

Министерство науки и высшего образования Российской Федерации Федеральное государственное бюджетное образовательное учреждение высшего образования

«Московский государственный технический университет имени Н.Э. Баумана (национальный исследовательский университет)» (МГТУ им. Н.Э. Баумана)

Факультет «Информатика и системы управления» Кафедра ИУ5 «Системы обработки информации и управления»

Лабораторная работа №2 по дисциплине «Технология машинного обучения» на тему:

Изучение библиотек обработки данных.

Выполнил: студент группы № ИУ5-62 Чернышев Павел подпись, дата

Проверил: Ю.Е. Гапанюк подпись, дата

Задание:

Часть 1.

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

Условие задания

- https://nbviewer.jupyter.org/github/Yorko/mlcourse_open/blob/master/jupyter_english/assignments demo/assignment01 pandas uci adult.ipynb?flush cache=true

Набор данных можно скачать здесь - https://archive.ics.uci.edu/ml/datasets/Adult

Пример решения задания - https://www.kaggle.com/kashnitsky/a1-demo-pandas-and-uci-adult-dataset-solution

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.

In [3]:

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

we don't like warnings

you can comment the following 2 lines if you'd like to

import warnings

warnings.filterwarnings('ignore')

In [4]:

data = pd.read_csv('adult.data.csv')
data.head()

Out[4]:

	age	workclass	fnlwgt	education	education- num	marital- status	occupation	relationship	race	sex	capital- gain	capital- loss	hours- per- week	native- country	salary
0	39	State-gov	77516	Bachelors	13	Never- married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United- States	<=50K
1	50	Self-emp- not-inc	83311	Bachelors	13	Married-civ- spouse	Exec- managerial	Husband	White	Male	0	0	13	United- States	<=50K
2	38	Private	215646	HS-grad	9	Divorced	Handlers- cleaners	Not-in-family	White	Male	0	0	40	United- States	<=50K
3	53	Private	234721	11th	7	Married-civ- spouse	Handlers- cleaners	Husband	Black	Male	0	0	40	United- States	<=50K
4	28	Private	338409	Bachelors	13	Married-civ- spouse	Prof- specialty	Wife	Black	Female	0	0	40	Cuba	<=50K

In [6]:

data['sex'].value_counts()

Out[6]:

Male 21790 Female 10771 Name: sex, dtype: int64

In [19]:

#df.loc['2012-Feb', 'Close'].mean()
#data.loc['age'].mean()
data.loc[data['sex'] == 'Female', 'age'].mean()
#data.loc[data['sex'] == 'Female'].mean()



Out[19]:

36.85823043357163

In [25]:

data.loc[data['native-country'] == 'Germany'].count() / data.shape[0] * 100

Out[25]:

age 0.420749
workclass 0.420749
fnlwgt 0.420749
education 0.420749
education-num 0.420749
marital-status 0.420749
occupation 0.420749
relationship 0.420749

```
sex
            0.420749
              0.420749
capital-gain
              0.420749
capital-loss
hours-per-week 0.420749
native-country 0.420749
            0.420749
salary
dtype: float64
In [27]:
data.loc[data['salary'] == '<=50K','age'].mean()
Out[27]:
36.78373786407767
In [28]:
data.loc[data['salary'] == '>50K', 'age'].mean()
Out[28]:
44.24984058155847
In [29]:
ages1 = data.loc[data['salary'] == '>50K', 'age']
ages2 = data.loc[data['salary'] == '<=50K', 'age']
print("The average age of the rich: {0} +- {1} years, poor - {2} +- {3} years.".format(
  round(ages1.mean()), round(ages1.std(), 1),
  round(ages2.mean()), round(ages2.std(), 1)))
The average age of the rich: 44 +- 10.5 years, poor - 37 +- 14.0 years.
In [32]:
data.loc[data['salary'] == '>50K', 'education'].value_counts()
Out[32]:
Bachelors
              2221
HS-grad
             1675
Some-college 1387
Masters
             959
Prof-school
              423
Assoc-voc
              361
              306
Doctorate
               265
Assoc-acdm
10th
11th
            60
7th-8th
             40
            33
12th
            27
9th
5th-6th
             16
1st-4th
             6
Name: education, dtype: int64
In [34]:
print(data.groupby(['sex', 'race'])['age'].mean())
sex
     race
Female Amer-Indian-Eskimo 37.117647
    Asian-Pac-Islander 35.089595
    Black
                    37.854019
    Other
                    31.678899
    White
                    36.811618
Male Amer-Indian-Eskimo 37.208333
    Asian-Pac-Islander 39.073593
    Black
                    37.682600
    Other
                    34.654321
    White
                    39.652498
Name: age, dtype: float64
```

race

0.420749

```
In [37]:
for (race, sex), sub_df in data.groupby(['race', 'sex']):
  print("Race: {0}, sex: {1}".format(race, sex))
  print(sub_df['age'].describe())
Race: Amer-Indian-Eskimo, sex: Female
count 119.000000
        37.117647
mean
std
      13.114991
       17.000000
min
25%
       27.000000
50%
       36.000000
75%
       46.000000
       80.000000
max
Name: age, dtype: float64
Race: Amer-Indian-Eskimo, sex: Male
count 192.000000
mean
       37.208333
std
      12.049563
       17.000000
min
25%
       28.000000
50%
       35.000000
75%
       45.000000
       82.000000
max
Name: age, dtype: float64
Race: Asian-Pac-Islander, sex: Female
count 346.000000
        35.089595
mean
std
      12.300845
       17.000000
min
25%
       25.000000
50%
       33.000000
75%
       43.750000
       75.000000
max
Name: age, dtype: float64
Race: Asian-Pac-Islander, sex: Male
count 693.000000
mean
        39.073593
std
      12.883944
       18.000000
min
25%
       29.000000
50%
       37.000000
75%
       46.000000
max
       90.000000
Name: age, dtype: float64
Race: Black, sex: Female
count 1555.000000
        37.854019
mean
std
       12.637197
       17.000000
min
25%
        28.000000
50%
        37.000000
        46.000000
75%
max
        90.000000
Name: age, dtype: float64
Race: Black, sex: Male
count 1569.000000
mean
        37.682600
std
       12.882612
min
       17.000000
25%
        27.000000
50%
        36.000000
75%
        46.000000
max
        90.000000
Name: age, dtype: float64
Race: Other, sex: Female
count 109.000000
        31.678899
mean
std
      11.631599
min
       17.000000
25%
       23.000000
50%
       29.000000
75%
       39.000000
       74.000000
Name: age, dtype: float64
Race: Other, sex: Male
count 162.000000
mean
        34.654321
      11.355531
std
       17.000000
min
```

```
75%
        42.000000
        77.000000
max
Name: age, dtype: float64
Race: White, sex: Female
count 8642.000000
mean
         36.811618
       14.329093
std
        17.000000
min
25%
        25.000000
50%
         35.000000
75%
         46.000000
max
        90.000000
Name: age, dtype: float64
Race: White, sex: Male
count 19174.000000
          39.652498
mean
std
        13.436029
        17.000000
min
25%
         29.000000
50%
         38.000000
75%
         49.000000
max
         90.000000
Name: age, dtype: float64
In [38]:
data.loc[data['salary'] == '>50K', 'marital-status'].value_counts()
Out[38]:
                      6692
Married-civ-spouse
Never-married
                     491
                   463
Divorced
Widowed
                    85
Separated
                    66
Married-spouse-absent
                         34
Married-AF-spouse
Name: marital-status, dtype: int64
In [39]:
data.loc[(data['sex'] == 'Male') &
   (data['marital-status'].isin(['Never-married',
                     'Separated',
                     'Divorced',
                     'Widowed'])), 'salary'].value_counts()
Out[39]:
<=50K 7552
>50K
        697
Name: salary, dtype: int64
In [43]:
data.loc[(data['sex'] == 'Male') &
   (data['marital-status'].str.startswith('Married')), 'salary'].value_counts()
Out[43]:
<=50K 7576
>50K
       5965
Name: salary, dtype: int64
In [44]:
data['hours-per-week'].max()
Out[44]:
99
In [47]:
```

data.loc[data['hours-per-week'] == data['hours-per-week'].max()].count()

25%

50%

26.000000

32.000000

```
Out[47]:
```

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

In [62]:

```
data.loc[(data['hours-per-week'] == data['hours-per-week'].max()) & (data['salary'] == '>50K')].count() / data.loc[data['salary']=='>50K'].count() *100
```

Out[62]:

0.318837 age workclass 0.318837 0.318837 fnlwgt education 0.318837 education-num 0.318837 marital-status 0.318837 occupation 0.318837 relationship 0.318837 0.318837 race 0.318837 sex capital-gain 0.318837 capital-loss 0.318837 hours-per-week 0.318837 native-country 0.318837 salary 0.318837 dtype: float64

In [64]:

Haiti

```
native-country
                 salary
             <=50K 40.164760
             >50K 45.547945
Cambodia
                <=50K 41.416667
             >50K 40.000000
               <=50K 37.914634
Canada
             >50K 45.641026
China
              <=50K 37.381818
             >50K 38.900000
Columbia
               <=50K 38.684211
             >50K 50.000000
              <=50K 37.985714
Cuba
             >50K 42.440000
Dominican-Republic
                   <=50K 42.338235
             >50K 47.000000
                <=50K 38.041667
Ecuador
             >50K 48.750000
               <=50K 36.030928
El-Salvador
             >50K 45.000000
England
                <=50K 40.483333
             >50K 44.533333
France
               <=50K 41.058824
             >50K 50.750000
Germany
                <=50K 39.139785
             >50K 44.977273
               <=50K 41.809524
Greece
             >50K 50.625000
Guatemala
                <=50K 39.360656
```

>50K 36.666667

<=50K 36.325000 >50K 42.750000

print(data.groupby(['native-country', 'salary'])['hours-per-week'].mean())

Mexico >50K 46.575758 <=50K 36.093750 Nicaragua >50K 37.500000 Outlying-US(Guam-USVI-etc) <=50K 41.857143 <=50K 35.068966 Peru >50K 40.000000 Philippines <=50K 38.065693 >50K 43.032787 Poland <=50K 38.166667 >50K 39.000000 Portugal <=50K 41.939394 >50K 41.500000 Puerto-Rico <=50K 38.470588 >50K 39.416667 Scotland <=50K 39.444444 >50K 46.666667 <=50K 40.156250 South >50K 51.437500 <=50K 33.774194 Taiwan >50K 46.800000 <=50K 42.866667 Thailand >50K 58.333333 o <=50K 37.058824 >50K 40.000000 Trinadad&Tobago **United-States** <=50K 38.799127 >50K 45.505369 <=50K 37.193548 Vietnam >50K 39.200000 <=50K 41.600000 Yugoslavia >50K 49.500000 Name: hours-per-week, Length: 82, dtype: float64

In []:

In [8]:

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

we don't like warnings

you can comment the following 2 lines if you'd like to

import warnings

warnings.filterwarnings('ignore')

In [9]:

import pandas as ps
from pandasql import sqldf
pysqldf = lambda q: sqldf(q, globals())

In [10]:

data_user_device = pd.read_csv('user_device.csv')
data_user_device.head()

Out[10]:

	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

In [11]:

data_user_usage = pd.read_csv('user_usage.csv')
data_user_usage.head()



Out[11]:

	outgoing_mins_per_month	outgoing_sms_per_month	montnly_mb	use_ia
C	21.97	4.82	1557.33	22787
1	1710.08	136.88	7267.55	22788
2	2 1710.08	136.88	7267.55	22789
3	94.46	35.17	519.12	22790
4	71.59	79.26	1557.33	22792

In [12]:

data_android_devices = pd.read_csv('android_devices.csv')
data_android_devices.head()



Out[12]:

Model	Device	Marketing Name	Retail Branding	
Smartfren Andromax AD681H	AD681H	NaN	NaN	0
FJL21	FJL21	NaN	NaN	1
Panasonic T31	T31	NaN	NaN	2
MediaPad 7 Youth 2	hws7721g	NaN	NaN	3

Retail Branding Marketing Name OC1020A Device OC1020A **Model** In [16]: pysqldf("""select outgoing_mins_per_month, monthly_mb from data_user_usage order by monthly_mb limit 10""") Out[16]: outgoing_mins_per_month monthly_mb 0 227.13 0.00 1 124.70 11.68 2 29.54 33.79 3 12.85 74.40 4 70.34 212.64 5 341.85 265.81 6 463.05 362.02 7 190.08 369.84 8 85.97 407.01 9 436.37 415.10

In [19]:

%%timeit
pysqldf (""" select * from data_user_usage as u join data_user_device as d on u.use_id = d.use_id """).head()

72.6 ms \pm 975 μ s per loop (mean \pm std. dev. of 7 runs, 10 loops each)

In []: