IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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18th October 2022

Outline

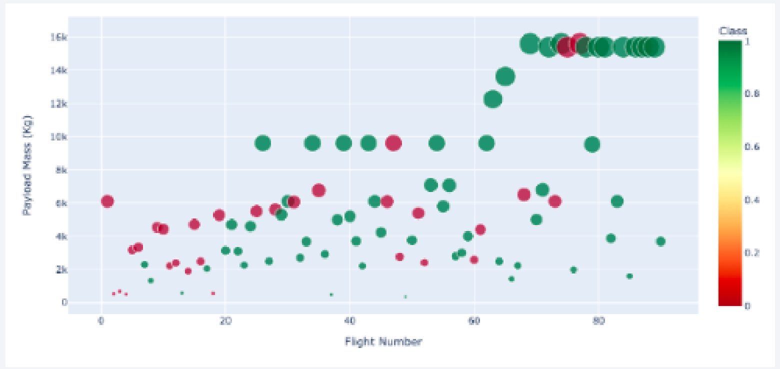
Executive Summary

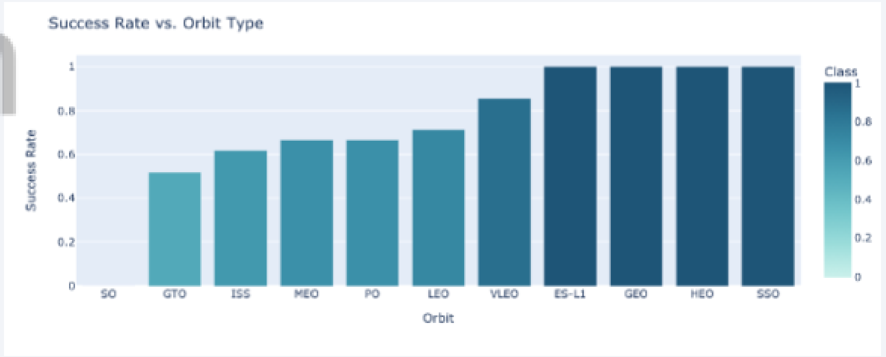
❑Summary of methodologies -

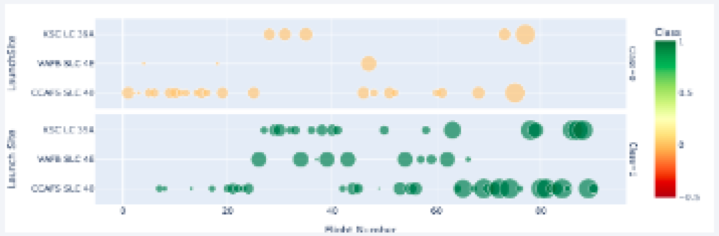
- Data Collection via API, SQL, and Web Scraping
- Data Wrangling and Analysis
- Interactive Map with Folium
- Predictive Analysis for each classification model

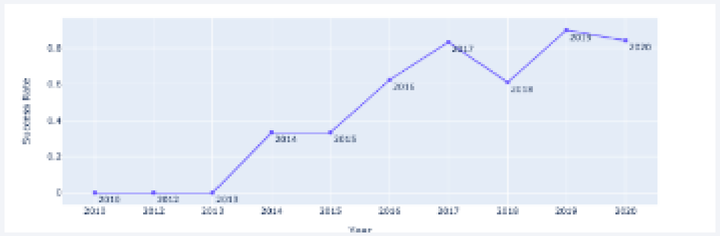
❑Summary of all results -

- Data Analysis along with Interactive Visualizations
- Best Model for Predictive Analysis









Orbit
SO
VLEO
MEO
HEO
SSO
ES-L1
GTO
PO
ISS
LEO

Introduction

❑Project background and context:

Here we will predict if the Falcon 9 first stage will land successfully. SpaceX advertises Falcon 9 rocket launches on its website, with a cost of 62 million dollars; other providers cost upwards of 165 million dollars each, much of the savings is because SpaceX can reuse the first stage. Therefore, if we can determine if the first stage will land successfully. This information can be used if an alternate company wants to bid against SpaceX for a rocket launch.

❑Problems you want to find answers:

- With what factors, the rocket will land successfully?
- The effect of each relationship of rocket variables on outcome.
- Conditions which will aid SpaceX have to achieve the best results.

Section 1

Methodology

Methodology

Executive Summary

❑ Data collection methodology:

- Via SpaceX Rest API
- Web Scrapping from Wikipedia

❑ Perform data wrangling:

- One hot encoding data fields for machine learning and dropping irrelevant columns (Transforming data for Machine Learning).

❑ Perform exploratory data analysis (EDA) using visualization and SQL:

- Scatter and bar graphs to show patterns between data.

❑ Perform interactive visual:

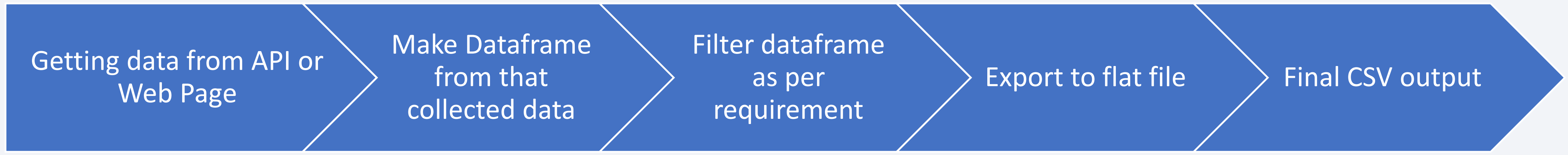
- Using Folium and Plotly Dash Visualizations.

❑ Perform predictive analysis using classification models:

- Build and 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.

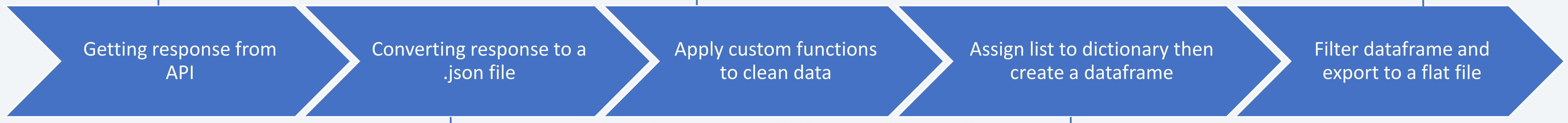

Getting data from API or Web Page
Make Dataframe from that collected data
Filter dataframe as per requirement
Export to flat file
Final CSV output

Data Collection – SpaceX API

```
spacex_url=https://api.spacexdata.com/v4/launches/past
response = requests.get(spacex_url)
```

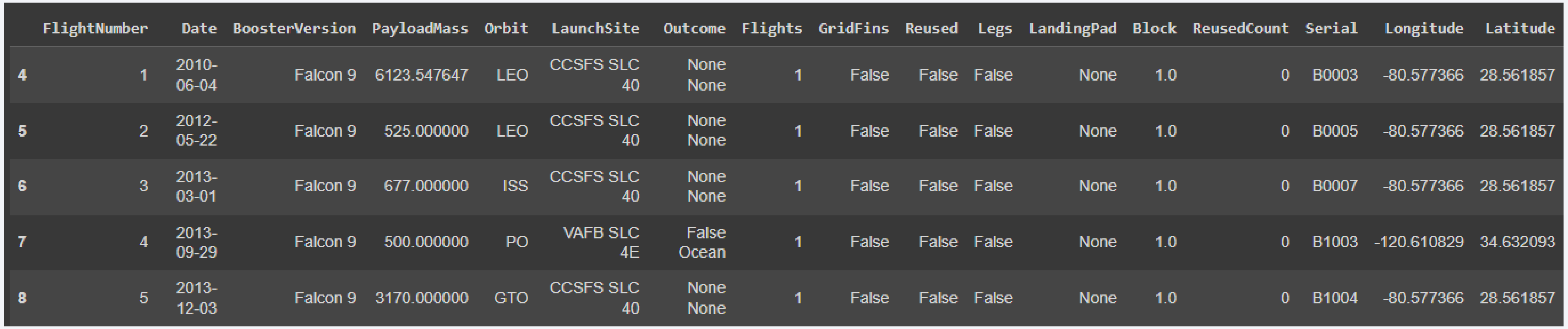
```
getBoosterVersion(data)
getLaunchSite(data)
getPayloadData(data)
getCoreData(data)
```

```
data_falcon9.drop(data_falcon9[data_falcon9['BoosterVersion']!='Falcon 9'].index, inplace = True
)
data_falcon9.loc[:,'FlightNumber'] = list(range(1, data_falcon9.shape[0]+1))
data_falcon9
data_falcon9.to_csv('csvs/dataset_part_1.csv', index=False)
```


Getting response from API
Converting response to a .json file
Apply custom functions to clean data
Assign list to dictionary then create a dataframe
Filter dataframe and export to a flat file

```
jlist = requests.get(static_json_url).json()
df2 = pd.json_normalize(jlist)
df2.head()
```

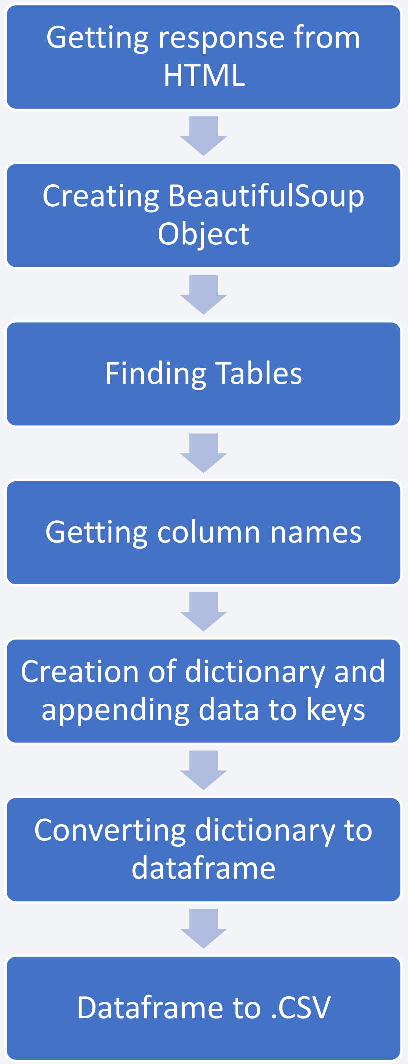
```
launch_dict = {'FlightNumber': list(data['flight_number']),
'Date': list(data['date']),
'BoosterVersion':BoosterVersion, . . .
```



	FlightNumber	Date	BoosterVersion	PayloadMass	Orbit	LaunchSite	Outcome	Flights	GridFins	Reused	Legs	LandingPad	Block	ReusedCount	Serial	Longitude	Latitude
4	1	2010-06-04	Falcon 9	6123.547647	LEO	CCSFS SLC 40	None None	1	False	False	False	None	1.0	0	B0003	-80.577366	28.561857
5	2	2012-05-22	Falcon 9	525.000000	LEO	CCSFS SLC 40	None None	1	False	False	False	None	1.0	0	B0005	-80.577366	28.561857
6	3	2013-03-01	Falcon 9	677.000000	ISS	CCSFS SLC 40	None None	1	False	False	False	None	1.0	0	B0007	-80.577366	28.561857
7	4	2013-09-29	Falcon 9	500.000000	PO	VAFB SLC 4E	False Ocean	1	False	False	False	None	1.0	0	B1003	-120.610829	34.632093
8	5	2013-12-03	Falcon 9	3170.000000	GTO	CCSFS SLC 40	None None	1	False	False	False	None	1.0	0	B1004	-80.577366	28.561857

Github URL

Data Collection - Scraping


Getting response from HTML
Creating BeautifulSoup Object
Finding Tables
Getting column names
Creation of dictionary and appending data to keys
Converting dictionary to dataframe
Dataframe to .CSV

```
static_url = "https://en.wikipedia.org/w/index.php?title=List_of_Falcon_9_and_Falcon_Heavy_launches&oldid=1027686922"
data  = requests.get(static_url).text
```

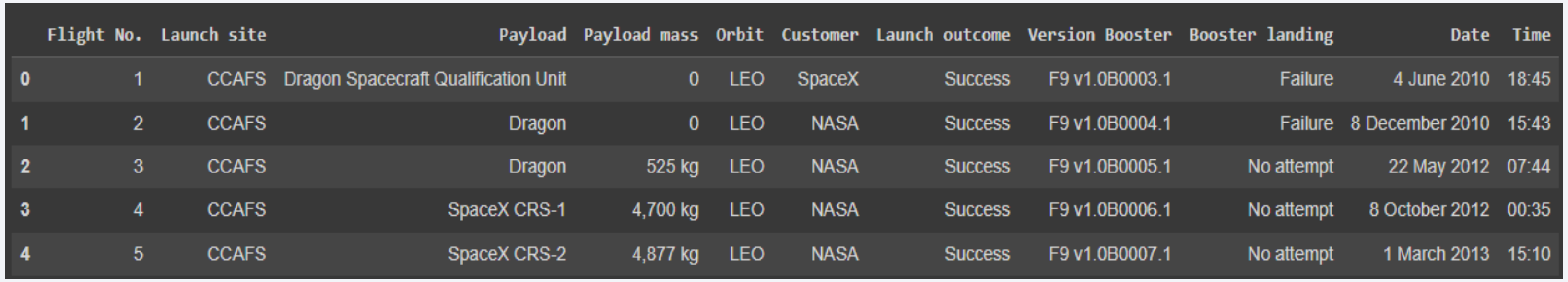
```
soup = BeautifulSoup(data, 'html5lib')
```

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

```
ths = first_launch_table.find_all('th')
for th in ths:
    name = extract_column_from_header(th)
    if name is not None and len(name) > 0:
        column_names.append(name)
```

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

Github URL



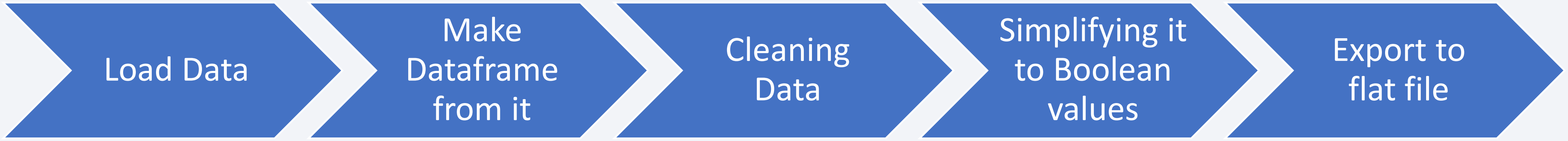
	Flight No.	Launch site	Payload	Payload mass	Orbit	Customer	Launch outcome	Version Booster	Booster landing	Date	Time
0	1	CCAFS	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	F9 v1.0B0003.1	Failure	4 June 2010	18:45
1	2	CCAFS	Dragon	0	LEO	NASA	Success	F9 v1.0B0004.1	Failure	8 December 2010	15:43
2	3	CCAFS	Dragon	525 kg	LEO	NASA	Success	F9 v1.0B0005.1	No attempt	22 May 2012	07:44
3	4	CCAFS	SpaceX CRS-1	4,700 kg	LEO	NASA	Success	F9 v1.0B0006.1	No attempt	8 October 2012	00:35
4	5	CCAFS	SpaceX CRS-2	4,877 kg	LEO	NASA	Success	F9 v1.0B0007.1	No attempt	1 March 2013	15:10

Data Wrangling

Data wrangling is the process of cleaning and unifying messy and complex data sets for easy access and analysis.

Here we mainly convert those outcomes into Training Labels with 1 means the booster successfully landed 0 means it was unsuccessful.

```
df['Class'] = df['Outcome'].apply(lambda landing_class: 0 if landing_class in bad_outcomes else 1)
```



Github URL

Data Wrangling

Calculate number of launches at each site

```
df['LaunchSite'].value_counts()
```

```
CCAFS SLC 40    55
KSC LC 39A      22
VAFB SLC 4E     13
```

Calculate number and occurrence of each orbit

```
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
```

Calculate number and occurrence of mission outcome per orbit type

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

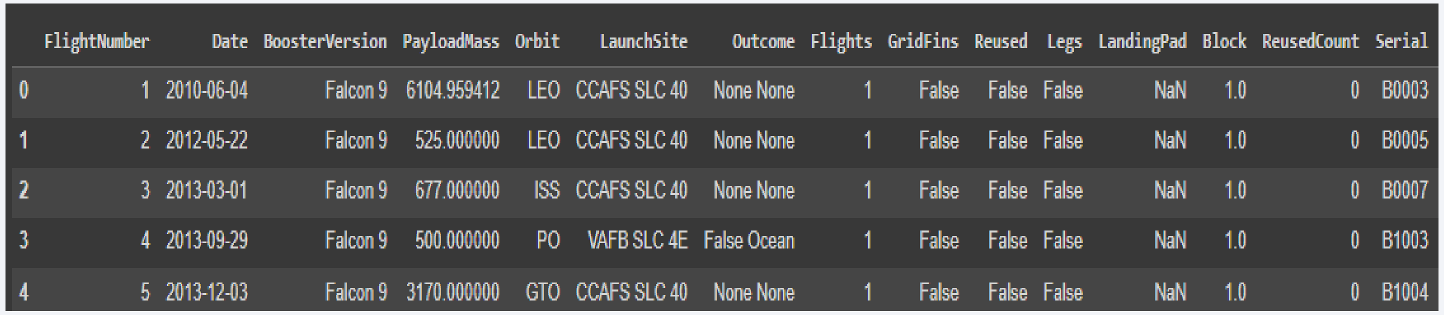
```
True ASDS      41
None None      19
True RTLS      14
False ASDS      6
True Ocean      5
None ASDS       2
False Ocean     2
False RTLS      1
```

```
df['Class'] = df['Outcome'].apply(lambda landing_class: 0 if landing_class in bad_outcomes else 1)
df[['Class']].head(8)
```

Create landing outcome from Outcome column

Export dataset as .CSV

```
df.to_csv("csvs/dataset_part_2.csv", index=False)
```

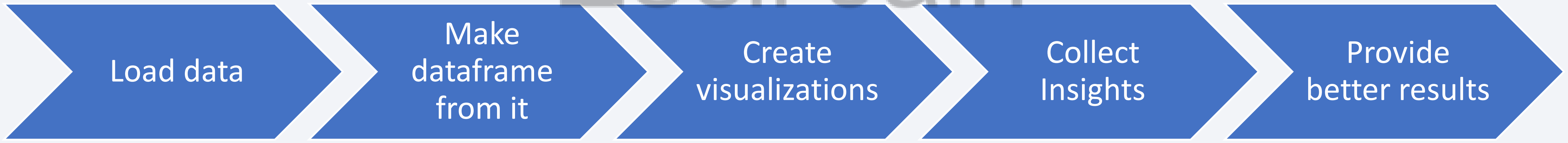


	FlightNumber	Date	BoosterVersion	PayloadMass	Orbit	LaunchSite	Outcome	Flights	GridFins	Reused	Legs	LandingPad	Block	ReusedCount	Serial
0	1	2010-06-04	Falcon 9	6104.959412	LEO	CCAFS SLC 40	None None	1	False	False	False	NaN	1.0	0	B0003
1	2	2012-05-22	Falcon 9	525.000000	LEO	CCAFS SLC 40	None None	1	False	False	False	NaN	1.0	0	B0005
2	3	2013-03-01	Falcon 9	677.000000	ISS	CCAFS SLC 40	None None	1	False	False	False	NaN	1.0	0	B0007
3	4	2013-09-29	Falcon 9	500.000000	PO	VAFB SLC 4E	False Ocean	1	False	False	False	NaN	1.0	0	B1003
4	5	2013-12-03	Falcon 9	3170.000000	GTO	CCAFS SLC 40	None None	1	False	False	False	NaN	1.0	0	B1004

Github URL

Exploratory Data Analysis

Exploratory data analysis is an approach of analyzing data sets to summarize their main characteristics, using statistical graphics and other data visualization methods.



EDA with Data Visualization

Scatter Graphs Drawn:

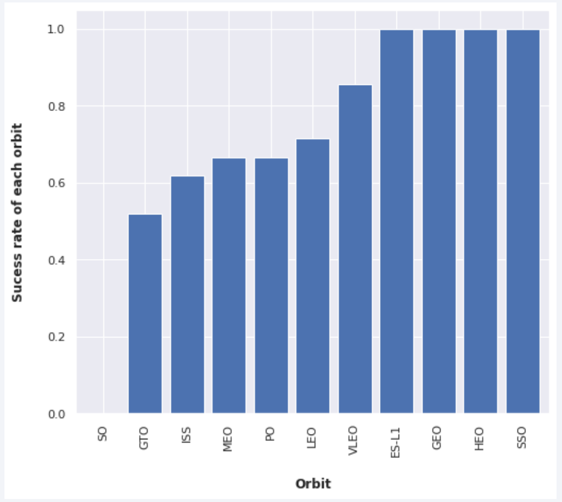
- Payload and Flight Number
- Flight Number and Launch Site
- Payload and Launch Site
- Flight Number and Orbit Type
- Payload and Orbit Type

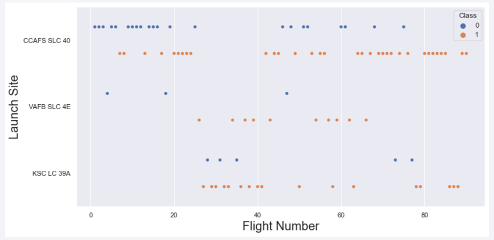
Scatter plots show dependency of attributes on each other. Once a pattern is determined from the graphs it's very easy to predict which factors will lead to maximum probability of success in both outcome and landing.

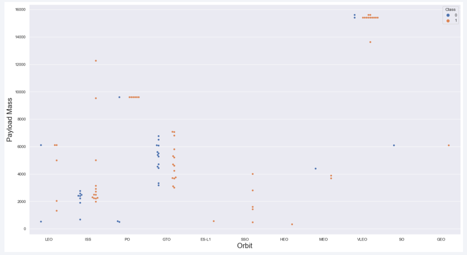
Bar Graph Drawn:

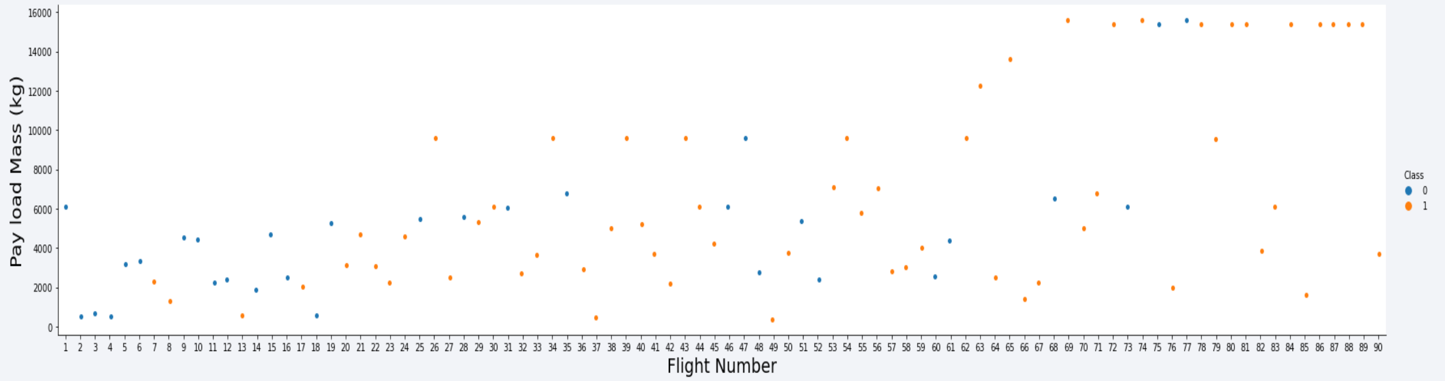
Success Rate VS. Orbit Type

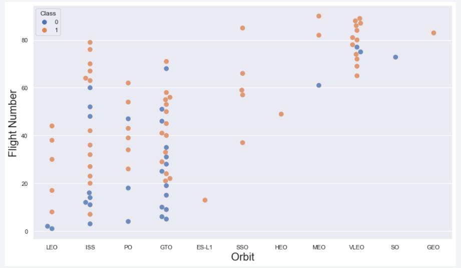
Bar graphs are easiest to interpret a relationship between attributes. Via this bar gra ph we can easily determine which orbits have the highest proba bility of success.

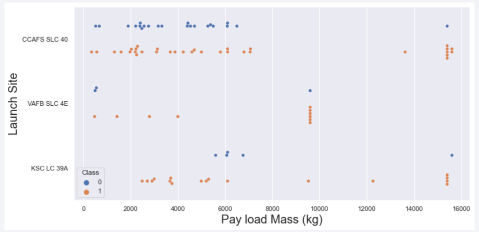












Github URL

EDA with SQL

SQL is an indispensable tool for Data Scientists and analysts as most of the real-world data is stored in databases. It's not only the standard language for Relational Database operations, but also an incredibly powerful tool for analyzing data and drawing useful insights from it. Here we use IBM's Db2 for Cloud, which is a fully managed SQL Database provided as a service.

```
!pip install sqlalchemy==1.3.9
!pip install ibm_db_sa
!pip install ipython-sql
%load_ext sql
```

```
%sql ibm_db_sa://my-username:my-password@my-hostname:my-port/my-db-name
%sql <your query>
```

We performed SQL queries to gather information from given dataset :

Displaying the names of the unique launch sites in the space mission

Display 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 F9v l.1

Listing the date where the successful landing outcome in drone ship was achieved

Listing the names of the boosters which have success in ground pad 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 the 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

Folium makes it easy to visualize data that's been manipulated in Python on an interactive leaflet map. We use the latitude and longitude coordinates for each launch site and added a Circle Mar ker around each launch site with a label of the name of the launch site. It is also easy to visua lize the number of success and failure for each launch site with Green and Red markers on the map.

Map Objects	Code	Result
Map Marker	folium.Marker()	Map object to make a mark on map.
Icon Marker	folium.Icon()	Create an icon on map.
Circle Marker	folium.Circle()	Create a circle where Marker is being placed.
Polyline	folium.Polyline()	Create a line between points.
Marker Cluster Object	MarkerCluster()	This is a good way to simplify a map containing many markers having the same coordinate.
AntPath	folium.plugins.AntPath()	Create an animated line between points.

Original Project - GitHub URL

Clean Distance Mar kers GitHub URL

Build a Dashboard with Plotly Dash

Pie Chart showing the total success for all sites or by certain launch site

Percentage of success in relation to launch site

Scatter Graph showing the correlation between Payload and Success for all sites or by certain launch site

It shows the relationship between Success rate and Booster Version Category.

Map Objects	Code	Result

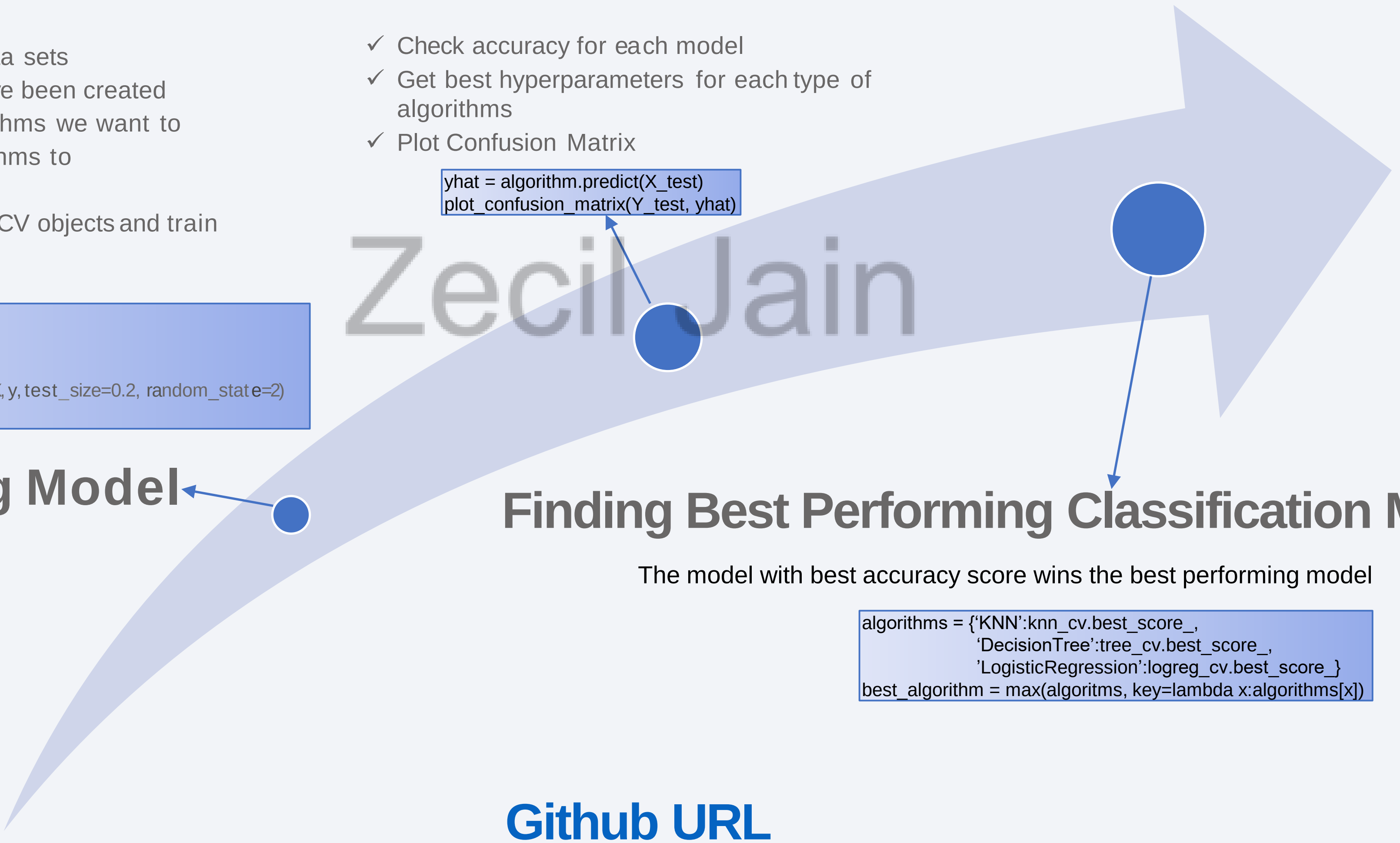
Dash and its components	*import* dash
	import dash_html_components as html
	import dash_core_components as dcc
	from dash.dependencies import Input, Output
		Plotly stewards Python's leading data viz and UI libraries. With Dash Open Source, Dash apps run on your local laptop or server. The Dash Core Component library contains a set of higher-level components like sliders,graphs, dropdowns, tables, and more.
		Dash provides all the available HTML tags as user-friendly Python classes.

Pandas	*import* pandas *as* pd	Fetching values from CSV and creating a dataframe
Plotly	*import* plotly.express *as* px	Plot the graphs with interactive plotly Library
Dropdown	dcc.Dropdown()	Create a dropdown for launch sites
Rangeslider	dcc.RangeSlider()	Create a rangeslider for Payload Mass range selection
Pie Chart	px.pie()	Creating the Pie graph for Success percentage display
Scatter Chart	px.scatter()	Creating the Scatter graph for correlation display

Github Code URL

Used Coursera’s Skills Network Labs to host a live website.

Predictive Analysis (Classification)



Building Model

- ✓ Load our feature engineered data into dataframe
- ✓ Transform it into NumPy arrays
- ✓ Standardize and transform data
- ✓ Split data into training and test data sets
- ✓ Check how many test samples have been created
- ✓ List down machine learning algorithms we want to use Set our parameters and algorithms to GridSearchCV
- ✓ Fit our datasets into the GridSearchCV objects and train our model

```
y = data['Class'].to_numpy()
transform = preprocessing.StandardScaler()
X = transform.fit(X).transform(X)
X_train, X_test, Y_train, Y_test = train_test_split(X, y, test_size=0.2, random_state=2)
Y_test.shape
```

Evaluating Model

- ✓ Check accuracy for each model
- ✓ Get best hyperparameters for each type of algorithms
- ✓ Plot Confusion Matrix

```
yhat = algorithm.predict(X_test)
plot_confusion_matrix(Y_test, yhat)
```

Finding Best Performing Classification Model

The model with best accuracy score wins the best performing model

```
algorithms = {'KNN':knn_cv.best_score_,
              'DecisionTree':tree_cv.best_score_,
              'LogisticRegression':logreg_cv.best_score_}
best_algorithm = max(algoritms, key=lambda x:algorithms[x])
```

Best Models

Github URL

Results

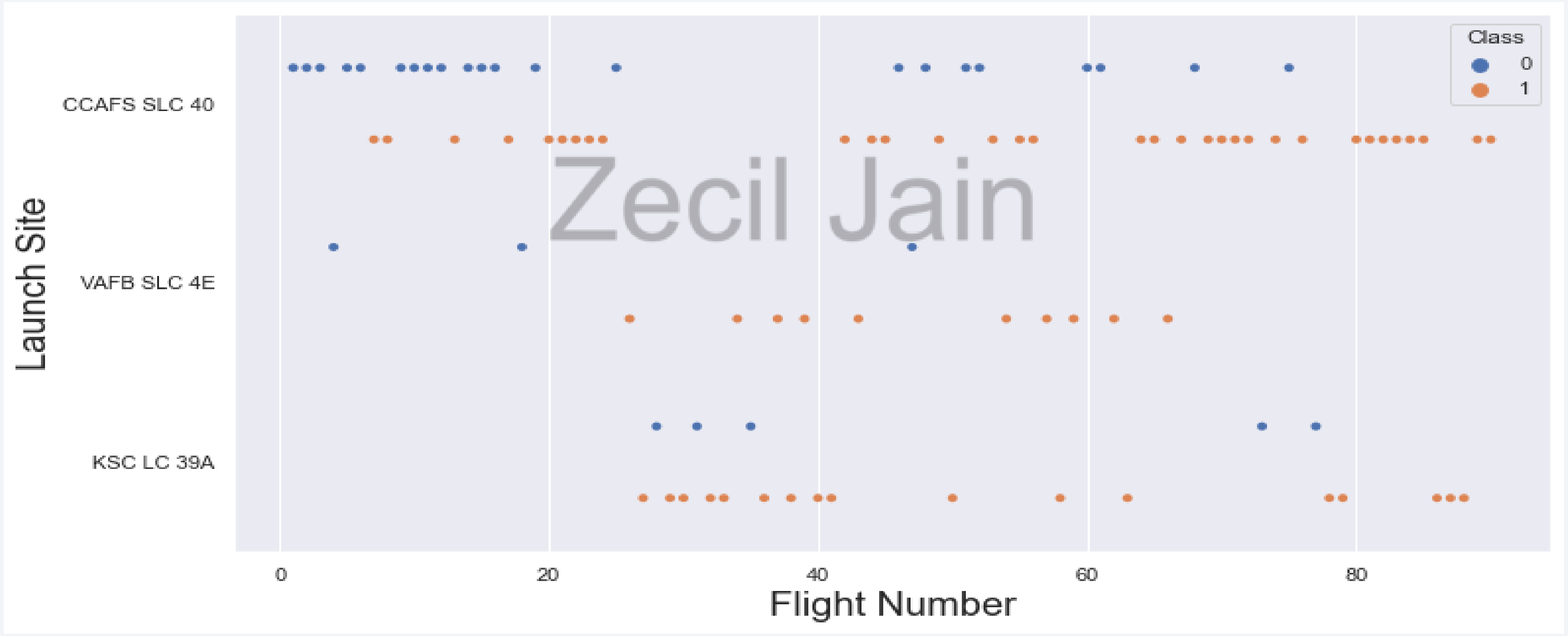
- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results

Section 2

Insights drawn from EDA

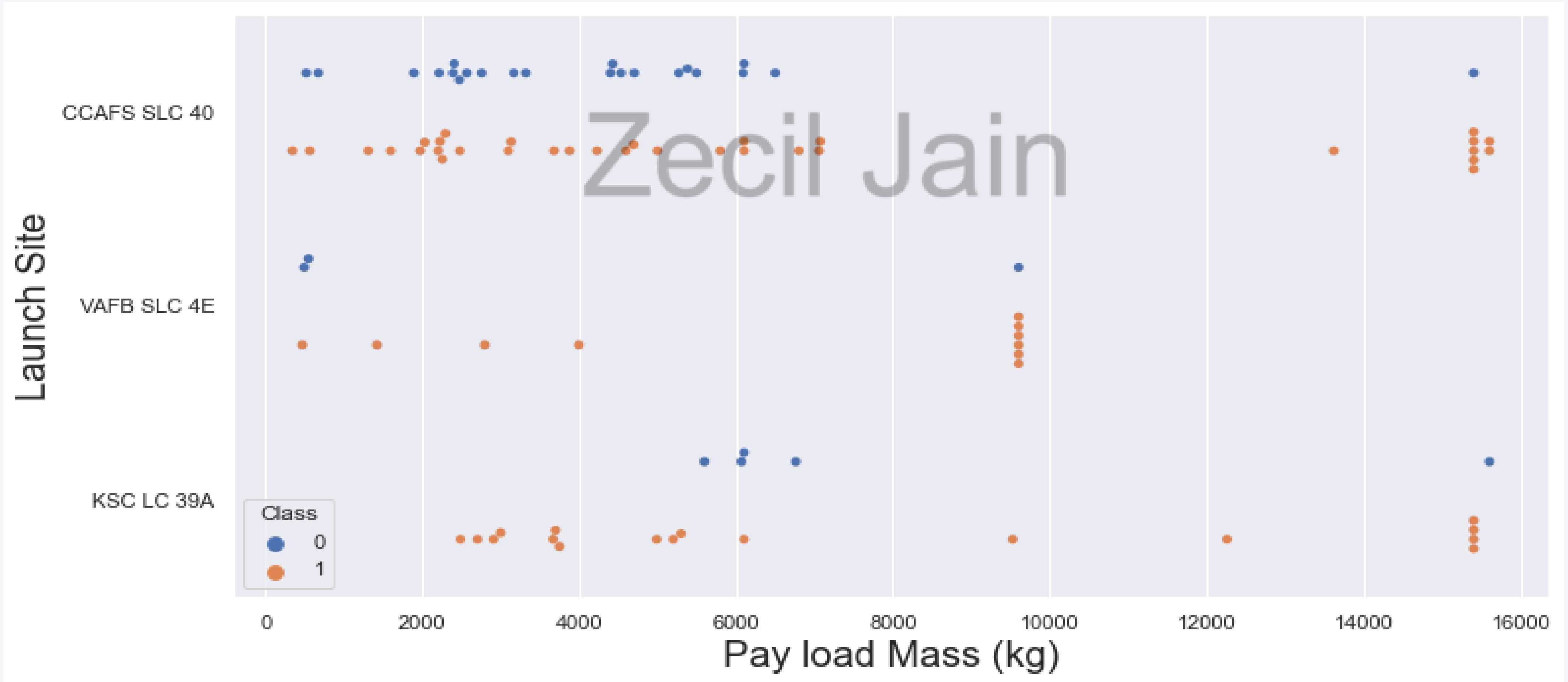
Flight Number vs. Launch Site

With higher flight numbers (greater than 30) the success rate for the Rocket is increasing.



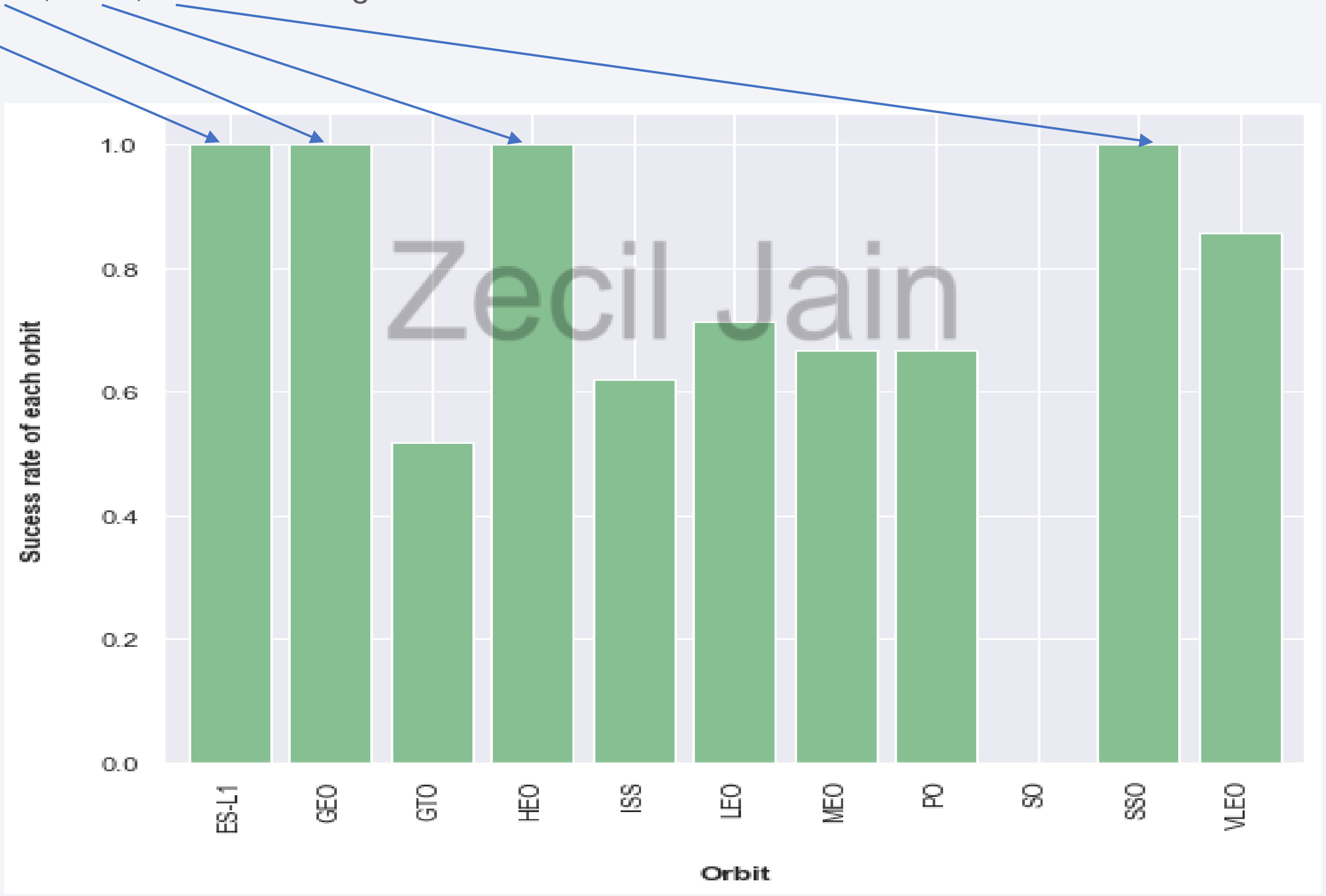
Payload vs. Launch Site

- The greater the payload mass (greater than 7000 Kg) higher the success rate for the Rocket. But there 's no clear pattern to take a decision, if the launch site is dependent on Payload Mass for a success launch.



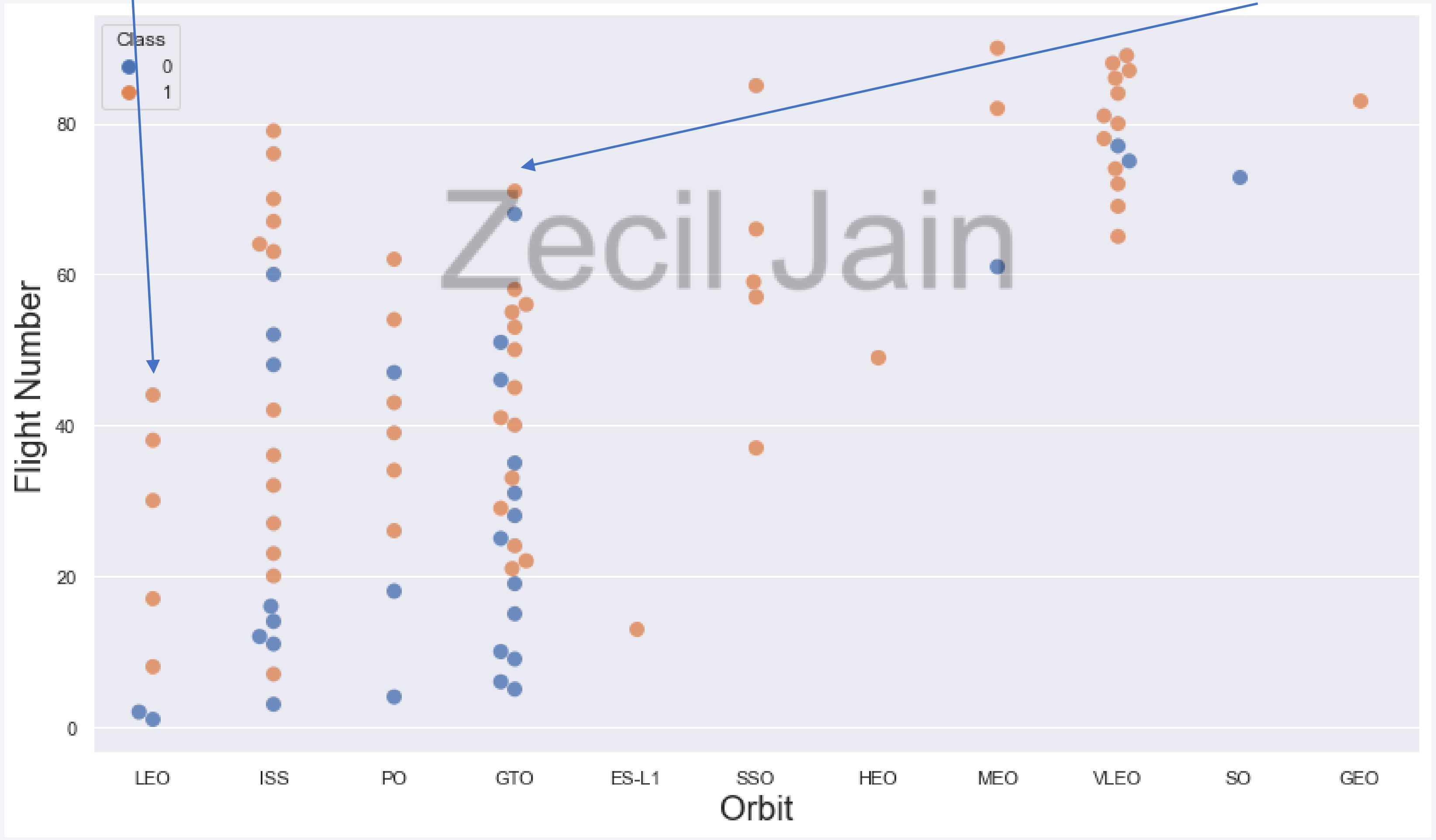
Success Rate vs. Orbit Type

- ES-L1, GEO, HEO, SS0 have highest success rates.



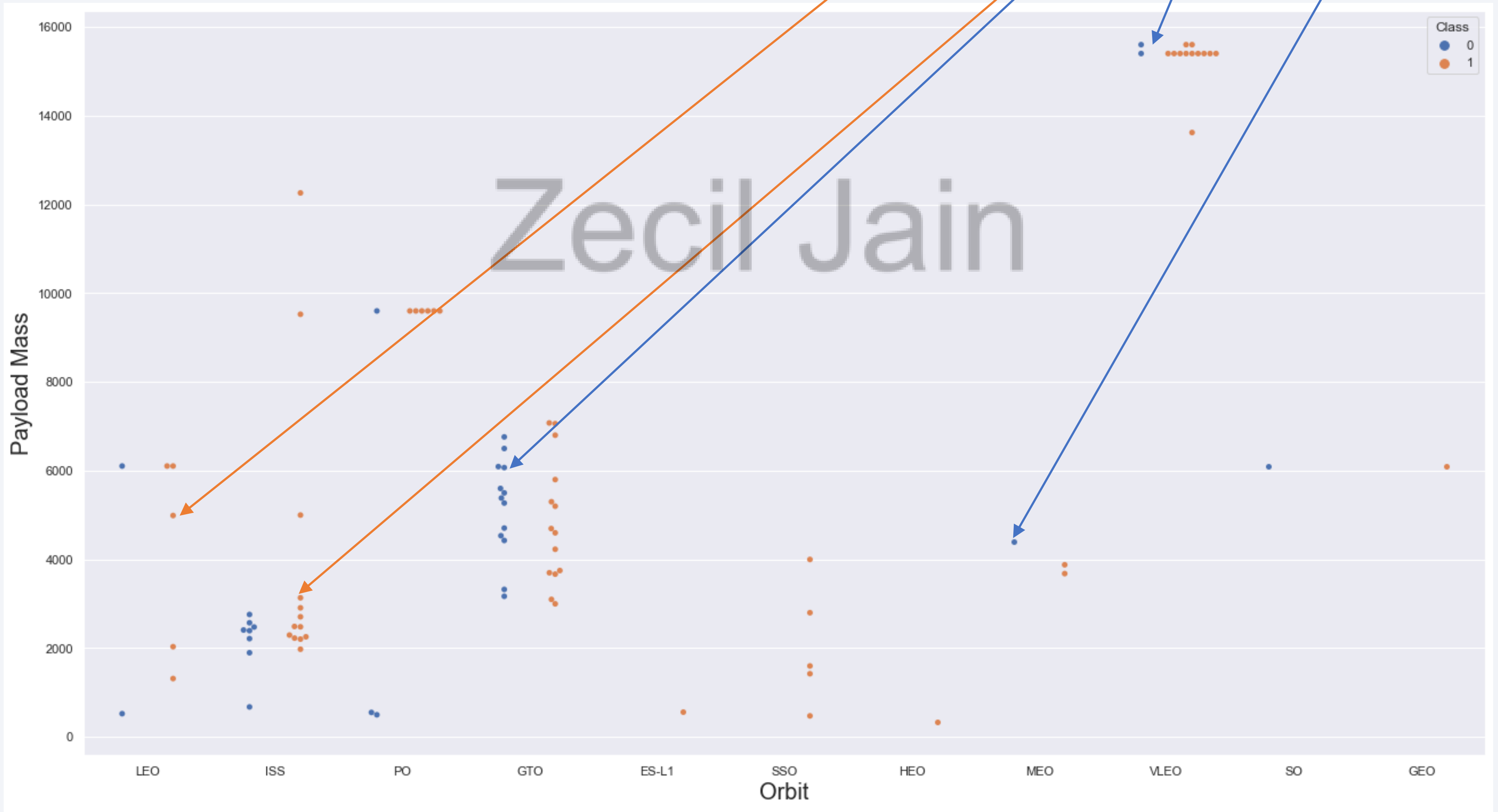
Flight Number vs. Orbit Type

- We see that for **LEO** orbit there's a clear indication that success increases with the number of flights
- On the other hand, there seems to be no relationship between flight number and the **GTO** orbit.



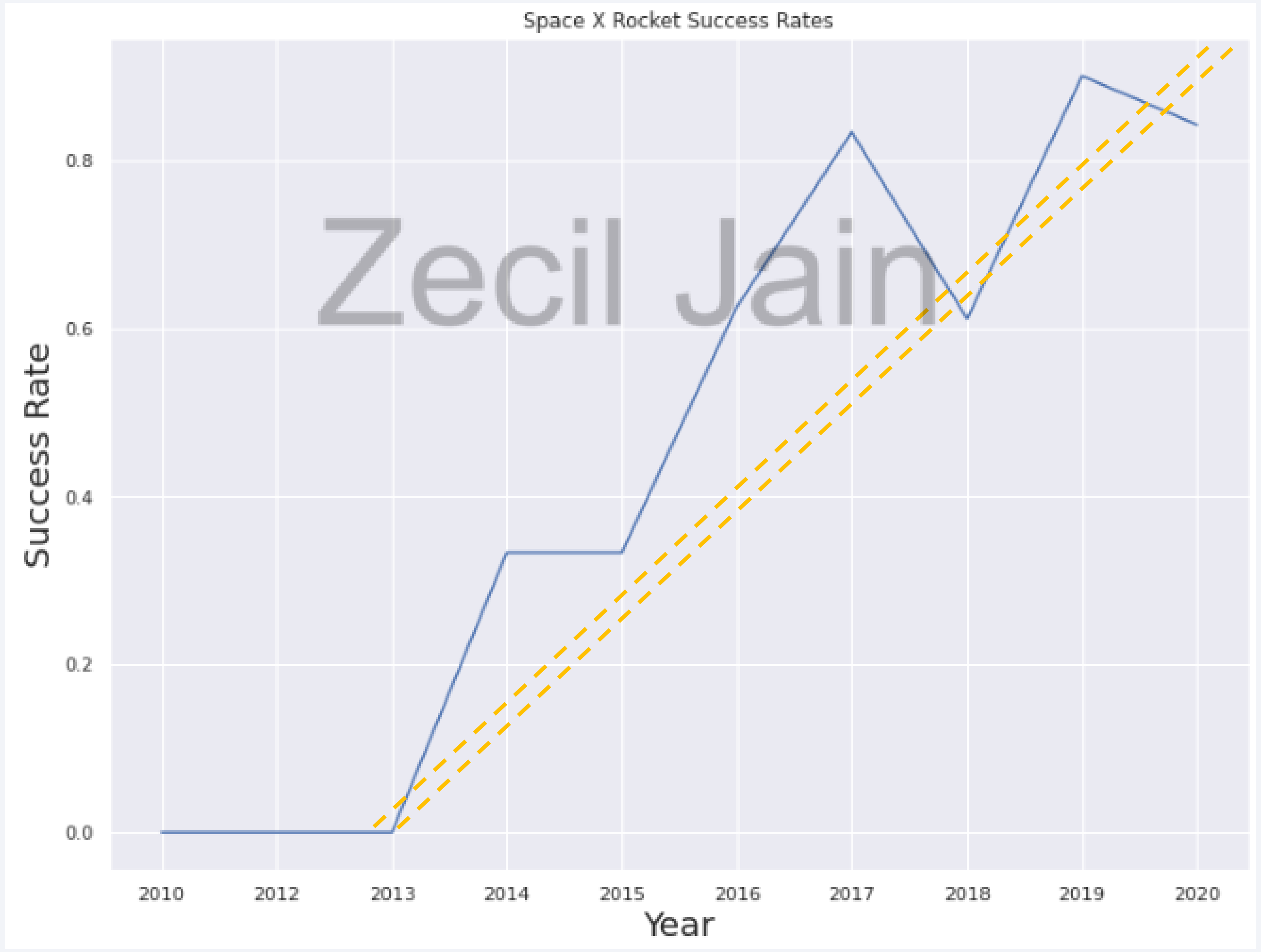
Payload vs. Orbit Type

- We observe that heavy payloads have a negative influence on **GTO, VLEO** and **MEO** orbits.
- Whereas there's a positive effect of the same on **LEO** and **ISS** orbits.



Launch Success Yearly Trend

We can observe that the success rate since 2013 kept increasing relatively though there is slight dip after 2017 and 2019.



All Launch Site Names

SQL Query

```
%sql SELECT DISTINCT LAUNCH_SITE as "Launch_Sites" FROM SPACEX;
```

Description

Using the word DISTINCT in the query we pull unique values for Launch_Site column from table SPACEX.

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

Launch Site Names Begin with 'CCA'

SQL Query

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

Description

Using keyword ‘LIMIT 5’ in the query we fetch 5 records from table SpaceX and with condition LIKE keyword with wildcard – ‘CCA%’. The percentage in the end suggests that the Launch_Site name must start with CCA.

DATE	time_utc_	booster_version	launch_site	payload	payload_mass__kg_	orbit	customer	mission_outcome	landing__outcome
2010-06-04	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
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)
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
2012-10-08	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
2013-03-01	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

Total Payload Mass

SQL Query

```
%sql SELECT SUM(PAYLOAD_MASS__KG_) AS "Total Payload Mass by NASA (CRS)" FROM SPACEX WHERE CUSTOMER = 'NASA (CRS)';
```

Description

Using the function SUM calculates the total in the column PAYLOAD_MASS_KG_ and WHERE clause filters the data to fetch Customers by name “NASA(CRS)”.

Total Payload Mass by NASA (CRS)
45596

Average Payload Mass by F9 v1.1

SQL Query

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

Description

Using the function AVG works out the average in the column PAYLOAD_MASS_KG_.
The WHERE clause filters the dataset to only perform calculations on Booster_version “F9 v1.1”.

Average Payload Mass by Booster Version F9 v1.1
2928

First Successful Ground Landing Date

SQL Query

```
%sql SELECT MIN(DATE) AS "First Succesful Landing Outcome in Ground Pad" FROM SPACEX \
WHERE LANDING__OUTCOME = 'Success (ground pad)';
```

Description

Using the function MIN works out the minimum in the column DATE and WHERE clause filters the dataset to only perform calculations on Landing_Outcome with value “Success (ground pad)”.

First Successful Landing Outcome in Ground Pad
2015-12-22

Successful Drone Ship Landing with Payload between 4000 and 6000

SQL Query

```
%sql SELECT BOOSTER_VERSION FROM SPACEX WHERE LANDING__OUTCOME = 'Success (drone ship)' \
AND PAYLOAD_MASS__KG_ > 4000 AND PAYLOAD_MASS__KG_ < 6000;
```

Description

Selecting only Booster_version,
WHERE clause filters the dataset to Landing_Outcome = Success (drone ship)

AND clause specifies additional filter conditions
PAYLOAD_MASS_KG_ > 4000 AND PAYLOAD_MASS_KG_ < 6000

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 Query

```
%sql SELECT sum(case when MISSION_OUTCOME LIKE '%Success%' then 1 else 0 end) AS "Successful Mission", \
   sum(case when MISSION_OUTCOME LIKE '%Failure%' then 1 else 0 end) AS "Failure Mission" \
FROM SPACEX;
```

Description

Selecting multiple count is a complex query. Here, we have used case clause within sub query for getting both success and failure counts in same query.

Case when MISSION_OUTCOME_LIKE ‘%Success%’ then 1 else 0 and returns a Boolean value which we sum to get the result needed.

Successful Mission	Failure Mission
100	1

Boosters Carried Maximum Payload

SQL Query

```
%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);
```

Description

Using the function MAX works out the maximum payload in the column PAYLOAD_MASS_KG_ in the sub query.

WHERE clause filters Booster Version which had that maximum payload.

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 Query

```
%sql SELECT {fn MONTHNAME(DATE)} as "Month", BOOSTER_VERSION, LAUNCH_SITE FROM SPACEX WHERE year(DATE) = '2015' AND \
LANDING__OUTCOME = 'Failure (drone ship)';
```

Description

We need to list the records which will display the month names, failure landing_outcomes in drone ship, booster_versions, launch_site for the months in the year 2015.

Via year function we extract the year and future where clause ‘Failure (drone ship)’ fetches our required values.

Also, here we are using {fn MONTHNAME(DATE)} to get the Month name.

Month	booster_version	launch_site
January	F9 v1.1 B1012	CCAFS LC-40
April	F9 v1.1 B1015	CCAFS LC-40

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

SQL Query

```
%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 ;
```

Description

Selecting only LANDING_OUTCOME,
WHERE clause filters the data with DATE BETWEEN '2010-06-04' AND '2017-03-20'

Grouping by LANDING_OUTCOME
Order by COUNT(LANDING_OUTCOME) in Descending Order.

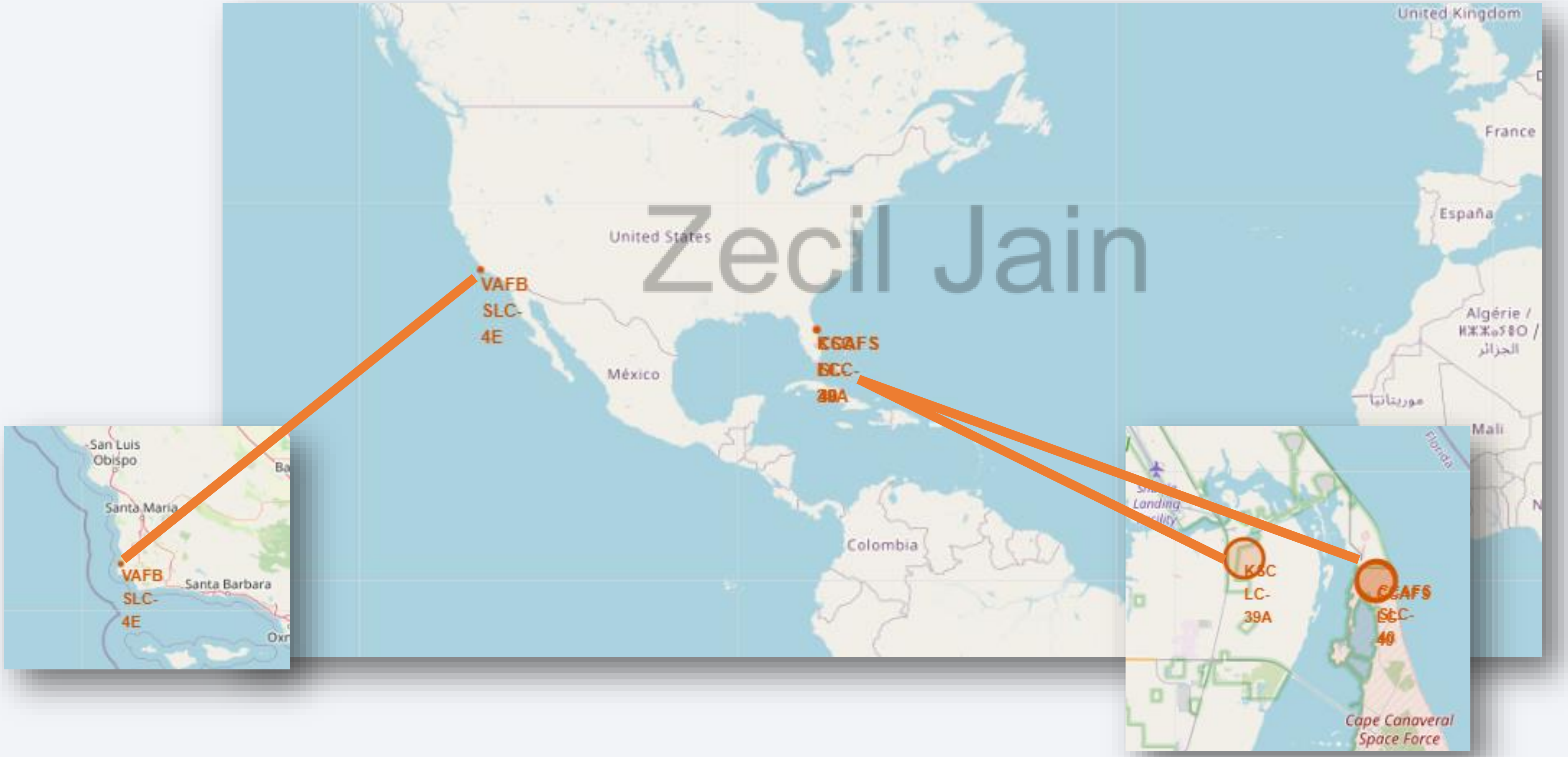
Landing Outcome	Total Count
No attempt	10
Failure (drone ship)	5
Success (drone ship)	5
Controlled (ocean)	3
Success (ground pad)	3
Failure (parachute)	2
Uncontrolled (ocean)	2
Precluded (drone ship)	1

Section 3

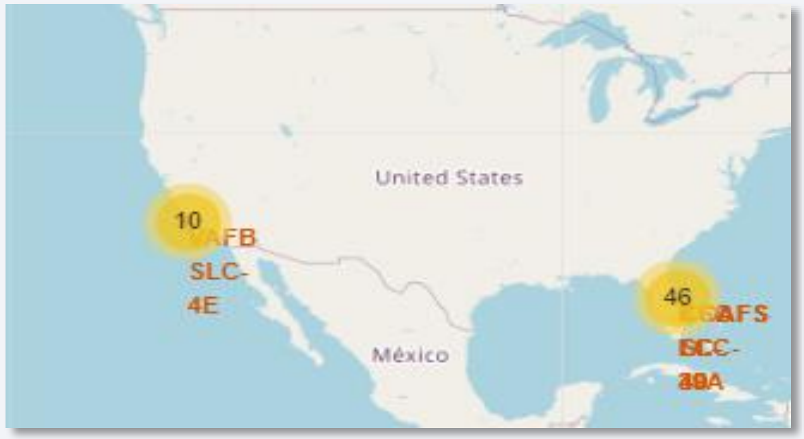
Launch Sites Proximities Analysis

All Launch Sites on Folium Map

- We can see the SpaceX launch sites are near to the United States of America coasts i.e., Florida and California regions.



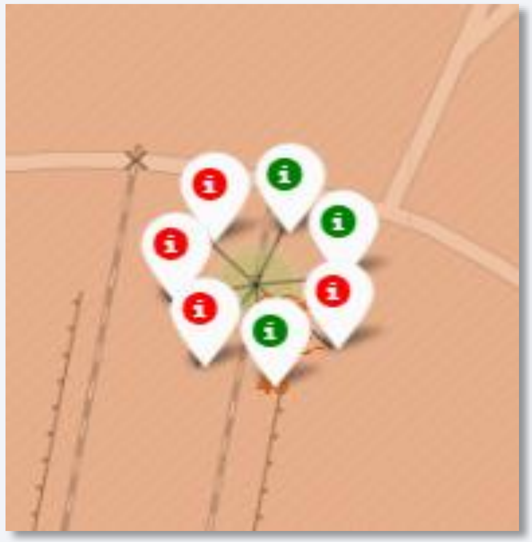
Color Labeled Launch Records



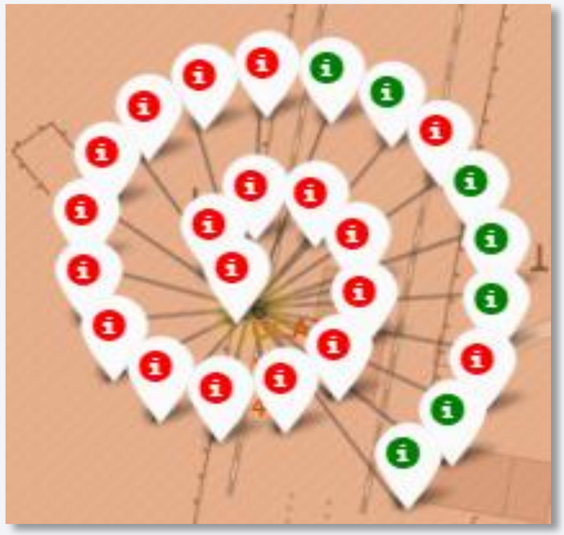
Green Marker 🟢 shows successful launches and Red marker 🔴 shows failures.

From these screenshots its easily understandable that KSC LC-39A has the maximum probability of success.

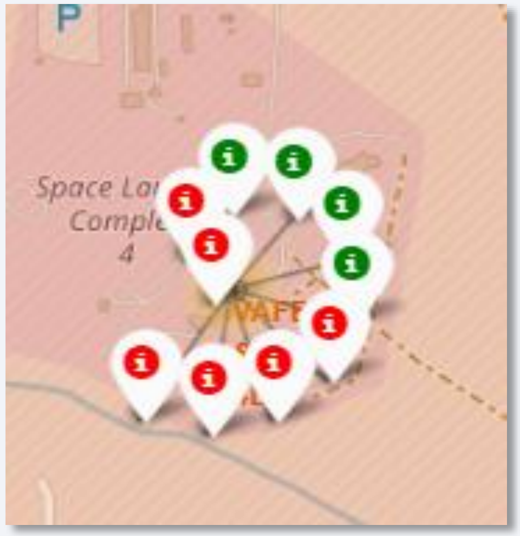
CCAFS SLC-40



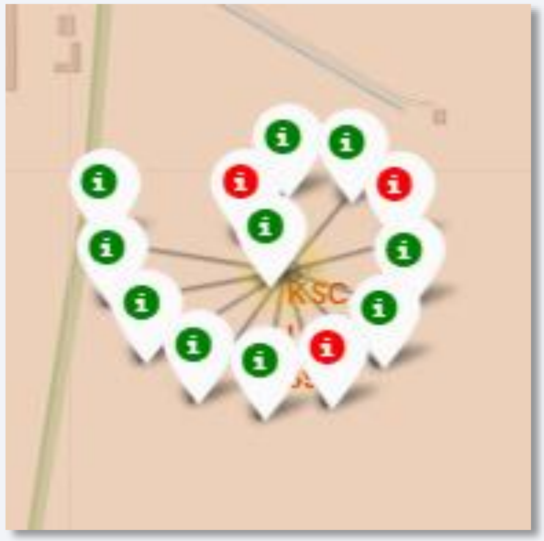
CCAFS LC-40



VAFB SLC-4E

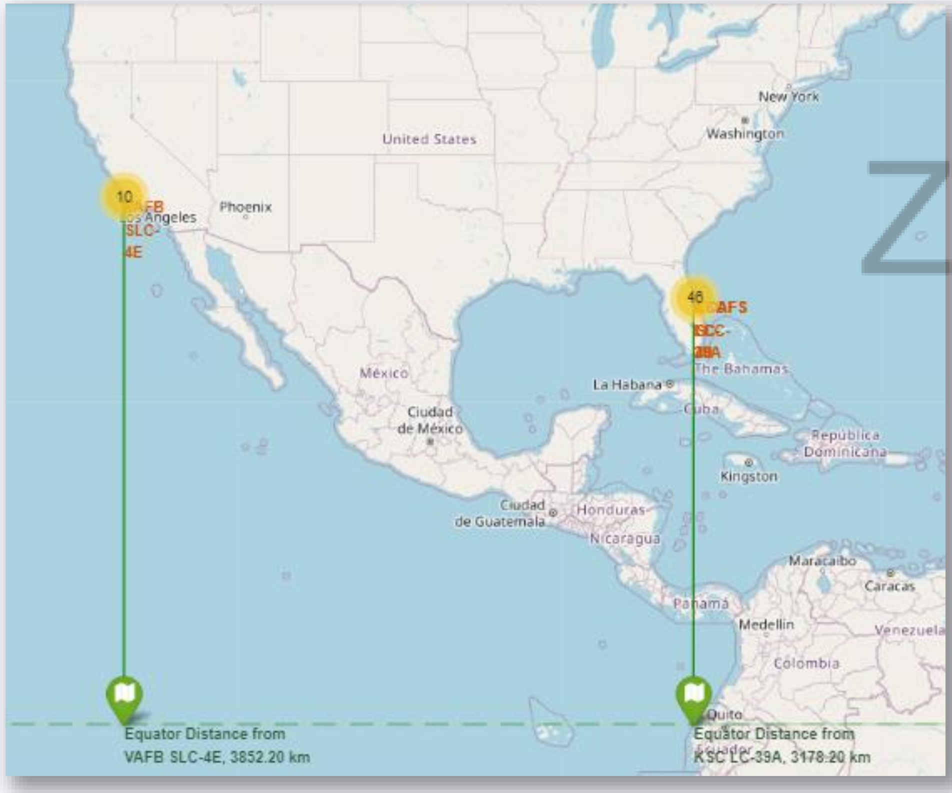


KSC LC-39A

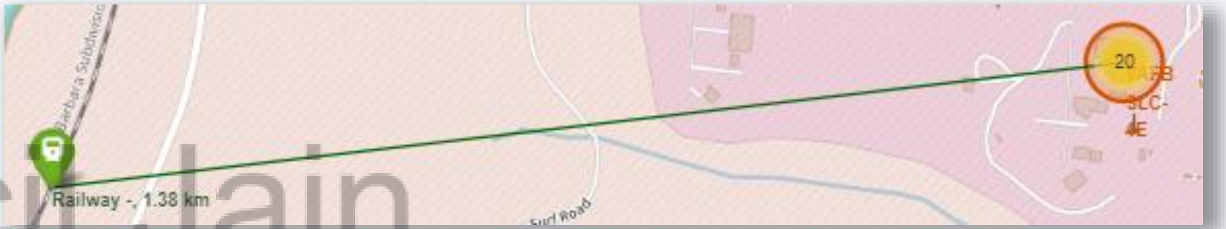


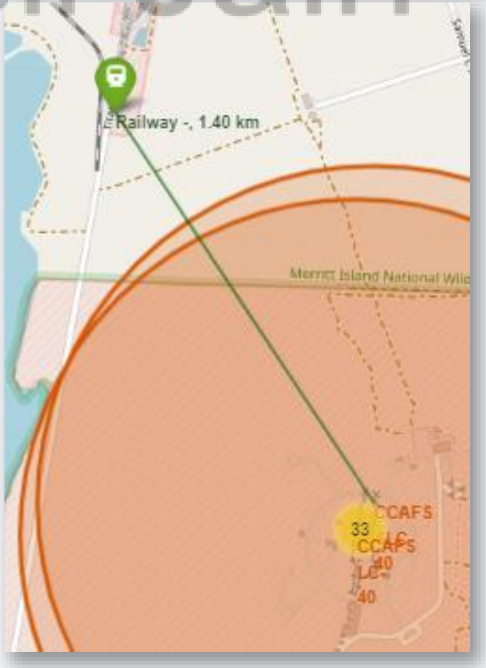
Launch Site Distance from Equator & Railways

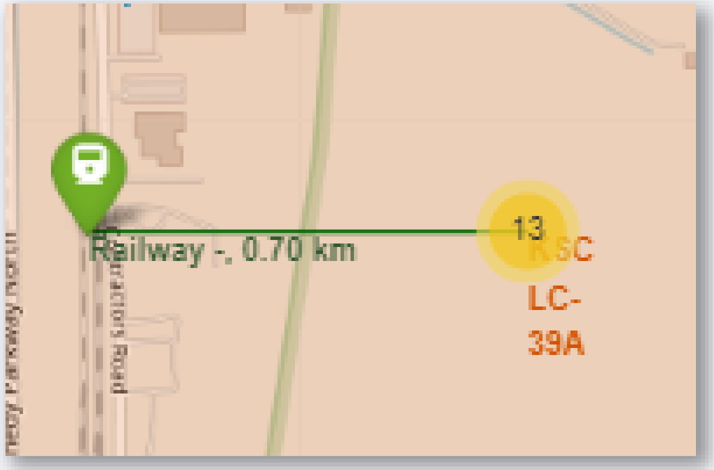
Distance from Equator is greater than 3000 Km for all sites.



Distance for all launch sites from railway tracks are greater than 0.7 Km for all sites. So, launch sites are not so far from railway tracks.

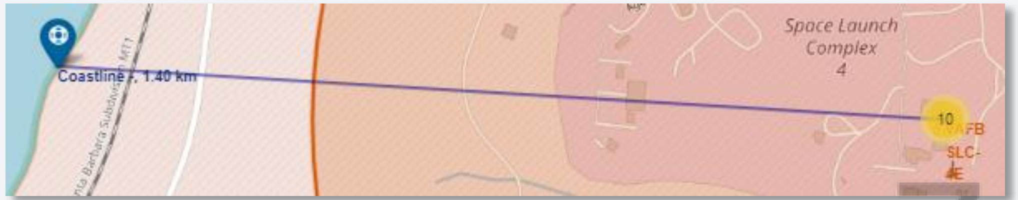


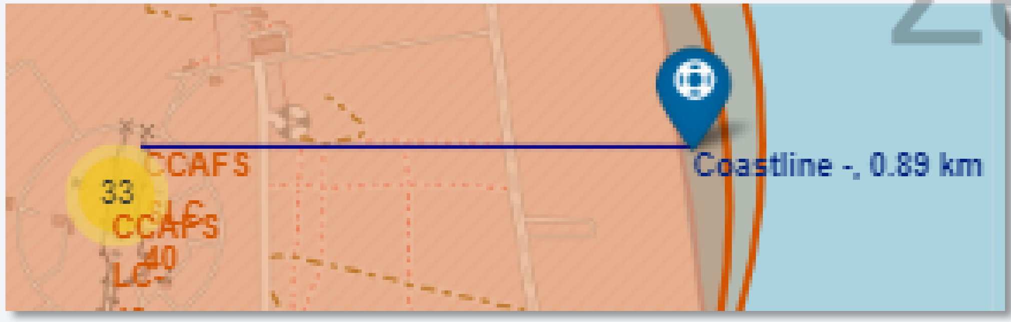


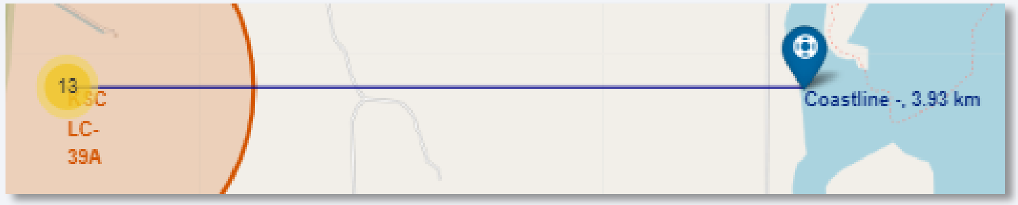


Launch Site Distance from Coastlines & Cities

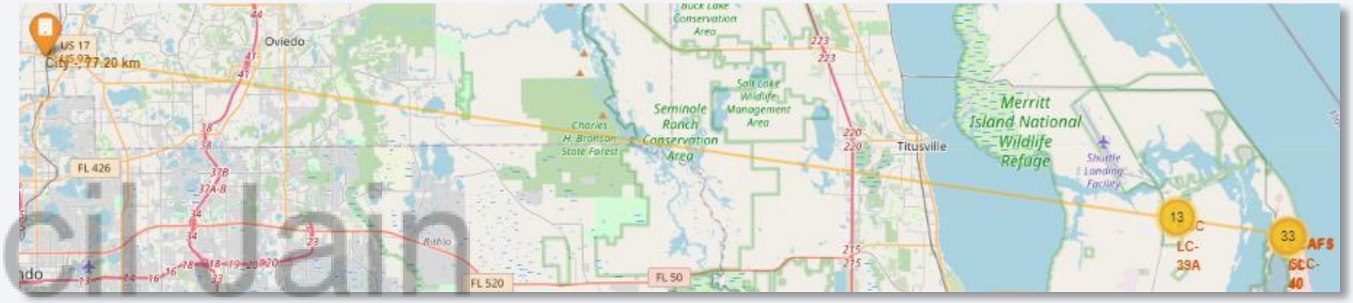
Distance for all launch sites from coastline is less than 4 km.

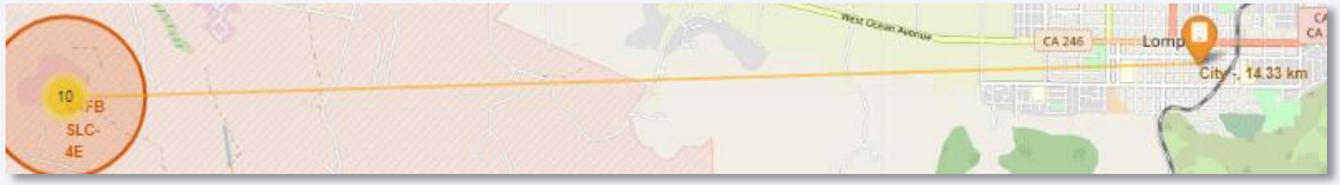


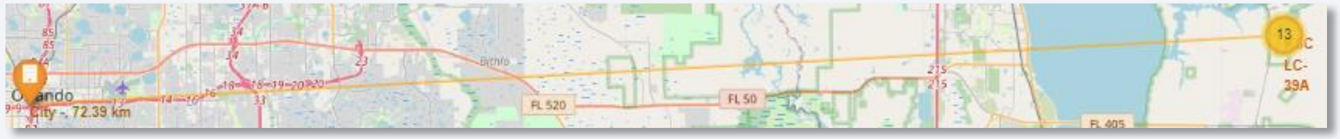




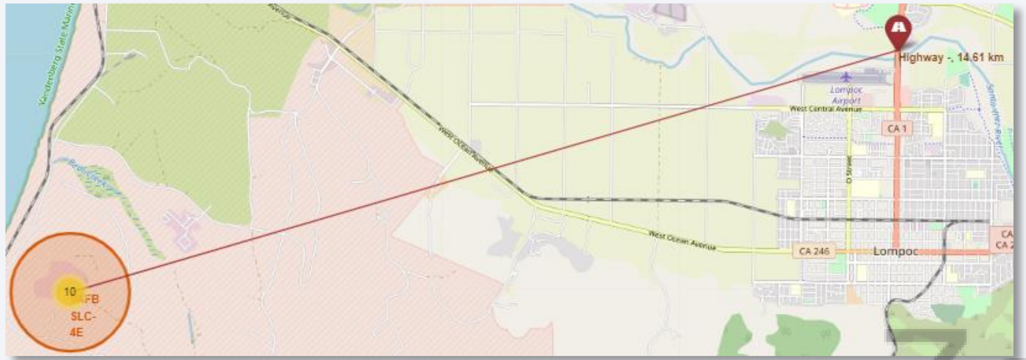
Distance for all launch sites from cities is greater than 14 Km for all sites. So, launch sites are far from cities.

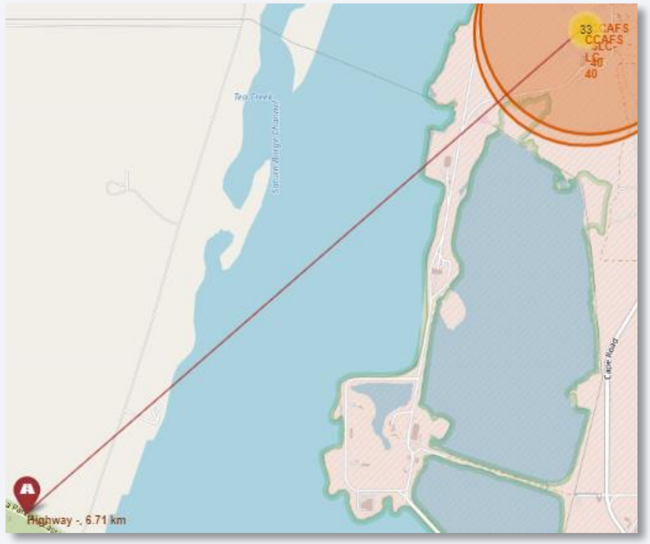


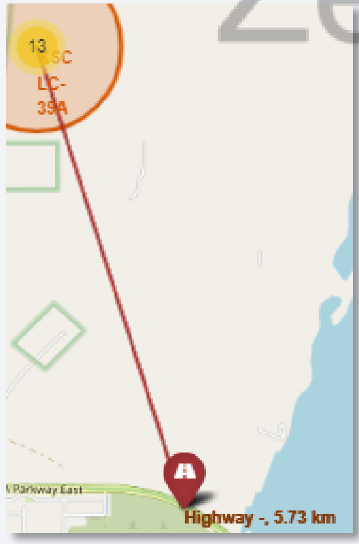




Launch Site Distance from Highways







Distance for all launch sites from highways is greater than 5 Km for all sites. So, launch sites are relatively far from highways.

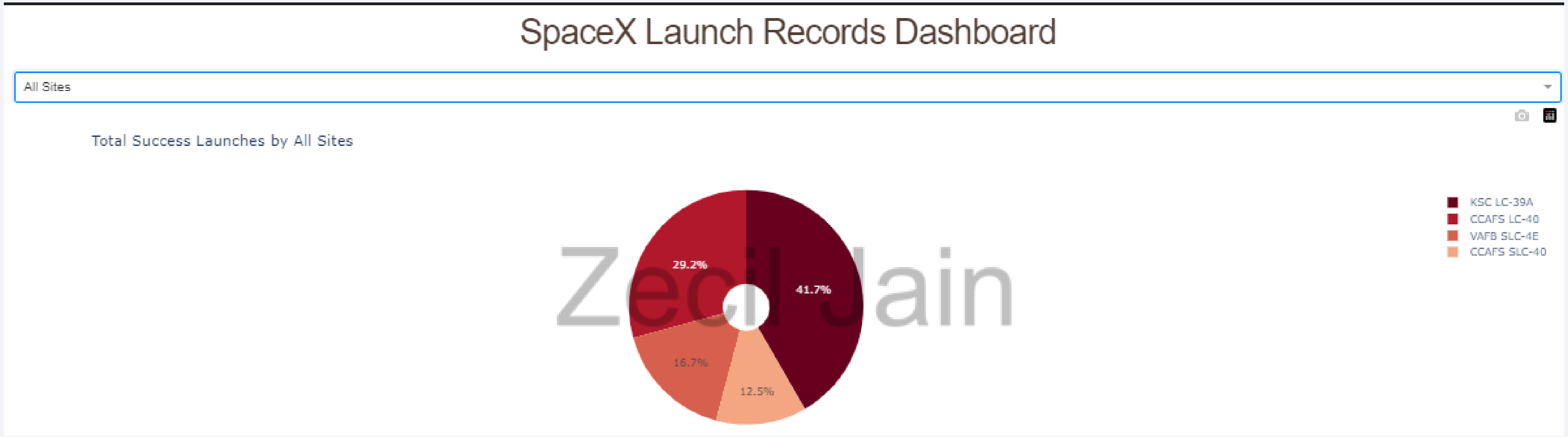
Conclusion:

- ❑ Are all launch sites in proximity to the Equator line?
- ✓ No (4000 Km > distance > 3000 Km)
- ❑ Are launch sites in close proximity to railways?
- ✓ Yes (2 Km > distance > .5 Km)
- ❑ Are launch sites in close proximity to highways?
- ✓ No (15 Km > distance > 5 Km)
- ❑ Are launch sites in close proximity to coastline?
- ✓ Yes (5 Km > distance > .5 Km)
- ❑ Do launch sites keep certain distance away from cities?
- ✓ Yes (15 Km > distance > 80 Km)

Section 4

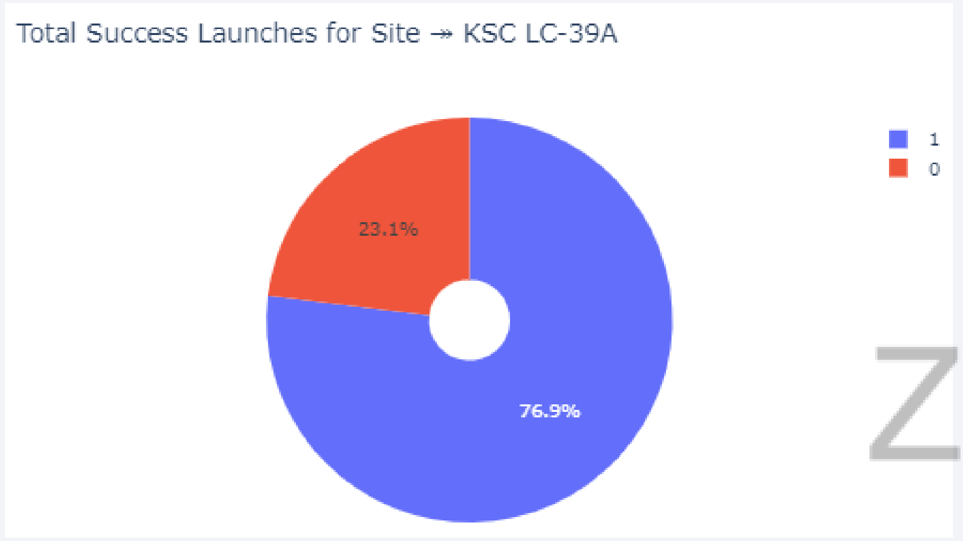
Build a Dashboard with Plotly Dash

Launch Success Count for All Sites



We can see that KSC LC-39A had the most successful launches from all the sites.

Launch Site with Highest Launch Success Ratio



KSC LC-39A achieved a 76.9% success rate while getting a 23.1% failure rate.

After visual analysis using the dashboard, we are able to obtain some insights to answer these questions:

- Which site has the highest launch success rate?

  KSC LC-39A

- Which payload range(s) has the highest launch success rate?

  2000kg-10000kg

- Which payload range(s) has the lowest launch success rate?

  0kg-1000kg

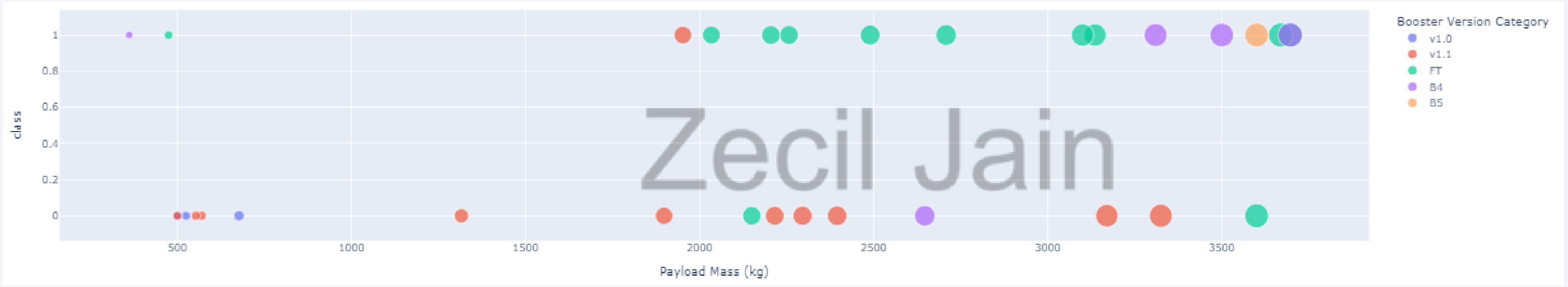
- Which F9 Booster version(v1.0, v.1.1, FT, B4, B5, etc.) has the highest launch success rate?

  FT

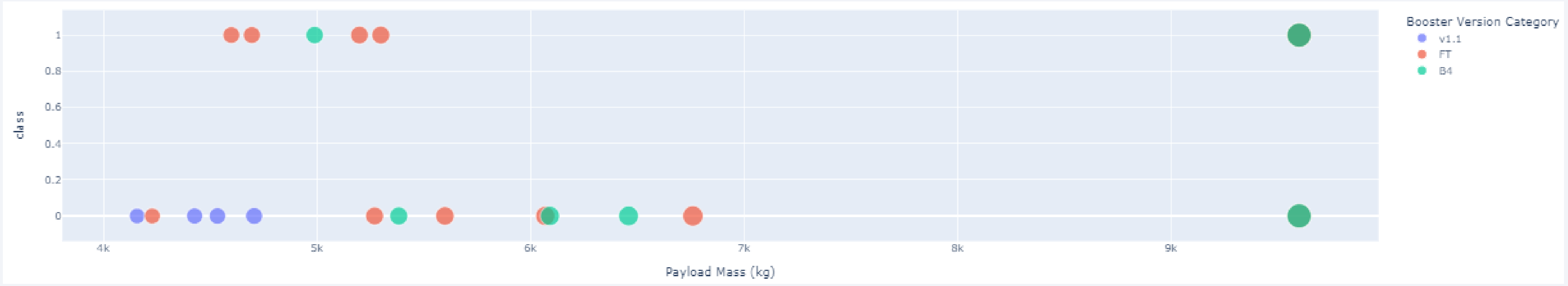
Payload vs. Launch Outcomes Scatter Plot for All Sites

- We can see the success rates for low weighted payloads is higher than the heavy weighted payloads.

Low Weighted Payload 0kg-4000kg



Heavy Weighted Payload 4000kg-10000kg



Section 5

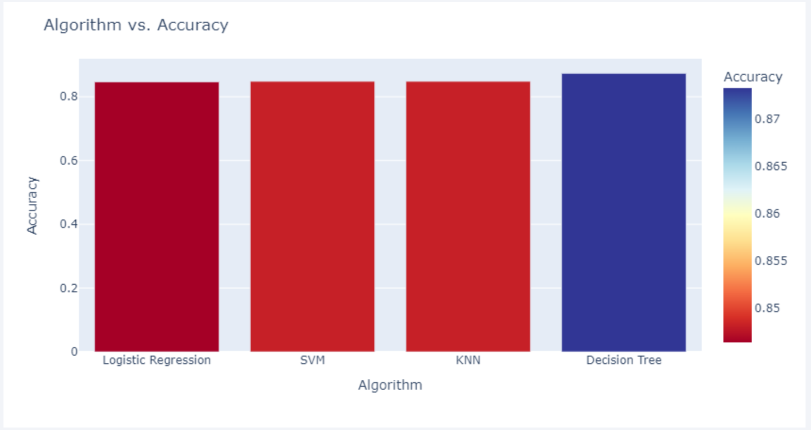
Predictive Analysis (Classification)

Classification Accuracy

As you can see our accuracy is extremely close, but we do have a clear winner which performs best – “Decision Tree” with a score of 0.8625

Algorithm	Accuracy	Accuracy on Test Data	Tuned Hyperparameters
Logistic Regression	0.846429	0.833334	{'C': 0.01, 'penalty': 'l2', 'solver': 'lbfgs'}
SVM	0.848214	0.833334	{'C': 1.0, 'gamma': 0.03162277660168379, 'kernel': 'sigmoid'}
KNN	0.848214	0.833334	{'algorithm': 'auto', 'n_neighbors': 10, 'p': 1}
Decision Tree	0.862500	0.833334	{'criterion': 'gini', 'max_depth': 10, 'max_features': 'sqrt', 'min_samples_leaf': 1, 'min_samples_split': 2, 'splitter': 'best'}

We trained four different models which each had an 83% accuracy rate



Confusion Matrix

Out here for all models unfortunately, we have same confusion matrix.

		Predicted Values		
		Predicted No	Predicted Yes	
Actual Values	Actual No	True Negative **TN = 3**	False Positive **FP = 3**	6
	Actual Yes	False Negative **FN = 0**	True Positive **TP = 12**	12
		3	15	Total Cases = 18

Accuracy: (TP + TN)/Total = (12 + 3) / 18 = 0.83333

Misclassification Rate: (FP + FN) / Total = (3 + 0) / 18 = 0.1667

True Positive Rate: TP / Actual Yes = 12 / 12 = 1

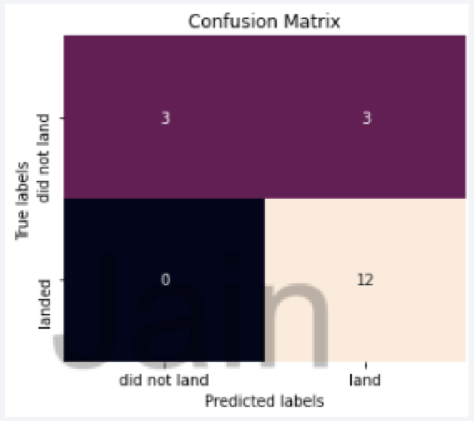
False Positive Rate: FP / Actual No = 3 / 6 = 0.5

True Negative Rate: TN / Actual No = 3 / 6 = 0.5

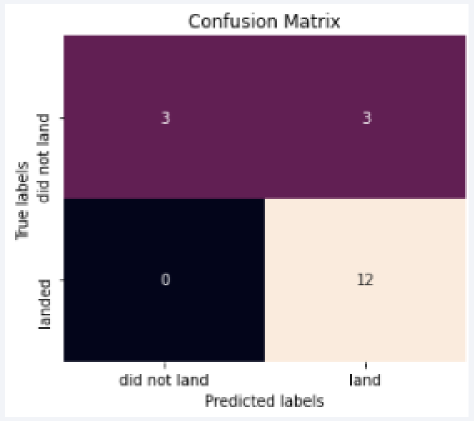
Precision: TP / Predicted Yes = 12 / 15 = 0.8

Prevalence: Actual Yes / Total = 12 / 18 = 0.6667

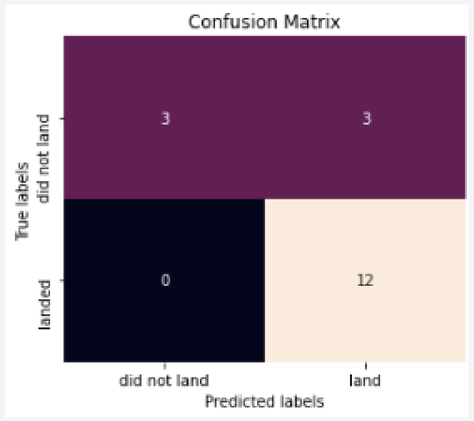
Logistic Regression



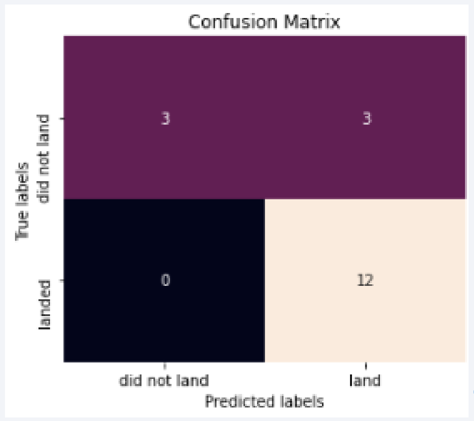
SVM

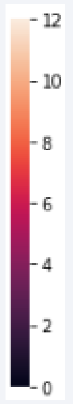


Decision Tree



KNN





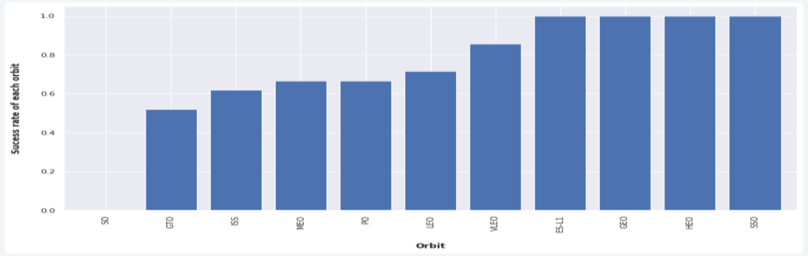
Conclusions

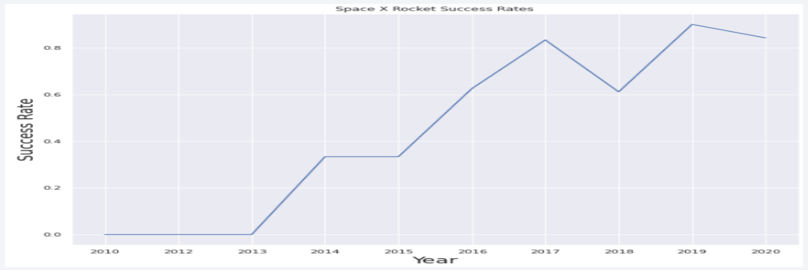
- ❖ Orbits ES-L1, GEO, HEO and SSO have highest success rates.

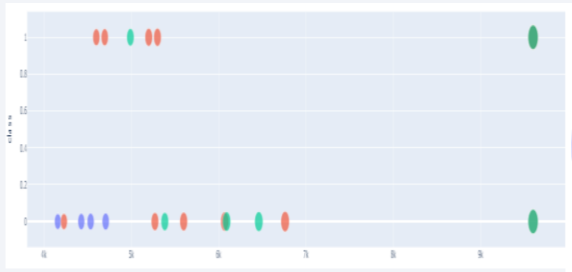
- ❖ Success rates for SpaceX launches have been increasing relatively with time and it looks like soon they will reach the required target.

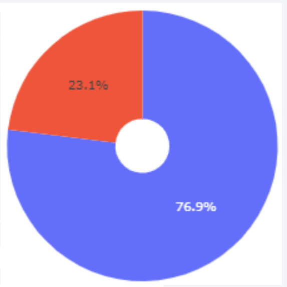
- ❖ KSC LC-39A had the most successful launches but increasing payload mass seems to have negative impact on the success.

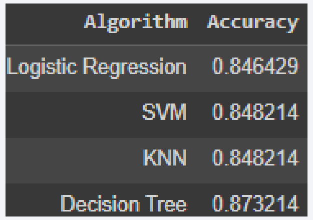
- ❖ Decision Tree Classifier Algorithm is the best suited Machine Learning Model with the provided dataset.



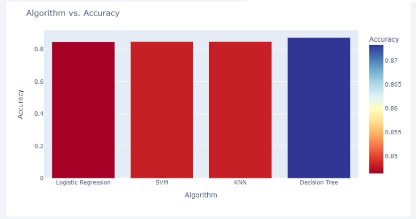








Algorithm	Accuracy
Logistic Regression	0.846429
SVM	0.848214
KNN	0.848214
Decision Tree	0.873214



Appendix

- Interactive Plotly
- Folium MeasureControl Plugin Tool
- Folium Custom Title Layers with Labels
- Basic Decision Tree Construction

Thank you!