assignment_26.1

January 13, 2019

1 Assignment: Income Prediction of Individuals Using XGBoost

1.1 Overview:

In this assignment I have used XGBoost to predict income of an individaul. This data was extracted from the census bureau database found at http://www.census.gov/ftp/pub/DES/www/welcome.html donated by Ronny Kohavi and Barry Becker, Data Mining and Visualization (Email: ronnyk@sgi.com)

Dataset Link: https://archive.ics.uci.edu/ml/machine-learning-databases/adult/

1.2 Preprocess Datasets:

In this step I have first all the loaded datasets given in adult.data.csv which is used for training purpose. I also loaded adult.test.csv which is used for training/validation purpose.

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib
        import matplotlib.pyplot as plt
        import seaborn as sns
        %matplotlib inline
        import statsmodels.api as sm
        import matplotlib.pyplot as plt
        from patsy import dmatrices
        from sklearn.linear_model import LogisticRegression
        from sklearn.cross_validation import train_test_split
        from sklearn import metrics
        from sklearn.cross_validation import cross_val_score
        from sklearn.metrics import accuracy_score
```

```
E:\anaconda\lib\site-packages\statsmodels\compat\pandas.py:56: FutureWarning: The pandas.core.c
  from pandas.core import datetools
E:\anaconda\lib\site-packages\sklearn\cross_validation.py:41: DeprecationWarning: This module w
  "This module will be removed in 0.20.", DeprecationWarning)
```

```
In [2]: pd.set_option('display.height', 1000)
        pd.set_option('display.max_rows', 1000)
```

```
pd.set_option('display.max_columns', 500)
pd.set_option('display.width', 1500)
```

In [3]:
```
# load adult.data.csv into application_train_data dataframe
#application_train_data = pd.read_csv('adult.data.csv', header=None)

application_train_data = pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning-da
print('Training data shape:',application_train_data.shape)
```

```
Training data shape: (32561, 15)
```

In [4]:
```
application_train_data.head()
```

Out[4]:

	0	1	2	3	4	5	
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-cleri
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-manager
2	38	Private	215646	HS-grad	9	Divorced	Handlers-clean
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-clean
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-special

In [5]:
```
column_list = ['AGE', 'WORKCLASS', 'FNLWGT', 'EDUCATION', 'EDUCATION_NUM', 'MARITAL_STA
application_train_data.columns = column_list
application_train_data['TARGET'] = application_train_data['TARGET'].apply(lambda x: 1 i
```

In [6]:
```
application_train_data.head()
```

Out[6]:

	AGE	WORKCLASS	FNLWGT	EDUCATION	EDUCATION_NUM	MARITAL_STATUS	
0	39	State-gov	77516	Bachelors	13	Never-married	
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	I
2	38	Private	215646	HS-grad	9	Divorced	Ha
3	53	Private	234721	11th	7	Married-civ-spouse	Ha
4	28	Private	338409	Bachelors	13	Married-civ-spouse	

In [7]:
```
# load adult.test.csv into application_test_data dataframe
#application_test_data = pd.read_csv('adult.test.csv', header=None)
application_test_data = pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning-dat
print('Test data shape:',application_test_data.shape)
```

```
Test data shape: (16281, 15)
```

In [8]:
```
application_test_data.columns = column_list
application_test_data['TARGET'] = application_test_data['TARGET'].apply(lambda x: 1 if
```

In [9]:
```
application_test_data.head()
```

Out[9]:

	AGE	WORKCLASS	FNLWGT	EDUCATION	EDUCATION_NUM	MARITAL_STATUS	
0	25	Private	226802	11th	7	Never-married	Machine
1	38	Private	89814	HS-grad	9	Married-civ-spouse	Farm
2	28	Local-gov	336951	Assoc-acdm	12	Married-civ-spouse	Prot
3	44	Private	160323	Some-college	10	Married-civ-spouse	Machine
4	18	?	103497	Some-college	10	Never-married	

1.3 Missing Data Analysis

In this step, we first get which all columns have missing values and then calculate percentage of records which have missing values in each column.

```
In [10]: application_train_data.isnull().any()
```

```
Out[10]: AGE               False
         WORKCLASS         False
         FNLWGT            False
         EDUCATION         False
         EDUCATION_NUM     False
         MARITAL_STATUS    False
         OCCUPATION        False
         RELATIONSHIP      False
         RACE              False
         SEX               False
         CAPITAL_GAIN      False
         CAPITAL_LOSS      False
         HOURS_PER_WEEK    False
         NATIVE_COUNTRY    False
         TARGET            False
         dtype: bool
```

```
In [11]: application_test_data.isnull().any()
```

```
Out[11]: AGE               False
         WORKCLASS         False
         FNLWGT            False
         EDUCATION         False
         EDUCATION_NUM     False
         MARITAL_STATUS    False
         OCCUPATION        False
         RELATIONSHIP      False
         RACE              False
         SEX               False
         CAPITAL_GAIN      False
         CAPITAL_LOSS      False
         HOURS_PER_WEEK    False
         NATIVE_COUNTRY    False
         TARGET            False
         dtype: bool
```

1.4 Interpretation

As there are no missing value columns, we can skip this

1.5 Analyze the data

1.6 Get statistical parameters of the training and test data

In [12]:
```
application_train_data.describe()
```

Out[12]:

	AGE	FNLWGT	EDUCATION_NUM	CAPITAL_GAIN	CAPITAL_LOSS	HOURS_PI
count	32561.000000	3.256100e+04	32561.000000	32561.000000	32561.000000	32561
mean	38.581647	1.897784e+05	10.080679	1077.648844	87.303830	40
std	13.640433	1.055500e+05	2.572720	7385.292085	402.960219	12
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	1
25%	28.000000	1.178270e+05	9.000000	0.000000	0.000000	40
50%	37.000000	1.783560e+05	10.000000	0.000000	0.000000	40
75%	48.000000	2.370510e+05	12.000000	0.000000	0.000000	45
max	90.000000	1.484705e+06	16.000000	99999.000000	4356.000000	99

In [13]:
```
application_test_data.describe()
```

Out[13]:

	AGE	FNLWGT	EDUCATION_NUM	CAPITAL_GAIN	CAPITAL_LOSS	HOURS_PI
count	16281.000000	1.628100e+04	16281.000000	16281.000000	16281.000000	16281
mean	38.767459	1.894357e+05	10.072907	1081.905104	87.899269	40
std	13.849187	1.057149e+05	2.567545	7583.935968	403.105286	12
min	17.000000	1.349200e+04	1.000000	0.000000	0.000000	1
25%	28.000000	1.167360e+05	9.000000	0.000000	0.000000	40
50%	37.000000	1.778310e+05	10.000000	0.000000	0.000000	40
75%	48.000000	2.383840e+05	12.000000	0.000000	0.000000	45
max	90.000000	1.490400e+06	16.000000	99999.000000	3770.000000	99

1.7 Interpretation:

From the statistics parameters, mean of fnlwght is very high value 1.894357e+05, so we need log transformation

1.8 Get the event rate

Event rate percentage is calculated by dividing number of 1 in INCOME field by total number of records multiplied by 100

In [14]:
```
event_rate = (sum(application_train_data.loc[application_train_data['TARGET']==1,'TARG
print("Event_Rate: " + str(event_rate) + "%")
```

```
Event_Rate: 24.080955744602438%
```

1.9 Interpretation:

From the Event Rate, it is clear that target income is imbalanced, hence we need to consider recall, precision in addition to accuracy

1.10 Analyze WORKCLASS vs TARGET

- Create count of each type of WORKCLASS
- Create a cross-tabulation bar plot between WORKCLASS vs TARGET

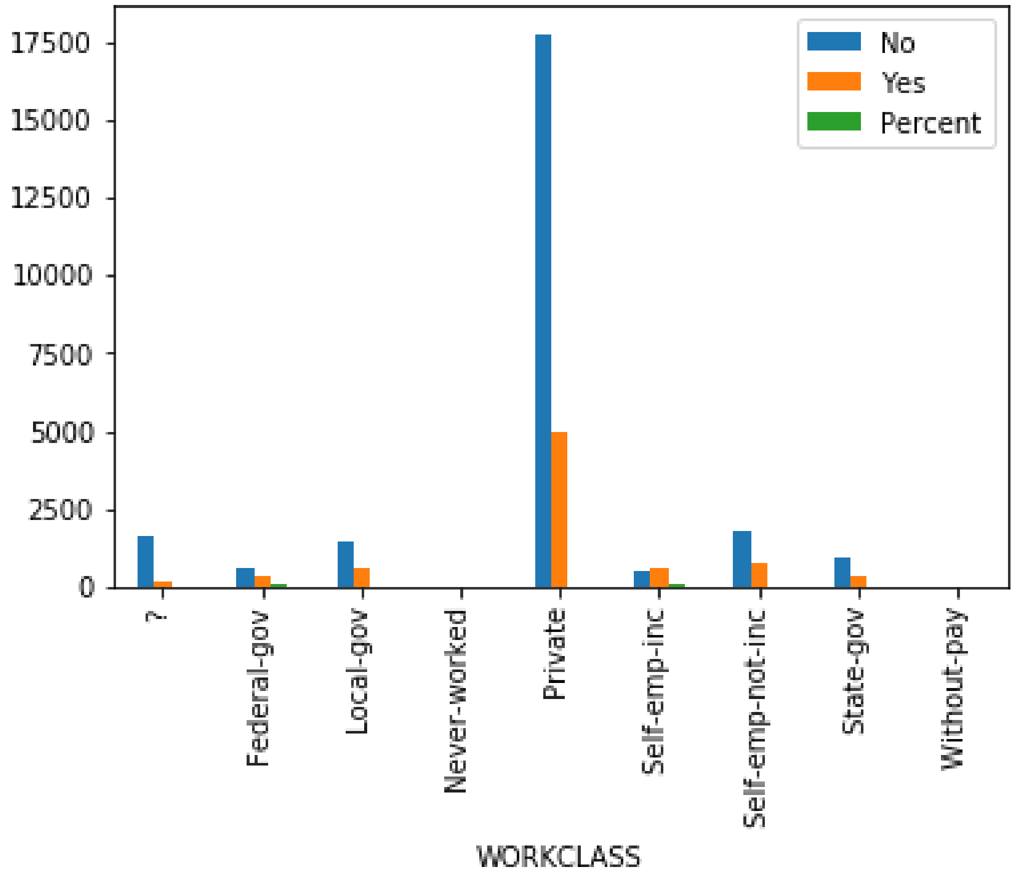
In [15]:
```
application_train_data['WORKCLASS'].value_counts()
```

Out[15]:
```
 Private             22696
 Self-emp-not-inc     2541
 Local-gov            2093
 ?                    1836
 State-gov            1298
 Self-emp-inc         1116
 Federal-gov           960
 Without-pay            14
 Never-worked            7
Name: WORKCLASS, dtype: int64
```

In [16]:
```
tab = pd.crosstab(index=application_train_data['WORKCLASS'],columns=application_train_
tab.columns = ['No','Yes']
tab['Percent'] = tab.Yes/(tab.No+tab.Yes) * 100
print(tab)
tab.plot(kind='bar')
```

```
                      No   Yes    Percent
WORKCLASS
 ?                  1645   191  10.403050
 Federal-gov         589   371  38.645833
 Local-gov          1476   617  29.479216
 Never-worked          7     0   0.000000
 Private           17733  4963  21.867289
 Self-emp-inc        494   622  55.734767
 Self-emp-not-inc   1817   724  28.492719
 State-gov           945   353  27.195686
 Without-pay          14     0   0.000000
```

Out[16]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x25a72bbb8d0>
```



1.11 Interpretation:

In terms of absolute numbers Private workclass have most number of people (4963) having > 50K income. However, percentage wise 21 percent of total private employees have mre tahn 50K income

% of Yes of Private employed 21.86% dividing by event rate, lift value = 21.86/24.08 = 0.91
% of Yes Self-emp-inc is 55.73 divinding by event rate, lift value = 55.73/24.08 = 2.31
% of Yes of Federal-gov is 38.65, dividing by event rate, lift value = 38.65/24.08 = 1.60
% of Yes of Local-gov is 29.48 dividing by event rate, lift value =29.48/24.08= 1.22
From the lift values, workcalss could be significant

1.12 Analyze EDUCATION vs TARGET

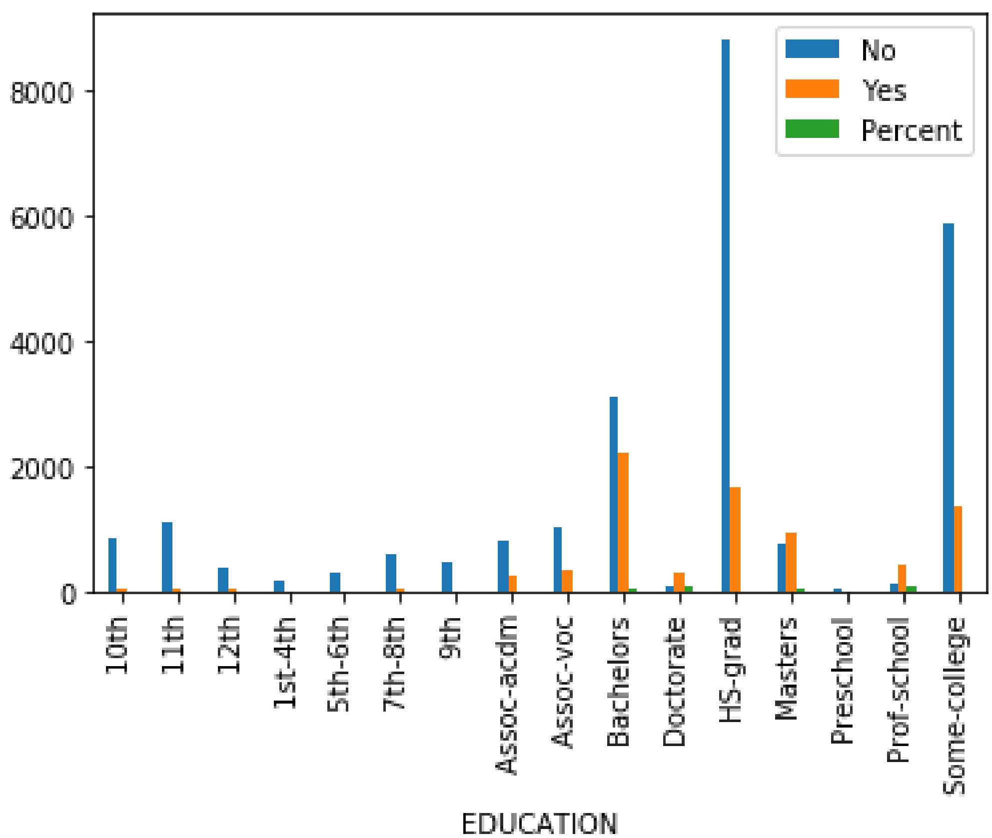
Create count of each type of EDUCATION Create a cross-tabulation bar plot between WORKCLASS vs TARGET

```
In [17]: tab = pd.crosstab(index=application_train_data['EDUCATION'],columns=application_train_
         tab.columns = ['No','Yes']
         tab['Percent'] = tab.Yes/(tab.No+tab.Yes) * 100
```

```python
print(tab)
tab.plot(kind='bar')
```

```
                 No   Yes    Percent
EDUCATION
 10th           871    62   6.645230
 11th          1115    60   5.106383
 12th           400    33   7.621247
 1st-4th        162     6   3.571429
 5th-6th        317    16   4.804805
 7th-8th        606    40   6.191950
 9th            487    27   5.252918
 Assoc-acdm     802   265  24.835989
 Assoc-voc     1021   361  26.121563
 Bachelors     3134  2221  41.475257
 Doctorate      107   306  74.092010
 HS-grad       8826  1675  15.950862
 Masters        764   959  55.658735
 Preschool       51     0   0.000000
 Prof-school    153   423  73.437500
 Some-college  5904  1387  19.023454
```

Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x25a72b250f0>



1.13 Interpretation

In terms of absoulute numbers bachelors degree have highest number of persons having > 50K income. In terms of percentage, doctorates have highest percentage of people having > 50K
% of Yes of Doctorate 74.09 dividing by event rate, lift value = 74.09/24.08 = 3.07
% of Yes Masters is 55.65 divinding by event rate, lift value = 55.65/24.08 = 2.31
% of Yes of Bachelors is 41.48, dividing by event rate, lift value = 41.48/24.08 = 1.72
% of Yes of HS-grad is 15.95 dividing by event rate, lift value = 15.95/24.08= 0.66
From the lift values, education could be significant

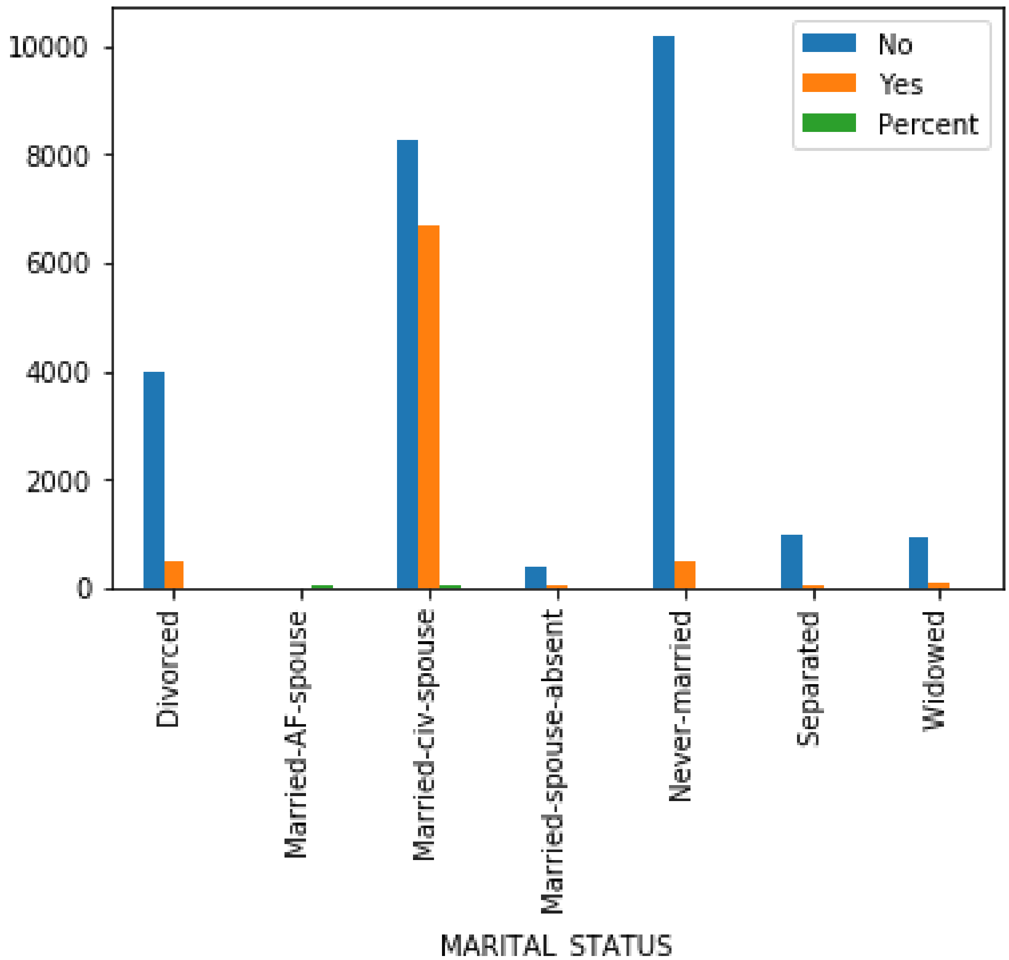
1.14 Analyze MARITAL_STATUS vs TARGET

Create count of each type of MARITAL_STATUS Create a cross-tabulation bar plot between MARITAL_STATUS vs TARGET

```
In [18]: tab = pd.crosstab(index=application_train_data['MARITAL_STATUS'],columns=application_t
         tab.columns = ['No','Yes']
         tab['Percent'] = tab.Yes/(tab.No+tab.Yes) * 100
         print(tab)
         tab.plot(kind='bar')
```

```
                          No   Yes    Percent
MARITAL_STATUS
 Divorced               3980   463  10.420887
 Married-AF-spouse        13    10  43.478261
 Married-civ-spouse     8284  6692  44.684829
 Married-spouse-absent   384    34   8.133971
 Never-married         10192   491   4.596087
 Separated               959    66   6.439024
 Widowed                 908    85   8.559919
```

```
Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x25a72de15f8>
```



Interpretation:

% of Yes of Married-civ-spouse 44.68 dividing by event rate, lift value = 44.68/24.08 = 1.86 % of Yes of Never-married 4.60 dividing by event rate, lift value = 4.60/24.08 = 0.19 % of Yes of Divorced 10.42 dividing by event rate, lift value = 10.42/24.08 = 0.43

From the lift values MARITAL_STATUS is a significant feature in determining person having income > 50K

1.15 Linear correlation analysis of fields:

TARGET, CAPITAL_GAIN, CAPITAL_LOSS, HOURS_PER_WEEK

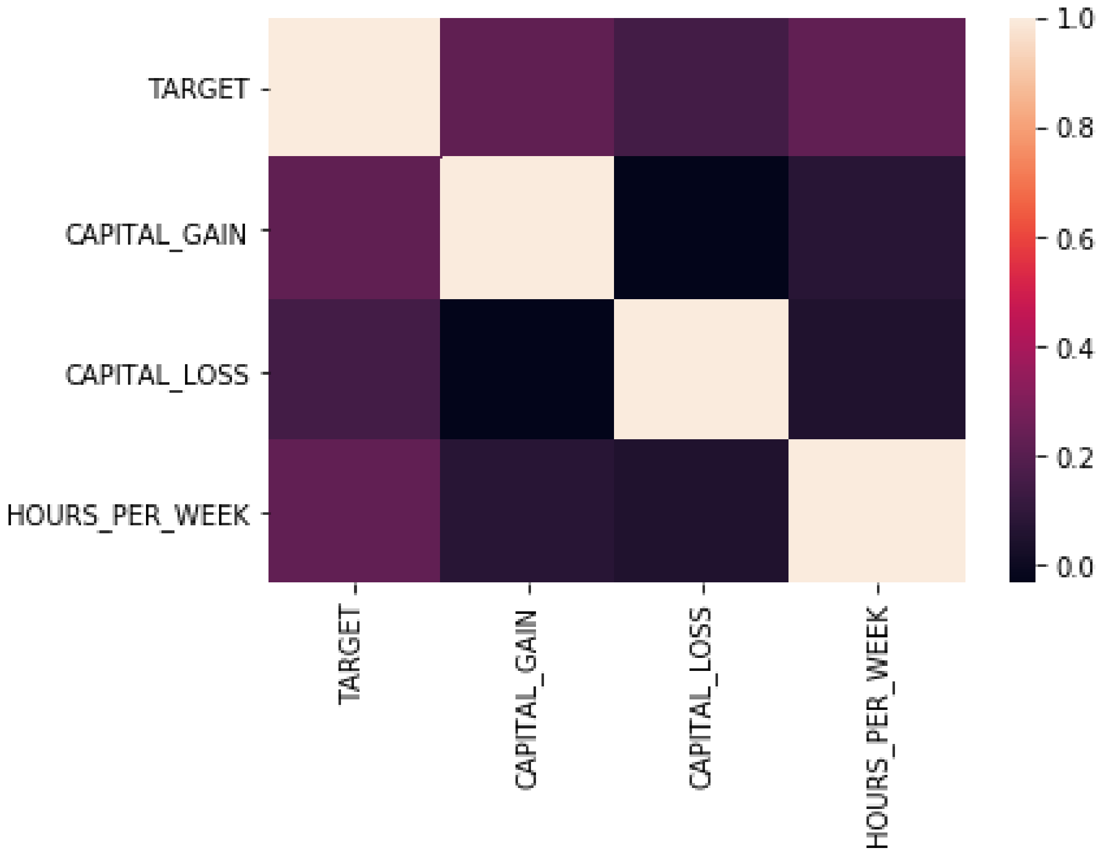
- First calculate correlation coefficinets
- Draw the heatmap

```
In [19]: cor = application_train_data[['TARGET','CAPITAL_GAIN','CAPITAL_LOSS','HOURS_PER_WEEK']
         print( "Correlation coefficients are:")
         print(str(cor))
```

```
sns.heatmap(cor)
```

```
Correlation coefficients are:
                  TARGET  CAPITAL_GAIN  CAPITAL_LOSS  HOURS_PER_WEEK
TARGET          1.000000      0.223329      0.150526        0.229689
CAPITAL_GAIN    0.223329      1.000000     -0.031615        0.078409
CAPITAL_LOSS    0.150526     -0.031615      1.000000        0.054256
HOURS_PER_WEEK  0.229689      0.078409      0.054256        1.000000
```

```
Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x25a734bab70>
```



1.16 Interpretation:

As all the correlation coefficients are low value, the fields TARGET, CAPITAL_GAIN, CAPITAL_LOSS, HOURS_PER_WEEK do not have correlation

1.17 Linear correlation analysis of fields:

TARGET, AGE, FNLWGT, EDUCATION_NUM

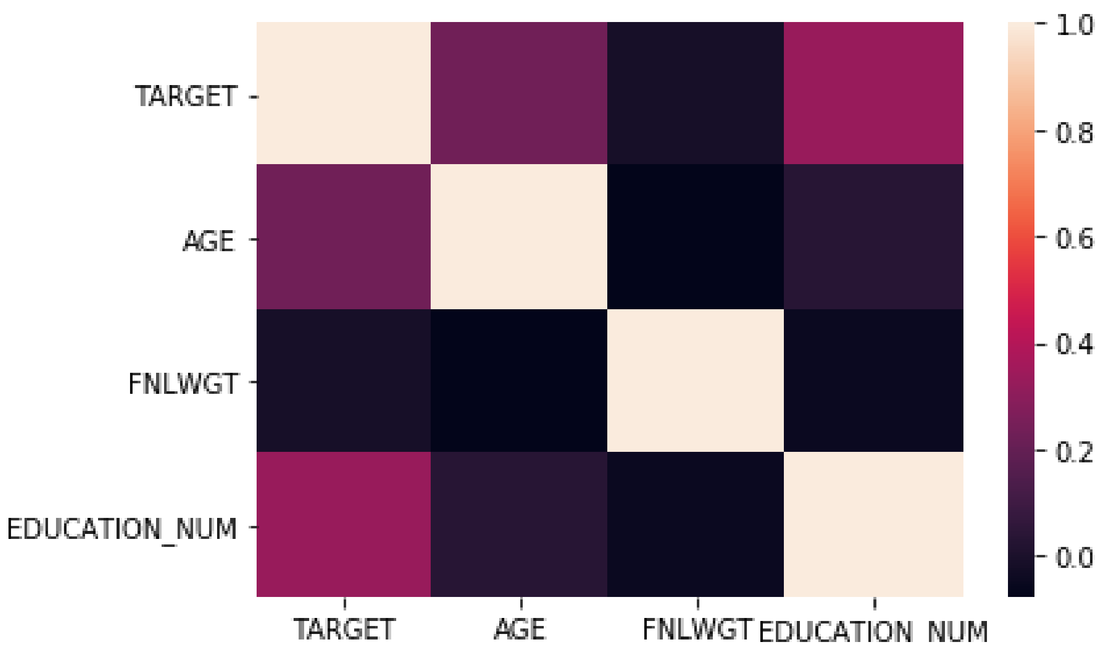
- First calculate correlation coefficinets
- Draw the heatmap

```
In [20]: cor = application_train_data[['TARGET','AGE','FNLWGT','EDUCATION_NUM']].corr()
         print( "Correlation coefficients are:")
         print(str(cor))

         sns.heatmap(cor)
```

```
Correlation coefficients are:
                 TARGET       AGE    FNLWGT  EDUCATION_NUM
TARGET         1.000000  0.234037 -0.009463       0.335154
AGE            0.234037  1.000000 -0.076646       0.036527
FNLWGT        -0.009463 -0.076646  1.000000      -0.043195
EDUCATION_NUM  0.335154  0.036527 -0.043195       1.000000
```

```
Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x25a73581cf8>
```



1.18 Interpretation:

From the heatmap it is clear that EDUCATION_NUM there is some corrrelation to TARGET

1.19 Field Transformations

i. Logarithmic Transformation: For highly-skewed feature distributions such as FNLWGT, CAPITAL_GAIN CAPITAL_LOSS, logarithmic transformation is done on the data so that the very large and very small values do not negatively affect the performance of a learning algorithm. Using a logarithmic transformation significantly reduces the range of values caused by outliers. Care must be taken when applying this transformation however: The logarithm of 0 is undefined, so we must translate the values by a small amount above 0 to apply the the logarithm successfully.

ii. Normalizing Numerical Features

In addition to performing transformations on features that are highly skewed, it is often good practice to perform some type of scaling on numerical features. Applying a scaling to the data does not change the shape of each feature's distribution (such as EDUCATION_NUM, AGE above); however, normalization ensures that each feature is treated equally when applying supervised learners. Note that once scaling is applied, observing the data in its raw form will no longer have the same original meaning, as exampled below.

iii.One hot encoding for categorical features Categorical variables having more than two possible vlaues are encoded using the one-hot encoding scheme. One-hot encoding creates a "dummy" variable for each possible category of each non-numeric feature. For example, assume someFeature has three possible entries: A, B, or C. We then encode this feature into someFeature_A, someFeature_B and someFeature_C.

iv. Label Encoding: Categorical variables having more than two possible are encoded using Label Encode to have values 0 and 1

In [21]:
```
# Perform log transformation
log_transform_fields = [ 'FNLWGT', 'CAPITAL_GAIN', 'CAPITAL_LOSS']

train_data = pd.DataFrame(data = application_train_data)
train_data[log_transform_fields] = application_train_data[log_transform_fields].apply

test_data = pd.DataFrame(data = application_test_data)
test_data[log_transform_fields] = application_test_data[log_transform_fields].apply(la
```

In [22]:
```
from sklearn.preprocessing import MinMaxScaler

# Initialize a scaler, then apply it to the features
scaler = MinMaxScaler() # default=(0, 1)

numerical = ['AGE','FNLWGT','EDUCATION_NUM', 'CAPITAL_GAIN', 'CAPITAL_LOSS']

temp1 = pd.DataFrame(data = train_data)
temp1[numerical] = scaler.fit_transform( train_data[numerical])
train_data = temp1

temp2 = pd.DataFrame(data = test_data)
temp2[numerical] = scaler.fit_transform( test_data[numerical])
test_data = temp2
```

In [23]:
```
train_data.head()
```

Out[23]:

	AGE	WORKCLASS	FNLWGT	EDUCATION	EDUCATION_NUM	MARITAL_STAT
0	0.301370	State-gov	0.384197	Bachelors	0.800000	Never-marr
1	0.452055	Self-emp-not-inc	0.399234	Bachelors	0.800000	Married-civ-spou
2	0.287671	Private	0.597596	HS-grad	0.533333	Divor
3	0.493151	Private	0.615275	11th	0.400000	Married-civ-spou
4	0.150685	Private	0.691582	Bachelors	0.800000	Married-civ-spou

1.20 Interpretation:

The accuracy score of original model is higher than reduced model. So I will stick with original model

In [24]:
```
#  One-hot encode the 'train_data' data using pandas.get_dummies()
categorical = ['WORKCLASS','EDUCATION','MARITAL_STATUS','OCCUPATION','RELATIONSHIP','I

train_data = pd.get_dummies(data = train_data, columns = categorical)

test_data = pd.get_dummies(data = test_data, columns = categorical)
```

In [25]:
```
# Drop the fields TARGET to create dataframe train_data_x
train_data_x = train_data.drop(['TARGET'], axis=1)

# Get only filed TARGET to create dataframe train_data_y
train_data_y = train_data['TARGET']
```

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

Out[26]:

	AGE	FNLWGT	EDUCATION_NUM	CAPITAL_GAIN	CAPITAL_LOSS	HOURS_PER_WEEK	WOR
0	0.301370	0.384197	0.800000	0.667492	0.0	40	
1	0.452055	0.399234	0.800000	0.000000	0.0	13	
2	0.287671	0.597596	0.533333	0.000000	0.0	40	
3	0.493151	0.615275	0.400000	0.000000	0.0	40	
4	0.150685	0.691582	0.800000	0.000000	0.0	40	

	SEX_ Male	NATIVE_COUNTRY_ ?	NATIVE_COUNTRY_ Cambodia	NATIVE_COUNTRY_ Canada	NA
0	1	0	0	0	
1	1	0	0	0	
2	1	0	0	0	
3	1	0	0	0	
4	0	0	0	0	

In [27]:
```
train_data_y.head()
```

Out[27]:
```
0    0
1    0
2    0
3    0
4    0
Name: TARGET, dtype: int64
```

In [28]:
```
# Drop the fields TARGET to create dataframe test_data_x
test_data_x = test_data.drop(['TARGET'], axis=1)

# Get only filed TARGET to create dataframe test_data_y
test_data_y = test_data['TARGET']
```

In [29]:
```
test_data_x.head()
```

Out[29]:

	AGE	FNLWGT	EDUCATION_NUM	CAPITAL_GAIN	CAPITAL_LOSS	HOURS_PER_WEEK	WORI
0	0.109589	0.599816	0.400000	0.000000	0.0	40	
1	0.287671	0.402918	0.533333	0.000000	0.0	50	
2	0.150685	0.683958	0.733333	0.000000	0.0	40	
3	0.369863	0.526083	0.600000	0.777174	0.0	40	
4	0.013699	0.433059	0.600000	0.000000	0.0	30	

	SEX_ Male	NATIVE_COUNTRY_ ?	NATIVE_COUNTRY_ Cambodia	NATIVE_COUNTRY_ Canada	NA
0	1	0	0	0	
1	1	0	0	0	
2	1	0	0	0	
3	1	0	0	0	
4	0	0	0	0	

In [30]:
```
test_data_y.head()
```

Out[30]:
```
0    0
1    0
2    0
3    0
4    0
Name: TARGET, dtype: int64
```

In [31]:
```
# Check if there is any field which is there in train_data_x but not in test_data_x a
train_col_set = set(train_data_x.columns.values.tolist())
test_col_set = set(test_data_x.columns.values.tolist())

train_minus_test_list = list(train_col_set - test_col_set)
test_minus_train_list = list(test_col_set - train_col_set)
```

In [32]:
```
train_minus_test_list
```

Out[32]:
```
['NATIVE_COUNTRY_ Holand-Netherlands']
```

In [33]:
```
test_minus_train_list
```

Out[33]:
```
[]
```

In [34]:
```
train_data_x = train_data_x.drop(['NATIVE_COUNTRY_ Holand-Netherlands'], axis=1)
```

1.21 Train using XGBClassifier and calulate accuracy score on test data

```
In [35]: from xgboost import XGBClassifier


         model = XGBClassifier(random_state=0)
         model.fit(train_data_x, train_data_y)
         test_predict = model.predict(test_data_x)
         acc_score = accuracy_score(test_predict, test_data_y)
         print("Accuracy Score: " + str(acc_score))
```

```
Accuracy Score: 0.8255021190344574
```

```
E:\anaconda\lib\site-packages\sklearn\preprocessing\label.py:151: DeprecationWarning: The trut
  if diff:
```

1.22 Conclusion:

By using XGBClassifier I got a accuracy of 82.55 on test data