Winning Space Race with Data Science

Ashwini Muralidhar Rao
14/02/2023

Outline

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

Executive Summary

The purpose of this study is to examine data on the SpaceX Falcon 9 obtained from multiple sources and use machine learning models to forecast the success of the first stage landing, giving other space agencies the choice of competing with SpaceX or not.

- Summary of methodologies
  - Data collection: Collect data through API and Web scraping
  - Data Wrangling: Transform data through data wrangling
  - Data exploration: Conduct exploratory data analysis with SQL and data visuals
  - Interactive dashboard: Build an interactive map with folium to analyze launch site proximity Build a dashboard to analyze launch records interactively with Plotly Dash
  - Predictive modelling: 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

- Project background and context
  - The space industry is becoming more and more mainstream and accessible to the general public as a result of recent advances in private space flight.
  - The cost of launch is still a major deterrent for new competitors entering the space race.
  - Approximately 62 million dollars are spent on each SpaceX flight, and stage 1 can be used again for subsequent launches.
  - This gives SpaceX a distinct advantage over rivals who typically spend more than 165 missions for each launch.
- Problems you want to find answers
  - Identify the success of SpaceX Falcon 9's first stage's landing.
  - Effects of various factors/parameters on the results of landing (such as launch site, payload mass, booster version, etc.)
  - Correlations between launch sites and success rate

Section 1

Methodology

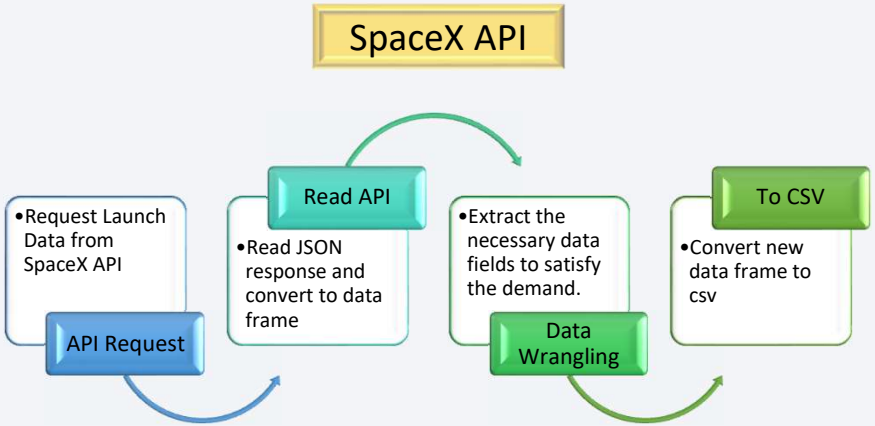
Methodology

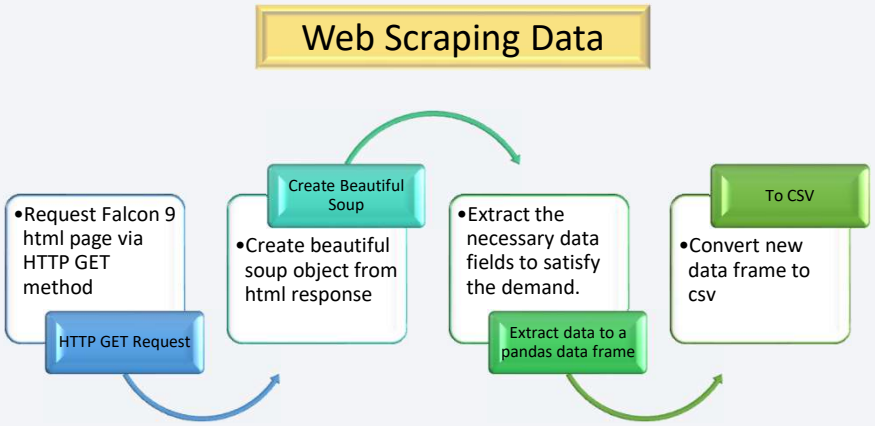
Executive Summary

- 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 in to 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

- The process of acquiring data from readily available sources is known as data collection. Structured, unstructured, or semi-structured data are all possible. Data was gathered for this project using the SpaceX API and web scraping Wiki pages for pertinent launch information.





Data Collection – SpaceX API

1. API Request and Read Response into Data frame
2. Set Global Variables
3. Helper functions with API calls to populate global variables
4. Construct data using dictionary
5. Convert dictionary to data frame, filter Flcon9 launches and convert to csv

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

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

```
In [6]: spacex_url="https://api.spacexdata.com/v4/launches/past"

In [7]: response = requests.get(spacex_url)
```

Now we decode the response content as a Json using `.json()` and turn it into a Pandas dataframe using `.json_normalize()`

```
In [18]: # Use json_normalize meethod to convert the json result into a dataframe
         data = pd.json_normalize(response.json())
```

2. Set Global Variables

```
In [21]: #Global variables
         BoosterVersion = []
         PayloadMass = []
         Orbit = []
         LaunchSite = []
         Outcome = []
         Flights = []
         GridFins = []
         Reused = []
         Legs = []
         LandingPad = []
         Block = []
         ReusedCount = []
         Serial = []
         Longitude = []
         Latitude = []
```

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

```
In [28]: 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}
```

3. 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)

5. Convert dictionary to data frame, filter Flcon9 launches and convert to csv

```
In [30]: # Create a data from launch_dict
         df_launch = pd.DataFrame(launch_dict)
```

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

GITHUB LINK

Data Collection - Scraping

1 Perform HTTP GET request Request HTML page

2. Create Beautiful Soup Object

3. Extract column names from HTML table header

4. Create dictionary with keys from extracted column names

5. Call helper functions and fill dict with launch records

6. Convert Dictionary to Data frame

1. Perform HTTP GET request and Request HTML page

```
static_url = "https://en.wikipedia.org/w/index.php?title=List_of_Falcon_9_and_Falcon_Heavy_launches&oldid=10276869
```

Next, request the HTML page from the above URL and get a `response` object

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
html_data = requests.get(static_url).text
```

2. Create a Beautiful Soup Object

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

3. Extract column names from HTML table header

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

Next, we just need to iterate through the `<th>` elements and apply the provided `extract_column_from_header()` to extrac

```
column_names = []

# Apply find_all() function with `th` element on first_launch_table
# Iterate each th element and apply the provided extract_column_from_header() to get a column name
# Append the Non-empty column name (`if name is not None and len(name) > 0`) into a list called column_names
colnames = soup.find_all('th')
for x in range (len(colnames)):
    name2 = extract_column_from_header(colnames[x])
    if (name2 is not None and len(name2) > 3):
        column_names.append(name2)
```

4. Create dictionary with keys from extracted column names

```
launch_dict= dict.fromkeys(column_names)

# Remove an irrelvant column
del launch_dict['Date and time ( )']

# Let's initial the launch_dict with each value t
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. Call helper functions and fill dict with launch records

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

6. Convert Dictionary to Data frame

```
df=pd.DataFrame(launch_dict)
```

```
df.to_csv('spacex_web_scraped.csv', index=False)
```

GITHUB LINK

Data Wrangling

1. Exploratory Data Analysis (EDA) was carried out to identify patterns in the data and provide labels for supervised model training.
2. The data collection included a variety of mission outcomes that were transformed into Training Labels, with 1 denoting a booster that successfully landed and 0 denoting one that failed to do so.
3. To construct labels, the following landing circumstances were taken into account: True Ocean denotes that the mission's results were successfully landed in a particular area of the ocean, while False Ocean denotes that the results were unsuccessfully landed in that area of the ocean.
4. RTLS denotes that the mission's results were successfully landed on a ground pad
5. False RTLS denotes that they unsuccessfully landed on a ground pad.
6. True ASDS means the mission outcome was successfully landed on a drone ship
7. False ASDS means the mission outcome was unsuccessfully landed on a drone ship

GITHUB LINK

EDA with Data Visualization

- **Scatter plot**: Demonstrates a connection or correlation between two variables, enabling the observation of patterns.
  - To visualize the relationships between the following:
    - ❖ Flight Number and Launch Site;
    - ❖ Payload and Launch Site;
    - ❖ Flight Number and Orbit Type; and
    - ❖ Payload and Orbit Type
- **Bar Chart**: Widely used to contrast the values of a variable at a particular time. Barcharts make it simple to identify which groups are the highest/most prevalent as well as how other groups contrast with one another. Each bar's length reflects how much the products it symbolizes are worth.
  - Plotted the following Bar chart to visualize:
    - ❖ Relationship between the success rate of each orbit type
- **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

GITHUB LINK

EDA with SQL

On an IBM DB2 cloud instance, the following SQL operations were carried out to better comprehend the SpaceX data set.

- ✓ List the specific names of the space mission's distinct launch sites.
- ✓ Show 5 records where the string "CCA" appears in the launch sites.
- ✓ Show the total payload mass carried by NASA's rockets (CRS)
- ✓ Show the average payload mass that the booster version F9 v1.1 can carry.
- ✓ Indicate the day on which the first successful ground pad landing occurred.
- ✓ Name the launchers with payload masses larger than 4,000 but less than 6,000 that have been successful in drone ships.
- ✓ Total the number of mission outcomes that were successful and unsuccessful.
- ✓ Name the booster models that have transported the most mass in payload. Employ a subquery
- ✓ List the names of the launch sites, drone ship booster versions, and failure landing results for the year 201510. Sort the number of landing outcomes between 2010 06 04 and 2017 03 20 in descending order, such as Success (ground pad) or Failure (drone ship).

GITHUB LINK

Build an Interactive Map with Folium

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 rateThe followingng 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 'foli um.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 torailways? YES
  - Are launch sites in close proximity tohighways? YES
  - Are launch sites in close proximity tocoastline? YES
  - Do launch sites keep certain distance away from cities? YES

GITHUB LINK

Build a Dashboard with Plotly Dash

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 Dashboardvisualsl 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 the following questions:

- Which site has the largest successful launches? KSC LC-39A with 10
- Which site has the highest launch success rate? KSC LC-39A with 76.9% success
- Which payload range(s) has the highest launch success rate? 2000 –5000 kg
- Which payload range(s) has the lowest launch success rate? 0-2000 and 5500 -7000
- Which F9 Booster version (v1.0, v1.1, FT, B4, B5, etc.) has the highest launch success rate? FT

GITHUB LINK

Predictive Analysis (Classification)

1. Read Dataset into Dataframe and create class array
2. Standardize the Data
3. Train/Test/Split data into training and test set
4. Create and refine Models
5. Find the Best Performing Model

1. Read Dataset into Dataframe and create class array

```
URL2 = 'https://cf-courses-data.s3.us.cloud-object-storage.a
resp2 = await fetch(URL2)
text2 = io.BytesIO((await resp2.arrayBuffer()).to_py())
X = pd.read_csv(text2)
```

```
Y = data['Class'].to_numpy()
```

2. Standardize the Data

```
# students get this
X= preprocessing.StandardScaler().fit(X).transform(X)
```

3. Train/Test/Split data into training and test set

```
# Split data for training and testing data sets
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)
print ('Train set:', X_train.shape,  Y_train.shape)
print ('Test set:', X_test.shape,  Y_test.shape)
```

4. Create and refine Models

- Create a Logistic Regression object and then create a GridSearchCV object
- Fit train data set in to the GridSearchCV object and train the Model
- Find and display best hyperparameters and accuracy score
- Check the accuracy on the test data by creating a confusion matrix
- Repeat above steps for Decision Tree, KNN, and SVM algorithms

```
parameters ={"C":[0.01,0.1,1],'penalty':['l2'], 'solver':['lbfgs']}
LR = LogisticRegression()
logreg_cv = GridSearchCV(LR, parameters,cv=10)
logreg_cv.fit(X_train, Y_train)
```

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

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

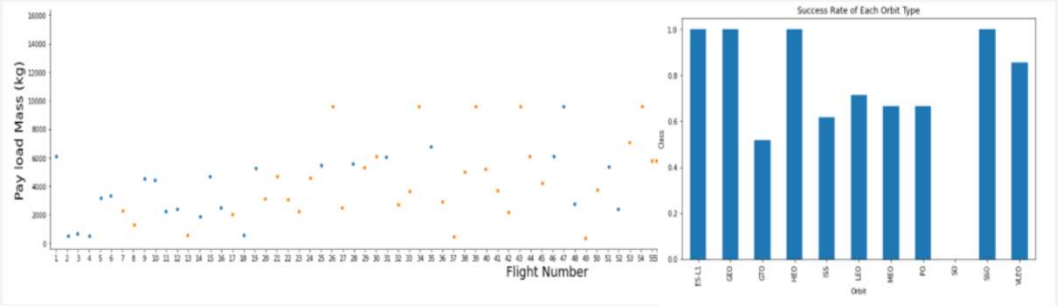
5. Find the Best Performing Model

	Algo Type	Accuracy Score	Test Data Accuracy Score
2	Decision Tree	0.875000	0.833333
3	KNN	0.848214	0.833333
1	SVM	0.848214	0.833333
0	Logistic Regression	0.846429	0.833333

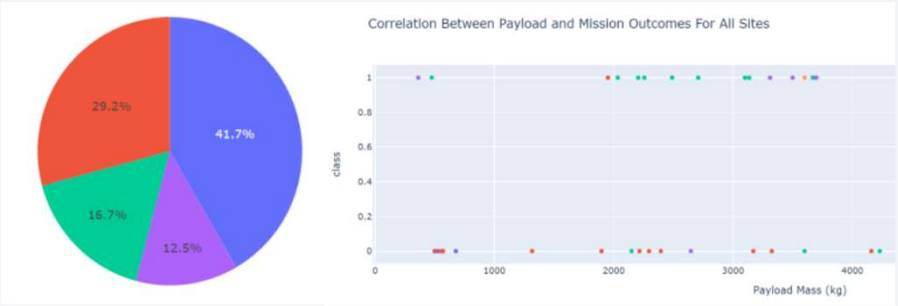
GITHUB LINK

Results

Exploratory data analysis results

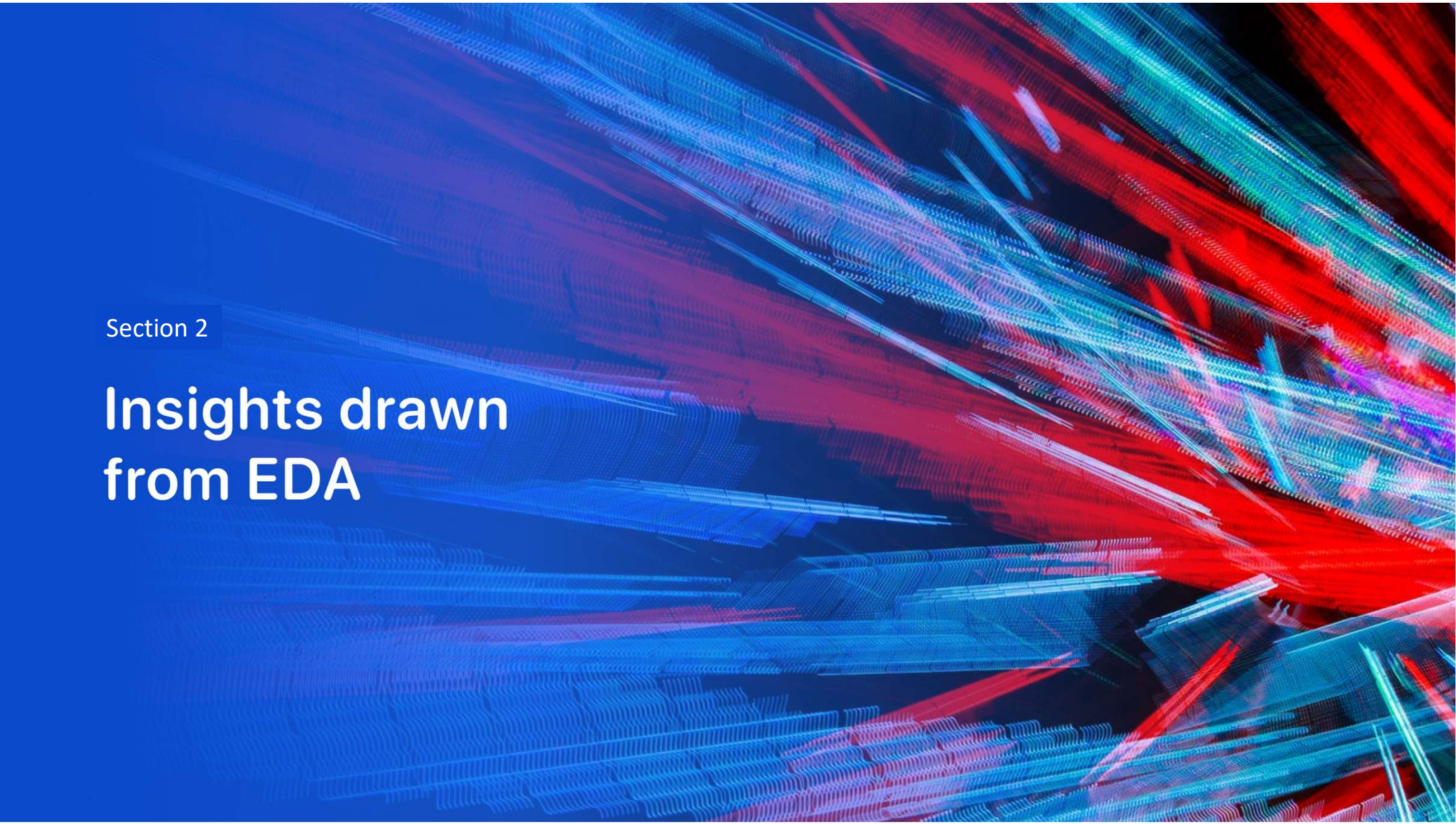


Interactive analytics demo in screenshots



Predictive analysis results

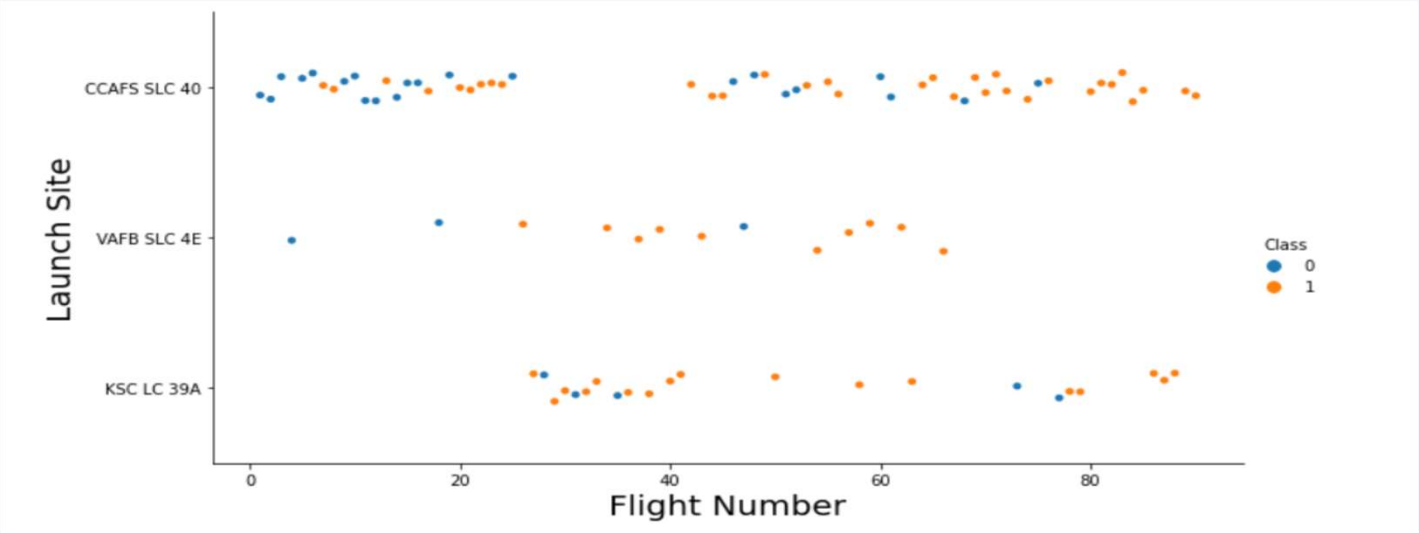
	Algo Type	Accuracy Score
2	Decision Tree	0.903571
3	KNN	0.848214
1	SVM	0.848214
0	Logistic Regression	0.846429



Section 2

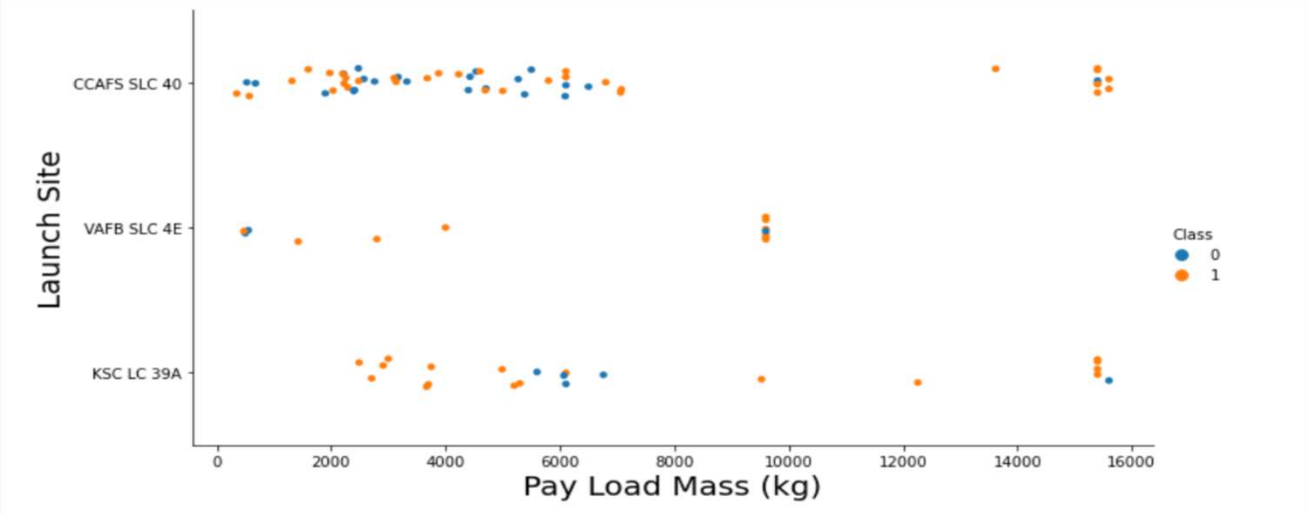
Insights drawn from EDA

Flight Number vs. Launch Site



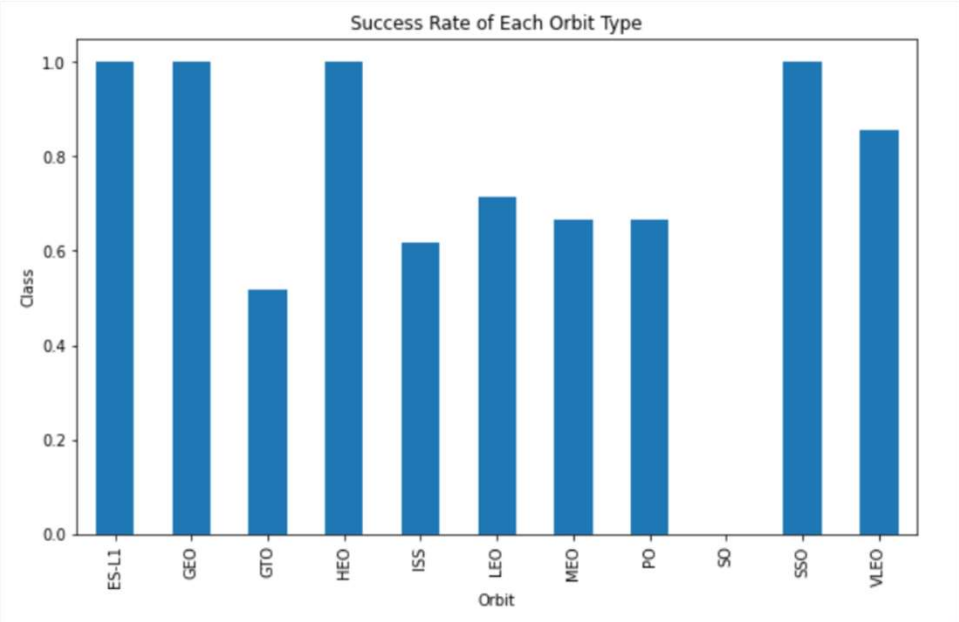
- Success rates (Class=1) increase as the number of flights increase
- For the launch site ‘KSC LC 39A’, it takes at least around 25 launches before a first successful launch

Payload vs. Launch Site



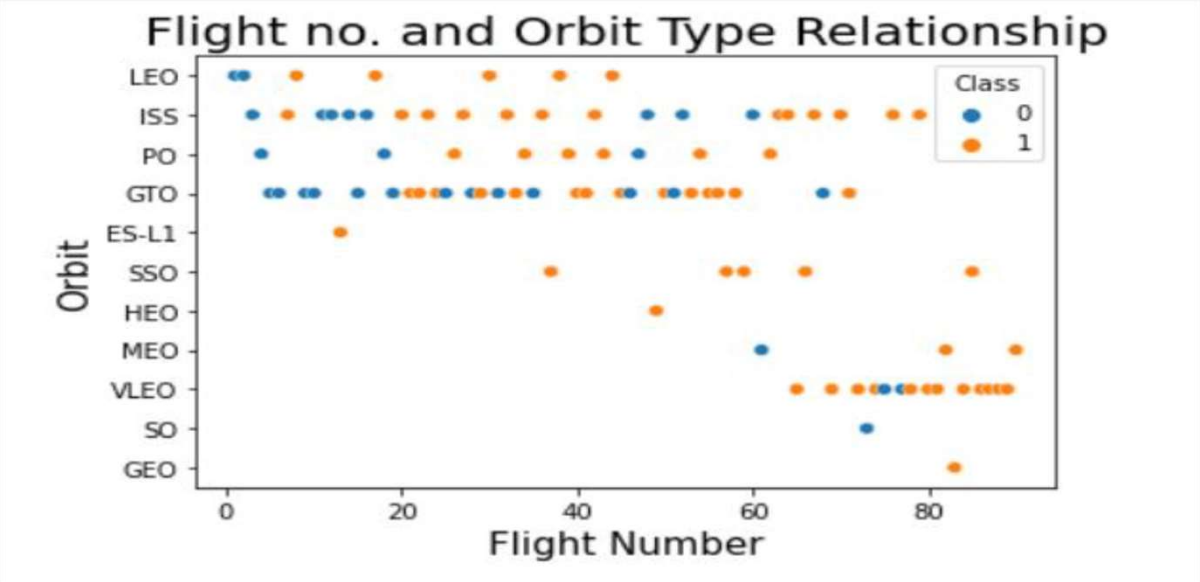
- For launch site 'VAFB SLC 4E', there are no rockets launched for payload greater than 10,000 kg
- The percentage of successful launches (Class=1) increases for launch site 'VAFB SLC 4E' as the payload mass increases
- There is no clear correlation or pattern between the launch site and payload mass

Success Rate vs. Orbit Type



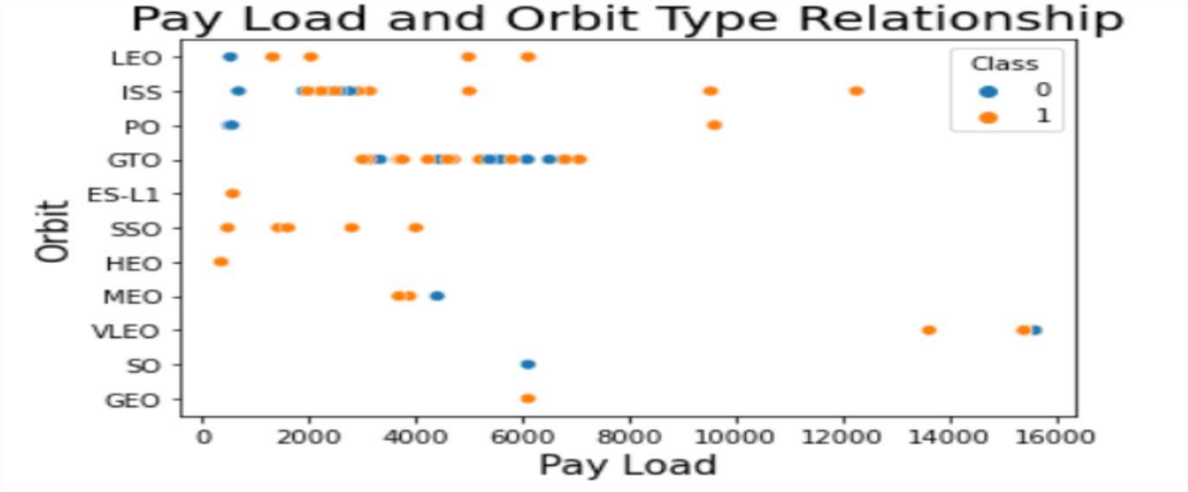
- Orbits ES-LI, GEO, HEO, and SSO have the highest success rates
- GTO orbit has the lowest success rate

Flight Number vs. Orbit Type



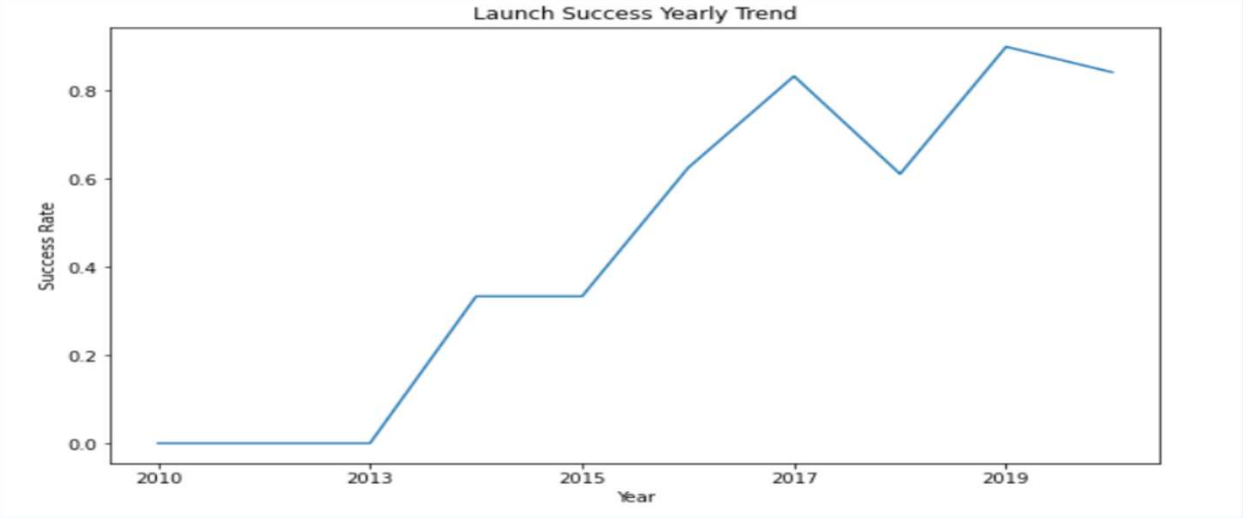
- For orbit VLEO, first successful landing (class=1) doesn't occur until 60+ number of flights
- For most orbits (LEO, ISS, PO, SSO, MEO, VLEO) successful landing rates appear to increase with flight numbers
- There is no relationship between flight number and orbit for GTO

Payload vs. Orbit Type



- Successful landing rates (Class=1) appear to increase with pay load 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



- 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:**

```
select distinct Launch_Site from spacextbl
```

- **Description:**
  - ‘distinct’ returns only unique values from the queries column (Launch_Site)
  - There are 4 unique launch sites
- **Result:**

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

Launch Site Names Begin with 'CCA'

- **Query:**

```
select * from spacextbl where Launch_Site LIKE 'CCA%' limit 5;
```

- **Description:**
  - Using the keyword ‘Like’ and format ‘CCA%’, returns records where ‘Launch Site’ column starts with “CCA”.
  - Limit 5, limits the number of returned records to 5
- **Result:**

DATE	time__utc_	booster_version	launch_site	payload	payload_mass__kg_	orbit	customer	mission_outcome	landing__outcome
2010-04-06	18:45:00	F9 v1.0 B0003	CCAFS LC-40	Dragon Spacecraft Qualification Unit	0	LEO	SpaceX	Success	Failure (parachute)
2010-08-12	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
2012-08-10	0:35:00	F9 v1.0 B0006	CCAFS LC-40	SpaceX CRS-1	500	LEO (ISS)	NASA (CRS)	Success	No attempt
2013-01-03	15:10:00	F9 v1.0 B0007	CCAFS LC-40	SpaceX CRS-2	677	LEO (ISS)	NASA (CRS)	Success	No attempt

Total Payload Mass

- **Query**:

```
select sum(PAYLOAD_MASS__KG_) from spacextbl where Customer = 'NASA (CRS)'
```

- **Description**:
  - ‘sum’ adds column ‘PAYLOAD_MASS_KG’ and returns total payload mass for customers named ‘NASA (CRS)’
- **Result**:

45596

Average Payload Mass by F9 v1.1

- **Query**:

```
select avg(PAYLOAD_MASS__KG_) from spacextbl where Booster_Version LIKE 'F9 v1.1'
```

- **Description**:
  - ‘avg’ keyword returns the average of payload mass in ‘PAYLOAD_MASS_KG’ column where booster version is ‘F9 v1.1’
- **Result**:

First Successful Ground Landing Date

- **Query**:

```
select min(Date) as min_date from spacextbl where Landing__Outcome = 'Success (ground pad)';
```

- **Description**:
  - ‘min(Date)’ selects the first or the oldest date from the ‘Date’ column where first successful landing on group pad was achieved
  - Where clause defines the criteria to return date for scenarios where ‘Landing_Outcome’ value is equal to ‘Success (ground pad)’
- **Result**:

min_date
2015-12-22

Successful Drone Ship Landing with Payload between 4000 and 6000

- **Query**:

```
select Booster_Version from spacextbl where (PAYLOAD_MASS__KG_> 4000 and PAYLOAD_MASS__KG_ < 6000)
and (Landing__Outcome = 'Success (drone ship)');
```

- **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**:

```
select Mission_Outcome, count(Mission_Outcome) as counts from spacextbl group by Mission_Outcome
```

- **Description**:
  - The 'group by' keyword arranges identical data in a column in to group
  - In this case, number of mission outcomes by types of outcomes are grouped in column 'counts'
- **Result**:

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

Boosters Carried Maximum Payload

- **Query**:

```
select Booster_Version, PAYLOAD_MASS__KG_ from spacextbl where PAYLOAD_MASS__KG_ = (select max(PAYLOAD_MASS__KG_) from spacextbl)
```

- **Description**:
  - The sub query returns the maximum payload mass by using keywork ‘max’ on the pay load mass column
  - The main query returns booster versions and respective payload mass where payload mass is maximum with value of 15600
- **Result**:

booster_version	payload_mass__kg_
F9 B5 B1048.4	15600
F9 B5 B1049.4	15600
F9 B5 B1051.3	15600
F9 B5 B1056.4	15600
F9 B5 B1048.5	15600
F9 B5 B1051.4	15600
F9 B5 B1049.5	15600
F9 B5 B1060.2	15600
F9 B5 B1058.3	15600
F9 B5 B1051.6	15600
F9 B5 B1060.3	15600
F9 B5 B1049.7	15600

2015 Launch Records

- **Query**:

```
select Landing__Outcome, Booster_Version, Launch_Site from spacextbl where Landing__Outcome = 'Failure (drone ship)' and year(Date) = '2015'
```

- **Description**:
  - The query lists 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' keywork extracts the year from column 'Date
  - 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**:

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

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

- **Query**:

```
select Landing__Outcome, count(*) as LandingCounts from spacextbl where Date between '2010-06-04' and '2017-03-20'
group by Landing__Outcome
order by count(*) desc;
```

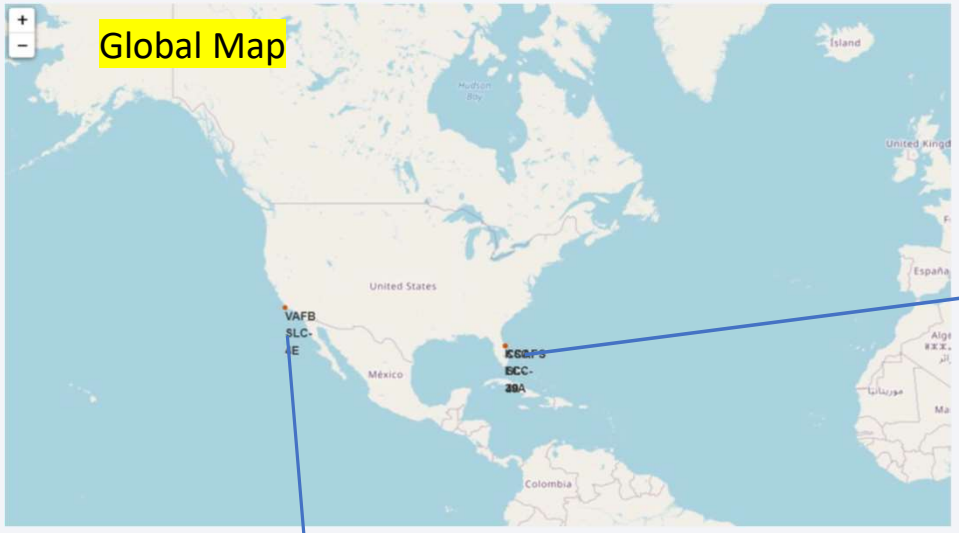
- **Description**:
  - The ‘group by’ key word arranges data in column ‘Landing__Outcome’ into groups
  - The ‘between’ and ‘and’ keywords return data that is between 2010-06-04 and 2017-03-20
  - The ‘order by’ keyword arranges the counts column in descending order
  - The result of the query is a ranked list of landing outcome counts per the specified date range
- **Result**:

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

Section 3

Launch Sites Proximities Analysis

SpaceX Falcon9 -Launch Sites Map



Global Map on the left-top 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.

Zoom1 and Zoom 2 into the launch sites to display 4 launch sites:

- VAFB SLC-4E (CA)
- CCAFS LC-40 (FL)
- KSC LC-39A (FL)
- CCAFS SLC-40 (FL)2

SpaceX Falon9 –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 greatest number of successful launches

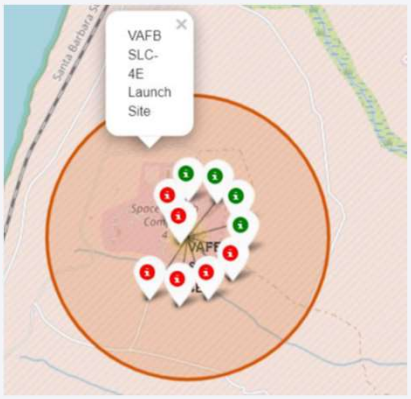


Fig 2 –VAFB Launch Site with success/failed markers

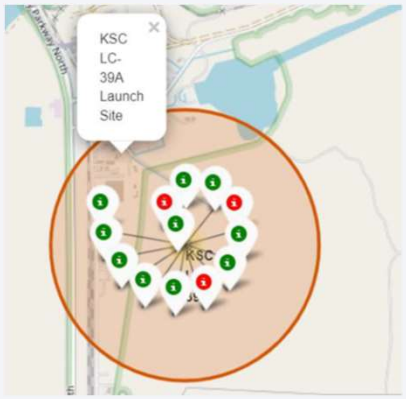


Fig 3 –KSC LC-39A success/failed markers

Fig 4 –CCAFS SLC-40 success/failed markers

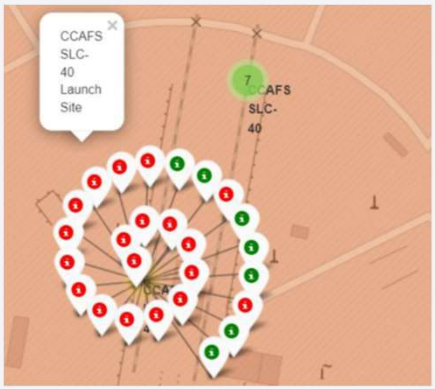


Fig 5 –CCAFS SLC-40 success/failed markers

SpaceX Falcon9 –Launch Site to proximity Distance Map

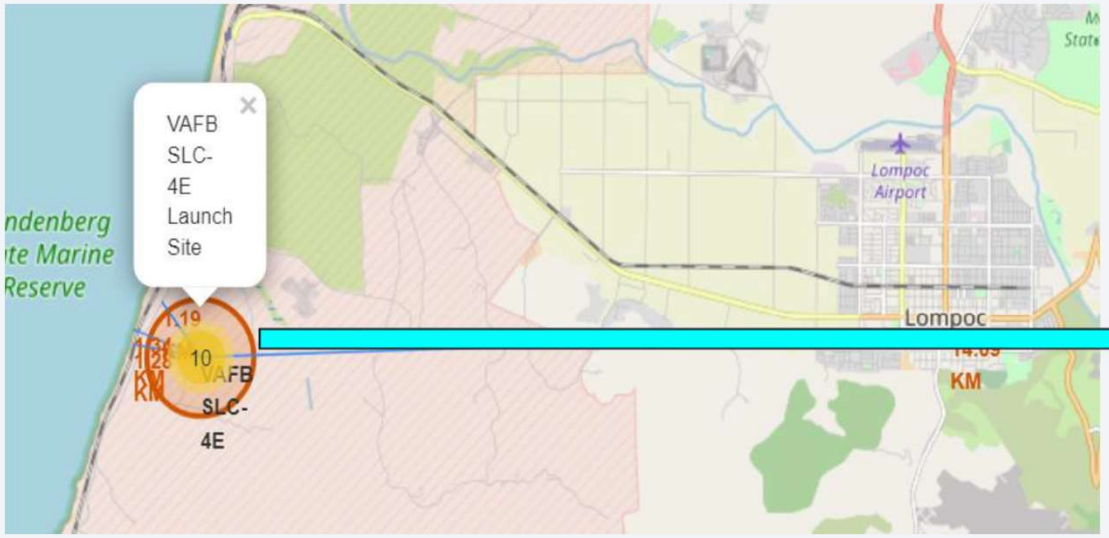


Fig 1 –Proximity site map for VAFB SLC-4E

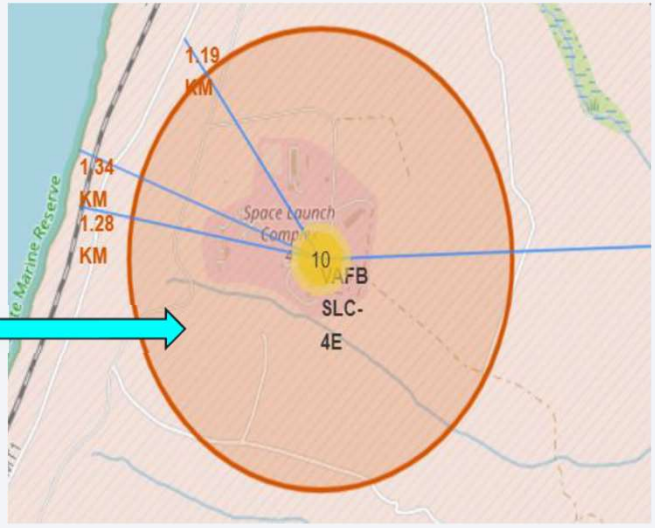
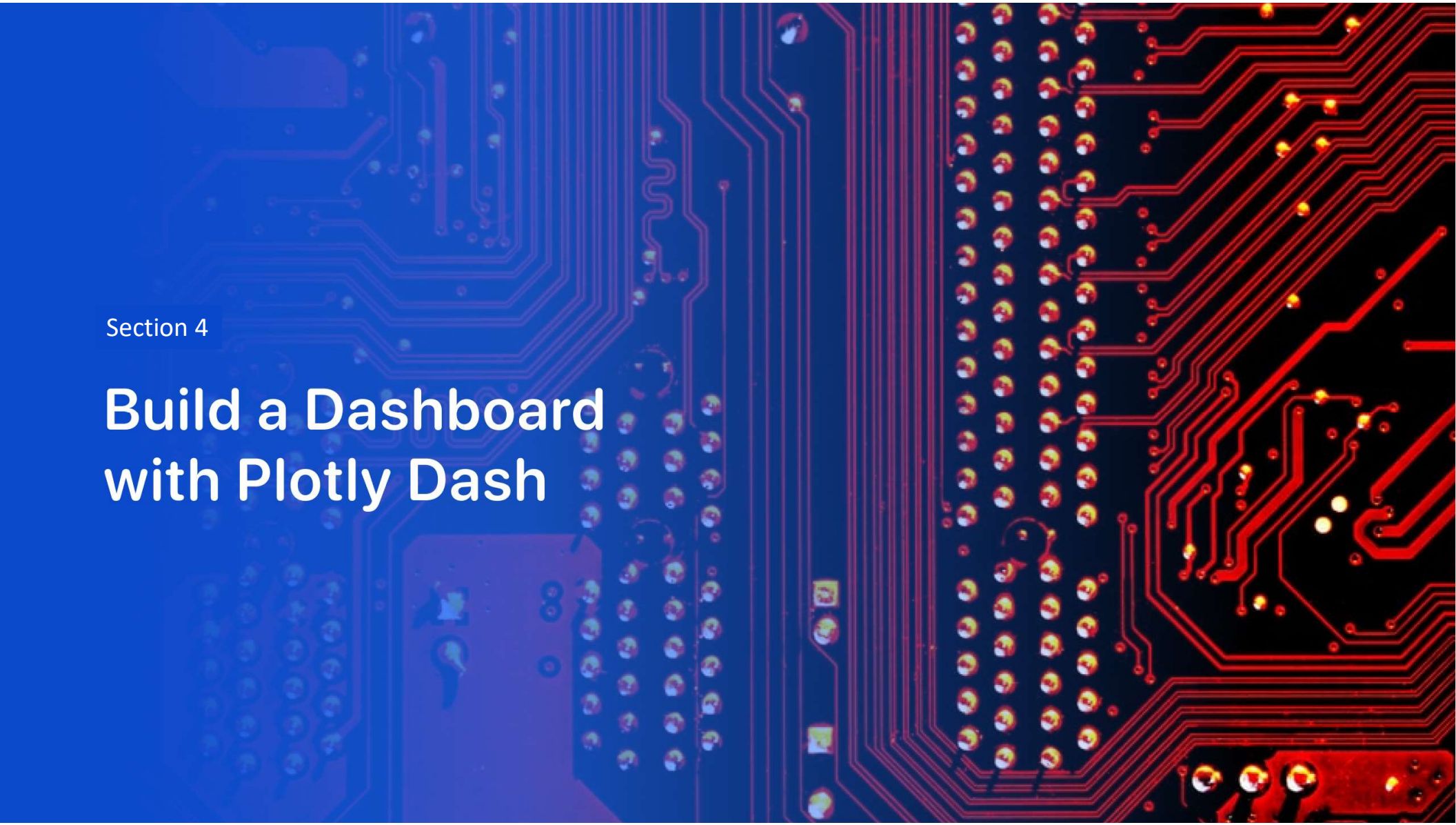


Fig 2 –Zoom in for sites –coastline, railroad, and highway

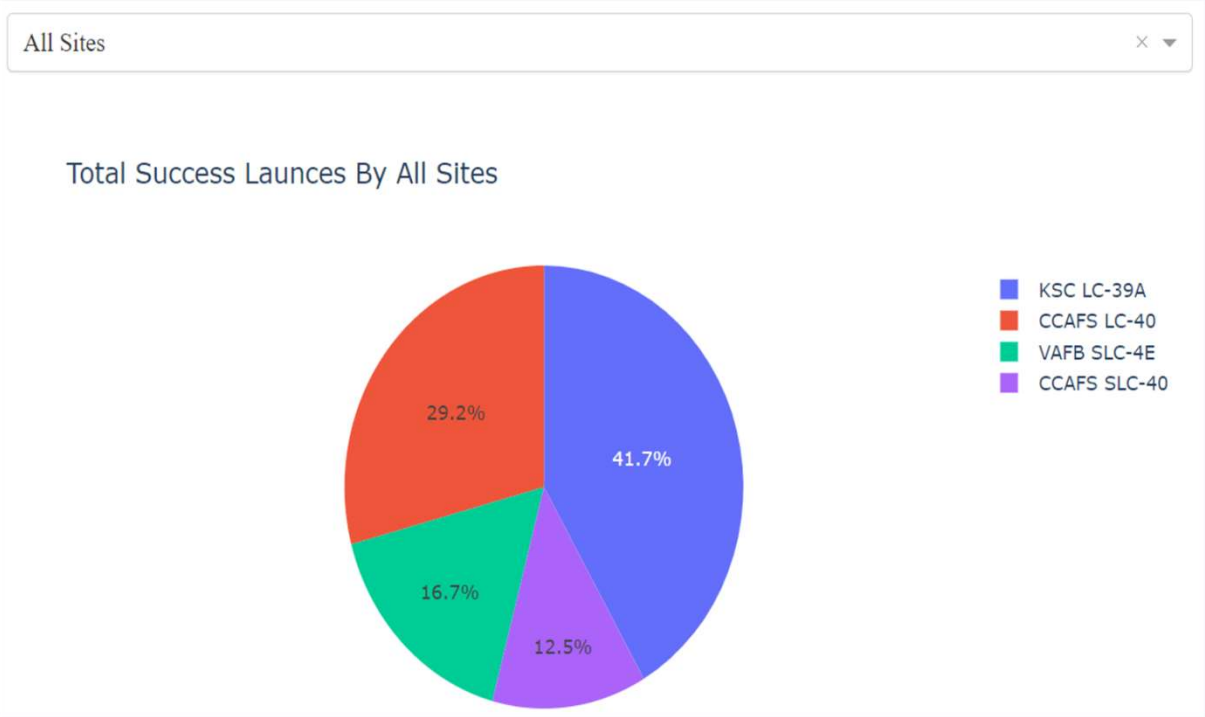
- Figure 1 displays all the proximity sites marked on the map for Launch Site VAFB SLC-4E. City Lompoc is located further away from Launch Site compared to other proximities such as coastline, railroad, highway, etc. The map also displays a marker with city distance from the Launch Site (14.09 km)
- 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 impactsto the general public and infrastructure. Launch Sites are strategically located near the coastline, railroad, and highways to provide easy access to resources.



Section 4

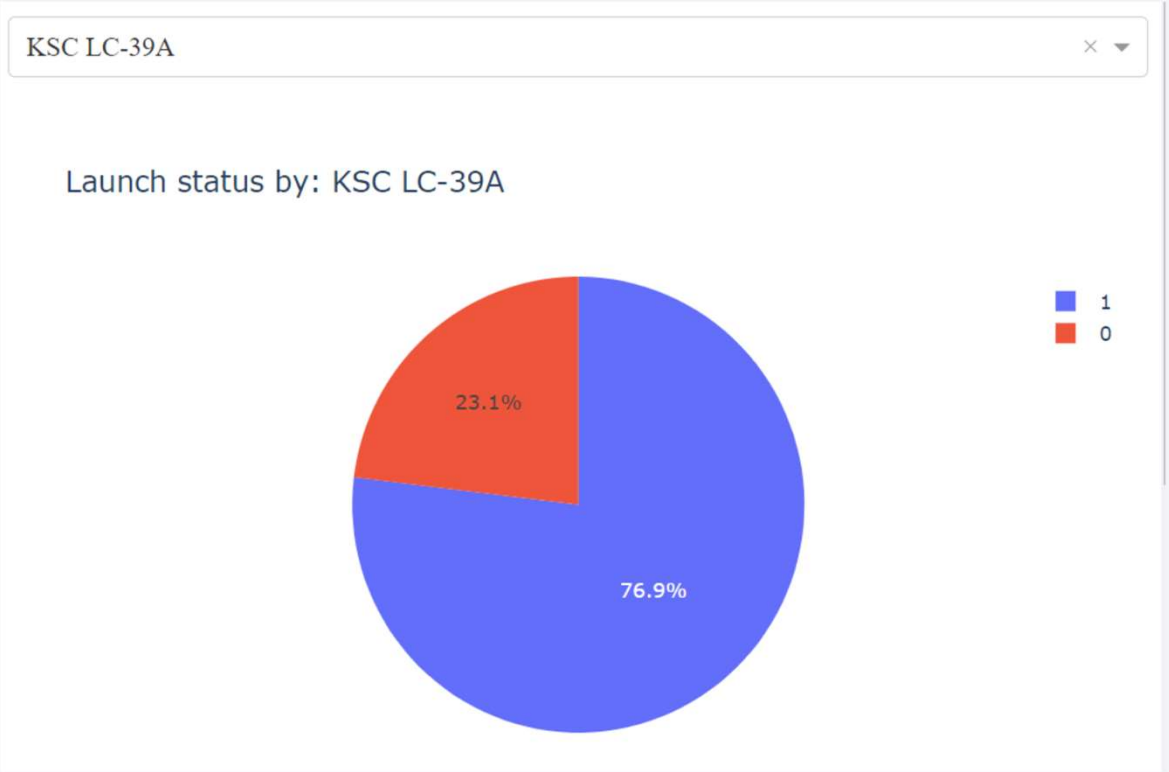
Build a Dashboard with Plotly Dash

Launch Success Counts For All Sites



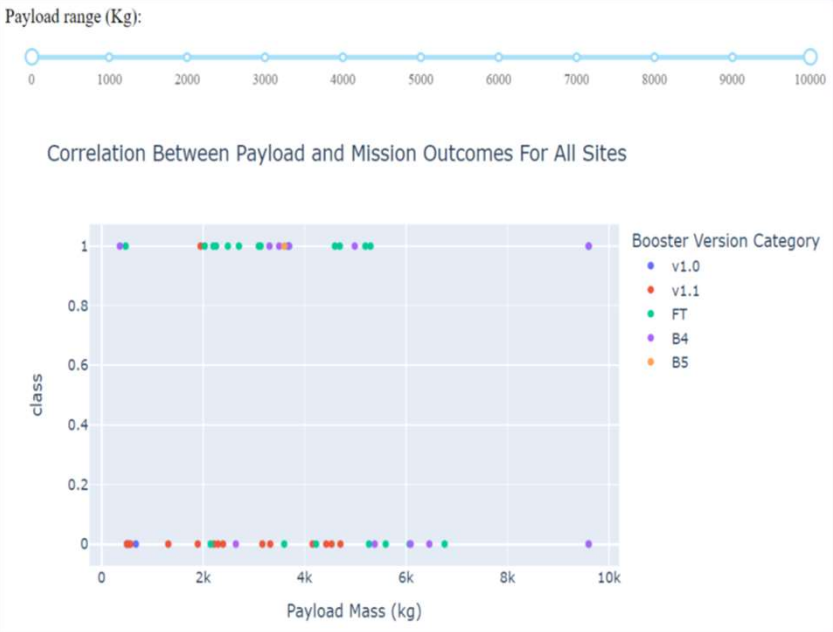
- Launch Site 'KSC LC-39A' has the highest launch success rate
- Launch Site 'CCAFS SLC-40' has the lowest launch success rate

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 successfailurerateis23.1%

Payload vs. Launch Outcome Scatter Plot for All Sites

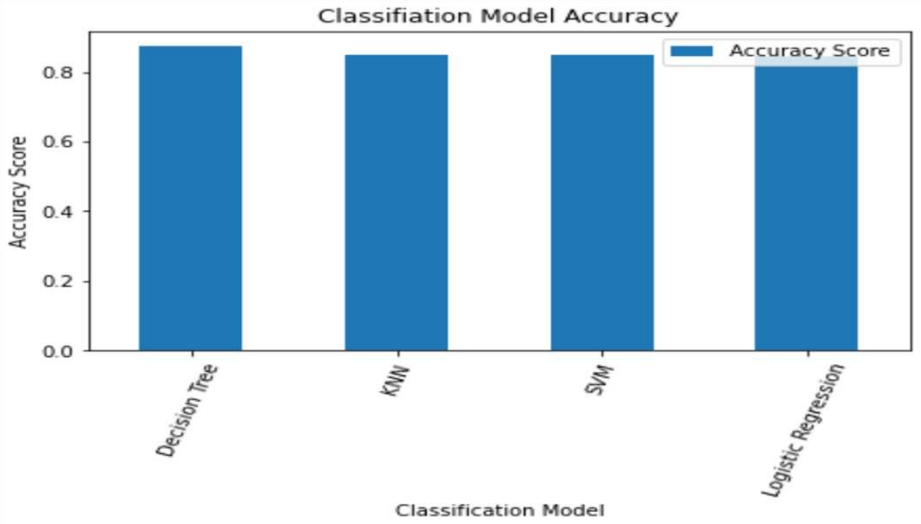


- Most successful launches are in the payload range from 2000 to about 5500
- Booster version category ‘FT’ has the most successful launches
- Only booster with a success launch when payload is greater than 6k is ‘B4’

Section 5

Predictive Analysis (Classification)

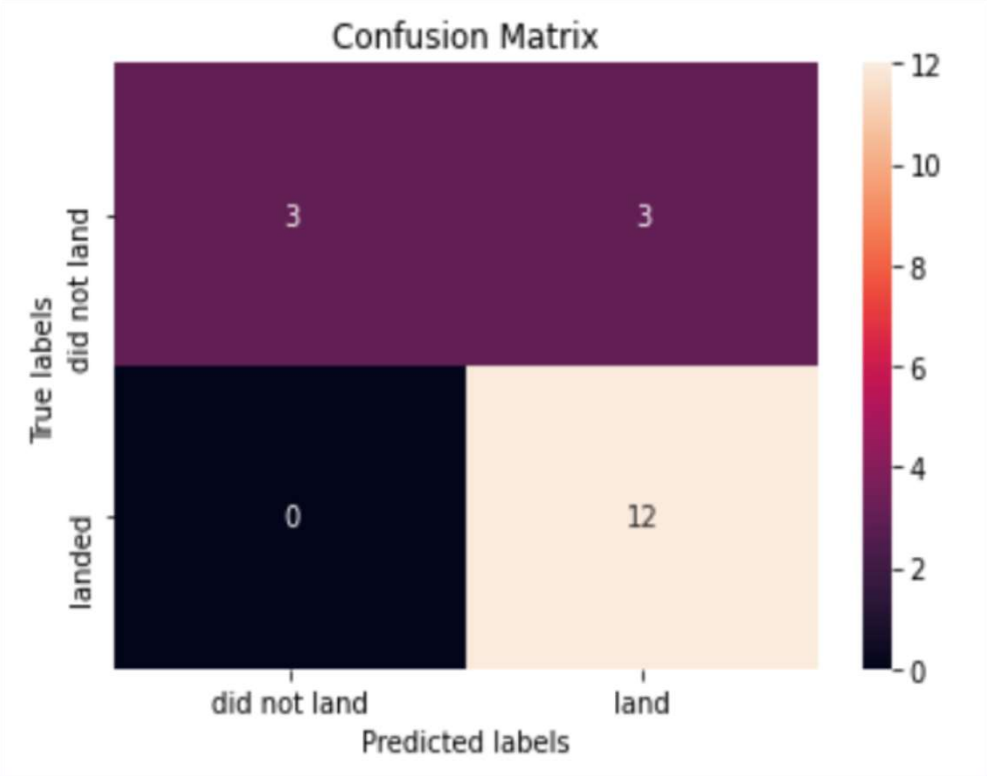
Classification Accuracy



	Algo Type	Accuracy Score	Test Data Accuracy Score
2	Decision Tree	0.875000	0.833333
3	KNN	0.848214	0.833333
1	SVM	0.848214	0.833333
0	Logistic Regression	0.846429	0.833333

- Based on the Accuracy scores and as also evident from the bar chart, the Decision Tree algorithm has the highest classification score with a value of .8750
- Accuracy Score on the test data is the same for all the classification algorithms based on the data set with a value of .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 the same for all the models (LR, SVM, Decision Tree, KNN)
- •Per the confusion matrix, the classifier made 18 predictions
- •12scenarios were predicted Yes for landing, and they did land successfully (True positive)
- •3scenarios (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% of the time ((TP + TN) / Total) with a misclassification or error rate ((FP + FN) / Total) of about 16.5%

Conclusions

- As the number of flights increases, 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 and Launch Site 'CCAFS SLC-40' has the lowest launch success rate
- Orbits ES-L1, GEO, HEO, and SSO have the highest launch success rates, and orbit GTO has the lowest
- Launch sites are located strategically away from the cities and closer to the coastline, railroads, and highways
- The best-performing Machine Learning Classification Model is the Decision Tree with an accuracy of about 87.5%. When the models were scored on the test data, the accuracy score was about 83% for all models. More data may be needed to further tune the models and find a potentially better fit.

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!