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

Лабораторная работа №2
по дисциплине
«Методы машинного обучения»
на тему
«Изучение библиотек обработки данных.»

Выполнил:
студент группы ИУ5-23М
Богомолов Д.Н.

Москва — 2020 г.

```
pip install pyreadline
```

```
Collecting pyreadline
  Downloading https://files.pythonhosted.org/packages/bc/7c/d724ef1ec3ab2125f38a1d532
     |████████████████████████████████| 112kB 3.4MB/s
Building wheels for collected packages: pyreadline
  Building wheel for pyreadline (setup.py) ... done
  Created wheel for pyreadline: filename=pyreadline-2.1-cp36-none-any.whl size=93834
  Stored in directory: /root/.cache/pip/wheels/70/66/59/590265c96902c7616243300c8f0d8
Successfully built pyreadline
Installing collected packages: pyreadline
Successfully installed pyreadline-2.1
```

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

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarnin
  import pandas.util.testing as tm
```

```
data = pd.read_csv("/content/drive/My Drive/survey.csv")
data.head()
```

	Timestamp	Age	Gender	Country	state	self_employed	family_history	treatment
0	2014-08-27 11:29:31	37	Female	United States	IL	NaN	No	Yes
1	2014-08-27 11:29:37	44	M	United States	IN	NaN	No	No
2	2014-08-27 11:29:44	32	Male	Canada	NaN	NaN	No	No
3	2014-08-27 11:29:46	31	Male	United Kingdom	NaN	NaN	Yes	Yes
4	2014-08-27 11:30:22	31	Male	United States	TX	NaN	No	No

```
data.shape # мы увидим информацию о размерности нашего датафрейма
data.info() # покажет информацию о размерности данных
          # описание индекса, количество not-a-number элементов
data.describe() # показывает статистики count,mean, std, min, 25%-50%-75% percentile,
data.nunique() # количество уникальных значений для каждого столбца
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1259 entries, 0 to 1258
Data columns (total 27 columns):
 #   Column                     Non-Null Count  Dtype 
---  ------                     --------------  ----- 
 0   Timestamp                  1259 non-null   object
 1   Age                        1259 non-null   int64 
 2   Gender                     1259 non-null   object
 3   Country                    1259 non-null   object
 4   state                      744 non-null    object
 5   self_employed              1241 non-null   object
 6   family_history             1259 non-null   object
 7   treatment                  1259 non-null   object
 8   work_interfere             995 non-null    object
 9   no_employees               1259 non-null   object
 10  remote_work                1259 non-null   object
 11  tech_company               1259 non-null   object
 12  benefits                   1259 non-null   object
 13  care_options               1259 non-null   object
 14  wellness_program           1259 non-null   object
 15  seek_help                  1259 non-null   object
 16  anonymity                  1259 non-null   object
 17  leave                      1259 non-null   object
 18  mental_health_consequence  1259 non-null   object
 19  phys_health_consequence    1259 non-null   object
 20  coworkers                  1259 non-null   object
 21  supervisor                 1259 non-null   object
 22  mental_health_interview    1259 non-null   object
 23  phys_health_interview      1259 non-null   object
 24  mental_vs_physical         1259 non-null   object
 25  obs_consequence            1259 non-null   object
 26  comments                   164 non-null    object
dtypes: int64(1), object(26)
memory usage: 265.7+ KB
Timestamp                    1246
Age                            53
Gender                         49
Country                        48
state                          45
self_employed                   2
family_history                  2
treatment                       2
work_interfere                  4
no_employees                    6
remote_work                     2
tech_company                    2
benefits                        3
care_options                    3
wellness_program                3
seek_help                       3
anonymity                       3
leave                           5
mental_health_consequence       3
phys_health_consequence         3
coworkers                       3
supervisor                      3
mental_health_interview         3
phys_health_interview           3
```

```
feature names = data columns tolist()
```

```
for column in feature_names:
    print (column)
    print (data[column].value_counts(dropna=False) )
```

```
Timestamp
2014-08-27 12:31:41    2
2014-08-27 12:37:50    2
2014-08-27 12:44:51    2
2014-08-27 15:23:51    2
2014-08-27 12:43:28    2
                      ..
2014-08-27 13:26:35    1
2014-09-04 08:35:49    1
2014-08-27 12:48:37    1
2014-08-27 15:59:47    1
2014-08-27 14:57:46    1
Name: Timestamp, Length: 1246, dtype: int64
Age
 29             85
 32             82
 26             75
 27             71
 33             70
 28             68
 31             67
 34             65
 30             63
 25             61
 35             55
 23             51
 24             46
 37             43
 38             39
 36             37
 39             33
 40             33
 43             28
 41             21
 22             21
 42             20
 21             16
 45             12
 46             12
 44             11
 19              9
 18              7
 20              6
 48              6
 50              6
 51              5
 56              4
 49              4
 57              3
 54              3
 55              3
 47              2
 60              2
 11              1
 8               1
 5               1
 99999999999     1
-1726            1
```

```
# Удаление колонок  содержащих пустые значения
```

```
data_new_1 = data.dropna(axis=1, how='any')
(data.shape, data_new_1.shape)
```

```
((1259, 27), (1259, 23))
```

```
# Удаление строк, содержащих пустые значения
data_new_2 = data.dropna(axis=0, how='any')
(data.shape, data_new_2.shape)
```

```
((1259, 27), (86, 27))
```

```
# Заполнение всех пропущенных значений нулями
# В данном случае это некорректно, так как нулями заполняются в том числе категориаль
data_new_3 = data.fillna(0)
data_new_3.head()
```

	Timestamp	Age	Gender	Country	state	self_employed	family_history	treatment
0	2014-08-27 11:29:31	37	Female	United States	IL	0	No	Yes
1	2014-08-27 11:29:37	44	M	United States	IN	0	No	No
2	2014-08-27 11:29:44	32	Male	Canada	0	0	No	No
3	2014-08-27 11:29:46	31	Male	United Kingdom	0	0	Yes	Yes
4	2014-08-27 11:30:22	31	Male	United States	TX	0	No	No

```
# Выберем числовые колонки с пропущенными значениями
# Цикл по колонкам датасета
num_cols = []
for col in data.columns:
    # Количество пустых значений
    temp_null_count = data[data[col].isnull()].shape[0]
    dt = str(data[col].dtype)
    if temp_null_count>0 and (dt=='float64' or dt=='int64'):
        num_cols.append(col)
        temp_perc = round((temp_null_count / total_count) * 100.0, 2)
        print('Колонка {}. Тип данных {}. Количество пустых значений {}, {}%.'.format
```

Разделим данные на 3 категории: мужчина, женщина и другие (сюда вошли те категории, к предыдущих двух, для примера - трансгендер).

```
male_terms = ["male", "m", "mal", "msle", "malr", "mail", "make", "cis male", "man",
female_terms = ["female", "f", "woman", "femake", "femaile", "femake", "cis female",

def clean_gender(response):
    if response.lower().rstrip() in male_terms:
        return "Male"
    elif response.lower().rstrip() in female_terms:
        return "Female"
    else:
        return "Other"

data['Gender'] = data["Gender"].apply(lambda x: clean_gender(x))
data.head()
```

	Timestamp	Age	Gender	Country	state	self_employed	family_history	treatment
0	2014-08-27 11:29:31	37	Female	United States	IL	NaN	No	Yes
1	2014-08-27 11:29:37	44	Male	United States	IN	NaN	No	No
2	2014-08-27 11:29:44	32	Male	Canada	NaN	NaN	No	No
3	2014-08-27 11:29:46	31	Male	United Kingdom	NaN	NaN	Yes	Yes
4	2014-08-27 11:30:22	31	Male	United States	TX	NaN	No	No

Возьмем эвристическую оценку, в каком возрасте могут работать люди: от 14 до 100 лет. И диапазон, преобразуем в формат Not-a-Number.

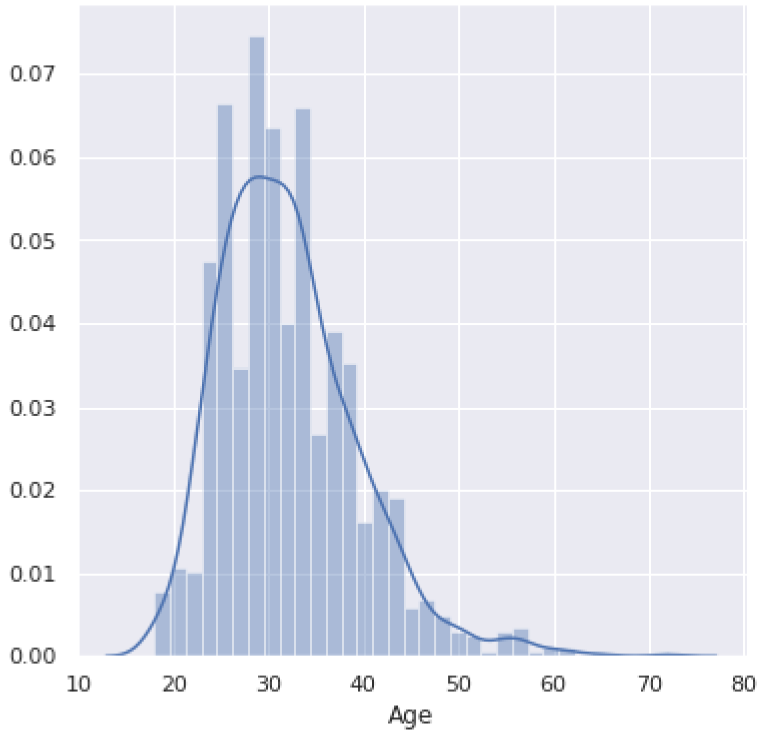
Double-click (or enter) to edit

```
data.Age.loc [(data.Age <14) | (data.Age> 100)] = np.nan
feature_names = data.columns.tolist()
for column in feature_names:
    print (column)
    print (data[column].value_counts(dropna=False) )
```

```
Timestamp
2014-08-27 12:31:41    2
2014-08-27 12:37:50    2
2014-08-27 12:44:51    2
2014-08-27 15:23:51    2
2014-08-27 12:43:28    2
                      ..
2014-08-27 13:26:35    1
2014-09-04 08:35:49    1
2014-08-27 12:48:37    1
2014-08-27 15:59:47    1
2014-08-27 14:57:46    1
Name: Timestamp, Length: 1246, dtype: int64
Age
29.0    85
32.0    82
26.0    75
27.0    71
33.0    70
28.0    68
31.0    67
34.0    65
30.0    63
25.0    61
35.0    55
23.0    51
24.0    46
37.0    43
38.0    39
36.0    37
39.0    33
40.0    33
43.0    28
22.0    21
41.0    21
42.0    20
21.0    16
45.0    12
46.0    12
44.0    11
19.0     9
NaN      8
18.0     7
20.0     6
50.0     6
48.0     6
51.0     5
56.0     4
49.0     4
57.0     3
55.0     3
54.0     3
60.0     2
47.0     2
62.0     1
58.0     1
53.0     1
61.0     1
```

Эти нулевые значения затем могут быть обработаны с использованием описанного выше диапазона для работающего человека, визуализируем распределение возраста, присутств

```
%matplotlib inline
import seaborn as sns
sns.set(color_codes=True)
plot = sns.distplot(data.Age.dropna())
plot.figure.set_size_inches(6,6)
```




```
# Выберем числовые колонки с пропущенными значениями
# Цикл по колонкам датасета

total_count = data.shape[0]
print('Всего строк: {}'.format(total_count))
num_cols = []
for col in data.columns:
    # Количество пустых значений
    temp_null_count = data[data[col].isnull()].shape[0]
    dt = str(data[col].dtype)
    if temp_null_count>0 and (dt=='float64' or dt=='int64'):
        num_cols.append(col)
        temp_perc = round((temp_null_count / total_count) * 100.0, 2)
        print('Колонка {}. Тип данных {}. Количество пустых значений {}, {}%.'.format
```

```
Всего строк: 1259
Колонка Age. Тип данных float64. Количество пустых значений 8, 0.64%.
```

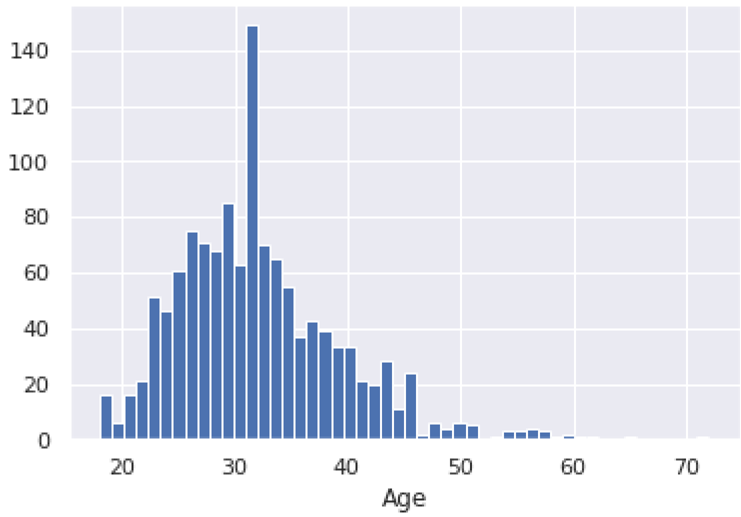
```
# Фильтр по колонкам с пропущенными значениями
data_num = data[num_cols]
data_num
```

	Age
0	37.0
1	44.0
2	32.0
3	31.0
4	31.0
...	...
1254	26.0
1255	32.0
1256	34.0
1257	46.0
1258	25.0

1259 rows × 1 columns

```
# Гистограмма по признакам
for col in data_num:
    plt.hist(data[col], 50)
    plt.xlabel(col)
    plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/numpy/lib/histograms.py:839: RuntimeWarning: i
  keep = (tmp_a >= first_edge)
/usr/local/lib/python3.6/dist-packages/numpy/lib/histograms.py:840: RuntimeWarning: i
  keep &= (tmp_a <= last_edge)
```




```
# Запоминаем индексы строк с пустыми значениями
flt_index = data[data['Age'].isnull()].index
flt_index
```

```
Int64Index([143, 364, 390, 715, 734, 989, 1090, 1127], dtype='int64')
```

```
# Проверяем что выводятся нужные строки
data[data.index.isin(flt_index)]
```

	Timestamp	Age	Gender	Country	state	self_employed	family_history	treatm
143	2014-08-27 12:39:14	NaN	Male	United States	MN	No	No	
364	2014-08-27 15:05:21	NaN	Male	United States	OH	No	No	
390	2014-08-27 15:24:47	NaN	Other	Zimbabwe	NaN	Yes	Yes	
715	2014-08-28 10:07:53	NaN	Male	United Kingdom	NaN	No	No	
734	2014-08-28 10:35:55	NaN	Male	United States	OH	No	No	
989	2014-08-29 09:10:58	NaN	Other	Bahamas, The	IL	Yes	Yes	
1090	2014-08-29 17:26:15	NaN	Male	United States	OH	Yes	No	
1127	2014-08-30 20:55:11	NaN	Other	United States	AL	Yes	Yes	

```
# фильтр по колонке
data_num[data_num.index.isin(flt_index)]['Age']
```

```
143     NaN
364     NaN
390     NaN
715     NaN
734     NaN
989     NaN
1090    NaN
1127    NaN
Name: Age, dtype: float64
```

```
data_num_MasVnrArea = data_num[['Age']]
data_num_MasVnrArea.head()
```

	Age
0	37.0
1	44.0
2	32.0
3	31.0
4	31.0

```
from sklearn.impute import SimpleImputer
from sklearn.impute import MissingIndicator
```

```
# Фильтр для проверки заполнения пустых значений
indicator = MissingIndicator()
mask_missing_values_only = indicator.fit_transform(data_num_MasVnrArea)
mask_missing_values_only
```

```
array([[False],
       [False],
       [False],
       ...,
       [False],
       [False],
       [False]])
```

```
strategies=['mean', 'median','most_frequent']
```

```
def test_num_impute(strategy_param):
    imp_num = SimpleImputer(strategy=strategy_param)
    data_num_imp = imp_num.fit_transform(data_num_MasVnrArea)
    return data_num_imp[mask_missing_values_only]
```

```
strategies[0], test_num_impute(strategies[0])
```

```
('mean',
 array([32.07673861, 32.07673861, 32.07673861, 32.07673861, 32.07673861,
        32.07673861, 32.07673861, 32.07673861]))
```

```
strategies[1], test_num_impute(strategies[1])
```

```
('median', array([31., 31., 31., 31., 31., 31., 31., 31.]))
```

```
strategies[2], test_num_impute(strategies[2])
```

```
('most_frequent', array([29., 29., 29., 29., 29., 29., 29., 29.]))
```

```
# Более сложная функция, которая позволяет задавать колонку и вид импьютации
def test_num_impute_col(dataset, column, strategy_param):
    temp_data = dataset[[column]]

```

```
    indicator = MissingIndicator()
    mask_missing_values_only = indicator.fit_transform(temp_data)

    imp_num = SimpleImputer(strategy=strategy_param)
    data_num_imp = imp_num.fit_transform(temp_data)

    filled_data = data_num_imp[mask_missing_values_only]

    return column, strategy_param, filled_data.size, filled_data[0], filled_data[fill
```

```
data[['Age']].describe()
```

	Age
count	1251.000000
mean	32.076739
std	7.288272
min	18.000000
25%	27.000000
50%	31.000000
75%	36.000000
max	72.000000

```
test_num_impute_col(data, 'Age', strategies[0])
```

```
('Age', 'mean', 8, 32.07673860911271, 32.07673860911271)
```

```
test_num_impute_col(data, 'Age', strategies[1])
```

```
('Age', 'median', 8, 31.0, 31.0)
```

```
test_num_impute_col(data, 'Age', strategies[2])
```

```
('Age', 'most_frequent', 8, 29.0, 29.0)
```

Часть 2.

- `age`: continuous.
- `workclass`: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Withou
- `fnlwgt`: continuous.
- `education`: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9t Doctorate, 5th-6th, Preschool.
- `education-num`: continuous.
- `marital-status`: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married

- `occupation` : Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces.
- `relationship`: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.
- `race`: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.
- `sex` : Female, Male.
- `capital-gain`: continuous.
- `capital-loss`: continuous.
- `hours-per-week`: continuous.
- `native-country`: United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Port Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Peru, Hong, Holand-Netherlands.
- `salary`: >50K,<=50K

```
import numpy as np
import pandas as pd
pd.set_option('display.max.columns', 100)
# to draw pictures in jupyter notebook
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
```

```
df = pd.read_csv('/content/adult.data.csv', sep=',')
df.head()
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife

1. How many men and women (*sex* feature) are represented in this dataset?

```
df.sex.value_counts()
```

```
Male      21790
Female    10771
Name: sex, dtype: int64
```

2. What is the average age (***age*** feature) of women?

```
df[df.sex == 'Female'].age.mean()
```

```
36.85823043357163
```

3. What is the percentage of German citizens (***native-country*** feature)?

```
df['native-country'].value_counts(normalize=True)['Germany']*100
```

```
0.42074874850281013
```

4-5. What are the mean and standard deviation of age for those who earn more than 50K per year (
50K per year?**

```
df.salary.value_counts()
```

```
<=50K    24720
>50K      7841
Name: salary, dtype: int64
```

```
df.groupby(by='salary').agg({'age':['mean','std']})
```

	age	
	mean	std
salary		
<=50K	36.783738	14.020088
>50K	44.249841	10.519028

6. Is it true that people who earn more than 50K have at least high school education? (***education*** ***Assoc-voc***, ***Masters*** or ***Doctorate*** feature)

```
df[df.salary=='>50K'].education.value_counts()
```

```
Bachelors       2221
HS-grad         1675
Some-college    1387
Masters          959
Prof-school      423
Assoc-voc        361
Doctorate        306
Assoc-acdm       265
10th              62
11th              60
7th-8th           40
12th              33
9th               27
5th-6th           16
1st-4th            6
Name: education, dtype: int64
```

No

7. Display age statistics for each race (*race* feature) and each gender (*sex* feature). Use *groupby(* men of *Amer-Indian-Eskimo* race.

```
df.groupby(by=['race', 'sex']).age.describe()
```

race	sex	count	mean	std	min	25%	50%	75%	max
Amer-Indian-Eskimo	**Female**	119.0	37.117647	13.114991	17.0	27.0	36.0	46.00	80.0
	Male	192.0	37.208333	12.049563	17.0	28.0	35.0	45.00	82.0
Asian-Pac-Islander	**Female**	346.0	35.089595	12.300845	17.0	25.0	33.0	43.75	75.0
	Male	693.0	39.073593	12.883944	18.0	29.0	37.0	46.00	90.0
Black	**Female**	1555.0	37.854019	12.637197	17.0	28.0	37.0	46.00	90.0
	Male	1569.0	37.682600	12.882612	17.0	27.0	36.0	46.00	90.0
Other	**Female**	109.0	31.678899	11.631599	17.0	23.0	29.0	39.00	74.0
	Male	162.0	34.654321	11.355531	17.0	26.0	32.0	42.00	77.0
White	**Female**	8642.0	36.811618	14.329093	17.0	25.0	35.0	46.00	90.0
	Male	19174.0	39.652498	13.436029	17.0	29.0	38.0	49.00	90.0

```
df1 = df.groupby(by=['race', 'sex']).age.describe()
df1.loc['Amer-Indian-Eskimo', 'Male']['max']
```

```
82.0
```

8. Among whom is the proportion of those who earn a lot (>50K) greater: married or single men (those who have a *marital-status* starting with *Married* (Married-civ-spouse, Married-spouse-abs

considered bachelors.

```
df[df.salary=='>50K'].groupby(by='marital-status').age.count()
```

```
marital-status
Divorced                  463
Married-AF-spouse          10
Married-civ-spouse       6692
Married-spouse-absent      34
Never-married             491
Separated                  66
Widowed                    85
Name: age, dtype: int64
```

answer = among married

9. What is the maximum number of hours a person works per week (*hours-per-week* feature)? Ho hours, and what is the percentage of those who earn a lot (>50K) among them?

```
#df.sort_values(by='hours-per-week', ascending=False)
mx = df['hours-per-week'].max()
mx
```

```
99
```

```
df[df['hours-per-week'] == mx].count()
```

```
age               85
workclass         85
fnlwgt            85
education         85
education-num     85
marital-status    85
occupation        85
relationship      85
race              85
sex               85
capital-gain      85
capital-loss      85
hours-per-week    85
native-country    85
salary            85
dtype: int64
```

```
df[df['hours-per-week'] == mx].salary.value_counts(normalize=True)
```

```
<=50K    0.705882
>50K     0.294118
Name: salary, dtype: float64
```

```

```

answer = 0.705882

10. Count the average time of work (*hours-per-week*) for those who earn a little and a lot (*salary*) these be for Japan?

```
# You code here
```

```
df.columns
```

```
Index(['age', 'workclass', 'fnlwgt', 'education', 'education-num',
       'marital-status', 'occupation', 'relationship', 'race', 'sex',
       'capital-gain', 'capital-loss', 'hours-per-week', 'native-country',
       'salary'],
      dtype='object')
```

```
df_hpw = df.groupby(by=['native-country', 'salary']).agg({'hours-per-week':'mean'})
```

```
df_hpw.loc['Japan']
```

salary	hours-per-week
<=50K	41.000000
>50K	47.958333

```
df1 = df.iloc[0:4]
df2 = df.iloc[50:53]
```

Получим из таблицы с исходными данными топ3 людей, чей возраст ме

```
!pip install pandasql
!pip install pandas

```

```
Requirement already satisfied: pandasql in /usr/local/lib/python3.6/dist-packages (0.
Requirement already satisfied: sqlalchemy in /usr/local/lib/python3.6/dist-packages (
Requirement already satisfied: numpy in /usr/local/lib/python3.6/dist-packages (from
Requirement already satisfied: pandas in /usr/local/lib/python3.6/dist-packages (from
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: python-dateutil>=2.6.1 in /usr/local/lib/python3.6/dis
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.6/dist-packages (fr
Requirement already satisfied: pandas in /usr/local/lib/python3.6/dist-packages (1.0.
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: numpy>=1.13.3 in /usr/local/lib/python3.6/dist-package
Requirement already satisfied: python-dateutil>=2.6.1 in /usr/local/lib/python3.6/dis
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.6/dist-packages (fr
```

```
import pandasql as ps
import pandas as pd
```

```
simple_query = '''
    SELECT
        age,
        workclass,
        fnlwgt,
        education
    FROM df
    WHERE age < 40
    ORDER BY age desc
    LIMIT 3

    '''
%time df_ps = ps.sqldf(simple_query, locals())
df_ps
```

```
CPU times: user 563 ms, sys: 41.9 ms, total: 605 ms
Wall time: 610 ms
```

	age	workclass	fnlwgt	education
0	39	State-gov	77516	Bachelors
1	39	Private	367260	HS-grad
2	39	Private	365739	Some-college

```
columns = ['age', 'workclass', 'fnlwgt', 'education']
%time df_pd = df.loc[df.age < 40, columns].sort_values(by='age', ascending=False).hea
df_pd
```

```
CPU times: user 9.93 ms, sys: 986 µs, total: 10.9 ms
Wall time: 13.3 ms
```

	age	workclass	fnlwgt	education
0	39	State-gov	77516	Bachelors
12603	39	Private	185053	HS-grad
1608	39	Private	379350	10th

```
def example2_pandasql(data):
    aggr_query = '''
        SELECT
            count(age) as count,
            avg(age)  as mean,
            min(age)   as mean
        FROM data
        GROUP BY race
        '''
    return ps.sqldf(aggr_query, locals()).set_index('age')
```

```
df.groupby(by=['race', 'sex']).age.describe()
```

race	sex	count	mean	std	min	25%	50%	75%	max
Amer-Indian-Eskimo	Female	119.0	37.117647	13.114991	17.0	27.0	36.0	46.00	80.0
	Male	192.0	37.208333	12.049563	17.0	28.0	35.0	45.00	82.0
Asian-Pac-Islander	Female	346.0	35.089595	12.300845	17.0	25.0	33.0	43.75	75.0
	Male	693.0	39.073593	12.883944	18.0	29.0	37.0	46.00	90.0
Black	Female	1555.0	37.854019	12.637197	17.0	28.0	37.0	46.00	90.0
	Male	1569.0	37.682600	12.882612	17.0	27.0	36.0	46.00	90.0
Other	Female	109.0	31.678899	11.631599	17.0	23.0	29.0	39.00	74.0
	Male	162.0	34.654321	11.355531	17.0	26.0	32.0	42.00	77.0
White	Female	8642.0	36.811618	14.329093	17.0	25.0	35.0	46.00	90.0
	Male	19174.0	39.652498	13.436029	17.0	29.0	38.0	49.00	90.0

```
%time pd.concat([df1, df2])
```

```
CPU times: user 5.93 ms, sys: 255 µs, total: 6.19 ms
Wall time: 6.84 ms
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband
50	25	Private	32275	Some-college	10	Married-civ-spouse	Exec-managerial	Wife
51	18	Private	226956	HS-grad	9	Never-married	Other-service	Own-child
52	47	Private	51835	Prof-school	15	Married-civ-spouse	Prof-specialty	Wife

Список литературы

[1] Гапанюк Ю. Е. Лабораторная работа «Разведочный анализ данных. Исследование и визуализация данных» [Электронный ресурс] // GitHub. – 2019. – Режим доступа: https://github.com/ugapanyuk/ml_course/wiki/LAB_EDA_VISUALIZATION (дата обращения: 15.02.2020).

[2] Scikit-learn. Boston house-prices dataset [Electronic resource] // Scikit-learn. — 2018. — Access mode: https://scikit- learn.org/0.20/modules/generated/sklearn.datasets.load_boston.html (online; accessed: 18.02.2020).

[3] Team The IPython Development. IPython 7.3.0 Documentation [Electronic resource] // Read the Docs. — 2019. — Access mode: https://ipython.readthedocs.io/en/ stable/ (online; accessed: 20.02.2020).

[4] Waskom M. seaborn 0.9.0 documentation [Electronic resource] // PyData. — 2018. — Access mode: https://seaborn.pydata.org/(online; accessed: 20.02.2020).

[5] pandas 0.24.1 documentation [Electronic resource] // PyData. — 2019. — Access mode: http://pandas.pydata.org/pandas-docs/stable/(online; accessed: 20.02.2020).