Winning Space Race with Data Science

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Outline

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Executive Summary

- SpaceY is a new commercial rocket launch provider who wants to bid against SpaceX.
- • SpaceX advertises launch services starting at $62 million for missions that allow some fuel to be reserved for landing the 1st stage rocket booster, so that it can be reused.
- • SpaceX public statements indicate a 1st stage Falcon 9 booster to cost upwards of $15 million to build without including R&D cost recoupment or profit margin.
- • Given mission parameters such as payload mass and desired orbit, the models produced in this report were able to predict the first stage rocket booster landing successfully with an accuracy level of 83.3%.
- • As a result, SpaceY will be able to make more informed bids against SpaceX by using 1st stage landing predictions as a proxy for the cost of a launch.

Introduction

Project background and context

- Space X advertises Falcon 9 rocket launches on its website with a cost of 62 million dollars; other providers cost upward of 165 million dollars each, much of the savings is because Space X can reuse the first stage. Therefore, if we can determine if the first stage will land, we can determine the cost of a launch.
- This information can be used if an alternate company wants to bid against space X for a rocket launch. This goal of the project is to create a machine learning pipeline to predict if the first stage will land successfully.

Problems you want to find answers

- What factors determine if the rocket will land successfully?
- The interaction amongst various features that determine the success rate of a successful landing.
- What operating conditions needs to be in place to ensure a successful landing program.

Section 1

Methodology

Methodology

Executive Summary → • Data collection methodology: → Data was collected using SpaceX API and web scraping from Wikipedia. → Perform data wrangling

→ One-hot encoding was applied to categorical features: → • Perform exploratory data analysis (EDA) using visualization and SQL → • Perform interactive visual analytics using Folium and Plotly Dash → • Perform predictive analysis using classification models

→ How to build, tune, evaluate classification models

Data Collection

Past launches [edit]

2010 to 2013 [edit]

[hide] Flight No.	Date and time (UTC)	Version, Booster [b]	Launch site	Payload[c]	Payload mass	Orbit	Customer	Launch outcome	Booster landing
1	4 June 2010, 18:45	F9 v1.0[7] B0003[8]	CCAFS, SLC-40	Dragon Spacecraft Qualification Unit		LEO	SpaceX	Success	Failure[9][10] (parachute)
	First flight of Falcon 9 v1.0.[11] Used a boilerplate version of Dragon capsule which was not designed to separate from the second stage. (more details below) Attempted to recover the first stage by parachuting it into the ocean, but it burned up on reentry, before the parachutes even go to deploy.[12]								
2	8 December 2010, 15:43[13]	F9 v1.0[7] B0004[8]	CCAFS, SLC-40	Dragon demo flight C1 (Dragon C101)		LEO (ISS)	NASA (COTS) NRO	Success[9]	Failure[9][14] (parachute)
	Maiden flight of SpaceX's Dragon capsule, consisting of over 3 hours of testing thruster maneuvering and then reentry.[15] Attempted to recover the first stage by parachuting it into the ocean, but it disintegrated upon reentry, again before the parachutes were deployed.[12] (more details below) It also included two CubeSats,[16] and a wheel of Brouère cheese. Before the launch, SpaceX discovered that there was a crack in the nozzle of the 2nd stage's Merlin vacuum engine. So Elon just had them cut off the end of the nozzle with a pair of shears and launched the rocket a few days later. After SpaceX had trimmed the nozzle, NASA was notified of the change and they agreed to it.[17]								
3	22 May 2012, 07:44[18]	F9 v1.0[7] B0005[8]	CCAFS, SLC-40	Dragon demo flight C2+[19] (Dragon C102)	525 kg (1,157 lb)[20]	LEO (ISS)	NASA (COTS)	Success[21]	No attempt
	The Dragon spacecraft demonstrated a series of tests before it was allowed to approach the International Space Station. Two days later, it became the first commercial spacecraft to board the ISS.[18] (more details below)								
4	8 October 2012, 00:35[22]	F9 v1.0[7] B0006[8]	CCAFS, SLC-40	SpaceX CRS-1[23] (Dragon C103)	4,700 kg (10,400 lb)	LEO (ISS)	NASA (CRS)	Success	No attempt
				Orbcomm-OG2[24]	172 kg (379 lb)[25]	LEO	Orbcomm	Partial failure[26]	
	CRS-1 was successful, but the secondary payload was inserted into an abnormally low orbit and subsequently lost. This was due to one of the nine Merlin engines shutting down during the launch, and NASA declining a second reignition, as per ISS visiting vehicle safety rules, the primary payload owner is contractually allowed to decline a second reignition. NASA stated that this was because SpaceX could not guarantee a high enough likelihood of the second stage completing the second burn successfully which was required to avoid any risk of secondary payload's collision with the ISS.[27][28][29]								
	1 March 2013,	F9 v1.0[7]	CCAFS,	SpaceX CRS-2[23]	4,877 kg	LEO	NASA	Success	No attempt

What the first page of launch data looked like on Wikipedia prior to web scraping

Data Collection

- API
- Acquired historical launch data from Open-Source REST API for SpaceX
- Requested and parsed the SpaceX launch data using the GET request
- Filtered the dataframe to only include Falcon 9 launches
- Replaced missing payload mass values from classified missions with mean

• Web Scraping

- Acquired historical launch data from Wikipedia page 'List of Falcon 9 and Falcon Heavy Launches'
- Requested the Falcon9 Launch Wiki page from its Wikipedia URL
- Extracted all column/variable names from the HTML table header
- Parsed the table and converted it into a Pandas data frame

Note: Falcon 9 launch dataset was limited to launches before December 7, 2020 per instructions.

Data Collection – SpaceX API

We used the get request to the

SpaceX API to collect data, clean the requested data and did some basic data wrangling and formatting.

The link to the notebook ishttps://github.com/Gaukarna/Final-Project-Applied-Data-Science-Capstone/blob/main/jupyter-labs-spacex-data-collection-api%20(1).ipynb

1. Get request for rocket launch data using API

```
In [6]: spacex_url="https://api.spacexdata.com/v4/launches/past"
```

```
In [7]: response = requests.get(spacex_url)
```

2. Use json_normalize method to convert json result to dataframe

```
In [12]: # Use json_normalize method to convert the json result into a dataframe

         # decode response content as json
         static_json_df = res.json()
```

```
In [13]: # apply json_normalize
         data = pd.json_normalize(static_json_df)
```

3. We then performed data cleaning and filling in the missing values

```
In [30]: rows = data_falcon9['PayloadMass'].values.tolist()[0]

         df_rows = pd.DataFrame(rows)
         df_rows = df_rows.replace(np.nan, PayloadMass)

         data_falcon9['PayloadMass'][0] = df_rows.values
         data_falcon9
```

Data Collection - Scraping

We applied web scrapping to webscrap Falcon 9 launch records with Beautiful Soup

We parsed the table and converted it into a pandas data frame.

The link to the notebook is https://github.com/Gaukarna/Final-Project-Applied-Data-Science-Capstone/blob/main/jupyter-labs-webscraping%20(1).ipynb

1. Apply HTTP Get method to request the Falcon 9 rocket launch page

```
In [4]: static_url = "https://en.wikipedia.org/w/index.php?title=List_of_Falcon_9_and_Falcon_Heavy_launches&oldid=1027686922"
```

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

Out[5]: 200
```

2. Create a BeautifulSoup object from the HTML response

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

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

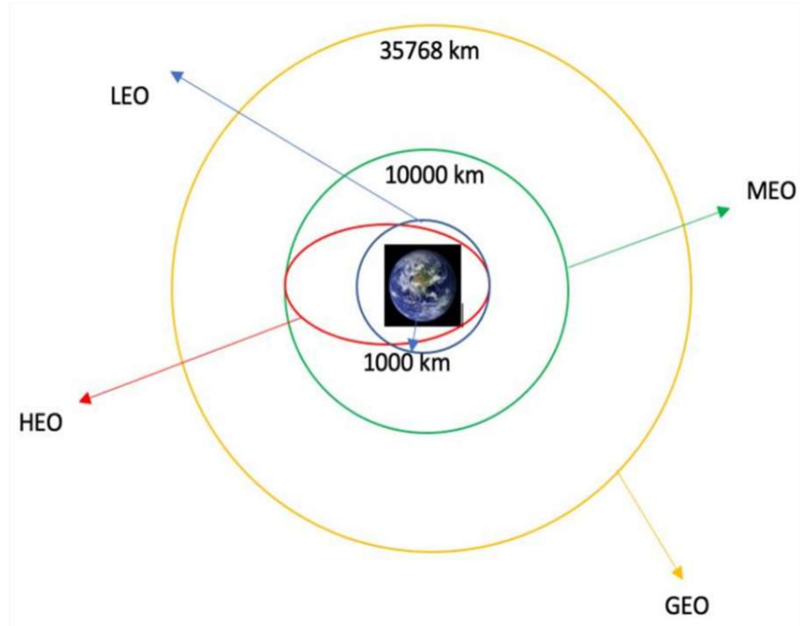
```
In [7]: # Use soup.title attribute
        soup.title

Out[7]: <title>List of Falcon 9 and Falcon Heavy launches - Wikipedia</title>
```

3. Extract all column names from the HTML table header

```
In [10]: column_names = []

         # Apply find_all() function with `th` element on first_launch_table
         # Iterate each th element and apply the provided extract_column_from_header() to get a column name
         # Append the Non-empty column name (`if name is not None and len(name) > 0`) into a list called column_names

         element = soup.find_all('th')
         for row in range(len(element)):
             try:
                 name = extract_column_from_header(element[row])
                 if (name is not None and len(name) > 0):
                     column_names.append(name)
             except:
                 pass
```

4. Create a dataframe by parsing the launch HTML tables
5. Export data to csv

Data Wrangling



WE PERFORMED EXPLORATORY DATA ANALYSIS AND DETERMINED THE TRAINING LABELS.

• WE CALCULATED THE NUMBER OF LAUNCHES AT EACH SITE, AND THE NUMBER AND OCCURRENCE OF EACH ORBITS

• WE CREATED LANDING OUTCOME LABEL FROM OUTCOME COLUMN AND EXPORTED THE RESULTS TO CSV.

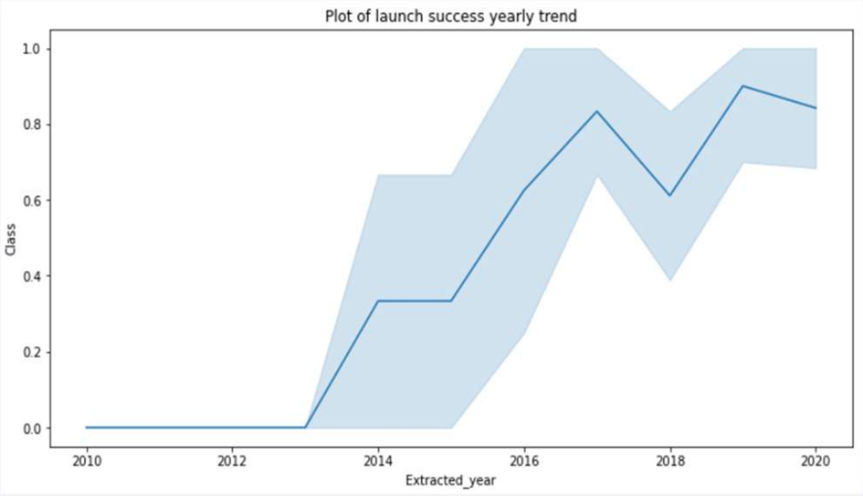
• THE LINK TO THE NOTEBOOK IS

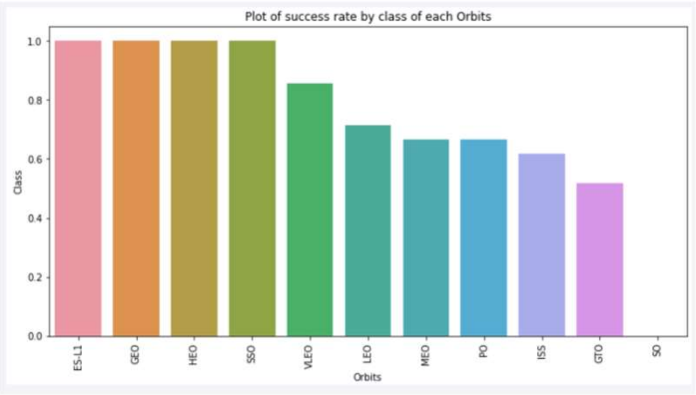
HTTPS://GITHUB.COM/GAUKARNA/FINAL-PROJECT-APPLIED-DATA-SCIENCE-CAPSTONE/BLOB/MAIN/LABS-JUPYTER-SPACEX-DATA%20WRANGLING.IPYNB

YNB.

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.





The link to the notebook is

https://github.com/Gaukarna/Final-Project-Applied-Data-Science-Capstone/blob/main/jupyter-labs-eda-dataviz.ipynb.jupyterlite.ipynb

EDA with SQL

We loaded the SpaceX dataset into a PostgreSQL database without leaving

the jupyter notebook.

- We applied EDA with SQL to get insight from the data. We wrote queries to

find out for instance:

- The names of unique launch sites in the space mission.

- The total payload mass carried by boosters launched by NASA (CRS)

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

- The total number of successful and failure mission outcomes

- The failed landing outcomes in drone ship, their booster version and launch site names.

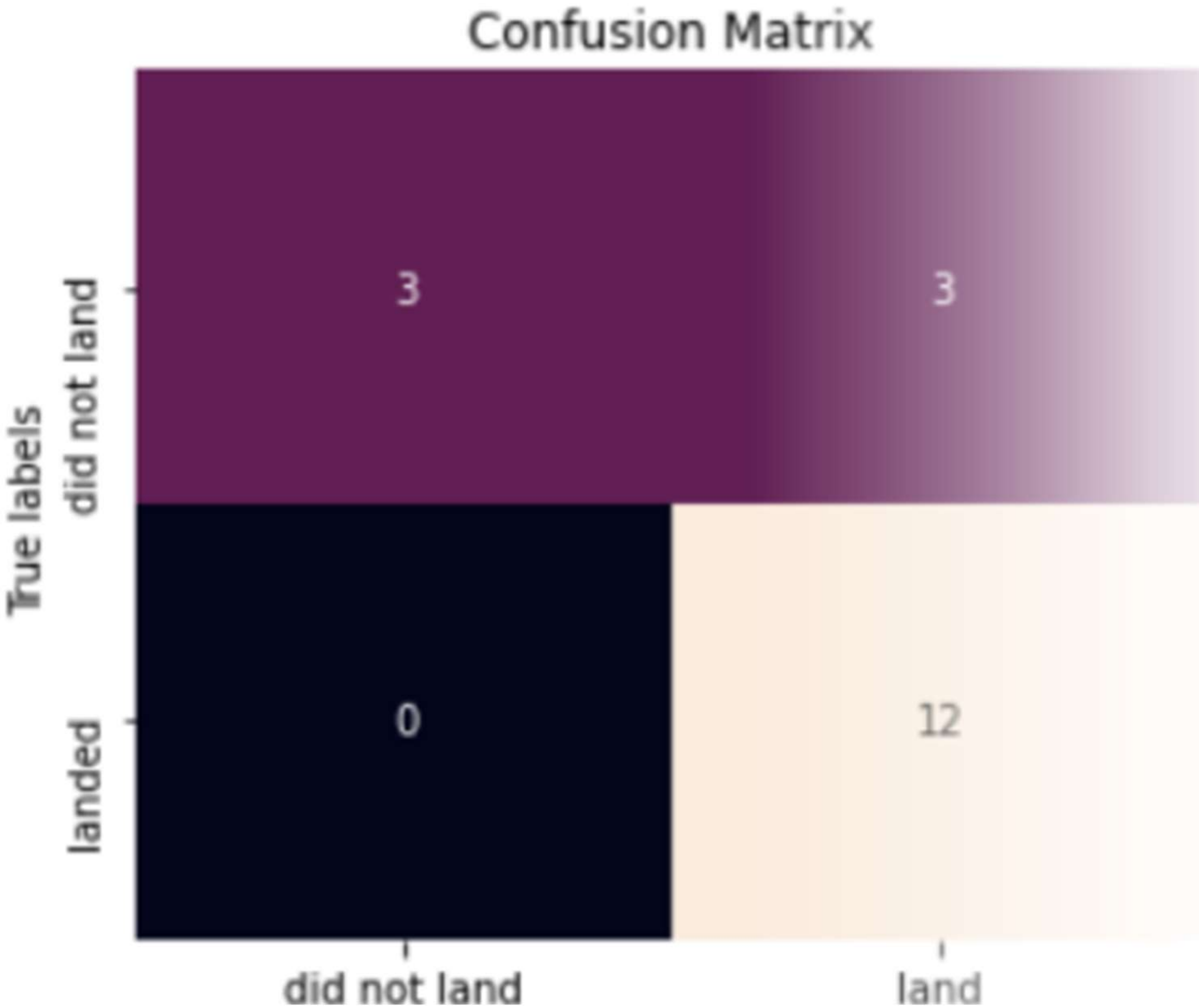
- The link to the notebook is https://github.com/Gaukarna/Final-Project-Applied-Data-Science-Capstone/blob/main/jupyter-labs-eda-sql-coursera_sqllite.ipynb

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.

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.
- The link to the notebook is https://github.com/Gaukarna/Final-Project-Applied-Data-Science-Capstone/blob/main/spacex_dash_app.py



Predictive Analysis (Classification)

- We loaded the data using numpy and pandas, transformed the data, split our data into training and testing.
- • We built different machine learning models and tune different hyperparameters using GridSearchCV.
- • We used accuracy as the metric for our model, improved the model using
- feature engineering and algorithm tuning.
- • We found the best performing classification model.
- • The link to the notebook is https://github.com/Gaukarna/Final-Project-Applied-Data-Science-Capstone/blob/main/SpaceX_Machine_Learning_Prediction_Part_5.jupyterlite.ipynb

Results

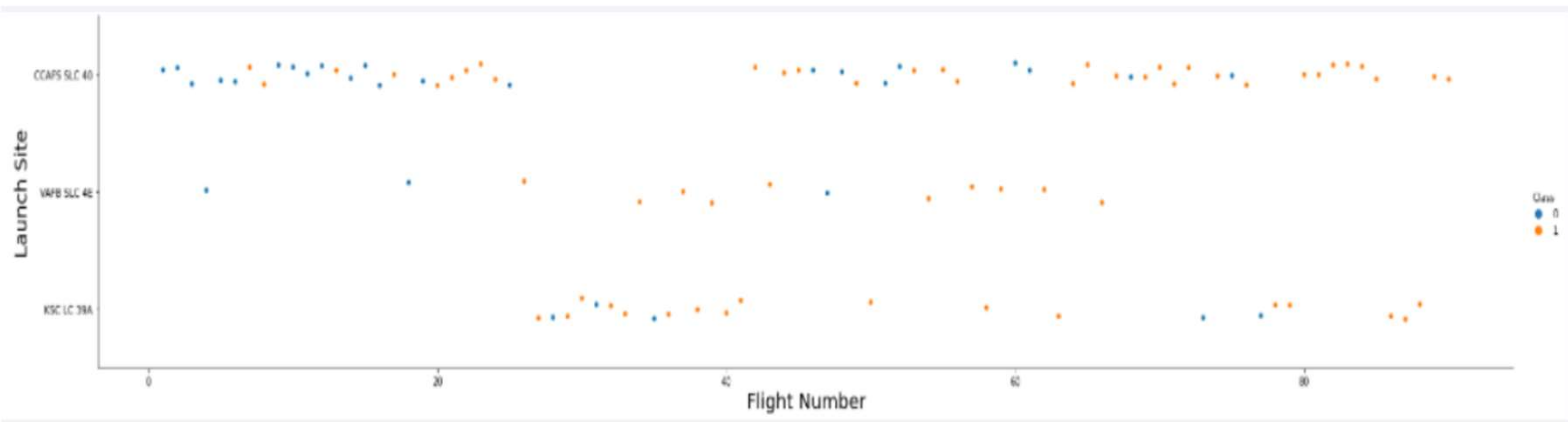
- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results

Section 2

Insights drawn from EDA

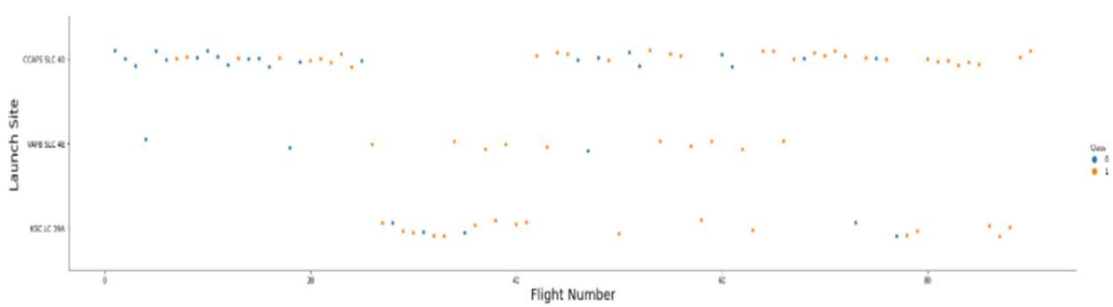
Flight Number vs. Launch Site

- • From the plot, we found that the larger the flight amount at a launch site, the greater the success rate at a launch site.

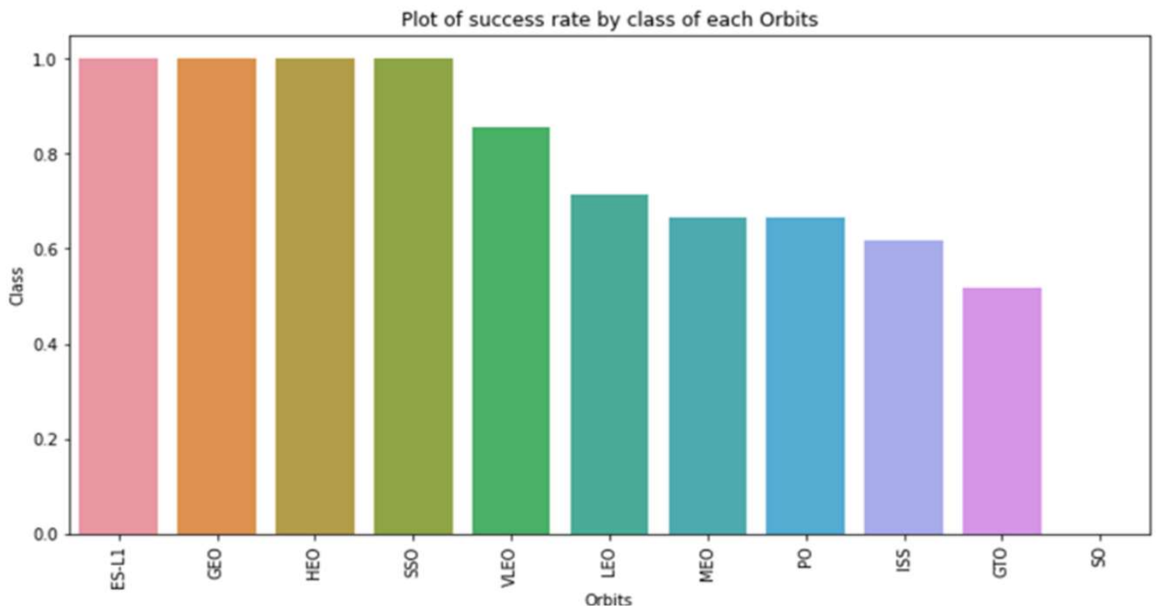


Payload vs. Launch Site

The greater the payload mass for launch site CCAFS SLC 40 the higher the success rate for the rocket.



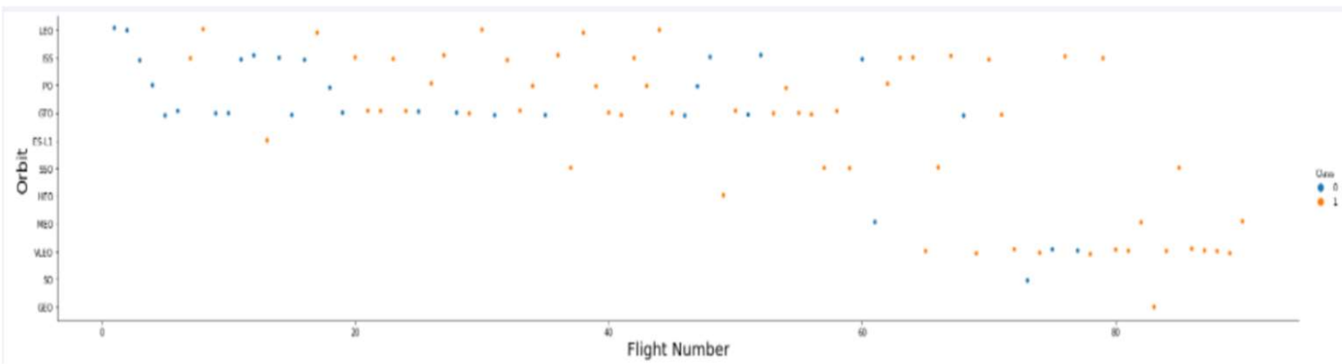
Success Rate vs. Orbit Type



From the plot, we can see that ES-L1, GEO, HEO, SSO, VLEO had the most success rate.

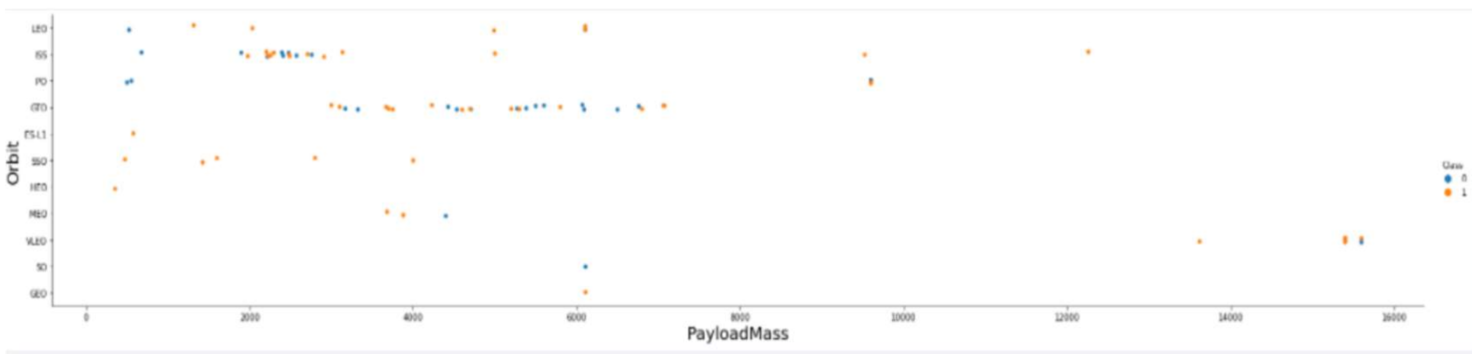
Flight Number vs. Orbit Type

- • The plot below shows the Flight Number vs. Orbit type. We observe that in the LEO orbit, success is related to the number of flights whereas in the GTO orbit, there is no relationship between flight number and the orbit.



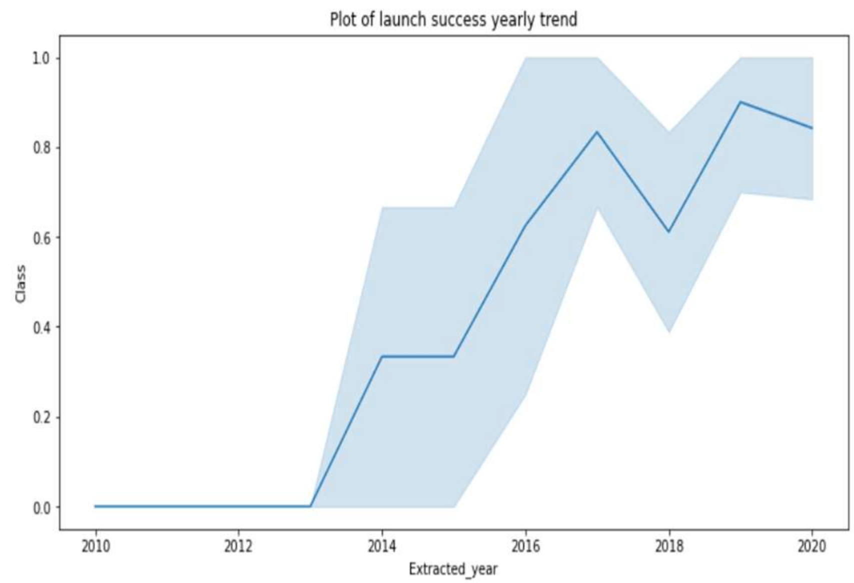
Payload vs. Orbit Type

- • We can observe that with heavy payloads, the successful landing are more for PO, LEO and ISS orbits.



Launch Success Yearly Trend

From the plot, we can observe that success rate since 2013 kept on increasing till 2020.



All Launch Site Names

- We used the key word DISTINCT to show only unique launch sites from the SpaceX data.

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

In [10]:
```
task_1 = '''
        SELECT DISTINCT LaunchSite
        FROM SpaceX
'''
create_pandas_df(task_1, database=conn)
```

Out[10]:

	launchsite
0	KSC LC-39A
1	CCAFS LC-40
2	CCAFS SLC-40
3	VAFB SLC-4E

Launch Site Names Begin with 'CCA'

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

In [11]:

```
task_2 = '''
        SELECT *
        FROM SpaceX
        WHERE LaunchSite LIKE 'CCA%'
        LIMIT 5
        '''
create_pandas_df(task_2, database=conn)
```

Out[11]:

	date	time	boosterversion	launchsite	payload	payloadmasskg	orbit	customer	missionoutcome	landingoutcome
0	2010-04-06	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
1	2010-08-12	15:43:00	F9 v1.0 B0004	CCAFS LC-40	Dragon demo flight C1, two CubeSats, barrel of...	0	LEO (ISS)	NASA (COTS) NRO	Success	Failure (parachute)
2	2012-05-22	07:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	No attempt
3	2012-08-10	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
4	2013-01-03	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

- We used the query above to display 5 records where launch sites begin with `CCA`

Total Payload Mass

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

In [12]:

```
task_3 = '''
        SELECT SUM(PayloadMassKG) AS Total_PayloadMass
        FROM SpaceX
        WHERE Customer LIKE 'NASA (CRS)'
        '''
create_pandas_df(task_3, database=conn)
```

Out[12]:

	total_payloadmass
0	45596

- We calculated the total payload carried by boosters from NASA as 45596 using the query below

Average Payload Mass by F9 v1.1

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

In [13]:

```
task_4 = '''
        SELECT AVG(PayloadMassKG) AS Avg_PayloadMass
        FROM SpaceX
        WHERE BoosterVersion = 'F9 v1.1'
        '''
create_pandas_df(task_4, database=conn)
```

Out[13]:

	avg_payloadmass
0	2928.4

- We calculated the average payload mass carried by booster version F9 v1.1 as 2928.4

First Successful Ground Landing Date

- We observed that the dates of the first successful landing outcome on ground pad was 22nd December 2015

In [14]:
```
task_5 = '''
        SELECT MIN(Date) AS FirstSuccessfull_landing_date
        FROM SpaceX
        WHERE LandingOutcome LIKE 'Success (ground pad)'
        '''
create_pandas_df(task_5, database=conn)
```

Out[14]:

	firstsuccessfull_landing_date
0	2015-12-22

Successful Drone Ship Landing with Payload between 4000 and 6000

- We used the WHERE clause to filter for boosters which have successfully landed on drone ship and applied the AND condition to determine successful landing with payload mass greater than 4000 but less than 6000

In [15]:

```
task_6 = '''
        SELECT BoosterVersion
        FROM SpaceX
        WHERE LandingOutcome = 'Success (drone ship)'
            AND PayloadMassKG > 4000
            AND PayloadMassKG < 6000
        '''
create_pandas_df(task_6, database=conn)
```

Out[15]:

	boosterversion
0	F9 FT B1022
1	F9 FT B1026
2	F9 FT B1021.2
3	F9 FT B1031.2

Total Number of Successful and Failure Mission Outcomes

- We used wildcard like '%' to filter for WHERE Mission Out come was a success or a failure.

List the total number of successful and failure mission outcomes

```
In [16]: task_7a = '''
                 SELECT COUNT(MissionOutcome) AS SuccessOutcome
                 FROM SpaceX
                 WHERE MissionOutcome LIKE 'Success%'
                 '''

         task_7b = '''
                 SELECT COUNT(MissionOutcome) AS FailureOutcome
                 FROM SpaceX
                 WHERE MissionOutcome LIKE 'Failure%'
                 '''
         print('The total number of successful mission outcome is:')
         display(create_pandas_df(task_7a, database=conn))
         print()
         print('The total number of failed mission outcome is:')
         create_pandas_df(task_7b, database=conn)
```

The total number of successful mission outcome is:

	successoutcome
0	100

The total number of failed mission outcome is:

Out[16]:

	failureoutcome
0	1

Boosters Carried Maximum Payload

- We determined the booster that have carried the maximum payload using a subquery in the WHERE clause and the MAX() function.

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

In [17]:

```
task_8 = '''
        SELECT BoosterVersion, PayloadMassKG
        FROM SpaceX
        WHERE PayloadMassKG = (
                                SELECT MAX(PayloadMassKG)
                                FROM SpaceX
                                )
        ORDER BY BoosterVersion
        '''
create_pandas_df(task_8, database=conn)
```

Out[17]:

	boosterversion	payloadmasskg
0	F9 B5 B1048.4	15600
1	F9 B5 B1048.5	15600
2	F9 B5 B1049.4	15600
3	F9 B5 B1049.5	15600
4	F9 B5 B1049.7	15600
5	F9 B5 B1051.3	15600
6	F9 B5 B1051.4	15600
7	F9 B5 B1051.6	15600
8	F9 B5 B1056.4	15600
9	F9 B5 B1058.3	15600
10	F9 B5 B1060.2	15600
11	F9 B5 B1060.3	15600

2015 Launch Records

- We used a combinations of the WHERE clause, LIKE, AND, and BETWEEN conditions to filter for failed landing outcomes in drone ship, their booster versions, and launch site names for year 2015

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

In [18]:

```
task_9 = '''
        SELECT BoosterVersion, LaunchSite, LandingOutcome
        FROM SpaceX
        WHERE LandingOutcome LIKE 'Failure (drone ship)'
            AND Date BETWEEN '2015-01-01' AND '2015-12-31'
        '''
create_pandas_df(task_9, database=conn)
```

Out[18]:

	boosterversion	launchsite	landingoutcome
0	F9 v1.1 B1012	CCAFS LC-40	Failure (drone ship)
1	F9 v1.1 B1015	CCAFS LC-40	Failure (drone ship)

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

- We selected Landing outcomes and the COUNT of landing outcomes from the data and used the WHERE clause to filter for landing outcomes BETWEEN 2010-06-04 to 2010-03-20.
- • We applied the GROUP BY clause to group the landing outcomes and the ORDER BY clause to order the grouped landing outcome in descending order.

Rank the count of landing outcomes (such as Failure (drone ship) or Success (ground pad))

In [19]:

```
task_10 = '''
        SELECT LandingOutcome, COUNT(LandingOutcome)
        FROM SpaceX
        WHERE DATE BETWEEN '2010-06-04' AND '2017-03-20'
        GROUP BY LandingOutcome
        ORDER BY COUNT(LandingOutcome) DESC
        '''
create_pandas_df(task_10, database=conn)
```

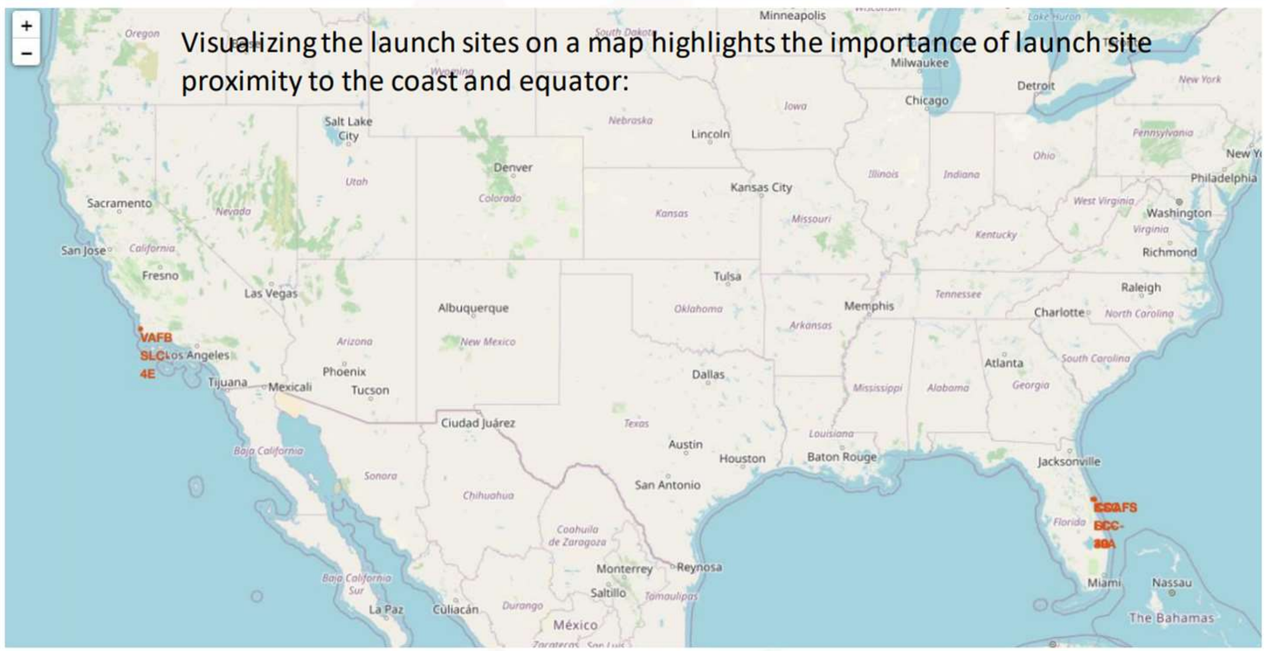
Out[19]:

	landingoutcome	count
0	No attempt	10
1	Success (drone ship)	6
2	Failure (drone ship)	5
3	Success (ground pad)	5
4	Controlled (ocean)	3
5	Uncontrolled (ocean)	2
6	Precluded (drone ship)	1
7	Failure (parachute)	1

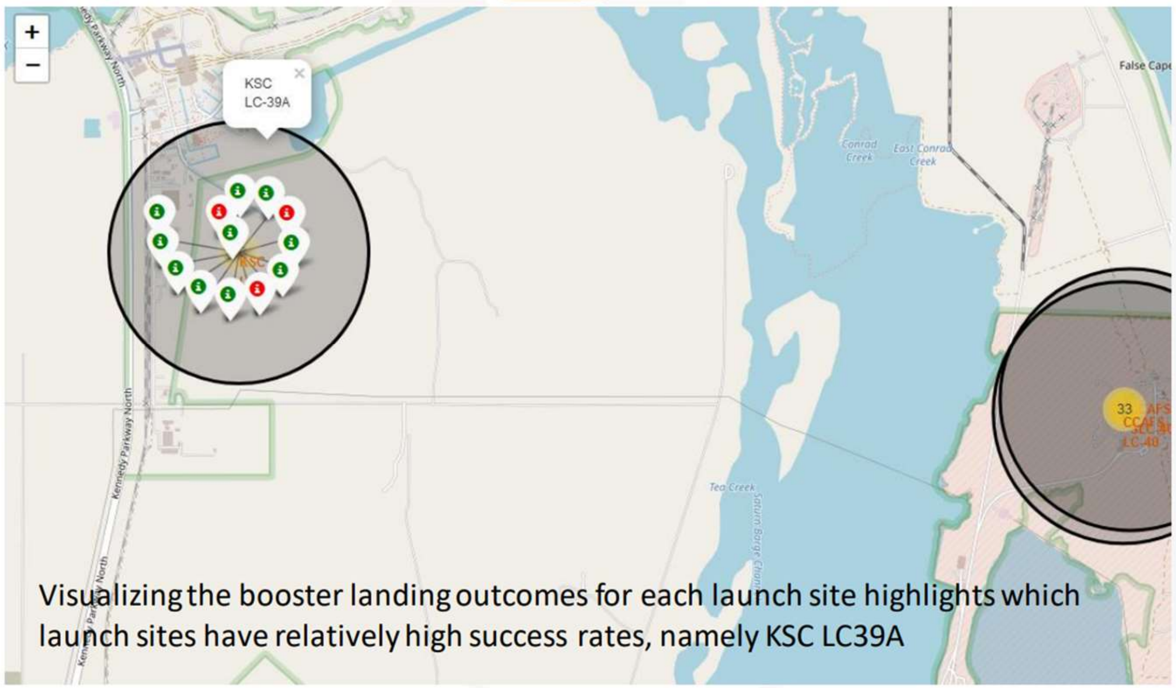
Section 3

Launch Sites Proximities Analysis

RESULTS LAUNCH SITE LOCATION ANALYSIS:1

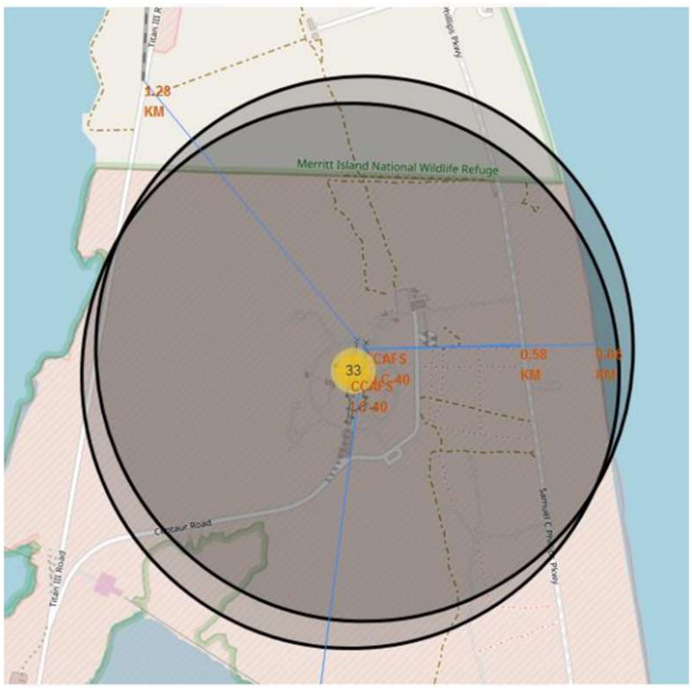


RESULTS LAUNCH SITE LOCATION ANALYSIS:2

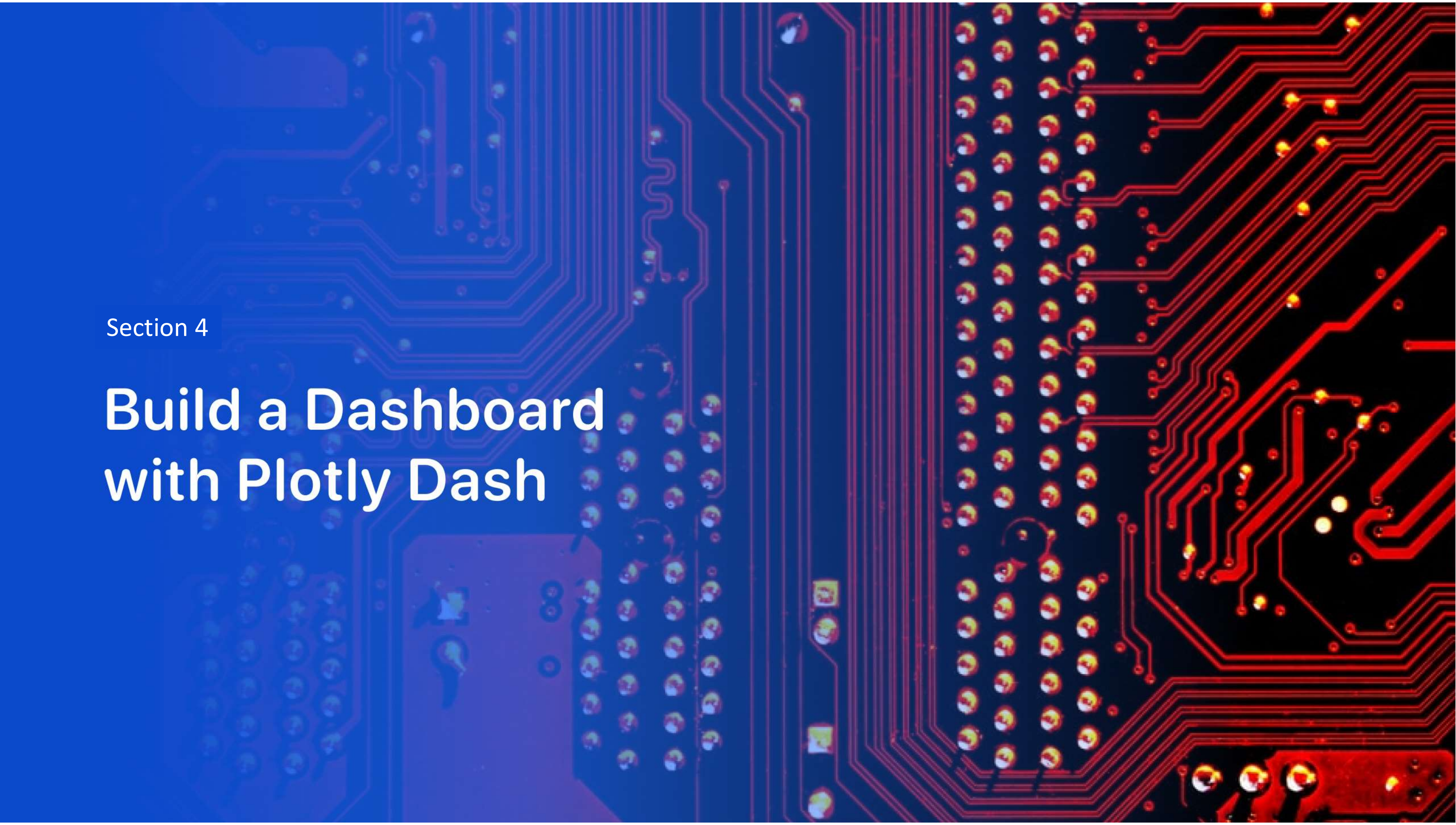


Visualizing the booster landing outcomes for each launch site highlights which launch sites have relatively high success rates, namely KSC LC39A

RESULTS LAUNCH SITE LOCATION ANALYSIS: 3



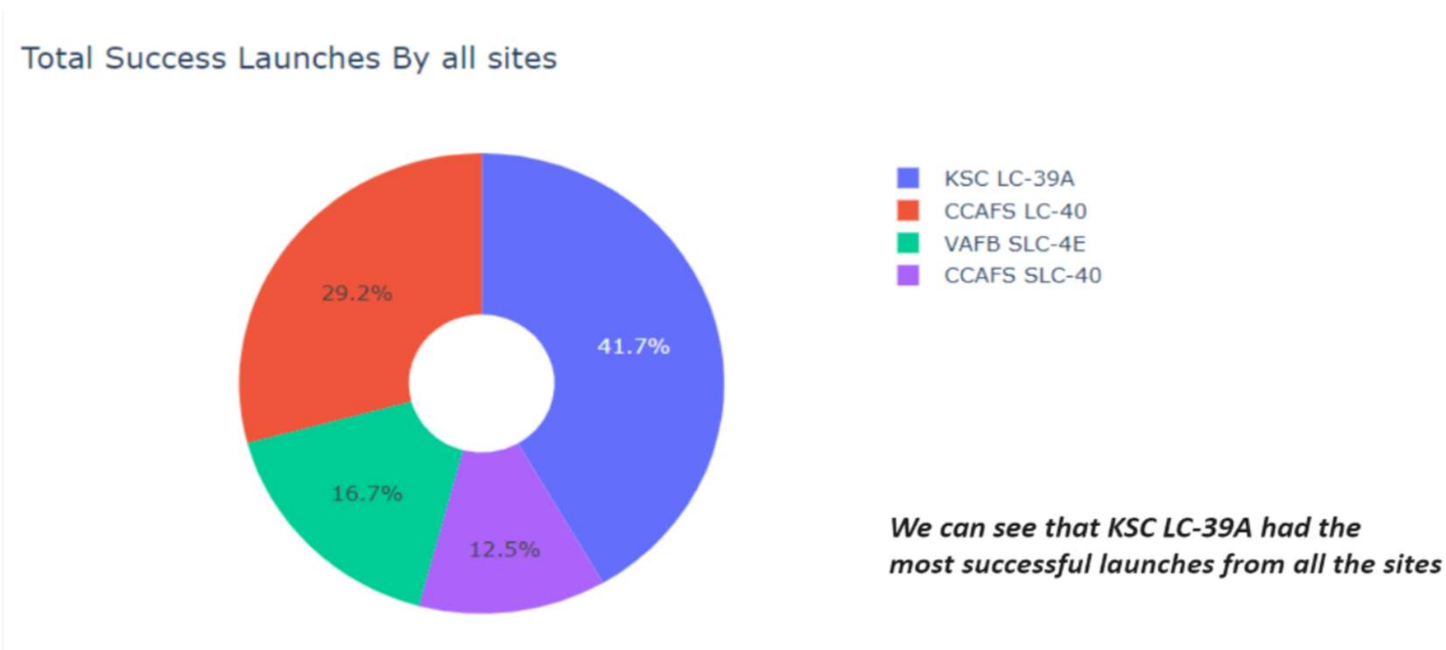
- Visualizing the railway, highway, coastline, and city proximities for each launch site
• Proximities for CCAFS SLC-40:
- • railway: 1.28 km
- • transporting heavy cargo
- • highway: 0.58 km
- • transporting personel and equipment
- • coastline: 0.86 km
- • optionality to abort launch and
- attempt water landing
- • minimizing risk from falling debris
- • city: 51.43 km
- • minimizing danger to population dense
- areas.



Section 4

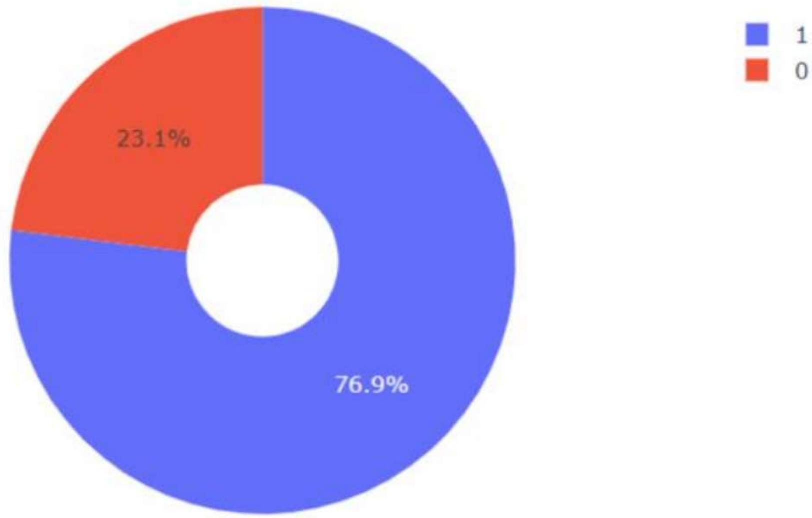
Build a Dashboard with Plotly Dash

Pie chart showing the success percentage achieved by each launch site1



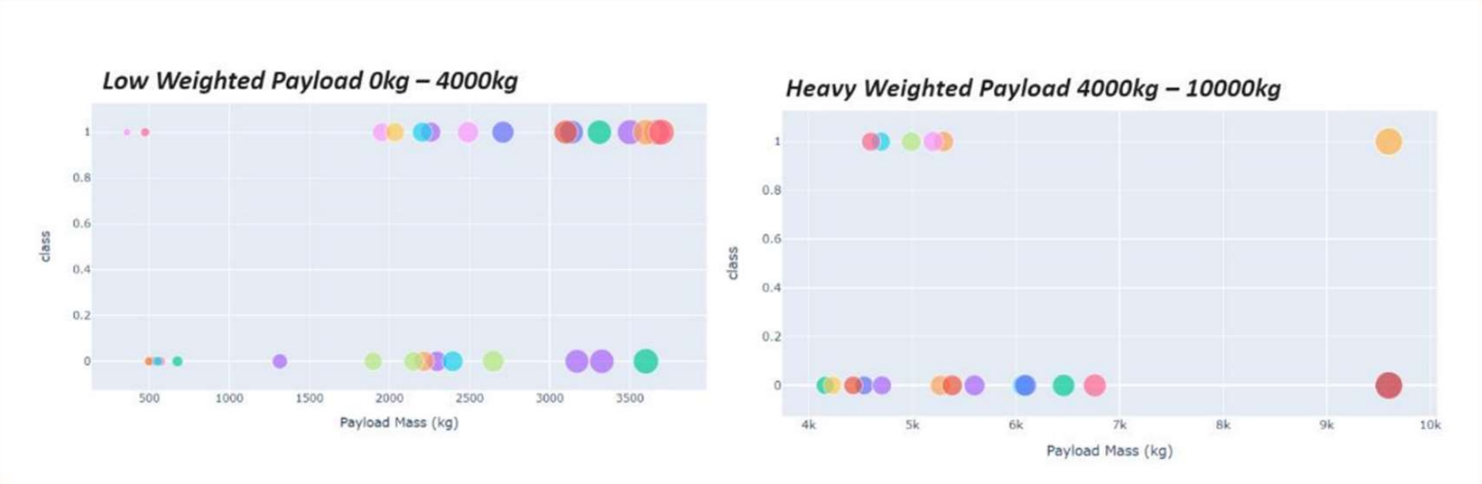
We can see that KSC LC-39A had the most successful launches from all the sites

Pie chart showing the Launch site with the highest launch success ratio2



KSC LC-39A achieved a 76.9% success rate while getting a 23.1% failure rate

Scatter plot of Payload vs Launch Outcome for all sites, with different payload selected in the range slider



We can see the success rate of low weighted payloads is higher than the heavy loaded payloads

Section 5

Predictive Analysis (Classification)

Results: Classification Accuracy

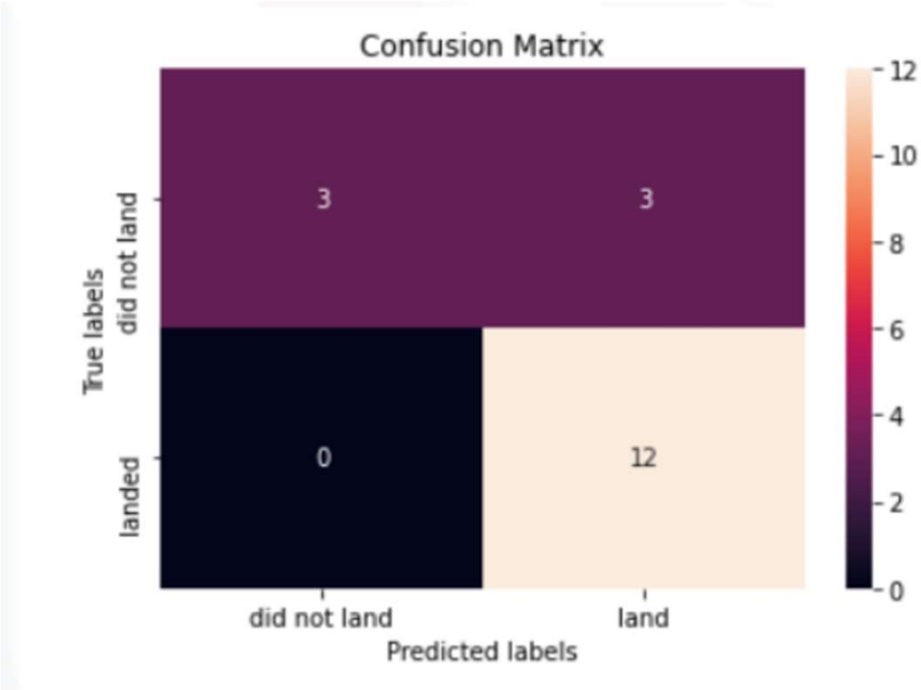

```
models = {'KNeighbors':knn_cv.best_score_,
              'DecisionTree':tree_cv.best_score_,
              'LogisticRegression':logreg_cv.best_score_,
              'SupportVector': svm_cv.best_score_}

bestalgorithm = max(models, key=models.get)
print('Best model is', bestalgorithm,'with a score of', models[bestalgorithm])
if bestalgorithm == 'DecisionTree':
    print('Best params is :', tree_cv.best_params_)
if bestalgorithm == 'KNeighbors':
    print('Best params is :', knn_cv.best_params_)
if bestalgorithm == 'LogisticRegression':
    print('Best params is :', logreg_cv.best_params_)
if bestalgorithm == 'SupportVector':
    print('Best params is :', svm_cv.best_params_)
```

```
Best model is DecisionTree with a score of 0.8732142857142856
Best params is : {'criterion': 'gini', 'max_depth': 6, 'max_features': 'auto', 'min_samples_leaf': 2, 'min_samples_split': 5, 'splitter': 'random'}
```

The Decision Tree classifier is the model with the highest classification accuracy.

Results: Confusion Matrix

- • The confusion matrices of the best performing models (4-way-tie) are the same
- • The major problem is false positives as evidenced by the models incorrectly predicting the 1st stage booster to land in 3 out of 18 samples in the test set



Conclusions

We can conclude that:

- The larger the flight amount at a launch site, the greater the success rate at a launch site.
- Launch success rate started to increase in 2013 till 2020.
- Orbits ES-L1, GEO, HEO, SSO, VLEO had the most success rate.
- KSC LC-39A had the most successful launches of any sites.
- The Decision tree classifier is the best machine learning algorithm for this task.

Appendix

1. **Notebooks to recreate dataset, analysis, and models:**
2. https://github.com/Gaukarna/Final-Project-Applied-Data-Science-Capstone/blob/main/jupyter-labs-spacex-data-collection-api%20(1).ipynb
3. https://github.com/Gaukarna/Final-Project-Applied-Data-Science-Capstone/blob/main/jupyter-labs-webscraping%20(1).ipynb
4. https://github.com/Gaukarna/Final-Project-Applied-Data-Science-Capstone/blob/main/labs-jupyter-spacex-Data%20wrangling.ipynb
5. https://github.com/Gaukarna/Final-Project-Applied-Data-Science-Capstone/blob/main/jupyter-labs-eda-sql-coursera_sqllite.ipynb
6. https://github.com/Gaukarna/Final-Project-Applied-Data-Science-Capstone/blob/main/jupyter-labs-eda-dataviz.ipynb.jupyterlite.ipynb
7. https://github.com/Gaukarna/Final-Project-Applied-Data-Science-Capstone/blob/main/Hands-on%20Lab-%20Interactive%20Visual%20Analytics%20with%20Folium%20lab.ipynb
8. https://github.com/Gaukarna/Final-Project-Applied-Data-Science-Capstone/blob/main/spacex_dash_app.py
9. https://github.com/Gaukarna/Final-Project-Applied-Data-Science-Capstone/blob/main/SpaceX_Machine_Learning_Prediction_Part_5.jupyterlite.ipynb

Thank you!