



IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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Executive Summary

- Summary of methodologies
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 - Machine Learning Prediction
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 - Predictive Analytics result

Introduction

- Project background and context
 - Space X 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 Space X 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 space X for a rocket launch. This goal of the project is to create a machine learning pipeline to predict if the first stage will land successfully.
- Problems you want to find answers
 - What factors determine if the rocket will land successfully?
 - The interaction amongst various features that determine the success rate of a successful landing.
 - What operating conditions needs to be in place to ensure a successful landing program.

Section 1

Methodology

Methodology

Executive Summary

- Data collection methodology:
 - Data was collected using SpaceX API and web scraping 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

- The data was collected using various methods
 - Data collection was done using get request to the SpaceX API.
 - Next, we decoded the response content as a Json using `.json()` function call and turn it into a pandas dataframe using `.json_normalize()`.
 - We then cleaned the data, checked for missing values and fill in missing values where necessary.
 - In addition, we performed web scraping from Wikipedia for Falcon 9 launch records with BeautifulSoup.
 - The objective was to extract the launch records as HTML table, parse the table and convert it to a pandas dataframe for future analysis.

Data Collection – SpaceX API

- We used the get request to the SpaceX API to collect data, clean the requested data and did some basic data wrangling and formatting.
- The link to the notebook is <https://github.com/HarshavardhanNaganagoudar/testrepo/blob/fced1cc62a91446d015de7b86517173798c6873c/Capstone%20project%20data%20science.ipynb>

```
returnigliadoppia(cori["Lunghezza"])
```

Now let's start requesting rocket launch data from SpaceX API with the following URL:

```
In [6]: spacex_url="https://api.spacexdata.com/v4/launches/past"
```

```
In [7]: response = requests.get(spacex_url)
```

Check the content of the response

```
In [8]: print(response.content)
```

```
b'{"fairings":{"reused":false,"recovery_attempt":false,"recovered":false,"ships":[],"links":{"N3_o.png","large":"https://images2.imgbox.com/40/e3/GypSkyF_o.png"},"reddit":{"campaign":null,'all':[],"original":[]},"presskit":null,"webcast":"https://www.youtube.com/watch?v=0a_00nJ_Y88",'om/2196-spacex-inaugural-falcon-1-rocket-lost-launch.html","wikipedia":"https://en.wikipedia.org0:00.000Z"},"static_fire_date_unix":1142553600,"net":false,"window":0,"rocket":"5e9d0d95eda69955t e":null,"reason":"merlin engine failure"}}, {"details":"Engine failure at 33 seconds and loss of v
```


Data Collection - Scraping

- We applied web scrapping to webscrap Falcon 9 launch records with BeautifulSoup
- We parsed the table and converted it into a pandas dataframe.
- The link to the notebook is <https://github.com/HarshavardhanaNaganagoudar/testrepo/blob/fced1cc62a91446d015de7b86517173798c6873c/Capstone%20project%20data%20science.ipynb>

```
In [9]: static_json_url='https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DS0321EN-Ski
We should see that the request was successfull with the 200 status response code

In [10]: response.status_code

Out[10]: 200

Now we decode the response content as a Json using .json() and turn it into a Pandas dataframe using .json_normalize

In [11]: # Use json_normalize meethod to convert the json result into a dataframe
data=pd.json_normalize(response.json())

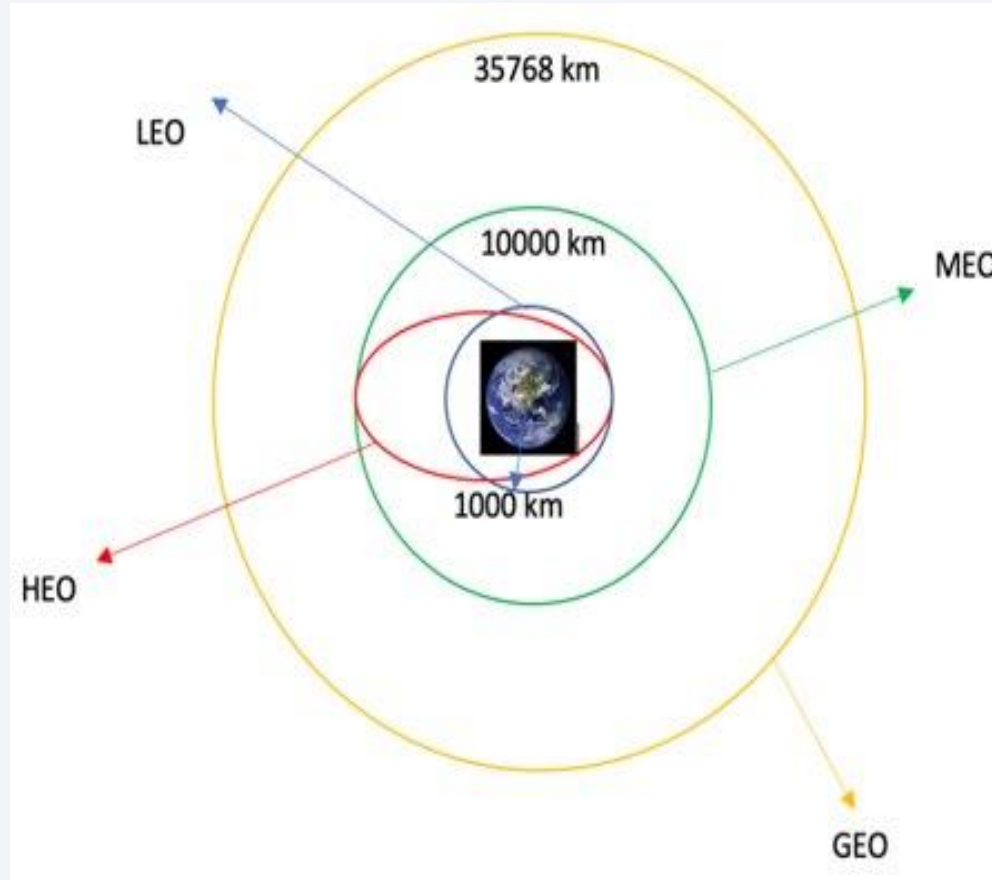
Using the dataframe data print the first 5 rows

In [12]: # Get the head of the dataframe
data.head()

Out[12]:
```

	static_fire_date_utc	static_fire_date_unix	net	window	rocket	success	failures	details
0	2006-03-17T00:00:00.000Z	1.142554e+09	False	0.0	5e9d0d95eda69955f709d1eb	False	[[{'time': 33, 'altitude': None, 'reason': 'merlin engine	Engine failure at 33 seconds and loss of vehicle

Data Wrangling

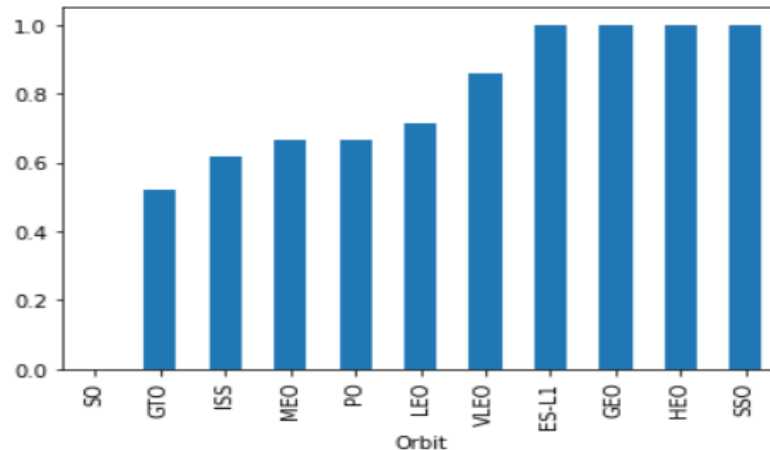


- We performed exploratory data analysis and determined the training labels.
- We calculated the number of launches at each site, and the number and occurrence of each orbits
- We created landing outcome label from outcome column and exported the results to csv.
- The link to the notebook is <https://github.com/HarshavardhanaNaganagoudar/testrepo/blob/fced1cc62a91446d015de7b86517173798c6873c/Data%20wrangling.ipynb>

EDA with Data Visualization

- We explored the data by visualizing the relationship between flight number and launch Site, payload and launch site, success rate of each orbit type, flight number and orbit type, the launch success yearly trend.

Out[12]: <AxesSubplot: xlabel='Orbit'>



- The link to the notebook is <https://github.com/HarshavardhanaNaga/nagoudar/testrepo/blob/fced1cc62a91446d015de7b86517173798c6873c/EDA%20with%20MATPLOTLIB.ipynb>

EDA with SQL

- We loaded the SpaceX dataset into a PostgreSQL database without leaving the jupyter notebook.
- We applied EDA with SQL to get insight from the data. We wrote queries to find out for instance:
 - The names of unique launch sites in the space mission.
 - The total payload mass carried by boosters launched by NASA (CRS)
 - The average payload mass carried by booster version F9 v1.1
 - The total number of successful and failure mission outcomes
 - The failed landing outcomes in drone ship, their booster version and launch site names.
- The link to the notebook is <https://github.com/HarshavardhanaNaganagoudar/testrepo/blob/fced1cc62a91446d015de7b86517173798c6873c/EDA%20with%20SQL.ipynb>

Build an Interactive Map with Folium

- We marked all launch sites, and added map objects such as markers, circles, lines to mark the success or failure of launches for each site on the folium map.
- We assigned the feature launch outcomes (failure or success) to class 0 and 1.i.e., 0 for failure, and 1 for success.
- Using the color-labeled marker clusters, we identified which launch sites have relatively high success rate.
- We calculated the distances between a launch site to its proximities. We answered some question for instance:
 - Are launch sites near railways, highways and coastlines.
 - Do launch sites keep certain distance away from cities.

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.
- The link to the notebook is <https://github.com/HarshavardhanaNaganagoudar/testrepo/blob/fced1cc62a91446d015de7b86517173798c6873c/EDA%20with%20MATPLOTLIB.ipynb>

Predictive Analysis (Classification)

- We loaded the data using numpy and pandas, transformed the data, split our data into training and testing.
- We built different machine learning models and tune different hyperparameters using GridSearchCV.
- We used accuracy as the metric for our model, improved the model using feature engineering and algorithm tuning.
- We found the best performing classification model.
- The link to the notebook is <https://github.com/HarshavardhanaNaganagoudar/testrepo/blob/fced1cc62a91446d015de7b86517173798c6873c/Machine%20learning%20classification.ipynb>

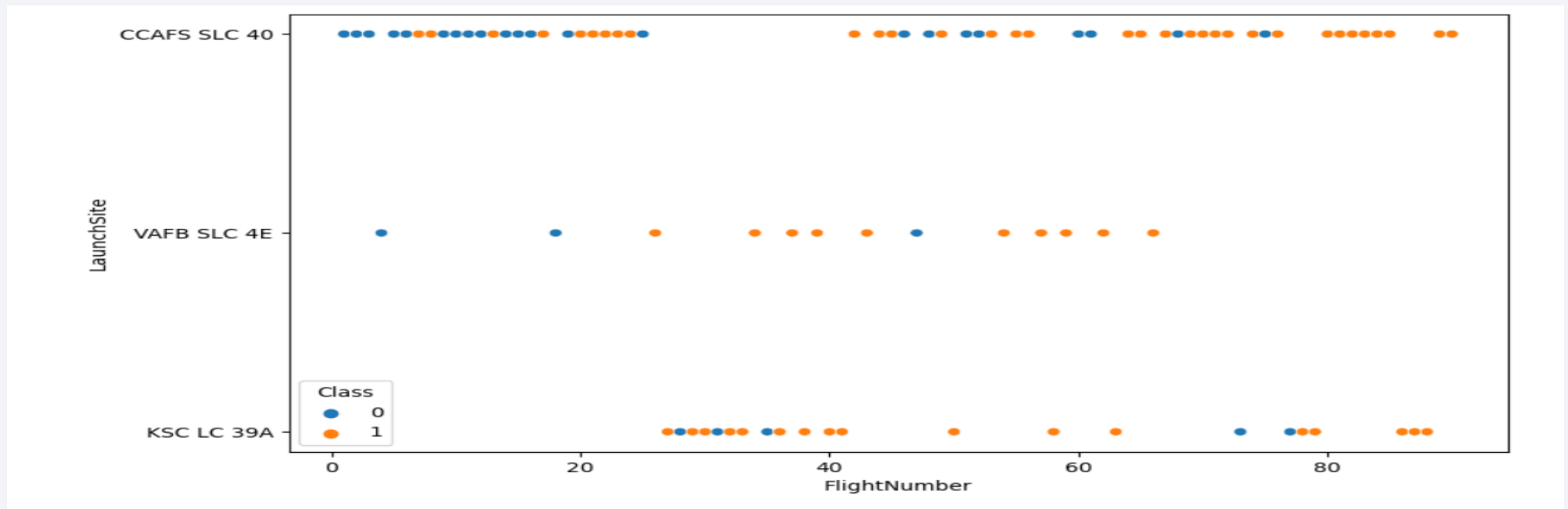
The background of the slide is an abstract composition. It features a dark blue base color. Overlaid on this are numerous diagonal streaks in shades of blue and red, creating a sense of motion or data flow. A faint, light blue grid pattern is also visible, particularly in the lower-left quadrant. The overall effect is high-tech and digital.

Section 2

Insights drawn from EDA

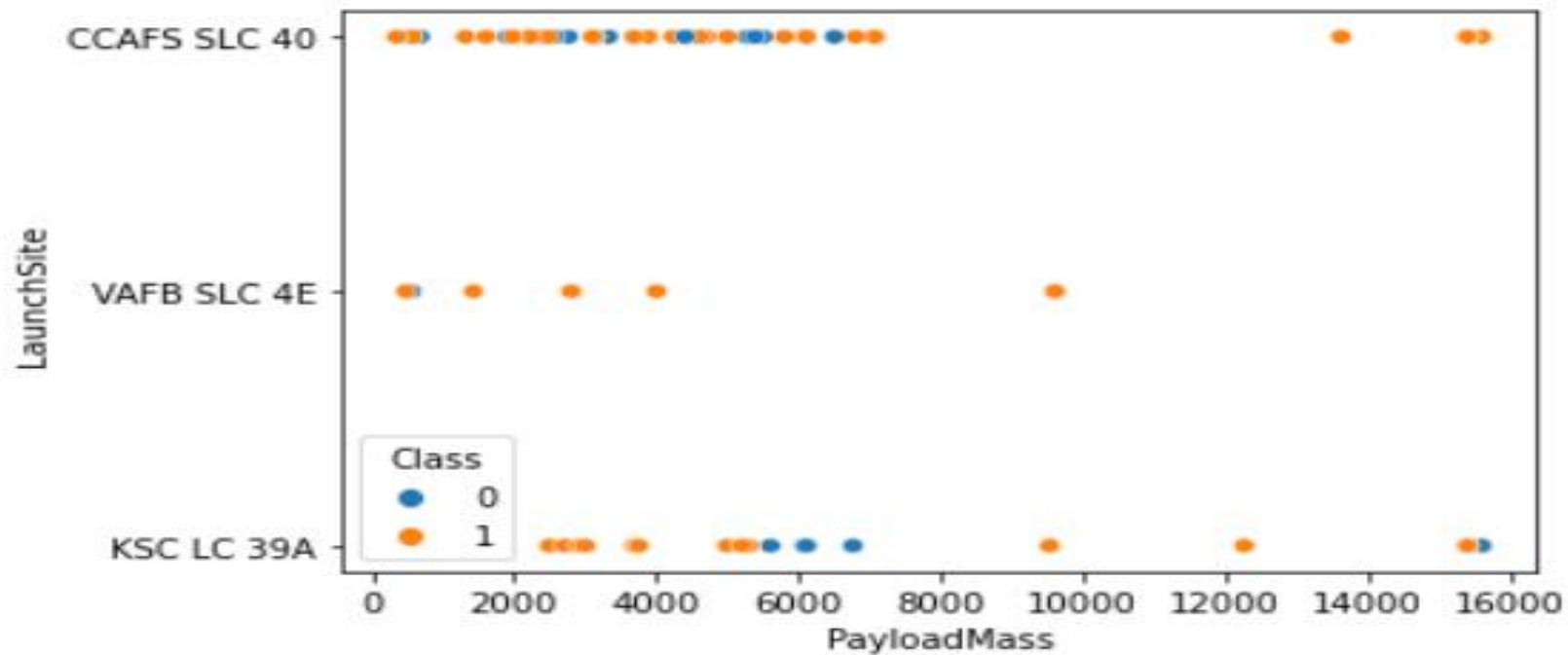
Flight Number vs. Launch Site

- From the plot, we found that the larger the flight amount at a launch site, the greater the success rate at a launch site.



Payload vs. Launch Site

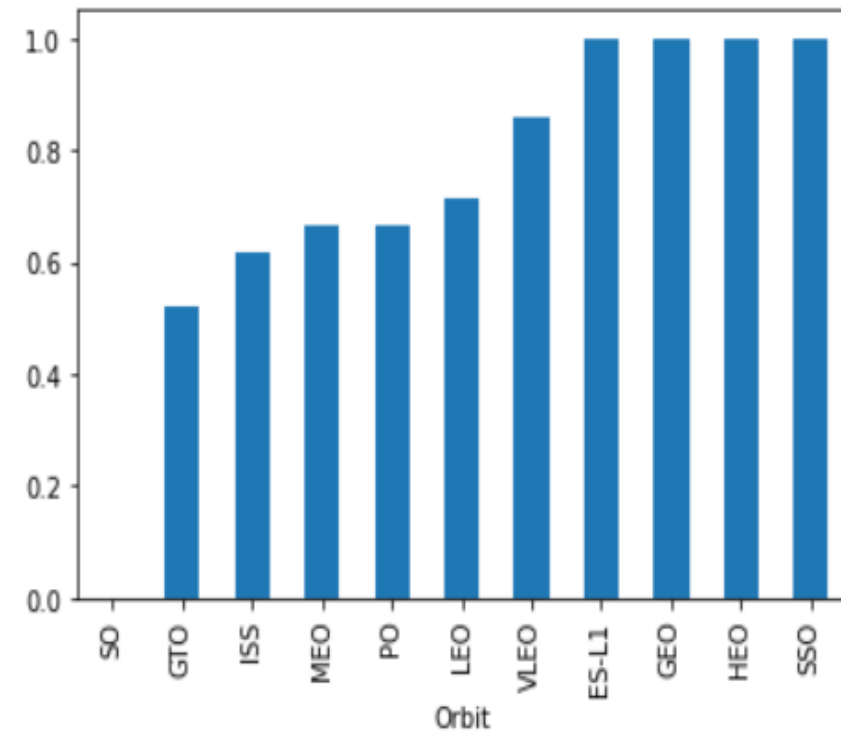
- we observe in Payload Vs. Launch Site scatter plot that, for the VAFB-SLC launch site there are no rockets launched for heavy payload mass(greater than 10000).



Success Rate vs. Orbit Type

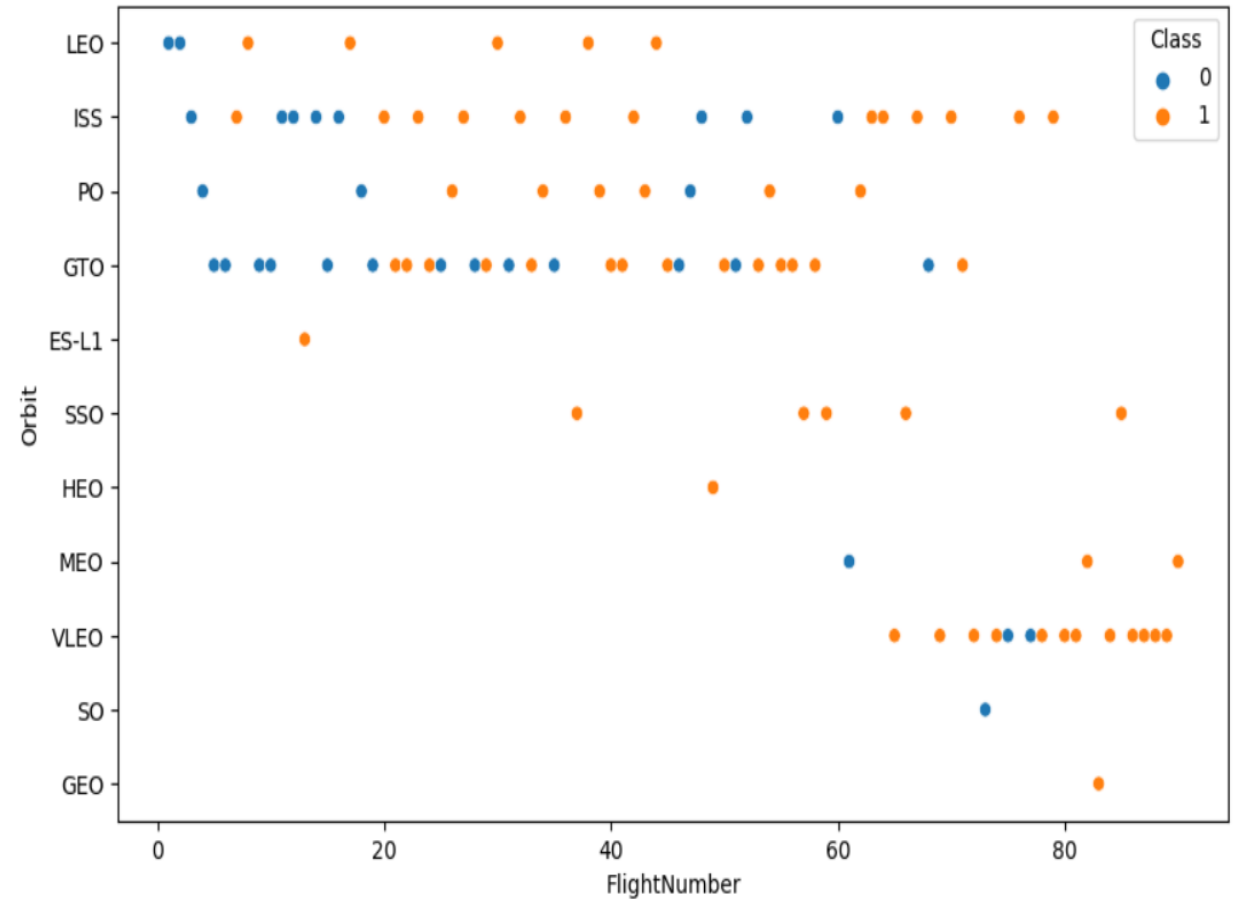
- From the plot, we can see that ES-L1, GEO, HEO, SSO, VLEO had the most success rate.

Out[12]: <AxesSubplot:xlabel='Orbit'>



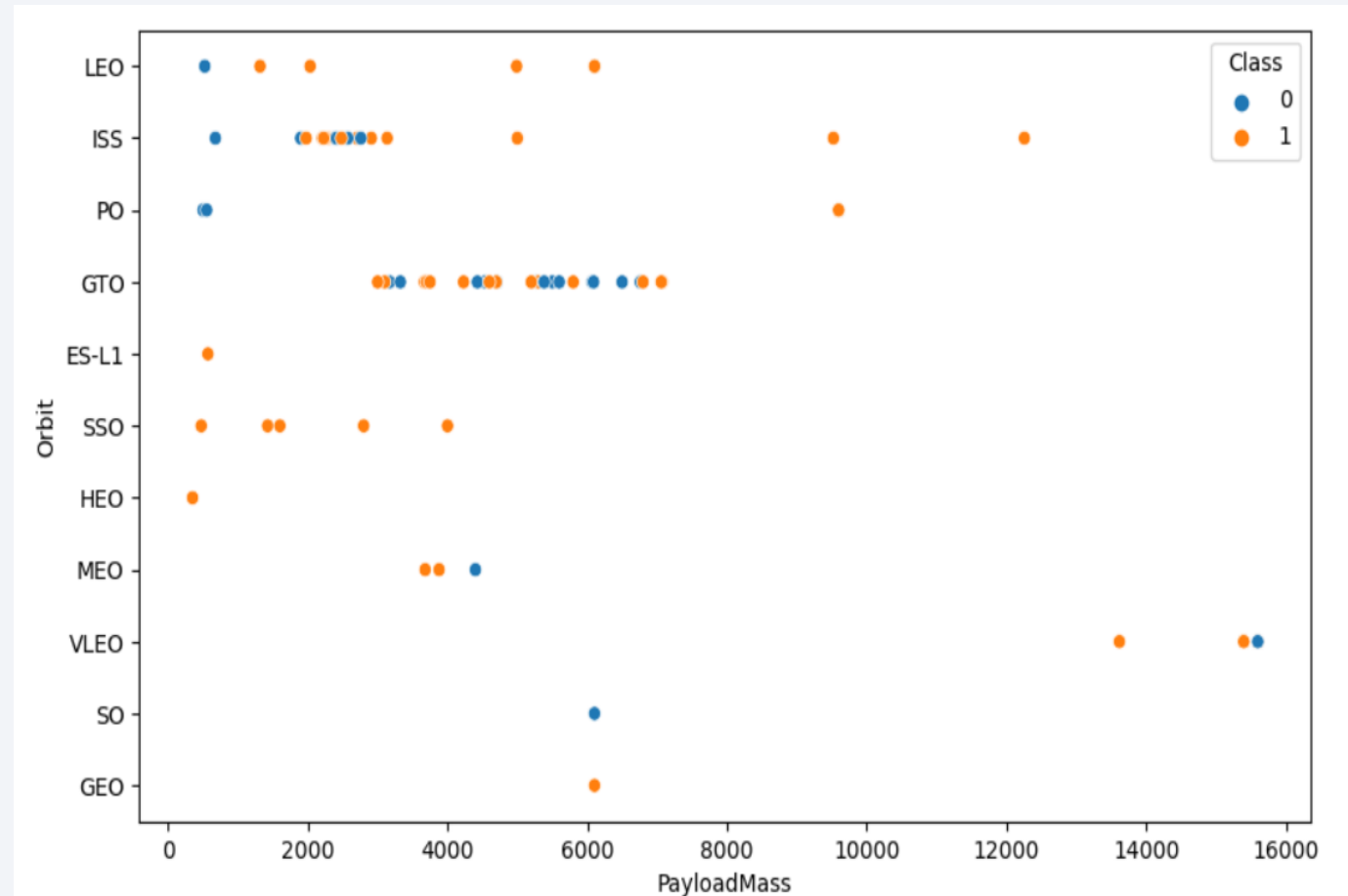
Flight Number vs. Orbit Type

- We can 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.



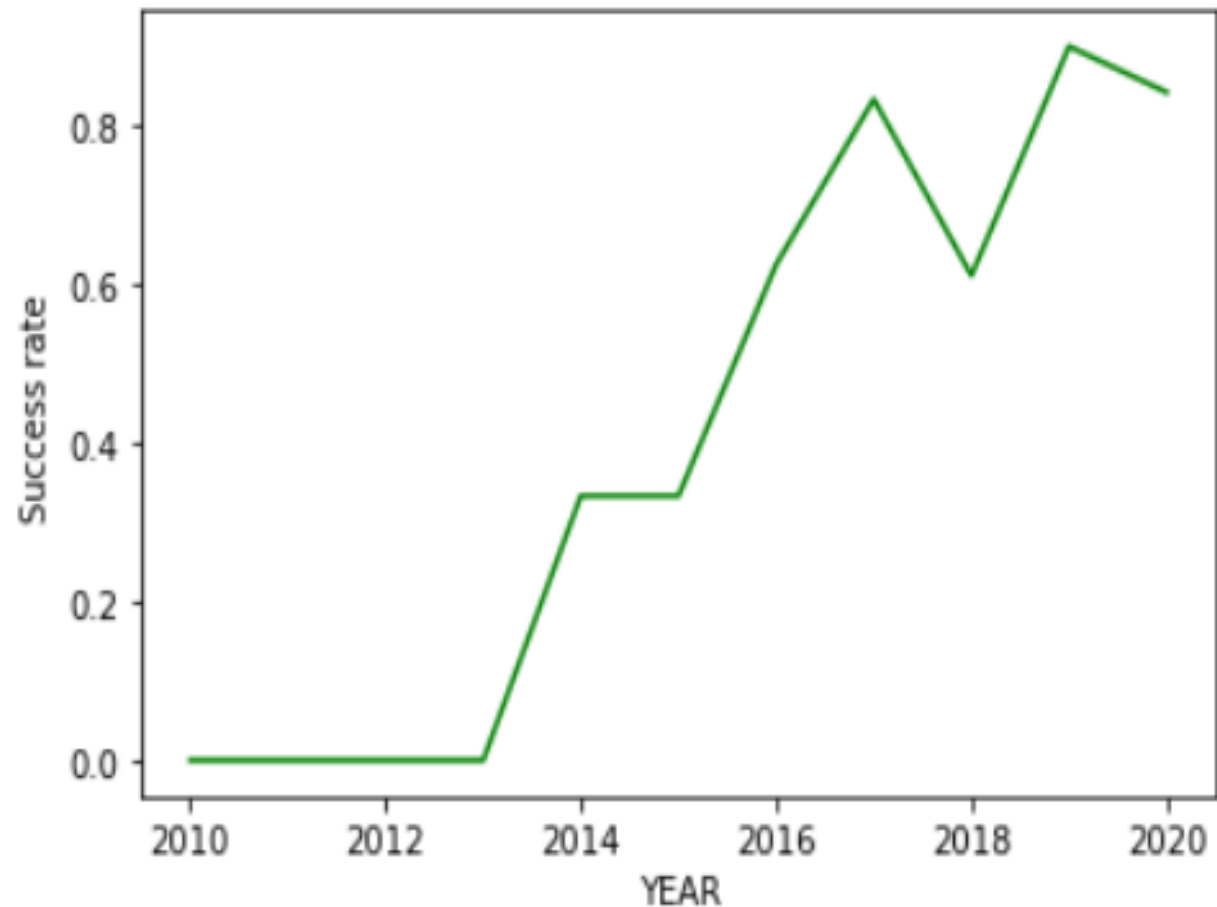
Payload vs. Orbit Type

- With heavy payloads the successful landing or positive landing rate are more for Polar, LEO and ISS.
- However for GTO we cannot distinguish this well as both positive landing rate and negative landing(unsuccesful mission) are both there.



Launch Success Yearly Trend

- From the plot, we can observe that success rate since 2013 kept on increasing till 2020.



All Launch Site Names

- We used the key word **DISTINCT** to show only unique launch sites from the SpaceX data.

In [13]:

```
%sql select distinct (launch_site) from spacextbl ;
```

```
* ibm_db_sa://nx181798:***@ba99a9e6-d59e-4883-8fc0-d6a8c9f7a08f.c1o  
  ibm_db_sa://nx181798:***@ba99a9e6-d59e-4883-8fc0-d6a8c9f7a08f.c1o
```

Done.

Out[13]: **launch_site**

CCAFS LC-40

CCAFS SLC-40

KSC LC-39A

VAFB SLC-4E

Launch Site Names Begin with 'CCA'

In [15]:

```
%sql select * from spacextbl where launch_site like ('CCA%') limit 5;
```

* ibm_db_sa://nxl81798:***@ba99a9e6-d59e-4883-8fc0-d6a8c9f7a08f.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:31321/BLU
ibm_db_sa://nxl81798:***@ba99a9e6-d59e-4883-8fc0-d6a8c9f7a08f.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:31321/blu
Done.

Out[15]:

DATE	time_utc	booster_version	launch_site	payload	payload_mass_kg	orbit	customer	mi
2010-06-04	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	
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	
2012-05-22	07:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	
2012-10-08	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	
2013-03-01	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	

- We used the query above to display 5 records where launch sites begin with `CCA`

Total Payload Mass

- We calculated the total payload carried by boosters from NASA as 45596 using the query below

In [16]:

```
%sql select sum(payload_mass_kg_) as total_payload from spacextbl where customer='NASA (CRS)';
```

```
* ibm_db_sa://nx181798:***@ba99a9e6-d59e-4883-8fc0-d6a8c9f7a08f.c1ogj3sd0tgtu0lqde00.databases.appdomaini  
ibm_db_sa://nx181798:***@ba99a9e6-d59e-4883-8fc0-d6a8c9f7a08f.c1ogj3sd0tgtu0lqde00.databases.appdomaini  
Done.
```

Out[16]: **total_payload**

```
45596
```

Average Payload Mass by F9 v1.1

- the average payload mass carried by booster version F9 v1.1 is 2534

```
In [17]: %sql select avg(payload_mass__kg_) as Avg_payload from spacextbl where booster_version like 'F9 v1.1%';

* ibm_db_sa://nx181798:***@ba99a9e6-d59e-4883-8fc0-d6a8c9f7a08f.c1ogj3sd0tgtu0lqde00.databases.appdomair
  ibm_db_sa://nx181798:***@ba99a9e6-d59e-4883-8fc0-d6a8c9f7a08f.c1ogj3sd0tgtu0lqde00.databases.appdomair
Done.

Out[17]: avg_payload
2534
```

First Successful Ground Landing Date

```
In [27]: %sql select min(date) as date from spacextbl where landing__outcome='Success (ground pad)';

* ibm_db_sa://nx181798:***@ba99a9e6-d59e-4883-8fc0-d6a8c9f7a08f.c1ogj3sd0tgtu0lqde00.databases
ibm_db_sa://nx181798:***@ba99a9e6-d59e-4883-8fc0-d6a8c9f7a08f.c1ogj3sd0tgtu0lqde00.databases
Done.

Out[27]:      DATE
2015-12-22
```

- We observed that the dates of the first successful landing outcome on ground pad was 22nd December 2015

Successful Drone Ship Landing with Payload between 4000 and 6000

```
In [20]: %sql select booster_version from spacextbl where landing__outcome='Success (drone ship)' and payload_mass__kg_ > 4000 and payload_mass__kg_ < 6000;
```

```
* ibm_db_sa://nxl81798:***@ba99a9e6-d59e-4883-8fc0-d6a8c9f7a08f.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:31321/BLUDB
  ibm_db_sa://nxl81798:***@ba99a9e6-d59e-4883-8fc0-d6a8c9f7a08f.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:31321/bludb
Done.
```

```
Out[20]: booster_version
```

```
F9 FT B1022
```

```
F9 FT B1026
```

```
F9 FT B1021.2
```

```
F9 FT B1031.2
```

- We used the **WHERE** clause to filter for boosters which have successfully landed on drone ship and applied the **AND** condition to determine successful landing with payload mass greater than 4000 but less than 6000

Total Number of Successful and Failure Mission Outcomes

In [23]:

```
%sql select mission_outcome, count(*) as total from spacextbl group by mission_outcome;
```

```
* ibm_db_sa://nx181798:***@ba99a9e6-d59e-4883-8fc0-d6a8c9f7a08f.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:31321/BLUDB
ibm_db_sa://nx181798:***@ba99a9e6-d59e-4883-8fc0-d6a8c9f7a08f.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:31321/bludb
Done.
```

Out[23]:

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

- We used wildcard like '%' to filter for **WHERE** Mission outcome was a success or a failure.

Boosters Carried Maximum Payload

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

```
In [24]: %sql select booster_version from spacextbl where payload_mass__kg_=(select max(payload_mass__kg_) from spacextbl) group by booster_version;

* ibm_db_sa://nx181798:***@ba99a9e6-d59e-4883-8fc0-d6a8c9f7a08f.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:31321/BLUDB
  ibm_db_sa://nx181798:***@ba99a9e6-d59e-4883-8fc0-d6a8c9f7a08f.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:31321/bludb
Done.
```

Out[24]: **booster_version**

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

- We determined the booster that have carried the maximum payload using a subquery in the **WHERE** clause and the **MAX()** function.

2015 Launch Records

```
In [25]: %sql select landing__outcome, booster_version, launch_site, date from spacextbl where date like ('%2015%') and landing__outcome = 'Failure (drone ship)'
```

```
* ibm_db_sa://nx181798:***@ba99a9e6-d59e-4883-8fc0-d6a8c9f7a08f.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:31321/BLUDB
```

```
ibm_db_sa://nx181798:***@ba99a9e6-d59e-4883-8fc0-d6a8c9f7a08f.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:31321/bludb
```

Done.

```
Out[25]: landing__outcome  booster_version  launch_site    DATE
```

```
Failure (drone ship)    F9 v1.1 B1012  CCAFS LC-40  2015-01-10
```

```
Failure (drone ship)    F9 v1.1 B1015  CCAFS LC-40  2015-04-14
```

- We used a combinations of the **WHERE** clause, **LIKE**, **AND**, and **BETWEEN** conditions to filter for failed landing outcomes in drone ship, their booster versions, and launch site names for year 2015

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

- We selected Landing outcomes and the **COUNT** of landing outcomes from the data and used the **WHERE** clause to filter for landing outcomes **BETWEEN** 2010-06-04 to 2017-03-20.
- We applied the **GROUP BY** clause to group the landing outcomes and the **ORDER BY** clause to order the grouped landing outcome in descending order.

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 [26]: %sql select landing_outcome, count(*) as total_no from spacextbl where date between '2010-06-04' and '2017-03-20' group by landing_outcome order by 2
```

```
* ibm_db_sa://nx181798:***@ba99a9e6-d59e-4883-8fc0-d6a8c9f7a08f.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:31321/BLUDB
ibm_db_sa://nx181798:***@ba99a9e6-d59e-4883-8fc0-d6a8c9f7a08f.c1ogj3sd0tgtu0lqde00.databases.appdomain.cloud:31321/bludb
Done.
```

```
Out[26]: landing_outcome total_no
```

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

A satellite view of Earth from space, showing the curvature of the planet and city lights at night. The image is a composite of a solid blue background on the left and a satellite photograph of Earth on the right. The Earth's surface is dark, with numerous bright yellow and orange lights representing cities and urban areas. The horizon of the Earth is visible as a curved line separating the dark surface from the deep blue of space.

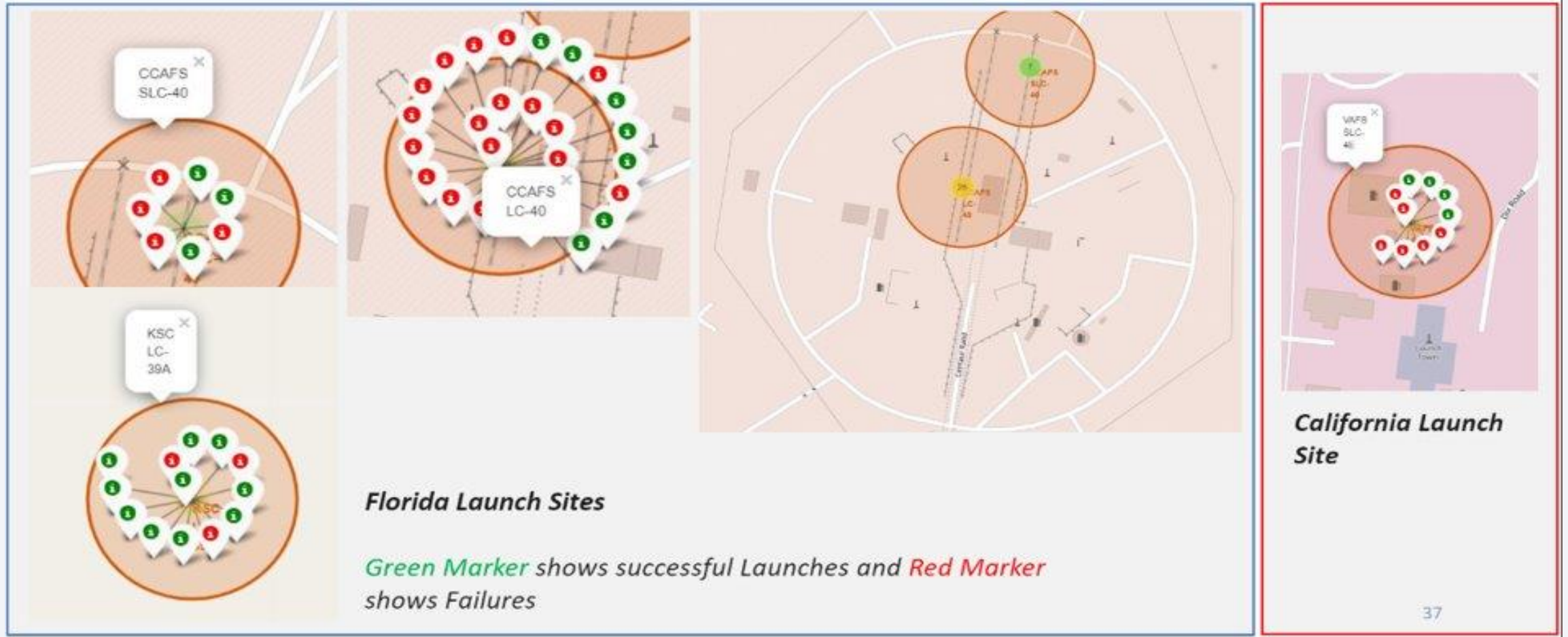
Section 3

Launch Sites Proximities Analysis

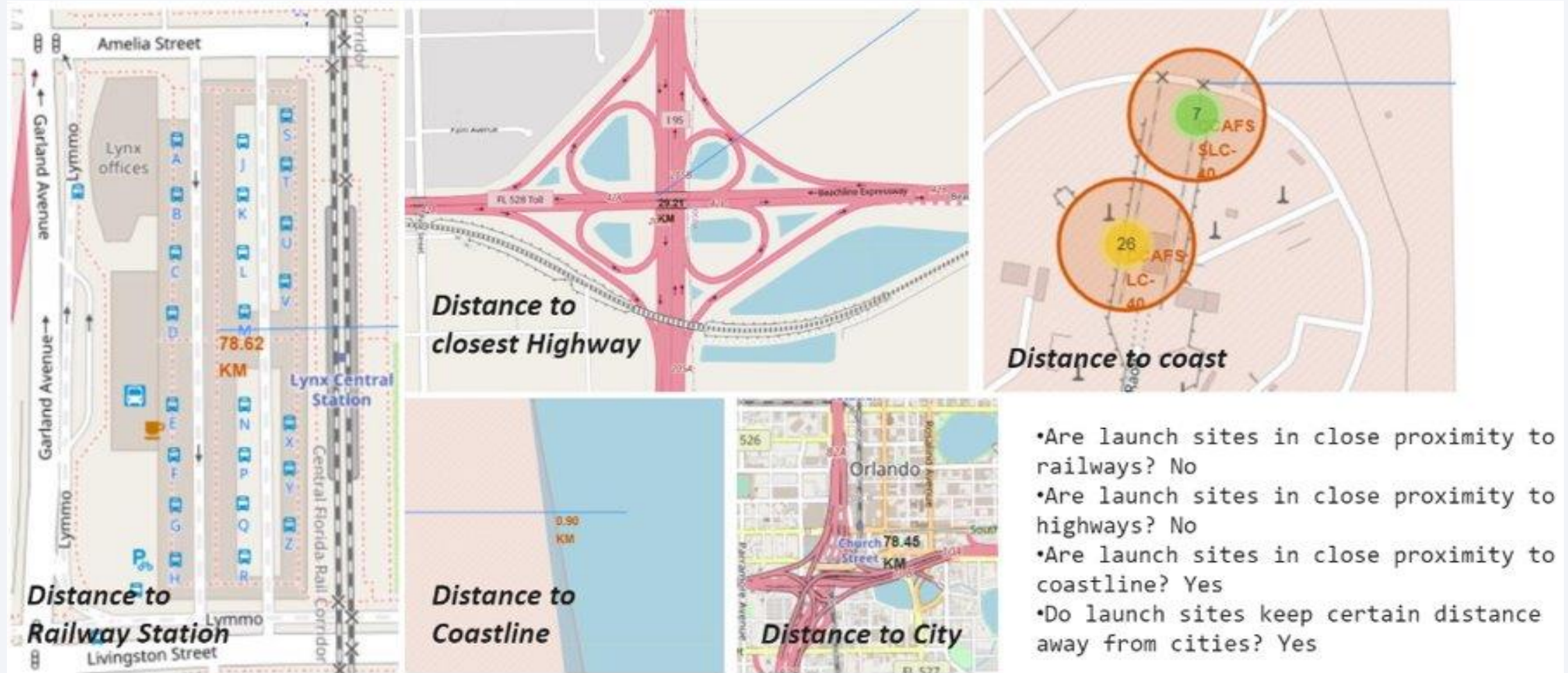
All launch sites global map markers



Markers showing launch sites with color labels



Launch Site distance to landmarks



- Are launch sites in close proximity to railways? No
- Are launch sites in close proximity to highways? No
- Are launch sites in close proximity to coastline? Yes
- Do launch sites keep certain distance away from cities? Yes

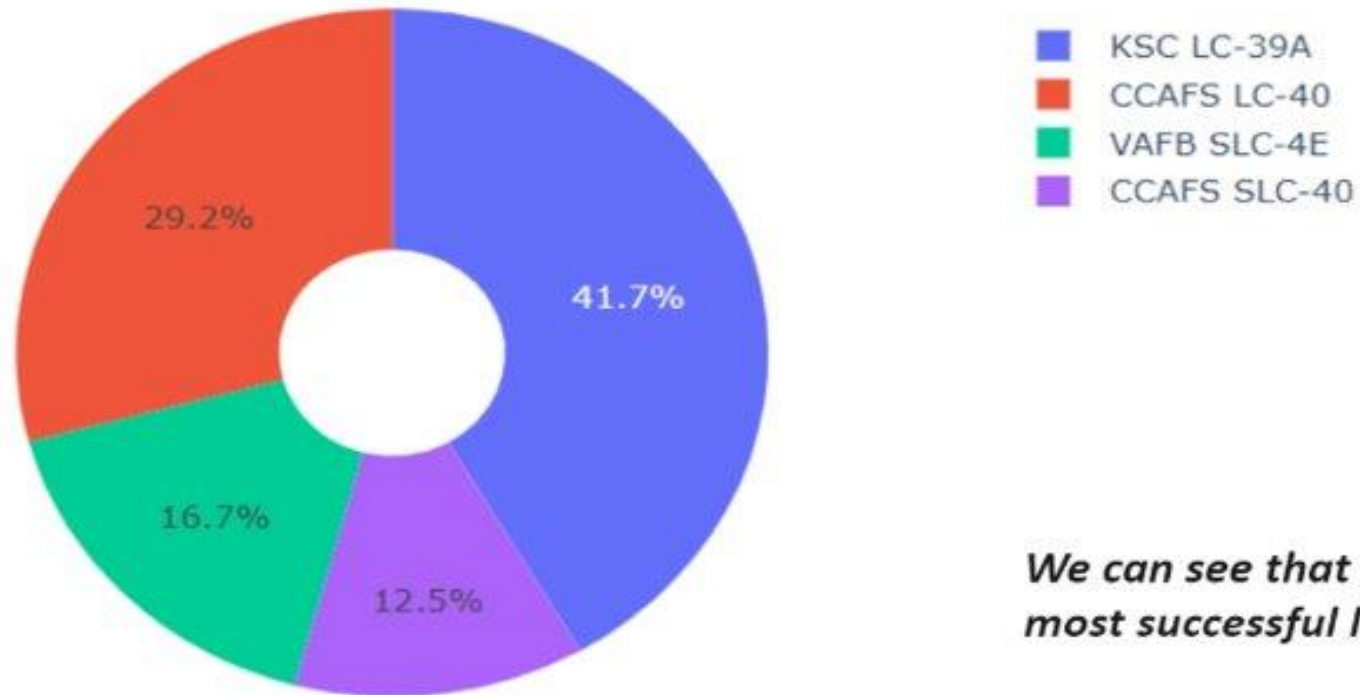


Section 4

Build a Dashboard with Plotly Dash

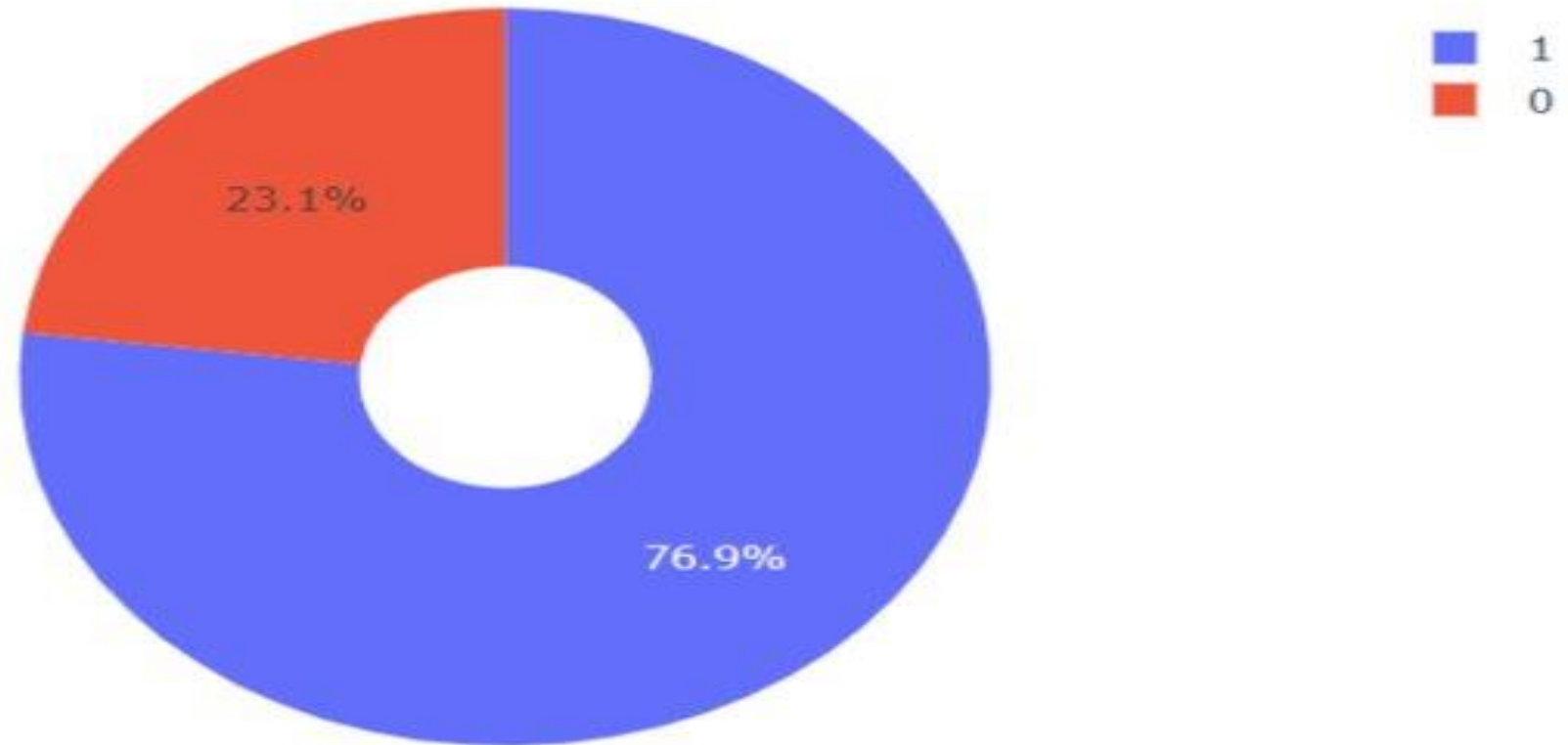
Pie chart showing the success percentage achieved by each launch site

Total Success Launches By all sites



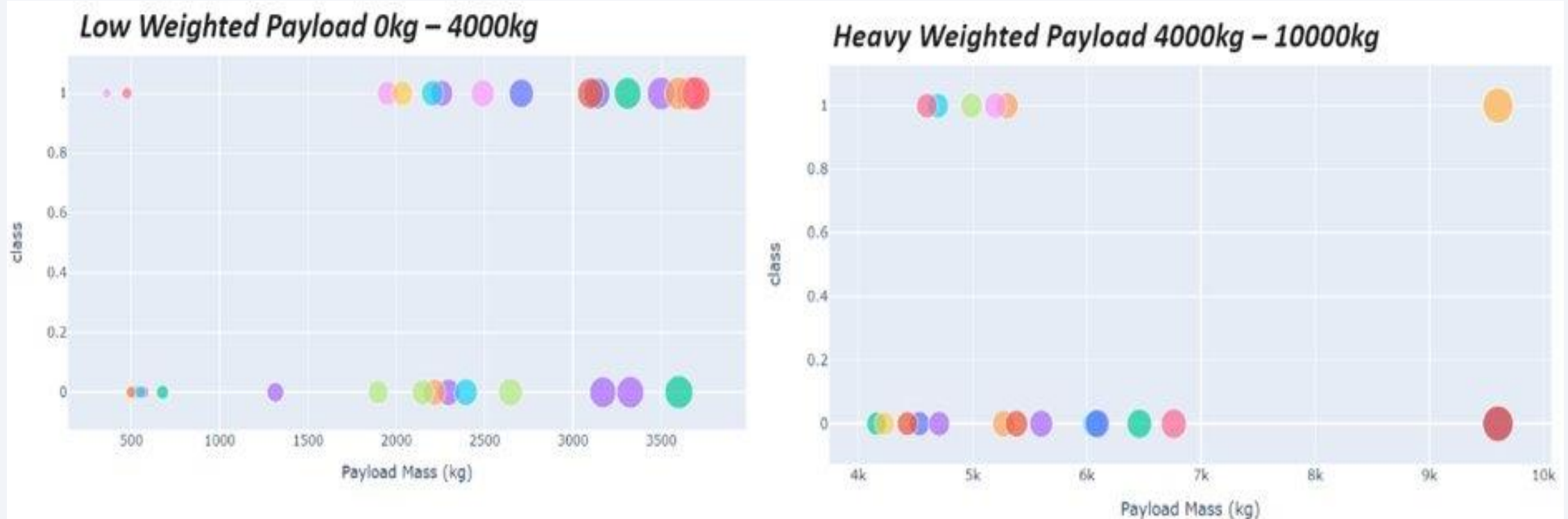
We can see that KSC LC-39A had the most successful launches from all the sites

Pie chart showing the Launch site with the highest launch success ratio



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

Scatter plot of Payload vs Launch Outcome for all sites, with different payload selected in the range slider



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

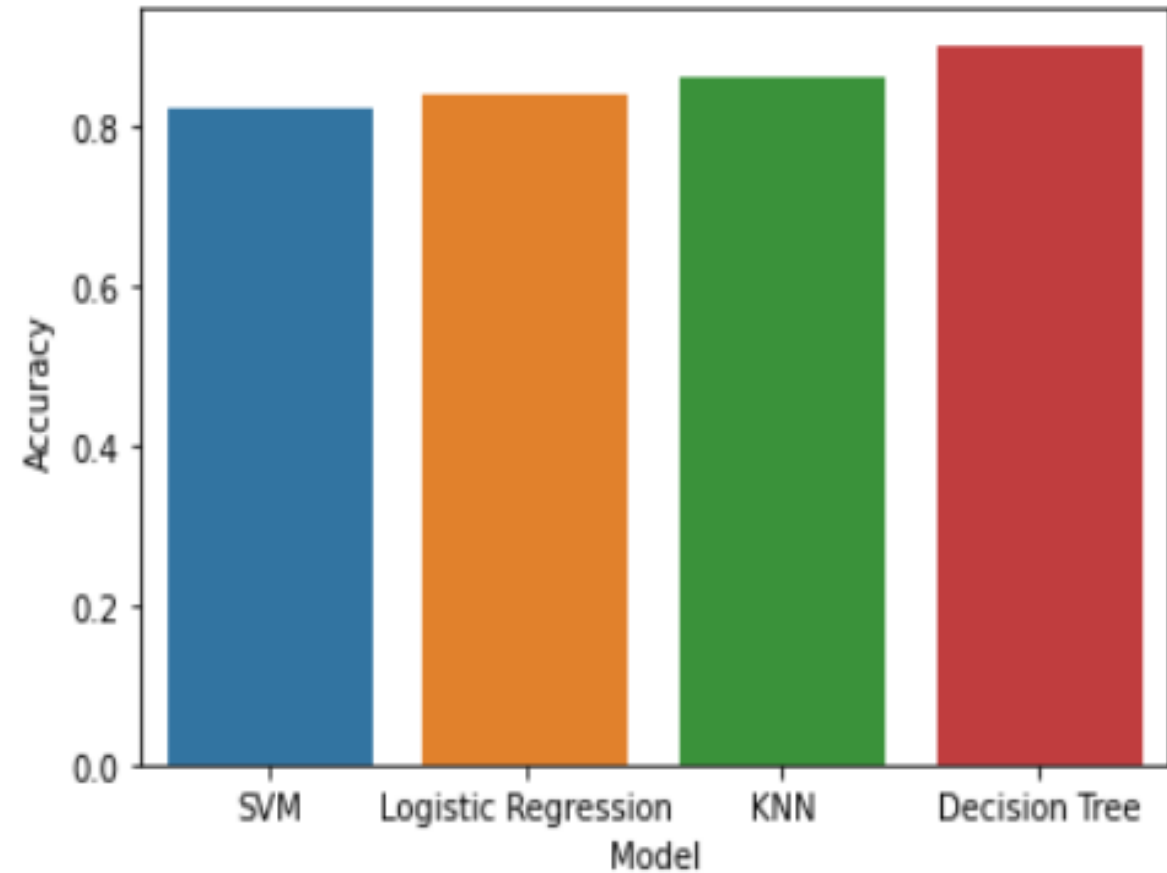


Section 5

Predictive Analysis (Classification)

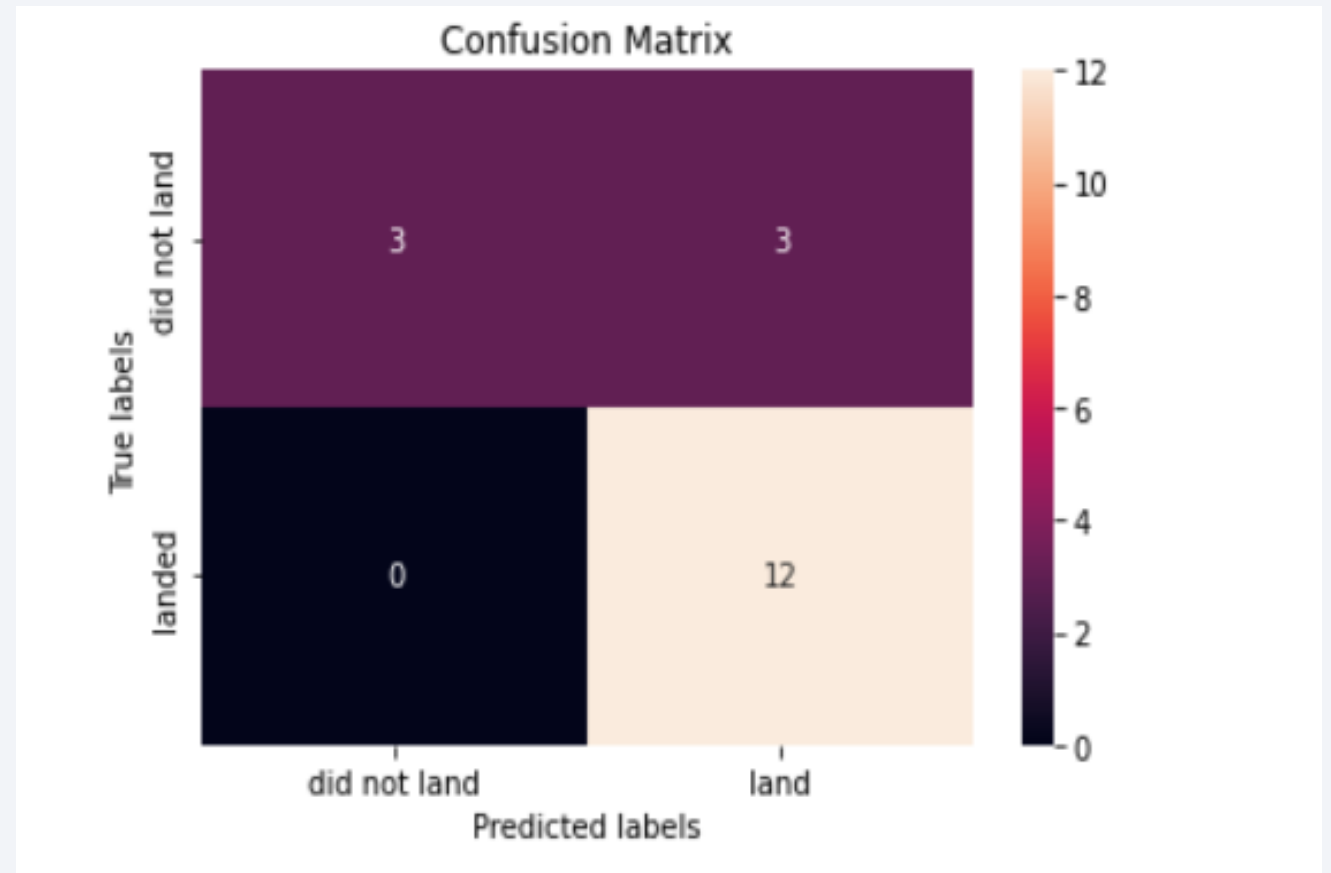
Classification Accuracy

- The decision tree classifier is the model with the highest classification accuracy



Confusion Matrix

- The confusion matrix for the decision tree classifier shows that the classifier can distinguish between the different classes. The major problem is the false positives .i.e., unsuccessful landing marked as successful landing by the classifier.



Conclusions

We can conclude that:

- The larger the flight amount at a launch site, the greater the success rate at a launch site.
- Launch success rate started to increase in 2013 till 2020.
- Orbits ES-L1, GEO, HEO, SSO, VLEO had the most success rate.
- KSC LC-39A had the most successful launches of any sites.
- The Decision tree classifier is the best machine learning algorithm for this task.

Thank you!

