## Московский государственный технический университет им. Н.Э. Баумана Факультет «Информатика и системы управления» Кафедра «Системы обработки информации и управления»



## **Лабораторная работа №4** по курсу «Методы машинного обучения»

«Создание рекомендательной модели»

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"_	_"_	2022 г.

ИСПОЛНИТЕЛЬ:

**import** numpy **as** np **import** pandas **as** pd

from typing import Dict, Tuple

from scipy import stats

from IPython.display import Image

from IPython.display import Image

from sklearn.feature\_extraction.text import CountVectorizer, TfidfVectorizer

from sklearn.datasets import load iris, load boston

from sklearn.model\_selection import cross\_val\_score

from sklearn model selection import train test split

from sklearn.neighbors import KNeighborsRegressor, KNeighborsClassifier

from sklearn.model\_selection import GridSearchCV, RandomizedSearchCV

from sklearn.metrics import accuracy score, balanced\_accuracy\_score

from sklearn.metrics import precision\_score, recall\_score, f1\_score, classification\_report

from sklearn.metrics import confusion matrix

from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor, export\_graphviz

from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor

from sklearn.ensemble import ExtraTreesClassifier, ExtraTreesRegressor

from sklearn.ensemble import GradientBoostingClassifier, GradientBoostingRegressor

from sklearn.ensemble import BaggingClassifier

from sklearn.ensemble import AdaBoostClassifier

from sklearn.metrics import mean\_absolute\_error, mean\_squared\_error, mean\_squared\_log\_error, median\_absolute\_error, r2\_score

from sklearn.metrics import roc curve, roc auc score

from sklearn.metrics.pairwise import cosine\_similarity, euclidean\_distances, manhattan\_distances

from collections import defaultdict

import seaborn as sns

import matplotlib.pyplot as plt

from matplotlib\_venn import venn2

%matplotlib inline

sns.set(style="ticks")

In [3]:

from google.colab import drive
drive.mount('/content/drive')

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force\_remount=True).

## Чтение и обработка данных

In [4]:

data = pd.read\_csv('/content/drive/MyDrive/Colab Notebooks/winemag-data-130k-v2.csv') data.head()

													Out	ıt[4]:
	Unnamed: 0	country	description	designation	points	price	province	region_1	region_2	taster_name	taster_twitter_handle	title	variety	1
0	0	Italy	Aromas include tropical fruit, broom, brimston	Vulkà Bianco	87	NaN	Sicily & Sardinia	Etna	NaN	Kerin O'Keefe	@kerinokeefe	Nicosia 2013 Vulkà Bianco (Etna)	White Blend	1
1	1	Portugal	This is ripe and fruity, a wine that is smooth	Avidagos	87	15.0	Douro	NaN	NaN	Roger Voss	@vossroger	Quinta dos Avidagos 2011 Avidagos Red (Douro)	Portuguese Red	Αv
2	2	US	Tart and snappy, the flavors of lime flesh and	NaN	87	14.0	Oregon	Willamette Valley	Willamette Valley	Paul Gregutt	@paulgwine	Rainstorm 2013 Pinot Gris (Willamette Valley)	Pinot Gris	Rai
3	3	US	Pineapple rind, lemon pith and orange blossom	Reserve Late Harvest	87	13.0	Michigan	Lake Michigan Shore	NaN	Alexander Peartree	NaN	St. Julian 2013 Reserve Late Harvest Riesling	Riesling	St
4	4	US	Much like the regular bottling from 2012, this	Vintner's Reserve Wild Child Block	87	65.0	Oregon	Willamette Valley	Willamette Valley	Paul Gregutt	@paulgwine	Sweet Cheeks 2012 Vintner's Reserve Wild Child	Pinot Noir	C

In [5]

```
Out[5]:
(129971, 14)
                                                                                                                                                         In [6]:
 description_data = data[data['description'].notnull()]
 description_data.shape
                                                                                                                                                        Out[6]:
(129971, 14)
                                                                                                                                                        In [7]:
 title = description_data['title'].values
 title[0:5]
                                                                                                                                                        Out[7]:
array(['Nicosia 2013 Vulkà Bianco (Etna)',
    'Quinta dos Avidagos 2011 Avidagos Red (Douro)',
    'Rainstorm 2013 Pinot Gris (Willamette Valley)',
    'St. Julian 2013 Reserve Late Harvest Riesling (Lake Michigan Shore)',
    "Sweet Cheeks 2012 Vintner's Reserve Wild Child Block Pinot Noir (Willamette Valley)"],
   dtype=object)
                                                                                                                                                         In [8]:
 descriptions = description_data['description'].values
 descriptions[0:5]
                                                                                                                                                        Out[8]:
array(["Aromas include tropical fruit, broom, brimstone and dried herb. The palate isn't overly expressive, offering unripened apple, citrus and dried sage alon
gside brisk acidity.",
    "This is ripe and fruity, a wine that is smooth while still structured. Firm tannins are filled out with juicy red berry fruits and freshened with acidity. It's alre
ady drinkable, although it will certainly be better from 2016.",
    'Tart and snappy, the flavors of lime flesh and rind dominate. Some green pineapple pokes through, with crisp acidity underscoring the flavors. The wine
was all stainless-steel fermented.',
    'Pineapple rind, lemon pith and orange blossom start off the aromas. The palate is a bit more opulent, with notes of honey-drizzled guava and mango givi
ng way to a slightly astringent, semidry finish.',
    "Much like the regular bottling from 2012, this comes across as rather rough and tannic, with rustic, earthy, herbal characteristics. Nonetheless, if you thin
k of it as a pleasantly unfussy country wine, it's a good companion to a hearty winter stew."],
   dtype=object)
                                                                                                                                                         In [9]:
 description_data.keys()
                                                                                                                                                        Out[9]:
Index(['Unnamed: 0', 'country', 'description', 'designation', 'points',
    'price', 'province', 'region_1', 'region_2', 'taster_name',
    'taster_twitter_handle', 'title', 'variety', 'winery'],
   dtype='object')
                                                                                                                                                       In [10]:
 wine_ids = description_data['Unnamed: 0'].values
 wine_ids
                                                                                                                                                      Out[10]:
array([
                    2, ..., 129968, 129969, 129970])
                                                                                                                                                       In [11]:
 %%time
 tfidf = TfidfVectorizer()
 description_matrix = tfidf.fit_transform(descriptions)
 description_matrix
CPU times: user 3.55 s, sys: 42.3 ms, total: 3.59 s
Wall time: 3.61 s
                                                                                                                                                       In [12]:
 description_matrix
                                                                                                                                                      Out[12]:
<129971x31275 sparse matrix of type '<class 'numpy.float64'>'
with 4475479 stored elements in Compressed Sparse Row format>
Фильтрация на основе содержания. Метод к-ближайших соседей
                                                                                                                                                       In [13]:
 class SimplerKnnRecomender:
  def __init__(self, X_matrix, X_ids, X_title, X_overview):
      Входные параметры:
     X_matrix - обучающая выборка (матрица объект-признак)
     X ids - массив идентификаторов объектов
```

```
X_title - массив названий объектов
     X_overview - массив описаний объектов
     #Сохраняем параметры в переменных объекта
     self._X_matrix = X_matrix
     self.df = pd.DataFrame(
        {'id': pd.Series(X ids, dtype='int'),
        'title': pd.Series(X_title, dtype='str'),
        'overview': pd.Series(X_overview, dtype='str'),
        'dist': pd.Series([], dtype='float')})
  def recommend_for_single_object(self, K: int, \
          X_matrix_object, cos_flag = True, manh_flag = False):
     Метод формирования рекомендаций для одного объекта.
     Входные параметры:
     К - количество рекомендуемых соседей
     X matrix object - строка матрицы объект-признак, соответствующая объекту
     cos_flag - флаг вычисления косинусного расстояния
     manh_flag - флаг вычисления манхэттэнского расстояния
     Возвращаемое значение: К найденных соседей
     scale = 1000000
     # Вычисляем косинусную близость
     if cos flag:
        dist = cosine similarity(self. X matrix, X matrix object)
        self.df['dist'] = dist * scale
        res = self.df.sort values(by='dist', ascending=False)
        # Не учитываем рекомендации с единичным расстоянием,
        # так как это искомый объект
        res = res[res['dist'] < scale]
     else:
        if manh_flag:
          dist = manhattan_distances(self._X_matrix, X_matrix_object)
          dist = euclidean_distances(self._X_matrix, X_matrix_object)
        self.df['dist'] = dist * scale
        res = self.df.sort values(by='dist', ascending=True)
        # Не учитываем рекомендации с единичным расстоянием,
        # так как это искомый объект
        res = res[res['dist'] > 0.0]
     # Оставляем К первых рекомендаций
     res = res.head(K)
     return res
                                                                                                                                                 In [14]:
test id = 11
print(title[test id])
print(descriptions[test_id])
Leon Beyer 2012 Gewurztraminer (Alsace)
This is a dry wine, very spicy, with a tight, taut texture and strongly mineral character layered with citrus as well as pepper. It's a food wine with its almost cris
p aftertaste.
                                                                                                                                                 In [15]:
test_matrix = description_matrix[test_id]
test_matrix
                                                                                                                                                Out[15]:
<1x31275 sparse matrix of type '<class 'numpy.float64'>'
with 25 stored elements in Compressed Sparse Row format>
                                                                                                                                                 In [16]:
skr1 = SimplerKnnRecomender(description matrix, wine ids, title, descriptions)
                                                                                                                                                 In [17]:
# 15 вин, наиболее похожих на Leon Beyer 2012 Gewurztraminer (Alsace)
# в порядке убывания схожести на основе косинусного сходства
rec1 = skr1.recommend_for_single_object(15, test_matrix)
```

rec1

dist	overview	title	id	
1000000.000000	This is a dry wine, very spicy, with a tight,	Leon Beyer 2012 Gewurztraminer (Alsace)	102760	102760
1000000.000000	This is a dry wine, very spicy, with a tight,	Leon Beyer 2012 Gewurztraminer (Alsace)	11	11
633624.990866	The wine is textured and tight with crisp acid	Domaine Michel Thomas et Fils 2015 Rosé (Sance	24045	24045
442624.176096	This wine is still tight and crisp. It has ple	Henri de Villamont 2014 Morgeot Premier Cru (	90700	90700
432556.705703	The wine is tight and nervy, very fresh, crisp	Schröder & Schÿler 2013 Chartron la Fleur (Bo	58330	58330
430242.028148	This taut and structured wine has weight as we	Maison Champy 2014 Viré-Clessé	66081	66081
428504.458538	This wine is tight, structured and taut. Still	Domaine Olivier Merlin 2014 Mâcon La Roche Vi	78572	78572
425886.605501	This rich and ripe wine is full of apricot and	Domaine Nigri 2013 Pierre de Lune (Jurançon Sec)	105230	105230
424385.444731	Tight and structured, this wine has minerality	Louis Max 2014 Mâcon-Villages	25907	25907
423757.525560	This crisp wine offers plenty of acidity as we	Joseph Drouhin 2013 Les Clos (Macon-Bussières)	99011	99011
421592.529700	Ripe Alvarinho gives a wine that is rich as we	Aveleda 2015 Alvarinho (Vinho Verde)	5406	5406
418388.507228	Very herbaceous in character, this is a wine t	Maison Malet Roquefort 2012 Léo de la Gaffeliè	22652	22652
416866.789965	Intensely peppery as well as fruity, this is a	Boeckel 2012 Vieilles Vignes Sylvaner (Alsace)	129715	129715
416866.789965	Intensely peppery as well as fruity, this is a	Boeckel 2012 Vieilles Vignes Sylvaner (Alsace)	119482	119482
411434.544994	This is crisp, fruity with apple and citrus fl	Moncigale 2014 Frais et Délicat Rosé (Coteaux	21920	21920

#При поиске с помощью Евклидова расстояния получаем такой же результат rec2 = skr1.recommend\_for\_single\_object(15, test\_matrix, cos\_flag = False) rec2

	id	title	overview	dist
24045	24045	Domaine Michel Thomas et Fils 2015 Rosé (Sance	The wine is textured and tight with crisp acid	8.560082e+05
90700	90700	Henri de Villamont 2014 Morgeot Premier Cru (	This wine is still tight and crisp. It has ple	1.055818e+06
58330	58330	Schröder & Schÿler 2013 Chartron la Fleur (Bo	The wine is tight and nervy, very fresh, crisp	1.065311e+06
66081	66081	Maison Champy 2014 Viré-Clessé	This taut and structured wine has weight as we	1.067481e+06
78572	78572	Domaine Olivier Merlin 2014 Mâcon La Roche Vi	This wine is tight, structured and taut. Still	1.069108e+06
105230	105230	Domaine Nigri 2013 Pierre de Lune (Jurançon Sec)	This rich and ripe wine is full of apricot and	1.071553e+06
25907	25907	Louis Max 2014 Mâcon-Villages	Tight and structured, this wine has minerality	1.072953e+06
99011	99011	Joseph Drouhin 2013 Les Clos (Macon-Bussières)	This crisp wine offers plenty of acidity as we	1.073539e+06
5406	5406	Aveleda 2015 Alvarinho (Vinho Verde)	Ripe Alvarinho gives a wine that is rich as we	1.075553e+06
22652	22652	Maison Malet Roquefort 2012 Léo de la Gaffeliè	Very herbaceous in character, this is a wine t	1.078528e+06
119482	119482	Boeckel 2012 Vieilles Vignes Sylvaner (Alsace)	Intensely peppery as well as fruity, this is a	1.079938e+06
129715	129715	Boeckel 2012 Vieilles Vignes Sylvaner (Alsace)	Intensely peppery as well as fruity, this is a	1.079938e+06
21920	21920	Moncigale 2014 Frais et Délicat Rosé (Coteaux	This is crisp, fruity with apple and citrus fl	1.084957e+06
92292	92292	Domaine Alban Roblin 2014 Rosé (Sancerre)	This is a fresh wine with caramel as well as r	1.087210e+06
96505	96505	Domaine Alban Roblin 2014 Rosé (Sancerre)	This is a fresh wine with caramel as well as r	1.087210e+06

# Манхэт тэнское расстояние дает несколько иные результаты поиска rec3 = skr1.recommend\_for\_single\_object(15, test\_matrix, cos\_flag = False, manh\_flag = True) rec3

In [18]:

Out[18]:

In [19]:

	id	title	overview	dist
24045	24045	Domaine Michel Thomas et Fils 2015 Rosé (Sance	The wine is textured and tight with crisp acid	3.865262e+06
22652	22652	Maison Malet Roquefort 2012 Léo de la Gaffeliè	Very herbaceous in character, this is a wine t	5.251729e+06
35502	35502	Château de Piote 2012 Perles (Crémant de Bord	Tight and sharp, this is an herbaceous wine wi	5.312967e+06
58330	58330	Schröder & Schÿler 2013 Chartron la Fleur (Bo	The wine is tight and nervy, very fresh, crisp	5.316624e+06
25907	25907	Louis Max 2014 Mâcon-Villages	Tight and structured, this wine has minerality	5.354298e+06
21920	21920	Moncigale 2014 Frais et Délicat Rosé (Coteaux	This is crisp, fruity with apple and citrus fl	5.452536e+06
97201	97201	Ravoire et Fils 2013 Domaine la Rabiotte Rosé	Tight, zingy and crisp, this wine has fresh, c	5.535851e+06
70762	70762	Château du Seuil 2015 Domaine du Seuil (Borde	The wine is tight and mineral in character. It	5.564448e+06
128577	128577	Ravoire et Fils 2014 Domaine Bel Eouve Rosé (C	This is a tangy, spicy wine, a character that	5.628584e+06
78572	78572	Domaine Olivier Merlin 2014 Mâcon La Roche Vi	This wine is tight, structured and taut. Still	5.644448e+06
92292	92292	Domaine Alban Roblin 2014 Rosé (Sancerre)	This is a fresh wine with caramel as well as r	5.653916e+06
96505	96505	Domaine Alban Roblin 2014 Rosé (Sancerre)	This is a fresh wine with caramel as well as r	5.653916e+06
108912	108912	Quinta do Portal 2012 Colheita Rosé (Douro)	This rosé is almost as rich as a red wine, the	5.701024e+06
66081	66081	Maison Champy 2014 Viré-Clessé	This taut and structured wine has weight as we	5.734040e+06

## Коллаборативная фильтрация. Метод на основе сингулярного разложения

Markus Huber 2009 Hugo Grüner Veltliner (Niede...

In [20]:

Out[19]:

data.head()

88898

88898

													Out[	20]:
	Unnamed: 0	country	description	designation	points	price	province	region_1	region_2	taster_name	taster_twitter_handle	title	variety	1
0	0	Italy	Aromas include tropical fruit, broom, brimston	Vulkà Bianco		NaN	Sicily & Sardinia	Etna	NaN	Kerin O'Keefe	@kerinokeefe	Nicosia 2013 Vulkà Bianco (Etna)	White Blend	ı
1	1	Portugal	This is ripe and fruity, a wine that is smooth	Avidagos	87	15.0	Douro	NaN	NaN	Roger Voss	@vossroger	Quinta dos Avidagos 2011 Avidagos Red (Douro)	Portuguese Red	Αv
2	2	US	Tart and snappy, the flavors of lime flesh and	NaN	87	14.0	Oregon	Willamette Valley	Willamette Valley	Paul Gregutt	@paulgwine	Rainstorm 2013 Pinot Gris (Willamette Valley)	Pinot Gris	Rai
3	3	US	Pineapple rind, lemon pith and orange blossom	Reserve Late Harvest		13.0	Michigan	Lake Michigan Shore	NaN	Alexander Peartree	NaN	St. Julian 2013 Reserve Late Harvest Riesling	Riesling	St
4	4	US	Much like the regular bottling from 2012, this	Vintner's Reserve Wild Child Block	87	65.0	Oregon	Willamette Valley	Willamette Valley	Paul Gregutt	@paulgwine	Sweet Cheeks 2012 Vintner's Reserve Wild Child	Pinot Noir	(

Very crisp fruit, with light acidity and a tau... 5.751297e+06

data3 = data[30000:55000]

In [21]:

# Количество уникальных дегустаторов len(data3['taster\_name'].unique())

In [22]:

Out[22]:

20

In [23]:

In [24]:

```
# Сформируем матрицу взаимодействий на основе рейтингов
# Используется идея из статьи - https://towardsdatascience.com/beginners-guide-to-creating-an-svd-recommender-system-1fd7326d1f65
def create utility matrix(data):
  itemField = 'title'
  userField = 'taster_name'
  valueField = 'points'
  userList = data[userField].tolist()
  itemList = data[itemField].tolist()
  valueList = data[valueField].tolist()
  users = list(set(userList))
  items = list(set(itemList))
  users_index = {users[i]: i for i in range(len(users))}
  pd_dict = {item: [0.0 for i in range(len(users))] for item in items}
  for i in range(0,data.shape[0]):
    item = itemList[i]
    user = userList[i]
    value = valueList[i]
    pd_dict[item][users_index[user]] = value
  X = pd.DataFrame(pd_dict)
  X.index = users
  itemcols = list(X.columns)
  items_index = {itemcols[i]: i for i in range(len(itemcols))}
```

%%time

user\_item\_matrix, users\_index, items\_index = create\_utility\_matrix(data3)

CPU times: user 762 ms, sys: 11.1 ms, total: 773 ms

return X, users index, items index

Wall time: 777 ms

In [26]:

In [25]:

user item matrix

Out[26]:

	Dão Sul 2006 Berço do Infante Red (Estremadura)	Lemelson 2009 Dry Riesling (Willamette Valley)	Jasper Hill 2014 Georgia's Paddo's Shiraz (Heathcote)	Bowers Harbor 2013 Langley Late Harvest Riesling (Old Mission Peninsula)	Stadt Krems 2012 Steinterrassen Riesling (Kremstal)	Youngberg Hill Vineyards 2012 Pinot Blanc (McMinnville)	Jaffurs 2013 Grenache (Santa Barbara County)	Pratsch 2012 Steinberg Grüner Veltliner (Niederösterreich)	Hunnicutt 2006 Zinfandel (Napa Valley)	Château Guilhem 2015 Pot de Vin Syrah Rosé (Pays d'Oc)	 Dão St 200 Quinta d Encontr Pret Branc Bag (Bairrada
NaN	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	92.0	0.0	 0.
Anna Lee C. Iijima	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.
Sean P. Sullivan	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.
Joe Czerwinski	0.0	0.0	91.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.
Alexander Peartree	0.0	0.0	0.0	88.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.
Lauren Buzzeo	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	83.0	 0.
Kerin O'Keefe	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.
Michael Schachner	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.
Susan Kostrzewa	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.
Fiona Adams	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.
Anne Krebiehl MW	0.0	0.0	0.0	0.0	0.0	0.0	0.0	92.0	0.0	0.0	 0.
Matt Kettmann	0.0	0.0	0.0	0.0	0.0	0.0	92.0	0.0	0.0	0.0	 0.
Carrie Dykes	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.
Jim Gordon	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.
Roger Voss	87.0	0.0	0.0	0.0	89.0	0.0	0.0	0.0	0.0	0.0	 88.
Mike DeSimone	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.
Virginie Boone	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.
Paul Gregutt	0.0	91.0	0.0	0.0	0.0	86.0	0.0	0.0	0.0	0.0	 0.
Christina Pickard	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.
Jeff Jenssen	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.

20 rows × 24517 columns

# Выделение тестовой строки

0.0

0.0

0.0

user\_item\_matrix\_\_test = user\_item\_matrix.loc[['Kerin O'Keefe']]
user\_item\_matrix\_\_test

										C	Out[27	]:
Dão Sul 2006 Berço do Infante Red (Estremadura)	Lemelson 2009 Dry Riesling (Willamette Valley)	Jasper Hill 2014 Georgia's Paddock Shiraz (Heathcote)	Bowers Harbor 2013 Langley Late Harvest Riesling (Old Mission Peninsula)	Stadt Krems 2012 Steinterrassen Riesling (Kremstal)	Youngberg Hill Vineyards 2012 Pinot Blanc (McMinnville)	Jaffurs 2013 Grenache (Santa Barbara County)	Pratsch 2012 Steinberg Grüner Veltliner (Niederösterreich)	Hunnicutt 2006 Zinfandel (Napa Valley)	Château Guilhem 2015 Pot de Vin Syrah Rosé (Pays d'Oc)	Quinta Enco ••• P Bra	ntro Preto anco Baga	V Z  (I

0.0

1 rows × 24517 columns

0.0

Kerin

O'Keefe

In [28]:

0.0

0.0

0.0

0.0

0.0 ...

0.0

<u>▶</u> In [27]:

taster\_names = np.delete(data3['taster\_name'].unique(), 0)
taster\_names = np.delete(taster\_names, 7)
taster\_names

Out[28]:

In [29]:

# Оставшаяся часть матрицы для обучения
user\_item\_matrix\_\_train = user\_item\_matrix.loc[taster\_names]
user\_item\_matrix\_\_train

Out[29]: **Bowers** Château Harbor Dão Sul Guilhem Jasper Hill 2013 **Jaffurs** Youngberg 2004 Lemelson Stadt Krems Hunnicutt 2015 Dão Sul 2006 Pratsch 2012 2014 Hill 2013 Quinta do Langley 2009 Dry 2012 2006 Pot de Steinberg Grüner Veltliner Vinevards Berço do Georgia's Grenache **Encontro** Late Riesling Steinterrassen Zinfandel Vin Infante Red Harvest 2012 Pinot Preto Paddock (Santa Riesling (Willamette (Napa Syrah Riesling (Niederösterreich) (Estremadura) Shiraz Blanc Barbara **Branco** Valley) (Kremstal) Valley) Rosé (Heathcote) (McMinnville) County) (Old Baga (Pays Mission (Bairrada) d'Oc) Peninsula) Jim 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 Gordon Michael 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 ... Schachner Matt 0.0 0.0 0.0 0.0 0.0 0.0 92.0 0.0 0.0 0.0 ... 0.0 Kettmann Sean P. 0.0 0.0 0.0 0.0 0.0 0.0 ... 0.0 0.0 0.0 0.0 0.0 Sullivan Roger 87.0 0.0 0.0 0.0 89.0 0.0 0.0 0.0 0.0 0.0 ... 88.0 Voss Virginie 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 ... 0.0 Boone Joe 0.0 0.0 91.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 ... 0.0 Czerwinski Paul 0.0 91.0 0.0 0.0 0.0 86.0 0.0 0.0 0.0 0.0 ... 0.0 Gregutt Mike 0.0 0.0 0.0 0.0 0.0 ... 0.0 0.0 0.0 0.0 0.0 0.0 **DeSimone** Jeff 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 Jenssen NaN 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 92.0 0.0 ... 0.0 Anna Lee 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 ... C. lijima Susan 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 ... 0.0 Kostrzewa Lauren 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 83.0 ... 0.0 Buzzeo Alexander 0.0 0.0 0.0 88.0 0.0 0.0 0.0 0.0 0.0 0.0 ... 0.0 Peartree Fiona 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 ... 0.0 **Adams** 

18 rows × 24517 columns

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%%time

Carrie

Dykes Christina

Pickard

U, S, VT = np.linalg.svd(user\_item\_matrix\_\_train.T) V = VT.T

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· - · · ·

CPU times: user 33.7 s, sys: 3.38 s, total: 37.1 s Wall time: 23.2 s

In [31]:

0.0

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```
# Матрица соотношения между дегустаторами и латентными факторами
 U.shape
                                                                                                                                                          Out[31]:
(24517, 24517)
                                                                                                                                                           In [32]:
 # Матрица соотношения между объектами и латентными факторами
V.shape
                                                                                                                                                          Out[32]:
(18, 18)
                                                                                                                                                           In [33]:
S.shape
                                                                                                                                                          Out[33]:
(18,)
                                                                                                                                                           In [34]:
 Sigma = np.diag(S)
Sigma.shape
                                                                                                                                                          Out[34]:
(18, 18)
                                                                                                                                                           In [35]:
 # Диагональная матрица сингулярных значений
Sigma
                                                                                                                                                          Out[35]:
array([[6328.37615756,
                          0.
                                     0.
                                               0.
       0.
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                                   , 3880.90866797,
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     3683.95055254.
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                825.2545062,
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     177.03107072,
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                           0.
                                     0.
       0.
               124.45882853]])
                                                                                                                                                         In [36]:
 # Используем 3 первых сингулярных значения
r=3
 Ur = U[:, :r]
 Sr = Sigma[:r, :r]
 Vr = V[:, :r]
 # Матрица соотношения между новым дегустатором и латентными факторами
 test_user = np.mat(user_item_matrix__test.values)
test_user.shape, test_user
                                                                                                                                                        Out[36]:
((1, 24517), matrix([[0., 0., 0., ..., 0., 0., 0.]]))
                                                                                                                                                         In [37]:
tmp = test_user * Ur * np.linalg.inv(Sr)
tmp
                                                                                                                                                        Out[37]:
matrix([[ 3.78394162e-04, -4.35827216e-06, -2.92218350e-18]])
                                                                                                                                                         In [38]:
test\_user\_result = np.array([tmp[0,0], tmp[0,1], tmp[0,2]])
test_user_result
                                                                                                                                                        Out[38]:
array([ 3.78394162e-04, -4.35827216e-06, -2.92218350e-18])
                                                                                                                                                         In [39]:
 # Вычисляем косинусную близость между текущим дегустатором
 # и остальными дегустаторами
 cos_sim = cosine_similarity(Vr, test_user_result.reshape(1, -1))
cos_sim[:10]
```

0.

0.

0.

0.

```
Out[39]:
array([[ 9.99999728e-01],
    [-1.44541469e-18],
    [ 3.53594407e-33],
    [3.06381034e-35],
    [-4.12491330e-04],
    [9.9999975e-01],
    [0.0000000e+00].
    [-1.04994959e-03],
    [0.00000000e+00],
    [0.00000000e+00]])
                                                                                                                                                  In [40]:
 # Преобразуем размерность массива
cos_sim_list = cos_sim.reshape(-1, cos_sim.shape[0])[0]
cos_sim_list[:10]
                                                                                                                                                 Out[40]:
array([ 9.99999728e-01, -1.44541469e-18, 3.53594407e-33, 3.06381034e-35,
    -4.12491330e-04, 9.99999975e-01, 0.00000000e+00, -1.04994959e-03,
    0.0000000e+00, 0.0000000e+00])
                                                                                                                                                  In [41]:
 # Находим наиболее близкого дегустатора
recommended_user_id = np.argsort(-cos_sim_list)[0]
recommended_user_id
                                                                                                                                                 Out[41]:
5
                                                                                                                                                  In [42]:
test_user
                                                                                                                                                 Out[42]:
matrix([[0., 0., 0., ..., 0., 0., 0.]])
                                                                                                                                                  In [43]:
 # Получение названия вина
wine_list = list(user_item_matrix.columns)
 def film_name_by_movieid(ind):
   try:
     wine = wine list[ind]
      #print(wineld)
     #flt_links = data3[data['movield'] == wineld]
     #tmdbld = int(flt_links['tmdbld'].values[0])
     #md_links = df_md[df_md['id'] == tmdbld]
     #res = md_links['title'].values[0]
     return wine
   except:
     return "
                                                                                                                                                  In [44]:
 # Вина, которые оценивал текущий дегустатор:
for idx, item in enumerate(np.ndarray.flatten(np.array(test_user))):
   if item > 0:
     film_title = film_name_by_movieid(idx)
     print('{} - {} - {}'.format(idx, film_title, item))
     if i==20:
        break
     else:
        i+=1
```

```
137 - Castelfeder 2012 Glener Pinot Nero (Alto Adige) - 88.0
146 - La Vis 2012 L'Altro Manzoni Incrocio Manzoni (Vigneti delle Dolomiti) - 87.0
164 - Cascina Luisin 2012 Paolin (Barbaresco) - 88.0
171 - Germano Ettore 2012 del Comune di Serralunga d'Alba (Barolo) - 91.0
203 - Stemmari 2012 Nero d'Avola (Terre Siciliane) - 86.0
224 - Castelli del Grevepesa 2009 Riserva Castello di Bibbione (Chianti Classico) - 90.0
226 - Pieropan 2009 Le Colombare (Recioto di Soave) - 90.0
259 - Villa Calcinaia 2012 Chianti Classico - 89.0
# Вина, ко торые оценивал наиболее схожий дегустатор:
recommended user item matrix = user item matrix.loc[['Roger Voss']]
for idx, item in enumerate(np.ndarray.flatten(np.array(recommended_user_item_matrix))):
   if item > 0:
     film_title = film_name_by_movieid(idx)
     print('{} - {} - {}'.format(idx, film_title, item))
     if i==20:
        break
     else:
        i+=1
0 - Dão Sul 2006 Berco do Infante Red (Estremadura) - 87.0
4 - Stadt Krems 2012 Steinterrassen Riesling (Kremstal) - 89.0
13 - Deco Provence - Villa Azur 2015 Rosé (Coteaux Varois en Provence) - 85.0
25 - Vignerons de Bel Air 2010 Hiver Gourmand (Morgon) - 86.0
29 - Cave du Marmandais 2011 Château Terrebert Malbec (Côtes du Marmandais) - 87.0
41 - Quinta Nova de Nossa Senhora do Carmo 2008 Referencia Grand Reserva Red (Douro) - 91.0
44 - Herdade do Perdigão 2009 Terras de Monforte Red (Alentejo) - 88.0
48 - Château L'Argilus du Roi 2011 Saint-Estèphe - 83.0
49 - Manuel Olivier 2010 Bourgogne - 85.0
53 - Château Paradis 2010 Red (Coteaux d'Aix-en-Provence) - 91.0
54 - Bernard Magrez 2011 Château du Galan (Haut-Médoc) - 90.0
55 - Quinta do Tedo 2009 Savedra Vintage (Port) - 90.0
63 - Domaine du Coudray 2015 Une Pointe d'Authenticité (Quincy) - 90.0
66 - Domaine des Cognettes 2005 Tentation Sélection Vieilles Vignes (Muscadet Sèvre et Maine) - 91.0
69 - Les Héritiers du Comte Lafon 2013 Viré-Clessé - 90.0
71 - Herdade dos Machados 2013 Santos Jorge Red (Alentejo) - 87.0
88 - Château Lafite Rothschild 2014 Carruades de Lafite (Pauillac) - 94.0
92 - Domaine Méo-Camuzet 2013 Gevrey-Chambertin - 90.0
100 - Château de Fuissé 2009 Tête de Cru (Pouilly-Fuissé) - 91.0
105 - Salomon-Undhof 2012 Hochterrassen Grüner Veltliner (Niederösterreich) - 85.0
Как видно, фильтрация на основе содержания и коллаборативная фильтрация показывают различные результаты работы в рамках
```

10 - Molino di Sant'Antimo 2010 Brunello di Montalcino - 93.0

106 - Feudo Principi di Butera 2015 Nero d'Avola (Sicilia) - 88.0

116 - Canella 2014 Extra Dry (Valdobbiadene Prosecco Superiore) - 89.0 124 - Conte Collalto NV Brut (Valdobbiadene Prosecco Superiore) - 89.0 126 - Rascioni e Cecconello 2015 Maremmino (Maremma) - 88.0

20 - Ca'Romè 2012 Chiaramanti (Barbaresco) - 88.0 32 - Nicolucci 2015 Tre Rocche Sangiovese (Romagna) - 88.0 39 - Dorigo 2013 Ribolla Gialla (Colli Orientali del Friuli) - 91.0 79 - Colutta 2013 Pinot Grigio (Colli Orientali del Friuli) - 88.0

87 - Poggio Scalette 2014 Chianti Classico - 88.0

18 - Feudi di San Gregorio 2013 Studi Campo Aperto (Fiano di Avellino) - 93.0

17 - Borgogno 2015 Dolcetto d'Alba - 89.0

рекомендательных систем

In [45]: