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```
# This Python 3 environment comes with many helpful analytics
libraries installed
# It is defined by the kaggle/python Docker image:
https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/"
directory
# For example, running this (by clicking run or pressing Shift+Enter)
will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/)
that gets preserved as output when you create a version using "Save &
Run All"
# You can also write temporary files to /kaggle/temp/, but they won't
be saved outside of the current session
```

```
/kaggle/input/anime-recommendations-database/rating.csv
/kaggle/input/anime-recommendations-database/anime.csv
```

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style="ticks")
```

Кодирование данных и масштабирование

```
data =
pd.read_csv('/kaggle/input/anime-recommendations-database/anime.csv',
sep=",")
```

```
data.shape
```

```
(12294, 7)
```

```
data.head()
```

```
   anime_id                              name  \
0     32281                    Kimi no Na wa.
1      5114  Fullmetal Alchemist: Brotherhood
2     28977                          Gintama°
3      9253                       Steins;Gate
4      9969                     Gintama&#039;

                                               genre   type episodes
rating  \
0               Drama, Romance, School, Supernatural  Movie        1
9.37
1  Action, Adventure, Drama, Fantasy, Magic, Mili...     TV       64
9.26
2  Action, Comedy, Historical, Parody, Samurai, S...     TV       51
9.25
3                                   Sci-Fi, Thriller     TV       24
9.17
4  Action, Comedy, Historical, Parody, Samurai, S...     TV       51
9.16

   members
0   200630
1   793665
2   114262
3   673572
4   151266
```

```python
for column in ['anime_id', 'name']:
    data = data.drop(column, axis=1)

data.head()
```

```
                                               genre   type episodes
rating  \
0               Drama, Romance, School, Supernatural  Movie        1
9.37
1  Action, Adventure, Drama, Fantasy, Magic, Mili...     TV       64
9.26
2  Action, Comedy, Historical, Parody, Samurai, S...     TV       51
9.25
3                                   Sci-Fi, Thriller     TV       24
9.17
4  Action, Comedy, Historical, Parody, Samurai, S...     TV       51
9.16

   members
0   200630
1   793665
2   114262
```

```
3    673572
4    151266
```

```python
data[['genre']]
```

```
                                                   genre
0                     Drama, Romance, School, Supernatural
1      Action, Adventure, Drama, Fantasy, Magic, Mili...
2      Action, Comedy, Historical, Parody, Samurai, S...
3                                      Sci-Fi, Thriller
4      Action, Comedy, Historical, Parody, Samurai, S...
...                                                  ...
12289                                             Hentai
12290                                             Hentai
12291                                             Hentai
12292                                             Hentai
12293                                             Hentai

[12294 rows x 1 columns]
```

```python
data.isnull().sum()
```

```
genre        62
type         25
episodes      0
rating      230
members       0
dtype: int64
```

```python
for null_rows in ['genre', 'type', 'rating']:
    data.dropna(subset=[null_rows], inplace=True)

data.isnull().sum()
```

```
genre       0
type        0
episodes    0
rating      0
members     0
dtype: int64
```

```python
data.shape
```

```
(12017, 5)
```

```python
data.dtypes.loc[lambda x: x == 'object']
```

```
genre       object
type        object
episodes    object
dtype: object
```

```python
genres = [genre for genres in data['genre'] for genre in
genres.split(', ')]
unique_genres = np.unique(genres)
print(len(unique_genres))
unique_genres
```

```
43
```

```
array(['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'], dtype='<U13')
```

```python
for genre in unique_genres:
    data[genre] = 0
for i, genres in data['genre'].items():
    for genre in genres.split(', '):
        data.at[i, genre] = 1
data.drop('genre', axis=1, inplace=True)
data.head()
```

```
    type episodes  rating  members  Action  Adventure  Cars  Comedy
Dementia  \
0  Movie        1    9.37   200630       0          0     0       0
0
1     TV       64    9.26   793665       1          1     0       0
0
2     TV       51    9.25   114262       1          0     0       1
0
3     TV       24    9.17   673572       0          0     0       0
0
4     TV       51    9.16   151266       1          0     0       1
0

   Demons  ...  Shounen Ai  Slice of Life  Space  Sports  Super Power
\
0       0  ...           0              0      0       0            0

1       0  ...           0              0      0       0            0

2       0  ...           0              0      0       0            0

3       0  ...           0              0      0       0            0

4       0  ...           0              0      0       0            0
```

```
   Supernatural  Thriller  Vampire  Yaoi  Yuri
0             1         0        0     0     0
1             0         0        0     0     0
2             0         0        0     0     0
3             0         1        0     0     0
4             0         0        0     0     0

[5 rows x 47 columns]
```

```
data.dtypes.loc[lambda x: x == 'object']
```

```
type        object
episodes    object
dtype: object
```

```
np.where(data['episodes']=='Unknown')[0].shape
```

```
(187,)
```

```
data = data.drop(data[data['episodes'] == 'Unknown'].index)
np.where(data['episodes']=='Unknown')[0].shape
```

```
(0,)
```

```
data['episodes'] = data['episodes'].map(int)
```

```
data['type'].unique()
```

```
array(['Movie', 'TV', 'OVA', 'Special', 'Music', 'ONA'], dtype=object)
```

```
from sklearn.preprocessing import OrdinalEncoder
oe = OrdinalEncoder()
data[['type']] = oe.fit_transform(data[['type']])
data.dtypes.loc[lambda x: x == 'object']
```

```
Series([], dtype: object)
```

```
data.dtypes.loc[lambda x: x == 'object']
```

```
Series([], dtype: object)
```

```
data.columns = [str(i) for i in data.columns]
data.describe()
```

```
               type      episodes        rating       members
Action  \
count  11830.000000  11830.000000  11830.000000  1.183000e+04
11830.000000
mean       3.037785     12.486729      6.484609  1.851100e+04
0.232291
std        1.811007     47.097131      1.019147  5.537144e+04
```

```
0.422311
min        0.000000      1.000000      1.670000  1.200000e+01
0.000000
25%        2.000000      1.000000      5.892500  2.322500e+02
0.000000
50%        3.000000      2.000000      6.570000  1.589500e+03
0.000000
75%        5.000000     12.000000      7.190000  9.832000e+03
0.000000
max        5.000000   1818.000000     10.000000  1.013917e+06
1.000000

          Adventure          Cars        Comedy      Dementia
Demons  \
count  11830.000000  11830.000000  11830.000000  11830.000000
11830.000000
mean       0.193829      0.006002      0.378952      0.020118
0.024260
std        0.395313      0.077241      0.485147      0.140411
0.153863
min        0.000000      0.000000      0.000000      0.000000
0.000000
25%        0.000000      0.000000      0.000000      0.000000
0.000000
50%        0.000000      0.000000      0.000000      0.000000
0.000000
75%        0.000000      0.000000      1.000000      0.000000
0.000000
max        1.000000      1.000000      1.000000      1.000000
1.000000

       ...    Shounen Ai  Slice of Life         Space        Sports  \
count  ...  11830.000000   11830.000000  11830.000000  11830.000000
mean   ...      0.005241       0.099746      0.031784      0.044548
std    ...      0.072207       0.299674      0.175431      0.206317
min    ...      0.000000       0.000000      0.000000      0.000000
25%    ...      0.000000       0.000000      0.000000      0.000000
50%    ...      0.000000       0.000000      0.000000      0.000000
75%    ...      0.000000       0.000000      0.000000      0.000000
max    ...      1.000000       1.000000      1.000000      1.000000

        Super Power  Supernatural      Thriller       Vampire
Yaoi  \
count  11830.000000  11830.000000  11830.000000  11830.000000
11830.000000
mean       0.037616      0.083939      0.007270      0.008453
0.003128
std        0.190274      0.277308      0.084955      0.091555
0.055840
min        0.000000      0.000000      0.000000      0.000000
```

```
0.000000
25%        0.000000      0.000000      0.000000      0.000000
0.000000
50%        0.000000      0.000000      0.000000      0.000000
0.000000
75%        0.000000      0.000000      0.000000      0.000000
0.000000
max        1.000000      1.000000      1.000000      1.000000
1.000000

               Yuri
count  11830.000000
mean       0.003466
std        0.058771
min        0.000000
25%        0.000000
50%        0.000000
75%        0.000000
max        1.000000

[8 rows x 47 columns]
```

```
from sklearn.preprocessing import MinMaxScaler, StandardScaler,
Normalizer

sc2 = StandardScaler()
sc2_data = sc2.fit_transform(data[['episodes', 'rating', 'members']])
sc2_data
```

```
array([[-0.24390475,  2.83130101,  3.28918118],
       [ 1.09381288,  2.7233631 , 13.99975827],
       [ 0.81777591,  2.71355056,  1.72932194],
       ...,
       [-0.18020391, -1.57452817, -0.33036483],
       [-0.24390475, -1.4764028 , -0.3311595 ],
       [-0.24390475, -1.00540102, -0.3317555 ]])
```

```
data[['episodes', 'rating', 'members']] = sc2_data
```

Предсказание

```
from sklearn.model_selection import train_test_split

(data['Hentai'] == 1).sum()
```

```
1099
```

```
target = data[['Hentai']]
data.drop('Hentai', axis=1, inplace=True)
```

```
target.shape
```

```
(11830, 1)
```

```
X_train, X_test, y_train, y_test = train_test_split(data.values,
target.values, test_size=0.2, random_state=42)
```

```
from typing import Dict

def accuracy_score_for_classes(
    y_true: np.ndarray,
    y_pred: np.ndarray) -> Dict[int, float]:
    """
    Вычисление метрики accuracy для каждого класса
    y_true - истинные значения классов
    y_pred - предсказанные значения классов
    Возвращает словарь: ключ - метка класса,
    значение - Accuracy для данного класса
    """
    # Для удобства фильтрации сформируем Pandas DataFrame
    d = {'t': y_true, 'p': y_pred}
    df = pd.DataFrame(data=d)
    # Метки классов
    classes = np.unique(y_true)
    # Результирующий словарь
    res = dict()
    # Перебор меток классов
    for c in classes:
        # отфильтруем данные, которые соответствуют
        # текущей метке класса в истинных значениях
        temp_data_flt = df[df['t']==c]
        # расчет accuracy для заданной метки класса
        temp_acc = accuracy_score(
            temp_data_flt['t'].values,
            temp_data_flt['p'].values)
        # сохранение результата в словарь
        res[c] = temp_acc
    return res

def print_accuracy_score_for_classes(
    y_true: np.ndarray,
    y_pred: np.ndarray):
    """
    Вывод метрики accuracy для каждого класса
    """
    accs = accuracy_score_for_classes(y_true, y_pred)
    if len(accs)>0:
        print('Метка \t Accuracy')
    for i in accs:
        print('{} \t {}'.format(i, accs[i]))
```

Логистическая регрессия

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import log_loss, accuracy_score

lg = LogisticRegression()
lg.fit(X_train, y_train.ravel())

LogisticRegression()

pred_y_test_proba = lg.predict_proba(X_test)
pred_y_test = np.argmax(pred_y_test_proba, axis=1)

print_accuracy_score_for_classes(y_test.ravel(), pred_y_test)

Метка       Accuracy
0     0.989242282507016
1     0.868421052631579

log_loss(y_test.ravel(), pred_y_test)

0.8074022103225739
```

SVM

```
from sklearn.svm import SVC, NuSVC, LinearSVC, OneClassSVM, SVR,
NuSVR, LinearSVR

def print_metrics_for_different_kernels(kernels, C):
    for kernel in kernels:
        svc = SVC(kernel=kernel, C=C, probability=True)
        svc.fit(X_train, y_train.ravel())

        pred_y_test_proba = svc.predict_proba(X_test)
        pred_y_test = np.argmax(pred_y_test_proba, axis=1)

        print('{}\nKernel \t {}'.format('='*10, kernel))

        print()
        print('Accuracy')
        print_accuracy_score_for_classes(y_test.ravel(), pred_y_test)
        print()

        log_loss_metric = log_loss(y_test.ravel(), pred_y_test)

        print('LgLoss \n{}'.format(log_loss_metric))
        print()
        print()

print_metrics_for_different_kernels(['poly', 'linear', 'rbf',
'sigmoid'], C=5)
```

```
==========
Kernel      poly

Accuracy
Метка       Accuracy
0     0.980355472404116
1     0.868421052631579

LgLoss
1.0968482857212323


==========
Kernel      linear

Accuracy
Метка       Accuracy
0     0.989242282507016
1     0.8596491228070176

LgLoss
0.8378702182592747


==========
Kernel      rbf

Accuracy
Метка       Accuracy
0     0.9897100093545369
1     0.8771929824561403

LgLoss
0.7617001984175225


==========
Kernel      sigmoid

Accuracy
Метка       Accuracy
0     0.999532273152479
1     0.0

LgLoss
3.488586908752252
```

Деревья решений

```
from sklearn.tree import DecisionTreeClassifier, export_graphviz

clf = DecisionTreeClassifier(random_state=1).fit(X_train,
y_train.ravel())

pred_y_test_proba = clf.predict_proba(X_test)
pred_y_test = np.argmax(pred_y_test_proba, axis=1)

print_accuracy_score_for_classes(y_test.ravel(), pred_y_test)
```

```
Метка       Accuracy
0      0.9831618334892422
1      0.881578947368421
```

```
log_loss(y_test.ravel(), pred_y_test)
```

```
0.9597422500060782
```

Важность признаков

```
sorted(list(zip(data.columns.values, clf.feature_importances_)),
key=lambda x: x[1], reverse=True)
```

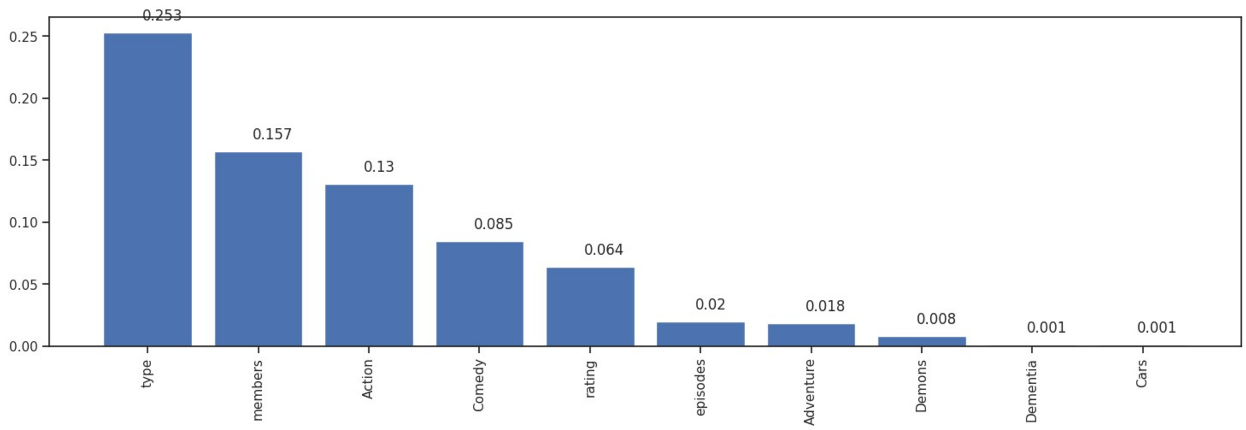
```
[('type', 0.2527704183313309),
 ('members', 0.15676888468880124),
 ('Action', 0.13043151984523027),
 ('Comedy', 0.08459507760958529),
 ('Drama', 0.06801037362106936),
 ('rating', 0.06382169379125198),
 ('Sci-Fi', 0.041008477242900916),
 ('Romance', 0.021820434812653947),
 ('episodes', 0.01976404648524759),
 ('Adventure', 0.018406162245900042),
 ('Slice of Life', 0.015427954579995988),
 ('Fantasy', 0.014505256822723554),
 ('Shounen', 0.013716738455562242),
 ('Mystery', 0.011128060612203339),
 ('Ecchi', 0.011105584899657269),
 ('Demons', 0.008260569522776577),
 ('Shoujo', 0.0075345502440438l),
 ('Music', 0.006301070869701497),
 ('Horror', 0.006251332476374522),
 ('Supernatural', 0.005863209981800086),
 ('Yuri', 0.005652866878554096),
 ('Military', 0.004976427975172386),
 ('Mecha', 0.004937906598608942),
 ('Magic', 0.004878675236535766),
 ('Kids', 0.004697779665013315),
 ('Psychological', 0.004031426089029916 5),
```

```
('Historical', 0.003432532525161955),
('Harem', 0.002115436330680849),
('Super Power', 0.0020084065670003823),
('Dementia', 0.0012262061568416598),
('Cars', 0.0012226519360972077),
('Parody', 0.001199002668913009),
('School', 0.0007928491034076275),
('Sports', 0.0006083677575086863),
('Martial Arts', 0.0003161198545848669),
('Yaoi', 0.00023988950197801 61),
('Police', 0.00017203801610060537),
('Game', 0.0),
('Josei', 0.0),
('Samurai', 0.0),
('Seinen', 0.0),
('Shoujo Ai', 0.0),
('Shounen Ai', 0.0),
('Space', 0.0),
('Thriller', 0.0),
('Vampire', 0.0)]
```

```
from operator import itemgetter

def draw_feature_importances(tree_model, X_dataset, top_feature_num=5,
figsize=(18,5)):
    """
    Вывод важности признаков в виде графика
    """
    # Сортировка значений важности признаков по убыванию
    list_to_sort = list(zip(X_dataset.columns.values,
tree_model.feature_importances_))[:top_feature_num]
    sorted_list = sorted(list_to_sort, key=itemgetter(1), reverse =
True)[:top_feature_num]
    # Названия признаков
    labels = [x for x,_ in sorted_list]
    # Важности признаков
    data = [x for _,x in sorted_list]
    # Вывод графика
    fig, ax = plt.subplots(figsize=figsize)
    ind = np.arange(len(labels))
    plt.bar(ind, data)
    plt.xticks(ind, labels, rotation='vertical')
    # Вывод значений
    for a,b in zip(ind, data):
        plt.text(a-0.05, b+0.01, str(round(b,3)))
    plt.show()
    return labels, data

labels, importance = draw_feature_importances(clf, data,
top_feature_num=10 )
```



Визуализация

```
import graphviz
from sklearn import tree

clf.classes_

array([0, 1])

class_names = ['No Hentai', 'Hentai']

tree.export_graphviz(clf, out_file='desision_tree.dot',
                           feature_names=data.columns.values.tolist(),

                           class_names=class_names,
                           filled=True, rounded=True,
special_characters=True)

dot_data = export_graphviz(clf, out_file=None,
                           feature_names=data.columns.values.tolist(),

                           class_names=class_names,
                           filled=True, rounded=True,
special_characters=True)
graph = graphviz.Source(dot_data)
graph
```