In [2]:

```
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 [59]:

```
data = pd.read_csv("C:/Users/VTsapiy/Desktop/лаба 2/adult.data.csv", names=['age', 'workcla
data.head()
```

Out[59]:

	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	Fe

In [60]:

```
data['sex'].count()
```

Out[60]:

32561

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

In [74]:

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

Out[74]:

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

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

In [75]:

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

Out[75]:

```
36.85823043357163
```

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

In [77]:

```
float((data['native-country'] == 'Germany').sum()) / data.shape[0]
```

Out[77]:

```
0.004207487485028101
```

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?

In [78]:

```
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: 44.0 +- 10.5 years, poor - 37.0 +- 14.0 years.
```

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)

In [81]:

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

Out[81]:

```
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)
```

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.

In [82]:

```
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
mean      37.117647
std       13.114991
min       17.000000
25%       27.000000
50%       36.000000
75%       46.000000
max       80.000000
Name: age, dtype: float64
Race: Amer-Indian-Eskimo, sex: Male
count    192.000000
mean      37.208333
std       12.049563
min       17.000000
25%       28.000000
50%       35.000000
75%       45.000000
max       82.000000
Name: age, dtype: float64
Race: Asian-Pac-Islander, sex: Female
count    346.000000
mean      35.089595
std       12.300845
min       17.000000
25%       25.000000
50%       33.000000
75%       43.750000
max       75.000000
Name: age, dtype: float64
Race: Asian-Pac-Islander, sex: Male
count    693.000000
mean      39.073593
std       12.883944
min       18.000000
25%       29.000000
50%       37.000000
75%       46.000000
max       90.000000
Name: age, dtype: float64
Race: Black, sex: Female
count    1555.000000
mean       37.854019
std        12.637197
min        17.000000
25%        28.000000
50%        37.000000
75%        46.000000
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
mean      31.678899
std       11.631599
min       17.000000
25%       23.000000
50%       29.000000
75%       39.000000
max       74.000000
Name: age, dtype: float64
Race: Other, sex: Male
count    162.000000
mean      34.654321
std       11.355531
min       17.000000
25%       26.000000
50%       32.000000
75%       42.000000
max       77.000000
Name: age, dtype: float64
Race: White, sex: Female
count    8642.000000
mean       36.811618
std        14.329093
min        17.000000
25%        25.000000
50%        35.000000
75%        46.000000
max        90.000000
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
```

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.

In [83]:

```
data.loc[(data['sex'] == 'Male') &
     (data['marital-status'].isin(['Never-married',
                                   'Separated',
                                   'Divorced',
                                   'Widowed'])), 'salary'].value_counts()
```

Out[83]:

```
<=50K    7552
>50K      697
Name: salary, dtype: int64
```

In [84]:

```
data.loc[(data['sex'] == 'Male') &
     (data['marital-status'].str.startswith('Married')), 'salary'].value_counts()
```

Out[84]:

```
<=50K    7576
>50K     5965
Name: salary, dtype: int64
```

In [85]:

```
data['marital-status'].value_counts()
```

Out[85]:

```
Married-civ-spouse       14976
Never-married            10683
Divorced                  4443
Separated                 1025
Widowed                    993
Married-spouse-absent      418
Married-AF-spouse           23
Name: marital-status, dtype: int64
```

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?

In [86]:

```
max_load = data['hours-per-week'].max()
print("Max time - {0} hours./week.".format(max_load))

num_workaholics = data[data['hours-per-week'] == max_load].shape[0]
print("Total number of such hard workers {0}".format(num_workaholics))

rich_share = float(data[(data['hours-per-week'] == max_load)
                 & (data['salary'] == '>50K')].shape[0]) / num_workaholics
print("Percentage of rich among them {0}%".format(int(100 * rich_share)))
```

```
Max time - 99 hours./week.
Total number of such hard workers 85
Percentage of rich among them 29%
```

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?

In [87]:

```
for (country, salary), sub_df in data.groupby(['native-country', 'salary']):
    print(country, salary, round(sub_df['hours-per-week'].mean(), 2))
```

```
? <=50K 40.16
? >50K 45.55
Cambodia <=50K 41.42
Cambodia >50K 40.0
Canada <=50K 37.91
Canada >50K 45.64
China <=50K 37.38
China >50K 38.9
Columbia <=50K 38.68
Columbia >50K 50.0
Cuba <=50K 37.99
Cuba >50K 42.44
Dominican-Republic <=50K 42.34
Dominican-Republic >50K 47.0
Ecuador <=50K 38.04
Ecuador >50K 48.75
El-Salvador <=50K 36.03
El-Salvador >50K 45.0
England <=50K 40.48
England >50K 44.53
France <=50K 41.06
France >50K 50.75
Germany <=50K 39.14
Germany >50K 44.98
Greece <=50K 41.81
Greece >50K 50.62
Guatemala <=50K 39.36
Guatemala >50K 36.67
Haiti <=50K 36.33
Haiti >50K 42.75
Holand-Netherlands <=50K 40.0
Honduras <=50K 34.33
Honduras >50K 60.0
Hong <=50K 39.14
Hong >50K 45.0
Hungary <=50K 31.3
Hungary >50K 50.0
India <=50K 38.23
India >50K 46.48
Iran <=50K 41.44
Iran >50K 47.5
Ireland <=50K 40.95
Ireland >50K 48.0
Italy <=50K 39.62
Italy >50K 45.4
Jamaica <=50K 38.24
Jamaica >50K 41.1
Japan <=50K 41.0
Japan >50K 47.96
Laos <=50K 40.38
Laos >50K 40.0
Mexico <=50K 40.0
Mexico >50K 46.58
Nicaragua <=50K 36.09
Nicaragua >50K 37.5
```

```
Outlying-US(Guam-USVI-etc) <=50K 41.86
Peru <=50K 35.07
Peru >50K 40.0
Philippines <=50K 38.07
Philippines >50K 43.03
Poland <=50K 38.17
Poland >50K 39.0
Portugal <=50K 41.94
Portugal >50K 41.5
Puerto-Rico <=50K 38.47
Puerto-Rico >50K 39.42
Scotland <=50K 39.44
Scotland >50K 46.67
South <=50K 40.16
South >50K 51.44
Taiwan <=50K 33.77
Taiwan >50K 46.8
Thailand <=50K 42.87
Thailand >50K 58.33
Trinadad&Tobago <=50K 37.06
Trinadad&Tobago >50K 40.0
United-States <=50K 38.8
United-States >50K 45.51
Vietnam <=50K 37.19
Vietnam >50K 39.2
Yugoslavia <=50K 41.6
Yugoslavia >50K 49.5
```

In [88]:

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

Out[88]:

native-country	?	Cambodia	Canada	China	Columbia	Cuba	Dominican-Republic	Ecuad
salary								
<=50K	40.164760	41.416667	37.914634	37.381818	38.684211	37.985714	42.338235	38.0416
>50K	45.547945	40.000000	45.641026	38.900000	50.000000	42.440000	47.000000	48.7500

2 часть

In [97]:

```python
import timeit
```

In [92]:

```
user_usage = pd.read_csv('C:/Users/VTsapiy/Desktop/лаба 2/user_usage.csv')
user_usage.head()
```

Out[92]:

	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

In [93]:

```
user_device = pd.read_csv('C:/Users/VTsapiy/Desktop/лаба 2/user_device.csv')
user_device.head()
```

Out[93]:

	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 [99]:

```
devices = pd.read_csv('C:/Users/VTsapiy/Desktop/лаба 2/android_devices.csv')
devices.head()
```

Out[99]:

	Retail Branding	Marketing Name	Device	Model
0	NaN	NaN	AD681H	Smartfren Andromax AD681H
1	NaN	NaN	FJL21	FJL21
2	NaN	NaN	T31	Panasonic T31
3	NaN	NaN	hws7721g	MediaPad 7 Youth 2
4	3Q	OC1020A	OC1020A	OC1020A

Запрос на соединение двух наборов данных в pandas

In [237]:

```
result = pd.merge(user_usage,
                  user_device[['use_id', 'platform', 'device']],
                  on='use_id')
result.head()
```

Out[237]:

	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

In [200]:

```
%timeit result
```

```
60.3 ns ± 3.2 ns per loop (mean ± std. dev. of 7 runs, 10000000 loops each)
```

Запрос на группировку набора данных с использованием функций агрегирования в pandas

In [108]:

```
user_usage.groupby('use_id', as_index=False).agg({"outgoing_sms_per_month": "sum"})
```

Out[108]:

	use_id	outgoing_sms_per_month
0	22787	4.82
1	22788	136.88
2	22789	136.88
3	22790	35.17
4	22792	79.26
...	...	...
235	25008	68.44
236	25040	36.50
237	25046	12.37
238	25058	120.46
239	25220	906.92

240 rows × 2 columns

In [203]:

```
result_2 = user_usage.groupby('use_id', as_index=False).agg({"outgoing_sms_per_month": "sum
```

In [ ]:

```
%timeit result_2
```

Запрос на соединение двух наборов данных в pandaSQL

In [110]:

```
import pandasql as ps
```

In [188]:

```
query_pandasql = '''
    SELECT u.use_id,
           u.monthly_mb,
           u.outgoing_sms_per_month,
           u2.device
    FROM   user_usage u
    LEFT JOIN
           user_device u2
            ON u.use_id = u2.use_id
    '''
pandasql_1 = ps.sqldf(query_pandasql, locals())
```

In [189]:

```
pandasql_1
```

Out[189]:

	use_id	monthly_mb	outgoing_sms_per_month	device
0	22787	1557.33	4.82	GT-I9505
1	22788	7267.55	136.88	SM-G930F
2	22789	7267.55	136.88	SM-G930F
3	22790	519.12	35.17	D2303
4	22792	1557.33	79.26	SM-G361F
...	...	...	...	...
235	25008	896.96	68.44	None
236	25040	2815.00	36.50	None
237	25046	6828.09	12.37	None
238	25058	1453.16	120.46	None
239	25220	3089.85	906.92	None

240 rows × 4 columns

In [193]:

```
worktime_3 = %timeit pandasql_1
```

```
61.1 ns ± 2.9 ns per loop (mean ± std. dev. of 7 runs, 10000000 loops each)
```

Запрос на группировку набора данных с использованием функций агрегирования в PandaSQL

In [178]:

```
query_pandasql_agg = '''
    SELECT
           u2.device,
           sum(u.outgoing_sms_per_month) total_outgoing_sms_per_month,
           avg(u.outgoing_mins_per_month) total_outgoing_mins_per_month
    FROM   user_usage u
    LEFT JOIN
           user_device u2
               ON u.use_id = u2.use_id
    GROUP BY
           u2.device
    ORDER BY 2 DESC

    '''
pandasql_2 = ps.sqldf(query_pandasql_agg, locals())
```

In [263]:

```
pandasql_2.head()
```

Out[263]:

	device	total_outgoing_sms_per_month	total_outgoing_mins_per_month
0	None	9763.77	414.376420
1	SM-G900F	2479.94	178.825333
2	GT-I9505	1076.33	162.770909
3	HTC One mini 2	981.99	78.800000
4	SM-G935F	891.46	325.834000

In [199]:

```
worktime_4 = %timeit pandasql_2
```

```
59.6 ns ± 1.79 ns per loop (mean ± std. dev. of 7 runs, 10000000 loops each)
```

Сравнение времени выполенния запроса pandas и pandasql на соединение таблиц

pandas = 60.3 ns ± 3.2 ns

pandasql = 61.1 ns ± 2.9 ns

Сравнение времени выполенния запроса pandas и pandasql на выполенение запросов с аггрегированными данными

pandas = 3.31 ms ± 461 µs

pandasql = 59.6 ns ± 1.79 ns

In [272]:

```
# pandasql code
def query_merge_pandasql(user_usage, user_device):
    simple_query_merge = '''
    SELECT
           u2.device,
           sum(u.outgoing_sms_per_month) total_outgoing_sms_per_month,
           avg(u.outgoing_mins_per_month) total_outgoing_mins_per_month
    FROM   user_usage u
    LEFT JOIN
           user_device u2
               ON u.use_id = u2.use_id
    GROUP BY
           u2.device
    ORDER BY 2 DESC

    '''
    return ps.sqldf(simple_query_merge, locals())

# pandas code
def query_merge_pandas(user_usage, user_device):
    return pd.merge(user_usage,
                    user_device[['use_id', 'platform', 'device']],
                    on='use_id')
```

In [274]:

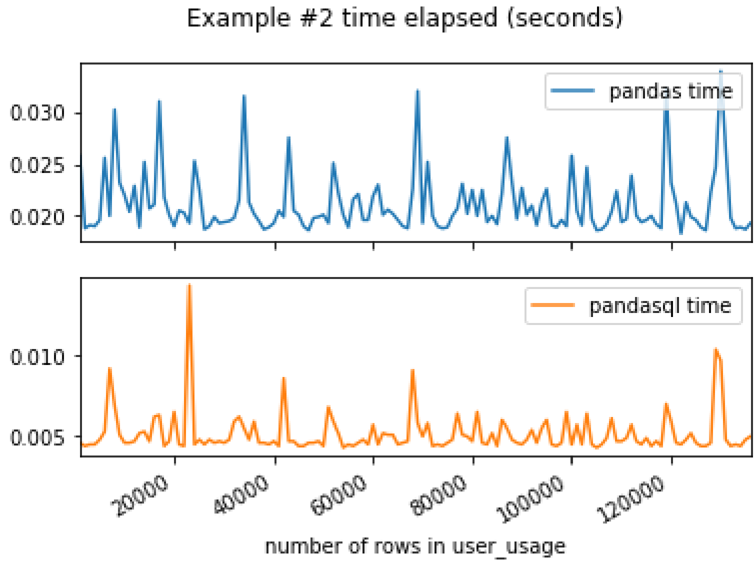
```
merge_times = []
for count in range(1000, 137000, 1000):
    pandasql_time = count_mean_time(query_merge_pandasql, [user_usage[:count], user_device]
    pandas_time = count_mean_time(query_merge_pandas, [user_usage[:count], user_device])
    merge_times.append({'count': count, 'pandasql_time': pandasql_time, 'pandas_time': panc
```

In [275]:

```
merge_times_df = pd.DataFrame(merge_times)
merge_times_df.columns = ['number of rows in user_usage', 'pandas time', 'pandasql time']
merge_times_df = merge_times_df.set_index('number of rows in user_usage')
```

In [276]:

```
merge_plot = merge_times_df.plot(title = 'Example #2 time elapsed (seconds)', subplots = Tr
```



In [265]:

```
#pandasql code
def query_pandasql(user_usage):
    aggr_query = '''
        SELECT
            avg(outgoing_mins_per_month) as outgoing_mins_per_month,
            use_id
        FROM user_usage
        GROUP BY use_id
        '''
    return ps.sqldf(aggr_query, locals()).set_index('use_id')

# pandas code
def query_pandas(user_usage):
    return pd.DataFrame(user_usage.groupby('use_id').outgoing_mins_per_month.mean())
```

In [266]:

```
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
```

In [268]:

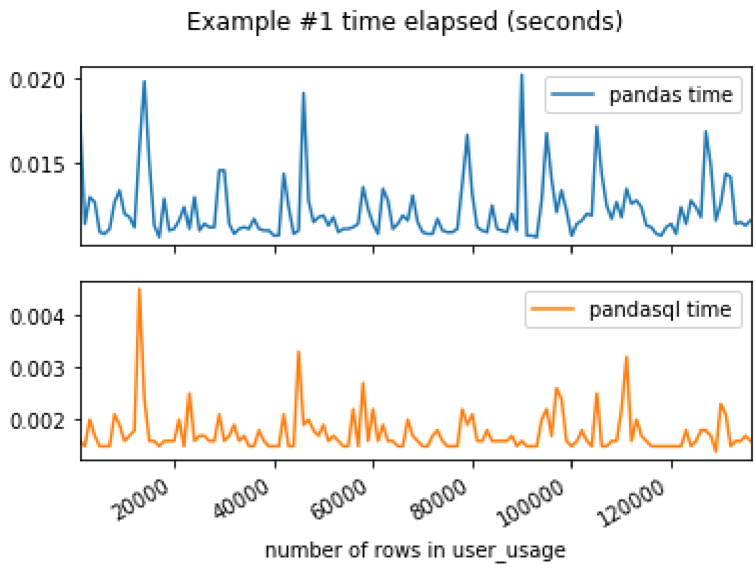
```
agg_times = []
for count in range(1000, 137000, 1000):
    pandasql_time = count_mean_time(query_pandasql, [user_usage[:count]])
    pandas_time = count_mean_time(query_pandas, [user_usage[:count]])
    agg_times.append({'count': count, 'pandasql_time': pandasql_time, 'pandas_time': pandas
```

In [270]:

```
agg_times_df = pd.DataFrame(agg_times)
agg_times_df.columns = ['number of rows in user_usage', 'pandas time', 'pandasql time']
agg_times_df = agg_times_df.set_index('number of rows in user_usage')
```

In [271]:

```
agg_plot = agg_times_df.plot(title = 'Example #1 time elapsed (seconds)', subplots = True)
```



In [ ]: