



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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The goal of this research is to analyze SpaceX Falcon 9 data collected through various sources and employ Machine Learning models to predict the success of first stage landing that provides other space agencies the ability to decide if they bid against SpaceX.

- **Summary of methodologies:** Following concepts and methods were used to collect and analyze data, build and evaluate machine learning models, and make predictions:
  - Collect data through API and Web scraping.
  - Transform data through data wrangling.
  - Conduct exploratory data analysis with SQL and data visuals.
  - Build an interactive map with folium to analyze launch site proximity.
  - Build a dashboard to analyze launch records interactively with Plotly Dash.
  - Finally, build a predictive model to predict if the first stage of Falcon 9 will land successfully.
- **Summary of all results:** This report will share results in various formats such as:
  - Data analysis results
  - Data visuals, interactive dashboards
  - Predictive model analysis results

# Introduction

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- **Project background and context**

- With the recent successes in private space travel, space industry is becoming more and more mainstream and accessible to general population. Cost of launch continues to remain a key barrier for new competitors to enter the space race.
- SpaceX with its first stage reuse capabilities offers a key advantage against its competitors. Each SpaceX launch costs around 62 million dollar and SpaceX can reuse stage 1 for future launches. This provides SpaceX a unique advantage where other competitors are spending around 165 million plus for each launch.

- **Problems you want to find answers**

- Determine if the first stage of SpaceX Falcon 9 will land successfully.
- Impact of different parameters/variables on the landing outcomes (e.g., launch site, payload mass, booster version, etc.).
- Correlations between launch sites and success rates.



Section 1

# Methodology

# Methodology

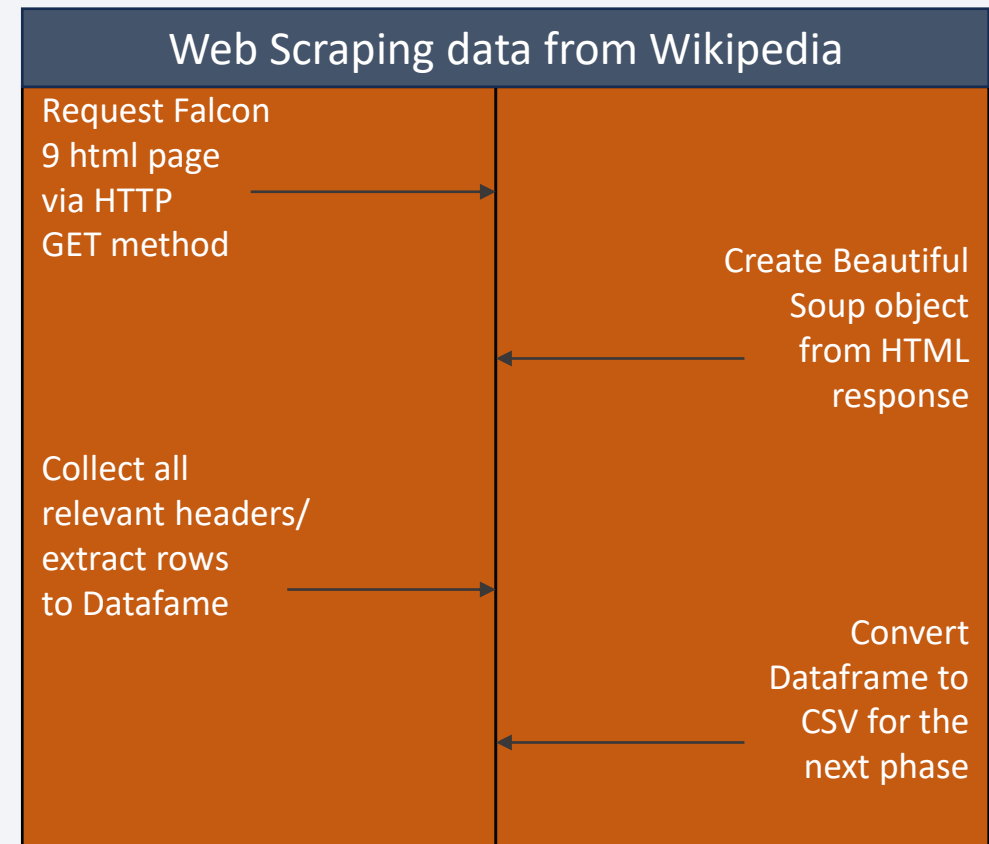
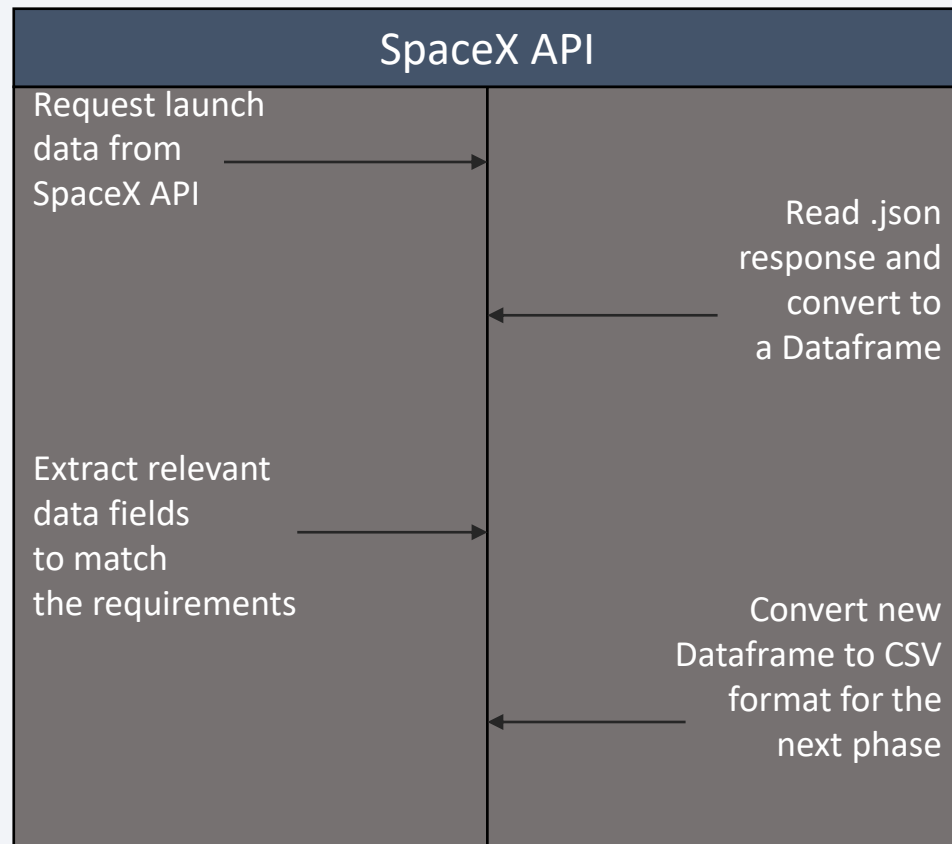
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## Executive Summary

- Data collection methodology:
  - SpaceX API
  - Web scrap Falcon 9 and Falcon Heavy launch records from Wikipedia ([link](#))
- Perform data wrangling
  - Determined labels for training the supervised models by converting mission outcomes into training labels (0-unsuccessful, 1-successful).
- Perform exploratory data analysis (EDA) using visualization and SQL
- Perform interactive visual analytics using Folium and Plotly Dash
- Perform predictive analysis using classification models
  - Created a column for 'class'; standardized and transformed data; train/test split data; find best classification algorithm (Logistic regression, SVM, Decision tree, & KNN) using test data.

# Data Collection

Data collection is the process of gathering data from available sources. This data can be structured, unstructured, or semi-structured. For this project, data was collected via SpaceX API and Web scrapping Wiki pages for relevant launch data.



# Data Collection – SpaceX API

1. API Request and read response into DF

2. Declare global variables

3. Call helper functions with API calls to populate global vars

4. Construct data using dictionary

5. Convert dictionary to Dataframe, filter for Falcon 9 launches, convert to CSV

1. Create API GET request, normalize data and read in to a Dataframe:

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

response = requests.get(spacex_url)

# Use json_normalize method to convert the json result into a dataframe
responsej=response.json()
data=pd.json_normalize(responsej)
```

2. Declare global variable lists that will store data returned by helper functions with additional API calls to get relevant data:

```
#Global variables
BoosterVersion = []
PayloadMass = []
Orbit = []
LaunchSite = []
Outcome = []
Flights = []
GridFins = []
Reused = []
Legs = []
LandingPad = []
Block = []
ReusedCount = []
Serial = []
Longitude = []
Latitude = []
```

3. Call helper functions to get relevant data where columns have IDs (e.g., rocket column is an identification number):

- getBoosterVersion(data)
- getLaunchSite(data)
- getPayloadData(data)
- getCoreData(data)

4. Construct dataset from received data & combine columns into a dictionary:

```
launch_dict = {'FlightNumber': list(data['flight_number']),
               'Date': list(data['date']),
               'BoosterVersion':BoosterVersion,
               'PayloadMass':PayloadMass,
               'Orbit':Orbit,
               'LaunchSite':LaunchSite,
               'Outcome':Outcome,
               'Flights':Flights,
               'GridFins':GridFins,
               'Reused':Reused,
               'Legs':Legs,
               'LandingPad':LandingPad,
               'Block':Block,
               'ReusedCount':ReusedCount,
               'Serial':Serial,
               'Longitude': Longitude,
               'Latitude': Latitude}
```

5. Create Dataframe from dictionary and filter to keep only the Falcon9 launches:

```
# Create a data from launch_dict
df=pd.DataFrame(dict([(key,pd.Series(value)) for key,value in launch_dict.items()])))

# Hint data['BoosterVersion']!='Falcon 1'
data_falcon9=df[df['BoosterVersion']!='Falcon 1']

data_falcon9.to_csv('dataset_part_1.csv', index=False)
```



# Data Collection – Scraping

1. Perform HTTP GET to request HTML page

2. Create Beautiful Soap object

3. Extract column names from HTML table header

4. Create Dictionary with keys from extracted column names

5. Call helper functions to fill up dict with launch records

6. Convert dictionary to Dataframe

1. Create API GET method to request Falcon9 launch HTML page:

```
static_url = "https://en.wikipedia.org/w/index.php?title=List_of_Falcon_9_and_Falcon_Heavy_launches&oldid=1027686922"  
data=requests.get(static_url).text
```

2. Create Beautiful Soap object:

```
soup=BeautifulSoup(data)
```

3. Find all the tables on the Wiki page and extract relevant column names from the HTML table header:

```
html_tables=soup.find_all('table')  
  
column_names = []  
  
# Apply find_all() function with `th` element o  
# Iterate each th element and apply the provide  
# Append the Non-empty column name (if name is  
  
for row in first_launch_table.find_all('th'):  
    col=extract_column_from_header(row)  
    if(col!=None and len(col)>0):  
        column_names.append(col)
```

4. Create an empty Dictionary with keys from extracted column names:

```
launch_dict= dict.fromkeys(column_names)  
  
# Remove an irrelevant column  
del launch_dict['Date and time ( )']  
  
# Let's initial the launch_dict with each value to be an empty list  
launch_dict['Flight No.'] = []  
launch_dict['Launch site'] = []  
launch_dict['Payload'] = []  
launch_dict['Payload mass'] = []  
launch_dict['Orbit'] = []  
launch_dict['Customer'] = []  
launch_dict['Launch outcome'] = []  
# Added some new columns  
launch_dict['Version Booster']=[]  
launch_dict['Booster landing']=[]  
launch_dict['Date']=[]  
launch_dict['Time']=[]
```

5. Fill up the launch\_dict with launch records extracted from table rows.

- Utilize following helper functions to help parse HTML data:

```
def date_time(table_cells):  
def booster_version(table_cells):  
def landing_status(table_cells):  
def get_mass(table_cells):
```

6. Convert launch\_dict to Dataframe:

```
df= pd.DataFrame({ key:pd.Series(value) for key, value in launch_dict.items() })
```

GitHub

# Data Wrangling

---

- Conducted Exploratory Data Analysis (EDA) to find patterns in data and define labels for training supervised models.
- The data set contained various mission outcomes that were converted into Training Labels with 1 meaning the booster successfully landed and 0 meaning booster was unsuccessful in landing. Following landing scenarios were considered to create labels:
  - True Ocean means the mission outcome was successfully landed to a specific region of the ocean.
  - False Ocean means the mission outcome was unsuccessfully landed to a specific region of the ocean.
  - True RTLS means the mission outcome was successfully landed to a ground pad.
  - False RTLS means the mission outcome was unsuccessfully landed to a ground pad.
  - True ASDS means the mission outcome was successfully landed on a drone ship.
  - False ASDS means the mission outcome was unsuccessfully landed on a drone ship.

# Data Wrangling – cont'd

## 1. Load dataset into Dataframe

### 1. Load SpaceX dataset (csv) into a Dataframe:

```
df=pd.read_csv("https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DS9321EN-SkillsNetwork/datasets/dataset_part_1.csv")
df.head(10)
```

	FlightNumber	Date	BoosterVersion	PayloadMass	Orbit	LaunchSite	Outcome	Flights	GridFins	Reused	Legs	LandingPad	Block	ReuseCount	Serial
0	1	2010-06-04	Falcon 9	6104.953412	LEO	CCAFS SLC 40	None	1	False	False	False	NaN	1.0	0	B0003
1	2	2012-05-22	Falcon 9	525.000000	LEO	CCAFS SLC 40	None	1	False	False	False	NaN	1.0	0	B0005
2	3	2013-03-01	Falcon 9	677.000000	ISS	CCAFS SLC 40	None	1	False	False	False	NaN	1.0	0	B0007

## 2. Find patterns in data

### 2. Find data patterns:

- Calculate the number of launches on each site

```
df['LaunchSite'].value_counts()
```

CCAFS SLC 40	55
KSC LC 39A	22
VAFB SLC 4E	13

- Calculate the number and occurrence of each orbit

```
df.Orbit.value_counts()
```

GTO	27
ISS	21
VLEO	14
PO	9
LEO	7
SFO	5
MEO	3
ES-L1	1
HEO	1
SO	1
GEO	1

- Calculate number/occurrence of mission outcomes per orbit type

```
landing_outcomes=df.Outcome.value_counts()
```

landing_outcomes	
True ASDS	41
None None	19
True RTLS	14
False ASDS	6
True Ocean	5
False Ocean	2
None ASDS	2
False RTLS	1

## 3. Create landing outcome label

### 3. Create a landing outcome label from Outcome column in the Dataframe:

```
landing_class=[]
#landing_class = 0 if bad_outcome
#landing_class = 1 otherwise
for val in df.Outcome:
    if val in bad_outcomes:
        landing_class.append(0)
    else:
        landing_class.append(1)
```

```
df['Class']=landing_class
df[['Class']].head(8)
```

# EDA with Data Visualization

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As part of the Exploratory Data Analysis (EDA), following charts were plotted to gain further insights into the dataset:

## 1. Scatter plot:

- Shows relationship or correlation between two variables making patterns easy to observe
- Plotted following charts to visualize:
  - Relationship between Flight Number and Launch Site
  - Relationship between Payload and Launch Site
  - Relationship between Flight Number and Orbit Type
  - Relationship between Payload and Orbit Type

## 2. Bar Chart:

- Commonly used to compare the values of a variable at a given point in time. Bar charts makes it easy to see which groups are highest/common and how other groups compare against each other. Length of each bar is proportional to the value of the items that it represents
- Plotted following Bar chart to visualize:
  - Relationship between success rate of each orbit type

## 3. Line Chart:

- Commonly used to track changes over a period of time. It helps depict trends over time.
- Plotted following Line chart to observe:
  - Average launch success yearly trend

# EDA with SQL

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To better understand SpaceX data set, following SQL queries/operations were performed on the Oracle database:

- 1) Display the names of the unique launch sites in the space mission.
- 2) Display 5 records where launch sites begin with the string 'CCA'.
- 3) Display the total payload mass carried by boosters launched by NASA (CRS).
- 4) Display average payload mass carried by booster version F9 v1.1.
- 5) List the date when the first successful landing outcome in ground pad was achieved.
- 6) List the names of the boosters which have success in drone ship and have payload mass greater than 4000 but less than 6000.
- 7) List the total number of successful and failure mission outcomes.
- 8) List the names of the booster\_versions which have carried the maximum payload mass. Use a subquery.
- 9) List the failed landing\_outcomes in drone ship, their booster versions, and launch site names for in year 2015.
- 10) 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.



# Build an Interactive Map with Folium

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- Folium interactive map helps analyze geospatial data to perform more interactive visual analytics and better understand factors such as location and proximity of launch sites that impact launch success rate.
- Following map object were created and added to the map:
  - Mark all launch sites on the map. This allowed to visually see the launch sites on the map.
    - Added 'folium.circle' and 'folium.marker' to highlight circle area with a text label over each launch site.
  - Added a 'MarkerCluster()' to show launch success (green) and failure (red) markers for each launch site.
  - Calculated distances between a launch site to its proximities (e.g., coastline, railroad, highway, city).
    - Added 'MousePosition()' to get coordinate for a mouse position over a point on the map.
    - Added 'folium.Marker()' to display distance (in KM) on the point on the map (e.g., coastline, railroad, highway, city).
    - Added 'folium.Polyline()' to draw a line between the point on the map and the launch site.
    - Repeated steps above to add markers and draw lines between launch sites and proximities – coastline, railroad, highway, city).
- Building the Interactive Map with Folium helped answered following questions:
  - Are launch sites in close proximity to railways? *YES*
  - Are launch sites in close proximity to highways? *YES*
  - Are launch sites in close proximity to coastline? *YES*
  - Do launch sites keep certain distance away from cities? *YES*

# Build a Dashboard with Plotly Dash

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- Built a Plotly Dash web application to perform interactive visual analytics on SpaceX launch data in real-time. Added Launch Site Drop-down, Pie Chart, Payload range slide, and a Scatter chart to the Dashboard.
  - Added a Launch Site Drop-down Input component to the dashboard to provide an ability to filter Dashboard visual by all launch sites or a particular launch site.
  - Added a Pie Chart to the Dashboard to show total success launches when 'All Sites' is selected and show success and failed counts when a particular site is selected.
  - Added a Payload range slider to the Dashboard to easily select different payload ranges to identify visual patterns.
  - Added a Scatter chart to observe how payload may be correlated with mission outcomes for selected site(s). The color-label Booster version on each scatter point provided missions outcomes with different boosters.
- Dashboard helped answer following questions:
  1. Which site has the largest successful launches? *KSC LC-39A with 10*
  2. Which site has the highest launch success rate? *KSC LC-39A with 76.9% success*
  3. Which payload range(s) has the highest launch success rate? *2000 – 5000 kg*
  4. Which payload range(s) has the lowest launch success rate? *0-2000 and 5500 - 7000*
  5. Which F9 Booster version (v1.0, v1.1, FT, B4, B5, etc.) has the highest launch success rate? *FT*

# Predictive Analysis (Classification)

1. Read dataset into Dataframe and create a 'Class' array

2. Standardize the data

3. Train/Test/Split data in to training and test data sets

4. Create and Refine Models

5. Find the best performing Model

1. Load SpaceX dataset (csv) into a Dataframe and create NumPy array from the column class in data:

```
URL1 = "https://cf-courses-data.s3.us.cloud-  
data = pd.read_csv(URL1)  
  
Y=data['Class'].to_numpy()  
Y
```

2. Standardize data in X then reassign to variable X using fit and transform:

```
transform = preprocessing.StandardScaler()  
transform.fit(X)  
X=transform.transform(X)  
X
```

3. Train/test/split X and Y into training and test datasets:

```
# Allows us to split our data into training and testing data  
from sklearn.model_selection import train_test_split
```

```
X_train, X_test, Y_train, Y_test = train_test_split( X, Y,  
test_size=0.2, random_state=2)
```

```
Y_test.shape  
  
(18,)
```

4. Create and refine Models based on following classification Algorithms: (below is SVM example)

- Create Support Vector Machine object and then create a GridSearchCV object
- Fit train dataset into the GridSearchCV object and train the Model

```
parameters = {'kernel':('linear', 'rbf','poly','rbf', 'sigmoid'),  
              'C': np.logspace(-3, 3, 5),  
              'gamma':np.logspace(-3, 3, 5)}  
  
svm = SVC()  
svm_cv=GridSearchCV(svm,parameters,cv=10)  
svm_cv.fit(X_train,Y_train)
```

- Find and display best hyperparameters and accuracy score

```
print("tuned hpyerparameters :(best parameters) ",svm_cv.best_params_)  
print("accuracy :",svm_cv.best_score_)
```

- Check the accuracy on the test data by creating a confusion matrix

```
yhat=svm_cv.predict(X_test)  
plot_confusion_matrix(Y_test,yhat)
```

- Repeat above steps for Logistic Regression, Decision Tree and KNN algorithms

5. Find the best performing model:

```
models=['Logistic Regression', 'Support Vector Machine', 'Decision Tree', 'K Nearest Neighbors']  
accuracy=[logreg_cv.best_score_,svm_cv.best_score_,tree_cv.best_score_,knn_cv.best_score_]
```

```
maxindex=np.argmax(accuracy)  
print(f'Best performing method: {models[maxindex]}')
```

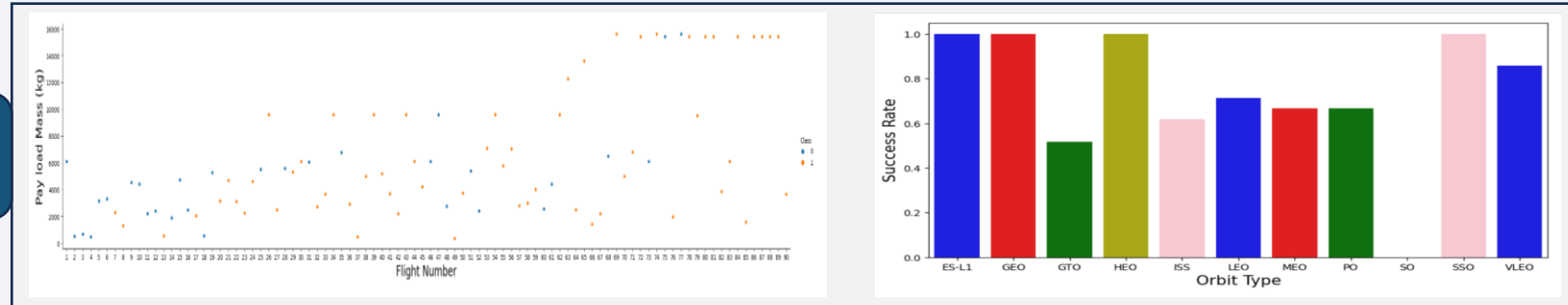
Best performing method: Decision Tree

[GitHub](#)

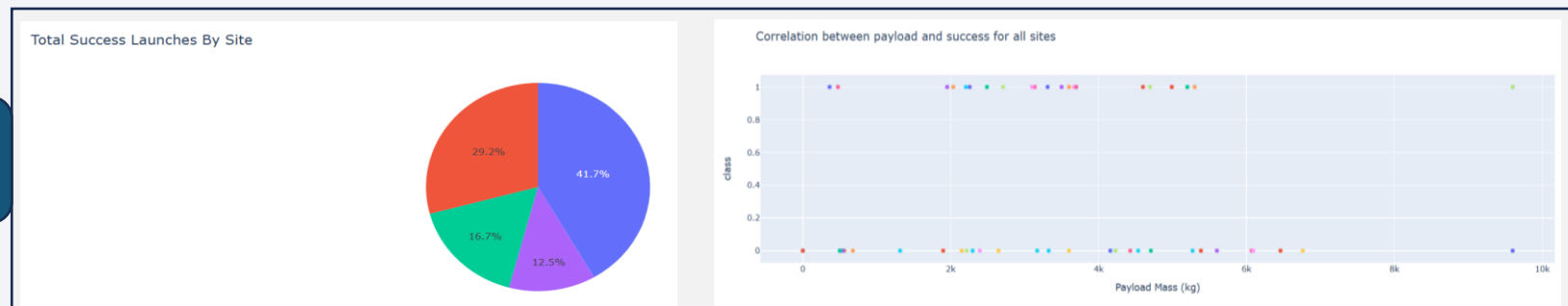
# Results

Following sections and slides explain results for:

## Exploratory data analysis results



## Interactive analytics results



## Predictive analysis results

	Model	Accuracy Score
0	Logistic Regression	0.846429
1	Support Vector Machine	0.848214
2	Decision Tree	0.876786
3	K Nearest Neighbors	0.848214



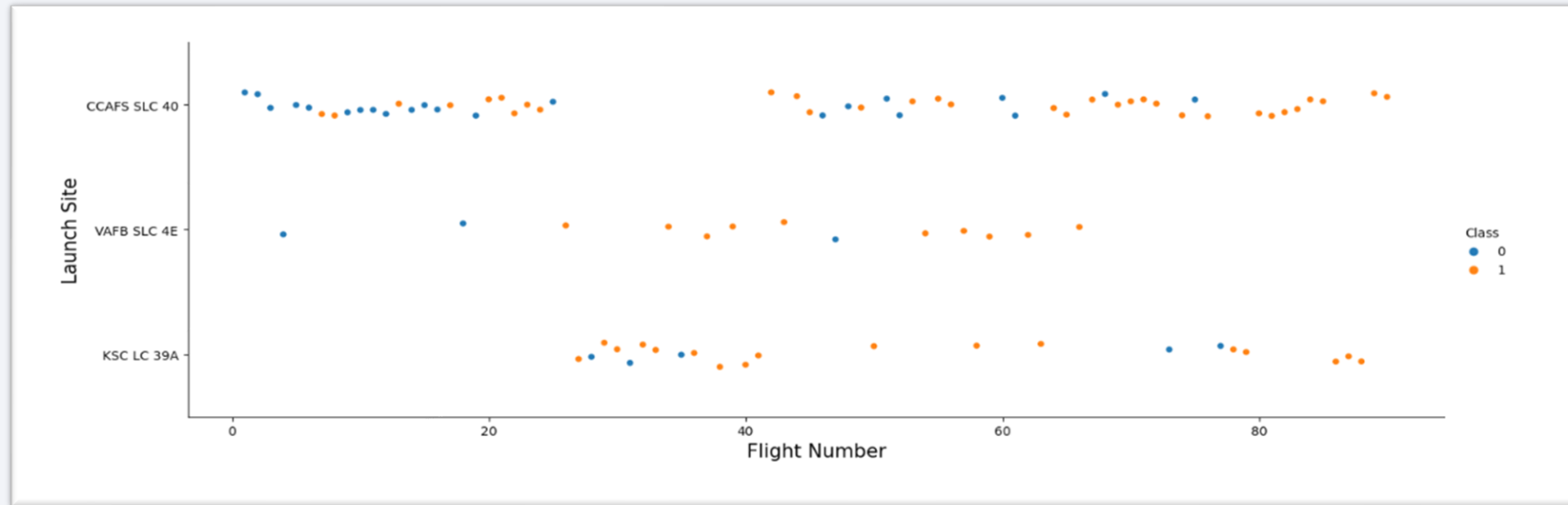


Section 2

# Insights drawn from EDA

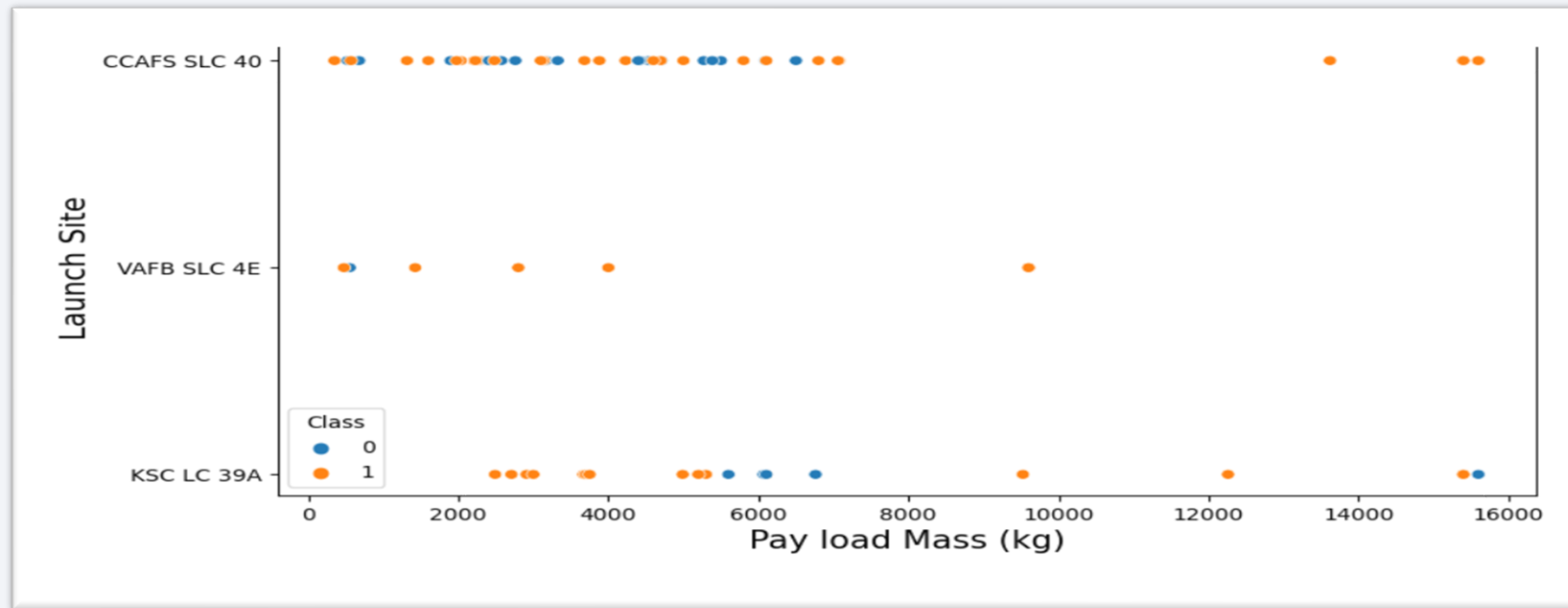


# Flight Number vs. Launch Site



- Success rates (Class=1) increases as the number of flights increase.
- For launch site 'KSC LC 39A', it takes at least around 25 launches before a first successful launch.

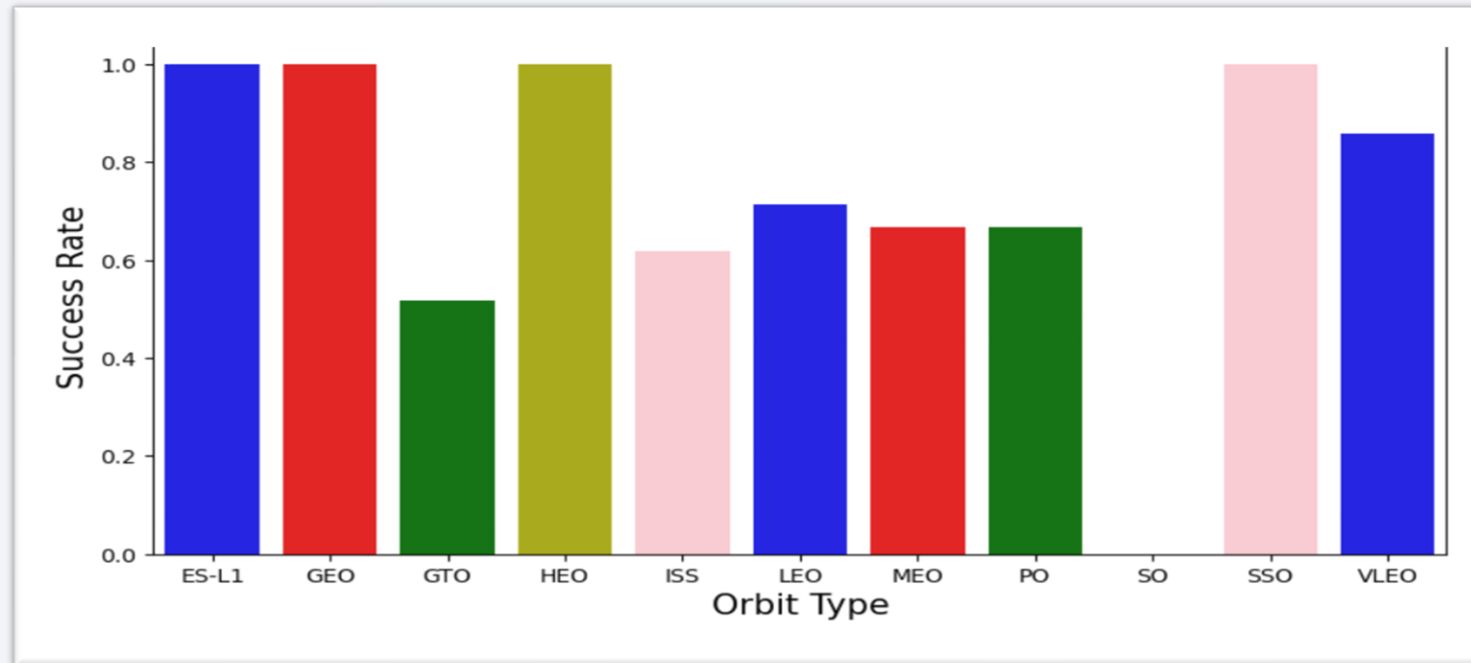
# Payload vs. Launch Site



- For launch site 'VAFB SLC 4E', there are no rockets launched for payload greater than 10,000 kg.
- Percentage of successful launch (Class=1) increases for launch site 'VAFB SLC 4E' as the payload mass increases.
- There is no clear correlation or pattern between launch site and payload mass.

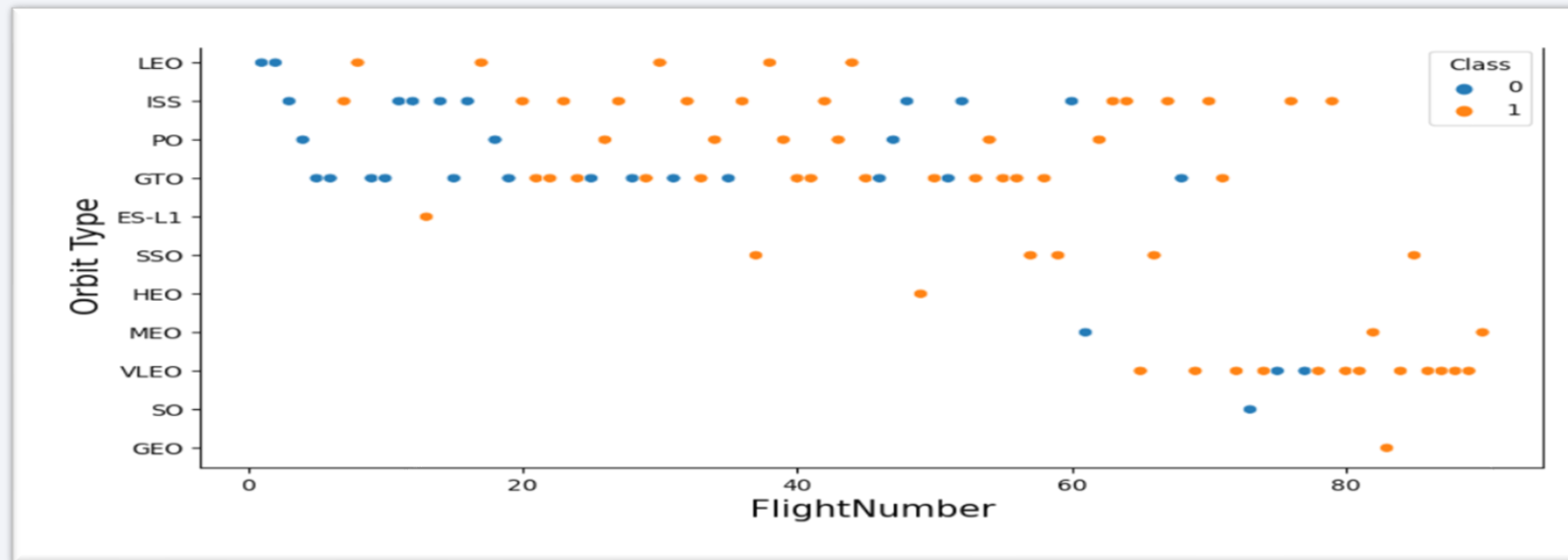
# Success Rate vs. Orbit Type

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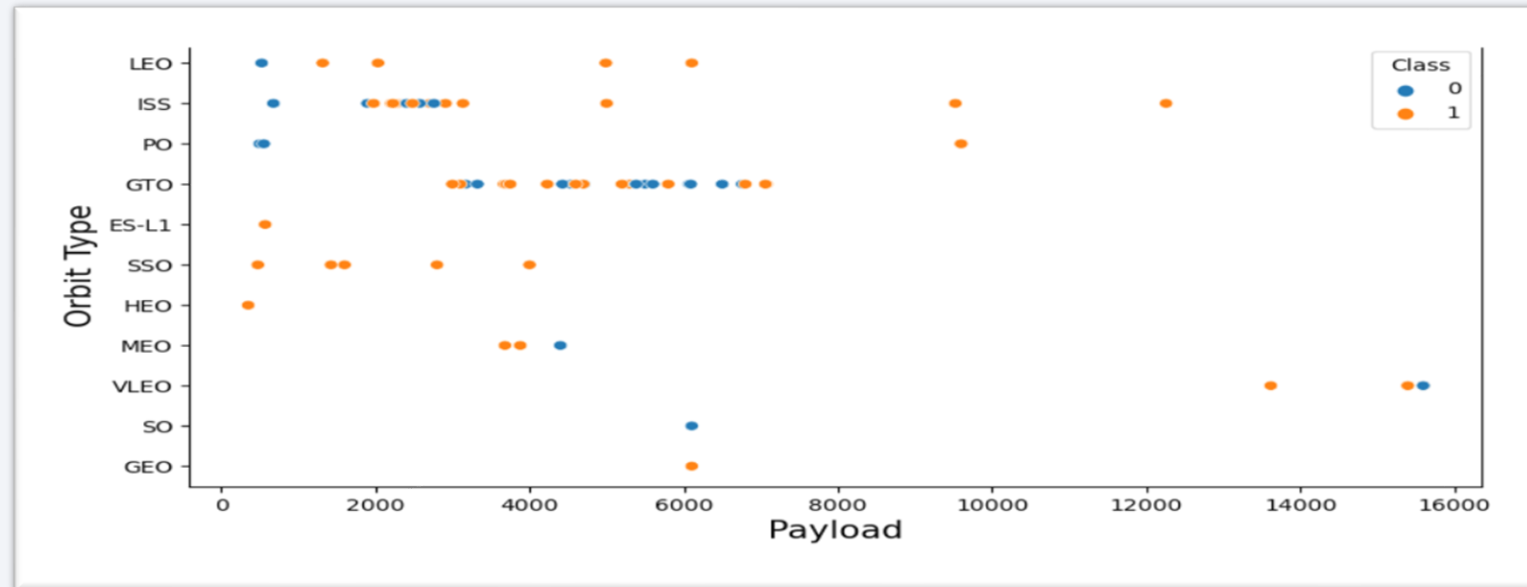
- Orbits ES-LI, GEO, HEO, and SSO have the highest success rates.
- SO orbit has the lowest success rate.

# Flight Number vs. Orbit Type



- For orbit VLEO, first successful landing (class=1) doesn't occur until 60+ number of flights.
- For most orbits (LEO, ISS, PO, SSO, MEO, VLEO) successful landing rates appear to increase with flight numbers.
- There is no relationship between flight number and orbit for GTO.

# Payload vs. Orbit Type

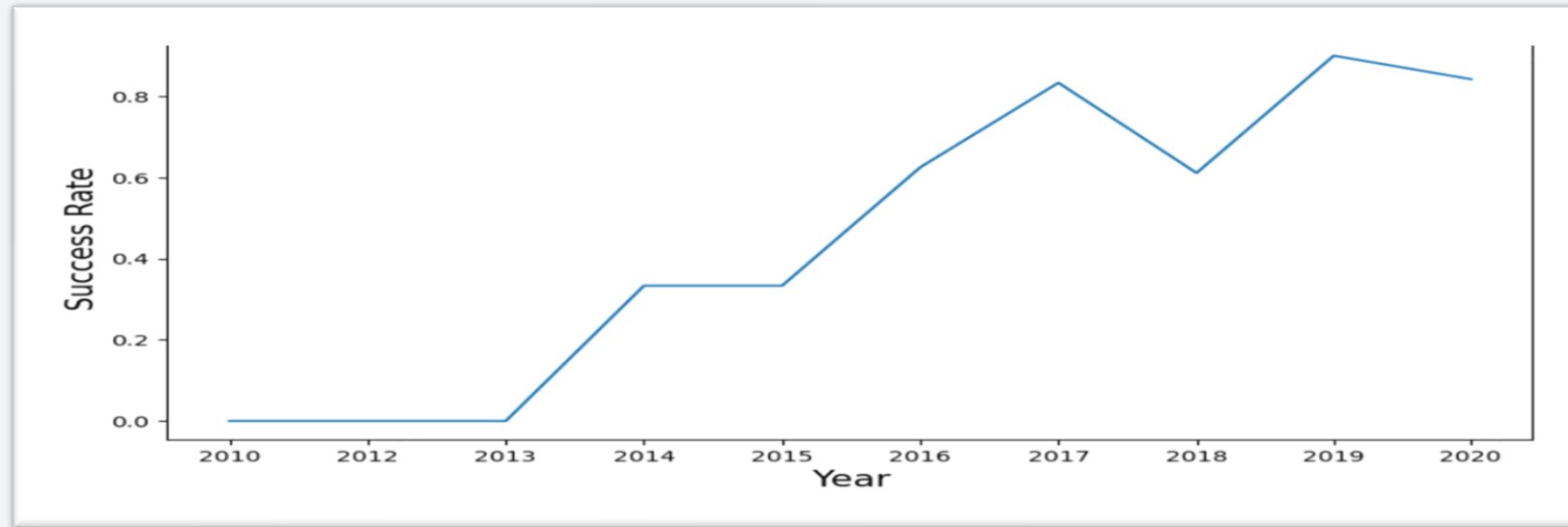


- Successful landing rates (Class=1) appear to increase with payload for orbits LEO, ISS, PO, and SSO.
- For GEO orbit, there is not clear pattern between payload and orbit for successful or unsuccessful landing.



# Launch Success Yearly Trend

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- Success rate (Class=1) increased by about 80% between 2013 and 2020.
- Success rates remained the same between 2010 and 2013 and between 2014 and 2015.
- Success rates decreased between 2017 and 2018 and between 2019 and 2020.

# All Launch Site Names

---

## Query:

```
%sql select distinct Launch_Site from spacetable
```

## Description:

- 'distinct' keyword returns only unique values from the query's column 'Launch\_Site'.
- There are 4 unique launch sites.

## Result:

launch_site
KSC LC-39A
CCAFS SLC-40
CCAFS LC-40
VAFB SLC-4E

# Launch Site Names Begin with 'CCA'

## Query:

```
%sql select * from(select * from spacetable where launch_site like 'CCA%') where rownum<=5
```

## Description:

- Using keyword 'like' and format 'CCA%', returns records where 'Launch\_Site' column starts with "CCA".
- 'rownum<=5', limits the number of returned records to 5.

## Result:

id	date_of	time_utc	booster_version	launch_site	payload	payload_mass__kg__	orbit	customer	mission_outcome	landing_outcome
85	2018-12-05 00:00:00	18:16:00	F9 B5B1050	CCAFS SLC-40	SpaceX CRS-16	2500	LEO (ISS)	NASA (CRS)	Success	Failure
86	2018-12-23 00:00:00	13:51:00	F9 B5B1054	CCAFS SLC-40	GPS III-01	4400	MEO	USAF	Success	No attempt
88	2019-02-22 00:00:00	1:45:00	F9 B5 B1048.3	CCAFS SLC-40	"Nusantara Satu, Beresheet Moon lander, S5"	4850	GTO	"PSN, SpaceIL / IAI"	Success	Success
90	2019-05-04 00:00:00	6:48:00	F9 B5B1056.1	CCAFS SLC-40	"SpaceX CRS-17, Starlink v0.9"	2495	LEO (ISS)	NASA (CRS)	Success	Success
91	2019-05-24 00:00:00	2:30:00	F9 B5 B1049.3	CCAFS SLC-40	"Starlink v0.9, RADARSAT Constellation"	13620	LEO	SpaceX	Success	Success

# Total Payload Mass

---

## Query:

```
%%sql select booster_version,sum(payload_mass_kg_)as total_payload_mass from spacetable where customer='NASA (CRS)'  
group by booster_version
```

## Description:

- 'sum()' adds column 'payload\_mass\_kg\_' and returns total payload mass carried by boosters launched by 'NASA (CRS)'.

## Result:

booster_version	total_payload_mass
F9 v1.1 B1010	2216
F9 FT B1035.2	2205
F9 B4 B1045.2	2697
F9 v1.0 B0006	500
F9 v1.1	2296
F9 FT B1035.1	2708
F9 B5 B1056.2	2268
F9 B5 B1059.2	1977
F9 B5 B1058.4	2972
F9 v1.1 B1012	2395
F9 v1.0 B0007	677
F9 v1.1 B1018	1952
F9 FT B1031.1	2490
F9 v1.1 B1015	1898
F9 FT B1021.1	3136
F9 FT B1025.1	2257
F9 B4 B1039.1	3310
F9 B4 B1039.2	2647
F9 B5B1050	2500
F9 B5B1056.1	2495

# Average Payload Mass by F9 v1.1

---

## Query:

```
%sql select avg(payload_mass_kg_) as average_payload_mass from spacetable where booster_version='F9 v1.1'
```

## Description:

- 'avg()' returns the average of payload mass in 'payload\_mass\_kg\_' column where booster version is 'F9 v1.1'.

## Result:

average_payload_mass
----------------------

2928.4
--------



# First Successful Ground Landing Date

---

## Query:

```
%sql select min(date_of) as first_successful_groundpad from spacetable where landing_outcome='Success (ground pad)'
```

## Description:

- 'min(date\_of)' selects the first or the oldest date from the 'date\_of' column where first successful landing on ground pad was achieved.
- where clause defines the criteria to return date for scenarios where 'landing\_outcome' value is equal to 'Success (ground pad)'.

## Result:

first_successful_groundpad
2015-12-22 00:00:00

# Successful Drone Ship Landing with Payload between 4000 and 6000

---

## Query:

```
%%sql
select distinct booster_version from spacetable where landing_outcome='Success (drone ship)' and payload_mass__kg_
between 4000 and 6000
```

## Description:

- The query finds the booster version where payload mass is greater than 4000 but less than 6000 and the landing outcome is success in drone ship.
- The 'and' operator in the where clause returns booster versions where both conditions in the where clause are true.

## Result:

booster_version
-----------------

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

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

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

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

# Total Number of Successful and Failure Mission Outcomes

---

## Query:

```
%sql select mission_outcome,count(*)as Count from spacetable group by mission_outcome
```

## Description:

- The 'group by' keyword arranges identical data in a column into group.
- In this case, number of mission outcomes by types of outcomes are grouped in column 'counts'.

## Result:

mission_outcome	count
Success (payload status unclear)	1
Success	99
Failure (in flight)	1

# Boosters Carried Maximum Payload

---

## Query:

```
%%sql
select booster_version as carrying_max_payload_mass from spacetable where payload_mass_kg_ =
(select max(payload_mass_kg_) from spacetable)
```

## Description:

- The sub query returns the maximum payload mass by using 'max()' on the 'payload\_mass\_kg\_' column.
- The main query returns booster versions where payload mass is maximum.

## Result:

carrying_max_payload_mass
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

---

## Query:

```
%%sql
select to_char(date_of,'month') as month,landing_outcome,booster_version,launch_site from spacetable where
landing_outcome='Failure (drone ship)' and extract(year from date_of)='2015'
```

## Description:

- The query lists month names, landing outcome, booster version, and the launch site where landing outcome is failed in drone ship and the year is 2015.
- The 'and' operator in the where clause returns booster versions where both conditions in the where clause are true.
- The 'year' keyword extracts the year from column 'date\_of'.
- The results identify launch site as 'CCAFS LC-40' and booster version as F9 v1.1 B1012 and B1015 that had failed landing outcomes in drop ship in the year 2015.

## Result:

month	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

## Query:

```
%%sql
select landing_outcome,count,dense_rank() over (order by count desc) rank from
(select landing_outcome, count(*) as count from spacetable where date_of between to_date('2010-06-04','YYYY-MM-DD') and
to_date('2019-03-20','YYYY-MM-DD') group by landing_outcome order by count(*))
```

## Description:

- The 'group by' keyword arranges data in column 'landing\_outcome' into groups.
- The 'between' and 'and' keywords return data that is between 2010-06-04 and 2017-03-20.
- The 'order by' keyword arranges the counts column in descending order.
- The result of the query is a ranked list of landing outcome counts as per the specified date range.

## Result:

landing_outcome	count	rank
No attempt	20	1
Success (drone ship)	14	2
Success	10	3
Success (ground pad)	9	4
Controlled (ocean)	5	5
Failure (drone ship)	5	5
Failure (parachute)	2	6
Uncontrolled (ocean)	2	6
Precluded (drone ship)	1	7
Failure	1	7

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 and a view of the Earth's surface, which is covered in a dense network of city lights and clouds. The lights are concentrated in the lower right portion of the image, while the upper left shows a clear blue sky.

Section 3

# Launch Sites Proximities Analysis



# SpaceX Falcon 9 - Launch Sites Map

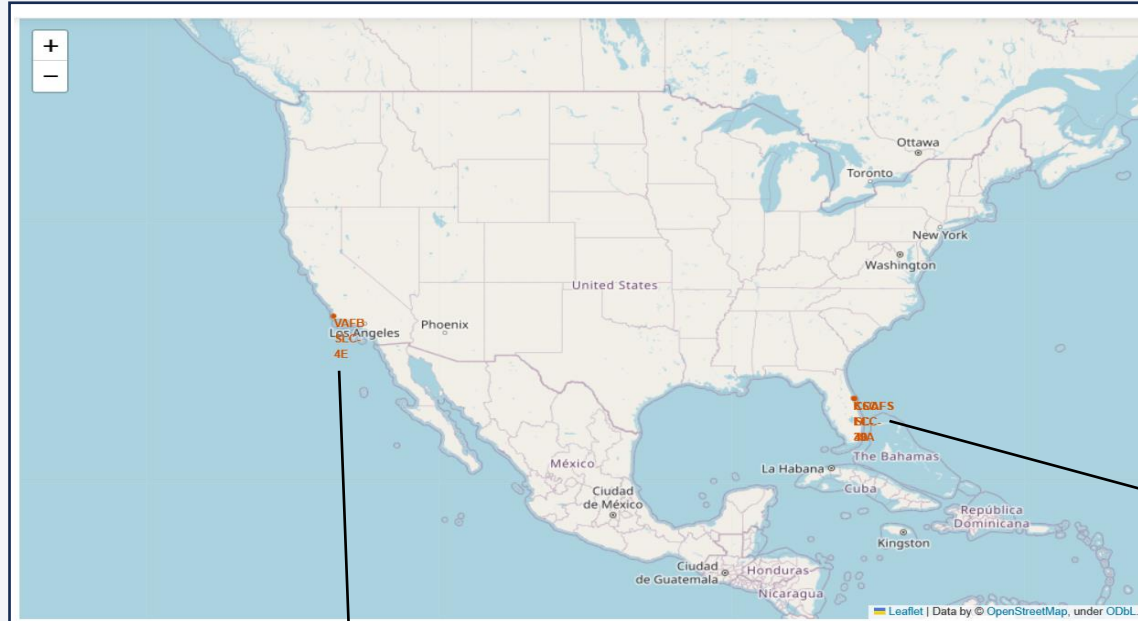


Fig 1 – Global Map

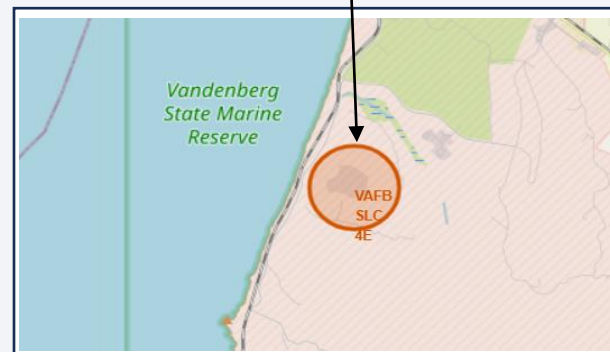


Fig 2 – Zoom 1

Figure 1 on left displays the Global map with Falcon 9 launch sites that are located in the United States (in California and Florida). Each launch site contains a circle, label, and a popup to highlight the location and the name of the launch site. It is also evident that all launch sites are near the coast.

Figure 2 and Figure 3 zoom in to the launch sites to display 4 launch sites:

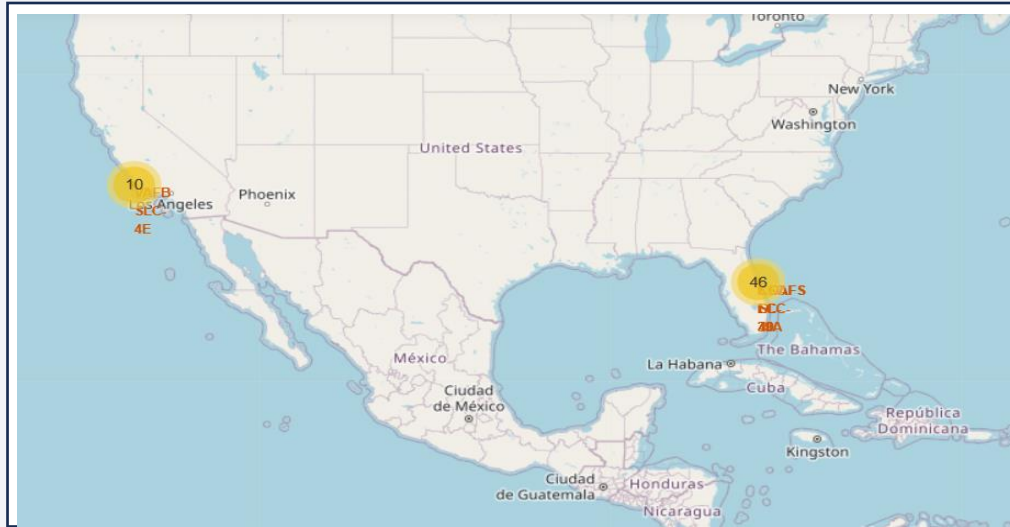
- VAFB SLC-4E (CA)
- CCAFS LC-40 (FL)
- KSC LC-39A (FL)
- CCAFS SLC-40 (FL)



Fig 3 – Zoom 2

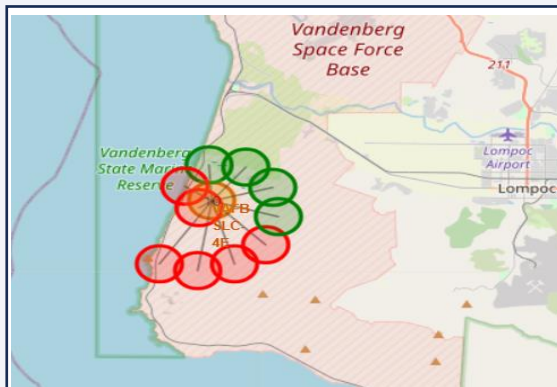


# SpaceX Falcon 9 – Success/Failed Launch Map for all Launch Sites

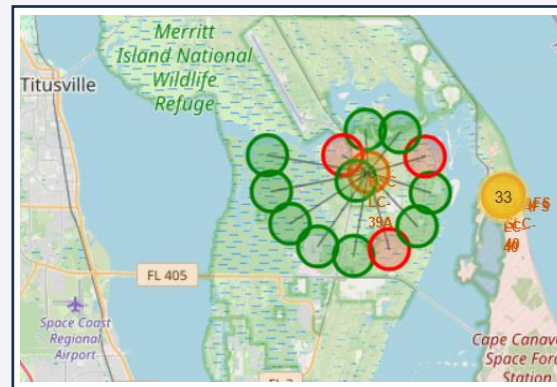


**Fig 1 – US map with all Launch Sites**

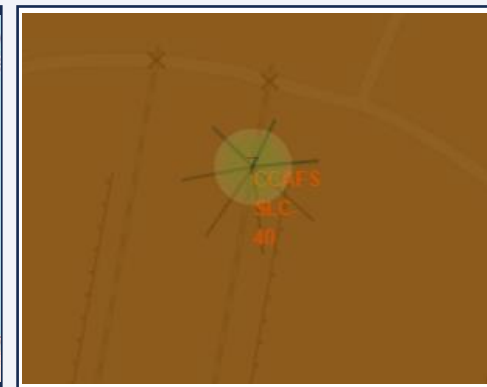
- Figure 1 is the US map with all the Launch Sites. The numbers on each site depict the total number of successful and failed launches.
- Figure 2, 3, 4, and 5 zoom in to each site and displays the success/fail markers with green as success and red as failed.
- By looking at each site map, KSC LC-39A Launch Site has the largest number of successful launches.



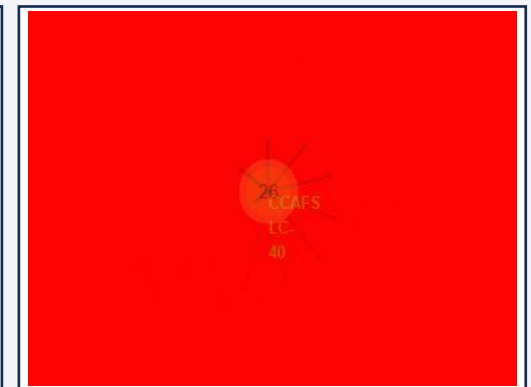
**Fig 2 – VAFB SLC-4E  
success/failed markers**



**Fig 3 – KSC LC-39A  
success/failed markers**



**Fig 4 – CCAFS SLC-40 success/failed markers**



**Fig 5 – CCAFS LC-40  
success/failed markers**

# SpaceX Falcon 9 – Launch Site to proximity Distance Map

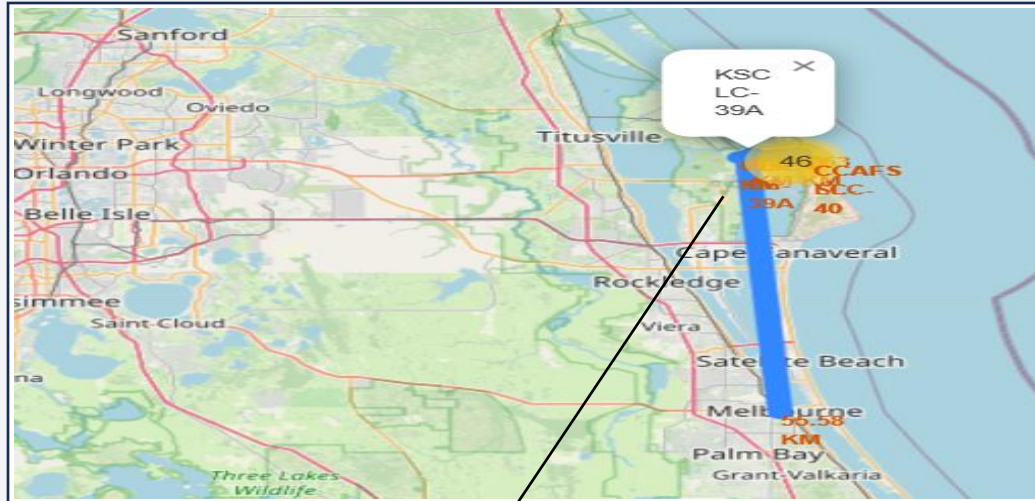


Fig 1 – Proximity site map for KSC LC-39A



Fig 2 – Zoom in for sites – coastline, railroad, and highway

- Figure 1 displays all the proximity sites marked on the map for Launch Site KSC LC-39A. City Melbourne is located further away from Launch Site compared to other proximities such as coastline, railroad, highway, etc. The map also displays a marker with city distance from the Launch Site (55.58 km).
- Figure 2 provides a zoom in view into other proximities such as coastline, railroad, and highway with respective distances from the Launch Site.
- In general, cities are located away from the Launch Sites to minimize impacts of any accidental impacts to the general public and infrastructure. Launch Sites are strategically located near the coastline, railroad, and highways to provide easy access to resources.

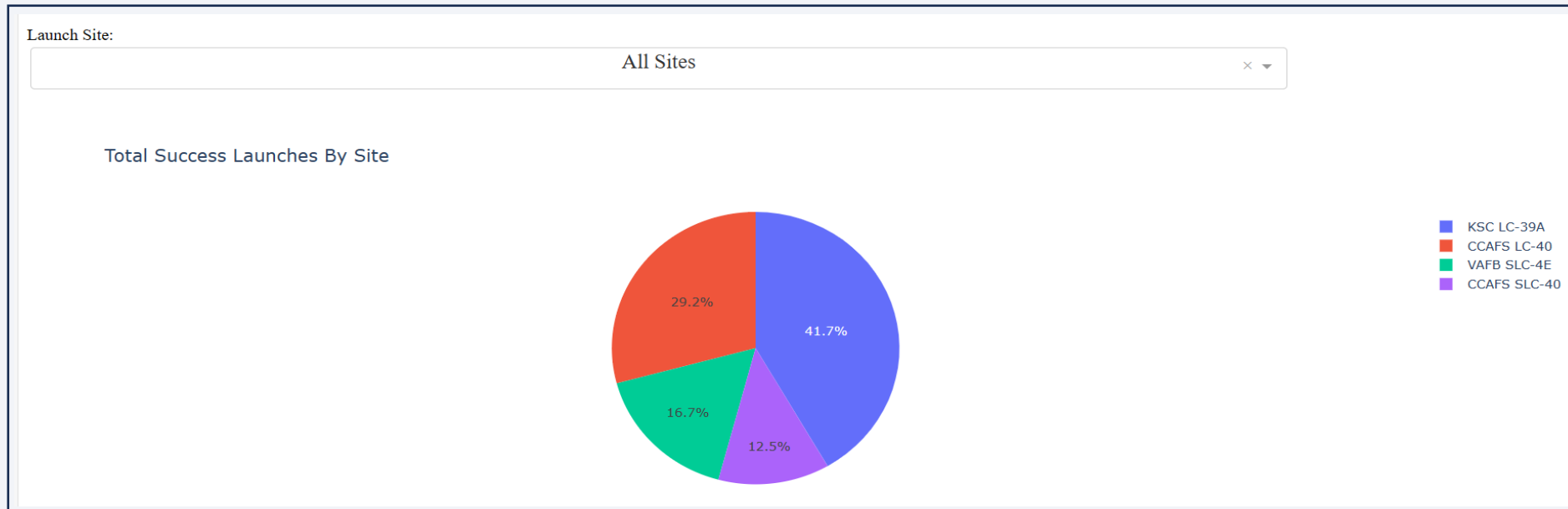




Section 4

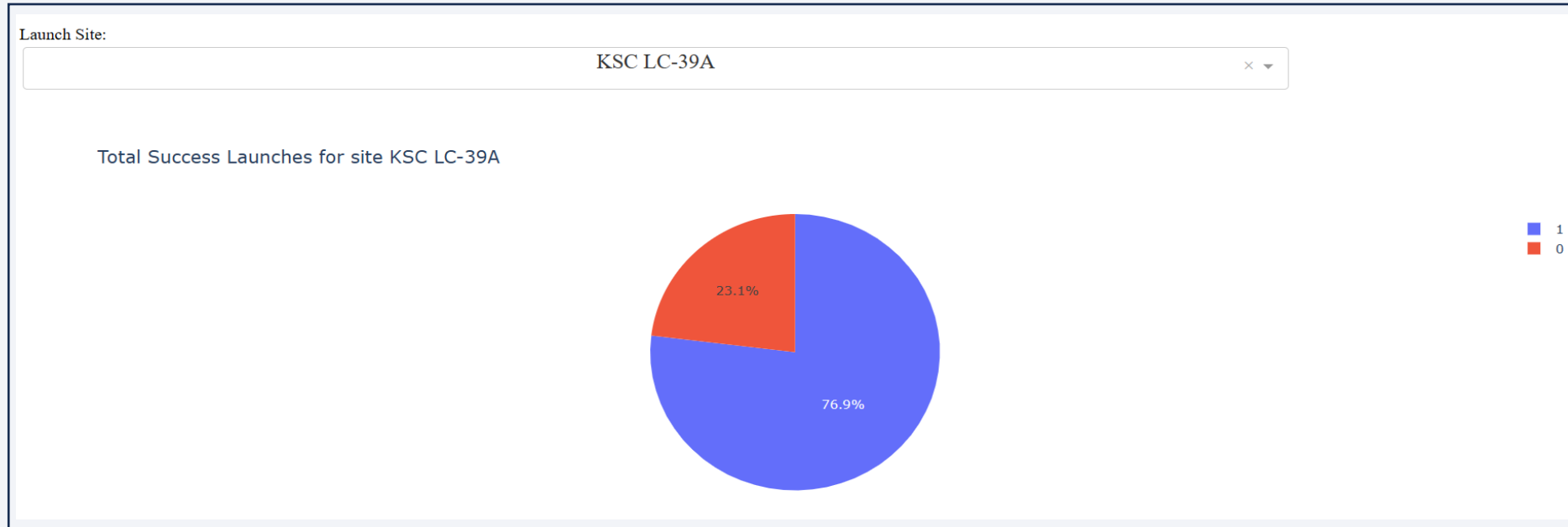
# Build a Dashboard with Plotly Dash

# Launch Success Counts For All Sites



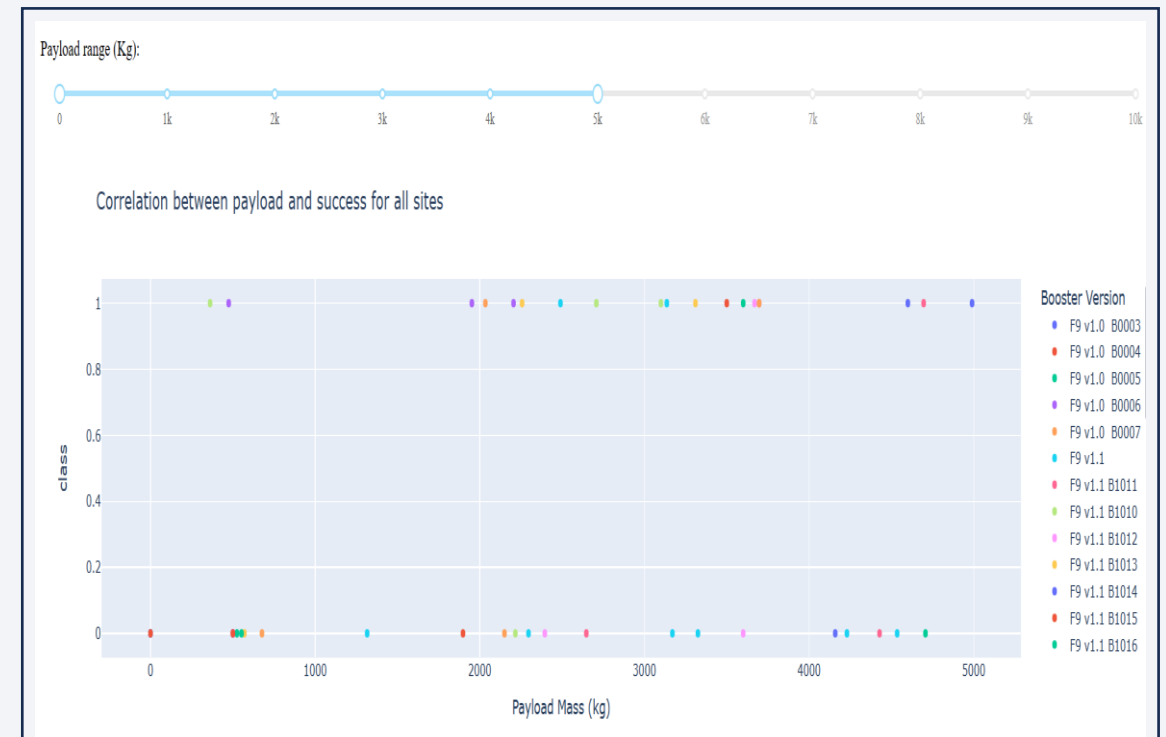
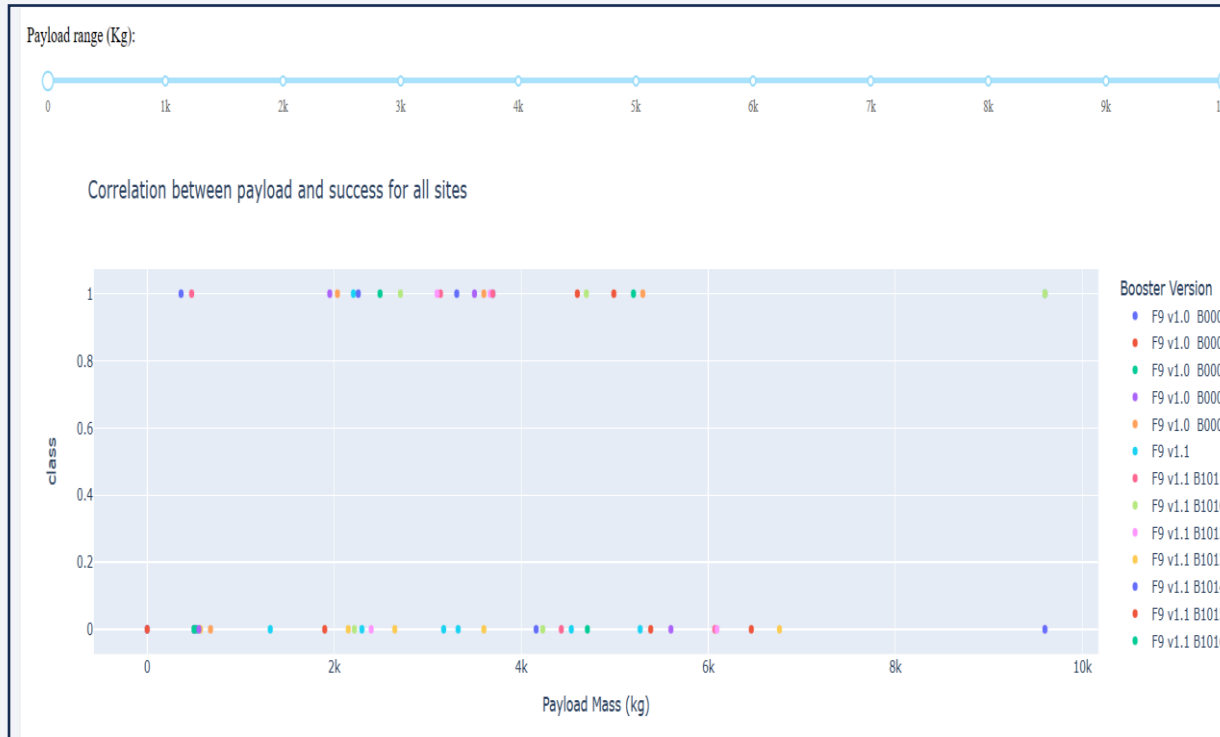
- Launch Site 'KSC LC-39A' has the highest launch success rate.
- Launch Site 'CCAFS SLC-40' has the lowest launch success rate.

# Launch Site with Highest Launch Success Ratio



- KSC LC-39A Launch Site has the highest launch success rate and count.
- Launch success rate is 76.9%.
- Launch success failure rate is 23.1%.

# Payload vs. Launch Outcome Scatter Plot for All Sites



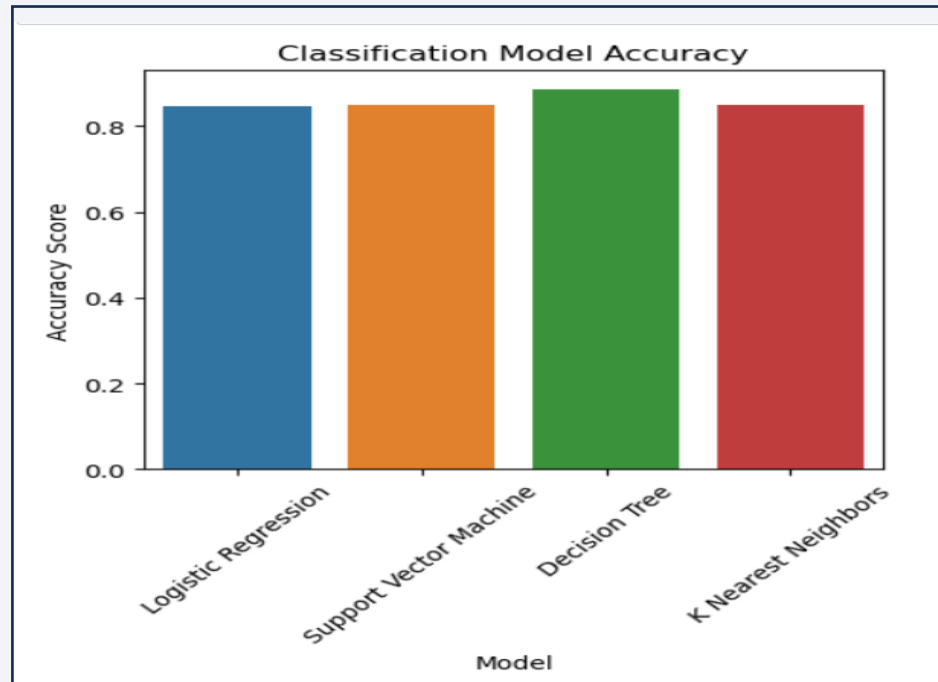
- Most successful launches are in the payload range from 2000 to 5000.
- Booster version category 'FT' has the most successful launches.
- Only booster version with a success launch when payload is greater than 6k is 'F9 B4 B1041.1'.

Section 5

# Predictive Analysis (Classification)



# Classification Accuracy

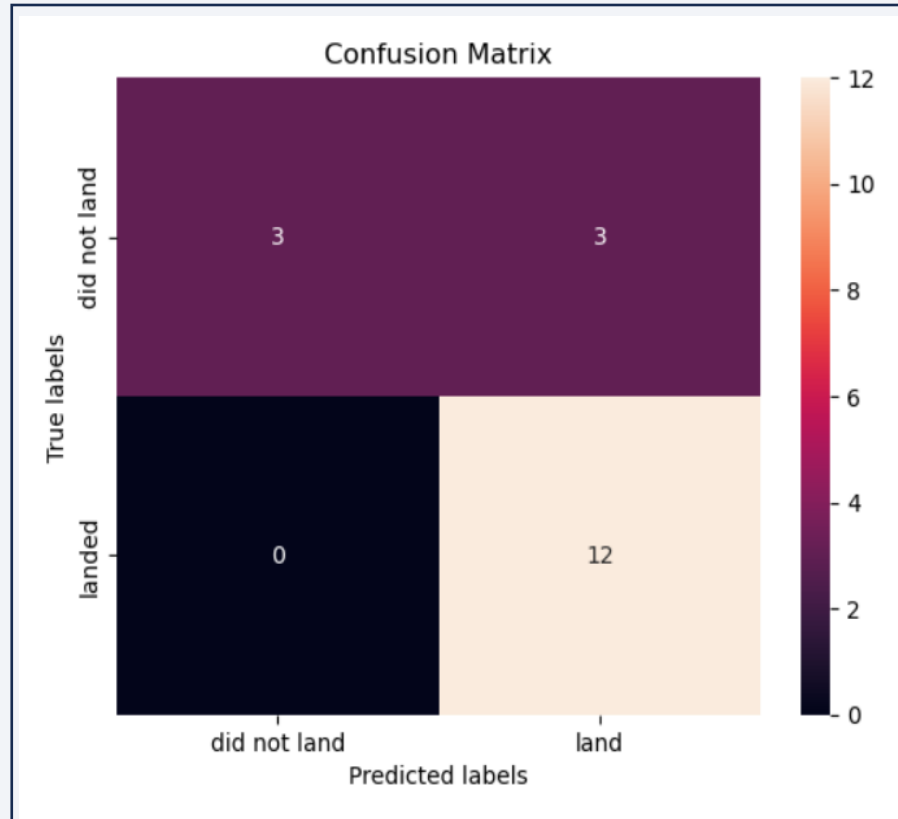


	Model	Accuracy Score	Test Data Accuracy Score
0	Logistic Regression	0.846429	0.833333
1	Support Vector Machine	0.848214	0.833333
2	Decision Tree	0.876786	0.833333
3	K Nearest Neighbors	0.848214	0.833333

- Based on the Accuracy scores and as also evident from the bar chart, Decision Tree algorithm has the highest classification score with a value of 0.876786.
- Accuracy Score on the test data is the same for all the classification algorithms based on the dataset with a value of 0.8333.
- Given that the Accuracy scores for classification algorithms are very close and the test scores are the same, we may need a broader dataset to further tune the models.



# Confusion Matrix



- The confusion matrix is same for all the models (LR, SVM, Decision Tree, KNN).
- As per the confusion matrix, the classifier made 18 predictions.
- 12 scenarios were predicted Yes for landing, and they did land successfully (True positive).
- 3 scenarios (top left) were predicted No for landing, and they did not land (True negative).
- 3 scenarios (top right) were predicted Yes for landing, but they did not land successfully (False positive).
- Overall, the classifier is correct about 83.33% of the time  $((TP + TN) / Total)$  with a misclassification or error rate  $((FP + FN) / Total)$  of about 16.67%.

# Conclusions

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- As the numbers of flights increase, the first stage is more likely to land successfully.
- Success rates appear to go up as Payload increases but there is no clear correlation between Payload mass and success rates.
- Launch success rate increased by about 80% from 2013 to 2020.
- Launch Site 'KSC LC-39A' has the highest launch success rate while Launch Site 'CCAFS SLC-40' has the lowest launch success rate.
- Orbits ES-L1, GEO, HEO, and SSO have the highest launch success rates while orbit SO the lowest.
- Launch sites are located strategically away from the cities and closer to coastline, railroads, and highways.
- The best performing Machine Learning Classification Model is the Decision Tree with an accuracy of about 87.67%. When the models were scored on the test data, the accuracy score was about 83.33% for all models. More data may be needed to further tune the models and find a potential better fit.

# Appendix

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**Project Link : [GitHub](#)**

Thank you!

