# SpaceX

***Capstone Project***

***Professional Certificate IBM Python for Data Science***

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# Outline

- Executive Summary
- Introduction
- Methodology
- Results
- Conclusion

# Executive Summary

## Methodologies Summary

- Data Collection using API
- Data Collection using Web Scraping
- Data Wrangling
- Exploratory Data Analysis using SQL
- Exploratory Data Analysis and Visualization
- Visual Analytics with Folium
- Machine learning Prediction

## Results Summary

- Exploratory Data Analysis result
- Dash in Screenshots
- Predictive Analytic result

# Introduction

## Target

The goal of this project is to design a Machine learning pipeline to predict if the first stage will land successfully.

## Context

SpaceX claims that Falcon 9 rocket launch cost 62 million; Other providers cost 165 million dollars. Much of the savings are because Space X can reuse the first stage. If we can determine if the first stage will land, we can determine the cost of the launch.

## Problems

Which factor can determine if the rocket will land successfully?

Which Interaction between various features can determine the success rate of a successful landing?

What conditions need to be ensured for a successful landing?

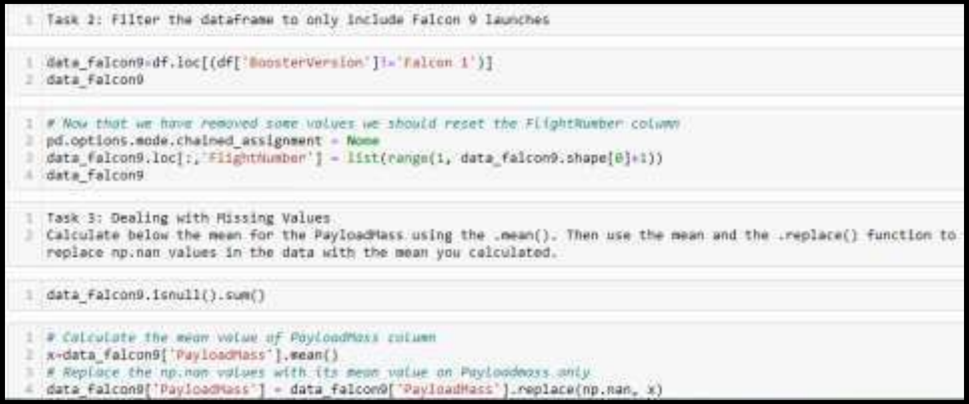
# Methodology

Data Collection using API
Data Collection using Web Scraping
Data Wrangling
Exploratory Data Analysis using SQL
Exploratory Data Analysis and Visualization
Visual Analytics with Folium
Machine learning Prediction

# The data was collected using various methods

- Data collection was done using get request to the SpaceX API.
- Next, the response content as a Json using .json() function call was decoded and turned into a pandas data frame using .json_normalize().
- Data were cleaned and checked for missing values and fill in missing values where necessary.
- In addition, we performed web scraping from Wikipedia for Falcon 9 launch records with BeautifulSoup.
- The objective was to extract the launch records as an HTML table, parse the table and convert it to a pandas data frame for future analysis.

# Data Collection – SpaceX API





- We used the get request to the SpaceX API to collect data:
- Clean the requested data and do some basic data wrangling and formatting.
- [The link to the notebook is https://github.com/GioFis/Data-Science-and-Machine-Learning-Capstone-Project/blob/main/jupyter-labs-spacex-data-collection-api.ipynb](https://github.com/GioFis/Data-Science-and-Machine-Learning-Capstone-Project/blob/main/jupyter-labs-spacex-data-collection-api.ipynb)

# Data Collection Scraping

```python
column_names = []

temp = first_launch_table.find_all('th')

for x in range(len(temp)):
        name=extract_column_from_header(temp[x])
        if name is not None and len(name)>0:
            column_names.append(name)
```

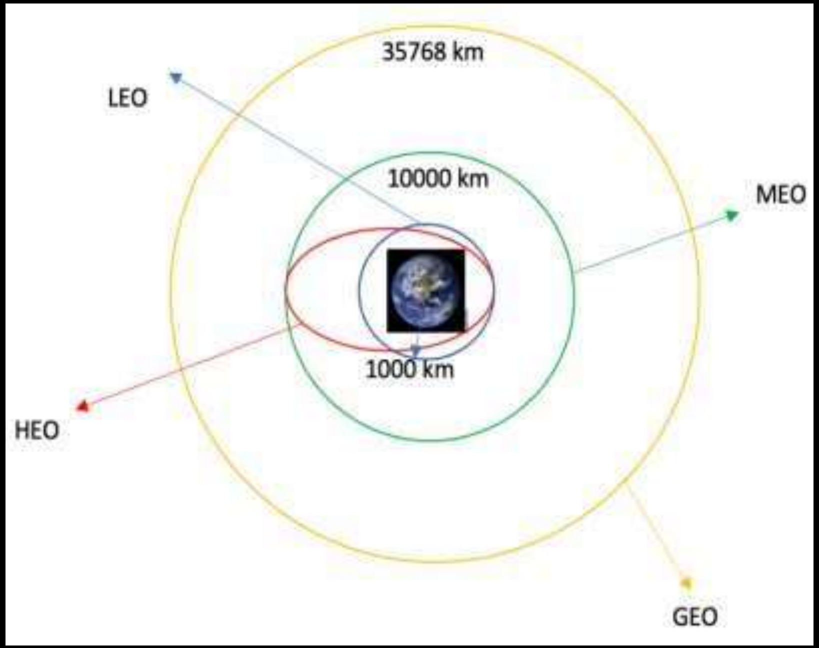
```python
launch_dict= dict.fromkeys(column_names)

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

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

- We applied web scrapping to web scrap Falcon 9 launch records with BeautifulSoup
- We parsed the table and converted it into a pandas data frame.
- [The link to the notebook is https://github.com/GioFis/Data-Science-and-Machine-Learning-Capstone-Project/blob/main/jupyter-labs-webscraping.ipynb](https://github.com/GioFis/Data-Science-and-Machine-Learning-Capstone-Project/blob/main/jupyter-labs-webscraping.ipynb)

# Data Wrangling




CAPE CANAVERAL SPACE LAUNCH COMPLEX 40
KENNEDY SPACE CENTER LAUNCH COMPLEX 39A
VANDENBERG AIR FORCE BASE SPACE LAUNCH COMPLEX 4E

- We performed exploratory data analysis and determined the training labels.
- We calculated the number of launches at each site, and the number and occurrence of each orbit
- We created a landing outcome label from the outcome column and exported the results to CSV.
- The link to the notebook is https://github.com/GioFis/Data-Science-and-Machine-Learning-Capstone-Project/blob/main/labs-jupyter-spacex-Data%20wrangling.ipynb

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

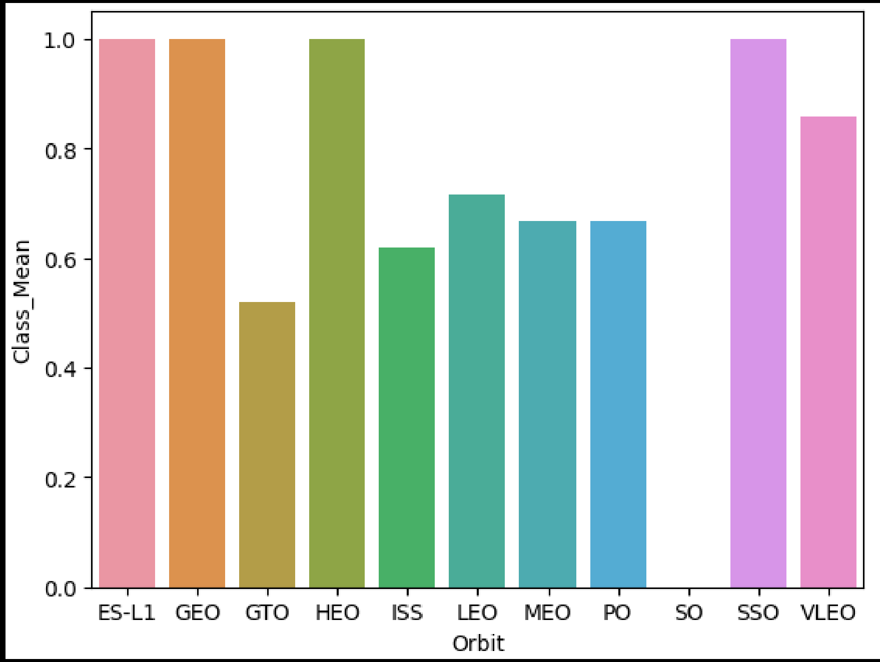
```
CCAFS SLC 40    55
KSC LC 39A      22
VAFB SLC 4E     13
Name: LaunchSite, dtype: int64
```

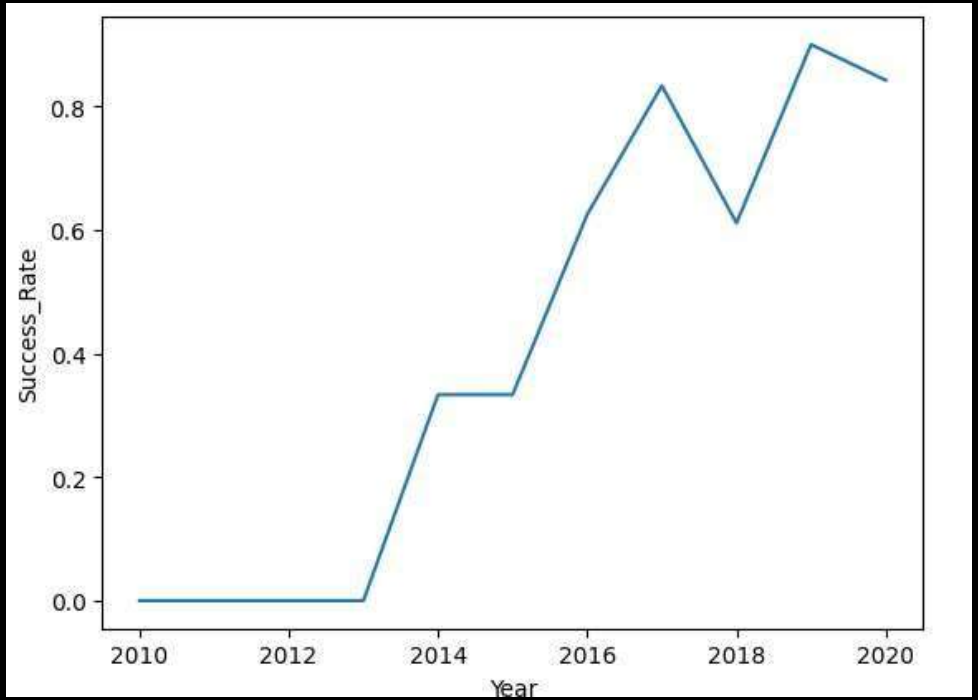
```
df['Class']=landing_class
df[['Class']].value_counts()
```

```
Class
1        60
0        30
dtype: int64
```

# EDA with Data Visualization

- We explored the data by visualizing the relationship between flight number and launch Site, payload and launch site, the success rate of each orbit type, flight number and orbit type, and the launch success yearly trend.




The link to the notebook is https://github.com/GioFis/Data-Science-and-Machine-Learning-Capstone-Project/blob/main/jupyter-labs-eda-dataviz.ipynb

# EDA with SQL

- We loaded the SpaceX dataset into a PostgreSQL database without leaving the jupyter notebook.
- We applied EDA with SQL to get insight from the data. We wrote queries to find out for instance:
  - The names of unique launch sites in the space mission.
  - The total payload mass carried by boosters launched by NASA (CRS)
  - The average payload mass carried by booster version F9 v1.1
  - The total number of successful and failure mission outcomes
  - The failed landing outcomes in drone ship, their booster version and launch site names.
- The link to the notebook https://github.com/GioFis/Data-Science-and-Machine-Learning-Capstone-Project/blob/main/eda-sql-edx.ipynb

# Build an Interactive Map with Folium

- We marked all launch sites and added map objects such as markers, circles, and lines to mark the success or failure of launches for each site on the folium map.
- We assigned the feature launch outcomes (failure or success) to classes 0 and 1.
- 0 for failure and 1 for success.
- Using the color-labeled marker clusters, we identified which launch sites have a relatively high success rate.
- We calculated the distances between a launch site to its proximities. We answered some questions, for instance:
  - Are launch sites near railways, highways, and coastlines?
  - Do launch sites keep a certain distance away from cities?

•https://github.com/GioFis/Data-Science-and-Machine-Learning-Capstone-Project/blob/main/lab_jupyter_launch_site_location.ipynb

# Built a Dashboard with Plotly Dash

- An interactive dashboard with Plotly dash was built
- We plotted pie charts showing the total launches by specific sites
- We plotted a scatter graph showing the relationship between Outcome and Payload Mass (Kg) for the different booster versions.
- The link to the notebook is https://github.com/GioFis/Data-Science-and-Machine-Learning-Capstone-Project/blob/main/spacex_dash.ipynb

# Predictive Analysis Classification

- Data have been loaded using NumPy and pandas, transformed, and split into training and testing.
- We built different machine learning models and tuned different hyperparameters using GridSearchCV.
- We used accuracy as the metric for our model and improved the model using feature engineering and algorithm tuning.
- We found the best performing classification model.
- The link to the notebook is https://github.com/GioFis/Data-Science-and-Machine-Learning-Capstone-Project/blob/main/SpaceX_Machine%20Learning%20Prediction.ipynb

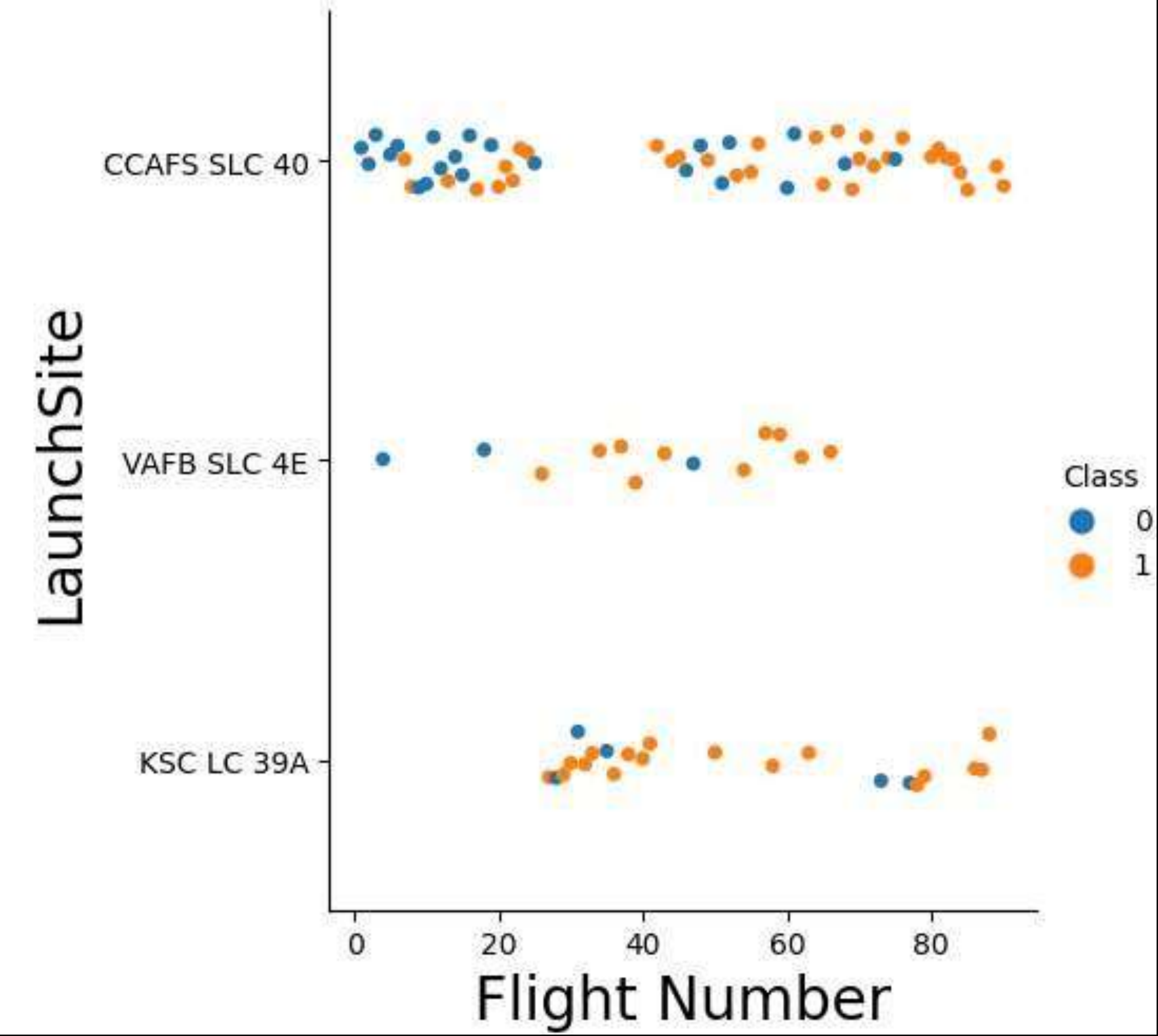
# Results

- EDA results
- Interactive Analytics demo in screenshots
- Predictive analysis results

# Insights from Exploratory data analysis

# Flight Number vs. Launch Site

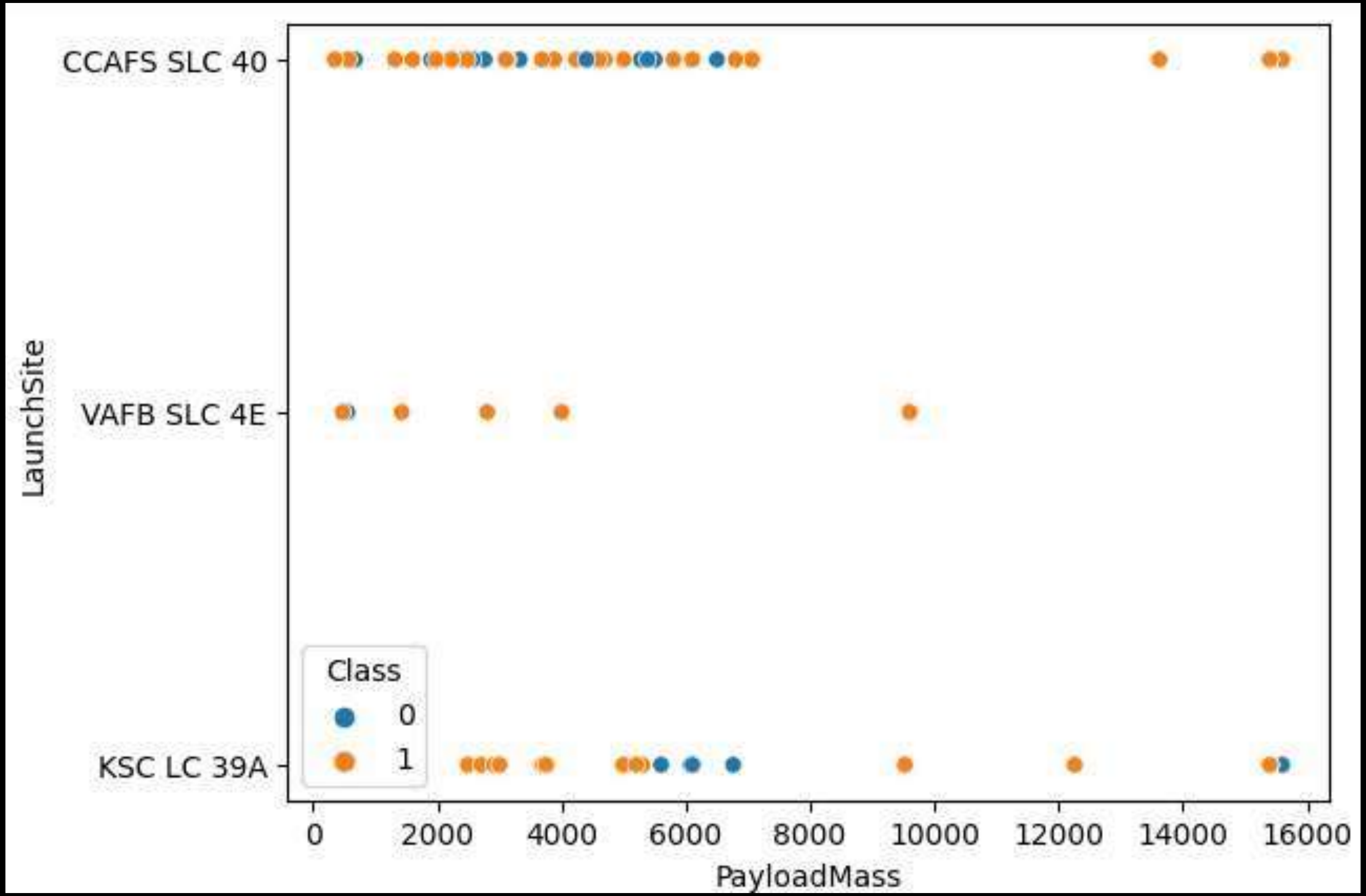
From this graph, we can deduce that CCAFS SLC 40 was the most used launch site, the progressively rare number of blue dots (failure) suggest a progressive improvement over time



# Payload vs Launch Site

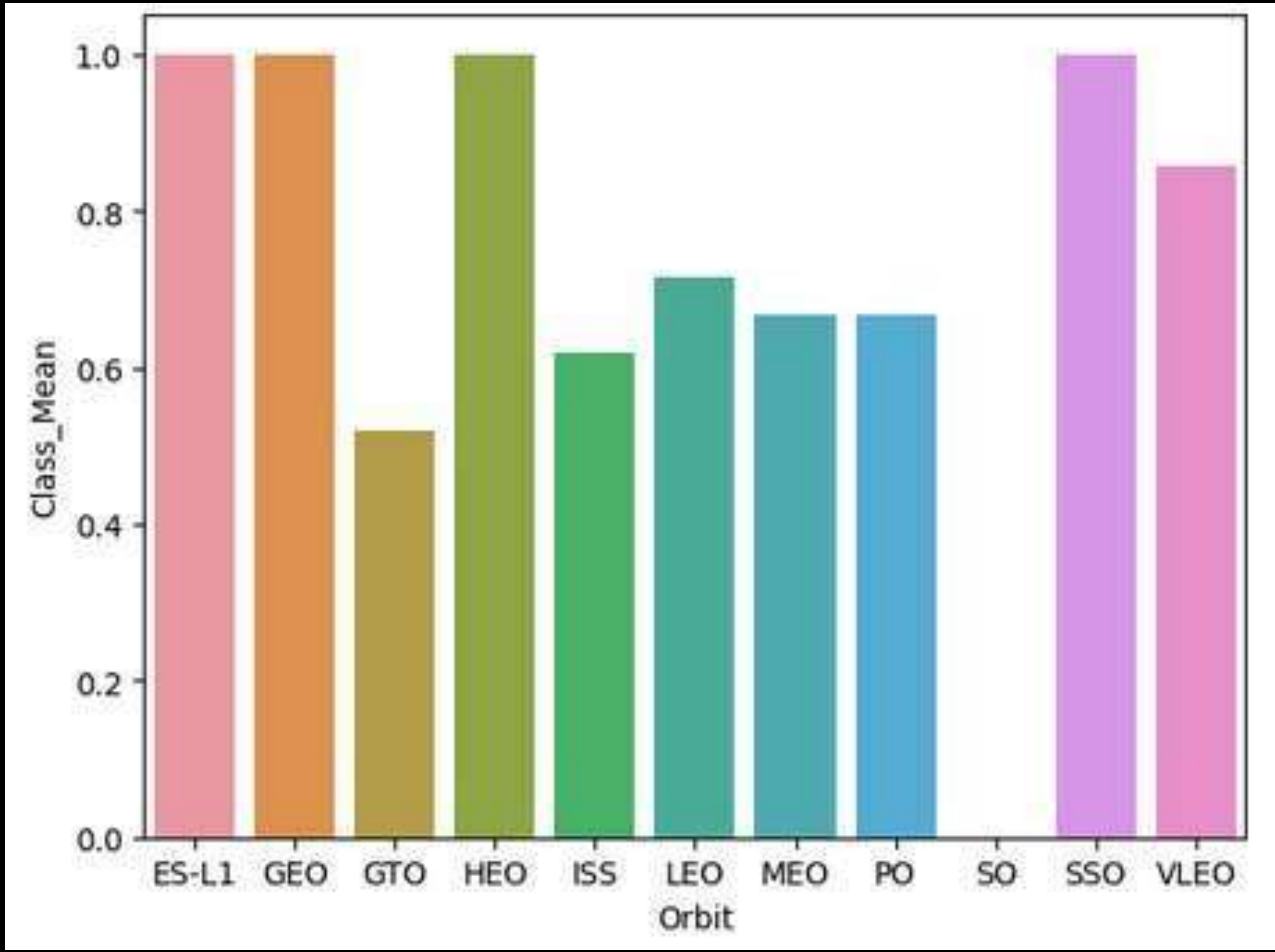
With a closer look at the graph, we can see that:

- payload mass >8k kg has a high success rate in all launch sites,
- 2k<Payload mass<8k Kg. We have a significant concentration of failure
- VAFB-SLC launch site, there are no rockets launched for heavy payload mass(greater than 10000)



# Success Rate vs Orbit Type

ES-L1, GEO, HEO, SSO, and VLEO had the most success rate, as we can see on this graph

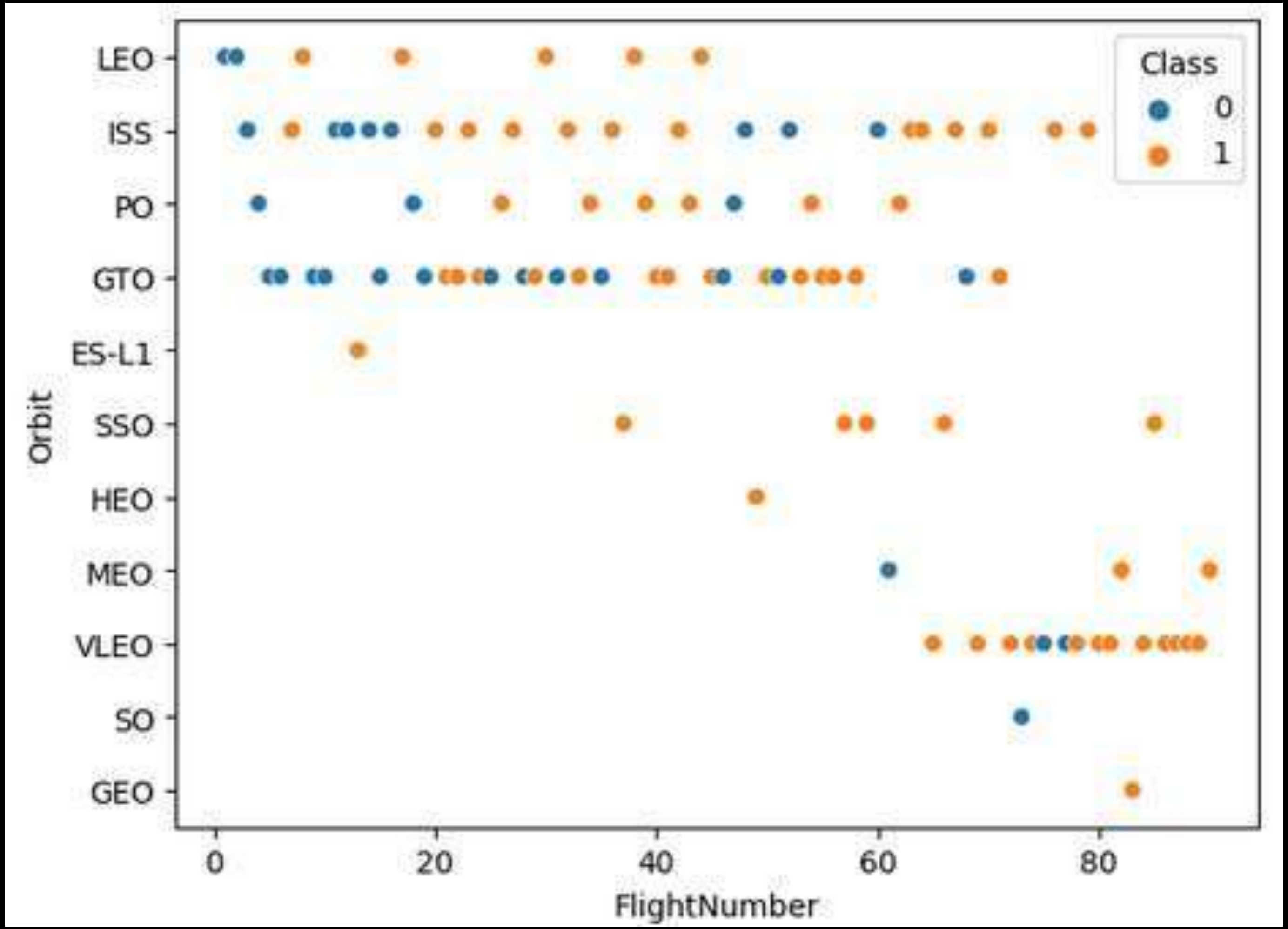


# Flight Number vs Orbit Type

- We observe that 51% of the 27 GTO Flight numbers have been successful

- LEO 71.5%
- ISS 62%
- VLEO 86%

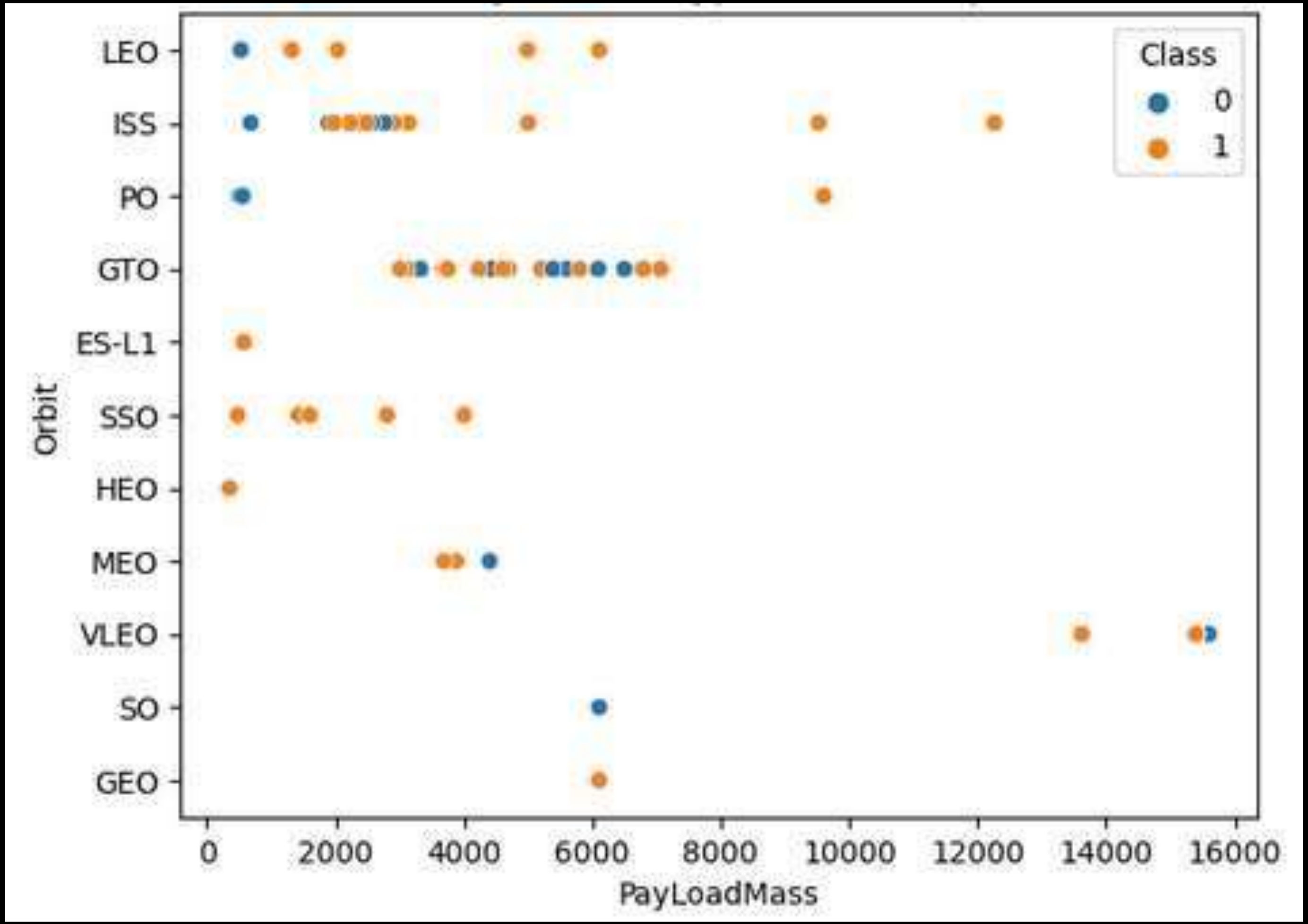
•ES-L1 and SSO performed well ( 100% successful ) but a fewer number of launches were committed to reach those orbits



# Payload vs Orbit Type

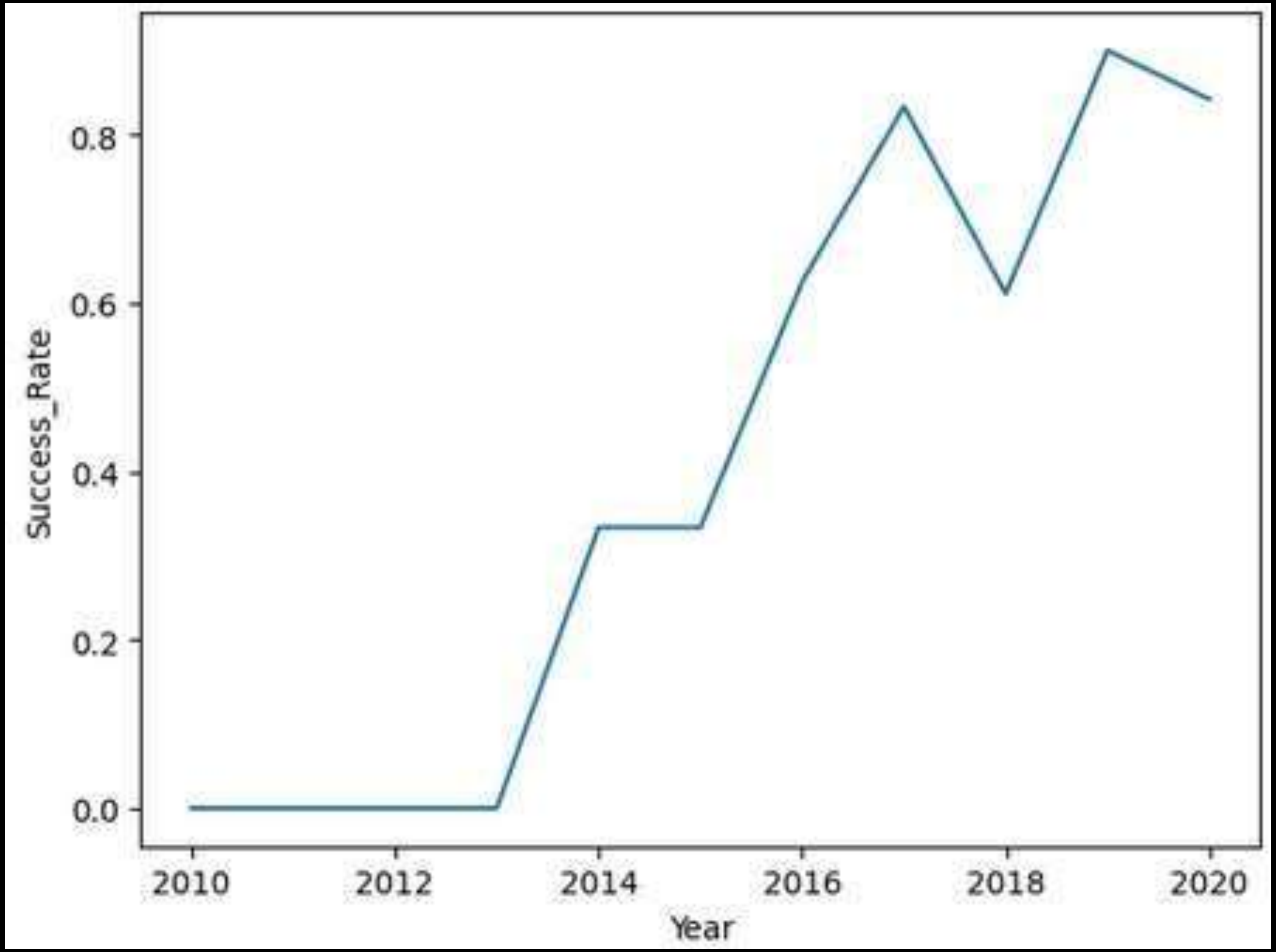
Successful landings of heavy payloads (more than 6000Kg) are more for LEO, ISS, and GTO orbits

A large part of the payload weight per launch was less than 6000Kg



# Launch Success Yearly Trend

Since 2013, the success rate kept on increasing till 2020, as we can see from this plot



the key word DISTINCT to show only unique launch sites

# All Launch Site Names

```
%sql SELECT DISTINCT(launch_site),COUNT(*) as count FROM SPACEXTBL GROUP BY launch_site;
```

```
 * ibm_db_sa://fbt48346:***@815fa4db-dc03-4c70-869a-a9cc13f33084.bs2io90l08kqb1od8lcg.databases.
Done.
```

| launch_site | COUNT |
|---|---|
| CCAFS LC-40 | 26 |
| CCAFS SLC-40 | 34 |
| KSC LC-39A | 25 |
| VAFB SLC-4E | 16 |

*Display 5 records where launch sites begin with the string 'KSC'*

```
%sql SELECT * FROM SPACEXTBL WHERE LAUNCH_SITE LIKE '%KSC%' LIMIT 5;
```

```
 * ibm_db_sa://fbt48346:***@815fa4db-dc03-4c70-869a-a9cc13f33084.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:30367/BLUDB
Done.
```

| column_0 | DATE | time__utc_ | booster_version | launch_site | payload | payload_mass__kg_ | orbit | customer | mission_outcome | landing__outcome |
|---|---|---|---|---|---|---|---|---|---|---|
| 29 | 2017-02-19 | 14:39:00 | F9 FT B1031.1 | KSC LC-39A | SpaceX CRS-10 | 2490 | LEO (ISS) | NASA (CRS) | Success | Success (ground pad) |
| 30 | 2017-03-16 | 06:00:00 | F9 FT B1030 | KSC LC-39A | EchoStar 23 | 5600 | GTO | EchoStar | Success | No attempt |
| 31 | 2017-03-30 | 22:27:00 | F9 FT B1021.2 | KSC LC-39A | SES-10 | 5300 | GTO | SES | Success | Success (drone ship) |
| 32 | 2017-01-05 | 11:15:00 | F9 FT B1032.1 | KSC LC-39A | NROL-76 | 5300 | LEO | NRO | Success | Success (ground pad) |
| 33 | 2017-05-15 | 23:21:00 | F9 FT B1034 | KSC LC-39A | Inmarsat-5 F4 | 6070 | GTO | Inmarsat | Success | No attempt |

We used the query above to see only 5 of all site ‘KSC’

# Launch Site Names Begin with KSC

# Total Payload Mass

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

```
%sql SELECT SUM(PAYLOAD_MASS__KG_) as Payload_NASA  FROM SPACEXTBL WHERE customer LIKE '%NASA%(CRS)%';

```

```
 * ibm_db_sa://fbt48346:***@815fa4db-dc03-4c70-869a-a9cc13f33084.bs2io90l08kqb1od8lcg.databases.appdomain.c
Done.
```

| payload_nasa |
| --- |
| 48213 |

Total Payload carried by boosters for NASA  (CRS) is 48213.

*Display average payload mass carried by booster version F9 v1.1*

```
%sql SELECT AVG(PAYLOAD_MASS__KG_) as AVG_MASS_F9_V1_1 FROM SPACEXTBL WHERE BOOSTER_VERSION LIKE '%F9%v1.1%';
```

```
 * ibm_db_sa://fbt48346:***@815fa4db-dc03-4c70-869a-a9cc13f33084.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:30
Done.
```

| avg_mass_f9_v1_1 |
|---|
| 2534 |

Calculated the average payload mass carried by booster F9 v1.1 as 2534

# Average Payload Mass by F9 v1.1

***List the date where the succesful landing outcome in drone ship was acheived.***

*Hint:Use min function*

```
%sql SELECT MIN(DATE) as First_Succesful_landing FROM SPACEXTBL WHERE LANDING__OUTCOME LIKE '%Success (drone ship)%';
```

```
 * ibm_db_sa://fbt48346:***@815fa4db-dc03-4c70-869a-a9cc13f33084.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:30367/BLUD
Done.
```

| first_succesful_landing |
| --- |
| 2016-05-27 |

We observed that the date of the first **successful landing outcome in the drone ship was 27th May 2016**

# First Successful Ground Landing Date

*List the names of the boosters which have success in ground pad and have payload mass greater than 4000 but less than 6000*

```
%sql SELECT booster_version as Succesful_booster_version, PAYLOAD_MASS__KG_ FROM SPACEXTBL
WHERE PAYLOAD_MASS__KG_>4000 and PAYLOAD_MASS__KG_<6000 and LANDING__OUTCOME LIKE '%Success (ground pad)%';
```

```
 * ibm_db_sa://fbt48346:***@815fa4db-dc03-4c70-869a-a9cc13f33084.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:30367/BLUDB
Done.
```

| succesful_booster_version | payload_mass__kg_ |
|---|---|
| F9 FT B1032.1 | 5300 |
| F9 B4 B1040.1 | 4990 |
| F9 B4 B1043.1 | 5000 |

Using WHERE clause to filter successfully landed booster on ship pad and applied AND condition

# 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***

```
%sql SELECT mission_outcome,COUNT(mission_outcome) as count FROM SPACEXTBL GROUP BY mission_outcome;
```

```
 * ibm_db_sa://fbt48346:***@815fa4db-dc03-4c70-869a-a9cc13f33084.bs2io90l08kqb1od8lcg.databases.appdomain.c
Done.
```

| mission_outcome | COUNT |
|---|---|
| Failure (in flight) | 1 |
| Success | 99 |
| Success (payload status unclear) | 1 |

*List the names of the booster_versions which have carried the maximum payload mass. Use a subquery*

```
%sql SELECT DISTINCT(BOOSTER_VERSION) from SPACEXTBL
WHERE PAYLOAD_MASS__KG_ = (select MAX(PAYLOAD_MASS__KG_) from SPACEXTBL);
```

```
 * ibm_db_sa://fbt48346:***@815fa4db-dc03-4c70-869a-a9cc13f33084.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:30367/BLUDB
Done.
```

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

- Determined the booster that has carried the maximum payload using a subquery in the WHERE clause and the MAX() function

# Boosters Carried Maximum Payload

*List the records which will display the month names, succesful landing_outcomes in ground pad ,booster versions, launch_site for the months in year 2017*

Note: SQLLite does not support monthnames. So you need to use substr(Date, 4, 2) as month to get the months and substr(Date,7,4)='2017' for year.

```
%sql SELECT substr(Date,6,2) as month, booster_version, launch_site  FROM SPACEXTBL
WHERE landing__outcome like '%Success (ground pad)';
```

```
 * ibm_db_sa://fbt48346:***@815fa4db-dc03-4c70-869a-a9cc13f33084.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:30367/BLUDB
Done.
```

| MONTH | booster_version | launch_site |
|---|---|---|
| 12 | F9 FT B1019 | CCAFS LC-40 |
| 07 | F9 FT B1025.1 | CCAFS LC-40 |
| 02 | F9 FT B1031.1 | KSC LC-39A |
| 01 | F9 FT B1032.1 | KSC LC-39A |
| 03 | F9 FT B1035.1 | KSC LC-39A |
| 08 | F9 B4 B1039.1 | KSC LC-39A |
| 07 | F9 B4 B1040.1 | KSC LC-39A |
| 12 | F9 FT B1035.2 | CCAFS SLC-40 |
| 08 | F9 B4 B1043.1 | CCAFS SLC-40 |

Using WHERE clause with LIKE, AND, and BETWEEN conditions to filter for failed landing outcomes in drone ships, their booster versions, and launch site names for the year 2015

# 2015 Launch Records

```
%sql SELECT DISTINCT(LANDING__OUTCOME),COUNT(*) as count FROM SPACEXTBL
WHERE DATE BETWEEN '2010-06-04' AND '2017-03-20' GROUP BY Landing__Outcome ORDER BY count DESC ;
```

```
 * ibm_db_sa://fbt48346:***@815fa4db-dc03-4c70-869a-a9cc13f33084.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:30367/BLUDB
Done.
```

| landing__outcome | COUNT |
|---|---|
| No attempt | 10 |
| Failure (drone ship) | 5 |
| Success (drone ship) | 5 |
| Success (ground pad) | 5 |
| Controlled (ocean) | 3 |
| Uncontrolled (ocean) | 2 |
| Failure (parachute) | 1 |
| Precluded (drone ship) | 1 |

We selected Landing outcomes and the COUNT of landing outcomes from the data and used the WHERE clause to filter for landing outcomes BETWEEN 2010-06-04 to 2010-03-20.

We applied the GROUP BY clause to group the landing outcomes and the ORDER BY clause to order the grouped landing outcome in descending order.

# Rank Landing Outcomes Between 2010 and 2017

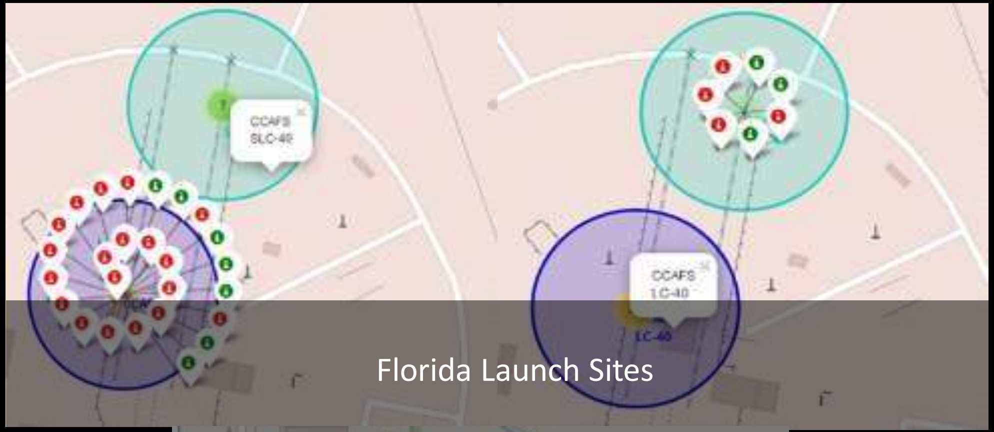
# Launch Sites with Folium

# All Launch sites in the global map

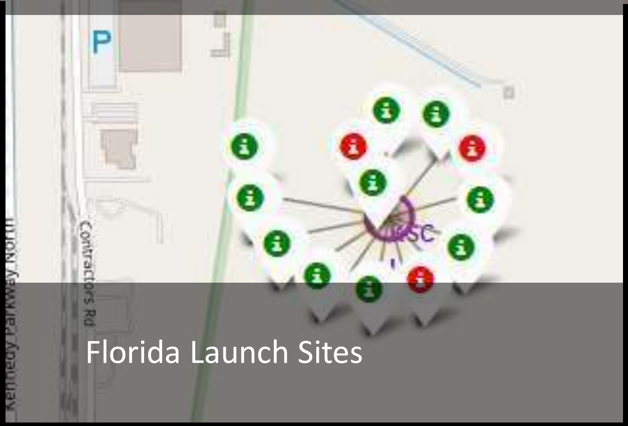
As we can see Space X launch sites are in USA, Florida and California

# Markers showing launch sites with color labels


California Launch Site



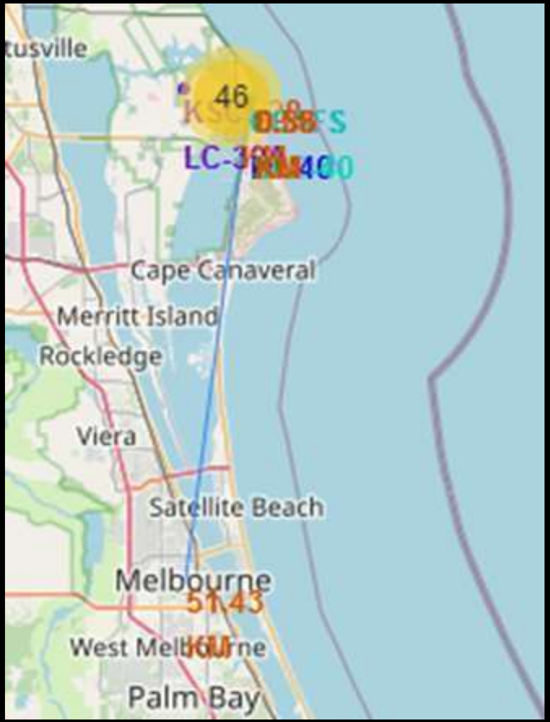
Florida Launch Sites



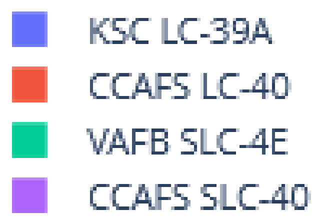

Florida Launch Sites

# Launch Site Distance to Landmarks

- Are launch sites near railways? 1.28km
- Are launch sites near highways? 30km
- Are launch sites near the coastline? 0.86km
- Do launch sites keep a certain distance away from cities? 51 km

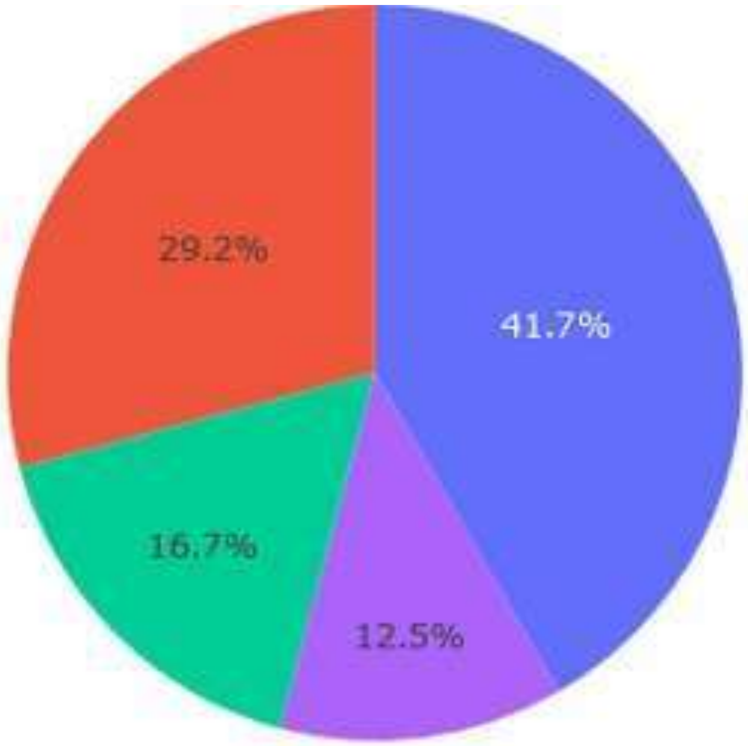



# Build a Dashboard with Plotly Dash



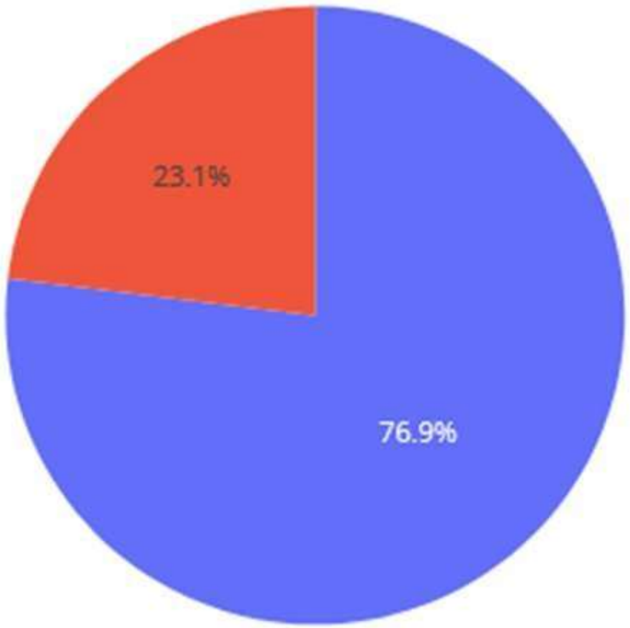

KSC LC-39A had the most successful of all the sites

# Total Success Launches By all sites



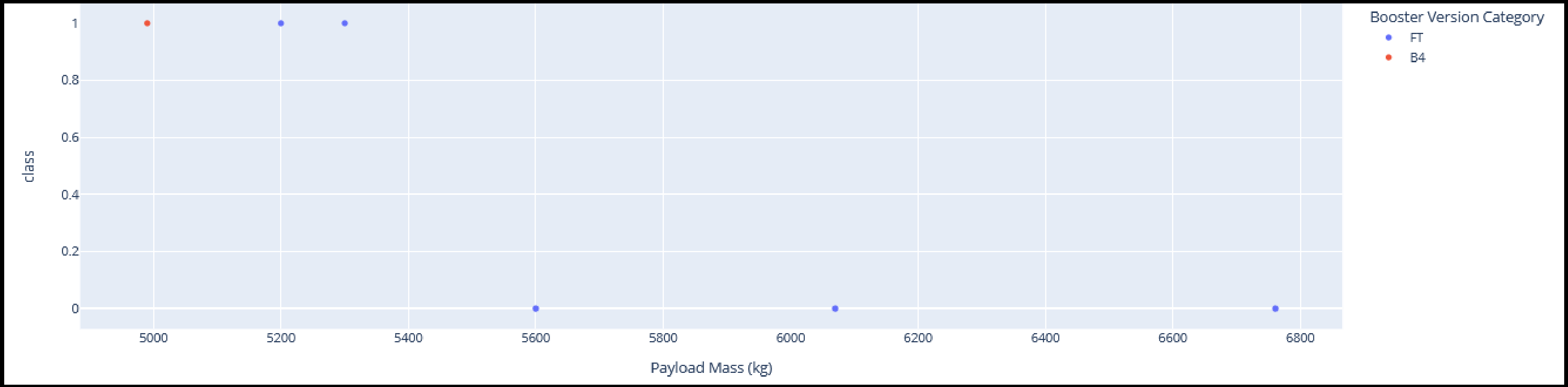

KSC LC-39A was the most successful of all the sites it achieved a 76.9% success rate while getting a 23.1% failure rate

# Launch Site with the highest launch success ratio



# Scatter plot
# Payload vs. Launch Outcome for all sites

Heavy Weighted Payload 4000 -10000 Kg




Low Weighted Payload 0-4000 Kg

# Predictive Analysis Classification

| | Method | Accuracy | Best score |
|---|---|---|---|
| 0 | Logistic regression | 0.833333 | 0.846429 |
| 1 | Support vector machine | 0.833333 | 0.848214 |
| 2 | Decision Tree classifier | 0.944444 | 0.891071 |
| 3 | K nearest neighbors | 0.833333 | 0.848214 |

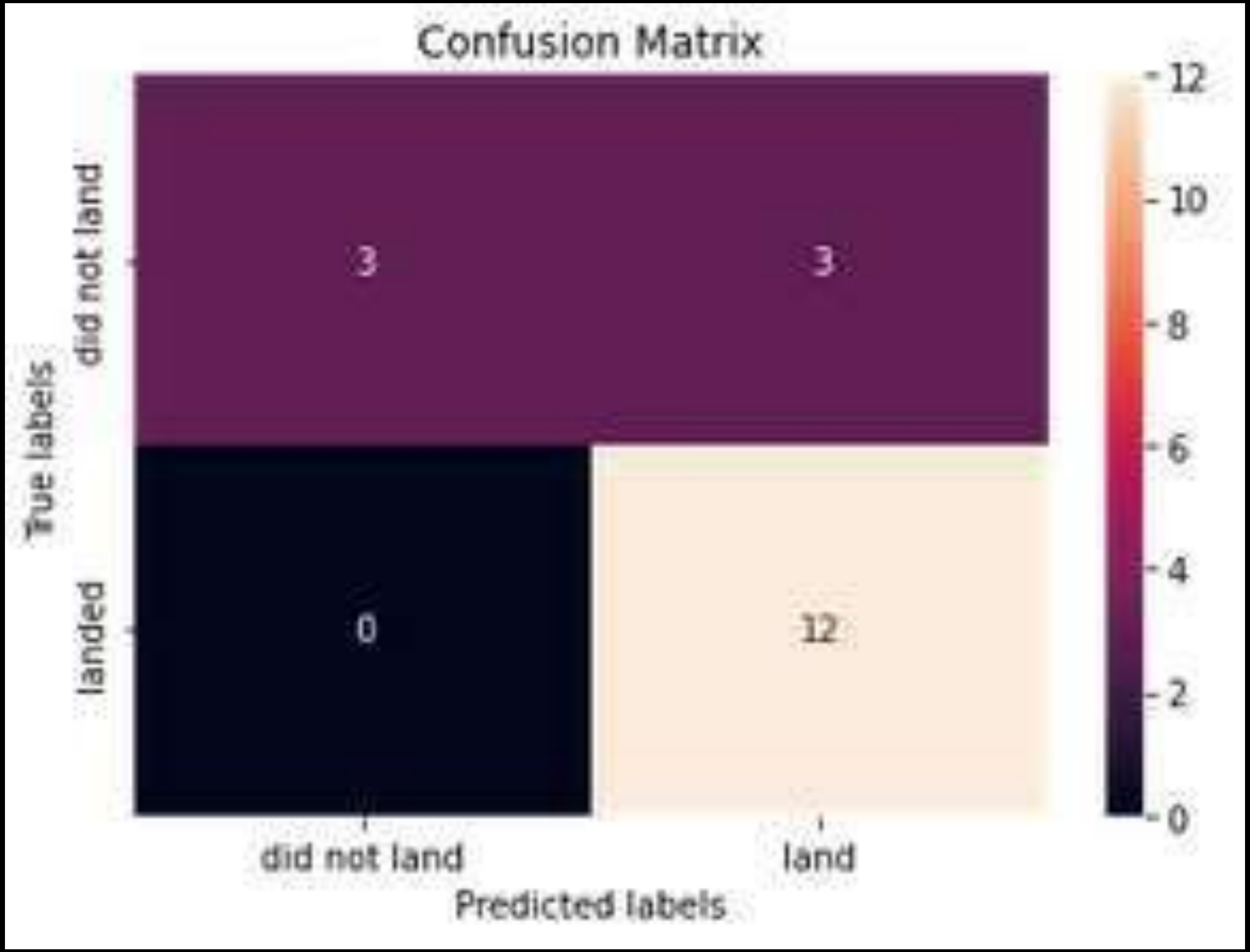
# Classification Accuracy

The decision tree classifier is the model with the highest classification accuracy

# Confusion Matrix

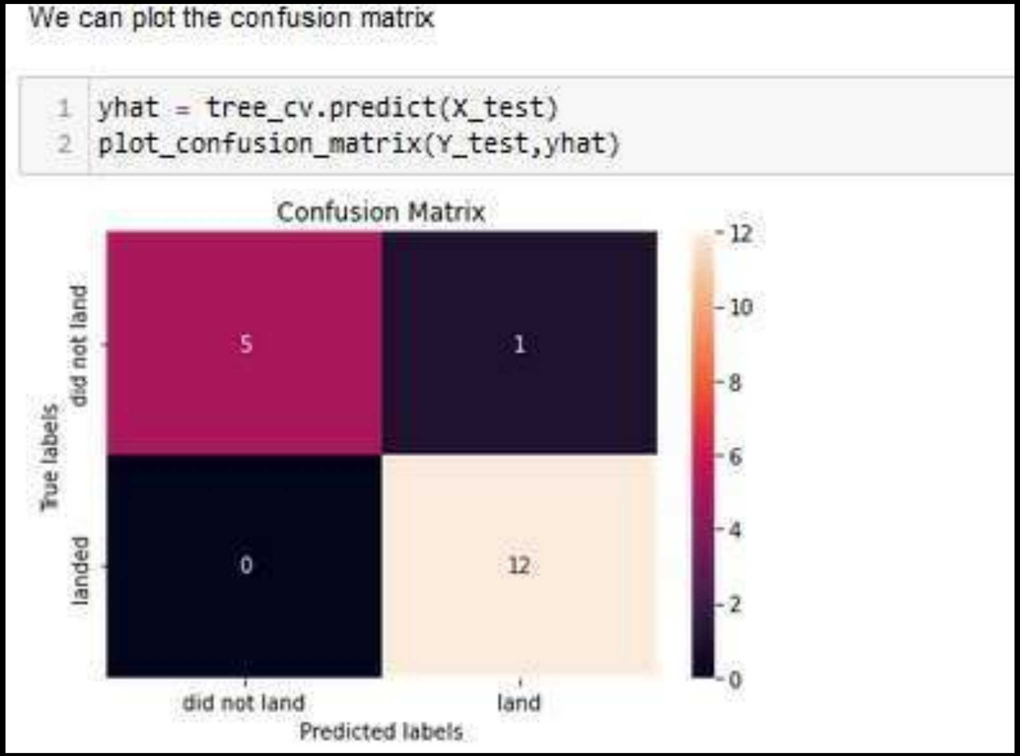
The confusion matrix shows that the classifier can distinguish between the different classes.

The major problem is the false positives, in this project, the unsuccessful landing is marked as a successful landing by the classifier



# Prediction tree classifier performs best

- Prediction tree classifier performs best in distinguishing false positives



# Conclusions

Seen these data, we can conclude that

- Launch success rate started to increase in 2013 till 2020
- Orbits ES-L1, GEO, HEO, SSO, and VLEO had the most success rate
- KSC LC-39A had the most successful launches of any sites
- The Decision tree classifier is the best machine learning algorithm for this task

# Thank you