Income

October 9, 2019

1 Problem setting

A polling institute wants to be able to estimate an individual's income from his/her personal data (see einkommen.train). To this aim, 30.000 individuals were interviewed concerning the features summarized below. For some of the individuals, not all features are available. Crucially, the income of only 5.000 of the interviewee's is known. Your task is to predict the income group of the remaining 25.000 interviewees and to prepare the data such that they can be used for further regression and correlation analyses.

Age

Employment type (Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked)

Weighting factor to compensate for an interview-dependent selection bias

Level of education (Bachelors, Some-college, HS-grad, Prof-school, Assoc-acdm, Assoc- voc, 1st-4th, 5th-6th, 7th-8th, 9th, 10th, 11th, 12th, Masters, Doctorate, Preschool)

Schooling/training period

Marital status (Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse)

Employment area (Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-shing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces)

Partnership (Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried)

Ethnicity (White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black)

Gender (Female, Male)

Gains on nancial assets

Losses on nancial assets

Weekly working time

Country of birth (United-States, Cambodia, England, Puerto-Rico, Canada, Ger- many, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ire- land, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hun- gary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trina- dad&Tobago, Peru, Hong Kong, Holand-Netherlands)

Income (50k, > 50k)

1.1 Introduce the Data

Task: Given attributes about a person, predict whether their income is <=50K or >50K

In [1]:
```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:
```python
# Import data and take a look
df = pd.read_csv('einkommen.train', names=['age','emplot-type','weight-factor',
                                           'level-edu','train-period','marital-statu',
                                           'employ-area','partnership','ethnicity',
                                           'gender','gains','losses','weekwtime',
                                           'country','income'])

df.head()
```

Out[2]:
```
   age         emplot-type  weight-factor   level-edu  train-period  \
0   39           State-gov          77516   Bachelors            13
1   50    Self-emp-not-inc          83311   Bachelors            13
2   38             Private         215646     HS-grad             9
3   53             Private         234721        11th             7
4   28             Private         338409   Bachelors            13

         marital-statu         employ-area     partnership ethnicity   gender  \
0        Never-married        Adm-clerical   Not-in-family     White     Male
1   Married-civ-spouse     Exec-managerial         Husband     White     Male
2             Divorced   Handlers-cleaners   Not-in-family     White     Male
3   Married-civ-spouse   Handlers-cleaners         Husband     Black     Male
4   Married-civ-spouse      Prof-specialty            Wife     Black   Female

   gains  losses  weekwtime         country  income
0   2174       0         40   United-States   <=50K
1      0       0         13   United-States   <=50K
2      0       0         40   United-States   <=50K
3      0       0         40   United-States   <=50K
4      0       0         40            Cuba   <=50K
```

In [3]:
```python
# the income of only 5.000 of the interviewees is known. so we drop all
# 25.000 interviewees.
df_train=df.drop(i for i in range(5000, 30000))
```

In [4]:
```python
df_train.head()
```

Out[4]:
```
   age         emplot-type  weight-factor   level-edu  train-period  \
0   39           State-gov          77516   Bachelors            13
1   50    Self-emp-not-inc          83311   Bachelors            13
2   38             Private         215646     HS-grad             9
3   53             Private         234721        11th             7
4   28             Private         338409   Bachelors            13

         marital-statu         employ-area     partnership ethnicity   gender  \
```

```
   0        Never-married        Adm-clerical   Not-in-family     White      Male
   1   Married-civ-spouse     Exec-managerial         Husband     White      Male
   2             Divorced   Handlers-cleaners   Not-in-family     White      Male
   3   Married-civ-spouse   Handlers-cleaners         Husband     Black      Male
   4   Married-civ-spouse      Prof-specialty            Wife     Black    Female

      gains  losses  weekwtime        country  income
   0   2174       0         40  United-States   <=50K
   1      0       0         13  United-States   <=50K
   2      0       0         40  United-States   <=50K
   3      0       0         40  United-States   <=50K
   4      0       0         40           Cuba   <=50K
```

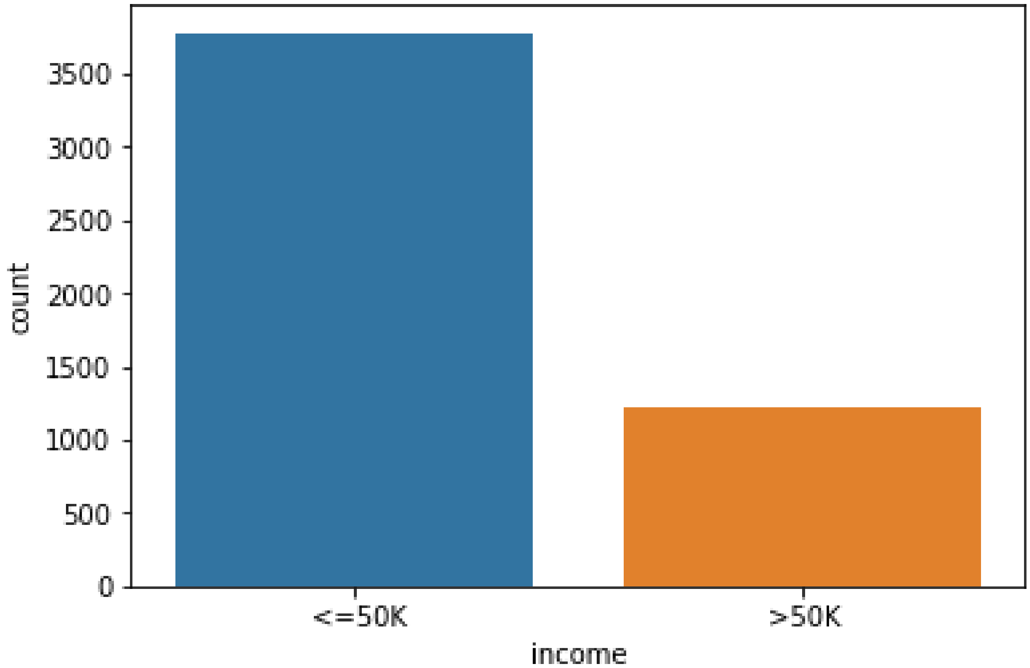
```
In [5]: df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5000 entries, 0 to 4999
Data columns (total 15 columns):
age                 5000 non-null int64
emplot-type         5000 non-null object
weight-factor       5000 non-null int64
level-edu           5000 non-null object
train-period        5000 non-null int64
marital-statu       5000 non-null object
employ-area         5000 non-null object
partnership         5000 non-null object
ethnicity           5000 non-null object
gender              5000 non-null object
gains               5000 non-null int64
losses              5000 non-null int64
weekwtime           5000 non-null int64
country             5000 non-null object
income              5000 non-null object
dtypes: int64(6), object(9)
memory usage: 625.0+ KB
```

```
In [6]: # Take a look at the outcome variable: 'income'
        print(df_train['income'].value_counts())
```

```
 <=50K    3779
 >50K     1221
Name: income, dtype: int64
```

```
In [7]: # Ploting the distribution of the income in the bar plot
        sns.countplot(x='income', data=df_train);
```

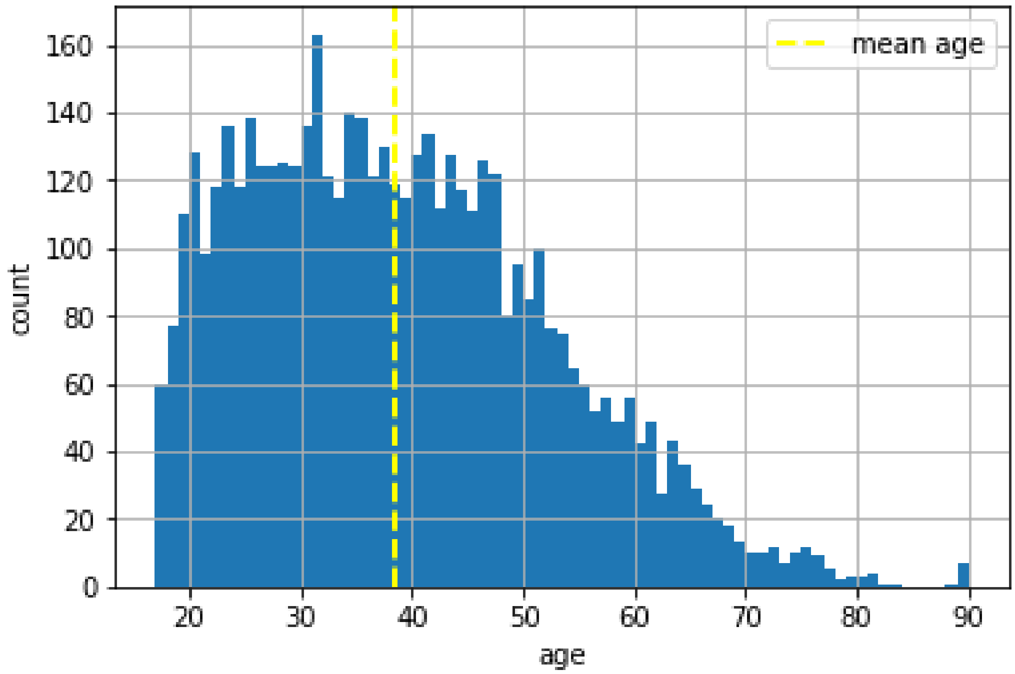


1.2 Exploring the data

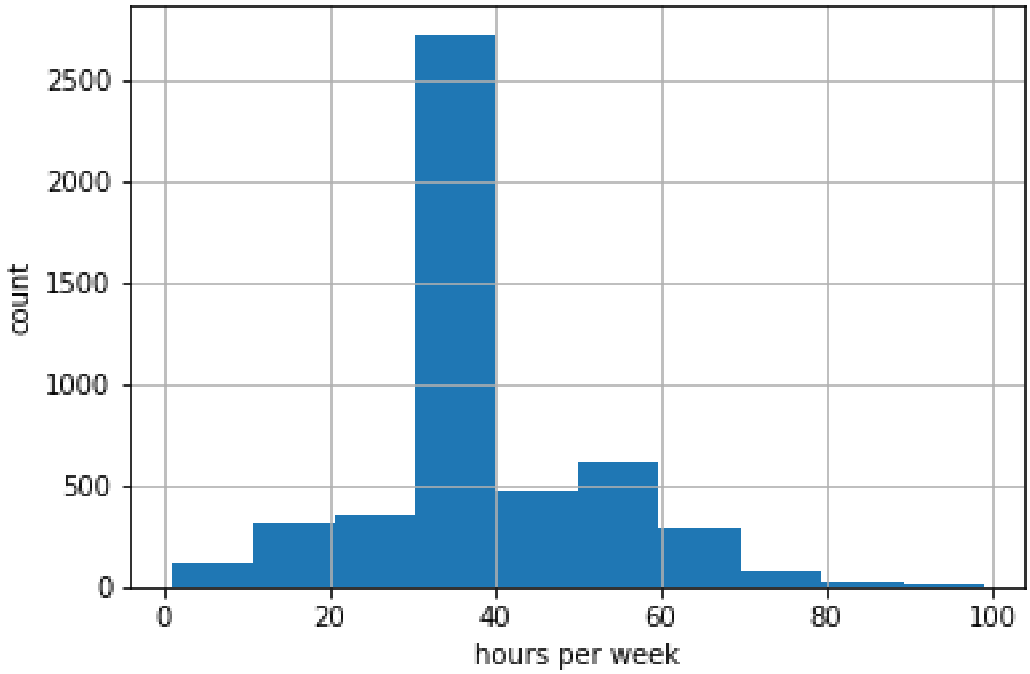
Lets now explore the data with few visualizations.

```
In [8]: # Assign outcome as 0 if income <=50K and as 1 if income >50K
        df_train['income'] = [0 if x == ' <=50K' else 1 for x in df_train['income']]

        # Assign X as a DataFrame of features and y as a Series of the outcome variable
        X = df_train.drop('income', 1)
        y = df_train.income
```

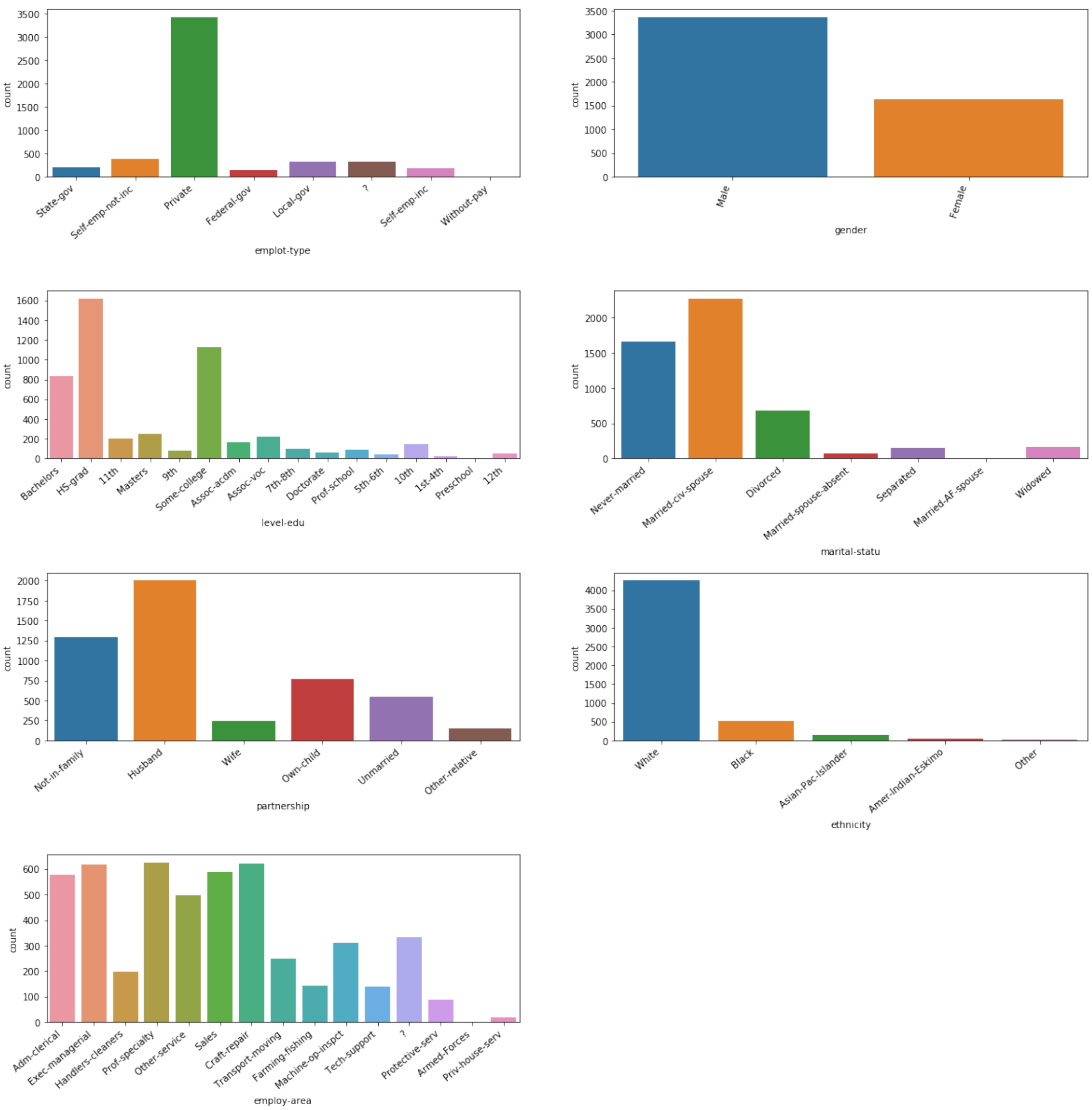
```
In [9]: # Age distribution
        ages = X['age'].hist(bins=max(X['age'])-min(X['age']))
        mean_val = np.mean(X['age'])
        plt.axvline(mean_val, linestyle='dashed', linewidth=2, color='yellow', label='mean age
        plt.xlabel('age')
        plt.ylabel('count')
        plt.legend()
        plt.show()
```



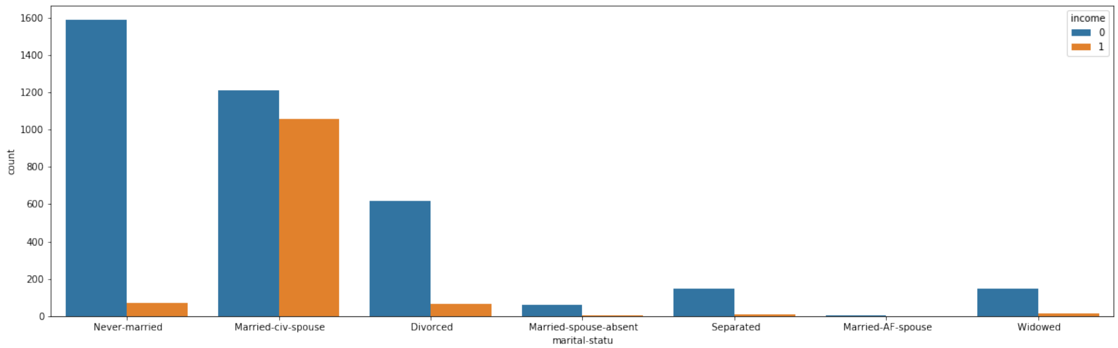

```
In [10]: X['weekwtime'].hist()
         plt.xlabel('hours per week')
         plt.ylabel('count')
         plt.show()
```



In [11]:
```
fig, axs = plt.subplots(ncols=2, nrows=4, figsize=(20, 20))
plt.subplots_adjust(hspace=0.68)
fig.delaxes(axs[3][1])

# Employment type
wc_plot = sns.countplot(X['emplot-type'], ax=axs[0][0])
wc_plot.set_xticklabels(wc_plot.get_xticklabels(), rotation=40, ha="right")

# Gender
ge_plot = sns.countplot(X['gender'], ax=axs[0][1])
ge_plot.set_xticklabels(ge_plot.get_xticklabels(), rotation=72, ha="right")

# Education level
ed_plot = sns.countplot(X['level-edu'], ax=axs[1][0])
ed_plot.set_xticklabels(ed_plot.get_xticklabels(), rotation=40, ha="right")

# Marital status
ms_plot = sns.countplot(X['marital-statu'], ax=axs[1][1])
ms_plot.set_xticklabels(ms_plot.get_xticklabels(), rotation=40, ha="right")

# Relationship
rel_plot = sns.countplot(X['partnership'], ax=axs[2][0])
rel_plot.set_xticklabels(rel_plot.get_xticklabels(), rotation=40, ha="right")

# Race
race_plot = sns.countplot(X['ethnicity'], ax=axs[2][1])
race_plot.set_xticklabels(race_plot.get_xticklabels(), rotation=40, ha="right")

# Occupation
occ_plot = sns.countplot(X['employ-area'], ax=axs[3][0])
occ_plot.set_xticklabels(occ_plot.get_xticklabels(), rotation=40, ha="right")

plt.show()
```



In [12]:
```
plt.figure(figsize=(20, 6))
sns.countplot(X['marital-statu'], hue=df_train['income'])
plt.show()
```



Inferences:

- Married citizens with spouse have higher chances of earning more than those who're unmarried/divorced/widowed/separated.
- A good marital relationship is also a key for earning more money.
- Males on an average make earn more than females.
- Higher Education can lead to higher income in most cases.
- Statistically (only), the Whites are always advantageous in salary.

1.3 Data cleaning

1.3.1 Handling Missing categorie

```
In [13]: # Handling Missing categorie by Replacing him by other categorie
         print(df_train['emplot-type'].value_counts())
```

```
 Private             3435
 Self-emp-not-inc     383
 ?                    331
 Local-gov            329
 State-gov            193
 Self-emp-inc         182
 Federal-gov          146
 Without-pay            1
Name: emplot-type, dtype: int64
```

```
In [14]: X['emplot-type'] = [' Other-emplot-type' if x == ' ?' else x for x in X['emplot-type']
```

```
In [15]: print(X['emplot-type'].value_counts())
```

```
 Private              3435
 Self-emp-not-inc      383
 Other-emplot-type     331
 Local-gov             329
 State-gov             193
```

```
 Self-emp-inc          182
 Federal-gov           146
 Without-pay             1
Name: emplot-type, dtype: int64
```

```
In [16]: print(df_train['employ-area'].value_counts())
```

```
 Prof-specialty       625
 Craft-repair         619
 Exec-managerial      618
 Sales                588
 Adm-clerical         576
 Other-service        495
 ?                    331
 Machine-op-inspct    312
 Transport-moving     247
 Handlers-cleaners    196
 Farming-fishing      143
 Tech-support         140
 Protective-serv       90
 Priv-house-serv       18
 Armed-Forces           2
Name: employ-area, dtype: int64
```

```
In [17]: X['employ-area'] = [' Other-employ-area' if x == ' ?' else x for x in X['employ-area']
```

```
In [18]: print(X['employ-area'].value_counts())
```

```
 Prof-specialty       625
 Craft-repair         619
 Exec-managerial      618
 Sales                588
 Adm-clerical         576
 Other-service        495
 Other-employ-area    331
 Machine-op-inspct    312
 Transport-moving     247
 Handlers-cleaners    196
 Farming-fishing      143
 Tech-support         140
 Protective-serv       90
 Priv-house-serv       18
 Armed-Forces           2
Name: employ-area, dtype: int64
```

1.3.2 Dealing with data types

Models can only handle numeric features Must convert categorical and ordinal features into numeric features

```
In [19]: # Decide which categorical variables you want to use in model
         for col_name in X.columns:
             if X[col_name].dtypes == 'object':
                 unique_cat = len(X[col_name].unique())
                 print("Feature '{col_name}' has {unique_cat} unique categories"
                       .format(col_name=col_name, unique_cat=unique_cat))
```

```
Feature 'emplot-type' has 8 unique categories
Feature 'level-edu' has 16 unique categories
Feature 'marital-statu' has 7 unique categories
Feature 'employ-area' has 15 unique categories
Feature 'partnership' has 6 unique categories
Feature 'ethnicity' has 5 unique categories
Feature 'gender' has 2 unique categories
Feature 'country' has 40 unique categories
```

```
In [20]: # Although, 'country' has a lot of unique categories,
         # most categories only have a few observations
         print(X['country'].value_counts().sort_values(ascending=False).head(10))
```

```
 United-States    4465
 Mexico            104
 ?                  97
 Canada             28
 Germany            22
 Philippines        22
 England            16
 El-Salvador        16
 Puerto-Rico        16
 Jamaica            15
Name: country, dtype: int64
```

```
In [21]: # In this case, bucket low frequecy categories as "Other"
         X['country'] = ['United-States ' if x == ' United-States' else 'Other' for x in X['co

         print(X['country'].value_counts().sort_values(ascending=False))
```

```
United-States     4465
Other              535
Name: country, dtype: int64
```

```
In [22]: X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5000 entries, 0 to 4999
Data columns (total 14 columns):
age               5000 non-null int64
emplot-type       5000 non-null object
weight-factor     5000 non-null int64
level-edu         5000 non-null object
train-period      5000 non-null int64
marital-statu     5000 non-null object
employ-area       5000 non-null object
partnership       5000 non-null object
ethnicity         5000 non-null object
gender            5000 non-null object
gains             5000 non-null int64
losses            5000 non-null int64
weekwtime         5000 non-null int64
country           5000 non-null object
dtypes: int64(6), object(8)
memory usage: 745.9+ KB
```

In [23]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
for col_name in X.columns:
        if X[col_name].dtypes == 'object':
            X[col_name]=le.fit_transform(X[col_name])
```

In [26]:
```
X.head()
```

Out[26]:

	age	emplot-type	weight-factor	level-edu	train-period	marital-statu
0	39	6	77516	9	13	4
1	50	5	83311	9	13	2
2	38	3	215646	11	9	0
3	53	3	234721	1	7	2
4	28	3	338409	9	13	2

	employ-area	partnership	ethnicity	gender	gains	losses	weekwtime
0	0	1	4	1	2174	0	40
1	3	0	4	1	0	0	13
2	5	1	4	1	0	0	40
3	5	0	2	1	0	0	40
4	10	5	2	0	0	0	40

	country
0	1
1	1
2	1
3	1
4	0

1.3.3 Handling missing data

An alternative solution is to use imputation - Replace missing value with another value - Strategies: mean, median, highest frequency value of given feature

```
In [27]: # How much of your data is missing?
         X.isnull().sum().sort_values(ascending=False).head()

         # Confirm All Missing Data is Handled
```

```
Out[27]: country      0
         weekwtime    0
         losses       0
         gains        0
         gender       0
         dtype: int64
```

```
In [28]: # Impute missing values using Imputer in sklearn.preprocessing
         #from sklearn.preprocessing import Imputer

         #imp = Imputer(missing_values='NaN', strategy='median', axis=0)
         #imp.fit(X)
         #X = pd.DataFrame(data=imp.transform(X) , columns=X.columns)
```

1.4 Model building

1.4.1 Build model using processed data

```
In [29]: # Importing objects from sklearn to help with the predictions.
         from sklearn.model_selection import train_test_split
         from sklearn.metrics import accuracy_score, precision_score,
                                     recall_score, confusion_matrix,
                                     precision_recall_curve
```

```
In [31]: # Use train_test_split in sklearn.cross_validation
         # to split data into train and test sets
         from sklearn.cross_validation import train_test_split

         X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                  train_size=0.70, random_state=1)
```

```
C:\Users\awdii\Anaconda3\lib\site-packages\sklearn\cross_validation.py:41: DeprecationWarning:
  "This module will be removed in 0.20.", DeprecationWarning)
```

```
In [32]: # Creating a confusion matrix.
         def CMatrix(CM, labels=['<=50K','>50K']):
             df = pd.DataFrame(data=CM, index=labels, columns=labels)
             df.index.name='TRUE'
             df.columns.name='PREDICTION'
```

```
    df.loc['TOTAL'] = df.sum()
    df['Total'] = df.sum(axis=1)
    return df
```

In [33]:
```
# Preparing a pandas DataFrame to analyze models (evaluation metrics).
metrics = pd.DataFrame(index=['accuracy', 'precision', 'recall'],
                       columns=['NULL','LogisticReg','ClassTree','RandomForest'])
```

1.5 The Null Model : Always predict the most common category

In [34]:
```
#######################
# The Null Model.
y_pred_test = np.repeat(y_train.value_counts().idxmax(), y_test.size)
metrics.loc['accuracy','NULL'] = accuracy_score(y_pred=y_pred_test, y_true=y_test)
metrics.loc['precision','NULL'] = precision_score(y_pred=y_pred_test, y_true=y_test)
metrics.loc['recall','NULL'] = recall_score(y_pred=y_pred_test, y_true=y_test)
accuracy_score(y_pred=y_pred_test, y_true=y_test)
```

```
C:\Users\awdii\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:1135: UndefinedMe
  'precision', 'predicted', average, warn_for)
```

Out[34]:
```
0.766
```

In [35]:
```
CM = confusion_matrix(y_pred=y_pred_test, y_true=y_test)
CMatrix(CM)
```

Out[35]:
```
PREDICTION  <=50K  >50K  Total
TRUE
<=50K        1149     0   1149
>50K          351     0    351
TOTAL        1500     0   1500
```

1.6 A. Logistic Regression.

In [36]:
```
# A. Logistic Regression.
# 1- Import the estimator object (model).
from sklearn.linear_model import LogisticRegression

# 2- Create an instance of the estimator.
logistic_regression = LogisticRegression()

# 3- Use the trainning data to train the estimator.
logistic_regression.fit(X_train, y_train)

# 4- Evaluate the model.
y_pred_test = logistic_regression.predict(X_test)
metrics.loc['accuracy','LogisticReg'] = accuracy_score(y_pred=y_pred_test, y_true=y_te
metrics.loc['precision','LogisticReg'] = precision_score(y_pred=y_pred_test, y_true=y_
```

```
metrics.loc['recall','LogisticReg'] = recall_score(y_pred=y_pred_test, y_true=y_test)

# Confusion Matrix.
CM = confusion_matrix(y_pred=y_pred_test, y_true=y_test)
CMatrix(CM)
```

Out[36]:

```
PREDICTION  <=50K  >50K  Total
TRUE
<=50K        1103    46   1149
>50K          250   101    351
TOTAL        1353   147   1500
```

1.7 B. Classification Trees.

In [37]:

```
# B. Classification Trees.
# 1- Import the estimator object (model).
from sklearn.tree import DecisionTreeClassifier

# 2- Create an instance of the estimator.
class_tree = DecisionTreeClassifier(min_samples_split=30,
                                    min_samples_leaf=10, random_state=10)

# 3- Use the trainning data to train the estimator.
class_tree.fit(X_train, y_train)

# 4- Evaluate the model.
y_pred_test = class_tree.predict(X_test)
metrics.loc['accuracy','ClassTree'] = accuracy_score(y_pred=y_pred_test, y_true=y_tes
metrics.loc['precision','ClassTree'] = precision_score(y_pred=y_pred_test, y_true=y_te
metrics.loc['recall','ClassTree'] = recall_score(y_pred=y_pred_test, y_true=y_test)

# Confusion Matrix.
CM = confusion_matrix(y_pred=y_pred_test, y_true=y_test)
CMatrix(CM)
```

Out[37]:

```
PREDICTION  <=50K  >50K  Total
TRUE
<=50K        1056    93   1149
>50K          158   193    351
TOTAL        1214   286   1500
```

1.8 C. Random Forest Classifier

In [38]:

```
# C. Random Forest Classifier.
# 1- Import the estimator object (model).
from sklearn.ensemble import RandomForestClassifier
```

```
# 2- Create an instance of the estimator.
random_forest = RandomForestClassifier()

# 3- Use the trainning data to train the estimator.
random_forest.fit(X_train, y_train)

# 4- Evaluate the model.
y_pred_test = random_forest.predict(X_test)
metrics.loc['accuracy','RandomForest'] = accuracy_score(y_pred=y_pred_test, y_true=y_t
metrics.loc['precision','RandomForest'] = precision_score(y_pred=y_pred_test, y_true=y
metrics.loc['recall','RandomForest'] = recall_score(y_pred=y_pred_test, y_true=y_test)

# Confusion Matrix.
CM = confusion_matrix(y_pred=y_pred_test, y_true=y_test)
CMatrix(CM)
```

Out[38]:

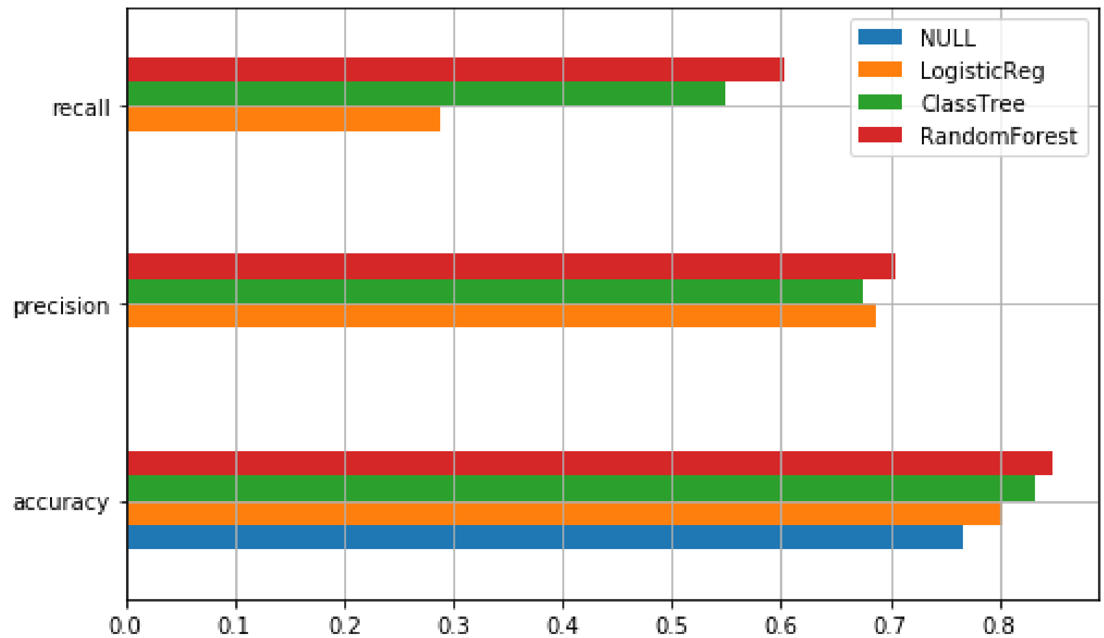
PREDICTION	<=50K	>50K	Total
TRUE			
<=50K	1060	89	1149
>50K	139	212	351
TOTAL	1199	301	1500

In [39]:
```
######################
# Comparing the models with percentages.
100*metrics
```

Out[39]:

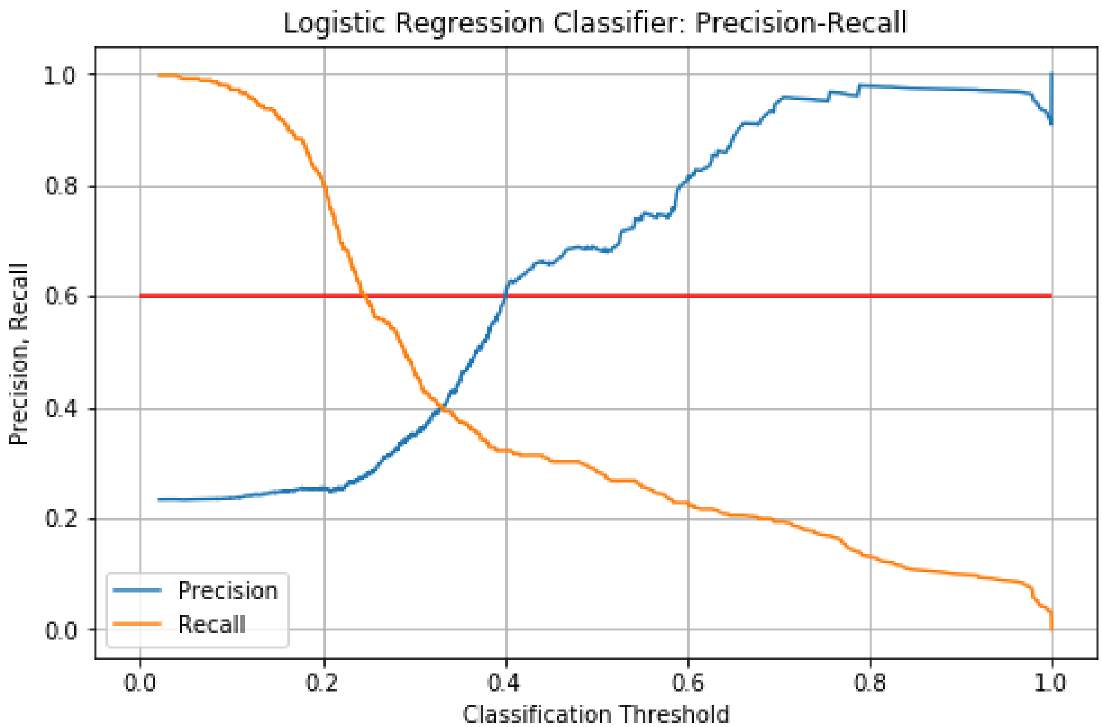
	NULL	LogisticReg	ClassTree	RandomForest
accuracy	76.6	80.2667	83.2667	84.8
precision	0	68.7075	67.4825	70.4319
recall	0	28.7749	54.9858	60.3989

In [40]:
```
# Comparing the models with a bar graph.
fig, ax = plt.subplots(figsize=(8,5))
metrics.plot(kind='barh', ax=ax)
ax.grid();
```



In [41]:
```
# Adjusting the precision and recall values for the logistic regression model

precision_lr, recall_lr, thresholds_lr = precision_recall_curve(y_true=y_test,
                    probas_pred=logistic_regression.predict_proba(X_test)[:,1])
```

In [42]:
```
# Creating a confusion matrix for modified Logistic Regression Classifier.
fig, ax = plt.subplots(figsize=(8,5))
ax.plot(thresholds_lr, precision_lr[1:], label='Precision')
ax.plot(thresholds_lr, recall_lr[1:], label='Recall')
ax.set_xlabel('Classification Threshold')
ax.set_ylabel('Precision, Recall')
ax.set_title('Logistic Regression Classifier: Precision-Recall')
ax.hlines(y=0.6, xmin=0, xmax=1, color='r')
ax.legend()
ax.grid();
```



1.9 Adjusting the threshold to 0.2.

```
In [43]: # Adjusting the threshold to 0.2.
         y_pred_proba = logistic_regression.predict_proba(X_test)[:,1]
         y_pred_test = (y_pred_proba >= 0.2).astype('int')

         # Confusion Matrix.
         CM = confusion_matrix(y_pred=y_pred_test, y_true=y_test)
         print('Recall: ', str(100*recall_score(y_pred=y_pred_test, y_true=y_test)) + '%')
         print('Precision: ', str(100*precision_score(y_pred=y_pred_test, y_true=y_test)) + '%
         CMatrix(CM)
```

```
Recall:  80.91168091168092%
Precision:  25.47085201793722%
```

```
Out[43]: PREDICTION  <=50K  >50K  Total
         TRUE
         <=50K         318   831   1149
         >50K           67   284    351
         TOTAL         385  1115   1500
```

We can see that Maritial statues, Working Hours and Sex really matters if you want to earn more than 50K per year. In contrary, the working class is not that important. Generally speaking, you will get equal opportunity if you work hard enough, no matter what kinds of job are you doing.

1.10 Prediction

predict the income group of the remaining 25.000 interviewees

```
In [44]: df_new=df.drop(i for i in range(0, 5000))
```

```
In [45]: Xnew = df_new.drop('income', 1)
```

```
In [46]: # Although, 'country' has a lot of unique categories,
         # most categories only have a few observations
         print(Xnew['country'].value_counts().sort_values(ascending=False).head(10))
```

```
 United-States    22406
 Mexico             498
 ?                  442
 Philippines        155
 Germany            100
 Puerto-Rico         96
 Canada              87
 India               82
 El-Salvador         80
 Cuba                73
Name: country, dtype: int64
```

```
In [47]: # In this case, bucket low frequecy categories as "Other"
         Xnew['country'] = ['United-States ' if x == ' United-States' else 'Other' for x in Xne

         print(Xnew['country'].value_counts().sort_values(ascending=False))
```

```
United-States     22406
Other              2594
Name: country, dtype: int64
```

```
In [48]: from sklearn.preprocessing import LabelEncoder
         le = LabelEncoder()
         for col_name in Xnew.columns:
                 if Xnew[col_name].dtypes == 'object':
                     Xnew[col_name]=le.fit_transform(Xnew[col_name])
```

```
In [49]: ynew = random_forest.predict(Xnew)
```

```
In [50]: df_new['income']=ynew
```

```
In [53]: df_new.head()
```

Out[53]:

```
      age     emplot-type  weight-factor     level-edu  train-period  \
5000   47    Self-emp-inc          79627   Prof-school            15
5001   55         Private         151474     Bachelors            13
5002   26         Private         132661       HS-grad             9
5003   28         Private         161674       HS-grad             9
5004   36         Private          62346       HS-grad             9

            marital-statu         employ-area     partnership ethnicity  \
5000             Divorced      Prof-specialty   Not-in-family     White
5001        Never-married        Tech-support  Other-relative     White
5002   Married-civ-spouse     Exec-managerial            Wife     White
5003        Never-married   Machine-op-inspct       Unmarried     White
5004   Married-civ-spouse        Craft-repair         Husband     Black

      gender  gains  losses  weekwtime        country  income
5000    Male  27828       0         50  United-States       1
5001  Female      0    1590         38  United-States       0
5002  Female   5013       0         40  United-States       0
5003  Female      0       0         40  United-States       0
5004    Male      0       0         40  United-States       0
```

In [52]:

```
# Ploting the distribution of the income in the bar plot
sns.countplot(x='income', data=df_new);
```