Data Science: Capstone Project Report

Executive Summary

The goal of this project is to predict the salary given some U.S. Census data. I selected this project in order to attempt to match the prediction accuracy cited in a 1996 paper, Improving the Accuracy of Naive-Bayes Classifiers: a Decision-Tree Hybrid.[1] A summary of the results is found in the file adult.names.

This is a classification problem. We don't predict the exact salary. Rather, we predict which class (>$50,000 or <=$50,000) that each individual belongs.

The key steps are importing the data set, cleaning the data set, creating and tuning a model, and evaluating the model against a validation data set. In the original data set work the authors listed the top 3 performing models: NBTree, C4.5, and Naive-Bayes. I choose a xgbTree, Naive-Bayes, and C5. I split the data set into a train_set and a test_set in order to avoid making any modelling decisions with the validation set. Then model parameters are tuned and evaluated against the test_set. Finally, the models make predictions for the validation set.

Methods

The data required minimal cleaning. I removed the observations with unknown values because the original researchers did.

First I build the data sets. The data files consist of two files: adult.data and adult.validation. I split the adult.data set into a train and test set. I train three models on the training data. When the models are built I use these models to predict the whether the salary of individuals in the validation set are greater than or less than or equal to $50,000.

Results

The original project used accuracy as evaluation function and so did I. One model, C5, out-performed the original models.

Original Model	Accuracy	My Model	Accuracy
NBTree	0.8590	xgbTree	0.8526
C4.5	0.8446	C5	0.8486
Naive-Bayes	0.8388	Naive-Bayes	0.8092

Conclusion

I've learned quite a bit during this course. I can build models that predict almost as well as others with much more experience than me. Of course, I've only learned how to use the tools that others have built. That counts as success for my first data science course.

A detailed exploratory data analysis follows.

[1] Kohavi, Ron, Scaling Up the Accuracy of Naive-Bayes Classifiers: a Decision-Tree Hybrid, Proceedings of the Second International Conference on Knowledge Discovery and Data Mining, 1996. http://www.aaai.org/Papers/KDD/1996/KDD96-033.pdf

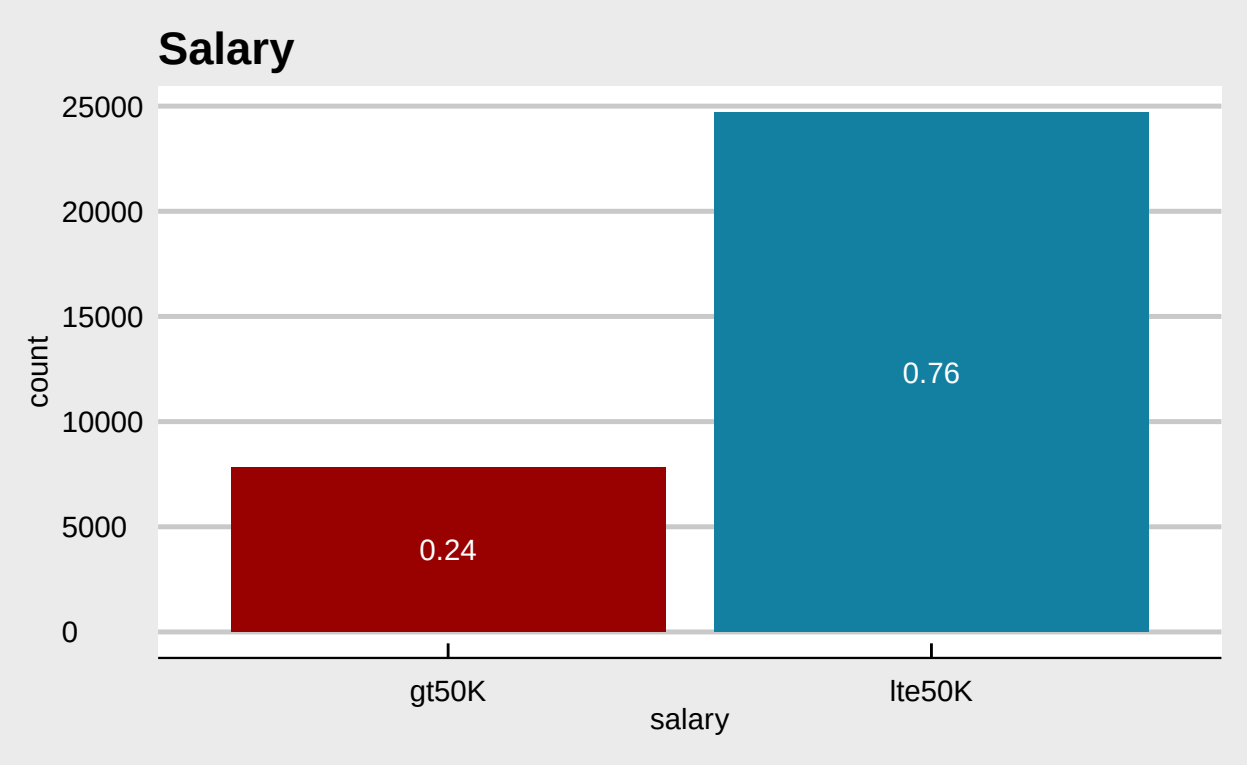
Basic Overview of Data

I obtained the data from https://archive.ics.uci.edu/ml/datasets/census+income. This data was oringally extracted from the 1994 census bureau database. The data was originally donated to the UCI by Ronny Kohavi and Barry Becker, Data Mining and Visualization Silicon Graphics, e-mail: ronnyk@sgi.com for questions. Extraction was done by Barry Becker from the 1994 Census database.

Structure

```
## 'data.frame':    32561 obs. of  15 variables:
##  $ age           : int  39 50 38 53 28 37 49 52 31 42 ...
##  $ workclass     : Factor w/ 9 levels " ?"," Federal-gov",..: 8 7 5 5 5 5 5 7 5 5 ...
##  $ fnlwgt        : int  77516 83311 215646 234721 338409 284582 160187 209642 45781 159449 ...
##  $ education     : Factor w/ 16 levels " 10th"," 11th",..: 10 10 12 2 10 13 7 12 13 10 ...
##  $ education.num : int  13 13 9 7 13 14 5 9 14 13 ...
##  $ marital.status: Factor w/ 7 levels " Divorced"," Married-AF-spouse",..: 5 3 1 3 3 3 4 3 5 3 ...
##  $ occupation    : Factor w/ 15 levels " ?"," Adm-clerical",..: 2 5 7 7 11 5 9 5 11 5 ...
##  $ relationship  : Factor w/ 6 levels " Husband"," Not-in-family",..: 2 1 2 1 6 6 2 1 2 1 ...
##  $ race          : Factor w/ 5 levels " Amer-Indian-Eskimo",..: 5 5 5 3 3 5 3 5 5 5 ...
##  $ sex           : Factor w/ 2 levels " Female"," Male": 2 2 2 2 1 1 1 2 1 2 ...
##  $ capital.gain  : int  2174 0 0 0 0 0 0 0 14084 5178 ...
##  $ capital.loss  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ hours.per.week: int  40 13 40 40 40 40 16 45 50 40 ...
##  $ native.country: Factor w/ 42 levels " ?"," Cambodia",..: 40 40 40 40 6 40 24 40 40 40 ...
##  $ salary        : Factor w/ 2 levels "gt50K","lte50K": 2 2 2 2 2 2 2 1 1 1 ...
```

Distribution of the response variable. We see this is a fairly unbalanced data set.



Univariate Distribution

Histograms

Let's take a look at the numeric variables. If we use AGE as a predictor we would likely center and normalize.

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
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```
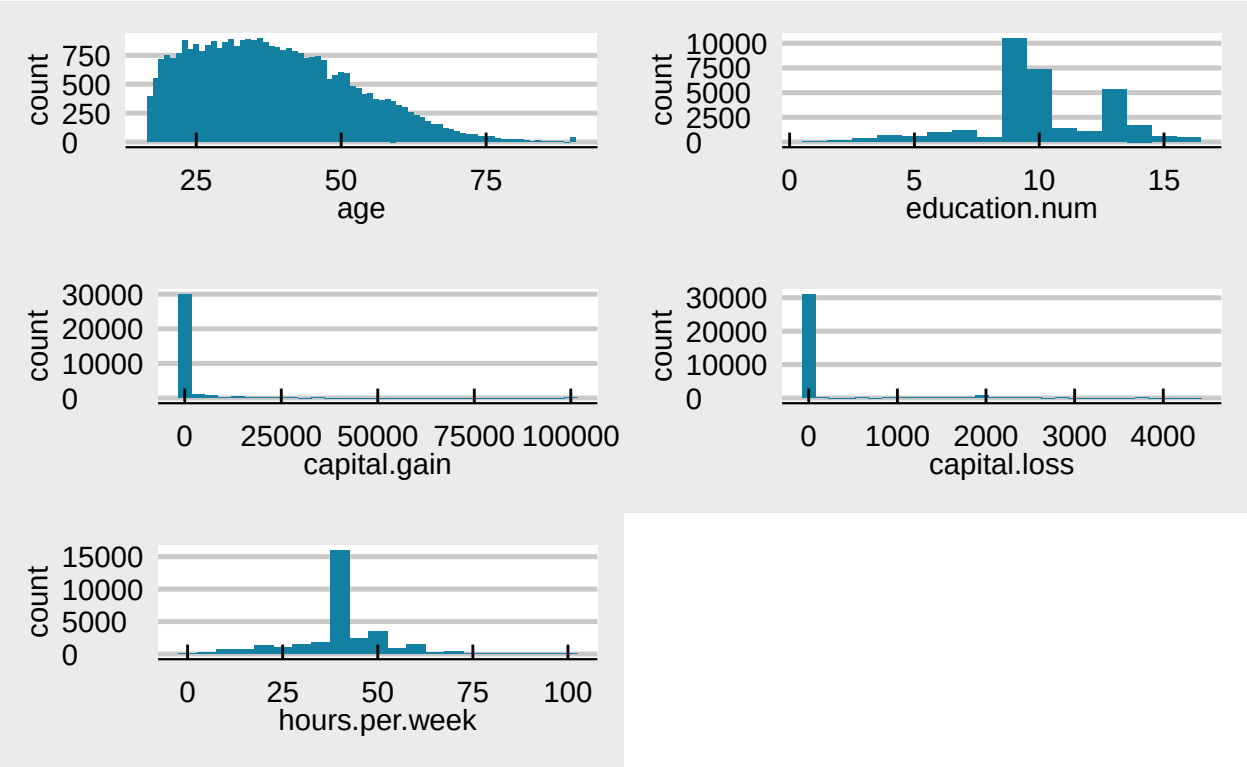
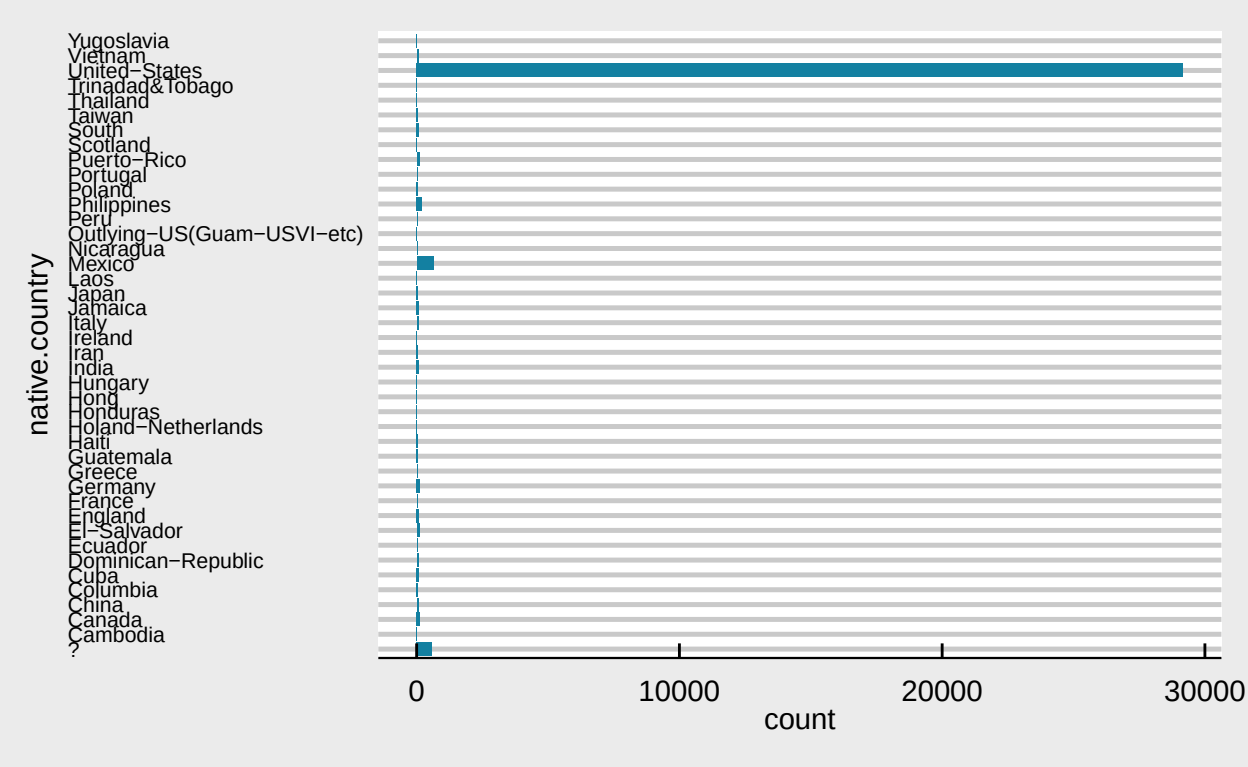



Next we look at the categorical data.


workclass
Without−pay
State−gov
Self−emp−not−inc
Self−emp−inc
Private
Never−worked
Local−gov
Federal−gov
?
0 5000 10000 15000 20000
count
education
Some−college
Prof−school
Preschool
Masters
HS−grad
Doctorate
Bachelors
Assoc−voc
Assoc−acdm
9th
7th−8th
5th−6th
1st−4th
12th
11th
10th
0 2500 5000 7500 10000
count
marital.status
Widowed
Separated
Never−married
Married−spouse−absent
Married−civ−spouse
Married−AF−spouse
Divorced
0 5000 10000 15000
count
occupation
Transport−moving
Tech−support
Sales
Protective−serv
Prof−specialty
Priv−house−serv
Other−service
Machine−op−inspct
Handlers−cleaners
Farming−fishing
Exec−managerial
Craft−repair
Armed−Forces
Adm−clerical
?
0 1000 2000 3000 4000
count
relationship
Wife
Unmarried
Own−child
Other−relative
Not−in−family
Husband
0 5000 10000
count
race
White
Other
Black
Asian−Pac−Islander
Amer−Indian−Eskimo
0 10000 20000
count
sex
Male
Female
0 5000 10000 15000 20000
count
salary
lte50K
gt50K
0 5000 10000 15000 20000 25000
count



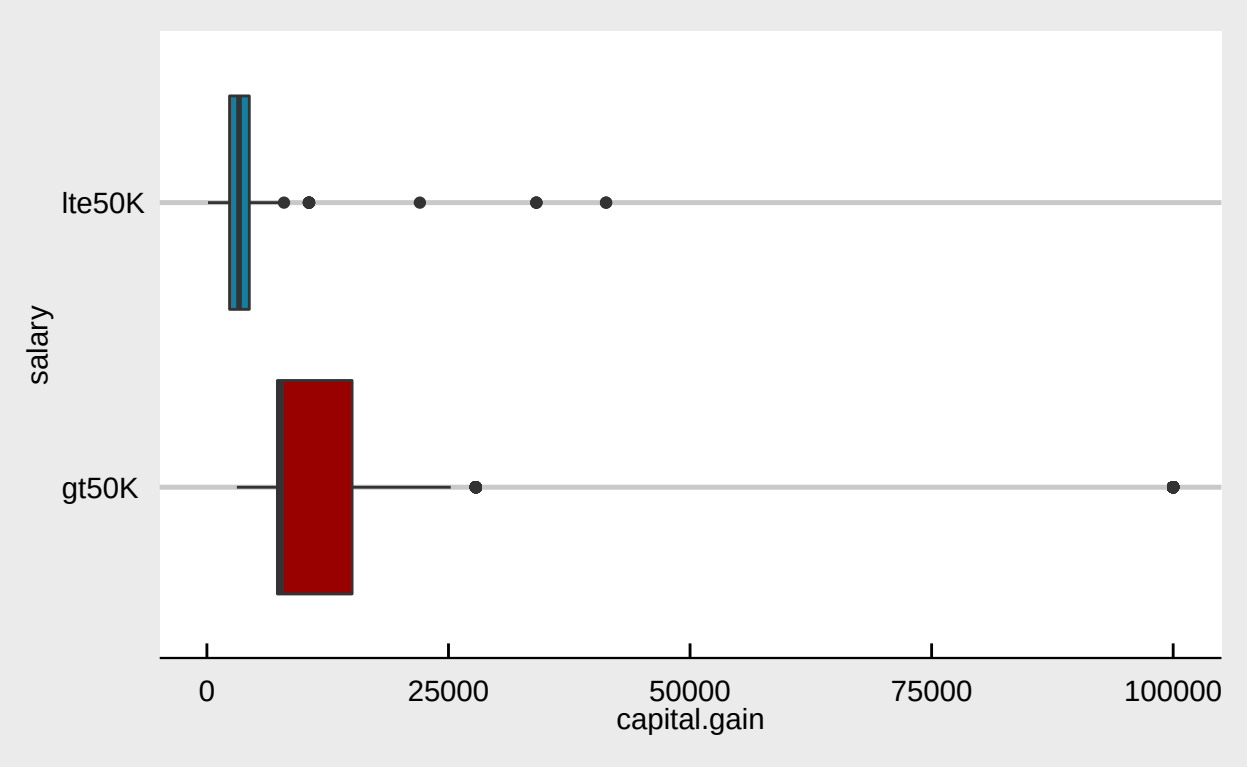
We remove those observations with an unknown value. We could have imputed the values, perhaps considering the distribution of known values. We did not because the original authors removed the data.

Bivariate

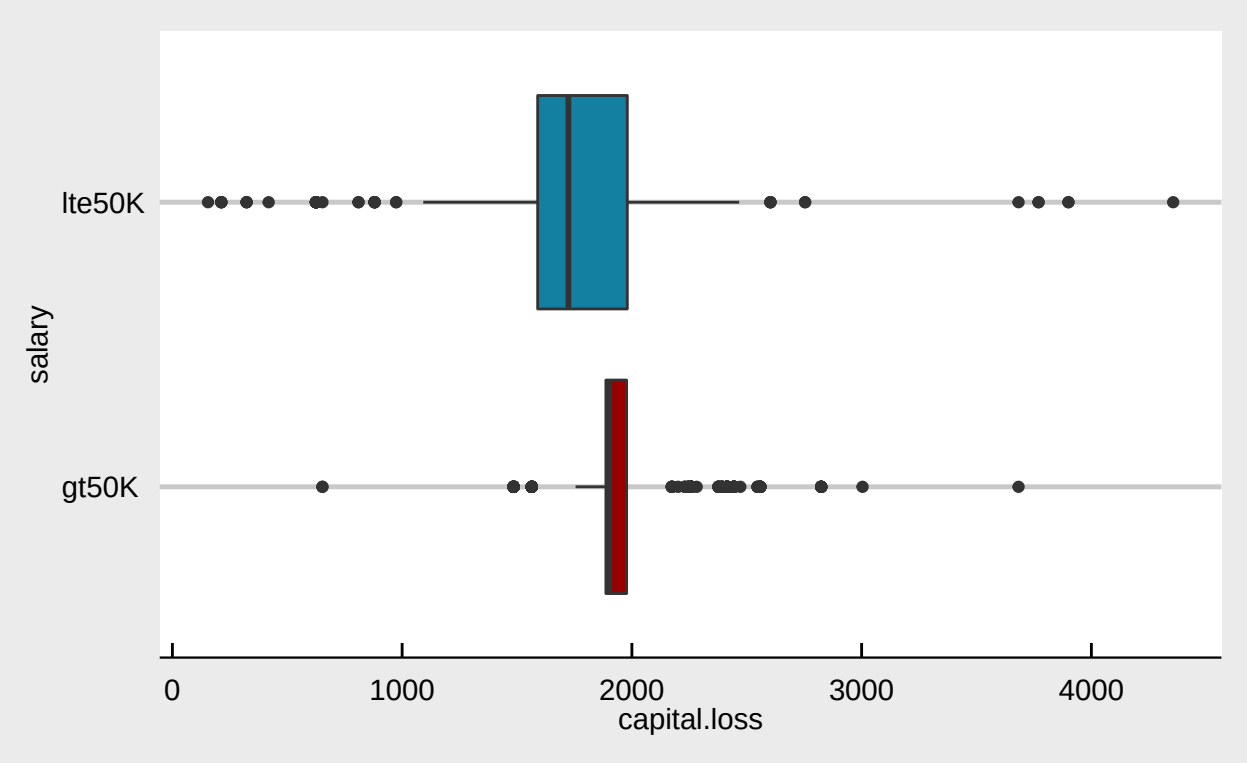
Response and predictor relationships

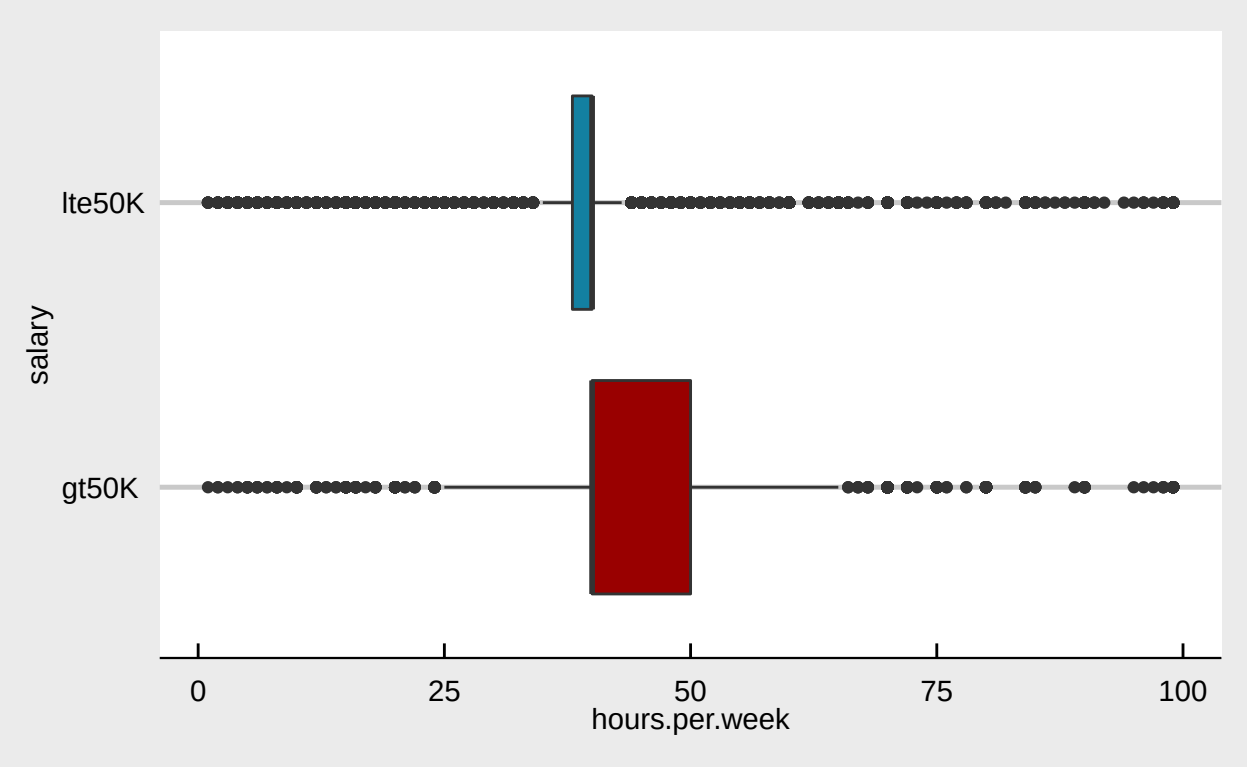
Continuous Predictors

We see that age can predict low salary for young adults.



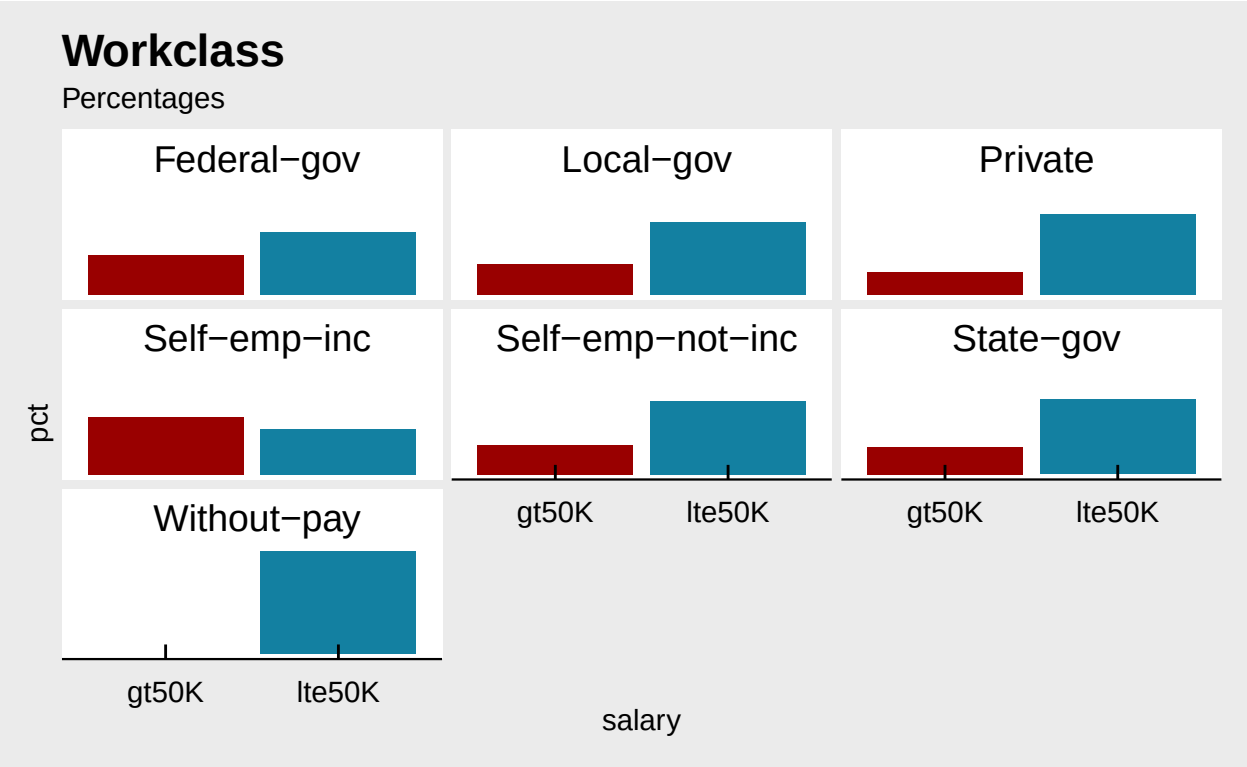
It appears that Capital Gain can also help predict salary. Capital Loss is not as helpful.

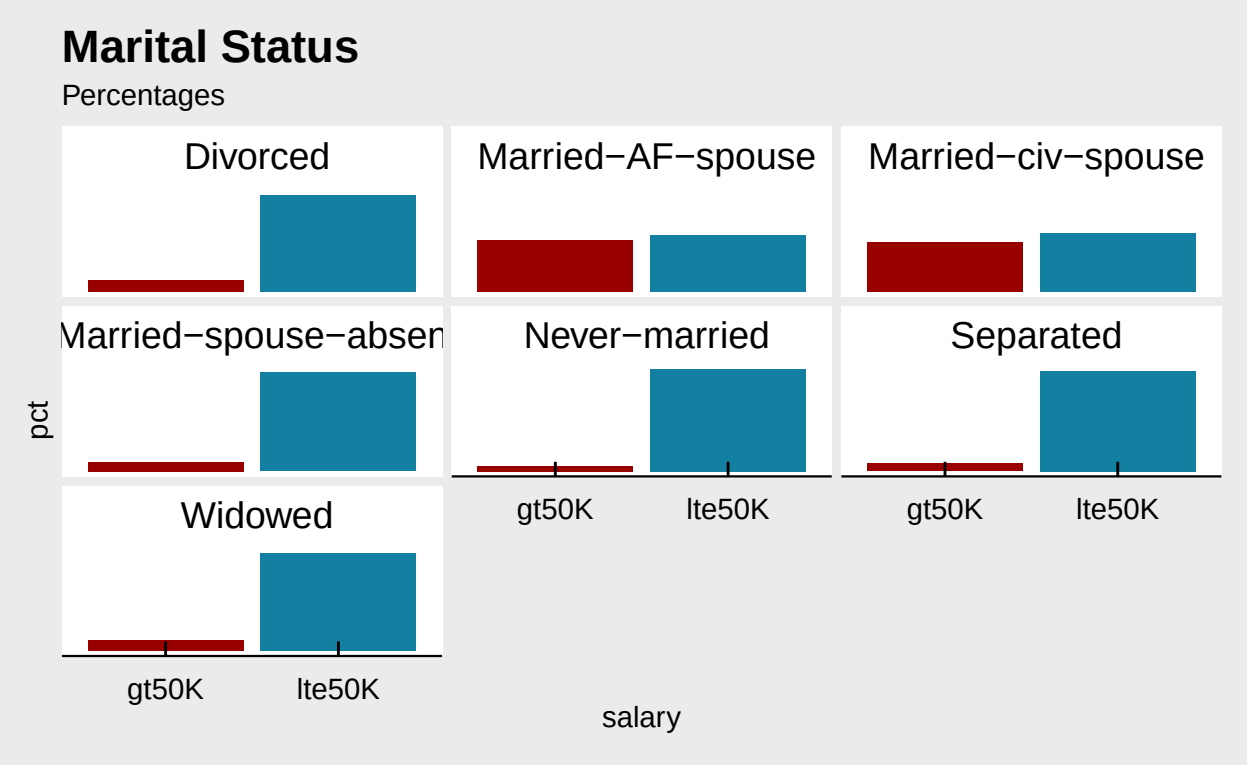


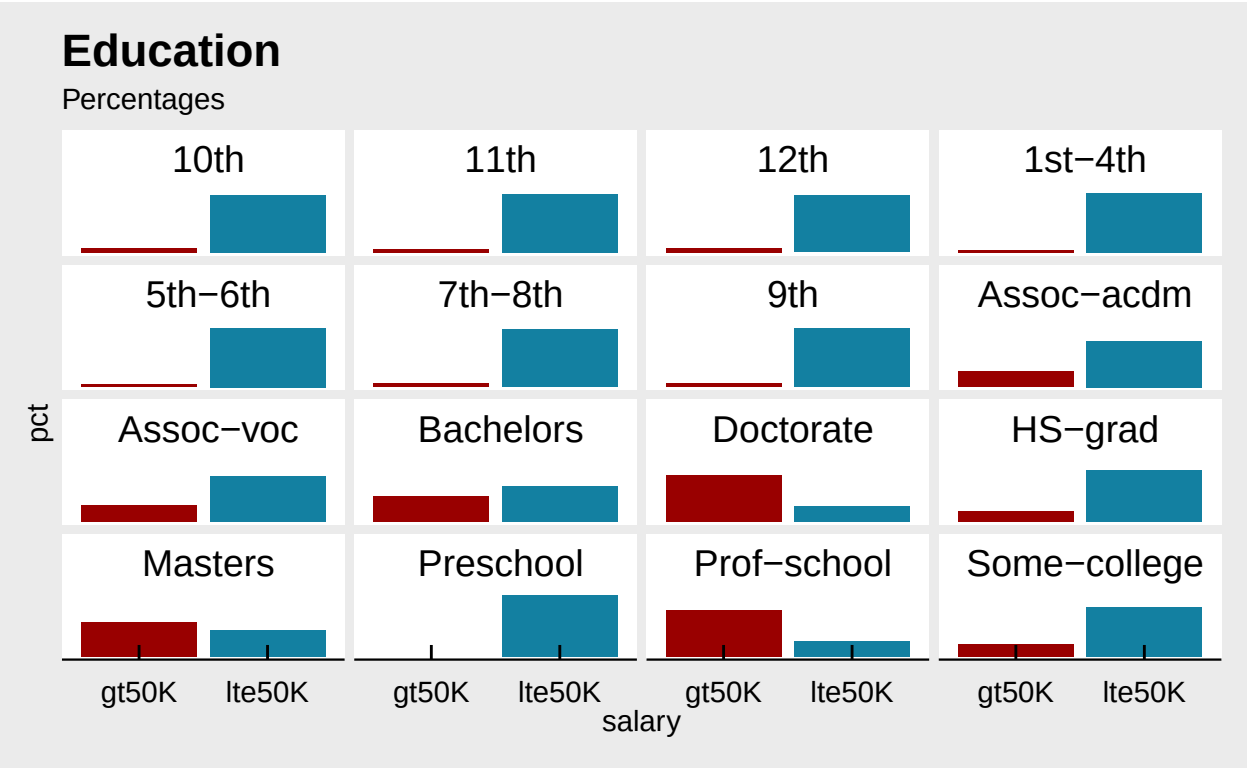

lte50K
gt50K
salary
0
25
50
75
100
hours.per.week

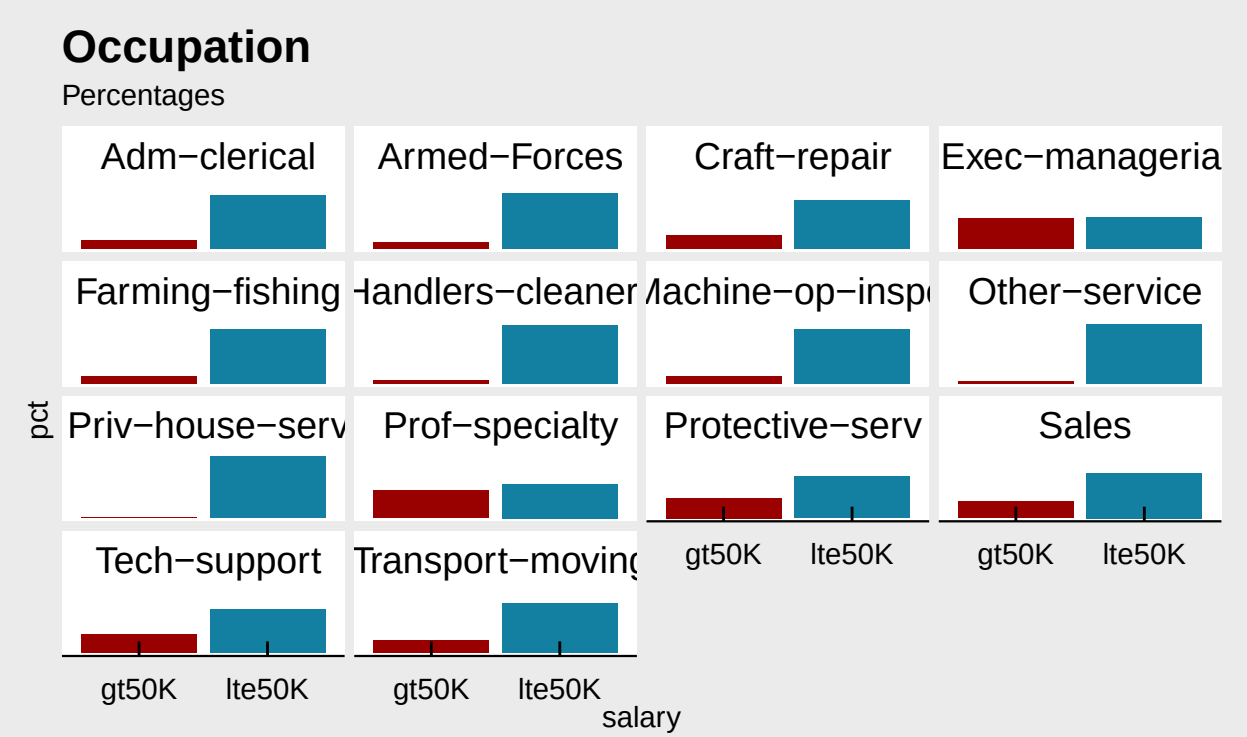
Categorical Predictors

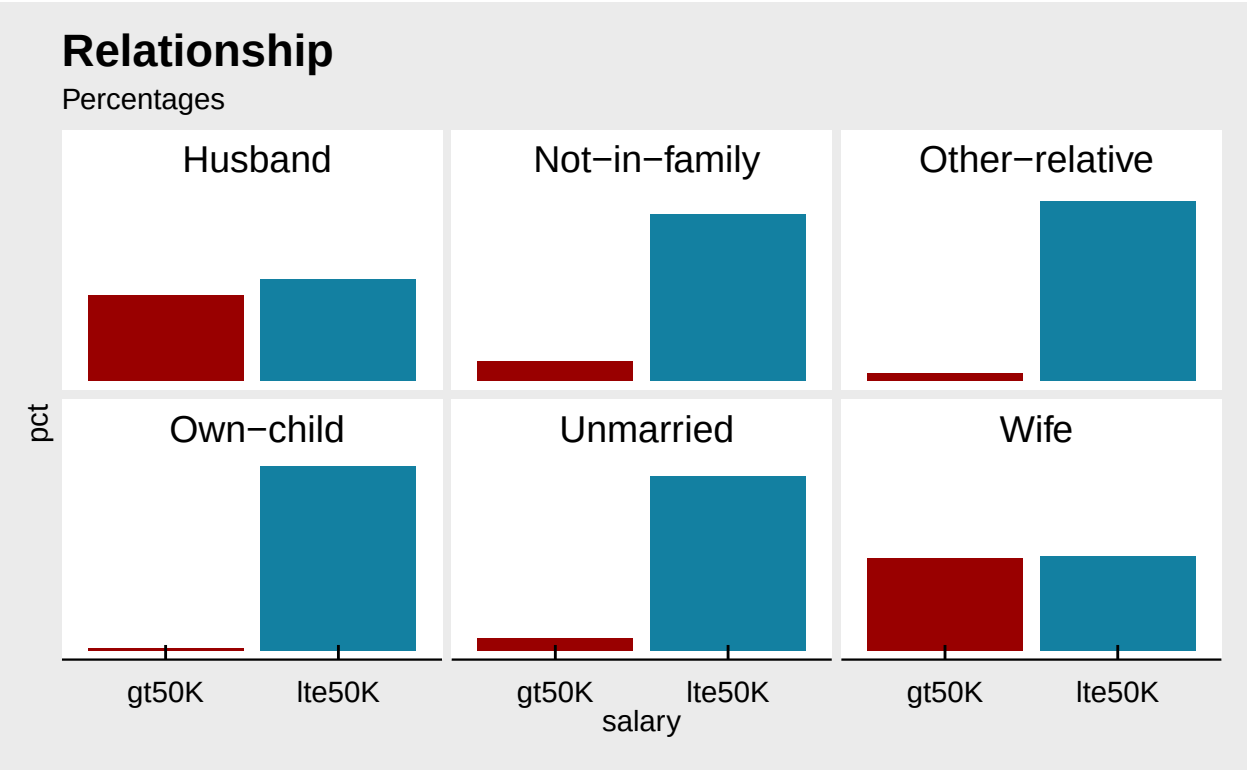
Looking at the categorical predictors we see several that appear useful. We will want to verify our intuition by considering independence using a Chi-Square test.

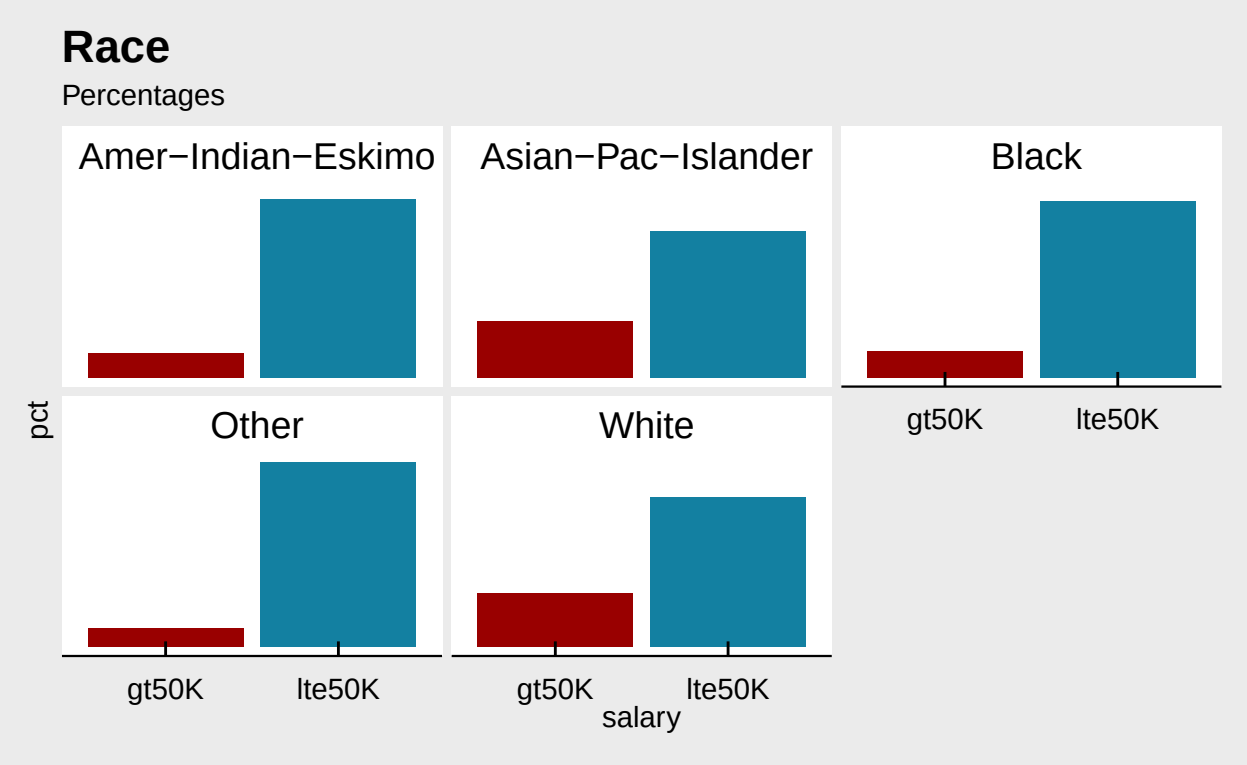


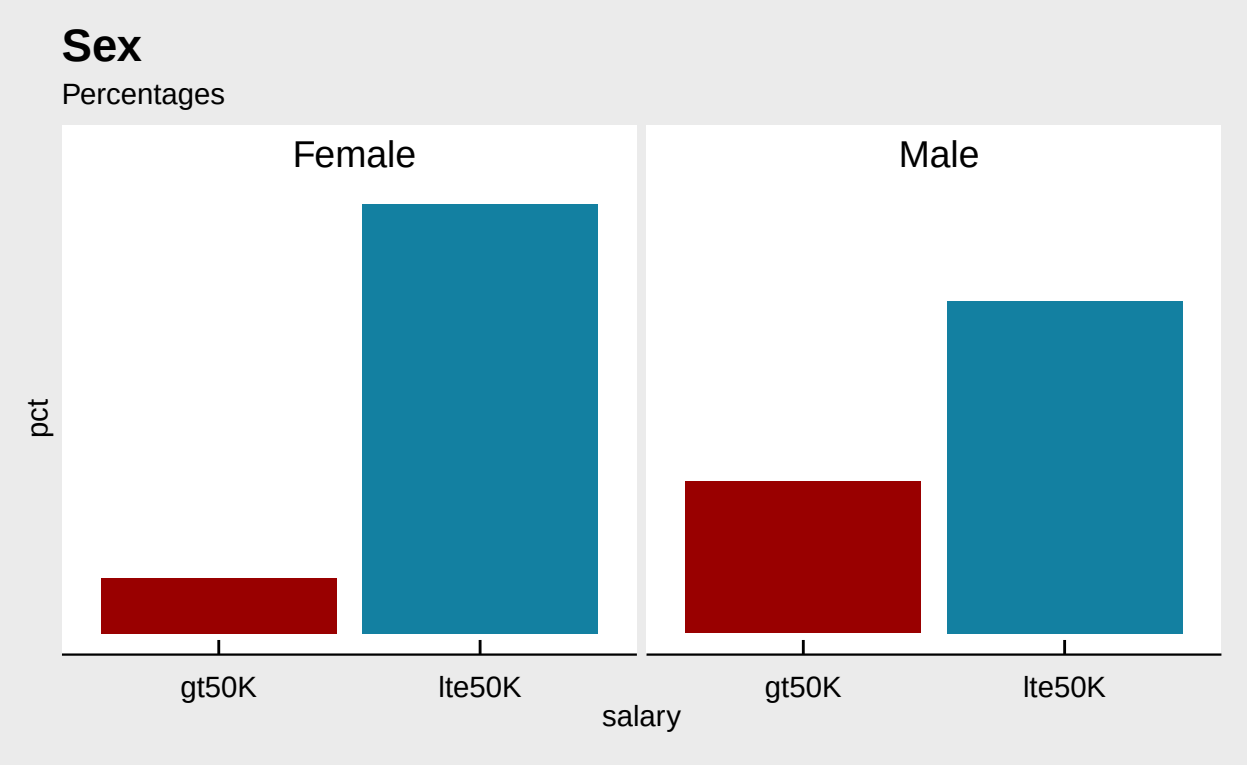

Marital Status
Percentages
Divorced
Married−AF−spouse
Married−civ−spouse
Married−spouse−absen
Never−married
Separated
Widowed
pct
gt50K
lte50K
salary

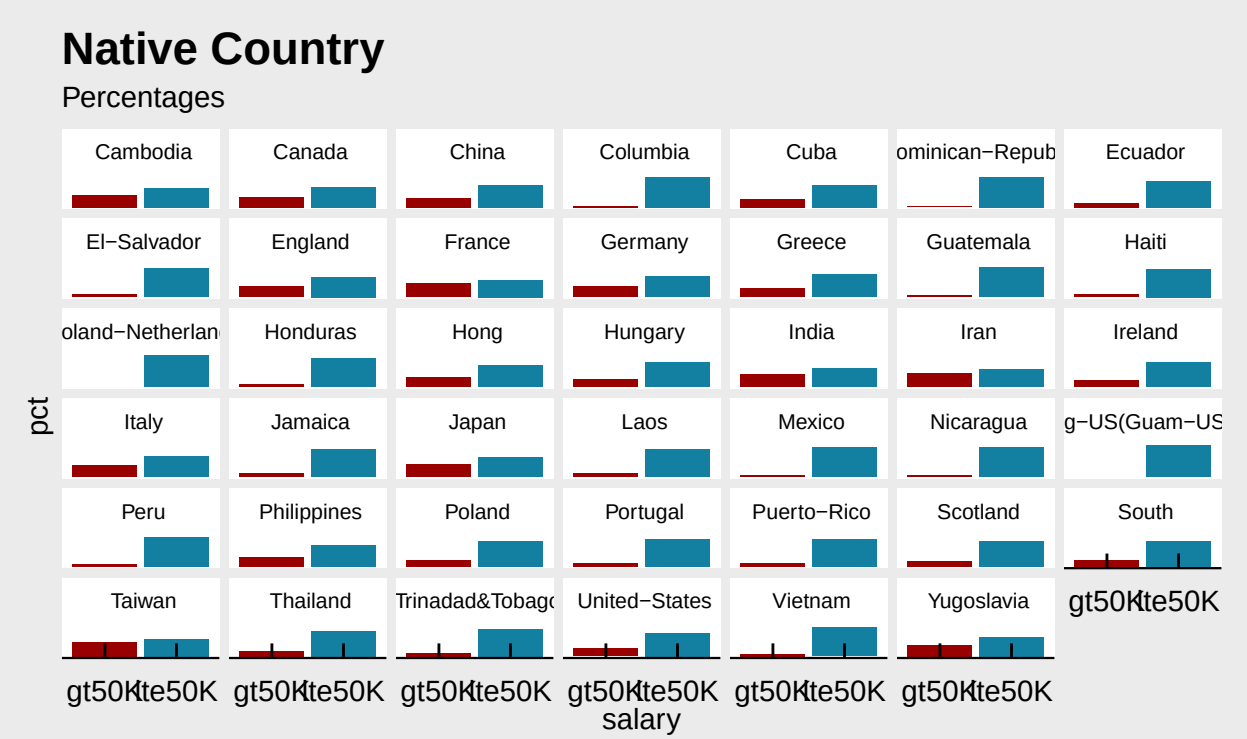

Education
Percentages
10th
11th
12th
1st−4th
5th−6th
7th−8th
9th
Assoc−acdm
Assoc−voc
Bachelors
Doctorate
HS−grad
Masters
Preschool
Prof−school
Some−college
pct
gt50K
lte50K
salary


Occupation
Percentages
Adm−clerical
Armed−Forces
Craft−repair
Exec−manageria
Farming−fishing
Handlers−cleaner
Machine−op−inspc
Other−service
Priv−house−serv
Prof−specialty
Protective−serv
Sales
Tech−support
Transport−moving
pct
gt50K
lte50K
salary


Relationship
Percentages
Husband
Not−in−family
Other−relative
Own−child
Unmarried
Wife
pct
gt50K
lte50K
salary


Race
Percentages
Amer−Indian−Eskimo
Asian−Pac−Islander
Black
Other
White
pct
gt50K
lte50K
salary


Sex
Percentages
Female
Male
pct
gt50K
lte50K
salary


Native Country
Percentages
Cambodia
Canada
China
Columbia
Cuba
ominican−Republ
Ecuador
El−Salvador
England
France
Germany
Greece
Guatemala
Haiti
oland−Netherlan
Honduras
Hong
Hungary
India
Iran
Ireland
Italy
Jamaica
Japan
Laos
Mexico
Nicaragua
g−US(Guam−US
Peru
Philippines
Poland
Portugal
Puerto−Rico
Scotland
South
Taiwan
Thailand
Trinadad&Tobago
United−States
Vietnam
Yugoslavia
pct
gt50K
lte50K
salary

We apply a Chi-Square test for independence for each variable against `salary`. We calculate the Cramer's V value for each variable against `salary`. We see that `workclass`, `occupation`, and `native.country` do not get a valid Cramer's V value since they fail to produce a correct Chi-Square test.

Those variables that are important to predicting salary are `education`, `marital.status`, `relationship`, and `sex`. If we run into model performance constraints we can reduce the categorical predictors to these.