IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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Outline

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

Executive Summary

- Summary of Methodologies

Goal: Predict Falcon 9 first-stage landing success (Class: 1 or 0) to assess cost viability.
Data Engineering: Data collected via API/Scraping, rigorously cleaned, features engineered (Orbit), and standardized.
EDA & Analytics: Comprehensive analysis using Visuals, SQL Queries for quantification, Folium for geospatial mapping, and a Plotly Dash interactive dashboard.
Predictive Modeling: Trained and optimized four classifiers (LR, SVM, KNN, DT) using GridSearchCV (CV=10) on scaled features.

- Summary of all results

Key Findings: Landing success is primarily driven by Orbit Type and Payload Mass.
Model Performance: Three models(LR, SVM, KNN) achieved a consistent Test Accuracy of ~= 08.333.
The Decision Tree model performed the worst on the test data with an accuracy of 0.6111.

Introduction

- SpaceX is an aerospace company focused on lowering the cost of space transportation.
- Project Context: Falcon 9 reusability is SpaceX’s core competitive advantage, enabling launch costs of ~ $62M versus competitors' >$165M.
- Problem Statement: Predicting the success of the first-stage return landing is critical for accurate launch cost forecasting and contract pricing.
- Our primary goal is to build a model to predict the binary target Class (1: Success, 0: Failure) based on pre-launch parameters.
  We aim to analyze historical Falcon 9 launch data to identify success patterns.

Section 1

Methodology

Methodology

Executive Summary

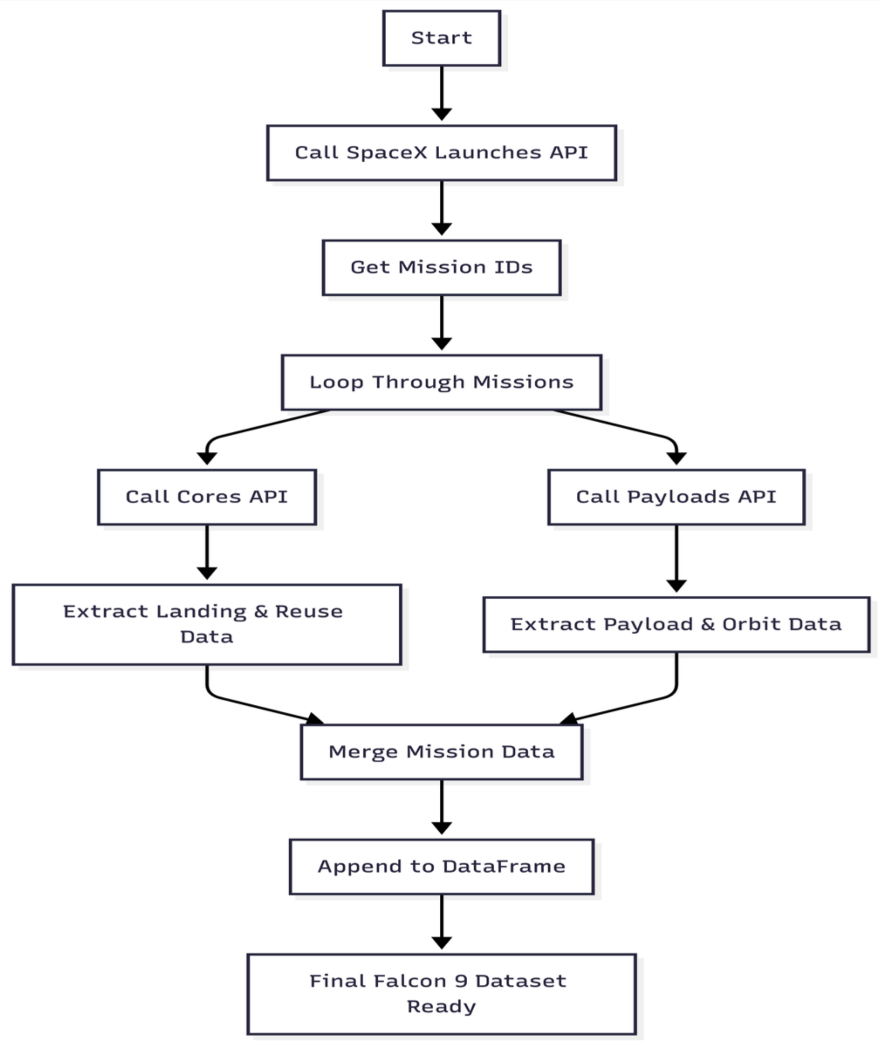
- Data collection methodology:
  - Describe how data was collected
- Perform data wrangling
  - Describe how data was processed
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
  - How to build, tune, evaluate classification models

Data Collection

- Source: Utilized the official SpaceX REST API to gather detailed telemetry, mission metadata, and core launch records.
- Initial Request: Sent the initial request to the main /launches or similar endpoint to retrieve all historical launch IDs.
- Iterative Process: Iterated through the list of launch IDs, sending granular requests to endpoints like /cores and /payloads to extract mission-specific data (e.g., core re-flight status, landing outcome, payload mass).
- Parsing: JSON responses were parsed using Python's json library to flatten nested structures and build the initial feature set DataFrame.
- Two primary data sources were used.
- Wikipedia provided historical mission records.

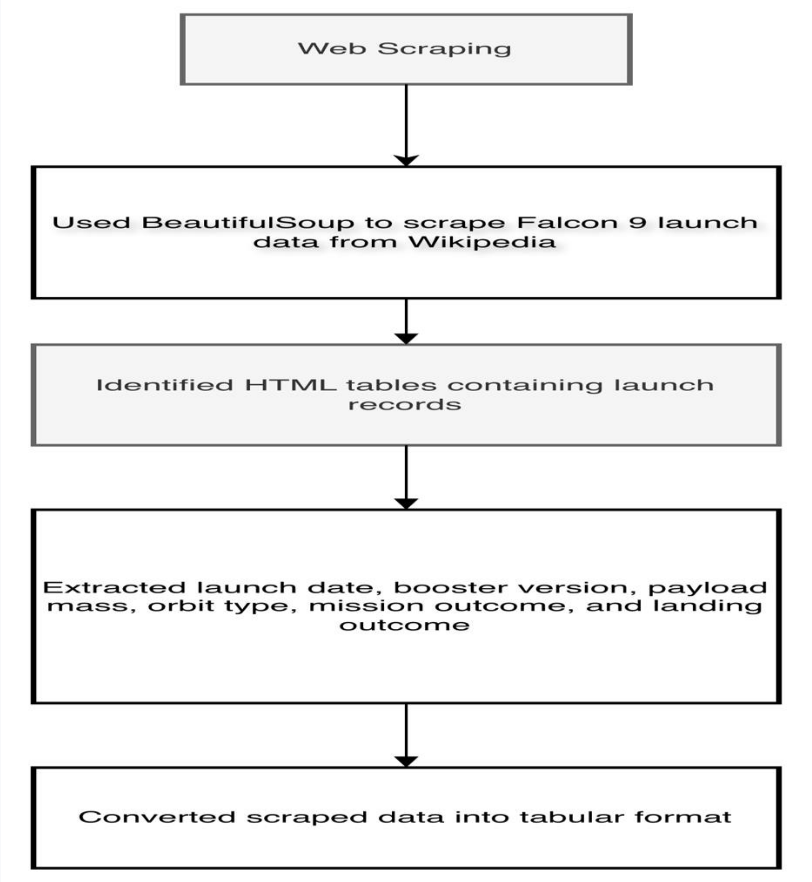
Data Collection – SpaceX API

- The flowchart in this slide, This diagram illustrates the process of building the comprehensive spacex_df from various API endpoints.
- Both datasets were combined to ensure completeness.
- The final dataset includes launch, payload, orbit, and landing outcome information.
- GitHub URL of the completed SpaceX API calls notebook: Gitbhub URL



Data Collection – Web Scraping

- Used Beautiful Soup to scrape Falcon 9 launch data from Wikipedia.
- Identified HTML tables containing launch records.
- Extracted launch date, booster version, payload mass, orbit type, mission outcome, and landing outcome.
- Completed notebook: [Github URL]



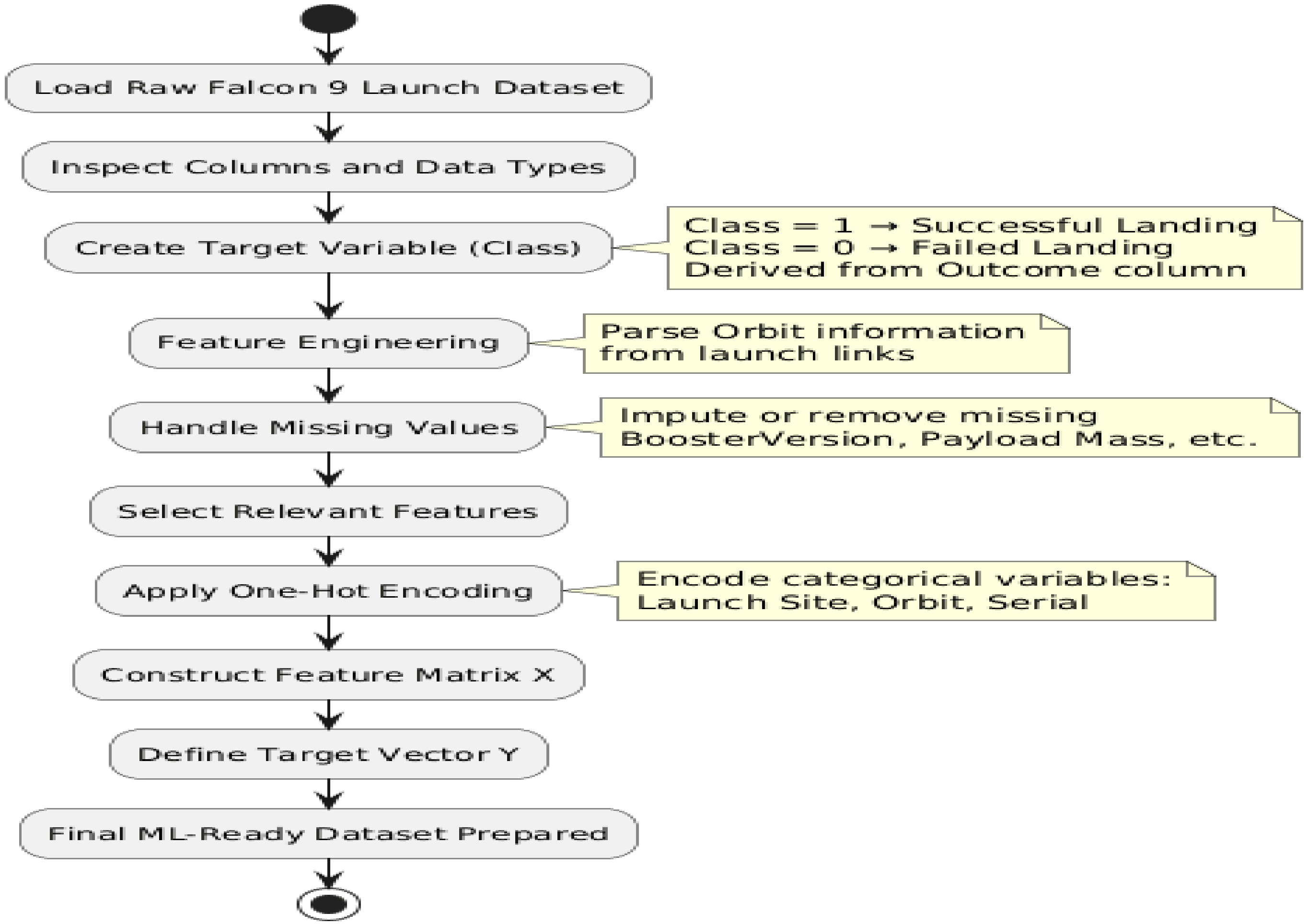
Data Wrangling

Goal: Convert raw launch records into a clean, machine-learning-ready X (features) and Y (target).

Key Steps:

- Target Creation: Class variable derived from the Outcome column (Success/Failure).
- Feature Engineering: Created the Orbit feature by parsing launch links.
- Missing Data: Handled sparse/missing values (e.g., in Booster Version or mass) using appropriate imputation.
- Categorical Encoding: Applied One-Hot Encoding to features like Launch Site, Orbit, and Serial to prepare the final feature matrix X.
- Github URL

Flowchart Diagram : Data Wrangling



EDA with Data Visualization

- Created scatter plots to analyze payload mass vs landing outcome as scatter plots reveal relationships and correlations.
- Visualized flight number vs landing success.
- Used bar charts to compare success rates by orbit type.
- Created line plots to analyze yearly success trends as line plots show performance trends over time.
- Visualization helps identify key predictive features.
- Github URL

EDA with SQL

- Loaded cleaned dataset into SQLite database.
- Used SQL queries for structured data analysis.
- SQL provided precise filtering and aggregation.
- Results supported insights from visualization analysis.
- SQL Queries Summary –
  Retrieved unique launch site names.
  Calculated total payload mass by customer.
  Computed average payload mass by booster version.
  Counted successful and failed landing outcomes.
- Github URL

EDA with SQL

- Display the names of the unique launch sites in the space mission :
  %sql SELECT DISTINCT Launch_Site FROM SPACEXTABLE;
- Display 5 records where launch sites begin with the string 'CCA' :
  %sql SELECT * FROM SPACEXTABLE WHERE "Launch_Site" LIKE 'CCA%'
  LIMIT 5;
- Display average payload mass carried by booster version F9 v1.1 :
  %sql SELECT AVG("PAYLOAD_MASS__KG_") FROM SPACEXTABLE WHERE
  "Booster_Version" = 'F9 v1.1';
- List the names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000 :
  %sql SELECT "Booster_Version" FROM SPACEXTABLE WHERE
  "Landing_Outcome" = 'Success (drone ship)' AND "PAYLOAD_MASS__KG_" >
  4000 AND "PAYLOAD_MASS__KG_" < 6000;

Build an Interactive Map with Folium

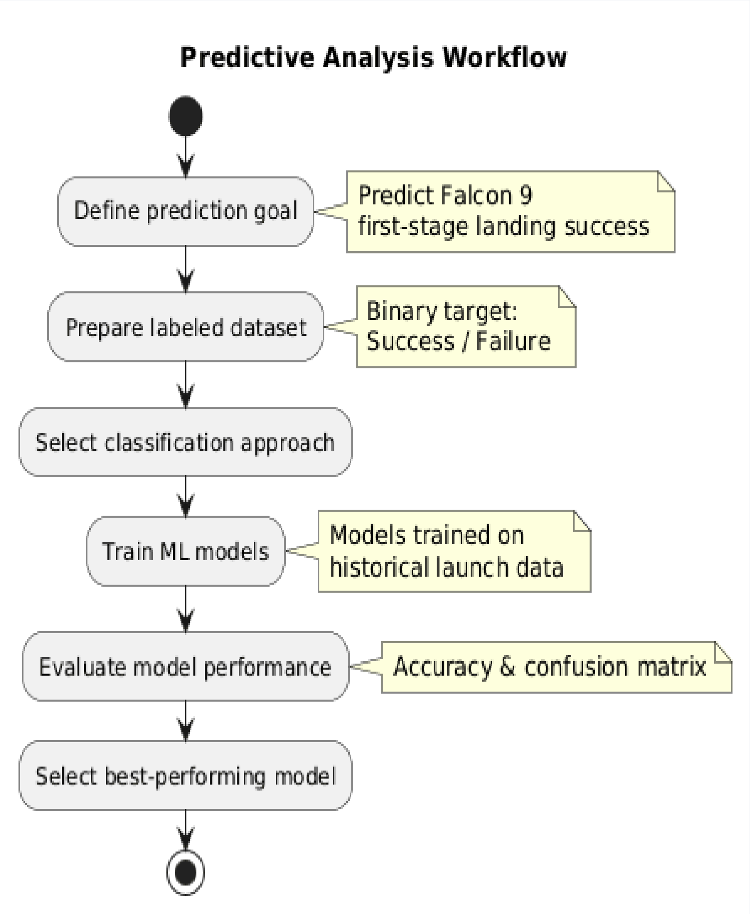
- Used Folium to build an interactive world map and added markers for SpaceX launch sites.
- Used color coding to show success and failure outcomes and enabled interactive exploration of launch locations.
- Methodology: Use of MarkerCluster for individual launch outcomes (Red/Green). Insight: Proximities of launch sites to safety zones (shorelines, cities).
- Markers are used for launch site locations, circles are used to represent proximity areas and lines are used to calculate distances to infrastructure.
- Popups are used to display site details.
- GitHub URL

Build a Dashboard with Plotly Dash

- Provides interactive filtering for stakeholders and peer-data-scientists.
- Dashboard allows users to select a Launch Site (Dropdown) or Payload Mass range (Slider) to dynamically update visual analytics.
- DCC Dropdown (Launch Site filter) dynamically updates the Plotly scatter plot (PayloadMass vs. Outcome)
- We have added a pie-chart, a range slider and scatter plot to our dashboard.
- Pie chart allows quick comparison of launch activity across sites, a range slider allows dynamic filtering of payload mass and users can explore different payload ranges to identify optimal conditions using scatter plot.
- GitHub URL

Predictive Analysis (Classification)

- The objective of predictive analysis is to forecast Falcon 9 first-stage landing success.
- A classification approach was selected because landing outcome is binary.
- The target variable represents successful or failed landings.
- Machine learning models were trained using historical launch data.
- Predictive analysis builds on insights from EDA and dashboard analysis.
- The goal is to identify the most accurate and reliable model.
- [GitHub URL]()



Results

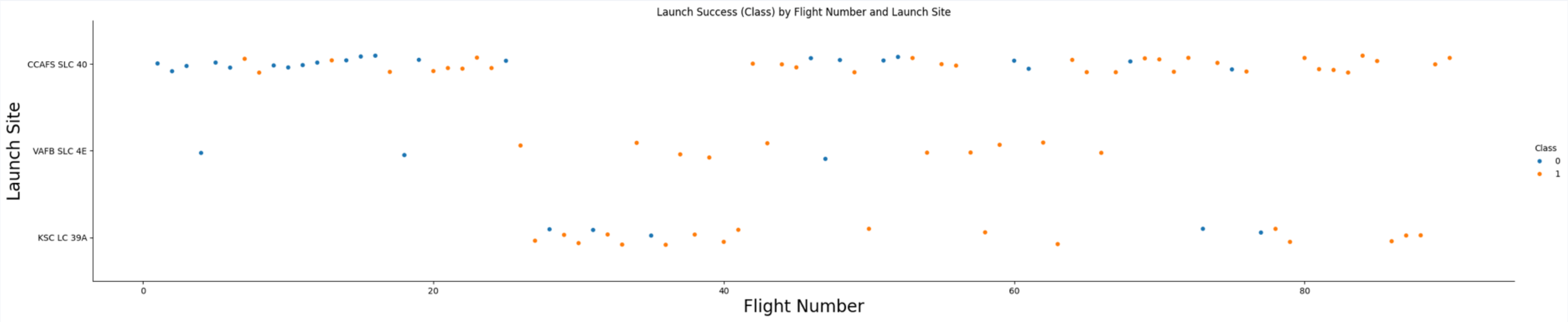
- Exploratory data analysis results: The exploratory analysis revealed a significant "learning curve" in SpaceX's landing technology, with success rates rising from 0.0 in 2010 to approximately 0.9 by 2019. Data visualization and SQL queries confirmed that technical maturity (Flight Number) is a more critical predictor of success than the specific launch site. Furthermore, analysis showed that heavier payload masses (exceeding 10,000 kg) do not decrease success rates; instead, the most recent heavy-lift missions show a high frequency of success, particularly in LEO and VLEO orbits. Conversely, GTO orbits remain the most challenging due to high-energy requirements, resulting in mixed outcomes regardless of payload mass.
- Predictive analysis results: The predictive modeling phase evaluated four classification algorithms optimized via GridSearchCV: Logistic Regression, SVM, KNN, and Decision Tree. Logistic Regression, SVM, and KNN tied for the highest test accuracy, each achieving a score of 0.8333. The Decision Tree model performed lower on the test set with an accuracy of 0.6111, likely due to the small test sample size. Confusion matrix analysis for the top models showed a 100% recall for successful landings, though they exhibited an "overly optimistic" bias by occasionally misclassifying failed attempts as successful.

Section 2

Insights drawn from EDA

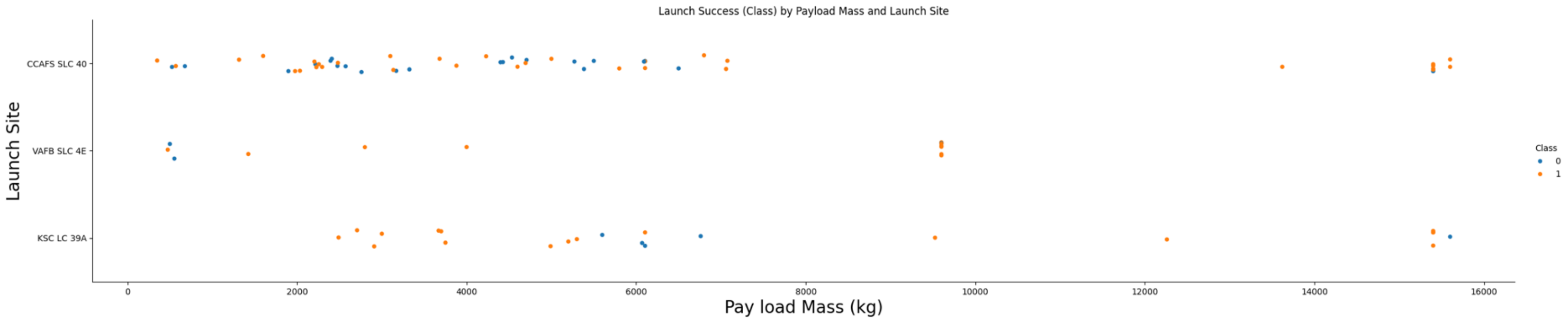
Flight Number vs. Launch Site

- As flight numbers increased, the success rate improved significantly across all sites, indicating a clear "learning curve" in landing technology.
- CCAFS SLC 40 hosted the majority of early experimental flights and failures, but transitioned to consistent success after flight 60.
- The data suggests that landing success is more dependent on the Flight Number (representing technical maturity) than the specific geographic Launch Site.



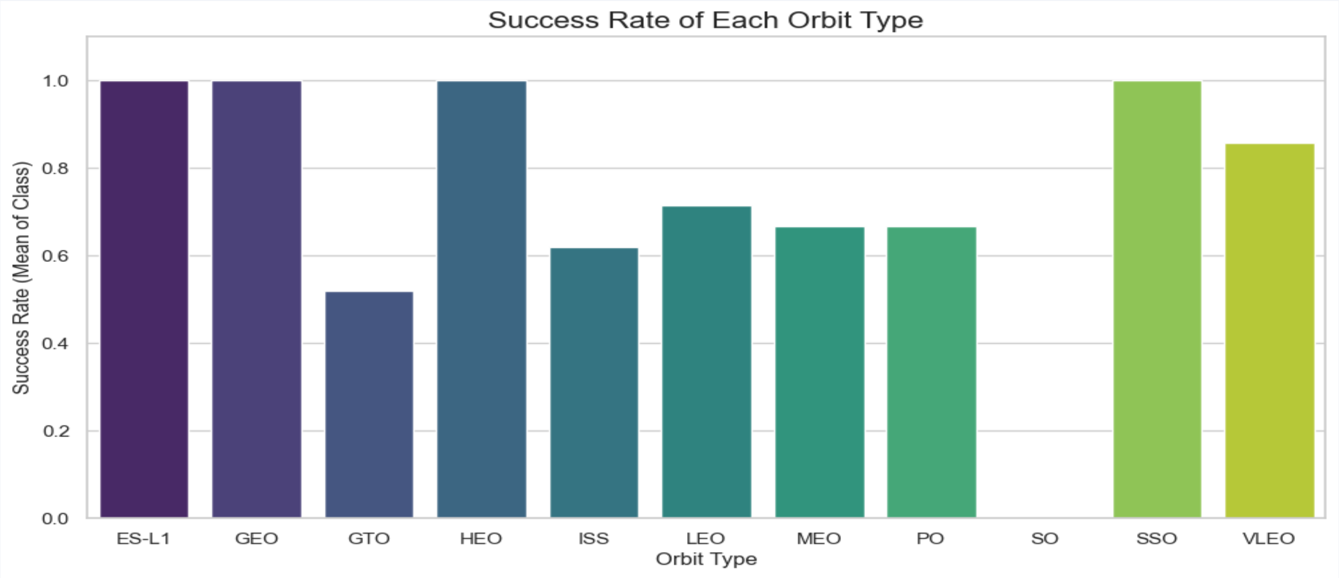
Payload vs. Launch Site

- For payloads exceeding 10,000 kg, there is a high density of successful landings (orange dots), particularly at KSC LC 39A and CCAFS SLC 40.
- Most launches from this site show high success rates across various payload masses, specifically showing dominance in the 3,000 kg to 6,000 kg range and the heavy 15,000+ kg range.
- The data suggests that heavier payload mass does not decrease the landing success rate; in fact, the most recent heavy-lift launches show a very high success frequency.



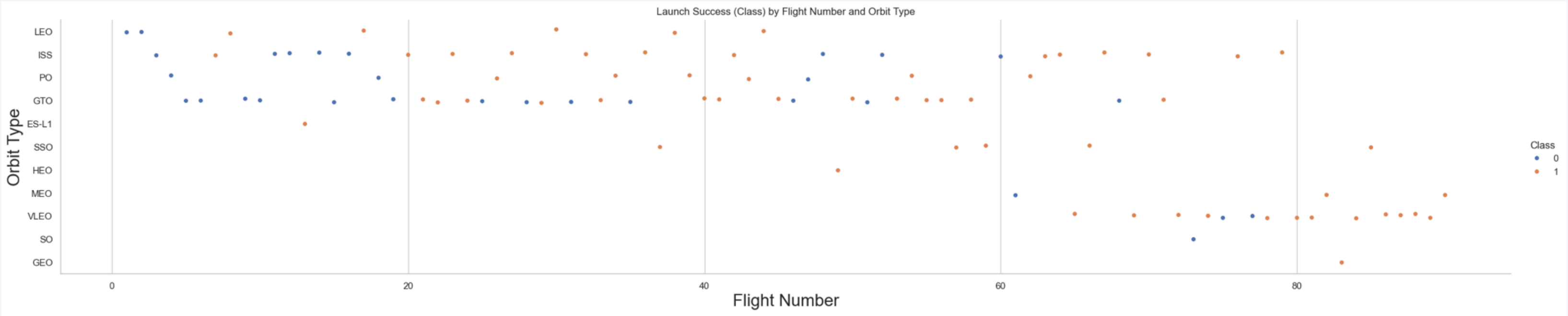
Success Rate vs. Orbit Type

- For payload masses exceeding 10,000 kg, there is a very high concentration of successful landings (orange dots), especially at sites KSC LC 39A and CCAFS SLC 40.
- There is no evidence that heavier payloads decrease success rates; in fact, the densest clusters of success are found in the highest payload categories across all major sites.



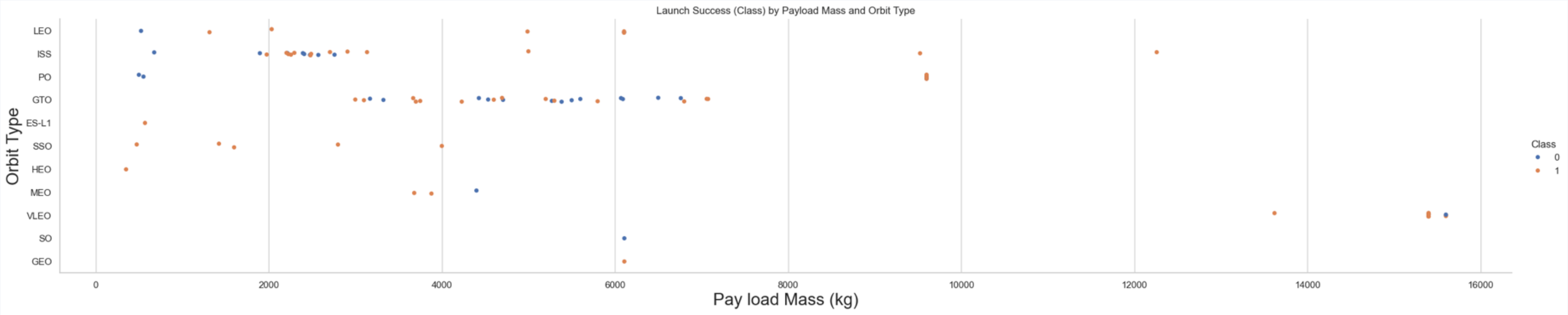
Flight Number vs. Orbit Type

- Similar to launch sites, success rates across different orbits improved significantly as the Flight Number increased, especially after flight 60.
- Orbit-Specific Reliability:
   - LEO and ISS: These orbits show a mix of early failures and successes, but transition to consistent success in later missions.
   - GTO: This orbit shows the most frequent landings and failures over time, reflecting the difficulty of returning from a Geostationary Transfer Orbit.
   - SSO, HEO, and MEO: Missions to these orbits are less frequent but show an exceptionally high success rate once the program reached its mid-stages.



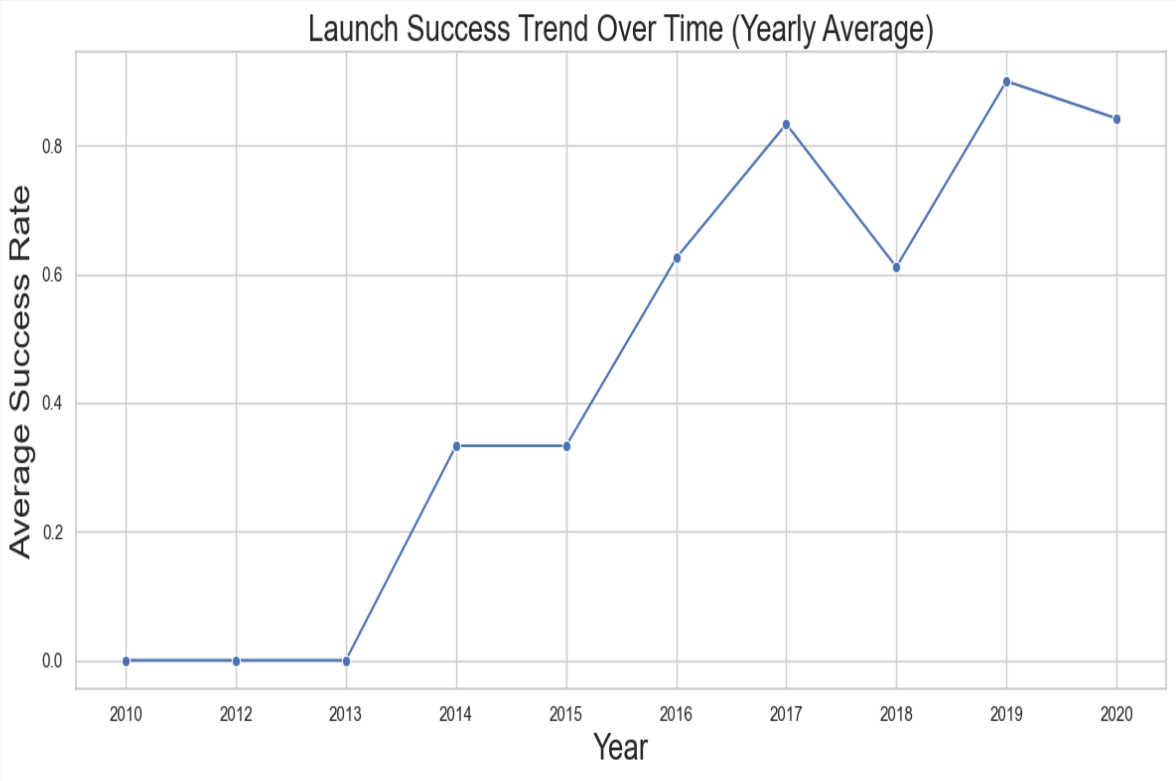
Payload vs. Orbit Type

- Similar to launch site trends, heavy payloads (exceeding 10,000 kg) sent to LEO or VLEO orbits demonstrate a consistently high success rate.
- The data indicates that while payload mass itself is not a direct predictor of failure, its interplay with specific orbit types shows that SpaceX has successfully optimized landing profiles for heavy-lift missions to LEO.
- The GTO orbit shows a more mixed success outcome across its entire payload range, suggesting that the high-energy requirements of this orbit introduce significant landing challenges regardless of the specific mass.



Launch Success Yearly Trend

- Data shows a clear upward trajectory in launch success rates, starting from 0.0 in 2010 and reaching a peak of approximately 0.9 by 2019.
- A significant jump occurred in 2014, followed by a steady climb through 2016, marking the period where landing technology began to stabilize and yield consistent results.



All Launch Site Names

- The dataset contains three primary unique launch sites:
    - CCAFS SLC 40: Cape Canaveral Space Force Station (Florida).
    - VAFB SLC 4E: Vandenberg Space Force Base (California).
    - KSC LC 39A: Kennedy Space Center (Florida).
    - CCAFS SLC-40
- The geographic distribution of these sites across both the Atlantic and Pacific coasts provides the necessary diversity to manage the wide variety of payload masses and orbit types observed in the Falcon 9 program. This infrastructure ensures that SpaceX can meet a broad range of commercial, governmental, and scientific mission requirements while maintaining a high launch frequency.

Launch Site Names Begin with 'CCA'

- The query specifically filters for **CCAFS SLC 40**, which is the only launch site in the dataset starting with "CCA".
- These records represent the earliest phase of the Falcon 9 program (2010–2014.
- These 5 records establish the performance baseline from which the program eventually achieved the high success rates seen in later years.

Flight Number	Date	BoosterVersion	PayloadMass	Orbit	LaunchSite	Class
1	2010-06-04	Falcon 9	6104.96	LEO	CCAFS SLC 40	0
2	2012-05-22	Falcon 9	525.00	LEO	CCAFS SLC 40	0
3	2013-03-01	Falcon 9	677.00	ISS	CCAFS SLC 40	0
5	2013-12-03	Falcon 9	3170.00	GTO	CCAFS SLC 40	0
6	2014-01-06	Falcon 9	3325.00	GTO	CCAFS SLC 40	0

Total Payload Mass

SUM("PAYLOAD_MASS__KG_")
45596

- The total payload mass of 45,596 kg carried by boosters for NASA (CRS) represents the cumulative weight of all cargo launched under the Commercial Resupply Services contracts.
- This total reflects the mass of numerous Dragon spacecraft missions designed to deliver essential supplies, scientific experiments, and hardware to the International Space Station (ISS).
- This value was derived by using the SUM aggregate function to total the PAYLOAD_MASS__KG_ column for all records where the Customer was identified as 'NASA (CRS)'.

Average Payload Mass by F9 v1.1

AVG("PAYLOAD_MASS__KG_")
2928.4

- The average payload mass of 2,928.4 kg for the F9 v1.1 booster version provides a snapshot of SpaceX's medium-lift capabilities during the early-to-mid stages of the Falcon 9 program.
- The F9 v1.1 was an early, less powerful iteration of the rocket compared to the modern Block 5 version, which explains why its average payload is significantly lower than current heavy-lift averages.
- This average reflects a variety of missions, including early Dragon resupply runs to the ISS and medium-sized commercial satellite deployments that defined the program between 2013 and 2016.
- Calculating this average allows engineers and analysts to benchmark the performance and fuel efficiency of this specific hardware generation against newer models.

First Successful Ground Landing Date

MIN(Date)
2015-12-22

- The date 2015-12-22 marks a historic milestone in aerospace history, representing the first time SpaceX successfully landed a Falcon 9 first stage on a terrestrial landing pad after an orbital mission.
- This specific launch (Orbital-2 mission) proved that returning an orbital-class booster to a ground pad for reuse was technically possible.
- It transitioned the program from "no attempt" or "failure" outcomes seen in early records to consistent terrestrial recovery.
- This success at Landing Zone 1 (LZ-1) at Cape Canaveral served as the primary proof-of-concept for SpaceX's reusability strategy to lower space access costs.

Successful Drone Ship Landing with Payload between 4000 and 6000

- The query identifies four specific boosters (F9 FT B1022, F9 FT B1026, F9 FT B1021.2, and F9 FT B1031.2) that met the rigorous criteria of a successful landing at sea while carrying a significant payload.
- These missions required a "Success (drone ship)" outcome, which is technically more difficult than a ground landing because the booster must land on a moving platform in the ocean.
- These specific boosters validated the Falcon 9's ability to recover stages even when high mission energy (required for heavier loads) didn't leave enough fuel for the booster to fly all the way back to a land-based pad.

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

Total Number of Successful and Failure Mission Outcomes

- The summary of mission outcomes indicates that the vast majority of SpaceX flights in this dataset were categorized as successful, with only a few exceptions due to flight anomalies or technical data gaps.
- The combined total of 99 successful missions demonstrates high operational reliability for the Falcon 9 program. The separate "Success " entry (with a trailing space) is a data entry artifact often found in this specific IBM dataset that should be treated as a standard successful mission.
- These outcomes focus purely on whether the payload reached its destination. Even if a booster failed to land (which occurred more frequently in early flights), the mission is still recorded as a "Success" if the primary customer payload was delivered correctly.

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

Boosters Carried Maximum Payload

- This query identifies a unique group of Falcon 9 Block 5 boosters that have all achieved the maximum payload capacity documented in this dataset: 15,600 kg.
- Every booster listed is associated with a Starlink v1.0 mission. SpaceX uses these internal launches to push the performance limits of their rockets, packing as many satellites as possible to maximize efficiency.
- All these boosters are the Block 5 variant, which features higher-thrust engines and structural improvements compared to earlier versions. This version was specifically designed for "high-mass" missions and easy reusability.

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

2015 Launch Records

- This query highlights the specific instances during the year 2015 when SpaceX attempted—but did not successfully complete—first-stage landings on an autonomous spaceport drone ship.
- The result focuses exclusively on the year 2015, identifying two specific failure events that occurred in January (Month 01) and April (Month 04).
- Both failures originated from CCAFS LC-40 in Cape Canaveral, showing that while the launches themselves were successful in delivering payloads, the recovery phase was still highly experimental.

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

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

- During these early years, SpaceX's priority was successfully reaching orbit rather than recovery, making "No attempt" the most frequent outcome.
- The equal split between Success (drone ship) and Failure (drone ship) reflects the challenging learning curve SpaceX faced while attempting to land on a moving platform at sea.
- This specific date range (ending in early 2017) captures the exact moment the program shifted from pure experimentation to consistent recovery success.

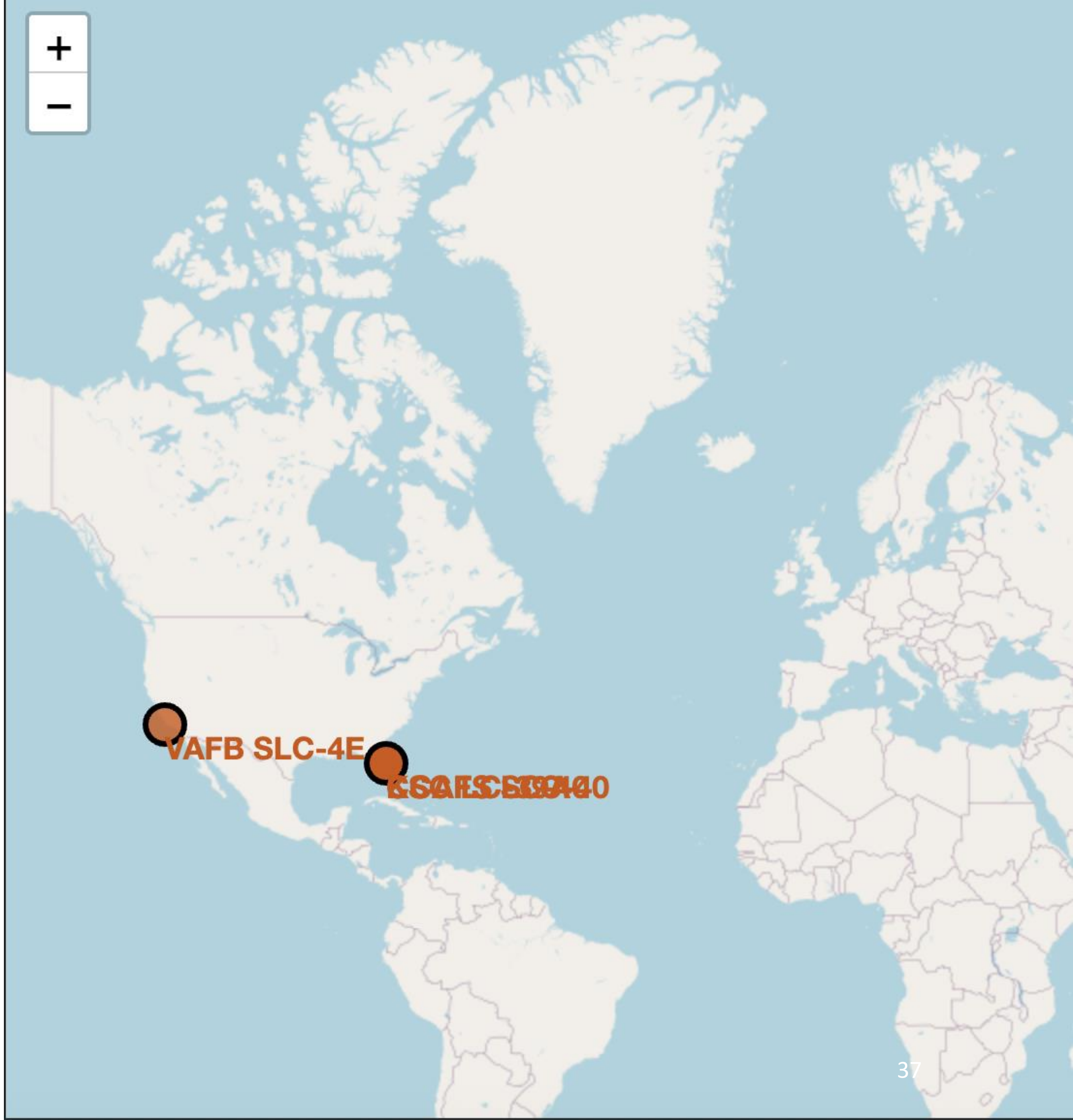
Landing_Outcome	Outcome_Count
No attempt	10
Success (drone ship)	5
Failure (drone ship)	5
Success (ground pad)	3
Controlled (ocean)	3
Uncontrolled (ocean)	2
Failure (parachute)	2
Precluded (drone ship)	1

Section 3

Launch Sites Proximities Analysis

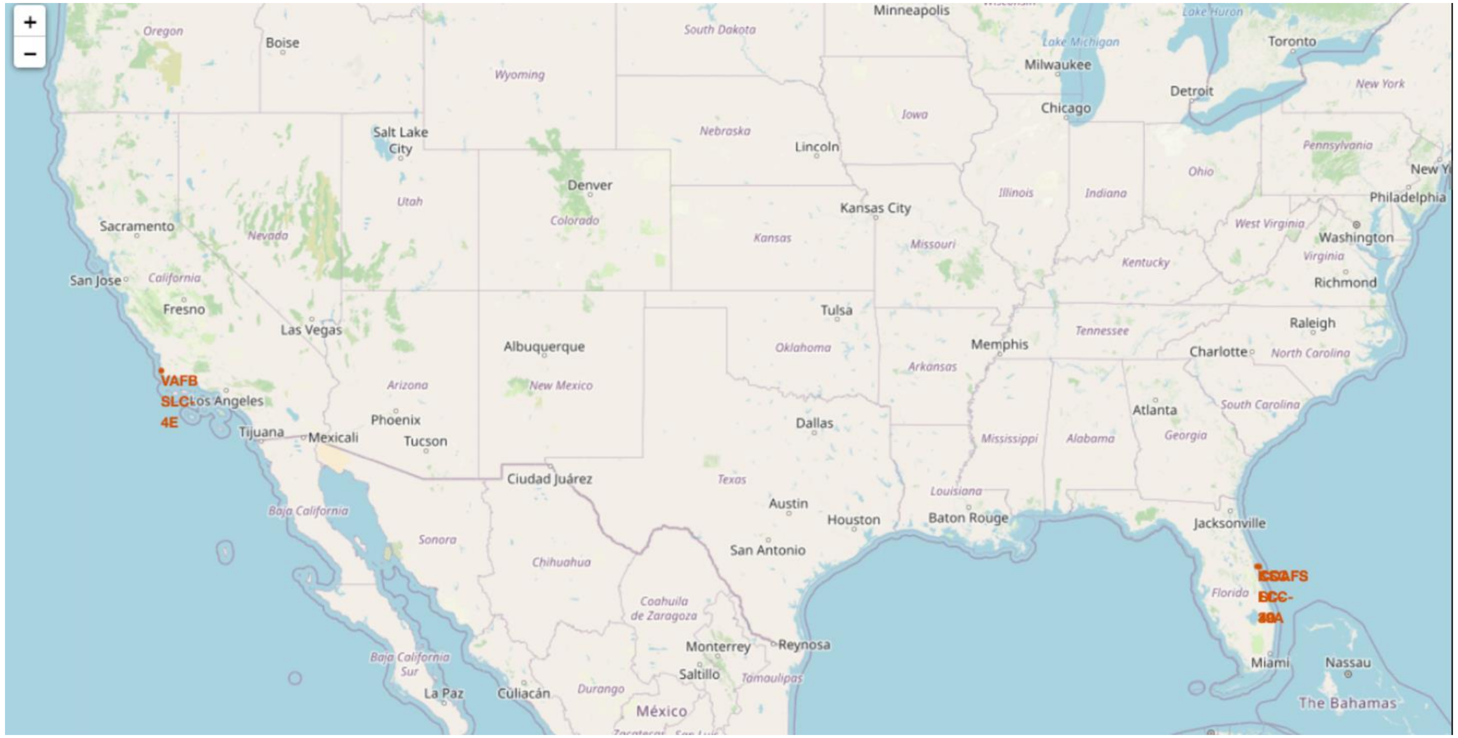
Launch Sites on a Folium Map

- The map identifies four unique launch sites situated on the East and West coasts of the United States: CCAFS LC-40, CCAFS SLC-40, KSC LC-39A (Florida), and VAFB SLC-4E (California).
- All markers are located directly adjacent to major coastlines, ensuring that flight paths are oriented over the ocean to maximize public safety during launch and landing maneuvers.
- The use of orange CircleMarkers and DivIcons provides a clear visual baseline for the next stage of analysis: mapping specific landing success and failure outcomes per site.
- [Dynamic Folium Map]



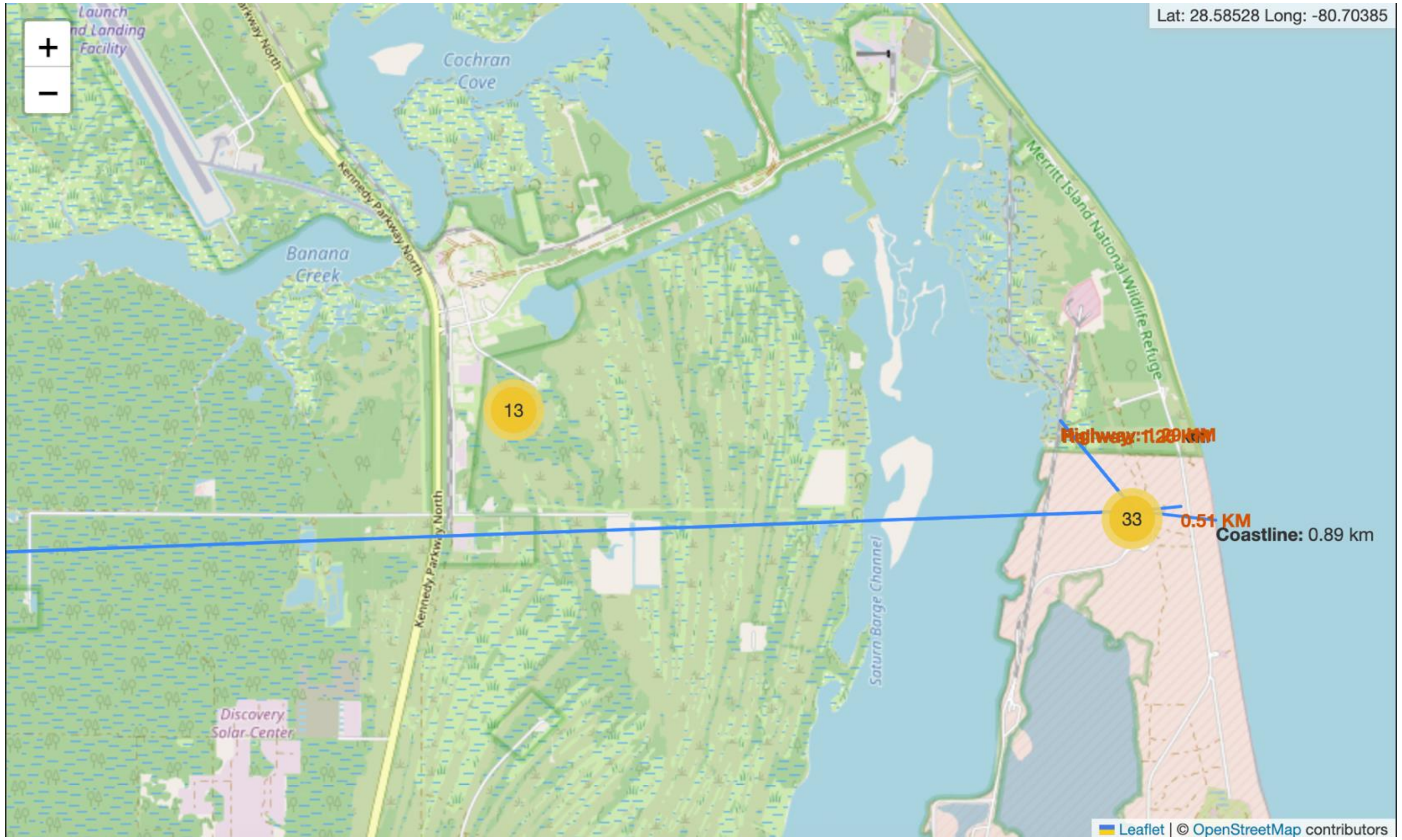
Color-labeled Launch Outcomes

- Displays every individual launch record in the data set, which includes multiple missions for each specific site.
- Uses color-coded markers to visualize the launch outcomes.
- Utilizes MarkerClusters. When you zoom out, multiple launches are grouped into a single bubble with a number; as you zoom in, they "cluster" out into individual success or failure markers.
- [Launch Sites HTML]



Launch Site Proximities

- All SpaceX launch sites are located in close proximity to the coastline (often <1 km away), which is a critical safety requirement. This ensures that any flight anomalies result in debris falling into the ocean rather than populated areas.
- Launch sites are intentionally positioned near existing highways and railways to facilitate the heavy logistics of transporting rocket stages and massive payload components.
- [Launch Site Proximities Map HTML]

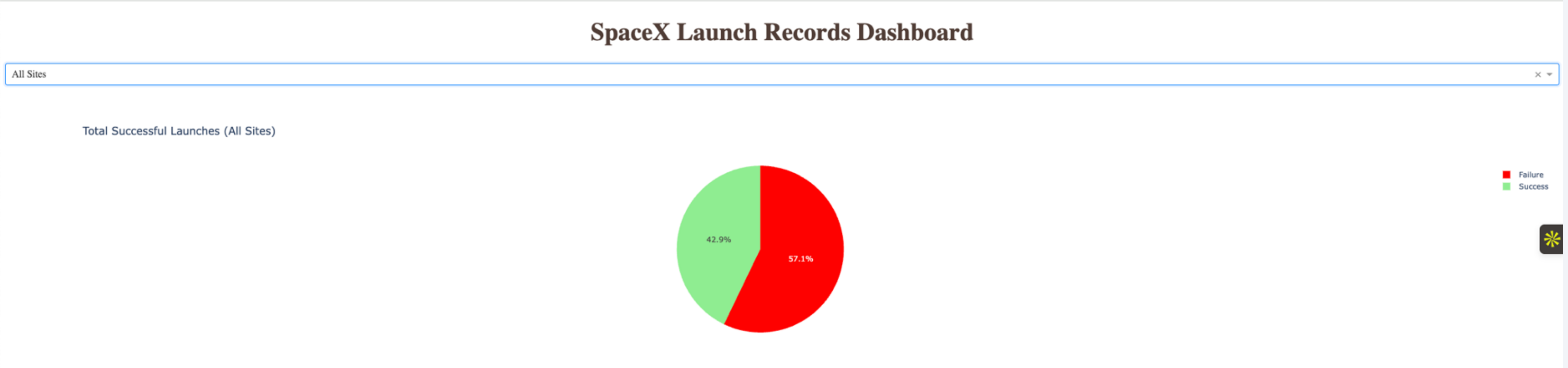


Section 4

Build a Dashboard with Plotly Dash

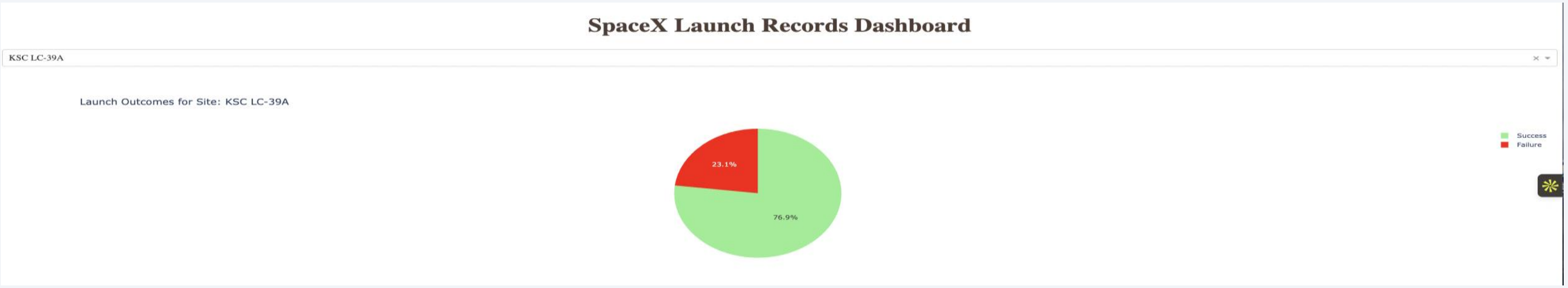
Interactive Visual Analysis: Launch Success Count by Site

- The pie chart is dynamically updated based on the "Select a Launch Site here" dropdown menu.
- When "All Sites" is selected, the chart visualizes the total successful launches (Class = 1) and how they are distributed among the different launch sites.
- Successes are typically represented in green, while failures are represented in red for clear visual distinction.



Highest Launch Success Ratio: KSC LC-39A

- The pie chart clearly shows that KSC LC-39A achieved a dominant success rate of 76.9% (the green section) compared to a failure rate of only 23.1% (the red section).
- This site's high ratio makes it the top-performing launch facility, significantly exceeding the performance of sites like CCAFS LC-40.
- The color-coded categories (Green for Success, Red for Failure) provide an immediate, at-a-glance understanding of mission reliability for stakeholders.



Payload-Success Correlation: Interactive Analysis of Mission Outcomes

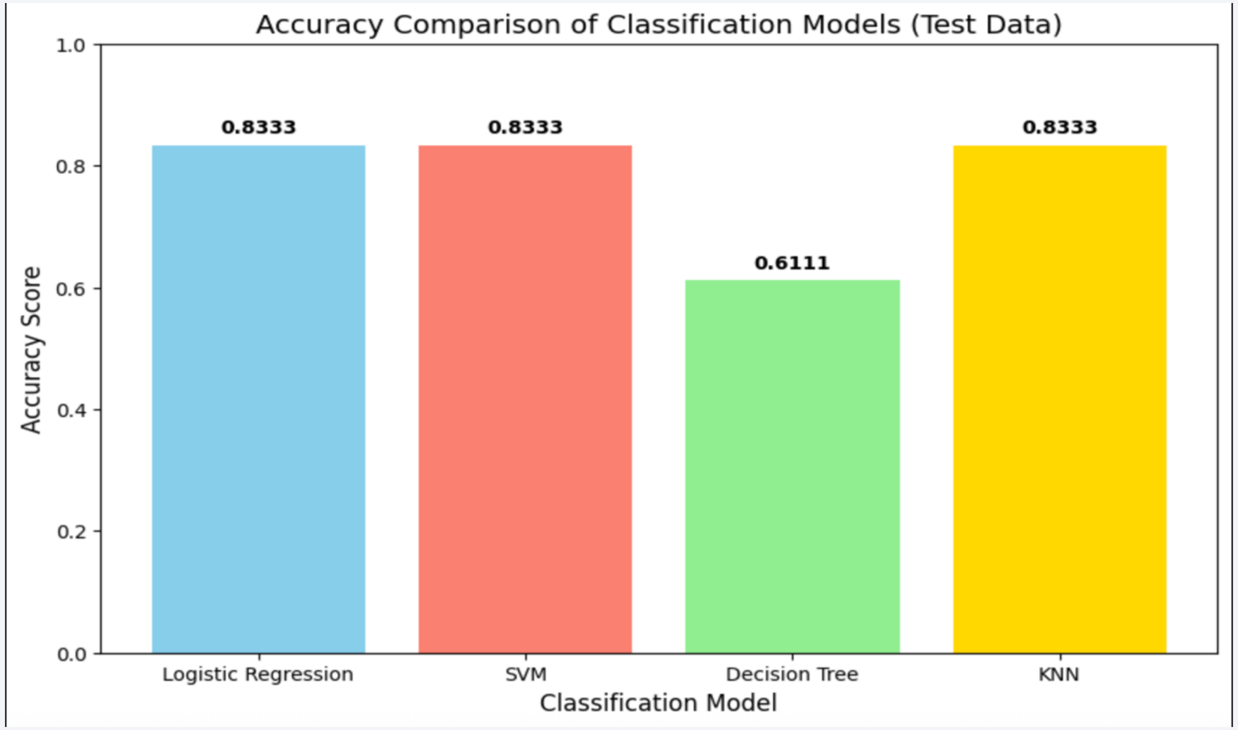
- The scatter plot dynamically updates based on the Payload Range Slider (set here from 2000 kg to 7000 kg) and the Launch Site Dropdown (filtered for KSC LC-39A).
- Successes (Class 1) are dominated by the FT (Falcon 9 Full Thrust) and B4 versions in this specific mass range, while the B5 version shows high reliability for early heavy-lift missions.
- For the KSC LC-39A site, there is a high density of successful landings (dots at Class 1) between 2500 kg and 5300 kg.

Section 5

Predictive Analysis (Classification)

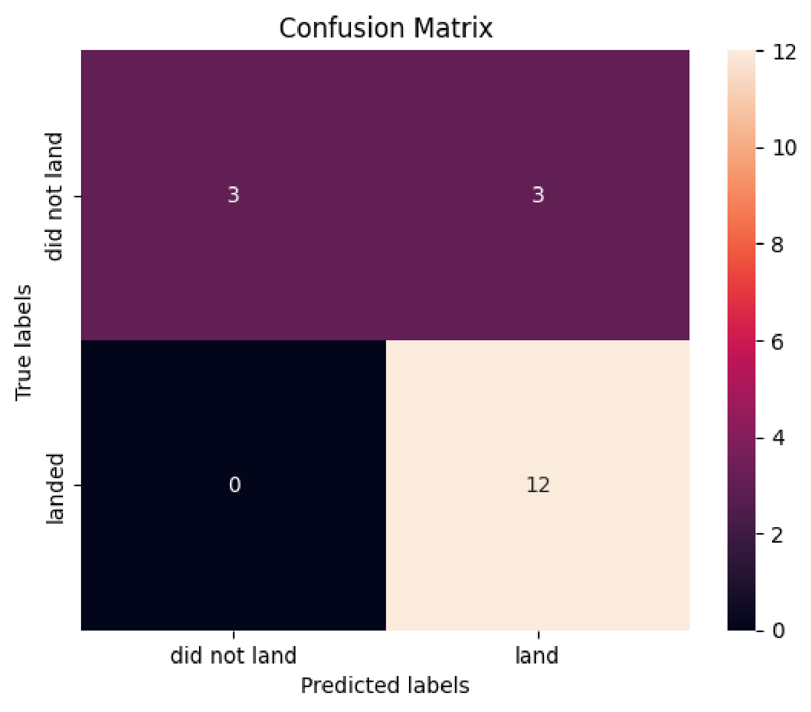
Classification Accuracy

- Logistic Regression, SVM, and KNN are tied for the highest accuracy with a score of 0.8333.
- The Decision Tree model performed the worst on the test data with an accuracy of 0.6111.
- The tie among the top three models is likely due to the small size of the test dataset (18 samples), where the models are all misclassifying the same number of data points.



Confusion Matrix

- Since Logistic Regression, SVM, and KNN all tied for the highest test accuracy of 0.8333, they share the same confusion matrix based on the test data results.
- All three top models are highly reliable at predicting successful landings (Recall = 100%), but they have a tendency to be "overly optimistic" by misclassifying some failed landings as successful.
- The best-performing models are excellent at identifying successful landings (100% recall for the "land" class). However, the main limitation identified in this lab is a "False Positive" problem: the models tend to be overly optimistic, occasionally predicting a successful landing when the first stage actually fails.



Conclusions

- Landing success rates showed a clear upward trajectory, starting from 0.0 in 2010 and peaking at approximately 0.9 by 2019. This indicates a significant "learning curve," with performance stabilizing and yielding consistent results after 2016.
- Data suggests technical maturity (Flight Number) is a stronger predictor of landing success than geographic Launch Site. Additionally, heavier payload masses do not decrease success rates; in fact, recent heavy-lift launches have shown high success frequency.
- While most orbits showed improved reliability over time, the Geostationary Transfer Orbit (GTO) remains challenging. Mixed success in GTO missions suggests that high-energy requirements introduce significant landing difficulties regardless of payload mass.
- Logistic Regression, SVM, and KNN tied for the highest test accuracy at 0.8333. These top-performing models demonstrate excellent reliability in identifying successful landings (100% recall), although they tend to be slightly over-optimistic, occasionally predicting success for failed landing attempts.
- SpaceX's success in first-stage reusability, proven by achieving a terrestrial landing pad recovery milestone in 2015, provides a core competitive advantage by significantly lowering space transportation costs.

Appendix

- SQL Query Samples:

1. Calculating the total payload mass for NASA (CRS)
   %sql SELECT SUM("PAYLOAD_MASS__KG_") FROM SPACEXTABLE WHERE Customer = 'NASA (CRS)';
2. Identifying the first successful ground landing date.
   %sql SELECT MIN(Date) FROM SPACEXTABLE WHERE "Landing_Outcome" = 'Success (ground pad)';
3. Rank the count of landing outcomes (such as Failure (drone ship) or Success (ground pad)) between the date 2010-06-04 and 2017-03-20, in descending order.
   %sql SELECT "Landing_Outcome", COUNT(*) AS "Outcome_Count" FROM SPACEXTABLE WHERE "Date" BETWEEN '2010-06-04' AND '2017-03-20' GROUP BY "Landing_Outcome" ORDER BY "Outcome_Count" DESC;

Appendix

- Data Cleaning Snippets:

1. Python code snippets showing how you handled missing values in the PayloadMass columns
```
# Calculate the mean value of PayloadMass column
mean_payload_mass = data_falcon9['PayloadMass'].mean()
# Replace the np.nan values with its mean value
data_falcon9['PayloadMass'].replace(np.nan, mean_payload_mass, inplace=True)
```

2. Filter the dataframe to only include `Falcon 9` launches
```
# Re-filter the DataFrame to keep only 'Falcon 9' launches, explicitly creating a copy
data_falcon9 = launch_data[launch_data['BoosterVersion'] == 'Falcon 9'].copy()
# Now, we can run the other commands safely:
data_falcon9.loc[:,'FlightNumber'] = list(range(1,data_falcon9.shape[0]+1))
```

Appendix

- Encoding Logic:

1. A snippet showing the application of One-Hot Encoding to categorical variables like LaunchSite, Orbit, and BoosterSerial.

```
# The categorical columns to encode
categorical_cols = ['Orbit', 'LaunchSite', 'LandingPad', 'Serial’]
# Use get_dummies() on the categorical columns
features_one_hot = pd.get_dummies(features, columns=categorical_cols)
# Display the results
print("First 5 rows of features_one_hot DataFrame:")
print(features_one_hot.head())
```

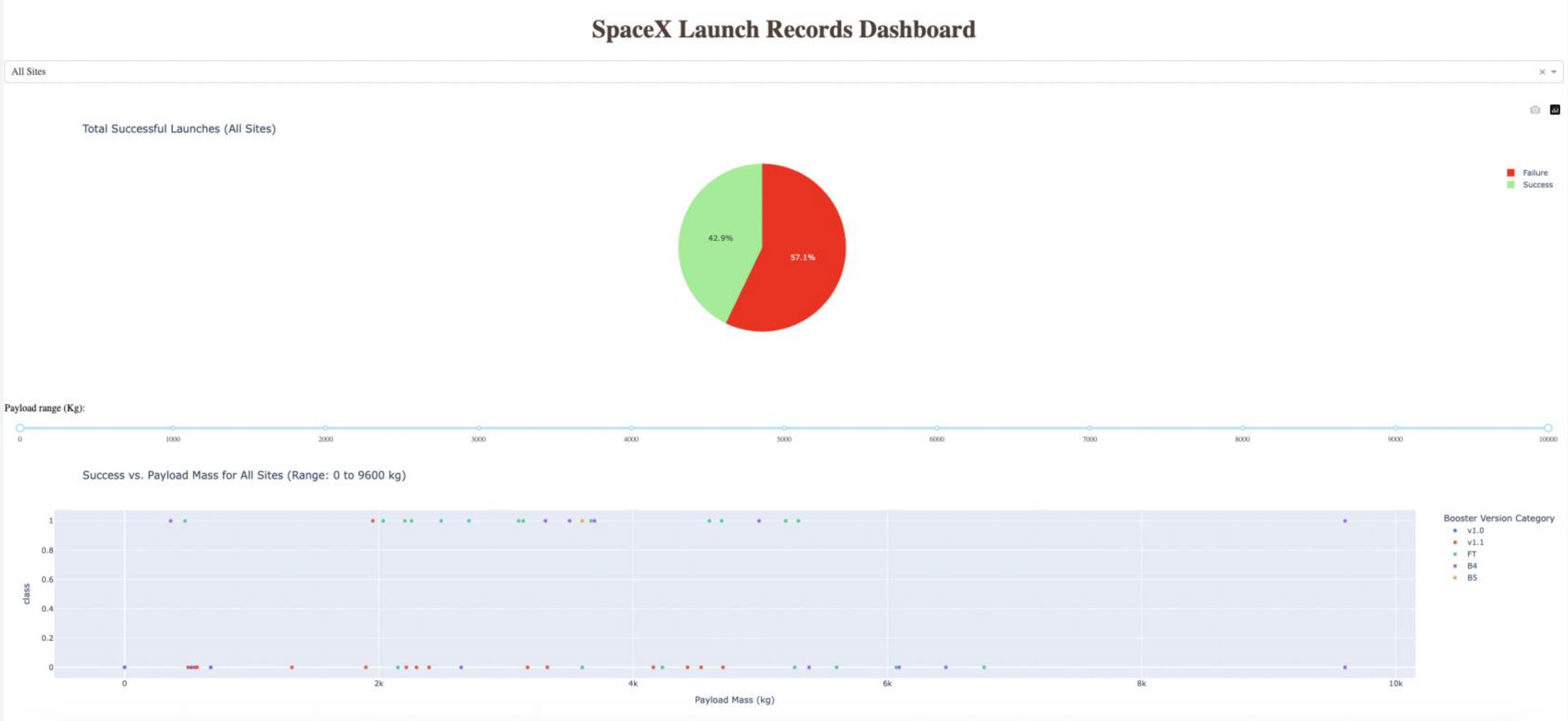
Appendix

- Yearly Trend Analysis
  A raw data table showing the average success rate trend from 2010 (0.0) to 2019 (~0.9)

	Orbit	Class
0	ES-L1	1.000000
1	GEO	1.000000
2	GTO	0.518519
3	HEO	1.000000
4	ISS	0.619048
5	LEO	0.714286
6	MEO	0.666667
7	PO	0.666667
8	SO	0.000000

Appendix

- Interactive Dashboard with Plotly Dash
  A Plotly Dash application for users to perform interactive visual analytics on SpaceX launch data in real-time.



Thank you!