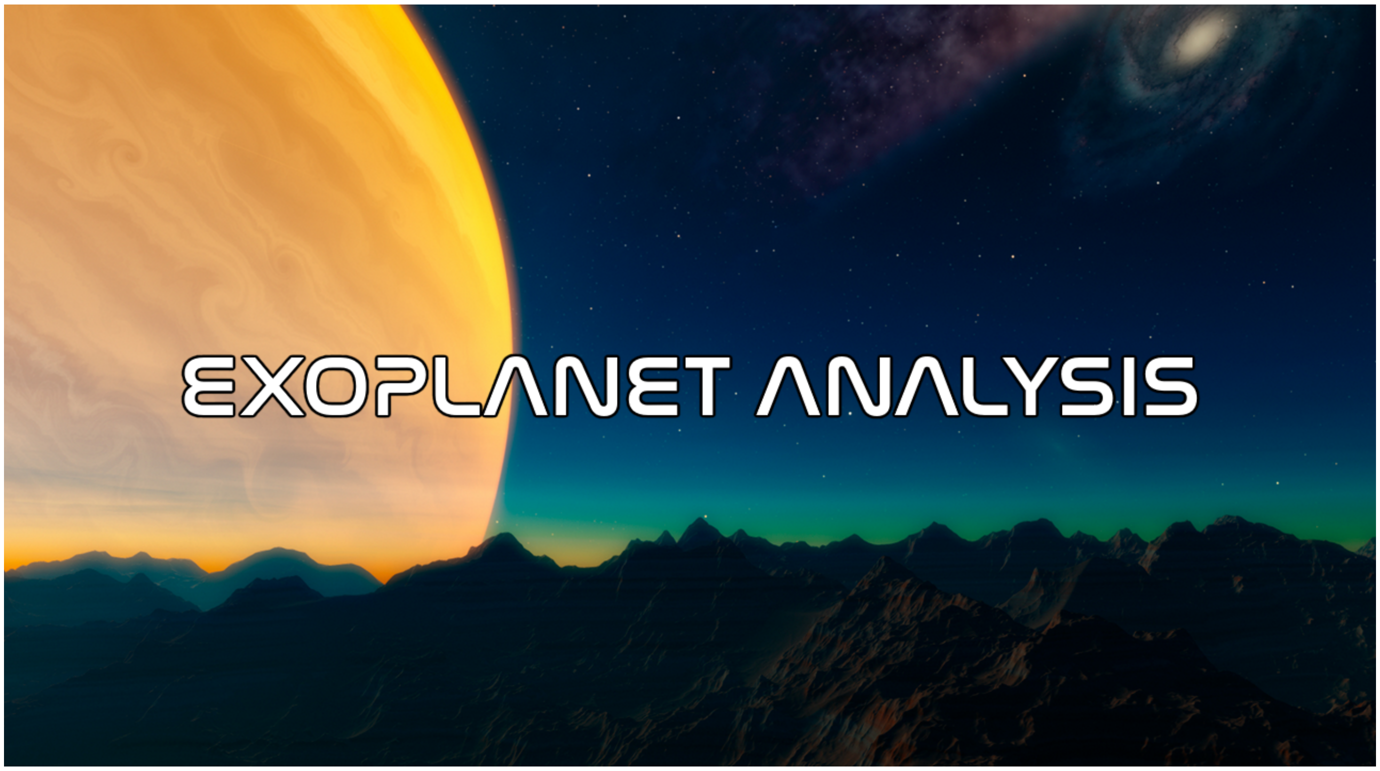


We will analyse the distributions of various extrasolar planets. We will group them into separate clusters, calculate missing information, find the most extreme known planets, and make predictions about the future.

Data has been retrieved from the NASA Exoplanet Archive on the following link: https://exoplanetarchive.ipac.caltech.edu/cgi-bin/TblView/nph-tblView?app=ExoTbls&config=PS

Firstly, we import the necessary libraries:

```
import pandas as pd
import numpy as np
import os
import random

import matplotlib.pyplot as plt
from matplotlib.pyplot import figure
import seaborn as sns

from math import pi
import math

from pandas.io.html import read_html
from urllib.error import HTTPError
import urllib.request
```

✓ 1m 11s completed at 7:02 PM

```
from sklearn.cluster import KMeans
from sklearn.cluster import SpectralClustering

sns.set(rc={"figure.figsize":(10, 4)})

pd.set_option('display.max_columns', None)
```

The data has been retrieved and is located on my google disk. Let us download it:

```
url = 'https://drive.google.com/uc?id=10leqQFcOz8GvXn6eUmJ9mx6Iph2goQ3e&export=download'
filename = 'exoplanets.csv'
urllib.request.urlretrieve(url, filename)

    ('exoplanets.csv', <http.client.HTTPMessage at 0x7f4897248dc0>)
```

Loading the Data

```
exoplanets = pd.read_csv('exoplanets.csv', parse_dates=[90])

    /usr/local/lib/python3.8/dist-packages/IPython/core/interactiveshell.py:3326: DtypeWa
      exec(code_obj, self.user_global_ns, self.user_ns)
```

We are dropping all data that does not concern the planet, the star or the system it is orbiting in. Exoplanet research is a relatively new field, and with less than 6000 confirmed exoplanets, there are many inaccuracies and insecurities concerning the general exoplanet population. Nevertheless, the data that is available can paint an interesting picture. We will be removing all upper and lower limits of data as well.

```
columnsToDrop = ["soltype", "pl_refname", "pl_controv_flag", "st_refname", "sy_refname", "r
                 "pl_orbpererr1", "pl_orbpererr2", "pl_orbperlim", "sy_vmagerr1", "sy_vmage
                 "sy_disterr1", "sy_disterr2", "st_loggerr1", "st_loggerr2", "st_logglim",
                 "pl_radj", "pl_radjerr1", "pl_radjerr2", "pl_radjlim", "pl_orbeccenerr1",
                 "st_masserr1", "st_masserr2", "st_masslim", "pl_orbeccenlim", "pl_insol",
                 "st_tefferr2", "st_tefflim", "st_raderr1", "st_raderr2", "st_radlim", "pl_
                 "st_logg", "st_metratio", "st_met" ]
exoplanets.drop(axis=1, labels=columnsToDrop, inplace=True)
```

Lets see what data remains within our dataset.

```
exoplanets.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 33829 entries, 0 to 33828
Data columns (total 18 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   pl_name         33829 non-null  object 
 1   hostname        33829 non-null  object 
 2   sy_snum         33829 non-null  int64  
 3   sy_pnum         33829 non-null  int64  
 4   discoverymethod  33829 non-null  object 
 5   disc_year       33829 non-null  int64  
 6   disc_facility   33829 non-null  object 
 7   pl_orbper       30957 non-null  float64
 8   pl_orbsmax      18521 non-null  float64
 9   pl_rade         23383 non-null  float64
 10  pl_bmasse       5043 non-null   float64
 11  pl_orbeccen     16923 non-null  float64
 12  pl_eqt          15396 non-null  float64
 13  st_spectype     1976 non-null   object 
 14  st_teff         31421 non-null  float64
 15  st_rad          31541 non-null  float64
 16  st_mass         28555 non-null  float64
 17  sy_dist         33029 non-null  float64
dtypes: float64(10), int64(3), object(5)
memory usage: 4.6+ MB
```

Features starting in “pl” relate to the planet, those that start with “st” relate to the star the planet orbits, and “sy” to the exoplanet system.

- pl_name, pl_orbper, pl_orbsmax, pl_rade, pl_bmasse, pl_orbeccen, pl_eqt are: the name, orbital period, orbital distance, planet's radius, planet's mass, orbital eccentricity, and the equilibrium temperature. These values (except the temperature) are expressed in Earth units.
- hostname - the name of the parent star
- sy_snum, sy_pnum, sy_dist are: the number of stars within the system, the number of other known exoplanets in the system, and the system's distance to Earth.
- discoverymethod, disc_year, disc_facility are: the method of exoplanet's discovery, the year of its discovery, and the science facility that discovered it.
- st_specttype, st_teff, st_rad, st_mass are: the parent star's spectral type, its temperature, radius, and mass. These values (except the temperature) are expressed in Solar units.

Cleaning the Data

We will be converting data to other types to speed up execution time and reduce the space occupied by the dataset. As well as calculating additional features.

```
# categorical data
exoplanets['discoverymethod'] = exoplanets['discoverymethod'].astype('category')
exoplanets['disc_facility'] = exoplanets['disc_facility'].astype('category')

# numberical data
exoplanets['sy_snum'] = exoplanets['sy_snum'].astype('int8')
exoplanets['sy_pnum'] = exoplanets['sy_pnum'].astype('int8')
exoplanets['disc_year'] = exoplanets['disc_year'].astype('int16')
```

When we take a look at the dateset now:

```
exoplanets.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 33829 entries, 0 to 33828
Data columns (total 18 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   pl_name          33829 non-null  object
 1   hostname         33829 non-null  object
 2   sy_snum          33829 non-null  int8
 3   sy_pnum          33829 non-null  int8
 4   discoverymethod  33829 non-null  category
 5   disc_year        33829 non-null  int16
 6   disc_facility    33829 non-null  category
 7   pl_orbper        30957 non-null  float64
 8   pl_orbsmax       18521 non-null  float64
 9   pl_rade          23383 non-null  float64
 10  pl_bmasse        5043 non-null   float64
 11  pl_orbeccen      16923 non-null  float64
 12  pl_eqt           15396 non-null  float64
 13  st_spectype      1976 non-null   object
 14  st_teff          31421 non-null  float64
 15  st_rad           31541 non-null  float64
 16  st_mass          28555 non-null  float64
 17  sy_dist          33029 non-null  float64
dtypes: category(2), float64(10), int16(1), int8(2), object(3)
memory usage: 3.6+ MB
```

The dataset size has been reduced by 1.3 MB. Now, lets take a look at our data:

```
exoplanets.head()
```

	pl_name	hostname	sy_snum	sy_pnum	discoverymethod	disc_year	disc_facilit
0	Kepler-10 b	Kepler-10	1	2	Transit	2011	Keple
1	Kepler-102 e	Kepler-102	1	5	Transit	2013	Keple

2	Kepler-1651 b	Kepler-1651	2	1	Transit	2017	Keple
3	Kepler-210 c	Kepler-210	1	2	Transit	2014	Keple

And a specific planet:

```
exoplanets.loc[exoplanets['pl_name'] == "TRAPPIST-1 b"]
```

	pl_name	hostname	sy_snum	sy_pnum	discoverymethod	disc_year	disc_fa
114	TRAPPIST-1 b	TRAPPIST-1	1	7	Transit	2016	Obse
115	TRAPPIST-1 b	TRAPPIST-1	1	7	Transit	2016	Obse
3123	TRAPPIST-1 b	TRAPPIST-1	1	7	Transit	2016	Obse
15455	TRAPPIST-1 b	TRAPPIST-1	1	7	Transit	2016	Obse

Here we see that there are multiple entries for each exoplanet. This is because the exoplanet archive keeps track of previous entries. We need a way to reduce the data down into one entry per planet.

The logic behind how we will do this is as follows:

1. We will create a separate dataframe, called "temp1" which contains the most recent data for each planet.
2. We will create another dataframe, called "temp2" that contains all other entries.
3. temp2, with its other entries, will be reduced to one entry per planet, taking the average of each column. In this way, we get the “most agreed upon” value for each data point.
4. We will merge the two dataframes, keeping only the “first” data point per each column, for each exoplanet.

In summary, we will take the most recent value provided, if thet value is missing, we will take the average of all older values.

```
temp1 = exoplanets.copy()
temp1.drop_duplicates(subset=["pl_name"], inplace=True, ignore_index=True)
```

Lets check this dataset really does contain only the newest datapoints for each planet.

```
temp1.loc[temp1['hostname'] == "TRAPPIST-1"]
```

	pl_name	hostname	sy_snum	sy_pnum	discoverymethod	disc_year	disc_facil
88	TRAPPIST-1 b	TRAPPIST-1	1	7	Transit	2016	La S Observat
89	TRAPPIST-1 c	TRAPPIST-1	1	7	Transit	2016	La S Observat
90	TRAPPIST-1 d	TRAPPIST-1	1	7	Transit	2016	La S Observat
91	TRAPPIST-1 e	TRAPPIST-1	1	7	Transit	2017	Mult Observato
92	TRAPPIST-1 f	TRAPPIST-1	1	7	Transit	2017	Mult Observato

Now, we create a dataframe that contains all older datapoints.

```
temp2 = exoplanets.copy()
temp2 = temp2[temp2.duplicated('pl_name') | ~temp2.duplicated('pl_name', keep=False)]
temp2= temp2.groupby('pl_name').mean()
temp2.reset_index(inplace=True)
```

```
temp2.loc[temp2['pl_name'] == "TRAPPIST-1 b"]
```

	pl_name	sy_snum	sy_pnum	disc_year	pl_orbper	pl_orbsmax	pl_rade	pl_bma
4947	TRAPPIST-1 b	1.0	7.0	2016.0	1.510848	0.011327	1.109	1.080

We see in the cell above that this dataframe does indeed contain the average of all older datapoints.

```
temp1 = pd.concat([temp1, temp2], ignore_index=True)
```

```
temp1.loc[temp1['pl_name'] == "TRAPPIST-1 b"]
```

	pl_name	hostname	sy_snum	sy_pnum	discoverymethod	disc_year	disc_fa
88	TRAPPIST-1 b	TRAPPIST-1	1.0	7.0	Transit	2016.0	Obse
10174	TRAPPIST-1	NaN	1.0	7.0	NaN	2016.0	

Within the temp1 dataframe we now have two rows for each planet. The first contains the newest data, and the second contains the average of the remaining rows. We will now take the "first" datapoint of each column for each exoplanet.

```
exoplanets = temp1.groupby('pl_name').first()
exoplanets.reset_index(inplace=True)
```

Lets take a look at one of the planets:

```
exoplanets.loc[exoplanets['pl_name'] == "TRAPPIST-1 b"]
```

	pl_name	hostname	sy_snum	sy_pnum	discoverymethod	disc_year	disc_fac
4947	TRAPPIST-1 b	TRAPPIST-1	1.0	7.0	Transit	2016.0	La Obser

How many values we are still missing?

```
exoplanets.isnull().sum(axis = 0)
```

```
pl_name              0
hostname             0
sy_snum              0
sy_pnum              0
discoverymethod      0
disc_year            0
disc_facility        0
pl_orbper          184
pl_orbsmax         281
pl_rade           1223
pl_bmasse         2831
pl_orbeccen        675
pl_eqt            1354
st_spectype       4684
st_teff            325
st_rad             453
st_mass             27
sy_dist            114
dtype: int64
```

Some missing values can be calculated, some can be found on the internet. First, lets handle orbital period and orbital distance.

The orbital distance (pl_orbsmax) and orbital period (pl_orbper) are closely related with Kepler's Third Law:

$$P^2 = a^2 * M$$

P = Period in years

a = semi major axis (SMA) in AU

M = mass of the star in solar masses

```
exoplanets[(exoplanets.pl_orbper.notnull() & exoplanets.pl_orbsmax.isnull() & exoplanets.st
```

```
     438
```

We have 438 planets with either a missing period or distance, and the other parameter available. We can calculate them both using the following functions:

```
def calcSMA(Period, solarMass):
  return round(((Period**2)*solarMass)**(1/3),5)

def calcPeriod(SMA, solarMass):
  return round(((SMA**3)/solarMass)**(0.5),5)
```

We will create temporary dataframes to calcualte the missing values and add them back into our original dataframe.

```
temp1 = exoplanets[(exoplanets.pl_orbper.notnull() & exoplanets.pl_orbsmax.isnull() & exopl
temp1.pl_orbsmax = calcSMA(temp1.pl_orbper/365.25, temp1.st_mass)
exoplanets = pd.concat([exoplanets, temp1], ignore_index=True)
exoplanets.drop_duplicates(subset=["pl_name"], keep='last', inplace=True, ignore_index=True
```

```
temp1 = exoplanets[(exoplanets.pl_orbper.isnull() & exoplanets.pl_orbsmax.notnull() & exopl
temp1.pl_orbper = calcPeriod(temp1.pl_orbsmax, temp1.st_mass)*365.25
exoplanets = pd.concat([exoplanets, temp1], ignore_index=True)
exoplanets.drop_duplicates(subset=["pl_name"], keep='last', inplace=True, ignore_index=True
```

```
exoplanets[(exoplanets.pl_orbper.notnull() & exoplanets.pl_orbsmax.isnull() & exoplanets.st
```

```
     0
```

We no longer have any planets with either a missing SMA or orbital period. There are systems which are missing their distance to the sun. We can find these distances using web-scraping. We will check the wiki page of each star and retrieve its distance to the sun.

The function for this is defined below:

```
def findDistance(hostname):
  page = 'https://en.wikipedia.org/wiki/NAMESYS'
  page = page.replace("NAMESYS", hostname)
  page = page.replace(" ", "%20")
  try:
    try:
      infoboxes = read_html(page, index_col=0, attrs={"class":"infobox"})

      try:
        distance1 = infoboxes[0].xs(u'Distance').values[0]
        distance2 = ''.join([str(elem) for elem in distance1]).replace(",", ".").replace("
        distance3 = round(float(distance2.lstrip().split(' ')[0])*0.3066,4)
        return distance3
      except KeyError as err:
        #print(f"{err} during the search for {hostname}")
        return None

    except ValueError as err:
      #print(f"{err} during the search for {hostname}")
      return None

  except HTTPError as err:
    if err.code == 404:
      #print(f"Cannot find the wiki page for {hostname}")
      return None
    else:
      raise


temp1 = exoplanets[exoplanets.sy_dist.isnull()].copy()
temp1["sy_dist"] = temp1.hostname.apply(lambda x: findDistance(x))
nFound = temp1[temp1.sy_dist.notnull()].groupby('hostname').first().pl_name.count()
exoplanets = pd.concat([exoplanets, temp1], ignore_index=True)
exoplanets.drop_duplicates(subset=["pl_name"], keep='last', inplace=True, ignore_index=True
print(f"{nFound} previously unknown system distances found")
```

```
     11 previously unknown system distances found
```

Lets try finding the star spectral types as well.

```
temp1 = exoplanets.groupby("hostname").first()["st_spectype"].isnull().sum()
print(f"{temp1} stars are missing their spectral type.")
```

```
     3503 stars are missing their spectral type.
```

```
def findStarType(hostname):
  page = 'https://en.wikipedia.org/wiki/NAMESYS'
  page = page.replace("NAMESYS", hostname)
  page = page.replace(" ", "%20")
  try:
    try:
      infoboxes = read_html(page, index_col=0, attrs={"class":"infobox"})

      try:
        value = infoboxes[0].xs(u'Spectral type').values[0]
        return value
      except KeyError as err:
        #print(f"{err} during the search for {hostname}")
        return None

    except ValueError as err:
      #print(f"{err} during the search for {hostname}")
      return None

  except HTTPError as err:
    if err.code == 404:
      #print(f"Cannot find the wiki page for {hostname}")
      return None
    else:
      raise


# scrapedStarTypes = exoplanets[exoplanets.st_spectype.isnull()].copy()
# scrapedStarTypes["st_spectype"] = scrapedStarTypes.hostname.apply(lambda x: findStarType(
# temp2 = scrapedStarTypes[scrapedStarTypes.st_spectype.notnull()].groupby('hostname').firs

# print(f"{temp2} previously unknown star types found")
```

The cell above takes a long time to execute, around 40 minutes. So we will just load its result with the cell below. You can run the cell above if you wish, but you need to skip the one immediately below.

```
urllib.request.urlretrieve("https://drive.google.com/uc?id=1xbGiJaON0zst06uv3_2O1tyjYosvMWH
scrapedStarTypes = pd.read_csv('scrapedStarTypes.csv', index_col=0)
scrapedStarTypes = scrapedStarTypes.reset_index(level=0)
```

Lets add the found stars into our dataset.

```
exoplanets = pd.concat([exoplanets, scrapedStarTypes], ignore_index=True)
exoplanets.drop_duplicates(subset=["pl_name"], keep='last', inplace=True, ignore_index=True
exoplanets["st_spectype"] = exoplanets.st_spectype.astype(str)
exoplanets["st_spectype"] = exoplanets.st_spectype.apply(lambda x: str(x[:2]))
exoplanets["st_spectype"] = exoplanets.st_spectype.apply(lambda x: None if x == "No" else x
exoplanets.st_spectype = exoplanets.st_spectype.apply(lambda x: None if x=="na" else x)


temp2 = exoplanets.groupby("hostname").first()["st_spectype"].isnull().sum()
```

```
print(f"{temp2} stars are missing their spectral type. We found {temp1-temp2} missing star
```

```
    3228 stars are missing their spectral type. We found 275 missing star types
```

An important property of planets is the Equilibrium Temperature. It can be calcualted using the temperature and the radius of the parent star, the distance to the planet, and its albedo. Source:https://www.astro.princeton.edu/~strauss/FRS113/writeup3/

We will be assuming an Albedo value of 0.28.

Lets see how many planets are missing their Equilibrium Temperatures.

```
exoplanets[exoplanets.st_teff.notnull() & exoplanets.pl_eqt.isnull() & exoplanets.st_rad.nc
```

```
    905
```

For these planets we will calculate the Equilibrium Temperature with the following function:

```
def calculateEQTemperature(solarRadi, SMAinAU, T):
  R = solarRadi * 696340
  SMA = SMAinAU * 150000000
  Albedo = 0.28
  return T*((R/(SMA*2))**(0.5))*((1-Albedo)**(1/4))
```

Lets see how well our equation performs on planets for which we know the equilibrium temperature:

```
eligible= exoplanets[exoplanets.st_teff.notnull() & exoplanets.pl_eqt.notnull() & exoplanet
eligible
```

```
    3841
```

We will perform the check with 3841 planets. We will create a separate dataframe to perform the calculation. We will calculate a delta temperature - a percentage value that tells us how wrong our calculated value is. We will then see how many planets fall within 10% of the expected value.

```
checkTemp = exoplanets[exoplanets.st_teff.notnull() & exoplanets.pl_eqt.notnull() & exoplar
checkTemp["calculatedTemp"] = calculateEQTemperature(checkTemp.st_rad, checkTemp.pl_orbsma
checkTemp["deltaTemp"] = checkTemp.pl_eqt/checkTemp.calculatedTemp
within10 = checkTemp[(checkTemp.deltaTemp > 0.9) & (checkTemp.deltaTemp < 1.1)].pl_name.cou
within1 = checkTemp[(checkTemp.deltaTemp > 0.99) & (checkTemp.deltaTemp < 1.01)].pl_name.cc
print(f"Of {eligible} planets, {within10/eligible:2.1%} fall within 10% of the real value.
Of 3841 planets, 79.5% fall within 10% of the real value. 23.5% within 1%
```

These values are acceptable, and we move forward with the calculation. We will calculate the missing values in a separate dataframe, concat it back into exoplanets, and keep the last row which contains the temperature.

```
temp1 = exoplanets[exoplanets.st_teff.notnull() & exoplanets.pl_eqt.isnull() & exoplanets.s
temp1.pl_eqt = calculateEQTemperature(temp1.st_rad, temp1.pl_orbsmax, temp1.st_teff)
exoplanets = pd.concat([exoplanets, temp1], ignore_index=True)
exoplanets.drop_duplicates(subset=["pl_name"], keep='last', inplace=True, ignore_index=True
```

Lets see how many eligible planets are missing their eq temperature now:

```
exoplanets[exoplanets.st_teff.notnull() & exoplanets.pl_eqt.isnull() & exoplanets.st_rad.nc
```

```
0
```

For the following missing values, we have no way of calculating, or retrieving them from elsewhere on the internet. We can however, calculate new variables that can be useful in our analysis.

```
exoplanets.isnull().sum(axis = 0)
```

```
pl_name              0
hostname             0
sy_snum              0
sy_pnum              0
discoverymethod      0
disc_year            0
disc_facility        0
pl_orbper           11
pl_orbsmax          16
pl_rade           1223
pl_bmasse         2831
pl_orbeccen        675
pl_eqt             449
st_spectype       4266
st_teff            325
st_rad             453
st_mass             27
sy_dist             96
ttv_flag          1509
dtype: int64
```

One of these useful variables, is the Earth Similarity Index. A scalar that attempts to reduce the dimensionality of the differences of planetary characteristic when compared to Earth. In other words, the closer the ESI value is to 1, the closer that planet is to being Earth.

It is explained in the *Earth Similarity Index and Habitability Studies of Exoplanets* paper.

Earth Similarity Index and Habitability Studies of Exoplanets: https://arxiv.org/ftp/arxiv/papers/1801/1801.07101.pdf

One of the variables needed for ESI, is the surface temperature. We can approximate it with the equation given in the paper above:

```
def calculateSurfaceTemp(pl_eqt):
  return 9.65 + 1.096 * pl_eqt


exoplanets["pl_sut"] = calculateSurfaceTemp(exoplanets.pl_eqt)
col = exoplanets.pop("pl_sut")
exoplanets.insert(13, col.name, col)
```

The surface temperatures have been calculated and moved to an appropriate position in the dataframe.

Next, we calculate the density of planets for which we know the mass and radius. All we need is the equation for the volume of the sphere, and the relationship between density, mass and volume:

$$V = \frac{4\pi r^3}{3}$$

V - volume

r - radius

$$D = \frac{M}{V}$$

D - density

M - mass

V - volume

```
def calculateDensity(pl_bmasse, pl_rade):
  pl_volume = 4/3*3.14159*(pl_rade**3)
  return pl_bmasse/pl_volume*4.1888

exoplanets["pl_dens"] = calculateDensity(exoplanets.pl_bmasse, exoplanets.pl_rade)
col = exoplanets.pop("pl_dens")
exoplanets.insert(11, col.name, col)
```

An escape velocity of a planet is the minimum speed an object needs to escape the planet's gravity.

$$V_e = \sqrt{\frac{2GM}{r}}$$

V_e - escape velocity

M - mass

G - gravitational constant (6.6743×10^{-11})

```
def calculateEscVelocity(M, R):
  G = 6.67*10**-11
  EscV = (2*G*M/R)**(0.5)
  return EscV*86580.8978
```

```
exoplanets["pl_escv"] = calculateEscVelocity(exoplanets.pl_bmasse, exoplanets.pl_rade)
col = exoplanets.pop("pl_escv")
exoplanets.insert(12, col.name, col)
```

We will also add the surface gravity to the equation:

$$g_s = \frac{GM}{r^2}$$

g_s - surface gravity

M - mass

G - gravitational constant (6.6743×10^{-11})

```
def calculateSurfaceGavity(pl_rade, pl_bmasse):
  mass = pl_bmasse*5.97*10**24
  radius = pl_rade*6371
  result = (6.674*10**-11*mass)/radius**2
  return result/1000000/9.816
```

```
exoplanets["pl_sug"] = calculateSurfaceGavity(exoplanets.pl_rade, exoplanets.pl_bmasse).as
col = exoplanets.pop("pl_sug")
exoplanets.insert(13, col.name, col)
```

The following equation has been adapted from the ESI calculation provided in the *Earth Similarity Index and Habitability Studies of Exoplanets* document. It consists of three “sub-indexes”; ESIi, ESIg, and ESIt.

$$ESIi = \sqrt{(1 - |\frac{R-1}{1+R}|^{0.57}) * (1 - |\frac{D-1}{1+D}|^{1.07})}$$

$ESIi$ - Earth Similarity Index of the planet's interior

$$ESIg = \sqrt{(1 - |\frac{V_e-1}{1+V_e}|^{0.7}) * (1 - |\frac{g_s-1}{1+g_s}|^{1.3})}$$

$ESIg$ *- Earth Similarity Index of the planet's gravity*

$ESIt = (1 - |\frac{T-1}{1+T}|)^{5.58}$
$ESIt$ *- Earth Similarity Index of the planet's temperature*

R - planet radius

D - planet density

V_e *- escape velocity*

g_s *- surface gravity*

T - surface temperature

$ESI = \sqrt[3]{ESIi * ESIg * ESIt}$
ESI *- Earth Similarity Index*

```
def calculateESI(T, EV, G, R, D):
  ESIi = (((1-abs(R-1)/abs(1+R))**0.57)*((1-abs(D-1)/abs(1+D))**1.07))**0.5
  ESIg = (((1-abs(EV-1)/abs(1+EV))**0.7)*((1-abs(G-1)/abs(1+G))**1.3))**0.5
  ESIt = (1-abs(T-288)/abs(288+T))**5.58
  return (ESIi*ESIg*ESIt)**(1/3)
```

```
exoplanets["ESI"] = calculateESI(exoplanets.pl_sut, exoplanets.pl_escv, exoplanets.pl_sug,
col = exoplanets.pop("ESI")
exoplanets.insert(4, col.name, col)
```

Lets take a look at our feature-complete dataset:

```
exoplanets.head()
```

	pl_name	hostname	sy_snum	sy_pnum	ESI	discoverymethod	disc_year	disc_fac
0	51 Eri b	51 Eri	3.0	1.0	NaN	Imaging	2015.0	(Obser
1	55 Cnc b	55 Cnc	2.0	5.0	NaN	Radial Velocity	1996.0	Obser
2	55 Cnc e	55 Cnc	2.0	5.0	0.060848	Radial Velocity	2004.0	McI Obser
3	AB Pic b	AB Pic	1.0	1.0	NaN	Imaging	2005.0	F Obser
4	AU Mic b	AU Mic	1.0	2.0	0.211262	Transit	2020.0	Tra Exc Survey S

b Survey S
(

Solar System Data

Lets prepare the data for solar system planets too. This will be useful for comparison. The data has been collected from: https://www.kaggle.com/datasets/jaredsavage/solar-system-major-bodies-data

The data has also been manually adapted to earth units.

```
urllib.request.urlretrieve("https://drive.google.com/uc?id=1ix2YDTpHo4Li3mcRg8ZAvlpqWa5ttn
solData = pd.read_csv('solData.csv')
```

```
solData["ESI"] = calculateESI(solData.pl_sut, solData.pl_escv, solData.pl_sug, solData.pl_
```

```
solData
```

	pl_name	hostname	sy_snum	sy_pnum	eccentricity	pl_dens	pl_sug	pl_escv	
0	Ceres	Sol	1	8	0.07582	0.391940	0.028571	0.045576	0
1	Uranus	Sol	1	8	0.04570	0.230340	0.905102	1.910634	3
2	Pluto	Sol	1	8	0.24880	0.342789	0.063265	0.108132	0
3	Neptune	Sol	1	8	0.01130	0.297084	1.137755	2.105451	3
4	Jupiter	Sol	1	8	0.04890	0.240533	2.529592	5.379803	10
5	Mars	Sol	1	8	0.09350	0.713527	0.378571	0.449508	0
6	Mercury	Sol	1	8	0.20560	0.984674	0.377551	0.379803	0
7	Saturn	Sol	1	8	0.05650	0.124619	1.065306	3.225201	9
8	Earth	Sol	1	8	0.01670	1.000000	1.000000	1.000000	1
9	Venus	Sol	1	8	0.00670	0.950921	0.905102	0.925827	0
10	Moon	Sol	1	8	0.05490	0.606500	0.165306	0.212690	0

Data Visualization and Analysis

The Record Holders

Highest ESI

```
print(f"{exoplanets[exoplanets.ESI == exoplanets.ESI.max()].pl_name.to_string(index=False)]
print(f"Its surface temperature is {float(exoplanets[exoplanets.ESI == exoplanets.ESI.max()
print(f"It is located {float(exoplanets[exoplanets.ESI == exoplanets.ESI.max()].sy_dist.to_
```

```
     TRAPPIST-1 e is the planet most similar to Earth. With an Earth Similarity Index of 0
     Its surface temperature is 10.5 degrees Celsius, and surface gravity 22.2% lower than
     It is located 40.7 light-years away from Earh.
```

First Exoplanets

```
print(f"{exoplanets[exoplanets.disc_year == exoplanets.disc_year.min()].head(1).pl_name.to_
print(f"They are located {float(exoplanets[exoplanets.disc_year == exoplanets.disc_year.mir
```

```
     PSR B1257+12 c and PSR B1257+12 d are the first extra-solar planets discovered in 199
     They are located 1956.94 light-years away from Earh.
```

Longest and Shortest Period

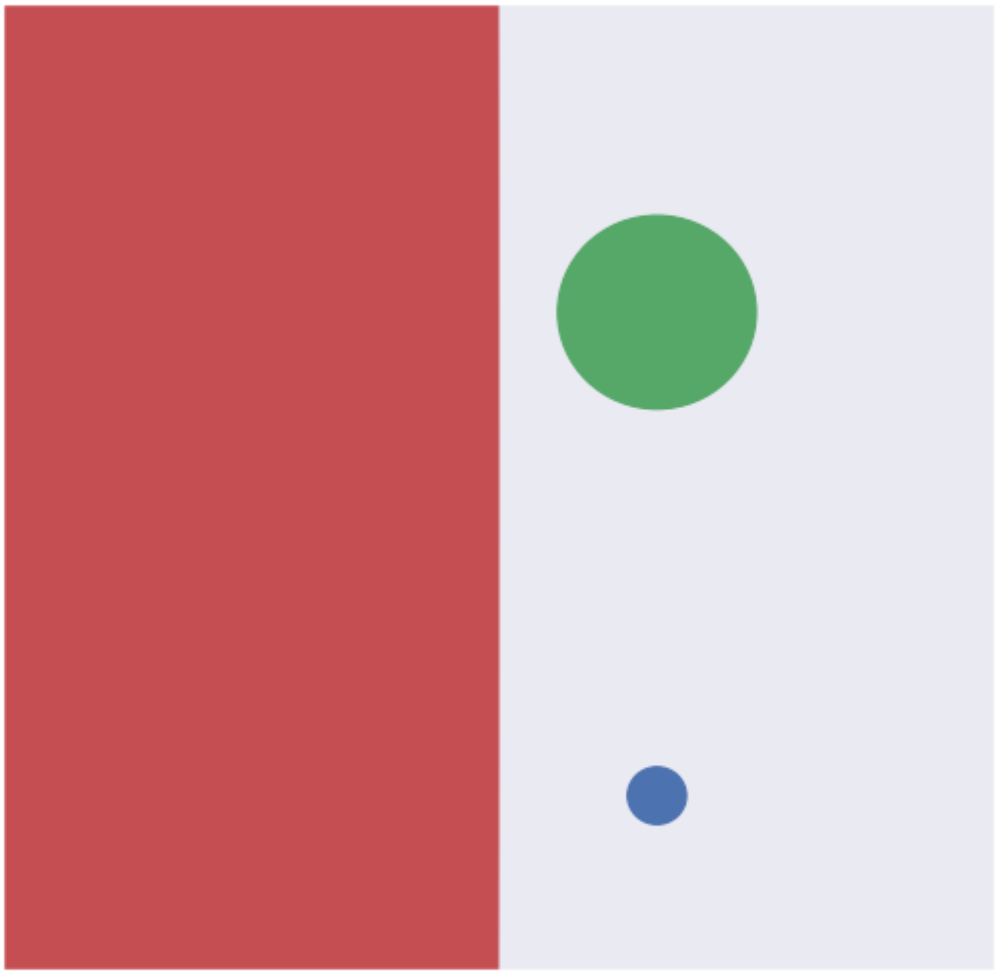
```
exoplanets.replace([np.inf, -np.inf], np.nan, inplace=True)
print(f"{exoplanets[exoplanets.pl_orbper == exoplanets.pl_orbper.max()].pl_name.to_string(i
print(f"Due to Kepler's Third Law, {exoplanets[exoplanets.pl_orbsmax == exoplanets.pl_orbsn
print(f"Its opposite is {exoplanets[exoplanets.pl_orbper == exoplanets.pl_orbper.min()].pl_
```

```
     COCONUTS-2 b is the planet with the longest orbital period. Its year lasts 1100616.01
     Due to Kepler's Third Law, COCONUTS-2 b is also the planet that orbits the farthest f
     Its opposite is PSR J1719-1438 b. Its year lasts just 2.18 hours! And is only 658240
```

Largest and Smallest

```
print(f"{exoplanets[exoplanets.pl_rade == exoplanets.pl_rade.max()].pl_name.to_string(index
print(f"{exoplanets[exoplanets.pl_rade == exoplanets.pl_rade.min()].pl_name.to_string(index
print(f"{exoplanets[exoplanets.pl_rade == exoplanets.pl_rade.max()].pl_name.to_string(index
plt.figure(figsize=(8, 8), dpi=80)
circle1 = plt.Circle((-449.5, 0.5), 450, color='r')
circle2 = plt.Circle((0.66, 0.68), 0.1, color='g')
circle3 = plt.Circle((0.66, 0.18), 0.1*exoplanets.pl_rade.min(), color='b')
plt.gca().add_patch(circle1).axes.get_xaxis().set_visible(False)
plt.gca().add_patch(circle2).axes.get_yaxis().set_visible(False)
plt.gca().add_patch(circle3);
```

```
HD 100546 b is the largest known exoplanet. It has a radius 77 times bigger than Eart
Kepler-37 b is the smallest. It has a radius 29.6% that of Earth's. That is smaller t
HD 100546 b (red), Earth (green), and Kepler-37 b (blue):
```



Most and Least Massive, & Escape Velocity

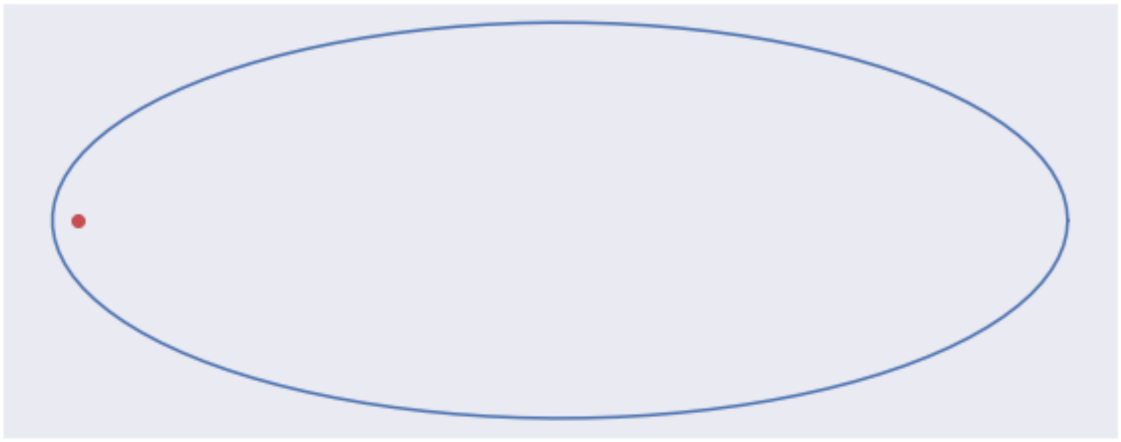
```
print(f"{exoplanets[exoplanets.pl_bmasse == exoplanets.pl_bmasse.max()].pl_name.to_string(i
print(f"It also has the highest escape velocity, at {exoplanets.pl_escv.max()*11.2:.5} km/s

print(f"{exoplanets[exoplanets.pl_bmasse == exoplanets.pl_bmasse.min()].pl_name.to_string(i
print(f"It however, does not have the lowest escape velocity. That title goes to {exoplanet
```

```
PH2 b is the most massive known exoplanet. It is 25426.4 times heavier than Earth.
It also has the highest escape velocity, at 583.15 km/s, 52.07 times larger than Eart
PSR B1257+12 b is the least massive exoplanet. It is 2.0% the mass of the Earth.
It however, does not have the lowest escape velocity. That title goes to Kepler-444 e
```

Most Eccentric Orbit

```
print(f"{exoplanets[exoplanets.pl_orbeccen == exoplanets.pl_orbeccen.max()].pl_name.to_stri
print(f"It goes from {(exoplanets.pl_orbeccen.max()+1)*float(exoplanets[exoplanets.pl_orbec
print(f"The red dot represents the star while the blue elipse represents the orbit of {exo
u=1     #x-position of the center
v=0.5    #y-position of the center
a=2     #radius on the x-axis
b=0.1561    #radius on the y-axis
t = np.linspace(0, 2*pi, 100)
plt.plot( u+a*np.cos(t) , v+b*np.sin(t) )
plt.plot(-0.90035,0.5, "ro")
plt.grid(color='lightgray',linestyle='--')
ax = plt.gca()
ax.axes.xaxis.set_ticklabels([])
ax.axes.yaxis.set_ticklabels([])
ax.grid(False)
plt.show()
```

```
HD 20782 b has the highest eccentricity at 0.95.
It goes from 2.6616 AU at its farthest, to 0.068 AU at the closest.
The red dot represents the star while the blue elipse represents the orbit of HD 2078
```



Hottest

```
print(f"{exoplanets[exoplanets.pl_eqt == exoplanets.pl_eqt.max()].pl_name.to_string(index=
print(f"That is {int(exoplanets.pl_eqt.max()) - 5778} degrees hotter than the surface of o
```

```
KOI-55 b has the highest equilibrium temperature at 7105K, or 6832 degrees celsius.
That is 1327 degrees hotter than the surface of our Sun!
```

Highest surface gravity

```
print(f"{exoplanets[exoplanets.pl_sug == exoplanets.pl_sug.max()].pl_name.to_string(index=
```

```
K2-137 b has the highest surface gravity, at 387gs.
```

Most and least dense

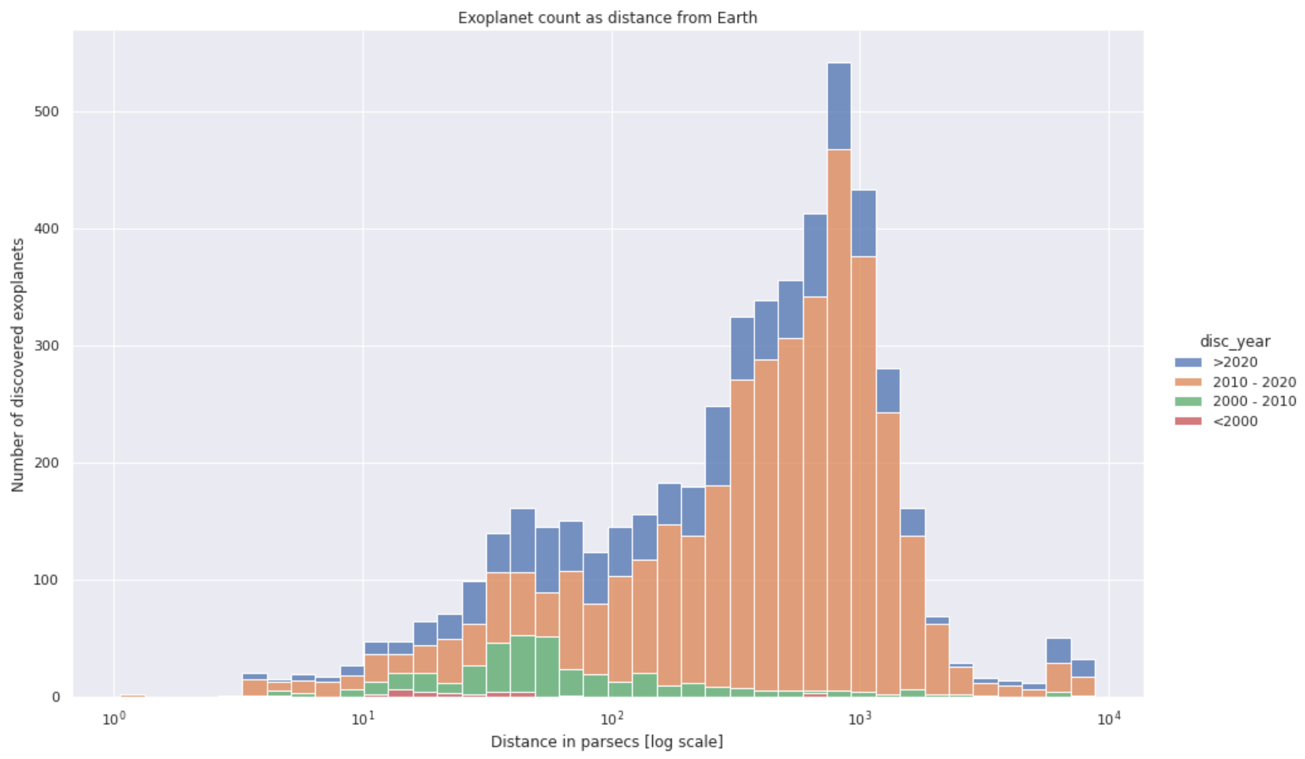
```
print(f"{exoplanets[exoplanets.pl_dens == exoplanets.pl_dens.max()].pl_name.to_string(inde
print(f"{exoplanets[exoplanets.pl_dens == exoplanets.pl_dens.min()].pl_name.to_string(inde
```

```
    KOI-4777.01 is the densest known exoplanet. It is 747 times denser than Earth.
    Kepler-444 e is the least dense exoplanet. It is 0.00699% Earth's density.
```

Count Plots

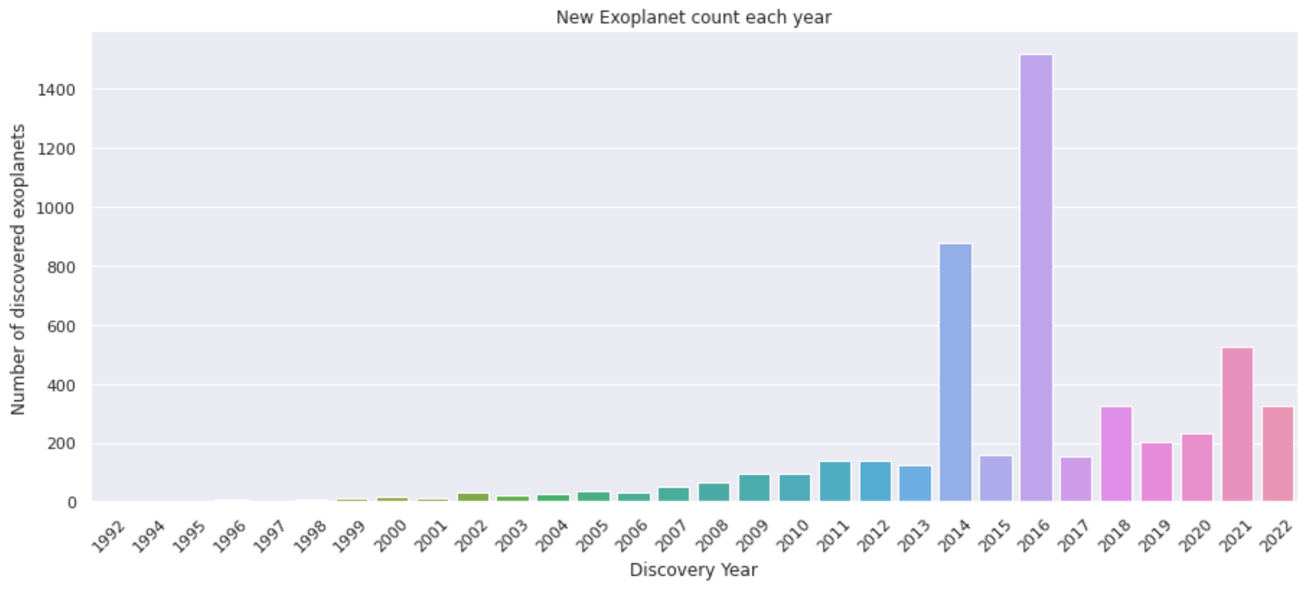
Lets plot the exoplanet systems according to their distance and discovery year. Note that one parces equals 3.26156 light-years.

```
temp1 = exoplanets.sort_values(by=["disc_year"], ascending=False).copy()
temp1.disc_year = temp1.disc_year.apply(lambda x: "<2000" if (x<2000) else ("2000 - 2010" :
ax = sns.displot(temp1, x="sy_dist", log_scale=True, height=8.3, aspect=13/8.3, hue="disc_y
ax.set(xlabel='Distance in parsecs [log scale]', ylabel='Number of discovered exoplanets',
plt.show()
```



The count plot per year:

```
temp1 = exoplanets.sort_values(by=["disc_year"], ascending=True).copy()
fig, ax = plt.subplots()
plt.gcf().set_size_inches((15, 6))

ax = sns.countplot(x=temp1.disc_year.astype("int16"))
ax.set(xlabel='Discovery Year', ylabel='Number of discovered exoplanets', title="New Exopla
plt.xticks(rotation=45)
plt.show()
```

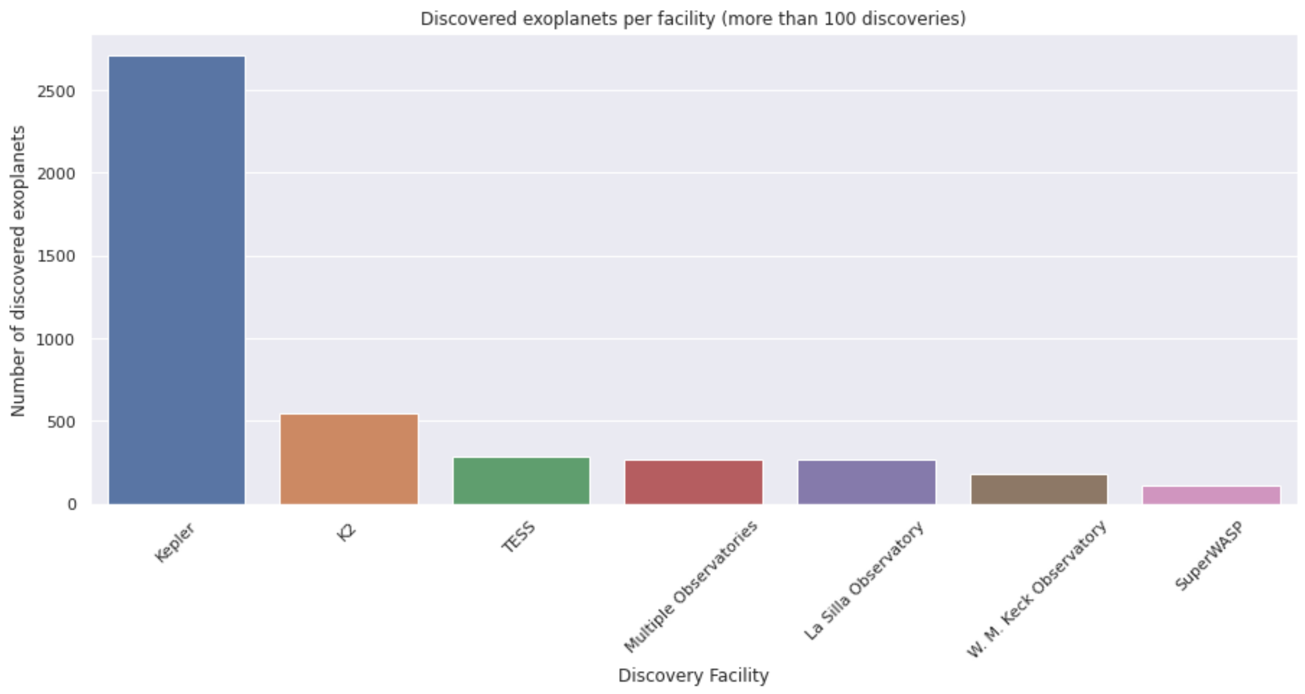


Why do we see a large jump in newly discovered exoplanets in 2014 and 2016? Because the Kepler space telescope responsible for the vast majority of exoplanet discoveries, released its data in those two years. We also see another uptick in 2018, when Kepler released its final data before being deactivated.

Let's take a look at the count plot of discovery facilities;

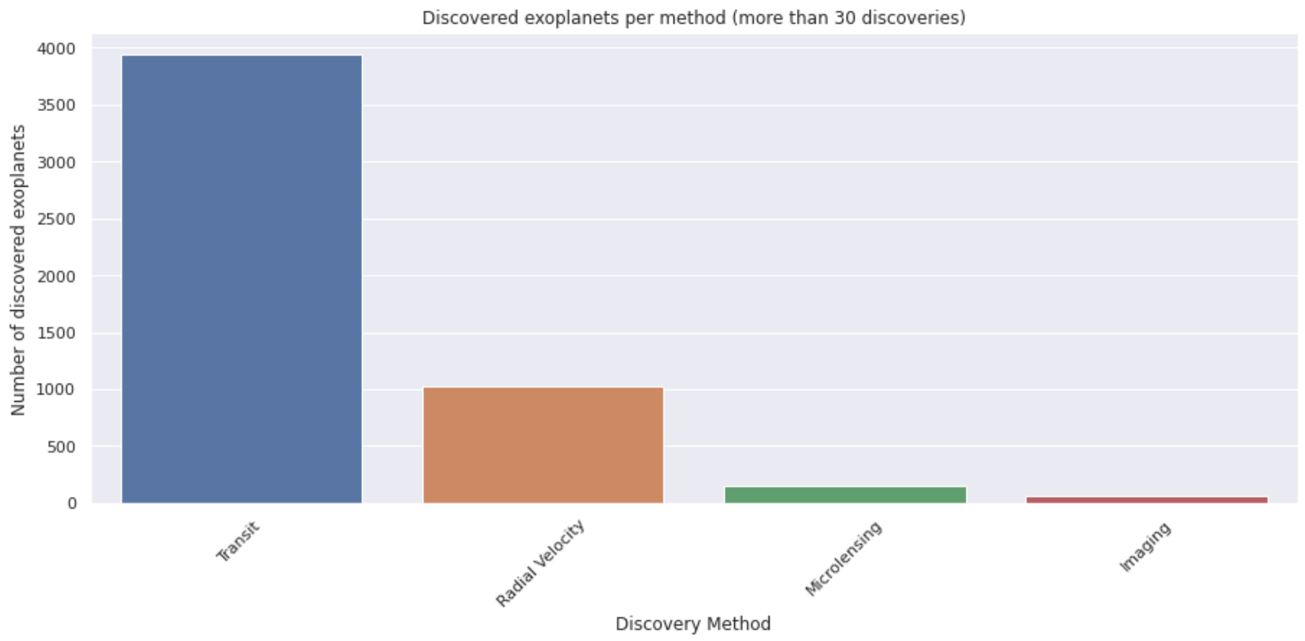
```
temp1 = exoplanets.groupby("disc_facility").pl_name.count()
temp1 = temp1.reset_index()
```

```
temp1.sort_values(by=["pl_name"], ascending=False, inplace=True)
temp1.disc_facility = temp1.disc_facility.apply(lambda x: ("TESS") if x== "Transiting Exop
temp1 = temp1[temp1['pl_name'] > 100]

fig, ax = plt.subplots()
plt.gcf().set_size_inches((15, 6))

ax = sns.barplot(data=temp1, x="disc_facility", y="pl_name")
ax.set(xlabel='Discovery Facility', ylabel='Number of discovered exoplanets', title="Disco
plt.xticks(rotation=45);
```



And the count plot of discovery methods;

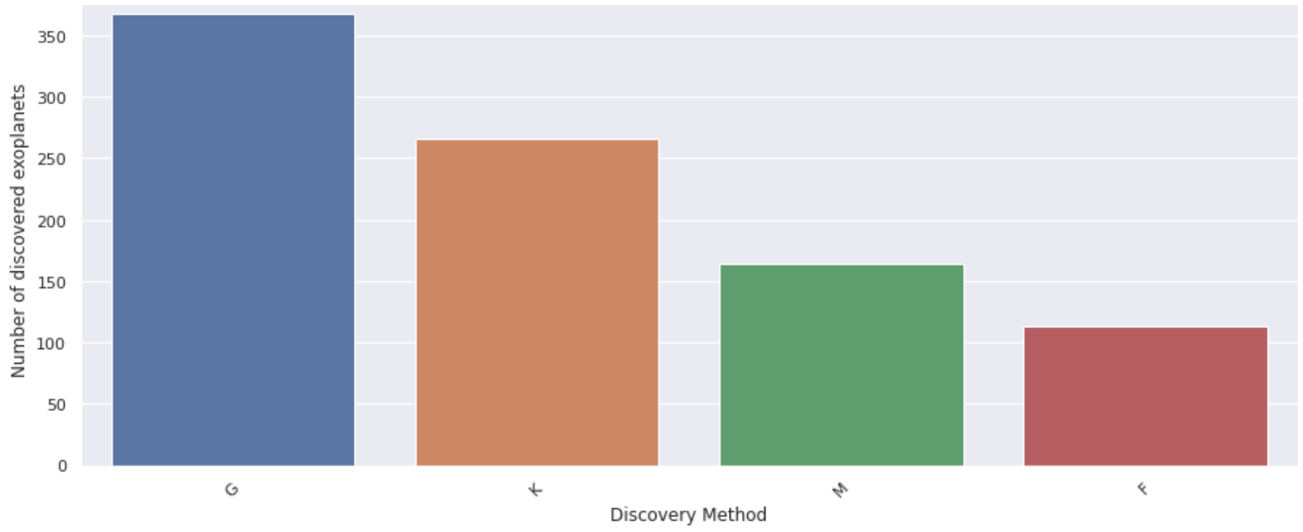
```
temp1 = exoplanets.groupby("discoverymethod").pl_name.count()
temp1 = temp1.reset_index()
temp1.sort_values(by=["pl_name"], ascending=False, inplace=True)
temp1 = temp1[temp1['pl_name'] > 30]

fig, ax = plt.subplots()
plt.gcf().set_size_inches((15, 6))

ax = sns.barplot(data=temp1, x="discoverymethod", y="pl_name")
ax.set(xlabel='Discovery Method', ylabel='Number of discovered exoplanets', title="Discove
plt.xticks(rotation=45);
```



Transit timing is the most common method of discovering exoplanets. It consists of staring at a star for long periods of time, and watching for periodic dips in the star's brightness caused by a transiting exoplanet. This introduces a strong discovery bias towards small stars (whose light can more easily be blocked), larger planets (that block more of their stats light), and shorter period planets (because they transit more often).

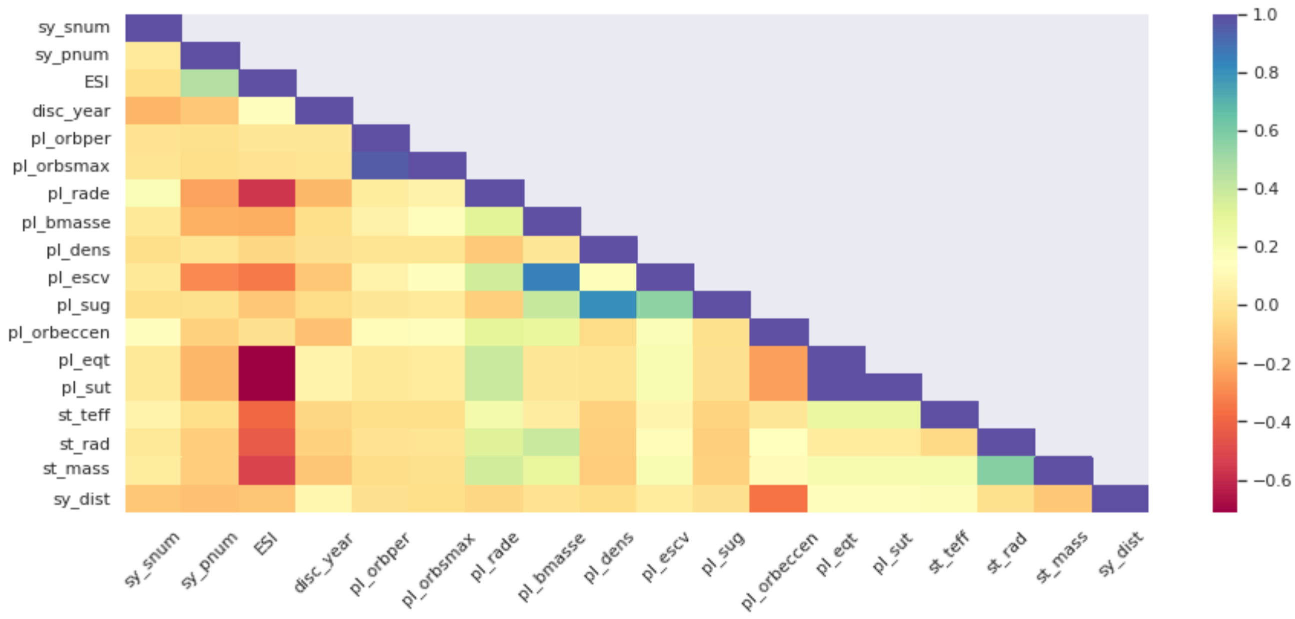
```
temp1 = exoplanets.copy()
temp1.st_spectype = temp1.st_spectype.str[:1]
temp1 = temp1.groupby("st_spectype").pl_name.count()
temp1 = temp1.reset_index()
temp1.sort_values(by=["pl_name"], ascending=False, inplace=True)
temp1 = temp1[temp1['pl_name'] > 30]

fig, ax = plt.subplots()
plt.gcf().set_size_inches((15, 6))

ax = sns.barplot(data=temp1, x="st_spectype", y="pl_name")
ax.set(xlabel='Discovery Method', ylabel='Number of discovered exoplanets', title="Discover
plt.xticks(rotation=45);
```

Discovered exoplanets per method (more than 30 discoveries), and for which we know the star type



Data correlation

```
temp1 = exoplanets.corr(method='pearson').where(np.tril(np.ones(exoplanets.corr(method='pea
fig, ax = plt.subplots(figsize=(15,6))
hmap=sns.heatmap(temp1,cmap="Spectral")
ax.set_xticklabels(ax.get_xticklabels(), rotation=45);
```



We see several features which are highly correlated. Such as equilibrium temperature (pl_eqt) and surface temperature (pl_sut) which makes a lot of sense, as we used a linear equation to connect the two. Planetary density (pl_dens) and planetary escape velocity (pl_escv) are similarly connected - as the density determines the velocity.

Observation 1: An interesting observation concerns the Earth similarity index (ESI) and the number of other planets found in the planetary system (sy_pnum). This suggests that more habitable planets, or those that are more earth-like, have a higher chance of forming with other planetary companions. This meshes well with the numerous theories that the large gas giants such as Jupiter and Saturn, played key roles in shepherding the formation of the Earth. And other exoplanets might do the same for their system's most habitable planets.

Observation 2: Another point to consider is the negative correlation between the distance to the exoplanet (sy_dist) and its orbital eccentricity (pl_orbeccen). We see this as the main discovery technique with which we can discover the eccentricity, is the radial velocity method. Where we measure the small changes in the motion of the parent star. These miniscule changes become much harder to detect with distance, and this is an example of selection bias. It is not that planets become less eccentric with distance from the earth, but our telescopes are not sensitive enough to probe those distant worlds in such a way as to reveal the most eccentric ones.

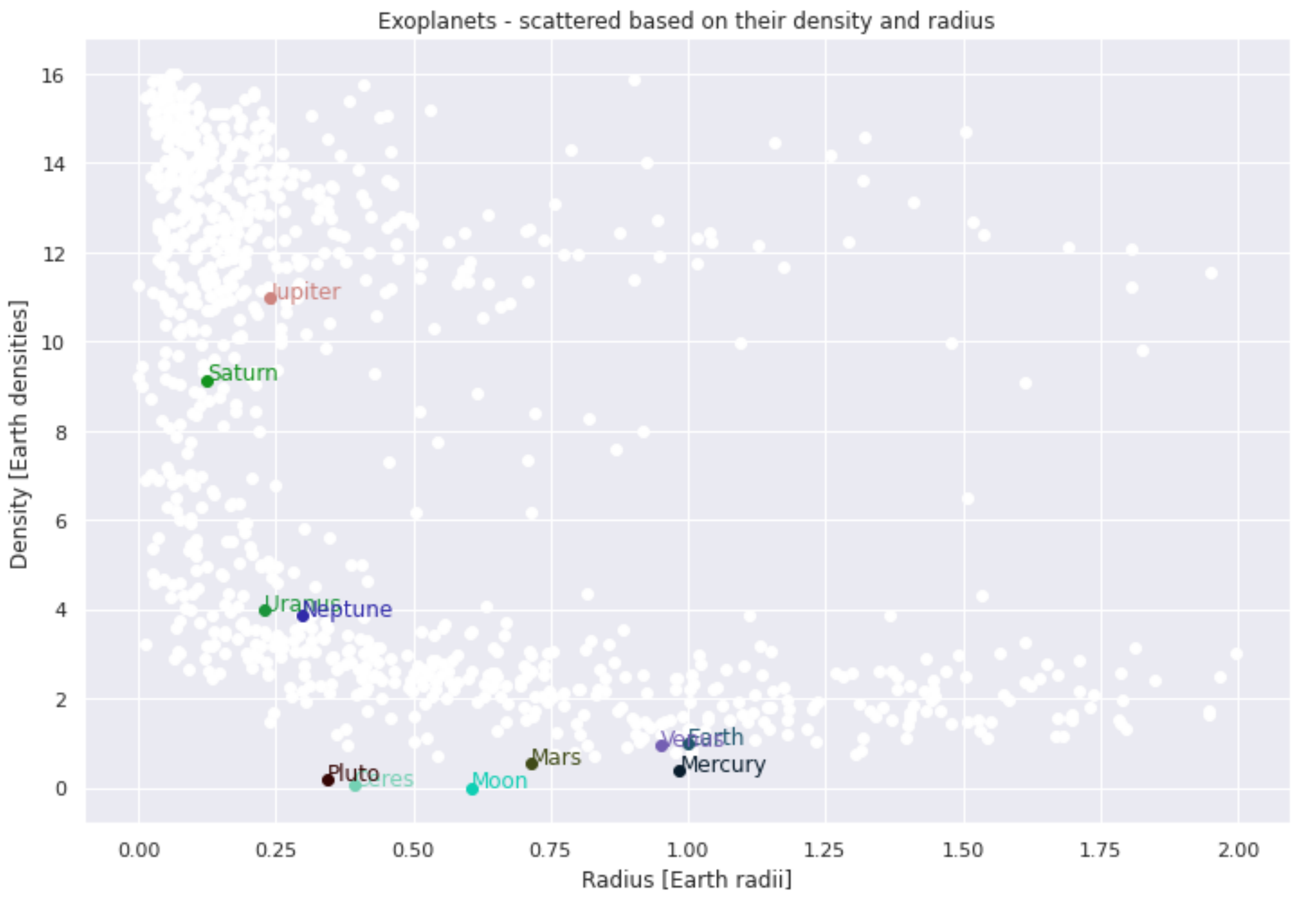
Clustering

Exoplanets can be best clustered using density and radius. We will be using Spectral Clustering, and focusing on planets with a density less than 2 times the Earth's, and a radius less than 16 times the Earth's.

First, we will take a look at all the exoplanets in this range, by plotting them onto a scatter plot. We will also load in the planets of our Solar System as a comparison.

```
temp1 = pd.DataFrame()
temp1["pl_dens"]=exoplanets[(exoplanets.pl_dens < 100000)].pl_dens
temp1["pl_rade"]=exoplanets[(exoplanets.pl_dens < 100000)].pl_rade


fig, ax = plt.subplots()
plt.gcf().set_size_inches((12, 8))

upperDenslimit = 2
upperRadelimit = 16
```

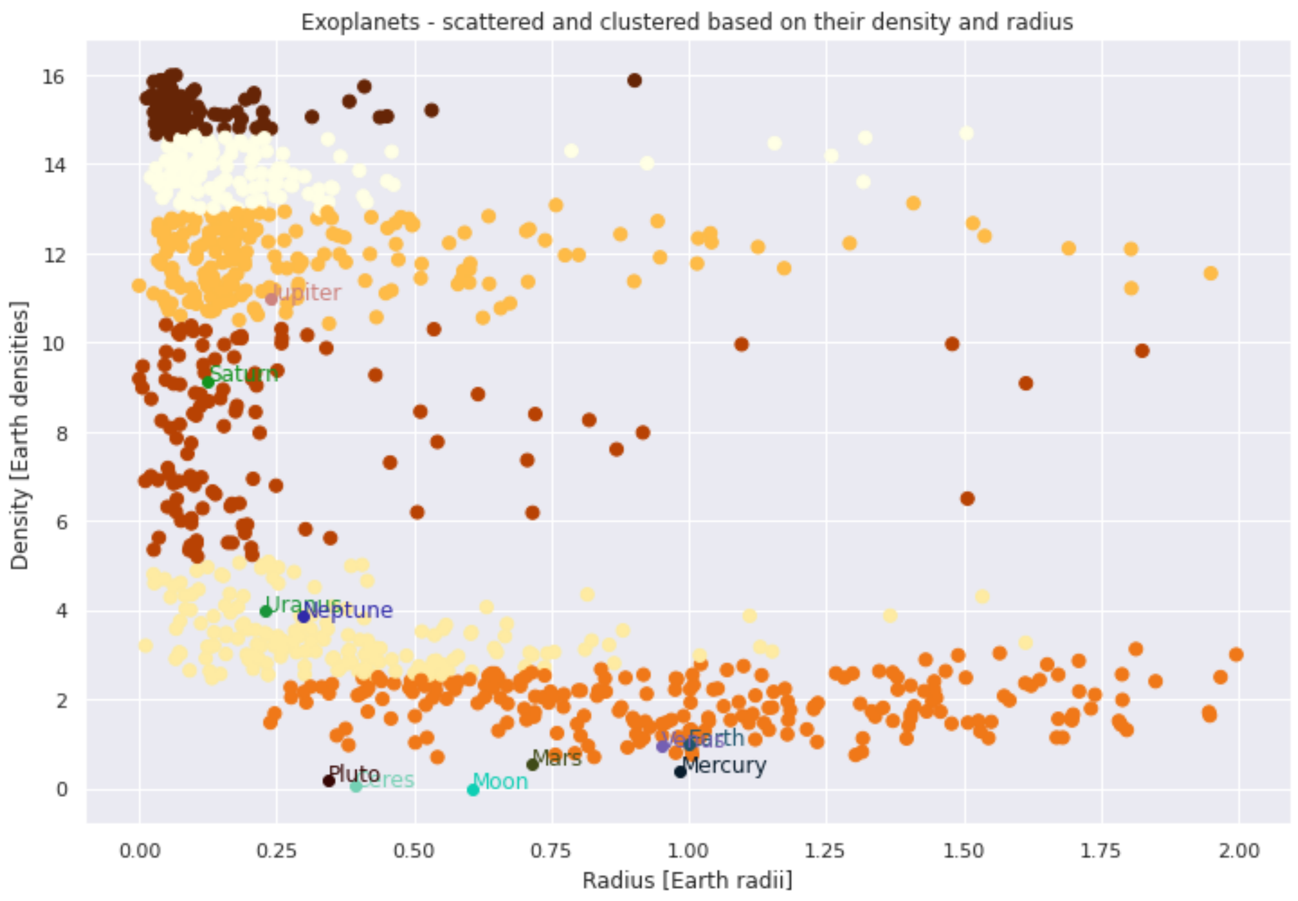
```
ax.scatter(temp1[(temp1.pl_dens<upperDenslimit) & (temp1.pl_rade<upperRadelimit)].pl_dens,

color = ["#"+''.join([random.choice('0123456789ABCDEF') for j in range(6)]) for i in range(

for ind in solData.index:
  ax.scatter(solData['pl_dens'][ind],solData['pl_rade'][ind],c=color[ind])
  ax.annotate(solData['pl_name'][ind], (solData['pl_dens'][ind],solData['pl_rade'][ind]), c

ax.set(xlabel='Radius [Earth radii]', ylabel='Density [Earth densities]', title="Exoplanets
```



Now we will cluster these datapoints into 6 clusters.

```
temp2 = pd.DataFrame()
temp2["pl_dens"] = temp1[(temp1.pl_dens<upperDenslimit) & (temp1.pl_rade<upperRadelimit)].p
temp2["pl_rade"] = temp1[(temp1.pl_dens<upperDenslimit) & (temp1.pl_rade<upperRadelimit)].p


fig, ax = plt.subplots()

plt.gcf().set_size_inches((12, 8))
model = SpectralClustering(n_clusters=6, affinity='nearest_neighbors',
                           assign_labels='kmeans')
```

```
                         assign_labels='kmeans')
labels = model.fit_predict(temp2)
ax.scatter(temp2.pl_dens, temp2.pl_rade, c=labels, s=50, cmap='YlOrBr');
for ind in solData.index:
  ax.scatter(solData['pl_dens'][ind],solData['pl_rade'][ind],c=color[ind])
  ax.annotate(solData['pl_name'][ind], (solData['pl_dens'][ind],solData['pl_rade'][ind]), c

ax.set(xlabel='Radius [Earth radii]', ylabel='Density [Earth densities]', title="Exoplanets
```



We clearly see the separation between the planet types within our own solar system.

1. Earth, Venus, Mars and Mercury are all in the “lowest” cluster. This can be though of as the Terrestrial Cluster.
2. Uranus and Neptune are in their own Ice Giant Cluster.
3. As a Gas Giant with an extremely low density (lower than water’s), Saturn belongs in the third cluster, the Puff Planet Cluster.
4. Jupiter is the largest Gas Giant, and belongs in his own cluster, the true Gas Giant Cluster.
5. & 6. The clusters above the Gas Giant, contains planets whose masses put Jupiter’s to shame. We have no planets in this range within our own planetary system.

Classification

We will manually set ranges and classes for variables such as mass, temperature and density, as proposed in this paper:

https://bit.ly/3jSfJ6M

I have used a modified system for classification, taking into account the "unknown densities" - densities many hundreds of times above Earth's.

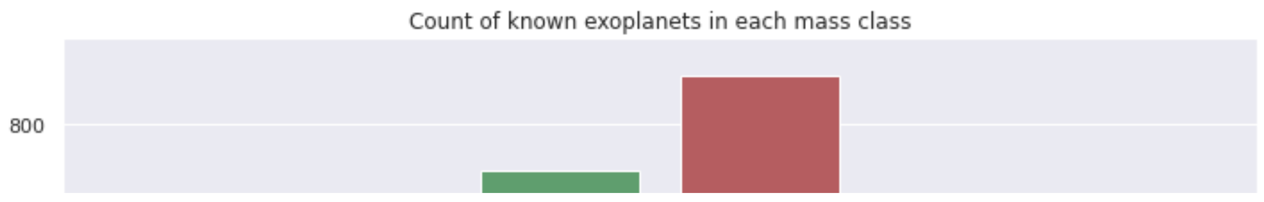
```
def classify(value, array):

  i = 0

  if value:
    while (value > array[1][i]) & (i <= len(array[1])):
      i = i + 1
    planetClass = array[0][i]
  else:
    planetClass = "?"

  return planetClass
```

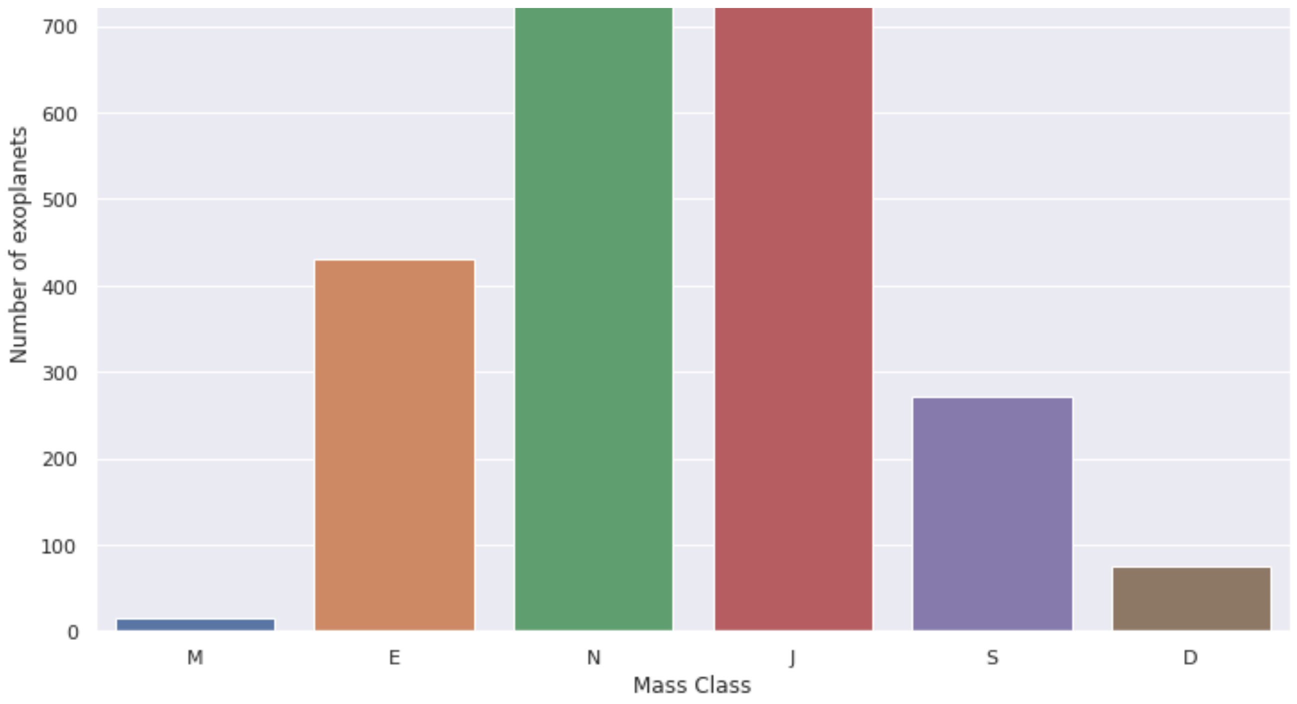
Each planet is classified based on the modified values presented in the paper.

```
exoplanets["massClass"] = exoplanets.apply(lambda x: classify(x.pl_bmasse, [["?", "M", "E",
exoplanets["tempClass"] = exoplanets.apply(lambda x: classify(x.pl_eqt, [["?", "F", "A", "W
exoplanets["planetClass"] = exoplanets.apply(lambda x: classify(x.pl_dens, [["?", "p", "g",
```

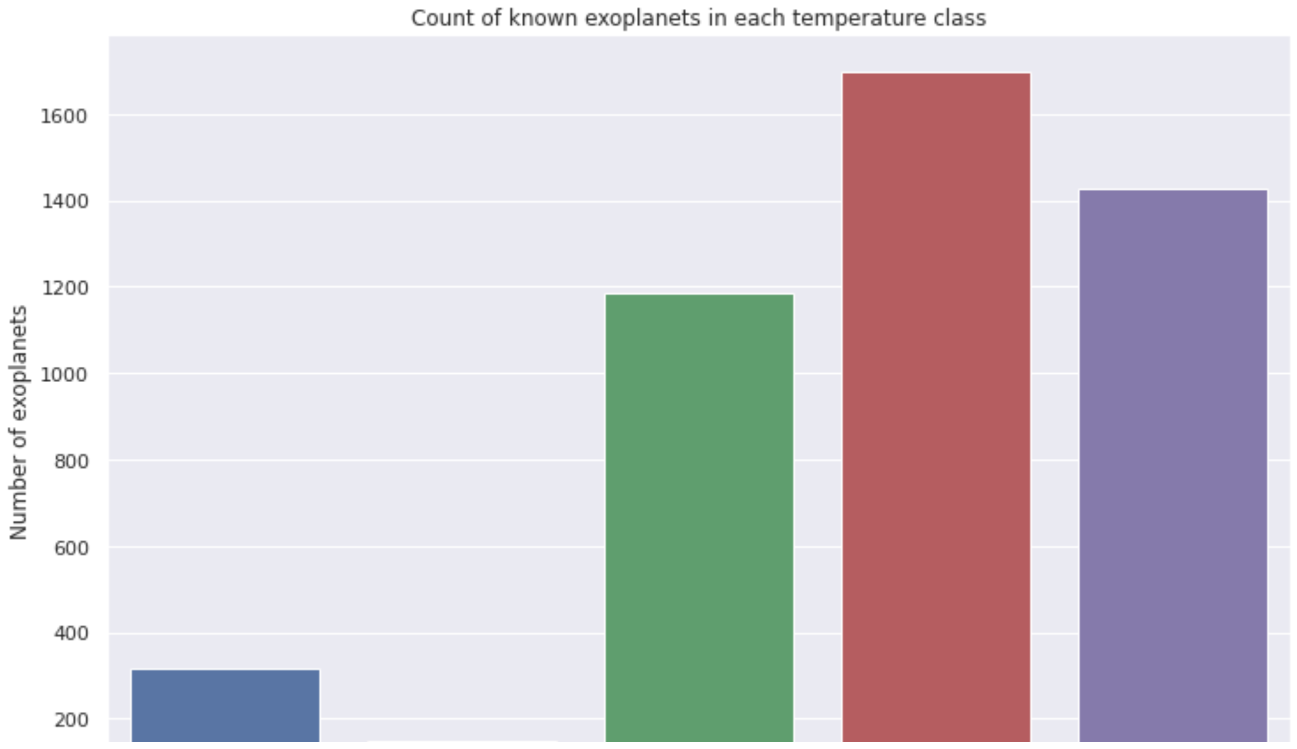
Lets take a look at the count plots for Mass, Temperature, and Density:

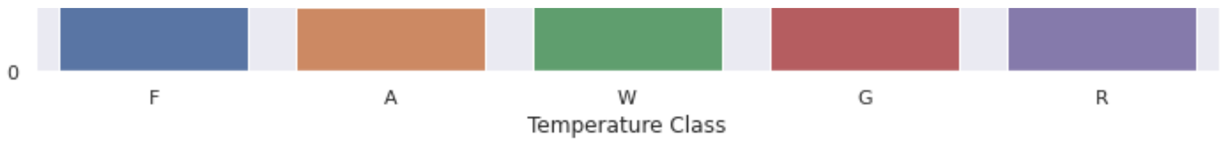
```
fig, ax = plt.subplots()
plt.gcf().set_size_inches((12, 8))

temp1 = exoplanets[exoplanets.massClass != "?"].copy()

ax = sns.countplot(x="massClass", data=temp1, order=["M", "E", "N", "J", "S", "D"])
ax.set(xlabel='Mass Class', ylabel='Number of exoplanets', title="Count of known exoplanets
```



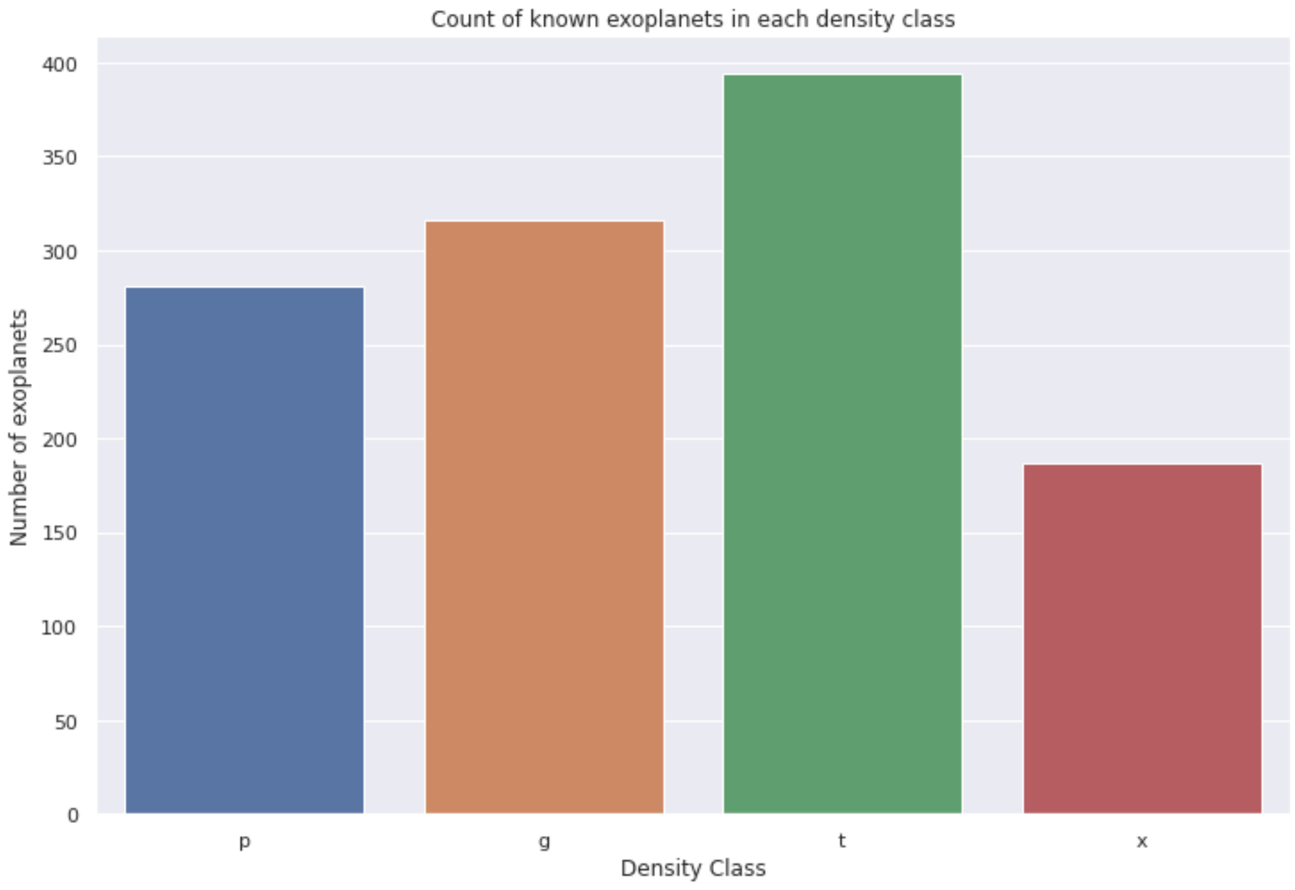


```
fig, ax = plt.subplots()
plt.gcf().set_size_inches((12, 8))

temp1 = exoplanets[exoplanets.tempClass != "?"].copy()

ax = sns.countplot(x="tempClass", data=temp1, order=["F", "A", "W", "G", "R"])
ax.set(xlabel='Temperature Class', ylabel='Number of exoplanets', title="Count of known exo
```





```
fig, ax = plt.subplots()
plt.gcf().set_size_inches((12, 8))

temp1 = exoplanets[exoplanets.planetClass != "?"].copy()

ax = sns.countplot(x="planetClass", data=temp1, order=["p", "g", "t", "x"])
ax.set(xlabel='Density Class', ylabel='Number of exoplanets', title="Count of known exoplar
```



Are there any exoplanets with the same classification as Earth? We are looking for a planet with a class of “EAt”.

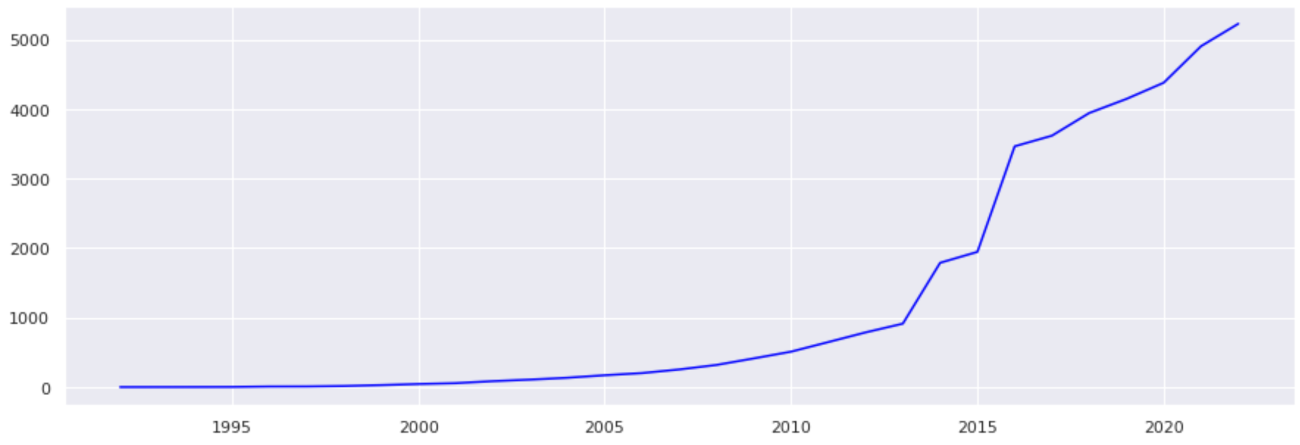
```
exoplanets[(exoplanets.massClass == "E") & (exoplanets.tempClass == "A") & (exoplanets.plar
```

	pl_name	hostname	sy_snum	sy_pnum	ESI	discoverymethod	disc_year
398	K2-18 b	K2-18	1.0	2.0	0.806230	Transit	2015.0
438	K2-3 d	K2-3	1.0	3.0	0.812223	Transit	2015.0
612	L 98-59 d	L 98-59	1.0	4.0	0.705965	Transit	2019.0
4313	TRAPPIST-1 e	TRAPPIST-1	1.0	7.0	0.941255	Transit	2017.0

All these worlds have ESI higher than any other object in the solar system besides Earth.

Predicting the next milestones in exoplanet discoveries

```
temp2 = exoplanets.groupby("disc_year").pl_name.count()
temp1 = temp2.cumsum()
plt.figure(figsize=(15,5))
plt.plot(temp1, c="blue")
plt.show()
```

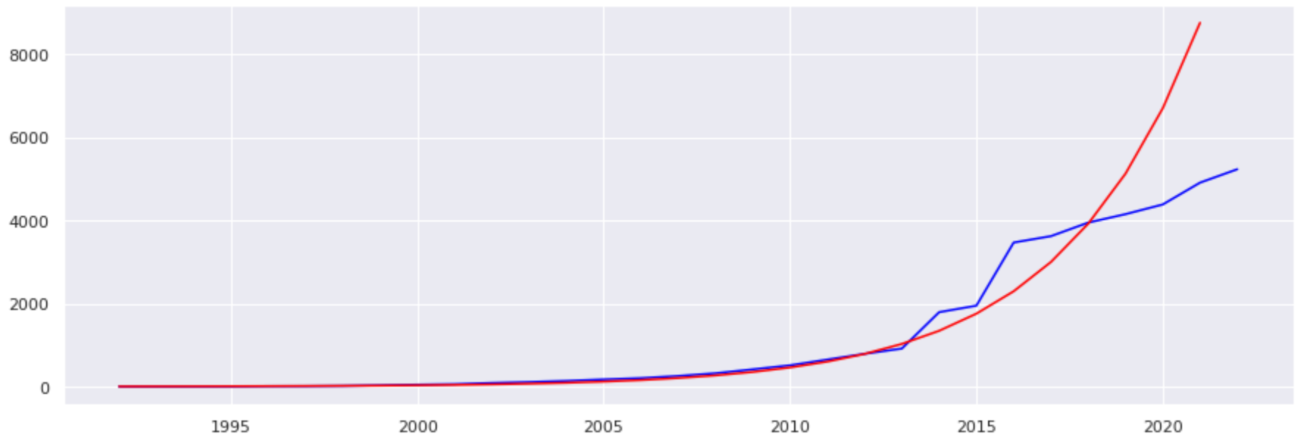


```
import numpy as np
from sklearn.linear_model import LinearRegression
```

```
temp2 = temp1
temp2 = temp2.to_frame()
temp2.rename(columns={'pl_name': 'y'}, inplace=True)
temp2["log_y"] = np.log(temp2.y)
temp2["year"] = temp2.index - 1991

# Create a numpy array of data:
x = temp2.year.to_numpy().reshape((-1, 1))
y = temp2.log_y.to_numpy()

# Create an instance of a linear regression model and fit it to the data with the fit() fur
model = LinearRegression().fit(x, y)

# The following section will get results by interpreting the created instance:

# Obtain the coefficient of determination by calling the model with the score() function, t
r_sq = model.score(x, y)
print('coefficient of determination:', r_sq)

# Print the Intercept:
print('intercept:', model.intercept_)

# Print the Slope:
print('slope:', model.coef_)

# Predict a Response and print it:
y_pred = model.predict(x)
print('Predicted response:', y_pred, sep='\n')
```

```
coefficient of determination: 0.9748802613653331
intercept: 1.0392566604749103
slope: [0.2679142]
Predicted response:
[1.30717086 1.84299927 2.11091347 2.37882768 2.64674188 2.91465609
 3.18257029 3.45048449 3.7183987  3.9863129  4.2542271  4.52214131
 4.79005551 5.05796971 5.32588392 5.59379812 5.86171232 6.12962653
 6.39754073 6.66545493 6.93336914 7.20128334 7.46919754 7.73711175
 8.00502595 8.27294016 8.54085436 8.80876856 9.07668277 9.34459697]
```

```
x = np.arange(1,100).reshape(-1,1)
y_pred = model.predict(x)
temp1=pd.DataFrame(x+1991, y_pred)
temp1 = temp1.reset_index()
temp1 = temp1.rename(columns={"index": "count"})
temp1["exo_count"] = temp1["count"].apply(lambda x: math.exp(x))
temp1.pop("count")
temp1 = temp1.rename(columns={0: "year"})
temp1 = temp1.set_index('year')
plt.figure(figsize=(15,5))
plt.plot(exoplanets.groupby("disc_year").pl_name.count().cumsum(), c ="blue")
plt.plot(temp1[:30], c ="red")
plt.show()
```



```
print("The model predicts:")
target = 10000
print(f"We will reach {target} known exoplanets by the end of {temp1['exo_count'].gt(targe
target = 100000
print(f"We will reach {target} known exoplanets by the end of {temp1['exo_count'].gt(targe
target = 1000000
print(f"We will reach {target} known exoplanets by the end of {temp1['exo_count'].gt(targe
target = 10000000
print(f"We will reach {target} known exoplanets by the end of {temp1['exo_count'].gt(targe
target = 100000000
print(f"We will reach {target} known exoplanets by the end of {temp1['exo_count'].gt(targe
target = 1000000000
print(f"We will reach {target} known exoplanets by the end of {temp1['exo_count'].gt(targe
```

```
The model predicts:
We will reach 10000 known exoplanets by the end of 2022.
We will reach 100000 known exoplanets by the end of 2031.
We will reach 1000000 known exoplanets by the end of 2039.
We will reach 10000000 known exoplanets by the end of 2048.
We will reach 100000000 known exoplanets by the end of 2056.
We will reach 1000000000 known exoplanets by the end of 2065.
```

Even though our predictions for the year 2022 are already wrong, the model confirms the findings of René Heller and László L. Kiss in their paper *"Exoplanet Vision 2050"* where they predict 100 000 000 known exoplanets by that year. Our model predicts the 100 000 000th planet will be discovered sometime in the latter half of 2056

Exoplanet Vision 2050: https://arxiv.org/pdf/1911.12114.pdf

When will humanity discover every single planet in our Galaxy?

Predictions for the exact number of planets within the Milky Way range from 100 to 200 billion. And if current trends continue:

```
print(f"Humanity will discover all of the Milky Way's planets sometime between {temp1['exo
```

```
    Humanity will discover all of the Milky Way's planets sometime between 2082 and 2085
```