adult-income-prediction-and-data-exploration

November 2, 2020

1 Adult Income Prediction and Data Exploration

[5]:
```python
# This Python 3 environment comes with many helpful analytics libraries␣
↪installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/
↪docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
from sklearn.preprocessing import LabelEncoder
import datetime
import matplotlib.pyplot as plt
import seaborn as sns
import urllib

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list␣
↪all files under the input directory

import os
for dirname, _, filenames in os.walk('./datasets/AdultIncome/'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 5GB to the current directory (/kaggle/working/) that gets␣
↪preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved␣
↪outside of the current session
```

```
./datasets/AdultIncome/adult.csv
```

We upload our dataset

[6]:
```python
adult_income = pd.read_csv("./datasets/AdultIncome/adult.csv")
```

We have a quick look at the table:

[7]:
```
adult_income.head()
```

[7]:
```
   age workclass  fnlwgt     education  education.num marital.status  \
0   90         ?   77053       HS-grad              9        Widowed
1   82   Private  132870       HS-grad              9        Widowed
2   66         ?  186061  Some-college             10        Widowed
3   54   Private  140359       7th-8th              4       Divorced
4   41   Private  264663  Some-college             10      Separated

          occupation   relationship   race     sex  capital.gain  \
0                  ?  Not-in-family  White  Female             0
1    Exec-managerial  Not-in-family  White  Female             0
2                  ?      Unmarried  Black  Female             0
3  Machine-op-inspct      Unmarried  White  Female             0
4     Prof-specialty      Own-child  White  Female             0

   capital.loss  hours.per.week native.country income
0          4356              40  United-States  <=50K
1          4356              18  United-States  <=50K
2          4356              40  United-States  <=50K
3          3900              40  United-States  <=50K
4          3900              40  United-States  <=50K
```

At first sight, the table seems to have null values. The `education.num` and `education` fields are the same, one is categorical and the other is numerical. Let's have a statistical look at the numerical values.

[8]:
```
adult_income.describe()
```

[8]:
```
                age        fnlwgt  education.num  capital.gain  capital.loss  \
count  32561.000000  3.256100e+04   32561.000000  32561.000000  32561.000000
mean      38.581647  1.897784e+05      10.080679   1077.648844     87.303830
std       13.640433  1.055500e+05       2.572720   7385.292085    402.960219
min       17.000000  1.228500e+04       1.000000      0.000000      0.000000
25%       28.000000  1.178270e+05       9.000000      0.000000      0.000000
50%       37.000000  1.783560e+05      10.000000      0.000000      0.000000
75%       48.000000  2.370510e+05      12.000000      0.000000      0.000000
max       90.000000  1.484705e+06      16.000000  99999.000000   4356.000000

       hours.per.week
count    32561.000000
mean        40.437456
std         12.347429
min          1.000000
25%         40.000000
50%         40.000000
75%         45.000000
max         99.000000
```

There might be some outliers in all numerical values.

[9]:
```
adult_income.head()
```

[9]:
```
   age workclass  fnlwgt     education  education.num marital.status  \
0   90         ?   77053       HS-grad              9        Widowed
1   82   Private  132870       HS-grad              9        Widowed
2   66         ?  186061  Some-college             10        Widowed
3   54   Private  140359       7th-8th              4       Divorced
4   41   Private  264663  Some-college             10      Separated

          occupation   relationship   race     sex  capital.gain  \
0                  ?  Not-in-family  White  Female             0
1    Exec-managerial  Not-in-family  White  Female             0
2                  ?      Unmarried  Black  Female             0
3  Machine-op-inspct      Unmarried  White  Female             0
4     Prof-specialty      Own-child  White  Female             0

   capital.loss  hours.per.week native.country income
0          4356              40  United-States  <=50K
1          4356              18  United-States  <=50K
2          4356              40  United-States  <=50K
3          3900              40  United-States  <=50K
4          3900              40  United-States  <=50K
```

1.0.1 What do we want to predict?

Our main goal is to predict if a person, given some certain features, has a high salary or not (A salary is considered high if it's above 50,000$ per year). This is contained in the `income` target

[ ]:
```

```

1.0.2 Exploring null values

[10]:
```
adult_income = adult_income.replace('?', np.NaN)
```

[11]:
```
adult_income.isna().sum()
```

[11]:
```
age                  0
workclass         1836
fnlwgt               0
education            0
education.num        0
marital.status       0
occupation        1843
relationship         0
race                 0
```

```
sex                  0
capital.gain         0
capital.loss         0
hours.per.week       0
native.country     583
income               0
dtype: int64
```

As we observe, `workclass`, `occupation` and `native.country`.

workclass The `workclass` feature is categorical. So we'll replace the null values setting the label `Unknown`.

```
[12]: adult_income['workclass'] = adult_income['workclass'].replace(np.NaN, 'Unknown')
```

```
[13]: adult_income['workclass'].isna().sum()
```

```
[13]: 0
```

```
[14]: adult_income[adult_income['workclass'] == 'Unknown']['workclass'].count()
```

```
[14]: 1836
```

occupation The `occupation` feature is categorical. So we'll replace the null values setting the label `Other`.

```
[15]: adult_income['occupation'] = adult_income['occupation'].replace(np.NaN, 'Other')
```

```
[16]: adult_income[adult_income['occupation'] == 'Other']['occupation'].count()
```

```
[16]: 1843
```

Native Country The `native.country` feature is categorical. So we'll also replace the null values setting the label `Other`.

```
[17]: adult_income['native.country'] = adult_income['native.country'].replace(np.NaN,␣
       ↪'Other')
```

```
[18]: adult_income[adult_income['native.country'] == 'Other']['native.country'].
       ↪count()
```

```
[18]: 583
```

Now there are no null values

```
[19]: adult_income.isna().sum()
```

[19]:
```
age               0
workclass         0
fnlwgt            0
education         0
education.num     0
marital.status    0
occupation        0
relationship      0
race              0
sex               0
capital.gain      0
capital.loss      0
hours.per.week    0
native.country    0
income            0
dtype: int64
```

1.0.3 Auxiliar functions

Before analyzing and exploring our dataset, We will create a auxiliar function to plot charts with certain parameters.

[20]:
```python
from matplotlib.ticker import FuncFormatter


def plot_features_income(data, column, type_names, size=(20, 10)):
    fig, ax = plt.subplots(figsize=size)
    barWidth = 0.25
    bars1 = list()
    bars2 = list()
    for col in type_names:
        dt = data[data[column] == col]
        count_up = dt[dt['income'] == '>50K']['income'].count()
        count_down = dt[dt['income'] == '<=50K']['income'].count()
        bars1.append(count_up)
        bars2.append(count_down)

    r1 = np.arange(len(bars1))
    r2 = [x + barWidth for x in r1]

    rects1 = plt.bar(r1, bars1, color='gold', width=barWidth,␣
 ↪edgecolor='white', label='More than 50K $')
    rects2 = plt.bar(r2, bars2, color='tomato', width=barWidth,␣
 ↪edgecolor='white', label='Less or Equal than 50K $')

    plt.xlabel(column, fontweight='bold')
    plt.ylabel('Income per number of people', fontweight='bold')
```

```
    plt.xticks([r + barWidth for r in range(len(bars1))], type_names,␣
↪rotation=30)
    plt.minorticks_on()
    plt.grid(b=True, which='minor', color='#999999', linestyle='-', alpha=0.4)

    heights_1 = list()
    for rect in rects1:
        height = rect.get_height()
        heights_1.append(height)

    heights_2 = list()
    for rect in rects2:
        height = rect.get_height()
        heights_2.append(height)

    count = 0
    for rect in rects1:
        h1 = heights_1[count]
        h2 = heights_2[count]
        ptg = (h1 / (h1 + h2)) * 100
        ax.text(rect.get_x() + rect.get_width()/2., 0.99*h1,
            '%d' % int(ptg) + "%", ha='center')
        count = count + 1

    count = 0
    for rect in rects2:
        h1 = heights_1[count]
        h2 = heights_2[count]
        ptg = (h2 / (h1 + h2)) * 100
        ax.text(rect.get_x() + rect.get_width()/2., h2,
            '%d' % int(ptg) + "%", ha='center', va='bottom')
        count = count + 1


    plt.tight_layout()
    plt.legend()
    plt.show()
```

[ ]:

```
```

2 Data Exploration

[21]:

```
adult_income.dtypes
```

```
[21]: age                int64
workclass         object
fnlwgt             int64
education         object
education.num      int64
marital.status    object
occupation        object
relationship      object
race              object
sex               object
capital.gain       int64
capital.loss       int64
hours.per.week     int64
native.country    object
income            object
dtype: object
```

2.1 Categorical features

We will first analyze our categorical features.

2.1.1 workclass

The `workclass` feature represents the kind of profession a person has. Let's see the relation between this feature and the `income` feature.

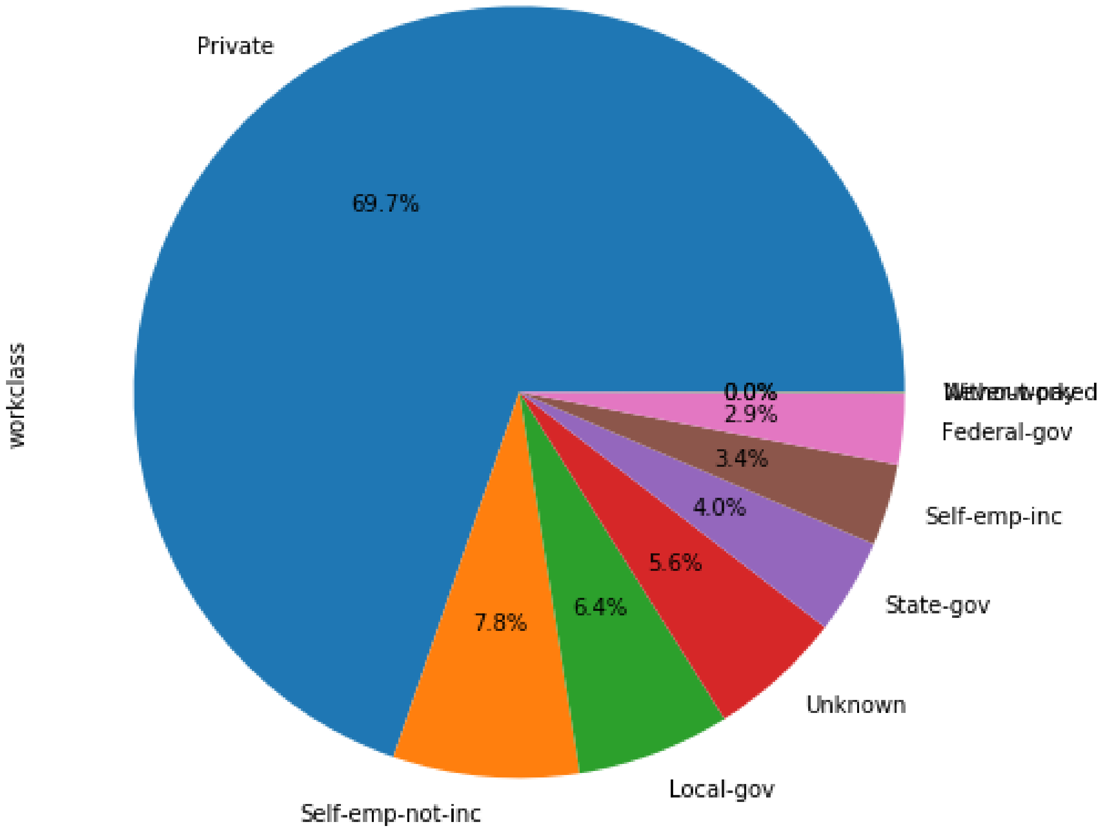
```
[22]: workclass_types = adult_income.workclass.unique()
```

```
[23]: workclass_types
```

```
[23]: array(['Unknown', 'Private', 'State-gov', 'Federal-gov',
       'Self-emp-not-inc', 'Self-emp-inc', 'Local-gov', 'Without-pay',
       'Never-worked'], dtype=object)
```

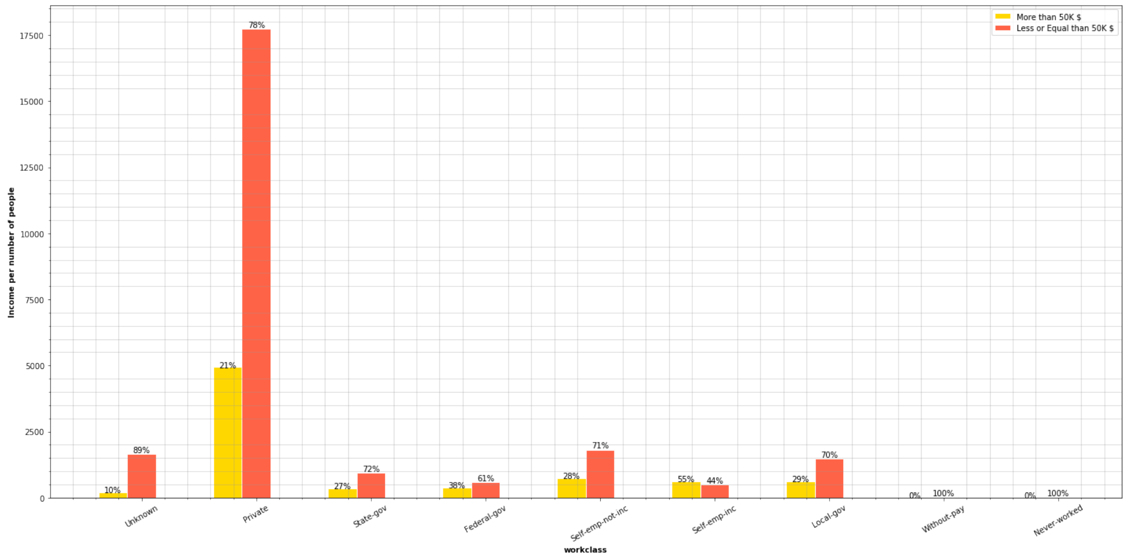
```
[24]: plt.figure(figsize=(8, 8))
adult_income['workclass'].value_counts().plot.pie(autopct='%1.1f%%')
```

```
[24]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1dbdf790>
```



We see that **60%** of people registered in the census work in the private sector. The rest is distribuited among between self-employement and public sector. We have a **5.6%** of jobs that are unknown. Now we we'll have a look at people earning more thatn 50,000$ depending on workclass.

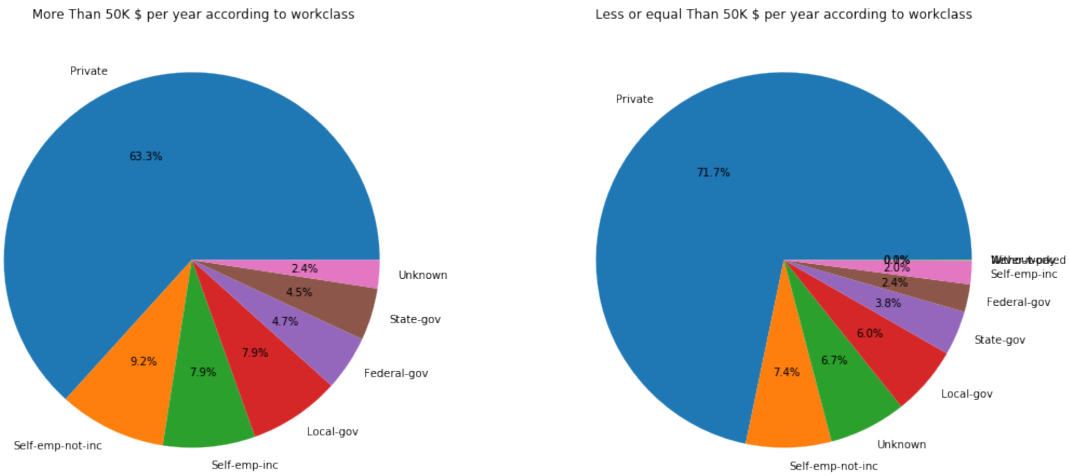
[25]:
```
plot_features_income(data=adult_income, column='workclass',␣
 ↪type_names=workclass_types)
```



For every workclass, except self-employement, there are more people earning below 50,000\$ than people earning more than 50,000\.$Privatesectorholdsmostofthejobs,havingthemajorityofthemasalarybelow50,000$. Now let's have a closer look high paid and non-high paid jobs.

[26]:
```
f,ax=plt.subplots(1,2,figsize=(18,8))
adult_income[adult_income['income'] == '>50K']['workclass'].value_counts().plot.
 ↪pie(autopct='%1.1f%%', ax=ax[0])
ax[0].set_title(' More Than 50K $ per year according to workclass')
ax[0].set_ylabel('')
adult_income[adult_income['income'] == '<=50K']['workclass'].value_counts().
 ↪plot.pie(autopct='%1.1f%%', ax=ax[1])
ax[1].set_title('Less or equal Than 50K $ per year according to workclass')
ax[1].set_ylabel('')
```

[26]:
```
Text(0, 0.5, '')
```



The observations in the **high salary chart** we draw is: * 63.3% of high paid jobs can be found in the private sector * 17.1% are self employed jobs * 2.4% are Unknown jobs * The rest are Goverment or civil servant jobs

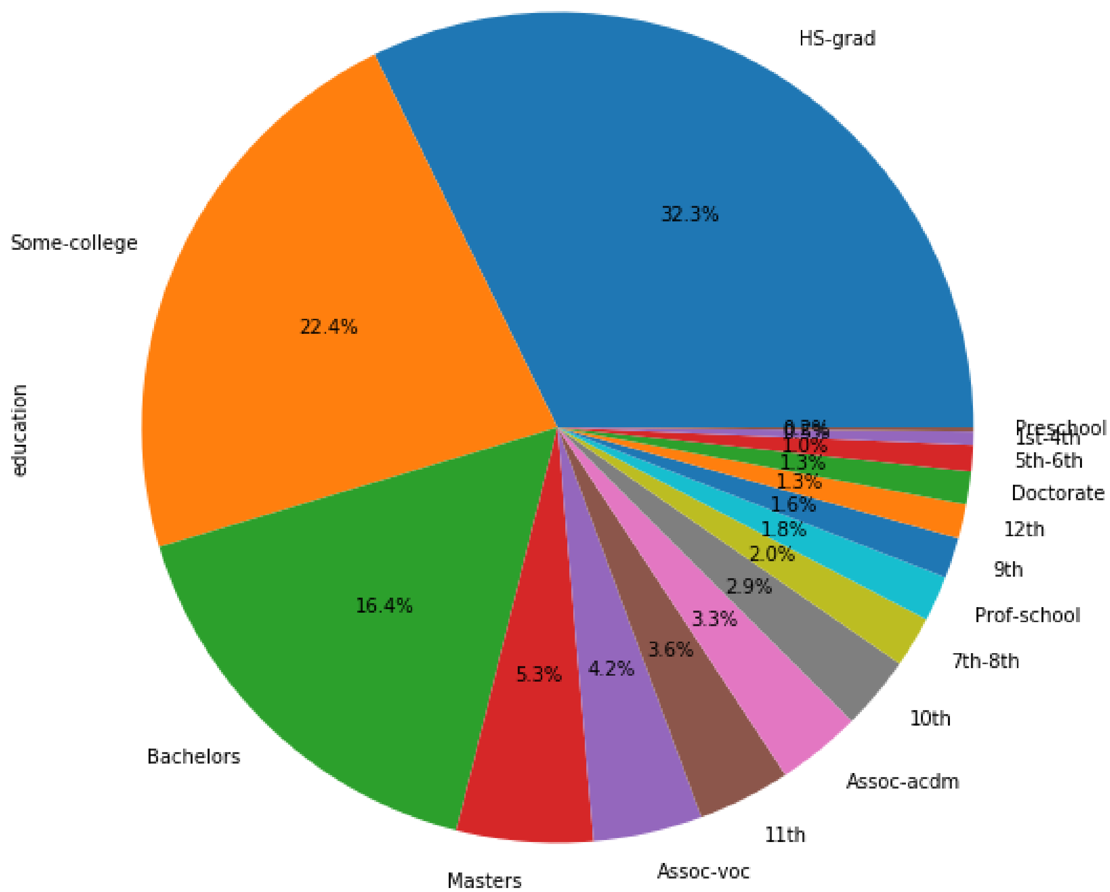
The observations in the **low salary chart** we draw is: * Most of the salaries under 50,000$ are in the private sector. * The rest of percentages are similar to the ones in the high salary sector.

2.1.2 Education

Let's have a look at the education feature.

[27]:
```
plt.figure(figsize=(10, 10))
adult_income['education'].value_counts().plot.pie(autopct='%1.1f%%')
```

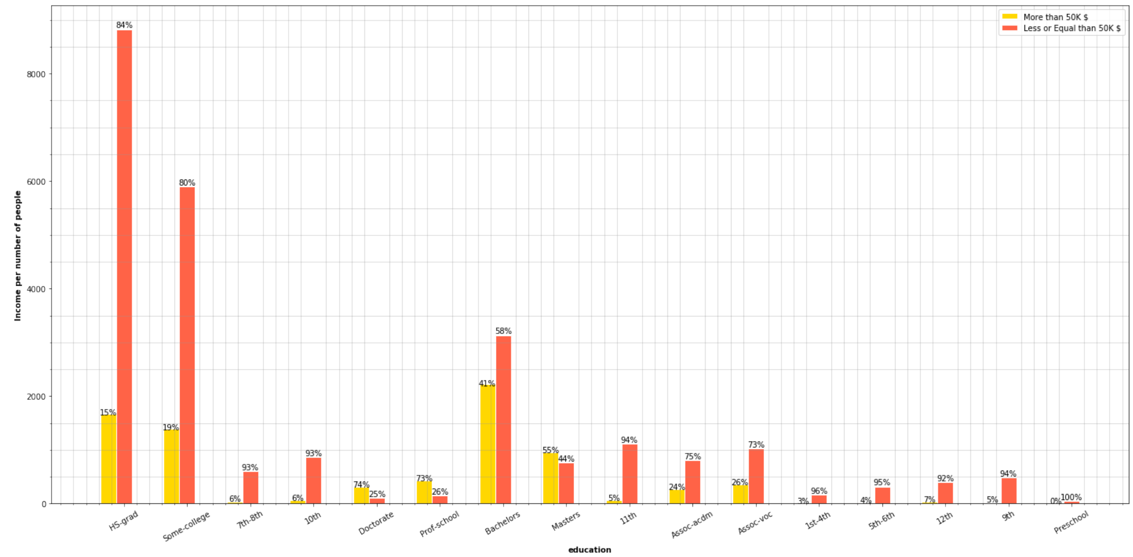
[27]: <matplotlib.axes._subplots.AxesSubplot at 0x109f80090>



We see that people's education scale in the census is very distributed.

[28]:
```
plt.figure(figsize=(20, 10))
education_types = adult_income.education.unique()
plot_features_income(data=adult_income, column='education',␣
↪type_names=education_types)
```

```
<Figure size 1440x720 with 0 Axes>
```

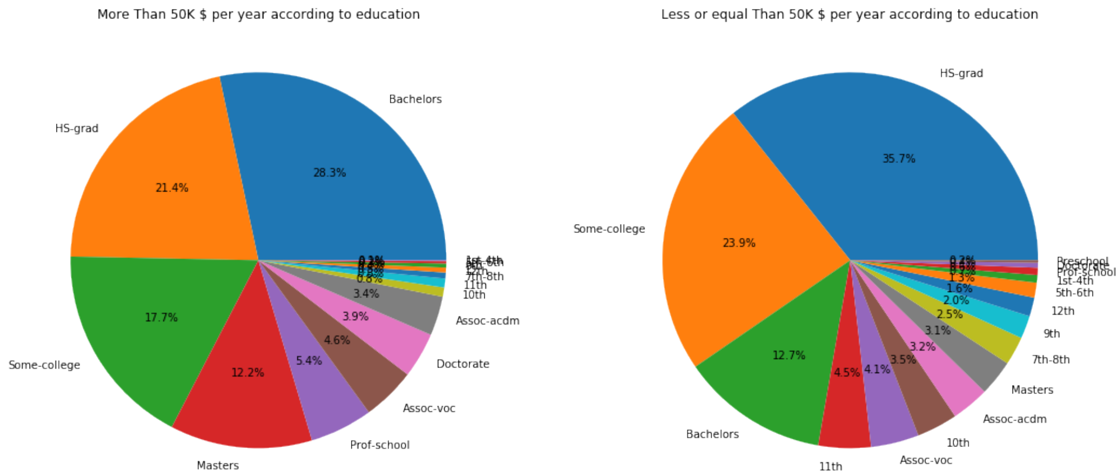


The charts plot some expectable information. We can see that most people who are school professors and most people holding a Master degree or a PhD earn more than 50,000\$ per year. It's interesting that the 41% of people owning a bachelor's degree tend to earn more than 50,000\$ a year. The observations we can draw here is that people who went to college and have professional degree tend to earn more than 50,000\$ per year.

Now, if we look at the charts below, among people earning more than 50,000\$ grouped by education we can see that half of the people have, at least, a college degree or are high school graduates (HS-grad). On the other hand, the other pie chart presents a similar distribuition but, as we saw in the previous charts, we can see that people earning a Master degree or a PhD tend to earn more than 50,000\$.

[29]:
```
f,ax=plt.subplots(1,2,figsize=(18,8))
adult_income[adult_income['income'] == '>50K']['education'].value_counts().plot.
↪pie(autopct='%1.1f%%', ax=ax[0])
ax[0].set_title('More Than 50K $ per year according to education')
ax[0].set_ylabel('')
adult_income[adult_income['income'] == '<=50K']['education'].value_counts().
↪plot.pie(autopct='%1.1f%%', ax=ax[1])
ax[1].set_title('Less or equal Than 50K $ per year according to education')
ax[1].set_ylabel('')
```

[29]:
```
Text(0, 0.5, '')
```

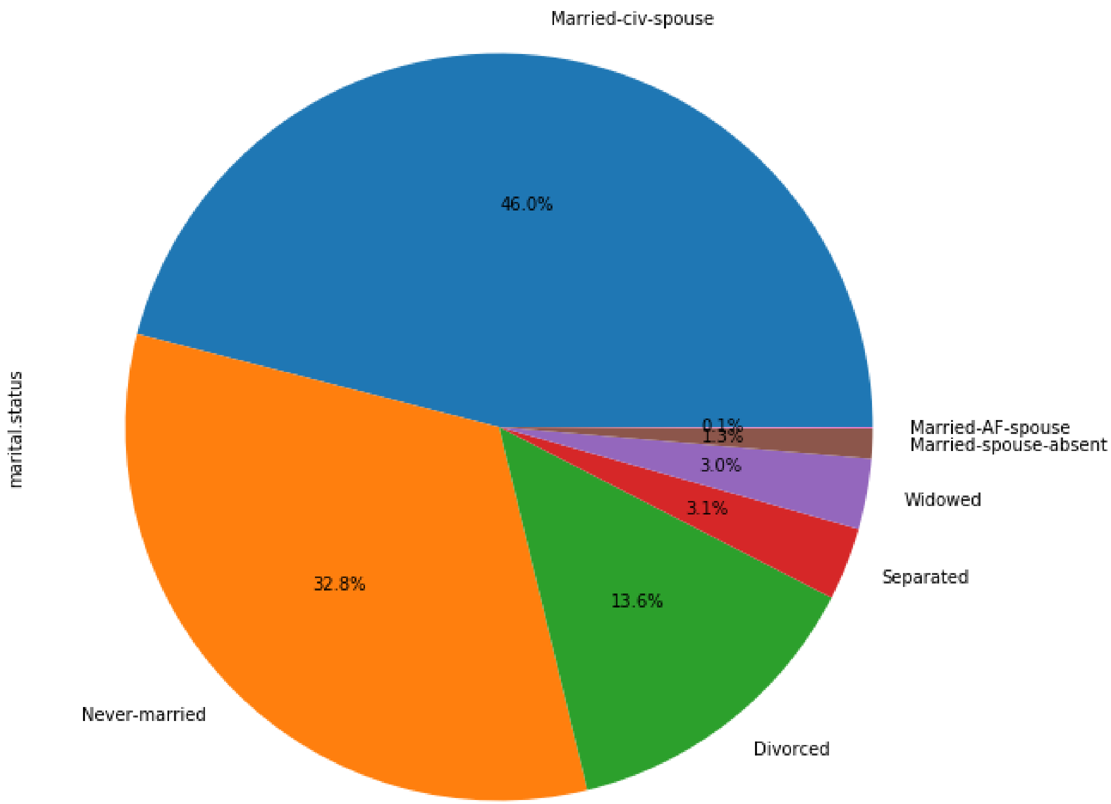


[ ]:

2.1.3 Marital status

[30]:
```
plt.figure(figsize=(10, 10))
adult_income['marital.status'].value_counts().plot.pie(autopct='%1.1f%%')
```

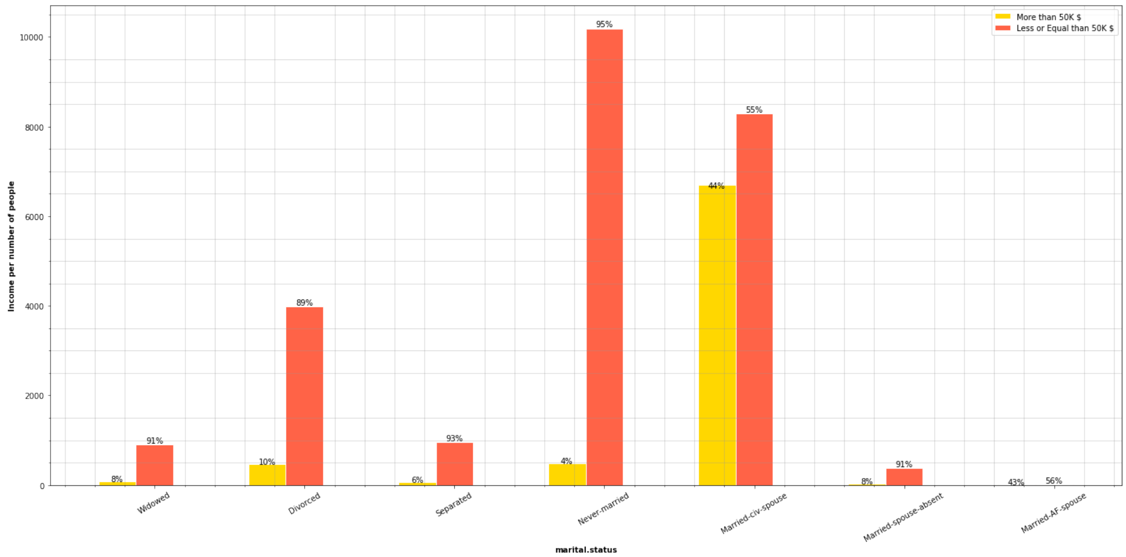
[30]: <matplotlib.axes._subplots.AxesSubplot at 0x1a20639e90>



The 46% of the people in the census are married, the 32% is single and the 13.6% is divorced.

[31]:
```
plt.figure(figsize=(20, 10))
marital_types = adult_income['marital.status'].unique()
plot_features_income(data=adult_income, column='marital.status',␣
 ↪type_names=marital_types)
```

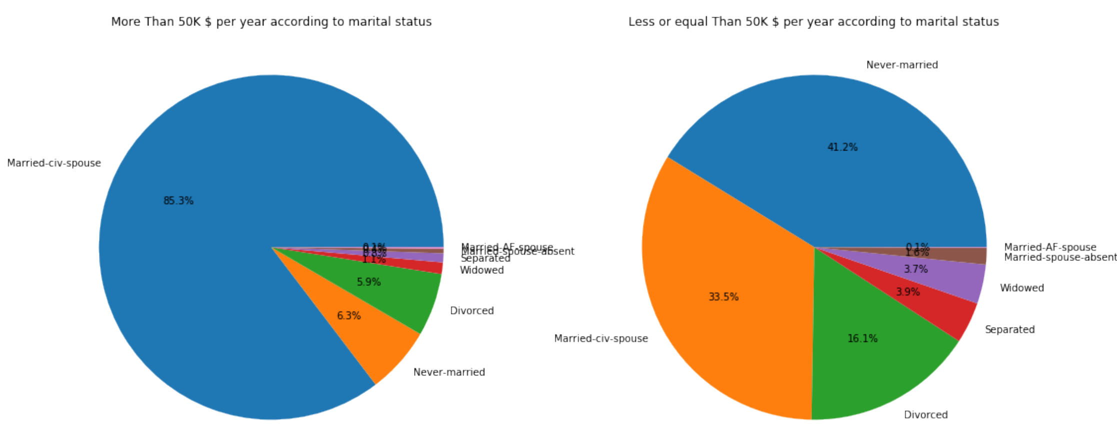
```
<Figure size 1440x720 with 0 Axes>
```



This is a very telling chart. As we can see, almost half of people who are married earn more than 50,000\$, $most people who are separated, divorced or single earn less than 50,000$
. Now let's separate the groups by people who earn more than 50,000\$ and less than 50,000\$.

[32]:
```
f,ax=plt.subplots(1,2,figsize=(18,8))
adult_income[adult_income['income'] == '>50K']['marital.status'].value_counts().
↪plot.pie(autopct='%1.1f%%', ax=ax[0])
ax[0].set_title('More Than 50K $ per year according to marital status')
ax[0].set_ylabel('')
adult_income[adult_income['income'] == '<=50K']['marital.status'].
↪value_counts().plot.pie(autopct='%1.1f%%', ax=ax[1])
ax[1].set_title('Less or equal Than 50K $ per year according to marital status')
ax[1].set_ylabel('')
```

[32]:
```
Text(0, 0.5, '')
```



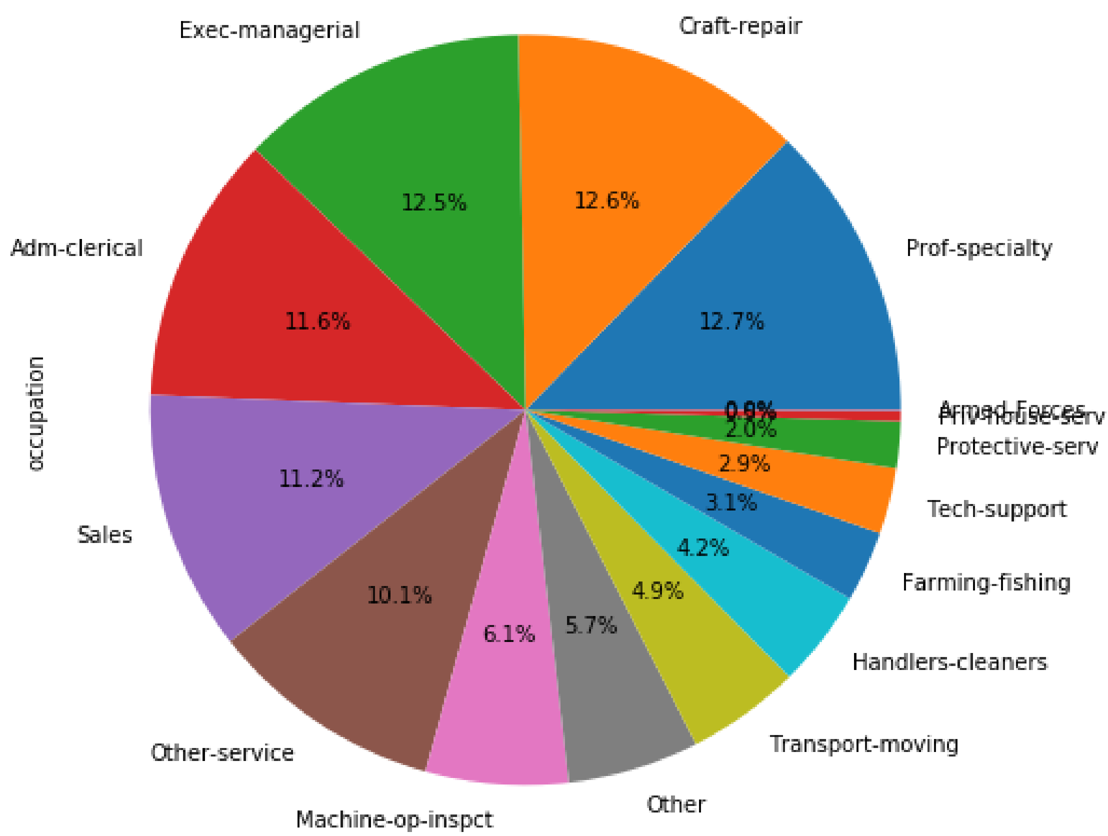
Most people earning more than 50,000\$ are married in a 85%, while they only represent a 33.5% of people earning less than 50,000\$.Averyinteresingfactisthatpeoplewhoearnlessthan50,000$ are either single or divorced, in other words, don't have partner.

2.1.4 occupation

We are taking a look at what kind of jobs have influence on salaries.

[33]:
```
plt.figure(figsize=(8, 8))
adult_income['occupation'].value_counts().plot.pie(autopct='%1.1f%%')
```

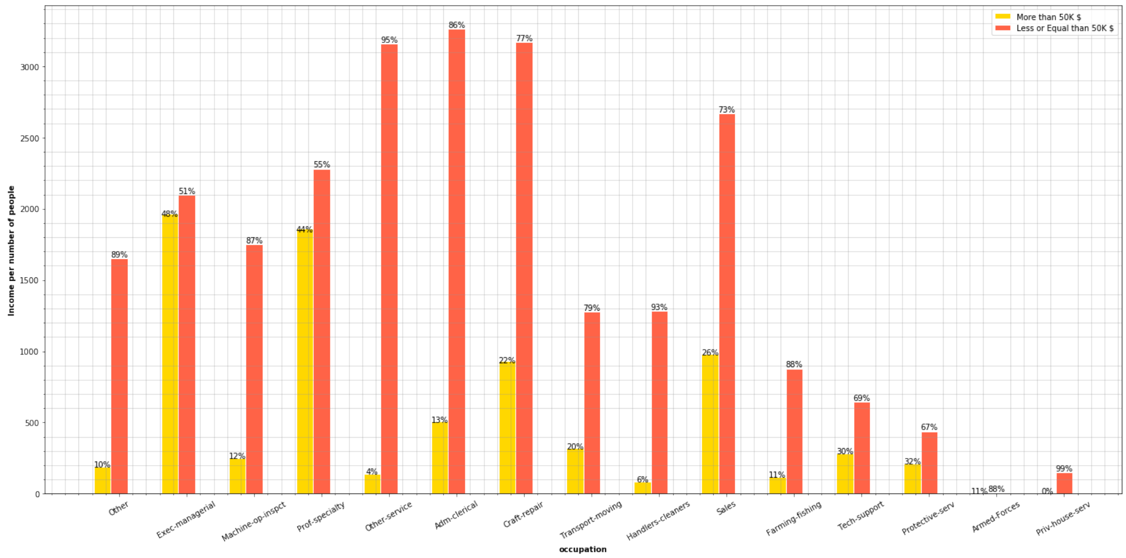
[33]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1f2e4ad0>



[34]:
```
plt.figure(figsize=(20, 10))
occupation_types = adult_income['occupation'].unique()
```

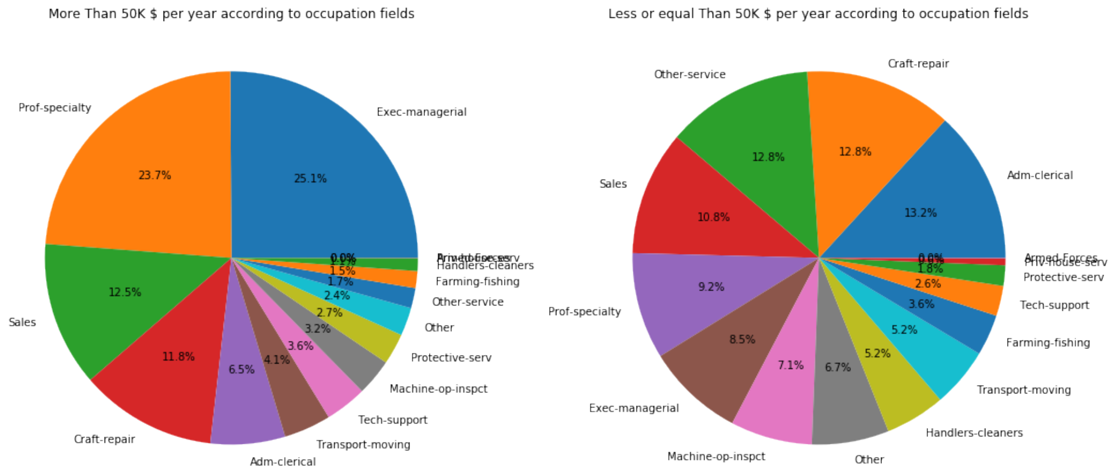
```
plot_features_income(data=adult_income, column='occupation',␣
↪type_names=occupation_types)
```

<Figure size 1440x720 with 0 Axes>



[35]:
```
f,ax=plt.subplots(1,2,figsize=(18,8))
adult_income[adult_income['income'] == '>50K']['occupation'].value_counts().
↪plot.pie(autopct='%1.1f%%', ax=ax[0])
ax[0].set_title('More Than 50K $ per year according to occupation fields')
ax[0].set_ylabel('')
adult_income[adult_income['income'] == '<=50K']['occupation'].value_counts().
↪plot.pie(autopct='%1.1f%%', ax=ax[1])
ax[1].set_title('Less or equal Than 50K $ per year according to occupation␣
↪fields')
ax[1].set_ylabel('')
```

[35]: Text(0, 0.5, '')

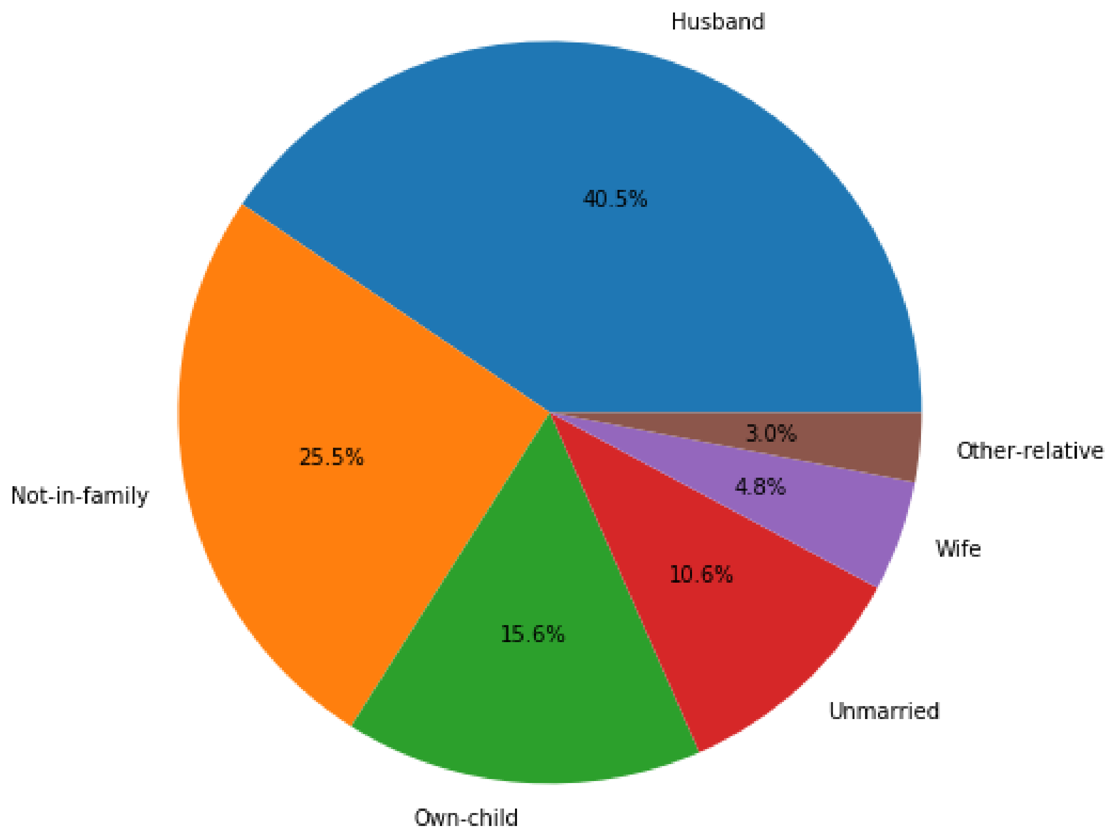


We can see that most well paid jobs are related to Executive Managers, specialized preoffesors, techology engineers and protection services.

2.1.5 Relationship

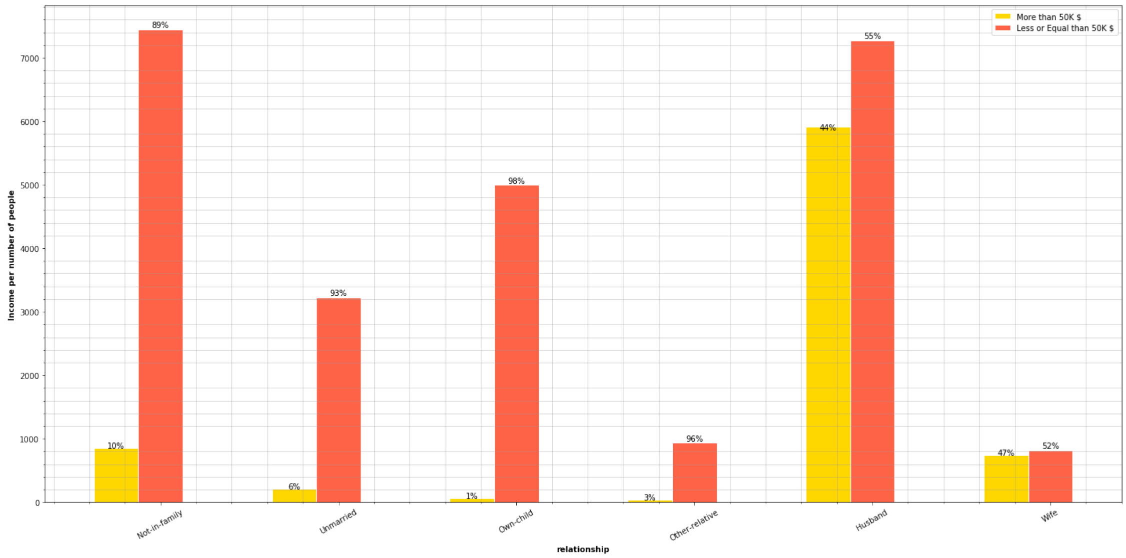
[36]:
```
plt.figure(figsize=(8, 8))
adult_income['relationship'].value_counts().plot.pie(autopct='%1.1f%%')
plt.ylabel('')
```

[36]: Text(0, 0.5, '')



[37]:
```
plt.figure(figsize=(20, 10))
relationships_types = adult_income['relationship'].unique()
plot_features_income(data=adult_income, column='relationship',␣
 ↪type_names=relationships_types)
```

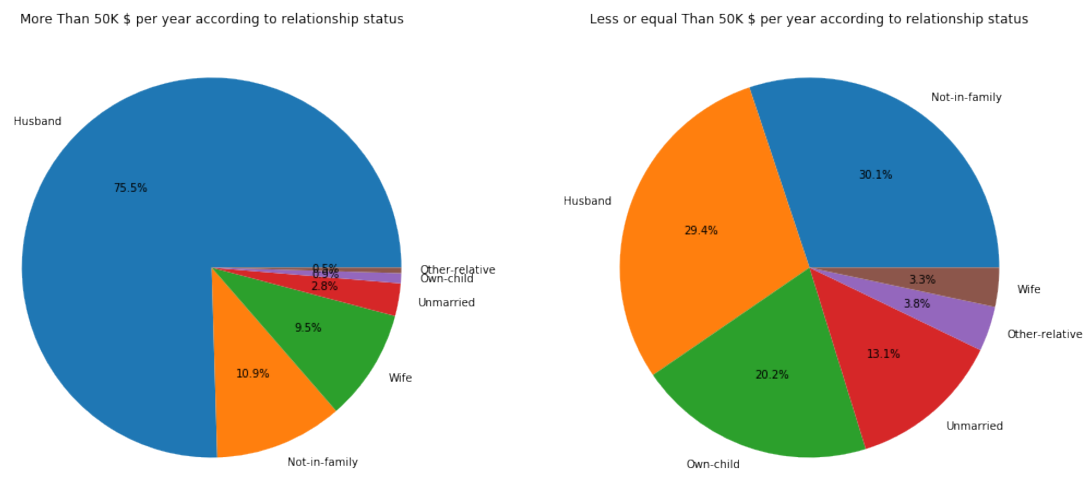
```
<Figure size 1440x720 with 0 Axes>
```



An interesting fact is that 44% of people earning more than 50,000\$ are married men, but it's even more interesting that the percentage of married women earning 50,000\$ is slightly higher. Let's divide the information by groups of people who earn more and less than 50,000\$.

[38]:
```
f,ax=plt.subplots(1,2,figsize=(18,8))
adult_income[adult_income['income'] == '>50K']['relationship'].value_counts().plot.pie(autopct='%1.1f%%', ax=ax[0])
ax[0].set_title('More Than 50K $ per year according to relationship status')
ax[0].set_ylabel('')
adult_income[adult_income['income'] == '<=50K']['relationship'].value_counts().plot.pie(autopct='%1.1f%%', ax=ax[1])
ax[1].set_title('Less or equal Than 50K $ per year according to relationship status')
ax[1].set_ylabel('')
```

[38]:
```
Text(0, 0.5, '')
```

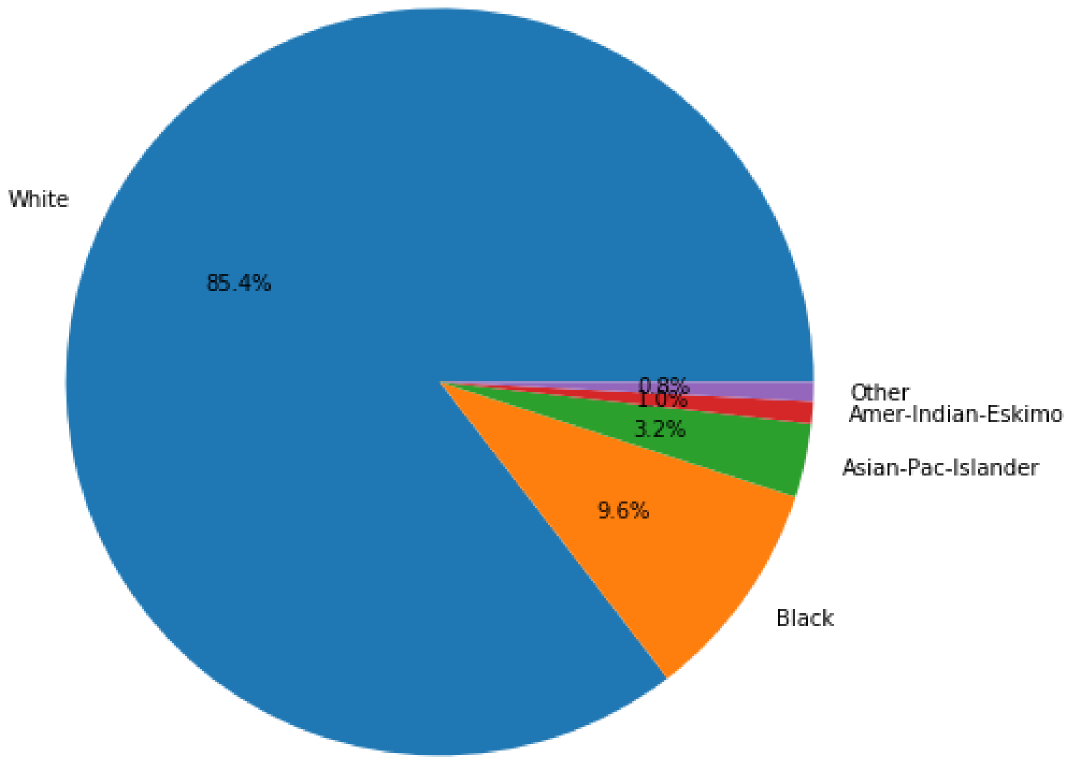


The pie charts show that, in general, most of people earning more than 50,000$ are married men. On the other pie charts the information is much more distribuited.

2.1.6 Race

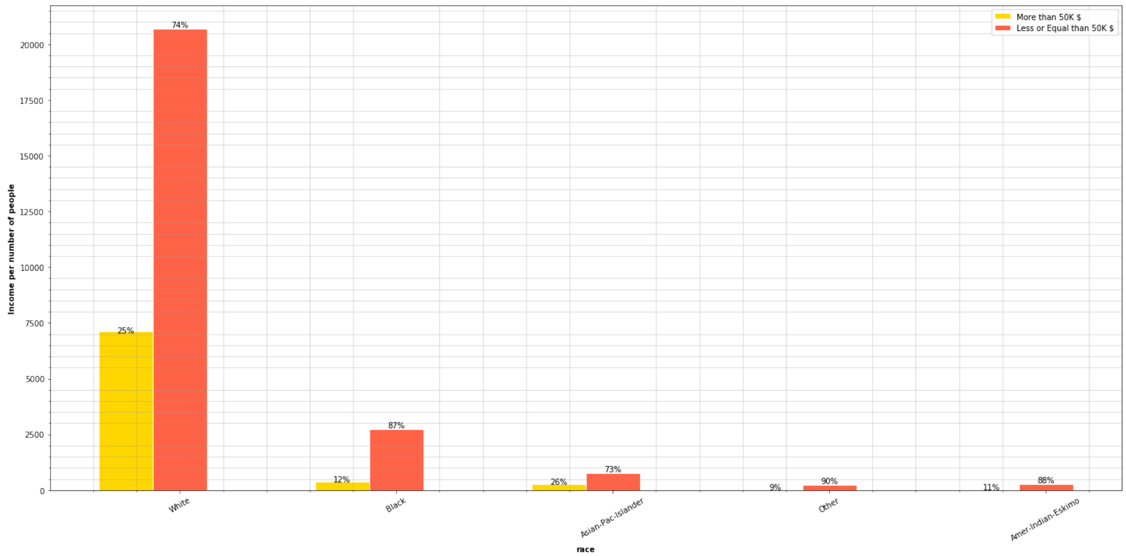
[39]:
```
plt.figure(figsize=(8, 8))
adult_income['race'].value_counts().plot.pie(autopct='%1.1f%%')
plt.ylabel('')
```

[39]: `Text(0, 0.5, '')`



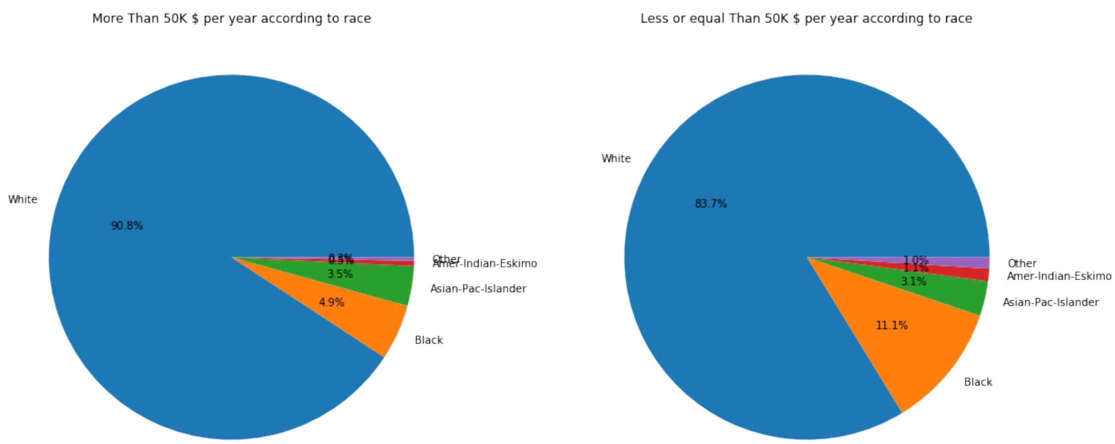
[40]:
```
plt.figure(figsize=(20, 10))
race_types = adult_income['race'].unique()
plot_features_income(data=adult_income, column='race', type_names=race_types)
```

```
<Figure size 1440x720 with 0 Axes>
```




```
[41]: f,ax=plt.subplots(1,2,figsize=(18,8))
adult_income[adult_income['income'] == '>50K']['race'].value_counts().plot.
 ↪pie(autopct='%1.1f%%', ax=ax[0])
ax[0].set_title('More Than 50K $ per year according to race')
ax[0].set_ylabel('')
adult_income[adult_income['income'] == '<=50K']['race'].value_counts().plot.
 ↪pie(autopct='%1.1f%%', ax=ax[1])
ax[1].set_title('Less or equal Than 50K $ per year according to race')
ax[1].set_ylabel('')
```

```
[41]: Text(0, 0.5, '')
```

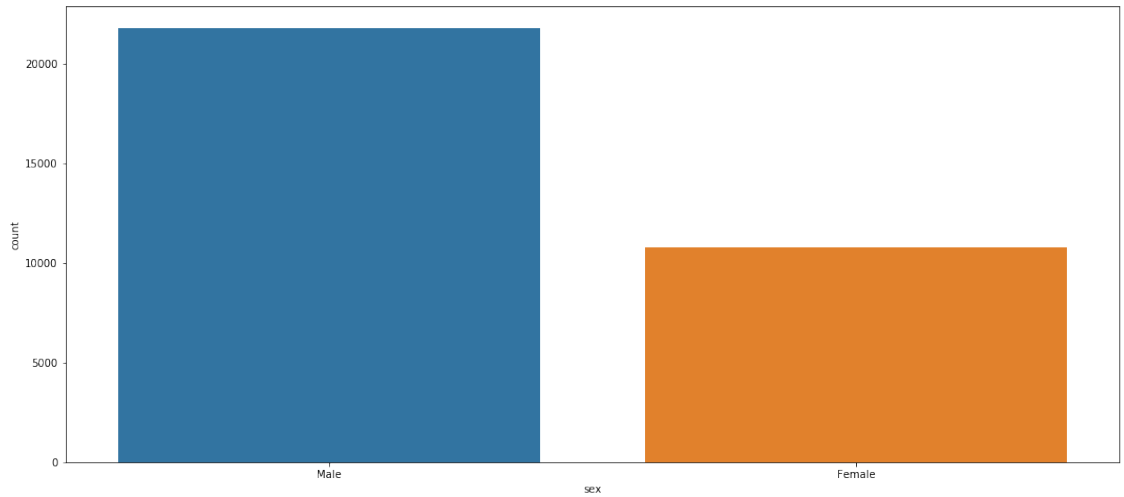


Statistically, there are more asians and whites earning more than 50,000$ than other races.

2.1.7 Sex

[42]:
```
plt.figure(figsize=(18, 8))
sns.countplot(adult_income['sex'], order = ['Male', 'Female'])
```

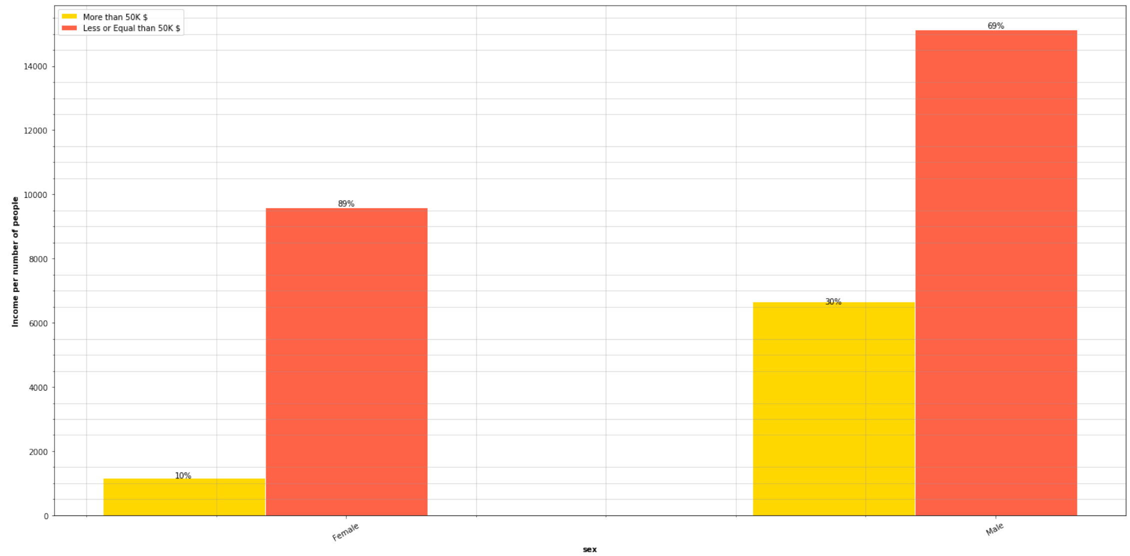
[42]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a200c8390>
```



The census registers more men than women.

[43]:
```
plt.figure(figsize=(20, 10))
race_types = adult_income['sex'].unique()
plot_features_income(data=adult_income, column='sex', type_names=race_types)
```

```
<Figure size 1440x720 with 0 Axes>
```

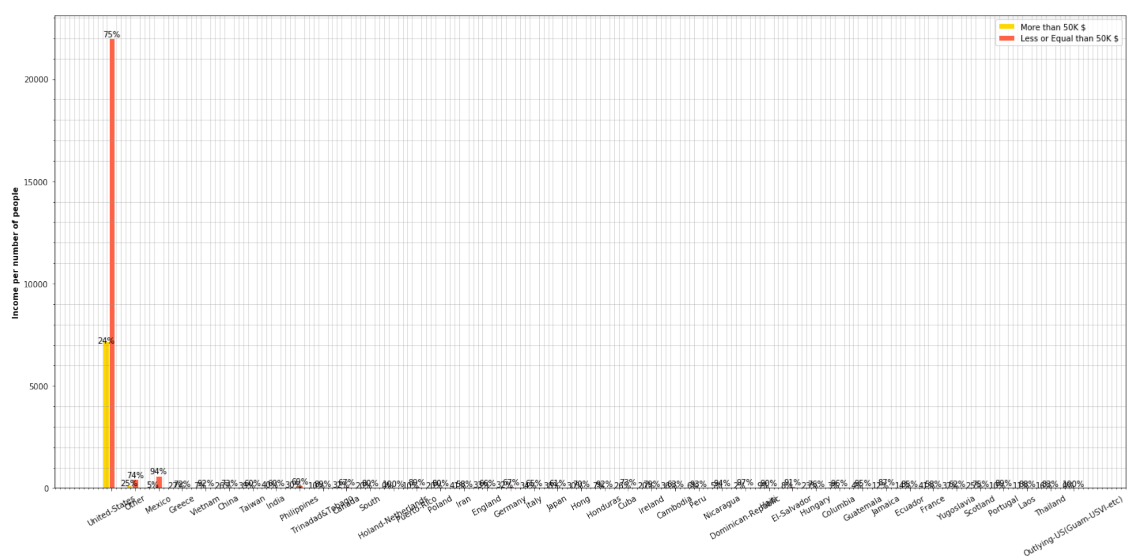


The chart show that 30% of men earn more than 50,000\$ while only 10% of women surpass that amount. In other words, there are 200% more men than women earning above 50,000 \$.

2.1.8 Native Country

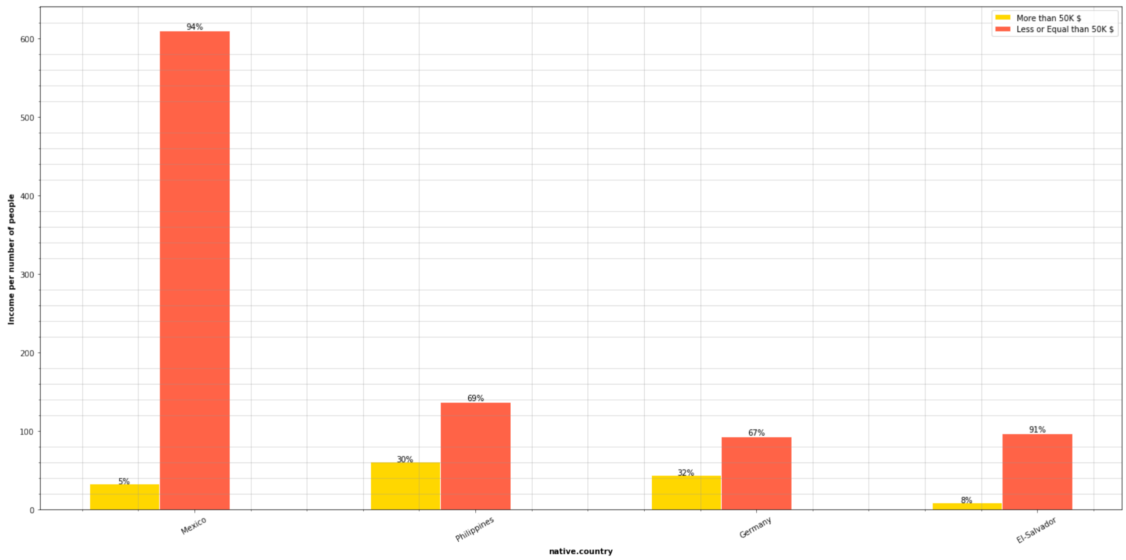
[44]:
```
plt.figure(figsize=(20, 10))
country_types = adult_income['native.country'].unique()
plot_features_income(data=adult_income, column='native.country', type_names=country_types)
```

```
<Figure size 1440x720 with 0 Axes>
```



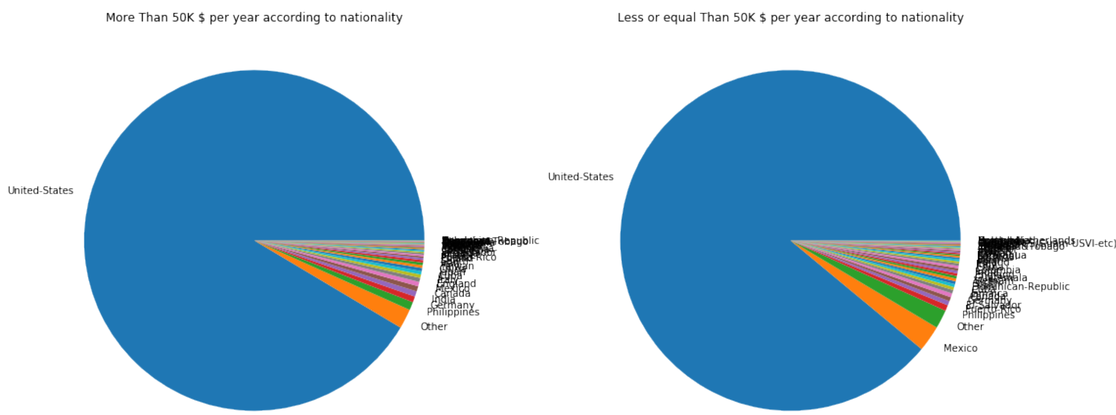
[45]:
```
plt.figure(figsize=(20, 10))
country_types = ['Mexico', 'Philippines', 'Germany', 'El-Salvador']
plot_features_income(data=adult_income, column='native.country',␣
↪type_names=country_types)
```

<Figure size 1440x720 with 0 Axes>



[46]:
```
f,ax=plt.subplots(1,2,figsize=(18,8))
adult_income[adult_income['income'] == '>50K']['native.country'].value_counts().
↪plot.pie(autopct='', ax=ax[0])
ax[0].set_title('More Than 50K $ per year according to nationality')
ax[0].set_ylabel('')
adult_income[adult_income['income'] == '<=50K']['native.country'].
↪value_counts().plot.pie(autopct='', ax=ax[1])
ax[1].set_title('Less or equal Than 50K $ per year according to nationality')
ax[1].set_ylabel('')
```

[46]: Text(0, 0.5, '')




```
[ ]:
```

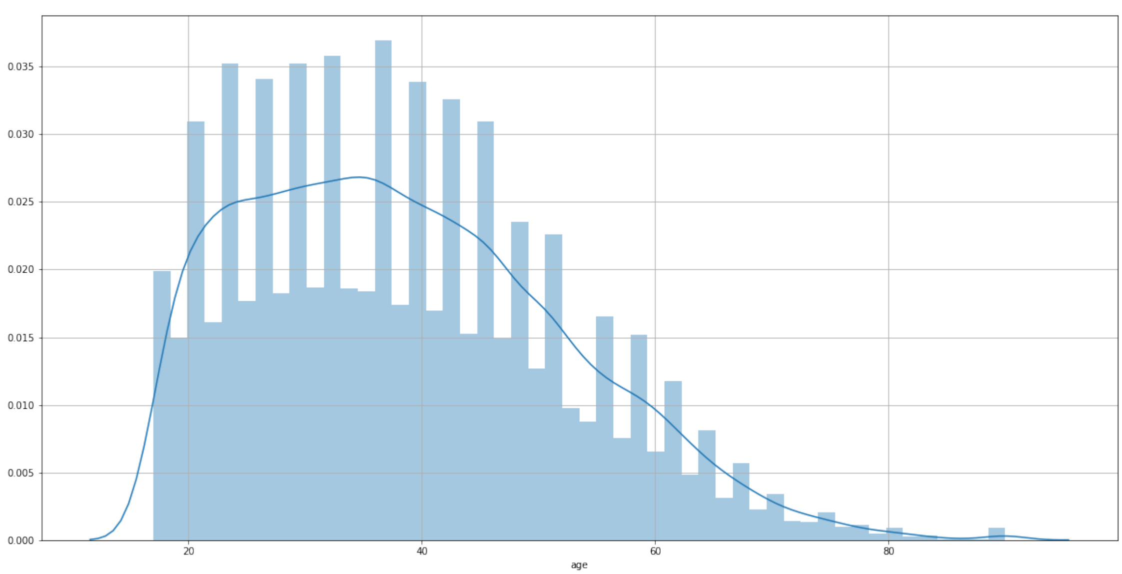
2.2 Numerical Analysis

2.2.1 Age

Now we'll take a lot at the age distribuition of the census.

```
[47]: plt.figure(figsize=(20,10))
      plt.grid()
      sns.distplot(adult_income['age'])
```

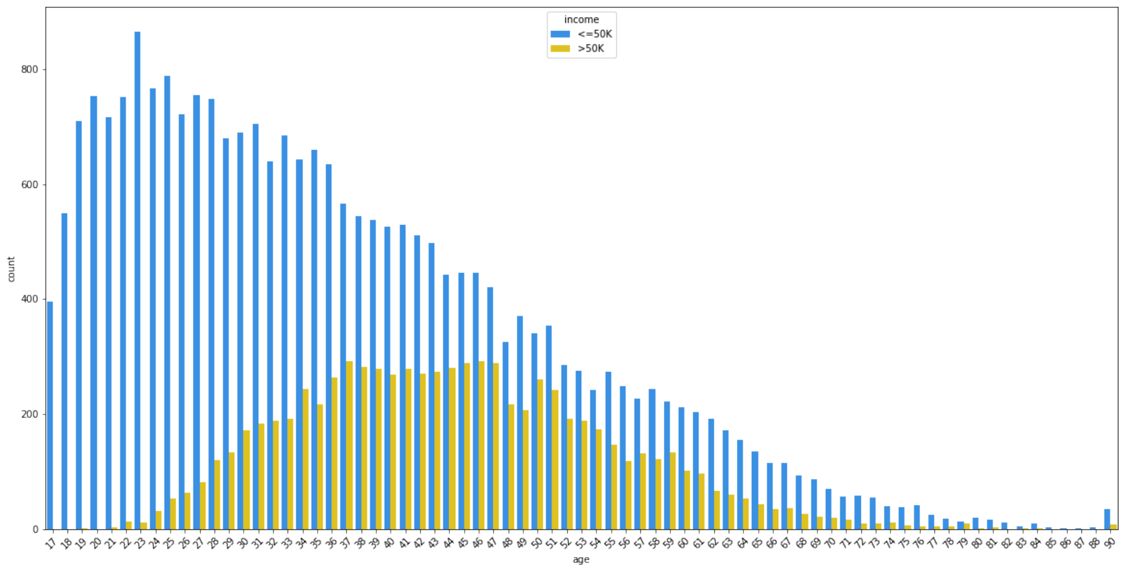
```
[47]: <matplotlib.axes._subplots.AxesSubplot at 0x1a20c55e90>
```



The age distribuition collected in the census is concentrated among from 20 y/o to the 50 y/o interval.

[48]:
```
plt.figure(figsize=(20, 10))
plt.xticks(rotation=45)
sns.countplot(adult_income['age'], hue=adult_income['income'], palette=['dodgerblue', 'gold'])
```

[48]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a21655a90>
```

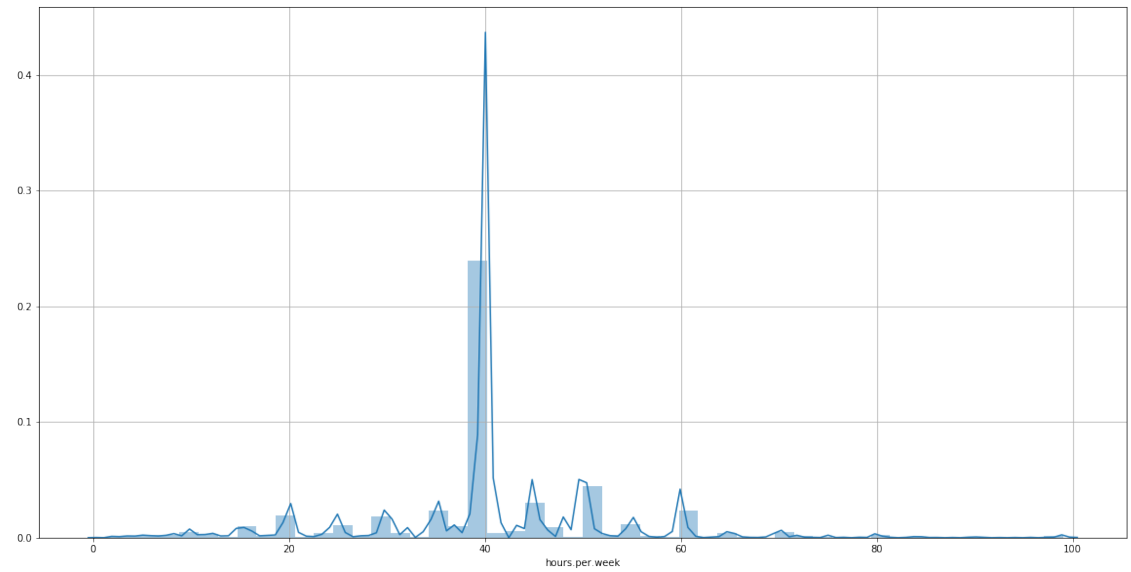


This is very interesting plot. As age grows, there are more people earning more than 50,000\$, so we can say that, generally, income is correllated to age.

2.2.2 Hours per week

[49]:
```
plt.figure(figsize=(20,10))
plt.grid()
sns.distplot(adult_income['hours.per.week'])
```

[49]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a20096c10>
```



The plot shows that most people in the census work 40 hours per week. Now, we'd like to know the hours per week distribuition of the people earning more than 50,000\$.

Normally, people who earn more than 50,000\$ per year have a 40 hours/week rutine. There are also a lot working for 45, 50 and 60 hours/week.

3 Multivariable analysis

After analysing each variable, we will apply a multivariable analysis combining several variables and correlations.

3.1 correlations

[50]:
```
numerical_dt = list(adult_income.select_dtypes(include=['float64', 'int64']).
    ↪columns)
```

[51]:
```
numerical_dt
```

[51]:
```
['age',
 'fnlwgt',
 'education.num',
 'capital.gain',
 'capital.loss',
 'hours.per.week']
```

[52]:
```
numerical_dt = np.asarray(numerical_dt)
```

[53]:
```
numerical_dt
```

```
[53]: array(['age', 'fnlwgt', 'education.num', 'capital.gain', 'capital.loss',
             'hours.per.week'], dtype='<U14')
```

```
[54]: num_dt = adult_income.loc[:, numerical_dt]
```

```
[55]: num_dt = num_dt.drop(columns='education.num')
```

```
[ ]:
```

```
[58]: plt.figure(figsize=(20,10))
      sns.heatmap(corr_matrix,
              xticklabels=corr_matrix.columns,
              yticklabels=corr_matrix.columns)
```

```
        ␣
 ↪---------------------------------------------------------------------------

       NameError                                 Traceback (most recent call␣
 ↪last)

       <ipython-input-58-dd5189355413> in <module>
         1 plt.figure(figsize=(20,10))
   ----> 2 sns.heatmap(corr_matrix,
         3         xticklabels=corr_matrix.columns,
         4         yticklabels=corr_matrix.columns)


       NameError: name 'corr_matrix' is not defined
```

```
<Figure size 1440x720 with 0 Axes>
```

The hitmap shows no evident high correlation cases among the numerical variables.

3.2 Analysis based on gender and age

After analyzing each of every feature we realized men to earn more than women, so we decided execute a better analysis on this field, so that we can draw some useful informations.

3.2.1 Gender and workclass

We're going to have a look at the relations between gender and workclass and occupations, and what kind of jobs women mostly occupy in the census.

```
[ ]: fig, axs = plt.subplots(1, 2, figsize=(20, 10))
     plt.figure(figsize=(20, 10))
```

```
sns.countplot(adult_income['workclass'], hue=adult_income['sex'], ax=axs[1],␣
 ↪palette=['pink', 'dodgerblue'], order=adult_income[adult_income['sex'] ==␣
 ↪'Female']['workclass'].value_counts().index)
sns.countplot(adult_income['occupation'], hue=adult_income['sex'], ax=axs[0],␣
 ↪palette=['pink', 'dodgerblue'], order=adult_income[adult_income['sex'] ==␣
 ↪'Female']['occupation'].value_counts().index)
plt.setp(axs[0].xaxis.get_majorticklabels(), rotation=45)
plt.setp(axs[1].xaxis.get_majorticklabels(), rotation=45)
plt.show()
```

Most women occupy the jobs related to clerical administration, cleaning services and other services, but jobs related to professor speciality, business and sales, engineering, technology, transport, protection service and primary sector are mostly occupied by men. It's also interesting to see that most gender gap in private sector and self employement is bigger than in other sectors.

3.2.2 Gender, Hours per week and Income

Let's see if there's any relationship between hours per week and income divided by gender.

[ ]:
```
fig, ax = plt.subplots(1, 2, figsize=(25, 8))
plt.xticks(rotation=45)
sns.violinplot(adult_income['sex'], adult_income['hours.per.week'],␣
 ↪hue=adult_income['income'], palette=['gold', 'dodgerblue'], ax=ax[0])
sns.stripplot(adult_income['sex'], adult_income['hours.per.week'],␣
 ↪hue=adult_income['income'], palette=['skyblue', 'tomato'], ax=ax[1])
ax[0].grid(True)
ax[1].grid(True)
```

The charts show that men work more for hours than women. The left chart show that, regardless of the income, there are more women working for less than men and the men chart is more distribuited above 40 hours per week. The right chart shows that men working more hours tend to earn more than 50,000\$. We see a concentration of red dots among the 40 and 60 hours/week interval. On the other hand, this concentration doesn't appear women side. Even though the hours per week gap between men and women is not so big, it's clear that there's no correlation between hours per week and income when it comes to women.

3.2.3 Age, gender and Hours per week

[ ]:
```
fig, ax = plt.subplots(1, 2, figsize=(30, 8))
plt.xticks(rotation=45)
sns.lineplot(adult_income['age'], adult_income['hours.per.week'],␣
 ↪hue=adult_income['income'], palette=['tomato', 'dodgerblue'], ax=ax[0])
sns.lineplot(adult_income['age'], adult_income['hours.per.week'],␣
 ↪hue=adult_income['sex'], palette=['tomato', 'dodgerblue'], ax=ax[1])
ax[0].grid(True)
ax[0].title.set_text("Age and Hours per week divided by Income")
ax[1].grid(True)
```

```
ax[0].title.set_text("Age and Hours per week divided by Gender")
```

We see a very interesting trend in chart above. Let's take a loot at the left chart first. As the age grows, there are more people earning more than 50,000\$ but work for more hours. In both cases, as age reaches the 60 year old, people tend to work for less hours but the number of people earning more than 50K increases. What's funny is that people who earn a lot start working for more hours when as they start turning 80.

The right chart shows very similar line paths. Men tend work for more hours than women, but as they get closer the standard retirement age, men and women work for the similar number of hours. What's very bizare, is that women who are 80 and 90 are the one working for more hours than the rest of ages.

3.3 Final observations and Conclusion after the Data Exploration

We analyzed and explored all the features of the dataset and their particularites, we want to summerise all the interesting facts we discovered and could help us predict whether a person earns more or less than 50,000 \$.Theinterestingobservationswedreware : * * *Workclasandoccupations * * * The55%ofselfemployedpeopleworkareself − employed * The63.3%ofthetotalpeopleinthecensusearningmorethan50, 000$ work in the private sector and the 71% of the total people in the census earning under 50,000\$ work in the private sector too. * If we focus only in the private sector, the 26% earn more than 50,000\$. * Thejobswerewecanfindmorepeopleearningabove50, 000$ are executive managers, protection services, college professors, engineering and jobs related to technology who are mostly occupied by men.

- **Education**
  - It's interesting that the 73% of the Professors, 74% of PhDs, the 55% of people owning a Master Degree and the 40% of Bachelors bachelors earn above 50,000\$.
  - We this information we can conclude that owning at least a college degree will increase your probabilities to earn 50,000 \$/year.
- **Gender, Marital Status and relationship**
  - The 85% of total people in the census earning more than 50,000\$ are married.
  - The 44% of people who are married earn more than 50,000\$.
  - The 44% of husbands earen more than 50,000\$.
  - The 47% of Wifes earn more than 50,000\$.
  - According to this info, being maried increases the probability of earning above 50,000\$.
- **Other interesting information**
  - The salary is directly related to age. The older people get, the more the surpass the 50,000\$ line.
  - Men work for more hourse than women in all ages but as they both get closer to the 60's they tend to work for similiar amount of hours per week.
  - People earning more than 50,000\$ per year tend to work for more hours too.
  - Men working for more than 40 hours per week tend to earn above 50,000\$ but women don't follow this trend and there's no correlation between hours per week and income when it comes to females.
- So we could say that a person who's likely to earn above 50.000\$/year is a person who:
  - Is male whose age is between 30 or over.
  - Married

- Whose job is related to bussines, engineering, college profesor, protection services, technical or IT field.
- Holds a master degree or a Phd.
- Works for more than 40 hours per week.
- Is American, Asian or European.

3.4 Data Cleaning and Formatting

Now that we've performed out data exploration and have drawn some assumptions, it's time to clean the data, format it and erase those rows and columns who are useless or could noise during our learning process.

[59]:
```
adult_income_prep = adult_income.copy()
```

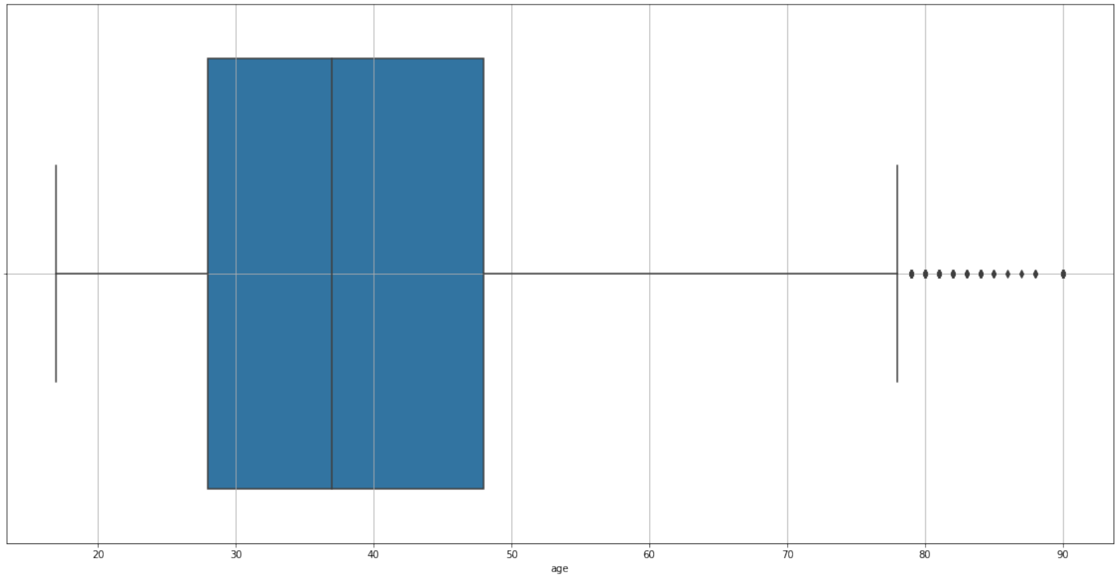
3.4.1 Outliers anomaly

Outliers can be very harmful for our learning models and can cause noise that can create distorsions in our predictions. We'll create an auxiliar function to erase the outliers in each numerical feature.

[60]:
```
def treat_outliers(data, column, upper=False, lower=False):
    Q1=adult_income_prep[column].quantile(0.25)
    Q3=adult_income_prep[column].quantile(0.75)
    IQR=Q3-Q1
    print(Q1)
    print(Q3)
    print(IQR)
    U_threshold = Q3+1.5*IQR
    #print(L_threshold, U_threshold)
    if upper:
        adult_income_prep[column] = adult_income_prep[adult_income_prep[column]␣
↪< U_threshold]
    if lower:
        adult_income_prep[column] = adult_income_prep[adult_income_prep[column]␣
↪>= U_threshold]
```

Checking outliers in the age feature

[61]:
```
plt.figure(figsize=(20,10))
sns.boxplot(data=adult_income_prep, x=adult_income_prep['age'])
plt.grid()
```

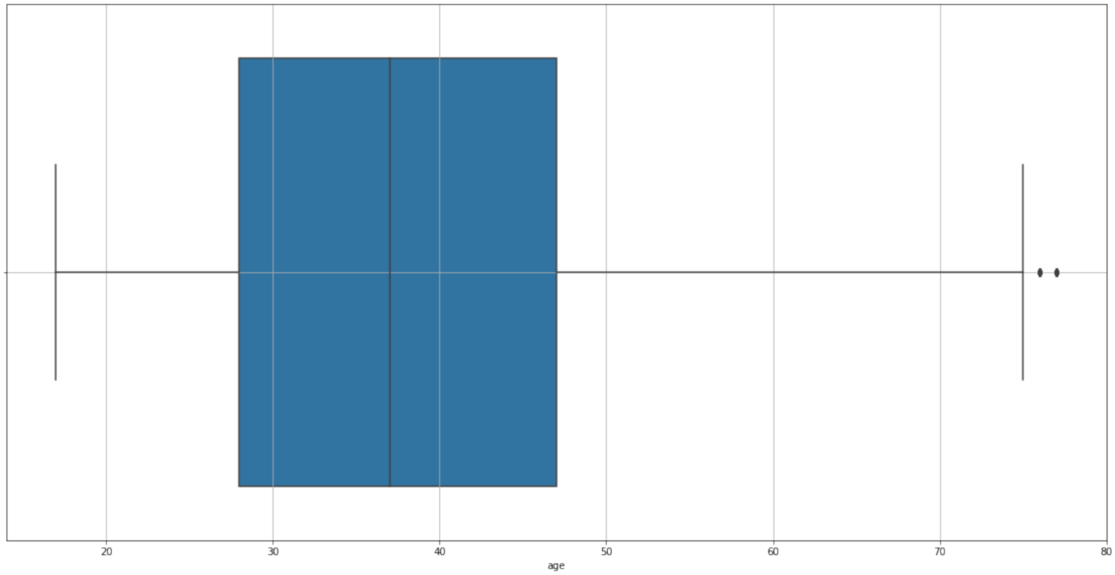


We found outliers in our chart, so we'll erase them.

[62]:
```
treat_outliers(data=adult_income_prep, column='age', upper=True)
```

```
28.0
48.0
20.0
```

[63]:
```
plt.figure(figsize=(20,10))
sns.boxplot(data=adult_income_prep, x=adult_income_prep['age'])
plt.grid()
```

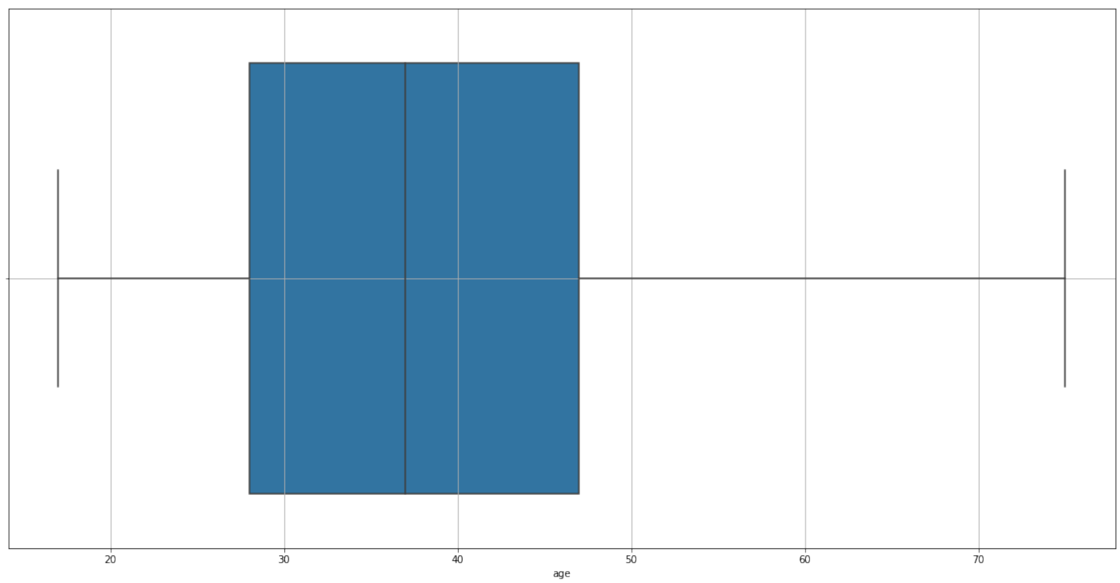


[64]:
```
treat_outliers(data=adult_income_prep, column='age', upper=True)
```

```
28.0
47.0
19.0
```

Let's check out now

[65]:
```
plt.figure(figsize=(20,10))
sns.boxplot(data=adult_income_prep, x=adult_income_prep['age'])
plt.grid()
```

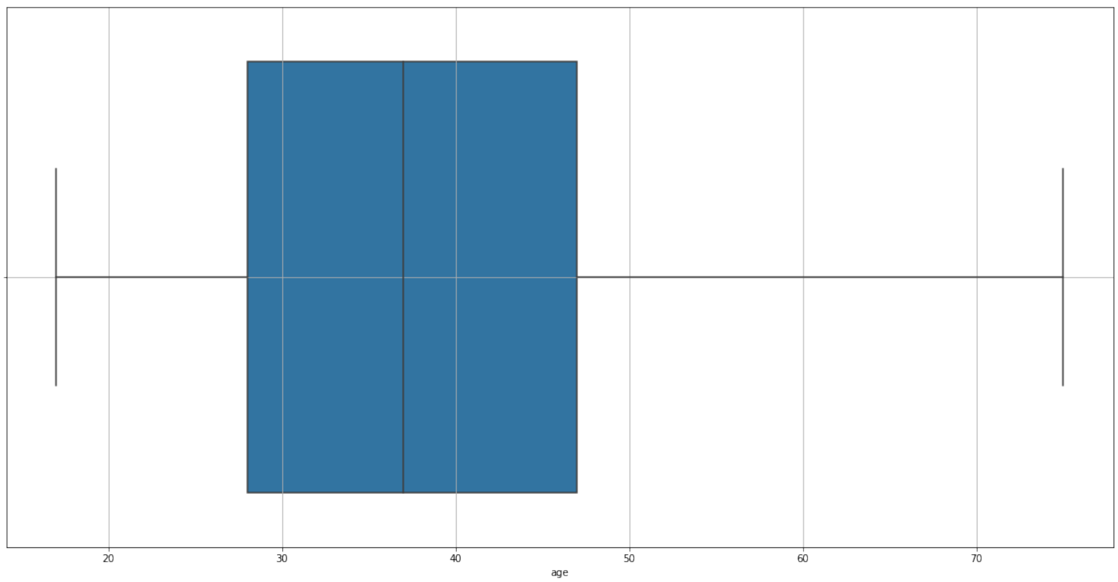


There are still to rows which age column contains an outlier.

[66]:
```
treat_outliers(data=adult_income_prep, column='age', upper=True)
```

```
28.0
47.0
19.0
```

[67]:
```
plt.figure(figsize=(20,10))
sns.boxplot(data=adult_income_prep, x=adult_income_prep['age'])
plt.grid()
```

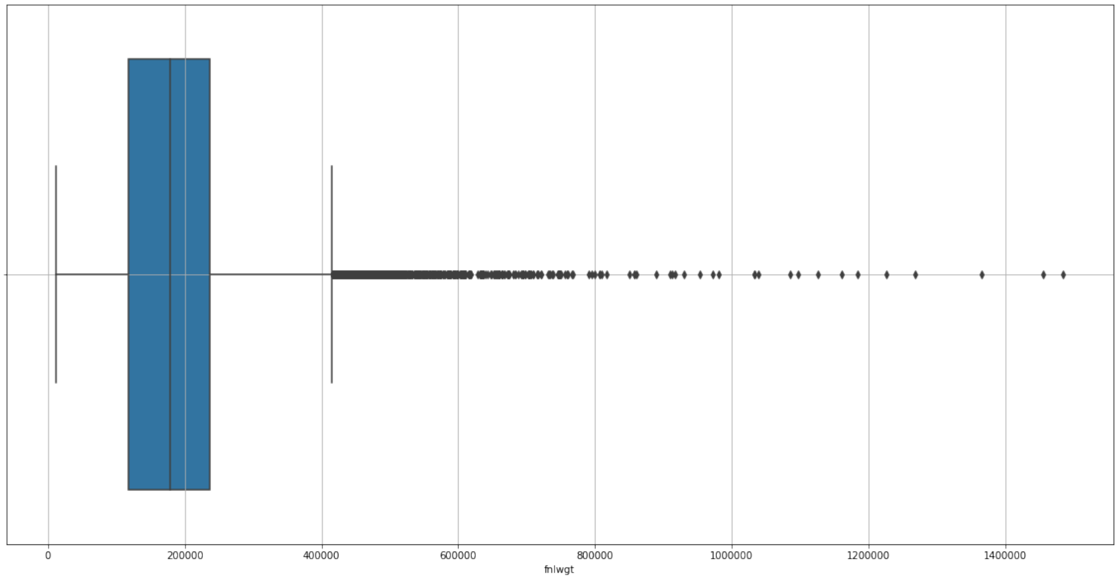


Now it's OK.

[ ]:

Removing outliers of final Weight

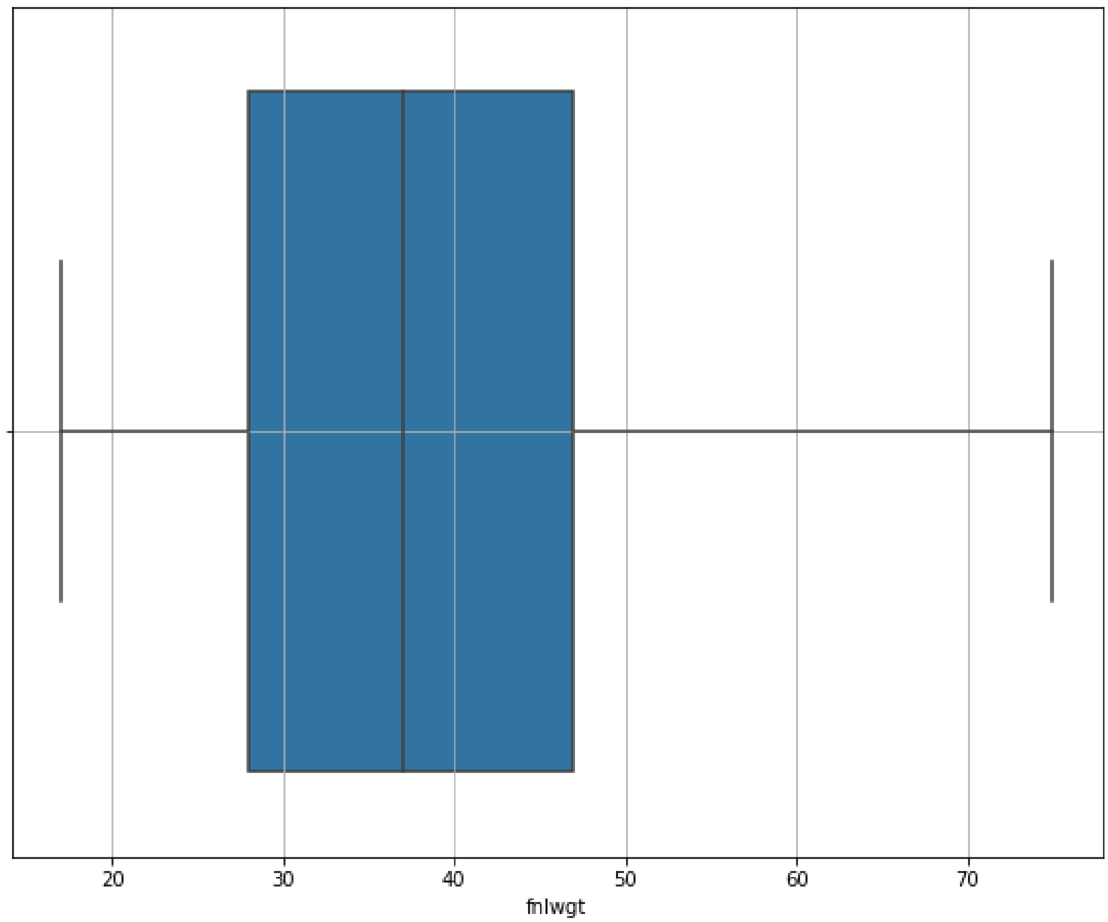
[68]:
```
plt.figure(figsize=(20,10))
sns.boxplot(data=adult_income_prep, x=adult_income_prep['fnlwgt'])
plt.grid()
```



[69]:
```
treat_outliers(data=adult_income_prep, column='fnlwgt', upper=True)
```

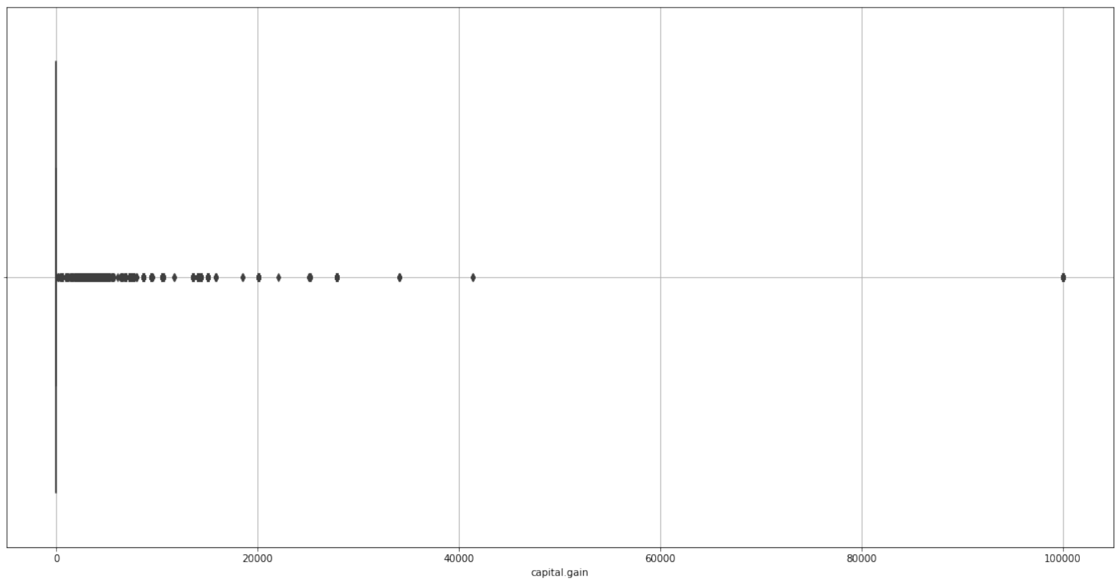
```
117827.0
237051.0
119224.0
```

[70]:
```
plt.figure(figsize=(10,8))
sns.boxplot(data=adult_income_prep, x=adult_income_prep['fnlwgt'])
plt.grid()
```

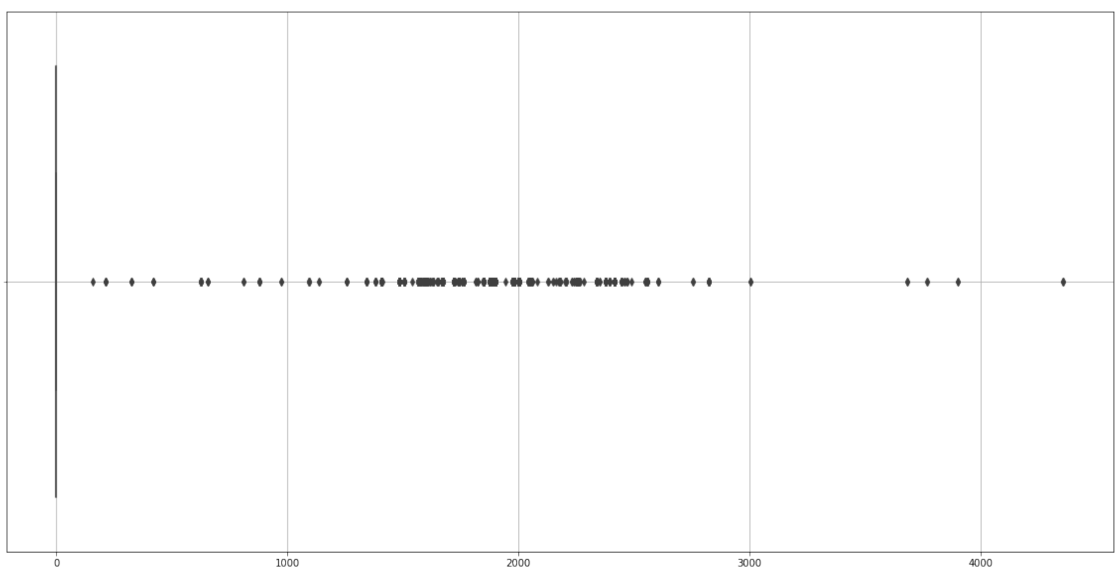


Checking outliers in Capital Gain and Loss

[71]:
```
plt.figure(figsize=(20,10))
sns.boxplot(data=adult_income_prep, x=adult_income_prep['capital.gain'])
plt.grid()
```



[72]:
```
plt.figure(figsize=(20,10))
sns.boxplot(data=adult_income_prep, x=adult_income_prep['capital.loss'])
plt.grid()
```



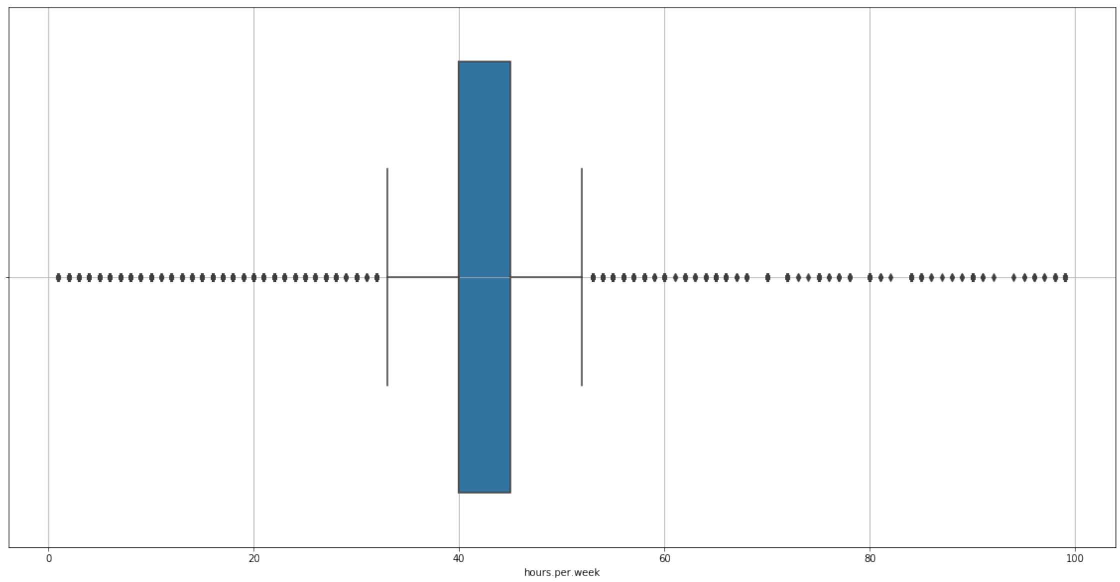
We realize `capital.gain` and `capital.loss` will disturb our learning process as they don't give any useful information either.

[73]:
```
adult_income_prep = adult_income_prep.drop(columns=['capital.gain', 'capital.
↪loss'])
```

[ ]:

Checking outliers of Hours per week

[74]:
```
plt.figure(figsize=(20,10))
sns.boxplot(data=adult_income_prep, x=adult_income_prep['hours.per.week'])
plt.grid()
```

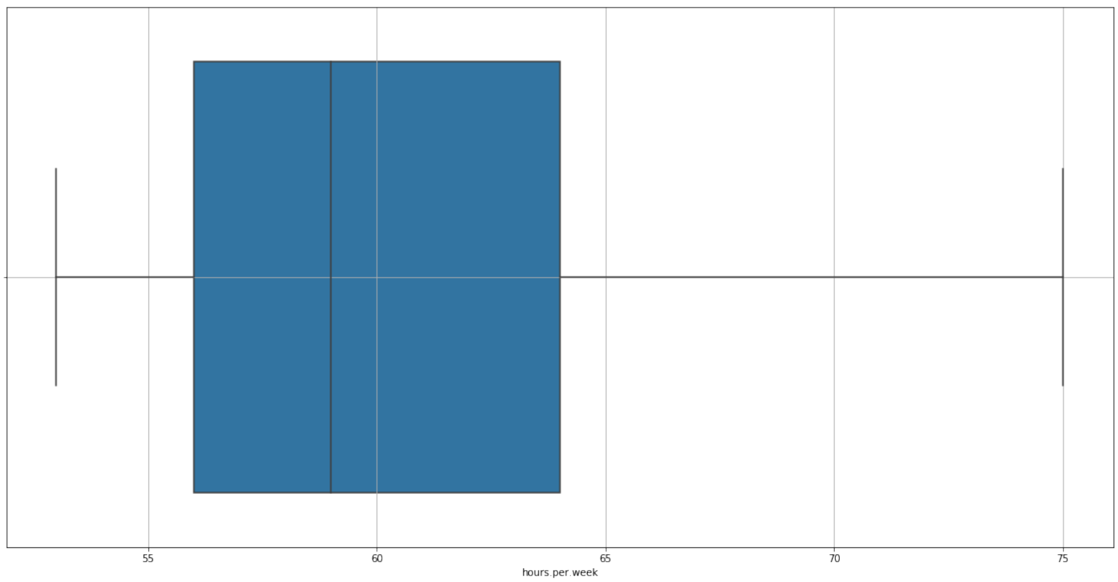


There are outliers, we must remove them.

[75]:
```
treat_outliers(data=adult_income_prep, column='hours.per.week', upper=True,␣
↪lower=True)
```

```
40.0
45.0
5.0
```

[76]:
```
plt.figure(figsize=(20,10))
sns.boxplot(data=adult_income_prep, x=adult_income_prep['hours.per.week'])
plt.grid()
```



Now it's alright. Let's see how our dataset is now.

[77]:
```
adult_income_prep.head()
```

[77]:
```
   age workclass fnlwgt     education  education.num marital.status  \
0  NaN   Unknown    NaN       HS-grad              9        Widowed
1  NaN   Private    NaN       HS-grad              9        Widowed
2   66   Unknown     66  Some-college             10        Widowed
3   54   Private     54       7th-8th              4       Divorced
4   41   Private     41  Some-college             10      Separated

          occupation   relationship   race     sex hours.per.week  \
0              Other  Not-in-family  White  Female            NaN
1    Exec-managerial  Not-in-family  White  Female            NaN
2              Other      Unmarried  Black  Female             66
3  Machine-op-inspct      Unmarried  White  Female             54
4     Prof-specialty      Own-child  White  Female            NaN

  native.country income
0  United-States  <=50K
1  United-States  <=50K
2  United-States  <=50K
3  United-States  <=50K
4  United-States  <=50K
```

We found new null values in the `age` and `fnlwgt` column. We have to fill it the median value.

[78]:
```python
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy="median")
```

[79]:
```python
adult_income_num = adult_income_prep[['age', 'fnlwgt', 'hours.per.week']]
```

[80]:
```python
adult_income_num.head()
```

[80]:

	age	fnlwgt	hours.per.week
0	NaN	NaN	NaN
1	NaN	NaN	NaN
2	66	66	66
3	54	54	54
4	41	41	NaN

[81]:
```python
imputer.fit(adult_income_num)
```

[81]:
```
SimpleImputer(add_indicator=False, copy=True, fill_value=None,
              missing_values=nan, strategy='median', verbose=0)
```

[82]:
```python
imputer.statistics_
```

[82]:
```
array([37., 37., 59.])
```

[83]:
```python
X = imputer.transform(adult_income_num)
```

[84]:
```python
X
```

[84]:
```
array([[37., 37., 59.],
       [37., 37., 59.],
       [66., 66., 66.],
       …,
       [40., 40., 59.],
       [58., 58., 58.],
       [22., 22., 59.]])
```

[85]:
```python
adult_tr = pd.DataFrame(X, columns=adult_income_num.columns)
```

[86]:
```python
adult_tr
```

[86]:

	age	fnlwgt	hours.per.week
0	37.0	37.0	59.0
1	37.0	37.0	59.0
2	66.0	66.0	66.0
3	54.0	54.0	54.0
4	41.0	41.0	59.0
…	…	…	…
32556	22.0	22.0	59.0

```
32557  27.0    27.0            59.0
32558  40.0    40.0            59.0
32559  58.0    58.0            58.0
32560  22.0    22.0            59.0

[32561 rows x 3 columns]
```

[87]:
```
adult_income_prep['age'] = adult_tr['age']
adult_income_prep['fnlwgt'] = adult_tr['fnlwgt']
adult_income_prep['hours.per.week'] = adult_tr['hours.per.week']
```

[88]:
```
adult_income_prep.head()
```

[88]:
```
    age workclass  fnlwgt     education  education.num marital.status  \
0  37.0   Unknown    37.0       HS-grad              9        Widowed
1  37.0   Private    37.0       HS-grad              9        Widowed
2  66.0   Unknown    66.0  Some-college             10        Widowed
3  54.0   Private    54.0       7th-8th              4       Divorced
4  41.0   Private    41.0  Some-college             10      Separated

          occupation   relationship   race     sex  hours.per.week  \
0              Other  Not-in-family  White  Female            59.0
1    Exec-managerial  Not-in-family  White  Female            59.0
2              Other      Unmarried  Black  Female            66.0
3  Machine-op-inspct      Unmarried  White  Female            54.0
4     Prof-specialty      Own-child  White  Female            59.0

  native.country income
0  United-States  <=50K
1  United-States  <=50K
2  United-States  <=50K
3  United-States  <=50K
4  United-States  <=50K
```

Alright, no null values now. Now let's change the income values by 1 and 0.

[89]:
```
adult_income_prep['income'] = adult_income_prep['income'].replace('<=50K', 0)
adult_income_prep['income'] = adult_income_prep['income'].replace('>50K', 1)
```

We'll erase the `education` feature because it's the same as `education.num`.

[90]:
```
adult_income_prep = adult_income_prep.drop(columns='education')
```

Category Encoding During our learning process, we can use non-numerical values, so it's better to encode our non-numerical features.

```
[91]: adult_income_prep.workclass = adult_income_prep.workclass.astype('category').
      ↪cat.codes
      adult_income_prep['marital.status'] = adult_income_prep['marital.status'].
      ↪astype('category').cat.codes
      adult_income_prep['occupation'] = adult_income_prep['occupation'].
      ↪astype('category').cat.codes
      adult_income_prep['relationship'] = adult_income_prep['relationship'].
      ↪astype('category').cat.codes
      adult_income_prep['race'] = adult_income_prep['race'].astype('category').cat.
      ↪codes
      adult_income_prep['sex'] = adult_income_prep['sex'].astype('category').cat.codes
      adult_income_prep['native.country'] = adult_income_prep['native.country'].
      ↪astype('category').cat.codes
```

```
[92]: adult_income_prep.head()
```

```
[92]:    age  workclass  fnlwgt  education.num  marital.status  occupation  \
      0  37.0          7    37.0              9               6           7
      1  37.0          3    37.0              9               6           3
      2  66.0          7    66.0             10               6           7
      3  54.0          3    54.0              4               0           6
      4  41.0          3    41.0             10               5          10

         relationship  race  sex  hours.per.week  native.country  income
      0             1     4    0            59.0              39       0
      1             1     4    0            59.0              39       0
      2             4     2    0            66.0              39       0
      3             4     4    0            54.0              39       0
      4             3     4    0            59.0              39       0
```

Now our dataset is ready for training.

4 Training and Comparing models

```
[93]: np.random.seed(1234)
```

We prepare out dataset and divide it into subsets.

```
[94]: y = adult_income_prep['income']
      X_prepared = adult_income_prep.drop(columns='income')
```

We import the `sklearn` library we need to partition the dataset into training and testing subsets.

```
[95]: from sklearn.model_selection import train_test_split
      train_X, val_X, train_y, val_y = train_test_split(X_prepared, y, random_state =␣
      ↪0)
```

We will use a crossvalidation to search for the best hyperparameters.

[96]:
```
from sklearn.model_selection import cross_val_score
```

We'll have to dictionaries containing the Mean Absolute Error and the accuracy value of each algorithm.

[97]:
```
MAE = dict()
Acc = dict()
```

4.1 Traditional ML Techniques: Logistic regression

We will perform a crossvalidated logistic regression to our dataset. From the Logistic Regression we will extract the coeficients/features who have a better or a worse influence on the prediction.

[98]:
```
from sklearn.linear_model import LogisticRegression
```

[99]:
```
log_model = LogisticRegression()
```

[100]:
```
score = cross_val_score(log_model, X_prepared, y,␣
 ↪scoring="neg_mean_absolute_error", cv=10)
```

```
/Users/morad/opt/anaconda3/lib/python3.7/site-
packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
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Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
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  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
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```

```
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```

```
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    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

[101]:

```
print("MAE score mean:\n", np.abs(score).mean())
```

```
MAE score mean:
 0.1939743749806691
```

[102]:

```
from sklearn.model_selection import GridSearchCV
```

[103]:

```
param_grid = [
    {'C': [0.001,0.01,0.1,1,10,100]},
]
grid_search = GridSearchCV(log_model, param_grid, cv=5,␣
 ↪scoring='neg_mean_squared_error')
grid_search.fit(train_X, train_y)
```

```
/Users/morad/opt/anaconda3/lib/python3.7/site-
packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed
to converge (status=1):
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```
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/Users/morad/opt/anaconda3/lib/python3.7/site-
```

```
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    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
```

```
regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/Users/morad/opt/anaconda3/lib/python3.7/site-
packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed
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```
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Increase the number of iterations (max_iter) or scale the data as shown in:
```

```
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
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    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/Users/morad/opt/anaconda3/lib/python3.7/site-
packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/Users/morad/opt/anaconda3/lib/python3.7/site-
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Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
```

```
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/Users/morad/opt/anaconda3/lib/python3.7/site-
packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed
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    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/Users/morad/opt/anaconda3/lib/python3.7/site-
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    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/Users/morad/opt/anaconda3/lib/python3.7/site-
packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed
to converge (status=1):
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Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

[103]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=LogisticRegression(C=1.0, class_weight=None, dual=False,
                                          fit_intercept=True,
                                          intercept_scaling=1, l1_ratio=None,
                                          max_iter=100, multi_class='auto',
                                          n_jobs=None, penalty='l2',
                                          random_state=None, solver='lbfgs',
                                          tol=0.0001, verbose=0,
                                          warm_start=False),
             iid='deprecated', n_jobs=None,
             param_grid=[{'C': [0.001, 0.01, 0.1, 1, 10, 100]}],
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
```

```
                scoring='neg_mean_squared_error', verbose=0)
```

[104]:
```python
grid_search.best_params_
```

[104]:
```
{'C': 100}
```

[105]:
```python
log_model = LogisticRegression(C=100, random_state=0)
```

[106]:
```python
log_model.fit(train_X, train_y)
```

```
/Users/morad/opt/anaconda3/lib/python3.7/site-
packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

[106]:
```
LogisticRegression(C=100, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=0, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

[107]:
```python
val_predictions = log_model.predict(val_X)
```

[108]:
```python
columns = adult_income_prep.drop(columns='income').columns
coefs = log_model.coef_[0]
print("Features - Coefs")
for index in range(len(coefs)):
    print(columns[index], ":", coefs[index])
```

```
Features - Coefs
age : 0.0591988304177485
workclass : -0.09002223884698841
fnlwgt : -0.014278177489885961
education.num : 0.37357447044203884
marital.status : -0.21856029678303646
occupation : -7.447641781696112e-05
relationship : -0.14266599757140028
race : 0.13047846851261513
sex : 1.0391318172666453
```

```
hours.per.week : -0.12302044432859731
native.country : 0.001667892121472329
```

It's pretty interesting to see what the logistic regression reveals. * Education, relationship, gender and race are the features which most positively have an impact on income * The hours per week and the final weight have a negative impact on income

Now, let's calculate the mean absolute error (MAE).

[109]:
```
from sklearn.metrics import mean_absolute_error
lm_mae = mean_absolute_error(val_y, val_predictions)
```

[110]:
```
from sklearn.metrics import accuracy_score
```

[111]:
```
lm_acc = accuracy_score(val_y, val_predictions)
MAE['lm'] = lm_mae
Acc['lm'] = lm_acc
```

[112]:
```
print("The mae is", lm_mae)
```

```
The mae is 0.19395651639847686
```

[113]:
```
print("The accuracy is", lm_acc * 100, "%")
```

```
The accuracy is 80.60434836015231 %
```

4.2 Modern ML techniques

We've performed a training and testing process using a traditional ML technique which was the Logistic Regression. Now, we'll use some modern classifers which are: * Random Forests * K Nearest Neighbours * Gradient Boosting Machine * Naive Bayes

For all of them we'll perform a crossvaliation to detect the best hyperparameters.

4.2.1 Random Forests

[114]:
```
from sklearn.ensemble import RandomForestClassifier
```

[115]:
```
param_grid = [
    {'n_estimators': [3, 10, 30], 'max_features': [2, 4, 6, 8]},
    {'bootstrap': [False], 'n_estimators': [3, 10], 'max_features': [2, 3, 4]}
]

forest_model = RandomForestClassifier()
grid_search = GridSearchCV(forest_model, param_grid, cv=5,␣
 ↪scoring='neg_mean_squared_error')
grid_search.fit(train_X, train_y)
```

[115]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=RandomForestClassifier(bootstrap=True, ccp_alpha=0.0,
                                              class_weight=None,
                                              criterion='gini', max_depth=None,
                                              max_features='auto',
                                              max_leaf_nodes=None,
                                              max_samples=None,
                                              min_impurity_decrease=0.0,
                                              min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_leaf=0.0,
                                              n_estimators=100, n_jobs=None,
                                              oob_score=False,
                                              random_state=None, verbose=0,
                                              warm_start=False),
             iid='deprecated', n_jobs=None,
             param_grid=[{'max_features': [2, 4, 6, 8],
                          'n_estimators': [3, 10, 30]},
                         {'bootstrap': [False], 'max_features': [2, 3, 4],
                          'n_estimators': [3, 10]}],
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='neg_mean_squared_error', verbose=0)
```

[116]:
```
grid_search.best_params_
```

[116]:
```
{'max_features': 2, 'n_estimators': 30}
```

[117]:
```
rf_model = RandomForestClassifier(max_features=2, n_estimators=30,␣
 ↪random_state=0)
```

[118]:
```
rf_model.fit(train_X, train_y)
```

[118]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=None, max_features=2,
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=30,
                       n_jobs=None, oob_score=False, random_state=0, verbose=0,
                       warm_start=False)
```

[119]:
```
val_predictions = rf_model.predict(val_X)
```

[120]:
```
rf_mae = mean_absolute_error(val_y, val_predictions)
```

[121]:
```
rf_mae
```

[121]: 0.18634074438029727

[122]:
```
rf_acc = accuracy_score(val_y, val_predictions)
```

[123]:
```
rf_acc
```

[123]: 0.8136592556197028

[124]:
```
MAE['rf'] = rf_mae
Acc['rf'] = rf_acc
```

4.2.2 Gradient Boosting Machine

[125]:
```
from sklearn.ensemble import GradientBoostingClassifier
```

[126]:
```
gbm_model = GradientBoostingClassifier(learning_rate=0.1, n_estimators=60,␣
 ↪max_features='sqrt', subsample=0.8, random_state=0)

param_grid = {'max_depth':range(5,16,2), 'min_samples_split':
 ↪range(200,1001,200)}

grid_search = GridSearchCV(gbm_model, param_grid, cv=5,␣
 ↪scoring='neg_mean_squared_error')
grid_search.fit(train_X, train_y)
```

[126]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=GradientBoostingClassifier(ccp_alpha=0.0,
                                                  criterion='friedman_mse',
                                                  init=None, learning_rate=0.1,
                                                  loss='deviance', max_depth=3,
                                                  max_features='sqrt',
                                                  max_leaf_nodes=None,
                                                  min_impurity_decrease=0.0,
                                                  min_impurity_split=None,
                                                  min_samples_leaf=1,
                                                  min_samples_split=2,
                                                  min_weight_fraction_leaf=0.0,
                                                  n_estimators=60,
                                                  n_iter_no_change=None,
                                                  presort='deprecated',
                                                  random_state=0, subsample=0.8,
                                                  tol=0.0001,
                                                  validation_fraction=0.1,
                                                  verbose=0, warm_start=False),
             iid='deprecated', n_jobs=None,
             param_grid={'max_depth': range(5, 16, 2),
```

```
                 'min_samples_split': range(200, 1001, 200)},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='neg_mean_squared_error', verbose=0)
```

[127]:
```
grid_search.best_params_
```

[127]:
```
{'max_depth': 7, 'min_samples_split': 800}
```

[128]:
```
gbm_model = GradientBoostingClassifier(max_depth=7, min_samples_split=800,␣
 ↪random_state=0)
```

[129]:
```
gbm_mae = mean_absolute_error(val_y, val_predictions)
```

[130]:
```
gbm_mae
```

[130]:
```
0.18634074438029727
```

[131]:
```
gbm_acc = accuracy_score(val_y, val_predictions)
```

[132]:
```
gbm_acc
```

[132]:
```
0.8136592556197028
```

[133]:
```
MAE['gbm'] = gbm_mae
Acc['gbm'] = gbm_acc
```

4.2.3 K-Nearest Neighbours

[134]:
```
from sklearn.neighbors import KNeighborsClassifier as KNN
```

[135]:
```
KNN
```

[135]:
```
sklearn.neighbors._classification.KNeighborsClassifier
```

[136]:
```
knn_model = KNN()

param_grid = {'n_neighbors':range(5,10,1)}

grid_search = GridSearchCV(knn_model, param_grid, cv=5,␣
 ↪scoring='neg_mean_squared_error')

grid_search.fit(train_X, train_y)
```

[136]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=KNeighborsClassifier(algorithm='auto', leaf_size=30,
                                            metric='minkowski',
                                            metric_params=None, n_jobs=None,
```

```
                                              n_neighbors=5, p=2,
                                              weights='uniform'),
             iid='deprecated', n_jobs=None,
             param_grid={'n_neighbors': range(5, 10)}, pre_dispatch='2*n_jobs',
             refit=True, return_train_score=False,
             scoring='neg_mean_squared_error', verbose=0)
```

[137]:
```
knn_params = grid_search.best_params_
knn_params
```

[137]:
```
{'n_neighbors': 8}
```

[138]:
```
knn_model = KNN(n_neighbors=8)
```

[139]:
```
knn_model.fit(train_X, train_y)
```

[139]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=8, p=2,
                     weights='uniform')
```

[140]:
```
val_predictions = knn_model.predict(val_X)
```

[141]:
```
knn_mae = mean_absolute_error(val_y, val_predictions)
```

[142]:
```
knn_mae
```

[142]:
```
0.18769192973836138
```

[143]:
```
knn_acc = accuracy_score(val_y, val_predictions)
```

[144]:
```
knn_acc
```

[144]:
```
0.8123080702616386
```

4.2.4 Naive Bayes

[145]:
```
from sklearn.naive_bayes import GaussianNB
```

[146]:
```
GNB = GaussianNB()
```

[147]:
```
GNB.fit(train_X, train_y)
```

[147]:
```
GaussianNB(priors=None, var_smoothing=1e-09)
```

[148]:
```
val_predictions = GNB.predict(val_X)
```

[149]:
```
GNB_mae = mean_absolute_error(val_y, val_predictions)
```

[150]:
```
GNB_mae
```

[150]: 0.22012037833190026

[151]:
```
GNB_acc = accuracy_score(val_y, val_predictions)
```

[152]:
```
GNB_acc
```

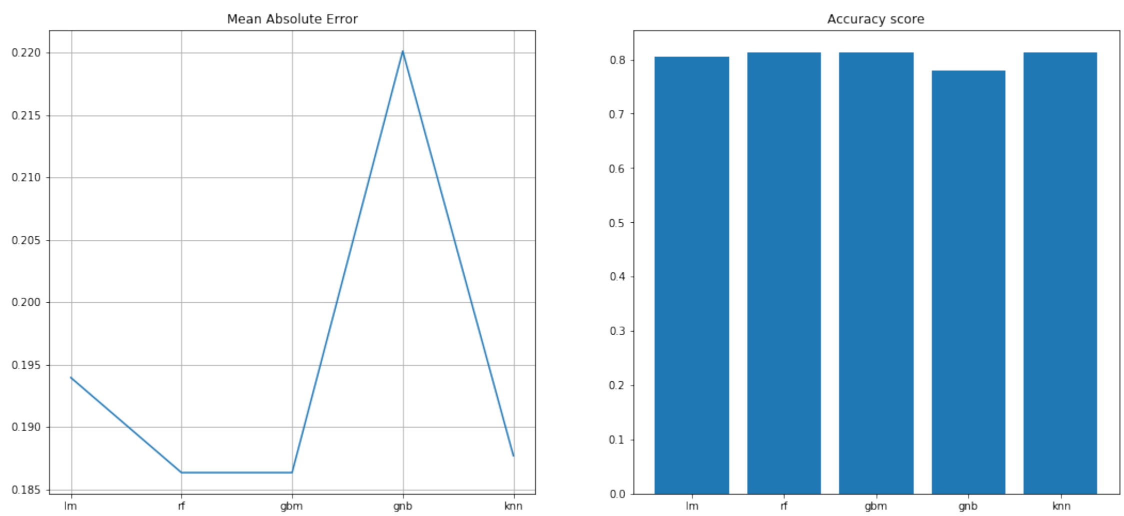
[152]: 0.7798796216680998

[153]:
```
MAE['gnb'] = GNB_mae
Acc['gnb'] = GNB_acc
```

[154]:
```
MAE['knn'] = knn_mae
Acc['knn'] = knn_acc
```

[155]:
```
f,ax=plt.subplots(1,2,figsize=(18,8))
ax[0].plot(list(MAE.keys()), list(MAE.values()))
ax[0].set_title("Mean Absolute Error")
ax[0].grid()
ax[1].bar(list(Acc.keys()), list(Acc.values()))
ax[1].set_title("Accuracy score")
```

[155]: Text(0.5, 1.0, 'Accuracy score')



Apparently the Random Forest Classifier is the best compared to the rest due the time Gradient Boosting needs to perform the training and testing with a 81.36% accuracy.

[ ]:
```
```