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Кафедра «Автоматизированные системы обработки информации и управления»



«Методы машинного обучения»

Отчет по Лабораторной работе №2

Изучение библиотек обработки данных

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Лабораторная работа №2. Изучение библиотек обработки данных.

Цель лабораторной работы: изучение библиотек обработки данных Pandas и PandaSQL.

Требования к отчету: отчет по лабораторной работе должен содержать:

- титульный лист; описание задания; текст программы;
- экранные формы с примерами выполнения программы.

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Задание:

Часть 1. Выполните первое демонстрационное задание "demo assignment" под названием "Exploratory data analysis with Pandas" со страницы курса https://mlcourse.ai/assignments (https://mlcourse.ai/assignments)

Условие задания

https://nbviewer.jupyter.org/github/Yorko/mlcourse_open/blob/master/jupyter_english/assignments_demo/assigflush_cache=true

(https://nbviewer.jupyter.org/github/Yorko/mlcourse_open/blob/master/jupyter_english/assignments_demo/assigned g flush_cache=true)

Часть 2. Выполните следующие запросы с использованием двух различных библиотек - Pandas и PandaSQL:

.

• один произвольный запрос на соединение двух наборов данных; один произвольный запрос на группировку набора данных с использованием функций агрегирования.

Сравните время выполнения каждого запроса в Pandas и PandaSQL.

Часть 1

Unique values of all features (for more information, please see the links above):

- age: continuous.
- workclass: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.
- fnlwgt: continuous.
- education: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool.
- education-num: continuous.
- marital-status: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouseabsent, Married-AF-spouse.
- occupation: Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlerscleaners, Machine-op-inspct, Adm-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-
- US(GuamUSVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland,
 Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti,
- Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-

In [5]:

```
import numpy
np
       import pandas
as pd
pd . set option ('display.max.columns',
100
       ) import seaborn
                                 sns
                           as
matplotlib inline
import matplotlib.pyplot as plt
sns . set ( style = "ticks" )
import warnings
warnings . filterwarnings ( 'ignore' )
In [6]:
data = pd.read_csv('D:/Загрузки/adult.data', header=None, names=['age','workclass','fnl
wgt', 'education',
                                                     'education-num','marital-status','oc
cupation',
                                                     'relationship','race','sex','capital
gain','capital-loss',
                                                     'hours-per-week', 'native-country', 's
alary']) data.head() Out[6]:
```

education- maritalage workclass fnlwgt education occupation relationship race num status

```
Never-
                                                                            Adm-
0
     39 State-gov
                         77516 Bachelors
                                                   13
                                                            Not-in-family
                                                                             White
                                                            married
                                                                          clerical
                                                           Married-
           Self-emp-
                                                                            Exec-
 1
     50 83311 Bachelors
                                  13
                                          civ-
                                                   Husband
                                                                    White not-inc
                                                                                     managerial spouse
                                                                        Handlers-
 2
     38 Private 215646 HS-grad 9
                                          Divorced
                                                                             White
                                                            Not-in-family
                                                                         cleaners
                                                           Married-
                                                                        Handlers-
     53 Private 234721 11th
                                                                    Black
 3
                                  7
                                           civ-
                                                   Husband
                                                                         cleaners
                                                            spouse
                                                           Married-
                                                                             Prof-
     28 Private 338409 Bachelors
                                           13
                                                            Wife
                                                                    Black
                                                   civ-
                                                                         specialty
                                                            spouse
```

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

```
data['sex'].value_counts()
Out[29]:
 Male
            21790
 Female
           10771
Name: sex, dtype: int64
2. What is the average age (age feature) of women?
In [41]:
data.loc[data['sex'] == 'Female'
                                              'age'
                                                                                     ] . mean ()
Out[41]:
36.85823043357163
3. What is the percentage of German citizens (native-country feature)?
In [54]:
data.loc[data['native-country'] == ' Germany', 'native-country'].value_counts()/data['n
ative-country'].count()*100 Out[54]:
 Germany
             0.420749
Name: native-country, dtype: float64
4-5. What are the mean and standard deviation of age for those who earn more than 50K per year
(salary feature) and those who earn less than 50K per year?
In [68]:
# mean and standard deviation of age for those who earn more than 50K
print("The average age is: {0} +- {1} years".format(
     round(data.loc[data['salary'] == ' >50K', 'age'].mean()),
 round(data.loc[data['salary'] == ' >50K', 'age'].std(), 1)))
The average age is: 44.0 +- 10.5 years
In [71]:
# mean and standard deviation of age for those who earn less than 50K
print("The average age is: {0} +- {1} years".format(
     round(data.loc[data['salary'] == ' <=50K', 'age'].mean()),</pre>
 round(data.loc[data['salary'] == ' <=50K', 'age'].std())))</pre>
The average age is: 37.0 +- 14.0 years
6. Is it true that people who earn more than 50K have at least high school education? (education –
Bachelors, Prof-school, Assoc-acdm, Assoc-voc, Masters or Doctorate feature)
In [81]: data.loc[data['salary'] == ' >50K',
```

'education'].unique()

```
Out[81]:
array([' HS-grad', ' Masters', ' Bachelors', ' Some-college',
' Assoc-voc', ' Doctorate', ' Prof-school', ' Assoc-acdm', ' 7th-8th', ' 12th', ' 10th', ' 11th', ' 9th', ' 5th-6th',
' 1st-4th'], dtype=object)
In [83]: print("Not all the people who earn more than 50K have at least high school
education")
Not all the people who earn more than 50K have at least high school educat
ion
7. Display age statistics for each race (race feature) and each gender (sex feature). Use groupby()
  anddescribe(). Find the maximum age of men of Amer-Indian-Eskimo race.
In [90]:
data1 = data.groupby(['race', 'sex'])
data1['age'].describe() Out[90]:
                               count
                                                       std min 25% 50%
                                                                             75% max
                                          mean
               race
                        sex
 Amer-Indian-Eskimo Female
                                119.0 37.117647 13.114991 17.0
                                                                       36.0
                                                                 27.0
                                                                            46.00
                                                                                   0.08
                               192.0 37.208333 12.049563 17.0
                                                                 28.0 35.0 45.00
                       Male
                                                                                   82.0
  Asian-Pac-Islander Female
                               346.0 35.089595 12.300845 17.0
                                                                 25.0 33.0 43.75 75.0
                               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
                                                                 23.0 29.0 39.00 74.0
                Other Female
                               109.0 31.678899 11.631599 17.0
                       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
```

Out[92]:

'age'].max()

82

8. Among whom is the proportion of those who earn a lot (>50K) greater: married or single men (marital-status feature)? Consider as married those who have a marital-status starting with Married (Married-civ-spouse, Married-spouse-absent or Married-AF-spouse), the rest are considered bachelors.

In [92]: data.loc[data['race'] == ' Amer-Indian-Eskimo',

Male 19174.0 39.652498 13.436029 17.0 29.0 38.0 49.00 90.0

```
In [120]:
data1 = data[data['sex'] == ' Male']
In [121]:

data2 = data1[data1['salary'] == ' >50K'].groupby('marital-status').count().reset_index
()[['marital-status', 'salary']]
data2_Out[121]:
```

marital-status salary

0	Divorced	284	
1	Married-AF	4	

```
2
               Married-civ-spouse 5938
                                      23
 3
               Married-spouse-absent
 4
               Never-married
                                325
 5
               Separated
                         49
 6
               Widowed
                         39
In [123]:
married_prop = data2[data2['marital-status'].str.startswith('
Married')].sum()[1] married_prop/data['marital-status'].count()*100 Out[123]:
18.319461932987316
In [124]:
single_prop = data2[~data2['marital-status'].str.startswith('
Married')].sum()[1] single prop/data['marital-status'].count()*100 Out[124]:
2.140597647492399
In [125]:
if married_prop > single_prop:
    print('The proportion of those who earn a lot (>50K) is greater among married men')
else:
         print('The proportion of those who earn a lot (>50K) is greater among single
 men')
The proportion of those who earn a lot (>50K) is greater among married men
9. What is the maximum number of hours a person works per week (hours-per-week feature)? How
many people work such a number of hours, and what is the percentage of those who earn a lot (>50K)
among them?
In [129]:
max_hours = data['hours-per-week'].max() print("The maximum number of hours
a person works per week is", max_hours)
The maximum number of hours a person works per week is 99
In [135]:
data1 = data.loc[data['hours-per-week'] == max_hours, 'salary'].count() print(data1,
"people work such a number of hours")
85 people work such a number of hours
In [152]:
percent = float(data['data['hours-per-week'] == max_hours) & (data['salary'] == ' >50K'
)].shape[0])/data1*100 print("The
percentage is", round(percent))
```

The percentage is 29.0

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

```
In [16]:
data3 = data.groupby(['native-country', 'salary']) pd.crosstab(data3['hours-per-
week'].describe().reset_index()[['native-country','salary','mean']]).T
 ______
                                          Traceback (most recent call las t)
TypeError
<ipython-input-16-0b282dafc892> in <module>
      1 data3 = data.groupby(['native-country', 'salary'])
----> 2 pd.crosstab(data3['hours-per-week'].describe().reset_index()[['nat
ivecountry','salary','mean']]).T
TypeError: crosstab() missing 1 required positional argument: 'columns'
In [18]:
pd.crosstab(data['native-country'], data['salary'],
                                                               values=data['hours-per-
week'], aggfunc=np.mean).T Out[18]:
                                                               Dominican-
native-
      ? Cambodia
                  Canada China Columbia
                                           Cuba
                                                 Ecu country
                                                              Republic
  salary
   <=50K 40.164760
                    41.416667 37.914634 37.381818 38.684211 37.985714
                                                                42.338235 38.04
>50K 45.547945 40.000000 45.641026 38.900000 50.000000 42.440000 47.000000 48.75 In [43]:
pd.crosstab(data.loc[data['native-country'] == ' Japan', 'native-country'], data['salar
y'],
                values=data['hours-per-week'], aggfunc=np.mean).T Out[43]:
native-country
                Japan
       salary
       <=50K 41.000000 >50K
            47.958333
```

Часть 2

In [45]:
Out[45]:

0	NaN	NaN	AD681H Sn	nartfren Andromax AD681H
1	NaN	NaN	FJL21	FJL21
2	NaN	NaN	T31	Panasonic T31
3	NaN	NaN h	nws7721g	MediaPad 7 Youth 2
4	3Q	OC1020A	OC1020A	OC1020A
n [47]	•			
android s.csv')	_	pd.read_csv('D:/Загрузк	и/Pandas-Merge-Tutorial-master/android_device
android	_devices.he	ad()		
user_de	vice = pd.re	ead_csv('D:/	Загрузки/Ра	<pre>ndas-Merge-Tutorial-master/user_device.csv')</pre>

use_id user_id platform_version device use_type_id

0	22782	26980	ios 10.2	iPhone7,2 2
1	22783	29628	android 6.0	Nexus 5 3
2	22784	28473	android 5.1	SM-G903F 1
3	22785	15200	ios 10.2	iPhone7,2 3
4	22786	28239	android 6.0	ONE E1003 1

In [49]:

user_usage = pd.read_csv('D:/Загрузки/Pandas-Merge-Tutorial-master/user_usage.csv')
user_usage.head() Out[49]:

outgoing_mins_per_month outgoing_sms_per_month monthly_mb use_id

0	21.97	4.82	1557.33	22787
1	1710.08	136.88	7267.55	22788
2	1710.08	136.88	7267.55	22789
3	94.46	35.17	519.12	22790
4	71.59	79.26	1557.33	22792

Использование Pandas

user_device.head() Out[47]:

Запрос на соединение двух наборов данных

In [52]:

Out[52]:

outgoing_mins_per_month outgoing_sms_per_month monthly_mb use_id platform device

GT 19505	android	22787	1557.33	4.82	21.97	0
SM G930F	android (22788	7267.55	136.88	1710.08	1
SM G930F	android (22789	7267.55	136.88	1710.08	2
D2303	android	22790	519.12	35.17	94.46	3
SM G361F	android (22792	1557.33	79.26	71.59	4
						4

Запрос на группировку набора данных с использованием функций агрегирования ${\tt In}$

[59]:

```
group_pd = user_device.groupby('platform').count().reset_index()[['platform','device']]
group_pd Out[59]:
```

platform device

0	android	184
1	ios 88	

Использование PandaSQL

In [61]:

```
import pandasql as ps
ps.sqldf('select * from user_device limit 5', locals())
```

Out[61]:

use_id user_id platform platform_version					device use_type_id	
0	22782	26980	ios	10.2	iPhone7,2	2
1	22783	29628	android	6.0	Nexus 5 3	
2	22784	28473	android	5.1	SM-G903F	1
3	22785	15200	ios	10.2	iPhone7,2	3
4	22786	28239	android	6.0	ONE E1003	1

Запрос на соединение двух наборов данных

In [64]:

```
In [66]:
group_ps = ps.sqldf('select platform, count(device) from user_device group by platform'
, locals())
group_ps
```

Out[66]:
join_ps = ps.sqldf('select * from user_usage join user_device on user_device.use_id = u
ser_usage.use_id', locals()) join_ps.head() Out[64]: outgoing_mins_per_month

outgoing_sms_per_month monthly_mb use_id use_id user_id

0	21.97	4.82	1557.33	22787	22787	12921
1	1710.08	136.88	7267.55	22788	22788	28714
2	1710.08	136.88	7267.55	22789	22789	28714
3	94.46	35.17	519.12	22790	22790	29592
4	71.59 platform count(device)	79.26	1557.33	22792	22792	28217

0 android 184

1 ios 88

Сравнение времени выполнения запросов библиотек Pandas и PandaSQL

In [86]:

```
import timeit

time_group_ps = timeit.timeit("group_ps", setup="from __main__ import group_ps", number
=1)
time_group_ps # 0.0000006999999868639861
```

Out[86]: 6.999999868639861e-

07

In [88]:

time_join_ps = timeit.timeit("join_ps", setup="from __main__ import join_ps", number=1)
time_join_ps # 0.00000039999997625272954

Out[88]: 3.9999997625272954e-

07

In [113]:

```
time_group_pd = timeit.timeit("group_pd", setup="from __main__ import group_pd", number
=1) time_group_pd #
0.0000005000000555810402
```

Out[113]: 5.000000555810402e-

```
In [104]:
time_join_pd = timeit.timeit("join_pd", setup="from __main__ import join_pd", number=1)
time_join_pd # 0.0000003000000106112566
Out[104]:
3.000000106112566e-07

In [114]:
if (time_group_ps > time_group_pd) & (time_join_ps > time_join_pd):
    print("Pandas is better")
else:
    print("PandaSQL is better")
```

Pandas is better