



IBM Developer  
SKILLS NETWORK

# Winning Space Race with Data Science

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# Outline

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

# Executive Summary

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## Summary of methodologies

- Logistic Regression
- Support Vector Machine
- Decision Tree
- K-Nearest Neighbors

Logistic Regression has the highest classification Accuracy

## Summary of all results

- Launch Success rate over 60% since 2016
- First successful landing on a ground pad at 12/12/2015
- Successful missions: 60
- Failed missions: 30
- KSC LC-39A is the site with the highest success rate

# Introduction

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- Prediction if the Falcon 9 first stage will land successfully.
- SpaceX 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 SpaceX can reuse the first stage.
- 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 SpaceX for a rocket launch.



Section 1

# Methodology

# Methodology

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## Executive Summary

- Data collection methodology:
  - Data have been retrieved from SpaceX API
- Perform data wrangling
  - Removing of “Falcon 1 launches” keeping only the Falcon 9 launches.
  - Reset the FlightNumber column
  - Dealing with Missing Values
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
  - Model Selection, Training, Tuning, Evaluation, Interpretation, Deployment

# Data Collection

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- Request to the SpaceX API (<https://api.spacexdata.com/v4/>)
- Web scraping to collect Falcon 9 historical launch records from a Wikipedia page

# Data Collection – SpaceX API

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- Get request to the SpaceX API
- Clean the requested data
- Create a dataframe
- Filter the dataframe to only include Falcon 9 launches
- Dealing with Missing Values

GitHub URL: <https://github.com/xaralabo/falcon/blob/main/jupyter-labs-spacex-data-collection-api.ipynb>



# Data Collection - Scraping

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- Web scraping to collect Falcon 9 historical launch records from a Wikipedia page
- Launch records are stored in a HTML table
- Extract Falcon 9 launch records HTML table from Wikipedia using BeautifulSoup
- Extract all column/variable names from the HTML table header
- Parse the table and convert it into a Pandas data frame
- Export to a CSV file

GitHub URL: <https://github.com/xaralabo/falcon/blob/main/jupyter-labs-webscraping.ipynb>

# Data Wrangling

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Sequentially the following flow:

- Data Collection
- Data Cleaning
- Data Transformation
- Data Validation
- Save Cleaned Data

GitHub URL: <https://github.com/xaralabo/falcon/blob/main/labs-jupyter-spacex-Data%20wrangling.ipynb>

# EDA with Data Visualization

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## Charts for Visualization

- Scatter plot of Flight Number vs. Launch Site
- Scatter plot of Payload vs. Launch Site
- Bar Graph of Payload vs. Launch Site
- Scatter Plot of Flight number vs. Orbit type
- Scatter plot of payload vs. orbit type
- Linear Graph with success Yearly Trend

GitHub: [https://github.com/xaralabo/falcon/blob/main/jupyter-labs-eda-sql-coursera\\_sqlite.ipynb](https://github.com/xaralabo/falcon/blob/main/jupyter-labs-eda-sql-coursera_sqlite.ipynb)

# EDA with SQL

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- `%sql select DISTINCT(Launch_Site) from SPACEXTABLE`
- `%sql select * from SPACEXTABLE WHERE Launch_Site LIKE 'CCA%' LIMIT 5`
- `%sql select sum() from SPACEXTABLE where Customer='NASA (CRS)'`
- `%sql select avg(PAYLOAD_MASS__KG_) from SPACEXTABLE where Booster_Version LIKE 'F9 v1.1'`
- `%sql select min(Date) from SPACEXTABLE where Landing_Outcome='Success'`
- `%sql select Booster_Version from SPACEXTABLE where Booster_Version='Success'`
- `%sql select Mission_Outcome, count(*) from SPACEXTABLE group by Mission_Outcome`
- `%sql select DISTINCT(Booster_Version) from SPACEXTABLE where PAYLOAD_MASS__KG_=(select max(PAYLOAD_MASS__KG_) from SPACEXTABLE)`
- `%sql select substr(Date, 6,2), Landing_Outcome, Booster_Version, Launch_Site from SPACEXTABLE where substr(Date,0,5)='2015'`
- `%sql select Landing_Outcome, count(*) from SPACEXTABLE where date >= '2010-06-04' and date <= '2017-03-20' group by Landing_Outcome`

GitHub: [https://github.com/xaralabo/falcon/blob/main/jupyter-labs-eda-sql-coursera\\_sqllite.ipynb](https://github.com/xaralabo/falcon/blob/main/jupyter-labs-eda-sql-coursera_sqllite.ipynb)

# Build an Interactive Map with Folium

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- All site's location have been added on a map using site's latitude and longitude coordinates
- Highlighted circle area with a text label for each location

GitHub: [https://github.com/xaralabo/falcon/blob/main/lab\\_jupyter\\_launch\\_site\\_location.ipynb](https://github.com/xaralabo/falcon/blob/main/lab_jupyter_launch_site_location.ipynb)

# Build a Dashboard with Plotly Dash

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- Pie chart with the total successful launches count for all sites
- Scatter chart for the correlation between payload and launch success

GitHub: [https://github.com/xaralabo/falcon/blob/main/spacex\\_dash\\_app.py](https://github.com/xaralabo/falcon/blob/main/spacex_dash_app.py)



# Predictive Analysis (Classification)

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- Problem Definition and Data Understanding
- Model Selection (Logistic Regression, Decision Trees, SVM, k-Nearest Neighbors)
- Data Splitting: Divided the dataset into training and testing sets
- Model Training: Trained each model on the training data and used basic evaluation metrics like accuracy to assess initial performance.
- Model Comparison: Analyzed metrics beyond accuracy and confusion matrices
- Model Testing and Deployment

GitHub: [https://github.com/xaralabo/falcon/blob/main/SpaceX\\_Machine%20Learning%20Prediction\\_Part\\_5.ipynb](https://github.com/xaralabo/falcon/blob/main/SpaceX_Machine%20Learning%20Prediction_Part_5.ipynb)

# Results

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- Launch Success rate over 60% since 2016
- First successful landing on a ground pad at 12/12/2015
- Successful missions: 60
- Failed missions: 30
- KSC LC-39A is the site with the highest success rate
- Logistic Regression Model has the highest classification Accuracy



The background of the slide is an abstract composition. It features a dark blue base color. Overlaid on this are numerous diagonal streaks in shades of red and cyan. A faint, light blue grid pattern is also visible, particularly in the lower half of the image. The overall effect is dynamic and technological.

Section 2

# Insights drawn from EDA

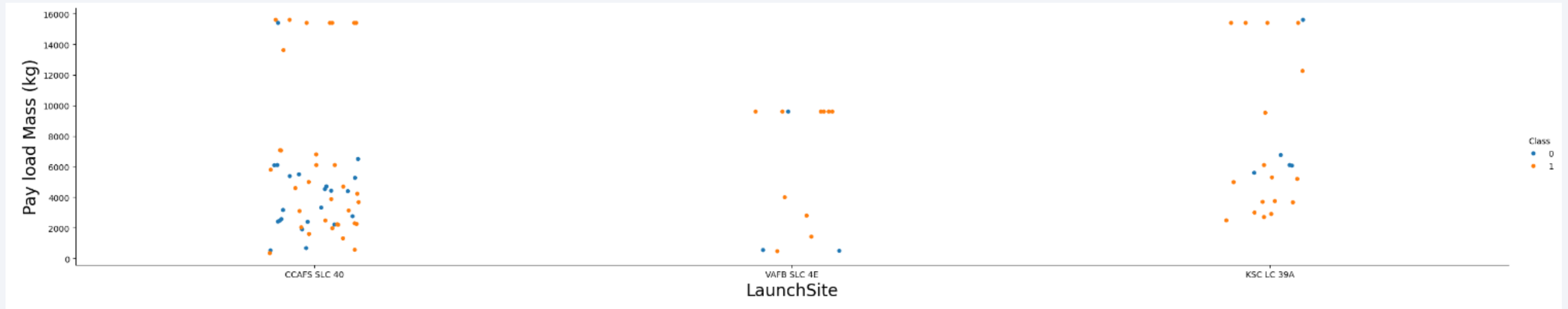


# Flight Number vs. Launch Site

- Scatter plot of Flight Number vs. Launch Site
- FlightNumber (indicating the continuous launch attempts.)
- Blue and Green Colors indicate the Class Hue



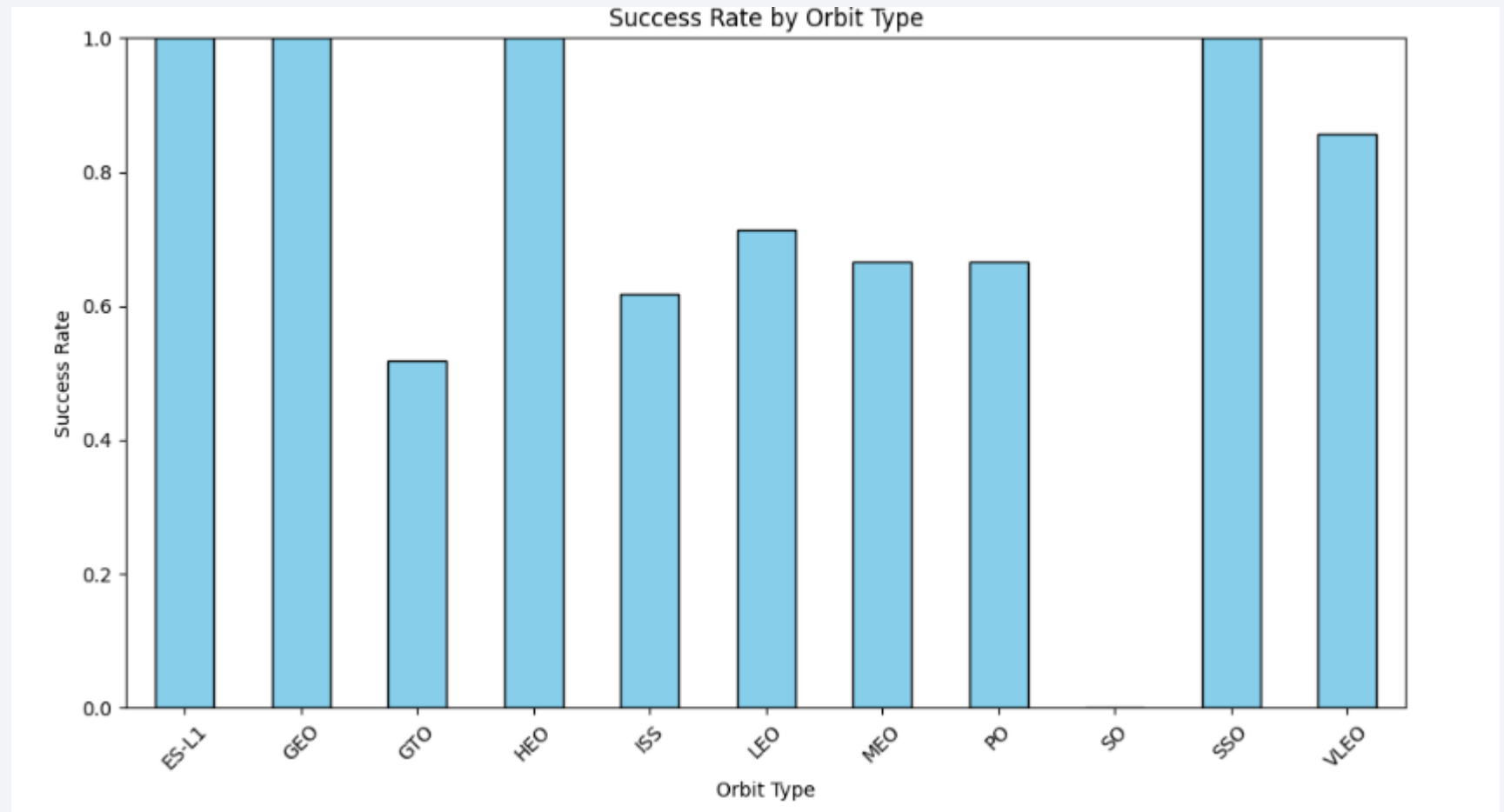
# Payload vs. Launch Site



- Scatter plot of Payload vs. Launch Site
- First Launch Site has the most cases
- Blue and orange colors indicate the class

# Success Rate vs. Orbit Type

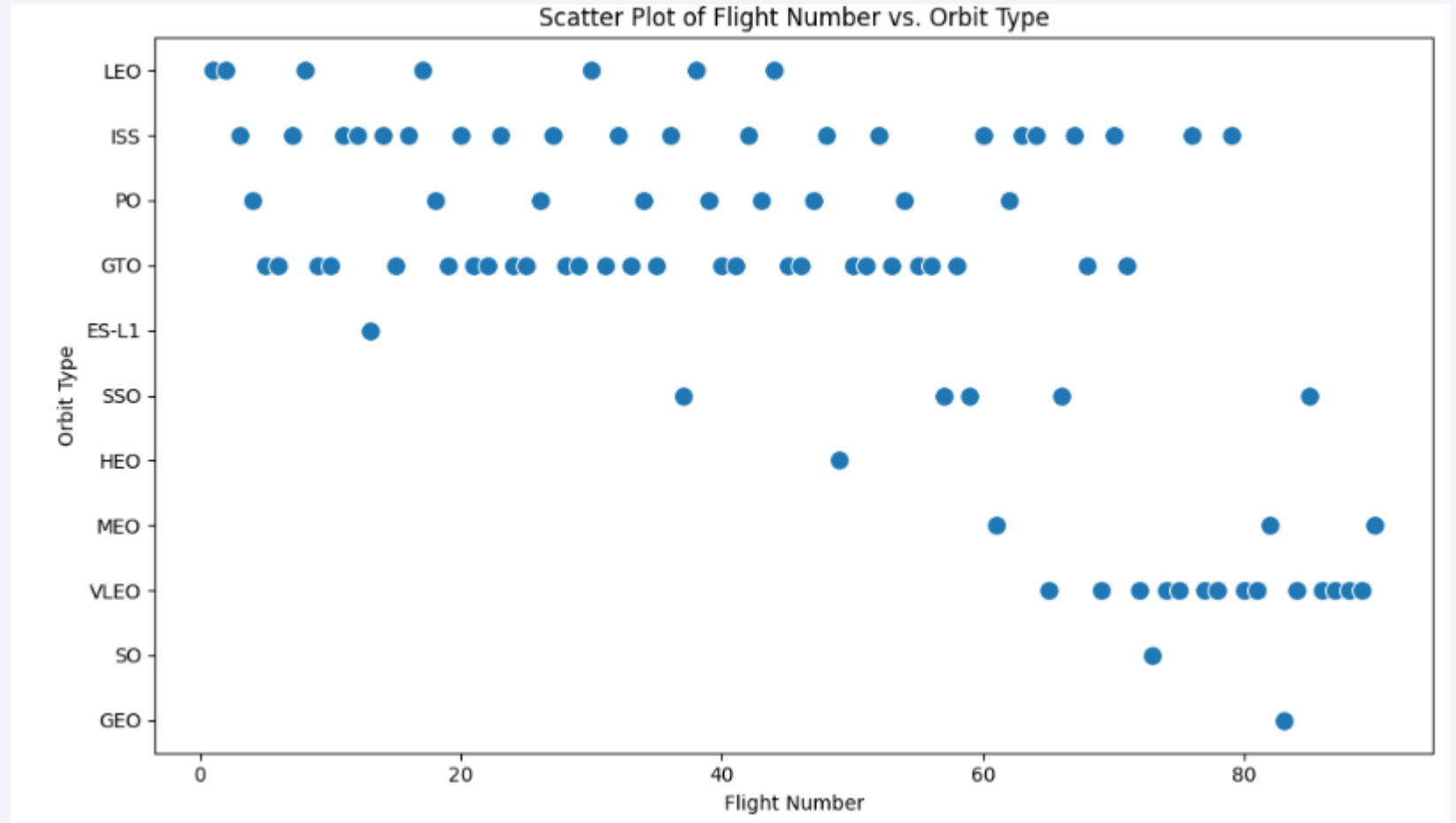
- Four Orbit Types have the highest Success Rate
- SO hasn't any success rate





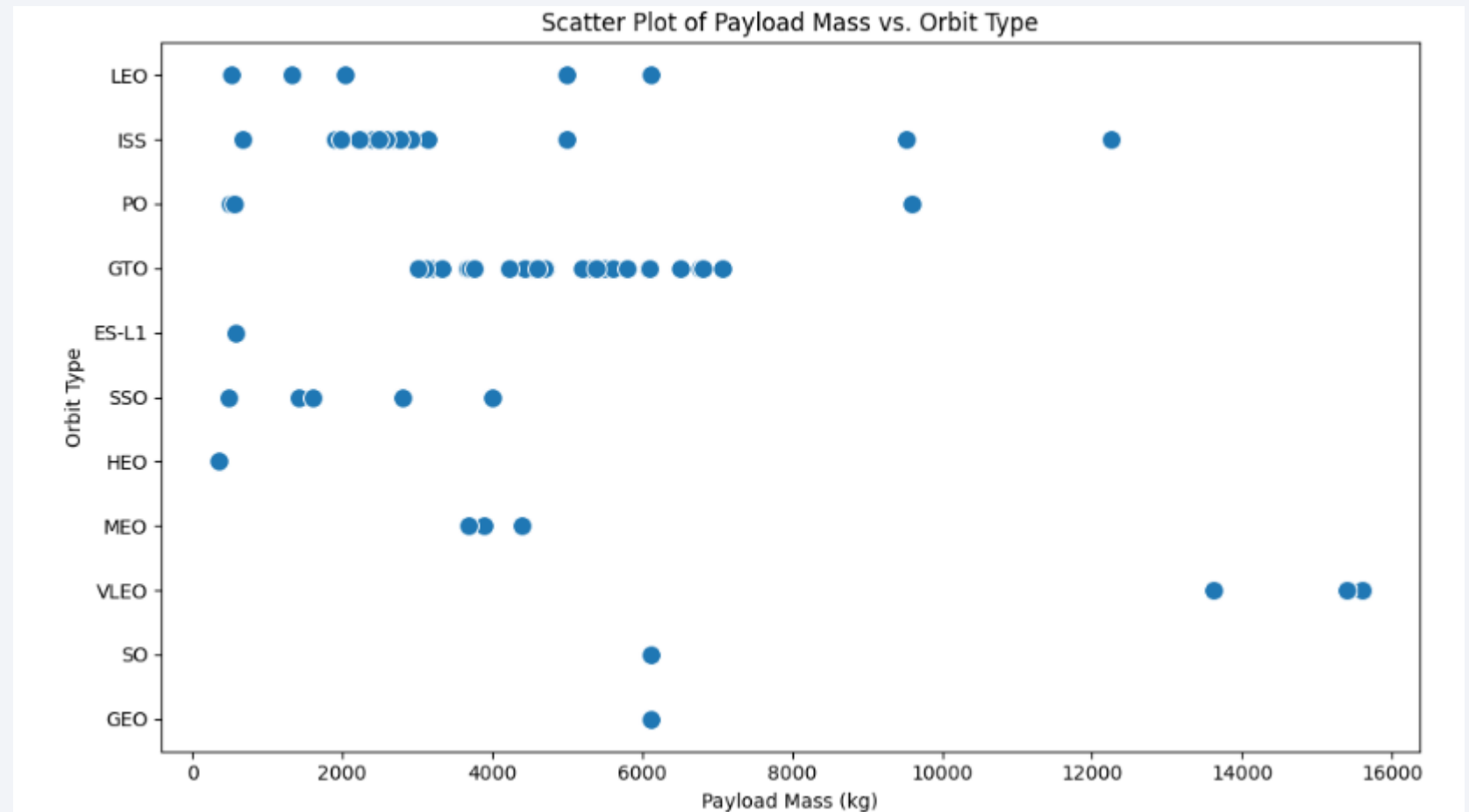
# Flight Number vs. Orbit Type

- Scatter Plot of Flight number vs. Orbit type



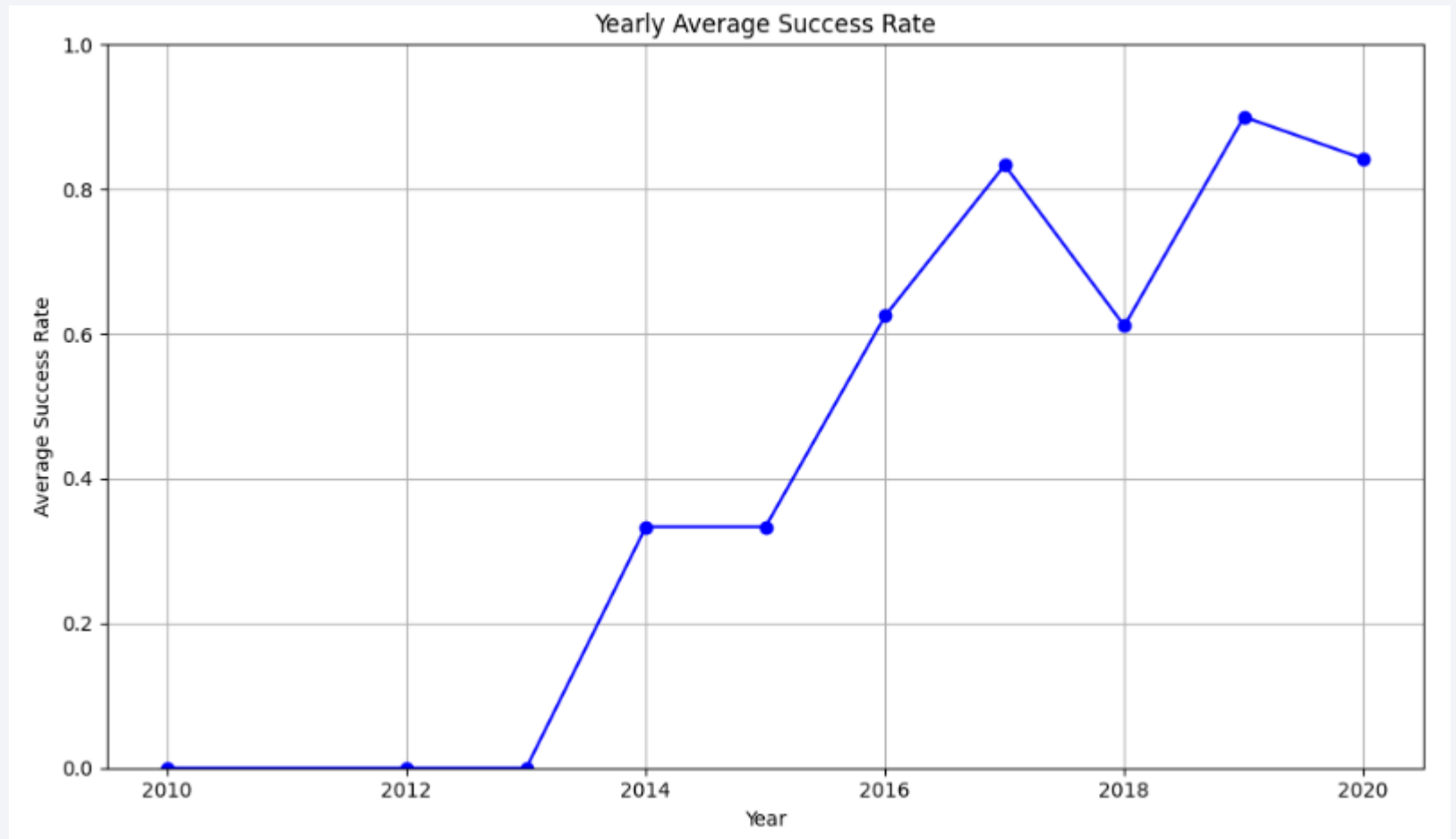
# Payload vs. Orbit Type

- Scatter plot of payload vs. orbit type
- GTO hasn't outlier values



# Launch Success Yearly Trend

- Zero success rate till 2013
- Success rate over 60% since 2016



# All Launch Site Names

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## Lanch Site Names

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

## Code

```
unique_launch_sites = df['LaunchSite'].unique()  
print("Unique Launch Sites:")  
print(unique_launch_sites)
```

# Launch Site Names Begin with 'CCA'

```
FlightNumber      Date BoosterVersion PayloadMass Orbit LaunchSite \
0                1  2010-06-04      Falcon 9  6104.959412  LEO  CCAFS SLC 40
1                2  2012-05-22      Falcon 9   525.000000  LEO  CCAFS SLC 40
2                3  2013-03-01      Falcon 9   677.000000  ISS  CCAFS SLC 40
4                5  2013-12-03      Falcon 9  3170.000000  GTO  CCAFS SLC 40
5                6  2014-01-06      Falcon 9  3325.000000  GTO  CCAFS SLC 40

Outcome  Flights  GridFins  Reused  Legs  LandingPad  Block  ReusedCount \
0  None  None      1      False  False  False      NaN      1.0          0
1  None  None      1      False  False  False      NaN      1.0          0
2  None  None      1      False  False  False      NaN      1.0          0
4  None  None      1      False  False  False      NaN      1.0          0
5  None  None      1      False  False  False      NaN      1.0          0

Serial  Longitude  Latitude  Class
0  B0003 -80.577366  28.561857  0
1  B0005 -80.577366  28.561857  0
2  B0007 -80.577366  28.561857  0
4  B1004 -80.577366  28.561857  0
5  B1005 -80.577366  28.561857  0
```

## Code

```
filtered_records = df[df['LaunchSite'].str.startswith('CCA', na=False)]

print(filtered_records.head(5))
```

# Total Payload Mass

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- Total payload carried by boosters from NASA

549446.3470588236 kg

Code

```
total_payload_mass = df['PayloadMass'].sum()  
print(f"Total Payload Mass Carried by Boosters: {total_payload_mass} kg")
```



# Average Payload Mass by F9 v1.1

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- Average Payload Mass Carried by Booster Version F9 v1.1: nan kg

- Code

```
f9_v1_1_payloads = df[df['BoosterVersion'] == 'F9 v1.1']  
  
massaverage_payload_mass = f9_v1_1_payloads['PayloadMass'].mean()  
  
print(f"Average Payload Mass Carried by Booster Version F9 v1.1: {average_payload_mass} kg")
```

# First Successful Ground Landing Date

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- Date of the first successful landing on a ground pad:

2015-12-22

- Code

```
ground_pad_success = df[df['LandingPad'].notna() & (df['Class'] == 1)]
```

```
first_success_date = ground_pad_success['Date'].min()
```

```
print(f"Date of the first successful landing on a ground pad: {first_success_date}")
```

# Successful Drone Ship Landing with Payload between 4000 and 6000

---

- Falcon 9 has been landed successfully
- Code

```
filtered_boosters = df[
    df['LandingPad'].notna() & # Ensures LandingPad is not NaN
    (df['Class'] == 1) & # Successful landings (Class == 1)
    (df['PayloadMass'] > 4000) & (df['PayloadMass'] < 6000) # Payload mass between 4000 and 6000
]
unique_boosters = filtered_boosters['BoosterVersion'].unique()
print("Boosters that successfully landed on a drone ship with specified LandingPad and payload mass
between 4000 and 6000 kg:")
print(unique_boosters)
```

# Total Number of Successful and Failure Mission Outcomes

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- Total number of successful missions: 60
- Total number of failed missions: 30

- Code:

```
outcome_counts = df['Class'].value_counts()
print("Total number of successful missions:", outcome_counts.get(1, 0))
print("Total number of failed missions:", outcome_counts.get(0, 0))
```

# Boosters Carried Maximum Payload

---

- Falcon 9 has carried the maximum payload mass
- Code

```
max_payload_mass = df['PayloadMass'].max()
```

```
boosters_with_max_payload = df[df['PayloadMass'] ==  
max_payload_mass]['BoosterVersion'].unique()
```

```
print(f"The booster(s) that carried the maximum payload mass of {max_payload_mass} kg:")
```

```
print(boosters_with_max_payload)
```

# 2015 Launch Records

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## Failed landing in drone ship for in year 2015

Failed landing outcomes on drone ship in 2015, along with their booster versions and launch site names:

	BoosterVersion	LaunchSite	Outcome
11	Falcon 9	CCAFS SLC 40	False ASDS
13	Falcon 9	CCAFS SLC 40	False ASDS
14	Falcon 9	CCAFS SLC 40	None None
15	Falcon 9	CCAFS SLC 40	None ASDS

## Code

```
df['Date'] = pd.to_datetime(df['Date'])

failed_drone_ship_landings_2015 = df[

    (df['Date'].dt.year == 2015) & # Filter for year 2015

    (df['Class'] == 0) # Filter for failed outcomes (Class == 0)

]

result = failed_drone_ship_landings_2015[['BoosterVersion', 'LaunchSite', 'Outcome']]

print("Failed landing outcomes on drone ship in 2015, along with their booster versions and launch site names:")

print(result)
```



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

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```
Ranked count of landing outcomes between 2010-06-04 and 2017-03-20:  
Outcome  
None None      9  
True ASDS      5  
False ASDS     4  
True Ocean     3  
True RTLS      3  
False Ocean    2  
None ASDS      2
```

- Code

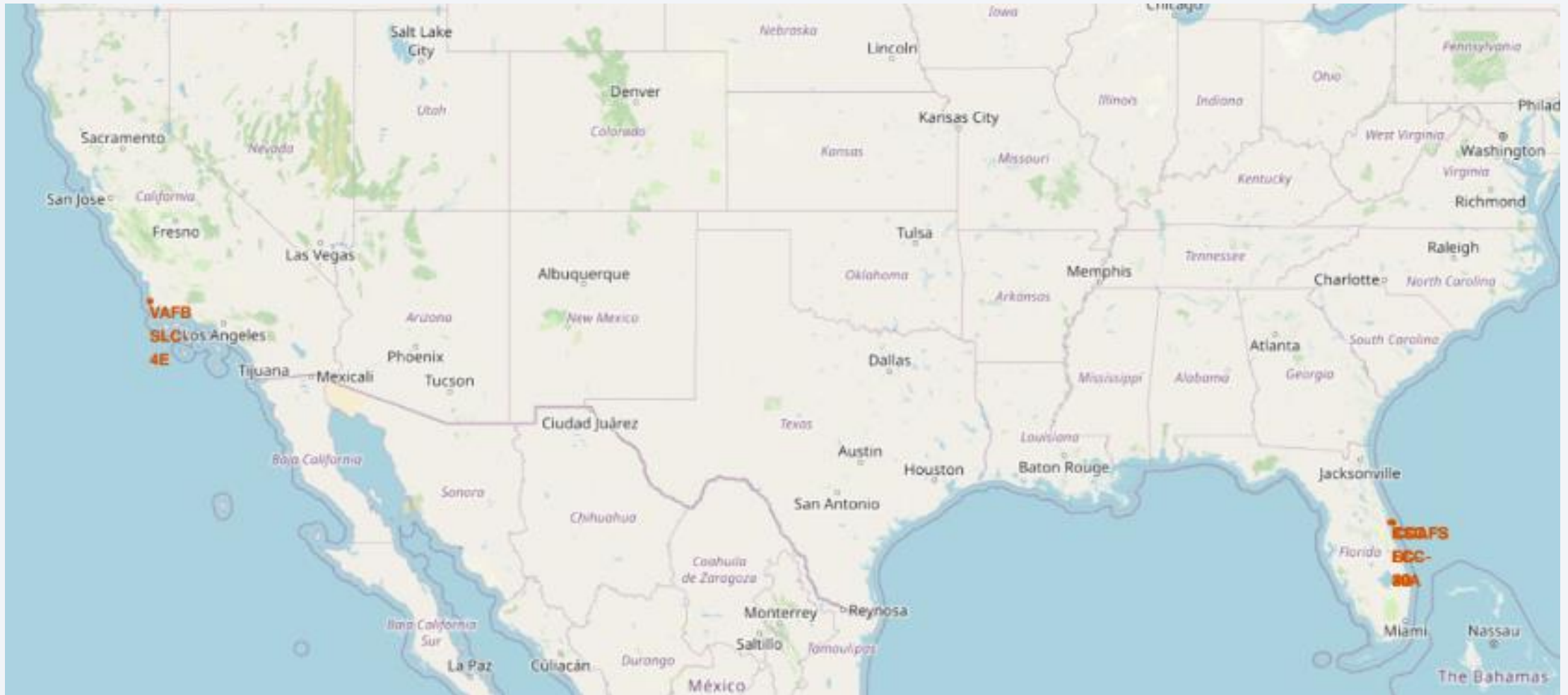
```
df['Date'] = pd.to_datetime(df['Date'])  
  
filtered_data = df[(df['Date'] >= '2010-06-04') & (df['Date'] <= '2017-03-20')]  
  
landing_outcome_counts = filtered_data['Outcome'].value_counts()  
  
landing_outcome_counts_sorted = landing_outcome_counts.sort_values(ascending=False)  
  
print("Ranked count of landing outcomes between 2010-06-04 and 2017-03-20:")  
  
print(landing_outcome_counts_sorted)
```

A satellite view of Earth from space, showing the curvature of the planet and city lights at night. The background is a deep blue gradient.

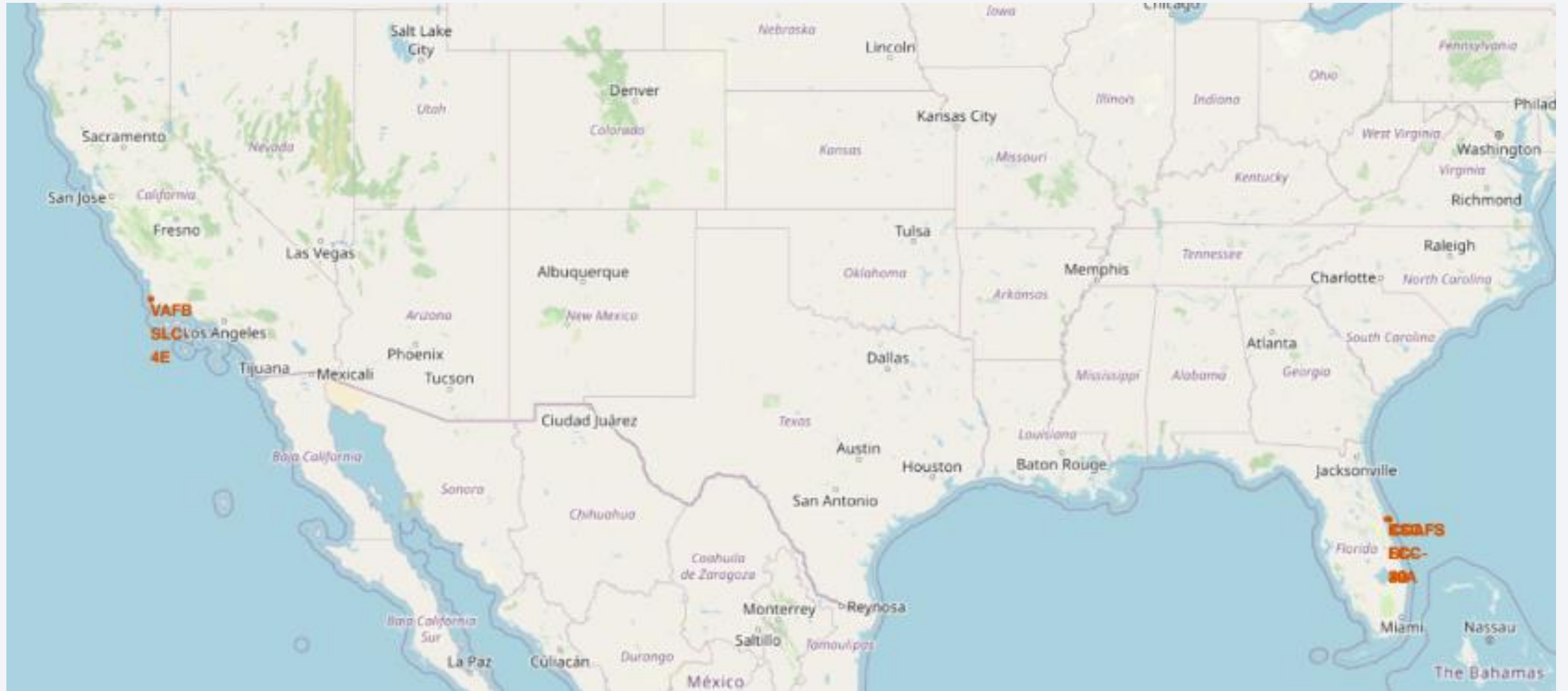
Section 3

# Launch Sites Proximities Analysis

# All Launch Sites

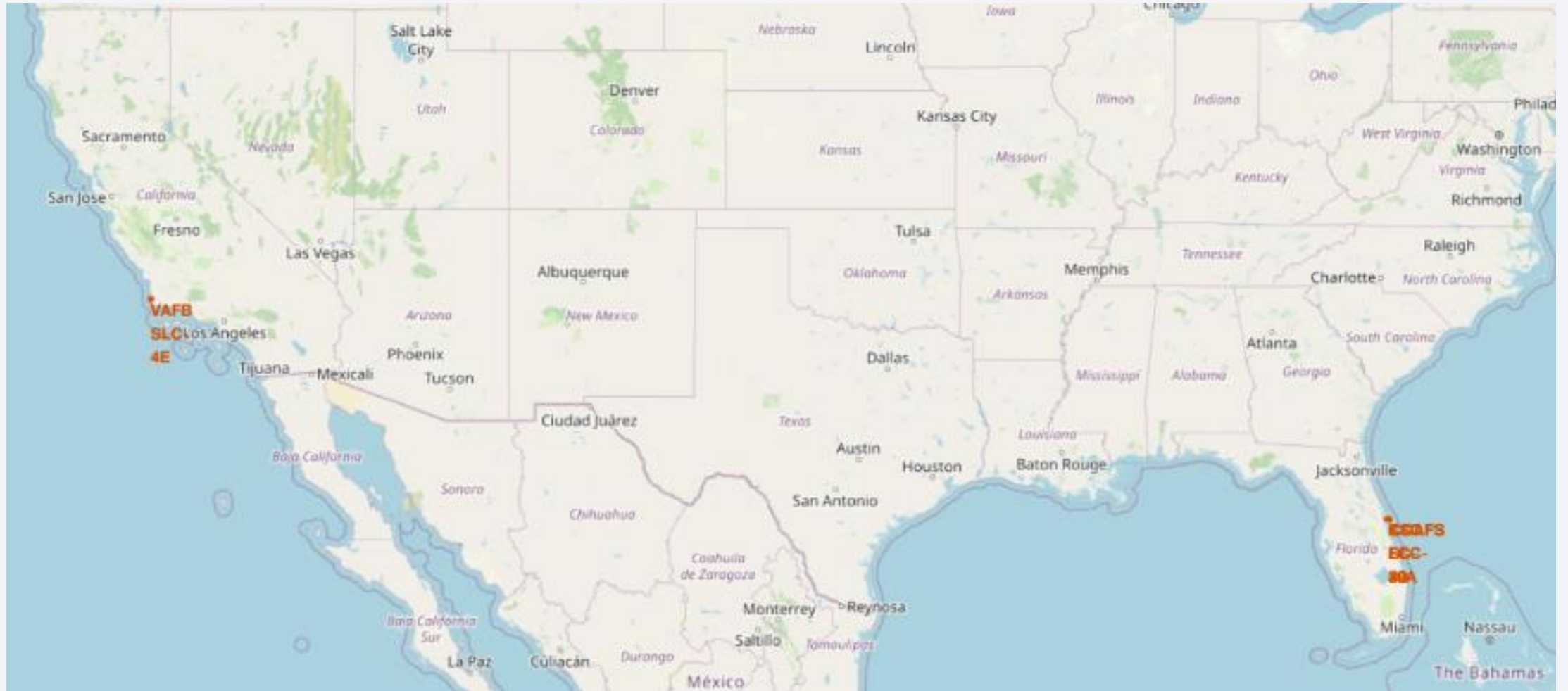


# Launch outcomes on the map





# Map



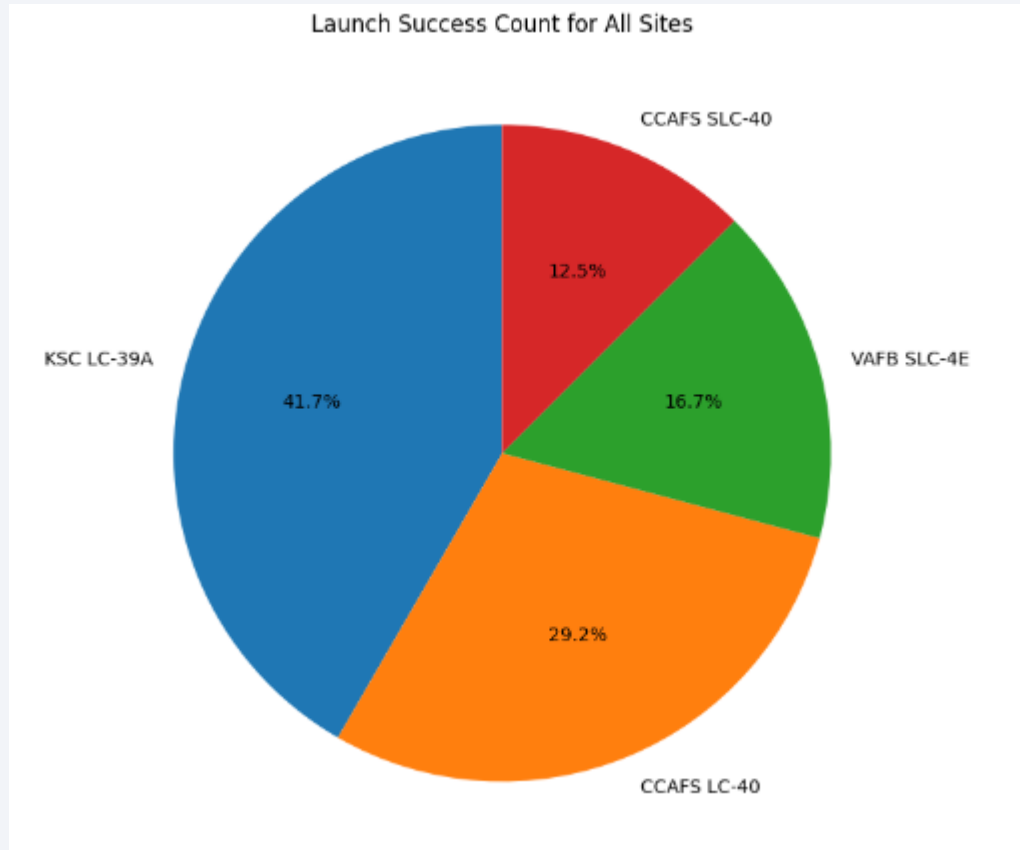


Section 4

# Build a Dashboard with Plotly Dash

# Launch Success Count for all sites

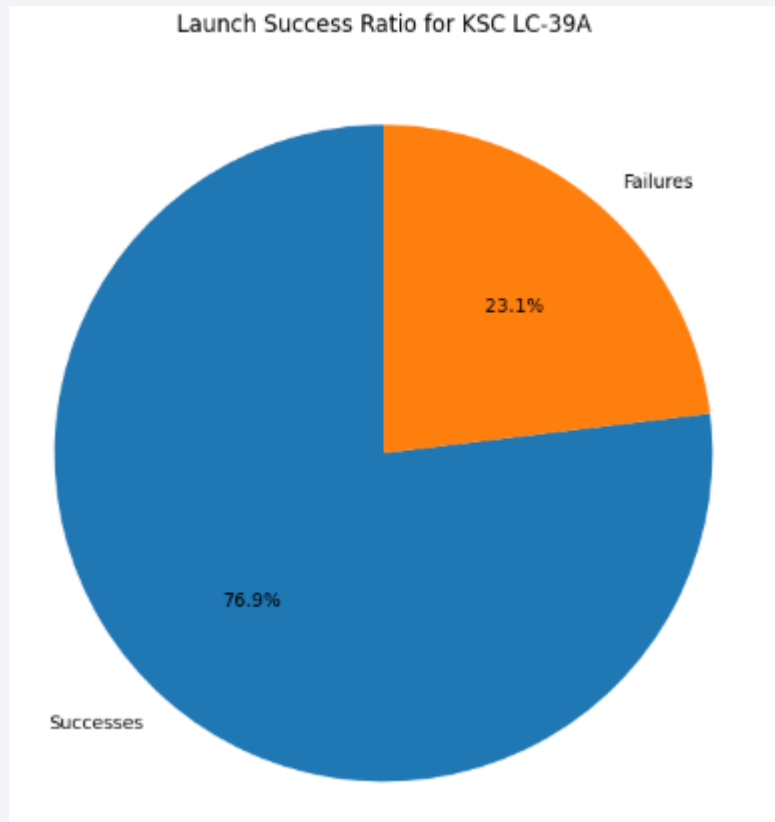
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KSC LC-39A has the highest success rate  
CAAFS SLC-40 has the lowest success rate

# Statistics for KSC LC-39A

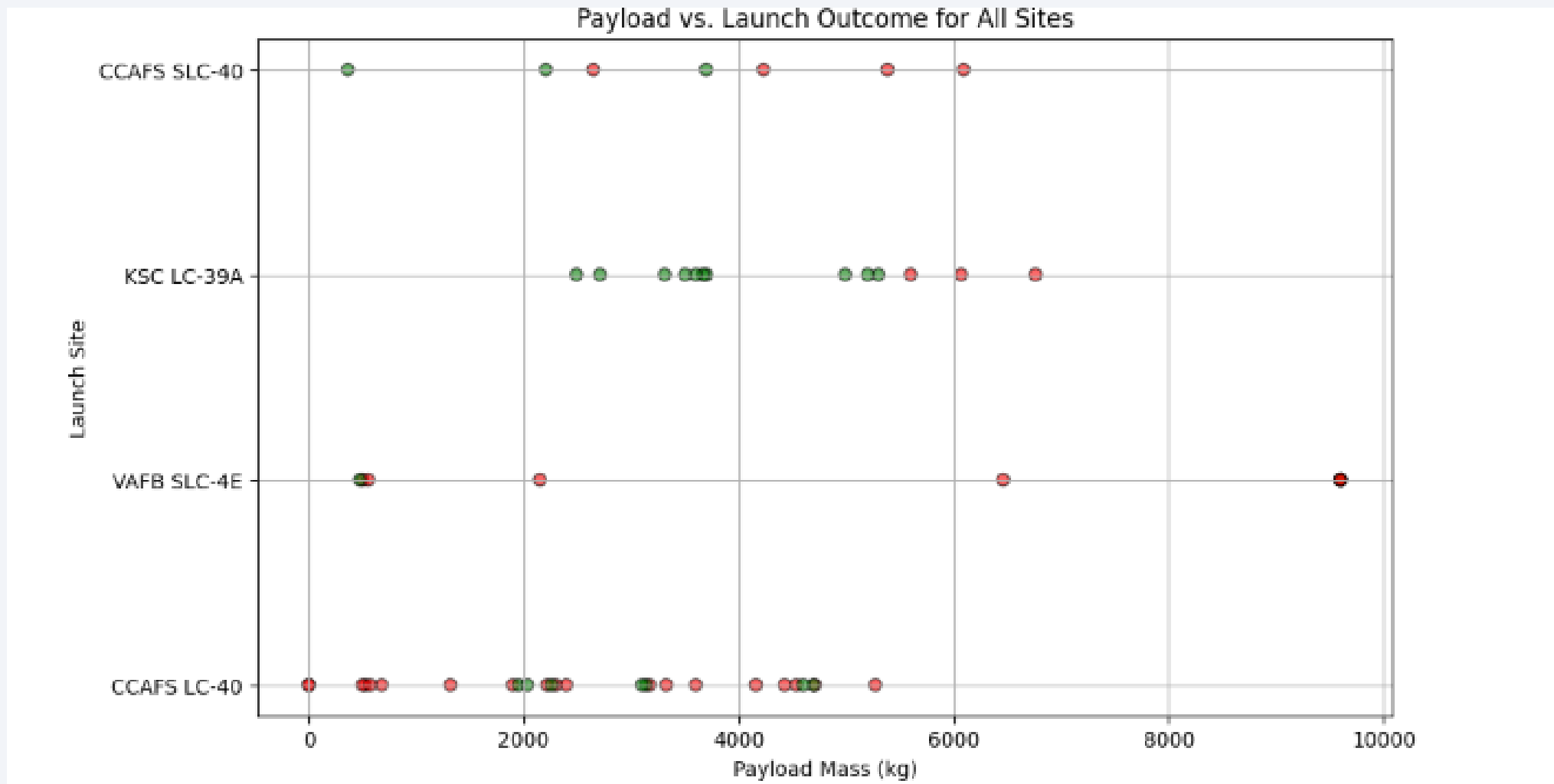
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KSC LC-39A is the site with the highest success rate



# Payload vs Launch Outcome

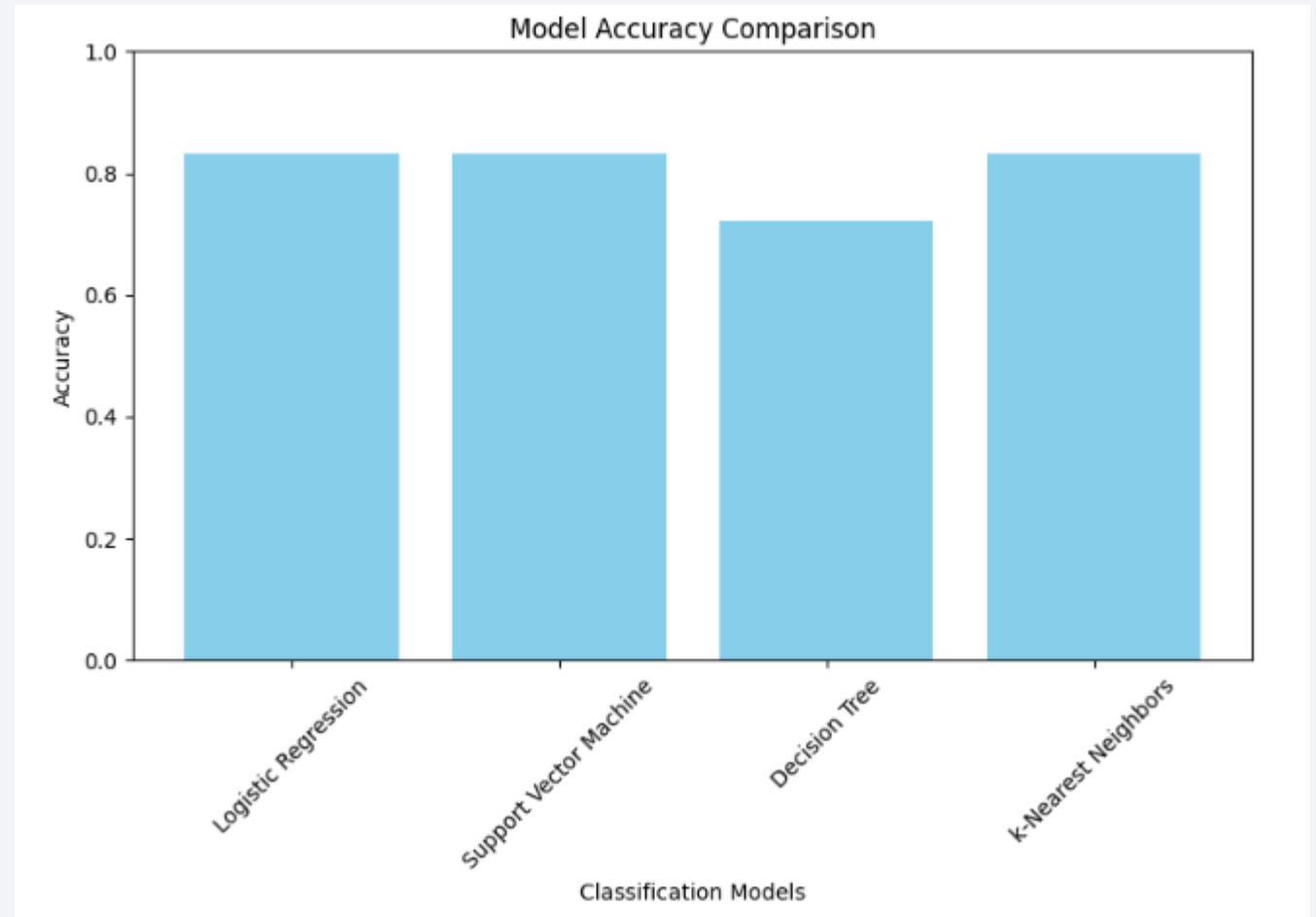


Section 5

# Predictive Analysis (Classification)

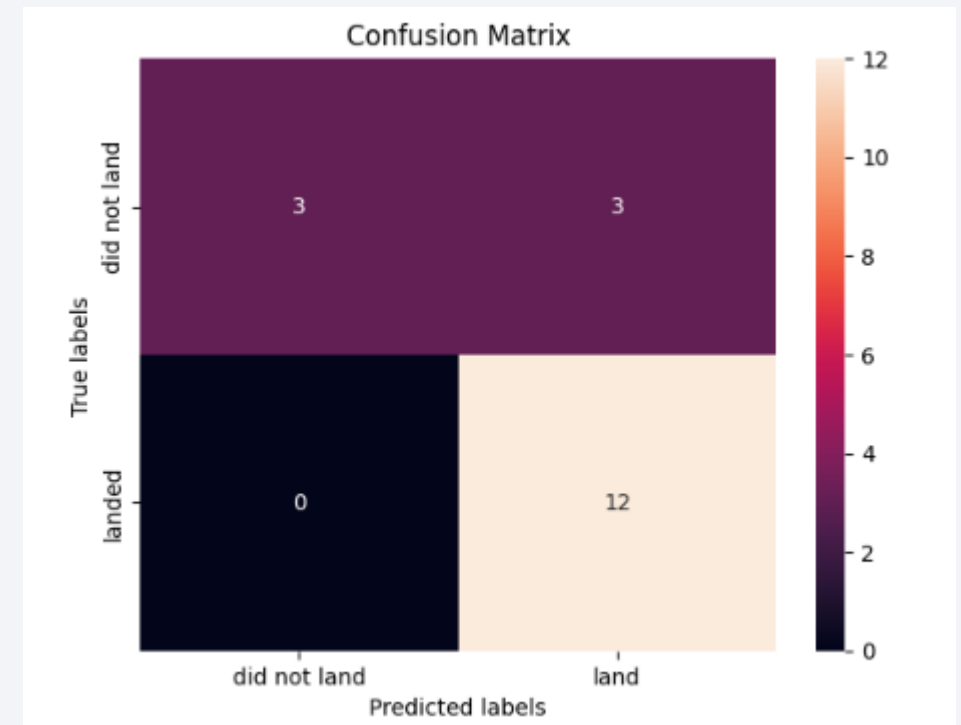
# Classification Accuracy

- Logistic Regression Model has the highest classification Accuracy



# Confusion Matrix

- Confusion matrix of the best performing model (Logistic Regression)
- Examining the confusion matrix, we see that logistic regression can distinguish between the different classes. We see that the problem is false positives.
- True Positive - 12 (True label is landed, Predicted label is also landed)
- False Positive - 3 (True label is not landed, Predicted label is landed)



# Conclusions

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- Launch Success rate over 60% since 2016
- First successful landing on a ground pad at 12/12/2015
- Successful missions: 60
- Failed missions: 30
- KSC LC-39A is the site with the highest success rate

# Appendix

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Python Libraries/Packages that were used:

- numpy
- pandas
- seaborn
- matplotlib
- sklearn
- requests
- piplite

Thank you!

