The U.S. Census

A socioeconomic look at factors indicative of wealth

"Any society, any nation, is judged on the basis of how it treats its weakest members -- the last, the least, the littlest." – (Cardinal Roger Mahoney, 1998, Creating a Culture of Life)

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Abstract

The purpose of this project is to identify key social/economic factors that are statistically proven to have strong influence on an individual's level of income. The task is to build predictive models which determine whether or not a person makes more than $50,000 per year. While the predictive algorithm will be the main focus of the work, we will also use data visualization and correlation analysis to take a look at other potential correlations, such as ethnicity to education levels, and gender to income, to extract further information beyond the predictive models.

Introduction

What is the American Dream? How do I achieve it? For many, that answer, and the path to it, will vary. Inevitably, those dreams will require money to pursue and maintain. News and media outlets regularly remind us that the paths for many Americans are impeded, and even blocked, due to a host of reasons. How can these roadblocks be overcome, and even removed, for future dream-seekers?

Once per decade, the United States government collects a wealth of information from and about its citizens. To the government, lobbyists, special interest and advocacy groups, this information is a goldmine; it is a reflection on the successes and, more importantly, the failures of the past decade's governance and social policy on the population.

Many questions can be answered with this trove of data. The aim of this paper, however, is to explore commonly cited reasons for income inequality in the United States, and test their validity.

Data Collection

The dataset used in this project was pulled from the UCI Machine Learning Repository[1], which further cites: *"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))" (University of California Irvine, 1994*). We concatenated their test and train sets, for a total of 48,842 observations and 15 attributes. In the modeling process, the variable "salary" is treated as the response, with string values of either "over 50k" or "below 50k", indicating personal level of wealth.

1 The dataset comes from USI Machine Learning website http://archive.ics.uci.edu/ml/datasets/Census+Income, which was extracted from the Census Bureau database found at http://www.census.gov/ftp/pub/DES/www/welcome.html.

Data Cleaning

Because the response variable, along with 8 predictor variables, are categorical, dummy variables were created in order to perform predictive algorithms and modeling. For the dependent variable "salary", the dummy labels were assigned as follows: 1 for observations of earning "over $50k" per year and 0 for earning "below $50k" per year. Similarly, the same was done with the independent variables. For example, "work class" was expanded to 9 dummy, binary variables, "education" to 17 variables, "marital status" to 7 variables, and so on. This expanded our dataset to 109 predictors, and 1 response variable, ready to enter the models.

Workclass	education	Marital-status	occupation	relationship	race	sex	native-country		
Private	Bachelors	Married-civ-spouse	Tech-support	Wife	White	Female	United-States	Italy	Nicaragua
Self-emp-not-inc	Some-college	Divorced	Craft-repair	Own-child	Asian-Pac-Islander	Male	Cambodia	Poland	Scotland
Self-emp-inc	11th	Never-married	Other-service	Husband	Amer-Indian-Eskimo		England	Jamaica	Thailand
Federal-gov	HS-grad	Separated	Sales	Not-in-family	Other		Puerto-Rico	Vietnam	Yugoslavia
Local-gov	Prof-school	Widowed	Exec-managerial	Other-relative	Black		Canada	Mexico	El-Salvador
State-gov	Assoc-acdm	Married-spouse-absent	Prof-specialty	Unmarried			Germany	Portugal	Trinadad&Tobago
Without-pay	Assoc-voc	Married-AF-spouse	Handlers-cleaners				Outlying-US(Guam-USVI-etc)	Ireland	Peru
Never-worked	9th		Machine-op-inspct				India	France	Hong
unknown	7th-8th		Adm-clerical				Japan	Dominican-Republic	Holand-Netherlands
	12th		Farming-fishing				Greece	Laos	
	Masters		Transport-moving				South	Ecuador	
	1st-4th		Priv-house-serv				China	Taiwan	
	10th		Protective-serv				Cuba	Haiti	
	Doctorate		Armed-Forces				Iran	Columbia	
	5th-6th		unknown				Honduras	Hungary	
	Preschool						Philippines	Guatemala	

The sub-categories of each categorical variable.

Because of the categorical nature of the data, outlier detection was not a concern and, in the data exploration, we found that the sample was generally representative of the population. Additionally, it is worth noting that we observed missing values in the original dataset, and replaced them with "unknown" values. All of the missing data points were categorical and we believed that it would be more appropriate to treat "unknown" as a single dummy variable, rather than deleting an entire instance, when other information in that observation was provided.

Data Exploration

As laid forth above, we sought to use our data to find if certain socioeconomic and demographic factors could predict whether or not an individual is wealthy (defined as making more than $50,000 per year). We looked for early indications through visualization of the data of what a regression model might include as important factors of wealth. Additionally, we used visualization to check for anomalies in the data. There were, intuitively, three factors which we felt would be major contributors to wealth: Education, Sex (gender), and Race. Good education, as the trope and mantra goes, is the key to a good job, which implies wealth. Sex and Race are frequently touted as reasons for income inequality as well, and we wished to test these notions.

First, we wanted to know if our sample was representative of the population, and Race is perhaps one of the easiest ways to measure this. Per the below, "White" is nearly the entire sample population of our dataset. However, these results are generally consistent with the 1990 Census (Appendix A.2). Dissimilar from the percentages in Appendix A.2, the UCI dataset does not include the Race category "Hispanic". UCI did not provide a reason for dropping this observation. However, and while this cannot be confirmed, it appears that the percentage overweight in the Race category "white" is roughly equal to the missing Hispanic value. Again referring to the Race "White", Appendix A.1 shows that the sample population is lopsided in a 2:1 gender split favoring males. Normally, genders are relatively equal in number, typically favoring females by a small percent *(Resident Population Estimates of the United States by Sex, Race, and Hispanic Origin, 2001)*. These two quirks aside, and given the overall sample size, we accepted this dataset as generally random, and as a representative sample of the population.

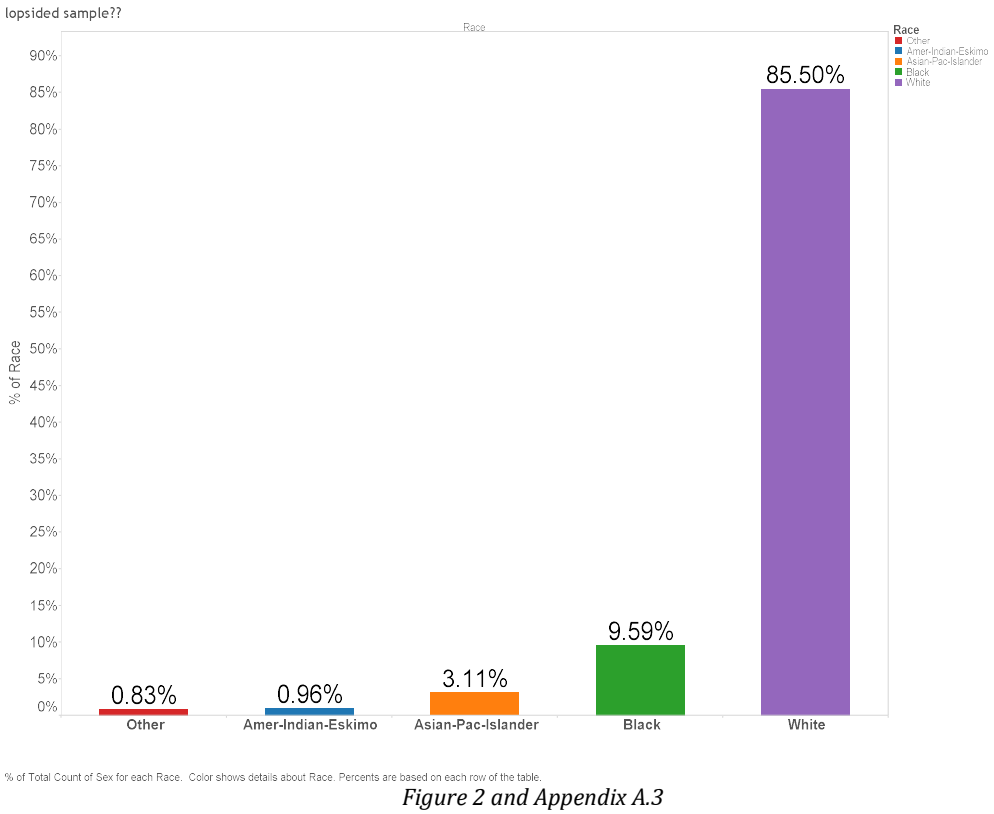


Figure 2 and Appendix A.3

After finding no critical issues with our dataset, we looked at the percentage of individuals at each education level making over $50,000 per year. As expected, the results show a positive trend where the higher the education level, the higher chances of earning more money. Yet there is some noise in this graph. For instance, it does not make sense for a pre-school student to be making any money given labor and education laws, and competency levels, among other issues.

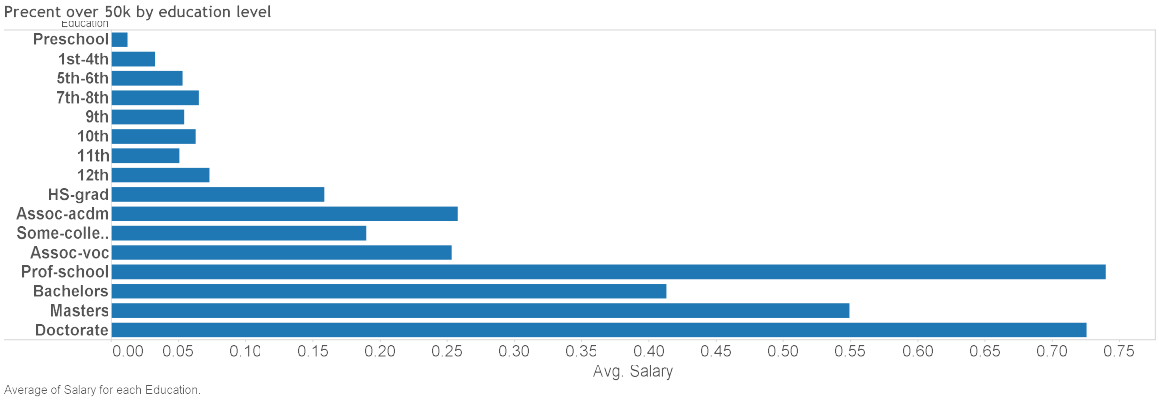


Figure 3 and Appendix A.4

To account for this, we look at education levels across all age groups sampled. Seen below is a graph of total white population by education levels[2] , which intuitively shows that certain percentages of the population achieve a particular level of education, and stop there until they die. This, despite the noise at the bottom of the graph, can most clearly be seen by the variable "high school grad", which is the first line under the thick, total population line. In other words, certain segments of the population may have not received a full education, yet have managed to do well for themselves in their adult years. As will be discussed later, this success may also be accounted for by other rationale.

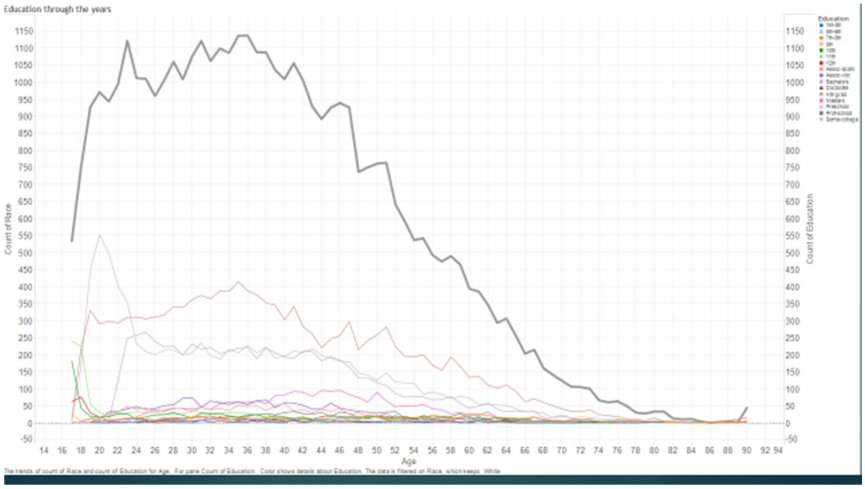


Figure 4 and Appendix A.5

[2] Using the category of Race = "White" made visualization of this point easier, because of the large sample size. While other Race categories more or less follow the same trend, their graphs are much more jagged and noisy due to less data.

If education could be indicative of wealth, does this apply equally across races and sex? The answer may not be so clear-cut when visualizing. Figures A.6 through A.9 in the appendix show the dispersion of higher education trends higher for the Race "Asian" while "White" and "Black" fall somewhere in the middle, and "Indian/Eskimo" lag behind. However, in the chart below, we see that the average of Black and White earning more than $50,000 per year are very far apart, and further see the gross inequality of the same between males and females.[3]

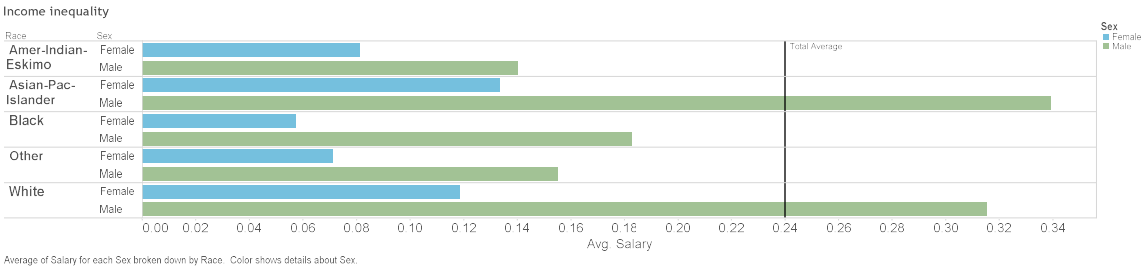


Figure 5 and Appendix A.10

With the added complexity of gender inequality, we looked at available potential explanatory factors, such as average hours worked. Below, we see that, on average, women worked about 4 hours less than men per week. While this may have some role in the results shown in figure 5, it is clearly not enough to explain the chasm between genders.

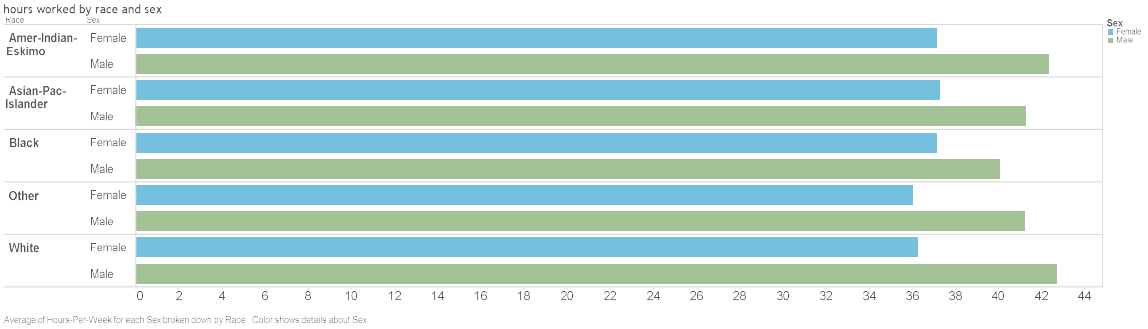


Figure 6 and Appendix A.11

By now, visualization has done its job in demonstrating that inequality does exist, and is perhaps explained by more than one factor. While these charts and figures may be enough for advocacy groups to fight for change, and government to review particular policies, we turned our focus to predictive modeling for a deeper analysis and potentially multiple causal factors.

[3] The graph shows each category compared to itself. For example, the blue bar categorized as "Asian Female" is the percent of Asian women who make over $50,000 per year. Thus, each category is out of a total possibility of 100%. The black horizontal line is the average of the whole sample, most likely buoyed by White Males.

Method 1 – GlmNet

The first and least meaningful method we tested was Glmnet, based on its ability to work with a binary predictor variable. GLMNet differs from Glm in that the method fits a generalized linear model via penalized maximum likelihood, with either lasso or elastic-net regularization, while Glm does not. This model tries to explain as much variance in the data as possible while keeping the model coefficients small. In addition to being fast, it can deal with the problem of sparsity in the input matrix X_i.

The algorithm of GlmNet is as follows:

$$\min_{\beta_0,\beta} \frac{1}{N} \sum_{i=1}^{N} w_i l(y_i, \beta_0 + \beta^T x_i) + \lambda \left[(1-\alpha)||\beta||_2^2/2 + \alpha||\beta||_1 \right]$$

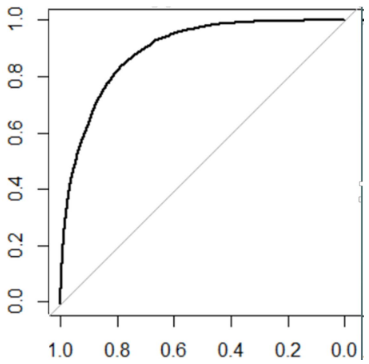
where variable w_i is the weight, l is the negative log-likelihood contribution for observation Xi, and α controls the penalty. Regularization parameter lambda (λ) covers the entire range, and penalizes the size of estimated coefficients *(Hastie & Qian, 2014).*

Using the following code, GlmNet suggested using 2 types of models:

```
> getModelInfo()$glmnet$type
[1] "Regression"     "Classification"
```

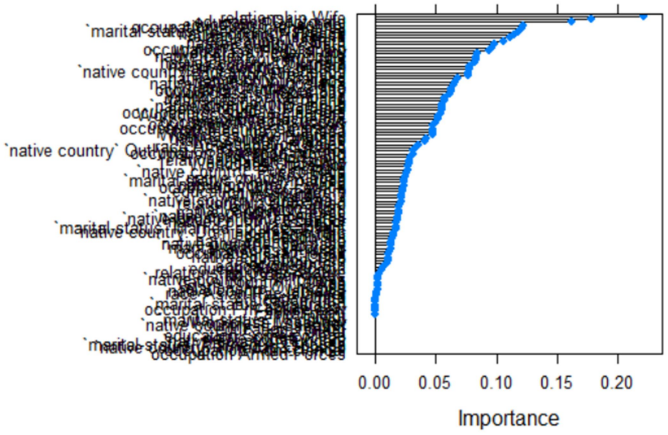
To test the predictive power of the model, we choose to split the data as 75% to train and 25% to test. Further, to show the accuracy of the model, we chose to use the Receiver Operating Characteristic (ROC) curve, further known as Area Under the Curve (AUC), as follows:

```
set.seed(3456)
splitIndex <- createDataPartition(census[,outcomeName],
                                  p = .75, list = FALSE, times = 1)
trainDF <- census[ splitIndex,]
testDF  <- census[-splitIndex,]

objControl <- trainControl(method='cv', number=3, returnResamp='none')
objModel <- train(trainDF[,predictorsNames], trainDF[,outcomeName],
                  method='glmnet',  metric = "RMSE", trControl=objControl)


predictions <- predict(object=objModel, testDF[,predictorsNames])

auc <- roc(testDF[,outcomeName], predictions)
print(auc$auc)


# Area under the curve: 0.8937
```

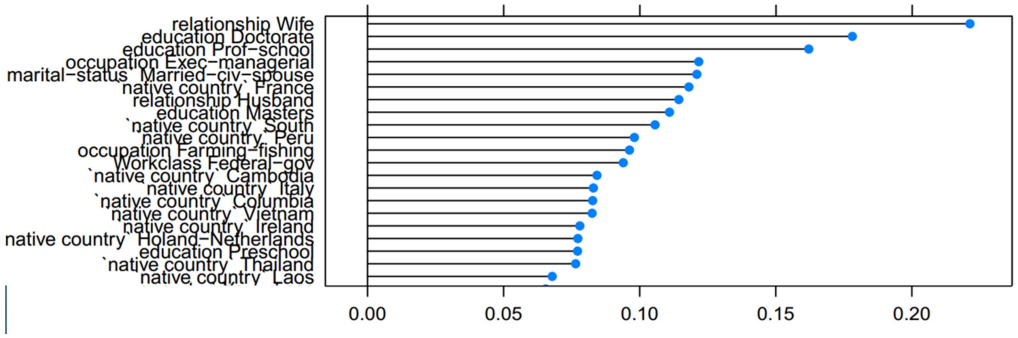


There is a lot of information to be derived from the AUC test, of which the most relevant to us is that the area under the curve is a measure of accuracy. An area of 1 represents a perfect test, and an area of .5 represents a worthless test. *(Kutner, Nachtsheim, & Neter, 2004)* For GlmNet, the AUC value (accuracy) is 89.75%.

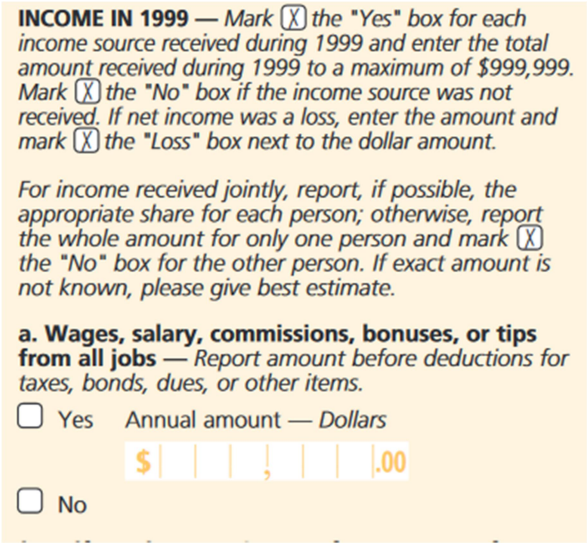
To help us understand which variables were important in the model derived by GlmNet, we used the function "varImp" (abbreviation for Variance Importance) in the caret package. The resulting bar chart may have values on both the positive and negative side, which translates to a positive or negative impact on our model:



Naturally, this output can be messy when dealing with so many variables. To make a clearer output, the top 22 variables were retained:



Per the cleaner output, the top influential variable is “Relationship_Wife”. There may be a few explanations as to why this variable stood out, not limited to a good education, or even reporting dual income, per the below Census snapshot. The second most important variable is “education_Doctorate”. This echoes the result from the data exploration; the better the education, the more likely he/she will have a high paying job.


INCOME IN 1999 — *Mark* X *the "Yes" box for each income source received during 1999 and enter the total amount received during 1999 to a maximum of $999,999. Mark* X *the "No" box if the income source was not received. If net income was a loss, enter the amount and mark* X *the "Loss" box next to the dollar amount.*

For income received jointly, report, if possible, the appropriate share for each person; otherwise, report the whole amount for only one person and mark X *the "No" box for the other person. If exact amount is not known, please give best estimate.*

a. Wages, salary, commissions, bonuses, or tips from all jobs — *Report amount before deductions for taxes, bonds, dues, or other items.*

☐ Yes Annual amount — *Dollars*

$, .00

☐ No

Figure 7 – sample Census Form[4]

Method 2 - Logistic Regression

Quite often, a research question will contain in the dataset a Y-variable that is binary, or yes/no. Historically, when such a question was being tested, methods such as Linear discriminant function analysis(LDFA) and ordinary least squares (OLS) would be used. However, both methods have strict assumptions surrounding the data, and often these assumptions are violated. For example, OLS assumes linearity and continuity in the dataset. Because of our dummy variables, this would violate the continuity assumption *(Peng, Lee, & Ingersoll, 2002)*.

To work around these strict assumptions, we turned to the logistic regression model. Logistic models are more apt to work with data which contains both continuous and categorical data, where the decision variable is dichotomous. *(UCLA, 2016).*

$$Logit(Y) = natural\log(odds) = \ln(\frac{\pi}{1-\pi}) = \alpha + \beta X$$

[4] **(U.S. Department of Commerce: Bureau of the Census, 2000)**

Using this regression method in SPSS yielded the following results:

Block 0: Beginning Block

Classification Table[a,b]

Observed			Predicted		
			salary		Percentage Correct
			0	1	
Step 0	salary	0	37155	0	100.0
		1	11687	0	.0
	Overall Percentage				76.1

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-1.157	.011	11893.487	1	.000	.315

Variables not in the Equation[a]

			Score	df	Sig.
Step 0	Variables	Age	2592.049	1	.000
		Workclass	341.088	1	.000
		WorkclassFederalgov	188.429	1	.000
		WorkclassLocalgov	58.392	1	.000
		WorkclassNeverworked	3.146	1	.076
		WorkclassPrivate	279.336	1	.000
		WorkclassSelfempinc	951.789	1	.000
		WorkclassSelfempnotinc	36.108	1	.000
		WorkclassStategov	9.059	1	.003
		WorkclassWithoutpay	2.395	1	.122
		fnlwgt	1.963	1	.161
		education10th	245.081	1	.000
		education11th	367.374	1	.000
		education12th	101.086	1	.000
		education1st4th	58.379	1	.000
		education5th6th	98.009	1	.000
		education7th8th	162.683	1	.000
		education9th	144.456	1	.000
		educationAssocacdm	3.174	1	.075

The first model of the output is a null model, which is to say SPSS fit a model with no predictors. The constant in the table labeled “Variables in the Equation” gives the unconditional log odds of variable admission to the model (i.e., admit=1).

This unfitted model is accompanied by a table labeled “Variables not in the Equation”, which gave the results of a score test known as the Lagrange multiplier test. The column labeled “Score” gave the estimated change in model fit if a term is added to the model, and the other two columns gave the degrees of freedom, and p-value (labeled “Sig.”) for the estimated change. Based on the p-value, almost all of the predictors shown were expected to improve the fit of the model.

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	22879.398	98	.000
	Block	22879.398	98	.000
	Model	22879.398	98	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	30871.284[a]	.374	.561

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

The second test (output shown above) gave the overall test and score for a model that includes the predictor variables. The chi-square value of 22879.398, with a p-value of less than 0.0005, suggested that the model as a whole fit significantly better than the null model.

Classification Table[a]

Observed			Predicted		
			salary		Percentage Correct
			0	1	
Step 1	salary	0	34641	2514	93.2
		1	4642	7045	60.3
	Overall Percentage				85.3

a. The cut value is .500

Variables in the Equation

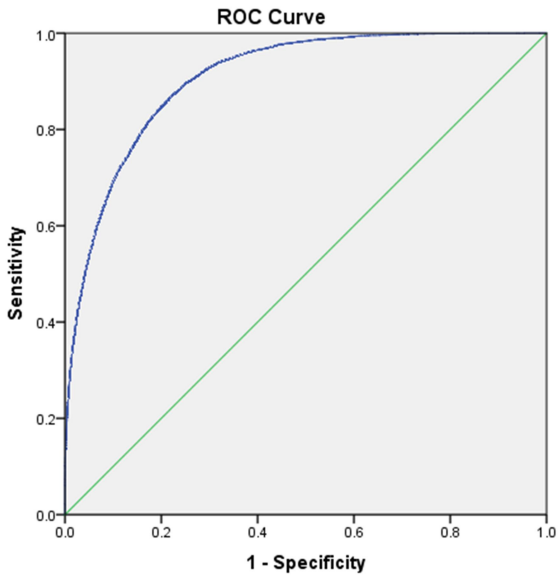
		Statistics					
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Age	.025	.001	348.674	1	.000	1.025
	Workclass	.246	.789	.097	1	.755	1.279
	WorkclassFederalgov	1.401	.787	3.171	1	.075	4.059
	WorkclassLocalgov	.761	.785	.938	1	.333	2.139
	WorkclassNeverworked	-16.456	10751.078	.000	1	.999	.000
	WorkclassPrivate	.908	.784	1.342	1	.247	2.479
	WorkclassSelfempinc	1.056	.786	1.806	1	.179	2.876
	WorkclassSelfempnotinc	.368	.785	.220	1	.639	1.445
	WorkclassStategov	.591	.787	.565	1	.452	1.807
	fnlwgt	.000	.000	30.147	1	.000	1.000
	education10th	-1.238	.130	90.950	1	.000	.290
	education11th	-1.135	.126	81.699	1	.000	.322
	education12th	-.708	.179	15.681	1	.000	.493
	education1st4th	-1.819	.399	20.816	1	.000	.162
	education5th6th	-1.383	.229	36.336	1	.000	.251

Additionally, this output included a classification table, which showed the overall usefulness of the model. As seen above, it accurately predicted/classified about 85% of the observations. In the table labeled “Variables in the Equation”, further diagnostics were given, such as the coefficients, their standard errors, the Wald test statistic with associated degrees of freedom and p-values, and the exponentiated coefficient (also known as an odds ratio).

Based on the p-values, there were 36 variables shown to be significant, some of which being age, education, native country relationship status, and occupation. This was a large model, so to reduce the dimensionality, we identified the most significant variables by looking at their odds ratio. Based on odds ratio, we found 18 significant variables:

Work Class	Education	Marital Status	Occupation	Native Country
Federal Gov't	Doctorate	Married Armed Forces Spouse	Executive / Managerial	Columbia
Never Worked	Masters	Married Civilian Spouse		Holand / Netherlands
Private	Preschool			Laos
Self Employed INC	Professional School			Trinidad & Tobago
				Vietnam

The final output below of interest was the Receiver Operating Characteristic curve. This model produces an ROC Curve accuracy rate of 90.80%, which means that the Logistic Regression model performed slightly better than GlmNet.



Method 3 – Gradient Boosting Machine

The last method we used was the Gradient Boosting Machine Model (GBM). With the versatility in the uses of GBM, a decision was made to use this as a classification method. The way this method works is similar to support vector machines, where it attempts to build a model by splitting the data through a hyperplane. The difference is that GBM is a type of ensemble method. That means that it is an additive model which runs several iterations to build a learning algorithm in a stage-wise manner. The end result is a model that finds a linear association between the past iterations. (Friedman, 2001) The figure below shows a step by step example of this process:

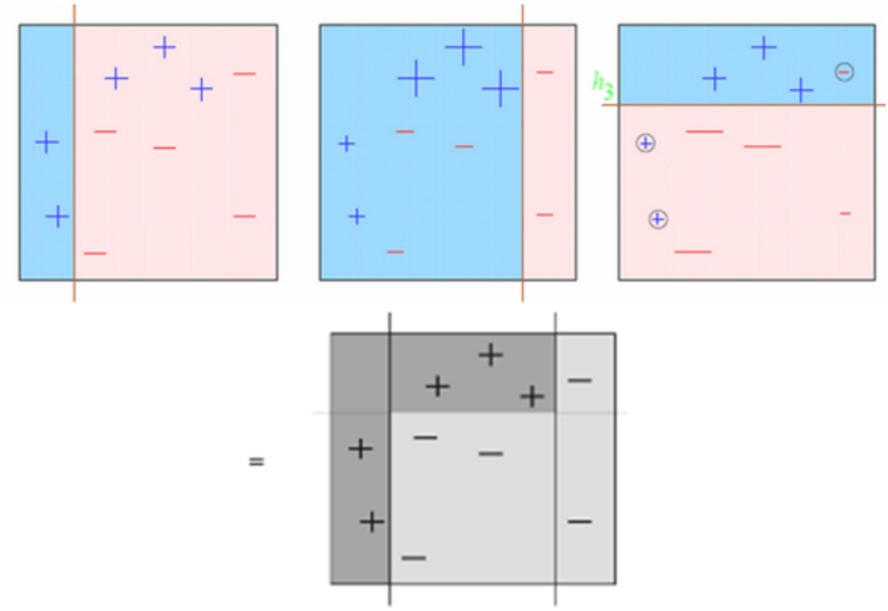


Figure 8 – the GBM Model procedure[5]

There are many benefits to using this type of machine learning algorithm. The first is that it prevents over fitting by choosing the optimal number of iterations to run through monitoring of prediction error. Gradient boosting is also typically used with decision trees, so there are strategies to overcome over fitting by changing a combination of parameters like the learning rate (shrinkage), depth of tree, and number of trees. With correct tuning parameters, GBM generally provides better results than other ensemble methods such as random forests (Friedman, 2001).

The Gradient Boosted Method was run in R using the gbm and caret packages. The first task was in creating a new variable to force GBM into using the classification mode instead of the original binary dependent variable:

```
#use gbm by first creating a new classification variable
census$salary2 <- ifelse(salary==1,'yes','no')
census$salary2 <- as.factor(census$salary2)
outcomeName <- 'salary2'
```

[5] Image source(Srivastava, 2015)

From there, the data was split into a test and train set to evaluate the model. Setting a seed guaranteed that we would get the same split in subsequent runs:

```
#splitting into train and test data
set.seed(1234)
splitIndex <- createDataPartition(census[,outcomeName], p = .75, list = FALSE, times = 1)
trainDF <- census[ splitIndex,]
testDF  <- census[-splitIndex,]
```

Using the caret package, we were able to get the most out of our model by controlling the resampling of the data through cross validation. In this case, we decided to cross-validate the data 10 times, therefore training it 10 times on different portions of the data to make sure we settled on the best tuning parameters.

Next we created the model and taught it how to recognize whether or not someone made above $50,000 per year:

```
objControl <- trainControl(method='cv', number=10, returnResamp='none', summaryFunction =
twoClassSummary, classProbs = TRUE)
objModel <- train(trainDF[,predictorsNames], trainDF[,outcomeName],
                  method='gbm',
                  trControl=objControl,
                  metric = "ROC",
                  preProc = c("center", "scale"))
```

Below is a sample output of the learning process as the model improved through each iteration. The "TrainDeviance" measures the error, which the model tries to minimize it after each new iteration:

Iter	TrainDeviance	ValidDeviance	StepSize	Improve
1	1.0638	nan	0.1	0.0185
2	1.0339	nan	0.1	0.0149
3	1.0099	nan	0.1	0.0117
4	0.9869	nan	0.1	0.0118
5	0.9707	nan	0.1	0.008
6	0.9516	nan	0.1	0.0095
7	0.9357	nan	0.1	0.0078
8	0.9242	nan	0.1	0.006
9	0.915	nan	0.1	0.0046
10	0.9024	nan	0.1	0.0063
20	0.8335	nan	0.1	0.0025
40	0.758	nan	0.1	0.0009
60	0.717	nan	0.1	0.001
80	0.6925	nan	0.1	0.0004
100	0.6751	nan	0.1	0.0004
120	0.6634	nan	0.1	0.0003
140	0.6544	nan	0.1	0.0001
150	0.6508	nan	0.1	0.0001

By running a summary of the model, we were given the relative importance of each independent variable, and were able to place weighted importance. It also minimized more than half of our original variables to zero, where we could conclude that they did not have an impact on the boosted method. The first figure below shows the most important factors, which are marital status, capital gain, and capital loss. The second figure indicates that more than half of the variables are classified as unimportant.

1	Relative Influence of Independent Variables	
2	`marital-status` Married-civ-spouse	37.53692617
3	`capital-gain`	23.07019642
4	`capital-loss`	6.34660483
5	Age	5.91152153
6	`hours-per-week`	4.45058102
7	occupation Prof-specialty	4.31077821
8	education Bachelors	3.66725941
9	occupation Exec-managerial	3.54987896
10	education Masters	2.5502487
11	education Prof-school	1.19383786
12	education Doctorate	0.96456148

1	Relative Influence of Independent Variables	
51	Workclass Never-worked	0
52	Workclass State-gov	0
53	Workclass Without-pay	0
54	education 12th	0
55	education Preschool	0
56	education Some-college	0
57	`marital-status` Divorced	0
58	`marital-status` Married-spouse-absent	0
59	`marital-status` Separated	0
60	`marital-status` Widowed	0
61	occupation ?	0

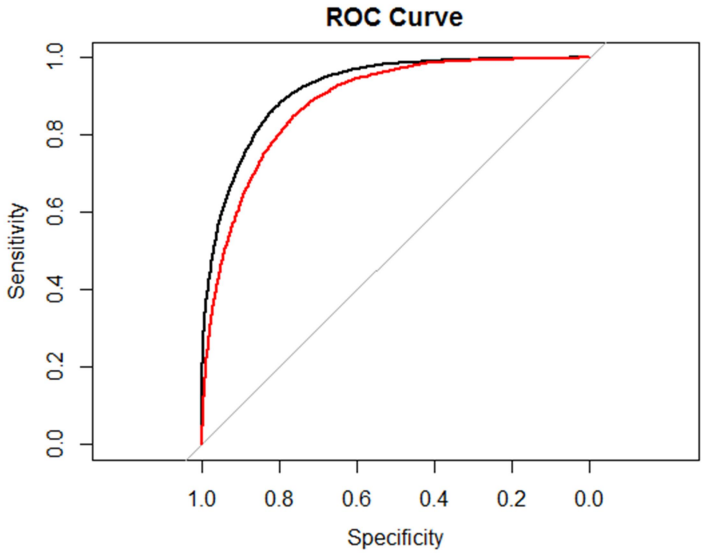
With the model completed, we were interested in how well it performed. The model was able to classify salary with 86.5% accuracy, by observing the type 1 and type 2 errors highlighted in the confusion matrix below:

```
> #find out accuracy of model
> predictions <- predict(object=objModel, testDF[,predictorsNames], type='raw')
> print(postResample(pred=predictions, obs=as.factor(testDF[,outcomeName])))
 Accuracy     Kappa
0.8649357 0.5932111

> confusionMatrix(objModel)
Cross-Validated (10 fold) Confusion Matrix

(entries are percentages of table totals)
```

```
          Reference
Prediction   no  yes
       no  72.4  9.9
       yes  3.7 14.0
```

Calculating the ROC, we observed that this method performed the best out of the three models used. The graph of the ROC curve also compares GBM in black to the GLMnet method in red. Clearly, GBM has outperformed since it has a larger area:

```
> auc <- roc(ifelse(testDF[,outcomeName]=="yes",1,0), predictions[[2]])
> print(auc$auc)
Area under the curve: 0.9193
```



Conclusions and Remarks

Of the three types of models we ran, they all performed very well. Despite a close performance by each model, the Gradient Boosting Machine performed the best. Depending on what is at stake, every additional percentage and even hundredth of a percentage of accuracy can make a big difference.

The Model Used	Area Under the Curve (AUC) Score
GlmNet	.8975
Logistic Regression	.9080
Gradient Boosting Machine (GBM) model	.9193

While there were few similarities between the variables deemed important by each model, the ones which were similar dealt with education levels and marital status. Education is rather intuitive to interpret, as one would expect a higher level of education to be correlated with more specialized fields, which are typically highly paid.

The marriage level is more difficult to interpret. As seen from the snippet of the Census, there is the possibility that a family who filled out the census reported their income as it was reported on their joint tax return. That is to say that they may not have delineated who earned how much. This creates the several possible scenarios. For example, two spouses could work and jointly earn over $50,000 if the census respondents reported their joint income, where they technically both earn less than $50,000 per year.

The dataset was not without its shortfalls. Not including the “Hispanic” category of race deviated from normal Census reporting, and would have been an interesting feature to measure. Further, the sample size was perhaps too low to more smoothly and accurately look at categories of Race outside of “White”. Perhaps more interesting is what we didn’t observe. For instance, none of the three models placed a high importance on race, nor on gender, despite visually significant differences between them. This is possibly due to having a dichotomous dependent variable, the effects of marriage and joint income, a combination of the two, or perhaps even other variations which we do not have the expertise to discern.

As a final note, future analysis of the same points (time-series) may be of additional use in terms of tracking trends in the areas we found to matter, such as levels of education achieved by the general population, and the health of the “institution of marriage”. Further, use of this

particular model on a future Census dataset can show whether or not there has been a shift in how wealth can be predicted, and if certain social issues still exist.

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Reference

Cover Image of Uncle Sam and the Census book was pulled from http://backstoryradio.org/files/2010/10/answersready.jpg. The full image can be found in the government archives at http://loc.gov/pictures/resource/cph.3g08370/.

Appendix

Figure A.1

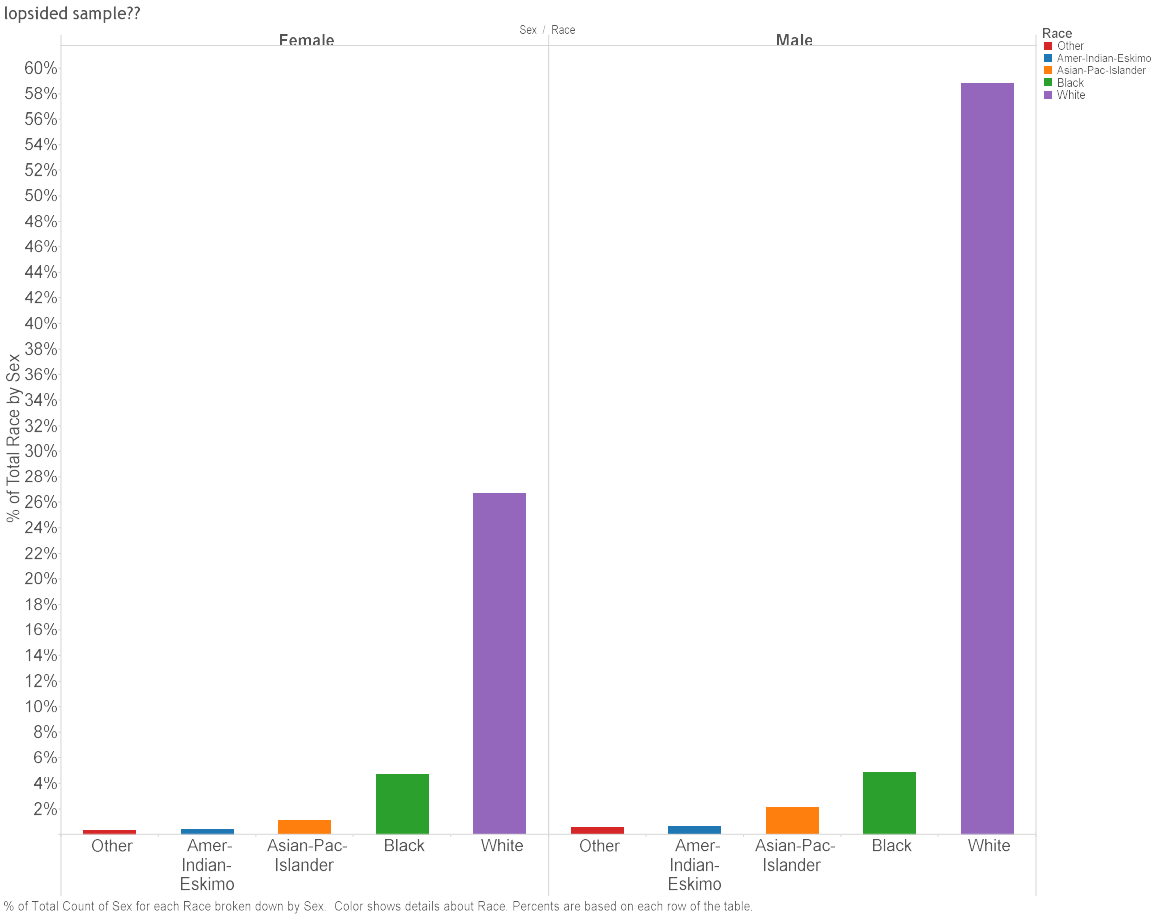


Figure A.2

Table 2
United States: population by race and Hispanic origin, 1960–99

Group	1960		1990		1999	
	Total (thousands)	Percentage of population	Total (thousands)	Percentage of population	Total (thousands)	Percentage of population
White	151,932	84.7	188,307	75.7	196,043	71.9
Black	18,872	10.5	29,299	11.8	33,088	12.1
Hispanic[a]	6,900	3.9	22,372	9.0	31,265	11.5
Asian and Pacific Islander[b]	878	0.5	6,992	2.8	10,219	3.7
American Indian, Eskimo, and Aleut	524	0.3	1,796	0.7	2,022	0.7
Other	218	0.1	—	—	—	—
Total	179,323	100.0	248,766	100.0	272,637	100.0

Sources: US Bureau of the Census, Census of Population 1960, Vol. 1: Characteristics of the Population, Part 1: United States Summary, Table 56. US Bureau of the Census, *Resident Population Estimates of the United States by Sex, Race, and Hispanic Origin: April 1, 1990 to June 1, 1999*.
Notes: a The estimate of the 1960 Hispanic population is from Cary Davis, Carl Haub, and JoAnne Willette, 1983. 'US Hispanics: Changing the Face of America.' *Population Bulletin*, Vol. 38, No. 3, p. 8, Table 2.
b For 1960, the Asian population comprises the categories 'Japanese,' and 'Chinese,' and 'Filipino' only. In subsequent years, Koreans, Vietnamese, Asian Indians, Samoans, Guamamians, and Hawaiians were also included.

Figure A.3

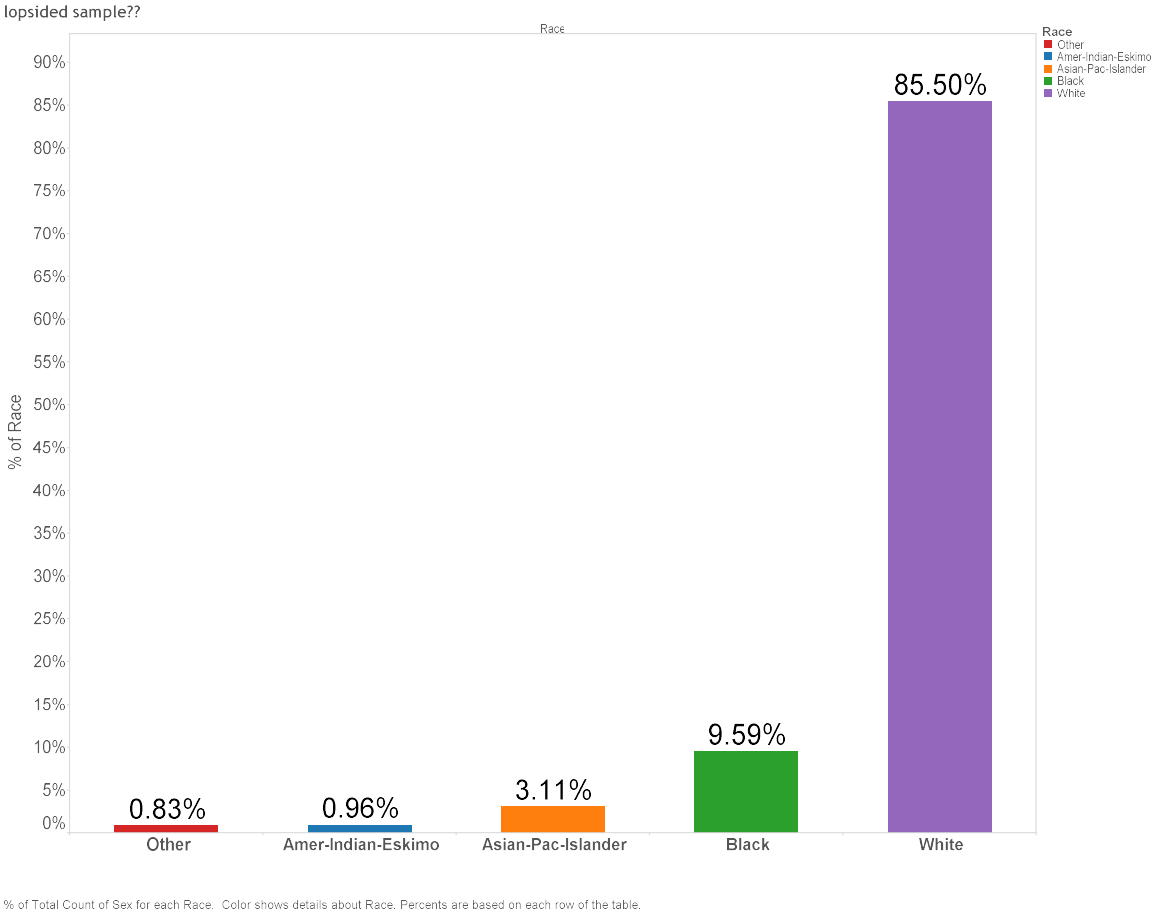


Figure A.4

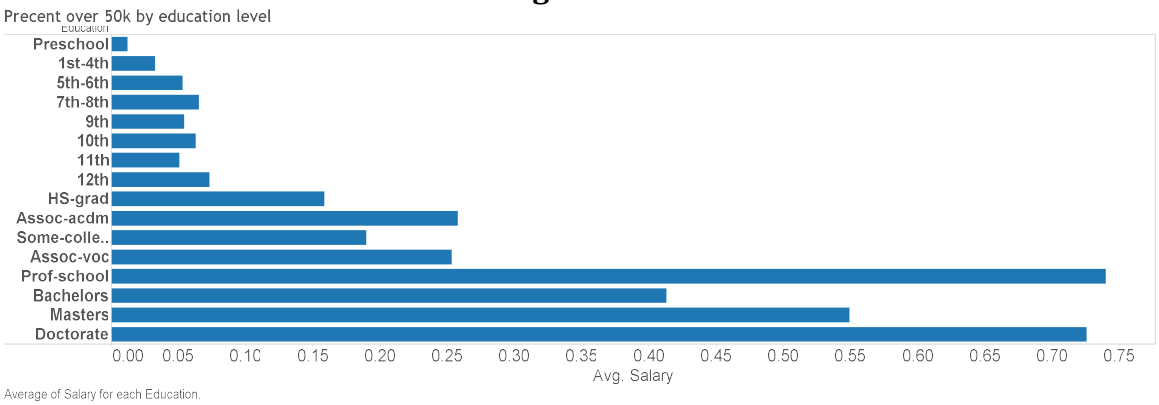


Figure A.5

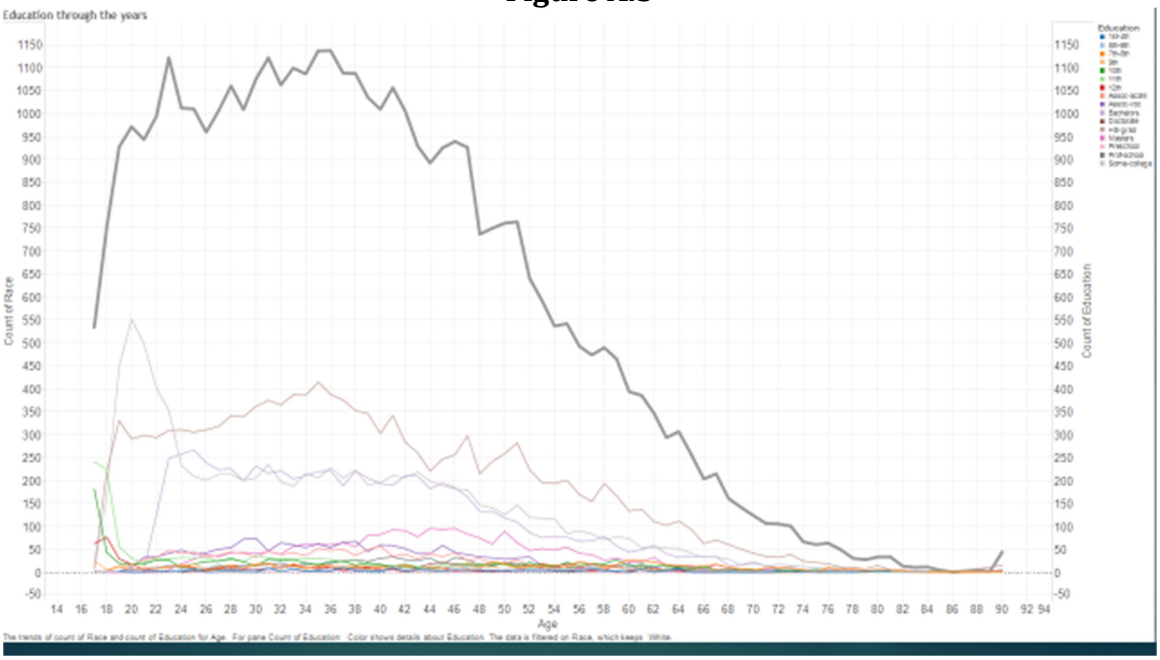


Figure A.6

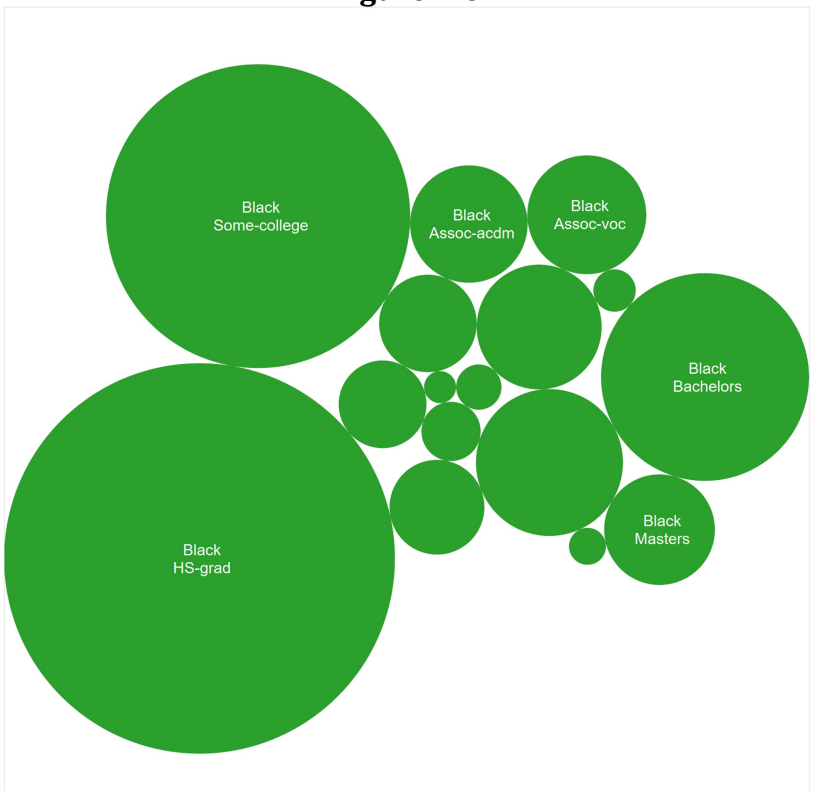


Figure A.7

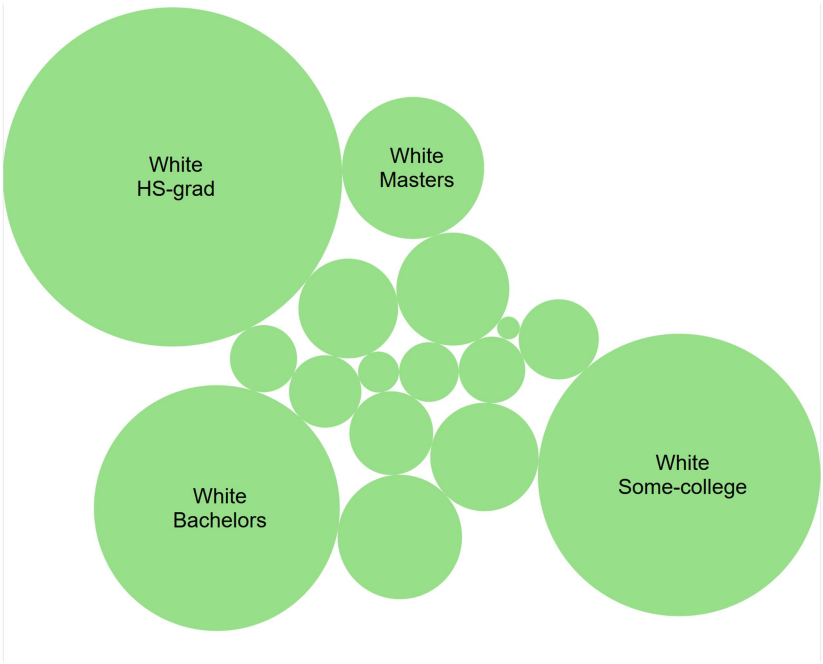


Figure A.8

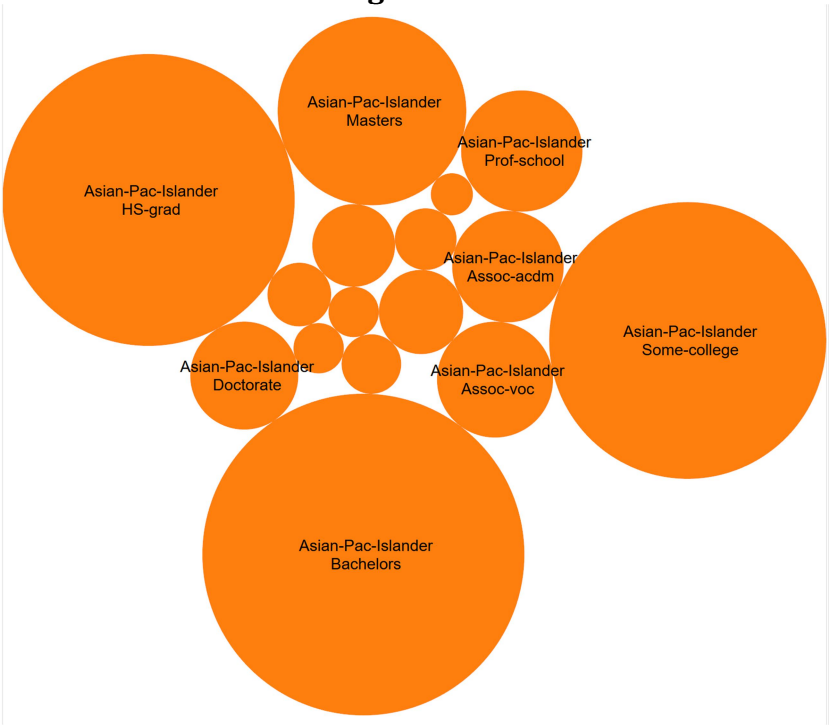


Figure A.9

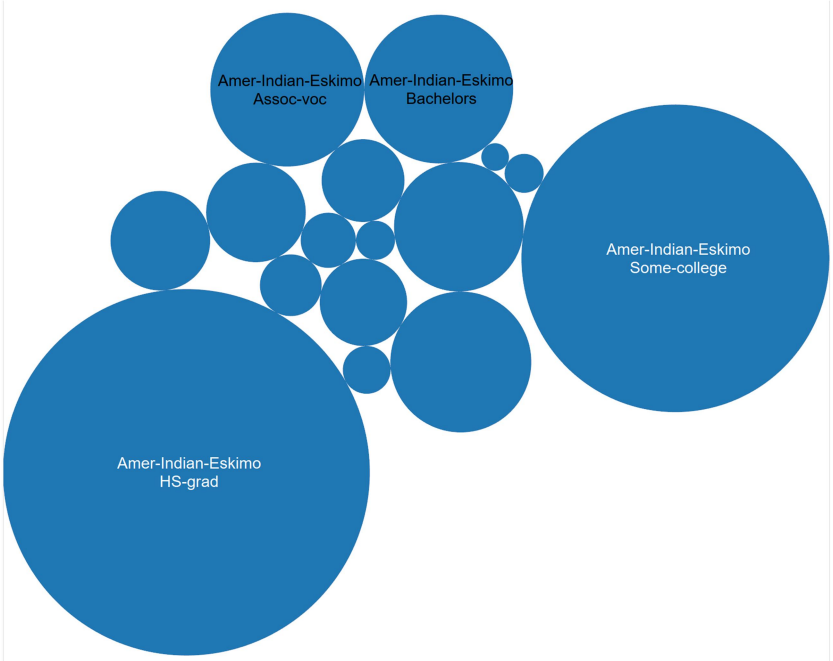
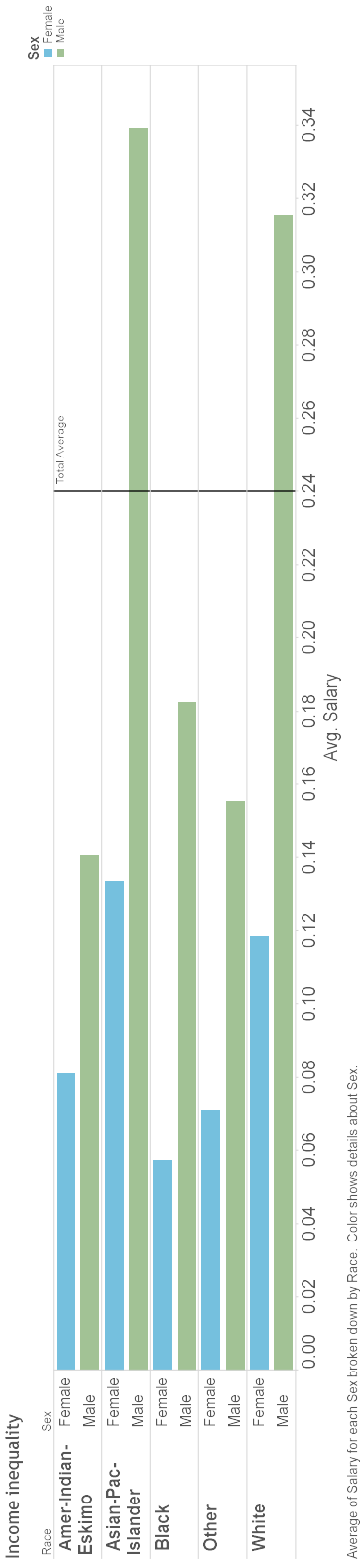
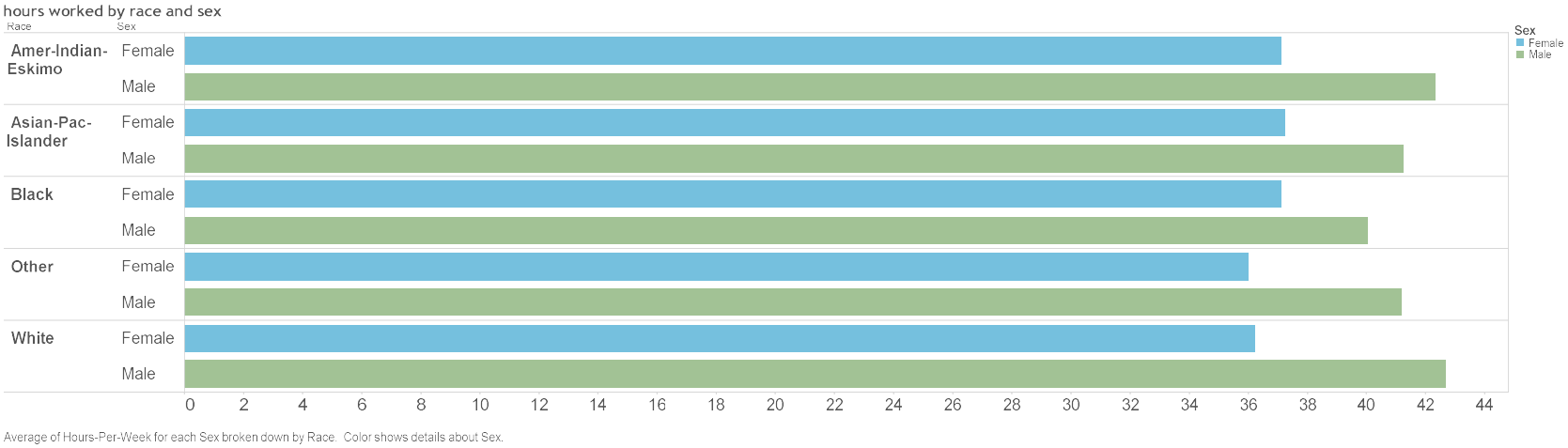


Figure A.10


Income inequality
Sex
Female
Male
Race
Amer-Indian-Eskimo
Asian-Pac-Islander
Black
Other
White
Total Average
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
0.16
0.18
0.20
0.22
0.24
0.26
0.28
0.30
0.32
0.34
Avg. Salary
Average of Salary for each Sex broken down by Race. Color shows details about Sex.

Appendix A.11


hours worked by race and sex
Race
Sex
Amer-Indian-Eskimo
Female
Male
Asian-Pac-Islander
Female
Male
Black
Female
Male
Other
Female
Male
White
Female
Male
0 2 4 6 8 10 12 14 16 18 20 22 24 26 28 30 32 34 36 38 40 42 44
Sex
Female
Male
Average of Hours-Per-Week for each Sex broken down by Race. Color shows details about Sex.

Individual Contributions

John Benischeck – Data visualization section and graphs. Compiled and edited paper.

Tommy Baw – GBM Model research, implementation, and writeup.

Shachi Parikh – Logistic Regression research, implementation, and writeup.

Xiaoqin Helen Yi – GlmNet research, implementation, and writeup.

Xiaomeng Blair Chen – data gathering and cleaning, introduction, and writeup.

Addressing Comments

We received no questions about our project.