



IBM Developer  
SKILLS NETWORK

# Winning Space Race with Data Science

Data Science Capstone Project Presentation

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# Outline

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

# Executive Summary

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- Summary of methodologies
  - Data collection
  - Data wrangling
  - EDA with data visualization
  - EDA with SQL
    - Building an interactive map with Folium
  - Building a Dashboard with Plotly Dash
  - Predictive analysis (Classification)
- Summary of all results
  - Exploratory data analysis results
  - Interactive analytics demo in screenshots
  - Predictive analysis results

# Introduction

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- **Project background and context**
  - The era of commercial space has arrived, and there are several companies that are making space travel affordable for everyone. Perhaps the most successful of them is SpaceX, and one of the reasons is that their rocket launch is relatively inexpensive. 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. Therefore, we will predict if the Falcon 9 first stage will land successfully. 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.
- **Problems you want to find answers**
  - Correlations between each rocket variables and successful landing rate
  - Conditions to get the best results and ensure the best successful landing rat



Section 1

# Methodology

# Methodology

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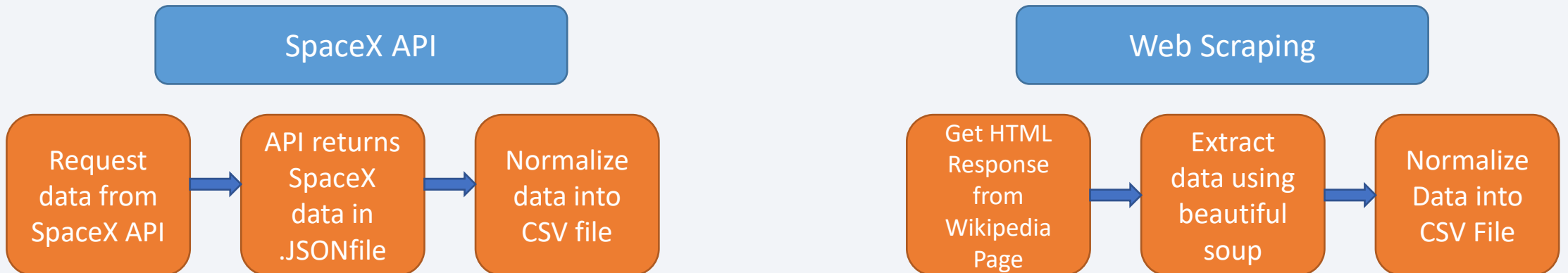
## Executive Summary

- Data collection methodology:
  - SpaceX API & Web Scraping Falcon 9 and Falcon Heavy Launches Records from Wikipedia
- Perform data wrangling
  - Convert outcomes into Training Labels with the booster successfully/unsuccessful landed
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
  - Find best Hyperparameter for SVM, Classification Trees and Logistic Regression

# Data Collection

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- The data collection process includes a combination of API requests from the SpaceX API and web scraping data from a table in the Wikipedia page of SpaceX, Falcon 9 and Falcon Heavy Launches Records.
  - o SpaceX API Data Columns: FlightNumber, Date, BoosterVersion, PayloadMass, Orbit, LaunchSite, Outcome, Flights, GridFins, Reused, Legs, LandingPad, Block, ReusedCount, Serial, Longitude, Latitude
- Wikipedia Web Scrape Data Columns: Flight No., Launch site, Payload, PayloadMass, Orbit, Customer, Launch outcome, Version Booster, Booster landing, Date, Time



# Data Collection - SpaceX API

1. Requesting rocket launch data from SpaceX API :

```
In [6]: spacex_url="https://api.spacexdata.com/v4/launches/past"
```

```
In [7]: response = requests.get(spacex_url)
```

Check the content of the response

2. Converting Response to a JSON File

```
In [9]: static_json_url='https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud'
```

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

```
In [10]: response.status_code
```

```
Out[10]: 200
```

Now we decode the response content as a json using `.json()` and turn it into a Pandas dataframe

```
In [11]: # Use json_normalize method to convert the json result into a dataframe
data = pd.json_normalize(response.json())
```

3. Using Custom Functions to Clean Data

```
In [16]: # Call getBoosterVersion
getBoosterVersion(data)
```

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

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

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

4. Combining the column into a dictionary to create data frame :

```
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}
```

Then, we need to create a Pandas data frame from the dictionary launch\_dict.

```
# Create a data from launch_dict
df = pd.DataFrame.from_dict(launch_dict)
```

5. Filtering Dataframe and exporting to a CSV

```
data_falcon9.loc[:, 'FlightNumber'] = list(range(1, data_falcon9.shape[0]+1))
data_falcon9
```

```
data_falcon9.to_csv('dataset_part\1.csv', index=False)
```



# Data Collection - Scraping

## 1. Getting response from HTML

```
# assign the response to a object
html_data = requests.get(static_url).text
```

## 2. Creating a BeautifulSoup object

```
soup = BeautifulSoup(html_data, 'html5lib')
```

## 3. Creating a BeautifulSoup object

```
html_tables = soup.find_all('table')
```

## 4. Extracting column name one by one

```
column_names = []

# Apply find_all() function with `th` element on first_launch_table
# Iterate each th element and apply the provided extract_column_from_header function
# Append the Non-empty column name (if name is not None and name is not empty)
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)
```

- [GitHub URL](#)

## 5. Creating an empty dictionary with keys

```
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 []
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. Filling up the launch\_dict with launch records (Too long to put in here, so please refer to the notebook)

```
df = pd.DataFrame.from_dict(launch_dict, orient="index").reset_index()
```

## 7. Creating a Dataframe and exporting it to a CSV

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

# Data Wrangling

---

- There are several cases in which the booster failed to successfully land on the dataset, and sometimes it attempted to land but failed because of accident.
  - True Ocean: the mission result has successfully landed in a specific area of the ocean
  - False Ocean: the mission result has not successfully landed in a specific area of the ocean
  - True RTLS: the mission result successfully landed on the ground pad
  - False RTLS: the mission result has not successfully landed on the ground pad
  - True ASDS: the mission result has successfully landed on the drone ship
  - False ASDS: the mission result has not landed on the drone ship
- Converting these results into training labels:
  - 1 = successful / 0 = failure
- [GitHub Link](#)

# Data Wrangling

1. Calculating the number of launches at each site

```
df.LaunchSite.value_counts()
```

2. Calculating the number and occurrence of each orbit

```
df.Orbit.value_counts()
```

3. Calculating the number and occurrence of mission outcome per orbit type

```
landing_outcomes = df.Outcome.value_counts()  
landing_outcomes
```

- [GitHub Link](#)

5. Creating a landing outcome label from Outcome column

```
landing_class = []  
  
for outcome in df['Outcome']:  
    if outcome in bad_outcomes:  
        landing_class.append(0)  
    else:  
        landing_class.append(1)
```

6. Calculating the success rate for every landing in dataset

```
df["Class"].mean()
```

```
0.6666666666666666
```

7. Exporting dataset to a CSV

```
df.to_csv("dataset_part\2.csv", index=False)
```

# EDA with Data Visualization

---

- **Scatter chart:**
  - Flight Number vs. Launch Site
  - Payload vs. Launch Site
  - Flight Number vs. Orbit Type
  - Payload vs. Orbit Type
  - A scatter plot shows how much one variable is affected by another. The relationship between two variables is called a correlation. This plot is generally composed of large data bodies.
- **Bar chart:**
  - Orbit Type vs. Success Rate
  - A Bar chart makes it easy to compare datasets between multiple groups at a glance. One axis represents a category and the other axis represents a discrete value. The purpose of this chart is to indicate the relationship between the two axes.
- **Line chart:**
  - Year vs. Success Rate
  - A Line chart shows data variables and trends very clearly and helps predict the results of data that has not yet been recorded.
- [GitHub URL](#)

# EDA with SQL

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- Loading the dataset into the corresponding table in a Db2 database, and executing SQL queries to answer following questions:
  - Displaying the names of the unique launch sites in the space mission
  - Displaying 5 records where launch sites begin with the string 'CCA'
  - Displaying the total payload mass carried by boosters launched by NASA (CRS)
  - Displaying average payload mass carried by booster version F9 v1.1
  - Listing the date when the first successful landing outcome in ground pad was achieved ○ Listing the names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000
  - Listing the total number of successful and failure mission outcomes ○ Listing the names of the booster\_versions which have carried the maximum payload mass
  - Listing the failed landing\_outcomes in drone ship, their booster versions, and launch site names for in year 2015
  - Ranking 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
- [GitHub URL](#)



# Build an Interactive Map with Folium

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- Objects created and added to a folium map:
  - Markers that show all launch sites on a map
  - Markers that show the success/failed launches for each site on the map
  - Lines that show the distances between a launch site to its proximities
- By adding these objects, following geographical patterns about launch sites are found:
  - Are launch sites in close proximity to railways? Yes
  - Are launch sites in close proximity to highways? Yes
  - Are launch sites in close proximity to coastline? Yes
  - Do launch sites keep certain distance away from cities? Yes
- [GitHub Link](#)/[IBM Cloud Link](#)

# Build a Dashboard with Plotly Dash

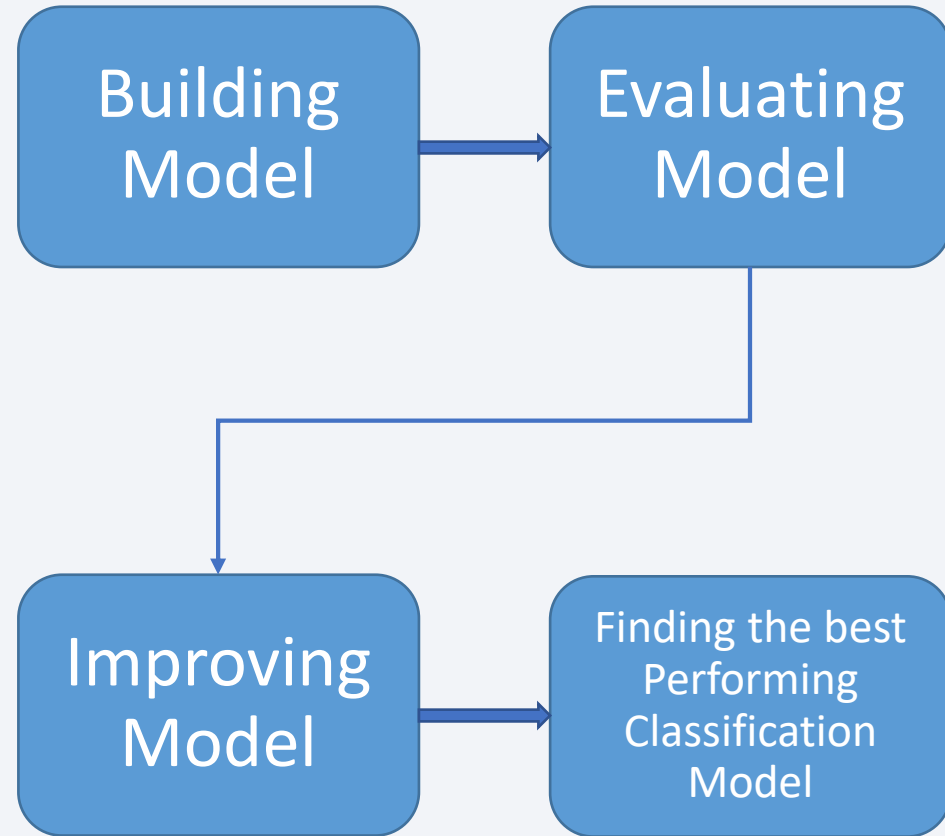
---

- The dashboard application contains a pie chart and a scatter point chart.
  - Pie chart :
    - For showing total success launches by sites
    - This chart can be selected to indicate a successful landing distribution across all launch sites or to indicate the success rate of individual launch sites.
  - Scatter chart :
    - For showing the relationship between Outcomes and Payload mass(Kg) by different boosters
    - Has 2 inputs: All sites/individual site & Payload mass on a slider between 0 and 10000 kg
    - This chart helps determine how success depends on the launch point, payload mass, and booster version categories.
- [GitHub URL](#)

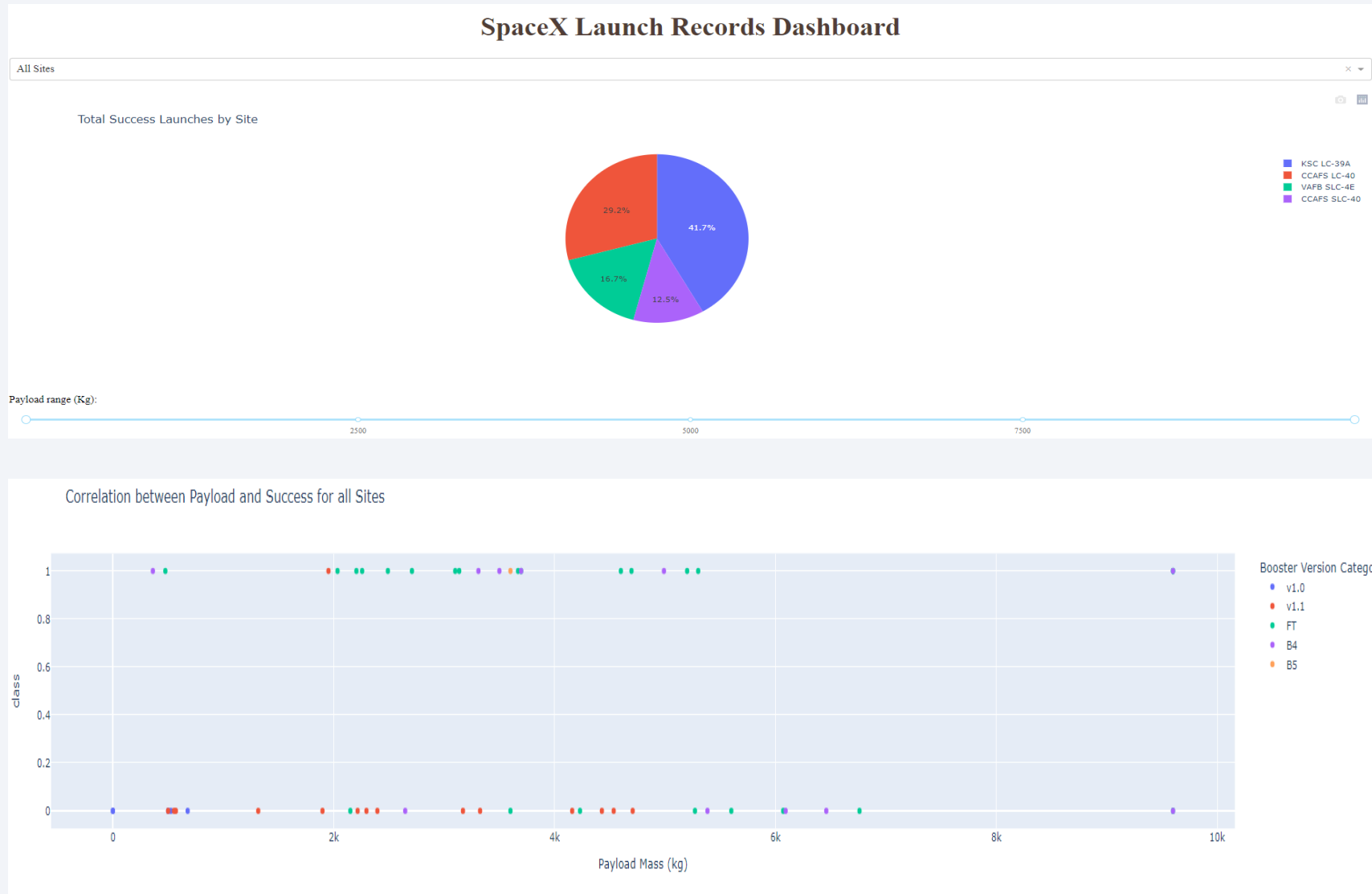
# Predictive Analysis (Classification)

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- Perform exploratory Data Analysis and determine Training Labels
  - Create a column for the class
  - Standardize the data
  - Split into training data and test data
- Find best Hyperparameter for SVM, Classification Trees and Logistic Regression
  - Find the method performs best using test data
- [GitHub URL](#)



# Results



- The left screenshot is a preview of the Dashboard with Plotly Dash.
- The results of EDA with visualization, EDA with SQL, Interactive Map with Folium, and Interactive Dashboard will be shown in the next slides.
- Comparing the accuracy of the four methods, all return the same accuracy of about 83% for test data.



The background of the slide is an abstract composition. It features a solid blue area on the left side, which transitions into a complex pattern of diagonal streaks and lines in shades of blue, red, and cyan on the right. These streaks have a textured, almost woven appearance, suggesting a digital or data-driven theme. The overall effect is dynamic and modern.

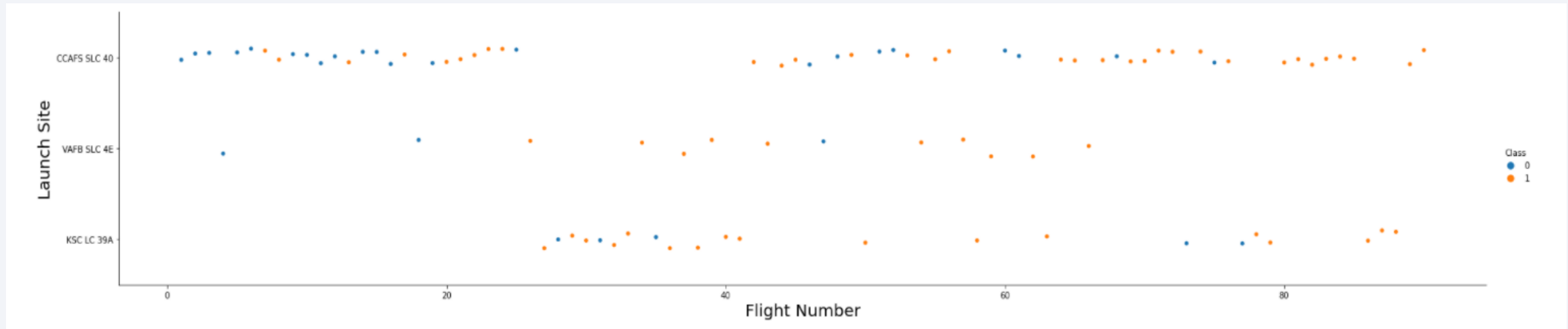
Section 2

# Insights drawn from EDA



# Flight Number vs. Launch Site

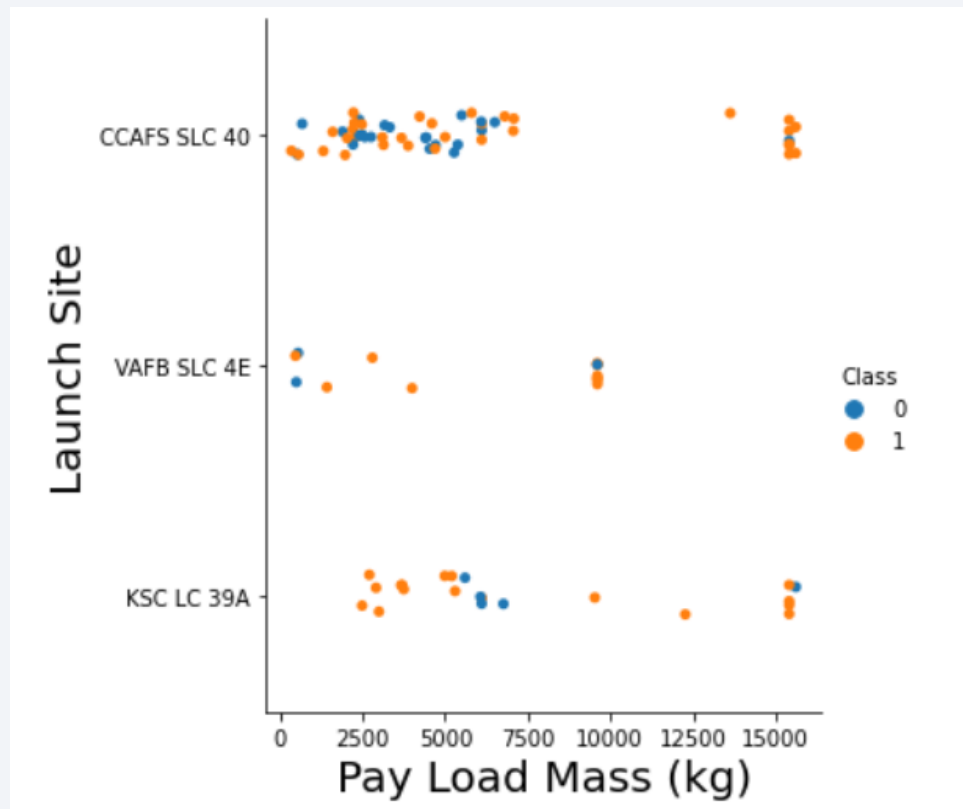
- Screenshot of the scatter plot with explanations



- Class 0 (blue) represents unsuccessful launch, and Class 1 (orange) represents successful launch.
- This figure shows that **the success rate increased as the number of flights increased.**
- As the success rate has increased considerably since the 20th flight, this point seems to be a big breakthrough.

# Payload vs. Launch Site

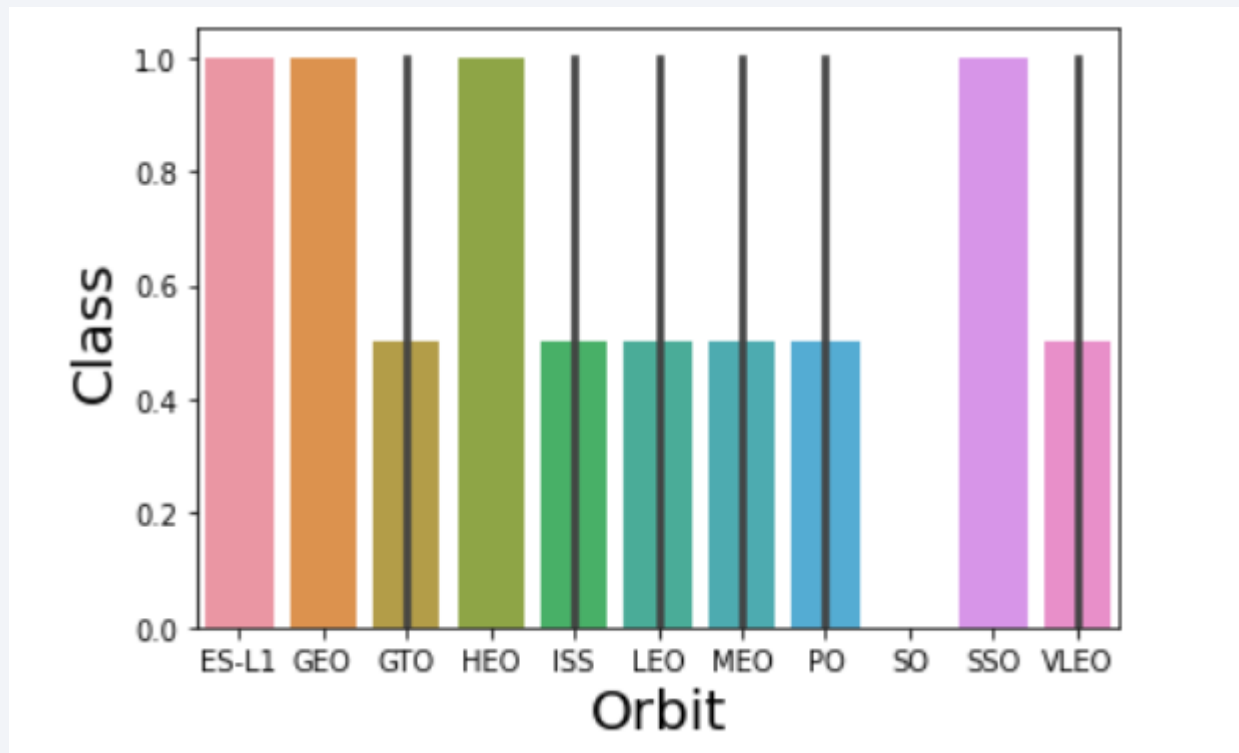
- Screenshot of the scatter plot with explanations



- Class 0 (blue) represents unsuccessful launch, and Class 1 (orange) represents successful launch.
- At first glance, the larger pay load mass, the higher the rocket's success rate, but it seems difficult to make decisions based on this figure because **no clear pattern can be found between successful launch and Pay Load Mass.**

# Success Rate vs. Orbit Type

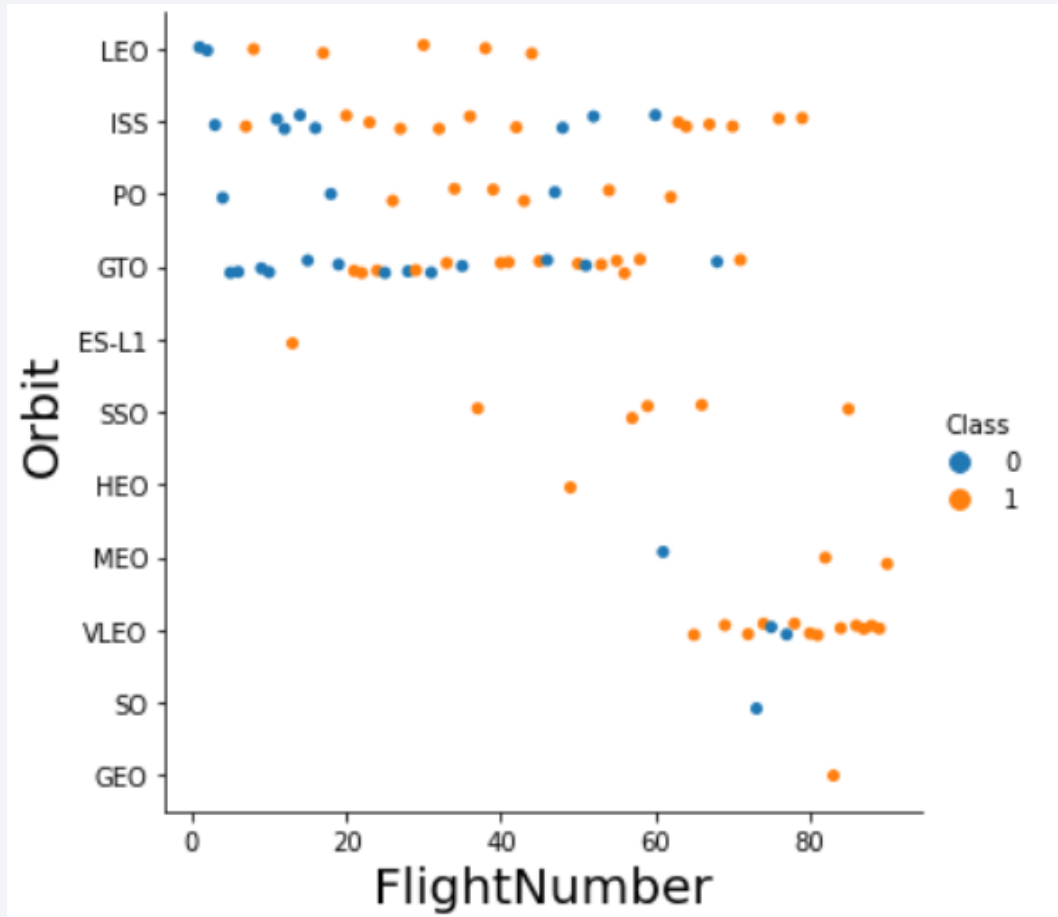
- Screenshot of the scatter plot with explanations :



- Orbit types SSO, HEO, GEO, and ES-L1 have the highest success rates (100%).
- On the other hand, the success rate of orbit type GTO is only 50%, and it is the lowest except for type SO, which recorded failure in a single attempt.

# Flight Number vs. Orbit Type

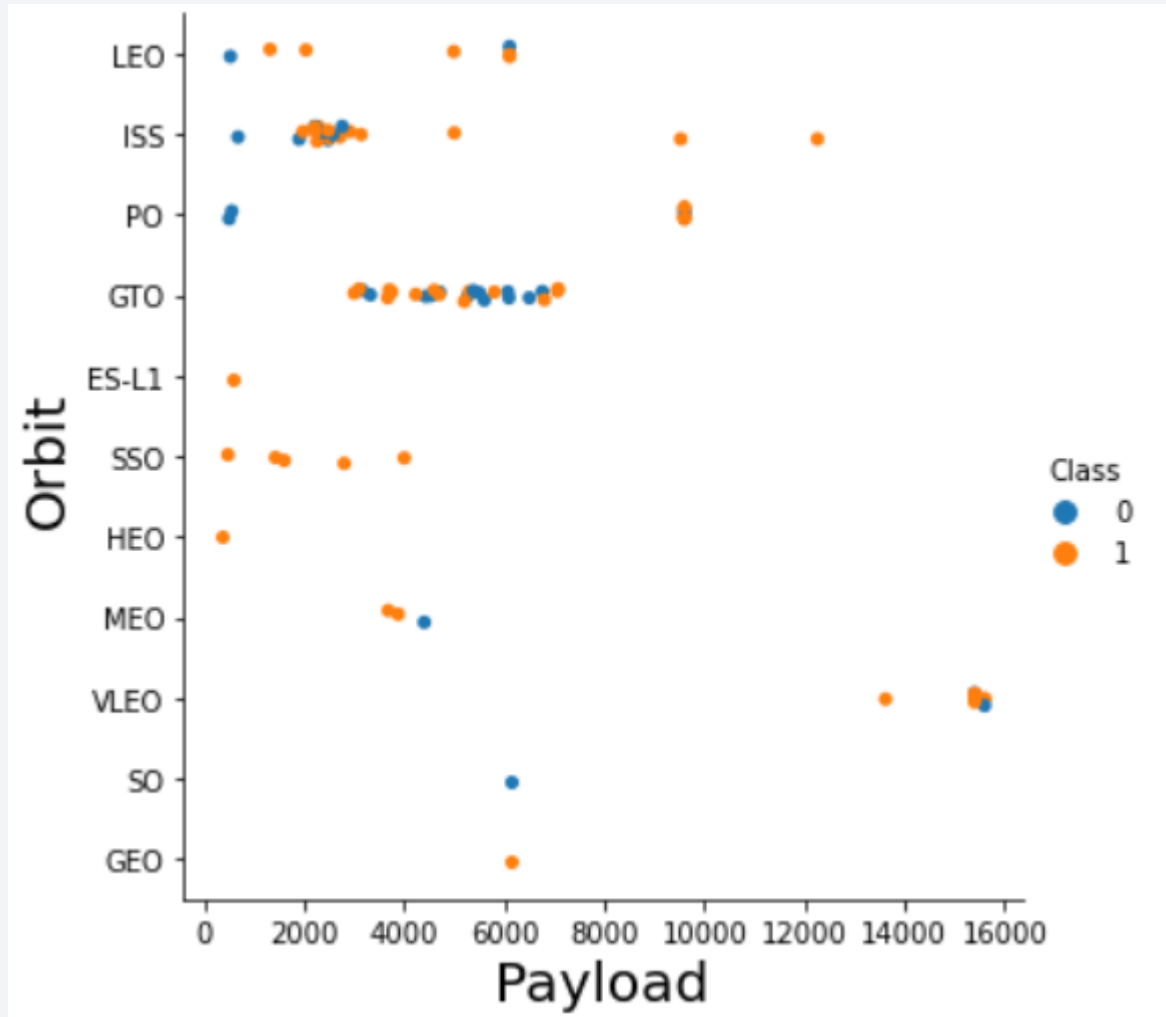
- Screenshot of the scatter plot with explanations :



- Class 0 (blue) represents unsuccessful launch, and Class 1 (orange) represents successful launch.
- In most cases, the launch outcome seems to be correlated with the flight number.
- On the other hand, in **GTO** orbit, there seems to be **no** relationship between flight numbers and success rate.
- SpaceX starts with LEO with a moderate success rate, and it seems that VLEO, which has a high success rate, is used the most in recent launches.

# Payload vs. Orbit Type

- Screenshot of the scatter plot with explanations :



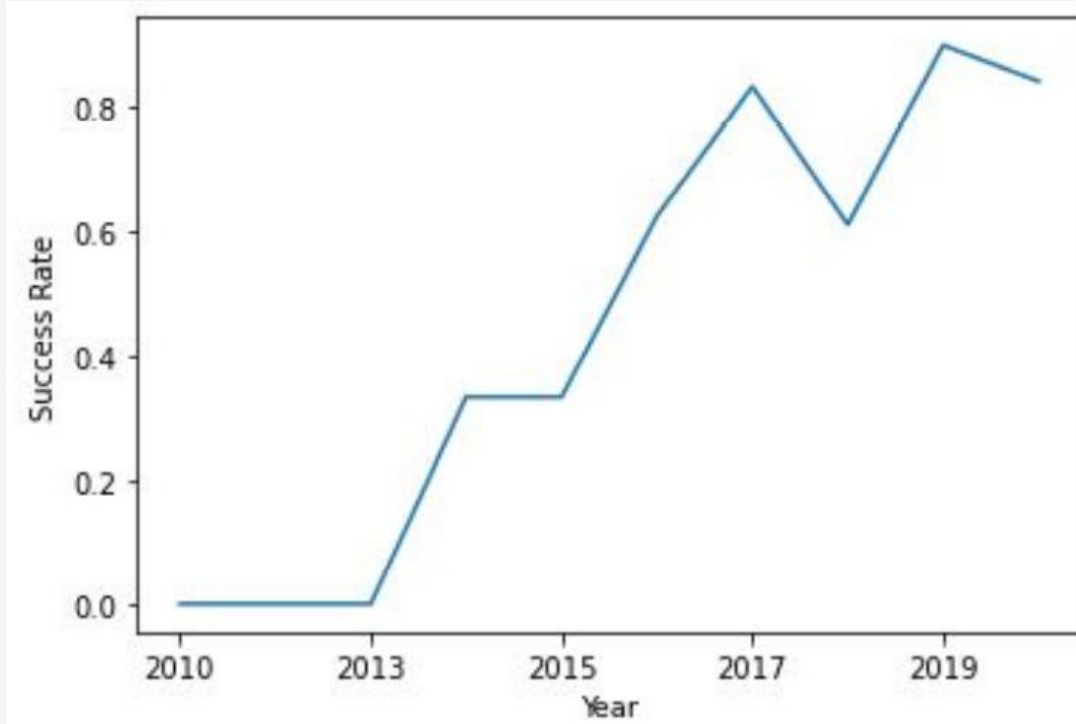
- Class 0 (blue) represents unsuccessful launch, and Class 1 (orange) represents successful launch.
- With heavy payloads the successful landing or positive landing rate are more for LEO and ISS.
- However, in the case of GTO, it is hard to distinguish between the positive landing rate and the negative landing because they are all gathered together



# Launch Success Yearly Trend

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- Screenshot of the scatter plot with explanations



- Since 2013, the success rate has continued to increase until 2017.
- The rate decreased slightly in 2018.
- Recently, it has shown a success rate of about 80%

# All Launch Site Names

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- Find the names of the unique launch sites (Query):

```
1 SELECT DISTINCT LAUNCH_SITE
2 FROM SPACEXTBL
```

- Result :

✓ SELECT DISTINCT LAUNCH_SITE FROM SPACEXTBL	
Result set 1	
LAUNCH_SITE	
CCAFS LC-40	
CCAFS SLC-40	
KSC LC-39A	
VAFB SLC-4E	

- When the SQL DISTINCT clause is used in the query, only unique values are displayed in the Launch\_Site column from the SpaceX table.
- There are four unique launch sites: CCAFS LC-40, CCAFS SLC-40, KSC LC-39A, VAFB SLC-4E

# Launch Site Names Begin with 'CCA'

- Find 5 records where launch sites begin with 'CCA' (Query)

```
select * from SPACEXTBL where LAUNCH_SITE like 'CCA%' limit 5
```

- Result :

✓ select \* from SPACEXTBL where LAUNCH\_SITE like 'CCA%' limit 5 Run time: 0.023 s

Result set 1				
DATE	TIME__UTC_	BOOSTER_VERSION	LAUNCH_SITE	PAYLOAD
2010-06-04	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Que
2010-12-08	15:43:00	F9 v1.0 B0004	CCAFS LC-40	Dragon demo flight C1.
2012-05-22	07:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2
2012-10-08	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1
2013-03-01	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2

- Only five records of the SpaceX table were displayed using LIMIT 5 clause in the query.
- Using the LIKE operator and the percent sign (%) together, the Launch\_Site name starting with CAA could be called

# Total Payload Mass

- Calculate the total payload carried by boosters from NASA (Query) :

```
SELECT SUM(PAYLOAD_MASS__KG_)
AS total_payload_mass_kg
FROM SPACEXTBL
WHERE CUSTOMER = 'NASA (CRS)'
```

```
SELECT SUM(PAYLOAD_MASS__KG_) AS
total_payload_mass_kg FROM SPACEXTBL
WHERE CUSTOMER = 'NASA (CRS)'
```

- Result :-

✓ SELECT SUM(PAYLOAD_MASS__KG_) AS total_payload_mass_kg FROM ...	
Result set 1	
TOTAL_PAYLOAD_MASS_KG	
45596	

- Using the SUM() function to calculate the sum of column PAYLOAD\_MASS\_\_KG
- 
- In the WHERE clause, filter the dataset to perform calculations only if Customer is NASA (CRS)

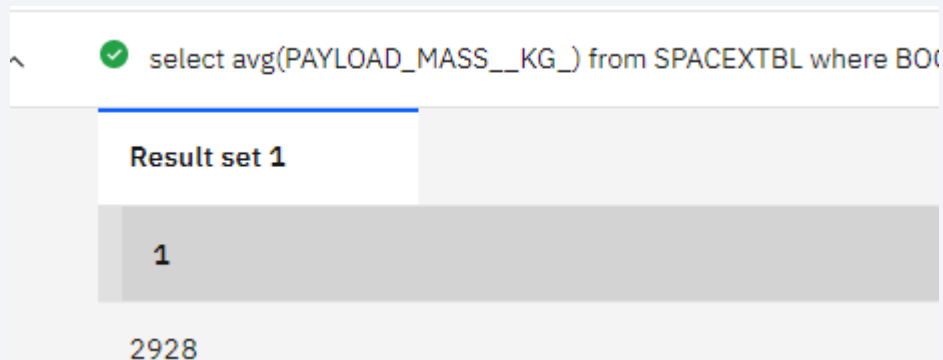
# Average Payload Mass by F9 v1.1

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

```
1 select avg(PAYLOAD_MASS__KG_)
2 from SPACEXTBL
3 where BOOSTER_VERSION = 'F9 v1.1'
```

```
select avg(PAYLOAD_MASS__KG_)
  from SPACEXTBL
 where BOOSTER_VERSION = 'F9 v1.1'
```

- Result :-



The screenshot shows a SQL query execution interface. At the top, a green checkmark indicates the query was successful. The query text is: `select avg(PAYLOAD_MASS__KG_) from SPACEXTBL where BOOSTER_VERSION = 'F9 v1.1'`. Below the query, a table titled "Result set 1" is displayed. The table has one column and one row. The value in the single row is 2928.

1
2928

- Using the AVG() function to calculate the average value of column PAYLOAD\_MASS\_\_KG\_.
- In the WHERE clause, filter the dataset to perform calculations only if Booster\_version is F9 v1.1



# First Successful Ground Landing Date

- Find the dates of the first successful landing outcome on ground pad (Query)

```
select min(DATE)
  from SPACEXTBL
 where Landing__Outcome = 'Success (ground pad)'
```

```
1 select min(DATE)
2   from SPACEXTBL
3  where Landing__Outcome = 'Success (ground pad)'
```

- Result :

✓ select min(DATE) from SPACEXTBL where Landing__Outcome = 'Success...	
Result set 1	
1	
2015-12-22	

- Using the MIN() function to find out the earliest date in the column DATE.
- In the WHERE clause, filter the dataset to perform a search only if Landing\_\_outcome is Success (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 (Query)

```
select BOOSTER_VERSION from SPACEXTBL
where Landing__Outcome = 'Success (drone ship)'
and PAYLOAD_MASS__KG_ > 4000 and PAYLOAD_MASS__KG_ < 6000
```

```
select BOOSTER_VERSION
from SPACEXTBL
where Landing__Outcome = 'Success (drone ship)'
and PAYLOAD_MASS__KG_ > 4000 and PAYLOAD_MASS__KG_ < 6000
```

- Report :

✓ select BOOSTER_VERSION from SPACEXTBL where Landin	
Result set 1	
BOOSTER_VERSION	
F9 FT B1022	
F9 FT B1026	
F9 FT B1021.2	
F9 FT B1031.2	

- In the WHERE clause, filter the dataset to perform a search if Landing\_\_outcome is Success (drone ship).
- Using the AND operator to display a record if additional condition PAYLOAD\_MASS\_\_KG\_ is between 4000 and 6000

# Total Number of Successful and Failure Mission Outcomes

- Calculate the total number of successful and failure mission outcomes (Query)

```
SELECT MISSION_OUTCOME, COUNT(*) AS total_number  
FROM SPACEXTBL GROUP BY MISSION_OUTCOME
```

```
SELECT MISSION_OUTCOME,  
COUNT(*) AS total_number  
FROM SPACEXTBL  
GROUP BY MISSION_OUTCOME
```

- Result :

SELECT MISSION_OUTCOME, COUNT(*) AS total_number FROM SPACEX...	
Result set 1	
MISSION_OUTCOME	TOTAL_NUMBER
Failure (in flight)	1
Success	99
Success (payload status unclear)	1

- Using the COUNT() function to calculate the total number of columns.
- Using the GROUP BY statement, groups rows that have the same values into summary rows to find the total number in each Mission\_outcome.
- According to the result, SpaceX seems to have successfully completed nearly 99% of its missions.

# Boosters Carried Maximum Payload

- List the names of the booster which have carried the maximum payload mass(Query)

```
select BOOSTER_VERSION
      from SPACEXTBL
     where PAYLOAD_MASS__KG_ = (select
max(PAYLOAD_MASS__KG_) from SPACEXTBL)
```

```
select BOOSTER_VERSION
      from SPACEXTBL
     where PAYLOAD_MASS__KG_ = (select max(PAYLOAD_MASS__KG_) from SPACEXTBL)
```

- Using a subquery, first, find the maximum value of the payload by using MAX() function, and second, filter the dataset to perform a search if PAYLOAD\_MASS\_\_KG\_ is the maximum value of the payload.
- According to the result, version F9 B5 B10xx.x boosters could carried the maximum payload

- Result:

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

# 2015 Launch Records

- List the failed landing\_outcomes in drone ship, their booster versions, and launch site names for in year 2015(Query)

```
SELECT  
LANDING__OUTCOME,BOOSTER_VERSION,LAUNCH_SITE  
FROM SPACEXTBL WHERE LANDING__OUTCOME =  
'Failure (drone ship)' AND YEAR(DATE) = '2015'
```

```
1 SELECT LANDING__OUTCOME,  
2     BOOSTER_VERSION,  
3     LAUNCH_SITE  
4  
5 FROM SPACEXTBL  
6 WHERE LANDING__OUTCOME = 'Failure (drone ship)'  
7     AND YEAR(DATE) = '2015'
```

- Result :

Result set 1			Find		
LANDING__OUTCOME	BOOSTER_VERSION	LAUNCH_SITE			
Failure (drone ship)	F9 v1.1 B1012	CCAFS LC-40			
Failure (drone ship)	F9 v1.1 B1015	CCAFS LC-40			

- In the WHERE clause, filter the dataset to perform a search if Landing\_\_outcome is Failure (drone ship).
  - Using the AND operator to display a record if additional condition YEAR is 2015.
- In 2015, there were two landing failures on drone ships

# 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(Query)

```
SELECT LANDING__OUTCOME,  
COUNT(LANDING__OUTCOME) AS total_number FROM  
SPACEXTBL WHERE DATE BETWEEN '2010-06-04' AND '2017-  
03-20' GROUP BY LANDING__OUTCOME ORDER BY  
total_number DESC
```

```
SELECT LANDING__OUTCOME,  
COUNT(LANDING__OUTCOME) AS total_number  
FROM SPACEXTBL  
WHERE DATE BETWEEN '2010-06-04' AND '2017-03-20'  
GROUP BY LANDING__OUTCOME  
ORDER BY total_number DESC
```

- In the WHERE clause, filter the dataset to perform a search if the date is between 2010-06-04 and 2017-03-20.
- Using the ORDER BY keyword to sort the records by total number of landing, and using DESC keyword to sort the records in descending order.
- According to the results, the number of successes and failures between 2010-06-04 and 2017-03-20 was similar

- Report :

Result set 1	
LANDING__OUTCOME	TOTAL_NUMBER
No attempt	10
Failure (drone ship)	5
Success (drone ship)	5
Controlled (ocean)	3
Success (ground pad)	3

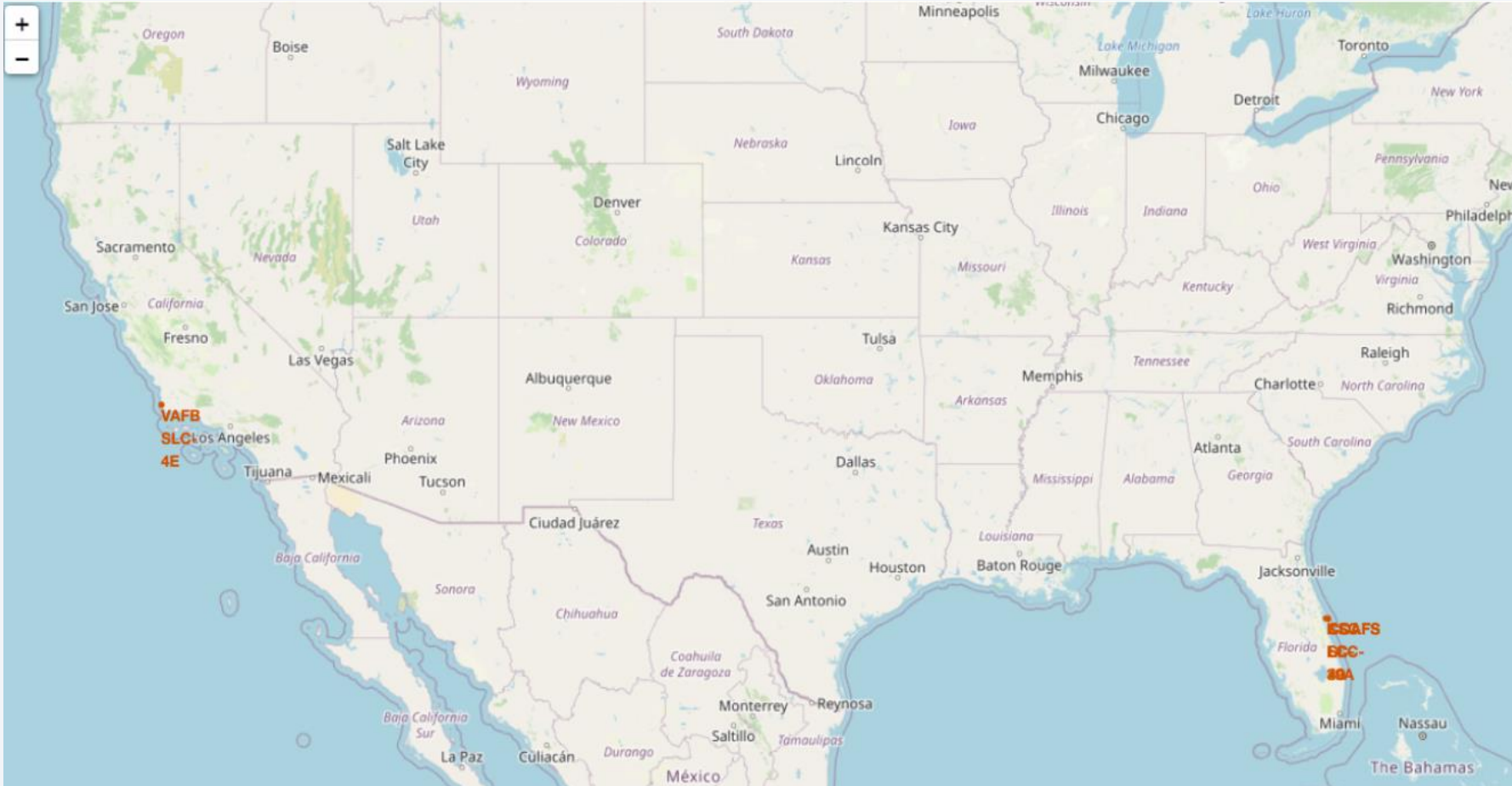
A satellite view of Earth from space, showing the curvature of the planet and city lights at night. The background is a deep blue gradient.

Section 3

# Launch Sites Proximities Analysis



# All Launch Sites' Locations



- The left map shows all SpaceX launch sites, and the right map also shows that all launch sites are in the United States.
- As can be seen on the map, all launch sites are near the coast

# Color-labeled Launch Outcomes



- By clicking on the marker clusters, successful landing (green) or failed landing (red) are displayed



# Proximities of Launch Sites



A railway map symbol may look like this:



A highway map symbol may look like this:



A city map symbol may look like this:



- It can be found that the launch site is close to railways and highways for transportation of equipment or personnel, and is also close to coastline and relatively far from the cities so that launch failure does not pose a threat



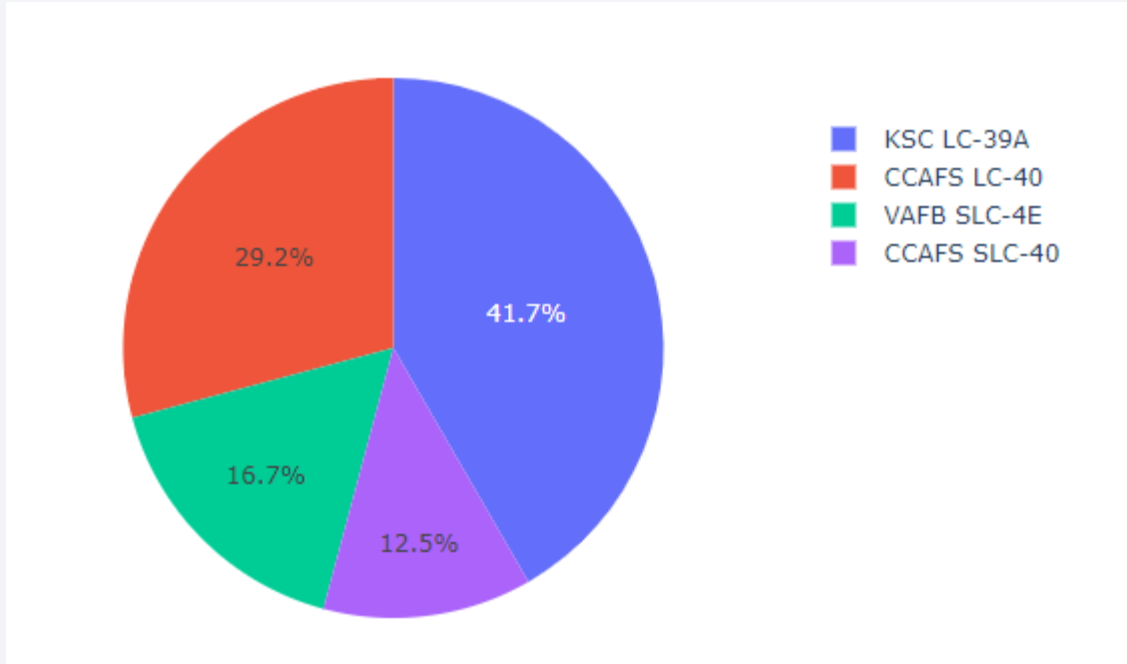


Section 4

# Build a Dashboard with Plotly Dash

# Total Success Launches By all sites

---

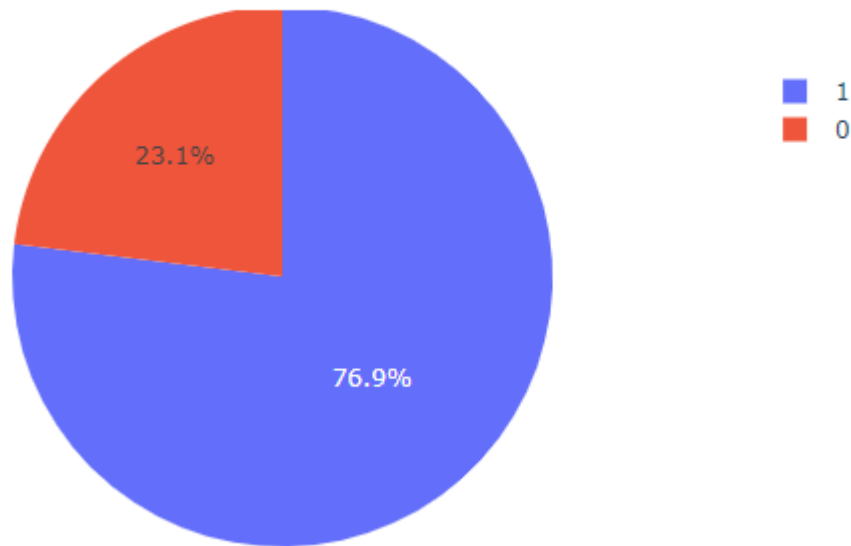


- KSLC-39A records the most launch success among all sites.
- The VAFB SLC-4E has the fewest launch success, possibly because
  - the data sample is small, or
  - because it is the only site located in California, so the launch difficulty on the west coast may be higher than on the east coast.

# Launch Site with Highest Launch Success Ratio

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Total Success Launches for KSC LC-39A



- KSLC-39A has the highest success rate with 10 landing successes (76.9%) and 3 landing failures (23.1%).

# Payload vs. Launch Outcome Scatter Plot for all sites



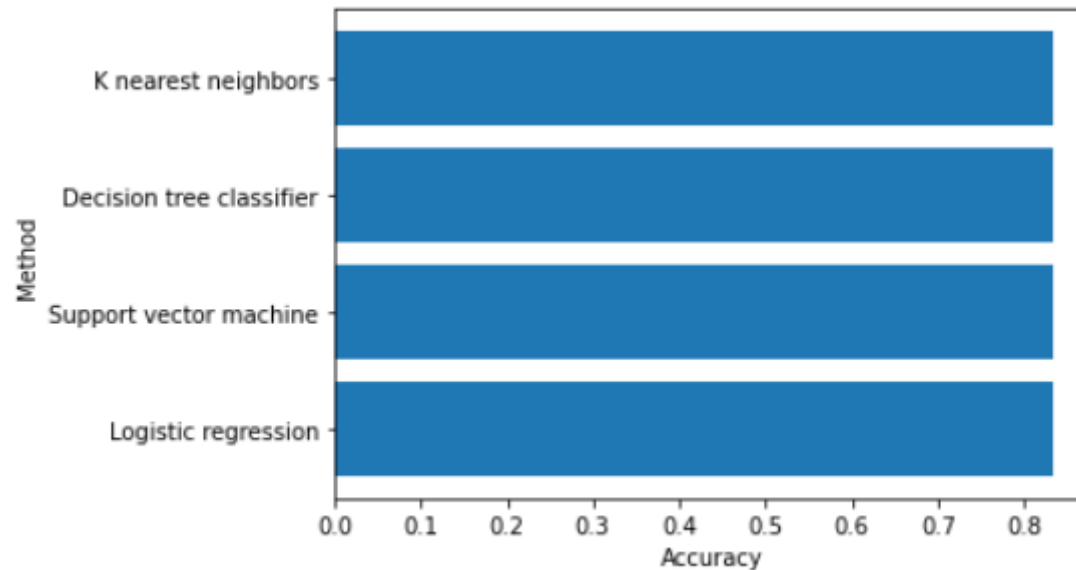
- These figures show that the launch success rate (class 1) for low weighted payloads(0-5000 kg) is higher than that of heavy weighted payloads(5000-10000 kg).



Section 5

# Predictive Analysis (Classification)

# Classification Accuracy

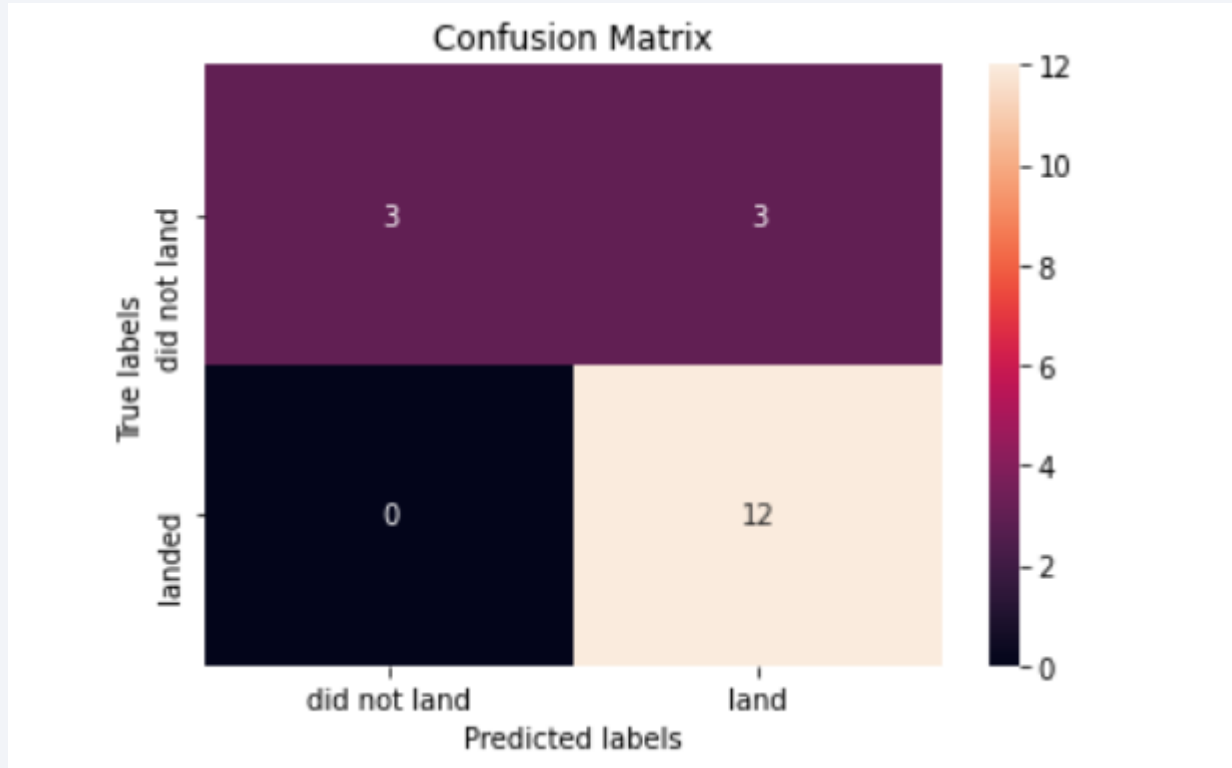


```
print("test set accuracy :",logreg_cv.score(X_test, Y_test))
```

```
test set accuracy : 0.8333333333333334
```

- In the test set, the accuracy of all models was virtually the same at 83.33%.
- It should be noted that the test size was small at 18.
- Therefore, more data is needed to determine the optimal model

# Confusion Matrix



- The confusion matrix is the same for all models because all models performed the same for the test set.
- The models predicted 12 successful landings when the true label was successful and 3 failed landings when the true label was failure. But there were also 3 predictions that said successful landings when the true label was failure (false positive).
- Overall, these models predict successful landings.

# Conclusions

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- Point 1 : As the number of flights increased, the success rate increased, and recently it has exceeded 80%.
- Point 2 : Orbital types SSO, HEO, GEO, and ES-L1 have the highest success rate (100%).
- Point 3 : The launch site is close to railways, highways, and coastline, but far from cities.
- Point 4 : KSLC-39A has the highest number of launch successes and the highest success rate among all sites.
- Point 5 : The launch success rate of low weighted payloads is higher than that of heavy weighted payloads.
- Point 6 : In this dataset, all models have the same accuracy (83.33%), but it seems that more data is needed to determine the optimal model due to the small data size.

# Appendix

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- [GitHub Link](#)
- [IBM Cloud Notebooks](#)



Thank you!

