IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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Outline

Executive Summary

- Summary of methodologies
  - Data Collection from ExpaceEx API and web scraping
  - Exploratory Data Analysis (EDA)
  - Prediction: Machine Learning Tool
- Summary of all results
  - Exploratory data analysis
  - Interactive analysis
  - Predictive analysis

Introduction

Hyperlink

SpaceX designs, manufactures and launches advanced rockets and spacecraft. The company was founded in 2002 to revolutionize space technology Using public information, as well machine learning tools, we are predicted the best place to make launches

Section 1

Methodology

Methodology

Hyperlink

Executive Summary

- Data collection methodology:
  - SpaceX API (link)
  - Web Scrapping from Wikipedia (link)
- Perform data wrangling
  - Filtering the data
  - Dealing with missing values.
  - To label de data label based on outcome data after summarizing and analyzing features;
- 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

Hyperlink

i) To get response response from API and convert the resulto to *.json* file

```python
static_json_url='https://cf-courses-data.s3.us.cloud-object-storage.appdomain.clo
response.status_code
# Use json_normalize meethod to convert the json result into a dataframe
response = requests.get(static_json_url).json()
df = pd.json_normalize(response)
```

Python

ii) Cleaning data

```python
# Call getLaunchSite
getLaunchSite(data)
```

[38] ✓ 50.6s

```python
# Call getPayloadData
getPayloadData(data)
```

[39] ✓ 48.6s

```python
# Call getCoreData
getCoreData(data)
```

[40] ✓ 48.5s

SpaceX API: https://api.spacexdata.com/v4/rockets/

Data Collection – SpaceX API

Hyperlink

iii) Converting list to a dataframe

Finally lets construct our dataset using the data we have obtained. We we combine the columns into a dictionary.

```
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}
```

iv) Filtering the dataframe and converting it to a *.csv* file

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

✓ 0.1s

Data Collection - Scraping

[Hyperlink]

i) Get a response from HTML adress

```
# use requests.get() method with the provided static_
# assign the response to a object
page = requests.get(static_url)
page.status_code
```

[12] ✓ 1.2s Python

```
200
```

ii) To create a BeautifulSoup Object

Create a `BeautifulSoup` object from the HTML `response`

```
# Use BeautifulSoup() to create a BeautifulSoup obje
soup = BeautifulSoup(page.text, 'html.parser')
```

[13] ✓ 1.3s Python

iii) To find the tables of interest

```
# Use the find_all function in the BeautifulSoup obj
# Assign the result to a list called `html_tables`
html_tables = soup.find_all('table')
```

[15] ✓ 0.9s Python

iv) To get the columns info

```
column_names = []

# Apply find_all() function with `th` element on fir
# Iterate each th element and apply the provided ext
# Append the Non-empty column name (`if name is not 
temp = soup.find_all('th')
for x in range(len(temp)):
    try:
     name = extract_column_from_header(temp[x])
     if (name is not None and len(name) > 0):
        column_names.append(name)
    except:
     pass
```

✓ 0.1s Python

Data Wrangling

[Hyperlink]

v) Creating a dictionary

```python
launch_dict= dict.fromkeys(column_names)

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

# Let's initial the launch_dict with each value to b
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']=[]
```

✓ 0.7s Python

ii) Appending data from all keys, converting to a dataframe and saving in *.csv*

```python
extracted_row = 0
#Extract each table
for table_number,table in enumerate(soup.find_all('table',"wikitable plainrowhead
    # get table row
    for rows in table.find_all("tr"):
        #check to see if first table heading is as number corresponding to launch
        if rows.th:
            if rows.th.string:
                flight_number=rows.th.string.strip()
                flag=flight_number.isdigit()
        else:
            flag=False
        #get table element
        row=rows.find_all('td')
        #if it is number save cells in a dictonary
        if flag:
```

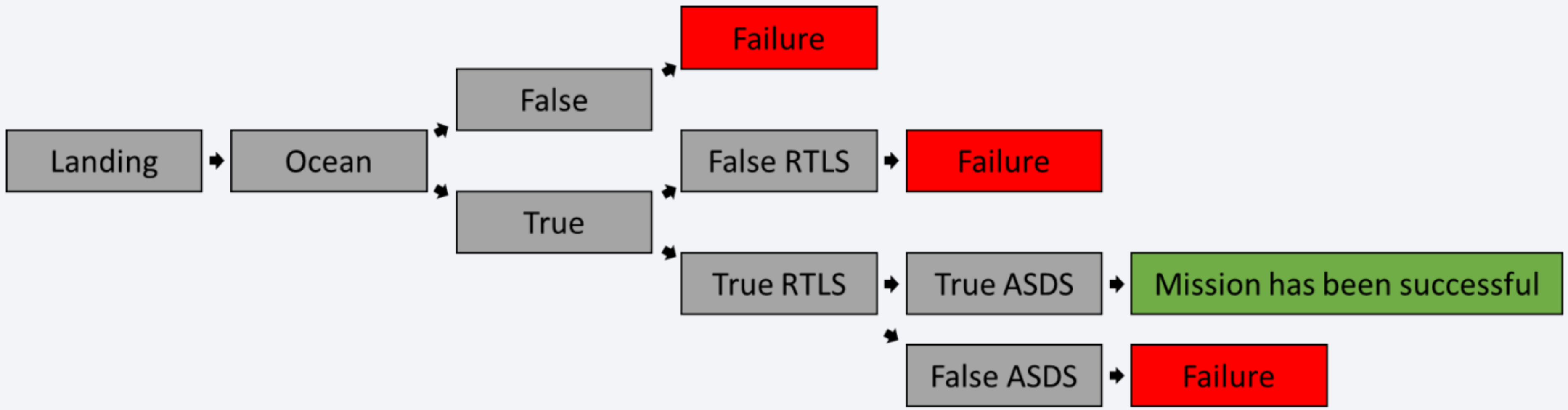
```python
headings = []
for key,values in dict(launch_dict).items():
    if key not in headings:
        headings.append(key)
    if values is None:
        del launch_dict[key]

def pad_dict_list(dict_list, padel):
    lmax = 0
    for lname in dict_list.keys():
        lmax = max(lmax, len(dict_list[lname]))
    for lname in dict_list.keys():
        ll = len(dict_list[lname])
        if  ll < lmax:
            dict_list[lname] += [padel] * (lmax - ll)
    return dict_list

pad_dict_list(launch_dict,0)

df = pd.DataFrame.from_dict(launch_dict)
df.head()
df.to_csv('spacex_web_scraped.csv', index=False)
```

✓ 0.1s

Data Wrangling

Hyperlink

Regarding the data analysis process, there are several cases in which the booster did not land successfully.



Data Wrangling

[Hyperlink]

i) Number of lauches

```
# Apply value_counts() on column LaunchSite
df["LaunchSite"].value_counts()
```

[34] ✓ 0.1s

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

ii) Number accourence of Earth orbit

```
# Apply value_counts on Orbit column
df["Orbit"].value_counts("Orbit")
```

[35] ✓ 0.1s

```
GTO      0.300000
ISS      0.233333
VLEO     0.155556
PO       0.100000
LEO      0.077778
SSO      0.055556
MEO      0.033333
HEO      0.011111
SO       0.011111
ES-L1    0.011111
GEO      0.011111
Name: Orbit, dtype: float64
```

iii) Number missoun outcome

```
# landing_outcomes = values on Outcome column
landing_outcomes = df["Outcome"].value_counts()
landing_outcomes
```

[44] ✓ 0.9s

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

iv) Creating a outcome label

```
for i,outcome in enumerate(landing_outcomes.keys()):
    print(i,outcome)
```

[37] ✓ 0.1s

```
0 True ASDS
1 None None
2 True RTLS
3 False ASDS
4 True Ocean
5 None ASDS
6 False Ocean
7 False RTLS
```

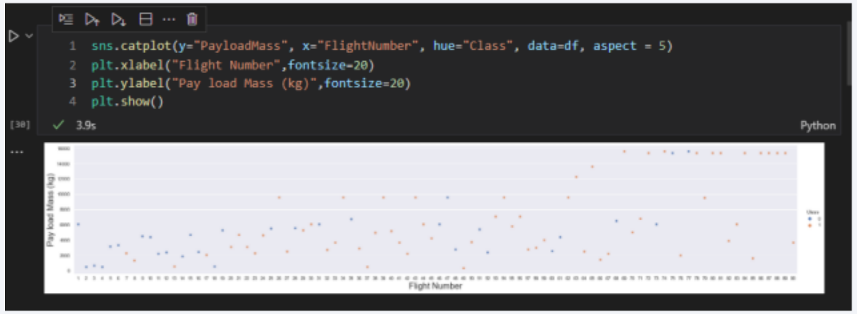
EDA with Data Visualization

Hyperlink

Scatter plots

Scatter plots showed the relationship between two variables (correlation)

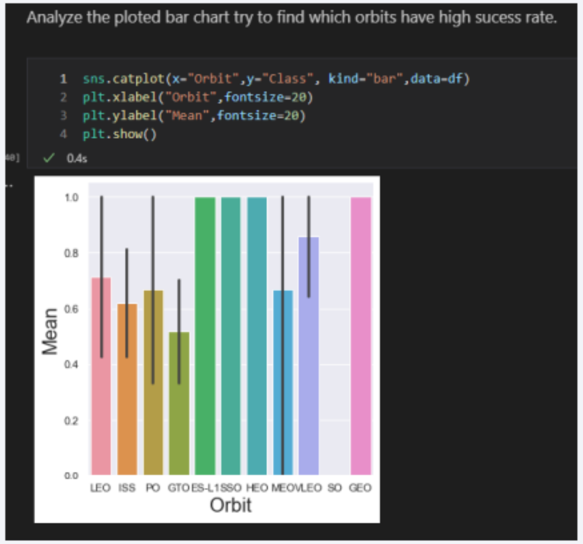
Flight Number VS. Payload Mass
Flight Number VS. Launch Site
Payload VS. Launch Site
Orbit VS. Flight Number
Payload VS. Orbit Type
Orbit VS. Payload Mass



Bar plots

Mean VS. Orbit

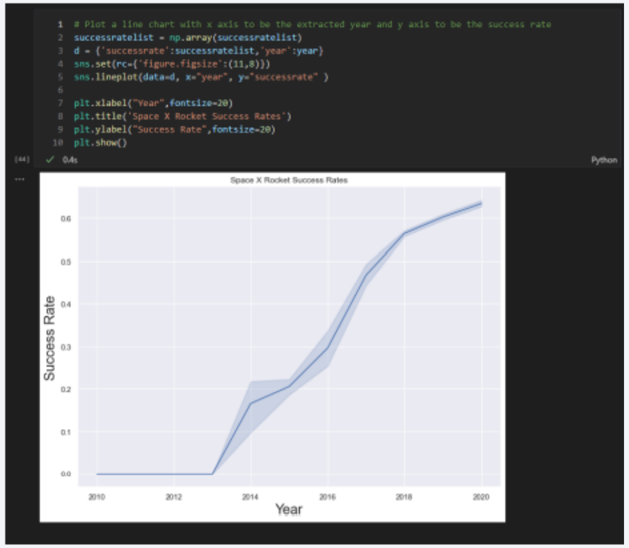
A bar diagram makes it easy to compare sets of data between different groups.



Line plots

Success Rate VS. Year

Line graphs are useful in that they show data variables and trends during the time



EDA with SQL

Hyperlink

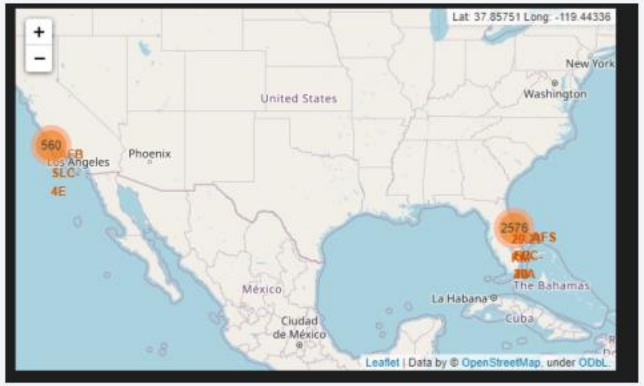
Please see bellow the SQL queries performed:

- Displaying the names of the unique launches sites in the space mission;
- Display 5 records where launch sites begin with ‘CCA’;
- Display the total payload mass carried by boosters launched by NASA;
- Display the average of the amount paid by booster version F9 v1.1;
- List of the dates of the first successful landing outcome;
- List of the names of the boosters which have success in drone ships and have payloads between 4000 and 6000;
- The total od number of successful and failure mission outcomes;
- List of the names of the *booster_version* which have carried the maximum payload mass;
- Listing the records which will display the successful *landing_outcomes* in the ground pad, booster versions, and launch site for the months in the year 2015;
- Ranking the count of successful *landing_outcomes* between the date 2010-06-04 and 2017-03-20.

Build an Interactive Map with Folium

[Hyperlink]

- To visualize the Launch Data into an interactive map:
  - We took the Latitude and Longitude Coordinates at each launch site and added a Circle Marker around each launch site with a label with the name of the launch site
  - We assigned the dataframe launch_outcomes and converted to classes 0 and 1 with Green and Red, respectively;
  - The red circles at each launch site coordinates with label showing launch site name;
- The objects are created to understand better the data problem. Also, we can easily show all launch sites and the successful and unsuccessful landings.



16

Build a Dashboard with Plotly Dash

Hyperlink

- The dashboard has a dropdown, pie chart and scatters plot:
  - The dropdown allows you to choose the launch site;
  - The pie chart shows the total of successful and unsuccessful launches sites selected from the dropdowns;
- Scatter Graph establishing the relationship with Outcome and Payload Mass (Kg) for the different Booster Versions:
  - It shows the relationship between two variables.
  - It is best to show you a non-linear pattern.
  - The range of data flow, maximum and minimum value, can be determined.
  - Observation and reading are straightforward

Predictive Analysis (Classification)

Hyperlink

Data Preparation

- Load our dataset into NumPy and Pandas
- Data transformation
- Split our data into training and test data sets

Model Preparation

- Check how many test samples we have
- Decide which type of machine learning algorithms we want to use
- Set our parameters and algorithms to GridSearchCV
- Training GridSearchCV

Model Evaluation

- Check the accuracy of each model
- Get tuned hyperparameters for each type of algorithm

Improving the model and finding the best classification model

- Feature Engineering
- Algorithm Tuning
- Comparison between methods
- The model with the best accuracy score wins the best-performing model

Results

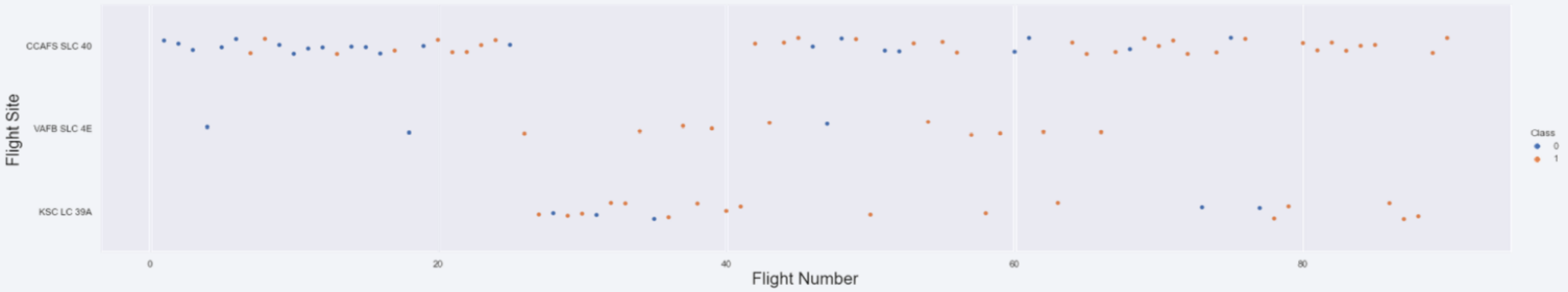
- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results

Section 2

Insights drawn from EDA

Flight Number vs. Launch Site

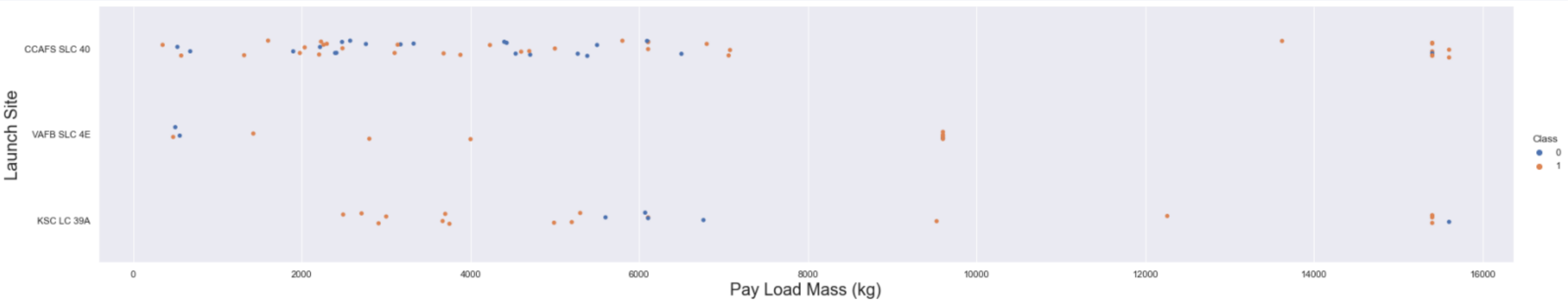
Hyperlink



It was observed, for each site, the success rate is increasing

Payload vs. Launch Site

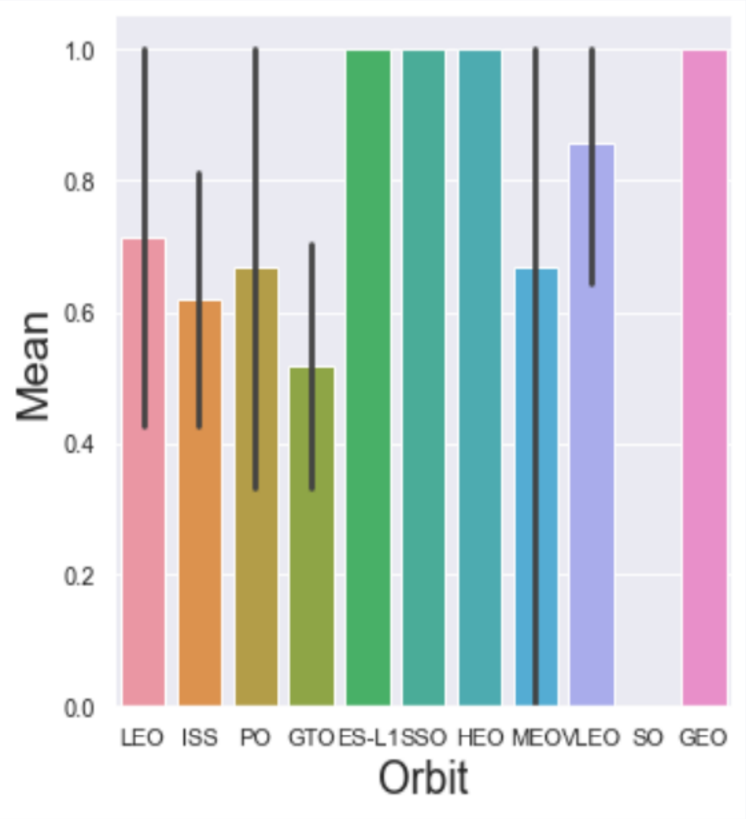
Hyperlink

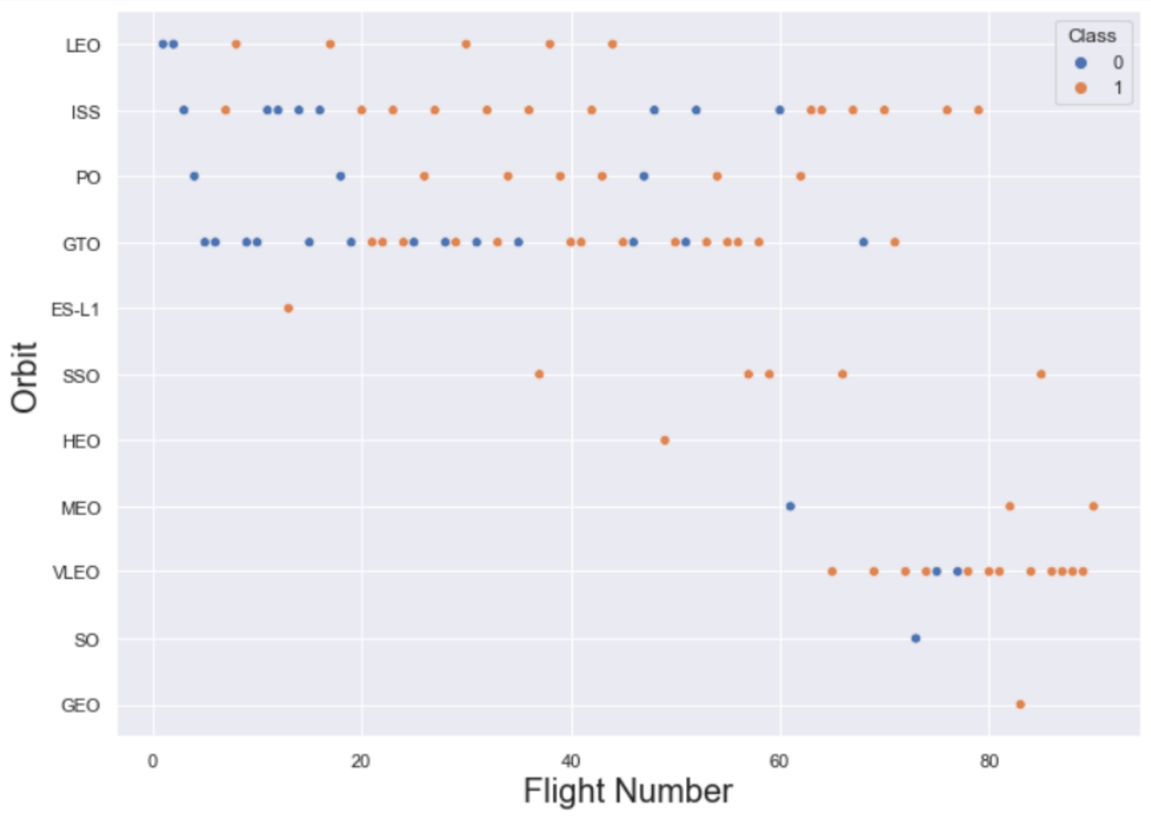


The heave impacts the launch site. Therefore, a heavier payload may be a consideration for a successful landing.

Success Rate vs. Orbit Type

Hyperlink





We found that the success rate increases with the number of flights for the LEO orbit. On the other hand, in other orbits, like GTO, it’s not related to success.

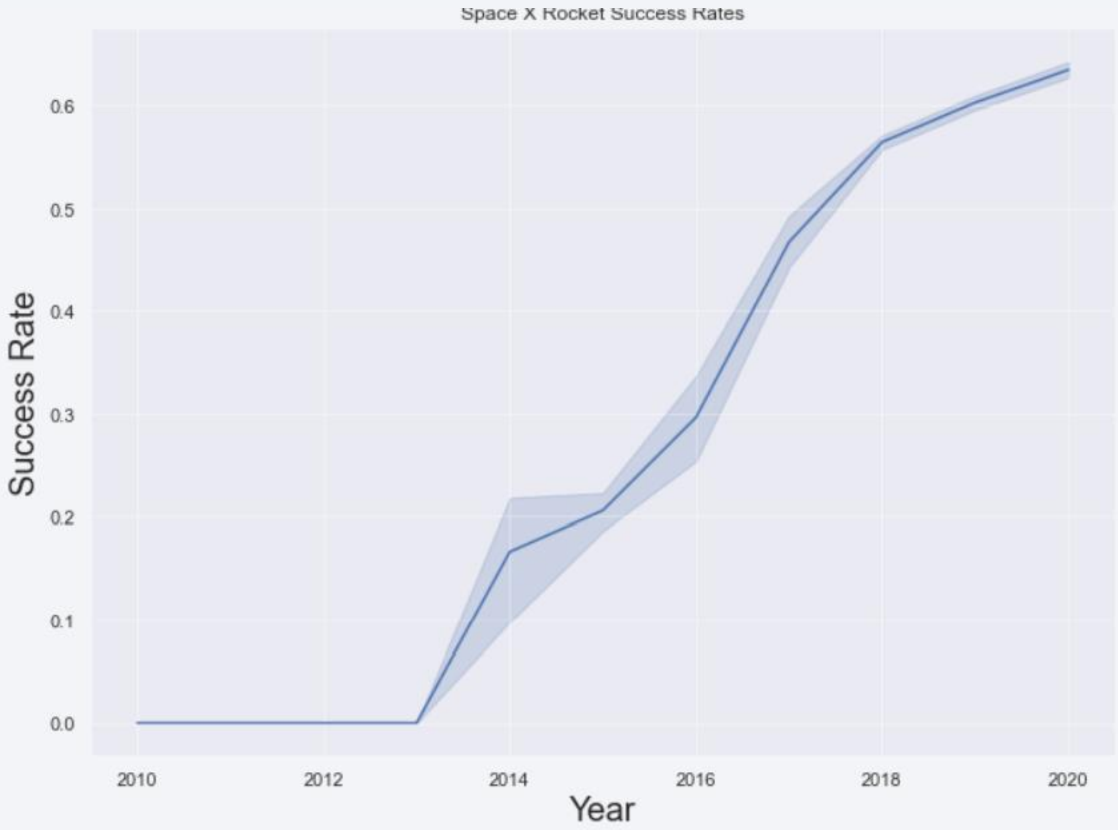
Payload vs. Orbit Type

Hyperlink

Heavy payloads have a negative influence on GTO orbits and positive on GTO and Polar LEO orbits.

Launch Success Yearly Trend

[Hyperlink](#)



Since 2013, the success rate has been increasing.

All Launch Site Names

Hyperlink

```
%sql select DISTINCT launch_site from SpaceX
```

Python

launch_site
CCAFS LC-40
CCAFS SLC-40
KSC LC-39A
VAFB SLC-4E

To use DESTINCT in a query remove all duplicated values

Launch Site Names Begin with 'CCA'

Hyperlink

```
%sql select * from SpaceX WHERE launch_site LIKE 'CCA%' limit 5
```

Python

DATE	time__utc_	booster_version	launch_site	payload	payload_mass__kg_	orbit	customer
2010-06-04	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX
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
2012-05-22	07:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)
2012-10-08	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)
2013-03-01	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)

To use WHERE followed by LIKE allows get the launchs that contain subsisting 'CCA', and getting only the 5 rows using LIMIT 5

Total Payload Mass

[Hyperlink]

```
1  %sql select SUM(payload_mass__kg_) from SpaceX where Customer = 'NASA (CRS)'
```

Python

1
45596

The query gives the sum of all payload where the customer is equal to NASA (CRS)

Average Payload Mass by F9 v1.1

Hyperlink

```
%sql select AVG(payload_mass__kg_) from SpaceX where Booster_Version = 'F9 v1.1'
```

1
2928

The WHERE clause filters the dataset to only perform calculations on Booster_version F9 v1.1

29

First Successful Ground Landing Date

Hyperlink

```
%sql select MIN(DATE) from SpaceX where landing__outcome = 'Success (ground pad)'
```

Python

1
2015-12-22

The WHERE clause filters the dataset to only perform calculations on Landing_Outcome = Success (ground pad) and get the first day

Hyperlink

Successful Drone Ship Landing with Payload between 4000 and 6000

```
%sql select DISTINCT booster_version from SpaceX where landing__outcome = 'Success
```

Python

booster_version
F9 FT B1021.2
F9 FT B1031.2
F9 FT B1022
F9 FT B1026

The query returns the booster version where landing was successful and payload was between 4k and 6k.

Hyperlink

Total Number of Successful and Failure Mission Outcomes

```
1  %sql SELECT mission_outcome, COUNT(*) FROM SpaceX GROUP BY mission_outcome
```

mission_outcome	2
Failure (in flight)	1
Success	99
Success (payload status unclear)	1

Using the function COUNT works out the amount

Boosters Carried Maximum Payload

Hyperlink

booster_version
F9 B5 B1048.4
F9 B5 B1049.4
F9 B5 B1051.3
F9 B5 B1056.4
F9 B5 B1048.5
F9 B5 B1051.4
F9 B5 B1049.5
F9 B5 B1060.2
F9 B5 B1058.3
F9 B5 B1051.6
F9 B5 B1060.3
F9 B5 B1049.7

Using the word SELECT in the query means that it will show values in the Booster_Version column from Space

2015 Launch Records

Hyperlink

DATE	landing_outcome	booster_version	launch_site
2015-01-10	Failure (drone ship)	F9 v1.1 B1012	CCAFS LC-40
2015-04-14	Failure (drone ship)	F9 v1.1 B1015	CCAFS LC-40

DATE LIKE puts the value of 2015

Hyperlink

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

DATE	time__utc_	booster_version	launch_site	payload	payload_mass__kg_	orbit	customer	mission_outcome	landing__outcome
2016-06-15	14:29:00	F9 FT B1024	CCAFS LC-40	ABS-2A Eutelsat 117 West B	3600	GTO	ABS Eutelsat	Success	Failure (drone ship)
2016-03-04	23:35:00	F9 FT B1020	CCAFS LC-40	SES-9	5271	GTO	SES	Success	Failure (drone ship)
2016-01-17	18:42:00	F9 v1.1 B1017	VAFB SLC-4E	Jason-3	553	LEO	NASA (LSP) NOAA CNES	Success	Failure (drone ship)
2015-04-14	20:10:00	F9 v1.1 B1015	CCAFS LC-40	SpaceX CRS-6	1898	LEO (ISS)	NASA (CRS)	Success	Failure (drone ship)
2015-01-10	09:47:00	F9 v1.1 B1012	CCAFS LC-40	SpaceX CRS-5	2395	LEO (ISS)	NASA (CRS)	Success	Failure (drone ship)
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)
2010-06-04	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)

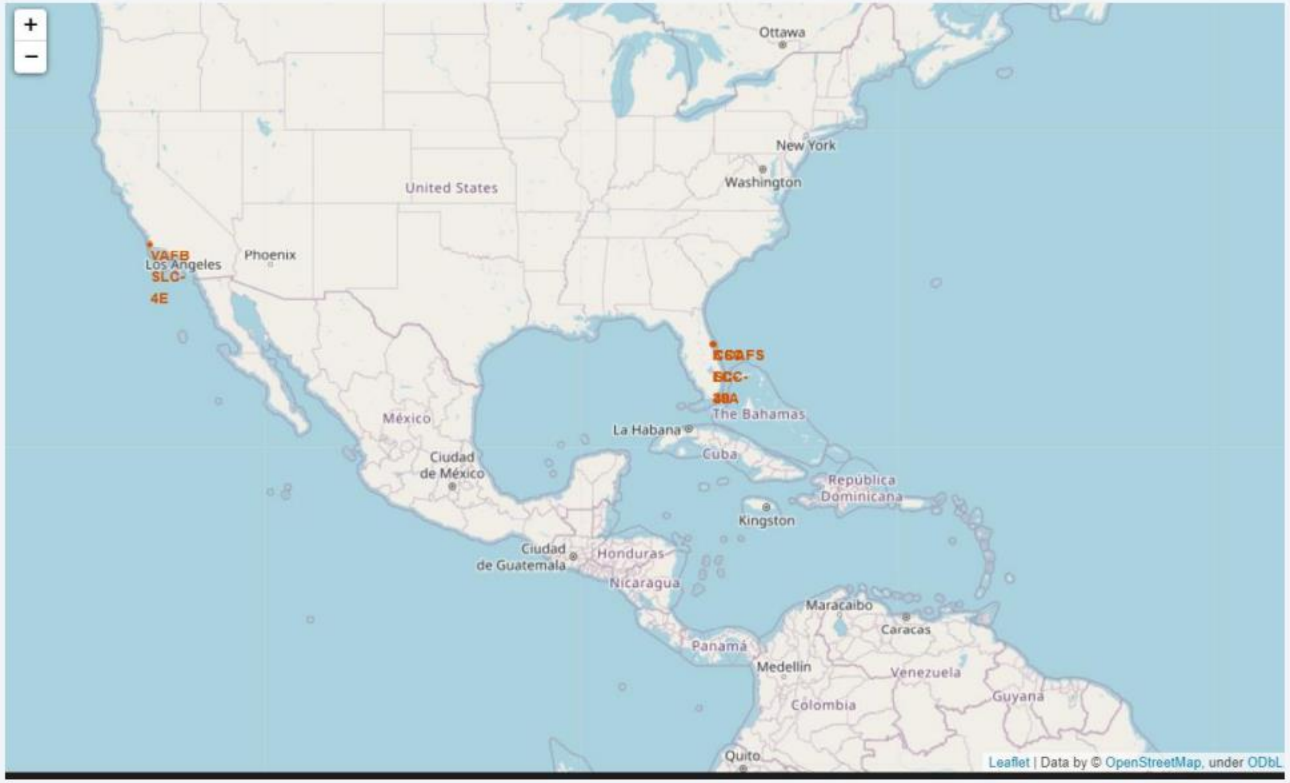
Function WHERE filters landing__outcome and LIKE (Success or Failure; AND (DATE between) DESC means its arranging the dataset into descending order

Section 3

Launch Sites Proximities Analysis

SpaceX in US

Hyperlink



SpaceX in the US

[Hyperlink](#)

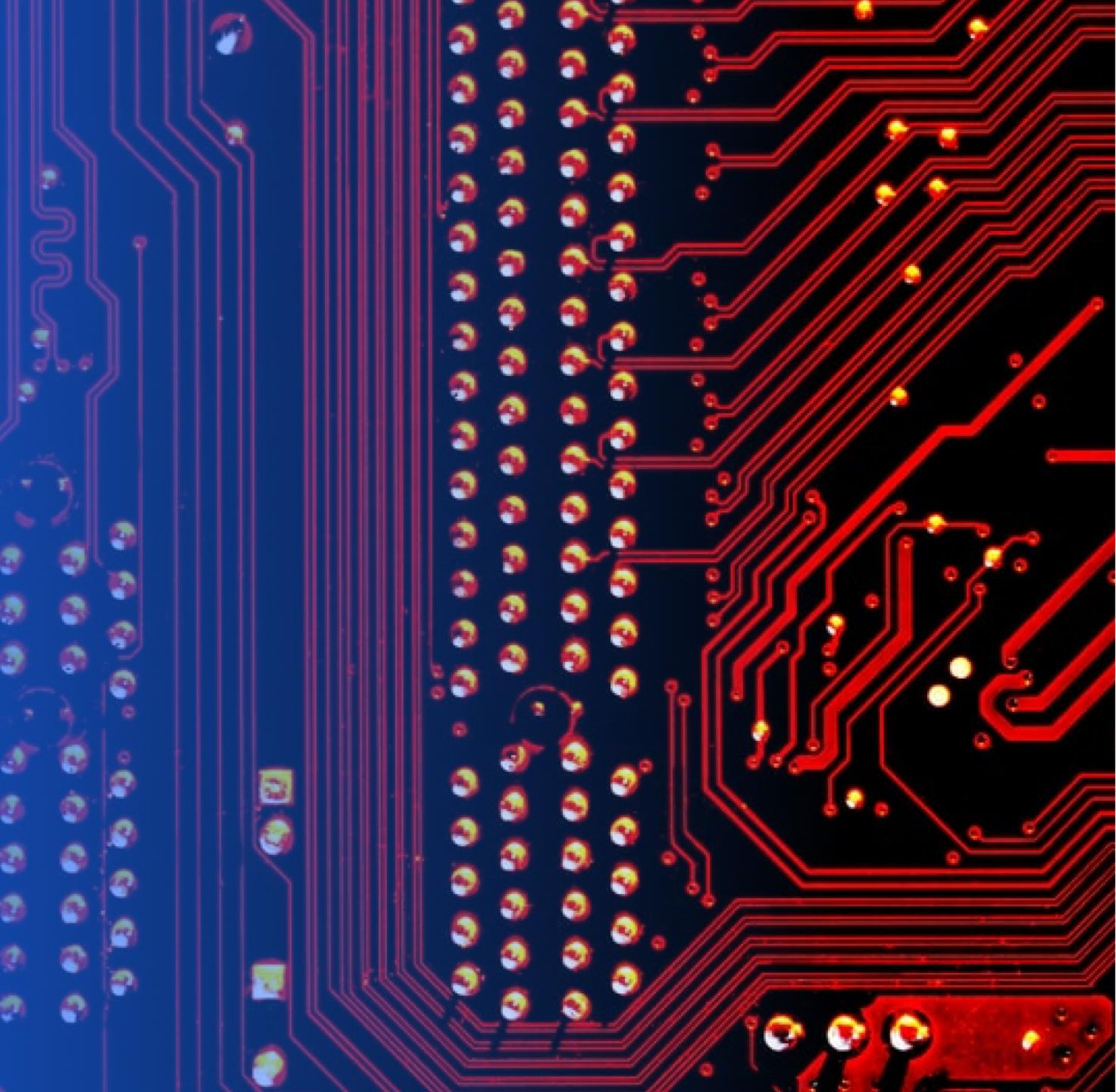
Color-labeled launch outcomes

[Hyperlink](#)

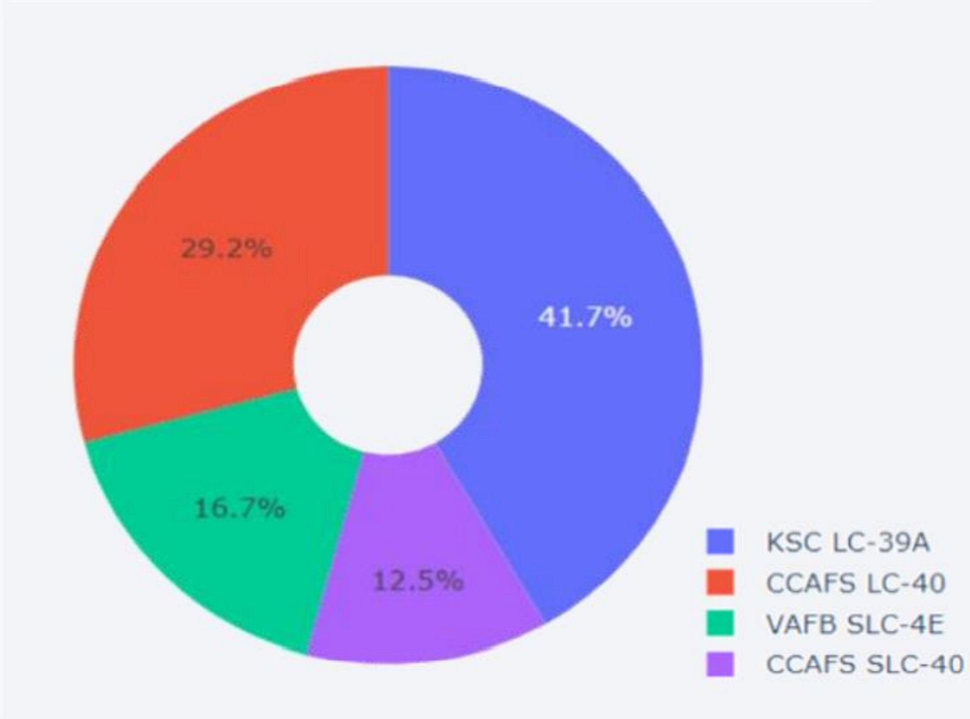
Color-labeled launch

Section 4

Build a Dashboard with Plotly Dash

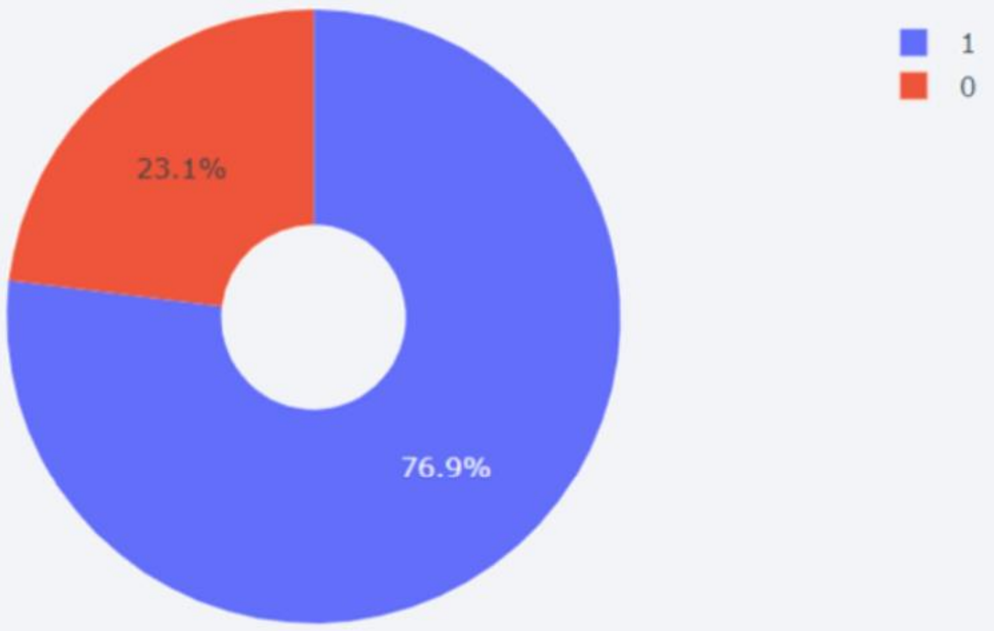


Pie chart showing the success %



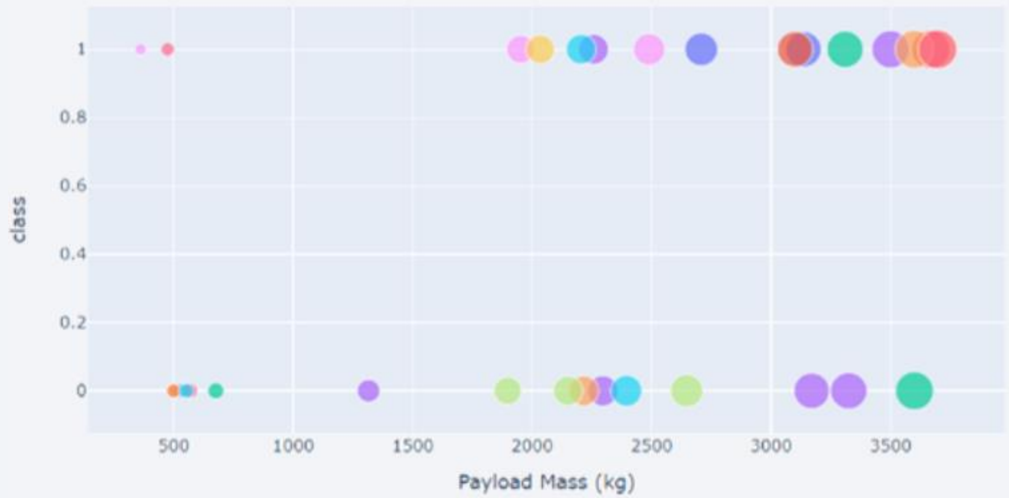
KSC had te most successful launches.

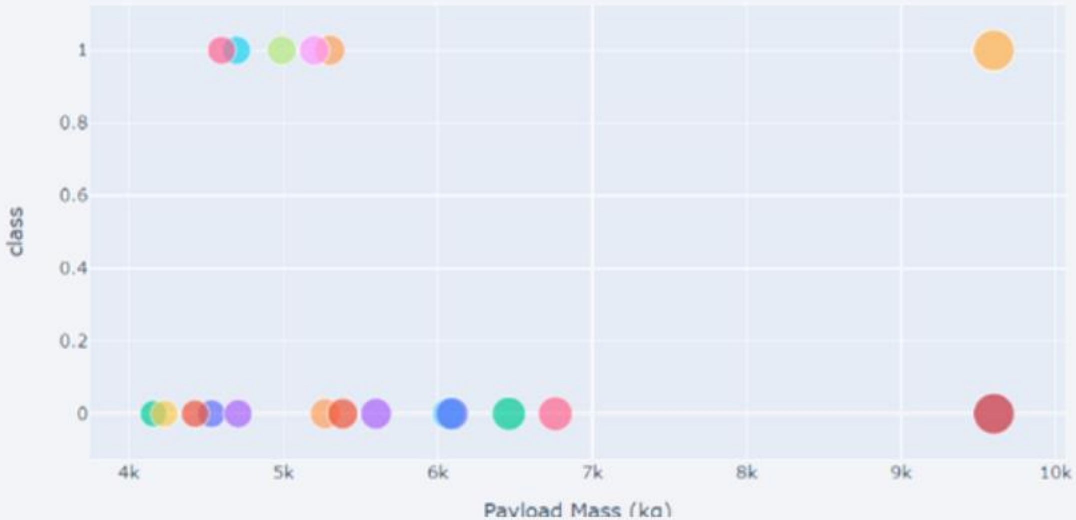
Pie chart showing the launch with the highest launch success ratio



KSC LC-39A achieved a 76,9% of success.

Scatter plot of payload x launch outcome for all sites, with different payload selected in the range slider





The success rates for low weighted payload is higher than the heavy weighted payloads.

Section 5

Predictive Analysis (Classification)

Hyperlink

Classification Accuracy

```python
parameters = {'criterion': ['gini', 'entropy'],
     'splitter': ['best', 'random'],
     'max_depth': [2*n for n in range(1,10)],
     'max_features': ['auto', 'sqrt'],
     'min_samples_leaf': [1, 2, 4],
     'min_samples_split': [2, 5, 10]}

tree = DecisionTreeClassifier()
```

[31] 0.1s Python

```python
tree_cv=GridSearchCV(tree, param_grid=parameters, cv=10)
tree_cv.fit(X_train,Y_train)
```

[32] 6.2s Python

```
GridSearchCV(cv=10, estimator=DecisionTreeClassifier(),
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [2, 4, 6, 8, 10, 12, 14, 16, 18],
                         'max_features': ['auto', 'sqrt'],
                         'min_samples_leaf': [1, 2, 4],
                         'min_samples_split': [2, 5, 10],
                         'splitter': ['best', 'random']})
```

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

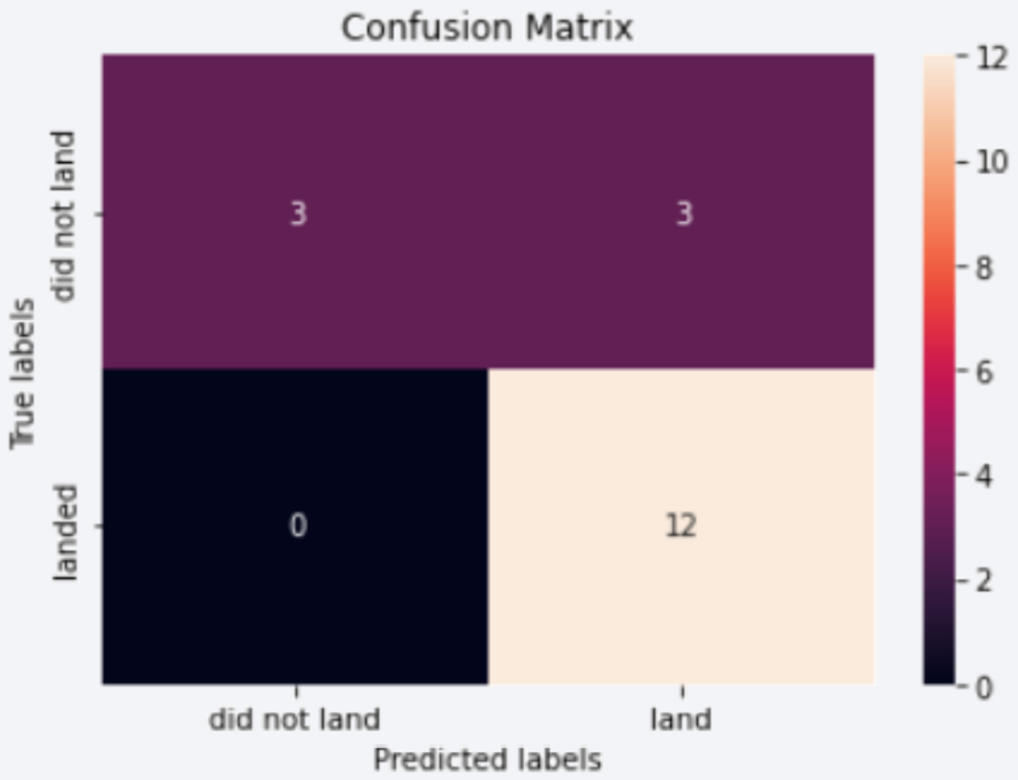
[33] 0.7s Python

```
tuned hpyerparameters :(best parameters)  {'criterion': 'gini', 'max_depth': 4, 'max_features': 'sqrt', 'min_samples_leaf': 1,
'min_samples_split': 2, 'splitter': 'random'}
accuracy : 0.8767857142857143
```

The decision tree was the best model based in the classification accuracy.

Hyperlink

Confusion Matrix



The confusion matrix for the decision tree classifier shows that the classifier can distinguish between the classes.

Hyperlink

Conclusions

- In conclusion, we can assume:
  - The larger the flight amount at a launch site;
  - The success rates for SpaceX launches is directly proportional time in years;
  - Orbits ES-L1, GEO, HEO, SSO, VLEO had the most success rate
  - The Decision tree classifier is the best machine learning algorithm for this task;

Thank you!