Final Project

Project Name: To Predict Income with the help of Machine Learning Model

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Course: DS 630 Machine learning

Professor: Dr. Wang

Objective: Predicting salary income class with help of machine learning model

Importing the libraries ¶

In [ ]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
from pandas.plotting import scatter_matrix
from sklearn.model_selection import train_test_split
from sklearn import metrics
import statsmodels.api as sm
from IPython.display import Markdown, display
from sklearn.metrics import roc_curve, auc
from sklearn import svm
from sklearn import tree
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import label_binarize
% matplotlib inline
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
```

Importing the adult dataset

In [ ]:
```
# Importing the dataset
from google.colab import files
uploaded = files.upload()
```

Choose Files No file chosen

Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving adult.csv to adult (2).csv
```

In [ ]:
```
import io
df = pd.read_csv(io.BytesIO(uploaded['adult.csv']))
```

Sample dataset for understanding

In [ ]:
```
df.head()
```

Out[ ]:

	age	workclass	fnlwgt	education	educational-num	marital-status	occupation	relationship	race	ge
0	25	Private	226802	11th	7	Never-married	Machine-op-inspct	Own-child	Black	
1	38	Private	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	
2	28	Local-gov	336951	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	
3	44	Private	160323	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	
4	18	?	103497	Some-college	10	Never-married	?	Own-child	White	Fe

In [ ]:
```
df.columns
```

Out[ ]:
```
Index(['age', 'workclass', 'fnlwgt', 'education', 'educational-num',
       'marital-status', 'occupation', 'relationship', 'race', 'gende
r',
       'capital-gain', 'capital-loss', 'hours-per-week', 'native-countr
y',
       'income'],
      dtype='object')
```

In [ ]:
```
print (df.shape)
```

```
(48842, 15)
```

The full dimension of data which is made up of 48842 rows and 15 columns.

In [ ]:
```
# Obtain summary stataistics of the data
df.describe()
```

Out[ ]:

	age	fnlwgt	educational-num	capital-gain	capital-loss	hours-per-week
count	48842.000000	4.884200e+04	48842.000000	48842.000000	48842.000000	48842.000000
mean	38.643585	1.896641e+05	10.078089	1079.067626	87.502314	40.422382
std	13.710510	1.056040e+05	2.570973	7452.019058	403.004552	12.391444
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	1.000000
25%	28.000000	1.175505e+05	9.000000	0.000000	0.000000	40.000000
50%	37.000000	1.781445e+05	10.000000	0.000000	0.000000	40.000000
75%	48.000000	2.376420e+05	12.000000	0.000000	0.000000	45.000000
max	90.000000	1.490400e+06	16.000000	99999.000000	4356.000000	99.000000

In [ ]:
```
# Investigate further to know the various types of the columns and count
of the data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48842 entries, 0 to 48841
Data columns (total 15 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   age              48842 non-null  int64 
 1   workclass        48842 non-null  object
 2   fnlwgt           48842 non-null  int64 
 3   education        48842 non-null  object
 4   educational-num  48842 non-null  int64 
 5   marital-status   48842 non-null  object
 6   occupation       48842 non-null  object
 7   relationship     48842 non-null  object
 8   race             48842 non-null  object
 9   gender           48842 non-null  object
 10  capital-gain     48842 non-null  int64 
 11  capital-loss     48842 non-null  int64 
 12  hours-per-week   48842 non-null  int64 
 13  native-country   48842 non-null  object
 14  income           48842 non-null  object
dtypes: int64(6), object(9)
memory usage: 5.6+ MB
```

Data cleaning or Data preprocessing

Missing Values

In [ ]:
```
# Counting the number of missing values for each feature
df.isnull().sum()
```

Out[ ]:
```
age                0
workclass          0
fnlwgt             0
education          0
educational-num    0
marital-status     0
occupation         0
relationship       0
race               0
gender             0
capital-gain       0
capital-loss       0
hours-per-week     0
native-country     0
income             0
dtype: int64
```

With the above results there are no null values but we still need to find out special characters present in the data.

Now we are further processing

Special Characters

In [ ]:
```
print ('Special Characters')
for i,j in zip(df.columns,(df.values.astype(str) == '?').sum(axis = 0)):
    if j > 0:
        print(str(i) + ': ' + str(j) + ' records')
```

```
Special Characters
workclass: 2799 records
occupation: 2809 records
native-country: 857 records
```

In [ ]:
```
# code will replace the special character to nan and then drop the colum
ns
df['native-country'] = df['native-country'].replace('?',np.nan)
df['workclass'] = df['workclass'].replace('?',np.nan)
df['occupation'] = df['occupation'].replace('?',np.nan)
#dropping the NaN rows now
df.dropna(how='any',inplace=True)
```

In [ ]:
```
#Finding if special characters are present in the data
df.isin(['?']).sum(axis=0)
```

Out[ ]:
```
age                0
workclass          0
fnlwgt             0
education          0
educational-num    0
marital-status     0
occupation         0
relationship       0
race               0
gender             0
capital-gain       0
capital-loss       0
hours-per-week     0
native-country     0
income             0
dtype: int64
```

In [ ]:
```
print (df.shape)
```

```
(45222, 15)
```

The data is reduced by 3620 rows

1. First, replace all the '?' with NaN(NaN is used as a placeholder for missing data in pandas), to do that, use python's string replace() function with NumPy's(imported as np earlier) nan.
2. Second, Use the .dropna() function to drop the rows with missing values. dropna() can drop either columns or rows, by default, it will delete rows if the axis keyword is not mentioned. how='any' will remove the rows if any missing values are present in them.

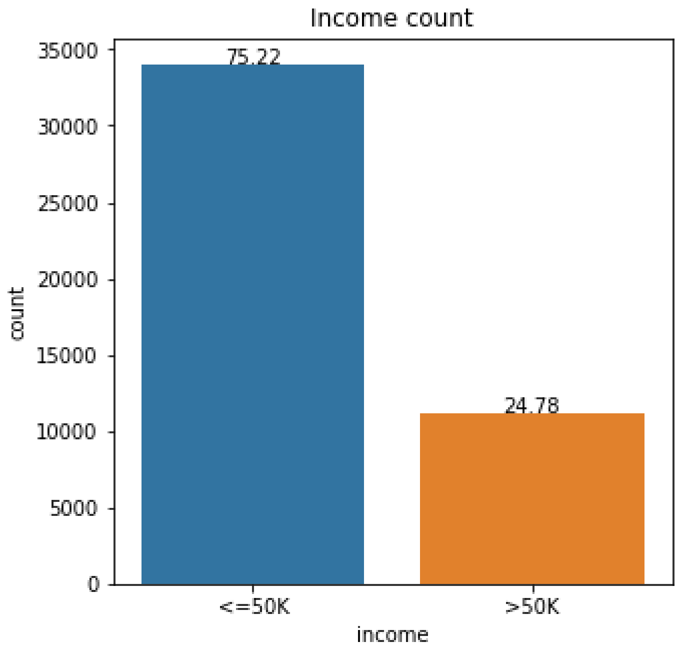
Exploratory data analysis

In [ ]:
```
df['income'].value_counts()
```

Out[ ]:
```
<=50K    34014
>50K     11208
Name: income, dtype: int64
```

Income target variable distribution

In [ ]:
```
plt.figure(figsize=(5,5))
total = float(len(df) )

ax = sns.countplot(x="income", data=df)
for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x()+p.get_width()/2.,
            height + 3,
            '{:1.2f}'.format((height/total)*100),
            ha="center")
plt.title('Income count')
plt.show()
```



In income there is 2 group, group1(who earns more than 50k) 25% belong to income and group2(who earns less than 50k) 75% belong to income

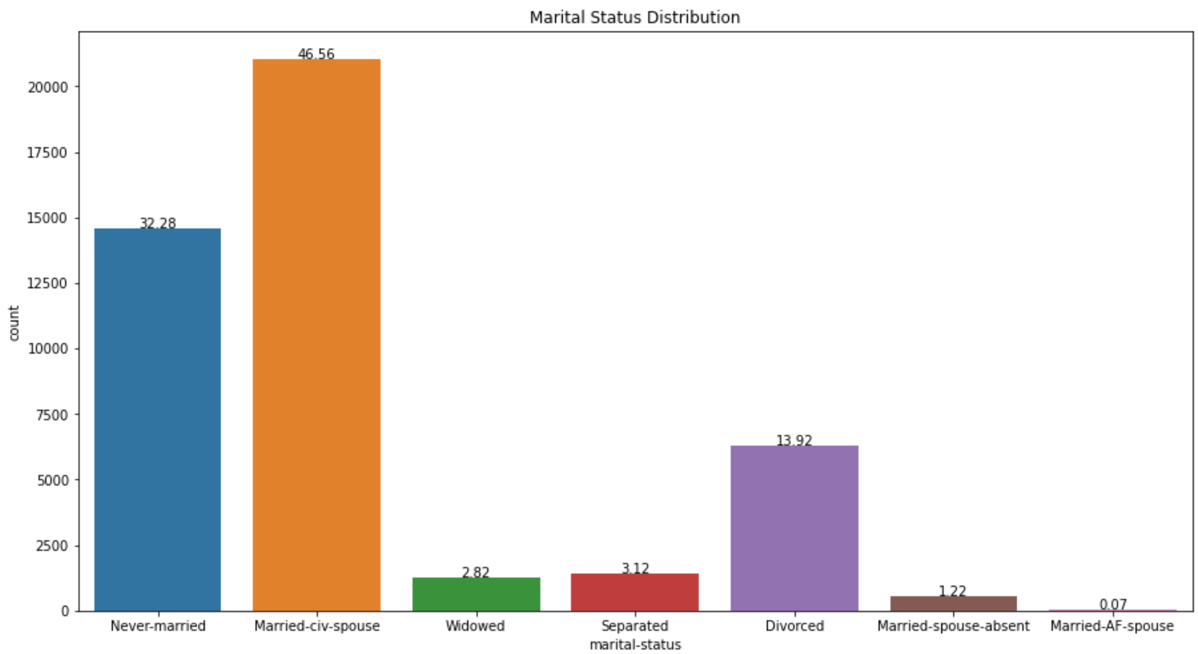
In [ ]:
```
df['gender'].value_counts()
```

Out[ ]:
```
Male      30527
Female    14695
Name: gender, dtype: int64
```

In [ ]:
```
# Creating a dictionary that contain the education and it's correspondin
g education level
edu_level = {}
for x,y in df[['educational-num','education']].drop_duplicates().itertup
les(index=False):
    edu_level[y] = x
```

Marital-status distribution

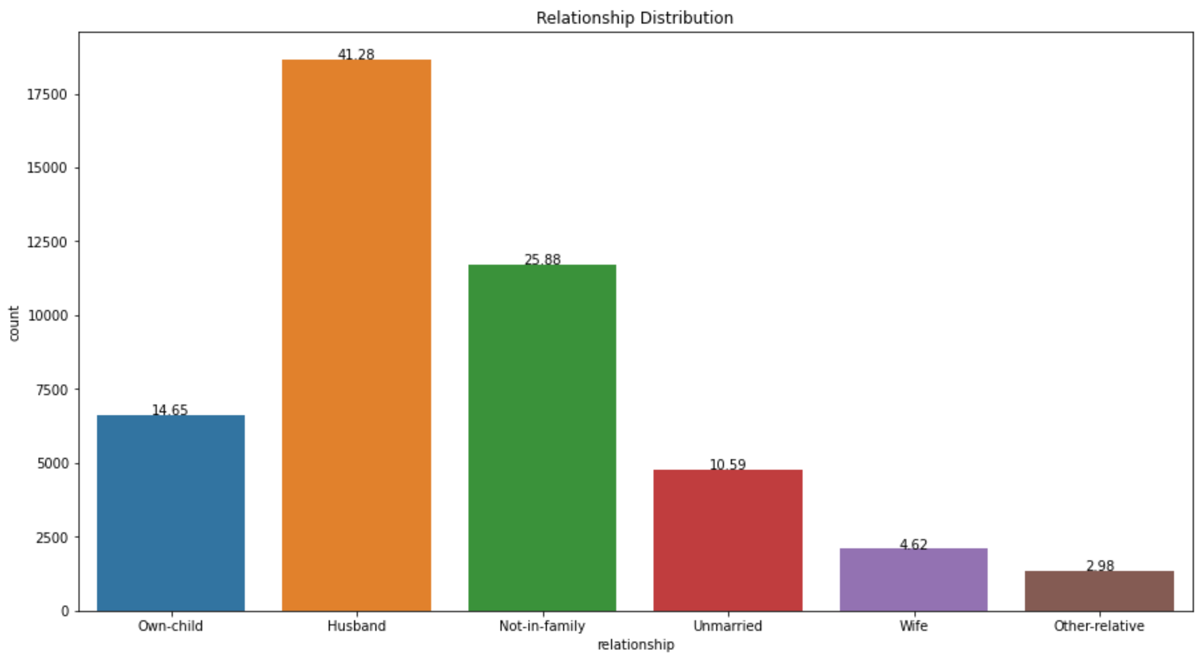
In [ ]:
```
plt.figure(figsize=(15,8))
total = float(len(df) )

ax = sns.countplot(x="marital-status", data=df)
for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x()+p.get_width()/2.,
            height + 3,
            '{:1.2f}'.format((height/total)*100),
            ha="center")
plt.title('Marital Status Distribution')
plt.show()
```



Married-civ-spouse has maximum number of samples. Married-AF-spouse has minimum number of obs.

Relationship distribution

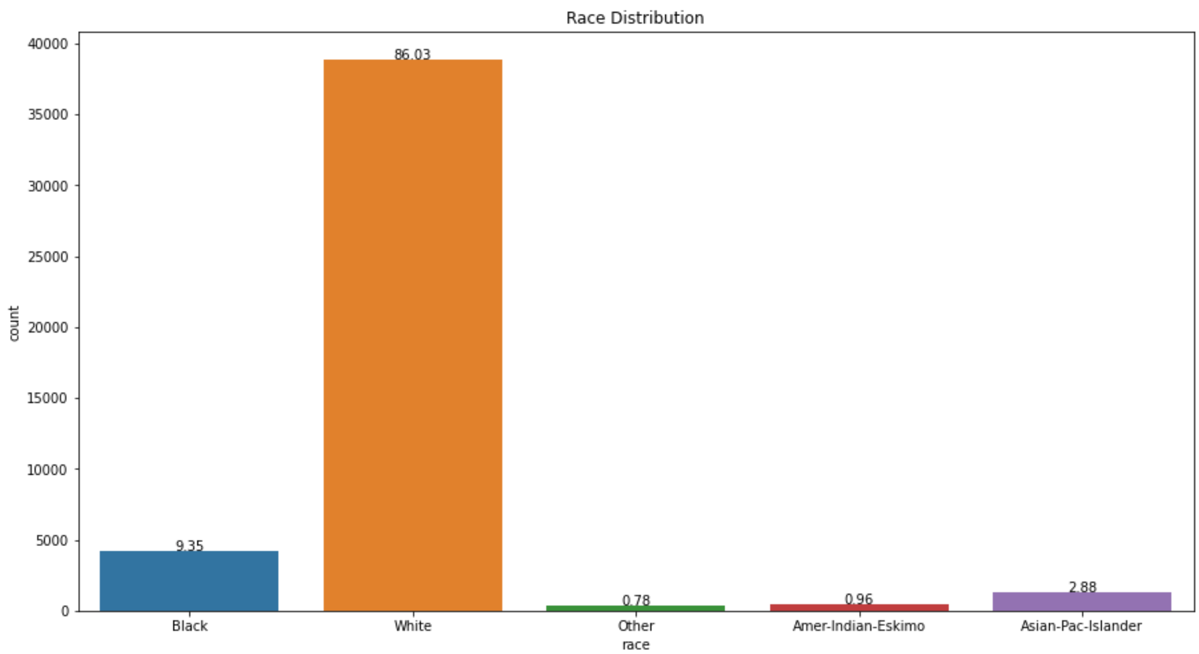
In [ ]:
```
plt.figure(figsize=(15,8))
total = float(len(df) )

ax = sns.countplot(x="relationship", data=df)
for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x()+p.get_width()/2.,
            height + 3,
            '{:1.2f}'.format((height/total)*100),
            ha="center")
plt.title('Relationship Distribution')
plt.show()
```



Husband has maximum percentage among all.

Race distribution

In [ ]:
```
plt.figure(figsize=(15,8))
total = float(len(df) )

ax = sns.countplot(x="race", data=df)
for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x()+p.get_width()/2.,
            height + 3,
            '{:1.2f}'.format((height/total)*100),
            ha="center")
plt.title('Race Distribution')
plt.show()
```



White is maximun among all about 85.50%. Black is second maximun.

Education level vs Income level

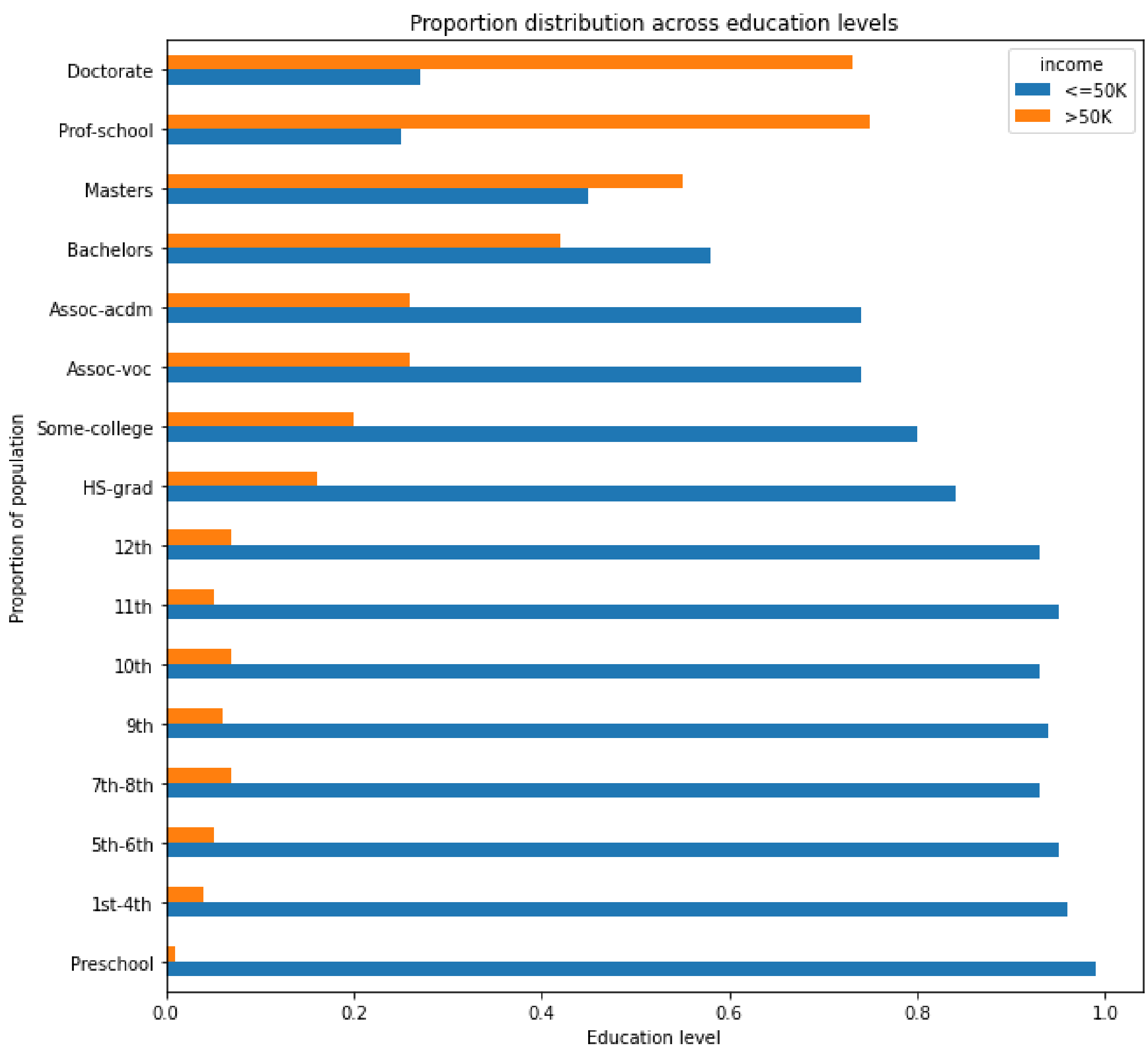
In [ ]:
```
adult = df
```

we are plotting this a bar graph to show the proportion of income classes versus education levels in the figure below.

we are going to see from the bar graph below that as the education level increase, the proportion of people who earn more than 50k a year also increase.

In [ ]:
```
import matplotlib.pyplot as plt
print ('Education vs Income')

education = round(pd.crosstab(adult.education, adult.income).div(pd.cros
stab(adult.education, adult.income).apply(sum,1),0),2)
education = education.reindex(sorted(edu_level, key=edu_level.get, rever
se=False))

ax = education.plot(kind ='barh', title = 'Proportion distribution acros
s education levels', figsize = (10,10))
# plot grouped bar chart

ax.set_xlabel('Education level')
ax.set_ylabel('Proportion of population')
plt.show()
```

```
Education vs Income
```

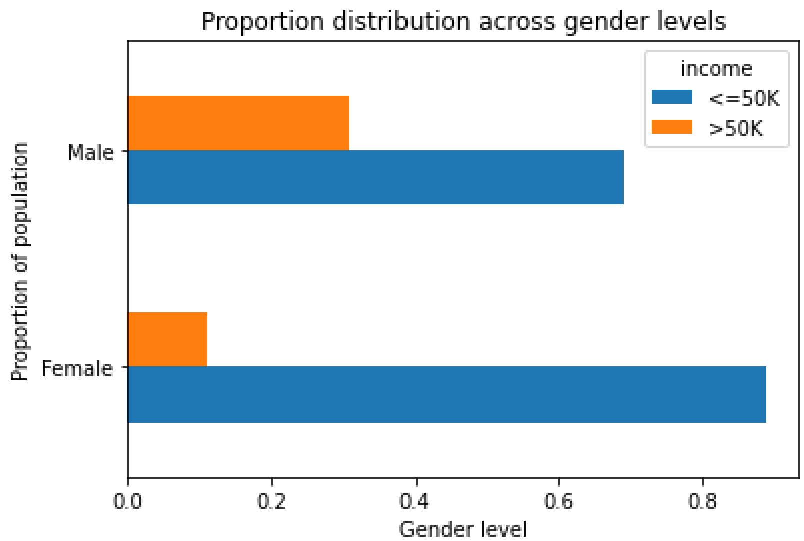


So the above graph saying only after doing master;s degree, majority people earning more than 50k per year

Gender and Income Distribution

1. List item
2. List item

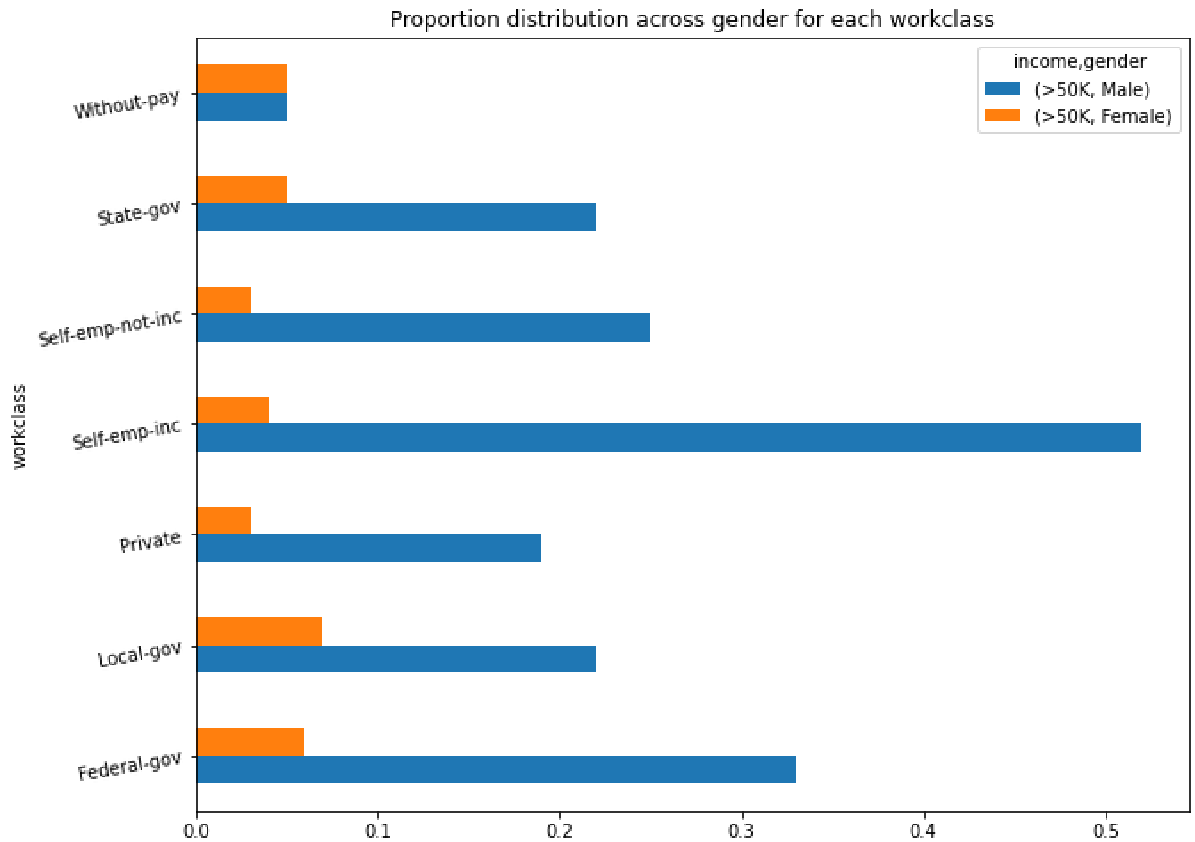
In [ ]:
```
gender = round(pd.crosstab(adult.gender, adult.income).div(pd.crosstab(a
dult.gender, adult.income).apply(sum,1),0),2)
gender.sort_values(by = '>50K', inplace = True)
ax = gender.plot(kind ='barh', title = 'Proportion distribution across g
ender levels')
ax.set_xlabel('Gender level')
ax.set_ylabel('Proportion of population')
plt.show()
```



From the above graph we can see the gap between male and females, but we do not have exact value of the income so we are limited to observe data

Work class with income

In [ ]:
```
gender_workclass = round(pd.crosstab(adult.workclass,
                                     [adult.income, adult.gender]).div(p
d.crosstab(adult.workclass,

[adult.income, adult.gender]).apply(sum,1),0),2)
gender_workclass[[('>50K','Male'), ('>50K','Female')]].plot(kind = 'bar
h',
                                                            title = 'Pro
portion distribution across gender for each workclass',
                                                            figsize = (1
0,8), rot = 10)
ax.set_xlabel('Gender level')
ax.set_ylabel('Proportion of population')
plt.show()
```

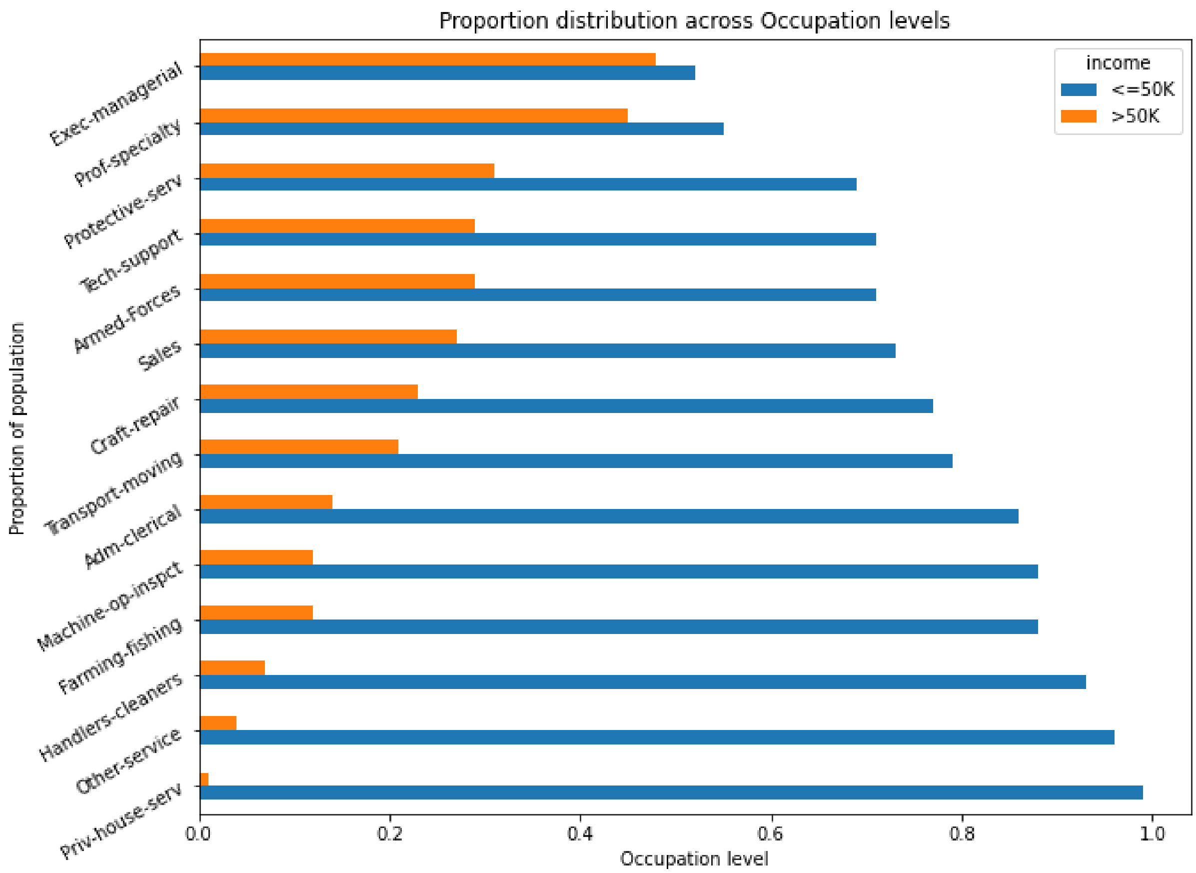


We see the above figure except 'without.pay' working class where both getting same pay scale but men's paid higher proportion earning more than 50k a year than women

Occupation vs proportion of population

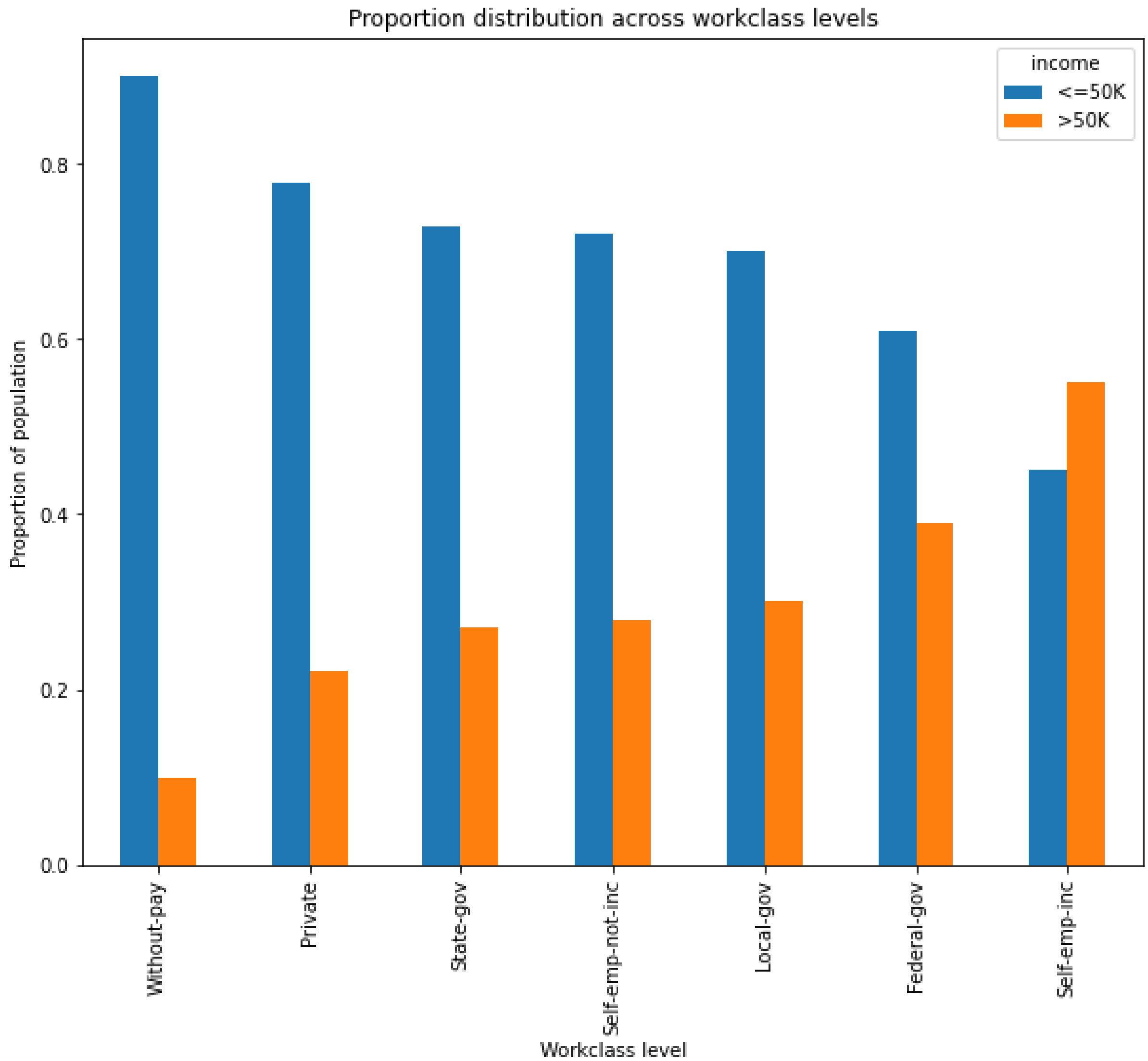
In [ ]:
```
occupation = round(pd.crosstab(adult.occupation, adult.income).div(pd.cr
osstab(adult.occupation, adult.income).apply(sum,1),0),2)
occupation.sort_values(by = '>50K', inplace = True)
ax = occupation.plot(kind ='barh', title = 'Proportion distribution acro
ss Occupation levels', figsize = (10,8), rot = 30)
ax.set_xlabel('Occupation level')
ax.set_ylabel('Proportion of population')
```

Out[ ]:
```
Text(0, 0.5, 'Proportion of population')
```



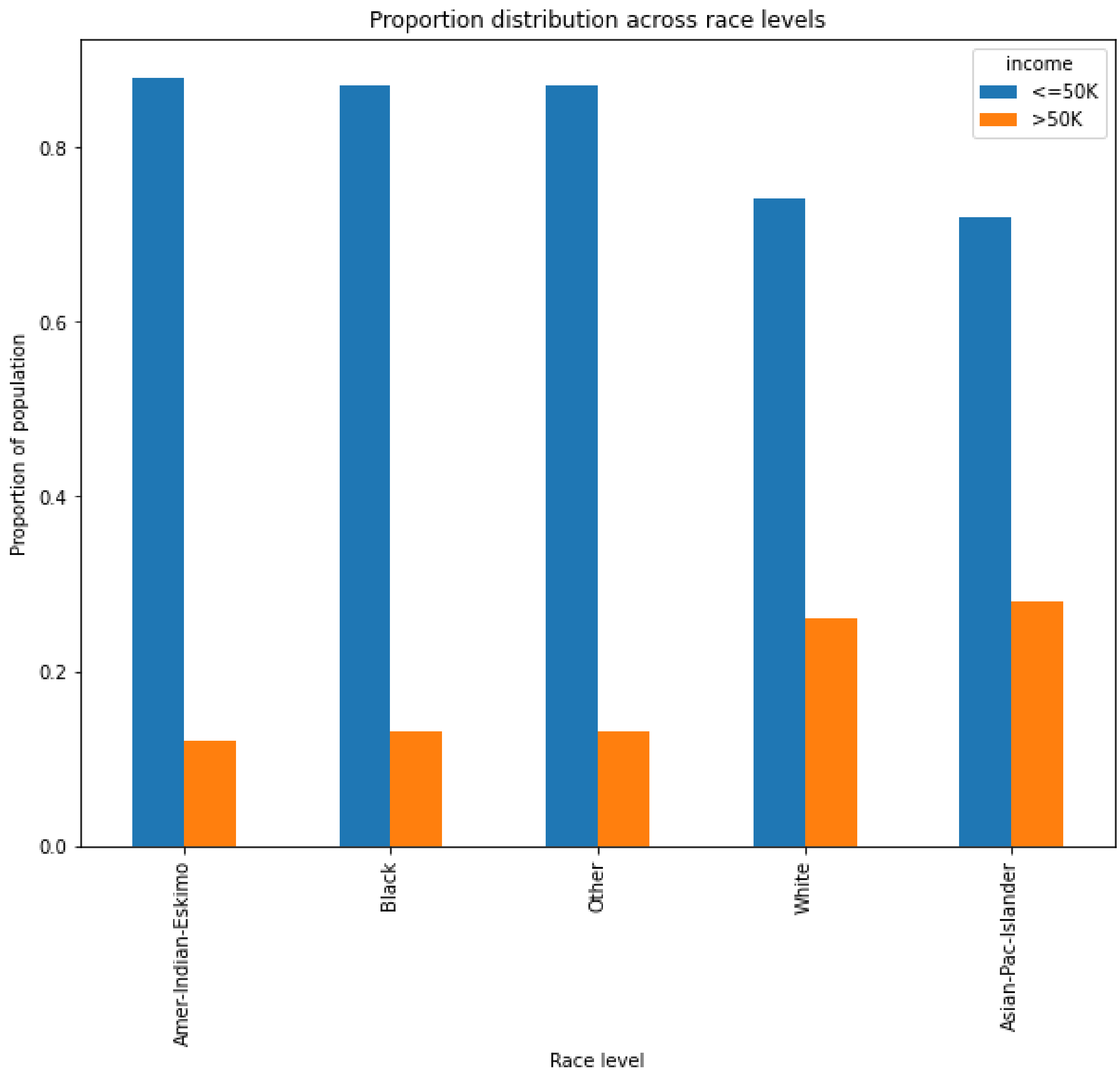
Population with work class distribution

In [ ]:
```
workclass = round(pd.crosstab(adult.workclass, adult.income).div(pd.cros
stab(adult.workclass, adult.income).apply(sum,1),0),2)
workclass.sort_values(by = '>50K', inplace = True)
ax = workclass.plot(kind ='bar', title = 'Proportion distribution across
workclass levels', figsize = (10,8))
ax.set_xlabel('Workclass level')
ax.set_ylabel('Proportion of population')
plt.show()
```



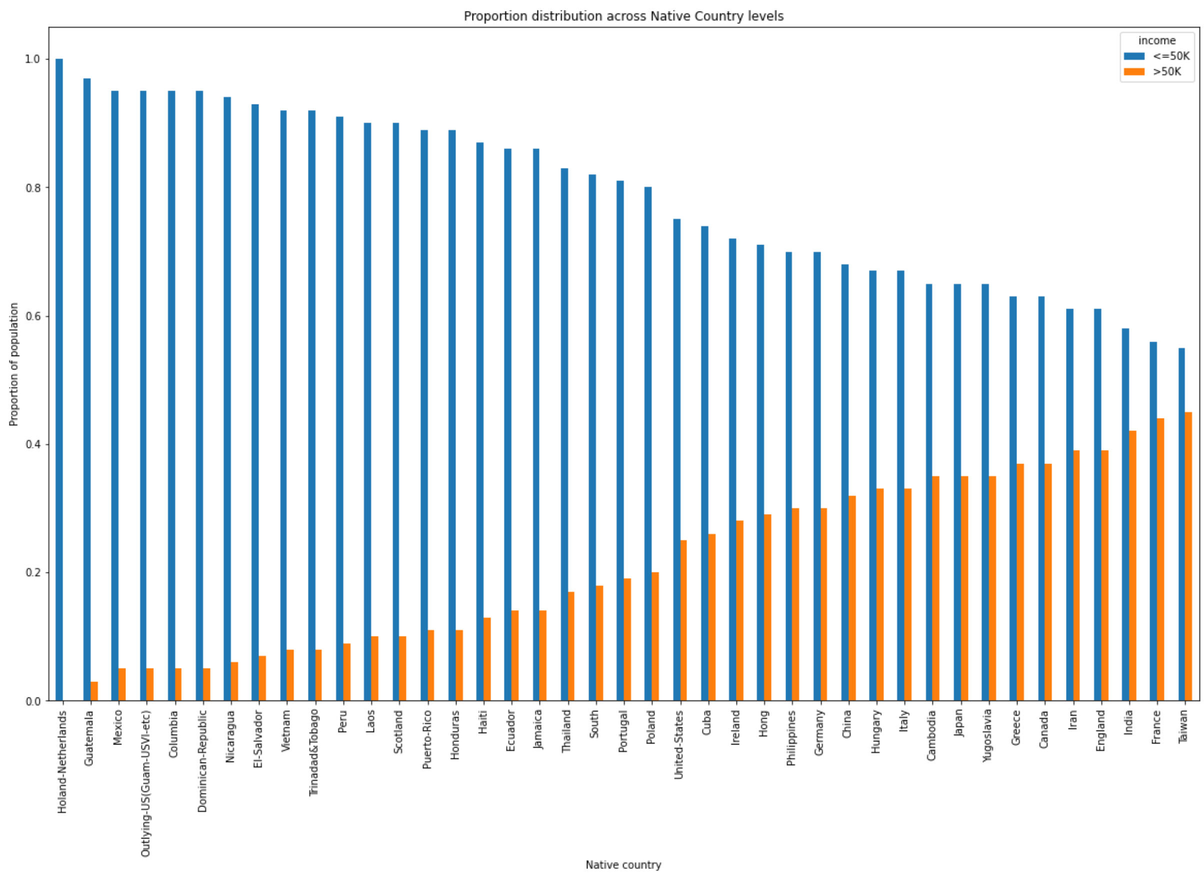
Population with Race distribution

In [ ]:
```
race = round(pd.crosstab(adult.race, adult.income).div(pd.crosstab(adult
.race, adult.income).apply(sum,1),0),2)
race.sort_values(by = '>50K', inplace = True)
ax = race.plot(kind ='bar', title = 'Proportion distribution across race
levels', figsize = (10,8))
ax.set_xlabel('Race level')
ax.set_ylabel('Proportion of population')
plt.show()
```



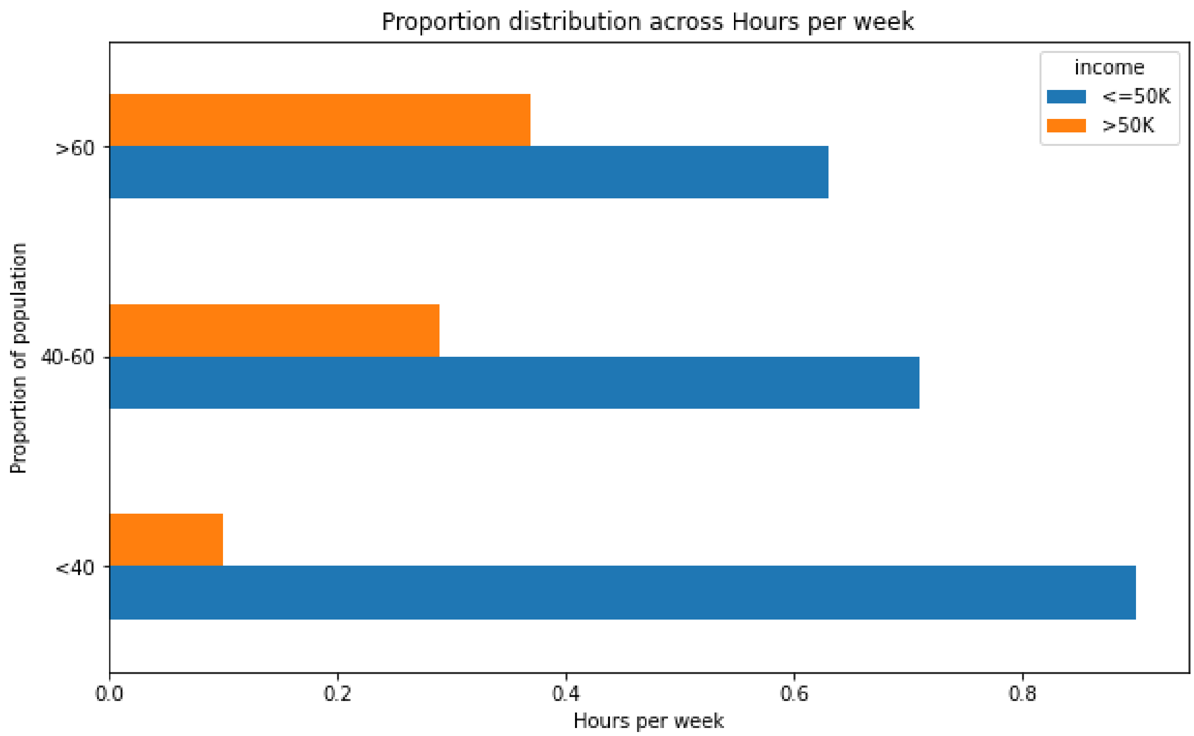
In [ ]:
```
native_country = round(pd.crosstab(adult['native-country'],
                                   adult.income).div(pd.crosstab(adult[
'native-country'], adult.income).apply(sum,1),0),2)
native_country.sort_values(by = '>50K', inplace = True)
ax = native_country.plot(kind ='bar', title = 'Proportion distribution a
cross Native Country levels', figsize = (20,12))
ax.set_xlabel('Native country')
ax.set_ylabel('Proportion of population')
```

Out[ ]:
```
Text(0, 0.5, 'Proportion of population')
```

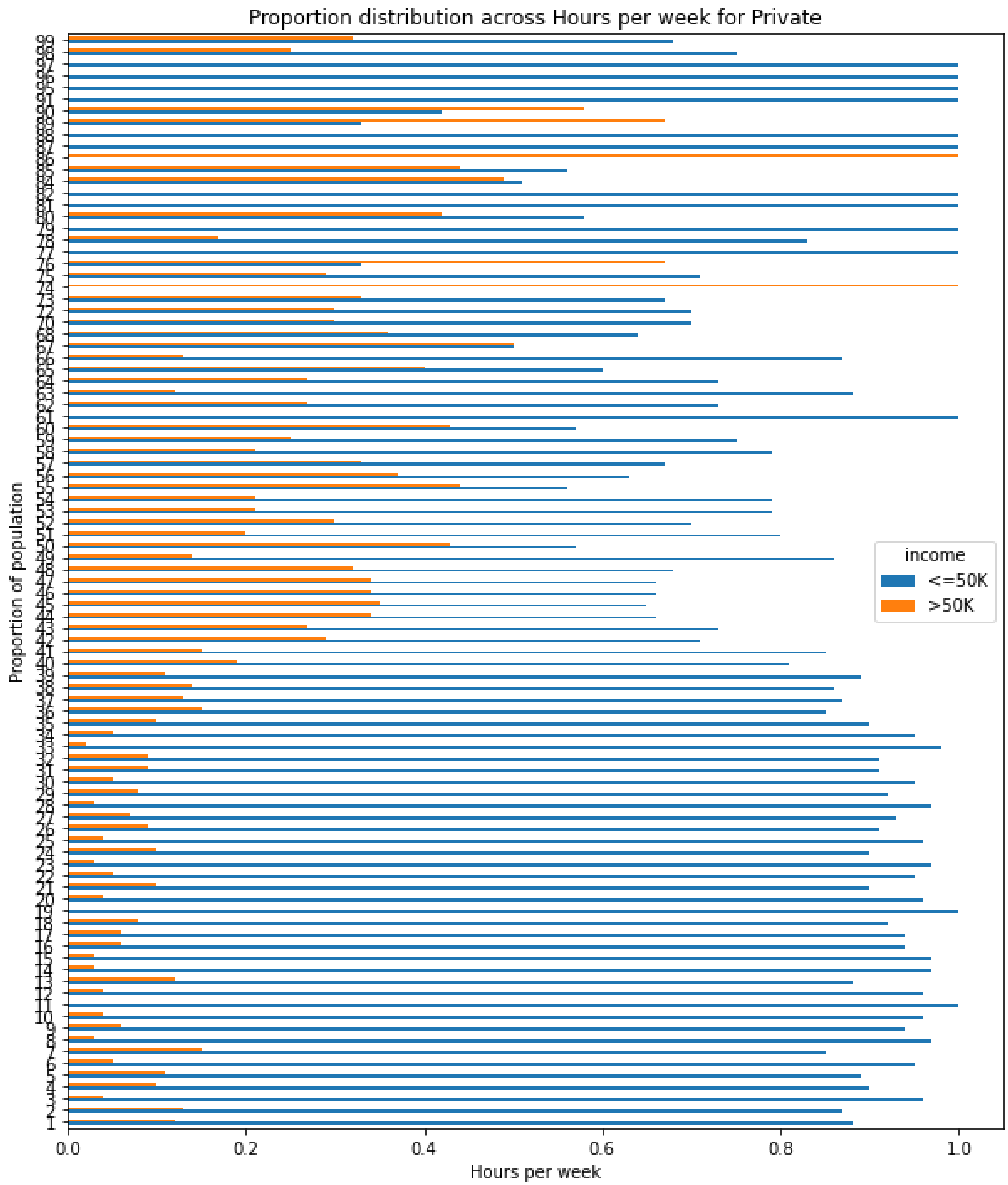


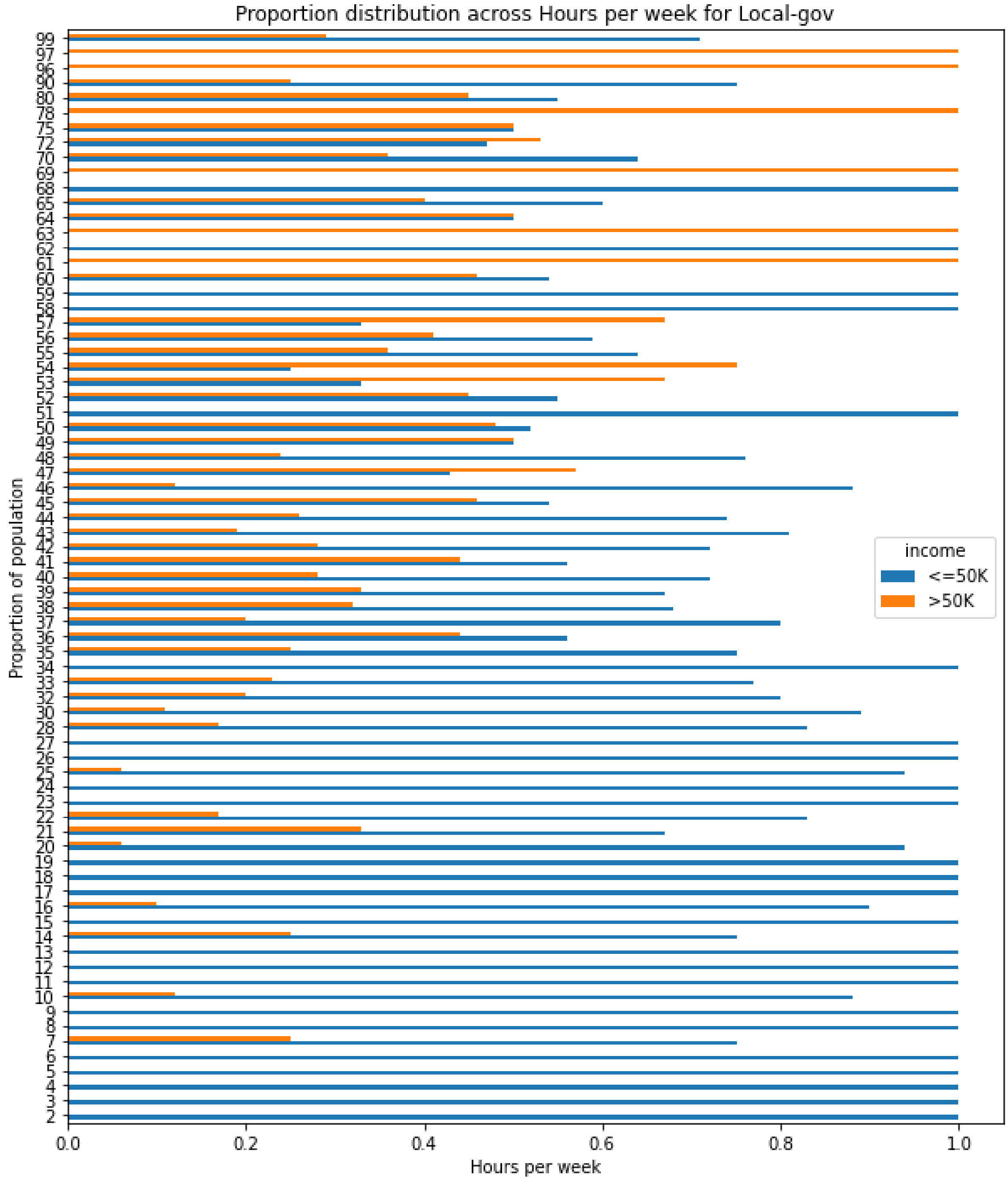
1. The above graph giving idea of the proporation of income class with the native country. we are noticing trend from the graph that south American has low proportion of people makes more than 50k.
2. On the other hand Asia, makes higher proportion of population have more than 50k a year.

In [ ]:
```
adult['hour_worked_bins'] = ['<40' if i < 40 else '40-60' if i <= 60 els
e '>60'  for i in adult['hours-per-week']]
adult['hour_worked_bins'] = adult['hour_worked_bins'].astype('category')
hours_per_week = round(pd.crosstab(adult.hour_worked_bins, adult.income)
.div(pd.crosstab(adult.hour_worked_bins, adult.income).apply(sum,1),0),2
)

hours_per_week.sort_values(by = '>50K', inplace = True)
ax = hours_per_week.plot(kind ='barh', title = 'Proportion distribution
 across Hours per week', figsize = (10,6))
ax.set_xlabel('Hours per week')
ax.set_ylabel('Proportion of population')
plt.show()
```



In [ ]:
```
for i in adult.workclass.unique():
    df = adult[adult.workclass == i]
    hours_per_week = round(pd.crosstab(df['hours-per-week'], df.income).
div(pd.crosstab(df['hours-per-week'], df.income).apply(sum,1),0),2)
    ax = hours_per_week.plot(kind ='barh', title = 'Proportion distribut
ion across Hours per week for '+ i, figsize = (10,12))
    ax.set_xlabel('Hours per week')
    ax.set_ylabel('Proportion of population')

plt.show()
```


Proportion distribution across Hours per week for Private
Proportion of population
Hours per week
income
<=50K
>50K


Proportion distribution across Hours per week for Local-gov
Proportion of population
Hours per week
income
<=50K
>50K
0.0
0.2
0.4
0.6
0.8
1.0
99
97
96
90
80
78
75
72
70
69
68
65
64
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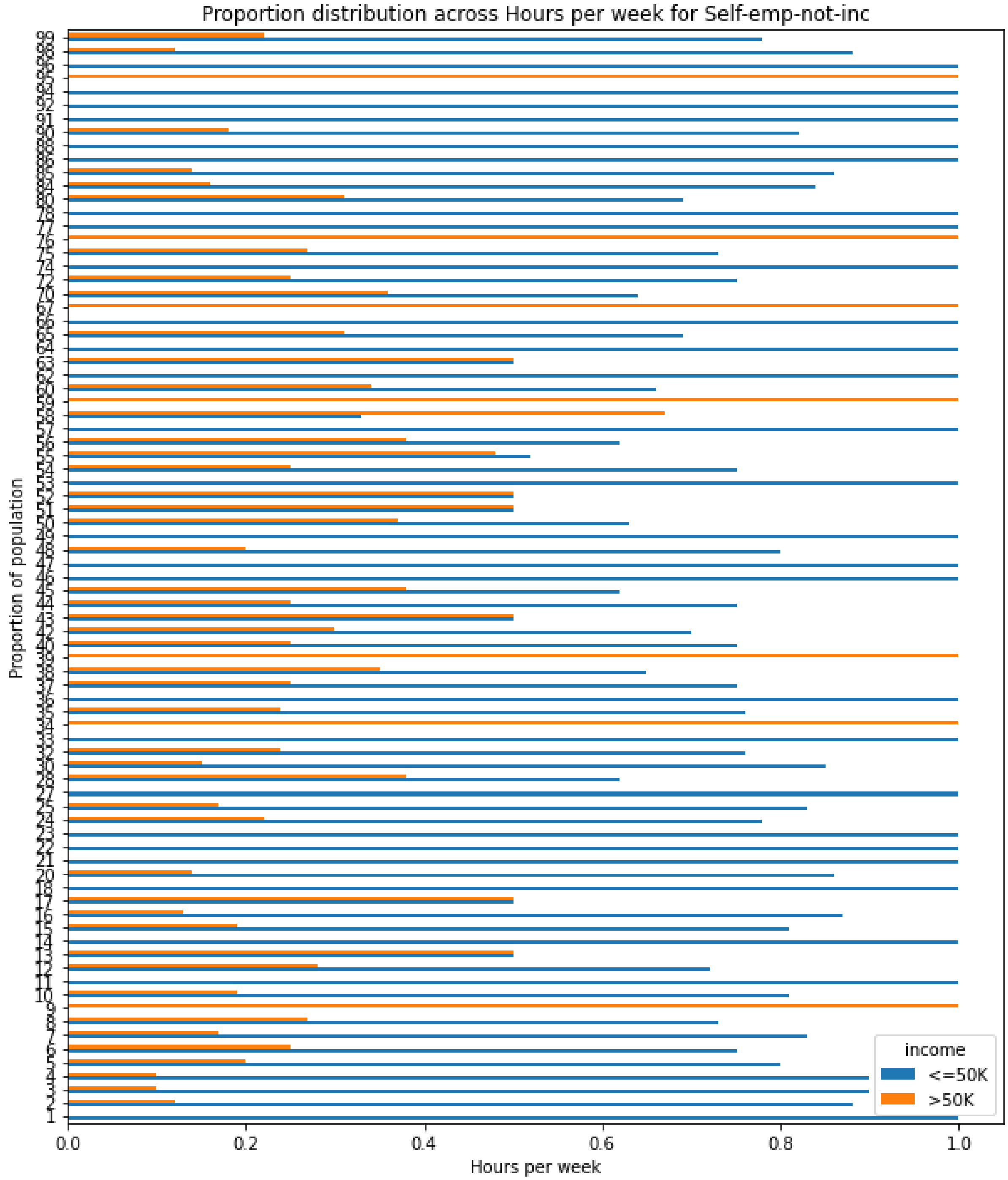
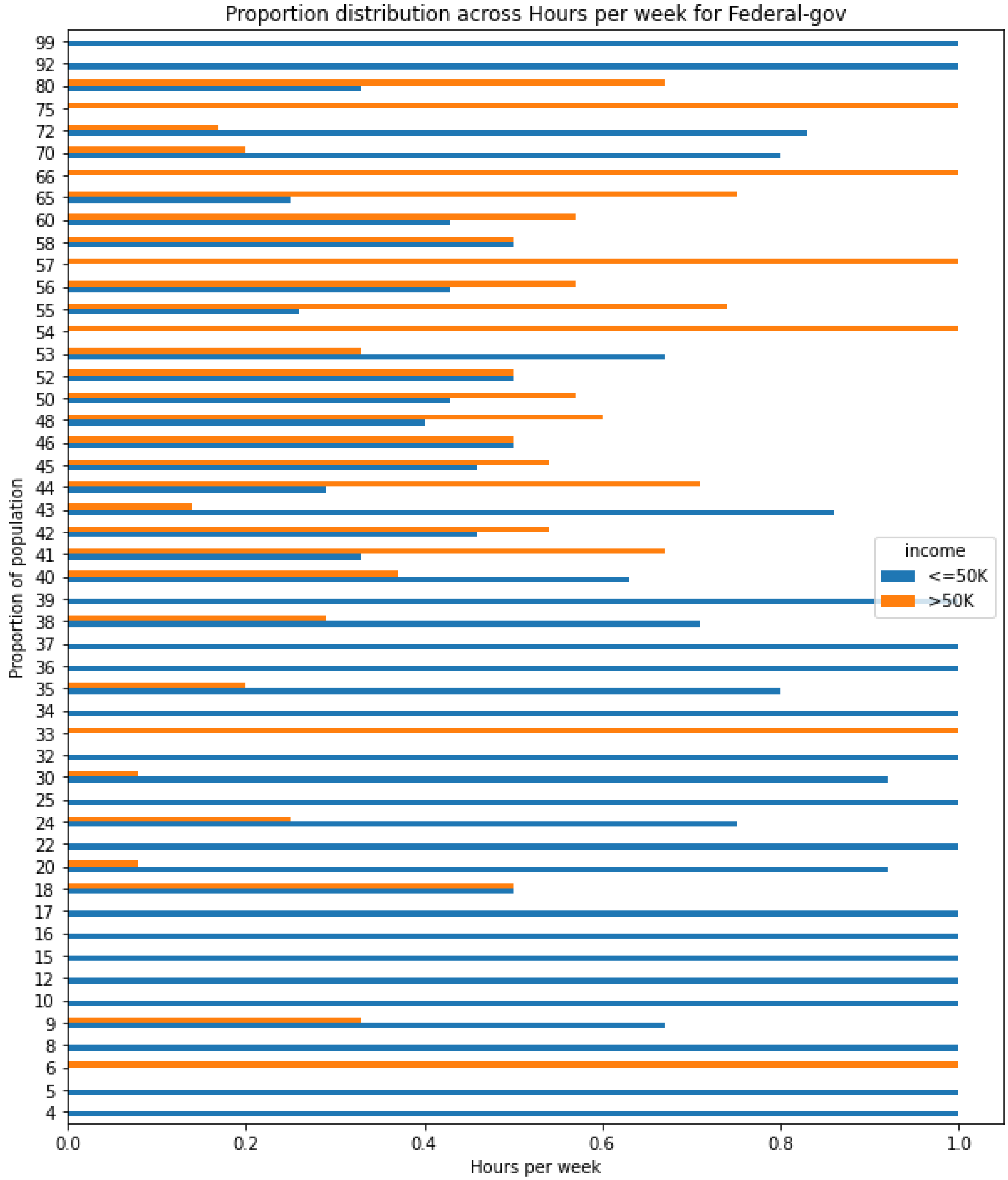

Proportion distribution across Hours per week for Self-emp-not-inc
Proportion of population
Hours per week
income
<=50K
>50K
0.0
0.2
0.4
0.6
0.8
1.0


Proportion distribution across Hours per week for Federal-gov
Proportion of population
Hours per week
income
<=50K
>50K
99
92
80
75
72
70
66
65
60
58
57
56
55
54
53
52
50
48
46
45
44
43
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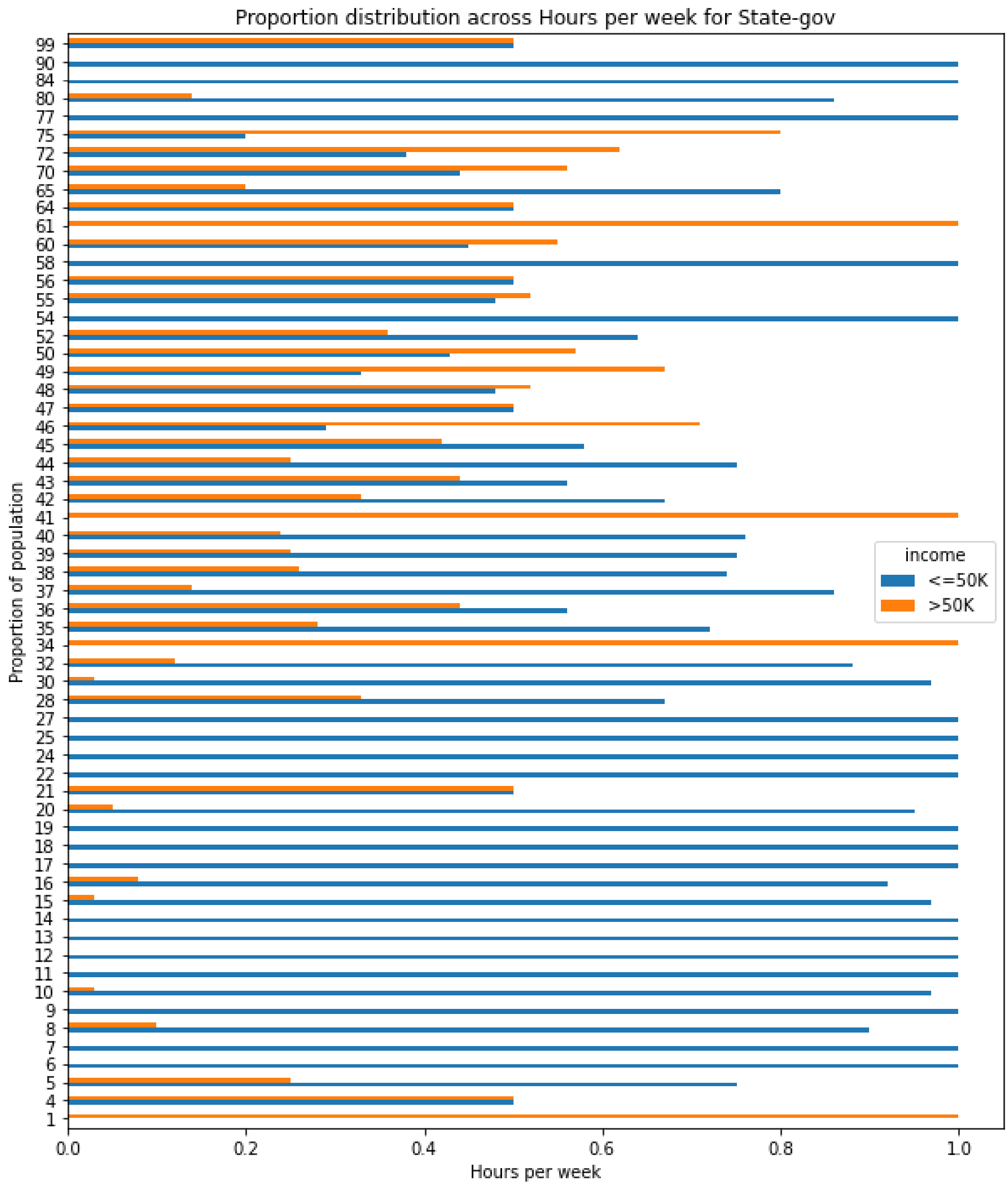
12
10
9
8
6
5
4
0.0
0.2
0.4
0.6
0.8
1.0


Proportion distribution across Hours per week for State-gov
Proportion of population
Hours per week
income
<=50K
>50K
99
90
84
80
77
75
72
70
65
64
61
60
58
56
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52
50
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14
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11
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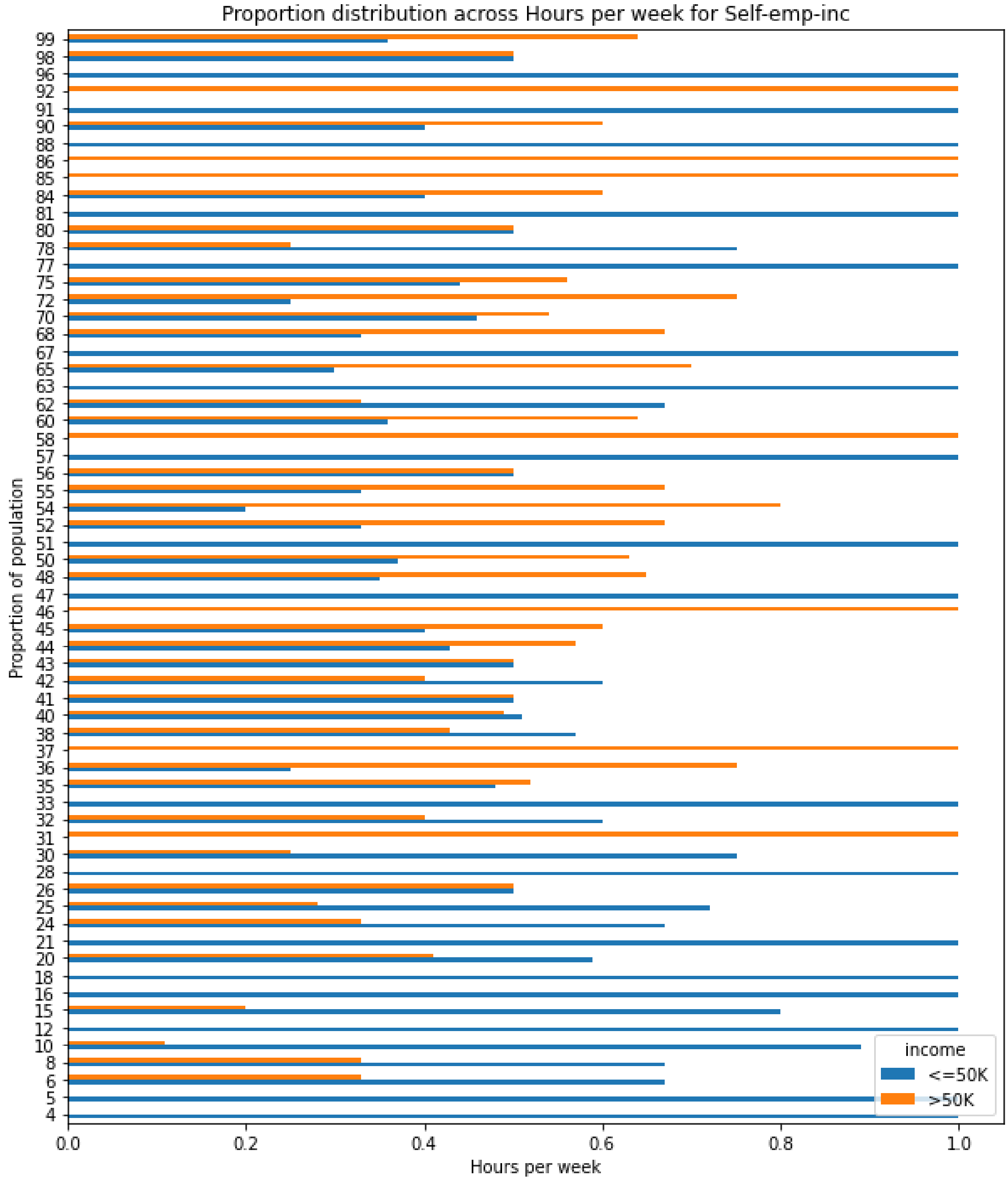
9
8
7
6
5
4
1
0.0
0.2
0.4
0.6
0.8
1.0


Proportion distribution across Hours per week for Self-emp-inc
Proportion of population
Hours per week
99
98
96
92
91
90
88
86
85
84
81
80
78
77
75
72
70
68
67
65
63
62
60
58
57
56
55
54
52
51
50
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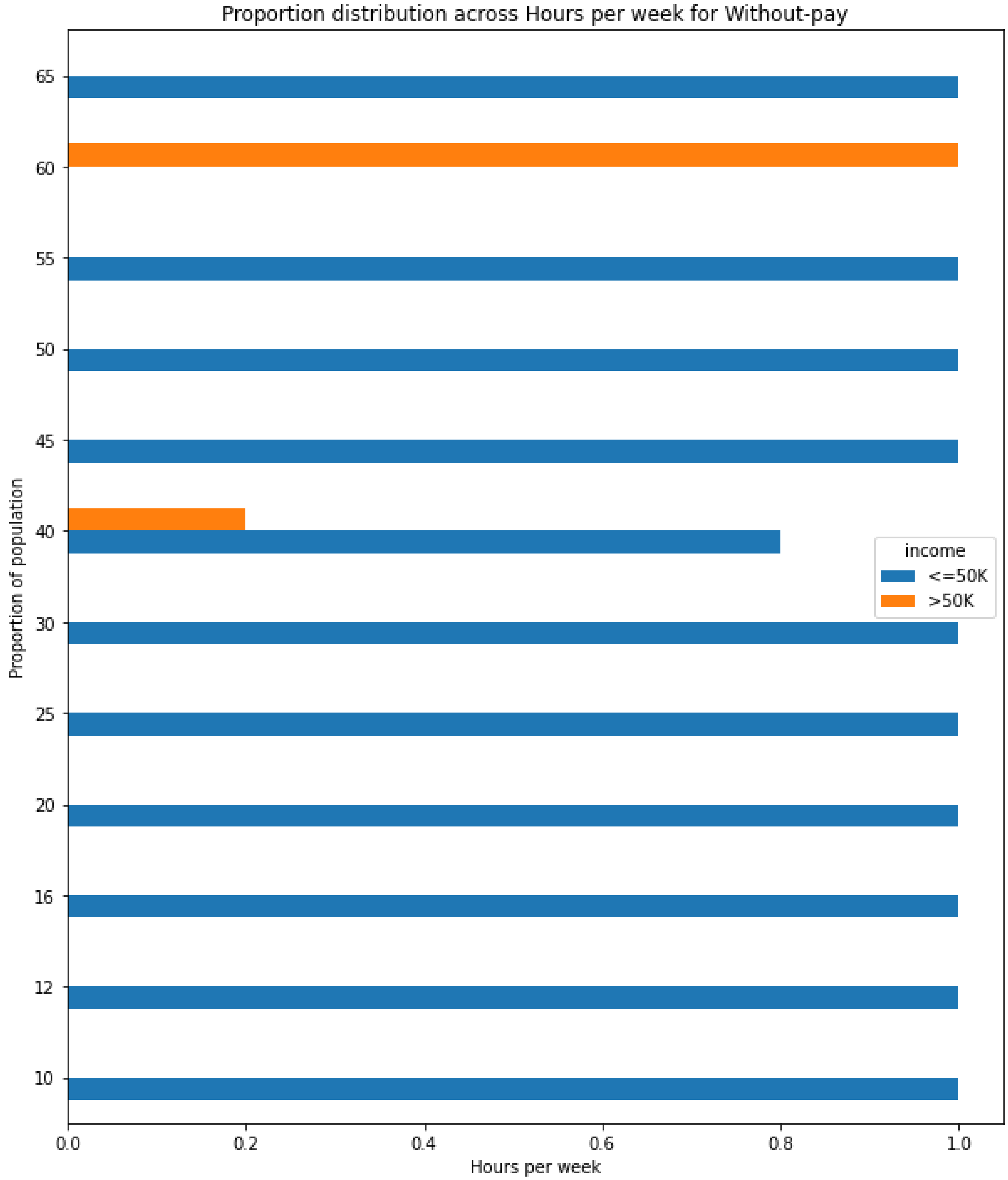
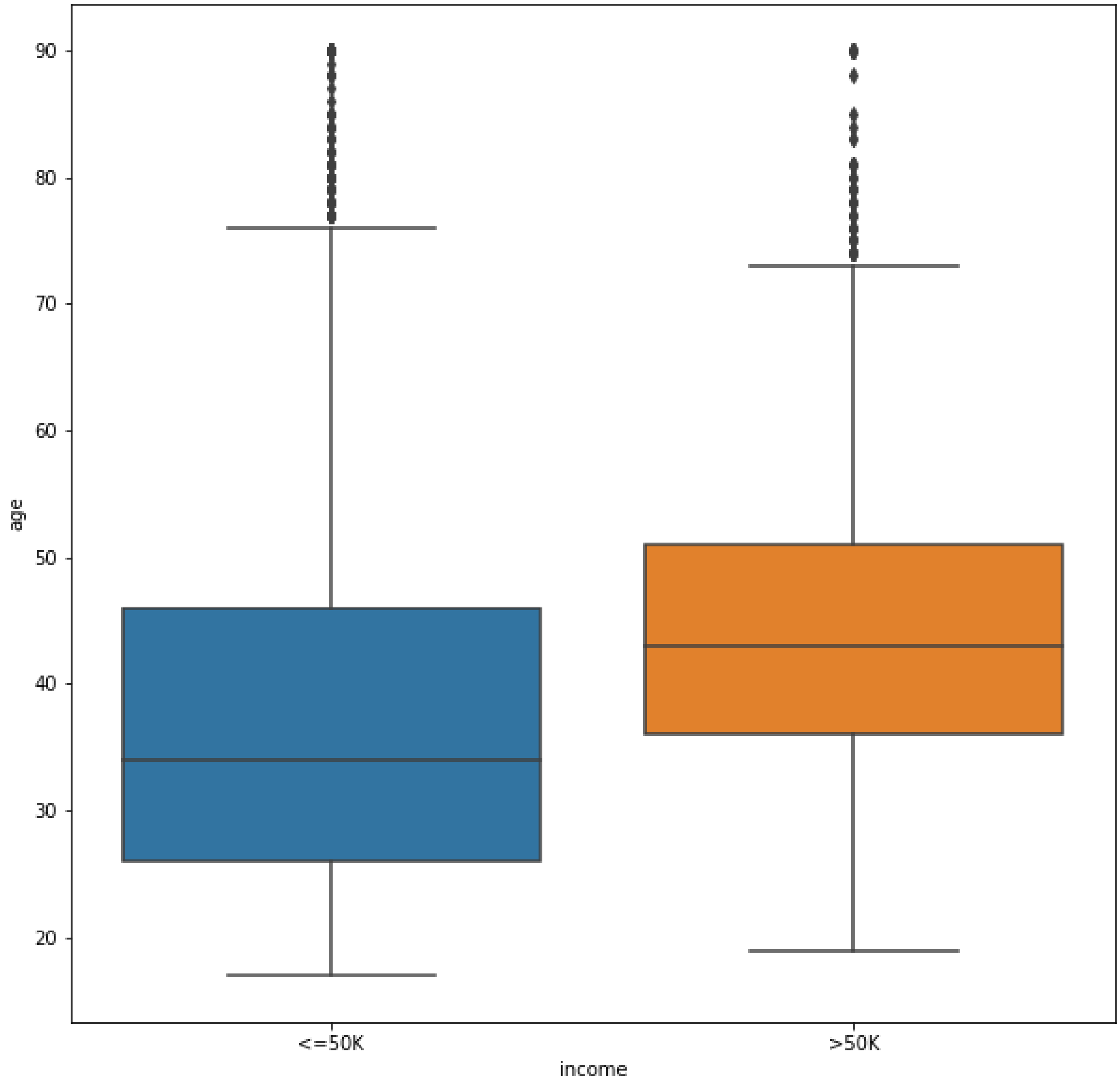
43
42
41
40
38
37
36
35
33
32
31
30
28
26
25
24
21
20
18
16
15
12
10
8
6
5
4
0.0
0.2
0.4
0.6
0.8
1.0
income
<=50K
>50K



Boxplot(Age with income)

In [ ]:
```
fig = plt.figure(figsize=(10,10))
sns.boxplot(x="income", y="age", data=adult)
plt.show()
```



In [ ]:
```
df = adult
```

In [ ]:
```
df[['income', 'age']].groupby(['income'], as_index=False).mean().sort_values(by='age', ascending=False)
```

Out[ ]:

	income	age
1	>50K	44.006067
0	<=50K	36.749427

The mean "age" for Income group(<=50k) is 36.8 years

And for Income group(>50k) is 44.2 years

Feature engineering

Machine Learning model requires input data in numerical notations to extract patterns from it and make predictions. But, not all the data provided in our source dataset is numerical. Some of the data provided are Categorical data like WorkClass, Education, Marital-Status, Occupation, Relationship, etc. we need to convert these into numerical notations.

In [ ]:
```
#running a loop of value_counts of each column to find out unique value
s.
for c in df.columns:
    print ("---- %s ---" % c)
    print (df[c].value_counts())
```

```
---- age ---
36    1283
33    1279
31    1274
35    1272
23    1241
      ...
85       5
88       5
86       1
87       1
89       1
Name: age, Length: 74, dtype: int64
---- workclass ---
Private             33307
Self-emp-not-inc     3796
Local-gov            3100
State-gov            1946
Self-emp-inc         1646
Federal-gov          1406
Without-pay            21
Name: workclass, dtype: int64
---- fnlwgt ---
203488    21
125892    18
120277    18
113364    17
126569    17
          ..
88440      1
176517     1
194956     1
201105     1
208174     1
Name: fnlwgt, Length: 26741, dtype: int64
---- education ---
HS-grad         14783
Some-college     9899
Bachelors        7570
Masters          2514
Assoc-voc        1959
11th             1619
Assoc-acdm       1507
10th             1223
7th-8th           823
Prof-school       785
9th               676
12th              577
Doctorate         544
5th-6th           449
1st-4th           222
Preschool          72
Name: education, dtype: int64
---- educational-num ---
9     14783
10     9899
13     7570
```

```
14     2514
11     1959
7      1619
12     1507
6      1223
4       823
15      785
5       676
8       577
16      544
3       449
2       222
1        72
Name: educational-num, dtype: int64
---- marital-status ---
Married-civ-spouse       21055
Never-married            14598
Divorced                  6297
Separated                 1411
Widowed                   1277
Married-spouse-absent      552
Married-AF-spouse           32
Name: marital-status, dtype: int64
---- occupation ---
Craft-repair         6020
Prof-specialty       6008
Exec-managerial      5984
Adm-clerical         5540
Sales                5408
Other-service        4808
Machine-op-inspct    2970
Transport-moving     2316
Handlers-cleaners    2046
Farming-fishing      1480
Tech-support         1420
Protective-serv       976
Priv-house-serv       232
Armed-Forces           14
Name: occupation, dtype: int64
---- relationship ---
Husband           18666
Not-in-family     11702
Own-child          6626
Unmarried          4788
Wife               2091
Other-relative     1349
Name: relationship, dtype: int64
---- race ---
White                 38903
Black                  4228
Asian-Pac-Islander     1303
Amer-Indian-Eskimo      435
Other                   353
Name: race, dtype: int64
---- gender ---
Male      30527
Female    14695
```

```
Name: gender, dtype: int64
---- capital-gain ---
0        41432
15024      498
7688       391
7298       351
99999      229
         ...
1731         1
22040        1
7262         1
1639         1
2387         1
Name: capital-gain, Length: 121, dtype: int64
---- capital-loss ---
0       43082
1902      294
1977      246
1887      228
2415       68
        ...
2201        1
1421        1
4356        1
2163        1
1870        1
Name: capital-loss, Length: 97, dtype: int64
---- hours-per-week ---
40    21358
50     4094
45     2602
60     2085
35     1776
      ...
69        1
94        1
79        1
82        1
87        1
Name: hours-per-week, Length: 96, dtype: int64
---- native-country ---
United-States                 41292
Mexico                          903
Philippines                     283
Germany                         193
Puerto-Rico                     175
Canada                          163
El-Salvador                     147
India                           147
Cuba                            133
England                         119
China                           113
Jamaica                         103
South                           101
Italy                           100
Dominican-Republic               97
Japan                            89
```

```
Guatemala                      86
Vietnam                        83
Columbia                       82
Poland                         81
Haiti                          69
Portugal                       62
Iran                           56
Taiwan                         55
Greece                         49
Nicaragua                      48
Peru                           45
Ecuador                        43
Ireland                        36
France                         36
Thailand                       29
Hong                           28
Cambodia                       26
Trinadad&Tobago                26
Yugoslavia                     23
Outlying-US(Guam-USVI-etc)     22
Laos                           21
Scotland                       20
Honduras                       19
Hungary                        18
Holand-Netherlands              1
Name: native-country, dtype: int64
---- income ---
<=50K    34014
>50K     11208
Name: income, dtype: int64
---- hour_worked_bins ---
40-60    33546
<40      10087
>60       1589
Name: hour_worked_bins, dtype: int64
```

Here we ran a for loop over all the columns using the .value_counts() function of Pandas which gets us the count of unique values.

We can see that some of the data provided are unique like the ‘workclass’ attribute which has only 7 distinct values

some columns have a lot of distinct values like fnlgwt attribute which has around 2000+ values. So, let’s drop the attributes that have noisy data.

In [ ]:
```
df.columns
```

Out[ ]:
```
Index(['age', 'workclass', 'fnlwgt', 'education', 'educational-num',
       'marital-status', 'occupation', 'relationship', 'race', 'gende
r',
       'capital-gain', 'capital-loss', 'hours-per-week', 'native-countr
y',
       'income', 'hour_worked_bins'],
      dtype='object')
```

In [ ]:
```
#dropping based on uniquness of data from the dataset
df.drop(['educational-num', 'hours-per-week', 'fnlwgt', 'capital-gain', 
'capital-loss', 'native-country','hour_worked_bins'], axis = 1, inplace=
True)
```

In [ ]:
```
df.columns
```

Out[ ]:
```
Index(['age', 'workclass', 'education', 'marital-status', 'occupation',
       'relationship', 'race', 'gender', 'income'],
      dtype='object')
```

In [ ]:
```
# Let's see how many unique categories we have in this gender property
gender = set(df['gender'])
print(gender)
```

```
{'Male', 'Female'}
```

In [ ]:
```
#Mapping the values to numerical values
#gender
df['gender'] = df['gender'].map({'Male': 0, 'Female': 1}).astype(int)

#race
df['race'] = df['race'].map({'Black': 0, 'Asian-Pac-Islander': 1, 'Othe
r': 2, 'White': 3, 'Amer-Indian-Eskimo': 4}).astype(int)

#marital
df['marital-status'] = df['marital-status'].map({'Married-spouse-absent'
: 0, 'Widowed': 1, 'Married-civ-spouse': 2, 'Separated': 3, 'Divorced': 
4,'Never-married': 5, 'Married-AF-spouse': 6}).astype(int)

#workclass
df['workclass'] = df['workclass'].map({'Self-emp-inc': 0, 'State-gov': 1
,'Federal-gov': 2, 'Without-pay': 3, 'Local-gov': 4,'Private': 5, 'Self-
emp-not-inc': 6}).astype(int)

#education
df['education'] = df['education'].map({'Some-college': 0, 'Preschool': 1
, '5th-6th': 2, 'HS-grad': 3, 'Masters': 4, '12th': 5, '7th-8th': 6, 'Pr
of-school': 7,'1st-4th': 8, 'Assoc-acdm': 9, 'Doctorate': 10, '11th': 11
,'Bachelors': 12, '10th': 13,'Assoc-voc': 14,'9th': 15}).astype(int)

#occupation
df['occupation'] = df['occupation'].map({ 'Farming-fishing': 1, 'Tech-su
pport': 2, 'Adm-clerical': 3, 'Handlers-cleaners': 4, 
 'Prof-specialty': 5,'Machine-op-inspct': 6, 'Exec-managerial': 7,'Priv-
house-serv': 8,'Craft-repair': 9,'Sales': 10, 'Transport-moving': 11, 'A
rmed-Forces': 12, 'Other-service': 13,'Protective-serv':14}).astype(int)

#relationship
df['relationship'] = df['relationship'].map({'Not-in-family': 0, 'Wife': 
1, 'Other-relative': 2, 'Unmarried': 3,'Husband': 4,'Own-child': 5}).ast
ype(int)
```

In [ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 45222 entries, 0 to 48841
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             45222 non-null  int64
 1   workclass       45222 non-null  int64
 2   education       45222 non-null  int64
 3   marital-status  45222 non-null  int64
 4   occupation      45222 non-null  int64
 5   relationship    45222 non-null  int64
 6   race            45222 non-null  int64
 7   gender          45222 non-null  int64
 8   income          45222 non-null  object
dtypes: int64(8), object(1)
memory usage: 4.7+ MB
```

In [ ]:
```
# Let's see how many unique categories we have in this property
income = set(df['income'])
print(income)
```

```
{'<=50K', '>50K'}
```

In [ ]:
```
#mapping the data into numerical data using map function
df['income'] = df['income'].map({'<=50K': 0, '>50K': 1}).astype(int)
```

In [ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 45222 entries, 0 to 48841
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             45222 non-null  int64
 1   workclass       45222 non-null  int64
 2   education       45222 non-null  int64
 3   marital-status  45222 non-null  int64
 4   occupation      45222 non-null  int64
 5   relationship    45222 non-null  int64
 6   race            45222 non-null  int64
 7   gender          45222 non-null  int64
 8   income          45222 non-null  int64
dtypes: int64(9)
memory usage: 4.7 MB
```

In [ ]:
```
df.head(5)
```

Out[ ]:

	age	workclass	education	marital-status	occupation	relationship	race	gender	income
0	25	5	11	5	6	5	0	0	0
1	38	5	3	2	1	4	3	0	0
2	28	4	9	2	14	4	3	0	1
3	44	5	0	2	6	4	0	0	1
5	34	5	13	5	13	0	3	0	0

Splitting the dataset into 70% of training and 30% testing data

In [ ]:
```
scaler = StandardScaler()
df1 = df.drop('income', axis=1)
X = scaler.fit_transform(df1)
y = df['income']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
random_state=11310)
```

Random Forest

In [ ]:
```
rf = RandomForestClassifier(n_estimators=150, random_state=123,max_depth
=6)
rf.fit(X_train, y_train)
```

Out[ ]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=Non
e,
                       criterion='gini', max_depth=6, max_features='aut
o',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=No
ne,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=150,
                       n_jobs=None, oob_score=False, random_state=123,
                       verbose=0, warm_start=False)
```

In [ ]:
```
y_pred = rf.predict(X_test)
print('Accuracy of Random Forest Classifier', metrics.accuracy_score(y_t
est, y_pred))
```

```
Accuracy of Random Forest Classifier 0.8146237193189356
```

Decision tree

In [ ]:
```
tree = DecisionTreeClassifier(max_depth=10, random_state=123)
tree.fit(X_train, y_train)
y_pred1= tree.predict(X_test)
print('Accuracy of Decision tree:', metrics.accuracy_score(y_test, y_pre
d1))
```

```
Accuracy of Decision tree: 0.8143288862681507
```

Random forest with grid search cv

In [ ]:
```
rfc=RandomForestClassifier(random_state=42)
param_grid = {
    'n_estimators': [200, 500],
    'max_features': ['auto', 'sqrt', 'log2'],
    'max_depth' : [4,5,6,7,8],
    'criterion' :['gini', 'entropy']
}
CV_rfc = GridSearchCV(estimator=rfc, param_grid=param_grid, cv= 5)
CV_rfc.fit(X_train, y_train)
```

Out[ ]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=RandomForestClassifier(bootstrap=True, ccp_alpha
=0.0,
                                              class_weight=None,
                                              criterion='gini', max_dep
th=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_s
tate=42,
                                              verbose=0, warm_start=Fal
se),
             iid='deprecated', n_jobs=None,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [4, 5, 6, 7, 8],
                         'max_features': ['auto', 'sqrt', 'log2'],
                         'n_estimators': [200, 500]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=Fa
lse,
             scoring=None, verbose=0)
```

In [ ]:
```
CV_rfc.best_params_
```

Out[ ]:
```
{'criterion': 'gini',
 'max_depth': 8,
 'max_features': 'log2',
 'n_estimators': 500}
```

In [ ]:
```
rfc1 = RandomForestClassifier(random_state=42, max_features='log2', n_es
timators= 500, max_depth=8, criterion='gini')
```

In [ ]:
```
rfc1.fit(X_train, y_train)
```

Out[ ]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=Non
e,
                       criterion='gini', max_depth=8, max_features='log
2',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=No
ne,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=500,
                       n_jobs=None, oob_score=False, random_state=42, v
erbose=0,
                       warm_start=False)
```

In [ ]:
```
y_pred2 = rfc1.predict(X_test)
print('Accuracy of Random Forest tree with grid search:', metrics.accura
cy_score(y_test, y_pred2))
```

```
Accuracy of Random Forest tree with grid search: 0.8240583769440555
```

Decision tree with grid search cv

In [ ]:
```
decision_tree = DecisionTreeClassifier()
decision_tree.fit(X_train, y_train)
```

Out[ ]:
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gin
i',
                       max_depth=None, max_features=None, max_leaf_node
s=None,
                       min_impurity_decrease=0.0, min_impurity_split=No
ne,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecate
d',
                       random_state=None, splitter='best')
```

In [ ]:
```
param_dict = {
    'min_samples_split': range(1,10),
    'max_depth': range(1,10),
    'min_samples_leaf' : range(1,5),
    'criterion' :['gini', 'entropy']
}
grid = GridSearchCV(decision_tree, param_grid=param_dict, cv=5, verbose=
1, n_jobs=-1)
grid.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 648 candidates, totalling 3240 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent work
ers.
[Parallel(n_jobs=-1)]: Done 202 tasks      | elapsed:    3.4s
[Parallel(n_jobs=-1)]: Done 1402 tasks      | elapsed:   26.0s
[Parallel(n_jobs=-1)]: Done 3240 out of 3240 | elapsed:  1.0min finishe
d
```

Out[ ]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=DecisionTreeClassifier(ccp_alpha=0.0, class_weig
ht=None,
                                              criterion='gini', max_dep
th=None,
                                              max_features=None,
                                              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,
                                              presort='deprecated',
                                              random_state=None,
                                              splitter='best'),
             iid='deprecated', n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': range(1, 10),
                         'min_samples_leaf': range(1, 5),
                         'min_samples_split': range(1, 10)},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=Fa
lse,
             scoring=None, verbose=1)
```

In [ ]:
```
grid.best_params_
```

Out[ ]:
```
{'criterion': 'entropy',
 'max_depth': 9,
 'min_samples_leaf': 4,
 'min_samples_split': 8}
```

In [ ]:
```
decision_tree1 = DecisionTreeClassifier(criterion = 'entropy',
 max_depth = 9,
 min_samples_leaf = 4,
 min_samples_split = 4)
```

In [ ]:
```
decision_tree1.fit(X_train, y_train)
```

Out[ ]:
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='ent
ropy',
                       max_depth=9, max_features=None, max_leaf_nodes=N
one,
                       min_impurity_decrease=0.0, min_impurity_split=No
ne,
                       min_samples_leaf=4, min_samples_split=4,
                       min_weight_fraction_leaf=0.0, presort='deprecate
d',
                       random_state=None, splitter='best')
```

In [ ]:
```
y_pred3 = decision_tree1.predict(X_test)
print('Accuracy of Decision tree with grid search:', metrics.accuracy_sc
ore(y_test, y_pred3))
```

```
Accuracy of Decision tree with grid search: 0.8152133854205056
```

Ada boost classifier

In [ ]:
```
from sklearn.ensemble import AdaBoostClassifier

ada = AdaBoostClassifier(n_estimators=100)
ada.fit(X_train, y_train)
ada_pred = ada.predict(X_test)
print('Accuracy of Adaboost:', metrics.accuracy_score(y_test, ada_pred))
```

```
Accuracy of Adaboost: 0.8283334561804379
```

Conclusion

- In the project, we have seen the highest accuracy was obatined from the **Adaboost classifier model.** The best accuracy we got on this dataset was **82.833%.**
- The accuracy was close to each other but Adaboost gave slightly better accuracy as compared to other two models which was used in this project.

TYPES OF MODEL	ACCURACY
RANDOM FOREST	81.462%
DECISION TREE	81.432%
RANDOM FOREST WITH GRID SEARCH	82.405%
DECISION TREE WITH GRID SEARCH	81.521%
ADABOOST	82.833%

What we have learned form this project?

We have learned so many concepts and practiced of machine learning, those are listed below:

1. We have learned about how to find out different types of analysis in EDA like three variable together (Population with work class distribution with Income)
2. In feature engineering we have learned about mapping and then using this function StandardScaler() to normalize data
3. Here we explored more deeper in scikit-learn libraries and its functions
4. We have learned several machine learning classifier models and Grid Search technique with deep understanding
5. Learning about how classifiers fits into the data and then comparing which classifiers are great for the model
6. Learning new concepts and methods to get accurate results in this test.

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