

SpaceX Falcon 9 First Stage Landing Prediction

Exploratory Data Analysis and Feature Engineering using Pandas and Matplotlib

-Exploratory Data Analysis

-Preparing Data Feature Engineering

```
import piplite
await piplite.install(['numpy'])
await piplite.install(['pandas'])
await piplite.install(['seaborn'])

# pandas is a software library written for the Python programming
language for data manipulation and analysis.
import pandas as pd
#NumPy is a library for the Python programming language, adding
support for large, multi-dimensional arrays and matrices, along with a
large collection of high-level mathematical functions to operate on
these arrays
import numpy as np
# Matplotlib is a plotting library for python and pyplot gives us a
MatLab like plotting framework. We will use this in our plotter
function to plot data.
import matplotlib.pyplot as plt
#Seaborn is a Python data visualization library based on matplotlib.
It provides a high-level interface for drawing attractive and
informative statistical graphics
import seaborn as sns

from js import fetch
import io

URL = "https://cf-courses-data.s3.us.cloud-object-
storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/datasets/
dataset_part_2.csv"
resp = await fetch(URL)
dataset_part_2_csv = io.BytesIO((await resp.arrayBuffer()).to_py())
df=pd.read_csv(dataset_part_2_csv)
df.head(5)
```

	FlightNumber	Date	BoosterVersion	PayloadMass	Orbit	
LaunchSite \						
0	1	2010-06-04	Falcon 9	6104.959412	LEO	CCAFS
SLC 40						
1	2	2012-05-22	Falcon 9	525.000000	LEO	CCAFS

SLC 40								
2	3	2013-03-01	Falcon 9	677.000000	ISS	CCAFS		
SLC 40								
3	4	2013-09-29	Falcon 9	500.000000	P0	VAFB		
SLC 4E								
4	5	2013-12-03	Falcon 9	3170.000000	GT0	CCAFS		
SLC 40								

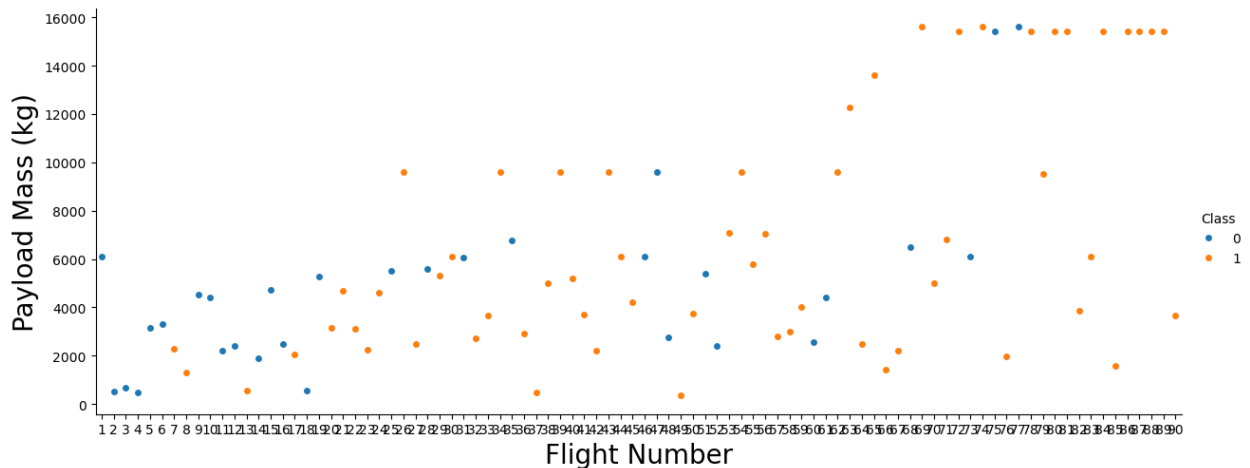
	Outcome	Flights	GridFins	Reused	Legs	LandingPad	Block	\
0	None None	1	False	False	False	NaN	1.0	
1	None None	1	False	False	False	NaN	1.0	
2	None None	1	False	False	False	NaN	1.0	
3	False Ocean	1	False	False	False	NaN	1.0	
4	None None	1	False	False	False	NaN	1.0	

	ReusedCount	Serial	Longitude	Latitude	Class
0	0	B0003	-80.577366	28.561857	0
1	0	B0005	-80.577366	28.561857	0
2	0	B0007	-80.577366	28.561857	0
3	0	B1003	-120.610829	34.632093	0
4	0	B1004	-80.577366	28.561857	0

```

sns.catplot(y="PayloadMass", x="FlightNumber", hue="Class", data=df,
aspect=2.5)
plt.xlabel("Flight Number", fontsize=20)
plt.ylabel("Payload Mass (kg)", fontsize=20)
plt.show()

```



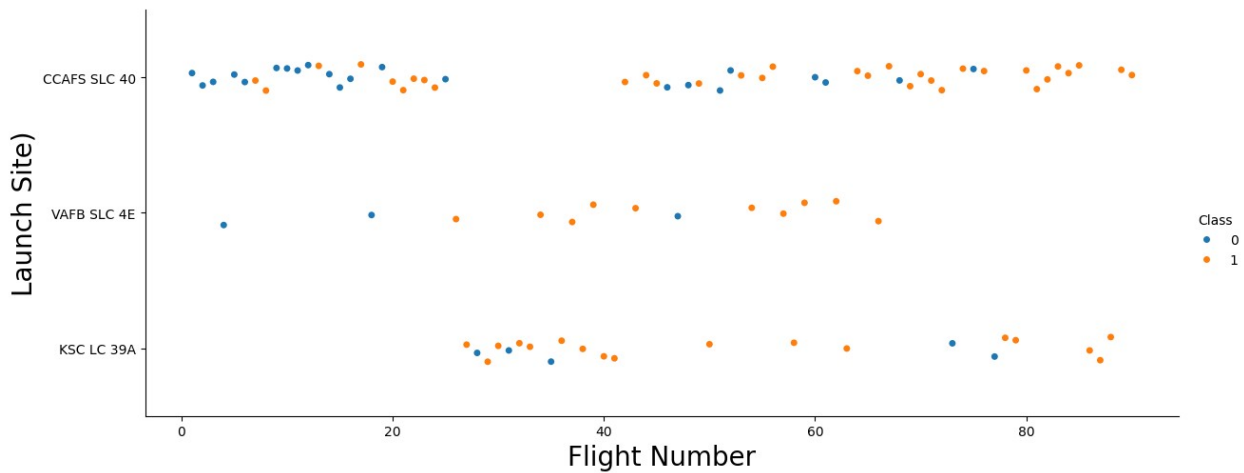
TASK 1: Visualize the relationship between Flight Number and Launch Site

```

sns.catplot(y="LaunchSite", x="FlightNumber", hue="Class", data=df,
aspect=2.5)
plt.xlabel("Flight Number", fontsize=20)

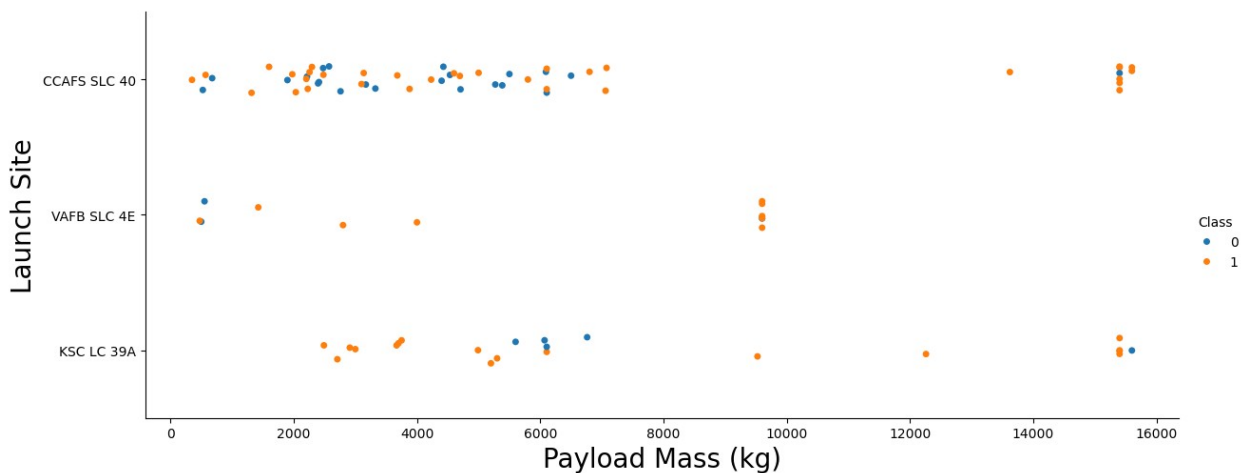
```

```
plt.ylabel("Launch Site", fontsize=20)
plt.show()
```



TASK 2: Visualize the relationship between Payload Mass and Launch Site

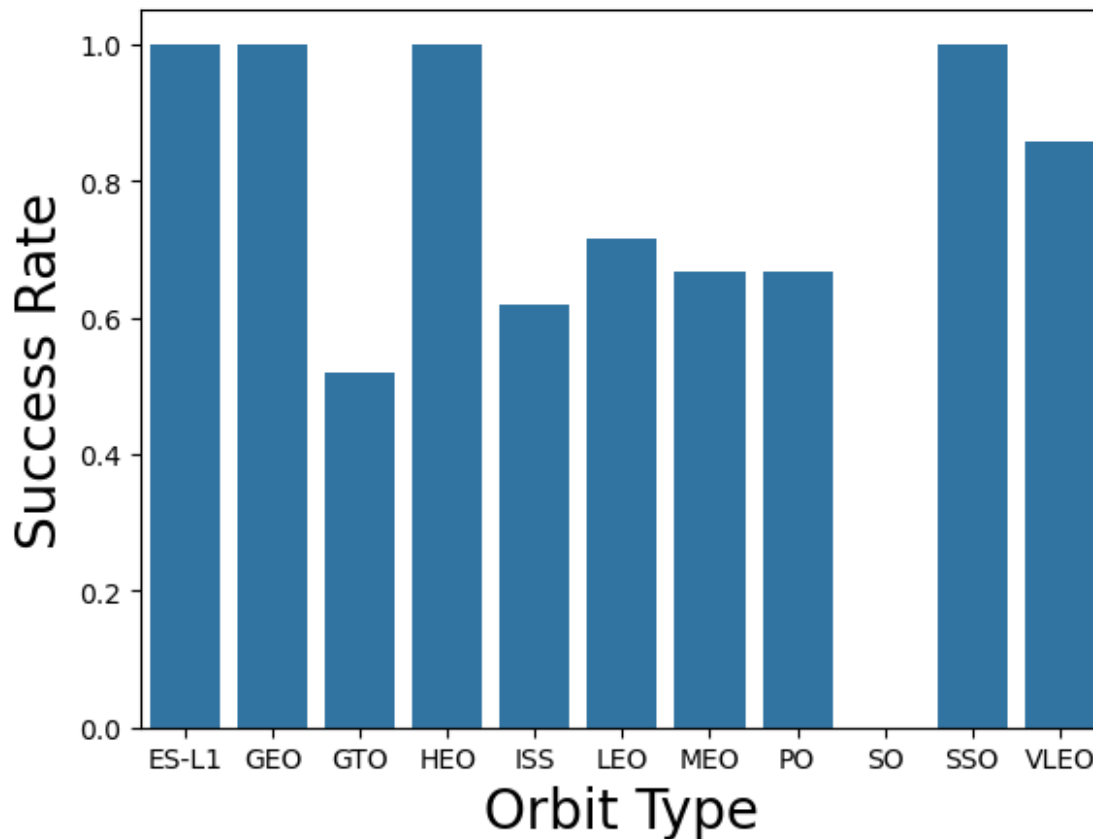
```
sns.catplot(y="LaunchSite", x="PayloadMass", hue="Class", data=df,
aspect=2.5)
plt.xlabel("Payload Mass (kg)", fontsize=20)
plt.ylabel("Launch Site", fontsize=20)
plt.show()
```



TASK 3: Visualize the relationship between success rate of each orbit type

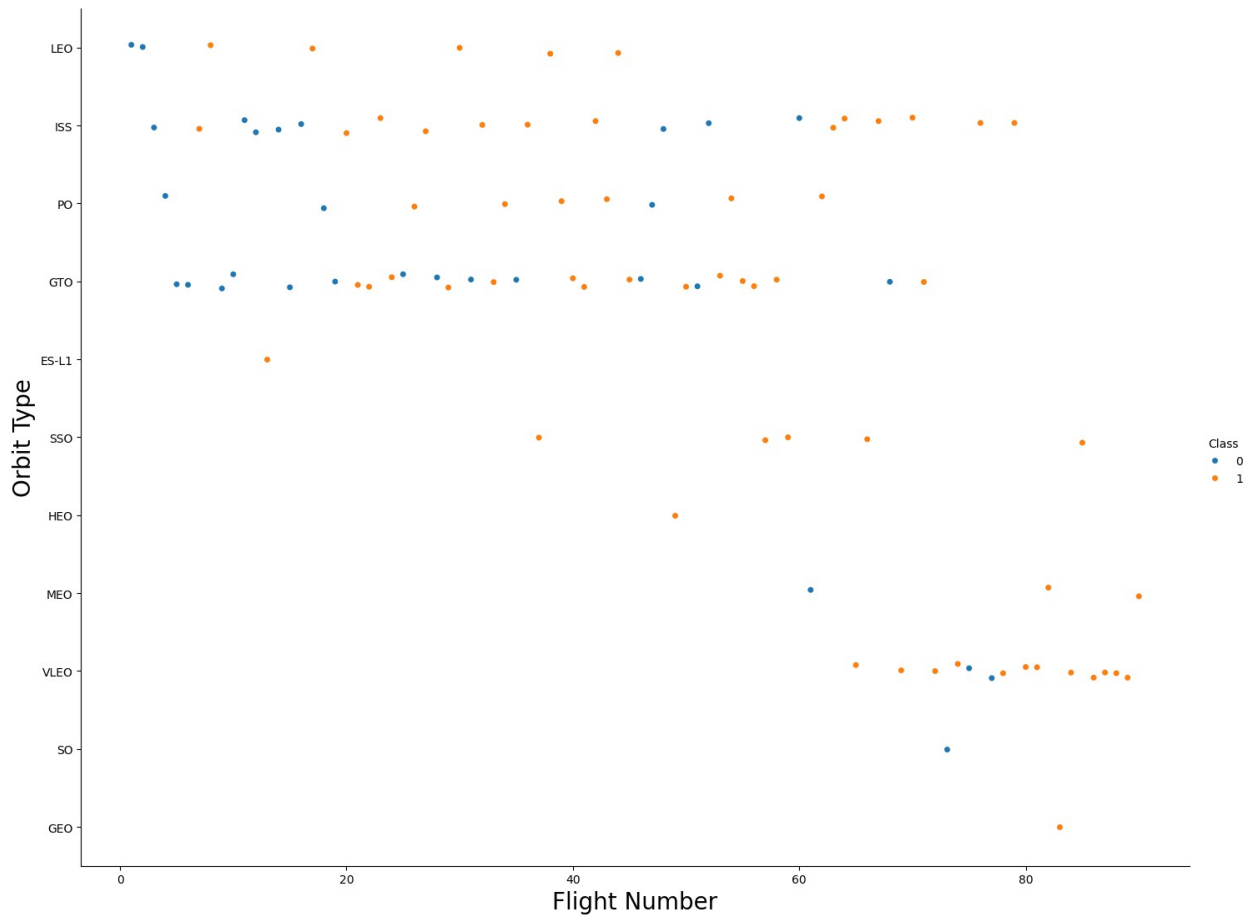
```
df_orbit = df.groupby(df['Orbit'], as_index=False).agg({"Class":
"mean"})
#df_orbit
sns.barplot(y="Class", x="Orbit", data=df_orbit)
```

```
plt.xlabel("Orbit Type", fontsize=20)
plt.ylabel("Success Rate", fontsize=20)
plt.show()
```



TASK 4: Visualize the relationship between FlightNumber and Orbit type

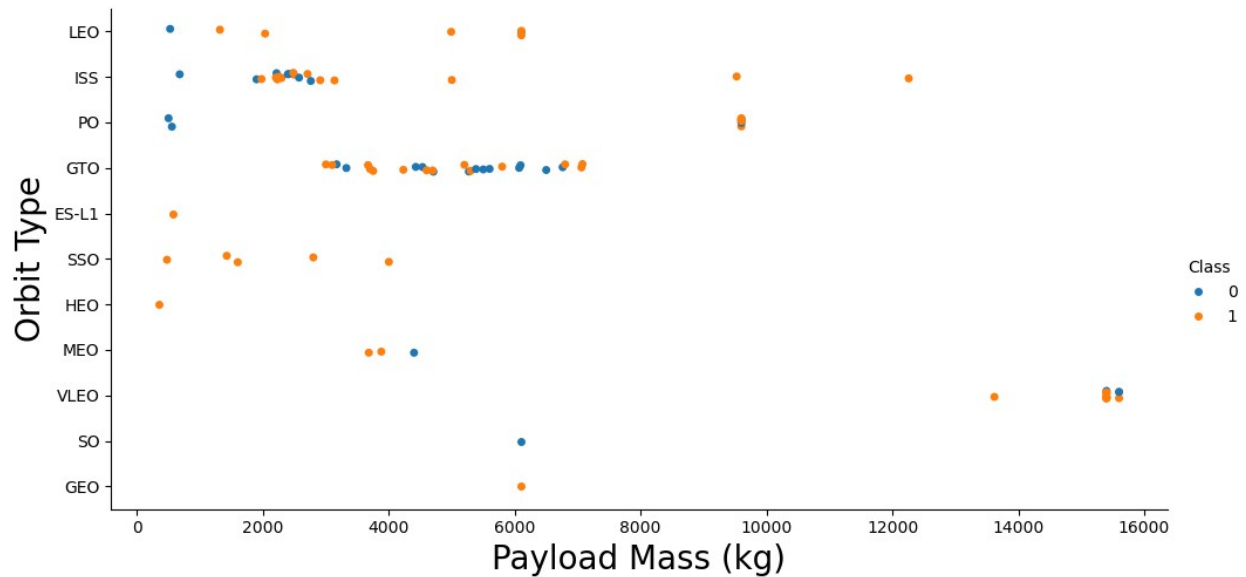
```
sns.catplot(y="Orbit", x="FlightNumber", hue="Class", data=df,
aspect=1.3, height=11)
plt.xlabel("Flight Number", fontsize=20)
plt.ylabel("Orbit Type", fontsize=20)
plt.show()
```



TASK 5: Visualize the relationship between Payload Mass and Orbit type

Plot a scatter point chart with x axis to be Payload Mass and y axis to be the Orbit, and hue to be the class value

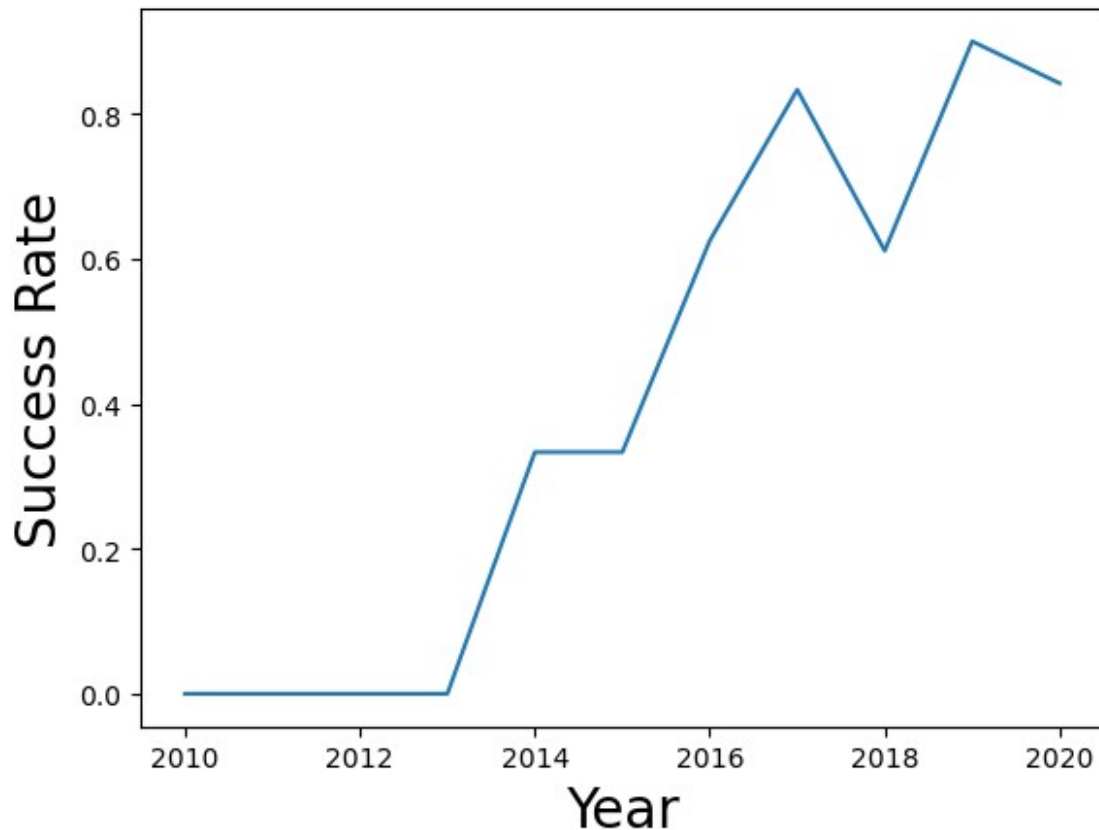
```
sns.catplot(y="Orbit", x="PayloadMass", hue="Class", data=df,
            aspect=2)
plt.xlabel("Payload Mass (kg)", fontsize=20)
plt.ylabel("Orbit Type", fontsize=20)
plt.show()
```



TASK 6: Visualize the launch success yearly trend

```
# add year column
df["Year"] = pd.DatetimeIndex(df["Date"]).year.astype(int)

df_year = df.groupby(df['Year'], as_index=False).agg({"Class":
"mean"})
#df_orbit
sns.lineplot(y="Class", x="Year", data=df_year)
plt.xlabel("Year", fontsize=20)
plt.ylabel("Success Rate", fontsize=20)
plt.show()
```



Features Engineering

We will select the features that will be used in success prediction in the future module.

```
features = df[['FlightNumber', 'PayloadMass', 'Orbit', 'LaunchSite',
'Flights', 'GridFins', 'Reused', 'Legs', 'LandingPad', 'Block',
'ReusedCount', 'Serial']]
features.head()
```

	FlightNumber	PayloadMass	Orbit	LaunchSite	Flights	GridFins
0	1	6104.959412	LEO	CCAFS SLC 40	1	False
1	2	525.000000	LEO	CCAFS SLC 40	1	False
2	3	677.000000	ISS	CCAFS SLC 40	1	False
3	4	500.000000	P0	VAFB SLC 4E	1	False
4	5	3170.000000	GT0	CCAFS SLC 40	1	False

	Legs	LandingPad	Block	ReusedCount	Serial
0	False	NaN	1.0	0	B0003
1	False	NaN	1.0	0	B0005
2	False	NaN	1.0	0	B0007
3	False	NaN	1.0	0	B1003
4	False	NaN	1.0	0	B1004

TASK 7: Create dummy variables to categorical columns

Use the function `get_dummies` and `features` dataframe to apply `OneHotEncoder` to the column `Orbits`, `LaunchSite`, `LandingPad`, and `Serial`. Assign the value to the variable `features_one_hot`, display the results using the method `head`. Your result dataframe must include all features including the encoded ones.

TASK 8: Cast all numeric columns to float64

Now that our `features_one_hot` dataframe only contains numbers, cast the entire dataframe to variable type `float64`

```
features_one_hot = features_one_hot.astype(float)
features_one_hot.dtypes

FlightNumber    float64
PayloadMass     float64
Flights         float64
GridFins        float64
Reused          float64
...
Serial_B1056    float64
Serial_B1058    float64
Serial_B1059    float64
Serial_B1060    float64
Serial_B1062    float64
Length: 81, dtype: object
```