Winning Space Race with Data Science

Jaylen Bailey
January 20, 2025

Outline

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

Executive Summary

- Summary of methodologies
  - Data collection and data wrangling
  - EDA with data visualization/SQL
  - Building an interactive map (Folium)
  - Building a Dashboard (Plotly Dash)
  - Predictive analysis (Classification)
- Summary of all results
  - EDA results
  - Interactive analytics
  - Predictive analysis

Introduction

- Project background and context
  - SpaceX has revolutionized the aerospace industry by prioritizing the development of reusable rockets, such as the Falcon 9, to reduce space exploration costs significantly. Successful landings are vital for reusability, enabling the company to recover and reuse rocket components, optimizing costs, and improving efficiency. This project analyzes historical launch data to understand better the factors contributing to landing success.
- Problems you want to find answers
  - The project addresses key questions: What factors most influence the success of Falcon 9 landings? How can these factors be used to predict future landing outcomes? Specifically, we seek to explore how variables like payload mass, launch site, and orbit type correlate with landing success and leverage machine learning models to forecast outcomes for future launches.

Section 1

Methodology

Methodology

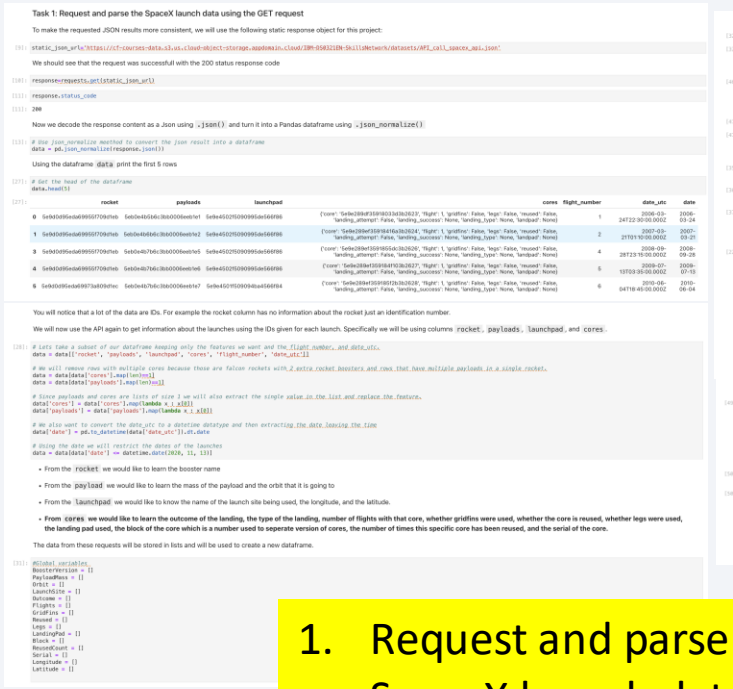
Executive Summary

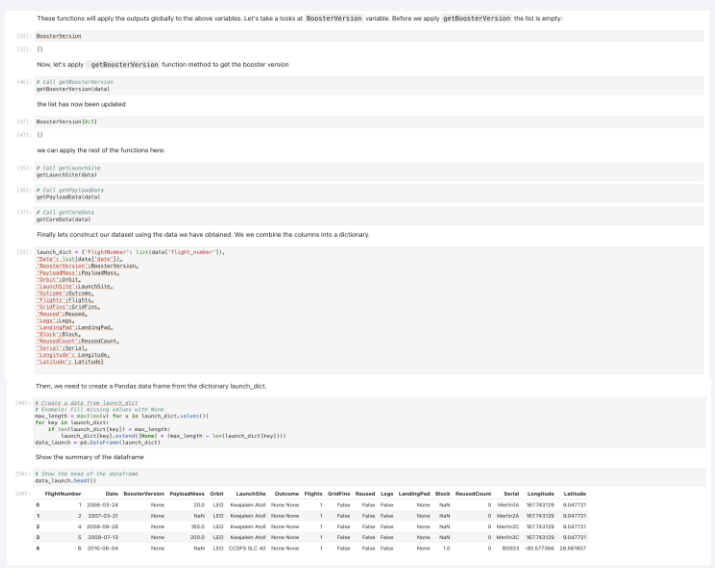
- Data collection methodology:
  - SpaceX Rest API
  - Web Scrapping from Wikipedia
- Perform data wrangling
  - One Hot Encoding for machine learning and removing any non-pertinent information from dataset.
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
  - Built classification models (Logistic Regression, Decision Tree, SVM, KNN).

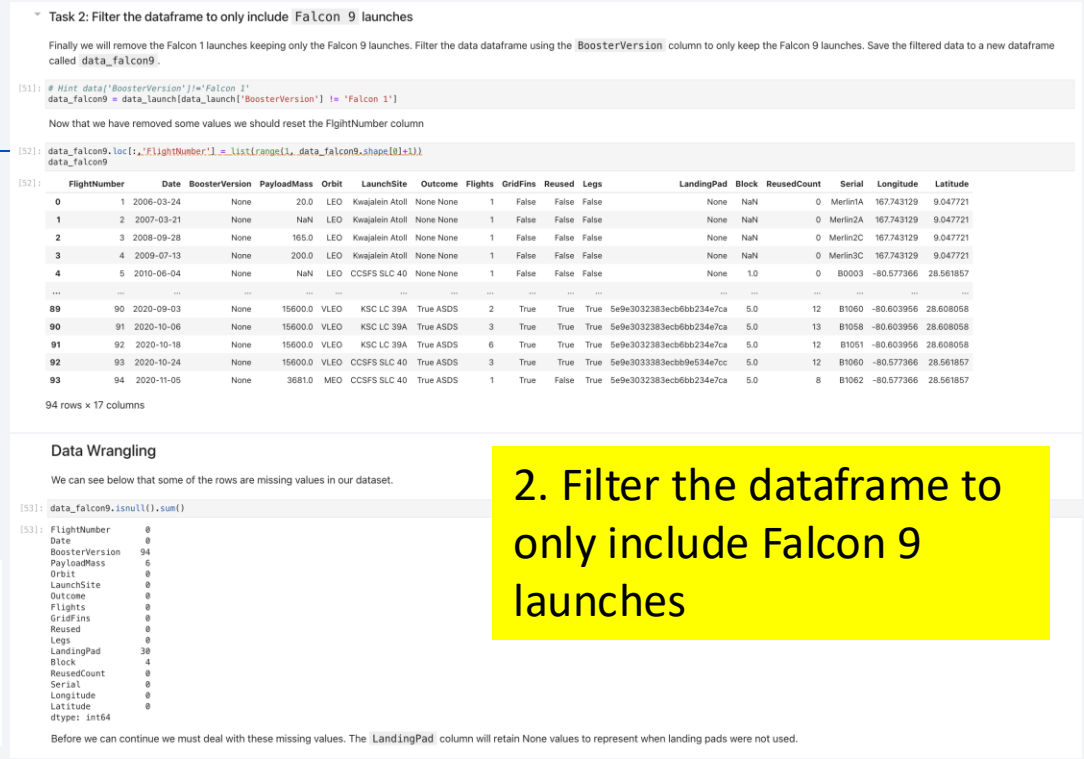
Data Collection

- **Primary Data Sources:**
  - **SpaceX REST API:** Retrieved detailed launch records (payload mass, orbit type, launch site, landing outcomes).
  - **Web Scraping:** Supplemented missing details from Wikipedia.
- **Data Wrangling and Preprocessing:**
  - Filtered dataset to include only Falcon 9 launches.
  - Addressed missing values
  - Encoded categorical variables like LaunchSite and Orbit for analysis.

Data Collection – SpaceX API







2. Filter the dataframe to only include Falcon 9 launches

1. Request and parse the SpaceX launch data using GET request

3. Dealing with Missing Values

https://github.com/jay1enbailey/Applied-Data-Science-Capstone/blob/main/jupyter-labs-spacex-data-collection-api.ipynb

Data Collection - Scraping

TASK 1: Request the Falcon9 Launch Wiki page from its URL

First, let's perform an HTTP GET method to request the Falcon9 Launch HTML page, as an HTTP response.

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

Create a `BeautifulSoup` object from the HTML `response`

```
[6]: # Use BeautifulSoup() to create a BeautifulSoup object from a response text content
     soup = BeautifulSoup(response.text, 'html')
```

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

```
[8]: # Use soup.title attribute
     soup.title
[8]: <title>List of Falcon 9 and Falcon Heavy launches - Wikipedia</title>
```

1. Request the Falcon9 Launch Wiki page from its URL

TASK 2: Extract all column/variable names from the HTML table header

Next, we want to collect all relevant column names from the HTML table header

Let's try to find all tables on the wiki page first. If you need to refresh your memory about `BeautifulSoup`, please check the external reference link towards the end of this lab

```
[9]: # Use the find_all function in the BeautifulSoup object, with element type `table`
     # Assign the result to a list called `html_tables`
     html_tables = soup.find_all('table')
```

Starting from the third table is our target table contains the actual launch records.

```
[10]: # Let's print the third table and check its content
      first_launch_table = html_tables[2]
      print(first_launch_table)
```

```
<table class="wikitable plainrowheaders collapsible" style="width: 100%;">
<tbody><tr>
<th scope="col">Flight No.
</th>
<th scope="col">Date and<br/>time (<a href="/wiki/Coordinated_Universal_Time" title="Coordinated Universal Time">UTC</a>)
</th>
<th scope="col"><a href="/wiki/List_of_Falcon_9_first-stage_boosters" title="List of Falcon 9 first-stage boosters">Version,<br/>Booster</a> <sup class
="reference" id="cite_ref-booster_11-0"><a href="#cite_note-booster-11"><span class="cite-bracket">[</span>b<span class="cite-bracket">]</span></a></sup>
</th>
```

2. Extract all column/variable names from the HTML table header

Next, we just need to iterate through the `<th>` elements and apply the provided `extract_column_from_header()` to extract column name one by one

```
[11]: 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
      tc = first_launch_table.find_all('th')
      for th in tc:...
          name = extract_column_from_header(th)
          if name is not None and len(name) > 0:
              column_names.append(name)
```

Check the extracted column names

```
[12]: print(column_names)
['Flight No.', 'Date and time ( )', 'Launch site', 'Payload', 'Payload mass', 'Orbit', 'Customer', 'Launch outcome']
```

TASK 3: Create a data frame by parsing the launch HTML tables

We will create an empty dictionary with keys from the extracted column names in the previous task. Later, this dictionary will be converted into a Pandas dataframe

```
[13]: launch_dict= dict.fromkeys(column_names)

      # Remove an irrelvant 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']=[]
```

Next, we just need to fill up the `launch_dict` with launch records extracted from table rows.

Usually, HTML tables in Wiki pages are likely to contain unexpected annotations and other types of noises, such as reference links `B0004.1[8]`, missing values `N/A [e]`, inconsistent formatting, etc.

To simplify the parsing process, we have provided an incomplete code snippet below to help you to fill up the `launch_dict`. Please complete the following code snippet with TODOs or you can choose to write your own logic to parse all launch tables:

```
[14]: extracted_row = 0
      #Extract each table
      for table_number,table in enumerate(soup.find_all('table',"wikitable plainrowheaders collapsible")):
         # get table row
          for rows in table.find_all("tr"):
              #check to see if first table heading is as number corresponding to launch a number
              if rows.th:
                  if rows.th.string:
                      flight_number=rows.th.string.strip()
                      flag=flight_number.isdigit()
              else:
                  flag=False
```

3. Create a data frame by parsing the launch HTML tables

```
[15]: for k in launch_dict.keys():
          print("Key {} => Len {}".format(k, len(k)))
```

```
Key Flight No. => Len 10
Key Launch site => Len 11
Key Payload => Len 7
Key Payload mass => Len 12
Key Orbit => Len 5
Key Customer => Len 8
Key Launch outcome => Len 14
Key Version Booster => Len 15
Key Booster landing => Len 15
Key Date => Len 4
Key Time => Len 4
```

After you have fill in the parsed launch record values into `launch_dict`, you can create a dataframe from it.

```
[18]: df= pd.DataFrame({ key:pd.Series(value) for key, value in launch_dict.items() })
```

...

We can now export it to a CSV for the next section, but to make the answers consistent and in case you have difficulties finishing this lab.

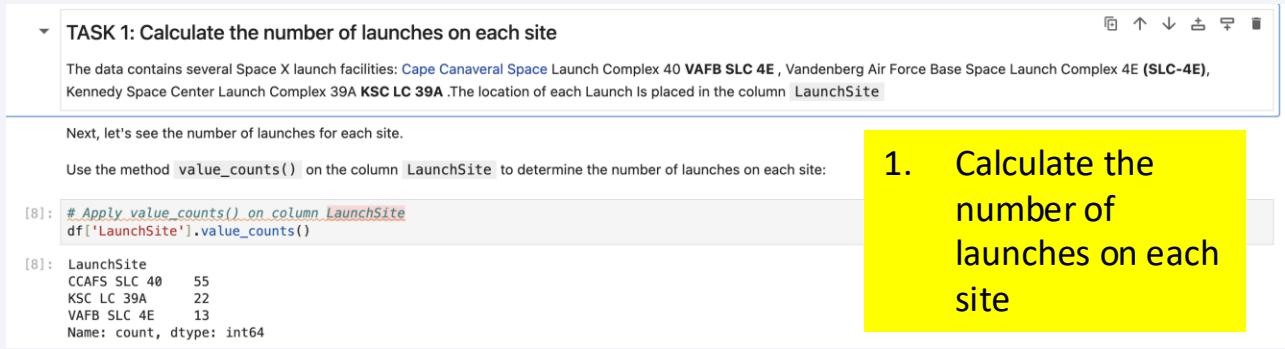
Following labs will be using a provided dataset to make each lab independent.

```
[19]: df.to_csv('spacex_web_scraped.csv', index=False)
```

df.to_csv('spacex_web_scraped.csv', index=False)

https://github.com/jay1enbailey/Applied-Data-Science-Capstone/blob/main/jupyter-labs-webscraping.ipynb

Data Wrangling



TASK 1: Calculate the number of launches on each site

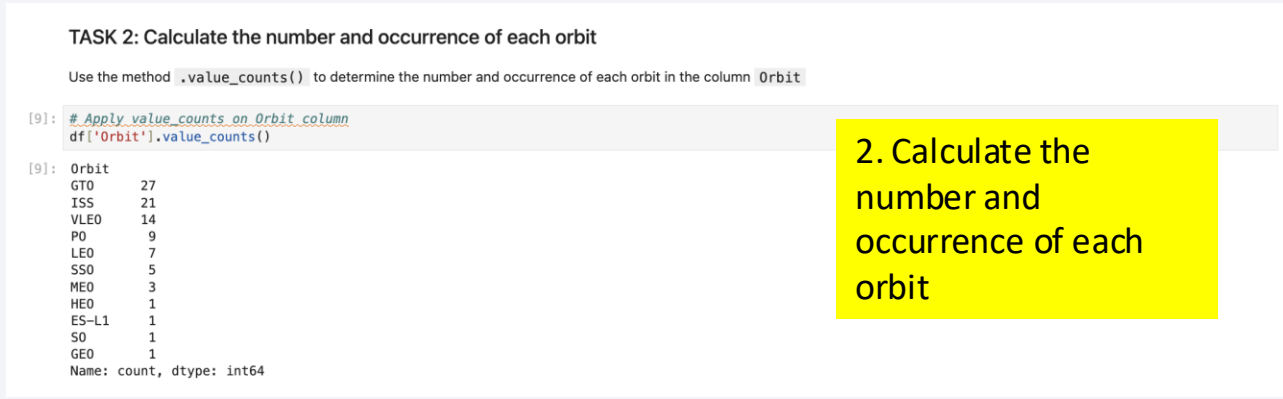
The data contains several Space X launch facilities: Cape Canaveral Space Launch Complex 40 **VAFB SLC 4E** , Vandenberg Air Force Base Space Launch Complex 4E **(SLC-4E)**, Kennedy Space Center Launch Complex 39A **KSC LC 39A** .The location of each Launch Is placed in the column `LaunchSite`

Next, let's see the number of launches for each site.

Use the method `value_counts()` on the column `LaunchSite` to determine the number of launches on each site:

```
[8]: # Apply value_counts() on column LaunchSite
     df['LaunchSite'].value_counts()

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

1. Calculate the number of launches on each site

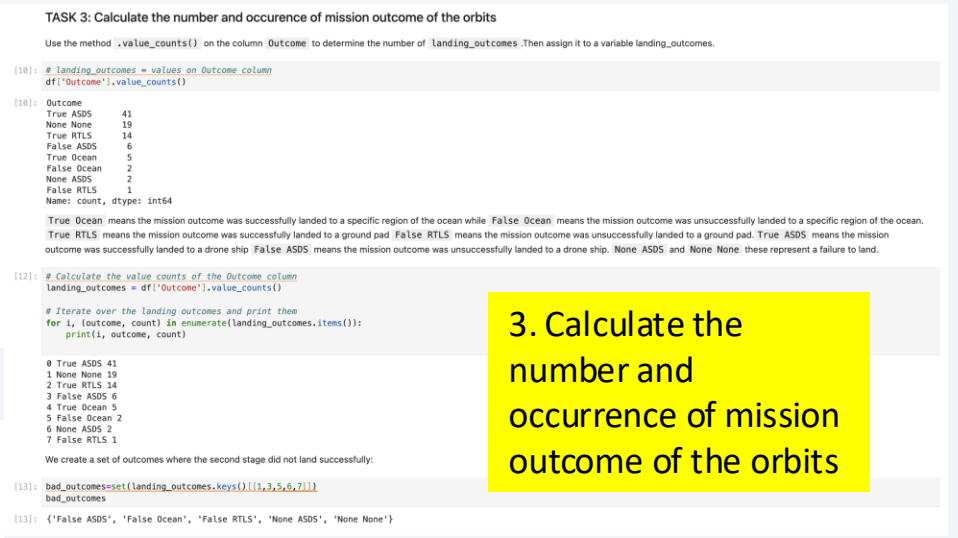


TASK 2: Calculate the number and occurrence of each orbit

Use the method `.value_counts()` to determine the number and occurrence of each orbit in the column `Orbit`

```
[9]: # Apply value_counts on Orbit column
     df['Orbit'].value_counts()

[9]: Orbit
     GTO      27
     ISS      21
     VLEO     14
     PO        9
     LEO       7
     SSO       5
     MEO       3
     HEO       1
     ES-L1     1
     SO        1
     GEO       1
     Name: count, dtype: int64
```

2. Calculate the number and occurrence of each orbit



TASK 3: Calculate the number and occurence of mission outcome of the orbits

Use the method `.value_counts()` on the column `Outcome` to determine the number of `landing_outcomes` .Then assign it to a variable landing_outcomes.

```
[10]: # landing_outcomes = values on Outcome column
      df['Outcome'].value_counts()

[10]: 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
      Name: count, dtype: int64
```

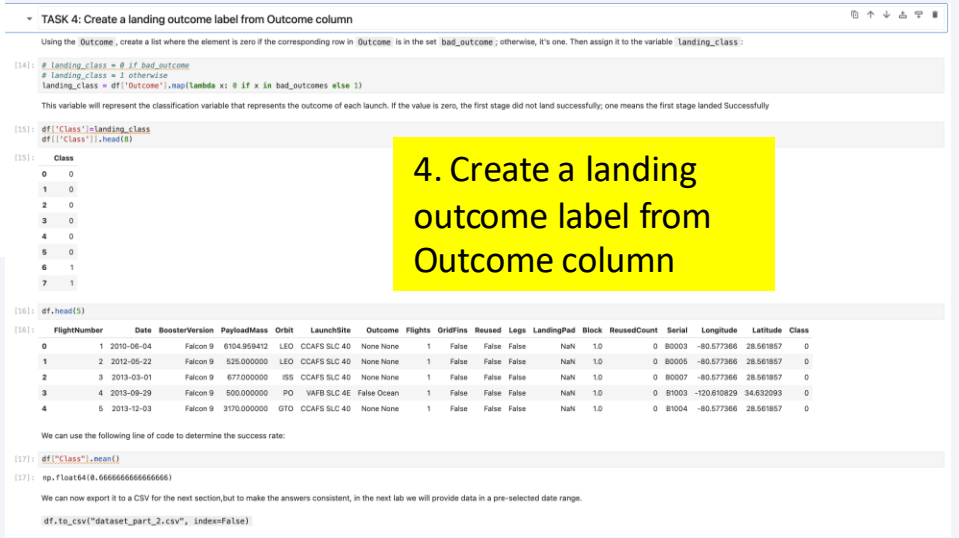
`True Ocean` means the mission outcome was successfully landed to a specific region of the ocean while `False Ocean` means the mission outcome was unsuccessfully landed to a specific region of the ocean. `True RTLS` means the mission outcome was successfully landed to a ground pad `False RTLS` means the mission outcome was unsuccessfully landed to a ground pad. `True ASDS` means the mission outcome was successfully landed to a drone ship `False ASDS` means the mission outcome was unsuccessfully landed to a drone ship. `None ASDS` and `None None` these represent a failure to land.

```
[12]: # Calculate the value counts of the Outcome column
      landing_outcomes = df['Outcome'].value_counts()

      # Iterate over the landing outcomes and print them
      for i, (outcome, count) in enumerate(landing_outcomes.items()):
          print(i, outcome, count)

      0 True ASDS 41
      1 None None 19
      2 True RTLS 14
      3 False ASDS 6
      4 True Ocean 5
      5 False Ocean 2
      6 None ASDS 2
      7 False RTLS 1
```

We create a set of outcomes where the second stage did not land successfully:

```
[13]: bad_outcomes=set(landing_outcomes.keys()[[1,3,5,6,7]])
      bad_outcomes

[13]: {'False ASDS', 'False Ocean', 'False RTLS', 'None ASDS', 'None None'}
```

3. Calculate the number and occurrence of mission outcome of the orbits



TASK 4: Create a landing outcome label from Outcome column

Using the `Outcome` , create a list where the element is zero if the corresponding row in `Outcome` is in the set `bad_outcome` ; otherwise, it's one. Then assign it to the variable `landing_class` :

```
[14]: # landing_class = 0 if bad_outcome
      # landing_class = 1 otherwise
      landing_class = df['Outcome'].map(lambda x: 0 if x in bad_outcomes else 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

```
[15]: df['Class']=landing_class
      df[['Class']].head(8)

[15]:   Class
      0     0
      1     0
      2     0
      3     0
      4     0
      5     0
      6     1
      7     1
```

4. Create a landing outcome label from Outcome column

```
[16]: df.head(5)

[16]:   FlightNumber  Date  BoosterVersion  PayloadMass  Orbit  LaunchSite  Outcome  Flights  GridFins  Reused  Legs  LandingPad  Block  ReusedCount  Serial  Longitude  Latitude  Class
      0  1  2010-06-04  Falcon 9  6104.959412  LEO  CCAFS SLC 40  None None  1  False  False  False  NaN  1.0  0  B0003  -80.577366  28.561857  0
      1  2  2012-05-22  Falcon 9  525.000000  LEO  CCAFS SLC 40  None None  1  False  False  False  NaN  1.0  0  B0005  -80.577366  28.561857  0
      2  3  2013-03-01  Falcon 9  677.000000  ISS  CCAFS SLC 40  None None  1  False  False  False  NaN  1.0  0  B0007  -80.577366  28.561857  0
      3  4  2013-09-29  Falcon 9  500.000000  PO  VAFB SLC 4E  False Ocean  1  False  False  False  NaN  1.0  0  B1003  -120.610829  34.632093  0
      4  5  2013-12-03  Falcon 9  3170.000000  GTO  CCAFS SLC 40  None None  1  False  False  False  NaN  1.0  0  B1004  -80.577366  28.561857  0
```

We can use the following line of code to determine the success rate:

```
[17]: df["Class"].mean()

[17]: np.float64(0.6666666666666666)
```

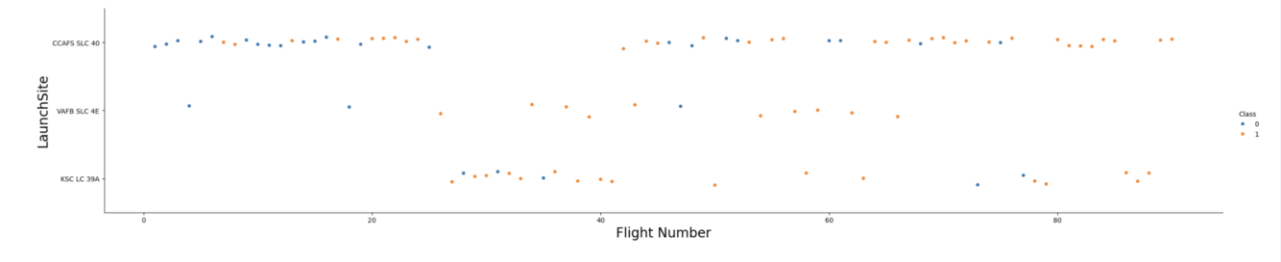
We can now export it to a CSV for the next section,but to make the answers consistent, in the next lab we will provide data in a pre-selected date range.

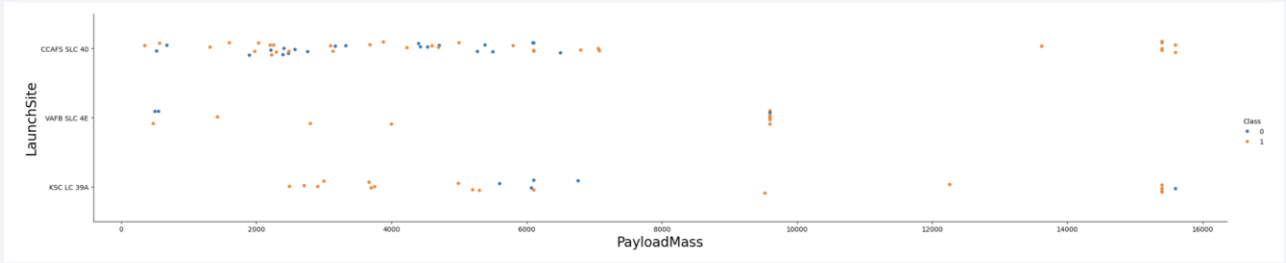
```
df.to_csv("dataset_part_2.csv", index=False)
```

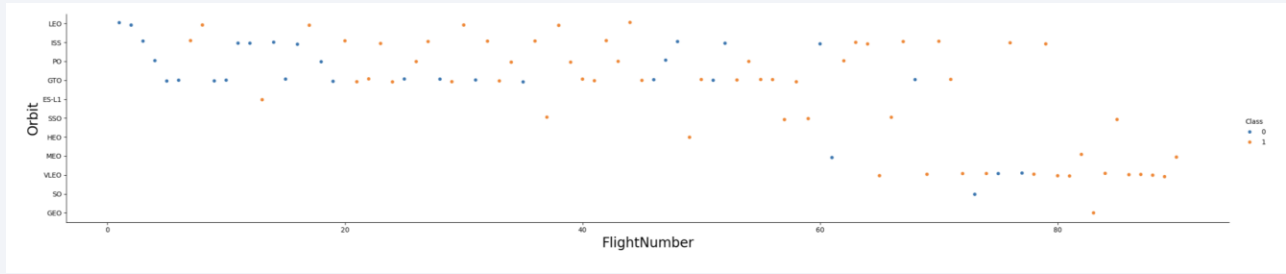
https://github.com/jay1enbailey/Applied-Data-Science-Capstone/blob/main/labs-jupyter-spacex-Data%20wrangling.ipynb

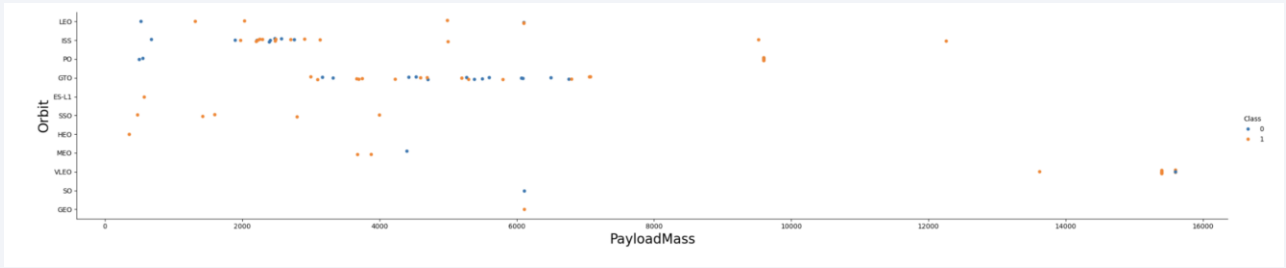
EDA with Data Visualization

Visualization of relationship between (1) Flight Number and Launch Site, (2) Payload and Launch Site, (3) Flight Number and Orbit type, (4) Payload and Orbit type

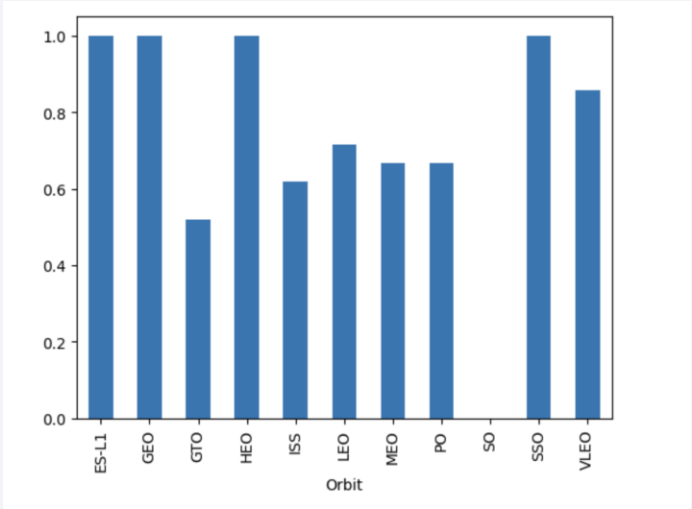


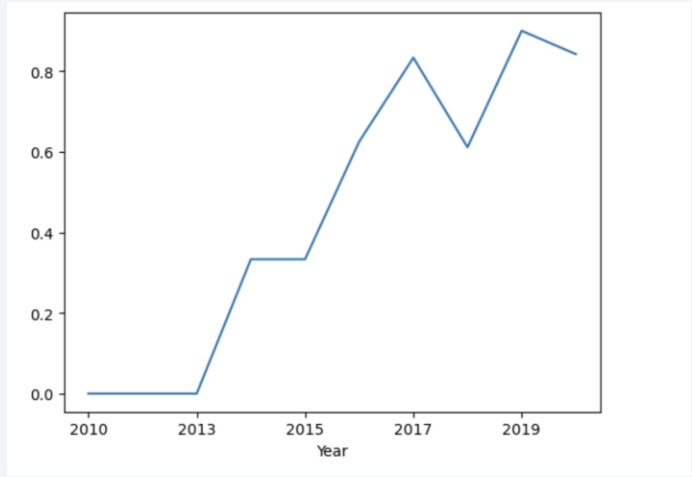






Bar chart was used to visualize the relationship between success rate of each orbit type; Line chart was used to visualize the launch success yearly trend





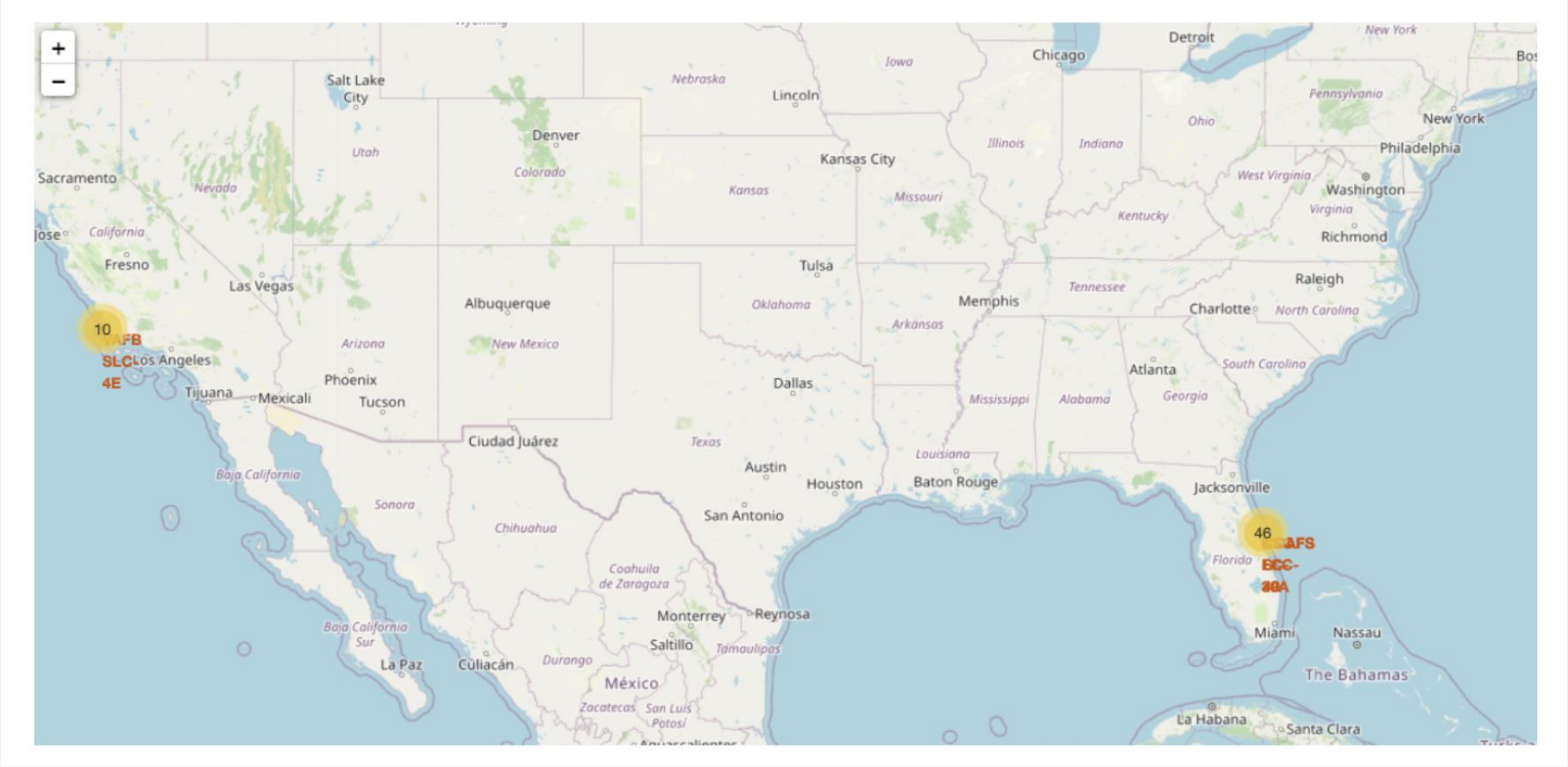
https://github.com/jay1enbailey/Applied-Data-Science-Capstone/blob/main/edadataviz.ipynb

EDA with SQL

https://github.com/jay1enbailey/Applied-Data-Science-Capstone/blob/main/jupyter-labs-eda-sql-coursera_sqllite.ipynb

- Display the names of the unique launch sites in the space mission
- Display 5 records where launch sites begin with the string 'CCA'
- Display the total payload mass carried by boosters launched by NASA (CRS)
- Display average payload mass carried by booster version F9 v1.1
- List the date when the first successful landing outcome in ground pad was achieved.
- List the names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000
- List the total number of successful and failure mission outcomes
- List the names of the booster_versions which have carried the maximum payload mass using a subquery
- 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.
- 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.

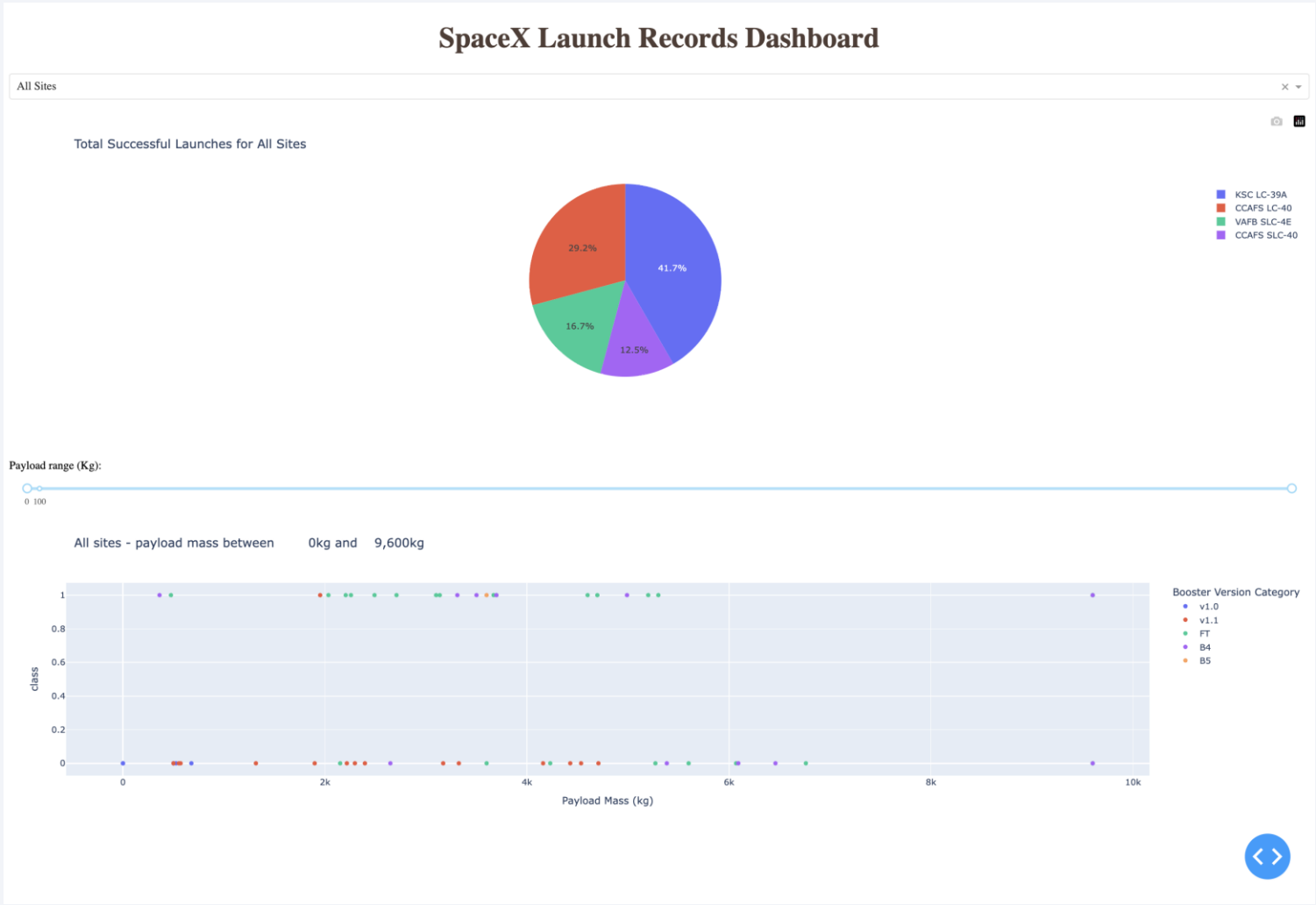
Build an Interactive Map with Folium



Map markers have been added to the map to find the right location for building a launch site

https://github.com/jay1enbailey/Applied-Data-Science-Capstone/blob/main/lab_jupyter_launch_site_location.ipynb

Build a Dashboard with Plotly Dash



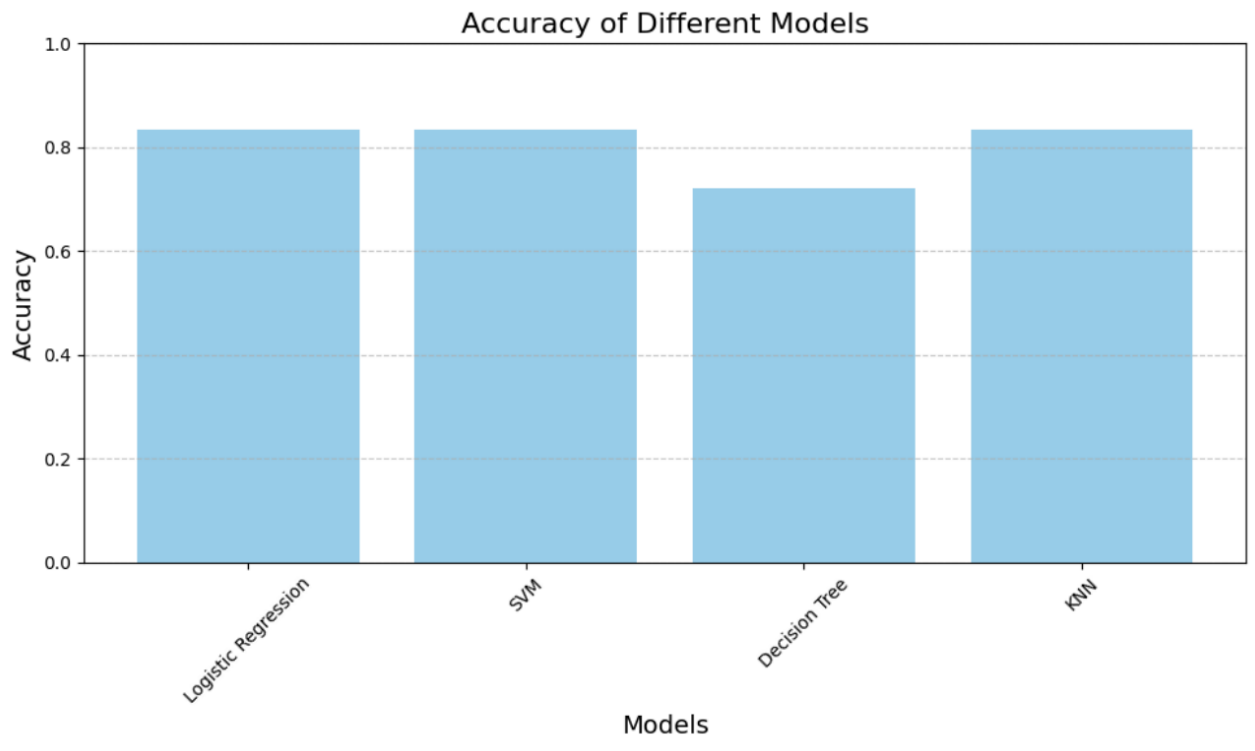
Dropdown option of pie chart created to show the success launches of all / each site

Scatter plot with payload range slider to show the success launches of all / each site by payload mass

https://github.com/jay1enbailey/Applied-Data-Science-Capstone/blob/main/spacex_dash_app.py

Predictive Analysis (Classification)

https://github.com/jay1enbailey/Applied-Data-Science-Capstone/blob/main/SpaceX_Machine%20Learning%20Prediction_Part_5.ipynb

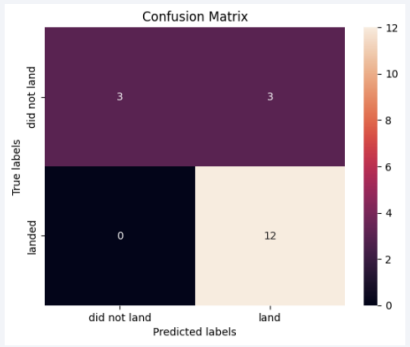


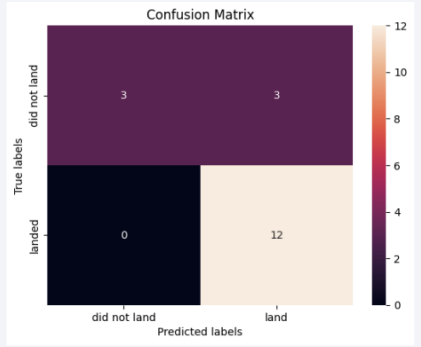
TASK 12

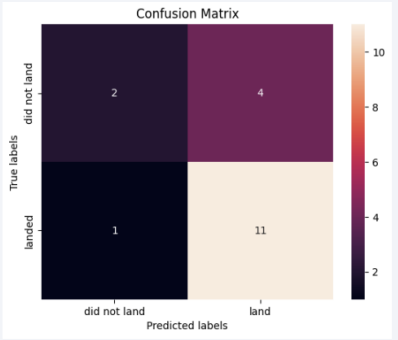
Find the method performs best:

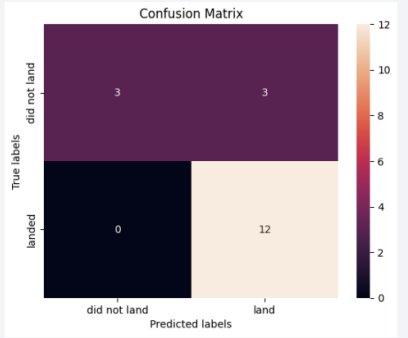
```
print('LR Accuracy:', '{:.2%}'.format(logreg_accuracy))
print( 'SVM Accuracy:', '{:.2%}'.format(svm_accuracy))
print('Decision Tree Accuracy:', '{:.2%}'.format(tree_accuracy))
print('KNN Accuracy:', '{:.2%}'.format(knn_accuracy))
```

```
LR Accuracy: 83.33%
SVM Accuracy: 83.33%
Decision Tree Accuracy: 72.22%
KNN Accuracy: 83.33%
```





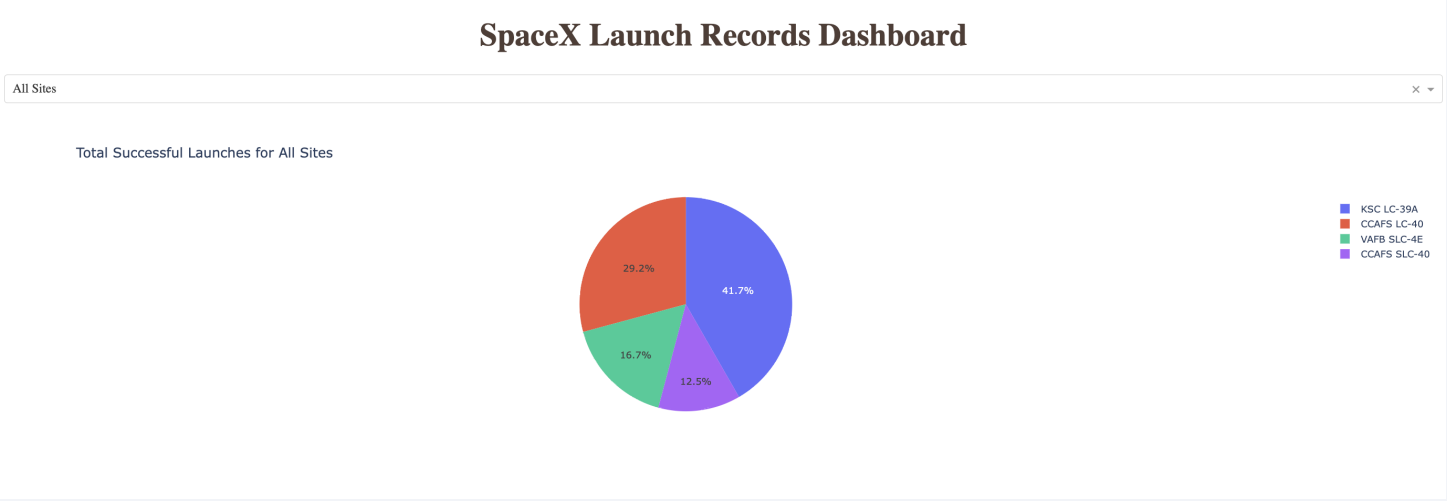




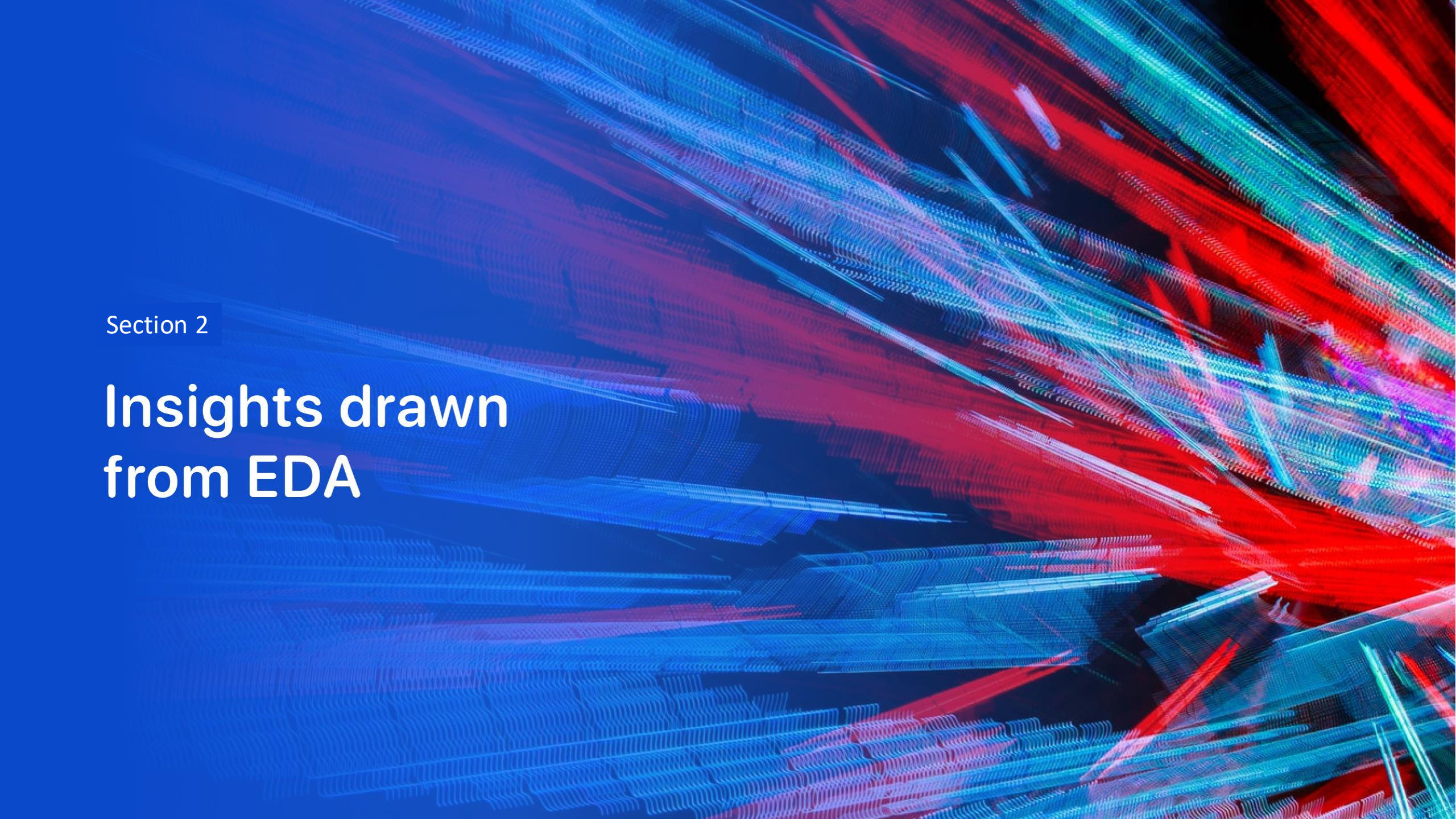
- The methods performed best are LR, SVM, KNN where all 3 achieved the highest accuracy of 83.33%.

Results

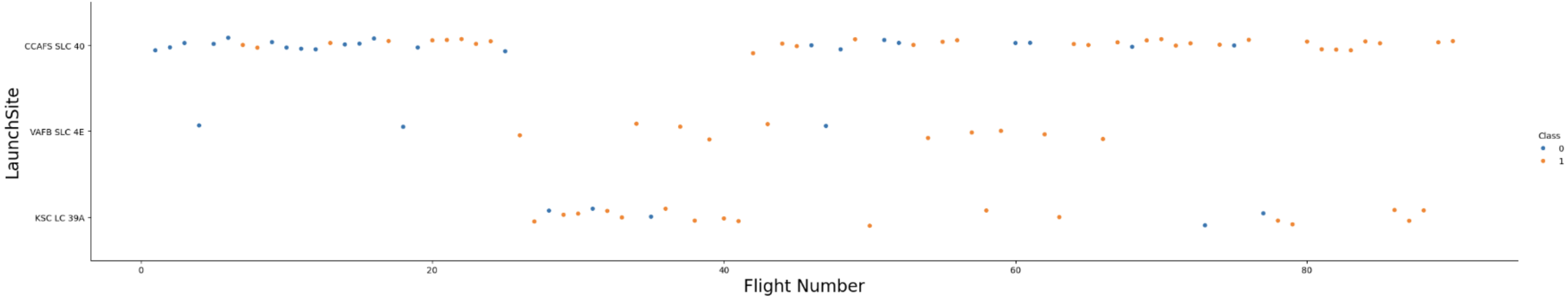
- LR, SVM, KNN performed best for forecasting outcomes in this data.
- Lighter payloads have a higher performance compared to heavier ones.
- The likelihood of a SpaceX launch succeeding increases with the number of years of experience, suggesting a trend towards flawless launches over time.
- KSC LC-39A has the highest number of successful launches compared to other launch sites.
- GEO,HEO,SSO,ES L1 exhibit the highest rates of successful launches.



KSC LC-39A has the highest number of successful launches

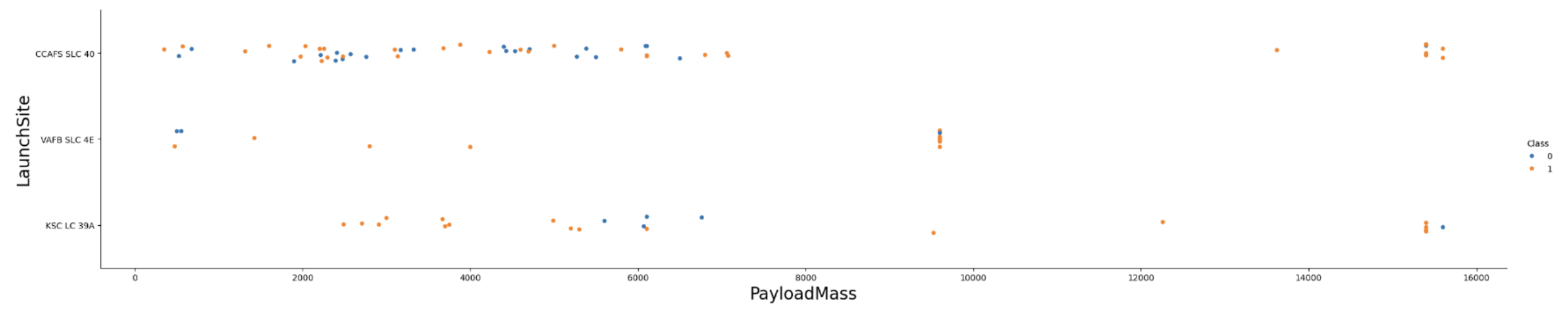

Section 2
Insights drawn from EDA

Flight Number vs. Launch Site



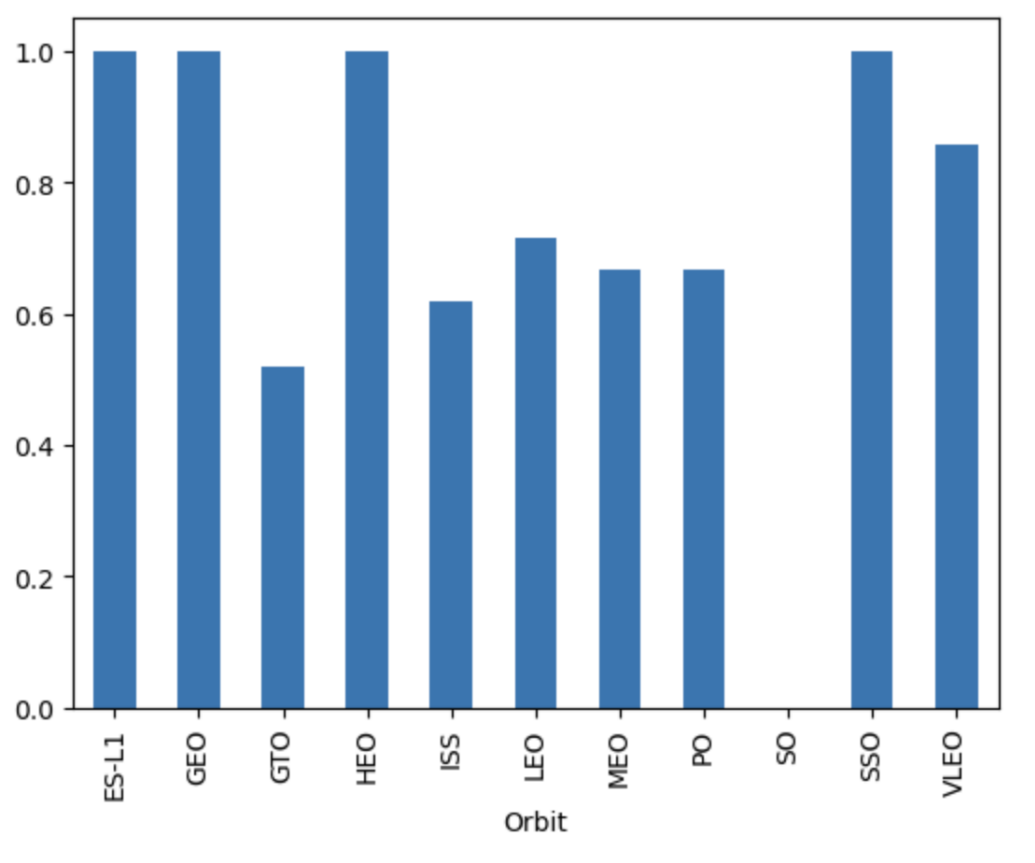
- Total number of launches from launch site CCAFS SLC 40 are higher than the other launch sites.

Payload vs. Launch Site



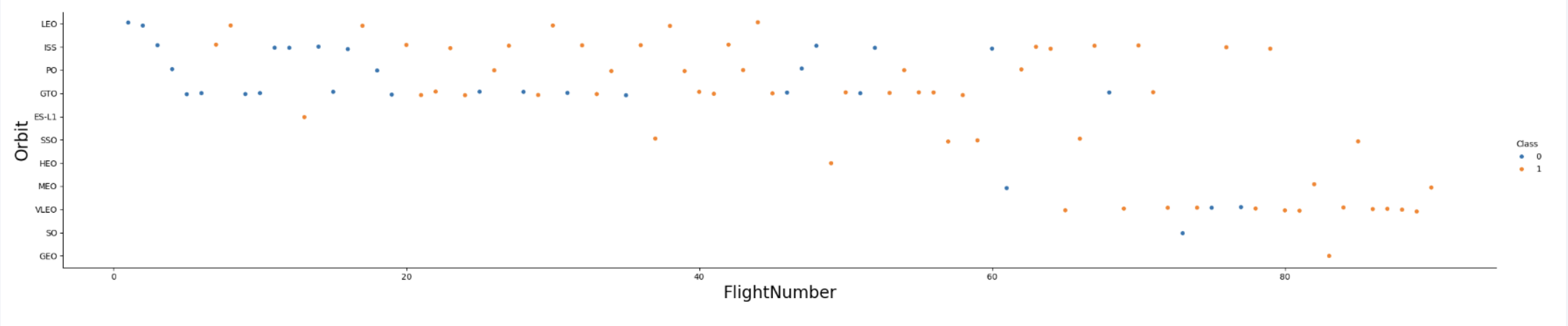
- Payloads with lower mass have more launches compared to those with higher mass across all three launch sites.

Success Rate vs. Orbit Type



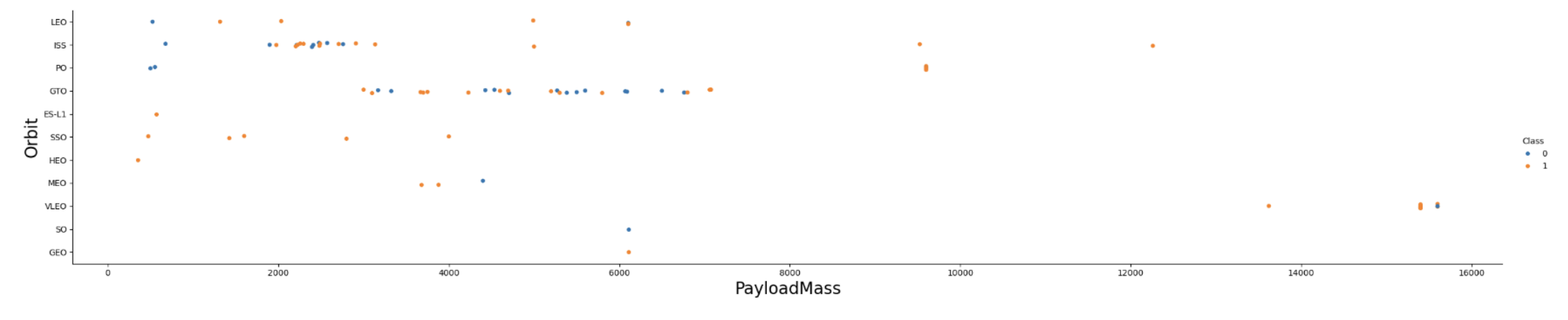
- The orbit types of ES-L1, GEO, HEO, SSO are among the highest success rates.

Flight Number vs. Orbit Type



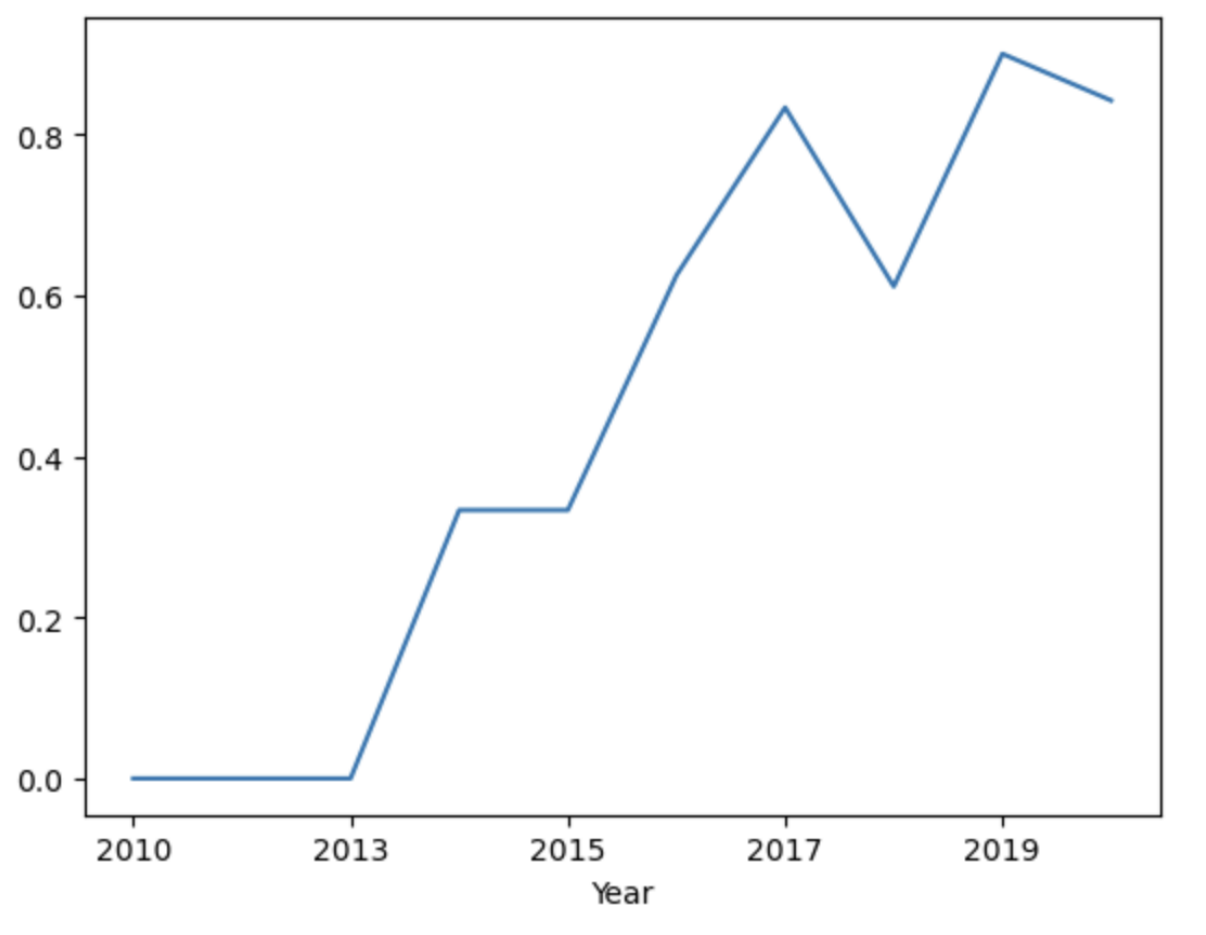
- Trends can be observed of shifting to VLEO launches in recent years.

Payload vs. Orbit Type



- Heavy payload tends to have higher successful landing rates for PO, LEO, and ISS orbits. GTO orbit success is less predictable with a close to equal mix of successes and failures.

Launch Success Yearly Trend



- The launch success rates have been increasing since 2013 till 2020, due to advancements in technology and experience.

All Launch Site Names

Task 1

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

```
[10]: sql SELECT DISTINCT LAUNCH_SITE FROM SPACEXTBL ORDER BY 1;
```

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

[10]:

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

- Performed an SQL query to obtain all launch site names

Launch Site Names Begin with 'CCA'

Task 2

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

[11]:
```
sql SELECT * FROM SPACEXTBL WHERE LAUNCH_SITE LIKE 'CCA%' LIMIT 5;
```

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

[11]:

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

- Find 5 records where launch sites begin with `CCA`

Total Payload Mass

Task 3

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

```
[13]: sql SELECT SUM(PAYLOAD_MASS__KG_) AS TOTAL_PAYLOAD FROM SPACEXTBL WHERE PAYLOAD  LIKE '%CRS%';
 * sqlite:///my_data1.db
Done.
```

[13]:

TOTAL_PAYLOAD
111268

- Calculate the total payload carried by boosters from NASA

Average Payload Mass by F9 v1.1

Task 4

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

```
[15]: sql SELECT AVG(PAYLOAD_MASS__KG_) AS AVG_PAYLOAD FROM SPACEXTBL WHERE BOOSTER_VERSION = 'F9 v1.1';
 * sqlite:///my_data1.db
Done.
```

[15]:

AVG_PAYLOAD
2928.4

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

First Successful Ground Landing Date

Task 5

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

Hint:Use min function

[22]:
```
%%sql
SELECT MIN(DATE) AS FIRST_SUCCESS_GP
FROM SPACEXTBL
WHERE "Landing_Outcome" = 'Success (ground pad)';
```

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

[22]:

FIRST_SUCCESS_GP
2015-12-22

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

Successful Drone Ship Landing with Payload between 4000 and 6000

Task 6

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

[23]:
```
%%sql
SELECT DISTINCT BOOSTER_VERSION
FROM SPACEXTBL
WHERE PAYLOAD_MASS__KG_ BETWEEN 4000 AND 6000
AND "Landing_Outcome" = 'Success (drone ship)';
```

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

[23]:

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

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

Total Number of Successful and Failure Mission Outcomes

Task 7

List the total number of successful and failure mission outcomes

```
[24]: sql SELECT MISSION_OUTCOME, COUNT(*) AS QTY FROM SPACEXTBL GROUP BY MISSION_OUTCOME ORDER BY MISSION_OUTCOME;
 * sqlite:///my_data1.db
Done.
```

[24]:

Mission_Outcome	QTY
Failure (in flight)	1
Success	98
Success	1
Success (payload status unclear)	1

- Calculate the total number of successful and failure mission outcomes

Boosters Carried Maximum Payload

Task 8

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

[25]:
```
sql SELECT DISTINCT BOOSTER_VERSION FROM SPACEXTBL WHERE PAYLOAD_MASS__KG_ = (SELECT MAX(PAYLOAD_MASS__KG_) FROM SPACEXTBL) ORDER BY BOOSTER_VERSION;
```

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

[25]:

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

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

2015 Launch Records

Task 9

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, 6,2) as month to get the months and substr(Date,0,5)='2015' for year.

[29]:
```
%%sql
SELECT BOOSTER_VERSION, LAUNCH_SITE
FROM SPACEXTBL
WHERE "Landing_Outcome" = 'Failure (drone ship)'
AND substr(DATE, 1, 4) = '2015';
```

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

[29]:

Booster_Version	Launch_Site
F9 v1.1 B1012	CCAFS LC-40
F9 v1.1 B1015	CCAFS LC-40

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

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

Task 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.

[30]:
```
%%sql
SELECT "Landing_Outcome", COUNT(*) AS QTY
FROM SPACEXTBL
WHERE DATE BETWEEN '2010-06-04' AND '2017-03-20'
GROUP BY "Landing_Outcome"
ORDER BY QTY DESC;
```

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

[30]:

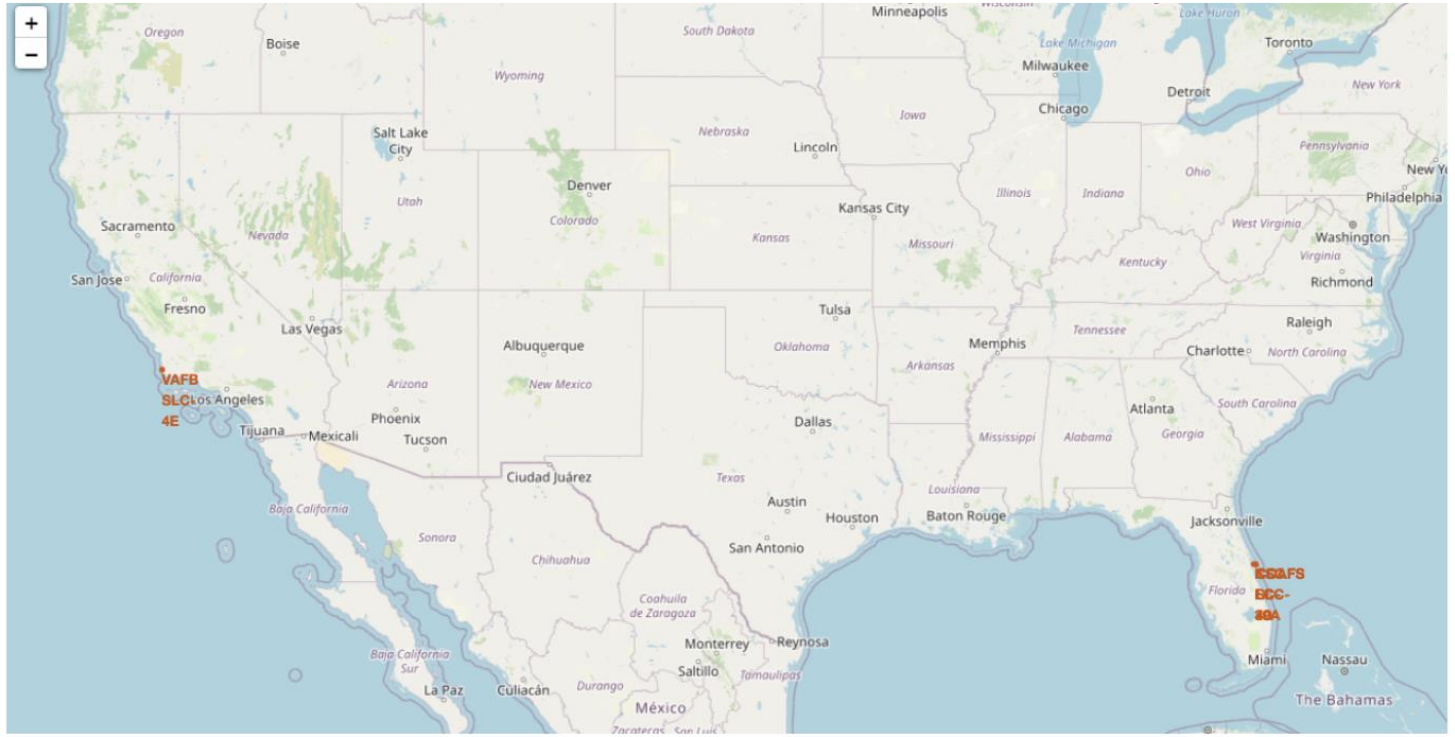
Landing_Outcome	QTY
No attempt	10
Success (drone ship)	5
Failure (drone ship)	5
Success (ground pad)	3
Controlled (ocean)	3
Uncontrolled (ocean)	2
Failure (parachute)	2
Precluded (drone ship)	1

- 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

Section 3

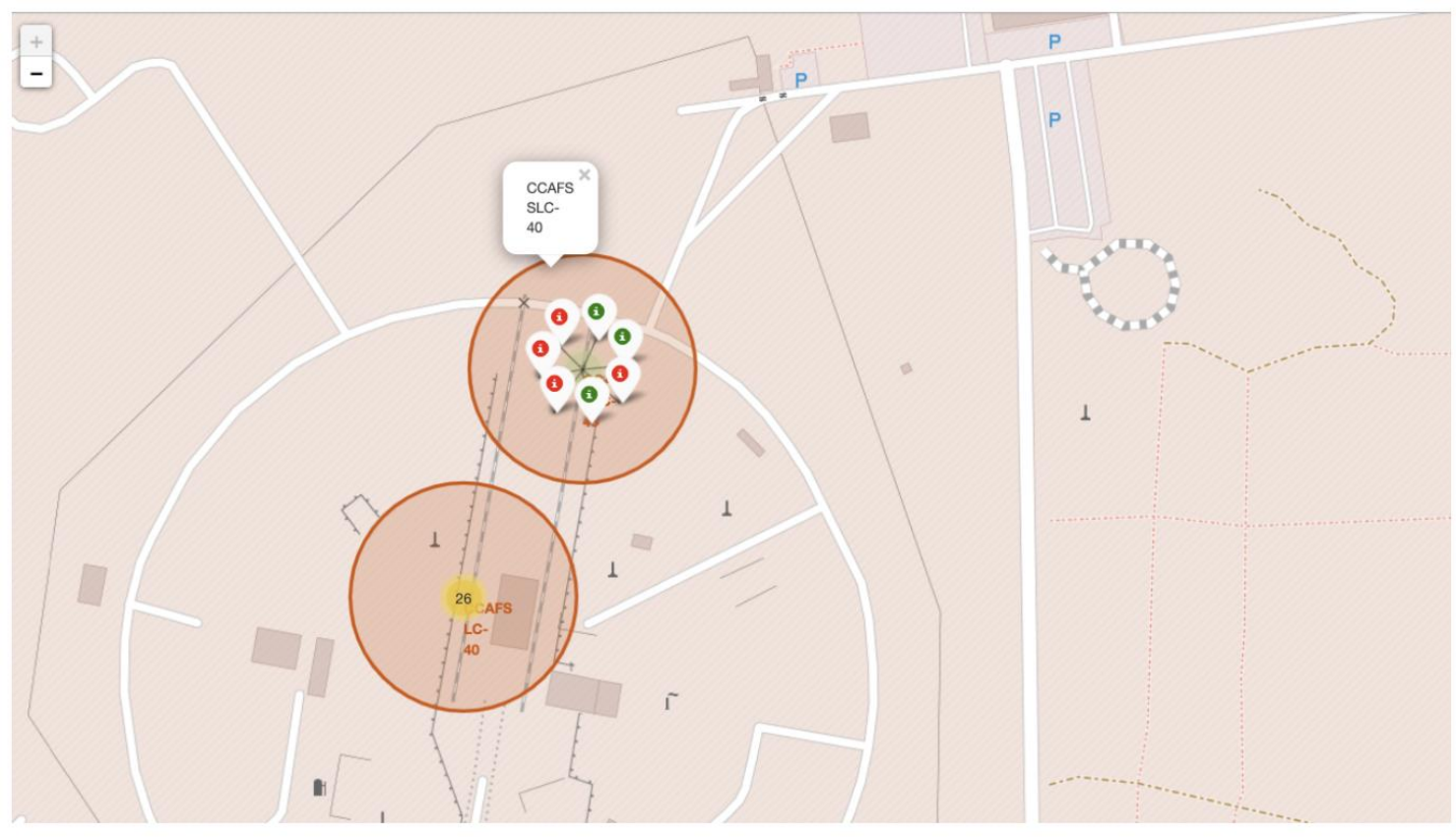
Launch Sites Proximities Analysis

All launch sites on a map



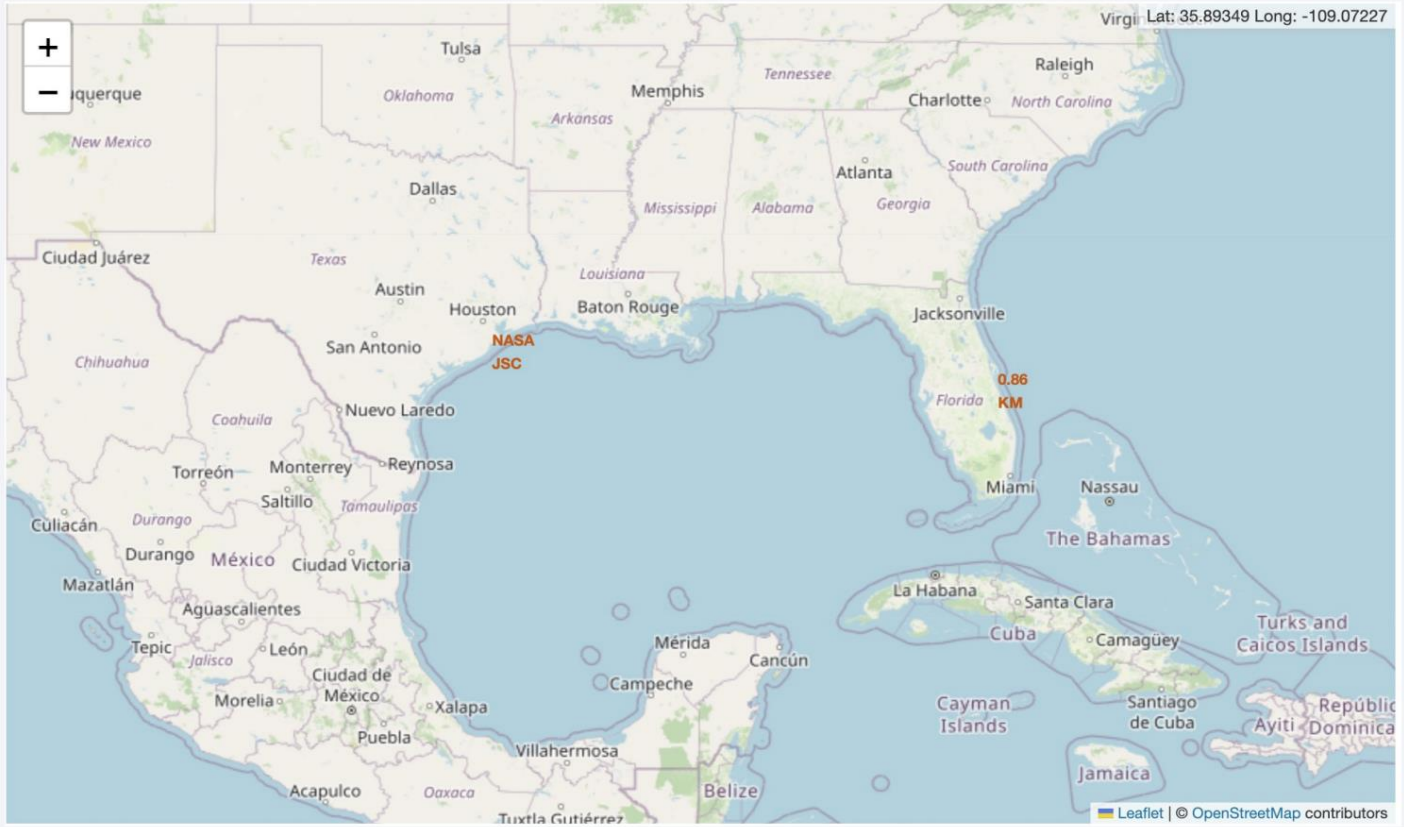
- Launch sites are labeled by a marker with their names on the map.

Success/Failed launches marked on the map

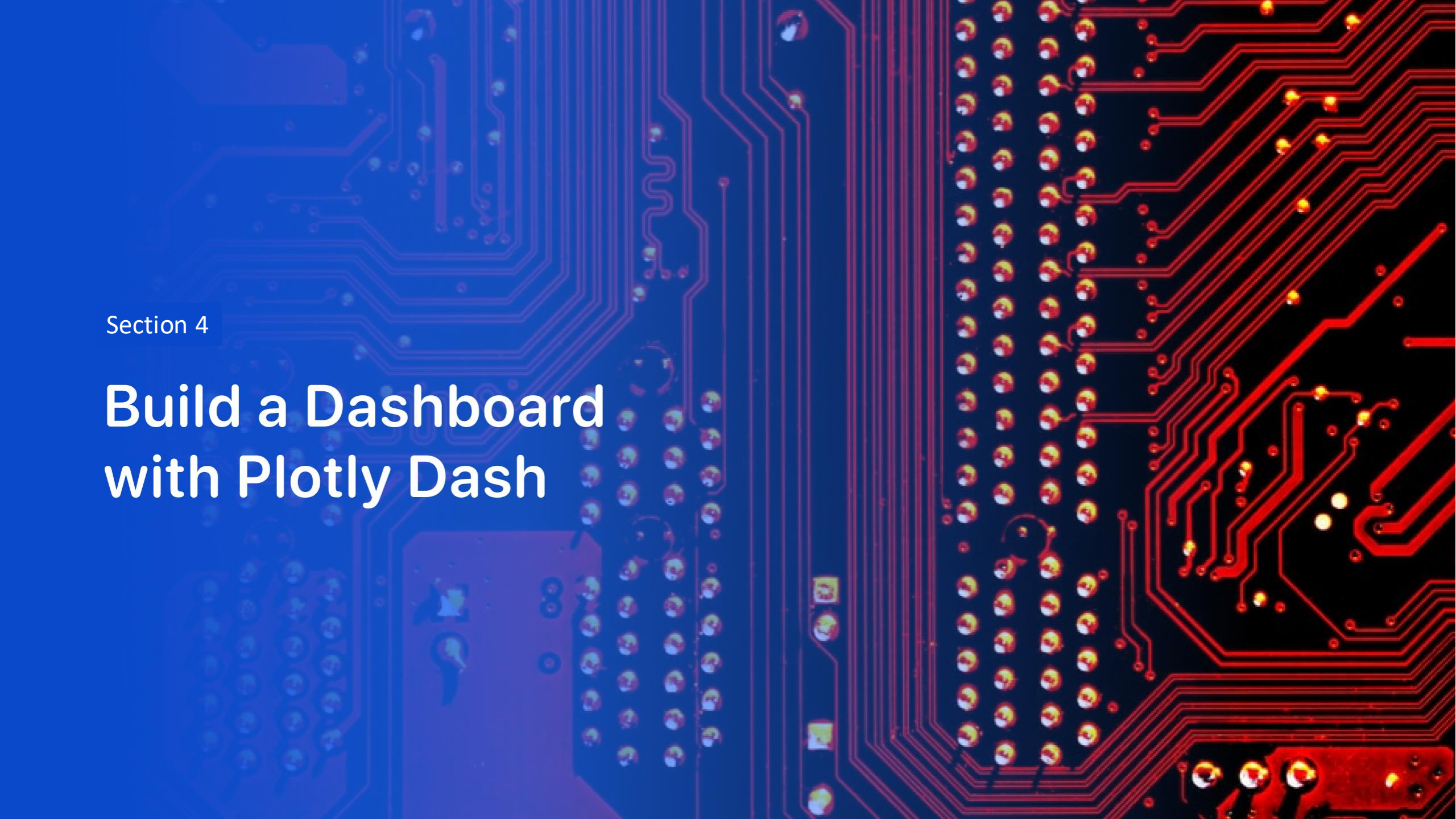


- Grouped in clusters on the map
- Labeled by green markers for successful launches, and red markers for unsuccessful ones.

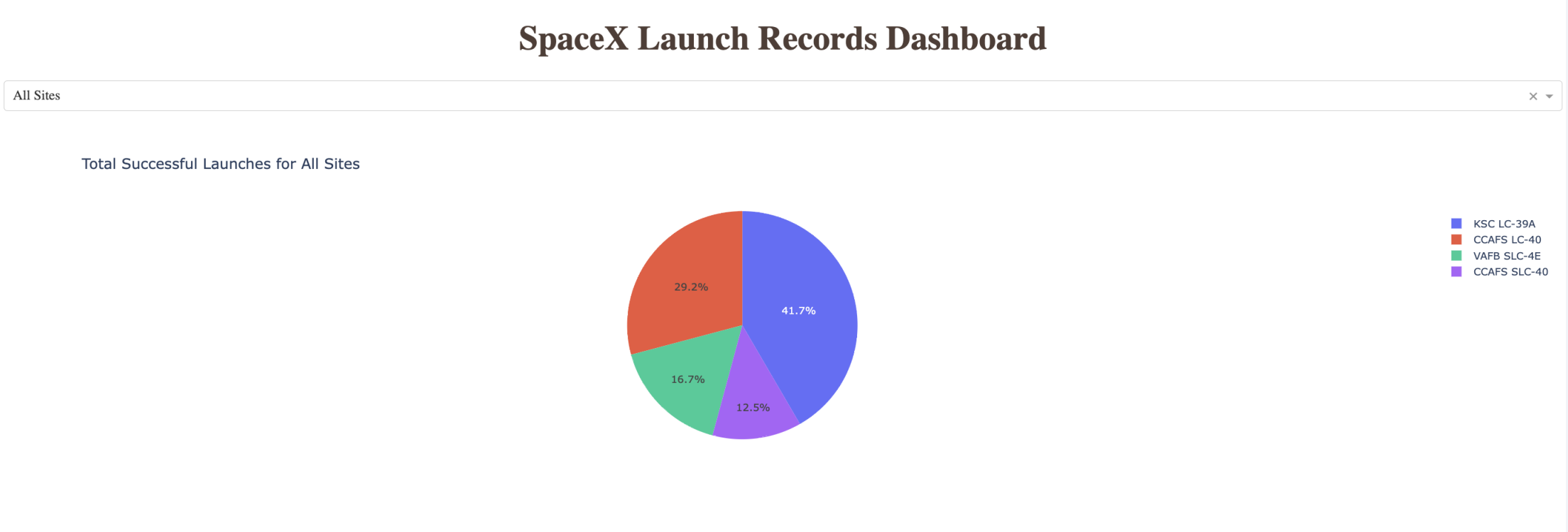
Distance between a launch site to its proximities



- Closest coastline from NASA JSC is marked as a point using MousePosition
- The distance between the coastline point and the launch site, which is approx. 0.86 km.

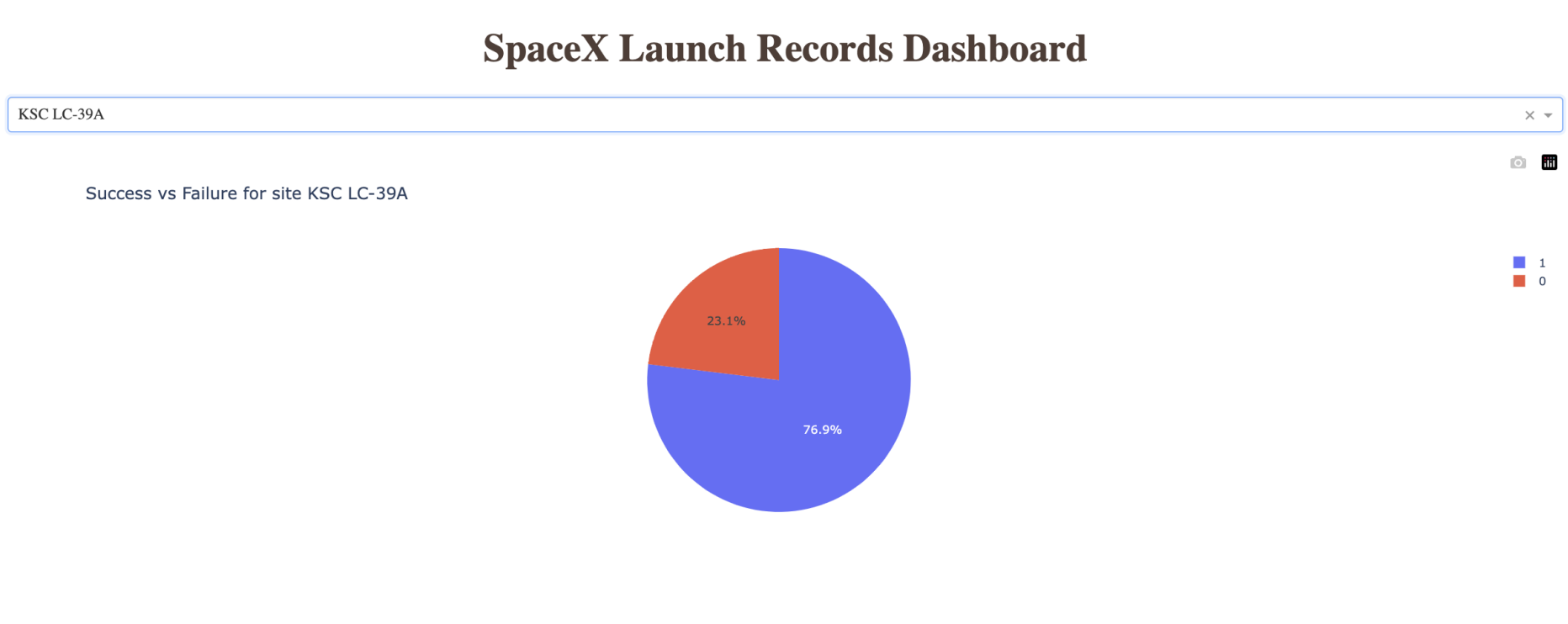

Section 4
Build a Dashboard with Plotly Dash

Total success launches for all sites



- KSC LC-39A - highest amount of success launches with 41.7% from the entire record
- CCAFS SLC-40 - lowest amount of success launches with only 12.5%.

Most successful launch site



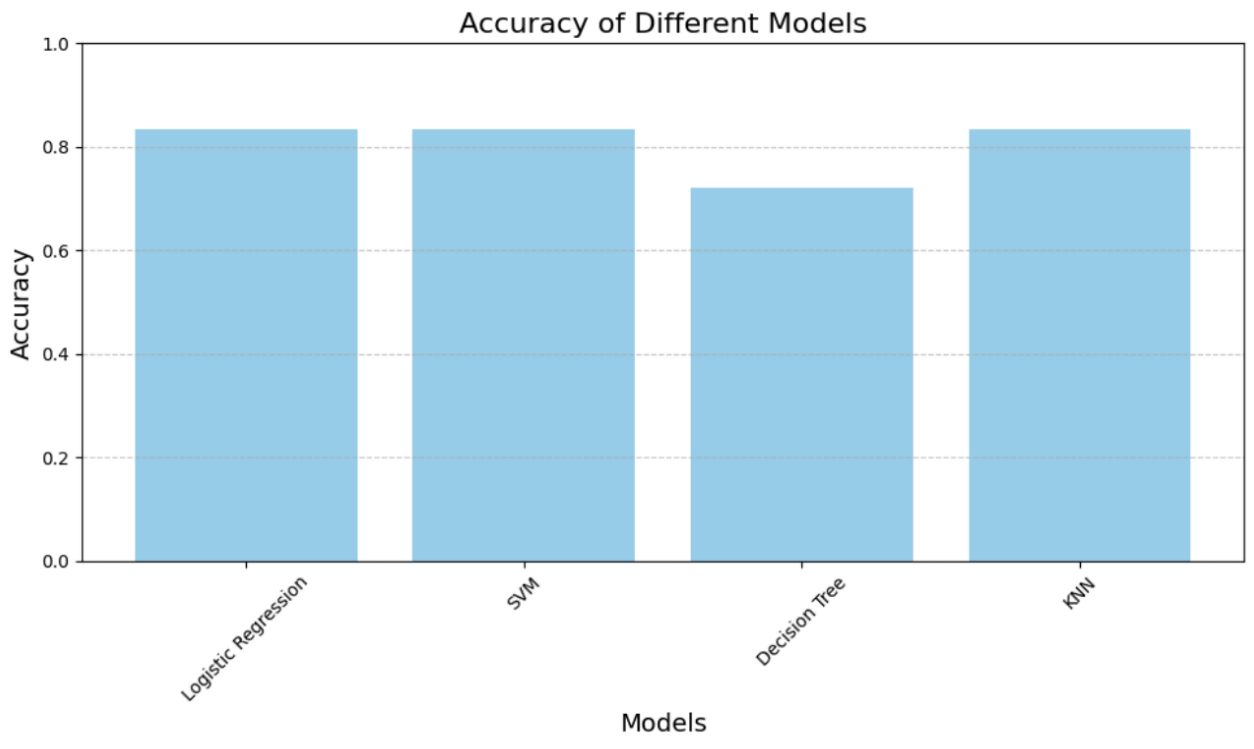
- KSC LC-39A, the launch site with highest amount of success, has a 76.9% success rate, and 23.1% failure rate.

Payload vs. Launch Outcome

Section 5

Predictive Analysis (Classification)

Classification Accuracy



TASK 12

Find the method performs best:

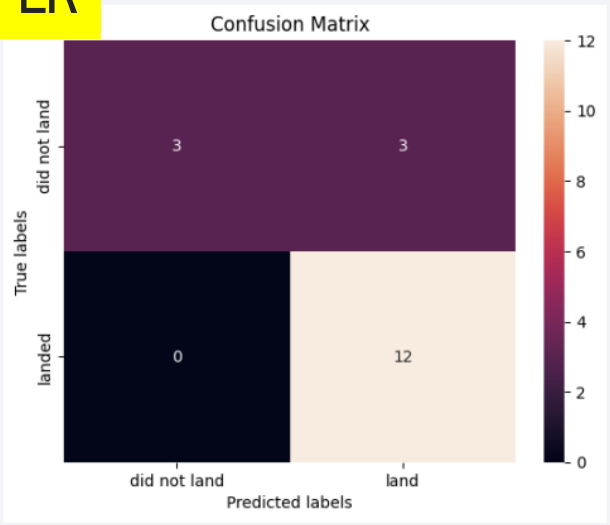
```
print('LR Accuracy:', '{:.2%}'.format(logreg_accuracy))
print( 'SVM Accuracy:', '{:.2%}'.format(svm_accuracy))
print('Decision Tree Accuracy:', '{:.2%}'.format(tree_accuracy))
print('KNN Accuracy:', '{:.2%}'.format(knn_accuracy))
```

```
LR Accuracy: 83.33%
SVM Accuracy: 83.33%
Decision Tree Accuracy: 72.22%
KNN Accuracy: 83.33%
```

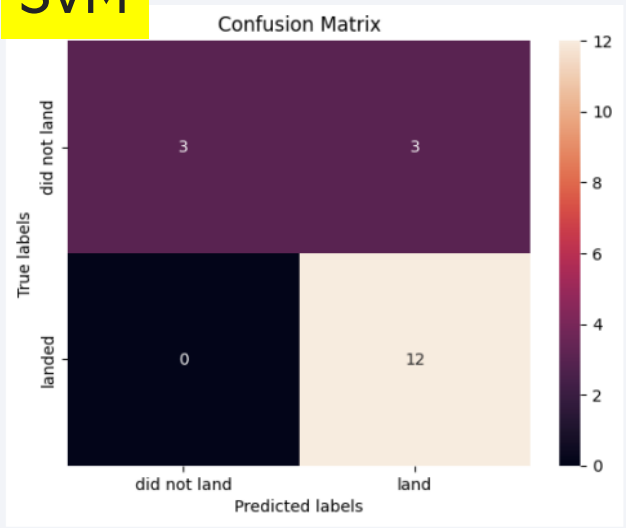
- The methods performed best are LR, SVM, KNN where all 3 achieved the highest accuracy of 83.33%.

Confusion Matrix

LR

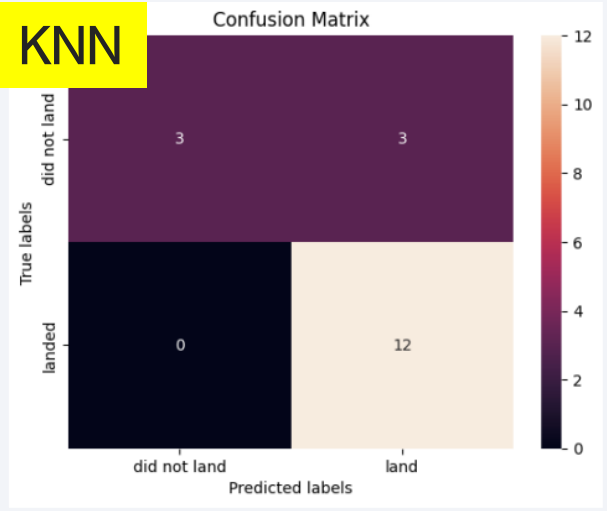


SVM



Decision Tree

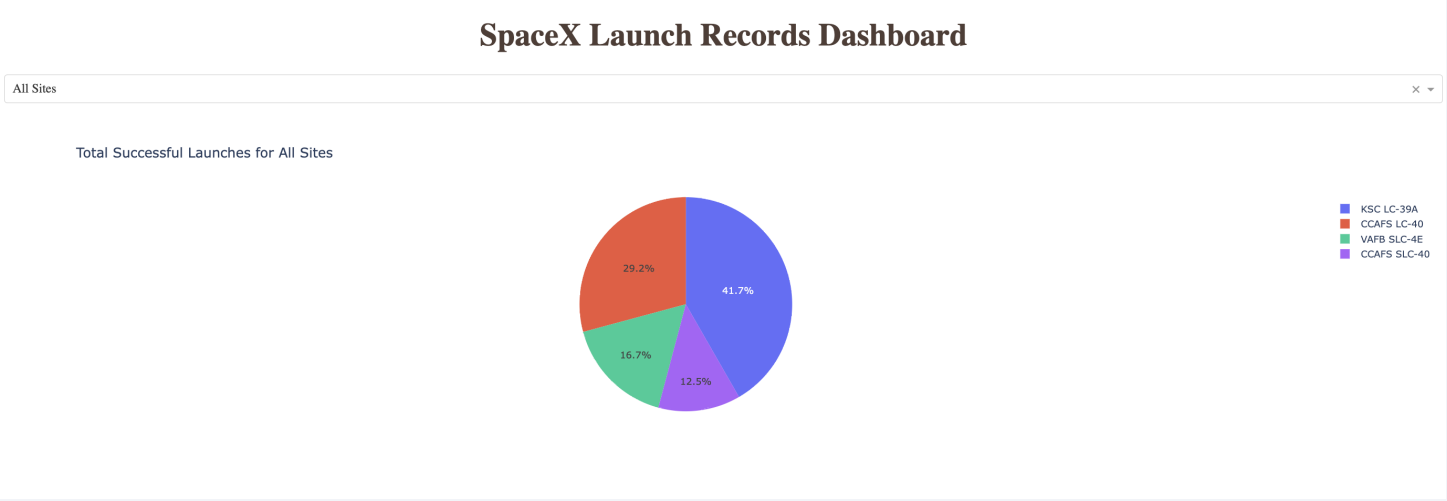
KNN



- LR, SVM, KNN models are good
  - Their confusion matrix show that they predicted all 12 successful landing correctly, with 0 error.
- The Decision Tree model only predicted 11 successful landing correctly
  - One of them wrongly predicted as a failed / did not land.
- LR, SVM, KNN models have the same accuracy of 83.33%

Conclusions

- LR, SVM, KNN performed best for forecasting outcomes in this data.
- Lighter payloads have a higher performance compared to heavier ones.
- The likelihood of a SpaceX launch succeeding increases with the number of years of experience, suggesting a trend towards flawless launches over time.
- KSC LC-39A has the highest number of successful launches compared to other launch sites.
- GEO,HEO,SSO,ES L1 exhibit the highest rates of successful launches.



KSC LC-39A has the highest number of successful launches

Thank you!