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# «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 <a href="https://mlcourse.ai/assignments">https://mlcourse.ai/assignments</a> (https://mlcourse.ai/assignments)

#### Условие задания

https://nbviewer.jupyter.org/github/Yorko/mlcourse open/blob/master/jupyter english/assignments demo/assig flush cache=true

(https://nbviewer.jupyter.org/github/Yorko/mlcourse\_open/blob/master/jupyter\_english/assignments\_demo/assign

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**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-

Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands. • salary: >50K,<=50K

### In [5]:

```
import numpy as np
import pandas as pd
pd.set_option('display.max.columns', 100)
import seaborn as sns
%matplotlib inline
import matplotlib.pyplot as plt
sns.set(style="ticks")
import warnings
warnings.filterwarnings('ignore')
```

### In [6]:

### education- maritalage workclass fnlwgt education occupation relationship race num status

0	39 State-gov	77516	Bachelo	ors	13	Never Not-in-f married	family	Adm- White clerical	
						Married	-		
	Self-emp	-						Exec-	
1	50 83311 Bad	helors	13	civ-	Husbar	nd	White	not-inc	managerial spouse
2	38 Private 215	646 HS-gra	d 9	Divorce	ed	Not-in-f	family	andlers- White leaners	
						Married		andlers-	
3	53 Private 234	721 11th	7	civ-	Husbar	nd	Black		
								leaners	
						spouse	Э		
						Married	-		
	00 5 :	400 5 1 1		4.0		1000	<b>5</b>	Prof-	
4	28 Private 338	409 Bachel	ors	13	civ-	Wife	Black		

spouse

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

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()),
round(data.loc[data['salary'] == ' <=50K', 'age'].std())))
The average age is: 37.0 +- 14.0 years</pre>
```

ion

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)

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]:
                                                                         75% max
                             count
                                       mean
                                                   std min 25% 50%
              race
                       sex
 Amer-Indian-Eskimo Female
                              119.0 37.117647 13.114991 17.0 27.0
                                                                  36.0
                                                                        46.00 80.0
                             192.0 37.208333 12.049563 17.0
                                                             28.0
                                                                   35.0
                                                                        45.00 82.0
                      Male
  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
In [92]: data.loc[data['race'] == ' Amer-Indian-Eskimo',
'age'].max()
Out[92]:
```

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 [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
Divorced 284
Married-AF-spouse 4
```

82

```
2
        Married-civ-spouse 5938
 3
     Married-spouse-absent
                         23
 4
           Never-married
                        325
 5
              Separated
                         49
               Widowed
 6
                         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')
         print('The proportion of those who earn a lot (>50K) is greater among single
else:
 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
TypeError
t)
<ipython-input-16-0b282dafc892> in <module>
      1 data3 = data.groupby(['native-country', 'salary'])
---> 2 pd.crosstab(data3['hours-per-week'].describe().reset index()[['nat ive-
country','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]:
native-
                                                                  Dominican-
               ? Cambodia
                              Canada
                                         China Columbia
                                                            Cuba
                                                                              Ecu
                                                                    Republic
country
  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]:

android\_devices = pd.read\_csv('D:/Загрузки/Pandas-Merge-Tutorial-master/android\_device
s.csv')
android\_devices.head()

### Out[45]:

In [49]:

	Retail Branding	Marketing Name	Device	Model
0	NaN	NaN	AD681H	Smartfren Andromax AD681H
1	NaN	NaN	FJL21	FJL21
2	NaN	NaN	T31	Panasonic T31
3	NaN	NaN	hws7721g	MediaPad 7 Youth 2
4	3Q	OC1020A	OC1020A	OC1020A
In	47 :			

user\_device = pd.read\_csv('D:/Загрузки/Pandas-Merge-Tutorial-master/user\_device.csv')
user\_device.head() Out[47]:

	use_id	user_id	platform	platfor	m_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	

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 21.97 4.82 1557.33 22787

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

# Запрос на соединение двух наборов данных

## In [52]:

### Out[52]:

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

# Запрос на группировку набора данных с использованием функций агрегирования In [59]:

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

	platform	device	
0	and	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	platfor	m_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]:

```
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	79.26	1557.33	22792	22792	28217

1

```
In [66]:
group_ps = ps.sqldf('select platform, count(device) from user_device group by platform'
, locals())
group_ps
Out[66]:
   platform count(device)
      android
                   184
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 #
0.00000050000000555810402
Out[113]: 5.000000555810402e-
07
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