IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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Outline

1. Executive Summary.
2. Introduction
3. Methodology
4. Results
5. Conclusion
6. Appendix

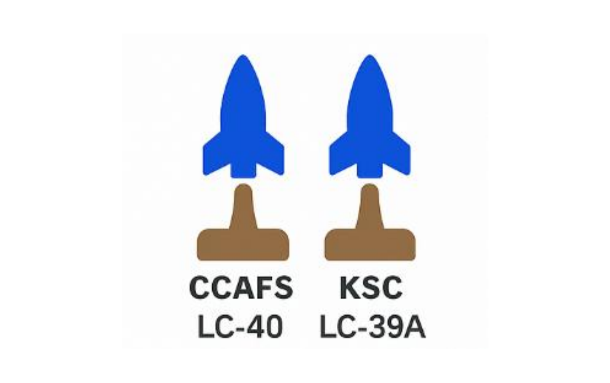
Executive Summary

Summary of methodologies

- Data Collection
- Data Cleansing and Transformation
- Exploratory Data Analysis (EDA)
- Geospatial Visualization
- SQL queries
- Predictive Analytics (ML)

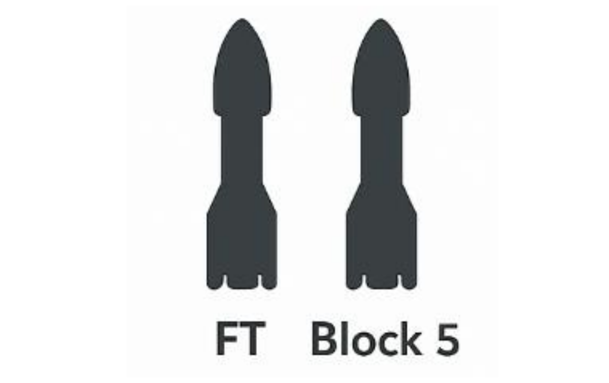
Executive Summary

Summary of all results

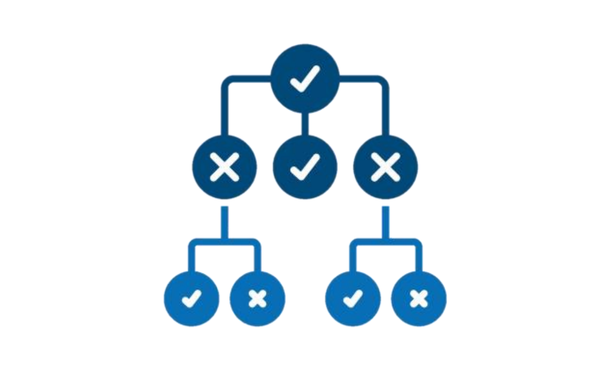


Most successful launch sites


Payload and success



Booster Versions


Best predictive model


Dashboard with Dash


Geospatial Analysis

Introduction

Project background and context

SpaceX has revolutionized the aerospace industry by using reusable rockets, which greatly reduces launch costs. However, predicting whether a rocket's first stage will land correctly remains a key challenge. This project aims to analyze, visualize, and predict the success of these landings using data science and machine learning techniques.

Problems you want to find answers

- Which launch sites have higher success rates?
- Is there a relationship between payload and probability of success?
- Which versions of boosters are most reliable?
- Can the results of a landing be predicted using classification models?
- How can interactive visualizations improve spatial and operational data analysis?

Section 1

Methodology

Methodology

Executive Summary

Data Collection

2 approaches were employed:

REST API: Using requests and json to extract structured data from public endpoints.
WEB SCRAPING: Using BeautifulSoup to extract data from HTML pages, such as financial income from companies.

Data Cleansing and Transformation

Implemented with pandas, it included renaming columns, handling null values, and converting data types to integrate them into subsequent analyses.

Exploratory Data Analysis (EDA)

Made using Plotly Express within an interactive dashboard in Dash. Drop-down menus, sliders, and pie and scatter charts were included to analyze relationships between variables such as launch site, payload, and success.

Geospatial Visualization

With Folium, launch locations were represented and clustering was applied to understand spatial patterns.

SQL queries

In notebooks, SQL magic cells were used to calculate key statistics such as success rates, mission counts, and payload averages.

Predictive Analytics (ML)

Classification models were developed using scikit-learn: Logistic Regression, SVM, Decision Tree and KNN.
Hyperparameters were optimized using GridSearchCV and performance was evaluated with confusion matrices.

Data Collection

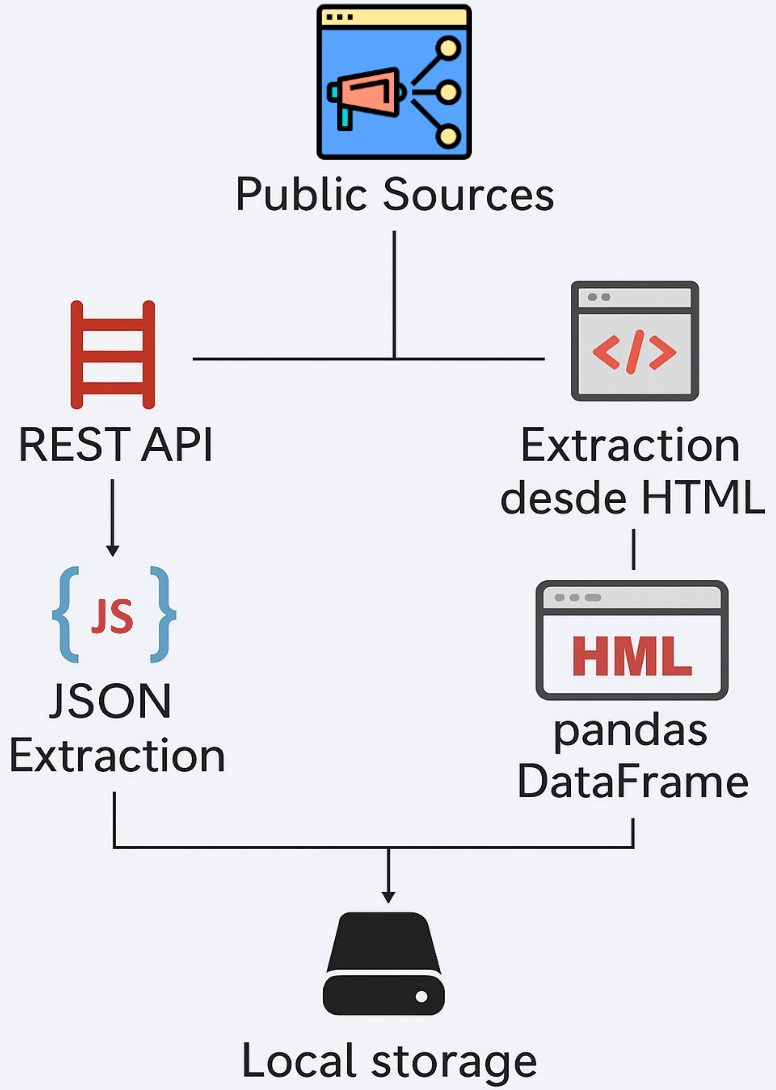
Two main approaches were used

1 **REST API:**

- We use the requests library to make HTTP calls.
- We extracted structured data in JSON format from public endpoints such as the SpaceX API.

2 **Web Scraping:**

- We apply BeautifulSoup to extract data from HTML pages.
- Financial information such as business revenue was collected from HTML tables.

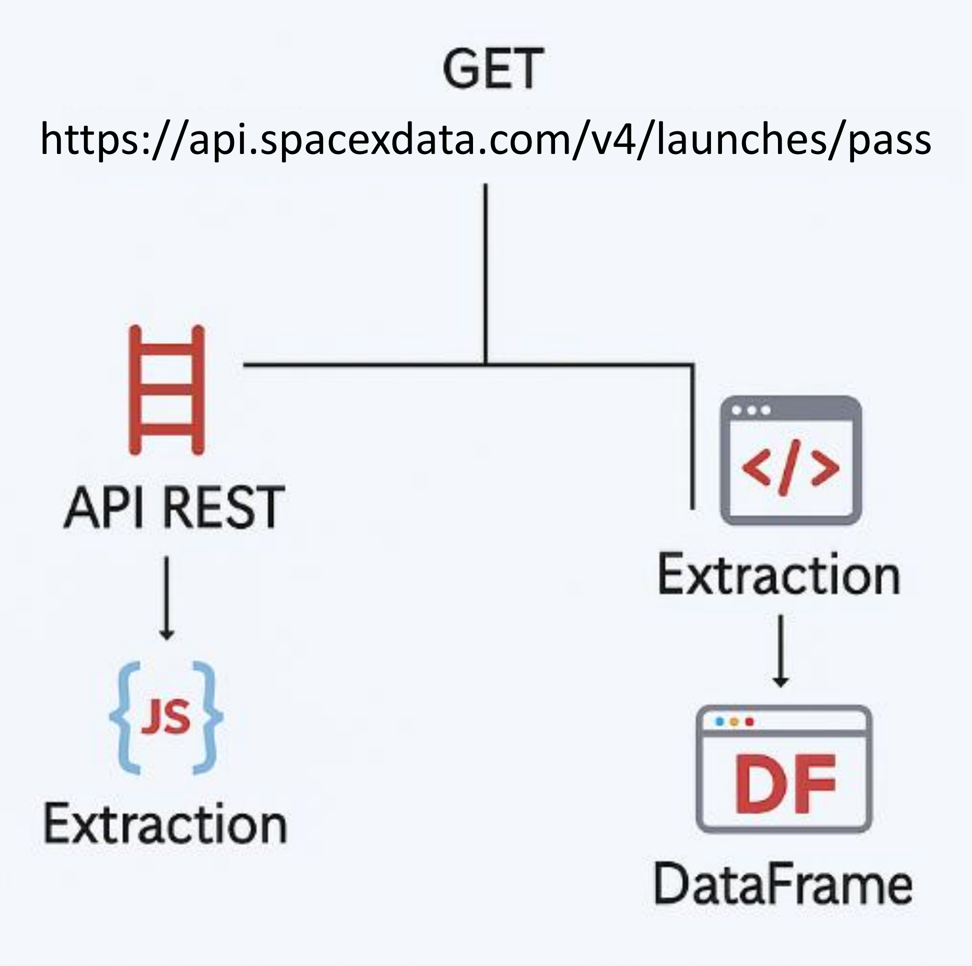


Data Collection – SpaceX API

La obtención de datos se realizó mediante llamadas a la API REST de SpaceX, utilizando solicitudes **GET** para acceder a información relacionada con lanzamientos. Se emplearon herramientas como requests y formatos JSON para estructurar los datos de respuesta.

Como referencia complementaria, se incluye la URL del repositorio en GitHub que contiene el notebook **“jupyter-labs-spacex-data-collection-api.ipynb”** con el código ejecutado y el resultado obtenido, permitiendo su revisión por parte de terceros y garantizando la transparencia del proceso.

LINK DE GITHUB
https://github.com/ClauLet/Ciencia-de-datos-aplicada-Capstone/blob/main/jupyter-labs-spacex-data-collection-api.ipynb



Data Collection - Scraping

HTTP request to the site with
`requests.get(‘~’)`

HTTP request to the site with
`BeautifulSoup(html,’html.parser’)`

Table Search with
`Soup.find_all( )`

Conversion to
`DataFrame`

Cleaning and local saving of the file
`.csv`

Web Scraping Process:

BeautifulSoup was used to extract HTML tables from public web pages. The content was analyzed using specific selectors and converted into DataFrame panda structures.

GitHub reference notebook:

It corresponds to the Web Scraping process and was implemented in the notebook called **"jupyter-labs-webscraping.ipynb“**

GITHUB
https://github.com/ClauLet/Ciencia-de-datos-aplicada-Capstone/blob/main/jupyter-labs-webscraping.ipynb

Data Wrangling

Standardizing Column Names

Columns were renamed as **'Launch Site'** to **Launch_Site** and **'class'** to Class to avoid access errors and ensure consistency in analysis.

1

Converting Data Types

Some values were converted to suitable types such as **int**, **float** or **datetime** to allow accurate calculations and visualizations.

2

Handling Null Values

Missing values **(NaN)** were identified and treated using methods such as imputation or selective deletion of irrelevant records.

3

Filtering relevant data

Removed unnecessary columns and filtered out key records such as payload dates or ranges **(Payload Mass (kg)).**

4

DataFrames Integration

All sets were combined or kept in panda **structures. DataFrame** to enable efficient handling and subsequent analysis.

5

GitHub reference notebook:

This process was implemented in the notebook called **"labs-jupyter-spacex-Data wrangling.ipynb"**

https://github.com/ClauLet/Ciencia-de-datos-aplicada-Capstone/blob/main/labs-jupyter-spacex-Data%20wrangling.ipynb

EDA with Data Visualization

Summary of the graphs used

Pie Chart:

To show the ratio of successful launches by launch site (facilitates visual comparison of performance by location).

Scatter Chart:

To analyze the relationship between payload and launch success (identify correlations or clusters of success).

Interactive filters (Dropdown and RangeSlider):

They were integrated to refine the data and observe behaviors by specific site and weight range.

Visualization Goals

1. Explore patterns of success based on variables such as launch site, booster type, and load weight.

2. Facilitate the identification of trends for data-driven decisions within space missions.

Notebook de referencia en GitHub:
https://github.com/ClauLet/Ciencia-de-datos-aplicada-Capstone

EDA with SQL

SQL queries performed

Success rates **(class = 1)** per launch site were queried using GROUP BY to identify the most effective sites.

The average payload **(Payload Mass (kg))** per type of booster **(Booster Version)** was calculated to determine its operational efficiency.

The total number of missions per site was determined using **COUNT(*) grouped** by **Launch_Site**.

WHERE filters were used to identify successful launches with loads above a certain threshold.

Results **(ORDER BY)** were ordered by success rate to facilitate hierarchical visualization.

GitHub reference notebook:

This process was implemented in the notebook called**“jupyter-labs-eda-sql-coursera_sqllite.ipynb”**

https://github.com/ClauLet/Ciencia-de-datos-aplicada-Capstone/blob/main/jupyter-labs-eda-sql-coursera_sqllite.ipynb

Build an Interactive Map with Folium

Added Map Objects

Markers:

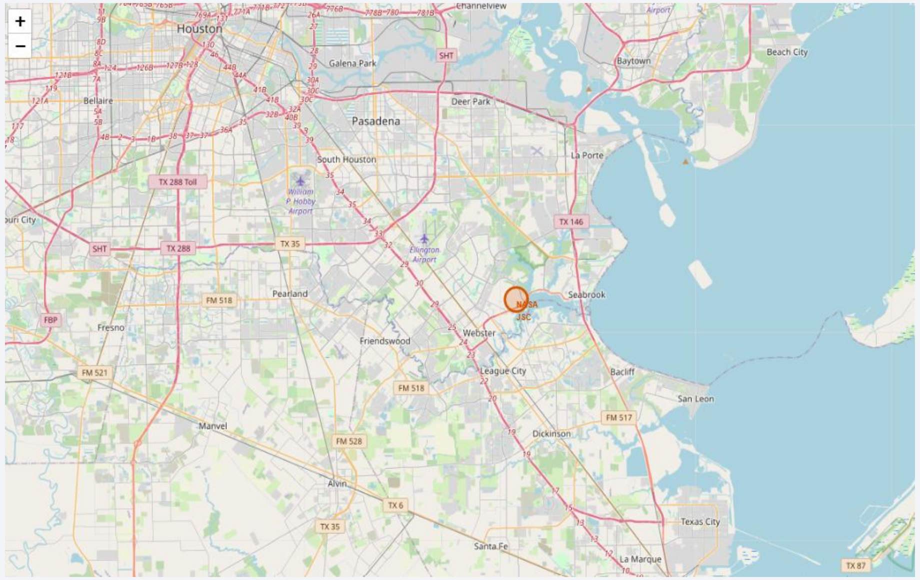
Markers were placed at each launch site to identify key locations on the map.

Circles:

Circles were used to highlight the proximity zone around each site, facilitating visual geographic analysis.

Interactive Pop-ups:

Added to bookmarks to display contextual information such as the site name or release result.



GitHub reference notebook:
This process was implemented in the notebook called“lab_jupyter_launch_site_location.ipynb”

https://github.com/ClauLet/Ciencia-de-datos-aplicada-Capstone/blob/main/lab_jupyter_launch_site_location.ipynb

Justification of Use

- Bookmarks make it easy to locate key sites.
- Circles help to visualize areas of influence and compare location with safe or dangerous areas.
- Pop-ups enrich visual exploration with data without overloading the map.

Build a Dashboard with Plotly Dash

Summary of aggregated graphs and interactions

Dropdown

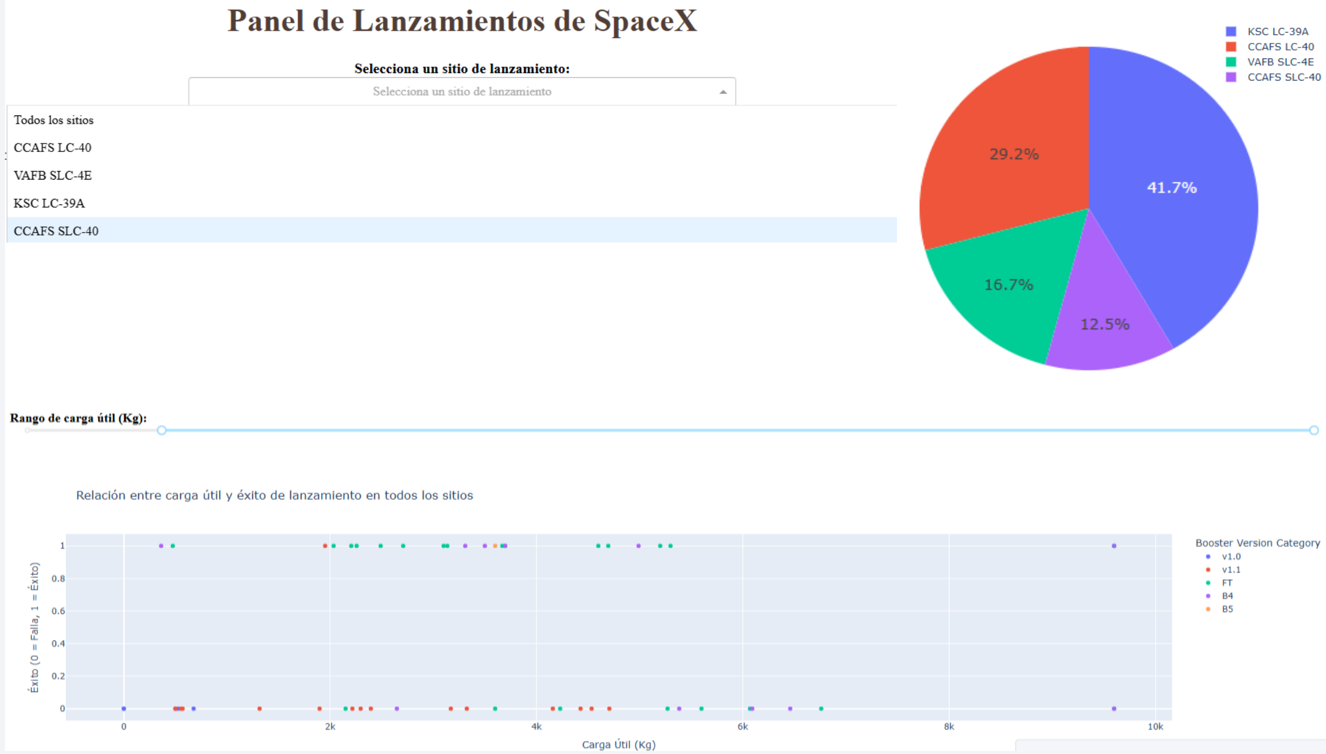
Allows you to select a specific launch site or view all of them together.

Scatter Chart

Relates payload mass to the success or failure of launches. It allows correlations between key variables to be observed.

Pie chart

Shows the ratio of successful launches by launch site. Used for quick visualization of overall performance by location.



Justification of the graphs and interactions

- These graphs were chosen because they allow us to visually compare success rates and explore relationships between technical variables (such as payload and type of booster).
- Interactions such as dropdown and slider make it possible to explore the data dynamically and intuitively without the need to modify the code.

GitHub reference notebook:

This process was implemented in the notebook called **"spacex-dash-app.py"**
https://github.com/ClauLet/Ciencia-de-datos-aplicada-Capstone/blob/main/spacex-dash-app.py

Predictive Analysis (Classification)

Process Overview

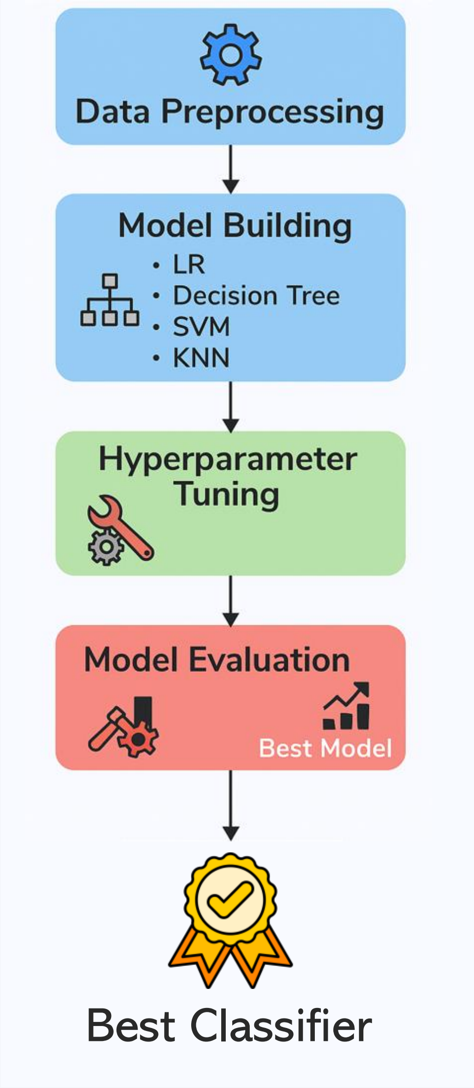
Four classification models were implemented:

- Logistic Regression
- Support Vector Machines (SVM)
- Decision Tree
- K-Nearest Neighbors (KNN).

Training/testing and cross-validation techniques were used to evaluate the performance of the models.

The hyperparameters of each model were optimized using GridSearchCV, evaluating metrics such as accuracy and confounding matrix.

The Decision Tree model was the most accurate with an accuracy of **88%** in the test data.



GitHub reference notebook:

This process was implemented in the notebook called"**SpaceX_Machine Learning Prediction_Part_5.ipynb**"

https://github.com/ClauLet/Ciencia-de-datos-aplicada-Capstone/blob/main/SpaceX_Machine%20Learning%20Prediction_Part_5.ipynb

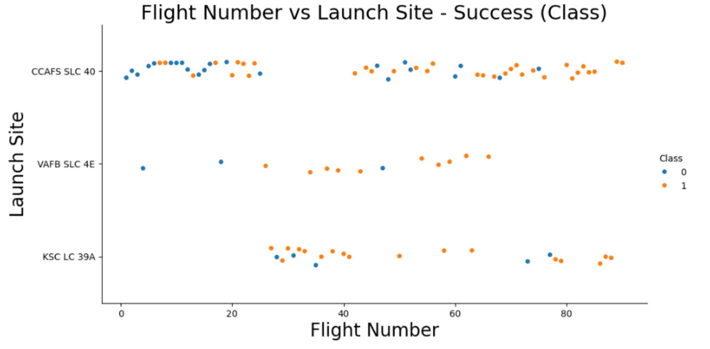
Results

Exploratory data analysis results

CCAFS LC-40 and KSC LC-39A were the most successful sites.

A positive correlation was identified between average payload and success.

The "FT" and "Block 5" boosters performed better.



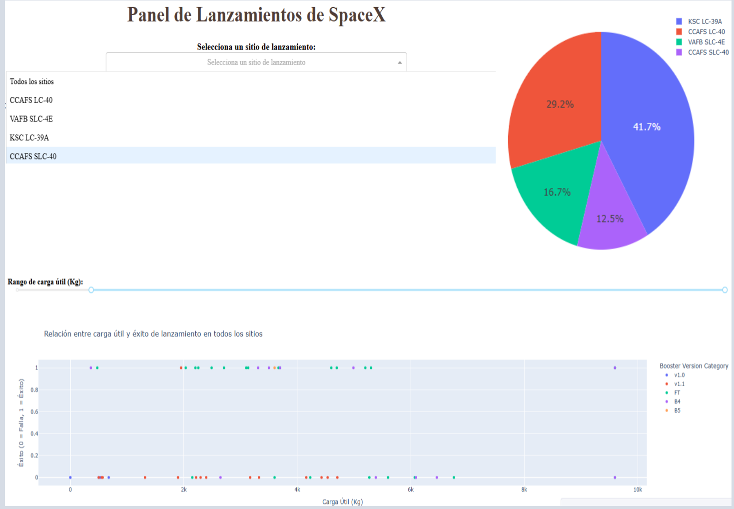
edadataviz.ipynb

Interactive analytics demo in screenshots

Drop-down menu to choose a site.

Pie chart of successes by site.

Payload slider and scatter plot to see impact.



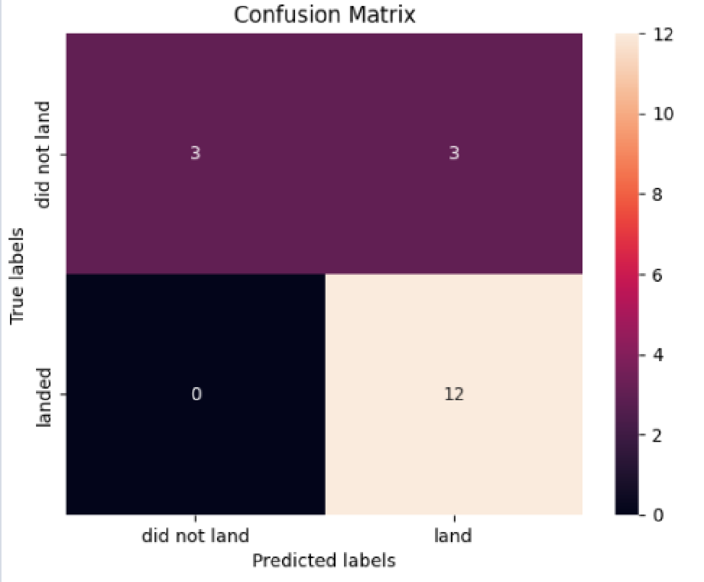
spacex-dash-app.py

Predictive analysis results

Logistic Regression, SVM, KNN and Decision Tree models were tested.

The Decision Tree obtained 83.3% accuracy.

Evaluation with GridSearchCV and confusion matrix.



SpaceX_Machine Learning Prediction_Part_5.ipynb

Section 2

Insights drawn from EDA

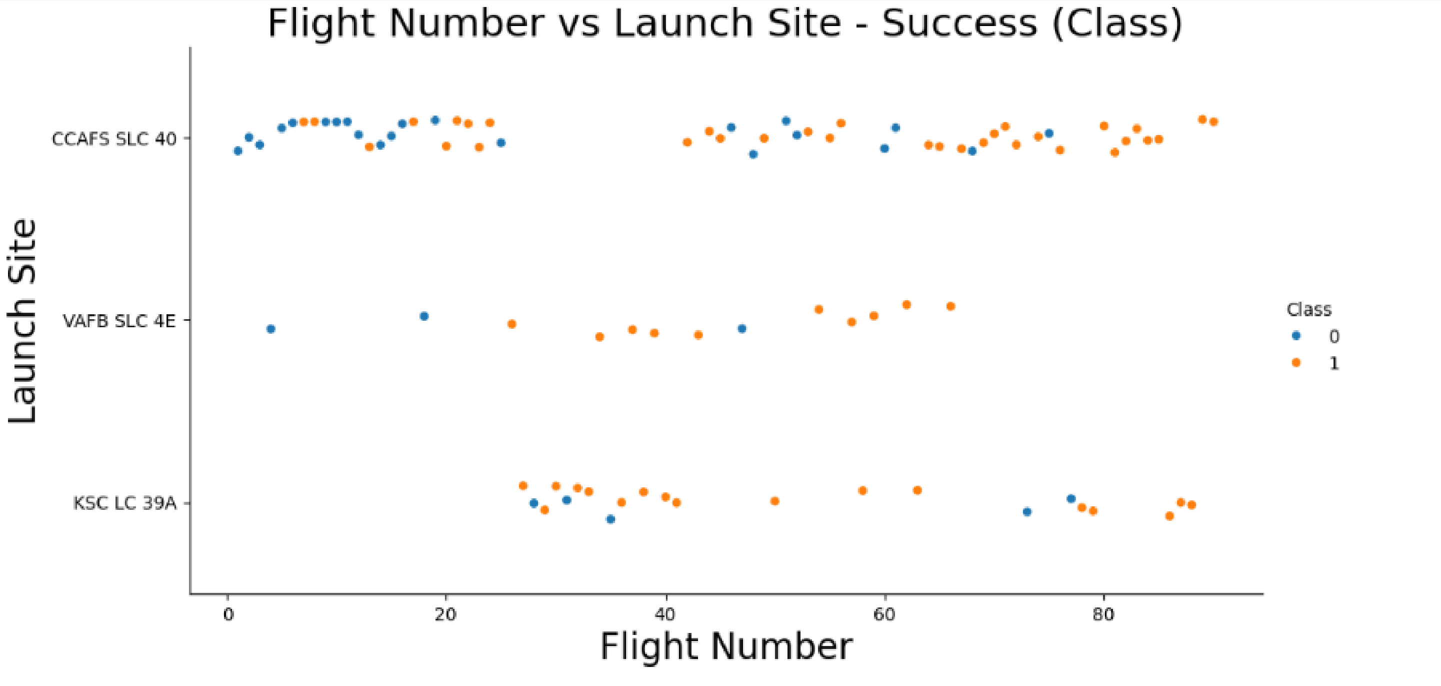
Flight Number vs. Launch Site

The scatter plot shows the relationship between the flight number (Flight Number) and the launch site (Launch Site), coding the success (Class) in colors.

CCAFS SLC 40:
This site shows a high number of releases spread over time. A transition from failures (Class 0) to successes (Class 1) is observed on subsequent flights, suggesting technological or logistical improvements as flights increase.

KSC LC 39A:
Although with fewer flights, this site presents a positive performance for the most part, with a higher proportion of successes.

VAFB SLC 4E:
It has fewer flights and a scattered mix between successes and failures, without a clear trend associated with the number of flights.



It is appreciated that more recent launches (higher flight number) tend to be more successful, especially at sites with more experience such as CCAFS SLC 40, which can indicate a positive learning curve.

Payload vs. Launch Site

Observed relationship

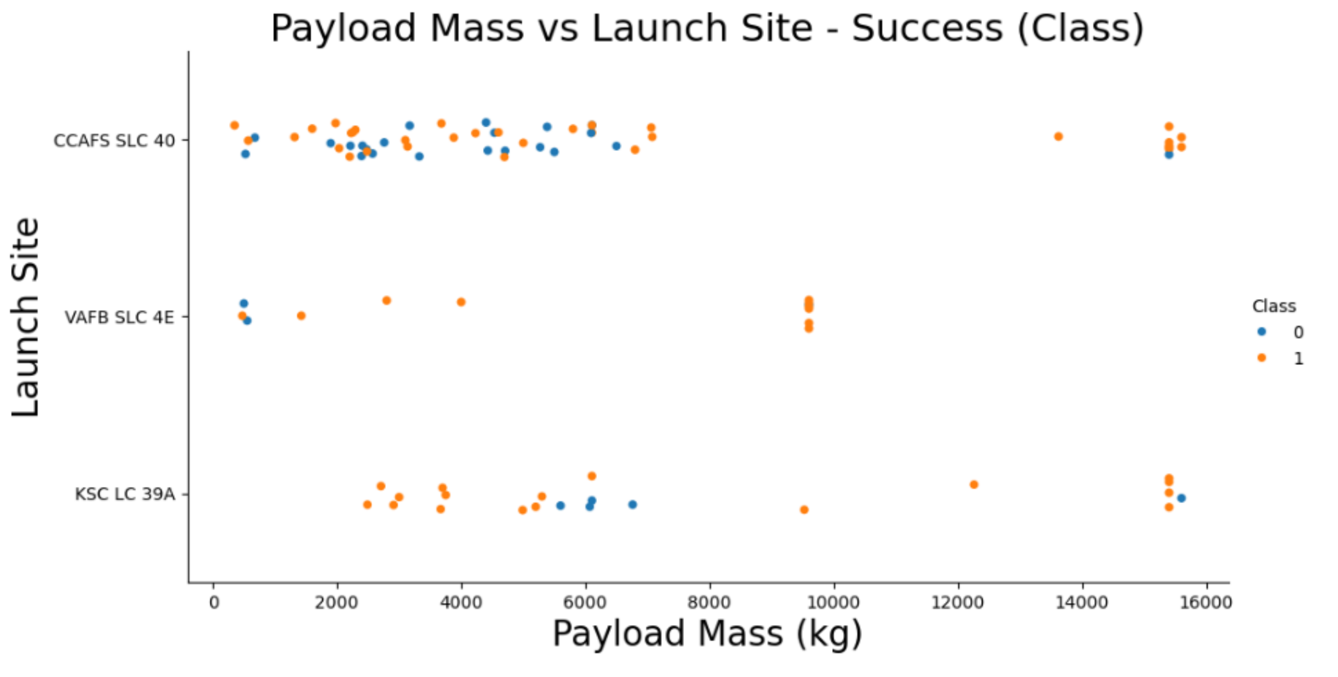
In general, there is a slight positive trend between higher payloads and the probability of success, although it is not conclusive for all sites.

Launch sites

CCAFS SLC 40:
It features a high concentration of successful launches (Class 1) with payloads from ~2000 to ~10000 kg, and some also above 14000 kg.

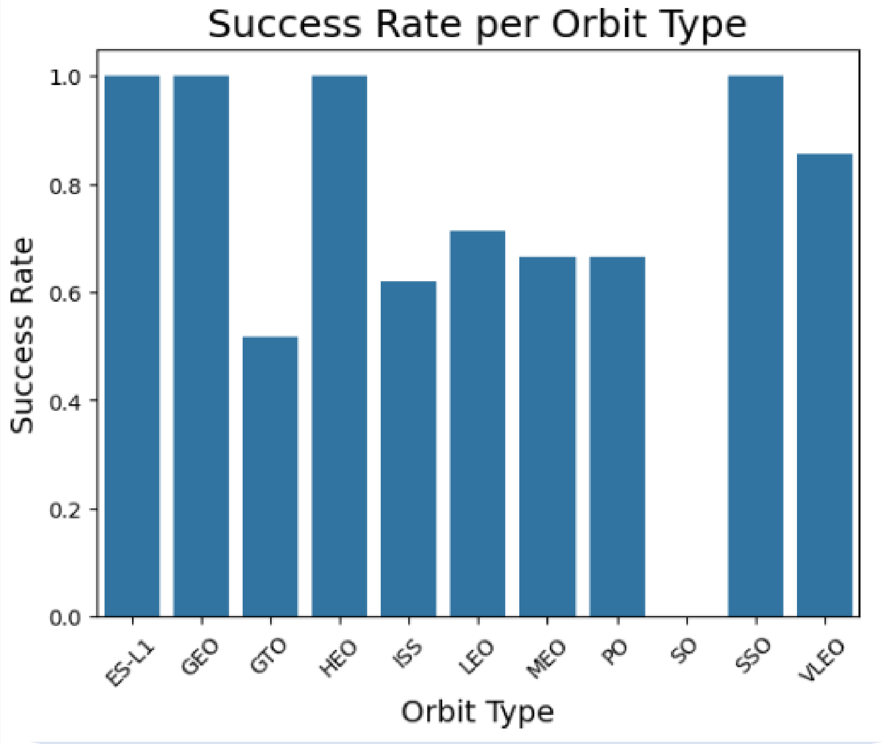
KSC LC 39A:
Similar to CCAFS, it has several successful launches for heavy loads (>10000 kg).

VAFB SLC 4E:
It does not register launches with loads greater than 10000 kg, which may be due to technical restrictions or logistical decisions.

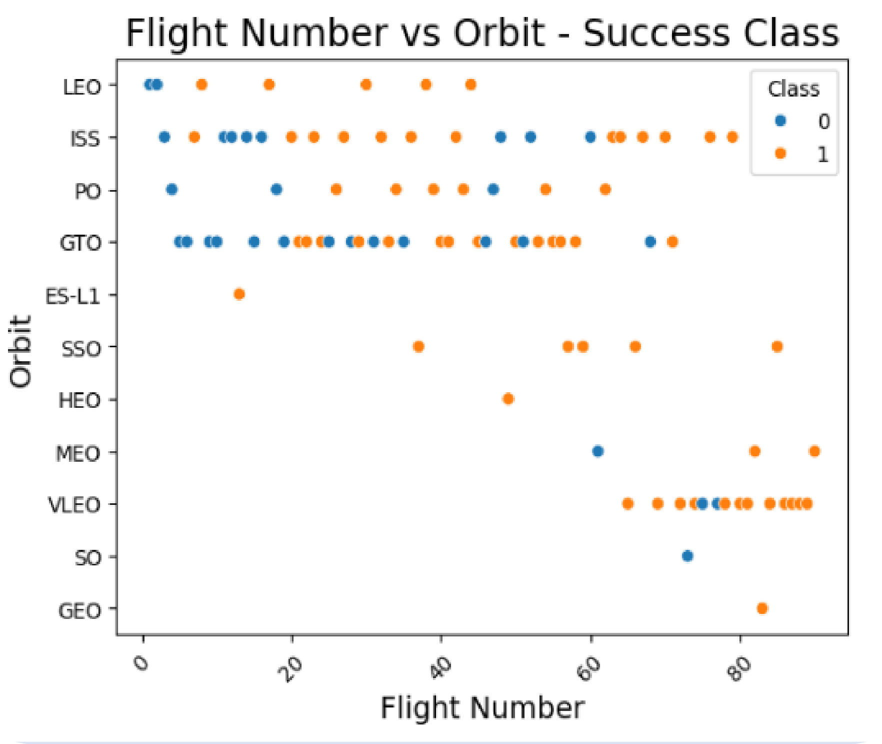


- Medium and high payloads appear to be associated with increased launch success, especially at CCAFS SLC 40 and KSC LC 39A sites.
- VAFB SLC 4E might not be a viable option for heavy loads, based on observed evidence.

Success Rate vs. Orbit Type



It is observed that the **ES-L1**, **HEO** and **SSO** orbits have a **100% success rate**, standing out as the most reliable. In contrast**,** **GTO** has the lowest success rate, indicating greater complexity or technical challenges in that type of orbit. Most other orbits maintain success rates in excess of **60%**, showing generally favorable performance.



In the **LEO** orbit, it can be seen that, the greater the number of flights, the greater the proportion of successful launches, suggesting an effect of accumulated experience or operational maturity. On the other hand, in **GTO** orbit, no clear relationship between the number of flights and success is identified, which could indicate more complex or less controllable technical factors.

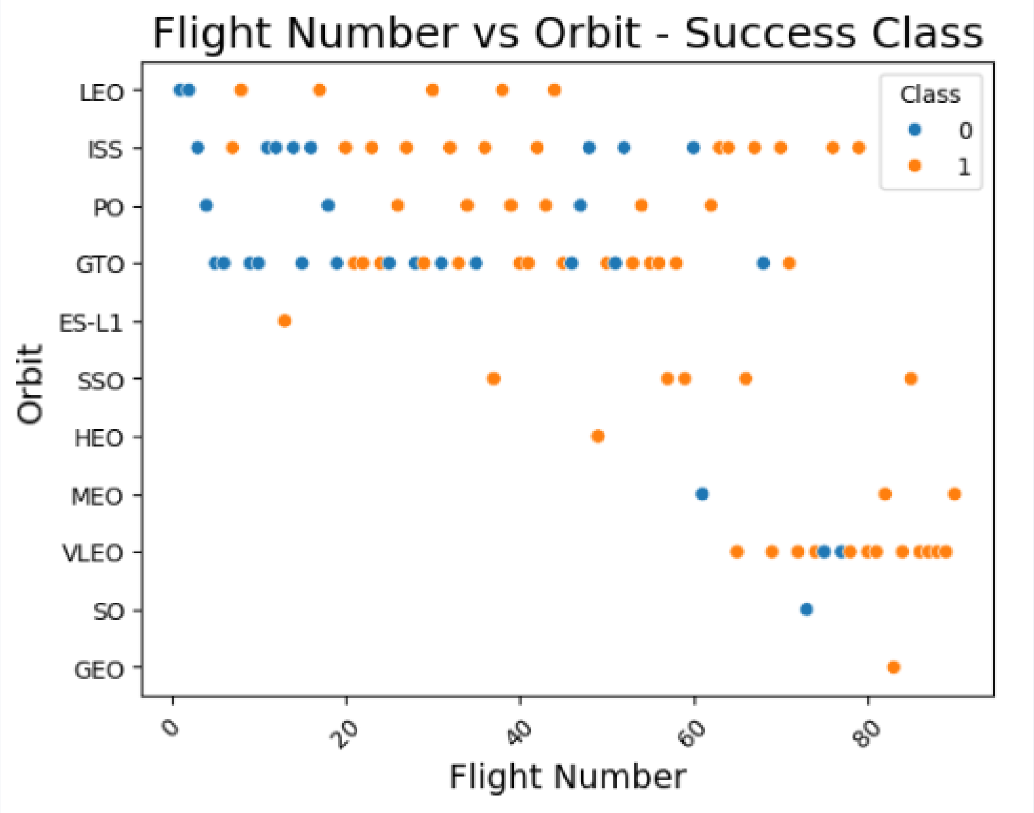
Flight Number vs. Orbit Type

In **LEO** orbit, a high success rate is observed, especially in the most recent flights (high flight numbers), suggesting cumulative learning and operational improvement.

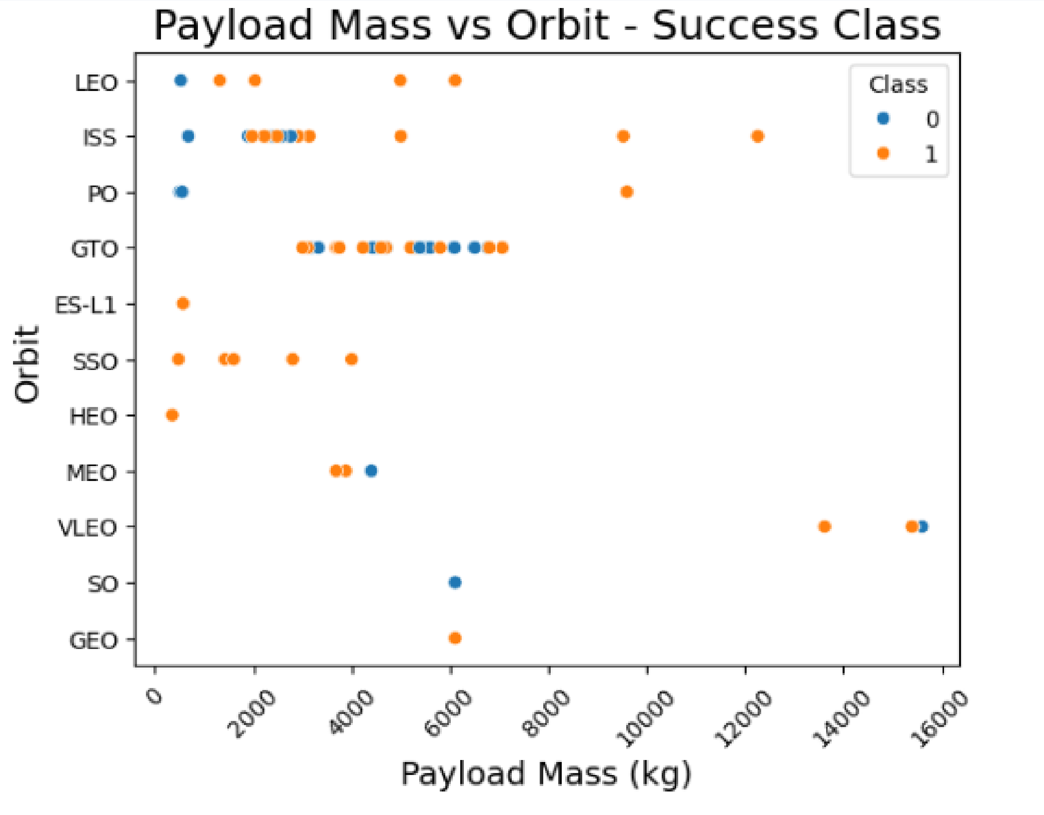
In **GTO** orbit, the results of success and failure are more randomly distributed, indicating that the number of flights does not guarantee success.

Orbits such as **ISS** and **PO** also show clearer success trends with higher number of flights.

In general, **success seems to correlate with accumulated experience** (FlightNumber) in some orbits, but not all.



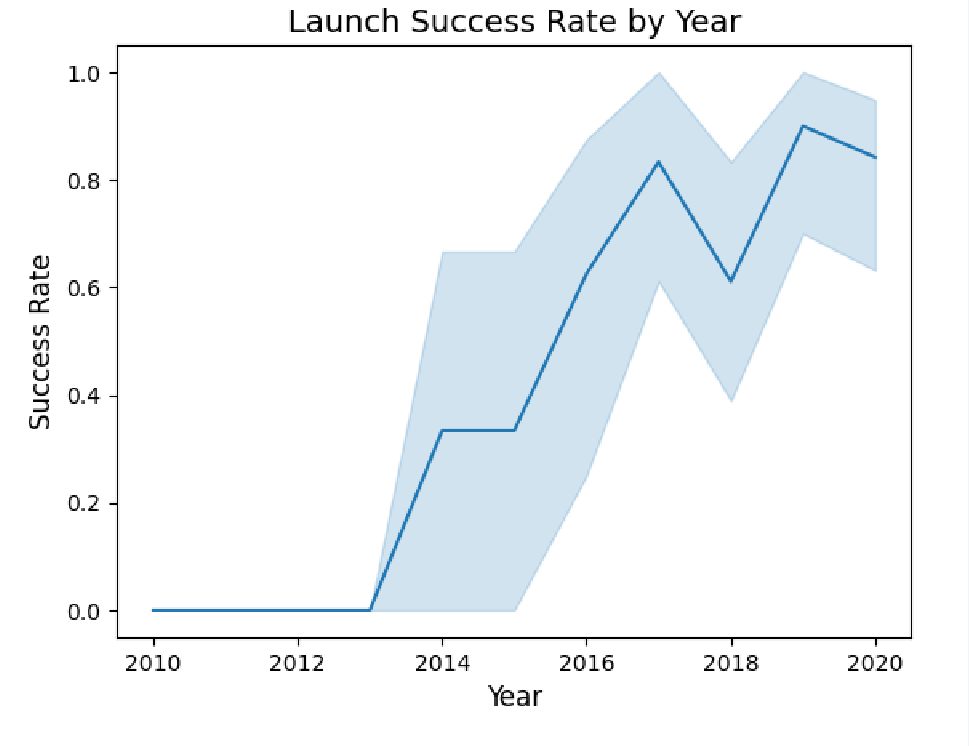
Payload vs. Orbit Type



The graph shows how the launch success rate varies depending on the type of orbit and the payload mass.
It is observed that in **Polar (PO), LEO**, and **ISS** orbits, launches with heavier payloads tend to have a higher success rate.
This suggests that these orbits could be better adapted or more optimized for larger payloads.

Launch Success Yearly Trend

The graph shows the evolution of the success rate in SpaceX launches from 2010 to 2020.
From 2013 onwards, a clear progressive improvement in the success rate has been observed, with peaks close to 100% in 2017 and 2019. This indicates that, over time, the company has optimized its technological and operational processes, achieving more reliable and consistent results in launches.



All Launch Site Names

A **SQL** query with **DISTINCT** was used to get the unique names of launch sites from the data table. This information is key to analyzing the individual performance of each site and its impact on the success rate of launches.

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

Launch Site Names Begin with 'CCA'

A **SQL** query with **LIKE 'CCA%'** was used to filter the first 5 launch site records that start with **"CCA".** This allows the identification of clusters or patterns associated with specific sites such as **CCAFS LC 40**

Date	Time (UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS__KG_	Orbit	Customer	Mission_Outcome	Landing_Outcome
2010-06-04	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
2010-12-08	15:43:00	F9 v1.0 B0004	CCAFS LC-40	Dragon demo flight C1, two CubeSats, barrel of Brouere cheese	0	LEO (ISS)	NASA (COTS) NRO	Success	Failure (parachute)
2012-05-22	7:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	No attempt
2012-10-08	0:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
2013-03-01	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

Total Payload Mass

Se realizó una consulta SQL para calcular la carga útil total transportada en misiones contratadas por **NASA (CRS)**.

What did this query do?

- Filtered all records where the **customer** is exactly "**NASA (CRS)**".
- He added up the payload (**PAYLOAD_MASS__KG_**) carried in those launches.
- The result was the total payload launched by specific missions of the **NASA CRS** (Commercial Resupply Services) program.

The result indicates that SpaceX's boosters have carried a total of **45.596 KG** **in these missions.**

Average Payload Mass by F9 v1.1

Executed Query

A **SQL** query was used to filter out all records where the rocket model was **F9 v1.1** and then calculated the **average payload (Payload_Mass__kg_)** carried by these launches.

Interpretation

The **F9 v1.1** model showed a consistent transport capacity, averaging close to **3,000 kg**, suggesting efficient use in medium-load missions.

The average payload carried by the **F9 v1.1** thruster was

2.928,4

KG

First Successful Ground Landing Date

Consultation carried out

A SQL query was executed that filters the logs with a successful landing on ground platform **(Landing_Outcome = 'Success (ground pad)')** and gets the oldest date **(MIN(Date)).**

Result obtained

The first recorded date of a successful landing on a ground platform was **December 22, 2015.**

Interpretation

This milestone represents a crucial technical breakthrough in rocket reusability, demonstrating that SpaceX was able to successfully recover a booster by landing on dry land, reducing future operating costs.

Successful Drone Ship Landing with Payload between 4000 and 6000

Consultation carried

The releases were leaked where:

The landing result was successful on a drone ship **(Landing_Outcome = 'Success (drone ship)')**The payload **(Payload_Mass__kg_)** was **between 4000 and 6000 kg.**

Result obtained

4 boosters were identified that met these conditions:

- **F9 FT B1022**
- **F9 FT B1026**
- **F9 FT B1021.2**
- **F9 FT B1031.2**

Interpretation

These results show the specific models of boosters that achieved successful landings on offshore platforms with medium loads, reflecting an advanced and consistent technical level under more demanding conditions.

Total Number of Successful and Failure Mission Outcomes

A query with **GROUP BY** was applied in column **Landing_Outcome** to obtain the total number of results for each type of mission.

Total Successful Missions

- Success: 38
- Success (drone ship): 14
- Success (ground pad): 9

TOTAL: 61 SUCCESSFUL MISSIONS.

Total Failed Missions

- Failure: 3
- Failure (drone ship): 5
- Failure (parachute): 2

TOTAL: 10 FAILED MISSIONS.

Interpretation

Most missions have had a successful landing, with the general success type being the most frequent. Failures occur mainly in attempts on drones and parachutes, although in a smaller proportion.

Boosters Carried Maximum Payload

A **SQL** subquery was used to identify the **maximum** value of column **Payload_Mass__kg_,** and then filtered all rows with that value to obtain the corresponding booster models.

Interpretation

These boosters stand out for having achieved the highest recorded value of payload carried, which evidences their high-performance capacity in critical missions.

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

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

Interpretation

In 2015, there were two failed landings on maritime platforms (drone ship). Both occurred at the CCAFS LC-40 launch site and used boosters from the F9 v1.1 version, specifically the B1012 (January) and B1015 (April) models.

The query selects records from the year **2015** in which the landing result was "Error (unmanned spacecraft)". To do this, the **SUBSTR()** function is used to extract the year and month from the **Date** column, specifically filtering out failed landings on maritime drones. Below are the values for the month, the **version of the booster**, **and the launch site**.

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

SQL query executed

The query selects the different types of landing results **(Landing_Outcome)** and counts how many times they occurred between June 4, 2010 and March 20, 2017. The records are grouped by type of landing and ordered in descending order according to their frequency.

Main results

- **No attempt** was the most common result, with 10 records.
- **Success (drone ship) and Failure (drone ship)** had the same frequency (5 cases each), highlighting the evolution in the development of successful drone landings.
- Other results such as **Success (ground pad)** and **Controlled (ocean)** were less frequent, showing diversity in recovery methods.

Interpretation

This ranking allows us to visualize the evolution and performance of SpaceX in different types of landings over the years, revealing both the number of attempts and the successes and failures in each type of platform.

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

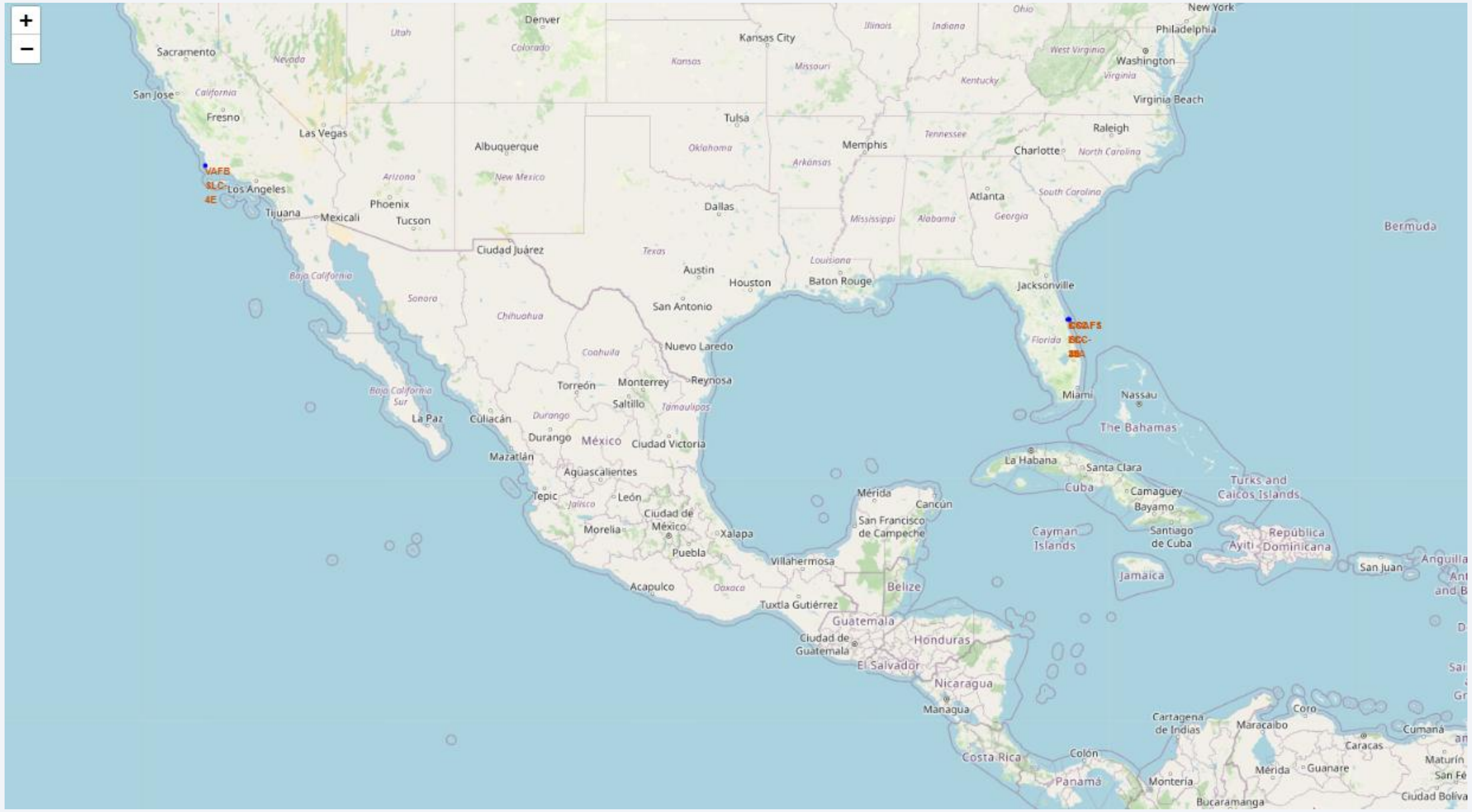
Section 3

Launch Sites Proximities Analysis

Global Map of SpaceX Launch Sites

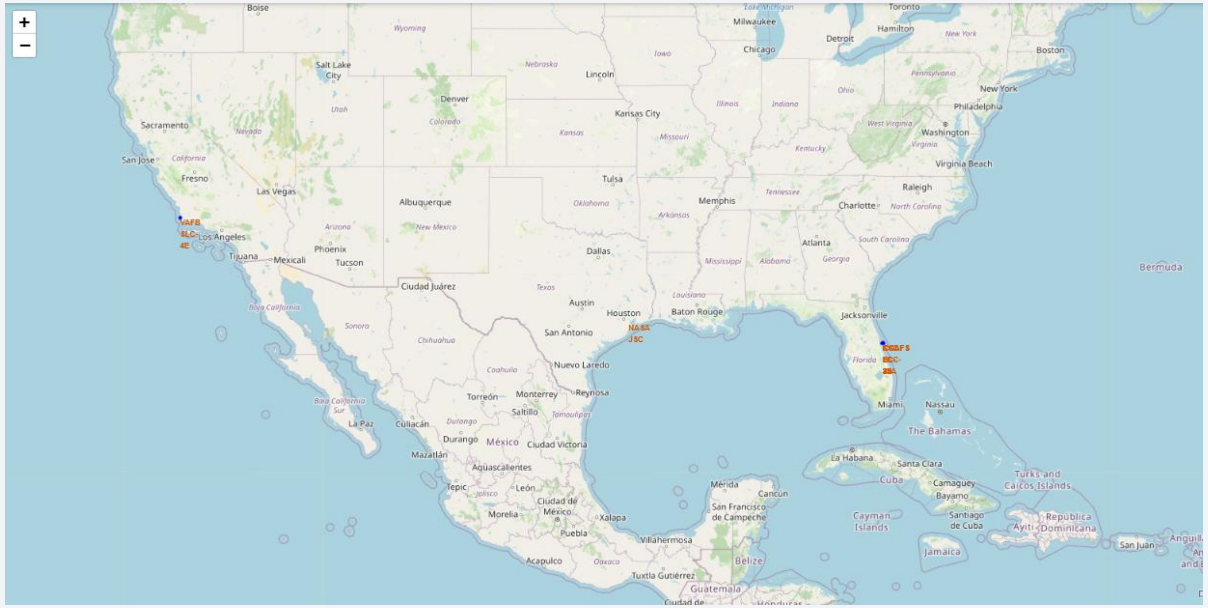
This map generated with **Folium** shows all the launch sites used by SpaceX, located using GPS coordinates. Each site is represented by a marker with its name and a blue circle to highlight its geographical location.

This visualization allows the spatial distribution of launch sites to be easily identified and serves as a basis for analyzing distances to nearby infrastructures in subsequent steps.



Launch Outcomes Visualization on Folium Map

This interactive map shows the launch sites marked with colors according to the outcome of each mission. Green dots indicate successful throws, while red dots represent failures.



Key elements visualized:

- Each marker represents a throw from a specific site.
- The color of the marker indicates the result of the throw (success or failure).
- The drop-down labels show details of the result for each item.

Key findings:

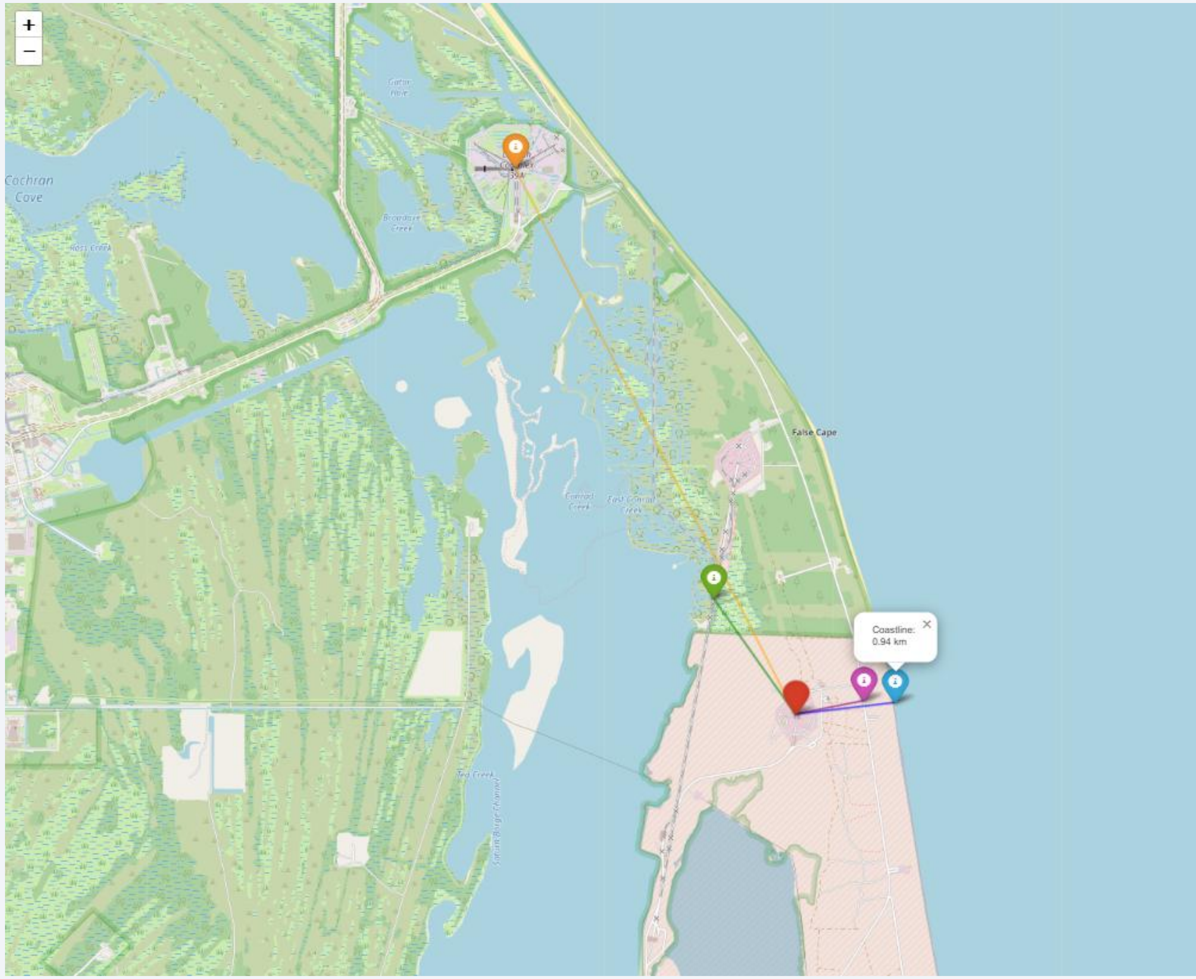
This visualization allows us to observe geographical patterns in the results, highlighting for example that certain sites have a higher proportion of successes than others.

Proximities to CCAFS LC-40 Launch Site

This map displays the spatial relationships between the selected launch site CCAFS LC-40 and nearby geographical features: coastline, railway, highway, and city.

Each location is marked with a colored icon and connected to the launch site via a straight line, annotated with the calculated distance in kilometers. These proximities are crucial for evaluating logistical accessibility and emergency response planning.

From the map, we can observe that the launch site is relatively close to the coastline and highway, enabling efficient transportation of equipment. The nearby railway and city provide additional infrastructure support.



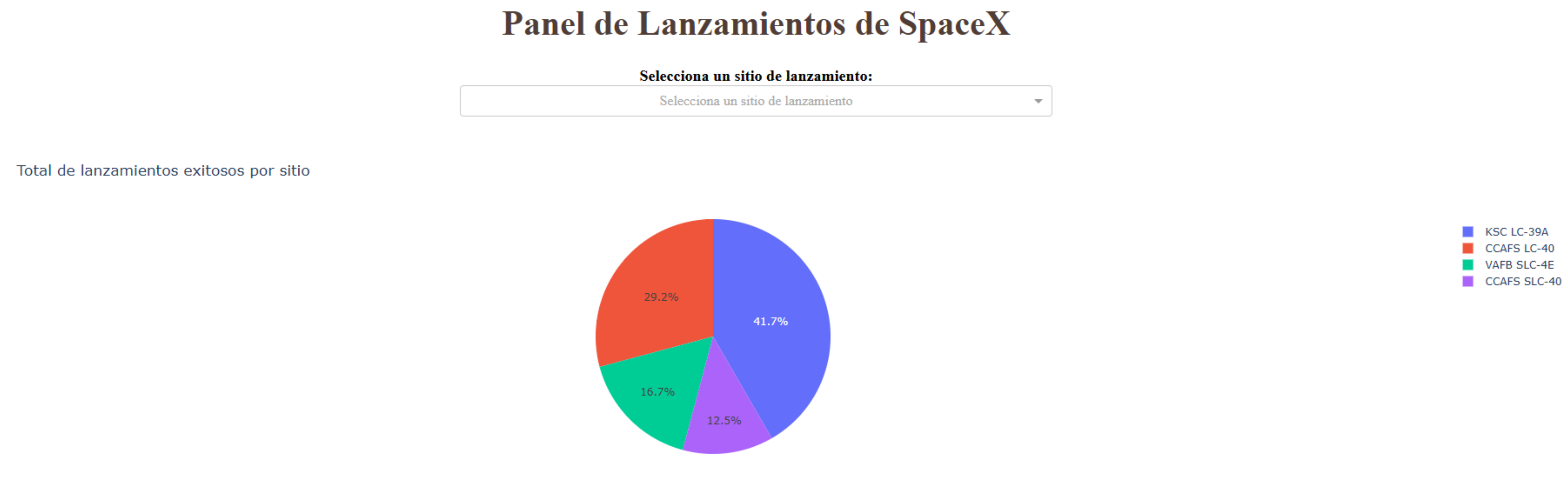
Section 4

Build a Dashboard with Plotly Dash

Launch Success Distribution by Site

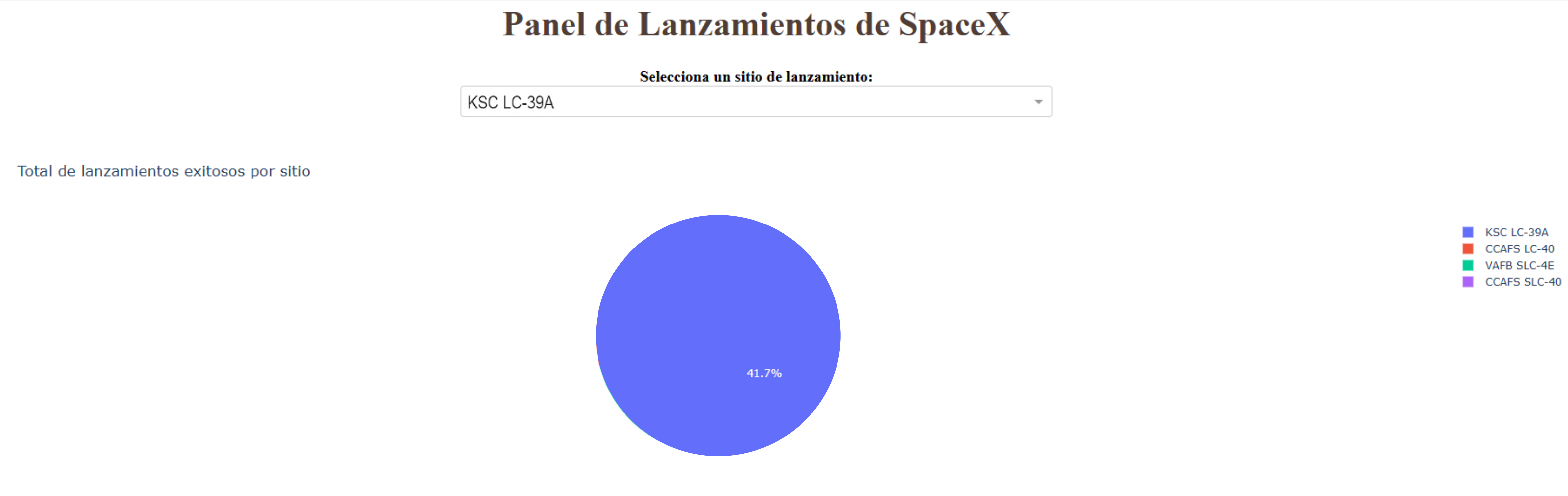
The pie chart represents the proportion of successful launches made from each of the launch sites. Each segment shows the success rate associated with the corresponding site. This graph allows you to visually identify which site has been the most active in terms of successful missions.

For example, the **KSC LC-39A** site leads with **more than 40%** of total successful launches, followed by **CCAFS LC-40**. This visualization helps to understand the operational relevance of each site in SpaceX's space program.



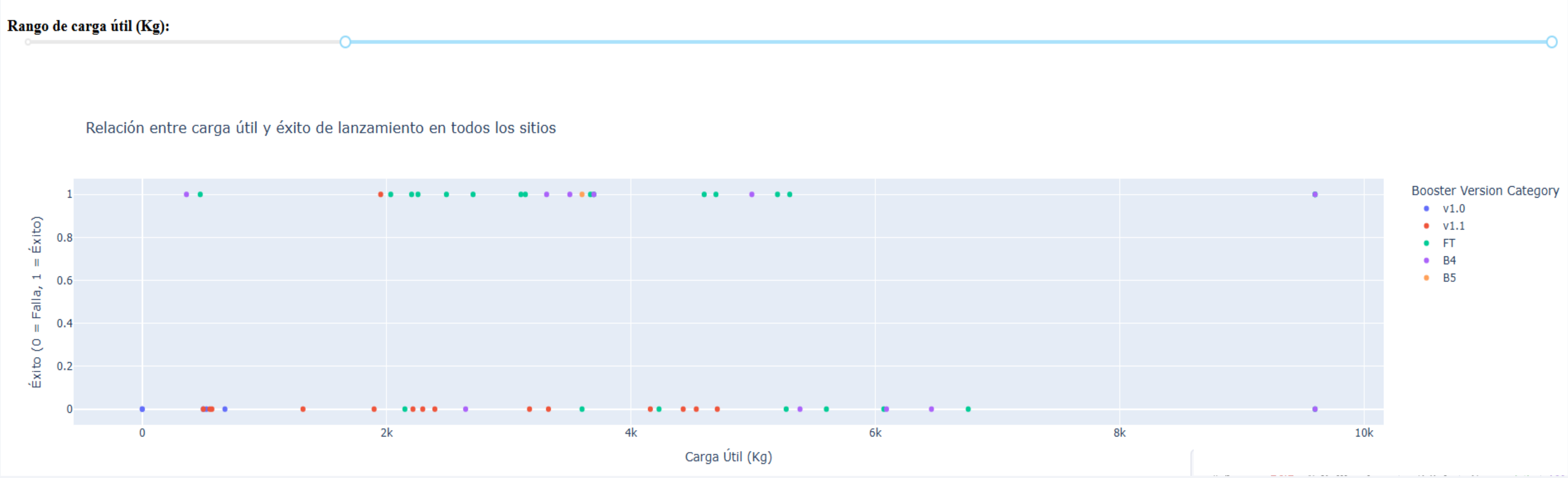
KSC LC-39A: Highest Launch Success Rate

This pie chart displays the launch outcomes for the site **KSC LC-39A**, which has the highest launch success ratio among all launch sites. The chart shows that **100% of launches from this site were successful**, representing a total of 41.7% of all successful SpaceX launches overall.
This insight highlights **KSC LC-39A** as the most reliable site in SpaceX's launch history.



Payload vs. Launch Outcome Scatter Plot Across All Sites

This visualization shows how launch success varies depending on the payload carried across sites.
Each point represents a launch, with the X-axis indicating the payload mass and the Y-axis the result (0 = failure, 1 = success).
It is observed that launches with payloads between 2000 and 4000 kg have a high success rate, especially with FT and B5 boosters.
This suggests that these models perform better in that payload range.
The slider allows you to explore different load combinations to analyze patterns of success.



Section 5

Predictive Analysis (Classification)

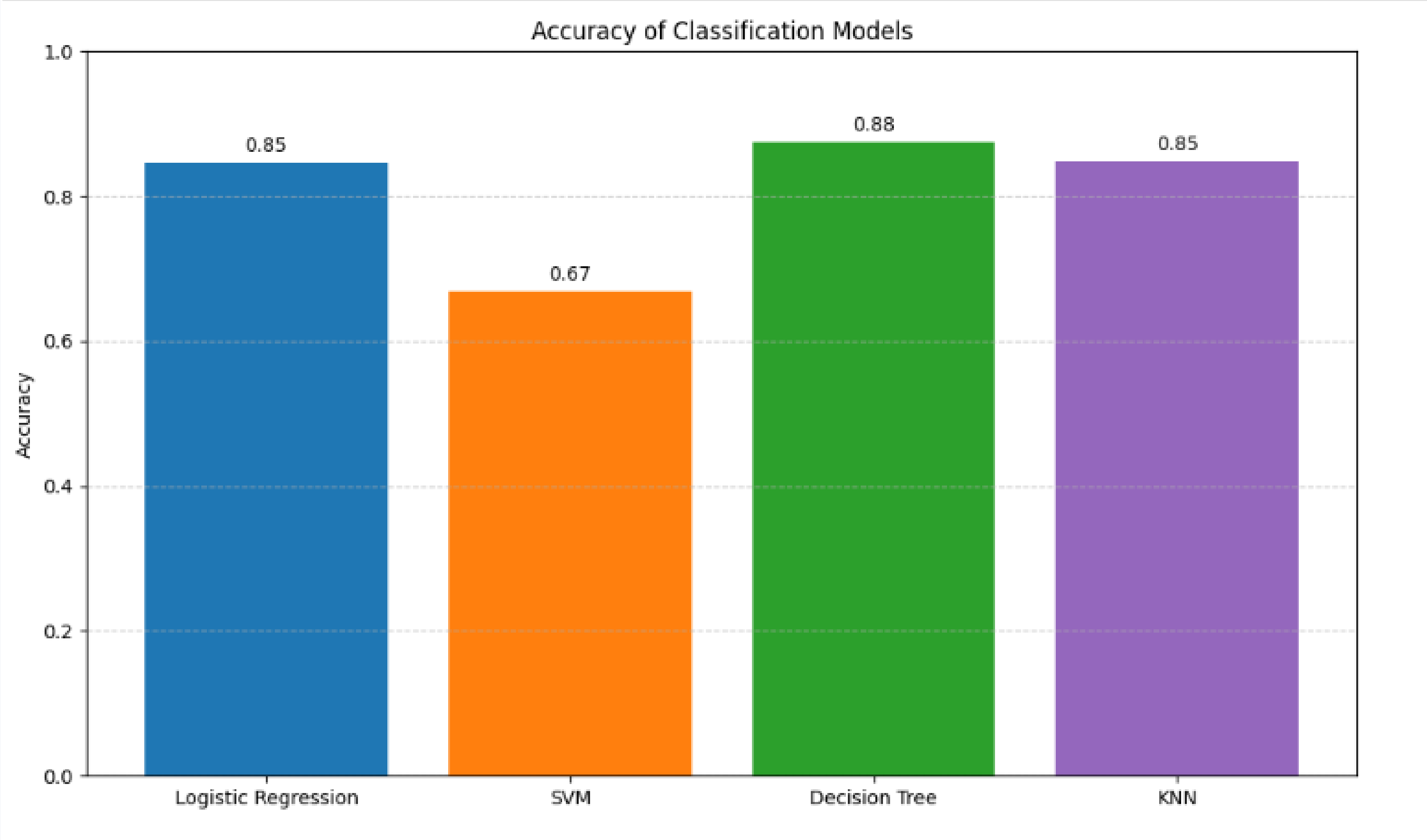
Classification Accuracy

The bar chart compares the classification accuracy of four predictive models:

Logistic Regression, Support Vector Machine **(SVM), Decision Tree**, and K-Nearest Neighbors **(KNN).**

Among these, the **Decision Tree** model achieved the highest accuracy with **0.88**, followed closely by Logistic Regression and **KNN (both at 0.85).**

SVM yielded the lowest accuracy at **0.67**, indicating it may not be the most effective model for this classification task.



This analysis helps identify the best-performing algorithm for predicting SpaceX launch outcomes.

Confusion Matrix

Confusion Matrix of the Best Performing Model

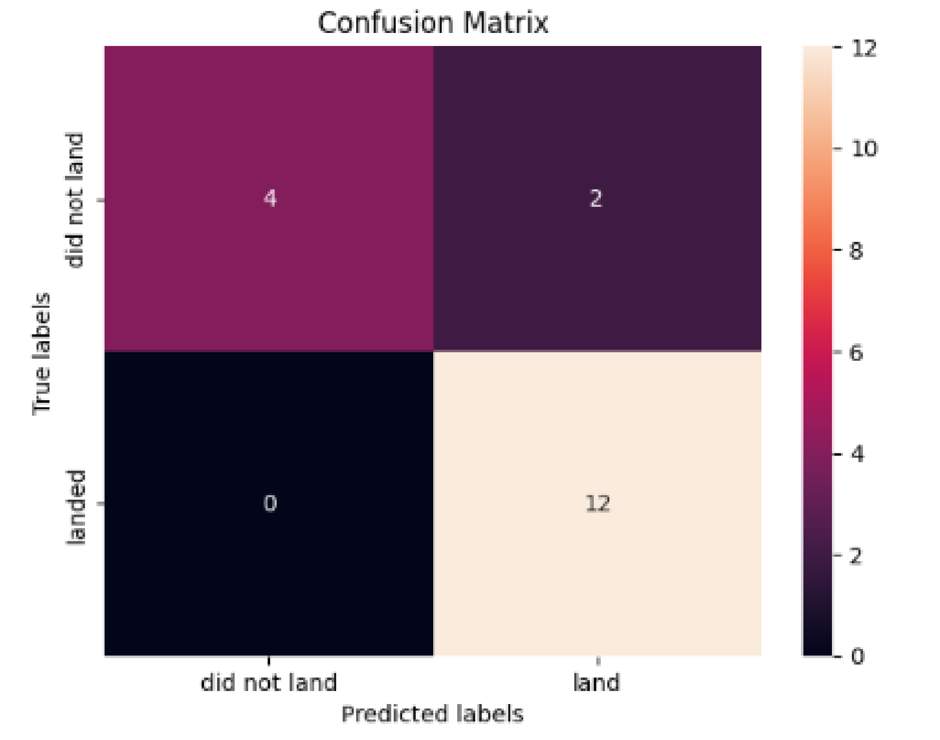
The following confusion matrix corresponds to the **Decision Tree**, the best-performing classification model with an accuracy of **88%**.

•**True Positives (TP = 12):** Correctly predicted landings

•**True Negatives (TN = 4):** Correctly predicted non-landings.

•**False Positives (FP = 2):** Incorrectly predicted landings that actually failed.

•**False Negatives (FN = 0):** No missed predictions of actual landings.



This result shows the model is highly reliable in identifying successful landings, with only minor confusion in predicting failed launches.

Conclusions

1 Geospatial visualization revealed that **KSC LC-39A** and **CCAFS LC-40 are** the most successful launch sites.

2 Payloads between **2000 and 4000 kg** combined with **FT** and **B5 boosters** showed the highest success rates.

3 The interactive dashboard enabled users to dynamically explore trends in success across payload and location.

4 Among the four models tested, the **Decision Tree** classifier achieved the highest prediction accuracy (**88%**).

5 Predictive models confirmed that **machine learning** can effectively classify the success of SpaceX landings.

Appendix

CODE NOTEBOOKS USED	Data Sources	Assets Created
• **lab_jupyter_launch_site_location.ipynb** – Geospatial proximity and marker visualization with Folium. • **spacex-dash-app.py** – Interactive dashboard using Plotly Dash. • **SpaceX_Machine Learning Prediction_Part_5.ipynb** – Model training and prediction (Logistic Regression, SVM, KNN, Decision Tree).	• SpaceX API: **https://api.spacexdata.com/v4/launches/past** • Revenue Data (scraped via BeautifulSoup	• Multiple pie charts, scatter plots, bar charts, and interactive visualizations. • SQL queries for mission statistics, payload analysis, and booster performance. • Machine learning models evaluated with accuracy metrics and confusion matrices.

https://github.com/ClauLet/Ciencia-de-datos-aplicada-Capstone

Thank you!