



IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

Gigih Pambuko
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Outline

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

Executive Summary

- Summary of methodologies
 - Data Collection via API, Web Scraping
 - Exploratory Data Analysis (EDA) with Data Visualization
 - EDA with SQL
 - Interactive Map with Folium
 - Dashboards with Plotly Dash
 - Predictive Analysis
- Summary of all results
 - Exploratory Data Analysis results
 - Interactive maps and dashboard
 - Predictive results

Introduction

- **Project background and context**

The aim of this project is to predict if the Falcon 9 first stage will successfully land. SpaceX says on its website that the Falcon 9 rocket launch cost 62 million dollars. Other providers cost upward of 165 million dollars each. The price difference is explained by the fact that SpaceX can reuse the first stage. By determining if the stage will land, we can determine the cost of a launch. This information is interesting for another company if it wants to compete with SpaceX for a rocket launch.

- **Problems you want to find answers**

1. What are the main characteristics of a successful or failed landing ?
2. What are the effects of each relationship of the rocket variables on the success or failure of a landing ?
3. What are the conditions which will allow SpaceX to achieve the best landing success rate ?

Section 1

Methodology

Methodology

Executive Summary

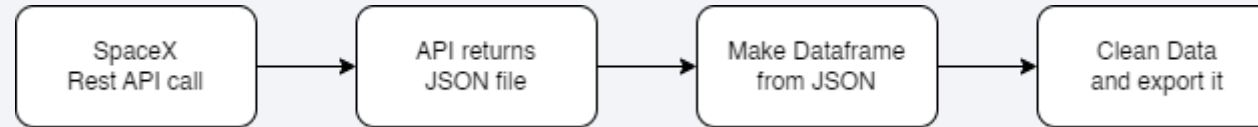
- Data collection methodology:
 - SpaceX REST API
 - Web Scrapping from Wikipedia
- Perform data wrangling
 - Dropping unnecessary columns
 - One Hot Encoding for classification models
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
 - How to build, tune, evaluate classification models

Data Collection

- Datasets are collected from Rest SpaceX API and webscrapping Wikipedia

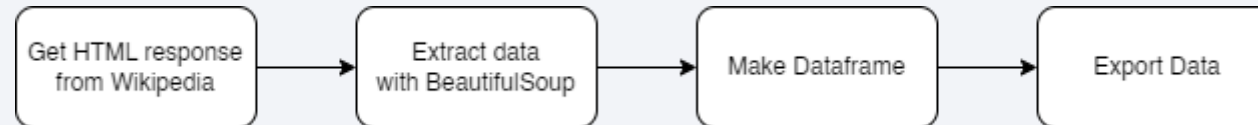
- The information obtained by the API are rocket, launches, payload information.

- The space X REST API URL is <https://api.spacexdata.com/v4/rockets/>



- The information obtained by the webscrapping of Wikipedia are launces, landing, payload information.

- URL is https://en.wikipedia.org/wiki/List_of_Falcon_9_and_Falcon_Heavy_launches



Data Collection – SpaceX API

1. Getting Response from API

```
[10]: static_json_url='https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/datasets/API_call_spacex_api.json'
```

We should see that the request was successful with the 200 status response code

```
[11]: response.status_code
```

```
[11]: 200
```

2. Convert Response to JSON File

```
[12]: # Use json_normalize meethod to convert the json result into a dataframe  
data = pd.json_normalize(response.json())
```

3. Transform data

```
[17]: # Call getBoosterVersion  
getBoosterVersion(data)
```

the list has now been update

```
[18]: BoosterVersion[0:5]
```

```
[18]: ['Falcon 1', 'Falcon 1', 'Falcon 1', 'Falcon 1', 'Falcon 9']
```

we can apply the rest of the functions here:

```
[19]: # Call getLaunchSite  
getLaunchSite(data)
```

```
[20]: # Call getPayloadData  
getPayloadData(data)
```

```
[21]: # Call getCoreData  
getCoreData(data)
```


Data Collection – SpaceX API

4. Create dictionary with data

```
[22]: launch_dict = {'FlightNumber': list(data['flight_number']),
                    'Date': list(data['date']),
                    'BoosterVersion': BoosterVersion,
                    'PayloadMass': PayloadMass,
                    'Orbit': Orbit,
                    'LaunchSite': LaunchSite,
                    'Outcome': Outcome,
                    'Flights': Flights,
                    'GridFins': GridFins,
                    'Reused': Reused,
                    'Legs': Legs,
                    'LandingPad': LandingPad,
                    'Block': Block,
                    'ReusedCount': ReusedCount,
                    'Serial': Serial,
                    'Longitude': Longitude,
                    'Latitude': Latitude}
```

5. Create dataframe

```
[23]: # Create a data from launch dict
data = pd.DataFrame.from_dict(launch_dict)
```

6. Filter dataframe

```
[25]: # Hint data['BoosterVersion']!='Falcon 1'
data_falcon9 = data[data['BoosterVersion'] != 'Falcon 1']
```

7. Export to file

```
[29]: data_falcon9.to_csv('dataset_part_1.csv', index=False)
```

Data Collection - Scraping

1. Getting Response from HTML

```
[5]: # use requests.get() method with the provided static_url
     # assign the response to a object
     data = requests.get(static_url).text
```

2. Create BeautifulSoup Object

```
[6]: # Use BeautifulSoup() to create a BeautifulSoup object from a response text content
     soup = BeautifulSoup(data, 'html.parser')
```

3. Find all tables

```
# Find all elements of type 'table' in the HTML
html_tables = soup.find_all('table')
```

4. Get column names

```
[10]: column_names = []
      # Apply find_all() function with `th` element on
      # Iterate each th element and apply the provided
      # Append the Non-empty column name (if name is n
      for row in first_launch_table.find_all('th'):
          name = extract_column_from_header(row)
          if (name != None and len(name) > 0):
              column_names.append(name)
```

Data Collection - Scraping

5. Create dictionary

```
[12]: launch_dict=dict.fromkeys(column_names)

# Remove an irrelevant column
del launch_dict['Date and time ( )']

# Let's initial the launch_dict with each value to be an empty list
launch_dict['Flight No.'] = []
launch_dict['Launch site'] = []
launch_dict['Payload'] = []
launch_dict['Payload mass'] = []
launch_dict['Orbit'] = []
launch_dict['Customer'] = []
launch_dict['Launch outcome'] = []
# Added some new columns
launch_dict['Version Booster']=[]
launch_dict['Booster landing']=[]
launch_dict['Date']=[]
launch_dict['Time']=[]
```

6. Add data to keys

```
extracted_row = 0
#Extract each table
for table_number,table in enumerate(soup.find_all('table')):
    # get table row
    for rows in table.find_all("tr"):
        #check to see if first table heading is as number
        if rows.th:
            if rows.th.string:
                flight_number=rows.th.string.strip()
                flag=flight_number.isdigit()
```

7. Create dataframe from dictionary & Export to file

```
df=pd.DataFrame(launch_dict)
```

```
df.to_csv('spacex_web_scraped.csv', index=False)
```

Data Wrangling

- In the dataset, there are several cases where the booster did not land successfully.
 - **True Ocean**, True RTLS, True ASDS means the mission has been successful.
 - **False Ocean**, False RTLS, False ASDS means the mission was a failure.
- We need to transform string variables into categorical variables where 1 means the mission has been successful and 0 means the mission was a failure.

Data Wrangling

1. Calculate launches number for each site

```
[8]: # Apply value_counts() on column LaunchSite
launches = df['LaunchSite'].value_counts()
launches

[8]: CCAFS SLC 40      55
      KSC LC 39A      22
      VAFB SLC 4E      13
      Name: LaunchSite, dtype: int64
```



2. Calculate the number and occurrence of each orbit

```
[9]: # Apply value_counts on Orbit column
occurrence = df['Orbit'].value_counts()
occurrence

[9]: GTO      27
      ISS      21
      VLEO     14
      PO       9
      LEO       7
      SSO       5
      MEO       3
      ES-L1     1
      HEO       1
      SO        1
      GEO       1
      Name: Orbit, dtype: int64
```

3. Calculate number and occurrence of mission outcome per orbit type

```
[10]: # landing_outcomes = values on Outcome column
landing_outcomes = df['Outcome'].value_counts()
landing_outcomes
```

```
[10]: True ASDS      41
      None None     19
      True RTLS     14
      False ASDS     6
      True Ocean     5
      False Ocean    2
      None ASDS      2
      False RTLS     1
      Name: Outcome, dtype: int64
```

4. Create landing outcome label from Outcome column

```
[13]: # landing_class = 0 if bad_outcome
      # landing_class = 1 otherwise
df['Class'] = df['Outcome'].apply(lambda x: 0 if x in bad_outcomes else 1)
df['Class'].value_counts()
```

```
[13]: 1      60
      0      30
      Name: Class, dtype: int64
```

5. Export file

```
[17]: df.to_csv("dataset_part_2.csv", index=False)
```

[Link to code](#)

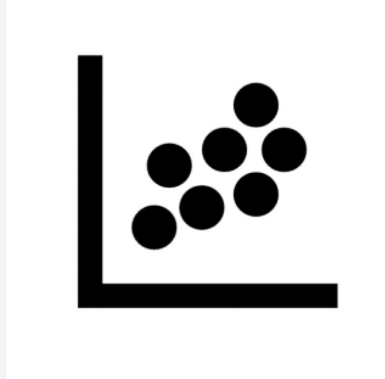
EDA with Data Visualization

Scatter Graphs

- Flight Number vs. Payload Mass
- Flight Number vs. Launch Site
- Payload vs. Launch Site
- Orbit vs. Flight Number
- Payload vs. Orbit Type
- Orbit vs. Payload Mass

Scatter plots show relationship between variables.

This relationship is called the correlation.



Bar Graph

- Success Rate vs Orbit

Bar graphs show the relationship between numeric and categorical variables.



Line Graph

- Success Rate vs Year

Line graphs show data variables and their trends. Line graphs can help to show global behavior and make prediction for unseen data.



EDA with SQL

We performed SQL queries to gather and understand data from dataset:

- Displaying the names of the unique launch sites in the space mission.
- Display 5 records where launch sites begin with the string 'CCA'
- Display the total payload mass carried by boosters launched by NASA (CRS).
- Display average payload mass carried by booster version F9 v1.1.
- List the date when the first successful landing outcome in ground pad was achieved.
- List the names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000.
- List the total number of successful and failure mission outcomes.
- List the names of the booster_versions which have carried the maximum payload mass.
- 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.
- Rank the count of successful landing_outcomes between the date 04-06-2010 and 20-03-2017 in descending order.

[Link to code](#)

Build an Interactive Map with Folium

Folium map object is a map centered on NASA Johnson Space Center at Houston, Texas

- Red circle at NASA Johnson Space Center's coordinate with label showing its name(*folium.Circle*, *folium.map.Marker*).
- Red circles at each launch site coordinates with label showing launch site name (*folium.Circle*, *folium.map.Marker*, *folium.features.DivIcon*).
- The grouping of points in a cluster to display multiple and different information for the same coordinates (*folium.plugins.MarkerCluster*).
- Markers to show successful and unsuccessful landings. **Green** for successful landing and **Red** for unsuccessful landing. (*folium.map.Marker*, *folium.Icon*).
- Markers to show distance between launch site to key locations (railway, highway, coastway, city) and plot a line between them. (*folium.map.Marker*, *folium.PolyLine*, *folium.features.DivIcon*)

These objects are created in order to understand better the problem and the data. We can show easily all launch sites, their surroundings and the number of successful and unsuccessful landings.

Build a Dashboard with Plotly Dash

Dashboard has dropdown, pie chart, rangeslider and scatter plot components

- Dropdown allows a user to choose the launch site or all launch sites (*dash_core_components.Dropdown*).
- Pie chart shows the total success and the total failure for the launch site chosen with the dropdown component (*plotly.express.pie*).
- Rangeslider allows a user to select a payload mass in a fixed range (*dash_core_components.RangeSlider*).
- Scatter chart shows the relationship between two variables, in particular Success vs Payload Mass (*plotly.express.scatter*).

Predictive Analysis (Classification)

Data Preparation

- Load dataset
- Normalize data
- Split data into training and test sets.

Model Preparation

- Selection of machine learning algorithms
- Set parameters for each algorithm to GridSearchCV
- Training GridSearchModel models with training dataset

Model Evaluation

- Get best hyperparameters for each type of model
- Compute accuracy for each model with test dataset
- Plot Confusion Matrix

Model Comparison

- Comparison of models according to their accuracy
- The model with the best accuracy will be chosen (see Notebook for result)

[Link to code](#)

Results

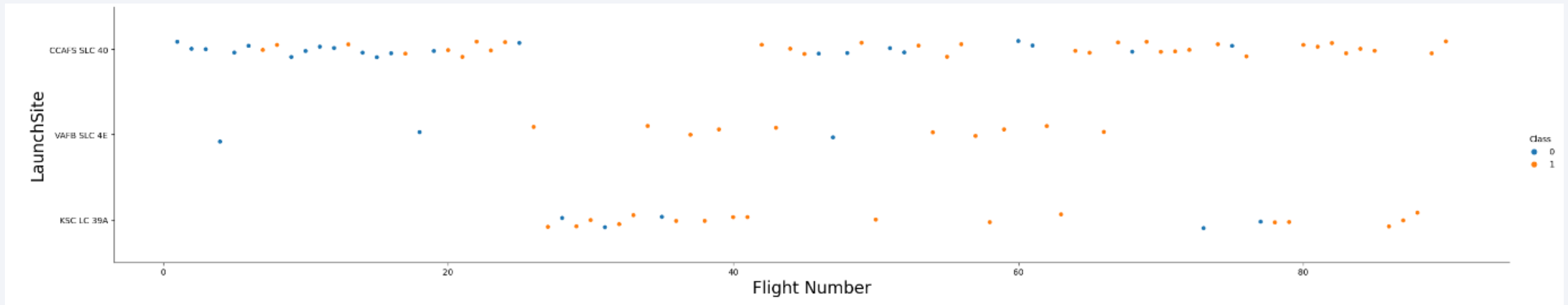
- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results

The background of the slide is an abstract composition. It features a dark blue base color. Overlaid on this are numerous diagonal streaks in shades of red and cyan. A faint, light blue grid pattern is also visible, particularly in the lower half of the image. The overall effect is dynamic and technological.

Section 2

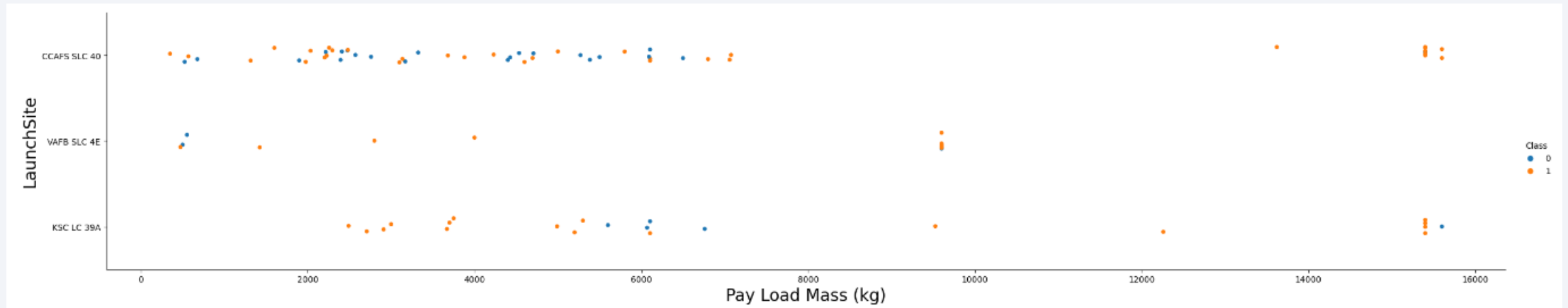
Insights drawn from EDA

Flight Number vs. Launch Site



We observe that, for each site, the success rate is increasing.

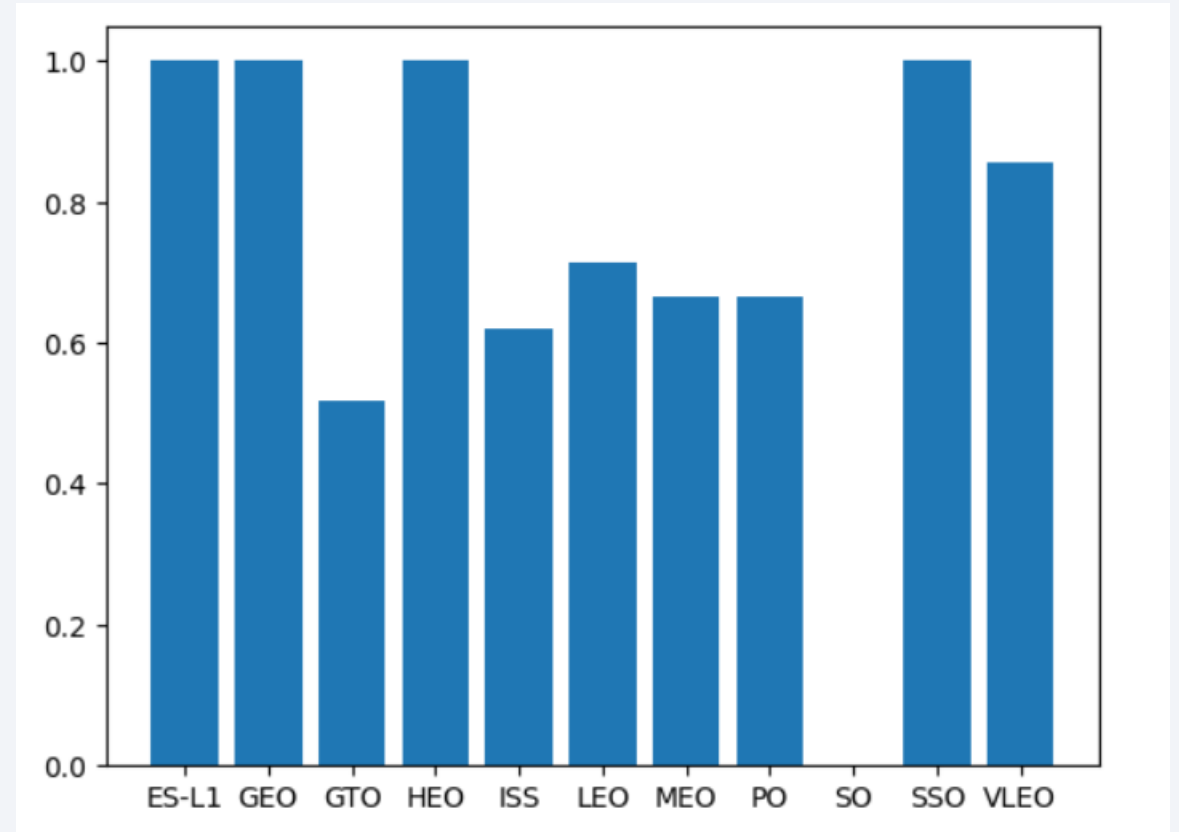
Payload vs. Launch Site



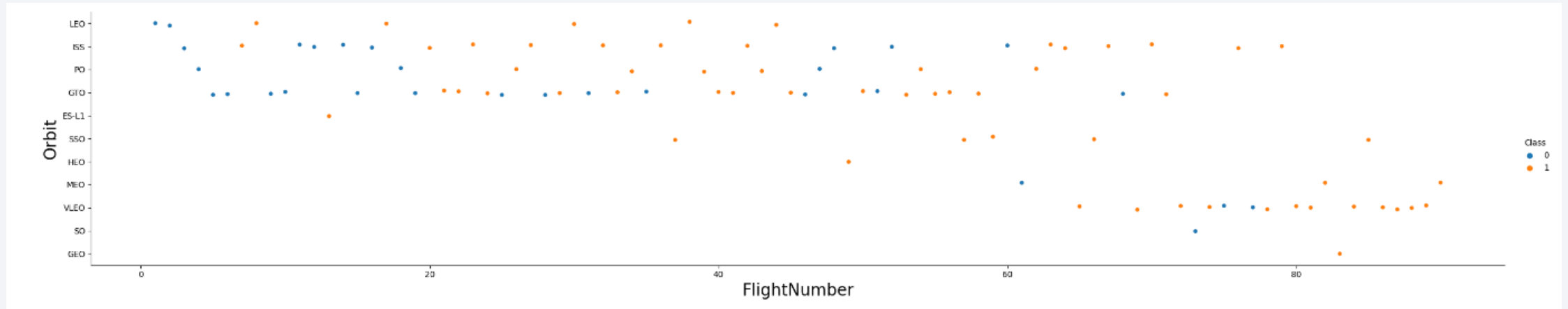
Depending on the launch site, a heavier payload may be a consideration for a successful landing. On the other hand, a too heavy payload can make a landing fail.

Success Rate vs. Orbit Type

With this plot, we can see success rate for different orbit types. We note that ES-L1, GEO, HEO, SSO have the best success rate.

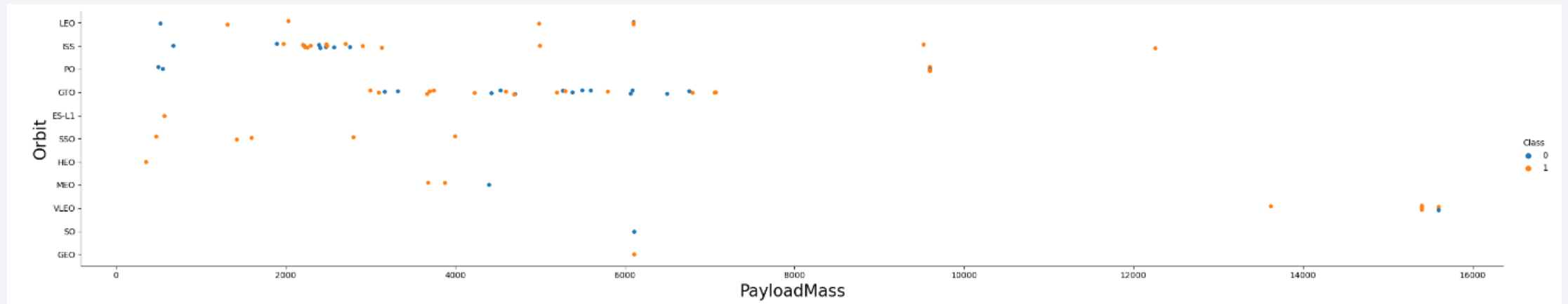


Flight Number vs. Orbit Type



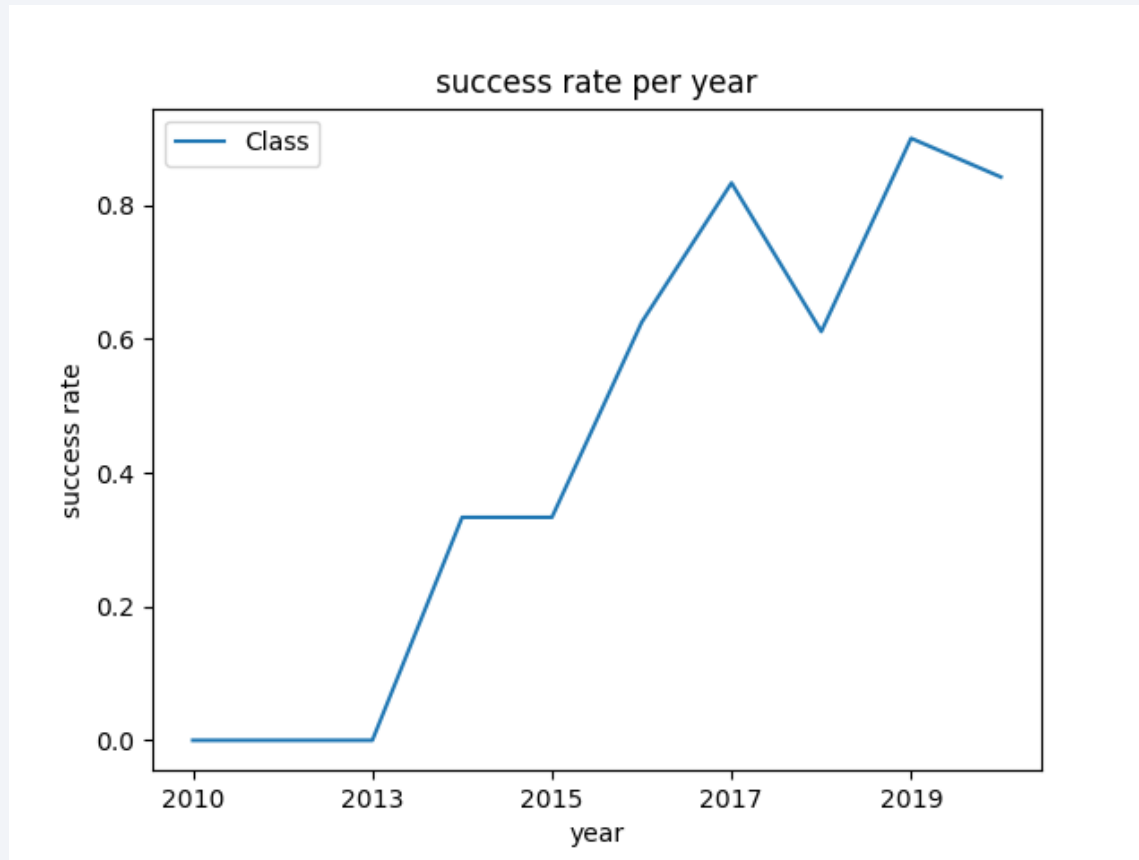
We notice that the success rate increases with the number of flights for the LEO orbit. For some orbits like GTO, there is no relation between the success rate and the number of flights. But we can suppose that the high success rate of some orbits like SSO or HEO is due to the knowledge learned during former launches for other orbits.

Payload vs. Orbit Type



The weight of the payloads can have a great influence on the success rate of the launches in certain orbits. For example, heavier payloads improve the success rate for the LEO orbit. Another finding is that decreasing the payload weight for a GTO orbit improves the success of a launch.

Launch Success Yearly Trend



Since 2013, we can see an increase in the Space X Rocket success rate.

All Launch Site Names

Query

[9]: %sql select distinct Launch_Site from SPACEXTABLE

* sqlite:///my_data1.db
Done.

Result

[9]: **Launch_Site**

CCAFS LC-40

VAFB SLC-4E

KSC LC-39A

CCAFS SLC-40

Explanation: The use of DISTINCT in the query allows to remove duplicate LAUNCH_SITE.

Launch Site Names Begin with 'CCA'

Query

```
%%sql
SELECT *
FROM SPACEXTABLE
WHERE Launch_Site LIKE '%CCA%'
LIMIT 5
```

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

Result

Date	Time (UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS_KG	Orbit	Customer	Mission_Outcome	Landing_Outcome
2010-04-06	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
2010-08-12	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	07:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	No attempt
2012-08-10	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
2013-01-03	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

Explanation:

The WHERE clause followed by LIKE clause filters launch sites that contain the substring CCA.

LIMIT 5 shows 5 records from filtering.

Total Payload Mass

Query

```
%%sql
SELECT Customer, SUM(PAYLOAD_MASS_KG_) AS total_PAYLOAD_MASS_KG
FROM SPACEXTABLE
WHERE Customer = 'NASA (CRS)'
GROUP BY Customer
```

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

Result

Customer	total_PAYLOAD_MASS_KG
NASA (CRS)	45596

Explanation:

This query returns the sum of all payload masses where the customer is NASA (CRS).

Average Payload Mass by F9 v1.1

Query

```
%%sql
SELECT Booster_Version, AVG(PAYLOAD_MASS_KG_) AS average_PAYLOAD_MASS_KG
FROM SPACEXTABLE
WHERE Booster_Version = 'F9 v1.1'
GROUP BY Booster_Version
```

Result

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

Booster_Version  average_PAYLOAD_MASS_KG
-----
F9 v1.1          2928.4
```

Explanation:

This query returns the average of all payload masses where the booster version contains the substring F9 v1.1.

First Successful Ground Landing Date

Query

```
%%sql
SELECT MIN(Date) AS first_sucesfull_landing_date
FROM SPACEXTABLE
WHERE Landing_Outcome = 'Success (ground pad)'

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

Result

```
first_sucesfull_landing_date
2015-12-22
```

Explanation:

With this query, we select the oldest successful landing.

The WHERE clause filters dataset in order to keep only records where landing was successful. With the MIN function, we select the record with the oldest date.

Successful Drone Ship Landing with Payload between 4000 and 6000

Query

```
%%sql
SELECT Booster_Version AS names_of_the_boosters
FROM SPACEXTABLE
WHERE Landing_Outcome = 'Success (drone ship)'
      AND PAYLOAD_MASS_KG_ > 4000
      AND PAYLOAD_MASS_KG_ < 6000
```

Result

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

names_of_the_boosters
-----
F9 FT B1022
F9 FT B1026
F9 FT B1021.2
F9 FT B1031.2
```

Explanation:

This query returns the booster version where landing was successful and payload mass is between 4000 and 6000 kg. The WHERE and AND clauses filter the dataset.

Total Number of Successful and Failure Mission Outcomes

Query



```
%%sql
SELECT Mission_Outcome, COUNT(*) AS total_outcomes
FROM SPACEXTABLE
GROUP BY Mission_Outcome;
```

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

Result



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

Explanation:

With the first SELECT, we show the queries counts total mission outcome. The group by classifies data record from mission outcome column.

Boosters Carried Maximum Payload

Query

```
%%sql
SELECT DISTINCT Booster_Version, PAYLOAD_MASS_KG_
FROM SPACEXTABLE
WHERE PAYLOAD_MASS_KG_ = (SELECT MAX(PAYLOAD_MASS_KG_) FROM SPACEXTABLE)
```

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

Result

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
F9 B5 B1049.5	15600
F9 B5 B1060.2	15600
F9 B5 B1058.3	15600
F9 B5 B1051.6	15600
F9 B5 B1060.3	15600
F9 B5 B1049.7	15600

Explanation:

We used a subquery to filter data by returning only the heaviest payload mass with MAX function. The main query uses subquery results and returns unique booster version (SELECT DISTINCT) with the heaviest payload mass.

2015 Launch Records

Query

```
%%sql
SELECT
CASE
  WHEN substr(Date, 6, 2) = '01' THEN 'January'
  WHEN substr(Date, 6, 2) = '02' THEN 'February'
  WHEN substr(Date, 6, 2) = '03' THEN 'March'
  WHEN substr(Date, 6, 2) = '04' THEN 'April'
  WHEN substr(Date, 6, 2) = '05' THEN 'May'
  WHEN substr(Date, 6, 2) = '06' THEN 'June'
  WHEN substr(Date, 6, 2) = '07' THEN 'July'
  WHEN substr(Date, 6, 2) = '08' THEN 'August'
  WHEN substr(Date, 6, 2) = '09' THEN 'September'
  WHEN substr(Date, 6, 2) = '10' THEN 'October'
  WHEN substr(Date, 6, 2) = '11' THEN 'November'
  WHEN substr(Date, 6, 2) = '12' THEN 'December'
END AS Month_Name,
Landing_Outcome,
Booster_Version,
Launch_Site
FROM SPACEXTABLE
WHERE substr(Date, 1, 4) = '2015'
AND Landing_Outcome = 'Failure (drone ship)'
```

Result

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

Month_Name	Landing_Outcome	Booster_Version	Launch_Site
October	Failure (drone ship)	F9 v1.1 B1012	CCAFS LC-40
April	Failure (drone ship)	F9 v1.1 B1015	CCAFS LC-40

Explanation:

This query returns month, booster version, launch site where landing was **unsuccessful** and landing date took place in 2015. Substr function process date in order to take month or year. Substr(Date,1, 4) shows year.

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

Query

```
%%sql
SELECT "Landing_Outcome", COUNT(*) as "Outcome_Count"
FROM SPACEXTABLE
WHERE "Date" >= '2010-06-04' AND "Date" <= '2017-03-20'
  AND ("Landing_Outcome" LIKE 'Success (ground pad)' OR "Landing_Outcome" LIKE 'Failure (drone ship)')
GROUP BY "Landing_Outcome"
ORDER BY "Outcome_Count" DESC
```

Result

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

Landing_Outcome	Outcome_Count
Success (ground pad)	5
Failure (drone ship)	5

Explanation:

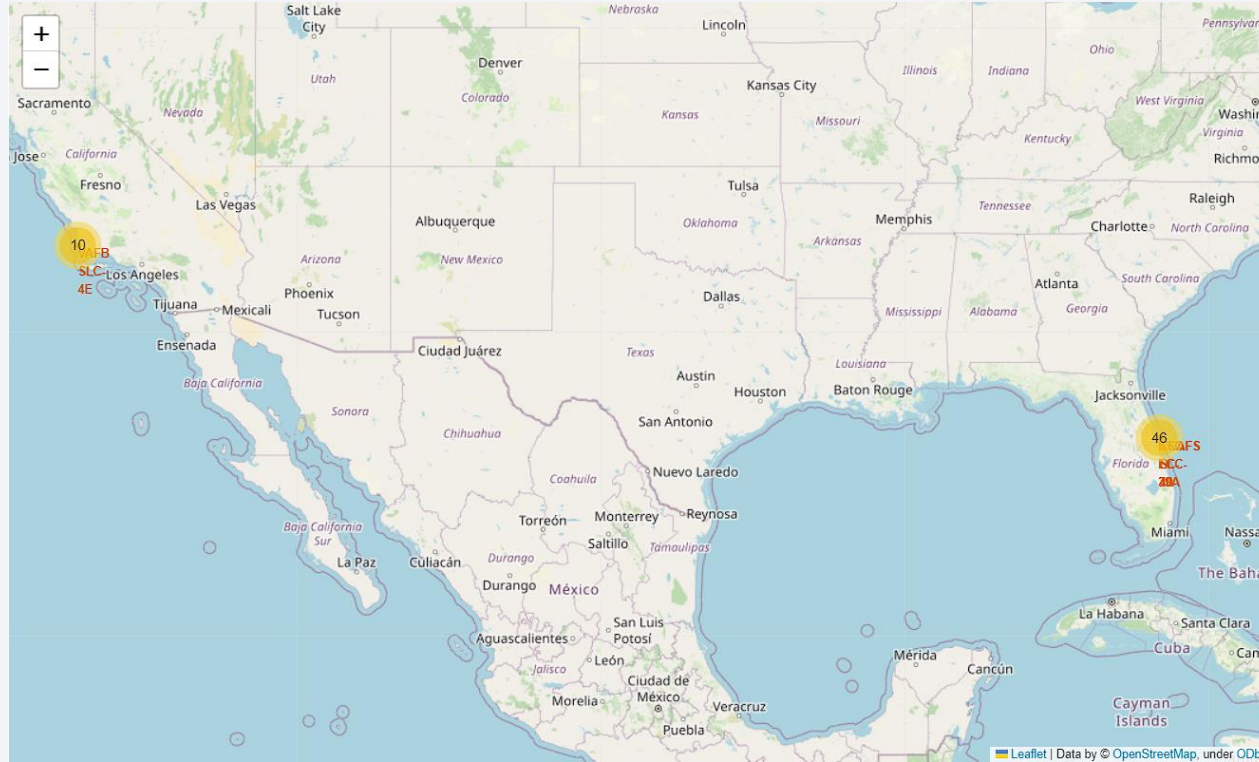
It focuses on missions that happened between June 4, 2010, and March 20, 2017. It counts how many times each outcome is labeled as either "Success (ground pad)" or "Failure (drone ship)". The code then shows these counts, arranging them from the most common outcome to the least common one.

A satellite view of Earth from space, showing the curvature of the planet and city lights at night. The background is a deep blue gradient.

Section 3

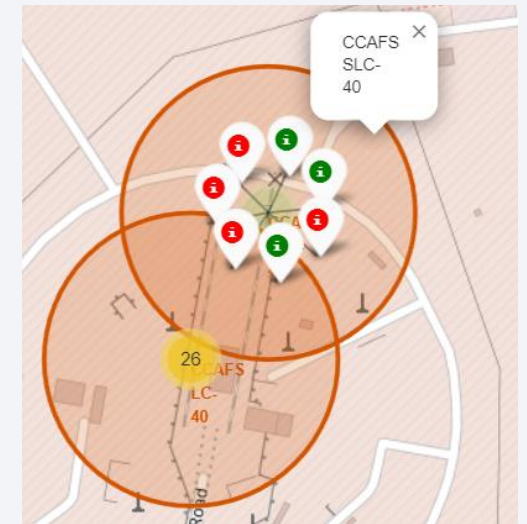
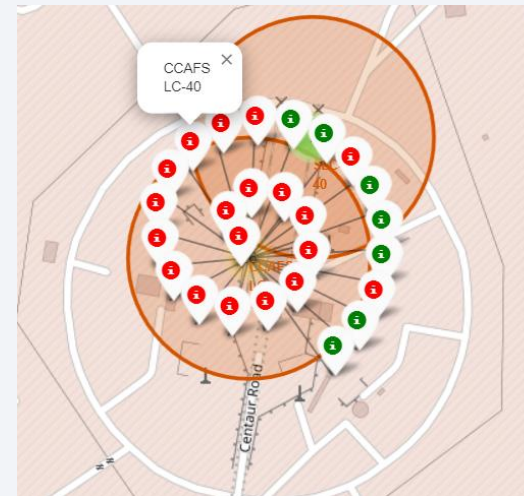
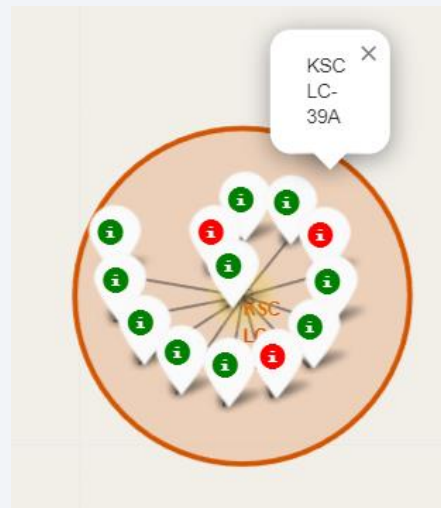
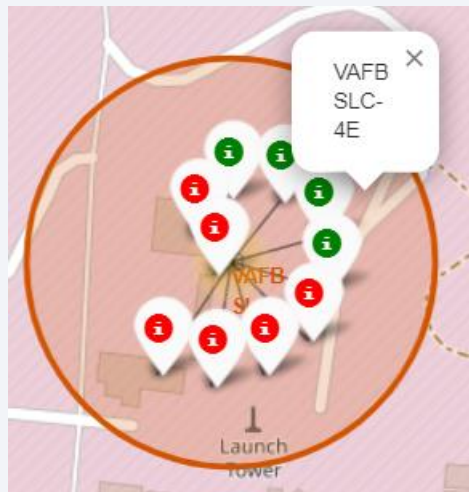
Launch Sites Proximities Analysis

Folium map – Ground Station



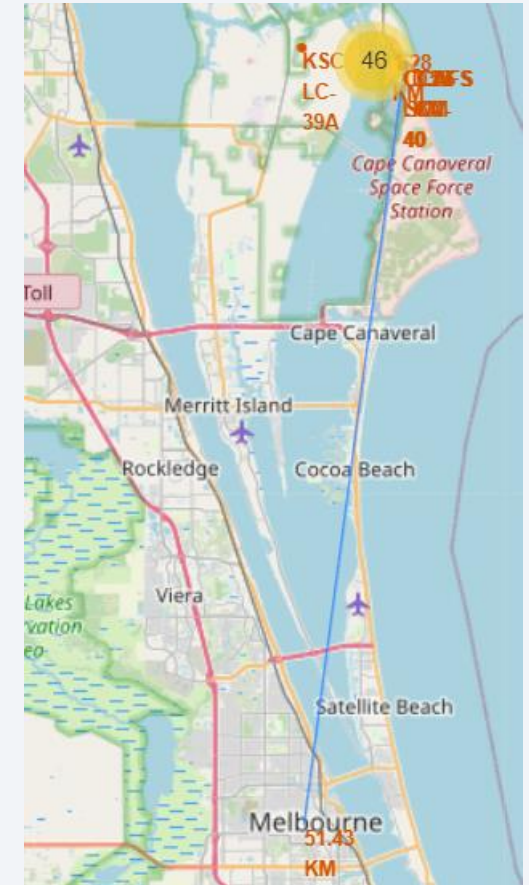
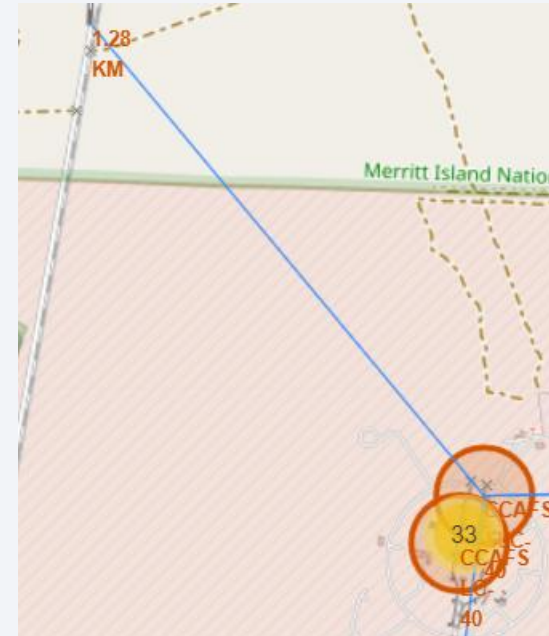
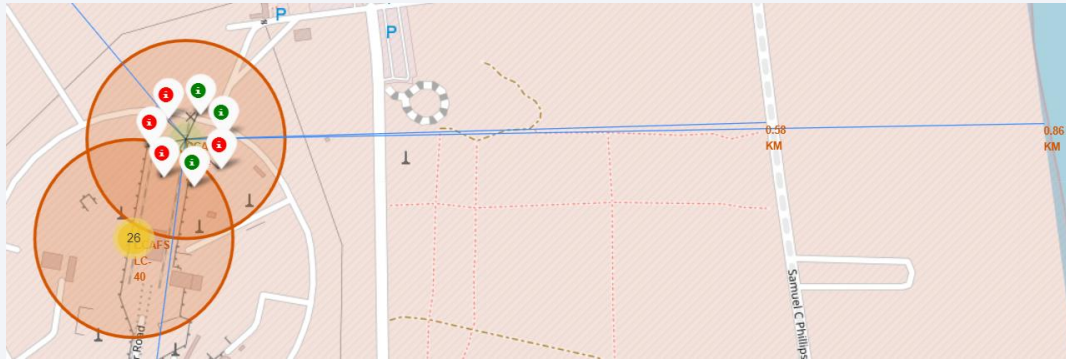
We see that Space X launch sites are located on the coast of the United States

Folium map – Color Labeled Markers



Green marker represents successful launches. Red marker represents unsuccessful launches. We note that KSC LC-39A has a higher launch success rate.

Folium map – Distance between CCAFS SLC-40 and its proximities



- Is CCAFS SLC-40 in close proximity to railways ? Yes
- Is CCAFS SLC-40 in close proximity to highways ? Yes
- Is CCAFS SLC-40 in close proximity to coastline ? Yes
- Do CCAFS SLC-40 keeps certain distance away from cities ? No



Section 4

Build a Dashboard with Plotly Dash

Dashboard – Total success by Site

Total Success Launches by Site



We see that KSC LC-39A has the best success rate of launches.

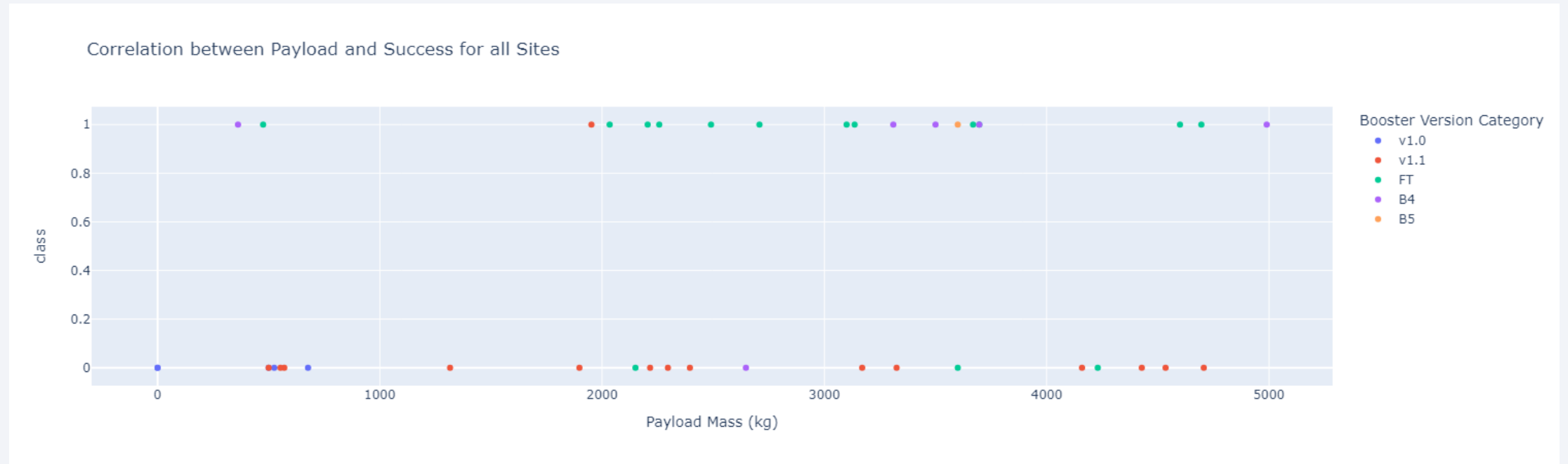
Dashboard – Total success launches for Site KSC LC-39 A

Total Success Launches for Site KSC LC-39A



We see that KSC LC-39A has achieved a 76.9% success rate while getting a 23.1% failure rate.

Dashboard –Payload mass vs Outcome for all sites with different payload mass selected



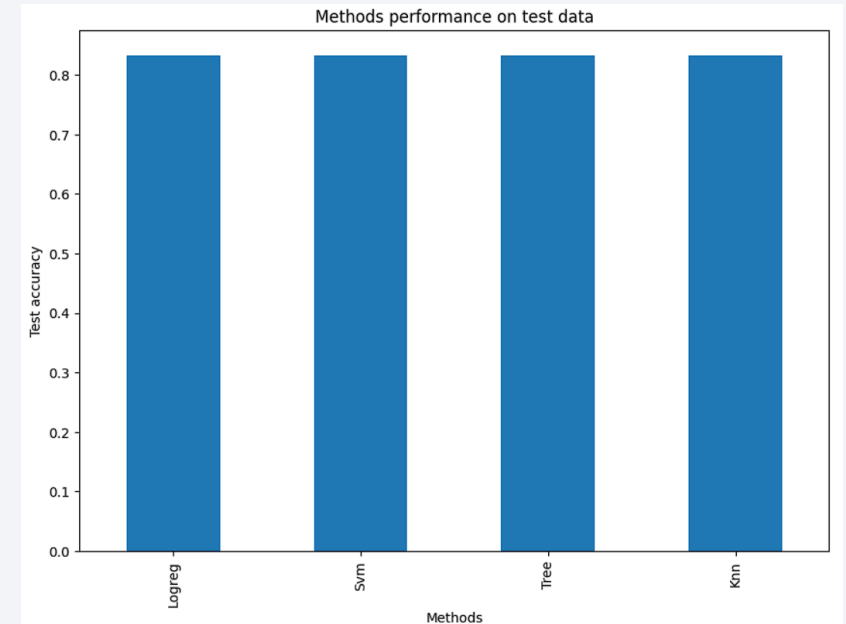
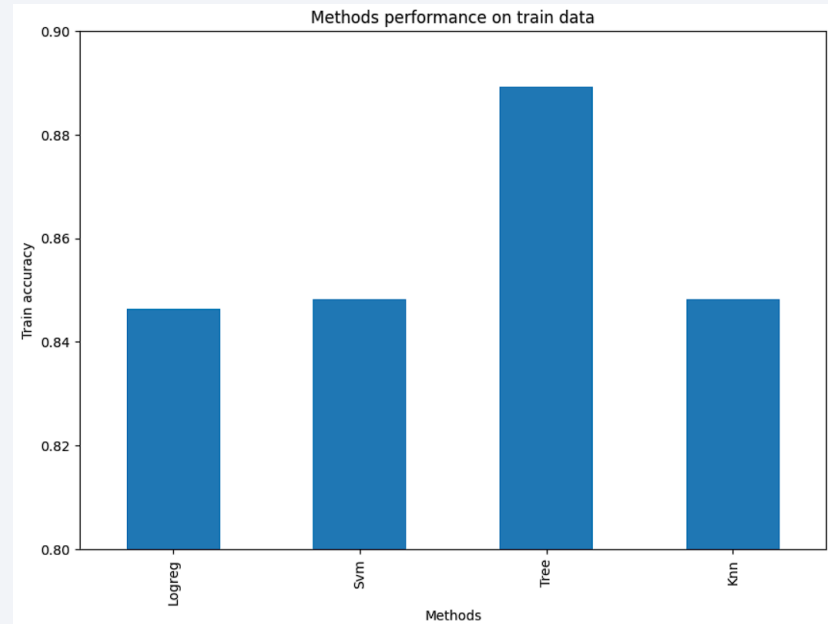
Low weighted payloads have a better success rate than the heavy weighted payloads.

Section 5

Predictive Analysis (Classification)

Classification Accuracy

	Accuracy Train	Accuracy Test
Tree	0.889286	0.833333
Knn	0.848214	0.833333
Svm	0.848214	0.833333
Logreg	0.846429	0.833333



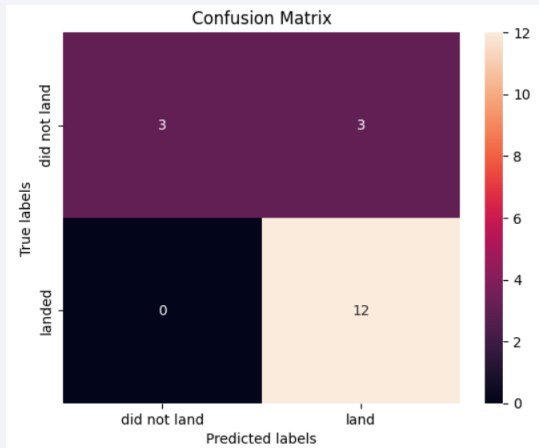
For accuracy test, all methods performed similar. We could get more test data to decide between them. But if we really need to choose one right now, we would take the decision tree.

```
print("tuned hyperparameters :(best parameters) ",tree_cv.best_params_)  
print("accuracy :",tree_cv.best_score_)
```

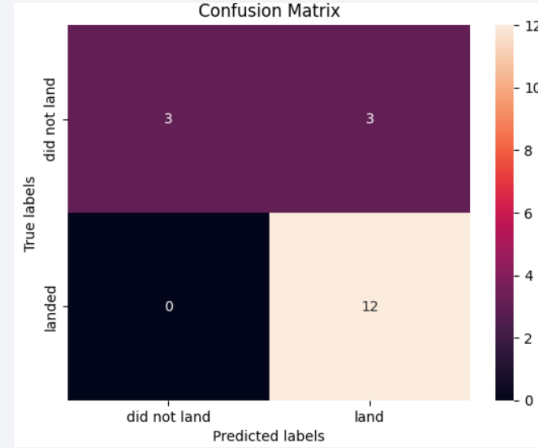
```
tuned hyperparameters :(best parameters) {'criterion': 'entropy', 'max_depth': 16, 'max_features': 'auto', 'min_samples_leaf': 4, 'min_samples_split': 2, 'splitter': 'random'}  
accuracy : 0.8892857142857142
```

Confusion Matrix

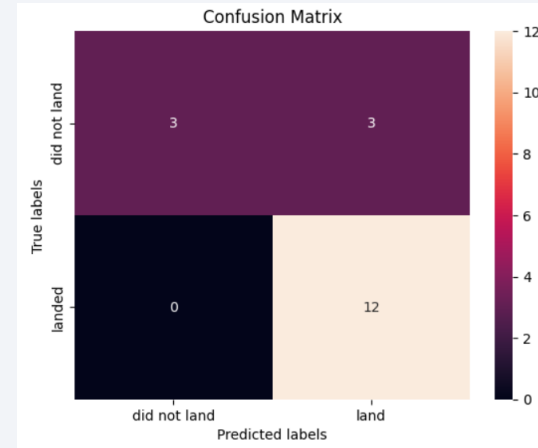
Logistic regression



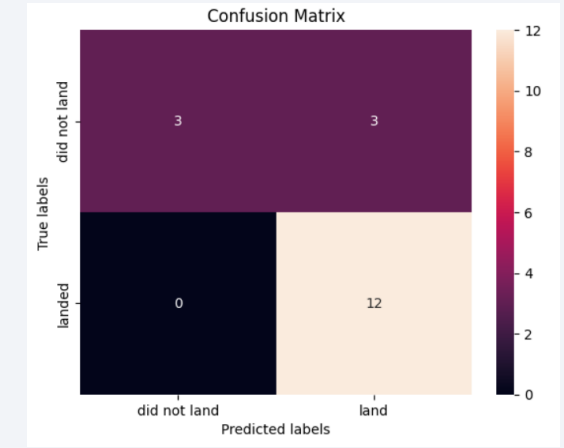
SVM



Decision Tree



KNN



As the test accuracy are all equal, the confusion matrices are also identical. The main problem of these models are false positives.

		Actual values	
		1	0
Predicted values	1	TP	FP
	0	FN	TN

Conclusions

- The success of a mission can be explained by several factors such as the launch site, the orbit and especially the number of previous launches. Indeed, we can assume that there has been a gain in knowledge between launches that allowed to go from a launch failure to a success.
- The orbits with the best success rates are GEO, HEO, SSO, ES-L1.
- Depending on the orbits, the payload mass can be a criterion to take into account for the success of a mission. Some orbits require a light or heavy payload mass. But generally low weighted payloads perform better than the heavy weighted payloads.
- With the current data, we cannot explain why some launch sites are better than others (KSC LC-39A is the best launch site). To get an answer to this problem, we could obtain atmospheric or other relevant data.
- For this dataset, we choose the Decision Tree Algorithm as the best model even if the test accuracy between all the models used is identical. We choose Decision Tree Algorithm because it has a better train accuracy.

Thank you!

