# Московский государственный технический университет им. Н.Э. Баумана Кафедра «Системы обработки информации и управления»

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

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### 0.1. Часть 1

Предварительно установим необходимые пакеты:

```
[0]: | !pip install -U seaborn | !pip install -U pandasql
```

Подключим пользователя к Google Drive:

```
[0]: !pip install -U -q PyDrive import os from pydrive.auth import GoogleAuth from pydrive.drive import GoogleDrive from google.colab import auth from oauth2client.client import GoogleCredentials
```

```
[0]: # 1. Authenticate and create the PyDrive client.
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)
```

```
[0]: # choose a local (colab) directory to store the data.
local_download_path = os.path.expanduser('~/Files')
try:
    os.makedirs(local_download_path)
except: pass
```

Подключим библиотеки для работы с датасетом:

```
[0]: import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import pandasql as ps
%matplotlib inline
sns.set(style="ticks")
import warnings
warnings.filterwarnings('ignore')
```

```
[7]: for f in file_list:
    # 3. Create & download by id.
    print('title: %s, id: %s' % (f['title'], f['id']))
    fname = os.path.join(local_download_path, f['title'])
    print('downloading to {}'.format(fname))
    f_ = drive.CreateFile({'id': f['id']})
    f_.GetContentFile(fname)
```

title: adult.dataset.csv, id: 1d9oaI8smgnh9JtdNmh30bc77CxoPyK-u downloading to /root/Files/adult.dataset.csv

```
[8]: data = pd.read_csv(fname, sep=",")
    data.head()
[8]:
                   workclass fnlwgt
                                       education education-num
       age
        39
                               77516
                                       Bachelors
                                                              13
                   State-gov
    1
        50
                               83311
                                       Bachelors
                                                              13
            Self-emp-not-inc
   2
        38
                     Private 215646
                                         HS-grad
                                                              9
   3
        53
                     Private 234721
                                                              7
                                            11th
   4
        28
                     Private 338409
                                       Bachelors
                                                              13
           marital-status
                                   occupation
                                                relationship
                                                               race
                                                                         sex
   0
                                 Adm-clerical
                                              Not-in-family
            Never-married
                                                              White
                                                                        Male
    1
      Married-civ-spouse
                             Exec-managerial
                                                     Husband
                                                                        Male
                                                              White
   2
                 Divorced Handlers-cleaners Not-in-family
                                                              White
                                                                        Male
   3 Married-civ-spouse Handlers-cleaners
                                                     Husband
                                                              Black
                                                                        Male
      Married-civ-spouse
                              Prof-specialty
                                                        Wife
                                                              Black Female
       capital-gain
                    capital-loss
                                   hours-per-week native-country salary
   0
                                                    United-States
                                                                   <=50K
               2174
                                                40
                                 0
    1
                  0
                                 0
                                                13
                                                    United-States <=50K
   2
                  0
                                 0
                                                40
                                                    United-States
                                                                   <=50K
   3
                  0
                                 0
                                                    United-States
                                                40
                                                                   <=50K
    4
                  0
                                 0
                                                40
                                                             Cuba <=50K
```

Выполнение непосредственно задач 1 части:

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

(Как много мужчин и женщин представлено на датасете?)

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

[9]: Male 21790 Female 10771

Name: sex, dtype: int64

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

(Какой средний возраст женщин?)

```
[10]: mean_age = data.loc[data['sex'] == 'Female', 'age'].mean()
print("Средний возраст: {0}".format(round(mean_age, 2)))
```

Средний возраст: 36.86

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

(Какой процент немецких граждан?)

Процент немецких граждан: 0.4207%

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?

(Какое среднее значение и среднее отклонение в возрасте у тех, кто зарабатывает >50k и тех, кто зарабатывает <=50k?)

```
Средний возраст >50K: 44 +- 10.52
Средний возраст <=50K: 37 +- 14.02
```

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)?

(Правда ли то, что люди, которые зарабатывают более 50k имеют как минимум школьное образование)

```
[13]: data.loc[data['salary'] == '>50K', 'education'].unique()
```

```
[13]: 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)
```

Так как есть значения '7th-8th', это утверждение неверно

7. 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.

(Выведите статистику по возрасту для каждой расы и пола. Найдите максимальный возраст мужчины расы Amer-Indian-Eskimo)

```
[14]: for (race, sex), sub_data in data.groupby(['race', 'sex']):
    print("Race: {0}, sex: {1}".format(race, sex))
    print(sub_data['age'].describe())
    print()
```

```
Race: Amer-Indian-Eskimo, sex: Female count 119.000000 mean 37.117647 std 13.114991
```

```
min
          17.000000
25%
          27.000000
50%
          36.000000
75%
          46.000000
max
          80.00000
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
mean
          35.089595
          12.300845
std
min
          17.000000
25%
          25.000000
50%
          33.000000
75%
          43.750000
          75.000000
max
Name: age, dtype: float64
Race: Asian-Pac-Islander, sex: Male
         693.000000
count
mean
          39.073593
std
          12.883944
min
          18.000000
25%
          29.000000
50%
          37.000000
75%
          46.000000
          90.000000
max
Name: age, dtype: float64
Race: Black, sex: Female
         1555.000000
count
           37.854019
mean
std
           12.637197
min
           17.000000
25%
           28.000000
50%
           37.000000
```

46.000000 90.000000

Name: age, dtype: float64

75%

max

5

```
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
           90.000000
max
```

Name: age, dtype: float64

Race: Other, sex: Female count 109.000000 mean 31.678899 std 11.631599 min 17.000000 25% 23.000000 50% 29.000000 75% 39.000000 max74.000000

Name: age, dtype: float64

Race: Other, sex: Male 162.000000 count 34.654321 mean std 11.355531 17.000000 min 25% 26.000000 50% 32.000000 75% 42.000000 77.000000 max

Name: age, dtype: float64

Race: White, sex: Female 8642.000000 count mean 36.811618 std 14.329093 min 17.000000 25% 25.000000 50% 35.000000 75% 46.000000 90.000000 max

Name: age, dtype: float64

Race: White, sex: Male count 19174.000000 mean 39.652498 std 13.436029 min 17.000000

```
25% 29.000000
50% 38.000000
75% 49.000000
max 90.000000
Name: age, dtype: float64
```

Максимальный возраст мужчин расы Amer-Indian-Eskimo: 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.

(Какова доля женатых и неженатых мужчин с заработком >50k?)

```
Доля женатых мужчин с заработком >50K: 44.05% Доля колостяков с заработком >50K: 8.45%
```

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?

(Какое максимальное число рабочих часов в неделю? Какое количество людей работает это число рабочих часов? Какова доля из этих людей, которые зарабатывают  $>50\mathrm{k?}$ )

Максимальное количество рабочих часов в неделю: 99 Количество людей, работающих 99 часов в неделю: 85 Доля людей с большим заработком среди тех, кто работает 99 часов в неделю: 29.41%

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?

(Подсчитайте среднее число часов в неделю для богатых (>50k) и бедных (<=50k) в каждой стране. Какое будет значение для Японии?)

```
[18]: pd.crosstab(data['native-country'], data['salary'], values=data['hours-per-week'], aggfunc=np.mean).T
```

```
[18]: native-country
                                 Cambodia
                                              Canada
                                                           China
                                                                   Columbia
                                                                            \
    salary
    <=50K
                     40.164760
                               41.416667
                                           37.914634
                                                      37.381818
                                                                  38.684211
                                40.000000 45.641026
    >50K
                     45.547945
                                                      38.900000
                                                                 50.000000
                                                      Ecuador El-Salvador
    native-country
                          Cuba
                               Dominican-Republic
    salary
    <=50K
                     37.985714
                                         42.338235
                                                    38.041667
                                                                  36.030928
                                                                  45.000000
                     42.440000
                                         47.000000
                                                    48.750000
    >50K
    native-country
                       England
                                           Portugal Puerto-Rico
                                                                    Scotland
    salary
    <=50K
                     40.483333
                                          41.939394
                                                       38.470588
                                                                  39.44444
    >50K
                     44.533333
                                          41.500000
                                                       39.416667 46.666667
    native-country
                        South
                                  Taiwan
                                           Thailand Trinadad&Tobago
    salary
                                          42.866667
    <=50K
                     40.15625
                               33.774194
                                                           37.058824
    >50K
                     51.43750
                               46.800000
                                          58.333333
                                                           40.000000
    native-country United-States
                                      Vietnam
                                               Yugoslavia
    salary
    <=50K
                         38.799127 37.193548
                                                     41.6
```

[2 rows x 42 columns]

```
Japan <=50K 41.0
Japan >50K 47.96
```

### 0.2. Часть 2

```
fnames = []
for f in file_list:
    # 3. Create & download by id.
    print('title: %s, id: %s' % (f['title'], f['id']))
    fnames.append(os.path.join(local_download_path, f['title']))
    print('downloading to {0}[{1}]'.format("fnames", len(fnames) - 1))
    f_ = drive.CreateFile({'id': f['id']})
    f_.GetContentFile(fnames[len(fnames) - 1])
```

title: mlm\_lab2\_2\_user\_usage.csv, id: 1\_13razXeHU4QVE1pk9qRAW7RqkKb622H downloading to fnames[0] title: mlm\_lab2\_2\_user\_device.csv, id: 1lsiiarkA556JV\_SCFb8YJKDnwmIDxk1x downloading to fnames[1] title: mlm\_lab2\_2\_android\_devices.csv, id: 1bcm-6KWZEAEmmYIFrsFd4w2oc06KOXWa downloading to fnames[2]

```
[22]: android_devices = pd.read_csv(fnames[2], sep=",")
android_devices.head()
```

```
Retail Branding Marketing Name
                                                                               Model
|22|:
                                              Device
     0
                     NaN
                                      NaN
                                               AD681H Smartfren Andromax AD681H
     1
                                                FJL21
                                                                               FJL21
                     NaN
                                       \mathtt{NaN}
     2
                     NaN
                                                  T31
                                                                      Panasonic T31
                                       {\tt NaN}
     3
                     NaN
                                      {\tt NaN}
                                            hws7721g
                                                                MediaPad 7 Youth 2
                      30
                                  OC1020A
                                              OC1020A
                                                                             OC1020A
```

```
[23]: user_usage = pd.read_csv(fnames[0], sep=",")
user_usage.head()
```

```
[23]:
        outgoing_mins_per_month outgoing_sms_per_month monthly_mb
                                                                        use_id
                                                               1557.33
                                                                         22787
     0
                           21.97
                                                     4.82
     1
                         1710.08
                                                   136.88
                                                               7267.55
                                                                         22788
     2
                         1710.08
                                                               7267.55
                                                   136.88
                                                                         22789
     3
                           94.46
                                                    35.17
                                                                519.12
                                                                         22790
     4
                           71.59
                                                    79.26
                                                               1557.33
                                                                         22792
     user_device = pd.read_csv(fnames[1], sep=",")
     user_device.head()
[24]:
        use_id user_id platform platform_version
                                                         device
                                                                  use_type_id
         22782
                  26980
                              ios
                                                10.2
                                                      iPhone7,2
                                                                            2
     0
     1
         22783
                  29628
                         android
                                                 6.0
                                                        Nexus 5
                                                                            3
     2
                                                 5.1
                                                       SM-G903F
                                                                             1
         22784
                  28473
                          android
                                                10.2
                                                                            3
     3
         22785
                                                      iPhone7,2
                   15200
                              ios
     4
         22786
                  28239
                          android
                                                 6.0
                                                      ONE E1003
                                                                             1
```

### 0.2.1. Произвольный запрос на соединение двух наборов данных

• Pandas

```
[26]: result = join_pandas(user_usage, user_device) print("{0} записей".format(result.shape[0])) result.head()
```

159 записей

```
[26]:
        outgoing_mins_per_month
                                  outgoing_sms_per_month
                                                            monthly_mb
                                                                         use_id
                                                                1557.33
     0
                           21.97
                                                      4.82
                                                                           22787
     1
                         1710.08
                                                                7267.55
                                                    136.88
                                                                          22788
     2
                                                                7267.55
                         1710.08
                                                    136.88
                                                                          22789
     3
                           94.46
                                                                          22790
                                                     35.17
                                                                519.12
     4
                           71.59
                                                     79.26
                                                                1557.33
                                                                          22792
```

```
platform device
0 android GT-I9505
1 android SM-G930F
2 android SM-G930F
3 android D2303
4 android SM-G361F
```

• PandaSQL

```
# PandaSQL can't find datasets without arguments
     def join_pandasql(user_usage, user_device):
       query = """SELECT
               use.*, dev.platform, dev.device
               user_usage use
            JOIN
               user_device dev
                  ON use.use_id = dev.use_id;"""
       return ps.sqldf(query, locals())
[28]: result = join_pandasql(user_usage, user_device)
     print("{0} записей".format(result.shape[0]))
     result.head()
    159 записей
[28]:
        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
       platform
                   device
    0 android GT-I9505
     1 android SM-G930F
     2 android SM-G930F
     3 android
                    D2303
     4 android SM-G361F
 [0]: | import time
     def count_mean_time(func, params, N = 5):
         total\_time = 0
         for i in range(N):
             time1 = time.time()
             if len(params) == 1:
                 tmp_df = func(params[0])
             elif len(params) == 2:
                 tmp_df = func(params[0], params[1])
             time2 = time.time()
             total_time += (time2 - time1)
         return total_time/N
```

• Оценка времени выполнения

```
[30]: all_use_id = user_usage.use_id.unique().tolist()
len(all_use_id)

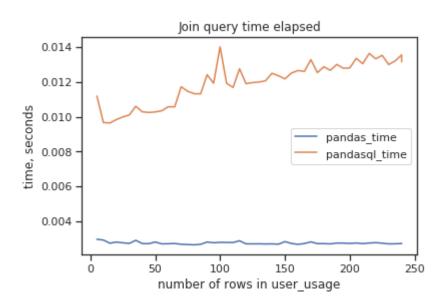
[30]: 240
```

```
[0]: join_times = []
for use_id_count in range(5, 250, 5):
    use_ids = all_use_id[:use_id_count]
    user_usage_sample = user_usage[user_usage.use_id.isin(use_ids)]
    user_device_sample = user_device[user_device.use_id.isin(use_ids)]
    count = user_usage_sample.shape[0]
    pandasql_time = count_mean_time(join_pandasql, [user_usage_sample,user_device_sample])
    pandas_time = count_mean_time(join_pandas, [user_usage_sample,user_device_sample])
    join_times.append({'count': count, 'pandasql_time': pandasql_time,user_device_sample})
    join_times.append({'count': count, 'pandasql_time': pandasql_time,user_device_sample})
```

```
[0]: join_times_df = pd.DataFrame(join_times).set_index('count')
```

```
[33]: ax = join_times_df.plot(title = 'Join query time elapsed')
ax.set_xlabel('number of rows in user_usage')
ax.set_ylabel('time, seconds')
```

[33]: Text(0, 0.5, 'time, seconds')



# 0.2.2. Произвольный запрос на группировку набора данных с использованием функций агрегирования

• Pandas

```
[0]: def aggregation_pandas(result):
       return result.groupby('platform', as_index=False).
      →agg({"outgoing_sms_per_month": "mean"})
[35]: | agg_result = aggregation_pandas(result)
     agg_result
|35|:
      platform outgoing_sms_per_month
    0 android
                              85.354586
     1
            ios
                             293.975000
       • PandaSQL
 [0]: def aggregation_pandasql(result):
       query = """SELECT
                 platform,
                 AVG(outgoing_sms_per_month) AS outgoing_sms_per_month
              FROM
                 result
              GROUP BY platform;
              \Pi/\Pi/\Pi
       return ps.sqldf(query, locals())
[37]: agg_result = aggregation_pandasql(result)
     agg_result
|37|:
      platform outgoing_sms_per_month
    0 android
                              85.354586
     1
            ios
                             293.975000
 [0]: aggregation_times = []
     for count in range(2, 160, 2):
         pandasql_time = count_mean_time(aggregation_pandasql, [result[:count]])
         pandas_time = count_mean_time(aggregation_pandas, [result[:count]])
         aggregation_times.append({'count': count, 'pandasql_time':__
      →pandasql_time, 'pandas_time': pandas_time})
 [0]: | aggregation_times_df = pd.DataFrame(aggregation_times)
     aggregation_times_df.columns = ['number of rows in result', 'pandas time', |
      →'pandasql time']
     aggregation_times_df = aggregation_times_df.set_index('number of rows in_
      →result')
[40]: ax = aggregation_times_df.plot(title = 'Aggregation time elapsed_
```

## Aggregation time elapsed (seconds)

