

#### Министерство образования и науки 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 СИСТЕМЫ ОБРАБОТКИ ИНФОРМАЦИИ И УПРАВЛЕНИЯ

Отчет по лабораторной работе № 2 «**Изучение библиотек обработки данных**» по курсу "Технологии машинного обучения"

Исполнитель: Студент группы ИУ5-63 Желанкина А.С. 28.02.2018

### Задание лабораторной работы

#### 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\_eng lish/assignments\_demo/assignment01\_pandas\_uci\_adult.ipynb?flush\_cache=true

Набор данных можно скачать здесь -

https://archive.ics.uci.edu/ml/datasets/Adult

#### 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.

# Экранные формы с текстом программы и примерами её выполнения

#### ЧАСТЬ 1

			umpy as andas as													
	<pre>url = 'https://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.data' data = pd.read_csv(url, sep=', ',header=None) data.head()</pre>															
							ernel_launch									
Out[2]:					as regex)		ot support r ou can avoid					ine='p		ion'		from
	'\s-	) are	e interp	oreted a	as regex)	; yo	ou can avoid	l this warni	ing by sp	ecifyi	ng eng	ine='p	oyth 11	ion'	•	
	0	0 39	e interp	2 77516	as regex)	4 13	ou can avoid 5 Never-	I this warni	7 Not-in-	8 White	ng eng	ine=';	11 0	12	13 United-	14

```
data.head()
Out[3]:
                                                                                                                        hours-
              age workclass fnlwgt education education num
                                                          marital-
status occupation relationship race
                                                                                                       capital-
                                                                                                               capital-
loss
                                                                                                                         per-
week
                                                                                                          gain
                                                           Never-
                                                                        Adm-
                                                                                                                           40
           0 39
                   State-gov 77516 Bachelors
                                                      13
                                                                             Not-in-family White
                                                                                                  Male
                                                                                                          2174
                                                                                                                     0
                                                           married
                                                                      clerical
                                                          Married-
                   Self-emp-
not-inc
                                                                       Exec-
              50
                              83311 Bachelors
                                                      13
                                                                                 Husband White
                                                                                                  Male
                                                                                                             0
                                                                                                                     0
                                                                                                                           13
                                                              civ-
                                                                   managerial
                                                           spouse
                                                                    Handlers-
           2 38
                      Private 215646
                                      HS-grad
                                                       9 Divorced
                                                                             Not-in-family White
                                                                                                  Male
                                                                                                             0
                                                                                                                     0
                                                                                                                           40
                                                          Married-
                                                                    Handlers-
           3 53
                      Private 234721
                                                                                 Husband Black
                                                                                                             0
                                                                                                                     0
                                          11th
                                                                                                  Male
                                                                                                                           40
                                                              civ-
                                                                     cleaners
                                                           spouse
In [4]: #How many men and women (sex feature) are represented in this dataset?
          print('Total people', data['sex'].count())
print(data['sex'].value_counts())
          Total people 32561
                   21790
          Male
          Female
                     10771
          Name: sex, dtype: int64
In [5]: #What is the average age (age feature) of women?
          average_age = 0
          counter = 0
          for i in range(data['sex'].count()):
              if data['sex'][i] == 'Female':
    counter += 1
                   average_age += data['age'][i]
          print('The average age of women is ', average_age / counter)
          The average age of women is 36.85823043357163
In [6]: #What is the percentage of German citizens (native-country feature)?
          counter_of_german = 0
          for country in data['native-country']:
              if country == 'Germany':
                   counter_of_german += 1
          print('The percentage of German citizens is '
                 counter_of_german / data['native-country'].count() * 100, '%')
          The percentage of German citizens is 0.42074874850281013 %
In [7]: #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?
          ages_of_rich = data.loc[data['salary'] == '>50K', 'age']
ages_of_poor = data.loc[data['salary'] == '<=50K', 'age']
print("The average age of the rich: {0} +- {1} years.\n\
The average age of the poor: {2} +- {3} years.".format(</pre>
          round(ages_of_rich.mean()), round(ages_of_rich.std(), 2),
round(ages_of_poor.mean()), round(ages_of_poor.std(), 2)))
The average age of the rich: 44 +- 10.52 years.
The average age of the poor: 37 +- 14.02 years.
In [8]: # 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)
          data.loc[data['salary'] == '>50K', 'education'].unique()
In [10]: #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.
          race_gender_age = data.groupby(['race', 'sex', 'age'])
          print(race_gender_age.describe())
```

```
The maximum age of men of Amer-Indian-Eskimo race is 82
                                         capital-gain
                                                                              std min
                                                 count
                                                               mean
                                     age
          Amer-Indian-Eskimo Female 17
                                                  2.0
                                                        527.500000
                                                                        745.997654 0.0
                                                         0.000000
                                                                          0.000000 0.0
                                     18
                                                  2.0
                                                  5.0
                                                           0.000000
                                                                          0.000000
                                     19
                                                                                    0.0
                                     21
                                                  4.0
                                                           0.000000
                                                                          0.000000
                                                                                    0.0
                                                  4.0 4307.250000
                                                                       6827.980442
                                     22
                                                                                    0.0
                                                                          0.000000
                                     23
                                                  4.0
                                                          0.000000
                                                                                    0.0
                                     24
                                                  3.0
                                                           0.000000
                                                                          0.000000
                                                                                    0.0
                                     25
                                                  4.0
                                                           0.000000
                                                                          0.000000
                                                                                    9.9
                                                         831.250000
                                     27
                                                  4.0
                                                                       1662.500000
                                                                                    0.0
                                     28
                                                   4.0
                                                           0.000000
                                                                          0.000000
                                     29
                                                  3.0
                                                           0.000000
                                                                          0.000000
                                                                                    0.0
        click to unscroll output; double click to hide
                                                           0.000000
                                                                          0.000000
                                     30
                                                   4.0
                                                                                    0.0
                                     31
                                                   7.0
                                                           0.000000
                                                                          0.000000
                                                                                    0.0
                                     32
                                                   1.0
                                                           0.000000
                                                                               NaN
                                                                                    0.0
                                                                          0.000000
                                     33
                                                  2.0
                                                           0.000000
                                                                                    0.0
In [11]: #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.
          print('Married men:\n')
print(data.loc[(data['sex'] == 'Male') & (data['marital-status'].str.startswith('Married')),
          'salary'].value_counts())
          Married men:
          <=50K
                   7576
                   5965
          >50K
          Name: salary, dtype: int64
          Single men:
                   7552
          <=50K
          >50K
                    697
          Name: salary, dtype: int64
In [16]: #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 among them?
          maximum = data['hours-per-week'].max()
          print('The maximum number of hours a person works per week is', maximum)
          hard = data[data['hours-per-week'] == maximum].shape[0]
          print(hard, 'people work such a number of hours')
          rich = float(data['hours-per-week'] == maximum) 8
                             (data['salary'] == '>50K')].shape[0]) / hard
          print('The percentage of those who earn a lot among them is', rich * 100, '%')
          The maximum number of hours a person works per week is 99
          85 people work such a number of hours
          The percentage of those who earn a lot among them is 29.411764705882355~\%
In [26]: #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?
          little = []
          lot = []
          country_salary = data.groupby(['native-country', 'salary'])
          for (country, salary), hours in country_salary:
    print(country, salary, int(hours['hours-per-week'].mean()))
          ? >50K 45
          Cambodia <=50K 41
Cambodia >50K 40
          Canada <=50K 37
          Canada >50K 45
          China <=50K 37
          China >50K 38
          Columbia <=50K 38
Columbia >50K 50
          Cuba <=50K 37
          Cuba >50K 42
          Dominican-Republic <=50K 42
          Dominican-Republic >50K 47
```

```
[ ] !pip3 install pandasql
               Collecting pandasql
                          \label{lower_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_power_pow
                       Requirement already satisfied: numpy in /usr/local/lib/python3.6/dist-packages (from pandasql) (1.14.6)
                       Requirement already satisfied: pandas in /usr/local/lib/python3.6/dist-packages (from pandasql) (0.22.0)
                       Requirement already satisfied: sqlalchemy in /usr/local/lib/python3.6/dist-packages (from pandasql) (1.2.18)
                       Requirement already satisfied: python-dateutil>=2 in /usr/local/lib/python3.6/dist-packages (from pandas->pandasql
                       Requirement already satisfied: pytz>=2011k in /usr/local/lib/python3.6/dist-packages (from pandas->pandasql) (2018
                       Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.6/dist-packages (from python-dateutil>=2->pandas
                      Building wheels for collected packages: pandasql
                          Building wheel for pandasql (setup.py) ... done
                          Stored in directory: /root/.cache/pip/wheels/53/6c/18/b87a2e5fa8a82e9c026311de56210b8d1c01846e18a9607fc9
                       Successfully built pandasql
                       Installing collected packages: pandasql
                       Successfully installed pandasql-0.7.3
                      import numpy as np
import pandas as pd
import pandasql as ps
>
             [28]
                        from time import time
                       url = 'https://archive.ics.uci.edu/ml/machine-learning-databases/breast-cancer-wisconsin/wdbc.data'
             [29]
                       data_diagnostic = pd.read_csv(url, sep=',',header=None)
data_diagnostic.columns = ['id'] + ['D' + str(i) for i in range(1, 32)]
data_diagnostic.head()
               \Box
                                                                                                                                                           D9 ...
                                        id D1
                                                          D2
                                                                      D3
                                                                                   D4
                                                                                                D5
                                                                                                               D6
                                                                                                                               D7
                                                                                                                                            DS
                                                                                                                                                                             D22
                                                                                                                                                                                        D23
                                                                                                                                                                                                      D24
                                                                                                                                                                                                                   D25
                                                                                                                                                                                                                                 D:
                                 842302 M 17.99 10.38 122.80 1001.0 0.11840 0.27760 0.3001 0.14710
                                                                                                                                                                    ... 25.38 17.33 184.60 2019.0 0.162
                                 842517 M 20.57 17.77 132.90 1326.0 0.08474 0.07864 0.0869 0.07017
                                                                                                                                                                     ... 24.99 23.41
                                                                                                                                                                                                 158.80
                        2 84300903 M 19.69 21.25
                                                                           130.00 1203.0 0.10960 0.15990 0.1974 0.12790
                                                                                                                                                                     ... 23.57 25.53
                                                                                                                                                                                                152.50
                                                                                                                                                                                                             1709.0 0.144
                        3 84348301 M 11.42 20.38
                                                                              77.58 386.1 0.14250 0.28390 0.2414 0.10520
                                                                                                                                                                    ... 14.91 26.50
                                                                                                                                                                                                   98.87
                                                                                                                                                                                                                567.7 0.209
                        4 84358402 M 20.29 14.34 135.10 1297.0 0.10030 0.13280 0.1980 0.10430
                                                                                                                                                                    ... 22.54 16.67 152.20 1575.0 0.137
                       5 rows × 32 columns
             [30] url = 'https://archive.ics.uci.edu/ml/machine-learning-databases/breast-cancer-wisconsin/wpbc.data'
                       data_prognostic = pd.read_csv(url, sep=',',header=None)
data_prognostic.columns = ['id'] + ['P' + str(i) for i in range(1, 35)]
data_prognostic.head()
               \Gamma
                                    id P1 P2
                                                               Р3
                                                                          P4
                                                                                        P5
                                                                                                     P6
                                                                                                                                  P8
                                                                                                                                                                                P26
                                                                                                                                                                                              P27
                                                                                                                                                                                                           P28
                                                                                                                                                                                                                         P29
                                                                                                                     P7
                                                                                                                                               P9 ...
                                                                                                                                                                   P25
                        0 119513
                                                   31 18.02 27.60 117.50 1013.0 0.09489 0.1036 0.1086
                                                                                                                                                      ... 139.70 1436.0 0.1195 0.1926 0.3140 0
                                 8423
                                                   61 17.99 10.38 122.80 1001.0 0.11840 0.2776 0.3001
                                                                                                                                                        ... 184.60 2019.0 0.1622 0.6656
                                                                                                                                                                                                                   0.7119 0
                                            Ν
                                                 116 21.37 17.44 137.50 1373.0 0.08836 0.1189 0.1255
                                                                                                                                                               159.10 1949.0 0.1188 0.3449 0.3414 0
                        2 842517
                                            Ν
                        3 843483 N 123 11.42 20.38 77.58 386.1 0.14250 0.2839 0.2414
                                                                                                                                                                98.87
                                                                                                                                                                             567.7 0.2098 0.8663 0.6869 0
                        4 843584 R 27 20.29 14.34 135.10 1297.0 0.10030 0.1328 0.1980
                                                                                                                                                      ... 152.20 1575.0 0.1374 0.2050 0.4000 0
                      5 rows × 35 columns
                      4
            [31] # 1 - diagnosis, 2 - radius, 22 - worst radius
t0_diagnostic = time()
aggregations_diagnostic = {
    'D22': lambda x: max(x)
}
>
                       print(data_diagnostic.groupby('D1').agg(aggregations_diagnostic))
t1_diagnostic = time()
print('It takes: ', t1_diagnostic - t0_diagnostic)
                                 D22
               \Gamma
                      D1
                            19.82
                            36.04
                      It takes: 0.005372047424316406
                       # 1 - diagnosis, 2 - radius, 22 - worst radius
t0_diagnostic = time()
aggr_query_diagnostic = '''
SELECT
                                                                                                                                                                                                                               :
                                    D1,
                                    max(D22)
                              FROM data_diagnostic
GROUP BY D1
```

```
print(ps.sqldf(aggr_query_diagnostic, locals()))
t1_diagnostic = time()
print('It takes: ', t1_diagnostic - t0_diagnostic)
         0
               D1 max(D22)
         \Box
             0 B 19.82
1 M 36.04
              It (diagnostic) takes: 0.04991793632507324
       t1 = time()
print(result)
print('It takes: ', t1 - t0)
         ₽
                        id D1 D2 D22 P1 P2
                   842517 M 20.57 24.99 N 116
843786 M 12.45 15.47 R 77
             0
             1
                    844359 M 18.25 22.88 N 60
                    844981 M 13.00 15.49 N 119
                    845636 M 16.02 19.19 N 123
       [36] t0 = time()
merge_query = '''
SELECT
d.id,
d.D1,
d.D2,
d.D22,
d.D22,
p.id
>
                      p.id,
p.P1,
p.P2
                  FROM data_diagnostic as d JOIN data_prognostic as p ON (d.id = p.id), GROUP BY p.id
              print(ps.sqldf(merge_query, locals()))
              t1 = time()
print('It takes: ', t1 - t0)
                     id D1 D2 D22
85715 M 13.17 15.67
                                                  id P1 P2
85715 N 111
                                   D2 D22
         ₽
             0
                     86208 M 20.26 24.22
                                                  86208 R
                                                               10
             1
                      86517 M 18.66 22.25
                                                   86517 N 108
                     87163 M 13.43 17.98
                                                   87163 N 84
                      87164 M 15.46 18.79
                                                   87164 N
                                                               98
              5
                     87880 M 13.81 19.20
                                                   87880 N 38
                      89122 M 19.40 23.79
              6
                                                   89122 N
                                                               17
```