Winning Space Race with Data Science

Ngoc Trang Dai VU

December 25, 2022

https://github.com/vntdai/Datascience_coursera

Outline

Executive Summary

- The Winning Space Race with Data Science Project (DS Project) goal is to determine the cost of each launch by training a machine learning model based on the public information to predict if SpaceX will reuse the first stage. The DS Project collects Data with API and with web scraping related Wiki pages. Data wrangling includes: Wrangling Data using an API, Sampling Data, and Dealing with Nulls. Applied exploratory data analysis (EDA) (with visualization and SQL) and interactive visual analytics (with Folium and Plotly Dash) allows to understand data and find the reasonable Training Labels for the Machine Learning models. For prediction were used the following classifiers: Logistic Regression, Support Vector machines, Decision Tree Classifier, and K-nearest neighbors.
- The DS Project applied the mentioned above methodologies to the SpaceX dataset and got some results:
- The launch success yearly trend demonstrates that the success rate since 2013 kept increasing till 2020. The plotted bar chart Success Rate vs. Orbit Type shows that orbits ES-L1, GEO, NEO and SSO have highest success rate.
- Interactive analytics with Folium showed that launch site VAFB SLC-4E is in very close proximity to the coast of Pacific Ocean and CCAFS SLC-40 site has a relatively highest number of flights. Plotly Dash was used for building an application for users to perform interactive visual analytics on SpaceX launch data in real-time. Pie chart of the launch site VAFB SLC-4E demonstrated highest launch success ratio.
- Predictive analysis results determined the same level of accuracy about 83% for all models. This is because the dataset is small and has a lesser values.

Introduction

- The commercial space age is here, companies are making space travel affordable for everyone. Perhaps the most successful is SpaceX. SpaceX's accomplishments include: sending spacecraft to the International Space Station. Starlink, a satellite internet constellation providing satellite Internet access. Sending manned missions to Space. One reason SpaceX can do this is the rocket launches are relatively inexpensive. SpaceX advertises Falcon 9 rocket launches on its website with a cost of 62 million dollars; other providers cost upwards of 165 million dollars each, much of the savings is because SpaceX can reuse the first stage. Therefore, if it can be determined if the first stage will land, it can be determined the cost of a launch.
- Spaces X's Falcon 9 launch like regular rockets. Unlike other rocket providers, SpaceX's Falcon 9 can recover the first stage. Sometimes the first stage does not land. Sometimes it will crash. Other times, Space X will sacrifice the first stage due to the mission parameters like payload, orbit, and customer.
- The Winning Space Race with Data Science Project (DS Project) goal is to determine the cost of each launch. It is done by gathering information about Space X and creating dashboards for the project. It is also determined if SpaceX will reuse the first stage by training a machine learning model and by using public information to predict if SpaceX will reuse the first stage. Instead of using rocket science to predict if the first stage will land successfully, a machine learning model will be trained using public information to predict if SpaceX will reuse the first stage.

Section 1

Methodology

Methodology

Executive Summary:

- The DS Project collects Data with API. The Data collection is started with the SpaceX REST API endpoints, or URL, api.spacexdata.com/v4/launches/past. Another popular data source for obtaining Falcon 9 Launch data is web scraping related Wiki pages.
- Data wrangling: to transform the raw data into a clean dataset which provides meaningful data the following procedure is applied: Wrangling Data using an API, Sampling Data, and Dealing with Nulls.
- Performing exploratory data analysis (EDA) using visualization and SQL.
- Performing interactive visual analytics using Folium and Plotly Dash.
- Performing predictive analysis using the following classification models: Logistic Regression, Support Vector machines, Decision Tree Classifier, and K-nearest neighbors.

Data Collection

- SpaceX launch data is gathered from an API, specifically the SpaceX REST API.
- The DS Project starts with the SpaceX REST API endpoints, or URL, api.spacexdata.com/v4/launches/past. This URL is used to target a specific endpoint of the API to get past launch data by request. The result can be viewed by calling the .json() method.
- The response will be in the form of a JSON, specifically a list of JSON objects which each represent a launch. To convert this JSON to a dataframe, the json_normalize function is used.
- The Python BeautifulSoup package is using to web scrape some HTML tables that contain valuable Falcon 9 launch records.
- Then the data from those tables are parsed and converted into a Pandas data frame for further visualization and analysis.

Data Collection – SpaceX API

- SpaceX launch data is gathered **from an API**, specifically the SpaceX REST API. The DS Project starts with the SpaceX REST API endpoints, or URL, api.spacexdata.com/v4/launches/past.
- This API provides data about launches, including information about the rocket used, payload delivered, launch specifications, landing specifications, and landing outcome.
- As a response from API the DS Project will get a list of JSON objects which each represent a launch. To convert this JSON to a dataframe, it is used the json_normalize function. This function allows to “normalize” the structured JSON data into a flat table.
- https://github.com/vntdai/Datascience_coursera/blob/main/Data_collection_API.ipynb

```
spacex_url = https://api.spacexdata.com/v4/launches/past

response = requests.get(spacex_url)

data = pd.json_normalize(response.json())
```

Data Collection - Scraping

- Another data source for obtaining Falcon 9 Launch data is web scraping related Wiki pages.
- The Python BeautifulSoup package is used to web scrape some HTML tables that contain valuable Falcon 9 launch records.
- The filtered launch data for the Falcon 9 have to be included only.

https://github.com/vntdai/Datascience_coursera/blob/main/Data_collection_Web_scraping.ipynb

```
static_soup = BeautifulSoup(response.text, "html.parser")


launch_df = pd.DataFrame(launch_dict)


data_falcon9 = launch_df[launch_df['BoosterVersion']!='Falcon 1']
```

Data Wrangling

- To transform the raw data into a clean dataset which provides meaningful data the following procedure is applied: Wrangling Data using an API, Sampling Data, and Dealing with Nulls.
- In some of the columns, there is an identification number, not actual data. The API is used again targeting another endpoint to gather specific data for each ID number. These functions are used: getBoosterVersion(data), getLaunchSite(data), getPayloadData(data), and getCoreData(data).
- The data are stored in lists and are used to create the dataset. In order to make the dataset viable for analysis it is necessary to deal with NULL values (by replacing with the mean (mean_value = data_falcon9['PayloadMass'].mean()) or using one hot encoding (data_falcon9['PayloadMass'].fillna(value=mean_value, inplace=True))):
- 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.
- The launch outcomes were converted into the column 'Class' with 1 means the booster successfully landed 0 means it was unsuccessful. The average success rate of Falcon 9 launch is about 67%.
- https://github.com/vntdai/Datascience_coursera/blob/main/Data_wrangling.ipynb

EDA

- Exploratory Data Analysis (EDA) is the first step of any data science project to find some patterns in the data and determine what would be the label for training supervised models.
- In the data set, there are several different cases where the booster did not land successfully. Sometimes a landing was attempted but failed due to an accident; for example, 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 on a drone ship False ASDS means the mission outcome was unsuccessfully landed on a drone ship. During the Data Wrangling stage those outcomes were converted into Training Labels with 1 means the booster successfully landed 0 means it was unsuccessful.
- The categorical variables are converted using one hot encoding, preparing the data for a machine learning model that predicts if the first stage will successfully land.

EDA with Data Visualization

The DS Project performs EDA with Data visualization by plotting the charts showing the relationships between different data like the following:

- Flight Number vs. Launch Site
- Payload vs. Launch Site
- Success Rate vs. Orbit Type
- Flight Number vs. Orbit Type
- Payload vs. Orbit Type
- Launch Success Yearly Trend

https://github.com/vntdai/Datascience_coursera/blob/main/EDA_Visualization.ipynb

EDA with SQL

The performed SQL queries:

- 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).
- 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.
- 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 successful landing_outcomes between the date 04-06-2010 and 20-03-2017 in descending order.
- https://github.com/vntdai/Datascience_coursera/blob/main/EDA_SQL.ipynb

Build an Interactive Map with Folium

- The launch success rate may depend on many factors such as payload mass, orbit type, as well as on the location and proximities of a launch site, i.e., the initial position of rocket trajectories. Finding an optimal location for building a launch site certainly also involves many factors by analyzing the existing launch site locations with more interactive visual analytics using Folium.
- Some geographical patterns about launch sites were created and added to the Folium Map:
    - all launch sites on a map;
    - the success/failed launches for each site on the map;
    - the distances between a launch site to its proximities.

https://github.com/vntdai/Datascience_coursera/blob/main/Interactive_Visual_Analytics_with_Folium.ipynb

Build a Dashboard with Plotly Dash

- Interactive visual analytics like Dashboard usually are built for stakeholders. Interactive visual analytics enables users to explore and manipulate data in an interactive and real-time way. Common interactions including filter, search, and link. With interactive visual analytics, users could find visual patterns faster and more effectively.
- The DS Project performed interactive visual analytics on SpaceX launch data in real-time. This dashboard application contains input components such as a dropdown list (to select one specific site) and a range slider to interact with a pie chart (visualizing launch success counts for all or with different boosters) and a scatter point chart (observe how payload may be correlated with mission outcomes for selected site(s) for all or with different boosters).

https://github.com/vntdai/Datascience_coursera/blob/main/Interactive_Dashboard_with_Plotly.py

Predictive Analysis (Classification)

- The DS Projects performs exploratory Data Analysis and determines Training Labels by following steps:
    - create a column for the class
    - standardize the data
    - split into training data and test data
- The model was trained and was performed with Grid Search, allowing to find the hyperparameters that allows a given algorithm to perform best. Logistic Regression, Support Vector Machines, Decision Tree Classifier, and K-nearest neighbors models were tested. The confusion matrixes were built. Using the best hyperparameter values, the model with the best accuracy was determined using the training data.
- https://github.com/vntdai/Datascience_coursera/blob/main/SpaceX_ML_Prediction.ipynb

Results

- The DS Project performs EDA with Data visualization by plotting the charts showing the relationships between different data. The scatter plot Flight Number vs. Launch Site shows that CCAFS SLC-40 site has a relatively highest number of flights. The plotted bar chart Success Rate vs. Orbit Type shows that orbits ES- L1, GEO, NEO and SSO have highest success rate. The launch success yearly trend demonstrates that the success rate since 2013 kept increasing till 2020 with one not really successful 2018.
- Interactive analytics with Folium allowed to generate a map with each site's location using site's latitude and longitude coordinates. The map can show, for example, that launch site VAFB SLC-4E is in very close proximity to the coast of Pacific Ocean; From the color-labeled markers in marker clusters, it should be able to easily identify which launch sites have relatively high success rates (like KSC LC-39A).
- Plotly Dash was used for building an application for users to perform interactive visual analytics on SpaceX launch data in real-time. Pie chart for the launch site VAFB SLC-4E with highest launch success ratio was selected. The Booster version on each scatter point on the success-payload-scatter-chart were color-labeled, so that it is possible to observe mission outcomes with different boosters.
- Predictive analysis used the following classification models: Logistic Regression, Support Vector machines, Decision Tree Classifier, and K-nearest neighbors. Predictive analysis results demonstrates the same level of accuracy about 83% for all models. This is because the dataset is small and has a lesser values.

Section 2

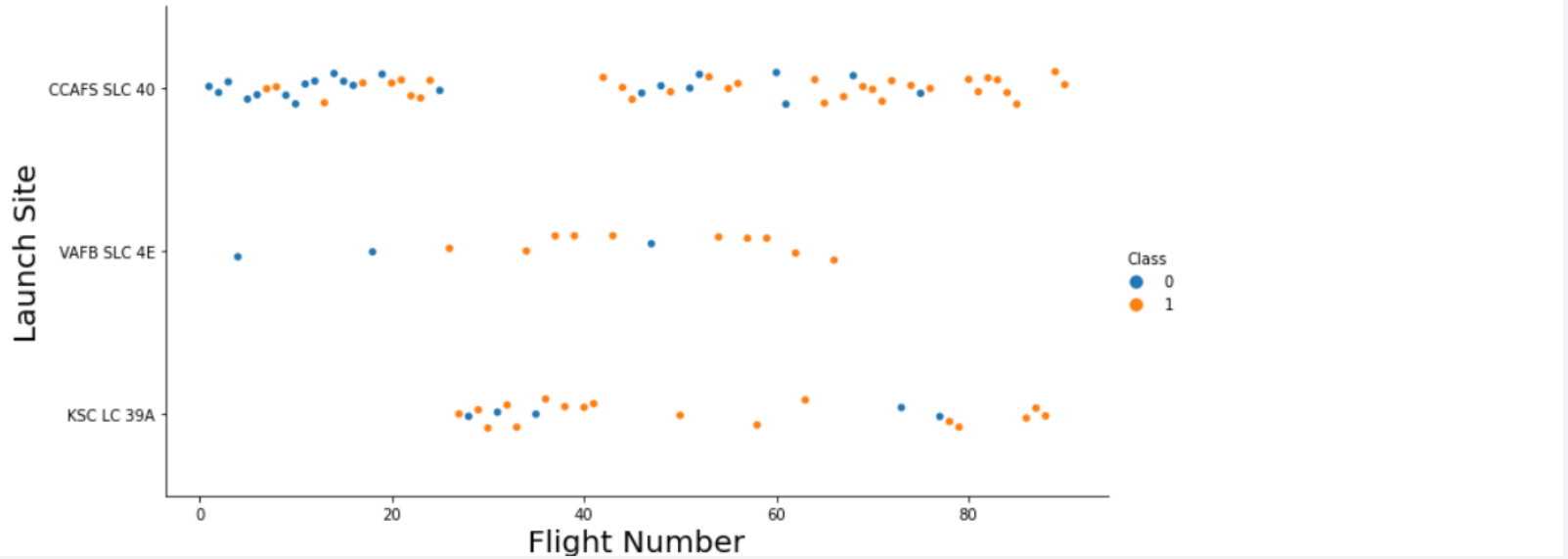
Insights drawn from EDA

Flight Number vs. Launch Site

TASK 1: Visualize the relationship between Flight Number and Launch Site

Use the function `catplot` to plot `FlightNumber` vs `LaunchSite`, set the parameter `x` parameter to `FlightNumber`,set the `y` to `Launch Site` and set the parameter `hue` to `'class'`

```
# Plot a scatter point chart with x axis to be Flight Number and y axis to be the launch site, and hue to be the class value
sns.catplot(y="LaunchSite", x="FlightNumber", hue="Class", data=df, aspect = 2)
plt.xlabel("Flight Number",fontsize=20)
plt.ylabel("Launch Site",fontsize=20)
plt.show()
```



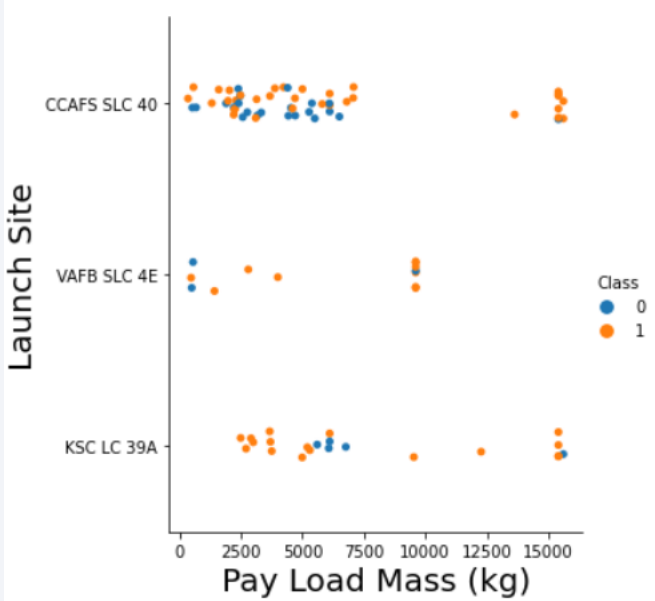
The scatter plot Flight Number vs. Launch Site shows that the different launch sites have different number of flights. CCAFS SLC-40 site has a relatively highest number of flights.

Payload vs. Launch Site

TASK 2: Visualize the relationship between Payload and Launch Site

We also want to observe if there is any relationship between launch sites and their payload mass.

```
# Plot a scatter point chart with x axis to be Pay Load Mass (kg) and y axis to be the launch site, and hue to be the class value
sns.catplot(y="LaunchSite", x="PayloadMass", hue="Class", data=df, aspect = 1)
plt.xlabel("Pay Load Mass (kg)",fontsize=20)
plt.ylabel("Launch Site",fontsize=20)
plt.show()
```



The scatter plot of Payload vs. Launch Site can demonstrate that for the VAFB-SLC 4E launch site there are no rockets launched for heavy payload mass (greater than 10000 kg).

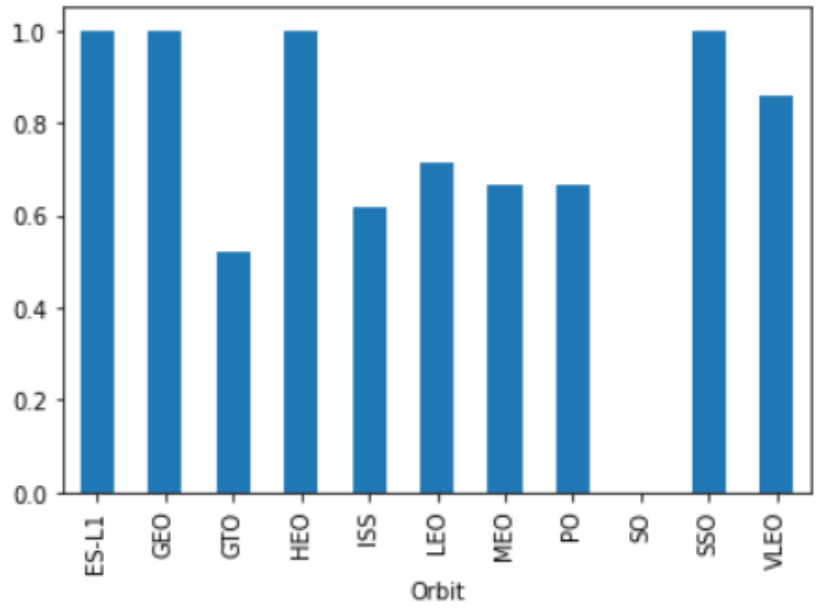
Success Rate vs. Orbit Type

TASK 3: Visualize the relationship between success rate of each orbit type

Next, we want to visually check if there are any relationship between success rate and orbit type.

Let's create a `bar chart` for the sucess rate of each orbit

```
# HINT use groupby method on Orbit column and get the mean of Class column
df.groupby('Orbit')['Class'].mean().plot.bar()
```



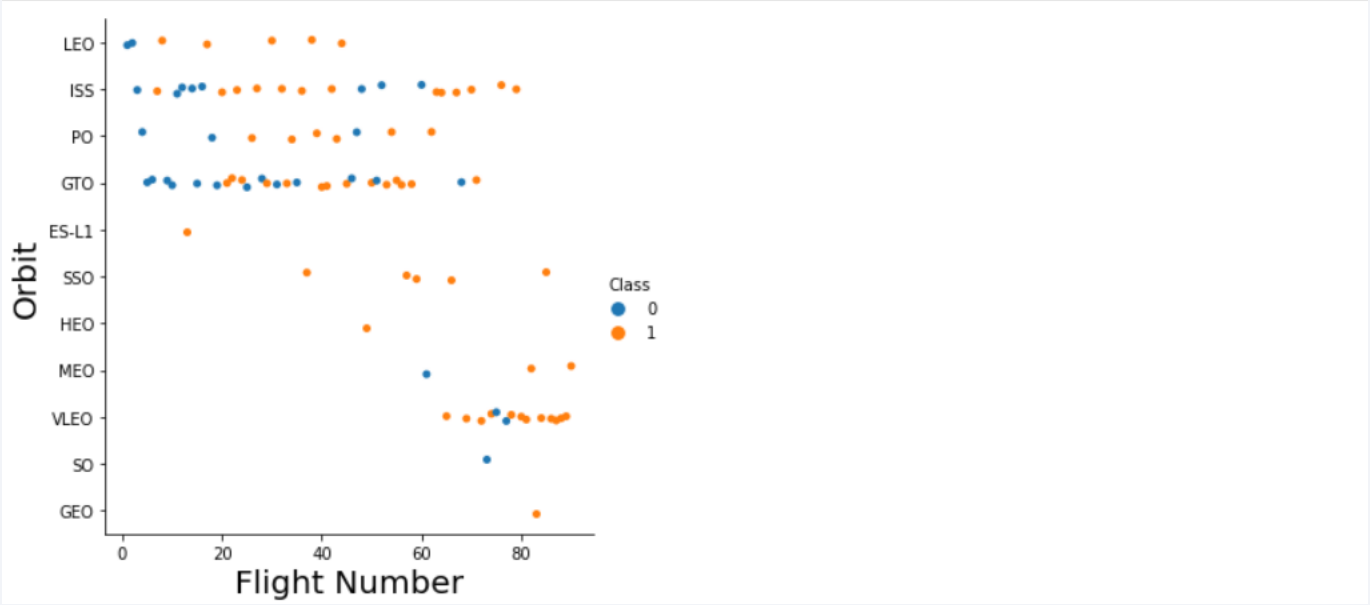
The plotted bar chart for the success rate of each orbit shows that orbits ES-L1, GEO, NEO and SSO have highest success rate.

Flight Number vs. Orbit Type

TASK 4: Visualize the relationship between FlightNumber and Orbit type

For each orbit, we want to see if there is any relationship between FlightNumber and Orbit type.

```
# Plot a scatter point chart with x axis to be FlightNumber and y axis to be the Orbit, and hue to be the class value
sns.catplot(y="Orbit", x="FlightNumber", hue="Class", data=df, aspect = 1)
plt.xlabel("Flight Number",fontsize=20)
plt.ylabel("Orbit",fontsize=20)
plt.show()
```



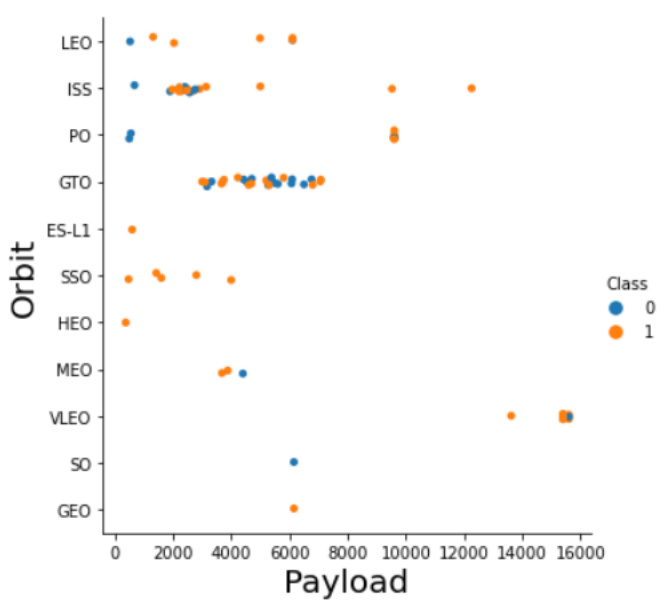
The scatter plot of Flight Number vs. Orbit Type can demonstrate that the LEO orbit the Success appears related to the number of flights; on the other hand, there seems to be no relationship between flight number when in ISS and GTO orbit.

Payload vs. Orbit Type

TASK 5: Visualize the relationship between Payload and Orbit type

Similarly, we can plot the Payload vs. Orbit scatter point charts to reveal the relationship between Payload and Orbit type

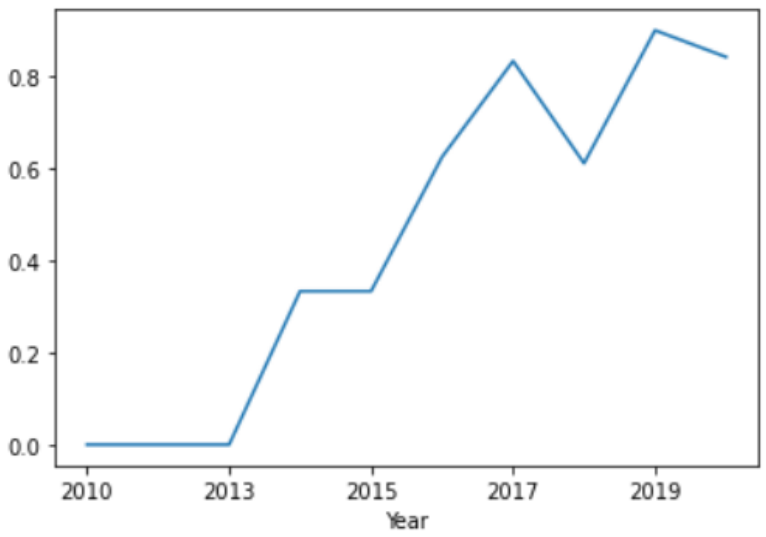
```
# Plot a scatter point chart with x axis to be Payload and y axis to be the Orbit, and hue to be the class value
sns.catplot(y="Orbit", x="PayloadMass", hue="Class", data=df, aspect = 1)
plt.xlabel("Payload",fontsize=20)
plt.ylabel("Orbit",fontsize=20)
plt.show()
```



With heavy payloads the successful landing or positive landing rate are more for Polar, LEO and ISS. However, for GTO positive landing rate and negative landing (unsuccessful mission) are both there here.

Launch Success Yearly Trend

```
# Plot a line chart with x axis to be the extracted year and y axis to be the success rate
temp_df = df.copy()
temp_df['Year'] = year
temp_df.groupby('Year')['Class'].mean().plot()
```



The launch success yearly trend demonstrates that the success rate since 2013 kept increasing until 2020 with one not successful 2018.

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

SQL queries to display the names of the unique launch sites in the space mission:

%%sql

SELECT DISTINCT LAUNCH_SITE FROM SPACEXTBL ORDER BY 1;

Launch Site Names Begin with 'CCA'

SQL queries to display 5 records where launch sites begin with the string 'CCA':

%%sql

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

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 attempt
08-10-2012	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
01-03-2013	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

Total Payload Mass

SQL queries to calculate the total payload mass carried by boosters launched by NASA (CRS):

%%sql

SELECT SUM(PAYLOAD_MASS__KG_) AS TOTAL_PAYLOAD FROM SPACEXTBL WHERE PAYLOAD LIKE '%CRS%';

Task 3

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

```
%%sql

SELECT SUM(PAYLOAD_MASS__KG_) AS TOTAL_PAYLOAD FROM SPACEXTBL WHERE PAYLOAD  LIKE '%CRS%';
```

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

TOTAL_PAYLOAD
111268

Average Payload Mass by F9 v1.1

SQL queries to calculate the average payload mass carried by booster version F9 v1.1:

```
%%sql

SELECT AVG(PAYLOAD_MASS__KG_) AS AVG_PAYLOAD FROM SPACEXTBL WHERE
BOOSTER_VERSION = 'F9 v1.1';
```

Task 4

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

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

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

AVG_PAYLOAD
2928.4

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

```
%%sql

SELECT "Landing _Outcome",count("Landing _Outcome")as LANDING_OUTCOME_COUNT,DATE

from SPACEXTBL where substr(Date,7,4) || substr(Date,4,2) || substr(Date,1,2) between '20100604'

and '20170320'and "Landing _Outcome" like "Success%"

group by "Landing _Outcome" order by count("Landing _Outcome") desc
```

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

Landing _Outcome	LANDING_OUTCOME_COUNT	Date
Success (drone ship)	5	08-04-2016
Success (ground pad)	3	22-12-2015

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

```
%%sql

SELECT DISTINCT BOOSTER_VERSION
FROM SPACEXTBL WHERE PAYLOAD_MASS__KG_ BETWEEN 4000 AND 6000
AND "LANDING _OUTCOME" like 'Success (drone ship)';
```

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

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

Total Number of Successful and Failure Mission Outcomes

Task 7

List the total number of successful and failure mission outcomes

```
%%sql
SELECT MISSION_OUTCOME, COUNT(*) AS QTY FROM SPACEXTBL GROUP BY MISSION_OUTCOME ORDER BY MISSION_OUTCOME;
```

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

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

Boosters Carried Maximum Payload

Task 8

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

```
%%sql

SELECT BOOSTER_VERSION FROM SPACEXTBL
WHERE PAYLOAD_MASS__KG_ = (SELECT MAX(PAYLOAD_MASS__KG_) FROM SPACEXTBL)
ORDER BY BOOSTER_VERSION;
```

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

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

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, 4, 2) as month to get the months and substr(Date,7,4)='2015' for year.

```
%%sql

SELECT BOOSTER_VERSION, LAUNCH_SITE, substr(Date, 4, 2) AS Month
FROM SPACEXTBL
WHERE substr(Date,7,4)='2015' AND "LANDING _OUTCOME" like 'Failure%'
GROUP BY substr(Date, 4, 2)
```

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

Booster_Version	Launch_Site	Month
F9 v1.1 B1012	CCAFS LC-40	01
F9 v1.1 B1015	CCAFS LC-40	04

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

Task 10

Rank the count of successful landing_outcomes between the date 04-06-2010 and 20-03-2017 in descending order.

```
%%sql

SELECT "Landing _Outcome",COUNT("Landing _Outcome") as LANDING_OUTCOME_COUNT,DATE
FROM SPACEXTBL WHERE substr(Date,7,4) || substr(Date,4,2) || substr(Date,1,2) between '20100604' and '20170320'
AND "LANDING _OUTCOME" like 'Success%'
GROUP BY "Landing _Outcome" ORDER BY COUNT("Landing _Outcome") DESC;
```

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

Landing _Outcome	LANDING_OUTCOME_COUNT	Date
Success (drone ship)	5	08-04-2016
Success (ground pad)	3	22-12-2015

Section 3

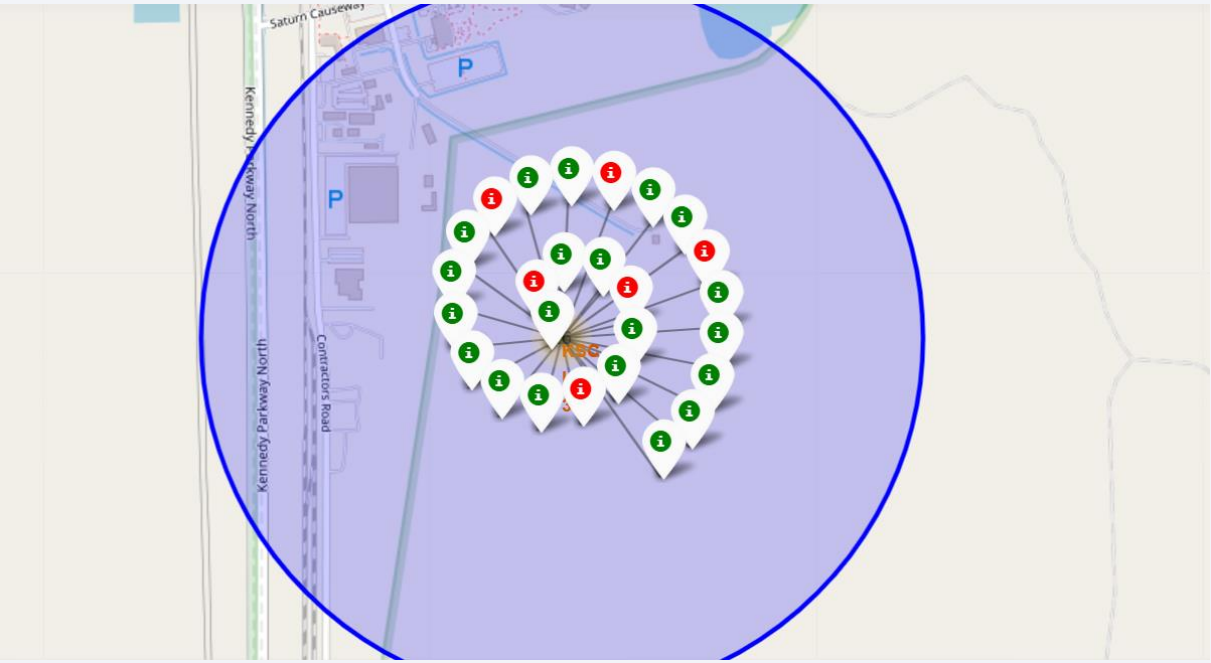
Launch Sites Proximities Analysis

All launch sites on a map

- Folium was used to add each site's location on a map using site's latitude and longitude coordinates (find below). Folium includes functions to create and add folium.Circle and folium. Marker for each launch site on the site map.
- The generated map with marked launch sites allows to explore the map by zoom-in/out the marked areas: and to see, for example, that launch site VAFB SLC-4E is in very close proximity to the coast of Pacific Ocean.

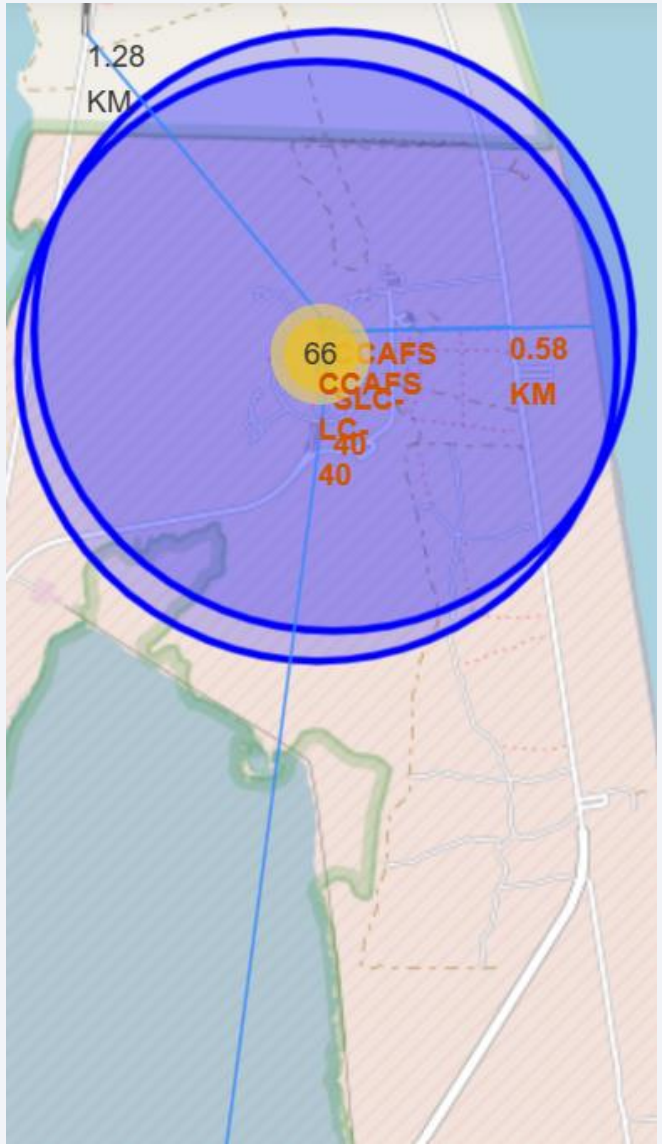
- All launch sites are in proximity to the Equator line and close to the coast. It is close the Equator line perhaps because it is more economical to get into space from the Equator (less expenses on fuel). The close proximity to the coast is of safety reasons as failed launches would occurs in the ocean.

The success/failed launches for each site on the map



- Marker clusters was used to simplify a map containing many markers having the same coordinate and to show the color-labeled launch outcomes on the map.
- If a launch was successful (class=1), then was used a green marker and if a launch was failed, was used a red marker (class=0)
- From the color-labeled markers in marker clusters, it should be able to easily identify which launch sites have relatively high success rates (like KSC LC-39A).

The distances between a launch site to its proximities



- Folium package has the several instruments using to explore and analyze the proximities of launch sites:

- MousePosition allows to get coordinate for a mouse over a point on the map based on their Lat and Long values;

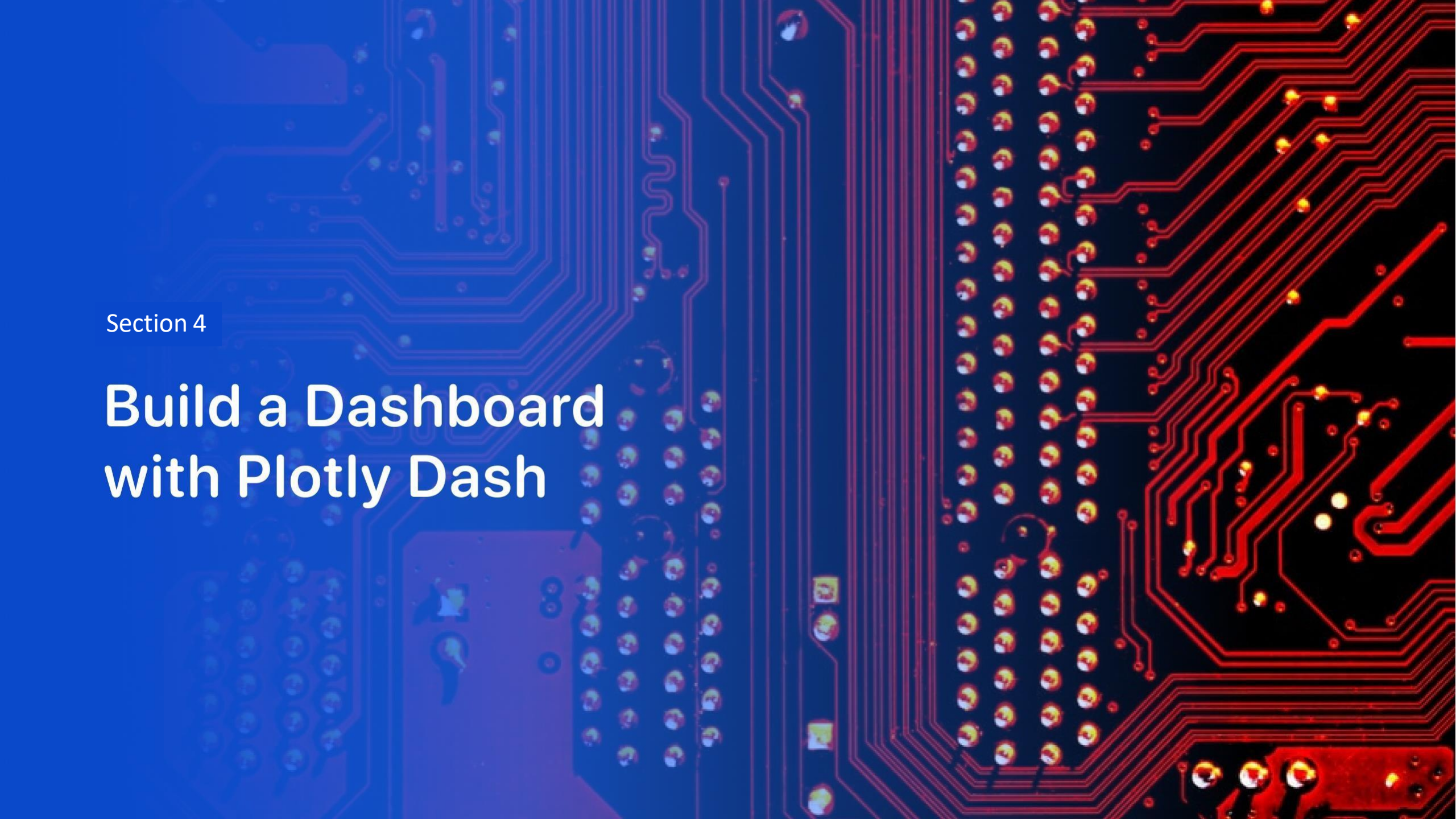
- After obtained its coordinate, a folium.Marker was created to show the distance;

- Folium.PolyLine draws a line between a launch site to its closest city, railway, highway, etc.

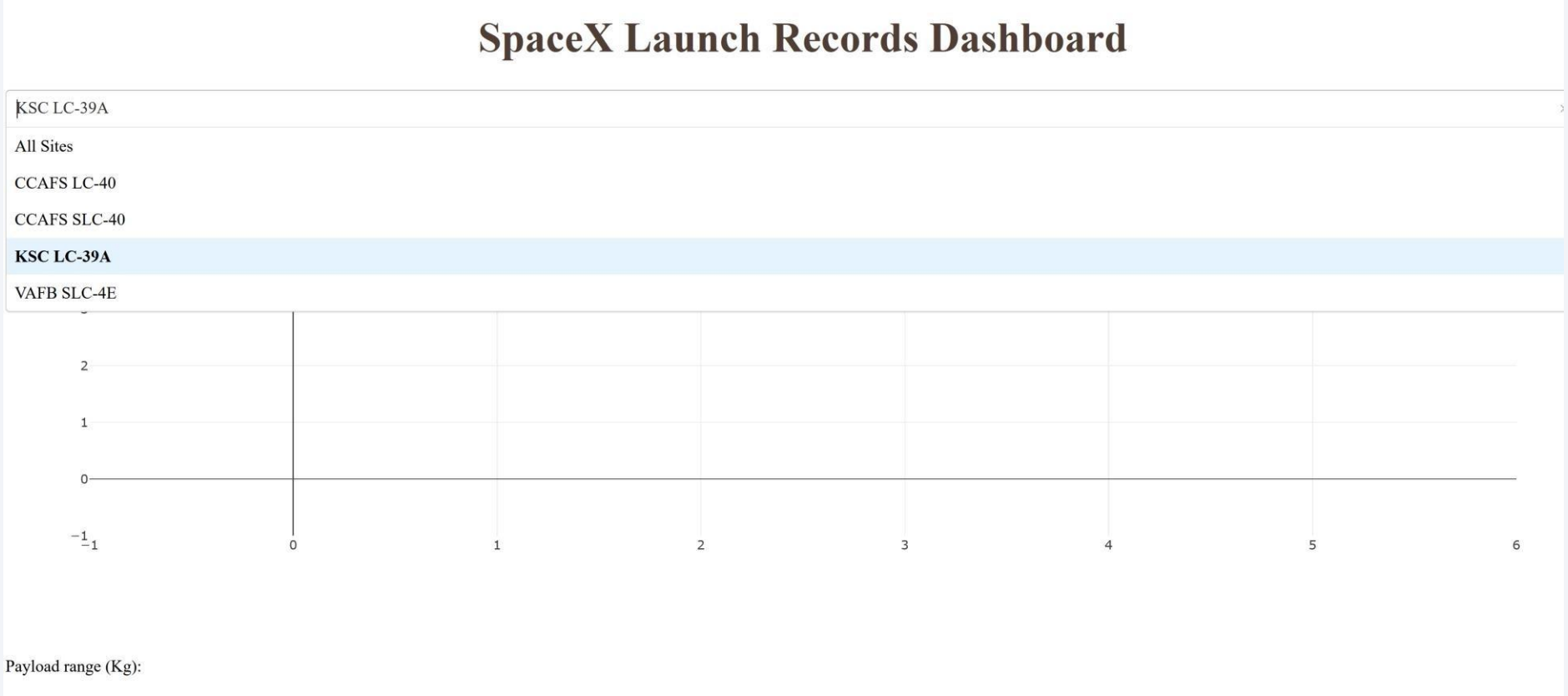
- For example, the proximities of launch site CCAFS SLC-40 to its closest city Titusville, railway and highway.

The proximities of launch site CCAFS SLC-40 from the following points:

- distance_highway = 0.5834695366934144 km
- distance_railroad = 1.2845344718142522 km
- distance_city (Cape Canaveral, Florida) = 19.625687088363627 km

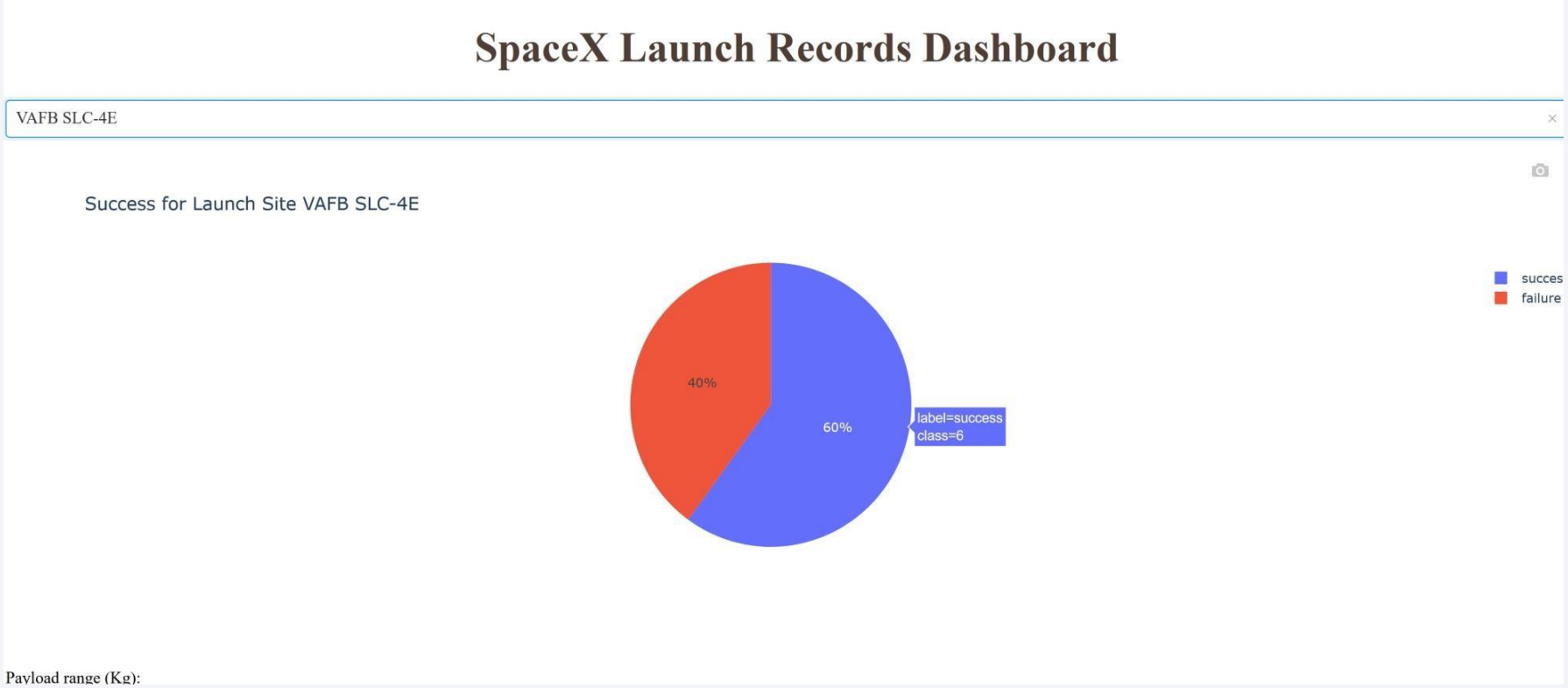

Section 4
Build a Dashboard with Plotly Dash

Launch Site Drop-down Input Component



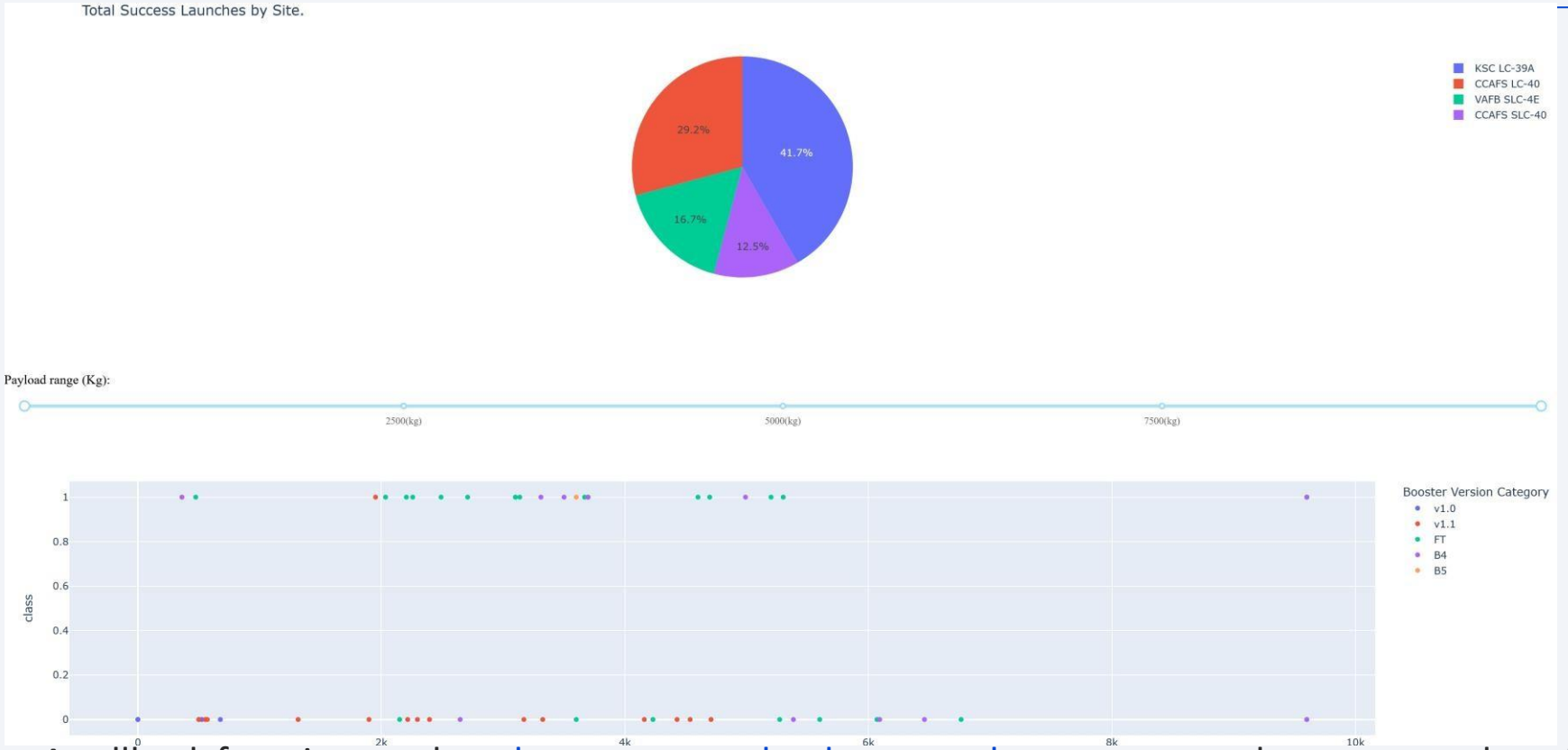
- Plotly Dash was used for building an application for users to perform interactive visual analytics on SpaceX launch data in real-time.
- There are four different launch sites and the completed dropdown menu allows to select one specific site and check its detailed success rate (class=0 vs. class=1) and see which one has the largest success count.

The pie-chart for the launch site with highest launch success ratio



- Dash callback function is a type of Python function which is automatically called by Dash whenever receiving an input component updates, such as a click or dropdown selecting event.
- The callback function is used to get the selected launch site from site-dropdown and render a pie chart visualizing launch success counts.
- Pie chart for the launch site VAFB SLC-4E with highest launch success ratio was selected.

Payload vs. Launch Outcome scatter plot for all sites

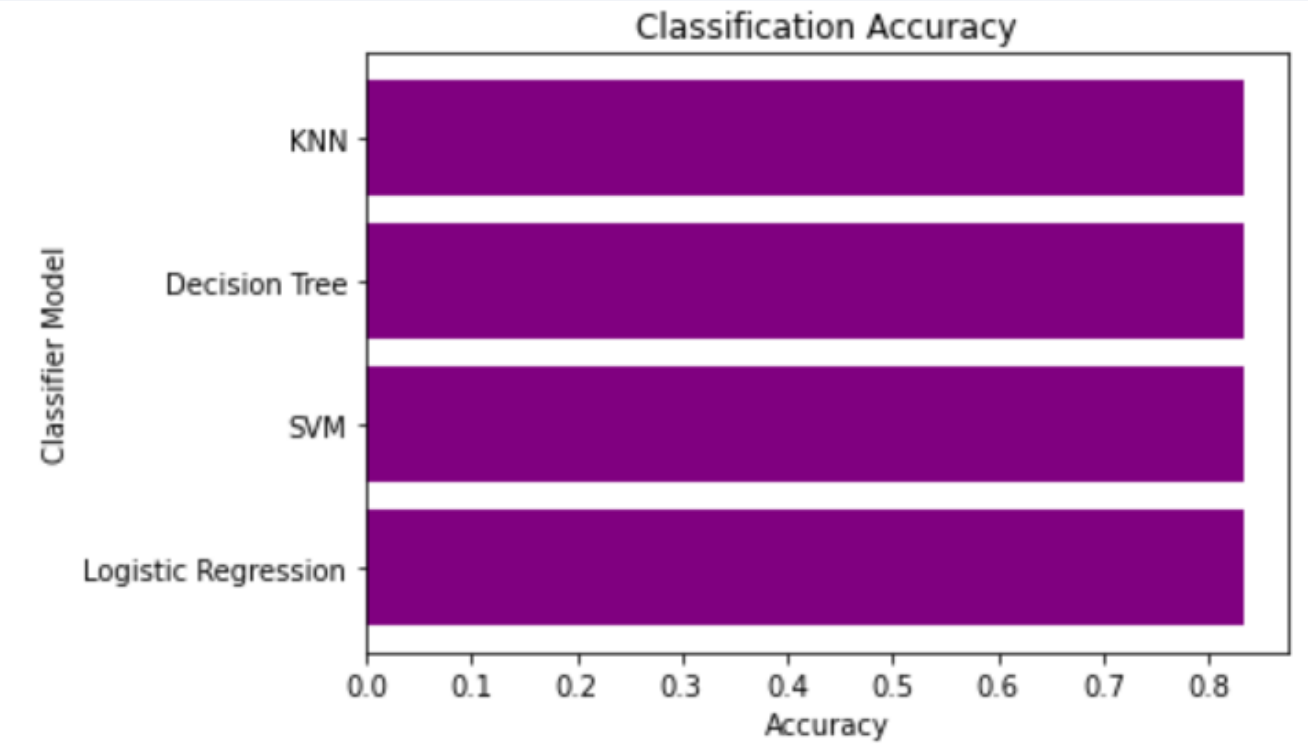


- A callback function renders the success-payload-scatter-chart scatter to plot a scatter plot with the x axis to be the payload and the y axis to be the launch outcome (i.e., class column). As such, it allows visually observe how payload may be correlated with mission outcomes for selected site(s). The Booster version on each scatter point were color-labeled, so that it is possible to observe mission outcomes with different boosters.
- Above a screenshots of Payload vs. Launch Outcome scatter plot for all sites, with different payload selected in the range slider.

Section 5

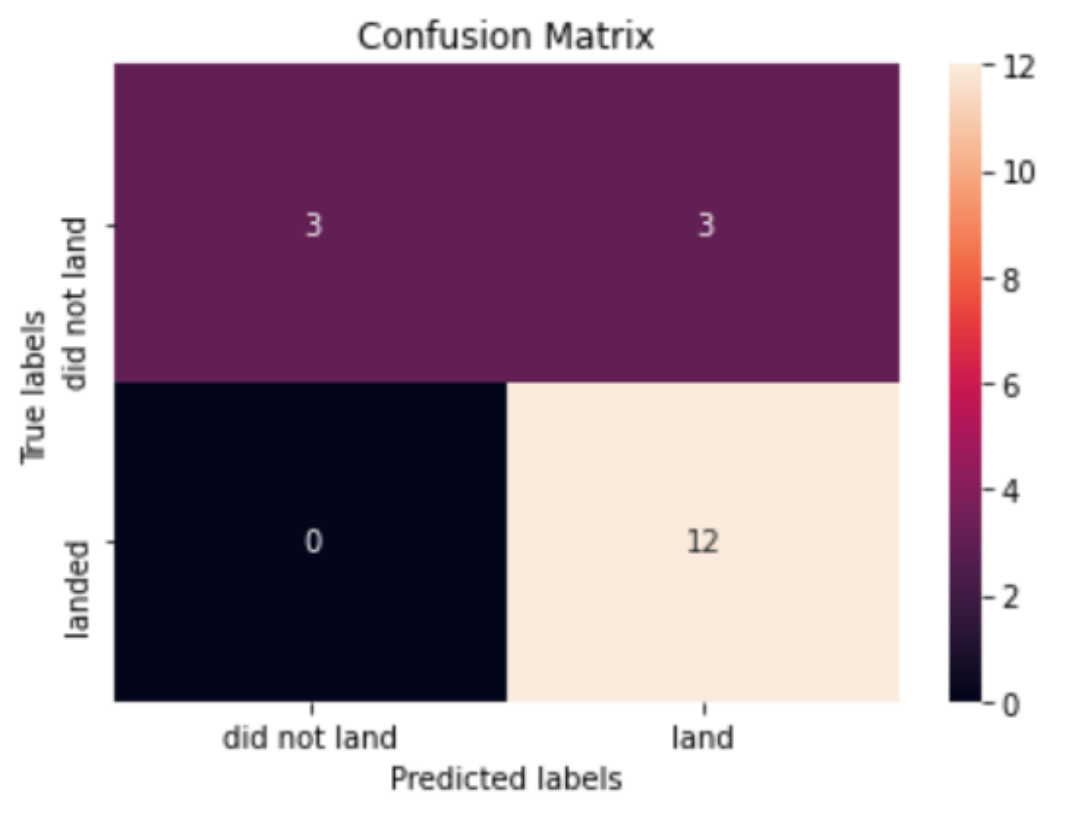
Predictive Analysis (Classification)

Classification Accuracy



- The DS Project created a machine learning pipeline to predict if the first stage will land given the prepared data.
- Predictive analysis used the following classification models: Logistic Regression, Support Vector machines, Decision Tree Classifier, and K-nearest neighbors.
- The results of the score are practically the same: 0.8333, and the confusion matrix looks the same for all classifier models. This is because the dataset is small and has lesser values.

Confusion Matrix



- The confusion matrix of the **Logistic Regression Model** shows that logistic regression can distinguish between the different classes – the classifier could predict 12 successful landed cases but the major problem is false positives.

Conclusions

- “The Winning Space Race with Data Science Project” (DS Project) goal was to determine the cost of each launch by training a machine learning model based on the public information to predict if SpaceX will reuse the first stage.
- The DS Project collected Data with API and with web scraping related Wiki pages and performed EDA with Data visualization by plotting the charts showing the relationships between different data. It showed that the launch success yearly trend demonstrates that the success rate since 2013 kept increasing till 2020.
- The interactive analytic with Folium could defined that the launch site KSC LC-39A has relatively high success rate. The built with Plotly Dashboard application helped users to perform interactive visual analytics on SpaceX launch data in real-time.
- Predictive analysis results demonstrates the same level of accuracy about 83% for all applied classifier models. This is because the dataset is small and has a lesser values.
- “The Winning Space Race with Data Science Project” could prove the positive perspective of using the Falcon 9 Rocket series whose launch progress can prove a reasonable cost. The results of the DS Project can be used if an alternate company wants to bid against SpaceX for a rocket launch.

Appendix

- Data Wrangling Result

	FlightNumber	Date	BoosterVersion	PayloadMass	Orbit	LaunchSite	Outcome	Flights	GridFins	Reused	Legs	LandingPad	Block	ReusedCount	Serial	Longitude	La
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	28.5
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	28.5
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	28.5
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	34.6
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	28.5
5	6	2014-01-06	Falcon 9	3325.000000	GTO	CCAFS SLC 40	None None	1	False	False	False	NaN	1.0	0	B1005	-80.577366	28.5
6	7	2014-04-18	Falcon 9	2296.000000	ISS	CCAFS SLC 40	True Ocean	1	False	False	True	NaN	1.0	0	B1006	-80.577366	28.5
7	8	2014-07-14	Falcon 9	1316.000000	LEO	CCAFS SLC 40	True Ocean	1	False	False	True	NaN	1.0	0	B1007	-80.577366	28.5
8	9	2014-08-05	Falcon 9	4535.000000	GTO	CCAFS SLC 40	None None	1	False	False	False	NaN	1.0	0	B1008	-80.577366	28.5
9	10	2014-09-07	Falcon 9	4428.000000	GTO	CCAFS SLC 40	None None	1	False	False	False	NaN	1.0	0	B1011	-80.577366	28.5

Thank you!