# Space X Falcon 9 Launch Analysis

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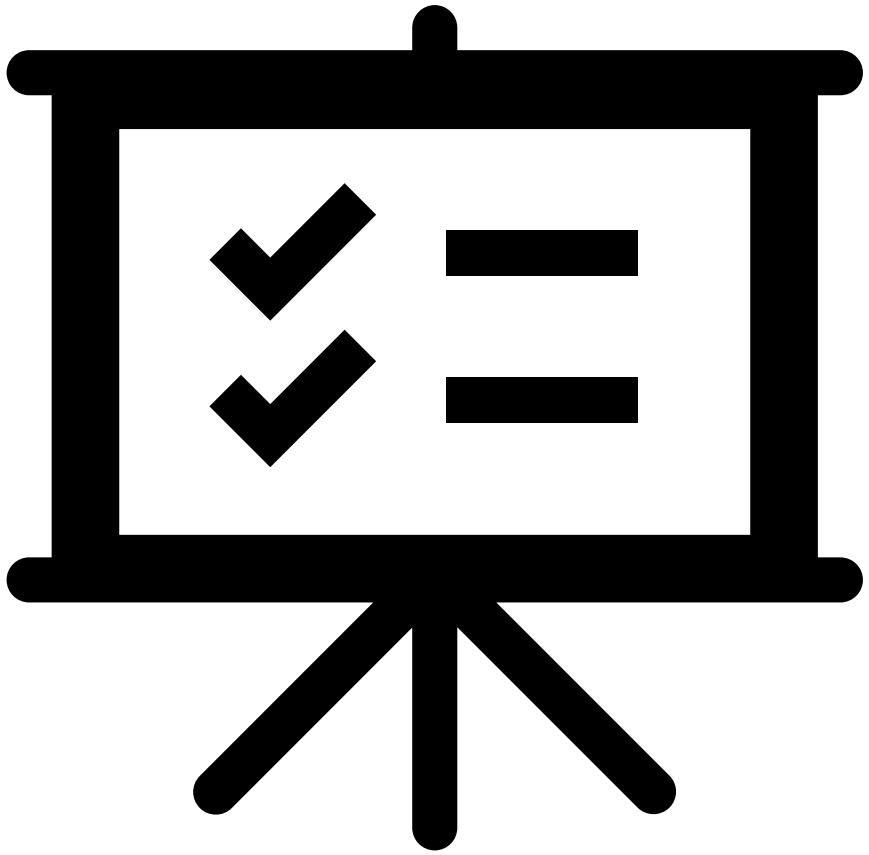


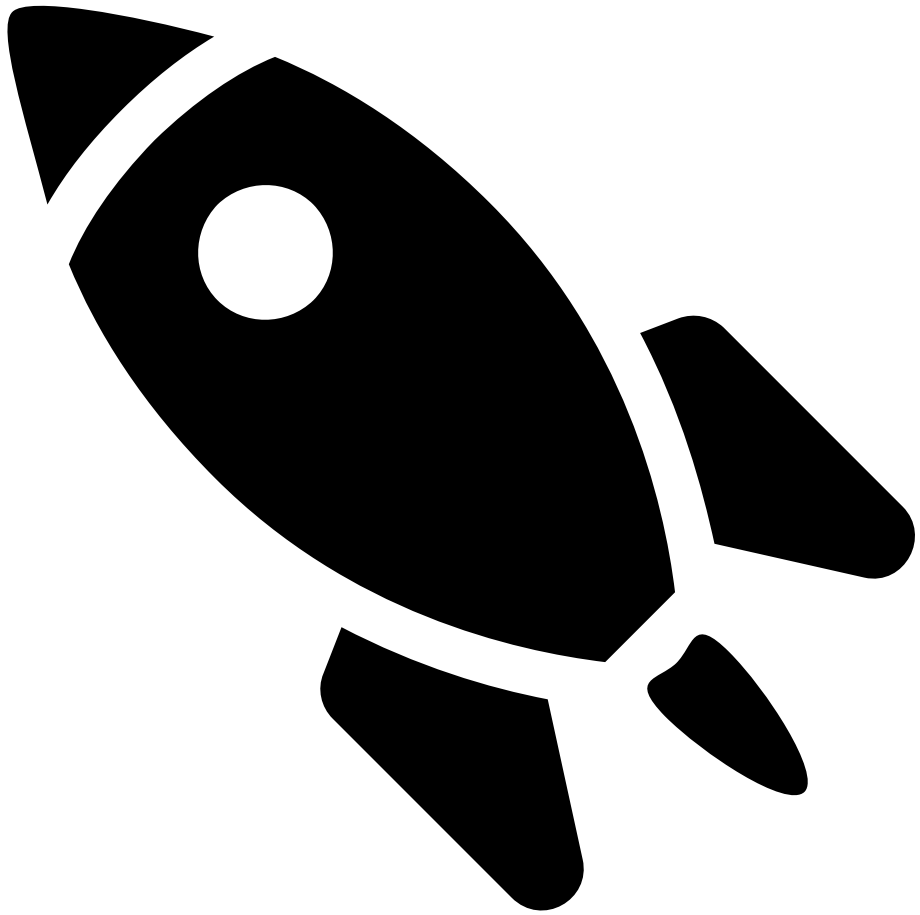
# EXECUTIVE SUMMARY

- We used data analysis methodologies to predict if a Space X Falcon 9 first-stage landing will be successful.
- Data collection and wrangling was necessary to conduct exploratory and predictive analyses.
- Exploratory Data Analysis provided insights on the relationship and weigh of variables.
- Geospatial analysis provided insight on common geographic features across launch sites.
- Several statistical models were tested:
  - Logistic Regression
  - SVM
  - Decision Tree
  - KNN

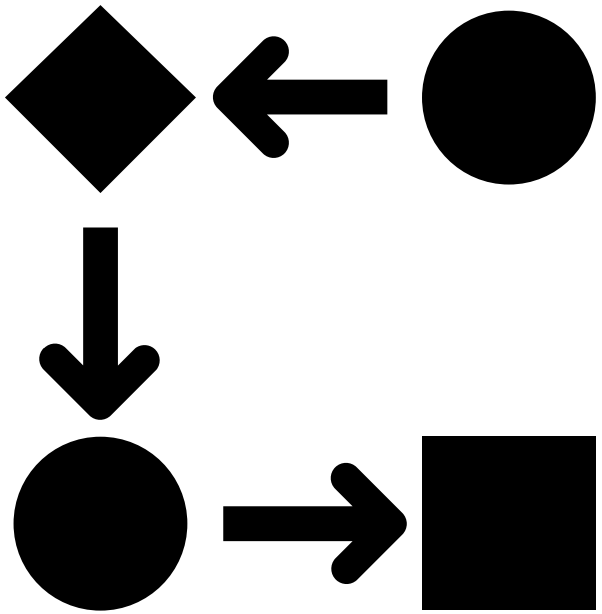
# INTRODUCTION

The project aims to predict if the first-stage Falcon 9 will land successfully. SpaceX reports that Falcon 9 rocket launches on its website with a cost of USD 62 million. Space X reports lower costs as it can reuse the first stage.

The advantage of predicting the landing outcome is that we could determine the cost of a launch. This information can be used if an alternate company wants to bid against SpaceX for a rocket launch.



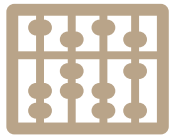
# Methodology



# METHODOLOGY OVERVIEW

- Data collection: API and web-scrapping.
- Data wrangling:
  - Exploratory Data Analysis (EDA) to conduct initial calculations to find preliminary patterns and determine how variables influence the launching outcome.
  - Tools: SQL, Pandas, Matplotlib
- Create interactive visuals for further exploratory analysis and data manipulation:
  - Geospatial visualization: Folium
  - Interactive analytics dashboard: Plotly Dash
- Machine Learning prediction models.

# Methodology: API Data Collection (Notebook)



## Preliminary steps

Import libraries.

Define functions to obtain data from API (https://api.spacexdata.com/v4/launches/past)

Convert JSON file into a pandas data frame.

## Data cleaning

Select subsets of data that are relevant for the anaylsis.

Change the date_utc format to a datetime data type.

## Create final data frame

Create empty lists corresponding to the data we will use for the analysis.

Use the defined functions to extract the desired values.

Create a dictionary using the lists as values.

Create a data frame using the dictionary.

# Methodology: Data Collection and Wrangling

With the resulting data frame, the next step was to deal with the NaN values in the PayloadMass column.

[27]:

| | FlightNumber | Date | BoosterVersion | PayloadMass | Orbit | LaunchSite | Outcome | Flights | GridFins | Reused | Legs | LandingPad | Block | ReusedCount | Serial | Longitude | Latitude |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **4** | 1 | 2010-06-04 | Falcon 9 | NaN | LEO | CCSFS SLC 40 | None None | 1 | False | False | False | None | 1.0 | 0 | B0003 | -80.577366 | 28.561857 |
| **5** | 2 | 2012-05-22 | Falcon 9 | 525.0 | LEO | CCSFS SLC 40 | None None | 1 | False | False | False | None | 1.0 | 0 | B0005 | -80.577366 | 28.561857 |
| **6** | 3 | 2013-03-01 | Falcon 9 | 677.0 | ISS | CCSFS SLC 40 | None None | 1 | False | False | False | None | 1.0 | 0 | B0007 | -80.577366 | 28.561857 |
| **7** | 4 | 2013-09-29 | Falcon 9 | 500.0 | PO | VAFB SLC 4E | False Ocean | 1 | False | False | False | None | 1.0 | 0 | B1003 | -120.610829 | 34.632093 |
| **8** | 5 | 2013-12-03 | Falcon 9 | 3170.0 | GTO | CCSFS SLC 40 | None None | 1 | False | False | False | None | 1.0 | 0 | B1004 | -80.577366 | 28.561857 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **89** | 86 | 2020-09-03 | Falcon 9 | 15600.0 | VLEO | KSC LC 39A | True ASDS | 2 | True | True | True | 5e9e3032383ecb6bb234e7ca | 5.0 | 12 | B1060 | -80.603956 | 28.608058 |
| **90** | 87 | 2020-10-06 | Falcon 9 | 15600.0 | VLEO | KSC LC 39A | True ASDS | 3 | True | True | True | 5e9e3032383ecb6bb234e7ca | 5.0 | 13 | B1058 | -80.603956 | 28.608058 |
| **91** | 88 | 2020-10-18 | Falcon 9 | 15600.0 | VLEO | KSC LC 39A | True ASDS | 6 | True | True | True | 5e9e3032383ecb6bb234e7ca | 5.0 | 12 | B1051 | -80.603956 | 28.608058 |
| **92** | 89 | 2020-10-24 | Falcon 9 | 15600.0 | VLEO | CCSFS SLC 40 | True ASDS | 3 | True | True | True | 5e9e3033383ecbb9e534e7cc | 5.0 | 12 | B1060 | -80.577366 | 28.561857 |
| **93** | 90 | 2020-11-05 | Falcon 9 | 3681.0 | MEO | CCSFS SLC 40 | True ASDS | 1 | True | False | True | 5e9e3032383ecb6bb234e7ca | 5.0 | 8 | B1062 | -80.577366 | 28.561857 |

90 rows × 17 columns

[60]:

```
# Calculate the mean value of PayloadMass column
PMmean = data_falcon9['PayloadMass'].mean()
# Replace the np.nan values with its mean value
data_falcon9['PayloadMass'] = data_falcon9['PayloadMass'].replace(np.nan, PMmean)
data_falcon9.isnull().sum()
```

[60]:

```
FlightNumber      0
Date              0
BoosterVersion    0
PayloadMass       0
Orbit             0
LaunchSite        0
Outcome           0
Flights           0
GridFins          0
Reused            0
Legs              0
LandingPad       26
Block             0
ReusedCount       0
Serial            0
Longitude         0
Latitude          0
dtype: int64
```

# Methodology: Web Scrapping Data Collection (Notebook)

## Preliminary steps

Import libraries.

Define functions to process tables after scraping the wiki site.

Request the wiki site (https://en.wikipedia.org/w/index.php?title=List_of_Falcon_9_and_Falcon_Heavy_launches&oldid=1027686922) and create BeautifulSoup objecto to obtain data.

## Extract table data

Use defined functions to extract data from the target table.

Create a list based on the table's headers.

## Create final data frame

Use the list as keys to create a dictionary with no values.

Fill the dictionaries values by parsing the table data.

Create a data frame using the dictionary.

# Methodology: EDA and Interactive Visual Analytics

SQL

I used SQL to further organize data and obtain useful information regarding launching events.

Libraries

I used several libraries to visualize and analyze data:

- Pandas: Organize and manipulate data.
- Matplotlib: Allowed me to ply data.
- Seaborn: Render visuals and analyze variables' relationships.
- Folium: Visualize geospatial data.
- Plotly Dash: Create an interactive dashboard to analyze data.

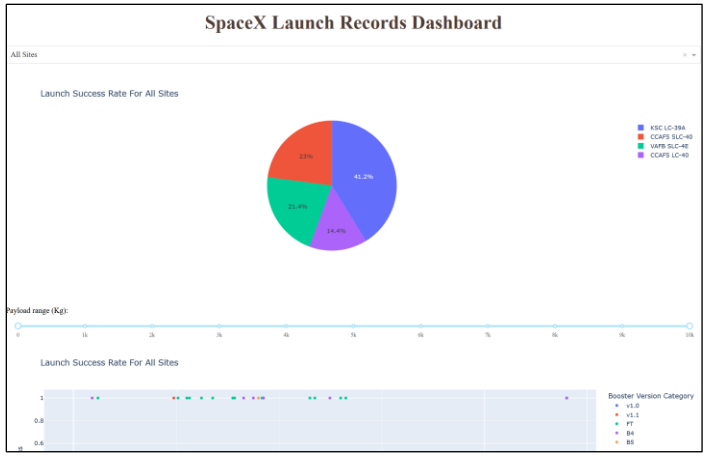
# Methodology: EDA with Pandas/Matplotlib, SQL, and Visual Analytics

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

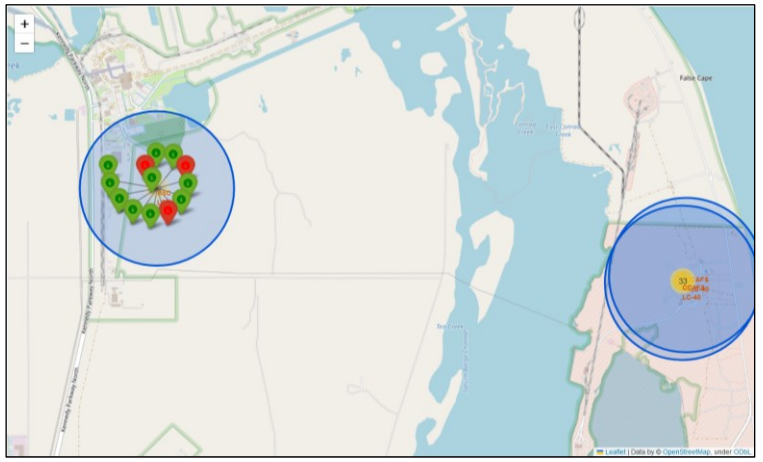
```
[17]: %sql SELECT BOOSTER_VERSION FROM SPACEXTBL WHERE PAYLOAD_MASS__KG_ = (SELECT MAX(PAYLOAD_MASS__KG_) FROM SPACEXTBL)
 * sqlite:///my_data1.db
Done.
```

| [17]: Booster_Version |
|---|
| F9 B5 B1048.4 |
| F9 B5 B1049.4 |
| F9 B5 B1051.3 |
| F9 B5 B1056.4 |
| F9 B5 B1048.5 |
| F9 B5 B1051.4 |
| F9 B5 B1049.5 |
| F9 B5 B1060.2 |
| F9 B5 B1058.3 |
| F9 B5 B1051.6 |
| F9 B5 B1060.3 |
| F9 B5 B1049.7 |

SQL sample

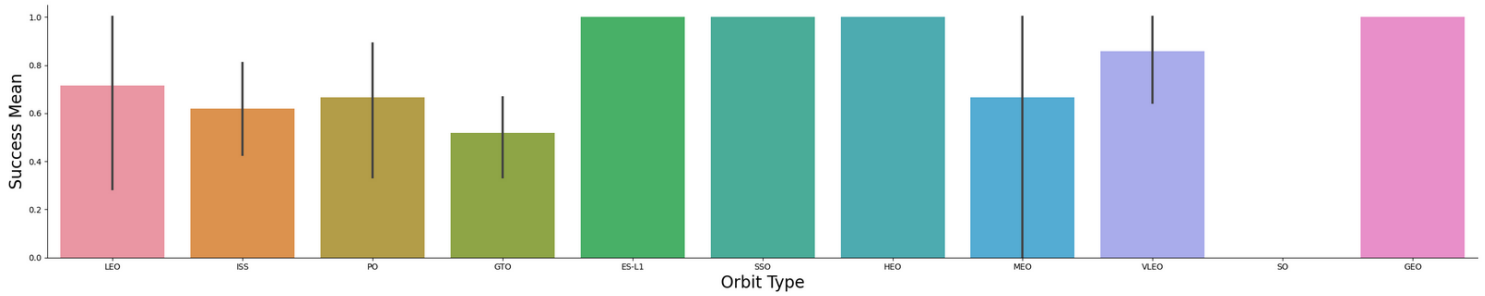



Dashboard overview



Folium sample

```
[11]: sns.catplot(x="Orbit",y="Class", kind="bar",data=df, aspect=5)
plt.xlabel("Orbit Type",fontsize=20)
plt.ylabel("Success Mean",fontsize=20)
plt.show()
```

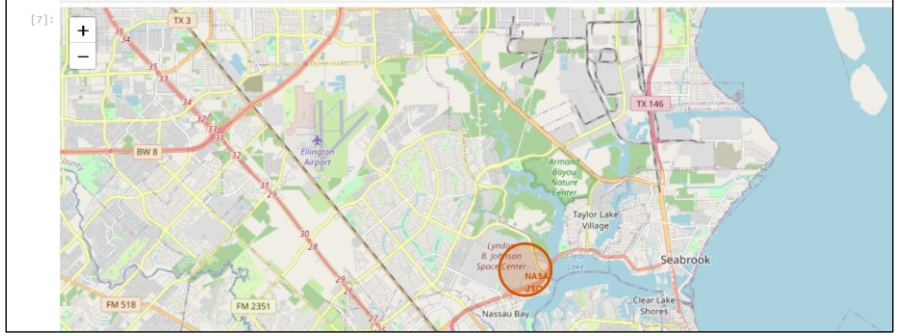



Matplotlib and seaborne sample

# Folium Peculiarities

- To elaborate more interactive and useful charts, I had to create additional elements:
  - Icons
  - Colored markers
  - Clusters
  - Lines

```
[7]: # Create a blue circle at NASA Johnson Space Center's coordinate with a popup label showing its name
circle = folium.Circle(nasa_coordinate, radius=1000, color='#d35400', fill=True).add_child(folium.Popup('NASA Johnson Space Center'))
# Create a blue circle at NASA Johnson Space Center's coordinate with a icon showing its name
marker = folium.map.Marker(
    nasa_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>' % 'NASA JSC',
        )
    )
site_map.add_child(circle)
site_map.add_child(marker)
```




Circle and name tags

```
[11]: # Apply a function to check the value of `class` column
# If class=1, marker_color value will be green
# If class=0, marker_color value will be red

def assign_marker_color(launch_outcome):
    if launch_outcome == 1:
        return 'green'
    else:
        return 'red'

spacex_df['marker_color'] = spacex_df['class'].apply(assign_marker_color)
spacex_df.tail(10)
```

[11]:

| | Launch Site | Lat | Long | class | marker_color |
|---|---|---|---|---|---|
| 46 | KSC LC-39A | 28.573255 | -80.646895 | 1 | green |
| 47 | KSC LC-39A | 28.573255 | -80.646895 | 1 | green |
| 48 | KSC LC-39A | 28.573255 | -80.646895 | 1 | green |
| 49 | CCAFS SLC-40 | 28.563197 | -80.576820 | 1 | green |
| 50 | CCAFS SLC-40 | 28.563197 | -80.576820 | 1 | green |
| 51 | CCAFS SLC-40 | 28.563197 | -80.576820 | 0 | red |
| 52 | CCAFS SLC-40 | 28.563197 | -80.576820 | 0 | red |
| 53 | CCAFS SLC-40 | 28.563197 | -80.576820 | 0 | red |
| 54 | CCAFS SLC-40 | 28.563197 | -80.576820 | 1 | green |
| 55 | CCAFS SLC-40 | 28.563197 | -80.576820 | 0 | red |

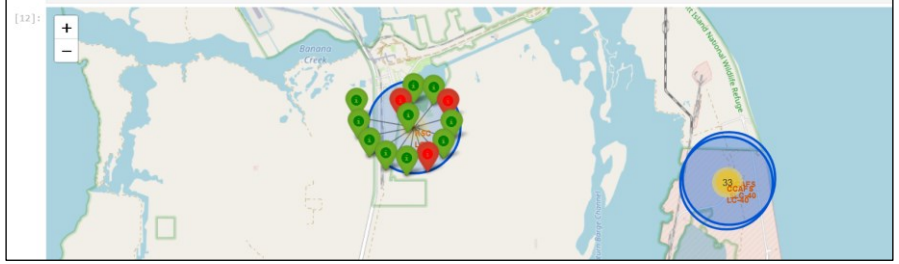
Creating color markers

```
[12]: # 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 index, record in spacex_df.iterrows():
    # TODO: Create and add a Marker cluster to the site map
    # marker = folium.Marker(...)

    folium.Marker(
        location=[record['Lat'], record['Long']],
        icon=folium.Icon(color=record['marker_color'], icon_color=record['marker_color'],
        popup=record['class'])
    ).add_to(marker_cluster)

site_map
```

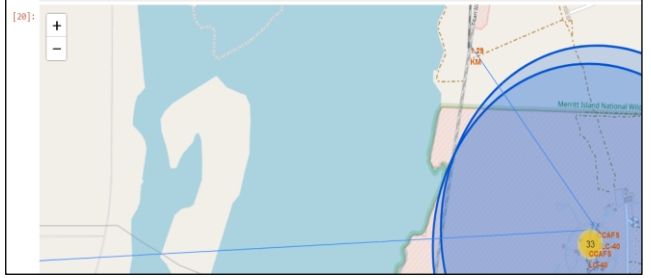



Clusters

```
[20]: launch_site_lat2, launch_site_lon2 = 28.563197, -80.576820
railway_lat, railway_lon = 28.57225, -80.58513  # coords for NASA Railway
distance_railway = calculate_distance(launch_site_lat2, launch_site_lon2, railway_lat, railway_lon)
distance_railway

distance_marker3 = folium.Marker(
   location=[railway_lat, railway_lon],
   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_railway),
       )
   )

line3=folium.PolyLine(locations=[[launch_site_lat2, launch_site_lon2], [railway_lat, railway_lon]], weight=1)
site_map.add_child(line3).add_child(distance_marker3)
```




Lines

# Methodology: Predictive Analysis

1. Standardize and normalize data.
2. Split the data into test and training sets for the machine learning models.
3. After training the model, conduct Grid Search to establish the best hyperparameters for the algorithms.
4. Train and test the following methods:
    - Logistic Regression (LR)
    - Support Vector Machine (SVM)
    - Decision Tree Classifier
    - K-Nearest Neighbors (KNN)
5. Determine the accuracy of each model and render a confusion matrix to determine the best predictive model for our data.

# Methodology: Predictive Analysis

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

[28]:
```
# students get this
X = preprocessing.StandardScaler().fit_transform(X)
X
```

[28]:
```
array([[-1.71291154e+00, -5.29526321e-17, -6.53912840e-01, ...,
        -8.35531692e-01,  1.93309133e+00, -1.93309133e+00],
       [-1.67441914e+00, -1.19523159e+00, -6.53912840e-01, ...,
        -8.35531692e-01,  1.93309133e+00, -1.93309133e+00],
       [-1.63592675e+00, -1.16267307e+00, -6.53912840e-01, ...,
        -8.35531692e-01,  1.93309133e+00, -1.93309133e+00],
       ...,
       [ 1.63592675e+00,  1.99100483e+00,  3.49060516e+00, ...,
         1.19684269e+00, -5.17306132e-01,  5.17306132e-01],
       [ 1.67441914e+00,  1.99100483e+00,  1.00389436e+00, ...,
         1.19684269e+00, -5.17306132e-01,  5.17306132e-01],
       [ 1.71291154e+00, -5.19213966e-01, -6.53912840e-01, ...,
        -8.35531692e-01, -5.17306132e-01,  5.17306132e-01]])
```

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`

[31]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=2)
```

we can see we only have 18 test samples.

[32]:
```
Y_test.shape
```

[32]:
```
(18,)
```

Standardizing and splitting procedures

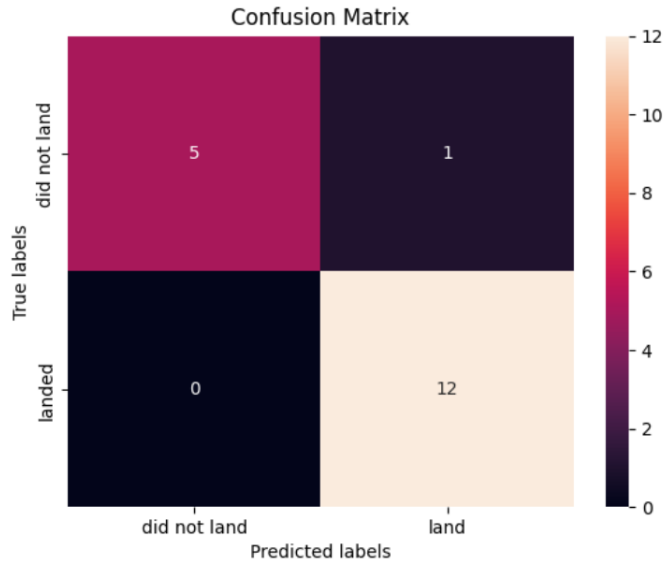
Calculate the accuracy on the test data using the method `score`:

[41]:
```
print('score on train data: ', logreg_cv.score(X_train, Y_train))  # R² score on train data
print('score on test data : ', logreg_cv.score(X_test, Y_test))  # R² score on test data
```

```
score on train data:  0.875
score on test data :  0.9444444444444444
```

Lets look at the confusion matrix:

[42]:
```
yhat=logreg_cv.predict(X_test)
plot_confusion_matrix(Y_test,yhat)
```

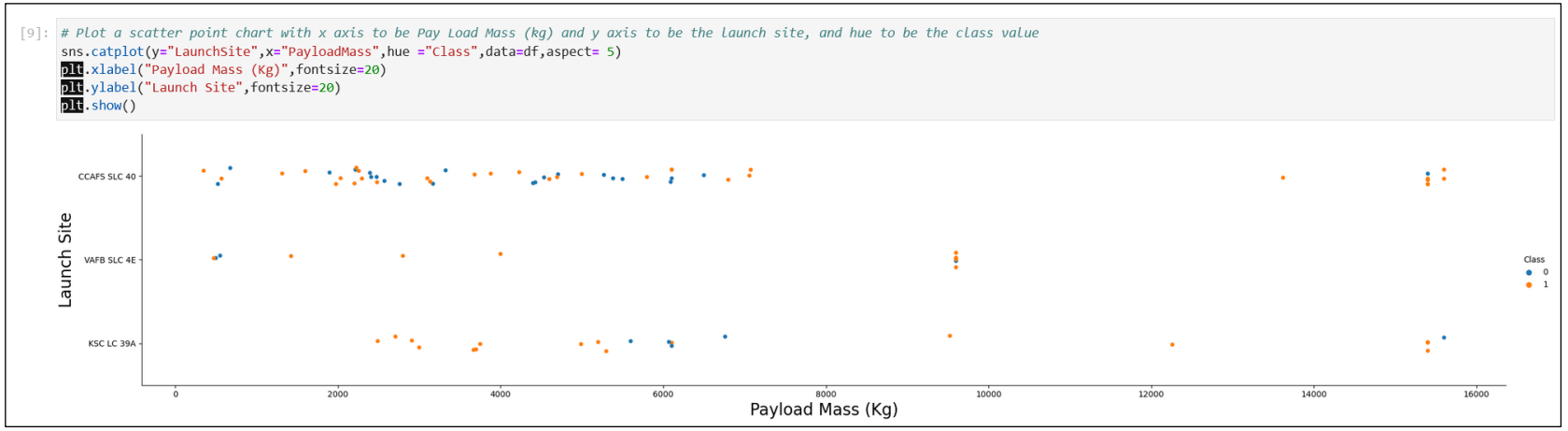



LR testing and confusion matrix example


RESULTS

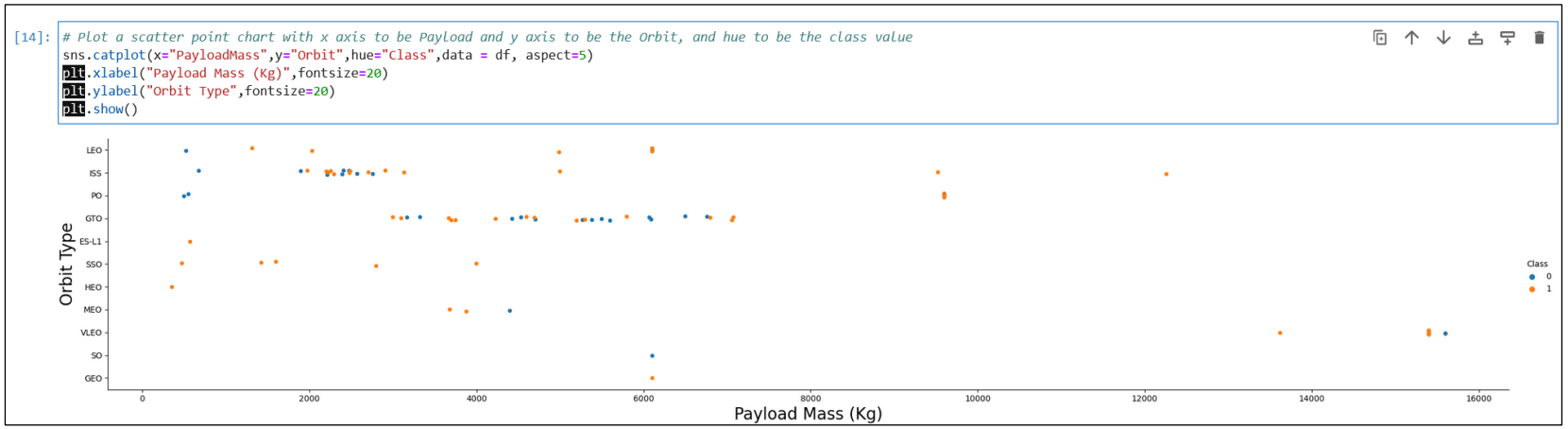
# EDA with Visualizations (Notebooks 1 & 2)

```
[9]: # 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("Payload Mass (Kg)",fontsize=20)
plt.ylabel("Launch Site",fontsize=20)
plt.show()
```




There are no rockets launched for heavy payload mass (greater than 10000Kg) for the VAFB-SLC launch site

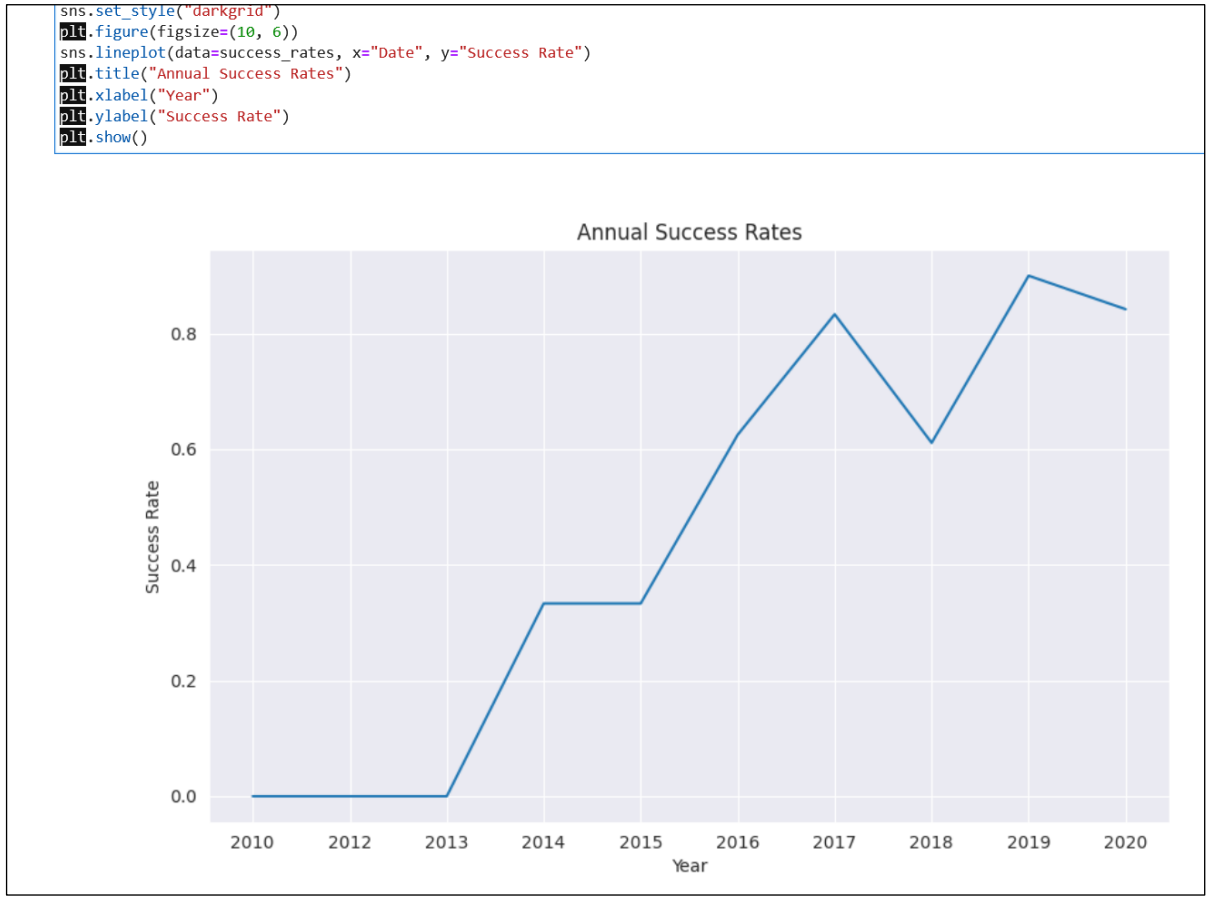
```
[14]: # Plot a scatter point chart with x axis to be Payload and y axis to be the Orbit, and hue to be the class value
sns.catplot(x="PayloadMass",y="Orbit",hue="Class",data = df, aspect=5)
plt.xlabel("Payload Mass (Kg)",fontsize=20)
plt.ylabel("Orbit Type",fontsize=20)
plt.show()
```




With heavy payloads the successful landing or positive landing rate are more for Polar, LEO and ISS

# EDA with Visualizations

```
sns.set_style("darkgrid")
plt.figure(figsize=(10, 6))
sns.lineplot(data=success_rates, x="Date", y="Success Rate")
plt.title("Annual Success Rates")
plt.xlabel("Year")
plt.ylabel("Success Rate")
plt.show()
```




Sucess rate since 2013 kept increasing, had a decrease in 2018, and a second fall in 2020.

# EDA with SQL (Notebook)

The estimations from SQL queries mainly provided an overview of our data and general insights on some of the variables.

```
[10]: %sql SELECT AVG(PAYLOAD_MASS__KG_) FROM SPACEXTBL WHERE BOOSTER_VERSION='F9 v1.1'
 * sqlite:///my_data1.db
Done.
[10]: AVG(PAYLOAD_MASS__KG_)
2928.4
```

Average payload mass carried by Falcon 9 booster

```
[47]: %sql SELECT BOOSTER_VERSION FROM SPACEXTBL WHERE PAYLOAD_MASS__KG_ between 4000 and 6000 AND "LANDING _OUTCOME"='Success (drone ship)'
 * sqlite:///my_data1.db
Done.
[47]: Booster_Version
F9 FT B1022
F9 FT B1026
F9 FT B1021.2
F9 FT B1031.2
```

Boosters with success outcome in drone ship and have payload mass greater than 4000 but less than 6000

# EDA with SQL

```
[29]: %sql SELECT "LANDING _OUTCOME", COUNT(*) as COUNT FROM SPACEXTBL \
          WHERE "DATE" BETWEEN '2010-06-04' and '2017-03-20' \
          GROUP BY "LANDING _OUTCOME" ORDER BY 2 DESC;
 * sqlite:///my_data1.db
Done.
```

[29]:

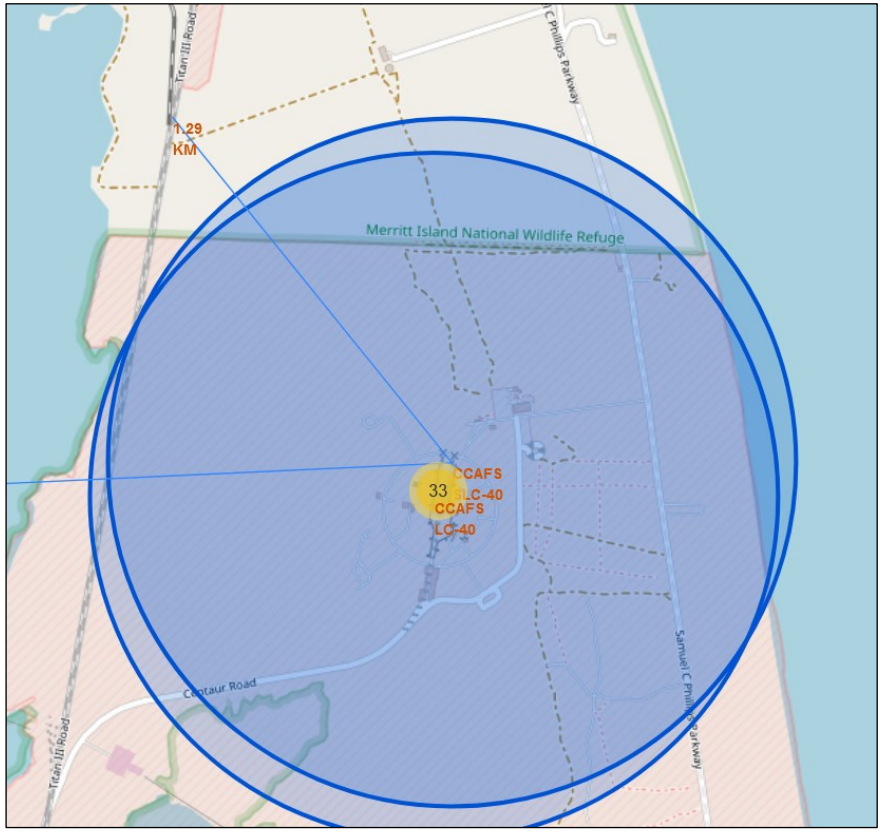
| Landing _Outcome | COUNT |
|---|---|
| No attempt | 10 |
| Success (drone ship) | 5 |
| Failure (drone ship) | 5 |
| Success (ground pad) | 3 |
| Controlled (ocean) | 3 |
| Uncontrolled (ocean) | 2 |
| Failure (parachute) | 2 |
| Precluded (drone ship) | 1 |

Count of successful landing outcomes between June 4, 2010, and March 20, 2017, in descending order

# Geospatial Results (Folium Notebook)

Based on geospatial data:

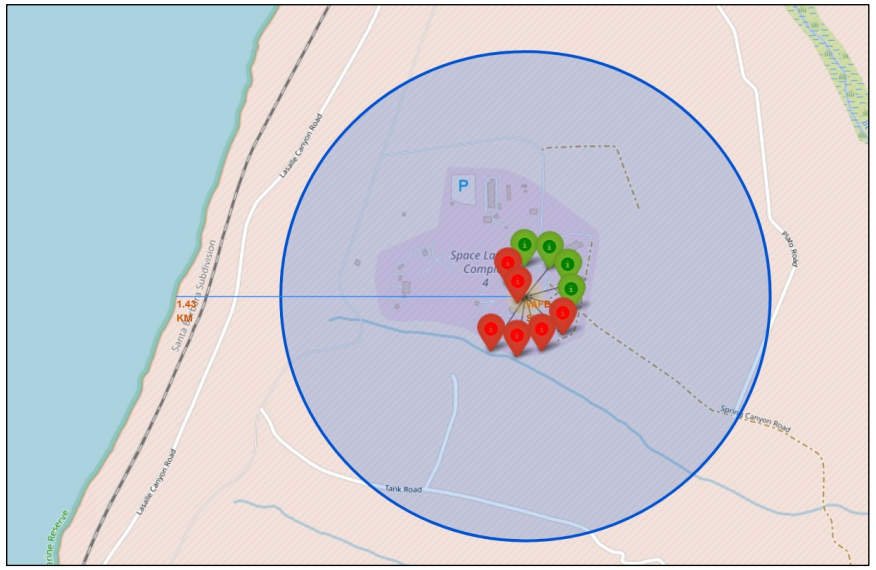
- All launch sites are near railways, likely to transport heavy machinery, pieces, and equipment necessary for the facilities' operations.
- Highways are relatively close to both locations in Florida, but farther away in California.
- All locations are near coastlines.
- And most launch sites are relatively far from cities. The California site is closer to Lompoc.
- Further, airports are close to all three facilities.



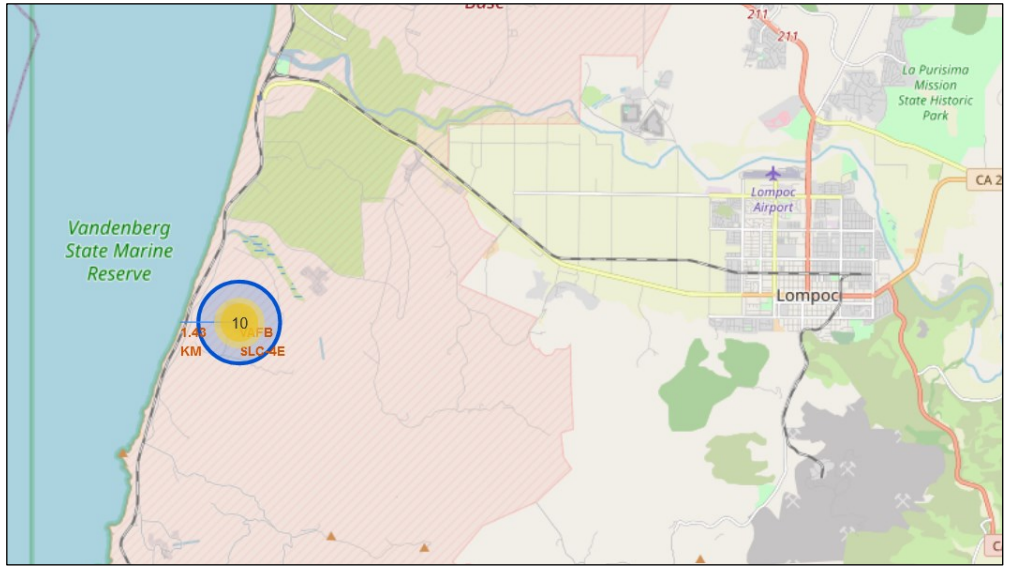

Railway distance from Florida sites.

The coastline is also close to the sites

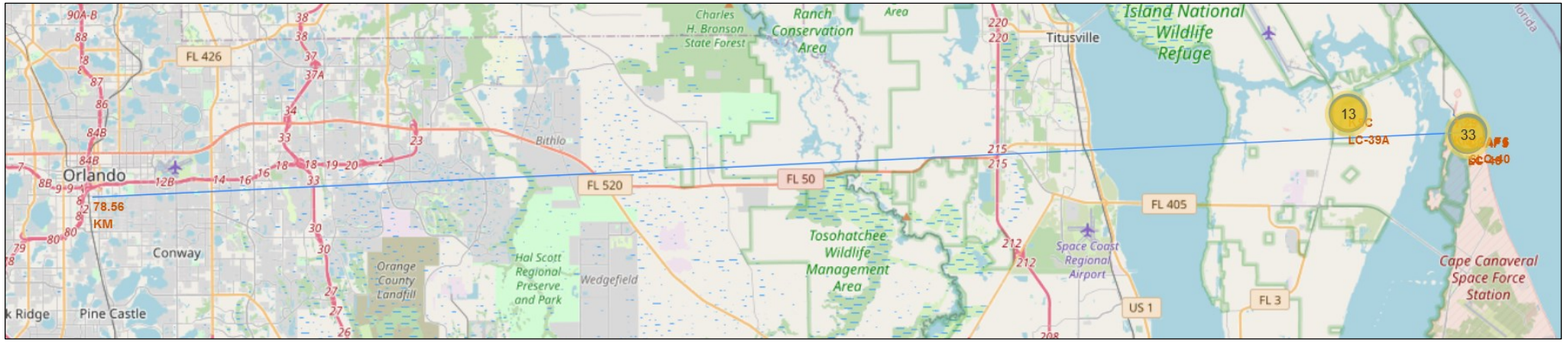
# Geospatial Results (Folium)




Distance to coastline from the California launch site

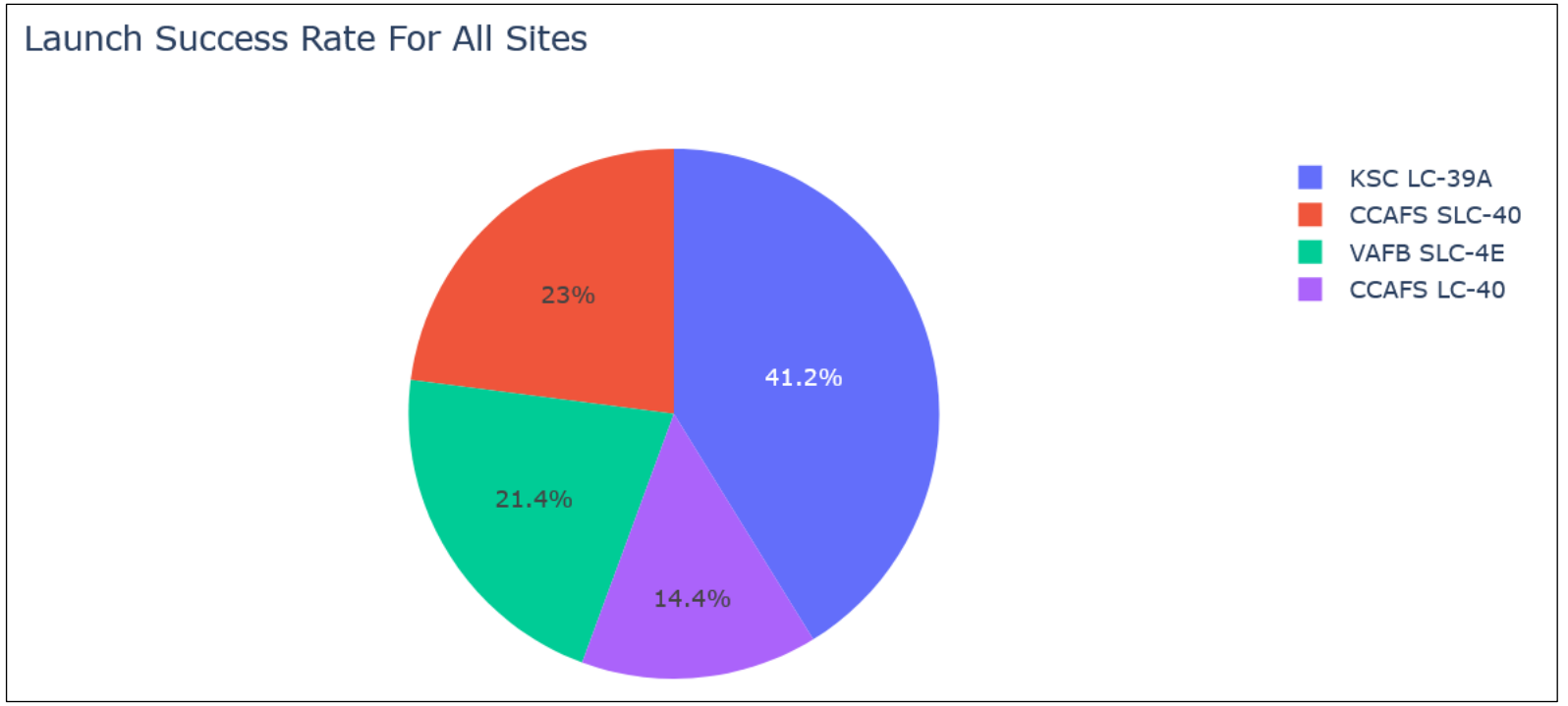



Airport and Lompoc city near VAFB SLC 4E



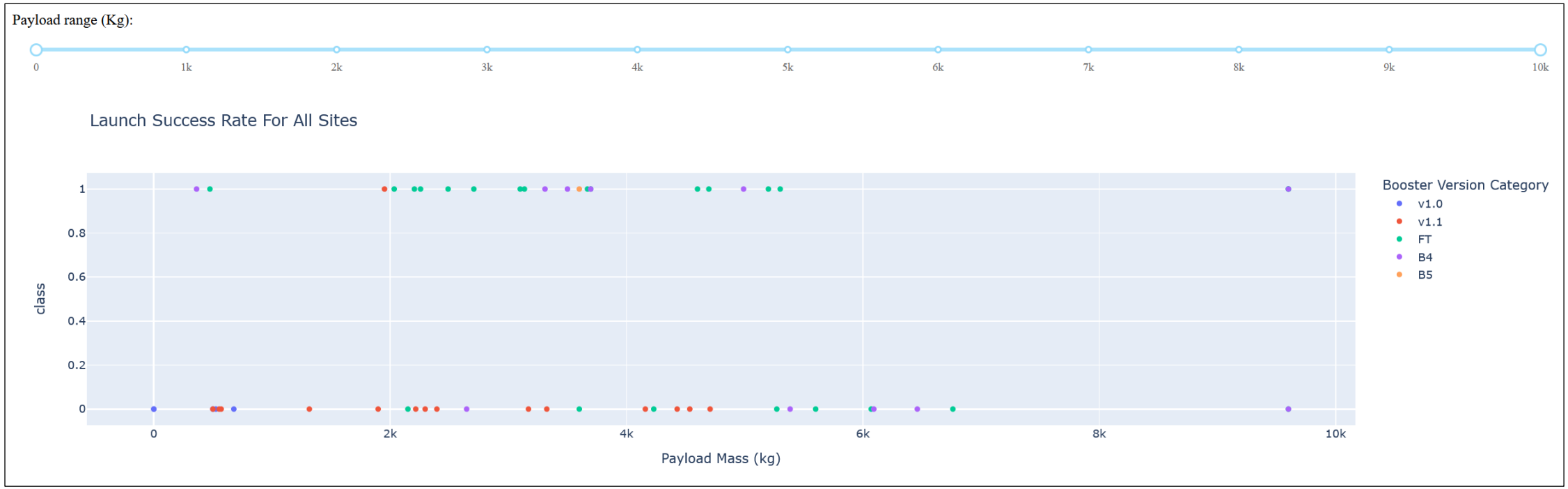

Distance to the nearest large city from a Florida launch site

# Dashboard Results (Link)




KSC LC-39A had the highest success rate compared to all other launch sites.

# Dashboard Results




The success rate of rockets with a payload mass higher than 6K had minimal success rates

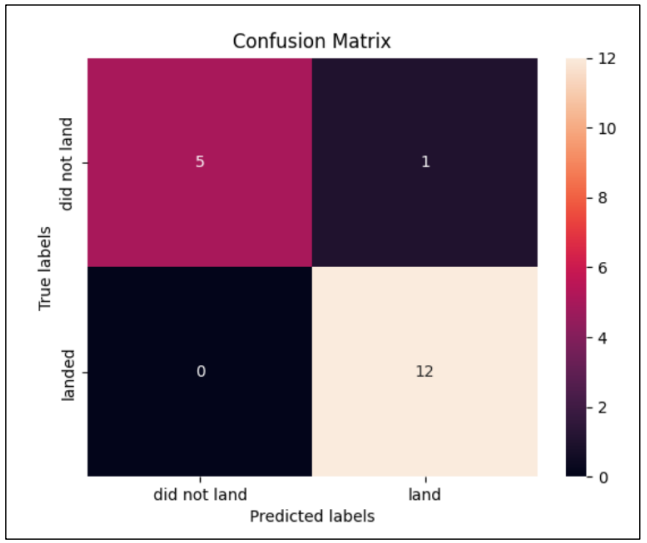

Predictive
Analysis

# Predictive Analysis (Notebook)

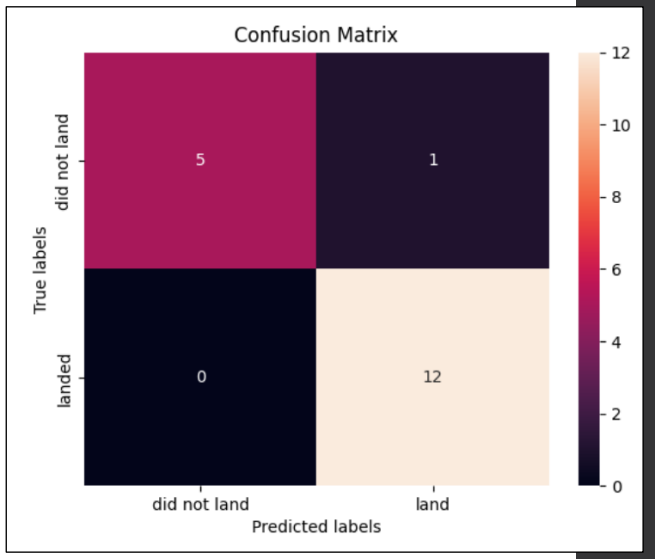
As stated in the methodology section, I prepared the data to run several predictive algorithms (LR, SVM, decision tree, and KNN).

The overall R scores of the predictive methods were as follow:

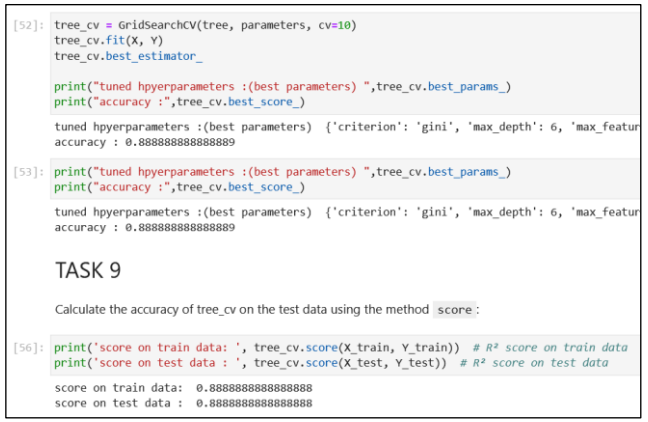
1. Logistic regression: 0.9444
2. Support vector machine: 0.9444
3. Decision tree: 0.888
4. K-Nearest Neighborh: 0.9444



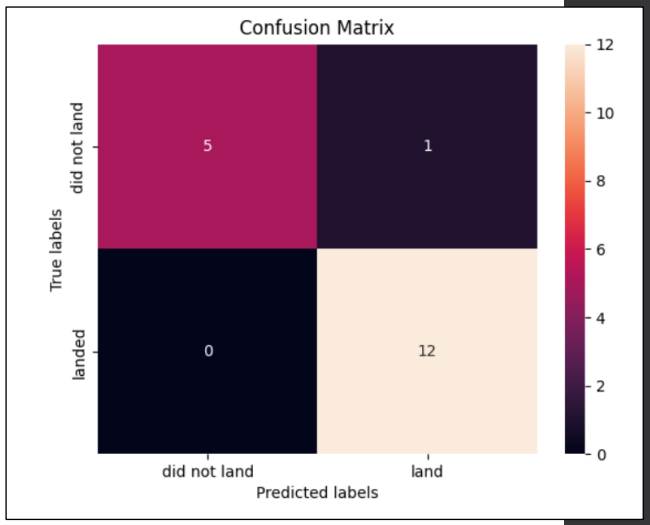

LR




SVM




Decision tree




KNN

# Conclusions

# Conclusions

Based on the EDA and the geospatial data analysis:

- The success rate at a launch site is likely to increase after several launches have taken place in that location.
- KSC LC-39A had the highest success rate compared to all other launch sites.
- There are no rockets launched for heavy payload mass (greater than 10000Kg) for the VAFB-SLC launch site.
- With heavy payloads the successful landing or positive landing rate are more for Polar, LEO and ISS.
- The geographic position of launch sites (near coastlines and railways, and further from urban centers) is highly likely due to safety and logistics.
- LR, SVM, and KNN had high R scores, eliciting high accuracy.
    - However, based on their confusion matrixes, false positives might remain an issue.
    - Thus, future changes might include collecting more data and review feature selection processes.


Thank you