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

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# 1. Цель лабораторной работы

Изучение библиотеки обработки данных Pandas

# 2. Задание

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

In this task you should use Pandas to answer a few questions about the Adult dataset: 1. How many men and women (sex feature) are represented in this dataset? 2. What is the average age (age feature) of women? 3. What is the percentage of German citizens (native-country feature)? 4. 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? 5. 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) 6. Display age statistics for each race (race feature) and each gender (sex feature). Use groupby() and describe(). Find the maximum age of men of Amer-Indian-Eskimo race. 7. 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. 8. 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? 9. 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?

Unique values of all features: * 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-spouse-absent, Married-AF-spouse. * occupation: Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, 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(Guam-USVI-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

# 3. Ход выполнения лабораторной работы

[1]:
```
# Импортируем необходимы библиотеки
import pandas as pd
# Устанавливаем ширину экрана для отчета
pd.set_option("display.width", 70)
```

```
# Загружаем данные
data = pd.read_csv('adult.data.csv')
data.head()
```

[1]:
```
   age         workclass  fnlwgt  education  education-num  \
0   39         State-gov   77516  Bachelors             13
1   50  Self-emp-not-inc   83311  Bachelors             13
2   38           Private  215646    HS-grad              9
3   53           Private  234721       11th              7
4   28           Private  338409  Bachelors             13

       marital-status         occupation   relationship   race  \
0       Never-married       Adm-clerical  Not-in-family  White
1  Married-civ-spouse    Exec-managerial        Husband  White
2            Divorced  Handlers-cleaners  Not-in-family  White
3  Married-civ-spouse  Handlers-cleaners        Husband  Black
4  Married-civ-spouse     Prof-specialty           Wife  Black

      sex  capital-gain  capital-loss  hours-per-week  \
0    Male          2174             0              40
1    Male             0             0              13
2    Male             0             0              40
3    Male             0             0              40
4  Female             0             0              40

  native-country salary
0  United-States  <=50K
1  United-States  <=50K
2  United-States  <=50K
3  United-States  <=50K
4           Cuba  <=50K
```

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

[2]:
```
data['sex'].value_counts()
```

[2]:
```
Male      21790
Female    10771
Name: sex, dtype: int64
```

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

[3]:
```
data.loc[data['sex'] == 'Female', 'age'].mean()
```

[3]:
```
36.85823043357163
```

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

[4]:
```
print("{}%".format(data[data["native-country"] == "Germany"].shape[0] /
 ↪data.shape[0]))
```

0.004207487485028101%

**4. 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?**

[5]:
```python
ages1 = data[data["salary"] == "<=50K"]["age"]
ages2 = data[data["salary"] ==  ">50K"]["age"]
print("<=50K: {0} ± {1} years".format(ages1.mean(), ages1.std()))
print(" >50K: {0} ± {1} years".format(ages2.mean(), ages2.std()))
```

```
<=50K: 36.78373786407767 ± 14.02008849082488 years
 >50K: 44.24984058155847 ± 10.519027719851826 years
```

**5. 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)**

[6]:
```python
high_educations = ["Bachelors", "Prof-school", "Assoc-acdm", "Assoc-voc",␣
 ↪"Masters", "Doctorate"]
def high_educated(e):
    return e in high_educations

data[data["salary"] == ">50K"]["education"].map(high_educated).all()
```

[6]:
```
False
```

**6. Display age statistics for each race (race feature) and each gender (sex feature). Use groupby() and describe(). Find the maximum age of men of Amer-Indian-Eskimo race.**

[7]:
```python
data.groupby(["race", "sex"])["age"].describe()
```

[7]:
```
                             count       mean        std   min  \
race               sex
Amer-Indian-Eskimo Female    119.0  37.117647  13.114991  17.0
                   Male      192.0  37.208333  12.049563  17.0
Asian-Pac-Islander Female    346.0  35.089595  12.300845  17.0
                   Male      693.0  39.073593  12.883944  18.0
Black              Female   1555.0  37.854019  12.637197  17.0
                   Male     1569.0  37.682600  12.882612  17.0
Other              Female    109.0  31.678899  11.631599  17.0
                   Male      162.0  34.654321  11.355531  17.0
White              Female   8642.0  36.811618  14.329093  17.0
                   Male    19174.0  39.652498  13.436029  17.0

                            25%   50%    75%   max
race               sex
Amer-Indian-Eskimo Female  27.0  36.0  46.00  80.0
                   Male    28.0  35.0  45.00  82.0
Asian-Pac-Islander Female  25.0  33.0  43.75  75.0
                   Male    29.0  37.0  46.00  90.0
```

```
Black                    Female  28.0  37.0  46.00  90.0
                         Male    27.0  36.0  46.00  90.0
Other                    Female  23.0  29.0  39.00  74.0
                         Male    26.0  32.0  42.00  77.0
White                    Female  25.0  35.0  46.00  90.0
                         Male    29.0  38.0  49.00  90.0
```

[8]:
```
data[(data["race"] == "Amer-Indian-Eskimo") & (data["sex"] ==␣
↪"Male")]["age"].max()
```

[8]: 82

**7. 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.**

[9]:
```
def is_married(m):
    return m.startswith("Married")

data["married"] = data["marital-status"].map(is_married)
(data[(data["sex"] == "Male") & (data["salary"] == ">50K")]
     ["married"].value_counts())
```

[9]:
```
True      5965
False      697
Name: married, dtype: int64
```

**8. 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?**

[10]:
```
m = data["hours-per-week"].max()
print("Maximum is {} hours/week.".format(m))

people = data[data["hours-per-week"] == m]
c = people.shape[0]
print("{} people work this time at week.".format(c))

s = people[people["salary"] == ">50K"].shape[0]
print("{0:%} get >50K salary.".format(s / c))
```

```
Maximum is 99 hours/week.
85 people work this time at week.
29.411765% get >50K salary.
```

**9. 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?**

[11]:
```
p = pd.crosstab(data["native-country"], data["salary"],
                values=data['hours-per-week'], aggfunc="mean")
p
```

[11]:
```
salary                           <=50K       >50K
native-country
?                           40.164760  45.547945
Cambodia                    41.416667  40.000000
Canada                      37.914634  45.641026
China                       37.381818  38.900000
Columbia                    38.684211  50.000000
Cuba                        37.985714  42.440000
Dominican-Republic          42.338235  47.000000
Ecuador                     38.041667  48.750000
El-Salvador                 36.030928  45.000000
England                     40.483333  44.533333
France                      41.058824  50.750000
Germany                     39.139785  44.977273
Greece                      41.809524  50.625000
Guatemala                   39.360656  36.666667
Haiti                       36.325000  42.750000
Holand-Netherlands          40.000000        NaN
Honduras                    34.333333  60.000000
Hong                        39.142857  45.000000
Hungary                     31.300000  50.000000
India                       38.233333  46.475000
Iran                        41.440000  47.500000
Ireland                     40.947368  48.000000
Italy                       39.625000  45.400000
Jamaica                     38.239437  41.100000
Japan                       41.000000  47.958333
Laos                        40.375000  40.000000
Mexico                      40.003279  46.575758
Nicaragua                   36.093750  37.500000
Outlying-US(Guam-USVI-etc)  41.857143        NaN
Peru                        35.068966  40.000000
Philippines                 38.065693  43.032787
Poland                      38.166667  39.000000
Portugal                    41.939394  41.500000
Puerto-Rico                 38.470588  39.416667
Scotland                    39.444444  46.666667
South                       40.156250  51.437500
Taiwan                      33.774194  46.800000
Thailand                    42.866667  58.333333
Trinadad&Tobago             37.058824  40.000000
United-States               38.799127  45.505369
Vietnam                     37.193548  39.200000
Yugoslavia                  41.600000  49.500000
```

[12]:
```
p.loc["Japan"]
```

[12]: 
```
salary
<=50K    41.000000
>50K     47.958333
Name: Japan, dtype: float64
```