

# logistic Regression Project:Asteroid Classification

## Data Acquisition

In [1]: #Import Libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [2]: #Load dataset

```
data=pd.read_csv(r"C:\Users\DD\Desktop\Asteroid\nasa.csv")
```

In [3]: `#read the data`  
data

Out[3]:

	Neo Reference ID	Name	Absolute Magnitude	Est Dia in KM(min)	Est Dia in KM(max)	Est Dia in M(min)	Est Dia in M(max)	Est Dia in Miles(min)	Est Dia in Miles(max)	Est Dia in Feet(min)	...	Asc Node Longitude
0	3703080	3703080	21.600	0.127220	0.284472	127.219878	284.472297	0.079051	0.176763	417.388066	...	314.373913
1	3723955	3723955	21.300	0.146068	0.326618	146.067964	326.617897	0.090762	0.202951	479.225620	...	136.717242
2	2446862	2446862	20.300	0.231502	0.517654	231.502122	517.654482	0.143849	0.321655	759.521423	...	259.475979
3	3092506	3092506	27.400	0.008801	0.019681	8.801465	19.680675	0.005469	0.012229	28.876199	...	57.173266
4	3514799	3514799	21.600	0.127220	0.284472	127.219878	284.472297	0.079051	0.176763	417.388066	...	84.629307
...	...	...	...	...	...	...	...	...	...	...	...	...
4682	3759007	3759007	23.900	0.044112	0.098637	44.111820	98.637028	0.027410	0.061290	144.723824	...	164.183305
4683	3759295	3759295	28.200	0.006089	0.013616	6.089126	13.615700	0.003784	0.008460	19.977449	...	345.225230
4684	3759714	3759714	22.700	0.076658	0.171412	76.657557	171.411509	0.047633	0.106510	251.501181	...	37.026468
4685	3759720	3759720	21.800	0.116026	0.259442	116.025908	259.441818	0.072095	0.161210	380.662441	...	163.802909
4686	3772978	3772978	19.109	0.400641	0.895860	400.640618	895.859655	0.248946	0.556661	1314.437764	...	187.642183

4687 rows × 40 columns



## Information about data set

In [4]: `data.shape`

Out[4]: (4687, 40)

In [5]: `#top 10 rows`  
`data.head(10)`

Out[5]:

	Neo Reference ID	Name	Absolute Magnitude	Est Dia in KM(min)	Est Dia in KM(max)	Est Dia in M(min)	Est Dia in M(max)	Est Dia in Miles(min)	Est Dia in Miles(max)	Est Dia in Feet(min)	...	Asc Node Longitude
0	3703080	3703080	21.6	0.127220	0.284472	127.219878	284.472297	0.079051	0.176763	417.388066	...	314.373913 60
1	3723955	3723955	21.3	0.146068	0.326618	146.067964	326.617897	0.090762	0.202951	479.225620	...	136.717242 42
2	2446862	2446862	20.3	0.231502	0.517654	231.502122	517.654482	0.143849	0.321655	759.521423	...	259.475979 64
3	3092506	3092506	27.4	0.008801	0.019681	8.801465	19.680675	0.005469	0.012229	28.876199	...	57.173266 51
4	3514799	3514799	21.6	0.127220	0.284472	127.219878	284.472297	0.079051	0.176763	417.388066	...	84.629307 49
5	3671135	3671135	19.6	0.319562	0.714562	319.561887	714.562102	0.198566	0.444008	1048.431420	...	178.971951 55
6	2495323	2495323	19.6	0.319562	0.714562	319.561887	714.562102	0.198566	0.444008	1048.431420	...	178.971953 55
7	2153315	2153315	19.2	0.384198	0.859093	384.197891	859.092601	0.238729	0.533815	1260.491809	...	112.562984 50
8	2162463	2162463	17.8	0.732074	1.636967	732.073989	1636.967205	0.454890	1.017164	2401.817627	...	80.211132 44
9	2306383	2306383	21.5	0.133216	0.297879	133.215567	297.879063	0.082776	0.185093	437.058960	...	2.613682 29

10 rows × 40 columns



```
In [6]: #bottom 10 rows  
data.tail(10)
```

Out[6]:

	Neo Reference ID	Name	Absolute Magnitude	Est Dia in KM(min)	Est Dia in KM(max)	Est Dia in M(min)	Est Dia in M(max)	Est Dia in Miles(min)	Est Dia in Miles(max)	Est Dia in Feet(min)	...	Asc Node Longitude
4677	3759644	3759644	24.500	0.033462	0.074824	33.462237	74.823838	0.020792	0.046493	109.784247	...	4.970984
4678	3358223	3358223	22.700	0.076658	0.171412	76.657557	171.411509	0.047633	0.106510	251.501181	...	231.238901
4679	3394709	3394709	26.300	0.014607	0.032662	14.606796	32.661790	0.009076	0.020295	47.922562	...	43.263028
4680	3608620	3608620	23.600	0.050647	0.113250	50.647146	113.250461	0.031471	0.070371	166.165182	...	175.870458
4681	3662283	3662283	20.700	0.192555	0.430566	192.555078	430.566244	0.119648	0.267541	631.742403	...	145.035928
4682	3759007	3759007	23.900	0.044112	0.098637	44.111820	98.637028	0.027410	0.061290	144.723824	...	164.183305
4683	3759295	3759295	28.200	0.006089	0.013616	6.089126	13.615700	0.003784	0.008460	19.977449	...	345.225230
4684	3759714	3759714	22.700	0.076658	0.171412	76.657557	171.411509	0.047633	0.106510	251.501181	...	37.026468
4685	3759720	3759720	21.800	0.116026	0.259442	116.025908	259.441818	0.072095	0.161210	380.662441	...	163.802909
4686	3772978	3772978	19.109	0.400641	0.895860	400.640618	895.859655	0.248946	0.556661	1314.437764	...	187.642183

10 rows × 40 columns



In [7]: *#describe the data*

```
data.describe(include='all')
```

Out[7]:

	Neo Reference ID	Name	Absolute Magnitude	Est Dia in KM(min)	Est Dia in KM(max)	Est Dia in M(min)	Est Dia in M(max)	Est Dia in Miles(min)	Est Dia in Miles(max)
<b>count</b>	4.687000e+03	4.687000e+03	4687.000000	4687.000000	4687.000000	4687.000000	4687.000000	4687.000000	4687.000000
<b>unique</b>	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
<b>top</b>	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
<b>freq</b>	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
<b>mean</b>	3.272298e+06	3.272298e+06	22.267865	0.204604	0.457509	204.604203	457.508906	0.127135	0.284283
<b>std</b>	5.486011e+05	5.486011e+05	2.890972	0.369573	0.826391	369.573402	826.391249	0.229642	0.513496
<b>min</b>	2.000433e+06	2.000433e+06	11.160000	0.001011	0.002260	1.010543	2.259644	0.000628	0.001404
<b>25%</b>	3.097594e+06	3.097594e+06	20.100000	0.033462	0.074824	33.462237	74.823838	0.020792	0.046493
<b>50%</b>	3.514799e+06	3.514799e+06	21.900000	0.110804	0.247765	110.803882	247.765013	0.068850	0.153954
<b>75%</b>	3.690060e+06	3.690060e+06	24.500000	0.253837	0.567597	253.837029	567.596853	0.157727	0.352688
<b>max</b>	3.781897e+06	3.781897e+06	32.100000	15.579552	34.836938	15579.552410	34836.938250	9.680682	21.646663

11 rows × 40 columns



```
In [8]: #it will display information about that object, including its data type, attributes, and methods, if available  
#This information is provided interactively to help you understand the object better.
```

```
data.info
```

Out[8]:	<bound method DataFrame.info of					Neo	Reference ID	Name	Absolute Magnitude	Est Dia in KM(min)	\
0	3703080	3703080				21.600		0.127220			
1	3723955	3723955				21.300		0.146068			
2	2446862	2446862				20.300		0.231502			
3	3092506	3092506				27.400		0.008801			
4	3514799	3514799				21.600		0.127220			
...	...	...				...		...			
4682	3759007	3759007				23.900		0.044112			
4683	3759295	3759295				28.200		0.006089			
4684	3759714	3759714				22.700		0.076658			
4685	3759720	3759720				21.800		0.116026			
4686	3772978	3772978				19.109		0.400641			
	Est Dia in KM(max)	Est Dia in M(min)	Est Dia in M(max)								\
0	0.284472	127.219878	284.472297								
1	0.326618	146.067964	326.617897								
2	0.517654	231.502122	517.654482								
3	0.019681	8.801465	19.680675								
4	0.284472	127.219878	284.472297								
...	...	...	...								
4682	0.098637	44.111820	98.637028								
4683	0.013616	6.089126	13.615700								
4684	0.171412	76.657557	171.411509								
4685	0.259442	116.025908	259.441818								
4686	0.895860	400.640618	895.859655								
	Est Dia in Miles(min)	Est Dia in Miles(max)	Est Dia in Feet(min)	...	...						\
0	0.079051	0.176763	417.388066	...							
1	0.090762	0.202951	479.225620	...							
2	0.143849	0.321655	759.521423	...							
3	0.005469	0.012229	28.876199	...							
4	0.079051	0.176763	417.388066	...							
...	...	...	...	...	...						
4682	0.027410	0.061290	144.723824	...							
4683	0.003784	0.008460	19.977449	...							
4684	0.047633	0.106510	251.501181	...							
4685	0.072095	0.161210	380.662441	...							
4686	0.248946	0.556661	1314.437764	...							
	Asc Node	Longitude	Orbital Period	Perihelion Distance	Perihelion Arg						\
0	314.373913	609.599786		0.808259	57.257470						
1	136.717242	425.869294		0.718200	313.091975						
2	259.475979	643.580228		0.950791	248.415038						

3	57.173266	514.082140	0.983902	18.707701
4	84.629307	495.597821	0.967687	158.263596
...	...	...	...	...
4682	164.183305	457.179984	0.741558	276.395697
4683	345.225230	407.185767	0.996434	42.111064
4684	37.026468	690.054279	0.965760	274.692712
4685	163.802909	662.048343	1.185467	180.346090
4686	187.642183	653.679098	0.876110	222.436688

	Aphelion	Dist	Perihelion	Time	Mean Anomaly	Mean Motion	Equinox	\
0	2.005764		2458161.642		264.837533	0.590551	J2000	
1	1.497352		2457794.969		173.741112	0.845330	J2000	
2	1.966857		2458120.468		292.893654	0.559371	J2000	
3	1.527904		2457902.337		68.741007	0.700277	J2000	
4	1.483543		2457814.455		135.142133	0.726395	J2000	
...	...		...		...	...	...	...
4682	1.581299		2457708.228		304.306024	0.787436	J2000	
4683	1.153835		2458087.617		282.978786	0.884117	J2000	
4684	2.090708		2458300.480		203.501147	0.521698	J2000	
4685	1.787733		2458288.261		203.524965	0.543767	J2000	
4686	2.071980		2458318.587		184.820424	0.550729	J2000	

## Hazardous

0	True
1	False
2	True
3	False
4	True
...	...
4682	False
4683	False
4684	False
4685	False
4686	False

[4687 rows x 40 columns]>

```
In [9]: #it provides a concise summary of the DataFrame's structure,  
#including the number of non-null values, data types of columns, and memory usage.  
#It's a useful method for quickly assessing the basic characteristics of your data.  
  
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4687 entries, 0 to 4686
Data columns (total 40 columns):
 #   Column           Non-Null Count Dtype  
 --- 
 0   Neo Reference ID    4687 non-null  int64   
 1   Name              4687 non-null  int64   
 2   Absolute Magnitude 4687 non-null  float64 
 3   Est Dia in KM(min) 4687 non-null  float64 
 4   Est Dia in KM(max) 4687 non-null  float64 
 5   Est Dia in M(min)  4687 non-null  float64 
 6   Est Dia in M(max)  4687 non-null  float64 
 7   Est Dia in Miles(min) 4687 non-null  float64 
 8   Est Dia in Miles(max) 4687 non-null  float64 
 9   Est Dia in Feet(min) 4687 non-null  float64 
 10  Est Dia in Feet(max) 4687 non-null  float64 
 11  Close Approach Date 4687 non-null  object  
 12  Epoch Date Close Approach 4687 non-null  float64 
 13  Relative Velocity km per sec 4687 non-null  float64 
 14  Relative Velocity km per hr  4687 non-null  float64 
 15  Miles per hour          4687 non-null  float64 
 16  Miss Dist.(Astronomical) 4687 non-null  float64 
 17  Miss Dist.(lunar)        4687 non-null  float64 
 18  Miss Dist.(kilometers)   4687 non-null  float64 
 19  Miss Dist.(miles)        4687 non-null  float64 
 20  Orbiting Body           4687 non-null  object  
 21  Orbit ID               4677 non-null  float64 
 22  Orbit Determination Date 4609 non-null  object  
 23  Orbit Uncertainty       4442 non-null  float64 
 24  Minimum Orbit Intersection 4371 non-null  float64 
 25  Jupiter Tisserand Invariant 4323 non-null  float64 
 26  Epoch Osculation        4211 non-null  float64 
 27  Eccentricity            4123 non-null  float64 
 28  Semi Major Axis         4061 non-null  float64 
 29  Inclination             4034 non-null  float64 
 30  Asc Node Longitude      4197 non-null  float64 
 31  Orbital Period          3784 non-null  float64 
 32  Perihelion Distance     3822 non-null  float64 
 33  Perihelion Arg          3836 non-null  float64 
 34  Aphelion Dist           4193 non-null  float64 
 35  Perihelion Time          4390 non-null  float64 
 36  Mean Anomaly             4534 non-null  float64 
 37  Mean Motion              4577 non-null  float64
```

```
38 Equinox          4642 non-null    object
39 Hazardous       4687 non-null    bool
dtypes: bool(1), float64(33), int64(2), object(4)
memory usage: 1.4+ MB
```

In [10]: `#any null value present`  
`data.isnull().values.any()`

Out[10]: True

In [11]: `# check the null values entirely present in the dataset`  
`data.isnull()`

Out[11]:

	Neo Reference ID	Name	Absolute Magnitude	Est Dia in KM(min)	Est Dia in KM(max)	Est Dia in M(min)	Est Dia in M(max)	Est Dia in Miles(min)	Est Dia in Miles(max)	Est Dia in Feet(min)	...	Asc Node Longitude	Orbital Period	Perihel Dist
0	False	False	False	False	False	False	False	False	False	False	...	False	False	I
1	False	False	False	False	False	False	False	False	False	False	...	False	False	I
2	False	False	False	False	False	False	False	False	False	False	...	False	False	I
3	False	False	False	False	False	False	False	False	False	False	...	False	False	I
4	False	False	False	False	False	False	False	False	False	False	...	False	False	I
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
4682	False	False	False	False	False	False	False	False	False	False	...	False	False	I
4683	False	False	False	False	False	False	False	False	False	False	...	False	False	I
4684	False	False	False	False	False	False	False	False	False	False	...	False	False	I
4685	False	False	False	False	False	False	False	False	False	False	...	False	False	I
4686	False	False	False	False	False	False	False	False	False	False	...	False	False	I

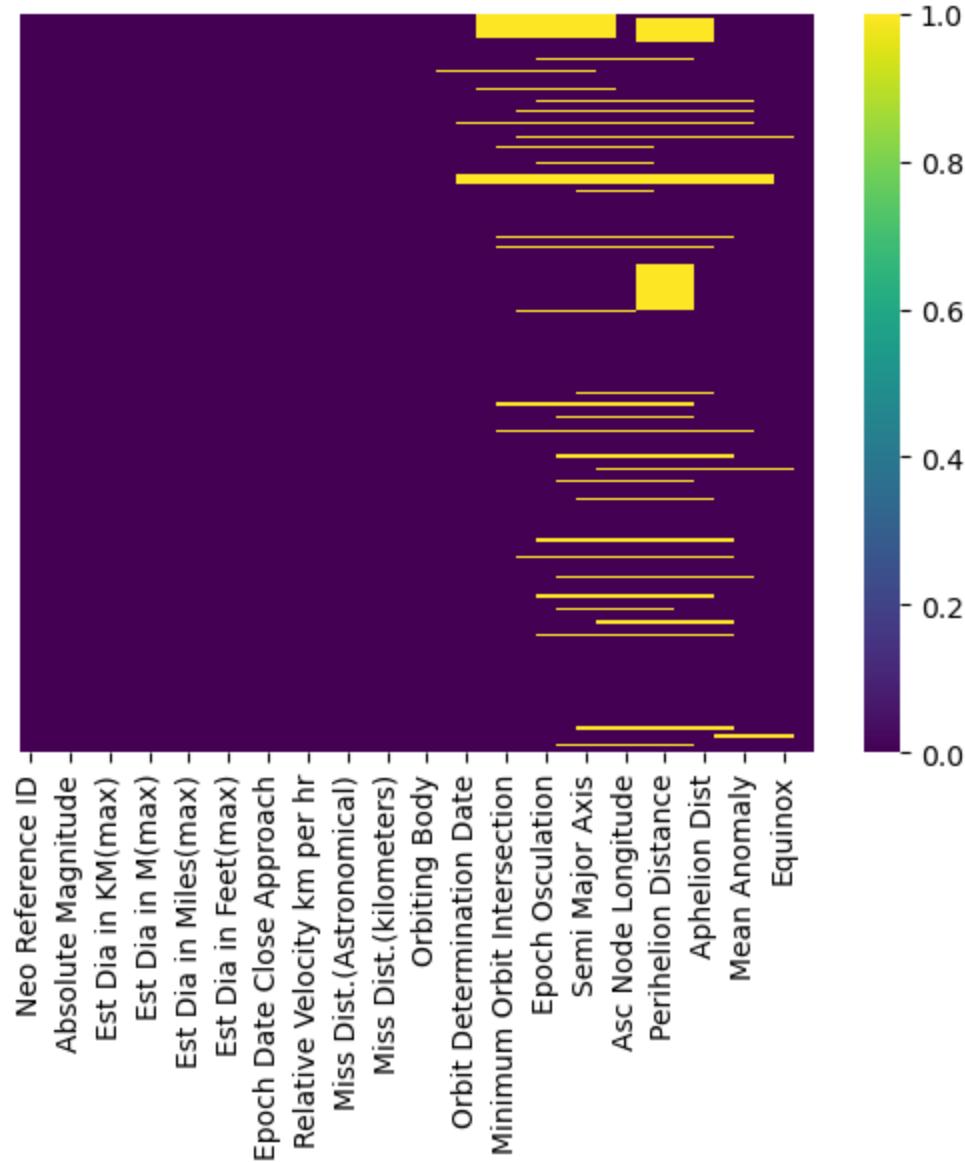
4687 rows × 40 columns

```
In [12]: # number of null values in each column  
data.isnull().sum()
```

```
Out[12]: Neo Reference ID      0
          Name            0
          Absolute Magnitude    0
          Est Dia in KM(min)   0
          Est Dia in KM(max)   0
          Est Dia in M(min)    0
          Est Dia in M(max)    0
          Est Dia in Miles(min) 0
          Est Dia in Miles(max) 0
          Est Dia in Feet(min)  0
          Est Dia in Feet(max)  0
          Close Approach Date   0
          Epoch Date Close Approach 0
          Relative Velocity km per sec 0
          Relative Velocity km per hr   0
          Miles per hour         0
          Miss Dist.(Astronomical) 0
          Miss Dist.(lunar)        0
          Miss Dist.(kilometers)   0
          Miss Dist.(miles)        0
          Orbiting Body           0
          Orbit ID                10
          Orbit Determination Date 78
          Orbit Uncertainty       245
          Minimum Orbit Intersection 316
          Jupiter Tisserand Invariant 364
          Epoch Osculation        476
          Eccentricity             564
          Semi Major Axis          626
          Inclination              653
          Asc Node Longitude       490
          Orbital Period           903
          Perihelion Distance      865
          Perihelion Arg            851
          Aphelion Dist             494
          Perihelion Time           297
          Mean Anomaly               153
          Mean Motion                 110
          Equinox                      45
          Hazardous                     0
          dtype: int64
```

```
In [13]: # to illustrate null values using heatmap  
sns.heatmap(data.isnull(), yticklabels=False,cmap="viridis")
```

Out[13]: <Axes: >



# Filling missing values

```
In [14]: # there is no need to fill the some data because there is no value for me so drop the data
data.drop(["Miss Dist.(Astronomical)", "Miss Dist.(lunar)", "Miss Dist.(miles)"
           , "Relative Velocity km per sec", "Est Dia in M(max)"
           , "Relative Velocity km per hr", "Est Dia in Feet(max)",
           "Est Dia in Feet(min)", "Est Dia in Miles(max)",
           "Est Dia in Miles(min)", "Est Dia in KM(max)", "Est Dia in KM(min)"
           , "Neo Reference ID", "Orbit ID", "Name", "Close Approach Date",
           "Equinox", "Epoch Date Close Approach", "Orbiting Body", "Orbit Determination Date"], axis=1, inplace=True)
```

```
In [15]: data.isnull().sum()
```

```
Out[15]: Absolute Magnitude          0
Est Dia in M(min)                 0
Miles per hour                   0
Miss Dist.(kilometers)           0
Orbit Uncertainty                245
Minimum Orbit Intersection         316
Jupiter Tisserand Invariant     364
Epoch Osculation                 476
Eccentricity                      564
Semi Major Axis                  626
Inclination                       653
Asc Node Longitude                490
Orbital Period                     903
Perihelion Distance               865
Perihelion Arg                    851
Aphelion Dist                     494
Perihelion Time                   297
Mean Anomaly                        153
Mean Motion                         110
Hazardous                           0
dtype: int64
```

```
In [16]: #fill my important data
data['Orbit Uncertainty']=data['Orbit Uncertainty'].fillna(data['Orbit Uncertainty'].mean())
data['Minimum Orbit Intersection']=data['Minimum Orbit Intersection'].fillna(data['Minimum Orbit Intersection'].mean())
data['Jupiter Tisserand Invariant']=data['Jupiter Tisserand Invariant'].fillna(data['Jupiter Tisserand Invariant'].mean())
data['Epoch Osculation']=data['Epoch Osculation'].fillna(data['Epoch Osculation'].mean())
data["Eccentricity"].fillna(data["Eccentricity"].mean(),inplace=True)
data['Semi Major Axis']=data['Semi Major Axis'].fillna(data['Semi Major Axis'].mean())
data['Inclination']=data['Inclination'].fillna(data['Inclination'].mean())
data['Asc Node Longitude']=data['Asc Node Longitude'].fillna(data['Asc Node Longitude'].mean())
```

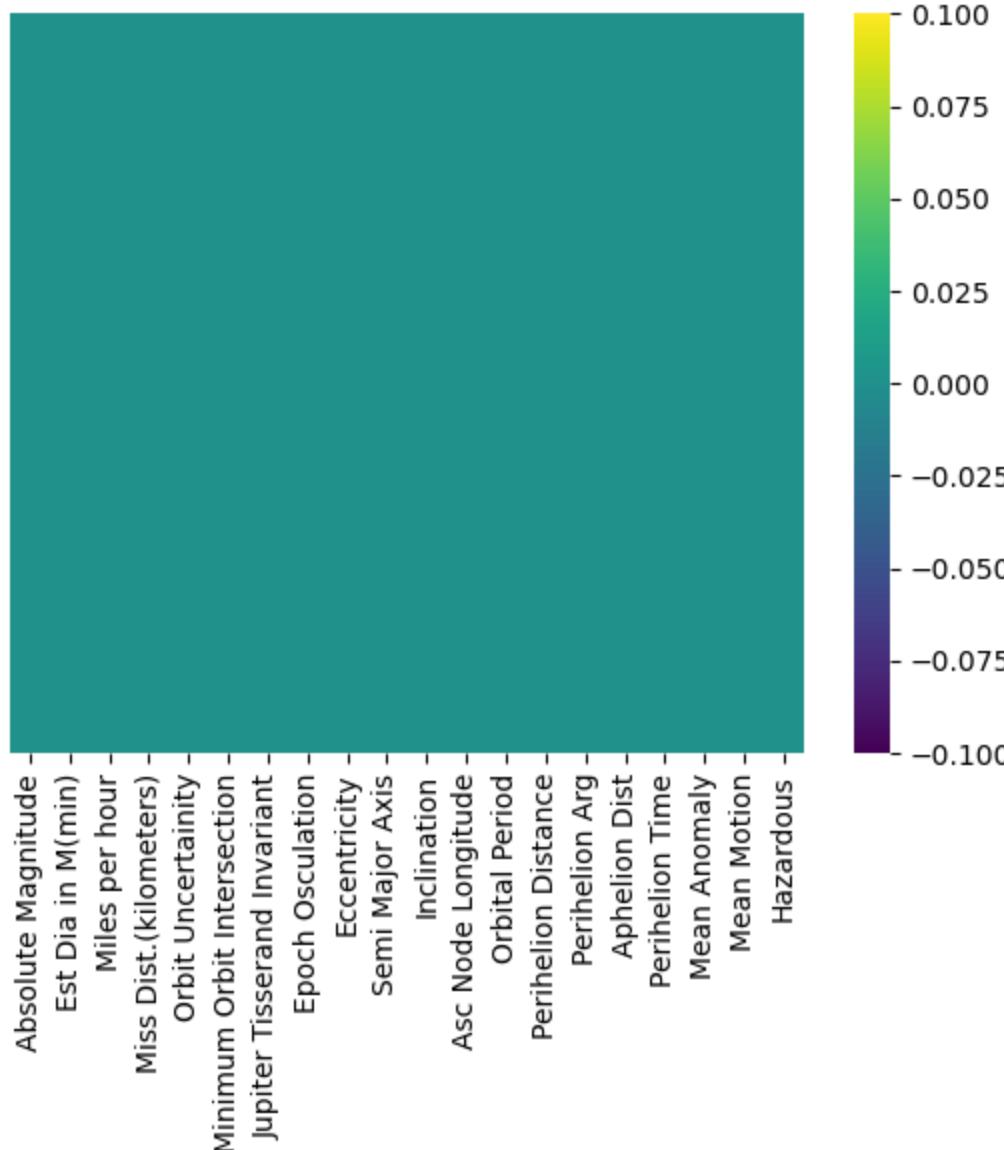
```
In [17]: data['Orbital Period']=data['Orbital Period'].fillna(data['Orbital Period'].mean())
data['Perihelion Distance']=data['Perihelion Distance'].fillna(data['Perihelion Distance'].mean())
data['Perihelion Arg']=data['Perihelion Arg'].fillna(data['Perihelion Arg'].mean())
data['Aphelion Dist']=data['Aphelion Dist'].fillna(data['Aphelion Dist'].mean())
data['Perihelion Time']=data['Perihelion Time'].fillna(data['Perihelion Time'].mean())
data['Mean Anomaly']=data['Mean Anomaly'].fillna(data['Mean Anomaly'].mean())
data['Mean Motion']=data['Mean Motion'].fillna(data['Mean Motion'].mean())
```

```
In [18]: data.isnull().sum()
```

```
Out[18]: Absolute Magnitude      0
Est Dia in M(min)            0
Miles per hour               0
Miss Dist.(kilometers)       0
Orbit Uncertainty             0
Minimum Orbit Intersection    0
Jupiter Tisserand Invariant  0
Epoch Osculation              0
Eccentricity                  0
Semi Major Axis                0
Inclination                   0
Asc Node Longitude             0
Orbital Period                 0
Perihelion Distance            0
Perihelion Arg                 0
Aphelion Dist                  0
Perihelion Time                 0
Mean Anomaly                   0
Mean Motion                     0
Hazardous                      0
dtype: int64
```

```
In [19]: # to illustrate null values using heatmap  
sns.heatmap(data.isnull(), yticklabels=False,cmap='viridis')
```

```
Out[19]: <Axes: >
```



```
In [20]: cat_data=data.select_dtypes(include=object)      # show catogorical data column  
num_data=data.select_dtypes(exclude=object)
```

```
In [21]: cat_data
```

Out[21]:

```
0  
1  
2  
3  
4  
...  
4682  
4683  
4684  
4685  
4686
```

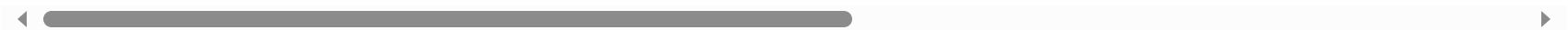
4687 rows × 0 columns

In [22]: num\_data

Out[22]:

	Absolute Magnitude	Est Dia in M(min)	Miles per hour	Miss Dist. (kilometers)	Orbit Uncertainty	Minimum Orbit Intersection	Jupiter Tisserand Invariant	Epoch Osculation	Eccentricity	Semi Major Axis	Inclination
0	21.600	127.219878	13680.509940	6.275369e+07	5.000000	0.025282	4.634000	2.458000e+06	0.425549	1.407011	6
1	21.300	146.067964	40519.173110	5.729815e+07	3.000000	0.186935	5.457000	2.458000e+06	0.351674	1.107776	28
2	20.300	231.502122	16979.661800	7.622912e+06	3.576317	0.082211	5.047591	2.457718e+06	0.381689	1.398264	13
3	27.400	8.801465	24994.839860	4.268362e+07	3.576317	0.082211	5.047591	2.457718e+06	0.381689	1.398264	13
4	21.600	127.219878	22012.954980	6.101082e+07	3.576317	0.082211	5.047591	2.457718e+06	0.381689	1.398264	13
...	...	...	...	...	...	...	...	...	...	...	...
4682	23.900	44.111820	49556.875550	6.187511e+06	8.000000	0.019777	5.156000	2.457638e+06	0.361512	1.161429	39
4683	28.200	6.089126	7214.337772	9.677324e+05	6.000000	0.006451	5.742000	2.458000e+06	0.073200	1.075134	5
4684	22.700	76.657557	16086.983630	9.126775e+06	6.000000	0.059972	4.410000	2.458000e+06	0.368055	1.528234	4
4685	21.800	116.025908	25393.489070	3.900908e+07	5.000000	0.177510	4.477000	2.458000e+06	0.202565	1.486600	21
4686	19.109	400.640618	80409.512650	6.916986e+07	6.000000	0.051777	4.108000	2.458000e+06	0.405642	1.474045	53

4687 rows × 20 columns

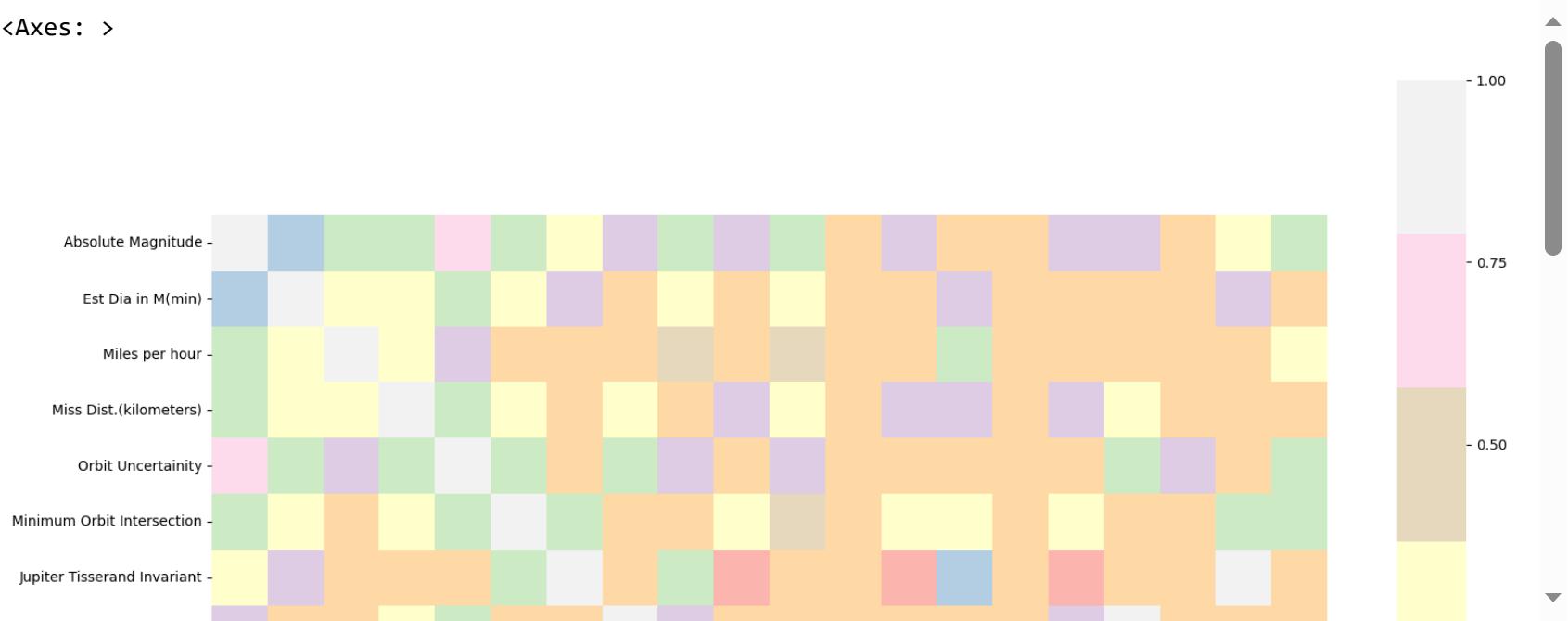


## Data Visualization

In [23]: *#Examining a correlation matrix of all the features*

```
corrrmat = data.corr()
plt.subplots(figsize=(18,18))
sns.heatmap(corrrmat,cmap="Pastel1", square=True)
```

Out[23]: <Axes: >



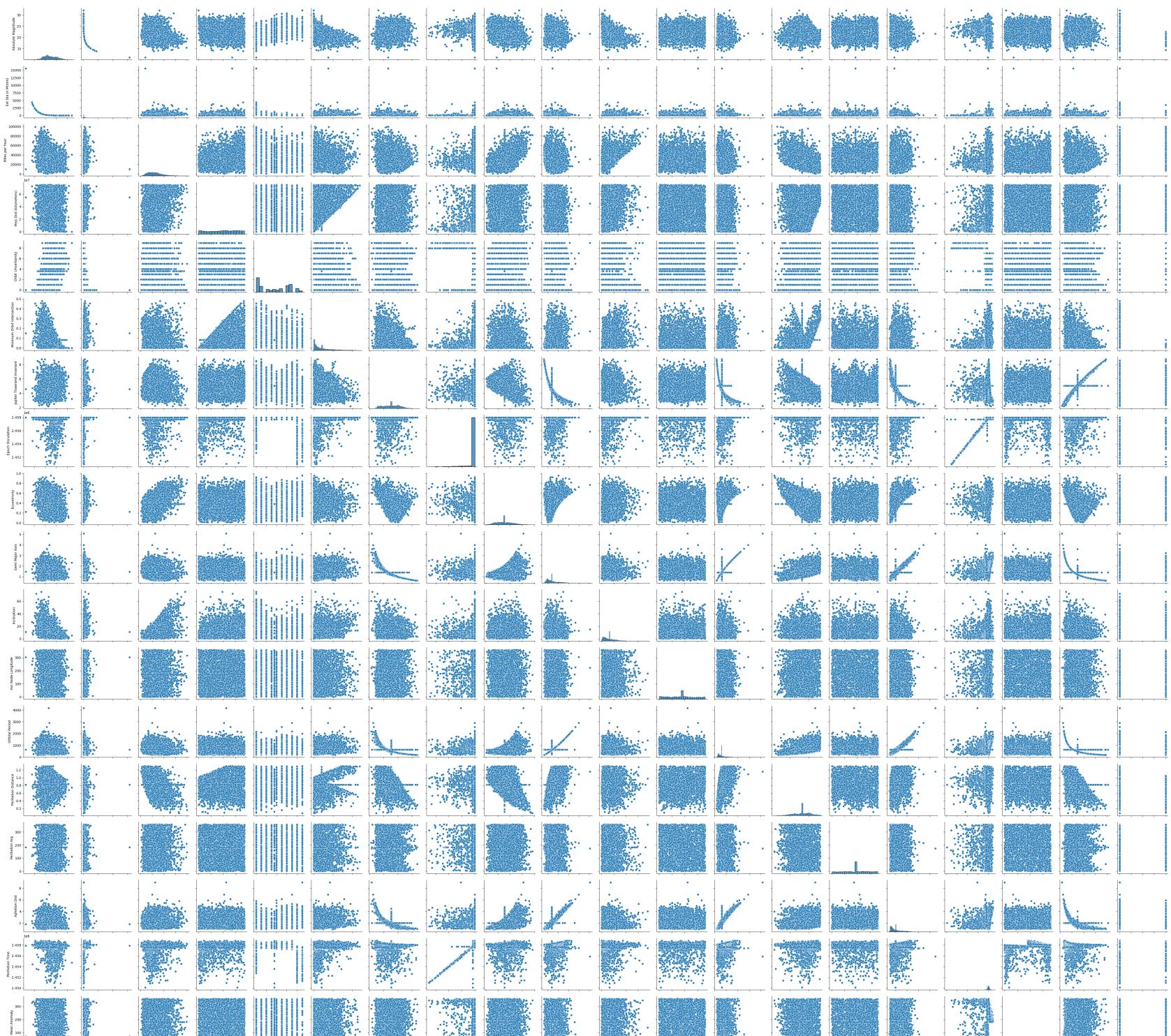
In [24]: `sns.pairplot(data)`

`<__array_function__ internals>:180: RuntimeWarning: Converting input from bool to <class 'numpy.uint8'> for compatibility.`

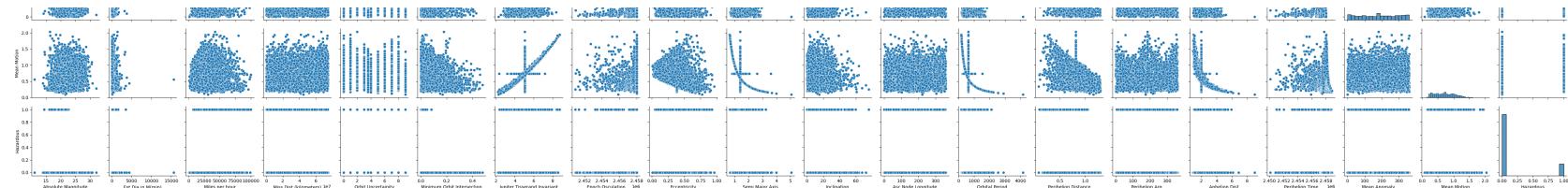
Out[24]: `<seaborn.axisgrid.PairGrid at 0x1f472fe1150>`



PRO 3 Logistic regression - Jupyter Notebook

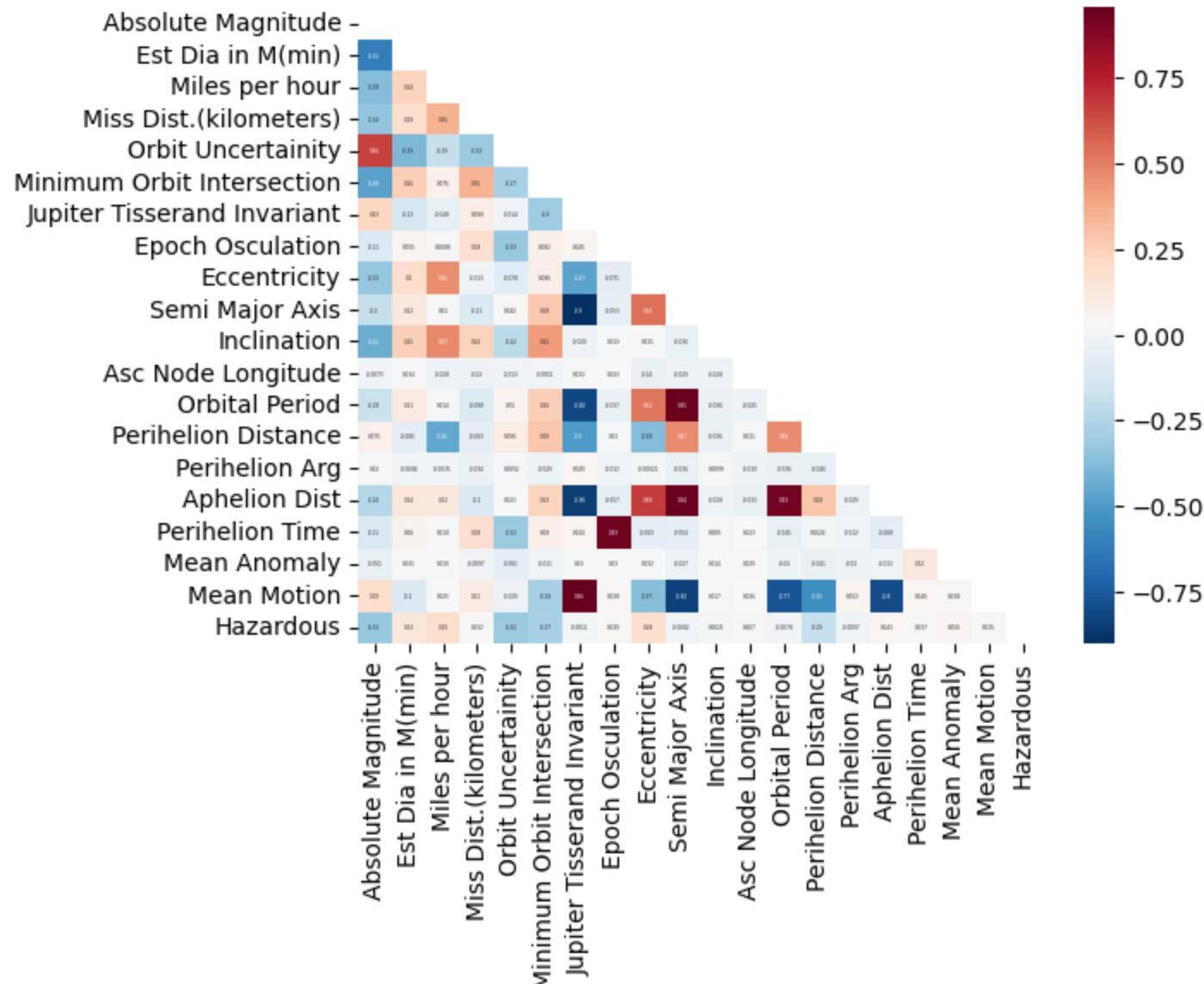


## PRO 3 Logistic regression - Jupyter Notebook

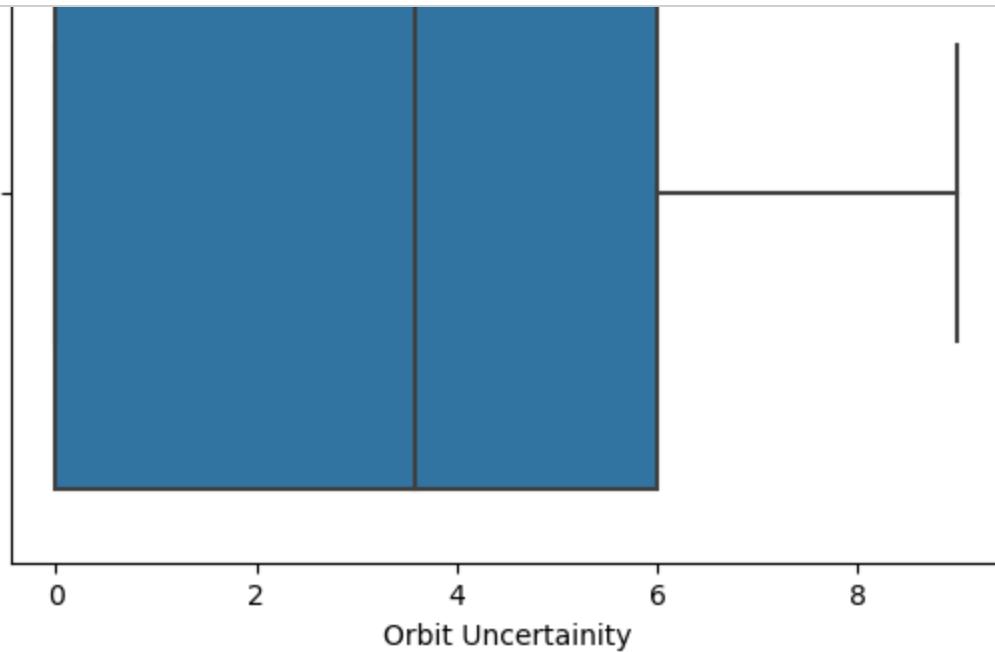


```
In [25]: corr=num_data.corr()
msk = np.triu(np.ones_like(corr))
sns.heatmap(corr,cmap=plt.cm.RdBu_r,annot=True,annot_kws={'size':2},mask=msk)
```

Out[25]: <Axes: >

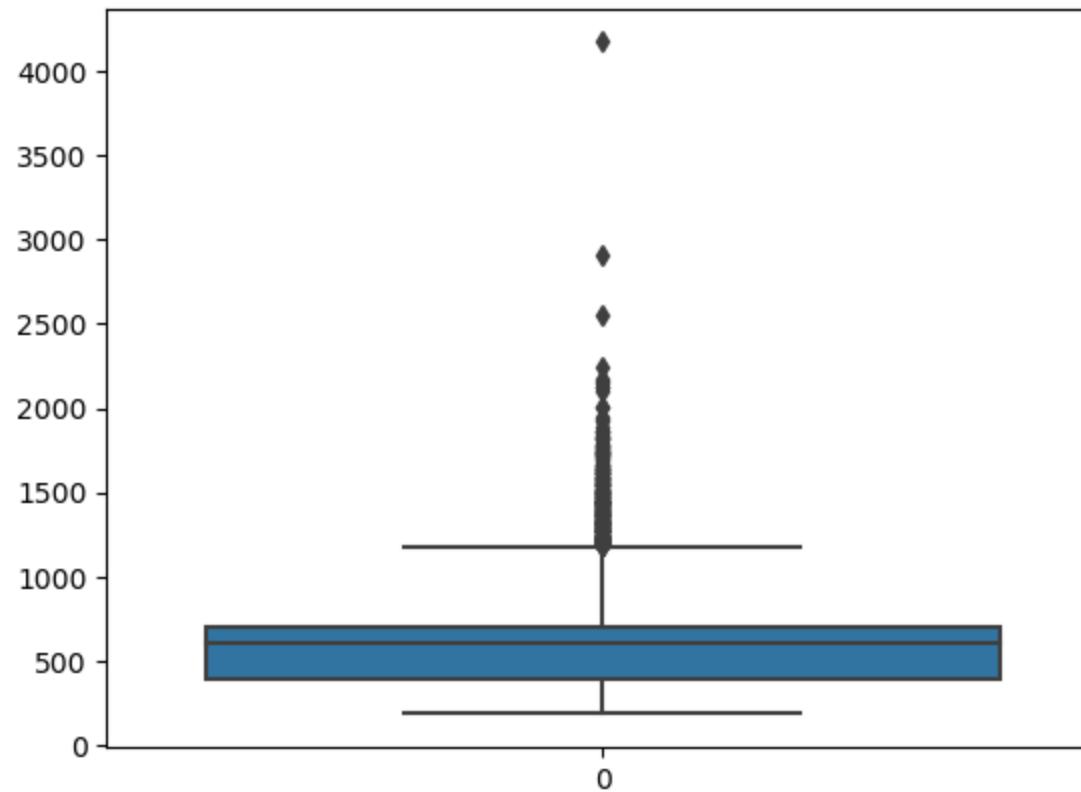


```
In [67]: for i in num_data.columns:  
    sns.boxplot(x=data[i]) # Use data instead of num_data here  
    plt.show()
```

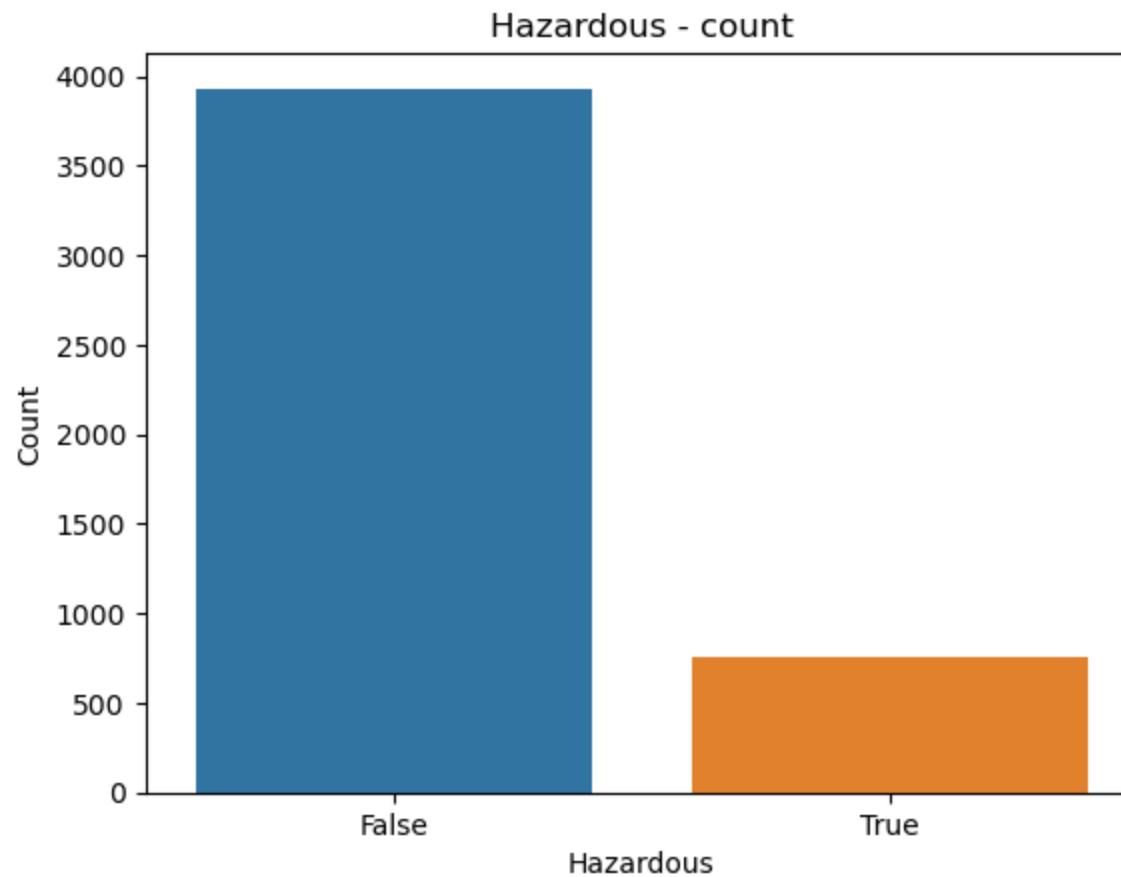


```
In [27]: sns.boxplot(data['Orbital Period'])
```

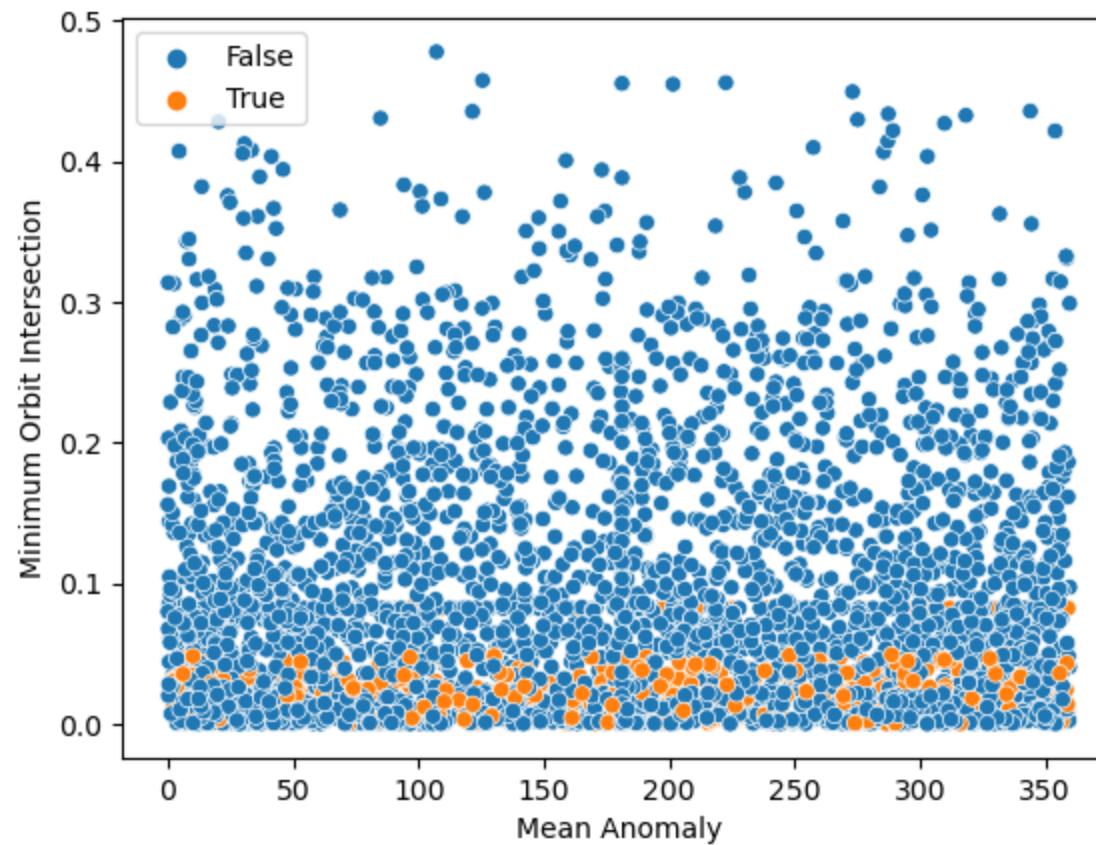
```
Out[27]: <Axes: >
```



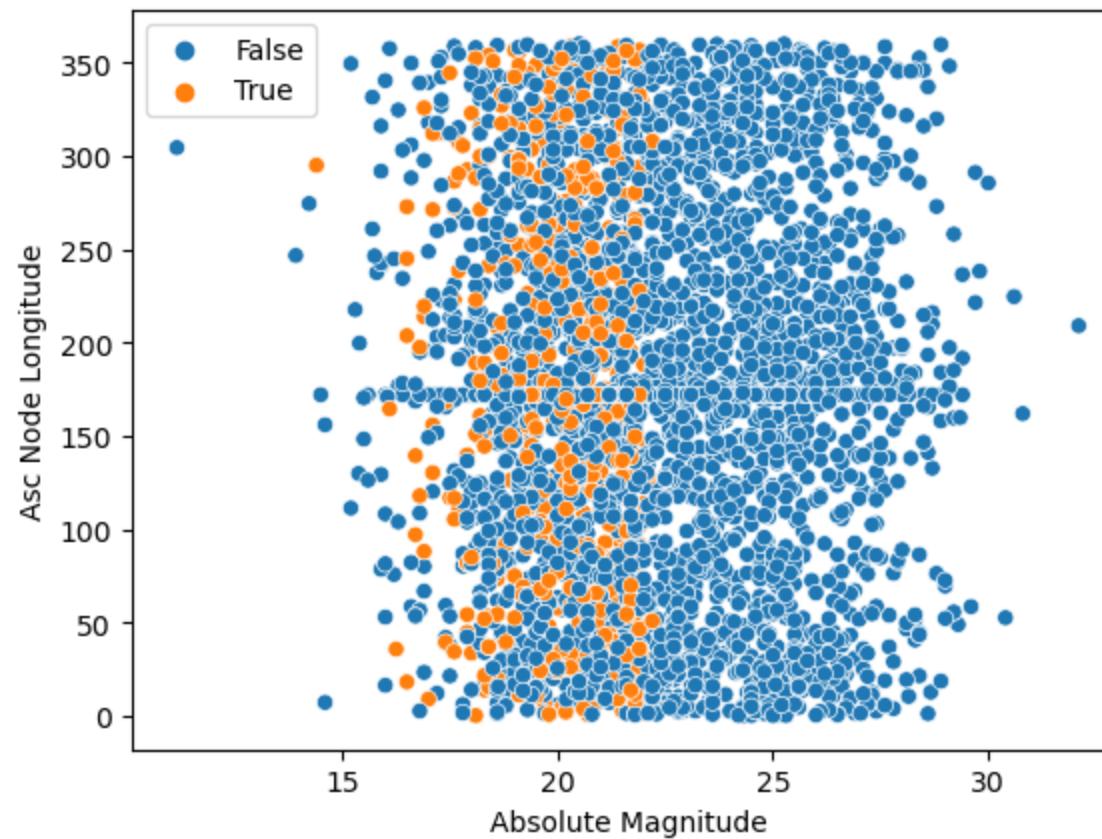
```
In [28]: a=data.groupby("Hazardous")["Hazardous"].count()
sns.barplot(x=a.index,y=a.values)
plt.title("Hazardous - count")
plt.xlabel("Hazardous")
plt.ylabel("Count")
plt.show()
```



```
In [29]: sns.scatterplot(x='Mean Anomaly',y='Minimum Orbit Intersection',color="b",hue="Hazardous",data=data)
plt.legend()
plt.show()
```

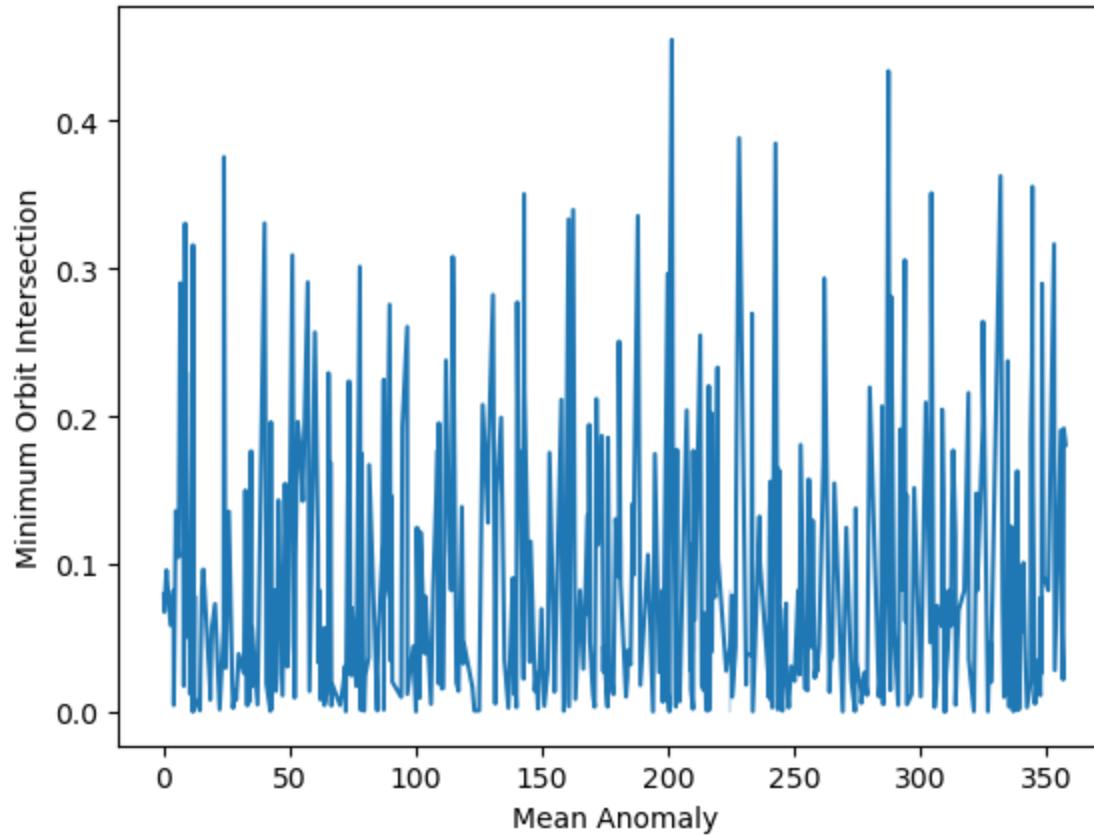


```
In [30]: sns.scatterplot(x='Absolute Magnitude',y='Asc Node Longitude',color="b",hue="Hazardous",data=data)
plt.legend()
plt.show()
```

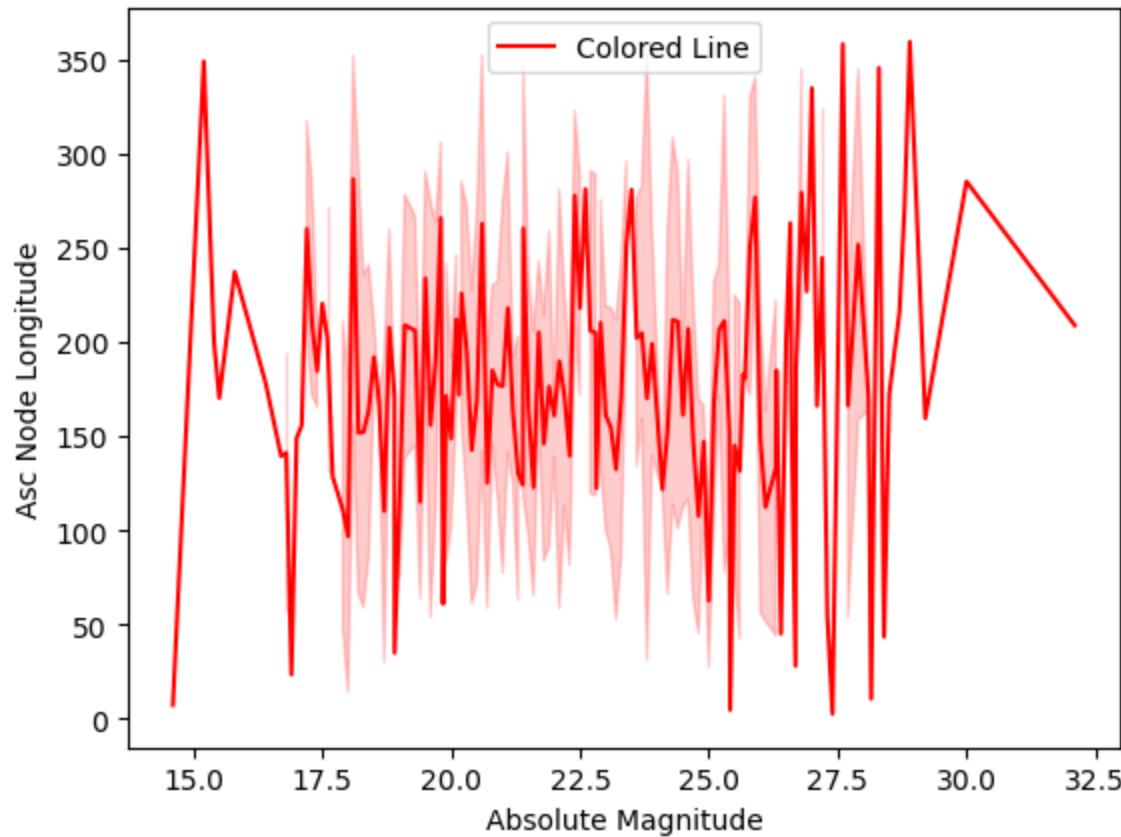


```
In [31]: x=data.sample(500)  
sns.lineplot(x='Mean Anomaly',y="Minimum Orbit Intersection",data=x)
```

```
Out[31]: <Axes: xlabel='Mean Anomaly', ylabel='Minimum Orbit Intersection'>
```



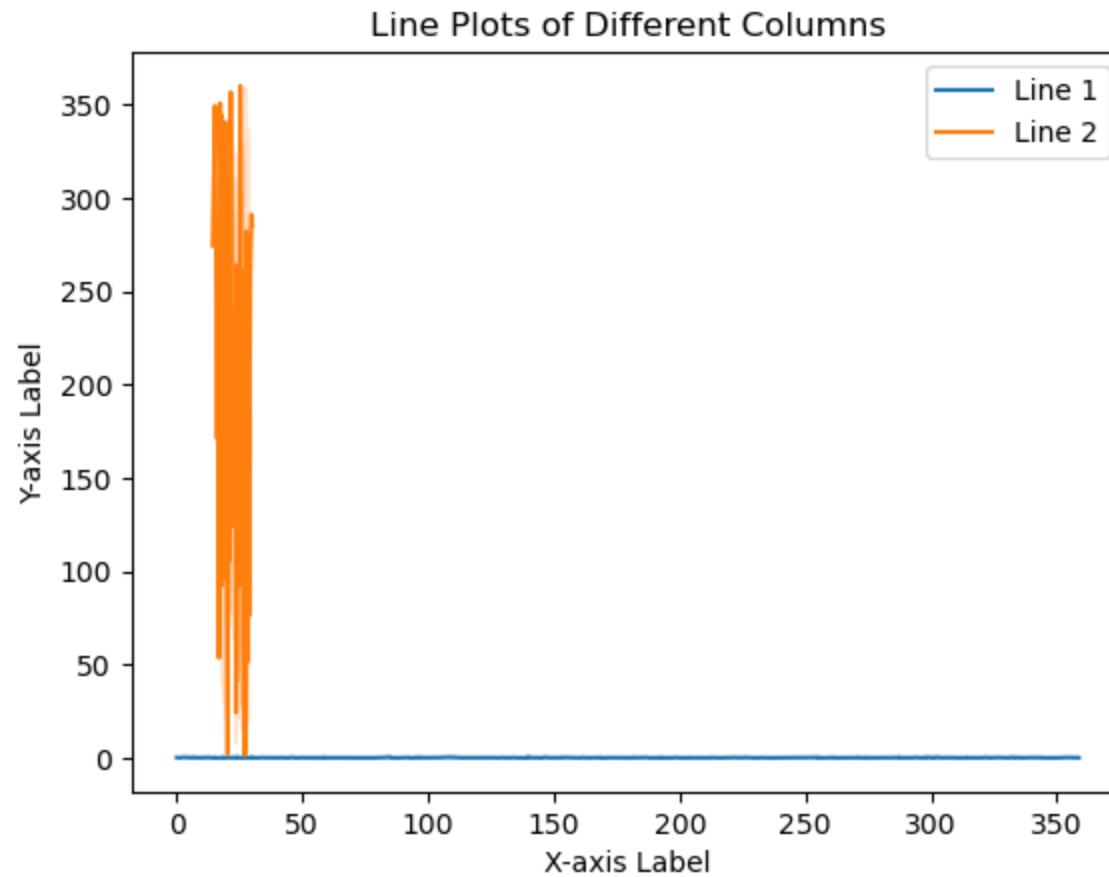
```
In [32]: sns.lineplot(x='Absolute Magnitude',y="Asc Node Longitude",data=x,color='red', label='Colored Line')
plt.show()
```



In [33]:

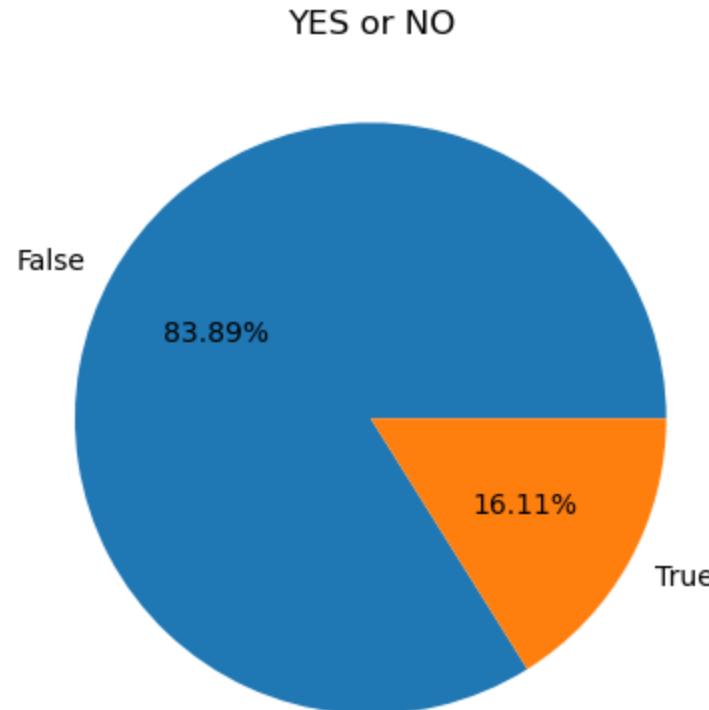
```
x = data.sample(500)
sns.lineplot(x='Mean Anomaly', y="Minimum Orbit Intersection", data=x, label='Line 1')# Create the first line
sns.lineplot(x='Absolute Magnitude', y="Asc Node Longitude", data=x, label='Line 2')# Create the second line p

plt.xlabel('X-axis Label')
plt.ylabel('Y-axis Label')
plt.title('Line Plots of Different Columns')
plt.legend()
plt.show()
```

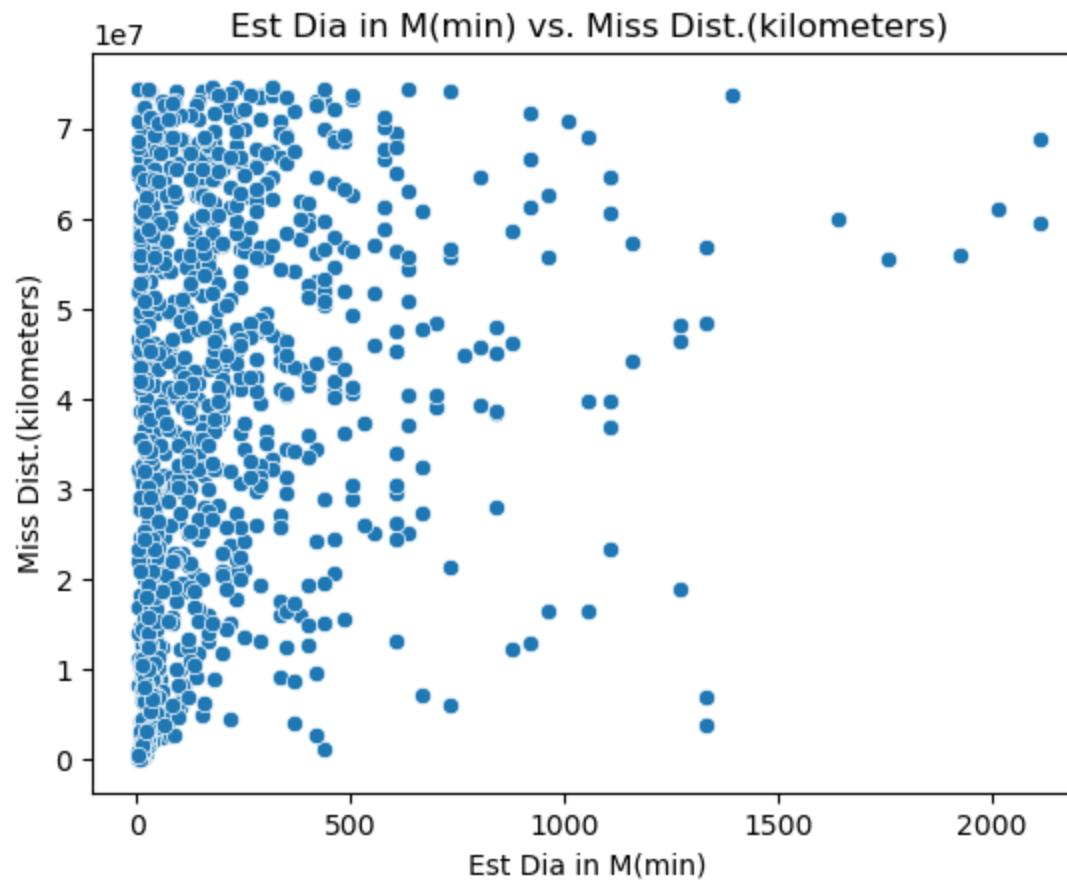


```
In [34]: b=data.groupby("Hazardous")["Hazardous"].count()
plt.pie(b,labels=b.index,autopct=".2f%%")
plt.title("YES or NO")
```

```
Out[34]: Text(0.5, 1.0, 'YES or NO')
```

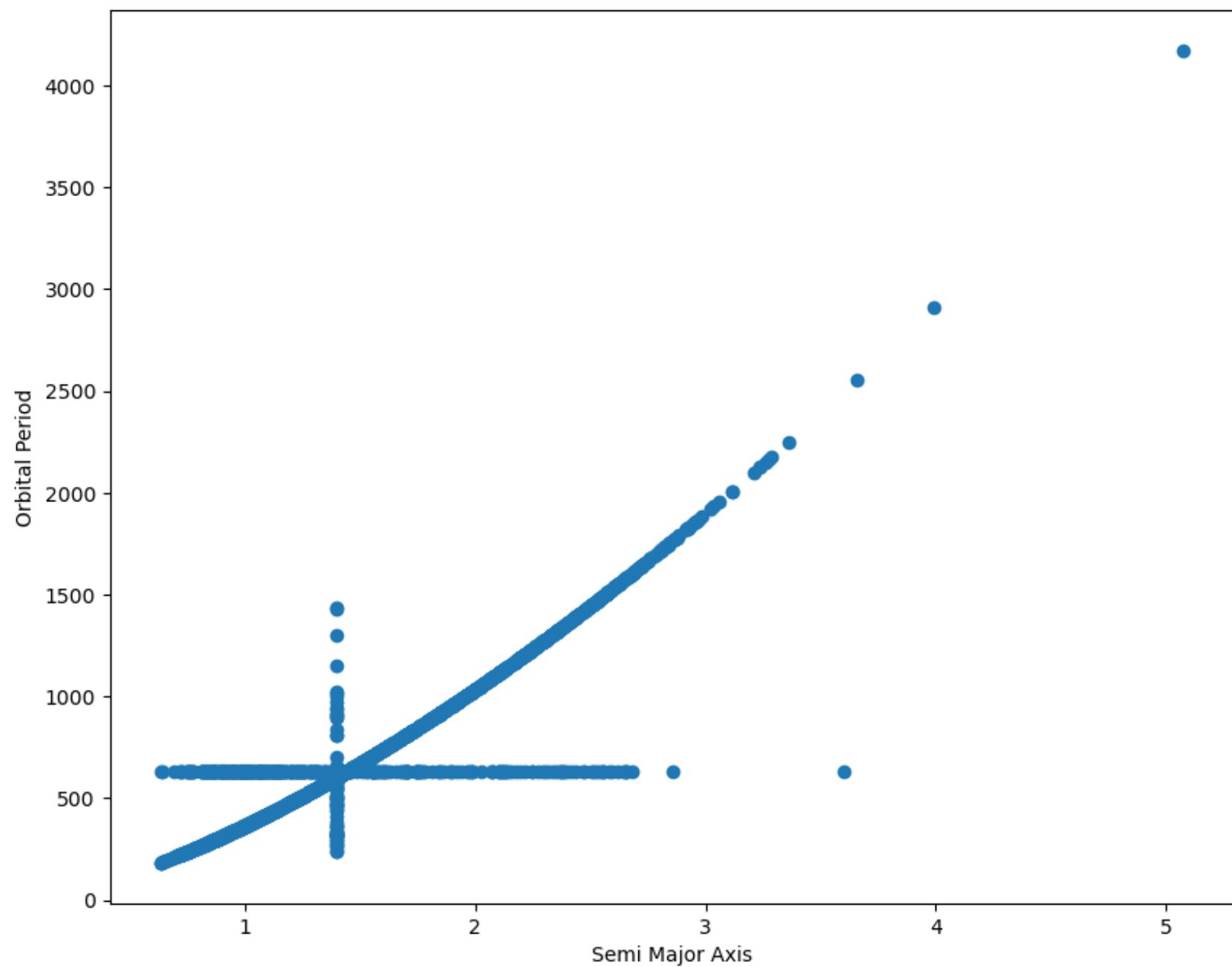


```
In [35]: x = data.sample(1000)
sns.scatterplot(x='Est Dia in M(min)', y='Miss Dist.(kilometers)', data=x)
plt.xlabel('Est Dia in M(min)')
plt.ylabel('Miss Dist.(kilometers)')
plt.title('Est Dia in M(min) vs. Miss Dist.(kilometers)')
plt.show()
```



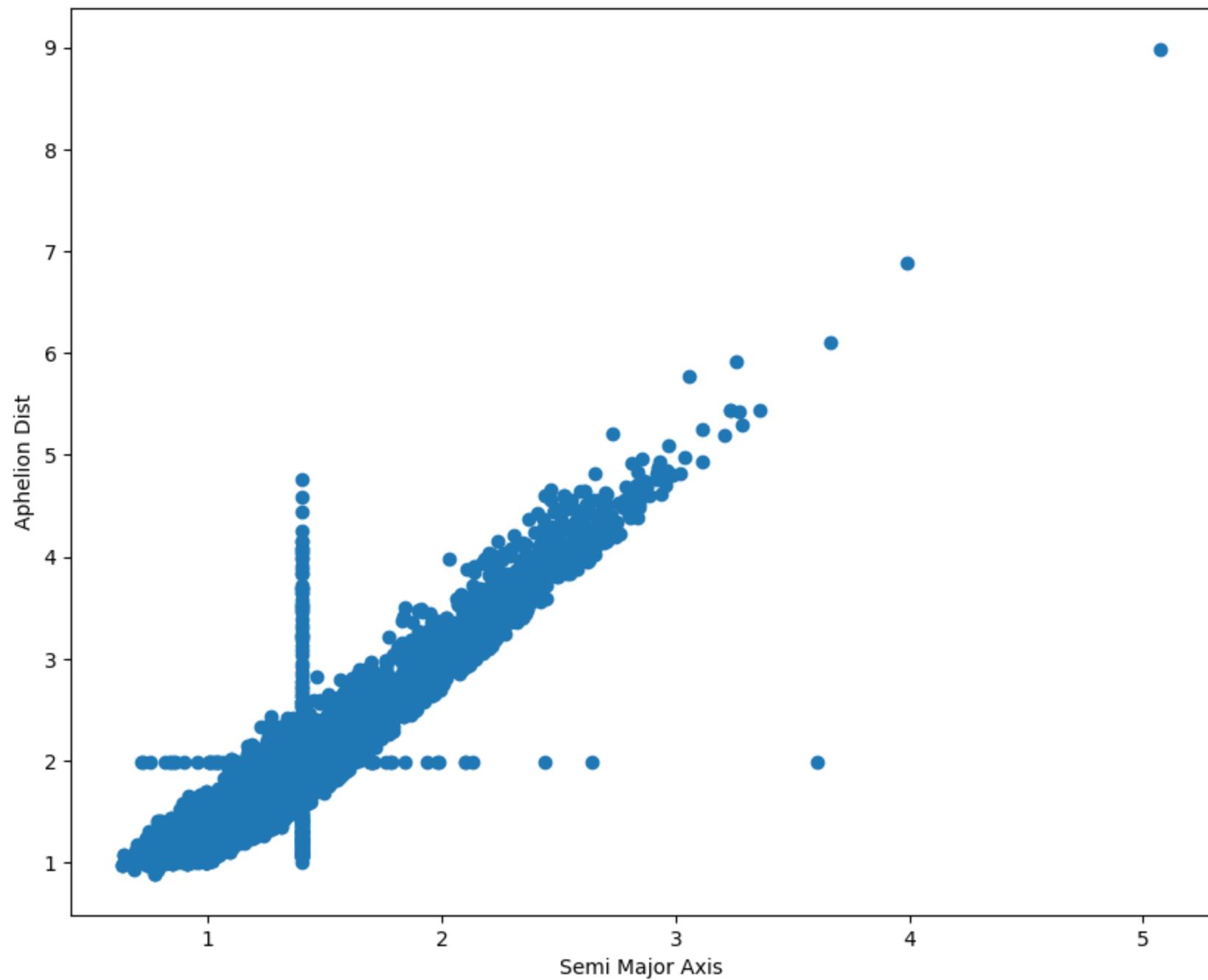
```
In [36]: plt.figure(figsize=(10, 8))

plt.scatter(data['Semi Major Axis'], data['Orbital Period'])
plt.xlabel('Semi Major Axis')
plt.ylabel('Orbital Period');
```



```
In [37]: plt.figure(figsize=(10, 8))

plt.scatter(data['Semi Major Axis'], data['Aphelion Dist'])
plt.xlabel('Semi Major Axis')
plt.ylabel('Aphelion Dist');
```



# Logistic Regression

In [38]:

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import mean_absolute_error,mean_squared_error,r2_score
from sklearn.preprocessing import OneHotEncoder,StandardScaler
from sklearn.compose import ColumnTransformer
import joblib
import warnings
warnings.filterwarnings("ignore")
```

In [39]:

```
X = data.drop(columns=['Hazardous'])
Y = data.Hazardous.astype(int)
```

In [40]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=88)
```

In [41]:

```
log=LogisticRegression()
log.fit(X_train, y_train)
```

Out[41]:

```
▼ LogisticRegression
  LogisticRegression()
```

In [42]:

```
print("Train Score",log.score(X_train, y_train))
```

Train Score 0.8362229927980794

In [43]:

```
print("Test Score",log.score(X_test, y_test))
```

Test Score 0.8454157782515992

```
In [44]: pred_train = log.predict(X_train)
pred_test = log.predict(X_test)
```

```
In [45]: from sklearn import metrics
print(metrics.classification_report(y_train,pred_train))
```

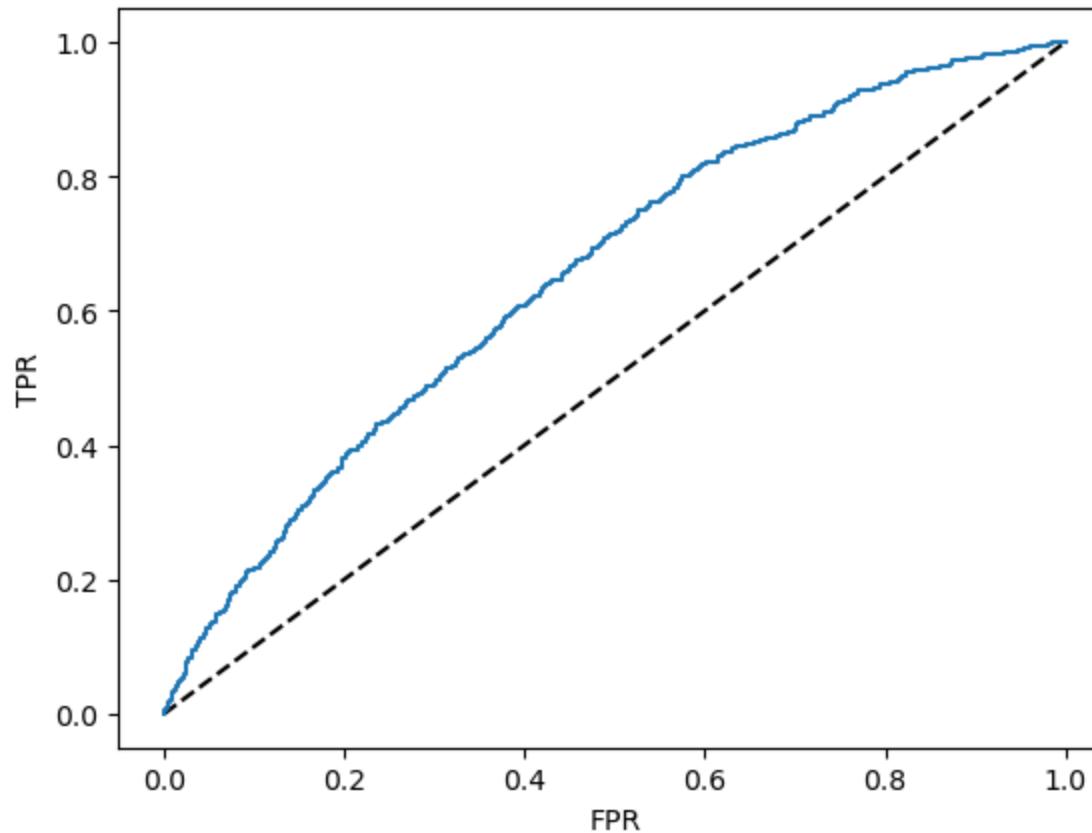
	precision	recall	f1-score	support
0	0.84	1.00	0.91	3140
1	0.33	0.01	0.02	609
accuracy			0.84	3749
macro avg	0.59	0.50	0.46	3749
weighted avg	0.76	0.84	0.77	3749

```
In [46]: print(metrics.classification_report(y_train,pred_train))
```

	precision	recall	f1-score	support
0	0.84	1.00	0.91	3140
1	0.33	0.01	0.02	609
accuracy			0.84	3749
macro avg	0.59	0.50	0.46	3749
weighted avg	0.76	0.84	0.77	3749

```
In [47]: roc=log.predict_proba(X_train)[:,1]
```

```
fpr,tpr,threshold = metrics.roc_curve(y_train, roc)
plt.plot([0,1],[0,1],'k--')
plt.plot(fpr,tpr,label='logistic')
plt.ylabel("TPR")
plt.xlabel("FPR")
plt.show()
```



```
In [48]: metrics.roc_auc_score(y_train,roc)
```

```
Out[48]: 0.6541652285777039
```

```
In [49]: from sklearn.metrics import matthews_corrcoef  
  
mcc=matthews_corrcoef(y_test,pred_test)  
print("MCC ",mcc)  
  
MCC  0.07984604966767538
```

```
In [50]: param_grid={  
    'penalty':['l1','l2'],#Lasso ridge  
    'C':[0.1,0.5,1,5,10]  
}
```

```
In [51]: from sklearn.model_selection import GridSearchCV  
grid=GridSearchCV(estimator=log,param_grid=param_grid,cv=5)
```

```
In [52]: grid.fit(X_train,y_train)
```

```
Out[52]:  
▶      GridSearchCV  
▶ estimator: LogisticRegression  
    ▶ LogisticRegression
```

```
In [53]: best_params_=grid.best_params_  
best_model=grid.best_estimator_
```

```
In [54]: y_pred=best_model.predict(X_test)
```

```
In [55]: from sklearn.metrics import accuracy_score , precision_score,recall_score,f1_score,roc_auc_score
```

```
In [56]: acc=accuracy_score(y_test,y_pred)  
pre=precision_score(y_test,y_pred)  
rec=recall_score(y_test,y_pred)  
f1=f1_score(y_test,y_pred)  
roc_auc=roc_auc_score(y_test,y_pred)
```

```
In [57]: print("Best Param: ",best_param)
print("Accuracy: ",acc)
print("Precision: ",pre)
print("Recall: ",rec)
print("f1 Scoer: ",f1)
print("AUC ROC: ",roc_auc)
```

```
Best Param: {'C': 0.1, 'penalty': 'l2'}
Accuracy: 0.8454157782515992
Precision: 0.6666666666666666
Recall: 0.0136986301369863
f1 Scoer: 0.02684563758389262
AUC ROC: 0.50621800193718
```

```
In [59]: from scipy.stats import loguniform
from sklearn.model_selection import RandomizedSearchCV
```

```
In [60]: logistic_random_param={'C':loguniform(1e-4,1e0),
                           'max_iter':(np.arange(100,800,10))}
grid=RandomizedSearchCV(estimator=log, param_distributions=logistic_random_param, cv=5)
```

```
In [61]: grid.fit(X_train,y_train)
```

```
Out[61]:
```

- ▶ RandomizedSearchCV
- ▶ estimator: LogisticRegression
  - ▶ LogisticRegression

```
In [62]: best_param = grid.best_params_
best_model = grid.best_estimator_
y_pred = best_model.predict(X_test)
```

```
In [63]: acc=accuracy_score(y_test,y_pred)
pre=precision_score(y_test,y_pred)
rec=recall_score(y_test,y_pred)
f1=f1_score(y_test,y_pred)
roc_auc=roc_auc_score(y_test,y_pred)
```

```
In [64]: print('Best Param:',best_param)
print('Accuracy:',acc)
print('Precision:',pre)
print('Recall:',rec)
print('F1Score:',f1)
print('ROC_AUC',roc_auc)
```

```
Best Param: {'C': 0.1565287725242802, 'max_iter': 550}
Accuracy: 0.8454157782515992
Precision: 0.6666666666666666
Recall: 0.0136986301369863
F1Score: 0.02684563758389262
ROC_AUC 0.50621800193718
```

```
In [ ]:
```