SpaceX Falcon 9 First Stage Landing Prediction

Assignment: Exploring and Preparing Data

Estimated time needed: **70** minutes

In this assignment, we will predict if the Falcon 9 first stage will land successfully. SpaceX advertises Falcon 9 rocket launches on its website with a cost of 62 million dollars; other providers cost upward of 165 million dollars each, much of the savings is due to the fact that SpaceX can reuse the first stage.

In this lab, you will perform Exploratory Data Analysis and Feature Engineering.

Falcon 9 first stage will land successfully

Several examples of an unsuccessful landing are shown here:

Most unsuccessful landings are planned. Space X performs a controlled landing in the oceans.

Objectives

Perform exploratory Data Analysis and Feature Engineering using `Pandas` and `Matplotlib`

- Exploratory Data Analysis
- Preparing Data Feature Engineering

Import Libraries and Define Auxiliary Functions

We will import the following libraries the lab

In [ ]:
```
# andas 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 sklearn.preprocessing import OneHotEncoder
```

Exploratory Data Analysis

First, let's read the SpaceX dataset into a Pandas dataframe and print its summary

In [ ]:
```
df=pd.read_csv("https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DS0321EN-SkillsNetwork/datasets/dataset_part_2.csv")

# If you were unable to complete the previous lab correctly you can uncomment and load this csv

# df = pd.read_csv('https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBMDeveloperSkillsNetwork-DS0701EN-SkillsNetwork/api/dataset_part_2.csv')

#df.head(5)

print(df)
```

```
    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    PO   VAFB SLC 4E
4              5  2013-12-03       Falcon 9   3170.000000   GTO  CCAFS SLC 40
..           ...         ...            ...           ...   ...           ...
85            86  2020-09-03       Falcon 9  15400.000000  VLEO    KSC LC 39A
86            87  2020-10-06       Falcon 9  15400.000000  VLEO    KSC LC 39A
87            88  2020-10-18       Falcon 9  15400.000000  VLEO    KSC LC 39A
88            89  2020-10-24       Falcon 9  15400.000000  VLEO  CCAFS SLC 40
89            90  2020-11-05       Falcon 9   3681.000000   MEO  CCAFS SLC 40

        Outcome  Flights  GridFins  Reused   Legs                LandingPad  \
0     None None        1     False   False  False                       NaN
1     None None        1     False   False  False                       NaN
2     None None        1     False   False  False                       NaN
3   False Ocean        1     False   False  False                       NaN
4     None None        1     False   False  False                       NaN
..          ...      ...       ...     ...    ...                       ...
85    True ASDS        2      True    True   True  5e9e3032383ecb6bb234e7ca
86    True ASDS        3      True    True   True  5e9e3032383ecb6bb234e7ca
87    True ASDS        6      True    True   True  5e9e3032383ecb6bb234e7ca
88    True ASDS        3      True    True   True  5e9e3033383ecbb9e534e7cc
89    True ASDS        1      True   False   True  5e9e3032383ecb6bb234e7ca

    Block  ReusedCount Serial   Longitude   Latitude  Class
0     1.0            0  B0003  -80.577366  28.561857      0
1     1.0            0  B0005  -80.577366  28.561857      0
2     1.0            0  B0007  -80.577366  28.561857      0
3     1.0            0  B1003 -120.610829  34.632093      0
4     1.0            0  B1004  -80.577366  28.561857      0
..    ...          ...    ...         ...        ...    ...
85    5.0            2  B1060  -80.603956  28.608058      1
86    5.0            2  B1058  -80.603956  28.608058      1
87    5.0            5  B1051  -80.603956  28.608058      1
88    5.0            2  B1060  -80.577366  28.561857      1
89    5.0            0  B1062  -80.577366  28.561857      1

[90 rows x 18 columns]
```

First, let's try to see how the `FlightNumber` (indicating the continuous launch attempts.) and `Payload` variables would affect the launch outcome.

We can plot out the `FlightNumber` vs. `PayloadMass` and overlay the outcome of the launch. We see that as the flight number increases, the first stage is more likely to land successfully. The payload mass is also important; it seems the more massive the payload, the less likely the first stage will return.

In [ ]:
```
sns.catplot(y="PayloadMass", x="FlightNumber", hue="Class", data=df, aspect = 5)
plt.xlabel("Flight Number",fontsize=20)
plt.ylabel("Pay load Mass (kg)",fontsize=20)
plt.show()
```

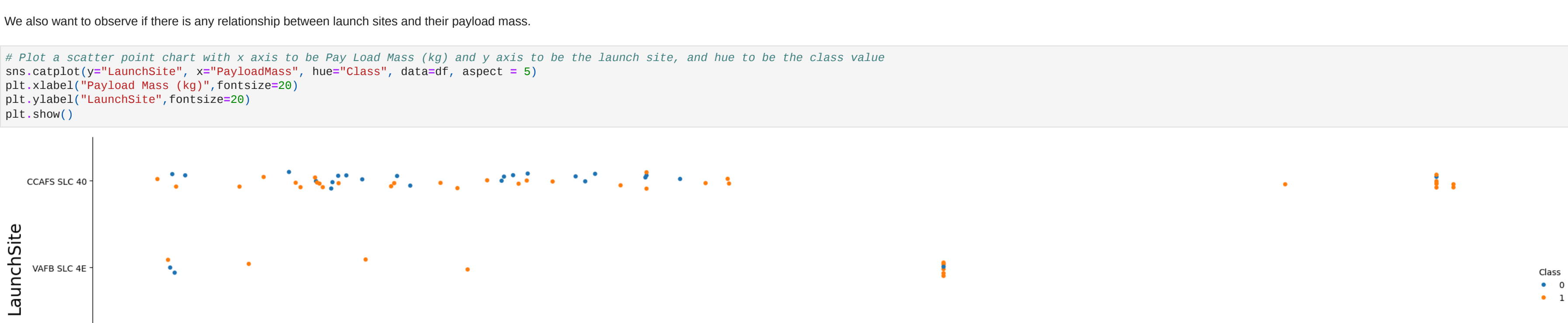
We see that different launch sites have different success rates. `CCAFS LC-40`, has a success rate of 60 %, while `KSC LC-39A` and `VAFB SLC 4E` has a success rate of 77%.

Next, let's drill down to each site visualize its detailed launch records.

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

Use the function `catplot` to plot `FlightNumber` vs `LaunchSite`, set the parameter `x` parameter to `FlightNumber`,set the `y` to `Launch Site` and set the parameter `hue` to `'class'`

In [ ]:
```
# Plot a scatter point chart with x axis to be Flight Number and y axis to be the launch site, and hue to be the class value
sns.catplot(y="LaunchSite", x="FlightNumber", hue="Class", data=df, aspect = 5)
plt.xlabel("Flight Number",fontsize=20)
plt.ylabel("LaunchSite",fontsize=20)
plt.show()
```

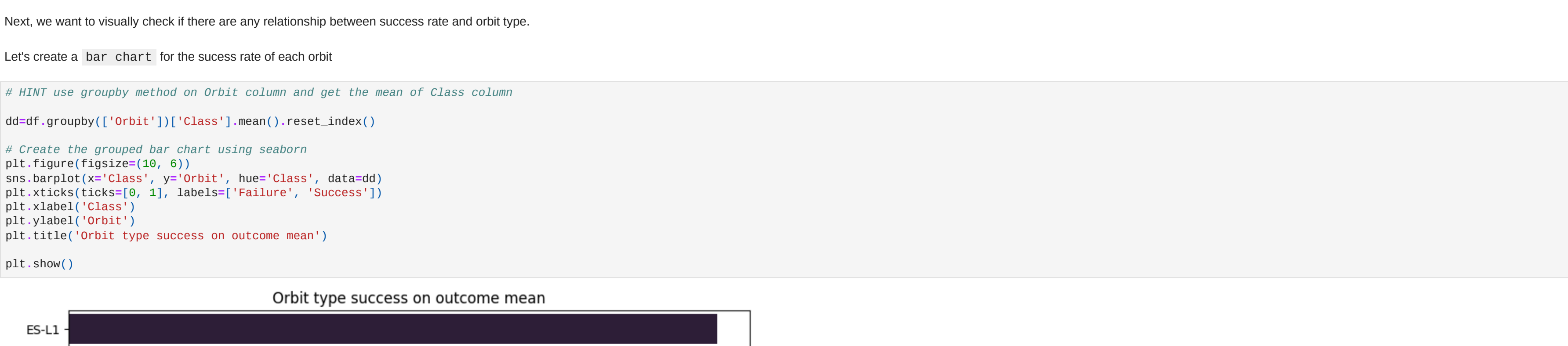


Now try to explain the patterns you found in the Flight Number vs. Launch Site scatter point plots.

TASK 2: Visualize the relationship between Payload and Launch Site

We also want to observe if there is any relationship between launch sites and their payload mass.

In [ ]:
```
# Plot a scatter point chart with x axis to be Pay Load Mass (kg) and y axis to be the launch site, and hue to be the class value
sns.catplot(y="LaunchSite", x="PayloadMass", hue="Class", data=df, aspect = 5)
plt.xlabel("Payload Mass (kg)",fontsize=20)
plt.ylabel("LaunchSite",fontsize=20)
plt.show()
```



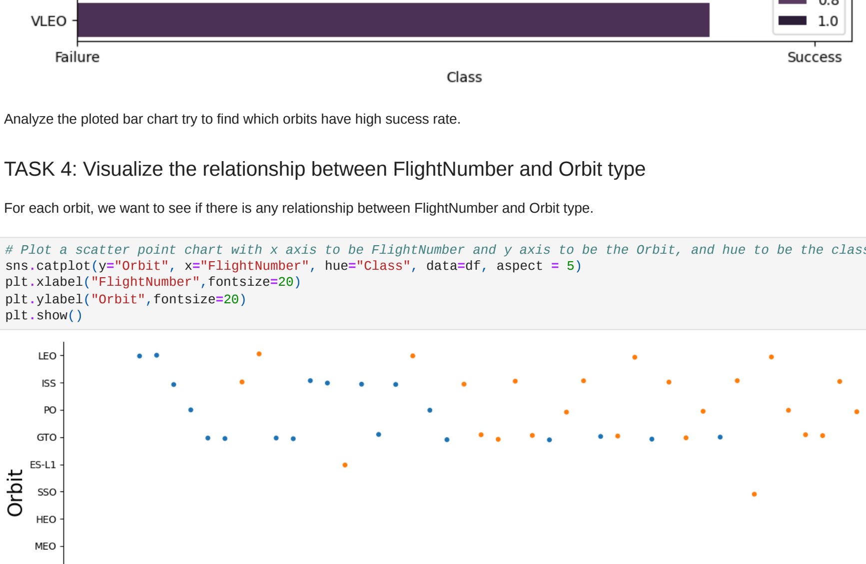
Now if you observe Payload Vs. Launch Site scatter point chart you will find for the VAFB-SLC launchsite there are no rockets launched for heavypayload mass(greater than 10000).

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

Next, we want to visually check if there are any relationship between success rate and orbit type.

Let's create a `bar chart` for the sucess rate of each orbit

In [ ]:
```
# HINT use groupby method on Orbit column and get the mean of Class column

dd=df.groupby(['Orbit'])['Class'].mean().reset_index()

# Create the grouped bar chart using seaborn
plt.figure(figsize=(10, 6))
sns.barplot(x='Class', y='Orbit', hue='Class', data=dd)
plt.xticks(ticks=[0, 1], labels=['Failure', 'Success'])
plt.xlabel('Class')
plt.ylabel('Orbit')
plt.title('Orbit type success on outcome mean')

plt.show()
```

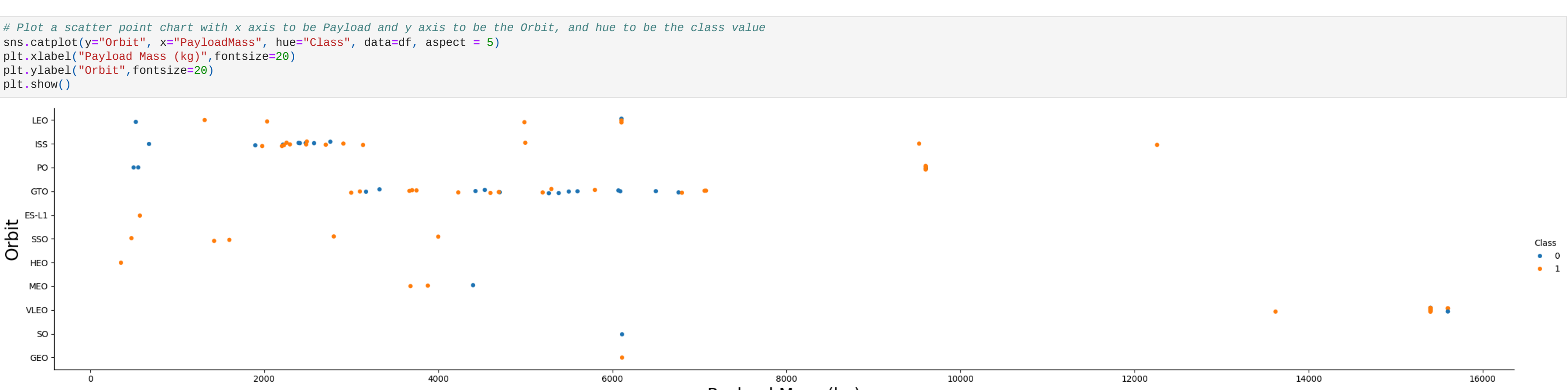


Analyze the ploted bar chart try to find which orbits have high sucess rate.

TASK 4: Visualize the relationship between FlightNumber and Orbit type

For each orbit, we want to see if there is any relationship between FlightNumber and Orbit type.

In [ ]:
```
# Plot a scatter point chart with x axis to be FlightNumber and y axis to be the Orbit, and hue to be the class value
sns.catplot(y="Orbit", x="FlightNumber", hue="Class", data=df, aspect = 5)
plt.xlabel("FlightNumber",fontsize=20)
plt.ylabel("Orbit",fontsize=20)
plt.show()
```

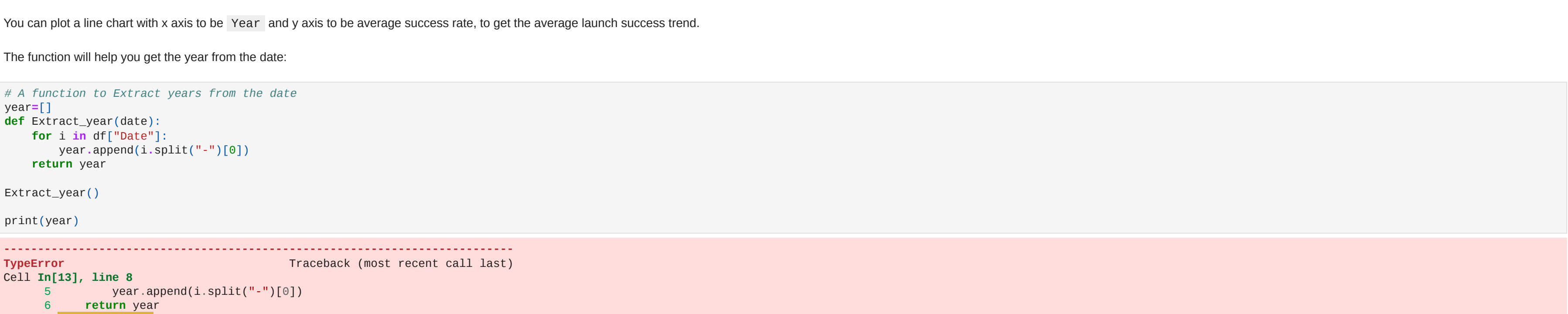


You should see that in the LEO orbit the Success appears related to the number of flights; on the other hand, there seems to be no relationship between flight number when in GTO orbit.

TASK 5: Visualize the relationship between Payload and Orbit type

Similarly, we can plot the Payload vs. Orbit scatter point charts to reveal the relationship between Payload and Orbit type

In [ ]:
```
# Plot a scatter point chart with x axis to be Payload 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 = 5)
plt.xlabel("Payload Mass (kg)",fontsize=20)
plt.ylabel("Orbit",fontsize=20)
plt.show()
```



With heavy payloads the successful landing or positive landing rate are more for Polar,LEO and ISS.

However for GTO we cannot distinguish this well as both positive landing rate and negative landing(unsuccessful mission) are both there here.

TASK 6: Visualize the launch success yearly trend

You can plot a line chart with x axis to be `Year` and y axis to be average success rate, to get the average launch success trend.

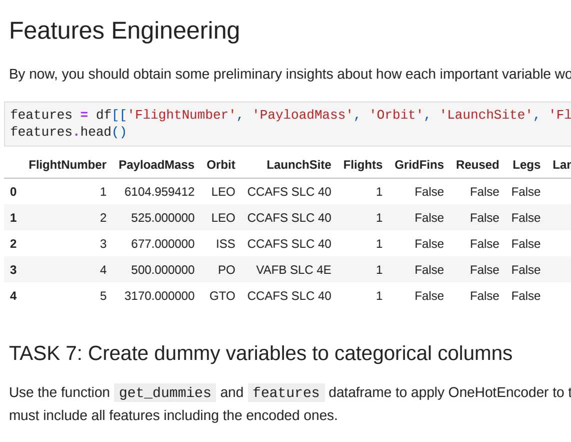
The function will help you get the year from the date:

In [ ]:
```
# A function to Extract years from the date
year=[]
def Extract_year(date):
    for i in df["Date"]:
        year.append(i.split("-")[0])
    return year

Extract_year()

print(year)
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
Cell In[13], line 8
      5         year.append(i.split("-")[0])
      6     return year
----> 8 Extract_year()
     10 print(year)

TypeError: Extract_year() missing 1 required positional argument: 'date'
```

In [ ]:
```
# Plot a line chart with x axis to be the extracted year and y axis to be the success rate
"""
may_flights = flights.query("month == 'May'")
sns.lineplot(data=may_flights, x="year", y="passengers")
"""
year=[]
for i in df["Date"]:
        year.append(i.split("-")[0])

df['Year']=year

sns.lineplot(data=df, x="Year", y="Class")
```

Out[ ]: `<Axes: xlabel='Year', ylabel='Class'>`



You can observe that the success rate since 2013 kept increasing till 2017 (stable in 2014) and after 2015 it started increasing.

Features Engineering

By now, you should obtain some preliminary insights about how each important variable would affect the success rate, we will select the features that will be used in success prediction in the future module.

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

Out[ ]:

	FlightNumber	PayloadMass	Orbit	LaunchSite	Flights	GridFins	Reused	Legs	LandingPad	Block	ReusedCount	Serial
0	1	6104.959412	LEO	CCAFS SLC 40	1	False	False	False	NaN	1.0	0	B0003
1	2	525.000000	LEO	CCAFS SLC 40	1	False	False	False	NaN	1.0	0	B0005
2	3	677.000000	ISS	CCAFS SLC 40	1	False	False	False	NaN	1.0	0	B0007
3	4	500.000000	PO	VAFB SLC 4E	1	False	False	False	NaN	1.0	0	B1003
4	5	3170.000000	GTO	CCAFS SLC 40	1	False	False	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.

In [ ]:
```
# HINT: Use get_dummies() function on the categorical columns
# Create an instance of OneHotEncoder
encoder = OneHotEncoder()

# Select the columns to encode
columns_to_encode = ['Orbit', 'LaunchSite', 'LandingPad', 'Serial']

# Fit and transform the selected columns
features_encoded = encoder.fit_transform(features[columns_to_encode])

# Create a new DataFrame with the encoded features
features_one_hot = pd.DataFrame(features_encoded.toarray(), columns=encoder.get_feature_names_out(columns_to_encode))

# Concatenate the original features with the encoded ones
features_one_hot = pd.concat([features_one_hot], axis=1)

# Display the first few rows of the resulting DataFrame
features_one_hot.head()
```

Out[ ]:

	Orbit_ES-L1	Orbit_GEO	Orbit_GTO	Orbit_HEO	Orbit_ISS	Orbit_LEO	Orbit_MEO	Orbit_PO	Orbit_SO	Orbit_SSO	...	Serial_B1048	Serial_B1049	Serial_B1050	Serial_B1051	Serial_B1054	Serial_B1056	Serial_B1058	Serial_B1059	Serial_B1060	Serial_B1062
0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 73 columns

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`

In [ ]:
```
# HINT: use astype function
# Cast the entire DataFrame to float64
features_one_hot = features_one_hot.astype(float)
features_one_hot.head()
```

Out[ ]:

	Orbit_ES-L1	Orbit_GEO	Orbit_GTO	Orbit_HEO	Orbit_ISS	Orbit_LEO	Orbit_MEO	Orbit_PO	Orbit_SO	Orbit_SSO	...	Serial_B1048	Serial_B1049	Serial_B1050	Serial_B1051	Serial_B1054	Serial_B1056	Serial_B1058	Serial_B1059	Serial_B1060	Serial_B1062
0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 73 columns

We can now export it to a **CSV** for the next section,but to make the answers consistent, in the next lab we will provide data in a pre-selected date range.

`features_one_hot.to_csv('dataset_part_3.csv', index=False)`

Authors

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Change Log

Date (YYYY-MM-DD)	Version	Changed By	Change Description
2021-10-12	1.1	Lakshmi Holla	Modified markdown
2020-09-20	1.0	Joseph	Modified Multiple Areas
2020-11-10	1.1	Nayef	updating the input data