IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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15 Jan 2023

Outline

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

Executive Summary

- Summary of methodologies
    1. Data Collection through API and Web Scraping
    2. Data Wrangling
    3. Exploratory Data Analysis with SQL and Data Visualization
    4. Interactive Visual Analytics with Folium
    5. Machine Learning Prediction
- Summary of all results
    - Exploratory Data Analysis result
    - Interactive analytics in screenshots
    - Predictive Analytics result

Introduction

Project background and context

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 upward 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, 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

- What factors determine if the rocket will land successfully?
- The relationship between the various features that determine the success rate of a successful landing.
- What conditions need to be implemented to ensure the best result
- how to determine the price of each launch?

Section 1

Methodology

Methodology

Executive Summary

- Data collection methodology:
  - API from SpaceX website
  - WebScraping from Wikipedia
- Perform data wrangling
  - One-hot encoding was applied to 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 collecting, measuring and analyzing different types of information using a set of standard validated techniques**. The main objective of data collection is to gather information-rich and reliable data, and analyze them to make critical business decisions.

The data was collected using various methods:

API

1. Getting data from API create a dataframe from this data
2. Then cleaned the data, checked for missing value and fill missing values where necessary
3. Filter the dataframe to only include Falcon 9 launches

WEBSCRAPING

1. We applied web scrapping to webscrap Falcon 9 launch records with BeautifulSoup
2. We parsed the table and converted it into a pandas dataframe

Data Collection – SpaceX API

Getting Response from API

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

response = requests.get(spacex_url)
```

Converting response to a .json file

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

static_json_url='https://cf-courses-data.s3.us.cloud-

# Get the head of the dataframe
data.head()
```

Apply custom functios to clean data

```
# Calculate the mean value of PayloadMass column
data_falcon9.describe()
mean=data_falcon9["PayloadMass"].mean()
# Replace the np.nan values with its mean value
data_falcon9["PayloadMass"]=data_falcon9["PayloadMass"].replace(np.nan,mean)
data_falcon9["PayloadMass"]

data_falcon9.isnull().sum()
```

Assign list to dictionary for dataframe

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

Filter only falcon 9 and export file (.csv)

```
data_falcon9= data[data.BoosterVersion =='Falcon 9']
data_falcon9

data_falcon9.to_csv('dataset_part_1.csv', index=False)
```

FlightNumber	Date	BoosterVersion	PayloadMass	Orbit	LaunchSite	Outcome	Flights	GridFins	Reused	Legs	LandingPad	Block	ReusedCount	Serial
1	2010-06-04	Falcon 9	NaN	LEO	CCSFS SLC 40	None None	1	False	False	False	None	1.0	0	B0003
2	2012-05-22	Falcon 9	525.0	LEO	CCSFS SLC 40	None None	1	False	False	False	None	1.0	0	B0005
3	2013-03-01	Falcon 9	677.0	ISS	CCSFS SLC 40	None None	1	False	False	False	None	1.0	0	B0007
4	2013-09-29	Falcon 9	500.0	PO	VAFB SLC 4E	False Ocean	1	False	False	False	None	1.0	0	B1003
5	2013-12-03	Falcon 9	3170.0	GTO	CCSFS SLC 40	None None	1	False	False	False	None	1.0	0	B1004

Notebook:

[Data Collection with API]

Data Collection – Scraping

Getting Response from HTML

```
static_url = "https://en.wikipedia.org
# assign the response to a object

response= requests.get(static_url)
```

Creating BeautifulSoup

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

Finding Tables and extract columns names

```
# Assign the result to a list called `html_tables`
html tables = soup.find all('table')

column_names = []

labels = first_launch_table.find_all('th')
for label in labels:
    name = extract_column_from_header(label)
   # header = str(label.text).strip()
    #header = str(header).split("($)Footnote", 1)[0]
    if name != None:
        if len(name) > 0:
            column_names.append(name)
```

Create an empty dictionary

```
launch_dict= dict.fromkeys(column_names)

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

# Let's initial the launch_dict with each value to be an empty list
launch_dict['Flight No.'] = []
launch dict['Launch site'] = []
```

Converting dictionary to daframe

```
headings = []
for key,values in dict(launch_dict).items():
    if key not in headings:
        headings.append(key)
    if values is None:
        del launch_dict[key]

def pad_dict_list(dict_list, padel):
    lmax = 0
    for lname in dict_list.keys():
        lmax = max(lmax, len(dict_list[lname]))
    for lname in dict_list.keys():
        ll = len(dict_list[lname])
        if  ll < lmax:
            dict_list[lname] += [padel] * (lmax - ll)
    return dict_list

pad_dict_list(launch_dict,0)

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

Export dataframe (.csv)

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

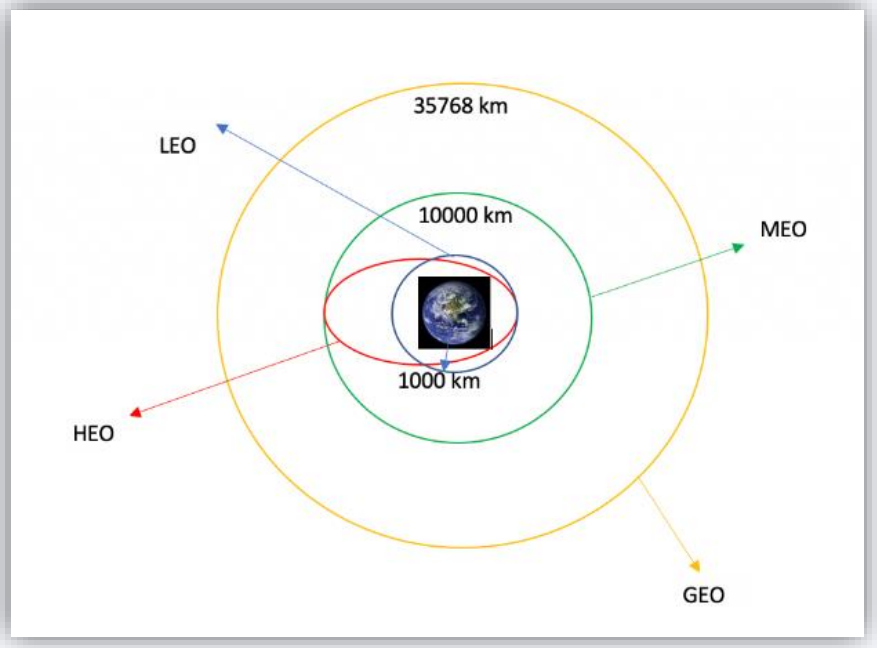
Notebook:

[Data collection WebScraping]

Data Wrangling

Data wrangling is **the process of removing errors and combining complex data sets to make them more accessible and easier to analyze**. You need to present your data wrangling process using key phrases and flowcharts

1. I did some exploratory data analysis (EDA) to find some patterns in the data and determine what the label would be for training supervised models.
2. Then I convert these results into training labels with **1** meaning the booster arrived successfully **0** meaning it was unsuccessful
3. I create a landing outcome label from **Outcome** column and
4. exported the results to **csv.**



Notebook:

Data Wrangling

Data Wrangling

Calculate the number and occurrence of each orbit

Calculate the number and occurence of mission outcome per orbit type

Create a landing outcome label from Outcome column

```
# Apply value_counts on Orbit column
df.value_counts("Orbit")
```

```
Orbit
GTO      27
ISS      21
VLEO     14
PO        9
LEO       7
SSO       5
MEO       3
ES-L1     1
GEO       1
HEO       1
SO        1
dtype: int64
```

```
# landing_outcomes = values on Outcome column
landing_outcomes= df.value_counts("Outcome")
landing_outcomes
```

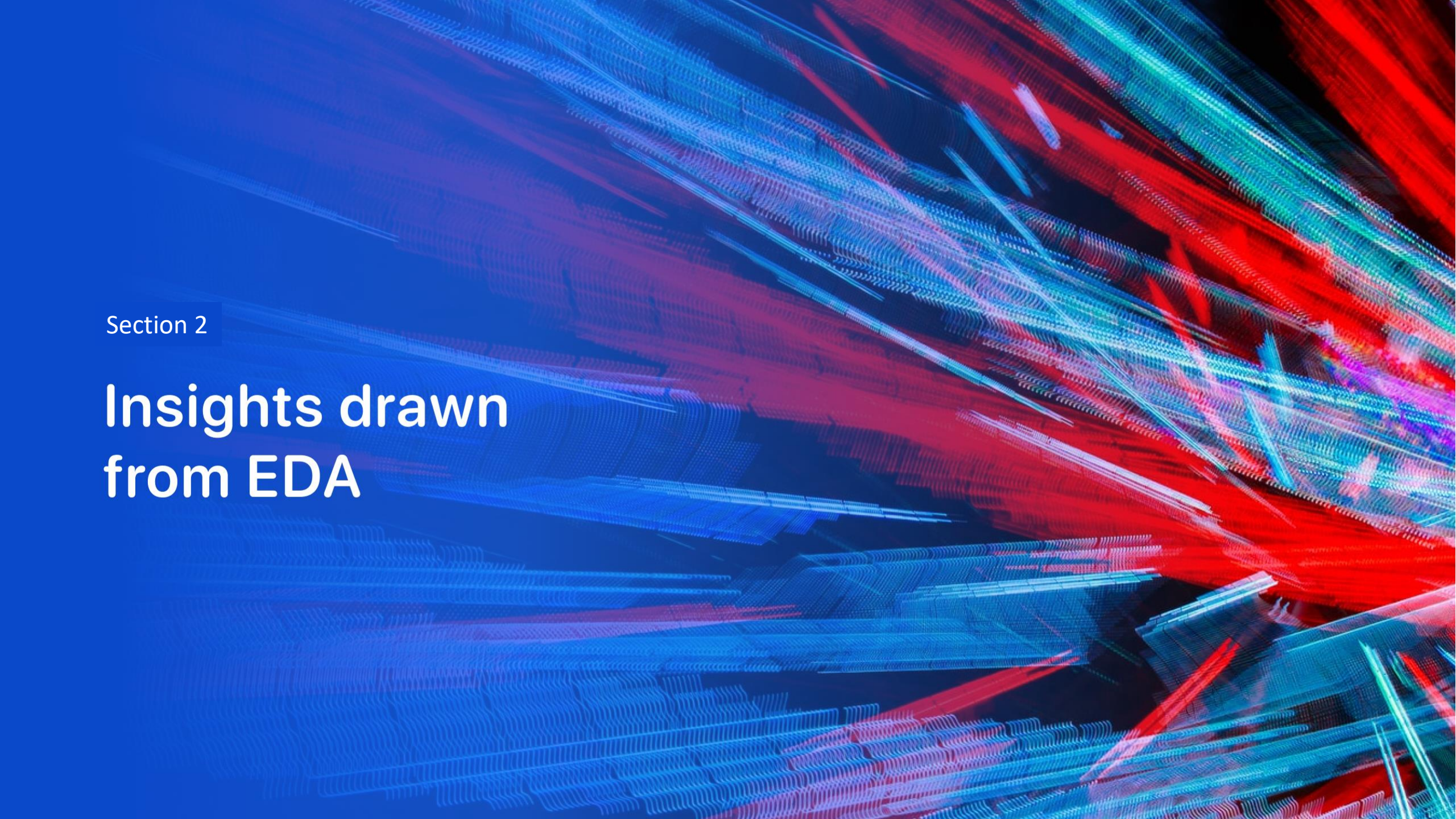
```
Outcome
True ASDS       41
None None       19
True RTLS       14
False ASDS       6
True Ocean       5
False Ocean      2
None ASDS        2
False RTLS       1
dtype: int64
```

```
df['Class']=landing_class
df[['Class']].head(8)
```

	Class
0	0
1	0
2	0
3	0
4	0
5	0
6	1
7	1

Notebook:

Data Wrangling


Section 2
Insights drawn from EDA

EDA with Data Visualization

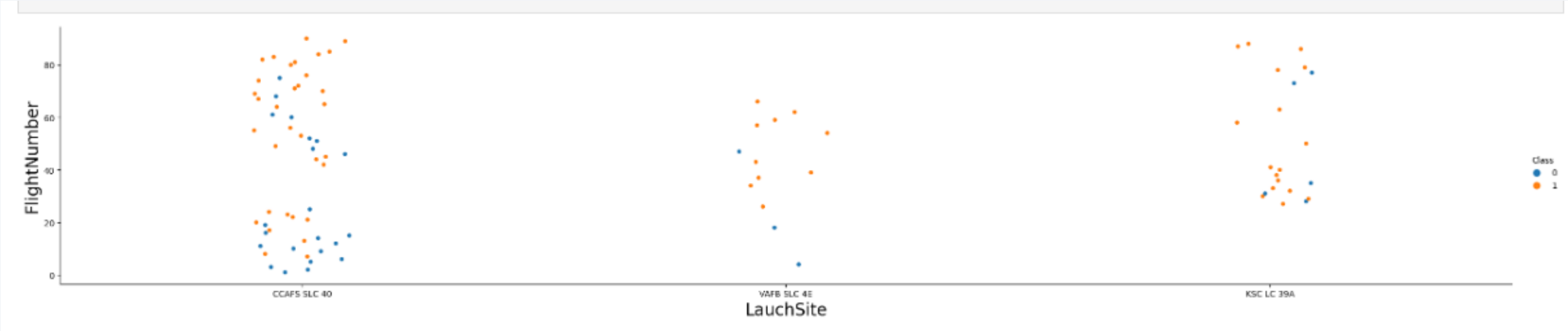
Perform exploratory Data Analysis and Feature Engineering using Pandas and Matplotlib

Next, let's drill down to each site visualize its detailed launch records.

Notebook:
EDA with data visualization

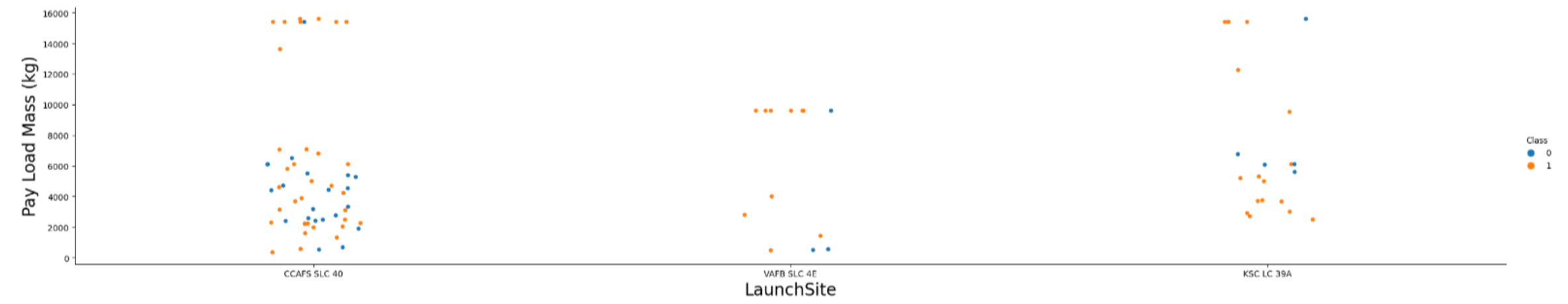
Flight Number vs Lauch Site

- CCAFS LC-40 has a success rate of 60 %,
- KSC LC-39A has a success rate of 77%,
- VAFB SLC 4E has a success rate of 77%.



Payload and Launch Site

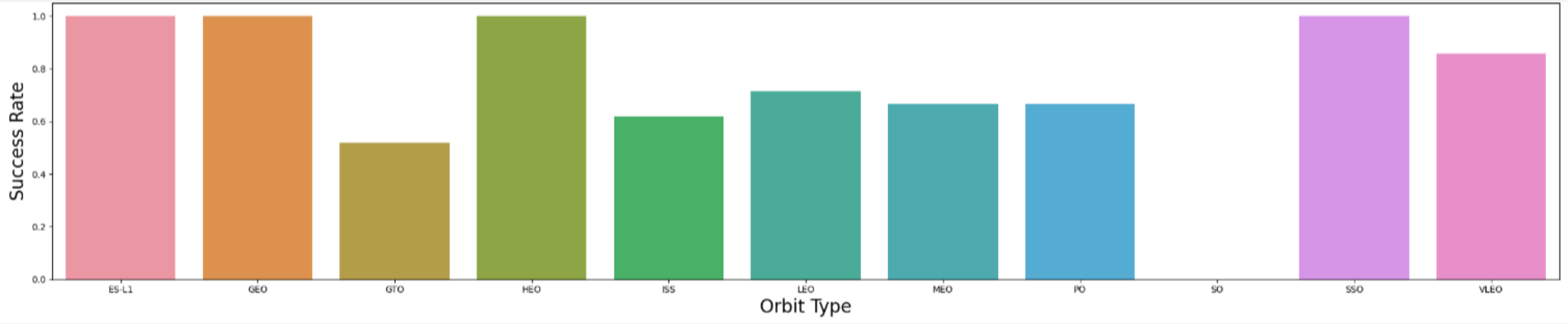
Now if you observe Payload Vs. Launch Site scatter point chart you will find for the **VAFB-SLC** launchsite there are no rockets launched for heavypayload mass(greater than 10000



Success rate of each orbit type

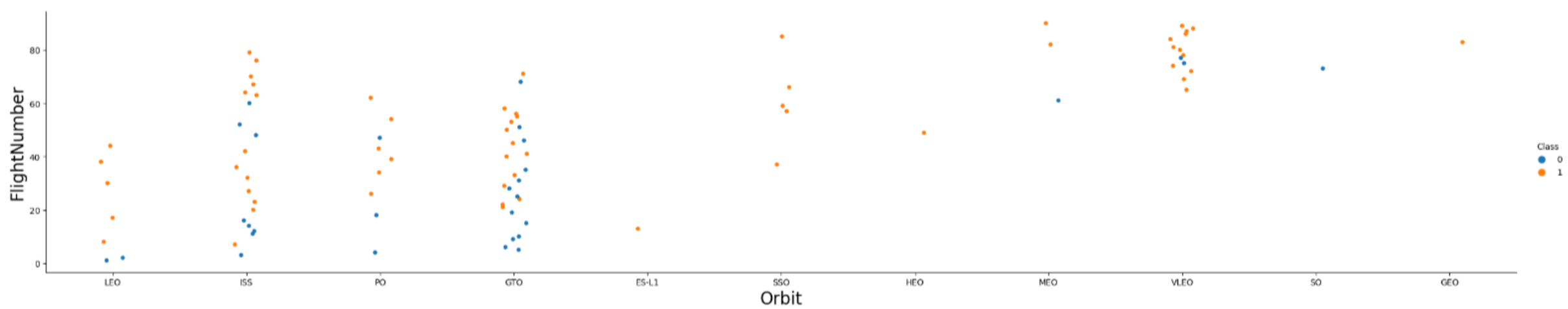
Analyze the ploted bar chart try to find which orbits have high sucess rate.

- GEO
- HEO
- SSO
- ES-L1



FlightNumber and Orbit type

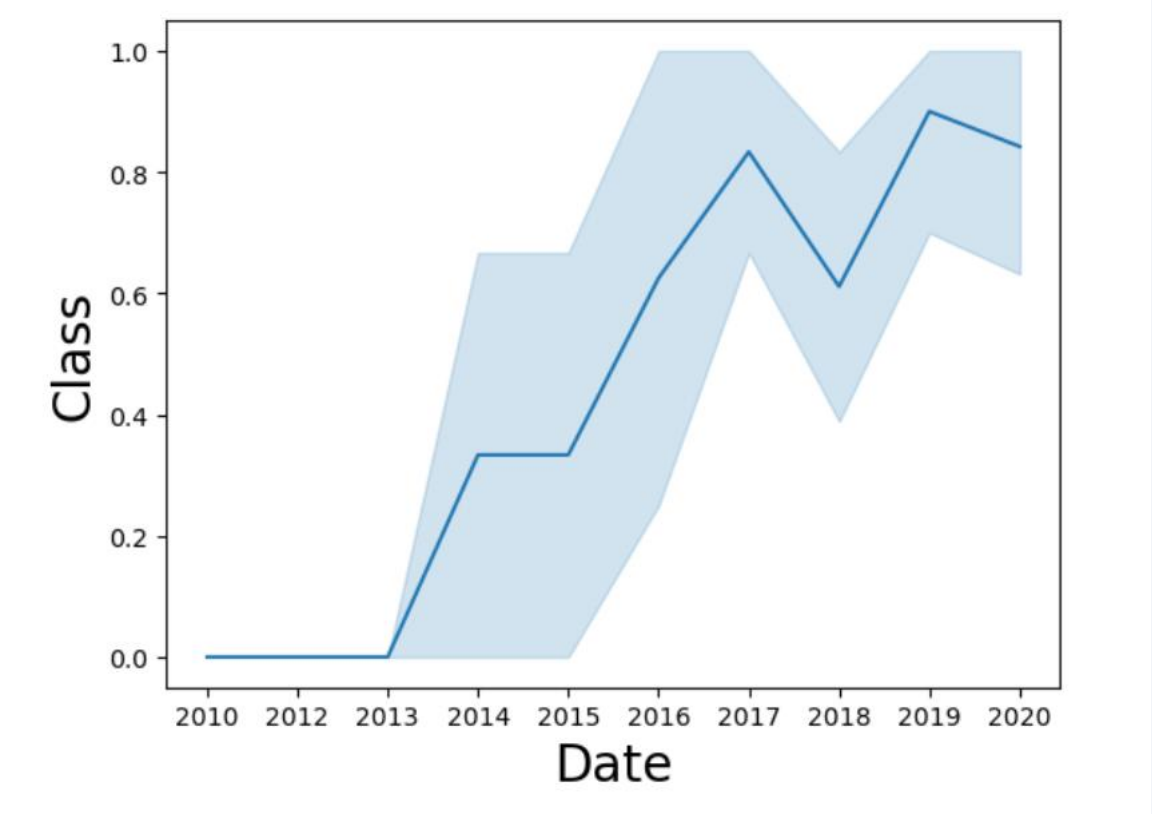
You should see that in the **LEO** orbit the Success appears related to the number of flights; on the other hand, there seems to be no relationship between flight number when in **GTO** orbit..



Visualize the launch success yearly trend

I draw a line graph with the x-axis as the Year and the y-axis as the average success rate, to get the average launch success trend.

We can observe that the sucess rate since 2013 kept increasing till 2020



EDA with SQL

SQL (Structured Query Language) is a standard language used for managing relational databases.

With SQL, you **can create, modify, and query** tables within a database, as well as manage users and permissions.

It also allows you to **select, insert, update and delete** data in a database.

SQL is a declarative language, which means that the user specifies what needs to be done, but not how it needs to be done.

Notebook:
EDA with SQL

1. Display the names of the unique launch sites in the space mission

RENAME TABLE from **SPACE_X** to **x**

```
%sql select distinct launch_site from x
```

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

2. Display 5 records where launch sites begin with the string 'CCA

```
%sql SELECT * FROM x WHERE launch_site LIKE 'CCA%' LIMIT 5;
```

DATE	time__utc_	booster_version	launch_site	payload	payload_mass__kg_	orbit	customer	mission_outcome	landing__outcome
04-06-2010	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
08-12-2010	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)
22-05-2012	07:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	No attempt
08-10-2012	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
01-03-2013	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

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

```
%sql SELECT customer,sum(payload_mass__kg_) as total_payload FROM x WHERE CUSTOMER = 'NASA (CRS)' group by CUSTOMER;
```

customer	total_payload
NASA (CRS)	45596

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

```
%sql select booster_version,avg(payload_mass__kg_) as average_payload_mass from x where booster_version='F9 v1.1' group by booster_version;
```

booster_version	average_payload_mass
F9 v1.1	2928

5. List the date when the first successful landing outcome in ground pad was acheived

```
%sql select DATE,landing__outcome from x where landing__outcome like 'Success (ground pad)' limit 1
```

DATE	landing__outcome
22-12-2015	Success (ground pad)

6.List the names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000

```
%sql select booster_version from x where landing__outcome
like 'Success (drone ship)' and 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

7. List the total number of successful and failure mission outcomes

```
%sql SELECT mission_outcome, COUNT(*) as total FROM x GROUP BY mission_outcome;
```

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

8. List the names of the booster_versions which have carried the maximum payload mass

```
%sql select distinct(booster_version),payload_mass__kg_ from x where payload_mass__kg_ in (select max(payload_mass__kg_) from x)
```

booster_version	payload_mass__kg_
F9 B5 B1048.4	15600
F9 B5 B1048.5	15600
F9 B5 B1049.4	15600
F9 B5 B1049.5	15600
F9 B5 B1049.7	15600
F9 B5 B1051.3	15600
F9 B5 B1051.4	15600
F9 B5 B1051.6	15600
F9 B5 B1056.4	15600
F9 B5 B1058.3	15600
F9 B5 B1060.2	15600
F9 B5 B1060.3	15600

9. List the failed landing_outcomes in drone ship, their booster versions, and launch site names for in year 2015

```
%sql select landing__outcome,booster_version,launch_site from x where landing__outcome= 'Failure (drone ship)' and date like '%2015'
```

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

10. Rank the count of landing outcomes (Failure (drone ship) or Success (ground pad)) between the date 2010-06-04 and 2017-03-20

```
%sql select landing__outcome,count(*),date
from x
where landing__outcome='Failure (drone ship)' or landing__outcome='Success (ground pad)'
and date>= '04-06-2010' and date<='20-03-2017'
group by landing__outcome,date
```

landing__outcome	2	DATE
Failure (drone ship)	1	04-03-2016
Success (ground pad)	1	07-09-2017
Success (ground pad)	1	08-01-2018
Failure (drone ship)	1	10-01-2015
Failure (drone ship)	1	14-04-2015
Success (ground pad)	1	14-08-2017
Failure (drone ship)	1	15-06-2016
Success (ground pad)	1	15-12-2017
Failure (drone ship)	1	17-01-2016
Success (ground pad)	1	18-07-2016
Success (ground pad)	1	19-02-2017

Section 3

Launch Sites Proximities Analysis

Build an Interactive Map with Folium

The launch success rate may depend on many factors such as payload mass, orbit type, and so on.

It may also depend on the location and proximities of a launch site, i.e., the initial position of rocket trajectories.

Finding an optimal location for building a launch site certainly involves many factors and hopefully we could discover some of the factors by analyzing the existing launch site locations.

Notebook:
Visual analitic with Folium

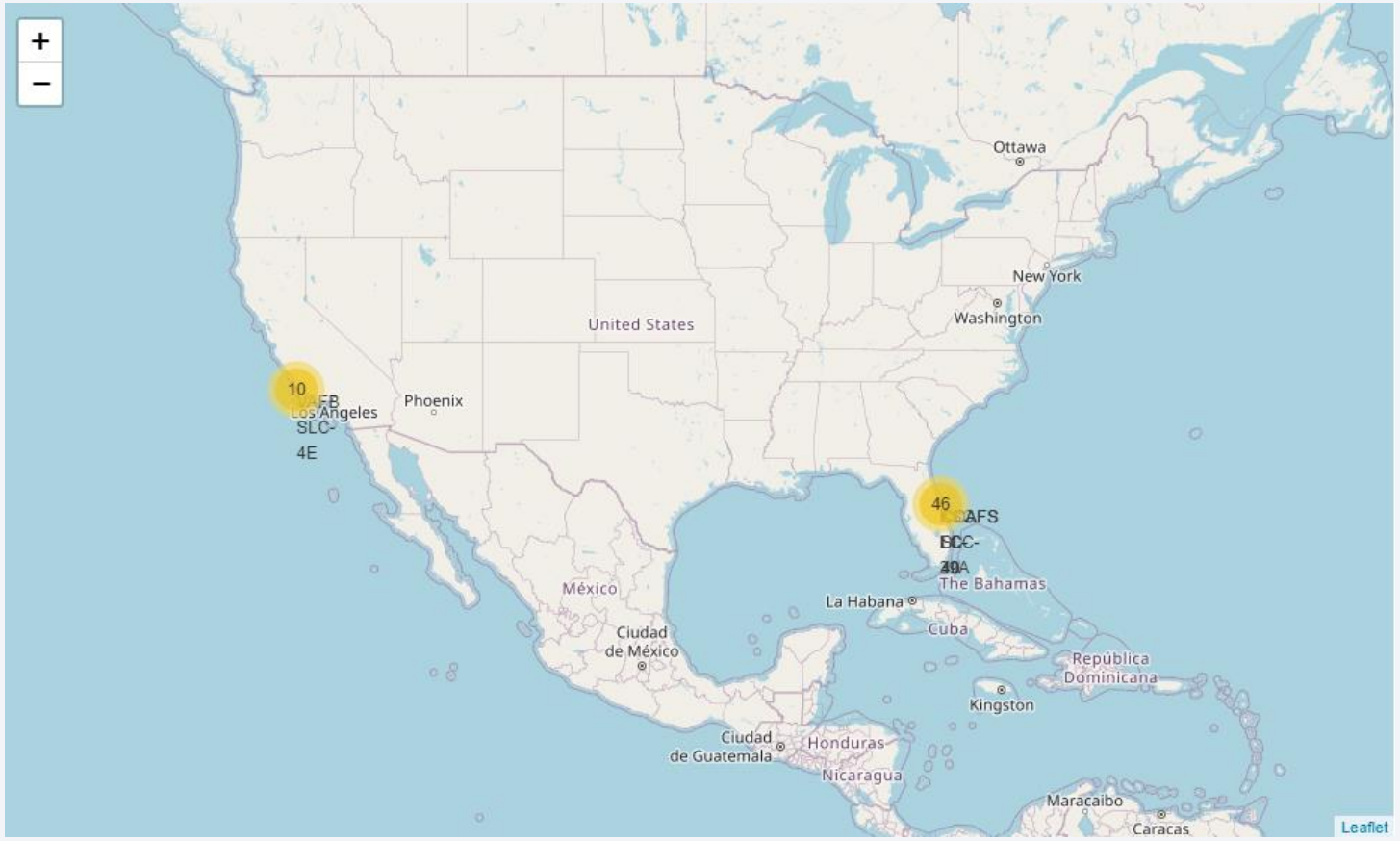
Launch sites global map

We can see that all launch sites are located in the united states, close to the coast and approximately close to the equator.

- In particular are located in Floria and California

Launch sites global map markers

We can see there are 10 lauch sites in California and 46 in Florida.

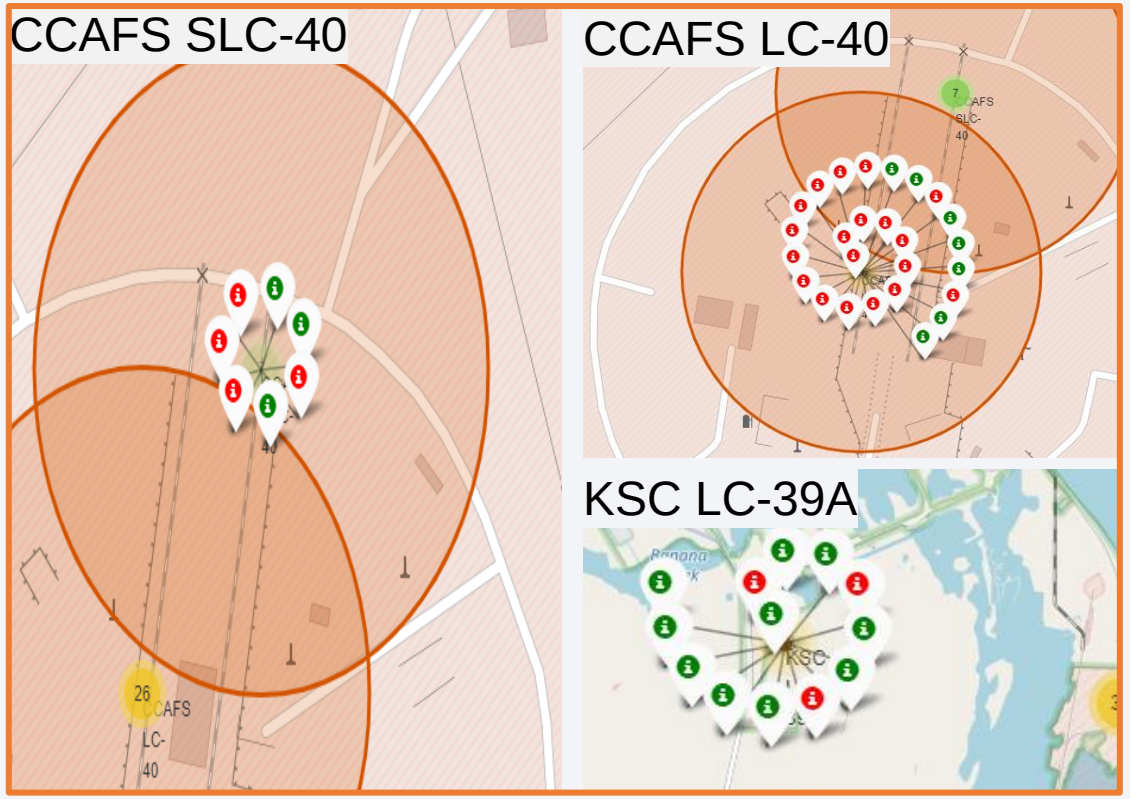


Mark the success/failed launches for each site on the map

Green markers show successful launches and Red markers show failures

- **CCAFS LC-40**: 7 success launches of 26
- **CCAFS SLC-40**: 3 success launches of 7
- **VAFB SLC-4E**: 4 success launches of 10
- **KSC LC-39A**: 10 success launches of 13

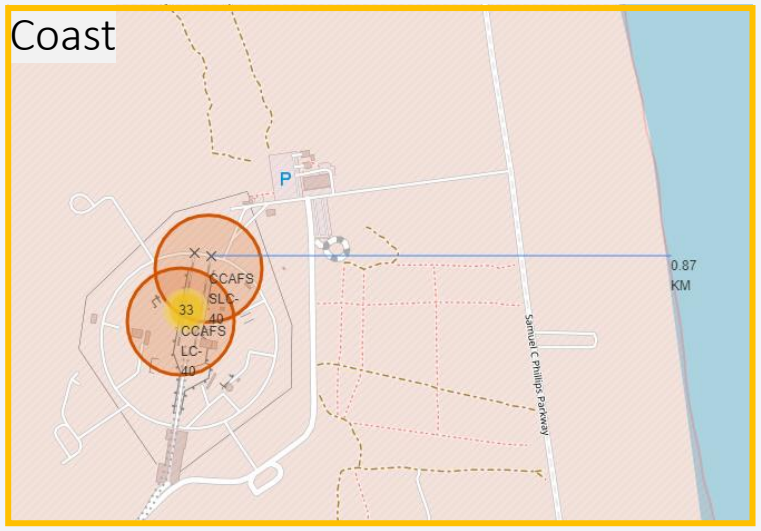
CALIFORNIA

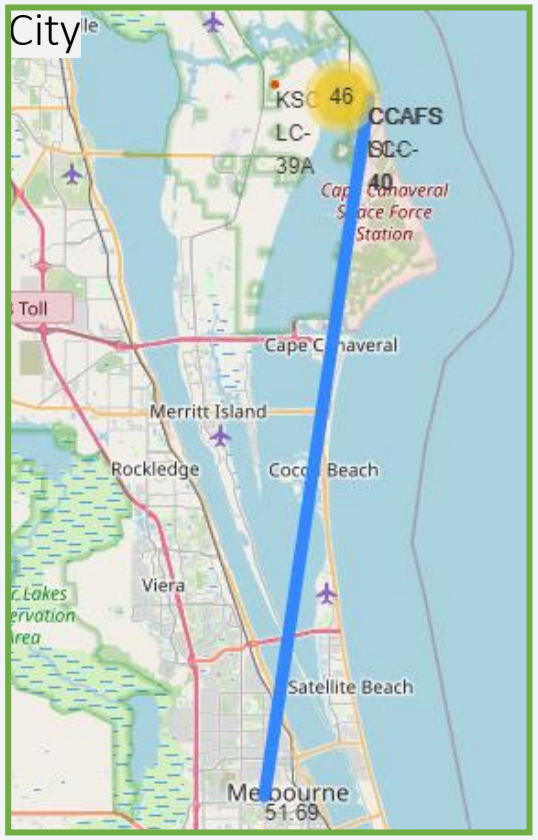


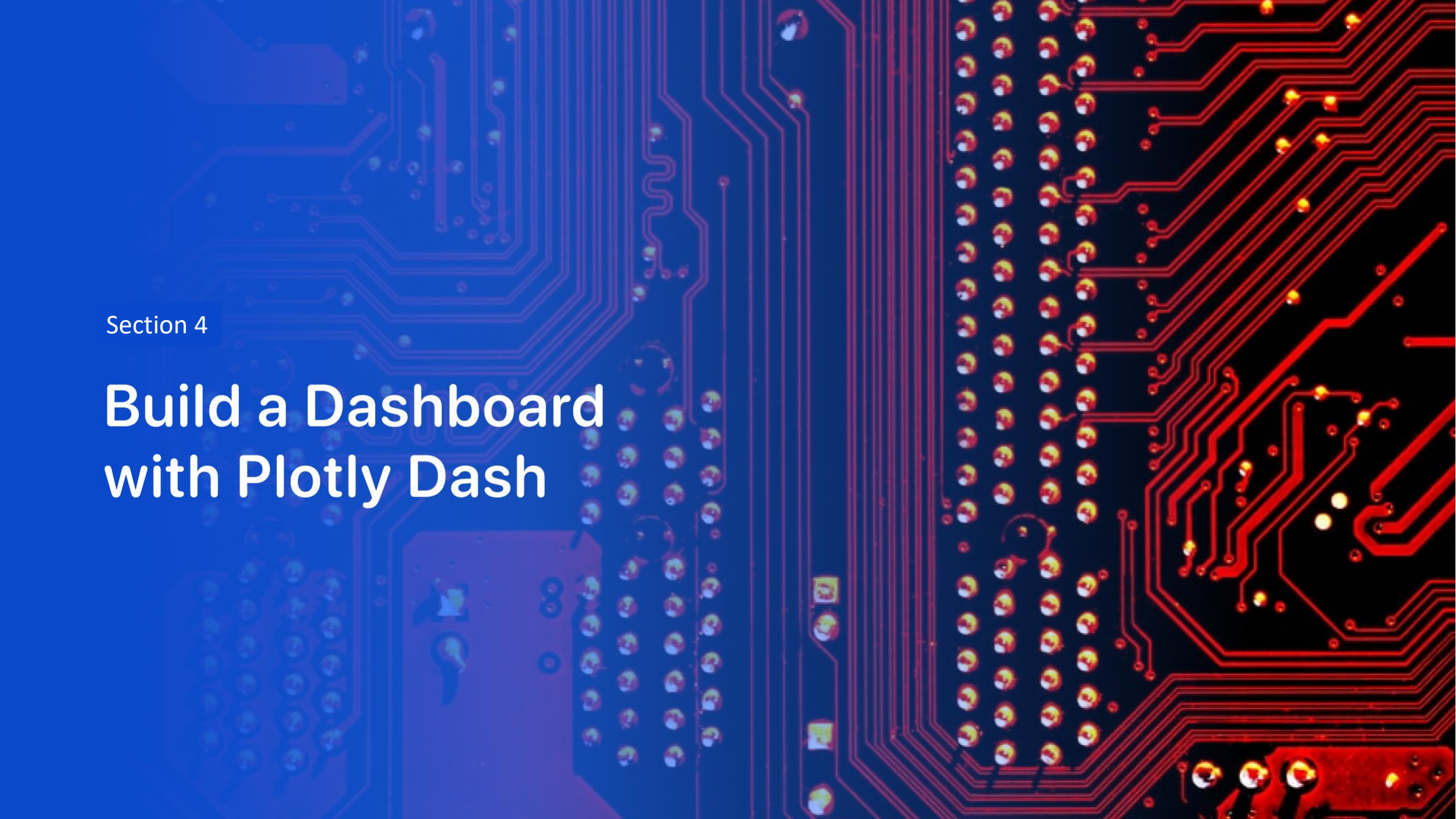
FLORIDA

Distances between a launch site to its proximities

- **Coast**: distance 0.87km
- **Railway**: distance 1.45 KM
- **Highway**: distance 11.16 KM
- **City**: distance 51.69 KM






Section 4
Build a Dashboard with Plotly Dash

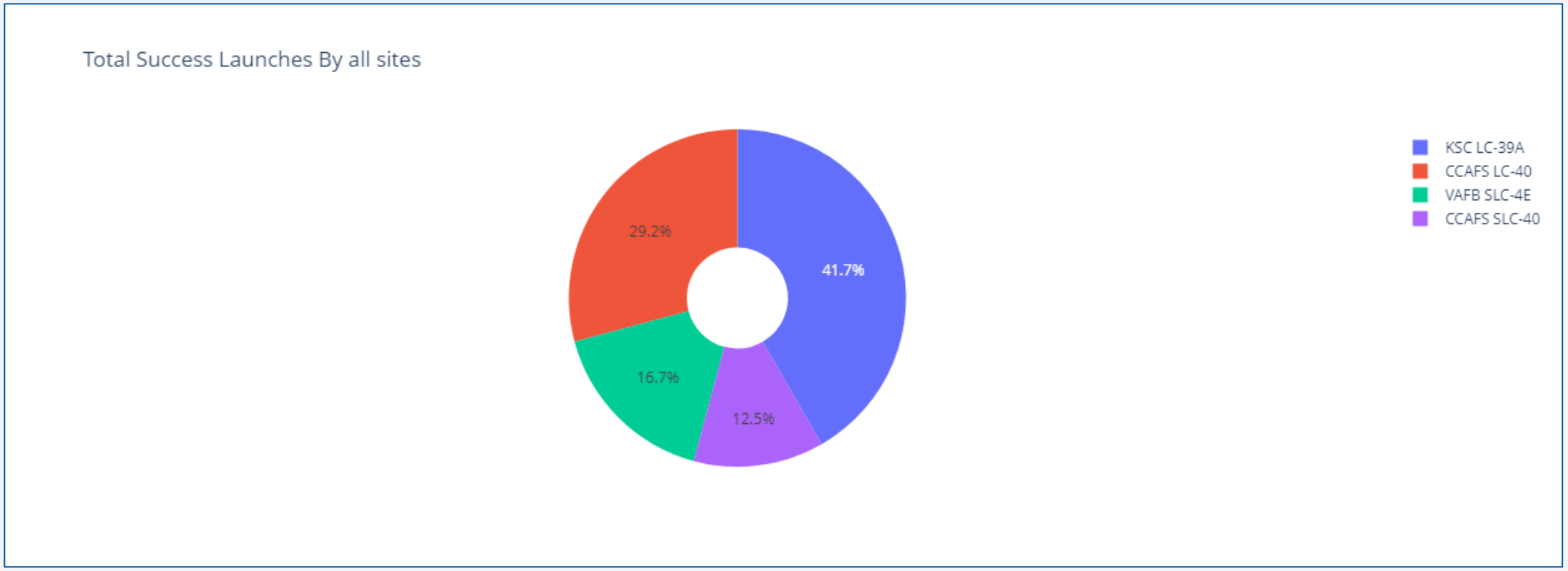
Build a Dashboard with Plotly Dash

- We built an interactive dashboard with Plotly dash
- We plotted pie charts showing the total launches by a certain sites
- We plotted scatter graph showing the relationship with Outcome and Payload Mass (Kg) for the different booster version.

Notebook:
Dash

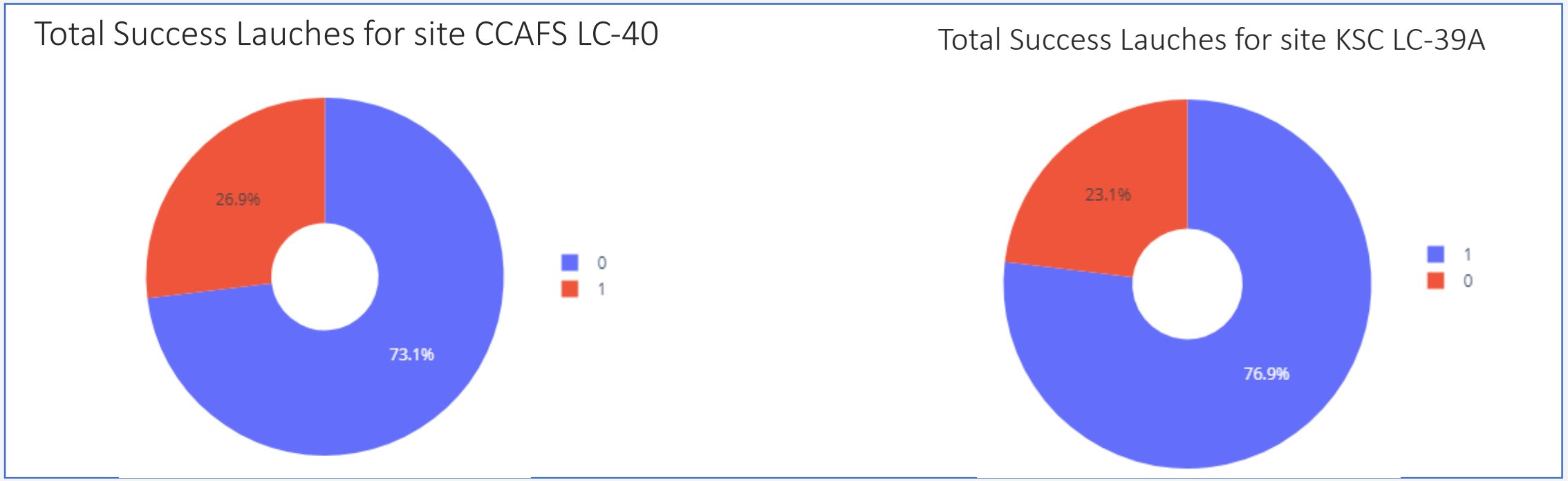
Success rate by each launch site (Pie Chart)

KSC LC-39A is more successful than other launched locations



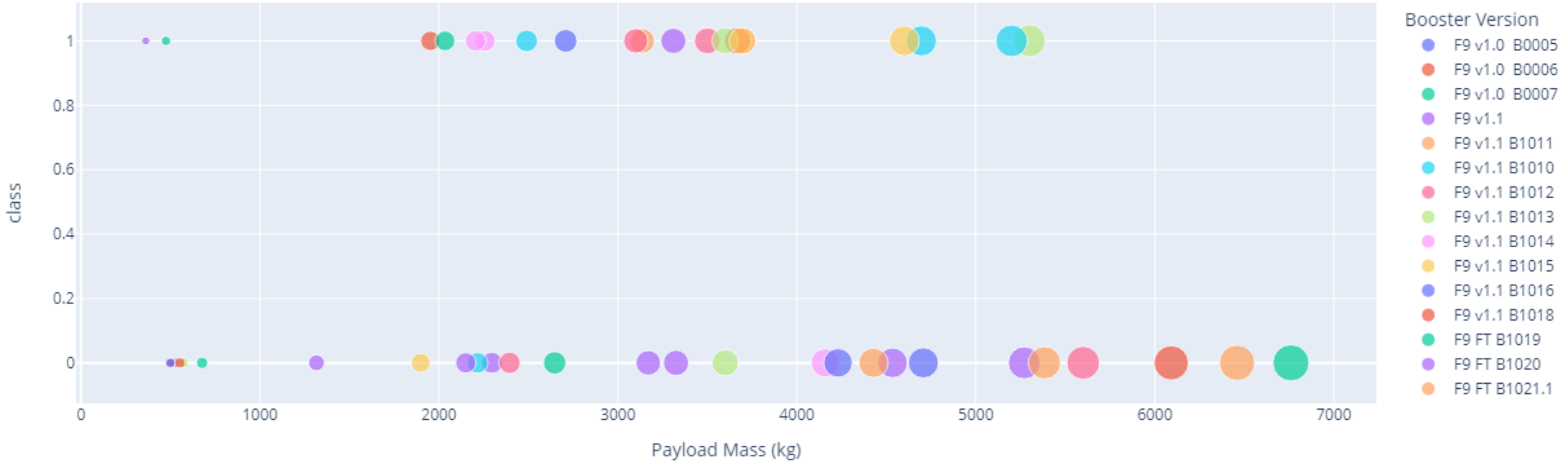
Success or failure percentage (Pie chart)

- KSC LC-39A has 76.9% success rate and 23.1% failure rate
- CCAFS LC-40 has 26.9% success rate and 73.1 failure rate



Payload vs Outcome for all booster version

The most successful launches center on boosters with weights ranging from 18,000 to 38,000



Section 5

Predictive Analysis (Classification)

Predictive Analysis (Classification)

We Perform exploratory Data Analysis and determine Training Labels

- create a column for the class and standardize the data
- Split into training data and test data
- Find best Hyperparameter for SVM, Classification Trees and Logistic Regression using GridSearchCV
- Find the method performs best using test data

Notebook:

Machine Learning Prediction

Classification Accuracy

```
method = {'Logistic Regression':logreg_cv.best_score_,'SVM':svm_cv.best_score_,'Decision Tree':tree_cv.best_score_,'KNN':knn_cv.best_score_,}
method_df = pd.DataFrame.from_dict(algorithms, orient='index', columns=['Accuracy'])
method_df
```

	Accuracy
Logistic Regression	0.846429
SVM	0.848214
Decision Tree	0.875000
KNN	0.848214

The method performs best is **Decision Tree** with a score: **0.875**

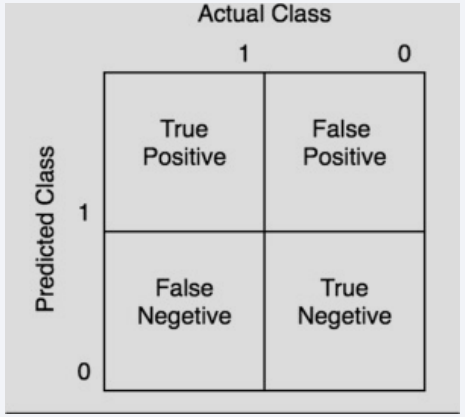
Decision Tree with the best parameters

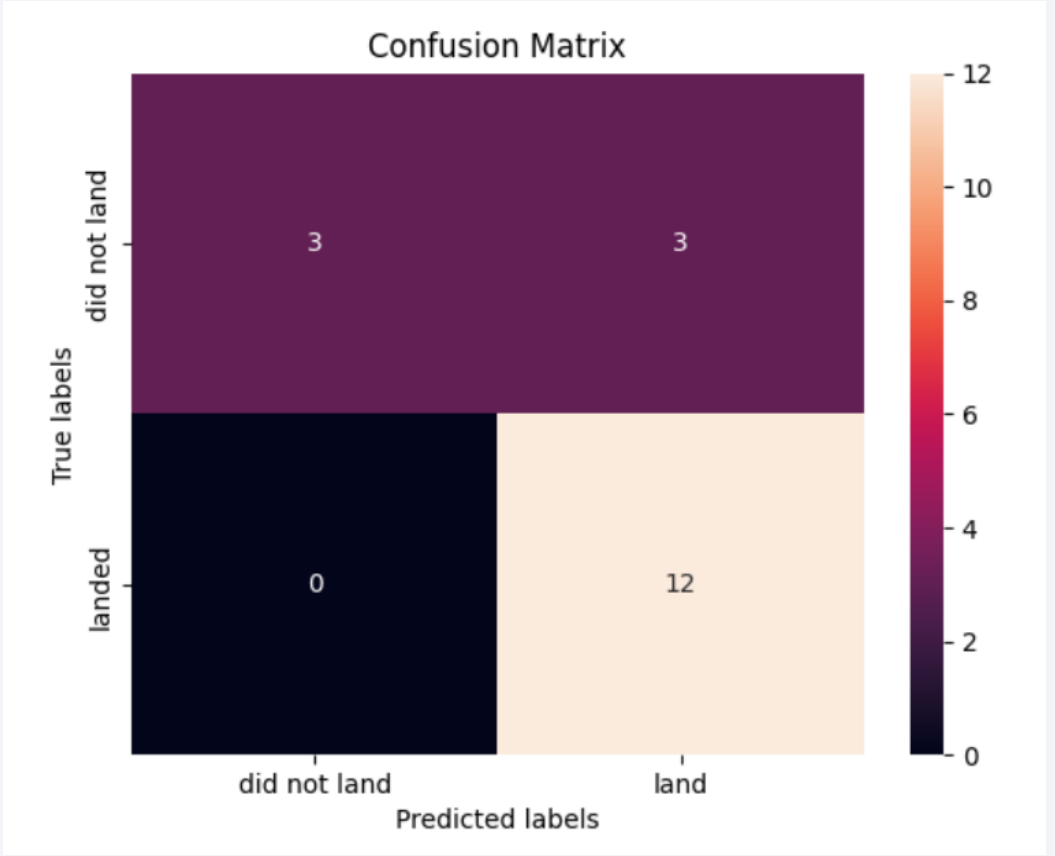
```
print("tuned hpyerparameters :(best parameters) ",tree_cv.best_params_)
print("accuracy :",tree_cv.best_score_)
```

```
tuned hpyerparameters :(best parameters)  {'criterion': 'gini', 'max_depth': 6, 'max_features': 'auto', 'min_samples_leaf': 1, 'min_samples_split': 10,
'splitter': 'random'}
accuracy : 0.875
```

Confusion Matrix

- By examining the confusion matrix, we can see that the **Decision Tree** knows how to distinguish between the different classes. positive.
- The main problem is **false positives**, i.e. failed landing marked as successful landing by the classifier.





Conclusion

On the basis of all that has been analysed, we can conclude by saying that:

- The **Decision Tree Classifier** is the best for Machine Learning for this dataset
- Ranging from 18,000 to 38,000 **Weighted payloads** perform better than the other payloads
- The launch success rate started to increase in 2013 until 2020
- We can see that **KSC LC-39A** had the most successful launches from all the sites
- Orbit **GEO,HEO,SSO,ES-L1** had the most Success Rate

Thank you!