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Отчет по лабораторной работе № 2

«Обработка пропусков в данных, кодирование категориальных признаков, масштабирование данных»
По курсу “ Методы машинного обучения”

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Цель лабораторной работы: изучение библиотек обработки данных Pandas и PandaSQL.

Задание

Часть 1. Выполните первое демонстрационное задание "demo assignment" под названием "Exploratory data analysis with Pandas" со страницы курса https://mlcourse.ai/assignments

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.

Выполнение работы

Часть 1

> *Примечание: из-за того, что условия задания на английском языке, то и последующее выполнение оформлено на языке источника, ввиду возможных различий при переводе.*

[4]
```
import numpy as np
import pandas as pd
pd.set_option('display.max.columns', 100)
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
# import warnings
# warnings.filterwarnings('ignore')
```

[ ]
```
import plotly.express as pl
from plotly.subplots import make_subplots
import plotly.graph_objects as go
```

[ ]
```
import statistics
import math
```

[ ]
```
data = pd.read_csv('/content/adult.data.csv')
data.head()
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black

[ ]
```
for colName in data.columns:
  print(colName)
```

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

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

```
sexStat = data['sex'].value_counts()
print(sexStat)
```

```
Male      21790
Female    10771
Name: sex, dtype: int64
```

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

```
[ ] womenData = data[data['sex'] == 'Female']
    averageWomanAge = np.mean(womenData['age'])
    print('Average woman age is ', averageWomanAge,'or rounded up', math.ceil(averageWomanAge))
```

```
Average woman age is  36.85823043357163 or rounded up 37
```

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

```
[ ] germanCitizensProportion = len(data[data['native-country']== 'Germany']) / len(data['native-country'])
    print('German citizens proportion is ', round( germanCitizensProportion * 100 , 2), '%')
```

```
German citizens proportion is  0.42 %
```

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?

```
[ ] salaryLess50K = data[data['salary']== '<=50K']
    salaryMore50K = data[data['salary']== '>50K']
```

```
[ ] print('People who has salary more than 50K per year:')
    print('Mean age: ', statistics.mean(salaryMore50K['age']))
    print('Standard deviation of age: ', statistics.stdev(salaryMore50K['age']))
    print('People who has salary less than 50K per year:')
    print('Mean age: ', statistics.mean(salaryLess50K['age']))
    print('Standard deviation of age: ', statistics.stdev(salaryLess50K['age']))
```

```
People who has salary more than 50K per year:
Mean age:  44.24984058155847
Standard deviation of age:  10.519027719851826
People who has salary less than 50K per year:
Mean age:  36.78373786407767
Standard deviation of age:  14.02008849082488
```

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)

Возможно, в задании ошибка, так как, я подозреваю, что тип образования HS-grad можно также отнести к high school education

- **Без включения HS-grad**

```
[ ] PieInfo = pd.DataFrame(data = salaryMore50K['education'].value_counts())
    PieInfo
```

	education
Bachelors	2221
HS-grad	1675
Some-college	1387
Masters	959
Prof-school	423
Assoc-voc	361
Doctorate	306
Assoc-acdm	265
10th	62
11th	60
7th-8th	40
12th	33
9th	27
5th-6th	16
1st-4th	6

```
[ ] def createHSProportion( HSgrades, PieInfo ):
      highEducationCounter = 0
      midleEducationCounter = 0
      for key in list(PieInfo.index.values):
        if(key in HSgrades):
          highEducationCounter += PieInfo['education'][key]
        else:
          midleEducationCounter += PieInfo['education'][key]
      aggregatedPieInfo = pd.DataFrame(data=[highEducationCounter, midleEducationCounter], columns=['count'], index=['High school education','Middle school education'])
      fig = pl.pie(aggregatedPieInfo, names=list(aggregatedPieInfo.index.values), values='count')
      fig.show()
```

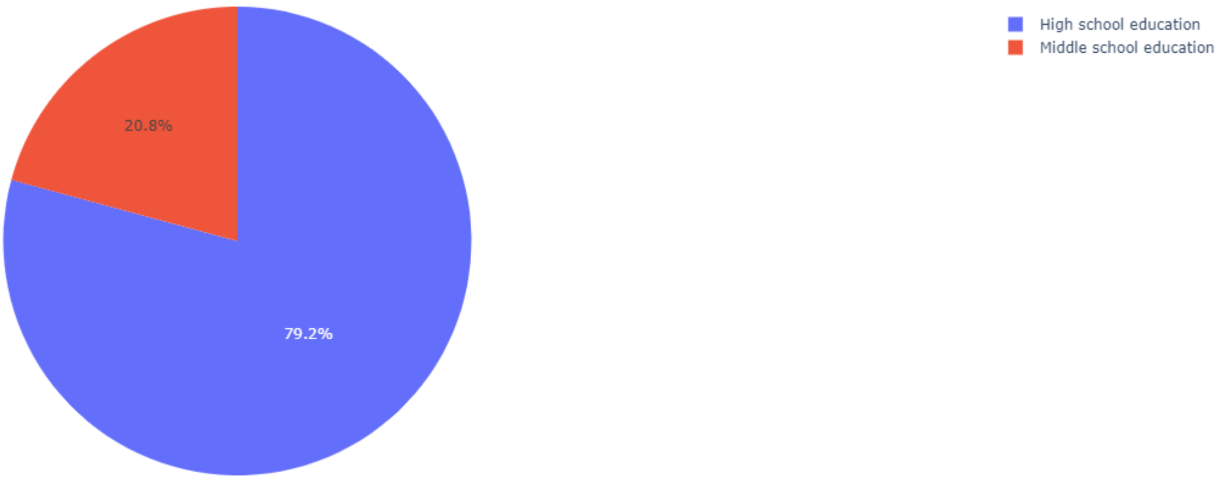
Have created function that helps make pie chart with proportions of high school education

```
[ ] createHSProportion(['Bachelors', 'Prof-school', 'Assoc-acdm', 'Assoc-voc', 'Masters', 'Doctorate'], PieInfo)
```

Answer: Actually, this is false. Not all people who earn more than 50K has a high school education and we can see that the about 57.8% of people has high education

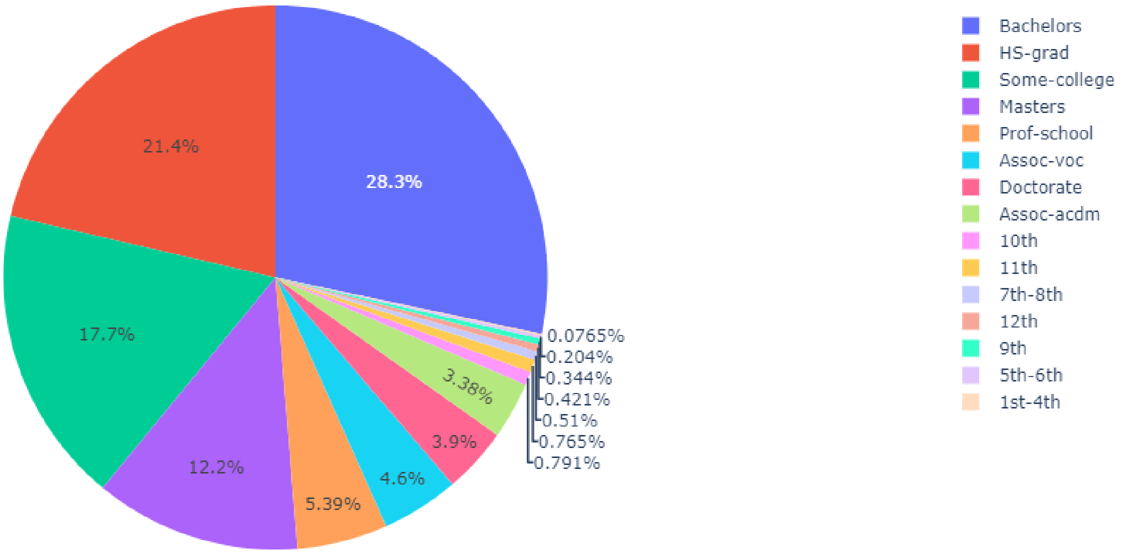
- **Включая HS-grad**

```
[ ] createHSProportion(['Bachelors', 'Prof-school', 'Assoc-acdm', 'Assoc-voc', 'Masters', 'Doctorate', 'HS-grad'], PieInfo)
```



Answer: Actually, this is true. Not all but a lot of people (about 79.2%) with great salary has a high school education

```
[ ] pl.pie(forPieInfo, names=list(forPieInfo.index.values), values='education')
```



Let's have a look how educated people with big salary. One of the biggest part from all has a Small-college grade (about 17.7%). Other the biggest parts (greater then 10%) of chart indicate that the people has a high school education

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.

- Female

```
[ ] data[data['sex'] == 'Female'].groupby(['race'])['age'].describe()
```

race	count	mean	std	min	25%	50%	75%	max
Amer-Indian-Eskimo	119.0	37.117647	13.114991	17.0	27.0	36.0	46.00	80.0
Asian-Pac-Islander	346.0	35.089595	12.300845	17.0	25.0	33.0	43.75	75.0
Black	1555.0	37.854019	12.637197	17.0	28.0	37.0	46.00	90.0
Other	109.0	31.678899	11.631599	17.0	23.0	29.0	39.00	74.0
White	8642.0	36.811618	14.329093	17.0	25.0	35.0	46.00	90.0

- Male

```
[ ] maleDescribeData = data[data['sex'] == 'Male'].groupby(['race'])['age'].describe()
    maleDescribeData
```

race	count	mean	std	min	25%	50%	75%	max
Amer-Indian-Eskimo	192.0	37.208333	12.049563	17.0	28.0	35.0	45.0	82.0
Asian-Pac-Islander	693.0	39.073593	12.883944	18.0	29.0	37.0	46.0	90.0
Black	1569.0	37.682600	12.882612	17.0	27.0	36.0	46.0	90.0
Other	162.0	34.654321	11.355531	17.0	26.0	32.0	42.0	77.0
White	19174.0	39.652498	13.436029	17.0	29.0	38.0	49.0	90.0

- Maximum age of men of Amer-Indian-Eskimo race

```
[ ] maleDescribeData['max']['Amer-Indian-Eskimo']
```

```
82.0
```

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.

```
[ ] PieInfo = pd.DataFrame(data = salaryMore50K['marital-status'].value_counts())
    PieInfo
```

	marital-status
Married-civ-spouse	6692
Never-married	491
Divorced	463
Widowed	85
Separated	66
Married-spouse-absent	34
Married-AF-spouse	10

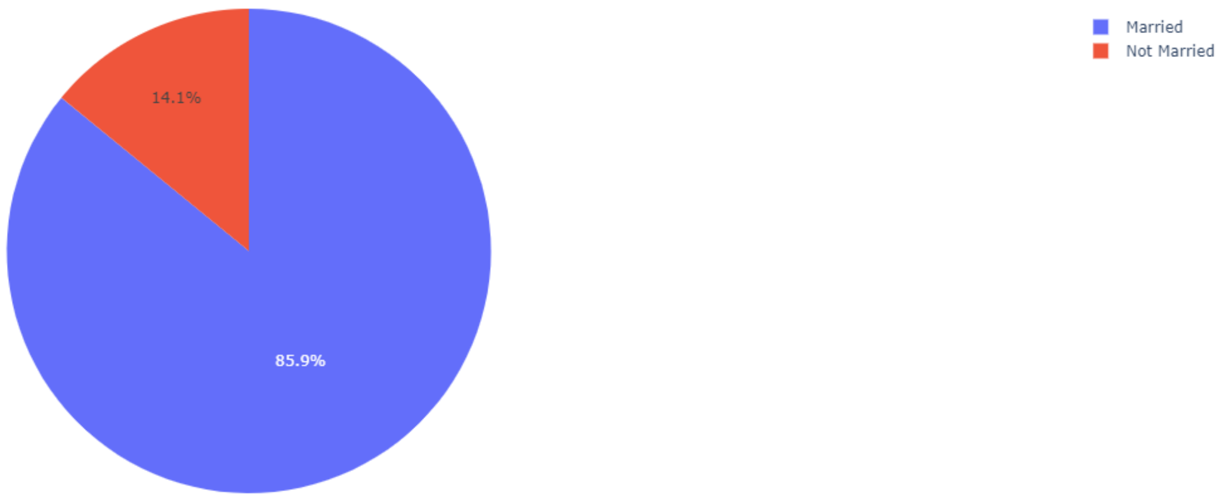
```
[ ] marriedStatus = ['Married-civ-spouse', 'Married-spouse-absent', 'Married-AF-spouse']

    MarriedCounter = 0
    NotMarriedCounter = 0

    for key in list(PieInfo.index.values):
      if(key in marriedStatus):
        MarriedCounter += PieInfo['marital-status'][key]
      else:
        NotMarriedCounter += PieInfo['marital-status'][key]

    aggregatedPieInfo = pd.DataFrame(data=[MarriedCounter, NotMarriedCounter], columns=['count'], index=['Married','Not Married'])

    pl.pie(aggregatedPieInfo, names=list(aggregatedPieInfo.index.values), values='count')
```



The biggest part of people with great salary are married (85.9%)

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?

- Maximum number of hours a person works per week

```
[ ] hoursPerWeekData = pd.DataFrame(data = data['hours-per-week'].value_counts())
    maxHoursPerWeek = max(hoursPerWeekData['hours-per-week'].index.values)
    maxHoursPerWeek
```

```
99
```

- Amount of people who works 99 hours per week

```
[ ] totalCountOfHardWorkers = hoursPerWeekData['hours-per-week'][maxHoursPerWeek]
    totalCountOfHardWorkers
```

```
85
```

- Proportion of hardworkers with big salary

```
[ ] hardworkersFrame = pd.DataFrame(data=data[data['hours-per-week']== maxHoursPerWeek])
    bigSalaryHardWorkersProportion = (hardworkersFrame['salary'].value_counts()['>50K'] / len(hardworkersFrame) )*100
    print(round(bigSalaryHardWorkersProportion, 2), '%')
```

```
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?

- Preparing data about people with the less salary

```
[ ] lessSalaryData = salaryLess50K.groupby(['native-country'])['hours-per-week'].describe()['mean']
    lessSalaryData = lessSalaryData.drop(lessSalaryData.index[0])
    lessSalaryData = lessSalaryData.rename("<=50K")
    len(lessSalaryData)
```

```
41
```

- Preparing data about people with the bigger salary

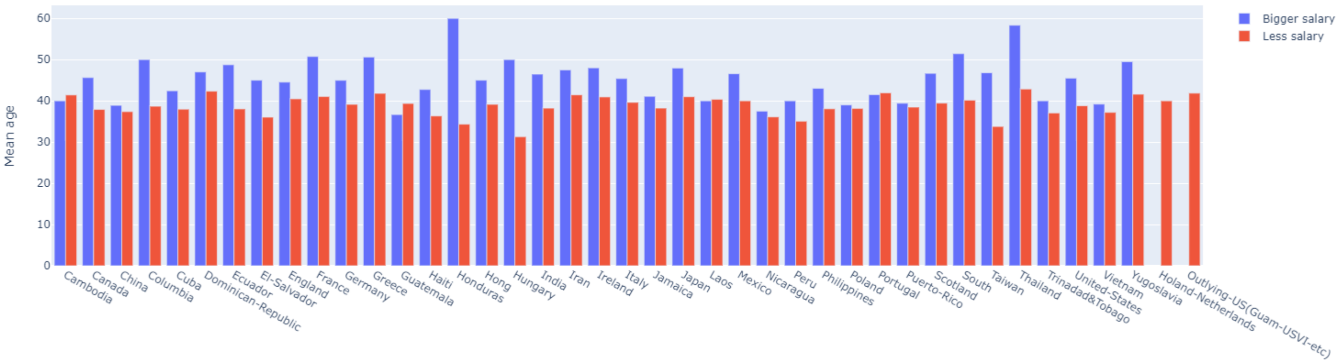
```
[ ] biggerSalaryData = salaryMore50K.groupby(['native-country'])['hours-per-week'].describe()['mean']
    biggerSalaryData = biggerSalaryData.drop(biggerSalaryData.index[0])
    biggerSalaryData = biggerSalaryData.rename(">50K")
    len(biggerSalaryData)
```

```
39
```

- Creating bar chart

```
[ ] dataForChart = pd.DataFrame(data=pd.concat([biggerSalaryData,lessSalaryData], ignore_index=False, axis=1))
    fig = go.Figure(data=[
        go.Bar(name='Bigger salary', x=dataForChart.index.values, y=dataForChart['>50K']),
        go.Bar(name='Less salary',  x=dataForChart.index.values, y=dataForChart['<=50K'])
    ])

    fig.update_layout(
        xaxis_title="Countries",
        yaxis_title="Mean age",
        barmode='group')
    fig.show()
```



- Information about Japan:

> Average age of people with salary greater then 50K

```
[ ] dataForChart['>50K']['Japan']
```

```
47.958333333333336
```

Average age of people with salary less then 50K

```
[ ] dataForChart['<=50K']['Japan']
```

```
41.0
```

Часть 2

```
[60] user_usage = pd.read_csv('/content/drive/My Drive/Colab Notebooks/MMO/2/user_usage.csv')
     user_device = pd.read_csv('/content/drive/My Drive/Colab Notebooks/MMO/2/user_device.csv')
     android_devices = pd.read_csv('/content/drive/My Drive/Colab Notebooks/MMO/2/android_devices.csv')
     print('user_usage\n',user_usage.head(2), '\n shape:', user_usage.shape)
     print('\nuser_device\n',user_device.head(2), '\n shape:', user_device.shape)
     print('\nandroid_devices\n', android_devices.head(2), '\n shape:', android_devices.shape )
```

```
user_usage
    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
 shape: (240, 4)

user_device
    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
 shape: (272, 6)

android_devices
   Retail Branding Marketing Name  Device                     Model
0              NaN            NaN  AD681H  Smartfren Andromax AD681H
1              NaN            NaN   FJL21                     FJL21
 shape: (14546, 4)
```

Соединение наборов данных с помощью Pandas

```
[36] def pandas_merge(user_usage, user_device):
       return  pd.merge(user_usage,
                 user_device[['use_id', 'platform', 'device']],
                 on='use_id')
     %time
     result =pandas_merge(user_usage, user_device)
     result.head()
```

```
CPU times: user 2 µs, sys: 1 µs, total: 3 µs
Wall time: 5.01 µs
```

	outgoing_mins_per_month	outgoing_sms_per_month	monthly_mb	use_id	platform	device
0	21.97	4.82	1557.33	22787	android	GT-I9505
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
4	71.59	79.26	1557.33	22792	android	SM-G361F

Соединение наборов данных с помощью PandaSQL

```
import pandasql as ps
def pandasql_merge(user_usage, user_device):
    aggr_query = '''
        SELECT user_usage.outgoing_mins_per_month ,
        user_usage.outgoing_sms_per_month, user_usage.monthly_mb,
        user_device.use_id, user_device.platform, user_device.device
        FROM user_usage,  user_device
        WHERE user_usage.use_id = user_device.use_id
        '''
    return ps.sqldf(aggr_query, locals())
%time
pandasql_merge(user_usage, user_device).head()
```

```
CPU times: user 2 µs, sys: 1 µs, total: 3 µs
Wall time: 6.91 µs
```

	outgoing_mins_per_month	outgoing_sms_per_month	monthly_mb	use_id	platform	device
0	21.97	4.82	1557.33	22787	android	GT-I9505
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
4	71.59	79.26	1557.33	22792	android	SM-G361F

Группировка набора данных с использованием функций агрегирования

Pandas:

```
[37] def pandas_agg(result):
       return result.groupby('device')['monthly_mb'].mean()

     %time
     res1 = pandas_agg(result)
     res1.head()
```

```
CPU times: user 2 µs, sys: 0 ns, total: 2 µs
Wall time: 4.53 µs
device
A0001    15573.33
C6603     1557.33
D2303      519.12
D5503     1557.33
D5803     1557.33
Name: monthly_mb, dtype: float64
```

PandaSQL:

```
[29] def pandasql_agg(result):
         aggr_query = '''
             SELECT
                 avg(monthly_mb) as avg_traffic, device
             FROM result
             GROUP BY device
             '''
         return ps.sqldf(aggr_query, locals())

     %time
     pandasql_agg(result).head()
```

```
CPU times: user 3 µs, sys: 0 ns, total: 3 µs
Wall time: 5.25 µs
```

	avg_traffic	device
0	15573.33	A0001
1	1557.33	C6603
2	519.12	D2303
3	1557.33	D5503
4	1557.33	D5803

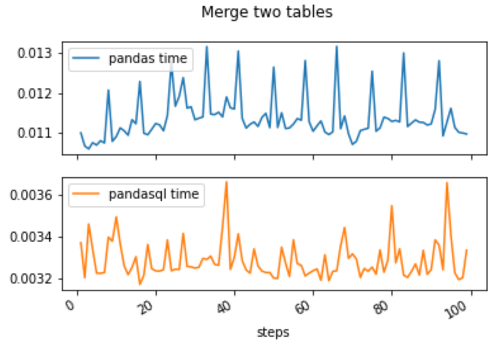
Сравнение времени выполнения.

```
[52] import time
     #  Метод подсчета времени
     def count_mean_time(func, params, N =50):
         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
```

```
[53] ex1_times = []
     for count in range(1, 100):
         pandasql_time = count_mean_time(pandasql_merge, [user_usage, user_device])
         pandas_time = count_mean_time(pandas_merge, [user_usage, user_device])
         ex1_times.append({'count': count, 'pandasql_time': pandasql_time, 'pandas_time': pandas_time})
```

```
[57] ex1_times_df = pd.DataFrame(ex1_times)
     ex1_times_df.columns = ['steps', 'pandas time', 'pandasql time']
     ex1_times_df = ex1_times_df.set_index('steps')

     ax = ex1_times_df.plot(title = 'Merge two tables', subplots = True)
```

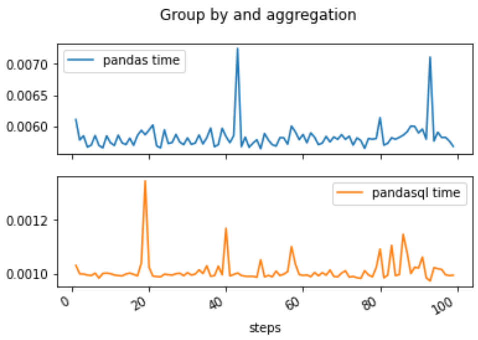


Сравнение времени выполнения объединения таблиц показало, что pandasql справляется с этой задачей быстрее, чем pandas.

```
[58] ex2_times = []
     for count in range(1, 100):
         pandasql_time = count_mean_time(pandasql_agg, [result])
         pandas_time = count_mean_time(pandas_agg, [result])
         ex2_times.append({'count': count, 'pandasql_time': pandasql_time, 'pandas_time': pandas_time})

     ex2_times_df = pd.DataFrame(ex2_times)
     ex2_times_df.columns = ['steps', 'pandas time', 'pandasql time']
     ex2_times_df = ex2_times_df.set_index('steps')

     ax = ex2_times_df.plot(title = 'Group by and aggregation', subplots = True)
```



Вывод: Возможно, ввиду небольшого объема данных, pandasql показал лучшее время выполнения, как запроса объединения двух таблиц, так и выполнения группировки с агрегатом.