IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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Outline

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Executive Summary

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

Introduction

Background

Our project is part of a big learning journey - the final course of the IBM Data Science series. Think of us as the brainy folks at SpaceY, a new company aiming to launch rockets just like SpaceX.

In this project, we will use the cool methodologies from data science to help SpaceY make smart choices when it comes to sending rockets into space, and maybe even outbid the big guys at SpaceX.

Business Problem

Here's the scoop: SpaceX is the big name in space because they figured out how to send rockets up without breaking the bank. They say it costs about 62 million dollars to launch their Falcon 9, which is way cheaper than what other companies charge. They save a bunch by reusing the first part of the rocket. Normally, that part alone could set you back over 15 million dollars, not even counting the money spent developing it.

But sometimes, SpaceX has to let that first part go - maybe the satellite they're carrying is super heavy, or they need to send it to a special place in space. When that happens, it's bye-bye savings. So, we're on a mission to guess if that rocket part is going to make it back safely or not. Getting this right could mean big savings, and that's a number any shareholder would like to see.

Section 1

Methodology

Methodology - Executive Summary

- Data collection methodology:
  - SpaceX Open Source Rest API
  - Web Scraping from Wikipedia page ‘List of Falcon 9 and Falcon Heavy Launches’
- Perform data wrangling
  - Transforming categorical data using One Hot Encoding for machine learning algorithms and removing any empty or unnecessary information from the 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
  - Logistic Regression, K-Nearest Neighbors, Support Vector Machines, and Decision Tree models have been developed to determine the most effective classification method.

Data Collection

The data sets are collected using 2 methods:

1) Request to the SpaceX API

- Gathered SpaceX's past launch data via their open-source API.
- Retrieved and processed this data with GET request.
- Ensured the data included only Falcon 9 launches.
- Filled in missing payload weights from secret missions with average values.

2) Web Scraping

- Requested past Falcon 9 and Falcon Heavy launch data from Wikipedia's relevant page.
- Accessed the Falcon 9 Launch page via its direct Wikipedia link.
- Extracted all the column names from the HTML table.
- Parsed and transformed the table into a Pandas data frame suitable for analysis.

Data Collection - SpaceX API

Task 1: Request and parse the SpaceX launch data using the GET request

To make the requested JSON results more consistent, we will use the following static response object for this project:

```
In [29]: static_json_url='https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/
```

We should see that the request was successfull with the 200 status response code

```
In [30]: response.status_code
Out[30]: 200
```

Now we decode the response content as a Json using `.json()` and turn it into a Pandas dataframe using `.json_normalize()`

```
In [31]: # Use json_normalize meethod to convert the json result into a dataframe
data = pd.json_normalize(response.json())
```

Using the dataframe `data` print the first 5 rows

```
In [32]: # Get the head of the dataframe
data.head()
Out[32]: static_fire_date_utc  static_fire_date_unix
```

Requested and parsed the data from SpaceX API using GET request

Finally lets construct our dataset using the data we have obtained. We we combine the columns into a dictionary.

```
In [41]: 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}
```

Then, we need to create a Pandas data frame from the dictionary launch_dict.

```
In [42]: # Create a data from launch_dict
df = pd.DataFrame.from_dict(launch_dict)
```

Show the summary of the dataframe

```
In [43]: # Show the head of the dataframe
df.head()
```

Stored the data and constructed the dataset into a new dictionary with relative columns

Task 2: Filter the dataframe to only include `Falcon 9` launches

Finally we will remove the Falcon 1 launches keeping only the Falcon 9 launches. Filter the data dataframe using the `BoosterVersion` column to only keep the Falcon 9 launches. Save the filtered data to a new dataframe called `data_falcon9`.

```
In [44]: # Hint data['BoosterVersion']!='Falcon 1'
data_falcon9 = df[df['BoosterVersion']!='Falcon 1']
```

Now that we have removed some values we should reset the FlgihtNumber column

```
In [45]: data_falcon9.loc[:,'FlightNumber'] = list(range(1, data_falcon9.shape[0]+1))
data_falcon9
```

Filtered the dataframe to only include Falcon 9 launches needed for the project analysis

Task 3: Dealing with Missing Values

Calculate below the mean for the `PayloadMass` using the `.mean()`. Then use the mean and the `.replace()` function to replace `np.nan` values in the data with the mean you calculated.

```
In [62]: # # Calculate the mean value of PayloadMass column
# # Replace the np.nan values with its mean value
payloadmass_avg = data_falcon9['PayloadMass'].mean()
data_falcon9['PayloadMass'].replace(np.nan, payloadmass_avg, inplace=True)
```

```
In [63]: data_falcon9.isnull().sum()
Out[63]: FlightNumber      0
Date              0
BoosterVersion    0
PayloadMass       0
Orbit             0
LaunchSite        0
Outcome           0
Flights           0
GridFins          0
Reused            0
Legs              0
LandingPad       26
Block             0
ReusedCount       0
Serial            0
Longitude         0
Latitude          0
dtype: int64
```

You should see the number of missing values of the `PayLoadMass` change to zero.

Now we should have no missing values in our dataset except for in `LandingPad`.

Cleaned the data and removed missing values of PayLoadMass

My GitHub reference: [1. Hands-on Lab_Complete the Data Collection API Lab.ipynb]

Data Collection - Web Scraping from Wikipedia

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.

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

response = requests.get(static_url)
print(response)
```

```
<Response [200]>
```

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

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

soup = BeautifulSoup(response.text)
```

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

```
In [7]:
# Use soup.title attribute
page_title = soup.title.string
print(page_title)
```

```
List of Falcon 9 and Falcon Heavy laun
```

Requested data from Wikipedia using HTTP GET request and BeautifulSoup

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

```
In [8]:
# 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.

```
In [9]:
# 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 hre
TC</a>)
</th>
<th scope="col"><a href="/wiki/List_of_Falcon_9_first-stage_boosters" title="List of Falcon 9 first-stage booster
```

Extracted all column/variable names from the HTML table header

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

```
In [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']=[]
```

Cleaned the column data, created an empty dictionary with extracted columns and appended the column names

```
# Booster landing
# TODO: Append the launch_outcome into launch_dict with key `Booster landing`
booster_landing = landing_status(row[8])
launch_dict['Booster landing'].append(booster_landing) #TODO-11
#print(booster_landing)
```

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

```
In [10]:
df= pd.DataFrame({ key:pd.Series(value) for key, value in launch_dict.items() })
df=pd.DataFrame(launch_dict)
df
```

Out[10]:

	Flight No.	Launch site	Payload	Payload mass	O[illegible]						
0	1	CCAFS	Dragon Spacecraft Qualification Unit	0	[illegible]						
1	2	CCAFS	Dragon	0	LEO	NASA (COTS)\nNRO	Success	F9 v1.0B0004.1	Failure	8 December 2010	15:43
2	3	CCAFS	Dragon	525 kg	LEO	NASA (COTS)	Success	F9 v1.0B0005.1	No attempt\n	22 May 2012	07:44

Created a data frame by parsing the launch HTML tables

My GitHub reference: [2. Hands-on Lab_Complete the Data Collection with Web Scraping lab.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:

```
In [5]:
# Apply value_counts() on column LaunchSite
launch_site_count = df['LaunchSite'].value_counts()
print(launch_site_count)
```

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

Calculated the number of launches of 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`

```
In [6]:
orbit_count = df['Orbit'].value_counts()
print(orbit_count)
```

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

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.

```
In [7]:
# landing_outcomes = values on Outcome column
landing_outcomes = df['Outcome'].value_counts()
print(landing_outcomes)
```

```
True ASDS      41
None None      19
True RTLS      14
False ASDS      6
True Ocean      5
False Ocean     2
None ASDS       2
```

Calculated the number and occurrence of each orbit and its mission outcome

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` :

```
In [10]:
# landing_class = 0 if bad_outcome
# landing_class = 1 otherwise
landing_class = []
for outcome in df['Outcome']:
    if outcome in bad_outcomes:
        landing_class.append(0)
    else:
        landing_class.append(1)
```

This variable will represent the classification variable that represents the outcome of each launch. If the value is zero, the first stage did not land successfully; one means the first stage landed Successfully

```
In [11]:
df['Class']=landing_class
df[['Class']].head(8)
```

Out[11]:

	Class
0	0

Created a landing outcome label form Outcome column

```
In [12]:
df.head(5)
```

Out[12]:

	FlightNumber	Date	BoosterVersion	PayloadMass	Orbit	LaunchSite	Outcome	Flights	GridFins	Reused	Legs	LandingPac
0	1	2010-06-04	Falcon 9	6104.959412	LEO	CCAFS SLC 40	None None	1	False	False	False	NaN
1	2	2012-05-22	Falcon 9	525.000000	LEO	CCAFS SLC 40	None None	1	False	False	False	NaN
2	3	2013-03-01	Falcon 9	677.000000	ISS	CCAFS SLC 40	None None	1	False	False	False	NaN
3	4	2013-09-29	Falcon 9	500.000000	PO	VAFB SLC 4E	False Ocean	1	False	False	False	NaN
4	5	2013-12-03	Falcon 9	3170.000000	GTO	CCAFS SLC 40	None None	1	False	False	False	NaN

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

```
In [13]:
df["Class"].mean()
```

```
Out[13]: 0.6666666666666666
```

Calculated the average success rate

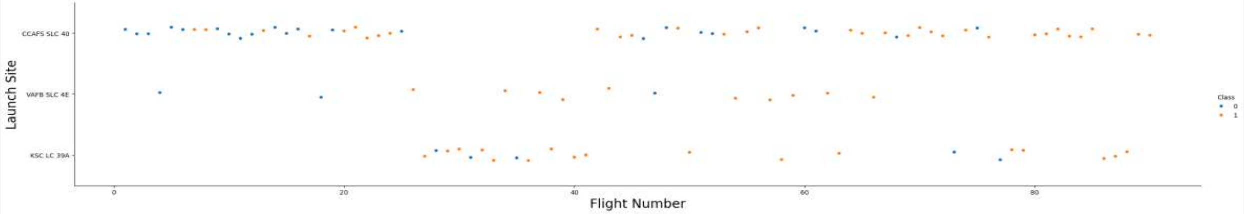
We can now export it to a CSV for the next section,but to make the answers consistent, in the next lab we will provide data in a pre-selected date range.

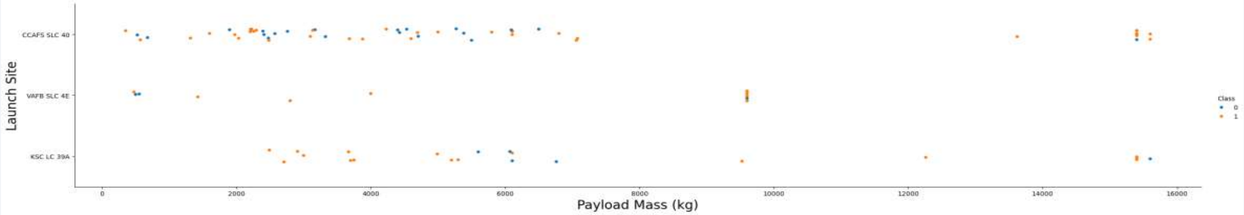
```
df.to_csv("dataset_part_2.csv", index=False)
```

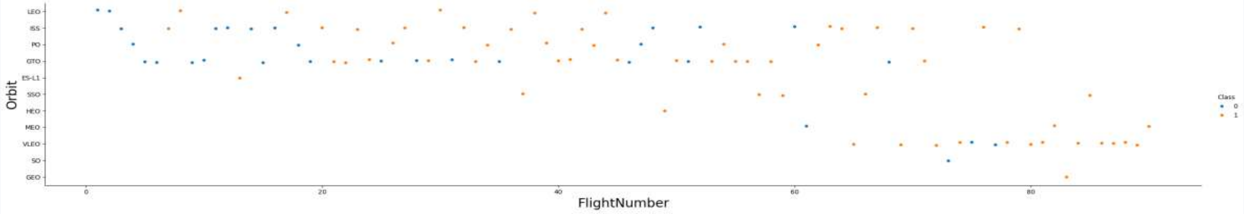

My GitHub reference: 3. Hands-on Lab_Data Wrangling.ipynb

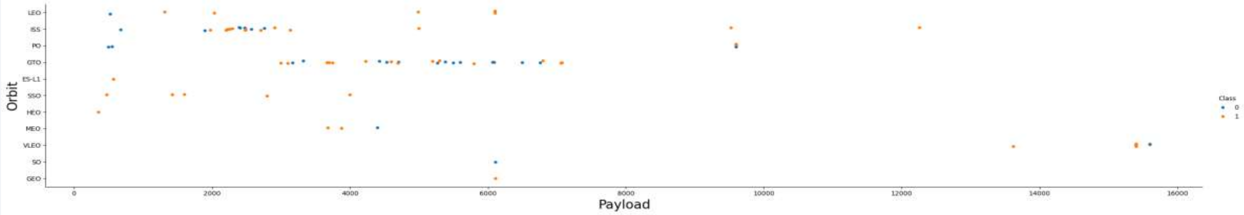
EDA with Data Visualization

Scatter point charts are used to visualize the relationship between (1) Flight Number and Launch Site, (2) Payload and Launch Site, (3) Flight Number and Orbit type, (4) Payload and Orbit type

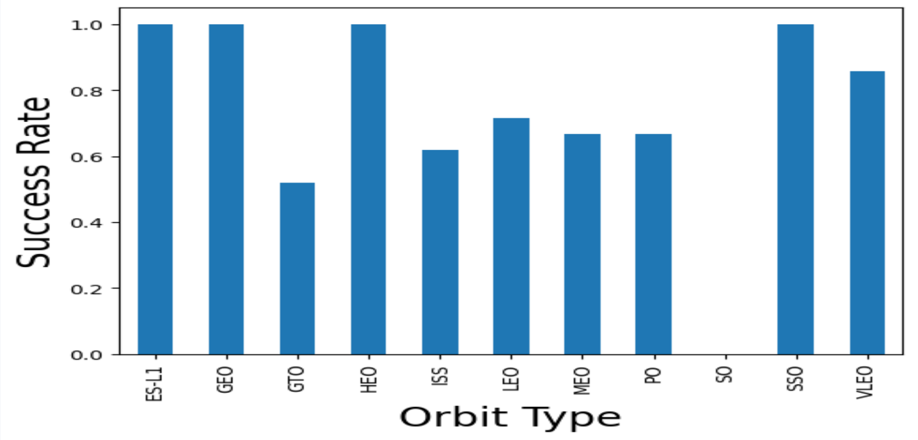


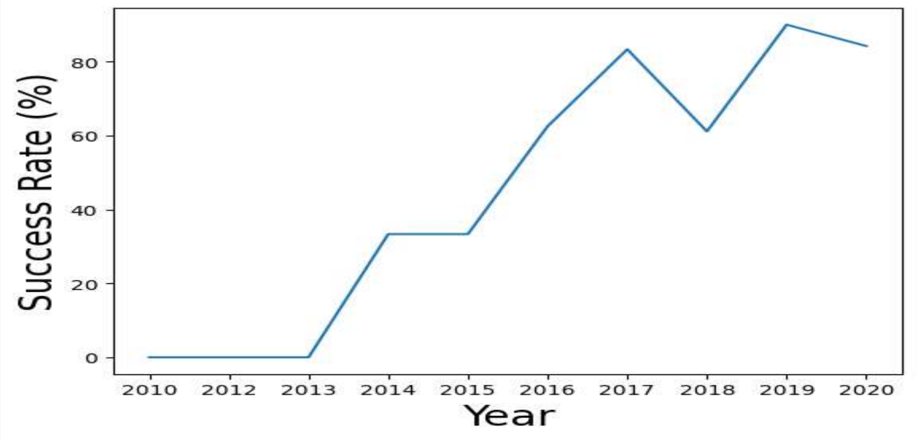






Bar chart was used to visualize the relationship between success rate of each orbit type; Line chart was used to visualize the launch success yearly trend





My GitHub reference: [5. EDA with Visualization Lab.ipynb]

EDA with SQL

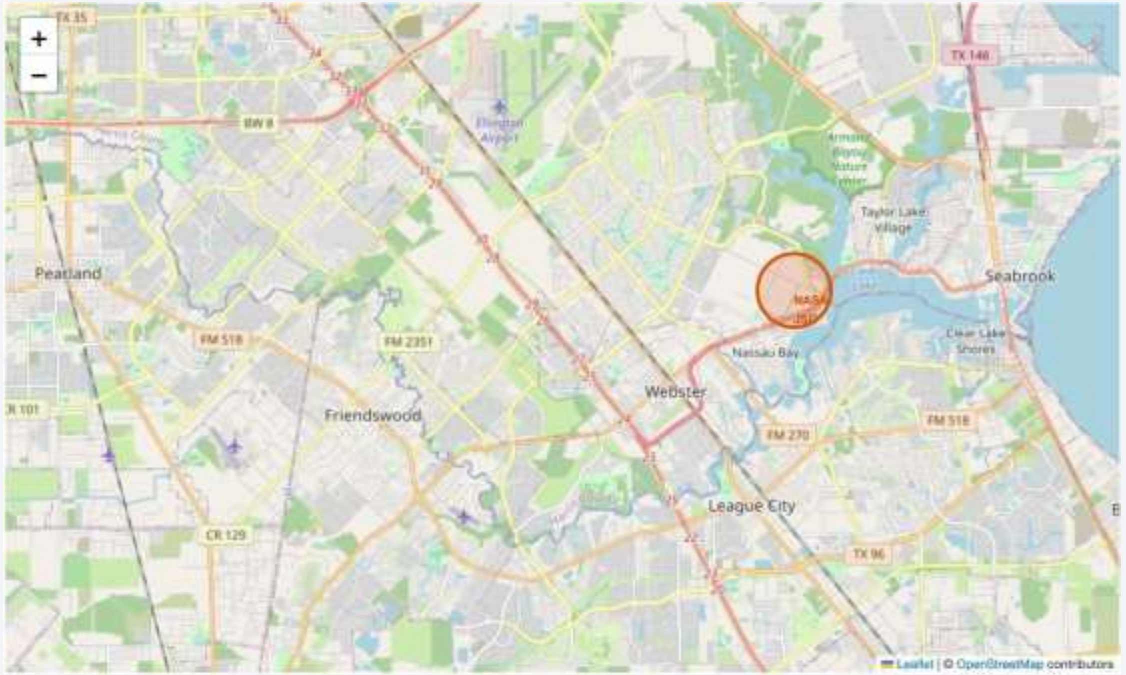
SQL queries are performed to:

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 average payload mass carried by booster version F9 v1.1
5. List the date when the first successful landing outcome in ground pad was achieved.
6. List the names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000
7. List the total number of successful and failure mission outcomes
8. List the names of the booster versions which have carried the maximum payload mass using a subquery
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.
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.

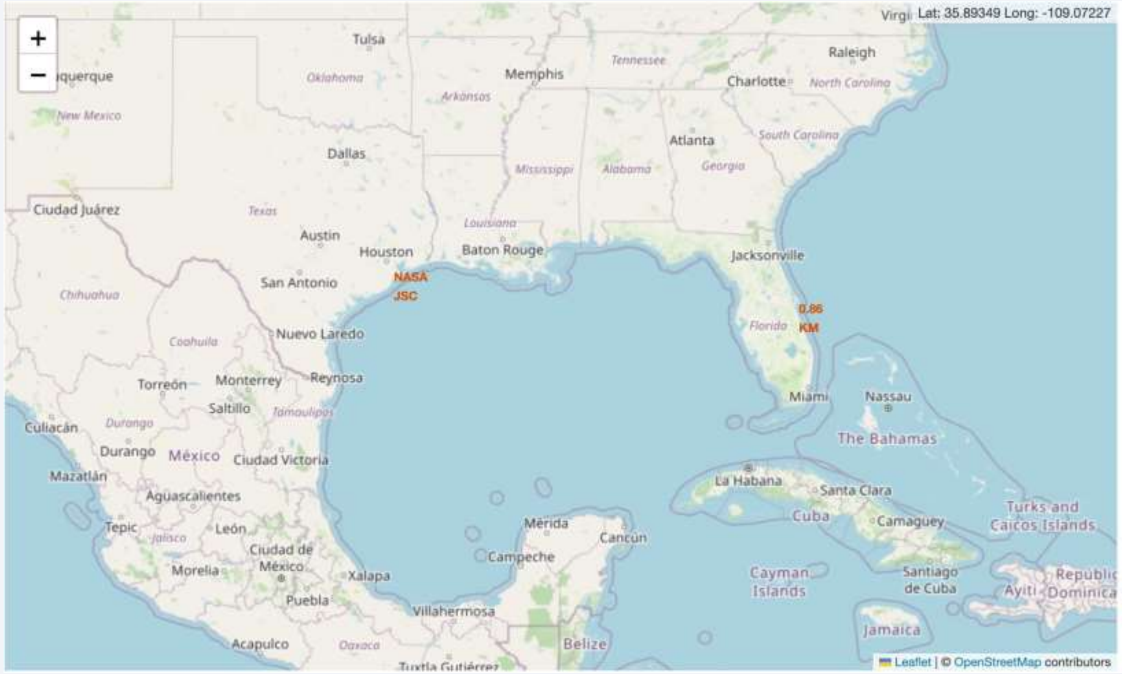
My GitHub reference: [4. Hands-on Lab_Complete the EDA with SQL.ipynb]

Build an Interactive Map with Folium

A circle marker was created to show NASA Johnson Space Center's coordinate

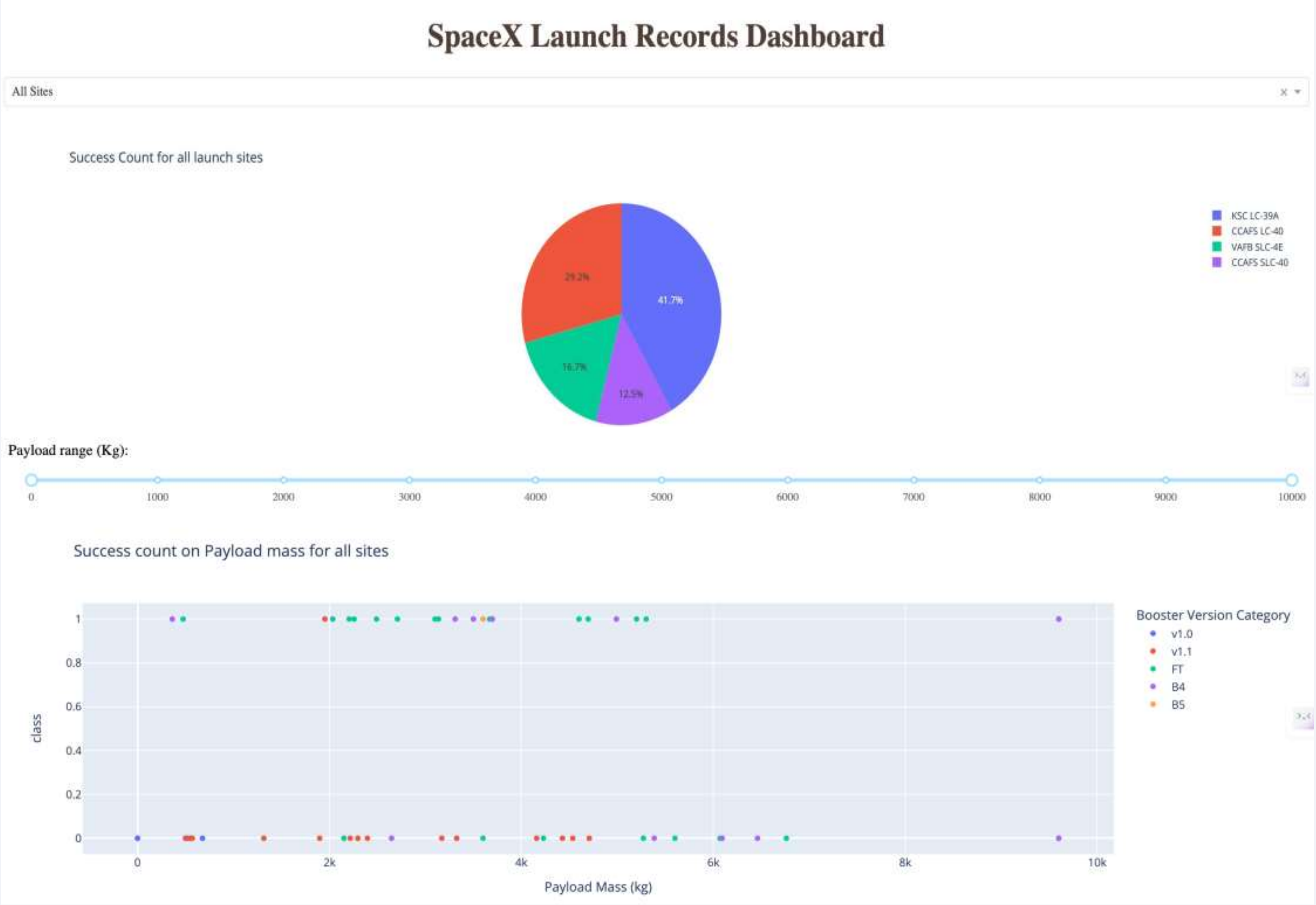


Distance marker was created to show distances between a launch site to its proximities



My GitHub reference: [6. Hands-on Lab_Interactive Visual Analytics with Folium lab.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

My GitHub reference: [7. Hands-on Lab_Build an Interactive Dashboard with Ploty Dash_spacex_dash_app.py]

Predictive Analysis (Classification)

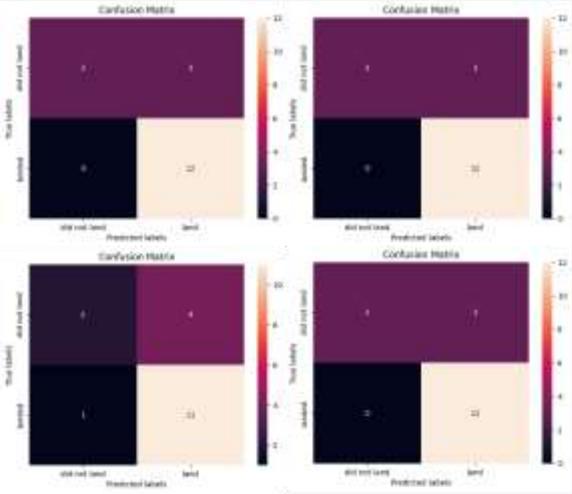
- LR, SVM, Decision Tree and KNN objects are created and fit with GridSearchCV object to find the best parameters, then the models are trained on the training set.
- The accuracy of test data are calculated for each machine learning model. It is found that the methods performed best are LR, SVM, KNN where all 3 achieved the highest accuracy of 83.33%.

TASK 12

Find the method performs best:

In [58]:
```
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))
```

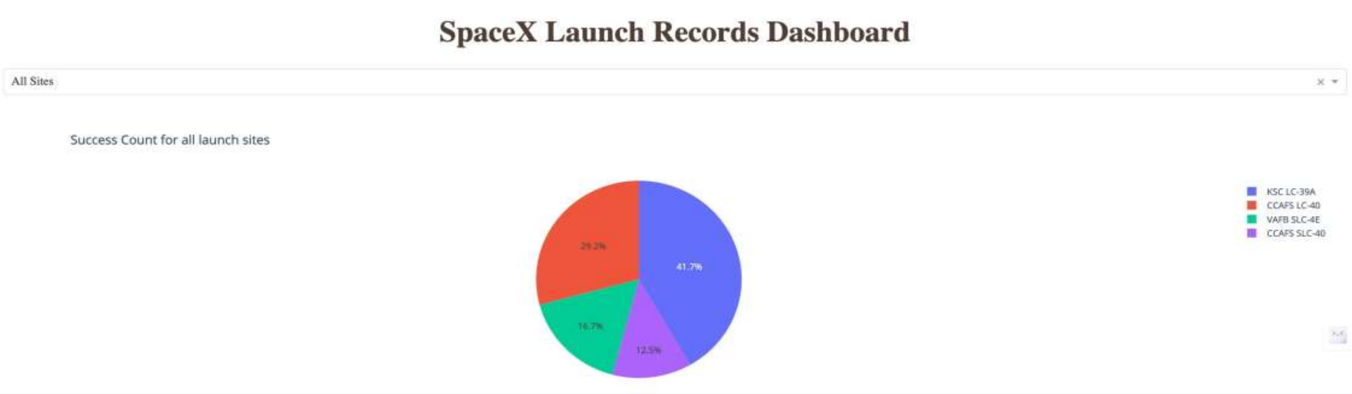
```
LR Accuracy: 83.33%
SVM Accuracy: 83.33%
Decision Tree Accuracy: 72.22%
KNN Accuracy: 83.33%
```



My GitHub reference: [8. Hands-on Lab_Complete the Machine Learning Prediction lab.ipynb]

Results

- LR, SVM, KNN are top-performing models 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.
- Launch Complex 39A at Kennedy Space Center has the highest number of successful launches compared to other launch sites.
- GEO,HEO,SSO,ES L1 orbit types exhibit the highest rates of successful launches.

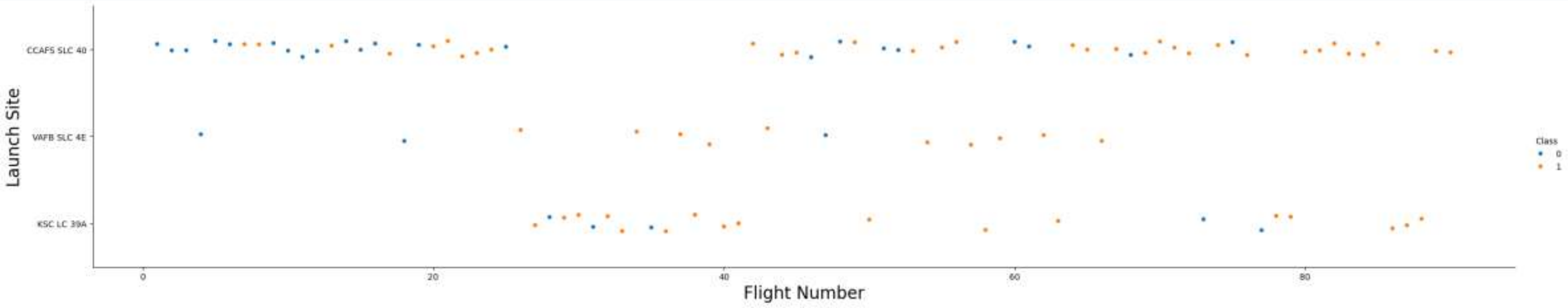


KSC LC-39A has the most successful launches overall

Section 2

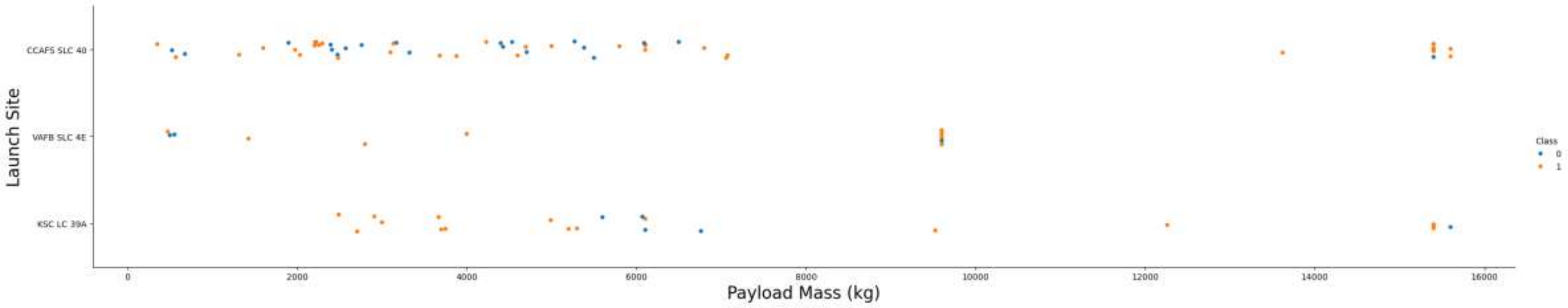
Insights drawn from EDA

Flight Number vs. Launch Site



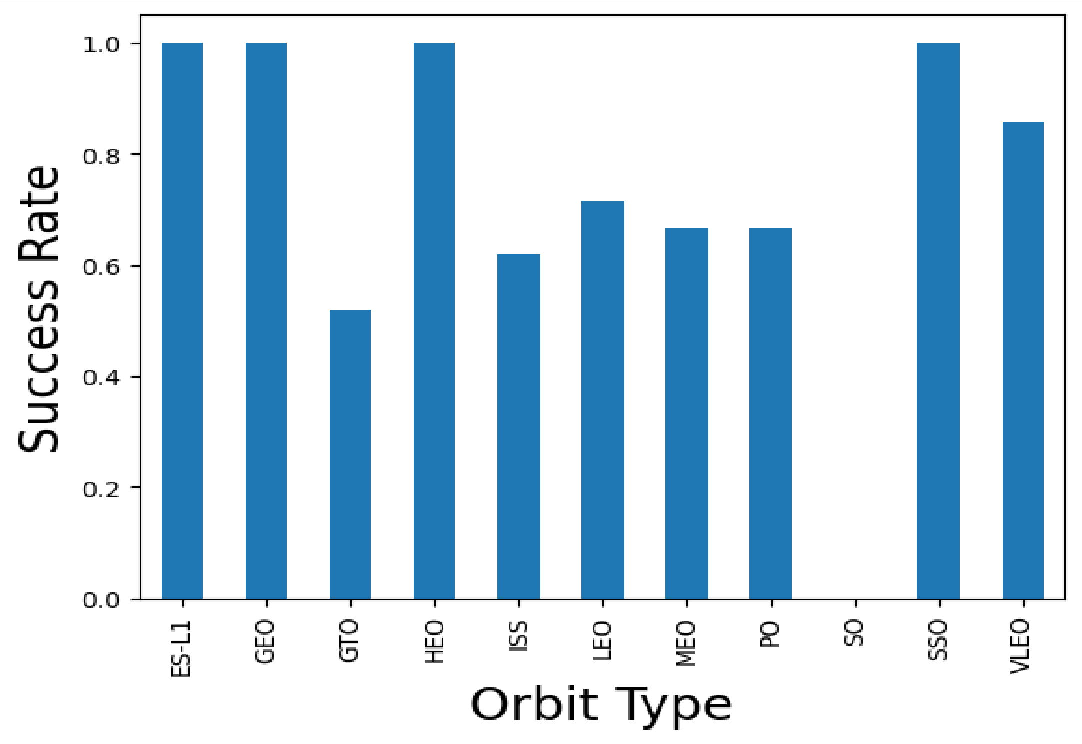
- Total number of launches from launch site CCAFS SLC40 are significantly higher than the other launch sites.

Payload vs. Launch Site



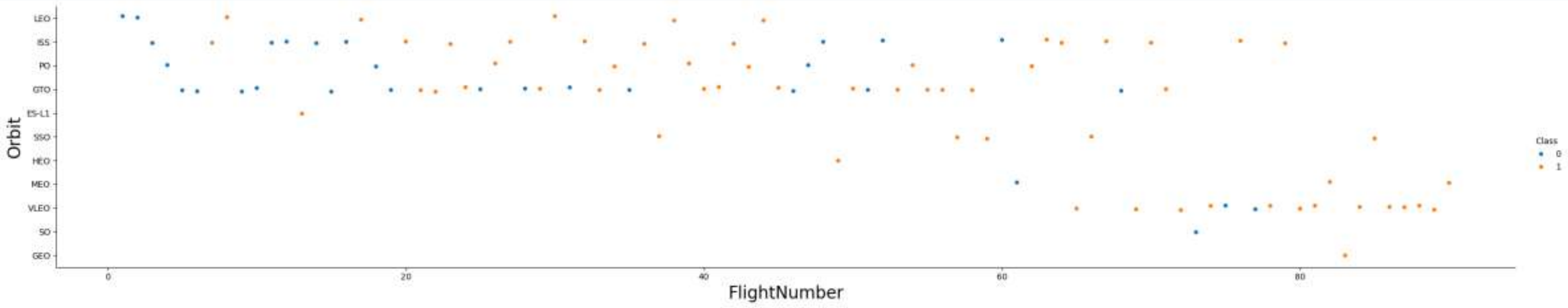
- Payloads with lower mass are have more launches compared to those with higher mass across all three launch sites.

Success Rate vs. Orbit Type



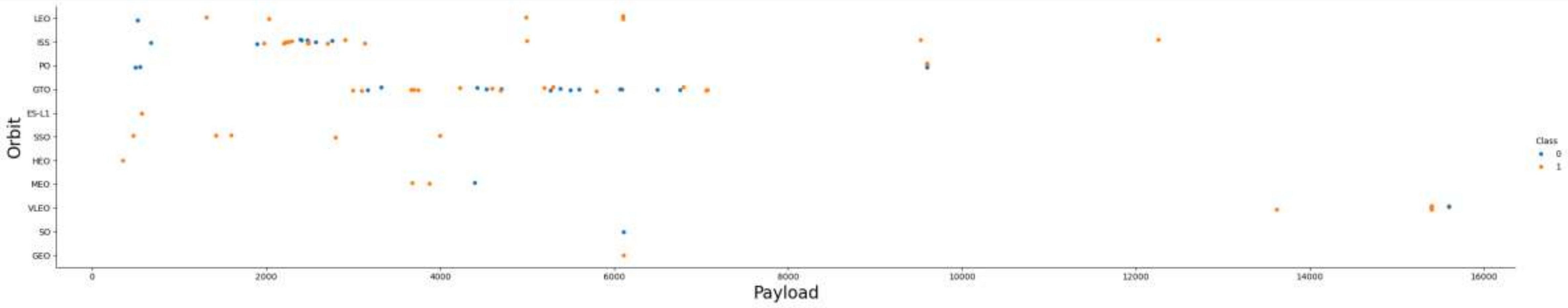
- Orbit types ES-L1, GEO, HEO, SSO have the highest success rate among all.

Flight Number vs. Orbit Type



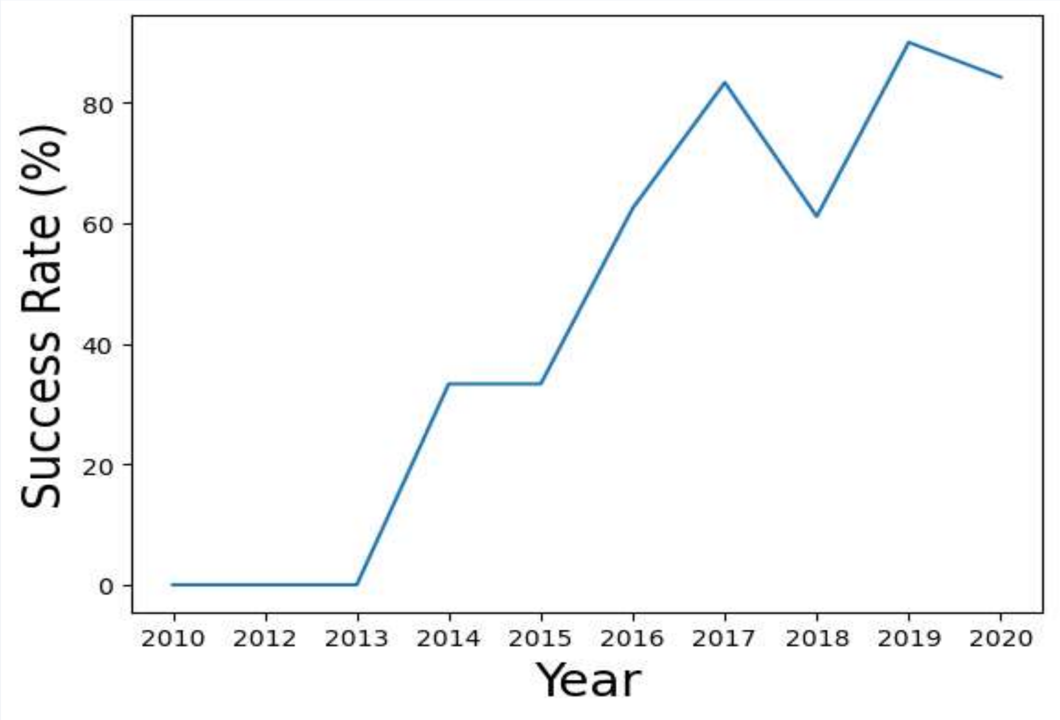
- LEO, ISS, PO, GTO orbits have the most launches in the earlier years, but it slowly shifted to VLEO orbit in the later years.

Payload vs. Orbit Type



- Heavy payloads tend to have higher successful landing rates for PO, LEO, and ISS orbits, but for GTO orbit, success is less predictable with an almost equal mix of successes and failures.

Launch Success Yearly Trend



- The success rate of launches have been increasing since 2013 till 2020, possibly due to technology advancement and experience.

All Launch Site Names

Task 1

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

```
In [15]: %sql select distinct Launch_Site FROM SPACEXTABLE

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

Out[15]:

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

- 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'

In [16]:
```
%sql select * from SPACEXTABLE where Launch_Site like 'CCA%' limit 5
```

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

Out[16]:

Date	Time (UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS__KG_	Orbit	Customer	Mission_Outcome	Landing_
2010-06-04	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (p
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 (p
2012-05-22	7:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	N
2012-10-08	0:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	N
2013-03-01	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	N

- Performed an SQL query to obtain 5 launch site names that begin with 'CCA'

Total Payload Mass

Task 3

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

```
In [17]: %sql select sum(PAYLOAD_MASS__KG_) from SPACEXTABLE where customer = 'NASA (CRS)'

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

Out[17]:

sum(PAYLOAD_MASS__KG_)
45596

- Performed an SQL query to obtain the total payload mass carried by boosters launched by NASA (CRS)

Average Payload Mass by F9 v1.1

Task 4

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

In [18]:
```
%sql select avg(PAYLOAD_MASS__KG_) from SPACEXTABLE where Booster_Version = 'F9 v1.1'
```

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

Out[18]:

avg(PAYLOAD_MASS__KG_)
2928.4

- Performed an SQL query to 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

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

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

Out[21]:

min(Date)
2015-12-22

- Performed an SQL query to find the dates of the first successful landing outcome on ground pad

Successful Drone Ship Landing with Payload between 4000 and 6000

```
%sql select distinct Booster_Version from SPACEXTABLE where Landing_Outcome = 'Success (drone ship)' and PAYLOAD_MASS_KG_ > 4000 and PAYLOAD_MASS_KG_ < 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

```
In [22]: %sql select distinct Booster_Version from SPACEXTABLE where Landing_Outcome = 'Success (drone ship)' and PAYLOAD_
```

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

Out[22]:

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

- Performed an SQL query to 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

In [23]:

```
%sql select distinct Mission_Outcome, count(*) from SPACEXTABLE group by Mission_Outcome
```

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

Out[23]:

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

- Performed an SQL query to calculate the total number of successful and failure mission outcomes

Boosters Carried Maximum Payload

%sql select Booster_Version from SPACEXTABLE where PAYLOAD_MASS_KG_ = (select max(PAYLOAD_MASS_KG_)from SPACEXTABLE)

Task 8

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

In [25]:

```
%sql select Booster_Version from SPACEXTABLE where PAYLOAD_MASS__KG_ = (select max(PAYLOAD_MASS__KG_)from SPACEXT
```

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

Out[25]:

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

- Performed an SQL query to list the names of the booster which have carried the maximum payload mass

2015 Launch Records

%sql select substr(Date, 6,2) as Month, Landing_Outcome, Booster_Version, Launch_Site from SPACEXTABLE where Landing_Outcome = 'Failure (drone ship)' and substr(Date,0,5) = '2015'

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.

In [26]:
```
%sql select substr(Date, 6,2) as Month, Landing_Outcome, Booster_Version, Launch_Site   from SPACEXTABLE where La
```

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

Out[26]:

Month	Landing_Outcome	Booster_Version	Launch_Site
01	Failure (drone ship)	F9 v1.1 B1012	CCAFS LC-40
04	Failure (drone ship)	F9 v1.1 B1015	CCAFS LC-40

- Performed an SQL query to 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

%sql select Landing_Outcome, count(*) as 'Count' from SPACEXTABLE where Date between '2010-06-04' and '2017-03-20' group by Landing_Outcome order by Count desc

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.

In [27]:
```
%sql select Landing_Outcome, count(*) as 'Count' from SPACEXTABLE where Date between '2010-06-04' and '2017-03-20
```

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

Out[27]:

Landing_Outcome	Count
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

- Performed an SQL query to 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

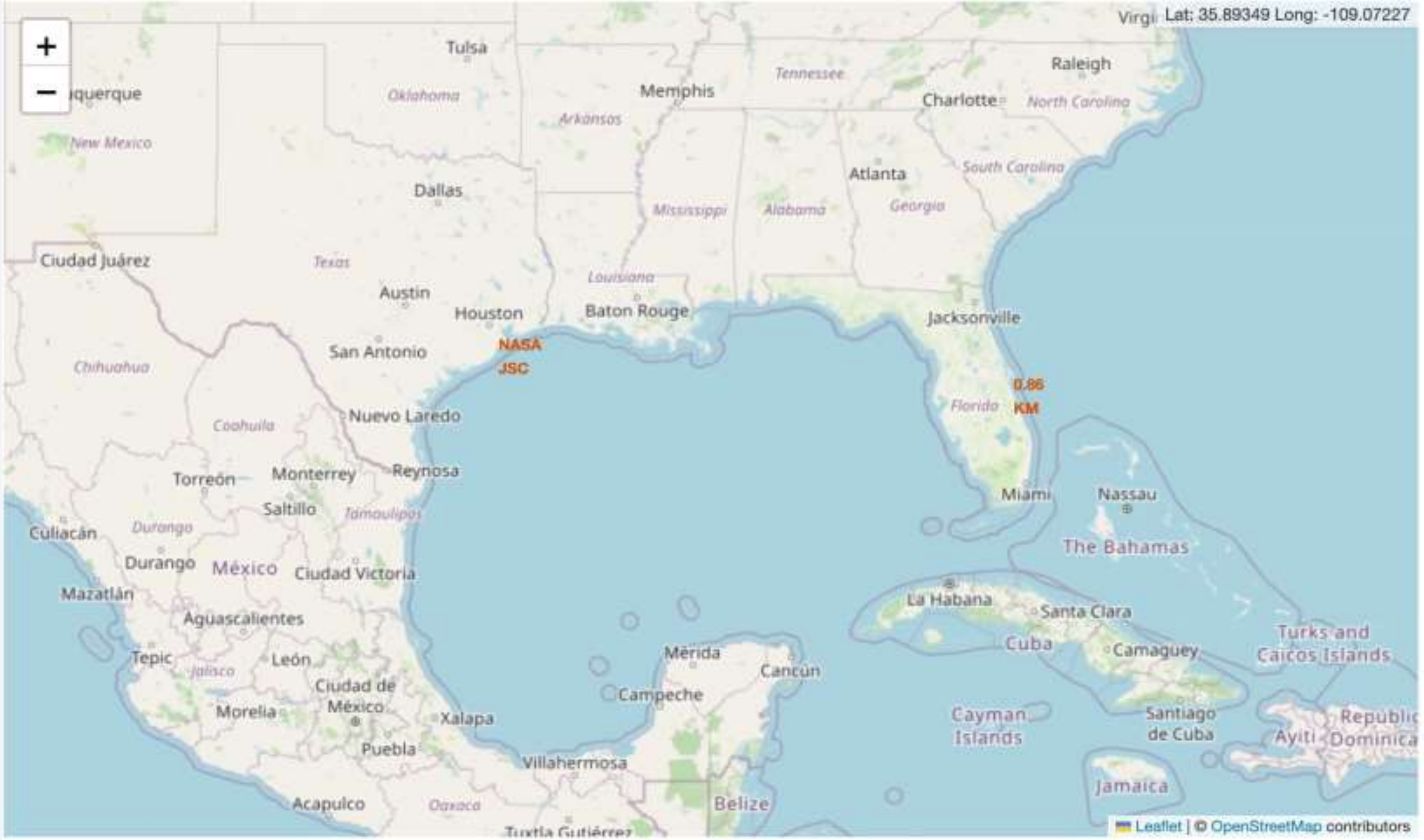
All launch sites on a map

- The launch sites are labelled by a marker with their names on the map.

All success/failed launches for each site on the map

- The launch records are grouped in clusters on the map, then labelled by green markers for successful launches, and red markers for unsuccessful ones.

Distances between a launch site to its proximities

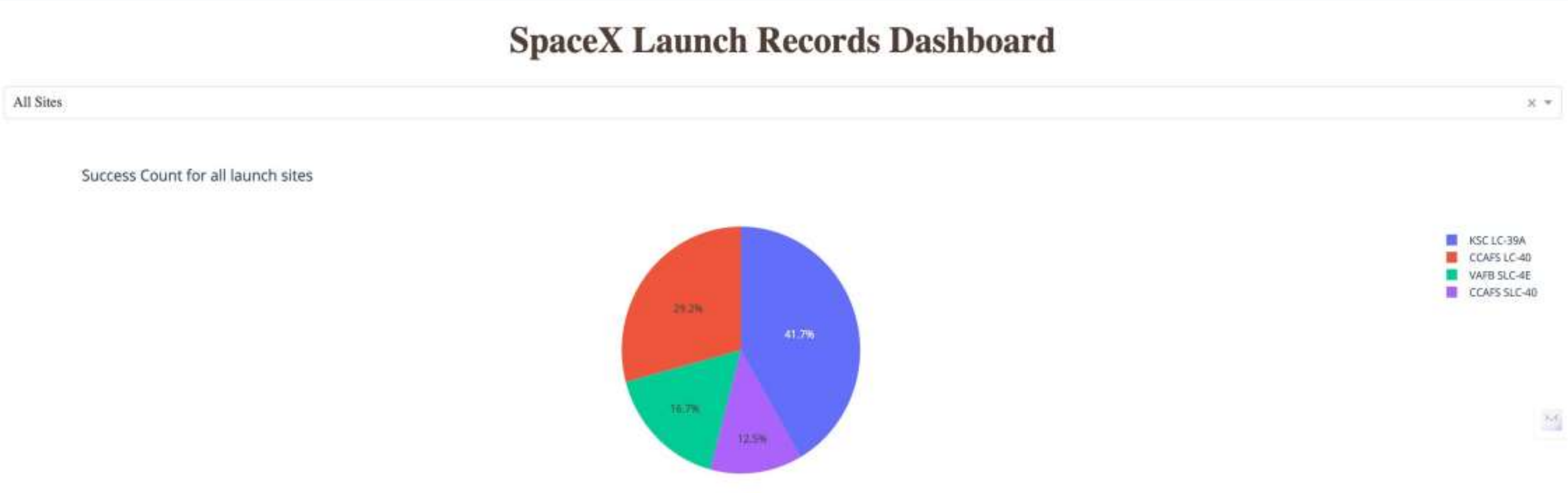


- The closest coastline from NASA JSC is marked as a point using MousePosition and the distance between the coastline point and the launch site, which is approximately 0.86 km.

Section 4

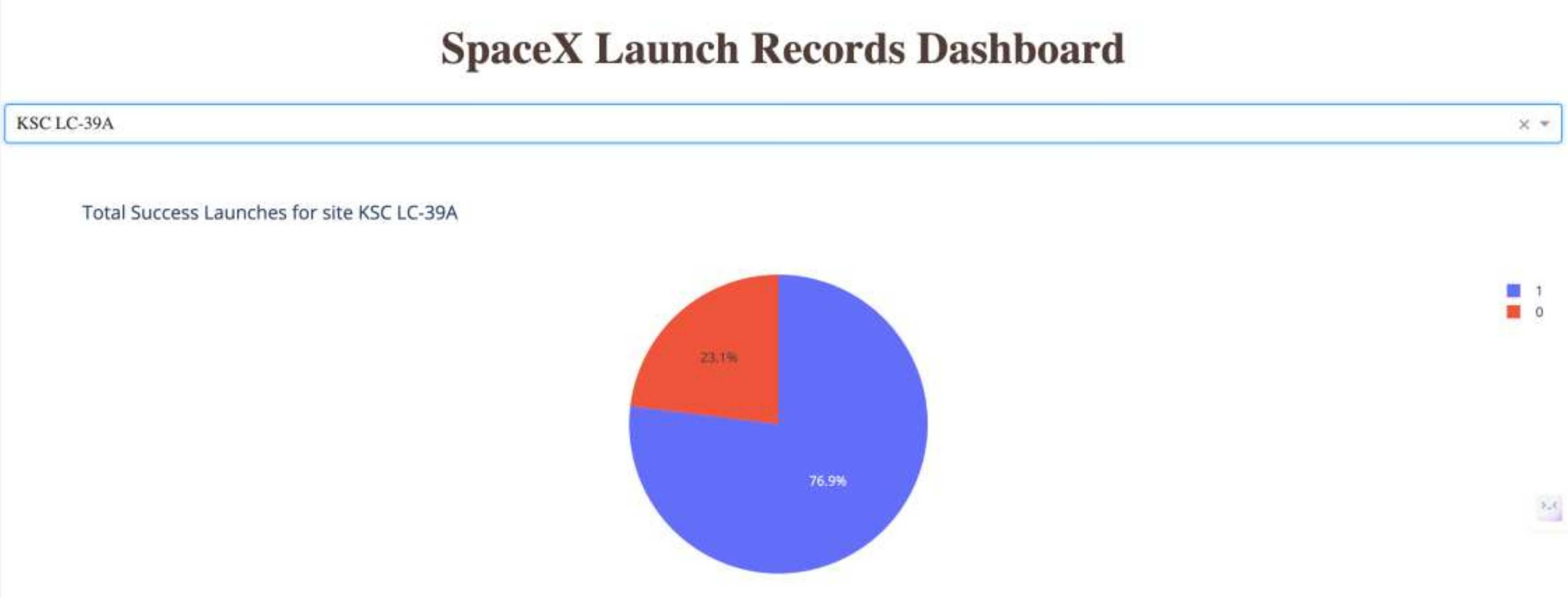
Build a Dashboard with Plotly Dash

Total success launches for all sites



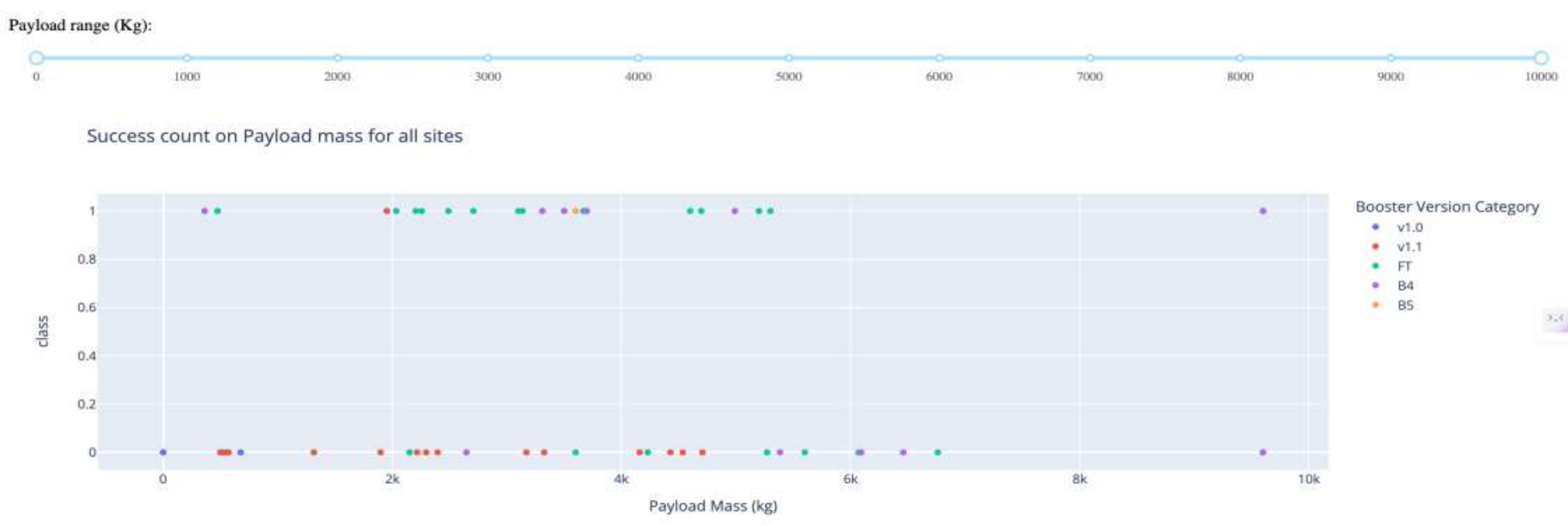
- KSC LC-39A has the highest amount of success launches with 41.7% from the entire record, whereas CCAFS SLC-40 has the lowest amount of success launches with only 12.5%.

Success ratio of the launch site with the highest success launches



- KSC LC-39A which is the launch site with highest amount of success, has a 76.9% success rate for the launches from its site, and 23.1% failure rate.

Payload vs. launch outcome

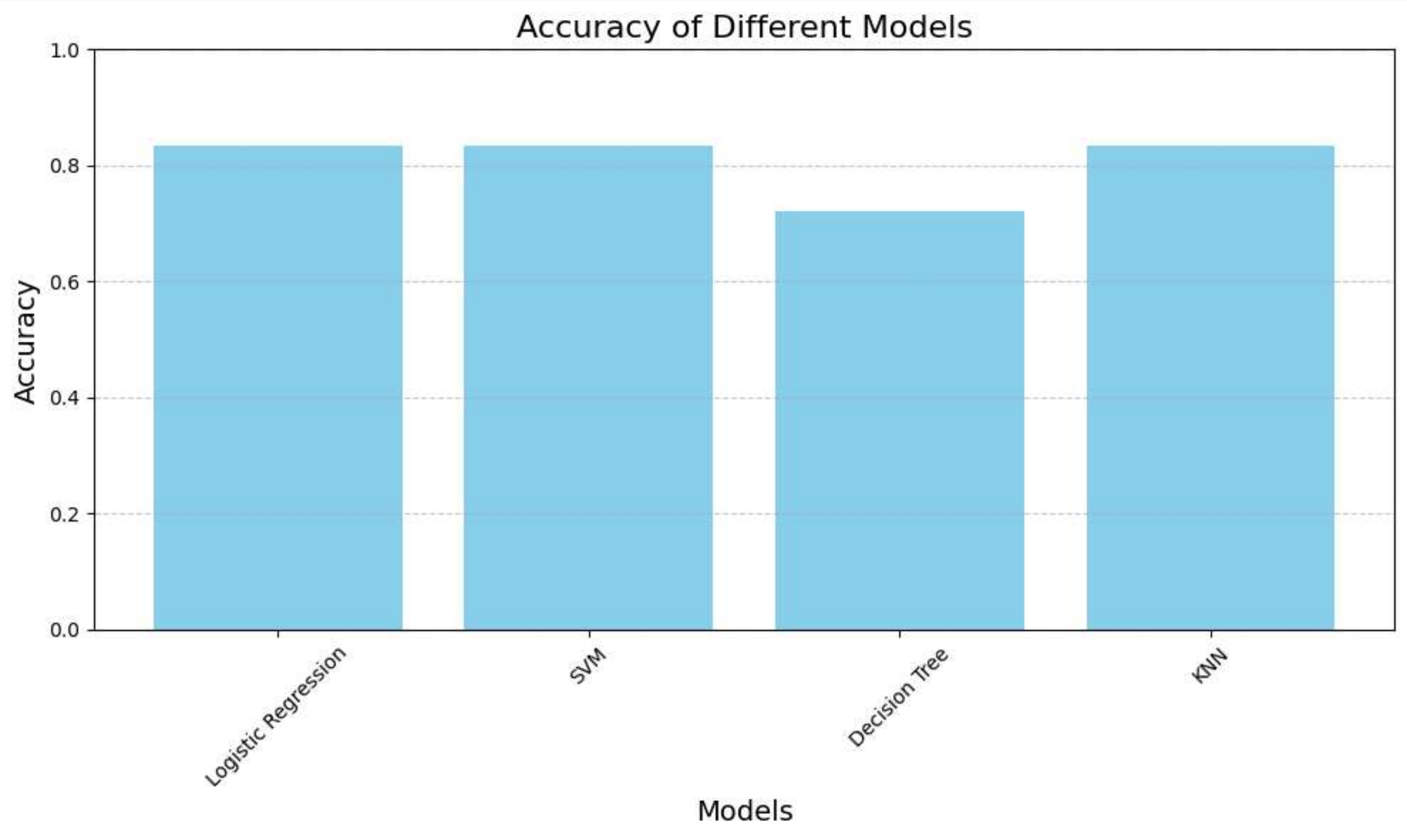


- The payload range that has the highest success launches is between 2,000 to 4,000 kg, which can be seen by the most number of plots in that range, followed by the payload range of 4,000 to 6,000 kg, with the second most number of plots.
- Booster version FT (green spots) has the highest success launches, followed by B4 (purple spots) with the second highest success launches, among all booster versions.

Section 5

Predictive Analysis (Classification)

Classification Accuracy



TASK 12

Find the method performs best:

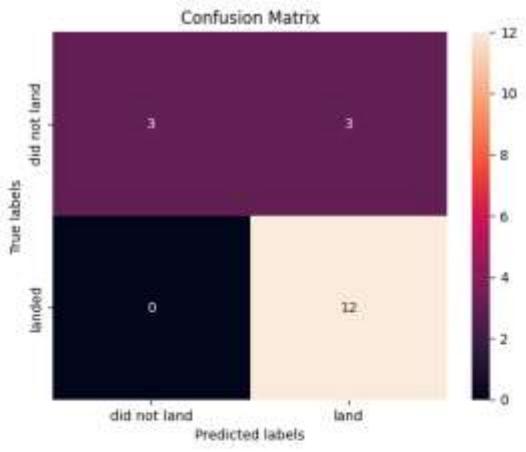
```
print('LR Accuracy:', '{:.2%}'.format(logreg_accuracy))
print( 'SVM Accuracy:', '{:.2%}'.format(svm_accuracy))
print('Decision Tree Accuracy:', '{:.2%}'.format(tree_accuracy))
print('KNN Accuracy:', '{:.2%}'.format(knn_accuracy))
```

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

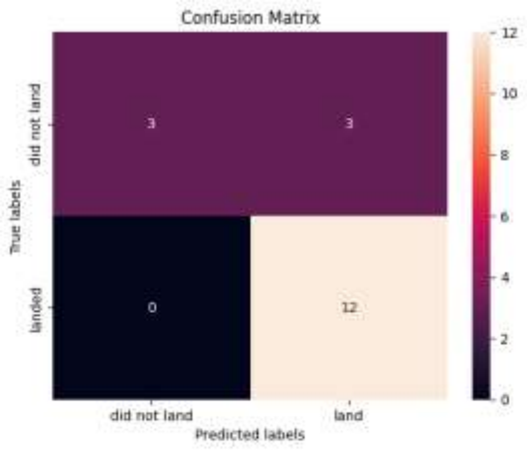
- The model that performed best are LR, SVM, KNN where all 3 achieved the highest accuracy of 83.33%.

Confusion Matrix

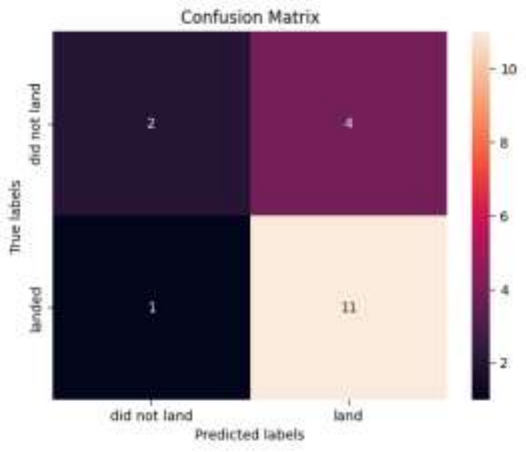
Confusion Matrix of LR



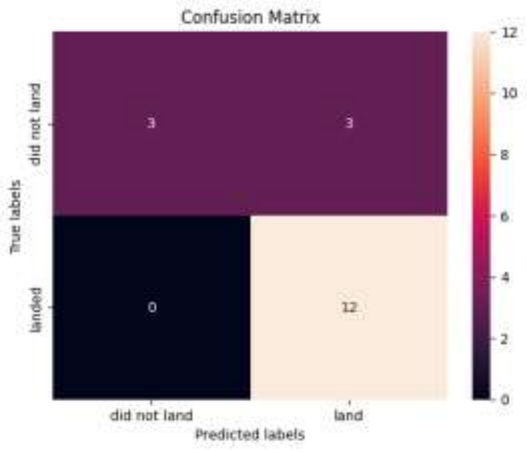
Confusion Matrix of SVM



Confusion Matrix of Decision Tree



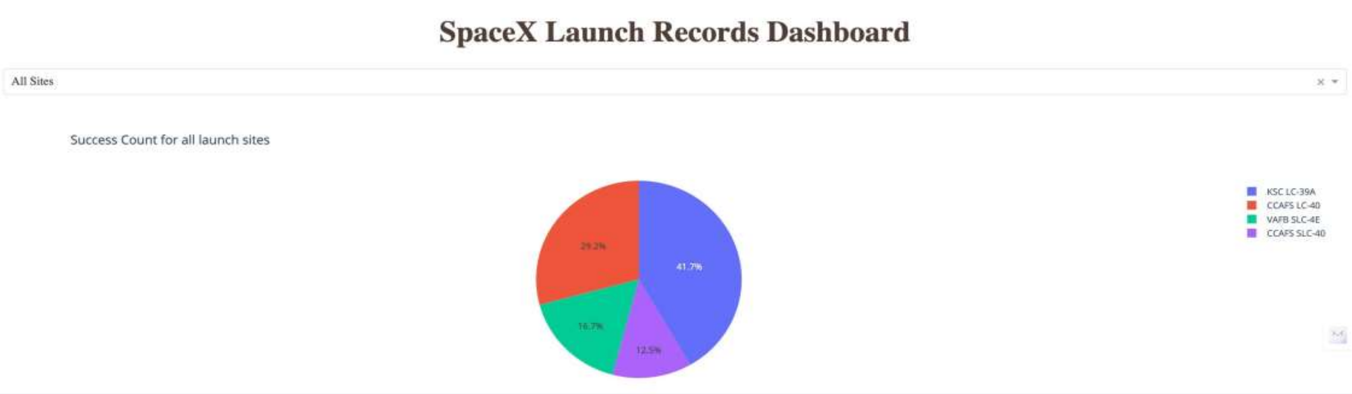
Confusion Matrix of KNN



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

Conclusions

- LR, SVM, KNN are top-performing models 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.
- Launch Complex 39A at Kennedy Space Center has the highest number of successful launches compared to other launch sites.
- GEO,HEO,SSO,ES L1 orbit types exhibit the highest rates of successful launches.



KSC LC-39A has the most successful launches overall

Thank you!