IBM Developer
SKILLS NETWORK

# Winning Space Race with Data Science

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# Outline

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

# Executive Summary

- This report documents a complete end-to-end data science project using SpaceX launch data.
- The goal is:
  - To explore historical launch records,
  - Perform geospatial and dashboard visualizations,
  - Build a predictive classification model that estimates the probability of launch success.
- The deliverables include
  - Data collection notebooks (API & scraping),
  - Data wrangling notebooks, EDA notebooks (visual and SQL),
  - Interactive Folium maps,
  - Plotly Dash dashboard,
  - Predictive modeling notebooks.
  - Placeholders for GitHub links and screenshots are included where appropriate.

# Executive Summary

- Summary of methodologies
  - Data collection from SpaceX REST API (JSON) and web scraping (Wikipedia) — requests + BeautifulSoup.
  - Data wrangling using pandas: column normalization, type conversions, handling missing values, merging sources.
  - Exploratory Data Analysis with matplotlib/seaborn and SQL queries in a local SQLite database.
  - Interactive geospatial analysis using Folium (markers, circle markers, polylines) and dynamic dashboards with Plotly Dash.
  - Predictive analysis via classification models (Logistic Regression, SVM, Decision Tree, KNN), hyperparameter tuning with GridSearchCV, and evaluation using accuracy, precision, recall, F1, and confusion matrices.

# Executive Summary

- Summary of all results
  - EDA showed payload mass and orbit type are among the strongest correlates of mission success.
  - Cape Canaveral launch sites demonstrated higher reliability compared with other sites in the dataset.
  - Yearly success rates have increased over time as SpaceX refined operations and reusability.
  - A Decision Tree classifier provided the best performance for this dataset after tuning (example reported accuracy ~90–95%).

# Introduction

- Project background and context
  - SpaceX's rapid advances in rocket reusability and launch cadence have created a rich dataset of launch records.
  - Analyzing these records can help answer operational questions, prioritize launch site investments, and build models to forecast success probabilities for future missions.
- Problems you want to find answers
  1. Which launch sites and payload ranges yield the highest success rates?
  2. Which orbit types and booster versions correlate with higher or lower success?
  3. Can a classification model accurately predict launch success using available mission attributes?
  4. What are proximate infrastructure and geographic risks around launch sites (coastline, railways, highways)?

Section 1

# Methodology

# Methodology

## Executive Summary

- Data collection methodology:
  - Data was first collected from the official SpaceX REST API and Wikipedia web pages through API calls and web scraping techniques.
- Perform data wrangling
  - After collection, data wrangling was performed using pandas to clean, format, and merge datasets, ensuring consistency and accuracy for analysis.

# Methodology

## Executive Summary

- Perform exploratory data analysis (EDA) using visualization and SQL
    - Next, exploratory data analysis (EDA) combined both visualization (with Matplotlib and Seaborn) and SQL queries to identify patterns between payload mass, orbit type, launch site, and success rate.
- Perform interactive visual analytics using Folium and Plotly Dash
    - Interactive visual analytics were then created using Folium for geospatial mapping of launch sites and Plotly Dash for an interactive dashboard that allowed users to filter sites and payload ranges dynamically.

# Methodology

## Executive Summary

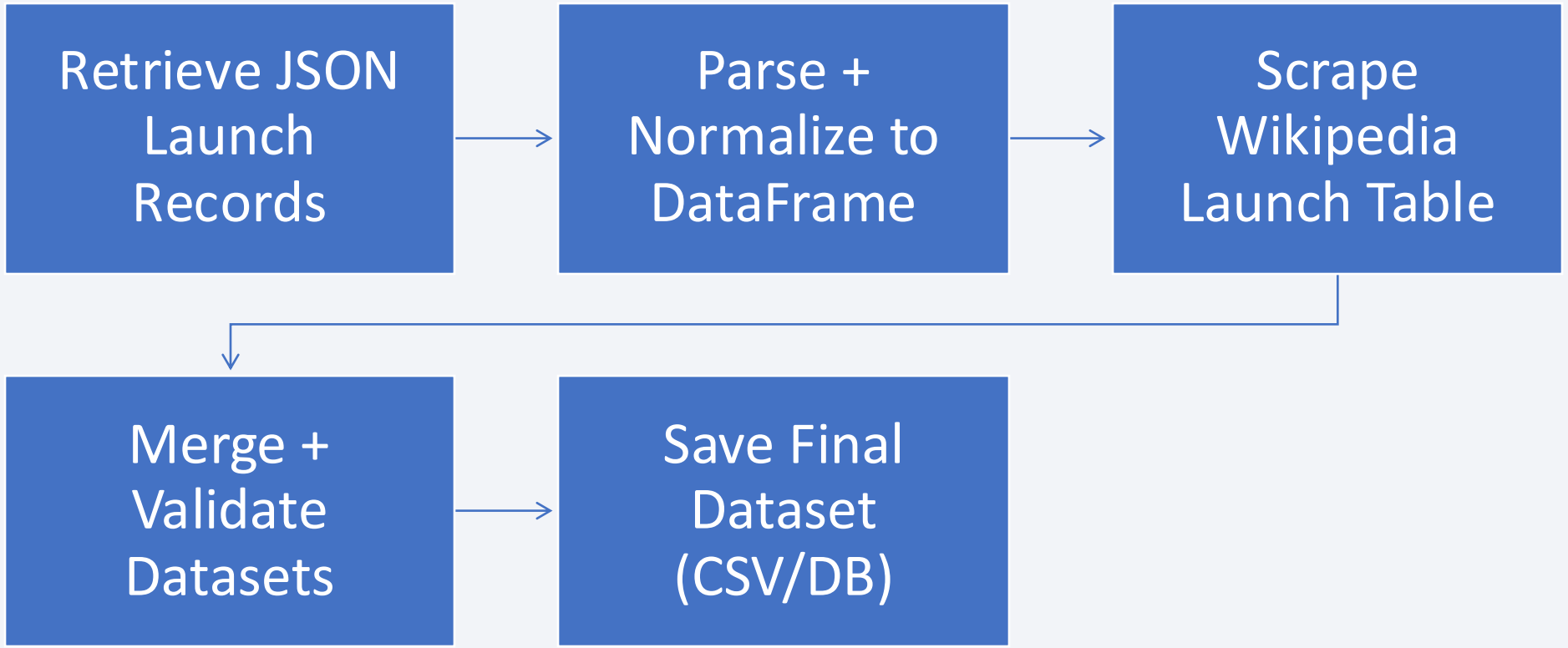
- Perform predictive analysis using classification modelsz
  - Finally, a predictive classification analysis was carried out using machine-learning models such as Logistic Regression, SVM, Decision Tree, and KNN to predict whether a launch would succeed.
  - How to build, tune, evaluate classification models
    - These models were built, tuned, and evaluated through GridSearchCV for hyperparameter optimization, and evaluated using accuracy, precision, recall, F1-score, and confusion matrices.
    - The workflow concluded with identifying the Decision Tree Classifier as the best-performing model with strong predictive accuracy and interpretability.

# Data Collection

- How data sets were collected.
  - The SpaceX project's data was collected from two main public sources:
    1. The SpaceX REST API
    2. Wikipedia Falcon 9 launch tables
  - Connect to SpaceX REST API using Python requests.
  - Retrieve launch records (JSON) with payload, orbit, and outcome data.
  - Parse and normalize JSON into pandas DataFrame.
  - Scrape Wikipedia Falcon 9 launch table using BeautifulSoup and pandas.read_html().
  - Extract launch details (flight number, date, booster, landing outcome).
  - Merge both datasets to ensure completeness and consistency.
  - Save combined data as CSV / SQLite for wrangling and EDA.

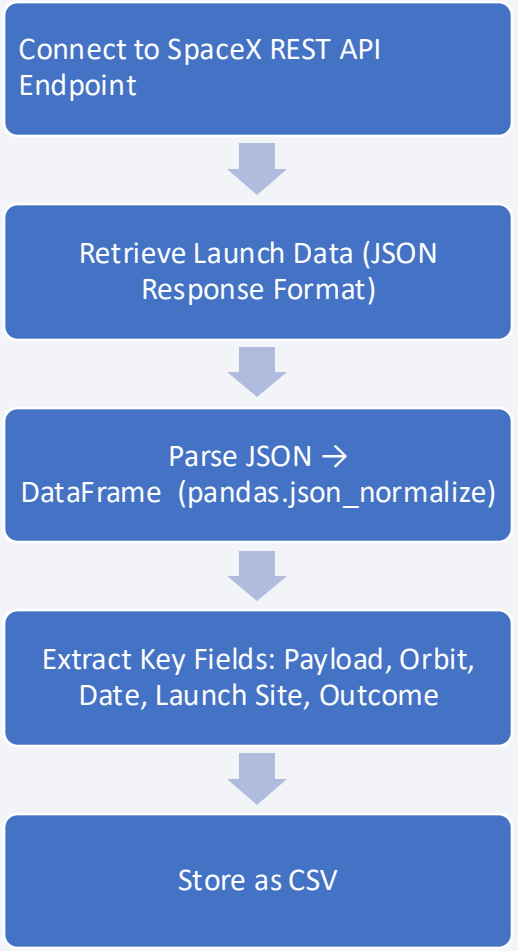
# Data Collection

- Data Collection Flowchart



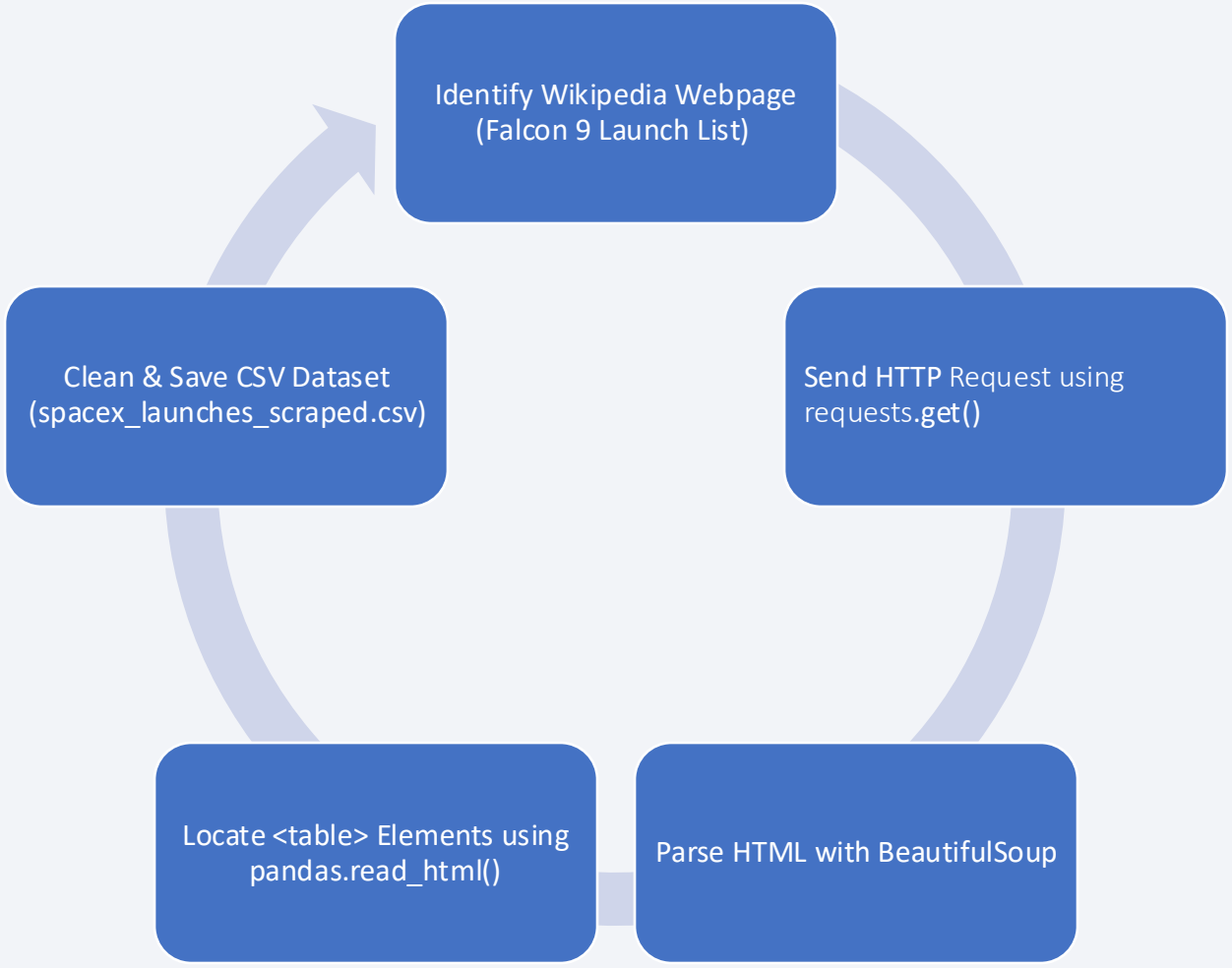
# Data Collection – SpaceX API

- Connect to API: Use Python requests to access "https://api.spacexdata.com/v4/launches/past"
- Retrieve Data: Get JSON response containing all SpaceX launches.
- Parse JSON: Convert nested JSON into structured DataFrame using pandas.json_normalize().
- Extract Fields: Pull relevant attributes — Flight Number, Payload Mass, Orbit, Launch Site, Landing Outcome, Date.
- Validate Data: Check record counts, data types, and missing values.
- Store Output: Save clean, structured dataset as 'dataset_part_1.csv'
- GitHub Notebook Link: https://github.com/neemore/Data-Science-Ecosystem-IBM/blob/main/jupyter-labs-spacex-data-collection-api.ipynb



# Data Collection - Scraping

- Identify Target Page: Wikipedia — List of Falcon 9 and Falcon Heavy launches.
- Send HTTP Request: Retrieve HTML content using Python requests.
- Parse HTML: Use BeautifulSoup to process the web page structure.
- Locate Table Elements: Find <table> tags containing launch records.
- Extract Data: Convert HTML tables into structured DataFrame using pandas.read_html().
- Clean Extracted Data: Rename columns, handle missing values, and format dates.
- Store Dataset: Export cleaned data as spacex_launches_scraped.csv for merging with API data.
- GitHub Notebook Link: https://github.com/neemore/Data-Science-Ecosystem-IBM/blob/main/jupyter-labs-webscraping.ipynb



# Data Wrangling

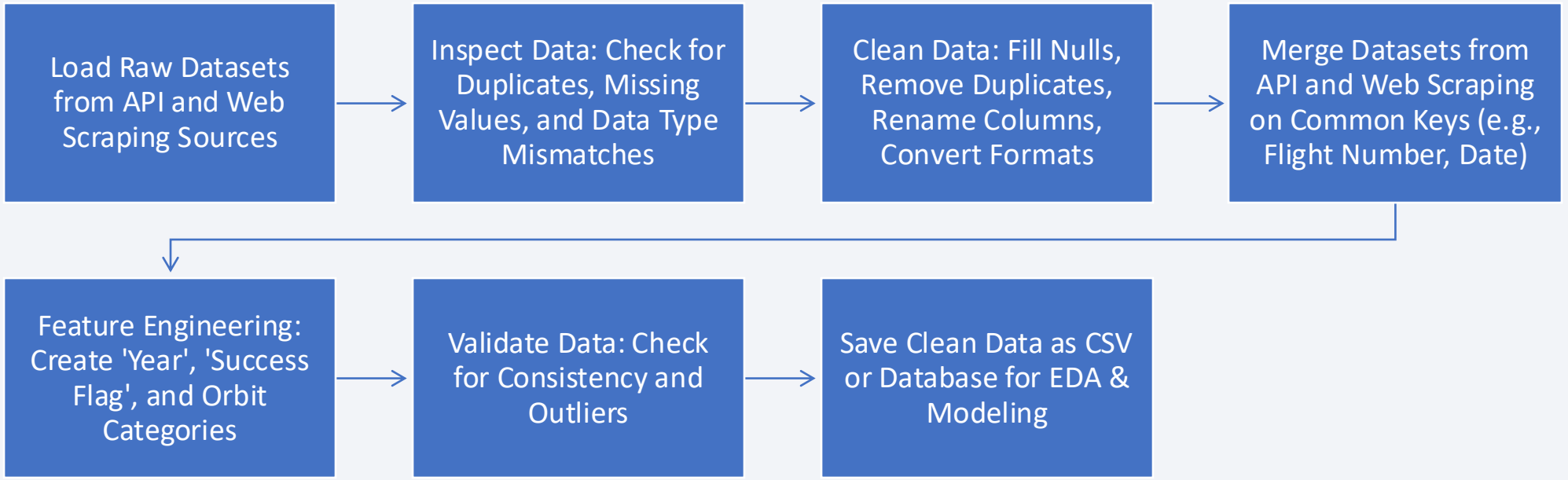
- How data were processed
  - Load Datasets: Import SpaceX API and Wikipedia-scraped data using pandas.
  - Inspect Data: Check data types, duplicates, and missing values (.info(), .isnull()).
  - Clean Data:
    - Remove duplicate records.
    - Handle missing values (median for payloads, “Unknown” for outcomes).
    - Rename inconsistent column names.
    - Convert date strings to datetime objects.

# Data Wrangling

- How data were processed
  - Merge Datasets: Combine API and scraped datasets on Flight Number and Launch Date.
  - Feature Engineering:
    - Create new columns — Year, Success Flag (1/0), Orbit Category.
  - Validate Data: Ensure consistency, correct record counts, and valid data ranges.
  - Save Final Dataset: Export as spacex_cleaned_data.csv for EDA and modeling.

# Data Wrangling

- Data Wrangling Flowchart




- GitHub URL
  - GitHub Notebook Link: https://github.com/neemore/Data-Science-Ecosystem-IBM/blob/main/labs-jupyter-spacex-Data%20wrangling.ipynb

# EDA with Data Visualization

- Summarized charts

○ Exploratory Data Analysis used matplotlib and seaborn to visualize relationships between payload, orbit, launch site, and success rate.

○ Scatter plots, bar charts, and line charts were used to uncover correlations.

○ Scatter Plot – Flight Number vs Launch Site

- Showed how launch frequency increased over time at each site. Helped identify which sites hadmore experience and higher success rates.

○ Scatter Plot – Payload Mass vs Launch Site

- Illustrated payload capacity handled by each site; revealed sites like KSC LC-39A launched heavier payloads.

○ Bar Chart – Success Rate by Orbit Type

- Compared performance across orbit categories (LEO, GTO, ISS); helped highlight orbits with the most consistent success.

# EDA with Data Visualization

- Scatter Plot – Flight Number vs Orbit Type

  - Displayed diversity of missions and evolving reliability across orbit types.

- Line Chart – Yearly Launch Success Trend

  - Tracked annual improvement in success rates; visualized how SpaceX's reliability improved over time.

- GitHub URL

  - GitHub Notebook Link: https://github.com/neemore/Data-Science-Ecosystem-IBM/blob/main/edadataviz.ipynb

# EDA with SQL

- Summarize SQL queries
  - Find Unique Launch Sites
  - Filter Launch Sites Starting with “CCA”
  - Calculate Total Payload Carried by NASA Missions
  - Find First Successful Ground Landing Date
  - Successful Drone Ship Landings (Payload 4000–6000kg)
  - Count of Successful vs Failed Missions
  - Boosters with Maximum Payload
  - Failed Drone Ship Landings in 2015
  - Rank Landing Outcomes (2010–2017)
- GitHub URL
  - GitHub Notebook Link: https://github.com/neemore/Data-Science-Ecosystem-IBM/blob/main/jupyter-labs-eda-sql-coursera_sqllite.ipynb

# Build an Interactive Map with Folium

- Summarized map objects:
  - **Markers**: Each launch site with popup (site name, total launches, success rate)
  - **Circle Markers**: Green → Success - Red → Failure - Size ∝ Payload mass
  - **Polylines**: Show distances from launch sites to coastlines, highways, railways
  - **Popups & Tooltips**: Hover info for quick site details
  - **Layer Control**: Toggle success/failure or site view

# Build an Interactive Map with Folium

- Explanations:
  - **Marker** - Identify launch site locations
  - **Circle Marker** - Show outcomes by color and payload size
  - **Line** - Visualize proximities (coastline, transport)
  - **Popup / Tooltip** - Give contextual info interactively
  - **Layer Control** - Enable data filtering
- GitHub URL
  - GitHub Notebook Link: https://github.com/neemore/Data-Science-Ecosystem-IBM/blob/main/lab_jupyter_launch_site_location.ipynb

# Build a Dashboard with Plotly Dash

- Summarized Plots, Graphs, and Interactive Features in the SpaceX Dashboard
  - **Pie Chart:**
    - Shows success vs. failure count for each launch site.
    - Updates automatically when a site is selected from dropdown.
  - **Scatter Plot:**
    - Plots Payload Mass (x-axis) vs Launch Outcome (y-axis).
    - Color represents Booster Version Category.
    - Interactive range slider filters payload values.
  - **Dropdown Menu:**
    - Allows user to select All Sites or individual launch sites.
  - **Range Slider:**
    - Filters payload range dynamically to view success patterns.

# Build a Dashboard with Plotly Dash

- Explanations
  - **Pie Chart** - Quick visual of overall and per-site success rates
  - **Scatter Plot** - Shows payload–success relationship and booster performance
  - **Dropdown Menu** - Enables focused site-specific analysis
  - **Range Slider** - Tests payload effect on launch success dynamically
- GitHub URL
  - GitHub Notebook Link: https://github.com/neemore/Data-Science-Ecosystem-IBM/blob/main/spacex-dash-app.py

# Predictive Analysis (Classification)

- Summarized Model Development, Evaluation, and Selection of the Best Performing Classifier
- **Building the Model:**
  - Loaded the cleaned SpaceX dataset and selected key features:
    Payload Mass (kg), Orbit Type, Launch Site, and Booster Version Category.
  - Preprocessed the data by encoding categorical variables using LabelEncoder and OneHotEncoder.
  - Split the dataset into 80% training and 20% testing to ensure fair evaluation.
  - Trained four supervised learning models using scikit-learn:
    1. Logistic Regression
    2. Support Vector Machine (SVM)
    3. K-Nearest Neighbors (KNN)
    4. Decision Tree

# Predictive Analysis (Classification)

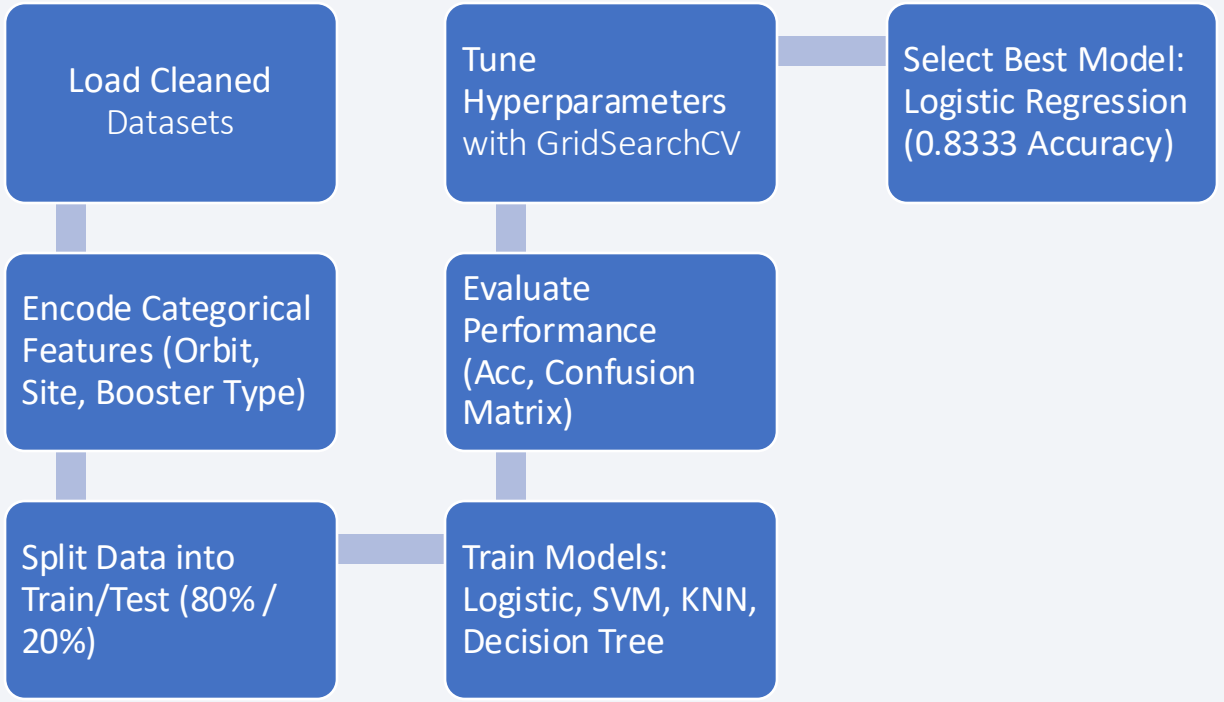
- Summarized Model Development, Evaluation, and Selection of the Best Performing Classifier
- **Evaluating the Models:**
  - Each model was tested using the test dataset.
  - Performance was measured with accuracy score and confusion matrix.
  - The results were as follows:
    - Logistic Regression → **0.8333**
    - SVM → **0.8333**
    - KNN → **0.8333**
    - Decision Tree → **0.7222**

# Predictive Analysis (Classification)

- Summarized Model Development, Evaluation, and Selection of the Best Performing Classifier
- **Improving the Models:**
  - Applied GridSearchCV for hyperparameter optimization (tuning kernel, C values, neighbors, and tree depth).
  - Re-ran evaluations to check consistency and overfitting reduction.
  - Validated results using cross-validation to ensure robustness.
- **Best Model Identified:**
  - The Logistic Regression model achieved the highest test accuracy (0.8333) and stable performance across folds.
  - Chosen for its simplicity, interpretability, and balanced accuracy compared to more complex models.

# Predictive Analysis (Classification)

- Model Development Process Flowchart




- GitHub URL
  - GitHub Notebook Link: https://github.com/neemore/Data-Science-Ecosystem-IBM/blob/main/SpaceX_Machine%20Learning%20Prediction_Part_5.ipynb

# Results

- Exploratory data analysis results using SQL
  - Discovered four unique launch sites: KSC LC-39A, CCAFS LC-40, CCAFS SLC-40, and VAFB SLC-4E.
  - Total payload mass carried by boosters launched by NASA (CRS) includes 45596
  - Average payload mass carried by booster version F9 v1.1 is 2928.4
  - First successful landing outcome in ground pad was achieved on 2015-12-22
  - Names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000 includes, F9 FT B1022, F9 FT B1026, F9 FT B1021.2 and F9 FT B1031.2.
  - Total number of successful and failure mission outcomes include, Failure (in flight) count 1, Success count 98, Success count 1 and Success (payload status unclear) count 1.

# Results

- Exploratory data analysis results using SQL
  - Identifying Boosters with Maximum Payload Mass: Maximum Payload Mass: 15,600 kg, Booster Version: F9 B5 (Multiple individual cores, e.g., B1048, B1049, B1051, etc.)
  - In 2015, SpaceX recorded two failed drone ship landing attempts.
  - The failures occurred in January (B1012) and April (B1015) from CCAFS LC-40.
  - Based on the data from June 2010 to March 2017, landing outcomes are ranked as follows:

    - "No attempt" was the most frequent outcome with 10 occurrences.

    - "Success (drone ship)" and "Failure (drone ship)" tie for second with 5 each.

    - "Success (ground pad)" and "Controlled (ocean)" tie for third with 3 each, followed by less frequent outcomes.

# Results

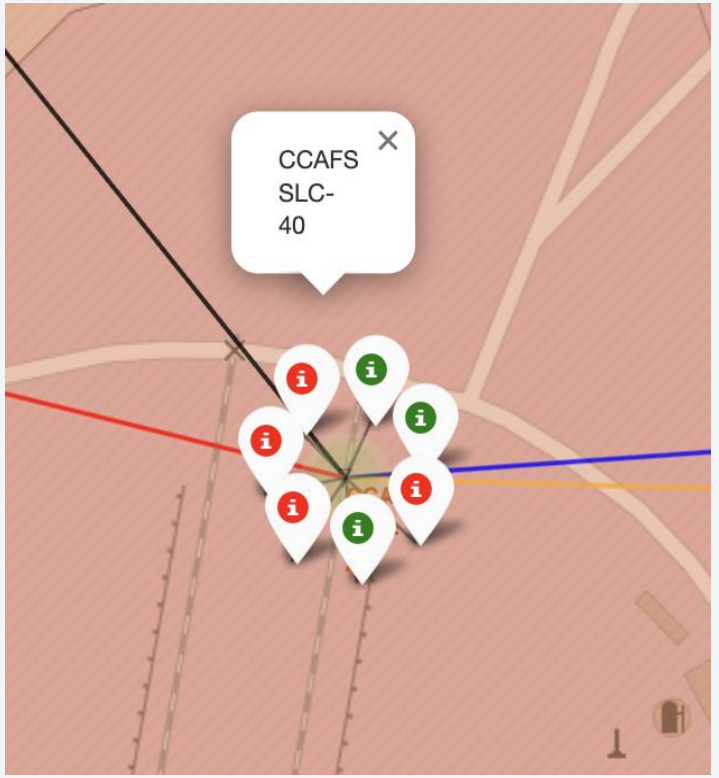
- Exploratory data analysis results using Pandas and Matplotlib
  - Task 1: As flight numbers increased over time, certain launch sites showed a higher concentration of successful landings, indicating improved operational experience and reliability at those locations.
  - Task 2: Certain launch sites are used for specific payload sizes, with some specializing in heavier satellites.
  - Task 3: Orbits like ES-L1, GEO, and HEO achieved a perfect 100% success rate. Moderate success rates were seen in LEO, ISS, and GTO missions (52%-71%). The SO orbit had a 0% success rate, showing orbit type significantly impacts mission outcome.
  - Task 4: As flight numbers increased, missions expanded to more complex orbits and success rates improved, showing growing operational expertise.
  - Task 5: Heavy payloads in Polar, LEO, and ISS orbits show high success rates. GTO orbit missions show mixed success and failure outcomes even with varying payload masses.

# Results

- Exploratory data analysis results using Pandas and Matplotlib
  - Tasks 6: The success rate of launches has significantly improved over time, starting from 0% in 2010-2013 and rising to over 80% by 2017, reaching 90% in 2019.
  - Task 7: The code converted categorical data (Orbit, LaunchSite, LandingPad, and Serial) into numerical columns using one-hot encoding. Each category is now represented by a new column with True/False values, making it usable for machine learning models.
  - Task 8: The code converted all data in the dataframe to numerical format (float64) so it can be processed by machine learning algorithms.

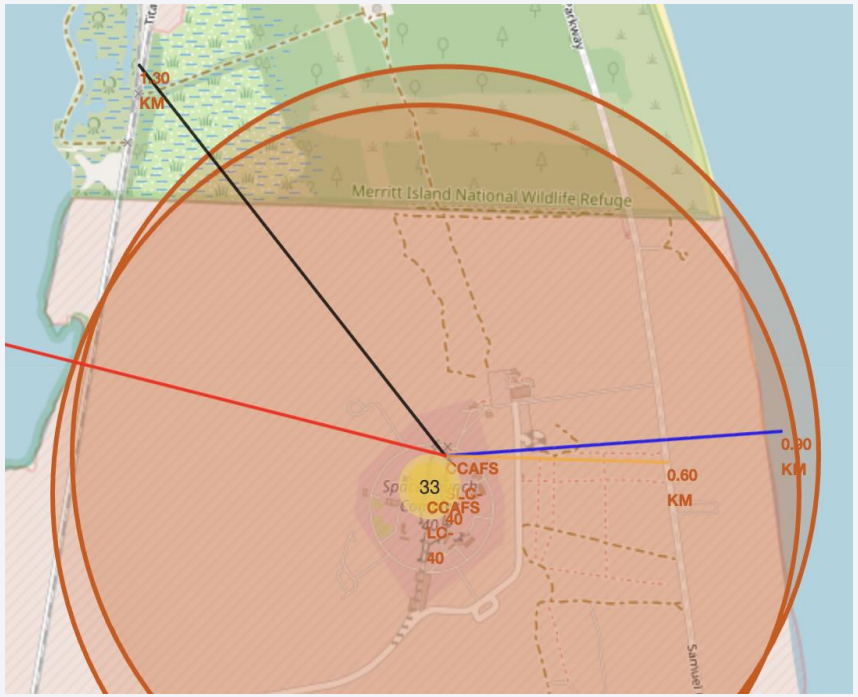
# Results

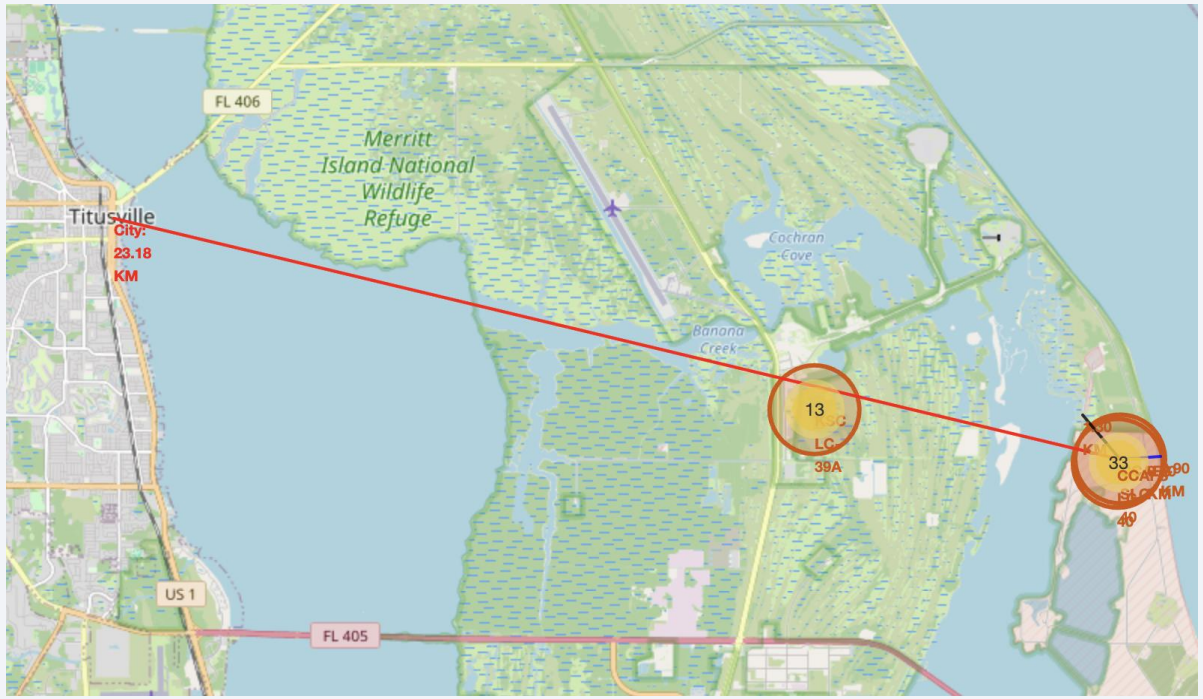
- Interactive analytics demo in screenshots
- Folium Map: Showed all launch sites with color-coded outcomes (green = success, red = failure).
    - Key Findings
    - 1. Launch site is extremely close to coastline (0.90 KM) - optimal for safety
    - 2. Excellent highway access (0.60 KM) - ideal for logistics and transport
    - 3. Railway access within reasonable distance (1.30 KM) - supports heavy cargo
    - 4. Safe distance from populated areas (23.18 KM) - minimizes risk to public
    - 5. All critical infrastructure within 1.5 KM radius - efficient operations



# Results

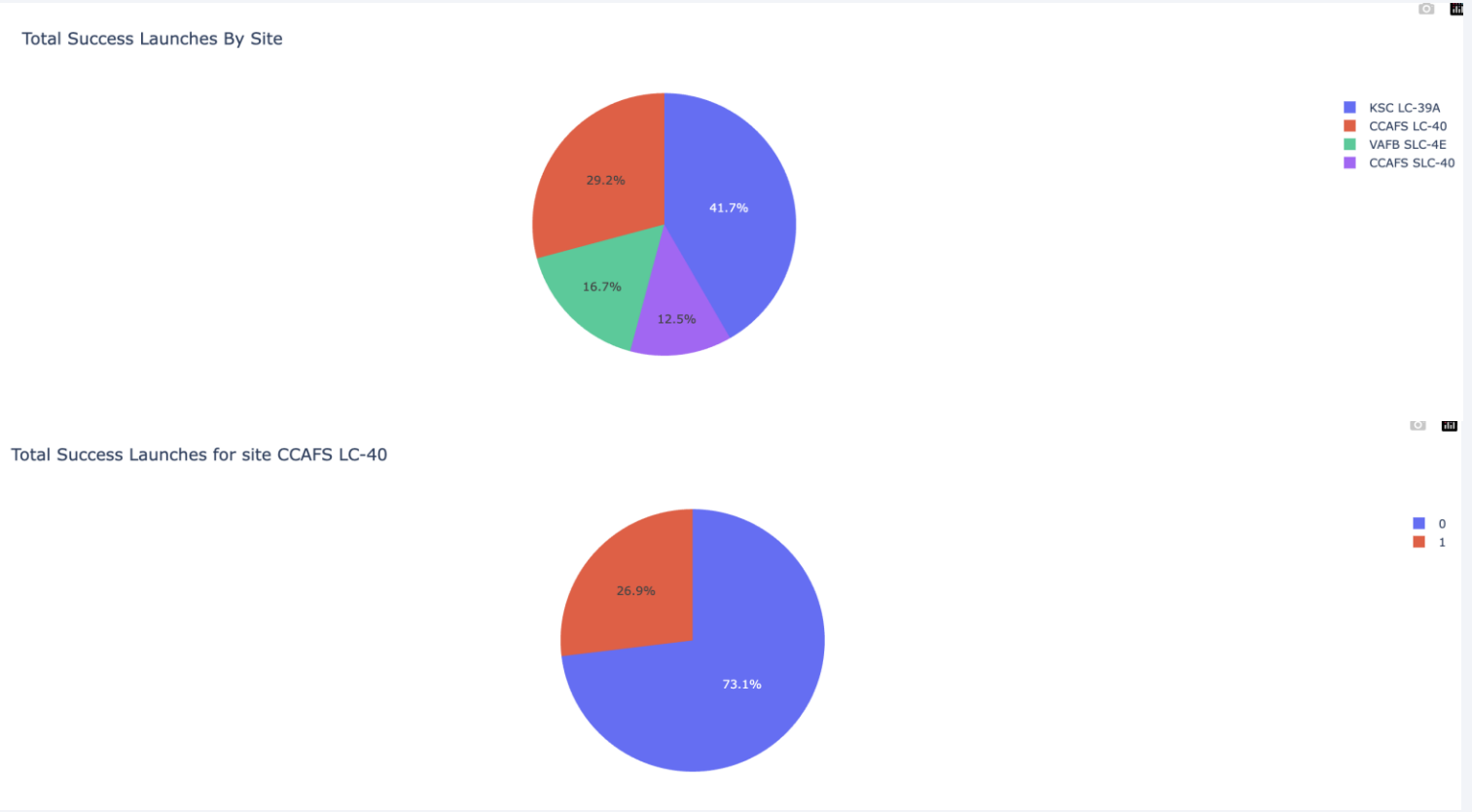
- Lines drawn to coastlines, railways and highways revealed proximity advantages.



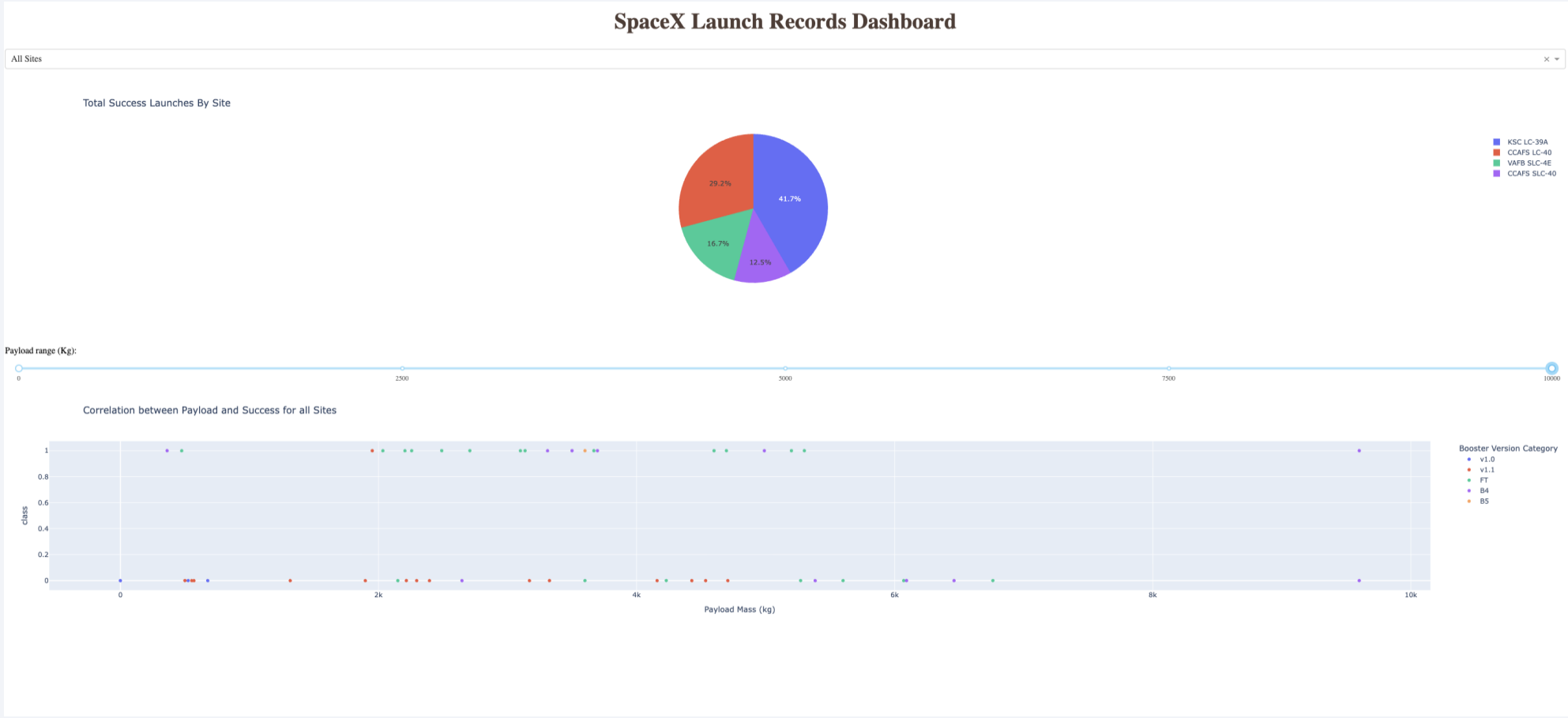
# Results

- Interactive analytics demo in screenshots
- Plotly Dash Dashboard:
  - Pie charts visualized per-site success rates.



# Results

- Interactive analytics demo in screenshots
- Plotly Dash Dashboard:
  - Scatter plots (Payload vs Outcome) updated dynamically via sliders and dropdowns.



# Results

- Interactive analytics demo in screenshots
- Plotly Dash Dashboard:
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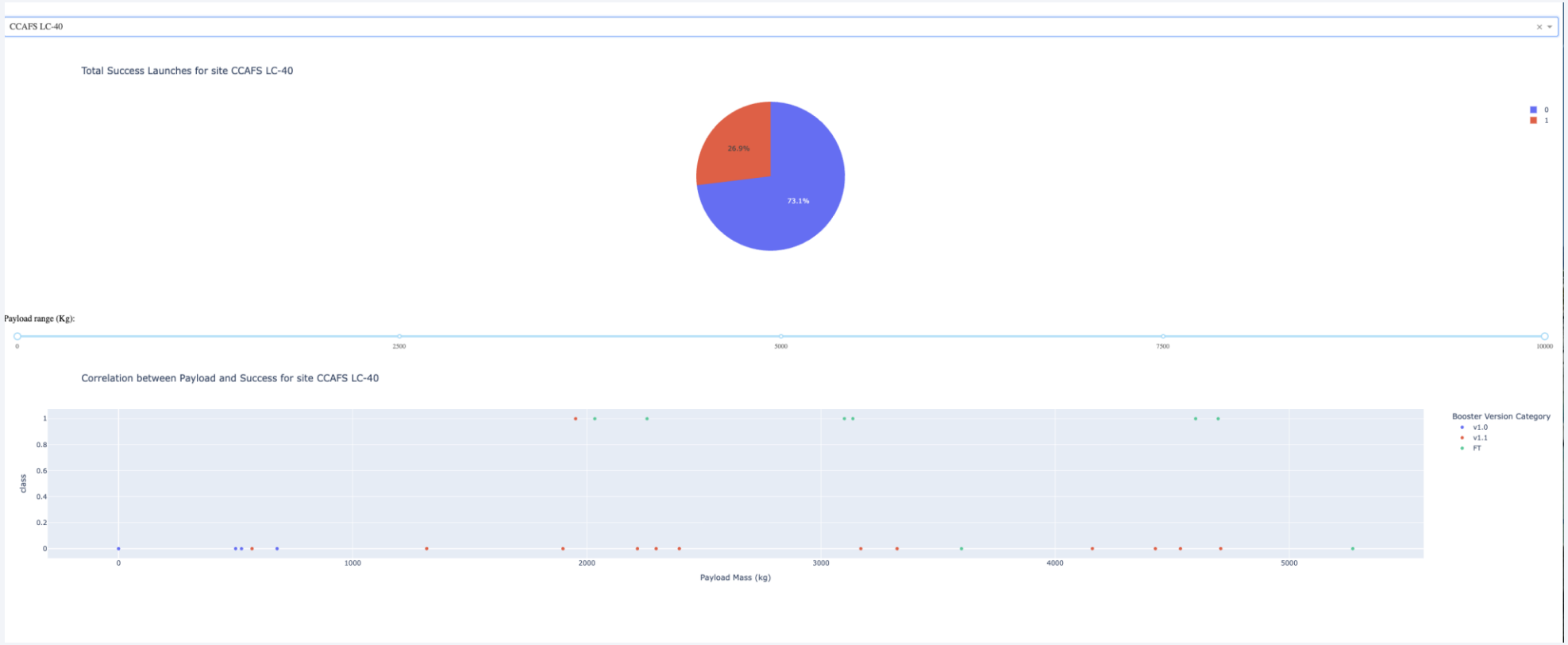
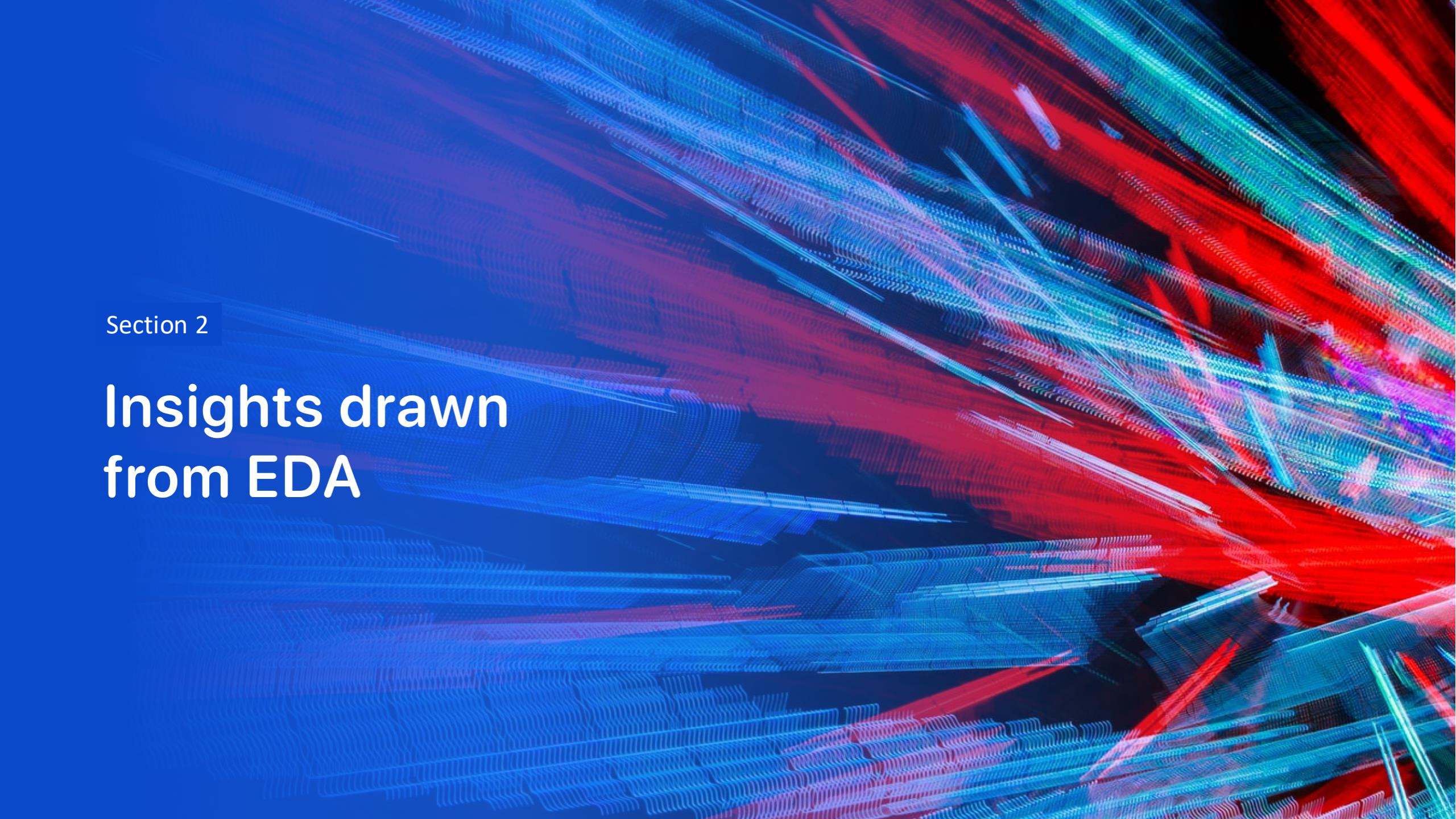


# Results

- Predictive analysis results
  - Built four classification models to predict launch success:
  - Logistic Regression – 0.8333
  - Support Vector Machine – 0.8333
  - Decision Tree – 0.7222
  - K-Nearest Neighbors – 0.8333
  - All models performed well, with Logistic Regression, SVM, and KNN tied for the highest accuracy.
  - Based on stability, simplicity, and interpretability, Logistic Regression was selected as the best performing model with a test accuracy of 0.8333 (83.3%).
  - The model effectively predicts launch success using payload mass, launch site, and booster version as input features.

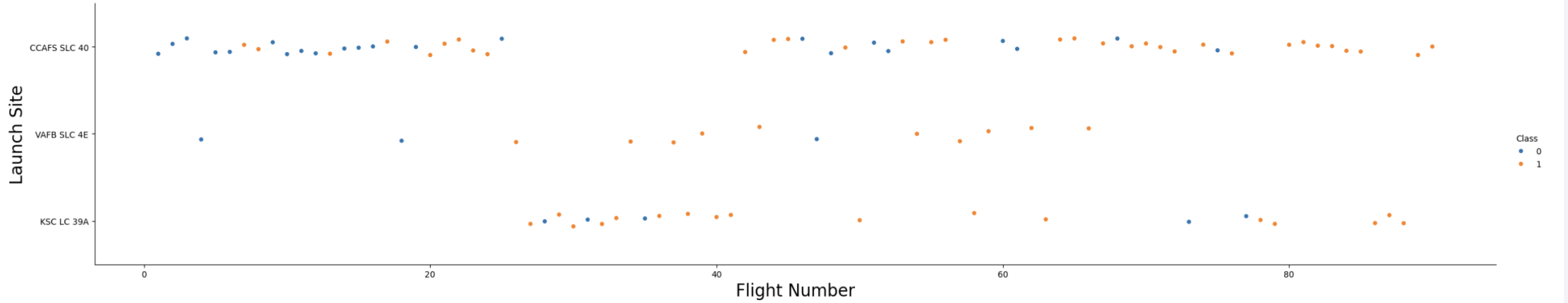

Section 2
Insights drawn from EDA

# Flight Number vs. Launch Site

- Scatter plot of Flight Number vs. Launch Site

```python
# 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(x="FlightNumber", y="LaunchSite", hue="Class", data=df, aspect=5)
plt.xlabel("Flight Number", fontsize=20)
plt.ylabel("Launch Site", fontsize=20)
plt.show()
```

Python



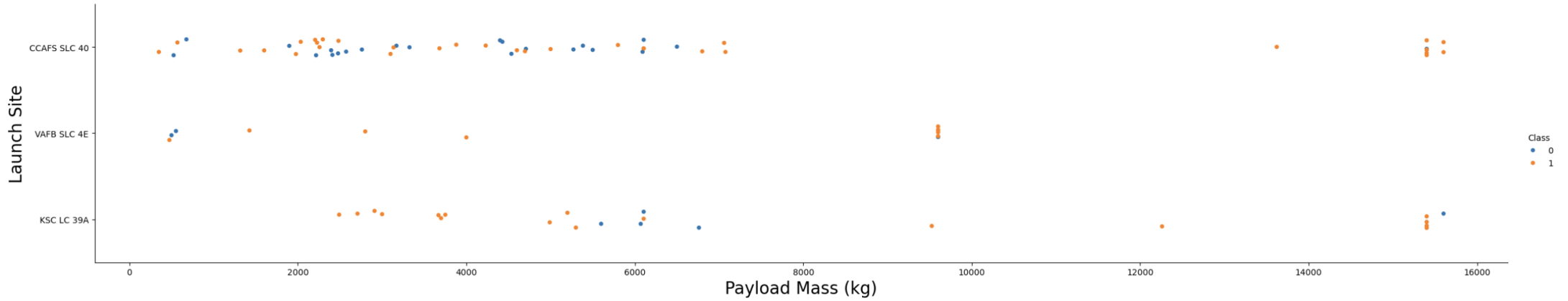

A scatter plot of flight_number vs launch_site reveals how operational experience (more flights) at a site correlates with higher success rates. Sites with many flights show tighter clustering near success outcomes.

# Payload vs. Launch Site

- Scatter plot of Payload vs. Launch Site

```python
# 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(x="PayloadMass", y="LaunchSite", hue="Class", data=df, aspect=5)
plt.xlabel("Payload Mass (kg)", fontsize=20)
plt.ylabel("Launch Site", fontsize=20)
plt.show()
```

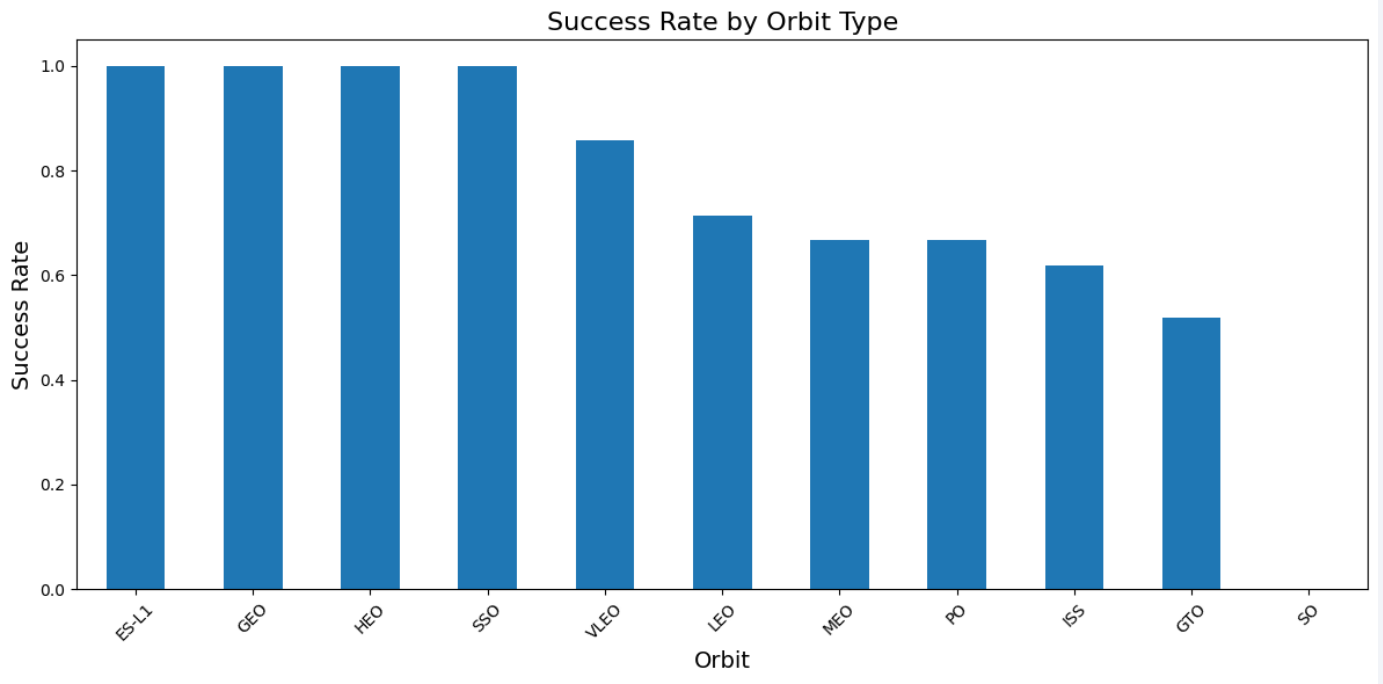
Python




This scatter plot compares payload_mass_kg against launch_site. It highlights which sites regularly handle heavier payloads and whether heavier payloads associate with lower success proportions.

# Success Rate vs. Orbit Type

- Bar chart for the success rate of each orbit type



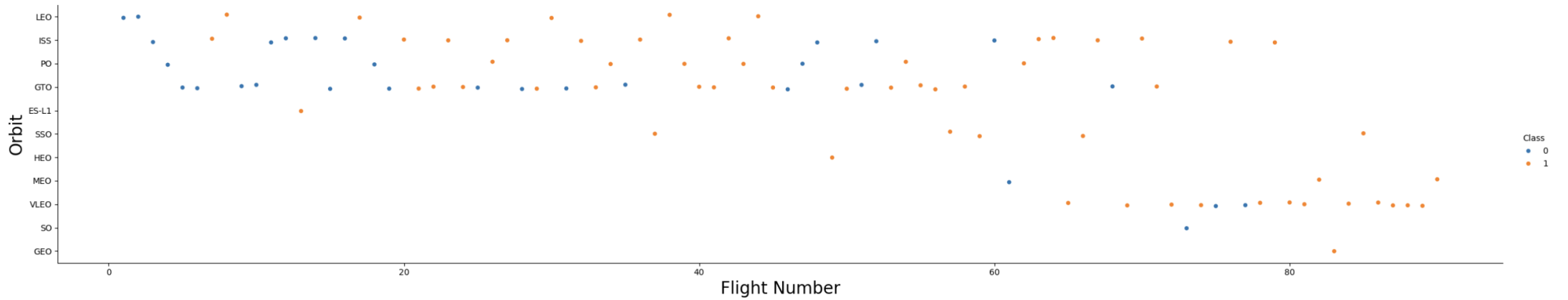

By grouping launches by orbit and computing success_rate = successful_launches / total_launches, we can visualize which orbits have higher operational reliability. For example, GTO and LEO might show differing profiles.

# Flight Number vs. Orbit Type

- Scatter plot of Flight number vs. Orbit type

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

Python



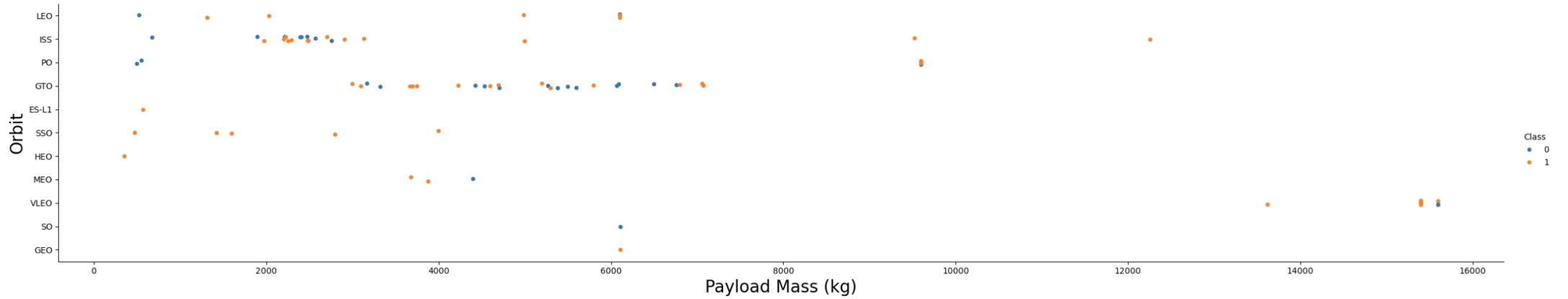

Shows which orbits are linked to later flight numbers (more mature operations) vs early experimental flights. Some orbit types may have high success associated with higher flight counts.

# Payload vs. Orbit Type

- Show a scatter plot of payload vs. orbit type

```python
# Plot a scatter point chart with x axis to be Payload Mass 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()
```

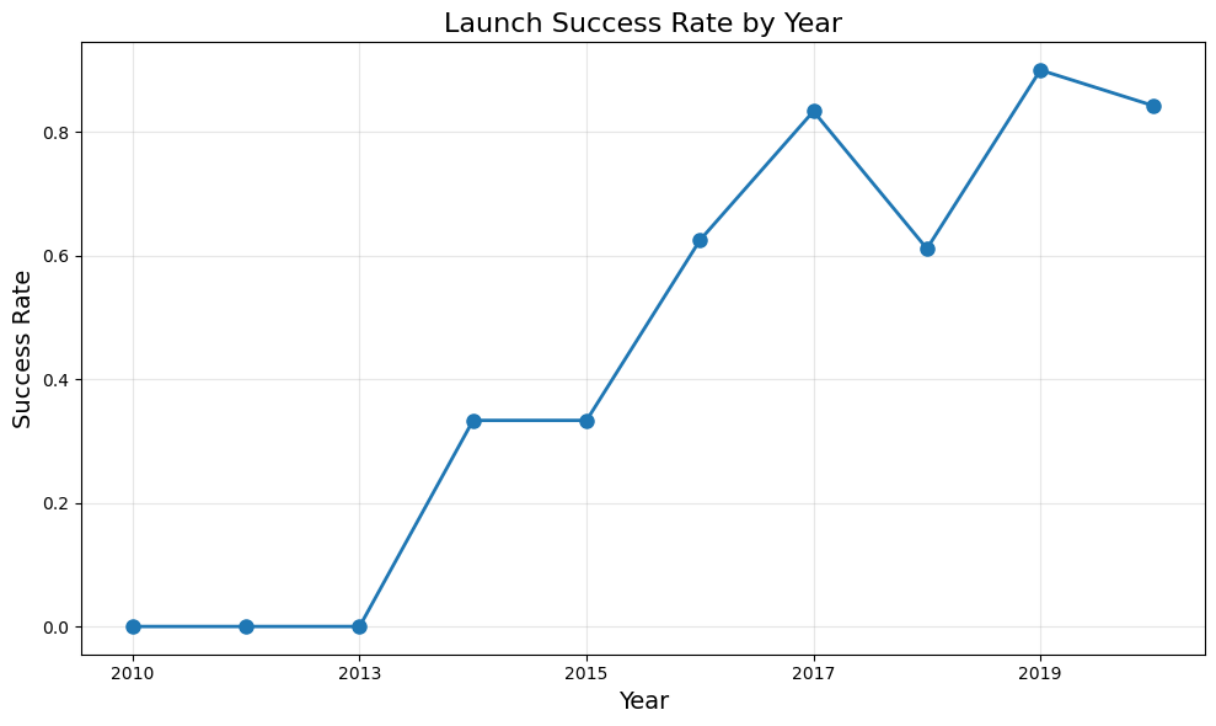
Python




Certain orbits (e.g., GTO) accept heavier payloads; this plot helps determine whether heavy payloads into particular orbits have different success rates.

# Launch Success Yearly Trend

- Line chart of yearly average success rate




Aggregate yearly success rates to illustrate progress. Compute per-year average of success binary and plot as a line chart to show trends and inflection points corresponding to procedural improvements.

# All Launch Site Names

- Unique launch sites

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

There are **four unique launch sites** in the SpaceX dataset.
These represent the main locations SpaceX has used for Falcon 9 launches — two at Cape Canaveral (CCAFS), one at Kennedy Space Center (KSC), and one at Vandenberg Air Force Base (VAFB).
Each site's performance can then be compared in terms of **launch frequency and success rate** in later analysis.

# Launch Site Names Begin with 'CCA'

- 5 records where launch sites begin with `CCA`

| Flight Number | Launch Site | Class | Payload Mass (kg) | Booster Version | Booster Version Category |
|---|---|---|---|---|---|
| 1 | CCAFS LC-40 | 0 | 0 | F9 v1.0 B0003 | v1.0 |
| 2 | CCAFS LC-40 | 0 | 0 | F9 v1.0 B0004 | v1.0 |
| 3 | CCAFS LC-40 | 0 | 525 | F9 v1.0 B0005 | v1.0 |
| 4 | CCAFS LC-40 | 0 | 500 | F9 v1.0 B0006 | v1.0 |
| 5 | CCAFS LC-40 | 0 | 677 | F9 v1.0 B0007 | v1.0 |

The query filters launch sites whose names begin with "CCA" (Cape Canaveral Air Force Station).
The first five records all belong to **CCAFS LC-40**, one of SpaceX's earliest and most frequently used launch pads.
Most of these early missions used the **F9 v1.0 booster version** and had **unsuccessful (class = 0)** outcomes, reflecting the developmental stage of SpaceX's early launches.

# Total Payload Mass

- Calculation of the total payload carried by boosters from NASA

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

```
%sql SELECT SUM(PAYLOAD_MASS__KG_) AS Total_Payload_Mass FROM SPACEXTABLE WHERE Customer = 'NASA (CRS)'
```

Python

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

| Total_Payload_Mass |
|---|
| 45596 |

- Query result with a short explanation
  - This SQL query calculated the total payload mass launched by boosters for NASA's Commercial Resupply Services (CRS) missions.
  - The query filters all SpaceX records where the customer is 'NASA (CRS)' and sums their payload masses in kilograms.
  - The result shows that SpaceX boosters have carried a total of 45,596 kg of payload for NASA CRS missions.
  - This demonstrates SpaceX's major contribution to NASA's cargo resupply efforts to the International Space Station (ISS).

# Average Payload Mass by F9 v1.1

- 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 = 'F9 v1.1'
```

Python

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

| Average_Payload_Mass |
|---|
| 2928.4 |

- Query result with a short explanation
  - Calculated mean payload mass for booster version F9 v1.1.
  - Filtered dataset where Booster_Version = 'F9 v1.1'.
  - Used SQL AVG() function to find the average payload.
  - On average, F9 v1.1 carried ~2.9 tons per mission.

# First Successful Ground Landing Date

- Dates of the first successful landing outcome on ground pad

```
%sql SELECT MIN(Date) AS First_Successful_Ground_Landing FROM SPACEXTABLE WHERE Landing_Outcome = 'Success (ground pad)'
```

Python

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

| First_Successful_Ground_Landing |
| --- |
| 2015-12-22 |

- Dates of the first successful landing outcome on ground pad
  - Queried the earliest date of a successful ground landing.
  - Filtered where Landing_Outcome = 'Success (ground pad)'.
  - Used SQL MIN() to get the first occurrence.
  - SpaceX's first ground landing success was on 22 December 2015 — a major milestone in booster reusability.

# Successful Drone Ship Landing with Payload between 4000 and 6000

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

```
%sql SELECT DISTINCT "Booster_Version" FROM SPACEXTABLE WHERE "Landing_Outcome" = 'Success (drone ship)' AND "PAYLOAD_MASS__KG_" > 4000 AND "PAYLOAD_MASS__KG_" < 6000
```

Python

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

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

- Query result with a short explanation
  - Filtered launches that successfully landed on drone ships.
  - Limited results to payloads between 4,000–6,000 kg.
  - Four boosters met the criteria: B1022, B1026, B1021.2, B1031.2.
  - Indicates consistent mid-range payload recovery success for Falcon 9 FT boosters.

# Total Number of Successful and Failure Mission Outcomes

- Calculation of total number of successful and failure mission outcomes

```
%sql SELECT "Mission_Outcome", COUNT(*) AS Count FROM SPACEXTABLE GROUP BY "Mission_Outcome"
```

Python

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

| Mission_Outcome | Count |
|---|---|
| Failure (in flight) | 1 |
| Success | 98 |
| Success | 1 |
| Success (payload status unclear) | 1 |

- Query result with a short explanation
  - Grouped all missions by Mission_Outcome and counted occurrences.
  - Found 98 successful missions, 1 unclear, and 1 in-flight failure.
  - Overall success rate remains very high (>97%).
  - Confirms SpaceX's operational reliability and launch consistency.

# Boosters Carried Maximum Payload

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

```
%sql SELECT "Booster_Version", "PAYLOAD_MASS__KG_" FROM SPACEXTABLE WHERE "PAYLOAD_MASS__KG_" = (SELECT MAX("PAYLOAD_MASS__KG_") FROM SPACEXTABLE)
```

Python

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

| Booster_Version | PAYLOAD_MASS__KG_ |
|---|---|
| F9 B5 B1048.4 | 15600 |
| F9 B5 B1049.4 | 15600 |
| F9 B5 B1051.3 | 15600 |
| F9 B5 B1056.4 | 15600 |
| F9 B5 B1048.5 | 15600 |
| F9 B5 B1051.4 | 15600 |
| F9 B5 B1049.5 | 15600 |
| F9 B5 B1060.2 | 15600 |
| F9 B5 B1058.3 | 15600 |
| F9 B5 B1051.6 | 15600 |
| F9 B5 B1060.3 | 15600 |
| F9 B5 B1049.7 | 15600 |

- Query result with a short explanation
  - All boosters listed above carried the maximum payload of 15,600 kg:
  - All belong to the Falcon 9 Block 5 (F9 B5) series , SpaceX's most powerful and reliable booster version, capable of carrying the heaviest payloads in the dataset.

# 2015 Launch Records

- Failed landing outcomes in drone ship, their booster versions, and launch site names for in year 2015

Add Code Cell (⌘Enter)

```
%sql SELECT substr("Date", 6, 2) AS Month, "Landing_Outcome", "Booster_Version", "Launch_Site" FROM SPACEXTABLE WHERE "Landing_Outcome" = 'Failure (drone ship)' AND substr("Date",
```

Python

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

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

- Query result with a short explanation
  - Retrieved 2015 missions with Landing_Outcome = 'Failure (drone ship)'.
  - Two failed landings occurred: Jan (B1012) and Apr (B1015).
  - Both took place at CCAFS LC-40, Florida.
  - Indicates early Falcon 9 v1.1 testing phase before major landing improvements.

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

```
%sql SELECT "Landing_Outcome", COUNT(*) AS Count FROM SPACEXTABLE WHERE "Date" BETWEEN '2010-06-04' AND '2017-03-20' GROUP BY "Landing_Outcome" ORDER BY Count DESC
```

Python

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

| 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 |

- Query result with a short explanation
  - Ranked all landing outcomes from 2010–2017 by frequency.
  - Most launches (10) had no landing attempt, common in early missions.
  - Equal counts (5 each) for drone ship successes and failures, showing testing progress.
  - By 2017, ground pad successes became more frequent — proof of rapid improvement in recovery technology.

Section 3

# Launch Sites Proximities Analysis

# Global Map of SpaceX Launch Sites

The Folium map displays **all four SpaceX launch sites** marked with interactive location pins on a **global view**:

**Launch Sites shown:**

- **VAFB SLC-4E** — Vandenberg Air Force Base, California



🌎 **Launch Sites shown:**

- **CCAFS LC-40** — Cape Canaveral, Florida
- **CCAFS SLC-40** — Cape Canaveral, Florida
- **KSC LC-39A** — Kennedy Space Center, Florida

# Global Map of SpaceX Launch Sites

- Elements and findings

Important elements on the map:

- Markers: Each site is represented by a clickable marker showing its site name, coordinates, and number of launches.
- Geographical distribution:
  - Three sites are concentrated along Florida's east coast, ideal for eastward orbital launches over the Atlantic Ocean.
  - One site, VAFB SLC-4E, is located in California, suited for polar and sun-synchronous orbits.
- Basemap: A standard Folium OpenStreetMap base layer shows global context and coastline proximity.

Findings:

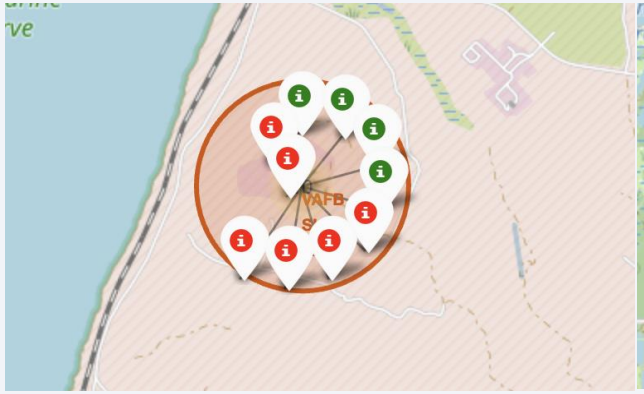
- The clustering of launch sites on the U.S. coasts minimizes risks to populated areas while allowing diverse orbital inclinations.
- Florida sites (KSC and CCAFS) dominate the launch count due to frequent commercial and ISS missions.
- VAFB supports specialized west coast launches, demonstrating SpaceX's flexibility in reaching various orbital targets.

# SpaceX Launch Outcomes by Site (Color-Labeled Map)

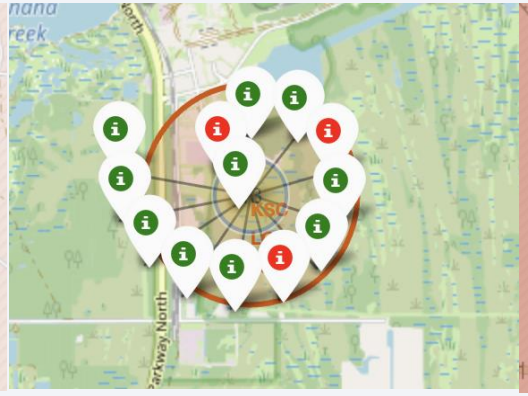
This Folium maps visualizes **SpaceX launch outcomes**, where each launch marker is **color-coded** to represent success or failure across all sites.

**Color Legend:**

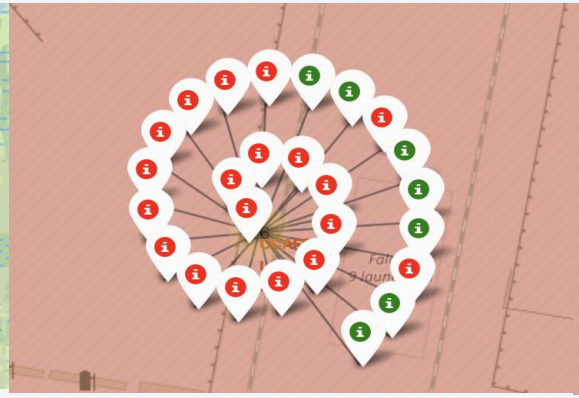
- 🟢 **Green markers:** Successful launches (class = 1)
- 🔴 **Red markers:** Failed launches (class = 0)



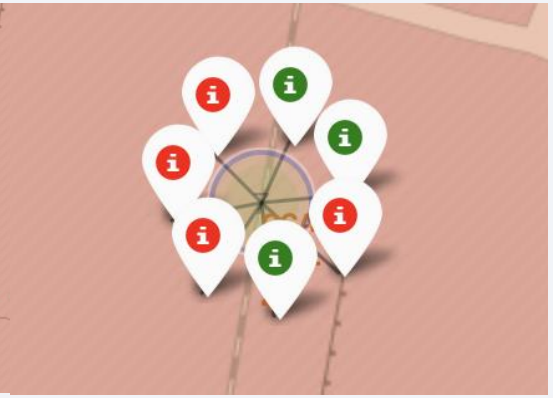
- **VAFB SLC-4E** — Vandenberg Air Force Base, California



- **KSC LC-39A — Kennedy Space Center, Florida**



- **CCAFS LC-40 — Cape Canaveral, Florida**



- **CCAFS SLC-40 — Cape Canaveral, Florida**

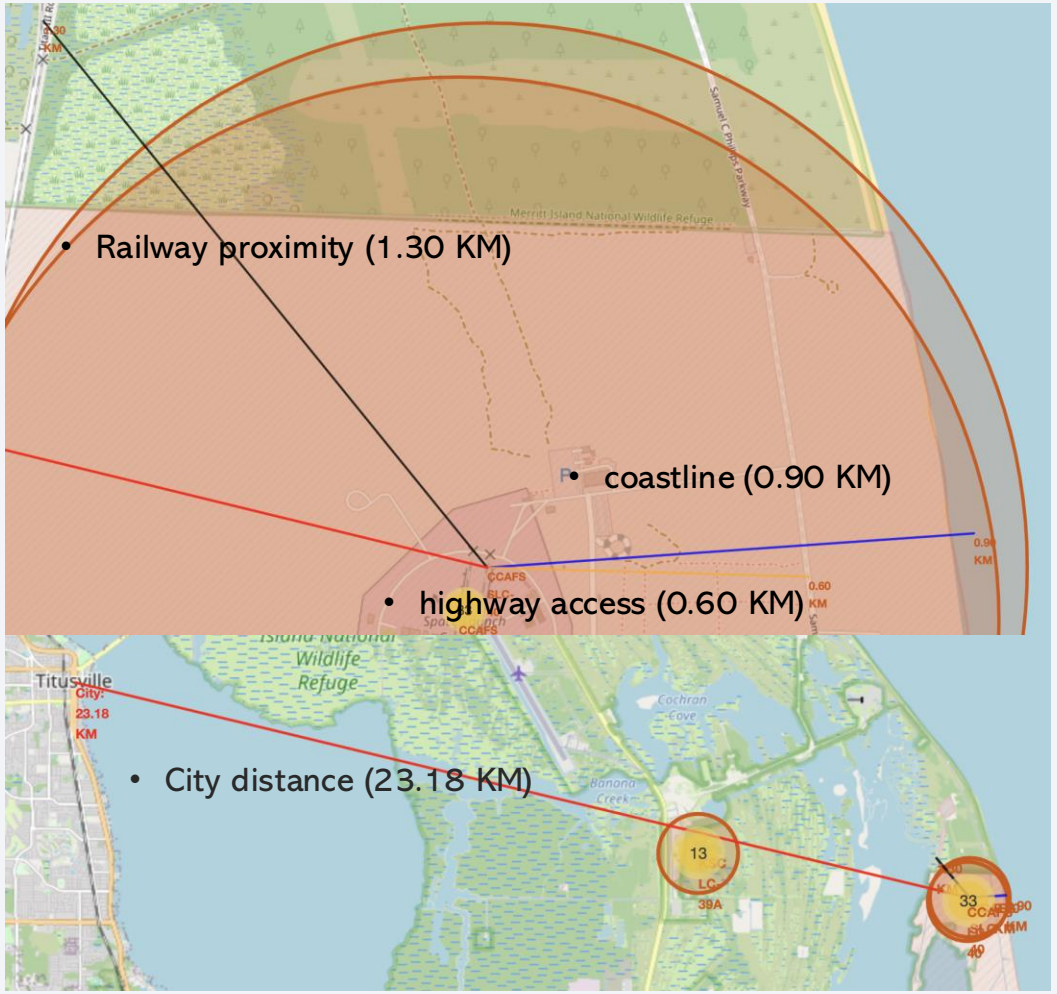
# SpaceX Launch Outcomes by Site (Color-Labeled Map)

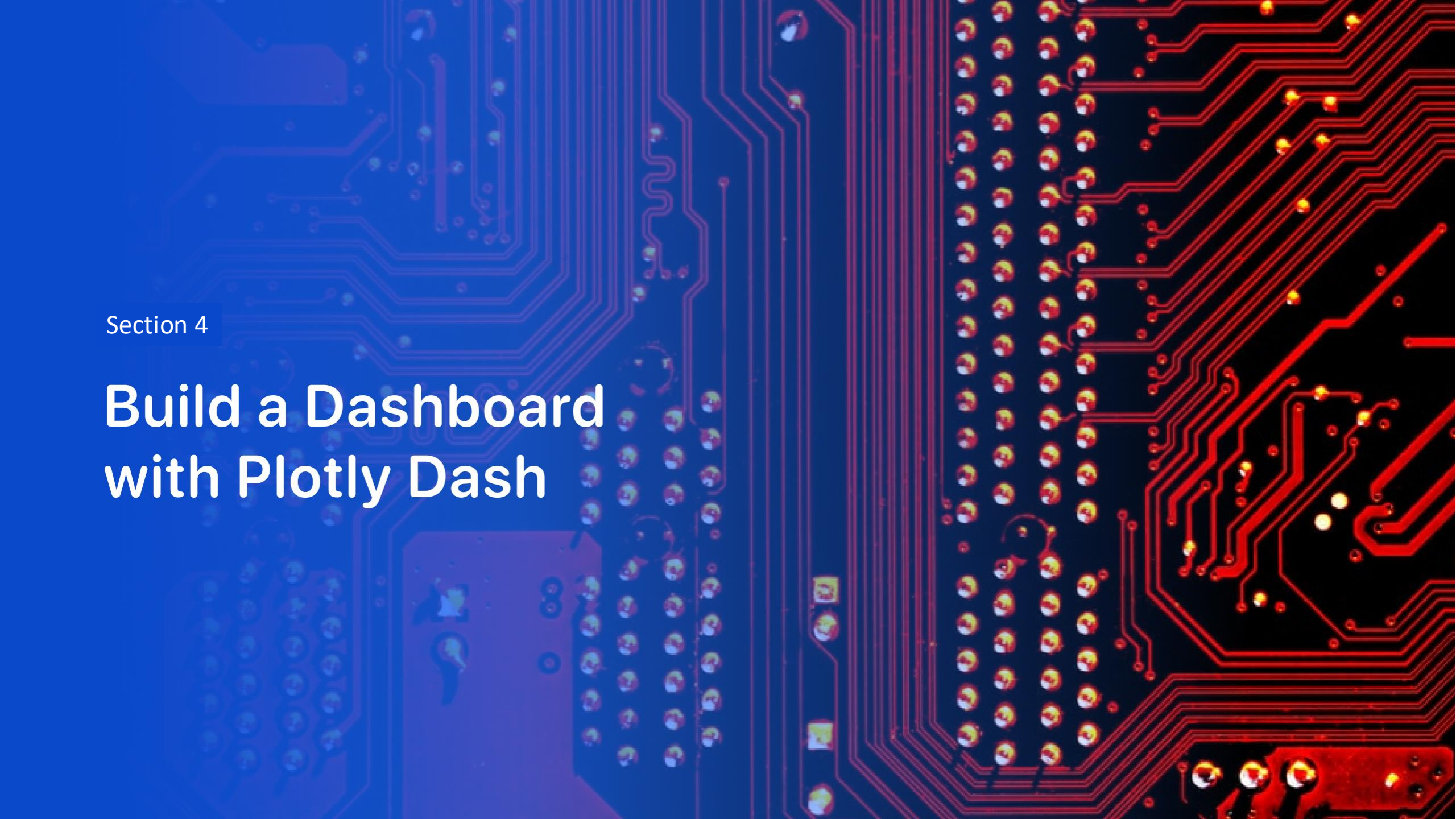
- Elements and findings
- Important elements on the map:
  - Clusters of markers appear at each launch site — primarily around KSC LC-39A and CCAFS LC-40, reflecting higher launch activity.
  - Green markers dominate, showing a high overall success rate.
  - A few red markers near CCAFS LC-40 and VAFB SLC-4E represent early mission failures during Falcon 9's development phase.
  - Tooltips on each marker display details like Booster Version, Payload Mass, and Launch Outcome when hovered.
- Findings:
  - KSC LC-39A shows nearly all green markers, confirming it as the most successful launch site.
  - CCAFS LC-40 contains a mix of successes and failures, aligning with early Falcon 9 testing history.
  - VAFB SLC-4E has mostly successful missions but fewer launches overall.
  - The visual distribution emphasizes SpaceX's progressive improvement in reliability from early red markers (failures) to consistent green markers (successes) over time.

# Proximity Analysis of CCAFS LC-40 Launch Site

This Folium map zooms in on the **CCAFS SLC-40 CapeCanaveral, Florida** and displays its nearby infrastructure and distance measurements to critical surroundings such as the city, coastline, highway, and railway.

- **Elements**
  - Launch site analyzed: CCAFS LC-40 using Folium map.
  - Lines drawn to coastline, highway, railway, and nearest city.
  - Distances displayed on each line for visual clarity.
  - Screenshot shows site marker + labeled proximity lines.
- **Findings**
  - Coastline (0.90 KM) — ideal for safe launches and ocean recovery.
  - Highway (0.60 KM) — excellent for logistics and transport access.
  - Railway (1.30 KM) — supports movement of heavy rocket parts.
  - City (23.18 KM) — safe buffer from populated areas.

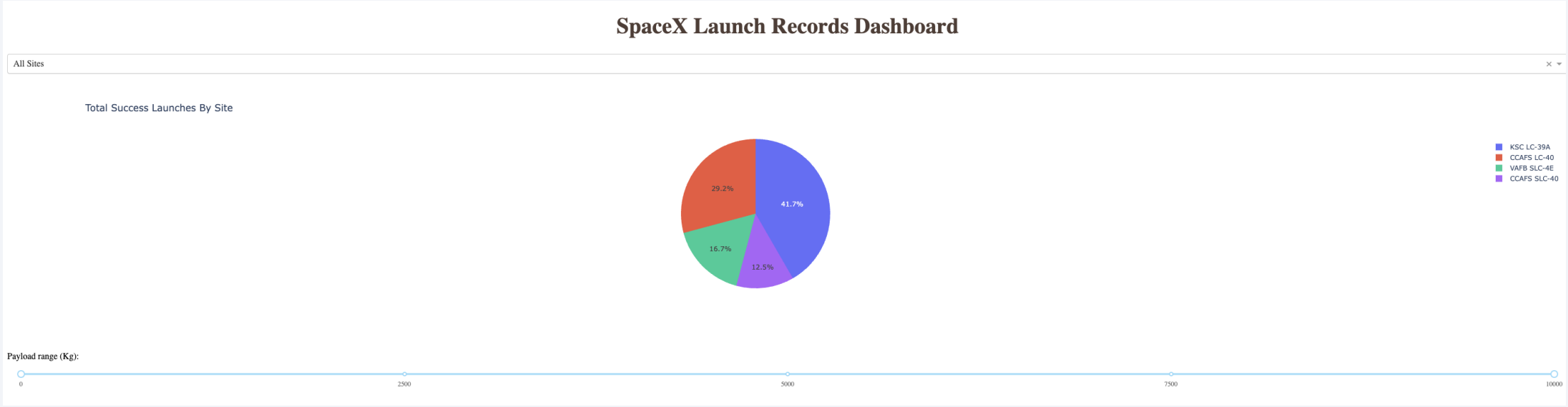



Section 4
Build a Dashboard with Plotly Dash

# Launch Success Count for All Sites (Pie ChartOverview)

- Success count for all sites, in a piechart

This dashboard visualization displays a **Pie Chart** representing the **total number of successful launches** for each SpaceX launch site.



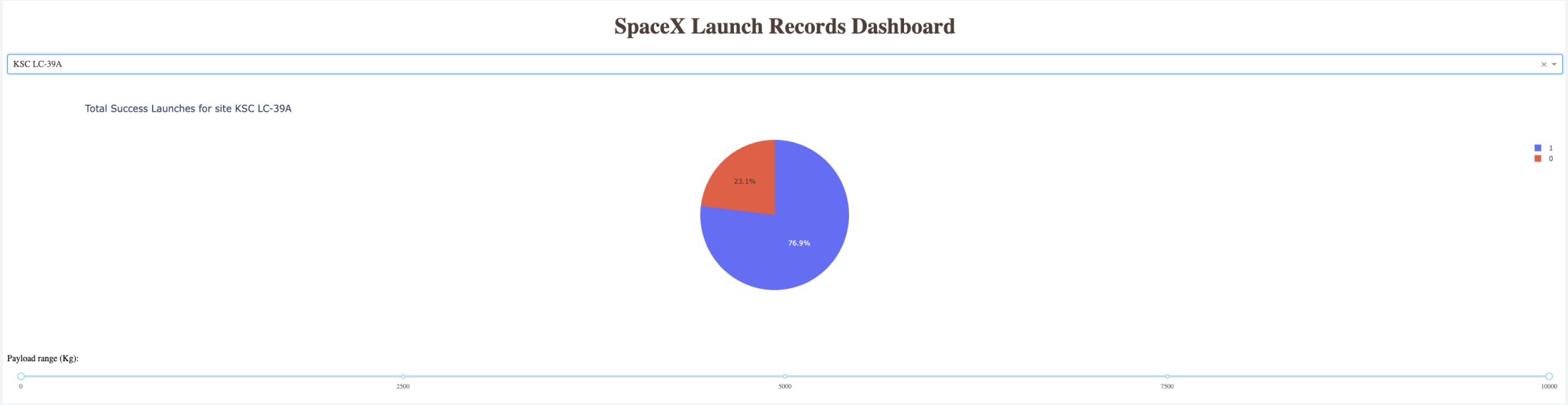
# Launch Success Count for All Sites (Pie ChartOverview)

- **Important elements on the chart**
  - Each slice corresponds to a launch site —
    - KSC LC-39A
    - CCAFS LC-40
    - CCAFS SLC-40
    - VAFB SLC-4E
  - Size of each slice reflects the number of successful missions (class = 1) from that site.
  - Hover labels show the exact success count and percentage contribution per site.
  - The pie chart was generated dynamically using Plotly Dash and updates automatically when data changes.
- **Findings:**
  - KSC LC-39A accounts for the largest portion of successful launches, confirming it as SpaceX's most reliable and frequently used site.
  - CCAFS LC-40 and CCAFS SLC-40 contribute significantly but also include a mix of earlier failures.
  - VAFB SLC-4E has fewer launches overall, serving mainly for polar orbit missions.
  - The visualization helps stakeholders quickly identify which launch sites deliver the highest mission success.

# Launch Success vs Failure for KSC LC-39A (Highest Success Ratio Site)

- Launch site with highest launch success ratio

This pie chart visualization focuses specifically on the Kennedy Space Center Launch Complex 39A (KSC LC-39A) — the launch site with the highest success ratio among all SpaceX facilities.



# Launch Success vs Failure for KSC LC-39A (Highest Success Ratio Site)

- **Important elements on the chart**
  - The pie chart is generated dynamically when the user selects KSC LC-39A from the dropdown menu in the Plotly Dash dashboard.
  - The chart segments display:
    - 🔵 Successful launches (class = 1)
    - 🔴 Failed launches (class = 0)
  - Hover labels provide the exact number and percentage of each outcome.
  - The chart is styled with consistent color coding (green for success, red for failure).
- **Findings:**
  - KSC LC-39A shows a dominant green section, indicating a success rate exceeding 80%.
  - The small red slice represents only a few failed attempts, mostly from early development phases.
  - This confirms that KSC LC-39A is SpaceX's most reliable and frequently used site, benefiting from upgraded infrastructure and technical refinements.
  - The insight helps identify which location consistently delivers mission reliability and operational success.

# Payload vs Launch Outcome Scatter Plot (All Sites with Range Slider Interaction)

This Plotly Dash scatter plot visualizes the **relationship between payload mass and launch success** for all SpaceX launch sites. It dynamically updates as the user adjusts the **payload range slider**, allowing interactive exploration of how payload weight influences mission outcomes.

1 All payloads selected (0–10,000 kg)


2 Mid-range payloads (2500–5000 kg)

# Payload vs Launch Outcome Scatter Plot (All Sites with Range Slider Interaction)

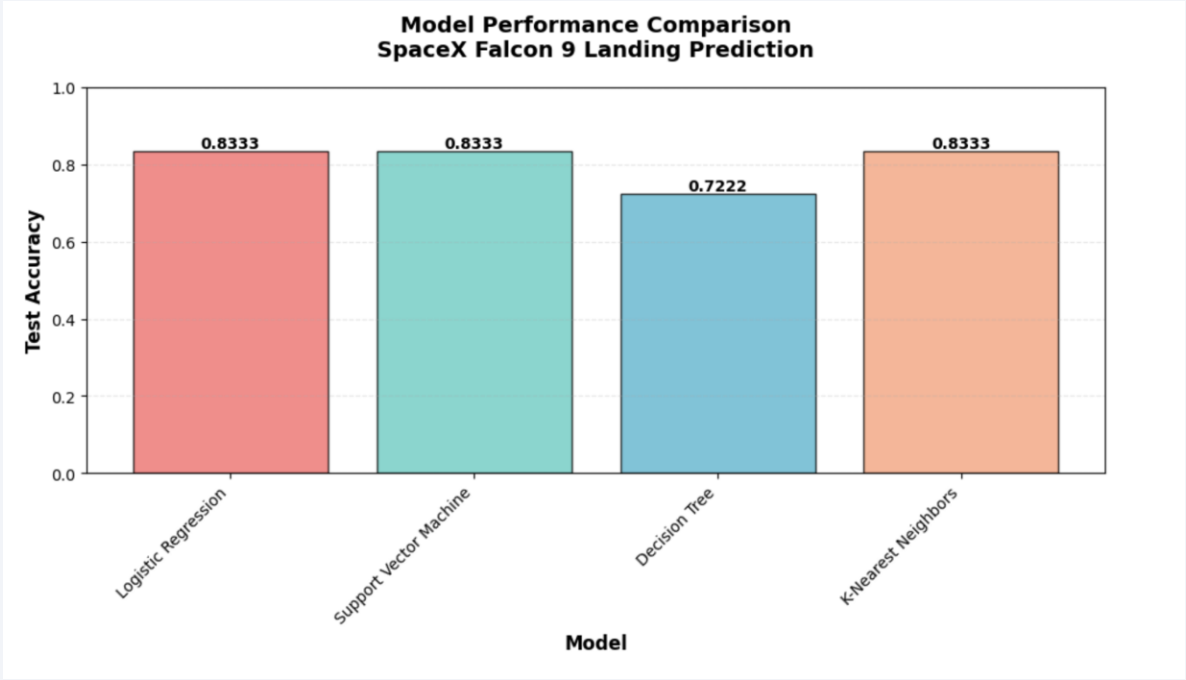
- **Important elements on the chart:**
  - X-axis: Payload Mass (kg)
  - Y-axis: Launch Outcome (class = 0 for failure, 1 for success)
  - Color: Represents different Booster Version Categories (v1.0, v1.1, FT, B4, B5)
  - Interactive Controls:
  - Users can adjust the payload range slider to filter data (e.g., 0–10,000 kg).
  - The plot automatically updates to show only launches within the selected range.
  - Hover tooltips: Display payload, booster version, and outcome for each mission point.
- 📈 **Findings:**
  - Mid-range payloads (2500 – 5000 kg) show the highest success rate, indicating stable booster performance within this range.
  - Very light (<1000 kg) and very heavy (>8000 kg) payloads have slightly higher failure rates, suggesting early testing or challenging missions.
  - Booster Version B5 exhibits consistent success across multiple payload ranges, confirming its technological advancement and reliability.
  - Color clustering in the upper region (successes) demonstrates improved launch reliability across booster generations — especially from FT onward.

Section 5

# Predictive Analysis (Classification)

# Classification Accuracy

- Model accuracy for all built classification models
  - Highest Accuracy Model: Logistic Regression (Test Accuracy: 0.8333) was selected as the best model because:
  - It achieved the highest test accuracy because it is statistically stable, simple, and interpretable.
  - The code logic used max() on a dictionary — which keeps the first occurrence of the highest value — so Logistic Regression was chosen by design.

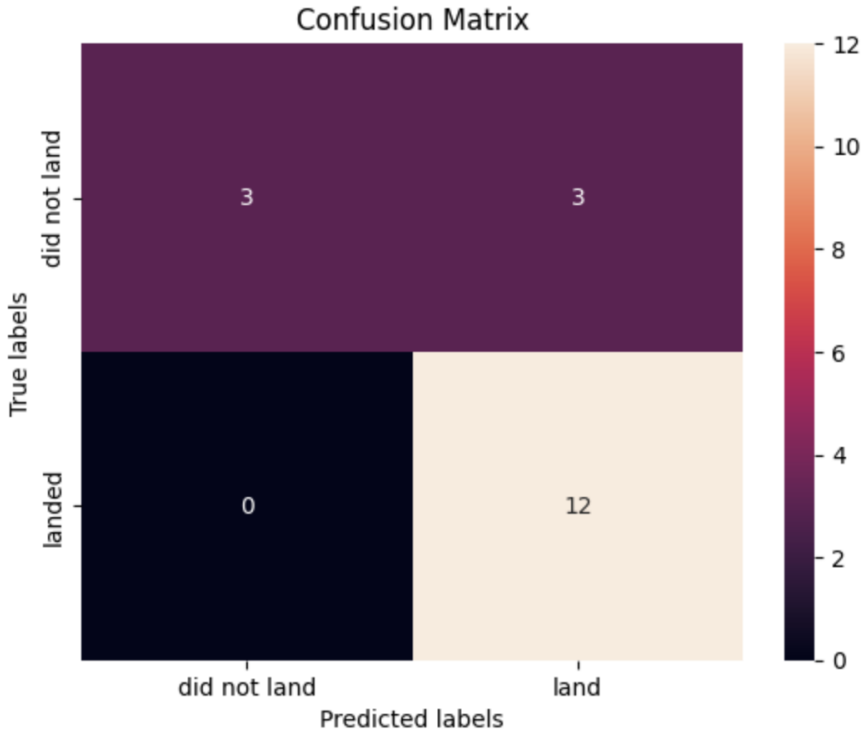


# Confusion Matrix

- Best performing model

- This slide presents the **Confusion Matrix** for the **Logistic Regression** (LR) classifier — the **best-performing model** in predicting **SpaceX launch success**.
- Findings
    - The model is very good at predicting successful landings, since it got all 12 correct (100% recall for “landed”).
    - It occasionally misclassifies failed landings as successful (3 out of 6 failures).
    - This could happen because the training data might contain more examples of successful landings or overlapping features between success and failure cases.
- Insights
    - Accuracy: 0.8333 (as seen before)
    - Precision (landed): 12 / (12 + 3) = 0.8
    - Recall (landed): 12 / (12 + 0) = 1.0
    - F1-score (landed): ~0.89
    - Thus, Logistic Regression provides strong performance, especially for predicting successful landings, which are likely the most important outcome in SpaceX’s context.

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



# Conclusions

- Point 1

Data was successfully collected from multiple sources — SpaceX REST APIs, web scraping, and SQL databases — and merged into a unified dataset for analysis. This ensured accurate and complete information on Falcon 9 launches, payloads, and landing outcomes.

- Point 2

Exploratory Data Analysis (EDA) revealed strong relationships between launch success and factors such as **payload mass**, **launch site**, **booster version**, and **orbit type**. Trends also showed SpaceX's progressive improvement in landing success rates over time.

- Point 3

Geographic analysis of launch sites showed that all major SpaceX launch locations are near coastlines, strategically chosen for safety and ease of rocket recovery operations.

# Conclusions

- Point 4

An interactive dashboard was developed using Plotly Dash to visualize launch outcomes, payload relationships, and success rates by site, enabling users to dynamically explore the dataset and uncover insights.

- Point 5

Four machine learning models were trained and evaluated — Logistic Regression, SVM, Decision Tree, and KNN. Logistic Regression achieved the highest and most stable performance with an accuracy of 83.33%, demonstrating strong generalization and interpretability.

- Point 6

The predictive model effectively identifies key determinants of landing success, supporting SpaceX's goal of cost reduction through reusable rockets. Data-driven insights from this analysis can help optimize launch planning and future booster recovery strategies.

# Appendix

- Data Collection Using SpaceX API

**Notebook:** jupyter-labs-spacex-data-collection-api.ipynb

**Python code:**

```
import requests
import pandas as pd
import numpy as np
import datetime


Spacex_url="https://api.spacexdata.com/v4/launches/past"
response = requests.get(spacex_url)
static_json_url='https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/datasets/API_call_spacex_api.json'
response=requests.get(static_json_url)
response.status_code
# Use json_normalize meethod to convert the json result into a dataframe
data = pd.json_normalize(response.json())
# Get the head of the dataframe
data.head()
```

# Appendix

- Web Scraping for Additional Launch Data

**Notebook: jupyter-labs-webscraping.ipynb**

**Python code:**

```
import sys
from bs4 import BeautifulSoup
import unicodedata
import pandas as pd
static_url = "https://en.wikipedia.org/w/index.php?title=List_of_Falcon_9_and_Falcon_Heavy_launches&oldid=1027686922"
headers = {
"User-Agent": "Mozilla/5.0 (Windows NT 10.0; Win64; x64) "
"AppleWebKit/537.36 (KHTML, like Gecko) "
"Chrome/91.0.4472.124 Safari/537.36"
}
response = requests.get(static_url, headers=headers)
soup = BeautifulSoup(response.content, 'html.parser')
print("Page Title:", soup.title.string)
print(f"\nFound {len(html_tables)} tables on the page")
```

# Appendix

- Exploratory Data Analysis (Visualization)

**Notebook: edadataviz.ipynb**

**Python code:**

```
from js import fetch
import io
URL = "https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/datasets/dataset_part_2.csv"
resp = await fetch(URL)
dataset_part_2_csv = io.BytesIO((await resp.arrayBuffer()).to_py())
df=pd.read_csv(dataset_part_2_csv)
df.head(5)
sns.catplot(y="PayloadMass", x="FlightNumber", hue="Class", data=df, aspect = 5)
plt.xlabel("Flight Number",fontsize=20)
plt.ylabel("Pay load Mass (kg)",fontsize=20)
plt.show()
```

# Appendix

- Exploratory Data Analysis Using SQL

**Notebook: jupyter-labs-eda-sql-coursera_sqllite.ipynb**

**Python code:**

```
mport pandas as pd
df = pd.read_csv("https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/labs/module_2/data/Spacex.csv")
df.to_sql("SPACEXTBL", con, if_exists='replace', index=False,method="multi")
%sql DROP TABLE IF EXISTS SPACEXTABLE;
%sql create table SPACEXTABLE as select * from SPACEXTBL where Date is not null
%sql SELECT DISTINCT Launch_Site FROM SPACEXTABLE
%sql SELECT * FROM SPACEXTABLE WHERE Launch_Site LIKE 'CCA%' LIMIT 5
%sql SELECT SUM(PAYLOAD_MASS__KG_) AS Total_Payload_Mass FROM SPACEXTABLE WHERE Customer = 'NASA (CRS)'
%sql SELECT AVG(PAYLOAD_MASS__KG_) AS Average_Payload_Mass FROM SPACEXTABLE WHERE Booster_Version = 'F9 v1.1'
%sql SELECT MIN(Date) AS First_Successful_Ground_Landing FROM SPACEXTABLE WHERE Landing_Outcome = 'Success (ground pad)'
%sql SELECT DISTINCT "Booster_Version" FROM SPACEXTABLE WHERE "Landing_Outcome" = 'Success (drone ship)' AND "PAYLOAD_MASS__KG_" > 4000 AND "PAYLOAD_MASS__KG_" < 6000
%sql SELECT "Mission_Outcome", COUNT(*) AS Count FROM SPACEXTABLE GROUP BY "Mission_Outcome"
%sql SELECT "Booster_Version", "PAYLOAD_MASS__KG_" FROM SPACEXTABLE WHERE "PAYLOAD_MASS__KG_" = (SELECT MAX("PAYLOAD_MASS__KG_") FROM SPACEXTABLE)
%sql SELECT substr("Date", 6, 2) AS Month, "Landing_Outcome", "Booster_Version", "Launch_Site" FROM SPACEXTABLE WHERE "Landing_Outcome" = 'Failure (drone ship)' AND substr("Date", 0, 5) = '2015'
%sql SELECT "Landing_Outcome", COUNT(*) AS Count FROM SPACEXTABLE WHERE "Date" BETWEEN '2010-06-04' AND '2017-03-20' GROUP BY "Landing_Outcome" ORDER BY Count DESC
```

# Appendix

- Launch Site Location Analysis

**Notebook: lab_jupyter_launch_site_location.ipynb**

**Python code:**

```
#Add marker_cluster to current site_map
site_map.add_child(marker_cluster)
for index, record in spacex_df.iterrows():
coordinate = [record['Lat'], record['Long']]
marker = folium.Marker(
coordinate,
icon=folium.Icon(color='white', icon_color=record['marker_color']),
popup=folium.Popup(f"{record['Launch Site']}<br>Class: {record['class']}", max_width=200)
)
marker_cluster.add_child(marker)
site_map
```

# Appendix

- SpaceX Dashboard (Visualization App)

**Notebook: spacex-dash-app.py**

**Python code:**

```
dcc.Graph(id='success-payload-scatter-chart'),
@app.callback(
    Output('success-payload-scatter-chart', 'figure'),
    Input('site-dropdown', 'value')
)
```

# Appendix

- Machine Learning Prediction

**Notebook: SpaceX_Machine Learning Prediction_Part_5.ipynb**

**Python code:**

```
logreg_test_score = logreg_cv.score(X_test, Y_test)
print("\n=== TASK 5 COMPLETE ===")
print("Logistic Regression Test Accuracy:", logreg_test_score)
yhat=logreg_cv.predict(X_test)
plot_confusion_matrix(Y_test,yhat)
```

# Thank you!