IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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Outline

- Executive Summary
- Introduction
- Methodology
- Results
- Conclusion
- Appendix

Executive Summary

- **Summary of methodologies**

This project implemented various data science techniques including data loading and reading, data wrangling, Exploratory Data Analysis with Data Visualization, Exploratory Data Analysis with SQL, data visualization, mapping, and creating Dashboards, and predictive analysis using various machine learning models.

- **Summary of all results**

The results illustrated the locations of space experiments with different landing outcomes, studied the patterns of data across launching sites, and demonstrated the predictive performance of different machine learning models with best hyperparameters and accuracy results.

Introduction

- **Project background and context**

SpaceX has become the most successful commercial space company by making space travel affordable through reusing of the rockets. Falcon 9 rocket in particular has led to significant reduction of the costs by enabling the reuse of the rocket in the first stage. Therefore, the prediction of the outcome of the first stage (i.e., failure or success in landing) can help determine the cost of a launch. This project will use publicly available data and machine learning techniques to predict if SpaceX will reuse the first stage.

- **Problems you want to find answers**

This project aims to examine how variables such as launch site, payload mass, number of flights, and orbits affect the success of the first stage landing and identify the predictive machine learning algorithms to best predict the class outcome.

Section 1

Methodology

Methodology

Executive Summary

- Data collection methodology:

  Data were collected from two main sources including SpaceX REST API endpoints and web scraping related Wikipages.

- Perform data wrangling

  Data wrangling in this project included creating dummy variables (one hot encoding) to convert categorical variables into multiple binary variables and identifying and handling of missing and null values.

Methodology

Executive Summary

- Perform exploratory data analysis (EDA) using visualization and SQL

Bar graphs, scatterplots, and descriptive statistics (such as minimum and sum) were used in this part to explore the links between success rate and other variables such as playload mass and launch sites.

- Perform interactive visual analytics using Folium and Plotly Dash

Geographical maps and dash boards were constructed in this part to communicate the patterns in data with regard to launch site, etc.

- Perform predictive analysis using classification models
    - In this part, different machine learning classification models were tuned and fit to data to predict the outcome of launch.

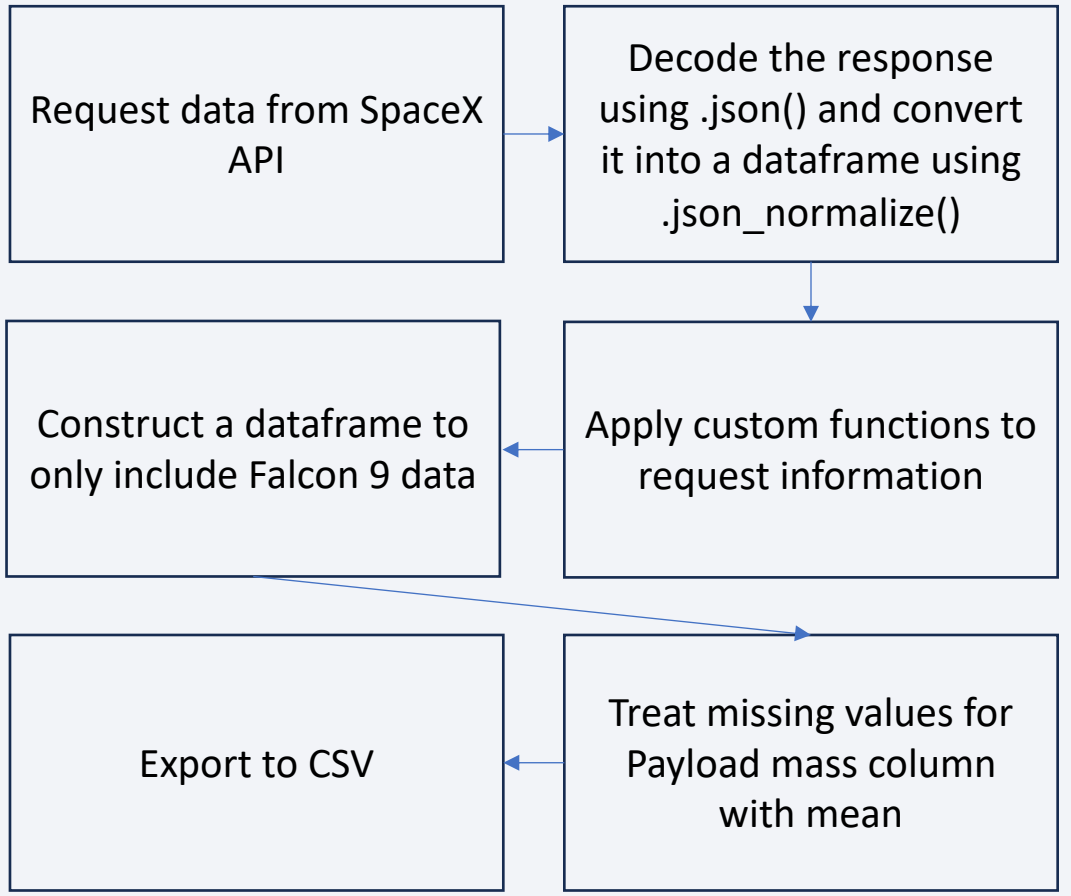
Data Collection

Data were collected from two main sources including SpaceX REST API endpoints and web scraping related Wikipages.

From SpaceX REST API the following data items were collected: FlightNumber, Date, BoosterVersion, PayloadMass, Orbit, LaunchSite, Outcome, Flights, GridFins, Reused, Legs, LandingPad, Block, ReusedCount, Serial, Longitude, Latitude

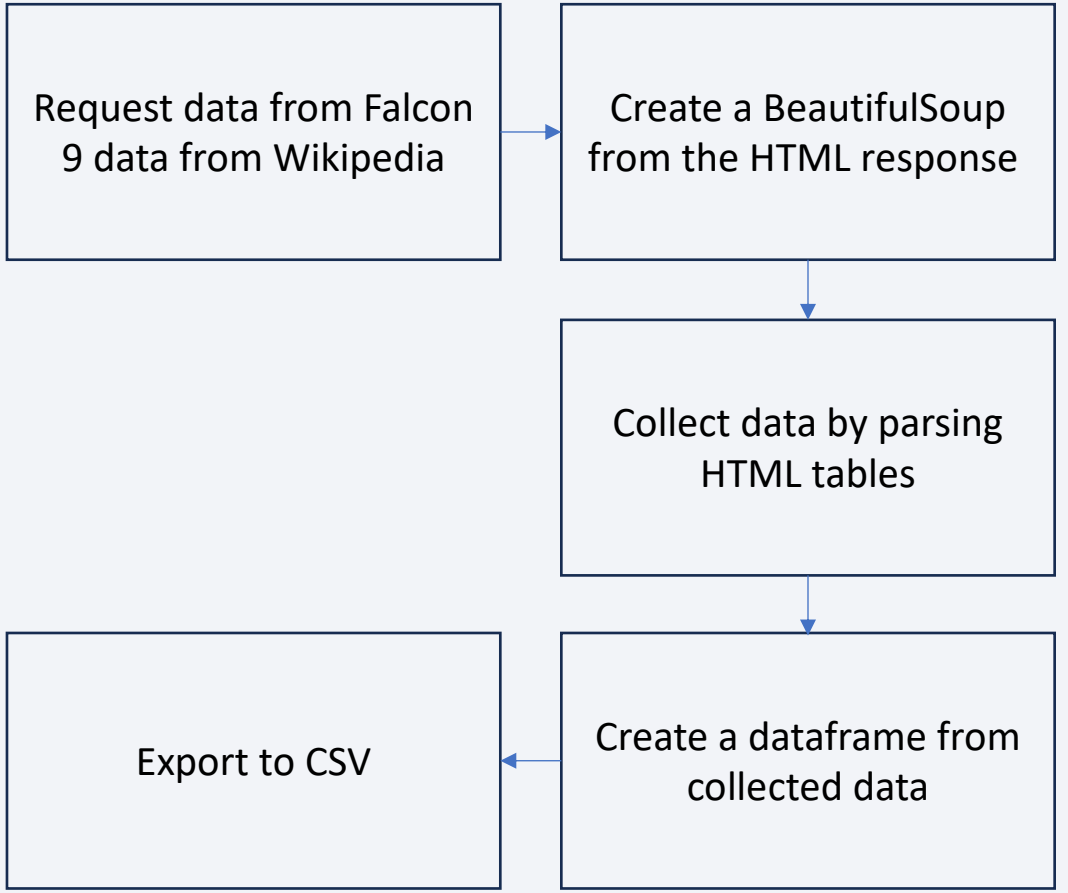
From HTML Web Scraping the following data were collected: Flight No., Launch site, Payload, PayloadMass, Orbit, Customer, Launch outcome, Version Booster, Booster landing, Date, Time

Data Collection – SpaceX API



Link to Github

Data Collection - Scraping

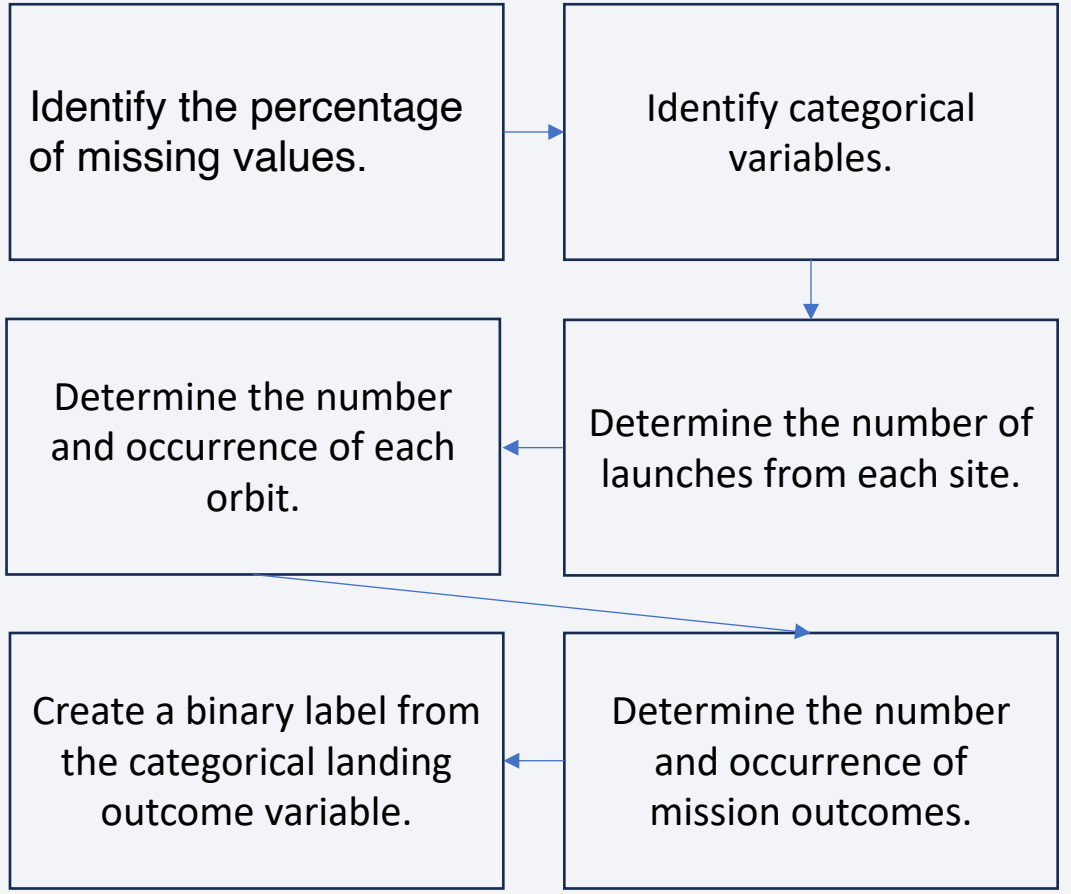


Link to Github

Data Wrangling

The main task in this part was to calculate the frequency and percentages of null variables, identify the variable types, calculate the number and occurrence of main mission outcomes, and label the landing outcomes data in “Outcome” to a binary ‘Class’ variable to present 0 for failure and 1 for success.

Link to Github



EDA with Data Visualization

In this task, scatter plots, bar charts, and trend line charts were plotted to illustrate the relationships between variables: Flight Number vs. Payload Mass (scatterplot), Flight Number vs. Launch Site (scatterplot, Payload Mass vs. Launch Site (scatterplot), Orbit Type vs. Success Rate (bar chart), Flight Number vs. Orbit Type (scatterplot), Payload Mass vs Orbit Type (scatterplot), and Success Rate (trend).

Link to Github

EDA with SQL

The following tasks were completed in this part:

- Display the names of the unique launch sites in the space mission
- Display records where launch sites begin with the string 'CCA'
- Display the total payload mass carried by boosters launched by NASA (CRS)
- Display average payload mass carried by booster version F9 v1.1
- 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 failed landing outcomes, their booster versions and launch site names for 2015
- Rank the count of landing outcomes between 2010-06-04 and 2017-03-20 in descending order.

Link to Github

Build an Interactive Map with Folium

In this task, the geographical location of the launch sites were illustrated on the folium map with the text, circles and markers, using their geographical coordinates (latitude and longitude). Also, proximity of the launch sites to Equator and coasts were explored. Also, colored markers (green for success, red for failure) were used to illustrate and identify the launch sites with high success rates. Finally, colored Lines were added to show distances between a launch site and its proximities (Railway, Highway, Coastline and Closest City).

Link to Github

Build a Dashboard with Plotly Dash

This task involved constructing a launch sites dropdown list (adding a dropdown list to enable launch site selection, development of a pie chart to show success launches, adding a pie chart to show the total successful launches count for all sites and the success vs. failed counts for the site for specific launch site selections), a slider of payload mass (adding a slider to select payload range, scatter chart of payload mass vs. success rate for the different booster versions and adding a scatter chart to show the correlation between payload and launch success.

Link to Github

Predictive Analysis (Classification)

In this task, data were split into training and test datasets based on 0.8/0.2 ratio. Then, different models were used to fit the data. The models included logistic regression, tree classifier, SVM, and K-nearest neighbor (KNN) classifiers. Finally, the best hypermeters and the accuracy of the models were determined.

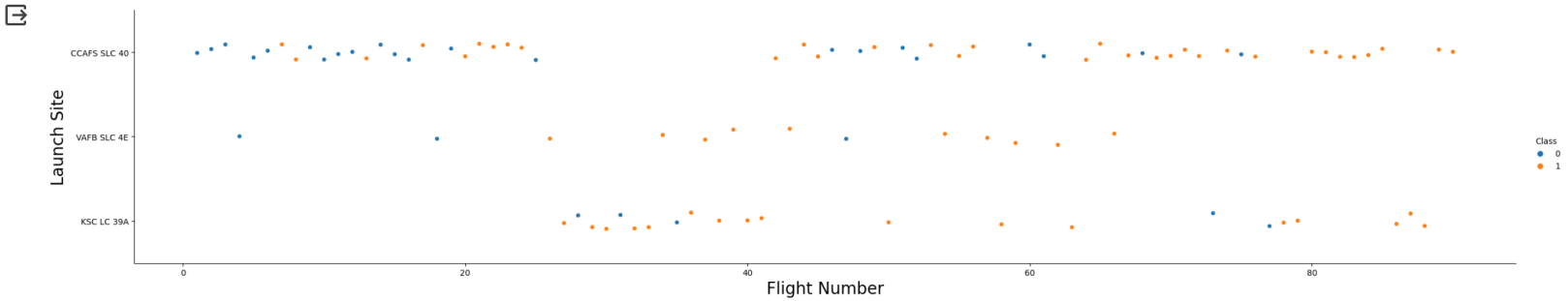
Link to Github

Results - Exploratory data analysis

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 = 5)
plt.xlabel("Flight Number",fontsize=20)
plt.ylabel("Launch Site",fontsize=20)
plt.show()
```

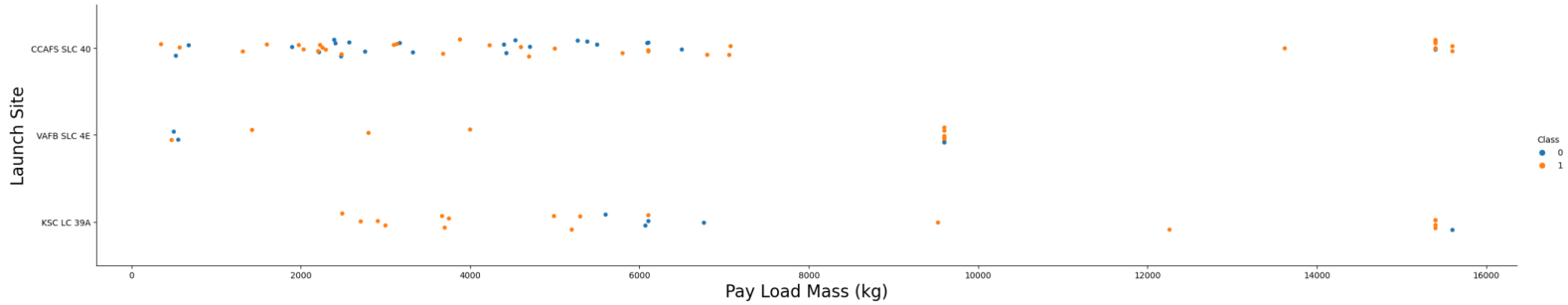


Results - Exploratory data analysis

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 = 5)
    plt.xlabel("Pay Load Mass (kg)",fontsize=20)
    plt.ylabel("Launch Site",fontsize=20)
    plt.show()
```



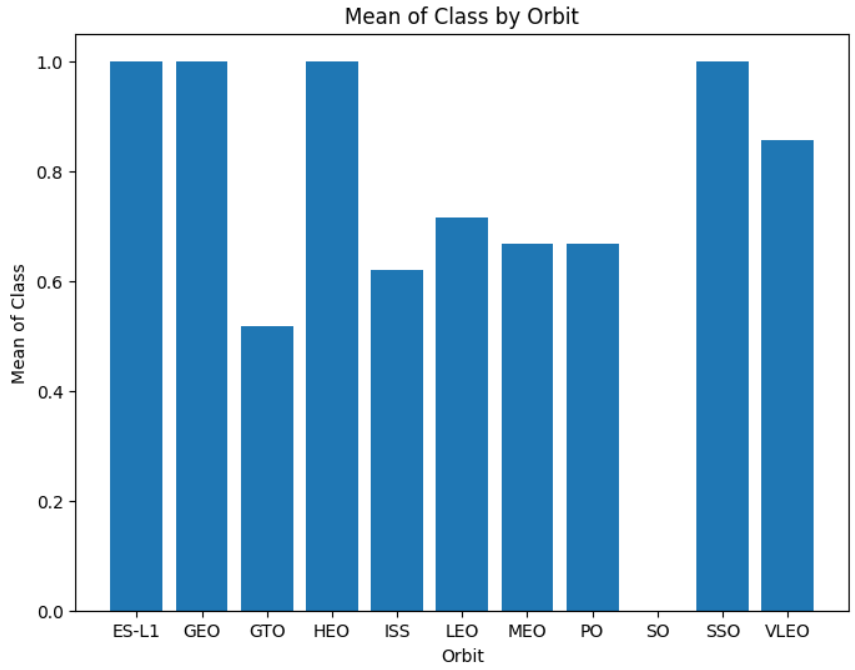
Results - Exploratory data analysis

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
# Group by 'Orbit' and calculate the mean of 'Class'
orbit_means = df.groupby('Orbit')['Class'].mean().reset_index()

# Create a bar chart to visualize the means
plt.figure(figsize=(8, 6))
plt.bar(orbit_means['Orbit'], orbit_means['Class'])
plt.xlabel('Orbit')
plt.ylabel('Mean of Class')
plt.title('Mean of Class by Orbit')
plt.show()
```

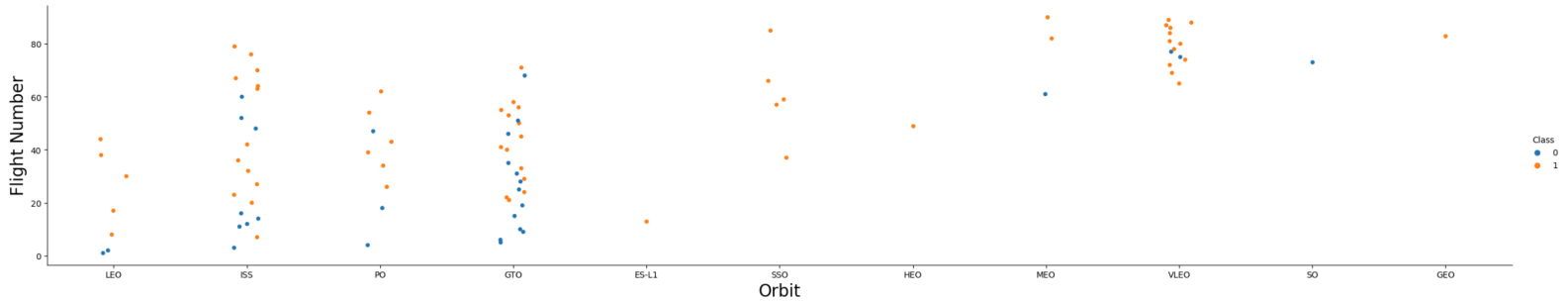


Results - Exploratory data analysis

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="FlightNumber", x="Orbit", hue="Class", data=df, aspect = 5)
    plt.xlabel("Orbit",fontsize=20)
    plt.ylabel("Flight Number",fontsize=20)
    plt.show()
```

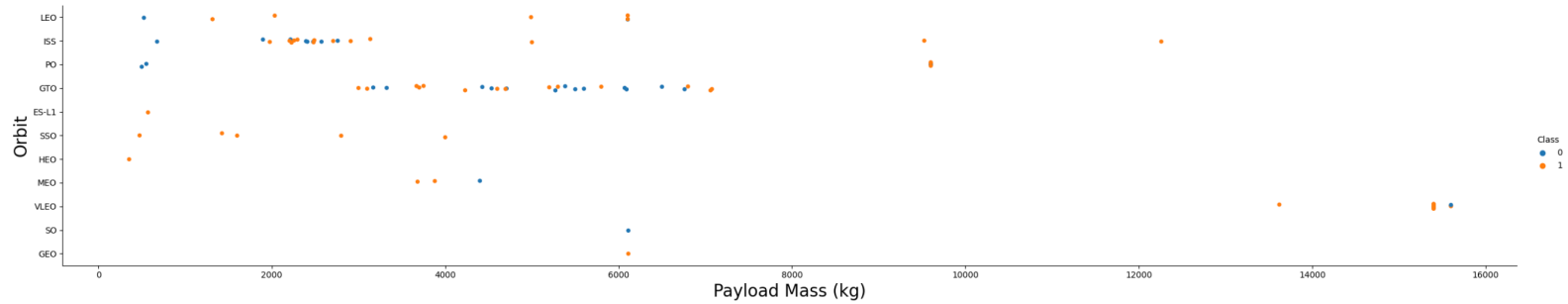


Results - Exploratory data analysis

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(x = 'PayloadMass', y = 'Orbit', hue = 'Class', data = df, aspect = 5)
    plt.xlabel('Payload Mass (kg)', fontsize = 20)
    plt.ylabel('Orbit', fontsize = 20)
    plt.show()
```



Results - Exploratory data analysis

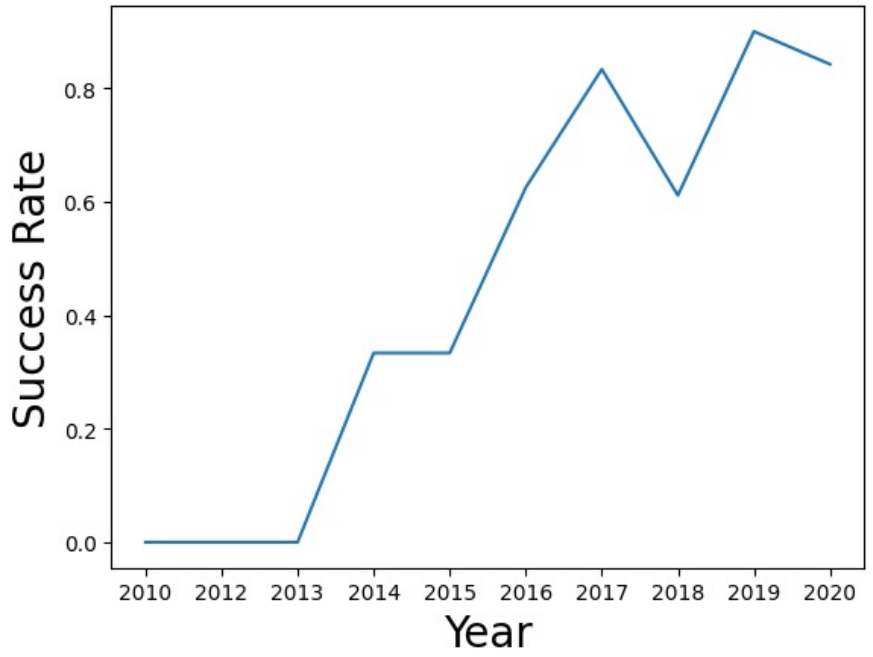
TASK 6: Visualize the launch success yearly trend

You can plot a line chart with x axis to be `Year` and y axis to be average success rate, to get the average launch success trend.

The function will help you get the year from the date:

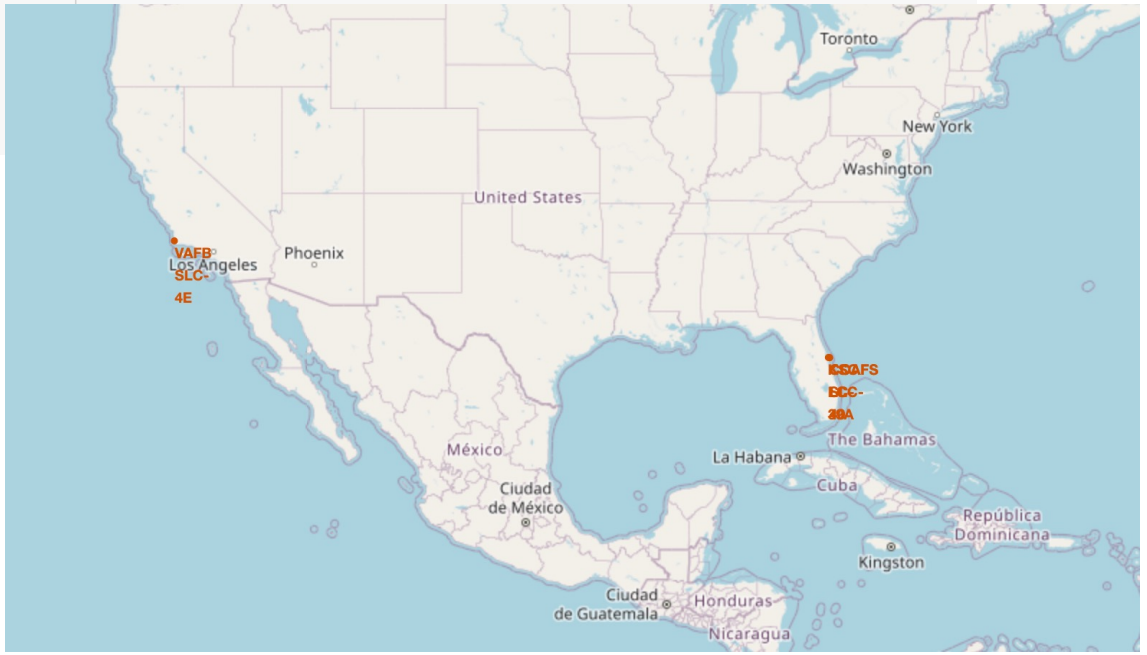
```
[ ] # A function to Extract years from the date
    year=[]
    def Extract_year(date):
        for i in df["Date"]:
            year.append(i.split("-")[0])
        return year
    Year1 = df[year]
```

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

    # Create a line chart to visualize the trend

    sns.lineplot(x = years.index, y = years)
    plt.xlabel('Year', fontsize = 20)
    plt.ylabel('Success Rate', fontsize = 20)
    plt.show()
```



Results - Interactive analytics demo in screenshots

```
# Initial the map
site_map = folium.Map(location=nasa_coordinate, zoom_start=5)
# For each launch site, add a Circle object based on its coordinate (Lat, Long) values. In addition, add Launch site name as a popup label
for launch_site, site_lat, site_long in zip(launch_sites_df['Launch Site'], launch_sites_df['Lat'], launch_sites_df['Long']):
    site_coordinate = [site_lat, site_long]

    circle = folium.Circle(site_coordinate, radius=1000, color='#d35400', fill=True).add_child(folium.Popup(launch_site))

    marker = folium.map.Marker(
        site_coordinate,
        # Create an icon as a text label
        icon=DivIcon(
            icon_size=(20, 20),
            icon_anchor=(0, 0),
            html='<div style="font-size: 12; color:#d35400;"><b>%s</b></div>' % launch_site,
            )
        )
    site_map.add_child(circle)
    site_map.add_child(marker)
site_map
```



Results - Interactive analytics demo in screenshots

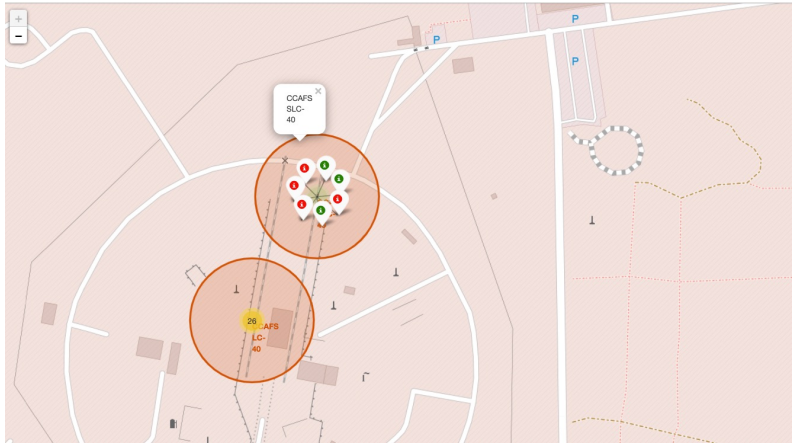
TODO: For each launch result in `spacex_df` data frame, add a `folium.Marker` to `marker_cluster`

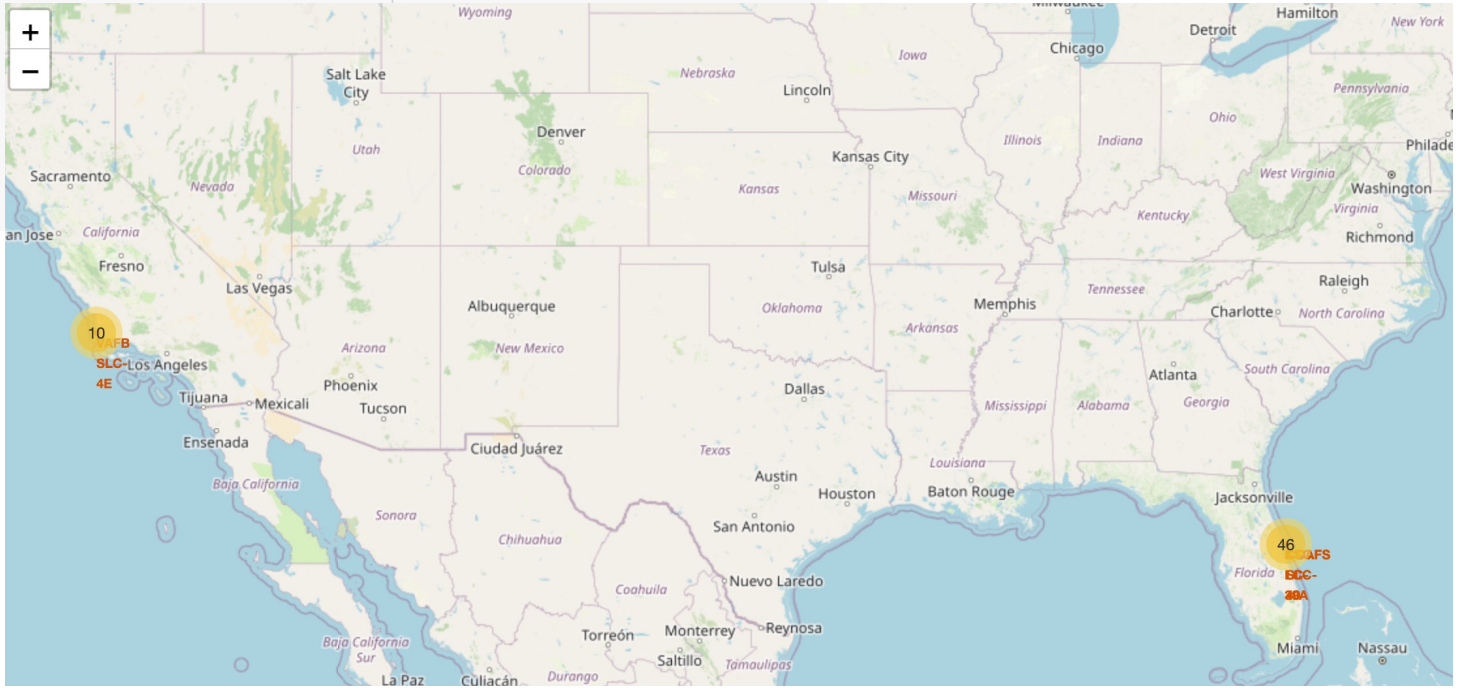
```
[ ]  # Add marker_cluster to current site_map
     site_map.add_child(marker_cluster)

     # for each row in spacex_df data frame
     # create a Marker object with its coordinate
     # and customize the Marker's icon property to indicate if this launch was successed or failed,
     # e.g., icon=folium.Icon(color='white', icon_color=row['marker_color']
     for site_lat, site_long, marker_color in zip(spacex_df['Lat'], spacex_df['Long'], spacex_df['marker_color']):
         site_coordinate = [site_lat, site_long]
         marker = folium.map.Marker(
             site_coordinate,
             # Create an icon as a text label
             icon=folium.Icon(color='white',
                              icon_color=marker_color)
         )
         marker.add_to(marker_cluster)

     site_map
```

Results - Interactive analytics demo in screenshots

TODO: For each launch result in `spacex_df` data frame, add a `folium.Marker` to `marker_cluster`

```
[ ]  # Add marker_cluster to current site_map
     site_map.add_child(marker_cluster)

     # for each row in spacex_df data frame
     # create a Marker object with its coordinate
     # and customize the Marker's icon property to indicate if this launch was successed or failed,
     # e.g., icon=folium.Icon(color='white', icon_color=row['marker_color']
     for site_lat, site_long, marker_color in zip(spacex_df['Lat'], spacex_df['Long'], spacex_df['marker_color']):
         site_coordinate = [site_lat, site_long]
         marker = folium.map.Marker(
             site_coordinate,
             # Create an icon as a text label
             icon=folium.Icon(color='white',
                              icon_color=marker_color)
         )
         marker.add_to(marker_cluster)

     site_map
```





Results - Interactive analytics demo in screenshots

```
[ ]  # find coordinate of the closet coastline
     # e.g.,: Lat: 28.56367  Lon: -80.57163
     # distance_coastline = calculate_distance(launch_site_lat, launch_site_lon, coastline_lat, coastline_lon)
     coastline_marker = [28.56293, -80.56803]
     launch_coordinate = [28.57337, -80.64669]
     distance_coastline = calculate_distance(coastline_marker[0], coastline_marker[1], launch_coordinate[0], launch_coordinate[1])
     distance_coastline  # distance in km
```

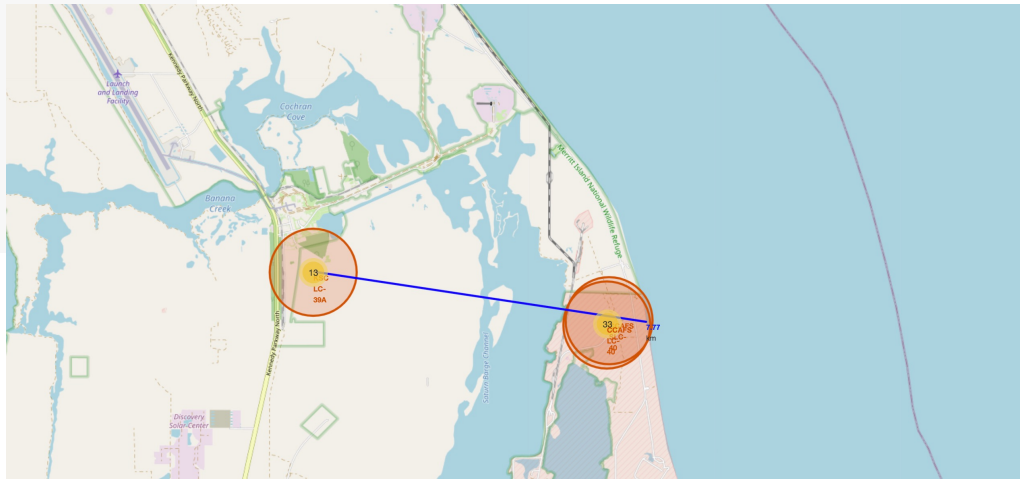
```
7.771346579504573
```

TODO: After obtained its coordinate, create a `folium.Marker` to show the distance

```
# Create and add a folium.Marker on your selected closest coastline point on the map
# Display the distance between coastline point and launch site using the icon property
# for example
# distance_marker = folium.Marker(
#    coordinate,
#    icon=DivIcon(
#        icon_size=(20,20),
#        icon_anchor=(0,0),
#        html='<div style="font-size: 12; color:#d35400;"><b>%s</b></div>' % "{:10.2f} KM".format(distance),
#        )
#    )
marker = folium.map.Marker(
        coastline_marker,
        # Create an icon as a text label
        icon=DivIcon(
            icon_size=(400, 400),
            icon_anchor=(0, 0),
            html='<div style="font-size:400; color:#0c10f2;"><b>%s</b></div>' % str(round(distance_coastline, 2))+' km',
            )
    )
marker.add_to(site_map)

site_map
```

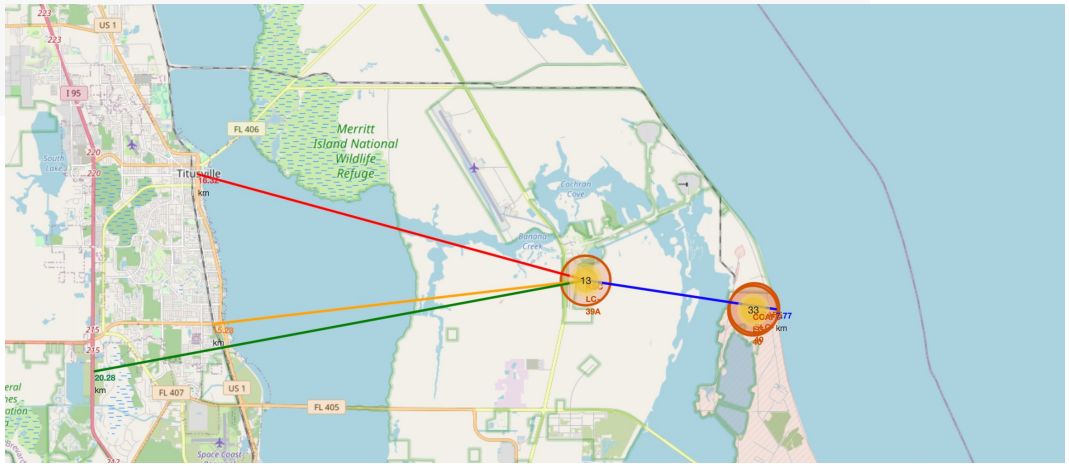
TODO: Draw a `PolyLine` between a launch site to the selected coastline point

```
# Create a `folium.PolyLine` object using the coastline coordinates and launch site coordinate
# lines=folium.PolyLine(locations=coordinates, weight=1)
folium.PolyLine([coastline_marker, launch_coordinate], color='blue').add_to(site_map)
site_map
```



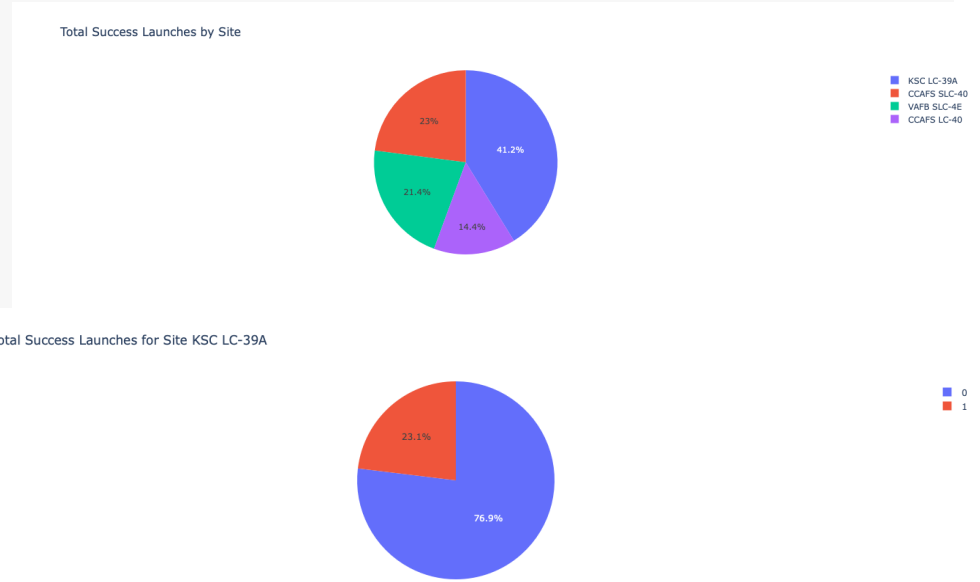
Results - Interactive analytics demo in screenshots

```
# Create a marker with distance to a closest city, railway, highway, etc.
# Draw a line between the marker to the launch site
city    = [28.61200, -80.80788]
railway = [28.55752, -80.80155]
highway   = [28.5402, -80.85079]

city_distance = calculate_distance(city[0], city[1], launch_coordinate[0], launch_coordinate[1])
railway_distance = calculate_distance(railway[0], railway[1], launch_coordinate[0], launch_coordinate[1])
highway_distance = calculate_distance(highway[0], highway[1], launch_coordinate[0], launch_coordinate[1])

colors = ['red','orange','green']
html_colors = ['#dc3545','#fd7e14','#198754']

for coordinate ,distance, color, html_color in zip([city, railway, highway], [city_distance, railway_distance, highway_distance], colors, html_colors):
    marker = folium.map.Marker(
            coordinate,
            # Create an icon as a text label
            icon=DivIcon(
                icon_size=(20,20),
                icon_anchor=(0,0),
                html='<div style="font-size: 12; color:'+html_color+';"><b>%s</b></div>' % str(round(distance, 2)) + 'km',
                )
            )
    marker.add_to(site_map)
    folium.PolyLine([coordinate, launch_coordinate], color=color).add_to(site_map)
site_map
```



Results - Exploratory data analysis

```
[ ]  # Create an app layout
     app.layout = html.Div(children=[html.H1('SpaceX Launch Records Dashboard',
                                             style={'textAlign': 'center', 'color': '#503D36',
                                                    'font-size': 40}),

     # TASK 1: Add a dropdown list to enable Launch Site selection
     # The default select value is for ALL sites
     dcc.Dropdown(id='site-dropdown', options=[{'label': 'All Sites', 'value': 'All Sites'}, {'label': 'CCAFS LC-40', 'value': 'CCAFS LC-40'}, {'label': 'VAFB SLC-4E', 'valu



     # TASK 2: Add a pie chart to show the total successful launches count for all sites
     # If a specific launch site was selected, show the Success vs. Failed counts for the site
                                     html.Div(dcc.Graph(id='success-pie-chart')),
                                     html.Br(),

                                     html.P("Payload range (Kg):"),
     # TASK 3: Add a slider to select payload range
                                     dcc.RangeSlider(id='payload-slider',
                                     min=0,
                                     max=10000,
                                     step=1000,
                                     marks={i: '{}'.format(i) for i in range(0, 10001, 1000)},
                                     value=[min_payload, max_payload]),

     # TASK 4: Add a scatter chart to show the correlation between payload and launch success
                                     html.Div(dcc.Graph(id='success-payload-scatter-chart')),
                                     ])
```



Results - Predictive analysis results

▼ TASK 1

Create a NumPy array from the column `Class` in `data`, by applying the method `to_numpy()` then assign it to the variable `Y`,make sure the output is a Pandas series (only one bracket df['name of column']).

```
[ ]  Y = pd.Series(data['Class'].to_numpy())
     Y.head(10)
```

```
0    0
1    0
2    0
3    0
4    0
5    0
6    1
7    1
8    0
9    0
dtype: int64
```

Results - Predictive analysis results

TASK 2

Standardize the data in `X` then reassign it to the variable `X` using the transform provided below.

```
[ ] # students get this
    transform = preprocessing.StandardScaler()
```

```
[ ] X = transform.fit(X).transform(X)
```

We split the data into training and testing data using the function `train_test_split`. The training data is divided into validation data, a second set used for training data; then the models are trained and hyperparameters are selected using the function `GridSearchCV`.

TASK 3

Use the function train_test_split to split the data X and Y into training and test data. Set the parameter test_size to 0.2 and random_state to 2. The training data and test data should be assigned to the following labels.

`X_train, X_test, Y_train, Y_test`

```
[ ] X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=2)
```

Results - Predictive analysis results

TASK 4

Create a logistic regression object then create a GridSearchCV object `logreg_cv` with cv = 10. Fit the object to find the best parameters from the dictionary `parameters`.

```
[ ] parameters ={'C':[0.01,0.1,1],
                 'penalty':['l2'],
                 'solver':['lbfgs']}
```

```
[ ] parameters ={"C":[0.01,0.1,1],'penalty':['l2'], 'solver':['lbfgs']}# l1 lasso l2 ridge
    lr=LogisticRegression()

    logreg_cv=GridSearchCV(lr, parameters, cv=10)
    logreg_cv.fit(X_train, Y_train)
```

GridSearchCV
estimator: LogisticRegression
LogisticRegression

TASK 5

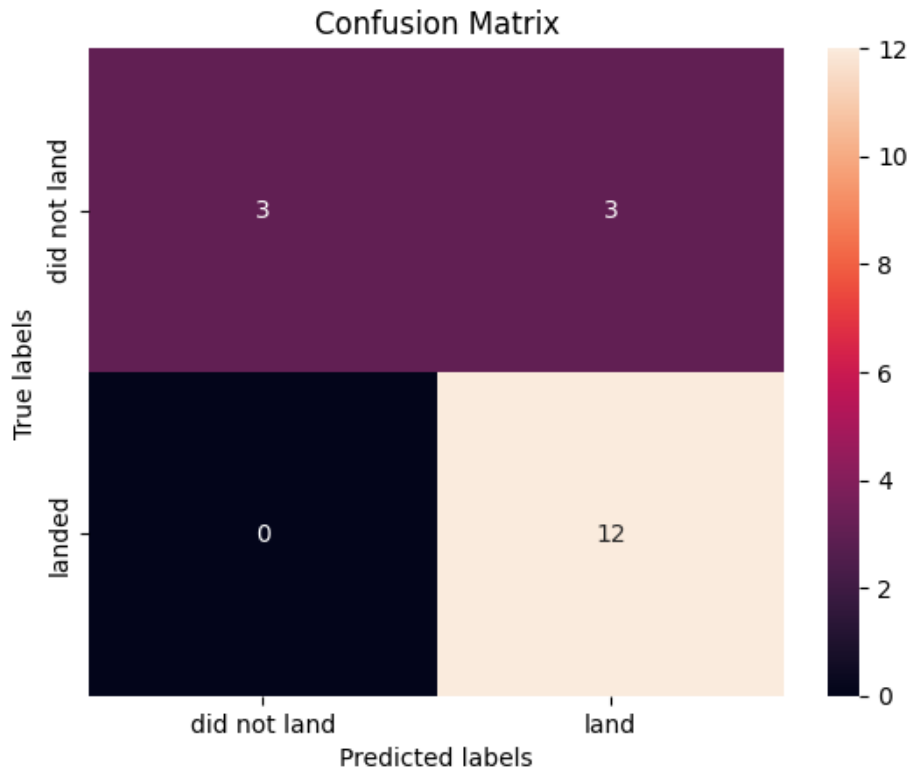
Calculate the accuracy on the test data using the method `score`:

```
[ ] logreg_accuracy = logreg_cv.score(X_test, Y_test)
    logreg_accuracy
```

```
0.8333333333333334
```

Lets look at the confusion matrix:

```
logreg_yhat=logreg_cv.predict(X_test)
plot_confusion_matrix(Y_test, logreg_yhat)
```



Results - Predictive analysis results

TASK 6

Create a support vector machine object then create a `GridSearchCV` object `svm_cv` with cv - 10. Fit the object to find the best parameters from the dictionary `parameters`.

```
[ ] parameters = {'kernel':('linear', 'rbf','poly','rbf', 'sigmoid'),
                  'C': np.logspace(-3, 3, 5),
                  'gamma':np.logspace(-3, 3, 5)}
    svm = SVC()
```

```
[ ] svm_cv = GridSearchCV(svm, parameters, cv=10)
    svm_cv.fit(X_train, Y_train)
```

▸ **GridSearchCV**
▸ **estimator: SVC**
▸ SVC

```
print("tuned hpyerparameters :(best parameters) ",svm_cv.best_params_)
print("accuracy :",svm_cv.best_score_)
```

```
tuned hpyerparameters :(best parameters)  {'C': 1.0, 'gamma': 0.03162277660168379, 'kernel': 'sigmoid'}
accuracy : 0.8482142857142856
```

+ Code + Text

TASK 7

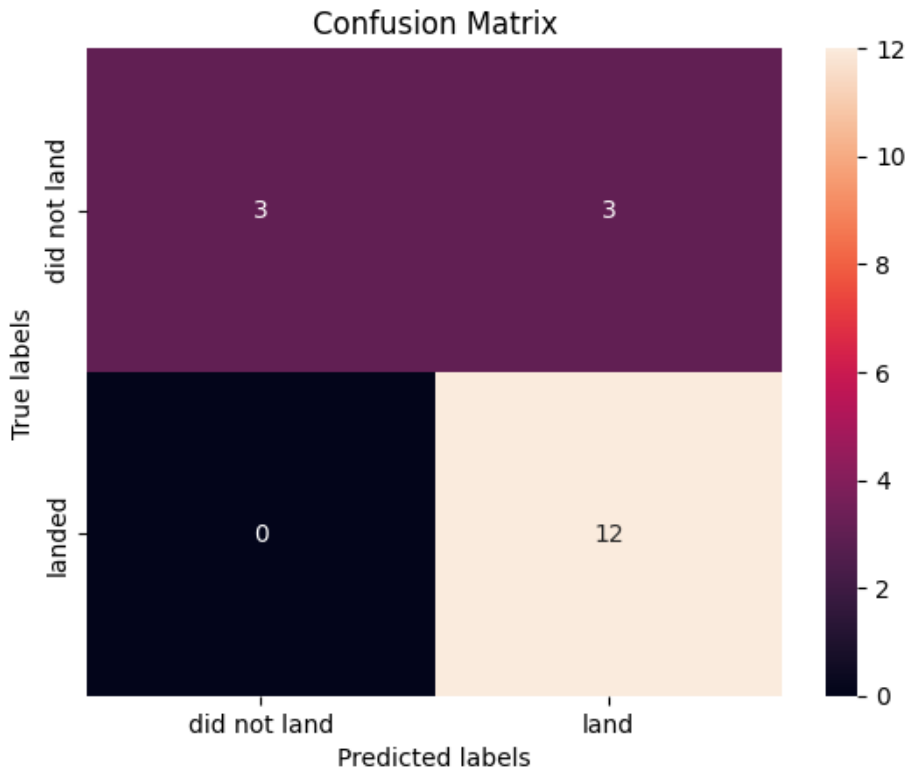
Calculate the accuracy on the test data using the method `score`:

```
[ ] svm_accuracy = svm_cv.score(X_test, Y_test)
    svm_accuracy
```

```
0.8333333333333334
```

We can plot the confusion matrix

```
svm_yhat=svm_cv.predict(X_test)
plot_confusion_matrix(Y_test, svm_yhat)
```



Results - Predictive analysis results

TASK 8

Create a decision tree classifier object then create a `GridSearchCV` object `tree_cv` with cv = 10. Fit the object to find the best parameters from the dictionary `parameters`.

```
parameters = {'criterion': ['gini', 'entropy'],
     'splitter': ['best', 'random'],
     'max_depth': [2*n for n in range(1,10)],
     'max_features': ['auto', 'sqrt'],
     'min_samples_leaf': [1, 2, 4],
     'min_samples_split': [2, 5, 10]}

tree = DecisionTreeClassifier()
```

```
tree_cv = GridSearchCV(tree, parameters, cv=10)
tree_cv.fit(X_train, Y_train)
```

+ Code + Text

```
print("tuned hpyerparameters :(best parameters) ",tree_cv.best_params_)
print("accuracy :",tree_cv.best_score_)
```

```
tuned hpyerparameters :(best parameters)  {'criterion': 'entropy', 'max_depth': 10, 'max_features': 'sqrt', 'min_samples_leaf': 4, 'min_samples_split'
accuracy : 0.8732142857142857
```

TASK 9

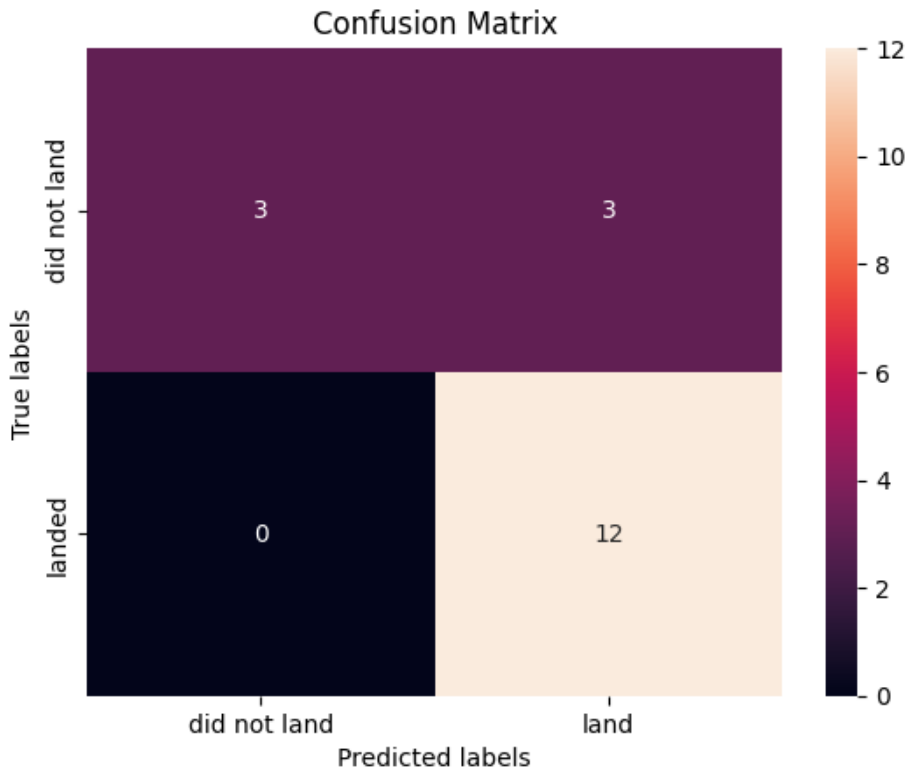
Calculate the accuracy of tree_cv on the test data using the method `score`:

```
tree_accuracy = tree_cv.score(X_test, Y_test)
tree_accuracy
```

```
0.7222222222222222
```

We can plot the confusion matrix

```
tree_yhat = svm_cv.predict(X_test)
plot_confusion_matrix(Y_test,tree_yhat)
```



Results - Predictive analysis results

TASK 10

Create a k nearest neighbors object then create a `GridSearchCV` object `knn_cv` with cv = 10. Fit the object to find the best parameters from the dictionary `parameters`.

```
[ ] parameters = {'n_neighbors': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10],
                  'algorithm': ['auto', 'ball_tree', 'kd_tree', 'brute'],
                  'p': [1,2]}

    KNN = KNeighborsClassifier()
```

```
knn_cv = GridSearchCV(KNN, parameters, cv=10)
knn_cv.fit(X_train, Y_train)
```

```
▸ GridSearchCV
▸ estimator: KNeighborsClassifier
    ▸ KNeighborsClassifier
```

```
[ ] print("tuned hpyerparameters :(best parameters) ",knn_cv.best_params_)
    print("accuracy :",knn_cv.best_score_)

    tuned hpyerparameters :(best parameters)  {'algorithm': 'auto', 'n_neighbors': 10, 'p': 1}
    accuracy : 0.8482142857142858
```

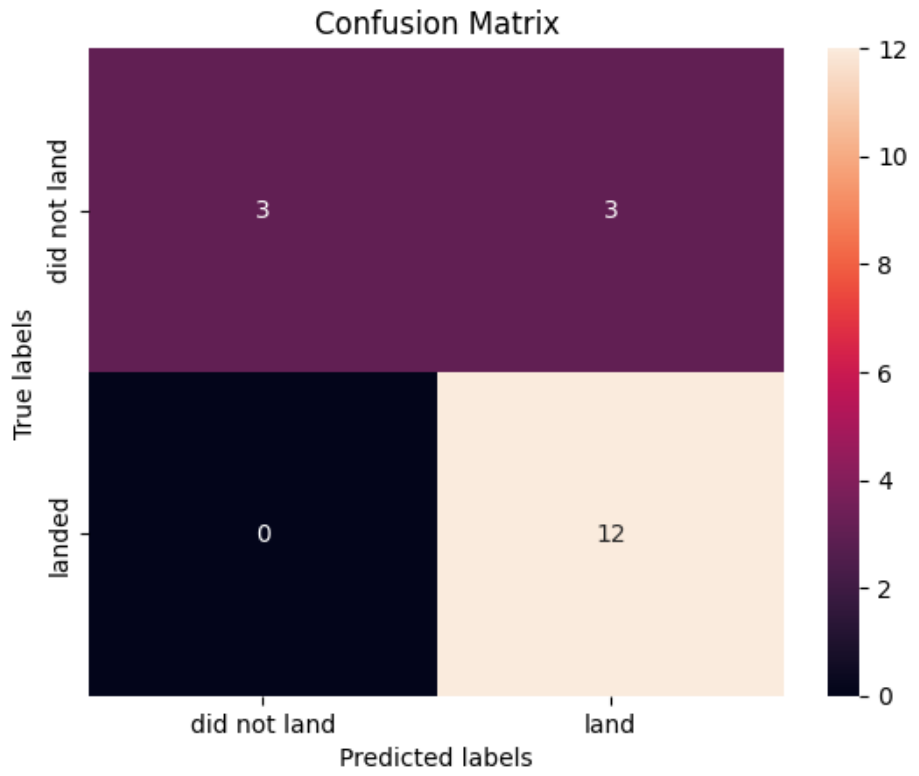
TASK 11

Calculate the accuracy of tree_cv on the test data using the method `score`:

```
[ ] knn_accuracy = knn_cv.score(X_test, Y_test)
    knn_accuracy

    0.8333333333333334
```

We can plot the confusion matrix

```
knn_yhat = knn_cv.predict(X_test)
plot_confusion_matrix(Y_test, knn_yhat)
```

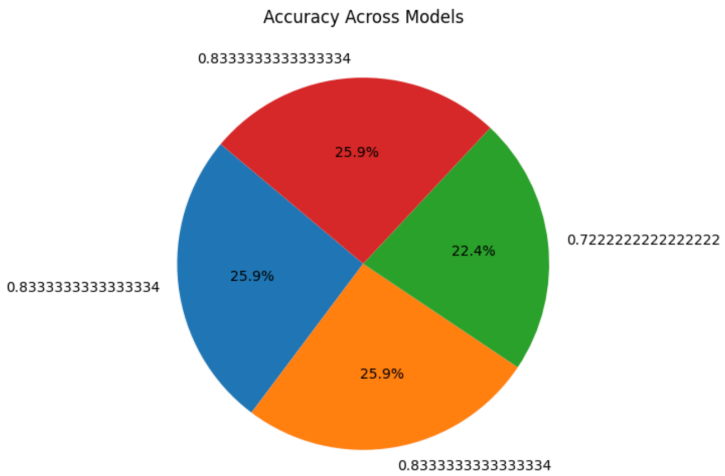


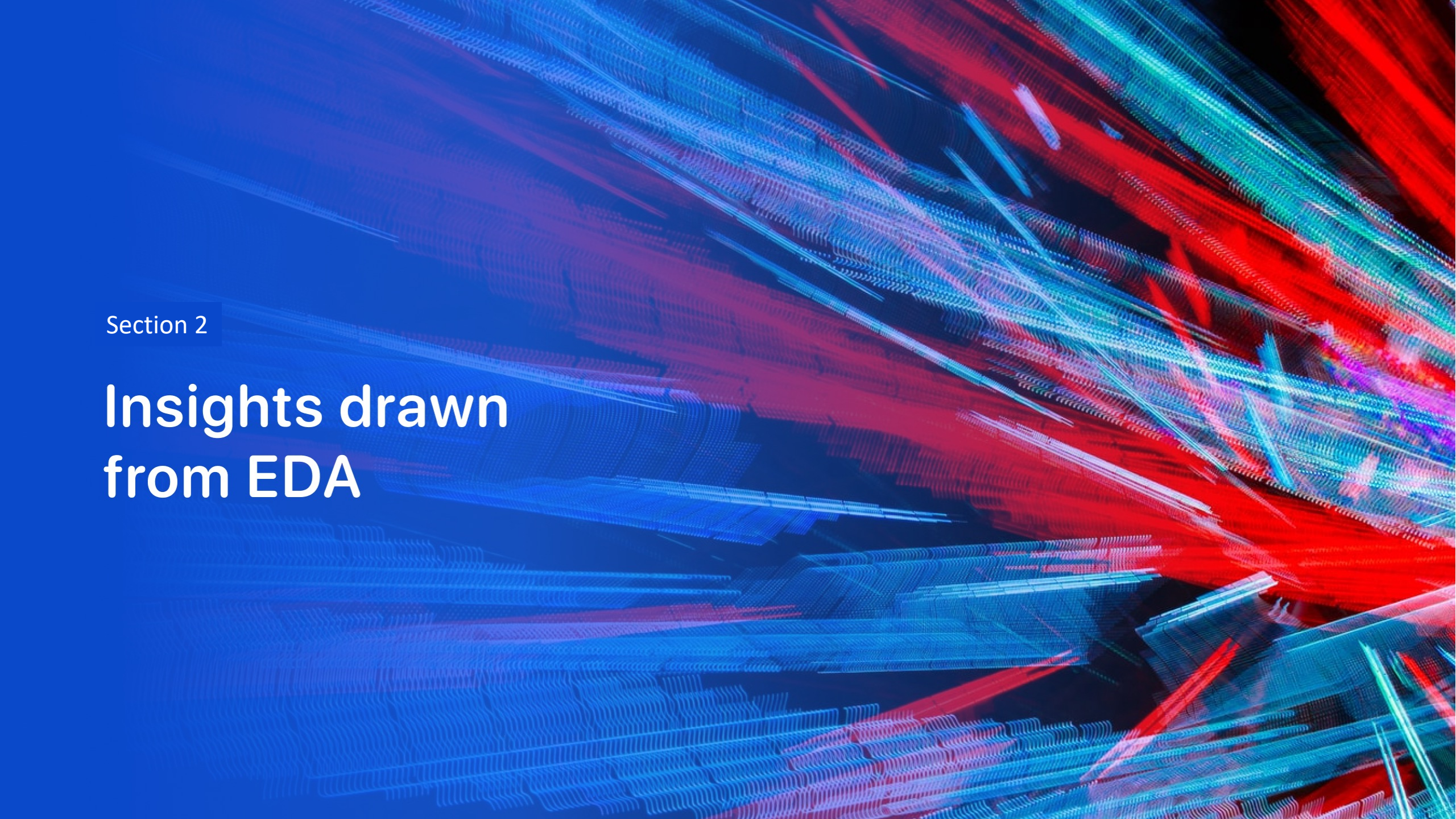
Results - Predictive analysis results

```
from sklearn.metrics import jaccard_score, f1_score

jaccard_scores = [
                  jaccard_score(Y_test, logreg_yhat, average='binary'),
                  jaccard_score(Y_test, svm_yhat, average='binary'),
                  jaccard_score(Y_test, tree_yhat, average='binary'),
                  jaccard_score(Y_test, knn_yhat, average='binary'),
                 ]

f1_scores = [
             f1_score(Y_test, logreg_yhat, average='binary'),
             f1_score(Y_test, svm_yhat, average='binary'),
             f1_score(Y_test, tree_yhat, average='binary'),
             f1_score(Y_test, knn_yhat, average='binary'),
            ]

accuracy = [logreg_accuracy, svm_accuracy, tree_accuracy, knn_accuracy]

scores = pd.DataFrame(np.array([jaccard_scores, f1_scores, accuracy]), index=['Jaccard_Score', 'F1_Score', 'Accuracy'] , columns=['LogReg', 'SVM', 'Tree', 'KNN'])
scores
```

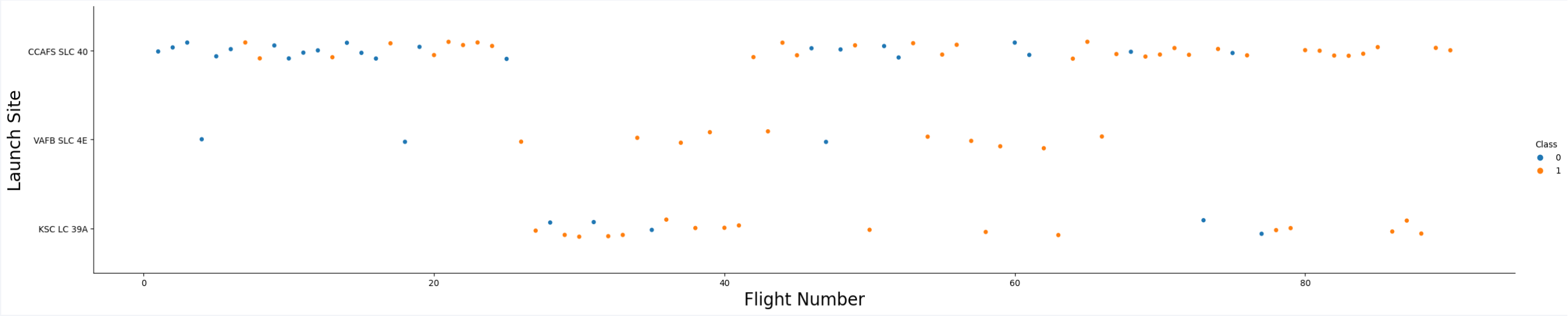
	LogReg	SVM	Tree	KNN
Jaccard_Score	0.800000	0.800000	0.800000	0.800000
F1_Score	0.888889	0.888889	0.888889	0.888889
Accuracy	0.833333	0.833333	0.722222	0.833333

```
import matplotlib.pyplot as plt

# Create a pie chart
plt.figure(figsize=(6, 6))  # Set the figure size
plt.pie(accuracy, labels=accuracy, autopct='%1.1f%%', startangle=140)  # 'autopct' adds percentage labels
plt.title('Accuracy Across Models')

# Display the pie chart
plt.show()
```



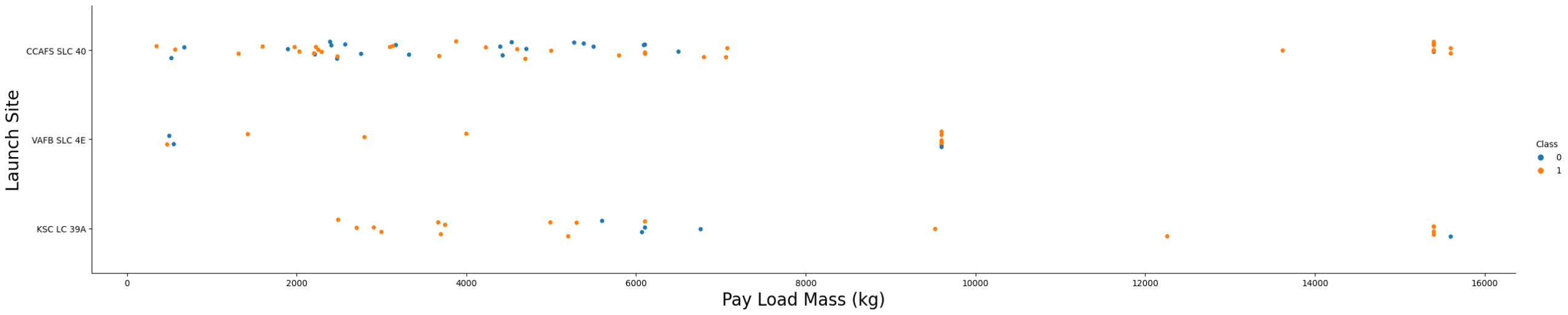

Section 2
Insights drawn from EDA

Flight Number vs. Launch Site



We learn that the increased flight numbers have lead to increased success rate across the launch sites.

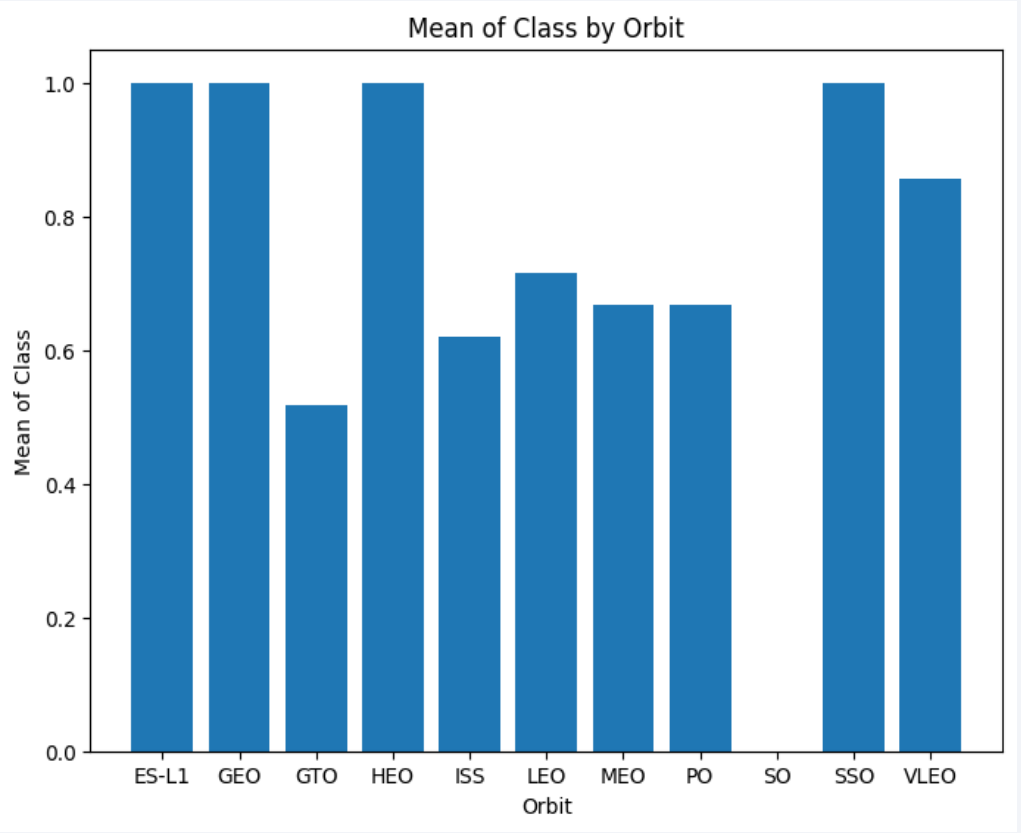
Payload vs. Launch Site



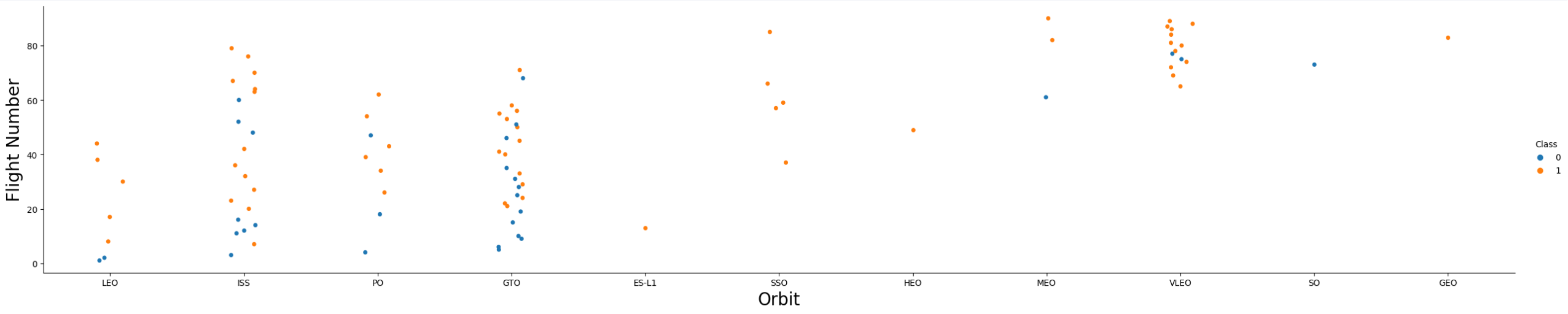
We learn that CCAFS SLC 40 is associated with higher success rates for high payload masses (such as greater than 15,000 kg). It is also clear that KSC LC 39A has experienced smaller failure rates for both small to high pay load masses.

Success Rate vs. Orbit Type

This bar chart shows ES-L1, SSO, GEO and HEO are the orbits associated with the highest success rates.

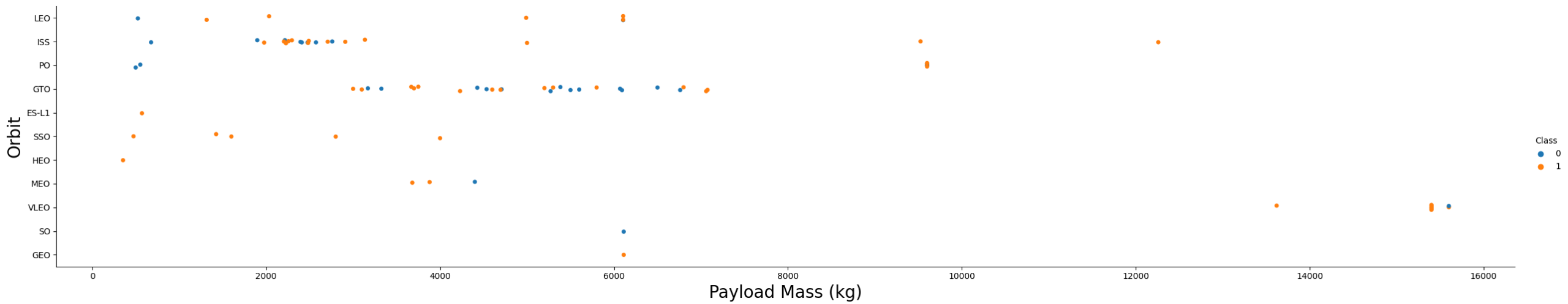


Flight Number vs. Orbit Type



We learn that VLEO is associated with very high success rates with great flight numbers. The pattern in most other orbits is scattered.

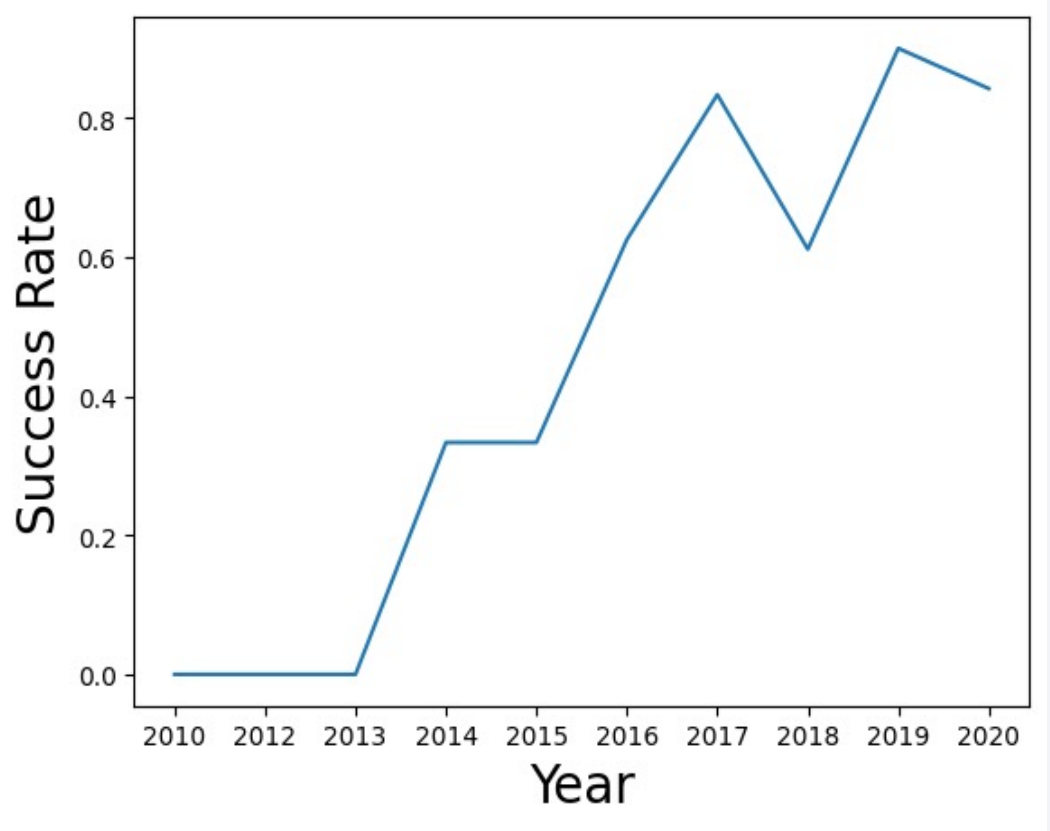
Payload vs. Orbit Type



We learn that for loads above 9000 kg, ISS and PO and VLEO represent success. Also, for loads between 4000 and 6000, LEO, ISS represent full success. For loads lesser than 4000 kg, MEO, HEO, SSO are the best success rate options.

Launch Success Yearly Trend

This trend chart show that the success rate has significantly improved in recent years.



All Launch Site Names

- Find the names of the unique launch sites

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

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

This value_count query shows the frequency of launches across three diverse launch sites.

Launch Site Names Begin with 'CCA'

- Find 5 records where launch sites begin with `CCA`.

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

```
[ ]  %sql select * from SPACEXTABLE 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
2010-04-06	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
2010-08-12	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)
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
2012-08-10	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
2013-01-03	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

This SQL SELECT query identifies 5 records with launch sites starting with CCA.

Total Payload Mass

- Calculate the total payload carried by boosters from NASA.

```
[ ]  %sql select sum(payload_mass__kg_) as total_payload_mass from SPACEXTABLE where customer = 'NASA (CRS)';
```

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

total_payload_mass
45596

This SQL SUM query calculates the total payload to be 45,596 kg.

Average Payload Mass by F9 v1.1

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

```
[ ]  %sql select avg(payload_mass__kg_) as average_payload_mass from SPACEXTABLE where booster_version like '%F9 v1.1%';
```

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

average_payload_mass
2534.6666666666665

This SQL AVG query calculates the average payload to be 2,534.66 kg.

First Successful Ground Landing Date

- Find the dates of the first successful landing outcome on ground pad.

```
[ ]  %sql select min(date) as first_successful_landing from SPACEXTABLE where Mission_Outcome = 'Success';
```

```
 * sqlite:///my_data1.db
Done.
first_successful_landing
2010-04-06
```

This SQL MIN query determines the first date for successful landing outcome to be 2010-04-06.

Successful Drone Ship Landing with Payload between 4000 and 6000

- List the names of boosters which have successfully landed on drone ship and had payload mass greater than 4000 but less than 6000

```
[ ] %sql select booster_version from SPACEXTABLE where Mission_Outcome = 'Success (drone ship)' and payload_mass__kg_ between 4000 and 6000;
```

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

Booster_Version

This SQL SELECT conditional query shows the boosters meeting the crtieria.

Total Number of Successful and Failure Mission Outcomes

- Calculate the total number of successful and failure mission outcomes.

```
[ ]  %sql select Mission_Outcome, count(*) as total_number from SPACEXTABLE group by Mission_Outcome;
```

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

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

This SQL Count query calculates the frequency of success and failure mission outcomes to be 100 success cases and 1 failure.

Boosters Carried Maximum Payload

- List the names of the booster which have carried the maximum payload mass

```
[ ]  %sql select booster_version from SPACEXTABLE where payload_mass__kg_ = (select max(payload_mass__kg_) from SPACEXTABLE);
```

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

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

This SQL conditional query determines the names of the booster meeting the crtieria.

2015 Launch Records

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

```
In [12]: %%sql select monthname(date) as month, date, booster_version, launch_site, landing__outcome from SPACEXDATASET
             where landing__outcome = 'Failure (drone ship)' and year(date)=2015;
 * ibm_db_sa://wzf08322:***@0c77d6f2-5da9-48a9-81f8-86b520b87518.bs2io90l08kqb1od8lcg.databases.appdomain.cloud:31198/bludb
Done.
```

Out[12]:

MONTH	DATE	booster_version	launch_site	landing__outcome
January	2015-01-10	F9 v1.1 B1012	CCAFS LC-40	Failure (drone ship)
April	2015-04-14	F9 v1.1 B1015	CCAFS LC-40	Failure (drone ship)

This SQL query determines the failed landing_outcomes in 2015.

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

- 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.

```
[ ]  %%sql select Mission_Outcome, count(*) as count_outcomes from SPACEXTABLE
           where date between '2010-06-04' and '2017-03-20'
           group by Mission_Outcome
           order by count_outcomes desc;
```

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

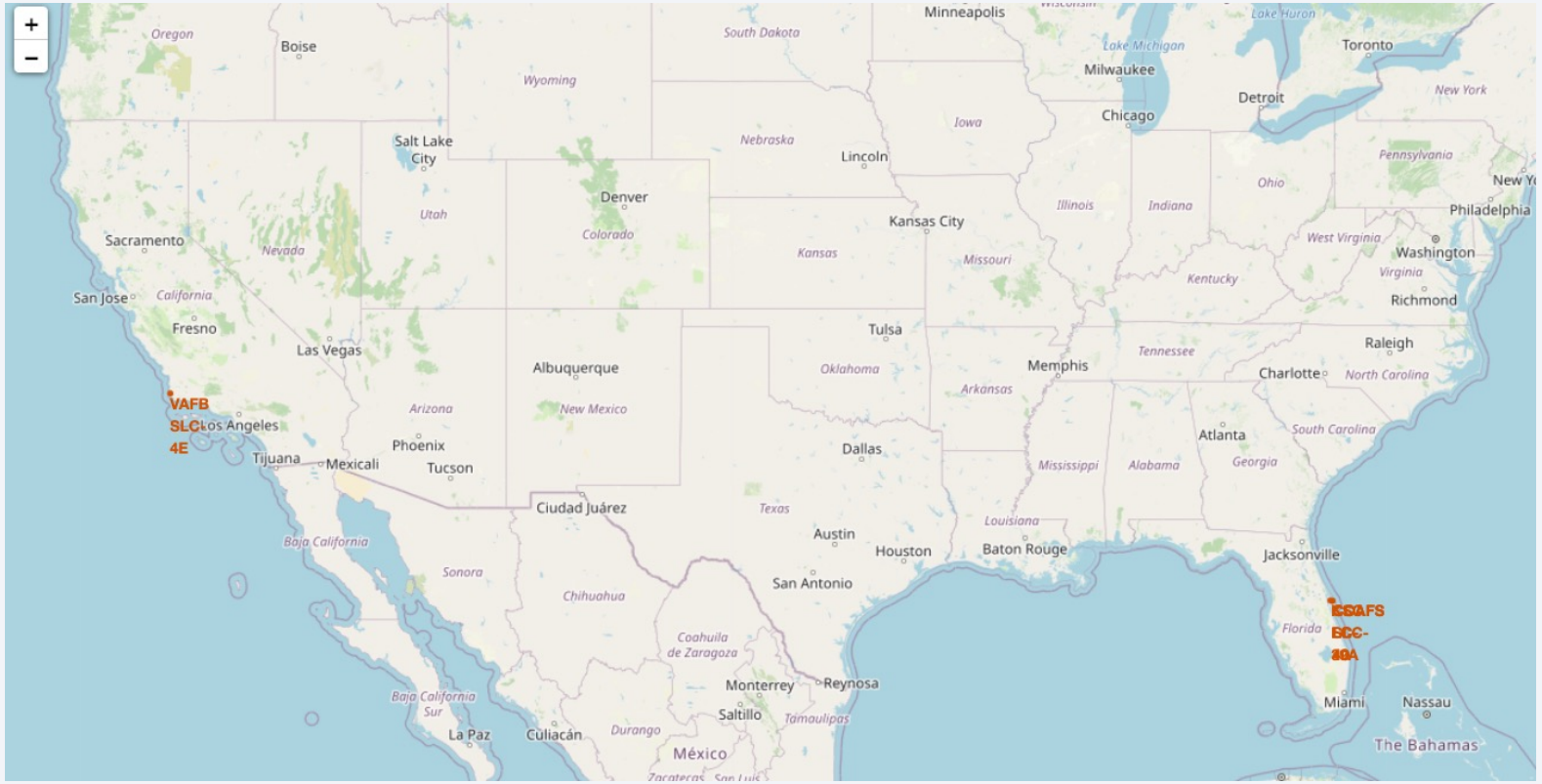
Mission_Outcome	count_outcomes
Success	31
Failure (in flight)	1

This SQL Count query determines the frequency of success and failure cases between the specified dates to be 31 success and 1 failure cases.


Section 3
Launch Sites
Proximities Analysis

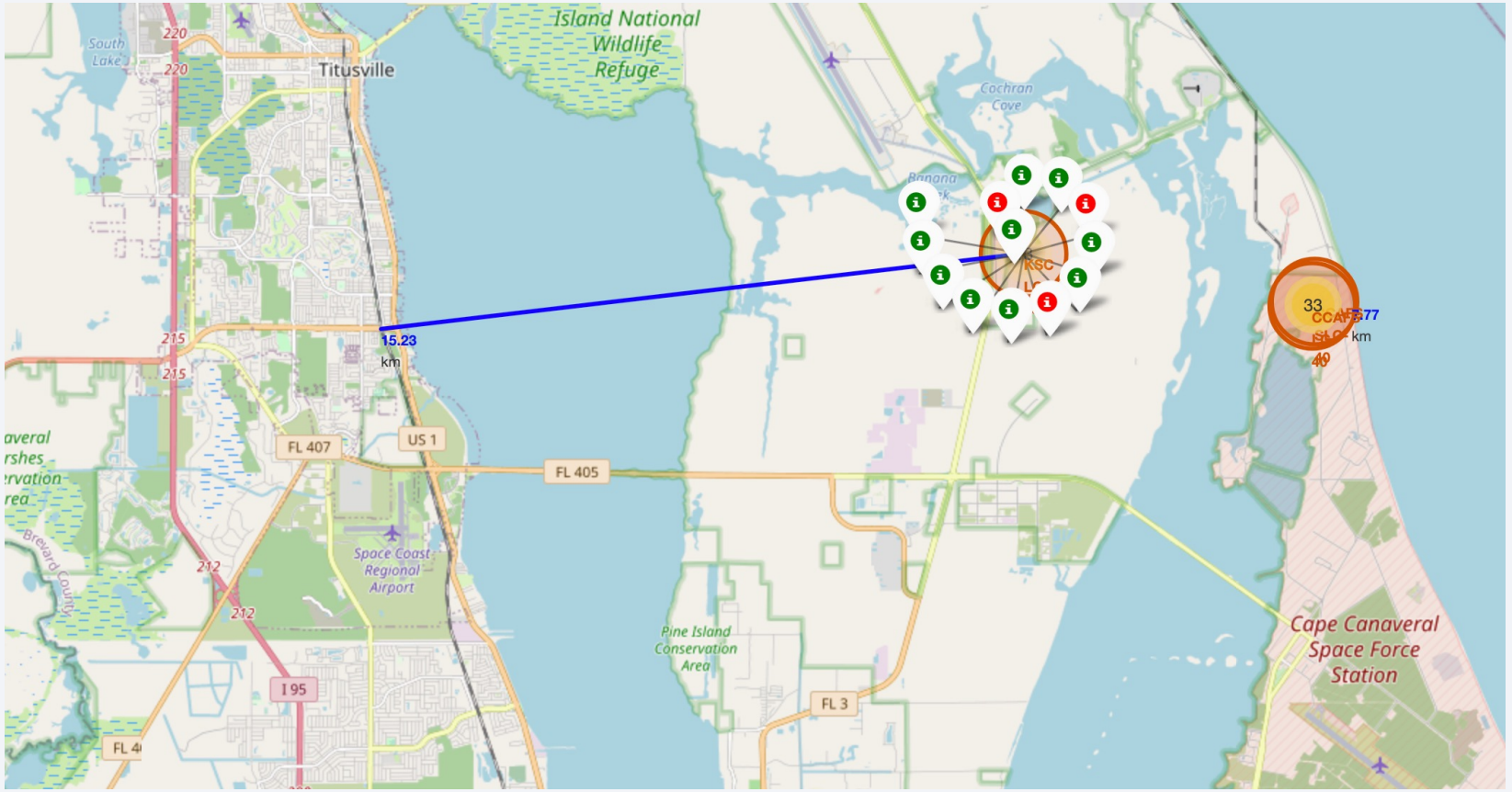
Geographical Location of Launch Sites

- The Launch sites are in very close proximity to the coastline on both east and west coasts of the United States.



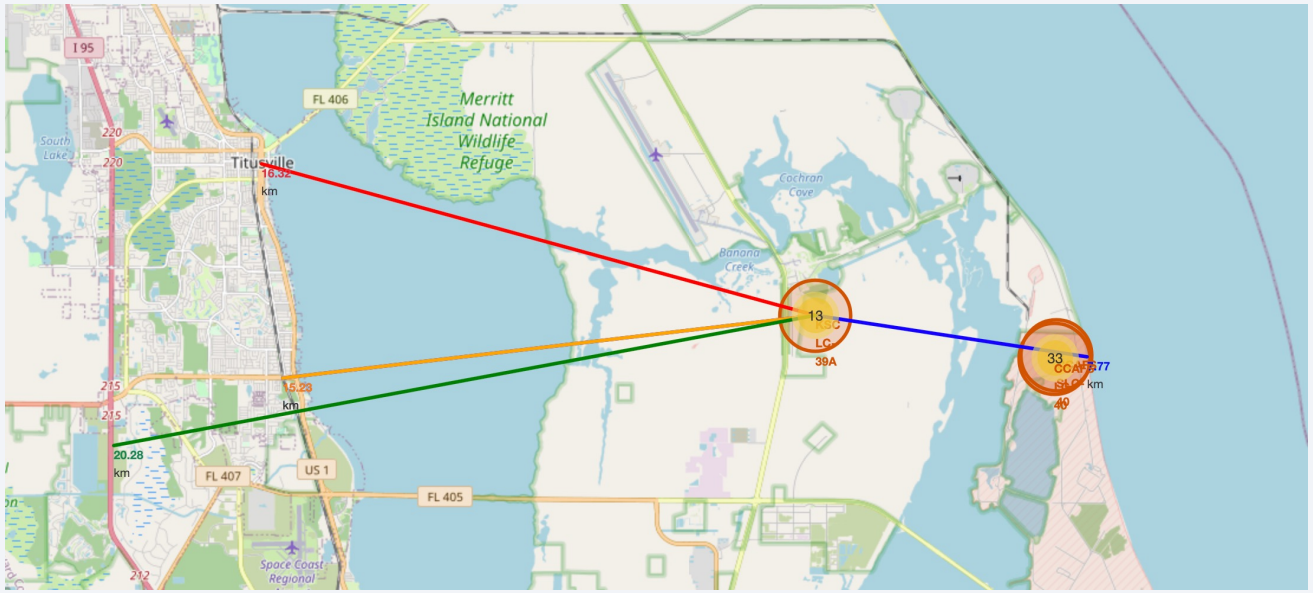
Success of Launches for KSC LC-39A

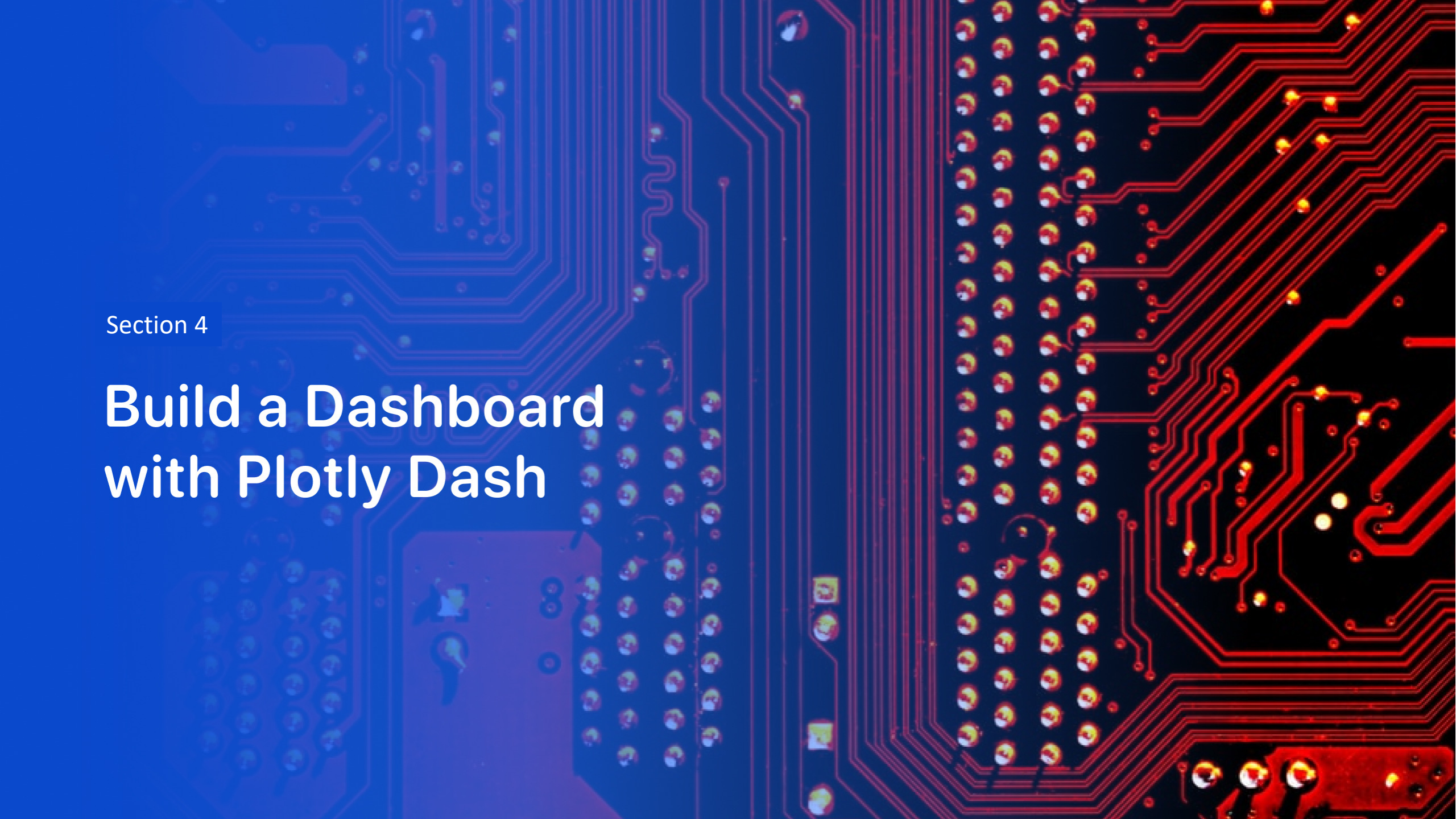
- This map shows successful (green) and failed launches for KSC LC-39A.



Proximity to Infrastructure

• The map of the launch site KSC LC-39A shows that closest railway, highway and city (Titusville), coastline are 15.23 km, 20.28 km, 7.77 km, and 16.32 km away.

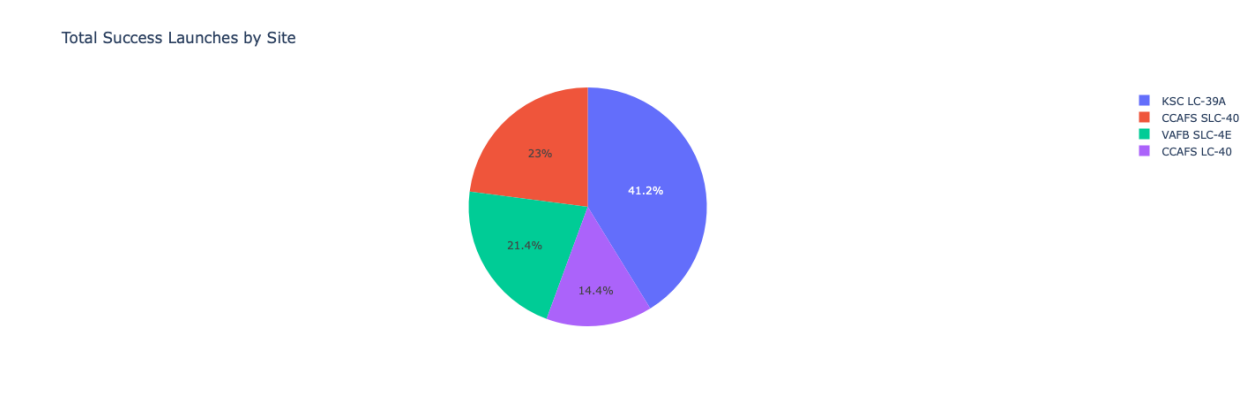



Section 4
Build a Dashboard with Plotly Dash

Dashboard for all launche sites

- Show the screenshot of launch success count for all sites, in a piechart

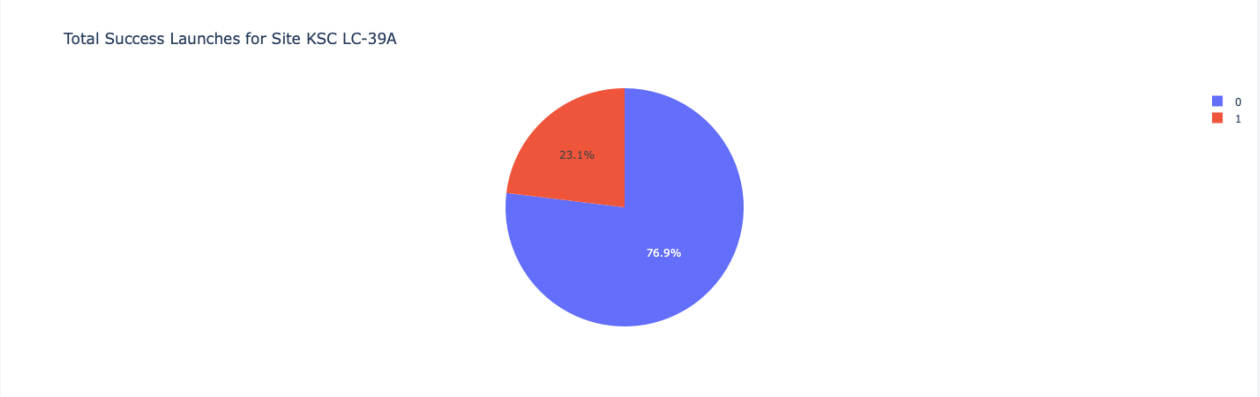
The chart clearly shows that KSC LC-39A has the most successful launches (41.2%).



Dashboard for the launch site with highest success

- Show the screenshot of the piechart for the launch site with highest launch success ratio

This chart shows that KSC LC-39A has the highest launch success rate (76.9%).



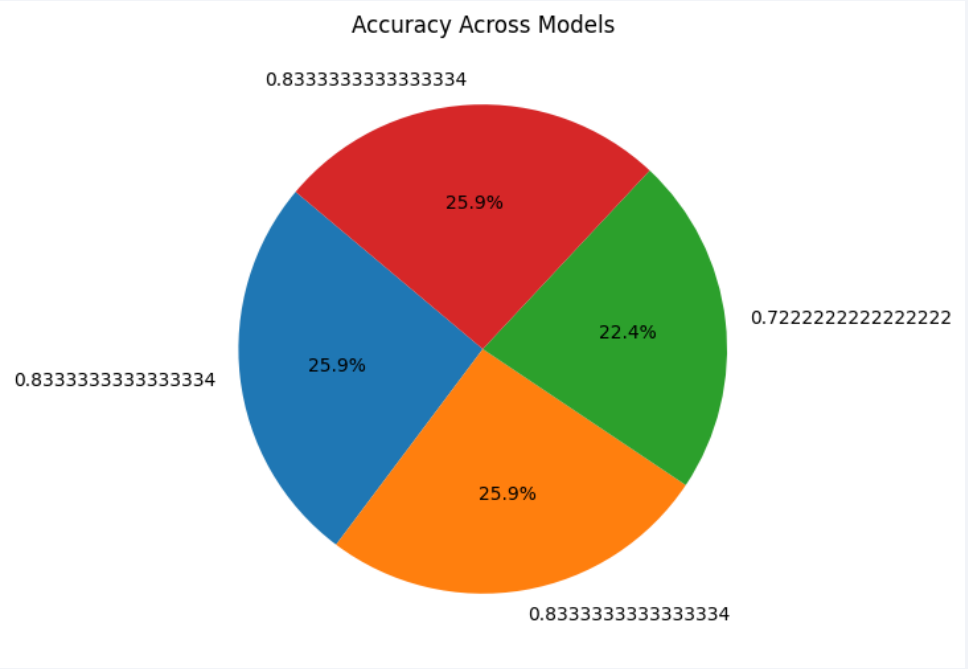
Section 5

Predictive Analysis (Classification)

Classification Accuracy

- Visualize the built model accuracy for all built classification models, in a bar chart. Find which model has the highest classification accuracy.

The results show that logistic regression, SVM and KNN have the highest performance.

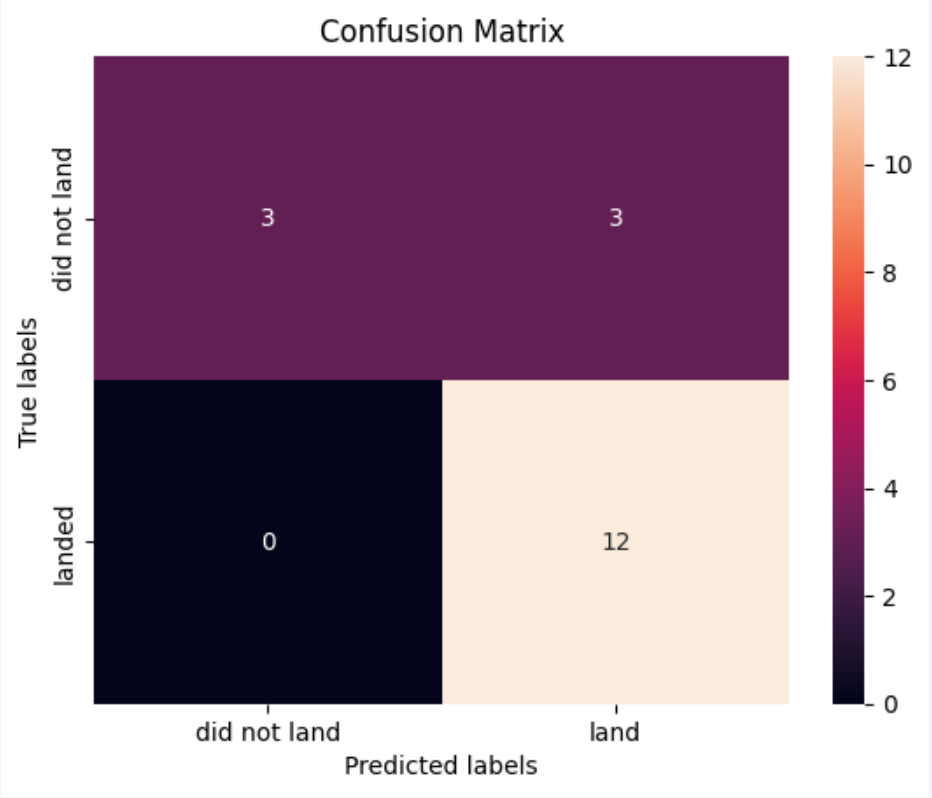


index	LogReg	SVM	Tree	KNN
Jaccard_Score	0.8	0.8	0.8	0.8
F1_Score	0.888888888888889	0.888888888888889	0.888888888888889	0.888888888888889
Accuracy	0.8333333333333334	0.8333333333333334	0.7222222222222222	0.8333333333333334

Confusion Matrix

- Show the confusion matrix of the best performing model with an explanation

The confusion Matrix for a high-performing model such as KNN shows 12 cases are true positives, 3 are true negatives, 3 are false positives and zero are false negatives.



Conclusions

- Logistic regression, SVM and KNN models performed equally well and high for this dataset.
- Decision Tree Model is the lowest performing model for this dataset.
- Launches associated with a low payload mass demonstrate better results than launches with a larger payload mass.
- Most of launch sites are in proximity to the Equator line and all the sites are in very close proximity to the coastline.
- The success rate of launches has significantly increased over the years.
- KSC LC-39A has the highest success rate of the launches from all the sites.

Thank you!