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Executive Summary

- Summary of methodologies

  - Data Collection through API

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  - Data Wrangling

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  - Interactive Visual Analytics with Folium

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  - Exploratory Data Analysis result

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  - Predictive Analytics result

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

- The data was collected using various methods

  - Data collection was done using get request to the SpaceX API.

  - Next, we decoded the response content as a Json using .json() function call and turn it into a pandas dataframe using .json_normalize().

  - We then cleaned the data, checked for missing values and fill in missing values where necessary.

  - In addition, we performed web scraping from Wikipedia for Falcon 9 launch records with BeautifulSoup.

  - The objective was to extract the launch records as HTML table, parse the table and convert it to a pandas dataframe for future analysis.

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 is IBM-Data-Science-Capstone/jupyter-labs-spacex-data-collection-api.ipynb at main · VijayaAnne/IBM-Data-Science-Capstone (github.com)

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 BeautifulSoup

- We parsed the table and converted it into a pandas dataframe.

- The link to the notebook is [IBM-Data-Science-Capstone/jupyter-labs-webscraping.ipynb at main · VijayaAnne/IBM-Data-Science-Capstone (github.com)](#)

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 IBM-Data-Science-Capstone/labs-jupyter-spacex-Data wrangling.ipynb at main · VijayaAnne/IBM-Data-Science-Capstone (github.com)

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.

Plot of launch success yearly trend

Plot of success rate by class of each Orbits
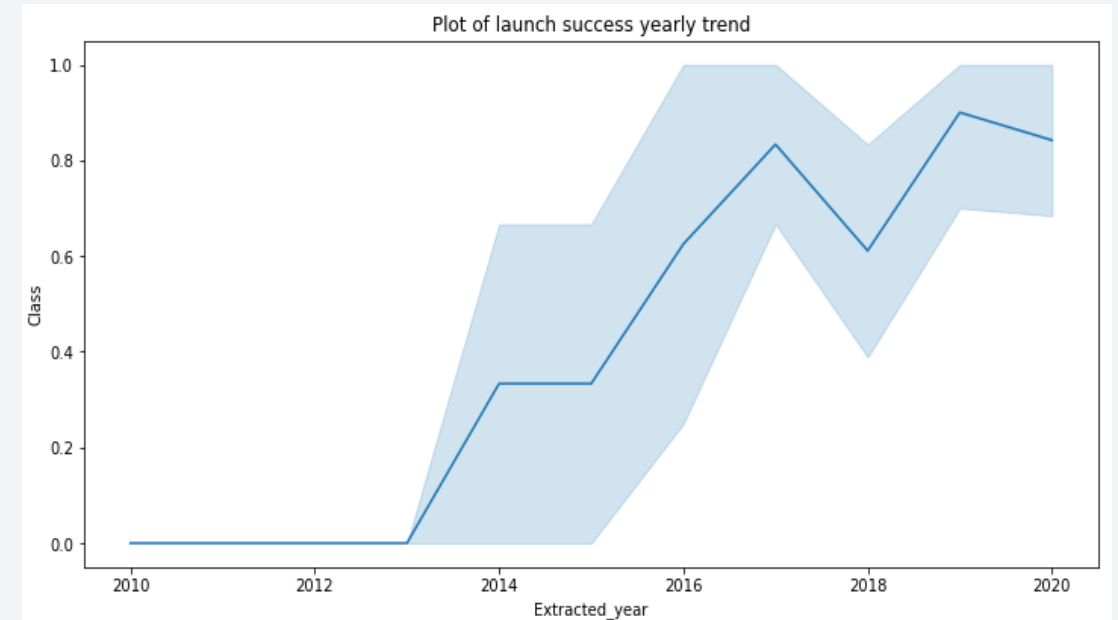
- The link to the notebook is IBM-Data-Science-Capstone/edadataviz.ipynb at main · VijayaAnne/IBM-Data-Science-Capstone (github.com)

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 IBM-Data-Science-Capstone/jupyter-labs-eda-sql-coursera_sqllite.ipynb at main · VijayaAnne/IBM-Data-Science-Capstone (github.com)

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 [IBM-Data-Science-Capstone/spacex_dash_app.py at main · VijayaAnne/IBM-Data-Science-Capstone (github.com)](#)

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 IBM-Data-Science-Capstone/SpaceX_Machine Learning Prediction_Part_5.ipynb at main · VijayaAnne/IBM-Data-Science-Capstone (github.com)

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.
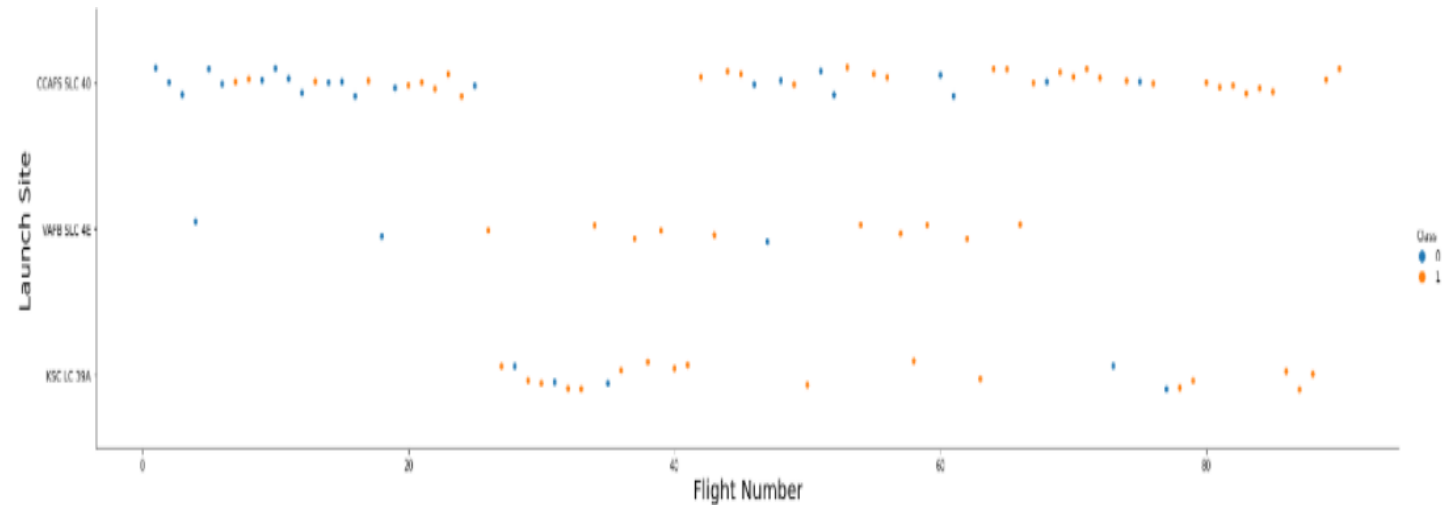
Success Rate vs. Orbit Type

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

Plot of success rate by class of each Orbits
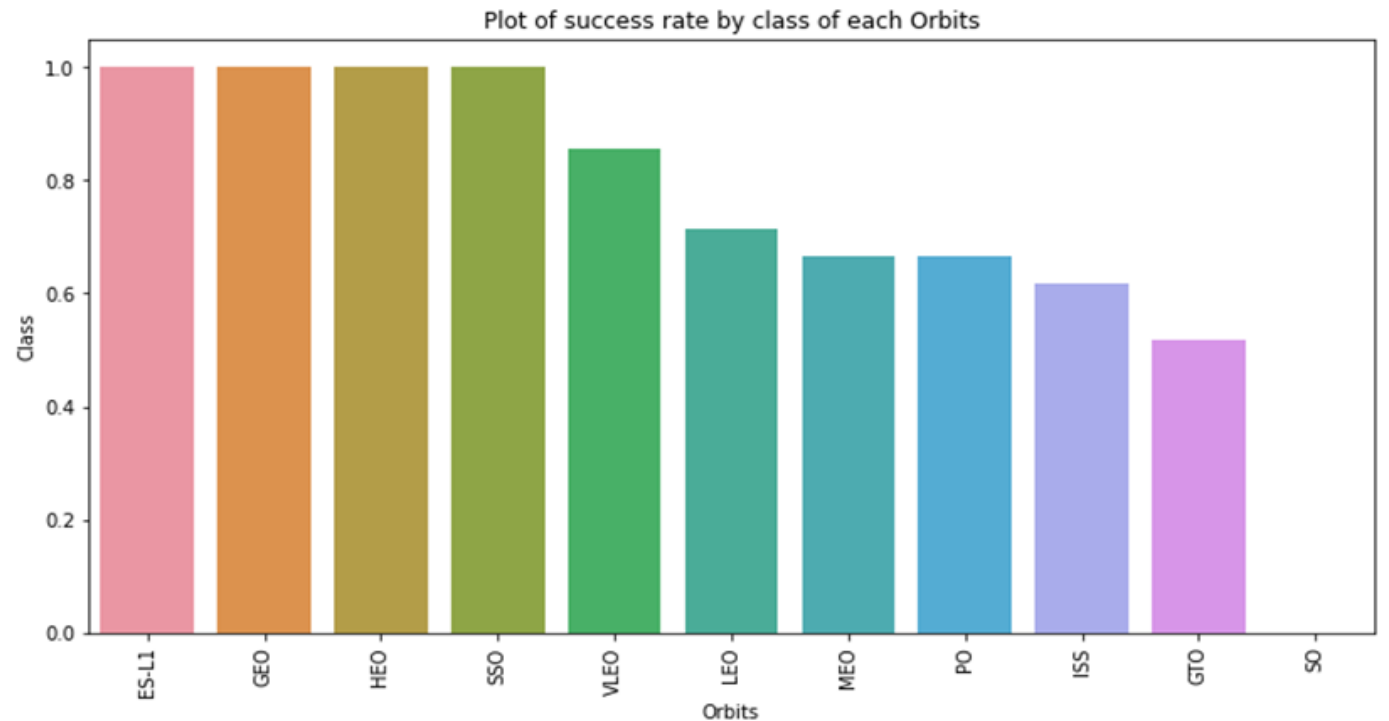
Flight Number vs. Orbit Type

- 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.
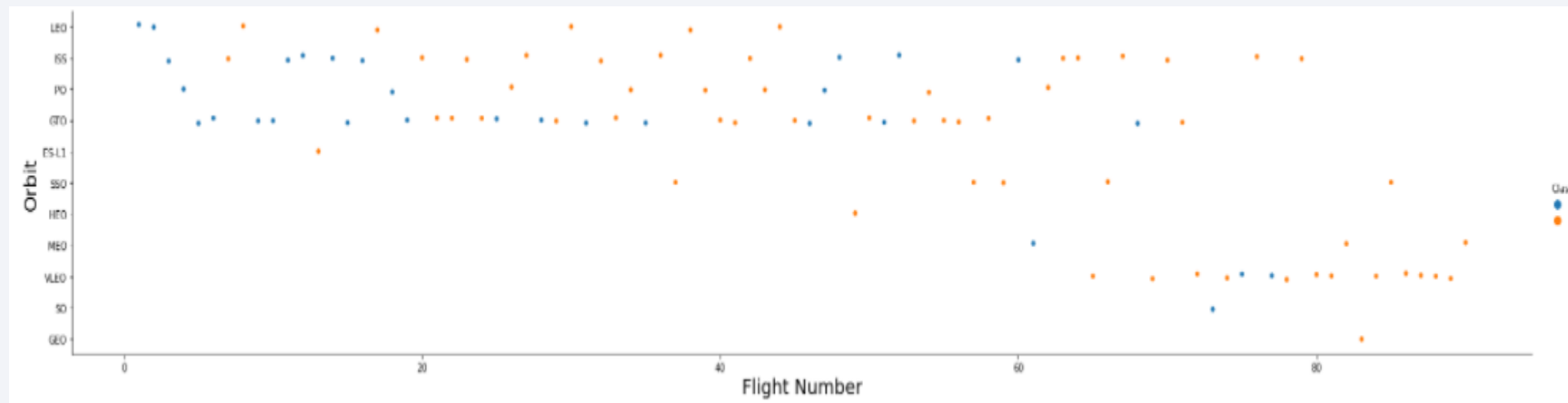
Payload vs. Orbit Type

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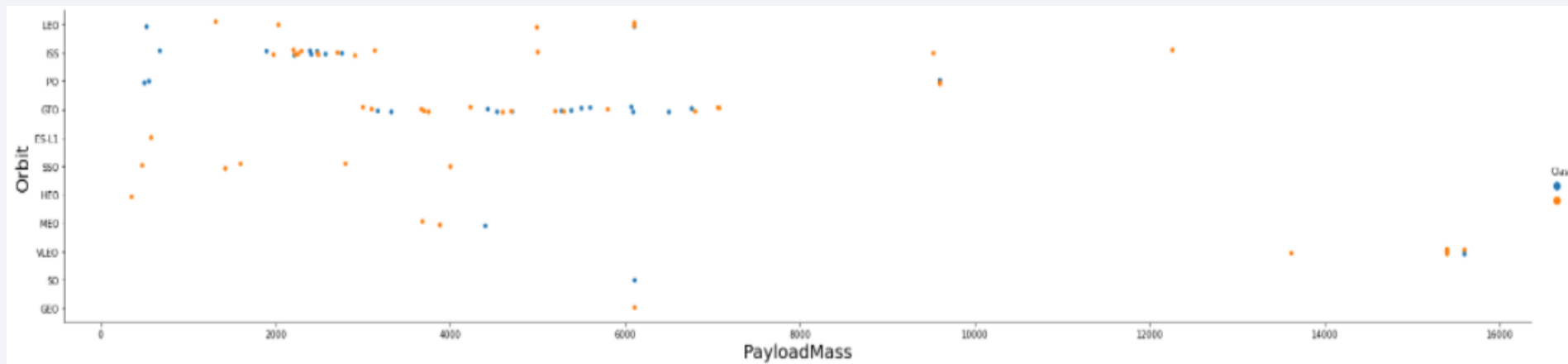
Launch Success Yearly Trend

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

Plot of launch success yearly trend
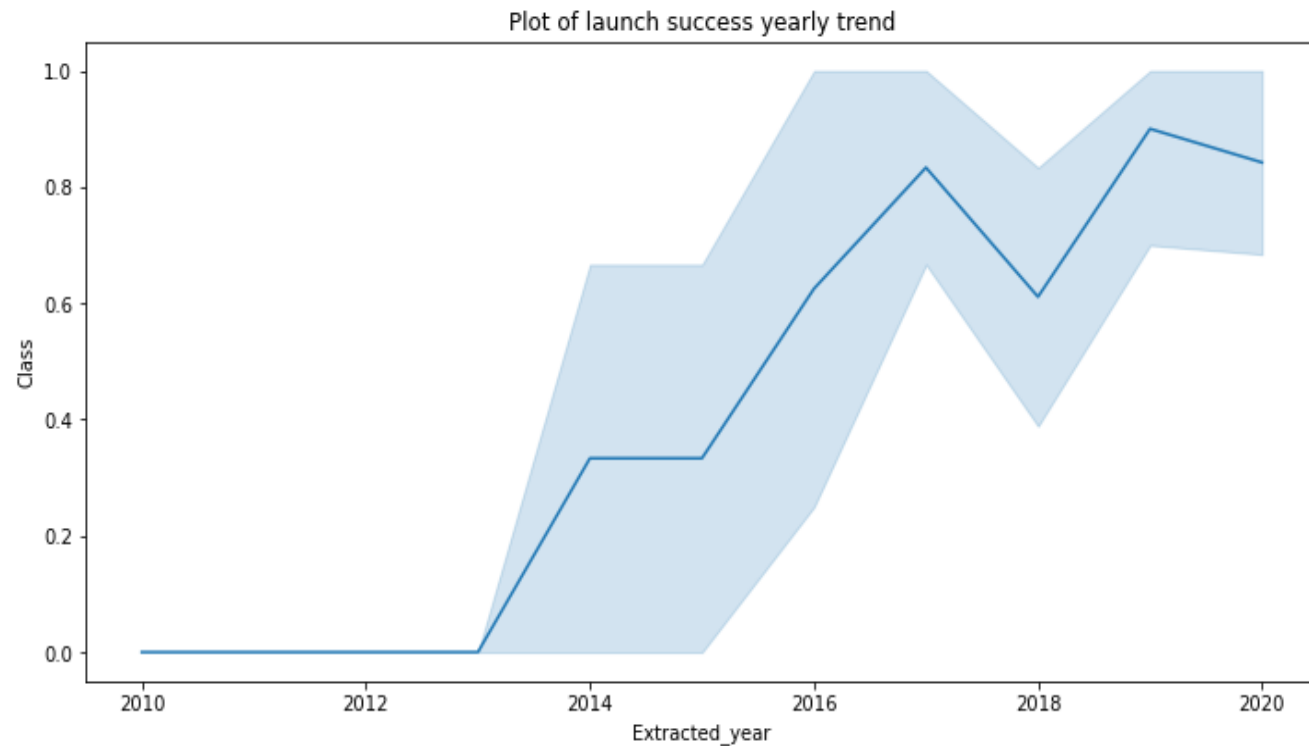
All Launch Site Names

- 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 [15]:  %sql SELECT DISTINCT Launch_Site    FROM SPACEXTABLE
```

* sqlite:///my_data1.db
Done.

Out[15]:
Launch_Site
CCAFS LC-40
VAFB SLC-4E
KSC LC-39A
CCAFS SLC-40

Launch Site Names Begin with 'CCA'

In [18]: `%sql SELECT *    FROM SPACEXTABLE WHERE Launch_Site LIKE 'CCA%' LIMIT 5`

* sqlite:///my_data1.db
Done.

Out[18]:

Date	Time (UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS__KG_	Orbit	Customer	Mission_Out
2010-06-04	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Su
2010-12-08	15:43:00	F9 v1.0 B0004	CCAFS LC-40	Dragon demo flight C1, two CubeSats, barrel of Brouere cheese	0	LEO (ISS)	NASA (COTS) NRO	Su
2012-05-22	7:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Su

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

Total Payload Mass

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

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

```
In [19]:  %%sql SELECT SUM(PAYLOAD_MASS__KG_     ) AS Total_PayloadMass
              FROM SPACEXTABLE
              WHERE Customer LIKE 'NASA (CRS)'
```

 * sqlite:///my_data1.db
Done.

Out[19]: **Total_PayloadMass**

45596

Average Payload Mass by F9 v1.1

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

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

```
In [20]:  %%sql SELECT AVG(PAYLOAD_MASS__KG_) AS Avg_PayloadMass
                 FROM SPACEXTABLE
                 WHERE Booster_Version = 'F9 v1.1'
```

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

Out[20]: **Avg_PayloadMass**

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

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

Hint:Use min function

```
In [21]:   %%sql SELECT MIN(Date) AS FirstSuccessfull_landing_date
               FROM SPACEXTABLE
               WHERE Landing_Outcome LIKE 'Success (ground pad)'
```

* sqlite:///my_data1.db
Done.

Out[21]: **FirstSuccessfull_landing_date**

2015-12-22

Successful Drone Ship Landing with Payload between 4000 and 6000

```
In [22]:   %%sql SELECT Booster_Version
                 FROM SPACEXTABLE
                 WHERE Landing_Outcome = 'Success (drone ship)'
                     AND PAYLOAD_MASS__KG_ > 4000
                     AND PAYLOAD_MASS__KG_ < 6000

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

Out[22]:

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

- 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

Total Number of Successful and Failure Mission Outcomes

```
In [28]:  %%sql SELECT COUNT(Mission_Outcome) AS SuccessOutcome
              FROM SPACEXTABLE
              WHERE Mission_Outcome LIKE 'Success%'

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

Out[28]: **SuccessOutcome**

                100

```
In [29]:  %%sql SELECT COUNT(Mission_Outcome) AS SuccessOutcome
              FROM SPACEXTABLE
              WHERE Mission_Outcome LIKE 'failure%'

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

Out[29]: **SuccessOutcome**

                1

- We used wildcard like '**%**' to filter for **WHERE** MissionOutcome was a success or a failure.

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 [30]:
```sql
%%sql SELECT Booster_Version, PAYLOAD_MASS__KG_
        FROM SPACEXTABLE
        WHERE PAYLOAD_MASS__KG_ = (
                                    SELECT MAX(PAYLOAD_MASS__KG_)
                                    FROM SPACEXTABLE
                                    )
        ORDER BY Booster_Version
```

* sqlite:///my_data1.db
Done.

Out[30]:

Booster_Version	PAYLOAD_MASS__KG_
F9 B5 B1048.4	15600
F9 B5 B1048.5	15600
F9 B5 B1049.4	15600
F9 B5 B1049.5	15600
F9 B5 B1049.7	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, month names, and launch site names for year 2015

```sql
In [31]:  %%sql  SELECT  substr(Date, 6,2) as month ,Booster_Version, Launch_Site, Landing_Outcome
             FROM SPACEXTABLE
             WHERE Landing_Outcome LIKE 'Failure (drone ship)'
                AND substr(Date,0,5)='2015'
```

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

Out[31]:

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

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

```
In [32]:  %%sql SELECT Landing_Outcome, COUNT(Landing_Outcome)
              FROM SPACEXTABLE
              WHERE DATE BETWEEN '2010-06-04' AND '2017-03-20'
              GROUP BY Landing_Outcome
              ORDER BY COUNT(Landing_Outcome) DESC
```

 * sqlite:///my_data1.db
Done.

Out[32]:

Landing_Outcome	COUNT(Landing_Outcome)
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

- 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.

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Section 4

Launch Sites
Proximities Analysis

All launch sites global map markers

We can see that the SpaceX launch sites are in the United States of America coasts. Florida and California

Markers showing launch sites with color labels

Florida Launch Sites

Green Marker shows successful Launches and Red Marker shows Failures

California Launch Site

Launch Site distance to landmarks

Distance to Railway Station

Distance to closest Highway

Distance to Coastline

Distance to City
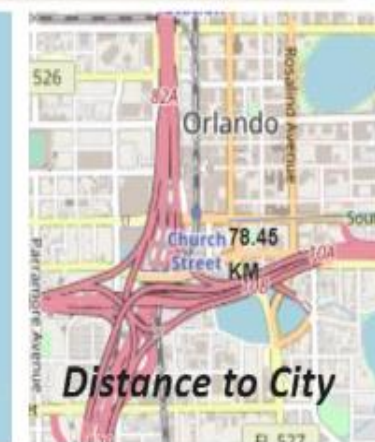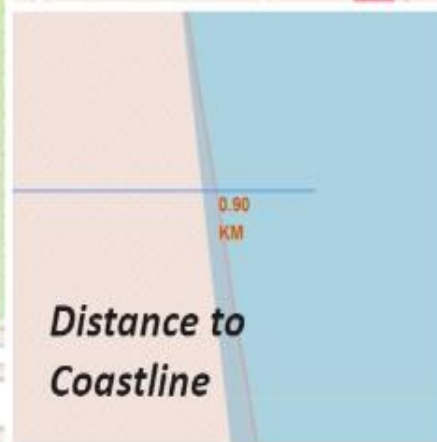
Distance to coast

- Are launch sites in close proximity to railways? No
- Are launch sites in close proximity to highways? No
- Are launch sites in close proximity to coastline? Yes
- Do launch sites keep certain distance away from cities? Yes

Section 5

Build a Dashboard
with Plotly Dash

Pie chart showing the success percentage achieved by each launch site

Total Success Launches By all sites

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

29.2%
41.7%
16.7%
12.5%

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 ratio

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

Low Weighted Payload 0kg – 4000kg

Heavy Weighted Payload 4000kg – 10000kg
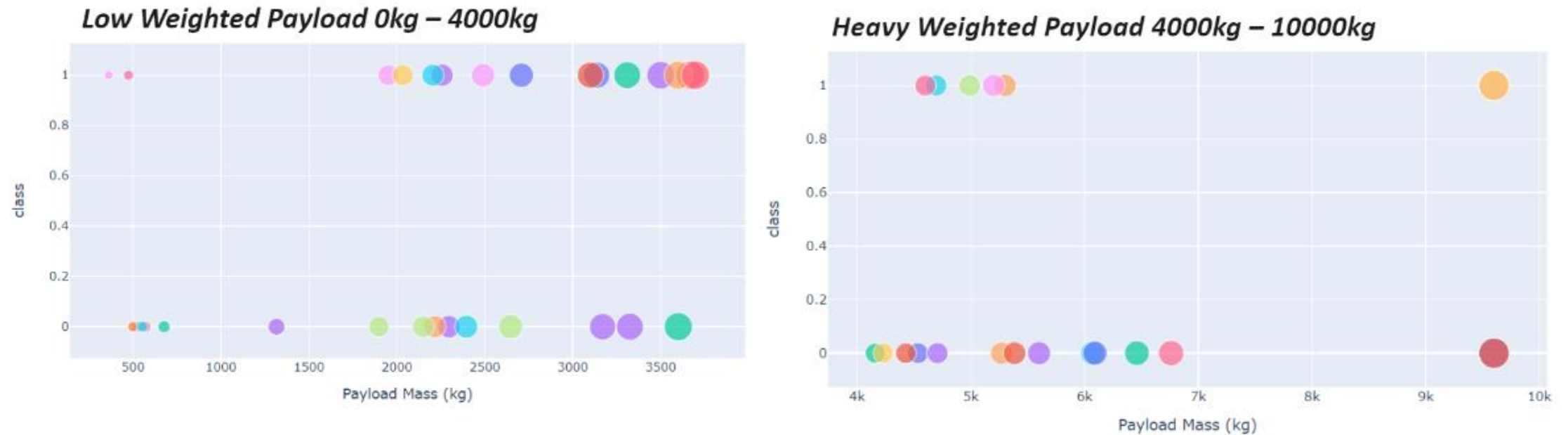
We can see the success rates for low weighted payloads is higher than the heavy weighted payloads

Section 6

Predictive Analysis
(Classification)

Classification Accuracy

- The decision tree classifier is the model with the highest 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'}
```

Confusion Matrix

- The confusion matrix for the decision tree classifier shows that the classifier can distinguish between the different classes. The major problem is the false positives .i.e., unsuccessful landing marked as successful landing by the classifier.
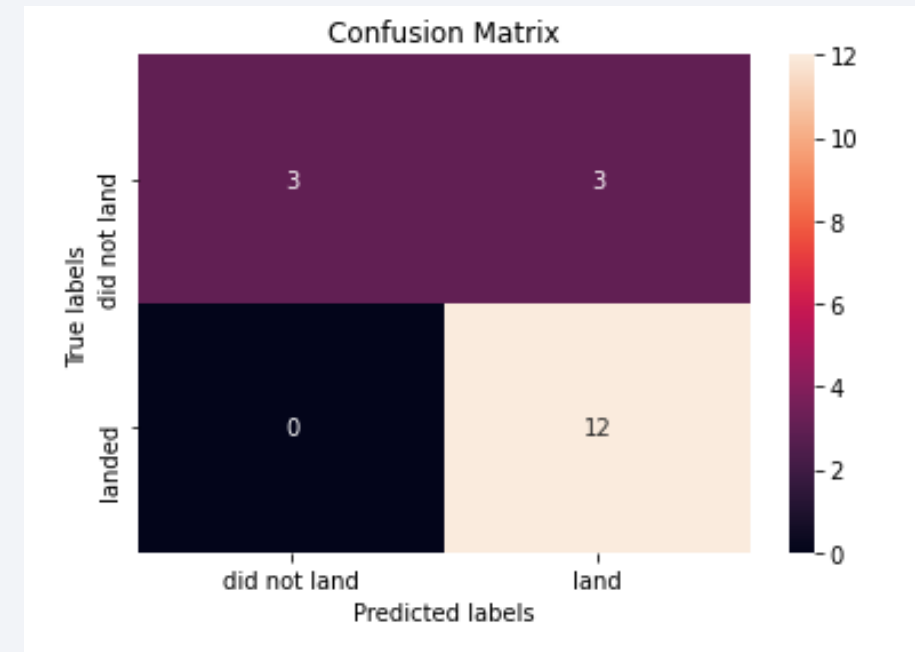
Conclusions

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.

Thank you!