Project 5 - Clustering

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1 SEN4018 - Data Science with Python

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1.1 PART I - Project Summary

This dataset provides the top popular anime by season. It includes the determined animes' qualifications based on their popularity. Characteristics of the published series have been categorized in several variations which is consisting some missing as well. The aim of this study is uncovering the functional data, notify conclusions and reinforce decision-making strategies in order to strengthen accountability. Our major finding on there is that when we analyzed our data, it has not a small number of neglectable outliers and noise. As a result of this outcome, we decided to use Density-Based Clustering strategy. Link of the dataset : https://www.kaggle.com/angadchau/anime-dataset?select=anime.csv

1.2 PART II - Dataset Description

Investigation of the dataset demonstrates to us that this dataset provides the top popular anime by season. It includes the determined animes' qualifications based on their popularity. Characteristics of the published series have been categorized in several variations which consist of some missing as well. Moreover, The sample amount is 2000 and this database includes 11 attributes. Lastly, the attribute types are "Name of the anime", "Rating", "Ranking"," Followers", "Type", "Episodes", "License", "Study", "Genre", "Demographics" and "Age".

Types of each attributes take place in the next part.

1.3 PART II(cont.) - Basic Descriptive Statistics

1.3.1 Import statements

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import math
```

1.3.2 Accessing the data

```
[ ]: df = pd.read_csv('anime.csv')
     df.head()
```

```
[ ]:                   Name of the anime  …                              Age
     0                        Death Note  …  R - 17+ (violence & profanity)
     1                 Shingeki no Kyojin  …  R - 17+ (violence & profanity)
     2  Fullmetal Alchemist: Brotherhood  …  R - 17+ (violence & profanity)
     3                   Sword Art Online  …       PG-13 - Teens 13 or older
     4                      One Punch Man  …  R - 17+ (violence & profanity)

     [5 rows x 11 columns]
```

1.3.3 Some statistics

Attributes

```
[ ]: df.dtypes
```

```
[ ]: Name of the anime     object
     Rating               float64
     Ranking                int64
     Followers             object
     Type                  object
     Episodes              object
     License               object
     Study                 object
     Genre                 object
     Demographics          object
     Age                   object
     dtype: object
```

Ranking feature is just numbers from 1 to 2000 so we do not need to find any outliers or other statistical information.

Episodes and Followers features are shown as object but in fact, their type is numerical. We will handle this on preprocessing part.

```
[ ]: dfRating = df.dropna(subset=['Rating'])
```

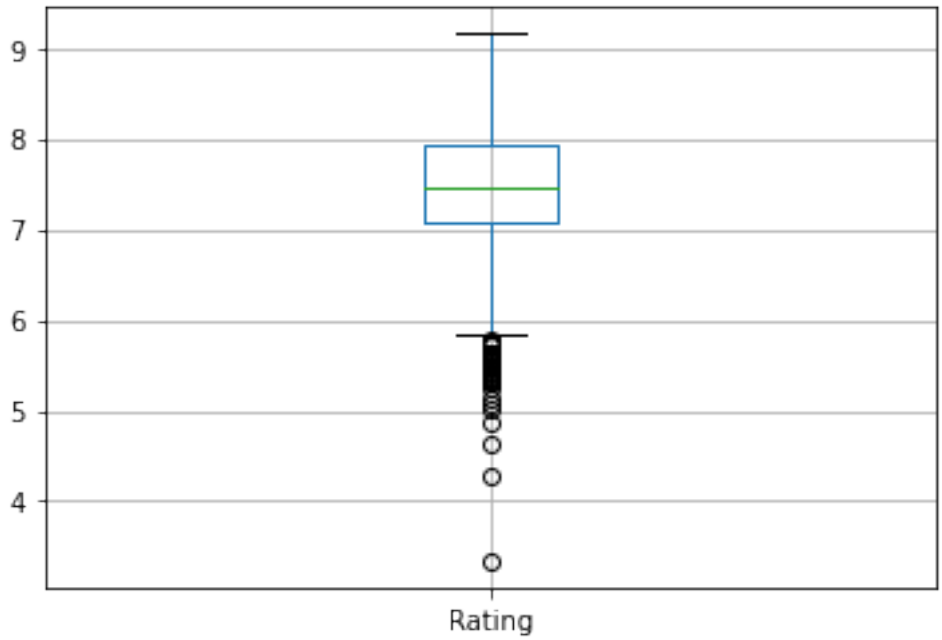
The dataframe without NaN data on 'Rating' column.

```
[ ]: dfRating.describe()['Rating']
```

```
[ ]: count    1979.000000
     mean        7.462567
     std         0.677055
     min         3.340000
     25%         7.090000
     50%         7.470000
```

```
75%          7.925000
max          9.160000
Name: Rating, dtype: float64
```

[ ]:
```
dfRating.boxplot(column=['Rating']);
```



[ ]:
```
quarter1 = dfRating.describe().Rating['25%']
quarter2 = dfRating.describe().Rating['50%']
quarter3 = dfRating.describe().Rating['75%']
meanRating = dfRating.describe().Rating['mean']
IQR = quarter3 - quarter1
lowerBound = quarter1 - (1.5 * IQR)
upperBound = quarter3 + (1.5 * IQR)
medianRating = dfRating.Rating.median()
rangeRating = dfRating.describe().Rating['max'] - dfRating.describe().
↪Rating['min']
```

[ ]:
```
print(f"Mean of the Rating column is {meanRating:f}" +
      f"\nLower bound of the box plot is {lowerBound}" +
      f"\nUpper bound of the box plot is {upperBound}" +
      f"\nMedian of the Rating column is {medianRating}" +
      f"\nRange of the Rating column is {rangeRating}")
```

```
Mean of the Rating column is 7.462567
Lower bound of the box plot is 5.8375
Upper bound of the box plot is 9.1775
```

```
Median of the Rating column is 7.47
Range of the Rating column is 5.82
```

[ ]:
```
upperOutliersRating = dfRating.loc[(dfRating['Rating'] > upperBound), ['Name of the anime','Rating']]
lowerOutliersRating = dfRating.loc[(dfRating['Rating'] < lowerBound), ['Name of the anime','Rating']]
ratingOutliers = pd.concat([lowerOutliersRating,upperOutliersRating])
ratingOutliers
```

[ ]:

	Name of the anime	Rating
170	Yakusoku no Neverland 2nd Season	5.45
251	School Days	5.59
583	Diabolik Lovers	5.24
726	Taboo Tattoo	5.76
745	Isekai Cheat Magician	5.41
805	Tsuujou Kougeki ga Zentai Kougeki de Ni-kai Ko…	5.55
888	Ousama Game The Animation	5.01
899	Mayoiga	5.51
907	Big Order (TV)	5.38
1059	Pupa	3.34
1105	Boku no Pico	4.27
1158	Glasslip	5.43
1160	Divine Gate	5.56
1177	Hyakuren no Haou to Seiyaku no Valkyria	5.71
1197	Fairy Gone	5.79
1225	Peter Grill to Kenja no Jikan	5.48
1304	Netsuzou TRap	5.35
1348	Sin: Nanatsu no Taizai	5.71
1364	Diabolik Lovers More,Blood	5.58
1380	Dies Irae	5.38
1522	Ore ga Suki nano wa Imouto dakedo Imouto ja Nai	4.88
1534	Wonder Egg Priority Special	5.08
1555	One Room	5.56
1576	Dokyuu Hentai HxEros	5.75
1599	Chaos Dragon: Sekiryuu Seneki	5.64
1644	Conception	4.62
1675	Hatsukoi Monster	5.54
1702	Hand Shakers	5.30
1734	Bloodivores	5.49
1738	Seisen Cerberus: Ryuukoku no Fatalités	5.62
1872	Ulysses: Jehanne Darc to Renkin no Kishi	5.33
1954	Bikini Warriors	5.13
1981	Shironeko Project: Zero Chronicle	5.32
1997	Iya na Kao sare nagara Opantsu Misete Moraitai	5.74

This table contains the outliers.

Null objects

```
[ ]: percentage = df.shape[0] / 100
     percentage
     df.isnull().sum()/percentage
```

```
[ ]: Name of the anime     0.00
     Rating               1.05
     Ranking              0.00
     Followers            0.00
     Type                 0.00
     Episodes             0.00
     License              0.00
     Study                0.00
     Genre                8.40
     Demographics        55.80
     Age                  0.00
     dtype: float64
```

We will use 'Other' tag for null 'Demographics' column data. For 'Rating' column we ignored null observations above. Null values mean that series is not started yet or they are just corrupted data.

```
[ ]: unknownEpisodes = df.loc[df['Episodes'] == 'Unknown'].count()['Episodes']
     print("Unknown episode count is " + str(unknownEpisodes))
```

```
Unknown episode count is 25
```

There are 25 'Unknown' values used for series that have not yet started or ended. For the 'Episodes' column, we may ignore these data or replace the 'unknown' value with the mean of the column according to the situation.

```
[ ]: df.loc[df['Type'] == 'Unknown', ['Name of the anime','Type']]
```

```
[ ]:              Name of the anime     Type
     1925  Bleach: Sennen Kessen-hen  Unknown
```

Since it is only 1 observation we will manually fill the 'Unknown' data with 'TV'.

```
[ ]: df.loc[df['Genre'].isnull() , ['Name of the anime', 'Genre', 'Rating']]
```

```
[ ]:                                      Name of the anime Genre  Rating
     22                                      Koe no Katachi   NaN    8.97
     60                                           Charlotte   NaN    7.75
     125           Kimetsu no Yaiba Movie: Mugen Ressha-hen   NaN    8.71
     140                                       Black Lagoon   NaN    8.03
     154   Youkoso Jitsuryoku Shijou Shugi no Kyoushitsu …   NaN    7.84
     …                                                  …   …      …
     1962                                Bishounen Tanteidan   NaN    7.21
     1975                                     Show By Rock!!   NaN    7.03
     1984                                        BanG Dream!   NaN    6.97
```

```
1989                            Haikyuu!!: vs. "Akaten"   NaN    7.77
1997     Iya na Kao sare nagara Opantsu Misete Moraitai   NaN    5.74

[168 rows x 3 columns]
```

There are 168 observations that has no Genre data. We cannot predict the genres so we will replace them with 'NA' (Not Available).

Attribute counts Names of the animes are all unique as expected. Rating and Ranking features are numerical data. Episodes and Followers data is nominal but should be numerical we will handle this on preprocessing part.

[ ]:
```
df.Type.value_counts()
```

[ ]:
```
TV         1462
Movie       267
OVA         130
Special      90
ONA          49
Music         1
Unknown       1
Name: Type, dtype: int64
```

[ ]:
```
df.Study.value_counts()
```

[ ]:
```
J.C.Staff                                          105
A-1 Pictures                                        96
Madhouse                                            91
Toei Animation                                      65
Studio Deen                                         65
                                                   ...
Kinema Citrus,       DR Movie                        1
Barnum Studio,       SILVER LINK.,       Connect     1
SANZIGEN                                            1
Ordet,       LIDENFILMS                             1
Wolfsbane                                           1
Name: Study, Length: 279, dtype: int64
```

There are multiple studies in one column seperated by comma. 3 columns are like that. We are going to handle this on preprocessing part.

[ ]:
```
df.Demographics.value_counts()
```

[ ]:
```
Shounen    510
Seinen     218
Shoujo     104
Josei       27
Kids        25
```

```
Name: Demographics, dtype: int64
```

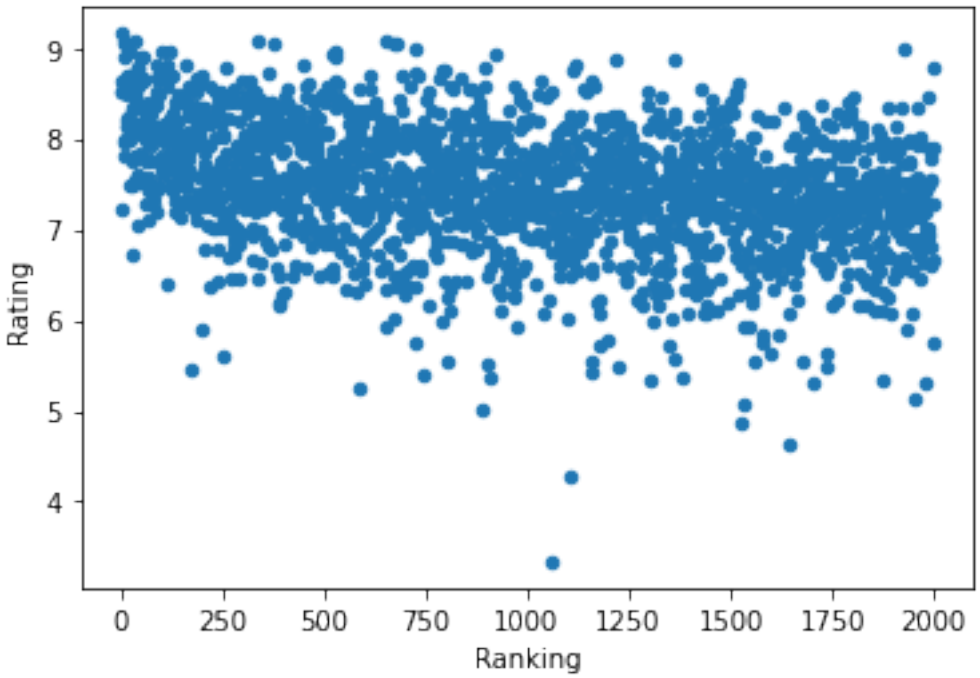
[ ]:
```
df.Age.value_counts()
```

[ ]:
```
PG-13 - Teens 13 or older         1288
R - 17+ (violence & profanity)     455
R+ - Mild Nudity                   180
PG - Children                       39
G - All Ages                        31
None                                 6
Rx - Hentai                          1
Name: Age, dtype: int64
```

None indicates there is no such an age gap data. We will leave it like that.

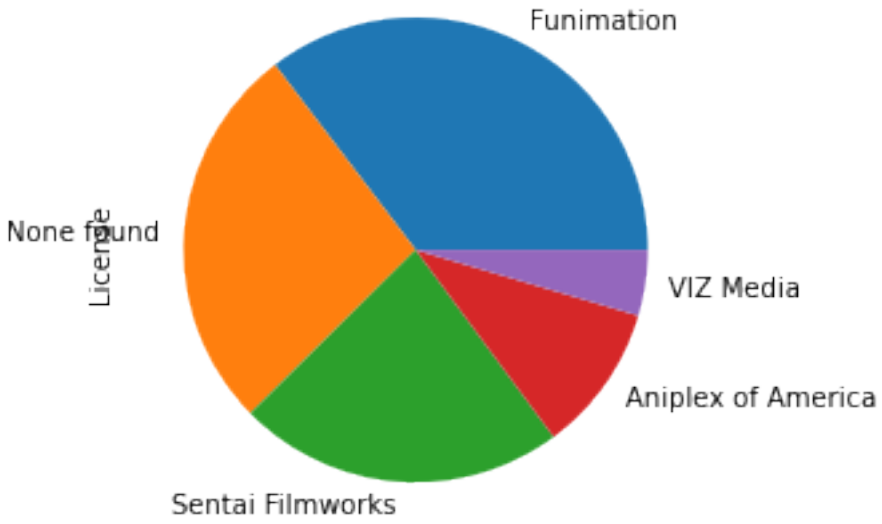
Some visualizations

[ ]:
```
df.plot("Ranking","Rating",kind = 'scatter');
```



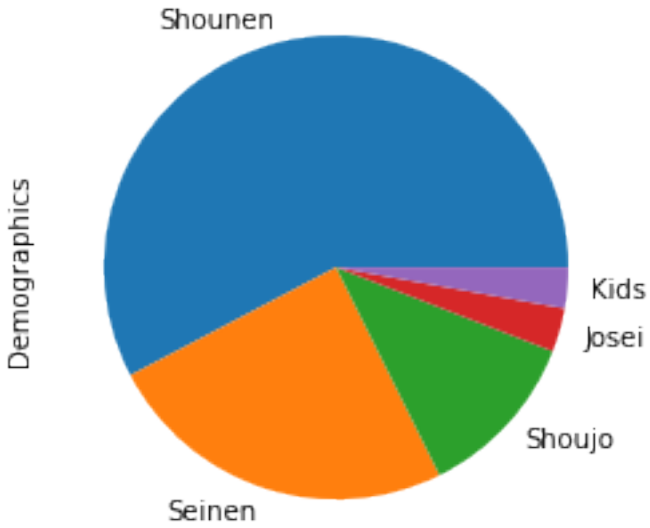
As it is seen, the rating score slightly decreases as the popularity decreases and there are some outliers.

[ ]:
```
df.License.value_counts().head().plot.pie();
```



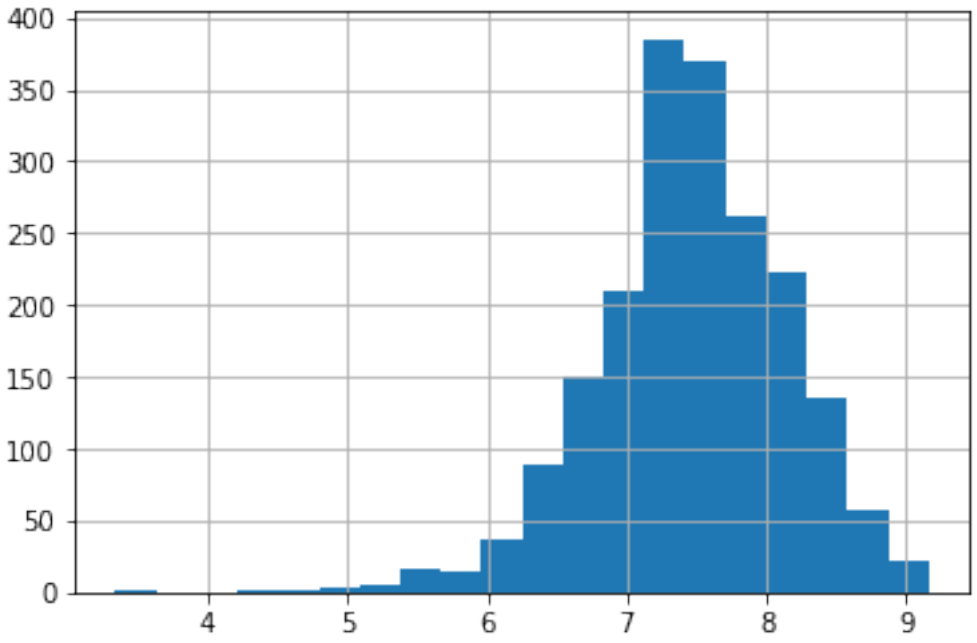
License distribution is shown.

```
[ ]: df.Demographics.value_counts().plot.pie();
```



Demography distribution is shown.

```
[ ]: dfRating['Rating'].hist(bins=20);
```



Rating distribution is shown.

All of the visualizations are just examples. Shown data is not preprocessed yet. More tidied up and correct data will be shown at Part IV with detailed visualizations.

1.4 PART III - Data Preprocessing

We are going to modify following features:

- Followers
- Type
- Episodes
- License
- Study
- Genre
- Demographics
- Age

We will not modify **Name of the anime** column because this column only contains unique series names and it does not need further modifications.

We will not modify **Rating** column because we already modified it above.

We will not modify **Ranking** column because there is no missing data and inconsistency issues.

We are going to modify **Followers** column because its type is shown in 'object' data type. We need to convert it to the numerical data type.

We are going to modify **Type** column because it contains missing values.

We are going to modify **Episodes** column with the same reason of **Followers** column. Additionaly, this column contains some missing values. We need to handle them.

We are going to modify **License** column because for some observations, it contains multiple licenses seperated by comma.

We are going to modify **Study** column for the same reason of **License** column.

We are going to modify **Genre** column for the same reson of **License** column. Additionally, there are some missing values. We need to handle them.

We are going to modify **Demographics** column because its half is missing.

We are going to modify **Age** column because there are missing values.

1.4.1 Followers column

We are going to delete commas in the data and parse it to the integer. We can use main dataFrame object here.

[ ]:
```
dfFollowers = df
dfFollowers['Followers'] = dfFollowers['Followers'].apply(lambda n: int(n.
 ↪replace(',','')))
dfFollowers.dtypes
```

[ ]:
```
Name of the anime     object
Rating               float64
Ranking                int64
Followers              int64
Type                  object
Episodes              object
License               object
Study                 object
Genre                 object
Demographics          object
Age                   object
dtype: object
```

1.4.2 Type column

We will clear missing data. We may name the values in numerical order.

Since there is only 1 missing data we will manually change it.

[ ]:
```
df.loc[df['Type'] == 'Unknown']
```

[ ]:
```
              Name of the anime  Rating  …  Demographics
Age
1925  Bleach: Sennen Kessen-hen     NaN  …       Shounen  PG-13 - Teens 13 or
older
```

```
[1 rows x 11 columns]
```

```
[ ]: df['Type'] = df['Type'].replace(['Unknown'], 'TV')
```

```
[ ]: df.iloc[1925]['Type']
```

```
[ ]: 'TV'
```

1.4.3 Episodes Column

We will replace 'Unknown' values to the mean of this column without 'Unknown' data. To take the mean we should first extract the rows with 'Unknown' values and parse the feature to the integer and take the mean. After that we will bring the rows back and change the 'Unknown' values with the mean.

```
[ ]: dfEpisodes = df.copy().loc[df['Episodes'] != 'Unknown']
dfUnknownEpisodes = df.copy().loc[df['Episodes'] == 'Unknown']
dfEpisodes['Episodes'] = dfEpisodes['Episodes'].apply(lambda n: int(n))
meanEpisodes = math.floor(dfEpisodes['Episodes'].mean())
meanEpisodes
```

```
[ ]: 16
```

```
[ ]: type(meanEpisodes)
```

```
[ ]: int
```

```
[ ]: dfUnknownEpisodes['Episodes'] = dfUnknownEpisodes['Episodes'].
 ↪replace(['Unknown'], meanEpisodes)
df = pd.concat([dfEpisodes,dfUnknownEpisodes])
df
```

```
[ ]:                                    Name of the anime  …
Age
0                                             Death Note  …  R - 17+ (violence
& profanity)
1                                      Shingeki no Kyojin  …  R - 17+ (violence
& profanity)
2                      Fullmetal Alchemist: Brotherhood  …  R - 17+ (violence
& profanity)
3                                       Sword Art Online  …       PG-13 - Teens
13 or older
4                                          One Punch Man  …  R - 17+ (violence
& profanity)
…                                                     …  …
…
1744                           Goblin Slayer 2nd Season  …  R - 17+ (violence
& profanity)
```

```
1776  Maou Gakuin no Futekigousha: Shijou Saikyou no…  …  R - 17+ (violence
& profanity)
1880  Dungeon ni Deai wo Motomeru no wa Machigatteir…  …       PG-13 - Teens
13 or older
1893                   Boku no Hero Academia 6th Season  …       PG-13 - Teens
13 or older
1925                            Bleach: Sennen Kessen-hen  …       PG-13 - Teens
13 or older

[2000 rows x 11 columns]
```

1.4.4 License Column

We are going to create a specific dataframe for these column because this column contains multiple variables. We need to modify them.

Firstly, we will use split method to seperate data with commas and put it into a dataframe. After that we will convert it to one column.

[ ]:
```
dfLicense = df['License'].str.split(',', expand=True)
dfLicense[['Name of the anime','Rating', 'Followers', 'Episodes','Ranking']] =␣
↪df[['Name of the anime','Rating', 'Followers', 'Episodes','Ranking']]
dfLicense
```

[ ]:
```
                      0                  1  … Episodes Ranking
0              VIZ Media               None  …       37       1
1             Funimation               None  …       25       2
2             Funimation  Aniplex of America  …       64       3
3     Aniplex of America               None  …       25       4
4              VIZ Media               None  …       12       5
…                    …                  …  …      …     …
1744          None found               None  …       16    1745
1776          None found               None  …       16    1777
1880          None found               None  …       16    1881
1893          None found               None  …       16    1894
1925          None found               None  …       16    1926

[2000 rows x 9 columns]
```

0,1,2 and 3 columns are licenses. We will melt them into one column.

[ ]:
```
meltedLicense = pd.melt(dfLicense, id_vars=('Name of the␣
↪anime','Rating','Followers','Episodes','Ranking'))
meltedLicense = meltedLicense.dropna(subset=['value'], how='any').
↪drop(['variable'], axis=1)
meltedLicense = meltedLicense.rename(columns={"value": "License"})
```

[ ]:
```
meltedLicense.loc[meltedLicense['Ranking'] == 144]
```

[ ]:
```
                Name of the anime  Rating  …  Ranking                License
142   Suzumiya Haruhi no Yuuutsu    7.85  …      144            Funimation
2142  Suzumiya Haruhi no Yuuutsu    7.85  …      144  Bandai Entertainment
4142  Suzumiya Haruhi no Yuuutsu    7.85  …      144  Kadokawa Pictures USA

[3 rows x 6 columns]
```

By using this dataframe we can count genres or make visualizations.

1.4.5 Study Column

We are going to use same logic with License column.

[ ]:
```
dfStudy = df['Study'].str.split(',', expand=True)
dfStudy[['Name of the anime','Rating', 'Followers', 'Episodes','Ranking']] =␣
↪df[['Name of the anime','Rating', 'Followers', 'Episodes','Ranking']]
dfStudy
```

[ ]:
```
                 0     1     2  … Followers  Episodes  Ranking
0         Madhouse  None  None  …   3150451        37        1
1       Wit Studio  None  None  …   3136959        25        2
2            Bones  None  None  …   2674846        64        3
3     A-1 Pictures  None  None  …   2583874        25        4
4         Madhouse  None  None  …   2577610        12        5
…              …   …   …   …  …         …         …
1744    None found  None  None  …     92642        16     1745
1776  SILVER LINK.  None  None  …     90837        16     1777
1880    None found  None  None  …     82464        16     1881
1893    None found  None  None  …     90132        16     1894
1925    None found  None  None  …     78243        16     1926

[2000 rows x 8 columns]
```

[ ]:
```
meltedStudy = pd.melt(dfStudy, id_vars=('Name of the␣
↪anime','Rating','Followers','Episodes','Ranking'))
meltedStudy = meltedStudy.dropna(subset=['value'], how='any').
↪drop(['variable'], axis=1)
meltedStudy = meltedStudy.rename(columns={"value": "Study"})
meltedStudy.Study = meltedStudy.Study.apply(lambda n: n.strip())
meltedStudy
```

[ ]:
```
                              Name of the anime  …    Study
0                                   Death Note  …  Madhouse
1                             Shingeki no Kyojin  …  Wit Studio
2             Fullmetal Alchemist: Brotherhood  …     Bones
3                             Sword Art Online  …  A-1 Pictures
4                                One Punch Man  …  Madhouse
…                                          …  …        …
```

```
5702                  Hori-san to Miyamura-kun  …                    Marone
5741                  Quanzhi Gaoshou Specials  …  Colored Pencil Animation
5840  Strike the Blood: Valkyria no Oukoku-hen  …                   Connect
5846                           FLCL Alternative  …                   Revoroot
5927                                 Ro-Kyu-Bu!  …               Studio Blanc

[2145 rows x 6 columns]
```

[ ]:
```
meltedStudy.loc[meltedStudy['Ranking'] == 117]
```

[ ]:
```
     Name of the anime  Rating  Followers  Episodes  Ranking           Study
115     Tokyo Ghoul:re    6.41     909814        12      117  Studio Pierrot
2115    Tokyo Ghoul:re    6.41     909814        12      117    Pierrot Plus
```

1.4.6 Genres Column

We are going to use same logic with License column.

[ ]:
```
dfGenres = df['Genre'].str.split(',', expand=True)
dfGenres[['Name of the anime','Rating', 'Followers',␣
 ↪'Episodes','Ranking','Type']] = df[['Name of the anime','Rating',␣
 ↪'Followers', 'Episodes','Ranking','Type']]
dfGenres
```

[ ]:
```
            0             1         2  … Episodes Ranking Type
0     Mystery  Supernatural  Suspense  …       37       1   TV
1      Action         Drama   Fantasy  …       25       2   TV
2      Action     Adventure    Comedy  …       64       3   TV
3      Action     Adventure   Fantasy  …       25       4   TV
4      Action        Comedy    Sci-Fi  …       12       5   TV
…       …            …       …  …       …      …  …
1744   Action     Adventure   Fantasy  …       16    1745   TV
1776      NaN           NaN       NaN  …       16    1777   TV
1880   Action     Adventure    Comedy  …       16    1881   TV
1893   Action        Comedy      None  …       16    1894   TV
1925   Action     Adventure    Comedy  …       16    1926   TV

[2000 rows x 13 columns]
```

[ ]:
```
meltedGenres = pd.melt(dfGenres, id_vars=('Name of the␣
 ↪anime','Rating','Followers','Episodes','Ranking','Type'))
meltedGenres = meltedGenres.dropna(subset=['value'], how='any').
 ↪drop(['variable'], axis=1)
meltedGenres = meltedGenres.rename(columns={"value": "Genre"})
```

For this way we can see genres by using the other columns. Rows which does not have any genres are excluded.

```
[ ]: meltedGenres.loc[meltedGenres['Ranking'] == 1]
```

```
[ ]:      Name of the anime  Rating  Followers  Episodes  Ranking Type         Genre
     0           Death Note    8.63    3150451        37        1   TV       Mystery
     2000        Death Note    8.63    3150451        37        1   TV  Supernatural
     4000        Death Note    8.63    3150451        37        1   TV      Suspense
```

By using this dataframe we can count genres or make visualizations.

1.4.7 Demographics Column

More than half of this column has missing data. We will change the missing data to 'Not Specified' state.

```
[ ]: df['Demographics'].fillna('Not Specified', inplace=True)
     df
```

```
[ ]:                                      Name of the anime  …
     Age
     0                                           Death Note  …  R - 17+ (violence
     & profanity)
     1                                     Shingeki no Kyojin  …  R - 17+ (violence
     & profanity)
     2                         Fullmetal Alchemist: Brotherhood  …  R - 17+ (violence
     & profanity)
     3                                      Sword Art Online  …       PG-13 - Teens
     13 or older
     4                                         One Punch Man  …  R - 17+ (violence
     & profanity)
     …                                                    …  …
     …
     1744                             Goblin Slayer 2nd Season  …  R - 17+ (violence
     & profanity)
     1776  Maou Gakuin no Futekigousha: Shijou Saikyou no…  …  R - 17+ (violence
     & profanity)
     1880  Dungeon ni Deai wo Motomeru no wa Machigatteir…  …       PG-13 - Teens
     13 or older
     1893                      Boku no Hero Academia 6th Season  …       PG-13 - Teens
     13 or older
     1925                            Bleach: Sennen Kessen-hen  …       PG-13 - Teens
     13 or older

     [2000 rows x 11 columns]
```

1.4.8 Age Column

We are going to do same thing on Demographics column. Only difference is we will replace 'None' value to 'Not Specified' value instead of filling the nulls.

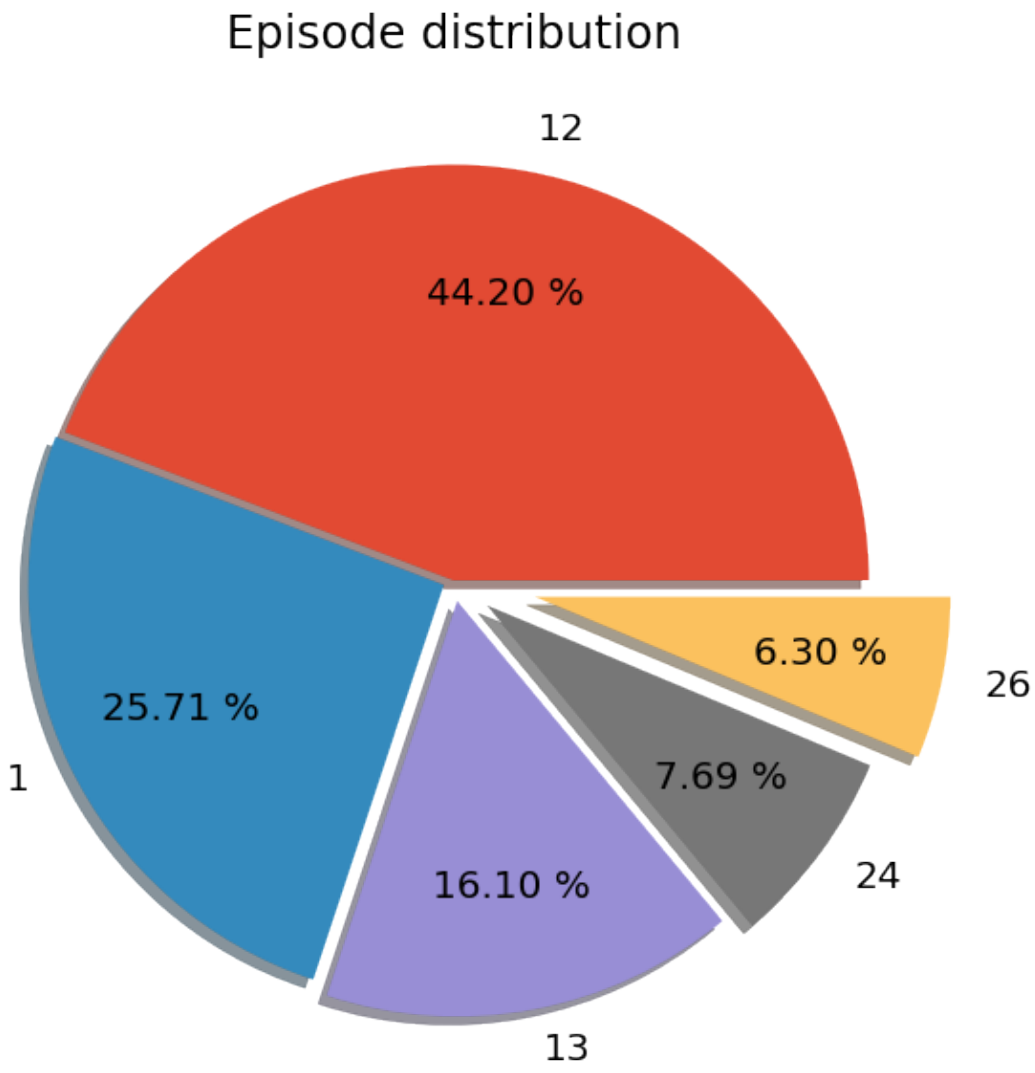
[ ]:
```
df['Age'].replace(['None'], 'Not Specified', inplace=True)
df.loc[df.Age == 'Not Specified']
```

[ ]:
```
                                    Name of the anime  …            Age
722                              Jujutsu Kaisen 0 Movie  …  Not Specified
1335  Sword Art Online: Progressive Movie - Hoshi Na…  …  Not Specified
1598                                          Mars Red  …  Not Specified
1970                                Kabukichou Sherlock  …  Not Specified
1991         Yuri!!! on Ice The Movie: Ice Adolescence  …  Not Specified
678                                        Chainsaw Man  …  Not Specified

[6 rows x 11 columns]
```

1.5 PART IV - Data Visualization

We are going to demonstrate 5 general visualizations and 2 boxplots for outliers.

[ ]:
```
plt.figure(figsize=(10, 10))
plt.style.use('ggplot')

episodesLabels = df.Episodes.value_counts().head().index.to_list()

plt.title('Episode distribution', fontsize=24)

plt.pie(df.Episodes.value_counts().head(),
        labels = episodesLabels,
        autopct = '%.2f %%', pctdistance = 0.7,
        textprops={'fontsize': 20},
        explode=[0,0.025,0.05,.1,.2],
        shadow=True)

plt.show()
```



As we can see Studios oftenly prefer 12-13 episodes for TV series and 1 episode for movies. We choose pie chart here because it is a type of graph that reflects the distribution data nicely.

[ ]:
```
popularGenresList = meltedGenres['Genre'].value_counts().head()
popularGenresList.index
```

[ ]:
```
Index(['Comedy', 'Action', 'Romance', 'Fantasy', 'Drama'], dtype='object')
```

[ ]:
```
popularTypesforGenres = np.array([meltedGenres.loc[meltedGenres['Genre'] ==␣
↪'Comedy']['Type'].value_counts()[:2],
                                  meltedGenres.loc[meltedGenres['Genre'] ==␣
↪'Action']['Type'].value_counts()[:2],
```

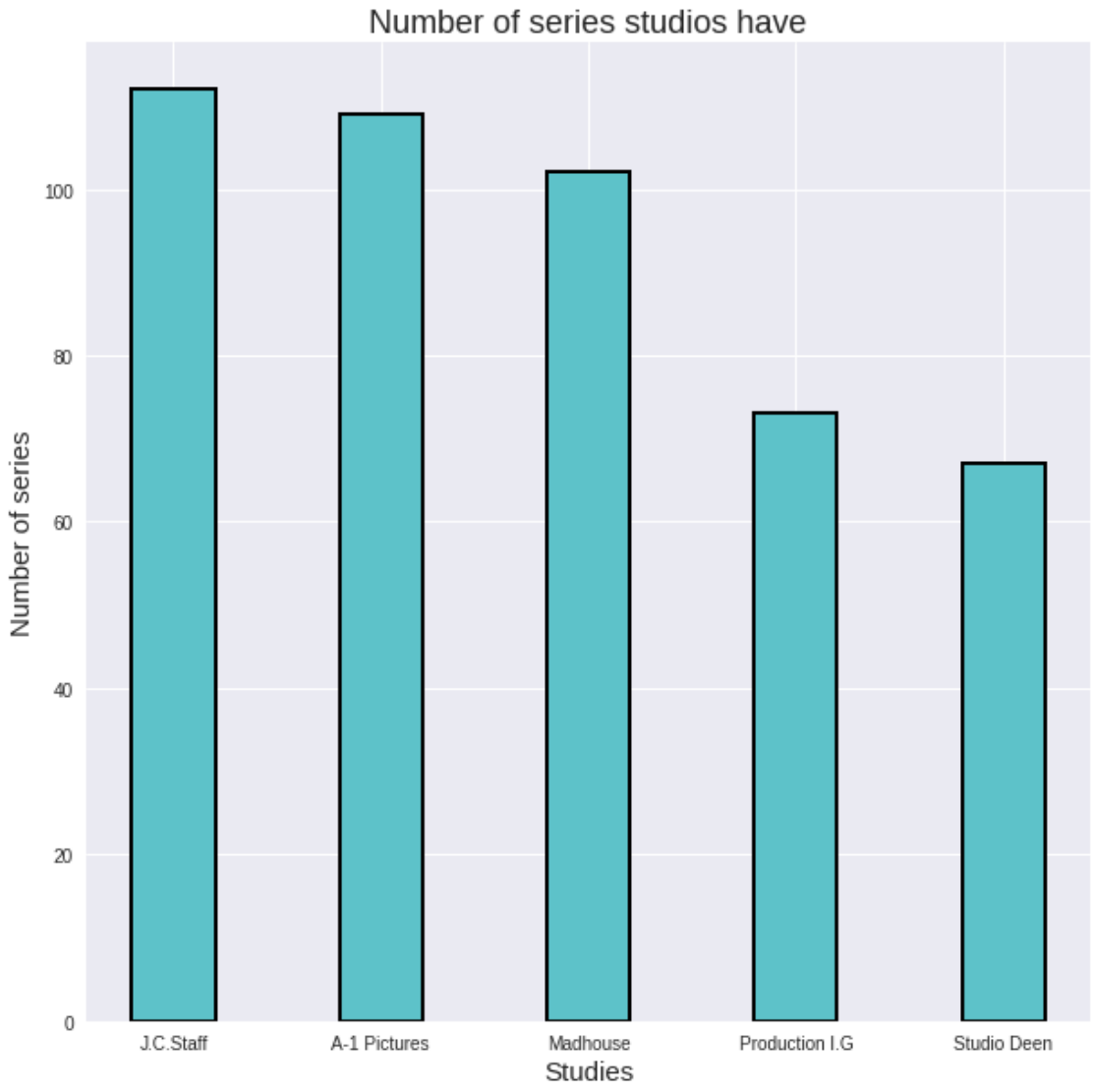
```
                                    meltedGenres.loc[meltedGenres['Genre'] ==␣
↪'Romance']['Type'].value_counts()[:2],
                                    meltedGenres.loc[meltedGenres['Genre'] ==␣
↪'Fantasy']['Type'].value_counts()[:2],
                                    meltedGenres.loc[meltedGenres['Genre'] ==␣
↪'Drama']['Type'].value_counts()[:2]])

typeLabels = ['TV', 'Movie', 'TV', 'Movie', 'TV', 'Movie', 'TV', 'Movie', 'TV',␣
↪'Movie']
```

[ ]:
```
fig, ax = plt.subplots(figsize=(12,12))
size = 0.4

plt.style.use('ggplot')

genreLabels = meltedGenres['Genre'].value_counts().head().index.to_list()

outer_colors = ['#23FF23',
                '#FF4400',
                '#0044FF',
                '#AACC00',
                '#FF44FF']
inner_colors = ['#63FF63', '#83FF83',
                '#FF5511', '#FF6424',
                '#1154FF', '#2264FF',
                '#CCBB21', '#BBBB42',
                '#EE44EE', '#DD33DD']

ax.pie(popularTypesforGenres.sum(axis=1), radius=1,
       wedgeprops=dict(width=size, edgecolor='w', linewidth=2),
       labels=genreLabels, labeldistance=0.7,
       textprops=dict(fontsize=16),
       colors=outer_colors,
       shadow=True)

ax.pie(popularTypesforGenres.flatten(), radius=1-size,
       wedgeprops=dict(width=size, edgecolor='w', linewidth=2),
       labels=typeLabels, labeldistance=0.75,
       textprops=dict(fontsize=11),
       colors=inner_colors,
       shadow=True)

ax.set_title('Most popular genres with most used series types',fontsize=22)
ax.set(aspect="equal")
plt.show()
```

Most popular 5 genres and their series type proportion is given. We choose nested pie chart here because it is a type of graph that reflects the nested distributions nicely.

[ ]:
```
fig, ax = plt.subplots(figsize=(10,10))

studyIndex = meltedStudy['Study'].value_counts()[:5].index.to_list()
studyValues = meltedStudy['Study'].value_counts()[:5].to_list()

ax.bar(studyIndex, studyValues, width = 0.4, color='#5dc2c9',
        edgecolor='#000000', linewidth=2)

ax.set_xlabel("Studies", fontsize=15)
```

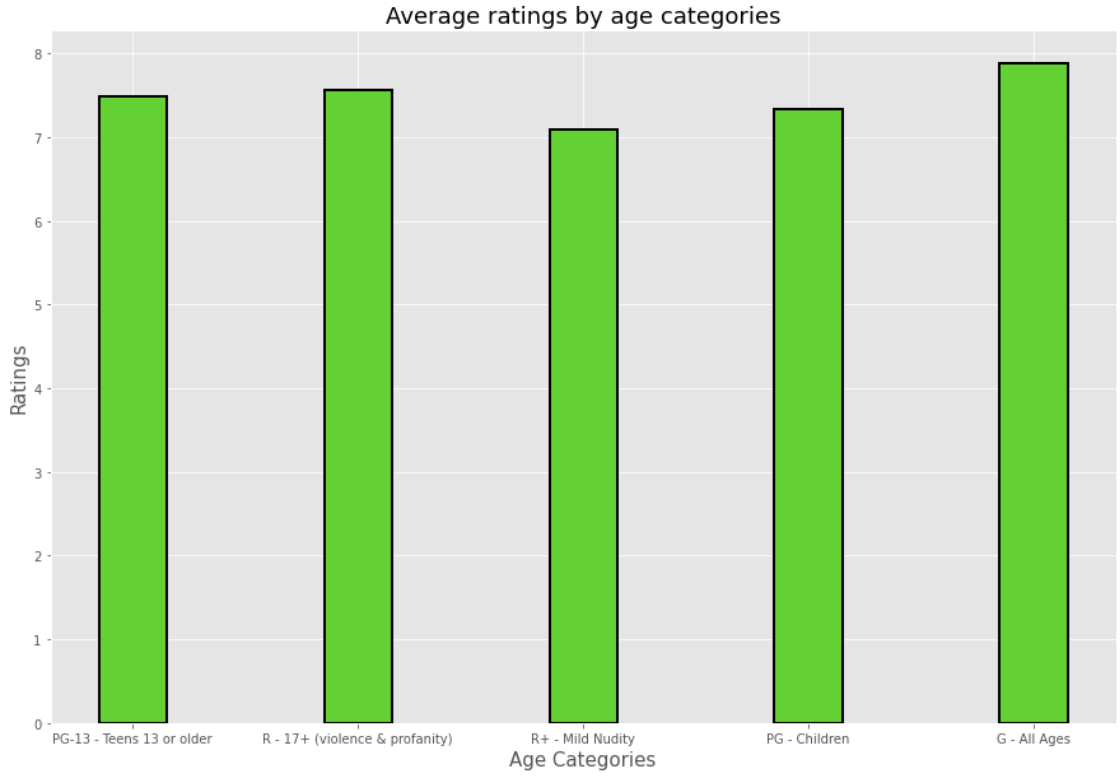
```
ax.set_ylabel("Number of series", fontsize=15)
ax.set_title("Number of series studios have", fontsize=18)

plt.show()
```



3 Studios have over 100+ series. We have used bar chart here because it looks nice when we make comparisons.

[ ]:
```
ageCategories = df['Age'].value_counts().head().index.to_list()
ageRatings = []

for age in ageCategories:
  ageRatings.append(df.loc[df['Age'] == age]['Rating'].mean())
```

```
fig, ax = plt.subplots(figsize=(15,10))

ax.bar(ageCategories, ageRatings, width = 0.3, color='#63d134',
        edgecolor='#000000', linewidth=2)

ax.set_xlabel("Age Categories", fontsize=15)
ax.set_ylabel("Ratings", fontsize=15)
ax.set_title("Average ratings by age categories", fontsize=18)

plt.show()
```



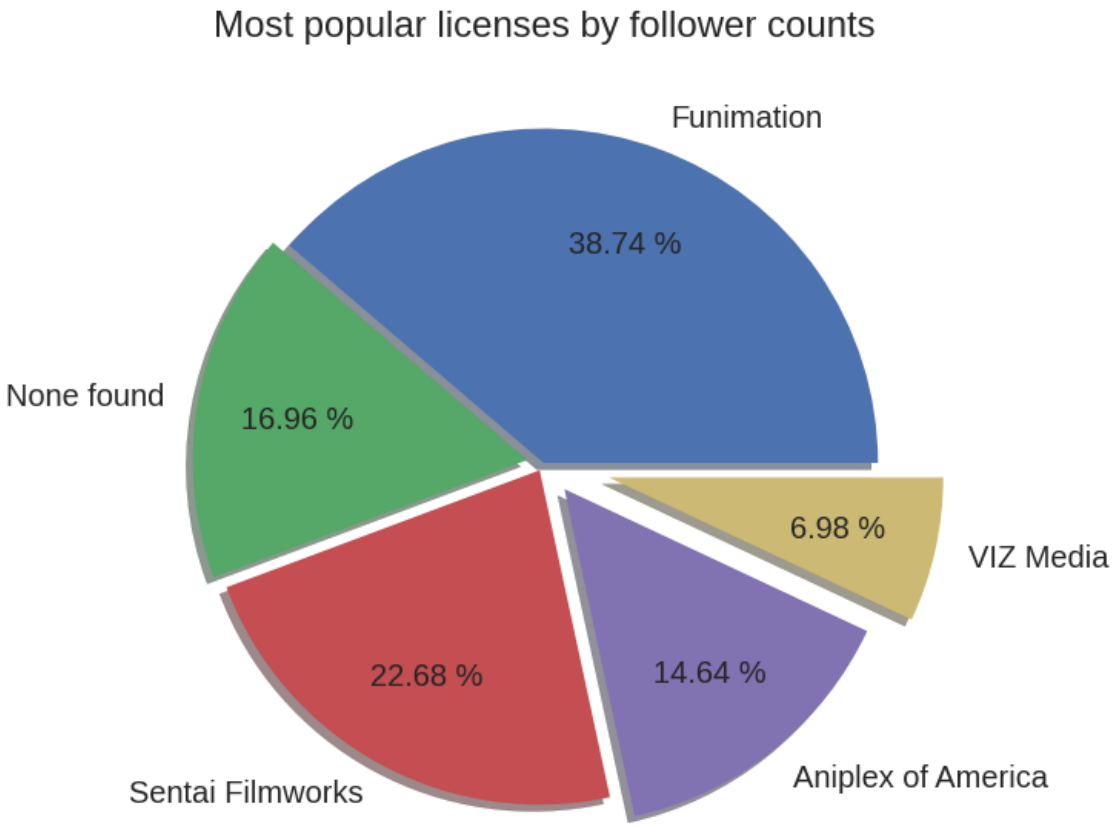
It is seen that the series appealing to the whole audience have a higher rating rate. We have used bar chart here because it looks nice when we make comparisons.

[ ]:
```
popularLicenses = meltedLicense['License'].value_counts().head().index.to_list()
followerCountLicense = []

for lic in popularLicenses:
  followerCountLicense.append(df.loc[df['License'] == lic]['Followers'].sum() /␣
 ↪10000000)
```

```
followerCountLicense
```

[ ]:
```
[18.0048575, 7.8806473, 10.5423784, 6.8058059, 3.2447358]
```

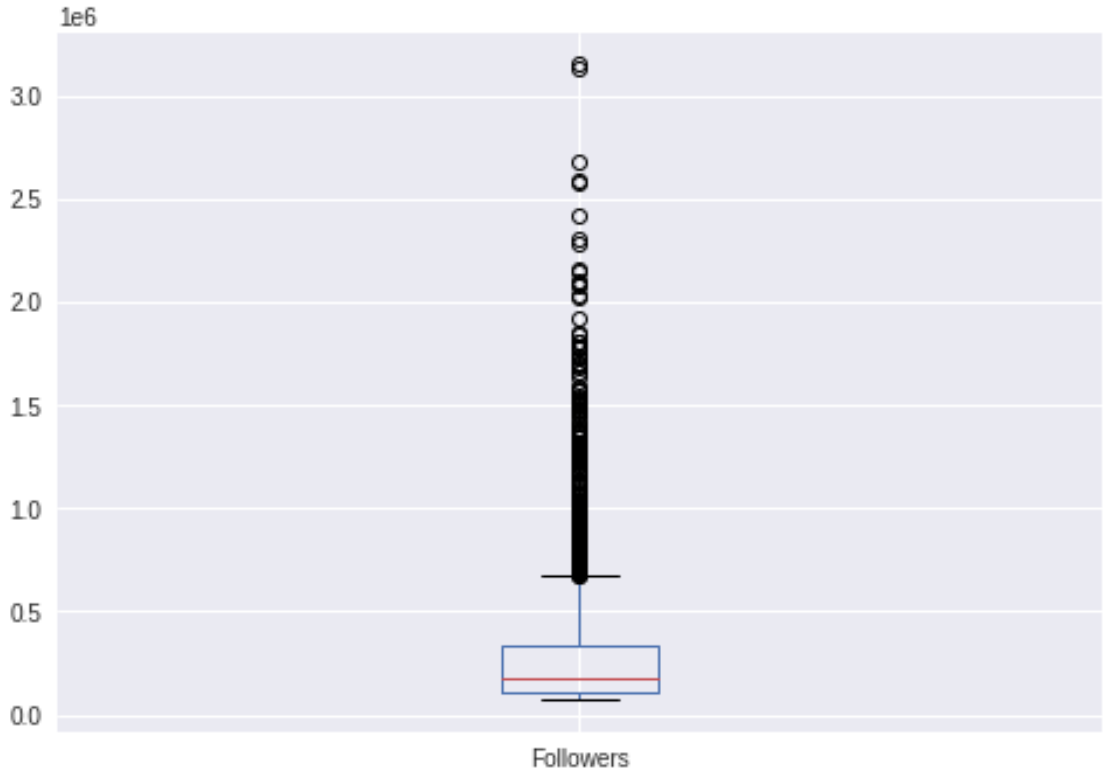
[ ]:
```
plt.figure(figsize=(10, 10))
plt.style.use('seaborn')

plt.title('Most popular licenses by follower counts', fontsize=24)

plt.pie(followerCountLicense,
        labels = popularLicenses,
        autopct = '%.2f %%', pctdistance = 0.7,
        textprops={'fontsize': 20},
        explode=[0,0.05,0.025,.1,.2],
        shadow=True)

plt.show()
```



Funimation has the most follower count by 18 million. We choose pie chart here because it is a type of graph that reflects the distributions nicely.

1.5.1 Outliers

[ ]:
```
df.boxplot(column=['Followers']);
```



[ ]:
```
df.describe().Followers
```

[ ]:
```
count    2.000000e+03
mean     3.073250e+05
std      3.512699e+05
min      7.244300e+04
25%      1.097425e+05
50%      1.764125e+05
75%      3.375495e+05
max      3.150451e+06
Name: Followers, dtype: float64
```

[ ]:
```
quarter1 = df.describe().Followers['25%']
quarter2 = df.describe().Followers['50%']
quarter3 = df.describe().Followers['75%']
meanRating = df.describe().Followers['mean']
IQR = quarter3 - quarter1
lowerBound = quarter1 - (1.5 * IQR)
```

```
upperBound = quarter3 + (1.5 * IQR)
medianFollowers = df.Followers.median()
rangeFollowers = df.describe().Followers['max'] - df.describe().Followers['min']
```

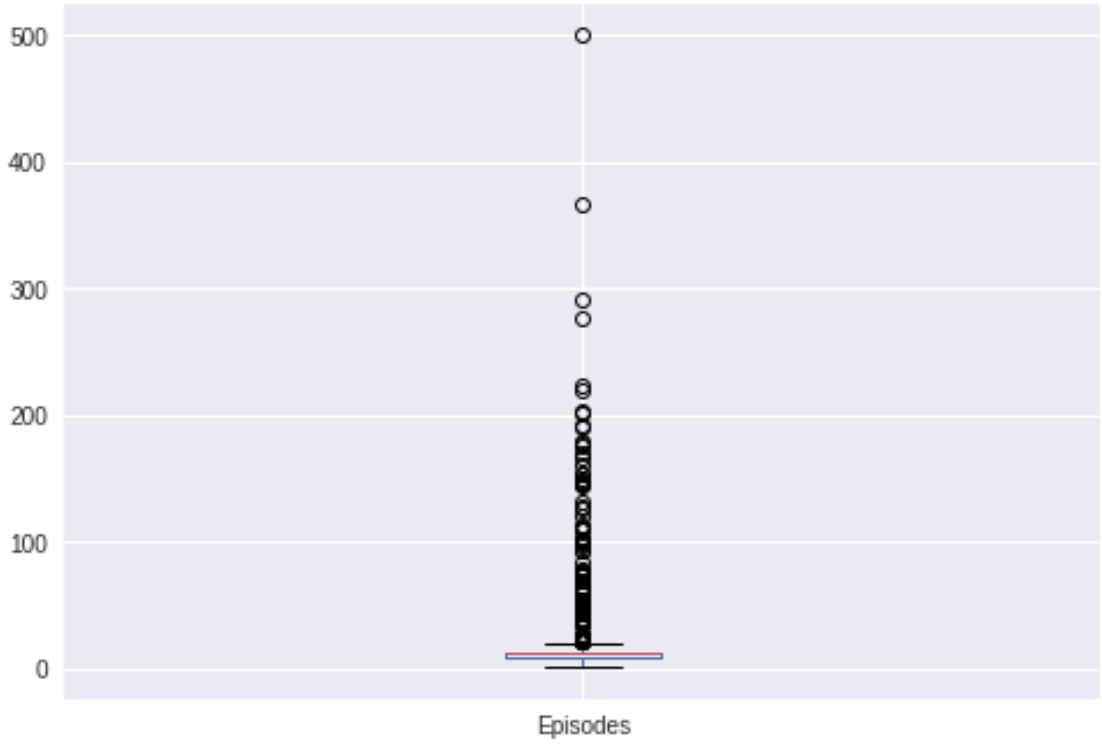
[ ]:
```
print(f"Mean of the Followers column is {meanRating:f}" +
      f"\nLower bound of the box plot is {lowerBound}" +
      f"\nUpper bound of the box plot is {upperBound}" +
      f"\nMedian of the Followers column is {medianRating}" +
      f"\nRange of the Followers column is {rangeRating}")
```

```
Mean of the Followers column is 307324.969500
Lower bound of the box plot is -231968.0
Upper bound of the box plot is 679260.0
Median of the Followers column is 176412.5
Range of the Followers column is 3078008.0
```

[ ]:
```
upperOutliersFollowers = df.loc[(df['Followers'] > upperBound), ['Name of the␣
↪anime','Followers']]
lowerOutliersFollowers = df.loc[(df['Followers'] < lowerBound), ['Name of the␣
↪anime','Followers']]
followersOutliers = pd.concat([lowerOutliersFollowers,upperOutliersFollowers])
followersOutliers.value_counts().size
```

[ ]:
```
202
```

[ ]:
```
df.boxplot(column=['Episodes']);
```



[ ]:
```
df.describe().Episodes
```

[ ]:
```
count    2000.000000
mean       16.133500
std        26.292705
min         1.000000
25%         8.000000
50%        12.000000
75%        13.000000
max       500.000000
Name: Episodes, dtype: float64
```

[ ]:
```
quarter1 = df.describe().Episodes['25%']
quarter2 = df.describe().Episodes['50%']
quarter3 = df.describe().Episodes['75%']
meanRating = df.describe().Episodes['mean']
IQR = quarter3 - quarter1
lowerBound = quarter1 - (1.5 * IQR)
upperBound = quarter3 + (1.5 * IQR)
medianEpisodes = df.Episodes.median()
rangeEpisodes = df.describe().Episodes['max'] - df.describe().Episodes['min']
```

[ ]:
```
print(f"Mean of the Episodes column is {meanRating:f}" +
      f"\nLower bound of the box plot is {lowerBound}" +
      f"\nUpper bound of the box plot is {upperBound}" +
      f"\nMedian of the Episodes column is {medianRating}" +
      f"\nRange of the Episodes column is {rangeRating}")
```

```
Mean of the Episodes column is 16.133500
Lower bound of the box plot is 0.5
Upper bound of the box plot is 20.5
Median of the Episodes column is 176412.5
Range of the Episodes column is 3078008.0
```

[ ]:
```
upperOutliersEpisodes = df.loc[(df['Episodes'] > upperBound), ['Name of the␣
 ↪anime','Episodes']]
lowerOutliersEpisodes = df.loc[(df['Episodes'] < lowerBound), ['Name of the␣
 ↪anime','Episodes']]
episodesOutliers = pd.concat([lowerOutliersEpisodes,upperOutliersEpisodes])
episodesOutliers.value_counts().size
```

[ ]:
```
436
```

As an example we already plotted Rating column's boxplot above. We will not plot Ranking column because it just contains number from 1 to 2000.

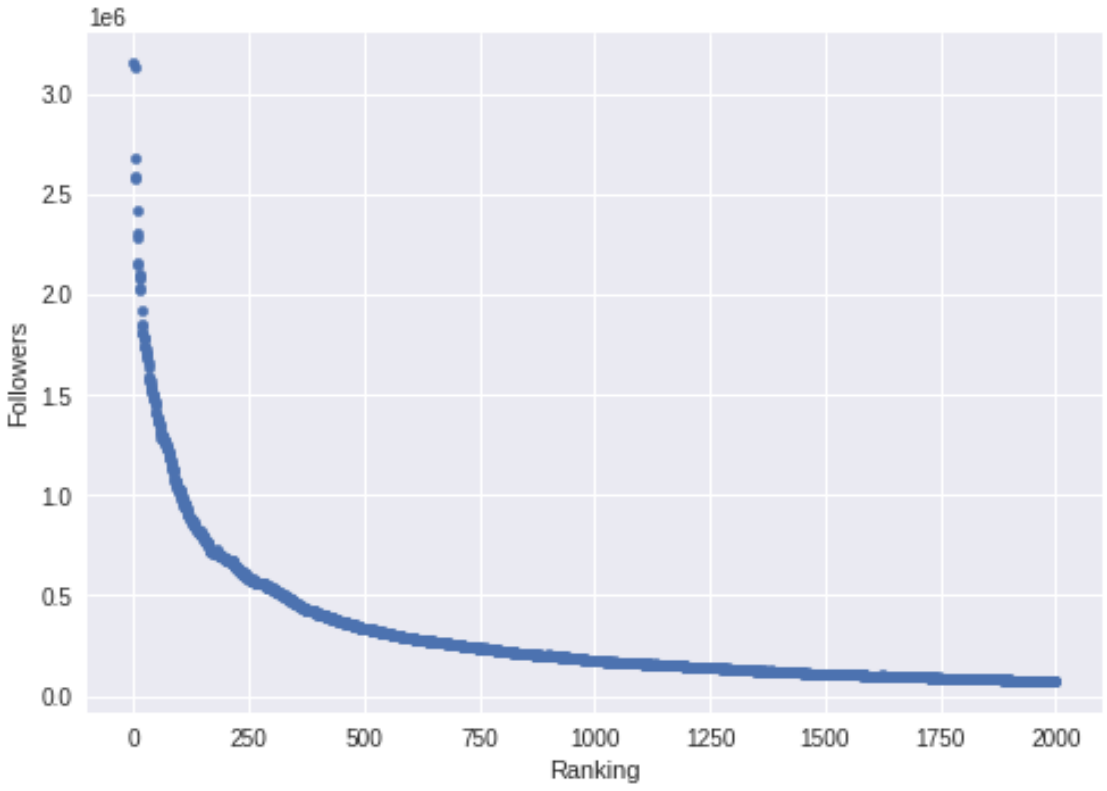
1.6 PART V - Data Analysis

In Part V, the results obtained from the analyzes so far will be shared and statistical analysis will be made about the visualizations in part 4. Columns will be explained in detail.

1.6.1 Column Details

- **'Name of the anime'** column has unique names with string object type. There are no missing values. Name of the anime in this column has the data in the next columns.
- **'Rating'** column has numerical variables in it. These values indicates the anime's rating. There was missing values but they are handled.
- **'Ranking'** column has numerical variables in it. These values shows the ranking of the anime by followers. It was discovered that there is a parabolic relationship between followers and ranking. You can see it below.

```
[ ]: df.plot("Ranking","Followers",kind = 'scatter');
```



- **'Followers'** column was containing string objects. We transformed them to integer objects. It indicates that anime has that many followers on the website.
- **'Type'** column contains categorical variables. There was a several missing values but they are handled on Part III. This column indicates the type of the series.

- **'Episodes'** column was containing string objects. We transformed them to integer objects. There were some missing data but they are replaced. This column indicates the episodes of the anime.
- **'License'** column was containing string objects. It still has string objects but for further usage, we have created a new dataframe for this column because sometimes it contains multiple variables in one column. In our new dataframe we seperated its data.
- **'Study'** column was containing string objects. This column has the same issue with the **License** column. We applied same logic to this column too.
- **'Genre'** column was containing string objects. This column has the same issue with the **License** column. We applied same logic to this column too. Additionally, this column was containing missing values but they are handled at Part III.
- **'Demography'** column contains categorical variables. They were many missing values but they are replaced with meaningful value.
- **'Age'** column contains categorical variables. They were some missing values but they are replaced with meaningful value.

1.6.2 Analyze statistics

- We have analyzed **episode distribution**. According to our preprocessed data, it is seen that production companies mostly prefer to present animes around 12 episodes and they make movies around 1 episode. However, it is also possible to see animes with episodes as high as 500. **22%** of the episode values are seen as outlier values.
- We have analyzed **most popular genres with most used series types**. By looking this data we can say that, for the most popular 5 genres, production companies production companies have performed it appropriate to present animes in TV or movie format. **90%** of the TV type is used.
- We have analyzed **number of series studios have**. According to this analysis, **25%** of the series held by only 5 studios.
- We have analyzed **average ratings by age categories**. As a result, it is seen that,G - All Ages category takes place in the top **25%** of the ratings.
- We have analyzed **most popular licenses by follower counts**. It is seen that Funimation license has the most followers. In the second place are the productions that are not licensed. In the distribution of the follower column, it was found that the first **10%** were seen as outliers.

1.7 PART VI - Machine Learning (ML) Implementation - Clustering

In Machine Learning Implementation, there are several ML strategies on clustering mechanism. Since our dataset has not a small number of neglectable outliers, Density- Based Clustering format would highly efficient for our Data Analysis approach. The light of this investigation, we choose the DBSCAN and OPTICS Machine Learning Algorithms for optimum Clustering observation.

1.7.1 DBScan Clustering

```
[ ]: from sklearn.cluster import DBSCAN
     from sklearn import metrics
     from sklearn.datasets import make_blobs
     from sklearn.preprocessing import StandardScaler
```

```
[ ]: db = DBSCAN(eps=0.2, min_samples=20)
     db2 = DBSCAN(eps=0.4, min_samples=6)
```

We created 2 dbscan objects with different parameters at here.

```
[ ]: clusterData = []

     dfRating = df.dropna(subset=['Rating'])

     clusterData = dfRating[['Followers','Rating']].to_numpy()
     clusterData = StandardScaler().fit_transform(clusterData)
     clusterData
```

```
[ ]: array([[ 8.05872636,  1.72471612],
            [ 8.02046334,  1.56220678],
            [ 6.70992096,  2.50771566],
            …,
            [-0.14784861,  0.72011293],
            [-0.30637412,  0.4246414 ],
            [-0.51844006, -0.07766019]])
```

Data scaling ve Transformation techniques are done.

```
[ ]: dbscanClustering = db.fit(clusterData)
     dbscanClustering2 = db2.fit(clusterData)
     clusterLabel = dbscanClustering.labels_
     clusterLabel2 = dbscanClustering2.labels_
     len(set(clusterLabel))
```

```
[ ]: 2
```

We created a model for 2 separate clusterings and we called a label. In the first label, 2 clusters appear.

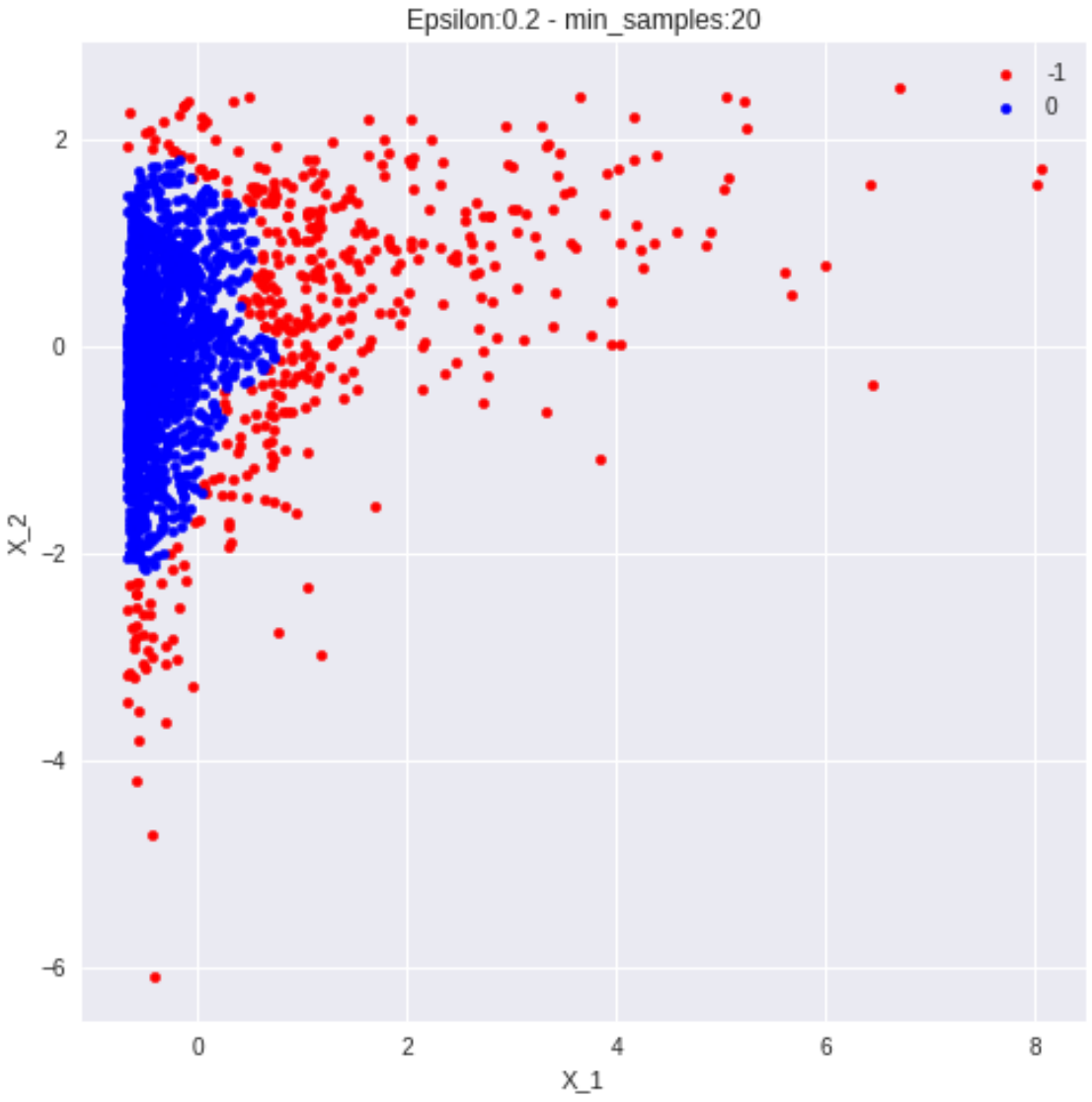
```
[ ]: len(set(clusterLabel2))
```

```
[ ]: 3
```

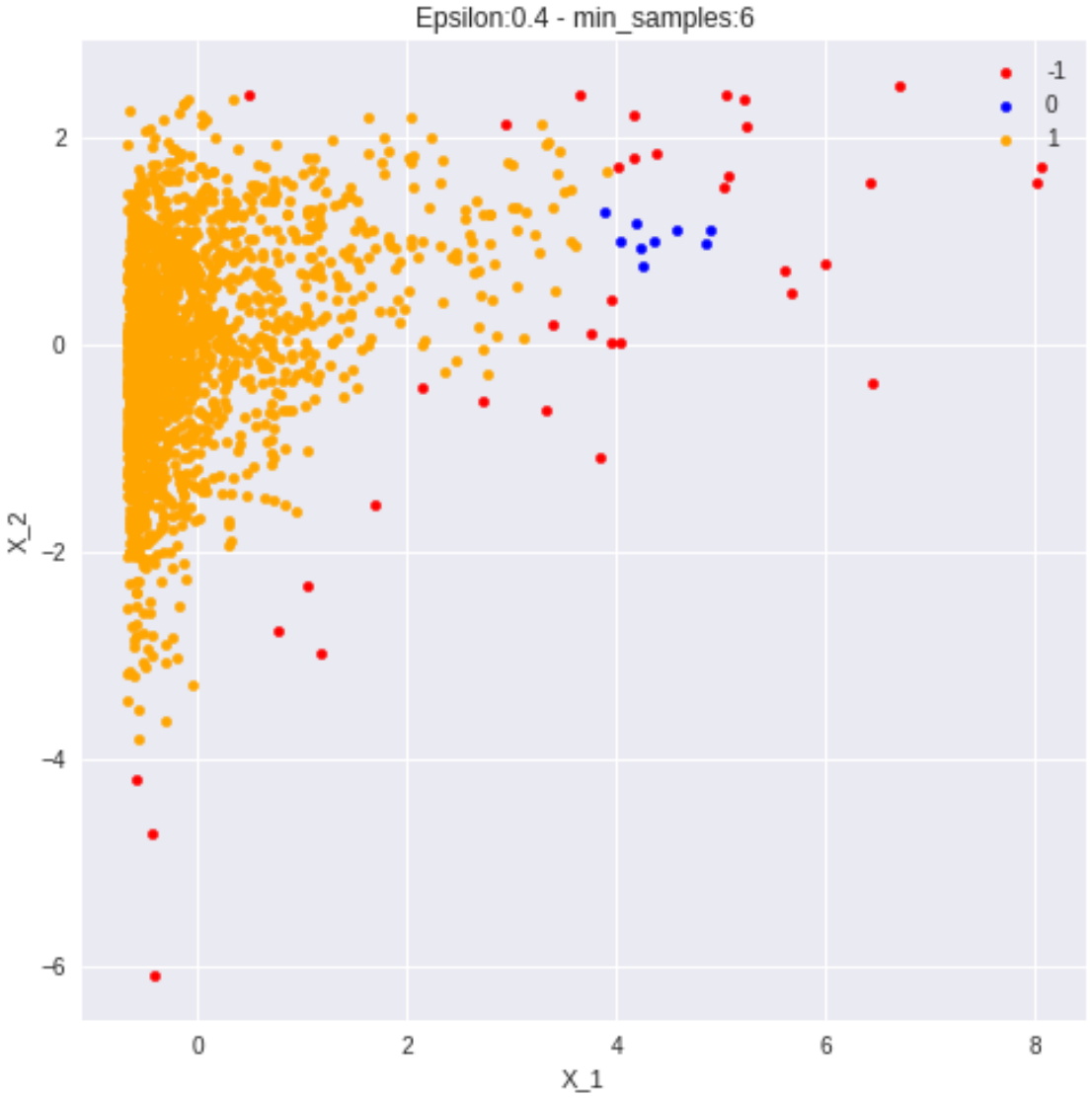
In the second label, there is 3 clusters appear.

```
[ ]: colors = {-1: 'red', 0:'blue', 1:'orange', 2:'green', 3:'black', 4:'purple'}
     dFrame = pd.DataFrame(dict(x=clusterData[:,0],
                                y=clusterData[:,1],
```

```
                              label=clusterLabel))
fig, ax = plt.subplots(figsize=(8,8))
grouped = dFrame.groupby('label')
for key, group in grouped:
  group.plot(ax=ax, kind='scatter', x='x', y='y', label=key, color=colors[key])

plt.xlabel('X_1')
plt.ylabel('X_2')
plt.title('Epsilon:0.2 - min_samples:20')
plt.show()
```



```
[ ]: dFrame = pd.DataFrame(dict(x=clusterData[:,0],
                               y=clusterData[:,1],
                               label=clusterLabel2))
     fig, ax = plt.subplots(figsize=(8,8))
     grouped = dFrame.groupby('label')
     for key, group in grouped:
       group.plot(ax=ax, kind='scatter', x='x', y='y', label=key, color=colors[key])

     plt.xlabel('X_1')
     plt.ylabel('X_2')
     plt.title('Epsilon:0.4 - min_samples:6')
     plt.show()
```



The result of the two tables, we can make interpretations. First of all, we visualize 2 different models. Then, we can see how the different parameters affect the results. As the epsilon value increases, even if the similarity is less, there is data included in the cluster. Also, when the value of the minimum samples decreases, the number of clusters increases.

1.7.2 Optics Clustering

[ ]:
```
from sklearn.cluster import OPTICS, cluster_optics_dbscan
from matplotlib import gridspec
from sklearn.preprocessing import normalize
```

[ ]:
```
dfOptics= df.dropna(subset=['Rating'])
drop_features = ['Name of the anime',␣
 ↪'Ranking','Type','Episodes','License','Study','Genre','Demographics','Age']
dfOptics = dfOptics.drop(drop_features, axis = 1)

clusterScaled = StandardScaler().fit_transform(dfOptics)

clusterNormalized = normalize(clusterScaled)
clusterNormalized = pd.DataFrame(clusterNormalized)

clusterNormalized.columns = dfOptics.columns
```

We create a data frame with the desired rows. Then we scale and transform the data and then, we normalized the data.

[ ]:
```
optics_model = OPTICS(min_samples = 10, xi = 0.1, min_cluster_size = 0.05)
optics_model2 = OPTICS(min_samples = 20, xi = 0.05, min_cluster_size = 0.1)

optics_model.fit(clusterNormalized)
optics_model2.fit(clusterNormalized)
```

[ ]:
```
OPTICS(min_cluster_size=0.1, min_samples=20)
```

We create OPTICS clustering models with 2 different parameters

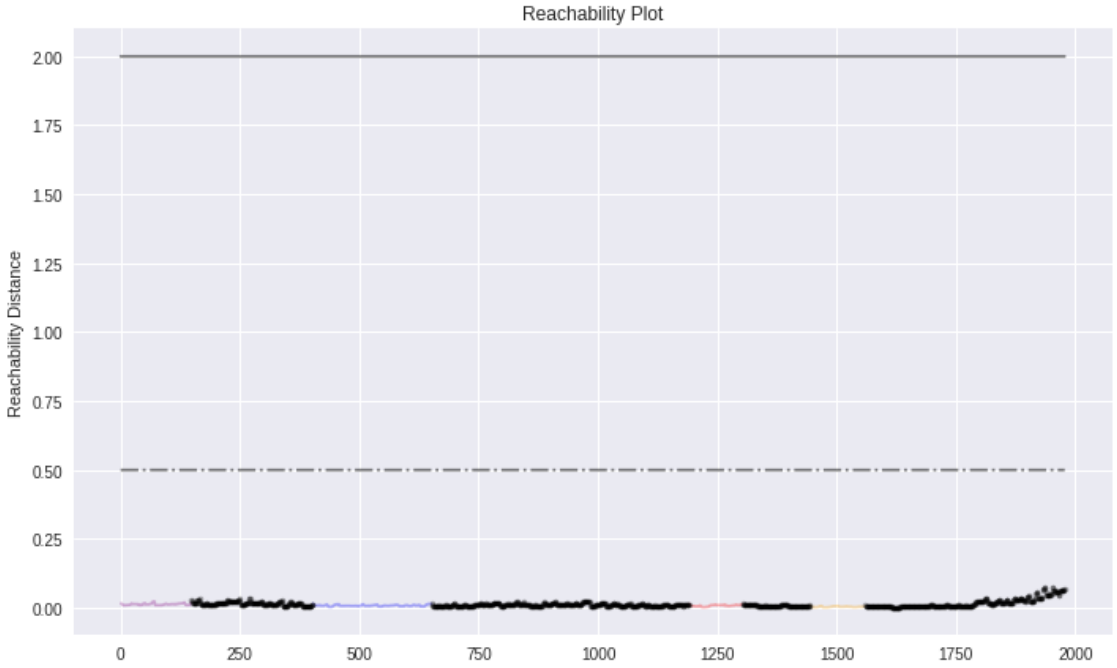
[ ]:
```
space = np.arange(len(clusterNormalized))
reachability = optics_model.reachability_[optics_model.ordering_]
labels = optics_model.labels_[optics_model.ordering_]

reachability2 = optics_model2.reachability_[optics_model2.ordering_]
labels2 = optics_model2.labels_[optics_model2.ordering_]
```

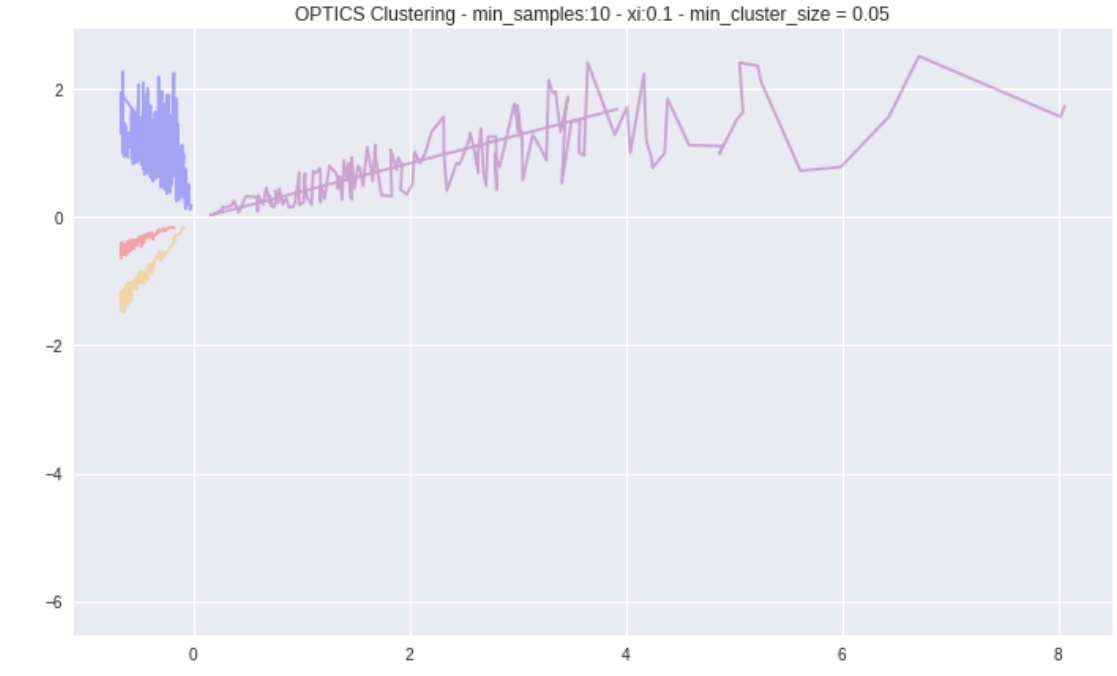
We store label and reachability information from 2 different created models.

https://scikit-learn.org/stable/auto_examples/cluster/plot_optics.html#sphx-glr-auto-examples-cluster-plot-optics-py

We benefited from this source.

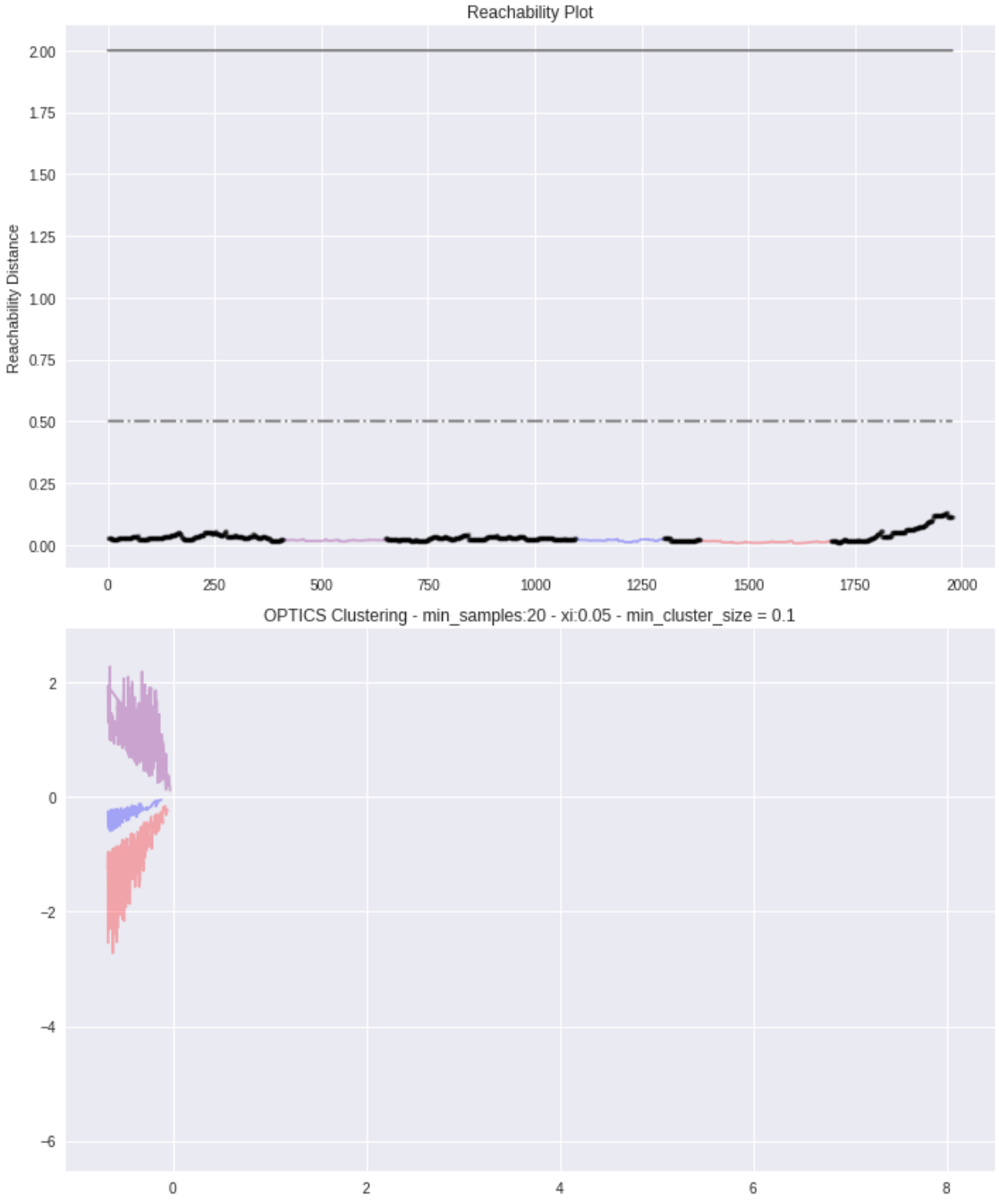
[ ]:
```
plt.figure(figsize =(10, 12))
G = gridspec.GridSpec(2, 1)
ax1 = plt.subplot(G[0, :])
ax2 = plt.subplot(G[1, 0])

colors = ['purple', 'blue', 'red', 'orange', 'green', 'black']
for Class, colour in zip(range(0, 5), colors):
    Xk = space[labels == Class]
    Rk = reachability[labels == Class]
    ax1.plot(Xk, Rk, colour, alpha = 0.3)
ax1.plot(space[labels == -1], reachability[labels == -1], 'k.', alpha = 0.3)
ax1.plot(space, np.full_like(space, 2., dtype = float), 'k-', alpha = 0.5)
ax1.plot(space, np.full_like(space, 0.5, dtype = float), 'k-.', alpha = 0.5)
ax1.set_ylabel('Reachability Distance')
ax1.set_title('Reachability Plot')

for Class, colour in zip(range(0, 5), colors):
    Xk = clusterData[optics_model.labels_ == Class]
    ax2.plot(Xk[:, 0], Xk[:, 1], colour, alpha = 0.3)

ax2.plot(clusterData[optics_model.labels_ == -1, 0],
        clusterData[optics_model.labels_ == -1, 1],
       'k+', alpha = 0.1)
ax2.set_title('OPTICS Clustering - min_samples:10 - xi:0.1 - min_cluster_size =␣
 ↪0.05')

plt.tight_layout()
plt.show()
```





[ ]:
```
plt.figure(figsize =(10, 12))
G = gridspec.GridSpec(2, 1)
ax1 = plt.subplot(G[0, :])
ax2 = plt.subplot(G[1, 0])

colors = ['purple', 'blue', 'red', 'orange', 'green']
```

```
for Class, colour in zip(range(0, 5), colors):
    Xk = space[labels2 == Class]
    Rk = reachability2[labels2 == Class]
    ax1.plot(Xk, Rk, colour, alpha = 0.3)
ax1.plot(space[labels2 == -1], reachability2[labels2 == -1], 'k.', alpha = 0.3)
ax1.plot(space, np.full_like(space, 2., dtype = float), 'k-', alpha = 0.5)
ax1.plot(space, np.full_like(space, 0.5, dtype = float), 'k-.', alpha = 0.5)
ax1.set_ylabel('Reachability Distance')
ax1.set_title('Reachability Plot')

for Class, colour in zip(range(0, 5), colors):
    Xk = clusterData[optics_model2.labels_ == Class]
    ax2.plot(Xk[:, 0], Xk[:, 1], colour, alpha = 0.3)

ax2.plot(clusterData[optics_model2.labels_ == -1, 0],
        clusterData[optics_model2.labels_ == -1, 1],
       'k+', alpha = 0.1)
ax2.set_title('OPTICS Clustering - min_samples:20 - xi:0.05 - min_cluster_size␣
 ↪= 0.1')

plt.tight_layout()
plt.show()
```

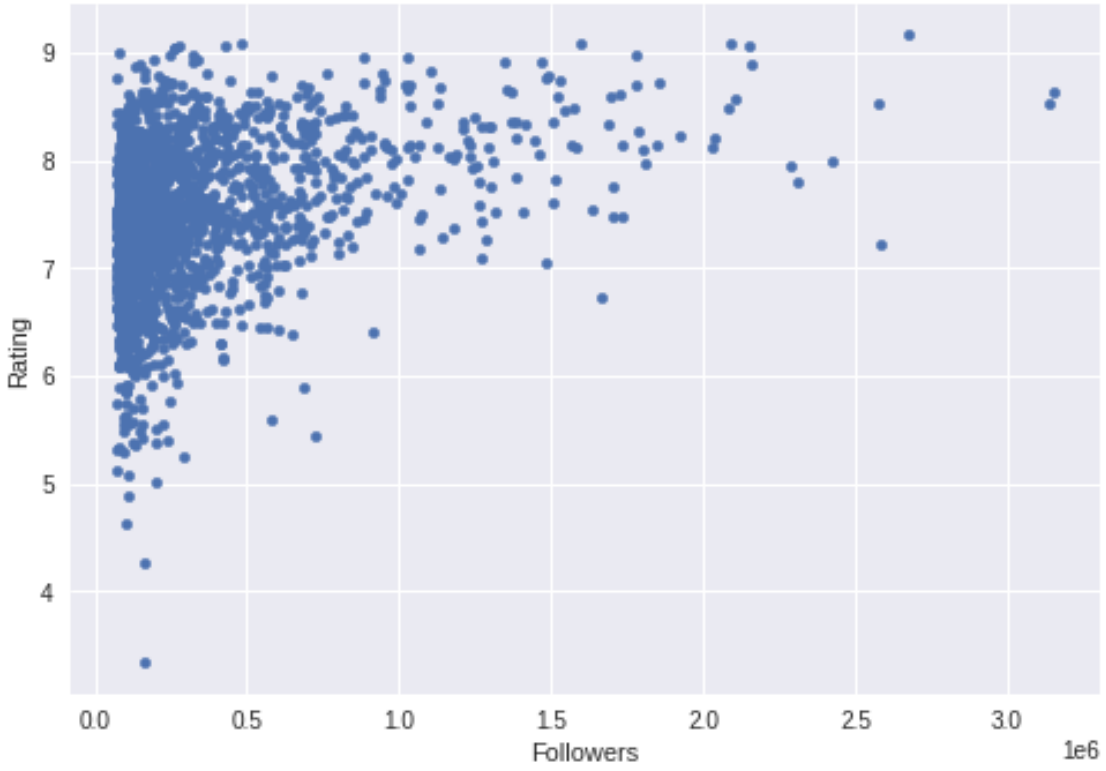


To begin with, we visualize 2 different models here. Then, we can see how the different parameters affect the results. When the value of the minimum samples decreases, the number of clusters increases. As the min_cluster size value decreases, the number of clusters tends to decrease. As the xi value increases, it tends to include the outliers in the cluster. Reducing the xi value is ignoring outliers more. As a result of two ML techniques, we determined the OPTICS methodology is better on our Data Analysis.

1.8 PART VII - Results

```
[ ]: When we analyzed our dataset, the main findings are our dataset has many␣
     ↪outliers and noise. For visualization, you can see the scatterplot which is␣
     ↪located at the bottom side.
```

```
[ ]: df.plot("Followers","Rating",kind = 'scatter');
```



Some columns had missing values but we handled them at pre-processing part. Some missing values are ignored and some of them are replaced with suitable values in an appropriate way. Then, we created some visualization that indicates two relationship of the columns to make clear in Part 4. At Part 5, we analyzed deeply the visual data. We made inferences for each of the visualizations. At Part 6, the light of the analysis has shown us that our data has lots of noise. Thats why, we determined the density based clustering. Then, we performed the DBSCAN and OPTICS as a 2 different Clustering Algorithms. When we analyzed the results of the clustering algorihms, we interpretted that the DBSCAN Clustering Algorithms would be perform better demonstration for our dataset.