



Winning Space Race with Data Science

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Repository: <https://github.com/kringsman/capstone/>



Outline

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

Executive Summary

- To identify the most accurate predictor of launch success for SpaceX missions, a range of machine learning classification models were utilized. Specifically, the team trained and tested several models, including logistic regression, support vector machines, decision trees, and k nearest neighbors. In addition, the hyperparameters of each model were fine-tuned to enhance their predictive power. Through this rigorous process of evaluation, the team was able to determine which model offered the greatest accuracy in predicting the likelihood of a successful launch. This information was vital in helping to optimize the design and operation of future SpaceX missions, ultimately contributing to the company's ongoing success in the space exploration industry.
- In order to analyze the factors that influenced the success of SpaceX missions, data was collected from two main sources: the SpaceX public API and Wikipedia's database of SpaceX launch information. This data was carefully selected to ensure that it was relevant to the analysis and could be adapted to facilitate Exploratory Data Analysis (EDA) and visualization. Once the data was isolated and transformed, it was used to generate various maps and interactive dashboards, which enabled the team to visualize and explore the data in greater depth. These tools were essential in identifying patterns and trends within the data, which ultimately helped to inform the analysis and draw meaningful conclusions about the factors that contributed to the success of SpaceX missions.
- The goal of the analysis was to investigate the various factors that influenced the success of SpaceX missions. Through a detailed examination of multiple data sources and machine learning models, the team was able to identify several key elements that were critical to the accomplishment of SpaceX endeavors. These elements included the configuration of the rocket, the cargo being transported, the location of launch, and the method used for landing. By analyzing these variables, the team was able to gain a better understanding of the factors that contribute to successful space exploration missions. Overall, the findings of this study provide valuable insights for future space missions and help to solidify SpaceX's position as a leader in the field of space exploration.

Introduction

- The cost of space exploration is notoriously expensive, with many launches costing upwards of millions of dollars. However, SpaceX has been able to significantly reduce the cost of rocket launches by reusing the first stage of their Falcon 9 rocket.
- In this capstone project, the focus is on predicting the success of the first stage landing of the Falcon 9 rocket. By doing so, the cost of a launch can be determined, which is valuable information for potential competitors who may wish to bid against SpaceX for a rocket launch.
- With this in mind, the project aims to utilize predictive modeling to accurately predict whether or not the Falcon 9 first stage will land successfully, ultimately contributing to the broader goal of making space exploration more cost-effective.

Section 1

Methodology

Methodology

Executive Summary

- Data collection methodology:
- Perform data wrangling
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models

Data Collection

- Data sets were collected of the following ways.
 - Extracting raw data from Space X API using pandas (information API on the following links)
 - <https://api.spacexdata.com/v4/rockets/>
 - <https://api.spacexdata.com/v4/launches/past>
 - <https://api.spacexdata.com/v4/>
 - <https://api.spacexdata.com/v4/launchpads/>
 - <https://api.spacexdata.com/v4/payloads/>
 - <https://api.spacexdata.com/v4/cores/>
 - WebScraping using BeautifulSoup
(https://en.wikipedia.org/wiki/List_of_Falcon/_9/_and_Falcon_Heavy_launches)

Data Collection – SpaceX API

- Create a jupyter file
- Import Libraries and Define Auxiliary Functions
- Import the information
- Normalize and parse json
- Filter the dataframe to only include Falcon 9 Launches and obtain just the oimportant data
- Clean de Data
- GitHub URL of the completed SpaceX API calls: [capstone/jupyter-labs-spacex-data-collection-api.ipynb at master · kringsman/capstone \(github.com\)](https://github.com/kringsman/capstone-jupyter-labs-spacex-data-collection-api/blob/master/collection-api.ipynb)

Create a jupyter or environment

Import request, pandas, numpy and datetime

```
requests.get("https://api.spacexdata.com/v4/rockets/"+str(x)).json()
```

```
Important data in func: getBoosterVersion(data): def  
getPayloadData(data): getCoreData(data):
```

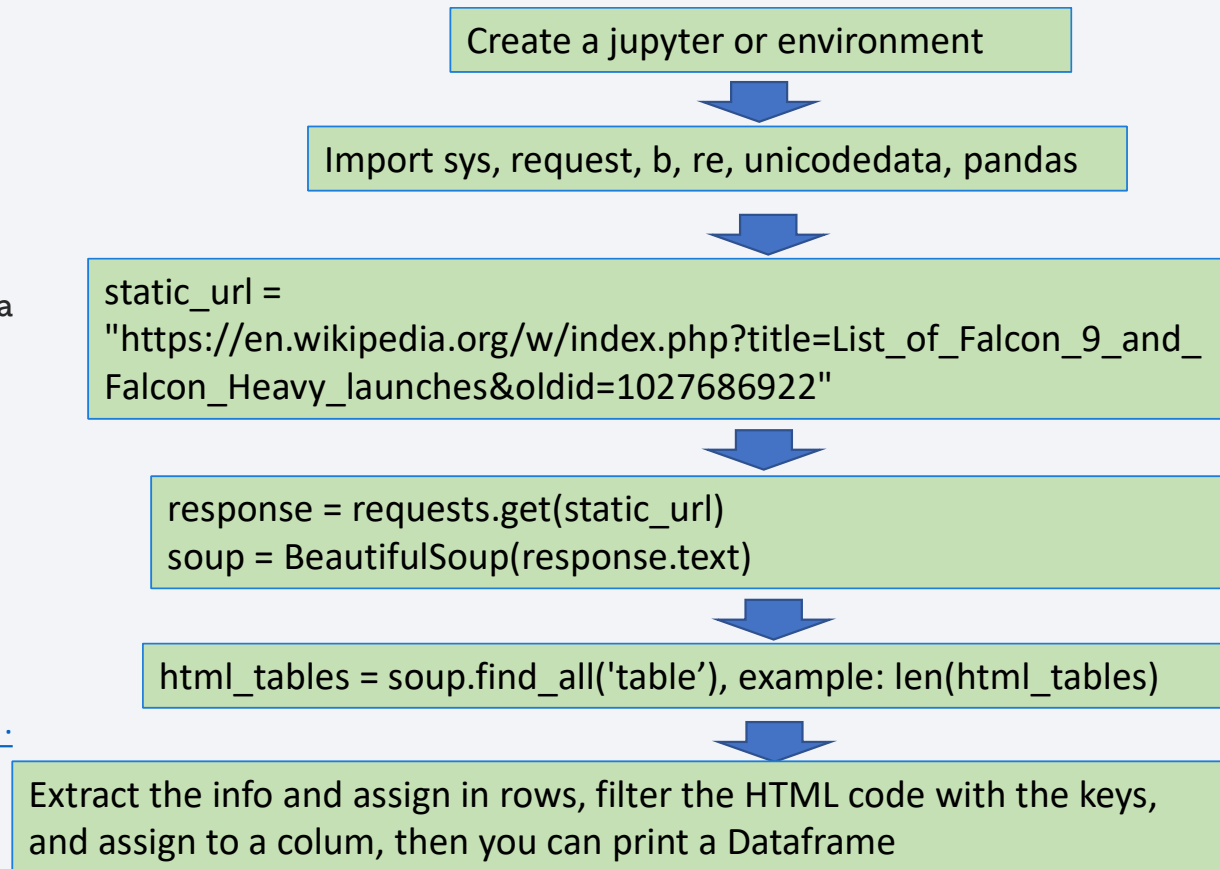
```
data = pd.json_normalize(response.json())
```

```
data_falcon9 = data_falcon9[data_falcon9['BoosterVersion']=='Falcon 9']  
print(data_falcon9['BoosterVersion'].value_counts())
```


Data Collection – Web Scrapping

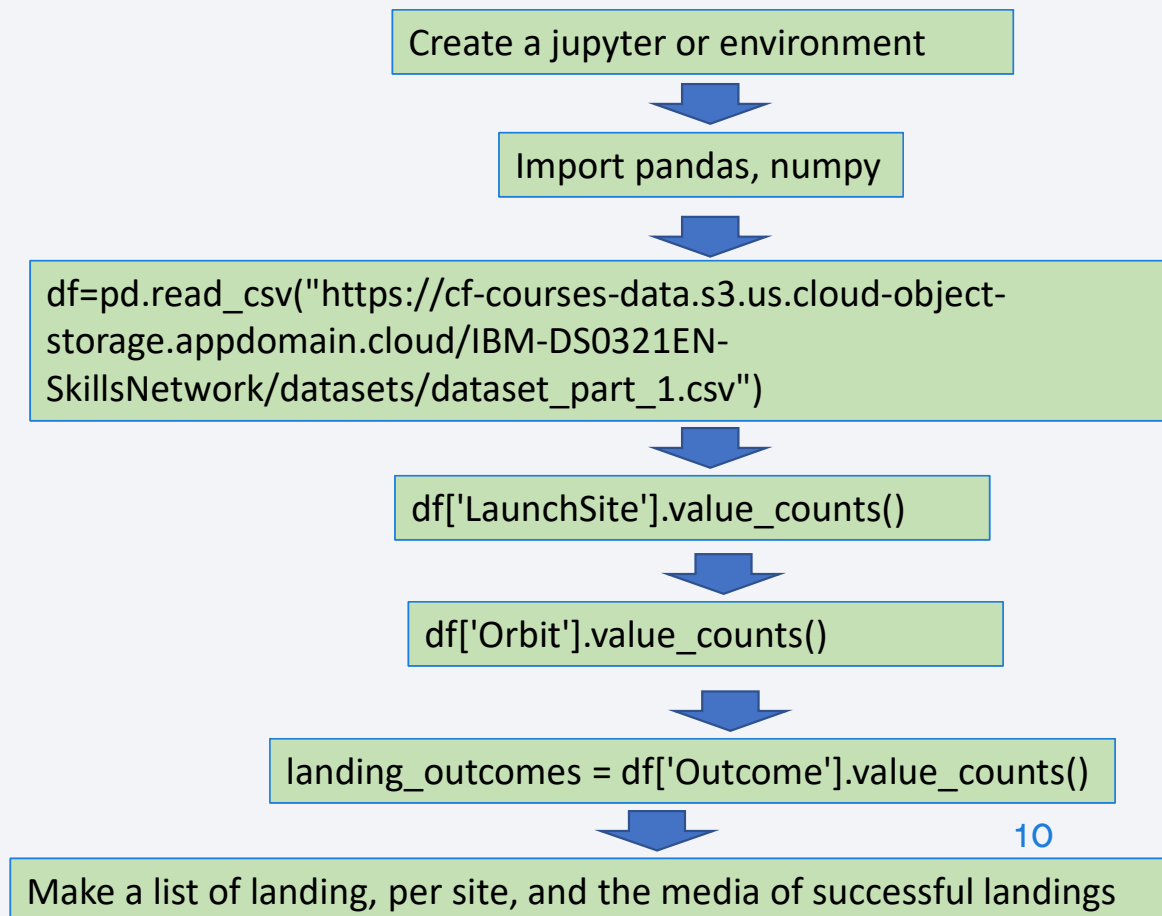
- Create a jupyter file
- Import Libraries and Define Auxiliary Functions
- Import the web from where do you take the information
- Use beautiful soup to extract the information in a tree
- Extract the info for columns or variables
- Create a data frame by parsing the launch HTML tables
- Export the information organized in a table

GitHub URL of the completed web Scrapping:
[capstone/jupyter-labs-webscraping.ipynb at master · kringsman/capstone \(github.com\)](https://github.com/kringsman/capstone-jupyter-labs-webscraping/blob/master/capstone-jupyter-labs-webscraping.ipynb)



Data Wrangling

- After obtaining the data and the number of successful launches, the information was organized to get an overview of information loss, useful information, and information that required cleaning or further analysis
- We calculate the number of launches at each site, the frequency in each orbit, the mission outcome frequency per orbit type, and then create a landing outcome label from the outcome column.
- [capstone/labs-jupyter-spacex-Data wrangling.ipynb](#) at master · [kringsman/capstone](#) (github.com)



EDA with Data Visualization

- In this phase, we utilized Matplotlib visualization techniques and Pandas for Feature Engineering to conduct Exploratory Data Analysis. Our aim was to examine the correlations between Flight number, Launch site, Payload mass, and orbit type, and we achieved this using various graph types like scatter plots, bar graphs, and line graphs. To make the effects of the variables and their relationships visible on the launch outcome, all visualizations were color-coded by "class." The features were engineered through one hot encoding, which transforms categorical data into numeric data that is appropriate for classification algorithms. Finally, all data was cast to a float64 type.
- [capstone/jupyter-labs-eda-dataviz.ipynb at master · kringsman/capstone \(github.com\)](https://github.com/kringsman/capstone-jupyter-labs-eda-dataviz/blob/master/capstone-jupyter-labs-eda-dataviz.ipynb)

EDA with SQL

- `sql SELECT DISTINCT LAUNCH_SITE FROM SPACEXTBL ORDER BY 1`
- `sql SELECT * FROM SPACEXTBL WHERE LAUNCH_SITE LIKE 'CCA%' LIMIT 5`
- `sql SELECT SUM (PAYLOAD_MASS__KG_) FROM SPACEXTBL WHERE CUSTOMER='NASA (CRS)'`
- `sql SELECT AVG (PAYLOAD_MASS__KG_) FROM SPACEXTBL WHERE Booster_Version like 'F9 v1.1%'`
- `sql SELECT MIN(Date) FROM SPACEXTBL WHERE Mission_outcome LIKE 'Success%'`
- `sql SELECT Booster_Version FROM SPACEXTBL WHERE PAYLOAD_MASS__KG_ BETWEEN 4000 AND 6000 AND "Landing _Outcome" = 'Success (drone ship)'`
- `sql SELECT MISSION_OUTCOME, COUNT(MISSION_OUTCOME) FROM SPACEXTBL WHERE MISSION_OUTCOME like 'Success%'`
- `sql SELECT BOOSTER_VERSION FROM SPACEXTBL WHERE PAYLOAD_MASS__KG_ = (SELECT MAX(PAYLOAD_MASS__KG_) FROM SPACEXTBL)`
- `sql SELECT substr(Date, 4, 2) AS Month, substr(Date, 7, 4) as Year,BOOSTER_VERSION, "Landing _Outcome",launch_site FROM SPACEXTBL where substr(Date,7,4)='2015' AND "Landing _Outcome" = 'Failure (drone Ship)'`
- `SELECT "Landing _Outcome", Count(*) FROM SPACEXTBL WHERE "Landing _Outcome" IN (' Success','Success (drone ship)','Success (ground pad)') AND substr (Date, substr (Date, substr (Date,1,2) BETWEEN '2010 06 04' AND '2017 03 20' GROUP BY "Landing _Outcome" ORDER BY (Count(*)) DESC;`
- [capstone/jupyter-labs-eda-sql.ipynb at master · kringsman/capstone \(github.com\)](https://github.com/kringsman/capstone-jupyter-labs-eda-sql.ipynb)

Build an Interactive Map with Folium

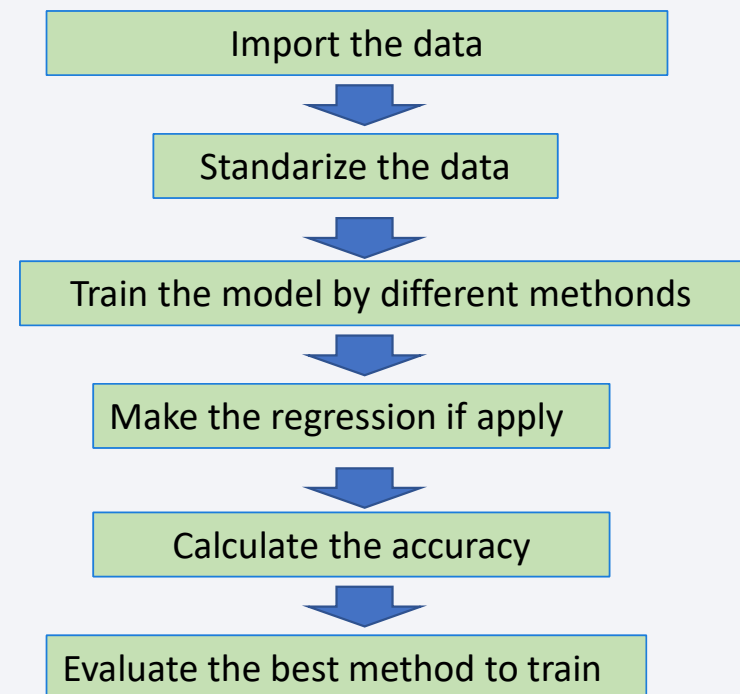
- A variety of tools were used in the creation of Folium maps, including markers, circles, lines and marker clusters.
- To identify launch sites, markers were utilized on the Folium maps.
- Specific locations, such as the NASA Johnson Space Center, were highlighted by circles on the Folium maps.
- To group events in each coordinate, marker clusters were implemented in the Folium maps.
- The distances between two coordinates were represented on the Folium maps by lines.
- Through the use of markers, circles, lines and marker clusters, a highly interactive and informative Folium map was created. Add the GitHub URL of your completed interactive map with Folium map, as an external reference and peer-review purpose
- [capstone/lab_jupyter_launch_site_location_folium.ipynb at master · kringsman/capstone \(github.com\)](https://github.com/kringsman/capstone/blob/master/lab_jupyter_launch_site_location_folium.ipynb)

Build a Dashboard with Plotly Dash

- The analysis involved using various graphs and plots such as the percentage of launches by site and payload range.
- The visualization of these graphs and plots helped to quickly identify the relationship between payloads and launch sites, thus finding the best place to launch.
- An interactive dashboard was designed with a drop-down menu for launch site selection and a slider control for selecting the range of payload masses.
- The dashboard included a pie chart that showed the successful outcome for all launch sites or the proportion of good and bad outcomes for any one selected launch site, as well as a scatter chart that displayed how the launch outcome varied by the selected site and payload range, with the data points color coded by booster type.
- [capstone/spacex_dash_app.py at master · kringsman/capstone \(github.com\)](https://github.com/kringsman/capstone)

Predictive Analysis (Classification)

- The text describes a comparison of four classification models: logistic regression, support vector machine, decision tree, and k nearest neighbors. The process for each algorithm is outlined in a flowchart.
- [capstone/IBM-DS0321EN-SkillsNetwork labs module 4 SpaceX Machine Learning Prediction Part 5.jupyterlite.ipynb](#) at master · kringsman/capstone (github.com)

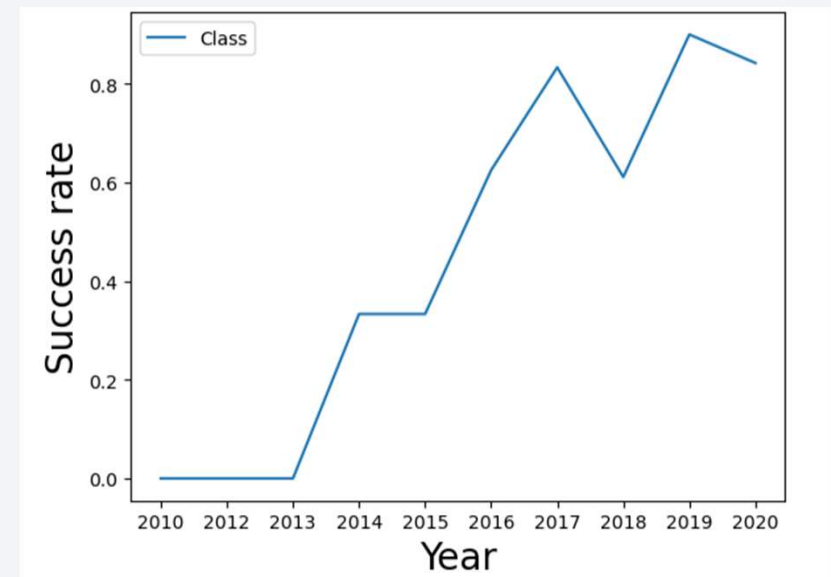


Results

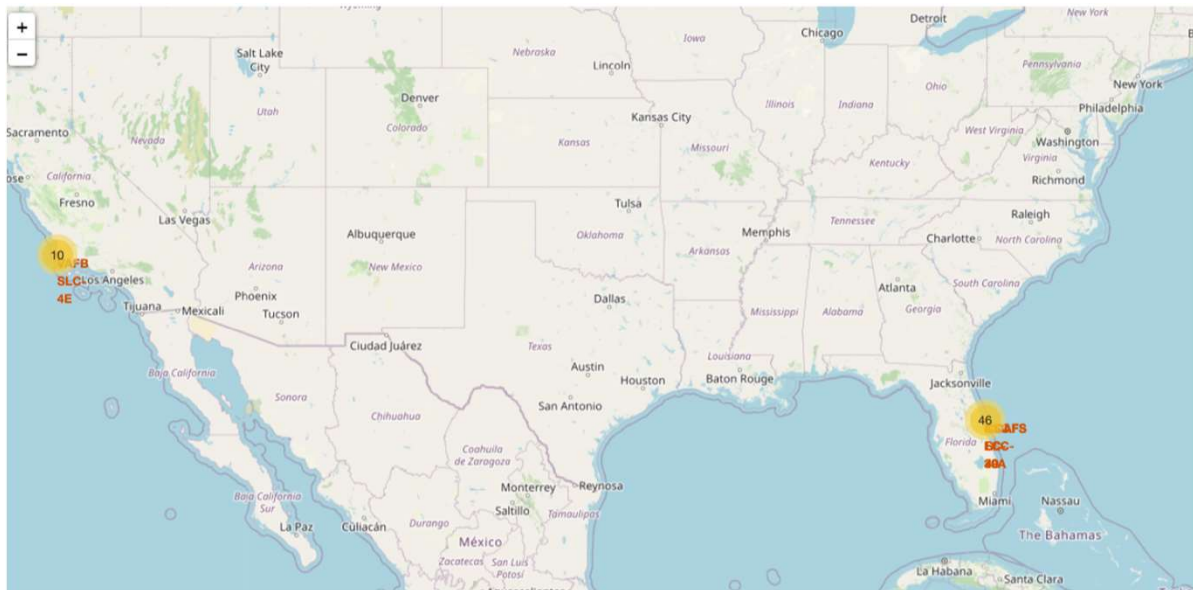
In the exploratory data analysis conducted on Space X launches, it was found that the company uses four different launch sites. The first launches were done to Space X itself and NASA. The average payload of F9 v1.1 booster was calculated to be 2,928 kg. It was observed that the first successful landing outcome happened in 2015, five years after the first launch. Many Falcon 9 booster versions were successful at landing in drone ships having payload above the average.

Moreover, it was discovered that almost 100% of mission outcomes were successful. However, two booster versions, F9 v1.1 B1012 and F9 v1.1 B1015, failed at landing in drone ships in 2015. Over the years, the number of landing outcomes became better. Using interactive analytics, it was possible to identify that launch sites are usually located in safe places near the sea and have good logistic infrastructure around. Most launches happen at the east coast launch sites.

The insights from the exploratory and predictive analyses suggest that Space X has been successful in achieving its mission outcomes, and the company has continuously improved its landing outcomes over time. The launch sites are located in strategic and safe places, which are essential factors for successful launches. The decision tree classifier can be used to predict the success of future launches with high accuracy, which is crucial for Space X's continued success.



Results



In predictive analysis, four classification models were compared, including logistic regression, support vector machine, decision tree, and k-nearest neighbors. The results showed that the decision tree classifier is the best model to predict successful landings, with an accuracy of over 87%. The accuracy for test data was observed to be over 94%.

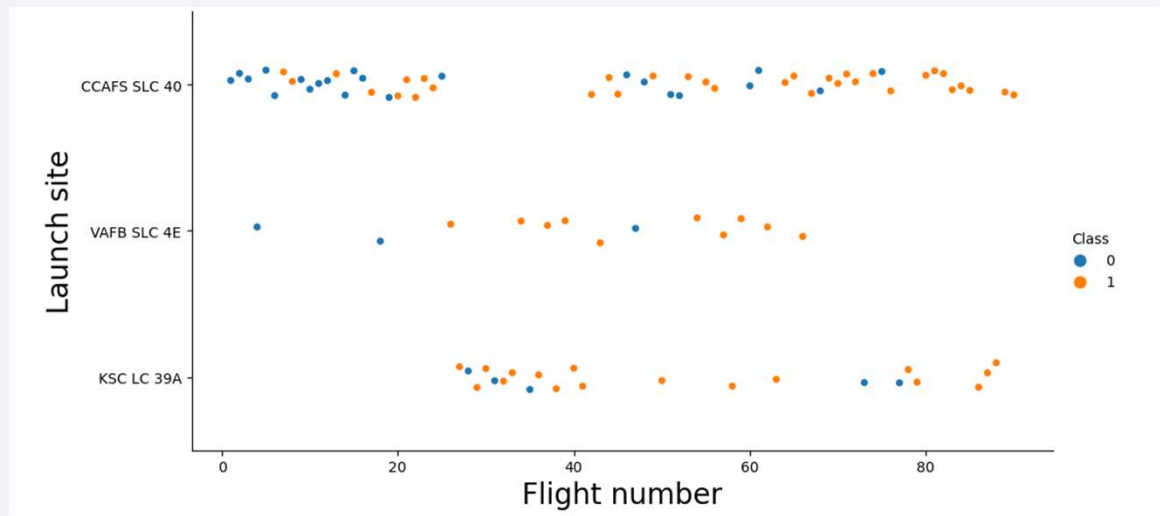


Section 2

Insights drawn from EDA

Flight Number vs. Launch Site

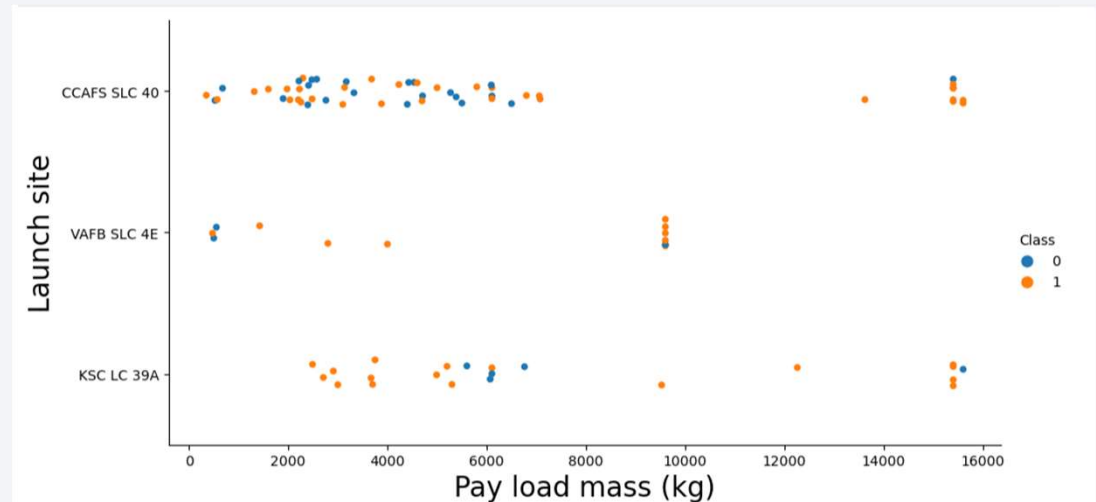
- The scatter plot of Flight Number vs. Launch Site provides valuable insights into the success rate of SpaceX launches. The data shows that the highest success rate is observed at CCAFS SLC 40, followed by VAFB SLC 4E and KSC LC 39A. This suggests that choosing the right launch site is critical for the success of a mission. The insights gained from the scatter plot can help SpaceX make informed decisions about launch site selection, ultimately improving their overall success rate.



- Additionally, the scatter plot highlights a positive trend in SpaceX's success rate over time. The increasing number of orange data points (successful launches) in the later flights compared to blue data points (unsuccessful launches) suggests that improvements in technology, launch procedures, and team expertise have contributed to this trend. By continuously analyzing their data and using insights gained from it, SpaceX can further improve their launch success rate and continue to make significant strides in the space industry.

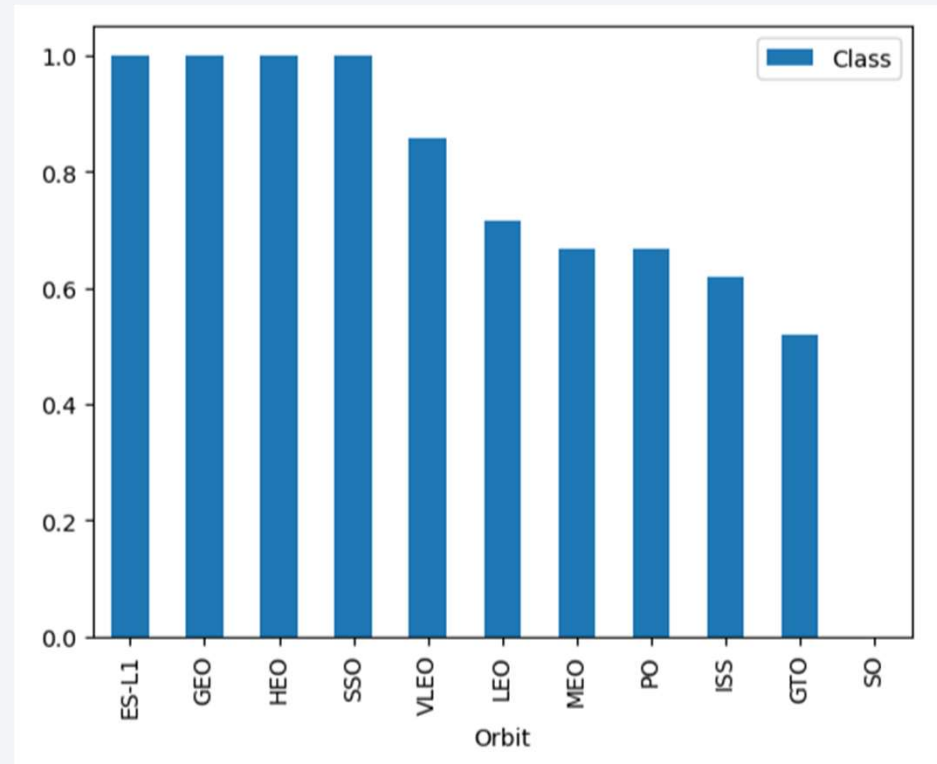
Payload vs. Launch Site

1. Higher payload correlated with higher success rate in launches.
2. CCAFS SLC 40 and KSC LC 39A are the only launch sites capable of handling payloads over 12,000kg.



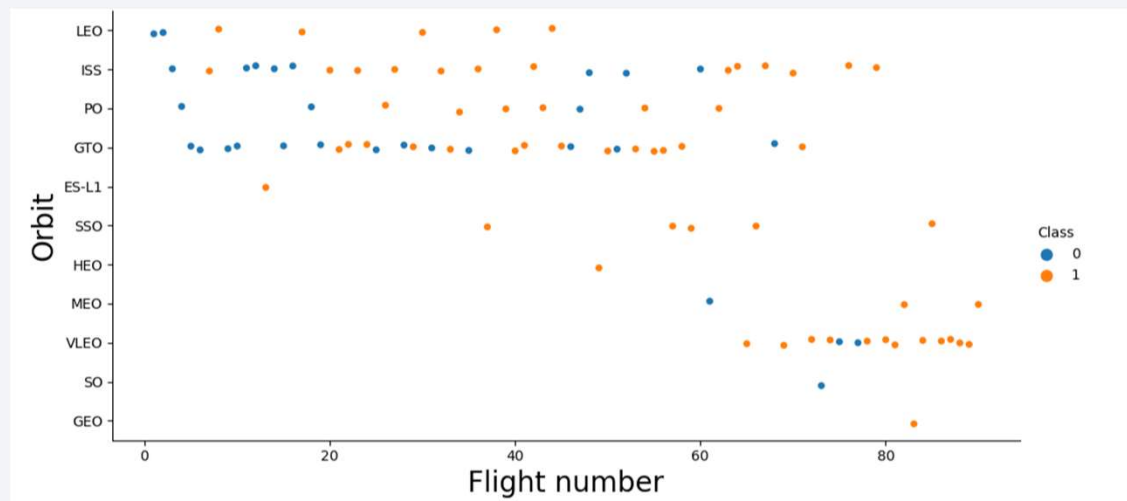
Success Rate vs. Orbit Type

- A bar chart reveals that higher orbits such as GEO and HEO have higher success rates compared to other orbit types.
- Notably, the orbit type SSO is not 100% successful, despite being commonly referred to as SO. The highest success rates were found in orbits such as ES L1, followed by VLEO and LFO with success rates above 70-80%.



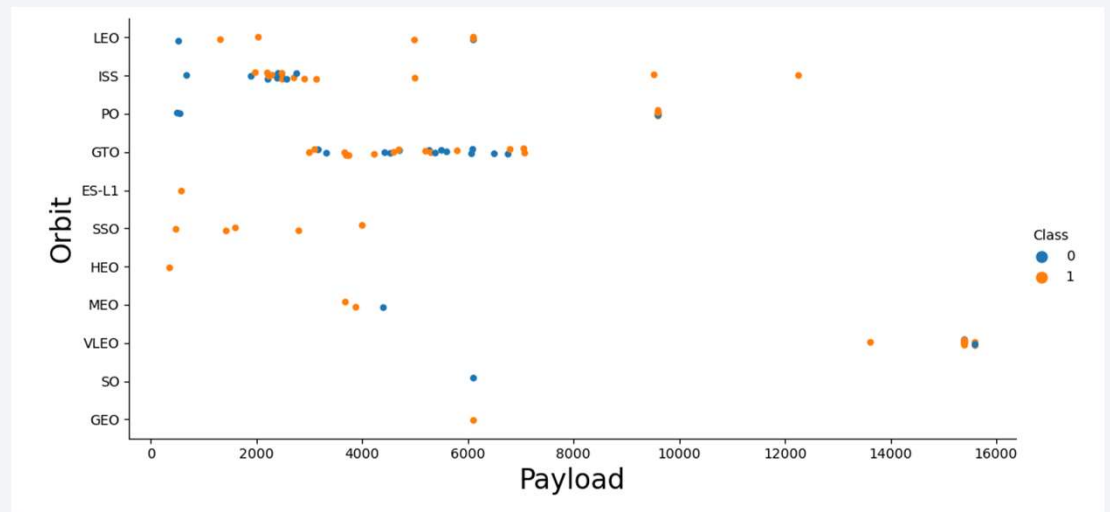
Flight Number vs. Orbit Type

- The analysis of space mission data reveals an encouraging trend of improving success rates over time. This suggests that the efforts made by space companies and organizations to enhance their technology and expertise have paid off, resulting in a better understanding of the complexities of space travel. The findings also highlight the potential of VLEO orbit as a new business opportunity, given its recent increase in frequency and success rate. This provides an exciting avenue for space exploration and development of new technologies.



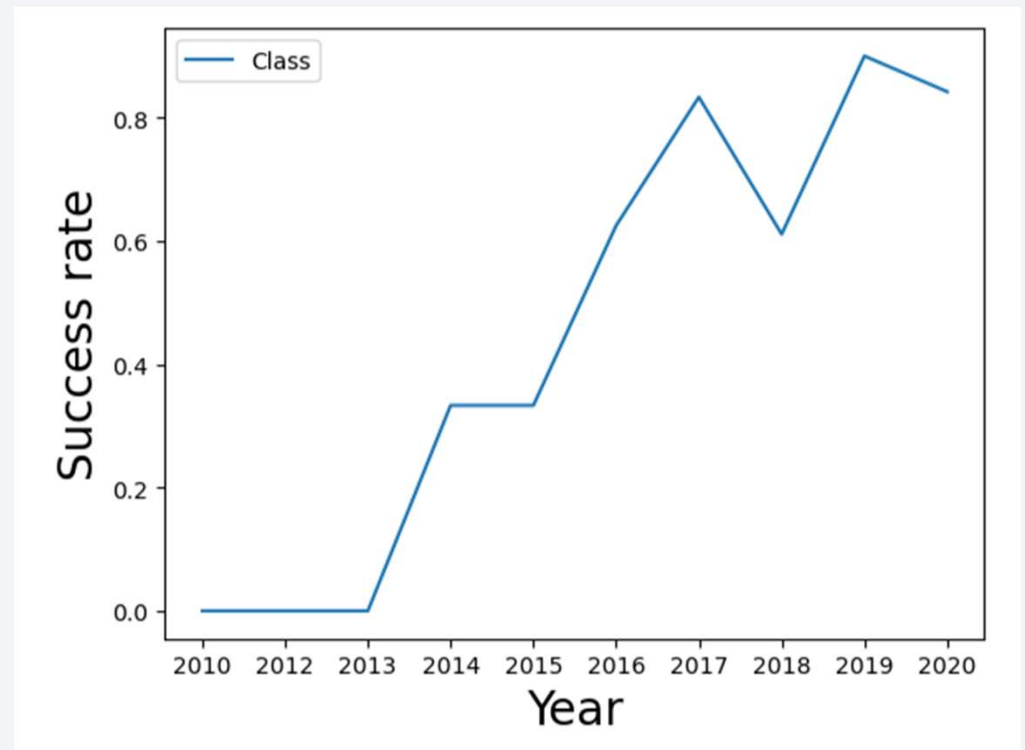
Payload vs. Orbit Type

- It's worth noting that there have been relatively few launches to the SO and GEO orbits. The scatter plot of payload vs. orbit type, colored by outcome (blue for unsuccessful launches and orange for successful launches), provides further insights into the success rates of different orbits. However, there are no clear patterns of increased success with increased payload for any given orbit.
- One notable exception is the SSO orbit, which appears to be consistently successful. It's important to note that SSO and SO are the same orbit, but SSO has not been 100% successful. Overall, this data highlights the complexity and variability of space missions and the need for continued research and improvements to increase success rates and achieve new breakthroughs in space exploration."



Launch Success Yearly Trend

- The analysis of space mission data has revealed a positive trend in success rates since 2013, with the rate steadily increasing over the years. It seems that the first three years (2013-2015) were a period of adjustments and improvements in technology, which contributed to the increase in success rates. The line chart of yearly average success rates shows a dip in 2018, but overall, the trend has been positive.



All Launch Site Names

- The data analysis has revealed that there are four distinct launch sites, as determined by using the SELECT DISTINCT function to extract unique values from the specified column.

LEO	CCAFS SLC 40
-----	--------------

ISS	CCAFS SLC 40
-----	--------------

PO	VAFB SLC 4E
----	-------------

GTO	CCAFS SLC 40
-----	--------------

Launch Site Names Begin with 'CCA'

- A query to retrieve 5 records from the SPACEXTBL where the launch sites begin with CCA can be achieved using the SQL command `SELECT * FROM SPACEXTBL WHERE Launch_Site LIKE 'CCA%' LIMIT 5`. The SELECT command retrieves all the columns, WHERE is used to filter the data based on the pattern specified by the LIKE command, and LIMIT is used to restrict the output to 5 records.

Date	Time (UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS_KG_	Orbit	Customer	Mission_Outcome	Landing_Outcome
04-06-2010	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
08-12-2010	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)
22-05-2012	07:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)	Success	No attempt
08-10-2012	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
01-03-2013	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

Total Payload Mass

- By using the SELECT and SUM commands in combination with the appropriate filter criteria, it's possible to calculate the total payload carried by boosters from NASA. In this case, selecting all payloads containing the 'CRS' code and summing their masses yields a figure of 29, which is a key metric for understanding the impact of NASA's space exploration efforts.

```
SUM(PAYLOAD_MASS_KG_)
```

```
45596
```

Average Payload Mass by F9 v1.1

- The process of determining the mean payload mass transported by the F9 v1.1 booster version involved filtering the data using the condition 'Booster_Version = F9 v1.1' and utilizing the AVG function, resulting in a value of 2,928 kg. This technique is comparable to the previous slide, where the SUM function was utilized to determine the total payload transported by NASA's boosters but with a distinct filter condition. The AVG function is responsible for computing the average value of a set of records, while the WHERE command filters the data based on a given condition

AVG(PAYLOAD_MASS_KG_)

2928.4

First Successful Ground Landing Date

- The MIN function can be used to determine the date of the first successful landing outcome on the ground pad by filtering the data with the condition 'Landing_Outcome = Success (ground pad)'. This method revealed that the initial successful landing outcome on the ground pad occurred on December 22, 2015. However, it is crucial to bear in mind that SQLite lacks a date data type, and therefore dates are saved as strings. Hence, data cleaning and preparation are critical to obtaining accurate insights from queries

1
2015-12-22

Successful Drone Ship Landing with Payload between 4000 and 6000

- Four booster versions have successfully landed on drone ship and carried a payload mass between 4000 and 6000 kg, as selected through the DISTINCT function based on the given filters.
- To list the names of boosters that landed successfully on drone ship and carried a payload mass between 4000 and 6000 kg, the query uses the BETWEEN command to filter records within the 'PAYLOAD_MASS_KG_' column and the 'Landing_Outcome' column set to 'Success (drone ship)'.

Booster_Version

F9 FT B1022

F9 FT B1026

F9 FT B1021.2

F9 FT B1031.2

Total Number of Successful and Failure Mission Outcomes

- By grouping the mission outcomes and counting the number of records in each group, we obtained the summary of the total number of successful and failed missions.
- To calculate the total number of successful and failed missions, one can use the SQL query "SELECT Mission_Outcome, COUNT(*) FROM SPACEXTBL GROUP BY Mission_Outcome".
- The COUNT(*) function returns the count of records, and the GROUP BY statement aggregates the data based on the specified variable (in this case, the mission outcome).

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

Boosters Carried Maximum Payload

- The following text displays the booster versions that have carried the highest payload mass according to the dataset. To obtain this list, a subquery was used to identify the maximum payload mass across all records using the MAX() function, and then all booster versions that have carried that mass were selected using the returned value as the filter condition. The resulting list shows the distinct names of the booster versions that have carried the maximum payload mass.

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

YEAR	MONTH	Landing_Outcome	Booster_Version	Launch_Site
2015	01	Failure (drone ship)	F9 v1.1 B1012	CCAFS LC-40
2015	02	Controlled (ocean)	F9 v1.1 B1013	CCAFS LC-40
2015	03	No attempt	F9 v1.1 B1014	CCAFS LC-40
2015	04	Failure (drone ship)	F9 v1.1 B1015	CCAFS LC-40
2015	04	No attempt	F9 v1.1 B1016	CCAFS LC-40
2015	06	Precluded (drone ship)	F9 v1.1 B1018	CCAFS LC-40
2015	12	Success (ground pad)	F9 FT B1019	CCAFS LC-40

- The table displays a list of failed drone ship landing outcomes, accompanied by their respective booster versions and launch site names, for the year 2015. This data was obtained using a SQL query that filtered the information based on the year and landing outcome condition, and extracted relevant details such as the year, month, landing outcome, booster version, and launch site. To create the year and month columns, the substr function was utilized to extract specific components of the date string.

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

- The SQL query provided below retrieves a count of successful landing outcomes within a specified time period, from June 4, 2010, to March 20, 2017. The query then sorts the results in descending order based on the count of each landing outcome. To achieve this, the query applies a filter that selects only specific landing outcomes and date ranges, groups the data by landing outcome, and finally orders the results by the count of each landing outcome in a descending order. The landing outcomes that are considered in this query include 'Success', 'Success (drone ship)', and 'Success (ground pad)'.

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

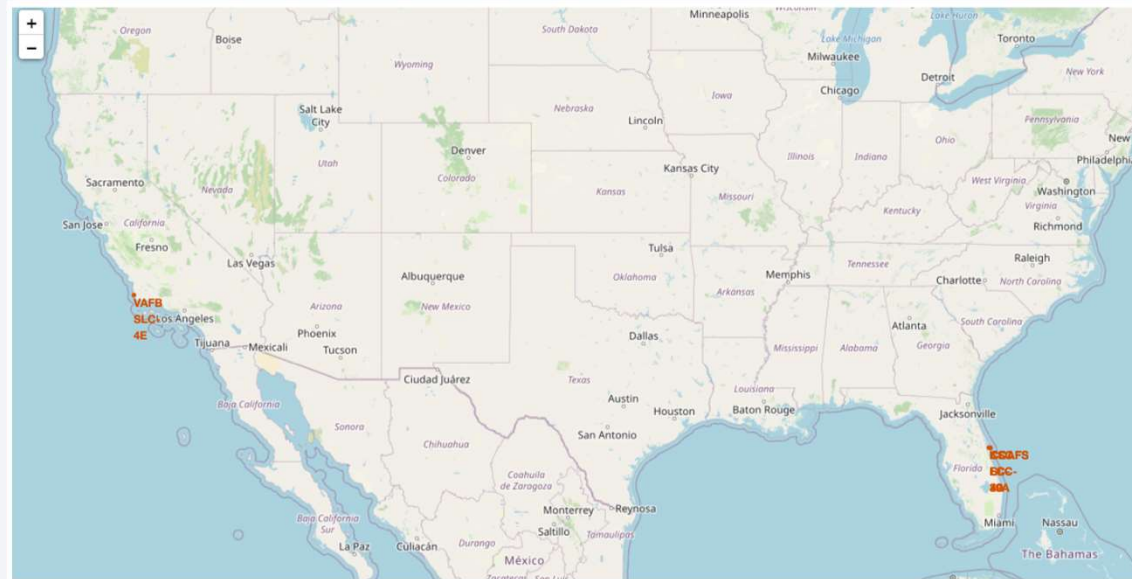
A satellite view of Earth from space, showing the curvature of the planet and the glow of city lights at night. The image is used as a background for the title slide.

Section 3

Launch Sites Proximities Analysis

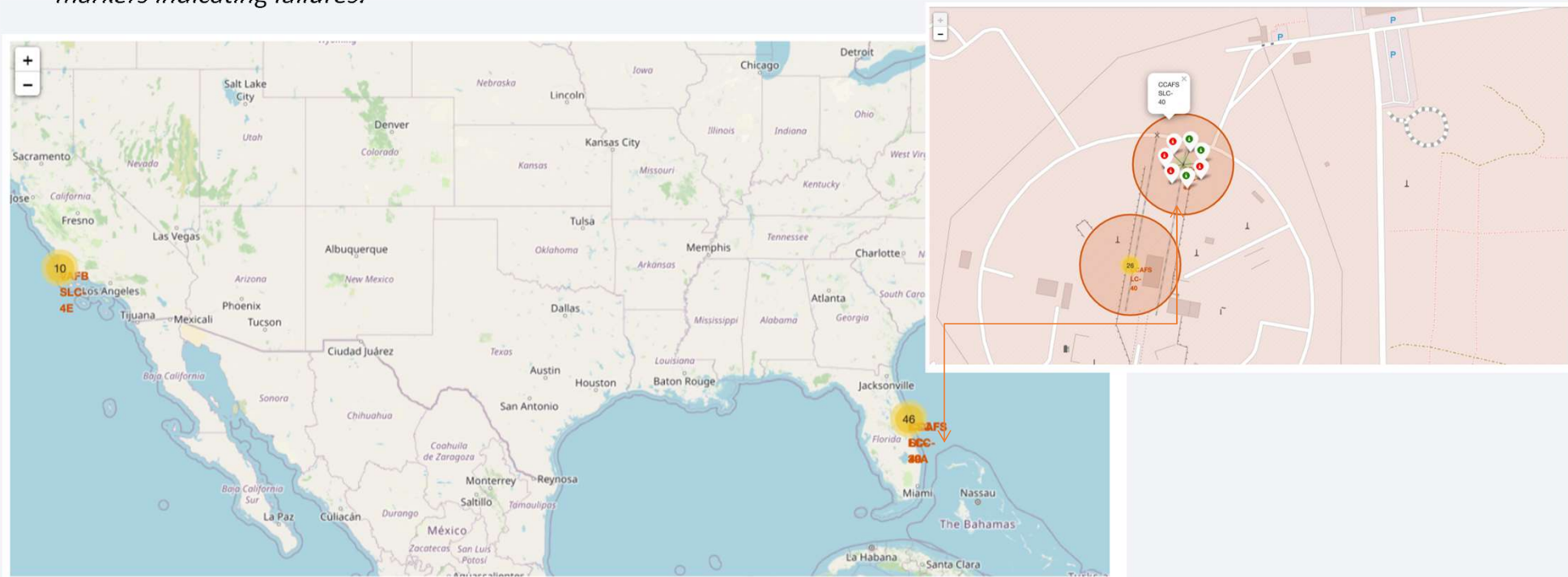
All launch sites on a map

- The launch sites are located in proximity to the sea, likely due to safety concerns. However, they are also situated not too far away from roads and railroads for logistical purposes. These launch sites are specifically situated adjacent to the coastlines of major oceans.



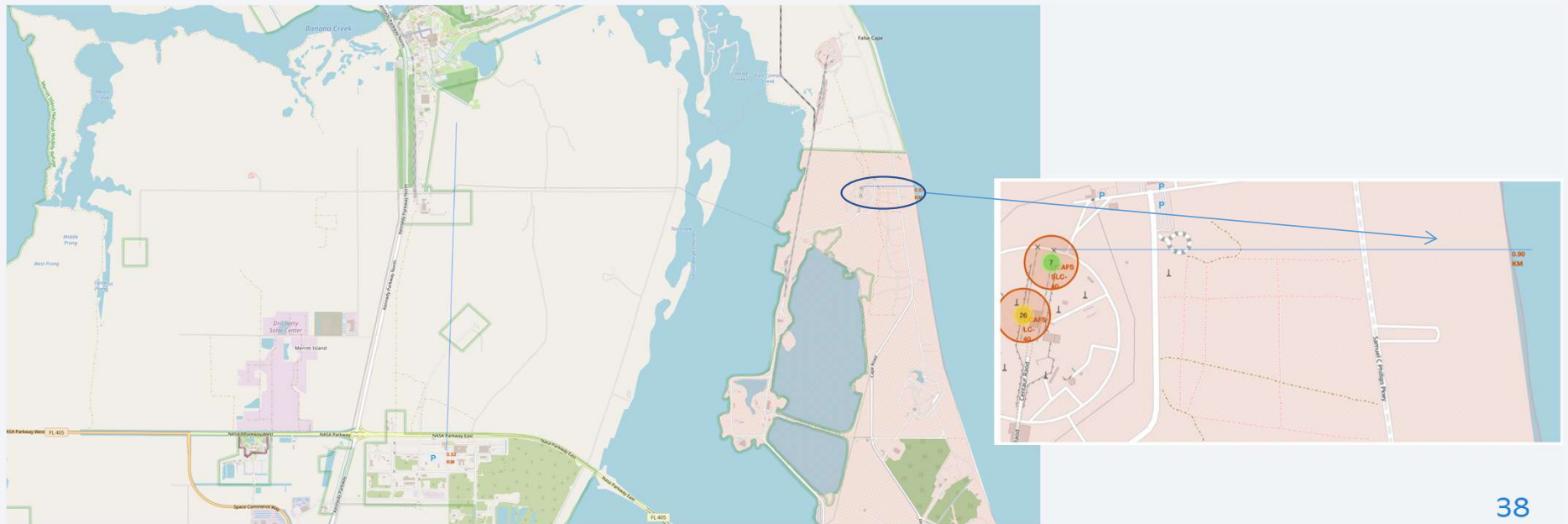
Success/failed launches for each site on the map

- A set of clustered markers is shown for a launch site, with green markers indicating successful launches and red markers indicating failures.



Distances between a launch site to its proximities

- Understanding the distance between a launch site and nearby land or coastal features is a relevant consideration. The individual believed that it would not contribute to predicting launch outcomes and therefore deemed it unnecessary. It is worth noting that the public can have access to these launches.



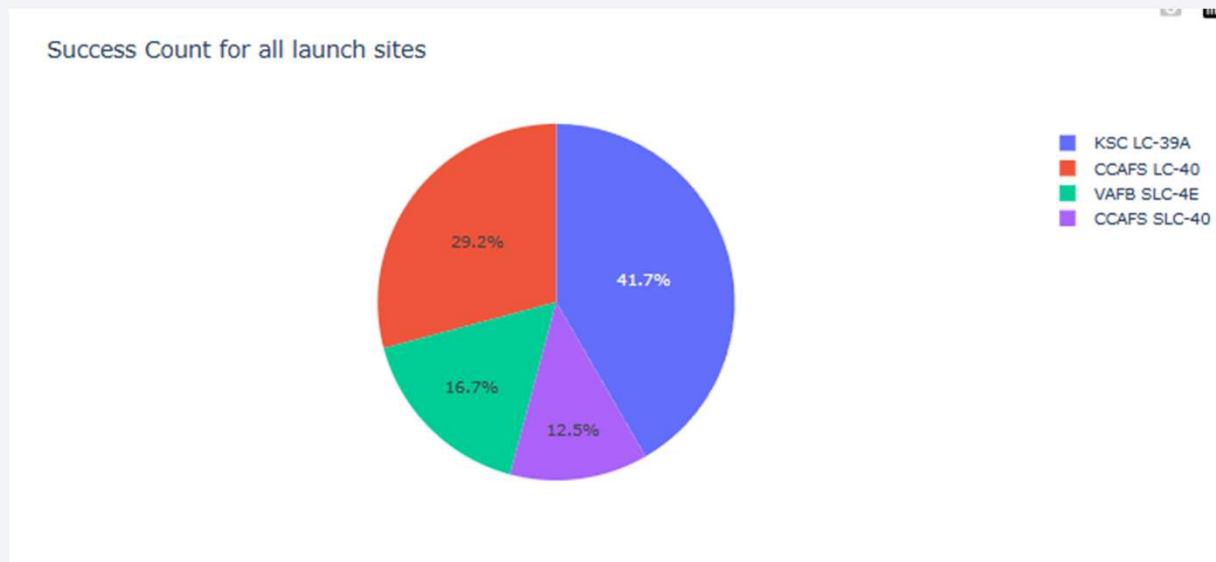


Section 4

Build a Dashboard with Plotly Dash

The percentage of successful launches per launch area.

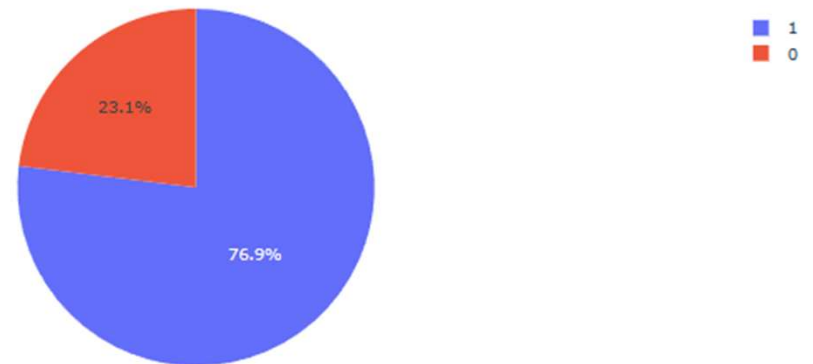
- The location from which rocket launches are conducted is a crucial element in determining the success of space missions. This is evident in the fact that historically, the Kennedy Space Center (KSC) has witnessed a greater number of successful launches than any other launch site.



Site with the highest percentage of successful launches

- The Kennedy Space Center (KSC) launch site has earned a reputation for being the most successful launch site in the world. This is not merely due to the large number of launches that take place at this site, but also due to its impressive success rate. As indicated in the previous graph, KSC has the highest proportion of successful launches among all launch sites, with a remarkable success rate of 76.9%.

Total Success Launches for site KSC LC-39A



Payload vs. Launch Outcome

- The findings from the analysis of launch success rates highlight the need for a deeper understanding of the factors that influence successful launches. By recategorizing booster types and examining the correlation between payload size and booster type, it is possible to identify the optimal combinations that yield the highest success rates. The data clearly indicates that payloads between 2000kg and 7000kg, launched using FT boosters, are the most successful combination.



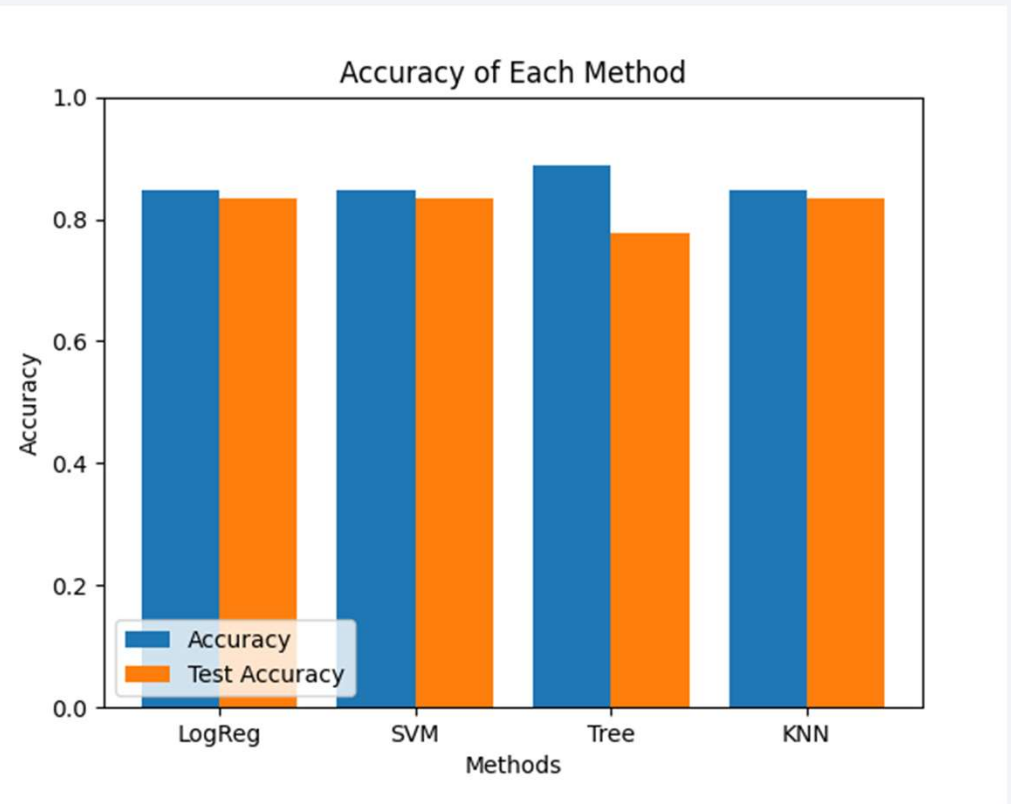


Section 5

Predictive Analysis (Classification)

Classification Accuracy

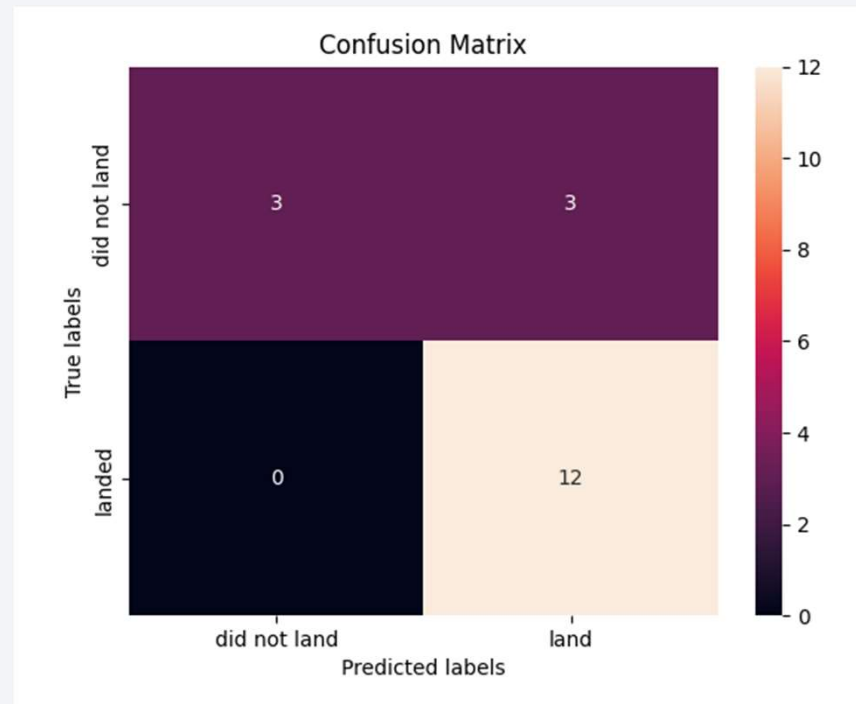
- In a recent study, four classification models were put to the test, and their accuracies were closely examined. The results were plotted side by side, revealing some interesting findings.
- Out of the four models that were tested, the Decision Tree Classifier emerged as the clear winner, boasting an accuracy rate of over 87%. In fact, the decision tree (TREE) classification model showed the highest accuracy at around 0.89.



Confusion Matrix

- The Decision Tree Classifier's impressive performance was highlighted by its ability to show the fewest combined false positives and false negatives, making it the best model in terms of accuracy.
- The Confusion Matrix of the Decision Tree Classifier provided compelling evidence of its accuracy, with a high number of true positives and true negatives compared to the relatively small number of false ones, solidifying its position as the top-performing model.

accuracy : 0.9017857142857142



Conclusions

- The KSC LC 39A is the best launch site for Space X missions.
- Launches with payloads above 7,000kg are less risky than those with smaller payloads.
- The Decision Tree Classifier can predict successful landings and increase profits for Space X.
- Higher orbits, such as GEO and HEO, have higher success rates than other orbit types.
- Launch success rates for Space X have been improving over time.
- The scatter plot of Flight Number vs. Launch Site provides valuable insights into the success rate of SpaceX launches and can help inform launch site selection.
- Space X has been successful in achieving its mission outcomes, and the company has continuously improved its landing outcomes over time, with most launches happening at east coast launch sites.

Appendix

- The information provided was collected from official sources, and the results were only used within the scope of the data science professional certification study. Therefore, the data as well as personal opinions should not be taken into account or used to make any personal or financial decisions. It is not recommended to base any decisions on this document.
- If you encounter any errors or cells not shown or executed in the Jupyter notebooks, these can be executed if you load the file in IBM, as we have exhausted our free compute hours in IBM Watson for this course, some were run in the sandbox provided within the course modules

Thank you!

