
IBM Developer
SKILLS NETWORK
Winning Space Race
with Data Science
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Outline

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

Executive Summary

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

- 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 mission 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
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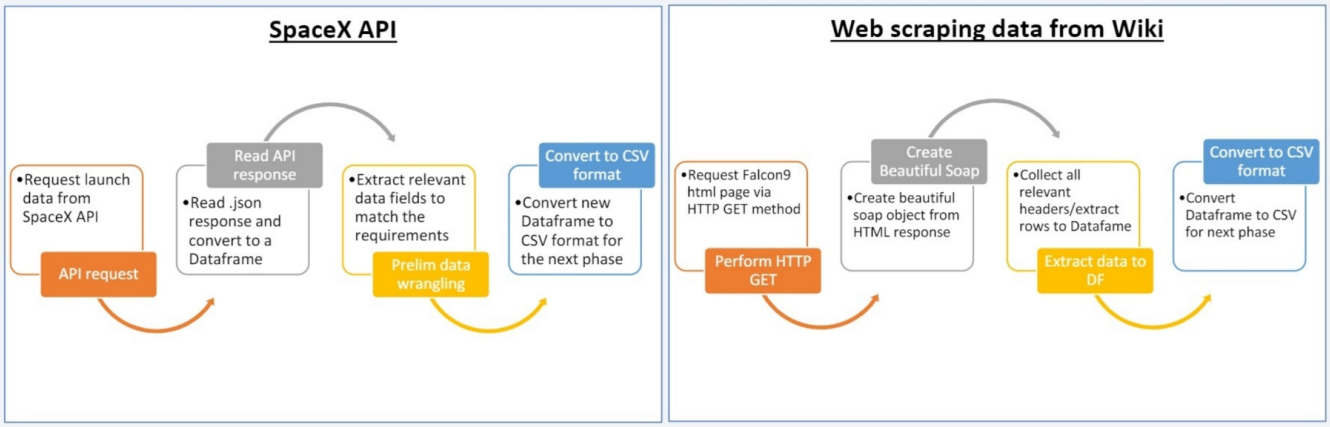
Methodology

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

- 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 Dict to Dataframe, filter for Falcon9 launches, covert 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 meethod to convert the json
data = pd.json_normalize(response.json())
```

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}
```

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

```
# Create a data from launch_dict
df_launch = pd.DataFrame(launch_dict)
```

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

```
data_falcon9.to_csv('dataset_part\_1.csv', index=False)
```

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Data Collection - Scraping

1. Perform HTTP GET to 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 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"

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

2. Create Beautiful Soup object

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

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 on firs
# Iterate each th element and apply the provided extr
# Append the Non-empty column name (`if name is not N
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 an empty 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 vc
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(launch_dict)
```

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Data Wrangling

- Conducted Exploratory Data Analysis (EDA) to find patters 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
  - 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

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Data Wrangling – cont'd

1. Load dataset in to Dataframe
2. Find patterns in data
3. Create landing outcome label

1. Load SpaceX dataset (csv) in to a Dataframe

```
df=pd.read_csv("https://cf-courses-data.s3.us.cloud-object-storage.appd
art_1.csv")
```

2. Find data patterns:

i. Calculate the number of launches on each site

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

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

ii. Calculate the number and occurrence of each orbit

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

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

iii. Calculate number/occurrence of mission outcomes per orbit type

```
landing_outcomes = df['Outcome'].value_counts()
```

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

```
# landing_class = 0 if bad_outcome
# landing_class = 1 otherwise

landing_class = []
for i in df['Outcome']:
    if i in bad_outcomes:
        landing_class.append(0)
    else:
        landing_class.append(1)
```

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

	Class
0	0
1	0
2	0
3	0
4	0

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EDA with Data Visualization

- 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

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EDA with SQL

- To better understand SpaceX data set, following SQL queries/operations were performed on an IBM DB2 cloud instance:

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

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Build an Interactive Map with Folium

- Folium interactive map helps analyze geospatial data to perform more interactive visual analytics and better understand factors such 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

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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.
  1. 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
  2. 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
  3. Added a Payload range slider to the Dashboard to easily select different payload ranges to identify visual patterns
  4. 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

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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) in to a Dataframe and create NumPy array from the column class in data

```
data = pd.read_csv("https://cf-courses-data.s3.us.cloud-object
et_part_2.csv")
```

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

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

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

3. Train/test/split X and Y in to training and test data sets.

```
# 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 based on following classification Algorithms: (below is LR example)
   i. Create Logistic Regression object and then create a GridSearchCV object
   ii. Fit train data set in to the GridSearchCV object and train the Model

```
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)
```

   iii. Find and display best hyperparameters and accuracy score

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

   iv. Check the accuracy on the test data by creating a confusion matrix

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

   v. Repeat above steps for Decision Tree, KNN, and SVM algorithms

3. Find the best performing model

```
Model_Performance_df = pd.DataFrame({'Algo Type': ['Logistic Regression', 'SVM','Decision Tree','KNN'],
'Accuracy Score': [logreg_cv.best_score_, svm_cv.best_score_, tree_cv.best_score_, knn_cv.best_score_],
'Test Data Accuracy Score': [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)]})
```

```
i = Model_Performance_df['Accuracy Score'].idxmax()
print('The best performing alogrithm is ' + Model_Performance_df['Algo Type'][i]
+ ' with score ' + str(Model_Performance_df['Accuracy Score'][i]))
```

The best performing alogrithm is Decision Tree with score 0.875

	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

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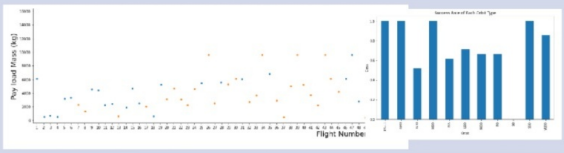
Results

Following sections and slides explain results for:

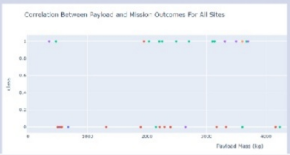
Exploratory data analysis results

- Samples:



Interactive analytics demo in screenshots

- Samples



Predictive analysis results

- Samples

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

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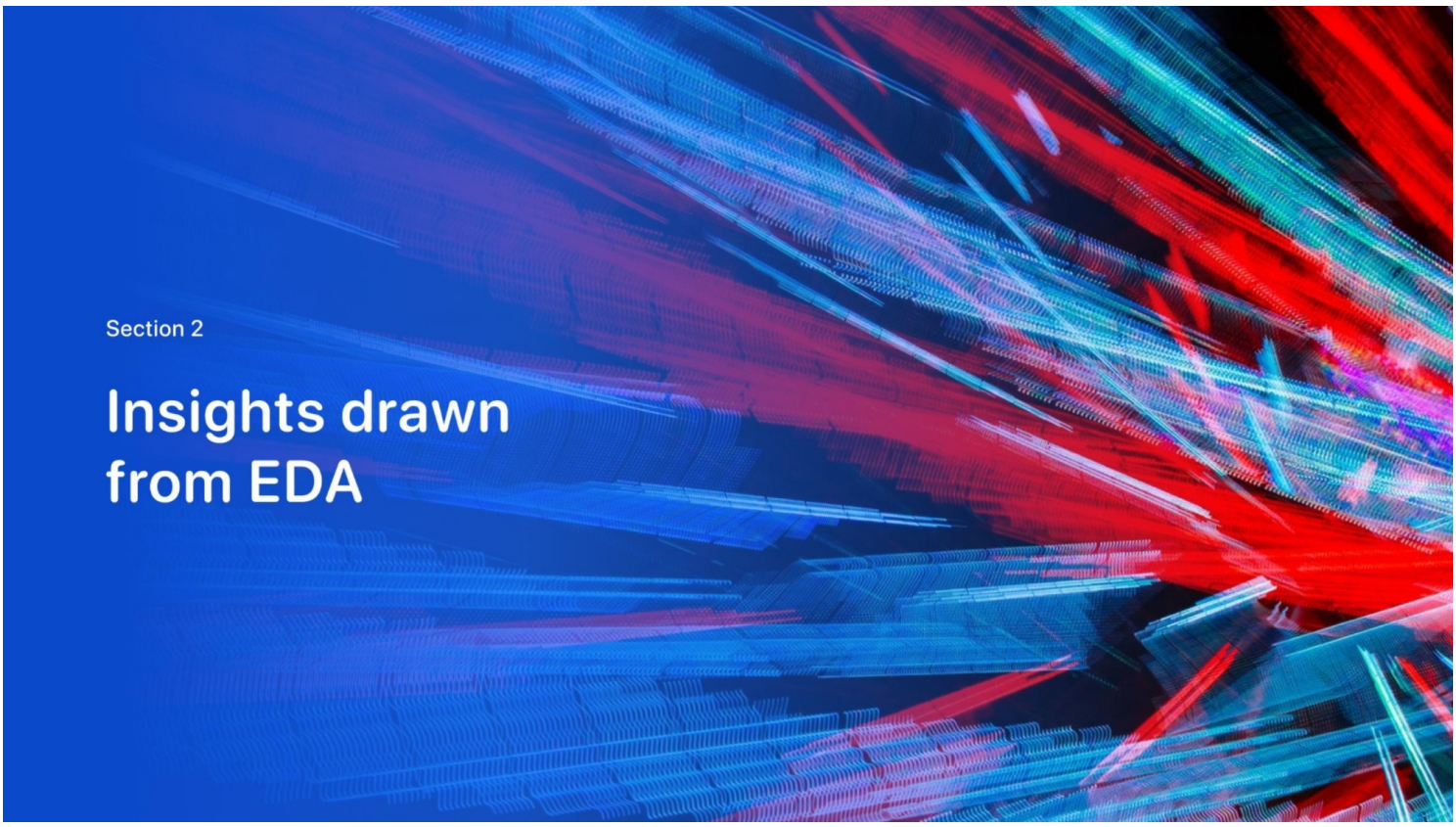
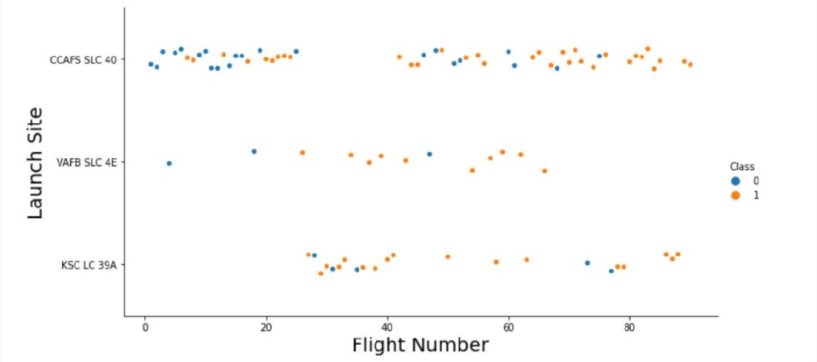
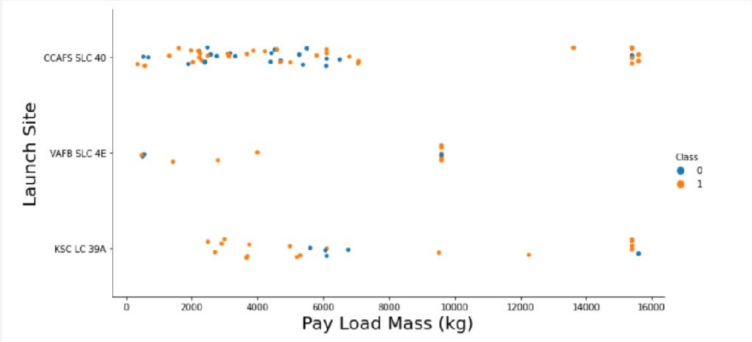

Section 2
Insights drawn
from EDA

Flight Number vs. Launch Site



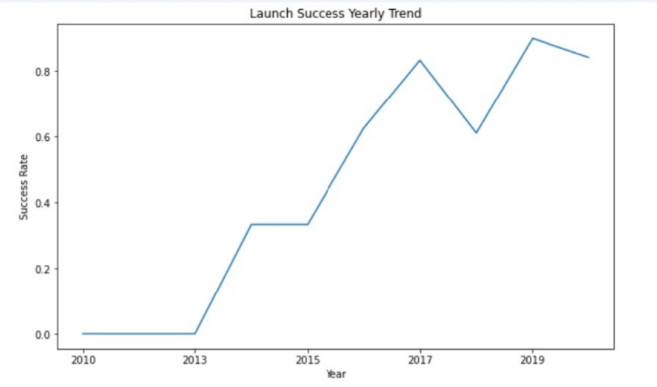
- Success rates (Class=1) increases as the number of flights increase
- For launch site 'KSC LC 39A', it takes at least around 25 launches before a first successful launch

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

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

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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

25