SPACE Y
FIRST STAGE REUSE

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06/25/2023

CONTENTS

EXECUTIVE SUMMARY

Summary of Methodologies

The Capstone project follows these steps:

1. Data Collection
2. Data Wrangling
3. Exploratory Data Analysis
4. Interactive Visual Analytics
5. Predictive Analysis

- **Summary of Results:**
- This project produced the following outputs and visualizations:
    1. Exploratory Data Analysis (EDA) results
    2. Geospatial analytics
    3. Interactive dashboard
    4. Predictive analysis of classification models

INTRODUCTION

- SpaceX launches Falcon 9 rockets at a cost of around
- $62m. This is considerably cheaper than other providers (which usually cost upwards of $165m), and much of the savings are because SpaceX can land, and then re-use the first stage of the rocket.
- If we can make predictions on whether the first stage will land, we can determine the cost of a launch, and use this information to assess whether or not an alternate company should bid and SpaceX for a rocket launch.
- This project will ultimately predict if the Space X Falcon 9 first stage will land successfully.

METHODOLOGY

1. Data Collection
    - I used GET requests to the SpaceX REST API
    - Web Scraping
2. Data Wrangling
    - Using the .fillna()method to remove NaN values
    - Using the .value_counts()method to determine the following:
        - Number of launches on each site
        - Number and occurrence of each orbit
        - Number and occurrence of mission outcome per orbit type
    - Creating a landing outcome label that shows the following:
        - 0 when the booster did not land successfully
        - 1 when the booster did land successfully
3. Exploratory Data Analysis
    - Using SQL queries to manipulate and evaluate the SpaceX dataset
    - Using Pandas and Matplotlib to visualize
4. Interactive Visual Analytics
    - Geospatial analytics using Folium
    - Creating an interactive dashboard using Plotly Dash
5. Data Modelling and Evaluation
    - Using Scikit-Learn to:
        - Pre-process (standardize) the data
        - Split the data into training and testing data using train_test_split
        - Train different classification models
        - Find hyperparameters using GridSearchCV
    - Plotting confusion matrices for each classification model
    - Assessing the accuracy of each classification

DATA COLLECTION SPACE X REST API

Here I have used the SpaceX API to retrieve data about launches, including information about the rocket used, payload etc.

1

- Make a GET response to the SpaceX REST API
- Convert the response to a .json file then to a Pandas DataFrame

2

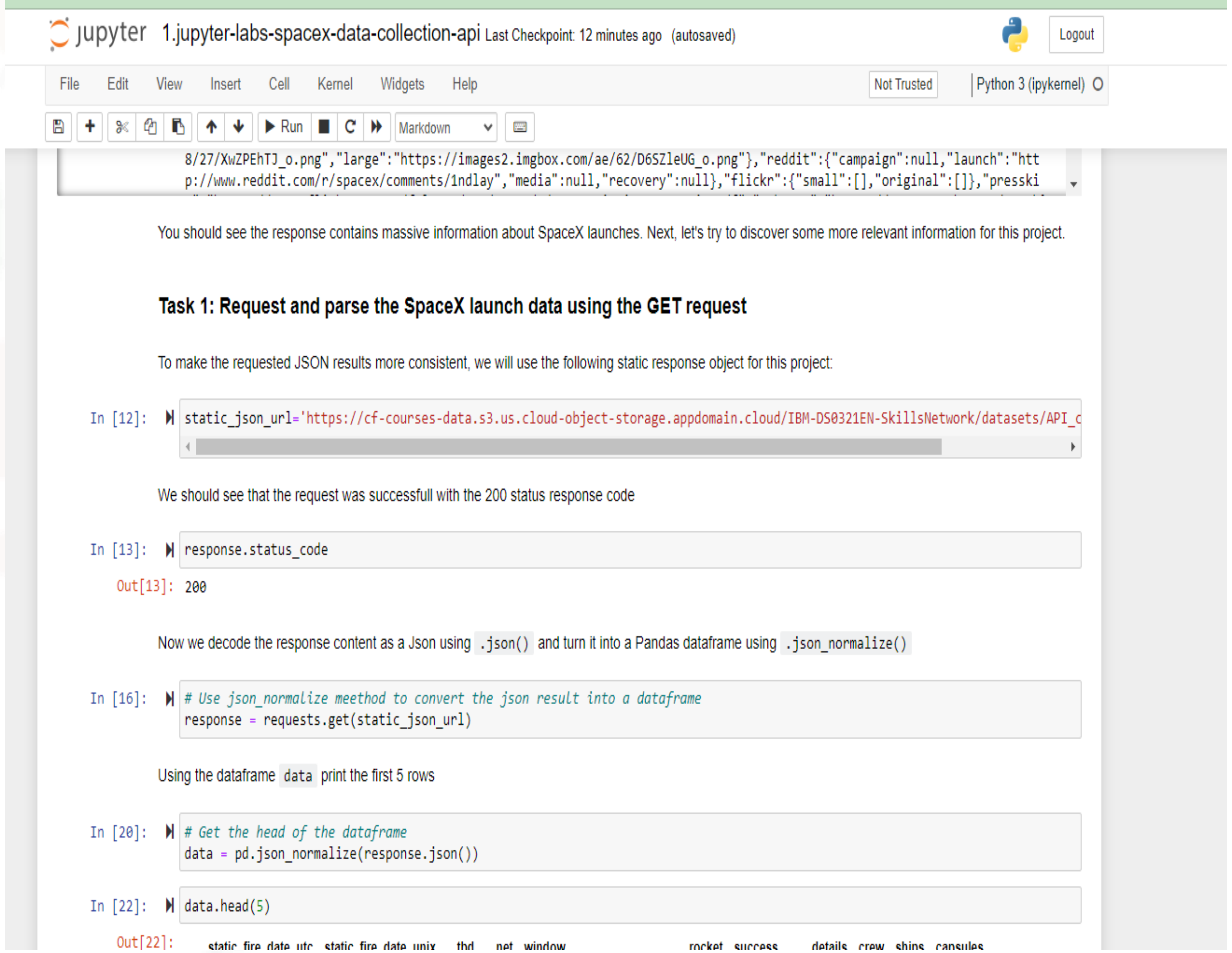
- Use custom logic to clean the data
- Define lists for data to be stored in
- Call custom functions to retrieve data and fill the lists
- Use these lists as values in a dictionary and construct the dataset

3

- Create a Pandas DataFrame from the constructed dictionary dataset

4

- Filter the DataFrame to only include Falcon 9 launches
- Reset the FlightNumber column
- Replace missing values of PayloadMass with the mean PayloadMass value



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SKILLS NETWORK

[GitHub Link](#)

DATA COLLECTION SPACE X REST API

1
- Make a GET response to the SpaceX REST API
- Convert the response to a .json file then to a Pandas DataFrame

2
- Use custom logic to clean the data (see Appendix)
- Define lists for data to be stored in
- Call custom functions (see Appendix) to retrieve data and fill the lists
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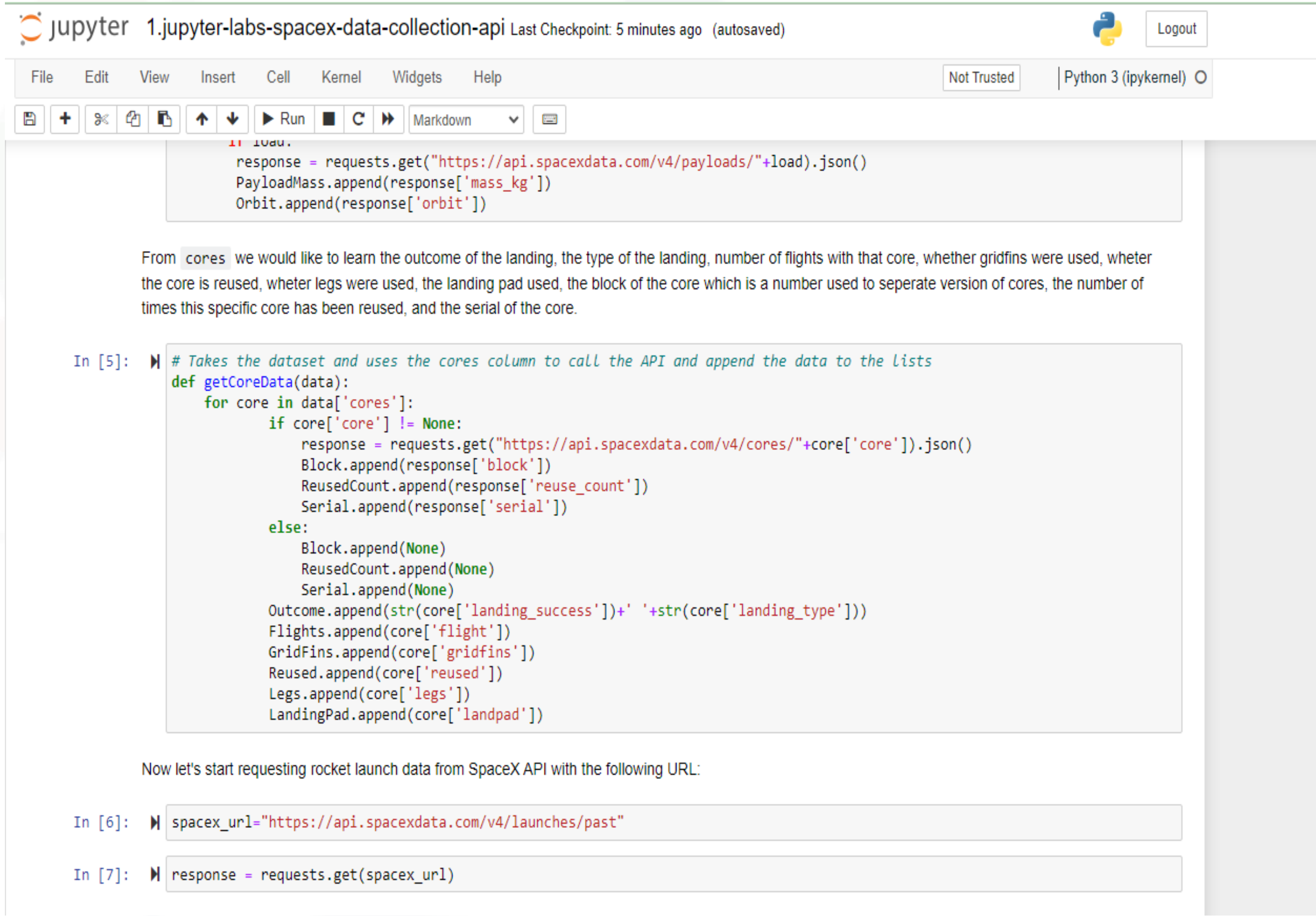



```python
        response = requests.get("https://api.spacexdata.com/v4/payloads/"+load).json()
        PayloadMass.append(response['mass_kg'])
        Orbit.append(response['orbit'])
```

From `cores` we would like to learn the outcome of the landing, the type of the landing, number of flights with that core, whether gridfins were used, wheter the core is reused, wheter legs were used, the landing pad used, the block of the core which is a number used to seperate version of cores, the number of times this specific core has been reused, and the serial of the core.

In [5]:
```python
# Takes the dataset and uses the cores column to call the API and append the data to the lists
def getCoreData(data):
    for core in data['cores']:
            if core['core'] != None:
                response = requests.get("https://api.spacexdata.com/v4/cores/"+core['core']).json()
                Block.append(response['block'])
                ReusedCount.append(response['reuse_count'])
                Serial.append(response['serial'])
            else:
                Block.append(None)
                ReusedCount.append(None)
                Serial.append(None)
            Outcome.append(str(core['landing_success'])+' '+str(core['landing_type']))
            Flights.append(core['flight'])
            GridFins.append(core['gridfins'])
            Reused.append(core['reused'])
            Legs.append(core['legs'])
            LandingPad.append(core['landpad'])
```

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

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

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

DATA COLLECTION – WEB SCRAPING

Web scraping to collect Falcon 9 historical launch records from a Wikipedia page titled List of Falcon 9 and Falcon Heavy launches.

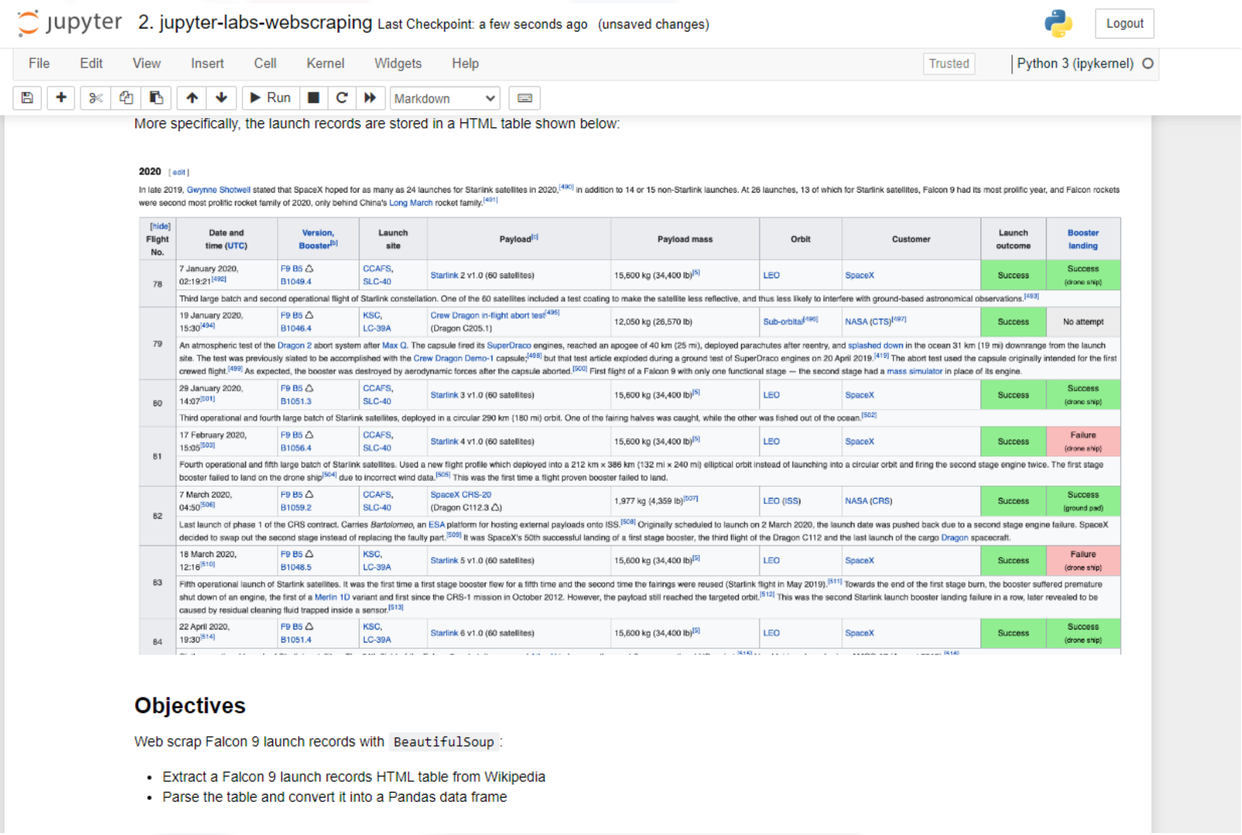
- Request the HTML page from the static URL
- Assign the response to an object

- Create a BeautifulSoup object from the HTML response object
- Find all tables within the HTML page

- Collect all column header names from the tables found within the HTML page

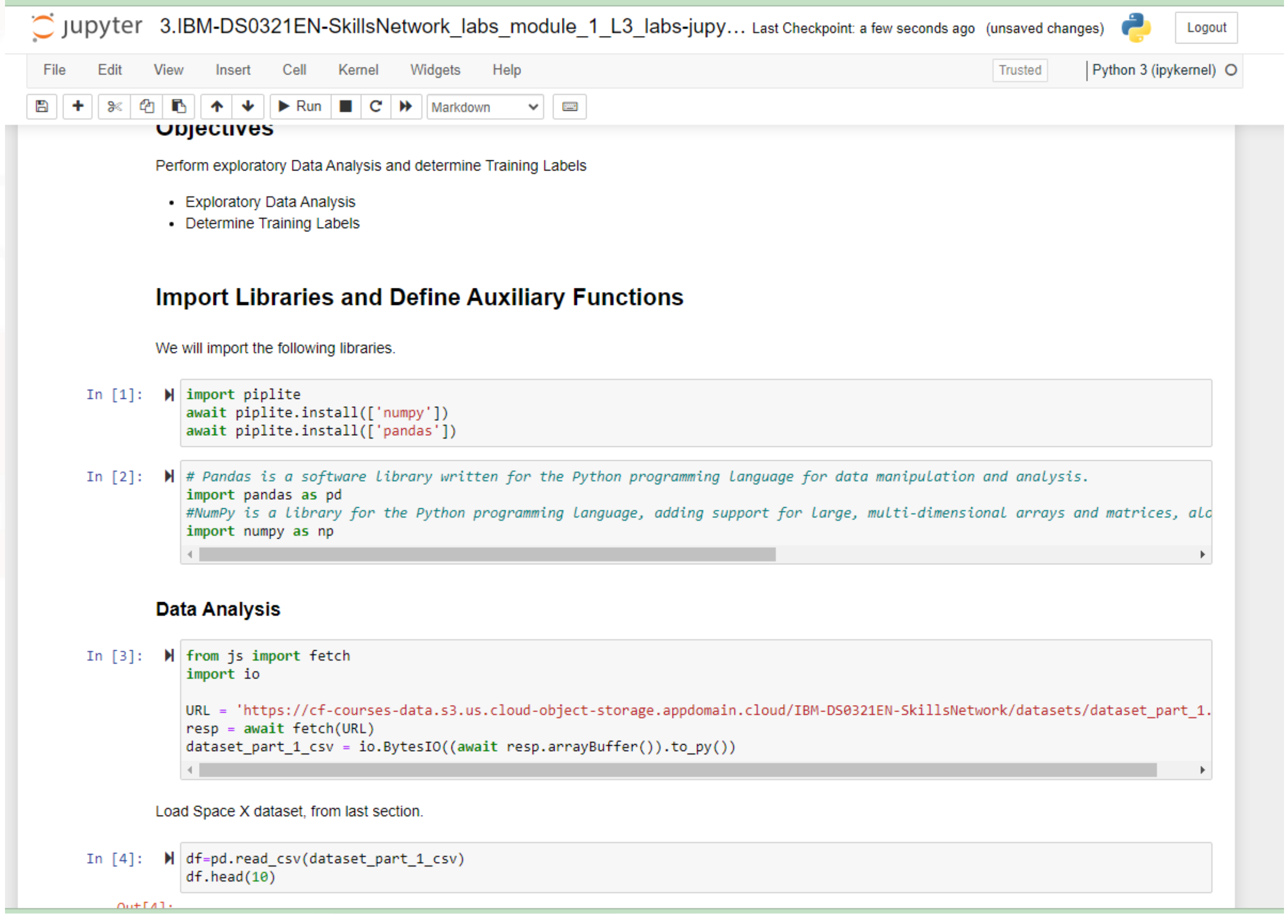
- Use the column names as keys in a dictionary
- Use custom functions and logic to parse all launch tables to fill the dictionary values

- Convert the dictionary to a Pandas DataFrame ready for export



DATA MANIPULATION/WRANGLING-PANDAS

1. Defining a set of unsuccessful outcomes
2. Creating a list, landing_class, where the element is 0 if the corresponding row in Outcome is in the set bad_outcome, otherwise, it's 1.
3. Create a Class column that contains the values from the list landing_class
4. Export the DataFrame as a .csv file



EXPLORATORY DATA ANALYSIS(EDA)-VISUALIZATION

SCATTER CHARTS

Scatter charts were produced to visualize the relationships between:

- Flight Number and Launch Site
- Payload and Launch Site
- Orbit Type and Flight Number
- Payload and Orbit Type

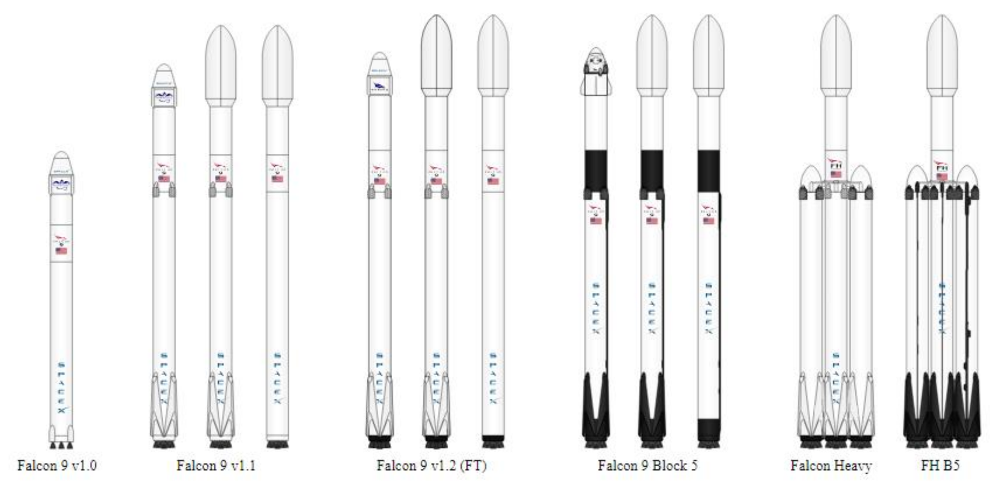
BAR CHART

A bar chart was produced to visualize the relationship between:

- Success Rate and Orbit Type

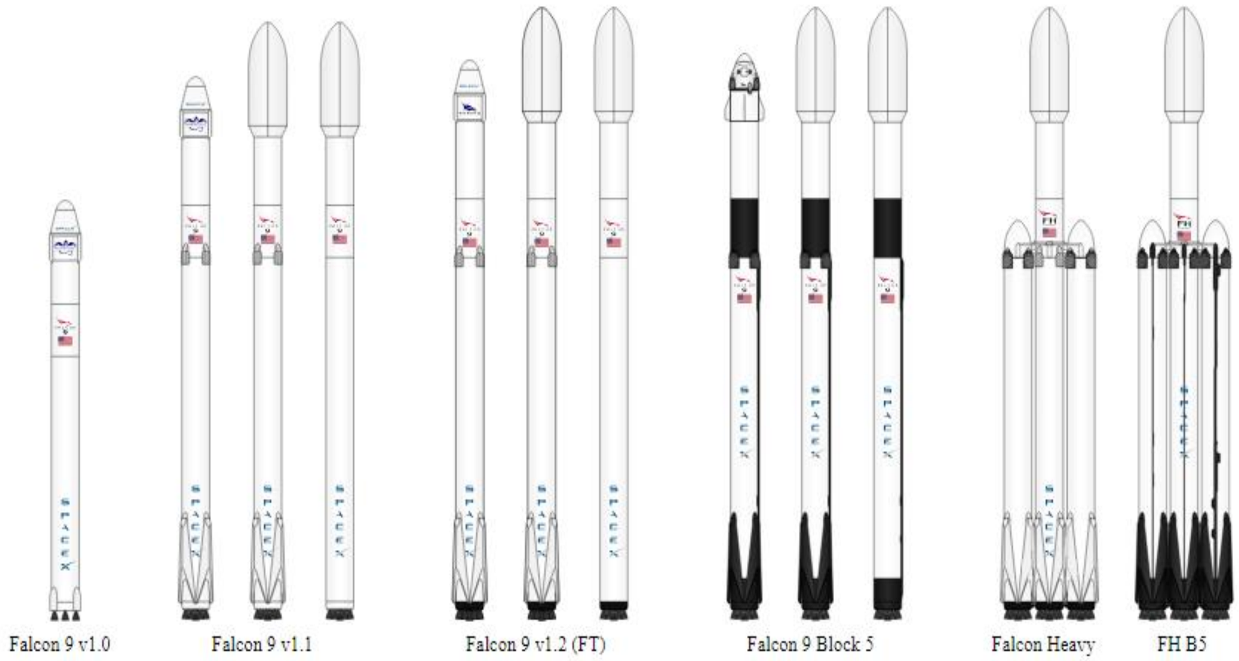
LINE CHARTS

- Success Rate and



Results

- Exploratory Data Analytics
- Interactive Data Analytics
- Predictive Analytics



EDA with Visualizations

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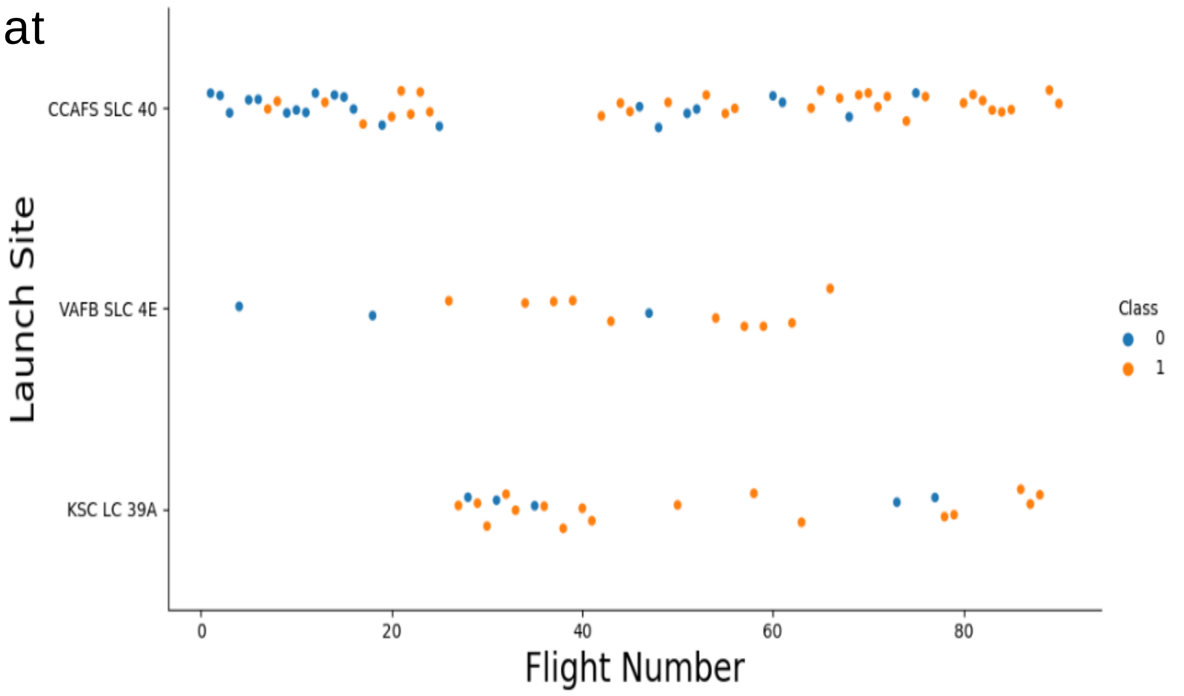
Launch Site Vs Flight Number (Cat plot)

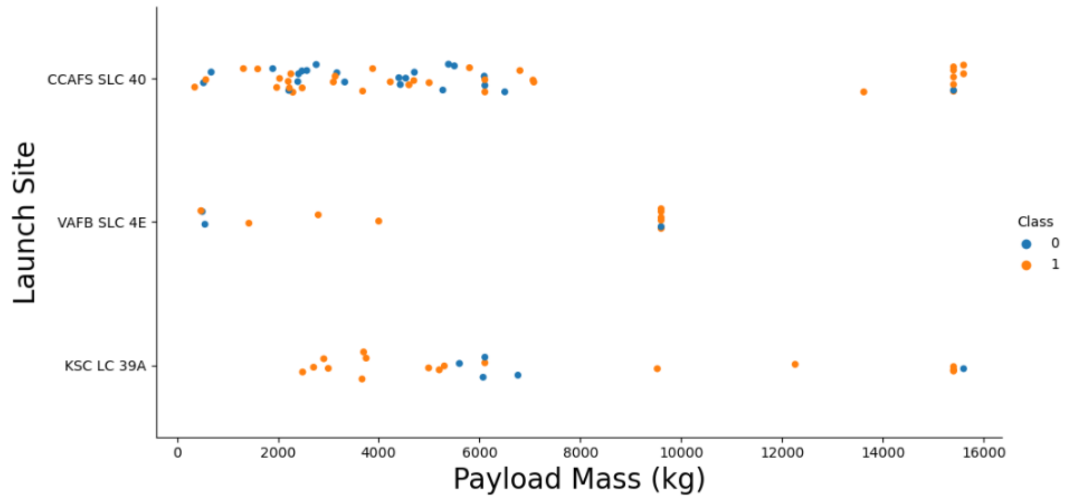
The Cat plot of Launch Site vs. Flight Number shows that:

- As the number of flights increases, the rate of success at a launch site increases.
- Most of the early flights (flight numbers < 30) were launched from CCAFS SLC 40, and were generally unsuccessful.
- The flights from VAFB SLC 4E also show this trend, that earlier flights were less successful.
- No early flights were launched from KSC LC 39A, so the launches from this site are more successful.
- Above a flight number of around 30, there are significantly more successful landings (Class = 1).



Launch Site vs Payload Mass

- The scatter plot of Launch Site vs. Payload Mass shows that:
- Above a payload mass of around 7000 kg, there are very few unsuccessful landings, but there is also far less data for these heavier launches.
- There is no clear correlation between payload mass and success rate for a given launch site.
- All sites launched a variety of payload masses, with most of the launches from CCAFS SLC 40 being comparatively lighter payloads (with some outliers).

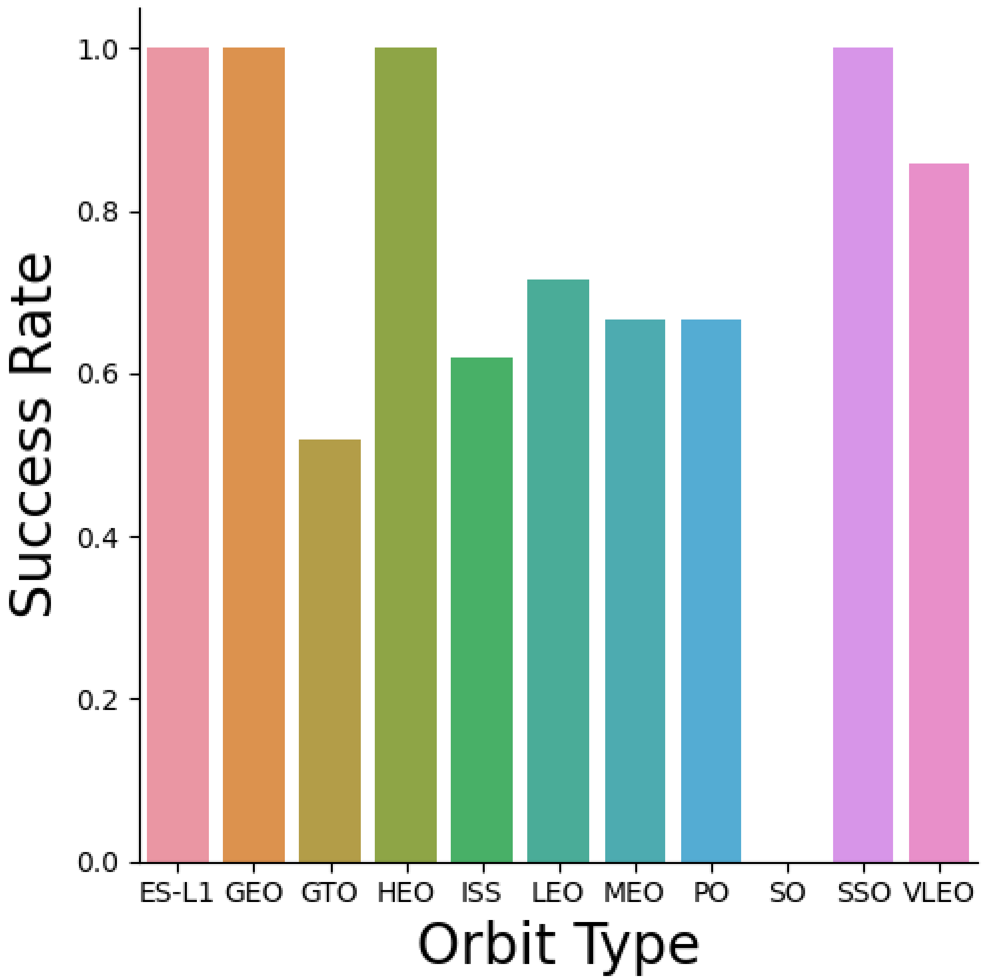


Success Rate vs Orbit Type

The bar chart of Success Rate vs. Orbit Type shows that the following orbits have the highest (100%) success rate:

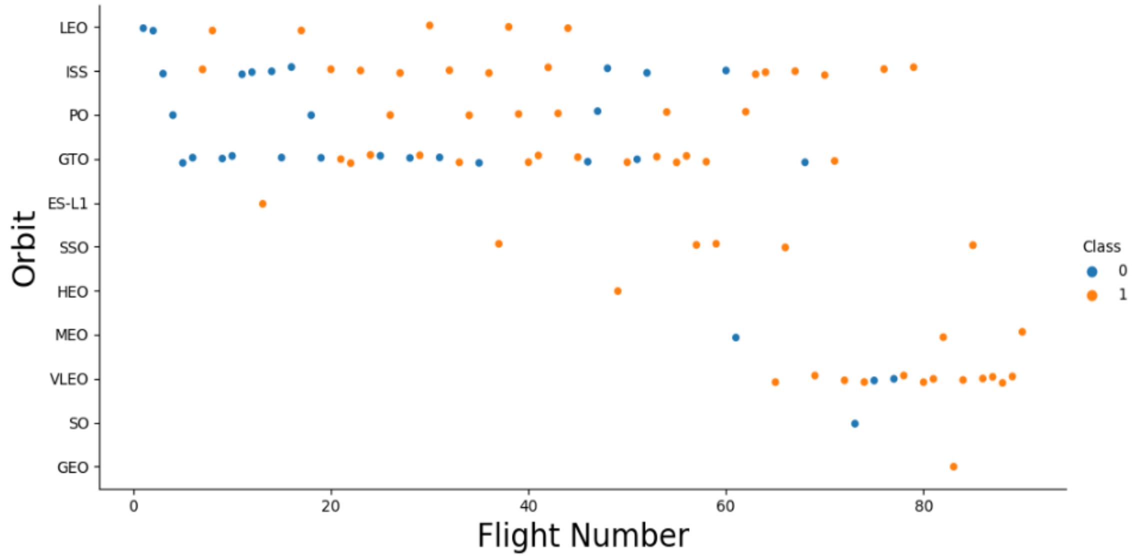
- ES-L1 (Earth-Sun First Lagrangian Point)
- GEO (Geostationary Orbit)
- HEO (High Earth Orbit)
- SSO (Sun-synchronous Orbit)

Observation: SO = 0% success rate



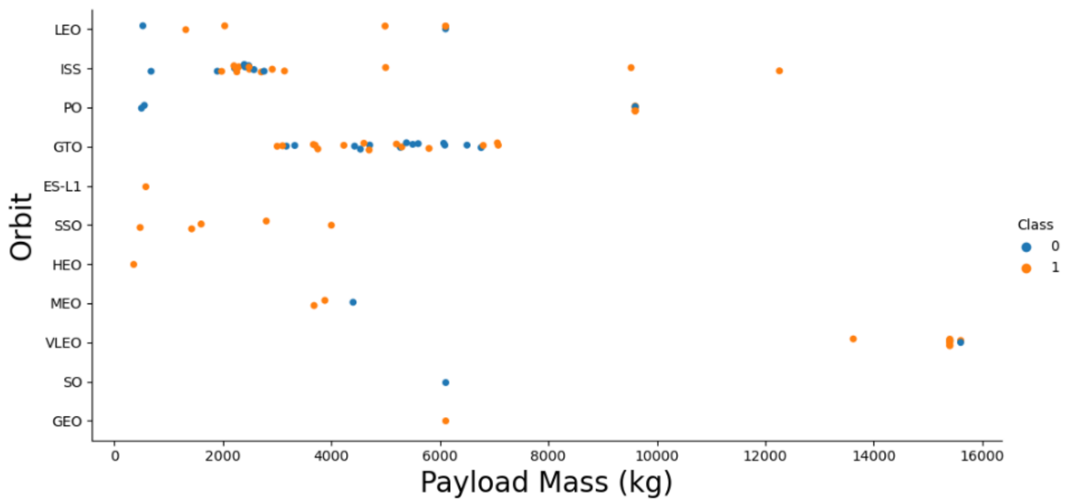
Orbit Type vs Flight Number

- This scatter plot of Orbit Type vs. Flight number shows a few useful things that the previous plots did not, such as:
  - The 100% success rate of GEO, HEO, and ES-L1 orbits can be explained by only having 1 flight into the respective orbits.
  - The 100% success rate in SSO is more impressive, with 5 successful flights.
  - There is little relationship between Flight Number and Success Rate for GTO.



Orbit Type vs Payload Mass

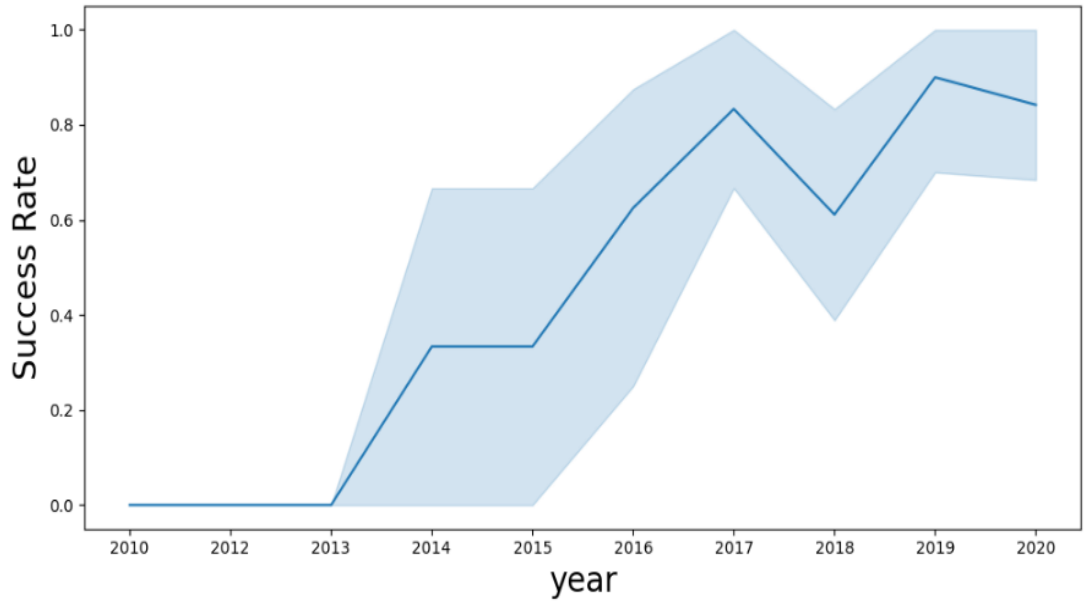
- This scatter plot of Orbit Type vs. Payload Mass shows that:
- The following orbit types have more success with
- heavy payloads:
  - PO (although the number of data points is small)
  - ISS
  - LEO
- For GTO, the relationship between payload mass and success rate is unclear.
- VLEO (Very Low Earth Orbit) launches are associated with heavier payloads, which makes intuitive sense.



Success Rate vs Year

The line chart of yearly average success rate shows that:

- Between 2010 and 2013, all landings were
- unsuccessful (as the success rate is 0).
- After 2013, the success rate generally increased, despite small dips in 2018 and 2020.
- After 2016, there was always a greater than 50% chance of success.



EDA with SQL

Launch Sites

```
Out[18]: ['CCAFS LC-40', 'VAFB SLC-4E', 'KSC LC-39A', 'CCAFS SLC-40', nan]
```

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

```
In [17]: %sql SELECT LAUNCH_SITE FROM SPACEXTBL WHERE LAUNCH_SITE LIKE 'CCA%' LIMIT 5;

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

Out[17]:

Launch_Site
CCAFS LC-40
CCAFS LC-40
CCAFS LC-40
CCAFS LC-40
CCAFS LC-40

Avg Payload Mass

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

In [19]:
```
%sql SELECT SUM(PAYLOAD_MASS__KG_) AS TOTAL_PAYLOAD_MASS FROM SPACEXTBL \
    WHERE CUSTOMER = 'NASA (CRS)';
```

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

Out[19]:

TOTAL_PAYLOAD_MASS
45596.0

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

]:
```
%sql SELECT AVG(PAYLOAD_MASS__KG_) AS AVERAGE_PAYLOAD_MASS FROM SPACEXTBL \
    WHERE BOOSTER_VERSION = 'F9 v1.1';
```

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

t[20]:

AVERAGE_PAYLOAD_MASS
2928.4

Successful Landing Dates

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

Hint:Use min function

```
%sql SELECT MIN(DATE) AS FIRST_SUCCESSFUL_GROUND_LANDING FROM SPACEXTBL WHERE LANDING_OUTCOME = 'Success (ground pad)';
```

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

0]:

FIRST_SUCCESSFUL_GROUND_LANDING
01/08/2018

```
%sql SELECT MAX(DATE) AS FIRST_SUCCESSFUL_GROUND_LANDING FROM SPACEXTBL WHERE LANDING_OUTCOME = 'Success (ground pad)';
```

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

1]:

FIRST_SUCCESSFUL_GROUND_LANDING
22/12/2015

Booster Versions

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

```
%sql SELECT BOOSTER_VERSION FROM SPACEXTBL WHERE (LANDING_OUTCOME = 'Success (drone ship)') AND (PAYLOAD_MASS__KG_ BETWEEN 40
```

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

9]:

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

Successful and Failure Missions

List the total number of successful and failure mission outcomes

```
:    %sql SELECT MISSION_OUTCOME, COUNT(MISSION_OUTCOME) AS TOTAL_NUMBER FROM SPACEXTBL GROUP BY MISSION_OUTCOME;
```

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

[42]:

Mission_Outcome	TOTAL_NUMBER
None	0
Failure (in flight)	1
Success	98
Success	1
Success (payload status unclear)	1

Booster Versions with Payloads

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

```
%sql SELECT DISTINCT(BOOSTER_VERSION) FROM SPACEXTBL \
    WHERE PAYLOAD_MASS__KG_ = (SELECT MAX(PAYLOAD_MASS__KG_) FROM SPACEXTBL);
```

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

4]:

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

Month and Year of Failure

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

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

```
%sql SELECT substr(Date,4,2) as month, DATE,BOOSTER_VERSION, LAUNCH_SITE, [LANDING_OUTCOME] FROM SPACEXTBL where [LANDING_OUT
```

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

;1]:

month	Date	Booster_Version	Launch_Site	Landing_Outcome
10	01/10/2015	F9 v1.1 B1012	CCAFS LC-40	Failure (drone ship)
04	14/04/2015	F9 v1.1 B1015	CCAFS LC-40	Failure (drone ship)

Count of Outcomes

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.

```
%sql SELECT [LANDING_OUTCOME], count(*) as count_outcomes FROM SPACEXTBL WHERE DATE between '04-06-2010' and '20-03-2017' grc
```

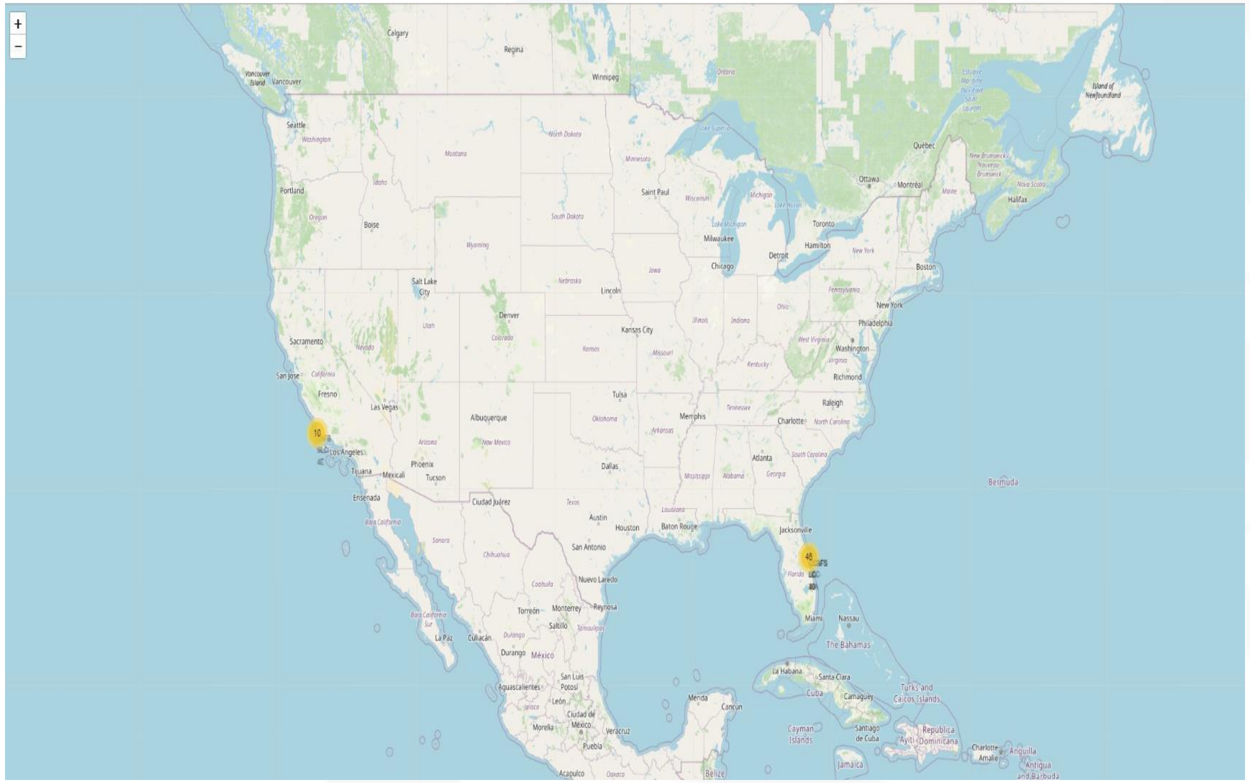
```
 * sqlite:///my_data1.db
Done.
```

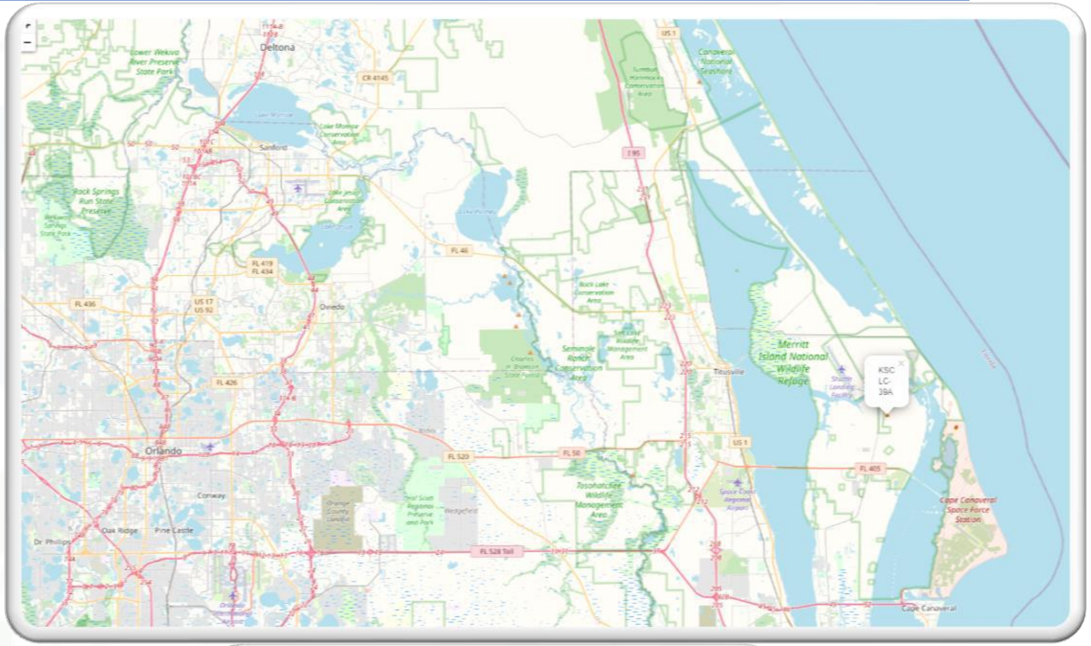
53]:

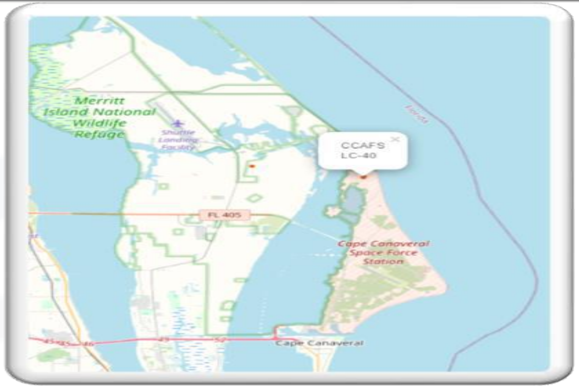
Landing_Outcome	count_outcomes
Success	20
No attempt	10
Success (drone ship)	8
Success (ground pad)	7
Failure (drone ship)	3
Failure	3
Failure (parachute)	2
Controlled (ocean)	2
No attempt	1

Launch Site Analysis- Folium Interactive Map

Launching Sites







Launch Outcomes

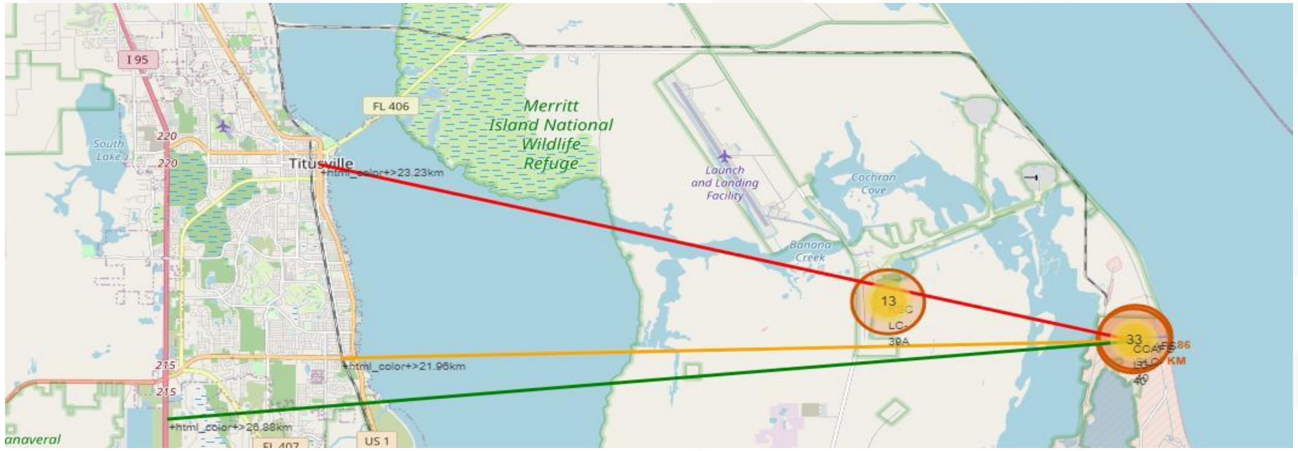
At Each Launch Site

- **Green** markers for successful launches
- **Red** markers for unsuccessful launches
- Launch site **CCAFS SLC-40** has a **3/7 success rate** (**42.9%)**

Distance to Proximities

CCAFS SLC-40

- **Coasts**: help ensure that spent stages dropped along the launch path or failed launches don't fall on people or property.
- **Safety / Security:** needs to be an exclusion zone around the launch site to keep unauthorized people away and keep people safe.
- **Transportation/Infrastructure and Cities**: need to be away from anything a failed launch can damage, but still close enough to roads/rails/docks to be able to bring people and material to or from it in support of launch activities.

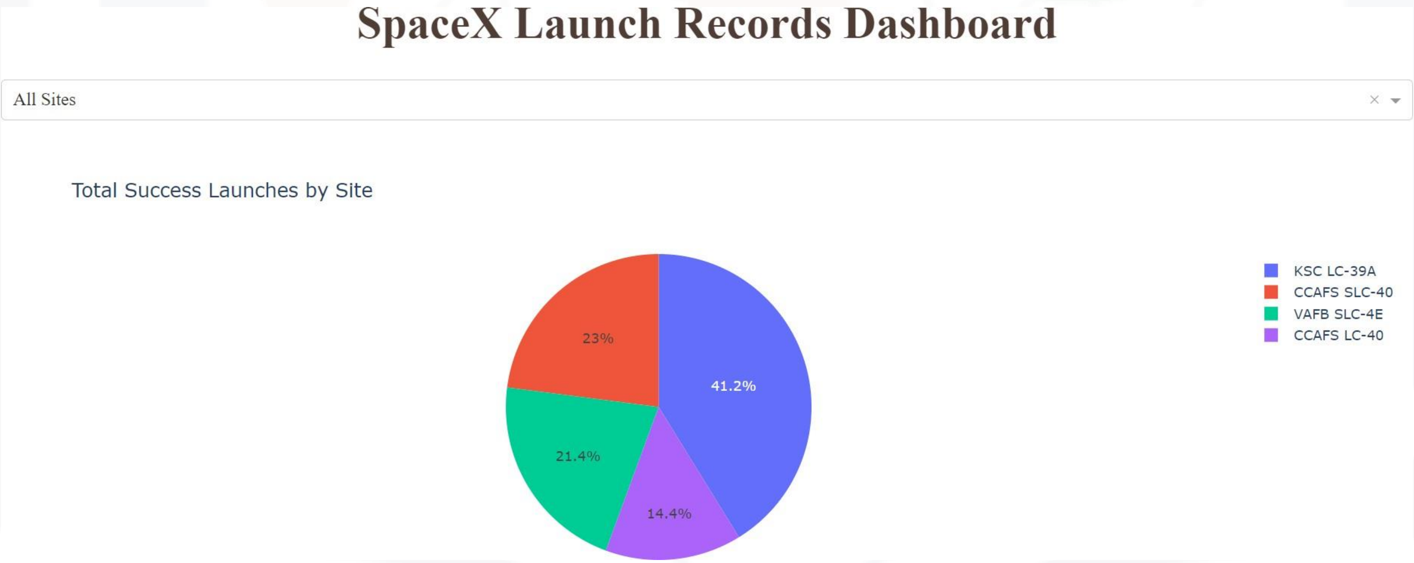


Plotly Analytics-Dashboards

Launch Success by Site

Success as Percent of Total

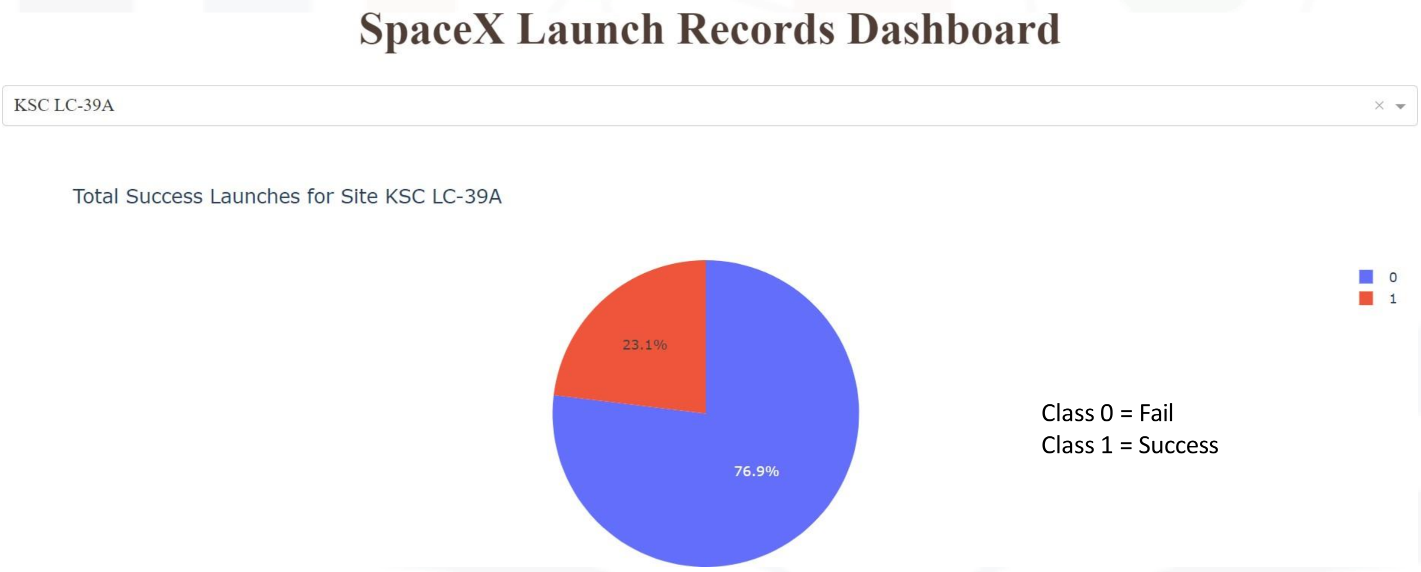
- **KSC LC-39A** has the **most successful launches** amongst launch sites (**41.2%**)



Launch Success (KSC LC-29A)

Success as Percent of Total

- **KSC LC-39A** has the **highest success rate** amongst launch sites (**76.9%**)
- 10 successful launches and 3 failed launches



Payload Mass and Success

By Booster Version

- **Payloads between 2,000 kg** and **5,000 kg** have the **highest success rate**
- 1 indicating successful outcome and 0 indicating an unsuccessful outcome

Predictive Analytics

Classification

Accuracy

- **All** the **models** performed at about the same level and had the **same scores** and **accuracy**. This is likely due to the **small dataset**. The **Decision Tree model slightly outperformed** the rest when looking at .best_score_
- .best_score_ is the average of all cv folds for a single combination of the parameters

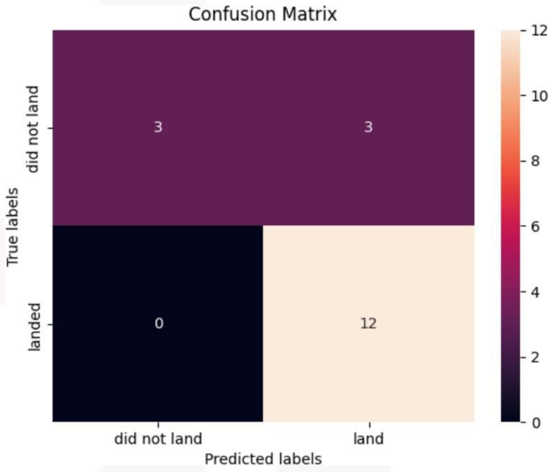
```
models = {'KNeighbors':knn_cv.best_score_,
              'DecisionTree':tree_cv.best_score_,
              'LogisticRegression':logreg_cv.best_score_,
              'SupportVector': svm_cv.best_score_}

bestalgorithm = max(models, key=models.get)
print('Best model is', bestalgorithm,'with a score of', models[bestalgorithm])
if bestalgorithm == 'DecisionTree':
    print('Best params is :', tree_cv.best_params_)
if bestalgorithm == 'KNeighbors':
    print('Best params is :', knn_cv.best_params_)
if bestalgorithm == 'LogisticRegression':
    print('Best params is :', logreg_cv.best_params_)
if bestalgorithm == 'SupportVector':
    print('Best params is :', svm_cv.best_params_)
```

```
Best model is DecisionTree with a score of 0.9017857142857142
Best params is : {'criterion': 'gini', 'max_depth': 16, 'max_features': 'auto', 'min_samples_leaf': 4, 'min_samples_split': 10, 'splitter': 'random'}
```

Confusion Matrices

- Confusion Matrix Outputs:
  - 12 True positive
  - 3 True negative
  - **3 False positive**
  - 0 False Negative
- **Precision** = TP / (TP + FP)
  - 12 / 15 = .80
- **Recall** = TP / (TP + FN)
  - 12 / 12 = 1
- **F1 Score** = 2 * (Precision * Recall) / (Precision + Recall)
  - 2 * (.8 * 1) / (.8 + 1) = .89
- **Accuracy** = (TP + TN) / (TP + TN + FP + FN) = .833



Conclusion

Observations:

- **Model Performance**: The models performed similarly on the test set with the decision tree model slightly outperforming
- **Equator**: Most of the launch sites are near the equator for an additional natural boost - due to the rotational speed of earth - which helps save the cost of putting in extra fuel and boosters
- **Coast**: All the launch sites are close to the coast
- **Launch Success**: Increases over time
- **KSC LC-39A**: Has the highest success rate among launch sites. Has a 100% success rate for launches less than 5,500 kg
- **Orbits**: ES-L1, GEO, HEO, and SSO have a 100% success rate
- **Payload Mass**: Across all launch sites, the higher the payload mass (kg), the higher the success rate

Conclusion

Things to Consider

- **Dataset**: A larger dataset will help build on the predictive analytics results to help understand if the findings can be generalizable to a larger data set
- **Feature Analysis / PCA**: Additional feature analysis or principal component analysis should be conducted to see if it can help improve accuracy

APPENDIX

- Custom functions for web scraping
- Custom logic to fill up the launch_dict values with values from the launch tables