Predicting Income

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How can different demographic and socioeconomic factors influence an individual's income?

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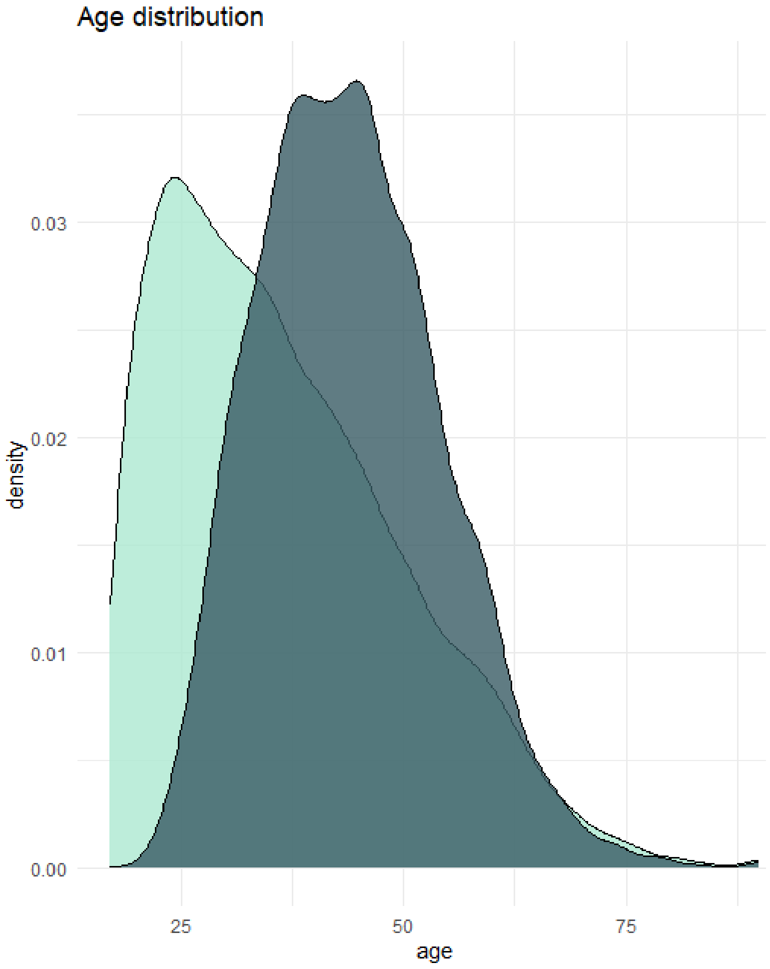
Summary

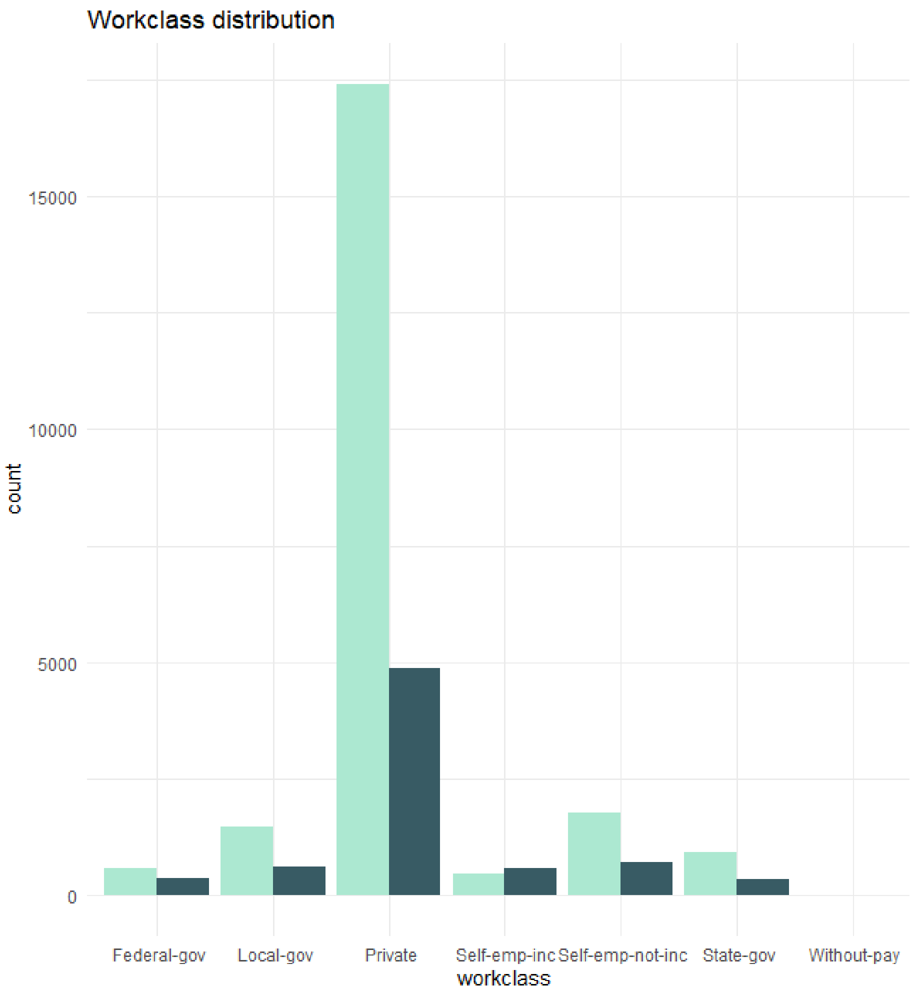
	age	workclass	education	education.num	marital.status	occupation	relationship	race	sex	hours.per.week	native.country	Income
1	39	State-gov	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	40	United-States	<=50K
2	50	Self-emp-not-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	13	United-States	<=50K
3	38	Private	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	40	United-States	<=50K
4	53	Private	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	40	United-States	<=50K
5	28	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	40	Cuba	<=50K
6	37	Private	Masters	14	Married-civ-spouse	Exec-managerial	Wife	White	Female	40	United-States	<=50K
7	49	Private	9th	5	Married-spouse-absent	Other-service	Not-in-family	Black	Female	16	Jamaica	<=50K
8	52	Self-emp-not-inc	HS-grad	9	Married-civ-spouse	Exec-managerial	Husband	White	Male	45	United-States	>50K
9	31	Private	Masters	14	Never-married	Prof-specialty	Not-in-family	White	Female	50	United-States	>50K
10	42	Private	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	40	United-States	>50K

```
      age                    workclass            education      education.num                  marital.status              occupation
 Min.   :17.00   Federal-gov     :  943   HS-grad     :9840   Min.   : 1.00   Divorced             : 4214   Prof-specialty :4038
 1st Qu.:28.00   Local-gov       : 2067   Some-college:6678   1st Qu.: 9.00   Married-AF-spouse    :   21   Craft-repair   :4030
 Median :37.00   Private         :22286   Bachelors   :5044   Median :10.00   Married-civ-spouse   :14065   Exec-managerial:3992
 Mean   :38.44   Self-emp-inc    : 1074   Masters     :1627   Mean   :10.12   Married-spouse-absent:  370   Adm-clerical   :3721
 3rd Qu.:47.00   Self-emp-not-inc: 2499   Assoc-voc   :1307   3rd Qu.:13.00   Never-married        : 9726   Sales          :3584
 Max.   :90.00   State-gov       : 1279   11th        :1048   Max.   :16.00   Separated            :  939   Other-service  :3212
                 Without-pay     :   14   (Other)     :4618                   Widowed              :  827   (Other)        :7585
         relationship                    race            sex          hours.per.week        native.country     Income
  Husband        :12463   Amer-Indian-Eskimo:  286   Female: 9782   Min.   : 1.00   United-States:27504   <=50K:22654
  Not-in-family  : 7726   Asian-Pac-Islander:  895   Male  :20380   1st Qu.:40.00   Mexico       :  610   >50K : 7508
  Other-relative :  889   Black             : 2817                  Median :40.00   Philippines  :  188
  Own-child      : 4466   Other             :  231                  Mean   :40.93   Germany      :  128
  Unmarried      : 3212   White             :25933                  3rd Qu.:45.00   Puerto-Rico  :  109
  Wife           : 1406                                             Max.   :99.00   Canada       :  107
                                                                                   (Other)       : 1516
```

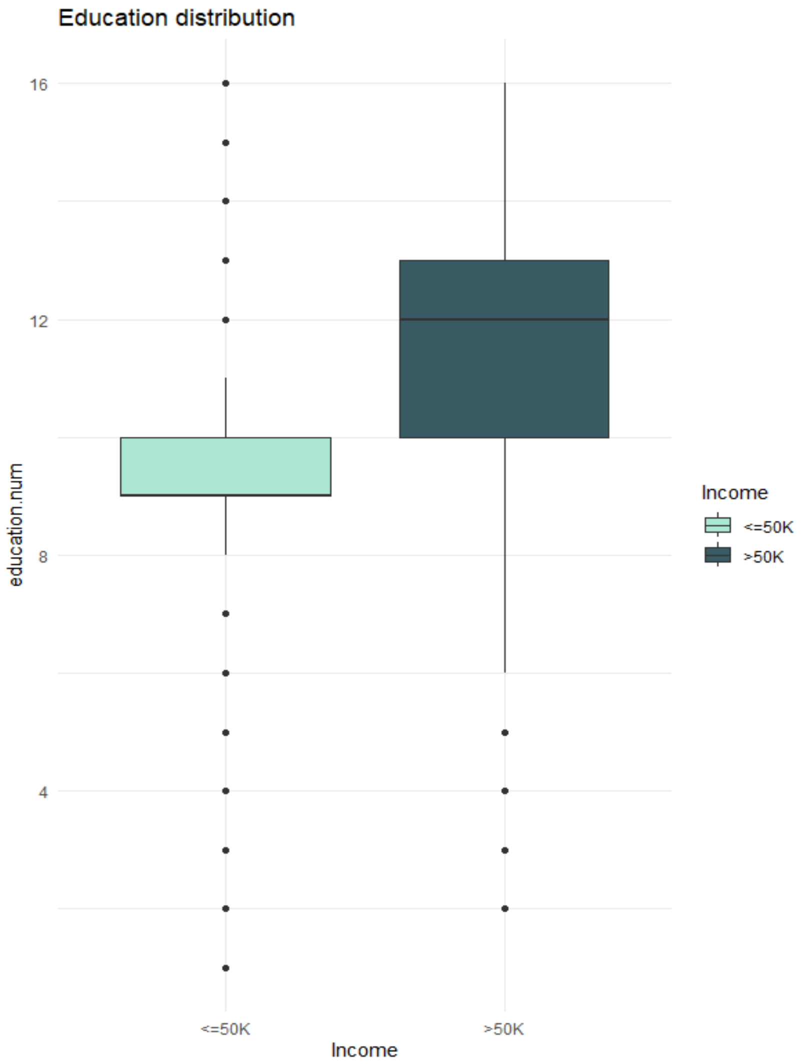
Summary



Age distribution
density
0.00
0.01
0.02
0.03
25
50
75
age



Workclass distribution
count
0
5000
10000
15000
Federal-gov
Local-gov
Private
Self-emp-inc
Self-emp-not-inc
State-gov
Without-pay
workclass



Education distribution
education.num
4
8
12
16
<=50K
>50K
Income
Income
<=50K
>50K

Logistic Regression

glm.fits=glm(Income~age+race+sex,data=data,family=binomial)

```
Call:
glm(formula = Income ~ age + race + sex, family = binomial, data = data)

Coefficients:
                        Estimate Std. Error z value Pr(>|z|)    
(Intercept)            -4.499147   0.194968 -23.076  < 2e-16 ***
age                     0.041907   0.001084  38.657  < 2e-16 ***
race Asian-Pac-Islander 0.996292   0.203434   4.897 9.71e-07 ***
race Black              0.177631   0.196261   0.905    0.365    
race Other             -0.206242   0.300408  -0.687    0.492    
race White              0.863006   0.188009   4.590 4.43e-06 ***
sex Male                1.212370   0.036295  33.404  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 33851  on 30161  degrees of freedom
Residual deviance: 30485  on 30155  degrees of freedom
AIC: 30499

Number of Fisher Scoring iterations: 5
```

```
Call:
glm(formula = Income ~ age + race + sex, family = binomial, data = train)

Coefficients:
                         Estimate Std. Error z value Pr(>|z|)    
(Intercept)             -4.509656   0.227008 -19.866  < 2e-16 ***
age                      0.043056   0.001259  34.209  < 2e-16 ***
race Asian-Pac-Islander  0.984789   0.236545   4.163 3.14e-05 ***
race Black               0.067566   0.229062   0.295 0.768020    
race Other              -0.296329   0.353763  -0.838 0.402228    
race White               0.825242   0.219210   3.765 0.000167 ***
sex Male                 1.218251   0.042073  28.955  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 25386  on 22620  degrees of freedom
Residual deviance: 22769  on 22614  degrees of freedom
AIC: 22783

Number of Fisher Scoring iterations: 5
```

```
        Income.num
glm.pred     0     1
       0 21244  7032
       1  1410   476
```

Accuracy: 72.01%

KNN Model:

```
train_features <- train[, c("age", "hours.per.week", "education.num")]
test_features <- test[, c("age", "hours.per.week", "education.num")]
```

Normalization

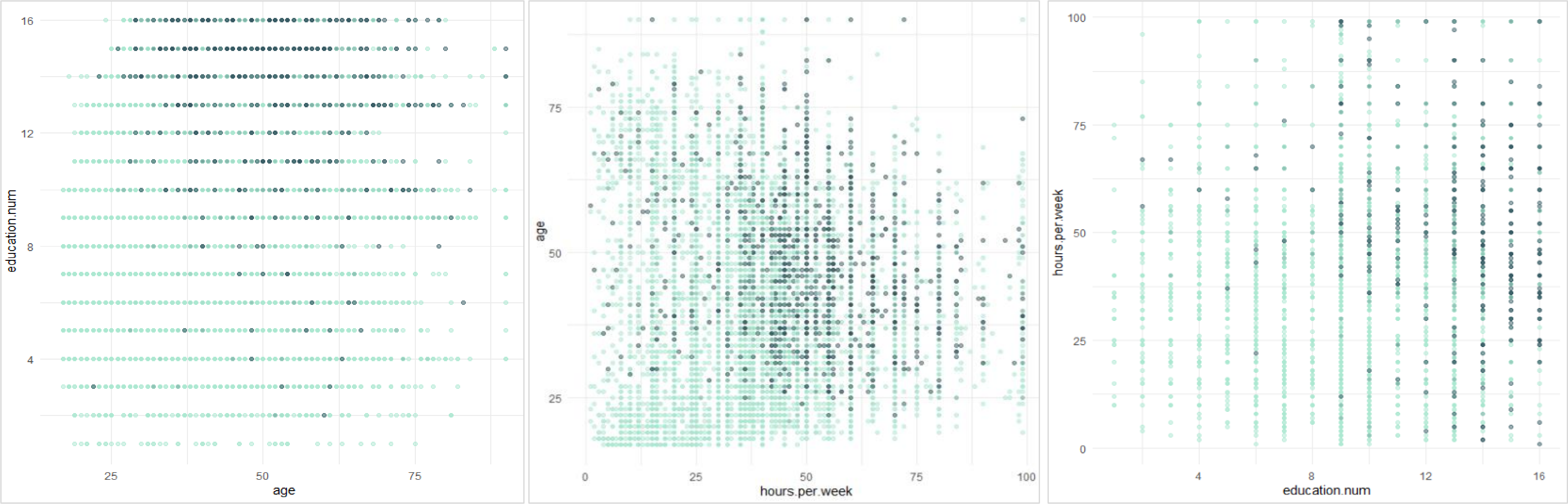
```
head(train_features)

##    age hours.per.week education.num
## 2   50             13            13
## 3   38             40             9
## 4   53             40             7
## 5   28             40            13
## 7   49             16             5
## 9   31             50            14

head(test_features)

##     age hours.per.week education.num
## 1    39             40            13
## 6    37             40            14
## 8    52             45             9
## 12   30             40            13
## 26   56             40            13
## 31   23             52            12
```

```
head(train_normalized)

##         age hours.per.week education.num
## 1 0.4520548      0.1224490     0.8000000
## 2 0.2876712      0.3979592     0.5333333
## 3 0.4931507      0.3979592     0.4000000
## 4 0.1506849      0.3979592     0.8000000
## 5 0.4383562      0.1530612     0.2666667
## 6 0.1917808      0.5000000     0.8666667

head(test_normalized)

##          age hours.per.week education.num
## 1 0.30136986      0.3979592     0.8000000
## 2 0.27397260      0.3979592     0.8666667
## 3 0.47945205      0.4489796     0.5333333
## 4 0.17808219      0.3979592     0.8000000
## 5 0.53424658      0.3979592     0.8000000
## 6 0.08219178      0.5204082     0.7333333
```

```
         Actual
Predicted    0    1
        0 5145 1137
        1  497  761
```

Accuracy: 78.33%

Which features are most predictive of higher income levels?



Tree Model

```
Call:
rpart(formula = Income.num ~ age + workclass + education + marital.status +
    occupation + relationship + hours.per.week + native.country +
    race + sex, data = train, method = "class")
  n= 24420

          CP nsplit rel error    xerror       xstd
1 0.12546721      0 1.0000000 1.0000000 0.01135538
2 0.01342168      2 0.7490656 0.7490656 0.01021201
3 0.01000000      5 0.7088005 0.7327557 0.01012442

Variable importance
  relationship marital.status      education     occupation            sex            age hours.per.week
            29             28             12             11              9              8              3
```

1 Relationship and Marital Status

2 Education

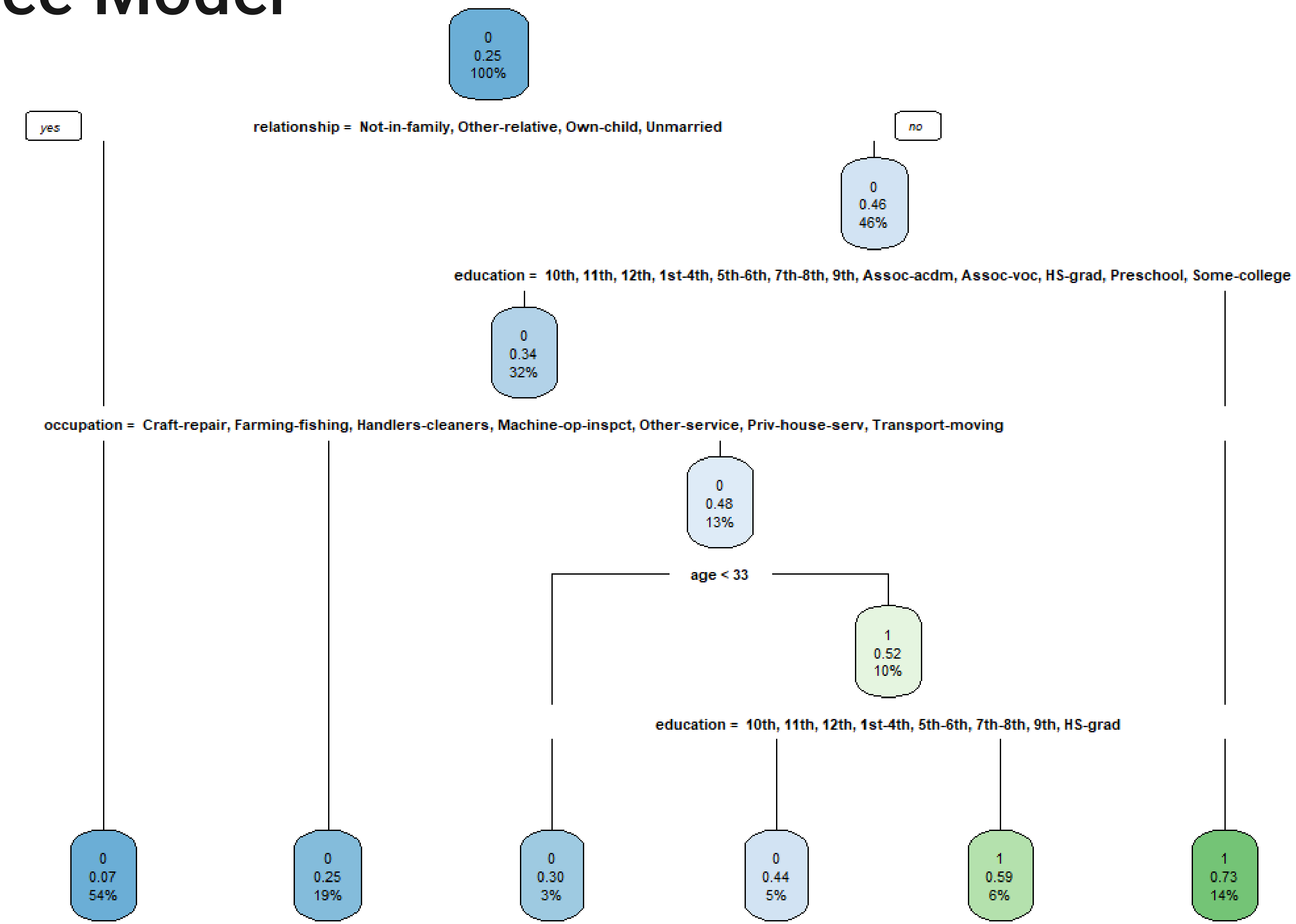
3 Occupation

4 Sex

5 Age

6 Hours per week

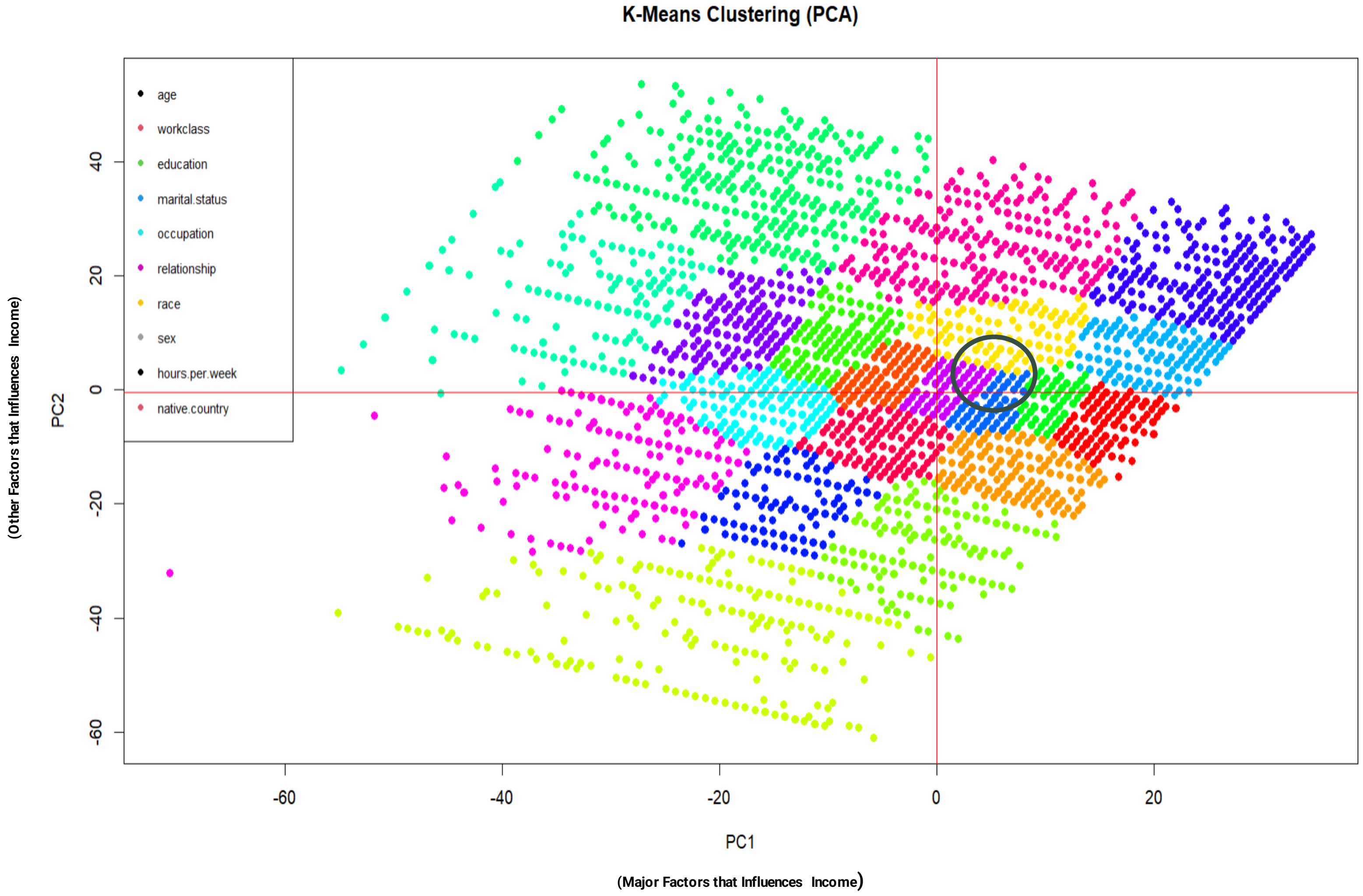
Tree Model



Key Insights

Root Node – Relationship
Education
Age
Occupation

Clustering



Top variables for PC1 (Accounts for 56.22% of variability):

1. Age
2. Hours per week
3. **Marital status:** Never-married, Married-civ-spouse
4. **Relationship:** Own-child
5. **Workclass:** Private, Self-emp-not-inc
6. **Sex:** Male
7. **Occupation:** Exec-managerial, Other-service

Top variables for PC2 (Accounts for 42.68% of variability):

1. Hours per week
2. Age
3. **Sex:** Male
4. **Occupation:** Other-service, Exec-managerial
5. **Marital status:** Married-civ-spouse, Widowed
6. **Education:** Bachelors
7. **Relationship:** Own-child, Unmarried

PCA Normalization Process

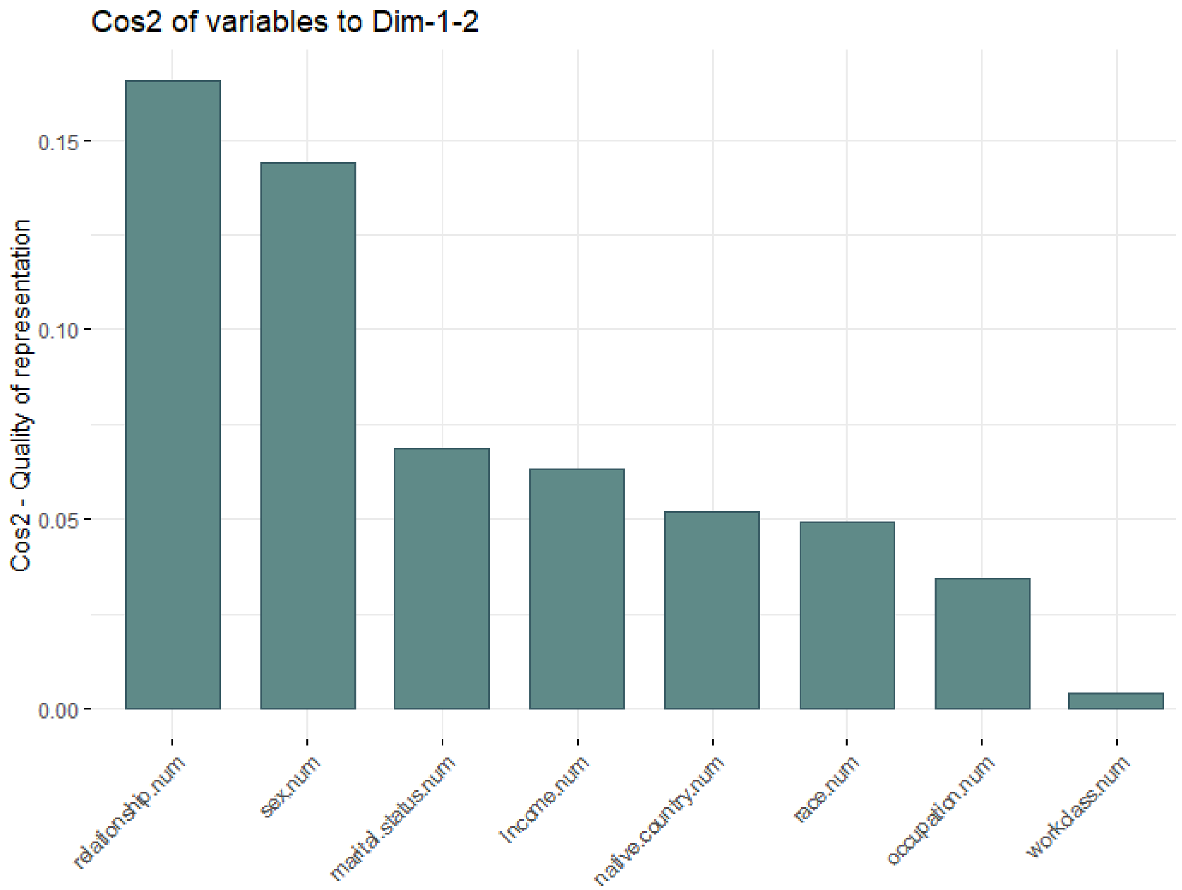
	workclass.num	marital.status.num	occupation.num	relationship.num
1	2.9359517	0.9478313	-1.4790301	-0.2612446
2	1.8876507	-0.3872683	-0.7345332	-0.8857223
3	-0.2089512	-1.7223678	-0.2382018	-0.2612446
4	-0.2089512	-0.3872683	-0.2382018	-0.8857223
5	-0.2089512	-0.3872683	0.7544608	2.2366662
6	-0.2089512	-0.3872683	-0.7345332	2.2366662

	race.num	sex.num	native.country.num	Income.num
1	0.3850415	0.6927947	0.2649196	-0.5756818
2	0.3850415	0.6927947	0.2649196	-0.5756818
3	0.3850415	0.6927947	0.2649196	-0.5756818
4	-2.0110019	0.6927947	0.2649196	-0.5756818
5	-2.0110019	-1.4433813	-5.3039463	-0.5756818
6	0.3850415	-1.4433813	0.2649196	-0.5756818

Importance of components:

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5
Standard deviation	0.6566579	0.3868625	0.3498713	0.3345691	0.30835196
Proportion of Variance	0.4128897	0.1433075	0.1172121	0.1071834	0.09104355
Cumulative Proportion	0.4128897	0.5561972	0.6734093	0.7805927	0.87163625

	Comp.6	Comp.7	Comp.8
Standard deviation	0.30385914	0.20426880	2.967518e-09
Proportion of Variance	0.08840979	0.03995396	8.432229e-18
Cumulative Proportion	0.96004604	1.00000000	1.000000e+00



THANK YOU