ADULT INCOME DATA

Final Project Report

Abstract

Predict the Adult Income data using USA Census Data
http://mlr.cs.umass.edu/ml/datasets/Adult

Shabbir Yousuf Ali – 039081070
CMKE 136 – Capstone Project
syali@ryerson.ca
https://github.com/shabbiryousufali/CKME136

Introduction

Predict whether income exceeds $50K/year based on census data. Also known as "Census Income" dataset. Extraction was done by Barry Becker from the 1994 Census database. Adult income helps to determine the growth of the country/region. In this study I will try to understand which factor(s) is/are more important in improving individual income. I will do the classification, regression and prediction to determine whether the income of adult is greater than 50K or not. I will explore the key attributes / factors that could affect the adult income (like higher education, age, area etc.)

Research Questions

1) How many adults have income less than 50K and greater than 50K
2) Individuals with higher education vs individuals with basis education
   a. Higher education means high income?
3) What factors/attributes should be considered to predict the income

Literature Review

The adult dataset was compiled by Barry Becker, who extracted the data from the US 1994 Census database. This dataset was given to Ron Kohavi who used it to study the effectiveness of a new machine learning algorithm he's proposed called the NBTree. According to Kohavi, the NBTree algorithm leverages the "surprising [accuracy]" of Naïve-Bayes and the scalability of Decision Trees. After the completion of Kohavi's paper in 1996, the dataset was donated and now hosted by the Machine Learning Group at UC Irvine

http://robotics.stanford.edu/~ronnyk/nbtree-talk.pdf
The paper by Ron Kohavi talks about a modified version of ID3 Decision Tree. The new algorithm is called NBTree, which induces a hybrid of decision-tree classifiers and Naïve-Bayes classifiers. The NBTree nodes contain univariate splits as regular decision-tree, but the leaves contain Naïve-Bayesian classifiers. Kohavi explains that the NBTree is a hybrid of naive bayes and a decision tree and is most suitable for scenarios where many attributes are significant in predicting the label, but they aren't all necessarily
conditionally independent

https://mpra.ub.uni-muenchen.de/83406/1/MPRA_paper_83406.pdf
S. M. Bekena, "Using decision tree classifier to predict income levels," MPRA Archive, 2017

In this study Random Forest Classifier machine learning algorithm is applied to predict income levels of individuals based on attributes including education, marital status, gender, occupation, country and others. Income levels are defined as a binary variable 0 for income <=50K/year and 1 for higher levels

https://link.springer.com/content/pdf/10.1023/B:MACH.0000011804.08528.7d.pdf
The paper by Jinyan Li introduces a new algorithm doesn't use distance as measurement but use frequency of an instance's subsets and the frequency-changing rate of the subsets among training classes to perform both knowledge discovery and classification tasks.

https://link.springer.com/content/pdf/10.1007/978-0-387-35592-4_12.pdf
Dennis P. Groth and Edward L. Robertson. An Entropy-based Approach to Visualizing Database Structure. VDB. 2002. The work by Dennis P. Groth talks about the use of entropy for visualizing database structure. Visualizing entropy of a relation provides a global perspective on the distribution of values and helps to identify areas within the relation where interesting relationships may be discovered.

http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.387.5068&rep=rep1&type=pdf
A. Lazar, "Income prediction via support vector machine," in 2004 International Conference on Machine Learning and Applications, 2004. Proceedings., Louisville, Kentucky, USA, 2004. In this paper, the effects of data reduction on the classification results of the SVM algorithm are presented. The training time and the performance of a SVM classifier where compared for six different subsets of the adult data set. Despite the vertically reduced datasets, good classification accuracy was obtained in faster time. The conclusion is very important especially for datasets with many variables that can be reduced by using the PCA method

After reading the above reviews, I have decided to use logistic regression, random forest and naïve bayes for my project. It is further supported by the fact that the project of predicting income from census data is a binary classification problem, as the target variable having binary output and data has mixed numerical and nominal attributes

I will use Logistic regression to predict income based on the p values. Random forest can be used for better performance.

Dataset

URL - http://mlr.cs.umass.edu/ml/machine-learning-databases/adult/

Extraction was done by Barry Becker from the 1994 Census database. A set of reasonably clean records was extracted using the following conditions: ((AAGE>16) && (AGI>100) && (AFNLWGT>1) && (HRSWK>0))

- The dataset has 14 attributes and 48842 number of instances.
  8 are categorical and 6 are numerical
- 48842 instances, mix of continuous and discrete (train=32561, test=16281)
- 45222 if instances with unknown values are removed (train=30162, test=15060)

Data Description

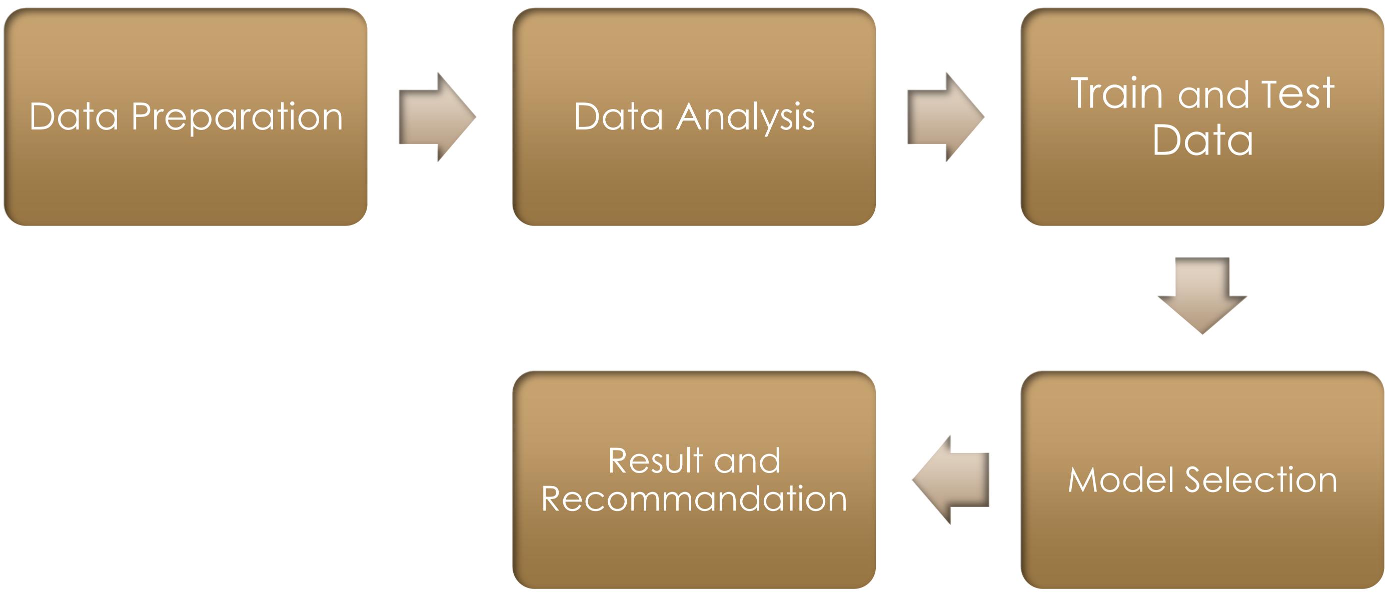
Attribute	Data Type	Description	Distinct Items
Age	Integer	Age of a person	17 is Minimum 90 is Maximum
Workclass	Categorical	Work Class	9 Distinct and Known Categories Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked Unknown Category ? = 1836
Fnlwgt	Integer	Final Weight	
education	Categorical	Highest education	16 Distinct Categories Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool
education-num	Integer	# of years of education	1 is Minimum 16 is Maximum
marital-status	Categorical	Marital Status	7 Distinct Categories Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse
occupation	Categorical	Person Occupation	15 Distinct and Known Categories Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces Unknown Category ? = 1843 records

relationship	Categorical	Role in a family	5 Distinct Categories Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried
race	Categorical		5 Distinct Categories White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black
sex	Categorical		2 Distinct Categories Male, Female
capital-gain	Integer	Gain during a year	
capital-loss	Integer	Losses during a year	
hours-per-week	Integer	work hours in a week	
native-country	Categorical	Native Country	42 Distinct Categories United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands Unknown Category ? = 583 records

Statistics

SEQ	Name	Min	Max	Mean	Median	SD	1st QU	3rd QU
1	Age	17.00	90.00	38.58	37.00	13.64	28.00	48.00
2	Education Num	1.0	16.0	10.58	10.00	2.57	9.00	12.00
3	Capital Gain	0.0	999	1078	0.0	7385.29	0.0	0.0
4	Capital Loss	0.0	4656.0	87.3	0.0	402.96	0.0	0.0
5	Hours per week	1.0	99.0	40.44	40.00	12.35	40.00	45.00

Approach



Step 1 – Data Preparation

The following data preparation tasks are conducted to make the data suitable for running the machine learning model

1) Download and load the data
2) Add headers to the data
3) Clean the data by removing the unknown values
4) Standard calculation can be performed on the integer attributes to get their statistical information (like mean, median etc.)
5) Categorical attributes (work class, occupation and native country) have missing information, we will remove the missing information to get more accurate result
6) Check if the data is normal or not and what attributes are the outliers

Result

Train data will contain 70% of the original data (i.e. 24421 records)
Test data will contain 30% of the original data (i.e. 8439 records)

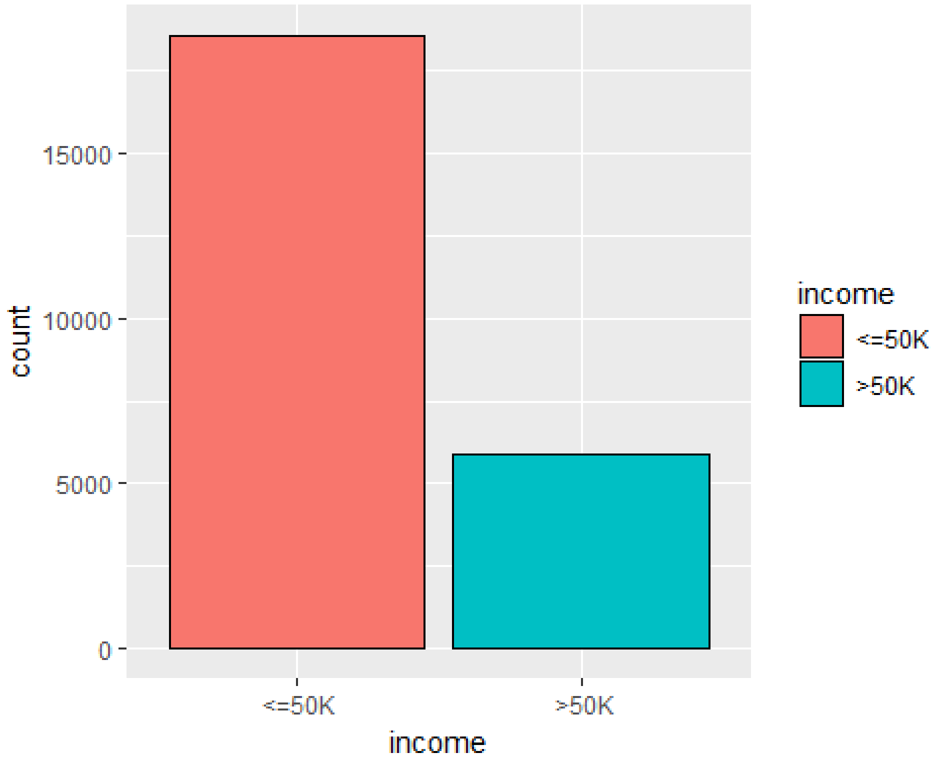
Step 2 – Data Analysis

We will do the complete analysis between attributes. Find the attribute relationship and dependencies; strong correlation vs weak correlation

1) Does Higher education mean high income?
   Study shows higher education means high income. As from the article published by Markus Hofmann in 2011 (View Link) , on page 11, figure 4
   When the education number attribute was plotted for the class labels it was found that the lower values tend to predominate in the 50K class which may indicate some predictive capability
2) Does age have any impact on the income?
3) Study by Sisay Menji Bekena 30 July 2017, clear shows that age has an impact on the income. The research on page 8 (View Link) shows the positive correlation with income. This show that marital status, capital gain, education, age and work hours (employment) determine much of the difference between low and high income levels

4) Which occupation pays the highest income?

Income distribution

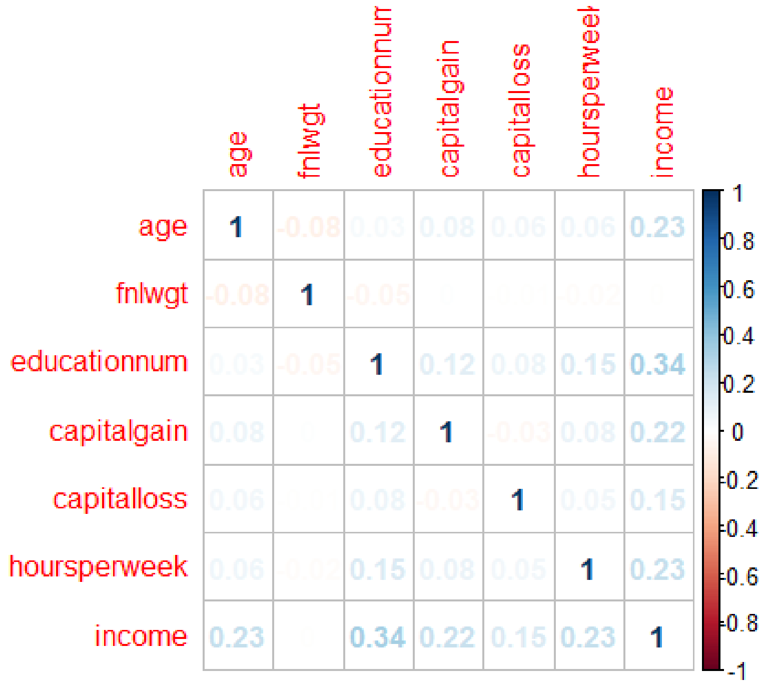


Above diagram shows the distribution of the income attribute.

Income <= 50K is approximately 76% where income > 50K is approximately 24%

Correlation

a. Between Numerical Attributes



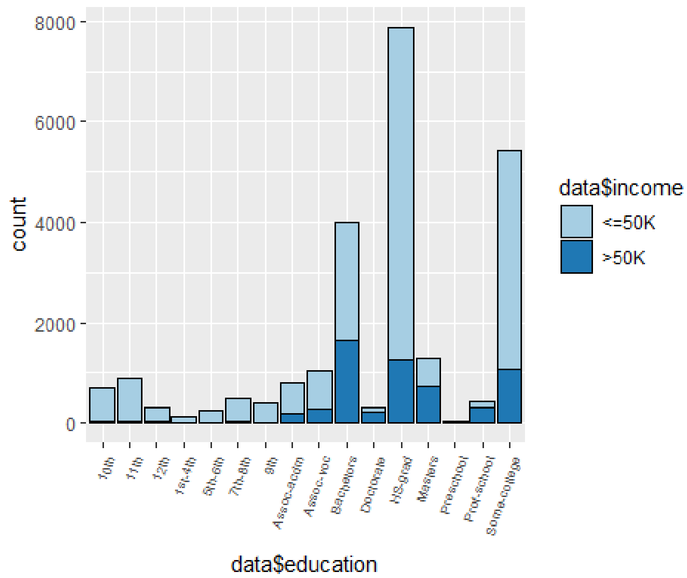
The correlation matrix created between the numerical attributes only.

Correlations shows that numeric attributes are related but they are not strongly correlated. Education has the highest correlation 0.33 with income followed by the Capital gain 0.22, age 0.24 and hours worked 0.23. The variables are positively correlated with each other

b. Between Categorical and Numerical (i.e. income)

Correlation between Education and Income

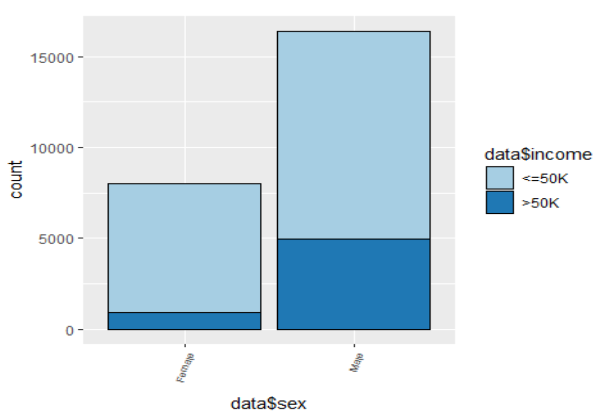
```
ggplot(data, aes(x=data$education,fill=data$income)) +
geom_bar(position = "stack", color = "black") +
theme(axis.text.x=element_text(angle = 70 , hjust= 1, size=7)) +
scale_fill_brewer(palette="Paired")
```



Result shows adults with higher education has earning > 50K. Adults with bachelor's degree have maximum number of earnings > 50K, followed by doctorate and masters. Adults with lower education level have maximum portion of income <= 50K

Correlation between Sex and Income

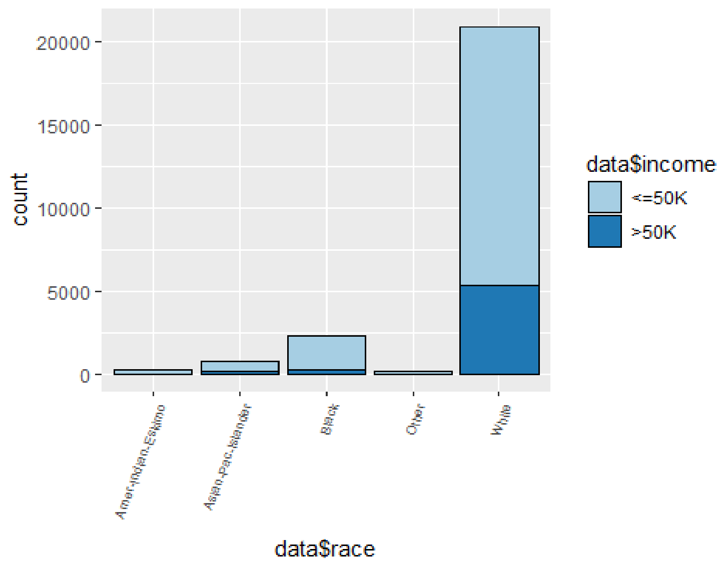
```
ggplot(data, aes(x=data$sex,fill=data$income)) + geom_bar(position = "stack", color = "black") + theme(axis.text.x=element_text(angle = 70 , hjust= 1, size=7)) + scale_fill_brewer(palette="Paired")
```



Result shows the ratio of male earning income > 50K is more than female

Correlation between Race and Income

```
ggplot(data, aes(x=data$race,fill=data$income)) + geom_bar(position = "stack", color = "black") + theme(axis.text.x=element_text(angle = 70 , hjust= 1, size=7)) + scale_fill_brewer(palette="Paired")
```

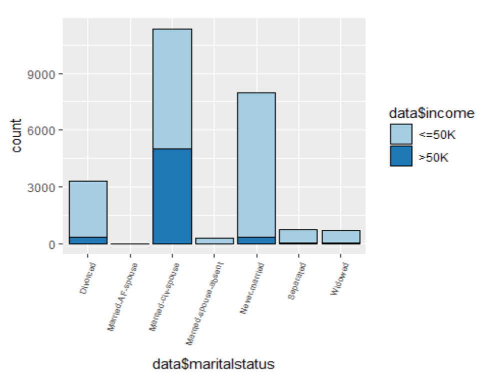


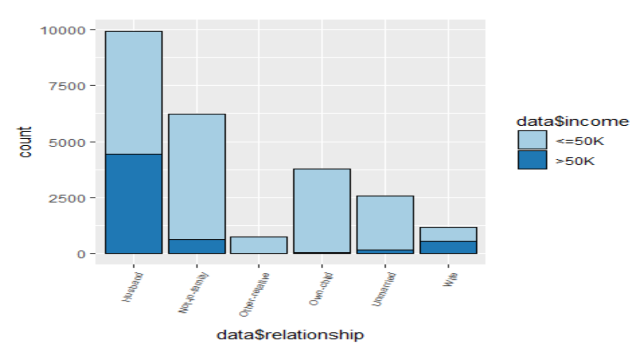
Result shows the highest earning adults are white followed by Black and Asia pacific

Correlation between Marital Status and Income

```
ggplot(data, aes(x=data$maritalstatus,fill=data$income)) + geom_bar(position = "stack", color = "black") + theme(axis.text.x=element_text(angle = 70 , hjust= 1, size=7)) + scale_fill_brewer(palette="Paired")
```

```
ggplot(data, aes(x=data$relationship,fill=data$income)) + geom_bar(position = "stack", color = "black") + theme(axis.text.x=element_text(angle = 70 , hjust= 1, size=7)) + scale_fill_brewer(palette="Paired")
```



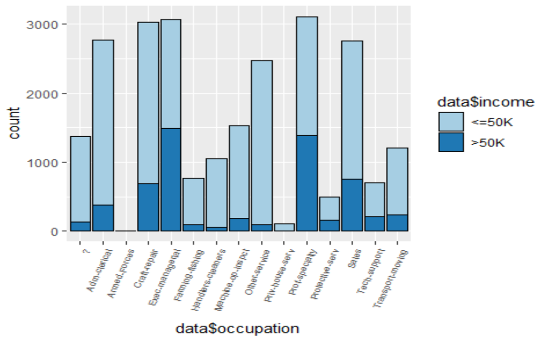


Shabbir Yousuf Ali (syali@ryerson.ca) **Student ID** 039081070
https://github.com/shabbiryousufali/CKME136

Results in both the graphs show that Male and married people are earning more than 50K, as compared to female and unmarried people

Correlation between Occupation and Income

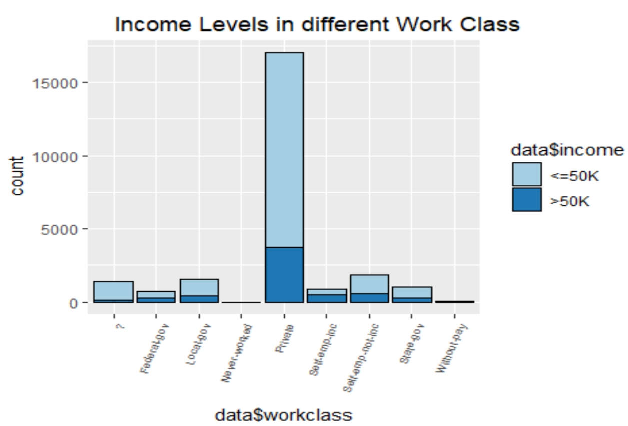
```
ggplot(data, aes(x=data$occupation,fill=data$income)) + geom_bar(position = "stack", color = "black") + theme(axis.text.x=element_text(angle = 70 , hjust= 1, size=7)) + scale_fill_brewer(palette="Paired")
```



Result shows adults with higher position like Manager, Professor are earning > 50K

Correlation between Work class and Income

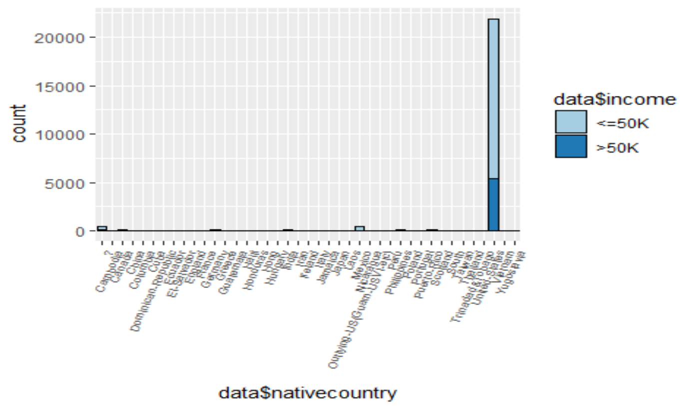
```
ggplot(data, aes(x=data$workclass,fill=data$income)) + geom_bar(position = "stack", color = "black") + ggtitle('     Income Levels in different Work Class')+ theme(axis.text.x=element_text(angle = 70 , hjust= 1, size=7))  + scale_fill_brewer(palette="Paired")
```



Result shows adults in private sector have maximum number of earning of > 50K

<u>Correlation between Native Country and Income</u>

```
ggplot(data, aes(x=data$nativecountry,fill=data$income)) +
geom_bar(position = "stack", color = "black") +
theme(axis.text.x=element_text(angle = 70 , hjust= 1, size=7)) +
scale_fill_brewer(palette="Paired")
```



Result shows majority of the adults belongs to the United States

Step 3 – Test and Train Data

Different classification algorithm will be used to test the train and test data; algorithms like Logistic Regression, Random Forest and Naïve Bayes. Similar approached was used in the paper by Ron Kohavi talks about a modified version of ID3 Decision Tree (View Link)

1) Train data will contain 70% of the original data (i.e. 24421 records)
2) Test data will contain 30% of the original data (i.e. 8439 records)

Step 4 – Model Selection

S. M. Bekena use the Random Forest Classifier machine learning algorithm to predict the income level (View Link). He achieved 85% accuracy by using the key attributes like marital status, capital gain, education, age and hours per week

Model used for the train and test data are

a. Decision Tree
b. Linear Regression
c. Random Forest

Random Forest Classifier will be used because the outcome (target) variable is binary variable (income level >50K or not). Also, the random forest has better accuracy as compared to Naïve Bayes classifier

The model with the highest accuracy will be selected as the final model

Decision Tree

```
Dectree<- rpart(income~ age+ workclass+ education+maritalstatus+
occupation+ sex +hoursperweek, data = traindata, method='class',cp =1e-
3)
```

Result using Traindata

```
Dectree.Ptrain <- predict(Dectree,newdata= traindata, type = 'class')
confusionMatrix(traindata$income,Dectree.Ptrain)
```

Prediction <=50K >50K <=50K 17328 1212 >50K 2576 3305	Accuracy : 0.8449 Sensitivity : 0.8706 Specificity : 0.7317 Pos Pred Value : 0.9346 Neg Pred Value : 0.5620 Prevalence : 0.8150

Result using Testdata

```
Dectree.pred.prob <- predict(Dectree, newdata = testdata, type =
'prob')
Dectree.pred <- predict(Dectree, newdata = testdata, type = 'class')
confusionMatrix(testdata$income,Dectree.pred)
```

Prediction <=50K >50K <=50K 5700 479 >50K 888 1072	Accuracy : 0.832 Sensitivity : 0.8652 Specificity : 0.6912 Pos Pred Value : 0.9225 Neg Pred Value : 0.5469 Prevalence : 0.8094

Linear Regression

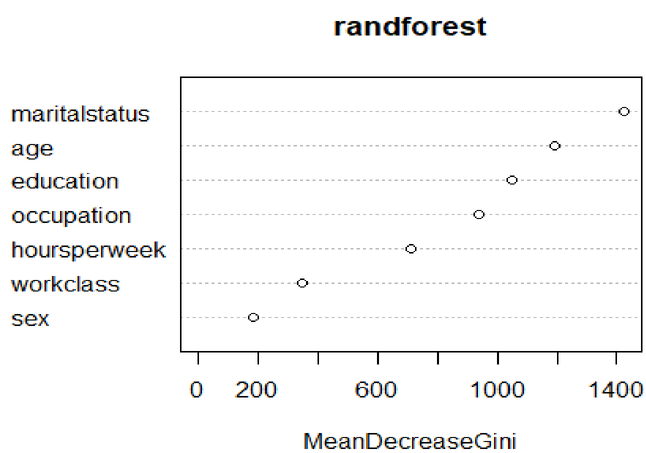
```
linReg <- glm(income ~ age+ workclass+ education+maritalstatus+
occupation+ sex +hoursperweek, data = traindata, family =
binomial('logit'))
```

```
pred1     <=50K   >50K
<=50K   17168   2644
>50K     1372   3237
```

Random Forest

```
randforest <- randomForest(income ~ age+ workclass+ education+
maritalstatus+occupation+ sex+hoursperweek, data = traindata, ntree =
500)
randforest.pred.prob <- predict(randforest, newdata = testdata, type =
'prob')
randforest.pred <- predict(randforest, newdata = testdata, type =
'class')
```

Prediction <=50K >50K <=50K 5699 480 >50K 830 1130	Accuracy : 0.839 Sensitivity : 0.8729 Specificity : 0.7019 Pos Pred Value : 0.9223 Neg Pred Value : 0.5765 Prevalence : 0.8022



Step 5 – Result and Recommendation

Result generated based on the previous steps

Compare the Algorithm

DECISION TREE

```
prtree <- prediction(Dectree.pred.prob[,2],testdata$income)
perftree  <- performance(prtree,measure="tpr",x.measure="fpr")
DTFrametree <- data.frame(FP=perftree@x.values[[1]],TP=perftree@y.value
s[[1]])
auctree <- performance(prtree, measure='auc')@y.values[[1]]
auctree
```

```
Result = 0.8500693
```

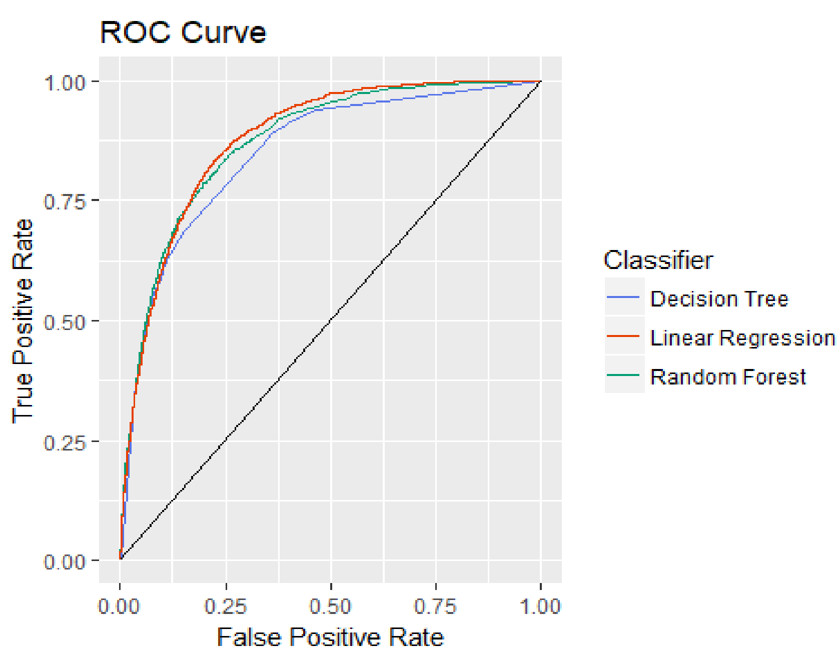
```
RANDOM FOREST
prRForest <- prediction(randforest.pred.prob[,2],testdata$income)
perfRForest  <- performance(prRForest,measure="tpr",x.measure="fpr")
DTFrameRForest <- data.frame(FP=perfRForest@x.values[[1]],TP=perfRFores
t@y.values[[1]])
aucFtree <- performance(prRForest, measure='auc')@y.values[[1]]
aucFtree
```

```
Result = 0.8733921
```

```
      LINEAR REGRESION
pr  <- prediction(prob,testdata$income)
perf <- performance(pr,measure="tpr", x.measure="fpr")
DtFrameReg <- data.frame(FP=perf@x.values[[1]],TP=perf@y.values[[1]])
aucRegresion <- performance(pr,measure='auc')@y.values[[1]]
aucRegresion
```

```
Result = 0.879603
```

Now plot the graph using Area Under Curve




```
auc <- rbind(aucRegresion,auctree,aucFtree)
rownames(auc) <- (c('Decision Tree', 'Random Forest', 'Linear
Regression'))
```

```
colnames(auc) <- 'ROC Curve Area'
round(auc, 6)
```

```
                  ROC Curve Area
Decision Tree           0.879603
Random Forest           0.850069
Linear Regression       0.873392
```

Recommendation

Linear regression has the highest area under curve (AUC) value, then random forest and lowest is with the decision tree. So, we selected linear regression as our final model for predicting income of an individual as it gives the largest area under the curve