

# Winning Space Race with Data Science

Gabriel Pinho 19-mar-2024



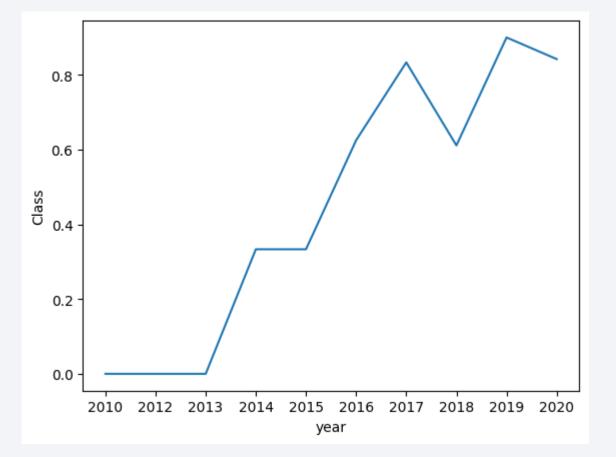
#### **Outline**

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

#### **Executive Summary**

- Summary of methodologies
  - EDA with SQL
  - EDA with data visualization
  - Maps with Folium
  - DashBoard with Plotly Dash

The main factor of success in launches is the experience gain in the firsts attempts, like we can below:



#### Introduction

#### Project background and context

- SpaceX advertises Falcon 9 rocket launches on its website with a cost of 62 million dollars; other providers cost upward of 165 million dollars each, much of the savings is because SpaceX can reuse the first stage.
- Problems you want to find answers
  - if we can determine if the first stage will land, we can determine the cost of a launch. This information can be used if an alternate company wants to bid against SpaceX for a rocket launch. In this project, we will predict if the Falcon 9 first stage will land successfully





# Methodology

#### **Executive Summary**

- Data collection methodology:
  - Data was collecting using spacex API
- Perform data wrangling
  - Several functions were created to process the data
- 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

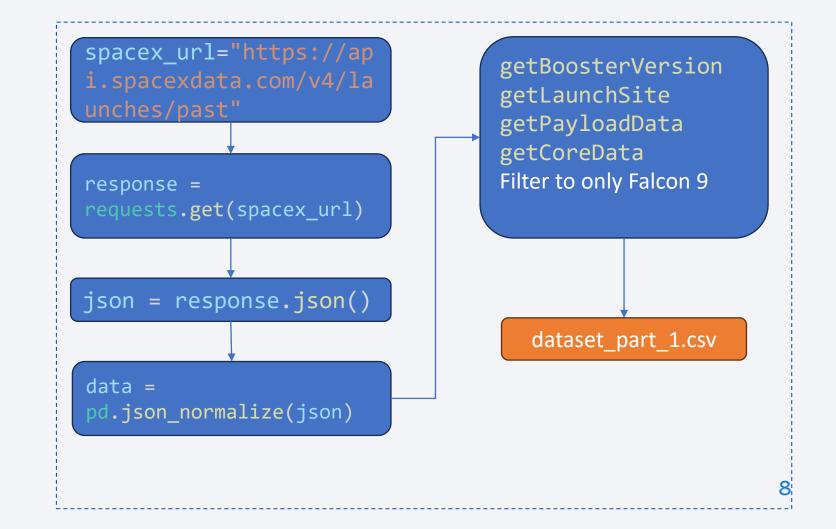
#### **Data Collection**

- Data was collecting using spacex API with python library request and the URL <a href="https://api.spacexdata.com/v4/launches/past">https://api.spacexdata.com/v4/launches/past</a>
- Several functions were created to process the data, mainly to:
  - filter only to include Falcon9 launches
  - Replace null entries in PayloadMass with its mean value
  - and to transform cathegorical data into numerical ones using one hot encoder (Pandas get\_dummies). Details of the functions in the flow chart next slide.

### Data Collection – SpaceX API

# Notebook with Data Collection

Estudos.IBM Data Science/10 Applied Data
 Science Capstone/notebooks/01 jupyter-labs-spacex-data-collection-api.ipynb at main gaugustop/Estudos.IB
 M Data Science (github.com)



### **Data Collection - Scraping**

# Notebook with Data Collection

Estudos.IBM Data Science/1

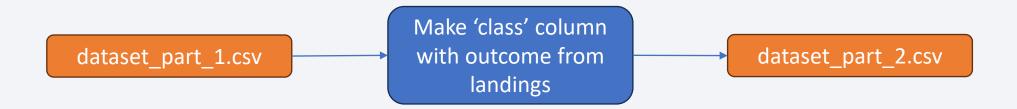
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 Science (github.com)

```
spacex_url="https://ap
i.spacexdata.com/v4/la
unches/past'
response =
requests.get(spacex_url)
json = response.json()
data =
pd.json_normalize(json)
```

# **Data Wrangling**

#### Github Link to data Wrangling Jupyter Notebook

• <u>Estudos.IBM Data Science/10 Applied Data Science Capstone/not ebooks/02 labs-jupyter-spacex-Data wrangling.ipynb at main · gaugustop/Estudos.IBM Data Science (github.com)</u>



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

- Charts ploted (to see if there is correlation between those variables)
  - Scatter plot: Pay load mass vs Flight Number
  - Scatter plot: Launch Site vs Flight Number
  - Scatter plot: Launch Site vs Payload mass
  - Bar plot: Class vs Orbit
  - Scatter plot: Orbit vs Flight Number
  - Scatter plot: Orbit vs Payload mass
  - Line chart: Class vs Year

#### Github Jupyter Notebook:

Estudos.IBM Data Science/10 Applied Data Science Capstone/not ebooks/04 jupyter-labs-edadataviz.ipynb at main · gaugustop/Estudos.IBM Data Science (github.com)

#### **EDA** with SQL

#### • SQL queries performed:

- select distinct(Launch Site) from spacextable
- select \* from spacextable where Launch\_Site like 'CCA%' limit 5
- select Customer, sum(PAYLOAD\_MASS\_\_KG\_) as 'total payload' from spacextable where Customer = "NASA (CRS)"
- select distinct(Booster\_Version) from spacextable where Booster\_Version like 'F9 v1.1%'
- select round(avg(PAYLOAD\_MASS\_\_KG\_),3) from spacextable where Booster\_Version like 'F9 v1.1%'
- select min(Date) as 'Date of first succesful landing' from spacextable where Landing\_Outcome like '%Success%'
- select Booster\_Version from spacextable where Landing\_Outcome = 'Success (drone ship)' and PAYLOAD\_MASS\_\_KG\_ between 4000 and 6000
- select Mission\_Outcome, count(Mission\_Outcome) as 'Count' from spacextable group by Mission\_Outcome
- select Booster\_Version from spacextable where PAYLOAD\_MASS\_\_KG\_ = (select max(PAYLOAD\_MASS\_\_KG\_) from spacextable)
- select Date, Booster\_Version, Launch\_Site, Landing\_Outcome, substr(Date, 6, 2) as month from spacextable where Landing\_Outcome = 'Failure (drone ship)' and substr(Date,0,5)='2015'
- select Landing\_Outcome, count(Landing\_Outcome) as Count from spacextable group by Landing\_Outcome having Date between '2010-06-042 and '2017-03-20' order by Count desc

#### **EDA** with SQL

#### Github Jupyter Notebook:

<u>Estudos.IBM Data Science/10 Applied Data Science Capstone/noteb ooks/03 jupyter-labs-eda-sql-coursera sqllite.ipynb at main · gaugustop/Estudos.IBM Data Science (github.com)</u>

# Build an Interactive Map with Folium

• Interactive maps were created using Folium, a Python Library. In order to better understand the geographic influence in launch success there were added to the maps: markers, marker clusters, distance from coastline and lines.

#### **Github Jupyter Notebook:**

Estudos.IBM Data Science/10 Applied Data Science Capstone/noteb ooks/05 lab jupyter launch site location.ipynb at main · gaugustop/Estudos.IBM Data Science (github.com)

### Build a Dashboard with Plotly Dash

• In the Dashboard with Plotly Dash, we have one dropdown to chose the Lauch Site, then a Pie chart showing the successful count per launch site (if one site is chosen then we see the proportion of success/failure of that site). Below that we have a payload mass range the user can chose and a scatter plot with class vs payload mass. This scatter plot also interacts with the dropdown.

#### Github Python file:

<u>Estudos.IBM Data Science/10 Applied Data Science Capstone/app/spacex dash app.py at main · gaugustop/Estudos.IBM Data Science (github.com)</u>

# Predictive Analysis (Classification)

- Summarize how you built, evaluated, improved, and found the best performing classification model
- The data were splitted into train and test (test size = 20%). For each model, there were created a GridSearch with cv = 10, some parameters were tested and the score was taken with the test set, also a confusion matrix was created for each model.
- Some classification models were tested:
  - Logistic regression
  - Support Vector Machine
  - Decision Tree Classifier
  - K Nearest Neighbors

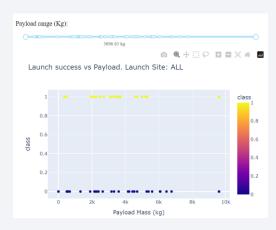
# Github Jupyter Notebook:

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Applied Data Science Capston
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gaugustop/Estudos.IBM Data S
cience (github.com)

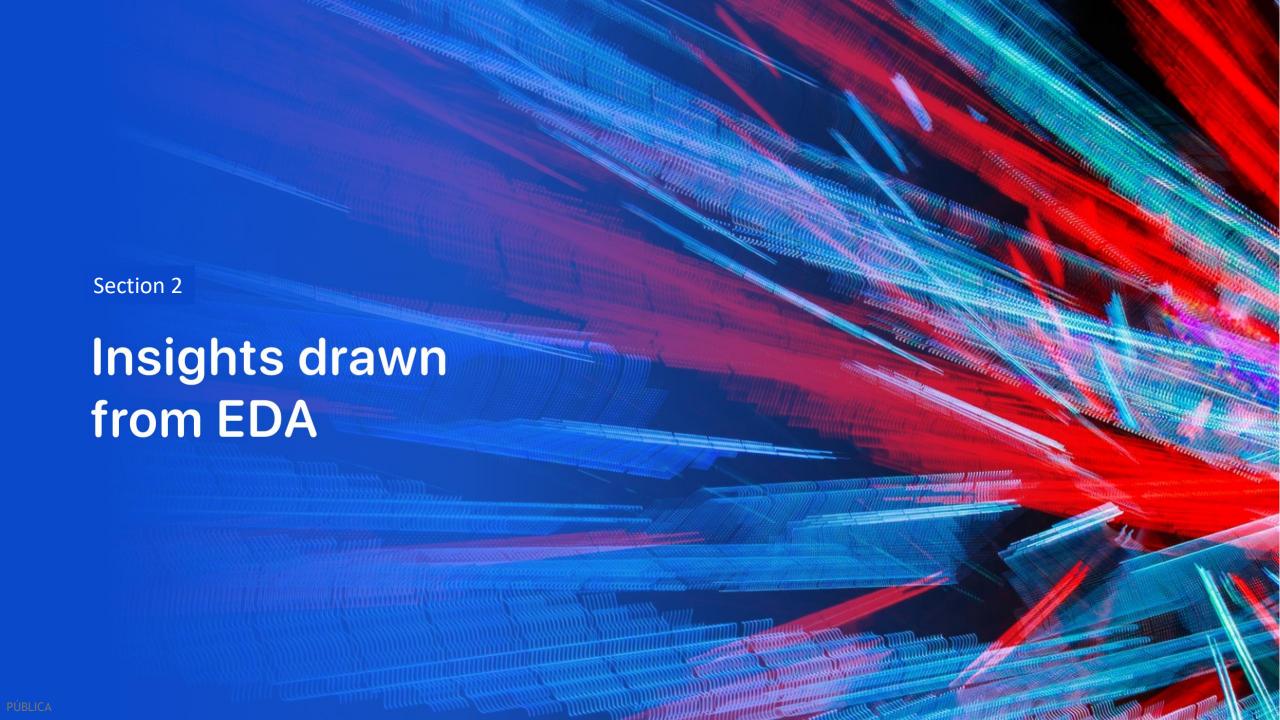
#### Results

- Exploratory data analysis results
  - Exploratory data analysis shown that we have a correlation between the launch site, number of the flight and payload mass in the success launch
- Interactive analytics with Plotly Dash



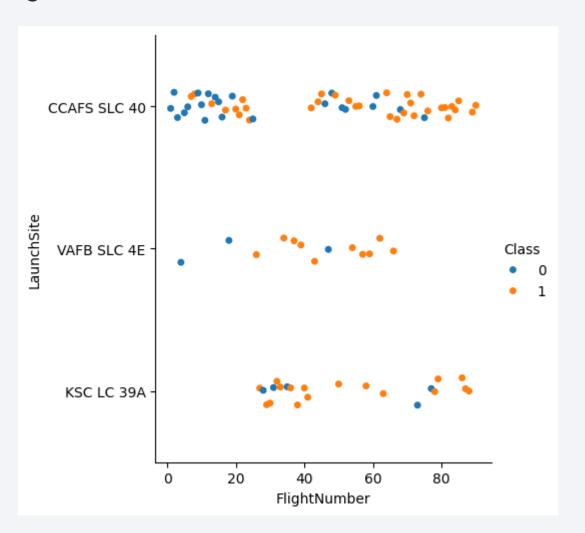


- Predictive analysis results
  - The best models tested were Logistic Regression, Support Vector Machine and K-Nearest Neighbors



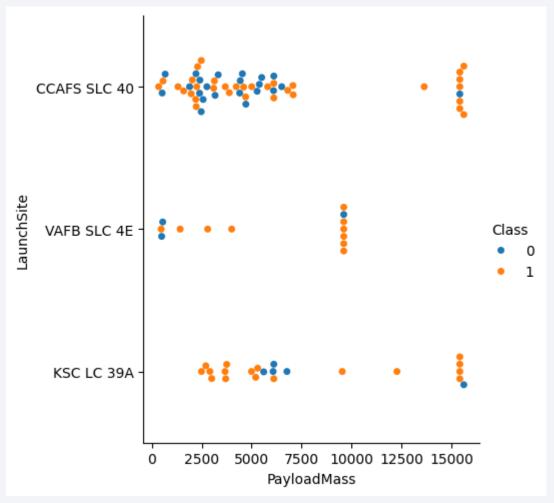
# Flight Number vs. Launch Site

• Scatter plot of Flight Number vs. Launch Site



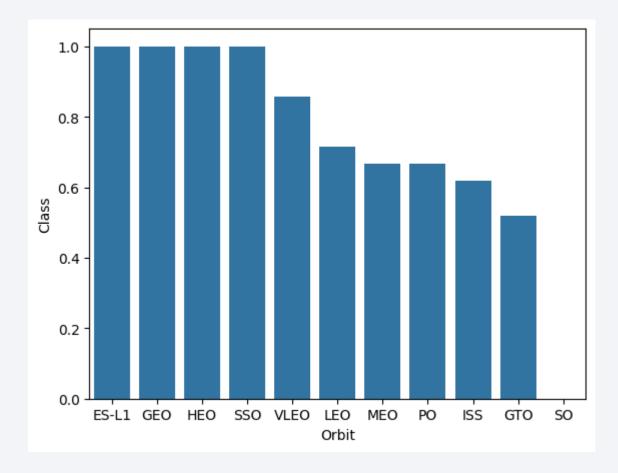
# Payload vs. Launch Site

• Scatter plot of Payload vs. Launch Site



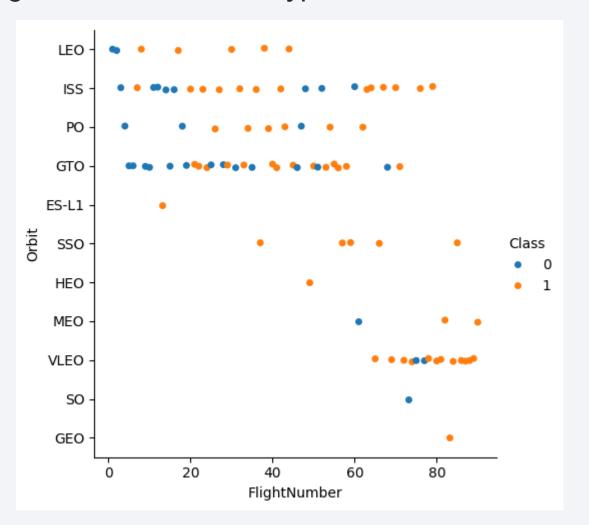
# Success Rate vs. Orbit Type

• Bar chart for the success rate of each orbit type



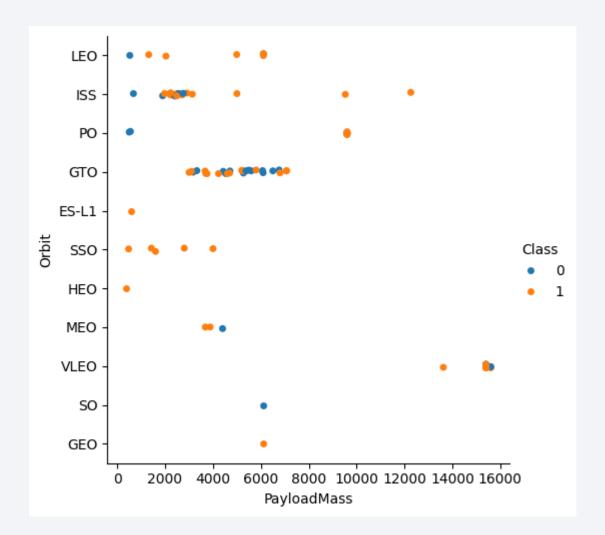
# Flight Number vs. Orbit Type

• Scatter plot of Flight number vs. Orbit type



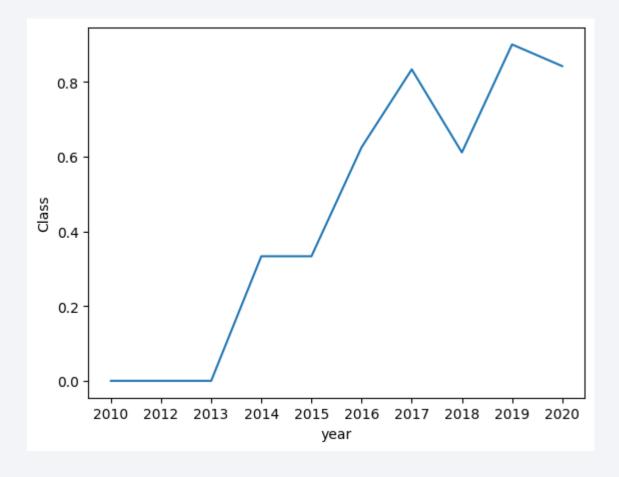
# Payload vs. Orbit Type

• Scatter plot of payload vs. orbit type



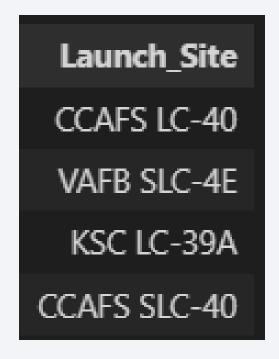
# Launch Success Yearly Trend

• Line chart of yearly average success rate



#### All Launch Site Names

- Names of the unique launch sites
- select distinct(Launch\_Site) from spacextable



# Launch Site Names Begin with 'CCA'

- 5 records where launch sites begin with `CCA`
- select \* from spacextable where Launch\_Site like 'CCA%' limit 5

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**

- Calculate the total payload carried by boosters from NASA
- select Customer, sum(PAYLOAD\_MASS\_\_KG\_) as 'total payload' from spacextable where Customer = "NASA (CRS)"

Customer total payload
NASA (CRS) 45596

# Average Payload Mass by F9 v1.1

- Calculate the average payload mass carried by booster version F9 v1.1
- select round(avg(PAYLOAD\_MASS\_\_KG\_),3) from spacextable where Booster Version like 'F9 v1.1%'

round(avg(PAYLOAD\_MASS\_\_KG\_),3)
2534.667

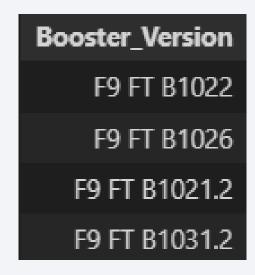
### First Successful Ground Landing Date

- Find the dates of the first successful landing outcome on ground pad
- select min(Date) as 'Date of first successful landing' from spacextable where Landing\_Outcome like '%Success%'

Date of first succesful landing 2015-12-22

#### 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
- select Booster\_Version from spacextable where Landing\_Outcome = 'Success' (drone ship)' and PAYLOAD\_MASS\_\_KG\_ between 4000 and 6000



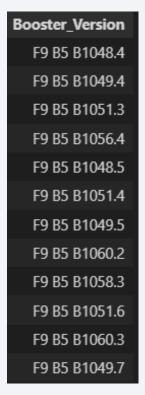
#### Total Number of Successful and Failure Mission Outcomes

- Calculate the total number of successful and failure mission outcomes
- select Mission\_Outcome, count(Mission\_Outcome) as 'Count' from spacextable group by Mission\_Outcome

Mission_Outcome	Count
Failure (in flight)	1
Success	98
Success	1
Success (payload status unclear)	1

# **Boosters Carried Maximum Payload**

- List the names of the booster which have carried the maximum payload mass
- select Booster\_Version from spacextable where PAYLOAD\_MASS\_\_KG\_ =
   (select max(PAYLOAD\_MASS\_\_KG\_) from spacextable)



#### 2015 Launch Records

- List the failed landing\_outcomes in drone ship, their booster versions, and launch site names for in year 2015
- select Date, Booster\_Version, Launch\_Site, Landing\_Outcome, substr(Date, 6, 2) as month from spacextable where Landing\_Outcome = 'Failure (drone ship)' and substr(Date, 0, 5) = '2015'

Date	Booster_Version	Launch_Site	Landing_Outcome	month
2015-01-10	F9 v1.1 B1012	CCAFS LC-40	Failure (drone ship)	01
2015-04-14	F9 v1.1 B1015	CCAFS LC-40	Failure (drone ship)	04

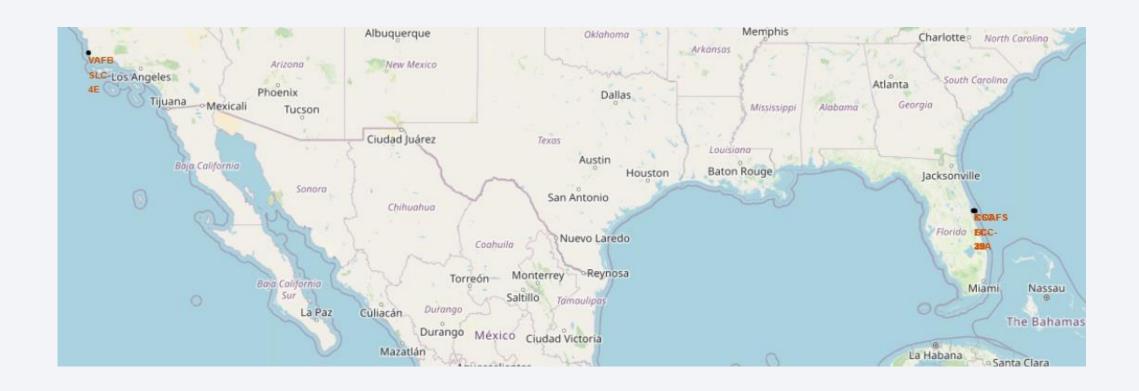
#### Rank Landing Outcomes Between 2010-06-04 and 2017-03-20

- 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 descending order
- select Landing\_Outcome, count(Landing\_Outcome) as Count from spacextable group by Landing\_Outcome having Date between '2010-06-04' and '2017-03-20' order by Count desc

Landing_Outcome	Count
No attempt	21
Success (drone ship)	14
Success (ground pad)	9
Failure (drone ship)	5
Controlled (ocean)	5
Uncontrolled (ocean)	2
Failure (parachute)	2
Precluded (drone ship)	1

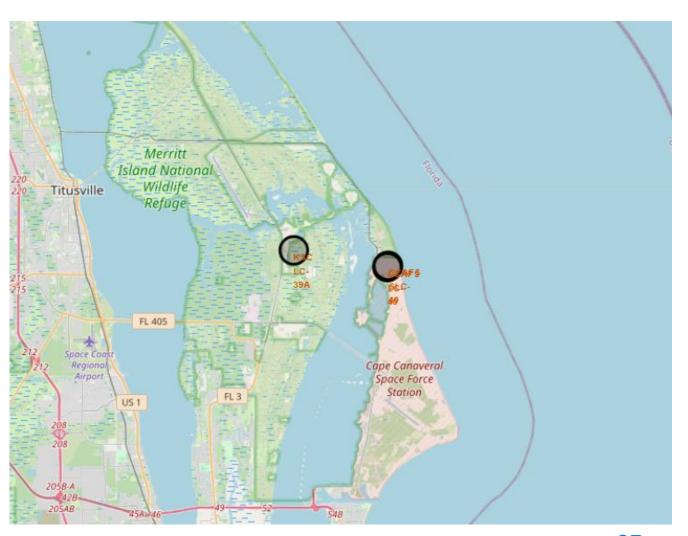


# Launch sites map

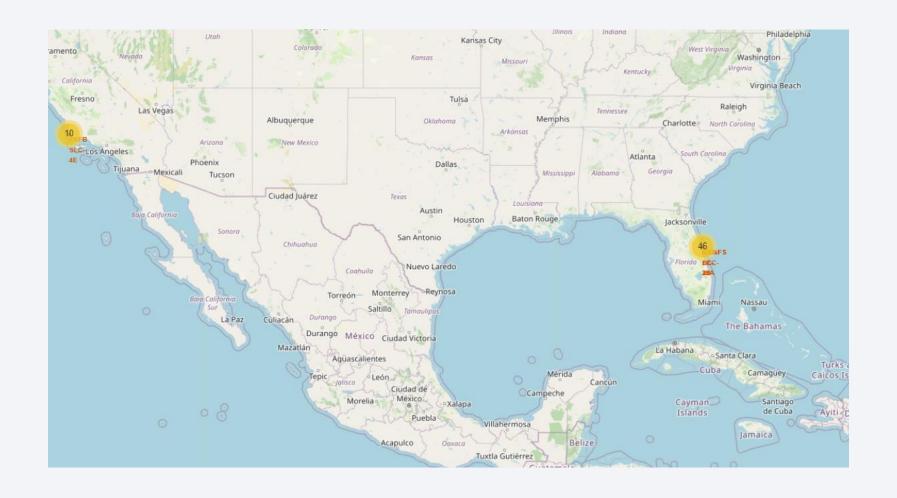


# Launch sites map

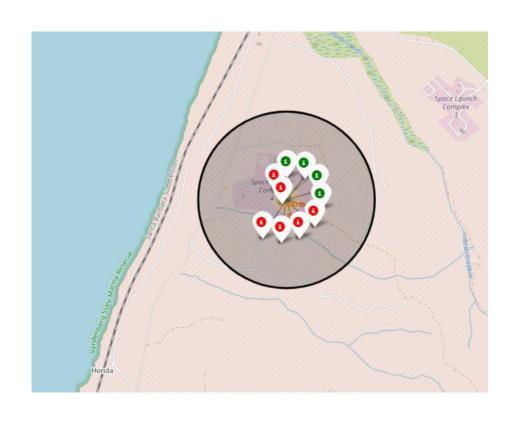


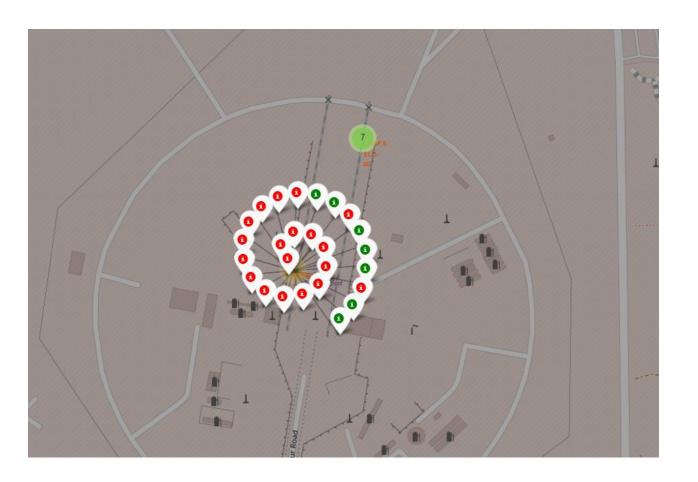


#### Launch Sites with outcomes



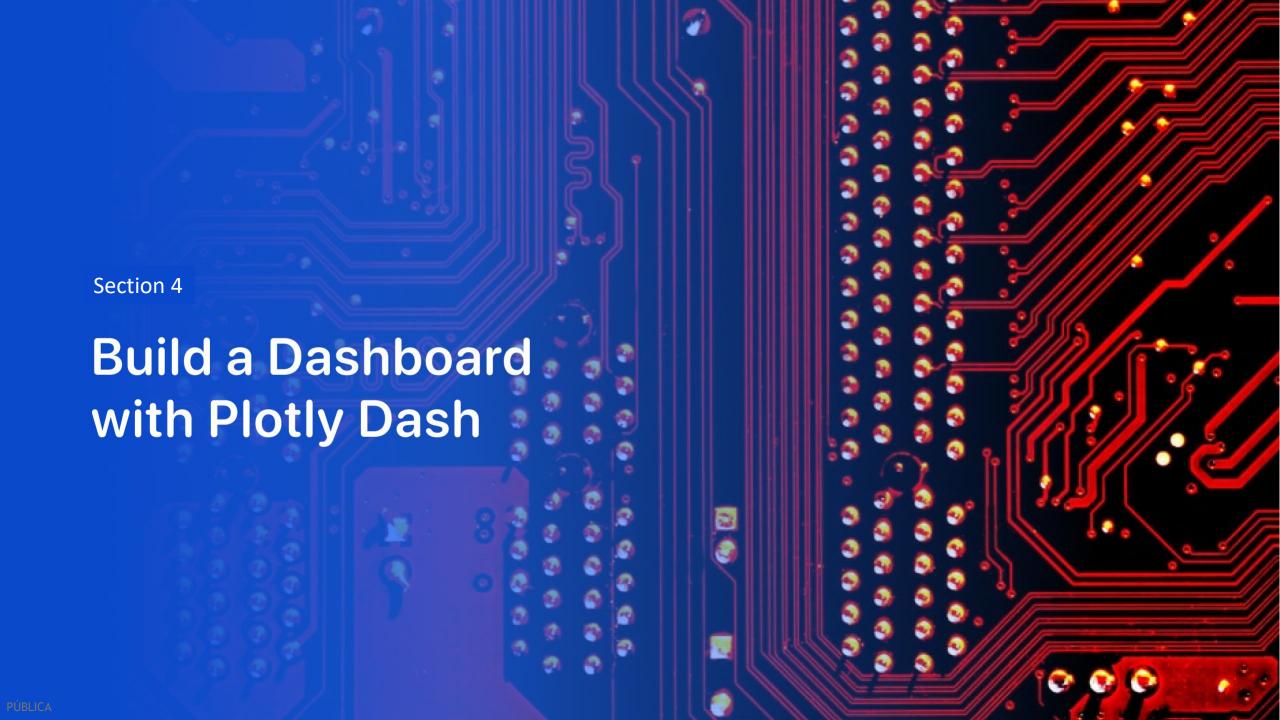
### Launch Sites with outcomes



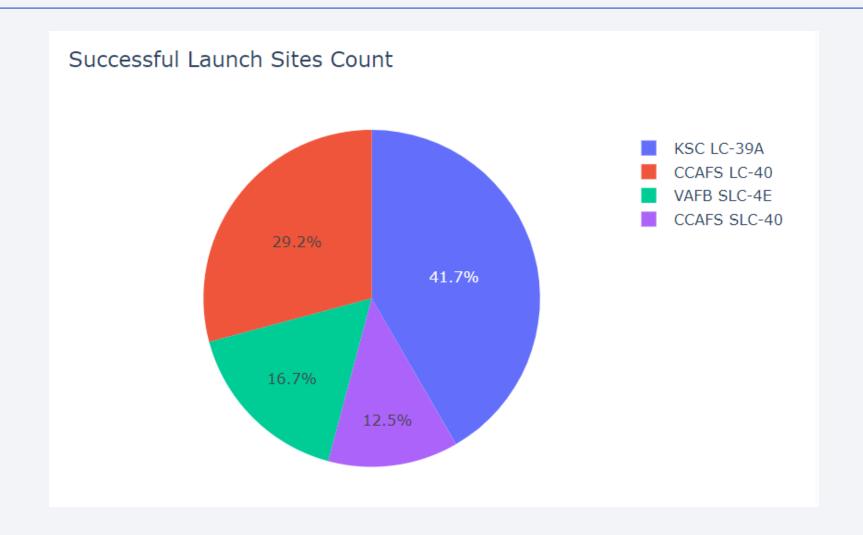


### Distance from coastline

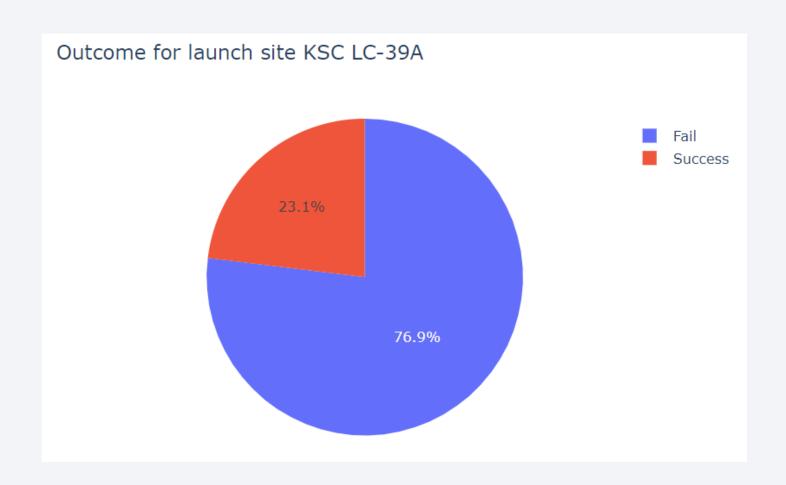




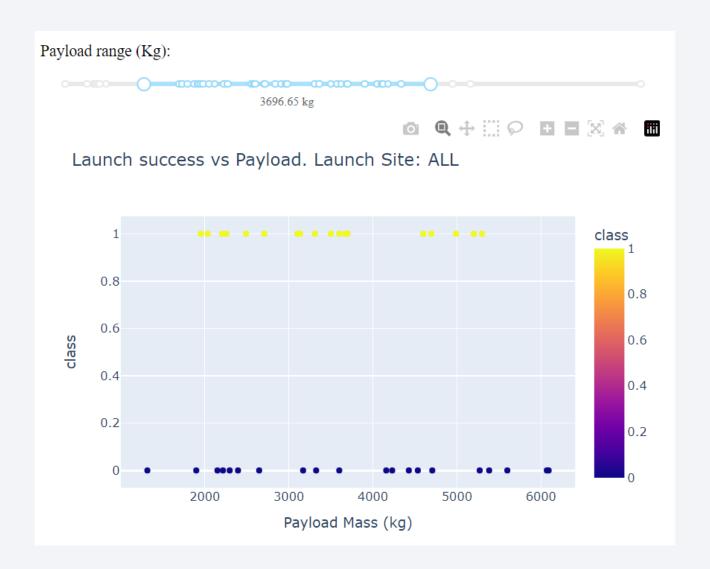
### Successful Launch Sites Count



## Outcome for launch site with highest success rate



## Payload Mass vs Launch outcome (all sites)

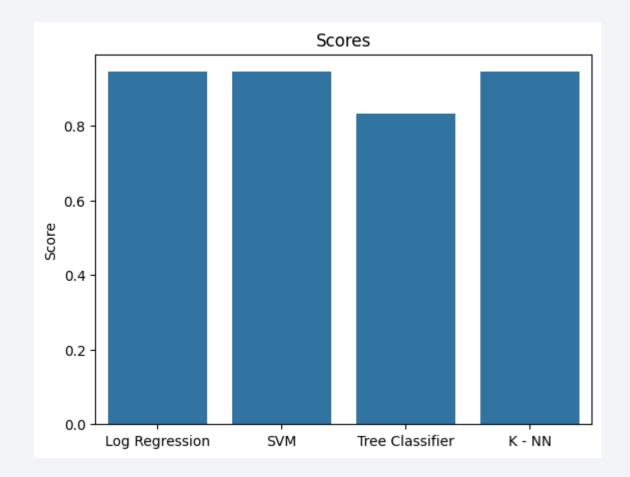




## Classification Accuracy

 Visualize the built model accuracy for all built classification models, in a bar chart

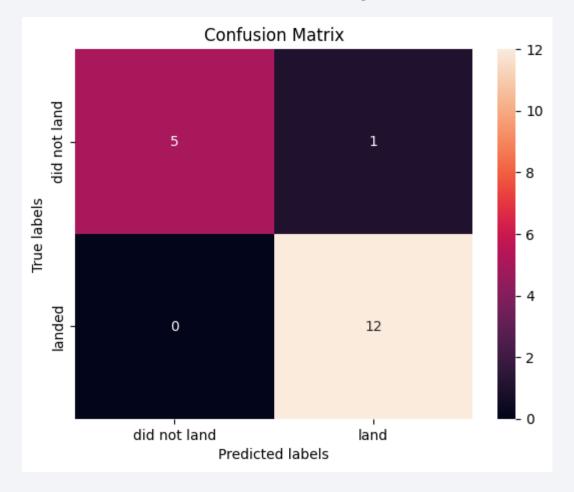
 Find which model has the highest classification accuracy: Log Reg, SVM and KNN



#### **Confusion Matrix**

• Show the confusion matrix of the best performing model with an

explanation



#### Conclusions

• The main factor of success in launches is the experience gain in the firsts attempts, we can see that in slide 24:

