IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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Outline

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- Results
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Executive Summary

Summary of methodologies:

- In this project, we present data collected from SpaceX and Wikipedia.
- We explored the data using Exploratory Data Analysis EDA using Python and SQL.
- Visualisation maps (Folium) and Dashboards were also generated to show relevant information as regards successful landings.
- Machine Learning models (Logistic Regression, Support Vector Machine, Decision Tree Classifier and K Nearest Neighbours) were also deployed to model the dataset.

Introduction

Project background and context

- The launching of a SpaceX Falcon 9 rockets cost approx. $62m
- This is way cheaper compared to other providers (Cost approx. $165m)
- The difference is price is because SpaceX rockets can land, and be re-used again.
- If we can determine if the first stage will land, we can determine the cost of the launch.
- This information will guide us if our new company Space Y should compete in the Space travel sector

Section 1

Methodology

Methodology

Executive Summary

- Data collection methodology:
  - Data was collected by using GET requests from SpaceX REST API
  - Web scraping from Wikipedia's page
- Perform data wrangling
  - Calculating number of launches and missions using the .value_counts() method
- 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

- Describe how data sets were collected.
- You need to present your data collection process use key phrases and flowcharts

Data Collection – SpaceX API

Step 1
Make GET requests from SpaceX REST API

```
spacex_url="https://api.spacexdata.com/v4/launches/past"
```

```
response = requests.get(spacex_url)
```

Convert the response to a .json file and use pandas to generate the data frame.

```
# Use json_normalize meethod to convert the json result into a dataframe

data = pd.json_normalize(response.json())
```

Step 3
Create Pandas Dataframe

```
# Create a data from launch_dict

data2 = pd.DataFrame(launch_dict)
```

Step 2
Clean Data

```
# We also want to convert the date_utc to a datetime datatype and then extracting the date leaving the time
data['date'] = pd.to_datetime(data['date_utc']).dt.date

# Using the date we will restrict the dates of the launches
data = data[data['date'] <= datetime.date(2020, 11, 13)]
```

Create Lists

Call Functions

Convert the response to a .json file

```
#Global variables
BoosterVersion = []
PayloadMass = []
Orbit = []
LaunchSite = []
Outcome = []
Flights = []
GridFins = []
Reused = []
Legs = []
LandingPad = []
Block = []
ReusedCount = []
Serial = []
Longitude = []
Latitude = []
```

Step 4
Filter Data in the dataframe, Replace missing values

```
# Replace the np.nan values with its mean value

temp = data_falcon9['PayloadMass'].replace(np.nan, pm_mean)
data_falcon9['PayloadMass'] = temp
data_falcon9
```

Data Collection - Scraping

Step 1
Request HTML page

```
static_url = "https://en.wikipedia.org/w/index.php?title=List_of_Falcon_9_and_Falcon_Heavy_launches&oldid=1027686922"
```

Assign response to an object

```
# assign the response to a object

page = requests.get(static_url)
```

Step 2
Create BeautifulSoup object

```
soup = BeautifulSoup(page.text, 'html.parser')
```

Fill all the table in the HTML Page

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

Step 3
Extract Column Names from tables in HTML Page

```
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() to get a column name
# Append the Non-empty column name (`if name is not None and len(name) > 0`) into a list called column_names

for i in first_launch_table.find_all('th'):
    if extract_column_from_header(i)!=None:
        if len(extract_column_from_header(i))>0:
            column_names.append(extract_column_from_header(i))
```

Step 4
Use column names as keys in dictionaries
Convert to Pandas

```
launch_dict= dict.fromkeys(column_names)

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

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

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

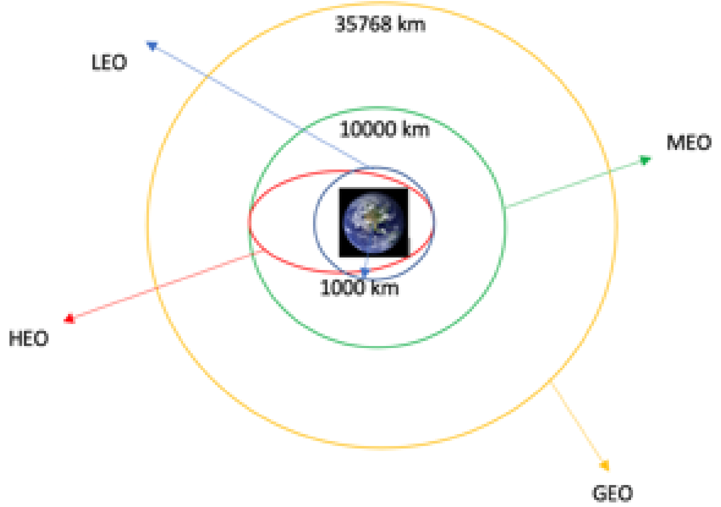
Data Wrangling

- The dataset contains several SpaceX launch facilities and each location is in the LaunchSite column.

```
# 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
```



- Initial Data Exploration [No of Launches, Occurrence of each Orbit, Landing outcome p

```
# Apply value_counts on Orbit column

df["Orbit"].value_counts()
```

```
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
```

```
# landing_outcomes = values on Outcome column

landing_outcomes = df["Outcome"].value_counts()
landing_outcomes
```

```
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
```

EDA with Data Visualization

- Exploratory Data Analysis was performed on certain variables and displayed using various tools

<u>SCATTER PLOTS</u>

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

<u>BAR CHARTS</u>

- Success Rate vs Orbit Type

<u>LINE CHARTS</u>

- Success Rate vs Year

**This analysis were used to compare relationships between different variables in the dataset

EDA with SQL

- Loading the Dataset using the IBM DB2 Database
- Query the Data using Python
- Performed different queries (10) to understand the dataset better
- Queries included [Displaying: names of unique launch sites, average payload mass carried by booster version etc……]

Build an Interactive Map with Folium

FOLIUM

- Visualising the Data on Folium was done in the following steps
  - Marking all the launch sites on a map
  - Marking successful and unsuccessful landing on the map
  - Calculating distance from launch sites to key locations (E.g. Railway, Highway and City)

Build a Dashboard with Plotly Dash

- Creating an interactive dashboard with Pie charts and Scatter Plots/Graphs
- Pie chart
  - Used to show distribution of successful launches across all launch sites
  - Shows success/failure ratio for each individual site
- Scatter plot
  - Shows us how success varies across different launch sites, payload mass and booster version

Predictive Analysis (Classification)

Model Development → **Model Evaluation** → **Best Fit Classification**

Steps for model development:

- Loading dataset
- Performing necessary data transformations (standardise and pre-process)
- Split data into training and test data sets, using train_test_split()
- Decide which type of machine learning algorithms are most appropriate
- Creating a GridSearchCV (Logreg, SVM, Decision Tree and KNN Model)
- Fitting the object to the parameters
- Using the training data set to train the model

- Plotting and examining the Confusion matrix
- Checking accuracy
- Checking tuned hyperparameters

- Review Accuracy Score
- Check which accuracy score is the highest to determine the best performing model

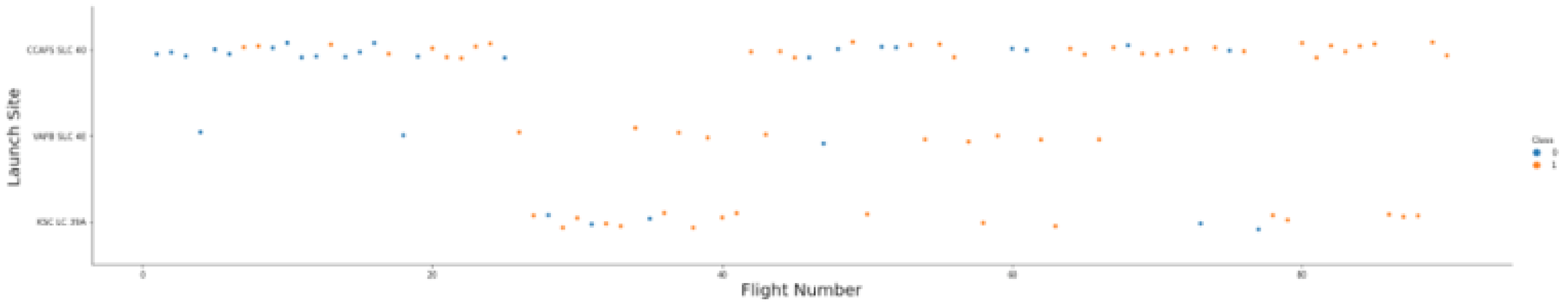
Results

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

Section 2

Insights drawn from EDA

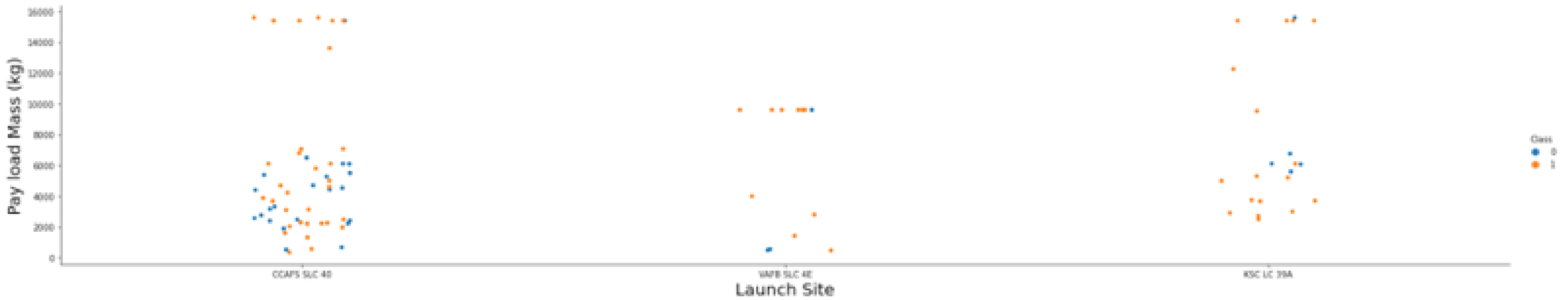
Flight Number vs. Launch Site



The scatter plot of Launch Site vs. Flight Number shows that:

- Increase in success rate at launch site.
- Most of the early flights that were launched from CCAFS SLC 40 were generally unsuccessful.
- Flights launched from KSC LC 39A were successful.

Payload vs. Launch Site



The scatter plot of Payload mass vs Launch Site shows that:

- Payload mass above 7000 kg have some successful landing, but little data for this launches
- There is no correlation between payload mass and success rate for launch sites

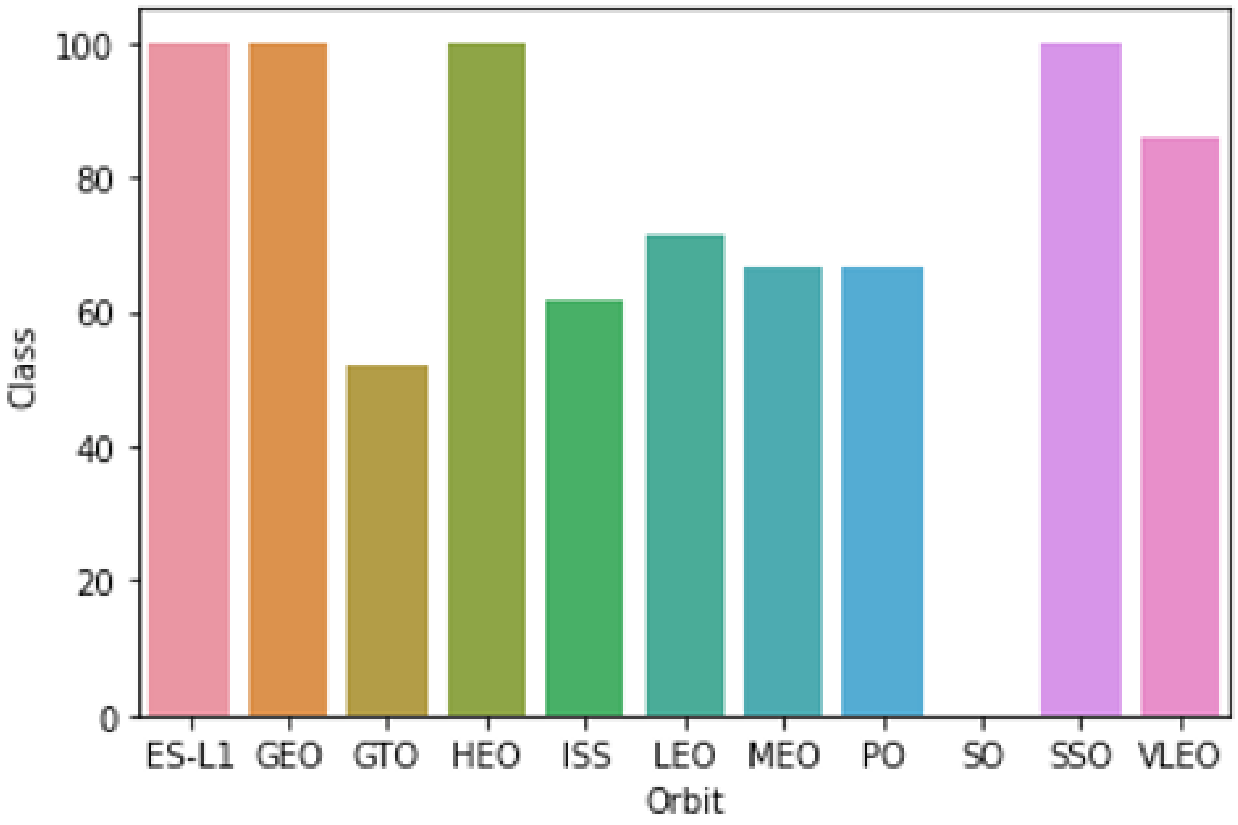
Success Rate vs. Orbit Type

- Orbits with 100% success rate

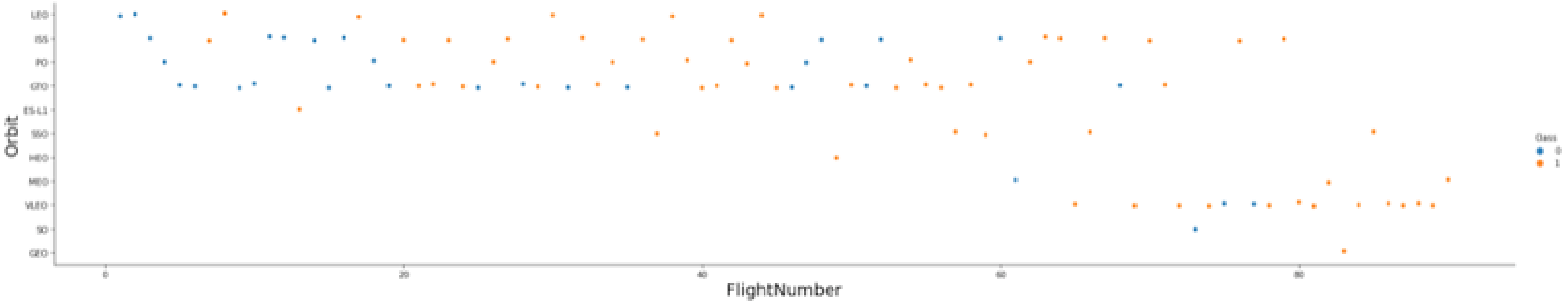
ES-L1 (Earth-Sun First Lagrangian Point),
GEO (Geostationary Orbit),
HEO (High Earth Orbit),
SSO (Sun-synchronous Orbit)

- Orbits with 0% success rate

SO (Heliocentric Orbit)



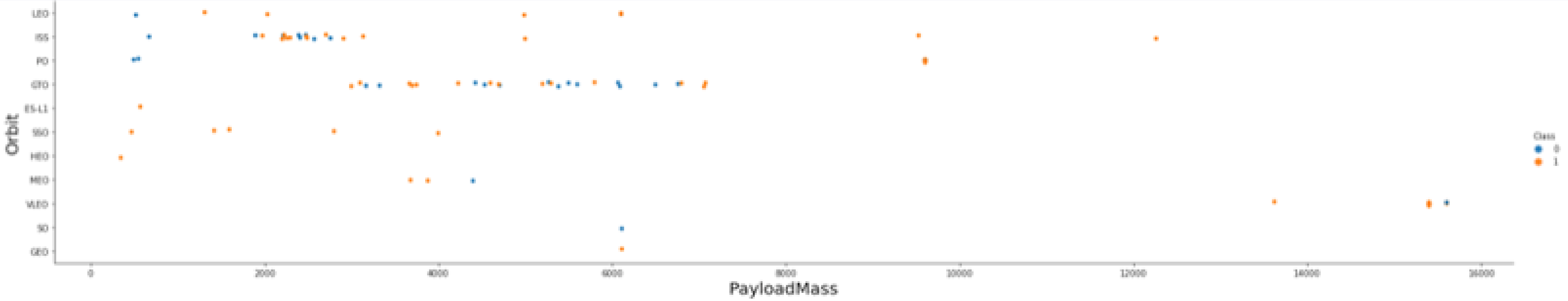
Flight Number vs. Orbit Type



The scatter plot of Orbit Type vs Flight Number shows that:

- The 100% success rate of GEO, HEO, and ES-L1 orbits can be explained by only having 1 flight into the respective orbits.
- Success rate in SSO is more impressive, with 5 successful flights.

Payload vs. Orbit Type

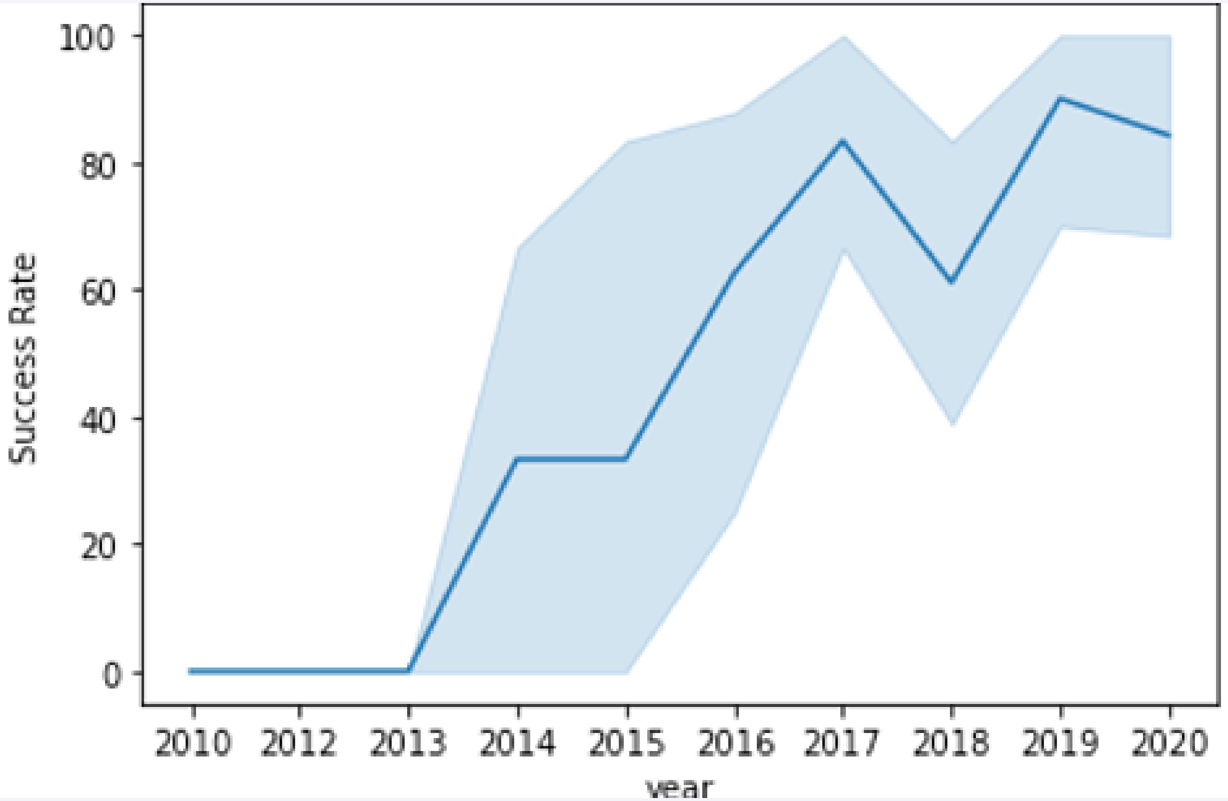


The scatter plot of Orbit Type vs Payload Mass shows that:

- Orbits types (PO, ISS and LEO) have more success with heavy payloads
- Relationship between payload mass and success rate in GTO is unclear.
- VLEO (Very Low Earth Orbit) launches are associated with heavier payloads.

Launch Success Yearly Trend

Between 2010 - 2013, all landings were unsuccessful
After 2013, success rate for launches increased (minor dips in 2018 and 2020)



All Launch Site Names

```
%sql SELECT UNIQUE(LAUNCH_SITE) FROM SPACEXTBL;
```

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

Launch Site Names Begin with 'CCA'

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

launch_site
CCAFS LC-40
CCAFS LC-40
CCAFS LC-40
CCAFS LC-40
CCAFS LC-40

Total Payload Mass

```
%sql SELECT SUM(PAYLOAD_MASS__KG_) AS TOTAL_PAYLOAD_MASS FROM SPACEXTBL \ WHERE CUSTOMER = 'N
ASA (CRS)';
```

sum_payload_mass_kg
45596

Average Payload Mass by F9 v1.1

```
%sql select avg(payload_mass__kg_) as Average from SPACEXDATASET where booster_version like 'F
9 v1.1%'
```

avg_payload_mass_kg
2928

First Successful Ground Landing Date

```
%sql select min(date) as Date from SPACEXDATASET where mission_outcome like 'Success'
```

first_success
2015-12-22

Successful Drone Ship Landing with Payload between 4000 and 6000

```
%sql select booster_version from SPACEXDATASET where (mission_outcome like 'Success')
AND (payload_mass__kg_ BETWEEN 4000 AND 6000) AND (landing__outcome like 'Success (drone ship)
')
```

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

Total Number of Successful and Failure Mission Outcomes

```
%sql SELECT mission_outcome, count(*) as Count FROM SPACEXDATASET GROUP by mission_outcome ORD
ER BY mission_outcome
```

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

Boosters Carried Maximum Payload

```
maxm = %sql select max(payload_mass__kg_) from SPACEXDATASET
maxv = maxm[0][0]
%sql select booster_version from SPACEXDATASET where payload_mass__kg_=(select max(payload_mas
s__kg_) from SPACEXDATASET)
```

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

```
%sql select MONTHNAME(DATE) as Month, landing__outcome, booster_version, launch_site
from SPACEXDATASET where DATE like '2015%' AND landing__outcome like 'Failure (drone ship)'
```

MONTH	landing__outcome	booster_version	payload_mass__kg_	launch_site
January	Failure (drone ship)	F9 v1.1 B1012	2395	CCAFS LC-40
April	Failure (drone ship)	F9 v1.1 B1015	1898	CCAFS LC-40

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

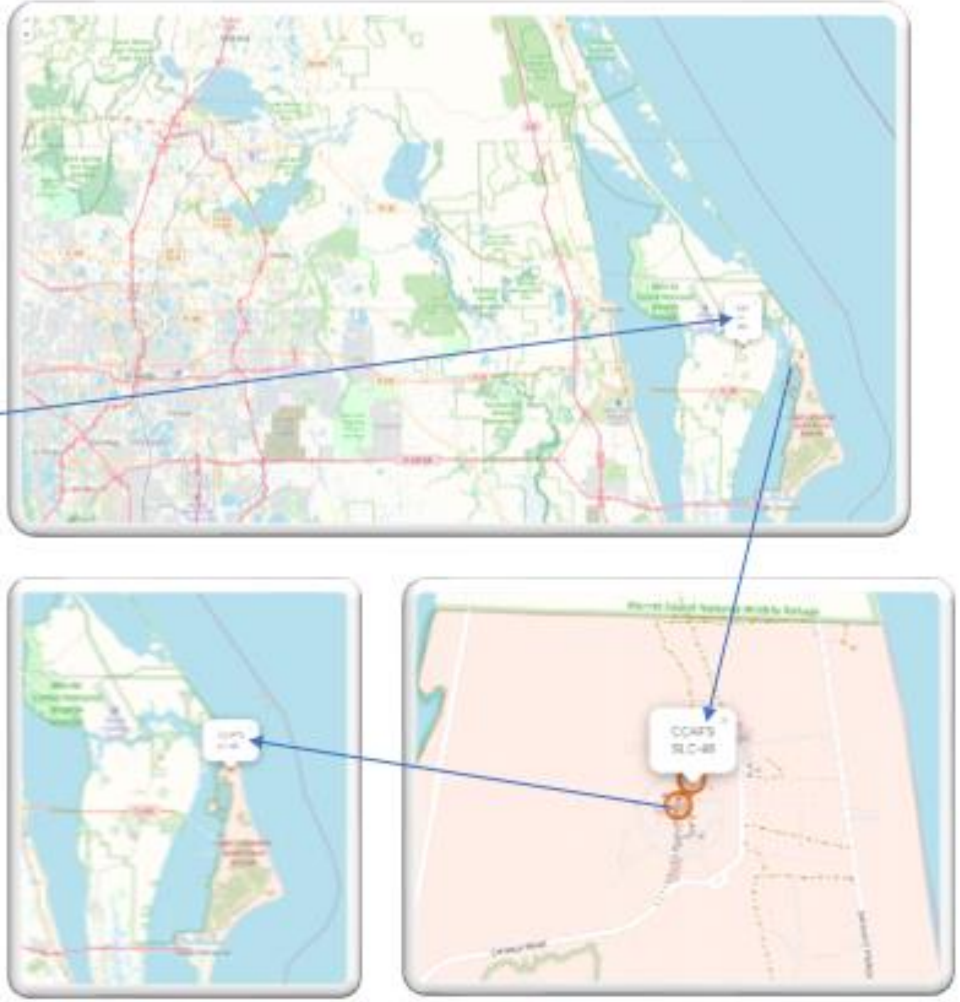
```
%sql select landing__outcome, count(*) as count from SPACEXDATASET
where Date >= '2010-06-04' AND Date <= '2017-03-20'
GROUP by landing__outcome ORDER BY count Desc
```

landing__outcome	no_outcome
Success (drone ship)	5
Success (ground pad)	3

Section 3

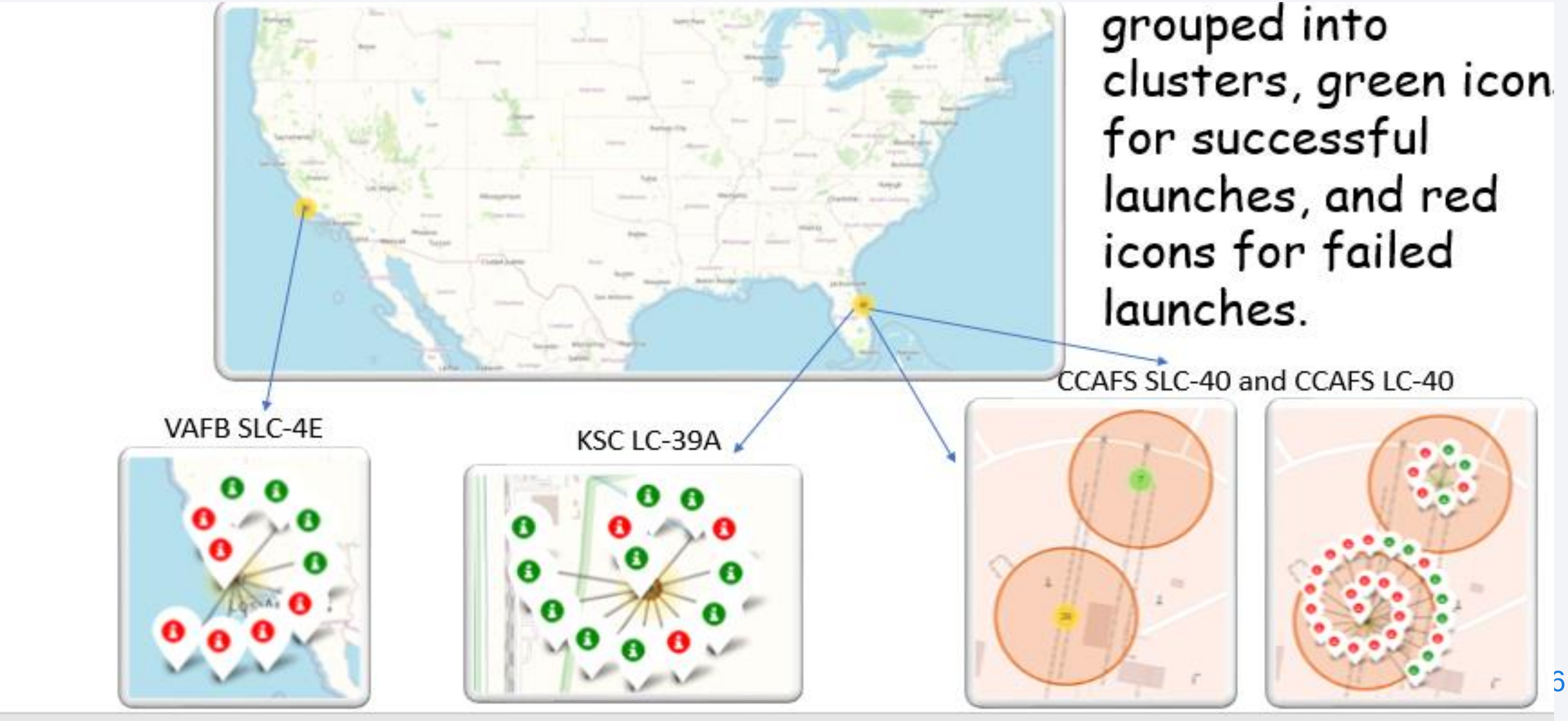
Launch Sites Proximities Analysis

Launch Site Locations



SpaceX launch sites are on coasts of the United States of America, specifically Florida and California.

Success and Failed Launches For Each Site



Location Proximities of Launch Sites to Key Locations

- Launch sites in close proximity to railways? YES.
- Launch sites in close proximity to highways? YES.

Nearest highway = 0.59km away.

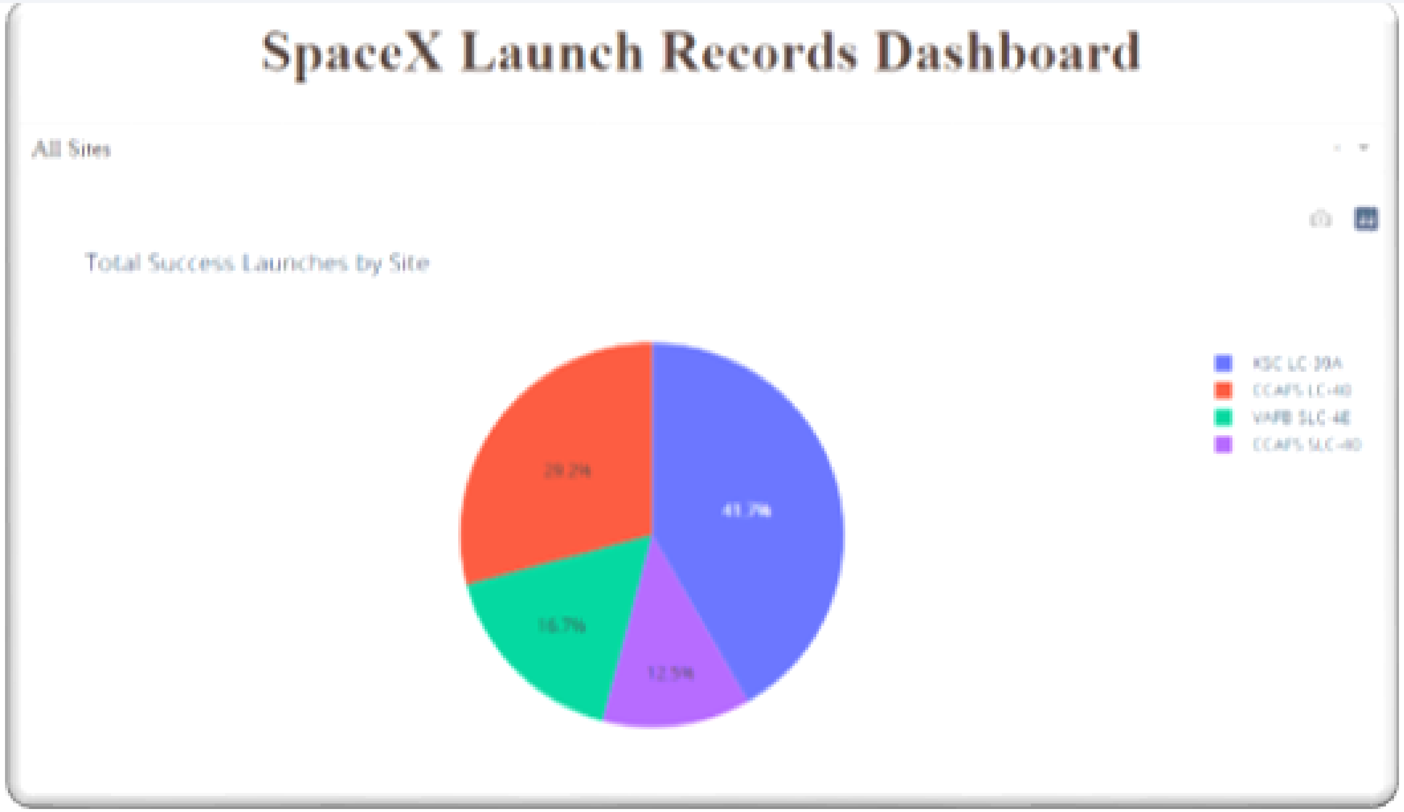
- Launch sites in close proximity to railways? YES.

Nearest railway = 1.29 km away.

Section 4

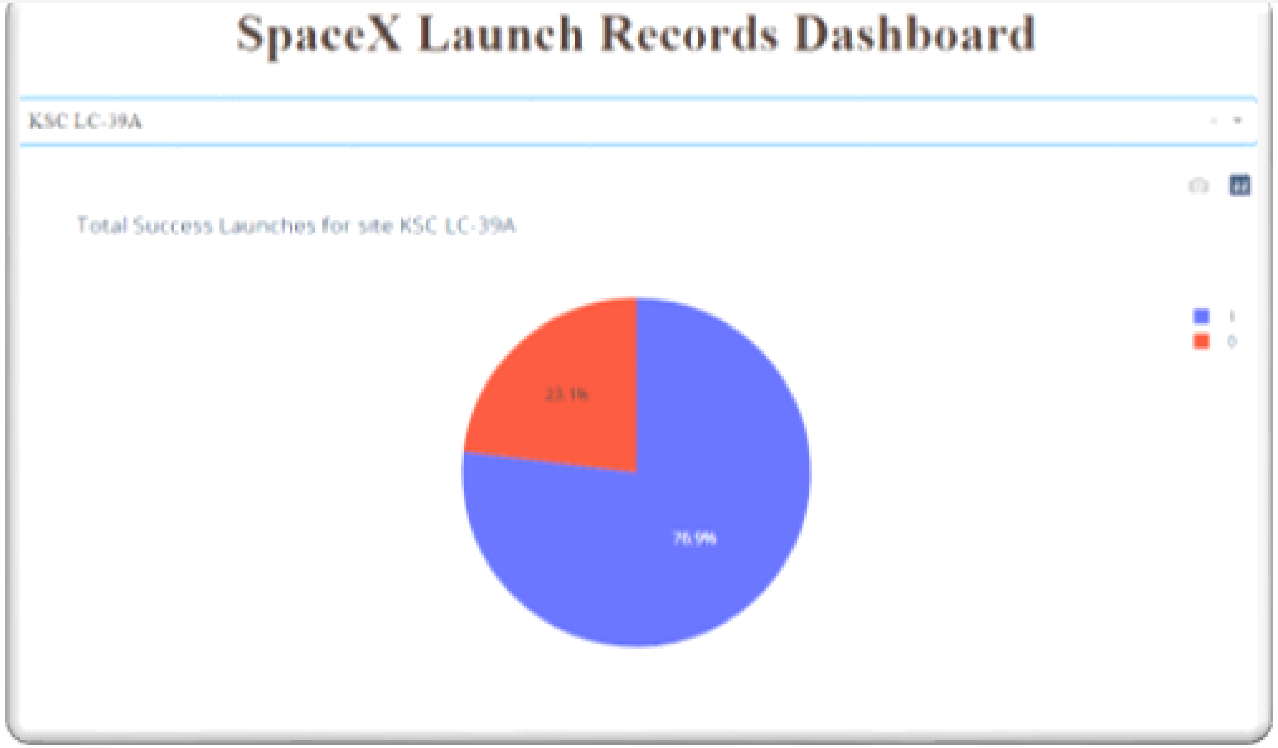
Build a Dashboard with Plotly Dash

Launch Success Count for All Sites



- The launch site KSC LC-39 A had the most successful launches, with 41.7% of the total successful launches.

Highest Launching Success Ratio



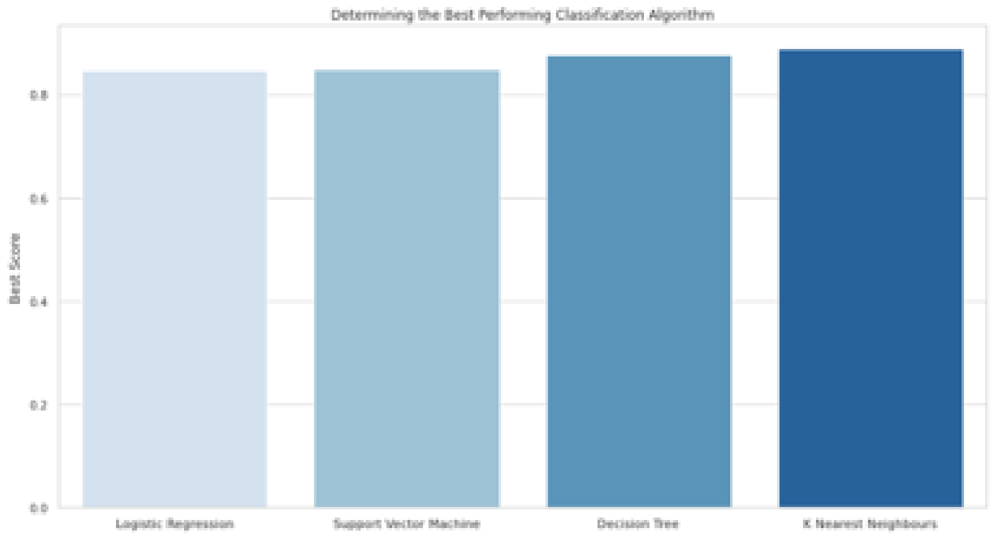
- Launch site KSC LC-39 also has the highest ratio success ratio with a ratio of 76.9%.

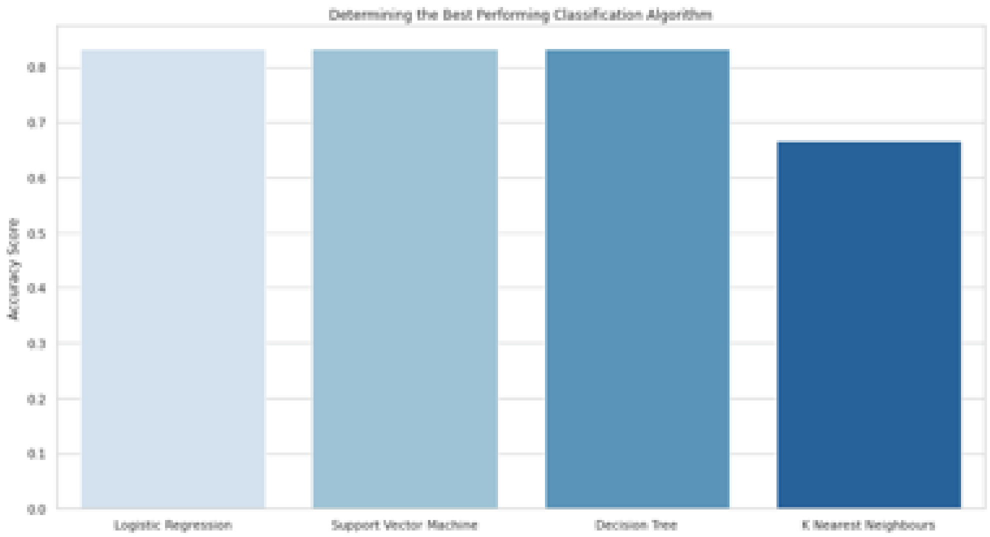
Payload Mass vs Success vs Booster version

Section 5

Predictive Analysis (Classification)

Classification Accuracy



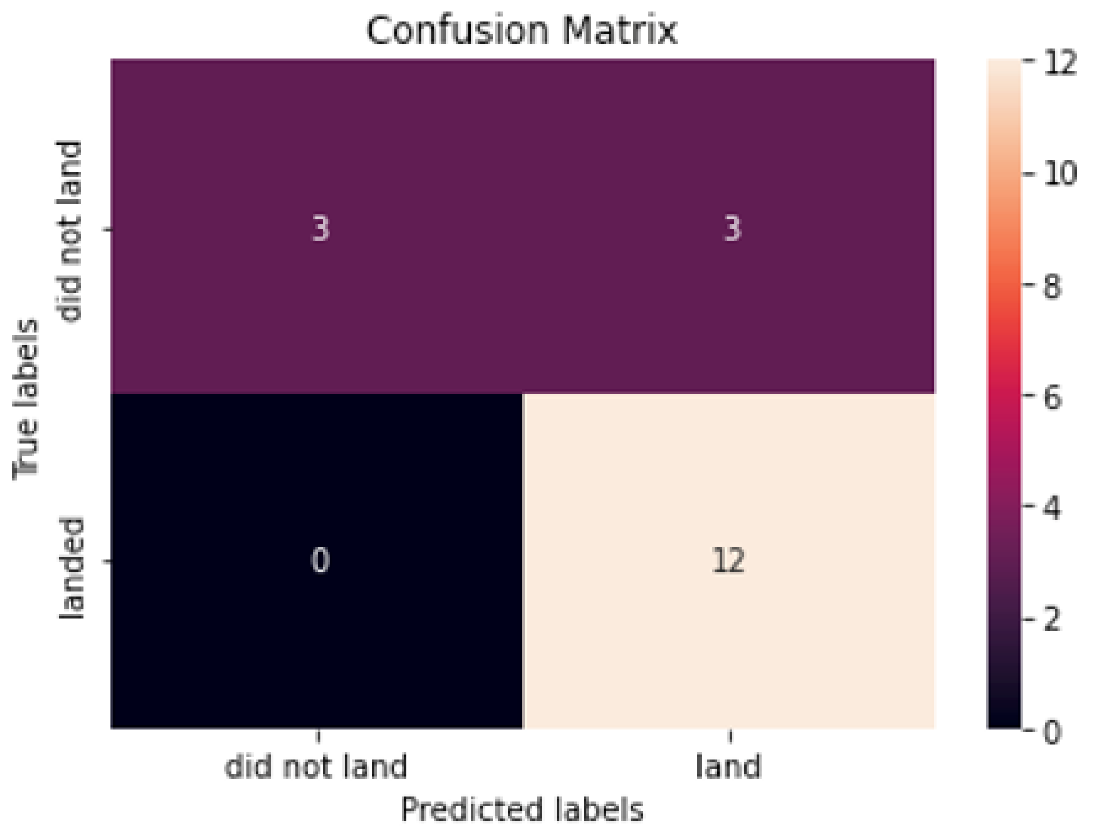


	Algorithm	Accuracy Score	Best Score
0	Logistic Regression	0.833333	0.846429
1	Support Vector Machine	0.833333	0.848214
2	Decision Tree	0.833333	0.876786
3	K Nearest Neighbours	0.666667	0.889286

- The Decision Tree model has the highest classification accuracy

Confusion Matrix

- The models predicted 12 successful landings when the true label was successful landing.
- The models predicted 3 unsuccessful landings when the true label was unsuccessful landing.
- The models predicted 3 successful landings when the true label was unsuccessful landings (false positives).



Conclusions

- As the number of flights increased, the rate of success at a launch site increased.
- Most of the early flights were unsuccessful.
- Between 2010 and 2013, all landings were unsuccessful
- After 2013, the success rate generally increased, despite small dips in 2018 and 2020.
- Orbit types ES-L1, GEO, HEO, and SSO, have the highest success rate of 100%.
- Launch site KSC LC-39 A had the most successful launches, with 41.7% of the total successful launches, and also the highest rate of successful launches, with a 76.9% success rate.

Appendix

- Include any relevant assets like Python code snippets, SQL queries, charts, Notebook outputs, or data sets that you may have created during this project
- https://github.com/PhuongAnhLy/IBM-Data-Science-Capstone-Project-Python

Thank you!