Министерство науки и высшего образования Российской Федерации
Федеральное государственное бюджетное образовательное учреждение высшего образования
«Московский государственный технический университет имени Н.Э. Баумана (национальный исследовательский университет)»
(МГТУ им. Н.Э. Баумана)

Факультет «Информатика и системы управления»

Кафедра ИУ5 «Системы обработки информации и управления»

Отчёт по домашнему заданию по дисциплине «Методы Машинного Обучения»

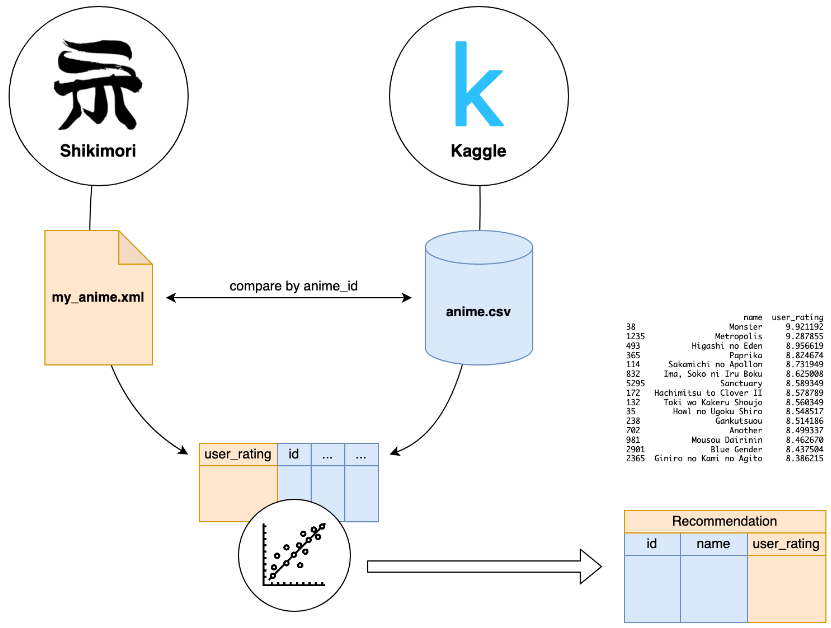
Выполнил:
студент группы № ИУ5-21М
Кучеренко Михаил Александрович
_____________, _________

Проверил:
к.т.н., доц., Ю.Е. Гапанюк
_____________, _________

2021 г.

Домашнее задание

Система рекомендаций Аниме




```python
import sys
sys.path.append('/Users/snipghost/anaconda3/bin/')
print(sys.version)
```

```
3.7.4 (default, Aug 13 2019, 15:17:50)
[Clang 4.0.1 (tags/RELEASE_401/final)]
```

```python
# Download personal anime list
!wget -O my_anime.xml https://shikimori.one/snipghost/list_export/animes.xml
```

```
--2021-06-18 15:07:56--  https://shikimori.one/snipghost/list_export/animes.xml
Распознаётся shikimori.one (shikimori.one)… 135.181.210.175
Подключение к shikimori.one (shikimori.one)|135.181.210.175|:443... соединение установлено.
HTTP-запрос отправлен. Ожидание ответа… 200 OK
Длина: нет данных [application/xml]
Сохранение в: «my_anime.xml»

my_anime.xml            [ <=>                  ] 302,88K  --.-KB/s    за 0,09s

2021-06-18 15:07:56 (3,14 MB/s) - «my_anime.xml» сохранён [310146]
```

```python
# Download anime recommendations database
!kaggle datasets download --force CooperUnion/anime-recommendations-database -f anime.csv
```

```
Downloading anime.csv to /Users/snipghost/Desktop/MMO/lab4
100%|████████████████████████████████████████| 915k/915k [00:00<00:00, 4.79MB/s]
100%|████████████████████████████████████████| 915k/915k [00:00<00:00, 4.78MB/s]
```

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import MultiLabelBinarizer, LabelBinarizer
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import RobustScaler
from sklearn.preprocessing import MaxAbsScaler
import seaborn as sns
%matplotlib inline
```

```python
df = pd.read_csv('anime.csv')
print(df.shape)
df.head()
```

```
(12294, 7)
```

```css
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	anime_id	name	genre	type	episodes	rating	members
0	32281	Kimi no Na wa.	Drama, Romance, School, Supernatural	Movie	1	9.37	200630
1	5114	Fullmetal Alchemist: Brotherhood	Action, Adventure, Drama, Fantasy, Magic, Mili...	TV	64	9.26	793665
2	28977	Gintama°	Action, Comedy, Historical, Parody, Samurai, S...	TV	51	9.25	114262
3	9253	Steins;Gate	Sci-Fi, Thriller	TV	24	9.17	673572
4	9969	Gintama'	Action, Comedy, Historical, Parody, Samurai, S...	TV	51	9.16	151266

Anime.csv

```
anime_id - myanimelist.net's unique id identifying an anime.
name - full name of anime.
genre - comma separated list of genres for this anime.
type - movie, TV, OVA, etc.
episodes - how many episodes in this show. (1 if movie).
rating - average rating out of 10 for this anime.
members - number of community members that are in this anime's "group".
```

```python
df1 = df[df.isna().any(axis=1)]
df1.shape
```

```
(277, 7)
```

```python
print(df.shape)
df = df.dropna()
print(df.shape)
df.reset_index(drop=True, inplace=True)
df.head()
```

```
(12294, 7)
(12017, 7)
```

```
.dataframe tbody tr th {
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}

.dataframe thead th {
    text-align: right;
}
```
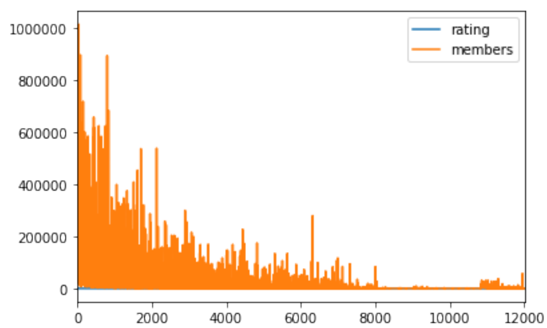
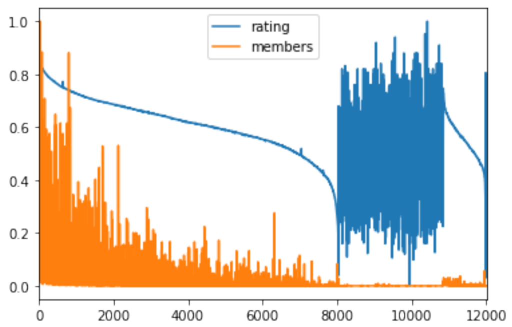
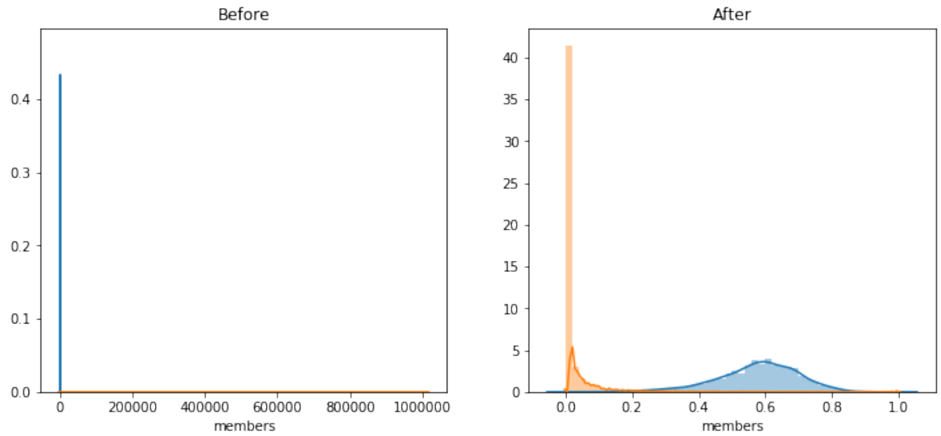

	anime_id	name	genre	type	episodes	rating	members
0	32281	Kimi no Na wa.	Drama, Romance, School, Supernatural	Movie	1	9.37	200630
1	5114	Fullmetal Alchemist: Brotherhood	Action, Adventure, Drama, Fantasy, Magic, Mili...	TV	64	9.26	793665
2	28977	Gintama°	Action, Comedy, Historical, Parody, Samurai, S...	TV	51	9.25	114262
3	9253	Steins;Gate	Sci-Fi, Thriller	TV	24	9.17	673572
4	9969	Gintama'	Action, Comedy, Historical, Parody, Samurai, S...	TV	51	9.16	151266

```python
# Построение плотности распределения
def draw_kde(col_list, df1, df2, label1, label2):
    fig, (ax1, ax2) = plt.subplots(
        ncols=2, figsize=(12, 5))
    # первый график
    ax1.set_title(label1)
    for col in col_list:
        sns.distplot(df1[col], ax=ax1)
    # второй график
    ax2.set_title(label2)
    for col in col_list:
        sns.distplot(df2[col], ax=ax2)
    plt.show()

def draw_data(col_list, df, df_scaled):
    df[col_list].plot()
    df_scaled[col_list].plot()
    plt.show()

def get_scaled(df, columns, scaler=StandardScaler()):
    data_scaled = scaler.fit_transform(df[columns])
    df_scaled = pd.DataFrame(data_scaled, columns=columns)
    draw_data(columns, df, df_scaled)
    draw_kde(columns, df, df_scaled, 'Before', 'After')
    return df_scaled

def apply_scaled(df, df_scaled, columns):
    for col in columns:
        df[f'{col}_scaled'] = df_scaled[col]
    return df
```

```python
df_scaled_maxmin = get_scaled(df, ['rating', 'members'], MinMaxScaler())
df = apply_scaled(df, df_scaled_maxmin, ['rating', 'members'])
df.head()
```








```
.dataframe tbody tr th {
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}

.dataframe thead th {
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}
```

	anime_id	name	genre	type	episodes	rating	members	rating_scaled	members_scaled
0	32281	Kimi no Na wa.	Drama, Romance, School, Supernatural	Movie	1	9.37	200630	0.924370	0.197867
1	5114	Fullmetal Alchemist: Brotherhood	Action, Adventure, Drama, Fantasy, Magic, Mili...	TV	64	9.26	793665	0.911164	0.782769
2	28977	Gintama°	Action, Comedy, Historical, Parody, Samurai, S...	TV	51	9.25	114262	0.909964	0.112683
3	9253	Steins;Gate	Sci-Fi, Thriller	TV	24	9.17	673572	0.900360	0.664323
4	9969	Gintama'	Action, Comedy, Historical, Parody, Samurai, S...	TV	51	9.16	151266	0.899160	0.149180

```
def normalize(df, cols):
    x = df[cols]
    print(x.shape)
    min_max_scaler = preprocessing.MinMaxScaler()
    x_scaled = min_max_scaler.fit_transform(x)
    print(x_scaled)
    print(x_scaled.shape)
    dataset = pd.DataFrame(x_scaled, columns = cols)
    print(dataset.shape)
    print(dataset.tail())
#     origin_columns = df.columns
#     df = df.drop(columns=cols)
#     df = pd.concat([df, dataset], ignore_index=True, axis=1)
#     df.columns = origin_columns
    for col in cols:
        df[col] = dataset[col]
```

```
    return df
```

```
df['episodes'] = pd.to_numeric(df['episodes'], errors='coerce')
df = df.fillna(df.mean())
df.head()
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	anime_id	name	genre	type	episodes	rating	members	rating_scaled	members_scaled
0	32281	Kimi no Na wa.	Drama, Romance, School, Supernatural	Movie	1.0	9.37	200630	0.924370	0.197867
1	5114	Fullmetal Alchemist: Brotherhood	Action, Adventure, Drama, Fantasy, Magic, Mili...	TV	64.0	9.26	793665	0.911164	0.782769
2	28977	Gintama°	Action, Comedy, Historical, Parody, Samurai, S...	TV	51.0	9.25	114262	0.909964	0.112683
3	9253	Steins;Gate	Sci-Fi, Thriller	TV	24.0	9.17	673572	0.900360	0.664323
4	9969	Gintama'	Action, Comedy, Historical, Parody, Samurai, S...	TV	51.0	9.16	151266	0.899160	0.149180

```
df = normalize(df, ['rating', 'members', 'episodes'])
df.head()
```

```
(12017, 3)
[[9.24369748e-01 1.97866664e-01 0.00000000e+00]
 [9.11164466e-01 7.82768603e-01 3.46725371e-02]
 [9.09963986e-01 1.12683141e-01 2.75178866e-02]
 ...
 [3.85354142e-01 2.04161139e-04 1.65107320e-03]
 [3.97358944e-01 1.60764569e-04 0.00000000e+00]
 [4.54981993e-01 1.28217141e-04 0.00000000e+00]]
(12017, 3)
(12017, 3)
         rating   members  episodes
12012  0.297719  0.000196  0.000000
12013  0.313325  0.000169  0.000000
12014  0.385354  0.000204  0.001651
12015  0.397359  0.000161  0.000000
12016  0.454982  0.000128  0.000000
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	anime_id	name	genre	type	episodes	rating	members	rating_scaled	members_scaled
0	32281	Kimi no Na wa.	Drama, Romance, School, Supernatural	Movie	0.000000	0.924370	0.197867	0.924370	0.197867
1	5114	Fullmetal Alchemist: Brotherhood	Action, Adventure, Drama, Fantasy, Magic, Mili...	TV	0.034673	0.911164	0.782769	0.911164	0.782769
2	28977	Gintama°	Action, Comedy, Historical, Parody, Samurai, S...	TV	0.027518	0.909964	0.112683	0.909964	0.112683
3	9253	Steins;Gate	Sci-Fi, Thriller	TV	0.012658	0.900360	0.664323	0.900360	0.664323
4	9969	Gintama'	Action, Comedy, Historical, Parody, Samurai, S...	TV	0.027518	0.899160	0.149180	0.899160	0.149180

```
def one_hot_encoding(df, cols):
    for col, col_type in cols:
        if col_type == list:
            col_data = df[col].str.split(', ')
            mlb = MultiLabelBinarizer()
        else:
            col_data = df[col]
            mlb = LabelBinarizer()
        mlb_data = mlb.fit_transform(col_data)
        encoded_data = pd.DataFrame(mlb_data, columns=mlb.classes_, index=col_data.index)

        for cls in mlb.classes_:
            if cls in df.columns.values:
                df = df.rename(columns={cls: '{}_{}'.format(cls, col)})

        print('Changing column: {} to: {}'.format(col, mlb.classes_))
        df = df.drop(columns=[col])
        df = pd.concat([df, encoded_data], axis=1)
    return df
```

```
df = df.drop(columns=['type'])
```

```
# df = one_hot_encoding(df, [('type', str), ('genre', list)])
df = one_hot_encoding(df, [('genre', list)])
# df = df.drop(columns=['OVA'])
df.head()
```

```
Changing column: genre to: ['Action' 'Adventure' 'Cars' 'Comedy' 'Dementia' 'Demons' 'Drama' 'Ecchi'
 'Fantasy' 'Game' 'Harem' 'Hentai' 'Historical' 'Horror' 'Josei' 'Kids'
 'Magic' 'Martial Arts' 'Mecha' 'Military' 'Music' 'Mystery' 'Parody'
 'Police' 'Psychological' 'Romance' 'Samurai' 'School' 'Sci-Fi' 'Seinen'
 'Shoujo' 'Shoujo Ai' 'Shounen' 'Shounen Ai' 'Slice of Life' 'Space'
 'Sports' 'Super Power' 'Supernatural' 'Thriller' 'Vampire' 'Yaoi' 'Yuri']
```

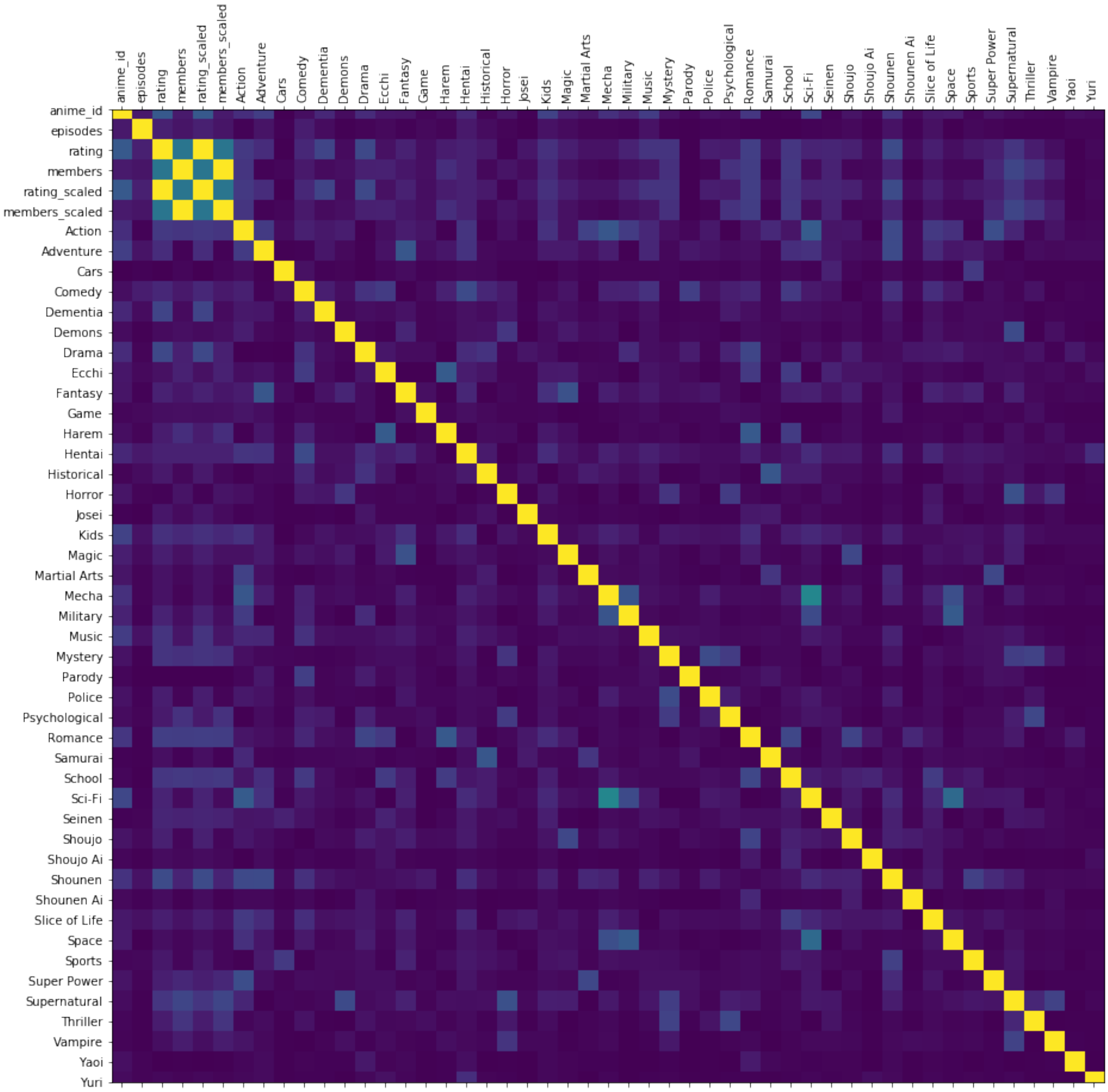
```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	anime_id	name	episodes	rating	members	rating_scaled	members_scaled	Action	Adventure	Cars	...	Shounen Ai	Sli Li
0	32281	Kimi no Na wa.	0.000000	0.924370	0.197867	0.924370	0.197867	0	0	0	...	0	0
1	5114	Fullmetal Alchemist: Brotherhood	0.034673	0.911164	0.782769	0.911164	0.782769	1	1	0	...	0	0
2	28977	Gintama°	0.027518	0.909964	0.112683	0.909964	0.112683	1	0	0	...	0	0
3	9253	Steins;Gate	0.012658	0.900360	0.664323	0.900360	0.664323	0	0	0	...	0	0
4	9969	Gintama'	0.027518	0.899160	0.149180	0.899160	0.149180	1	0	0	...	0	0

5 rows × 50 columns

```python
def plot_corr_matrix(df,size=15):
    corr = df.corr().abs()
    fig, ax = plt.subplots(figsize=(size, size))
    ax.matshow(corr)
    plt.xticks(range(len(corr.columns)), corr.columns)
    plt.yticks(range(len(corr.columns)), corr.columns)
    plt.xticks(rotation=90)
    return corr
```

```python
corr = plot_corr_matrix(df)
```




```
def drop_correlated(df, corr_matrix, threshold=0.5):
    upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(np.bool))
    to_drop = [column for column in upper.columns if any(upper[column] > 0.5)]
    df = df.drop(columns=to_drop)
    return df
```

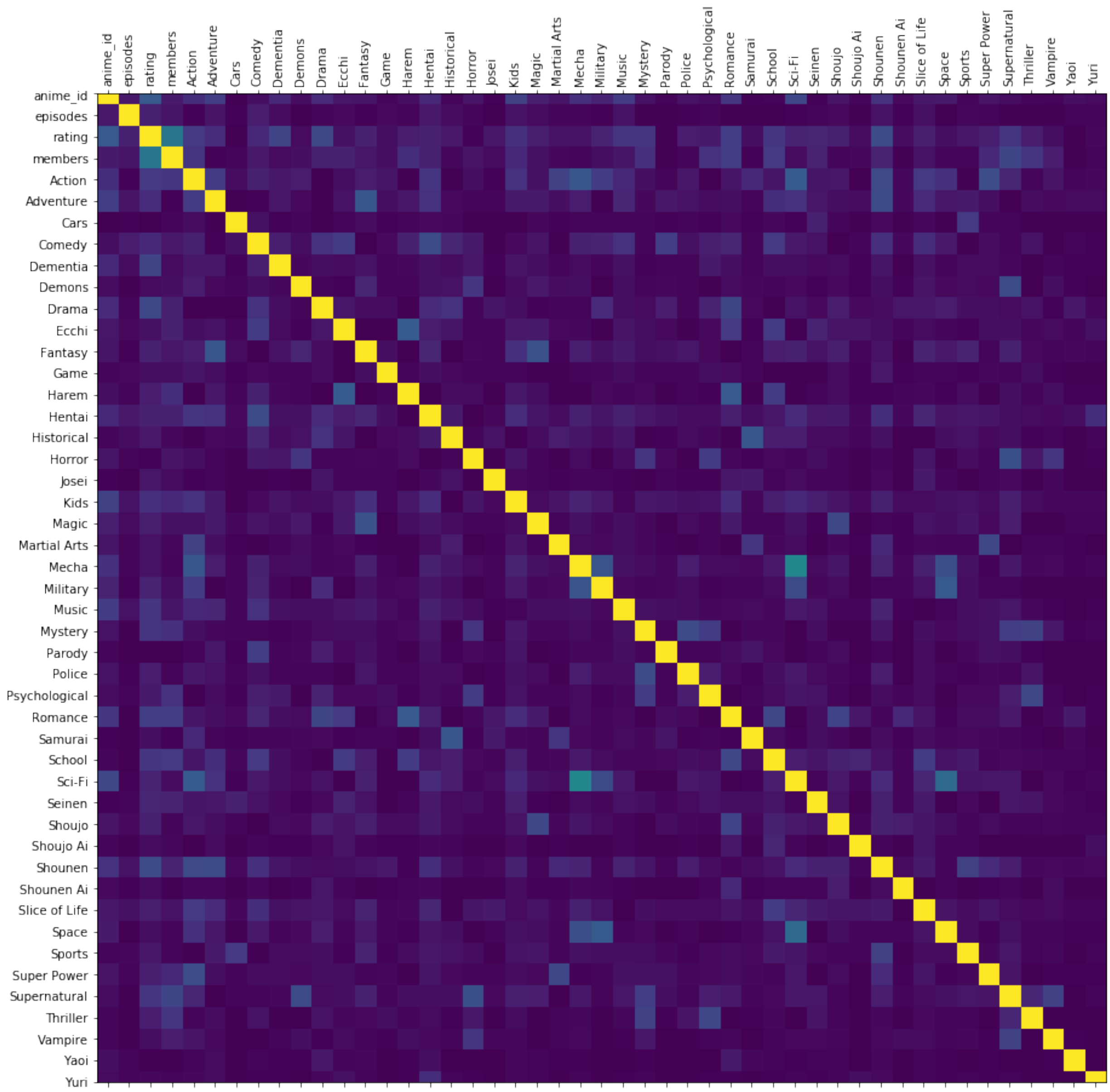
```
df = drop_correlated(df, corr)
df.head()
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	anime_id	name	episodes	rating	members	Action	Adventure	Cars	Comedy	Dementia	...	Shounen Ai	Slice of Life	Space
0	32281	Kimi no Na wa.	0.000000	0.924370	0.197867	0	0	0	0	0	...	0	0	0
1	5114	Fullmetal Alchemist: Brotherhood	0.034673	0.911164	0.782769	1	1	0	0	0	...	0	0	0
2	28977	Gintama°	0.027518	0.909964	0.112683	1	0	0	1	0	...	0	0	0
3	9253	Steins;Gate	0.012658	0.900360	0.664323	0	0	0	0	0	...	0	0	0
4	9969	Gintama'	0.027518	0.899160	0.149180	1	0	0	1	0	...	0	0	0

5 rows × 48 columns

```
corr = plot_corr_matrix(df)
```




```
df['user_rating'] = pd.Series(np.zeros(df.shape[0]))
df.head()
df.tail()
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	anime_id	name	episodes	rating	members	Action	Adventure	Cars	Comedy	Dementia	...	Slice of Life	Space	Sports
12012	9316	Toushindai My Lover: Minami tai Mecha-Minami	0.000000	0.297719	0.000196	0	0	0	0	0	...	0	0	0
12013	5543	Under World	0.000000	0.313325	0.000169	0	0	0	0	0	...	0	0	0
12014	5621	Violence Gekiga David no Hoshi	0.001651	0.385354	0.000204	0	0	0	0	0	...	0	0	0
12015	6133	Violence Gekiga Shin David no Hoshi: Inma Dens...	0.000000	0.397359	0.000161	0	0	0	0	0	...	0	0	0
12016	26081	Yasuji no Pornorama: Yacchimae!!	0.000000	0.454982	0.000128	0	0	0	0	0	...	0	0	0

5 rows × 49 columns

```python
import xml.etree.ElementTree as ET

tree = ET.parse('my_anime.xml')
root = tree.getroot()
anime_list = root.findall('anime')

for anime in anime_list:
    idx = anime.find('series_animedb_id')
    title = anime.find('series_title')
    score = anime.find('my_score')
    list_has = df['anime_id'] == float(idx.text)
    if not list_has.empty and float(score.text) != 0.0:
        df.loc[list_has, 'user_rating'] = float(score.text)

df.head()
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	anime_id	name	episodes	rating	members	Action	Adventure	Cars	Comedy	Dementia	...	Slice of Life	Space	Sports
0	32281	Kimi no Na wa.	0.000000	0.924370	0.197867	0	0	0	0	0	...	0	0	0
1	5114	Fullmetal Alchemist: Brotherhood	0.034673	0.911164	0.782769	1	1	0	0	0	...	0	0	0
2	28977	Gintama°	0.027518	0.909964	0.112683	1	0	0	1	0	...	0	0	0
3	9253	Steins;Gate	0.012658	0.900360	0.664323	0	0	0	0	0	...	0	0	0
4	9969	Gintama'	0.027518	0.899160	0.149180	1	0	0	1	0	...	0	0	0

5 rows × 49 columns

```
df.corr().abs()['user_rating'][:].sort_values(ascending=False)
```

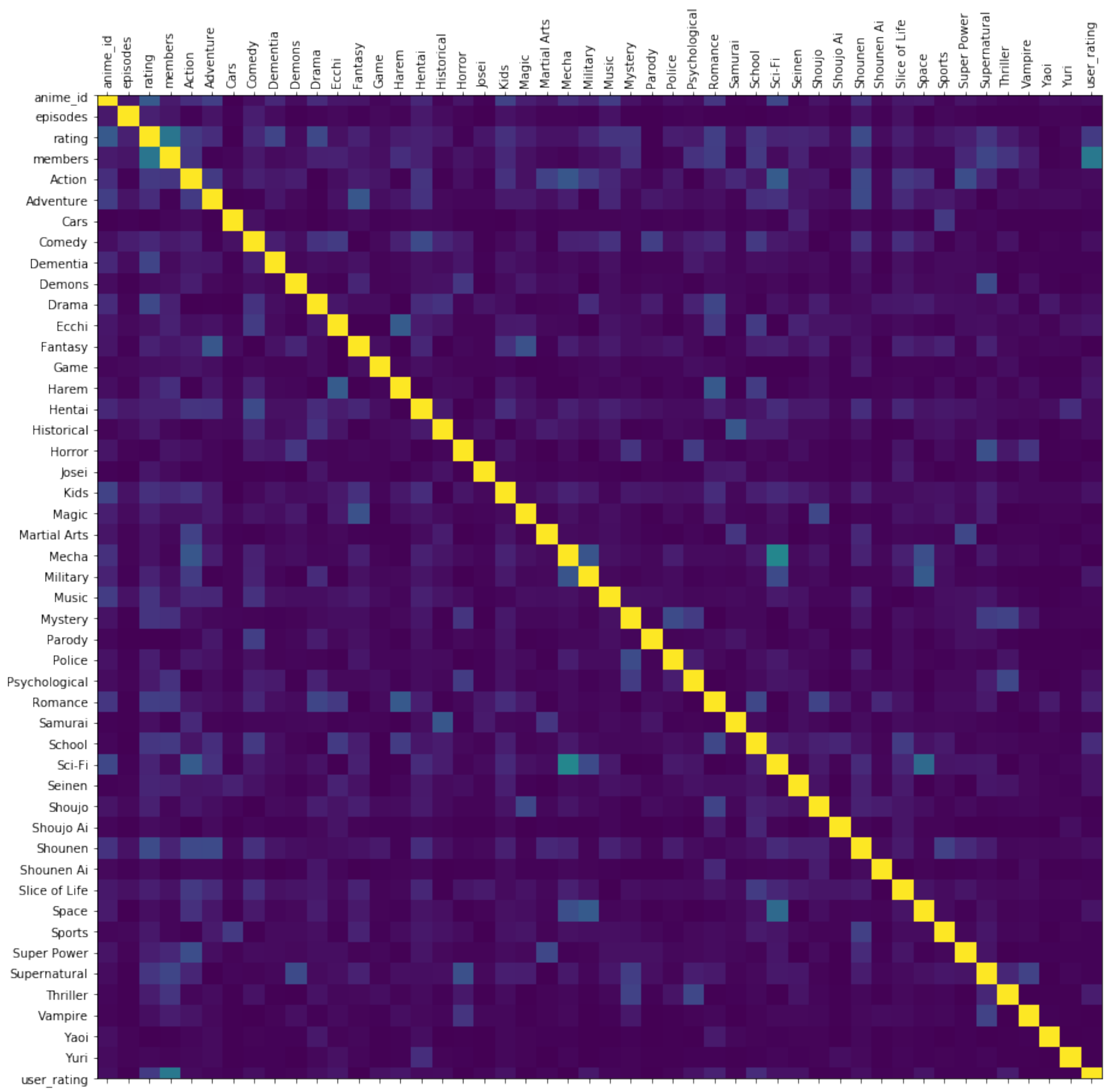
```
user_rating      1.000000
members          0.398669
rating           0.169579
School           0.124686
Romance          0.091002
Thriller         0.077548
Military         0.063860
Harem            0.061067
Ecchi            0.060635
Space            0.052915
Kids             0.050718
Seinen           0.049713
Sci-Fi           0.048391
Psychological    0.048230
Game             0.044487
Shounen          0.039878
Drama            0.038032
anime_id         0.036035
Comedy           0.035542
Historical       0.032808
Hentai           0.029237
Action           0.027912
Martial Arts     0.019517
Adventure        0.017990
Josei            0.017673
Music            0.016990
Samurai          0.014442
Demons           0.014098
Police           0.013589
Mystery          0.012704
Slice of Life    0.012673
Supernatural     0.011336
Dementia         0.010951
Cars             0.010110
Shounen Ai       0.009378
Sports           0.008986
Shoujo Ai        0.008749
Super Power      0.008040
Yuri             0.007620
Magic            0.007353
Yaoi             0.007335
Shoujo           0.005842
episodes         0.004312
Parody           0.003515
Vampire          0.002828
Fantasy          0.002147
Mecha            0.001743
Horror           0.001663
Name: user_rating, dtype: float64
```

```
pred_val = 'user_rating'
c = list(df.columns)
c.remove('anime_id')
```

```
c.remove('name')
c.remove(pred_val)

e = df[pred_val] != 0.0
X_train = pd.DataFrame(df[e][c])
Y_train = pd.DataFrame(df[e][pred_val])
print(X_train.shape)

e = df[pred_val] == 0.0
X = pd.DataFrame(df[e][c])
print(X.shape)
```

```
(225, 46)
(11792, 46)
```

```
corr = plot_corr_matrix(df)
```




```
from sklearn.model_selection import KFold
from sklearn.metrics import mean_squared_error, mean_absolute_error

from sklearn.linear_model import LinearRegression, BayesianRidge, LogisticRegression
from sklearn.neural_network import MLPClassifier

from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
```

```
def calc_scores(model, X, Y, test=None):
    if test is not None:
        Xr = X.iloc[test,:]
        Yr = Y.iloc[test,:]
    else:
        Xr = X
        Yr = Y
    Y_pred = model.predict(Xr)
    score_r2 = model.score(Xr, Yr.values.ravel())
    score_rmse = mean_squared_error(Yr, Y_pred)
    score_abs = mean_absolute_error(Yr, Y_pred)
    return (score_r2, score_rmse, score_abs)
```

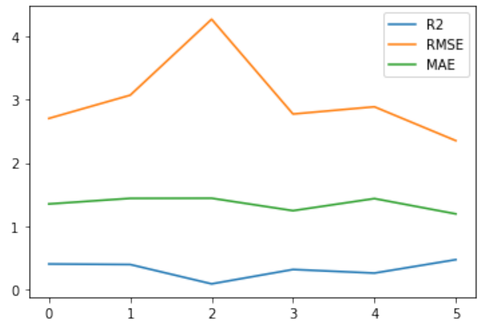
```
def fit_predict(model, X_train, Y_train, X, rst=21, print_size=15):
    scores_1 = []
    scores_2 = []
    scores_3 = []

    kfold = KFold(n_splits=5, shuffle=True, random_state=rst)
    for i, (train, test) in enumerate(kfold.split(X_train, Y_train)):
        model.fit(X_train.iloc[train,:], Y_train.iloc[train,:].values.ravel())
        scores = calc_scores(model, X_train, Y_train, test)
        scores_1.append(scores[0])
        scores_2.append(scores[1])
        scores_3.append(scores[2])

    model.fit(X_train, Y_train.values.ravel())

    scores = calc_scores(model, X_train, Y_train)
    scores_1.append(scores[0])
    scores_2.append(scores[1])
    scores_3.append(scores[2])

    x = np.arange(0, 6, 1)
    plt.plot(x, scores_1)
    plt.plot(x, scores_2)
    plt.plot(x, scores_3)
    labels = ['R2', 'RMSE', 'MAE']
    plt.legend(labels)
    plt.show()

    # Условие по которому вы выбираете TEST выборку
    # это может быть просто df.iloc[test,:] (срез)
    e = df[pred_val] == 0.0

    Y = pd.DataFrame(df[e])
    Y[pred_val] = model.predict(X)
    print(Y.sort_values(by=[pred_val], ascending=False)[['name', pred_val]].head(print_size))
```

```
models = [
    BayesianRidge(),
    LinearRegression(),
    RandomForestRegressor(),
    GradientBoostingRegressor(),
# Classificasion methods
#     LogisticRegression(),
#     MLPClassifier(),
]
```

```
def solve(models, X_train, Y_train, X):
    for model in models:
        print('Model:', type(model).__name__)
        fit_predict(model, X_train, Y_train, X)
        print('\n\n\n')
```

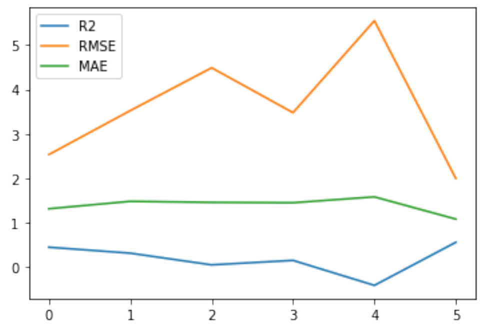
```
solve(models, X_train, Y_train, X)
```

```
Model: BayesianRidge
```




```
                        name  user_rating
38                   Monster     9.921192
1235              Metropolis     9.287855
493          Higashi no Eden     8.956619
365                  Paprika     8.824674
114       Sakamichi no Apollon     8.731949
832      Ima, Soko ni Iru Boku     8.625008
5295               Sanctuary     8.589349
172     Hachimitsu to Clover II     8.578789
132       Toki wo Kakeru Shoujo     8.560349
35          Howl no Ugoku Shiro     8.548517
238               Gankutsuou     8.514186
702                  Another     8.499337
981          Mousou Dairinin     8.462670
2901             Blue Gender     8.437504
2365  Giniro no Kami no Agito     8.386215
```

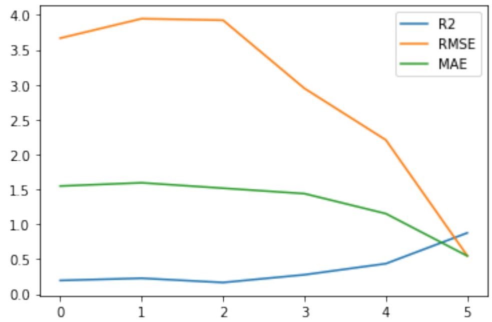
```
Model: LinearRegression
```




```
                                                    name  user_rating
38                                               Monster    12.283960
172                                  Hachimitsu to Clover II    10.572720
1235                                          Metropolis    10.544546
114                                   Sakamichi no Apollon    10.361105
365                                              Paprika    10.340557
325                                   Hachimitsu to Clover    10.086614
596                                     Psycho-Pass Movie     9.805784
68                              Shouwa Genroku Rakugo Shinjuu     9.743177
493                                      Higashi no Eden     9.624178
91                                        Shinsekai yori     9.561978
75      Ghost in the Shell: Stand Alone Complex 2nd GIG     9.502509
137   Detective Conan Movie 06: The Phantom of Baker...     9.491569
633                                         Paradise Kiss     9.471116
601                                   Vampire Hunter D (2000)     9.439421
93                                          Chihayafuru 2     9.426317
```

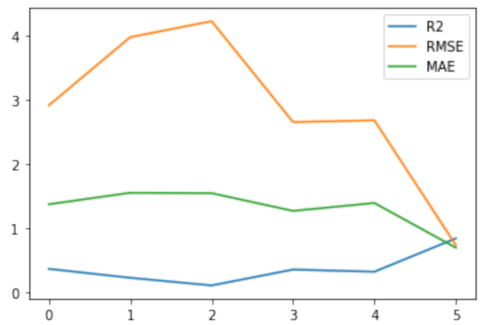
```
Model: RandomForestRegressor
```

```
/Users/snipghost/opt/anaconda3/lib/python3.7/site-packages/sklearn/ensemble/forest.py:245: FutureWarning: The default value of n_estimators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```




```
                                                    name  user_rating
18                            Ookami Kodomo no Ame to Yuki          9.6
53                     Rainbow: Nisha Rokubou no Shichinin          9.5
10                                   Clannad: After Story          9.4
21    Rurouni Kenshin: Meiji Kenkaku Romantan - Tsui...          9.2
68                        Shouwa Genroku Rakugo Shinjuu          9.2
93                                       Chihayafuru 2          9.1
45                         Kara no Kyoukai 5: Mujun Rasen          9.1
38                                             Monster          9.0
47                                 Ping Pong The Animation          9.0
36                                   Fate/Zero 2nd Season          9.0
1073                               Waga Seishun no Arcadia          9.0
31                                   Natsume Yuujinchou Go          8.9
51                                   Aria The Origination          8.9
34                                  Natsume Yuujinchou Shi          8.8
55         Tengen Toppa Gurren Lagann Movie: Lagann-hen          8.8
```

```
Model: GradientBoostingRegressor
```




```
                                                    name  user_rating
45                         Kara no Kyoukai 5: Mujun Rasen     9.979689
21    Rurouni Kenshin: Meiji Kenkaku Romantan - Tsui...     9.686625
53                     Rainbow: Nisha Rokubou no Shichinin     9.407639
68                        Shouwa Genroku Rakugo Shinjuu     9.270985
38                                             Monster     9.232541
60                                   Hotarubi no Mori e     9.232013
36                                   Fate/Zero 2nd Season     9.157793
93                                       Chihayafuru 2     9.076980
77          Kara no Kyoukai 7: Satsujin Kousatsu (Kou)     8.896145
9538                   Mirai ni Mukete: Bousai wo Kangaeru     8.876312
75      Ghost in the Shell: Stand Alone Complex 2nd GIG     8.801777
10                                   Clannad: After Story     8.798712
240                          Nodame Cantabile: Paris-hen     8.747536
35                                   Howl no Ugoku Shiro     8.721789
50                                  Yojouhan Shinwa Taikei     8.706756
```

Выводы:

Эмпирически выявлено, что лучший результат дают регрессионные модели. Задача оказалось довольно простой и предобработка данных почти не влияет на результат, для получения высокой точности предсказаний вполне достаточно было провести one-hot-encoding жанров, преобразовать их в тэги (может быть несколько на каждый сериал), и нормализовать рейтинг.

Измененение характера распределения оценок на нормальное не повлияло положительно на точность.

```

```