IBM Developer SKILLS NETWORK

Winning Space Race with Data Science

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Outline

- Executive Summary
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- Methodology
- Results
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Executive Summary

Summary of methodologies

1. Data Collection - gathering data
2. Data Wrangling – cleaning & preparing data
3. Exploratory Data Analysis
4. Interactive Visual Analytics
5. Predictive Analysis

Summary of results

1. Exploratory Data Analysis results of SQL and visualization
2. Interactive analytics results of Folium and Dash
3. Predictive analysis results

Introduction

The commercial space age is here, companies are making space travel affordable for everyone. Talking about affordability, the agency that we can first think of is SpaceX which was founded in 2002 by Elon Musk with the goal of reducing space transportation costs. It's accomplishments include: Sending spacecraft to the International Space Station. Starlink, a satellite internet constellation providing satellite Internet access and many more.

One reason SpaceX can do this is the rocket launches are relatively inexpensive, 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.

As a Data Scientist at SpaceY Corp., I will be predicting if the SpaceX Falcon 9 first stage will land successfully, if the first stage can be reused and as a result to determine the price of each launch. I will achieve this by training a machine learning model and use public information to make the required prediction.

Section 1

Methodology

Methodology

Summary

- Data collection methodology:
  - Obtained the launch data from SpaceX REST API & also by Web Scrapping with Beautiful Soup.
- Perform data wrangling:
  - The booster landings outcomes are converted to training labels using Exploratory data analysis.
- Perform exploratory data analysis (EDA) using visualization and SQL:
  - Performed visualization with pandas & matplotlib and executed SQL queries for EDA.
- Perform interactive visual analytics using Folium and Plotly Dash:
  - Used Folium maps to find geographical patterns and built a dashboard with the Plotly Dash to get more insights.
- Perform predictive analysis using classification models:
  - Built machine learning models to make the prediction and find best model.

Data Collection

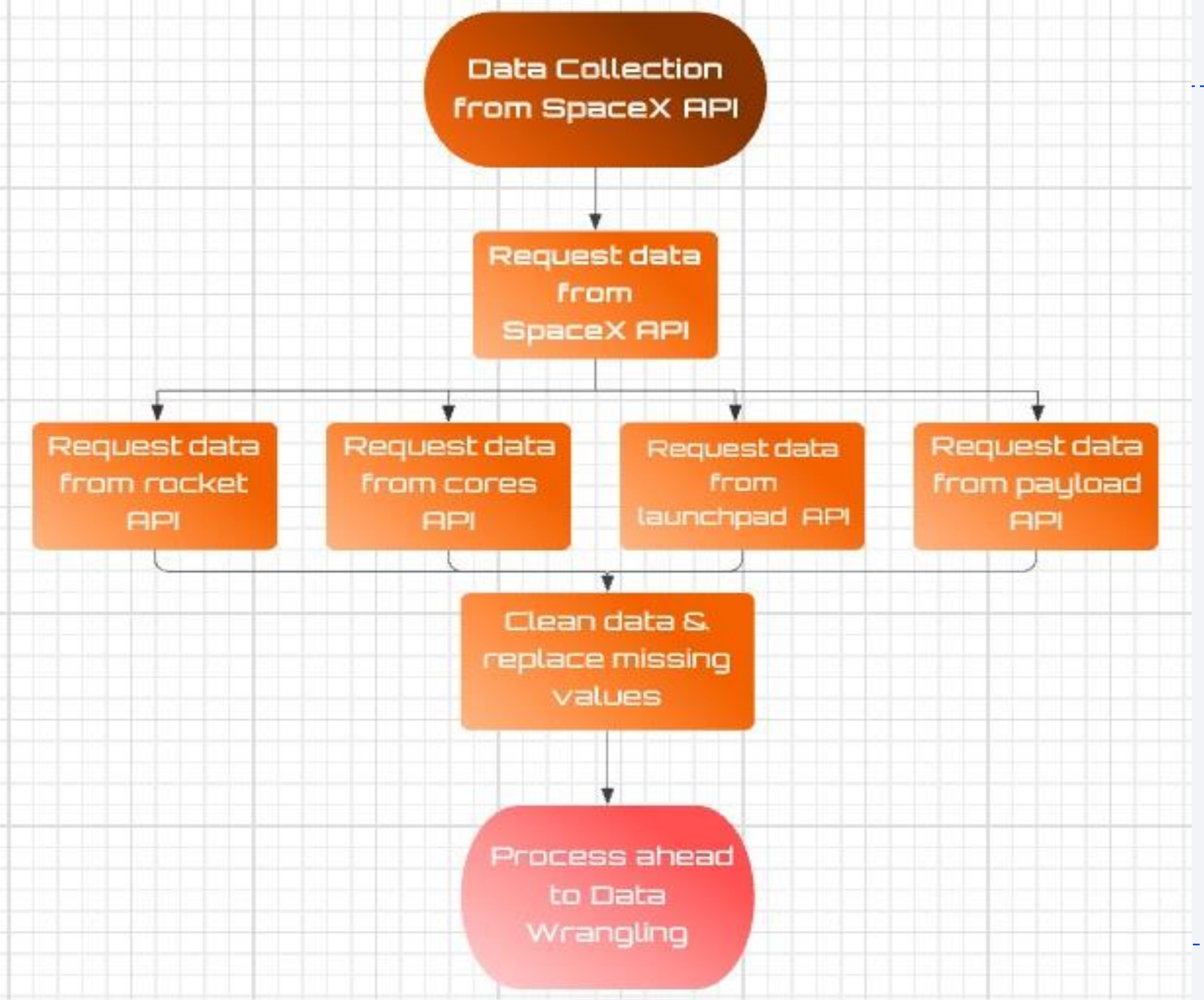
- The initial step of Collecting SpaceX Falcon 9 launch data is fulfilled using two methodologies as follows:

1) From API:- using the get() method from requests library the launch data is collected from SpaceX REST API.

2) From Web Page:- web scrapping Falcon 9 historical launch records from Wikipedia webpage titled 'List of Falcon 9 and Falcon heavy launches' with BeautifulSoup.

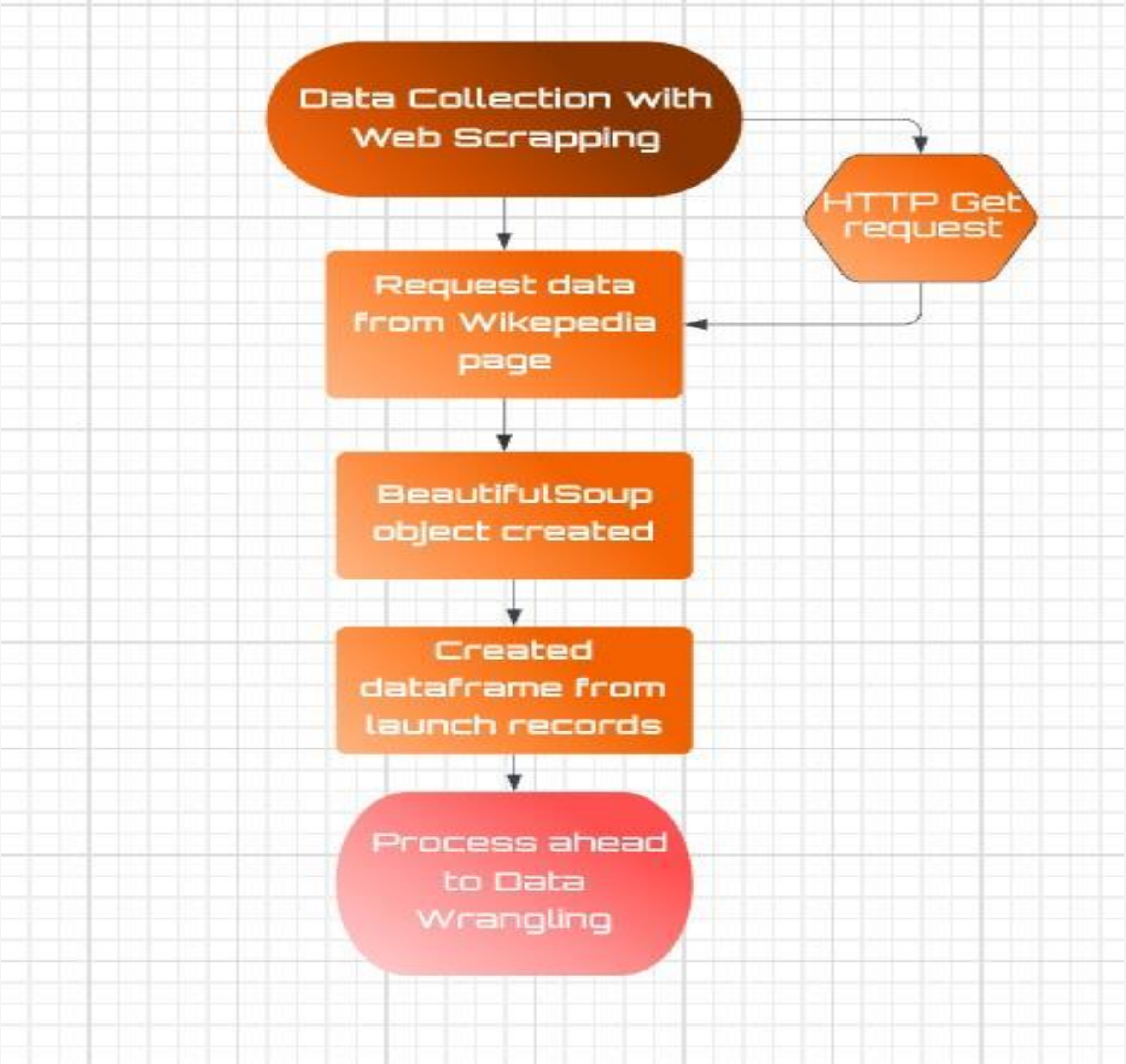
Data Collection – SpaceX API

- Requested rocket launch data from SpaceX API using get() method from requests library.
- Parsed the launch data to a JSON and then converted it to a dataframe.
- Removed irrelevant features and removed all launches data except the Falcon 9 launches.
- Replaced missing values with the mean of respective column.



Data Collection - Scraping

- Performed HTTP GET request to the Falcon9 Launch HTML page.
- Created a BeautifulSoup object using response text content.
- Created dataframe from parsed launch record values.



Data Wrangling

- Analyzed the number of launches on each site, each orbit and outcome.
- Categorized outcomes as landing labels, where 0 represents unsuccessful landing and 1 for successful landing.
- Created a new dataframe with an added Class column containing the landing labels.

EDA with Data Visualization

- Plots used for exploratory data analysis to visualize valuable insights.
- Made scatter plots of
  1. Flight Number vs Payload Mass
  2. Flight Number vs Launch Site
  3. Payload Mass vs Launch Site
  4. Flight Number vs Orbit Type
  5. Payload Mass vs Orbit Type, each with Class overlay.
- Created bar plot to visualize success rate of each orbit.
- Used line plot to visualize launch success yearly trend.

EDA with SQL

- Executed SQL queries for exploratory data analysis.
- Displayed following SQL queries:-

- ✓ Display the names of the unique launch sites in the space mission.
- ✓ Display 5 records where launch sites begin with the string 'CCA'.
- ✓ Display the total payload mass carried by boosters launched by NASA (CRS).
- ✓ Display average payload mass carried by booster version F9 v1.1.
- ✓ List the date when the first successful landing outcome in ground pad was achieved.
- ✓ List the names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000.
- ✓ List the total number of successful and failure mission outcomes.
- ✓ List the names of the booster_versions which have carried the maximum payload mass.
- ✓ List the failed landing_outcomes in drone ship, their booster versions, and launch site names for in year 2015.
- ✓ Rank the count of landing outcomes between the date 2010-06-04 and 2017-03-20, in descending order.

Build an Interactive Map with Folium

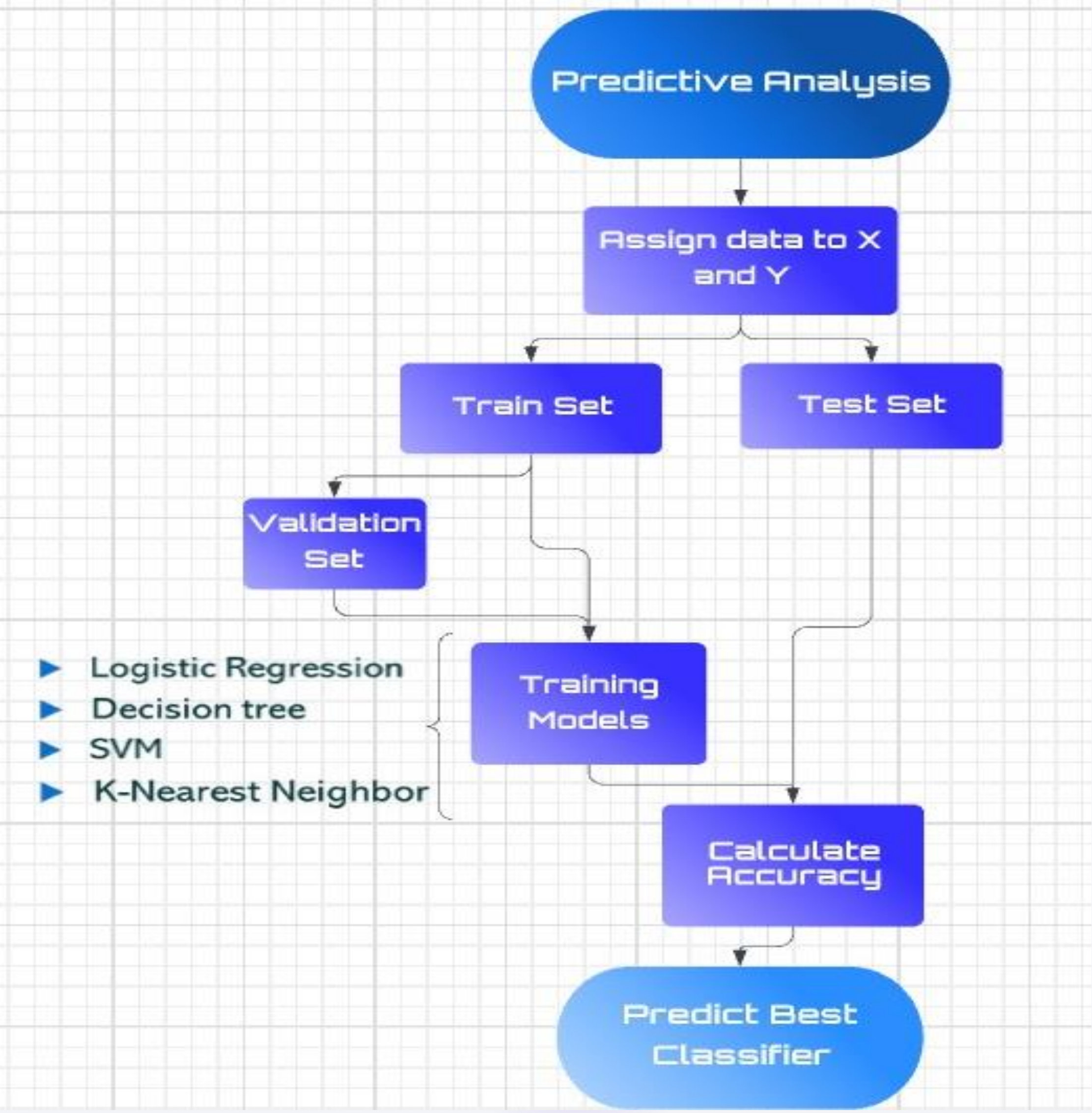
- Folium map objects used to build an Interactive Map are markers, circles and polylines.
- Created a map with center location as NASA Johnson Space Center at Houston, Texas, to visualize and draw insights of SpaceX launch sites.
- Marked the success and failed launches for each site on the map using markers.

Build a Dashboard with Plotly Dash

- The dashboard was build using the Dash framework and deployed on Google Cloud Platform. You can review the live application here and the source.
- The first interactive component is a **Dropdown** list, where you can select all sites or any specific launch site to plot the graphs for.
- Added a pie chart to the Dashboard showing comparison between success Vs failed launches of selected site or count of successful launches of all sites.
- Then a Scatter Plot is displayed, where the launch outcome in relation to the payload mass can be analyzed. Each point on this graph is colored according to the booster version label on the right side.
- Added a scatter plot to show the correlation between payload mass and launch success.

Predictive Analysis (Classification)

- Obtained and standardized feature data in X and assigned Class data to Y.
- Data spilt into train & test data and training data further divided to validation data.
- Created models of Logistic Regression, Support Vector Machine, Decision tree classifier and K-Nearest Neighbor and calculated validation set accuracy and test set accuracy of each model.
- Plotted Confusion Matrix of each model.
- Observed that all four models have same accuracy score of 83.3% and hence cannot determine best classifier.



Results

- Exploratory data analysis results:
  - ❖ As the flight number increases, the first stage is more likely to land successfully.
  - ❖ Rockets with payload mass less than 8000kg are highly preferred for launches.
  - ❖ Orbits ES-L1, GEO, HEO, SSO have the highest success rates.
  - ❖ Since 2013, the launch success rate kept increasing till 2020.
  - ❖ First successful landing outcome on ground pad was on 2015-12-22.
- Interactive analytics results:
  - ❖ Site KSC LC-39A has the highest success rate & CCAFS LC-40 has lowest.
  - ❖ Launch sites are in close proximity to railways, highways and coastline but located far away from the cities.
- Predictive analysis results:
  - ❖ All the four classification models have the same Accuracy Score which is 0.833.

Section 2

Insights drawn from EDA

Flight Number vs. Launch Site

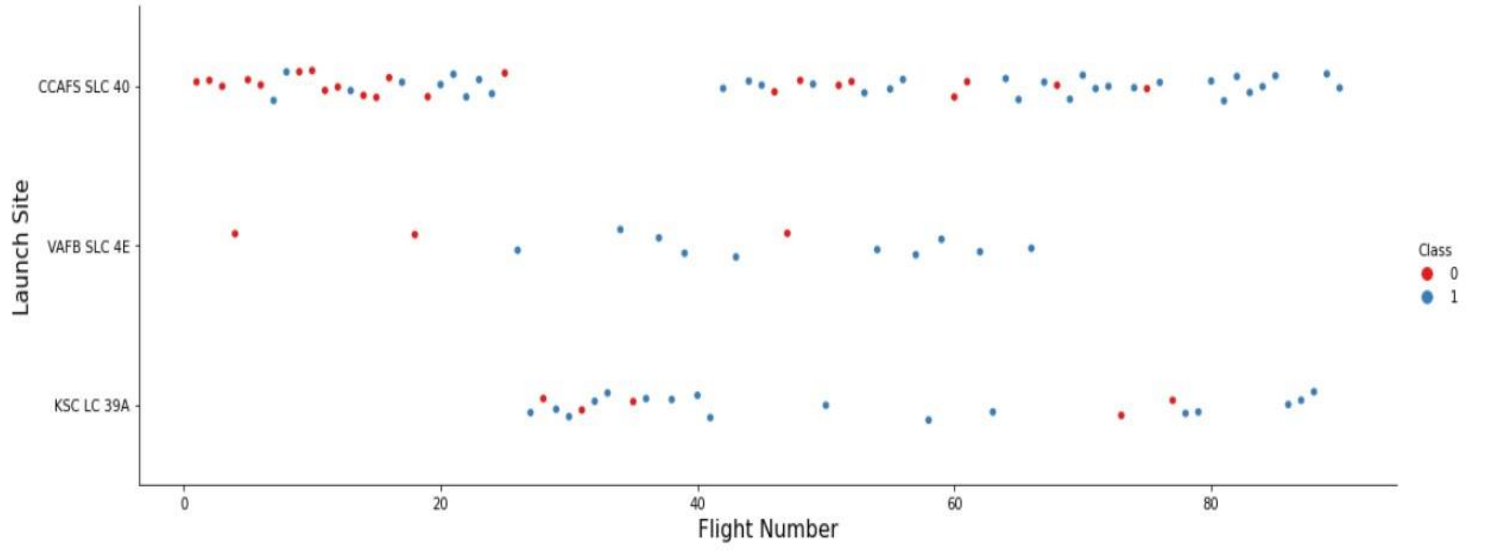
- Observations of scatter plot of Flight Number vs. Launch Site with Class as overlay:-

  1. Launch sites KSC LC-39A and have higher success rates than VAFB SLC 4E and CCAFS LC-40.
  2. As the flight number increases, the first stage is more likely to land successfully

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'`

In [36]:
```
# 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=3 , palette="Set1")
plt.xlabel("Flight Number" , fontsize=15)
plt.ylabel("Launch Site" , fontsize = 15)
plt.show()
```



Payload vs. Launch Site

- Observations of scatter plot of Payload Mass vs. Launch Site with Class as overlay:-

  1. Rockets with payload mass less than 8000kg are highly preferred for launches.

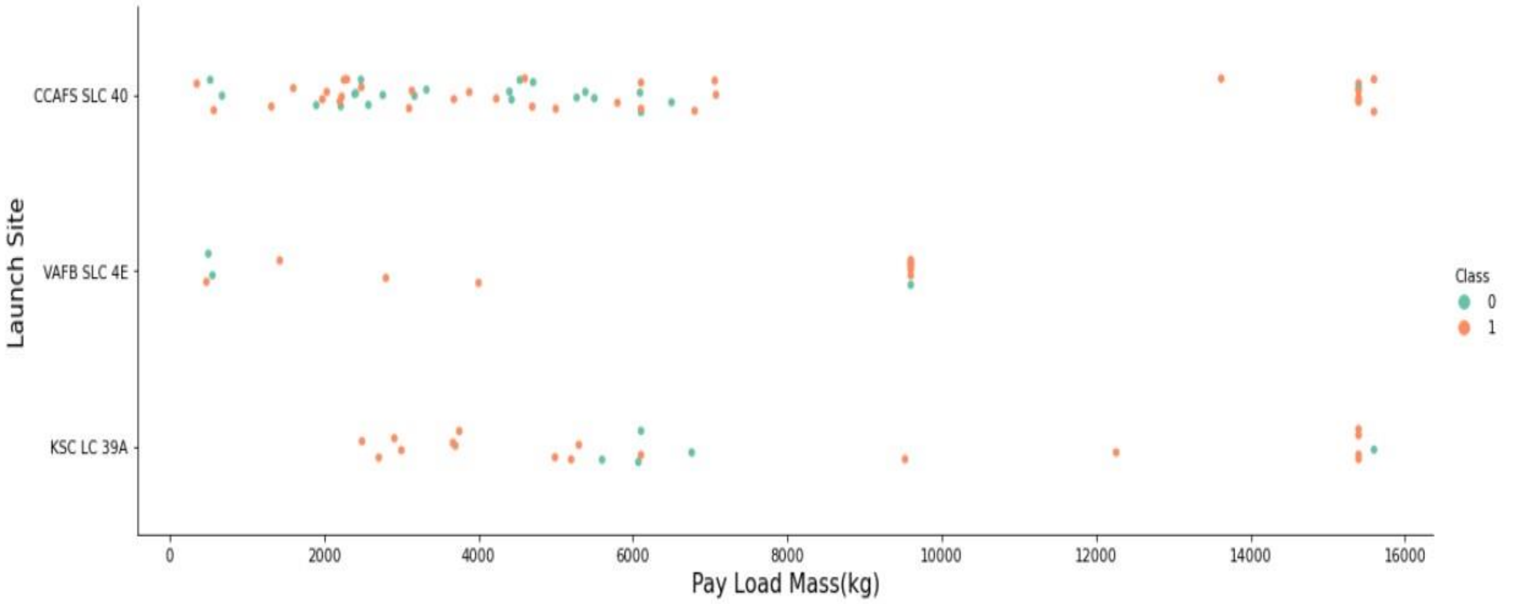
  2. No rockets launched from VAFB SLC 4E launch site having payload mass greater than 10000kg

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.

In [37]:

```
# 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 valu
e
sns.catplot(y="LaunchSite" , x="PayloadMass" , data=df , hue="Class" , aspect=3 , palette="Set2")
plt.xlabel("Pay Load Mass(kg)" , fontsize=15)
plt.ylabel("Launch Site" , fontsize=15)
plt.show()
```



Success Rate vs. Orbit Type

- Observations of bar plot of Success Rate vs. Orbit Type:-

  1. Orbits ES-L1, GEO, HEO, SSO have the highest success rates.

  2. Approximately no success rate for orbit type 'SO'

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

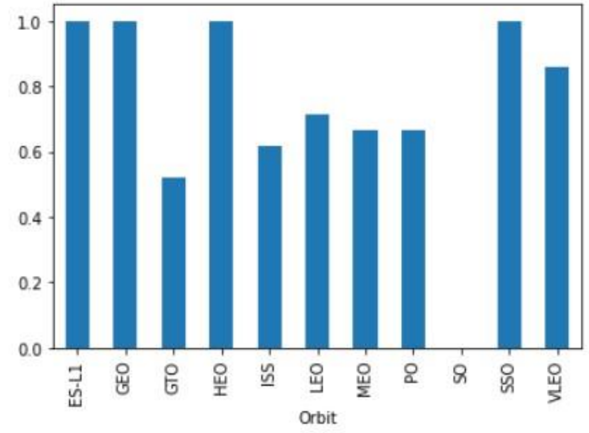
In [38]:
```
# HINT use groupby method on Orbit column and get the mean of Class column
df_grp = df.groupby(['Orbit']).mean()['Class']

df_grp.head()
```

Out[38]:
```
Orbit
ES-L1    1.000000
GEO      1.000000
GTO      0.518519
HEO      1.000000
ISS      0.619048
Name: Class, dtype: float64
```

In [39]:
```
df_grp.plot(kind='bar')
```

Out[39]: <AxesSubplot:xlabel='Orbit'>



Flight Number vs. Orbit Type

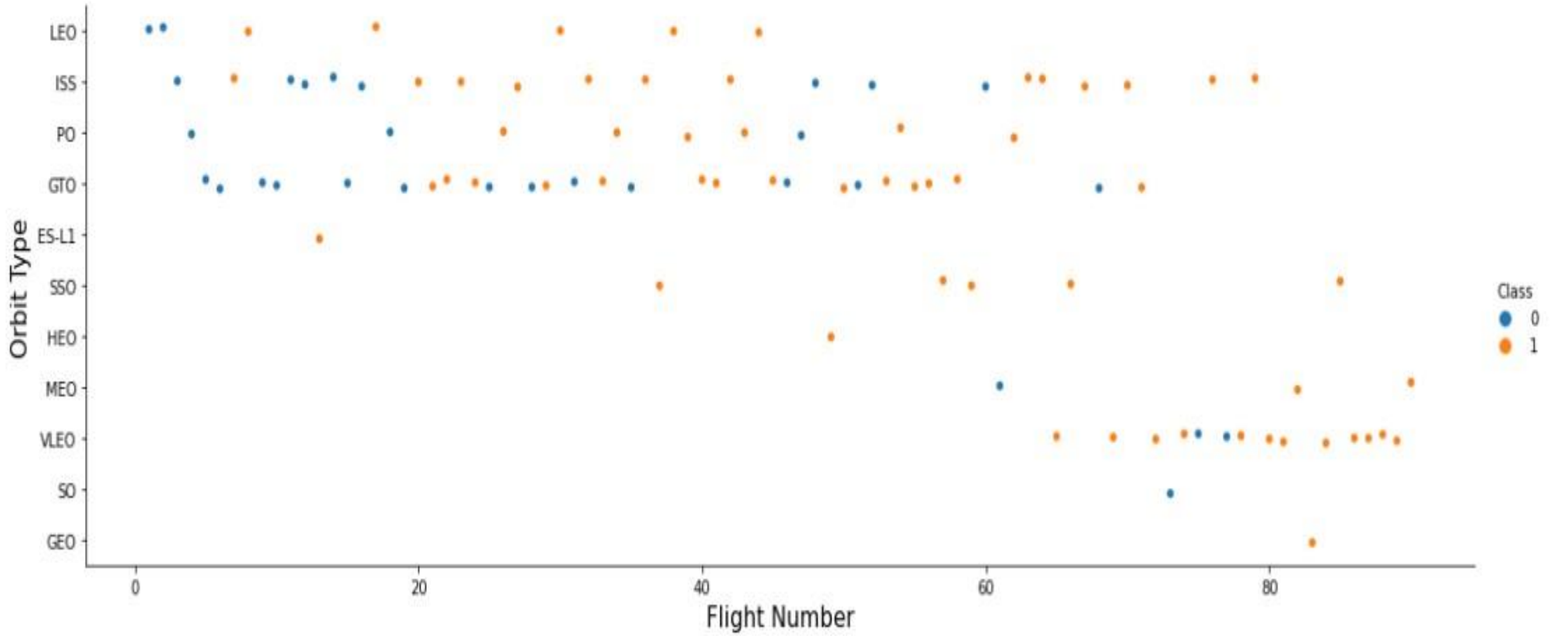
- Observations of scatter plot of Flight Number vs. Orbit Type:-

1. Success rate in LEO orbit increases with increase in Flight number.
2. Orbit VLEO has higher success rate when flight number is more than 60.
3. Orbits SSO, HEO, GEO and ES-L1 have 100% success rate, irrespective of 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.

In [40]:
```
# 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" , data=df , hue="Class" , aspect=3)
plt.xlabel("Flight Number" , fontsize=15)
plt.ylabel("Orbit Type" , fontsize=15)
plt.show()
```



Payload vs. Orbit Type

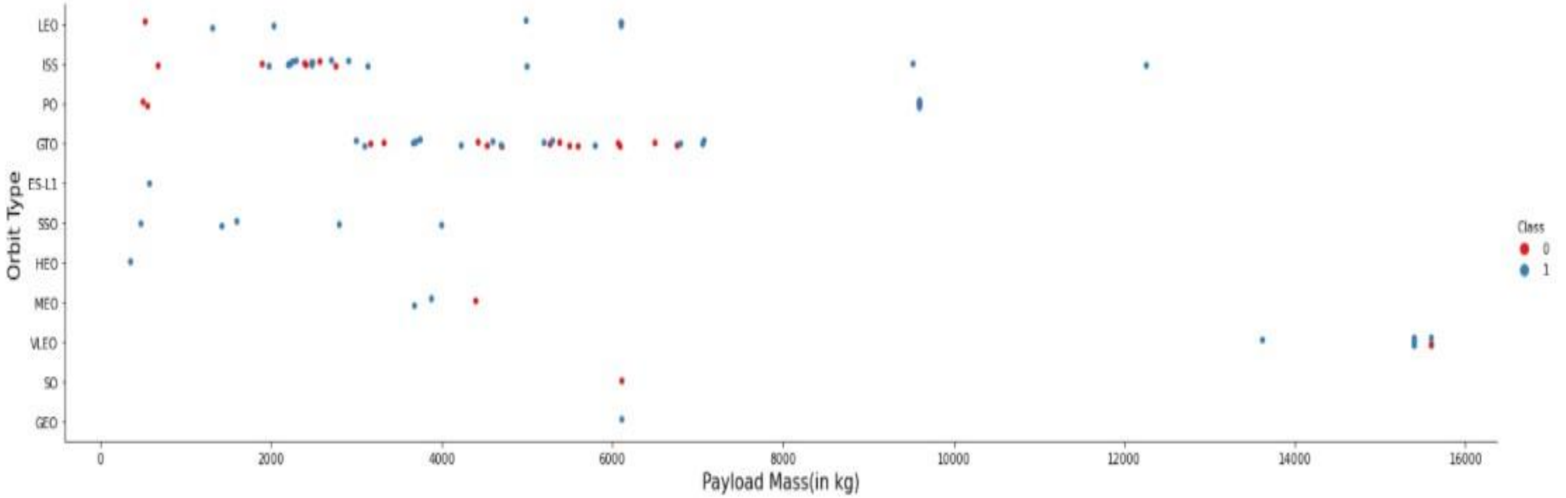
- Observations of scatter plot of Payload Mass vs. Orbit Type:-

  1. Success rates of orbits LEO, ISS, PO increases with heavy payloads.
  2. SSO, HEO, ES-L1 have successful landings with lighter payloads.
  3. For orbit GTO no relationship observed.

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

In [41]:
```
# 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" , data=df , hue="Class" , aspect=4 , palette="Set1")
plt.xlabel("Payload Mass(in kg)" , fontsize=15)
plt.ylabel("Orbit Type" , fontsize=15)
plt.show()
```



Launch Success Yearly Trend

- Observations of line plot of Launch Success yearly trend:-

  1. Since 2013, the launch success rate kept increasing till 2020, with a drastic downfall in 2018.

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:

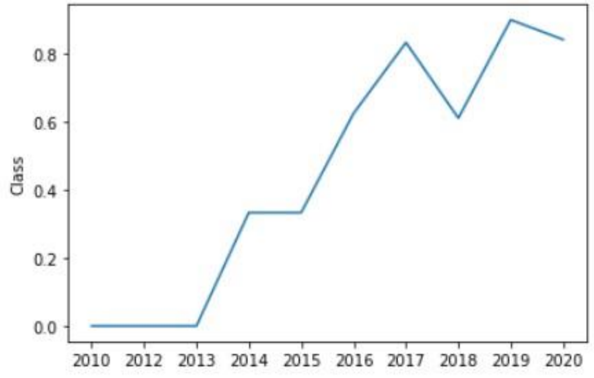
In [42]:
```
# A function to Extract years from the date
year=[]
def Extract_year(date):
    for i in df["Date"]:
        year.append(i.split("-")[0])
    return year
```

In [43]:
```
# Plot a line chart with x axis to be the extracted year and y axis to be the success rate
Year = Extract_year(df['Date'])

df_yr = pd.DataFrame(Year , columns=['ExtractedYear'])
df_yr['Class'] = df['Class']

sns.lineplot(y=df_yr.groupby(['ExtractedYear'])['Class'].mean(0) , x=np.unique(df_yr['ExtractedYear']))
```

Out[43]: <AxesSubplot:ylabel='Class'>



All Launch Site Names

- Used DISTINCT with SELECT statement to find unique launch site names.

Task 1

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

In [34]:
```
%sql select distinct(launch_site) from SPACEXDATASET
```

```
 * ibm_db_sa://hkq84699:***@8e359033-a1c9-4643-82ef-8ac06f5107eb.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:30120/bludb
Done.
```

Out[34]:

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

Launch Site Names Begin with 'CCA'

- Used LIMIT with SELECT statement to get first 5 rows WHERE launch site starting with ‘CCA’

Task 2

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

In [35]:
```
%sql select * from SPACEXDATASET where launch_site like 'CCA%' limit 5
```

```
 * ibm_db_sa://hkq84699:***@8e359033-a1c9-4643-82ef-8ac06f5107eb.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:30120/bludb
Done.
```

Out[35]:

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

- Used SUM() function with SELECT statement to get total payload mass of NASA(CRS)

Task 3

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

```
In [36]: %sql select sum(payload_mass__kg_) as Total_Payload_Mass from SPACEXDATASET where customer= 'NASA (CRS)'
```

```
 * ibm_db_sa://hkq84699:***@8e359033-a1c9-4643-82ef-8ac06f5107eb.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:30120/bludb
Done.
```

Out[36]:

total_payload_mass
45596

Average Payload Mass by F9 v1.1

- Used AVG() function with SELECT statement to get average payload mass carried by booster version F9 v1.1

Task 4

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

In [37]:
```
%sql select avg(payload_mass__kg_) as Average_Payload_Mass from SPACEXDATASET where booster_version= 'F9 v1.1'
```

```
 * ibm_db_sa://hkq84699:***@8e359033-a1c9-4643-82ef-8ac06f5107eb.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:30120/bludb
Done.
```

Out[37]:

average_payload_mass
2928

First Successful Ground Landing Date

- Used MIN function with SELECT statement to get date of the first successful landing outcome on ground pad

Task 5

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

Hint:Use min function

```
In [38]: %sql select min(DATE) as First_Successful_Landing from SPACEXDATASET where landing__outcome= 'Success (ground pad)'
```

```
 * ibm_db_sa://hkq84699:***@8e359033-a1c9-4643-82ef-8ac06f5107eb.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:30120/bludb
Done.
```

Out[38]:

first_successful_landing
2015-12-22

Successful Drone Ship Landing with Payload between 4000 and 6000

- Used AND to satisfy 2 conditions in 1 query and obtain boosters which have successfully landed on drone ship and had payload mass greater than 4000 but less than 6000

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

In [39]:
```
%sql select booster_version as Booster_Names from SPACEXDATASET where landing__outcome='Success (drone ship)' and payload_mass__kg_ between 4000 and 6000
```

```
 * ibm_db_sa://hkq84699:***@8e359033-a1c9-4643-82ef-8ac06f5107eb.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:30120/bludb
Done.
```

Out[39]:

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

Total Number of Successful and Failure Mission Outcomes

- Used COUNT function with SELECT statement to total number of mission outcomes, grouped by type of mission outcome.

Task 7

List the total number of successful and failure mission outcomes

In [40]:
```
%sql select mission_outcome , count(mission_outcome) as Total_Number from SPACEXDATASET group by mission_outcome
```

```
 * ibm_db_sa://hkq84699:***@8e359033-a1c9-4643-82ef-8ac06f5107eb.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:30120/bludb
Done.
```

Out[40]:

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

Boosters Carried Maximum Payload

- Used a subquery and MAX() function to list booster names which have carried the maximum payload mass.

Task 8

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

In [41]:
```
%sql select booster_version from SPACEXDATASET where payload_mass__kg_ = (select max(payload_mass__kg_) from SPACEXDATASET)
```

```
 * ibm_db_sa://hkq84699:***@8e359033-a1c9-4643-82ef-8ac06f5107eb.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:30120/bludb
Done.
```

Out[41]:

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

2015 Launch Records

- Used AND to satisfy 2 conditions in 1 query and failed landing outcomes in drone ship, their booster versions, and launch site names for in year 2015 using YEAR() function.

Task 9

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

In [42]:
```
%sql select landing__outcome, booster_version, launch_site from SPACEXDATASET where landing__outcome='Failure (drone ship)' and YEAR(DATE)=2015
```

```
 * ibm_db_sa://hkq84699:***@8e359033-a1c9-4643-82ef-8ac06f5107eb.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:30120/bludb
Done.
```

Out[42]:

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

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

- Used AND to satisfy 2 conditions in 1 query and rank the count of landing outcomes grouped by type of outcome between the date 2010-06-04 and 2017-03-20 using GROUP BY clause, in descending order using ORDER BY clause.

Task 10

Rank 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

In [43]:

```
%sql select landing__outcome , count(landing__outcome) as Count from SPACEXDATASET where DATE between '2010-06-04' and '2017-03-20' group by landing__outcome order by count(landing__outcome) desc
```

```
 * ibm_db_sa://hkq84699:***@8e359033-a1c9-4643-82ef-8ac06f5107eb.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:30120/bludb
Done.
```

Out[43]:

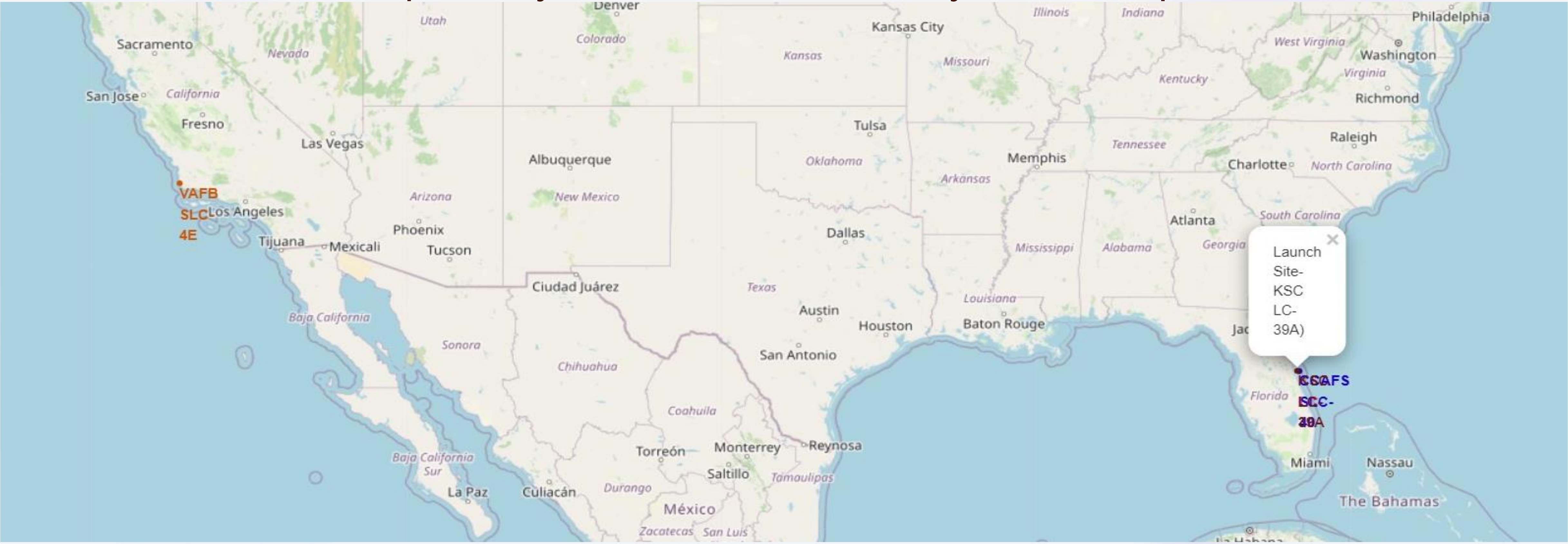
landing__outcome	COUNT
No attempt	10
Failure (drone ship)	5
Success (drone ship)	5
Controlled (ocean)	3
Success (ground pad)	3
Failure (parachute)	2
Uncontrolled (ocean)	2
Precluded (drone ship)	1

Section 3

Launch Sites Proximities Analysis

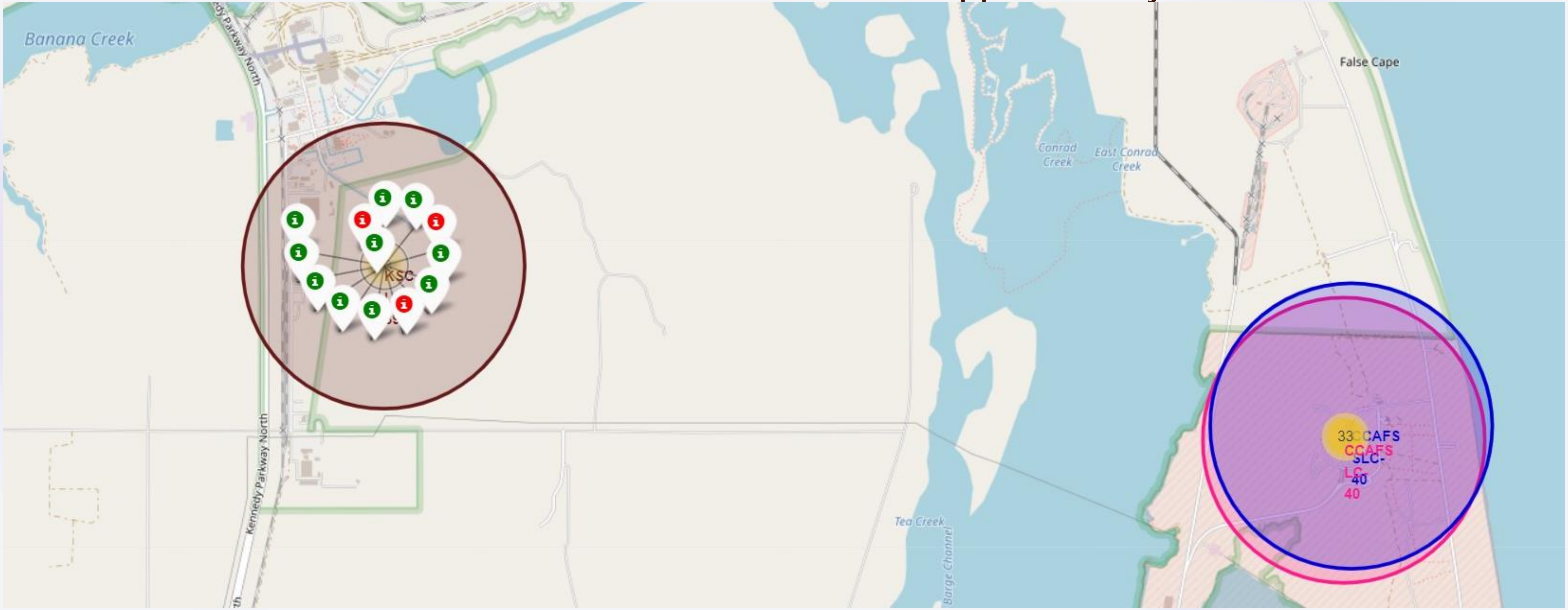
Visualize Launch Sites

- Launch Site VAFB SLC-4E is located on farther west as compared to the other 3 sites, which are in proximity.
- The launch sites are in proximity to the coast but far away from the Equator line.



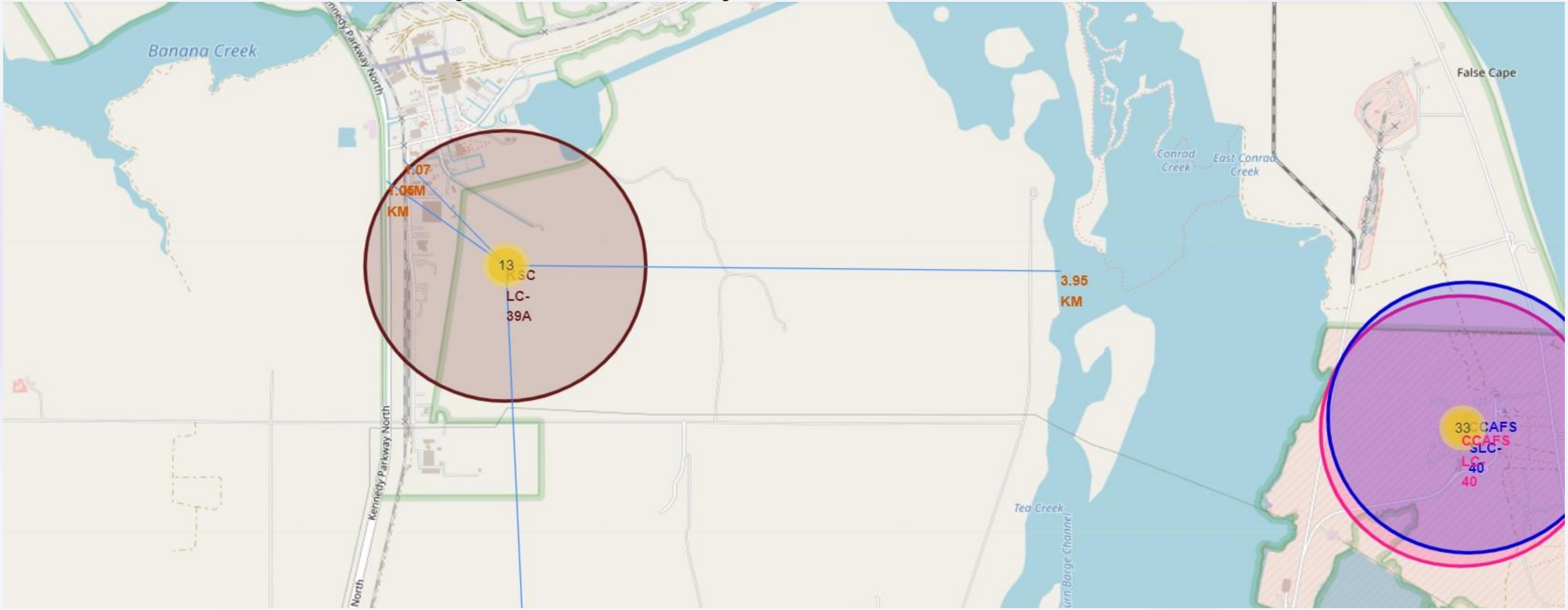
Visualize launch outcome of each site

- Launch Site KSC LC-39A has the highest success rate of approximately 77%.
- Launch Site CCAFS LC-40 has the lowest success rate of approximately 27%



Calculate distance of sites to its proximities

- The launch sites are in close proximity to railways, highways and coastline.
- The launch sites are usually located far away from the cities.

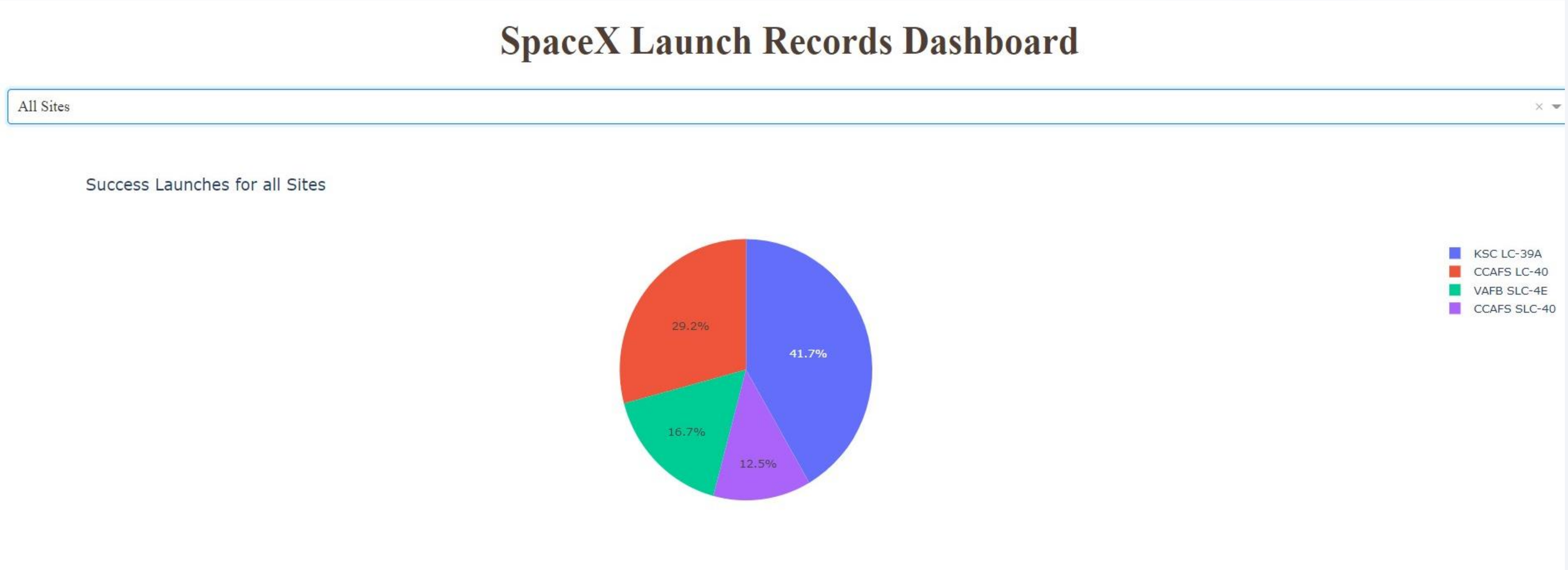


Section 4

Build a Dashboard with Plotly Dash

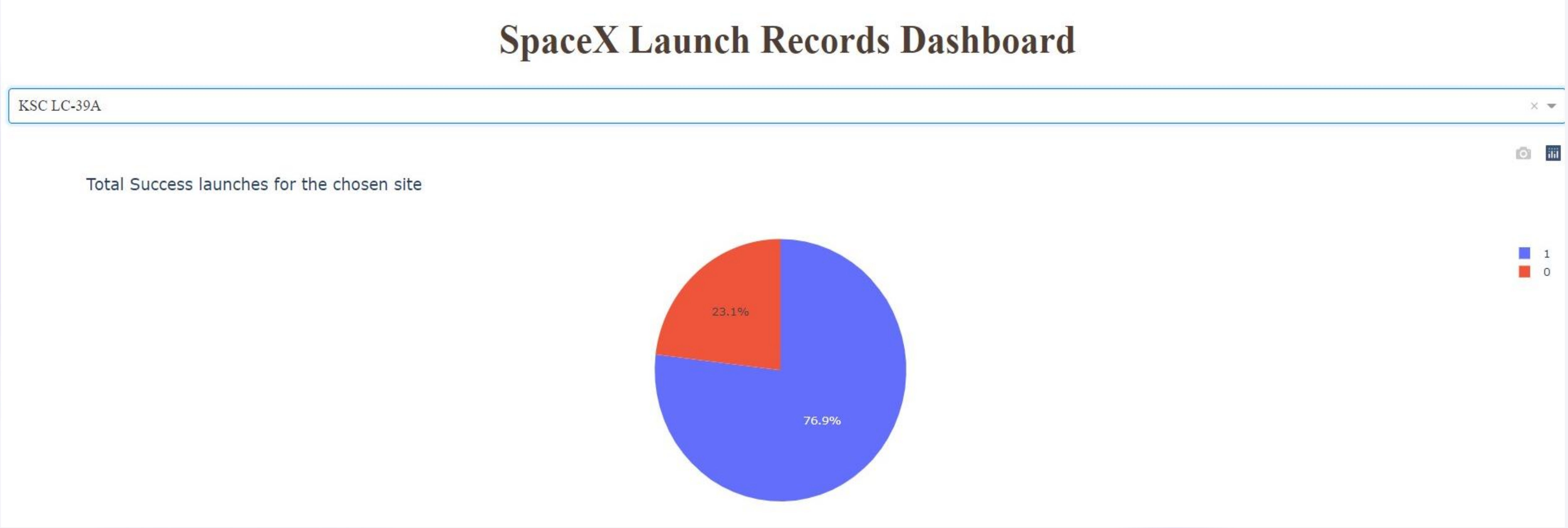
Compare success rates of all sites

- Selecting All Sites from dropdown, shows pie chart of total successful launch for all four sites.
- KSC LC-39A has the highest number of success launches.



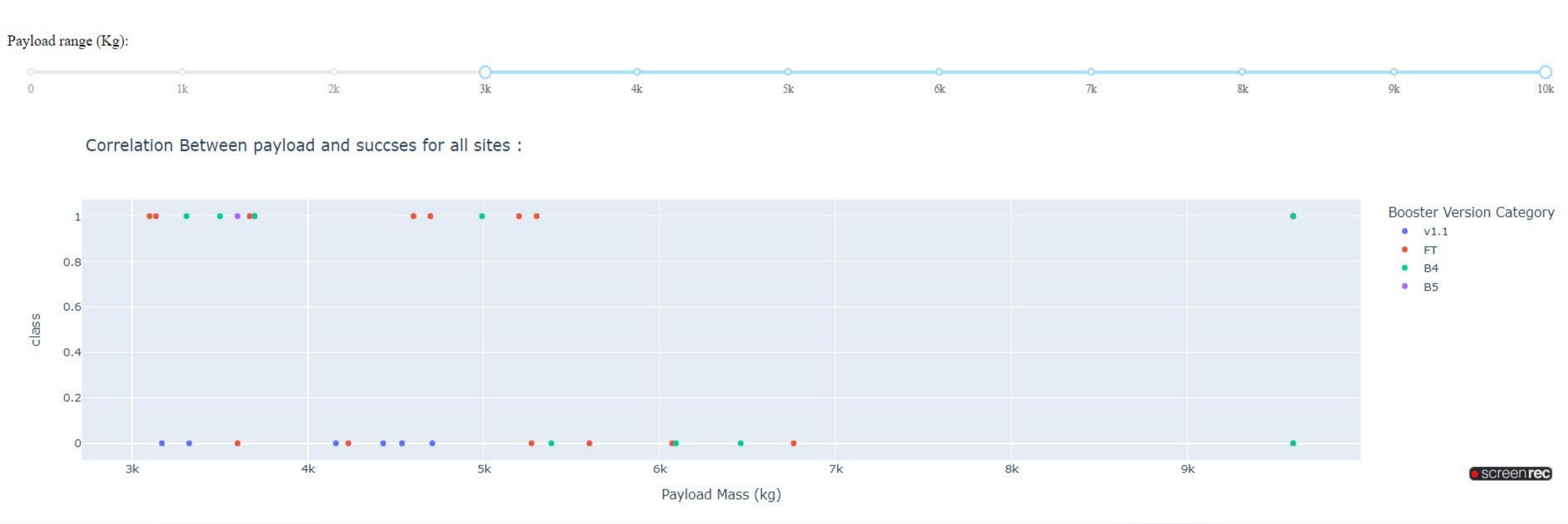
Success launches of chosen site

- Success rate of launch site KSC LC-39A is 76.9%, which denotes out of all the launches from this site, the first stage of most launches land successfully and hence can be reused.



Correlation between payload and success rate

- Altered the range of payload mass by sliding to 3000kg-10000kg.
- From scatter plot we observe, booster version FT has a high success rate within selected range of payload mass whereas no success with booster version v1.1.



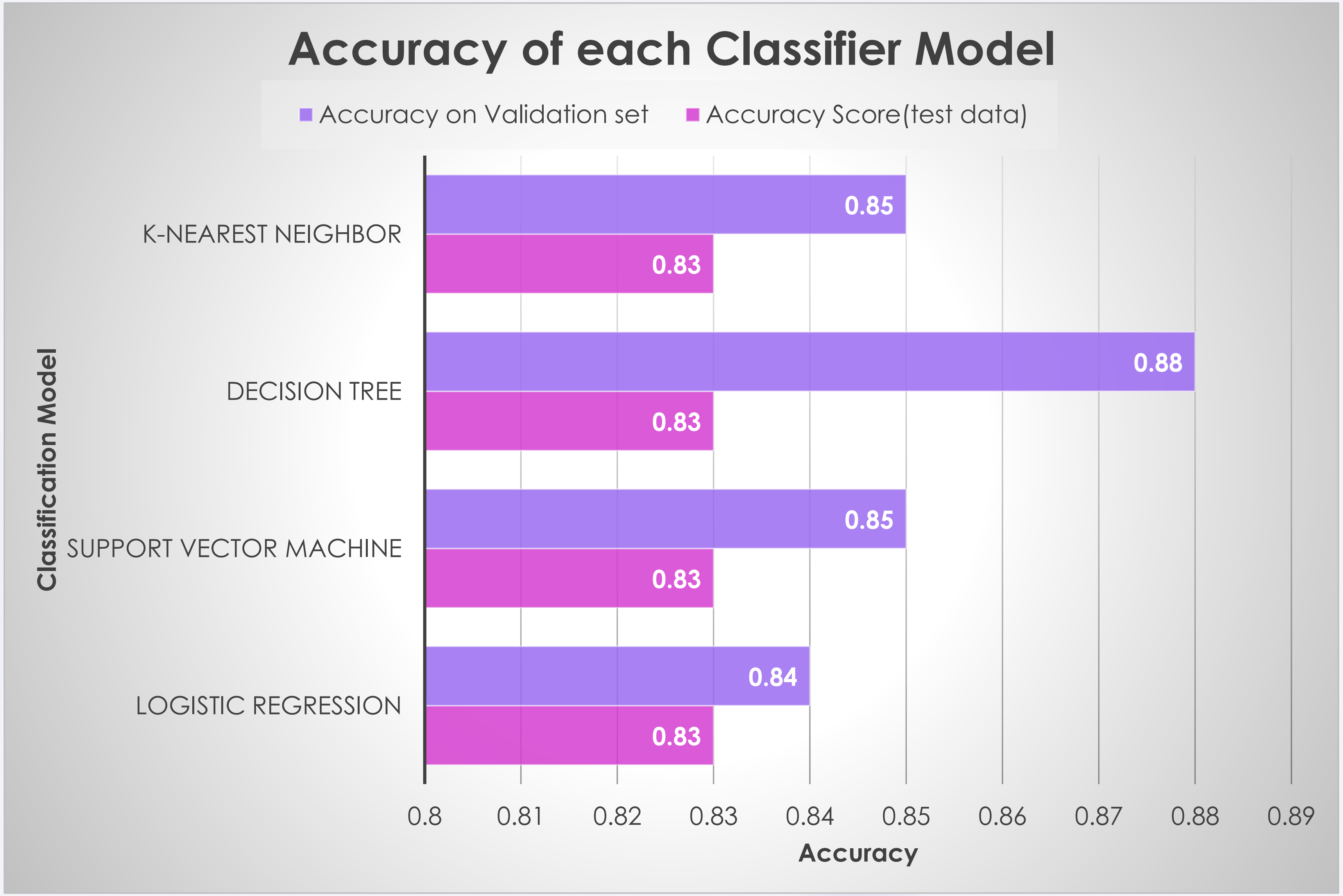
Section 5

Predictive Analysis (Classification)

Classification Accuracy

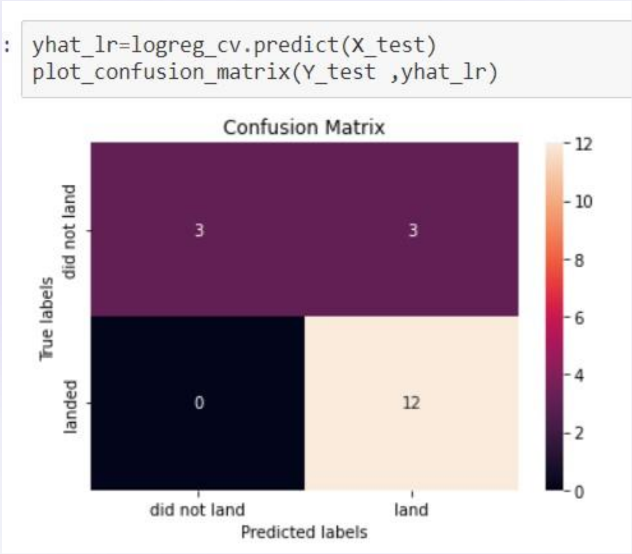
- All the four classification models have the same Accuracy Score which is 0.833.

- Hence cannot determine the best out of the four models that has highest classification accuracy.

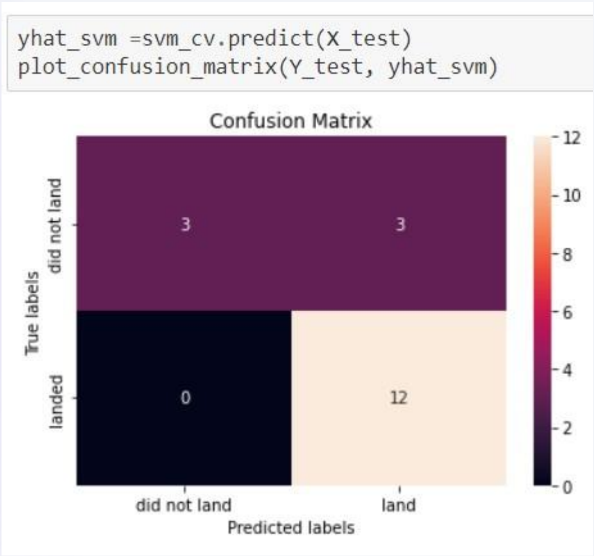


Confusion Matrix

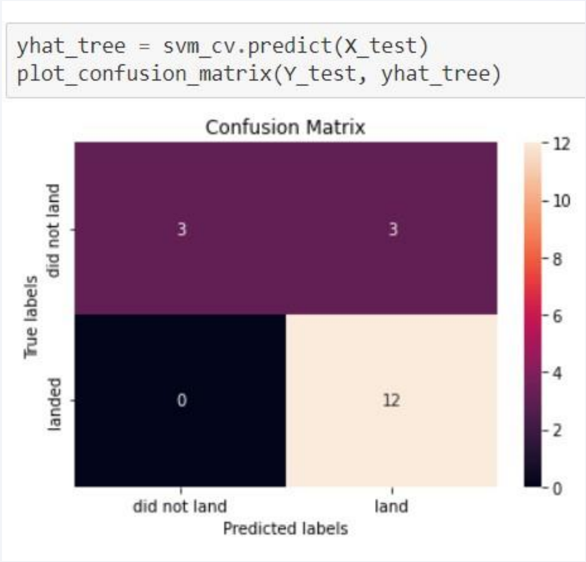
- As observed in previous results, all the four models have the same Accuracy Score and its difficult to determine the best classification model.
- The Confusion Matrices of each model depicts similar performance of each model.



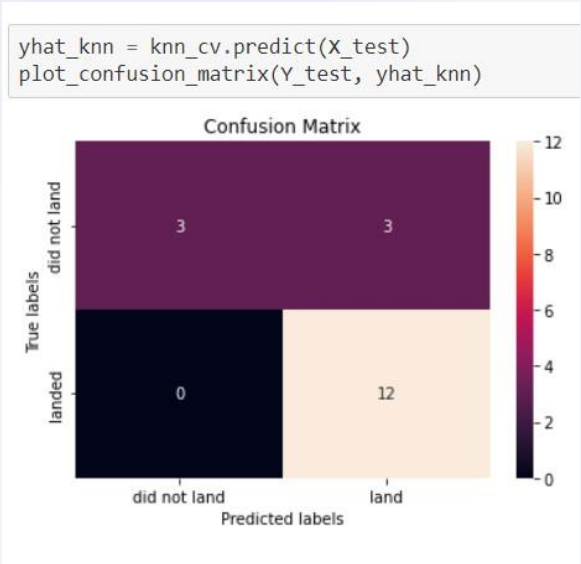
Logistic Regression



SVM



Decision Tree



K-Nearest Neighbor

Conclusions

- Launch Site KSC LC-39A has the highest success rate of landing and is more preferable for launches where first stage needs to be reused.
- To have more successful landings, orbits ES-L1, GEO, HEO, SSO can be chosen.
- As the number of flight increases, the first stage is more likely to land successfully, thereby more chances of it to be reused.
- The best accuracy of classification model is 0.833.
- Starting from 2013, there has been an increase in successful landings and so with the classification model we may predict an increase in successful first stage landings which will lead to cost reduction of each launch.

Appendix

- The Python code to obtain the Test Accuracy Score using the method accuracy_score() and comparing with the models created is as below:

Find the method performs best:

```
from sklearn import metrics
print("Accuracy score of LR model is:" , metrics.accuracy_score(Y_test , yhat_lr))
print("Accuracy score of SVM model is:" , metrics.accuracy_score(Y_test , yhat_svm))
print("Accuracy score of Decision Tree model is:" , metrics.accuracy_score(Y_test , yhat_tree))
print("Accuracy score of KNN model is:" , metrics.accuracy_score(Y_test , yhat_knn))
```

```
Accuracy score of LR model is: 0.8333333333333334
Accuracy score of SVM model is: 0.8333333333333334
Accuracy score of Decision Tree model is: 0.8333333333333334
Accuracy score of KNN model is: 0.8333333333333334
```

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Thank you!