



IBM Developer  
SKILLS NETWORK

# Winning Space Race with Data Science

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# Outline

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

# Executive Summary

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## **Summary of methodologies used**

- CRISP-DM (Cross-Industry Standard Process for Data Mining)
- Feature Engineering

## **Summary of all results**

# Introduction

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## **Project background and context**

The commercial space age is booming, and companies like Virgin Galactic, Rocket Lab, Blue Origin, and SpaceX are making space travel more accessible and affordable. SpaceX, in particular, has made significant strides in reducing the cost of space launches, primarily through the ability to reuse the first stage of its Falcon 9 rocket.

This capstone project puts you in the role of a data scientist working for Space Y, a new rocket company seeking to compete with SpaceX. Your task is to develop a machine learning model that can predict whether SpaceX will reuse the first stage of its Falcon 9 rocket for a given launch. This information will be crucial in determining the price of each launch for Space Y.

## **Problems we want to find answers**

- Determining the Cost of Launch
- Predicting First Stage Reusability
- Creating Dashboards for Data Analysis





Section 1

# Methodology

# Methodology

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## Executive Summary

### **Data collection methodology**

- We obtained data from two distinct sources, drawing information from both Wikipedia and an external API.

### **Perform data wrangling**

- The gathered data underwent enrichment through the generation of a final outcome label, derived from a comprehensive analysis of summarized features and outcome data

# Methodology

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## Executive Summary

### **Next Steps during EDA was performed**

- Calculate the number of launches on each site: This will help us understand the distribution of launches across different launch sites.
- Calculate the number and occurrence of each orbit: This will help us understand the types of orbits that SpaceX typically targets.
- Calculate the number and occurrence of mission outcome of the orbits: This will help us understand the success rate of SpaceX launches for different orbits.
- Create a landing outcome label from Outcome column: This will create a new binary variable that indicates whether the first stage of the Falcon 9 rocket landed successfully or not. This will be the target variable for our machine learning model.

# Methodology

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## Executive Summary

**To build, tune, and evaluate classification models, follow these steps:**

- Prepare the data: clean, explore, and engineer features.
- Choose a classification algorithm and split data into training and testing sets.
- Train the model and tune hyperparameters for optimal performance.
- Evaluate the model using metrics like accuracy, precision, recall, and F1-score.
- Analyze misclassified examples and error types to improve the model.
- Compare different models and select the best one based on performance trade-offs.
- Use visualizations, feature importance, and cross-validation for deeper understanding.
- Deploy the chosen model for real-world use.



# Data Collection

## How data sets were collected.

To ensure data accuracy and completeness, we utilized both Wikipedia and an API to collect relevant information.

```
df=pd.read_csv("https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/datasets/dataset_part_1.csv")
df.head(10)
```

	FlightNumber	Date	BoosterVersion	PayloadMass	Orbit	LaunchSite	Outcome	Flights	GridFins	Reused	Legs	LandingPad	Block	ReusedCount	Serial	Longitude	Latitude
0	1	2010-06-04	Falcon 9	6104.959412	LEO	CCAFS SLC 40	None None	1	False	False	False	NaN	1.0	0	B0003	-80.577366	28.561857
1	2	2012-05-22	Falcon 9	525.000000	LEO	CCAFS SLC 40	None None	1	False	False	False	NaN	1.0	0	B0005	-80.577366	28.561857
2	3	2013-03-01	Falcon 9	677.000000	ISS	CCAFS SLC 40	None None	1	False	False	False	NaN	1.0	0	B0007	-80.577366	28.561857
3	4	2013-09-29	Falcon 9	500.000000	PO	VAFB SLC 4E	False Ocean	1	False	False	False	NaN	1.0	0	B1003	-120.610829	34.632093
4	5	2013-12-03	Falcon 9	3170.000000	GTO	CCAFS SLC 40	None None	1	False	False	False	NaN	1.0	0	B1004	-80.577366	28.561857
5	6	2014-01-06	Falcon 9	3325.000000	GTO	CCAFS SLC 40	None None	1	False	False	False	NaN	1.0	0	B1005	-80.577366	28.561857
6	7	2014-04-18	Falcon 9	2296.000000	ISS	CCAFS SLC 40	True Ocean	1	False	False	True	NaN	1.0	0	B1006	-80.577366	28.561857
7	8	2014-07-14	Falcon 9	1316.000000	LEO	CCAFS SLC 40	True Ocean	1	False	False	True	NaN	1.0	0	B1007	-80.577366	28.561857
8	9	2014-08-05	Falcon 9	4535.000000	GTO	CCAFS SLC 40	None None	1	False	False	False	NaN	1.0	0	B1008	-80.577366	28.561857
9	10	2014-09-07	Falcon 9	4428.000000	GTO	CCAFS SLC 40	None None	1	False	False	False	NaN	1.0	0	B1011	-80.577366	28.561857

# Data Collection – SpaceX API

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I created a new repository called "ibm\_ds\_cert" on GitHub, which contains the Jupyter notebook for the web scraping and data visualization of the SpaceX dataset. You can find the repository [here](#).

The notebook includes various visualizations, such as scatter plots, bar charts, and line charts, to explore the relationships between different variables and gain insights into the SpaceX dataset.

Now let's start requesting rocket launch data from SpaceX API with the following URL:

```
spacex_url="https://api.spacexdata.com/v4/launches/past"
```

```
response = requests.get(spacex_url)
```

# Data Collection - Scraping

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## TASK 1: Request the Falcon9 Launch Wiki page from its URL

First, let's perform an HTTP GET method to request the Falcon9 Launch HTML page, as an HTTP response.

```
# use requests.get() method with the provided static_url
# assign the response to a object
response = requests.get(static_url)
```

Create a `BeautifulSoup` object from the HTML `response`

```
# Use BeautifulSoup() to create a BeautifulSoup object from a response text content
soup = BeautifulSoup(response.text, 'html.parser')
```

Print the page title to verify if the `BeautifulSoup` object was created properly

```
# Use soup.title attribute
soup.title.text
```

```
'List of Falcon 9 and Falcon Heavy launches - Wikipedia'
```

## TASK 2: Extract all column/variable names from the HTML table header

Next, we want to collect all relevant column names from the HTML table header

Let's try to find all tables on the wiki page first. If you need to refresh your memory about `BeautifulSoup`

```
# Use the find_all function in the BeautifulSoup object, with element type 'table'
# Assign the result to a list called 'html_tables'
```

```
html_tables = [item for item in soup.find_all('table')]
```

```
# html_tables = [item.text for item in soup.find_all('table')] #readable variant
```

# Data Wrangling

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## Data Wrangling processed steps:

- Analyze Launch Distribution: Determine the number of launches conducted at each launch site.
- Characterize Orbit Types: Quantify the frequency of each orbit type targeted by SpaceX missions.
- Assess Orbit-Specific Mission Outcomes: Evaluate the success rate of SpaceX missions for each orbit type.
- Derive Landing Outcome Indicator: Create a binary variable indicating whether the Falcon 9 rocket's first stage successfully landed.

I created a new repository called "ibm\_ds\_cert" on GitHub, which contains the Jupyter notebook for the DW and data visualization of the SpaceX dataset. You can find the repository [here](#). The notebook includes various visualizations, such as scatter plots, bar charts, and line charts, to explore the relationships between different variables and gain insights into the SpaceX dataset.

# EDA with Data Visualization

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## Visualizations and Purposes

- Scatter plot: To understand the distribution of flight numbers across different launch sites, payload weight variations, and any patterns or trends between flight numbers and orbit types.
- Bar chart: To compare the success rates of SpaceX missions for different orbit types and assess whether payload weight is influenced by the targeted orbit type.
- Line chart: To analyze the overall trend of SpaceX launch success over the years.
- Data type conversion: To convert categorical variables into numerical representations for machine learning modeling and ensure consistent data type for numerical variables.

I created a new repository called "ibm\_ds\_cert" on GitHub, which contains the Jupyter notebook for the data visualization of the SpaceX dataset. You can find the repository [here](#). The notebook includes various visualizations, such as scatter plots, bar charts, and line charts, to explore the relationships between different variables and gain insights into the SpaceX dataset.



# EDA with SQL

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## Summary of SQL Queries without Code

- Extracted a list of all distinct launch sites from the space mission data.
- Identified five records where the launch site name began with the string 'CCA'.
- Calculated the total payload mass carried by boosters launched by NASA (CRS) missions.
- Retrieved the date of the first successful landing outcome achieved on a ground pad.
- Listed the booster names associated with successful drone ship landings and payload masses between 4000 and 6000.
- Counted the total number of successful and failure mission outcomes across all launches.
- Identified the booster versions that had carried the maximum payload mass.

I created a new repository called "ibm\_ds\_cert" on GitHub, which contains the Jupyter notebook for the queering of the SpaceX dataset. You can find the repository [here](#). The notebook includes codes to explore the relationships between different variables and gain insights into the SpaceX dataset.

# Build an Interactive Map with Folium

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**The summary of the map objects I created and added to a folium map.**

Launch Sites:

- Blue circles with popup labels and icons.
- Green for successful, red for failed launches.

Proximity Distance:

- Marker clusters and polylines.
- Distance displays on markers and polylines.

I created a new repository called "ibm\_ds\_cert" on GitHub, which contains the Jupyter notebook for the data visualization of the SpaceX dataset. You can find the repository [here](#). The notebook includes various visualizations, such as scatter plots, bar charts, and line charts, to explore the relationships between different variables and gain insights into the SpaceX dataset.

# Build a Dashboard with Plotly Dash

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## What plots/graphs and interactions you have added to a dashboard

- Added a drop-down input component to select a launch site.
- Added a callback function to render a pie chart visualizing launch success counts based on the selected site.
- Added a range slider to select a payload range.
- Added a callback function to render a scatter plot visualizing the relationship between payload and launch outcome.

I created a new repository called "ibm\_ds\_cert" on GitHub, which contains the Jupyter notebook for the data visualization of the SpaceX dataset. You can find the repository [here](#). The notebook includes various visualizations, such as scatter plots, bar charts, and line charts, to explore the relationships between different variables and gain insights into the SpaceX dataset.

# Predictive Analysis (Classification)

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## **Summary on how we built, evaluated, improved, and found the best performing classification model**

- Convert a data column to a NumPy array and Pandas Series
- Standardize data and split it into training and test sets
- Train and evaluate logistic regression, support vector machine, decision tree classifier, and K nearest neighbors models

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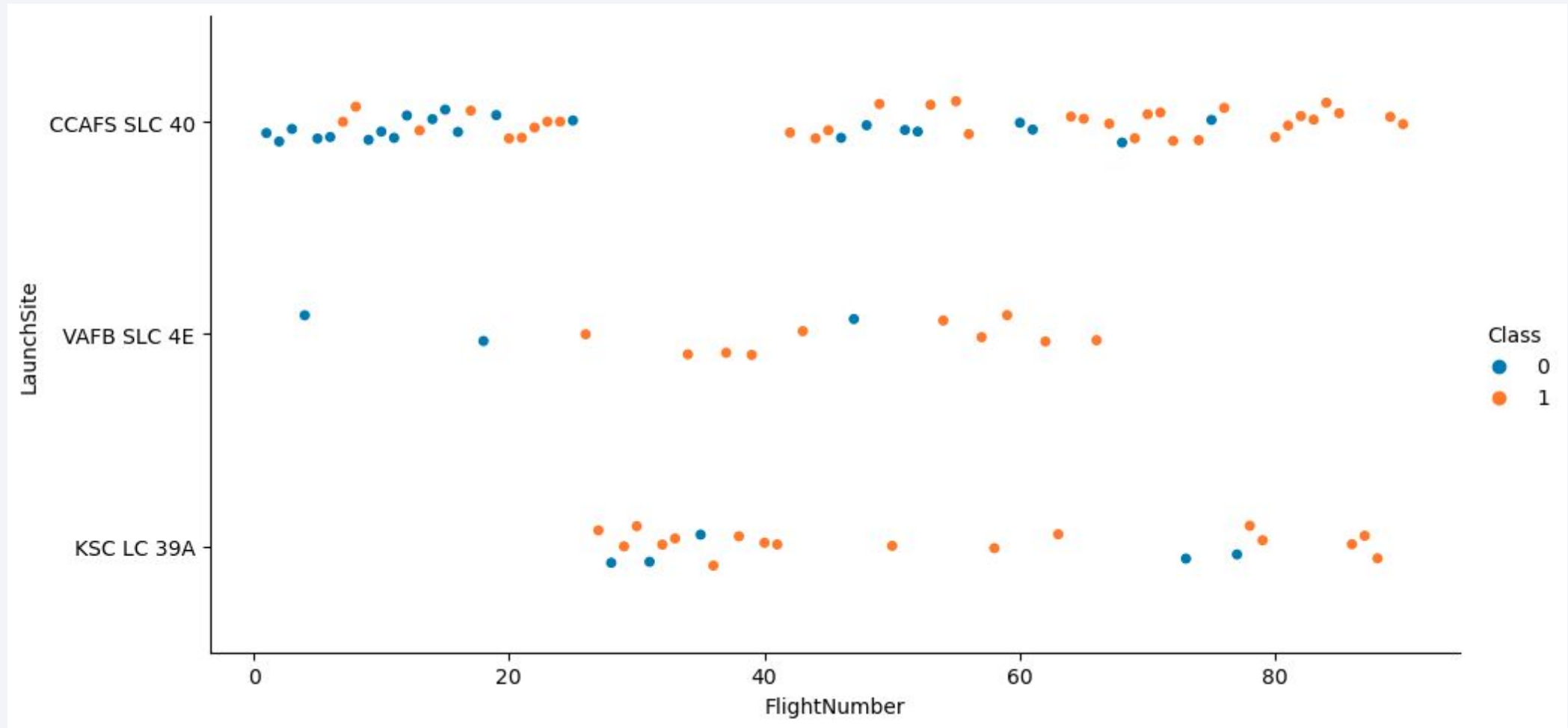
The background of the slide is a complex, abstract composition. It features a dark blue base color on the left, which transitions into a vibrant, multi-colored area on the right. This transition is achieved through a series of diagonal, overlapping bands and streaks in shades of red, teal, and light blue. A fine, grid-like pattern is visible throughout the image, particularly in the teal and red areas, giving it a digital or data-driven appearance. The overall effect is one of dynamic movement and high-tech aesthetics.

Section 2

# Insights drawn from EDA

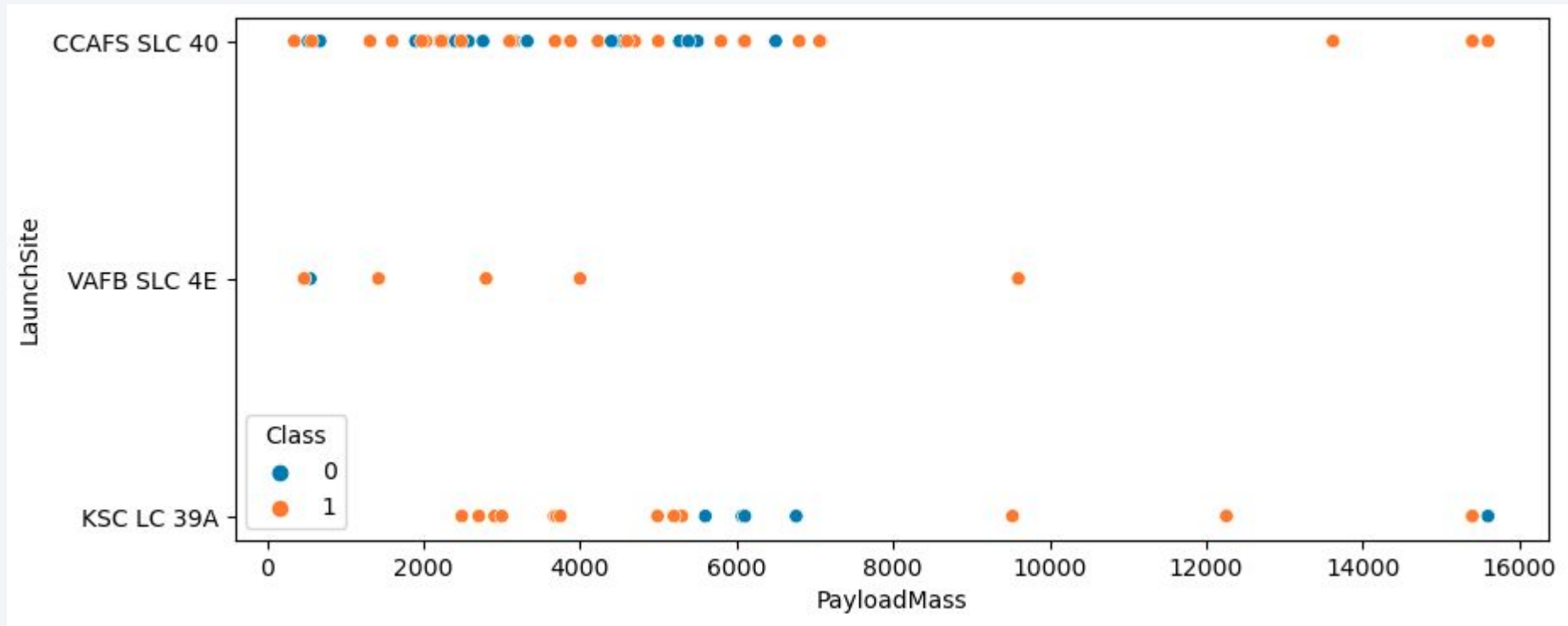


# Flight Number vs. Launch Site



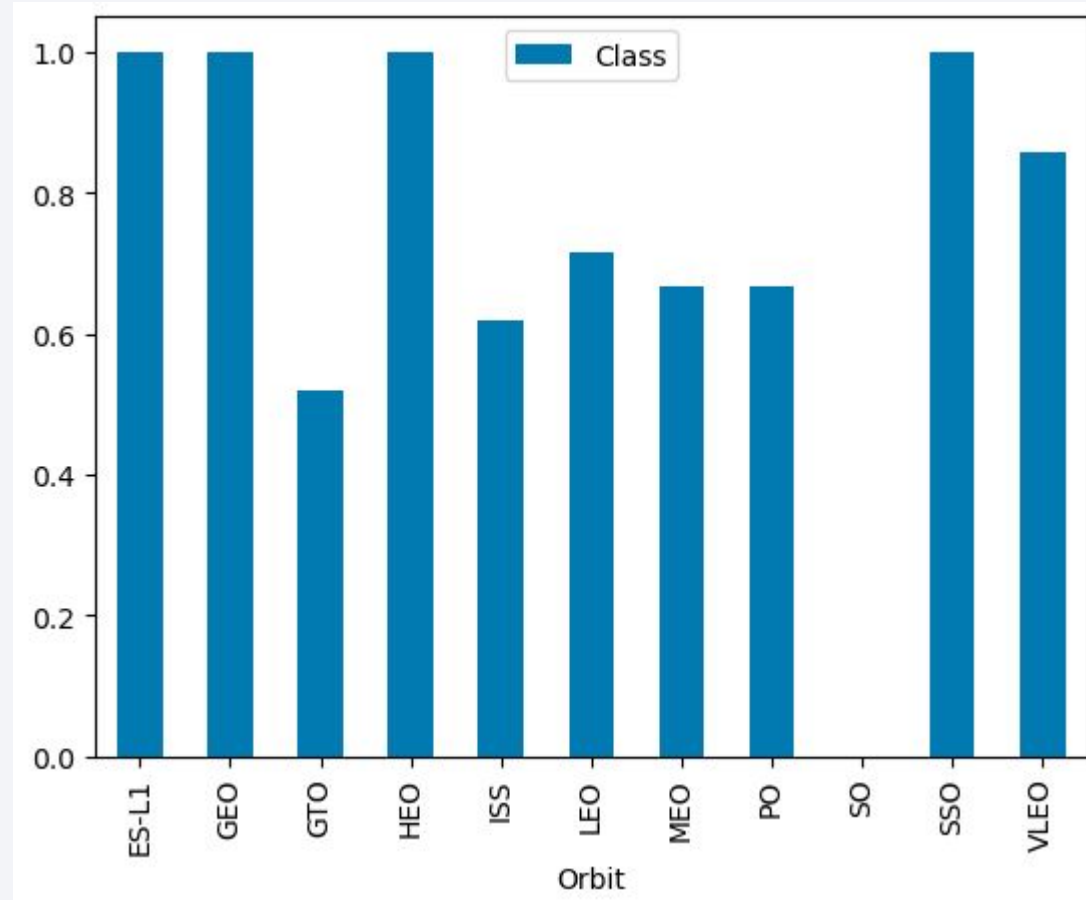
# Payload vs. Launch Site

---

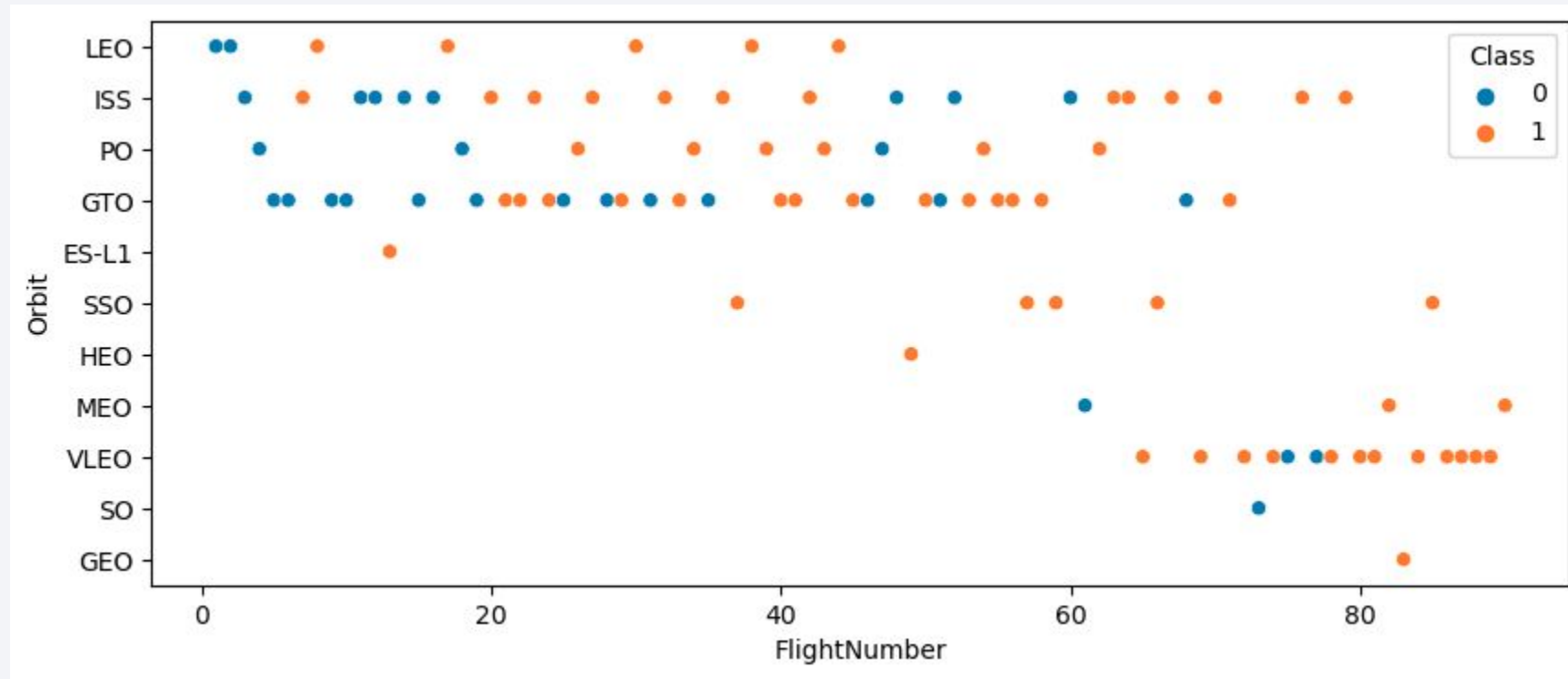


# Success Rate vs. Orbit Type

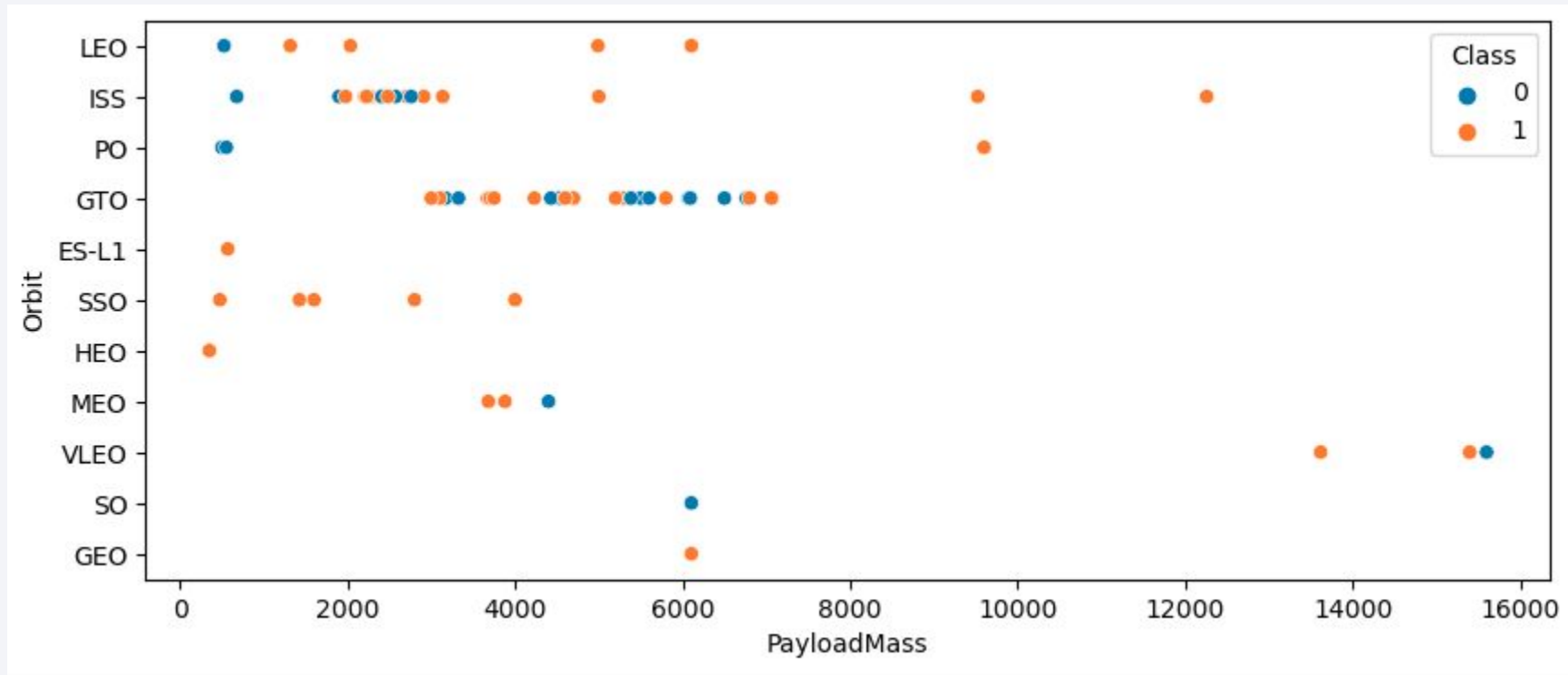
---



# Flight Number vs. Orbit Type



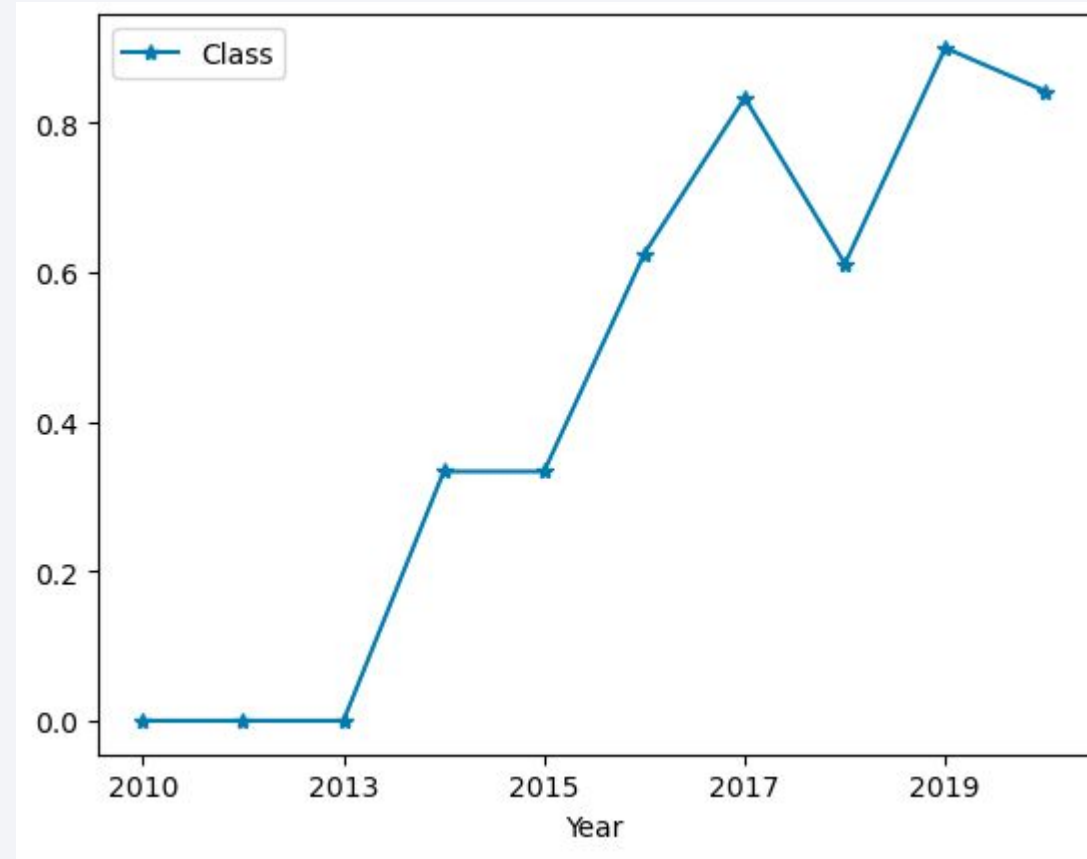
# Payload vs. Orbit Type





# Launch Success Yearly Trend

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# All Launch Site Names

---

Display the names of the unique launch sites in the space mission

```
%sql
```

```
select distinct  
  Launch_Site  
from SPACEXTBL
```

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

Done.

Launch_Site
-------------

CCAFS LC-40
-------------

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

KSC LC-39A
------------

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

# Launch Site Names Begin with 'CCA'

Display 5 records where launch sites begin with the string 'CCA'

```
%%sql
select
  *
from SPACEXTBL
where Launch_Site like 'CCA%'
limit 5
```

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

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

---

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

```
%sql  
  
select  
    sum(PAYLOAD_MASS_KG_) total_payload_mass  
from SPACEXTBL  
where Customer = 'NASA (CRS)'
```

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

```
Done.
```

```
total_payload_mass
```

```
45596
```

# Average Payload Mass by F9 v1.1

---

Display average payload mass carried by booster version F9 v1.1

```
%%sql  
  
select  
    avg(PAYLOAD_MASS__KG_) avg_payload_mass  
from SPACEXTBL  
where Booster_Version like '%F9 v1.1%'
```

\* sqlite:///my\_data1.db

Done.

avg_payload_mass
------------------

2534.6666666666665
--------------------



# First Successful Ground Landing Date

---

List the date when the first succesful landing outcome in ground pad was acheived.

*Hint: Use min function*

```
: %sql
select
    min(Date) date
from SPACEXTBL
where Landing_Outcome='Success (ground pad)'

* sqlite:///my_data1.db
Done.
:      date
-----
2015-12-22
```

# Successful Drone Ship Landing with Payload between 4000 and 6000

---

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 distinct
  Booster_Version
from SPACEXTBL
where Landing_Outcome='Success (drone ship)'
and PAYLOAD_MASS_KG_ between 4000 and 6000
```

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

Done.

Booster_Version
-----------------

F9 FT B1022
-------------

F9 FT B1026
-------------

F9 FT B1021.2
---------------

F9 FT B1031.2
---------------

# Total Number of Successful and Failure Mission Outcomes

---

```
List the total number of successful and failure mission outcomes

: %%sql

select
  case
    when Mission_Outcome like '%success%' then 'success'
    else 'failure'
  end outcome,
  count(1) c
from SPACEXTBL
group by 1

* sqlite:///my_data1.db
Done.

: outcome  c
-----
failure   1
success  100
```

# Boosters Carried Maximum Payload

List the names of the booster\_versions which have carried the maximum payload mass. Use a subquery

```
%%sql
```

```
select distinct
    Booster_Version
from SPACEXTBL
where PAYLOAD_MASS_KG_ = (select max(PAYLOAD_MASS_KG_) max_mass from SPACEXTBL)
```

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

Done.

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

---

List the records which will display the month names, failure landing\_outcomes in drone ship ,booster versions, launch\_site for the months in year 2015.

**Note: SQLite does not support monthnames. So you need to use substr(Date, 6,2) as month to get the months and substr(Date,0,5)='2015' for year.**

```
%%sql

select
    substr(Date, 6, 2) month,
    Landing_Outcome,
    Booster_Version,
    Launch_Site
from SPACEXTBL
where Date like '2015%'
and Landing_Outcome = 'Failure (drone ship)'
```

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

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

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

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(*) c
from SPACEXTBL
where Date between '2010-06-04' and '2017-03-20'
group by 1 order by 2 desc
```

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

Landing_Outcome	c
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

A satellite view of Earth from space, showing the curvature of the planet and city lights at night. The image is a composite of a dark blue sky with stars and a view of the Earth's surface from space. The Earth's surface is mostly dark, with a thin layer of atmosphere visible along the horizon. The city lights are concentrated in the lower right quadrant, showing a dense network of urban areas. The text "Section 3" is overlaid on the left side of the image.

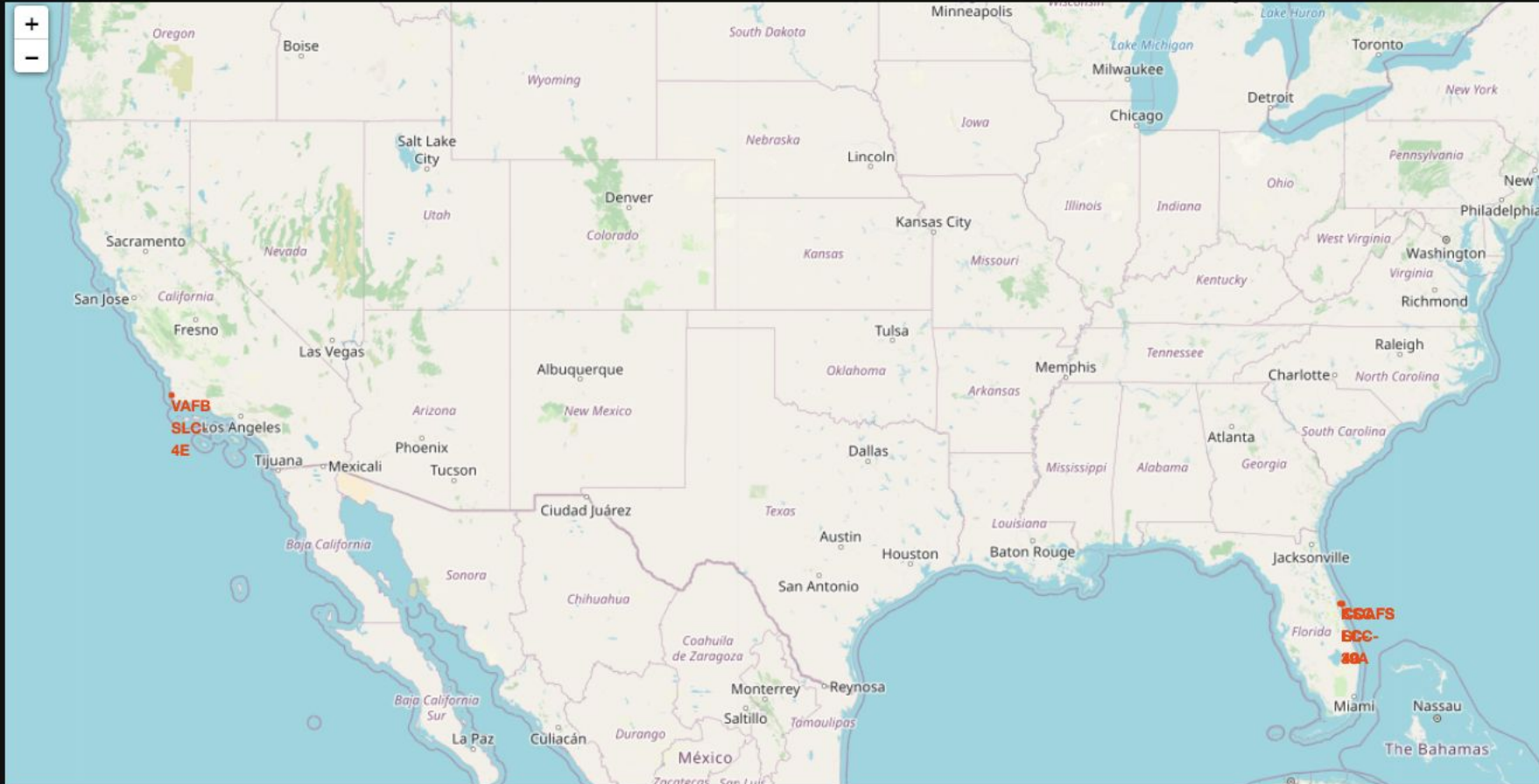
Section 3

# Launch Sites Proximities Analysis

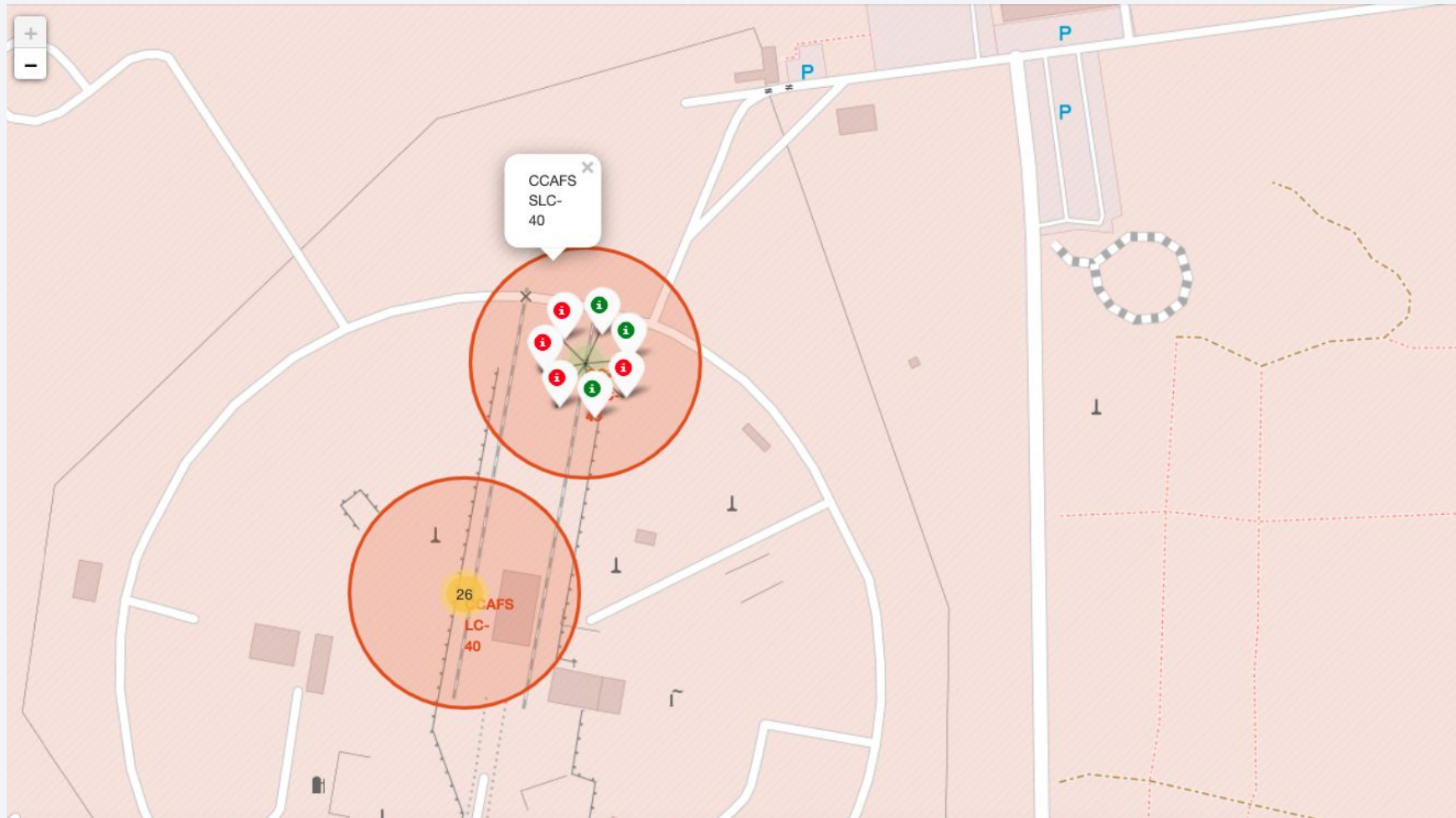


## Global map markers denoting the locations of all launch sites.

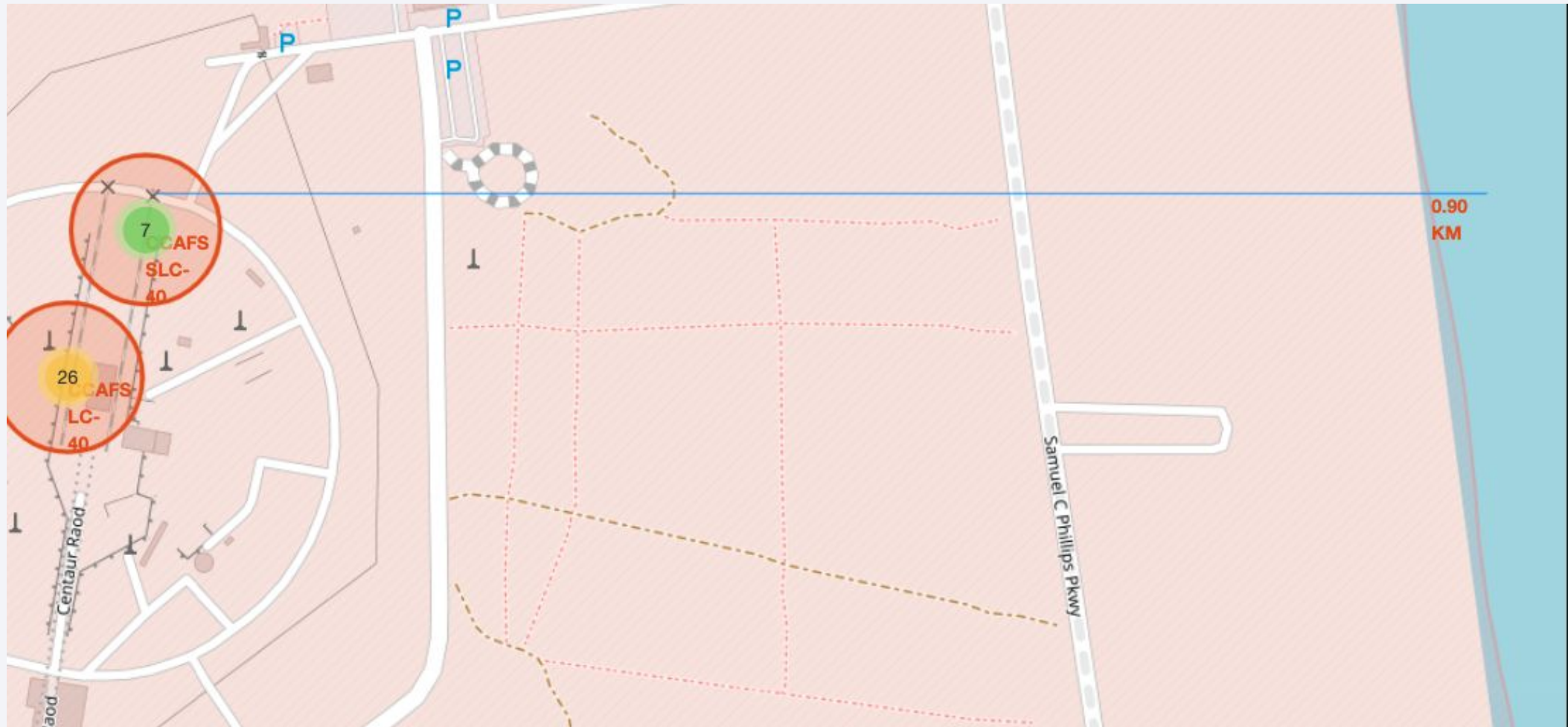
The generated map with marked launch sites should look similar to the following:



Color-labeled markers indicating different launch sites on a map.



## Distance from Launch Sites to Landmarks







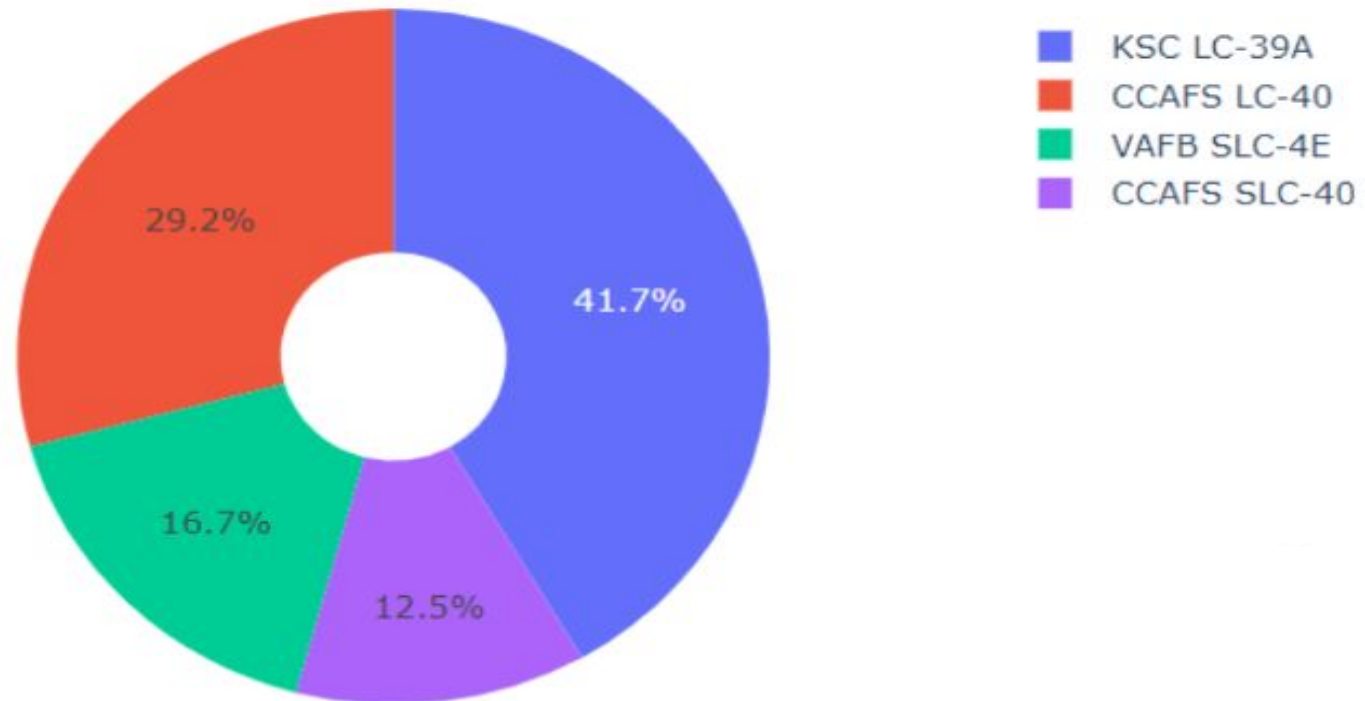
Section 4

# Build a Dashboard with Plotly Dash

A visually engaging pie chart illustrating the success percentages attained by individual launch sites.

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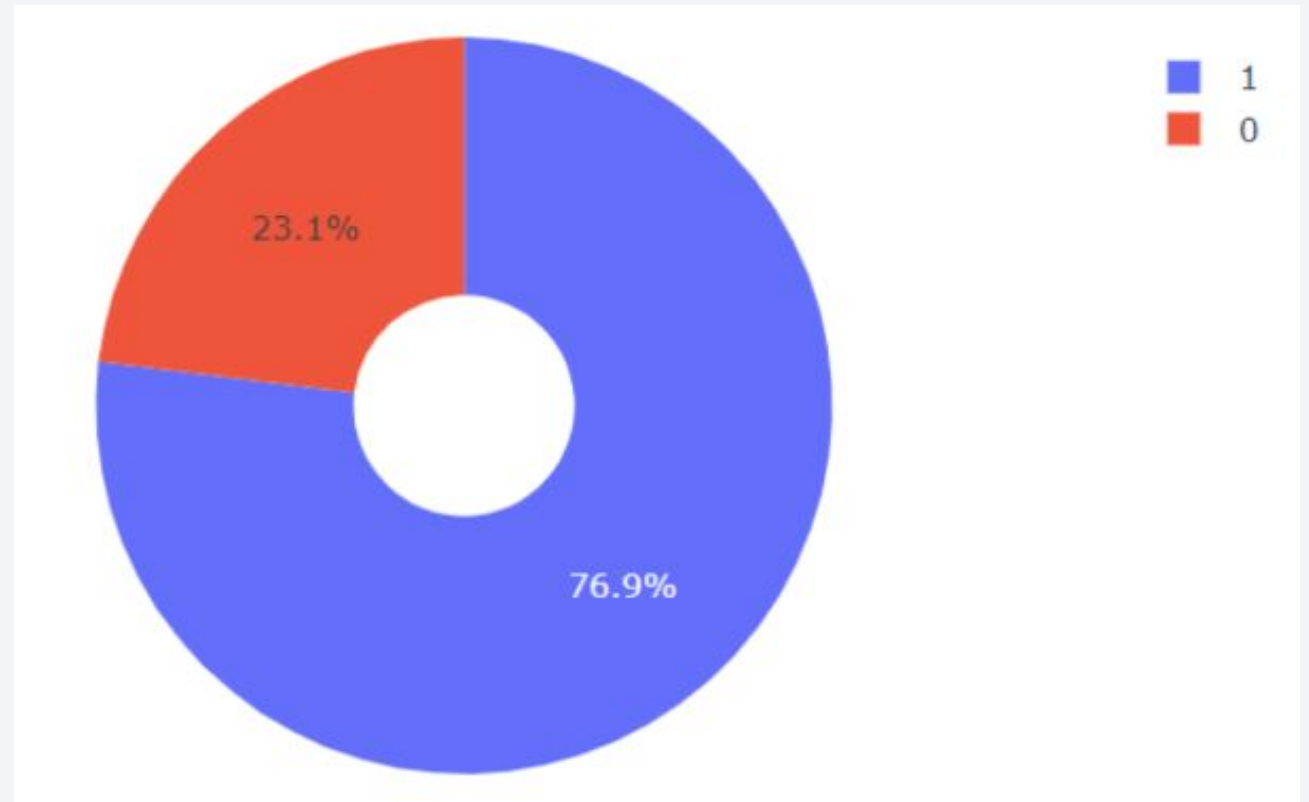
Total Success Launches By all sites



A pie chart highlighting the launch site with the highest success ratio.

---

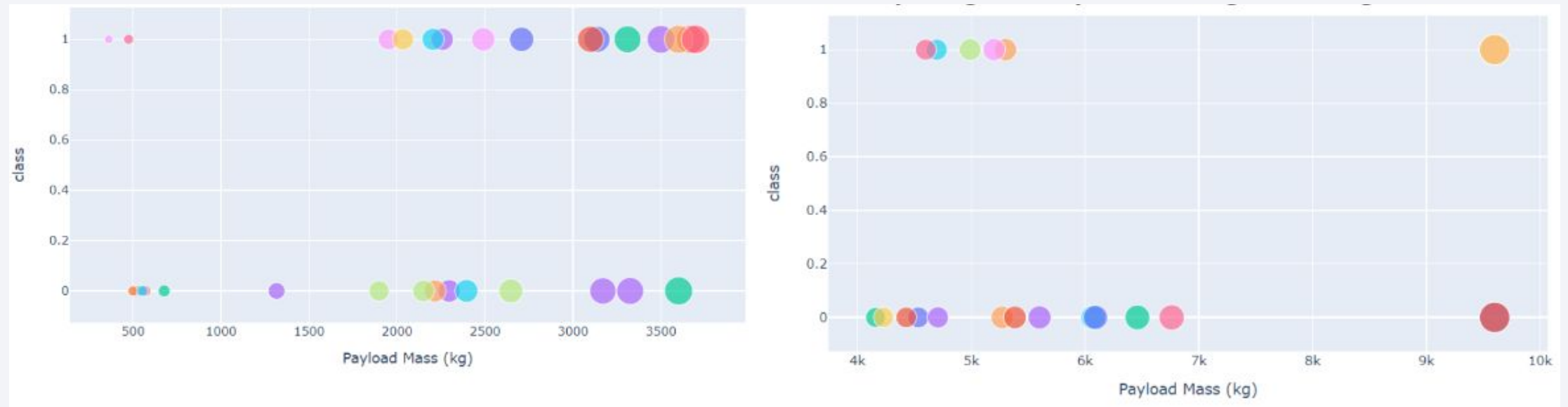
Kennedy Space Center Launch Complex 39A (KSC LC-39A) boasts the highest success rate among launch sites.





A scatter plot illustrating the relationship between Payload and Launch Outcome for all launch sites, with the ability to select different payload ranges using a range slider.

---





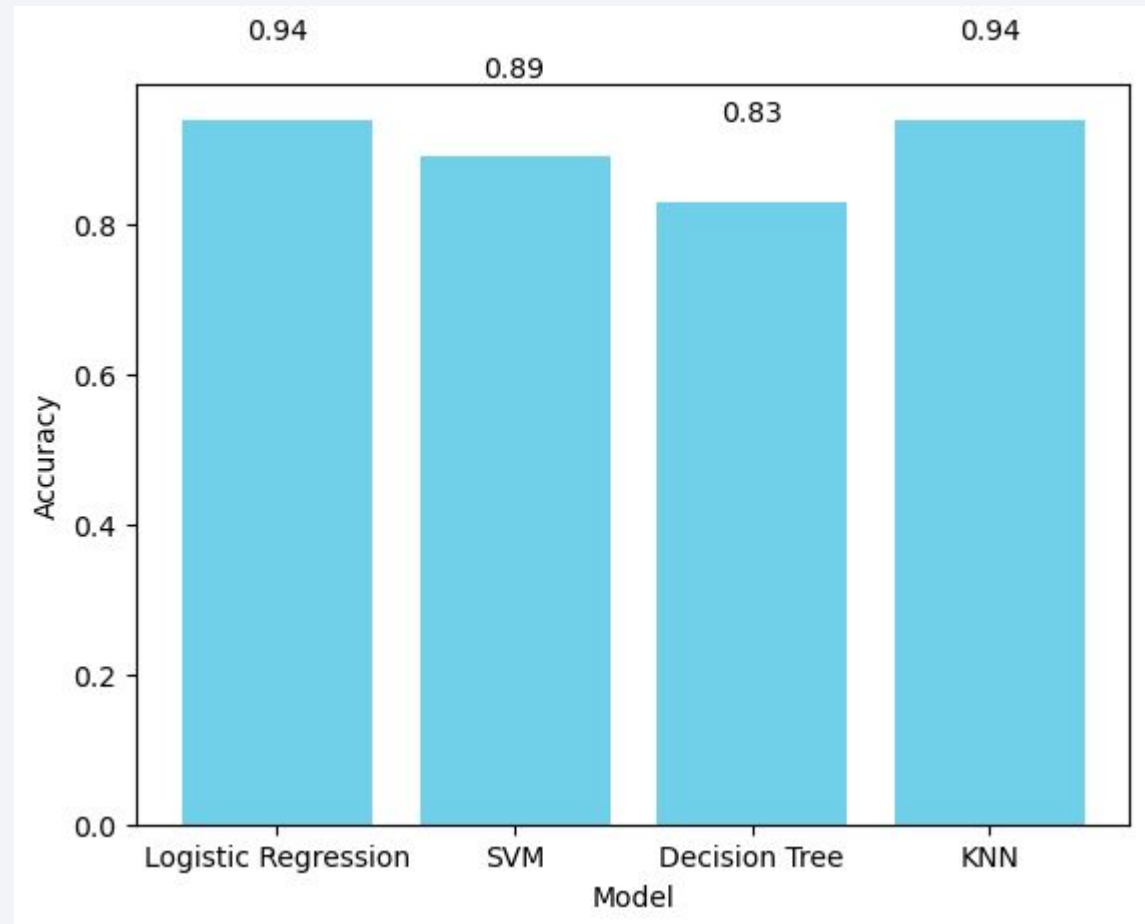
Section 5

# Predictive Analysis (Classification)

# Classification Accuracy

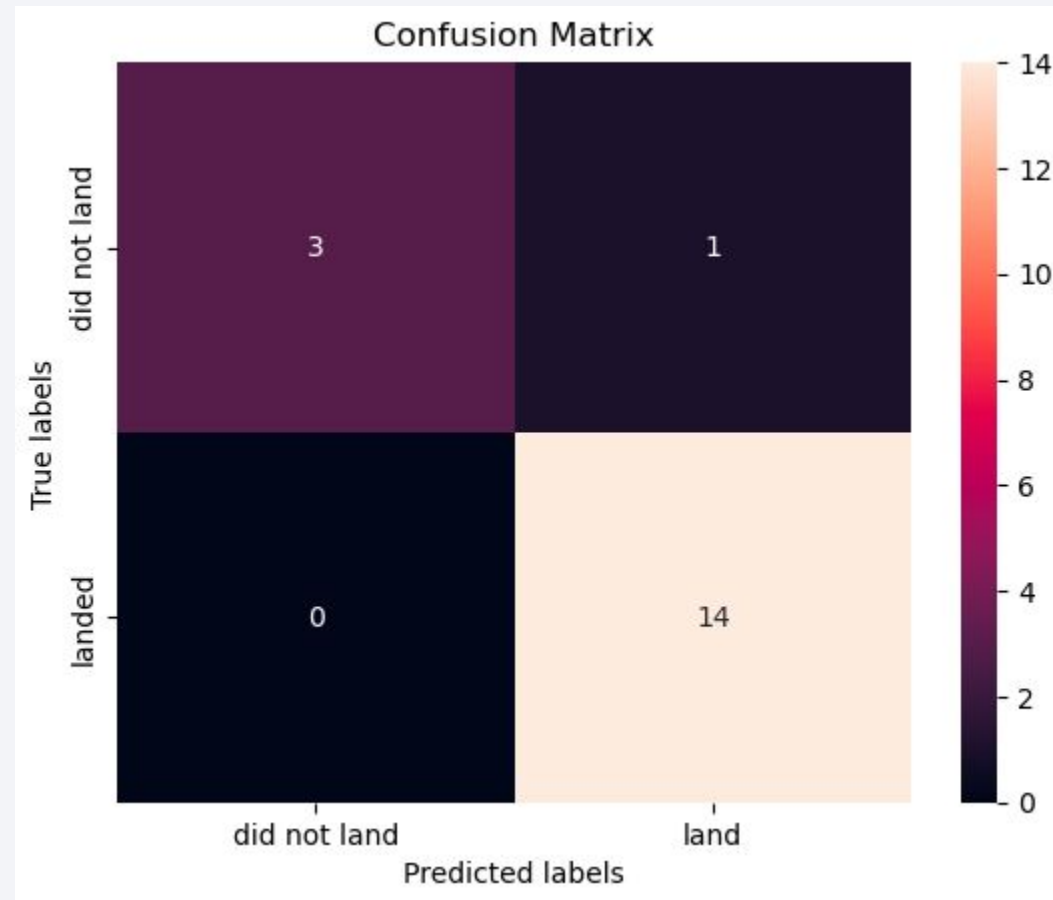
---

LR and KNN exhibit identical levels of accuracy.



# Confusion Matrix

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# Conclusions

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- The greater the flight count at a launch site, the higher its success rate.
- The launch success rate showed an upward trend from 2013 to 2020.
- Among all sites, KSC LC-39A recorded the highest number of successful launches.
- LR and KNN exhibit identical levels of accuracy and emerged as the most effective machine learning algorithm in our case.



Thank you!

