Министерство науки и высшего образования Российской Федерации
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«Московский государственный технический университет имени Н.Э. Баумана
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Факультет «Информатика и системы управления»

Кафедра ИУ5 «Системы обработки информации и управления»

Отчёт по лабораторной работе
по дисциплине «Методы Машинного Обучения»

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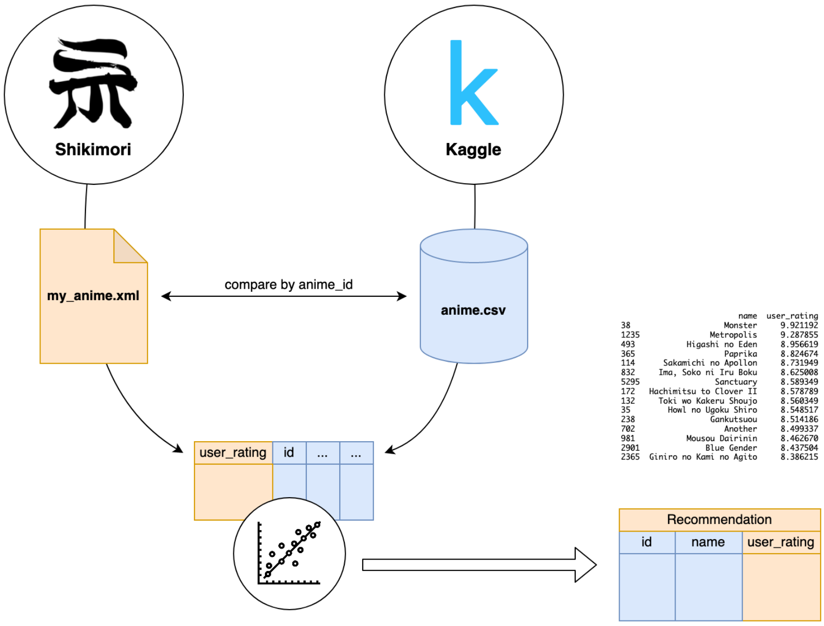
2021 г.

Лабораторная работа №4

Система рекомендаций Аниме




```
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)]
```

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

```
--2021-06-18 08:30:10--  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 0,1s

2021-06-18 08:30:10 (3,06 MB/s) - «my_anime.xml» сохранён [310146]
```

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

```
Downloading anime.csv to /Users/snipghost/Desktop
100%|████████████████████████████████████████| 915k/915k [00:00<00:00, 4.41MB/s]
100%|████████████████████████████████████████| 915k/915k [00:00<00:00, 4.37MB/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
```

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

```
(12294, 7)
```

	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)
```

	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

```
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()
```

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

```
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
```

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

```python
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
```

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

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

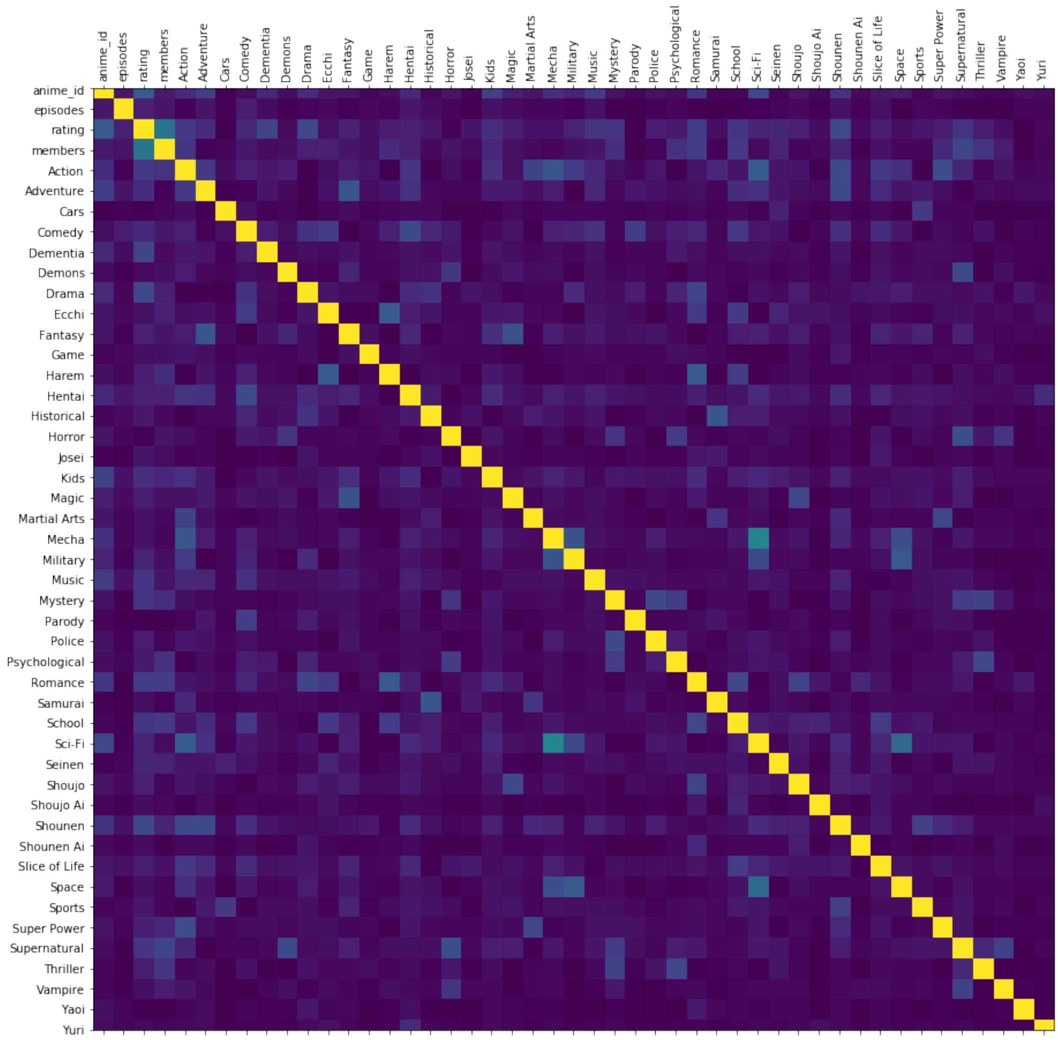
```
Changing column: genre to: ['Action' 'Adventure' 'Cars' 'Comedy' 'Dementia' 'Demons' 'Drama' 'Ecchi'
 'Fantasy' 'Game' 'Harem' 'Hentai' 'Historical' 'Horror' 'Josei' 'Kids'
 'Magic' 'Martial Arts' 'Mecha' 'Military' 'Music' 'Mystery' 'Parody'
 'Police' 'Psychological' 'Romance' 'Samurai' 'School'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

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

5 rows × 48 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)
```



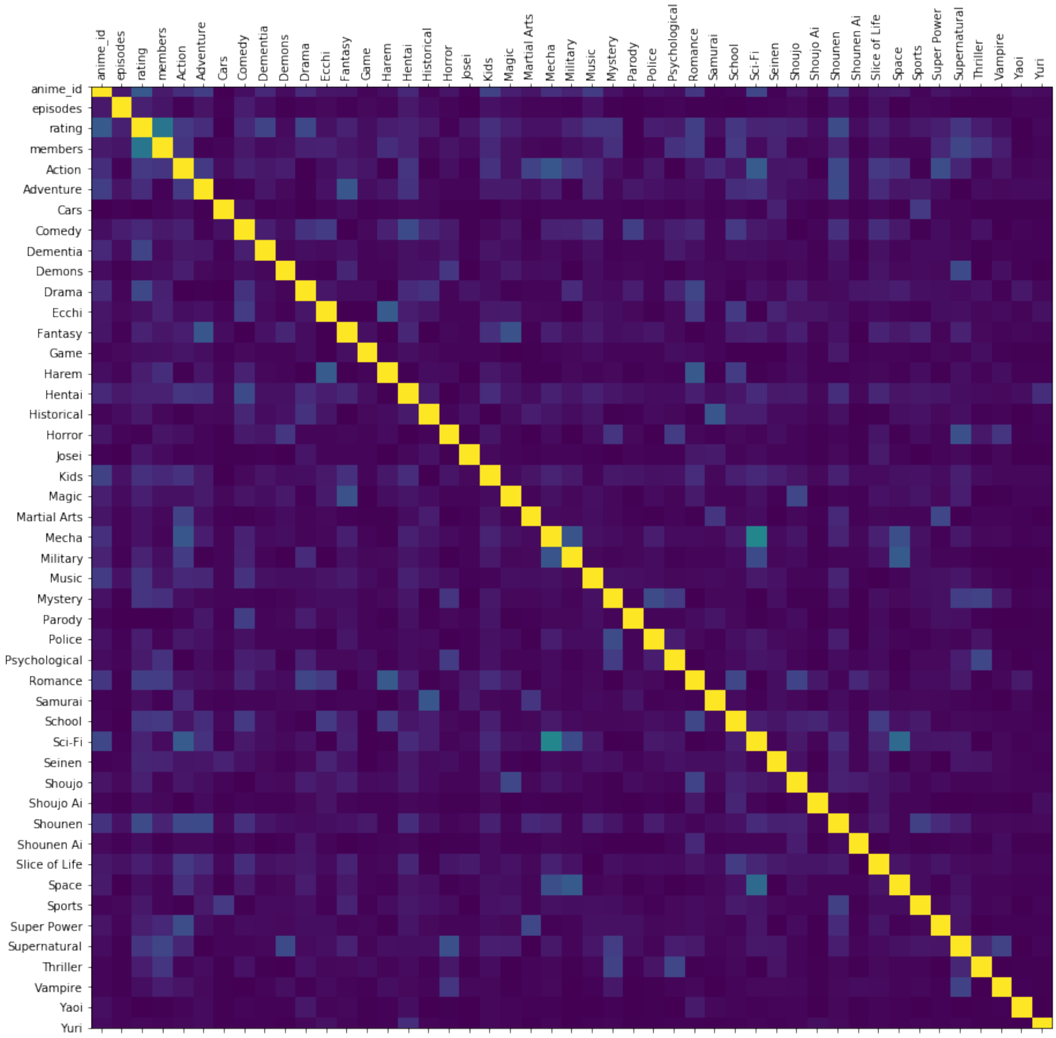

```
def drop_correlated(df, corr_matrix, threshold=0.5):
    upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(np.bool))
    to_drop = [column for column in upper.columns if any(upper[column] > 0.5)]
    df = df.drop(columns=to_drop)
    return df
```

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

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

5 rows × 48 columns

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




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

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

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

5 rows × 49 columns

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

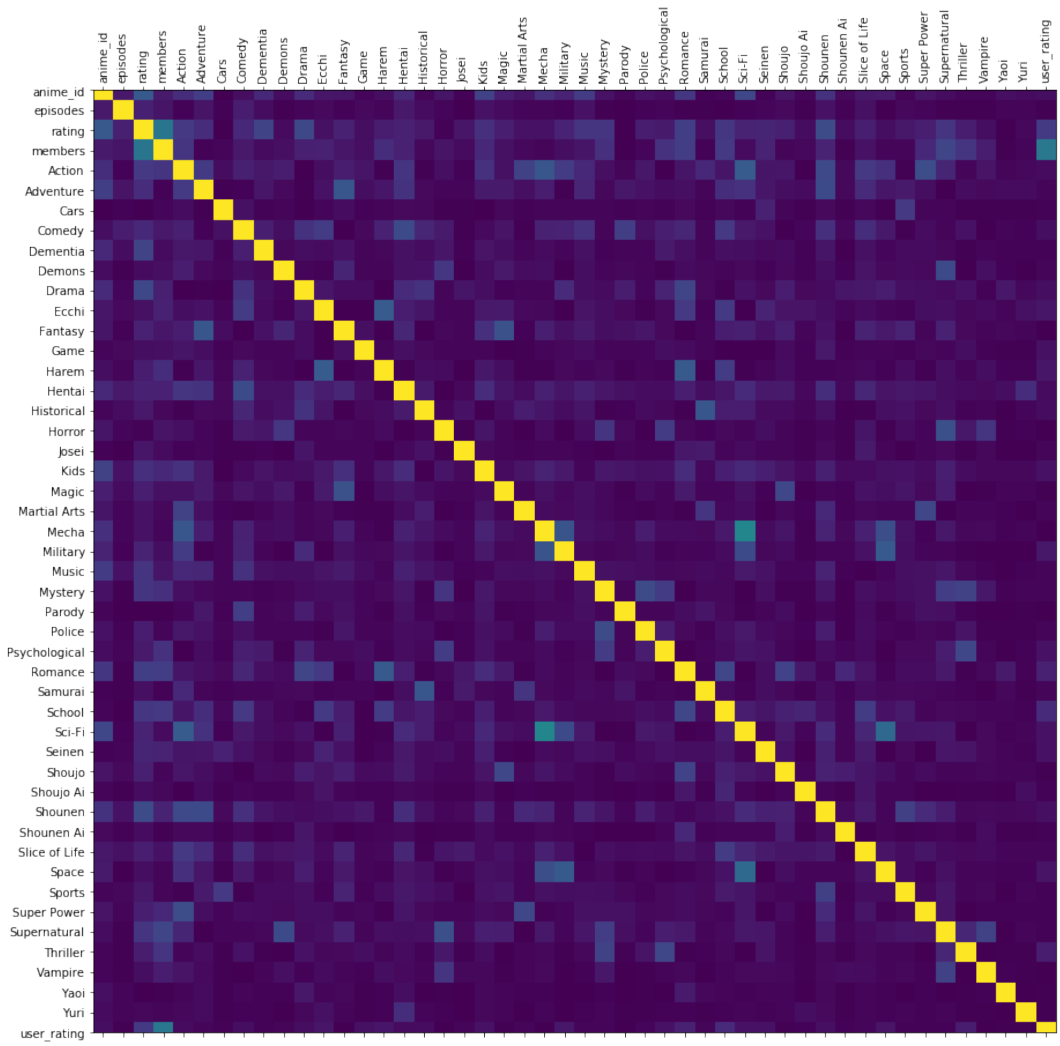
```
user_rating      1.000000
members          0.398669
rating           0.169579
School           0.124686
Romance          0.091002
Thriller         0.077548
Military         0.063860
Harem            0.061067
Ecchi            0.060635
Space            0.052915
Kids             0.050718
Seinen           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
```

```python
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)
```

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



```python
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
```

```python
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)
```

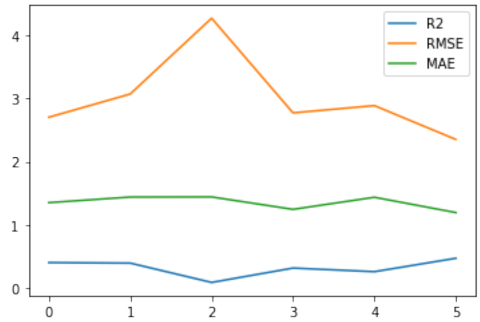
```python
def fit_predict(model, X_train, Y_train, X, rst=21, print_size=15):
    scores_1 = []
    scores_2 = []
    scores_3 = []

    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))
```

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

```python
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')
```

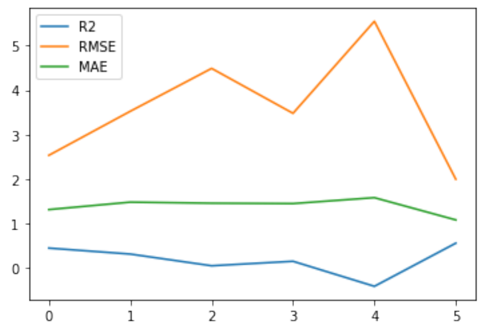
```
solve(models, X_train, Y_train, X)
```

```
Model: BayesianRidge
```



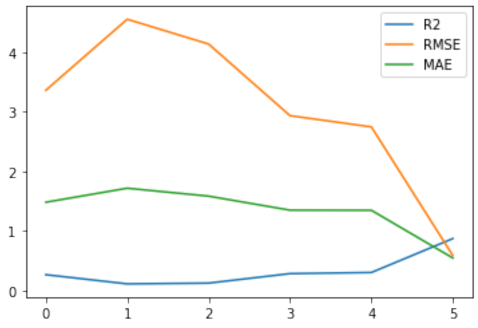

```
                        name  user_rating
38                   Monster     9.921192
1235              Metropolis     9.287855
493          Higashi no Eden     8.956619
365                  Paprika     8.824674
114       Sakamichi no Apollon     8.731949
832      Ima, Soko ni Iru Boku     8.625008
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
```



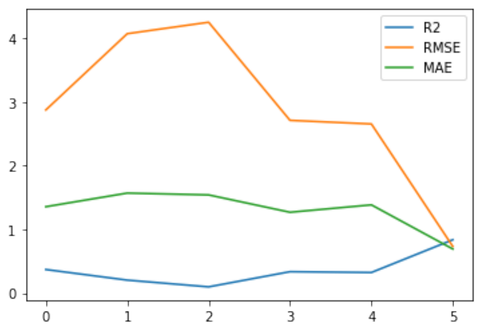

```
                                           name  user_rating
38                                      Monster    12.283960
172                     Hachimitsu to Clover II    10.572720
1235                                 Metropolis    10.544546
114                        Sakamichi no Apollon    10.361105
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
```




```
                                                 name  user_rating
50                            Yojouhan Shinwa Taikei          9.3
21     Rurouni Kenshin: Meiji Kenkaku Romantan - Tsui...          9.2
26                  Monogatari Series: Second Season          9.2
10                              Clannad: After Story          9.1
10739                    Yakusoku: Africa Mizu to Midori          9.1
60                                Hotarubi no Mori e          9.1
9046                                    Kahei no Umi          9.1
8      Gintama Movie: Kanketsu-hen - Yorozuya yo Eien...          9.0
45                       Kara no Kyoukai 5: Mujun Rasen          9.0
19                       Code Geass: Hangyaku no Lelouch          9.0
38                                             Monster          9.0
6                                  Hunter x Hunter (2011)          9.0
9                                Gintama&#039;: Enchousen          9.0
13                    Code Geass: Hangyaku no Lelouch R2          8.9
53                   Rainbow: Nisha Rokubou no Shichinin          8.9
```

```
Model: GradientBoostingRegressor
```




```
                                                name  user_rating
45                      Kara no Kyoukai 5: Mujun Rasen     9.875052
21    Rurouni Kenshin: Meiji Kenkaku Romantan - Tsui...     9.663214
53                 Rainbow: Nisha Rokubou no Shichinin     9.337465
60                                  Hotarubi no Mori e     9.232013
38                                             Monster     9.226272
36                                 Fate/Zero 2nd Season     9.157793
68                     Shouwa Genroku Rakugo Shinjuu     9.060116
93                                      Chihayafuru 2     8.926881
9538                   Mirai ni Mukete: Bousai wo Kangaeru     8.876312
77                Kara no Kyoukai 7: Satsujin Kousatsu (Kou)     8.825971
10                              Clannad: After Story     8.798712
75          Ghost in the Shell: Stand Alone Complex 2nd GIG     8.744925
35                                   Howl no Ugoku Shiro     8.721789
50                             Yojouhan Shinwa Taikei     8.668339
269                                Mobile Suit Gundam 00     8.657001
```

Выводы:

Эмпирически выявлено, что лучший результат дают регрессионные модели.

Из графиков RMSE-метрики следует, что модель GradientBoostingRegressor превосходит остальные.
Хоть все модели и выдали разные списки рекомендаций - они значительно пересекаются между собой, так все 4 модели прогнозируют высокую пользовательскую оценку аниме-сериалу Monster.
Причем рекоменации аниме значительно совпадают с моим собственным списком "запланировано к просмотру".