

Winning Space Race with Data Science

<Name> <Date>



Outline

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

Executive Summary

- Summary of methodologies
 - Data Collection with API
 - Data Colleciton with Web Scrapping
 - Data Wrangling
 - Exploratory Analysis with SQL
 - Exploratory Analysis with Visualization
 - Interactive Visualization with Folium
 - Machine Learning Prediction
- Summary of all results
 - Analysis Result
 - Prediction result from Machine Learning

Introduction

SpaceX is a revolutionary company who has disrupt the space industry by offering a rocket launches specifically Falcon 9 as low as 62 million dollars; while other providers cost upward of 165 million dollar each. Most of this saving thanks to SpaceX astounding idea to reuse the first stage of the launch by re-land the rocket to be used on the next mission. Repeating this process will make the price down even further. As a data scientist of a startup rivaling SpaceX, the goal of this project is to create the machine learning pipeline to predict the landing outcome of the first stage in the future. This project is crucial in identifying the right price to bid against SpaceX for a rocket launch.

The problems included:

- Identifying all factors that influence the landing outcome.
- The relationship between each variables and how it is affecting the outcome.
- The best condition needed to increase the probability of successful landing.



Methodology

Executive Summary

- Data collection methodology:
 - Data was collected using SpaceX REST API and web scrapping from Wikipedia
- Perform data wrangling
 - Data was processed using one-hot encoding for categorical 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
 - How to build, tune, evaluate classification models

Data Collection

Data collection is the process of gathering and measuring information on targeted variables in an established system, which then enables one to answer relevant questions and evaluate outcomes.

As mentioned, the dataset was collected by REST API and Web Scrapping from Wikipedia.

For REST API, its started by using the get request. Then, we decoded the response content as Json and turn it into a pandas dataframe using json_normalize(). We then cleaned the data, checked for missing values and fill with whatever needed.

For web scrapping, we will use the BeautifulSoup to extract the launch records as HTML table, parse the table and convert it to a pandas dataframe for further analysis

Data Collection – SpaceX API

Get request for rocket launch data using API

Use json_normalize method to convert json result to dataframe

Performed data cleaning and filling the missing value

https://github.com/ThLeroy61/SpaceX-Data-Science-Coursera/blob/main/Data%20Collection%20API.ipy nb

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

response = requests.get(spacex_url)

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

```
# Lets take a subset of our dataframe keeping only the features we want a
nd the flight number, and date utc.
data = data[['rocket', 'payloads', 'launchpad', 'cores', 'flight number',
'date utc']]
# We will remove rows with multiple cores because those are falcon rocket
s with 2 extra rocket boosters and rows that have multiple payloads in a
single rocket.
data = data[data['cores'].map(len)==1]
data = data[data['payloads'].map(len)==1]
# Since payloads and cores are lists of size 1 we will also extract the s
ingle value in the list and replace the feature.
data['cores'] = data['cores'].map(lambda x : x[0])
data['payloads'] = data['payloads'].map(lambda x : x[0])
# We also want to convert the date utc to a datetime datatype and then ex
tracting 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)]
```

Data Collection - Scraping

Request the Falcon9 Launch Wiki page from url

Create a BeautifulSoup from the HTML response

Extract all column/variable names from the HTML header

https://github.com/ThLeroy61/SpaceX-Data-Science-Coursera/blob/main/Webscrapping.ipynb

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

```
# Use BeautifulSoup() to create a BeautifulSoup object from a response te
xt content
soup = BeautifulSoup(data, 'html.parser')
```

Data Wrangling

Data Wrangling is the process of cleaning and unifying messy and complex data sets for easy access and Exploratory Data Analysis (EDA).

We will first calculate the number of launches on each site, then calculate the number and occurrence of mission outcome per orbit type. We then create a landing outcome label from the outcome column.

This will make it easier for further analysis, visualization, and ML. Lastly, we will export the result to a CSV.

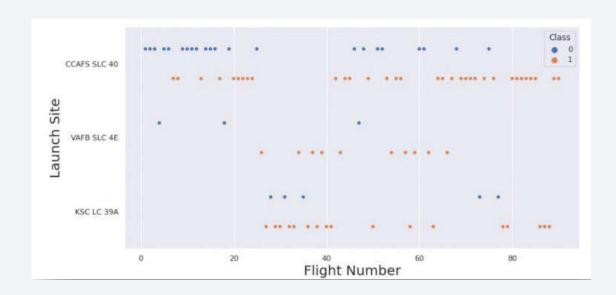
https://github.com/ThLeroy61/SpaceX-Data-Science-Coursera/blob/main/Data%20Wrangling.ipynb

EDA with Data Visualization

We first started by using scatter graph to find the relationship between the attributes such as between:

- Payload and Flight Number.
- Flight Number and Launch Site.
- Payload and Launch Site.
- Flight Number and Orbit Type.
- Payload and Orbit Type.

Scatter plots show dependency of attributes on each other. Once a pattern is determined from the graphs. It's very easy to see which factors affecting the most to the success of the landing outcomes.



https://github.com/ThLeroy61/SpaceX-Data-Science-Coursera/blob/main/EDA%20Data%20Viz.ipynb

EDA with Data Visualization

Once we get a hint of the relationships using scatter plot. We will then use further visualization tools such as bar graph and line plots graph for further analysis.

Bar graphs is one of the easiest way to interpret the relationship between the attributes. In this case, we will use the bar graph to determine which orbits have the highest probability of success.

We then use the line graph to show a trends or pattern of the attribute over time which in this case, is used for see the launch success yearly trend.

We then use Feature Engineering to be used in success prediction in the future module by created the dummy variables to categorical columns.

https://github.com/ThLeroy61/SpaceX-Data-Science-Coursera/blob/main/EDA%20Data%20Viz.ipynb

EDA with SQL

Using SQL, we had performed many queries to get better understanding of the dataset, Ex:

- Displaying the names of the launch sites.
- Displaying 5 records where launch sites begin with the string 'CCA'.
- Displaying the total payload mass carried by booster launched by NASA (CRS).
- Displaying the 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 sites names for in year 2015.
- Rank the count of landing outcomes or success between the date 2010-06-04 and 2017-03-20, in descending order.

Build an Interactive Map with Folium

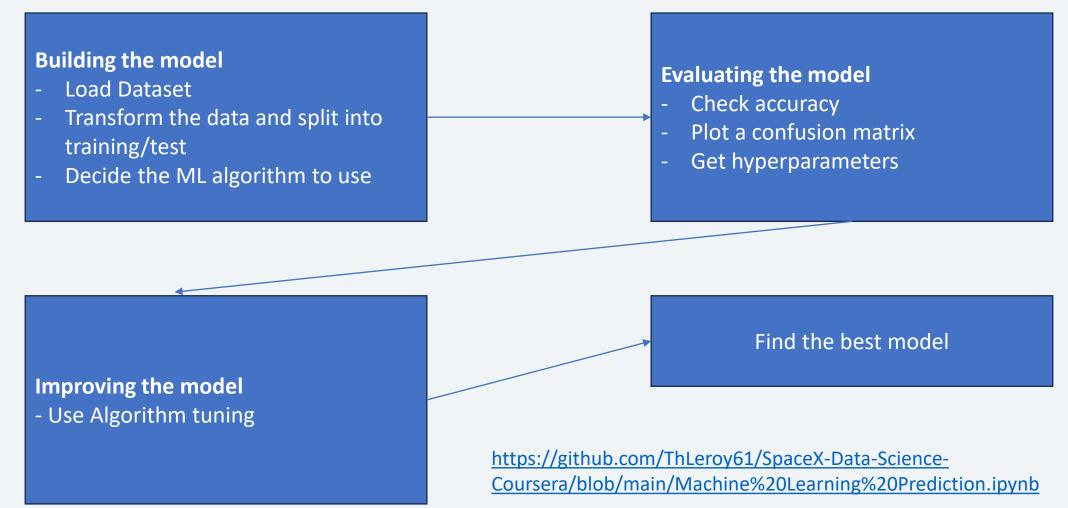
To visualize the launch data into an interactive map. We took the latitude and longitude coordinates at each launch site and added a circle marker around each launch site with a label of the name of the launch site.

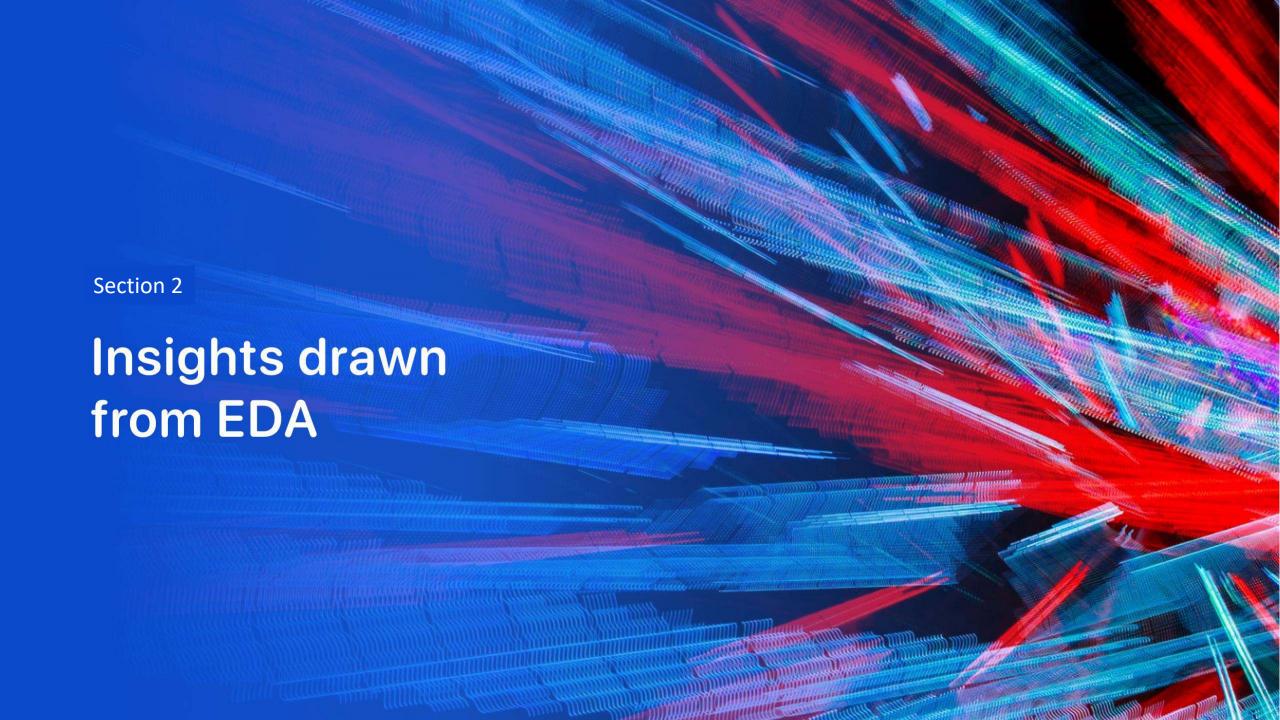
We then used the Haversine's formula to calculated the distance of the launch sites to various landmark to find answer to the questions of:

- How close the launch sites with railways, highways and coastlines?
- How close the launch sites with nearby cities?

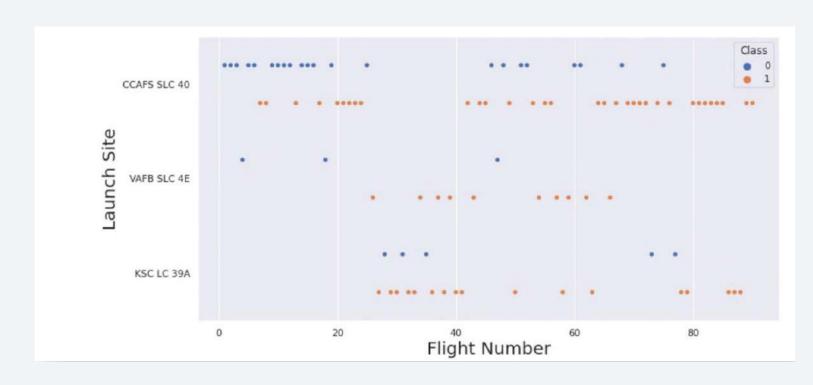
https://github.com/ThLeroy61/SpaceX-Data-Science-Coursera/blob/main/lab_jupyter_launch_site_location.ipynb

Predictive Analysis (Classification)





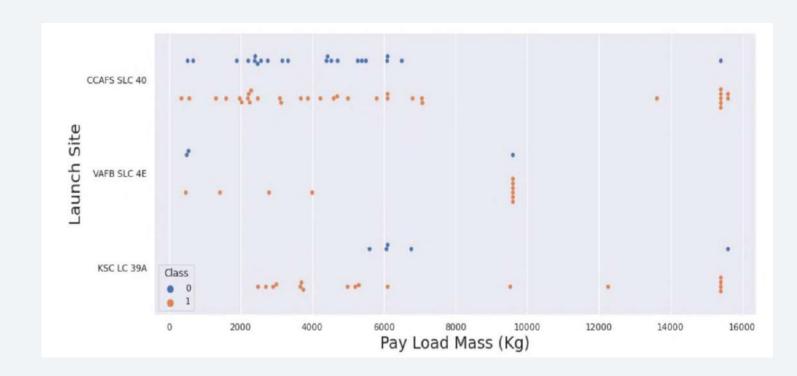
Flight Number vs. Launch Site



This scatter plot shows that the larger the flights amount of the launch site, the greater the the success rate will be.

However, site CCAFS SLC40 shows the least pattern of this.

Payload vs. Launch Site



This scatter plot shows once the pay load mass is greater than 7000kg, the probability of the success rate will be highly increased.

However, there is no clear pattern to say the launch site is dependent to the pay load mass for the success rate.

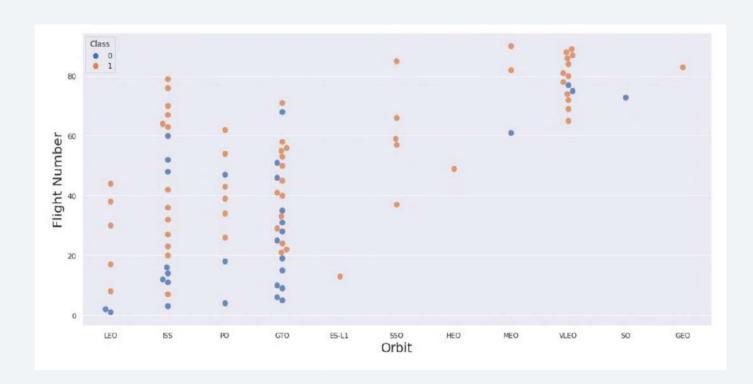
Success Rate vs. Orbit Type



This figure depicted the possibility of the orbits to influences the landing outcomes as some orbits has 100% success rate such as SSO, HEO, GEO AND ES-L1 while SO orbit produced 0% rate of success.

However, deeper analysis show that some of this orbits has only 1 occurrence such as GEO, SO, HEO and ES-L1 which mean this data need more dataset to see pattern or trend before we draw any conclusion.

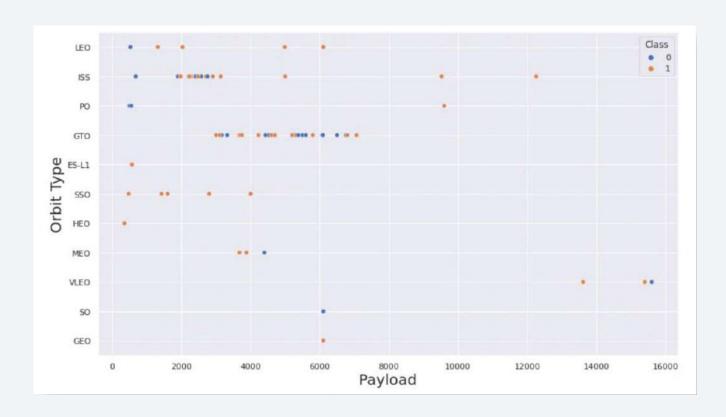
Flight Number vs. Orbit Type



This scatter plot shows that generally, the larger the flight number on each orbits, the greater the success rate (especially LEO orbit) except for GTO orbit which depicts no relationship between both attributes.

Orbit that only has 1 occurrence should also be excluded from above statement as it's needed more dataset.

Payload vs. Orbit Type

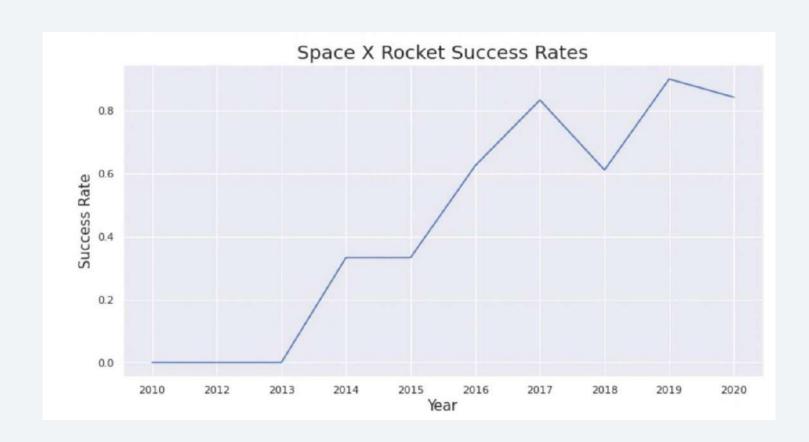


Heavier payload has positive impact on LEO, ISS and PO orbit. However, it has negative impact on MEO and VLEO orbit.

GTO orbit seem to depict no relation between the attributes.

Meanwhile, again, SO, GEO and HEO orbit need more dataset to see any pattern or trend.

Launch Success Yearly Trend



This figures clearly depicted and increasing trend from the year 2013 until 2020.

If this trend continue for the next year onward, the success rate will steadily increase until reaching 1% success rate.

All Launch Site Names

```
In [5]:
         %sql SELECT DISTINCT LAUNCH_SITE as "Launch_Sites" FROM SPACEX;
         * ibm db sa://zpw86771:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.clogj3
        sd0tgtu0lqde00.databases.appdomain.cloud:32731/bludb
        Done.
         Launch_Sites
Out[5]:
         CCAFS LC-40
        CCAFS SLC-40
          KSC LC-39A
         VAFB SLC-4E
```

Launch Site Names Begin with 'CCA'

[11]:		FRO WHE LIM	ECT * M SpaceX RE Launc IT 5	hSite LIKE 'CC							
ut[11]:		date	time	boosterversion	launchsite	payload	payloadmasskg	orbit	customer	missionoutcome	landingoutcome
	0	2010-04- 06	18:45:00	F9 v1.0 B0003	CCAFS LC- 40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
	1	2010-08- 12	15:43:00	F9 v1.0 B0004	CCAFS LC- 40	Dragon demo flight C1, two CubeSats, barrel of	0	LEO (ISS)	NASA (COTS) NRO	Success	Failure (parachute)
	2	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
	3	2012-08-	00:35:00	F9 v1.0 B0006	CCAFS LC-	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt

Total Payload Mass

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

```
*sql SELECT SUM(PAYLOAD_MASS__KG_) AS "Total Payload Mass by NASA (CRS)
```

* ibm_db_sa://zpw86771:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.clogj3sd0tgtu0lqde00.databases.appdomain.cloud:32731/bludb

Total Payload Mass by NASA (CRS)

45596

Average Payload Mass by F9 v1.1

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

```
%sql SELECT AVG(PAYLOAD_MASS__KG_) AS "Average Payload Mass by Booster
WHERE BOOSTER_VERSION = 'F9 v1.1';
```

* ibm_db_sa://zpw86771:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.clogj3sd0tgtu0lqde00.databases.appdomain.cloud:32731/bludb
Done.

Average Payload Mass by Booster Version F9 v1.1

2928

First Successful Ground Landing Date

First Succesful Landing Outcome in Ground Pad

```
%sql SELECT MIN(DATE) AS "First Successful Landing Outcome in Ground Pad
WHERE LANDING_OUTCOME = 'Success (ground pad)';

* ibm_db_sa://zpw86771:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.clogj3
sd0tgtu0lqde00.databases.appdomain.cloud:32731/bludb
Done.
```

2015-12-22

Successful Drone Ship Landing with Payload between 4000 and 6000

```
*sql SELECT BOOSTER VERSION FROM SPACEX WHERE LANDING OUTCOME = 'Success (drone ship)' \
AND PAYLOAD MASS KG > 4000 AND PAYLOAD MASS KG < 6000;
* ibm db sa://zpw86771:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.clogj3sd0tgtu0lqde00.datab
ases.appdomain.cloud:32731/bludb
Done.
booster_version
   F9 FT B1022
   F9 FT B1026
  F9 FT B1021.2
  F9 FT B1031.2
```

Total Number of Successful and Failure Mission Outcomes

List the total number of successful and failure mission outcomes

```
%sql SELECT COUNT(MISSION OUTCOME) AS "Successful Mission" FROM SPACEX WHERE MISSION OUTCOME LIKE 'Success%';
```

* ibm_db_sa://zpw86771:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.clogj3sd0tgtu0lqde00.databases.appdomain.cloud:32731/bludb Done.

Successful Mission

100

```
*sql SELECT COUNT(MISSION_OUTCOME) AS "Failure Mission" FROM SPACEX WHERE MISSION_OUTCOME LIKE 'Failure%';
```

* ibm_db_sa://zpw86771:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.clogj3sd0tgtu0lqde00.databases.appdomain.cloud:32731/bludb
Done.

Failure Mission

1

Boosters Carried Maximum Payload

%sql SELECT DISTINCT BOOSTER_VERSION AS "Booster Versions which carried the Maximum Payload Mass" FROM SPACEX
WHERE PAYLOAD_MASS__KG_ =(SELECT MAX(PAYLOAD_MASS__KG_) FROM SPACEX);

* ibm_db_sa://zpw86771:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.clogj3sd0tgtu0lqde00.databases.appdomain.cloud:32731/bludb

Done.

Booster Versions which carried the Maximum Payload Mass

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

2015 Launch Records

```
%sql SELECT BOOSTER_VERSION, LAUNCH_SITE FROM SPACEX WHERE DATE LIKE '2015-%' AND \
LANDING__OUTCOME = 'Failure (drone ship)';

* ibm_db_sa://zpw86771:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.clogj3sd0tgtu0lqde00.
databases.appdomain.cloud:32731/bludb
Done.
booster_version launch_site

F9 v1.1 B1012 CCAFS LC-40
F9 v1.1 B1015 CCAFS LC-40
```

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

```
%sql SELECT LANDING__OUTCOME as "Landing Outcome", COUNT(LANDING__OUTCOME) AS "Total Count" FROM SPACEX \
WHERE DATE BETWEEN '2010-06-04' AND '2017-03-20' \
GROUP BY LANDING__OUTCOME \
ORDER BY COUNT(LANDING__OUTCOME) DESC;
```

* ibm_db_sa://zpw86771:***@fbd88901-ebdb-4a4f-a32e-9822b9fb237b.clogj3sd0tgtu0lqde00.databases.appdomain.c loud:32731/bludb Done.

Landing Outcome Total Count

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



<Folium Map Screenshot 1>

• Replace <Folium map screenshot 1> title with an appropriate title

• Explore the generated folium map and make a proper screenshot to include all launch sites' location markers on a global map

<Folium Map Screenshot 2>

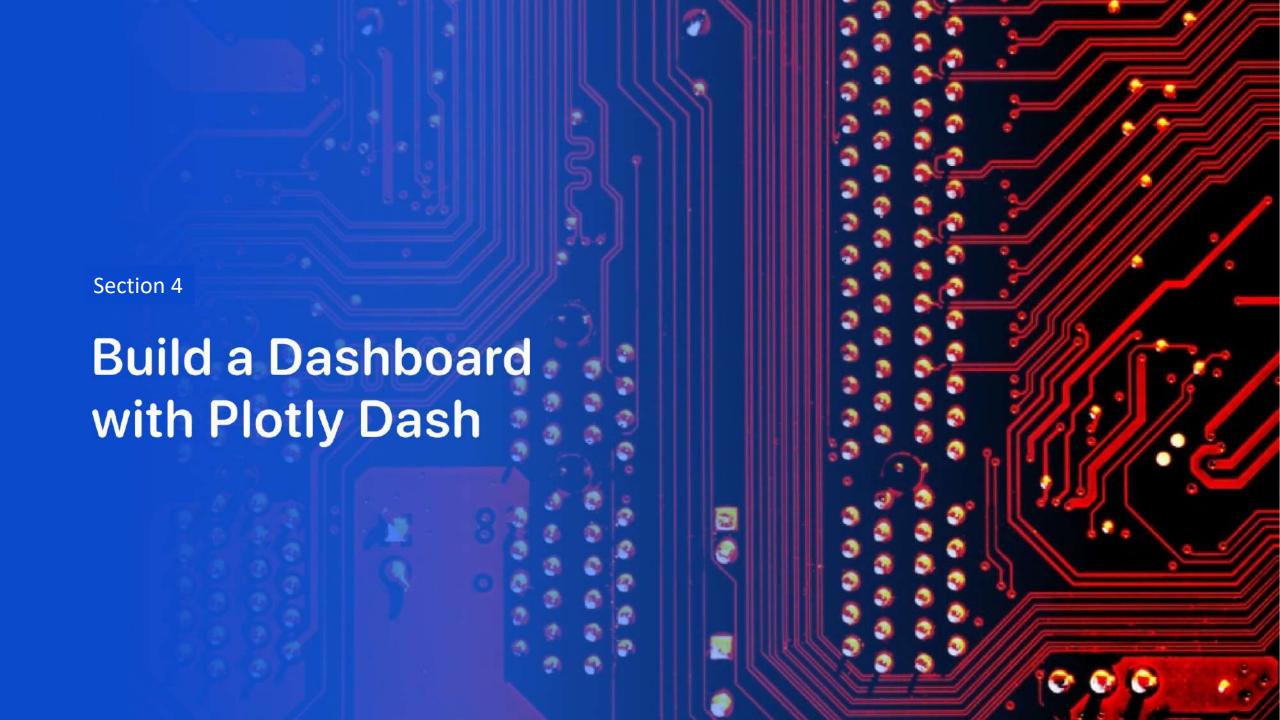
Replace <Folium map screenshot 2> title with an appropriate title

 Explore the folium map and make a proper screenshot to show the colorlabeled launch outcomes on the map

<Folium Map Screenshot 3>

Replace <Folium map screenshot 3> title with an appropriate title

• Explore the generated folium map and show the screenshot of a selected launch site to its proximities such as railway, highway, coastline, with distance calculated and displayed



< Dashboard Screenshot 1>

Replace < Dashboard screenshot 1> title with an appropriate title

• Show the screenshot of launch success count for all sites, in a piechart

< Dashboard Screenshot 2>

Replace <Dashboard screenshot 2> title with an appropriate title

• Show the screenshot of the piechart for the launch site with highest launch success ratio

< Dashboard Screenshot 3>

Replace <Dashboard screenshot 3> title with an appropriate title

• Show screenshots of Payload vs. Launch Outcome scatter plot for all sites, with different payload selected in the range slider

• Explain the important elements and findings on the screenshot, such as which payload range or booster version have the largest success rate, etc.



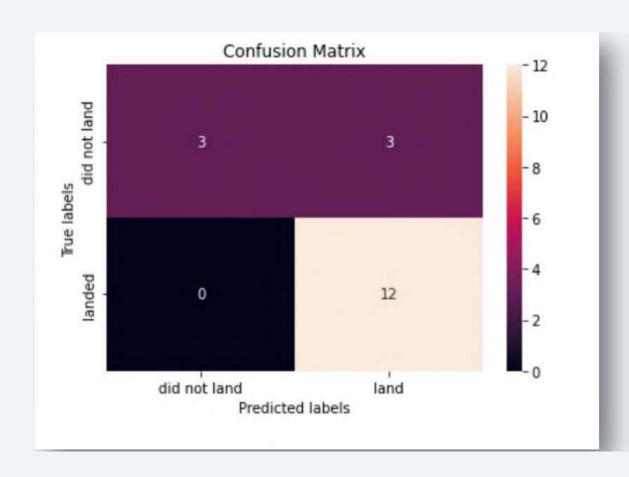
Classification Accuracy

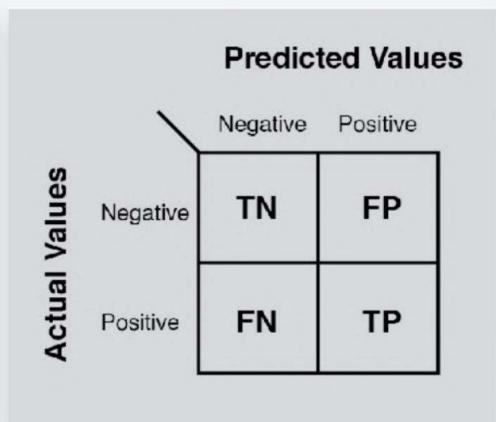
As we can see, by using the code as below: we could identify that the best algorithm to be the Tree Algorithm which have the highest classification accuracy.

```
algorithms = {'KNN':knn_cv.best_score_,'Tree':tree_cv.best_score_,'LogisticRegression':logreg_cv.best_score_}
bestalgorithm = max(algorithms, key=algorithms.get)
print('Best Algorithm is',bestalgorithm,'with a score of',algorithms[bestalgorithm])
if bestalgorithm == 'Tree':
    print('Best Params is :',tree_cv.best_params_)
if bestalgorithm == 'KNN':
    print('Best Params is :',knn_cv.best_params_)
if bestalgorithm == 'LogisticRegression':
    print('Best Params is :',logreg_cv.best_params_)

Best Algorithm is Tree with a score of 0.9017857142857142
Best Params is : {'criterion': 'entropy', 'max_depth': 10, 'max_features': 'auto', 'min_samples_leaf': 2, 'min_samples_split': 10, 'splitter': 'random'}
```

Confusion Matrix





Conclusions

We can conclude that:

- The Tree Classifier Algorithm is the best Machine Learning approach for this dataset.
- The low weighted payloads (which define as 4000kg and below) performed better than the heavy weighted payloads.
- Starting from the year 2013, the success rate for SpaceX launches is increased, directly proportional time in years to 2020, which it will eventually perfect the launches in the future.
- KSC LC-39A have the most successful launches of any sites; 76.9%
- SSO orbit have the most success rate; 100% and more than 1 occurrence.

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

