IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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July 23, 2024

Outline

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- Methodology
- Results
- Conclusion
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Executive Summary

- 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 in screenshots
  - Predictive Analytics result

Introduction

Space X advertises Falcon 9 rocket launches on its site for $62 million, significantly less than competitors' offerings which start at $165 million per launch. This cost disparity is largely due to Space X's ability to reuse the first stage. Therefore, accurately predicting the first stage landing can directly influence launch costs. This predictive capability is crucial for other companies wishing to compete with Space X in rocket launch bids. The objective of this project is to develop a machine learning pipeline for precisely predicting the success of the first stage landing.

- Finding answers to problems:
  - What factors contribute to the successful landing of a rocket?
  - The interplay of different factors determines the success rate of a landing.
  - What operational conditions must be met 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 gathered through diverse methodologies:

Initially, data collection involved making GET requests to the SpaceX API.

↓

Subsequently, the JSON response content was decoded using the `.json()` function and converted into a pandas dataframe using `.json_normalize()`.

↓

Following this, we conducted data cleaning, addressed missing values, and filled them appropriately.

↓

Additionally, we utilized web scraping techniques with BeautifulSoup to extract Falcon 9 launch records from Wikipedia. The goal was to retrieve launch data stored in HTML tables, parse it, and convert it into a pandas dataframe for subsequent 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/fran-carrillo/spaceY/blob/main/jupyter-labs-spacex-data-collection-api.ipynb

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

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

In [9]: static_json_url='https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/datasets/API_
```

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

n [26]: # Hint data['BoosterVersion']!='Falcon 1'
        filt = df['BoosterVersion']!= 'Falcon 1'
        data_falcon9 = df.loc[filt]
        data_falcon9.head

In [27]: data_falcon9.loc[:,'FlightNumber'] = list(range(1, data_falcon9.shape[0]+1))
         data_falcon9

In [3]: # Calculate the mean value of PayloadMass column
        plm_mean = data_falcon9['PayloadMass'].mean()
        print(plm_mean)
```

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/fran-carrillo/spaceY/blob/main/jupyter-labs-webscraping.ipynb

```
In [4]: static_url = "https://en.wikipedia.org/w/index.php?title=List_of_Falcon_9_and_Falcon_Heavy_launches&oldid=1027686922"
```

```
In [5]: # use requests.get() method with the provided static_url
        # assign the response to a object

        html_data = requests.get(static_url)
```

```
In [6]: # Use BeautifulSoup() to create a BeautifulSoup object from a response text content

        beautiful_soup = BeautifulSoup(html_data.text, 'html.parser')
```

Print the page title to verify if the `BeautifulSoup` object was created properly

```
In [7]: # Use soup.title attribute

        beautiful_soup.title

Out[7]: <title>List of Falcon 9 and Falcon Heavy launches - Wikipedia</title>
```

```
In [10]: column_names = []

         # Apply find_all() function with `th` element on first_launch_table
         # Iterate each th element and apply the provided extract_column_from_header() to get a column name
         # Append the Non-empty column name (`if name is not None and len(name) > 0`) into a list called column_names


         element = beautiful_soup.find_all('th')
         for row in range(len(element)):
             try:
                 name = extract_column_from_header(element[row])
                 if (name is not None and len(name) > 0):
                     column_names.append(name)
             except:
                 pass
```

Check the extracted column names

```
In [11]: print(column_names)

['Flight No.', 'Date and time ( )', 'Launch site', 'Payload', 'Payload mass', 'Orbit', 'Customer', 'Launch outcome', 'Flight
No.', 'Date and time ( )', 'Launch site', 'Payload', 'Payload mass', 'Orbit', 'Customer', 'Launch outcome', 'Flight No.', 'Da
```

Data Wrangling

- We conducted exploratory data analysis to define the training labels.
- This involved calculating the frequency of launches at each site and the distribution of orbits.
- From the outcome column, we generated landing outcome labels and saved the results to a CSV file.

- The link for this notebook is https://github.com/fran-carrillo/spaceY/blob/main/labs-jupyter-spacex-Data%20wrangling.ipynb

In [7]:
```python
# Apply value_counts() on column LaunchSite
df['LaunchSite'].value_counts()
```

Out[7]:
```
CCAFS SLC 40    55
KSC LC 39A      22
VAFB SLC 4E     13
Name: LaunchSite, dtype: int64
```

In [8]:
```python
# Apply value_counts on Orbit column
df['Orbit'].value_counts()
```

Out[8]:
```
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
```

In [9]:
```python
landing_outcomes = df.value_counts('Outcome')
landing_outcomes
```

Out[9]:
```
Outcome
True ASDS      41
None None      19
True RTLS      14
False ASDS      6
True Ocean      5
False Ocean     2
None ASDS       2
False RTLS      1
dtype: int64
```

In [15]:
```python
# landing_class = 0 if bad_outcome
# landing_class = 1 otherwise

landing_class = []
for outcome in df['Outcome']:
    if outcome in bad_outcomes:
        landing_class.append(0)
    else:
        landing_class.append(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

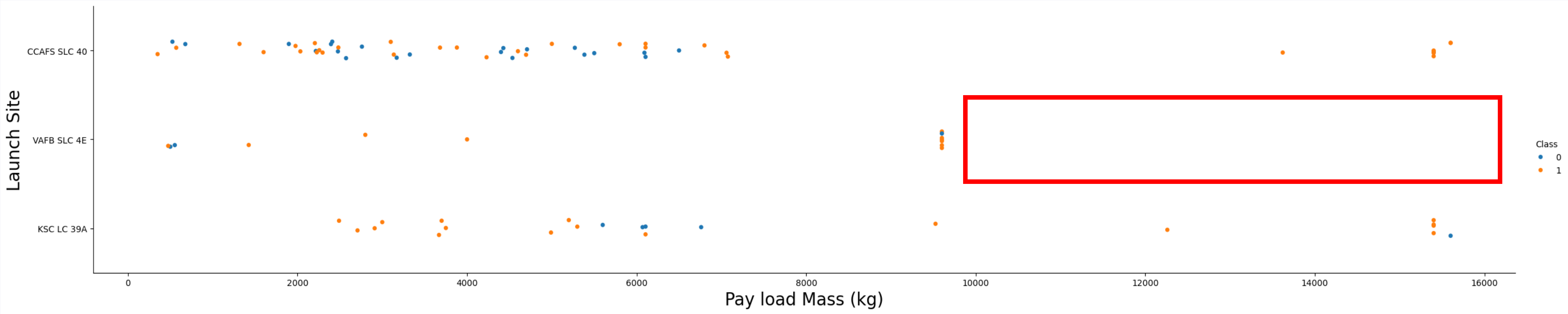
In [16]:
```python
df['Class']=landing_class
df[['Class']].head(8)
```

EDA with Data Visualization (I)

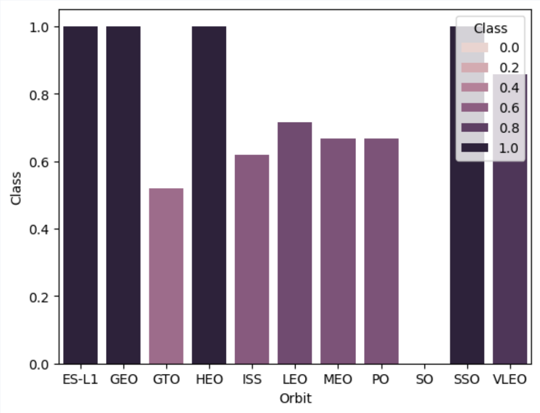
We conducted data exploration by visualizing several relationships:

- ✓ The correlation between flight number and launch site.
- ✓ The connection between payload and launch site.
- ✓ The success rates across different orbit types.
- ✓ The relationship between flight number and orbit type.
- ✓ The annual trend in launch success rates.

EDA with Data Visualization (II)

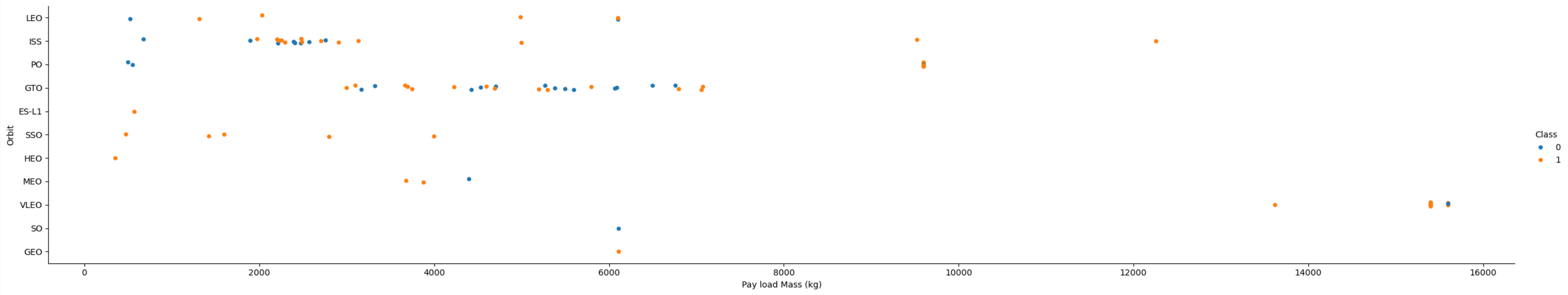


For the VAFB-SLC launchsite there are no rockets launched for heavypayload mass.

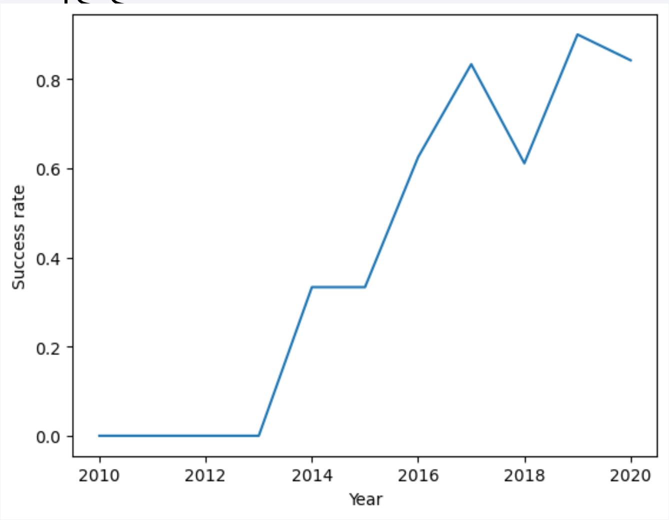


The orbits ES-L1, GEO, HEO, SSO and VLEO have the highest success rates.

EDA with Data Visualization (III)



With heavy payloads the successful landing or positive landing rate are more for Polar,LEO and ISS



The sucess rate since 2013 kept increasing until 2020.

- The link for this notebook is https://github.com/fran-carrillo/spaceY/blob/main/edadataviz.ipynb

EDA with SQL

- We imported the SpaceX dataset within the Jupyter Notebook environment.
- Using SQL for exploratory data analysis, we executed queries to uncover key insights such as:
  - Identifying the unique launch sites involved in the space missions.
  - Five records where launch sites begin with 'CCA'.
  - Calculating the total payload mass carried by boosters launched by NASA (CRS).
  - Determining the average payload mass carried by booster version F9 v1.1.
  - Tabulating the total number of successful and failed mission outcomes.
  - List the names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000.
  - Extracting details on failed landing outcomes on drone ships, including their booster version and launch site names.
  - Listing the records which display the month names, failure landing_outcomes in drone ship ,booster versions, launch_site for the months in year 2015.
  - 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.
- The link for this notebook is https://github.com/fran-carrillo/spaceY/blob/main/jupyter-labs-eda-sql-coursera_sqllite.ipynb

Build an Interactive Map with Folium

We annotated all launch sites and incorporated map elements such as markers, circles, and lines on a Folium map to indicate the success or failure of launches at each site.

- Launch outcomes (failure or success) were categorized into classes: 0 for failure and 1 for success.
- Using color-coded marker clusters, we identified launch sites with notably high success rates.
- We also computed distances from each launch site to nearby features and addressed questions such as:
- Proximity of launch sites to railways, highways, and coastlines.
- Whether launch sites maintain a specified distance from urban areas.

- The link to this notebook is https://github.com/fran-carrillo/spaceY/blob/main/lab_jupyter_launch_site_location.ipynb

Build a Dashboard with Plotly Dash

- We developed an interactive dashboard using Plotly Dash.
- In the dashboard, we included pie charts depicting the total launches from specific sites.
- Additionally, we created scatter plots to visualize the relationship between launch outcomes and payload mass (in kilograms) across various booster versions.

- **The link to this notebook is** https://github.com/fran-carrillo/spaceY/blob/main/spacex_dash_app%20(1).py

Predictive Analysis (Classification)

- We loaded and transformed the data using numpy and pandas, then divided it into training and testing sets.
- Next, we constructed multiple machine learning models and fine-tuned their hyperparameters using GridSearchCV.
- Our evaluation metric was accuracy, and we enhanced the model through feature engineering and algorithm refinement.
- Ultimately, we identified the best-performing classification model.

- The link to this notebook is https://github.com/fran-carrillo/spaceY/blob/main/SpaceX_Machine%20Learning%20Prediction_Part_5.ipynb

Results

✓Exploratory data analysis results

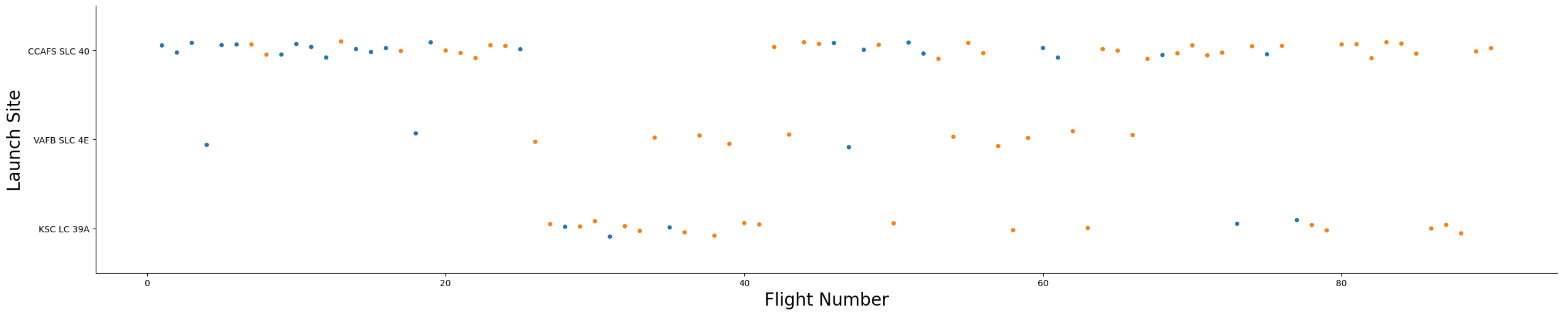
✓Interactive analytics demo in screenshots

✓Predictive analysis results

Section 2

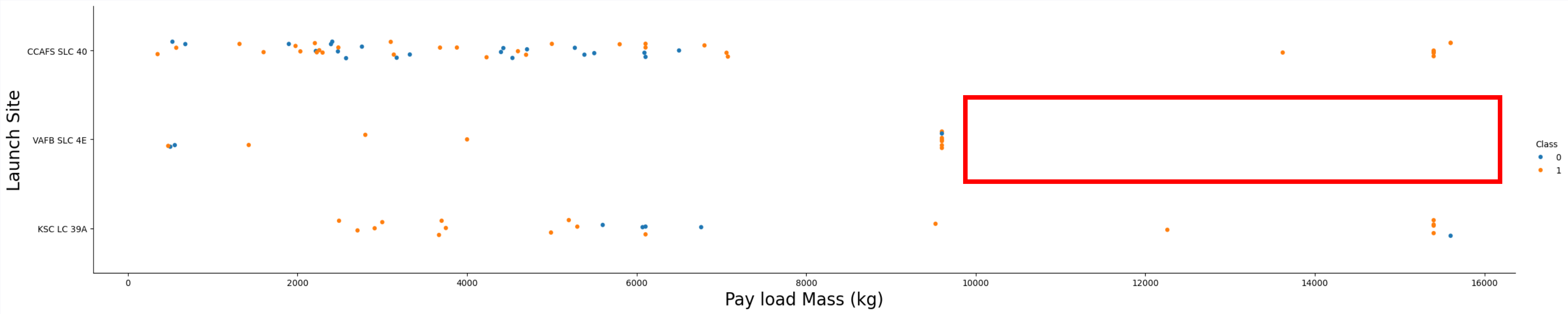
Insights drawn from EDA

Flight Number vs. Launch Site



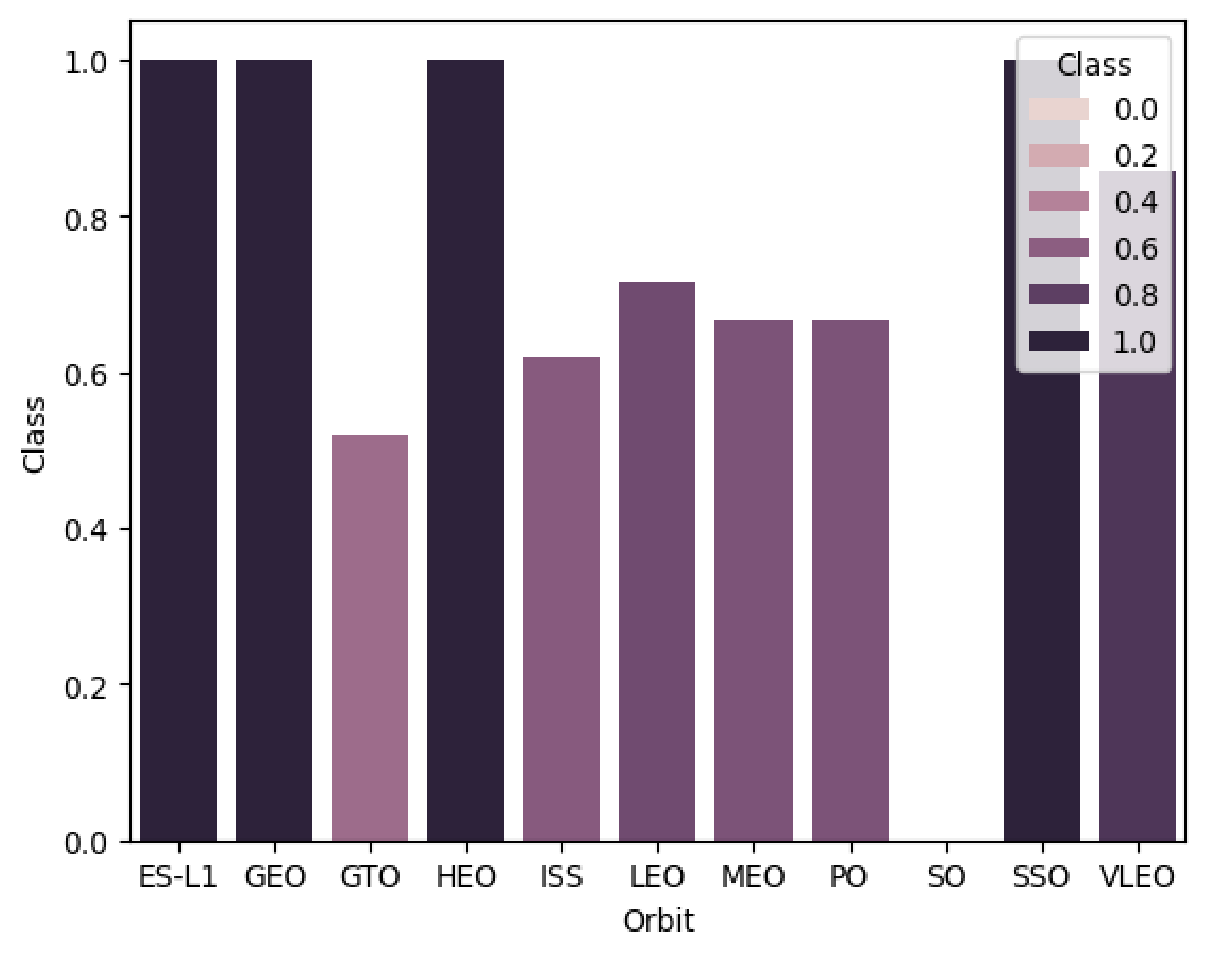
We observed a positive correlation between the number of flights at a launch site and its success rate.

Payload vs. Launch Site



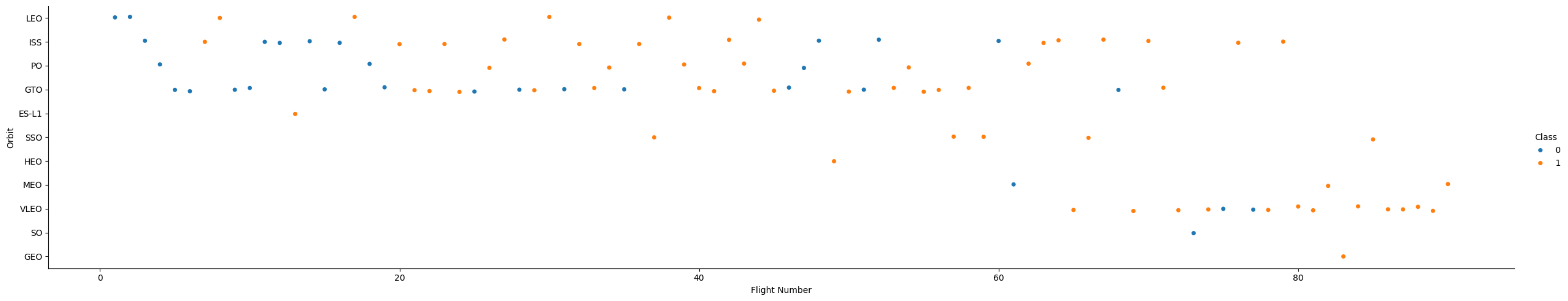
For the VAFB-SLC launchsite there are no rockets launched for heavypayload mass.

Success Rate vs. Orbit Type



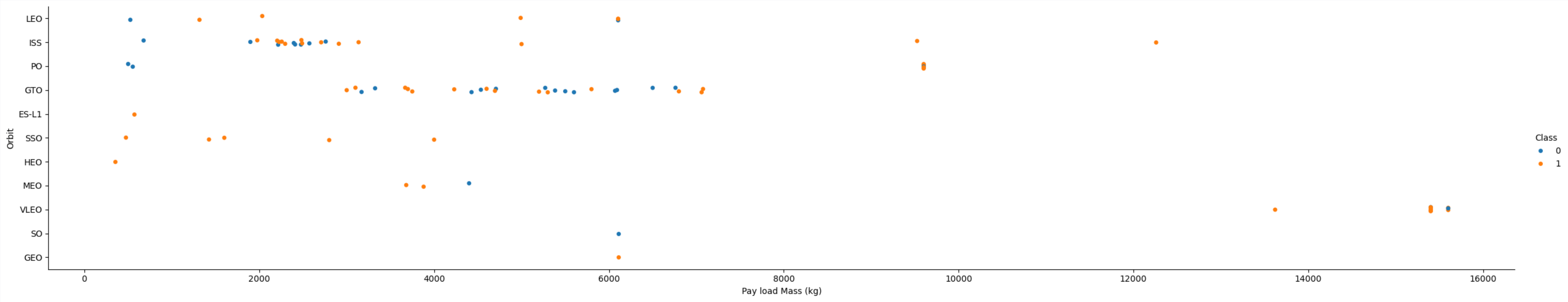
The orbits ES-L1, GEO, HEO, SSO and VLEO have the highest success rates.

Flight Number vs. Orbit Type



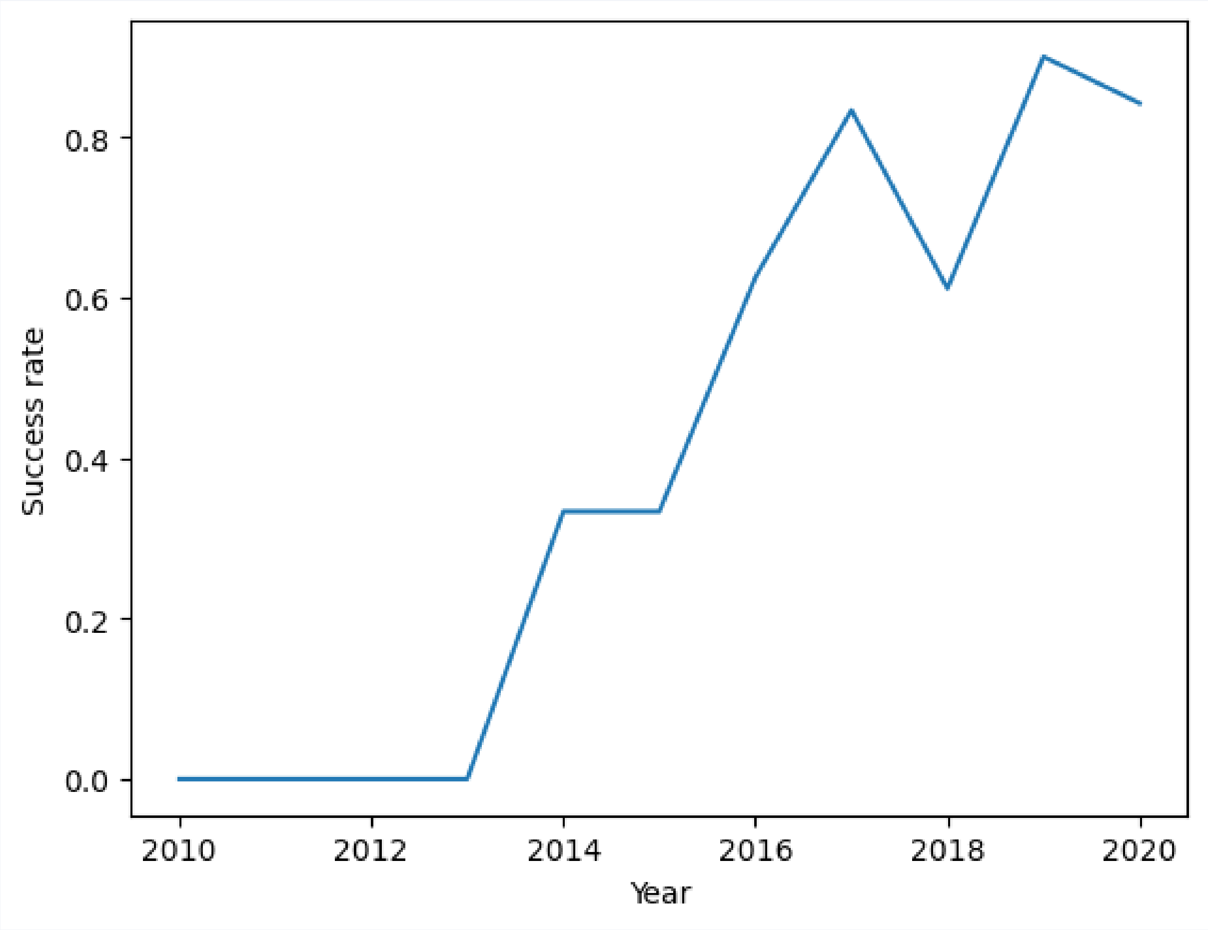
In the LEO orbit, success seems to be related to the number of flights. Conversely, in the GTO orbit, there appears to be no relationship between flight number and success.

Payload vs. Orbit Type



- With heavy payloads the successful landing or positive landing rate are more for Polar,LEO and ISS.
- However, for GTO, it's difficult to distinguish between successful and unsuccessful landings as both outcomes are present.

Launch Success Yearly Trend



The sucess rate since 2013 kept increasing until 2020.

All Launch Site Names

In [12]:
```
%sql select DISTINCT Launch_Site from SPACEXTABLE
```

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

Out[12]:

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

We utilized the keyword DISTINCT to display only unique launch sites from the SpaceX data.

Launch Site Names Begin with 'CCA'

In [23]:
```
%sql SELECT * FROM SPACEXTABLE WHERE Launch_Site LIKE 'CCA%' limit 5
```

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

Out[23]:

Date	Time (UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS__KG_	Orbit	Customer	Mission_Outcome	Landing_Outcon
2010-06-04	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachut
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 (parachut
2012-05-22	7:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	No attem
2012-10-08	0:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attem
2013-03-01	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attem

We used the query above to retrieve 5 records where launch sites start with CCA.

Total Payload Mass

```
In [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

We determined that the total payload carried by boosters from NASA was 45,596 units using the query above. For that, we used SELECT SUM to display the total payload mass carried.

Average Payload Mass by F9 v1.1

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

In [18]:
```
%sql SELECT AVG(PAYLOAD_MASS__KG_) FROM SPACEXTABLE WHERE Booster_Version='F9 v1.1'
```

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

Out[18]:

AVG(PAYLOAD_MASS__KG_)
2928.4

We calculated the average payload mass carried by booster version F9 v1.1 as 2928.4. For that, we used the keywords SELECT AVG and WHERE to display the average.

First Successful Ground Landing Date

```
In [21]:  %sql SELECT MIN(Date) FROM SPACEXTABLE WHERE Landing_Outcome='Success (ground pad)'

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

Out[21]:

MIN(Date)
2015-12-22

We observed that the dates of the first successful landing outcome on ground pad was Dec 22, 2015. For that, we used SELECT MIN to select the date of the first succesful landing (the lower number, the elder)

Successful Drone Ship Landing with Payload between 4000 and 6000

In [26]:
```
%sql SELECT * FROM SPACEXTABLE WHERE Landing_Outcome='Success (drone ship)' AND PAYLOAD_MASS__KG_>4000 AND PAYLOAD_MASS__
```

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

Out[26]:

Date	Time (UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS__KG_	Orbit	Customer	Mission_Outcome	Landing_Outcome
2016-05-06	5:21:00	F9 FT B1022	CCAFS LC-40	JCSAT-14	4696	GTO	SKY Perfect JSAT Group	Success	Success (drone ship)
2016-08-14	5:26:00	F9 FT B1026	CCAFS LC-40	JCSAT-16	4600	GTO	SKY Perfect JSAT Group	Success	Success (drone ship)
2017-03-30	22:27:00	F9 FT B1021.2	KSC LC-39A	SES-10	5300	GTO	SES	Success	Success (drone ship)
2017-10-11	22:53:00	F9 FT B1031.2	KSC LC-39A	SES-11 / EchoStar 105	5200	GTO	SES EchoStar	Success	Success (drone ship)

We used the WHERE clause to filter for boosters that successfully landed on a drone ship. Additionally, we applied an AND condition to identify cases where the landing was successful and the payload mass was between 4000 and 6000 units.

Total Number of Successful and Failure Mission Outcomes

```
In [40]: %sql SELECT COUNT(Mission_Outcome) FROM SPACEXTABLE WHERE Mission_Outcome LIKE 'Success%'

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

Out[40]:

COUNT(Mission_Outcome)
100

```
In [41]: %sql SELECT COUNT(Mission_Outcome) FROM SPACEXTABLE WHERE Mission_Outcome LIKE'Failure%'

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

Out[41]:

COUNT(Mission_Outcome)
1

In this slide we can see that the Successful missions were 100 and only one mission outcome was a failure.

We used '%' to filter for WHERE MissionOutcome was a success or a failure.

Boosters Carried Maximum Payload

In [48]:
```
%sql SELECT Booster_Version FROM SPACEXTABLE WHERE PAYLOAD_MASS__KG_ = (SELECT MAX(PAYLOAD_MASS__KG_) FROM SPACEXTABLE)
```

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

Out[48]:

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

To determine which boosters carried maximum payload, we used a subquery in the WHERE clause and the MAX() function.

2015 Launch Records

In [49]:
```
%sql select substr(Date, 6,2), Landing_Outcome, Booster_Version, Launch_Site FROM SPACEXTABLE WHERE substr(Date,0,5)='201
```

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

Out[49]:

substr(Date, 6,2)	Landing_Outcome	Booster_Version	Launch_Site
01	Failure (drone ship)	F9 v1.1 B1012	CCAFS LC-40
04	Failure (drone ship)	F9 v1.1 B1015	CCAFS LC-40

We used a combination of the WHERE clause, LIKE, AND, and BETWEEN conditions to filter for failed landing outcomes on drone ships, including their booster versions and launch site names, specifically for the year 2015.

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

```
[11]: ıding_Outcome, COUNT(Landing_Outcome) AS 'NUMBER OF LANDING OUTCOMES' FROM SPACEXTABLE WHERE DATE BETWEEN '2010-06-04' AND '2017-03-20' GROUP BY Landing_Outcome ORDER BY COUNT(Landing_Outcome) DE

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

[11]:

Landing_Outcome	NUMBER OF LANDING OUTCOMES
No attempt	10
Success (drone ship)	5
Failure (drone ship)	5
Success (ground pad)	3
Controlled (ocean)	3
Uncontrolled (ocean)	2
Failure (parachute)	2
Precluded (drone ship)	1

We selected landing outcomes and the count of landing outcomes from the data, filtering for landing outcomes between June 4, 2010, and March 20, 2010, using the WHERE clause.

We then used the GROUP BY clause to group the landing outcomes and the ORDER BY clause to sort the grouped landing outcomes in descending order.

```
%sql SELECT Landing_Outcome, COUNT(Landing_Outcome) AS 'NUMBER OF LANDING OUTCOMES' FROM SPACEXTABLE WHERE DATE BETWEEN '2010-06-04' AND '2017-03-20' GROUP BY
  Landing_Outcome ORDER BY COUNT(Landing_Outcome) DESC
```

SQL code

TASK 1:

```
%sql SELECT * FROM SPACEXTABLE
```

```
%sql select DISTINCT Launch_Site from SPACEXTABLE
```

TASK 2:

```
%sql SELECT * FROM SPACEXTABLE WHERE Launch_Site LIKE 'CCA%' limit 5
```

TASK 3:

```
%sql SELECT SUM(PAYLOAD_MASS__KG_) FROM SPACEXTABLE WHERE Customer='NASA (CRS)'
```

TASK 4:

```
%sql SELECT AVG(PAYLOAD_MASS__KG_) FROM SPACEXTABLE WHERE Booster_Version='F9 v1.1'
```

TASK 5:

```
%sql SELECT MIN(Date) FROM SPACEXTABLE WHERE Landing_Outcome='Success (ground pad)'
```

SQL code (II)

TASK6:

%sql SELECT * FROM SPACEXTABLE WHERE Landing_Outcome='Success (drone ship)' AND PAYLOAD_MASS__KG_>4000 AND PAYLOAD_MASS__KG_<6000

TASK 7:

%sql SELECT COUNT(Mission_Outcome) FROM SPACEXTABLE WHERE Mission_Outcome LIKE 'Success%'

%sql SELECT COUNT(Mission_Outcome) FROM SPACEXTABLE WHERE Mission_Outcome LIKE'Failure%'

TASK 8:

%sql SELECT Booster_Version FROM SPACEXTABLE WHERE PAYLOAD_MASS__KG_ = (SELECT MAX(PAYLOAD_MASS__KG_) FROM SPACEXTABLE)

TASK 9:

%sql select substr(Date, 6,2), Landing_Outcome, Booster_Version, Launch_Site FROM SPACEXTABLE WHERE substr(Date,0,5)='2015' AND Landing_Outcome='Failure (drone ship)'

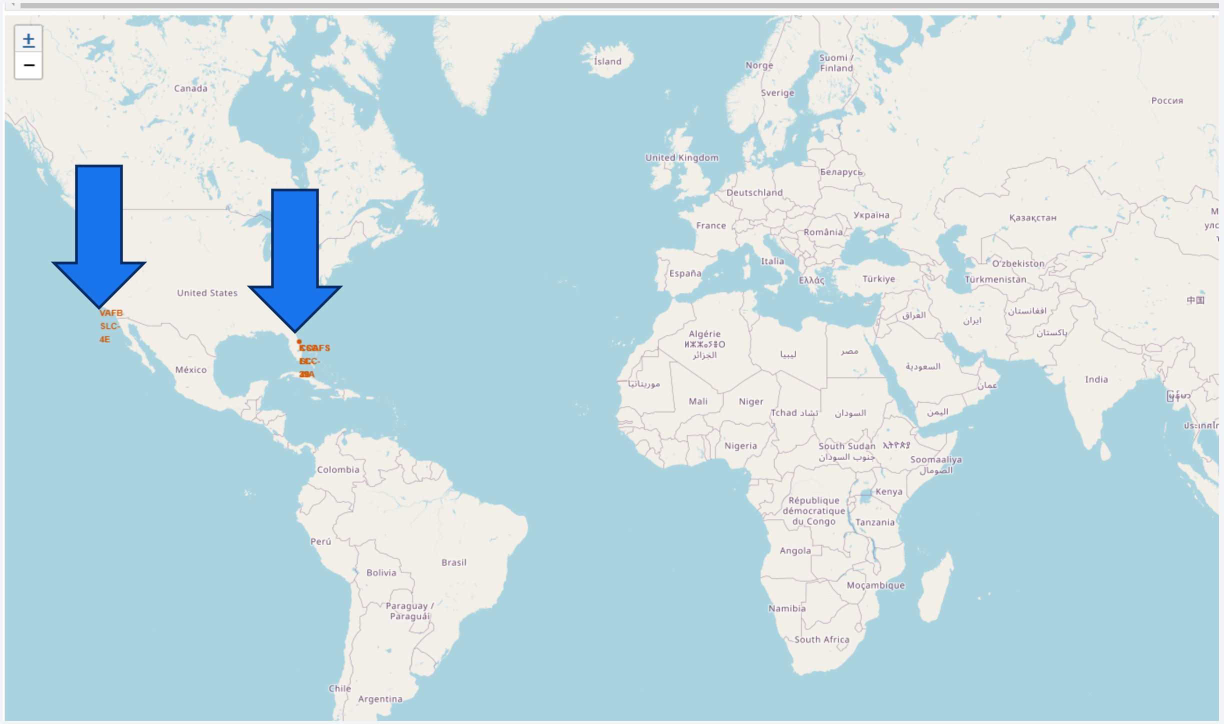
TASK 10:

%sql SELECT Landing_Outcome, COUNT(Landing_Outcome) AS 'NUMBER OF LANDING OUTCOMES' FROM SPACEXTABLE WHERE DATE BETWEEN '2010-06-04' AND '2017-03-20' GROUP BY Landing_Outcome ORDER BY COUNT(Landing_Outcome) DESC

Section 3

Launch Sites Proximities Analysis

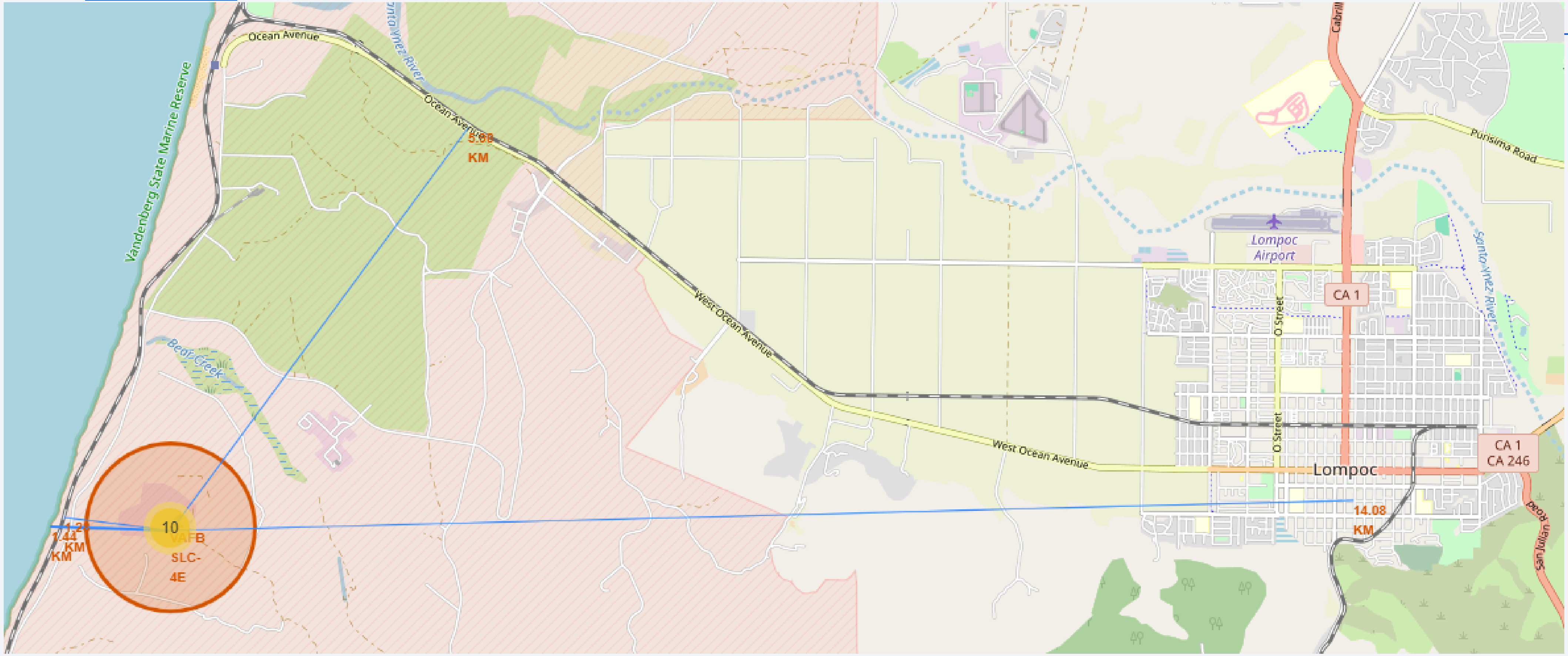
Global map of all launch sites



Space X launch sites are either in the west coast of the US (California) or east coast (Florida)

Successful (green) and failure (red) launches

Distance of different points of interest from launch site



All launch sites are far away from railways, highways and cities, and keep close to the coastline

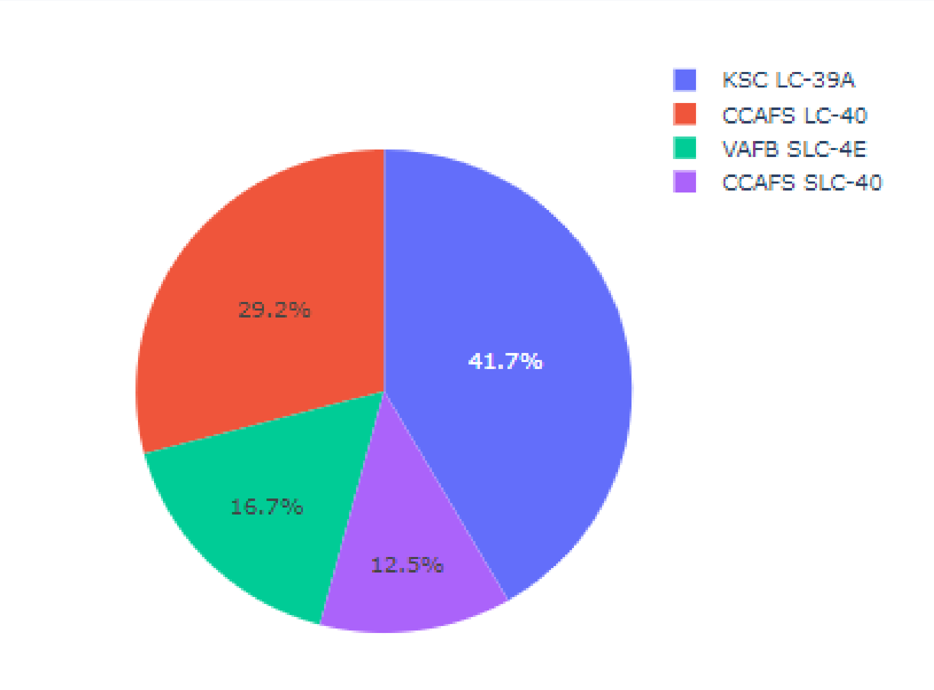
Section 4

Build a Dashboard with Plotly Dash

NASA's Kennedy Space Center has the highest Launch success rate

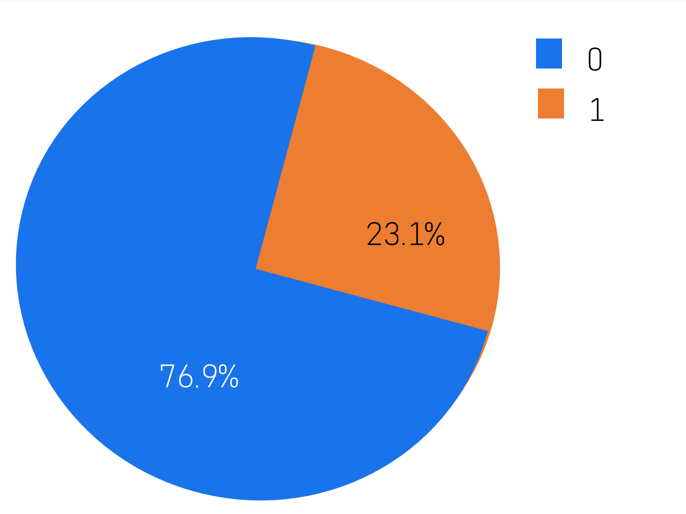
- NASA's **Kennedy Space Center (KSC LC-39A)** in Merritt Island, Florida.

- East coast launch sites at Florida have higher Launch success rate than VAFB at Santa Barbara, CA.

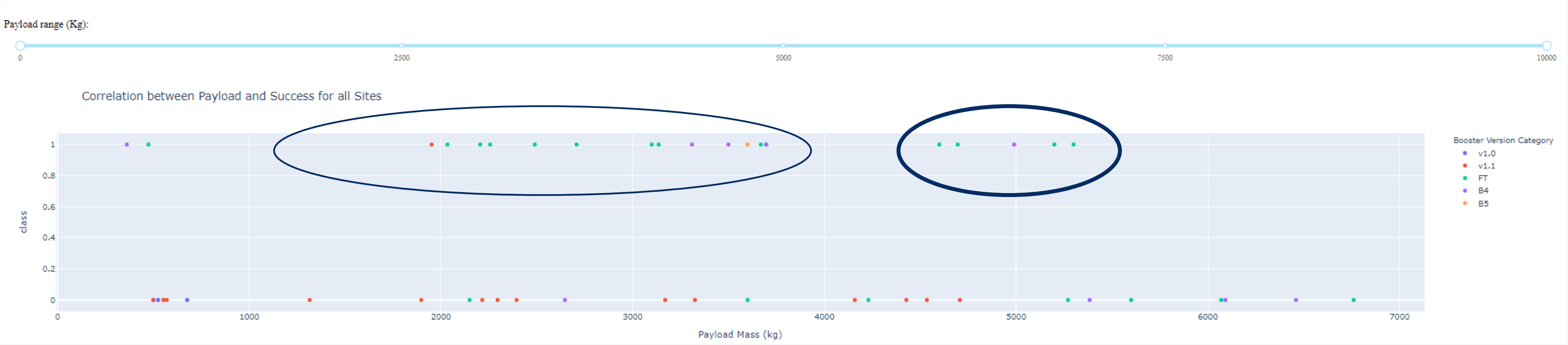


NASA's Kennedy Space Center has the highest Launch success rate

KSC LC-39A has a 77% success rate and a 23% of failure rate



Scatter plot of Payload vs Launch Outcome for all sites



Higher success rates for low weighted payloads (left circle) than heavy wieghted payloads (right circle)

Section 5

Predictive Analysis (Classification)

Classification Accuracy

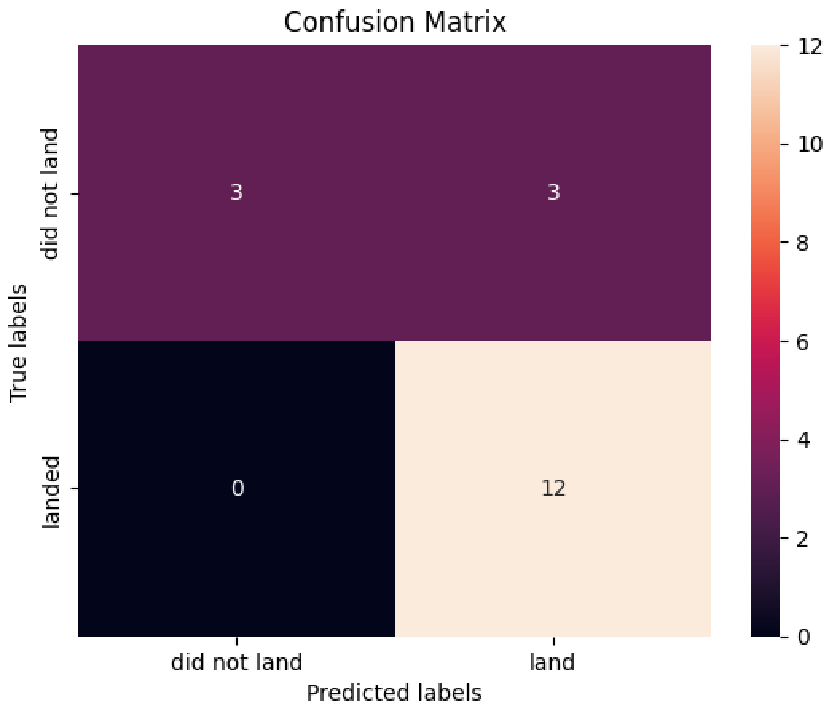
In [37]:
```
print('lr accuracy =', '{:.2%}'.format(logreg_cv.best_score_))
print('svm accuracy =', '{:.2%}'.format(svm_cv.best_score_))
print('tree accuracy =', '{:.2%}'.format(tree_cv.best_score_))
print('knn accuracy =', '{:.2%}'.format(knn_cv.best_score_))
```

```
lr accuracy = 84.64%
svm accuracy = 84.82%
tree accuracy = 87.14%
knn accuracy = 84.82%
```

The decision tree classifier is the model that has the highest classification accuracy.

Confusion Matrix

In [27]:
```
yhat = tree_cv.predict(X_test)
plot_confusion_matrix(Y_test,yhat)
```



The confusion matrix of the decision tree classifier reveals its ability to distinguish between different classes. The primary issue lies in false positives, where unsuccessful landings are incorrectly classified as successful.

Conclusions

Based on our analysis, we can conclude the following:

- There is a positive correlation between the number of flights at a launch site and its success rate.
- The launch success rate has shown a steady increase from 2013 to 2020.
- Orbits ES-L1, GEO, HEO, SSO, and VLEO exhibited the highest success rates.
- KSC LC-39A had the highest number of successful launches among all sites.
- The decision tree classifier stands out as the optimal machine learning algorithm for this specific task.

Thank you!