01_analyse_raw_data

January 19, 2020

1 EDA on raw data (after collect)

This notebook main goal is to : - Understand what is in the data : plot variables one by one, missing values, etc. - See which data are correlated - Removes useless variables : too much missing values, too correlated with other variables. - See if data is biased on protected attributes

1.1 Load packages

[1]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
from IPython.display import display, Markdown

# transparentai package : https://github.com/Nathanlauga/transparentai
from transparentai.datasets import ClassificationDataset
import transparentai.explore as explore
```

[2]:
```
PROJECT_PATH = '..'
```

1.2 Load data informations

[3]:
```
df_details = pd.read_csv(f'{PROJECT_PATH}/01_collect/columns_informations.csv')
```

[4]:
```
df_details
```

[4]:
```
  dataset           column   dtype  is_protected      new_name  \
0    adult             age   int64             1           NaN
1    adult       workclass  object             0           NaN
2    adult          fnlwgt   int64             0  final_weight
3    adult       education  object             0           NaN
4    adult  educational-num   int64             0           NaN
5    adult  marital-status  object             1           NaN
6    adult      occupation  object             0           NaN
7    adult    relationship  object             0           NaN
8    adult            race  object             1           NaN
```

```
9    adult           gender  object            1          NaN
10   adult     capital-gain   int64            0          NaN
11   adult     capital-loss   int64            0          NaN
12   adult   hours-per-week   int64            0          NaN
13   adult   native-country  object            1          NaN
14   adult           income  object            0          NaN

                                            description
0                                    Age of the person
1                 Workclass of the person (e.g. Private)
2   final weight, which is the number of units in …
3                                      Education level
4                     Education level (numerical format)
5                                       Marital status
6                                     Field occupation
7                                 Current relationship
8                                            Ethnicity
9                                       Female or Male
10                                     Gain of capital
11                                     Loss of capital
12                 number of working hours during a week
13                                      Native country
14                           Target : income > 50K or not
```

1.3 Load data using data informations

[5]:
```python
dfs = {}
datasets = df_details['dataset'].unique()

for dataset in datasets:
    dataset_detail = df_details[df_details['dataset'] == dataset]

    dtypes, columns = dataset_detail['dtype'], dataset_detail['column']
    dtypes = pd.Series(dtypes.values,index=columns)

    parse_dates = list()
    for var, dtype in dtypes.iteritems():
        if 'datetime' in dtype:
            parse_dates.append(var)

    dtypes = dtypes.str.replace(r'datetime.*','str')

    dfs[dataset] = pd.read_csv(f'{PROJECT_PATH}/_data/{dataset}.csv',
                               dtype=dtypes.to_dict(),
                               parse_dates=parse_dates
                              )
```

```
    columns = np.where(dataset_detail['new_name'].isna(), columns,␣
↪dataset_detail['new_name'])
    dfs[dataset].columns = columns
```

1.4 Display shape & head

[6]:
```
for dataset in dfs:
    display(Markdown(f'#### {dataset}, {dfs[dataset].shape}'))
    display(dfs[dataset].head())
```

adult, (48842, 15)

```
   age  workclass  final_weight     education  educational-num  \
0   25    Private        226802          11th                7
1   38    Private         89814       HS-grad                9
2   28  Local-gov        336951    Assoc-acdm               12
3   44    Private        160323  Some-college               10
4   18          ?        103497  Some-college               10

       marital-status         occupation relationship   race  gender  \
0       Never-married  Machine-op-inspct    Own-child  Black    Male
1  Married-civ-spouse    Farming-fishing      Husband  White    Male
2  Married-civ-spouse    Protective-serv      Husband  White    Male
3  Married-civ-spouse  Machine-op-inspct      Husband  Black    Male
4       Never-married                  ?    Own-child  White  Female

   capital-gain  capital-loss  hours-per-week native-country income
0             0             0              40  United-States  <=50K
1             0             0              50  United-States  <=50K
2             0             0              40  United-States   >50K
3          7688             0              40  United-States   >50K
4             0             0              30  United-States  <=50K
```

1.5 Set datasets into differents variables

Here we just have one dataset `adult`, but if in the next versions we had some others datasets it's important to set them into distinct variables.

[7]:
```
adult = dfs['adult']
del dfs
```

1.6 Analyse : missing values

[8]:
```
help(explore.show_missing_values)
```

```
Help on function show_missing_values in module transparentai.explore.explore:

show_missing_values(df)
    Show a bar plot that display percentage of missing values on columns that
have some.
    If no missing value then it use `display` & `Markdown` functions to indicate
it.

    Parameters
    ----------
    df: pd.DataFrame
        Dataframe to inspect
```

[9]:
```
display(Markdown('#### Missing values for adult dataset'))
explore.show_missing_values(adult)
```

Missing values for adult dataset No missing value.

1.7 Analyse : plot each variable

1.7.1 Using MLHelper

[10]:
```
from transparentai.utils import remove_var_with_one_value
adult = remove_var_with_one_value(adult)
```

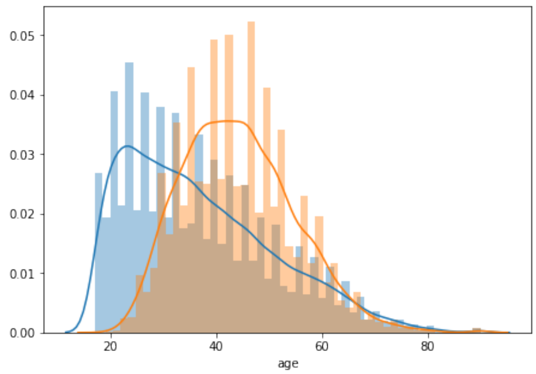
[11]:
```
help(explore.show_df_vars)
```

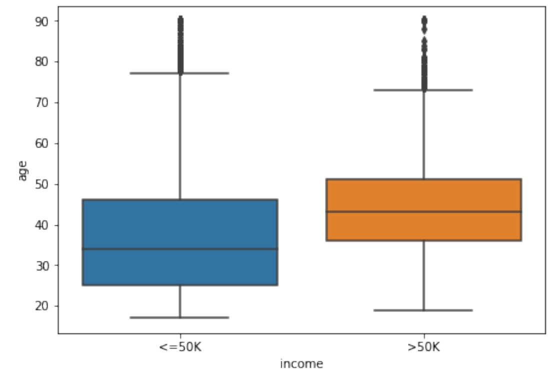
```
Help on function show_df_vars in module transparentai.explore.explore:

show_df_vars(df, target=None)
    Show all variables with graphics to understand each variable.
    If target is set, complement visuals will be added to take a look on the
    influence that a variable can have on target

    Data type handle : categorical, numerical, datetime

    Parameters
    ----------
    df: pd.DataFrame
        Dataframe to inspect
    target: str (optional)
        Target column for classifier
```

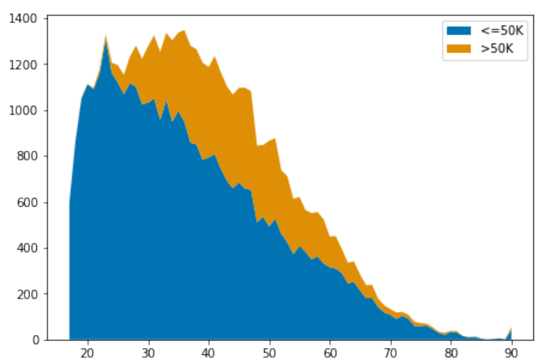
[12]:
```
explore.show_df_vars(df=adult, target='income')
```

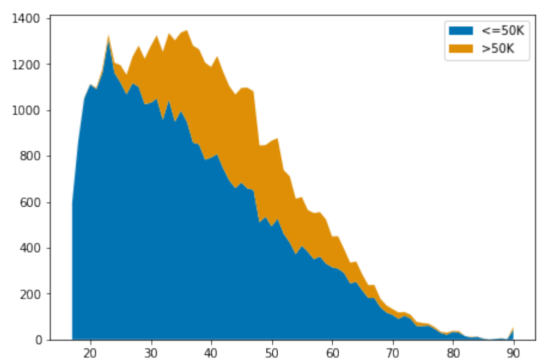
1.7.2 Numerical variables

age : 0 nulls, 74 unique vals, most common: {36: 1348, 35: 1337}

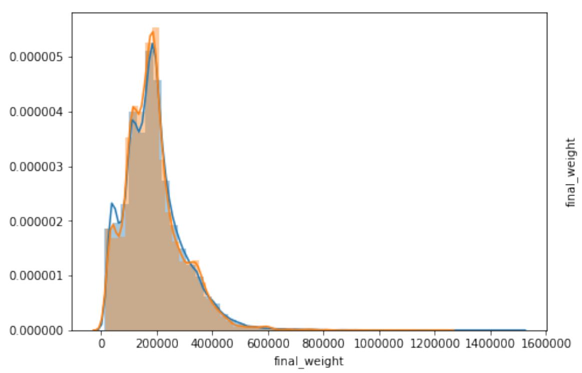


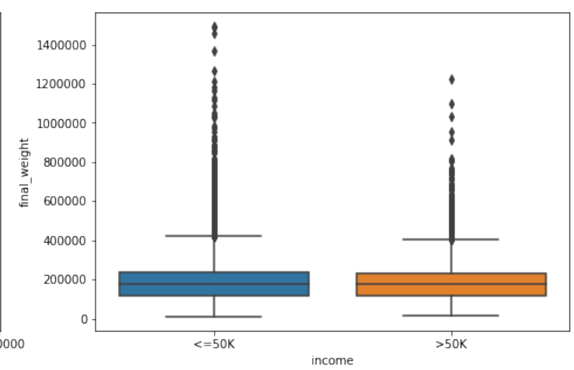


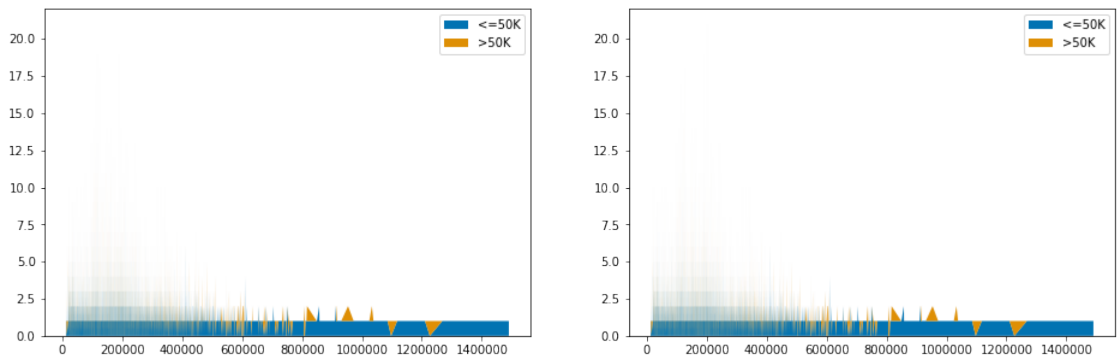




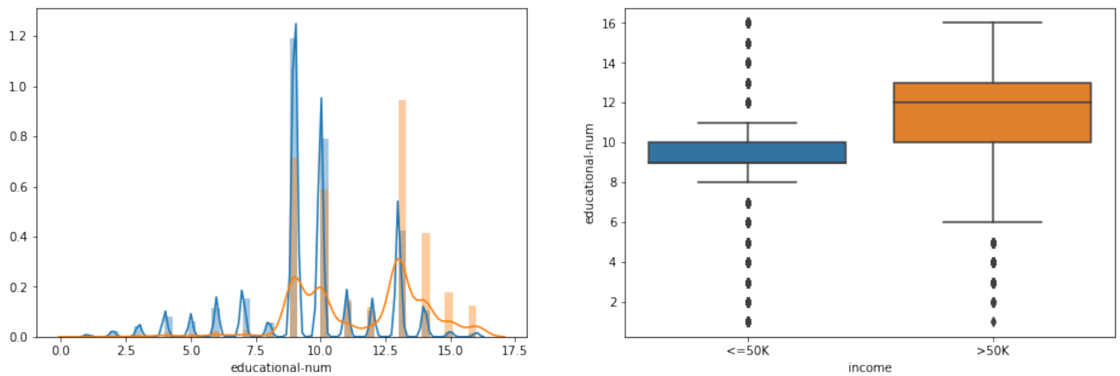
final_weight : 0 nulls, 28523 unique vals, most common: {203488: 21, 190290: 19}

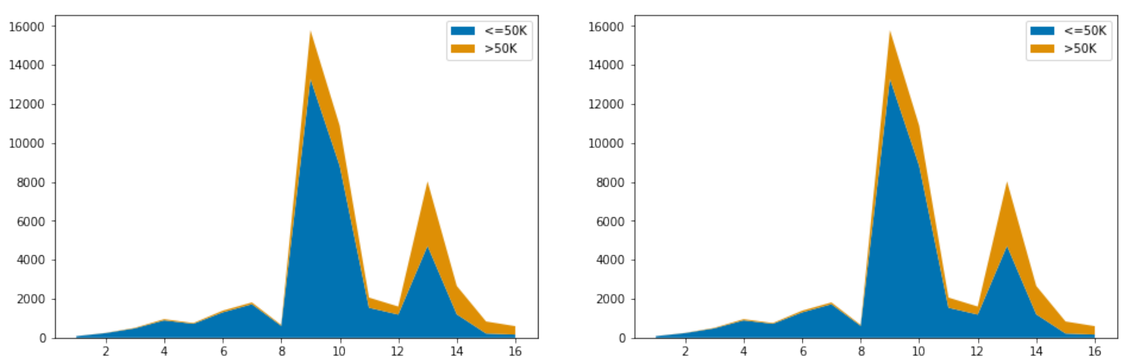




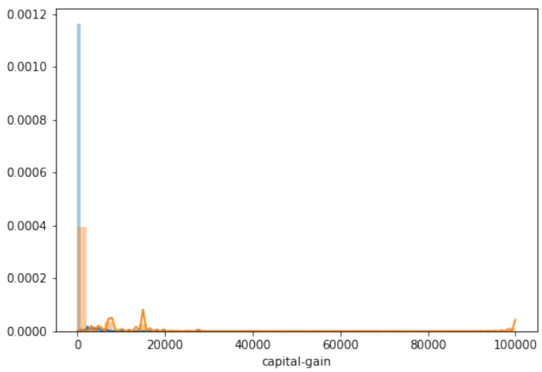


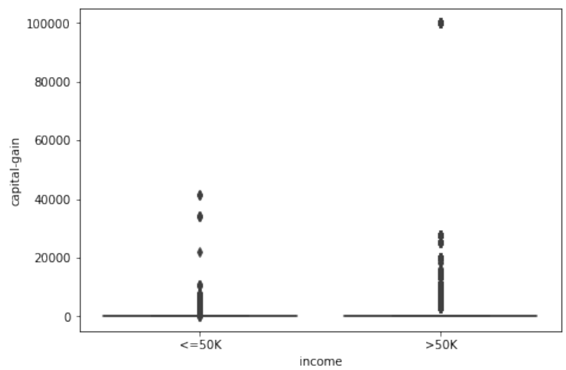
educational-num : 0 nulls, 16 unique vals, most common: {9: 15784, 10: 10878}

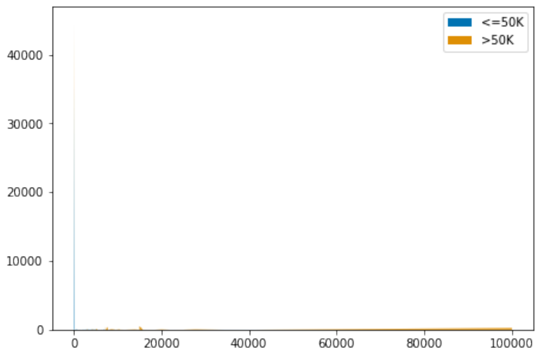


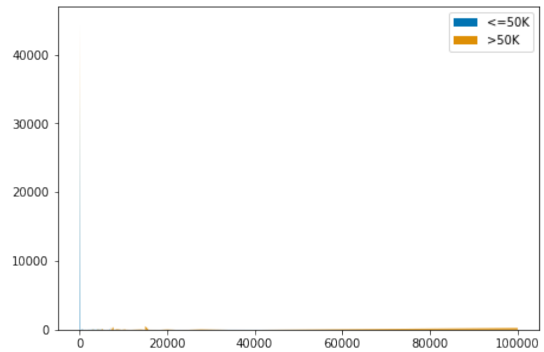


capital-gain : 0 nulls, 123 unique vals, most common: {0: 44807, 15024: 513}

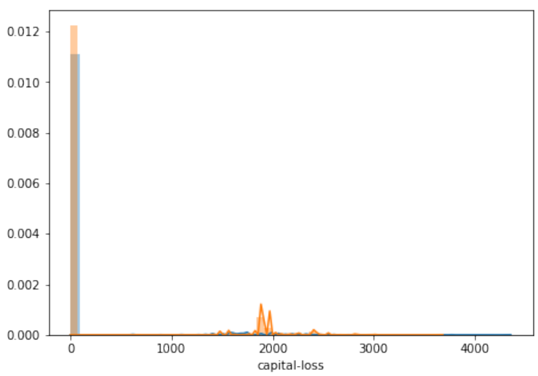


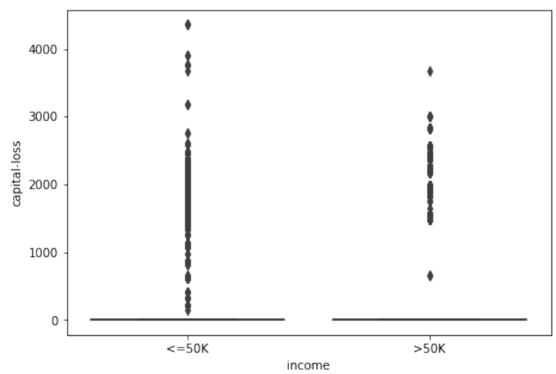


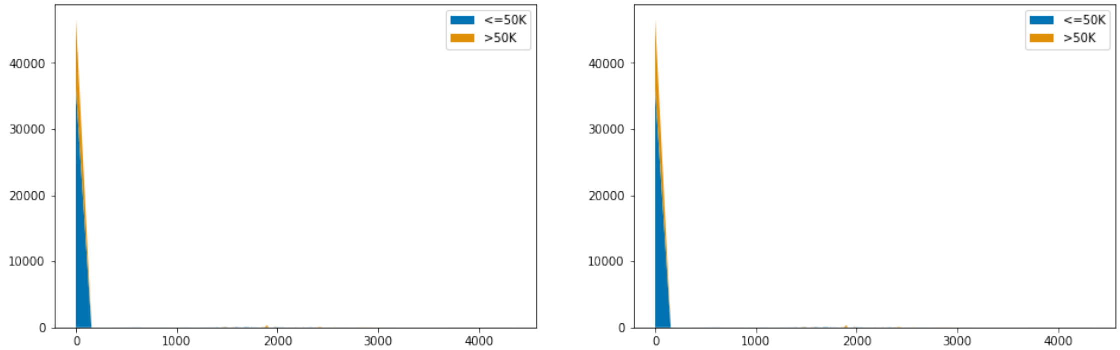




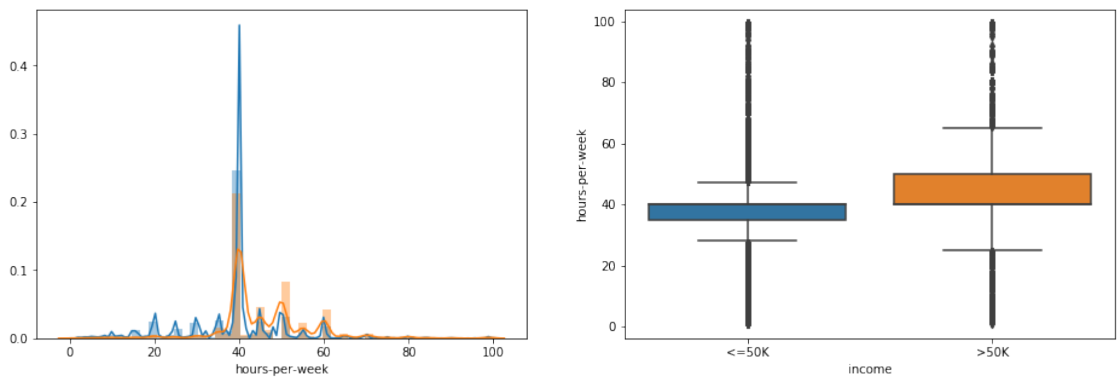
capital-loss : 0 nulls, 99 unique vals, most common: {0: 46560, 1902: 304}

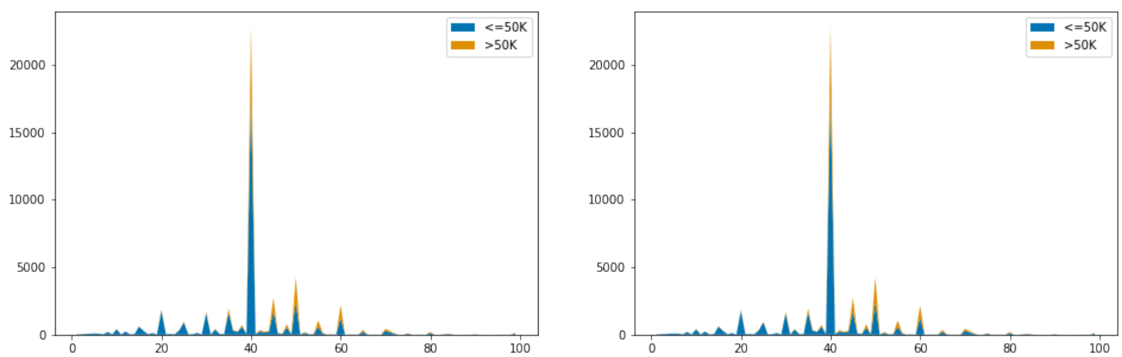






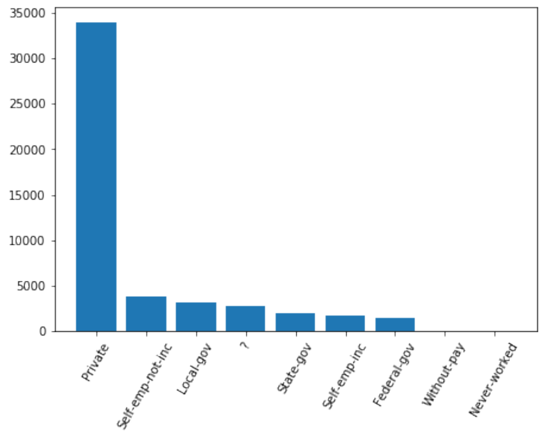
hours-per-week : 0 nulls, 96 unique vals, most common: {40: 22803, 50: 4246}

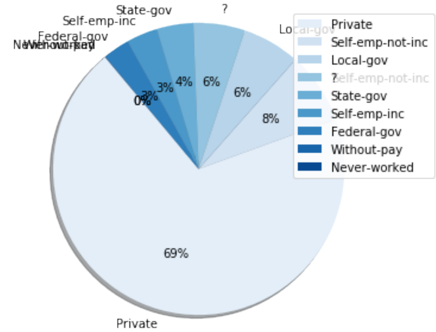


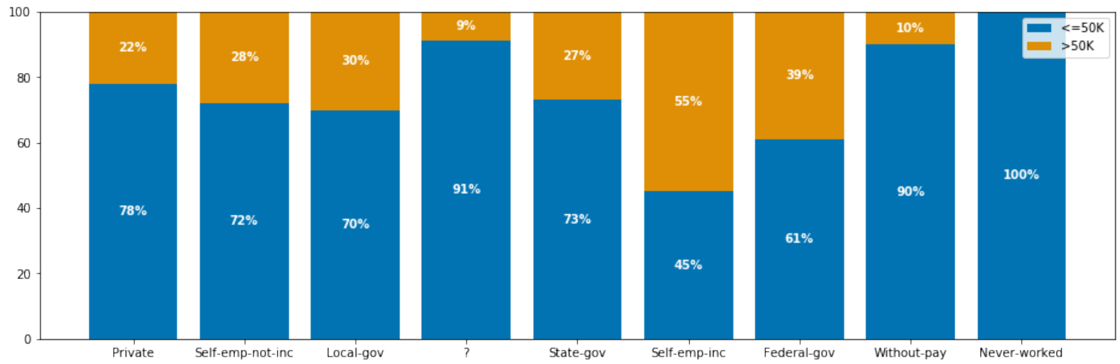


1.7.3 Categorical variables

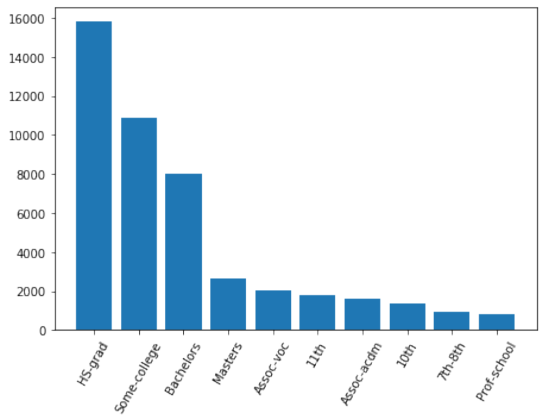
workclass : 0 nulls, 9 unique vals, most common: {'Private': 33906, 'Self-emp-not-inc': 3862}

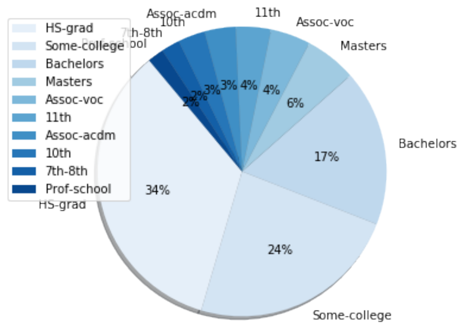


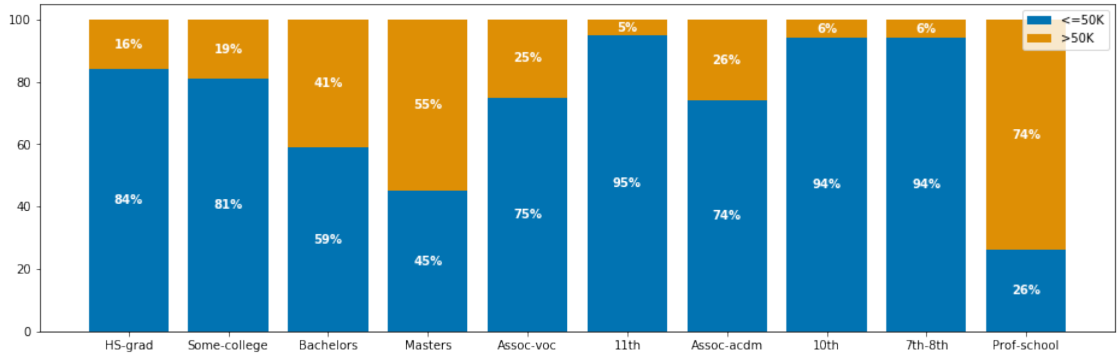




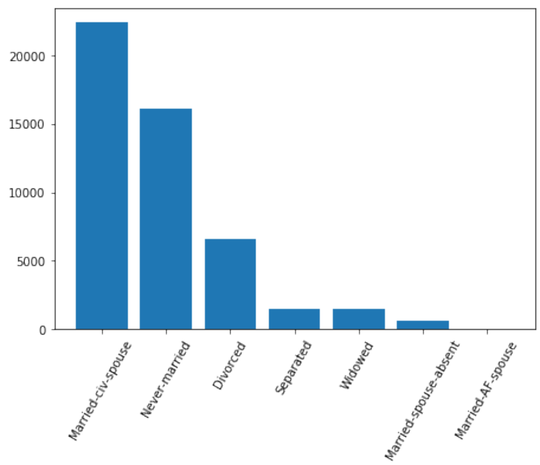
education : 0 nulls, 16 unique vals, most common: {'HS-grad': 15784, 'Some-college': 10878}

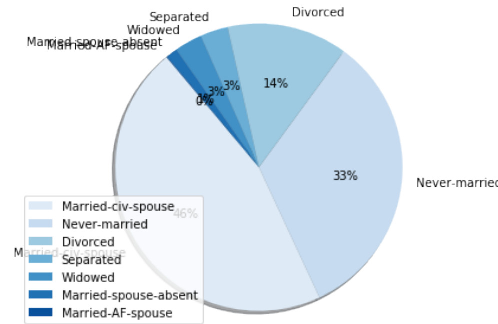


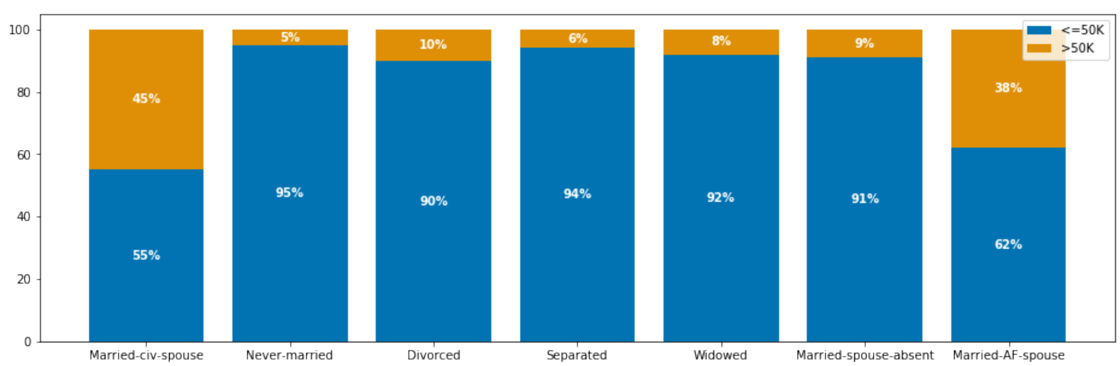




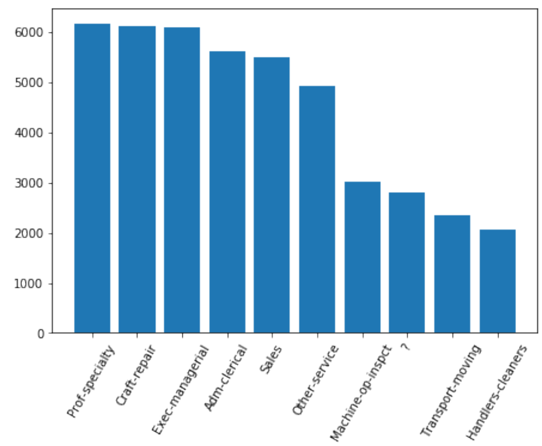
marital-status : 0 nulls, 7 unique vals, most common: {'Married-civ-spouse': 22379, 'Never-married': 16117}

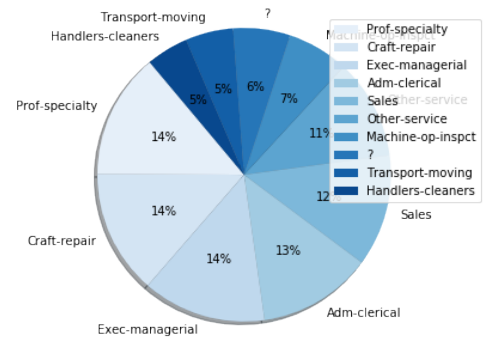


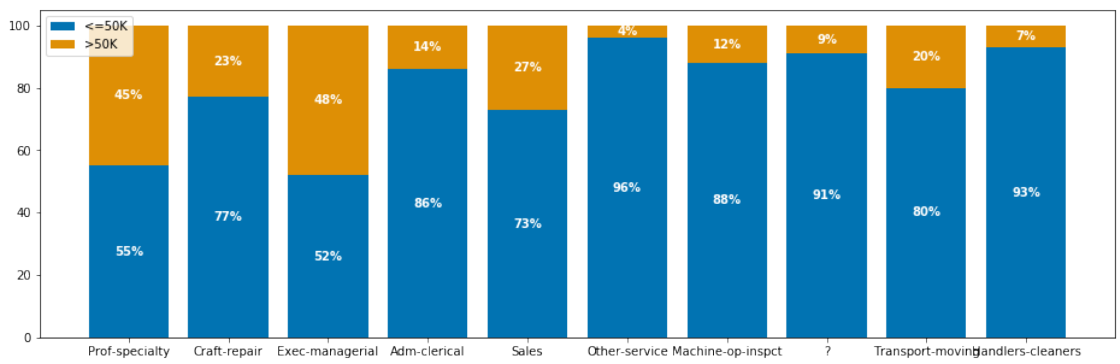




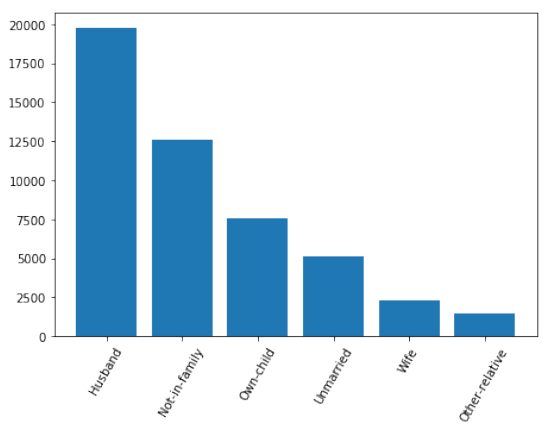
occupation : 0 nulls, 15 unique vals, most common: {'Prof-specialty': 6172, 'Craft-repair': 6112}

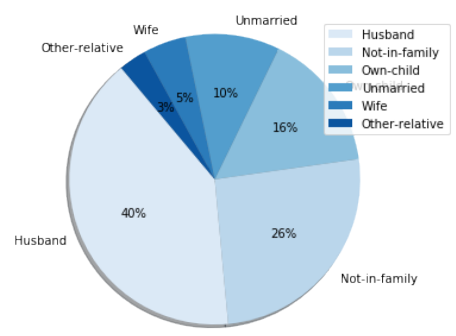


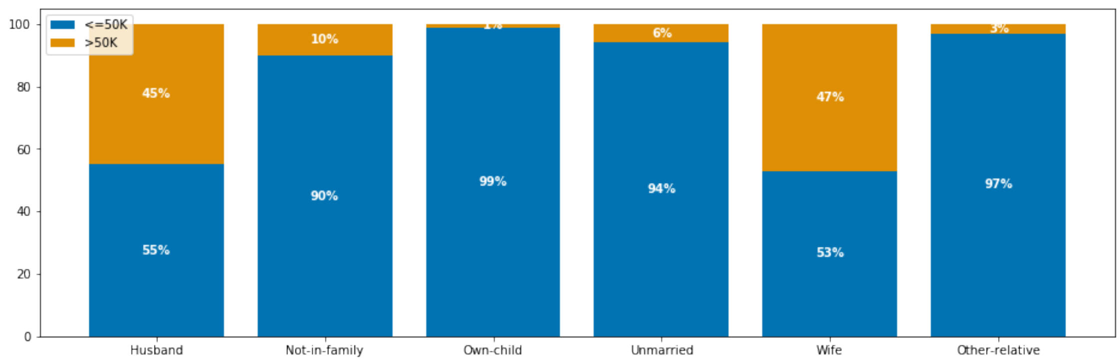




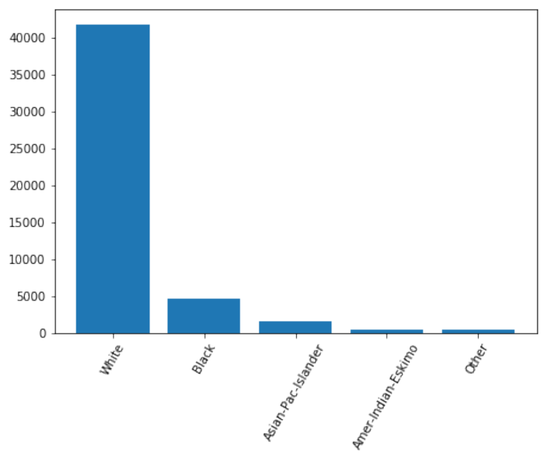
relationship : 0 nulls, 6 unique vals, most common: {'Husband': 19716, 'Not-in-family': 12583}

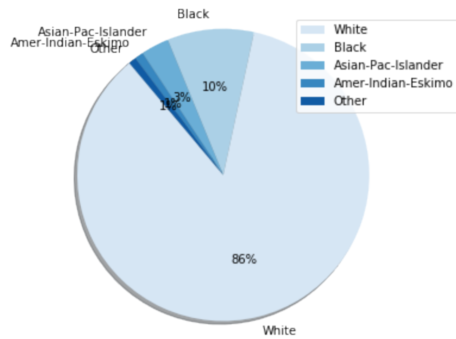


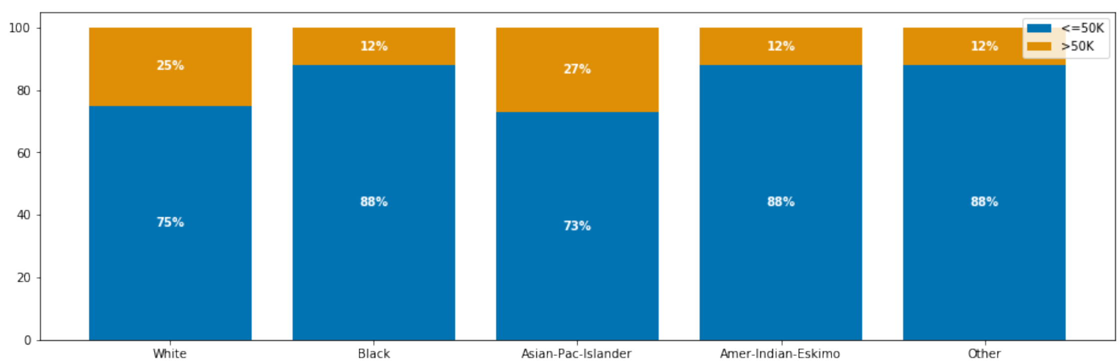




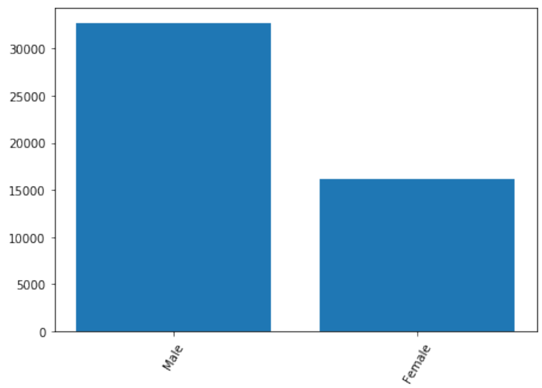
race : 0 nulls, 5 unique vals, most common: {'White': 41762, 'Black': 4685}

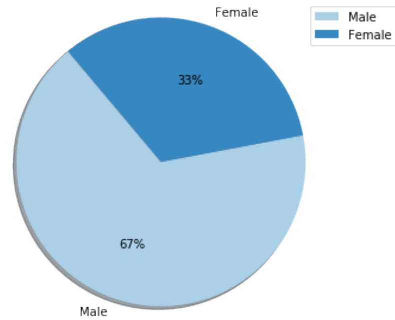


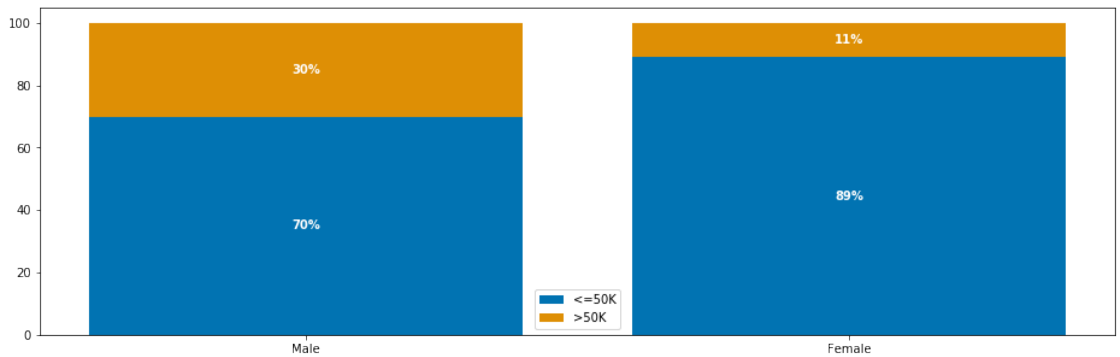




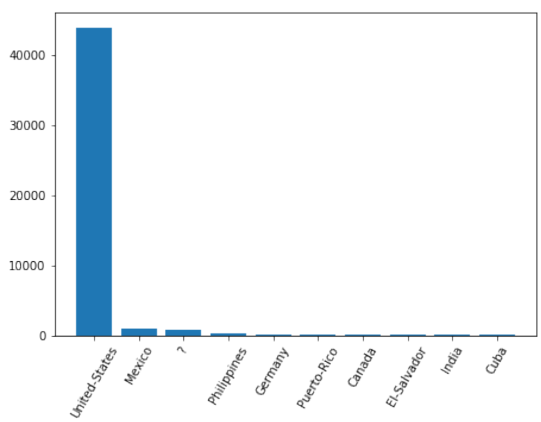
gender : 0 nulls, 2 unique vals, most common: {'Male': 32650, 'Female': 16192}

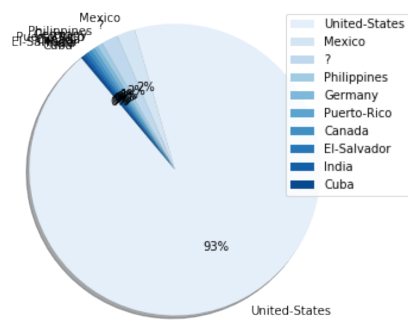


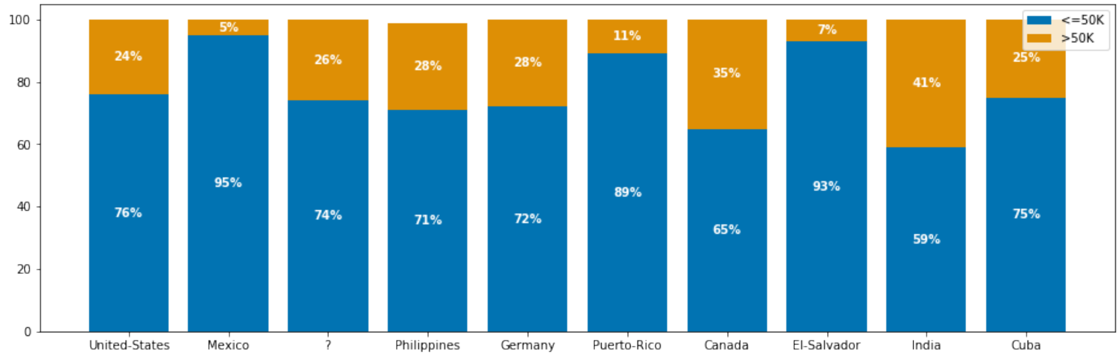




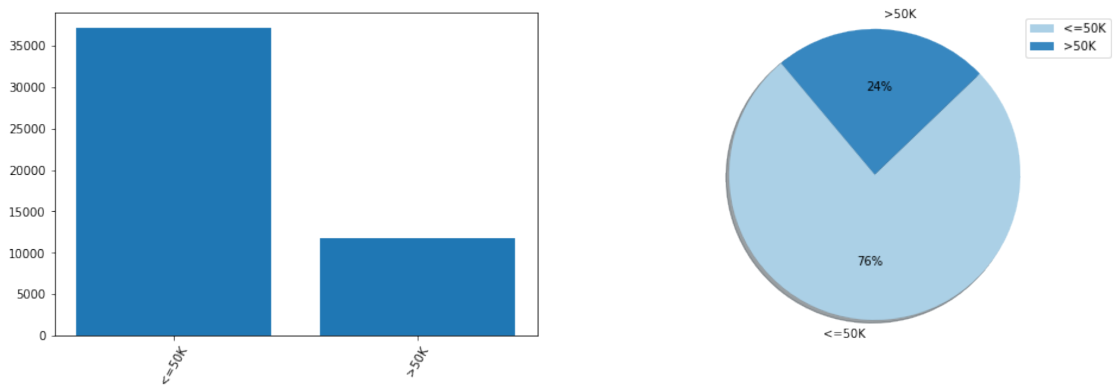
native-country : 0 nulls, 42 unique vals, most common: {'United-States': 43832, 'Mexico': 951}

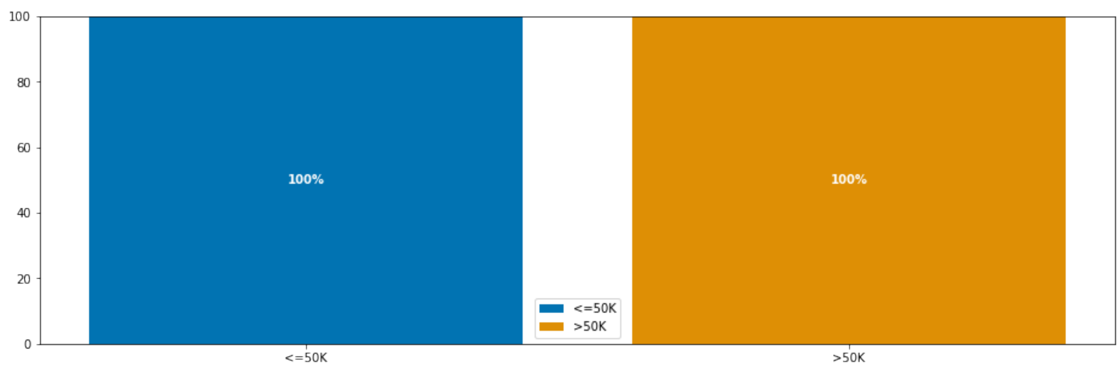






income : 0 nulls, 2 unique vals, most common: {'<=50K': 37155, '>50K': 11687}





1.7.4 Datetime variables

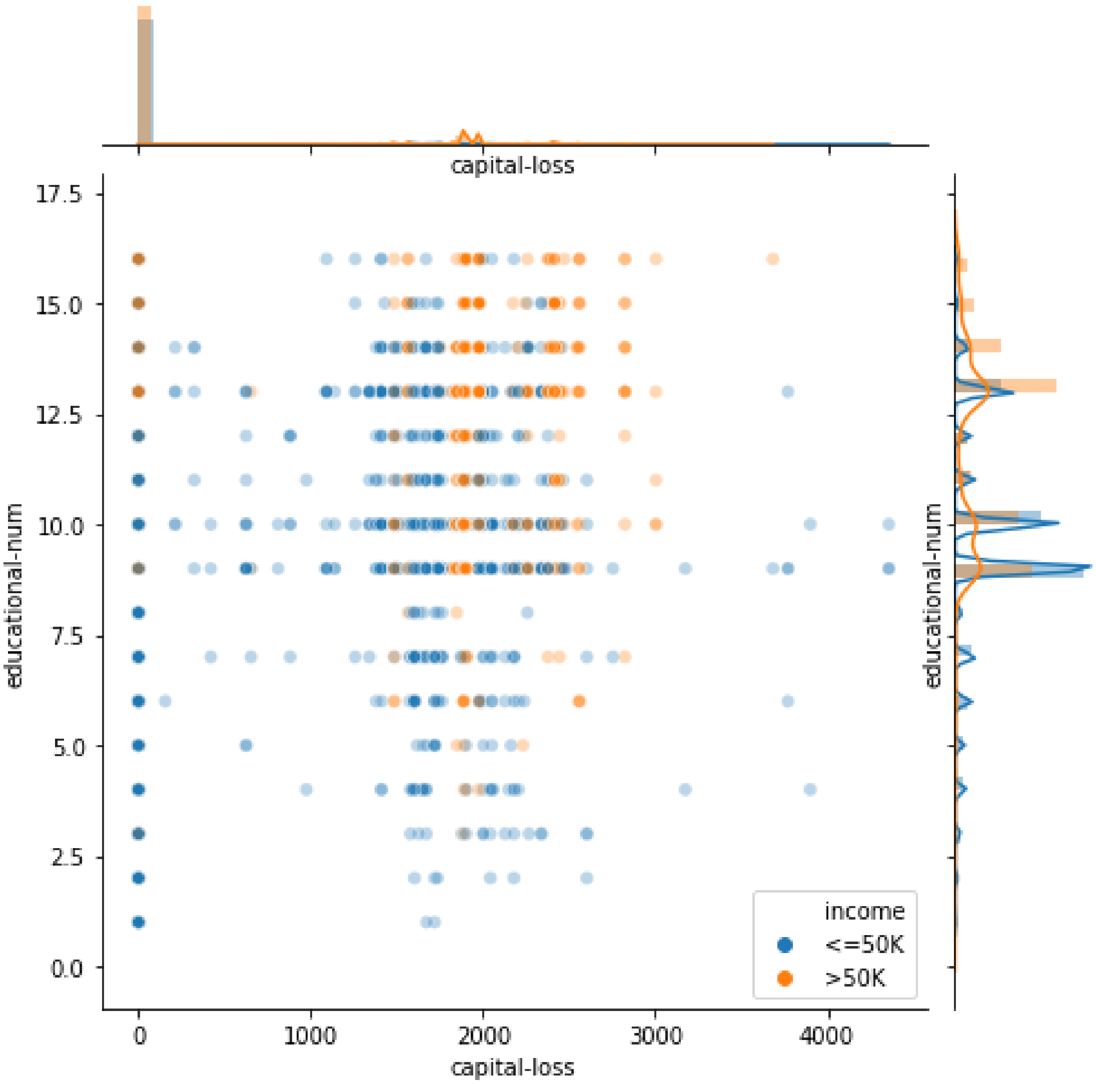
[13]:
```
help(explore.show_df_numerical_relations)
```

```
Help on function show_df_numerical_relations in module
```

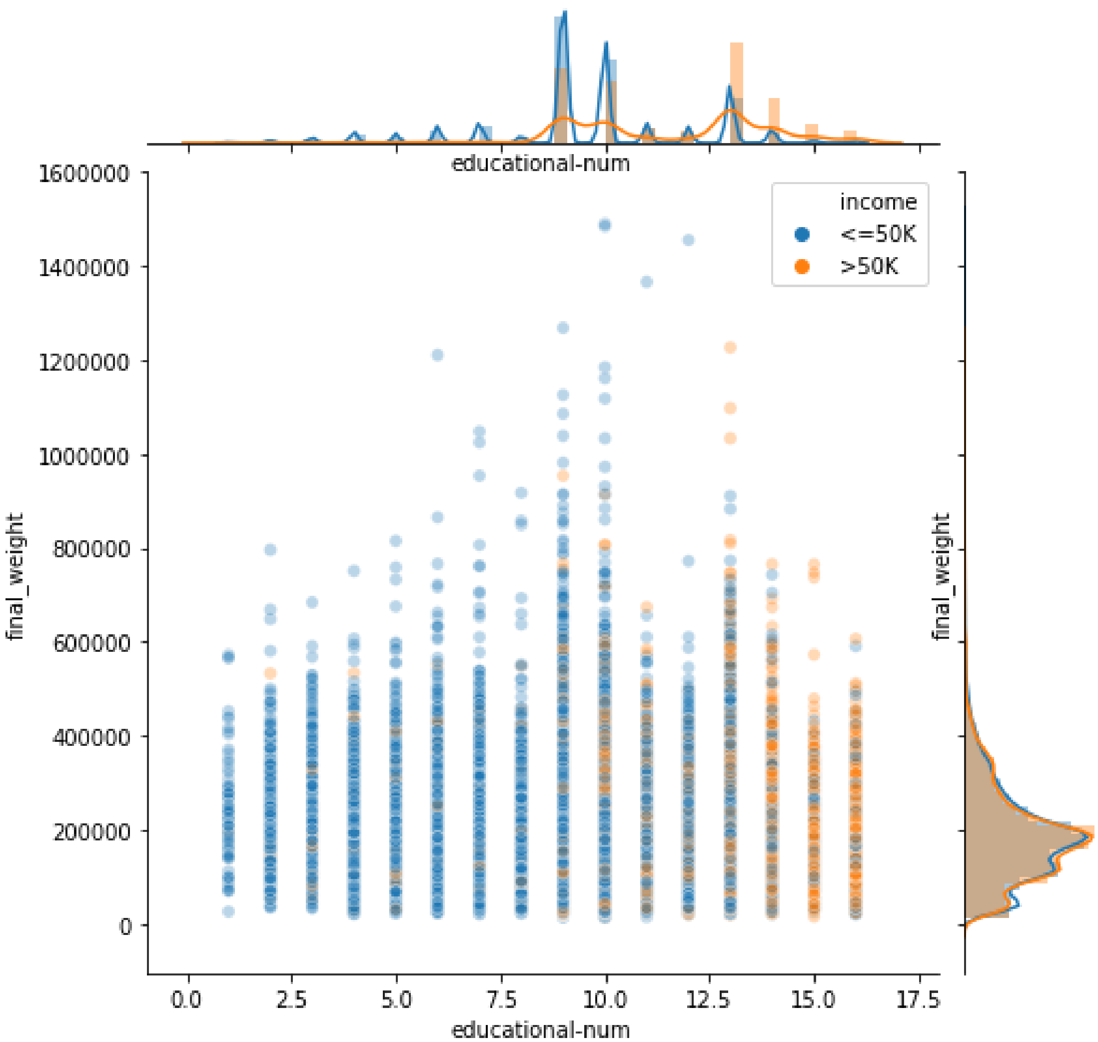
```
transparentai.explore.explore:

show_df_numerical_relations(df, target=None)
    Show all numerical variables 2 by 2 with graphics understand their relation.
    If target is set, separate dataset for each target value.

    Parameters
    ----------
    df: pd.DataFrame
        Dataframe to inspect
    target: str (optional)
        Target column for classifier
```

[14]:
```
explore.show_df_numerical_relations(df=adult, target='income')
```

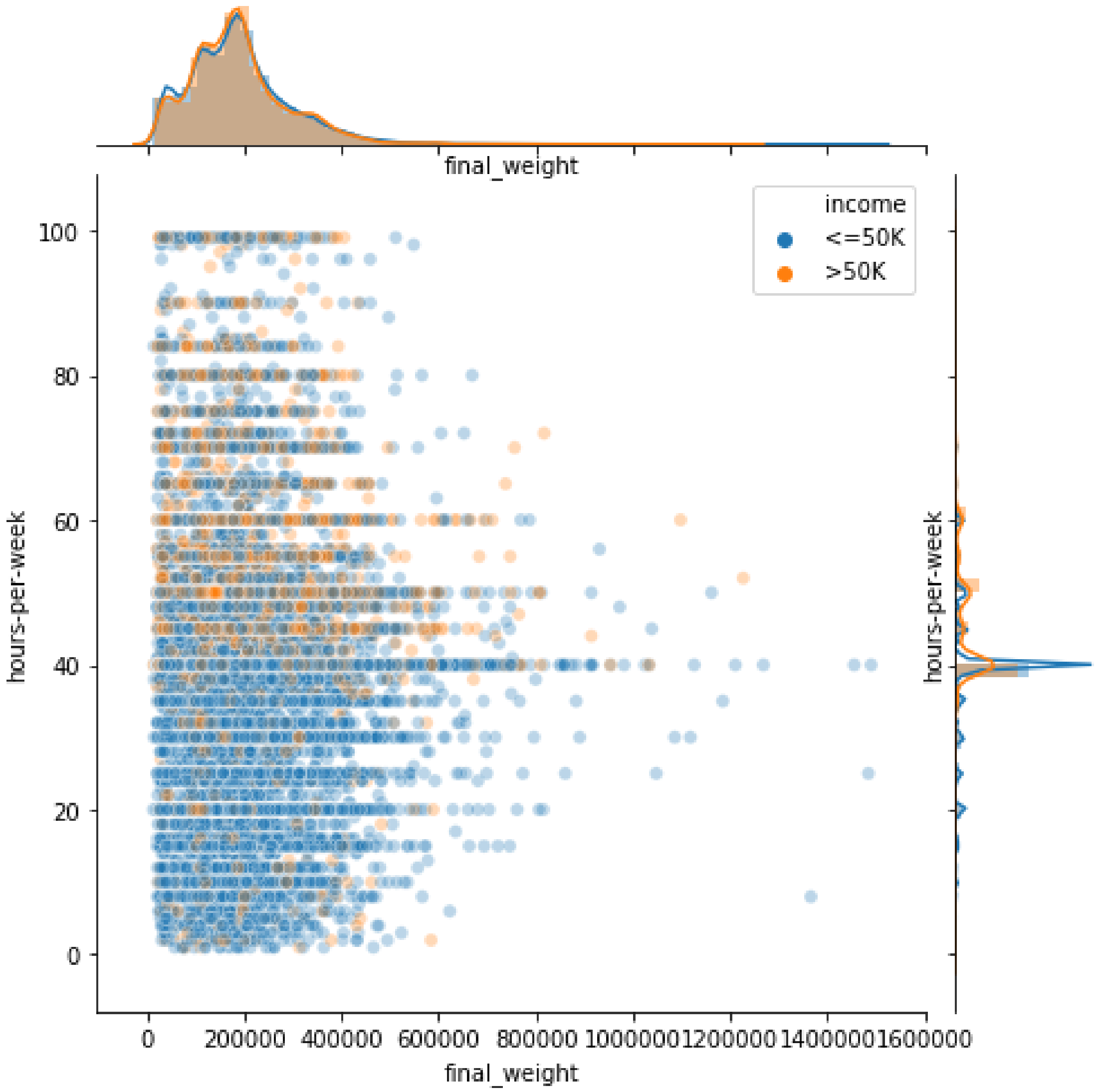
Joint plot for **capital-loss** & **educational-num**



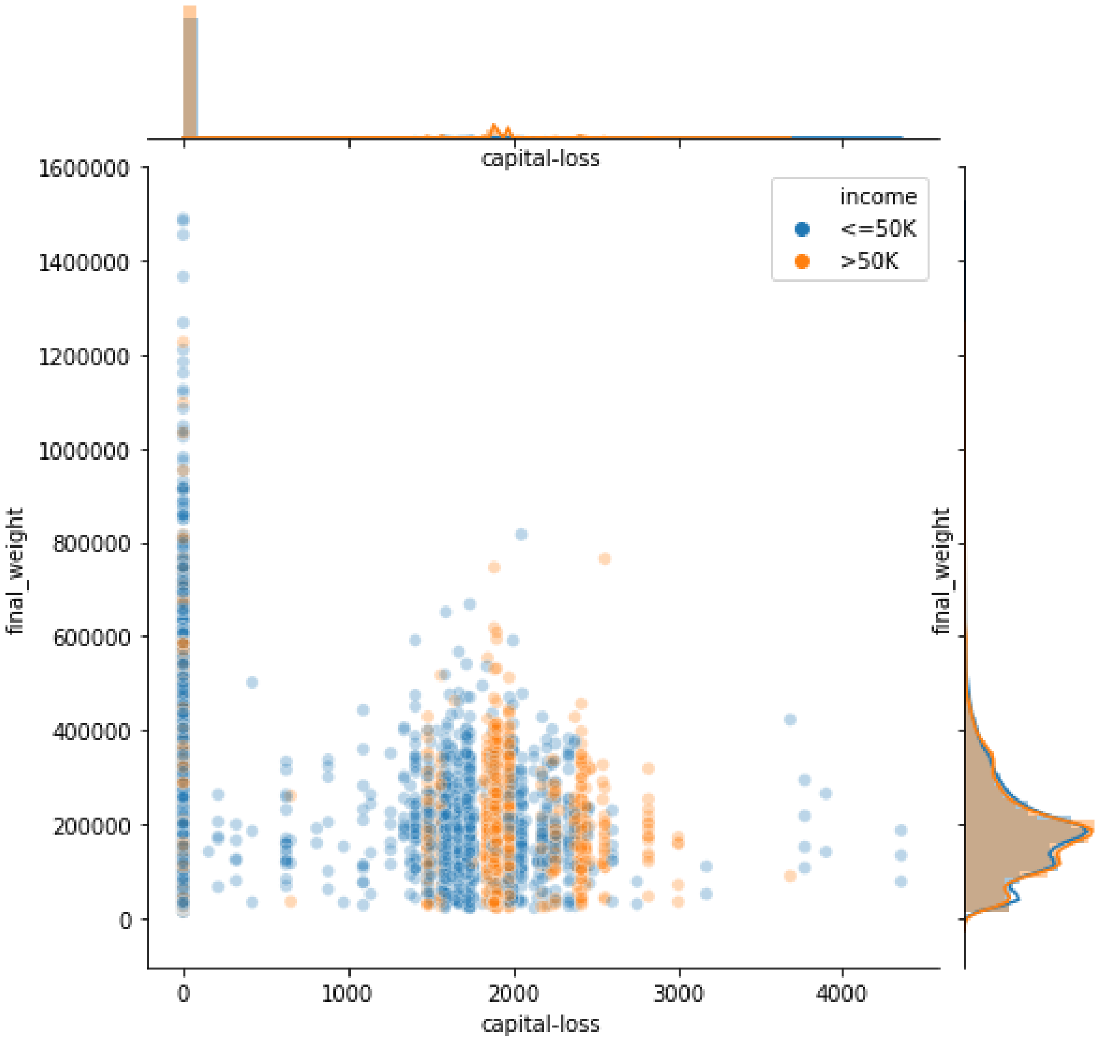
Joint plot for **educational-num** & **final_weight**



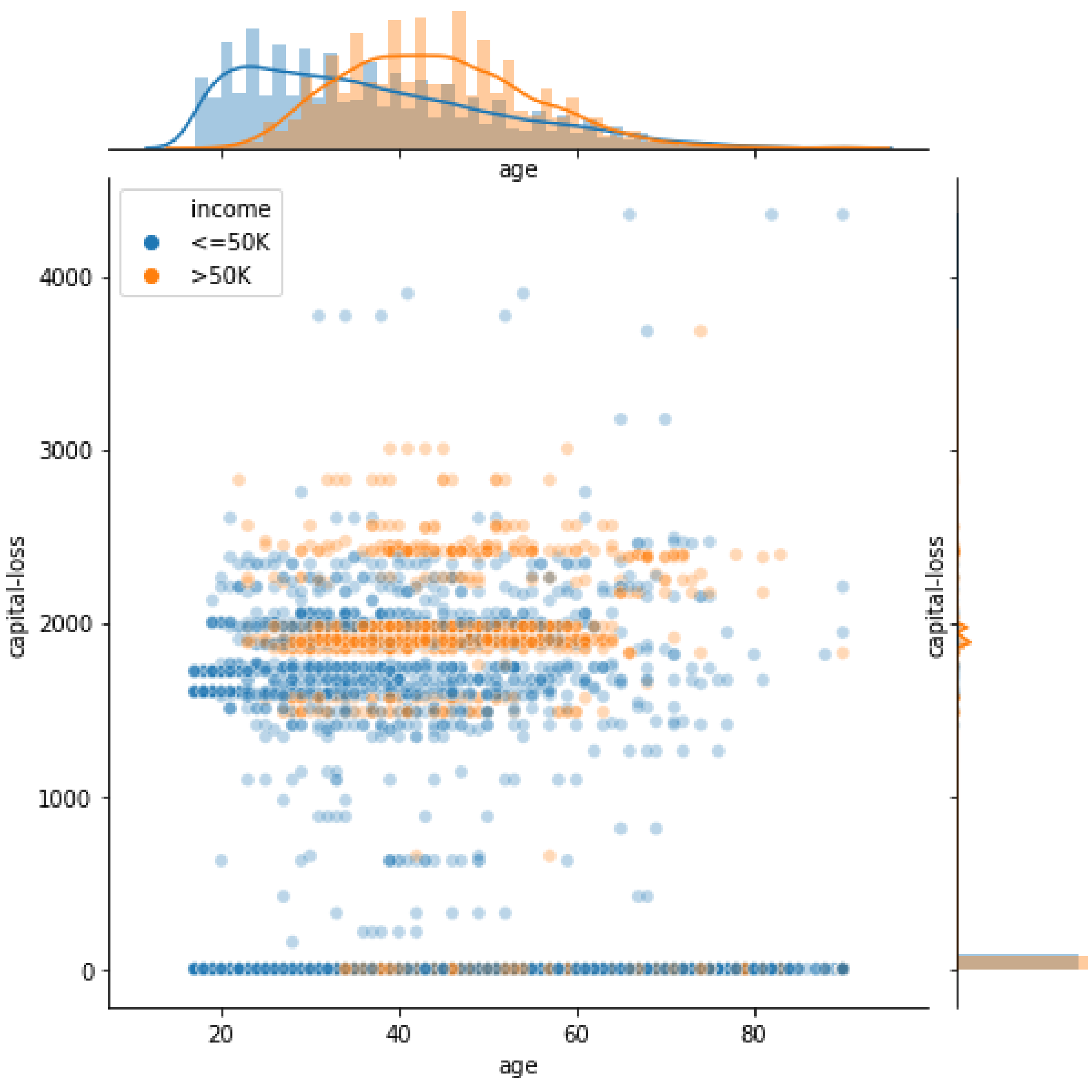
Joint plot for **final_weight** & **hours-per-week**



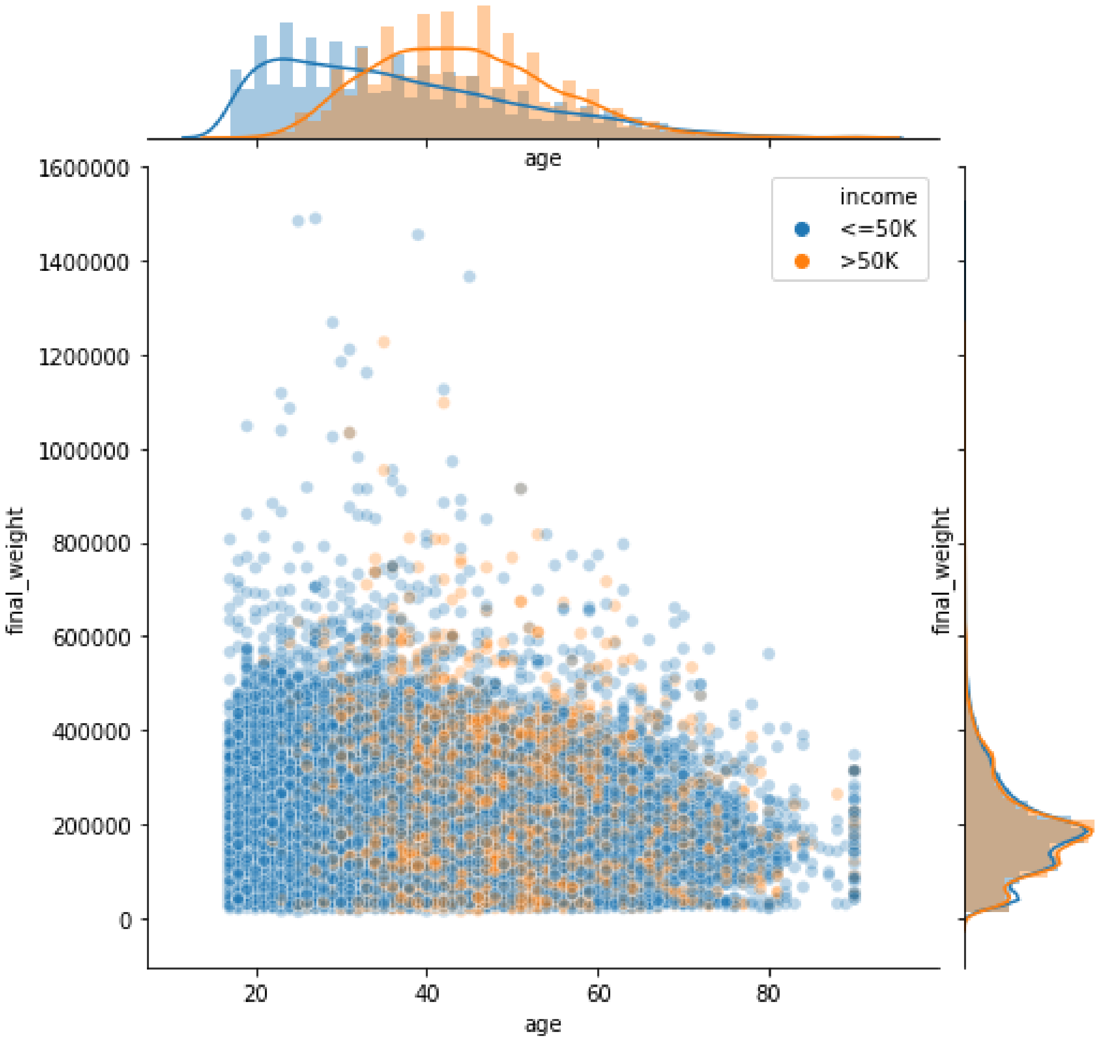
Joint plot for **capital-loss** & **final__weight**



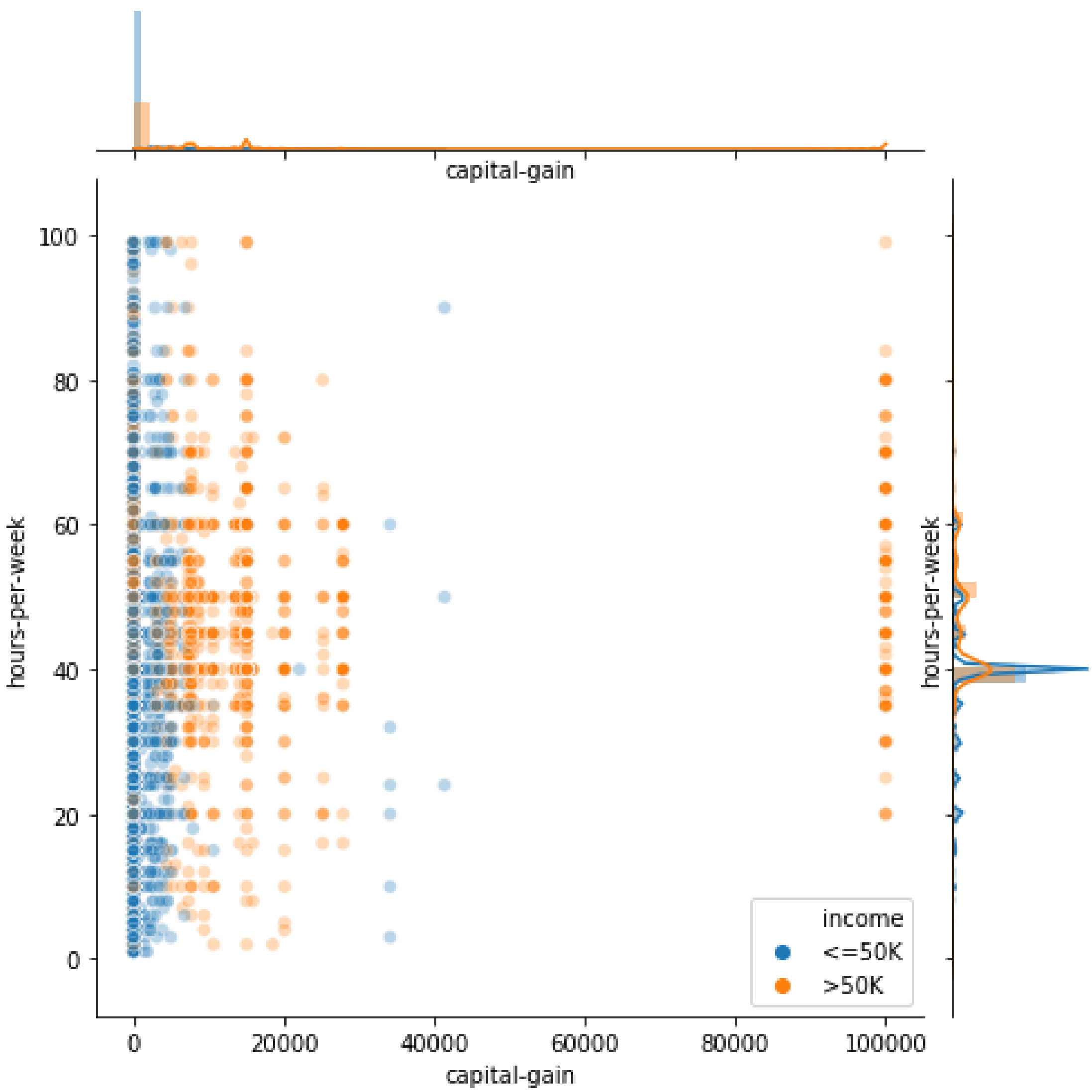
Joint plot for **age** & **capital-loss**



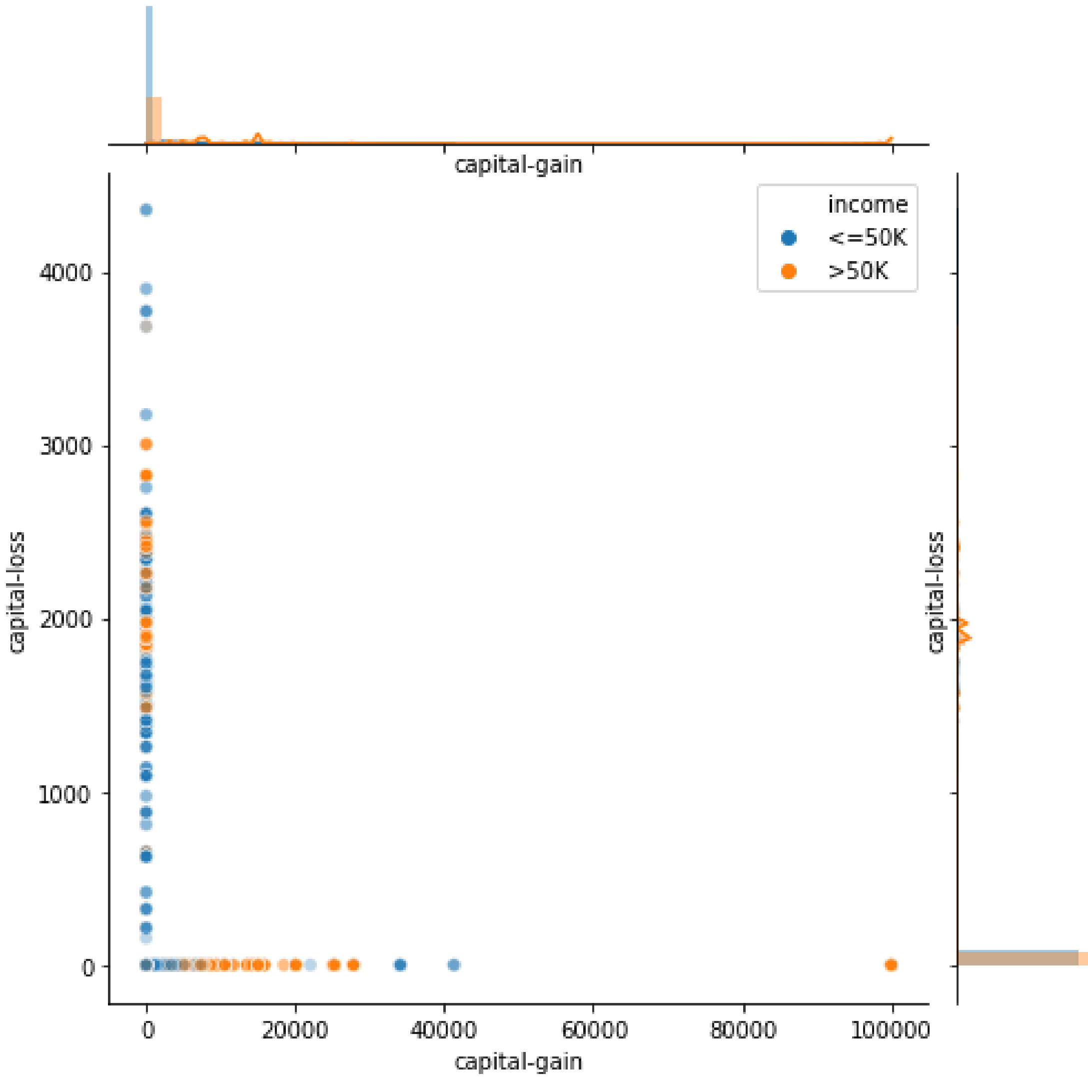
Joint plot for **age** & **final_weight**



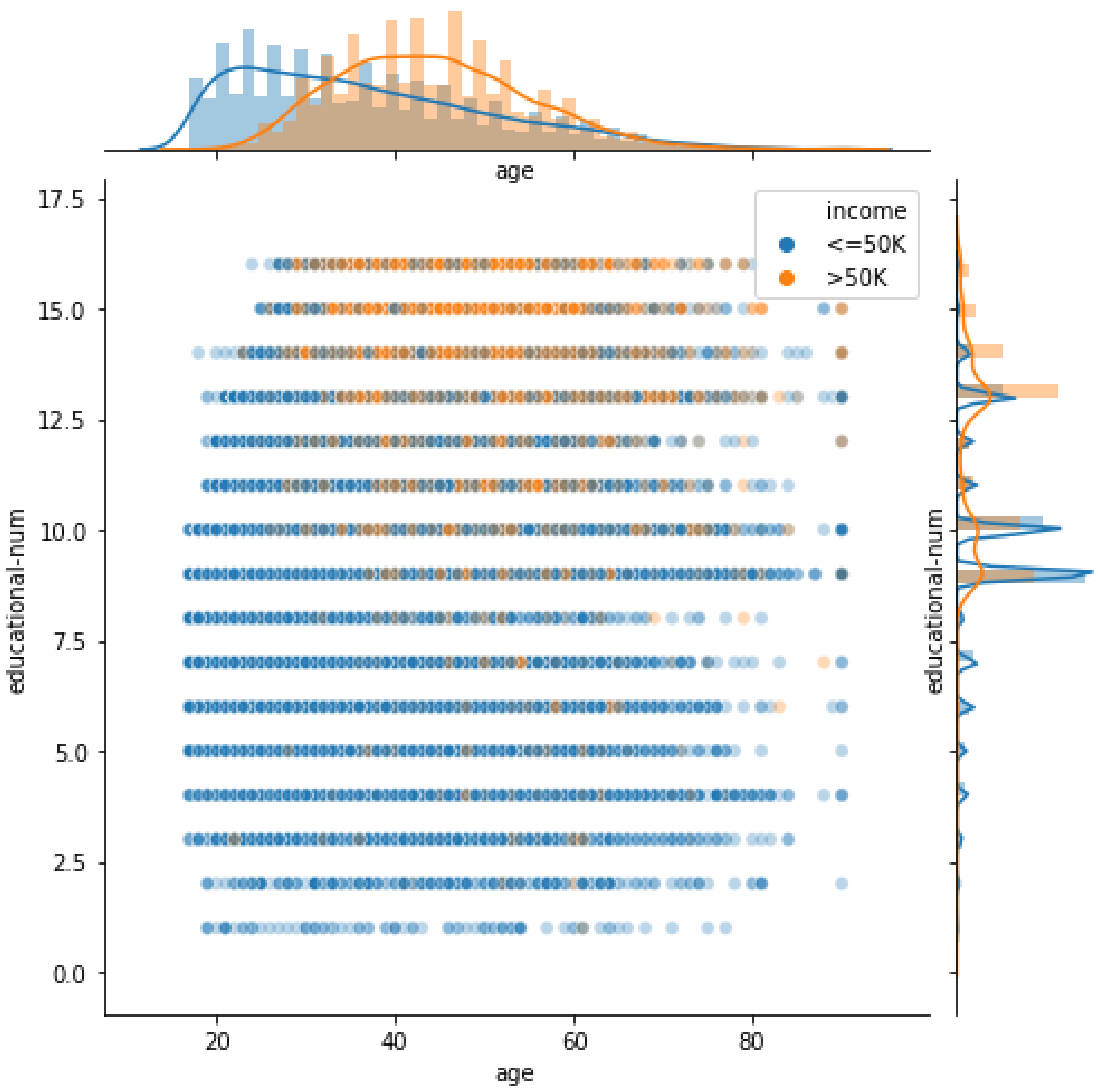
Joint plot for **capital-gain** & **hours-per-week**



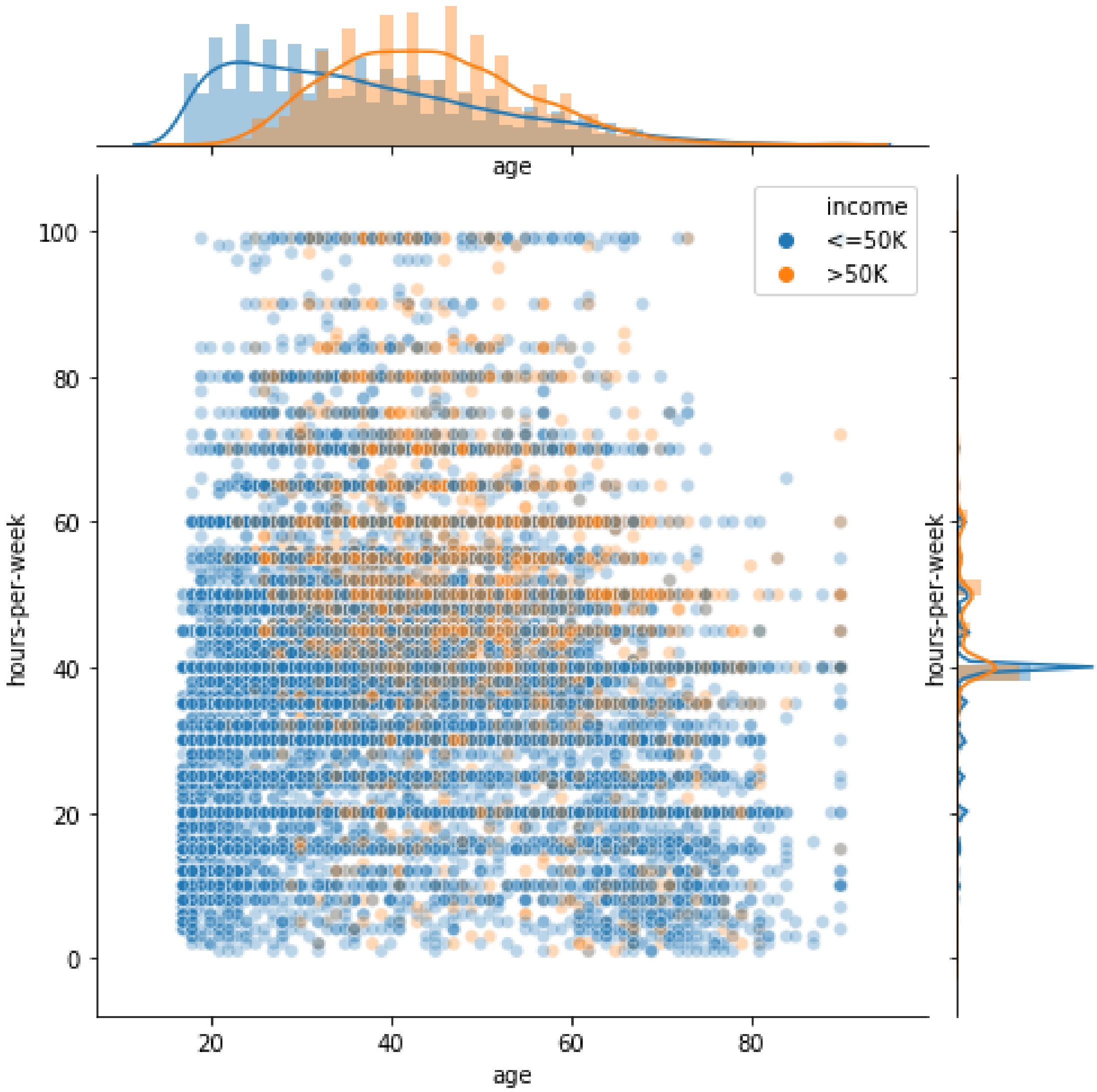
Joint plot for **capital-gain** & **capital-loss**



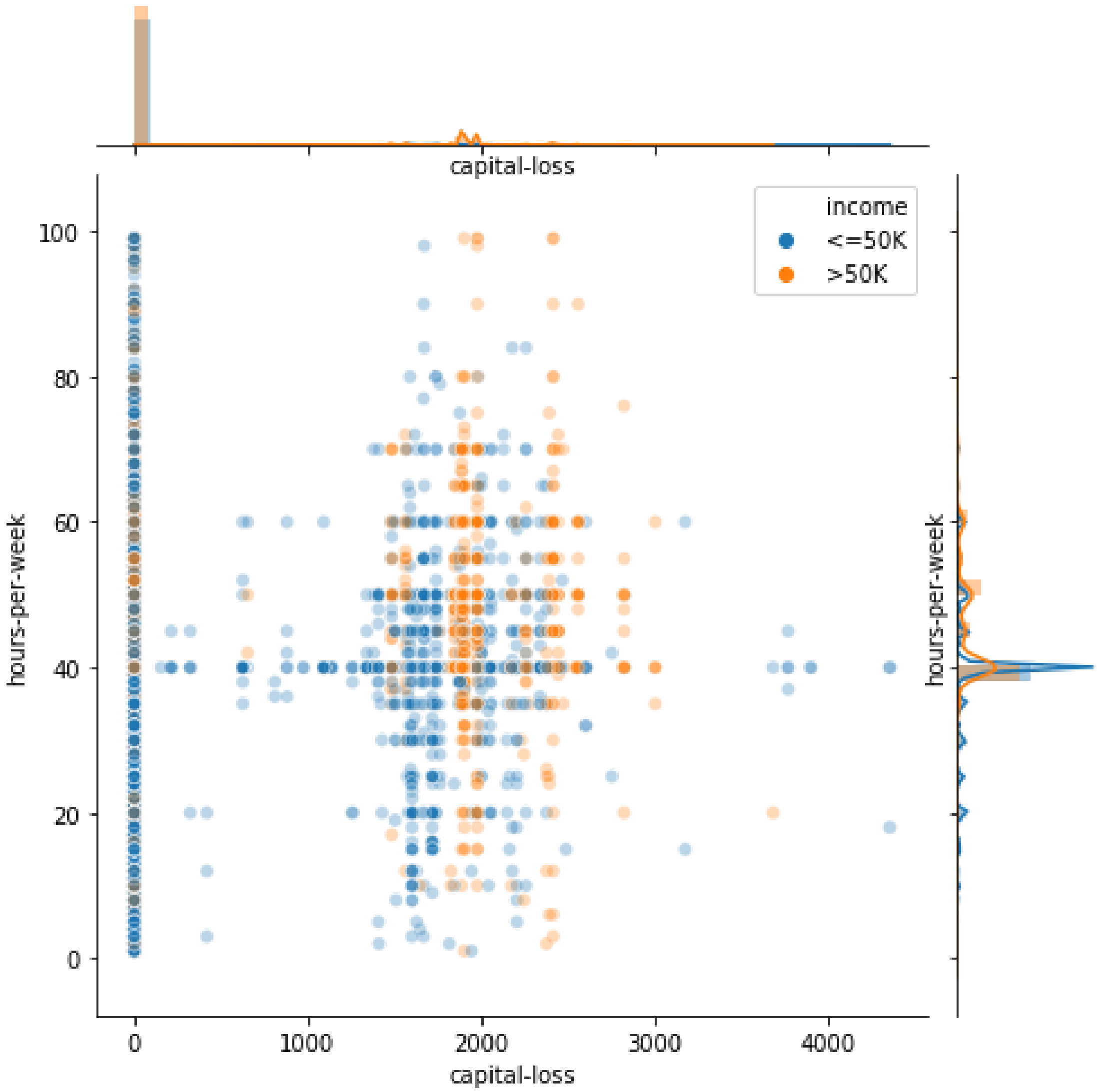
Joint plot for **age** & **educational-num**



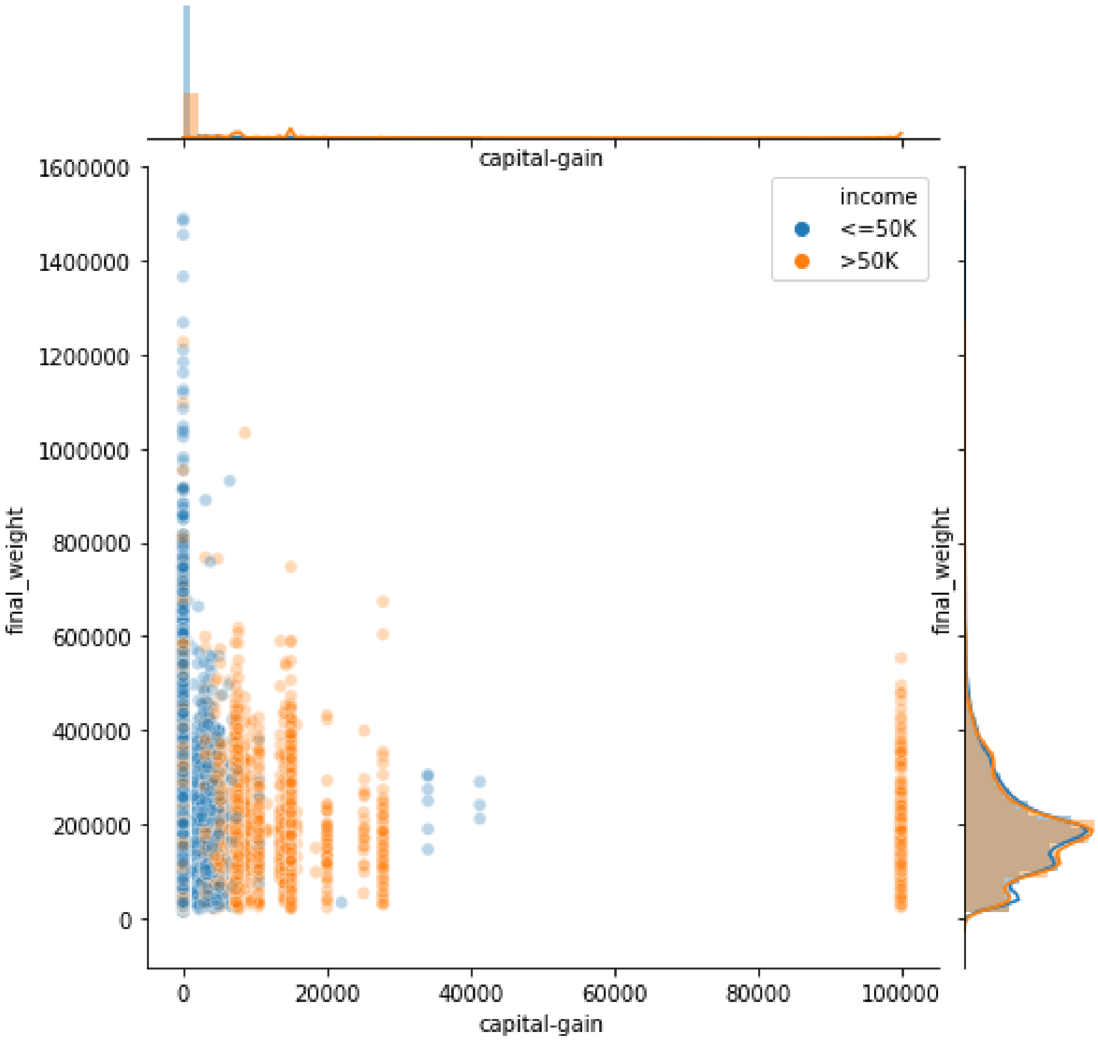
Joint plot for **age** & **hours-per-week**



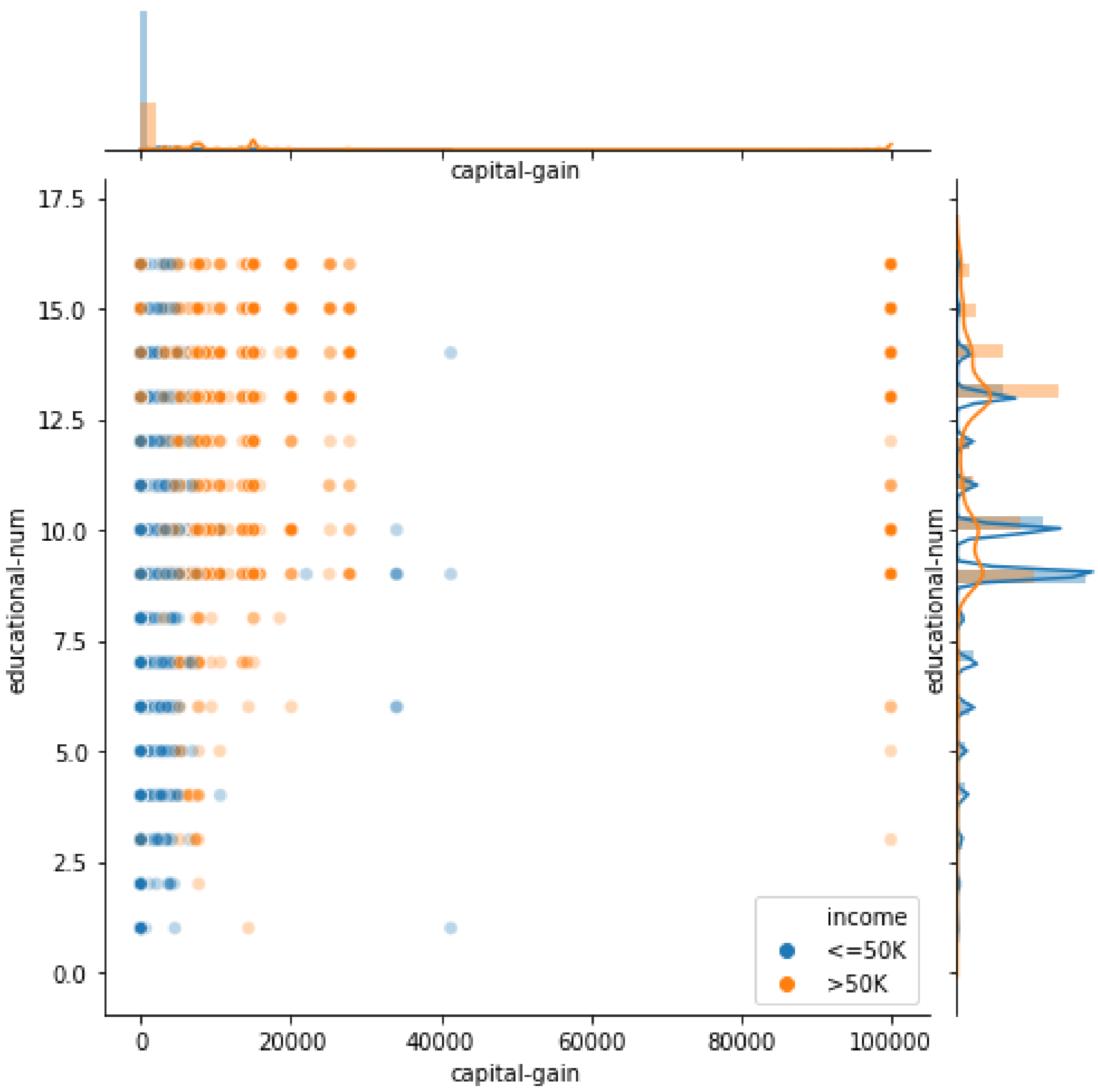
Joint plot for **capital-loss** & **hours-per-week**



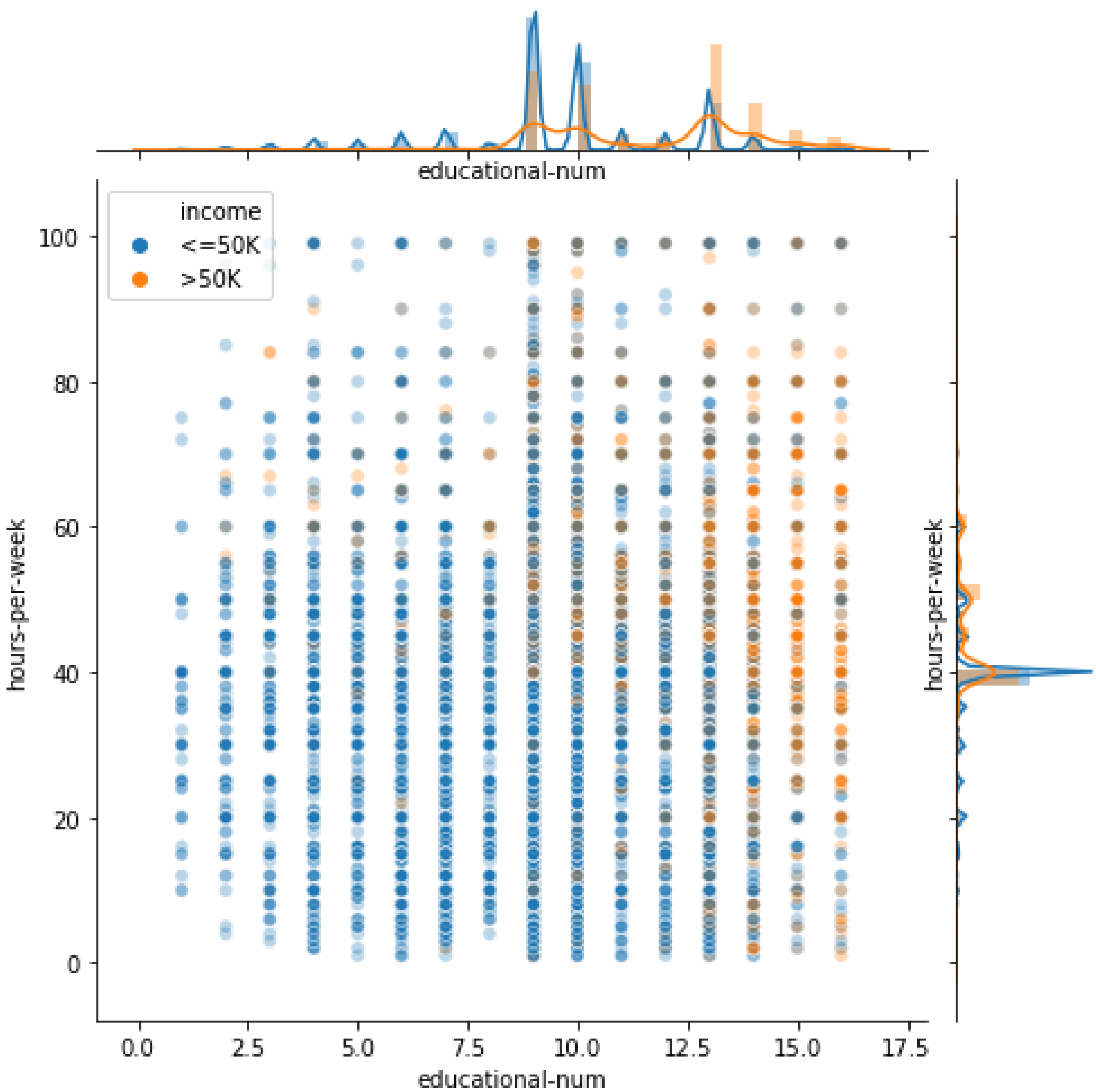
Joint plot for **capital-gain** & **final_weight**



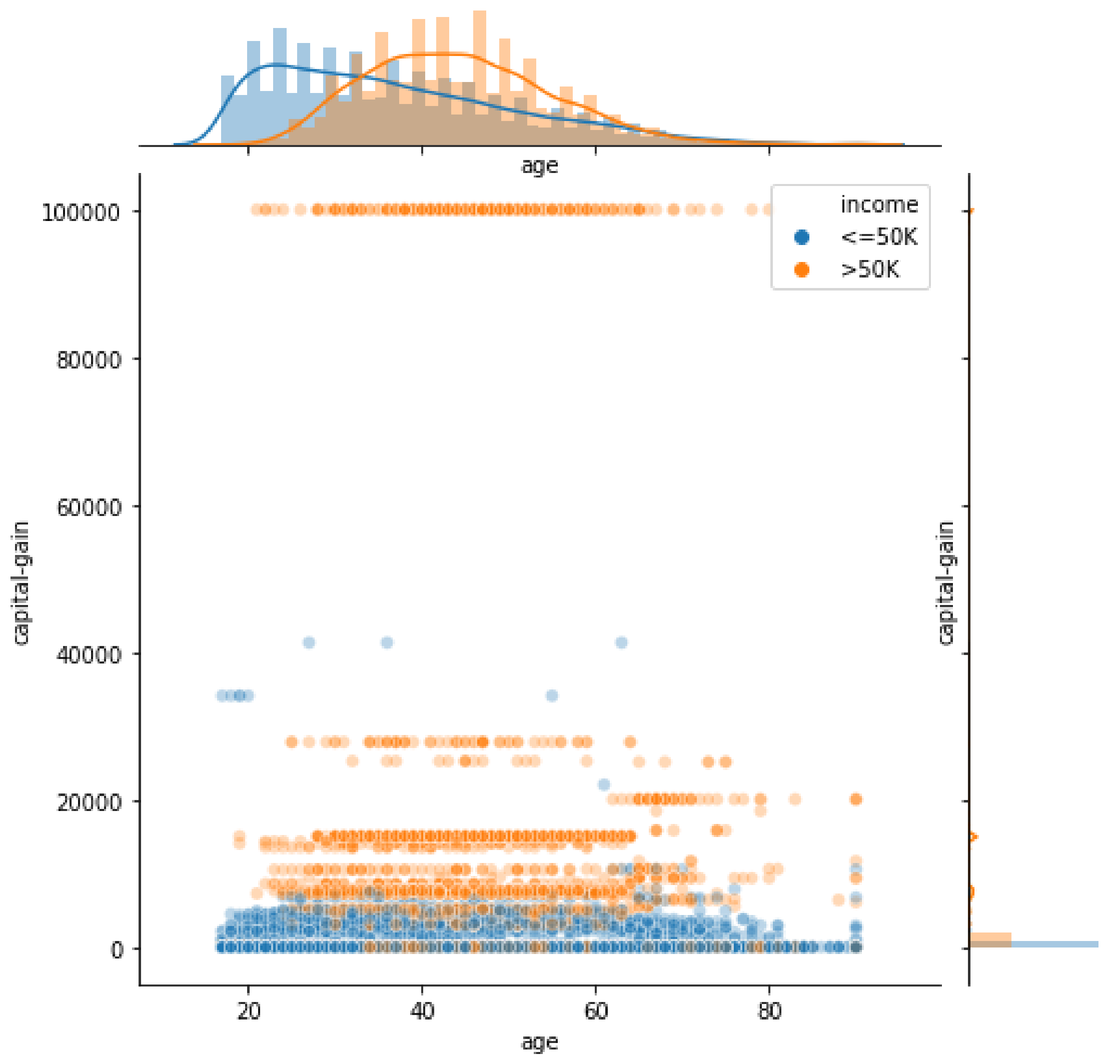
Joint plot for **capital-gain** & **educational-num**



Joint plot for **educational-num** & **hours-per-week**



Joint plot for **age** & **capital-gain**

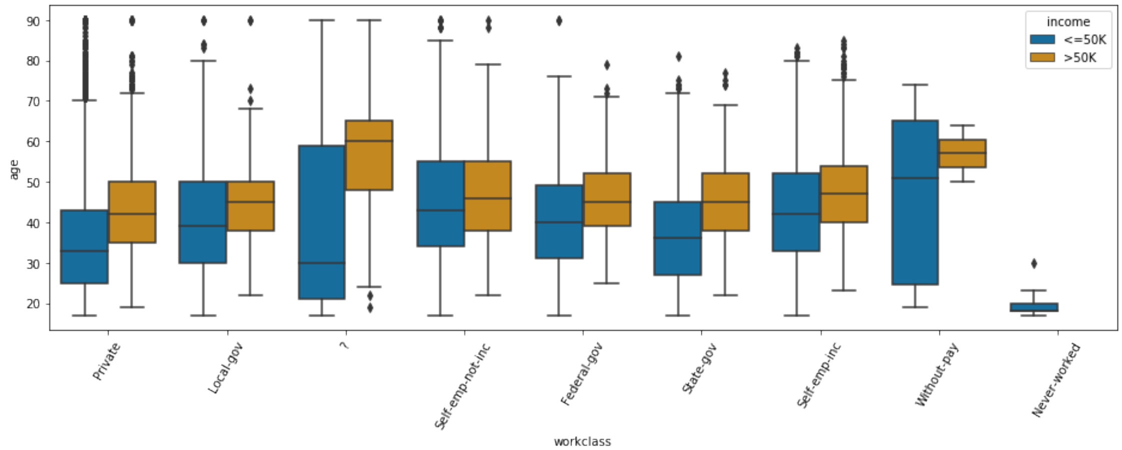


[15]:
```
help(explore.show_df_num_cat_relations)
```

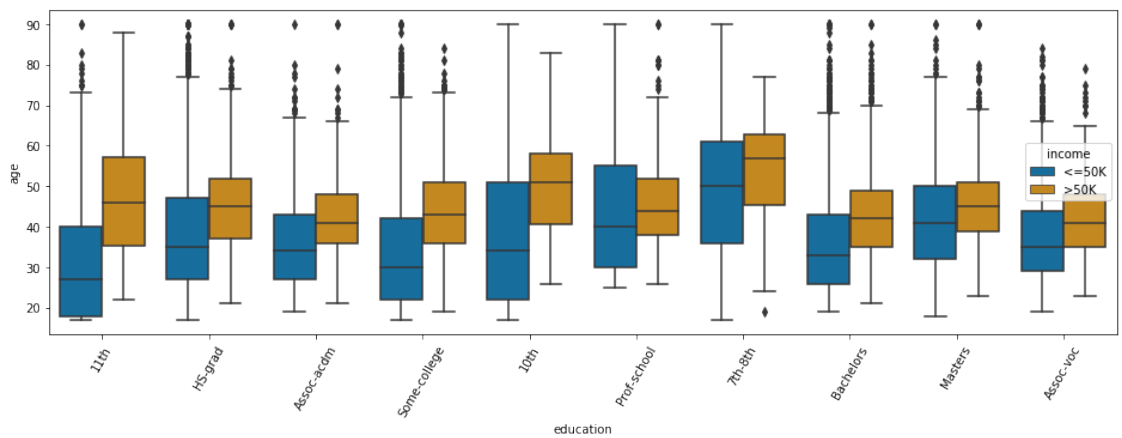
```
Help on function show_df_num_cat_relations in module
transparentai.explore.explore:

show_df_num_cat_relations(df, target=None)
    Show boxplots for each pair of categorical and numerical variables
    If target is set, separate dataset for each target value.

    Parameters
    ----------
    df: pd.DataFrame
        Dataframe to inspect
    target: str (optional)
        Target column for classifier
```

```
[16]: explore.show_df_num_cat_relations(df=adult, target='income')
```

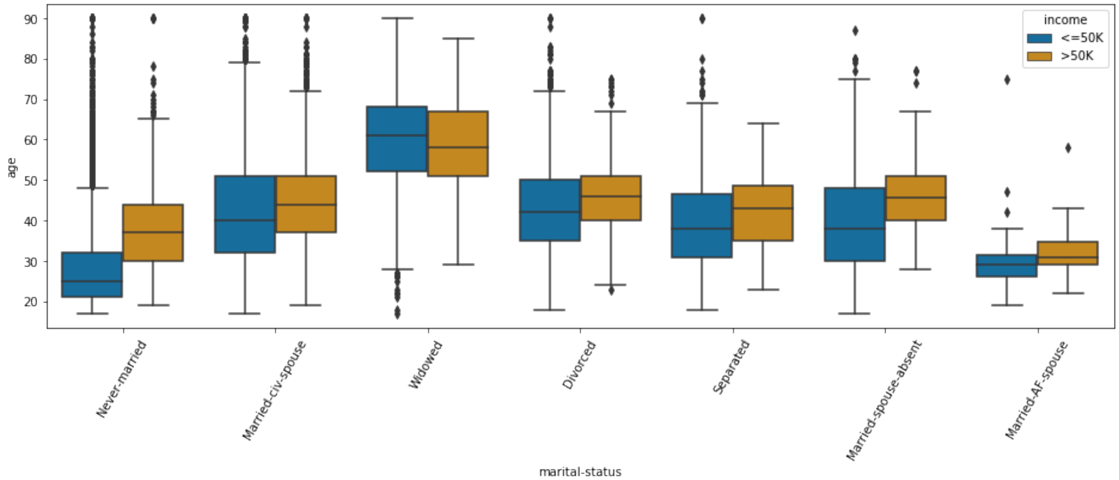
Box plot for **workclass** & **age**



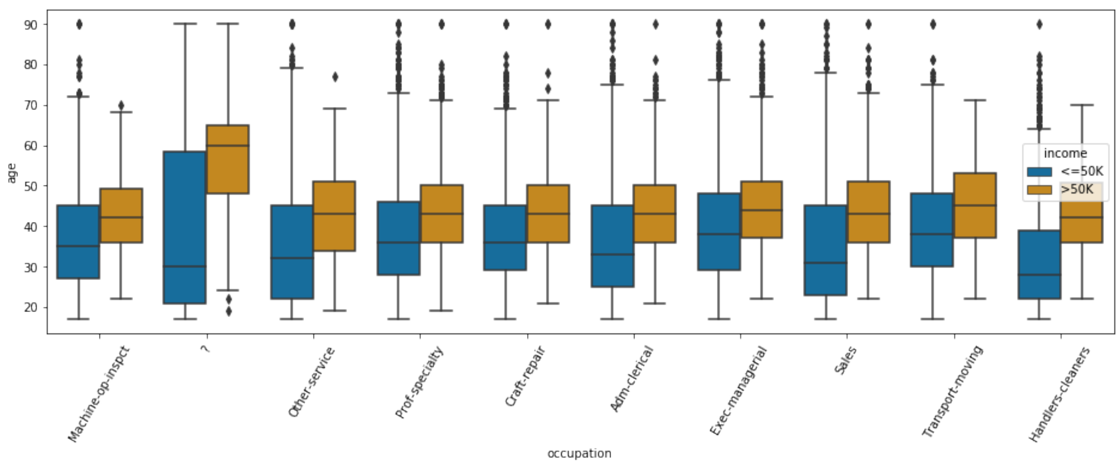
Box plot for **education** & **age**



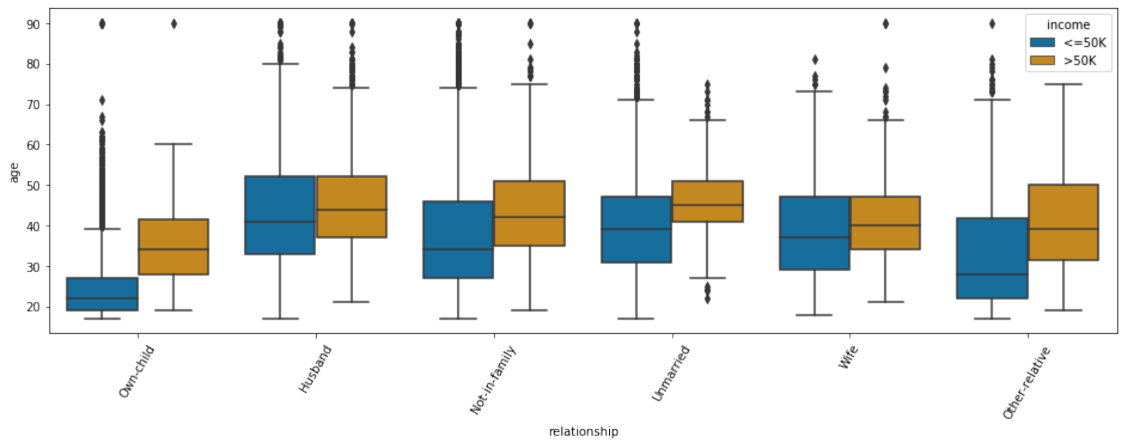
Box plot for **marital-status** & **age**



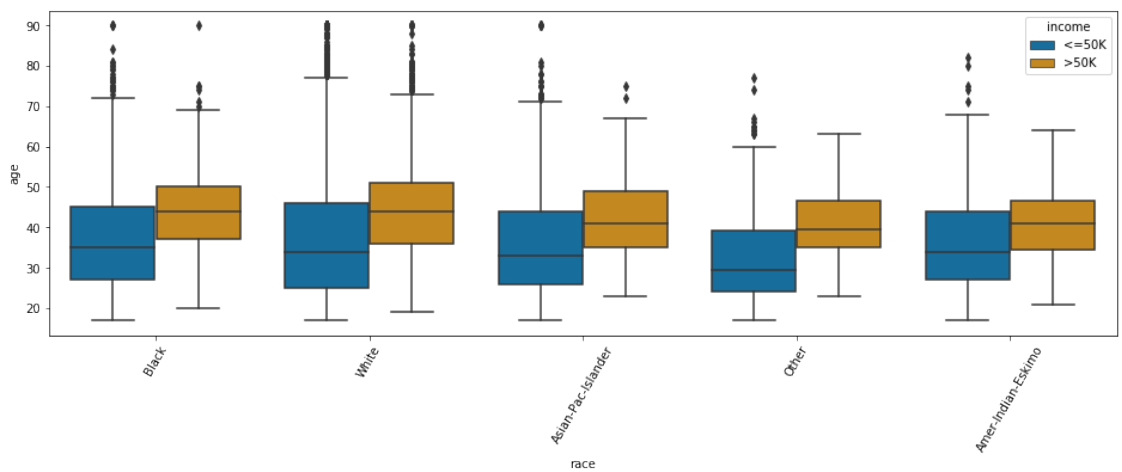
Box plot for **occupation** & **age**



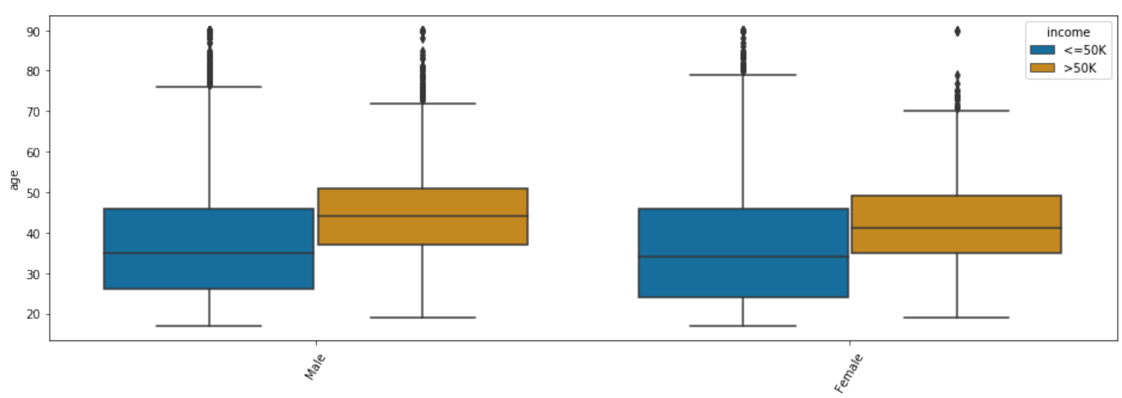
Box plot for **relationship** & **age**



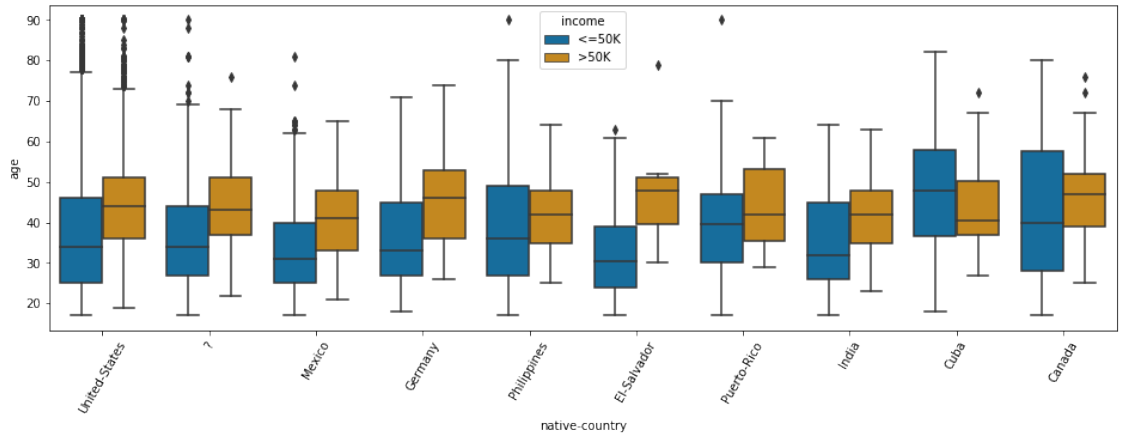
Box plot for **race** & **age**



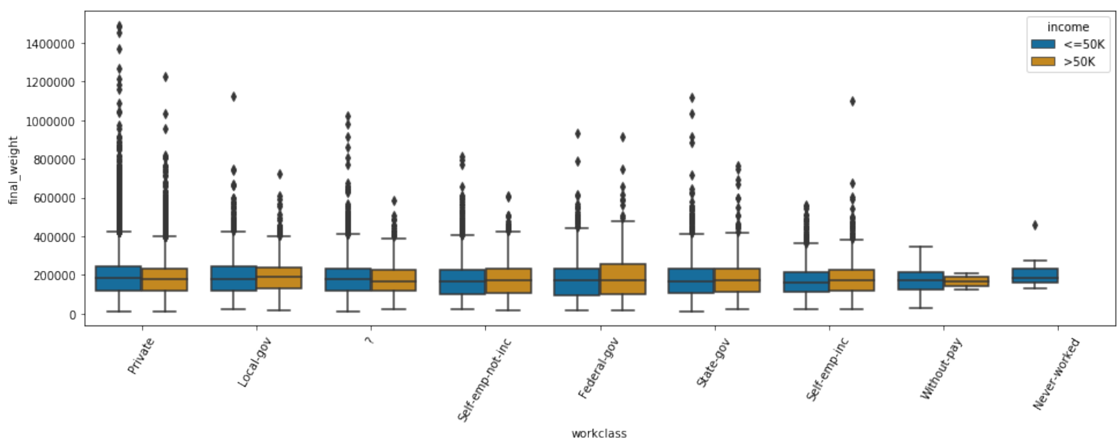
Box plot for **gender** & **age**



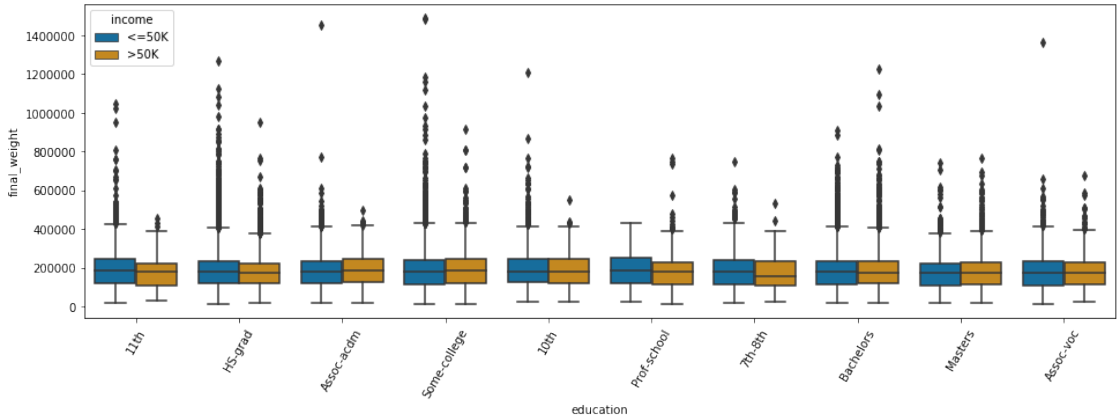
Box plot for **native-country** & **age**



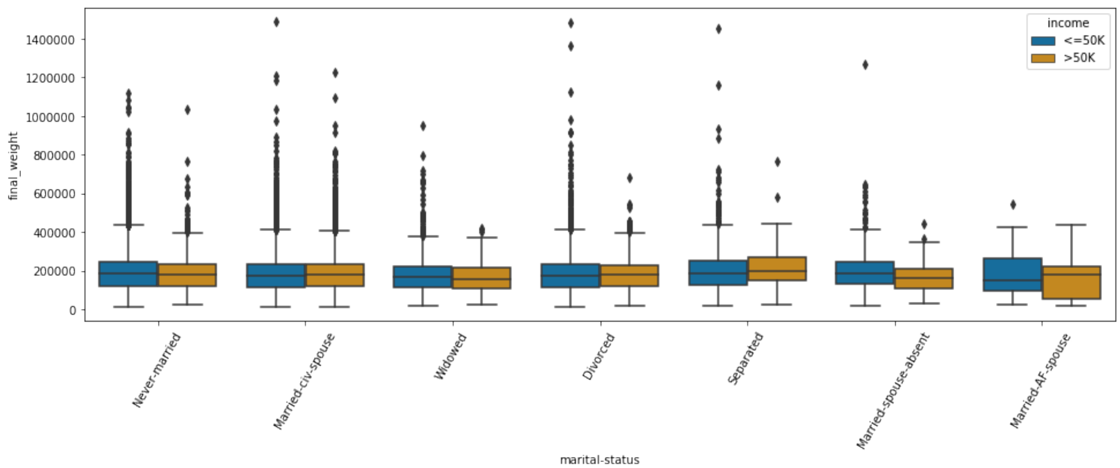
Box plot for **workclass** & **final_weight**



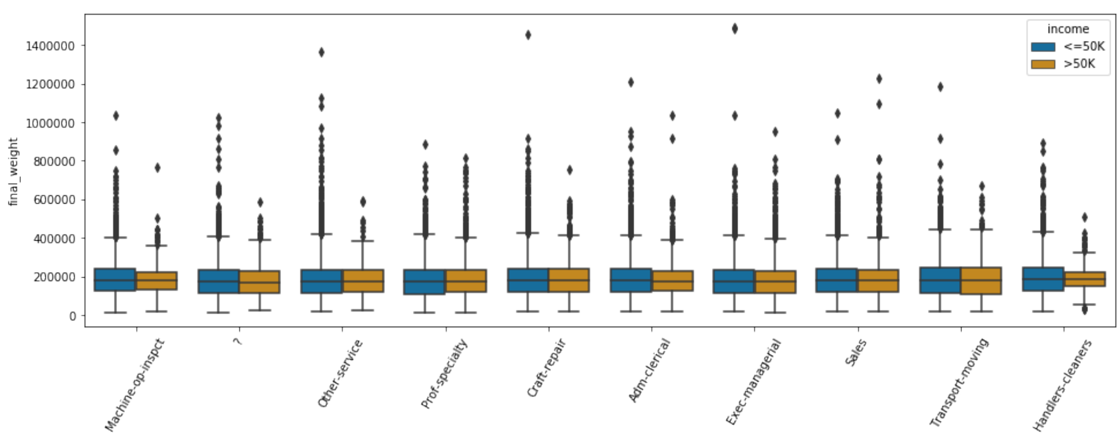
Box plot for **education** & **final_weight**



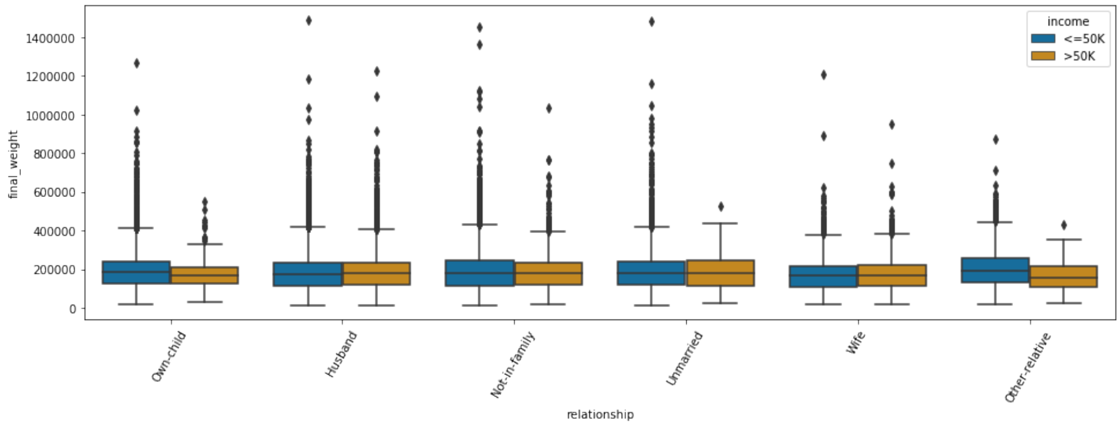
Box plot for **marital-status** & **final_weight**



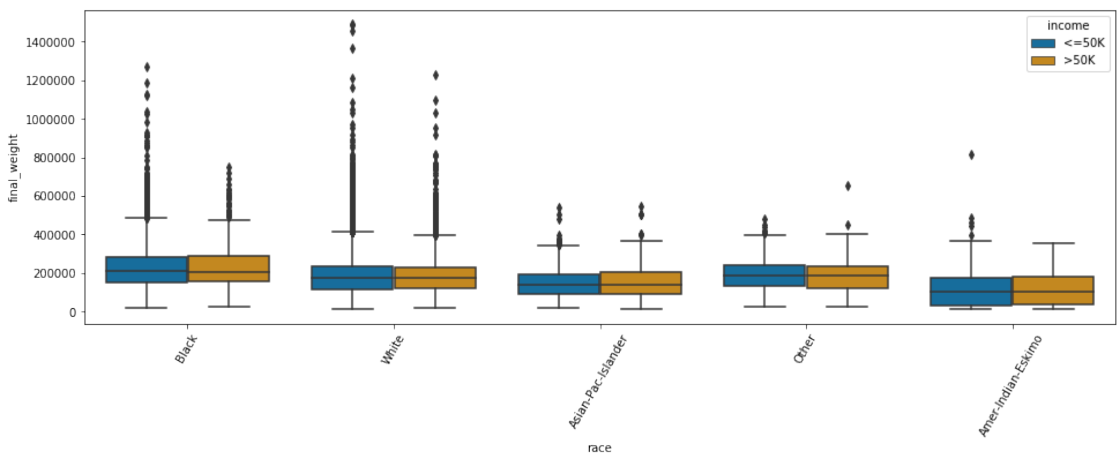
Box plot for **occupation** & **final_weight**



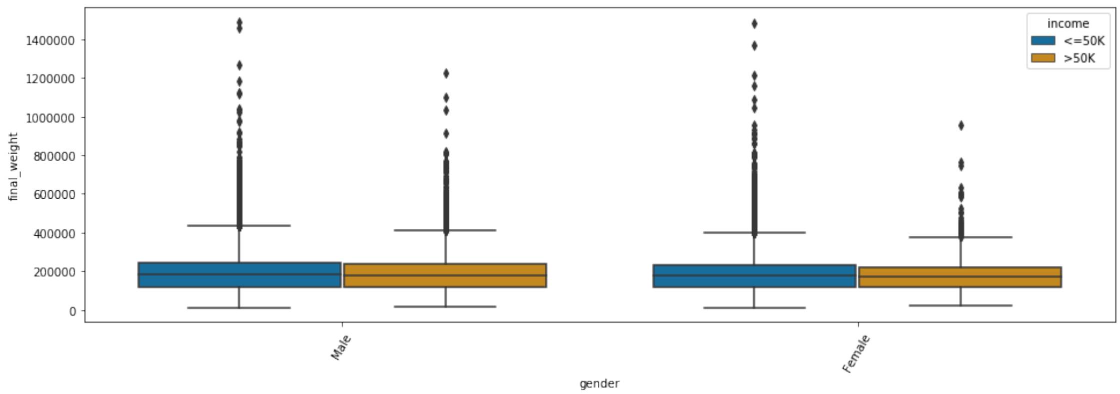
Box plot for **relationship** & **final__weight**



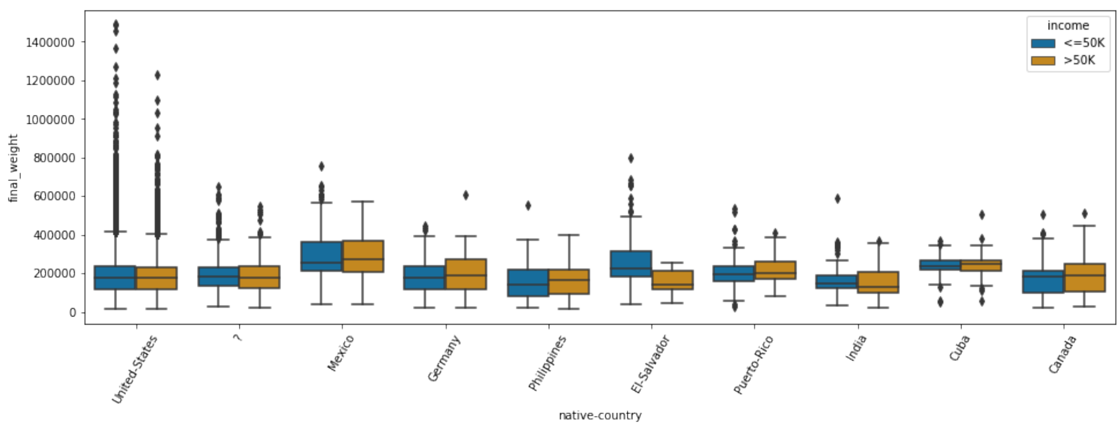
Box plot for **race** & **final__weight**



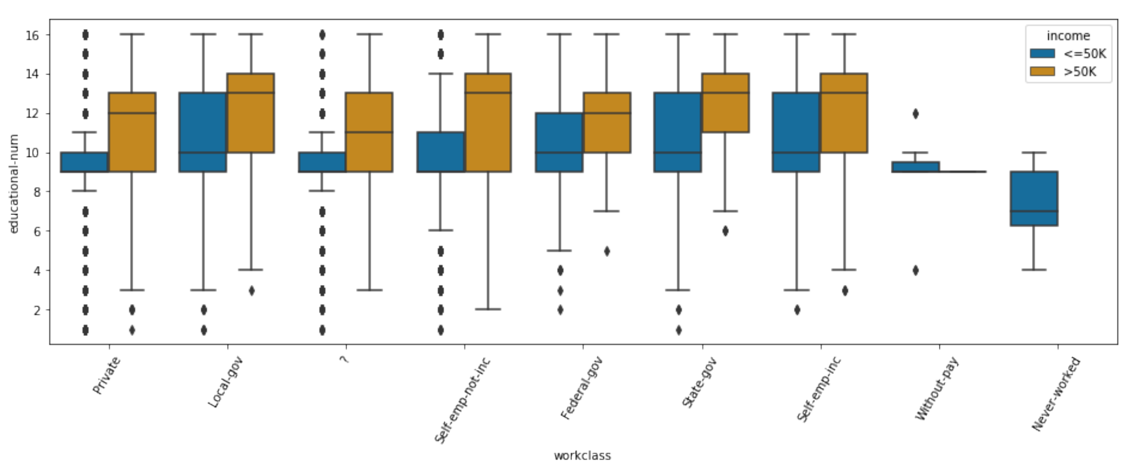
Box plot for **gender** & **final__weight**



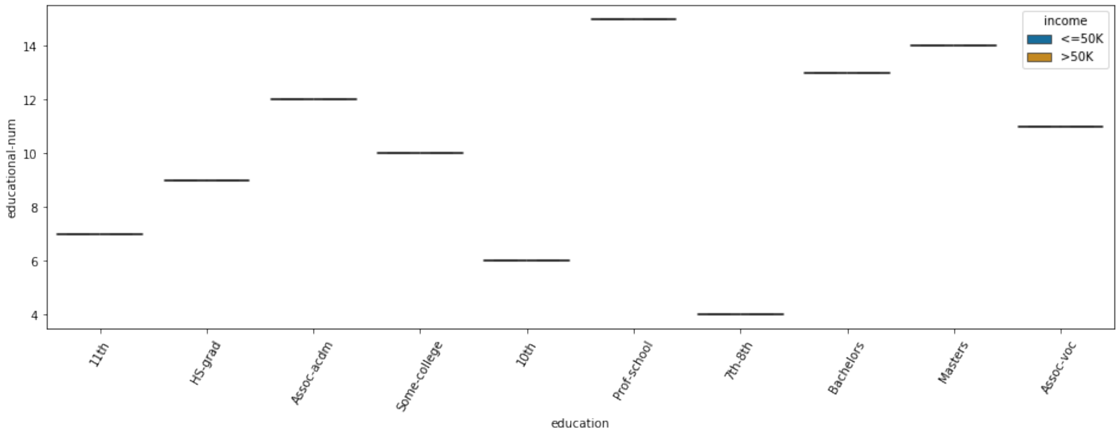
Box plot for **native-country** & **final_weight**



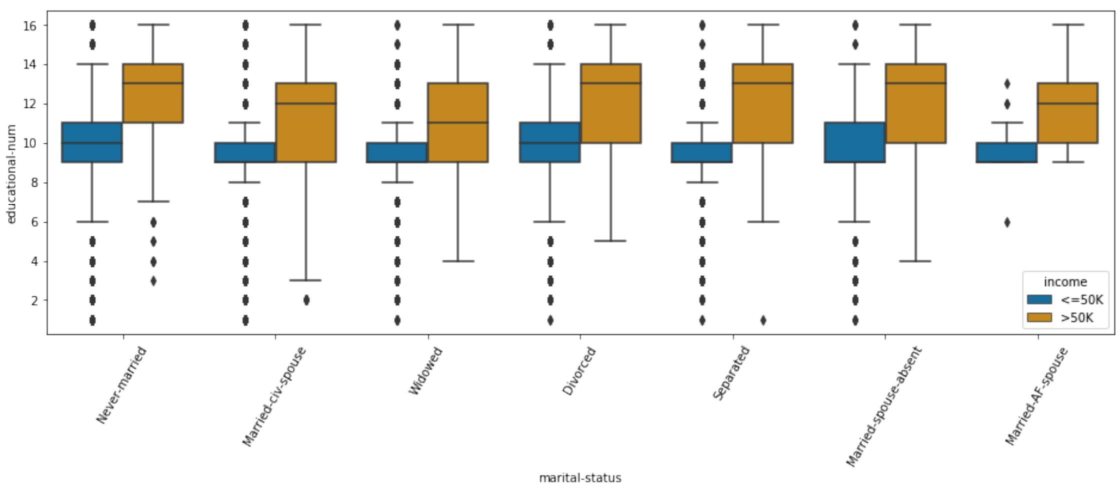
Box plot for **workclass** & **educational-num**



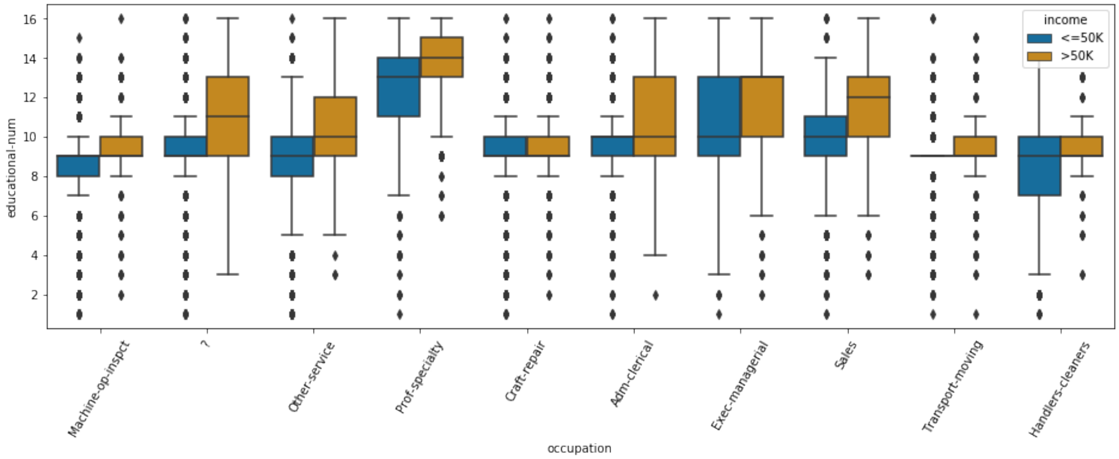
Box plot for **education** & **educational-num**



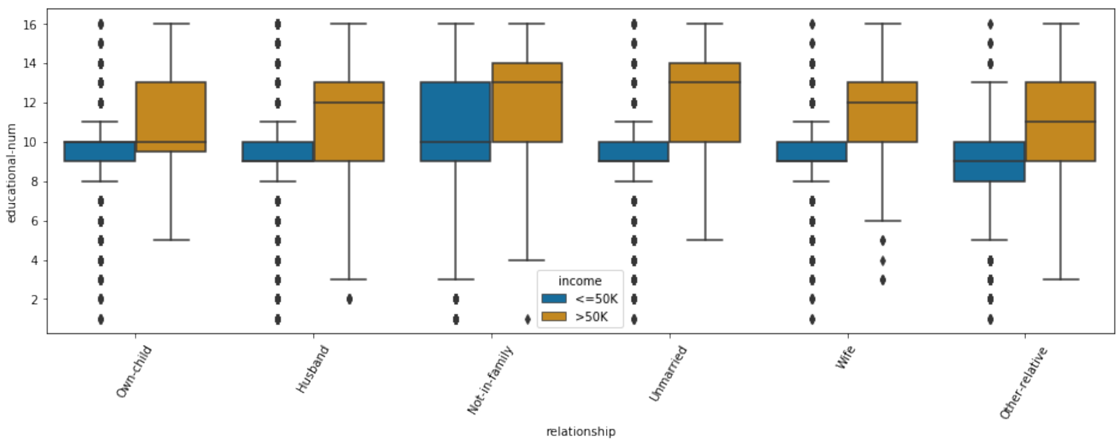
Box plot for **marital-status** & **educational-num**



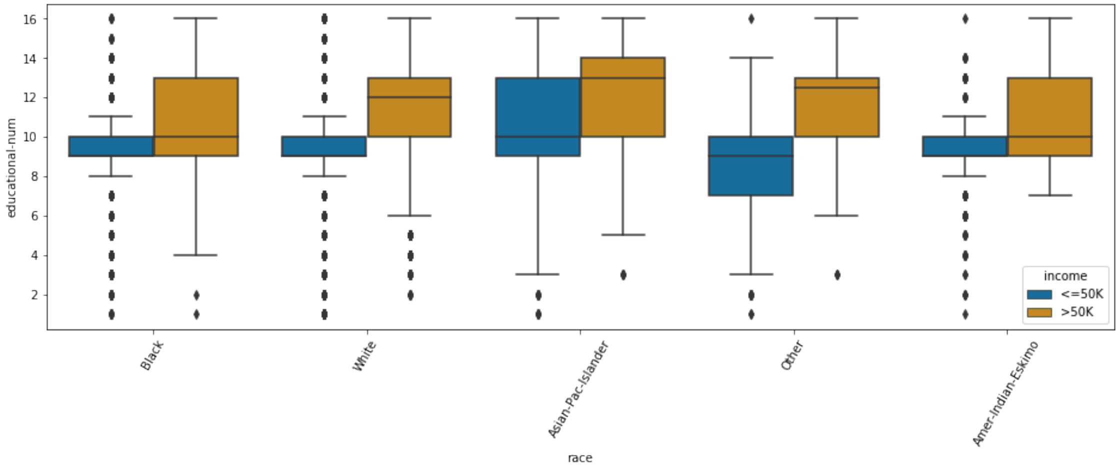
Box plot for **occupation** & **educational-num**



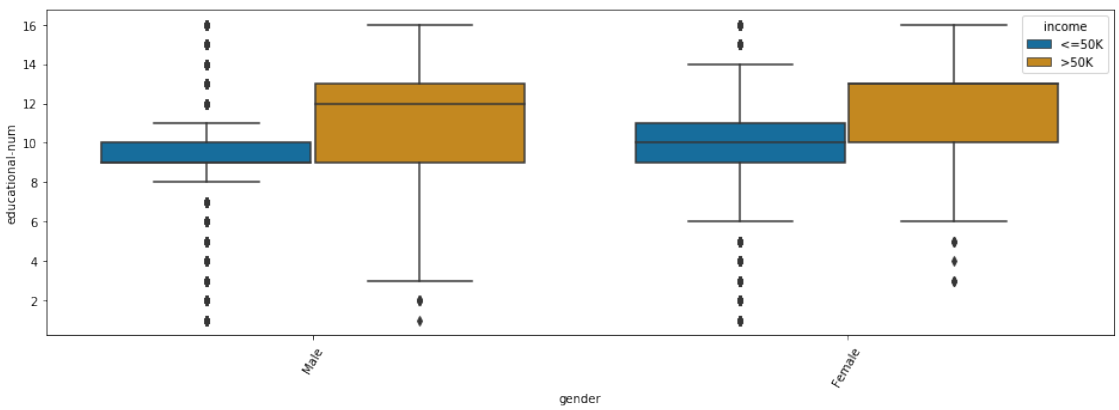
Box plot for **relationship** & **educational-num**



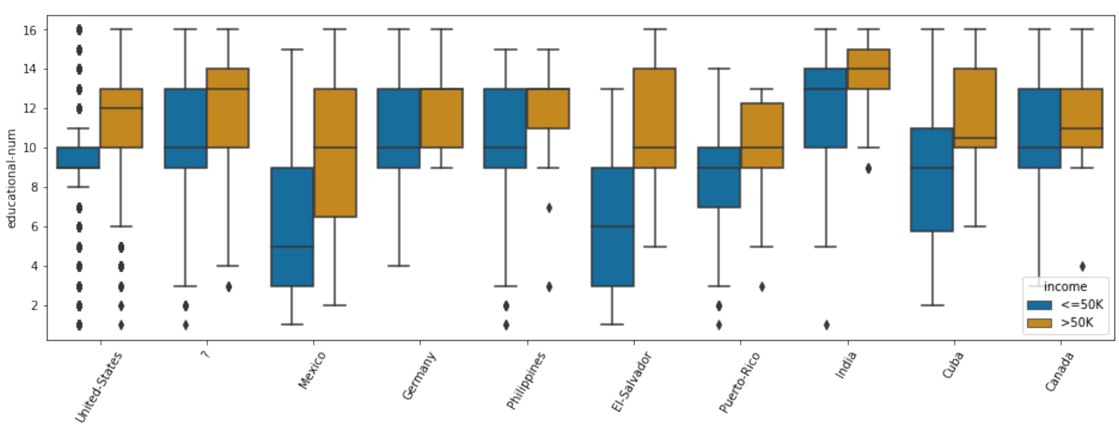
Box plot for **race** & **educational-num**



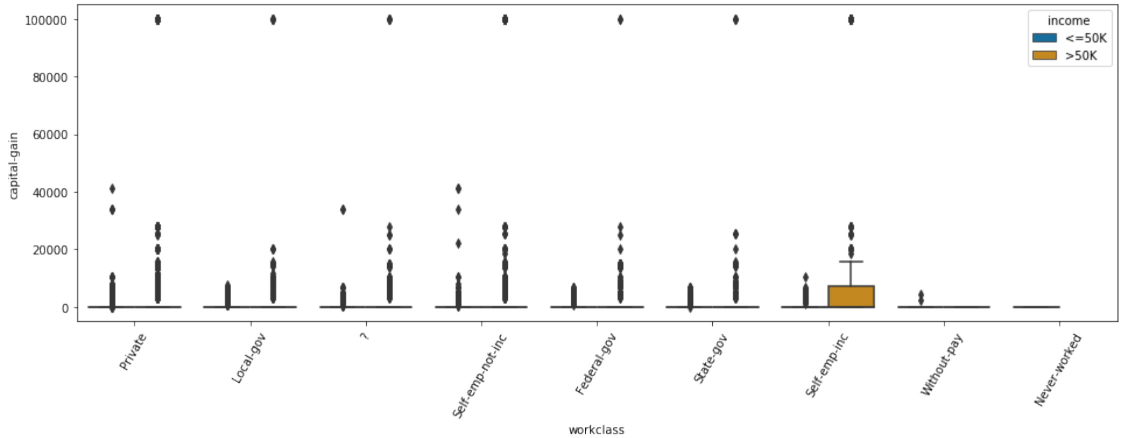
Box plot for **gender** & **educational-num**



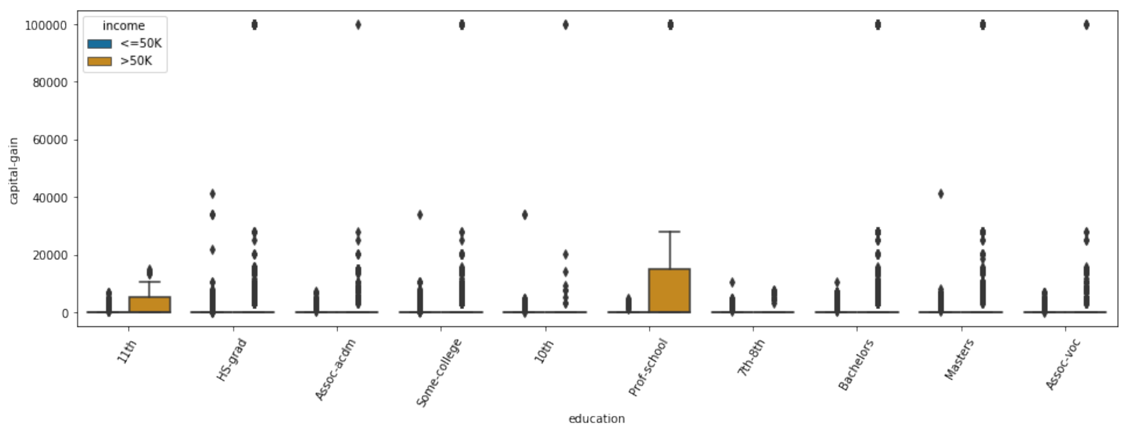
Box plot for **native-country** & **educational-num**



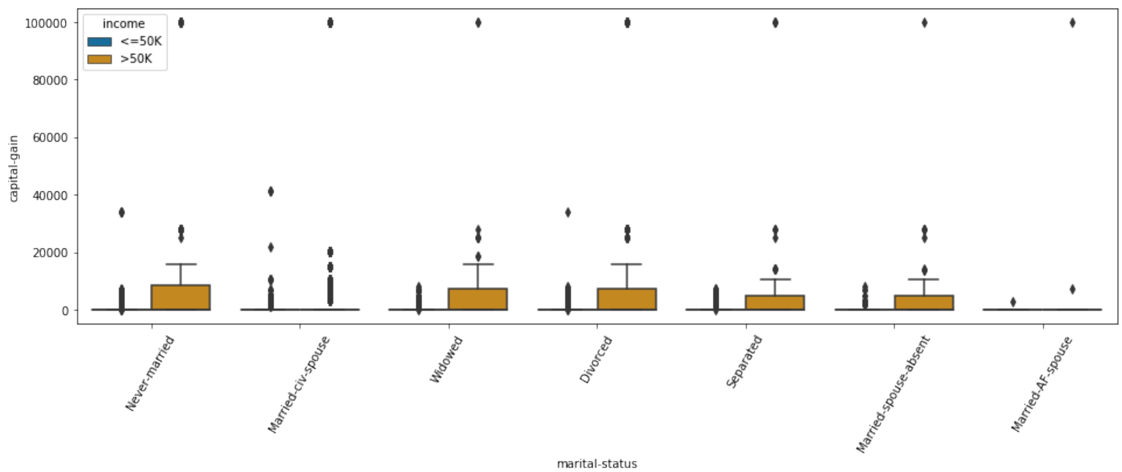
Box plot for **workclass** & **capital-gain**



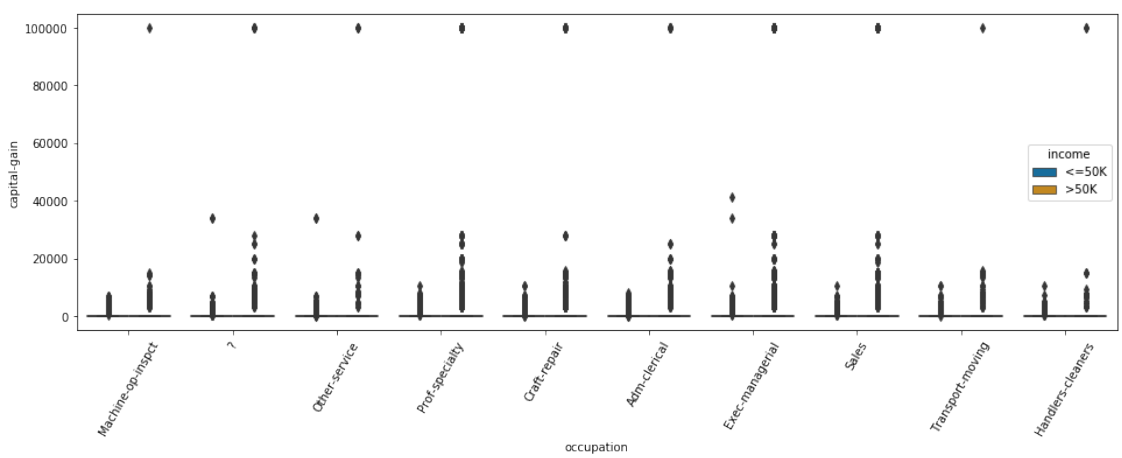
Box plot for **education** & **capital-gain**



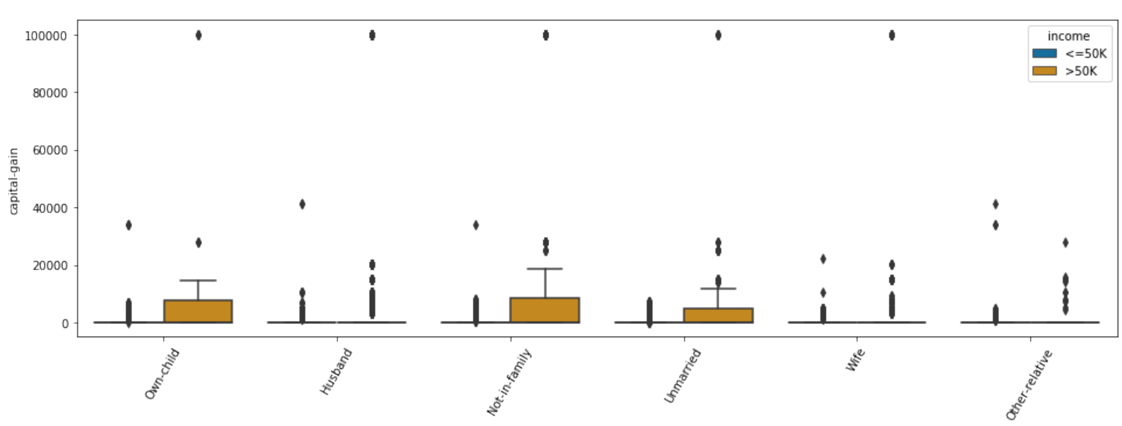
Box plot for **marital-status** & **capital-gain**



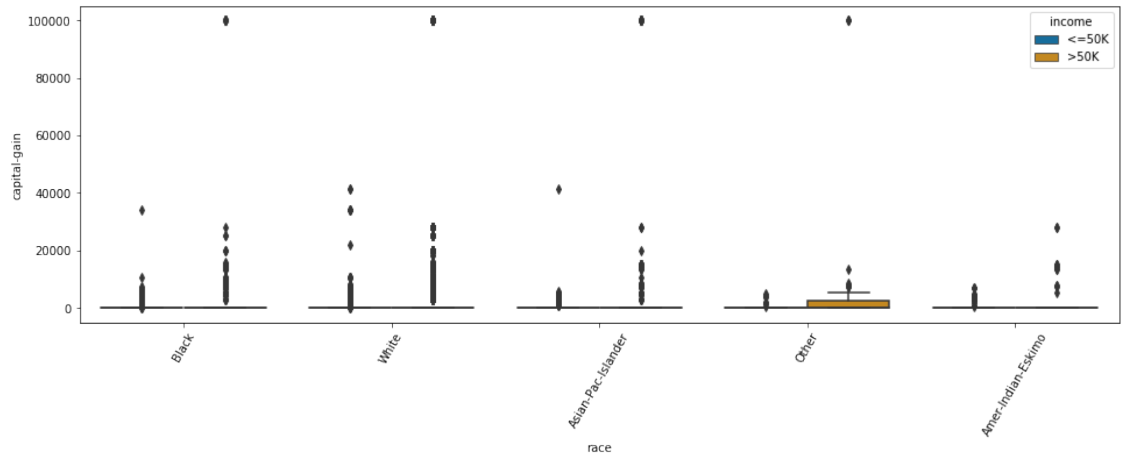
Box plot for **occupation** & **capital-gain**



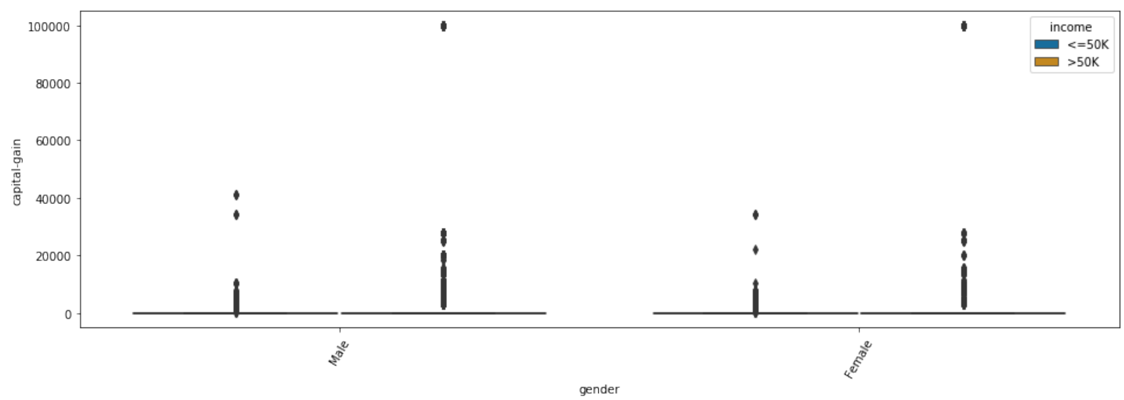
Box plot for **relationship** & **capital-gain**



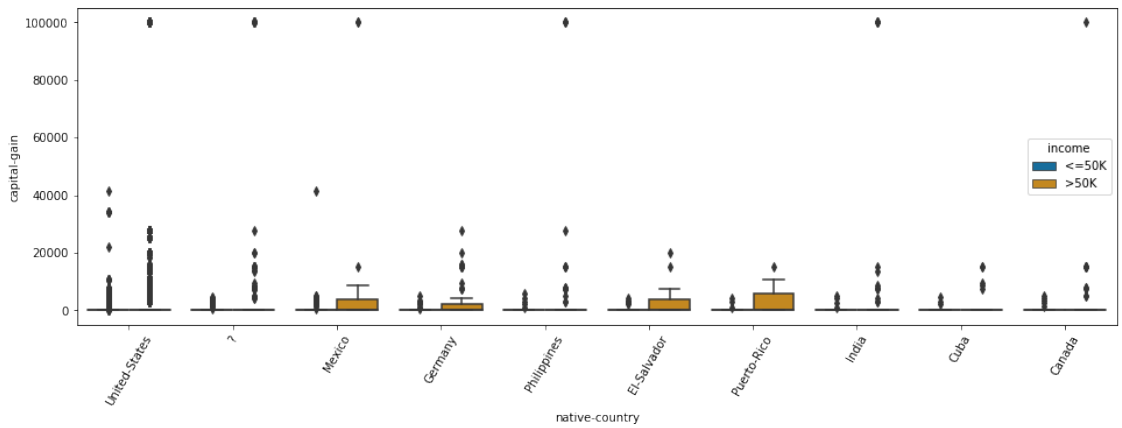
Box plot for **race** & **capital-gain**



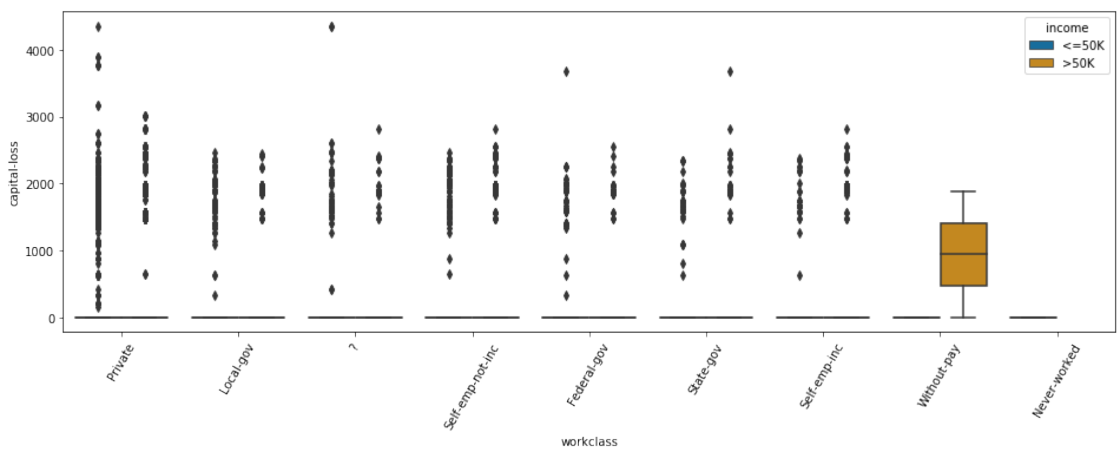
Box plot for **gender** & **capital-gain**



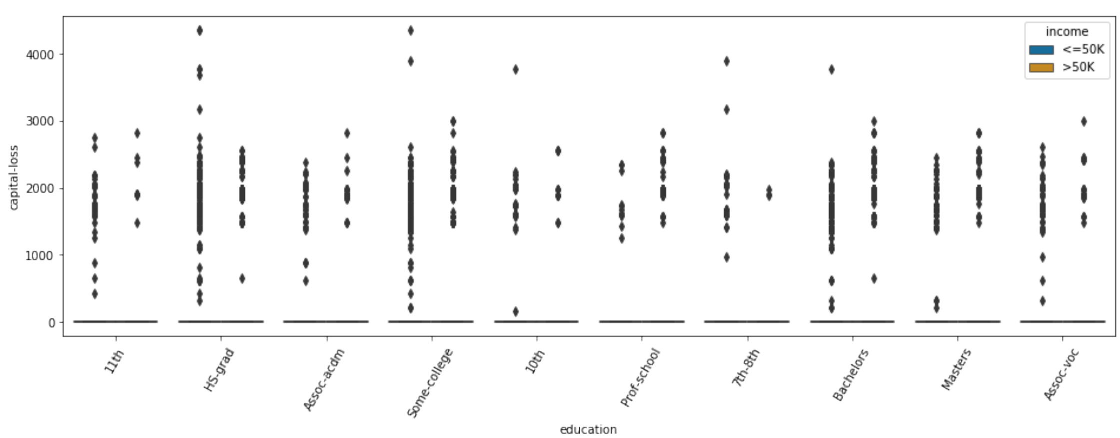
Box plot for **native-country** & **capital-gain**



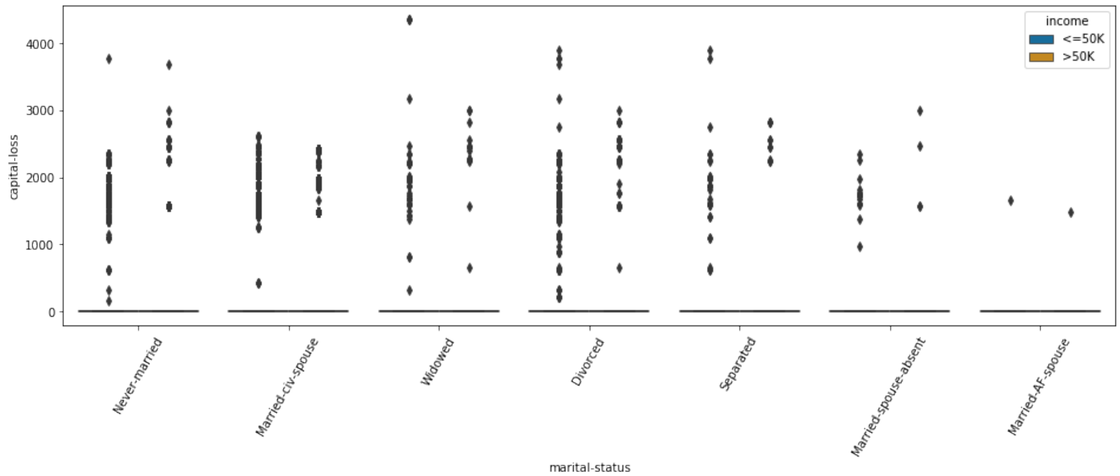
Box plot for **workclass** & **capital-loss**



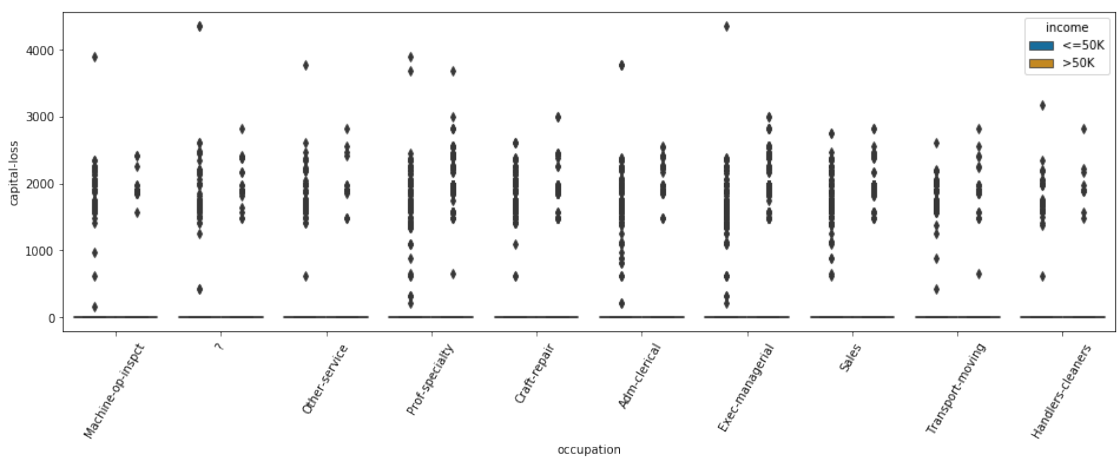
Box plot for **education** & **capital-loss**



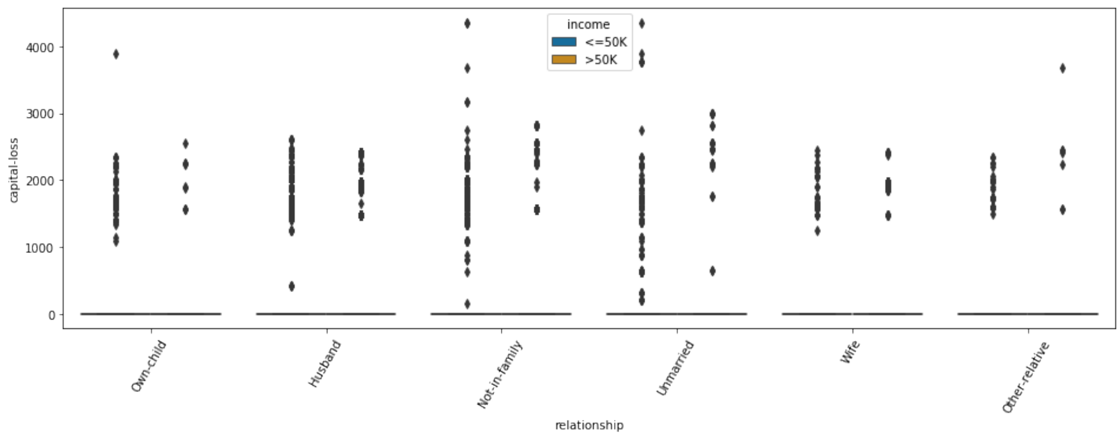
Box plot for **marital-status** & **capital-loss**



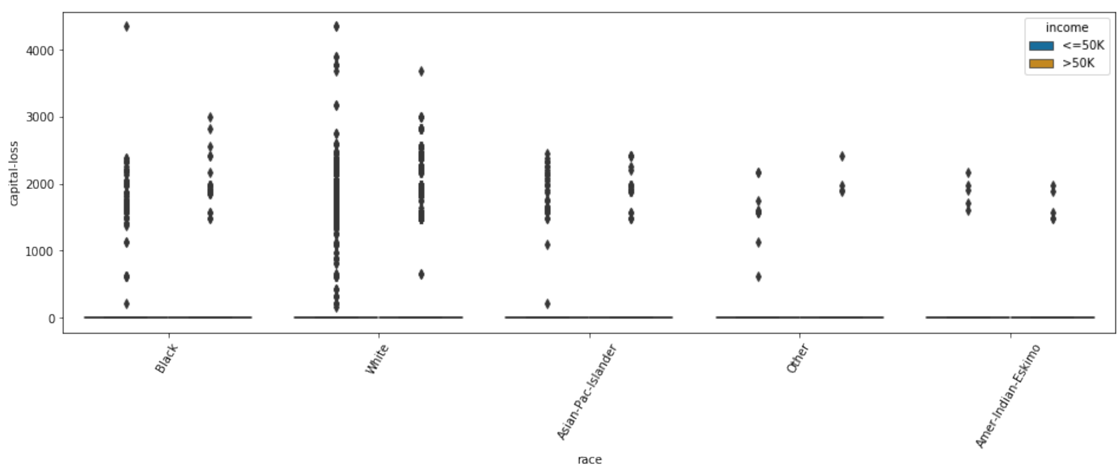
Box plot for **occupation** & **capital-loss**



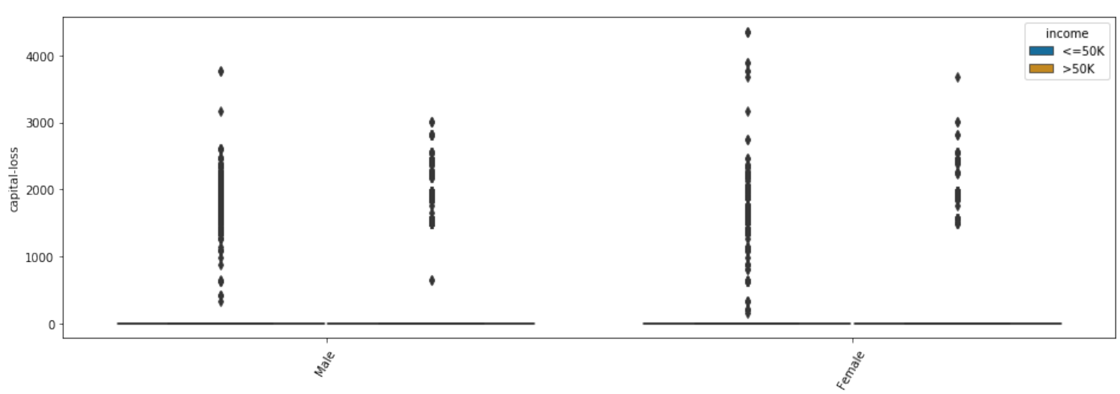
Box plot for **relationship** & **capital-loss**



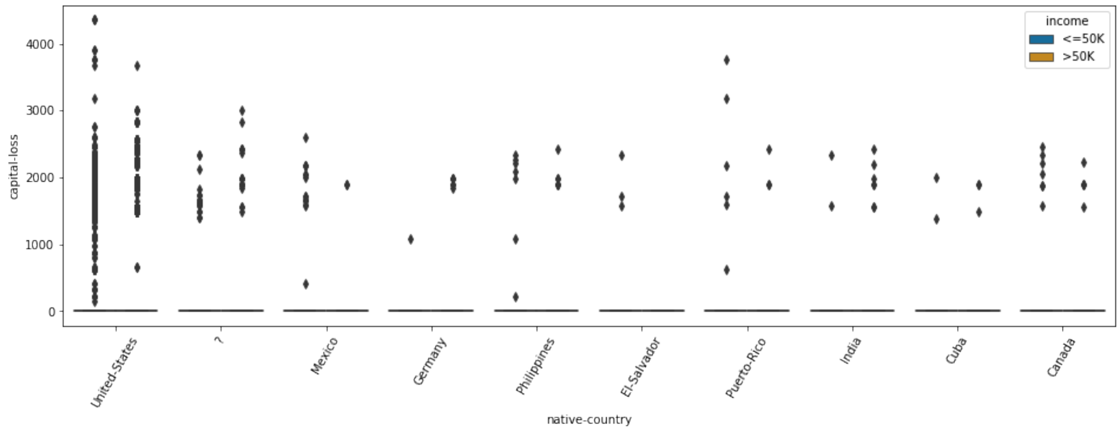
Box plot for **race** & **capital-loss**



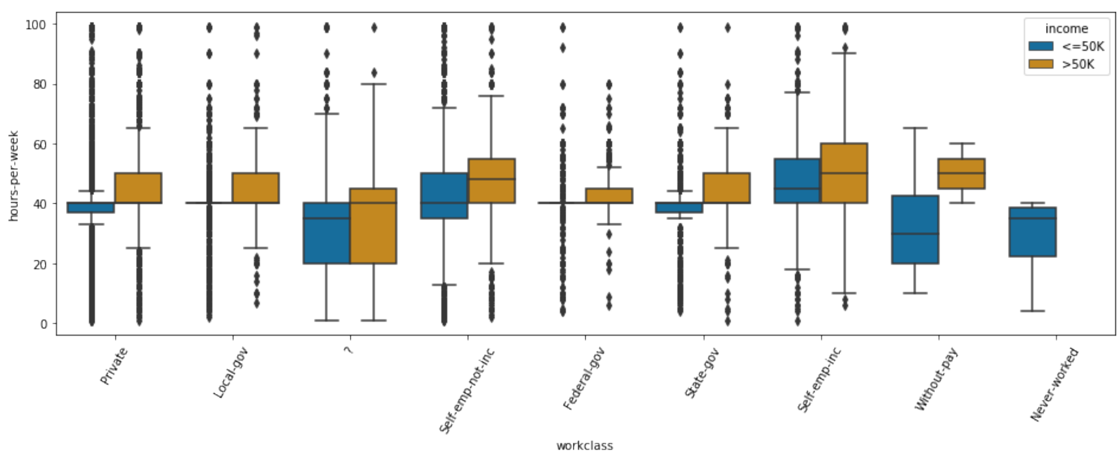
Box plot for **gender** & **capital-loss**



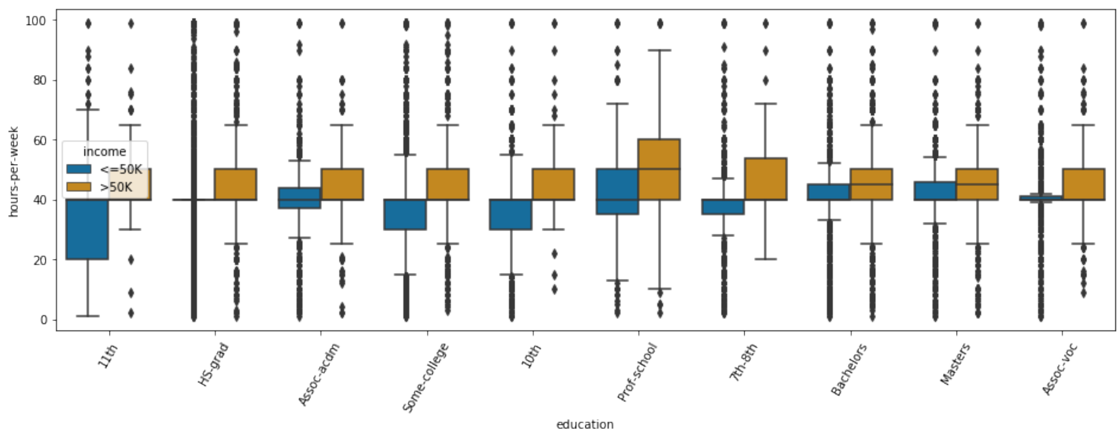
Box plot for **native-country** & **capital-loss**



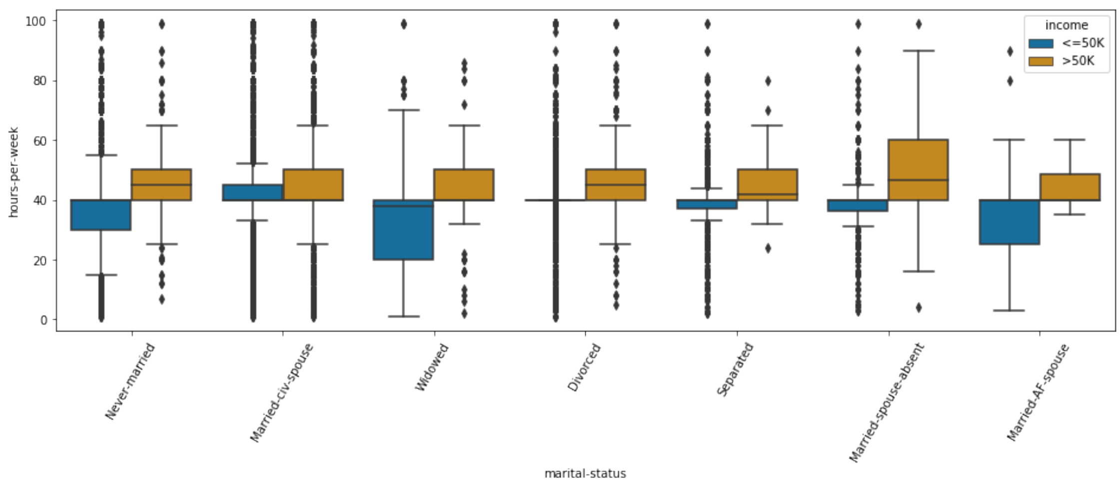
Box plot for **workclass** & **hours-per-week**



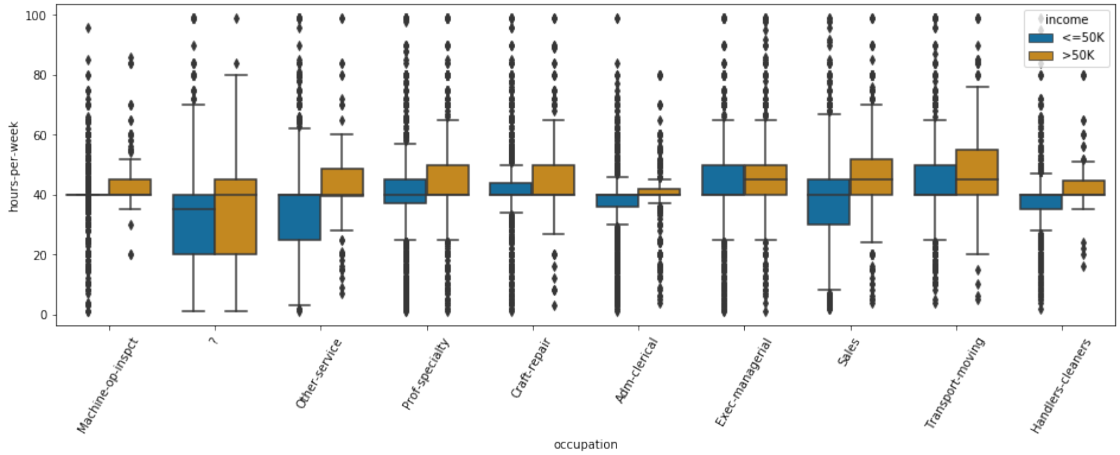
Box plot for **education** & **hours-per-week**



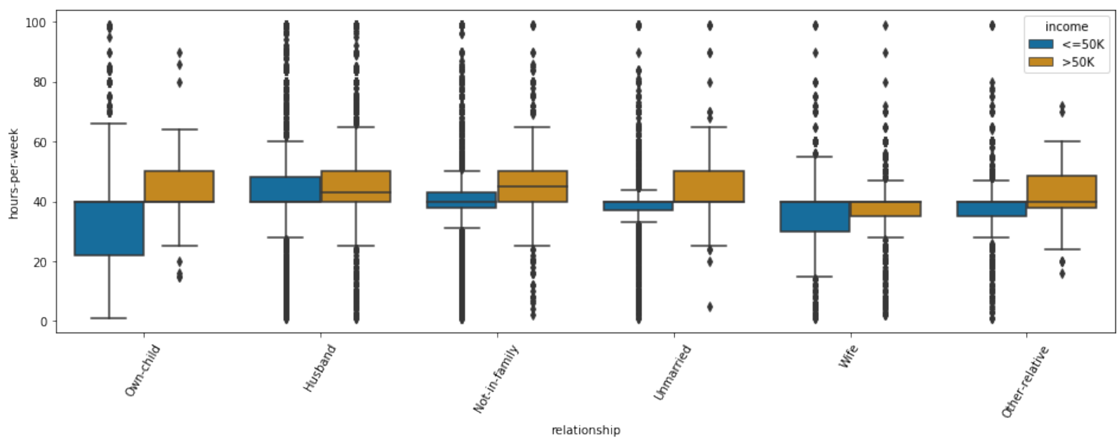
Box plot for **marital-status** & **hours-per-week**



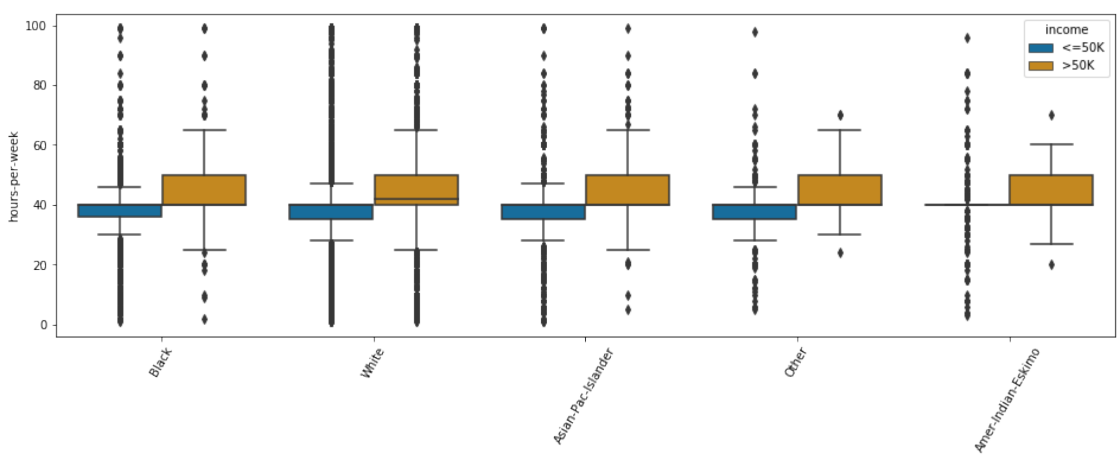
Box plot for **occupation** & **hours-per-week**



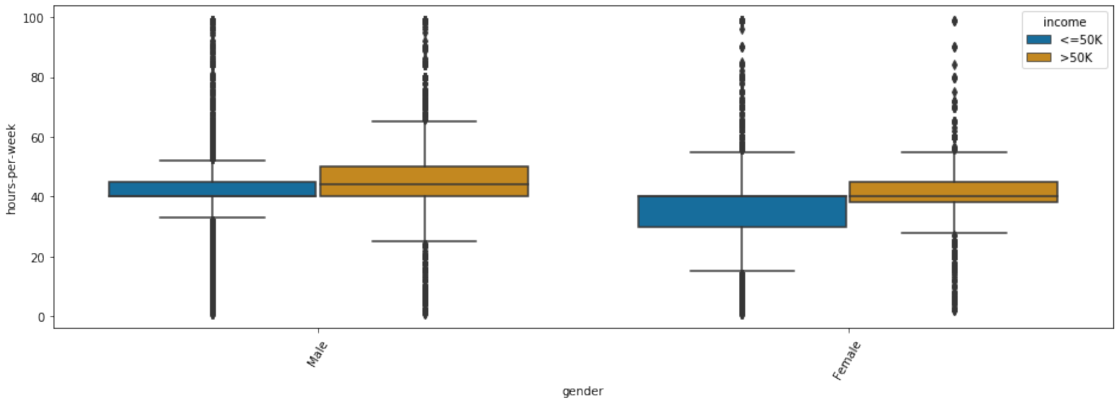
Box plot for **relationship** & **hours-per-week**



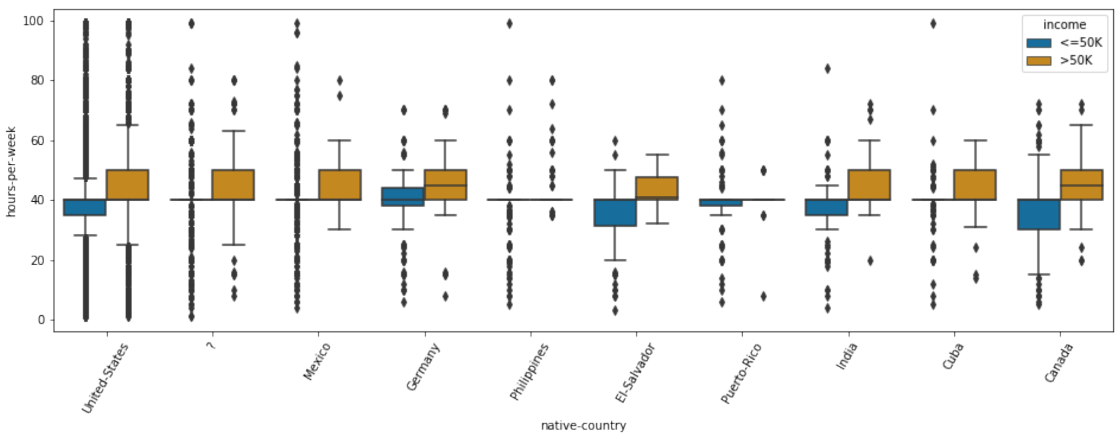
Box plot for **race** & **hours-per-week**



Box plot for **gender** & **hours-per-week**



Box plot for **native-country** & **hours-per-week**



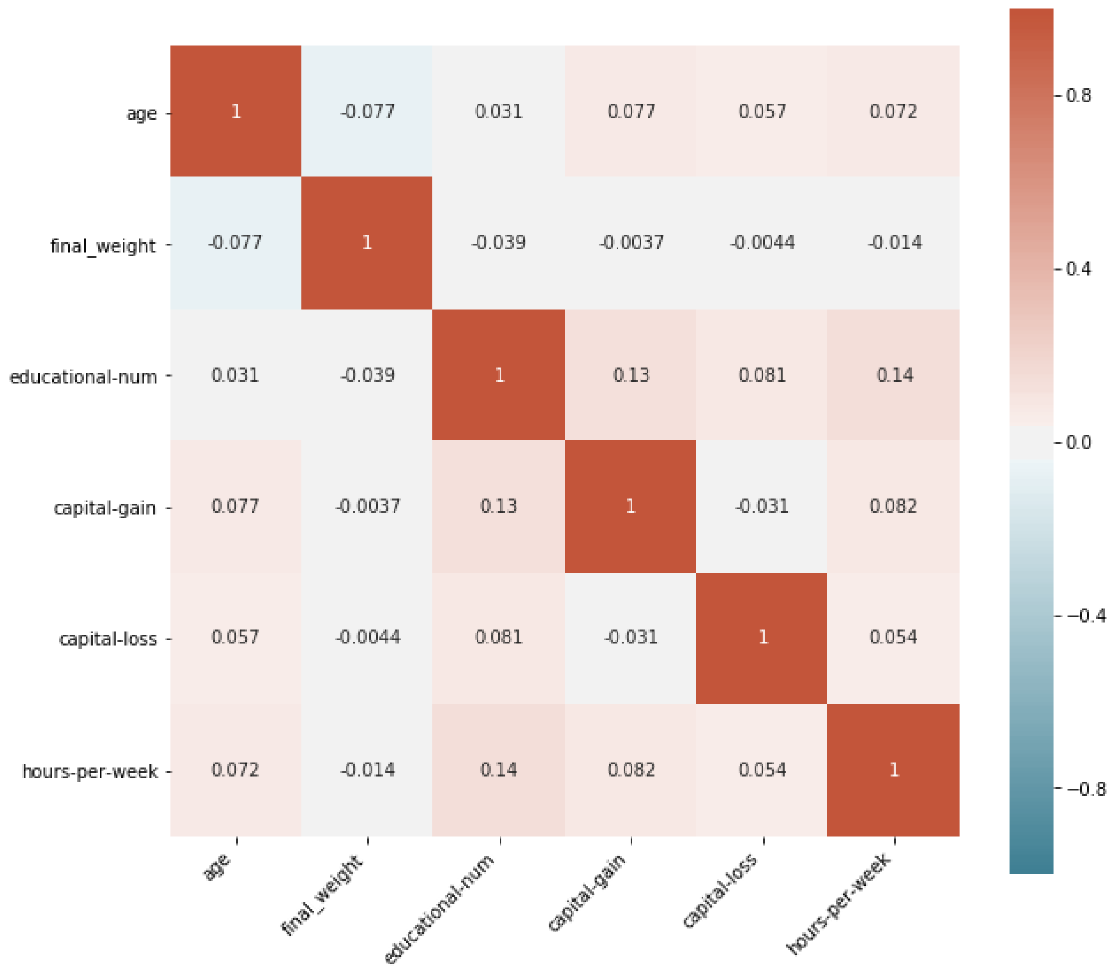
[17]:
```
help(explore.show_df_correlations)
```

```
Help on function show_df_correlations in module transparentai.explore.explore:

show_df_correlations(df)
    Show differents correlations matrix for 3 cases :
    - numerical to numerical (using Pearson coeff)
    - categorical to categorical (using Cramers V & Chi square)
    - numerical to categorical (discrete) (using Point Biserial)

    Parameters
    ----------
```

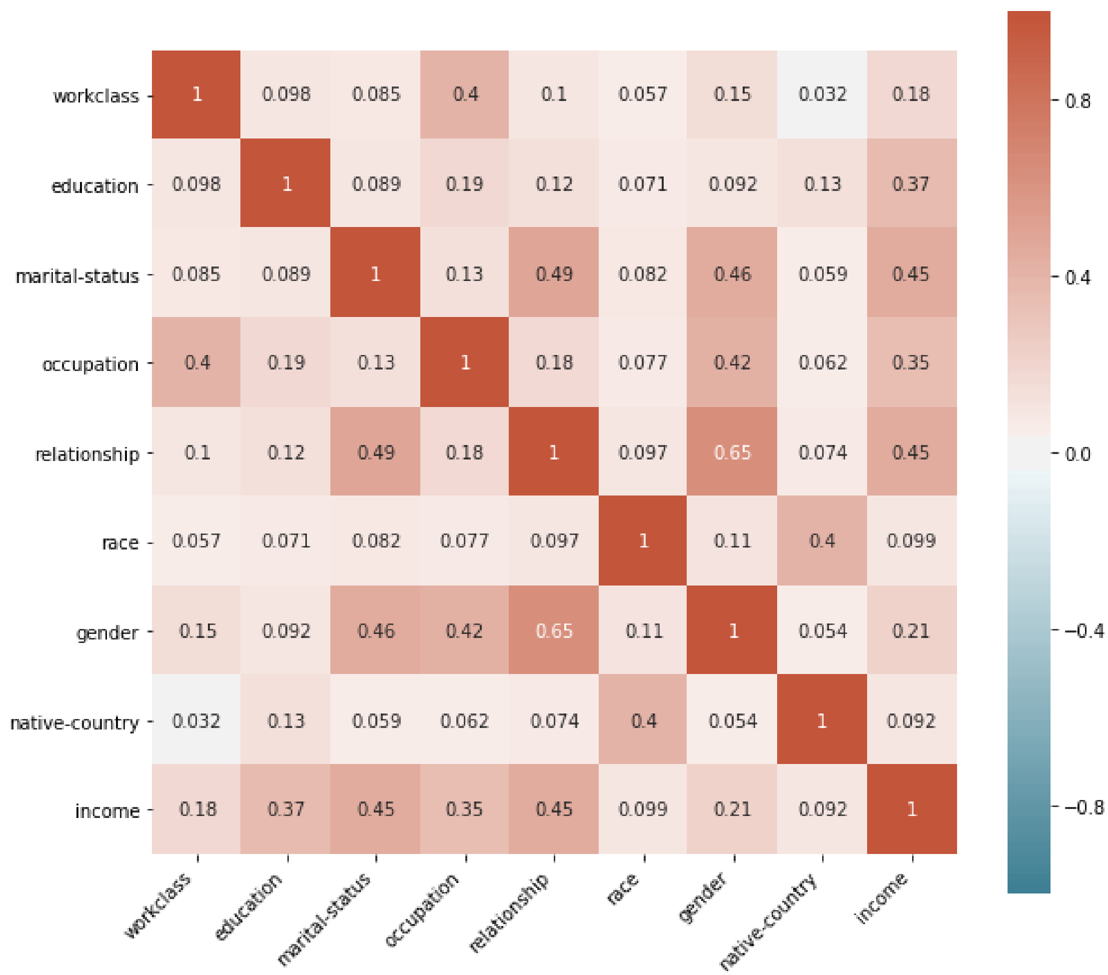
```
df: pd.DataFrame
    Dataframe to inspect
```

[18]:
```
explore.show_df_correlations(df=adult)
```

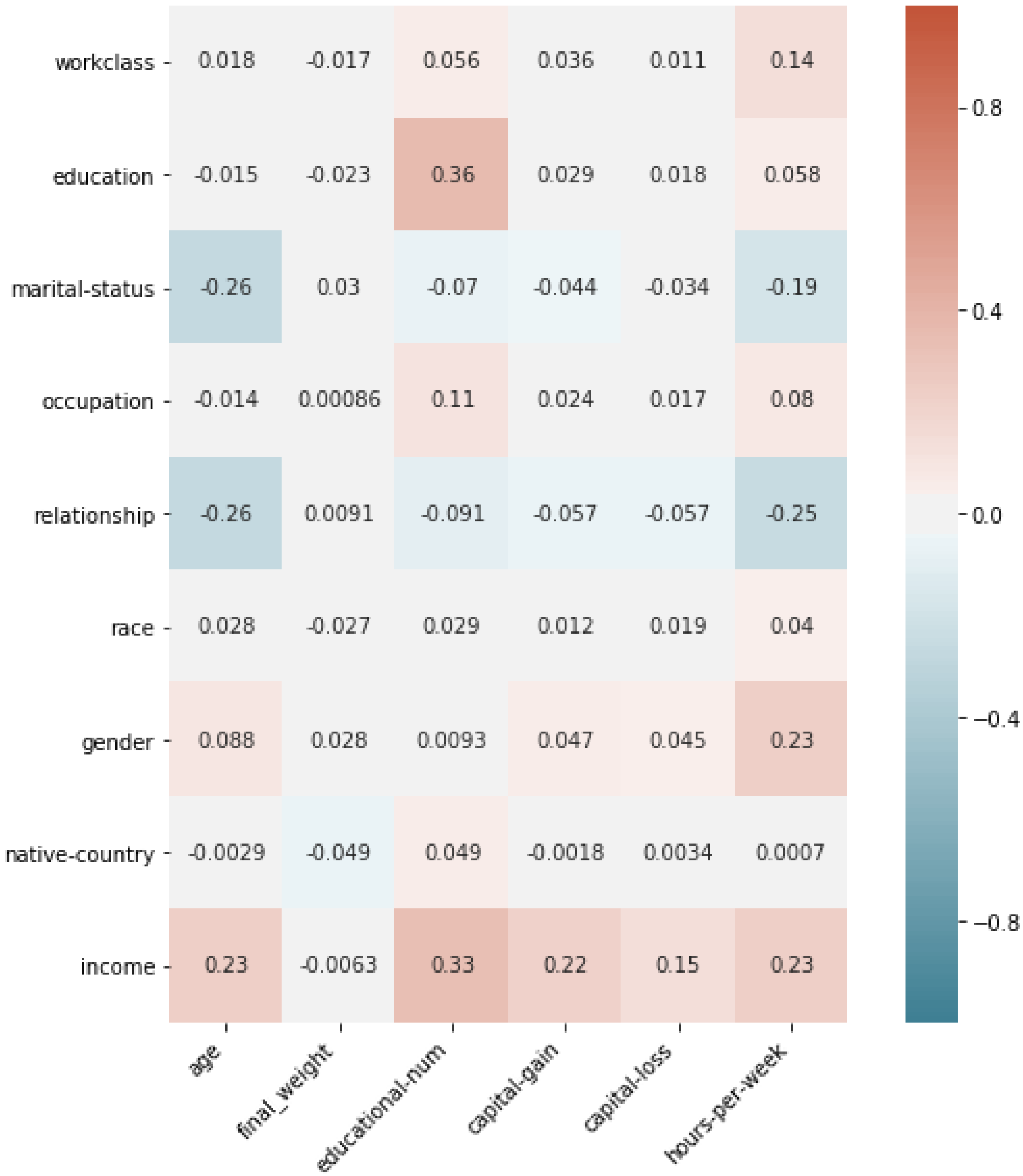
Pearson correlation matrix for numerical variables



Cramers V correlation matrix for categorical variables



Point Biserial correlation matrix for numerical & categorical variables



1.8 Handle dataset bias

Now let's take a look on dataset bias.

[19]:
```
protected_vars = df_details[df_details['is_protected'] == 1]
protected_vars = np.where(protected_vars['new_name'].isna(),␣
 ↪protected_vars['column'], protected_vars['new_name'])

for var in protected_vars:
```

```
    display(Markdown(f'#### {var}'))
    display(adult[var].unique())
```

age

```
array([25, 38, 28, 44, 18, 34, 29, 63, 24, 55, 65, 36, 26, 58, 48, 43, 20,
       37, 40, 72, 45, 22, 23, 54, 32, 46, 56, 17, 39, 52, 21, 42, 33, 30,
       47, 41, 19, 69, 50, 31, 59, 49, 51, 27, 57, 61, 64, 79, 73, 53, 77,
       80, 62, 35, 68, 66, 75, 60, 67, 71, 70, 90, 81, 74, 78, 82, 83, 85,
       76, 84, 89, 88, 87, 86])
```

marital-status

```
array(['Never-married', 'Married-civ-spouse', 'Widowed', 'Divorced',
       'Separated', 'Married-spouse-absent', 'Married-AF-spouse'],
      dtype=object)
```

race

```
array(['Black', 'White', 'Asian-Pac-Islander', 'Other',
       'Amer-Indian-Eskimo'], dtype=object)
```

gender

```
array(['Male', 'Female'], dtype=object)
```

native-country

```
array(['United-States', '?', 'Peru', 'Guatemala', 'Mexico',
       'Dominican-Republic', 'Ireland', 'Germany', 'Philippines',
       'Thailand', 'Haiti', 'El-Salvador', 'Puerto-Rico', 'Vietnam',
       'South', 'Columbia', 'Japan', 'India', 'Cambodia', 'Poland',
       'Laos', 'England', 'Cuba', 'Taiwan', 'Italy', 'Canada', 'Portugal',
       'China', 'Nicaragua', 'Honduras', 'Iran', 'Scotland', 'Jamaica',
       'Ecuador', 'Yugoslavia', 'Hungary', 'Hong', 'Greece',
       'Trinadad&Tobago', 'Outlying-US(Guam-USVI-etc)', 'France',
       'Holand-Netherlands'], dtype=object)
```

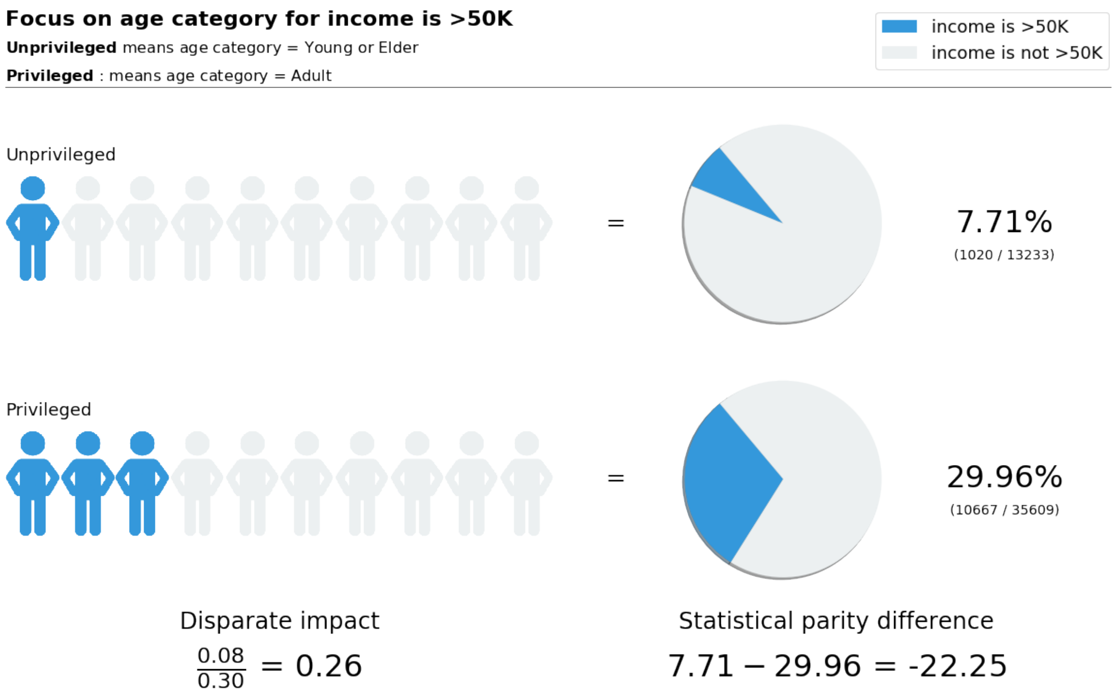
Convert age into a categorical variable for this purpose with the following rule : - if age < 26 then `Young` - else if age < 61 then `Adult` - else `Elder`

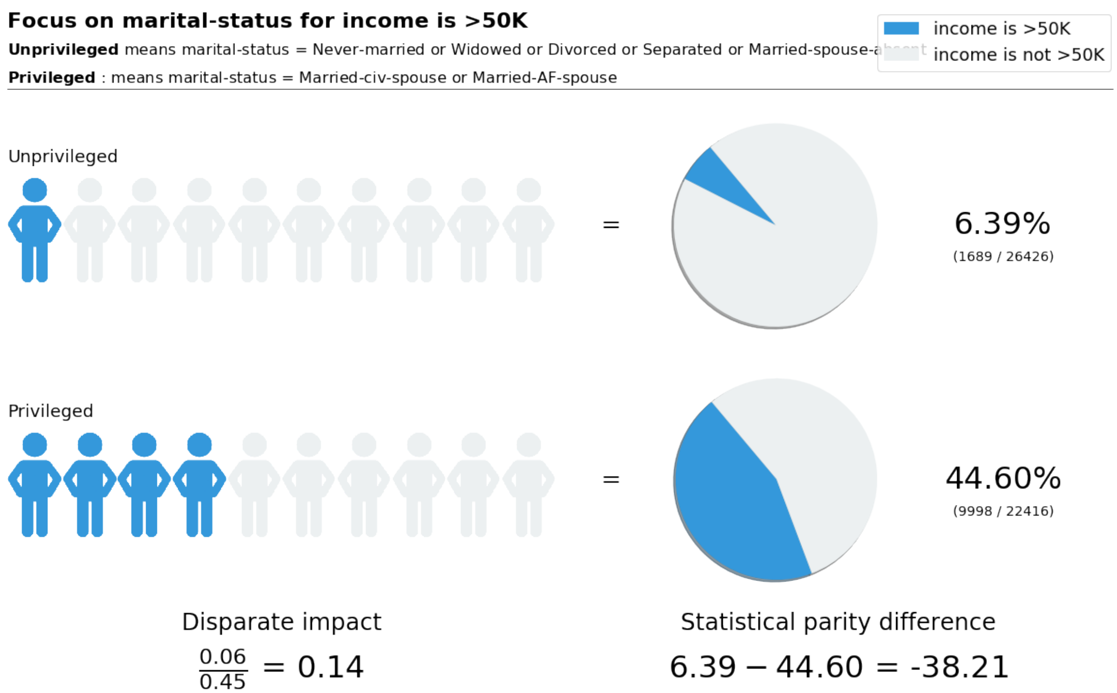
[20]:
```
adult['age category'] = np.where(adult['age'] < 26, 'Young',
                                 np.where(adult['age'] < 61, 'Adult','Elder'))
```

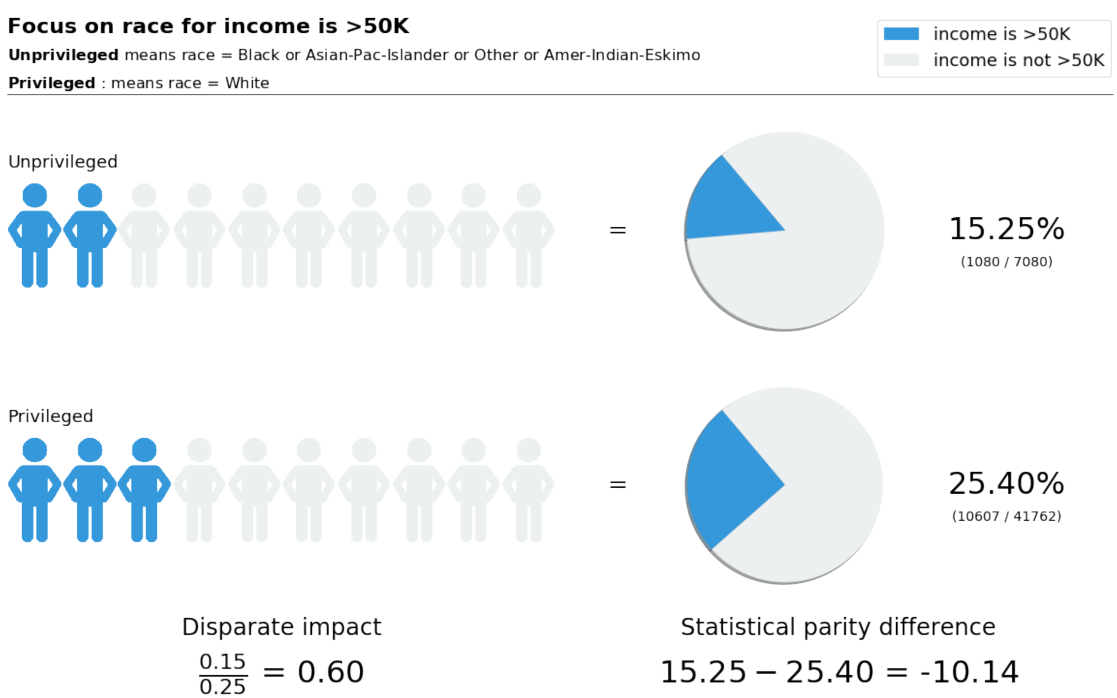
1.9 Using transparentai ClassificationDataset dataset

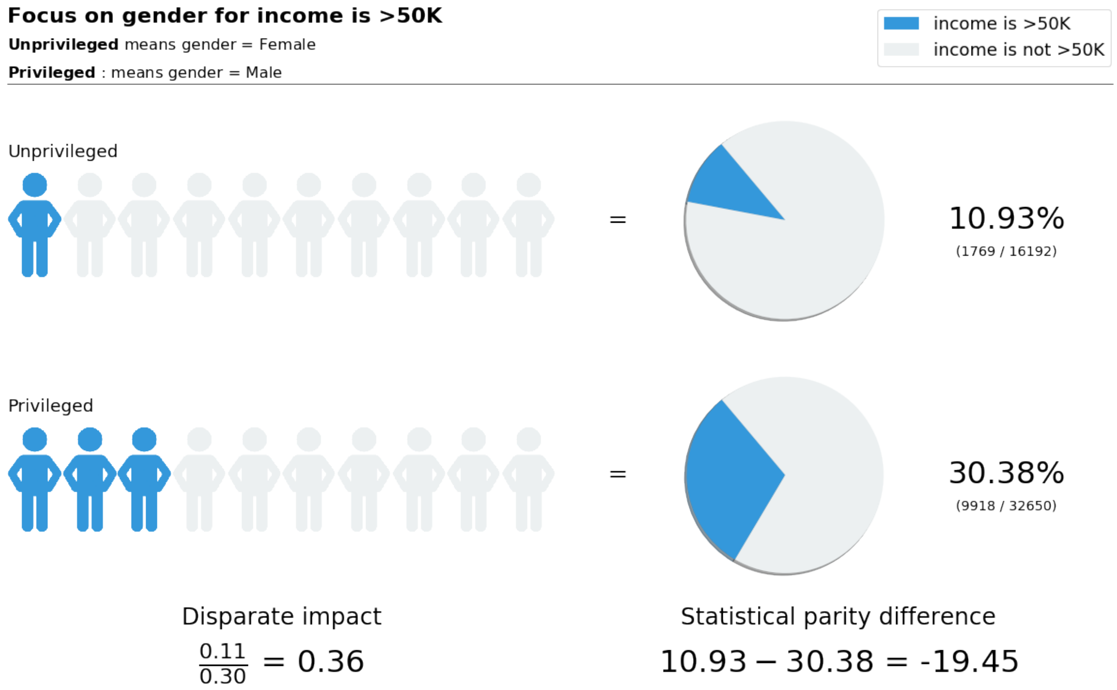
[21]:
```
target = 'income'
privileged_values = {
    'age category': ['Adult'],
    'marital-status': ['Married-civ-spouse','Married-AF-spouse'],
    'race': ['White'],
    'gender': ['Male']
}
fair_dataset = ClassificationDataset(df=adult,
                                     label_name=target,
                                     privileged_values=privileged_values)
```

[22]:
```
fair_dataset.show_bias_metrics(label_value='>50K')
```




Focus on marital-status for income is >50K
Unprivileged means marital-status = Never-married or Widowed or Divorced or Separated or Married-spouse-a
Privileged : means marital-status = Married-civ-spouse or Married-AF-spouse
income is >50K
income is not >50K
Unprivileged
=
6.39%
(1689 / 26426)
Privileged
=
44.60%
(9998 / 22416)
Disparate impact
0.06 / 0.45 = 0.14
Statistical parity difference
6.39 − 44.60 = -38.21


Focus on race for income is >50K
Unprivileged means race = Black or Asian-Pac-Islander or Other or Amer-Indian-Eskimo
Privileged : means race = White
income is >50K
income is not >50K
Unprivileged
=
15.25%
(1080 / 7080)
Privileged
=
25.40%
(10607 / 41762)
Disparate impact
0.15 / 0.25 = 0.60
Statistical parity difference
15.25 − 25.40 = -10.14



1.10 Insight from previous graphics

Now you have a lot of informations about your dataset ! You can go deeper by transform your data and re-execute a notebook with this template if necessary.

Don't forget to detail your insight about this dataset on a worksheet or slides so that business people may understand what you found without going into this notebook by themselves

1.11 The end.

Thanks for reading. *Nathan*