Project_2_2

July 28, 2020

1 Project 2 Exercise 2. Adult dataset preprocessing

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from os import walk
import re
```

1.1 1. Read files

[2]:
```
data_path = './data'
```

[3]:
```
for root, dirs, files in walk(data_path):
    all_files = [data_path+'/'+file for file in files if file.split('.')[-1] in␣
 ↪['data', 'names']]

for file_num in range(len(all_files)):
    print(f'#{file_num} ->', all_files[file_num])
```

```
#0 -> ./data/adult.names
#1 -> ./data/adult.data
#2 -> ./data/old.adult.names
```

[4]:
```
# in here we choose the index from above result. for example here we want data␣
 ↪file with index 2
# and data names file with index 3

names_index = 0
data_index = 1


# open names file
names_file = [line.strip() for line in open(all_files[names_index], 'r').
 ↪readlines()]
```

```
print_flag = False
attrs = []
for line in names_file:
    if len(line) > 0 and line[0] != '|':
        print_flag = True

    if print_flag:
        print(line)
        attr = re.findall("([\w\-]*)\(*\)*:", line)

        if len(attr) > 0:
            print(attr)
            attrs.append(attr[0])


attrs.append('income')

# print all attributes
print('attributes count: ', len(attrs), '\n'*2)
print(attrs)
```

```
>50K, <=50K.

age: continuous.
['age']
workclass: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov,
State-gov, Without-pay, Never-worked.
['workclass']
fnlwgt: continuous.
['fnlwgt']
education: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm,
Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th,
Preschool.
['education']
education-num: continuous.
['education-num']
marital-status: Married-civ-spouse, Divorced, Never-married, Separated, Widowed,
Married-spouse-absent, Married-AF-spouse.
['marital-status']
occupation: Tech-support, Craft-repair, Other-service, Sales, Exec-managerial,
Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-
fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces.
['occupation']
relationship: Wife, Own-child, Husband, Not-in-family, Other-relative,
Unmarried.
['relationship']
race: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.
```

```
['race']
sex: Female, Male.
['sex']
capital-gain: continuous.
['capital-gain']
capital-loss: continuous.
['capital-loss']
hours-per-week: continuous.
['hours-per-week']
native-country: United-States, Cambodia, England, Puerto-Rico, Canada, Germany,
Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran,
Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal,
Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia,
Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador,
Trinadad&Tobago, Peru, Hong, Holand-Netherlands.
['native-country']
attributes count:  15
```

```
['age', 'workclass', 'fnlwgt', 'education', 'education-num', 'marital-status',
'occupation', 'relationship', 'race', 'sex', 'capital-gain', 'capital-loss',
'hours-per-week', 'native-country', 'income']
```

[5]:
```
data_df = pd.read_csv(all_files[data_index])
data_df.columns = attrs
data_df = data_df.replace('?', np.NaN)
data_df
```

[5]:

	age	workclass	fnlwgt	education	education-num	\
0	50	Self-emp-not-inc	83311	Bachelors	13	
1	38	Private	215646	HS-grad	9	
2	53	Private	234721	11th	7	
3	28	Private	338409	Bachelors	13	
4	37	Private	284582	Masters	14	
…	…	…	…	…	…	
32555	27	Private	257302	Assoc-acdm	12	
32556	40	Private	154374	HS-grad	9	
32557	58	Private	151910	HS-grad	9	
32558	22	Private	201490	HS-grad	9	
32559	52	Self-emp-inc	287927	HS-grad	9	

	marital-status	occupation	relationship	race	\
0	Married-civ-spouse	Exec-managerial	Husband	White	
1	Divorced	Handlers-cleaners	Not-in-family	White	
2	Married-civ-spouse	Handlers-cleaners	Husband	Black	
3	Married-civ-spouse	Prof-specialty	Wife	Black	
4	Married-civ-spouse	Exec-managerial	Wife	White	

```
…                    …                  …              …      …
32555   Married-civ-spouse        Tech-support            Wife   White
32556   Married-civ-spouse   Machine-op-inspct         Husband   White
32557              Widowed        Adm-clerical       Unmarried   White
32558        Never-married        Adm-clerical       Own-child   White
32559   Married-civ-spouse     Exec-managerial            Wife   White

            sex  capital-gain  capital-loss  hours-per-week  native-country  \
0          Male             0             0              13   United-States
1          Male             0             0              40   United-States
2          Male             0             0              40   United-States
3        Female             0             0              40            Cuba
4        Female             0             0              40   United-States
…         …           …            …              …              …
32555    Female             0             0              38   United-States
32556      Male             0             0              40   United-States
32557    Female             0             0              40   United-States
32558      Male             0             0              20   United-States
32559    Female         15024             0              40   United-States

       income
0       <=50K
1       <=50K
2       <=50K
3       <=50K
4       <=50K
…       …
32555   <=50K
32556    >50K
32557   <=50K
32558   <=50K
32559    >50K

[32560 rows x 15 columns]
```

1.2 2. Columns and Rows counts

[6]:
```
print('Columns counts: ',len(data_df.columns))
print('Row counts: ', len(data_df))
```

```
Columns counts:  15
Row counts:  32560
```

1.3 3 & 4 . Miss values count

[7]:
```
pd.DataFrame(data_df.isna().any())
```

[7]:
```
                     0
age              False
workclass        False
fnlwgt           False
education        False
education-num    False
marital-status   False
occupation       False
relationship     False
race             False
sex              False
capital-gain     False
capital-loss     False
hours-per-week   False
native-country   False
income           False
```

1.4 5. Fill missing values by imputing them

[8]:
```
cols_with_missing = [col for col in data_df.columns if data_df[col].isnull().
 ↪any()]
print('Columns with missing values: ', cols_with_missing)

# for missing values we can use simple imputer to fill missing values...
# from sklearn.impute import SimpleImputer
# my_imputer = SimpleImputer()
# imputed_data_df = pd.DataFrame(my_imputer.fit_transform(data_df))
# imputed_data_df.columns = data_df.columns
# data_df = imputed_data_df

# Actually!!! ther is an easier way to handle missing values...
# we can just simply DROP them! :)))

data_df = data_df.drop(cols_with_missing, axis=1)
data_df
```

```
Columns with missing values:  []
```

[8]:

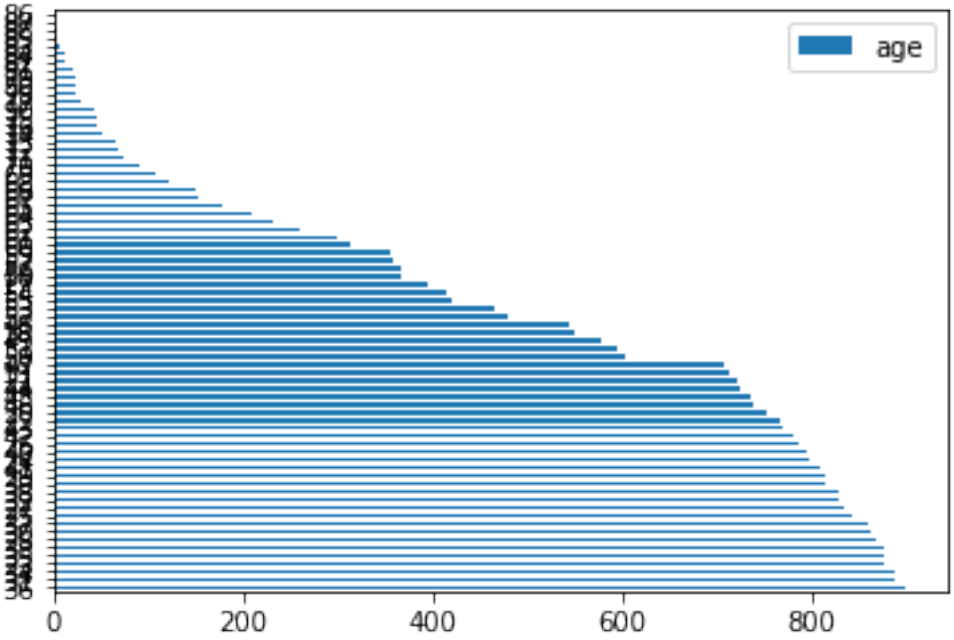
	age	workclass	fnlwgt	education	education-num	\
0	50	Self-emp-not-inc	83311	Bachelors	13	
1	38	Private	215646	HS-grad	9	
2	53	Private	234721	11th	7	

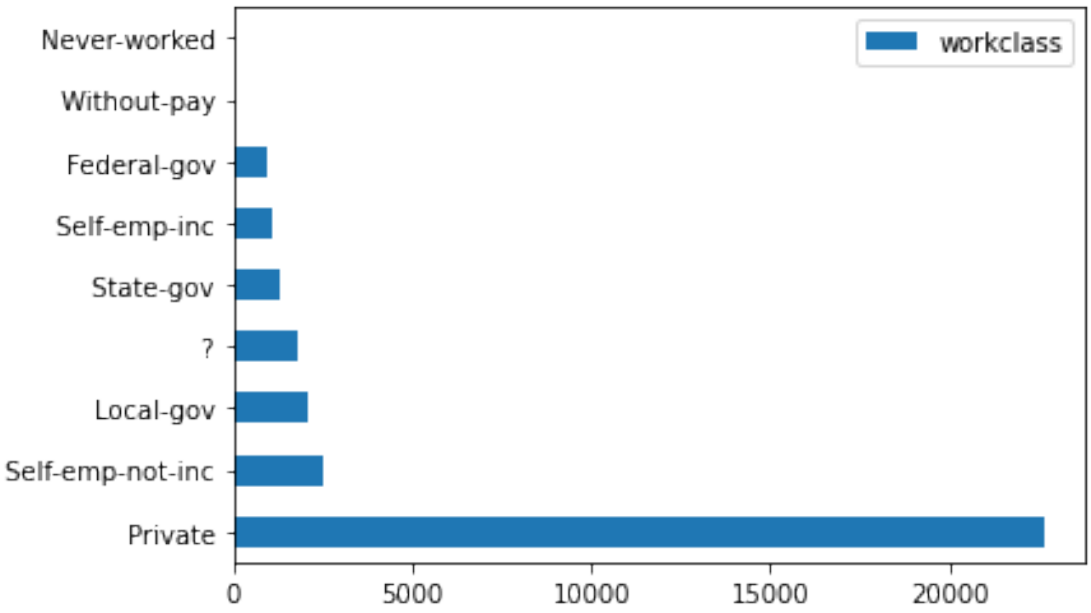
```
3       28            Private  338409    Bachelors             13
4       37            Private  284582      Masters             14
…    …                …     …          …             …
32555   27            Private  257302   Assoc-acdm             12
32556   40            Private  154374      HS-grad              9
32557   58            Private  151910      HS-grad              9
32558   22            Private  201490      HS-grad              9
32559   52       Self-emp-inc  287927      HS-grad              9

           marital-status          occupation    relationship    race  \
0       Married-civ-spouse     Exec-managerial         Husband   White
1                 Divorced   Handlers-cleaners   Not-in-family   White
2       Married-civ-spouse   Handlers-cleaners         Husband   Black
3       Married-civ-spouse      Prof-specialty            Wife   Black
4       Married-civ-spouse     Exec-managerial            Wife   White
…                      …                …             …     …
32555   Married-civ-spouse        Tech-support            Wife   White
32556   Married-civ-spouse   Machine-op-inspct         Husband   White
32557              Widowed        Adm-clerical       Unmarried   White
32558        Never-married        Adm-clerical       Own-child   White
32559   Married-civ-spouse     Exec-managerial            Wife   White

          sex  capital-gain  capital-loss  hours-per-week  native-country  \
0        Male             0             0              13   United-States
1        Male             0             0              40   United-States
2        Male             0             0              40   United-States
3      Female             0             0              40            Cuba
4      Female             0             0              40   United-States
…       …           …           …             …              …
32555  Female             0             0              38   United-States
32556    Male             0             0              40   United-States
32557  Female             0             0              40   United-States
32558    Male             0             0              20   United-States
32559  Female         15024             0              40   United-States

       income
0       <=50K
1       <=50K
2       <=50K
3       <=50K
4       <=50K
…       …
32555   <=50K
32556    >50K
32557   <=50K
32558   <=50K
32559    >50K
```

```
[32560 rows x 15 columns]
```

1.5 6. Graph of each values of each column

[ ]:
```
for col in data_df.columns:
        each_value_count = pd.DataFrame(data_df[col].value_counts())
        each_value_count.plot.barh()
```

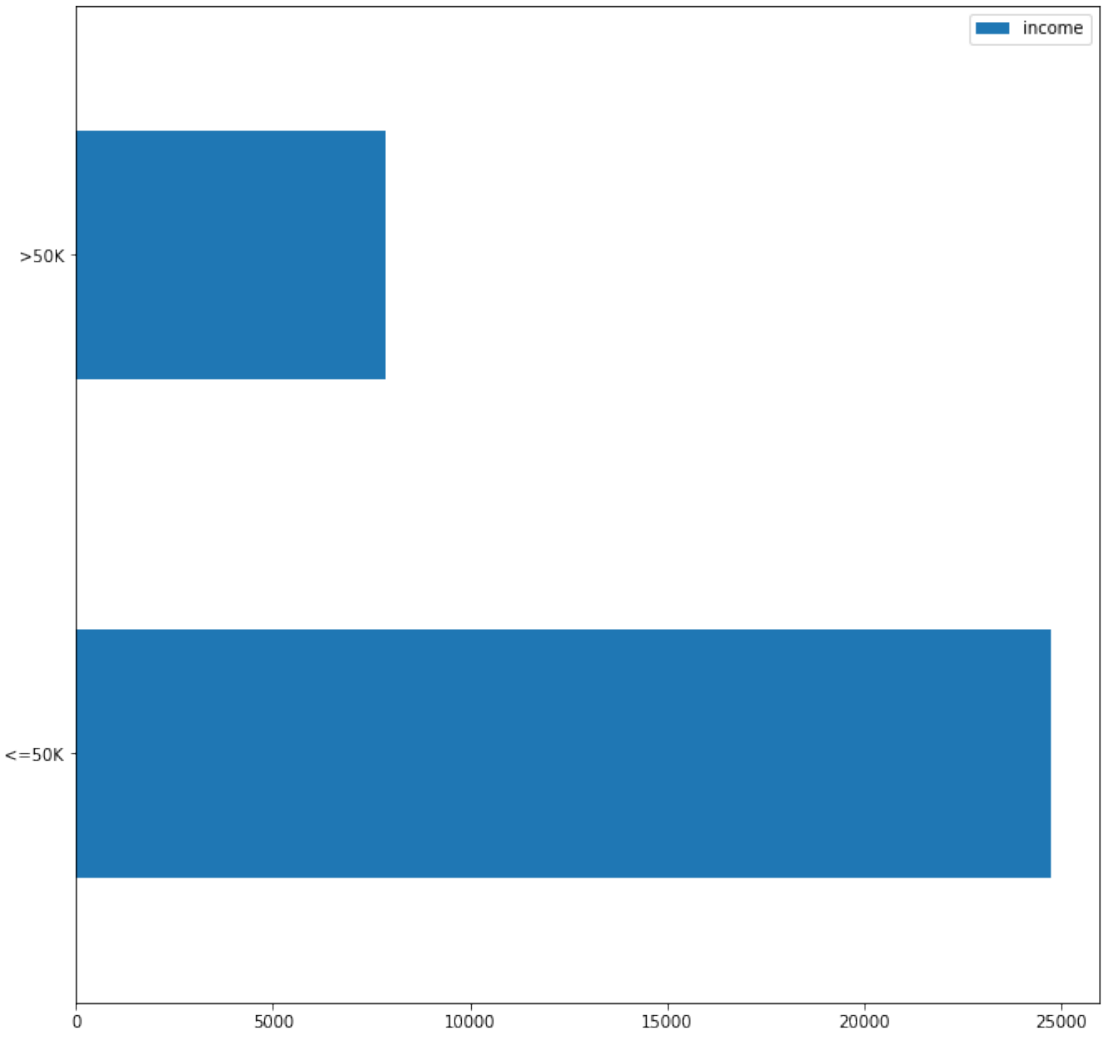




1.6 7. Draw class value counts

[10]:
```
value_count = pd.DataFrame(data_df['income'].value_counts())
value_count.plot.barh(figsize=(11,11))
```

[10]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f31a4b780f0>
```


income
>50K
<=50K
0
5000
10000
15000
20000
25000