Adult_Income_Analysis

February 19, 2020

0.1 Outline:

1. Preliminary Data Analysis
2. Exploratory Data Analysis
3. Data Transformations
4. Model Development & Classification
5. Model Evaluation
6. Conclusion

[1]:

```
#importing necessary libraries
import pandas as pd
from IPython.display import Markdown, display
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc
import numpy as np
from sklearn import metrics

def printmd(string):
    display(Markdown(string))


from sklearn.linear_model import LogisticRegression
from sklearn import svm
from sklearn import tree
from sklearn.ensemble import RandomForestClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.ensemble import AdaBoostClassifier
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
```

[2]:
```python
#importing the raw data files as well as with cross validation performed
adult = pd.read_csv('adult.csv')
column_names = ['age', 'workclass', 'fnlwgt', 'education',␣
 ↪'educational-num','marital-status', 'occupation', 'relationship', 'race',␣
 ↪'gender','capital-gain', 'capital-loss', 'hours-per-week',␣
 ↪'native-country','income']

train = pd.read_csv('adult_data.txt', sep=",\s", header=None, names =␣
 ↪column_names, engine = 'python')
test = pd.read_csv('adult_test.txt', sep=",\s", header=None, names =␣
 ↪column_names, engine = 'python')
test['income'].replace(regex=True,inplace=True,to_replace=r'\.',value=r'')

adult = pd.concat([test,train])
adult.reset_index(inplace = True, drop = True)
```

---

1 1. Preliminary Data Analysis

[3]:
```python
# Setting all the categorical columns to type category
for col in set(adult.columns) - set(adult.describe().columns):
    adult[col] = adult[col].astype('category')

printmd('## 1.1 Columns and their types')
print(adult.info())
```

1.1 1.1 Columns and their types

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48842 entries, 0 to 48841
Data columns (total 15 columns):
age                48842 non-null int64
workclass          48842 non-null category
fnlwgt             48842 non-null int64
education          48842 non-null category
educational-num    48842 non-null int64
marital-status     48842 non-null category
occupation         48842 non-null category
relationship       48842 non-null category
race               48842 non-null category
gender             48842 non-null category
capital-gain       48842 non-null int64
capital-loss       48842 non-null int64
hours-per-week     48842 non-null int64
native-country     48842 non-null category
```

```
income             48842 non-null category
dtypes: category(9), int64(6)
memory usage: 2.7 MB
None
```

[4]:
```
adult.head()
```

[4]:
```
   age  workclass  fnlwgt     education  educational-num      marital-status  \
0   25    Private  226802          11th                7       Never-married
1   38    Private   89814       HS-grad                9  Married-civ-spouse
2   28  Local-gov  336951    Assoc-acdm               12  Married-civ-spouse
3   44    Private  160323  Some-college               10  Married-civ-spouse
4   18          ?  103497  Some-college               10       Never-married

          occupation relationship   race  gender  capital-gain  capital-loss  \
0  Machine-op-inspct    Own-child  Black    Male             0             0
1    Farming-fishing      Husband  White    Male             0             0
2    Protective-serv      Husband  White    Male             0             0
3  Machine-op-inspct      Husband  Black    Male          7688             0
4                  ?    Own-child  White  Female             0             0

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

[5]:
```
printmd('## 1.2 Summary Statistics')
adult.describe()
```

1.2 1.2 Summary Statistics

[5]:
```
                age        fnlwgt  educational-num  capital-gain  \
count  48842.000000  4.884200e+04     48842.000000  48842.000000
mean      38.643585  1.896641e+05        10.078089   1079.067626
std       13.710510  1.056040e+05         2.570973   7452.019058
min       17.000000  1.228500e+04         1.000000      0.000000
25%       28.000000  1.175505e+05         9.000000      0.000000
50%       37.000000  1.781445e+05        10.000000      0.000000
75%       48.000000  2.376420e+05        12.000000      0.000000
max       90.000000  1.490400e+06        16.000000  99999.000000

       capital-loss  hours-per-week
count  48842.000000    48842.000000
mean      87.502314       40.422382
std      403.004552       12.391444
```

```
min         0.000000        1.000000
25%         0.000000       40.000000
50%         0.000000       40.000000
75%         0.000000       45.000000
max      4356.000000       99.000000
```

[6]:
```
# Checking for missing values
printmd('## 1.3 Missing values')
for i,j in zip(adult.columns,(adult.values.astype(str) == '?').sum(axis = 0)):
    if j > 0:
        printmd(str(i) + ': ' + str(j) + ' records')
```

1.3 1.3 Missing values

workclass: 2799 records

occupation: 2809 records

native-country: 857 records

1.3.1 Replacing missing values with appropriate ones

I fill the missing values in each of the three columns by predicting their values. For each of the three columns, I use all the attributes (including 'income') as independent variables and treat that column as the dependent variable, making it a multi-class classification task. I use three classification algorithms, namely, logistic regression, decision trees and random forest to predict the class when the value is missing ('?'). I then take a majority vote amongst the three classifiers to be the class of the missing value. In case of a tie, I pick the majority class of that column using the entire dataset.

[7]:
```
# Create one hot encoding of the categorical columns in the data frame.
def oneHotCatVars(df, df_cols):

    df_1 = adult_data = df.drop(columns = df_cols, axis = 1)
    df_2 = pd.get_dummies(df[df_cols])

    return (pd.concat([df_1, df_2], axis=1, join='inner'))
```

[8]:
```
printmd('## 1.4 Filling in missing values for Attribute workclass')

test_data = adult[(adult.workclass.values == '?')].copy()
test_label = test_data.workclass

train_data = adult[(adult.workclass.values != '?')].copy()
train_label = train_data.workclass

test_data.drop(columns = ['workclass'], inplace = True)
train_data.drop(columns = ['workclass'], inplace = True)
```

```
train_data = oneHotCatVars(train_data, train_data.select_dtypes('category').
 ↪columns)
test_data = oneHotCatVars(test_data, test_data.select_dtypes('category').
 ↪columns)

log_reg = LogisticRegression()
log_reg.fit(train_data, train_label)
log_reg_pred = log_reg.predict(test_data)


clf = tree.DecisionTreeClassifier()
clf = clf.fit(train_data, train_label)
clf_pred = clf.predict(test_data)

r_forest = RandomForestClassifier(n_estimators=10)
r_forest.fit(train_data, train_label)
r_forest_pred = r_forest.predict(test_data)

majority_class = adult.workclass.value_counts().index[0]

pred_df =  pd.DataFrame({'RFor': r_forest_pred, 'DTree' : clf_pred, 'LogReg' :␣
 ↪log_reg_pred})
overall_pred = pred_df.apply(lambda x: x.value_counts().index[0] if x.
 ↪value_counts()[0] > 1 else majority_class, axis = 1)

adult.loc[(adult.workclass.values == '?'),'workclass'] = overall_pred.values
print(adult.workclass.value_counts())
print(adult.workclass.unique())
```

1.4 1.4 Filling in missing values for Attribute workclass

```
/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.py:432:
FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify a
solver to silence this warning.
  FutureWarning)
/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.py:469:
FutureWarning: Default multi_class will be changed to 'auto' in 0.22. Specify
the multi_class option to silence this warning.
  "this warning.", FutureWarning)
```

```
Private             36346
Self-emp-not-inc     3872
Local-gov            3138
State-gov            1983
Self-emp-inc         1696
Federal-gov          1432
Never-worked          354
```

```
Without-pay            21
?                       0
Name: workclass, dtype: int64
[Private, Local-gov, Self-emp-not-inc, Federal-gov, State-gov, Self-emp-inc,
Never-worked, Without-pay]
Categories (8, object): [Private, Local-gov, Self-emp-not-inc, Federal-gov,
State-gov, Self-emp-inc, Never-worked, Without-pay]
```

[9]:

```
printmd('## 1.5 Filling in missing values for Occupation occupation')

test_data = adult[(adult.occupation.values == '?')].copy()
test_label = test_data.occupation

train_data = adult[(adult.occupation.values != '?')].copy()
train_label = train_data.occupation

test_data.drop(columns = ['occupation'], inplace = True)
train_data.drop(columns = ['occupation'], inplace = True)

train_data = oneHotCatVars(train_data, train_data.select_dtypes('category').
 ↪columns)
test_data = oneHotCatVars(test_data, test_data.select_dtypes('category').
 ↪columns)

log_reg = LogisticRegression()
log_reg.fit(train_data, train_label)
log_reg_pred = log_reg.predict(test_data)


clf = tree.DecisionTreeClassifier()
clf = clf.fit(train_data, train_label)
clf_pred = clf.predict(test_data)

r_forest = RandomForestClassifier(n_estimators=10)
r_forest.fit(train_data, train_label)
r_forest_pred = r_forest.predict(test_data)


majority_class = adult.occupation.value_counts().index[0]

pred_df =  pd.DataFrame({'RFor': r_forest_pred, 'DTree' : clf_pred, 'LogReg' :␣
 ↪log_reg_pred})
overall_pred = pred_df.apply(lambda x: x.value_counts().index[0] if x.
 ↪value_counts()[0] > 1 else majority_class, axis = 1)

adult.loc[(adult.occupation.values == '?'),'occupation'] = overall_pred.values
print(adult.occupation.value_counts())
```

```
print(adult.occupation.unique())
```

1.5 1.5 Filling in missing values for Occupation occupation

```
/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.py:432:
FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify a
solver to silence this warning.
  FutureWarning)
/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.py:469:
FutureWarning: Default multi_class will be changed to 'auto' in 0.22. Specify
the multi_class option to silence this warning.
  "this warning.", FutureWarning)
```

```
Prof-specialty       7761
Craft-repair         6398
Exec-managerial      6173
Adm-clerical         5870
Sales                5637
Other-service        5194
Machine-op-inspct    3077
Transport-moving     2398
Handlers-cleaners    2109
Farming-fishing      1501
Tech-support         1465
Protective-serv       990
Priv-house-serv       254
Armed-Forces           15
?                       0
Name: occupation, dtype: int64
[Machine-op-inspct, Farming-fishing, Protective-serv, Prof-specialty, Other-
service, …, Tech-support, Sales, Priv-house-serv, Transport-moving, Armed-
Forces]
Length: 14
Categories (14, object): [Machine-op-inspct, Farming-fishing, Protective-serv,
Prof-specialty, …, Sales, Priv-house-serv, Transport-moving, Armed-Forces]
```

[10]:
```
printmd('## 1.6 Filling in missing values for Native Country')

test_data = adult[(adult['native-country'].values == '?')].copy()
test_label = test_data['native-country']

train_data = adult[(adult['native-country'].values != '?')].copy()
train_label = train_data['native-country']

test_data.drop(columns = ['native-country'], inplace = True)
train_data.drop(columns = ['native-country'], inplace = True)
```

```
train_data = oneHotCatVars(train_data, train_data.select_dtypes('category').
 ↪columns)
test_data = oneHotCatVars(test_data, test_data.select_dtypes('category').
 ↪columns)

log_reg = LogisticRegression()
log_reg.fit(train_data, train_label)
log_reg_pred = log_reg.predict(test_data)


clf = tree.DecisionTreeClassifier()
clf = clf.fit(train_data, train_label)
clf_pred = clf.predict(test_data)

r_forest = RandomForestClassifier(n_estimators=10)
r_forest.fit(train_data, train_label)
r_forest_pred = r_forest.predict(test_data)


majority_class = adult['native-country'].value_counts().index[0]

pred_df =  pd.DataFrame({'RFor': r_forest_pred, 'DTree' : clf_pred, 'LogReg' :␣
 ↪log_reg_pred})
overall_pred = pred_df.apply(lambda x: x.value_counts().index[0] if x.
 ↪value_counts()[0] > 1 else majority_class, axis = 1)

adult.loc[(adult['native-country'].values == '?'),'native-country'] =␣
 ↪overall_pred.values
print(adult['native-country'].value_counts())
print(adult['native-country'].unique())
```

1.6 1.6 Filling in missing values for Native Country

```
/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.py:432:
FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify a
solver to silence this warning.
  FutureWarning)
/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.py:469:
FutureWarning: Default multi_class will be changed to 'auto' in 0.22. Specify
the multi_class option to silence this warning.
  "this warning.", FutureWarning)
/opt/anaconda3/lib/python3.7/site-packages/sklearn/svm/base.py:929:
ConvergenceWarning: Liblinear failed to converge, increase the number of
iterations.
  "the number of iterations.", ConvergenceWarning)
```

```
United-States                 44638
```

```
Mexico                          964
Philippines                     305
Germany                         206
Puerto-Rico                     184
Canada                          182
India                           156
El-Salvador                     155
Cuba                            138
China                           127
England                         127
South                           121
Jamaica                         107
Italy                           105
Dominican-Republic              104
Japan                            95
Guatemala                        88
Poland                           87
Vietnam                          86
Columbia                         85
Haiti                            75
Taiwan                           67
Portugal                         67
Iran                             59
Nicaragua                        49
Greece                           49
Peru                             46
Ecuador                          46
France                           38
Ireland                          37
Hong                             32
Thailand                         31
Cambodia                         28
Trinadad&Tobago                  27
Laos                             24
Yugoslavia                       23
Outlying-US(Guam-USVI-etc)       23
Scotland                         21
Honduras                         20
Hungary                          19
Holand-Netherlands                1
?                                 0
Name: native-country, dtype: int64
[United-States, Peru, Guatemala, Mexico, Dominican-Republic, …, Greece,
Trinadad&Tobago, Outlying-US(Guam-USVI-etc), France, Holand-Netherlands]
Length: 41
Categories (41, object): [United-States, Peru, Guatemala, Mexico, …,
Trinadad&Tobago, Outlying-US(Guam-USVI-etc), France, Holand-Netherlands]
```

[11]:
```
# Resetting the categories
adult['workclass'] = adult['workclass'].cat.remove_categories('?')
adult['occupation'] = adult['occupation'].cat.remove_categories('?')
adult['native-country'] = adult['native-country'].cat.remove_categories('?')
```

[12]:
```
printmd ('## 1.7 Correlation Matrix')
display(adult.corr())
```

1.7 1.7 Correlation Matrix

```
                     age    fnlwgt  educational-num  capital-gain  \
age             1.000000 -0.076628         0.030940      0.077229
fnlwgt         -0.076628  1.000000        -0.038761     -0.003706
educational-num 0.030940 -0.038761         1.000000      0.125146
capital-gain    0.077229 -0.003706         0.125146      1.000000
capital-loss    0.056944 -0.004366         0.080972     -0.031441
hours-per-week  0.071558 -0.013519         0.143689      0.082157

                 capital-loss  hours-per-week
age                  0.056944        0.071558
fnlwgt              -0.004366       -0.013519
educational-num      0.080972        0.143689
capital-gain        -0.031441        0.082157
capital-loss         1.000000        0.054467
hours-per-week       0.054467        1.000000
```

We see that none of the columns are highly correlated.

---

2 2. Exploratory Data Analysis

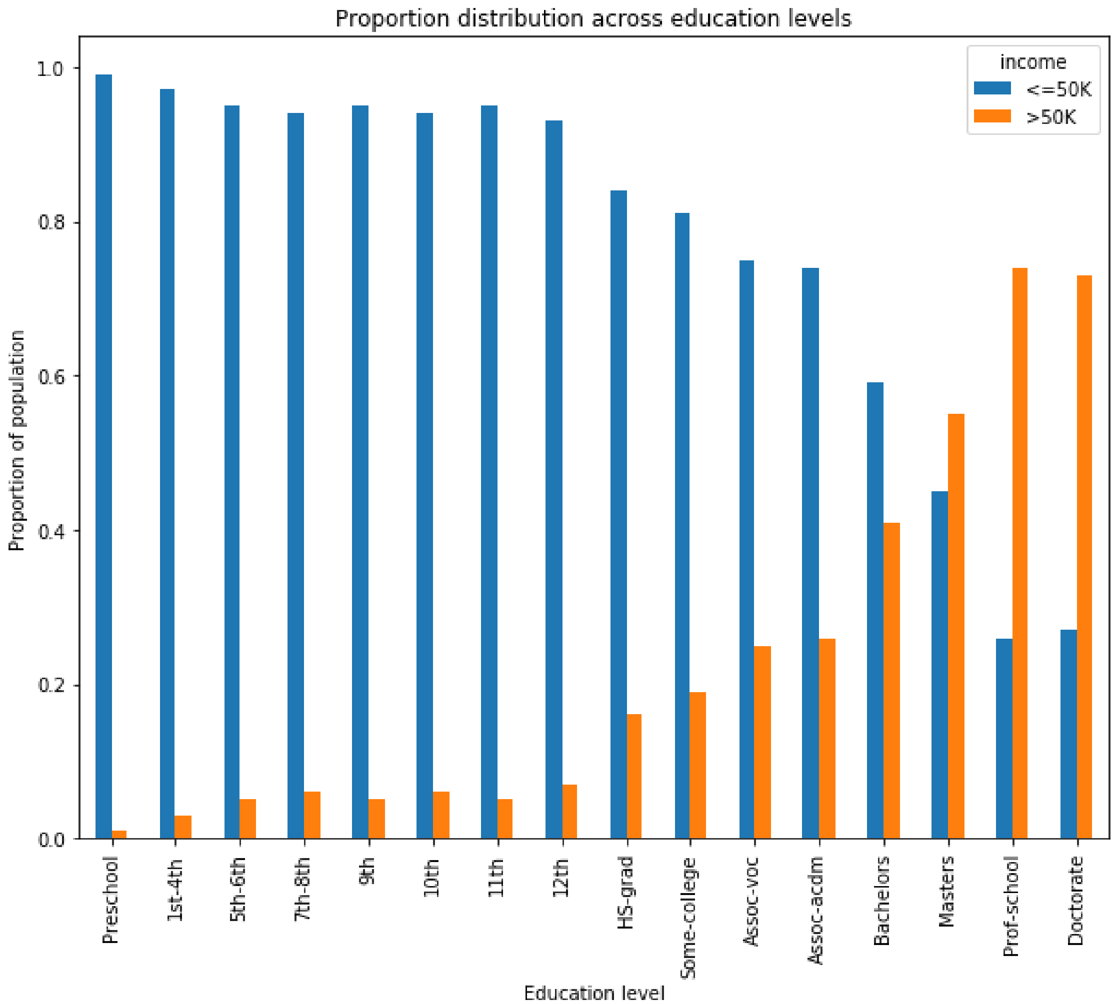
[13]:
```
# Creating a dictionary that contain the education and it's corresponding␣
↪education level
edu_level = {}
for x,y in adult[['educational-num','education']].drop_duplicates().
↪itertuples(index=False):
    edu_level[y] = x
```

[14]:
```
printmd('## 2.1 Education vs Income')

education = round(pd.crosstab(adult.education, adult.income).div(pd.
↪crosstab(adult.education, adult.income).apply(sum,1),0),2)
education = education.reindex(sorted(edu_level, key=edu_level.get,␣
↪reverse=False))
```

```
ax = education.plot(kind ='bar', title = 'Proportion distribution across␣
↪education levels', figsize = (10,8))
ax.set_xlabel('Education level')
ax.set_ylabel('Proportion of population')

printmd('I plot a bar graph showing the proportion of income classes across␣
↪education levels \
        in the figure below. As one would expect, we 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. It is interesting to note that only after a master\'s degree,␣
↪the proportion of \
        people earning more than 50k a year, is a majority.')
```

2.1 2.1 Education vs Income

I plot a bar graph showing the proportion of income classes across education levels in the figure below. As one would expect, we 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. It is interesting to note that only after a master's degree, the proportion of people earning more than 50k a year, is a majority.

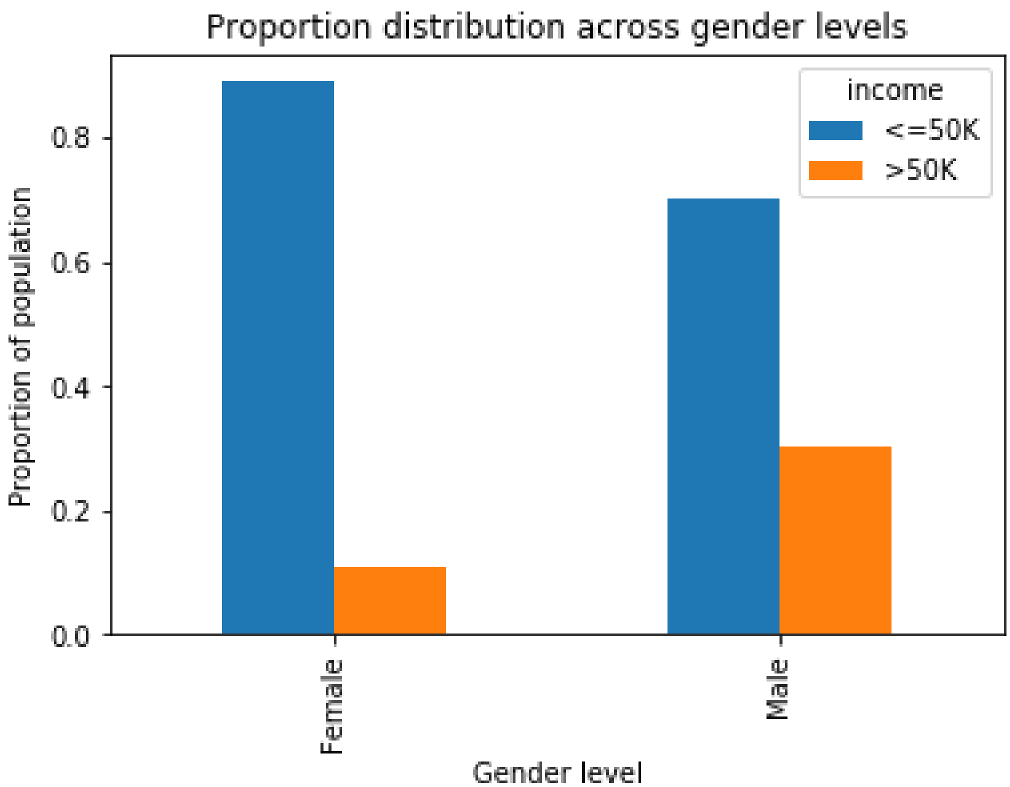


[15]:
```
printmd('## 2.2 Gender vs Income')

gender = round(pd.crosstab(adult.gender, adult.income).div(pd.crosstab(adult.
 ↪gender, adult.income).apply(sum,1),0),2)
gender.sort_values(by = '>50K', inplace = True)
ax = gender.plot(kind ='bar', title = 'Proportion distribution across gender␣
 ↪levels')
ax.set_xlabel('Gender level')
ax.set_ylabel('Proportion of population')

printmd('We plot a bar graph showing the proportion of income classes across␣
 ↪the genders in figure \
        below. From the graph, at an overall view, there exists a wage gap␣
 ↪between females and males. \
```

```
        Since we do not have the exactly value of the income, we are limited to␣
↪only observing that the \
        proportion of males earning more than 50k a year is more than double of␣
↪their female counterparts. \
        ')
```

2.2 2.2 Gender vs Income

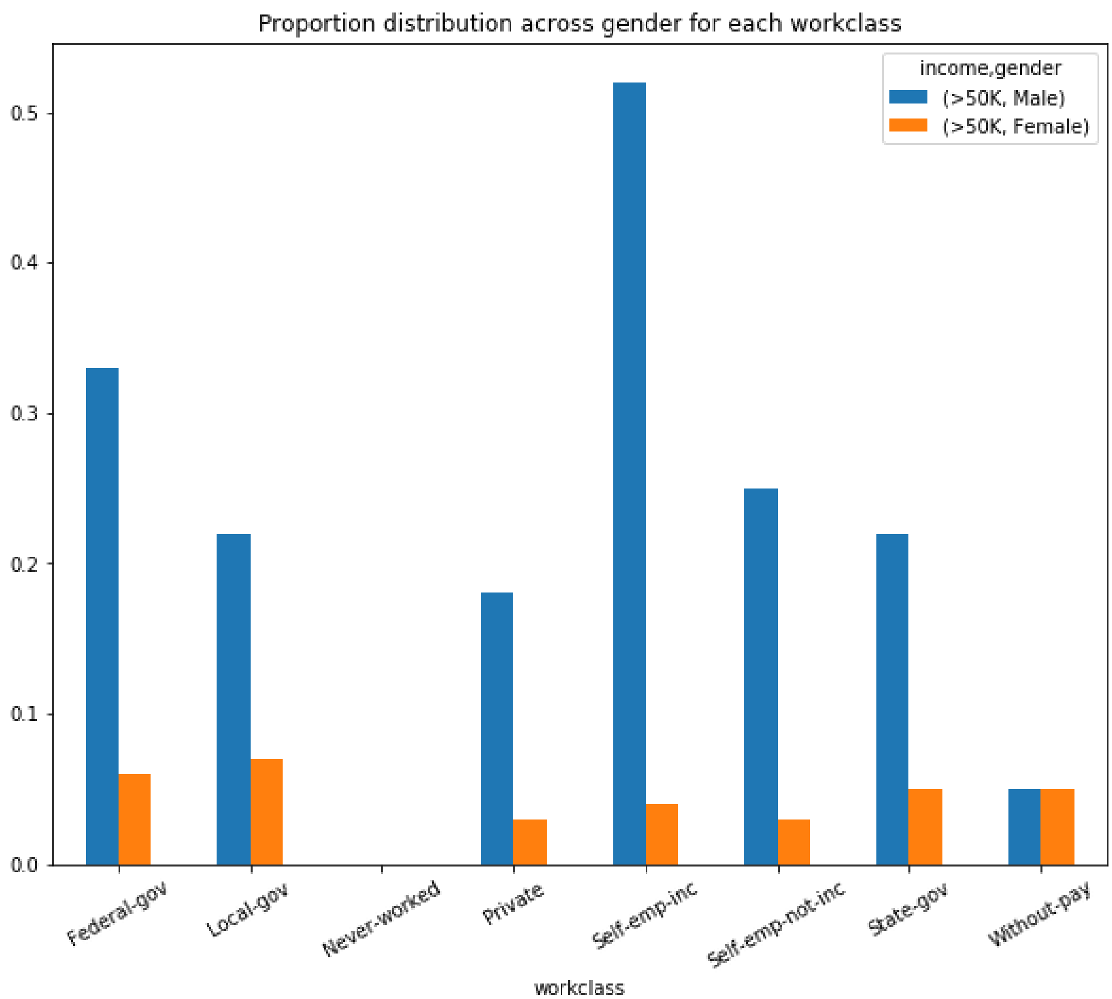
We plot a bar graph showing the proportion of income classes across the genders in figure below. From the graph, at an overall view, there exists a wage gap between females and males. Since we do not have the exactly value of the income, we are limited to only observing that the proportion of males earning more than 50k a year is more than double of their female counterparts.



[16]:
```
gender_workclass = round(pd.crosstab(adult.workclass, [adult.income, adult.
 ↪gender]).div(pd.crosstab(adult.workclass, [adult.income, adult.gender]).
 ↪apply(sum,1),0),2)
gender_workclass[[('>50K','Male'), ('>50K','Female')]].plot(kind = 'bar', title␣
 ↪= 'Proportion distribution across gender for each workclass', figsize =␣
 ↪(10,8), rot = 30)
ax.set_xlabel('Gender level')
ax.set_ylabel('Proportion of population')
```

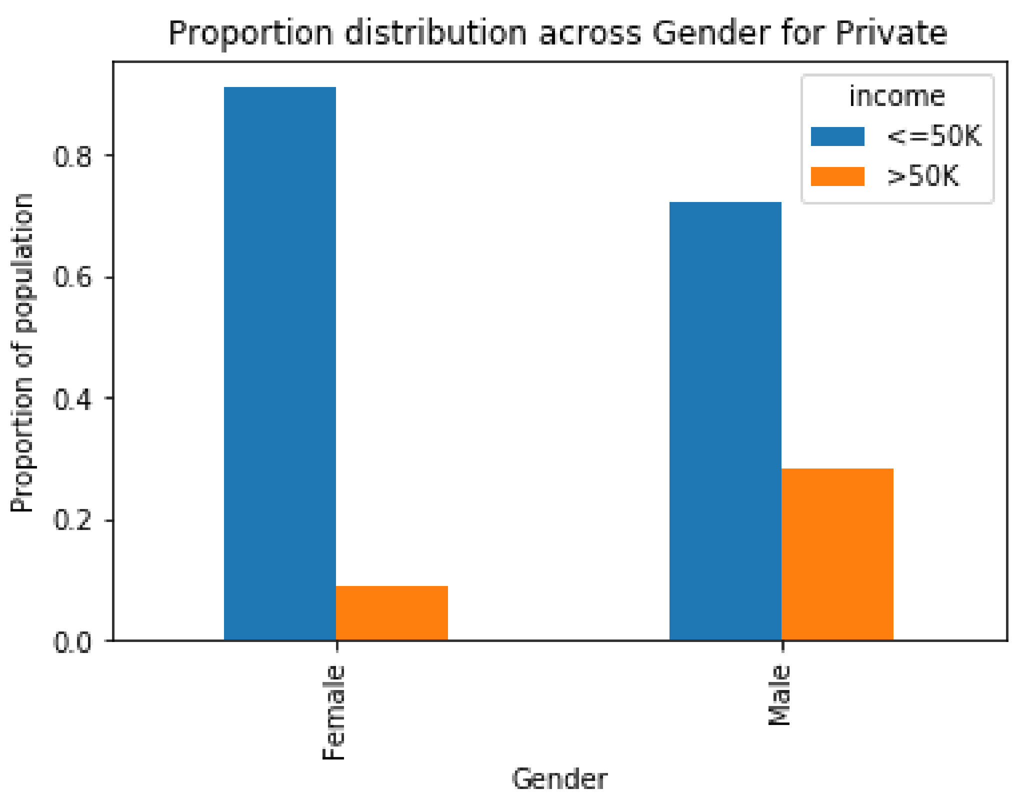
```
printmd('Taking a closer look at the disparity in income between men and women,␣
↪plot the \
        proportion of men and women who earn more than 50k a year, across all␣
↪the working \
        classes as seen in Fig. 3. We see that men always have a higher␣
↪proportion earning \
        more than 50k a year than women, except for the \'without.pay\' working␣
↪class, where \
        they have the same proportion.')
```

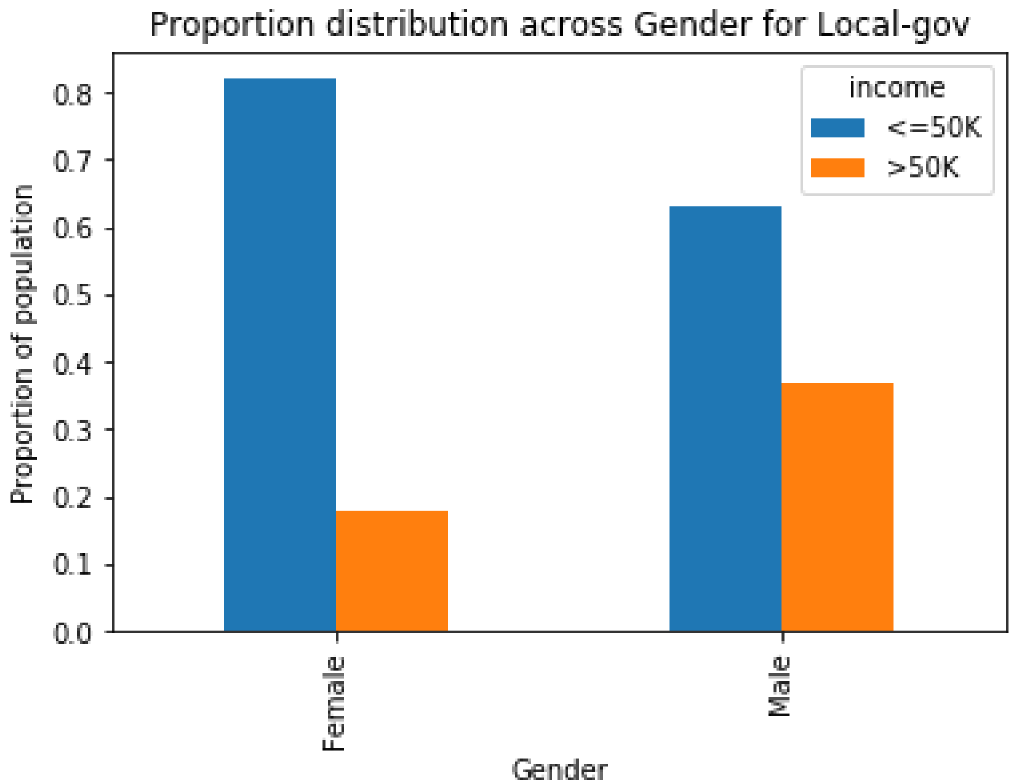
Taking a closer look at the disparity in income between men and women, plot the proportion of men and women who earn more than 50k a year, across all the working classes as seen in Fig. 3. We see that men always have a higher proportion earning more than 50k a year than women, except for the ‘without.pay’ working class, where they have the same proportion.

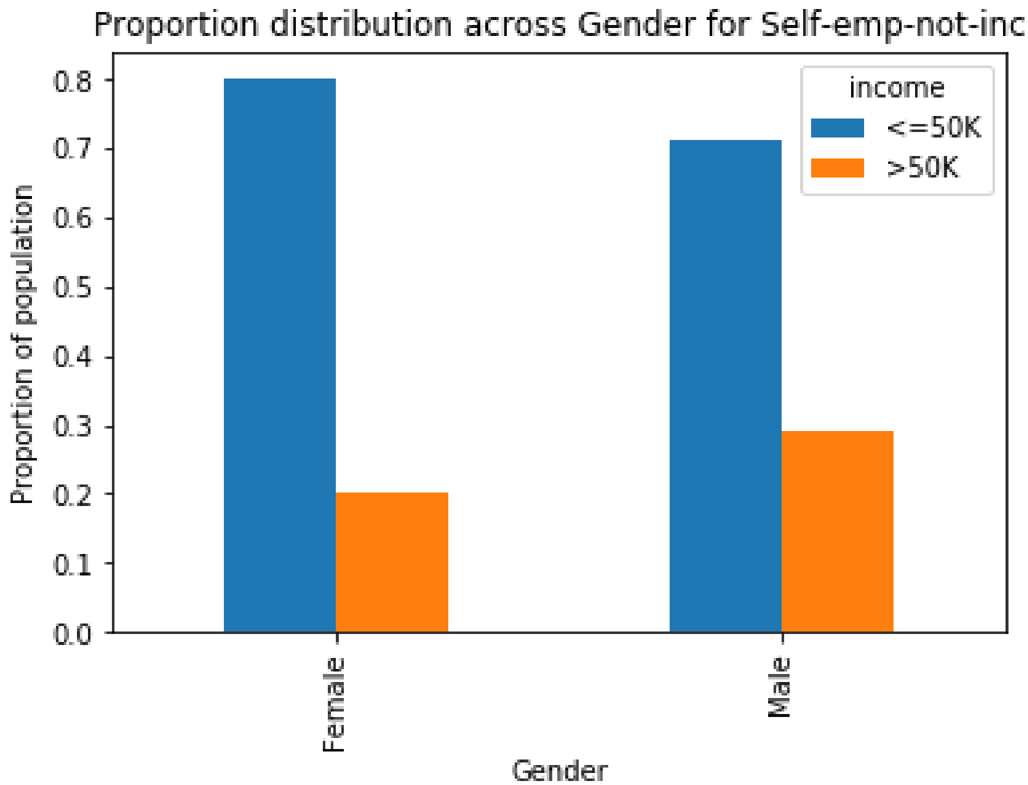


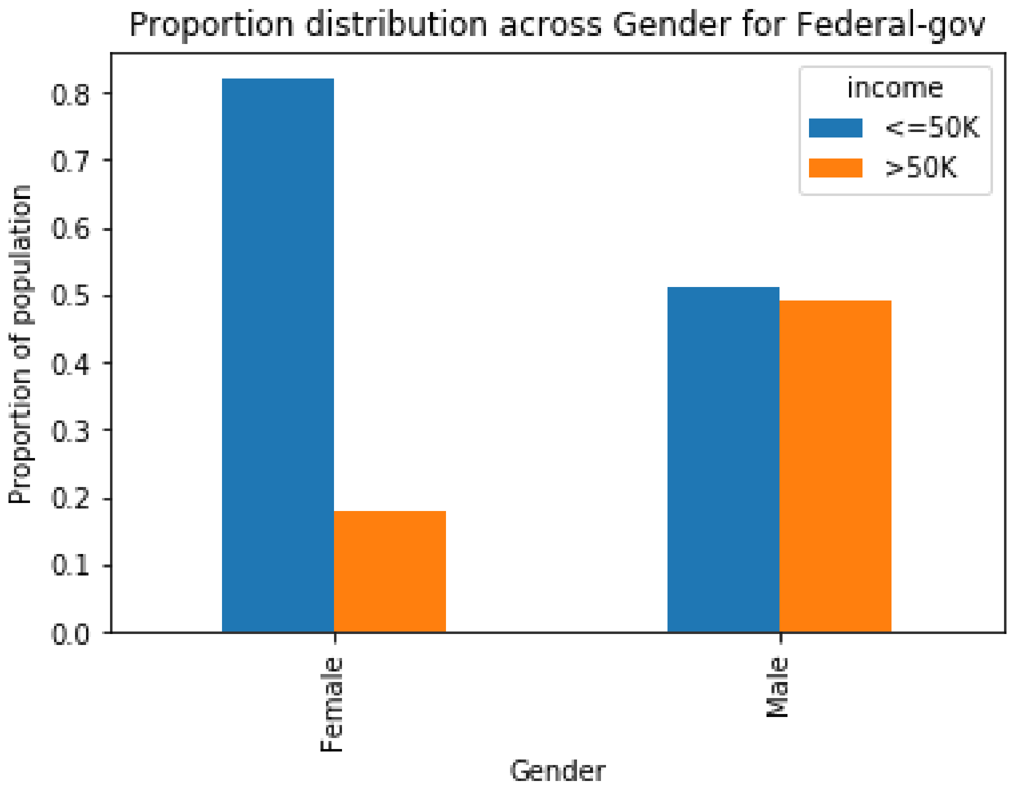
[17]:
```
printmd('### Gender across working classes')

for i in adult.workclass.unique():
    df = adult[adult.workclass == i]
    hours_per_week = round(pd.crosstab(df.gender, df.income).div(pd.crosstab(df.
 ↪gender, df.income).apply(sum,1),0),2)
    #hours_per_week.sort_values(by = '>50K', inplace = True)
    ax = hours_per_week.plot(kind ='bar', title = 'Proportion distribution␣
 ↪across Gender for '+ i)
    ax.set_xlabel('Gender')
    ax.set_ylabel('Proportion of population')
    print()
```

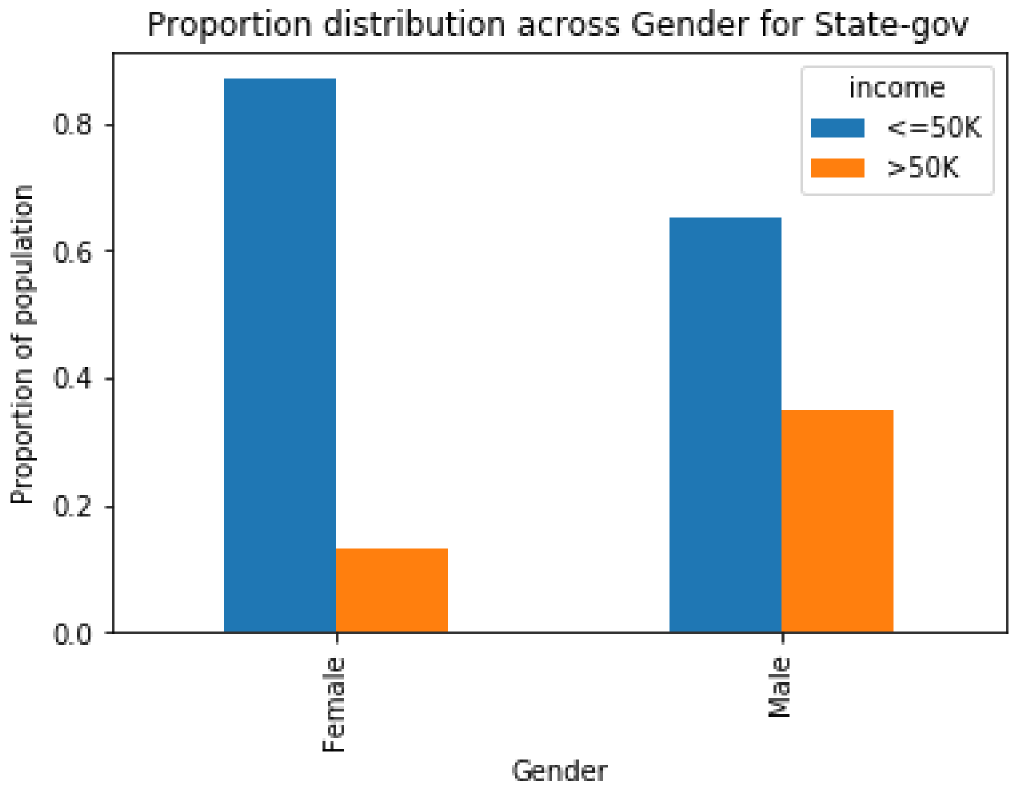
2.2.1 Gender across working classes

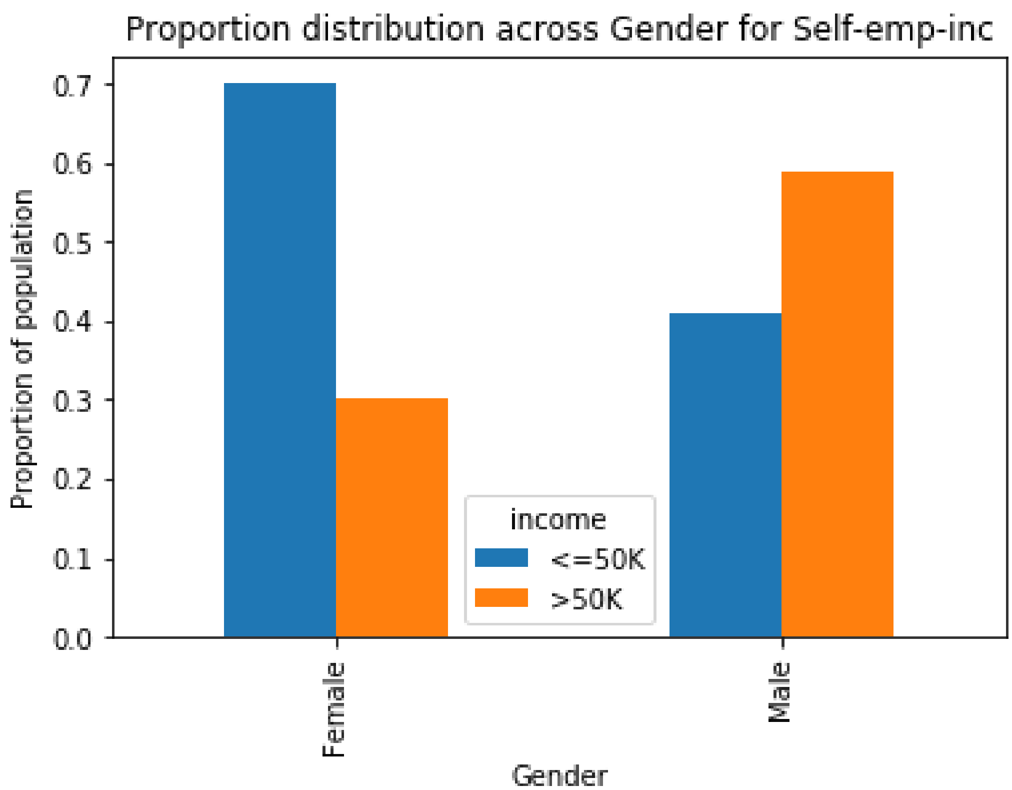


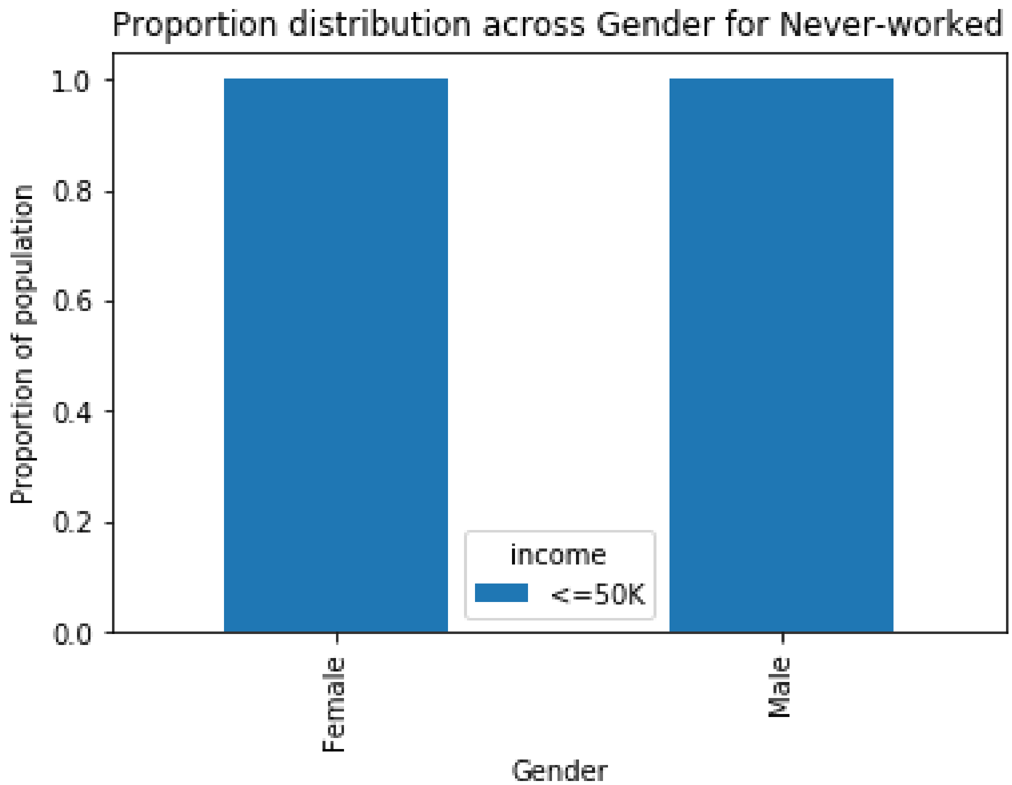

Proportion distribution across Gender for Local-gov
income
<=50K
>50K
Proportion of population
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Female
Male
Gender

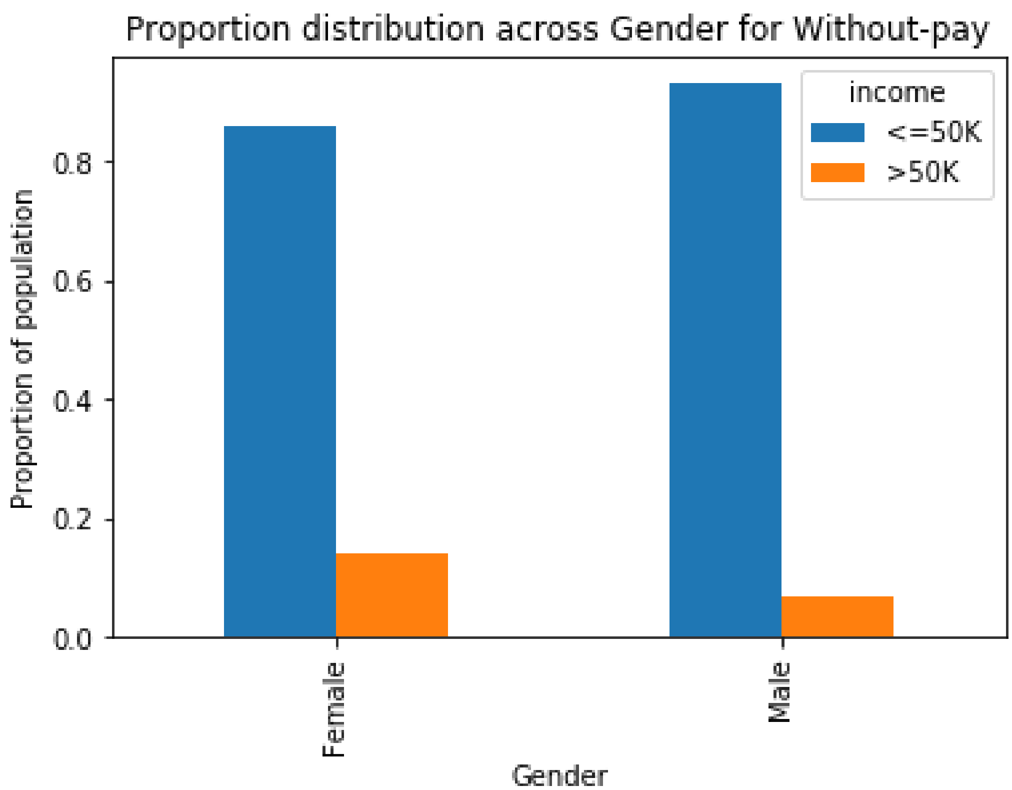

Proportion distribution across Gender for Self-emp-not-inc
Proportion of population
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
income
<=50K
>50K
Female
Male
Gender


Proportion distribution across Gender for Federal-gov
income
<=50K
>50K
Proportion of population
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Female
Male
Gender


Proportion distribution across Gender for State-gov
Proportion of population
0.0
0.2
0.4
0.6
0.8
income
<=50K
>50K
Female
Male
Gender

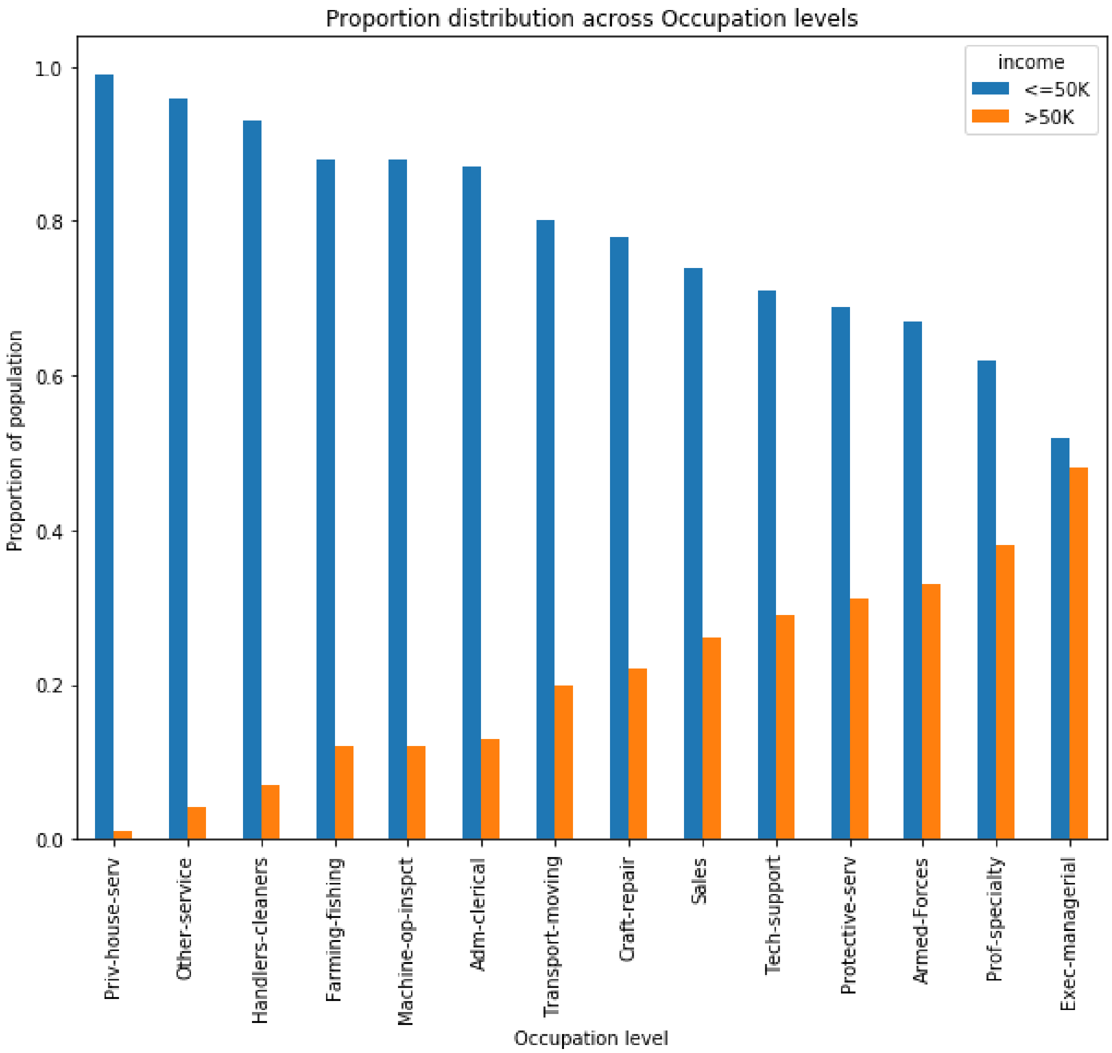

Proportion distribution across Gender for Self-emp-inc
Proportion of population
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
income
<=50K
>50K
Female
Male
Gender


Proportion distribution across Gender for Never-worked
Proportion of population
1.0
0.8
0.6
0.4
0.2
0.0
income
<=50K
Female
Male
Gender



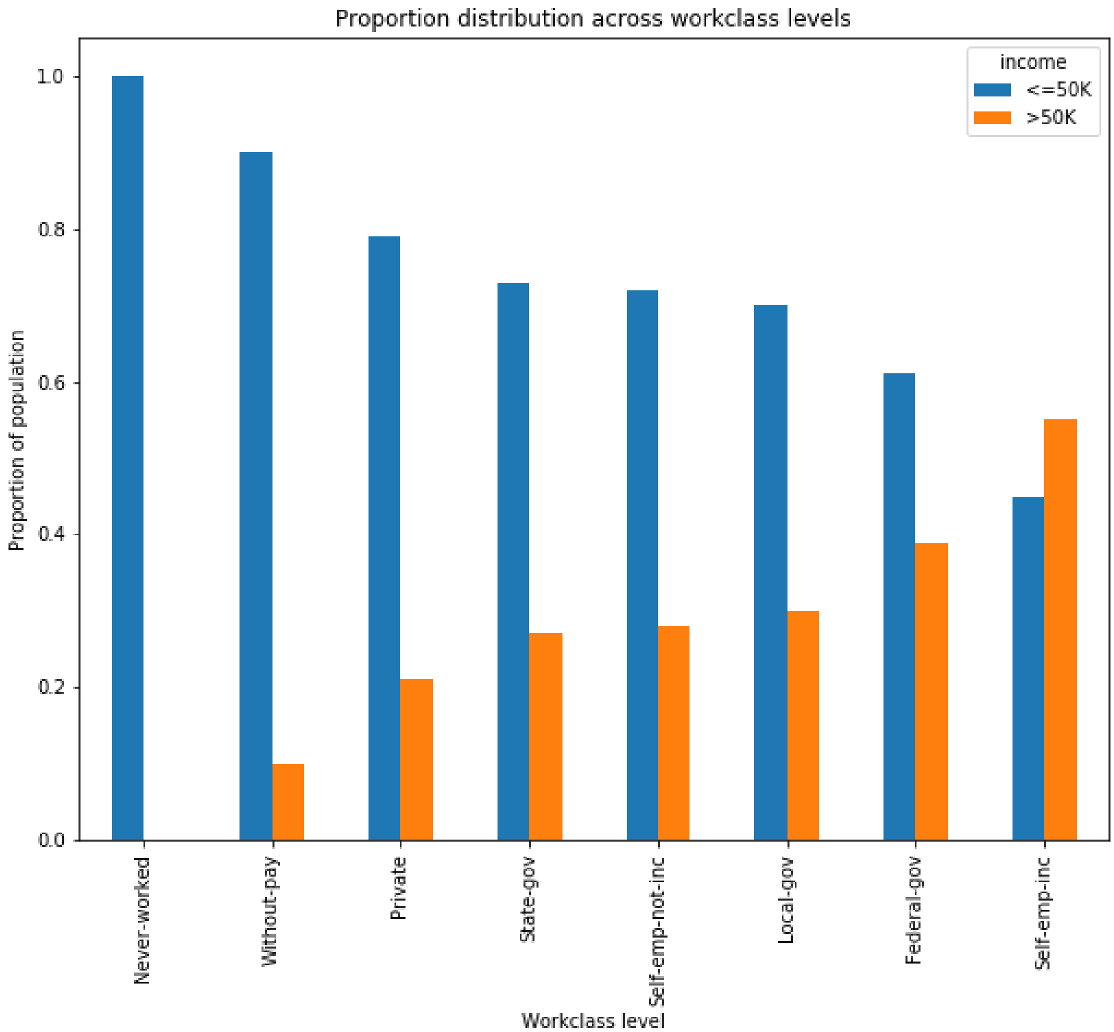
[18]:
```
printmd('## 2.3. Occupation vs Income')

occupation = round(pd.crosstab(adult.occupation, adult.income).div(pd.
 ↪crosstab(adult.occupation, adult.income).apply(sum,1),0),2)
occupation.sort_values(by = '>50K', inplace = True)
ax = occupation.plot(kind ='bar', title = 'Proportion distribution across␣
 ↪Occupation levels', figsize = (10,8))
ax.set_xlabel('Occupation level')
ax.set_ylabel('Proportion of population')

print()
```

2.3 2.3. Occupation vs Income



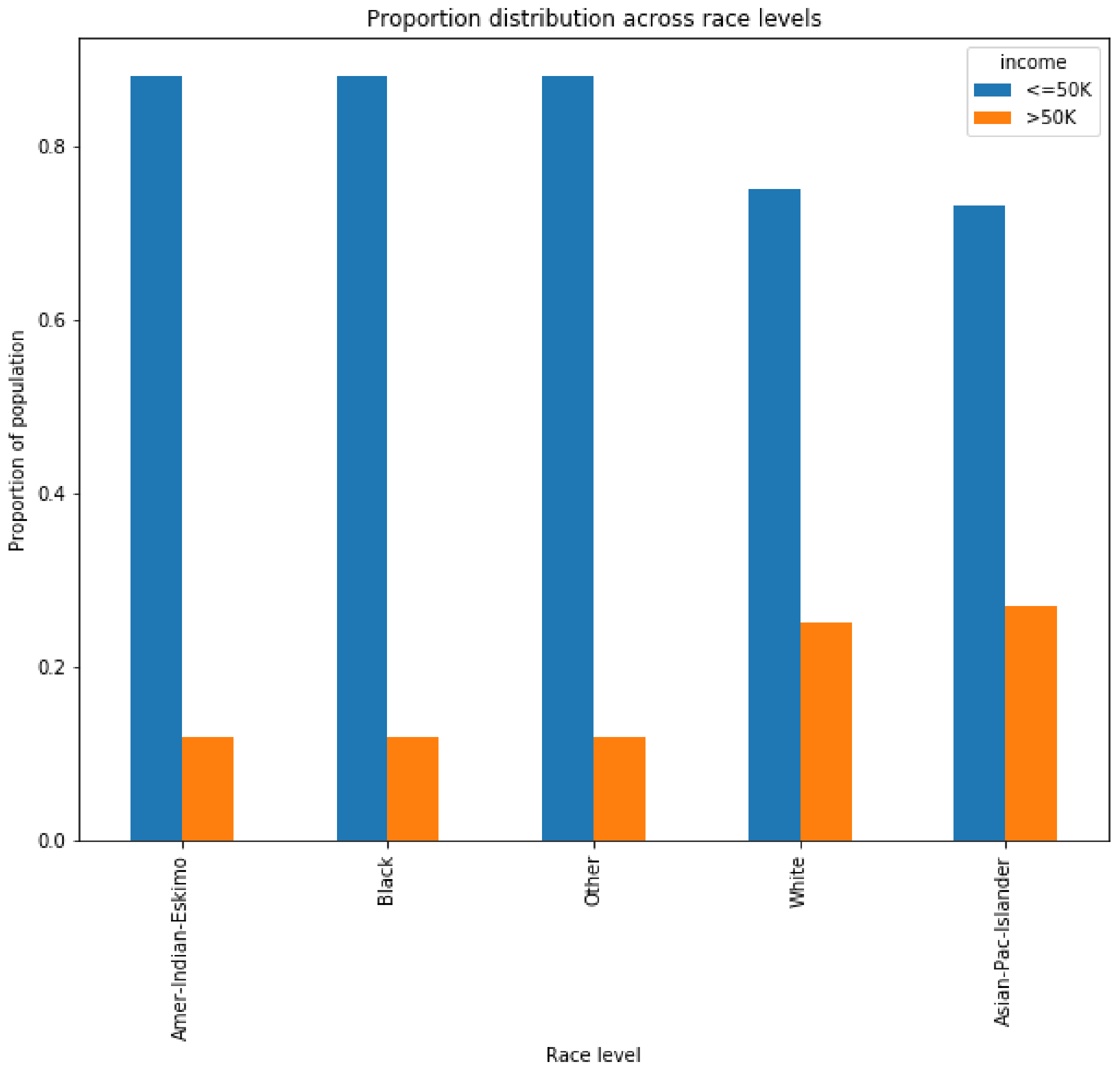
[19]:
```
printmd('## 2.4. Workclass vs Income')

workclass = round(pd.crosstab(adult.workclass, adult.income).div(pd.
 ↪crosstab(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')

print()
```

2.4 2.4. Workclass vs Income



[20]:
```
printmd('## 2.5. Race vs Income')

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')

print()
```

2.5 2.5. Race vs Income

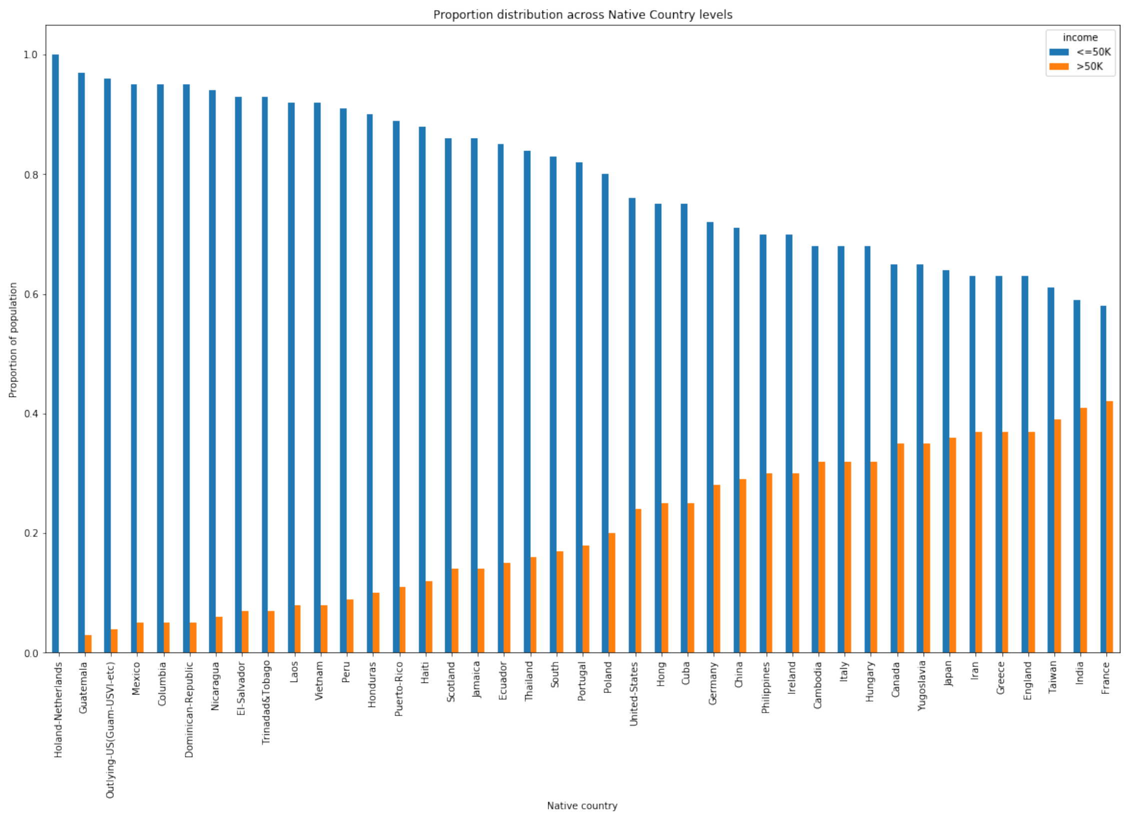


[21]:
```
printmd('## 2.6. Native Country')

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 across␣
 ↪Native Country levels', figsize = (20,12))
ax.set_xlabel('Native country')
ax.set_ylabel('Proportion of population')

printmd('I plot a bar graph showing the proportion of income classes across the␣
 ↪native country in figure \
        below. From the graph, we notice a trend in positioning of the country.␣
 ↪South American country are \
```

```
        at the left end of the plot, with low proportion of population that␣
↪make more than 50k a year. The \
        United States is located somewhat centrally, and at the right are␣
↪countries from Europe and Asia, \
        with higher proportion of population that make more than 50k a year.')
```

2.6 2.6. Native Country

I plot a bar graph showing the proportion of income classes across the native country in figure below. From the graph, we notice a trend in positioning of the country. South American country are at the left end of the plot, with low proportion of population that make more than 50k a year. The United States is located somewhat centrally, and at the right are countries from Europe and Asia, with higher proportion of population that make more than 50k a year.

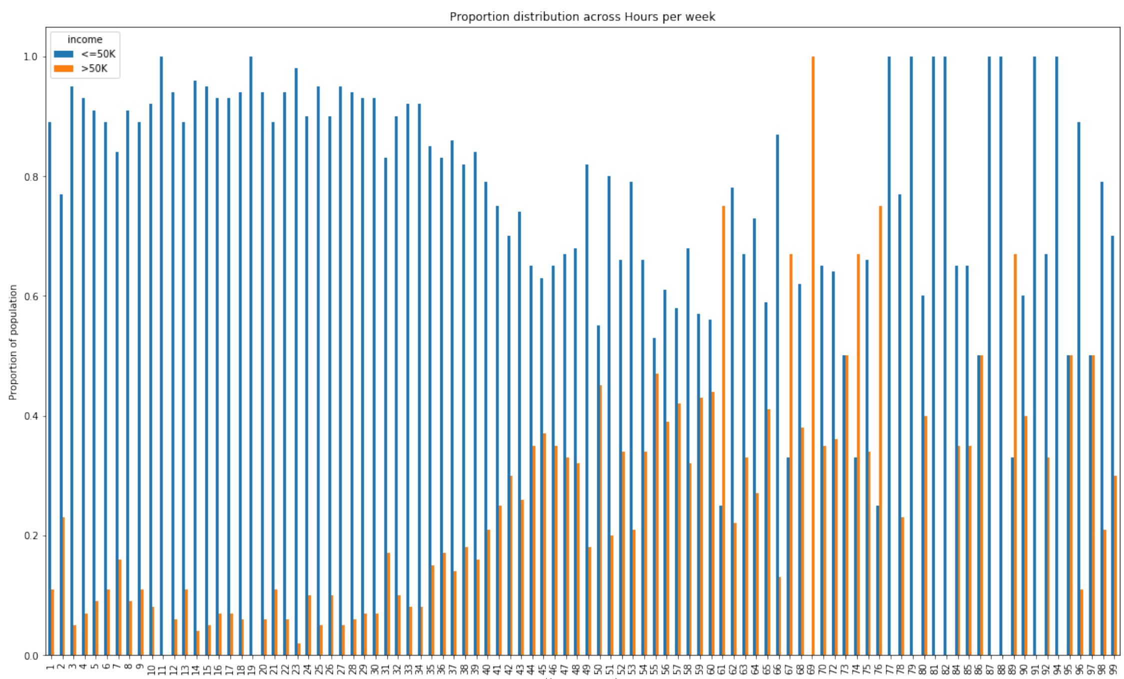



```
[22]: printmd('## 2.7. Hours per week vs Income')

hours_per_week = round(pd.crosstab(adult['hours-per-week'], adult.income).
 ↪div(pd.crosstab(adult['hours-per-week'], adult.income).apply(sum,1),0),2)
# hours_per_week.sort_values(by = '>50K', inplace = True)
ax = hours_per_week.plot(kind ='bar', title = 'Proportion distribution across␣
 ↪Hours per week', figsize = (20,12))
```

```
ax.set_xlabel('Hours per week')
ax.set_ylabel('Proportion of population')

printmd('I plot a bar graph showing the proportion of income classes across the␣
↪hours worked. \
        We would expected to notice a trend that higher the hours worked per␣
↪week, the higher the proportion \
        of population making more than 50k a year. However, this was not␣
↪necessarily true from the graph. \
        For several hours instance (for example, where hours worked was 77, 79,␣
↪81, 82, 87, 88 and so on) \
        no one earned more than 50k a year. ')
```

2.7 2.7. Hours per week vs Income

I plot a bar graph showing the proportion of income classes across the hours worked. We would expected to notice a trend that higher the hours worked per week, the higher the proportion of population making more than 50k a year. However, this was not necessarily true from the graph. For several hours instance (for example, where hours worked was 77, 79, 81, 82, 87, 88 and so on) no one earned more than 50k a year.

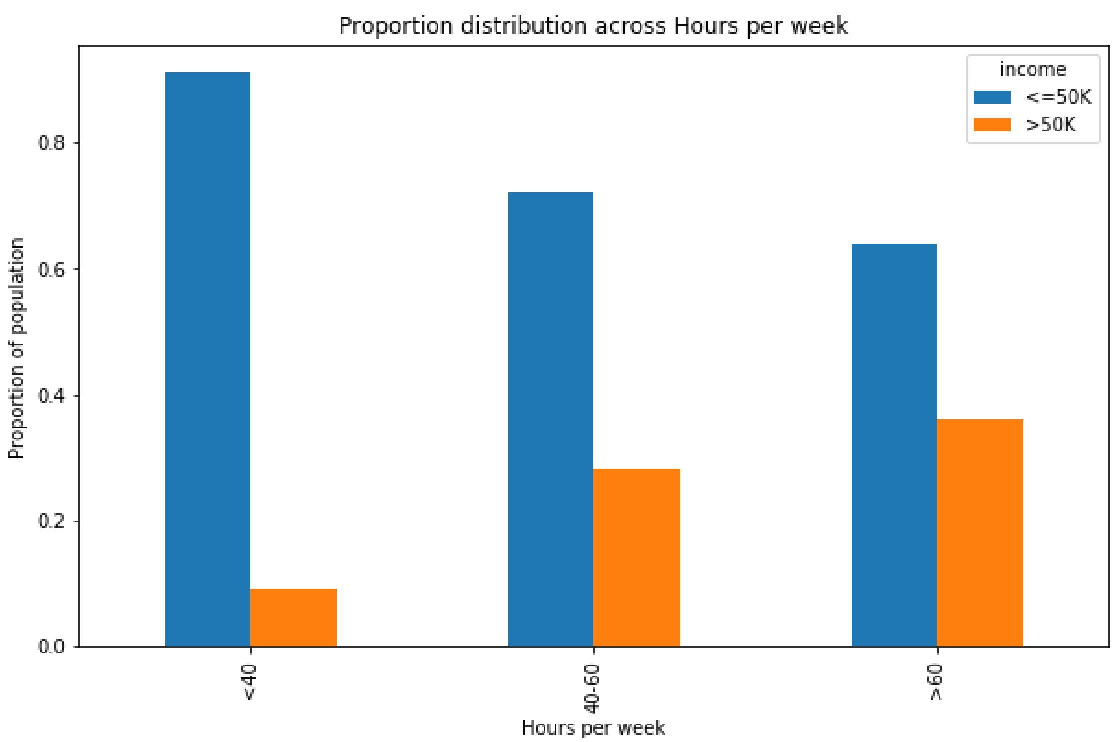


[23]:
```
printmd('### 2.7.1 Hours per week with categories')

adult['hour_worked_bins'] = ['<40' if i < 40 else '40-60' if i <= 60 else '>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 ='bar', title = 'Proportion distribution across␣
 ↪Hours per week', figsize = (10,6))
ax.set_xlabel('Hours per week')
ax.set_ylabel('Proportion of population')

printmd('Therefore, I decided to transform this column into 3 categories, less␣
 ↪than 40 hours, \
        40 to 60 hours and greater than 60 hours. Plotting a bar graph with␣
 ↪these 3 categories, \
        we can see from the figure below that there is an increasing trend in␣
 ↪the proportion of \
        population making more than 50k a year.')
```

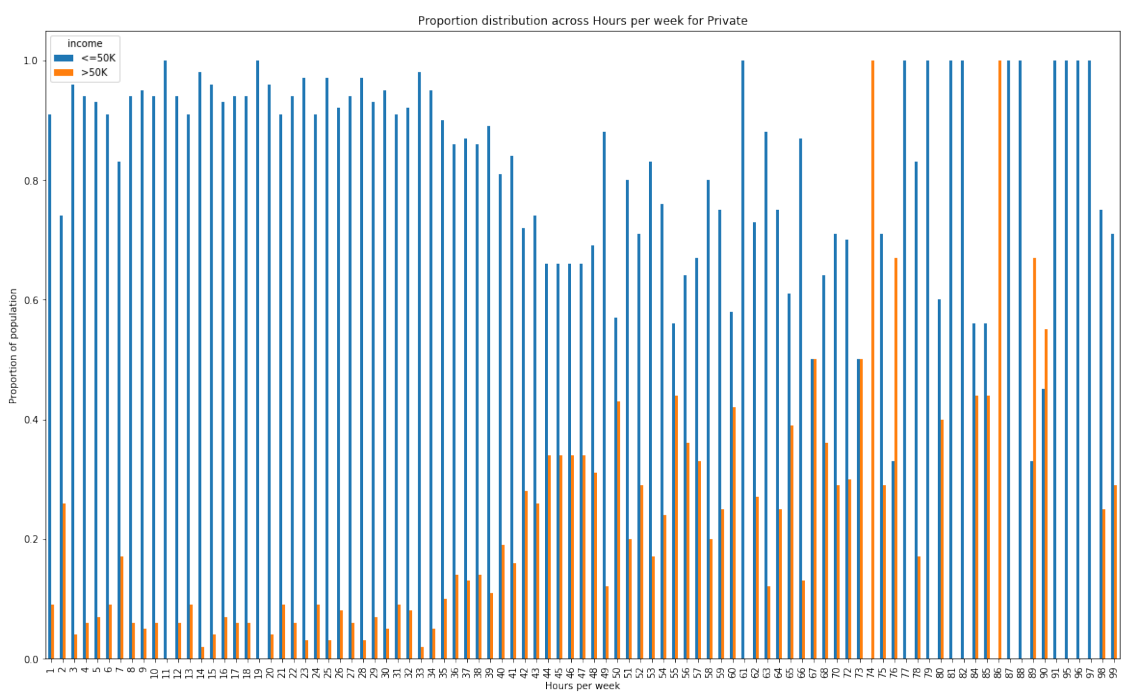
2.7.1 2.7.1 Hours per week with categories

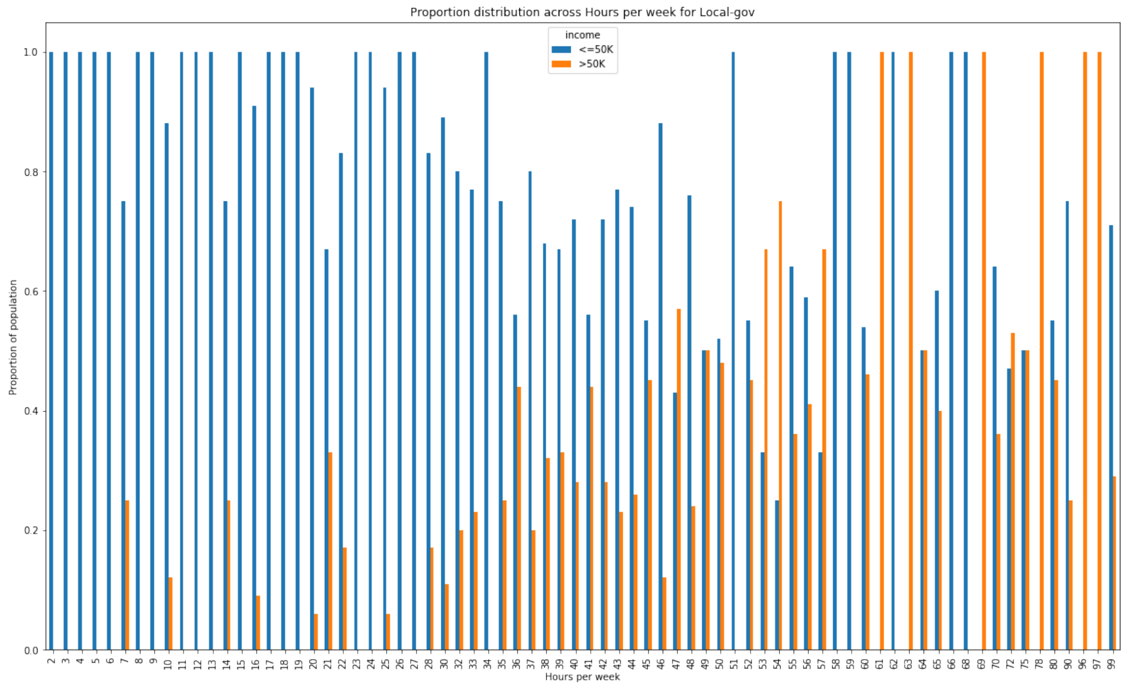
Therefore, I decided to transform this column into 3 categories, less than 40 hours, 40 to 60 hours and greater than 60 hours. Plotting a bar graph with these 3 categories, we can see from the figure below that there is an increasing trend in the proportion of population making more than 50k a year.

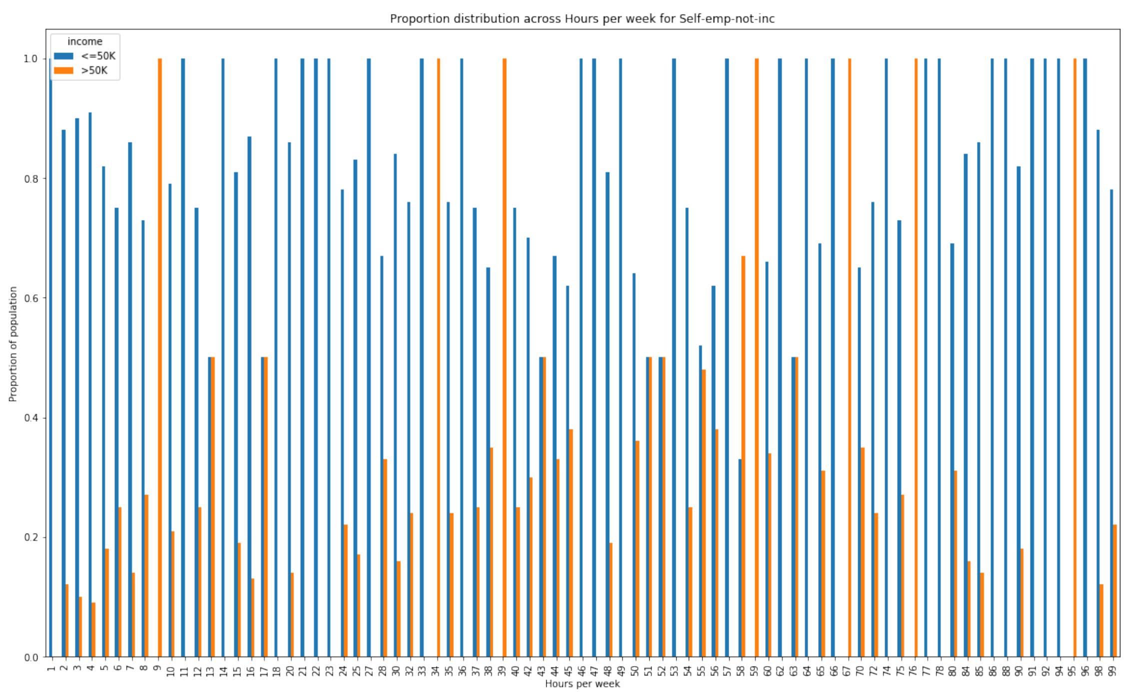


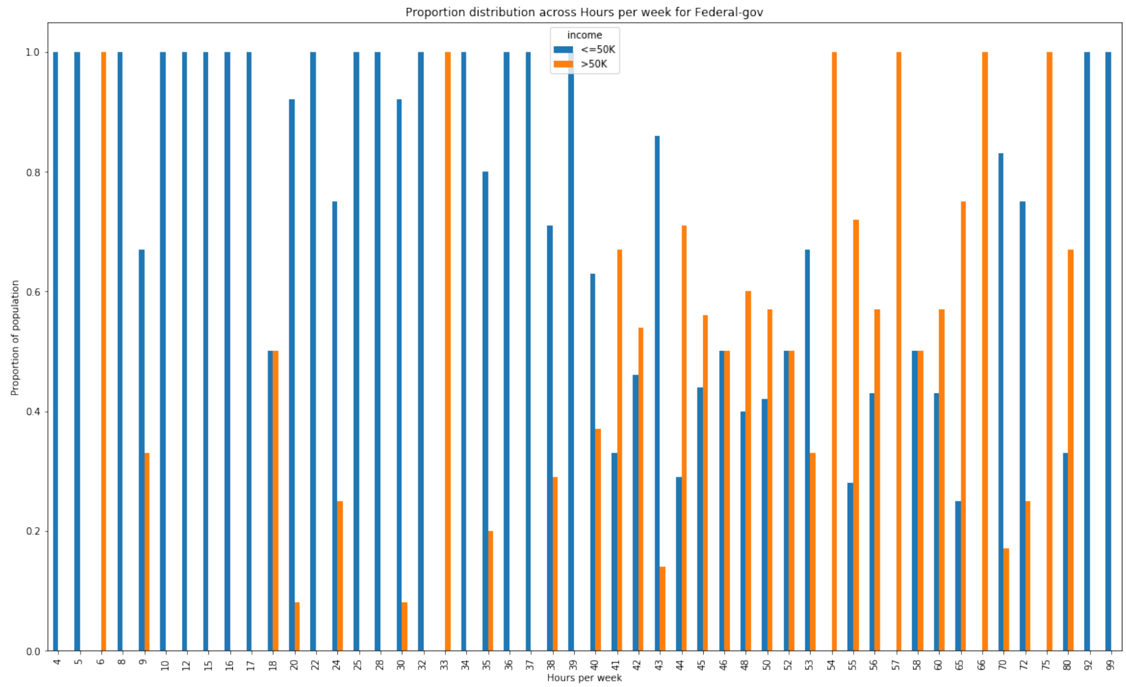
[24]:
```
printmd('### 2.7.2 Hours worked across working classes')

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)
    # hours_per_week.sort_values(by = '>50K', inplace = True)
    ax = hours_per_week.plot(kind ='bar', title = 'Proportion distribution␣
↪across Hours per week for '+ i, figsize = (20,12))
    ax.set_xlabel('Hours per week')
    ax.set_ylabel('Proportion of population')

    print()
```

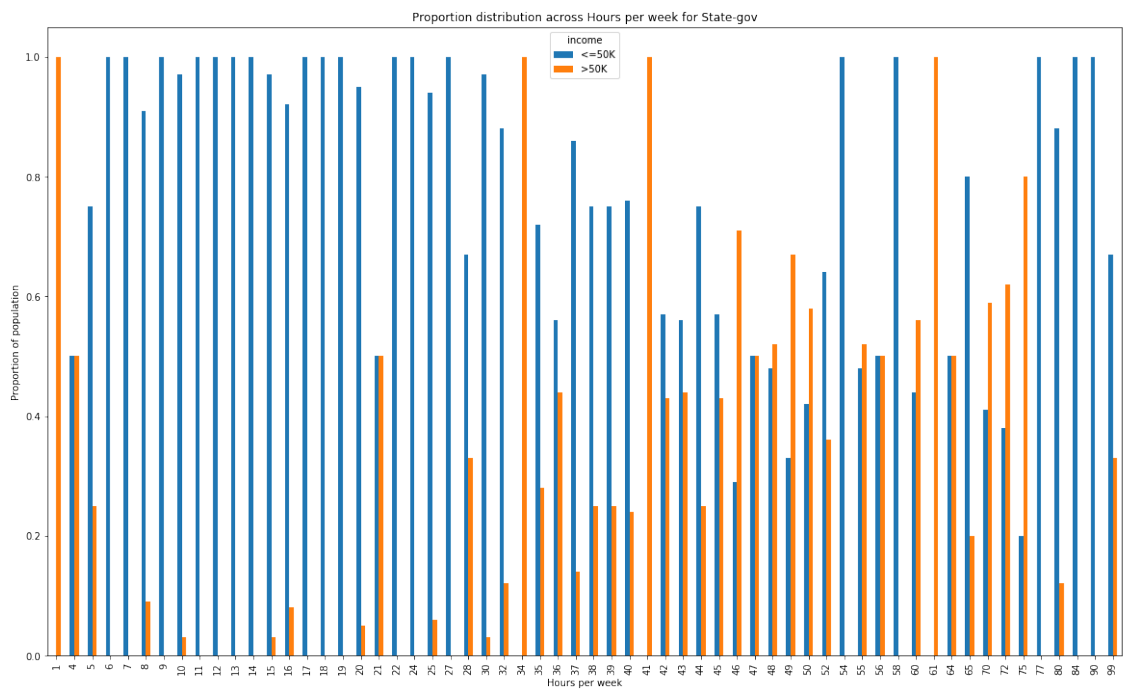
2.7.2 2.7.2 Hours worked across working classes

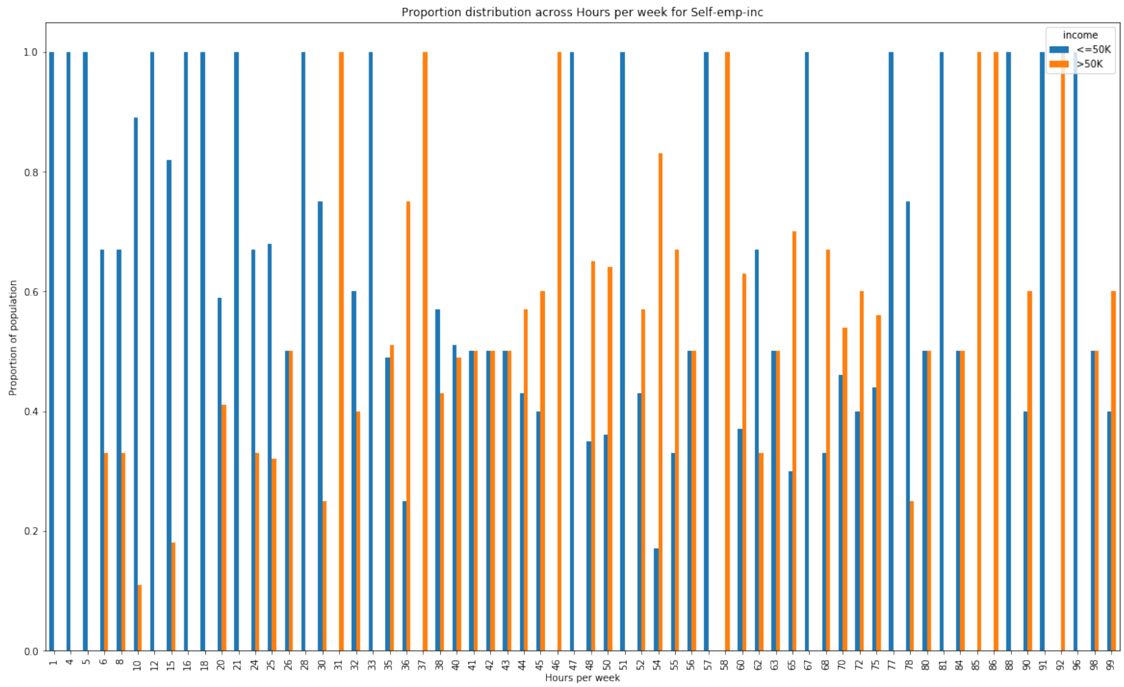


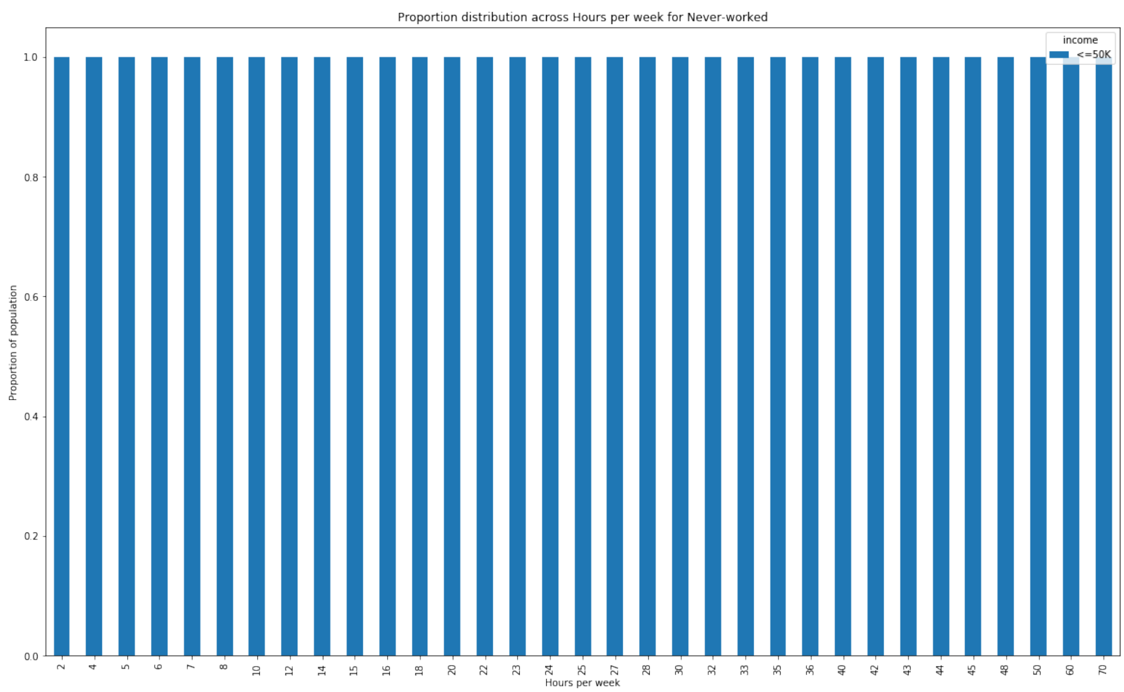

Proportion distribution across Hours per week for Local-gov
income
<=50K
>50K
Proportion of population
Hours per week

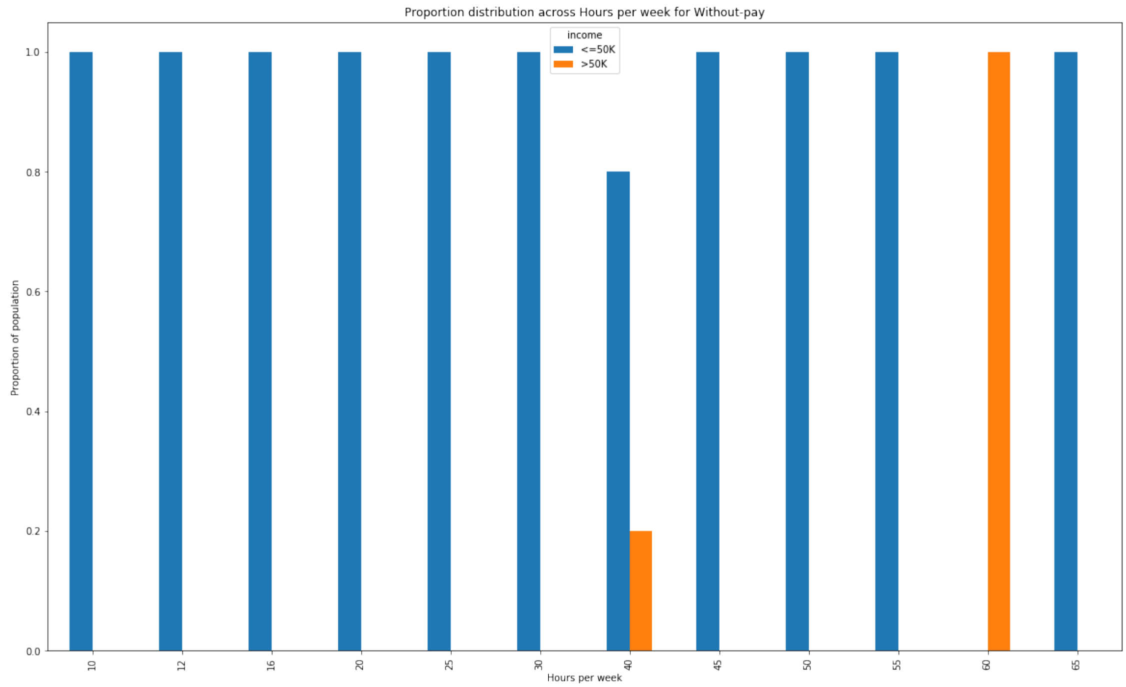

Proportion distribution across Hours per week for Self-emp-not-inc
income
<=50K
>50K
Proportion of population
Hours per week


Proportion distribution across Hours per week for Federal-gov
income
<=50K
>50K
Proportion of population
Hours per week


Proportion distribution across Hours per week for State-gov
income
<=50K
>50K
Proportion of population
Hours per week


Proportion distribution across Hours per week for Self-emp-inc
income
<=50K
>50K
Proportion of population
Hours per week


Proportion distribution across Hours per week for Never-worked
income
<=50K
Proportion of population
Hours per week



---

3 3. Data Transformations

3.1 3.1. Feature Selection

[25]:
```
# Remove education and fnlwgt
adult.drop(columns = ['education','fnlwgt','hours-per-week'], inplace = True)

printmd('* We have 2 features that convey the same meaning, \'education\' \
        and \'educational-num\'. To avoid the effect of this attribute on the␣
↪models to be \
        overstated, I am not going to use the categorical education attribute.')
printmd('* I use the categorical Hours work column and drop the␣
↪\'hour-per-week\' column')
printmd('* Also, I chose not to use the \'Fnlwgt\' attribute that is used by␣
↪the census, \
        as the inverse of sampling fraction adjusted for non-response and over␣
↪or under sampling \
        of particular groups. This attribute does not convey individual related␣
↪meaning.')
```

- We have 2 features that convey the same meaning, 'education' and 'educational-num'. To avoid the effect of this attribute on the models to be overstated, I am not going to use the categorical education attribute.

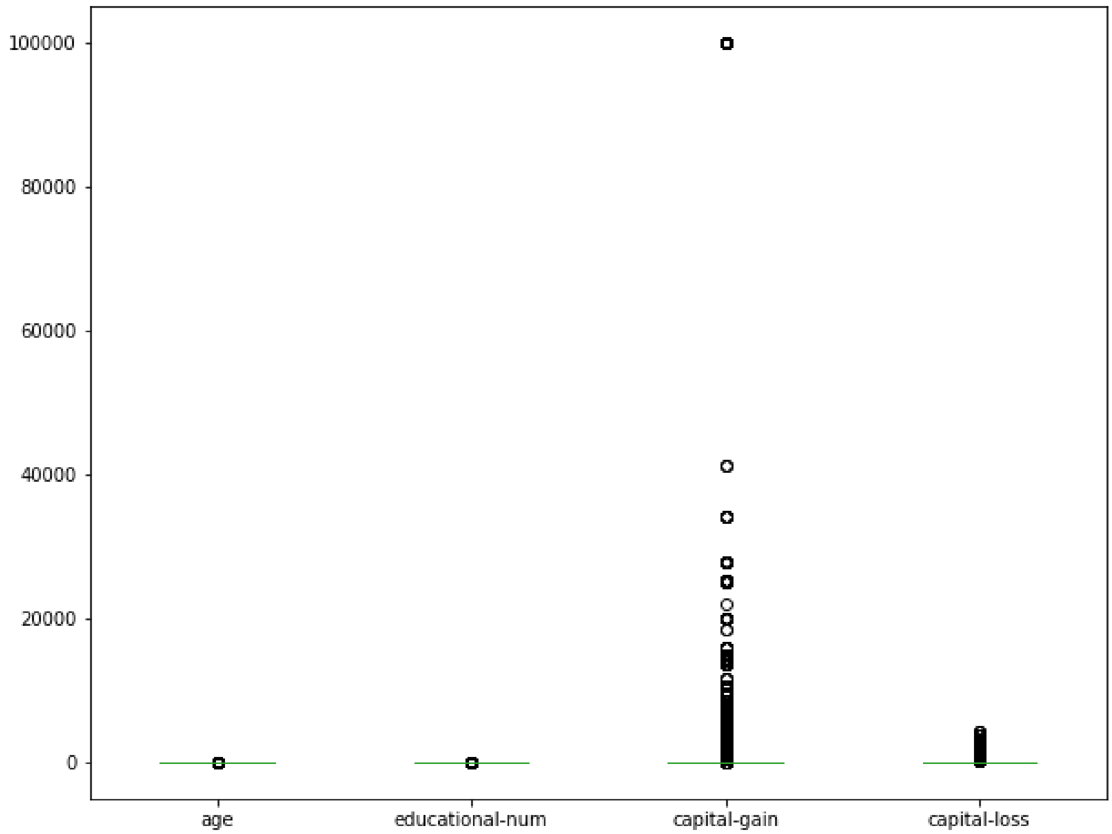
- I use the categorical Hours work column and drop the 'hour-per-week' column
- Also, I chose not to use the 'Fnlwgt' attribute that is used by the census, as the inverse of sampling fraction adjusted for non-response and over or under sampling of particular groups. This attribute does not convey individual related meaning.

3.2 3.2 Normalization

[26]:
```
printmd('## Box plot')
adult.select_dtypes(exclude = 'category').plot(kind = 'box', figsize = (10,8))
```

3.3 Box plot

[26]: <matplotlib.axes._subplots.AxesSubplot at 0x1a2049d490>



Normalization happens on the training dataset, by removing the mean and scaling to unit variance. These values are stored and then later applied to the test data before the test data is passed to the model for prediction.

4 4. Model Development & Classification

4.1 4.1. Data Preparation

One-hot encoding is the process of representing multi-class categorical features as binary features, one for each class. Although this process increases the dimensionality of the dataset, classification algorithms tend to work better on this format of data.

I use one-hot encoding to represent all the categorical features in the dataset.

[27]:
```
# Data Prep
adult_data = adult.drop(columns = ['income'])
adult_label = adult.income


adult_cat_1hot = pd.get_dummies(adult_data.select_dtypes('category'))
adult_non_cat = adult_data.select_dtypes(exclude = 'category')

adult_data_1hot = pd.concat([adult_non_cat, adult_cat_1hot], axis=1,␣
↪join='inner')
```

[28]:
```
# Train - Test split
train_data, test_data, train_label, test_label =␣
↪train_test_split(adult_data_1hot, adult_label, test_size  = 0.25)
```

[29]:
```
# Normalization
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()

# Fitting only on training data
scaler.fit(train_data)
train_data = scaler.transform(train_data)

# Applying same transformation to test data
test_data = scaler.transform(test_data)
```

[30]:
```
def model_eval(actual, pred):

    confusion = pd.crosstab(actual, pred, rownames=['Actual'],␣
↪colnames=['Predicted'])
    TP = confusion.loc['>50K','>50K']
    TN = confusion.loc['<=50K','<=50K']
    FP = confusion.loc['<=50K','>50K']
    FN = confusion.loc['>50K','<=50K']

    accuracy = ((TP+TN))/(TP+FN+FP+TN)
    precision = (TP)/(TP+FP)
    recall = (TP)/(TP+FN)
```

```
    f_measure = (2*recall*precision)/(recall+precision)
    sensitivity = TP / (TP + FN)
    specificity = TN / (TN + FP)
    error_rate = 1 - accuracy

    out = {}
    out['accuracy'] =  accuracy
    out['precision'] = precision
    out['recall'] = recall
    out['f_measure'] = f_measure
    out['sensitivity'] = sensitivity
    out['specificity'] = specificity
    out['error_rate'] = error_rate

    return out
```

4.2 4.2. Model Development

4.2.1 4.2.1. Decision Tree

For the decision tree classifier, I experimented with the splitting criteria, minimum samples required to split, max depth of the tree, minimum samples required at the leaf level and the maximum features to consider when looking for the best split. The following values of the parameters attained the best accuracy during classification. Results in the table below.

- **Splitting criteria:** Gini Index (Using Gini Index marginally outperformed Entropy with a higher accuracy.)
- **Min samples required to split:** 5% (Best amongst 1%, 10% and 5%.)
- **Max Depth:** None
- **Min samples required at leaf:** 0.1 % (Best amongst 1%, 5% and 0.1%.)
- **Max features:** number of features (Performs better than 'auto', 'log2' and 'sqrt'.)

[31]:
```
# Gini
clf_gini = tree.DecisionTreeClassifier(criterion = 'gini', min_samples_split =␣
↪0.05, min_samples_leaf = 0.001, max_features = None)
clf_gini = clf_gini.fit(train_data, train_label)
clf_gini_pred = clf_gini.predict(test_data)
DTree_Gini = model_eval(test_label, clf_gini_pred)
print('Desicion Tree using Gini Index : %.2f percent.' %␣
↪(round(DTree_Gini['accuracy']*100,2)))



# Entropy
clf_entropy = tree.DecisionTreeClassifier(criterion = 'entropy',␣
↪min_samples_split = 0.05, min_samples_leaf = 0.001)
clf_entropy = clf_entropy.fit(train_data, train_label)
clf_entropy_pred = clf_entropy.predict(test_data)
DTree_Entropy = model_eval(test_label, clf_entropy_pred)
```

```
print('Desicion Tree using Entropy : %.2f percent.' %␣
↪(round(DTree_Entropy['accuracy']*100,2)))


printmd('### Model Evaluation ')
ovl_dtree = round(pd.DataFrame([DTree_Entropy, DTree_Gini], index =␣
↪['DTree_Entropy','DTree_Gini']),4)
display(ovl_dtree)
```

```
Desicion Tree using Gini Index : 84.68 percent.
Desicion Tree using Entropy : 84.64 percent.
```

4.2.2 Model Evaluation

```
               accuracy  precision  recall  f_measure  sensitivity  \
DTree_Entropy    0.8464     0.7579  0.5483     0.6363       0.5483
DTree_Gini       0.8468     0.7559  0.5530     0.6387       0.5530

               specificity  error_rate
DTree_Entropy       0.9432      0.1536
DTree_Gini          0.9421      0.1532
```

4.2.3 4.2.2. Artificial Neural Network

For the ANN classifier, I experimented with the activation function, the solver for weight optimization, regularization term and learning schedule for weight updates. The following values of the parameters attained the best accuracy during classification. Other parameters were neither applicable to the 'adam' solver nor did it improve the performance of the model. Results in the table below.

- **Activation:** Logistic (Marginally outperformed 'relu', 'tanh' and 'identity' functions.)
- **Solver:** Adam (Works well on relatively large datasets with thousands of training samples or more)
- **Alpha:** 1e-4 (Best amongst 1, 1e-1, 1e-2, 1e-3, 1e-4 and 1e-5)
- **Learning Rate:** 'invscaling' (Gradually decreases the learning rate at each time step 't' using an inverse scaling exponent of 'power_t'.)

[32]:
```
# Tan H
ann_tanh = MLPClassifier(activation = 'tanh', solver='lbfgs', alpha=1e-1,␣
↪hidden_layer_sizes=(10, 2), random_state=1, warm_start=True)
ann_tanh.fit(train_data, train_label)
ann_tanh_pred = ann_tanh.predict(test_data)
ANN_TanH = model_eval(test_label, ann_tanh_pred)
print('ANN using TanH and lbfgs solver : %.2f percent.' %␣
↪(round(ANN_TanH['accuracy']*100,2)))
```

```
# Relu
ann_relu = MLPClassifier(activation = 'relu', solver='adam', alpha=1e-1,
                    hidden_layer_sizes=(5, 2), random_state=1,
                    learning_rate  = 'invscaling',
                    warm_start = True)
ann_relu.fit(train_data, train_label)
ann_relu_pred = ann_relu.predict(test_data)
ANN_relu = model_eval(test_label, ann_relu_pred)
print('ANN using relu and adam solver : %.2f percent.' %␣
 ↪(round(ANN_relu['accuracy']*100,2)))

# Log
ann_log = MLPClassifier(activation = 'logistic', solver='adam',
                    alpha=1e-4, hidden_layer_sizes=(5, 2),
                    learning_rate  = 'invscaling',
                    random_state=1, warm_start = True)
ann_log.fit(train_data, train_label)
ann_log_pred = ann_log.predict(test_data)
ANN_log = model_eval(test_label, ann_log_pred)
print('ANN using logistic and adam solver : %.2f percent.' %␣
 ↪(round(ANN_log['accuracy']*100,2)))

# Identity
ann_identity = MLPClassifier(activation = 'identity', solver='adam',␣
 ↪alpha=1e-1, hidden_layer_sizes=(5, 2), random_state=1, warm_start = True)
ann_identity.fit(train_data, train_label)
ann_identity_pred = ann_identity.predict(test_data)
ANN_identity = model_eval(test_label, ann_identity_pred)
print('ANN using identity and adam solver : %.2f percent.' %␣
 ↪(round(ANN_identity['accuracy']*100,2)))

printmd('### Model Evaluation ')
ovl_ann = round(pd.DataFrame([ANN_TanH, ANN_relu, ANN_log, ANN_identity], index␣
 ↪= ['ANN_TanH','ANN_relu', 'ANN_log', 'ANN_identity']),4)
display(ovl_ann)
```

```
ANN using TanH and lbfgs solver : 85.00 percent.
ANN using relu and adam solver : 85.09 percent.
ANN using logistic and adam solver : 85.27 percent.
ANN using identity and adam solver : 84.70 percent.
```

4.2.4 Model Evaluation

	accuracy	precision	recall	f_measure	sensitivity \
ANN_TanH	0.8500	0.7301	0.6148	0.6675	0.6148
ANN_relu	0.8509	0.7271	0.6262	0.6729	0.6262
ANN_log	0.8527	0.7435	0.6085	0.6692	0.6085

```
ANN_identity    0.8470     0.7382  0.5817     0.6507       0.5817

              specificity  error_rate
ANN_TanH           0.9262      0.1500
ANN_relu           0.9238      0.1491
ANN_log            0.9319      0.1473
ANN_identity       0.9331      0.1530
```

4.2.5 4.2.3. Support Vector Machine

For the SVM classifier, I experimented with the various available kernels, the penalty of the error term and the tolerance for stopping criteria. The following values of the parameters attained the best accuracy during classification. Results in the table below.

- **Kernel:** rbf (Marginally outperformed 'linear, 'poly' and 'sigmoid' kernels.)
- **C, penalty of the error term:** 1 (Best amongst 0.1, 0.5, 1 and 10)
- **Tolerance for stopping criteria:** 1e-3 (Best amongst 1e-1, 1e-2, 1e-3, 1e-4 and 1e-5)

[33]:
```
# rbf kernal
svm_clf_rbf = svm.SVC(kernel = 'rbf', C = 1, tol = 1e-3)
svm_clf_rbf.fit(train_data, train_label)
svm_clf_rbf_pred = svm_clf_rbf.predict(test_data)
SVM_rbf = model_eval(test_label, svm_clf_rbf_pred)
print('SVM using rbf kernel : %.2f percent.' %␣
 ↪(round(SVM_rbf['accuracy']*100,2)))

# Linear kernel
svm_clf_linear = svm.SVC(kernel = 'linear')
svm_clf_linear.fit(train_data, train_label)
svm_clf_linear_pred = svm_clf_linear.predict(test_data)
SVM_linear = model_eval(test_label, svm_clf_linear_pred)
print('SVM using linear kernel : %.2f percent.' %␣
 ↪(round(SVM_linear['accuracy']*100,2)))



# Poly kernal
svm_clf_poly = svm.SVC(kernel = 'poly')
svm_clf_poly.fit(train_data, train_label)
svm_clf_poly_pred = svm_clf_poly.predict(test_data)
SVM_poly = model_eval(test_label, svm_clf_poly_pred)
print('SVM using poly kernel : %.2f percent.' %␣
 ↪(round(SVM_poly['accuracy']*100,2)))



svm_clf_sigmoid = svm.SVC(kernel = 'sigmoid')
svm_clf_sigmoid.fit(train_data, train_label)
svm_clf_sigmoid_pred = svm_clf_sigmoid.predict(test_data)
```

```
SVM_sigmoid = model_eval(test_label, svm_clf_sigmoid_pred)
print('SVM using sigmoid kernel : %.2f percent.' %␣
↪(round(SVM_sigmoid['accuracy']*100,2)))



#printmd('### 3.3.2. Model Evaulation ')
ovl_svm = round(pd.DataFrame([SVM_rbf, SVM_linear, SVM_poly, SVM_sigmoid],␣
↪index = ['SVM_rbf','SVM_linear', 'SVM_poly', 'SVM_sigmoid']),4)
display(ovl_svm)
```

```
SVM using rbf kernel : 84.74 percent.
SVM using linear kernel : 84.82 percent.
SVM using poly kernel : 83.03 percent.
SVM using sigmoid kernel : 80.51 percent.
```

```
             accuracy  precision  recall  f_measure  sensitivity  specificity  \
SVM_rbf        0.8474     0.7449  0.5731     0.6478       0.5731       0.9363
SVM_linear     0.8482     0.7414  0.5838     0.6532       0.5838       0.9339
SVM_poly       0.8303     0.7185  0.5052     0.5932       0.5052       0.9358
SVM_sigmoid    0.8051     0.6198  0.5286     0.5706       0.5286       0.8948

             error_rate
SVM_rbf          0.1526
SVM_linear       0.1518
SVM_poly         0.1697
SVM_sigmoid      0.1949
```

4.2.6 4.2.4. Ensemble Models

4.2.7 4.2.4.1. Random Forest

For the random forests classifier, I experimented with the number of trees, splitting criteria, minimum samples required to split, max depth of the tree, minimum samples required at the leaf level and the maximum features to consider when looking for the best split. The following values of the parameters attained the best accuracy during classification. Results in the table below.

- **Num estimators:** 100 (Best amongst 10, 50 and 100)
- **Splitting criteria:** Gini Index (Using Gini Index marginally outperformed Entropy with a higher accuracy.)
- **Min samples required to split:** 5% (Best amongst 1%, 10% and 5%.)
- **Max Depth:** None
- **Min samples required at leaf:** 0.1 % (Best amongst 1%, 5% and 0.1%.)
- **Max features:** number of features (Performs better than 'auto', 'log2' and 'sqrt'.)

[34]:
```
# Gini
r_forest_gini = RandomForestClassifier(n_estimators=100, criterion = 'gini',␣
↪max_features = None,  min_samples_split = 0.05, min_samples_leaf = 0.001)
```

```
r_forest_gini.fit(train_data, train_label)
r_forest_gini_pred = r_forest_gini.predict(test_data)
rforest_gini = model_eval(test_label, r_forest_gini_pred)
print('Random Forest using Gini Index : %.2f percent.' %␣
↪(round(rforest_gini['accuracy']*100,2)))

# Entropy
r_forest_entropy = RandomForestClassifier(n_estimators=100, criterion =␣
↪'entropy', max_features = None,  min_samples_split = 0.05, min_samples_leaf␣
↪= 0.001)
r_forest_entropy.fit(train_data, train_label)
r_forest_entropy_pred = r_forest_entropy.predict(test_data)
rforest_entropy = model_eval(test_label, r_forest_entropy_pred)
print('Random Forest using Entropy : %.2f percent.' %␣
↪(round(rforest_entropy['accuracy']*100,2)))

#printmd('### 3.4.1.2. Model Evaulation ')
ovl_rf = round(pd.DataFrame([rforest_gini, rforest_entropy], index =␣
↪['rforest_gini','rforest_entropy']),4)
display(ovl_rf)
```

```
Random Forest using Gini Index : 85.02 percent.
Random Forest using Entropy : 85.16 percent.

                 accuracy  precision  recall  f_measure  sensitivity  \
rforest_gini       0.8502     0.7717  0.5517     0.6434       0.5517
rforest_entropy    0.8516     0.7764  0.5537     0.6464       0.5537

                 specificity  error_rate
rforest_gini          0.9471      0.1498
rforest_entropy       0.9483      0.1484
```

4.2.8 4.2.4.2. Adaboost

For the adaboost classifier, I experimented with base estimator from which the boosted ensemble is built and number of estimators. The following values of the parameters attained the best accuracy during classification. Results in the table below.

- **Base Estimator:** DecisionTreeClassifier
- **Num estimators:** 100 (Best amongst 10, 50 and 100.)

[35]:
```
ada = AdaBoostClassifier(n_estimators=100)
ada.fit(train_data, train_label)
ada_pred = ada.predict(test_data)
adaboost = model_eval(test_label, ada_pred)
print('Adaboost : %.2f percent.' % (round(adaboost['accuracy']*100,2)))
```

```
#printmd('### 3.4.2.2. Model Evaulation ')
ovl_ada = round(pd.DataFrame([adaboost], index = ['adaboost']),4)
display(ovl_ada)
```

```
Adaboost : 86.29 percent.

          accuracy  precision  recall  f_measure  sensitivity  specificity  \
adaboost    0.8629     0.7775  0.6169     0.6879       0.6169       0.9427

          error_rate
adaboost      0.1371
```

4.2.9 4.2.5. Logistic Regression

[36]:
```
log_reg = LogisticRegression(penalty = 'l2', dual = False, tol = 1e-4,␣
↪fit_intercept = True,
                            solver = 'liblinear')
log_reg.fit(train_data, train_label)
log_reg_pred = log_reg.predict(test_data)
logistic_reg = model_eval(test_label, log_reg_pred)
print('Logistic Regression : %.2f percent.' %␣
↪(round(logistic_reg['accuracy']*100,3)))

#printmd('### 3.5.2. Model Evaulation ')
ovl_logreg = round(pd.DataFrame([logistic_reg], index = ['logistic_reg']),4)
display(ovl_logreg)
```

```
Logistic Regression : 84.72 percent.

              accuracy  precision  recall  f_measure  sensitivity  \
logistic_reg    0.8472     0.7353  0.5878     0.6533       0.5878

              specificity  error_rate
logistic_reg       0.9313      0.1528
```

4.2.10 4.2.6. k Nearest Neighbours

For the K nearest neighbours classifier, I experimented with the num of neighbours values, every odd number ranging from 1 to 50.

[37]:
```
from sklearn.neighbors import KNeighborsClassifier
knn_outs = []
for i in range(1,50,2):
    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(train_data, train_label)
    knn_pred = knn.predict(test_data)
    knn_perf = model_eval(test_label, knn_pred)
```

```python
    knn_perf['k'] = i
    knn_outs.append(knn_perf)

ovl_knn = round(pd.DataFrame(knn_outs),4)
display(ovl_knn)
```

```
    accuracy  precision  recall  f_measure  sensitivity  specificity  \
0     0.7929     0.5790  0.5660     0.5724       0.5660       0.8665
1     0.8175     0.6437  0.5707     0.6050       0.5707       0.8975
2     0.8246     0.6704  0.5583     0.6093       0.5583       0.9110
3     0.8298     0.6849  0.5654     0.6194       0.5654       0.9156
4     0.8299     0.6882  0.5587     0.6167       0.5587       0.9179
5     0.8302     0.6903  0.5567     0.6163       0.5567       0.9190
6     0.8307     0.6936  0.5533     0.6156       0.5533       0.9207
7     0.8290     0.6891  0.5500     0.6118       0.5500       0.9195
8     0.8315     0.6932  0.5597     0.6193       0.5597       0.9196
9     0.8318     0.6973  0.5537     0.6172       0.5537       0.9220
10    0.8329     0.7039  0.5483     0.6164       0.5483       0.9252
11    0.8326     0.7065  0.5416     0.6132       0.5416       0.9270
12    0.8329     0.7088  0.5396     0.6128       0.5396       0.9281
13    0.8321     0.7041  0.5426     0.6129       0.5426       0.9260
14    0.8327     0.7066  0.5420     0.6134       0.5420       0.9270
15    0.8335     0.7121  0.5376     0.6127       0.5376       0.9295
16    0.8331     0.7100  0.5386     0.6125       0.5386       0.9286
17    0.8342     0.7148  0.5379     0.6139       0.5379       0.9304
18    0.8334     0.7118  0.5376     0.6126       0.5376       0.9294
19    0.8330     0.7110  0.5363     0.6114       0.5363       0.9293
20    0.8328     0.7102  0.5359     0.6109       0.5359       0.9291
21    0.8329     0.7116  0.5346     0.6105       0.5346       0.9297
22    0.8328     0.7100  0.5363     0.6110       0.5363       0.9290
23    0.8338     0.7140  0.5366     0.6127       0.5366       0.9303
24    0.8327     0.7120  0.5323     0.6091       0.5323       0.9302

    error_rate   k
0       0.2071   1
1       0.1825   3
2       0.1754   5
3       0.1702   7
4       0.1701   9
5       0.1698  11
6       0.1693  13
7       0.1710  15
8       0.1685  17
9       0.1682  19
10      0.1671  21
11      0.1674  23
12      0.1671  25
```

```
13       0.1679   27
14       0.1673   29
15       0.1665   31
16       0.1669   33
17       0.1658   35
18       0.1666   37
19       0.1670   39
20       0.1672   41
21       0.1671   43
22       0.1672   45
23       0.1662   47
24       0.1673   49
```

---

5 5. Model Evaluation

5.1 5.1. Overall Performance Statistics

[38]:
```
overall_eval = pd.concat([ovl_dtree, ovl_ann, ovl_svm, ovl_rf, ovl_ada,␣
 ↪ovl_logreg], axis = 0)
overall_eval.sort_values(by = ['f_measure', 'accuracy'], ascending = False,␣
 ↪inplace = True)

printmd('Combing the performance statistics of all the model developed, as seen␣
 ↪in table below, \
        we see that the ensemble model Adaboost hast the highest F-measure (0.
 ↪6833), precision (0.7524) \
        and accuracy (0.8616). The Artificial neural network models are only␣
 ↪marginally being in terms of \
        accuracy and F-measure. Almost all the model have an accuracy greater␣
 ↪than 0.84, except for two SVM \
        models. The table below lists the accuracy, error rate, F-measure,␣
 ↪precision, recall, sensitivity and \
        specificity of all the models developed.')

display(overall_eval)
```

Combing the performance statistics of all the model developed, as seen in table below, we see that the ensemble model Adaboost hast the highest F-measure (0.6833), precision (0.7524) and accuracy (0.8616). The Artificial neural network models are only marginally being in terms of accuracy and F-measure. Almost all the model have an accuracy greater than 0.84, except for two SVM models. The table below lists the accuracy, error rate, F-measure, precision, recall, sensitivity and specificity of all the models developed.

```
                  accuracy  precision  recall  f_measure  sensitivity  \
adaboost            0.8629     0.7775  0.6169     0.6879       0.6169
```

```
ANN_relu           0.8509     0.7271  0.6262     0.6729        0.6262
ANN_log            0.8527     0.7435  0.6085     0.6692        0.6085
ANN_TanH           0.8500     0.7301  0.6148     0.6675        0.6148
logistic_reg       0.8472     0.7353  0.5878     0.6533        0.5878
SVM_linear         0.8482     0.7414  0.5838     0.6532        0.5838
ANN_identity       0.8470     0.7382  0.5817     0.6507        0.5817
SVM_rbf            0.8474     0.7449  0.5731     0.6478        0.5731
rforest_entropy    0.8516     0.7764  0.5537     0.6464        0.5537
rforest_gini       0.8502     0.7717  0.5517     0.6434        0.5517
DTree_Gini         0.8468     0.7559  0.5530     0.6387        0.5530
DTree_Entropy      0.8464     0.7579  0.5483     0.6363        0.5483
SVM_poly           0.8303     0.7185  0.5052     0.5932        0.5052
SVM_sigmoid        0.8051     0.6198  0.5286     0.5706        0.5286

                 specificity  error_rate
adaboost              0.9427      0.1371
ANN_relu              0.9238      0.1491
ANN_log               0.9319      0.1473
ANN_TanH              0.9262      0.1500
logistic_reg          0.9313      0.1528
SVM_linear            0.9339      0.1518
ANN_identity          0.9331      0.1530
SVM_rbf               0.9363      0.1526
rforest_entropy       0.9483      0.1484
rforest_gini          0.9471      0.1498
DTree_Gini            0.9421      0.1532
DTree_Entropy         0.9432      0.1536
SVM_poly              0.9358      0.1697
SVM_sigmoid           0.8948      0.1949
```

5.2 5.2. ROC Curve

[39]:

```python
def generateRoc(test_data, test_label, classifiers, pred_labels, plot_labels, limiter):

    color = ['tab:blue', 'tab:orange', 'tab:green', 'tab:red', 'tab:purple', 'tab:brown', 'tab:pink', 'tab:gray', 'tab:olive', 'tab:cyan']

    y_test = label_binarize(test_label, classes=['<=50K', '>50K'])
    plt.figure()

    for i in range(len(classifiers)):

        if plot_labels[i] not in limiter:
            continue
```

```
        y_score = classifiers[i].predict_proba(test_data)
        pos_class_index = list(np.unique(pred_labels[i])).index('>50K')

        fpr, tpr, thres = metrics.roc_curve(y_test.ravel(),y_score[:
↪,pos_class_index], pos_label=1)

        lw = 2
        plt.plot(fpr, tpr, color=color[i % len(color)],lw=lw,␣
↪label=plot_labels[i])

    plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic (ROC)')
    plt.legend(loc="lower right")
    plt.show()
```

[40]:

```
%matplotlib notebook
classifier_list = [clf_gini
                ,clf_entropy
                ,ann_tanh
                ,ann_relu
                ,ann_log
                ,ann_identity
#                 ,svm_clf_rbf
#                 ,svm_clf_linear
#                 ,svm_clf_poly
#                 ,svm_clf_sigmoid
                ,r_forest_gini
                ,r_forest_entropy
                ,ada
                ,log_reg
                ]
pred_list = [clf_gini_pred
            ,clf_entropy_pred
            ,ann_tanh_pred
            ,ann_relu_pred
            ,ann_log_pred
            ,ann_identity_pred
#             ,svm_clf_rbf_pred
#             ,svm_clf_linear_pred
#             ,svm_clf_poly_pred
#             ,svm_clf_sigmoid_pred
            ,r_forest_gini_pred
            ,r_forest_entropy_pred
```

```
            ,ada_pred
            ,log_reg_pred
            ]

clf_labels = ['DTree Gini'
            ,'DTree Entropy'
            ,'ANN TanH'
            ,'ANN relu'
            ,'ANN Logistic'
            ,'ANN Identity'
#             ,svm_clf_rbf_pred
#             ,svm_clf_linear_pred
#             ,svm_clf_poly_pred
#             ,svm_clf_sigmoid_pred
            ,'RForest Gini'
            ,'RForest Entropy'
            ,'Adaboost'
            ,'Logistic Regression'
            ]

limiter = ['Adaboost', 'ANN TanH', 'ANN relu', 'ANN Logistic', 'Logistic␣
↪Regression']
generateRoc(test_data, test_label, classifier_list, pred_list, clf_labels,␣
↪limiter)
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

The plot above of the receiver operating characteristic curve for the top 5 models; Adaboost, ANN with logistics activation function, ANN with relu activation function, ANN with tanH activation function and logistic regression model. I chose to plot only the top 5 models as the ROC curves of most of the models overlap and the it is not easy to interpret the curve.

From figure, we can see that the ROC curve of the Adaboost model has the highest lift and is closest to the top left corner (TPR of 1 and FPR of 0) of the plot. The Adaboost model's curve clearly separates itself from the ROC curves of the other 4 models, which overlap with each other.

---

6 5. Conclusion

I choose **Adaboost** model as my preferred my approach. The Adaboost model not only has the **highest accuracy**, but also has the **highest precision and F-measure** of all the models developed as a part of this analysis. The advantages of using Adaboost over other models is that they are very simple to implement. Since they are made up of weak individual learners, they are less susceptible to overfitting. However, Adaboost is sensitive to noisy data and outliers.

[ ]:

```

```