

# Winning Space Race with Data Science

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#### Outline

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

#### **Executive Summary**

- Methodology
  - First, collect data
  - Second, analyze data with:
    - Visualize data statistics
    - Interactive dashboard
    - Maps
  - Third, build a machine learning (ML) model to predict a mission success
- Summary of all results
  - Exploratory data analysis to see what variables are related to success
  - 4 different ML models to predict success

#### Introduction

- SpaceX is an American company founded in 2002 by Elon Musk who in words of Donald J Trump 'is doing the rocket, he likes rockets, and does good at rockets too'. <u>Click here</u>.
- The objective of this project is to understand what leads to the success or failure of a rocket mission, and be able to predict if a mission will be successful or not



# Methodology

#### 1. Data collection:

- SpaceX API
- WebScrapping

#### 2. Data wrangling

- Prepare data for analysis
- Calculate landing sites, orbits, and outcomes

#### 3. Data visualization

- Scatterplots, bar charts, and time line trends
- Calculate landing sites, orbits, and outcomes

#### 4. SQL queries

#### 5. Folium maps

- · Show location of launch sites
- Show successes/failures at each launch site

#### 6. Plotly Dashboard

- Success Pie chart and correlation chart between payload and sucess
- Interactive

# 7. Predictive analysis using ML classification models

 4 models: Logistic regression, Support Vector machines, Decision trees, and k-nearest neighbors

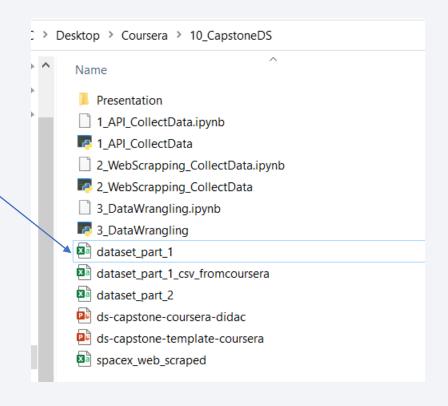
#### **Data Collection**

• 2 alternative methods to collect data:

1. SpaceX API

2. WebScrapping Wikipedia page "List of Falcon 9 and Falcon Heavy launches"

• (use a static version of the link)



Save in .csv

format

## Data Collection - SpaceX API

1. Request the SpaceX launches data by calling the SpaceX API. Normalize json.

```
# Better use this static link than the one above for this course
static_json_url = 'https://cf-courses-data.s3.us.cloud-object-stor
response = requests.get(static_json_url)
data = pd.json_normalize(response.json())
```

- 2. Convert it into a readable pandas dataframe (see code for details)
  - 3. Filter the dataframe to include only Falcon 9 Launches

```
data_falcon9 = df[df['BoosterVersion']!='Falcon 1']
```

4. Replace missing 'PayLoadMass' values by the mean of the column

```
# Calculate the mean value of PayloadMass column
PayloadMass_mean = data_falcon9['PayloadMass'].mean()
# Replace the np.nan values with its mean value
data_falcon9['PayloadMass'] = data_falcon9['PayloadMass'].fillna(PayloadMass_mean)
```

## Data Collection - WebScraping

 Get data from the url using 'requests.get' # To keep the lab tasks consistent, you will be asked to scrape the data from # a snapshot of the List of Falcon 9 and Falcon Heavy launches Wikipage updated on 9th June 2021 static\_url = "https://en.wikipedia.org/w/index.php?title=List\_of\_Falcon\_9\_and\_Falcon\_Heavy\_Launched # Use requests.get() method with the provided static\_url and assign the response to a object response = requests.get(static\_url).text

2. Turn it into a 'Beautiful Soup object'

# Use BeautifulSoup() to create a BeautifulSoup object from a response text content
soup = BeautifulSoup(response, "html5lib")

3. Turn html code into pandas df (see code)

Code link in GitHub

# **Data Wrangling**

1. Calculate landings on each site

```
df.value_counts('LaunchSite')
'''
LaunchSite
CCAFS SLC 40 55
KSC LC 39A 22
VAFB SLC 4E 13
```

3. Calculate the number of occurrences of mission outcome per orbit type

```
landing outcomes = df.value counts('Outcome')
Outcome
True ASDS
              41 -- success
              19 -- fail
None None
True RTLS
              14 -- success
False ASDS
               6 -- fail
               5 -- success
True Ocean
               2 -- fail
False Ocean
               2 -- fail
None ASDS
               1 -- fail
False RTLS
```

2. Calculate the number and occurrence of each orbit

```
df.value counts('Orbit')
Orbit
GTO
         27
ISS
         21
         14
VLEO
PO
LE0
SS0
MEO
ES-L1
GE0
HE0
SO.
```

4. Create a 0-1 landing outcome label 'Class'. And calculate success rate with it

```
# Success rate
df["Class"].mean()
0.6666
```

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

- Categorical scatterplots: To see the relation between success and
  - Launch Site and flight number
  - Launch site and payload
  - Flight number and orbit type
  - Payload and orbit type
- Bar charts
  - Success rate by orbit type
- Time trends
  - Success rate change over time

#### **EDA** with SQL

- 1. Display names launch sites
- Display 5 records where launch sites begin by 'CAA'
- Display total payload mass by boosters launched by NASA
- 4. Display average payload mass carried by booster version F9 v1.1
- 5. List date when the first successful landing outcome in a ground pad was achieved

- 6. List names successful boosters where payload mass (4000,6000)
- 7. List number of success/fail missions
- 8. List Names of booster versions that have carried the maximum payload mass
- 9. List full records in year 2015
- 10. Rank the count of successful landing outcomes between the date 04-06-2010 and 20-03-2017.

Code link in GitHub

### Build an Interactive Map with Folium

- Map 1: Markers showing location of launch sites in the US
- Map 2: Markers also show the number of success missions at each site
- Map 3: Show lines that measure proximity to objects

Code link in Github

#### Build a Dashboard with Plotly Dash

- Pie chart showing success/failure.
  - Interactivity: select site
- Correlation between payload and success.
  - Interactivity: Choose payload range and site.

Code link in GitHub

# Predictive Analysis (Classification)

- Build 4 Machine Learning Models:
  - Logistic Regression
  - Support Vector Machines (SVM)
  - K-Nearest Neighbors (KNN)
  - Decision Trees
- Evaluate performance:
  - Cross validation: Split sample into train and test. Measure accuracy in the test (and train) sample
- Choice:
  - Almost identical performance
  - Decision trees marginally better

Code link in GitHub

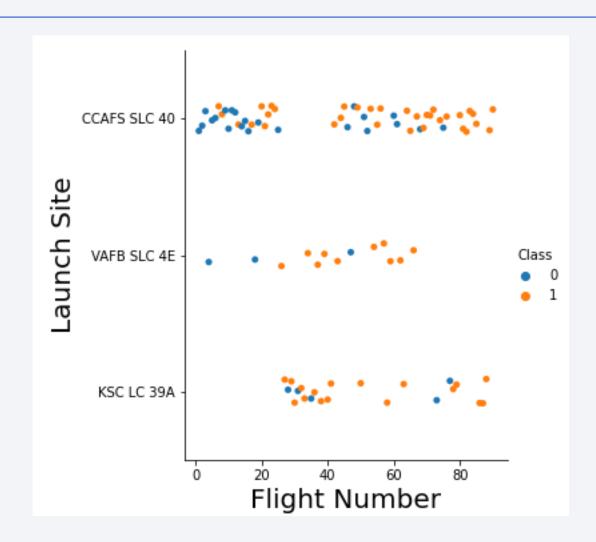
#### Results

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



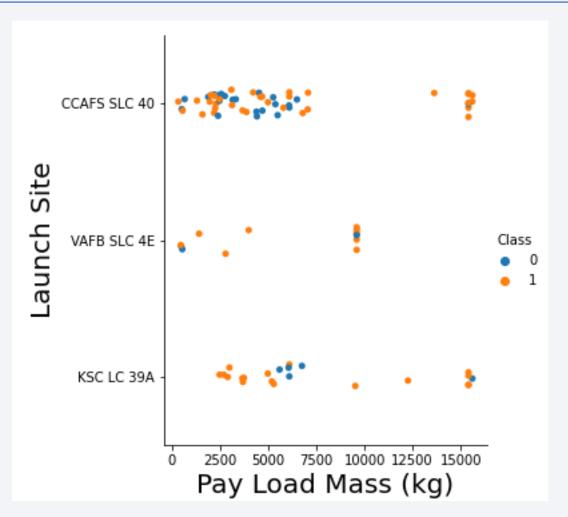
## Flight Number vs. Launch Site

- CCAFS SLC 40 most used launch site
- VAFB SLC 4E least used launch site
- First flights fail more often
- Last flights succeed more
- Important success increase in CCAFS SLC 40



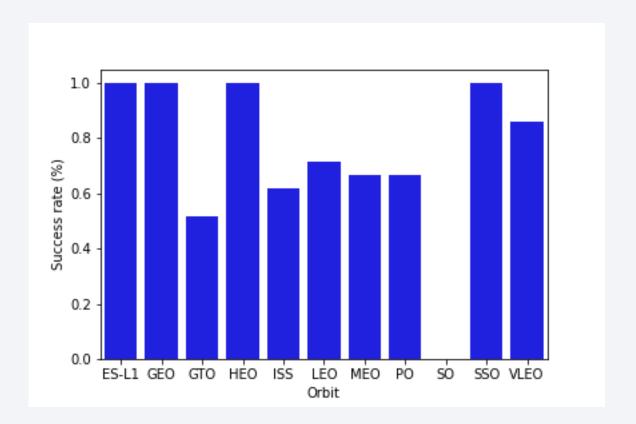
## Payload vs. Launch Site

- CCAFS SLC 40 performs better with high payload mass
- VAFB SLC 4E never has a mass above 10000



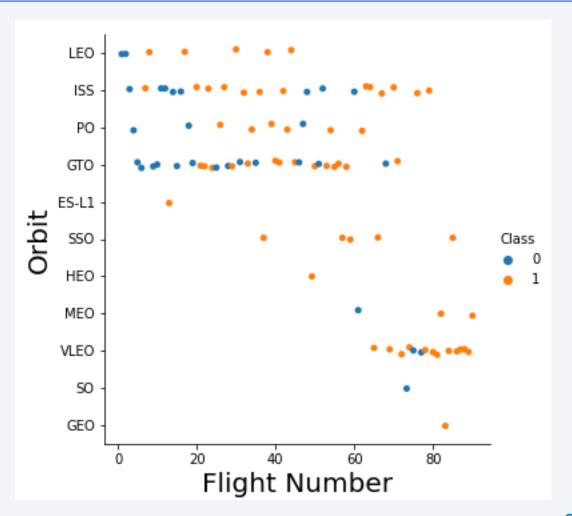
# Success Rate vs. Orbit Type

- Several Orbit types have
   100% success rate
- SO 0% has 0% success rate
- Small sample size in some Orbits may lead to the high/low success rates



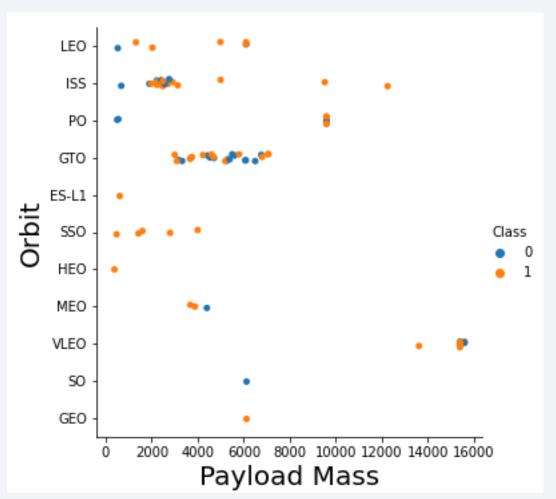
# Flight Number vs. Orbit Type

- Over time there is a shift from some orbit types to others
- Again, first flights perform worse



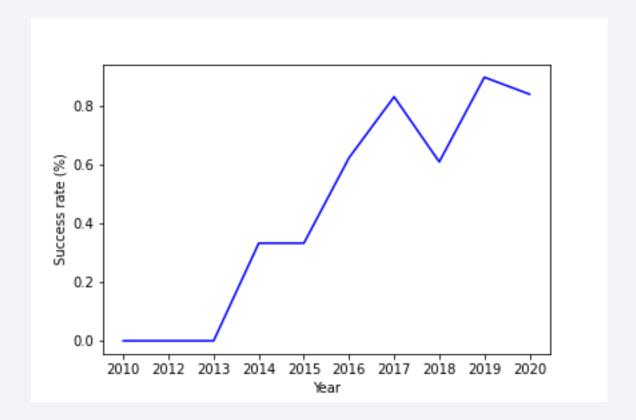
# Payload vs. Orbit Type

 Some orbit types have more often high payloads than others



## Launch Success Yearly Trend

- Big increase in the success rate from 2010 to 2017
- After that the success rate did not increase significantly and in 2018 was lower than in 2017



#### All Launch Site Names

• Find the names of the unique launch sites



• 4 sites, already seen

# Launch Site Names Begin with 'CCA'

• Find 5 records where launch sites begin with `CCA`

| Date           | Time<br>(UTC) | Booster_Version | Launch_Site     | Payload   | PAYLOAD_MASSKG_ | Orbit        | Customer           | Mission_Outcome | Landing<br>_Outcome    |
|----------------|---------------|-----------------|-----------------|---|-----------------|--------------|--------------------|-----------------|------------------------|
| 04-06-<br>2010 | 18:45:00      | F9 v1.0 B0003   | CCAFS LC-<br>40 | Dragon Spacecraft Qualification<br>Unit                             | 0               | LEO          | SpaceX             | Success         | Failure<br>(parachute) |
| 08-12-<br>2010 | 15:43:00      | F9 v1.0 B0004   | CCAFS LC-<br>40 | Dragon demo flight C1, two<br>CubeSats, barrel of Brouere<br>cheese | 0               | LEO<br>(ISS) | NASA<br>(COTS) NRO | Success         | Failure<br>(parachute) |
| 22-05-<br>2012 | 07:44:00      | F9 v1.0 B0005   | CCAFS LC-<br>40 | Dragon demo flight C2   | 525             | LEO<br>(ISS) | NASA<br>(COTS)     | Success         | No attempt             |
| 08-10-<br>2012 | 00:35:00      | F9 v1.0 B0006   | CCAFS LC-<br>40 | SpaceX CRS-1  | 500             | LEO<br>(ISS) | NASA (CRS)         | Success         | No attempt             |
| 01-03-<br>2013 | 15:10:00      | F9 v1.0 B0007   | CCAFS LC-<br>40 | SpaceX CRS-2  | 677             | LEO<br>(ISS) | NASA (CRS)         | Success         | No attempt             |

- This is an example of 5 records launches from CCAFS LC-40
- There are more than 5 records

# **Total Payload Mass**

Calculate the total payload carried by boosters from NASA

• That's a lot of Kg!

## Average Payload Mass by F9 v1.1

Calculate the average payload mass carried by booster version F9 v1.1



The average is around of 2500Kg

## First Successful Ground Landing Date

• Find the dates of the first successful landing outcome on ground pad



• Until 2017 there was no successful landing outcome on 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



Four different types

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

• Calculate the total number of successful and failure mission outcomes



• Very high success rate!

# **Boosters Carried Maximum Payload**

• List the names of the booster which have carried the maximum payload mass



Many different boosters can carry the maximum payload mass

#### 2015 Launch Records

• List the failed landing outcomes in drone ship, their booster versions, and launch site names for in year 2015

| MONTH | Booster_Version | Launch_Site |
|-------|-----------------|-------------|
| 01    | F9 v1.1 B1012   | CCAFS LC-40 |
| 04    | F9 v1.1 B1015   | CCAFS LC-40 |

These failed

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

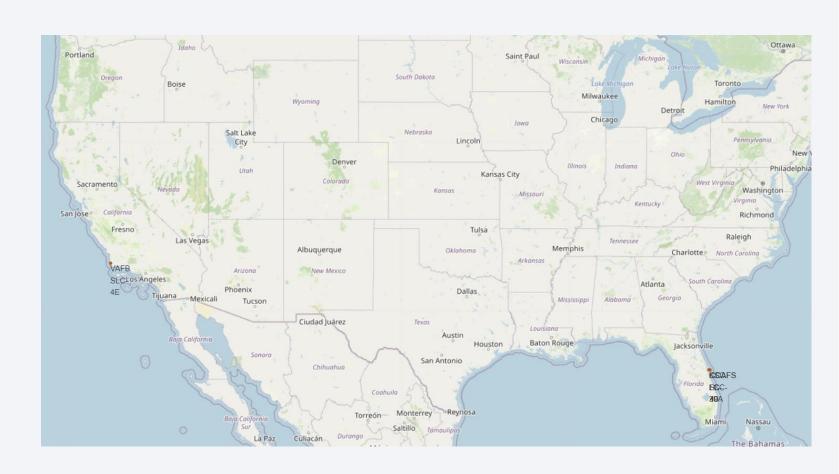
 Rank the count of landing outcomes (such as Failure (drone ship) or Success (ground pad)) between the date 2010-06-04 and 2017-03-20, in descending order

| Landing _Outcome     | COUNT("LANDING _OUTCOME") |
|----------------------|---------------------------|
| Success              | 20                        |
| Success (drone ship) | 8                         |
| Success (ground pad) | 6                         |
|                      |                           |



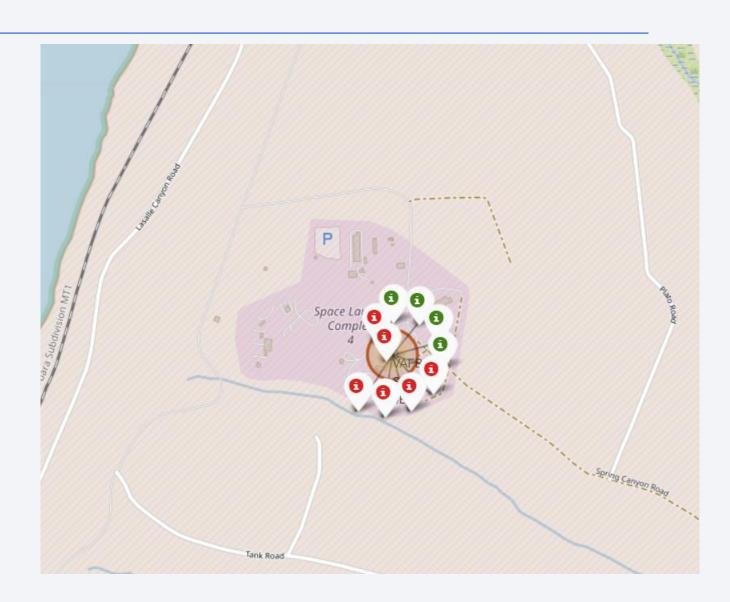
#### **Location Launch sites**

- All launch sites are in California or Florida
- Which are closer to the equator and closer to the sea



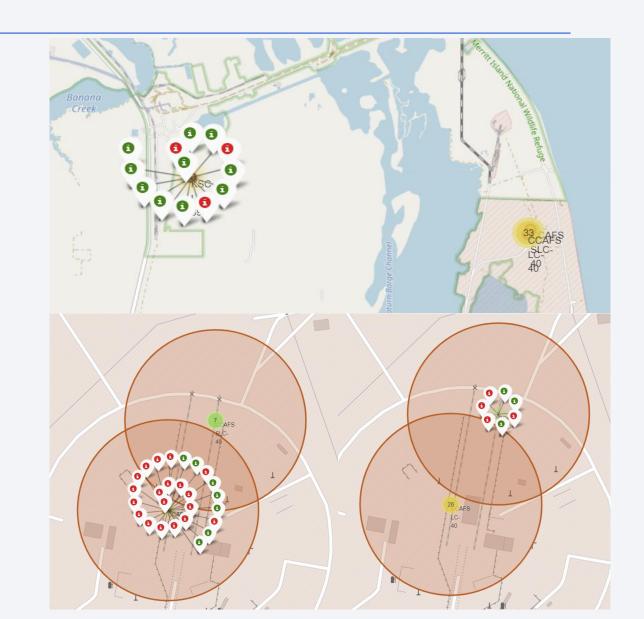
# Launch sites success/failure - California

- Launch site in California
- High failure rate



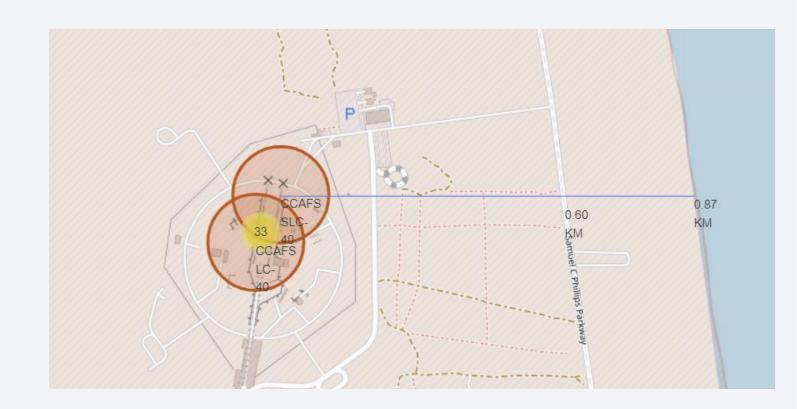
#### Launch sites success/failure - Florida

- The map on top shows the 3 launch sites in Florida. Plus the success/failures in one of the
- The bottom maps show the success/failures in the other 2 launch sites
- The launch site on the West has higher success rate than the others



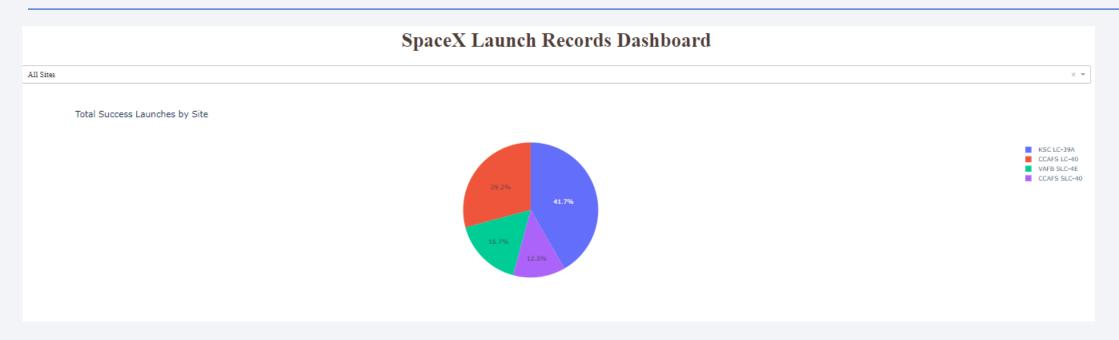
# Launch site proximites

- The launch site CCAFS SLC-40 is at
  - 0.6km from a road
  - 0.87km from the sea



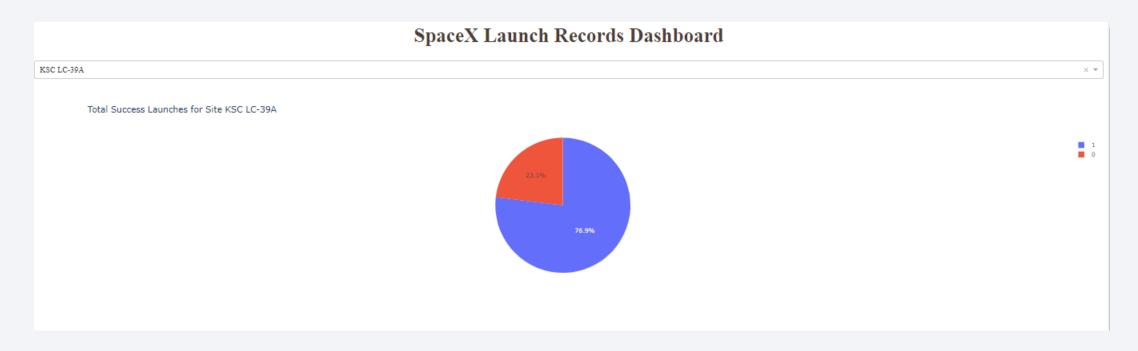


## Dashboard: Successful outcomes by site



• KSC-LC-39A has the highest number of successful missions 41.7%

# Dashboard: Site with highest success rate



• KSC-LC-39A also has the highest success rate

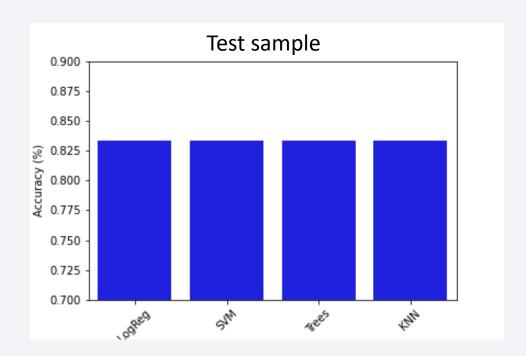
## Dashboard: Correlation Payload and success

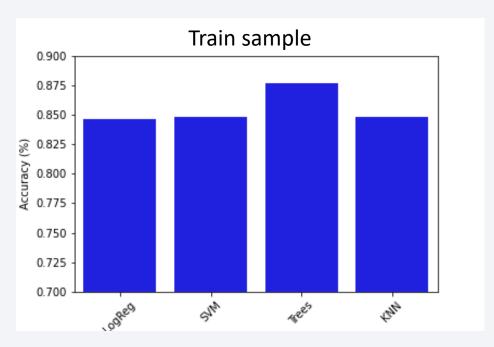


- Correlation between payload and success in KSC LC-39A
- · Missions with higher payload are more likely to fail



## **Classification Accuracy**

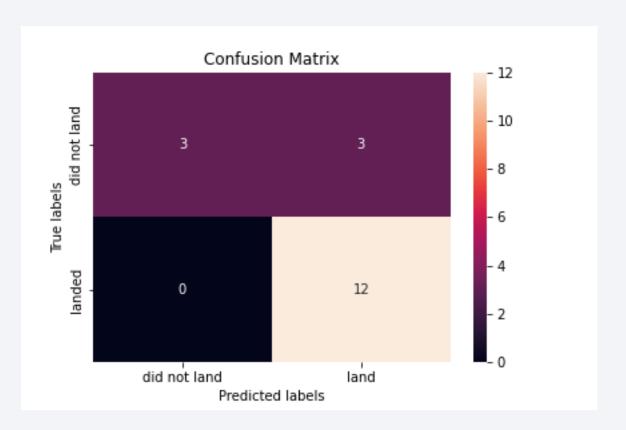




- Same accuracy in the test sample
- Decision trees have higher accuracy in the train sample

#### **Confusion Matrix**

All models have the same confusion matrix



#### Conclusions

- The four ML models perform almost equally in predicting the success of a mission
- Decision Trees is slightly better at prediction

