Data Science Capstone Project: SPACEX

By

Sayeda Fatima

Outline

Executive Summary

Introduction

Methodology

Results

Conclusion

Appendix

Summary of Methodologies

- Data Collection was carried out through SPACE X Rest API
- Data Wrangling employed One-Hot Coding
- Exploratory Data Analysis (EDA) using SQL and Visualizations
- Interactive Visual Analytics using Folium and Plotly-Dash
- Predictive Analysis using Machine Learning Algorithms

Summary of Results

- Data Analysis revealed relationships between variables and conditions determining success or failure
- Interactive Visualizations achived
- Best Predictive Modelling is Machine Learning

Project Background and Context

- The aim of this project is to predict success or failure of Falcon 9’s landings. SpaceX’s website records Falcon 9 rocket’s launch cost as $62 million in contrast to $165 million by other providers. The price difference is due to SpaceX’s ability to reuse its first stage. Hence, by predicting success of landing, the cost of launch can be estimated. Consequently, this information can be useful for other providers competing with SpaceX for rocket launches.

Problems requiring resolution

- What are the main characteristics of a successful or failed landing?
- What are the impacts of variable relationships on landing success or failure?
- What are the conditions which will facilitate SpaceX in acquiring best landing success rates?

Data Collection

- SPACE X Rest API

Exploratory Data Analysis (EDA)

- Visualizations
- SQL

Predictive Analysis

- Classification Models

Data Wrangling

- Unwanted Column Drop
- One-Hot Coding

Interactive Visual Analytics

- Folium
- Plotly Dash

Data Collection Methodology

The following methods have been employed:

API Data Extraction

- Importing json file from: "https://api.spacexdata.com/v4/launches/past"

Pandas Data Transformation

- Importing selected columns from json data into pandas dataframe

Data Filteration

- Filtering 'Falcon9' rows
- "Payload" Missing Value replacement with average values

Data Wrangling Methodology

The following methods have been employed:

Data Upload

- "csv" conversion to Dataframe

Data Analysis

Task 1: Calculating "Number of Launches"
Task 2: Calculating "Orbit Occurrences"

EDA & IVA Methodology

The following methods have been employed:

Folium,
an interactive leaflet map

The following folium methodology was employed:
- **Reverse Geo-coding to find State names with Launch Site concentration**
- **Marking of Launch sites**
- **Marking of Successful/Failed launches**
- **Marking distance between launch sites and proximities**

Plotly Dash,
an interactive framework for building ML & data science web apps

The following plotly dash method was employed:
- **Creation of App Layout**
- **Creation of Callback Functions for Pie Chart**
- **Creation of Callback Functions for Scatter Chart with Slider**

Predictive Analysis Methodology

The following methods have been employed:

Decision Trees which employs a top-down approach to a dataset and tries to group data on the basis of dissimilarity till a certain degree of similarity is attained

K-Nearest Neighbors (KNN) which classifies a given dataset elements on the basis of similarity or closeness

Support Vector Machines (SVM) which finds the best hyperplane to divide a given dataset into two classes

Logistic Regression which estimates the probability of an event occurring, like yes or no, based on selected dataset of independent variables.

Data Collection Results

API Data Extraction

	static_fire_date_utc	static_fire_date_unix	tbd	net	window	rocket	success	details	crew	ships	capsules	p
0	2006-03-17T00:00:00.000Z	1.142554e+09	False	False	0.0	5e9d0d95eda69955f709d1eb	False	Engine failure at 33 seconds and loss of vehicle	[]	[]	[]	[5eb0e4b5b6c3bb0006
1	None	NaN	False	False	0.0	5e9d0d95eda69955f709d1eb	False	Successful first stage burn and transition to second stage, maximum altitude 289 km, Premature engine	[]	[]	[]	[5eb0e4b6b6c3bb0006

Pandas Data Transformation

	FlightNumber	Date	BoosterVersion	PayloadMass	Orbit	LaunchSite	Outcome	Flights	GridFins	Reused	Legs	LandingPad	Block	ReusedCount	Seri
0	1	2006-03-24	Falcon 1	20.0	LEO	Kwajalein Atoll	None None	1	False	False	False	None	NaN	0	Merlin1
1	2	2007-03-21	Falcon 1	NaN	LEO	Kwajalein Atoll	None None	1	False	False	False	None	NaN	0	Merlin2
2	4	2008-09-28	Falcon 1	165.0	LEO	Kwajalein Atoll	None None	1	False	False	False	None	NaN	0	Merlin2
3	5	2009-07-13	Falcon 1	200.0	LEO	Kwajalein Atoll	None None	1	False	False	False	None	NaN	0	Merlin3
4	6	2010-06-04	Falcon 9	NaN	LEO	CCSFS SLC 40	None None	1	False	False	False	None	1.0	0	B00(

Data Filtration

	FlightNumber	Date	BoosterVersion	PayloadMass	Orbit	LaunchSite	Outcome	Flights	GridFins	Reused	Legs	LandingPad	Block	Reus
4	1	2010-06-04	Falcon 9	NaN	LEO	CCSFS SLC 40	None None	1	False	False	False	None	1.0	
5	2	2012-05-22	Falcon 9	525.0	LEO	CCSFS SLC 40	None None	1	False	False	False	None	1.0	
6	3	2013-03-01	Falcon 9	677.0	ISS	CCSFS SLC 40	None None	1	False	False	False	None	1.0	

Data Wrangling Results I

Number of Launches

Maximum launches From "CCAFS SLC 40"

TASK 1: Calculate the number of launches on each site

The data contains several Space X launch facilities: Cape Canaveral Space Launch Complex 40 VAFB SLC 4E , Vandenberg Air Force Base Space Launch Complex 4E (SLC-4E), Kennedy Space Center Launch Complex 39A KSC LC 39A .The location of each Launch Is placed in the column `LaunchSite`

Next, let's see the number of launches for each site.
Use the method `value_counts()` *on the column* `LaunchSite` *to determine the number of launches on each site:*

In [5]:
```
# Apply value_counts() on column LaunchSite
df['LaunchSite'].value_counts()
```

Out[5]:
```
CCAFS SLC 40    55
KSC LC 39A      22
VAFB SLC 4E     13
Name: LaunchSite, dtype: int64
```

Number of Orbital Occurances

Orbit "GTO" exhibited Maximum Occurances

TASK 2: Calculate the number and occurrence of each orbit ¶

Use the method `.value_counts()` *to determine the number and occurrence of each orbit in the column* `Orbit`

In [6]:
```
# Apply value_counts on Orbit column
df['Orbit'].value_counts()
```

Out[6]:
```
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
```

Data Wrangling Results 2

Mission Outcome Occurrences

60 True Outcomes

New Column Creation for Labelling

Copied "Outcomes" Column to New "Class" Column

TASK 3: Calculate the number and occurence of mission outcome per orbit type

Use the method `.value_counts()` on the column `Outcome` to determine the number of `landing_outcomes`. Then assign it to a variable landing_outcomes.

In [7]:
```
# landing_outcomes = values on Outcome column
landing_outcomes = df['Outcome'].value_counts()
landing_outcomes
```

Out[7]:
```
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
```

In [8]:
```
for i,outcome in enumerate(landing_outcomes.keys()):
    print(i,outcome)
```

```
0 True ASDS
1 None None
2 True RTLS
3 False ASDS
4 True Ocean
5 False Ocean
6 None ASDS
7 False RTLS
```

We create a set of outcomes where the second stage did not land successfully:

In [9]:
```
bad_outcomes=set(landing_outcomes.keys()[[1,3,5,6,7]])
bad_outcomes
```

Out[9]:
```
{'False ASDS', 'False Ocean', 'False RTLS', 'None ASDS', 'None None'}
```

TASK 4: Create a landing outcome label from Outcome column

Using the `Outcome`, create a list where the element is zero if the corresponding row in `Outcome` is in the set `bad_outcome`; otherwise, it's one. Then assign it to the variable `landing_class`:

In [10]:
```
# landing_class = 0 if bad_outcome
# landing_class = 1 otherwise
df['Class'] = df['Outcome'].apply(lambda landing_class: 0 if landing_class in bad_outcomes else 1)
```

This variable will represent the classification variable that represents the outcome of each launch. If the value is zero, the first stage did not land successfully; one means the first stage landed Successfully

In [11]:
```
df[['Class']].head(8)
```

Out[11]:

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

In [12]:
```
df.head(3)
```

Out[12]:

	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

We can use the following line of code to determine the success rate:

In [13]:
```
df["Class"].mean()
```

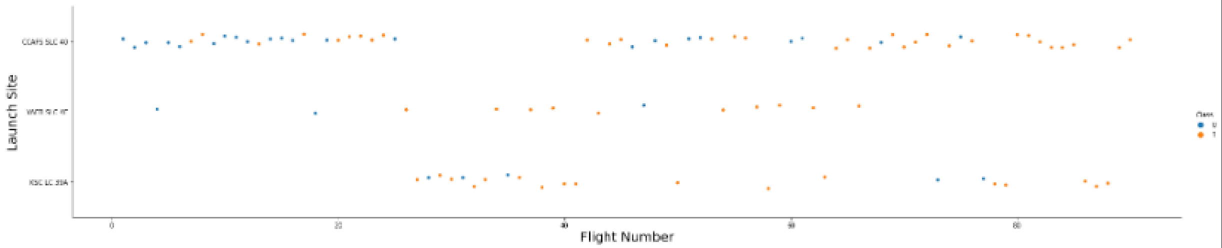
Out[13]: 0.6666666666666666

EDA Interactive Visuals Results I

TASK 1: Visualize the relationship between Flight Number and Launch Site

Use the function `catplot` to plot `FlightNumber` vs `LaunchSite`, set the parameter `x` parameter to `FlightNumber`, set the `y` to `Launch Site` and set the parameter `hue` to `'class'`

```
# Plot a scatter point chart with x axis to be Flight Number and y axis to be the launch site, and hue to be the class value
sns.catplot(y="LaunchSite", x="FlightNumber", hue="Class", data=df, aspect = 5)
plt.xlabel("Flight Number",fontsize=20)
plt.ylabel("Launch Site",fontsize=20)
plt.show()
```



Interpretation

Task 1: Increase in success rate for each site

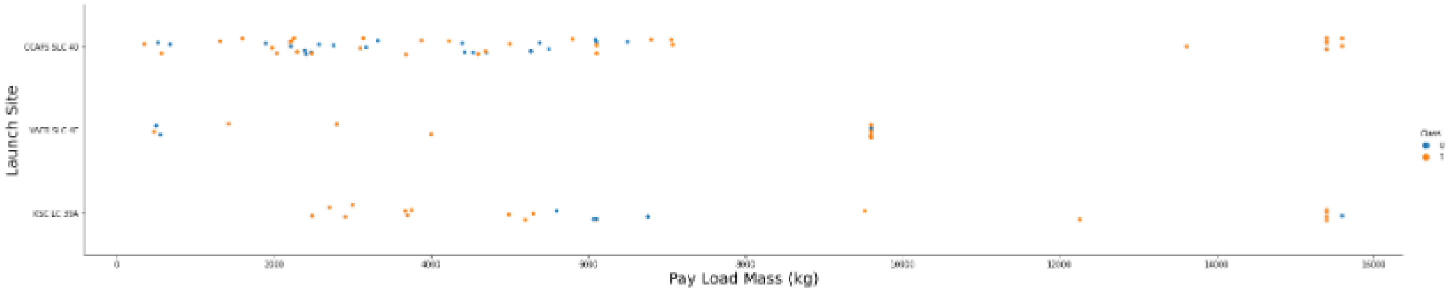
Task 2: Landing Failures seem to be related to excessive payload

Task 3: Best success rate was exhibited by "ES-L1", "GEO", "HEO" & "SSO"

TASK 2: Visualize the relationship between Payload and Launch Site

We also want to observe if there is any relationship between launch sites and their payload mass.

```
# Plot a scatter point chart with x axis to be Pay Load Mass (kg) and y axis to be the launch site, and hue to be the class
sns.catplot(y="LaunchSite", x="PayloadMass", hue="Class", data=df, aspect = 5)
plt.xlabel("Pay Load Mass (kg)",fontsize=20)
plt.ylabel("Launch Site",fontsize=20)
plt.show()
```



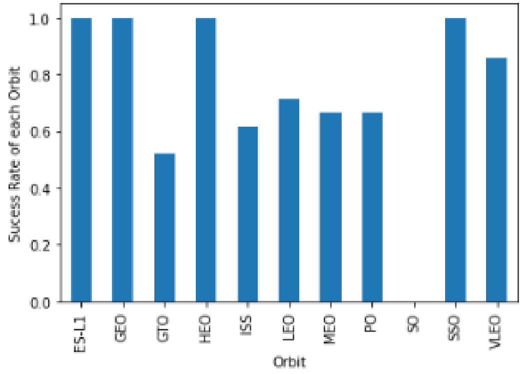
TASK 3: Visualize the relationship between success rate of each orbit type

Next, we want to visually check if there are any relationship between success rate and orbit type.

Let's create a `bar chart` for the sucess rate of each orbit

```
# HINT use groupby method on Orbit column and get the mean of Class column
data = df.groupby('Orbit')['Class'].mean()
ax = data.plot(kind='bar')
ax.set_xlabel("Orbit")
ax.set_ylabel("Sucess Rate of each Orbit")
```

```
Text(0, 0.5, 'Sucess Rate of each Orbit')
```



EDA Interactive Visuals Results 2

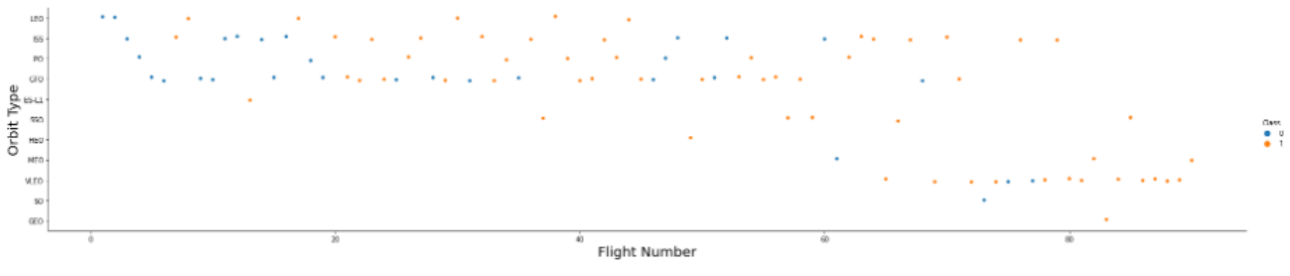
Task 4

There is an increase in success rate with number of flights

TASK 4: Visualize the relationship between FlightNumber and Orbit type

For each orbit, we want to see if there is any relationship between FlightNumber and Orbit type.

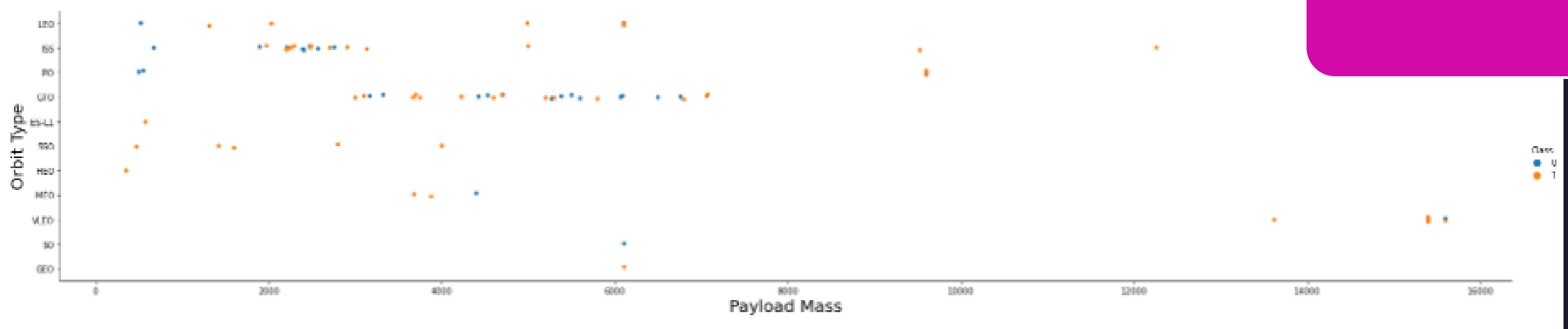
```
# Plot a scatter point chart with x axis to be FlightNumber and y axis to be the Orbit, and hue to be the class value
sns.catplot(y="Orbit", x="FlightNumber", hue="Class", data=df, aspect = 5)
plt.xlabel("Flight Number",fontsize=20)
plt.ylabel("Orbit Type",fontsize=20)
plt.show()
```



TASK 5: Visualize the relationship between Payload and Orbit type

Similarly, we can plot the Payload vs. Orbit scatter point charts to reveal the relationship between Payload and Orbit type

```
# Plot a scatter point chart with x axis to be Payload and y axis to be the Orbit, and hue to be the class value
sns.catplot(y="Orbit", x="PayloadMass", hue="Class", data=df, aspect = 5)
plt.xlabel("Payload Mass",fontsize=20)
plt.ylabel("Orbit Type",fontsize=20)
plt.show()
```



Task 5

Increased "Payload Mass" increases success rate in some Orbits like "LEO" while decreasing "Payload Mass" increases success rate in some Orbits like " GTO "

EDA Interactive Visuals Results 3

Tasks 6

There is a general increase in success rate since "2013"

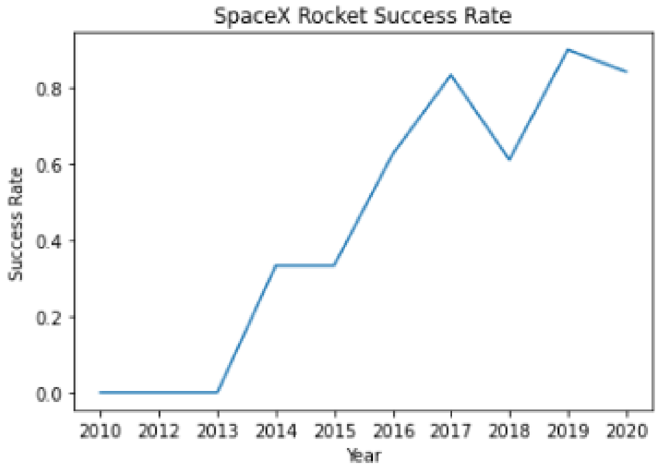
TASK 6: Visualize the launch success yearly trend

You can plot a line chart with x axis to be `Year` and y axis to be average success rate, to get the average launch success trend.

The function will help you get the year from the date:

```
# A function to Extract years from the date
year=[]
def Extract_year(date):
    for i in df["Date"]:
        year.append(i.split("-")[0])
    return year

```

```
# Plot a line chart with x axis to be the extracted year and y axis to be the success rate
df['Year'] = Extract_year(df["Date"])
df_groupby_year = df.groupby("Year",as_index=False)["Class"].mean()
#Plotting Line Chart
sns.lineplot(data = df_groupby_year, x="Year", y="Class")
plt.xlabel("Year")
plt.title('SpaceX Rocket Success Rate')
plt.ylabel("Success Rate")
plt.show()
```



EDA Interactive Visuals Results 4

Task 7 & 8

"One Hot Coding" transposed features columns as float

TASK 7: Create dummy variables to categorical columns

Use the function `get_dummies` and `features` dataframe to apply OneHotEncoder to the column `Orbits`, `LaunchSite`, `LandingPad`, and `Serial`. Assign the value to the variable `features_one_hot`, display the results using the method head. Your result dataframe must include all features including the encoded ones.

```
# HINT: Use get_dummies() function on the categorical columns
one_hot_coding = features

one_hot_coding = pd.concat([one_hot_coding,
                            pd.get_dummies(df['Orbit']),
                            pd.get_dummies(df['LaunchSite']),
                            pd.get_dummies(df['LandingPad']),
                            pd.get_dummies(df['Serial'])], axis=1)

one_hot_coding.drop(['Orbit', 'LaunchSite', 'LandingPad', 'Serial'], axis = 1, inplace=True)

one_hot_coding.head()
```

	FlightNumber	PayloadMass	Flights	GridFins	Reused	Legs	Block	ReusedCount	ES-L1	GEO	...	B1048	B1049	B1050	B1051	B1054	B1056	B1058	B1
0	1	6104.959412	1	False	False	False	1.0	0	0	0	...	0	0	0	0	0	0	0	
1	2	525.000000	1	False	False	False	1.0	0	0	0	...	0	0	0	0	0	0	0	
2	3	677.000000	1	False	False	False	1.0	0	0	0	...	0	0	0	0	0	0	0	
3	4	500.000000	1	False	False	False	1.0	0	0	0	...	0	0	0	0	0	0	0	
4	5	3170.000000	1	False	False	False	1.0	0	0	0	...	0	0	0	0	0	0	0	

TASK 8: Cast all numeric columns to `float64`

Now that our `features_one_hot` dataframe only contains numbers cast the entire dataframe to variable type `float64`

```
# HINT: use astype function
one_hot_coding = one_hot_coding.astype(float)
one_hot_coding
```

	FlightNumber	PayloadMass	Flights	GridFins	Reused	Legs	Block	ReusedCount	ES-L1	GEO	...	B1048	B1049	B1050	B1051	B1054	B1056	B1058	B
0	1.0	6104.959412	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
1	2.0	525.000000	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
2	3.0	677.000000	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
3	4.0	500.000000	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
4	5.0	3170.000000	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
85	86.0	15400.000000	2.0	1.0	1.0	1.0	5.0	2.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
86	87.0	15400.000000	3.0	1.0	1.0	1.0	5.0	2.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	1.0	
87	88.0	15400.000000	6.0	1.0	1.0	1.0	5.0	5.0	0.0	0.0	...	0.0	0.0	0.0	1.0	0.0	0.0	0.0	
88	89.0	15400.000000	3.0	1.0	1.0	1.0	5.0	2.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
89	90.0	3681.000000	1.0	1.0	0.0	1.0	5.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

EDAwith SQL I

Bonus Task

Local SQL Database Creation achieved from csv

Tasks

1) 4 Unique Launch Sites were found
2) Records of Launch Sites Like 'CCA' achieved

Task 1: Display the names of the unique launch sites in the space mission

```
#### Establish Connection with Locally Created Database ##################################################
conn = sqlite3.connect('SPACEX.db')
cursor = conn.cursor() # Create Handle
#### CODE ##################################################################################################
q= "SELECT DISTINCT [Launch_Site] as 'Launch_Sites' FROM SPACEX ORDER BY [Launch_Site] ASC;"
pd.read_sql_query(q,conn)
```

	Launch_Sites
0	CCAFS LC-40
1	CCAFS SLC-40
2	KSC LC-39A
3	VAFB SLC-4E

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

```
#### Establish Connection with Locally Created Database ###########################################################
conn = sqlite3.connect('SPACEX.db')
cursor = conn.cursor() # Create Handle
#### CODE #########################################################################################################
q= "SELECT * FROM SPACEX WHERE [Launch_Site] LIKE 'CCA%' LIMIT 5;"
pd.read_sql_query(q,conn)
```

	Date	Time (UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS__KG_	Orbit	Customer	Mission_Outcome	Landing _Outcome
0	04-06-2010	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
1	08-12-2010	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	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
3	08-10-2012	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
4	01-03-2013	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

EDAwith SQL Results 2

Tasks

3) Total "**Payload Mass**" carried by Boosters is 45596
4) Average "**Payload Mass**" by Booster F9 v1.1 is 2535

5) First Successful Landing was in 2017
6) 4 successful Boosters between "**Payload Mass**" 4000 and 600

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

```
#### Establish Connection with Locally Created Database ####################################################
conn = sqlite3.connect('SPACEX.db')
cursor = conn.cursor() # Create Handle
#### CODE ###################################################################################################
q= "SELECT SUM(PAYLOAD_MASS__KG_) AS 'Total Payload Mass by NASA (CRS)' FROM SPACEX WHERE [Customer] = 'NASA (CRS)'"
pd.read_sql_query(q,conn)
```

	Total Payload Mass by NASA (CRS)
0	45596

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

```
#### Establish Connection with Locally Created Database ####################################################
conn = sqlite3.connect('SPACEX.db')
cursor = conn.cursor() # Create Handle
#### CODE ###################################################################################################
q= "SELECT AVG(PAYLOAD_MASS__KG_) AS 'Average Payload Mass by Booster Ver F9 v1.1' FROM SPACEX \
WHERE BOOSTER_VERSION LIKE '%F9 v1.1%';"
pd.read_sql_query(q,conn)
```

	Average Payload Mass by Booster Ver F9 v1.1
0	2534.666667

Task 5: List the date when the first succesful landing outcome in ground pad was acheived.

Hint:Use min function

```
#### Establish Connection with Locally Created Database ####################################################
conn = sqlite3.connect('SPACEX.db')
cursor = conn.cursor() # Create Handle
#### CODE ###################################################################################################

q ="SELECT MIN(Date) AS 'First Succesful Landing Outcome in Ground Pad' FROM SPACEX \
WHERE [Landing _Outcome] = 'Success (ground pad)';"
pd.read_sql_query(q,conn)
```

	First Succesful Landing Outcome in Ground Pad
0	01-05-2017

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

```
#### Establish Connection with Locally Created Database ####################################################
conn = sqlite3.connect('SPACEX.db')
cursor = conn.cursor() # Create Handle
#### CODE ###################################################################################################
q= "SELECT [Booster_Version] AS 'Booster Versions' FROM SPACEX WHERE [Landing _Outcome] = 'Success (drone ship)' \
AND [PAYLOAD_MASS__KG_] > 4000 AND PAYLOAD_MASS__KG_ < 6000;"
pd.read_sql_query(q,conn)
```

	Booster Versions
0	F9 FT B1022
1	F9 FT B1026
2	F9 FT B1021.2
3	F9 FT B1031.2

EDA with SQL Results 3

Tasks

7) Total Successful & Failed Outcomes are 101
8) Sub-query returned 11 Boosters with Max "Payload Mass"
9) "Year 2015" Analysis displayed 2 failed landing outcomes
10) 34 Successful Outcomes between "2010-17"

Task 7: List the total number of successful and failure mission outcomes

```
#### Establish Connection with Locally Created Database ######################################################
conn = sqlite3.connect('SPACEX.db')
cursor = conn.cursor() # Create Handle
#### CODE ####################################################################################################
q= "SELECT COUNT(Mission_Outcome) AS 'Total Number of Successful & Failed Outcomes' FROM SPACEX \
WHERE [Mission_Outcome] LIKE 'Success%' OR [Mission_Outcome] LIKE 'Failure%';"
pd.read_sql_query(q,conn)
```

	Total Number of Successful & Failed Outcomes
0	101

Task 8: List the names of the booster_versions which have carried the maximum payload mass. Use a subquery

```
#### Establish Connection with Locally Created Database ######################################################
conn = sqlite3.connect('SPACEX.db')
cursor = conn.cursor() # Create Handle
#### CODE ####################################################################################################
q= "SELECT DISTINCT [Booster_Version] AS 'Booster Versions with Max Payload Mass' FROM SPACEX \
WHERE PAYLOAD_MASS__KG_ =(SELECT MAX(PAYLOAD_MASS__KG_) FROM SPACEX);"
pd.read_sql_query(q,conn)
```

	Booster Versions with Max Payload Mass
0	F9 B5 B1048.4
1	F9 B5 B1049.4
2	F9 B5 B1051.3
3	F9 B5 B1056.4
4	F9 B5 B1048.5
5	F9 B5 B1051.4
6	F9 B5 B1049.5
7	F9 B5 B1060.2
8	F9 B5 B1058.3
9	F9 B5 B1051.6
10	F9 B5 B1060.3
11	F9 B5 B1049.7

Task 9: List the records which will display the month names, failure landing_outcomes in drone ship ,booster versions, launch_site for the months in year 2015.

Note: SQLLite does not support monthnames. So you need to use substr(Date, 4, 2) as month to get the months and substr(Date,7,4)='2015' for year.

```
#### Establish Connection with Locally Created Database ######################################################
conn = sqlite3.connect('SPACEX.db')
cursor = conn.cursor() # Create Handle
#### CODE ####################################################################################################
q= "SELECT DISTINCT [Booster_Version] AS 'Booster Ver', \
[Landing _Outcome] as 'Landing Outcome', \
substr([Date], 4, 2) AS 'Month', \
[Launch_Site] AS 'Launch Site' FROM SPACEX \
WHERE [Date] LIKE '%-2015' AND [Landing _Outcome] = 'Failure (drone ship)';"
pd.read_sql_query(q,conn)
```

	Booster Ver	Landing Outcome	Month	Launch Site
0	F9 v1.1 B1012	Failure (drone ship)	01	CCAFS LC-40
1	F9 v1.1 B1015	Failure (drone ship)	04	CCAFS LC-40

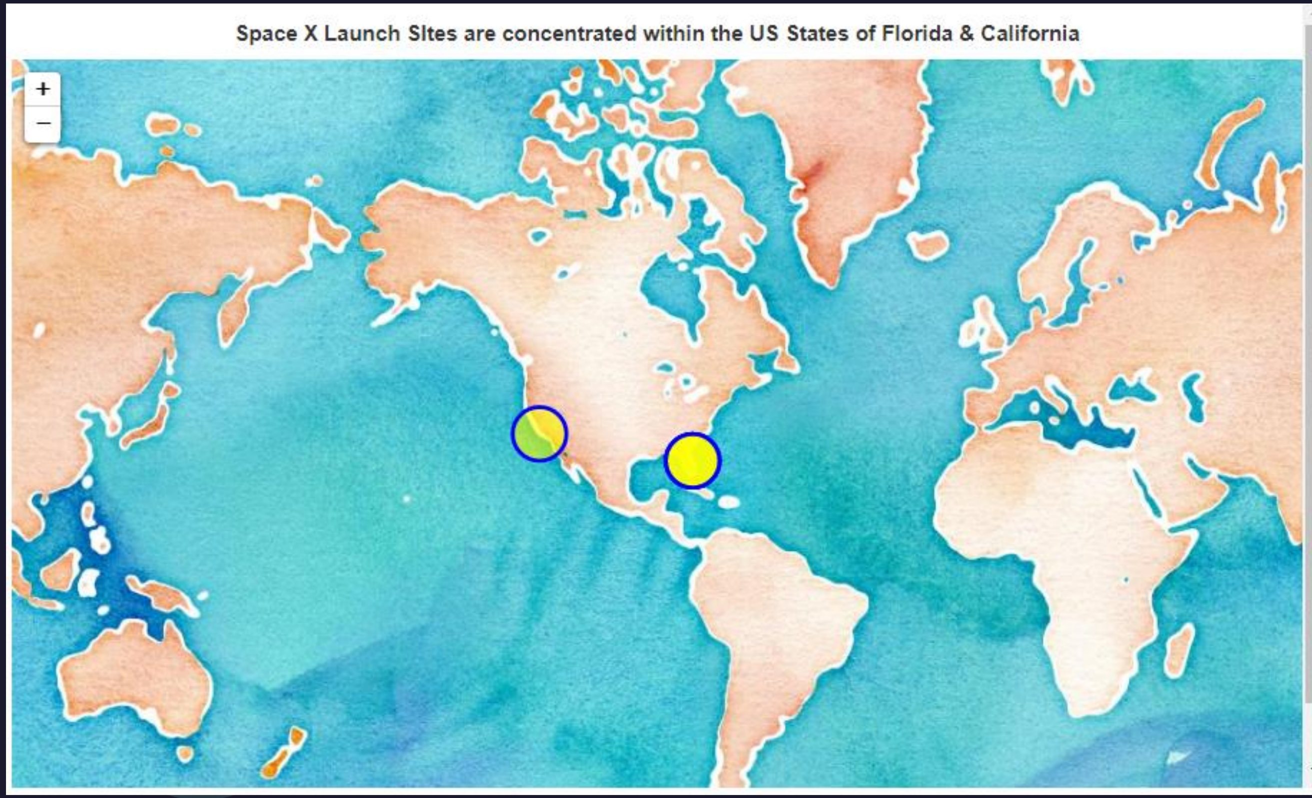
Task 10: Rank the count of successful landing_outcomes between the date 04-06-2010 and 20-03-2017 in descending order.

```
#### Establish Connection with Locally Created Database ######################################################
conn = sqlite3.connect('SPACEX.db')
cursor = conn.cursor() # Create Handle
#### CODE ####################################################################################################
q= "SELECT [Landing _Outcome] as 'Landing Outcome' , COUNT([Landing _Outcome]) AS 'Count' FROM SPACEX \
WHERE [Date] BETWEEN '04-06-2010' AND '20-03-2017' AND [Landing _Outcome] LIKE '%Success%' \
GROUP BY  [Landing _Outcome] ORDER BY COUNT([Landing _Outcome]) DESC ;"
pd.read_sql_query(q,conn)
```

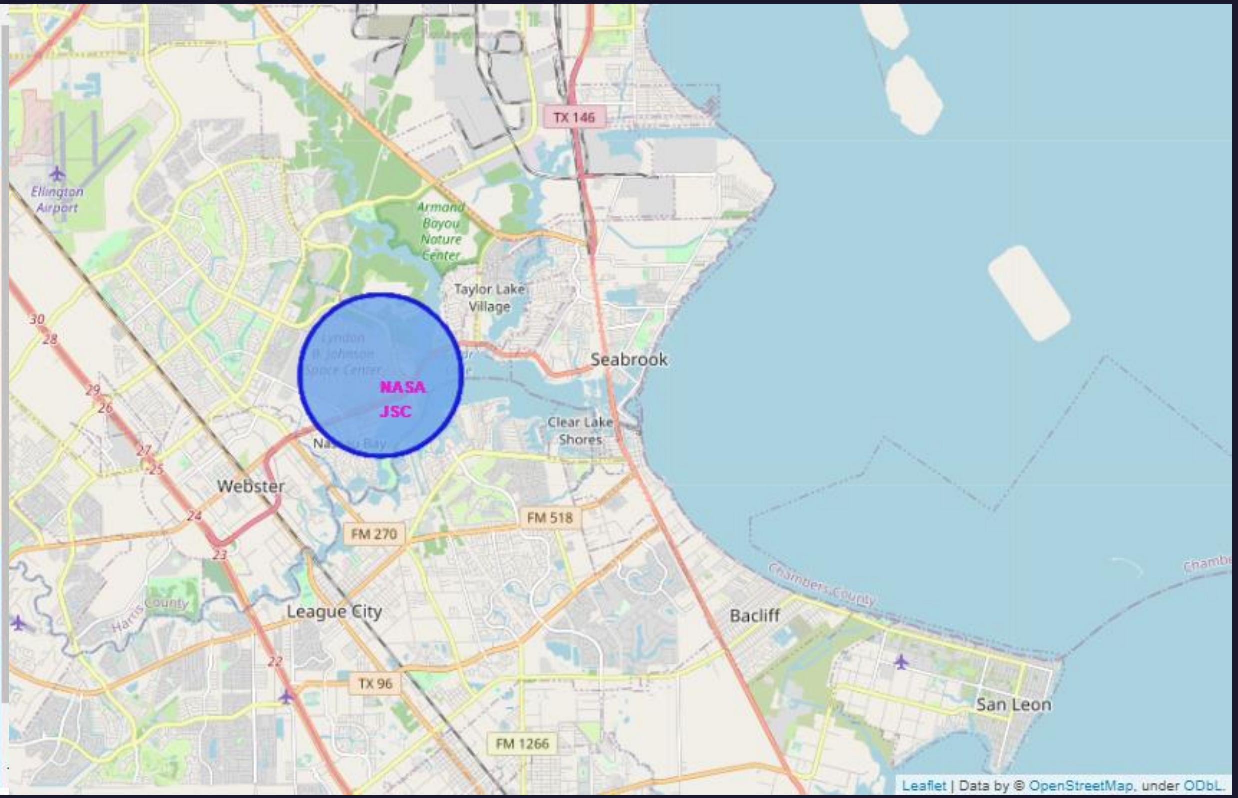
	Landing Outcome	Count
0	Success	20
1	Success (drone ship)	8
2	Success (ground pad)	6

Interactive Visual Analysis
Folium Results 1

Bonus Task: Displaying Concentration of Space X Launch Sites

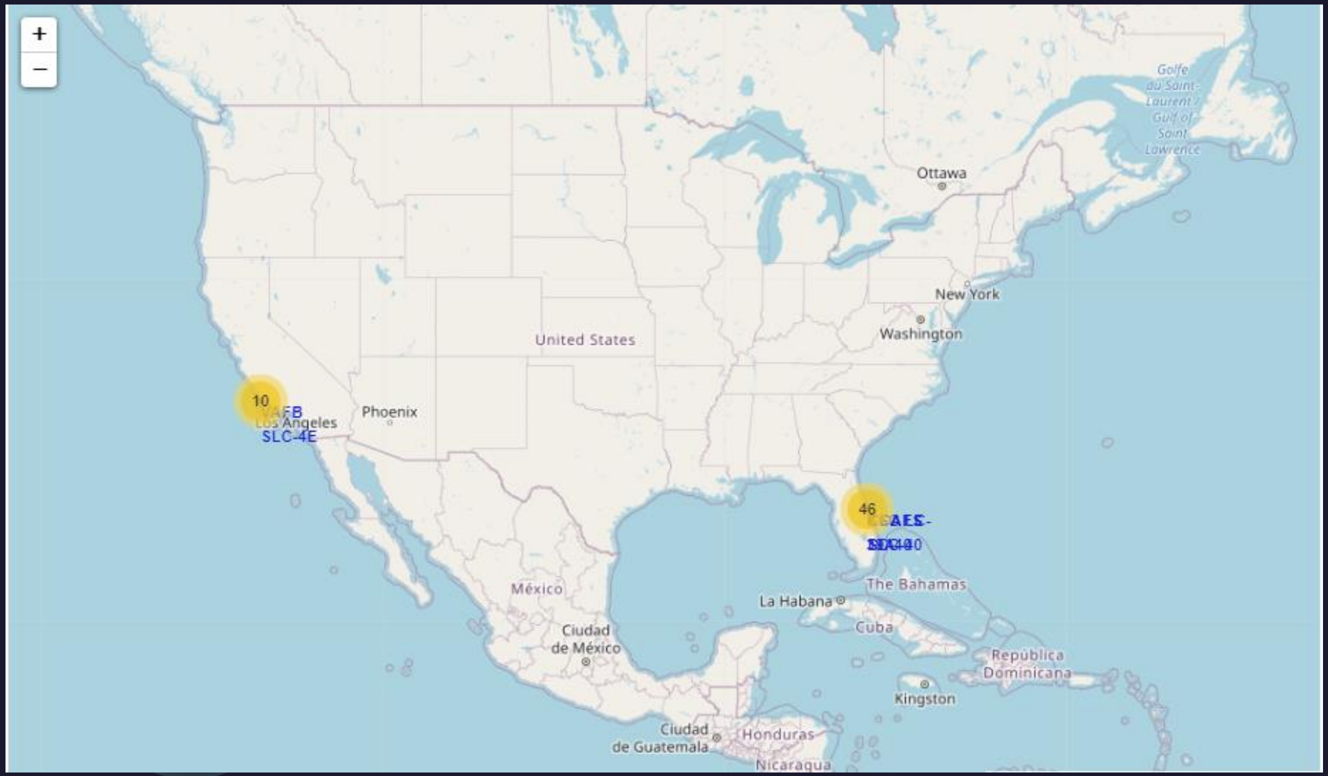


Task 1: Displaying 'NASA Johnson Space Center'

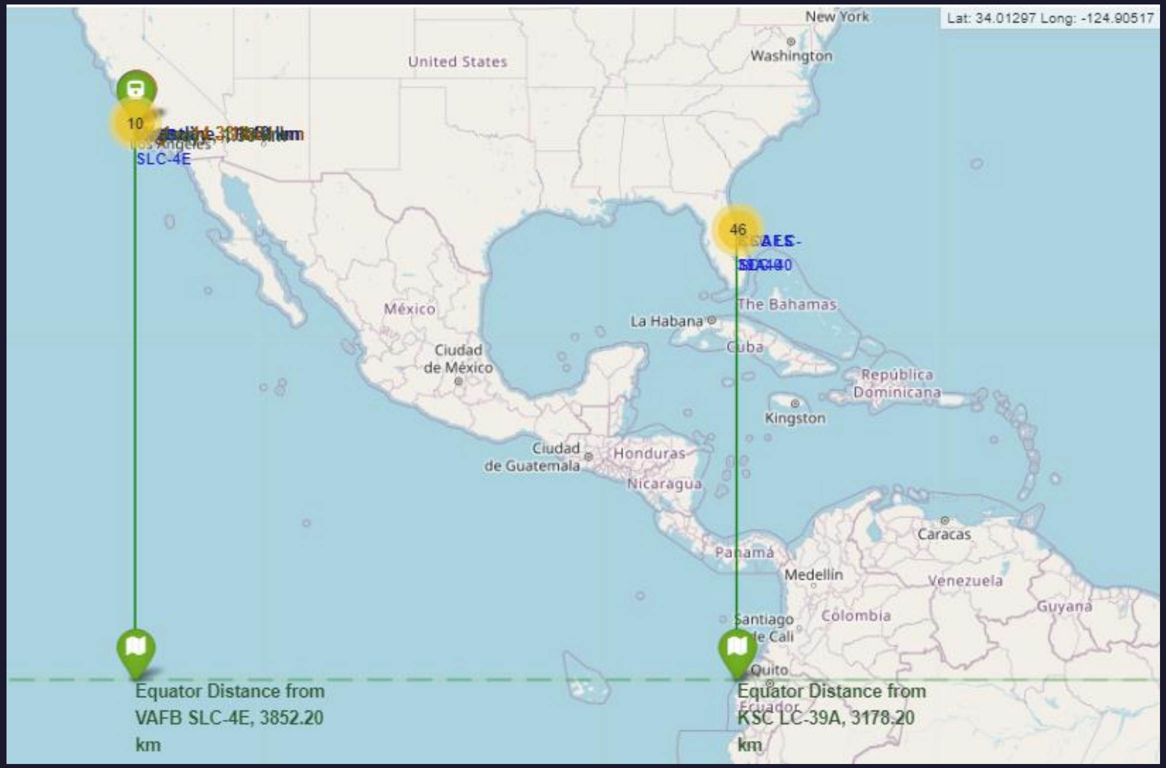


Interactive Visual Analysis
Folium Results 2

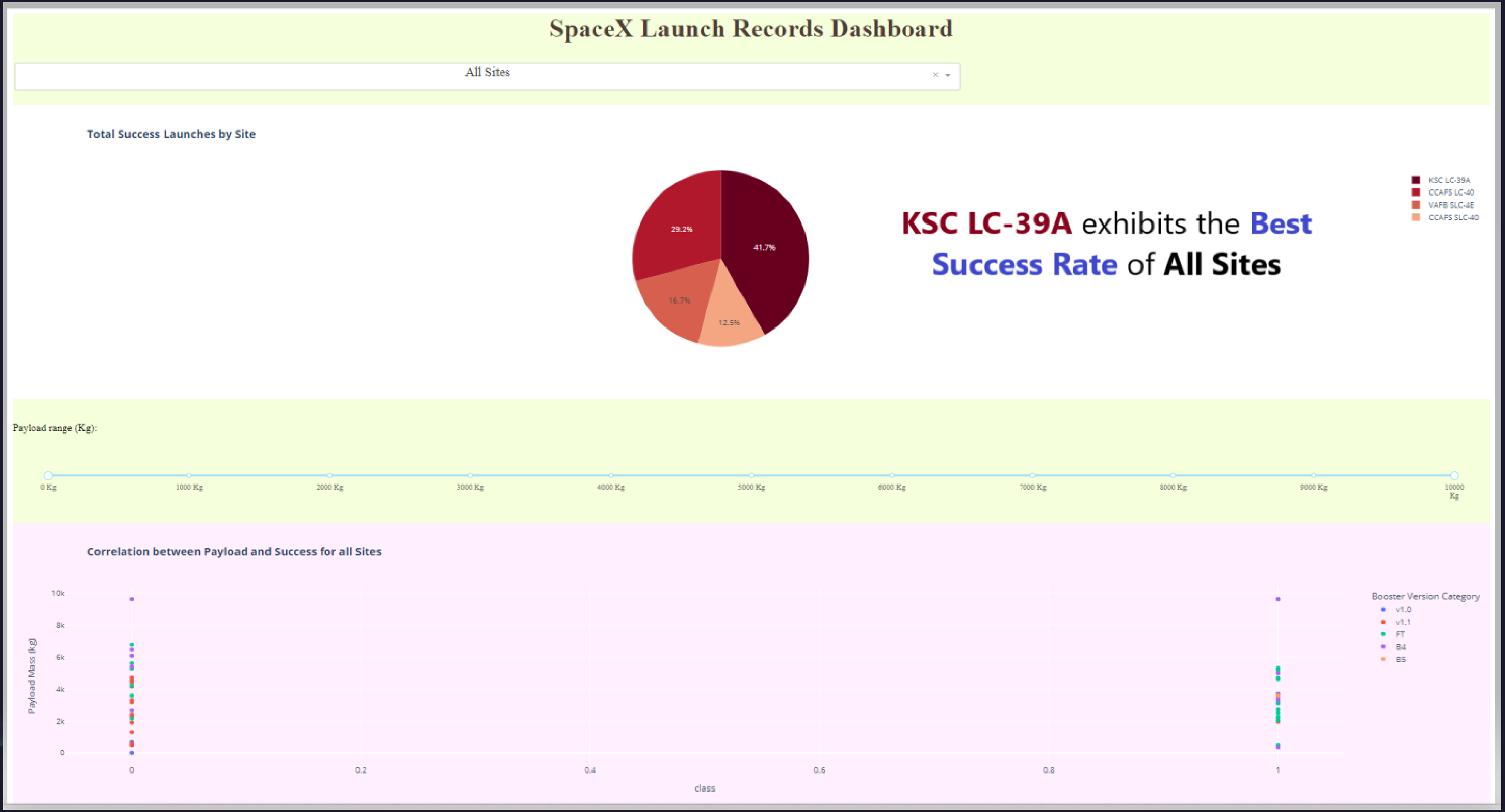
Task 2: Displaying Successful/Failed Launches



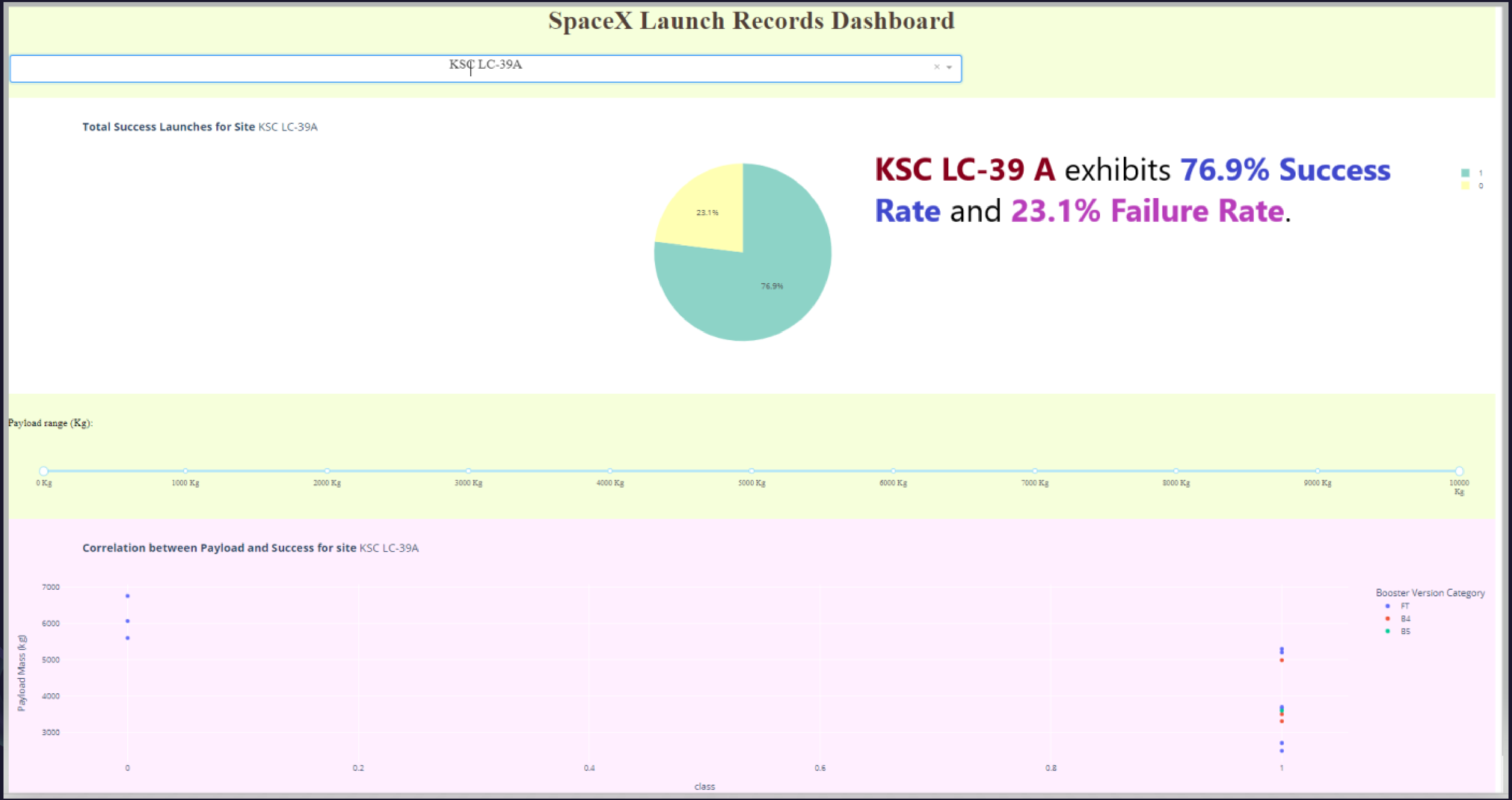
Task 3: Displaying Distances between Launch Sites to its Proximities



Interactive Visual Analysis: Plotly Dash All Sites Results

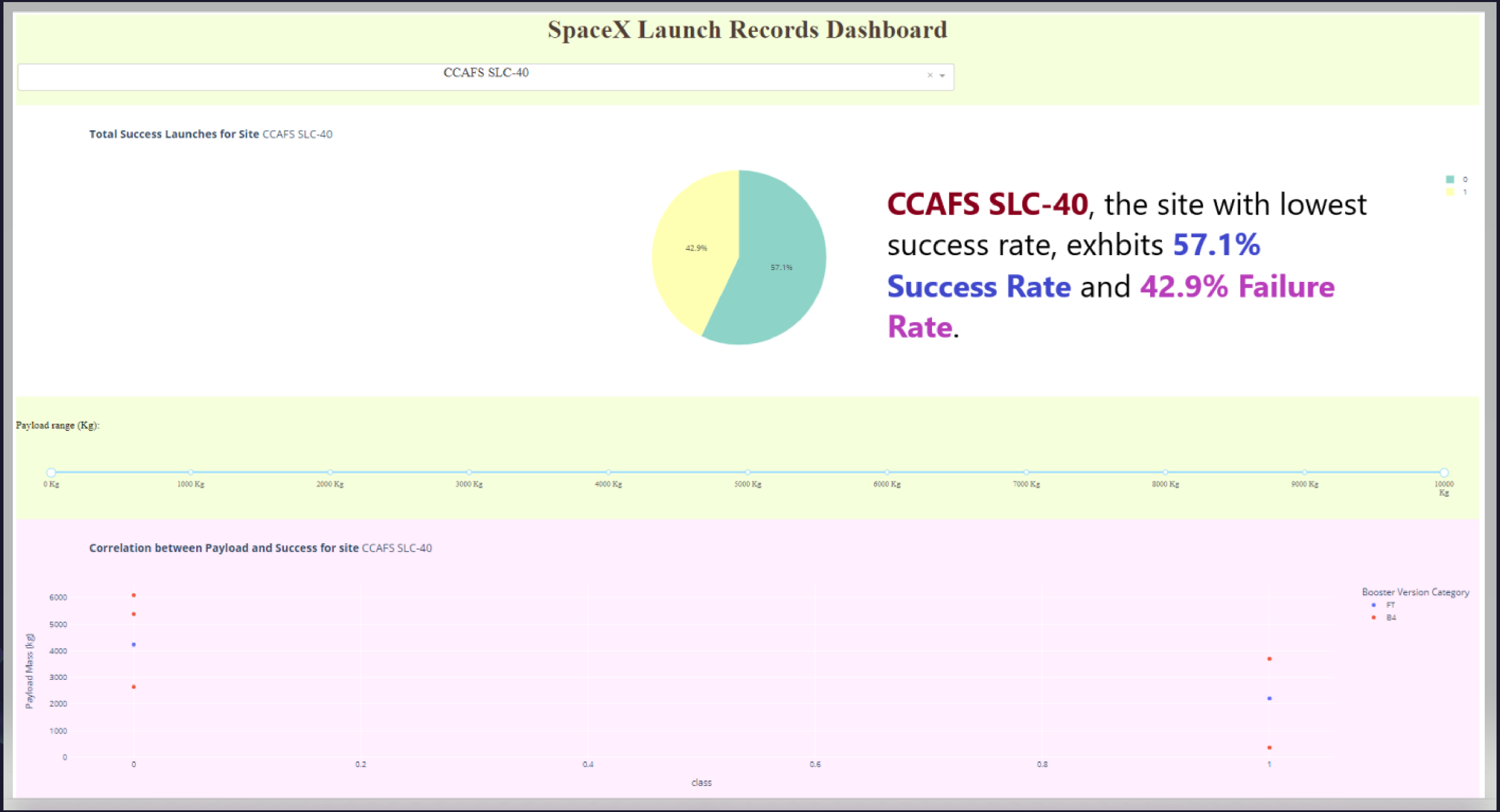


Interactive Visual Analysis: Plotly Dash KSC LC-39 A Site Results



KSC LC-39 A exhibits **76.9% Success Rate** and **23.1% Failure Rate**.

Interactive Visual Analysis: Plotly Dash CCAFS SLC-40 Site Results



CCAFS SLC-40, the site with lowest success rate, exhbits **57.1% Success Rate** and **42.9% Failure Rate**.

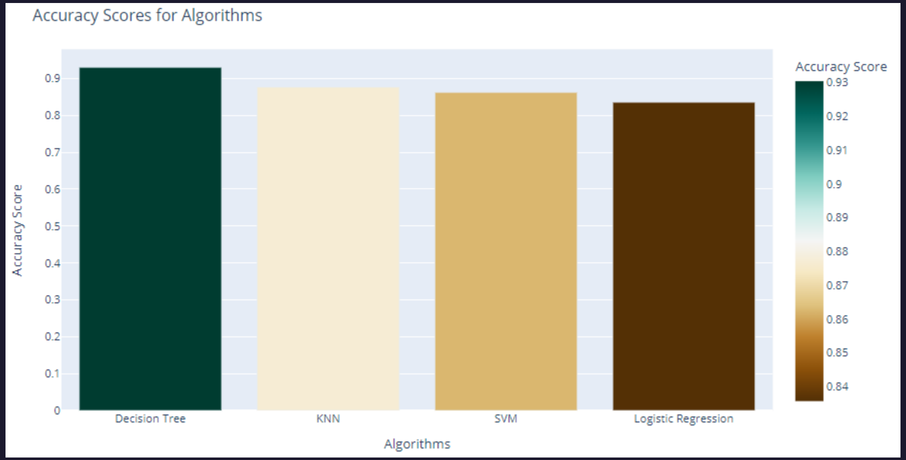
Predictive Analysis Results

The BEST MODEL is Decision Tree which yielded the Highest Accuracy Score of 0.9303571428571429

	Algorithms	Accuracy Score
1	Decision Tree	0.930357
0	KNN	0.876786
3	SVM	0.862500
2	Logistic Regression	0.835714

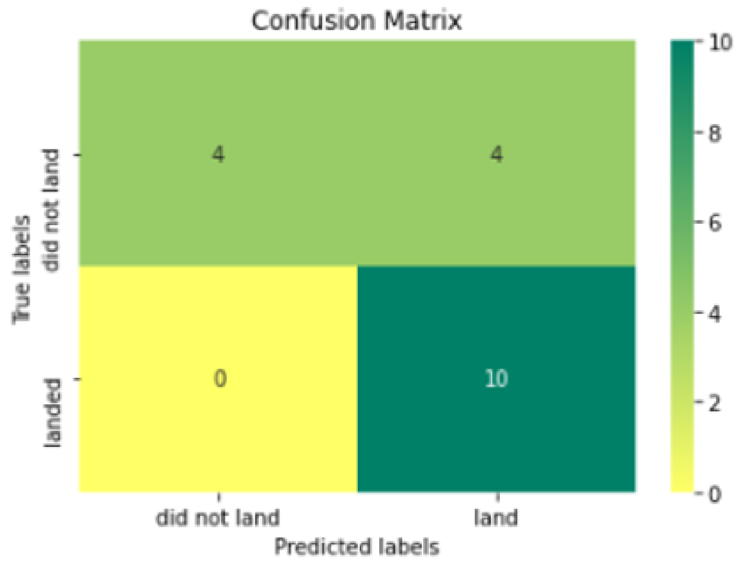
With the Highest Accuracy Score on Train Data, Decision Tree is the winner among all models.

```
        SUMMARY RESULTS:
After Tuning, Best Hpyerparameters for Descision Tree were:
{'criterion': 'entropy', 'max_depth': 18, 'max_features': 'sqrt', 'min_samples_leaf': 1, 'min_samples_split': 5, 'splitter': 'b
est'}
With Accuracy Score: 0.9303571428571429
Accuracy for Descision Tree on Test Data using the Method 'Score' was: 0.7777777777777778

##############################################################################################################################

After Tuning, Best Hpyerparameters for KNeighbors Classifier were:
{'algorithm': 'auto', 'n_neighbors': 4, 'p': 1}
With Accuracy Score: 0.8767857142857143
Accuracy for K Nearest Neighbors on Test Data using the Method 'Score' was: 0.7777777777777778

##############################################################################################################################

After Tuning, Best Hpyerparameters for Support Vector Machines were:
{'C': 1.0, 'gamma': 0.03162277660168379, 'kernel': 'sigmoid'}
With Accuracy Score: 0.8625
Accuracy for Support Vector Machines on Test Data using the Method 'Score' was: 0.7777777777777778

##############################################################################################################################

After Tuning, Best Hpyerparameters for Logistic Regression were:
{'C': 0.01, 'penalty': 'l2', 'solver': 'newton-cg'}
With Accuracy Score: 0.8357142857142857
Accuracy for Logistic Regression on Test Data using the Method 'Score' was: 0.7222222222222222

##############################################################################################################################
```

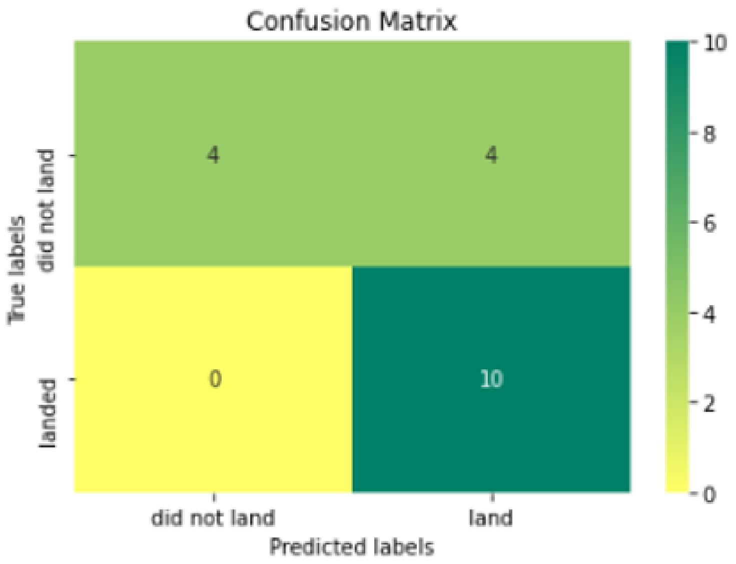


Logistic Regression (LR)

Support Vector Machines (SVM)



Descision Tree (DT)



K Nearest Neighbor(KNN)

Predictive Analysis Results

After tuning for best hyper-parameters, accuracy on Test Data using method score was the same for all models except Logistic Regression (LR). This is why, the confusion matrix for LR is different while for the rest it is the same

Application of Creativity Beyond Template

Exploratory Data Analysis

- **SQL:** Local Database Creation was achieved for subsequent SQL EDA

SPACEX.db
C:\Users\[redacted]Documents\PythonScripts\DATA S...

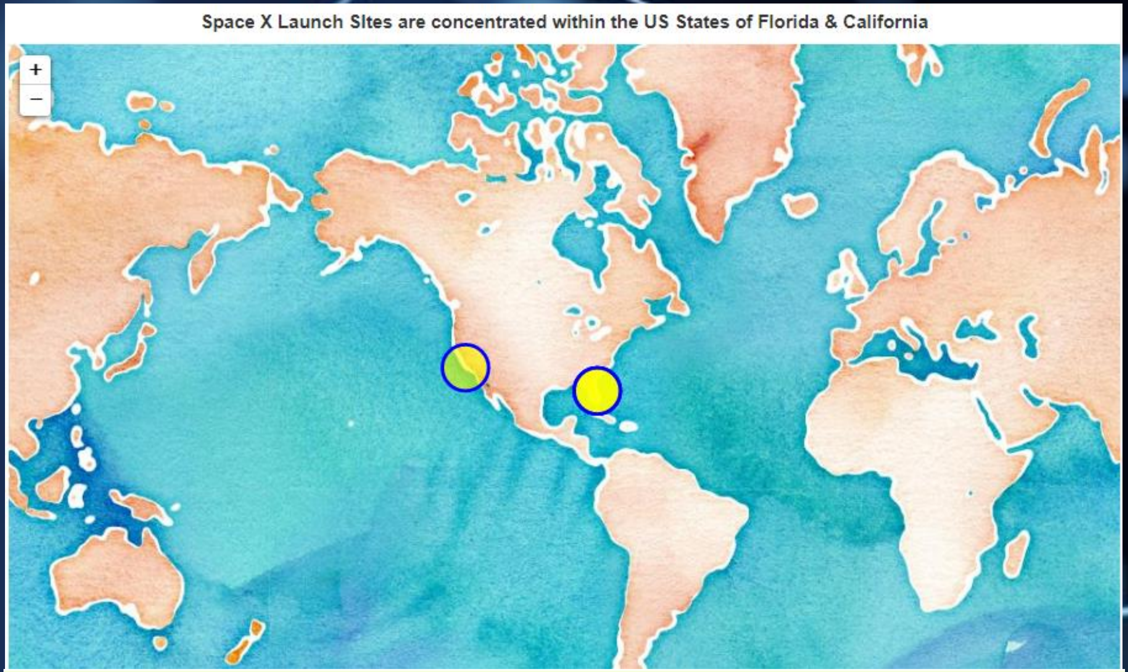
```
############# LOAD DATA ##########################################################################################
# Specify CSV File Location
csv = "C:/Users/fatima.s/Downloads/Spacex.csv"

# Import Spacex.csv to Dataframe
print("Reading Spacex.CSV")
Spacex_data = pd.read_csv(csv, sep = ',')
Spacex_df = pd.DataFrame(Spacex_data)
print("Spacex Data Info: ",Spacex_df.shape)
print("Spacex Data: ",Spacex_df.head(2))
# Get Column List
Spacex_column_list = (list(Spacex_df.columns))
print(list(Spacex_df.columns))
# Remove brackets and speech marks from column names; format for Making Database Table
print('SPACEX COLUMN LIST:\n {}'.format(' '.join('[{}] VARCHAR,'.format(i) for i in Spacex_column_list)))#For Making Databas

############# CREATE NEW LOCAL DATABASE ##########################################################################

#Create New Database..............See: https://datatofish.com/create-database-python-using-sqlite3/
# Establish Connection
conn = sqlite3.connect('SPACEX.db')
#Create Handle (cursor)
cursor = conn.cursor()

############# CREATE NEW DATABASE TABLE ##########################################################################

# Delete SPACEX table if already exists
cursor.execute("DROP TABLE IF EXISTS SPACEX")
print("Table dropped... ")
conn.commit() #Commit your changes in the database

#######################################

# Create SPACEX Table....Copy printed Column List, look at column values, change from VARCHAR to another Data Type if needed
print("Creating Empty SPACEX Table")
cursor.execute('''
          CREATE TABLE IF NOT EXISTS SPACEX
          ([Date] VARCHAR, [Time (UTC)] VARCHAR, [Booster_Version] VARCHAR, [Launch_Site] VARCHAR, [Payload] VARCHAR,
          [PAYLOAD_MASS__KG_] INTEGER, [Orbit] VARCHAR, [Customer] VARCHAR, [Mission_Outcome] VARCHAR,
          [Landing _Outcome] VARCHAR)
          ''')

########################################
# Append Spacex_df to 'SPACEX' table
table_name = 'SPACEX'
conn.commit()

print("Appending df to SPACEX Table")
Spacex_df.to_sql(table_name, conn, if_exists='append', index=False)
```

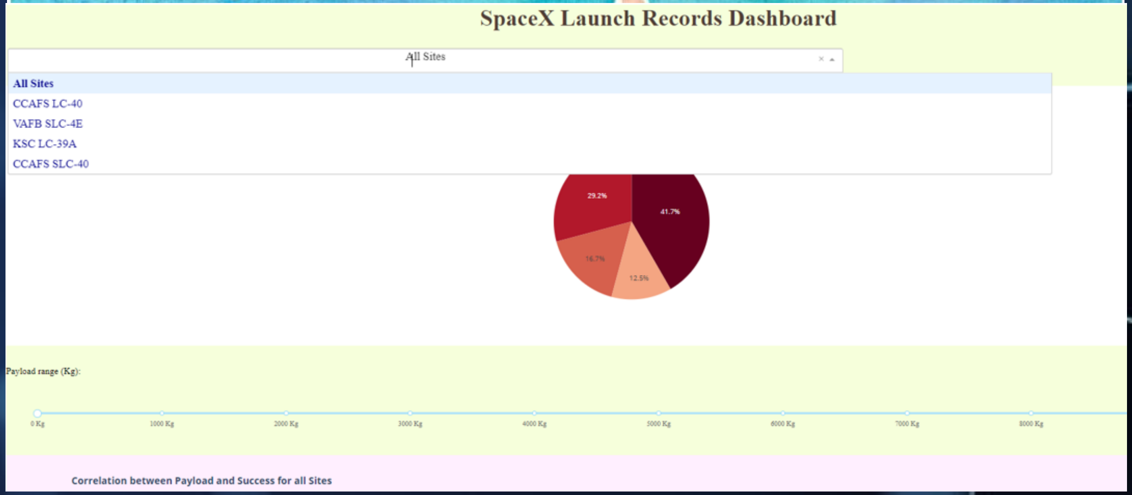
Application of Creativity Beyond Template

Interactive Visual Analytics

- **Folium:** Reverse Geo-coding to find State names with Launch Site concentration

- **Plotly Dash:** Colored dropdown list, app background coloring & pie chart color change





Application of Creativity Beyond Template

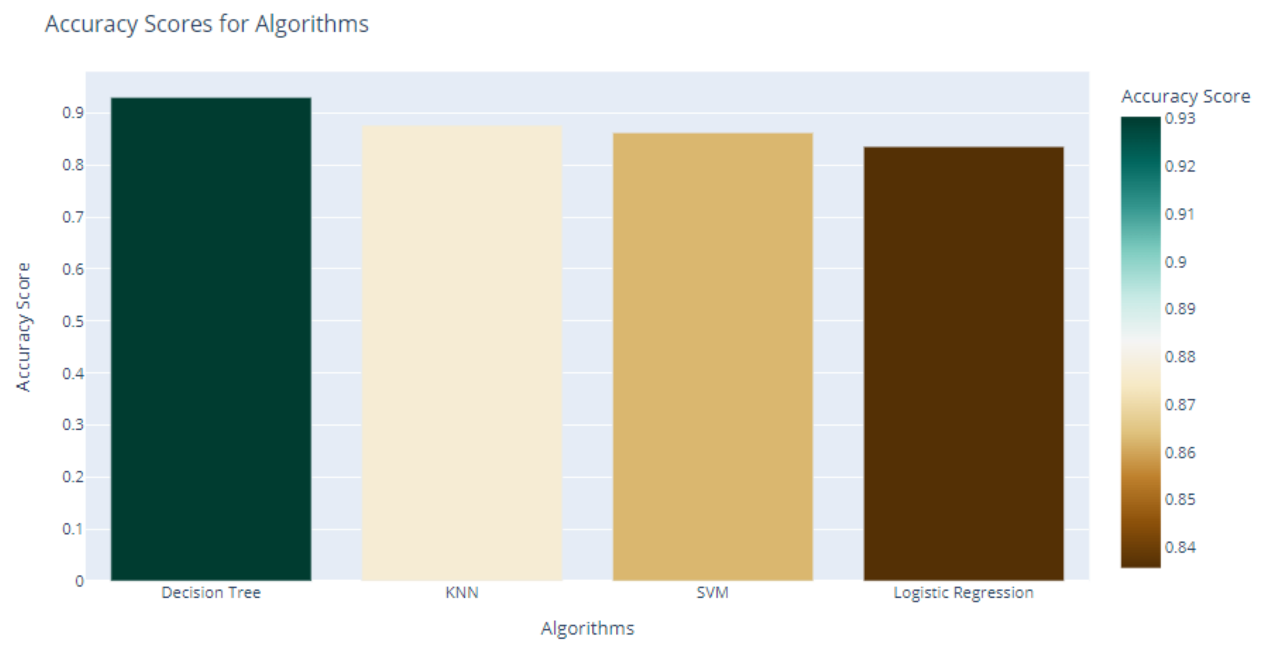
Predictive Analysis:

- **Plotting of Accuracy Scores as Bar Chart to furnish visual insight of modelling accuracy results**

Plotting Accuracy Scores as Bar Chart

See More on Plotly Color Scales: https://plotly.com/python/colorscales/#color-scales-in-plotly-express

```
import plotly.express as px
import plotly.graph_objects as go

scale_color = px.colors.diverging.BrBG #Example: scale_color = ["yellow", "red", "green", "blue"] #'Inferno'
#fig = px.bar(df, x='Algorithms', y='Accuracy Score', hover_data=['Algorithms', 'Accuracy Score'], color='Accuracy Score', c
fig = px.bar(df, x='Algorithms', y='Accuracy Score', hover_data=['Algorithms', 'Accuracy Score'], color='Accuracy Score',
             color_continuous_scale=scale_color)


fig.update_layout(title='Accuracy Scores for Algorithms', xaxis_title='Algorithms', yaxis_title='Accuracy Score' )
fig.show()
```



- Mission success is influenced by factors like, orbit, launch site and number of previous launches since they furnish insight to ensure future success

- Most successful launch site is “KCS LC-39A” but underlying factors cannot be identified with current data

- Orbits with best success rate are GEO, HEO, SSO, ES-L1

- Depending on particular orbits, increase or decrease of Payload Mass seems to be a significant factor

- Predictive Analysis using Machine Learning can be best achieved by Decision Tree Modelling due to its high accuracy score with training data

- Falcon 9’s success may go beyond identified factors and may be related to other variables like engine composition, material, etc.
- The success of best launch sites may be related to weather conditions or atmospheric variables which needs to be explored further
- Cost of successful orbital landing can be reduced by multiple relaunches


THANK YOU