

Winning Space Race with Data Science

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Outline

- Executive Summary
- Introduction
- Methodology
- Results
- Conclusion
- Appendix

Executive Summary

- **Summary of Methodologies:**

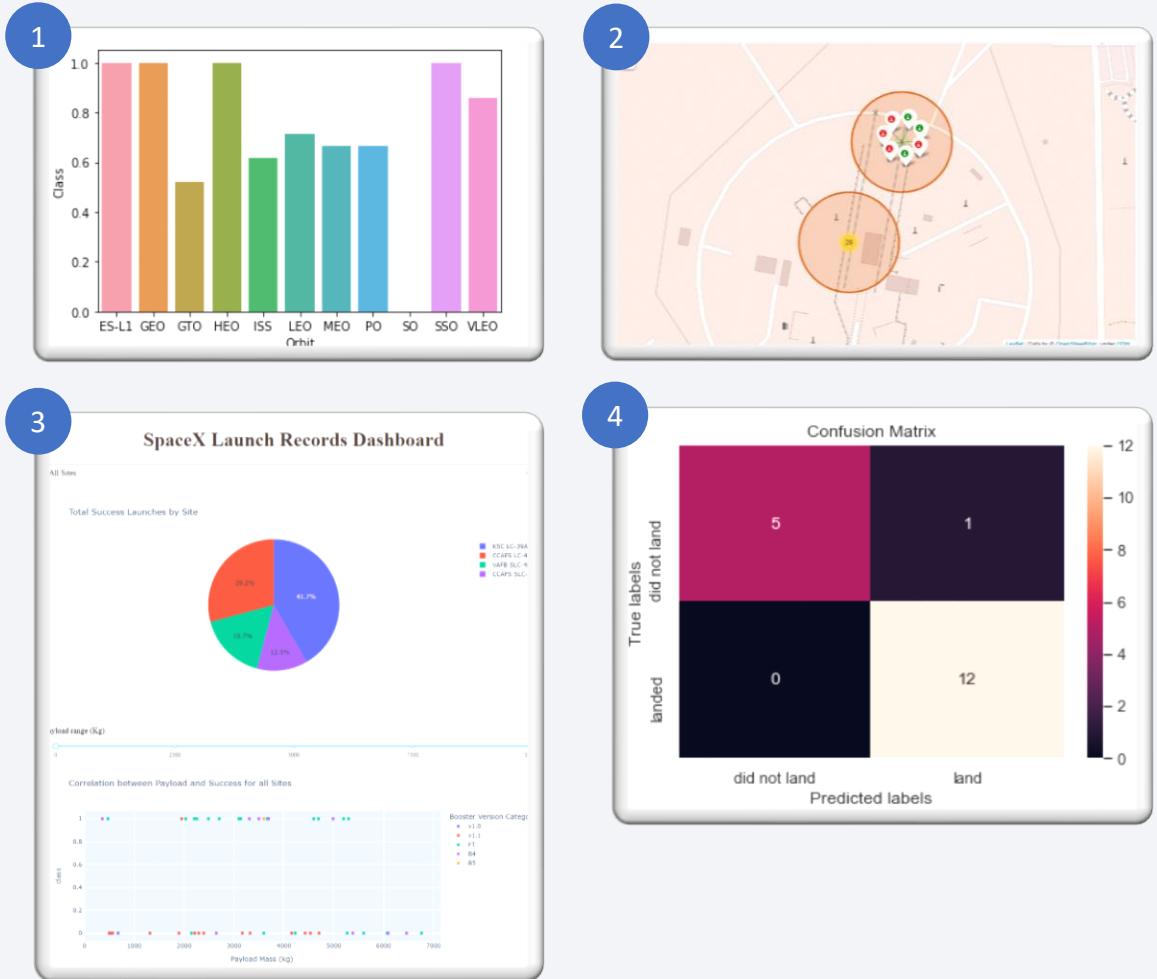
This project follows these steps:

- Data Collection
- Data Wrangling
- Exploratory Data Analysis
- Interactive Visual Analytics
- Predictive Analysis (Classification)

- **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.**

Section 1

Methodology

Methodology

Executive Summary

- Data collection methodology:
 - Making GET requests to the SpaceX REST API
 - Web Scraping
- Perform 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
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
 - 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 model

Data Collection – SpaceX API

Using the SpaceX API to retrieve data about launches, including information about the rocket used, payload delivered, launch specifications, landing specifications, and landing outcome.

- 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
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

```
1 spacex_url="https://api.spacexdata.com/v4/launches/past"
response = requests.get(spacex_url)

# Use json_normalize method to convert the json result into a dataframe
data = pd.json_normalize(response.json())
```

```
2 #Global variables
BoosterVersion = []
PayloadMass = []
Orbit = []
LaunchSite = []
Outcome = []
Flights = []
GridFins = []
Reused = []
Legs = []
LandingPad = []
Block = []
ReusedCount = []
Serial = []
Longitude = []
Latitude = []
```

```
# Call getBoosterVersion
getBoosterVersion(data)

# Call getLaunchSite
getLaunchSite(data)

# Call getPayloadData
getPayloadData(data)

# Call getCoreData
getCoreData(data)
```

```
launch_dict = {'FlightNumber': list(data['flight_number']),
'Date': list(data['date']),
'BoosterVersion':BoosterVersion,
'PayloadMass':PayloadMass,
'Orbit':Orbit,
'LaunchSite':LaunchSite,
'Outcome':Outcome,
'Flights':Flights,
'GridFins':GridFins,
'Reused':Reused,
'Legs':Legs,
'LandingPad':LandingPad,
'Block':Block,
'ReusedCount':ReusedCount,
'Serial':Serial,
'Longitude': Longitude,
'Latitude': Latitude}
```

```
3 # Create a data from launch_dict
df = pd.DataFrame.from_dict(launch_dict)
```

```
4 data_falcon9 = df[df['BoosterVersion']!='Falcon 1']
```

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

```
# Calculate the mean value of PayloadMass column and Replace the np.nan values with its mean value
data_falcon9 = data_falcon9.fillna(value={'PayloadMass': data_falcon9['PayloadMass'].mean()})
```

Data Collection - Scraping

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

1

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

2

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

3

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

4

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

5

- Convert the dictionary to a Pandas DataFrame ready for export

1

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

# use requests.get() method with the provided static_url
response = requests.get(static_url)
# assign the response to a object
data = response.text
```

2

```
soup = BeautifulSoup(data, 'html5lib')
html_tables = soup.find_all('table')
```

3

```
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

for row in first_launch_table.find_all('th'):
    name = extract_column_from_header(row)
    if(name != None and len(name) > 0):
        column_names.append(name)
```

4

```
launch_dict= dict.fromkeys(column_names)

# Remove an irrelevant column
del launch_dict['Date and time ( )']

# Let's initial the launch_dict with each value to be an empty list
launch_dict['Flight No.']= []
launch_dict['Launch site']= []
launch_dict['Payload']= []
launch_dict['Payload mass']= []
launch_dict['Orbit']= []
launch_dict['Customer']= []
launch_dict['Launch outcome']= []
# Added some new columns
launch_dict['Version Booster']= []
launch_dict['Booster landing']= []
launch_dict['Date']= []
launch_dict['Time']= []
```

5

```
df = pd.DataFrame(launch_dict)
```

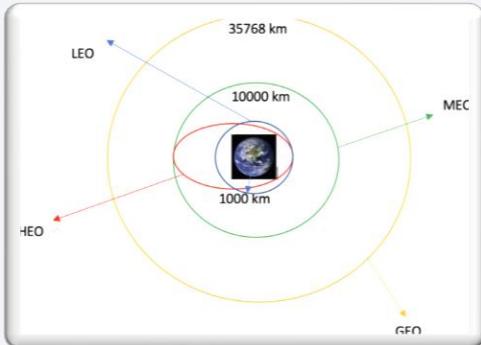
8

[GitHub Link](#)

Data Wrangling

Context:

- The SpaceX dataset contains several Space X launch facilities, and each location is in the **LaunchSite** column.
- Each launch aims to a dedicated orbit, and some of the common orbit types are shown in the figure below. The orbit type is in the **Orbit** column.



Data Wrangling:

- To determine whether a booster will successfully land, it is best to have a binary column, i.e., where the value is 1 or 0, representing the success of the landing.
- This is done by:
 - Defining a set of unsuccessful (bad) outcomes, **bad_outcome**
 - 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.
 - Create a **Class** column that contains the values from the list **landing_class**
 - Export the DataFrame as a .csv file.

1

```
bad_outcomes=set(landing_outcomes.keys()|[1,3,5,6,7])  
bad_outcomes  
{'False ASDS', 'False Ocean', 'False RTLS', 'None ASDS', 'None None'}
```

2

```
# 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)
```

3

```
df['Class']=landing_class
```

4

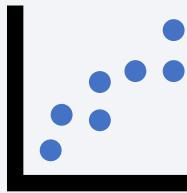
```
df.to_csv("dataset_part\2.csv", index=False)
```

EDA with Data 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



Scatter charts are useful to observe relationships, or correlations, between two numeric variables.

BAR CHART

A bar chart was produced to visualize the relationship between:

- Success Rate and Orbit Type

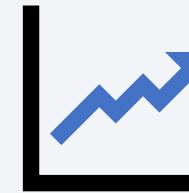


Bar charts are used to compare a numerical value to a categorical variable. Horizontal or vertical bar charts can be used, depending on the size of the data.

LINE CHARTS

Line charts were produced to visualize the relationships between:

- Success Rate and Year (i.e. the launch success yearly trend)



Line charts contain numerical values on both axes and are generally used to show the change of a variable over time.

EDA with SQL

To gather some information about the dataset, some SQL queries were performed.

The SQL queries performed on the data set were used to:

1. Display the names of the unique launch sites in the space mission
2. Display 5 records where launch sites begin with the string 'CCA'
3. Display the total payload mass carried by boosters launched by NASA (CRS)
4. Display the average payload mass carried by booster version F9 v1.1
5. List the date when the first successful landing outcome on a ground pad was achieved
6. List the names of the boosters which had success on a drone ship and a payload mass between 4000 and 6000 kg
7. List the total number of successful and failed mission outcomes
8. List the names of the booster versions which have carried the maximum payload mass
9. List the failed landing outcomes on drone ships, their booster versions, and launch site names for 2015
10. Rank the count of landing outcomes (such as Failure (drone ship) or Success (ground pad)) between the date 2010-06-04 and 2017-03-20, in descending order

Build an Interactive Map with Folium

The following steps were taken to visualize the launch data on an interactive map:

1. Mark all launch sites on a map
 - Initialise the map using a Folium **Map** object
 - Add a **folium.Circle** and **folium.Marker** for each launch site on the launch map
2. Mark the success/failed launches for each site on a map
 - As many launches have the same coordinates, it makes sense to cluster them together.
 - Before clustering them, assign a marker colour of successful (class = 1) as green, and failed (class = 0) as red.
 - To put the launches into clusters, for each launch, add a **folium.Marker** to the **MarkerCluster()** object.
 - Create an icon as a text label, assigning the **icon_color** as the **marker_colour** determined previously.
3. Calculate the distances between a launch site to its proximities
 - To explore the proximities of launch sites, calculations of distances between points can be made using the Lat and Long values.
 - After marking a point using the Lat and Long values, create a **folium.Marker** object to show the distance.
 - To display the distance line between two points, draw a **folium.PolyLine** and add this to the map.

Build a Dashboard with Plotly Dash

The following plots were added to a Plotly Dash dashboard to have an interactive visualisation of the data:

1. Pie chart (`px.pie()`) showing the total successful launches per site
 - This makes it clear to see which sites are most successful
 - The chart could also be filtered (using a `dcc.Dropdown()` object) to see the success/failure ratio for an individual site

2. Scatter graph (`px.scatter()`) to show the correlation between outcome (success or not) and payload mass (kg)
 - This could be filtered (using a `RangeSlider()` object) by ranges of payload masses
 - It could also be filtered by booster version

Predictive Analysis (Classification)

The following steps were taking to develop, evaluate, and find the best performing classification model:

Model Development



- To prepare the dataset for model development:
 - Load dataset
 - Perform necessary data transformations (standardise and pre-process)
 - Split data into training and test data sets, using `train_test_split()`
 - Decide which type of machine learning algorithms are most appropriate
- For each chosen algorithm:
 - Create a `GridSearchCV` object and a dictionary of parameters
 - Fit the object to the parameters
 - Use the training data set to train the model

Model Evaluation



- For each chosen algorithm:
 - Using the output `GridSearchCV` object:
 - Check the tuned hyperparameters (`best_params_`)
 - Check the accuracy (`score` and `best_score_`)
 - Plot and examine the Confusion Matrix

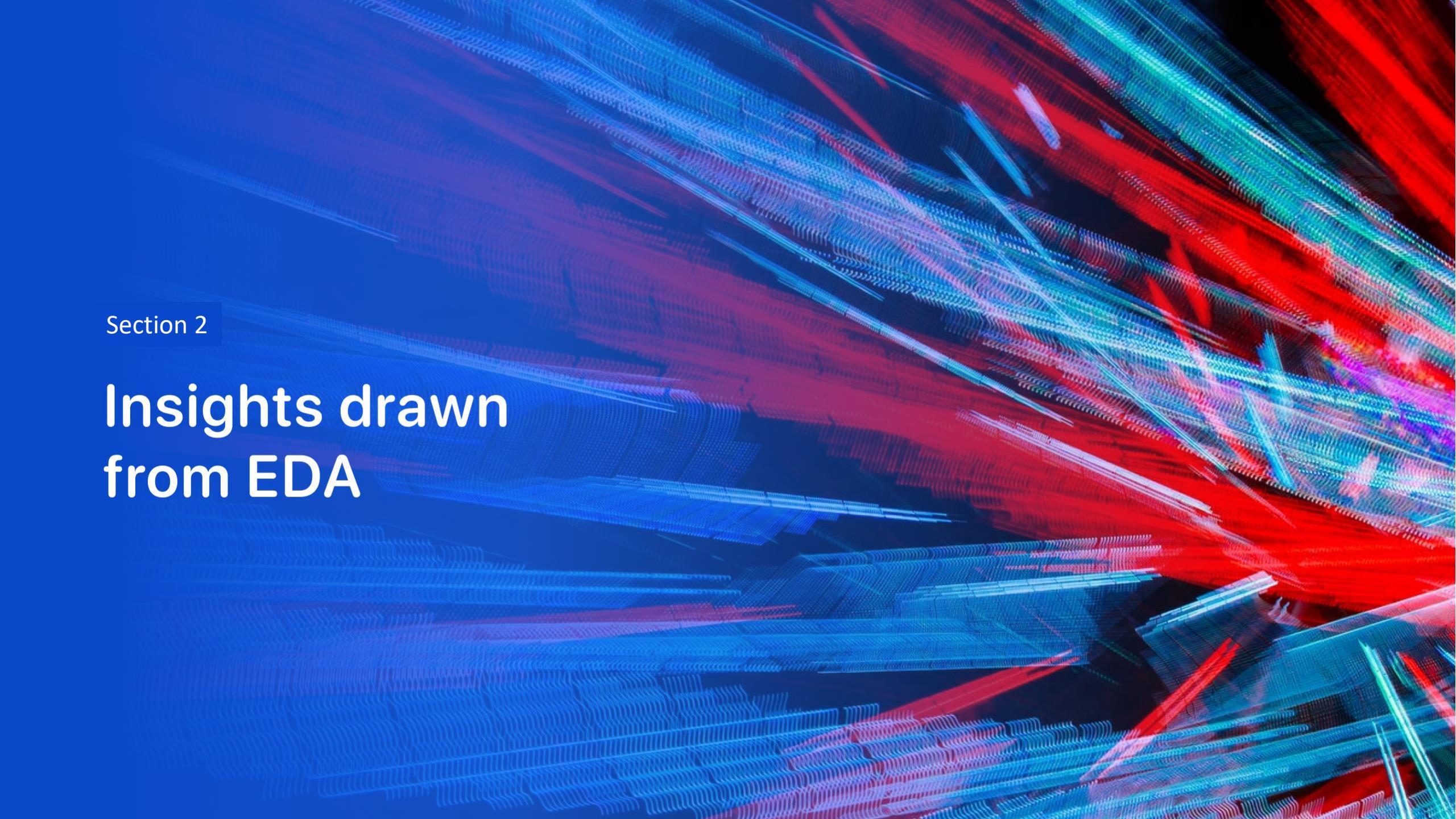
Finding the Best Classification Model



- Review the accuracy scores for all chosen algorithms
- The model with the highest accuracy score is determined as the best performing model

Results

- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results

The background of the slide features a complex, abstract digital visualization. It consists of numerous thin, glowing lines that create a sense of depth and motion. The lines are primarily blue and red, with some green and purple highlights. They form a grid-like structure that curves and twists across the frame, resembling a three-dimensional space or a network of data points. The overall effect is futuristic and dynamic.

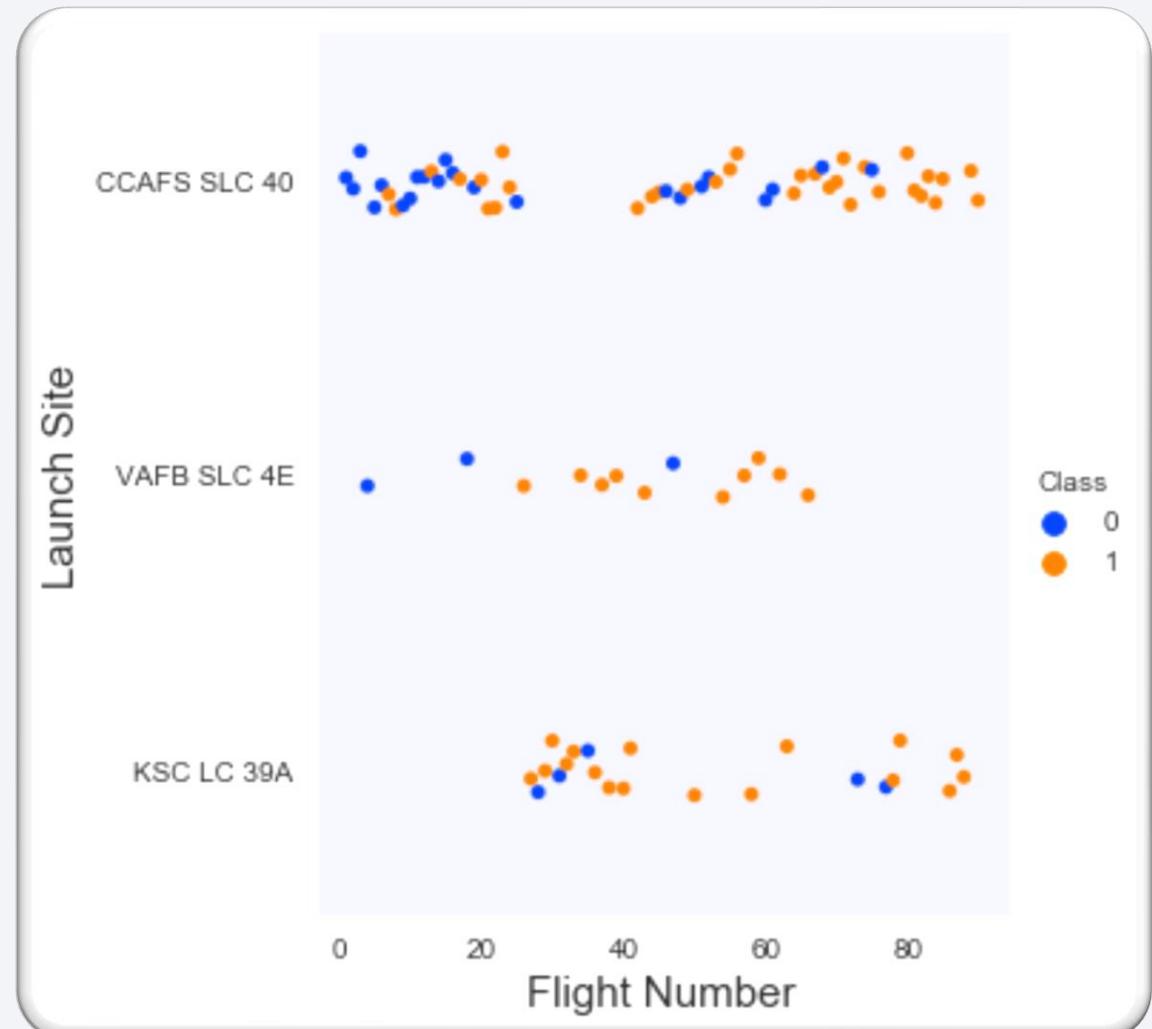
Section 2

Insights drawn from EDA

Flight Number vs. Launch Site

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

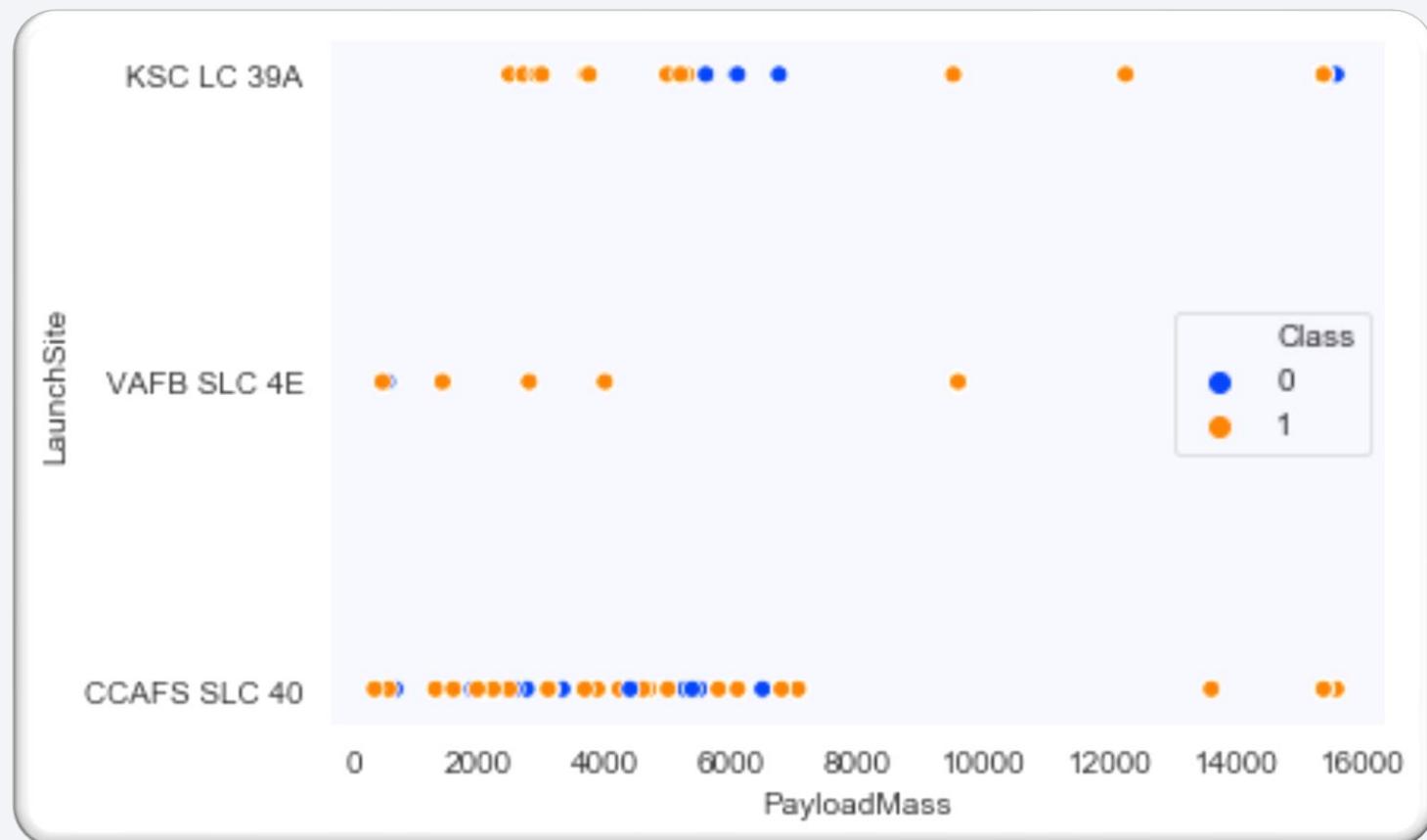
- As the number of flights increases, the rate of success at a launch site increases.
- Most of the early flights (flight numbers < 30) were launched from CCAFS SLC 40, and were generally unsuccessful.
- The flights from VAFB SLC 4E also show this trend, that earlier flights were less successful.
- No 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).



Payload vs. Launch Site

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).



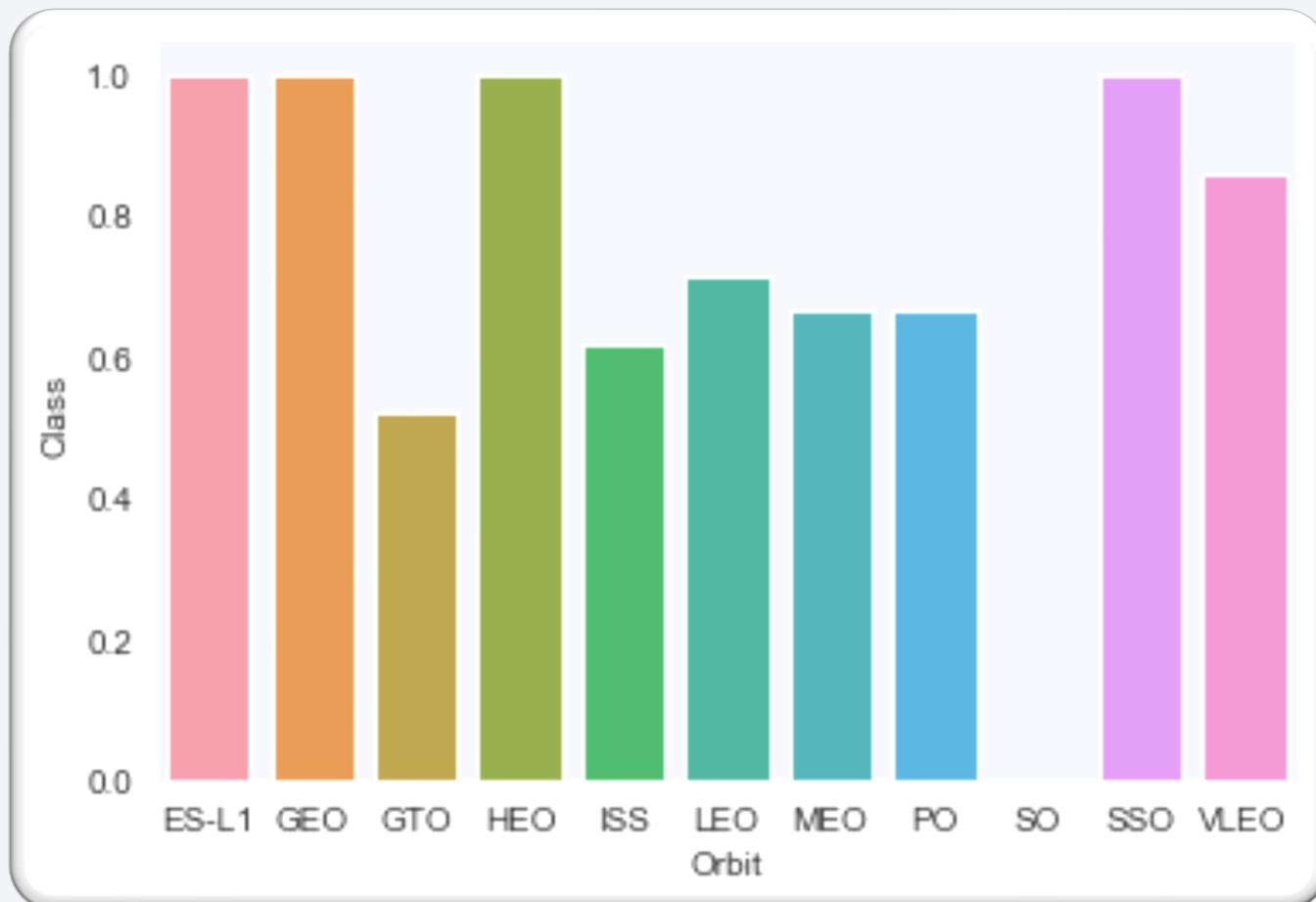
Success Rate vs. Orbit Type

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)

The orbit with the lowest (0%) success rate is:

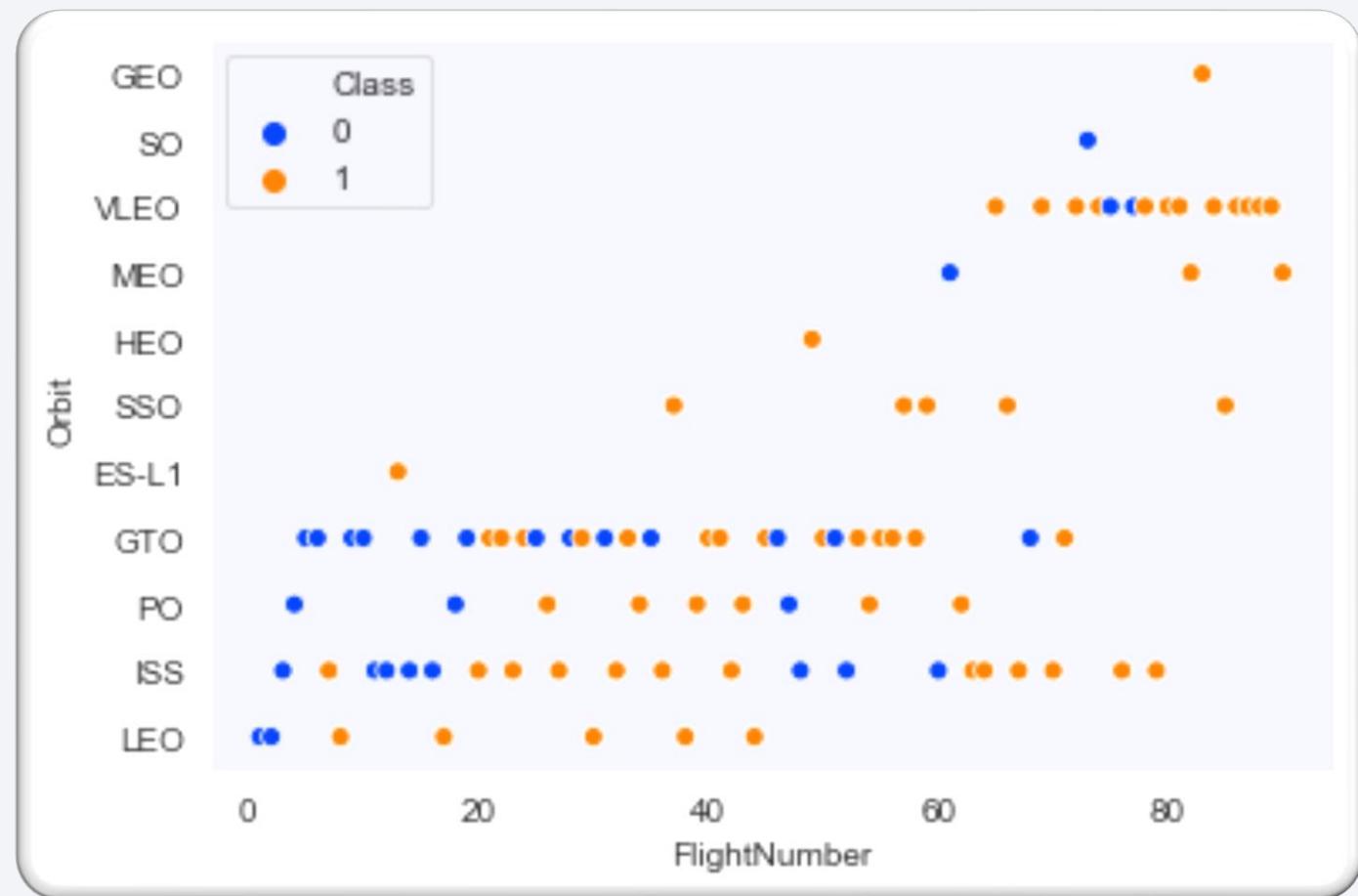
- SO (Heliocentric Orbit)



Flight Number vs. Orbit Type

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.
 - Generally, as Flight Number increases, the success rate increases. This is most extreme for LEO, where unsuccessful landings only occurred for the low flight numbers (early launches).



Payload vs. Orbit Type

This scatter plot of Orbit Type vs. Payload Mass shows that:

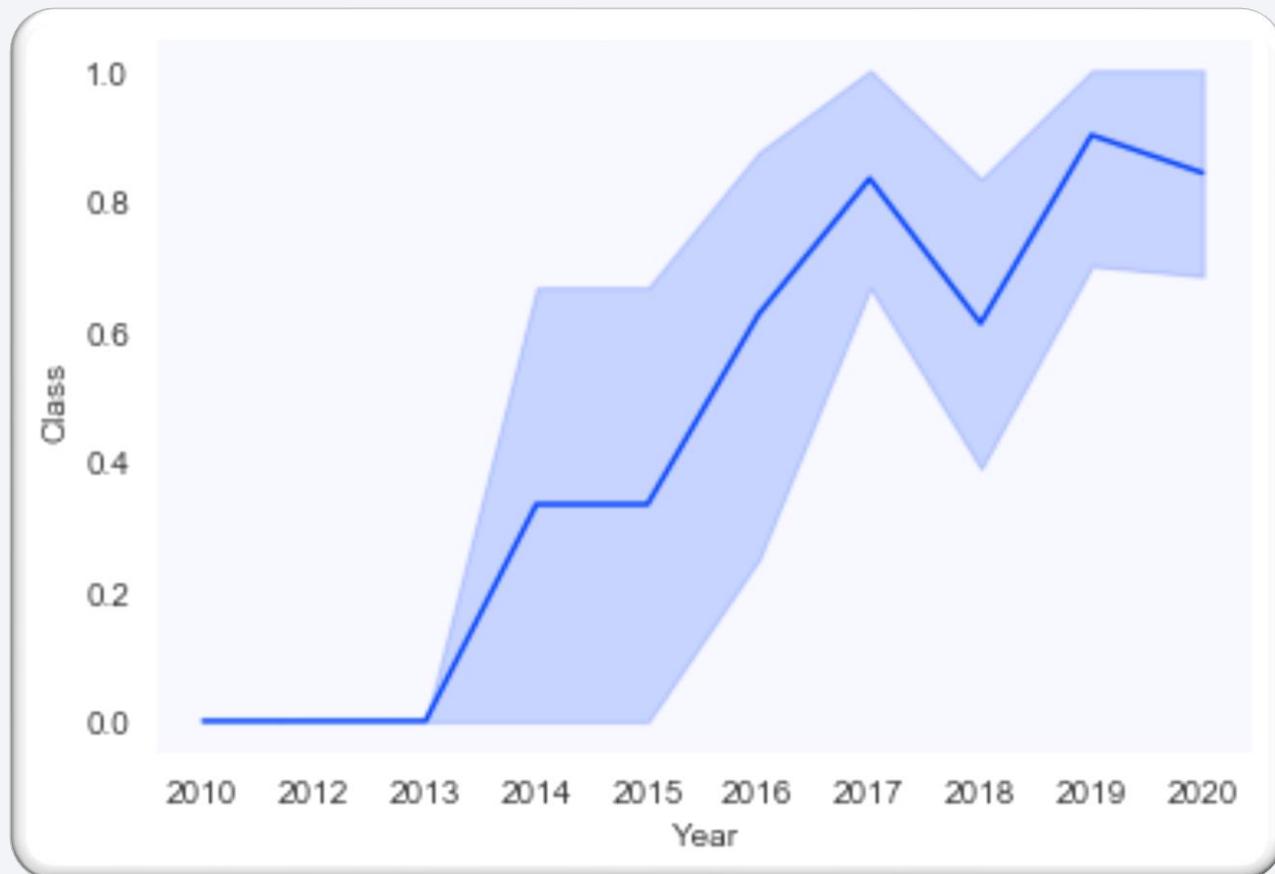
- The following orbit types have more success with heavy payloads:
 - PO (although the number of data points is small)
 - ISS
 - LEO
- For GTO, the relationship between payload mass and success rate is unclear.
- VLEO (Very Low Earth Orbit) launches are associated with heavier payloads, which makes intuitive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



Launch Success Yearly Trend

The line chart of yearly average success rate shows that:

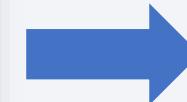
- Between 2010 and 2013, all landings were unsuccessful (as the success rate is 0).
- After 2013, the success rate generally increased, despite small dips in 2018 and 2020.
- After 2016, there was always a greater than 50% chance of success.



All Launch Site Names

Find the names of the unique launch sites.

```
● ● ●  
1 %sql SELECT UNIQUE(LAUNCH_SITE) FROM SPACEXTBL;
```



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

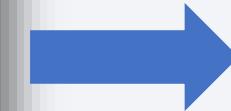
The word **UNIQUE** returns only unique values from the **LAUNCH_SITE** column of the **SPACEXTBL** table.

Launch Site Names Begin with 'CCA'

Find 5 records where launch sites begin with 'CCA'.



```
1 %sql SELECT LAUNCH_SITE FROM SPACEXTBL WHERE LAUNCH_SITE LIKE 'CCA%' LIMIT 5;
```



launch_site
CCAFS LC-40

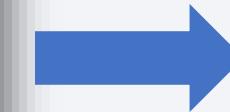
LIMIT 5 fetches only 5 records, and the **LIKE** keyword is used with the wild card '**CCA%**' to retrieve string values beginning with '**CCA**'.

Total Payload Mass

Calculate the total payload carried by boosters from NASA.



```
1 %sql SELECT SUM(PAYLOAD_MASS__KG_) AS TOTAL_PAYLOAD_MASS FROM SPACEXTBL \
2      WHERE CUSTOMER = 'NASA (CRS)';
```

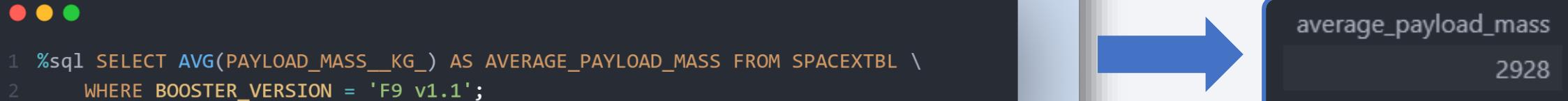


total_payload_mass
45596

The **SUM** keyword is used to calculate the total of the **LAUNCH** column, and the **SUM** keyword (and the associated condition) filters the results to only boosters from NASA (CRS).

Average Payload Mass by F9 v1.1

Calculate the average payload mass carried by booster version F9 v1.1.



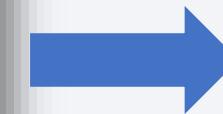
The **AVG** keyword is used to calculate the average of the **PAYLOAD_MASS__KG_** column, and the **WHERE** keyword (and the associated condition) filters the results to only the F9 v1.1 booster version.

First Successful Ground Landing Date

Find the dates of the first successful landing outcome on ground pad.



```
1 %sql SELECT MIN(DATE) AS FIRST_SUCCESSFUL_GROUND_LANDING FROM SPACEXTBL \
2      WHERE LANDING__OUTCOME = 'Success (ground pad)';
```



first_successful_ground_landing
2015-12-22

The **MIN** keyword is used to calculate the minimum of the **DATE** column, i.e. the first date, and the **WHERE** keyword (and the associated condition) filters the results to only the successful ground pad landings.

Successful Drone Ship Landing with Payload between 4000 and 6000

List the names of boosters which have successfully landed on drone ship and had payload mass greater than 4000 but less than 6000.

```
● ● ●  
1 %sql SELECT BOOSTER_VERSION FROM SPACEXTBL \  
2 WHERE (LANDING_OUTCOME = 'Success (drone ship)') AND (PAYLOAD_MASS_KG_ BETWEEN 4000 AND 6000);
```

The diagram illustrates a data flow from a query result to a table of booster versions. On the left, a dark grey rectangular box contains a command-line interface (CLI) query. This query selects the 'BOOSTER_VERSION' column from the 'SPACEXTBL' table, filtering for entries where the 'LANDING_OUTCOME' is 'Success (drone ship)' and the 'PAYLOAD_MASS_KG_' value is between 4000 and 6000. An arrow points from this box to a blue-bordered table on the right. The table has a single column labeled 'booster_version'. It lists four distinct values: 'F9 FT B1022', 'F9 FT B1026', 'F9 FT B1021.2', and 'F9 FT B1031.2'.

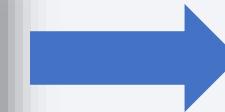
booster_version
F9 FT B1022
F9 FT B1026
F9 FT B1021.2
F9 FT B1031.2

The **WHERE** keyword is used to filter the results to include only those that satisfy both conditions in the brackets (as the **AND** keyword is also used). The **BETWEEN** keyword allows for $4000 < x < 6000$ values to be selected.

Total Number of Successful and Failure Mission Outcomes

Calculate the total number of successful and failure mission outcome.

```
1 %sql SELECT MISSION_OUTCOME, COUNT(MISSION_OUTCOME) AS TOTAL_NUMBER FROM SPACEXTBL GROUP BY MISSION_OUTCOME;
```



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

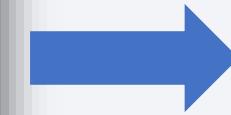
The **COUNT** keyword is used to calculate the total number of mission outcomes, and the **GROUP BY** keyword is also used to group these results by the type of mission outcome.

Boosters Carried Maximum Payload

List the names of the booster which have carried the maximum payload mass.



```
1 %sql SELECT DISTINCT(BOOSTER_VERSION) FROM SPACEXTBL \
2      WHERE PAYLOAD_MASS__KG_ = (SELECT MAX(PAYLOAD_MASS__KG_) FROM SPACEXTBL);
```



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

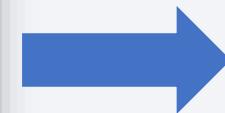
A subquery is used here. The **SELECT** statement within the brackets finds the maximum payload, and this value is used in the **WHERE** condition. The **DISTINCT** keyword is then used to retrieve only distinct /unique booster versions.

2015 Launch Records

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



```
1 %sql SELECT BOOSTER_VERSION, LAUNCH_SITE FROM SPACEXTBL \
2 WHERE (LANDING_OUTCOME = 'Failure (drone ship)') AND (EXTRACT(YEAR FROM DATE) = '2015');
```



booster_version	launch_site
F9 v1.1 B1012	CCAFS LC-40
F9 v1.1 B1015	CCAFS LC-40

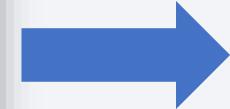
The **WHERE** keyword is used to filter the results for only failed landing outcomes, **AND** only for the year of 2015.

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

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.



```
1 %sql SELECT LANDING_OUTCOME, COUNT(LANDING_OUTCOME) AS TOTAL_NUMBER FROM SPACEXTBL \
2 WHERE DATE BETWEEN '2010-06-04' AND '2017-03-20' \
3 GROUP BY LANDING_OUTCOME \
4 ORDER BY TOTAL_NUMBER DESC;
```



landing_outcome	total_number
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

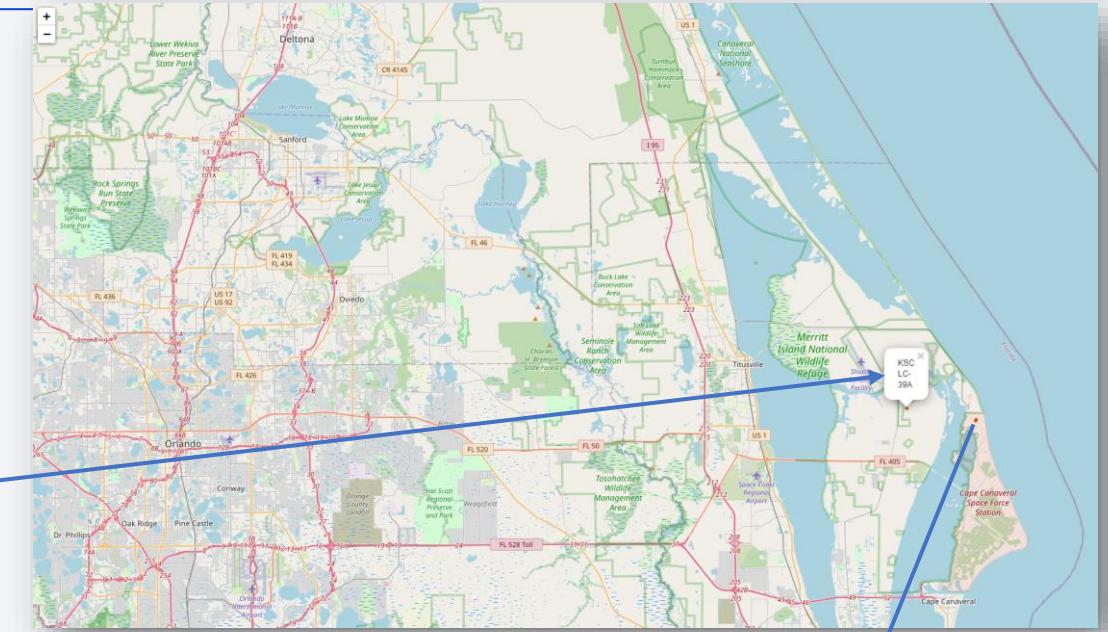
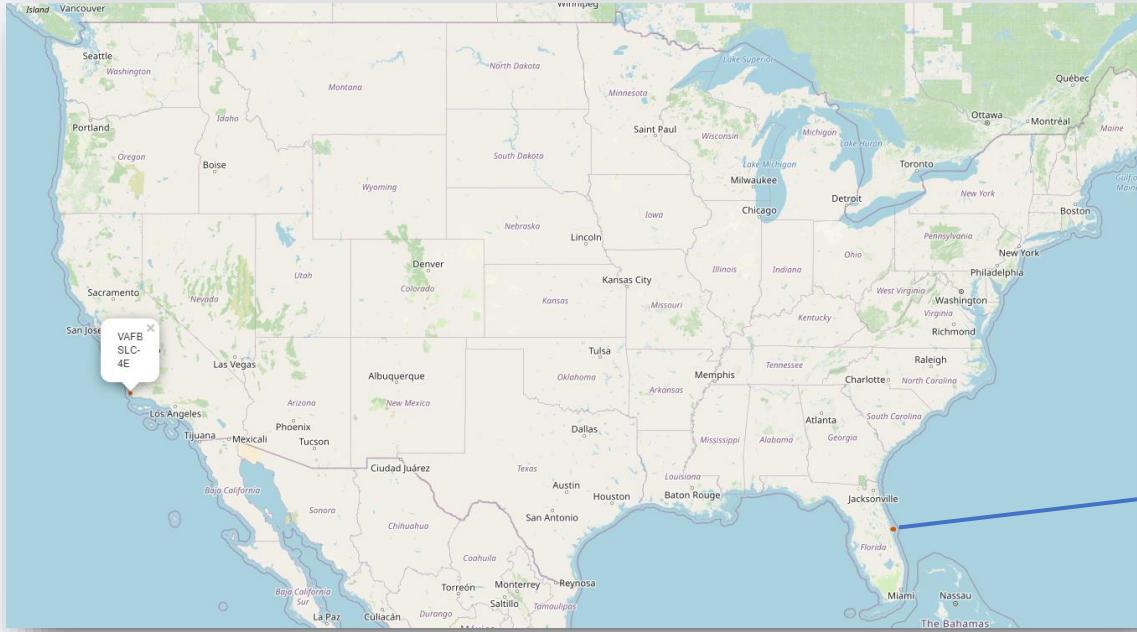
The **WHERE** keyword is used with the **BETWEEN** keyword to filter the results to dates only within those specified. The results are then grouped and ordered, using the keywords **GROUP BY** and **ORDER BY**, respectively, where **DESC** is used to specify the descending order.

The background of the slide is a photograph taken from space at night. It shows the curvature of the Earth's horizon against a dark blue sky. Numerous glowing yellow and white points represent city lights, concentrated in coastal and urban areas. In the upper right quadrant, there are bright green and yellow bands of light, likely the Aurora Borealis or Australis. The overall atmosphere is dark and mysterious.

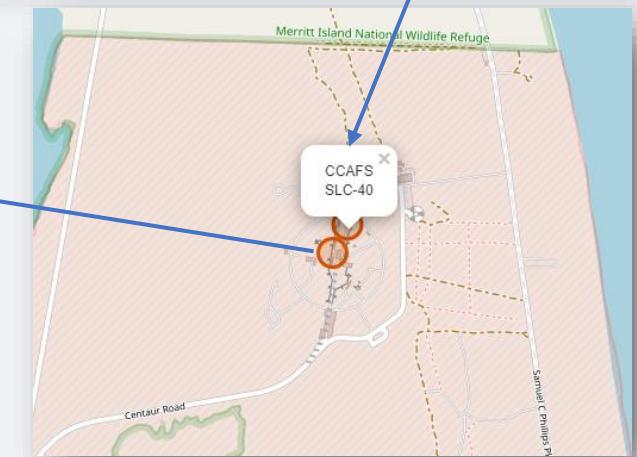
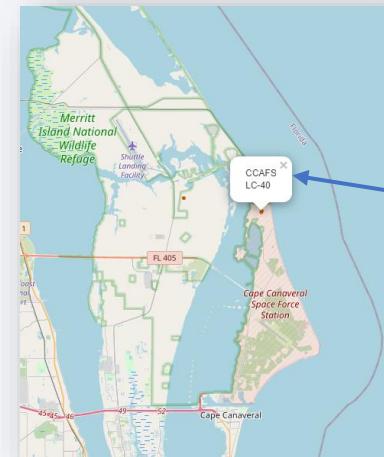
Section 3

Launch Sites Proximities Analysis

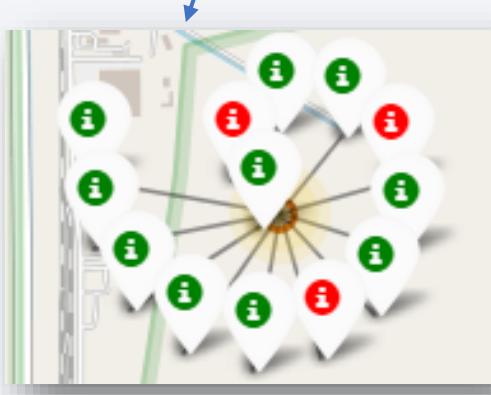
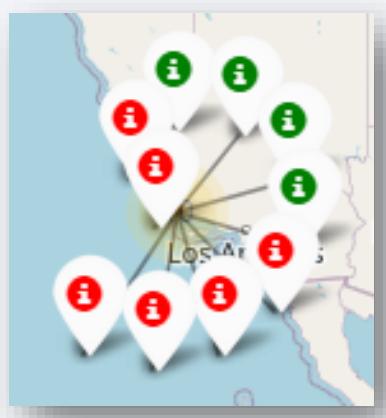
All Launch Sites On a Map



All SpaceX launch sites are on coasts of the United States of America, specifically Florida and California.



Success/Failed Launches for Each Site

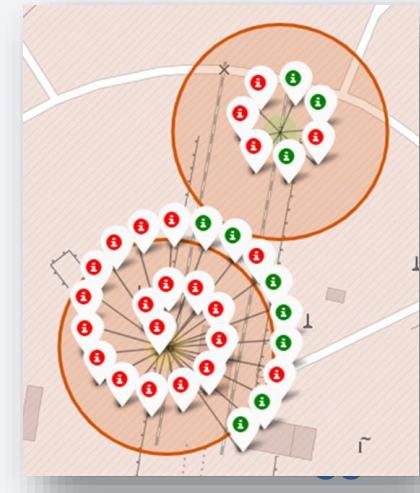


Launches have been grouped into clusters, and annotated with **green icons** for successful launches, and **red icons** for failed launches.

CCAFS SLC-40 and CCAFS LC-40

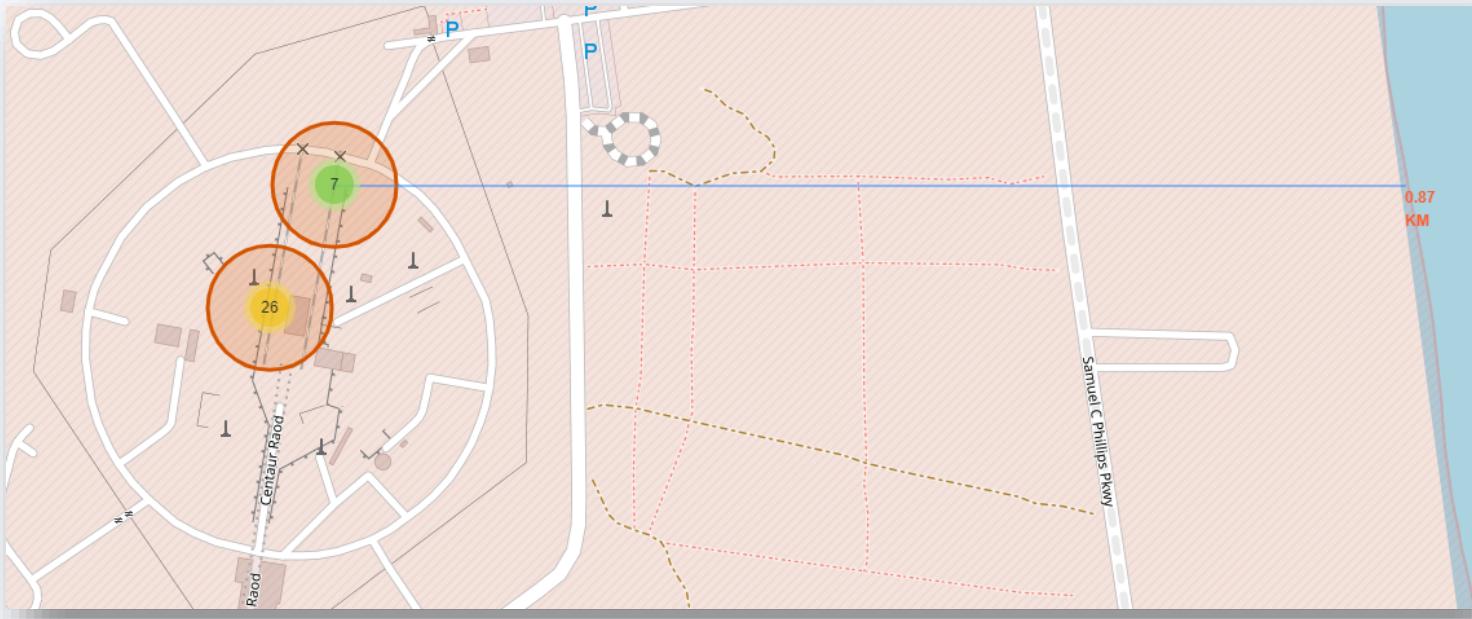
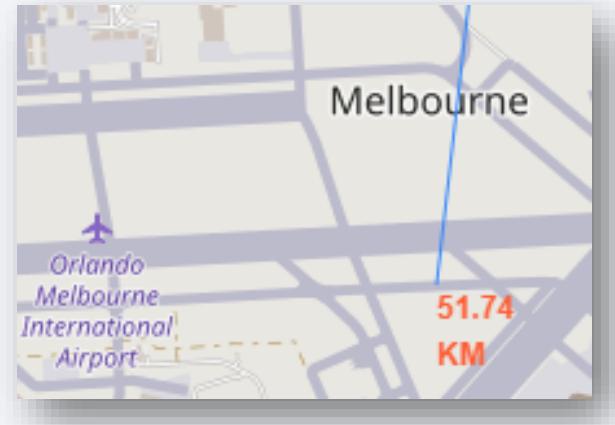


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Proximity of Launch Sites to Other Points of Interest

Using the **CCAFS SLC-40** launch site as an example site, we can understand more about the placement of launch sites.



Are launch sites in close proximity to railways?

- **YES.** The coastline is only 0.87 km due East.

Are launch sites in close proximity to highways?

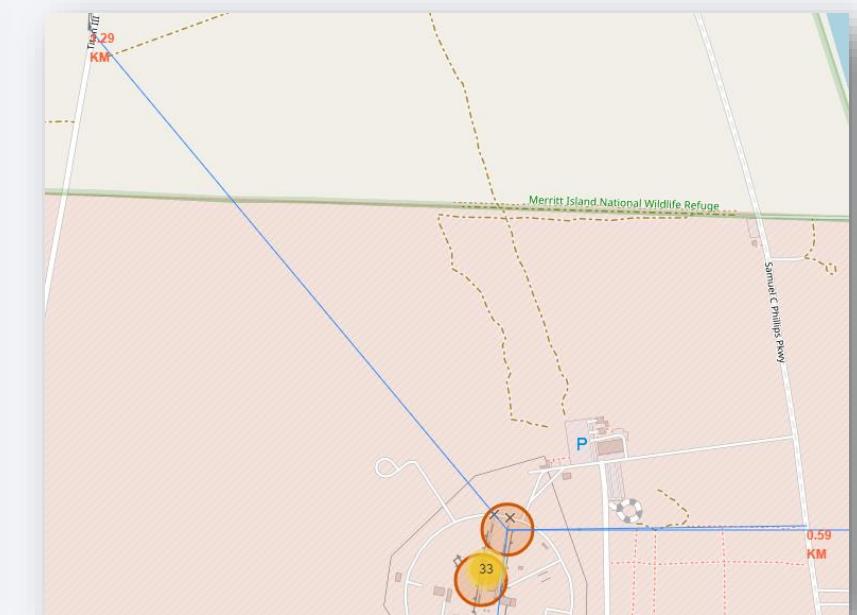
- **YES.** The nearest highway is only 0.59km away.

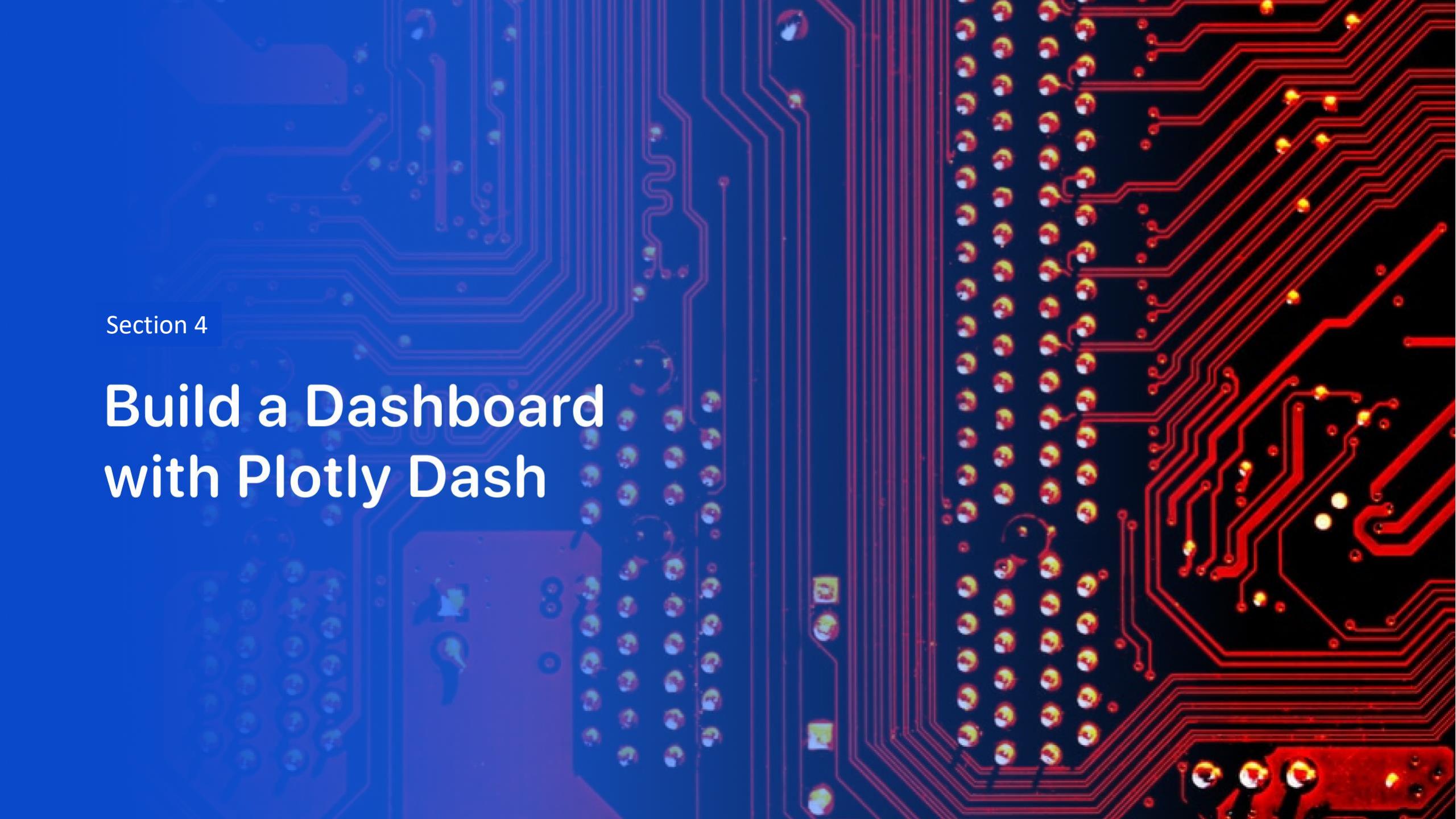
Are launch sites in close proximity to railways?

- **YES.** The nearest railway is only 1.29 km away.

Do launch sites keep certain distance away from cities?

- **YES.** The nearest city is 51.74 km away.

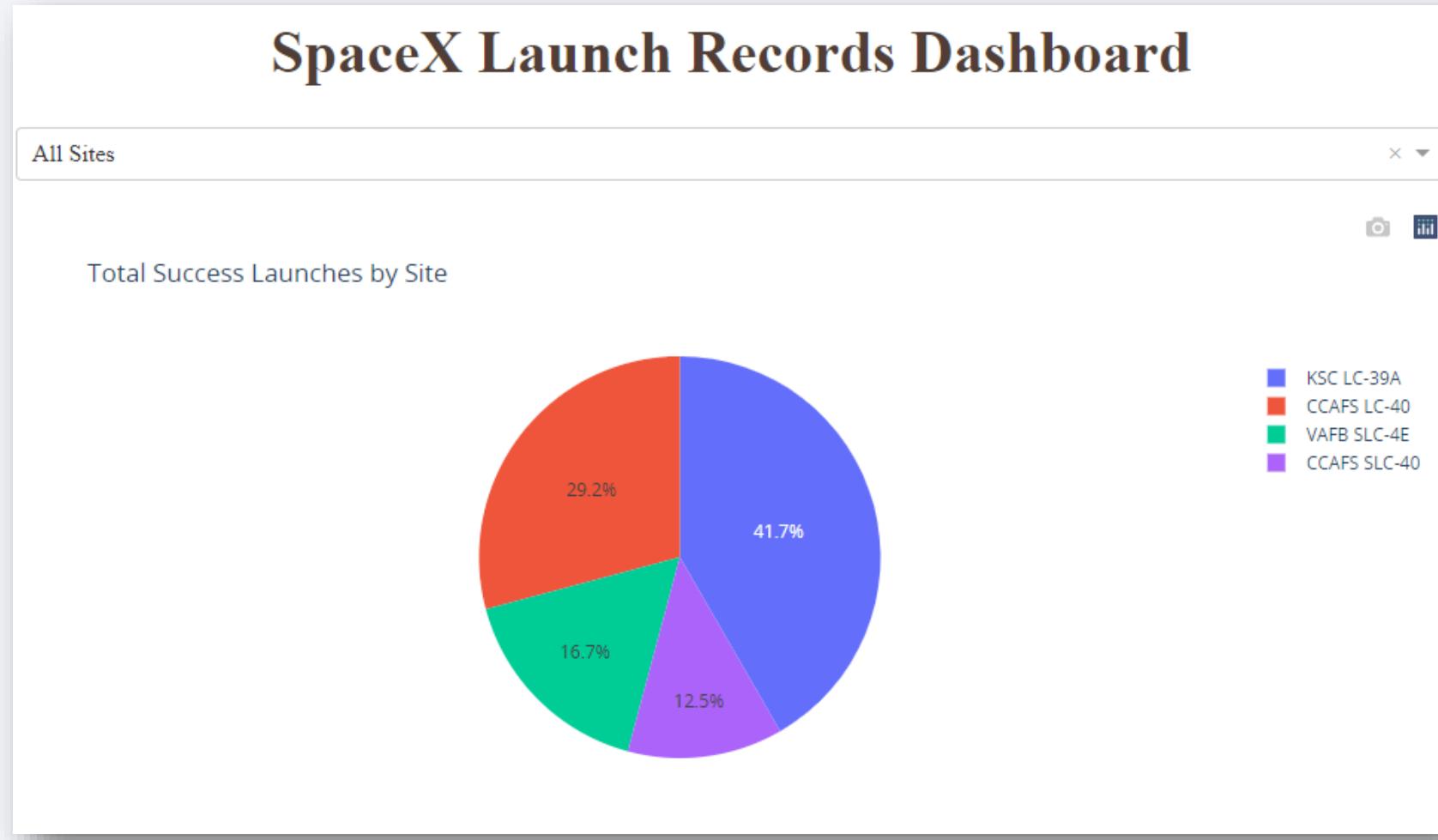




Section 4

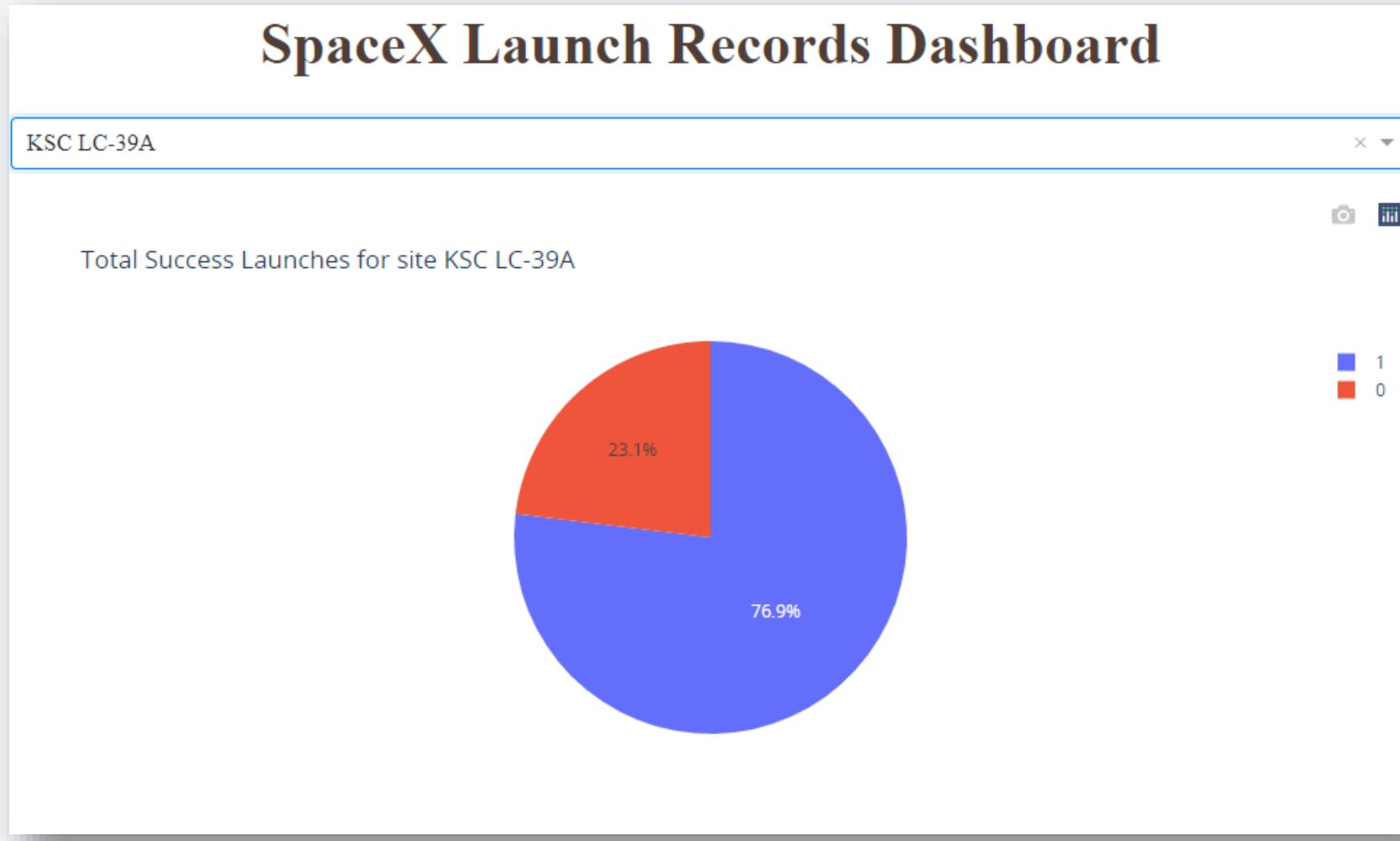
Build a Dashboard with Plotly Dash

Launch Success Count for All Sites



The launch site **KSC LC-39 A** had the most successful launches, with 41.7% of the total successful launches.

Pie Chart for the Launch Site with Highest Launch Success Ratio

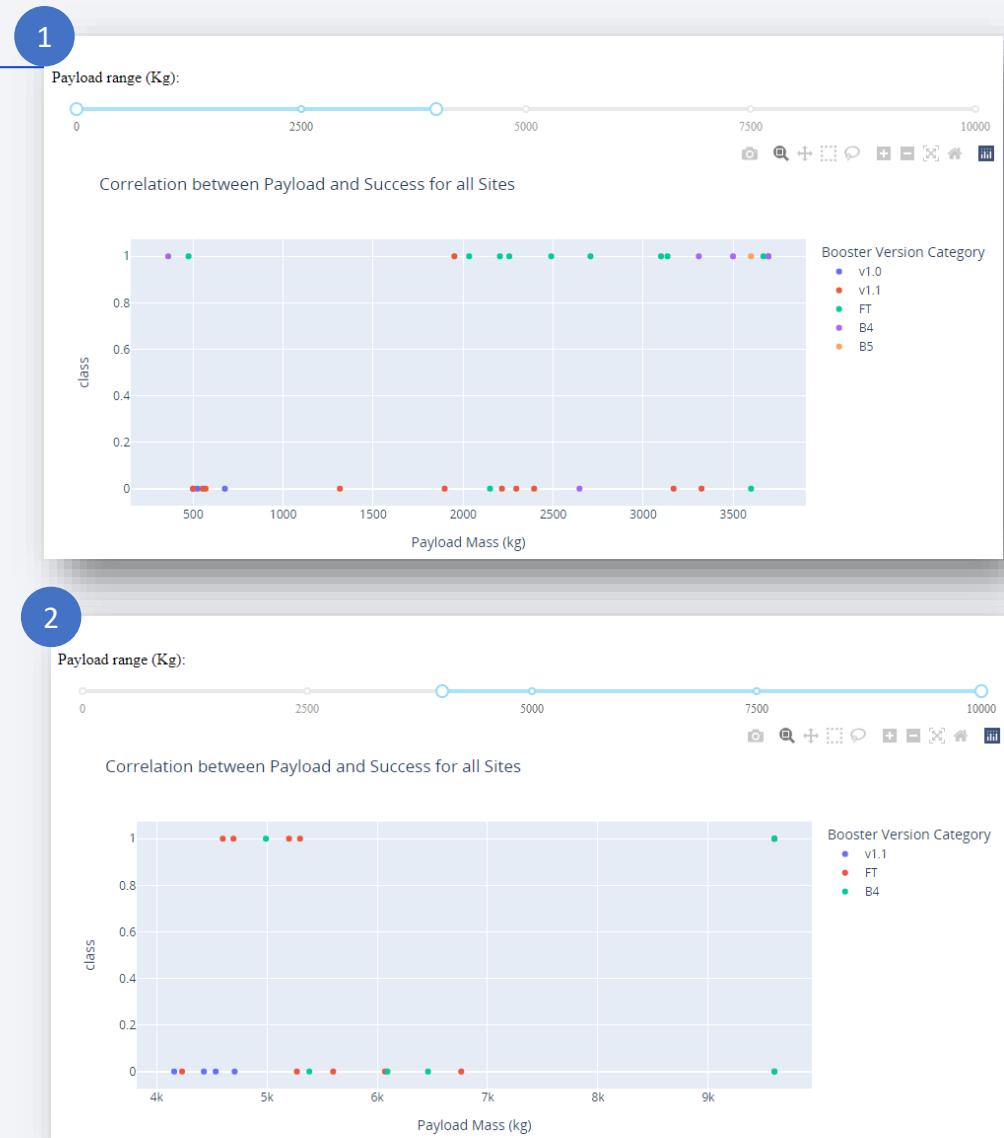


The launch site **KSC LC-39 A** also had the highest rate of successful launches, with a 76.9% success rate.

Launch Outcome VS. Payload Scatter Plot for All Sites



- Plotting the launch outcome vs. payload for all sites shows a gap around 4000 kg, so it makes sense to split the data into 2 ranges:
 - 0 – 4000 kg (low payloads)
 - 4000 – 10000 kg (massive payloads)
- From these 2 plots, it can be shown that **the success for massive payloads is lower than that for low payloads.**
- It is also worth noting that some booster types (v1.0 and B5) have not been launched with massive payloads.



The background of the slide features a dynamic, abstract design. It consists of several thick, curved lines that transition from a bright yellow at the top right to a deep blue at the bottom left. These lines create a sense of motion and depth, resembling a tunnel or a stylized landscape. The overall effect is modern and professional.

Section 5

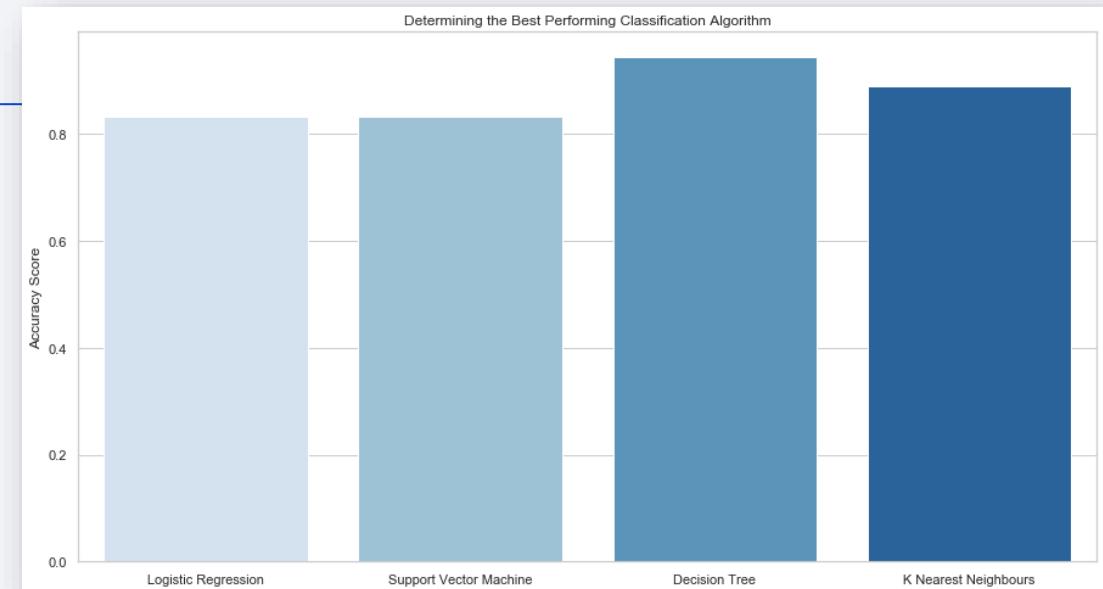
Predictive Analysis (Classification)

Classification Accuracy

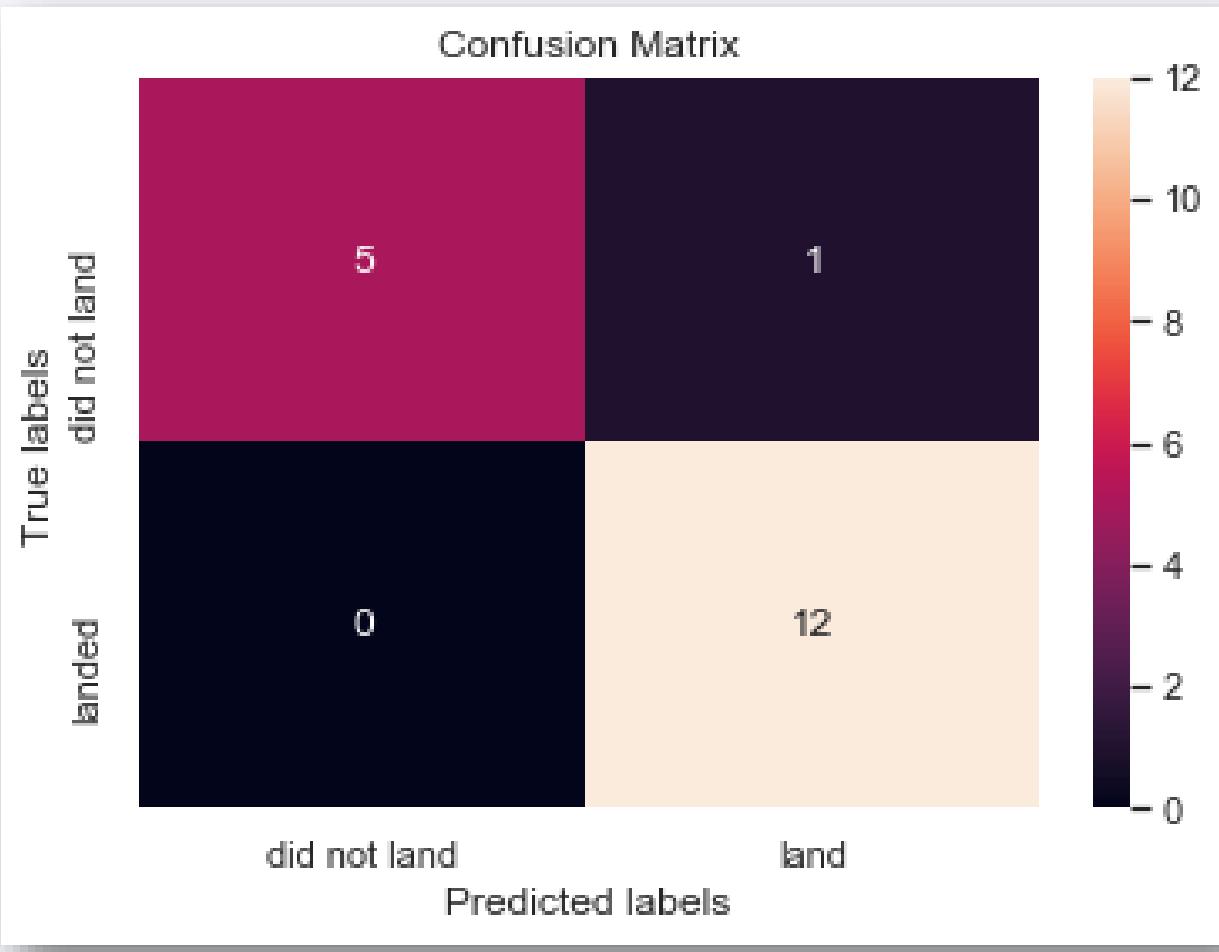
Plotting the Accuracy Score and Best Score for each classification algorithm produces the following result:

- The **Decision Tree** model has the highest classification accuracy
 - The Accuracy Score is 94.44%
 - The Best Score is 90.36%

Algorithm	Accuracy Score	Best Score
Logistic Regression	0.833333	0.846429
Support Vector Machine	0.833333	0.848214
Decision Tree	0.944444	0.903571
K Nearest Neighbours	0.888889	0.876786



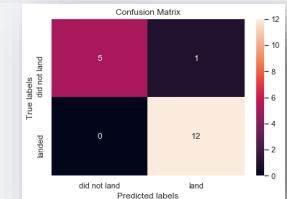
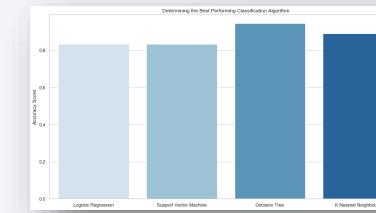
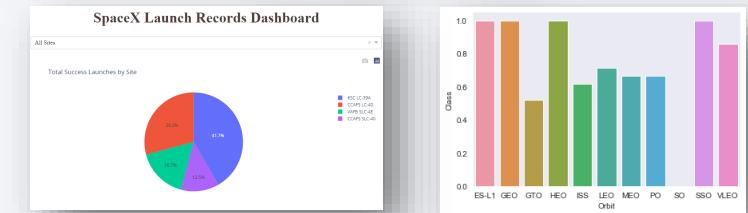
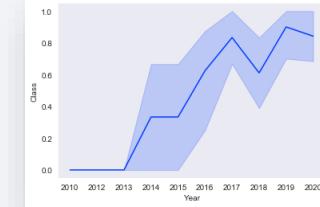
Confusion Matrix



- As shown previously, best performing classification model is the **Decision Tree** model, with an accuracy of 94.44%.
- This is explained by the confusion matrix, which shows only 1 out of 18 total results classified incorrectly (a false positive, shown in the top-right corner).
- The other 17 results are correctly classified (5 did not land, 12 did land).

Conclusions

- As the number of flights increases, the rate of success at a launch site increases, with most early flights being unsuccessful. I.e. with more experience, the success rate increases.
 - 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.
- Orbit types ES-L1, GEO, HEO, and SSO, have the highest (100%) success rate.
 - 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.
 - The orbit types PO, ISS, and LEO, have more success with heavy payloads:
 - VLEO (Very Low Earth Orbit) launches are associated with heavier payloads, which makes intuitive sense.
- The launch site **KSC LC-39 A** had the most successful launches, with 41.7% of the total successful launches, and also the highest rate of successful launches, with a 76.9% success rate.
- The success for massive payloads (over 4000kg) is lower than that for low payloads.
- The best performing classification model is the Decision Tree model, with an accuracy of 94.44%.



Appendix

DATA COLLECTION – Space x REST API

- Custom functions to retrieve the required information
- Custom logic to clean the data

```
# Lets take a subset of our dataframe keeping only the features we want and the flight number, and date_utc.  
data = data[['rocket', 'payloads', 'launchpad', 'cores', 'flight_number', 'date_utc']]  
  
# We will remove rows with multiple cores because those are falcon rockets with 2 extra rocket boosters  
# and rows that have multiple payloads in a single rocket.  
data = data[data['cores'].map(len)==1]  
data = data[data['payloads'].map(len)==1]  
  
# Since payloads and cores are lists of size 1 we will also extract the single value in the list and replace the feature.  
data['cores'] = data['cores'].map(lambda x : x[0])  
data['payloads'] = data['payloads'].map(lambda x : x[0])  
  
# We also want to convert the date_utc to a datetime datatype and then extracting the date leaving the time  
data['date'] = pd.to_datetime(data['date_utc']).dt.date  
  
# Using the date we will restrict the dates of the launches  
data = data[data['date'] <= datetime.date(2020, 11, 13)]
```

Python

From the `rocket` column we would like to learn the booster name.

```
# Takes the dataset and uses the rocket column to call the API and append the data to the list  
def getBoosterVersion(data):  
    for x in data['rocket']:  
        response = requests.get("https://api.spacexdata.com/v4/rockets/"+str(x)).json()  
        BoosterVersion.append(response['name'])
```

Python

From the `launchpad` we would like to know the name of the launch site being used, the longitude, and the latitude.

```
# Takes the dataset and uses the Launchpad column to call the API and append the data to the list  
def getLaunchSite(data):  
    for x in data['launchpad']:  
        response = requests.get("https://api.spacexdata.com/v4/launchpads/"+str(x)).json()  
        Longitude.append(response['longitude'])  
        Latitude.append(response['latitude'])  
        LaunchSite.append(response['name'])
```

Python

From the `payload` we would like to learn the mass of the payload and the orbit that it is going to.

```
# Takes the dataset and uses the payloads column to call the API and append the data to the lists  
def getPayloadData(data):  
    for load in data['payloads']:  
        response = requests.get("https://api.spacexdata.com/v4/payloads/"+load).json()  
        PayloadMass.append(response['mass_kg'])  
        Orbit.append(response['orbit'])
```

Python

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, whether the core is reused, whether legs were used, the landing pad used, the block of the core (which is a number used to separate versions of cores), the number of times this specific core has been reused, and the serial of the core.

```
[...]  
# 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'])
```

Python

Appendix

DATA COLLECTION – WEB SCRAPING

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

```
def date_time(table_cells):  
    """  
    This function returns the data and time from the HTML table cell  
    Input: the element of a table data cell extracts extra row  
    """  
    return [date_time.strip() for date_time in list(table_cells.strings)][0:2]  
  
def booster_version(table_cells):  
    """  
    This function returns the booster version from the HTML table cell  
    Input: the element of a table data cell extracts extra row  
    """  
    out=''.join([booster_version for i,booster_version in enumerate( table_cells.strings) if i%2==0][0:-1])  
    return out  
  
def landing_status(table_cells):  
    """  
    This function returns the landing status from the HTML table cell  
    Input: the element of a table data cell extracts extra row  
    """  
    out=[i for i in table_cells.strings][0]  
    return out  
  
def get_mass(table_cells):  
    mass=unicodedata.normalize("NFKD", table_cells.text).strip()  
    if mass:  
        mass.find("kg")  
        new_mass=mass[0:mass.find("kg")+2]  
    else:  
        new_mass=0  
    return new_mass  
  
def extract_column_from_header(row):  
    """  
    This function returns the landing status from the HTML table cell  
    Input: the element of a table data cell extracts extra row  
    """  
    if (row.br):  
        row.br.extract()  
    if row.a:  
        row.a.extract()  
    if row.sup:  
        row.sup.extract()  
  
    column_name = ' '.join(row.contents)  
  
    # Filter the digit and empty names  
    if not(column_name.strip().isdigit()):  
        column_name = column_name.strip()  
    return column_name
```

```
extracted_row = 0  
#Extract each table  
for table_number,table in enumerate(soup.find_all('table','wikitable plainrowheaders collapsible')):  
    # get table row  
    rows=table.findAll('tr')  
    #check to see if first table heading is a number corresponding to Launch a number  
    if rows:  
        if rows[0].string:  
            flight_number=rows[0].string.strip()  
            flag=flight_number.isdigit()  
        else:  
            flag=False  
        #get table element  
        rows=rows.findAll('td')  
        #if it is number save cells in a dictionary  
        if flag:  
            extracted_row += 1  
            # Flight Number value  
            # Append the flight_number into launch_dict with key 'Flight No.'  
            launch_dict["Flight No."].append(flight_number)  
  
            # Date value  
            #Append the date into launch_dict with key 'Date'  
            datatimelist=date_time(rows[0])  
            date = datatimelist[0].strip(',')  
            launch_dict["Date"].append(date)  
  
            # Time value  
            #Append the time into launch_dict with key 'Time'  
            time = datatimelist[1]  
            launch_dict["Time"].append(time)  
  
            # Booster version  
            #Append the bv into launch_dict with key 'Version Booster'  
            bv=booster_version(rows[1])  
            if not(bv):  
                bv=row[1].a.string  
            launch_dict["Version Booster"].append(bv)  
  
            # Launch Site  
            #Append the bv into launch_dict with key 'Launch site'  
            launch_site = row[2].a.string  
            launch_dict["Launch site"].append(launch_site)  
  
            # Payload  
            #Append the payload into launch_dict with key 'Payload'  
            payload = row[3].a.string  
            launch_dict['Payload'].append(payload)  
  
            # Payload Mass  
            #Append the payload_mass into launch_dict with key 'Payload mass'  
            payload_mass = get_mass(rows[4])  
            launch_dict['Payload mass'].append(payload_mass)  
  
            # Orbit  
            #Append the orbit into launch_dict with key 'Orbit'  
            orbit = row[5].a.string  
            launch_dict['Orbit'].append(orbit)  
  
            # Customer  
            #Append the customer into launch_dict with key 'Customer'  
            if row[6].a != None:  
                customer = row[6].a.string  
            else:  
                customer = 'None'  
  
            launch_dict['Customer'].append(customer)  
  
            # Launch outcome  
            #Append the launch_outcome into launch_dict with key 'Launch outcome'  
            launch_outcome = list(rows[7].strings)[8]  
            launch_dict['Launch outcome'].append(launch_outcome)  
  
            # Booster Landing  
            #Append the booster_landing into launch_dict with key 'Booster Landing'  
            booster_landing = landing_status(rows[8])  
            launch_dict['Booster landing'].append(booster_landing)  
  
    print("Flight Number: {flight_number}, Date: {date}, Time: {time} \n \\\n " +  
          "Booster Version (bv), Launch Site: {launch_site} \n \\\n " +  
          "Payload: {payload}, Orbit: {orbit} \n \\\n " +  
          "Customer: {customer}, Launch Outcome: {launch_outcome} \\\n " +  
          "Booster Landing: {booster_landing} \n \\\n " +  
          "***")
```

Thank you!

