

Winning Space Race with Data Science

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Outline

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

Executive Summary

- Summary of methodologies
- Summary of all results:
 - By using different classification models such as Logsitic Regression, Support Vector Machine, Decision Tree, and K nearest neighbor.
 - Gainning accuracy of 83.33%, 83.33%, 77.8%, 83.33% respectively.

Introduction

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



Methodology

Executive Summary

- Data collection methodology:
 - Data were collected by using wget with URL
- Perform data wrangling
 - Data were processed by removing null value, using standard scaler to normalize them, as well as encode categorical data
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
 - Built classification models by applying packages from Sklearn and tune model using GridSearchCV. Using AUC-ROC curve, confusion matrix, and F1 score to evaluats

Data Collection

- Describe how data sets were collected.
- You need to present your data collection process use key phrases and flowcharts

```
spacex_csv_file = wget.download('ht
```

```
1 %sql sqlite:///my_datal.db
UsageError: Line magic function

1 import pandas as pd
2 df = pd.read_csv("https://c.
3 df.to_sql("SPACEXTBL", con,
```

data = pd. read_csv("https://cf-courses-dat

df=pd. read_csv("https://cf-courses-data.s3.us.cloud-object-storage.apj

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

	FlightNumber	Date	Booste	rVersion	Payloa	dMass	Orbit	Launch Site	Outcome	Flights	GridFins	Reused	Legs	Landin	gPad	Block	Reu
0	1	2010- 06-04		Falcon 9	6104.	959412	LEO	CCAFS SLC 40	None None	1	False	False	False		NaN	1.0	
1	2	2012- 05-22		Falcon 9	525.	000000	LEO	CCAFS SLC 40	None None	1	False	False	False		NaN	1.0	
2	3	2013- 03-01		Falcon 9	677.	000000	ISS	CCAFS SLC 40	None None	1	False	False	False		NaN	1.0	
3	4	2013- 09-29		Falcon 9	500.	000000	PO	VAFB SLC 4E	False Ocean	1	False	False	False		NaN	1.0	
4	5	2013- 12-03		Falcon 9	3170.	000000	GTO	CCAFS SLC 40	None None	1	False	False	False		NaN	1.0	
	FlightNumber	Payloa	adMass	Flights	Block	Reuse	dCount	Orbit_ES- L1	Orbit_GEO	Orbit_	GTO Orbi	t_HEO C	Orbit_IS	s s	erial_	B1058	s
0	1.0	6104.	.959412	1.0	1.0		0.0	0.0	0.0)	0.0	0.0	0.	0		0.0	
1	2.0	525.	.000000	1.0	1.0		0.0	0.0	0.0)	0.0	0.0	0.	0		0.0	
2	3.0	677.	.000000	1.0	1.0		0.0	0.0	0.0)	0.0	0.0	1.	0		0.0	
3	4.0	500.	.000000	1.0	1.0		0.0	0.0	0.0)	0.0	0.0	0.	0		0.0	
4	5.0	3170.	.000000	1.0	1.0		0.0	0.0	0.0)	1.0	0.0	0.	0		0.0	
85	86.0	15400.	.000000	2.0	5.0		2.0	0.0	0.0)	0.0	0.0	0.	0		0.0	
86	87.0	15400.	.000000	3.0	5.0		2.0	0.0	0.0)	0.0	0.0	0.	0		1.0	
87	88.0	15400.	.000000	6.0	5.0		5.0	0.0	0.0)	0.0	0.0	0.	0		0.0	
88	89.0	15400.	.000000	3.0	5.0		2.0	0.0	0.0)	0.0	0.0	0.	0		0.0	
89	90.0	3681.	.000000	1.0	5.0		0.0	0.0	0.0)	0.0	0.0	0.	0		0.0	

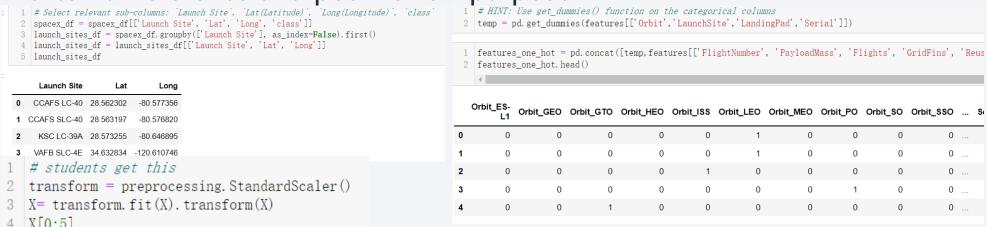
Data Collection - Scraping

 Present your web scraping process using key phrases and flowcharts data = pd.read_csv("https://cf-courses-data.s3.us.cloudobject-storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/datasets/dataset_part_2.csv")

 Add the GitHub URL of the completed web scraping notebook, as an external reference and peer-review purpose spacex_csv_file = wget.download('https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DSO321EN-SkillsNetwork/datasets/spacex_launch_geo.csv')

Data Wrangling

- Describe how data were processed
 - Built classification models by applying packages from Sklearn and tune model using GridSearchCV. Using AUC-ROC curve, confusion matrix, and F1 score to evaluats
- You need to present your data wrangling process using key phrases and flowcharts
- Add the GitHub URL of your completed data wrangling related notebooks, as an external reference and peer-review purpose



EDA with Data Visualization

- Summarize what charts were plotted and why you used those charts
 - Flight number V.S. Pay load mass(Scatter plot) to find out the outcome of the launch
 - Success rate of each orbit (Bar chart) to see which orbit perform better.
 - Year V.S. success rate(line chart) to find out how our tech perform when time goes by

 Add the GitHub URL of your completed EDA with data visualization notebook, as an external reference and peer-review purpose

EDA with SQL

- Using bullet point format, summarize the SQL queries you performed
 - Find unique launch sites in the space mission: %sql Select DISTINCT LAUNCH_SITE FROM SPACEXTBL
 - Show 5 records where launch sites begin with string 'CCA': SELECT * FROM SPACEXTBL WHERE LAUNCH SITE LIKE 'CCA%' LIMIT 5
 - Total payload mass: SELECT SUM(PAYLOAD_MASS_KG_) FROM SPACEXTBL WHERE CUSTOMER =
 'NASA (CRS)'
 - Find certain payload mass based on different booster bersion
 - Ground pad where first landing were successfully achieved
 - Name of booster when payload mass was between a certain range
 - Number of total outcomes
 - Outcomes between certain date range

Build an Interactive Map with Folium

- Summarize what map objects such as markers, circles, lines, etc. you created and added to a folium map
 - Using circle and add child to certain location to mark where it is; using marker to mark the size of the icon and color
 - Using folium. Map to show the whole map of USA; using circle to mark the radius and color as well as creating child.
 - Using mousePosition to get coordinate for a mouse over a point on the map
 - Using folium.Marker to mark the distance between to locations

Build a Dashboard with Plotly Dash

- Summarize what plots/graphs and interactions you have added to a dashboard
- Explain why you added those plots and interactions
- Add the GitHub URL of your completed Plotly Dash lab, as an external reference and peer-review purpose

Predictive Analysis (Classification)

- Summarize how you built, evaluated, improved, and found the best performing classification model
 - First by splitting the data into training and testing set
 - Using models from Sklearn packages to train each training set and then find out their accuracy
 - By using metrics like confusion matrix, F1 score and AUC-ROC curve we can directly see how the model perform on the data set
 - Besides decision tree, the other three models (logistic regression, SVM, KNN) have the same accuracy

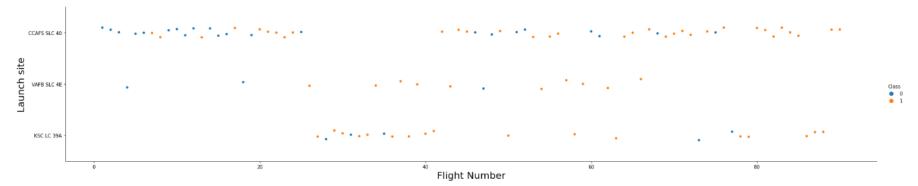
Results

- Exploratory data analysis results
- Interactive analytics demo in screenshots
- Predictive analysis results



Flight Number vs. Launch Site

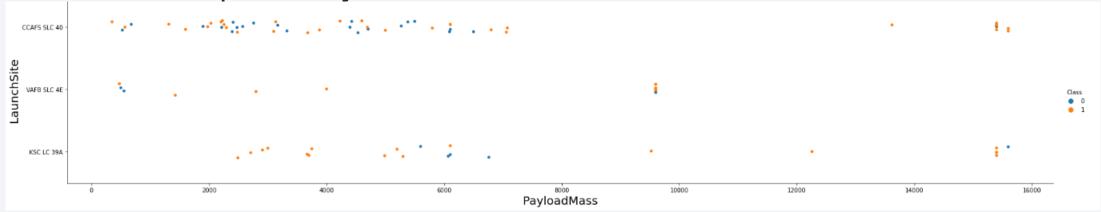
Show a scatter plot of Flight Number vs. Launch Site



• The x-axis is flight number and y-axis is launch site. We can see that CCAFS SLC 40 site ahs the most flight number and VAFB SLC 4E has the least number of flights

Payload vs. Launch Site

Show a scatter plot of Payload vs. Launch Site

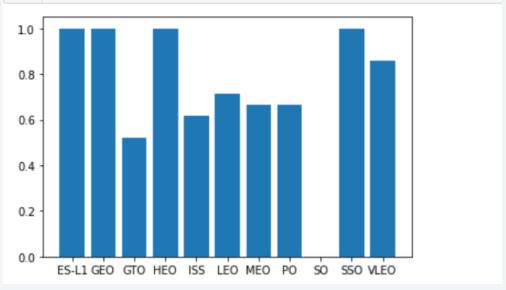


• Most of the payload are less than 8000, and still, CCAFS SLC 40 has most of the flights.

Success Rate vs. Orbit Type

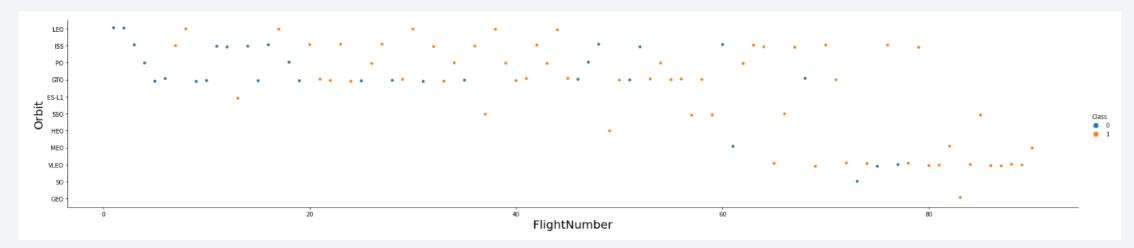
 Show a bar chart for the success rate of each orbit type

```
2  orbit = df[['Orbit','Class']].groupby('Orbit').mean()
3
4  plt.bar(orbit.index.values, orbit['Class'])
5
6  plt.show()
```



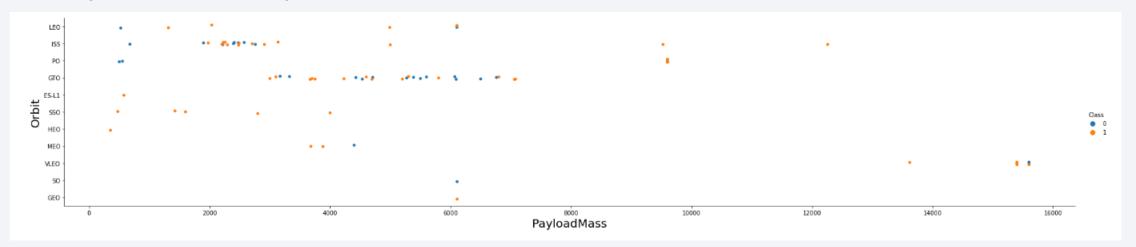
Flight Number vs. Orbit Type

 Show a scatter point of Flight number vs. Orbit type



Payload vs. Orbit Type

 Show a scatter point of payload vs. orbit type



Launch Success Yearly Trend

• Show a line chart of yearly average success rate

All Launch Site Names

• Find the names of the unique launch sites

%sq1 SELECT Distinct LAUNCH_SITE FROM SPACEXTBL

* ibm_db_sa://kcq64325:***@dashdb-txn-sbox-yp-da1
Done.
launch_site

CCAFS LC-40

CCAFS SLC-40

KSC LC-39A

VAFB SLC-4E

Launch Site Names Begin with 'CCA'

• Find 5 records where launch sites begin with `CCA`

%sq1 SELECT * FROM SPACEXTBL WHERE LAUNCH_SITE LIKE 'CCA%' LIMIT 5														
* ibm_db_sa://kcq64325:***@dashdb-txn-sbox-yp-da109-04.services.da1.bluemix.net:50000/BLUDB Done.														
DATE	time_utc_	booster_version	launch_site	payload	payload_masskg_	orbit	customer	mission_outcome	landing_outcome					
2010-06-04	18:45:00	F9 v1.0 B0003	CCAFS LC-40	None	0	LEO	SpaceX	Success	Failure (parachute)					
2010-12-08	15:43:00	F9 v1.0 B0004	CCAFS LC-40	None	0	LEO (ISS)	NASA (COTS) NRO	Success	Failure (parachute)					
2012-05-22	07:44:00	F9 v1.0 B0005	CCAFS LC-40	None	525	LEO (ISS)	NASA (COTS)	Success	No attempt					
2012-10-08	00:35:00	F9 v1.0 B0006	CCAFS LC-40	None	500	LEO (ISS)	NASA (CRS)	Success	No attempt					
2013-03-01	15:10:00	F9 v1.0 B0007	CCAFS LC-40	None	677	LEO (ISS)	NASA (CRS)	Success	No attempt					

Total Payload Mass

Calculate the total payload carried by boosters from NASA

```
%sq1 SELECT SUM(PAYLOAD_MASS__KG_) FROM SPACEXTBL WHERE CUSTOMER='NASA (CRS)'
```

* ibm_db_sa://kcq64325:***@dashdb-txn-sbox-yp-da109-04.services.da1.bluemix.ne⁻Done.

1

45596

Average Payload Mass by F9 v1.1

Calculate the average payload mass carried by booster version F9 v1.1

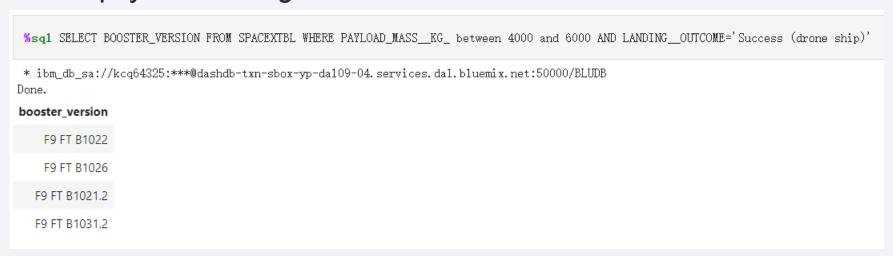
First Successful Ground Landing Date

• Find the dates of the first successful landing outcome on ground pad

```
%sq1 SELECT min(DATE) FROM SPACEXTBL WHERE LANDING_OUTCOME='Success (ground pad)'
* ibm_db_sa://kcq64325:***@dashdb-txn-sbox-yp-da109-04.services.da1.bluemix.net:500
Done.
1
2015-12-22
```

Successful Drone Ship Landing with Payload between 4000 and 6000

 List the names of boosters which have successfully landed on drone ship and had payload mass greater than 4000 but less than 6000



Total Number of Successful and Failure Mission Outcomes

Calculate the total number of successful and failure mission outcomes

```
%sq1 SELECT COUNT(*) FROM SPACEXTBL WHERE MISSION_OUTCOME LIKE '%Success%' OR MISSION_OUTCOME LIKE '%Failure%'
* ibm_db_sa://kcq64325:***@dashdb-txn-sbox-yp-da109-04.services.da1.bluemix.net:50000/BLUDB
Done.
101
```

Boosters Carried Maximum Payload

List the names of the booster which have carried the maximum payload mass

%sq1 SELECT BOOSTER_VERSION FROM SPACEXTBL WHERE PAYLOAD_MASS__KG_ = (SELECT MAX(PAYLOAD_MASS__KG_) FROM SPACEXTBL)

* ibm_db_sa://kcq64325:***@dashdb-txn-sbox-yp-da109-04.services.da1.bluemix.net:50000/BLUDB 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 failed landing_outcomes in drone ship, their booster versions, and launch site names for in year 2015

```
%sq1 SELECT TO_CHAR(TO_DATE(MONTH("DATE"), 'MM'), 'MONTH') AS MONTH_NAME, \
    LANDING_OUTCOME AS LANDING_OUTCOME, \
    BOOSTER_VERSION AS BOOSTER_VERSION, \
    LAUNCH_SITE AS LAUNCH_SITE \
    FROM SPACEXTBL WHERE LANDING_OUTCOME = 'Failure (drone ship)' AND "DATE" LIKE '%2015%'

* ibm_db_sa://kcq64325:***@dashdb-txn-sbox-yp-da109-04.services.da1.bluemix.net:50000/BLUDEDone.

month_name landing_outcome booster_version launch_site

JANUARY Failure(drone ship) F9 v1.1 B1012 CCAFS LC-40

APRIL Failure(drone ship) F9 v1.1 B1015 CCAFS LC-40
```

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

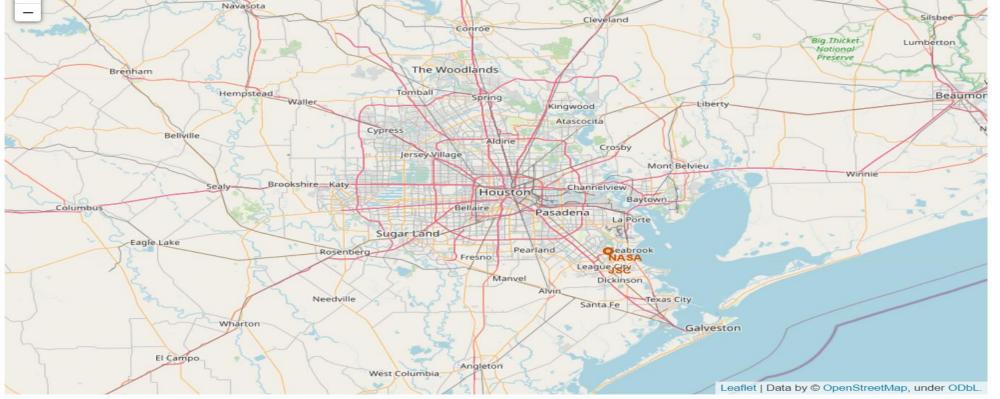
• Rank the count of landing outcomes (such as Failure (drone ship) or Success (ground pad)) between the date 2010-06-04 and 2017-03-20, in

```
%sq1 SELECT "DATE", COUNT(LANDING_OUTCOME) as COUNT FROM SPACEXTBL \
    WHERE "DATE" BETWEEN '2010-06-04' and '2017-03-20' AND LANDING_OUTCOME LIKE '%Success%' \
    GROUP BY "DATE" \
    ORDER BY COUNT (LANDING_OUTCOME) DESC
* ibm db_sa://kcq64325:***@dashdb-txn-sbox-yp-da109-04.services.da1.bluemix.net:50000/BLUDB
Done.
     DATE COUNT
2015-12-22
2016-04-08
2016-05-06
2016-05-27
2016-07-18
2016-08-14
2017-01-14
2017-02-19
```

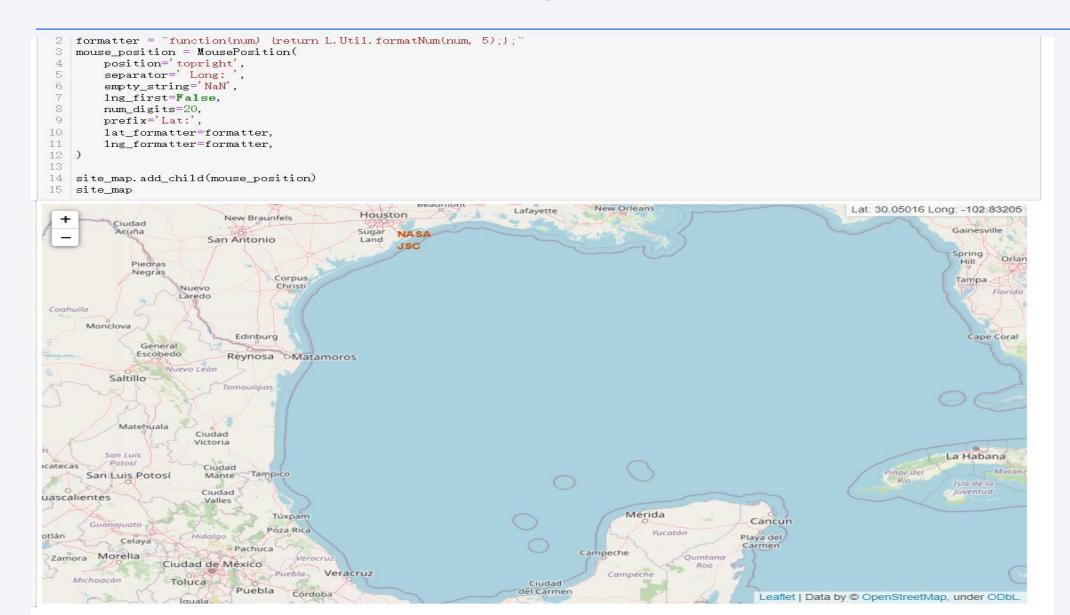


Houston NASA map

```
2 | circle = folium. Circle (nasa_coordinate, radius=1000, color='#d35400', fill=True). add_child(folium. Popup('NASA Johnson Space Center'))
 3 # Create a blue circle at NASA Johnson Space Center's coordinate with a icon showing its name
   marker = folium. map. Marker (
        nasa_coordinate,
 6
        # Create an icon as a text label
        icon=DivIcon(
8
            icon_size=(20, 20),
9
            icon_anchor=(0,0),
            html='<div style="font-size: 12; color:#d35400;"><b>%s</b></div>' % 'NASA JSC',
10
11
12
13 site_map.add_child(circle)
14 site map. add child(marker)
                               Navasota
                                                                                                                      Big Thicket
                                                                                                                                    Lumberton
                                                                                                                       Preserve
```



Distance Calculation Map

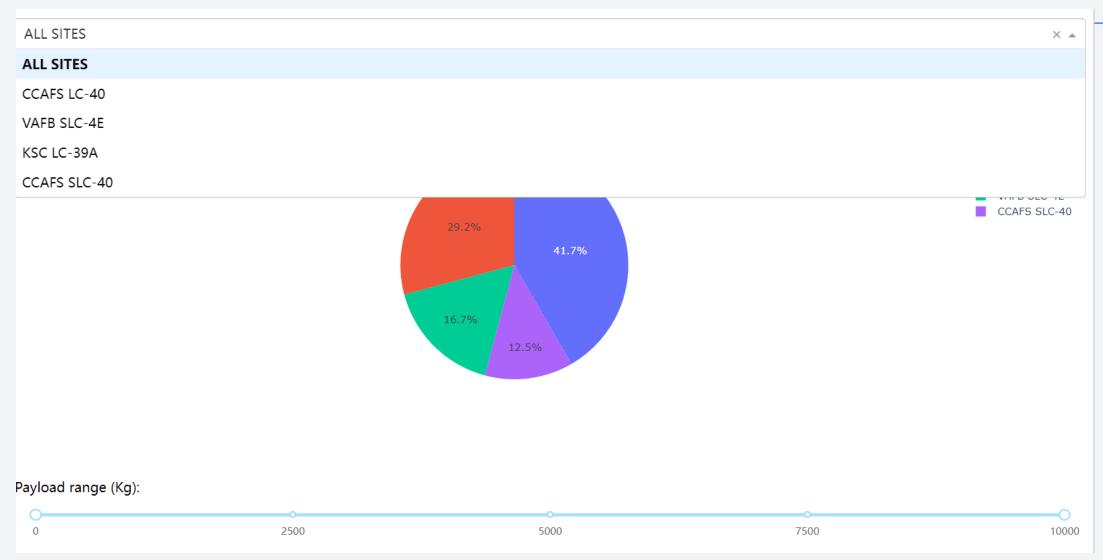


Southern map

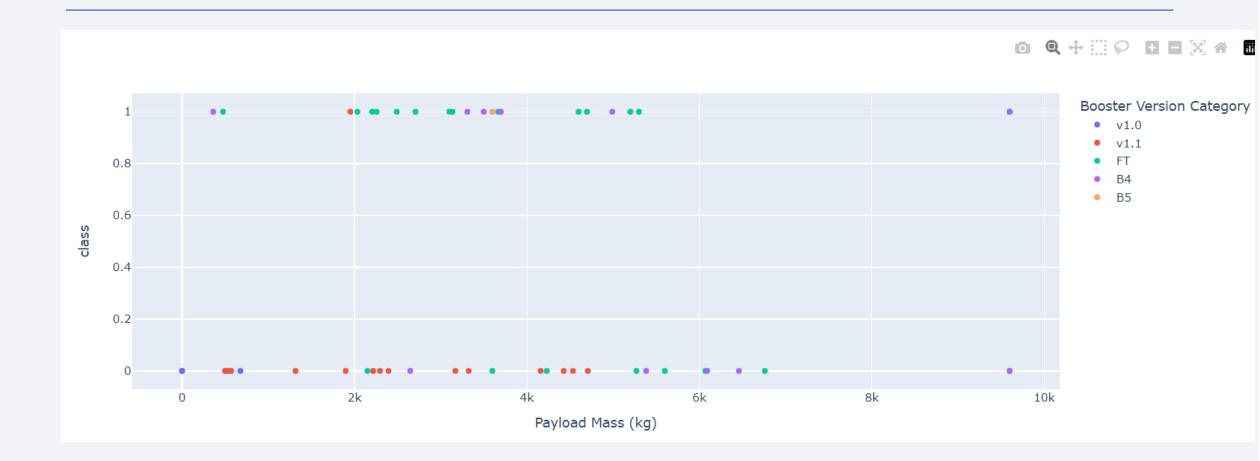
```
24 site_map.add_child(distance_marker)
          25 # closest railroad line
          26 coordinates = [[launch_site_lat, launch_site_lon], closest_railroad]
              lines=folium.PolyLine(locations=coordinates, weight=1)
              site_map.add_child(lines)
          30 # closest city marker
          31 distance_marker = folium. Marker(
                 closest_city,
                 icon=DivIcon(
          34
                      icon_size=(20, 20),
          35
                      icon_anchor=(0,0),
          36
                     html='<div style="font-size: 12; color:#d35400;"><b>%s</b></div>' % "{:10.2f} KM".format(distance_city),
          37
          39 site_map.add_child(distance_marker)
           40 # closest city line
          41 | coordinates = [[launch_site_lat, launch_site_lon], closest_city]
           42 lines=folium.PolyLine(locations=coordinates, weight=1)
           43 site_map.add_child(lines)
Out[23]:
                                                                                                                                 Lat: 2.6477 Long: -50.99357
                                          Nassau
                                      The Bahamas
                        La Habana
          Cancún
                                                               República
                              Islands
                                              de Cuba
                                                         Ayiti Dominicana
                                                                                          Antigua
                                                                                         and Barbuda
          Honduras
                                                                                           Saint Vincent
            Nicaragua
                                                                                             and the
                                                                                            Grenadines
           Managua
                                                           Maracaibo
                                                                                    Cumaná
                                                Barranquilla
                                                                                            and Tobago
                                                                           Caracas
                                                                                        Maturin
                                                                 Barinas
                                                                                         San Félix
                              Panamá
                                              Monteria
                                                                                    Ciudad Bolivar
                                                                                                      Georgetown
                                                                               Venezuela
                                               Medellin
                                              Manizales
                                                       Colombia
```



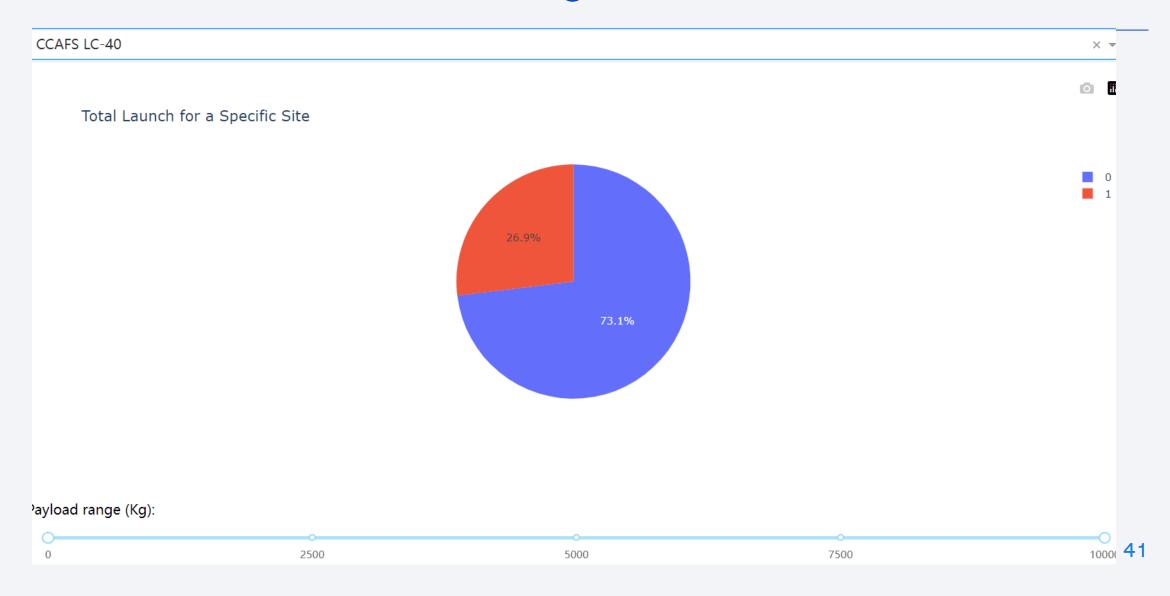
Sites V.S. payload range



Payload V.S. Class



Site that has the most flights

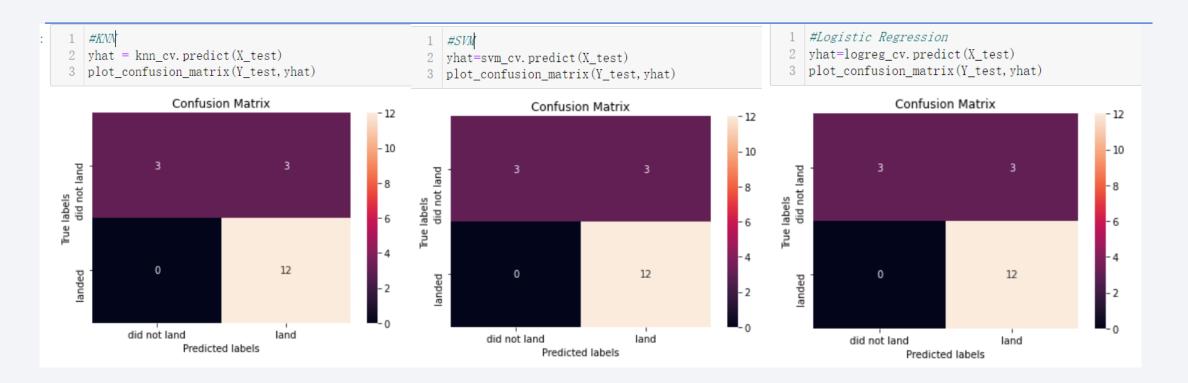




Classification Accuracy

```
1 accuracy_1st = [logreg_cv.score(X_test, Y_test), svm_cv.score(X_test, Y_test), tree_cv.score(X_test, Y_test), knn_cv.score(X_test, Y_test)
 2 | name_1st = ['LR', 'SVM', 'DT', 'KNN']
 3 plt.bar(name_lst, accuracy_lst)
<BarContainer object of 4 artists>
 0.8 -
 0.7 -
 0.6 -
 0.5 -
 0.4
 0.3 -
 0.2 -
 0.1 -
 0.0
                      SVM
          LR
                                  DT
                                              KNN
```

Confusion Matrix



Conclusions

- Point 1
- Point 2
- Point 3
- Point 4

•

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

