IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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Outline

- Executive Summary
- Introduction
- Methodology
- Results
- Conclusion

Executive Summary

- **Summary of methodologies**
  - Data collection
  - Data wrangling
  - EDA with SQL
  - EDA with data visualization
  - 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

- 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

Requested and parsed the data from SpaceX API using GET request

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:

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

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

```
[24]: response=requests.get(static_json_url)

[25]: response.status_code

[25]: 200
```

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

```
[26]: # 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

```
[27]: # Get the head of the dataframe
data.head()
```

[27]:

static_fire_date_utc	static_fire_date_unix	tbd	net	window	rocket	success	details	crew	ships

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

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`.

```
[39]: # Hint data['BoosterVersion']!='Falcon 1'
data_falcon9 = data2[data2['BoosterVersion']!='Falcon 1']
```

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

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

```
/home/jupyterlab/conda/envs/python/lib/python3.7/site-packages/pandas/core/indexing.py:1773: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self._setitem_single_column(ilocs[0], value, pi)
```

[40]:

	FlightNumber	Date	BoosterVersion	PayloadMass	Orbit	LaunchSite	Outcome	Flights	GridFins	Reused	Legs
4	1	2010-06-04	Falcon 9	NaN	LEO	CCSFS SLC 40	None None	1	False	False	False
5	2	2012-05-22	Falcon 9	525.0	LEO	CCSFS SLC 40	None None	1	False	False	False

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

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

```
[37]: # Create a data from launch_dict
data2 = pd.DataFrame(launch_dict)
```

Show the summary of the dataframe

```
[38]: # Show the head of the dataframe
data2.head()
```

[38]:

	FlightNumber	Date	BoosterVersion	PayloadMass	Orbit	LaunchSite	Outcome	Flights	GridFins	Reused	Legs	LandingP
0	1	2006-03-24	Falcon 1	20.0	LEO	Kwajalein Atoll	None None	1	False	False	False	No
1	2	2007-03-21	Falcon 1	NaN	LEO	Kwajalein Atoll	None None	1	False	False	False	No
2	4	2008-09-28	Falcon 1	165.0	LEO	Kwajalein Atoll	None None	1	False	False	False	No
3	5	2009-07-13	Falcon 1	200.0	LEO	Kwajalein Atoll	None None	1	False	False	False	No
4	6	2010-06-04	Falcon 9	NaN	LEO	CCSFS SLC 40	None None	1	False	False	False	No

Cleaned the data and removed missing values of PayLoadMass

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.

```
[42]: # Calculate the mean value of PayloadMass column
payload_mean = data_falcon9['PayloadMass'].mean()
# Replace the np.nan values with its mean value
data_falcon9['PayloadMass'] = data_falcon9['PayloadMass'].replace(np.nan, payload_mean)
data_falcon9.isnull().sum()
data_falcon9.to_csv('dataset_part_1.csv', index=False)
```

```
/home/jupyterlab/conda/envs/python/lib/python3.7/site-packages/ipykernel_launcher.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  after removing the cwd from sys.path.
```

GitHub reference: https://github.com/Sorushberlin/Applied-Data-Science-Capstone/blob/c22e1dcd89484e59097cb08795c725aaedf93008/1.%20Hands-on%20Lab_Complete%20the%20Data%20Collection%20API%20Lab.ipynb.ipynb

Data Collection - Scraping

Requested data from Wikipedia using HTTP GET request and BeautifulSoup

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.

```
[22]: # 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`

```
[23]: # 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

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

```
List of Falcon 9 and Falcon Heavy launches - Wikipedia
```

Extracted all column/variable names from the HTML table header

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

```
[25]: # 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.

```
[26]: # 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>
```

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

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

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

[32]:

	Flight No.	Launch site	Payload	Payload mass	Orbit	Customer	Launch outcome	Version Booster	Booster landing	Date	Time
0	1	CCAFS	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success\n	F9 v1.07B0003.18	Failure	4 June 2010	18:45
1	2	CCAFS	Dragon	0	LEO	NASA (COTS)\nNRO	Success	F9 v1.07B0004.18	Failure	8 December 2010	15:43
2	3	CCAFS	Dragon	525 kg	LEO	NASA (COTS)	Success	F9 v1.07B0005.18	No attempt\n	22 May 2012	07:44
3	4	CCAFS	SpaceX CRS-1	4,700 kg	LEO	NASA (CRS)	Success\n	F9 v1.07B0006.18	No attempt	8 October 2012	00:35
4	5	CCAFS	SpaceX CRS-2	4,877 kg	LEO	NASA (CRS)	Success\n	F9 v1.07B0007.18	No attempt\n	1 March 2013	15:10
...	...	...	...	...	...	...	...	...	...	...	...
116	117	CCSFS	Starlink	15,600 kg	LEO	SpaceX	Success\n	F9 B5B1051.10657	Success	9 May 2021	06:42

GitHub reference:

https://github.com/Sorushberlin/Applied-Data-Science-Capstone/blob/790f09dff94e20362ea7f30aef52861f98ffb6b4/2.%20Hands-on%20Lab_Complete%20the%20Data%20Collection%20with%20Web%20Scraping%20lab.ipynb.ipynb

Data Wrangling

Calculated the number of launches of each site

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:

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

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

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

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`

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

```
[11]: 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
```

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

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.

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

```
[12]: 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
```

Created a landing outcome label form Outcome column

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` :

```
[15]: # 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

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

```
[16]:
```

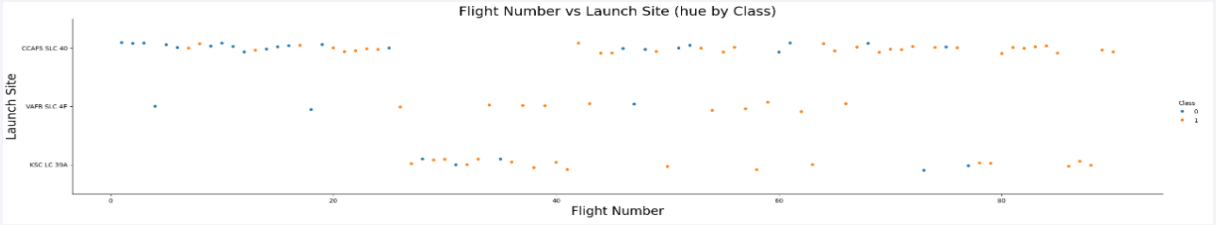
	Class
0	0
1	0
2	0
3	0
4	0
5	0

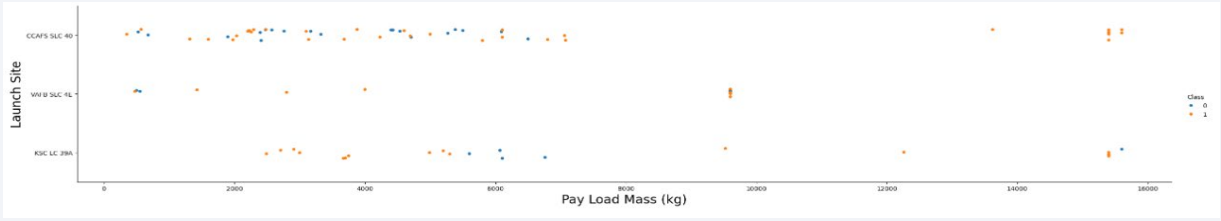
GitHub reference: https://github.com/Sorushberlin/Applied-Data-Science-Capstone/blob/a415c1b563066afdd7eca4a767f1b3500b1f6cb6/3.%20Hands-on%20Lab_Data%20Wrangling.ipynb.ipynb

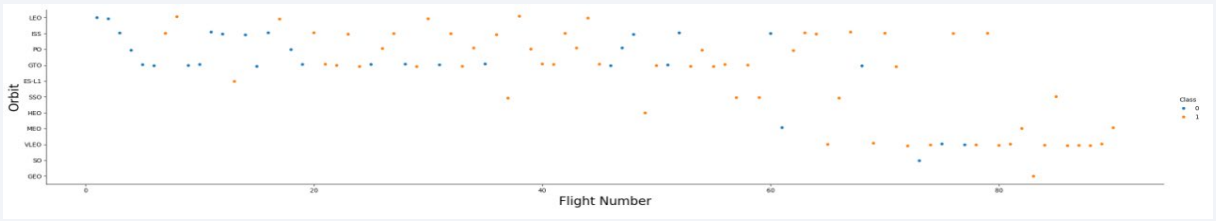
EDA with Data Visualization

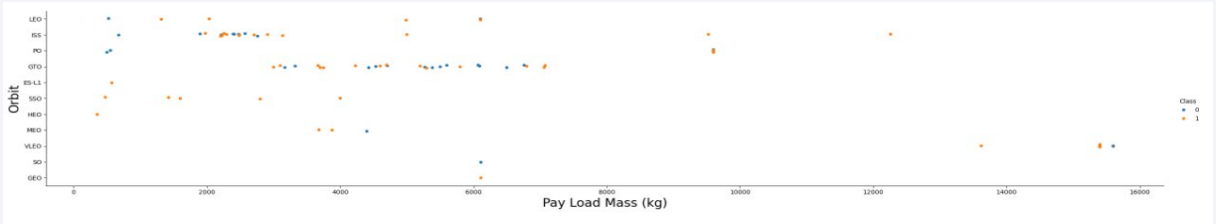
We explored the data by visualizing the relationship between flight number and launch Site, payload and launch site, success rate of each orbit type, flight number and orbit type, the launch success yearly trend.

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

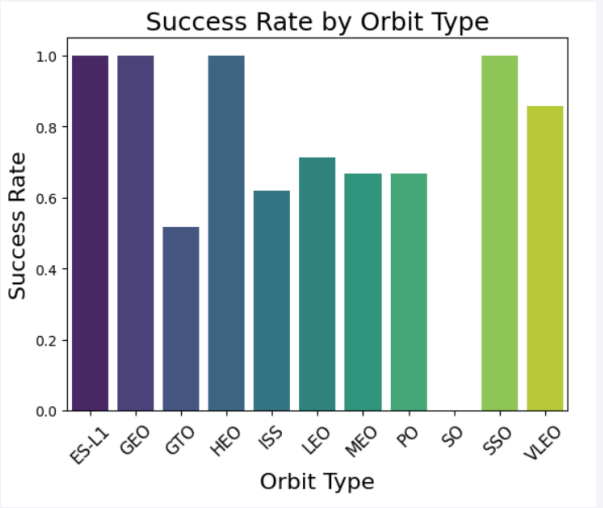


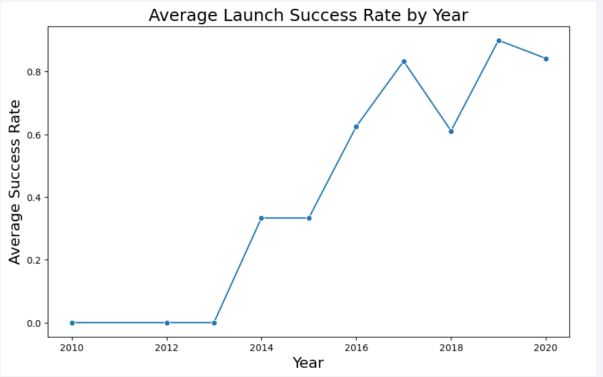






Bar chart was used to visualize the relationship between success rate of each orbit type; Line chart was used to visualize the launch success yearly trend





GitHub reference: https://github.com/Sorushberlin/Applied-Data-Science-Capstone/blob/83176815371107467ed9b62f593cb6d370e3aa95/5.%20EDA%20with%20Visualization%20Lab.ipynb.ipynb

EDA with SQL

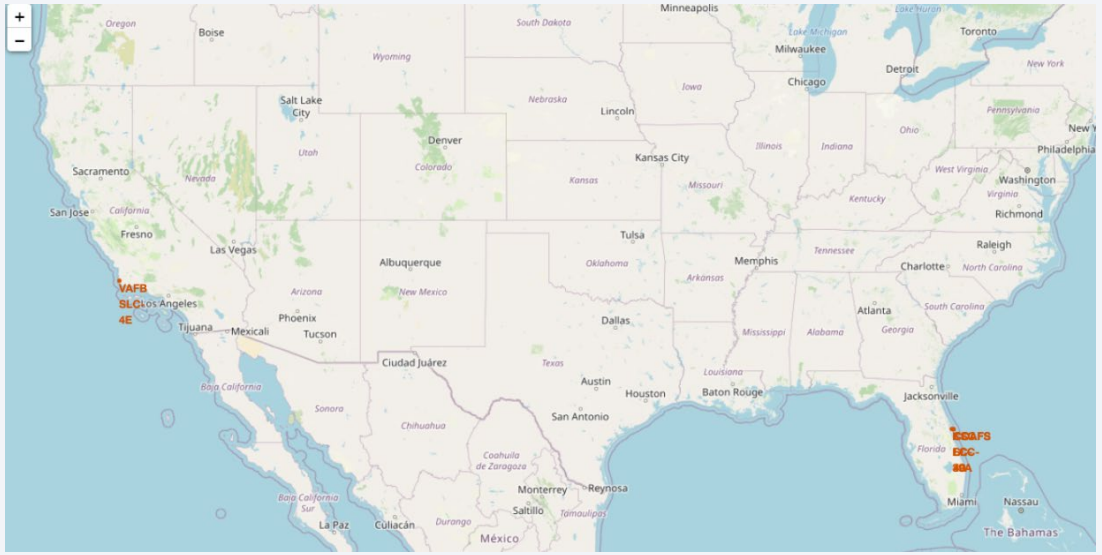
SQL queries are performed to:

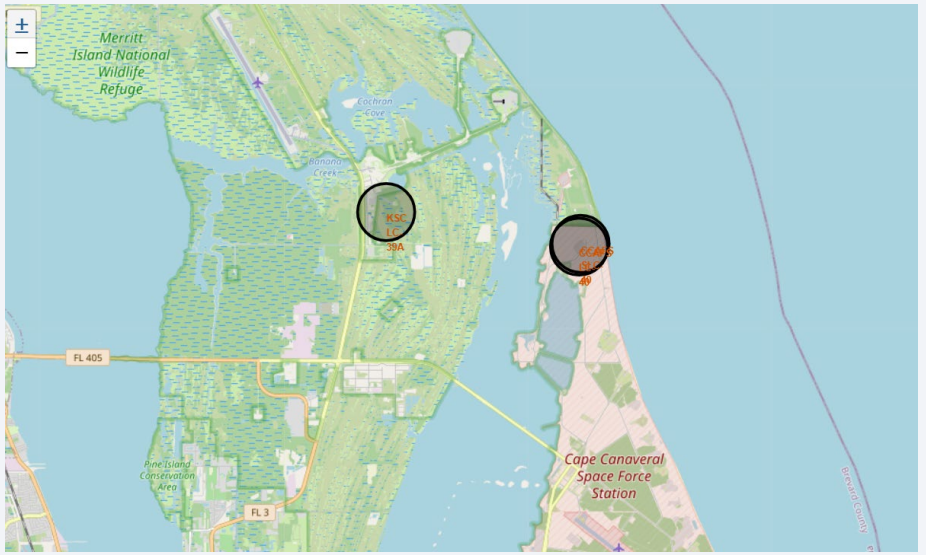
1. Display the names of the unique launch sites in the space mission
2. Display 5 records where launch sites begin with the string 'CCA’
3. Display the total payload mass carried by boosters launched by NASA (CRS)
4. Display average payload mass carried by booster version F9 v1.1
5. List the date when 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.

GitHub reference: https://github.com/Sorushberlin/Applied-Data-Science-Capstone/blob/70a0ce53ce7550a7b8618bdba1dabd969c2f78dc/4.%20Hands-on%20Lab_Complete%20the%20EDA%20with%20SQL.ipynb.ipynb

Build an Interactive Map with Folium

- We marked all launch sites, and added map objects such as markers, circles, lines to mark the success or failure of launches for each site on the folium map.
- We assigned the feature launch outcomes (failure or success) to class 0 and 1.i.e., 0 for failure, and 1 for success.
- Using the color-labeled marker clusters, we identified which launch sites have relatively high success rate.
- We calculated the distances between a launch site to its proximities. We answered some question for instance:
  - Are launch sites near railways, highways and coastlines.
  - Do launch sites keep certain distance away from cities.

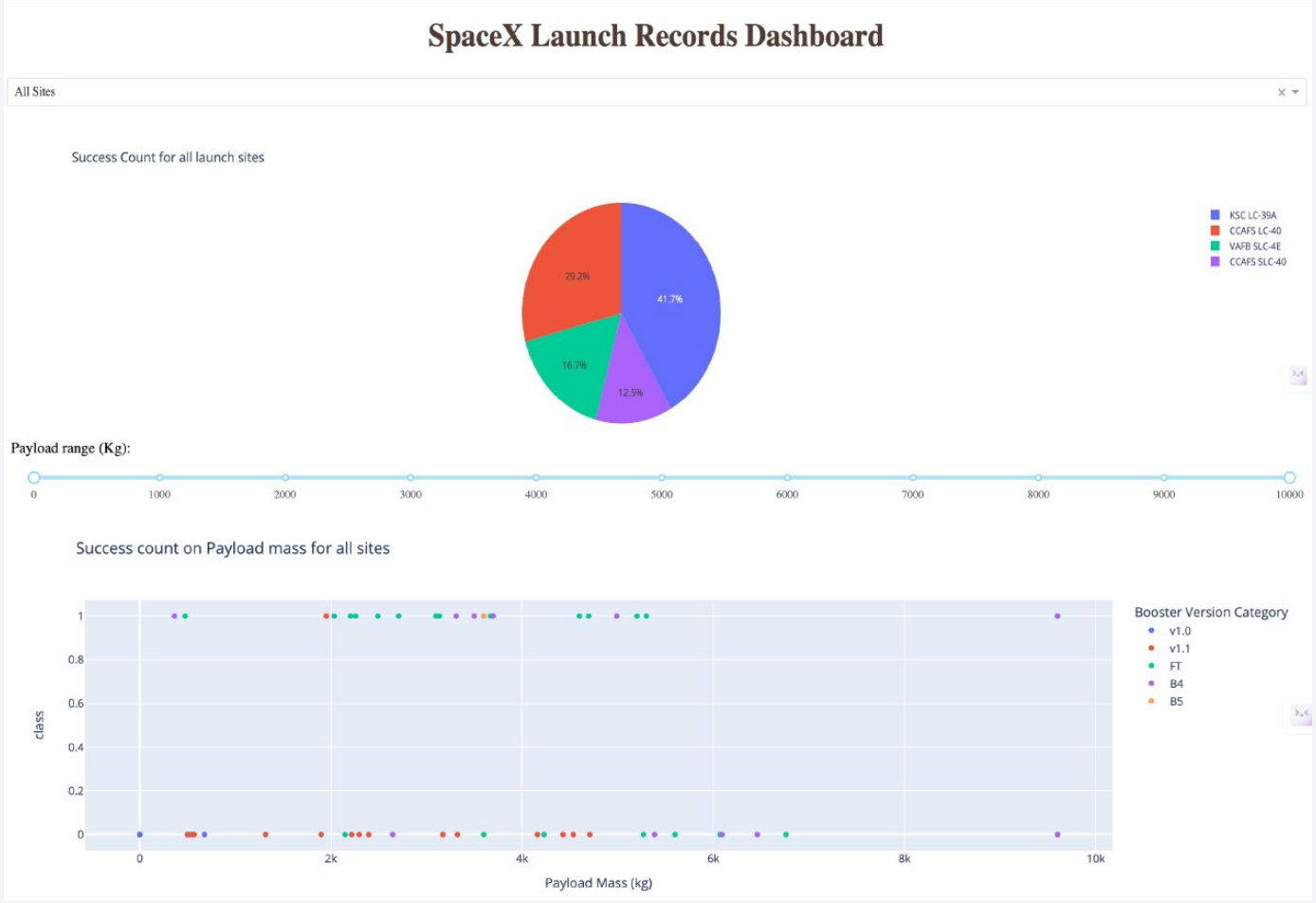




GitHub reference: https://github.com/Sorushberlin/Applied-Data-Science-Capstone/blob/6f3f84ed568c60f490d3bb9b13a43a3a1f2bd256/6.%20Hands-on%20Lab_Interactive%20Visual%20Analytics%20with%20Folium%20lab.ipynb.ipynb

Build a Dashboard with Plotly Dash

- We built an interactive dashboard with Plotly dash
- We plotted pie charts showing the total launches by a certain sites
- We plotted scatter graph showing the relationship with Outcome and Payload Mass (Kg) for the different booster version.

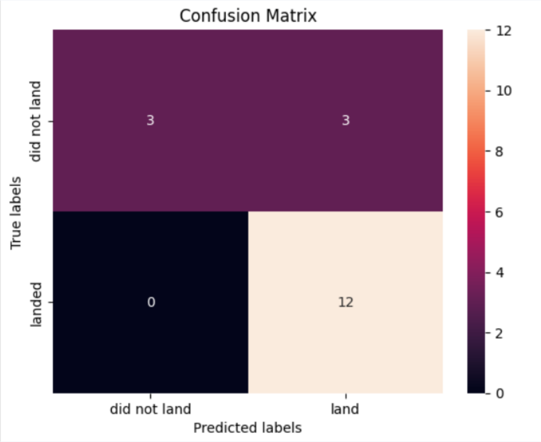


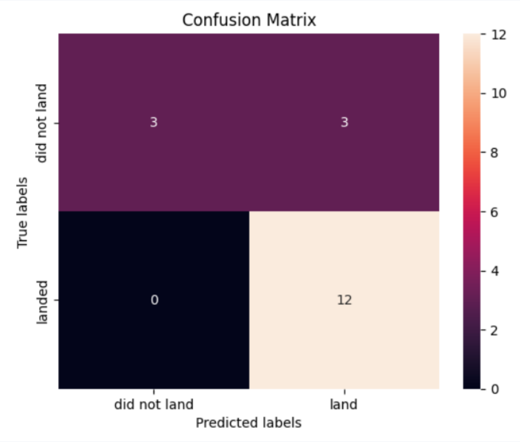
GitHub reference: https://github.com/Sorushberlin/Applied-Data-Science-Capstone/blob/bb797250e1253841416e0e005eafd57a07c66d01/7.%20Hands-on%20Lab_Build%20an%20Interactive%20Dashboard%20with%20Ploty%20Dash_spacex_dash_app.py

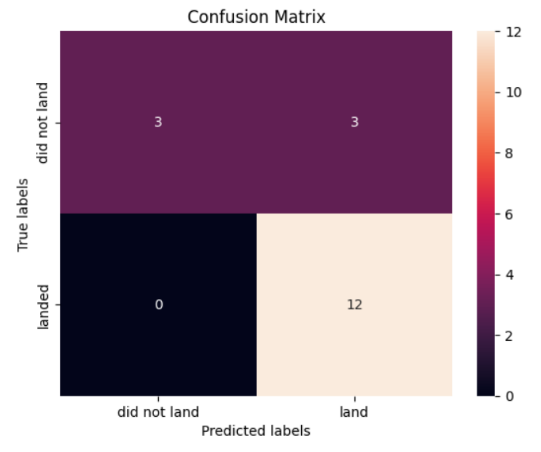
Predictive Analysis (Classification)

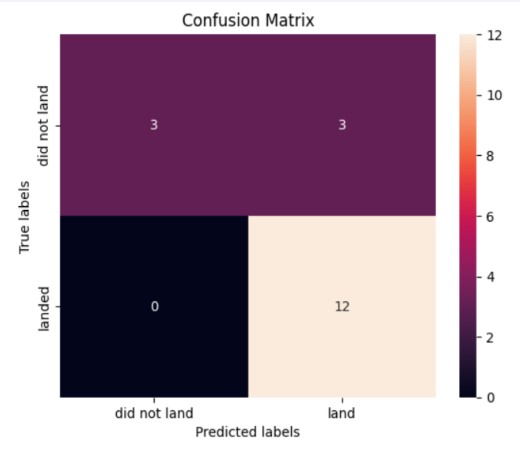
LR, SVM, Decision Tree and KNN objects are created and fit with GridSearchCV object to find the best parameters, then the models are trained on the training set.

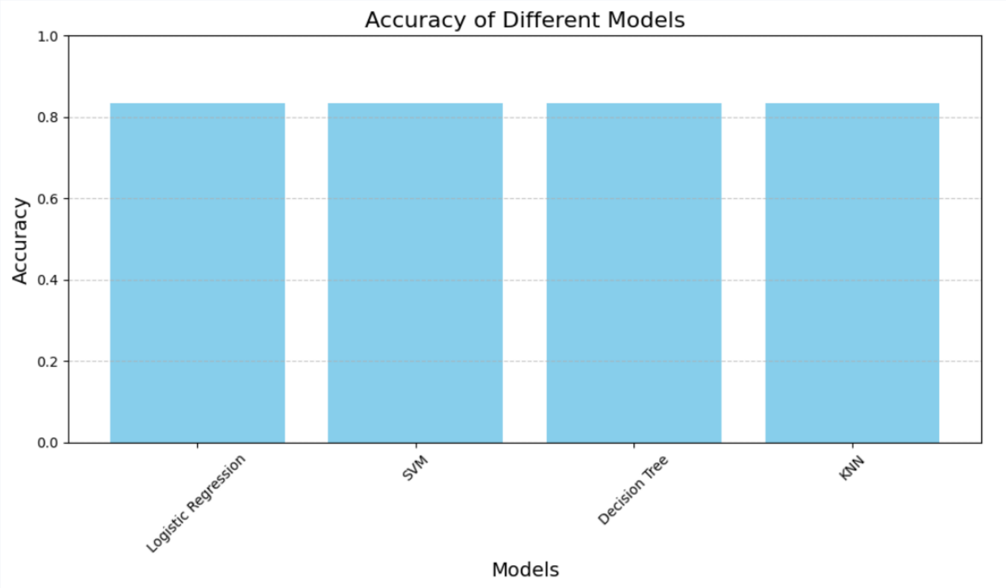
The accuracy of test data are calculated for each machine learning model. It is found that the methods performed best are LR, SVM, KNN and Decision Tree where all 4 achieved the highest accuracy of 83.33%.











GitHub reference: https://github.com/Sorushberlin/Applied-Data-Science-Capstone/blob/3014560da6e62680e6f7368c6ff07d7efb945a29/8.%20Hands-on%20Lab_Complete%20the%20Machine%20Learning%20Prediction%20lab.ipynb.ipynb

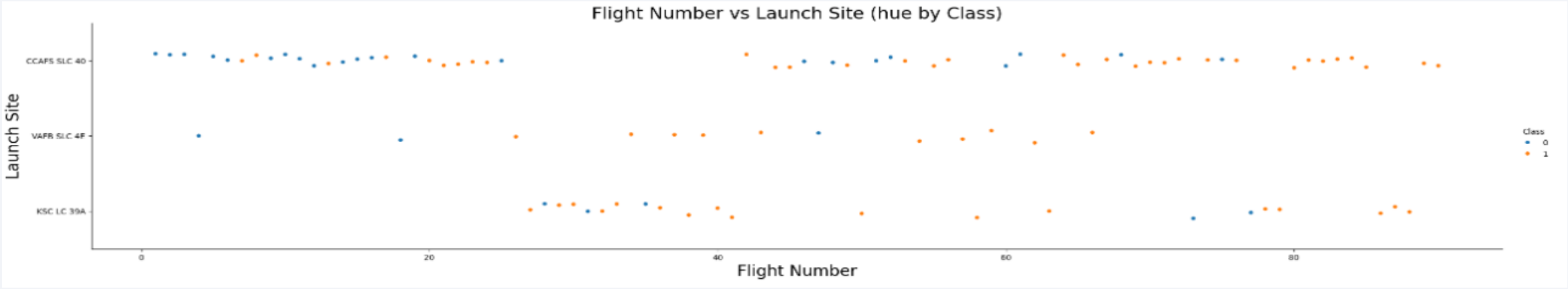
Results

- 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.

Section 2

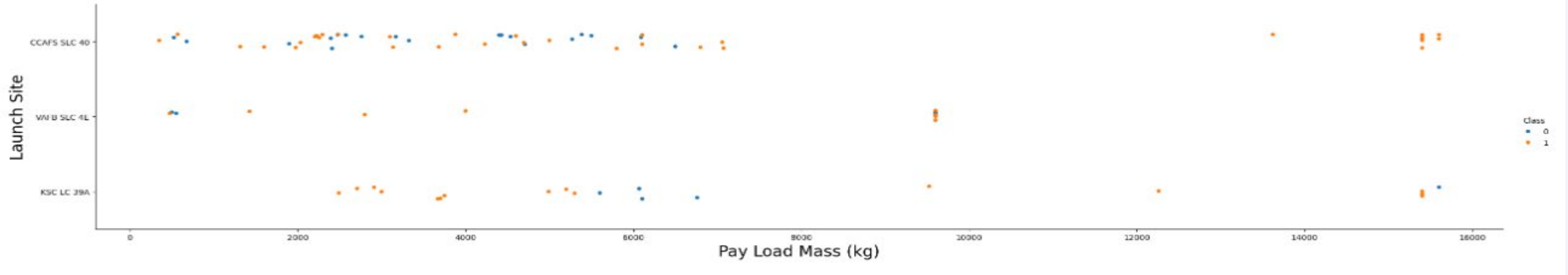
Insights drawn from EDA

Flight Number vs. Launch Site



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

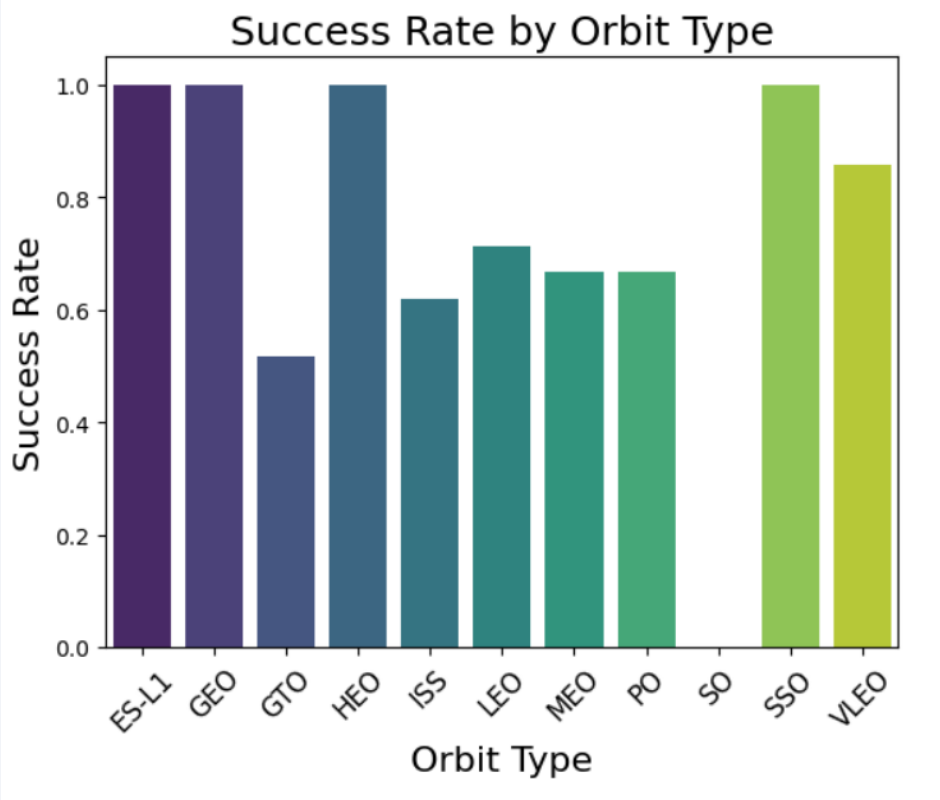
Payload vs. Launch Site



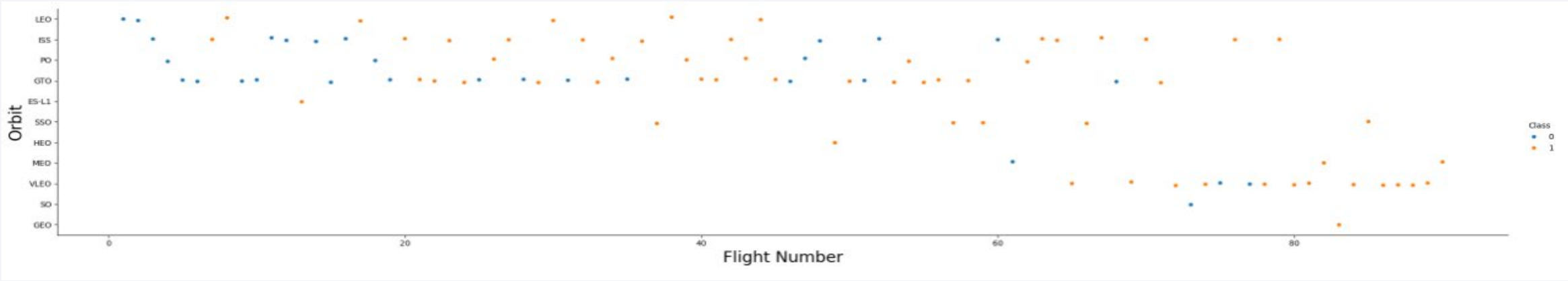
Payloads with lower mass are have more launches compared to those with higher mass across all three launch sites.

Success Rate vs. Orbit Type

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

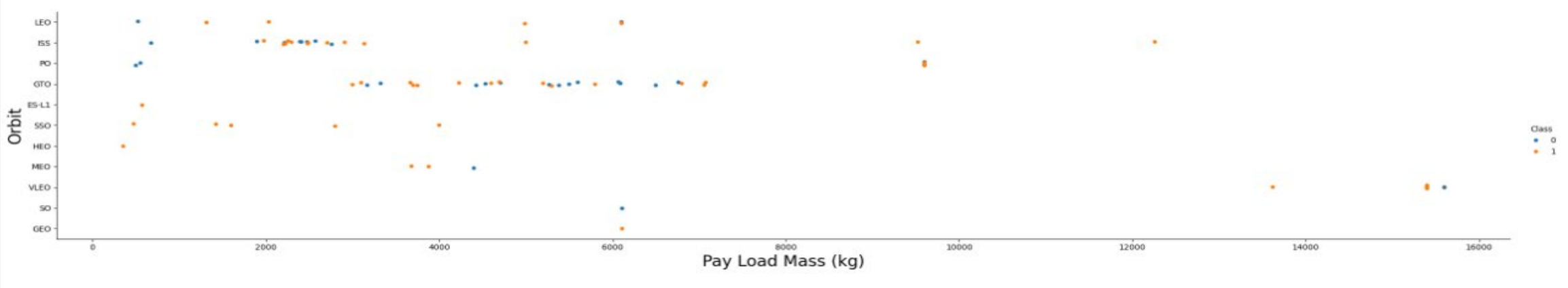


Flight Number vs. Orbit Type



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

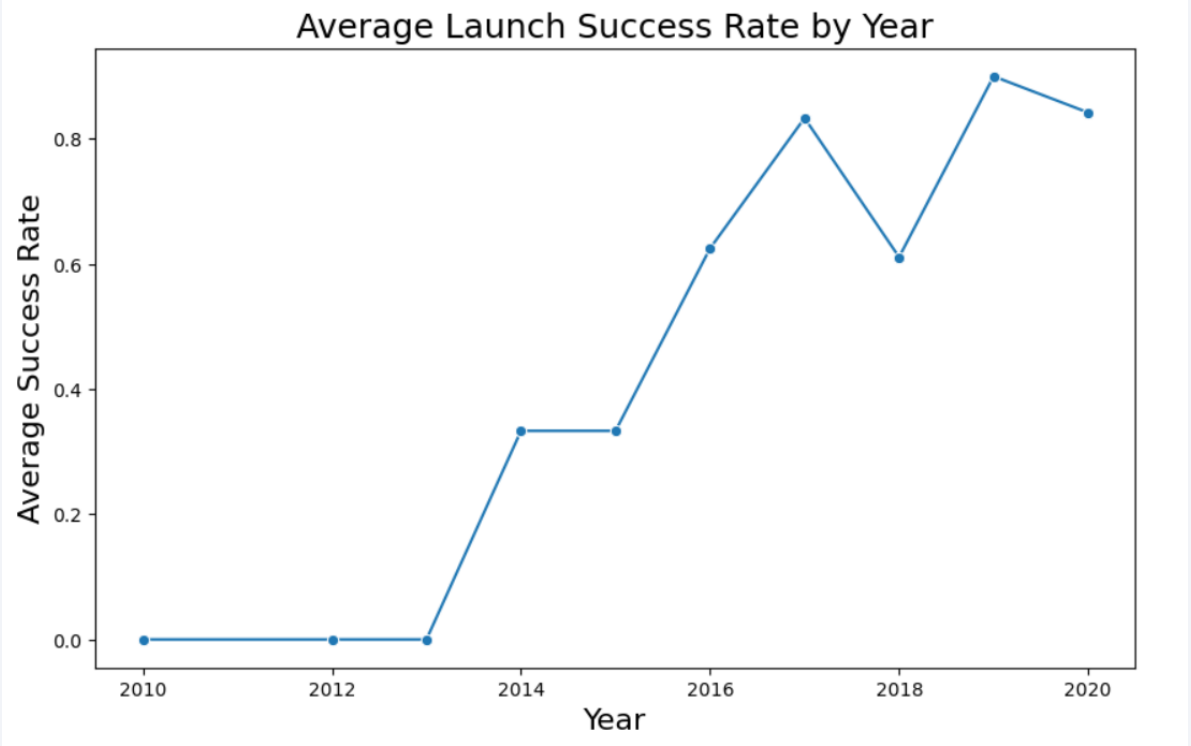
Payload vs. Orbit Type



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

Performed an SQL query to obtain all launch site names.

Task 1

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

```
%sql SELECT DISTINCT LAUNCH_SITE FROM SPACEXTBL ORDER BY 1;
```

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

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

Launch Site Names Begin with 'CCA'

Performed an SQL query to obtain 5 launch site names that begin with ‘CCA’.

Task 2

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

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

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

Date	Time (UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS__KG_	Orbit	Customer	Mission_Outcome	Landing_Outcome
04-06-2010	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute
08-12-2010	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
22-05-2012	07:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	No attemp
08-10-2012	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attemp
01-03-2013	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attemp

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.

The dates of the first successful landing outcome on ground pad was 22ndDecember 2015.

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

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

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

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

Performed an SQL query to 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.

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

%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'

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

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

%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

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.

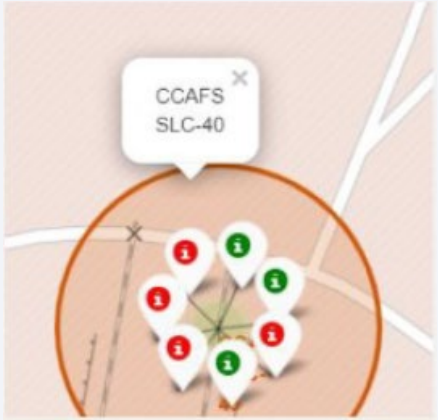
Section 3

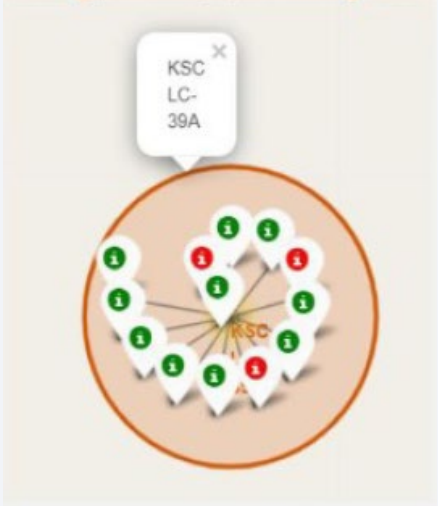
Launch Sites Proximities Analysis

All launch sites on a map

The launch sites are labelled by a marker with their names on the map.
The SpaceX launch sites are in California and Florida.

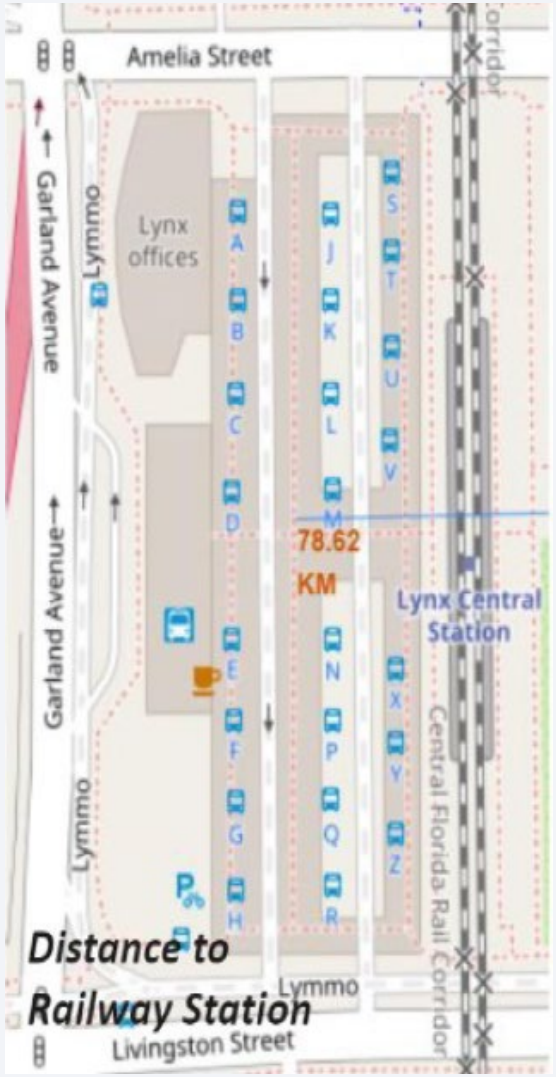
All success/failed launches for each site on the map



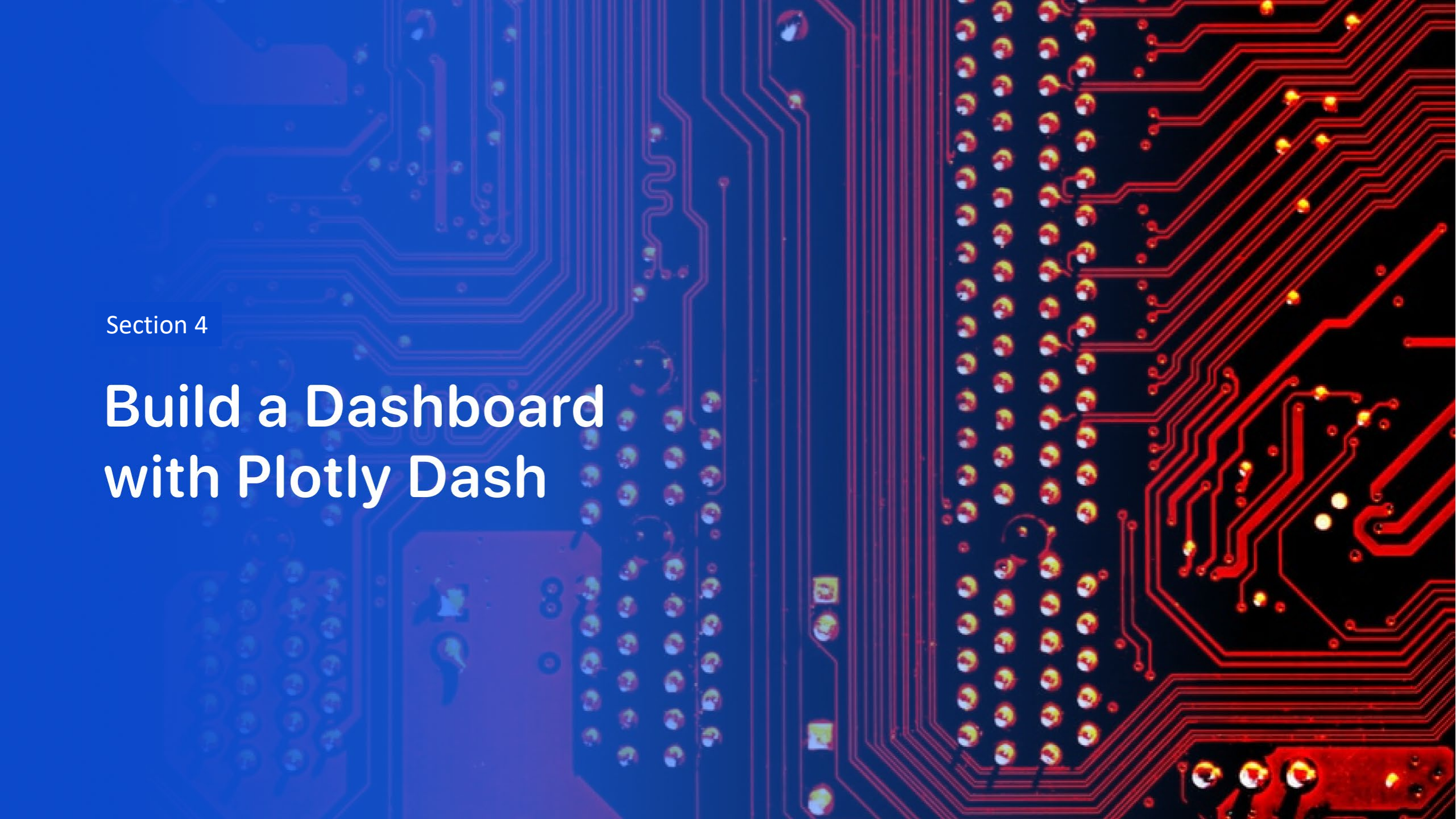


The launch records are grouped in clusters on the map, then labelled by green markers for successful launches, and red markers for Unsuccessful ones.

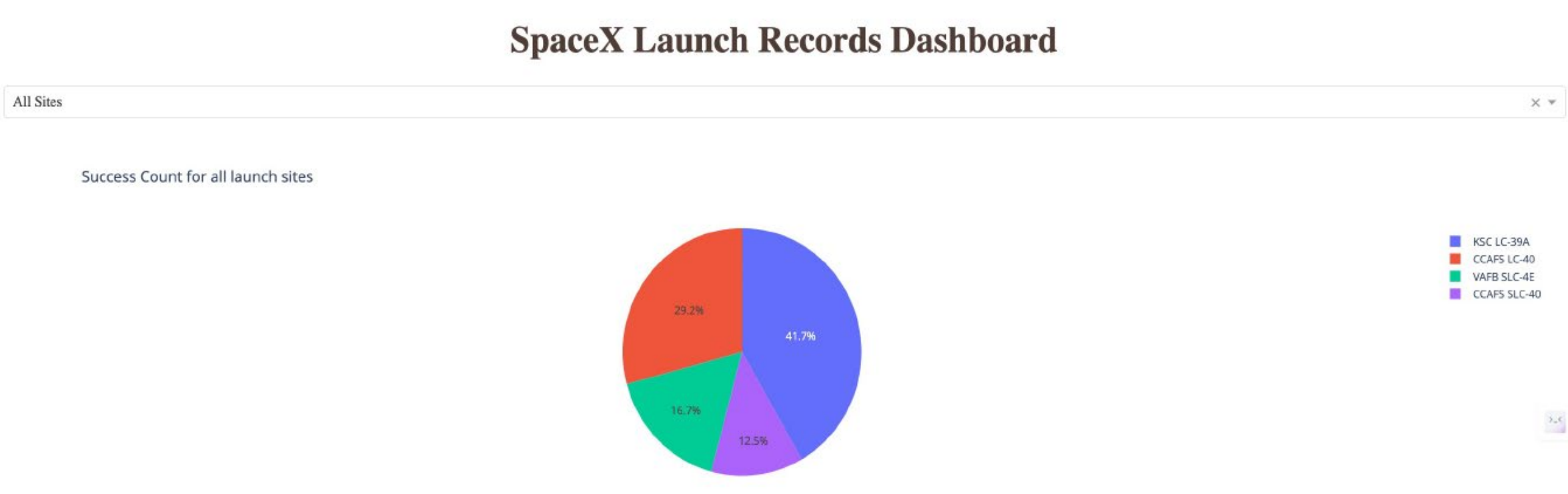
Launch Site distance to landmarks



The closest coastline from NASA JSC is marked as a red point using MousePosition and the distance between the coastline point and the launch site, which is approximately 0.90km.

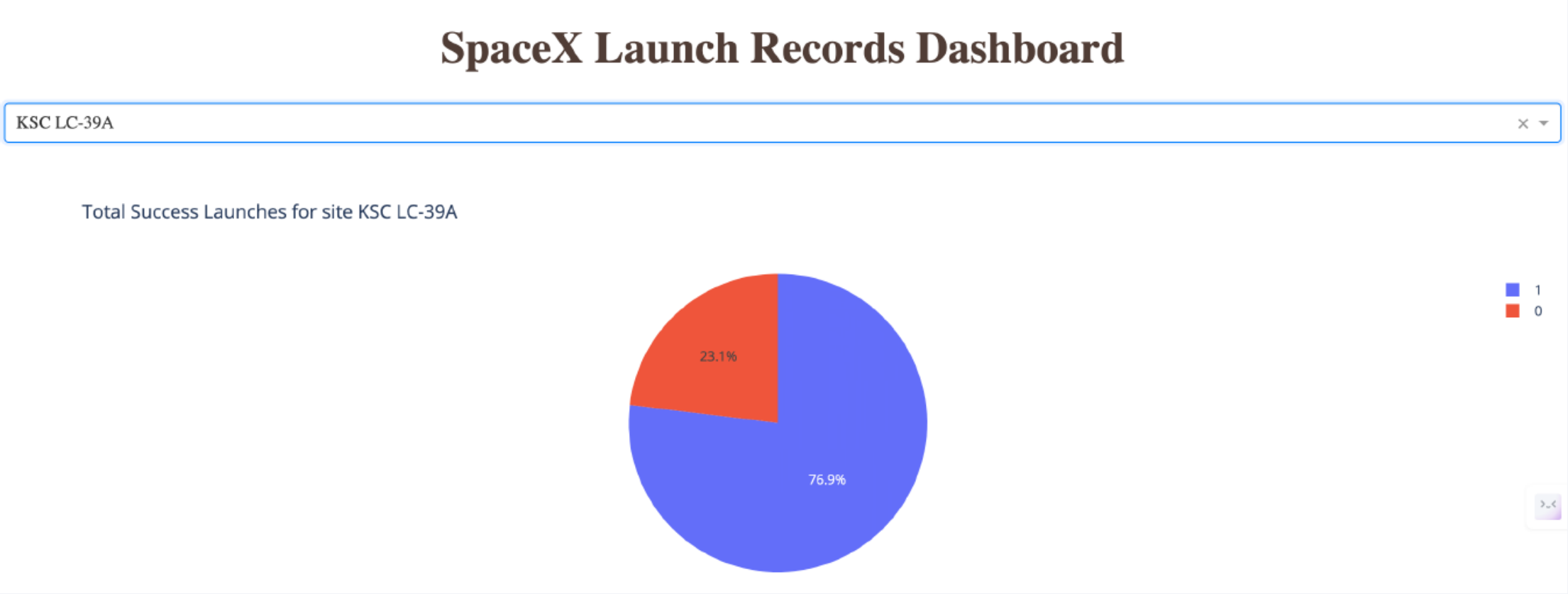

Section 4
Build a Dashboard with Plotly Dash

Pie chart showing the success percentage achieved by each launch site



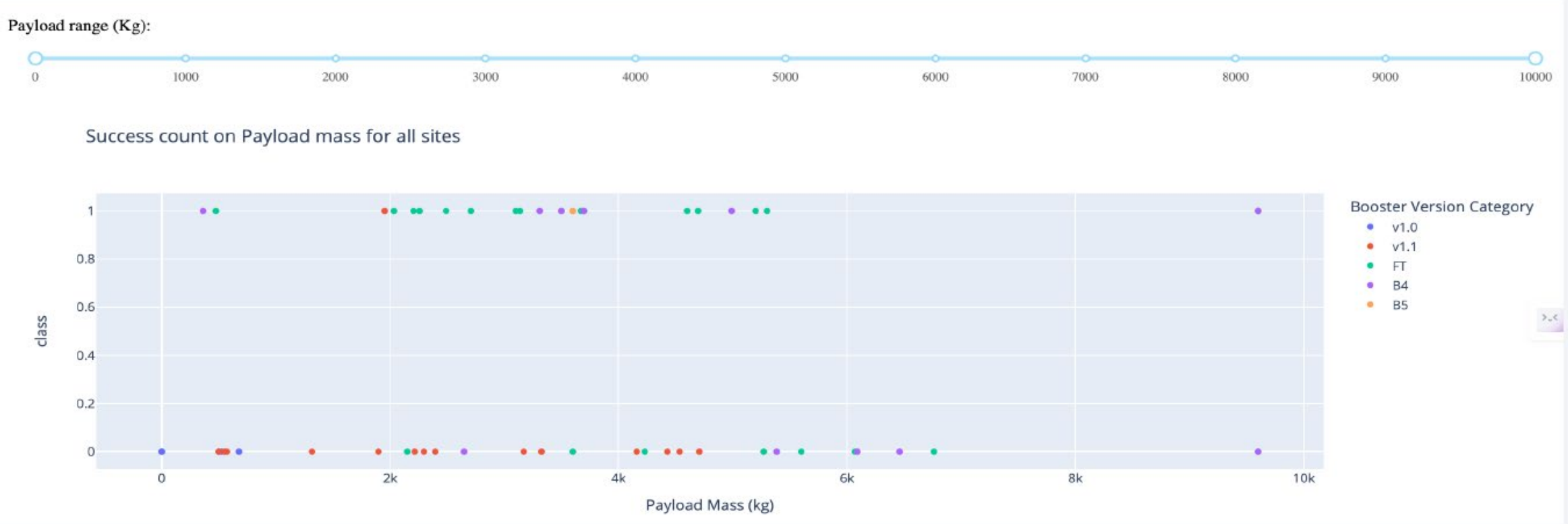
KSC LC-39A has the highest amount of success launches with 41.7% from the entire record, whereas CCAFS SLC-40 has the lowest amount of success launches with only 12.5%.

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)

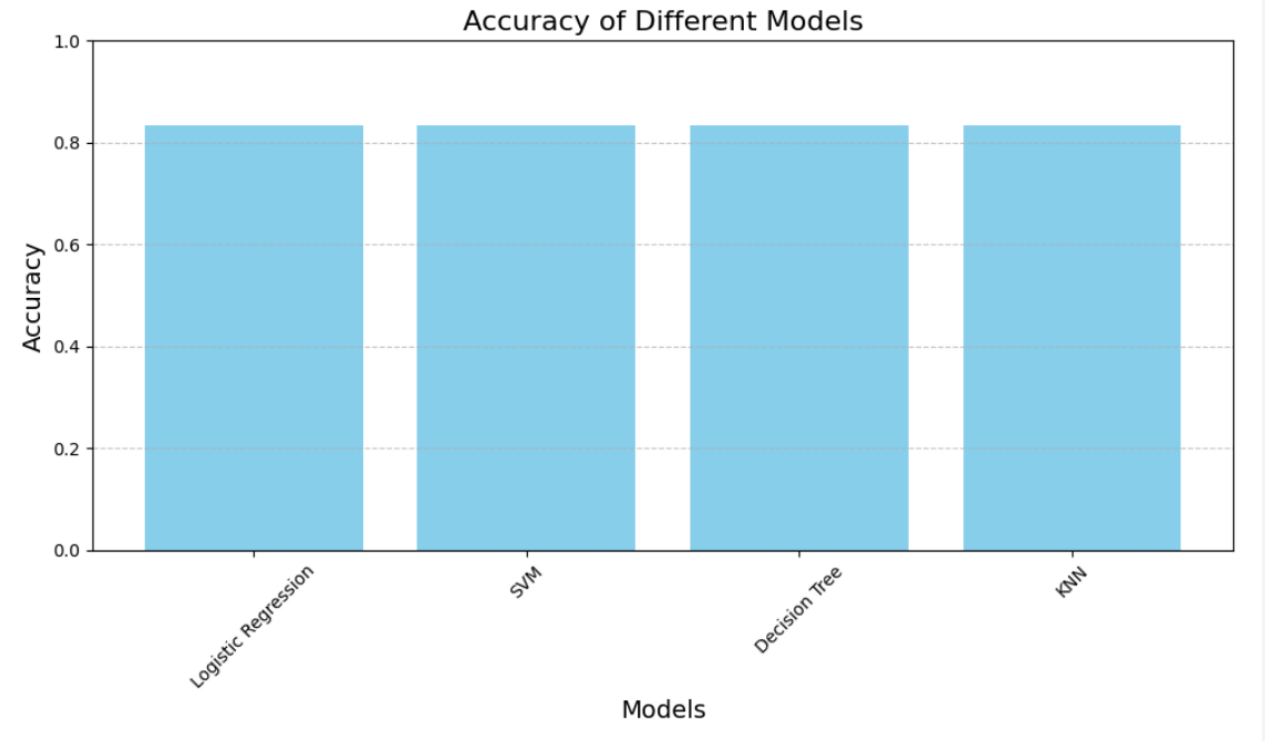
Classification Accuracy

Find the method performs best:

In [30]:
```
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: 83.33%
KNN Accuracy: 83.33%
```

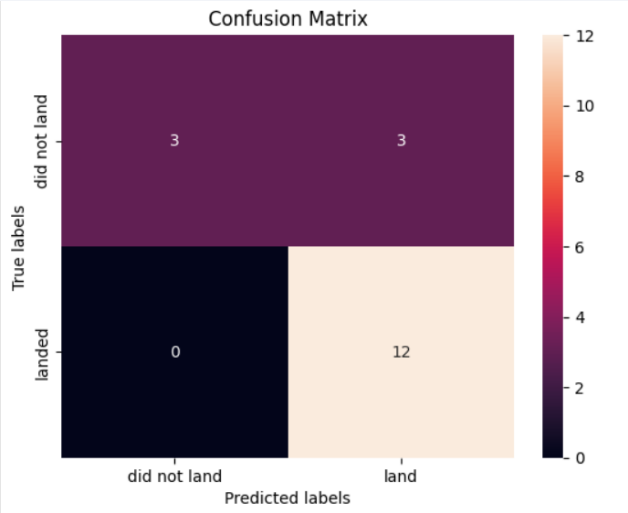
In [31]:
```
import matplotlib.pyplot as plt

# Accuracy values
accuracies = [logreg_accuracy, svm_accuracy, tree_accuracy, knn_accuracy]
models = ['Logistic Regression', 'SVM', 'Decision Tree', 'KNN']

# Plotting
plt.figure(figsize=(10, 6))
plt.bar(models, accuracies, color='skyblue')
plt.xlabel('Models', fontsize=14)
plt.ylabel('Accuracy', fontsize=14)
plt.title('Accuracy of Different Models', fontsize=16)
plt.ylim(0, 1)  # Set y-axis limit from 0 to 1 for percentage accuracy
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.xticks(rotation=45)  # Rotate x-axis labels for better readability
plt.tight_layout()
plt.show()
```



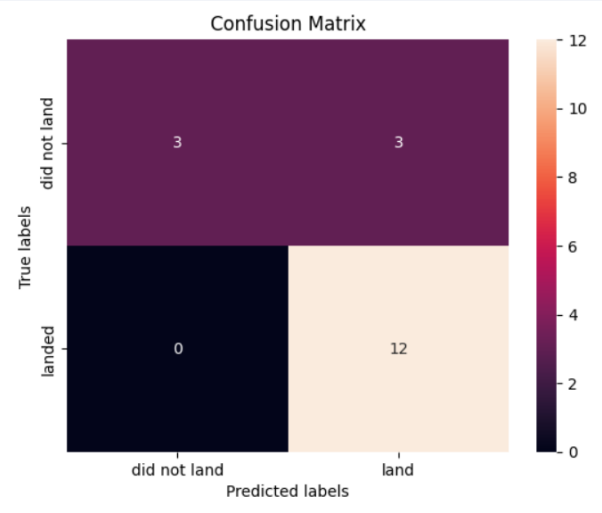
The model that performed best are LR, SVM, KNN and Decision Tree where all 4 achieved the highest accuracy of 83.33%.

Confusion Matrix

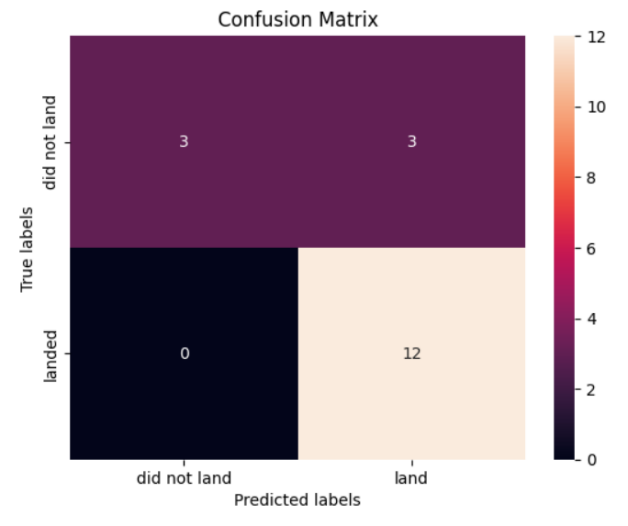
Confusion Matrix of LR



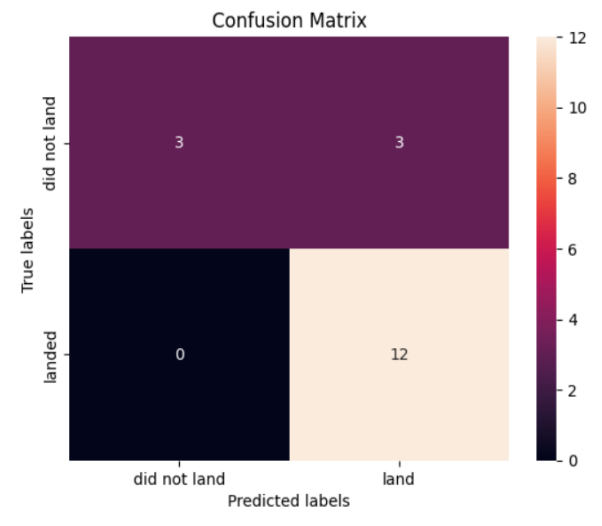
Confusion Matrix of SVM



Confusion Matrix of Decision Tree



Confusion Matrix of KNN



- LR, SVM, KNN and Decision Tree models are good as their confusion matrix show that they predicted all 12 successful landing correctly, with 0 error.
- LR, SVM, KNN and Decision Tree 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.

Thank you!