



IBM Developer  
SKILLS NETWORK

# Winning Space Race with Data Science

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18<sup>th</sup> December 2023



# Outline

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Executive  
Summary



Introduction



Methodology



Results



Conclusion



Appendix

# Executive Summary

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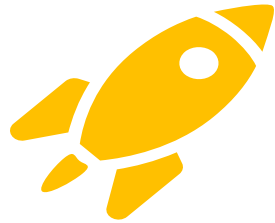
## Summary of methodologies

- Data Collection through API
- Data Collection with Web Scraping
- Data Wrangling
- Exploratory Data Analysis with SQL
- Exploratory Data Analysis with Data Visualization
- Interactive Visual Analytics with Folium
- Machine Learning Prediction

## Summary of all results

- Exploratory Data Analysis result
- Interactive analytics
- 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. The goal of this project is to train a machine learning model and use public information 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

Clean the Data

Dealing with Missing Values

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

Build, tune, evaluate classification models

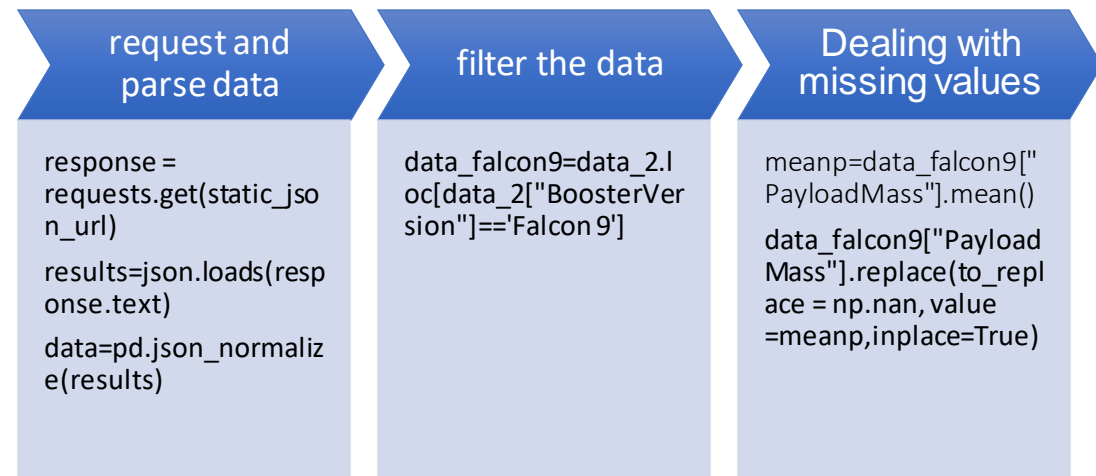


# Data Collection

- The data was collected using two methods
  - First Data collection was done using get request to the SpaceX API.
  - Then, we decoded the response content as a Json using `.json()` and turn it into a pandas dataframe using `.json_normalize()` method.
  - Next, we clean the data and dealing with missing values.
  - 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

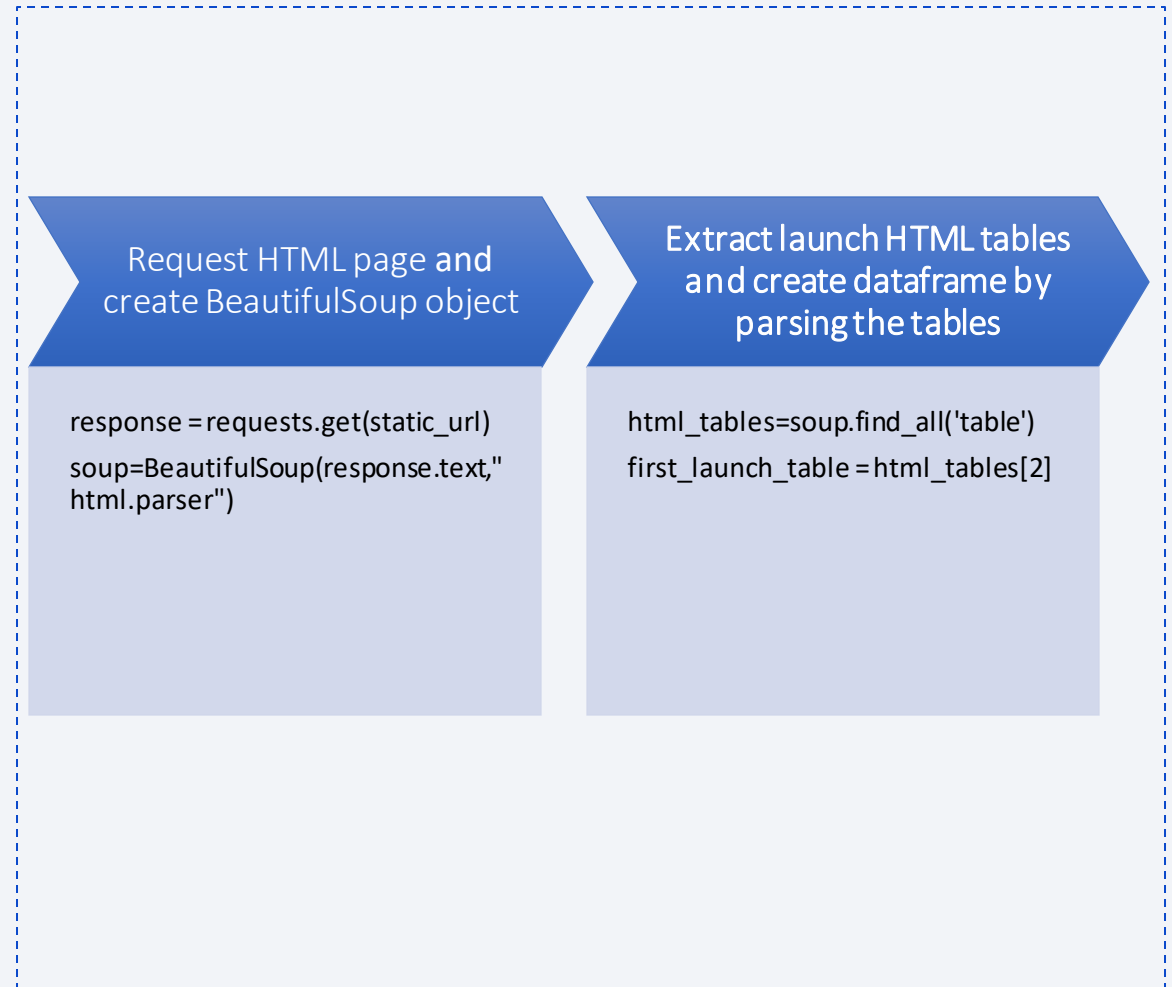
- We request and parse the SpaceX launch data using the GET request, filter the data to only include Falcon9 launches and dealing with missing values.
- The link to the notebook is [https://github.com/dodemabiteniwe/IBM\\_ds\\_CapstProject/blob/d42d70ad51ca91ee808d2bd11ada223bbb1ced02/jupyter-labs-spacex-data-collection-api.ipynb](https://github.com/dodemabiteniwe/IBM_ds_CapstProject/blob/d42d70ad51ca91ee808d2bd11ada223bbb1ced02/jupyter-labs-spacex-data-collection-api.ipynb)





# 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/dodemabiteniwe/IBM\\_ds\\_CapstProject/blob/d42d70ad51ca91ee808d2bd11ada223bbb1ced02/jupyter-labs-webscraping.ipynb](https://github.com/dodemabiteniwe/IBM_ds_CapstProject/blob/d42d70ad51ca91ee808d2bd11ada223bbb1ced02/jupyter-labs-webscraping.ipynb)



# Data Wrangling

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We calculated the number of launches at each site

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We calculated the number and occurrence of each orbits

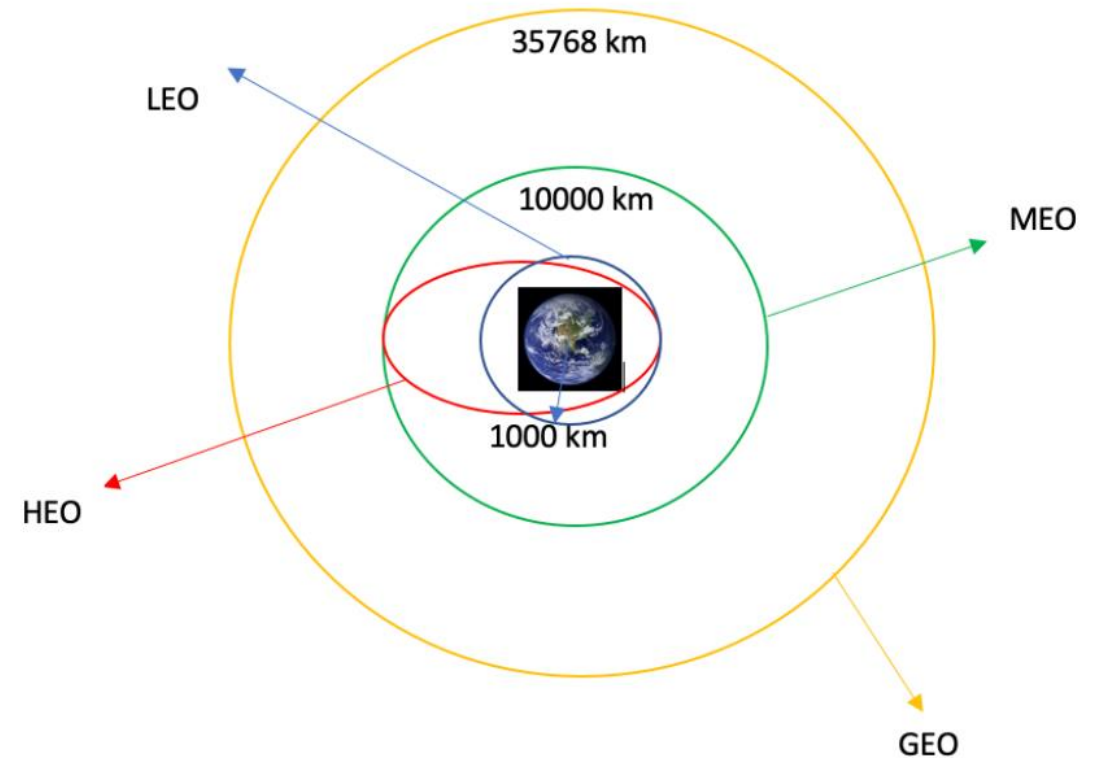
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We calculated the number and occurrence of mission outcome of the orbits

---

We created landing outcome label from outcome column and exported the results to csv.

The link to the notebook is [https://github.com/dodemabiteniwe/IBM\\_ds\\_CapstProject/blob/d42d70ad51ca91ee808d2bd11ada223bbb1ced02/labs\\_jupyter\\_spacex\\_Data%20wrangling2.ipynb](https://github.com/dodemabiteniwe/IBM_ds_CapstProject/blob/d42d70ad51ca91ee808d2bd11ada223bbb1ced02/labs_jupyter_spacex_Data%20wrangling2.ipynb)





# EDA with Data Visualization

- We explored the data by visualizing the relationship between:
  - flight number and payload
  - flight number and launch Site,
  - payload and launch site,
  - success rate of each orbit type and flight number and orbit type.
- The goal was to see how these variables evolve together and how they affect the launch outcome
- We explored the launch success yearly trend.
- The link to the notebook is [https://github.com/dodemabiteniwe/IBM\\_ds\\_CapstProject/blob/d42d70ad51ca91ee808d2bd11ada223bbb1ced02/labs%20EDA%20dataviz%20Dodema2.ipynb](https://github.com/dodemabiteniwe/IBM_ds_CapstProject/blob/d42d70ad51ca91ee808d2bd11ada223bbb1ced02/labs%20EDA%20dataviz%20Dodema2.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/dodemabiteniwe/IBM\\_ds\\_CapstProject/blob/d42d70ad51ca91ee808d2bd11ada223bbb1ced02/jupyter-labs-eda-sql-edx\\_sqlite\(1\).ipynb](https://github.com/dodemabiteniwe/IBM_ds_CapstProject/blob/d42d70ad51ca91ee808d2bd11ada223bbb1ced02/jupyter-labs-eda-sql-edx_sqlite(1).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.

The link to the notebook is [https://github.com/dodemabiteniwe/IBM\\_ds\\_CapstProject/blob/d42d70ad51ca91ee808d2bd11ada223bbb1ced02/lab\\_jupyter\\_launch\\_site\\_location.jupyterlite.ipynb](https://github.com/dodemabiteniwe/IBM_ds_CapstProject/blob/d42d70ad51ca91ee808d2bd11ada223bbb1ced02/lab_jupyter_launch_site_location.jupyterlite.ipynb)



# 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/dodemabiteniwe/IBM\\_ds\\_CapstProject/blob/d42d70ad51ca91ee808d2bd11ada223bbb1ced02/spacex\\_dash\\_app.py](https://github.com/dodemabiteniwe/IBM_ds_CapstProject/blob/d42d70ad51ca91ee808d2bd11ada223bbb1ced02/spacex_dash_app.py)

# Predictive Analysis (Classification)

- We Perform exploratory Data Analysis and determine Training Labels:
  - create a column for the class
  - Standardize the data
  - Split into training data and test data
- We built different machine learning models and tune different hyperparameters using GridSearchCV:
  - Logistic Regression
  - SVM
  - Classification Trees
  - k nearest neighbors
- We found the best performing classification model.
- The link to the notebook is [https://github.com/dodemabiteniwe/IBM\\_ds\\_CapstProject/blob/d42d70ad51ca91ee808d2bd11ada223bbb1ced02/SpaceX\\_Machine\\_Learning\\_Prediction\\_Part\\_5.jupyterlite\(2\).ipynb](https://github.com/dodemabiteniwe/IBM_ds_CapstProject/blob/d42d70ad51ca91ee808d2bd11ada223bbb1ced02/SpaceX_Machine_Learning_Prediction_Part_5.jupyterlite(2).ipynb)

# Results



EXPLORATORY DATA  
ANALYSIS RESULTS



INTERACTIVE ANALYTICS  
DEMO IN SCREENSHOTS



PREDICTIVE ANALYSIS  
RESULTS



The background of the slide is an abstract composition. It features a solid blue area on the left side, which transitions into a dynamic pattern of diagonal streaks in shades of blue, red, and cyan on the right. These streaks vary in thickness and intensity, creating a sense of motion and depth. A faint, light-blue grid pattern is visible across the entire image, adding a technical or digital feel to the design.

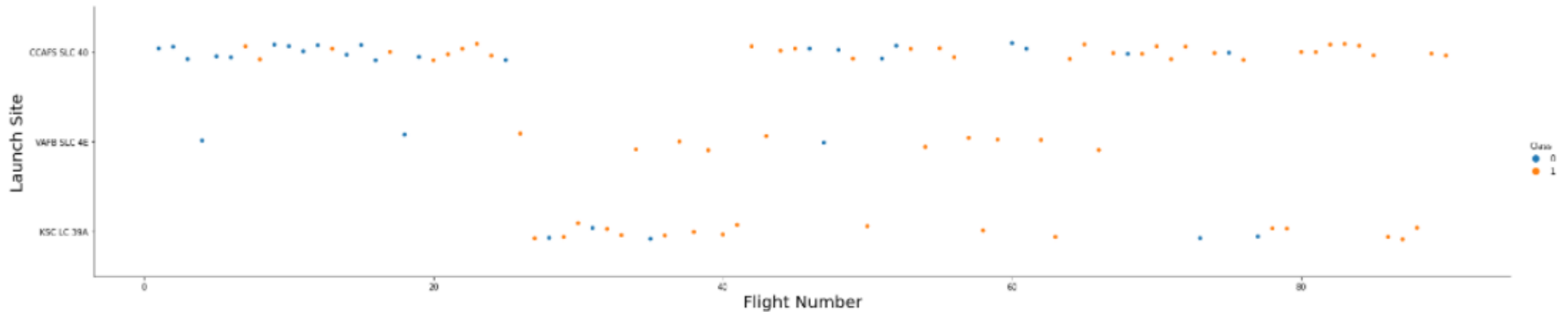
Section 2

# Insights drawn from EDA

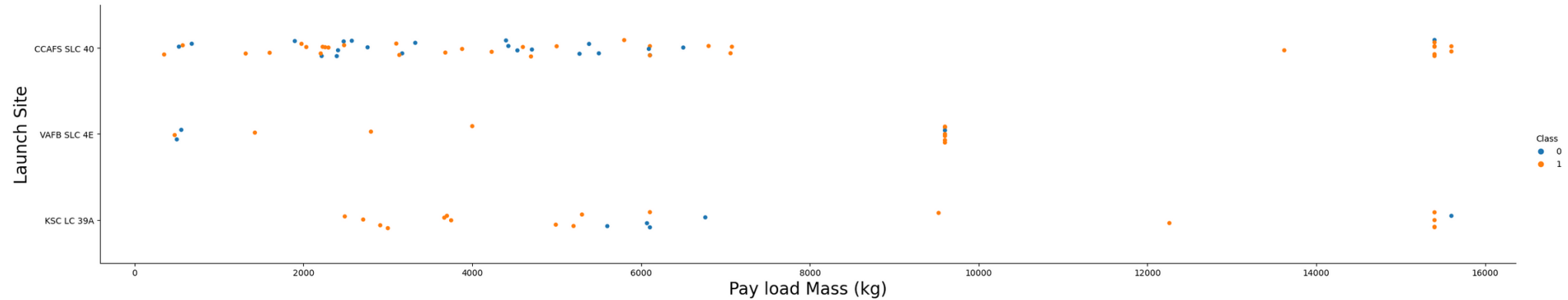


# Flight Number vs. Launch Site

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



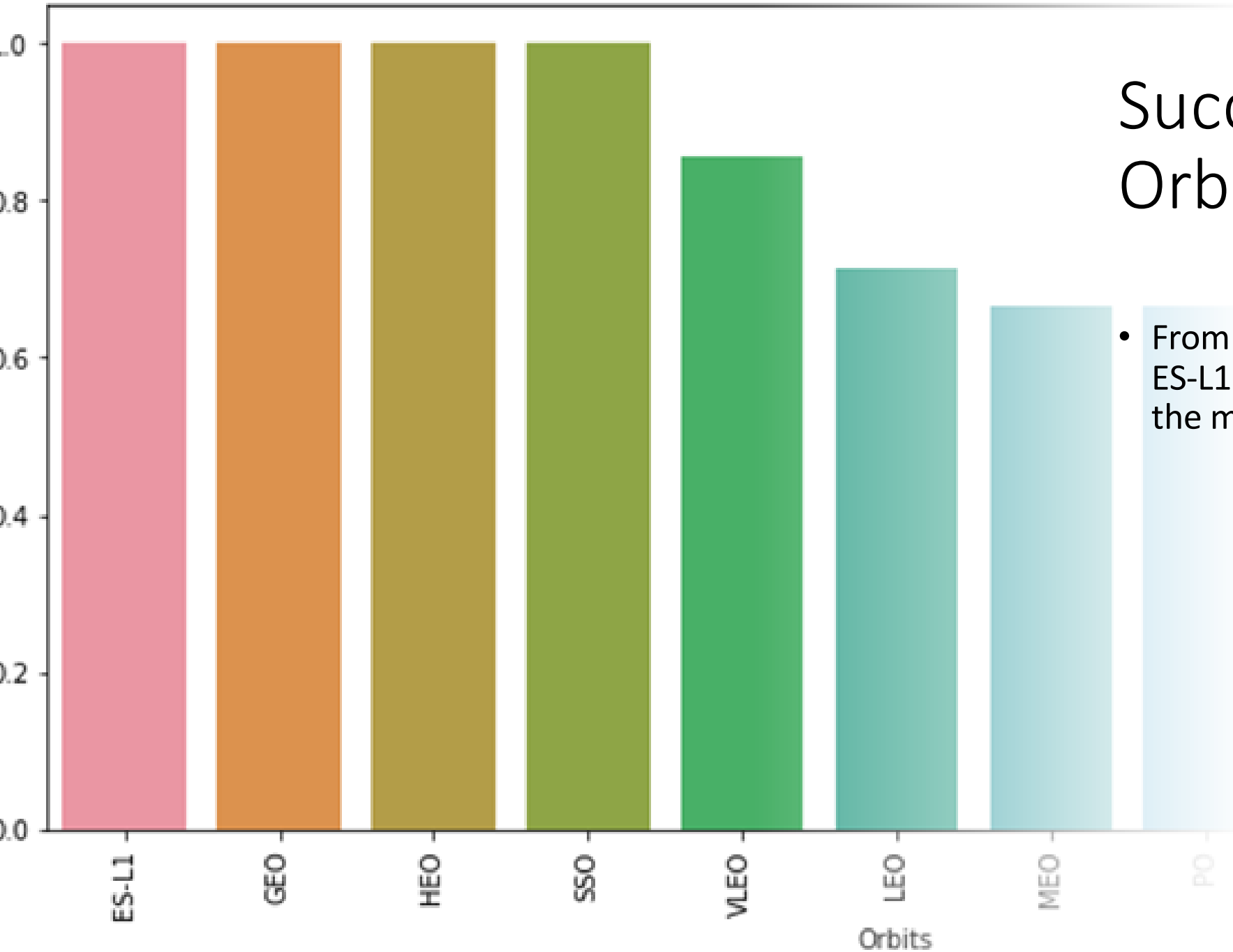




## Payload vs. Launch Site

- The greater the payload mass for launch site CCAFS SLC 40 the higher the success rate for the rocket
- We can also see that for the VAFB-SLC launchsite there are no rockets launched for heavypayload mass(greater than 10000).

Plot of success rate by class of each Orbits

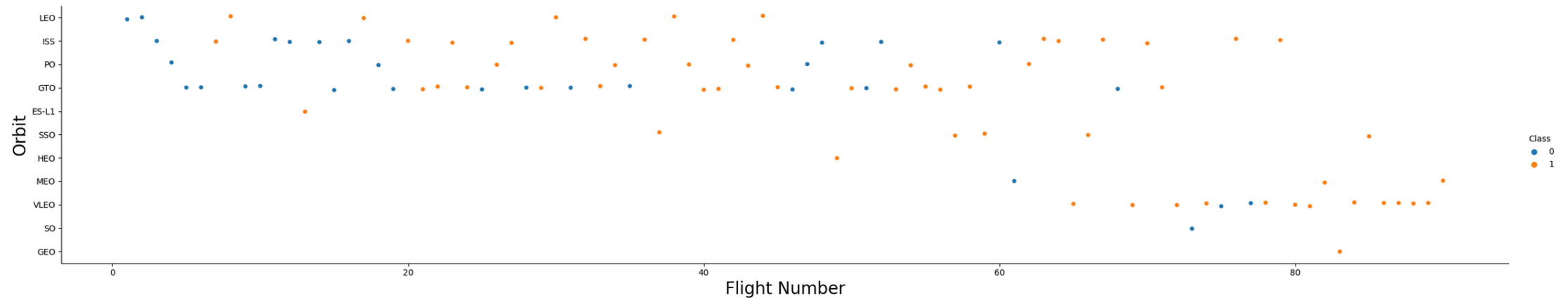


## Success Rate vs. Orbit Type

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

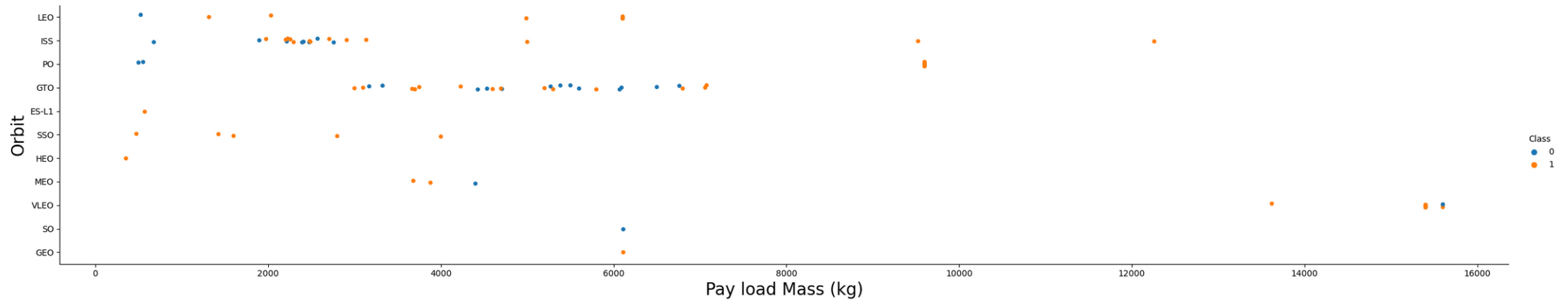
# Flight Number vs. Orbit Type

- We observe that in the LEO orbit, success is related to the number of flights whereas in the GTO orbit; on the other hand, there seems to be no relationship between flight number when in GTO orbit.

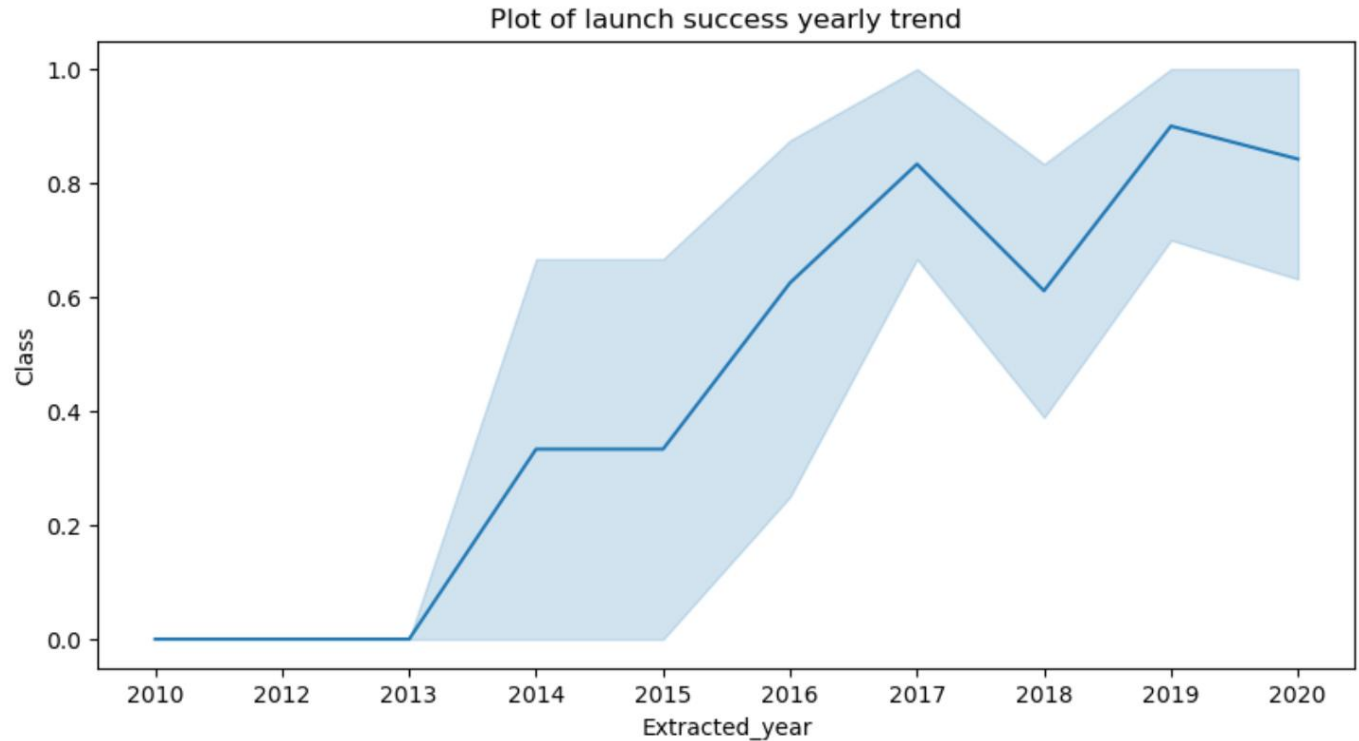


# Payload vs. Orbit Type

- 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



# Launch Success Yearly Trend



- From the plot, we can observe that success rate since 2013 kept increasing till 2017 (stable in 2014) and after 2017 it started increasing.



# All Launch Site Names

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

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

```
Entrée [14]: %sql select distinct "Launch_Site" from SPACEXTABLE
```

```
* sqlite:///my_data1.db  
Done.
```

```
Out[14]:
```

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

# Launch Site Names Begin with 'KSC'

*Display 5 records where launch sites begin with the string 'KSC'*

```
Entrée [15]: %sql select * from SPACEXTABLE where "Launch_Site" like 'KSC%' limit 5
```

```
* sqlite:///my_data1.db  
Done.
```

```
Out[15]:
```

Date	Time (UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS_KG_	Orbit	Customer	Mission_Outcome	Landing_Outcome
2017-02-19	14:39:00	F9 FT B1031.1	KSC LC-39A	SpaceX CRS-10	2490	LEO (ISS)	NASA (CRS)	Success	Success (ground pad)
2017-03-16	6:00:00	F9 FT B1030	KSC LC-39A	EchoStar 23	5600	GTO	EchoStar	Success	No attempt
2017-03-30	22:27:00	F9 FT B1021.2	KSC LC-39A	SES-10	5300	GTO	SES	Success	Success (drone ship)
2017-05-01	11:15:00	F9 FT B1032.1	KSC LC-39A	NROL-76	5300	LEO	NRO	Success	Success (ground pad)
2017-05-15	23:21:00	F9 FT B1034	KSC LC-39A	Inmarsat-5 F4	6070	GTO	Inmarsat	Success	No attempt

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

# Total Payload Mass

---

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

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

```
Entrée [16]: %sql select SUM("PAYLOAD_MASS_KG_") from SPACEXTABLE where "Customer" = 'NASA (CRS)'
```

```
* sqlite:///my_data1.db  
Done.
```

```
Out[16]: SUM("PAYLOAD_MASS_KG_")
```

45596
-------

# Average Payload Mass by F9 v1.1

- We calculated the average payload mass carried by booster version F9 v1.1 as 2928.4

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

```
Intrée [10]: %sql select AVG("PAYLOAD_MASS_KG_") from SPACEXTABLE where "Booster_Version" = 'F9 v1.1'
```

```
* sqlite:///my_data1.db  
Done.
```

```
Out[10]:  AVG("PAYLOAD_MASS_KG_")
```

2928.4
--------

## First Successful Ground Landing Date

- We observed that the dates of the first successful landing outcome on ground pad was 08<sup>th</sup> April 2016

```
Entrée [11]: %sql select MIN("Date") from SPACEXTABLE where "Landing_Outcome" like '%Success (drone ship)%'
```

```
* sqlite:///my_data1.db  
Done.
```

```
Out[11]: MIN("Date")
```

```
2016-04-08
```



## Successful Drone Ship Landing with Payload between 4000 and 6000

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

```
Entrée [13]: %sql select "Booster_Version" from SPACEXTABLE  
             where "Landing_Outcome" like 'Success (ground pad)' and "PAYLOAD_MASS__KG_" between 4000 and 6000
```

```
* sqlite:///my_data1.db  
Done.
```

```
Out[13]:
```

Booster_Version
F9 FT B1032.1
F9 B4 B1040.1
F9 B4 B1043.1

## Total Number of Successful and Failure Mission Outcomes

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

```
Entrée [ ]: %sql select "Mission_Outcome", count(*) as SuccessOutcome from SPACEXTABLE where "Mission_Outcome" like '%Success%'
* sqlite:///my_data1.db
Done.
```

```
Out[14]:
```

Mission_Outcome	SuccessOutcome
Success	100

```
Entrée [15]: %sql select "Mission_Outcome", count(*) as FailureOutcome from SPACEXTABLE where "Mission_Outcome" like '%Failure%'
* sqlite:///my_data1.db
Done.
```

```
Out[15]:
```

Mission_Outcome	FailureOutcome
Failure (in flight)	1

# Boosters Carried Maximum Payload

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

```
Entrée [21]: %sql select "Booster_Version" from SPACEXTABLE where "PAYLOAD_MASS_KG_"=(select MAX("PAYLOAD_MASS_KG_") from SPACEXTABLE)
* sqlite:///my_data1.db
Done.
```

Out[21]:

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

# 2017 Launch Records

- We used a combinations of the **WHERE** clause, **LIKE** and **AND** to filter for failed landing outcomes in drone ship, their booster versions, and launch site names for year 2017

```
Entrée [17]: %sql select substr(Date,6,2),"Landing_Outcome","Booster_Version",  
"Launch_Site" from SPACEXTABLE where "Landing_Outcome" like '%Success (ground pad)%' and substr(Date,0,5)='2017'  
  
* sqlite:///my_data1.db  
Done.
```

```
Out[17]:
```

substr(Date,6,2)	Landing_Outcome	Booster_Version	Launch_Site
02	Success (ground pad)	F9 FT B1031.1	KSC LC-39A
05	Success (ground pad)	F9 FT B1032.1	KSC LC-39A
06	Success (ground pad)	F9 FT B1035.1	KSC LC-39A
08	Success (ground pad)	F9 B4 B1039.1	KSC LC-39A
09	Success (ground pad)	F9 B4 B1040.1	KSC LC-39A
12	Success (ground pad)	F9 FT B1035.2	CCAFS SLC-40

# 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.

```
Entrée [18]: %sql select "Landing_Outcome", count(*) as "number",  
|"Date" from SPACEXTABLE where "Date" between '2010-06-04' and '2017-03-20' group by "Landing_Outcome" order by "number" desc
```

```
* sqlite:///my_data1.db  
Done.
```

```
Out[18]:
```

Landing_Outcome	number	Date
No attempt	10	2012-05-22
Success (drone ship)	5	2016-04-08
Failure (drone ship)	5	2015-01-10
Success (ground pad)	3	2015-12-22
Controlled (ocean)	3	2014-04-18
Uncontrolled (ocean)	2	2013-09-29
Failure (parachute)	2	2010-06-04
Precluded (drone ship)	1	2015-06-28



Section 4

# Launch Sites Proximities Analysis

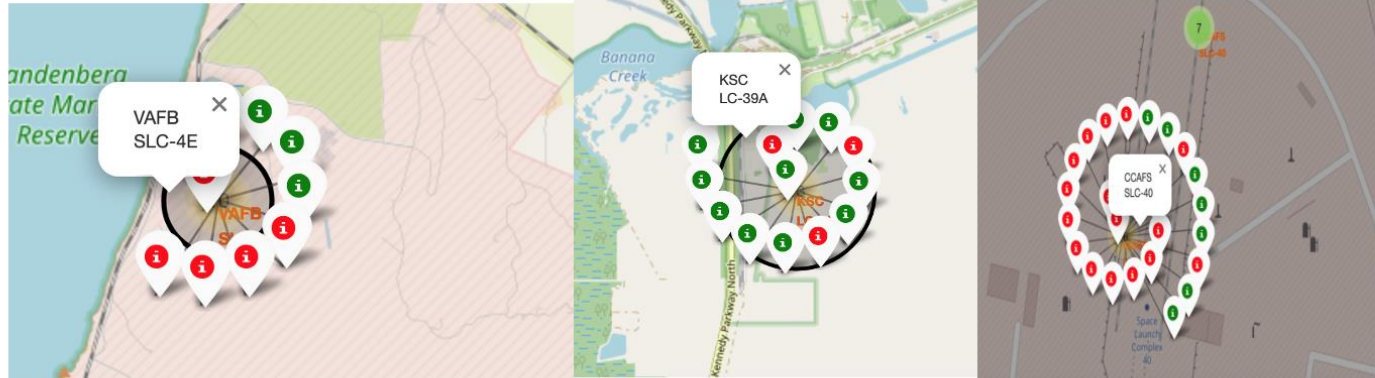


# All launch sites global map markers

- We can see that the SpaceX launch sites are in the United States of America coasts, Florida and California

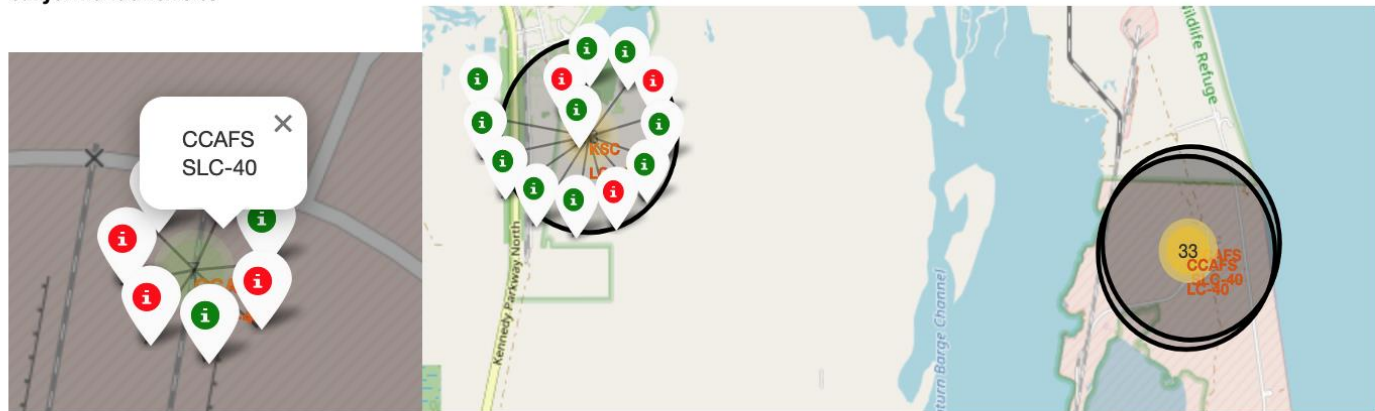


Markers  
showing  
launch sites  
with color  
labels



Florida launch site

California launch site



Florida launch site

**Green Marker** shows Successful Launches and **Red Marker** shows Failures



Distance for the launch site to the coastline



railway, highway, coastline



Distance to highway



- Are launch sites in close proximity to the coastline? YES
- Are launch sites in close proximity to the railway? YES
- Are launch sites in close proximity to the highway? YES
- Do launch sites keep certain distances from the cities? YES

# Launch Site distance to landmarks

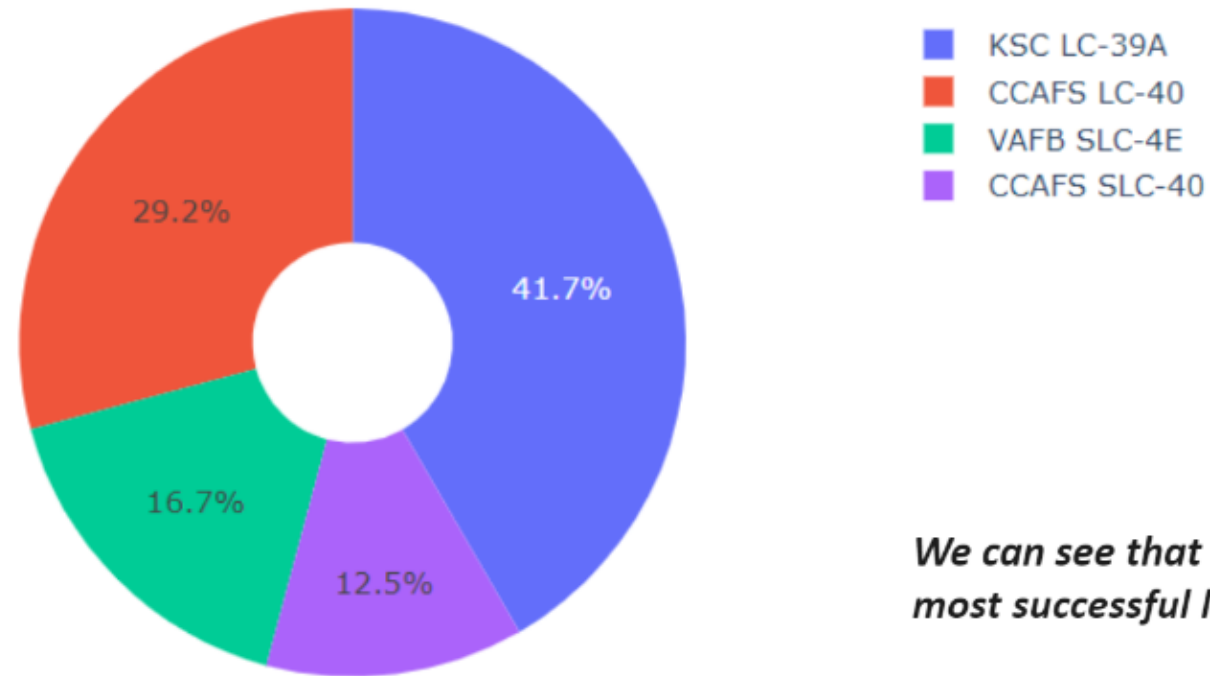


Section 5

# Build a Dashboard with Plotly Dash

# Pie chart showing the success percentage achieved by each launch site

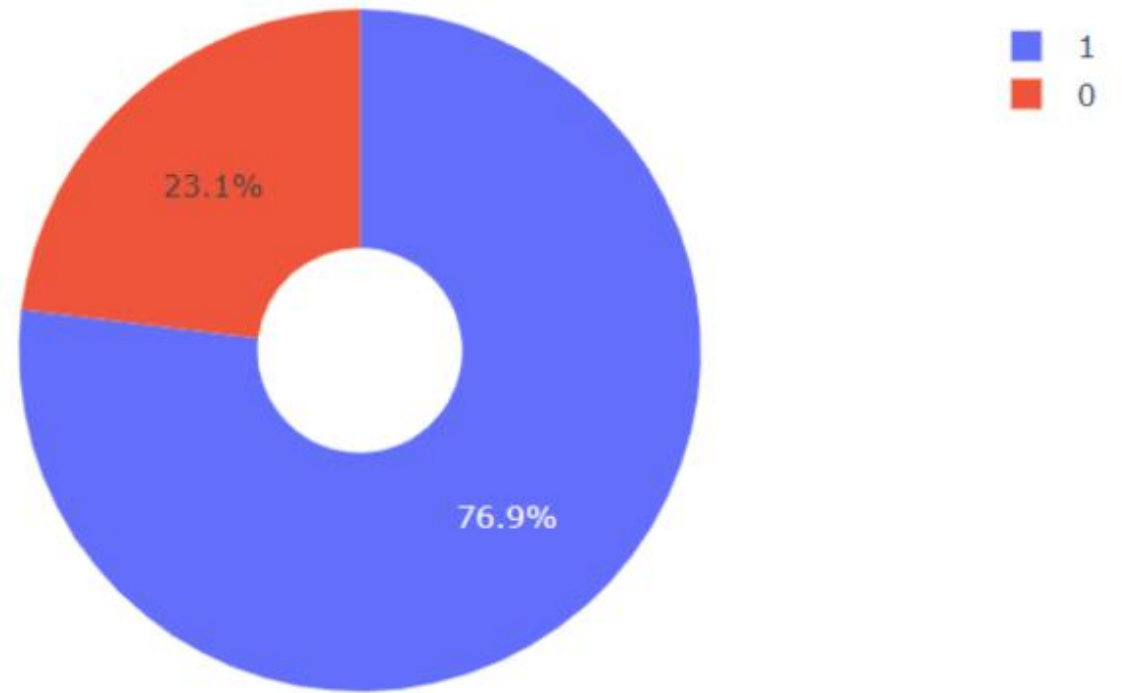
Total Success Launches By all sites



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



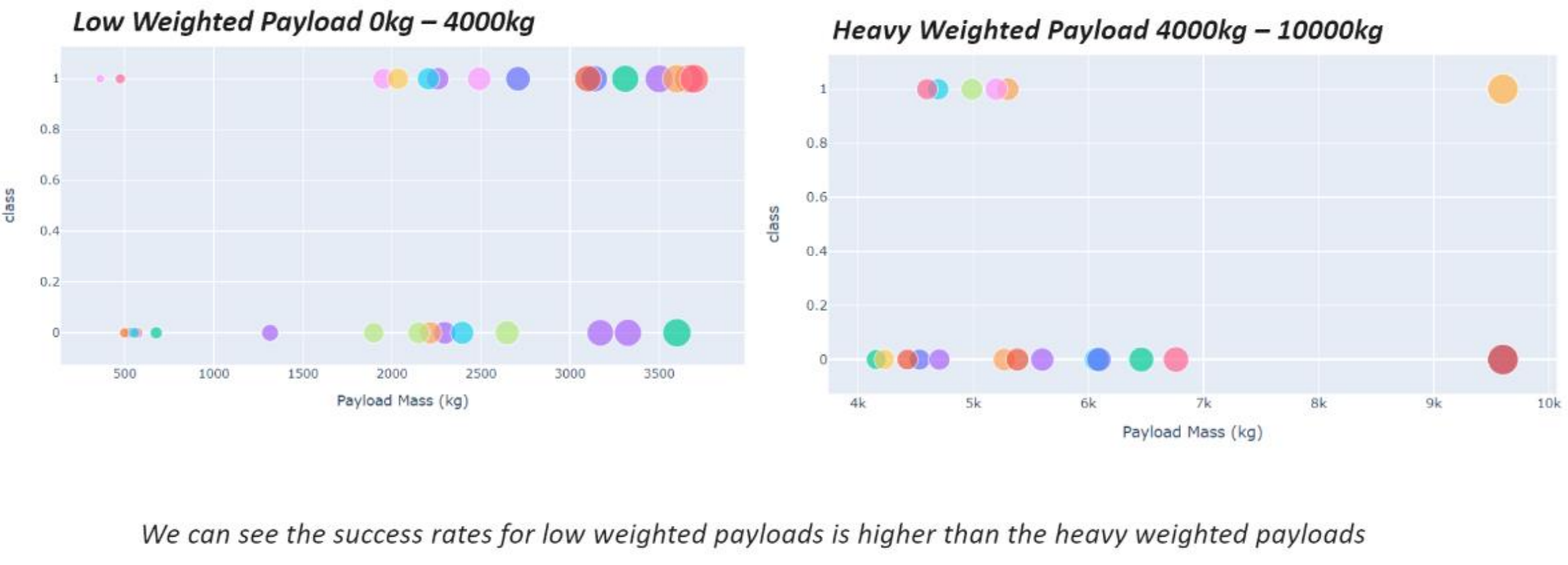
Pie chart  
showing the  
Launch site  
with the  
highest launch  
success ratio



*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



Section 6

# Predictive Analysis (Classification)

# Classification Accuracy

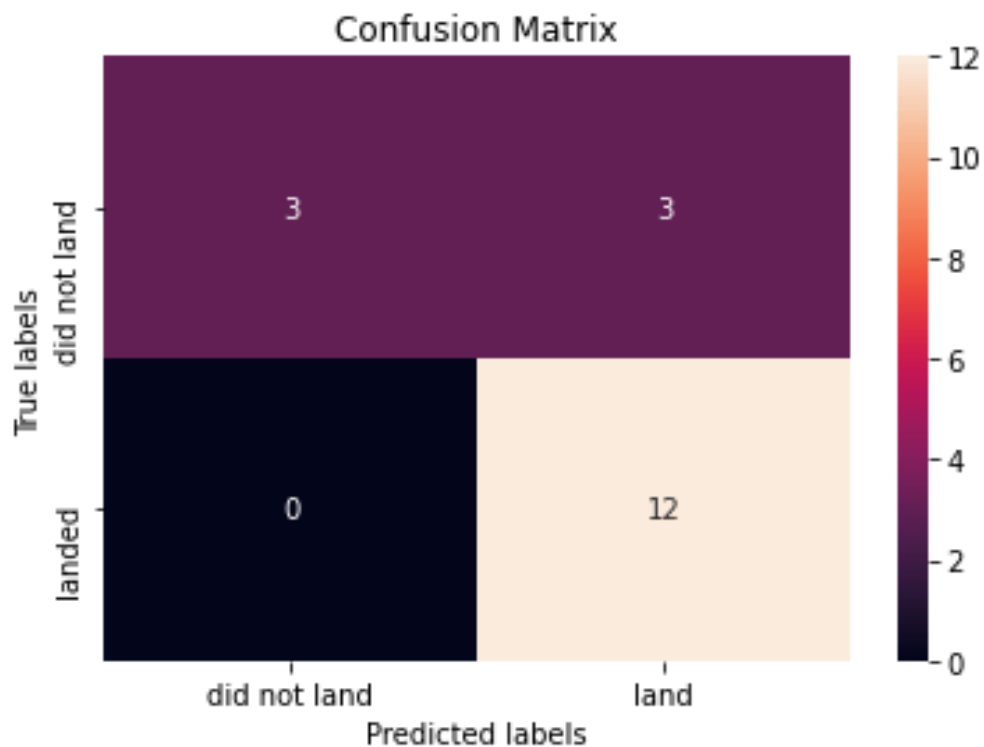
- The decision tree classifier is the model with the highest classification accuracy

```
Entrée [37]: models_scor = {'KNeighbors': knn_cv.best_score_,
                             'DecisionTree': tree_cv.best_score_,
                             'LogisticRegression': logreg_cv.best_score_,
                             'SupportVector': svm_cv.best_score_}

best_method = max(models_scor, key=models_scor.get)
print('method performs best:', best_method, 'with a score of', models_scor[best_method])
if best_method == 'LogisticRegression':
    print('Best params is :', logreg_cv.best_params_)
if best_method == 'SupportVector':
    print('Best params is :', svm_cv.best_params_)
if best_method == 'DecisionTree':
    print('Best params is :', tree_cv.best_params_)
if best_method == 'KNeighbors':
    print('Best params is :', knn_cv.best_params_)

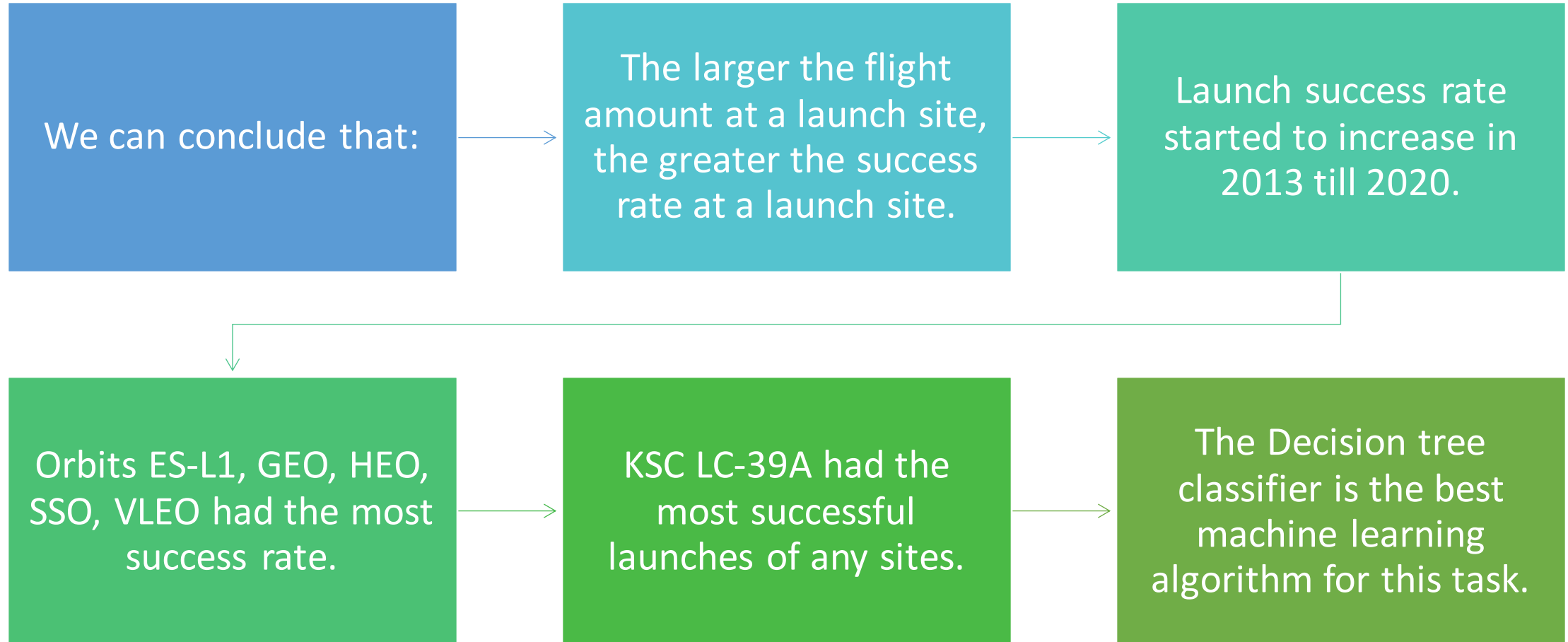
method performs best: DecisionTree with a score of 0.8767857142857143
Best params is : {'criterion': 'gini', 'max_depth': 4, 'max_features': 'sqrt', 'min_samples_leaf': 1, 'min_samples_split': 10,
'splitter': 'random'}
```

# 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





Thank you!

