



IBM Developer
SKILLS NETWORK

Winning Space Race with Data Science

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<2023-09-15>



Outline

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

Executive Summary

- Summary of methodologies
- Summary of all results

Introduction

- Project background and context
- Problems you want to find answers



Section
1

Methodology

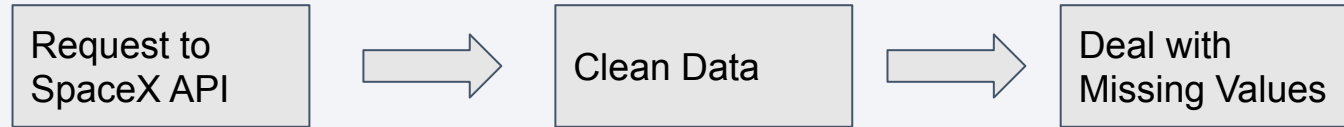
Methodology

Executive Summary

- Data collection methodology:
 - Data was collected from the SpaceX website using HTTP request API
- Perform data wrangling
 - Missing values have been replaced with the mean
- 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 has been standardized, split into train/test datasets, and then best hyperparameter was found for SVM, Classification Trees and Logistic Regression

Data Collection

- Data was collected from the SpaceX website using HTTP request API



Data Collection – SpaceX API

- Present your data collection with SpaceX REST calls using key phrases and flowcharts
- Add the GitHub URL of the completed SpaceX API calls notebook (must include completed code cell and outcome cell), as an external reference and peer-review purpose

GET

```
requests.get(spacex_url)
```

NORMALIZE

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

FILL NAN

```
data_falcon9.isnull().sum()
```


Data Collection - Scraping

- Present your web scraping process using key phrases and flowcharts
- Add the GitHub URL of the completed web scraping notebook, as an external reference and peer-review purpose

GET

```
r = requests.get(static_url)
```

BEAUTIFUL SOUP PARSER

```
soup = BeautifulSoup(data, "html.parser")
```

FIND TABLES

```
html_tables = soup.find_all('table')
```

Data Wrangling

- Calculate the number of launches on each site
- Calculate the number and occurrence of each orbit
- Calculate the number and occurrence of mission outcome per orbit type
- Create a landing outcome label from Outcome column

EDA with Data Visualization

- CATPLOT
 - Visualize the relationship between Flight Number and Launch Site
 - Visualize the relationship between Payload and Launch Site
 - Visualize the relationship between FlightNumber and Orbit type
- BAR CHART
 - Visualize the relationship between success rate of each orbit type
- LINE CHART
 - Visualize the launch success yearly trend

EDA with SQL

- `read_sql('select * from spacexdata', conn)`
- `read_sql('select distinct Launch_Site from spacexdata', conn)`
- `read_sql("select * from spacexdata where Launch_Site like 'CCA%' limit 5", conn)`
- `read_sql("select avg(PAYLOAD_MASS__KG_) from spacexdata where Booster_Version='F9 v1.1'", conn)`
- `read_sql("select min(Date) from spacexdata where Landing__Outcome='Success (ground pad)'", conn)`

Build an Interactive Map with Folium

- Markers for all launch sites
- Markers for the success/failed launches for each site
- Link of distances between a launch site to its proximities

Build a Dashboard with Plotly Dash

- Dropdown list to enable Launch Site selection
- Pie chart to show the total successful launches count for all sites
- Slider to select payload range
- Scatter chart to show the correlation between payload and launch success

Predictive Analysis (Classification)

- Standardize the data
- Split into training data and test data
- Find best Hyperparameter for SVM, Classification Trees and Logistic Regression
- Find the method performs best using test data

Results

- Scores on test data for each method
 - Logistic Regression: 0.944
 - SVM: 0.944
 - Decision Tree: 0.888
 - KNN: 0.888

The background of the slide is a complex, abstract composition. It features a dark blue base color. Overlaid on this are numerous diagonal streaks and bands of lighter blue and vibrant red. These streaks vary in thickness and intensity, creating a sense of motion and depth. A faint, white grid pattern is also visible, particularly in the upper right quadrant, where it intersects with the colored streaks. The overall effect is a high-tech, digital aesthetic.

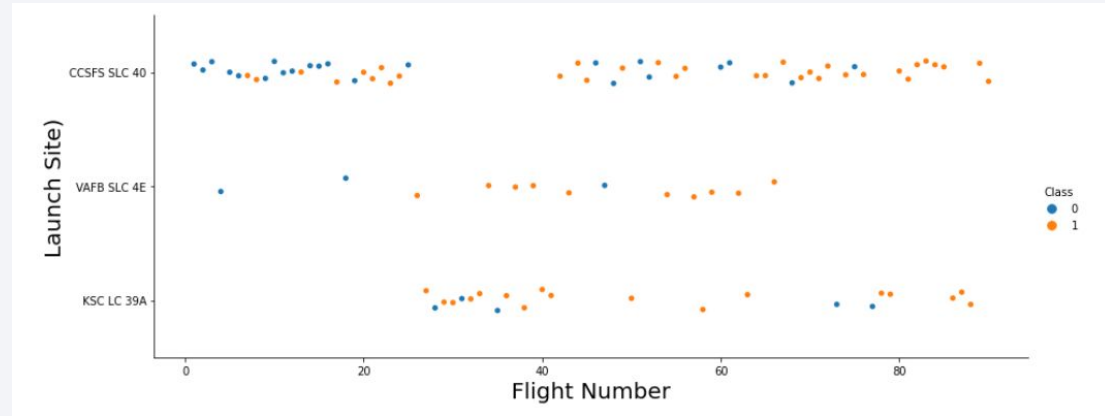
Section

2

Insights drawn from EDA

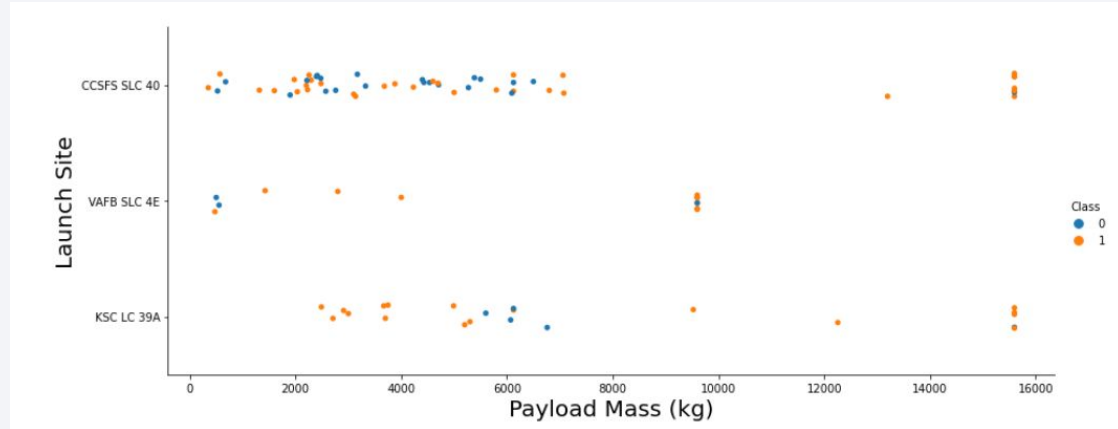
Flight Number vs. Launch Site

- Low and high flight numbers have been largely launched from CCSFS SLC 40
- Mid flight numbers have been launched from VAFB SLC 4E
- Mid flight numbers have been launched from VAFB SLC 4E



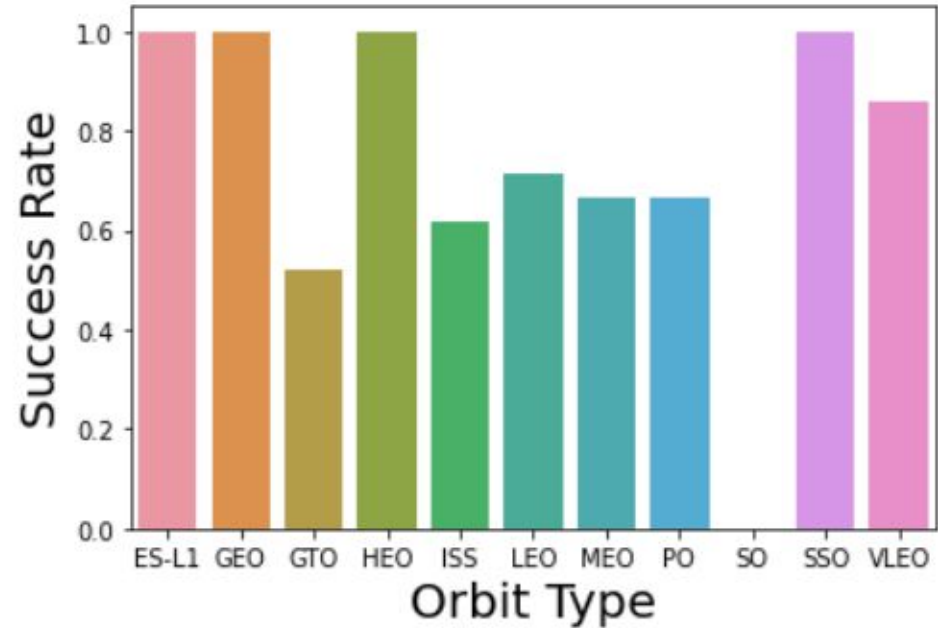
Payload vs. Launch Site

- Lighter payloads have been largely launched from CCSFS SLC 40
- Mid weight payloads have been launched from VAFB SLC 4E
- Mid weight payloads have been launched from VAFB SLC 4E



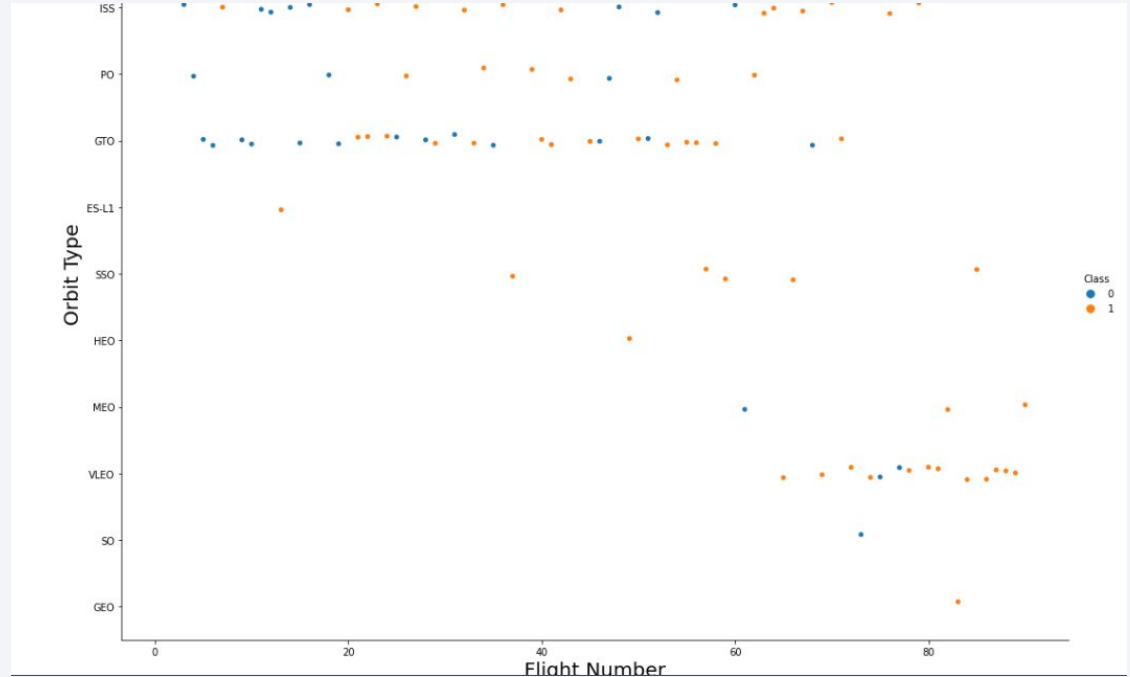
Success Rate vs. Orbit Type

- Almost all orbit types except SO had success rate higher than 50%
- Success rate was exceptional for orbit type ES-L1, GEO, HEO, SSO with 100%



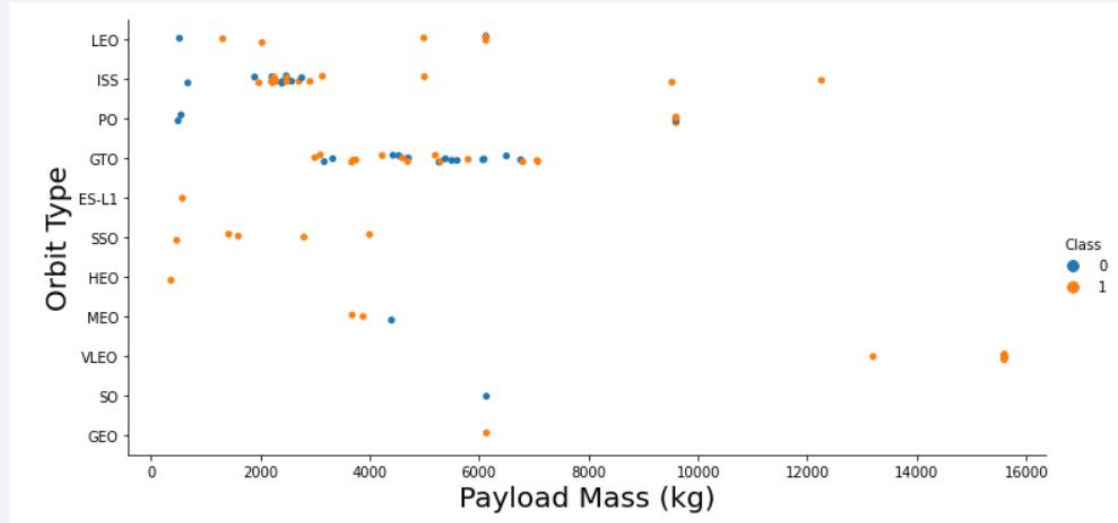
Flight Number vs. Orbit Type

- For LEO, higher flight number resulted in higher success rate
- For GTO, there is no such relationship



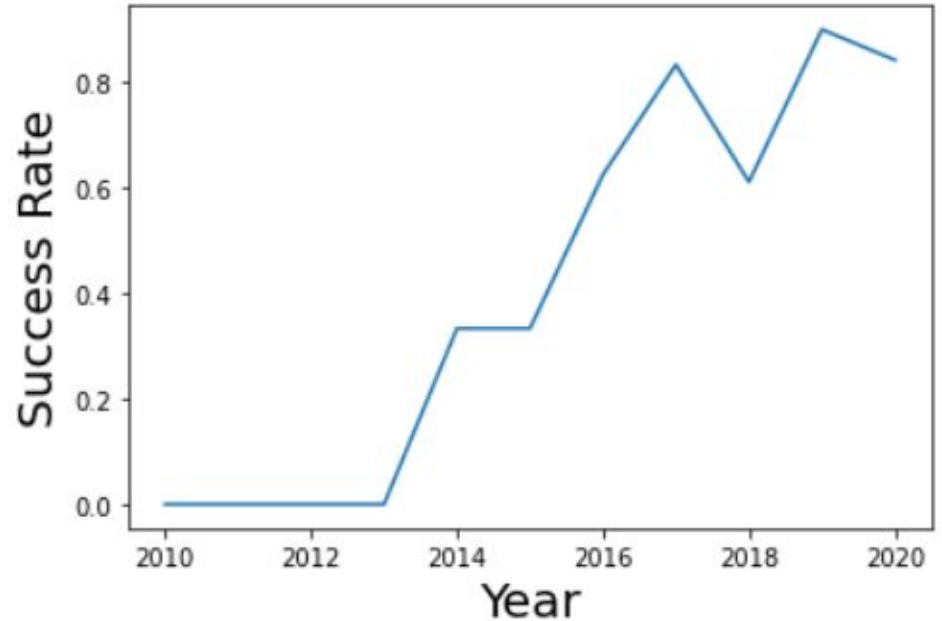
Payload vs. Orbit Type

- For Polar, LEO and ISS, higher payload resulted in higher success rate



Launch Success Yearly Trend

- Success rate has been increasing since 2013



All Launch Site Names

- CCAFS LC-40
 - VAFB SLC-4E
 - KSC LC-39A
 - CCAFS SLC-40
-
- `pd.read_sql('select distinct Launch_Site from spacexdata', conn)`

Launch Site Names Begin with 'CCA'

- `pd.read_sql("select * from spacexdata where Launch_Site like 'CCA%' limit 5", conn)`

	index	Date	Time_(UTC)	Booster_Version	Launch_Site	Payload	PAYLOAD_MASS_KG_	Orbit	Customer
0	0	2010-06-04 00:00:00	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX
1	1	2010-12-08 00:00:00	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
2	2	2012-05-22 00:00:00	07:44:00	F9 v1.0 B0005	CCAFS LC-40	Dragon demo flight C2	525	LEO (ISS)	NASA (COTS)
3	3	2012-10-08 00:00:00	00:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)
4	4	2013-03-01 00:00:00	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)

Total Payload Mass

- 45596
- `pd.read_sql("select sum(PAYLOAD_MASS__KG_) from spacexdata where Customer='NASA (CRS)'", conn)`

Average Payload Mass by F9 v1.1

- 2928.4
- `pd.read_sql("select avg(PAYLOAD_MASS__KG_) from spacexdata where Booster_Version='F9 v1.1'", conn)`

First Successful Ground Landing Date

- 2015-12-22 00:00:00
- `pd.read_sql("select min(Date) from spacexdata where Landing__Outcome='Success (ground pad)", conn)`

Successful Drone Ship Landing with Payload between 4000 and 6000

- F9 FT B1022
 - F9 FT B1026
 - F9 FT B1021.2
 - F9 FT B1031.2
-
- `pd.read_sql("select distinct Booster_Version from spacexdata where Landing__Outcome='Success (drone ship)' and PAYLOAD_MASS__KG_ between 4000 and 6000", conn)`

Total Number of Successful and Failure Mission Outcomes

- Failure 1
 - Success 100
-
- `pd.read_sql("select substr(Mission_Outcome,1,7) as Mission_Outcome, count(*) from spacexdata group by 1", conn)`

Boosters Carried Maximum Payload

- 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
-
- `pd.read_sql("select distinct Booster_Version from spacexdata where
PAYLOAD_MASS__KG_ = (select max(PAYLOAD_MASS__KG_) from spacexdata)",
conn)`

2015 Launch Records

Landing__Outcome	Booster_Version	Launch_Site
Failure (drone ship)	F9 v1.1 B1012	CCAFS LC-40
Failure (drone ship)	F9 v1.1 B1015	CCAFS LC-40
Failure (drone ship)	F9 v1.1 B1017	VAFB SLC-4E
Failure (drone ship)	F9 FT B1020	CCAFS LC-40
Failure (drone ship)	F9 FT B1024	CCAFS LC-40

- `pd.read_sql("select distinct Landing__Outcome, Booster_Version, Launch_Site from spacexdata where Landing__Outcome='Failure (drone ship)'", conn)`

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

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

- `pd.read_sql("select Landing__Outcome, count(*) from spacexdata where Date between '2011-06-04' and '2017-03-20' group by Landing__Outcome order by 2 desc", conn)`

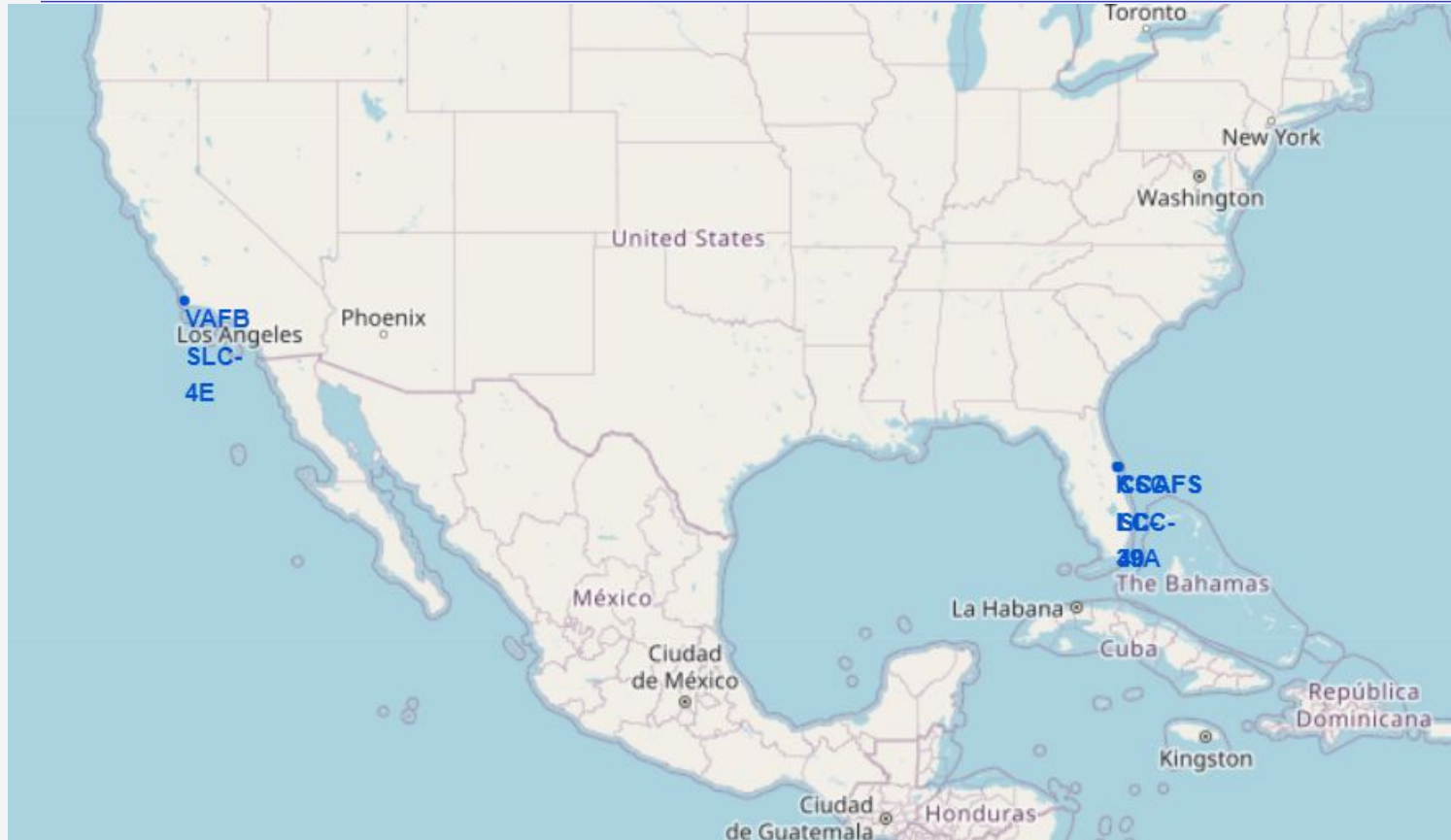
A satellite view of Earth from space, showing the curvature of the planet and city lights at night. The image is a composite of a dark blue sky with stars and a view of the Earth's surface from space. The Earth's surface is mostly dark, with bright yellow and orange lights from cities and towns visible, particularly along the coastlines and in the lower right quadrant. The horizon of the Earth is visible as a thin, curved line separating the dark surface from the black space.

Section

3

Launch Sites Proximities Analysis

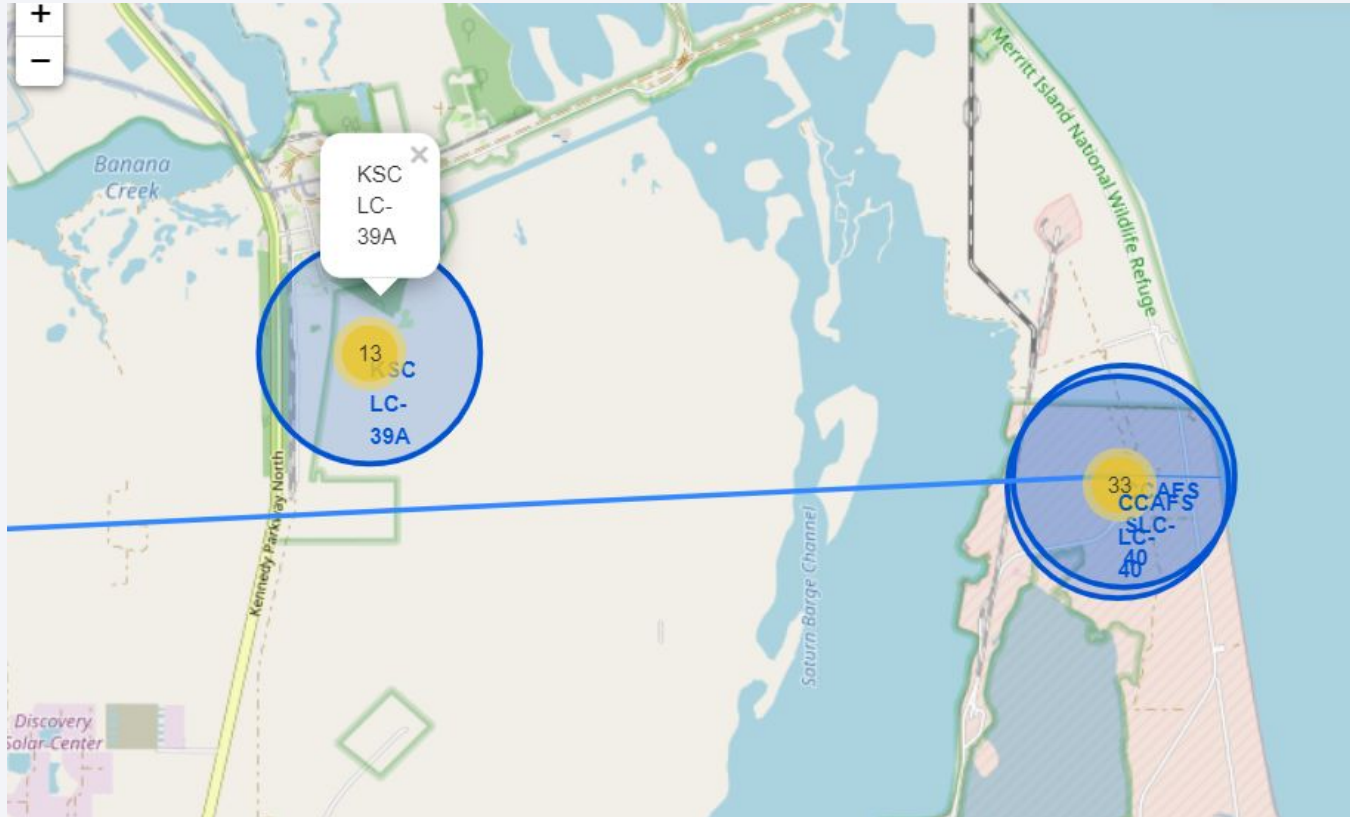
<Folium Map Screenshot 1>



<Folium Map Screenshot 2>



<Folium Map Screenshot 3>





Section

4

Build a Dashboard with Plotly Dash

<Dashboard Screenshot 1>

- Replace <Dashboard screenshot 1> title with an appropriate title
- Show the screenshot of launch success count for all sites, in a piechart
- Explain the important elements and findings on the screenshot

<Dashboard Screenshot 2>

- Replace <Dashboard screenshot 2> title with an appropriate title
- Show the screenshot of the piechart for the launch site with highest launch success ratio
- Explain the important elements and findings on the screenshot

<Dashboard Screenshot 3>

- Replace <Dashboard screenshot 3> title with an appropriate title
- Show screenshots of Payload vs. Launch Outcome scatter plot for all sites, with different payload selected in the range slider
- Explain the important elements and findings on the screenshot, such as which payload range or booster version have the largest success rate, etc.



Section

5

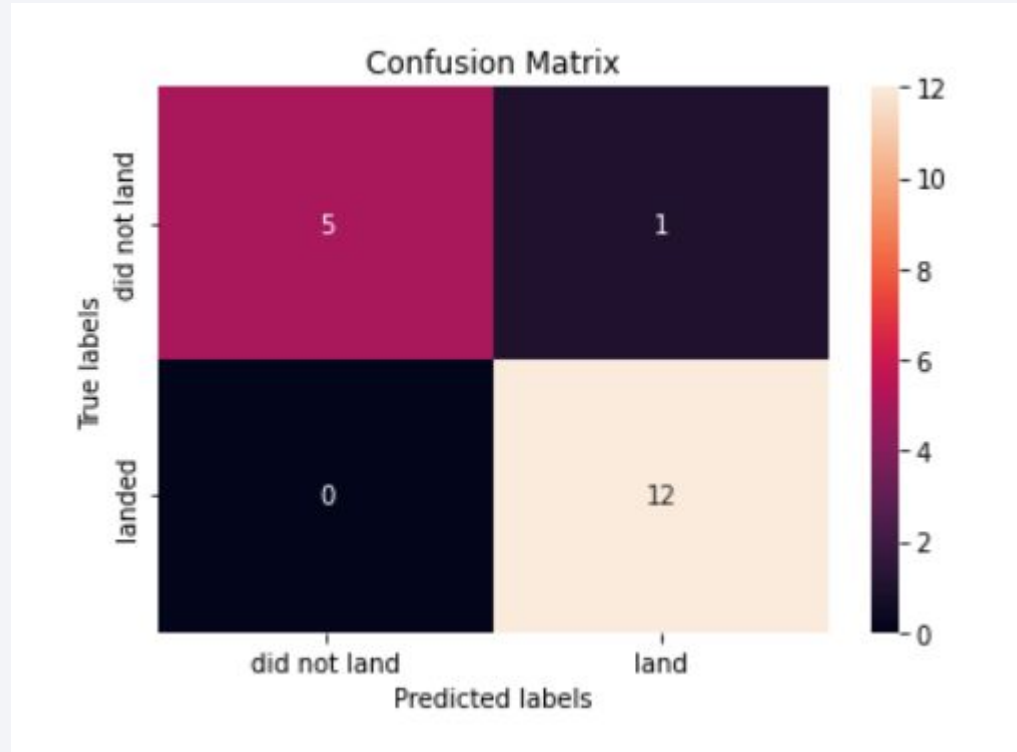
Predictive Analysis (Classification)

Classification Accuracy

- Visualize the built model accuracy for all built classification models, in a bar chart
- Find which model has the highest classification accuracy

Confusion Matrix

- SVM performed well with the score of 0.944



Conclusions

- SpaceX data was collected, analyzed as well as visualized to evaluate different relationships among the variables and the success rate
- SVM performed well among the classification models tested with the score of 0.944

Appendix

- Include any relevant assets like Python code snippets, SQL queries, charts, Notebook outputs, or data sets that you may have created during this project

Thank you!

