DS Midterm Project

July 1, 2021

1 Exoplanet Dataset Machine Learning Model

1.1 INTRODUCTION

1.1.1 DOMAIN AREA

We are creating a machine learning model that will identify clusters of exoplanets based on common characteristics and inform our view of the universe highlighting commonalities, divergences and distribution within the discovered exoplanets. It intends also to be a starting point for monitoring the evolution of discoveries and update in real time our evolving comprehension of the universe.

1.1.2 DATASET

The purpouse of this project is to analyze and describe the Open Exoplanet Dataset available in Kaggle : https://www.kaggle.com/mrisdal/open-exoplanet-catalogue

The dataset contains the characteristics of all discovered exoplanets. Data fields include planet and host star attributes, discovery methods, and date of discovery.

Data was originally collected and continues to be updated by Hanno Rein at the Open Exoplanet Catalogue Github repository.

The database is licensed under an MIT license. If you use it for a scientific publication, please include a reference to the Open Exoplanet Catalogue: https://github.com/OpenExoplanetCatalogue/open_exoplanet_catalogue on GitHub or to this arXiv paper: http://arxiv.org/abs/1211.7121

1.1.3 OBJECTIVES

The objective of the project is to use a wide array of techniques and visualization to provide compelling insights into the vast exoplanet dataset. I am interested in exploring statistical data and clustering of planets by characteristics and find insights.

1.2 IMPLEMENTATION

1.2.1 READ AND CONVERT THE DATASET

[172]:
```
# we import pandas library to avail of the dataframe structure and it␣
↪flexibility and to use it to read the dataset
import pandas as pd
df = pd.read_csv('oec.csv')
df
```

[172]:
```
       PlanetIdentifier  TypeFlag  PlanetaryMassJpt  RadiusJpt   PeriodDays  \
0           HD 143761 b         0            1.0450        NaN    39.845800
1           HD 143761 c         0            0.0790        NaN   102.540000
2           KOI-1843.03         0            0.0014      0.054     0.176891
3           KOI-1843.01         0               NaN      0.114     4.194525
4           KOI-1843.02         0               NaN      0.071     6.356006
…                   …         …                 …          …           …
3579          eta Cet b         0            2.4600        NaN   407.300000
3580          eta Cet c         0            3.1600        NaN   744.300000
3581        HD 108874 b         0            1.3600        NaN   395.400000
3582        HD 108874 c         0            1.0180        NaN  1605.800000
3583     Kepler-1473 b         0               NaN      0.106    14.427355

       SemiMajorAxisAU  Eccentricity  PeriastronDeg  LongitudeDeg  \
0               0.2196         0.037         270.60           NaN
1               0.4123         0.050         190.00           NaN
2               0.0048           NaN            NaN           NaN
3               0.0390           NaN            NaN           NaN
4               0.0520           NaN            NaN           NaN
…                    …             …              …             …
3579            1.2700         0.170         247.20           NaN
3580            1.9300         0.020          36.67           NaN
3581            1.0510         0.070            NaN           NaN
3582            2.6800         0.250            NaN           NaN
3583               NaN           NaN            NaN           NaN

       AscendingNodeDeg  …  LastUpdated  RightAscension     Declination  \
0                   NaN  …     16/07/11        16 01 03        +33 18 13
1                   NaN  …     16/07/11        16 01 03        +33 18 13
2                   NaN  …     13/07/15     19 00 03.14     +40 13 14.7
3                   NaN  …          NaN     19 00 03.14     +40 13 14.7
4                   NaN  …          NaN     19 00 03.14     +40 13 14.7
…                     …  …            …               …               …
3579                NaN  …     15/12/11  01 08 35.39148  -10 10 56.1570
3580                NaN  …     15/12/11  01 08 35.39148  -10 10 56.1570
3581                NaN  …     10/12/29        12 30 26        +22 52 47
3582                NaN  …     10/12/29        12 30 26        +22 52 47
```

```
3583              NaN  …    16/05/10       19 22 33       +48 59 46

     DistFromSunParsec  HostStarMassSlrMass HostStarRadiusSlrRad  \
0               17.236                0.889                1.362
1               17.236                0.889                1.362
2                  NaN                0.460                0.450
3                  NaN                0.460                0.450
4                  NaN                0.460                0.450
…                  …                   …                   …
3579            37.990                1.700               14.300
3580            37.990                1.700               14.300
3581            68.500                1.000                1.220
3582            68.500                1.000                1.220
3583               NaN                1.090                1.090

     HostStarMetallicity HostStarTempK  HostStarAgeGyr    ListsPlanetIsOn
0                  -0.31        5627.0             NaN  Confirmed planets
1                  -0.31        5627.0             NaN  Confirmed planets
2                   0.00        3584.0             NaN      Controversial
3                   0.00        3584.0             NaN      Controversial
4                   0.00        3584.0             NaN      Controversial
…                   …            …              …                 …
3579                0.12        4528.0             NaN  Confirmed planets
3580                0.12        4528.0             NaN  Confirmed planets
3581                0.14        5407.0             NaN  Confirmed planets
3582                0.14        5407.0             NaN  Confirmed planets
3583               -0.01        6046.0             NaN  Confirmed planets

[3584 rows x 25 columns]
```

1.2.2 PREPROCESS THE DATA

[173]:
```
# We can now go ahead to check if there are problematic rows or columns that␣
↪could affect our analysis
# We want to be safe that our data has the best possible structure for our␣
↪purpouses.
# We can see for example that in the data we have a lot of NaN data present.
# We want therefore understand better how this missing data is distributed and␣
↪how it can affect our analysis.

df.isna().sum()
```

[173]:
```
PlanetIdentifier          0
TypeFlag                  0
PlanetaryMassJpt       2271
RadiusJpt               810
```

```
PeriodDays                 99
SemiMajorAxisAU          2178
Eccentricity             2476
PeriastronDeg            3256
LongitudeDeg             3541
AscendingNodeDeg         3538
InclinationDeg           2919
SurfaceTempK             2843
AgeGyr                   3582
DiscoveryMethod            63
DiscoveryYear              10
LastUpdated                 8
RightAscension             10
Declination                10
DistFromSunParsec        1451
HostStarMassSlrMass       168
HostStarRadiusSlrRad      321
HostStarMetallicity      1075
HostStarTempK             129
HostStarAgeGyr           3067
ListsPlanetIsOn             0
dtype: int64
```

We can see that some colums such as TypeFlag are not missing any data while others such as AgeGyr are almost totally empty. We will have to decide if this can create bias in our analysis and how to rectify it. Clearly we can remove the columns with little or no data that do not bring any added value to our model and that will only drain memory and resources. If we use info() we can see that we are consuming over 700.1+ KB of memory.

[174]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3584 entries, 0 to 3583
Data columns (total 25 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   PlanetIdentifier      3584 non-null   object
 1   TypeFlag              3584 non-null   int64
 2   PlanetaryMassJpt      1313 non-null   float64
 3   RadiusJpt             2774 non-null   float64
 4   PeriodDays            3485 non-null   float64
 5   SemiMajorAxisAU       1406 non-null   float64
 6   Eccentricity          1108 non-null   float64
 7   PeriastronDeg         328 non-null    float64
 8   LongitudeDeg          43 non-null     float64
 9   AscendingNodeDeg      46 non-null     float64
 10  InclinationDeg        665 non-null    float64
 11  SurfaceTempK          741 non-null    float64
```

```
 12  AgeGyr              2 non-null      float64
 13  DiscoveryMethod     3521 non-null   object
 14  DiscoveryYear       3574 non-null   float64
 15  LastUpdated         3576 non-null   object
 16  RightAscension      3574 non-null   object
 17  Declination         3574 non-null   object
 18  DistFromSunParsec   2133 non-null   float64
 19  HostStarMassSlrMass 3416 non-null   float64
 20  HostStarRadiusSlrRad 3263 non-null  float64
 21  HostStarMetallicity 2509 non-null   float64
 22  HostStarTempK       3455 non-null   float64
 23  HostStarAgeGyr      517 non-null    float64
 24  ListsPlanetIsOn     3584 non-null   object
dtypes: float64(18), int64(1), object(6)
memory usage: 700.1+ KB
```

[175]:
```python
#let us remove the colums with less than 100 non-null values
df = df.drop(columns = ['LongitudeDeg','AscendingNodeDeg','AgeGyr'])
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3584 entries, 0 to 3583
Data columns (total 22 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   PlanetIdentifier     3584 non-null   object
 1   TypeFlag             3584 non-null   int64
 2   PlanetaryMassJpt     1313 non-null   float64
 3   RadiusJpt            2774 non-null   float64
 4   PeriodDays           3485 non-null   float64
 5   SemiMajorAxisAU      1406 non-null   float64
 6   Eccentricity         1108 non-null   float64
 7   PeriastronDeg        328 non-null    float64
 8   InclinationDeg       665 non-null    float64
 9   SurfaceTempK         741 non-null    float64
 10  DiscoveryMethod      3521 non-null   object
 11  DiscoveryYear        3574 non-null   float64
 12  LastUpdated          3576 non-null   object
 13  RightAscension       3574 non-null   object
 14  Declination          3574 non-null   object
 15  DistFromSunParsec    2133 non-null   float64
 16  HostStarMassSlrMass  3416 non-null   float64
 17  HostStarRadiusSlrRad 3263 non-null   float64
 18  HostStarMetallicity  2509 non-null   float64
 19  HostStarTempK        3455 non-null   float64
 20  HostStarAgeGyr       517 non-null    float64
 21  ListsPlanetIsOn      3584 non-null   object
dtypes: float64(15), int64(1), object(6)
```

```
memory usage: 616.1+ KB
```

We can see that our memory usage has gone down to 600 KB, which will come handy especially with visualizations plotting time. Furthermore we have removed clutter that is not bringing any added value to our analysis.

We must also consider fot the NaN values in the remaining column if it makes sense to use dropna() to remove them from the dataset or use fillna() for example to replace them with other values. For the moment i will leave them in the dataset since given the dataset origin and being hard to collect data we cannot pretend a too clean dataset and we will have to deal with the limitations of exoplanet hunting. We will eventually reconsider our decision when the exploration of the dataset provide further insights to support a decision on this.

1.2.3 IDENTIFY KEY SERIES

1.2.4 STATISTICAL SUMMARY OF THE DATA

[176]:
```
# Let us describe the dataset with some common statistical summaries
df.describe()
```

[176]:
```
          TypeFlag  PlanetaryMassJpt    RadiusJpt     PeriodDays  \
count  3584.000000       1313.000000  2774.000000    3485.000000
mean      0.097656          2.890944     0.371190     537.248317
std       0.424554         10.204485     0.416871    7509.660676
min       0.000000          0.000008     0.002300       0.090706
25%       0.000000          0.150000     0.141062       4.757940
50%       0.000000          0.940000     0.209600      13.071630
75%       0.000000          2.500000     0.321518      49.514000
max       3.000000        263.000000     6.000000  320000.000000

       SemiMajorAxisAU  Eccentricity  PeriastronDeg  InclinationDeg  \
count      1406.000000   1108.000000     328.000000      665.000000
mean          2.000170      0.166910     150.363823       82.973840
std          19.352699      0.189760     117.859945       21.402768
min           0.004420      0.000000    -233.000000       -0.000543
25%           0.053000      0.020000      66.750000       85.058000
50%           0.169500      0.100000     139.700000       87.800000
75%           1.250000      0.247282     243.000000       89.140000
max         662.000000      0.956000     791.000000      305.000000

       SurfaceTempK  DiscoveryYear  DistFromSunParsec  HostStarMassSlrMass  \
count    741.000000    3574.000000        2133.000000          3416.000000
mean     871.714170    2013.300504         554.912346             0.983225
std      699.314463       6.159674         847.566803             0.319063
min      102.200000    1781.000000           1.295000             0.012000
25%      321.800000    2013.000000          60.000000             0.830000
50%      719.600000    2014.000000         333.000000             0.977000
```

```
75%     1310.900000    2016.000000         773.130000              1.105000
max     7112.000000    2017.000000        8500.000000              4.500000

       HostStarRadiusSlrRad  HostStarMetallicity  HostStarTempK  \
count           3263.000000          2509.000000    3455.000000
mean               1.495629             0.016228    5505.514501
std                3.071298             0.193495    1204.271777
min                0.000014            -2.090000     540.000000
25%                0.810000            -0.050000    5113.000000
50%                1.000000             0.020000    5634.000000
75%                1.250000             0.100000    5940.000000
max               51.100000             0.560000   29300.000000

       HostStarAgeGyr
count      517.000000
mean         4.635355
std          4.657679
min          0.002200
25%          2.000000
50%          4.000000
75%          6.300000
max         80.000000
```

MEASURES OF CENTRAL TENDENCY

[177]:
```python
# calculate mean (average value of the data)
print ("Mean values in the distribution")
df.mean()
```

```
Mean values in the distribution
```

[177]:
```
TypeFlag                   0.097656
PlanetaryMassJpt           2.890944
RadiusJpt                  0.371190
PeriodDays               537.248317
SemiMajorAxisAU            2.000170
Eccentricity               0.166910
PeriastronDeg            150.363823
InclinationDeg            82.973840
SurfaceTempK             871.714170
DiscoveryYear           2013.300504
DistFromSunParsec        554.912346
HostStarMassSlrMass        0.983225
HostStarRadiusSlrRad       1.495629
HostStarMetallicity        0.016228
HostStarTempK           5505.514501
HostStarAgeGyr             4.635355
```

```
dtype: float64
```

[178]:
```
# calculate median (middle value in the distribution)
print ("Median values in the distribution")
df.median()
```

```
Median values in the distribution
```

[178]:
```
TypeFlag                   0.00000
PlanetaryMassJpt           0.94000
RadiusJpt                  0.20960
PeriodDays                13.07163
SemiMajorAxisAU            0.16950
Eccentricity               0.10000
PeriastronDeg            139.70000
InclinationDeg            87.80000
SurfaceTempK             719.60000
DiscoveryYear           2014.00000
DistFromSunParsec        333.00000
HostStarMassSlrMass        0.97700
HostStarRadiusSlrRad       1.00000
HostStarMetallicity        0.02000
HostStarTempK           5634.00000
HostStarAgeGyr             4.00000
dtype: float64
```

[179]:
```
# calculate Mode (most common value in the distribution)
print ("Mode")
df.mode()
```

```
Mode
```

[179]:
```
   PlanetIdentifier  TypeFlag  PlanetaryMassJpt  RadiusJpt   PeriodDays  \
0      Kepler-953 b       0.0               1.9      0.178     0.448413
1      Kepler-953 c       NaN               NaN      0.211     1.257850
2               NaN       NaN               NaN        NaN     5.287898
3               NaN       NaN               NaN        NaN     5.334084
4               NaN       NaN               NaN        NaN     8.600154
5               NaN       NaN               NaN        NaN     8.980000
6               NaN       NaN               NaN        NaN     9.109671
7               NaN       NaN               NaN        NaN    54.155743
8               NaN       NaN               NaN        NaN   125.632430
9               NaN       NaN               NaN        NaN   217.831763
10              NaN       NaN               NaN        NaN   290.000000
11              NaN       NaN               NaN        NaN   324.000000
12              NaN       NaN               NaN        NaN   883.000000
13              NaN       NaN               NaN        NaN   962.000000
```

```
14             NaN       NaN               NaN        NaN   1107.592300
15             NaN       NaN               NaN        NaN   1276.000000
16             NaN       NaN               NaN        NaN   4640.000000
17             NaN       NaN               NaN        NaN  10000.000000

    SemiMajorAxisAU  Eccentricity  PeriastronDeg  InclinationDeg  \
0               2.0           0.0            0.0            86.8
1               NaN           NaN            NaN            89.7
2               NaN           NaN            NaN             NaN
3               NaN           NaN            NaN             NaN
4               NaN           NaN            NaN             NaN
5               NaN           NaN            NaN             NaN
6               NaN           NaN            NaN             NaN
7               NaN           NaN            NaN             NaN
8               NaN           NaN            NaN             NaN
9               NaN           NaN            NaN             NaN
10              NaN           NaN            NaN             NaN
11              NaN           NaN            NaN             NaN
12              NaN           NaN            NaN             NaN
13              NaN           NaN            NaN             NaN
14              NaN           NaN            NaN             NaN
15              NaN           NaN            NaN             NaN
16              NaN           NaN            NaN             NaN
17              NaN           NaN            NaN             NaN

    SurfaceTempK  … LastUpdated  RightAscension Declination  \
0          149.6  …    16/05/10        01 37 54   -60 30 42
1          182.8  …         NaN             NaN         NaN
2         1070.0  …         NaN             NaN         NaN
3         1100.0  …         NaN             NaN         NaN
4         1200.0  …         NaN             NaN         NaN
5         1480.0  …         NaN             NaN         NaN
6         1600.0  …         NaN             NaN         NaN
7         2000.0  …         NaN             NaN         NaN
8            NaN  …         NaN             NaN         NaN
9            NaN  …         NaN             NaN         NaN
10           NaN  …         NaN             NaN         NaN
11           NaN  …         NaN             NaN         NaN
12           NaN  …         NaN             NaN         NaN
13           NaN  …         NaN             NaN         NaN
14           NaN  …         NaN             NaN         NaN
15           NaN  …         NaN             NaN         NaN
16           NaN  …         NaN             NaN         NaN
17           NaN  …         NaN             NaN         NaN

   DistFromSunParsec HostStarMassSlrMass  HostStarRadiusSlrRad  \
0               39.4                 1.0                   1.0
```

```
1                 NaN                 NaN                   NaN
2                 NaN                 NaN                   NaN
3                 NaN                 NaN                   NaN
4                 NaN                 NaN                   NaN
5                 NaN                 NaN                   NaN
6                 NaN                 NaN                   NaN
7                 NaN                 NaN                   NaN
8                 NaN                 NaN                   NaN
9                 NaN                 NaN                   NaN
10                NaN                 NaN                   NaN
11                NaN                 NaN                   NaN
12                NaN                 NaN                   NaN
13                NaN                 NaN                   NaN
14                NaN                 NaN                   NaN
15                NaN                 NaN                   NaN
16                NaN                 NaN                   NaN
17                NaN                 NaN                   NaN

    HostStarMetallicity  HostStarTempK  HostStarAgeGyr   ListsPlanetIsOn
0                  0.04         5940.0             3.0  Confirmed planets
1                   NaN            NaN             NaN                NaN
2                   NaN            NaN             NaN                NaN
3                   NaN            NaN             NaN                NaN
4                   NaN            NaN             NaN                NaN
5                   NaN            NaN             NaN                NaN
6                   NaN            NaN             NaN                NaN
7                   NaN            NaN             NaN                NaN
8                   NaN            NaN             NaN                NaN
9                   NaN            NaN             NaN                NaN
10                  NaN            NaN             NaN                NaN
11                  NaN            NaN             NaN                NaN
12                  NaN            NaN             NaN                NaN
13                  NaN            NaN             NaN                NaN
14                  NaN            NaN             NaN                NaN
15                  NaN            NaN             NaN                NaN
16                  NaN            NaN             NaN                NaN
17                  NaN            NaN             NaN                NaN

[18 rows x 22 columns]
```

[180]:

```python
# we can also restrict our focus to a specific column
count = df['RadiusJpt'].value_counts()
print(count)
mode = df['RadiusJpt'].mode()
print(mode)
```

```
0.2110    16
```

```
0.1780    16
0.1360    15
0.1700    14
0.1280    13
          ..
1.4200     1
1.5900     1
0.0966     1
1.1940     1
0.5720     1
Name: RadiusJpt, Length: 1137, dtype: int64
0    0.178
1    0.211
dtype: float64
```

MEASURES OF SPREAD

[181]:
```python
#Standard Deviation
#It quantifies the variation from the mean
# High values means more spread
# Low values means less spread

print ("Standard Deviation")
df.std()
```

```
Standard Deviation
```

[181]:
```
TypeFlag                    0.424554
PlanetaryMassJpt           10.204485
RadiusJpt                   0.416871
PeriodDays               7509.660676
SemiMajorAxisAU            19.352699
Eccentricity                0.189760
PeriastronDeg             117.859945
InclinationDeg             21.402768
SurfaceTempK              699.314463
DiscoveryYear               6.159674
DistFromSunParsec         847.566803
HostStarMassSlrMass         0.319063
HostStarRadiusSlrRad        3.071298
HostStarMetallicity         0.193495
HostStarTempK            1204.271777
HostStarAgeGyr              4.657679
dtype: float64
```

[182]:
```python
# Skew
# less than -1 is skewed to the left
# More than 1 is skewed to the right
```

```
# Between -1 and 1 is symmetric

print ("Skew")
df.skew()
```

```
Skew
```

[182]:
```
TypeFlag                 4.252992
PlanetaryMassJpt        17.207769
RadiusJpt                2.672376
PeriodDays              31.819143
SemiMajorAxisAU         29.401792
Eccentricity             1.558577
PeriastronDeg            0.368739
InclinationDeg           0.006816
SurfaceTempK             2.547872
DiscoveryYear          -21.735357
DistFromSunParsec        5.031595
HostStarMassSlrMass      1.599861
HostStarRadiusSlrRad     9.842093
HostStarMetallicity     -1.892852
HostStarTempK           10.993621
HostStarAgeGyr           8.471431
dtype: float64
```

[183]:
```
# Kurtosis
# Kurtosis obtained using Fisher’s definition of kurtosis (kurtosis of normal␣
↪== 0.0). Normalized by N-1.

print ("Kurtosis")
df.kurtosis().round(2)
```

```
Kurtosis
```

[183]:
```
TypeFlag                  16.58
PlanetaryMassJpt         382.89
RadiusJpt                 14.24
PeriodDays              1164.78
SemiMajorAxisAU          972.79
Eccentricity               2.18
PeriastronDeg              1.89
InclinationDeg            23.91
SurfaceTempK              16.13
DiscoveryYear            726.99
DistFromSunParsec         34.34
HostStarMassSlrMass       11.83
HostStarRadiusSlrRad     120.03
```

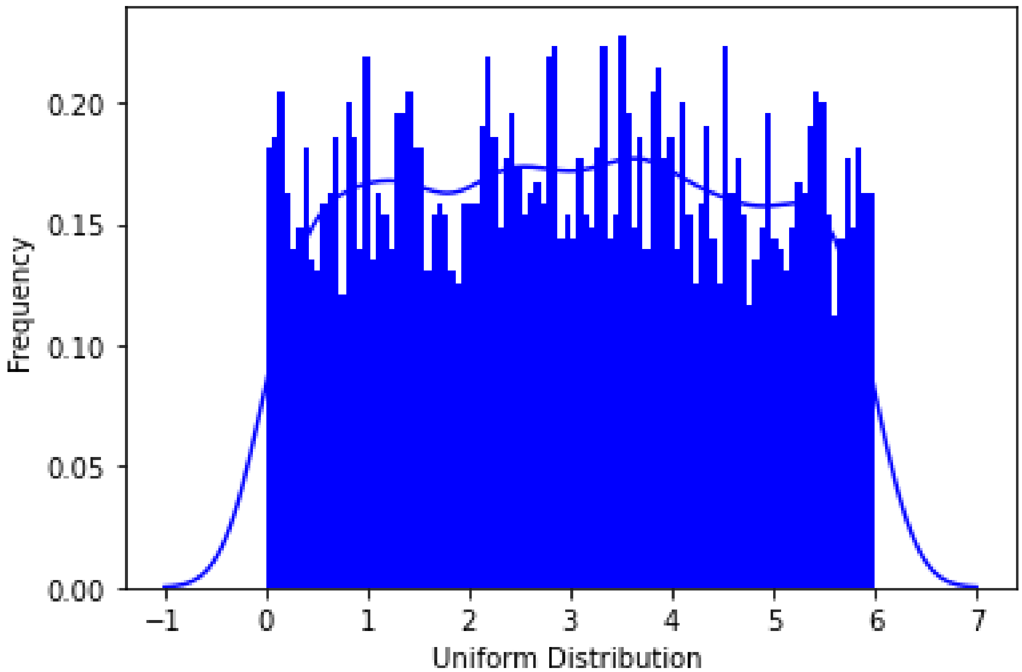
```
HostStarMetallicity       14.64
HostStarTempK            206.58
HostStarAgeGyr           132.10
dtype: float64
```

TYPE OF DISTRIBUTION We can see the distribution of a specific variable. For example the Radius of the planet from a minimum of 0 to a maximum of 6 Jupiters is shown below.

[184]:
```
# Uniform  distribution

from scipy.stats import uniform
import seaborn as sns

data_uniform = uniform.rvs(size=len(df["RadiusJpt"]), loc = 0 , scale=6)

ax = sns.distplot(data_uniform,
                  bins=100,
                  kde=True,
                  color='blue',
                  hist_kws={"linewidth": 15,'alpha':1})
ax.set(xlabel='Uniform Distribution ', ylabel='Frequency')
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2551:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```

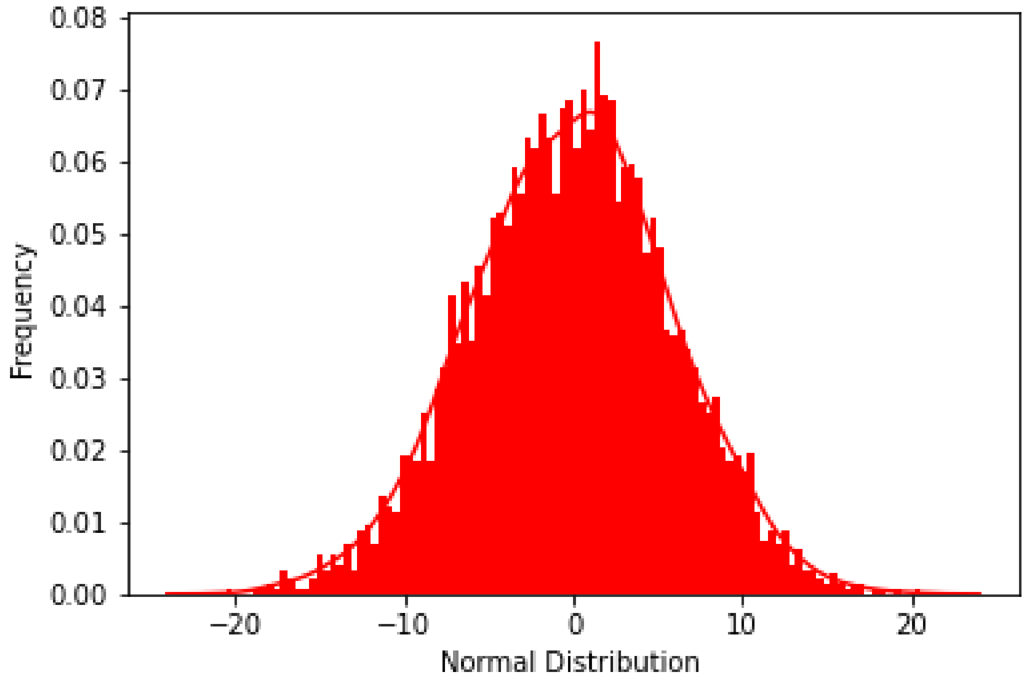
[184]:
```
[Text(0.5, 0, 'Uniform Distribution '), Text(0, 0.5, 'Frequency')]
```



[185]:
```
# Normal  distribution

from scipy.stats import norm


data_norm = norm.rvs(size=len(df["RadiusJpt"]), loc = 0 , scale=6)

ax = sns.distplot(data_norm,
                  bins=100,
                  kde=True,
                  color='red',
                  hist_kws={"linewidth": 15,'alpha':1})
ax.set(xlabel='Normal Distribution ', ylabel='Frequency')
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2551:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```

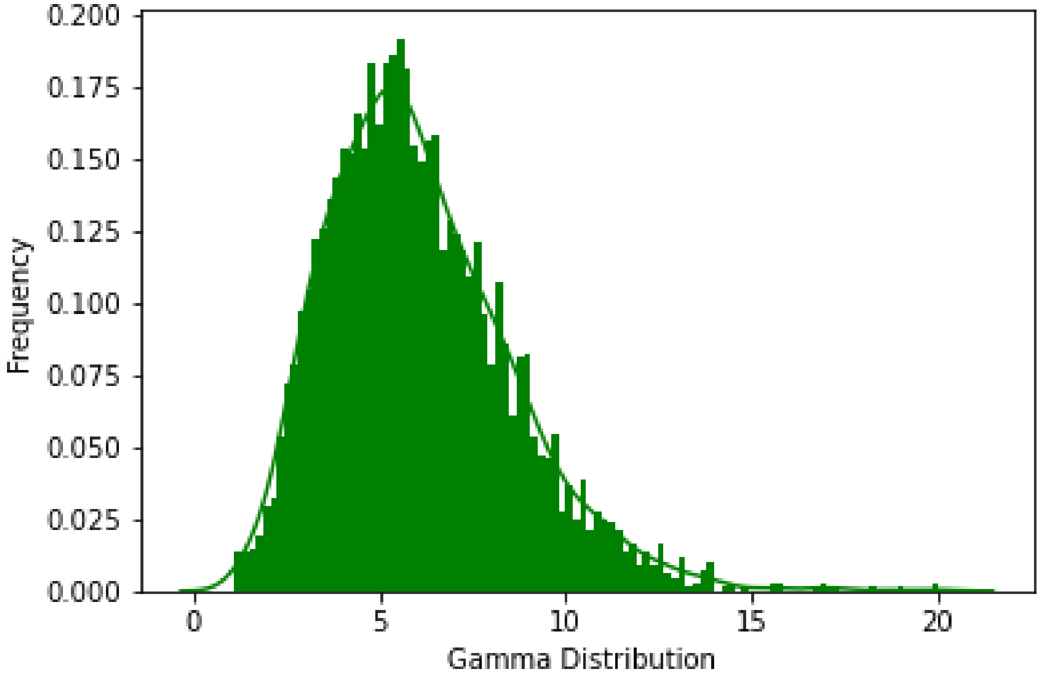
[185]: [Text(0.5, 0, 'Normal Distribution '), Text(0, 0.5, 'Frequency')]



[186]:
```
# Gamma  distribution

from scipy.stats import gamma


data_gamma = gamma.rvs(size=len(df["RadiusJpt"]), a=6)

ax = sns.distplot(data_gamma,
                  bins=100,
                  kde=True,
                  color='green',
                  hist_kws={"linewidth": 15,'alpha':1})
ax.set(xlabel='Gamma Distribution ', ylabel='Frequency')
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2551:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```

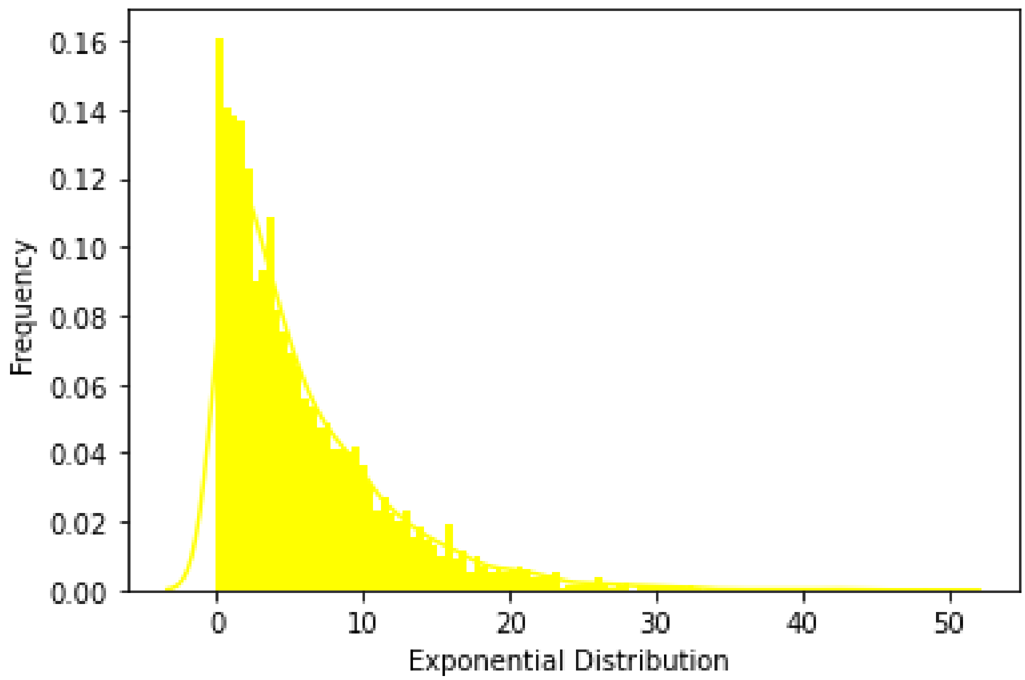
[186]: [Text(0.5, 0, 'Gamma Distribution '), Text(0, 0.5, 'Frequency')]



[187]:
```
# Exponential  distribution

from scipy.stats import expon


data_exp = expon.rvs(size=len(df["RadiusJpt"]), scale=6, loc=0)

ax = sns.distplot(data_exp,
                  bins=100,
                  kde=True,
                  color='yellow',
                  hist_kws={"linewidth": 15,'alpha':1})
ax.set(xlabel='Exponential Distribution ', ylabel='Frequency')
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2551:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```

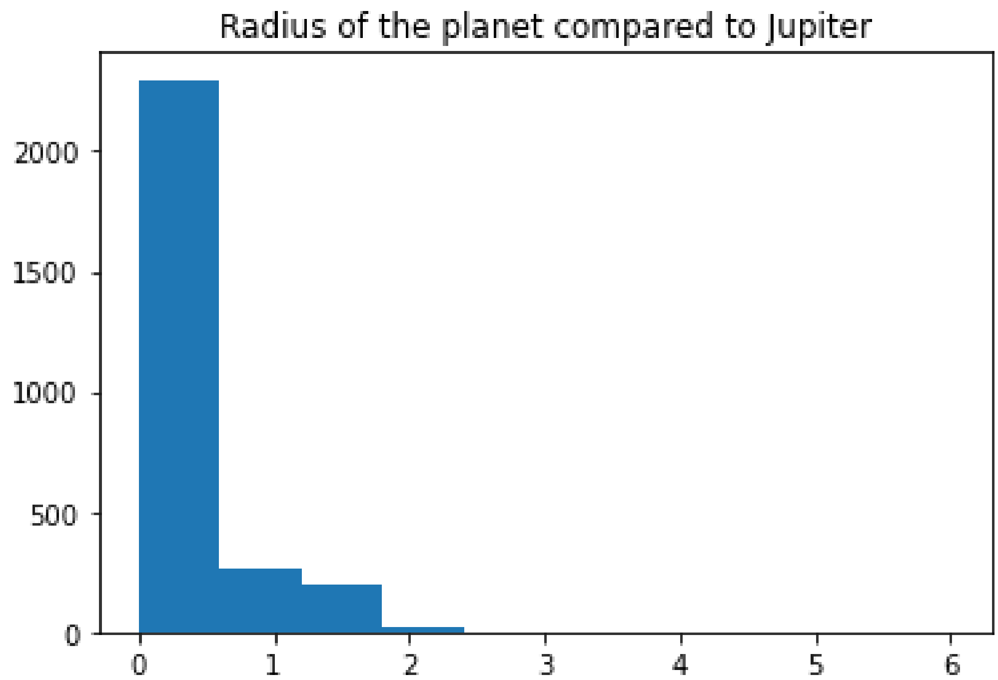
[187]: `[Text(0.5, 0, 'Exponential Distribution '), Text(0, 0.5, 'Frequency')]`



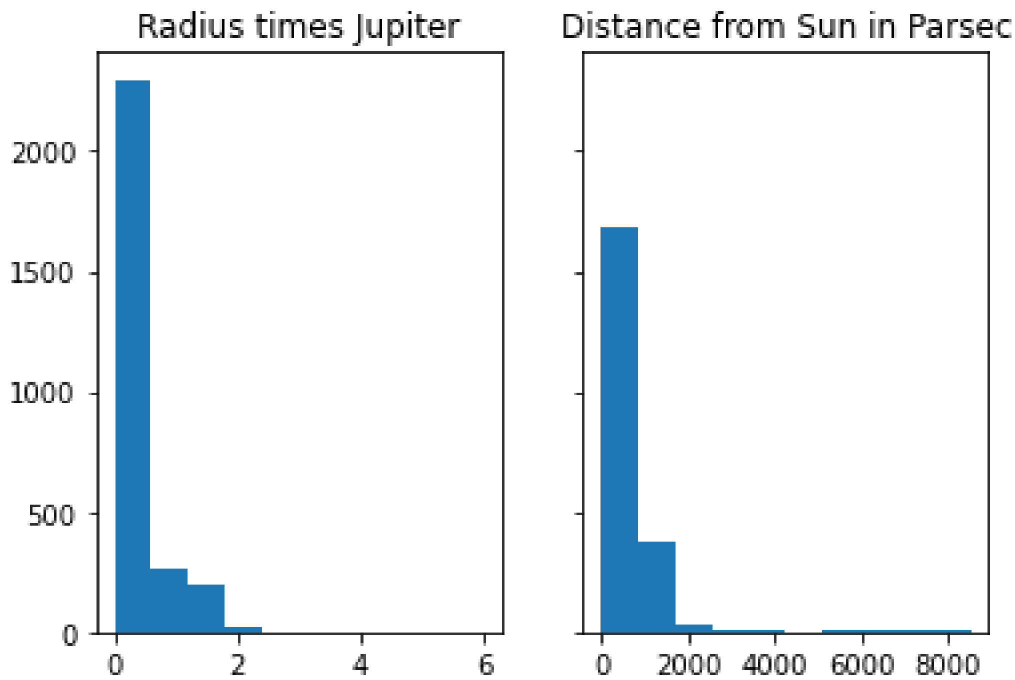
1.2.5 VISUALIZATIONS

6. Visualise key data series within the dataset by using the appropriate graphs. This can be done by using Python libraries, such as Matplotlib. Accompany any diagram with explanations. Draw conclusions based on the diagrams, which otherwise, without visualisation, would be difficult or impossible.

[188]:
```
#let us start with a simple plot with Matplotlib library
import matplotlib.pyplot as plt

plt.hist(df["RadiusJpt"])
plt.title('Radius of the planet compared to Jupiter')

plt.show()
```



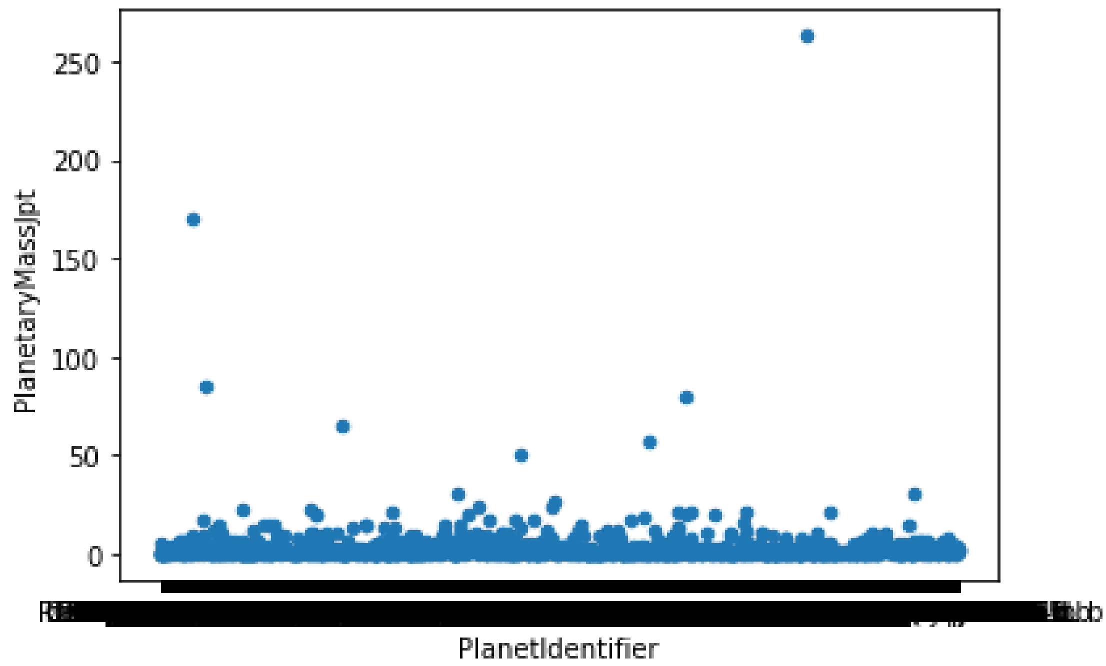
[189]:
```
#let's add other columns to our plot and tweak the histogram to better show the␣
↪values
fig, axes = plt.subplots(1,2,sharey=True)
axes[0].hist(df["RadiusJpt"])
axes[1].hist(df['DistFromSunParsec'])
#plt.hist(df["RadiusJpt"])
axes[0].set_title('Radius times Jupiter')


#plt.hist(df['DistFromSunParsec'])
axes[1].set_title('Distance from Sun in Parsec')

plt.show()
```



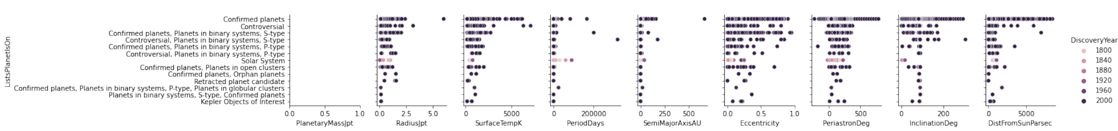
We can see in a much clearer way than compared to raw data how the values are distributed.

[190]:
```
# we can use a Scatter plot to see the distribution between two columns or␣
↪attributes
# In the example below we want to see how the Planetary mass is distributed in␣
↪the dataset
# we can see that there is an outlier planet with a mass of over 250 (263 as␣
↪per max value in the describe table above)
# the majority though are under 10 as per scatter plot below
df.plot.scatter('PlanetIdentifier','PlanetaryMassJpt')
```

[190]: <AxesSubplot:xlabel='PlanetIdentifier', ylabel='PlanetaryMassJpt'>



[191]:
```python
#if we want to compare multiple variables though we can use a tool such as␣
↪pairplot below.

#pairplot will need a tidy data with no empty values in this case we use a␣
↪linear interpolation to fill the missing values.
dfclean = df.interpolate(method='linear')


import seaborn as sns
sns.pairplot(dfclean,
             y_vars=["ListsPlanetIsOn"],
             x_vars=['PlanetaryMassJpt', "RadiusJpt",␣
↪"SurfaceTempK","PeriodDays","SemiMajorAxisAU","Eccentricity","PeriastronDeg","InclinationDe
             hue= "DiscoveryYear",
             height=2.5
            );
```



1.2.6 DATA REGRESSION MODEL

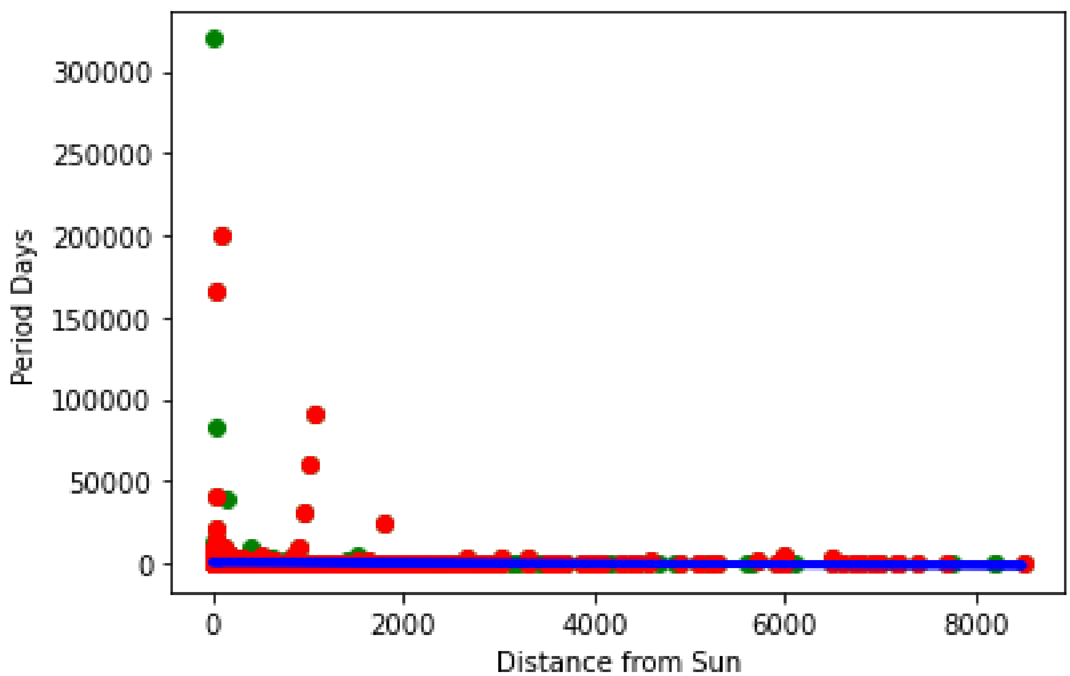
7. Identify the features and the labels, which will be used in the data regression model and justify why they were selected. Explain their importance for the process of building the ML model. Build a regression model by using appropriate Python library, such as Weka or Scikit-learns. Describe the employed ML algorithm and the reasons for choosing it. Run and test the machine learning model.

SCIKIT-LEARNS REGRESSION MODELS As in the pairplot above we will select a predictor variable and a dependent variable. I want to analyze the relationship between the distance from the sun and the period which by Kepler third law shoud be linear. The choice of the features can be complicated. In general we want to use our expertise of the subject our experience in dealing with similar datasets and of course we want to experiment many possibilities to find insights.

[233]:
```
import numpy as np
from sklearn.linear_model import LinearRegression

#select features

X = dfclean[["DistFromSunParsec"]]
y = dfclean[["PeriodDays"]]



#let us try and find a straight line between the data points to predict future␣
↪values

model = LinearRegression().fit(X,y)

yfit = model.predict(X)


plt.scatter(X,y,c='green')
plt.plot(X,yfit,linewidth=3,c="blue")
plt.xlabel('Distance from Sun')
plt.ylabel('Period Days')
print("Coefficient of correlation:")
print(model.coef_)
print("Intercept:")
print(model.intercept_)

#train the model

from sklearn.model_selection import train_test_split
Xtrain,Xtest,ytrain,ytest = train_test_split(X,y,test_size=1/4,random_state=0)

model = LinearRegression().fit(Xtrain,ytrain)
```

```
ypred = model.predict(Xtest)
plt.scatter(Xtrain,ytrain,c='red')

plt.xlabel('Distance from Sun')
plt.ylabel('Period Days')
#evaluate the model
from sklearn.metrics import mean_squared_error
import math

#calculate RMSE (Root Mean Squared Error) to evaluate the accuracy of the model
MSE = mean_squared_error(ytest, ypred)
print ("RMSE:")
RMSE = math.sqrt(MSE)
print(RMSE)
```

```
Coefficient of correlation:
[[-0.2225497]]
Intercept:
[650.6001912]
RMSE:
11154.530251142676
```



1.3 CONCLUSIONS

The result provided corroborate Kepler third law although the model given the high RMSE is certainly not a good one. Such an high RMSE would warrant either changing the selected features or modify our parameters. The issue here is that we have imputed many values since we were facing an high amount of NaN, and this has added to noise and outliers which are tweaking the model. Although not very accurate though support my first hipotesis and we can repeat the same with different features. It can certainly be used with similar datasets in other domain areas. I have also used R in the past and from a statistics and machine learning point of view is a valid programming language to consider as an alternative to Python for ML analysis. Just as Python has a strong ecosystem of libraries and markdown functionalites similar to Jupyter.

[ ]:
```

```