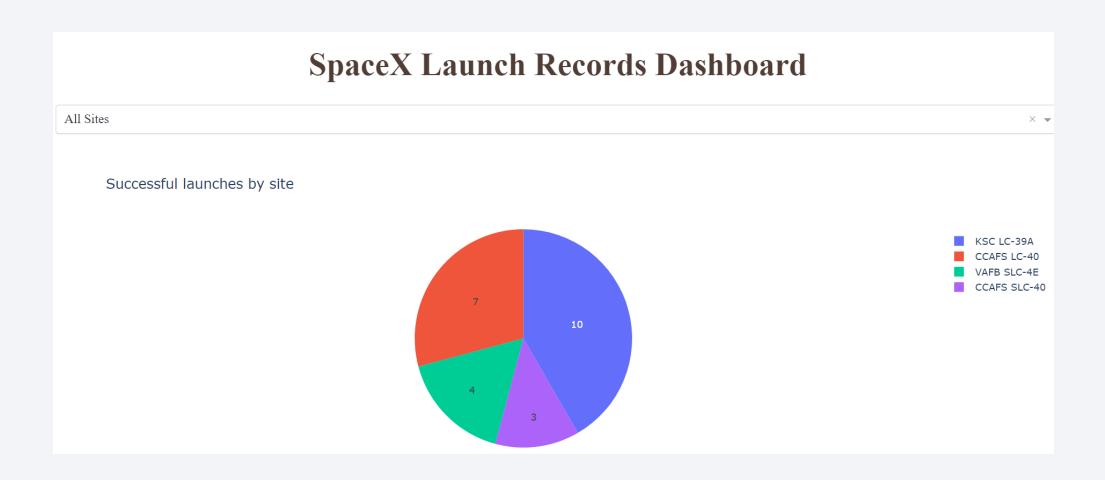
• Cape Canaveral LC39A concentrating success outcome

### Service Infrastructure close to the launch site



- Railway, roads and airport closer to the launch site are for use of the base
- Closest cities are more than 15 km from the base

# First Stage success landing per site

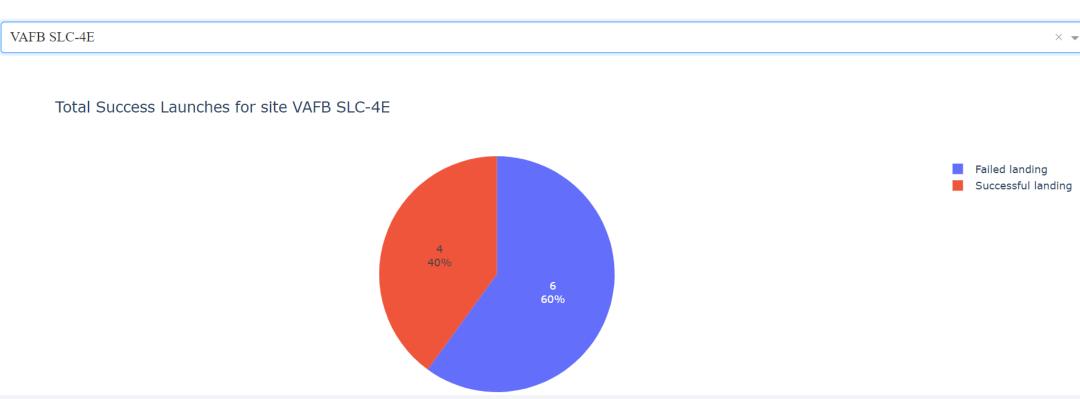


# First Stage landing x payload and booster version



### VAFB SLC 4E



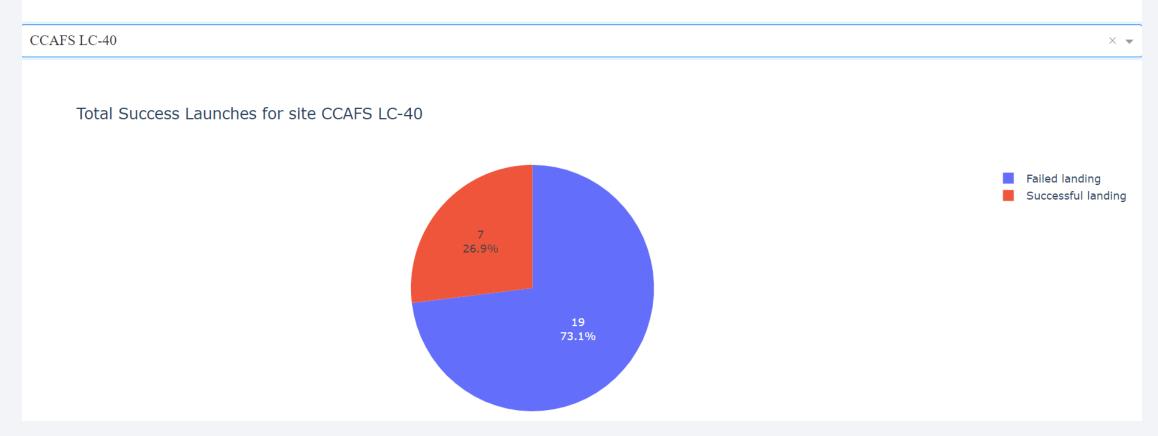


# VAFB SLC 4E x Payload and Booster version

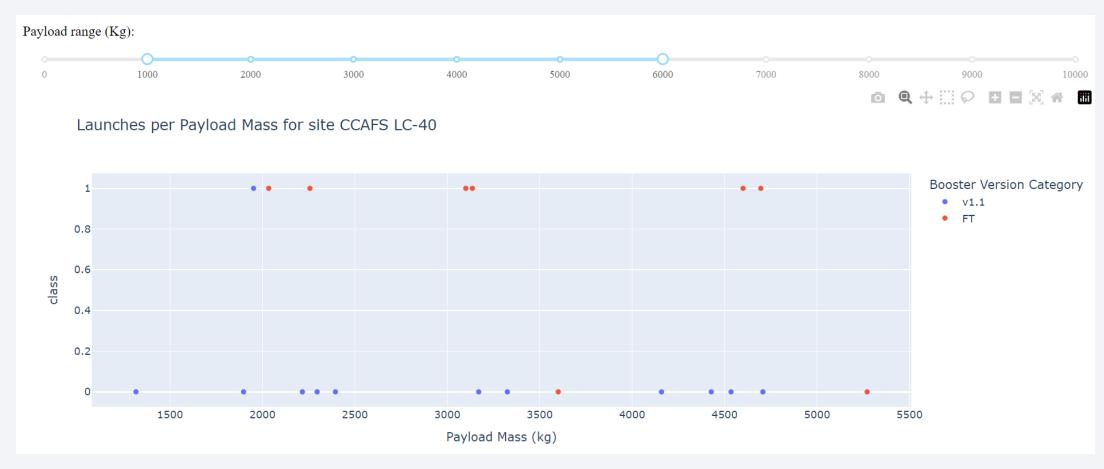


### **CCAAFS LC40**

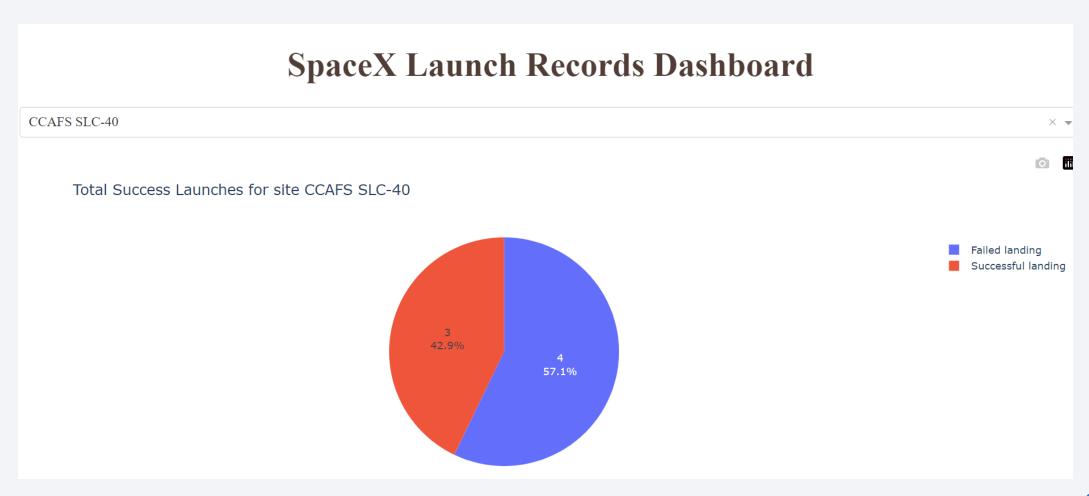
### **SpaceX Launch Records Dashboard**



### **CCAAFS LC40**



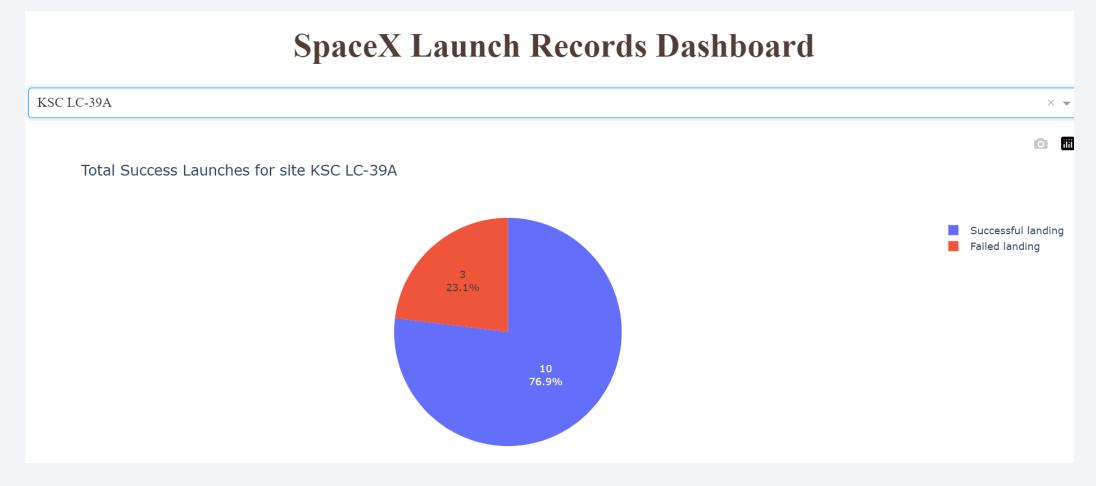
### **CCAAFS SLC40**



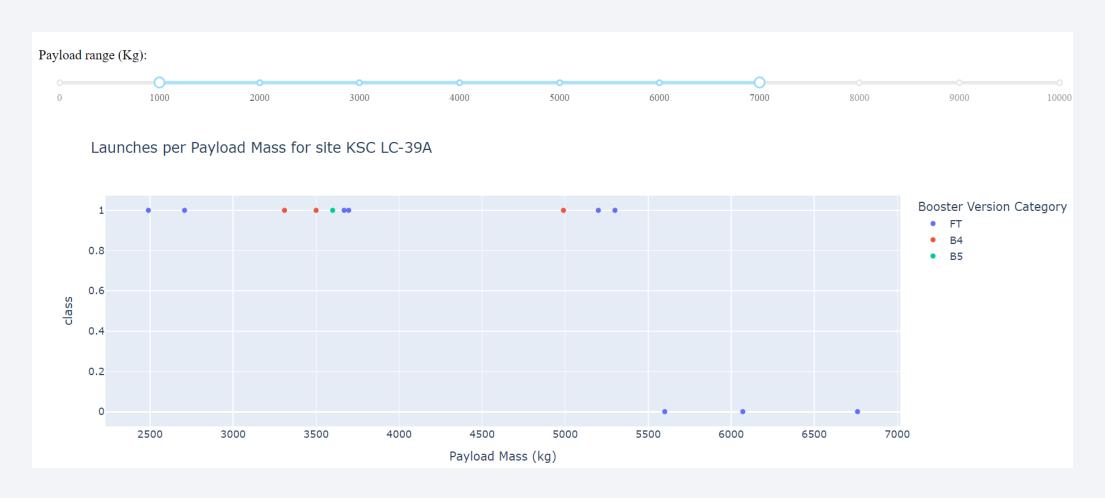
# CCAAFS SLC40 x Payload and Booster Version



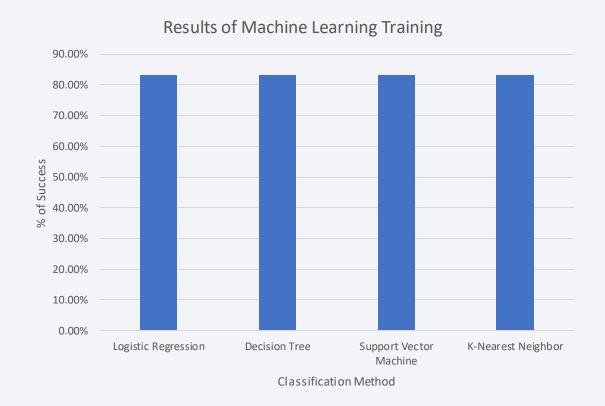
### KSC LC39A



# KSC LC39A x Payload and Booster version

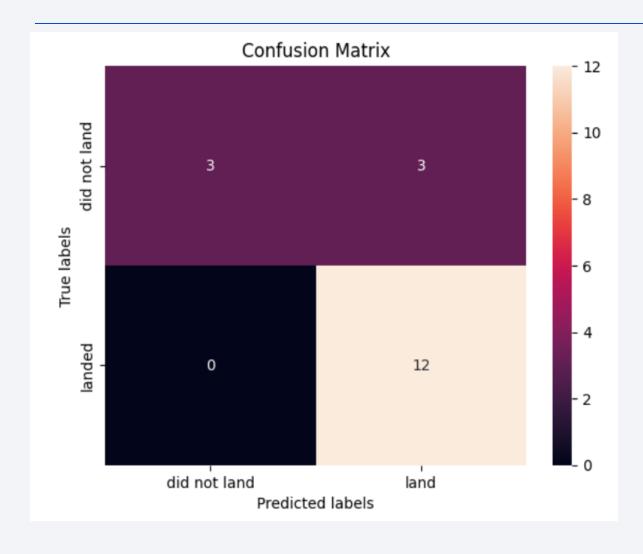


# Classification Accuracy



 All methods had a similar accuracy of 83,33%, in predicting the landing outcome.

### **Confusion Matrix**



- All four models tested resulted in similar results on our Test Set
- No false negatives were predicted, but we had 3 false positives out of 18 samples resulting in an accuracy of 83,33%

### **Conclusions**

The best set of parameters for each method are:

- Logistic regression: {'C': 0.01, 'penalty': 'l2', 'solver': 'lbfgs'}
- SVM: {'C': 1.0, 'gamma': 0.03162277660168379, 'kernel': 'sigmoid'}
- Decision Tree: {'criterion': 'gini', 'max\_depth': 4, 'max\_features': 'sqrt', 'min\_samples\_leaf': 2, 'min\_samples\_split': 2, 'splitter': 'best'}
- KNN: {'algorithm': 'auto', 'n\_neighbors': 10, 'p': 1}

Highest accuracy on the Train set was achieved at Decision Tree (88.9%) the other methods achieves 84%.

On the Test Set the accuracy achieved was 83.3%.