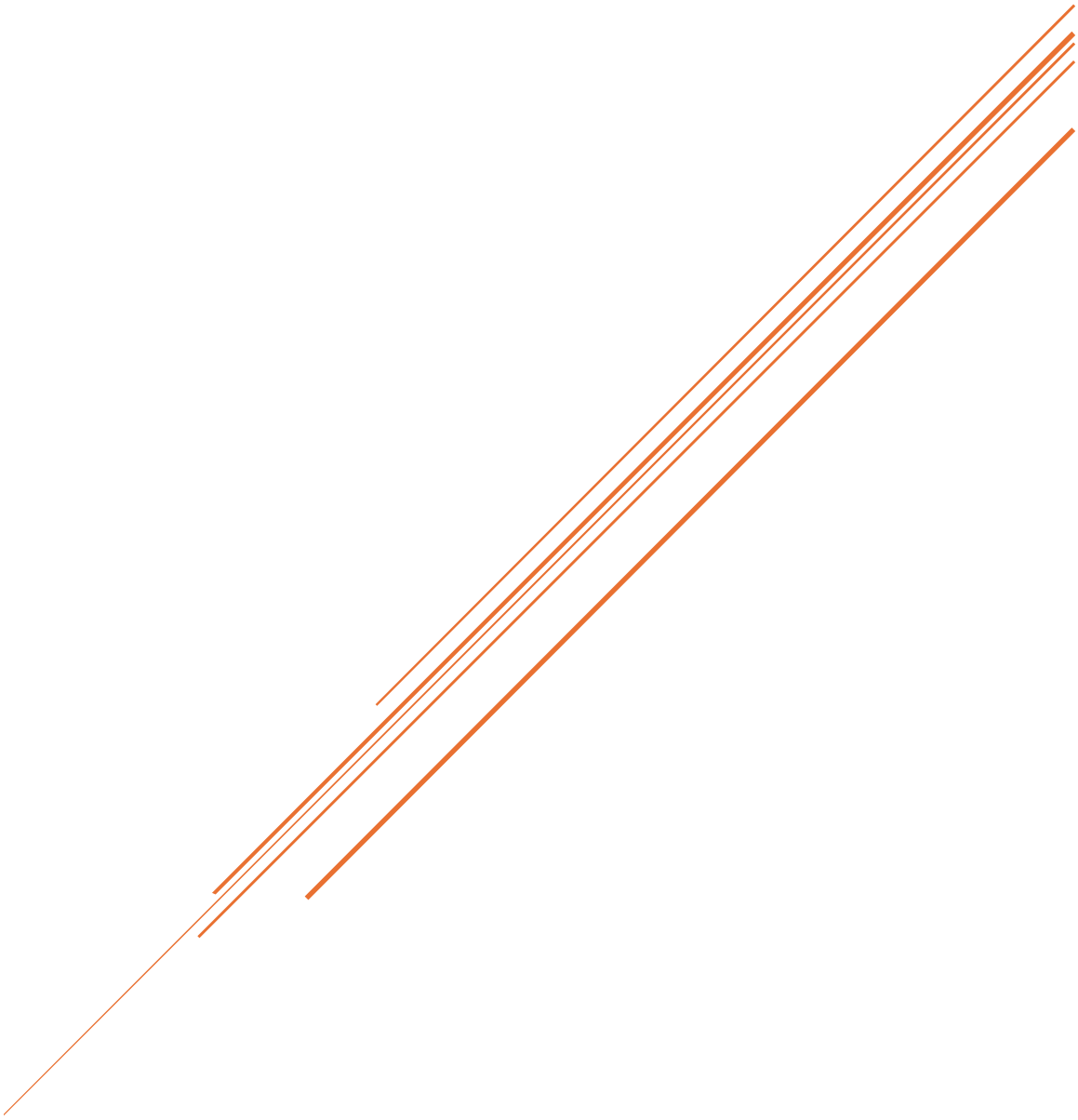
# United States Census

## Data Mining Project



# Contents

# Part 1. PreprocessingS

## Reduce to 5000 data points

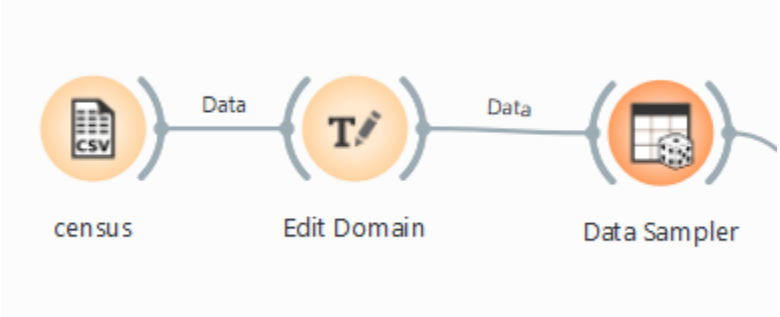



*Figure 1 Data Sampler Node*

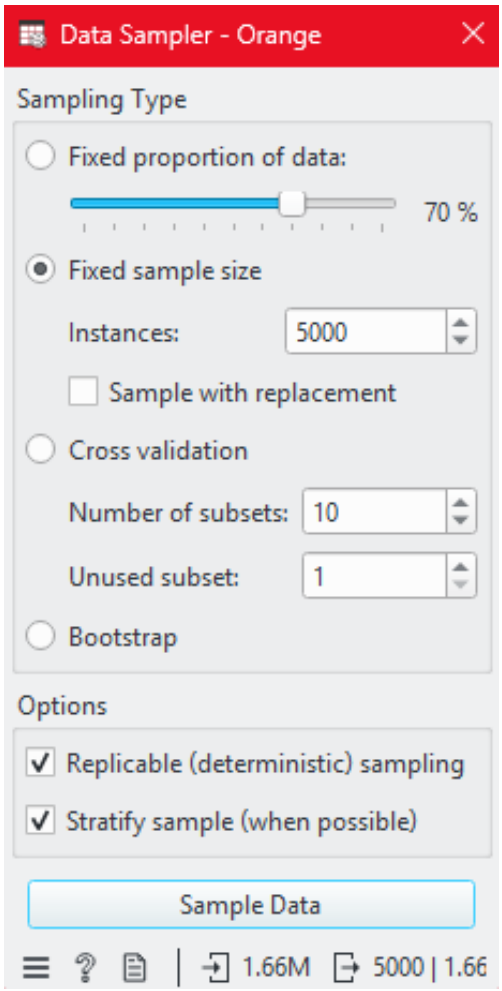



*Figure 2 Data Sampler Settings*

The dataset has been reduced to 5000 points using Data Sampler to speed up computations.

## Modify data structure

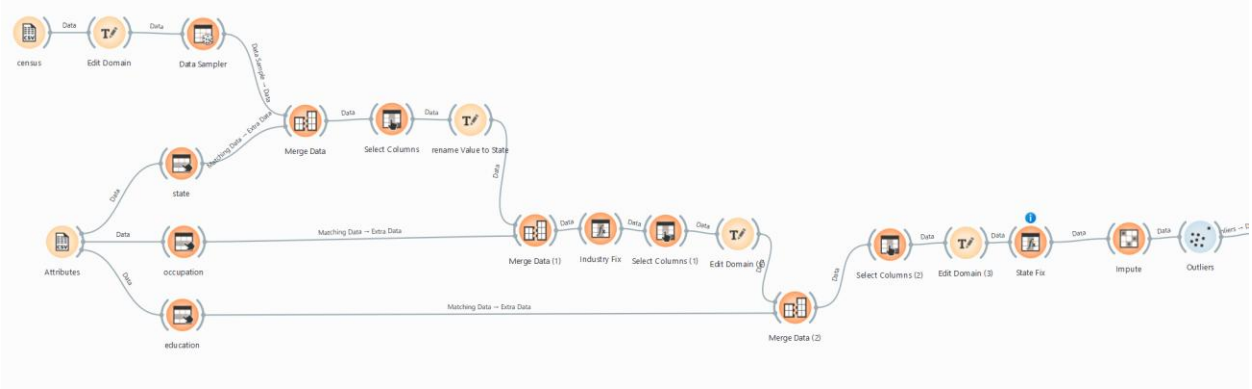



*Figure 3 Preprocessing nodes*

| | income | State | Industry | education_lvl | age | CoW | education | marital | occupation | PoB | hours | sex | race |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 182 | 82500 | Arkansas | CON | High-School | 64 | Government E... | 16 | Married | 6730 | US | 40 | Male | white |
| 183 | 30000 | New Hampshire | OFF | Post-High-School | 28 | Private Employee | 19 | Married | 5140 | US | 40 | Male | white |
| 184 | 120000 | Nevada | PRT | Post-High-School | 45 | Government E... | 19 | Married | 3740 | US | 56 | Male | non-white |
| 185 | 44000 | Ohio | RPR | High-School | 34 | Private Employee | 17 | Married | 7100 | US | 40 | Male | white |
| 186 | 38000 | Maryland | CLN | High-School | 57 | Government E... | 16 | Married | 4220 | US | 40 | Male | white |
| 187 | 22000 | California | OFF | High-School | 20 | Private Employee | 16 | Separated | 5240 | non-US | 40 | Female | non-white |
| 188 | 19600 | New York | EAT | No diploma | 24 | Private Employee | 14 | Married | 4030 | non-US | 18 | Female | non-white |
| 189 | 69400 | Nebraska | MGR | Post-High-School | 68 | Private Employee | 19 | Married | 10 | US | 40 | Female | white |
| 190 | 35000 | Pennsylvania | OFF | Post-High-School | 62 | Private Employee | 19 | Married | 5120 | US | 40 | Female | white |
| 191 | 1500 | Connecticut | TRN | Post-High-School | 21 | Private Employee | 18 | Single | 9645 | US | 8 | Female | white |
| 192 | 95000 | Florida | ENG | Bachelor's degree | 49 | Private Employee | 21 | Married | 1450 | US | 40 | Male | white |
| 193 | 1400 | Tennessee | EAT | No diploma | 18 | Private Employee | 14 | Single | 4130 | US | 10 | Male | white |
| 194 | 50000 | Nevada | MGR | Associate's degree | 40 | Self-Employed | 20 | Married | 310 | non-US | 60 | Male | non-white |
| 195 | 161000 | New Jersey | BUS | Professional degree beyond a ... | 55 | Private Employee | 23 | Married | 650 | US | 45 | Male | white |
| 196 | 283000 | North Carolina | EAT | No diploma | 57 | Private Employee | 14 | Married | 4020 | US | 35 | Male | non-white |
| 197 | 15000 | Massachusetts | MED | High-School | 19 | Private Employee | 16 | Single | 3424 | US | 36 | Female | white |
| 198 | 18000 | Illinois | EAT | Post-High-School | 37 | Private Employee | 18 | Married | 4110 | US | 20 | Female | white |
| 199 | 30000 | Massachusetts | EAT | No diploma | 30 | Private Employee | 11 | Married | 4020 | non-US | 40 | Male | non-white |
| 200 | 22900 | Louisiana | EAT | Post-High-School | 25 | Private Employee | 19 | Single | 4110 | non-US | 40 | Female | non-white |
| 201 | 36000 | Michigan | SAL | Associate's degree | 59 | Self-Employed | 20 | Married | 4820 | non-US | 50 | Male | non-white |
| 202 | 103000 | Missouri | MGR | Bachelor's degree | 61 | Private Employee | 21 | Married | 10 | US | 45 | Male | white |
| 203 | 120000 | New York | PRT | Bachelor's degree | 43 | Government E... | 21 | Married | 3740 | US | 36 | Male | white |
| 204 | 50000 | Washington | OFF | Post-High-School | 24 | Private Employee | 19 | Single | 5000 | US | 40 | Female | non-white |
| 205 | 59000 | Maine | PRD | High-School | 38 | Private Employee | 17 | Married | 7700 | US | 48 | Male | white |
| 206 | 30000 | Arizona | CON | High-School | 59 | Private Employee | 16 | Separated | 6410 | US | 40 | Male | white |
| 207 | 35000 | Minnesota | SAL | High-School | 19 | Private Employee | 16 | Married | 4720 | US | 35 | Female | white |
| 208 | 150000 | Wisconsin | MGR | Master's degree | 51 | Private Employee | 22 | Married | 140 | US | 45 | Male | white |
| 209 | 192000 | Maine | TRN | High-School | 66 | Self-Employed | 16 | Single | 9130 | US | 60 | Male | white |
| 210 | 157000 | New York | MGR | Bachelor's degree | 65 | Private Employee | 21 | Divorced | 440 | US | 50 | Male | white |
| 211 | 60000 | Georgia | TRN | Post-High-School | 56 | Private Employee | 19 | Divorced | 9130 | US | 70 | Male | non-white |
| 212 | 17500 | Mississippi | TRN | High-School | 32 | Private Employee | 16 | Single | 9600 | US | 30 | Male | white |
| 213 | 48000 | New Jersey | MED | Professional degree beyond a ... | 64 | Self-Employed | 23 | Married | 3100 | US | 20 | Male | white |
| 214 | 6940 | North Carolina | CON | Post-High-School | 64 | Self-Employed | 18 | Married | 6230 | US | 35 | Male | white |
| 215 | 1500 | Pennsylvania | TRN | No diploma | 17 | Private Employee | 15 | Single | 9645 | US | 25 | Male | white |
| 216 | 50000 | New Hampshire | BUS | Master's degree | 30 | Government E... | 22 | Married | 710 | US | 38 | Male | white |
| 217 | 20400 | New York | CON | No diploma | 61 | Private Employee | 14 | Divorced | 6260 | US | 40 | Male | white |
| 218 | 55000 | New York | OFF | Master's degree | 31 | Private Employee | 22 | Separated | 5740 | US | 40 | Female | non-white |
| 219 | 32000 | Florida | OFF | High-School | 62 | Private Employee | 17 | Married | 5000 | US | 40 | Female | white |
| 220 | 1000 | Georgia | OFF | Post-High-School | 22 | Private Employee | 19 | Married | 5400 | US | 4 | Female | white |
| 221 | 50000 | Texas | CMS | Bachelor's degree | 35 | Government E... | 21 | Single | 2011 | US | 50 | Female | white |
| 222 | 25000 | Maryland | MED | Bachelor's degree | 22 | Private Employee | 21 | Single | 3500 | US | 30 | Female | white |
| 223 | 36000 | Florida | CLN | High-School | 50 | Private Employee | 16 | Separated | 4210 | US | 40 | Male | white |
| 224 | 80260 | Indiana | PRD | Bachelor's degree | 72 | Private Employee | 21 | Married | 8130 | US | 20 | Male | white |
| 225 | 15000 | Maine | CLN | No diploma | 33 | Self-Employed | 15 | Married | 4230 | US | 15 | Female | white |
| 226 | 20800 | South Carolina | CLN | High-School | 50 | Government E... | 17 | Married | 4220 | US | 40 | Female | non-white |
| 227 | 111000 | North Carolina | MGR | Master's degree | 45 | Government E... | 22 | Divorced | 230 | US | 40 | Female | white |
| 228 | 41000 | Wisconsin | PRD | High-School | 39 | Private Employee | 17 | Married | 8990 | US | 40 | Male | white |
| 229 | 2400 | Texas | EAT | Post-High-School | 19 | Private Employee | 18 | Single | 4055 | US | 15 | Female | white |
| 230 | 200000 | Michigan | MGR | Bachelor's degree | 56 | Private Employee | 21 | Married | 10 | non-US | 45 | Male | non-white |

*Figure 4 Preprocessing final output*

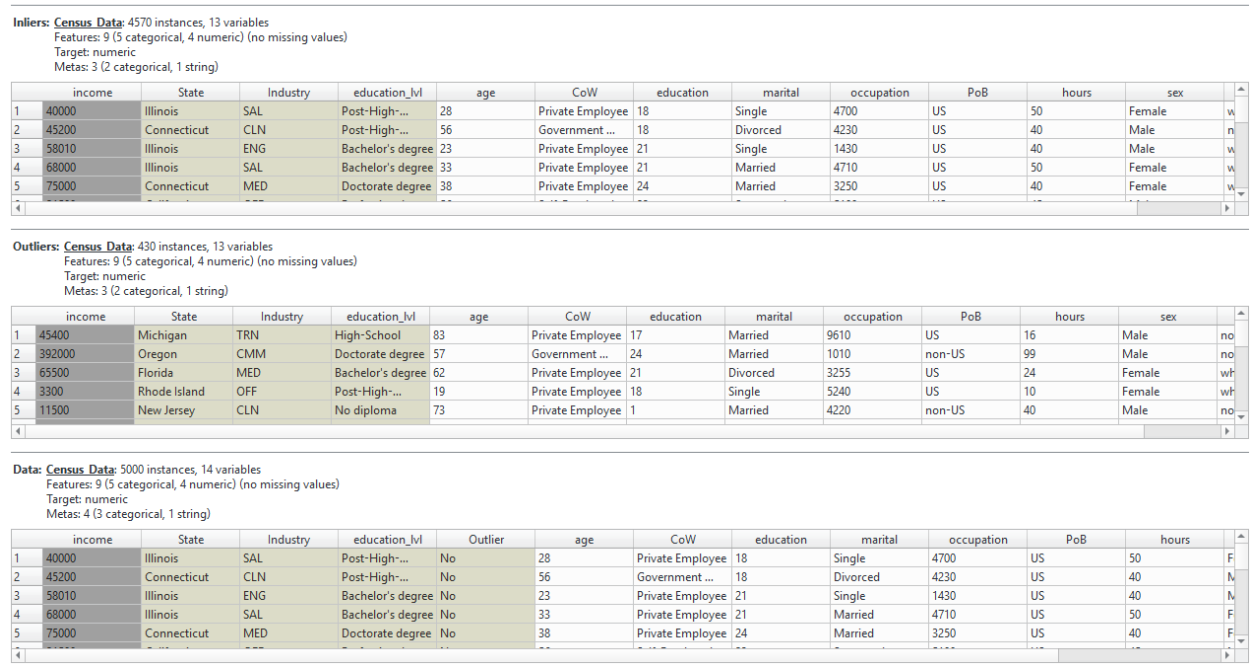
The data in the census file has been modified to display the data structure for:

- COW as private employee, government employee, self-employed, no pay. No data points exist for “unemployed”. (categorical)
- Education as no diploma, high-school, post-high-school, etc. while maintaining the numeric value associated with each data point. (categorical + numeric)

- Marital as single, married, widowed, divorced, separated. (categorical)
- Occupation as the first 3 digits of the industry title while maintaining the original numeric value. (text + numeric)
- PoB as US/ non-US. (categorical)
- Sex as male or female. (categorical)
- Race as white or non-white. (categorical)
- State as state's name. (categorical)

## Handle missing data or Outliers

There are no missing data in datasets. However, there were a total of 430 datapoints which involved Outliers which were removed using Local Outlier Factor.



**Inliers:** Census_Data: 4570 instances, 13 variables
Features: 9 (5 categorical, 4 numeric) (no missing values)
Target: numeric
Metas: 3 (2 categorical, 1 string)

| | income | State | Industry | education_lvl | age | CoW | education | marital | occupation | PoB | hours | sex | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 40000 | Illinois | SAL | Post-High-... | 28 | Private Employee | 18 | Single | 4700 | US | 50 | Female | w |
| 2 | 45200 | Connecticut | CLN | Post-High-... | 56 | Government ... | 18 | Divorced | 4230 | US | 40 | Male | n |
| 3 | 58010 | Illinois | ENG | Bachelor's degree | 23 | Private Employee | 21 | Single | 1430 | US | 40 | Male | w |
| 4 | 68000 | Illinois | SAL | Bachelor's degree | 33 | Private Employee | 21 | Married | 4710 | US | 50 | Female | w |
| 5 | 75000 | Connecticut | MED | Doctorate degree | 38 | Private Employee | 24 | Married | 3250 | US | 40 | Female | w |

**Outliers:** Census_Data: 430 instances, 13 variables
Features: 9 (5 categorical, 4 numeric) (no missing values)
Target: numeric
Metas: 3 (2 categorical, 1 string)

| | income | State | Industry | education_lvl | age | CoW | education | marital | occupation | PoB | hours | sex | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 45400 | Michigan | TRN | High-School | 83 | Private Employee | 17 | Married | 9610 | US | 16 | Male | no |
| 2 | 392000 | Oregon | CMM | Doctorate degree | 57 | Government ... | 24 | Married | 1010 | non-US | 99 | Male | no |
| 3 | 65500 | Florida | MED | Bachelor's degree | 62 | Private Employee | 21 | Divorced | 3255 | US | 24 | Female | wh |
| 4 | 3300 | Rhode Island | OFF | Post-High-... | 19 | Private Employee | 18 | Single | 5240 | US | 10 | Female | wh |
| 5 | 11500 | New Jersey | CLN | No diploma | 73 | Private Employee | 1 | Married | 4220 | non-US | 40 | Male | no |

**Data:** Census_Data: 5000 instances, 14 variables
Features: 9 (5 categorical, 4 numeric) (no missing values)
Target: numeric
Metas: 4 (3 categorical, 1 string)

| | income | State | Industry | education_lvl | Outlier | age | CoW | education | marital | occupation | PoB | hours | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 40000 | Illinois | SAL | Post-High-... | No | 28 | Private Employee | 18 | Single | 4700 | US | 50 | F |
| 2 | 45200 | Connecticut | CLN | Post-High-... | No | 56 | Government ... | 18 | Divorced | 4230 | US | 40 | M |
| 3 | 58010 | Illinois | ENG | Bachelor's degree | No | 23 | Private Employee | 21 | Single | 1430 | US | 40 | M |
| 4 | 68000 | Illinois | SAL | Bachelor's degree | No | 33 | Private Employee | 21 | Married | 4710 | US | 50 | F |
| 5 | 75000 | Connecticut | MED | Doctorate degree | No | 38 | Private Employee | 24 | Married | 3250 | US | 40 | F |

*Figure 5 Outliers node results*

# Exploratory Data Analysis

**Feature Statistics**

| | Name | Distribution | Mean | Mode | Median | Dispersion | Min. | Max. | Missing |
|---|---|---|---|---|---|---|---|---|---|
| N | income |  | 56519.8 | 50000 | 39300 | 1.26636 | 150 | 830000 | 0 (0 %) |
| N | occupation |  | 4146.93 | 2310 | 4150 | 0.639558 | 10 | 9830 | 0 (0 %) |
| N | age |  | 42.898 | 52 | 43 | 0.350743 | 17 | 90 | 0 (0 %) |
| N | hours |  | 38.3967 | 40 | 40 | 0.317445 | 1 | 96 | 0 (0 %) |
| N | education |  | 18.5987 | 16 | 19 | 0.169695 | 1 | 24 | 0 (0 %) |
| C | State |  | | California | | 3.5 | | | 0 (0 %) |
| C | education_lvl |  | | High-School | | 1.82 | | | 0 (0 %) |
| C | marital |  | | Married | | 1.09 | | | 0 (0 %) |
| C | CoW |  | | Private Employee | | 0.77 | | | 0 (0 %) |
| C | sex |  | | Male | | 0.692 | | | 0 (0 %) |
| C | race |  | | white | | 0.526 | | | 0 (0 %) |
| C | PoB |  | | US | | 0.422 | | | 0 (0 %) |

*Table 1 Feature Statistics results*

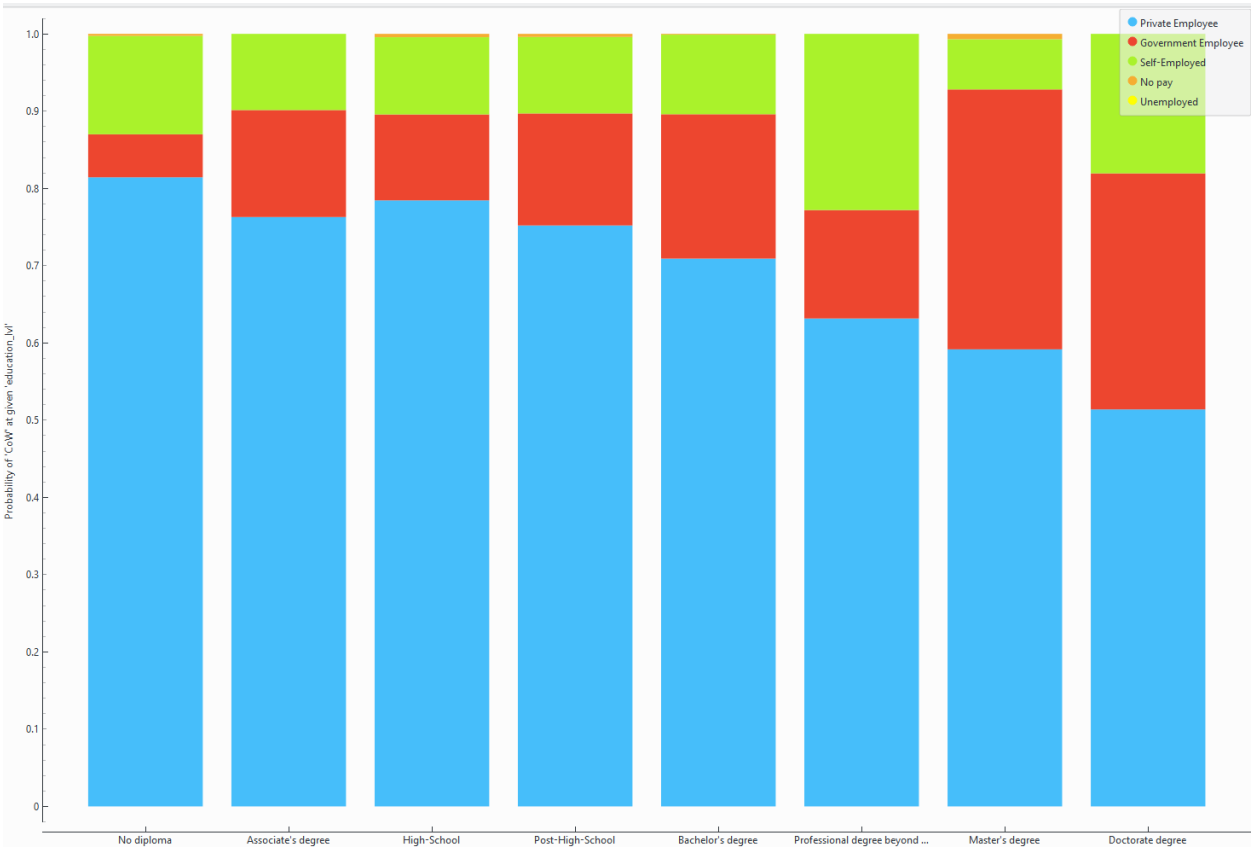



*Table 2 CoW by education level*

| | | # | Univar. reg. | RR...fF |
|---|---|---|---|---|
| 1 | N occupation | | NA | 0.100 |
| 2 | N age | | NA | 0.089 |
| 3 | N hours | | NA | 0.079 |
| 4 | N education | | NA | 0.077 |
| 5 | C marital | 5 | NA | 0.058 |
| 6 | C CoW | 5 | NA | 0.016 |
| 7 | C PoB | 2 | NA | 0.012 |
| 8 | C race | 2 | NA | 0.008 |
| 9 | C sex | 2 | NA | 0.007 |

*Figure 6 Ranking variables importance*

The distribution of the numerical variables of the data set along with some statistically relevant features are visualized above.

## Part 2. Fairness in income distribution

### Income Histogram

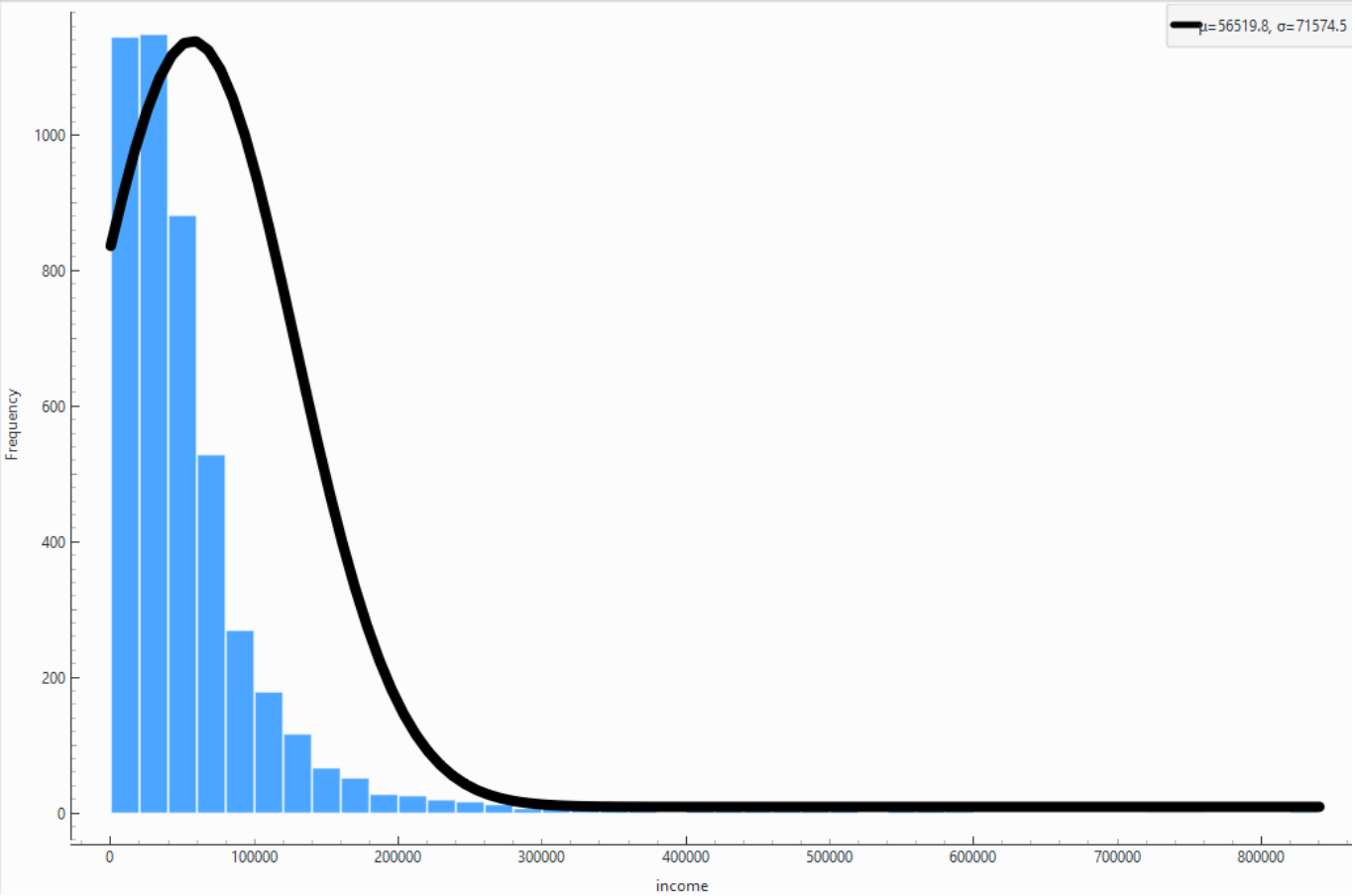



*Table 3 Income Histogram*

## Log(Income) Histogram

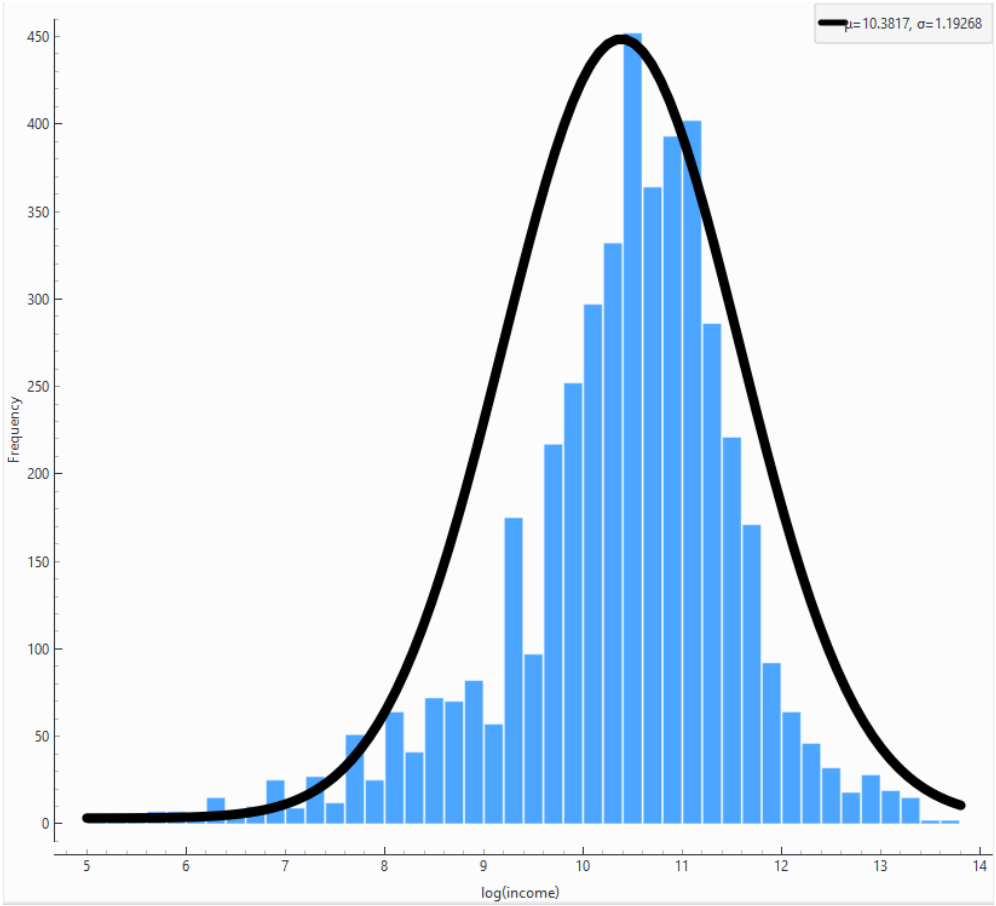



*Table 4 Log(Income) Histogram*

## Zipf plot for income distribution

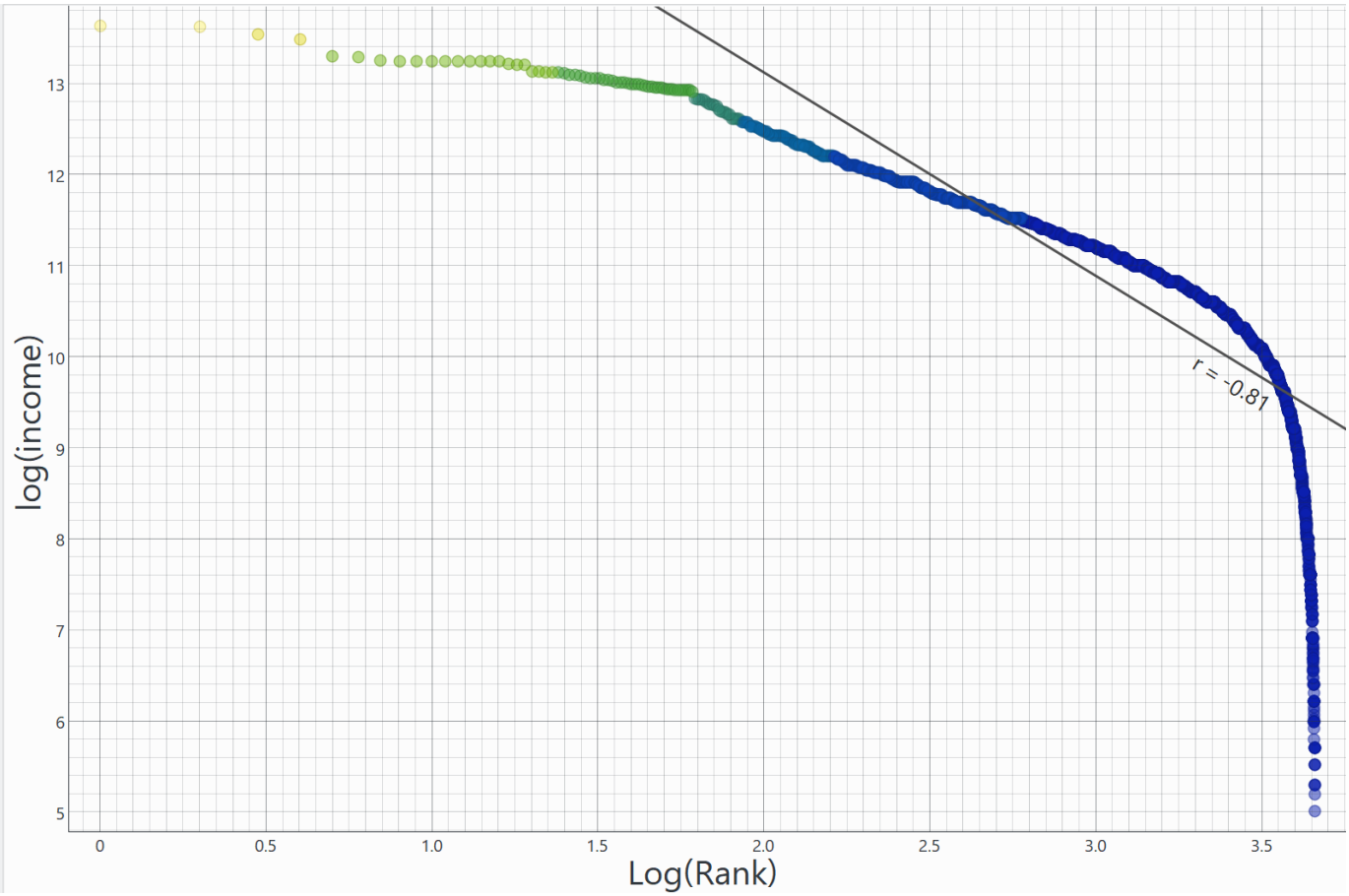



*Table 5 Zipf Plot*

## Results interpretation

The log transformation has increased the correlation coefficients (data is more spread). This suggests a more linear relationship between the variables. The log(income) graph is more useful as it helps identify patterns which may be less apparent in the regular income/frequency histogram. The Zipf plot graph checks if the income has followed a Pareto distribution and can be used to understand inequality in income (how top earners compare vs the rest). The results:

A) Log(income) plot: data appears to be normally distributed with a mean log(income) of 10.3817 and SD of 1.93.
B) Zipf plot: the data in the upper tail appears to follow a power-law distribution (Pareto's principle) due to its linearity, indicating that a very small number of individuals hold significantly higher incomes.

## Visualization of income distribution by sex, race and PoB

The three attributes vs income are visualized using box plot graphs.

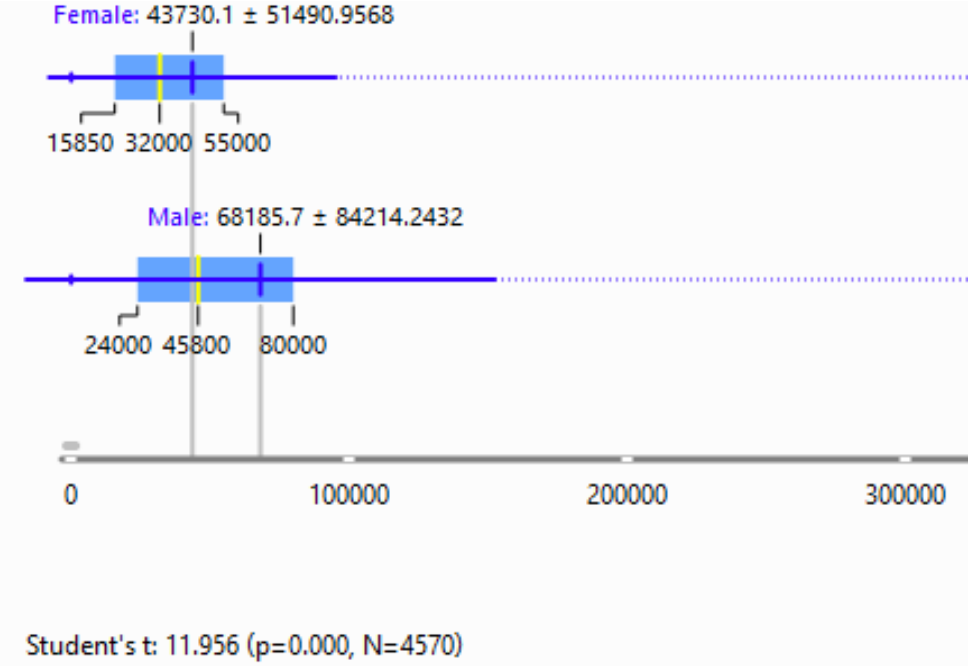



*Table 6 Box Plot of income vs sex*

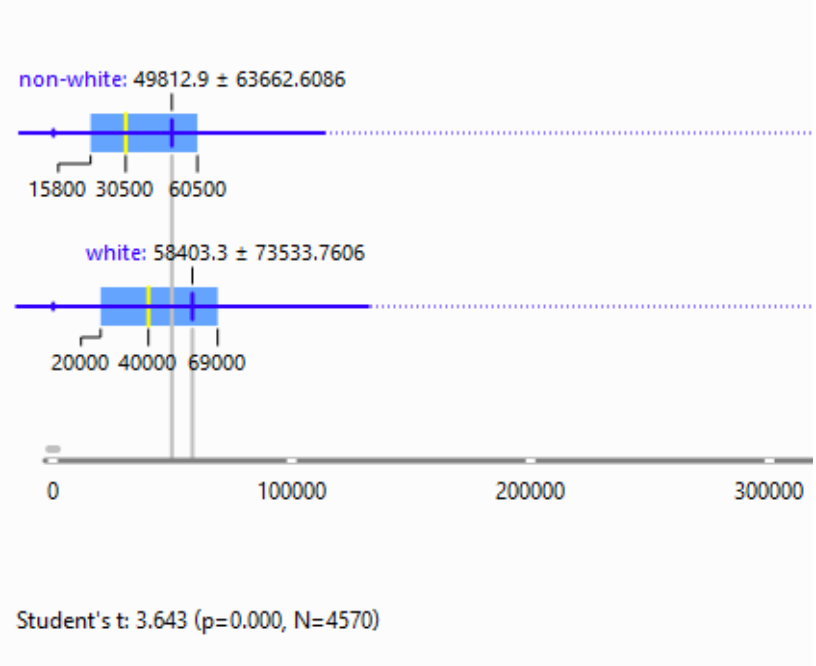



*Table 7 Box Plot of income vs race*

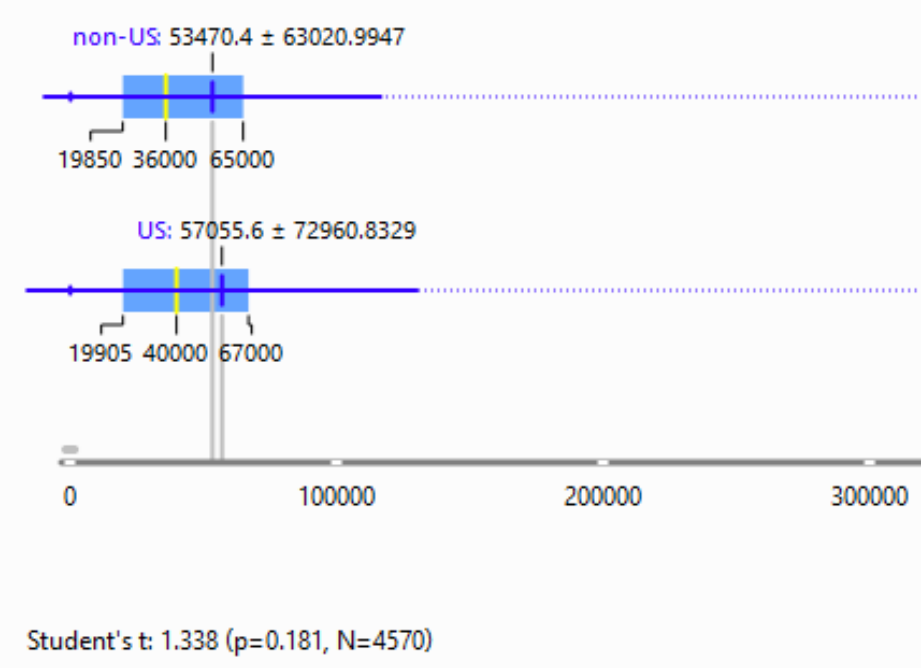



*Table 8 Box Plot of income vs PoB*

## Compute t-test and comment on findings

The results are summarized in the table below:

| Category | Mean Income | Standard Deviation | Median | Interquartile Range (IQR) | t-test values | p-value | Sample Size (N) |
|---|---|---|---|---|---|---|---|
| **Gender** | | | | | | | |
| **Female** | 43,730.1 | 51,490.9568 | 32,000 | 15,850 - 55,000 | 11.956 | 0.000 | 4,570 |
| **Male** | 68,185.7 | 84,214.2432 | 45,800 | 24,000 - 80,000 | | | |
| **Race** | | | | | | | |
| **Non-White** | 49,812.9 | 63,662.6086 | 30,500 | 15,800 - 60,500 | 3.643 | 0.000 | 4,570 |
| **White** | 58,403.3 | 73,533.7606 | 44,000 | 20,000 - 69,000 | | | |
| **Nationality** | | | | | | | |
| **Non-US** | 53,470.4 | 63,020.9947 | 36,000 | 19,850 - 65,000 | 1.338 | 0.181 | 4,570 |
| **US** | 57,055.6 | 72,960.8329 | 40,000 | 19,905 - 67,000 | | | |

*Table 9 Tabular t-test results*

The t-test results show statistically significant differences between gender and race. The p-value of 0.0 indicates that the difference is highly unlikely to be caused by random chance for those two variables. The t-test result and p-value of 0.181 indicate that PoB is not a statistically significant variable.

## Scatter plots of income vs age, weekly hours and education level

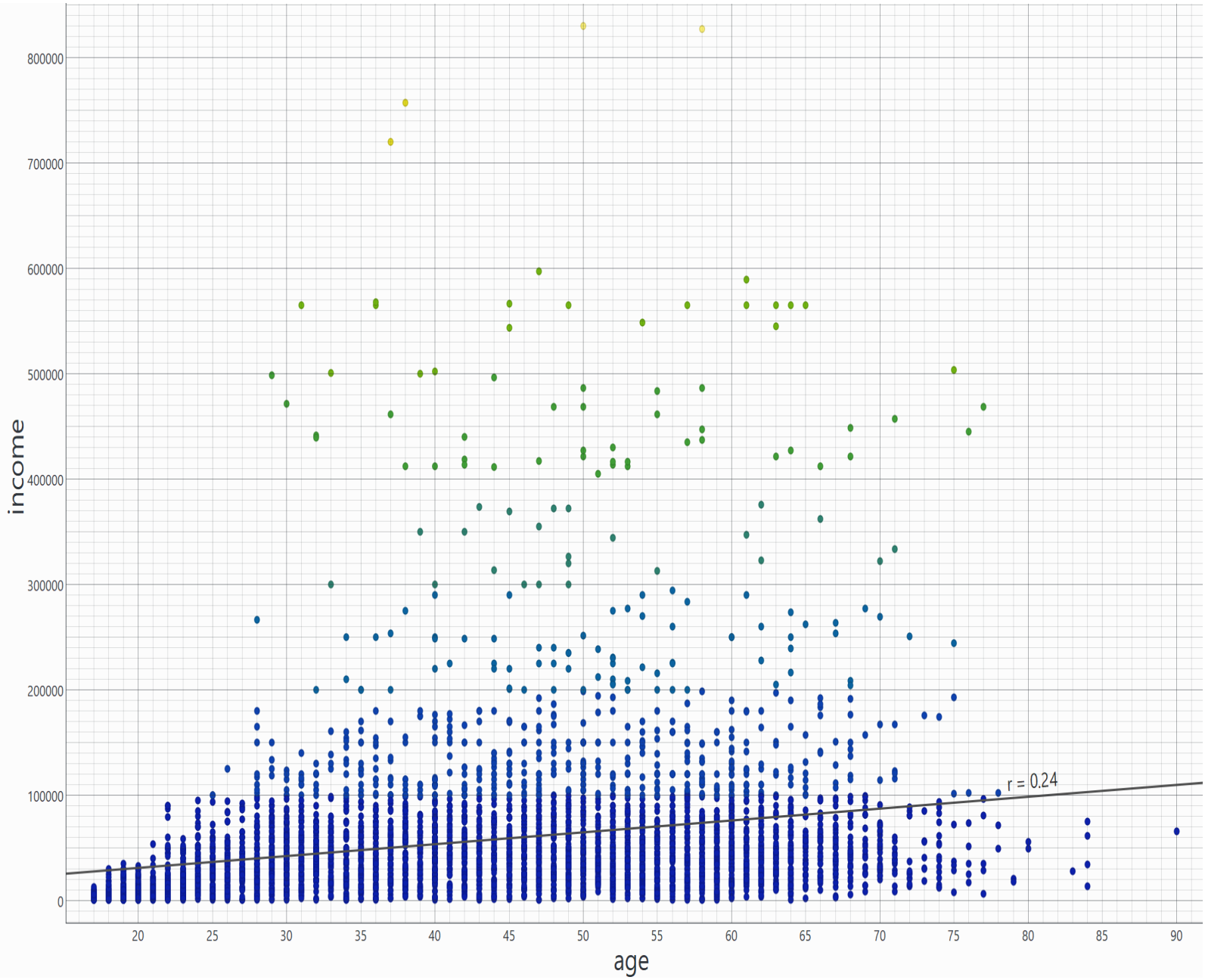



*Figure 7 Income vs age*

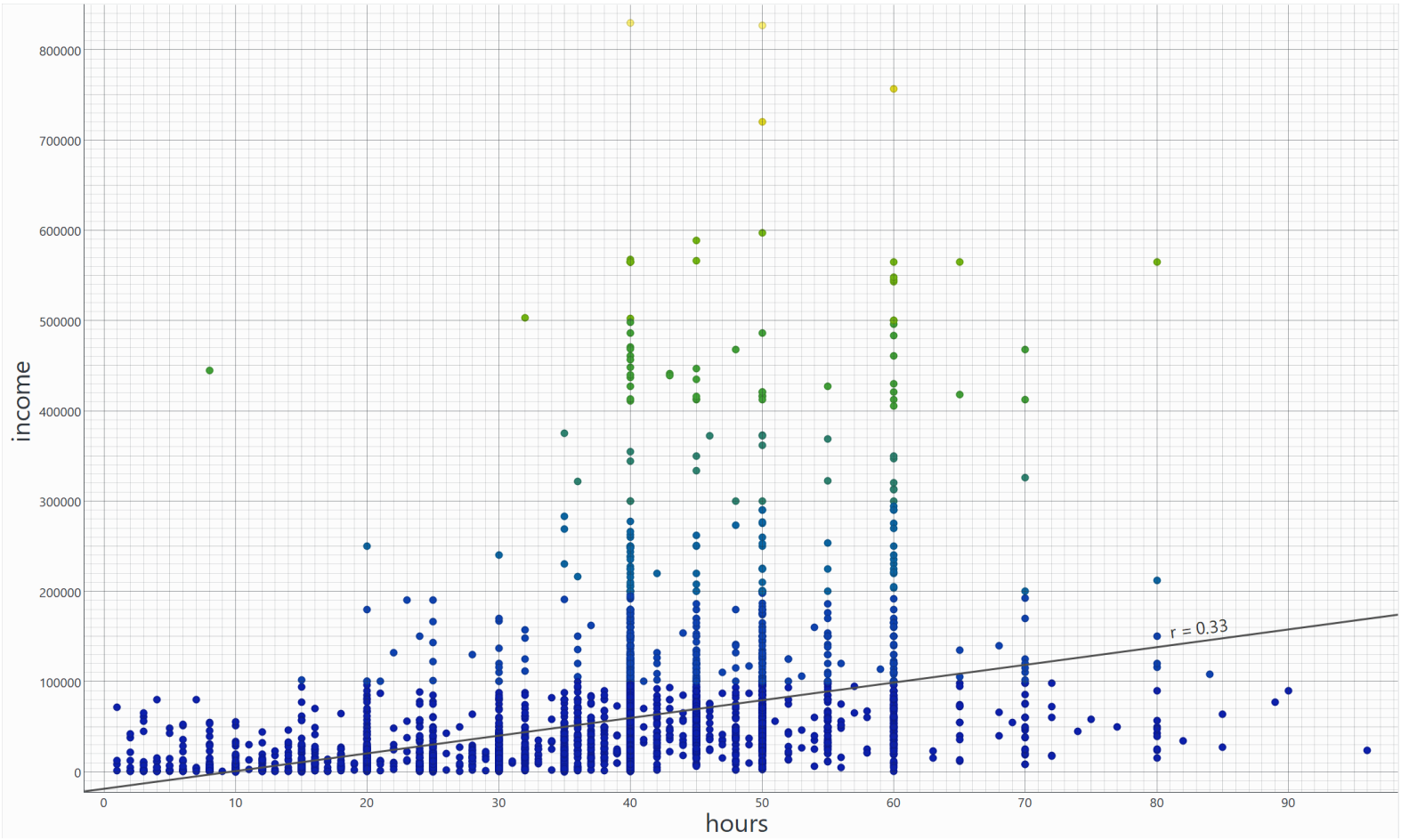



*Figure 8 Income vs hours*

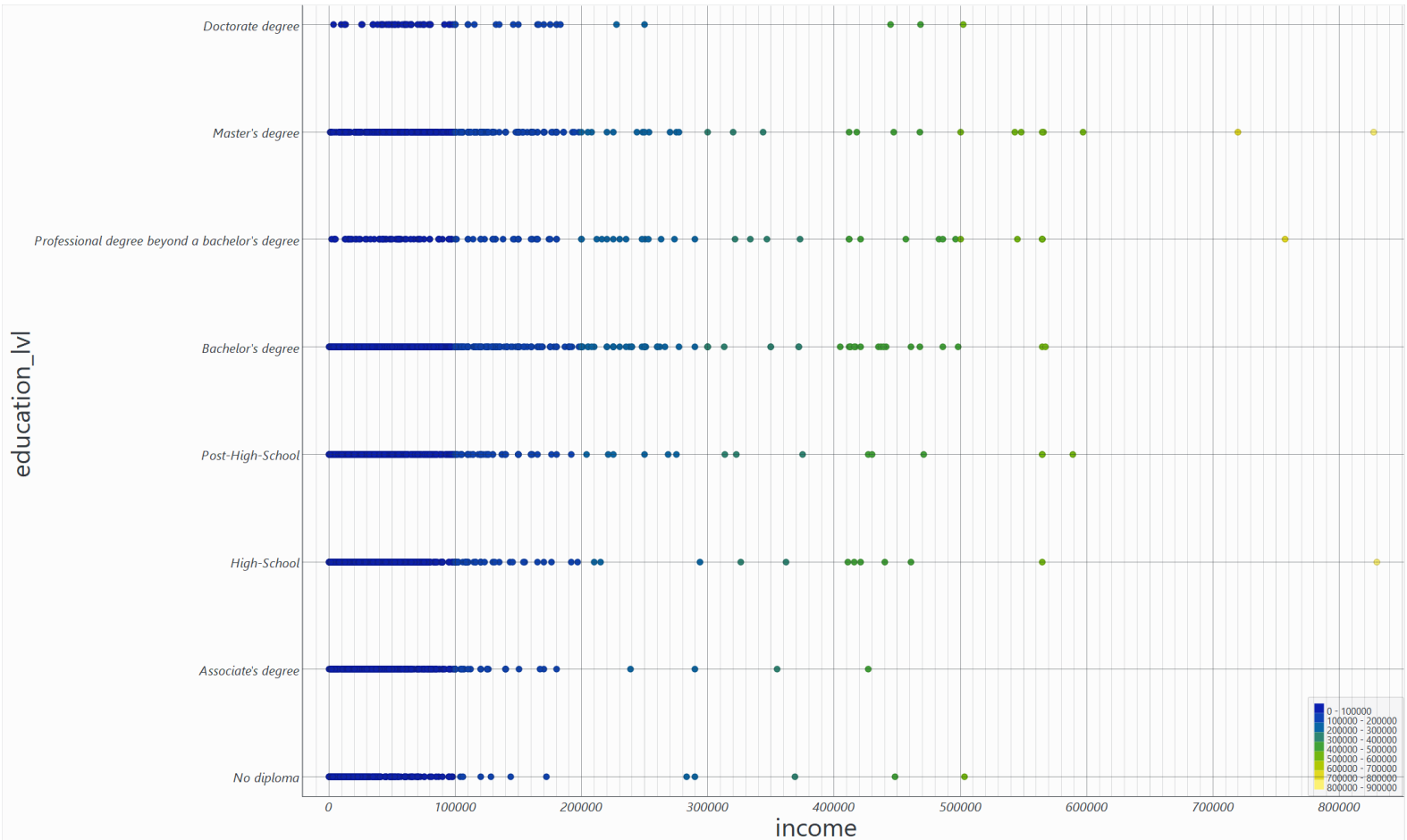



*Figure 9 Income vs Edu_lvl*

## Pearson's Correlation for income

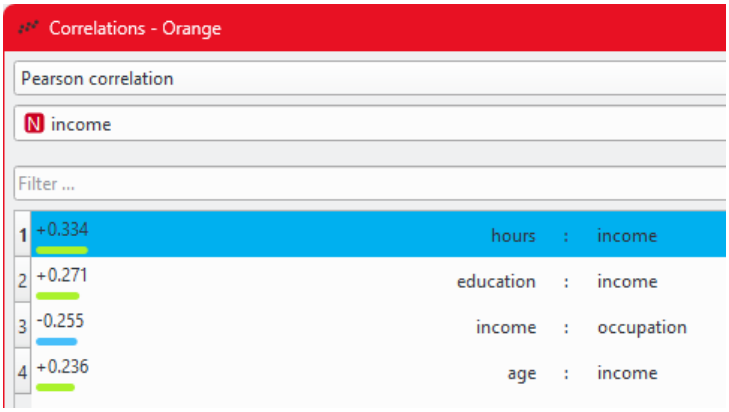



*Figure 10 Pearson's Correlation for income*

## Log(income) scatter plots

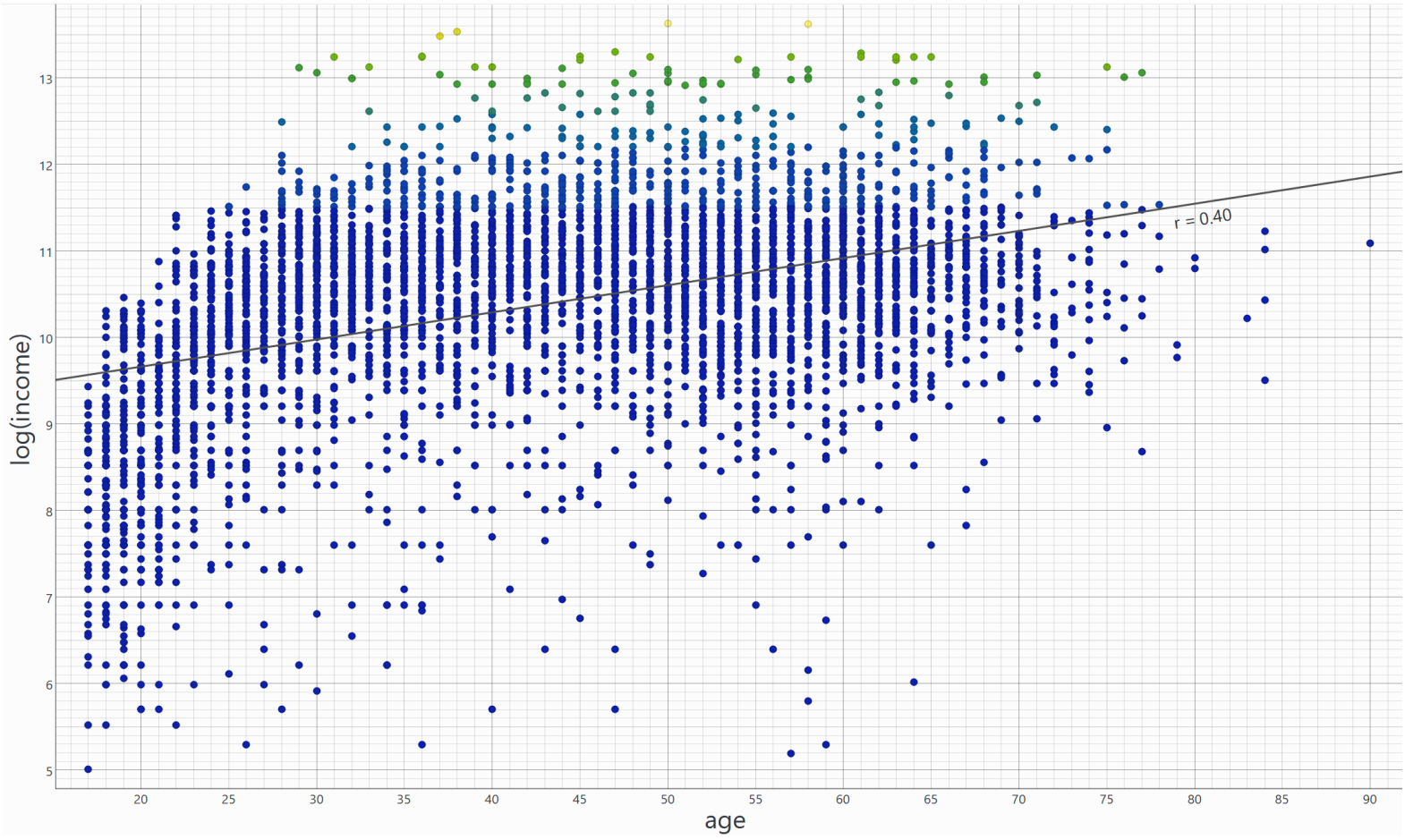



*Figure 11 log(income) vs age*

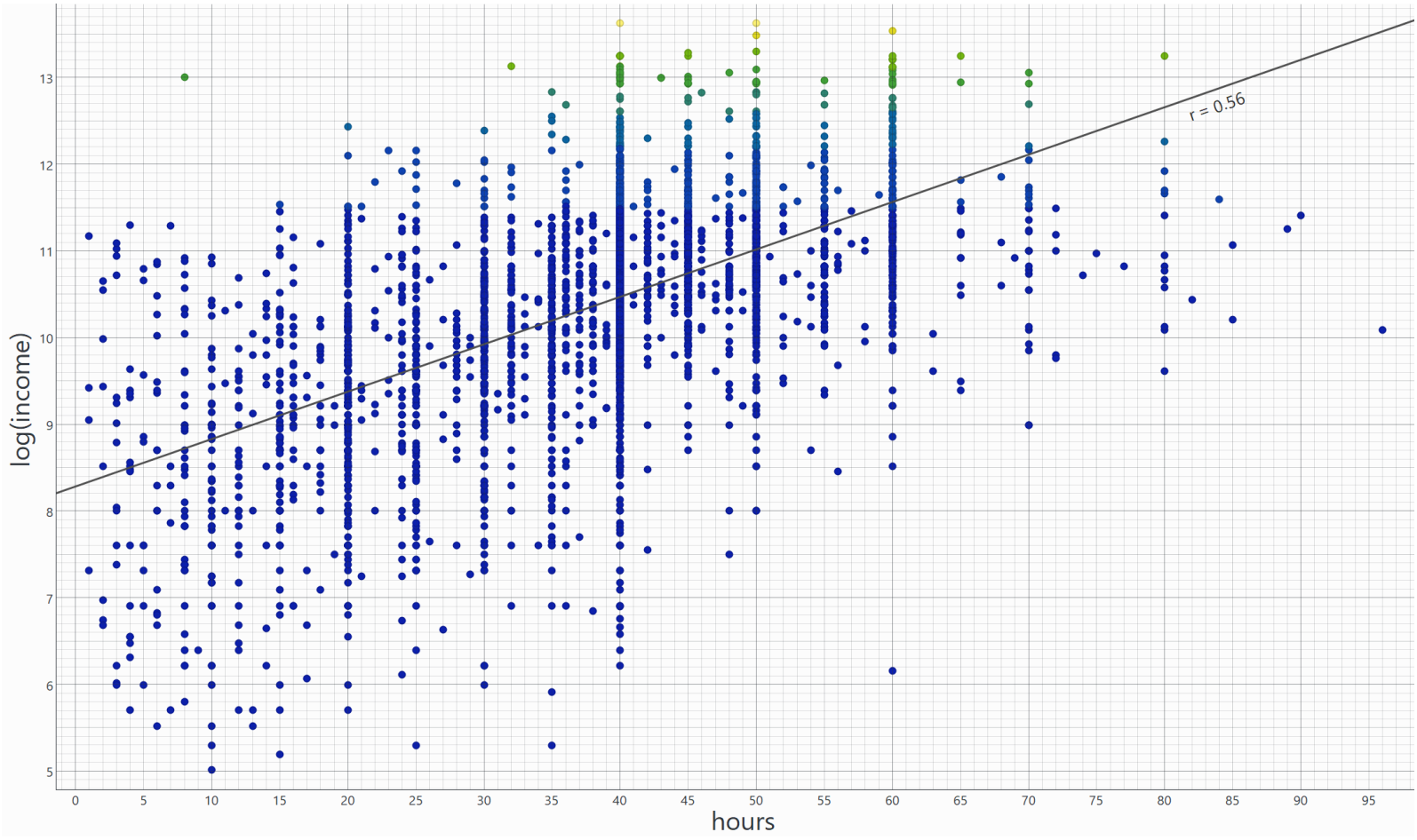



*Figure 12 log(income) vs hours*

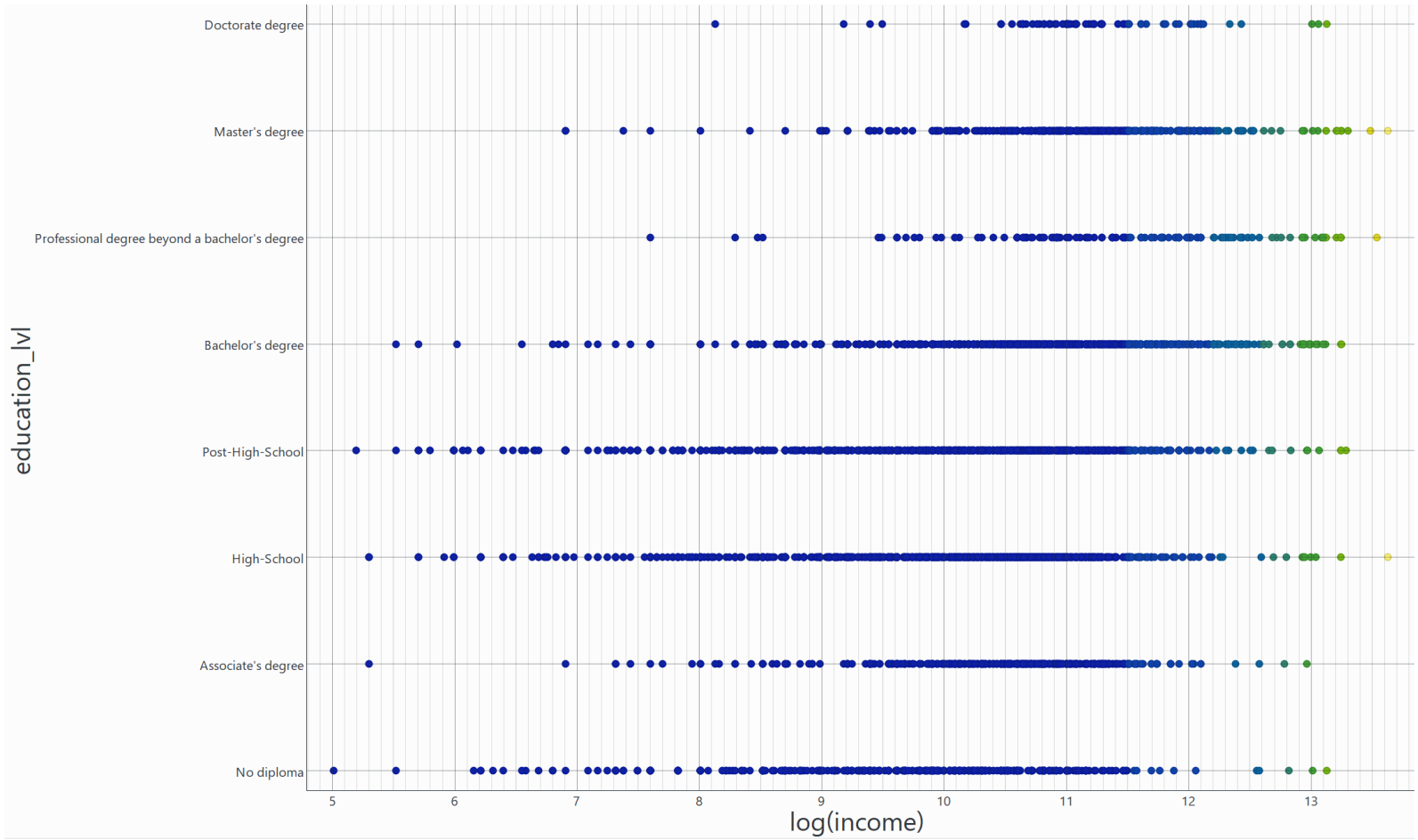



*Figure 13log(income) vs edu_lvl*

## Pearson's Correlation for log(income)

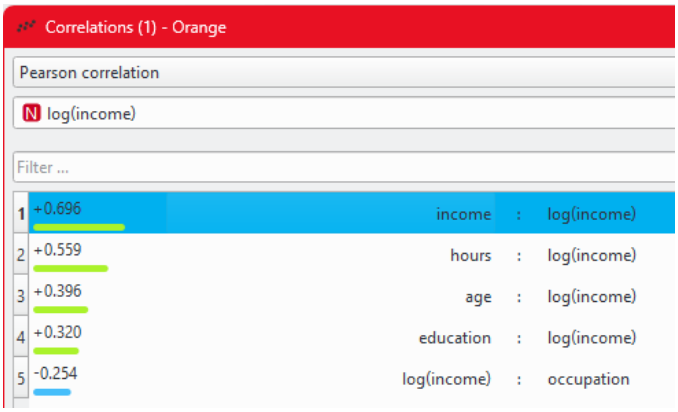



*Figure 14 Pearson's Correlation for log(income)*

## Comment on findings

The usage of log transformations (log(income)) has reduced the influence of outliers and the impact of data variance. This makes the correlations of the variables more reliable and meaningful. The log(income)'s variable correlation was higher than those of income for the aforementioned reasons and the more meaningful variables are now in the order hours, age, education, occupation.

# Part 3. Predicting Income

## Mean income vs education level

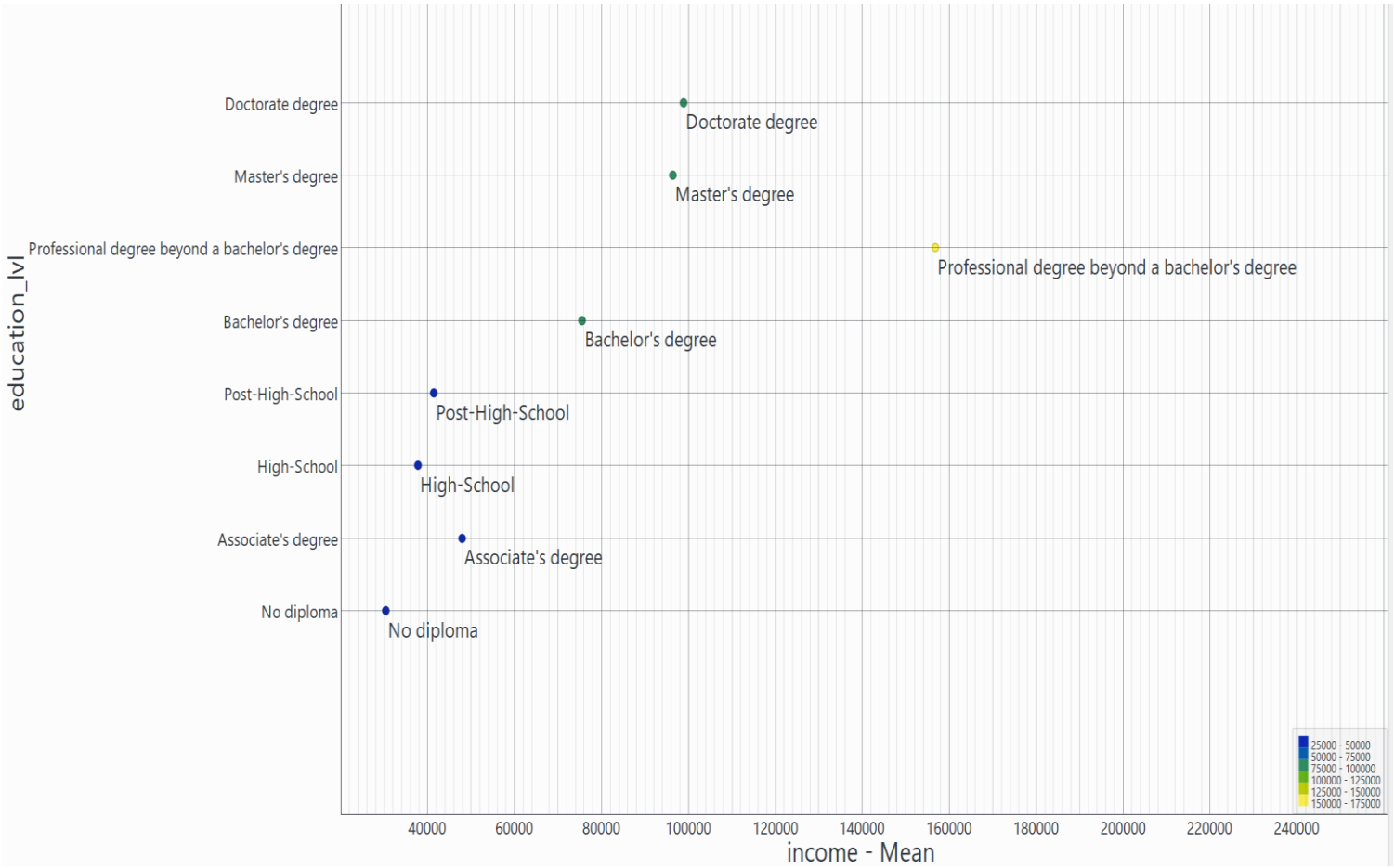



*Figure 15 mean income vs edu_lvl*

## Estimate a monetary value for education

The mean income corresponding to the total years of education is visualized.

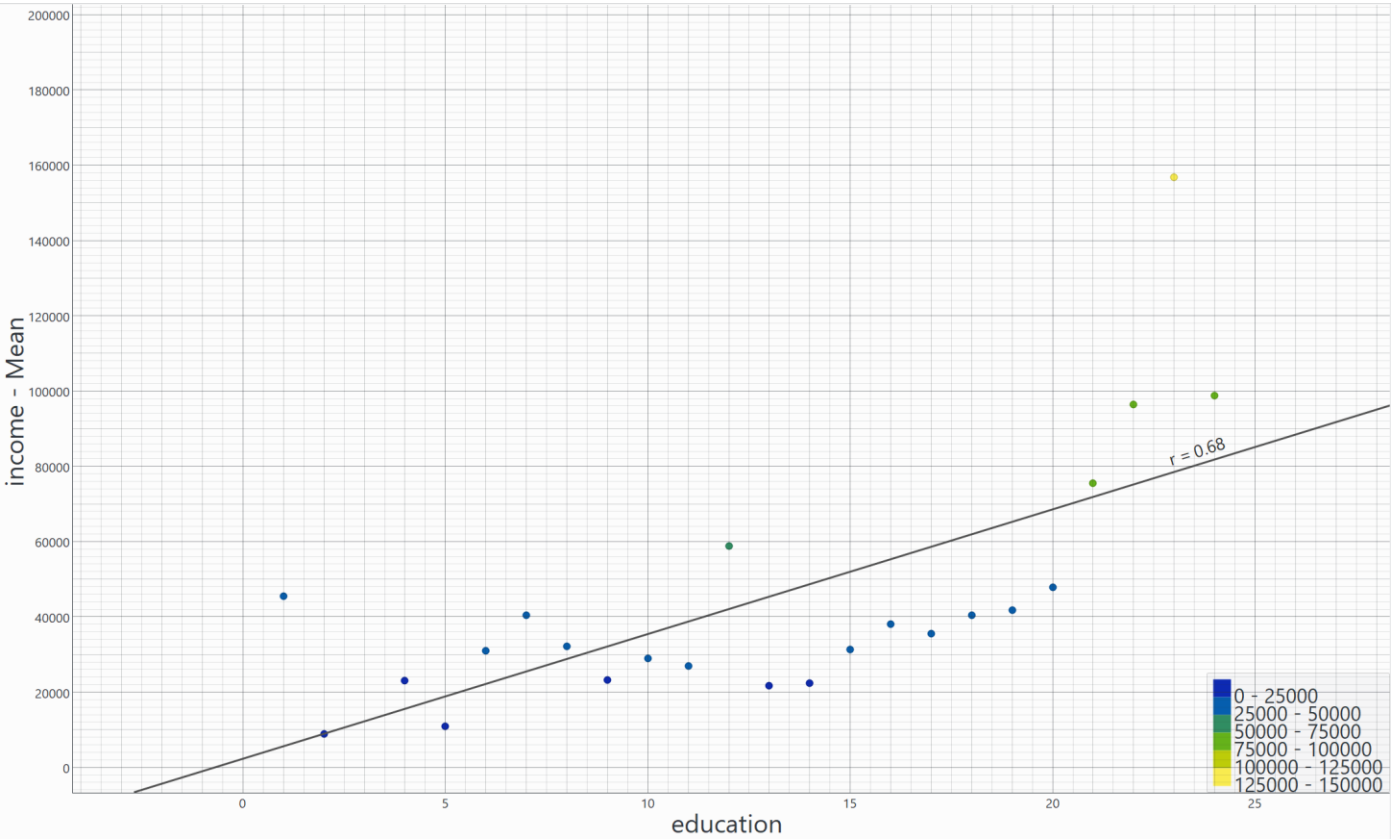



*Figure 16 mean income vs years of education*

Linear regression is used to calculate the monetary value of each year of education as well as the y-intercept.

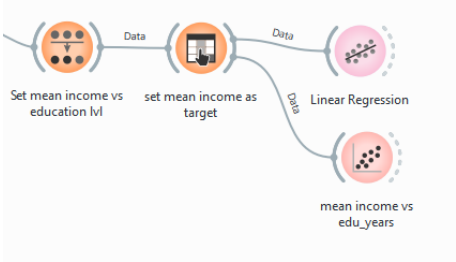



*Figure 17 Linear Regression results*

**Coefficients:** coefficients: 2 instances, 2 variables
Features: numeric (no missing values)
Metas: string

| | name | coef |
|---|---|---|
| 1 | intercept | 2289.87 |
| 2 | education | 3312.65 |

*Figure 18 linear regression Orange nodes*

## Analysis Limitation

This analysis does not factor in other important variables such as age, hours, industry type, CoW, experience, skills or the state. This omission can greatly imbalance the data.

The intercept assumes an annual income of $2289.87 at 0 years of education. Furthermore, the results of low years of education might not be useful or realistic.

By looking at education level vs mean-income (figure15), higher levels of education do not necessarily translate to a significant increase in mean-income, which suggests non-linearity.

## Split population into high and low income

By connecting a formula node to the data set, a new categorical variable (income_class) is created to split the population into different income groups.

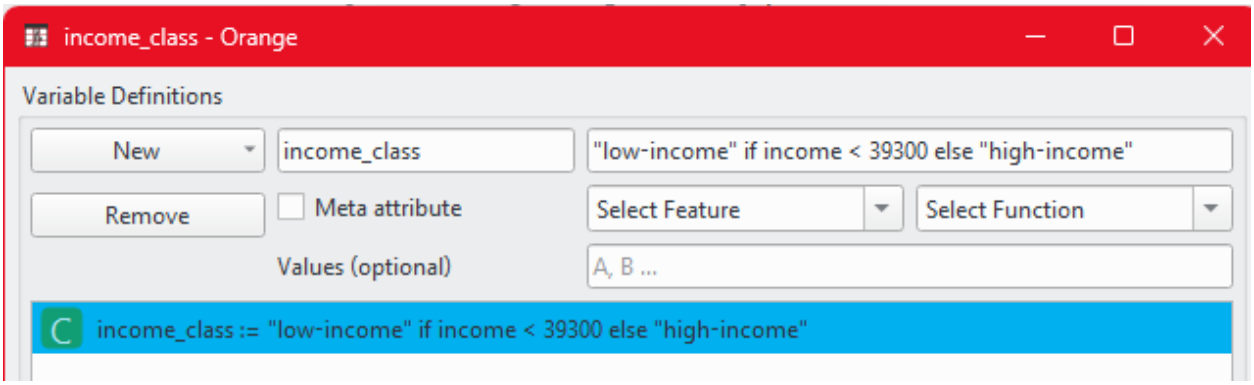



*Figure 19 income_class node settings*

## Use different classifier models to predict which subgroup a person belongs to

After setting “income_class” as target and ignoring the variable “income”, 5 models were attached to a “test and score” node and the results were analyzed.

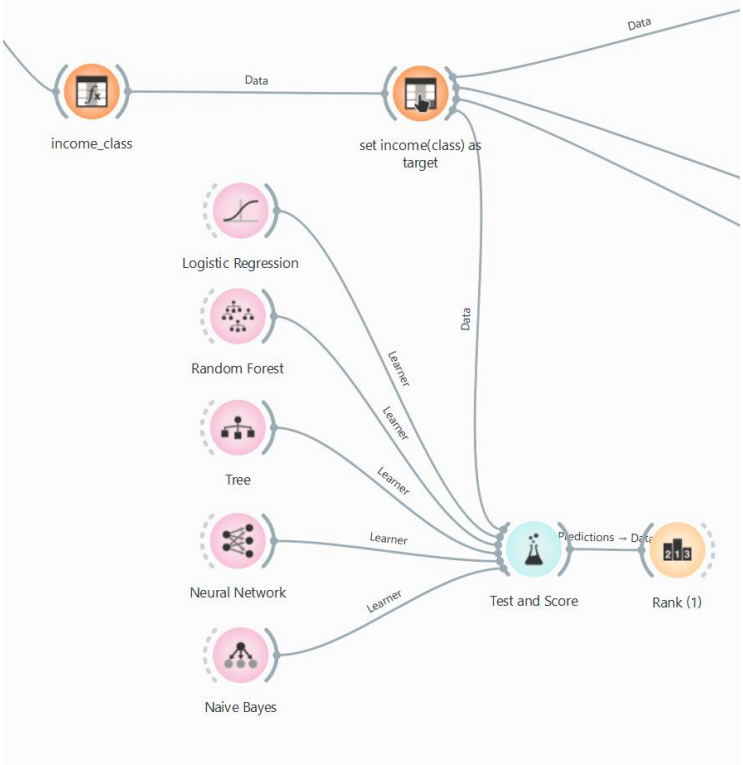



*Figure 20 Models used in analysis*

The results are displayed below:

| Model | AUC | CA | F1 | Prec | Recall | MCC |
|---|---|---|---|---|---|---|
| Logistic Regression | 0.851 | 0.767 | 0.766 | 0.767 | 0.767 | 0.533 |
| Random Forest | 0.853 | 0.771 | 0.771 | 0.772 | 0.771 | 0.543 |
| Tree | 0.722 | 0.737 | 0.737 | 0.738 | 0.737 | 0.476 |
| Neural Network | 0.857 | 0.768 | 0.768 | 0.768 | 0.768 | 0.536 |
| Naive Bayes | 0.852 | 0.762 | 0.762 | 0.762 | 0.762 | 0.525 |

Compare models by: Area under ROC curve  Negligible diff.: 0.1

| | Logistic ... | Random ... | Tree | Neural N... | Naive Ba... |
|---|---|---|---|---|---|
| Logistic Regression | | 0.396 | 0.999 | 0.054 | 0.399 |
| Random Forest | 0.604 | | 1.000 | 0.283 | 0.580 |
| Tree | 0.001 | 0.000 | | 0.001 | 0.000 |
| Neural Network | 0.946 | 0.717 | 0.999 | | 0.813 |
| Naive Bayes | 0.601 | 0.420 | 1.000 | 0.187 | |

*Figure 21 Model results*

Out all the models, Neural Network performed the best based on its high AUC score, F1 score and MCC. A side-by-side comparison shows its performance against the other models.

## Collect feature ranking

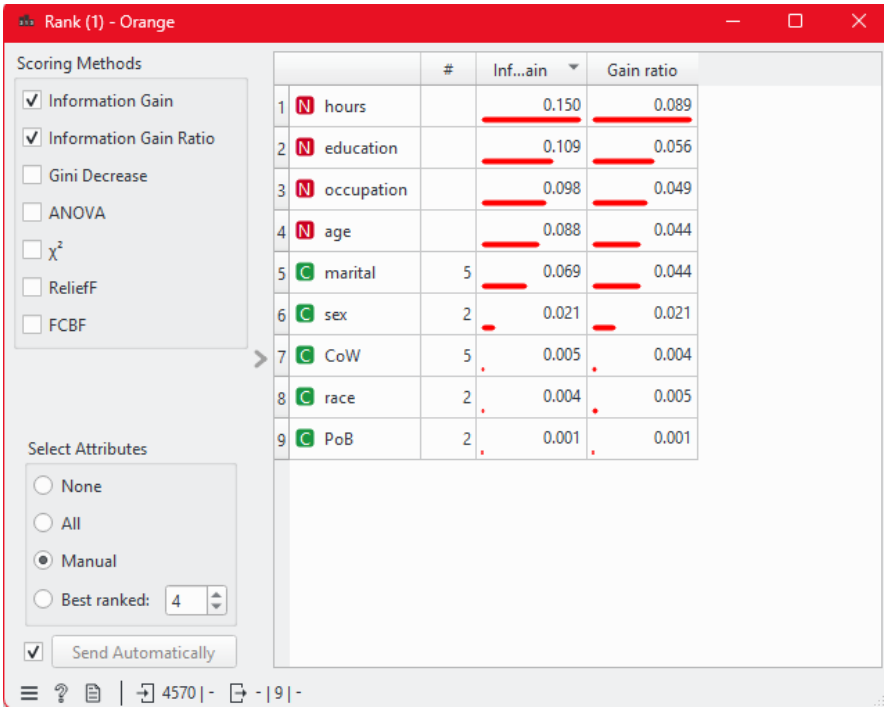



*Figure 22 Feature ranking of data*

The best predictors of income_class in order of importance appear to be

- Hours
- Education
- Occupation
- Age

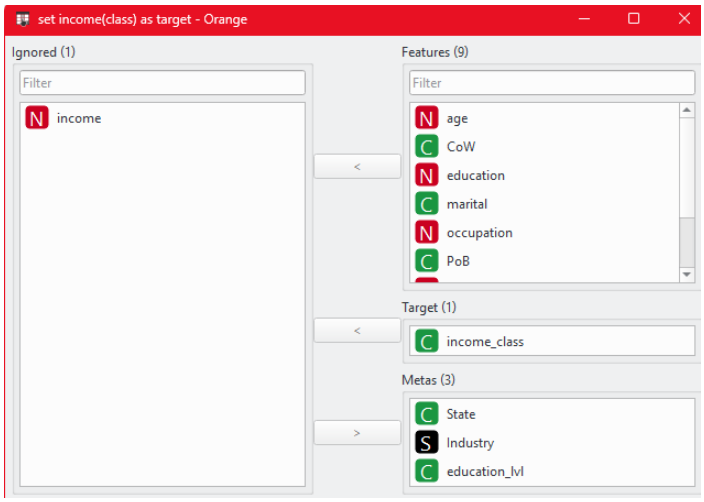



*Figure 23 setting income_class as target*

Income is ignored to avoid contamination of the results.

## Train selected model on data

A “data sampler” node is used to split the data into training (67%) and testing data (33%).

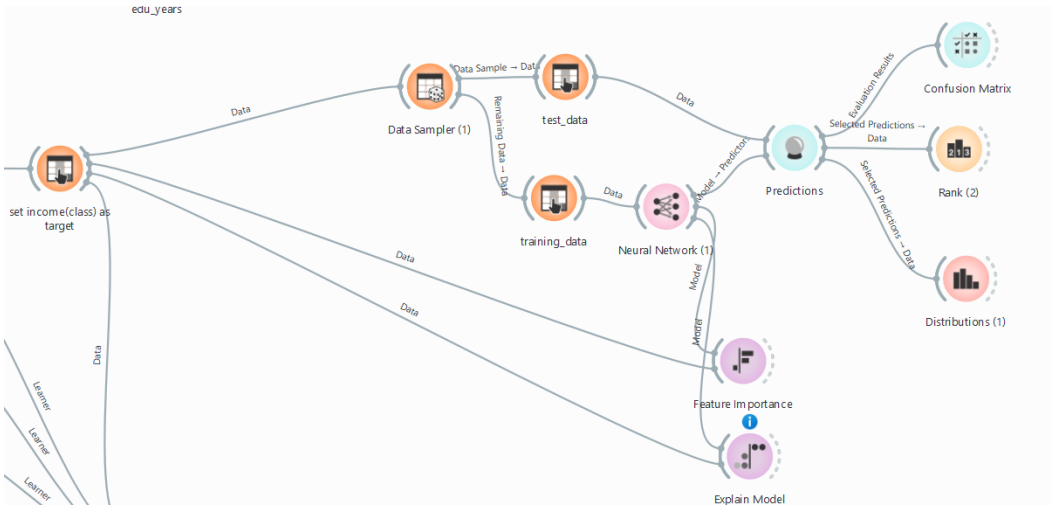



*Figure 24 Node setup for data training*

The results of the model and explainability techniques are displayed below.

| Actual \ Predicted | high-income | low-income | Σ |
|---|---|---|---|
| high-income | 79.8 % | 20.2 % | 732 |
| low-income | 24.9 % | 75.1 % | 731 |
| Σ | 766 | 697 | 1463 |

*Figure 25 Confusion Matrix results*

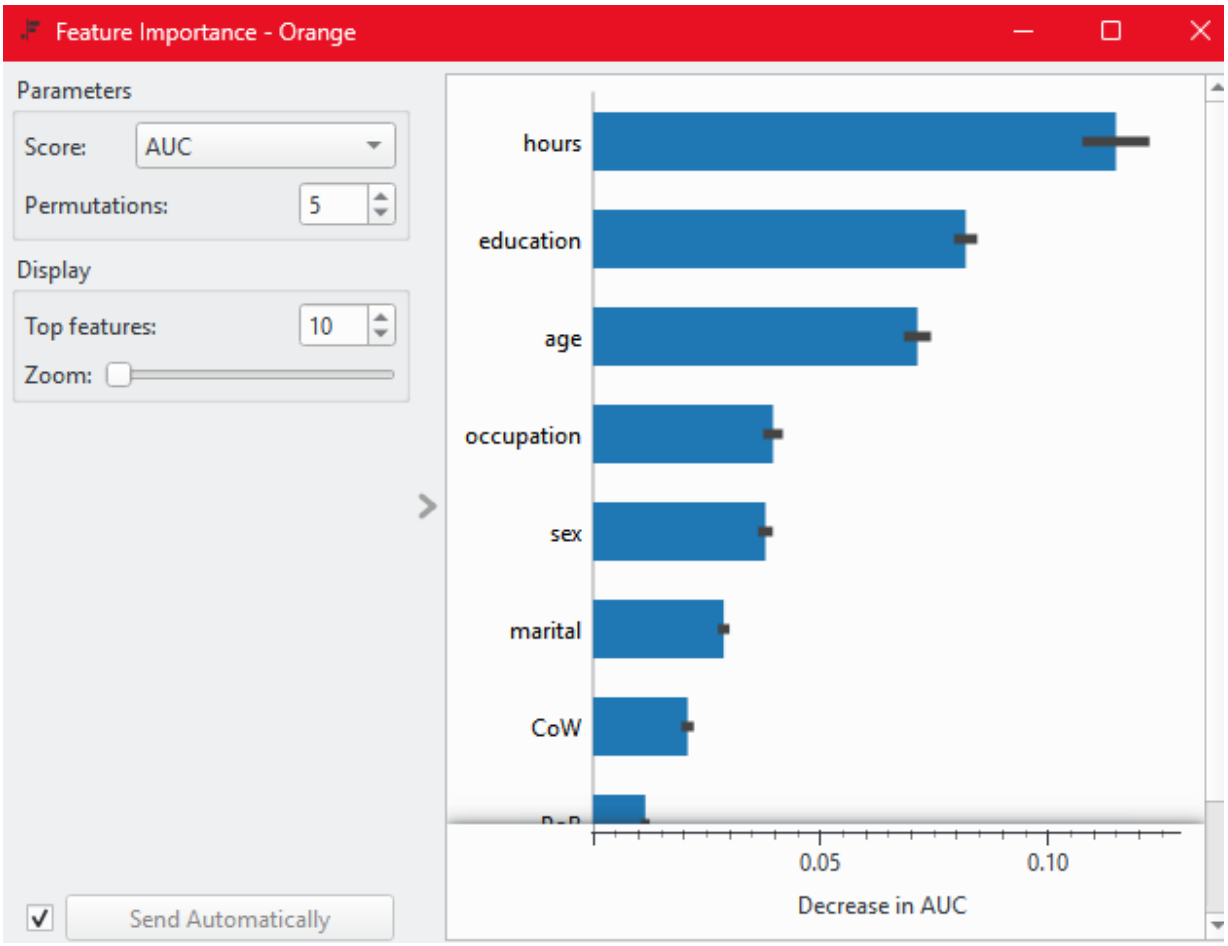



*Figure 26 Feature Importance results*

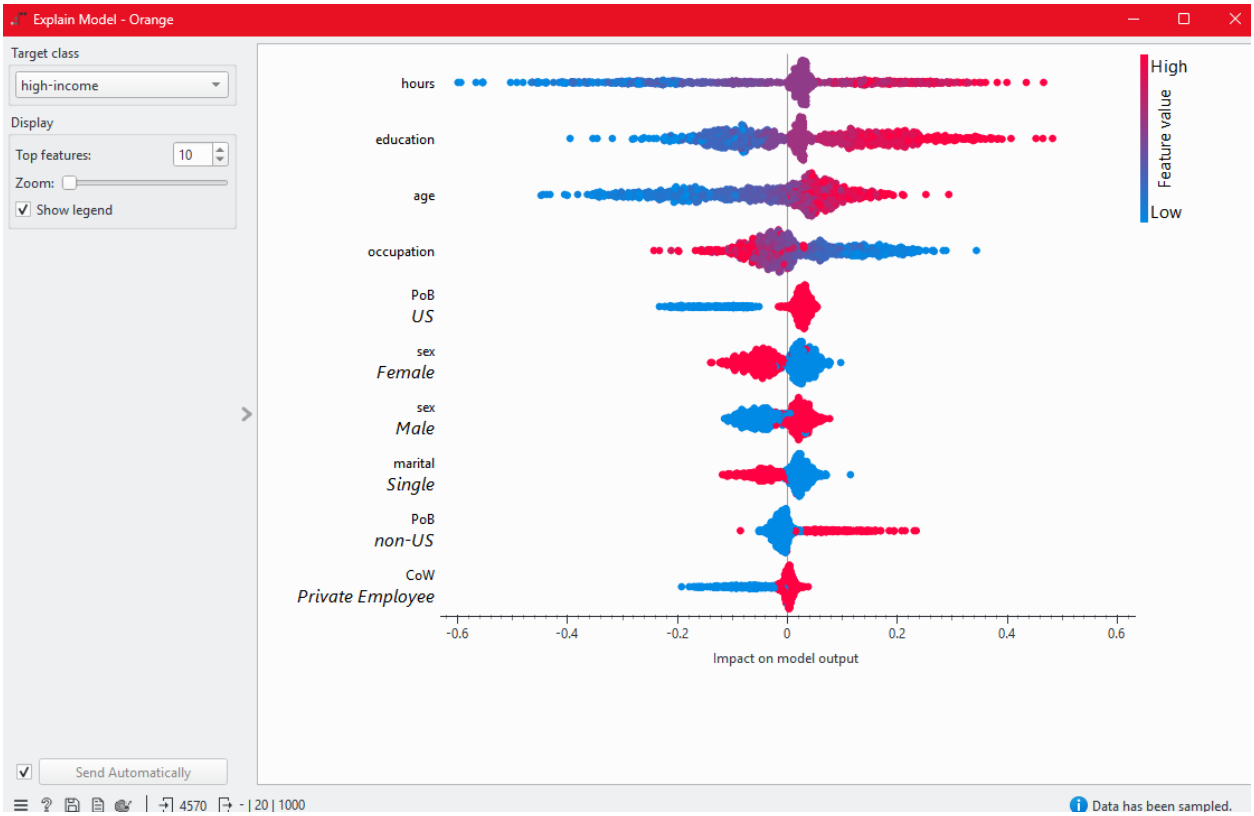



*Figure 27 Explain Model results*

## Compare results and comment on findings

Both analyses highlight the same variables as having a strong impact on income levels. The explained model results shows a more nuanced impact of each variable while the feature importance shows a more general impact. The results mostly agree with each other; however the importance of variables slightly changes.

# Part 4. Demographics of US elections

## Plot the election results, mean income and mean educational attainment levels on the US map.

Data from the Census file is grouped by State, and Puerto Rico before merging it to Voting.csv. The data in Voting is cleaned to display one row for each State, showing who won only the winning candidate. The variables mean income, mean years in education and income level for each state are added to the dataset.

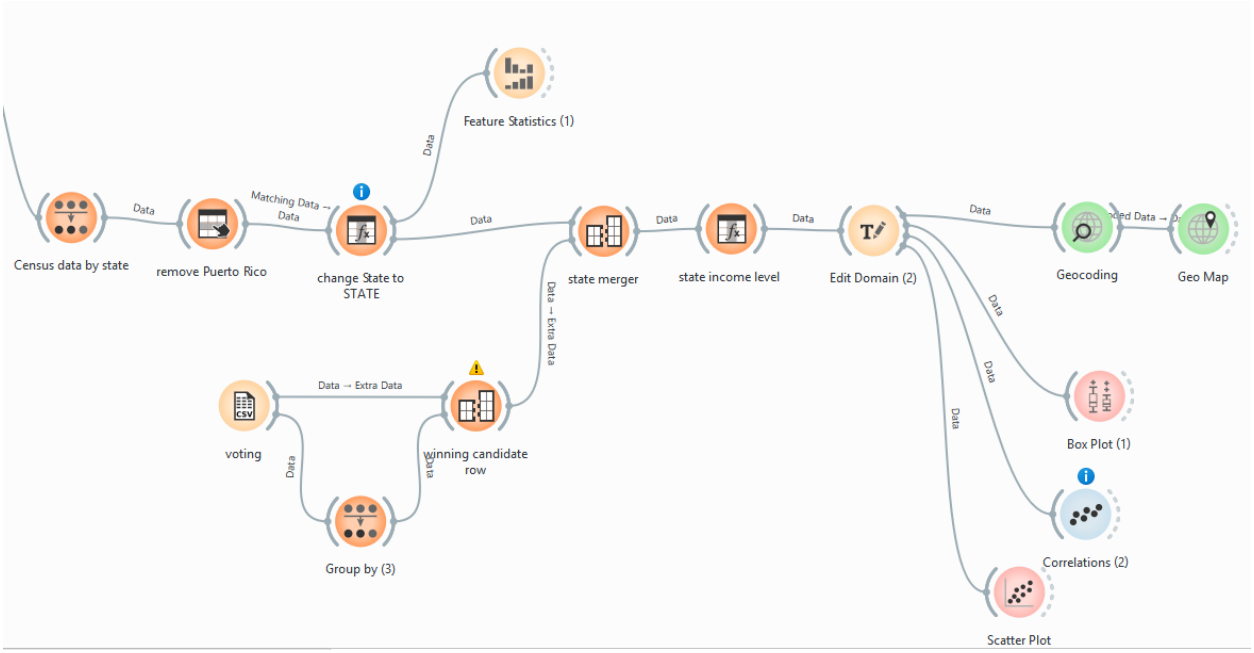



*Figure 28 Part 4 Orange node setup*

- Election Results (Red for Republican/ Blue for Democrat)


*Figure 29 Election results mapped*

- Income level per State

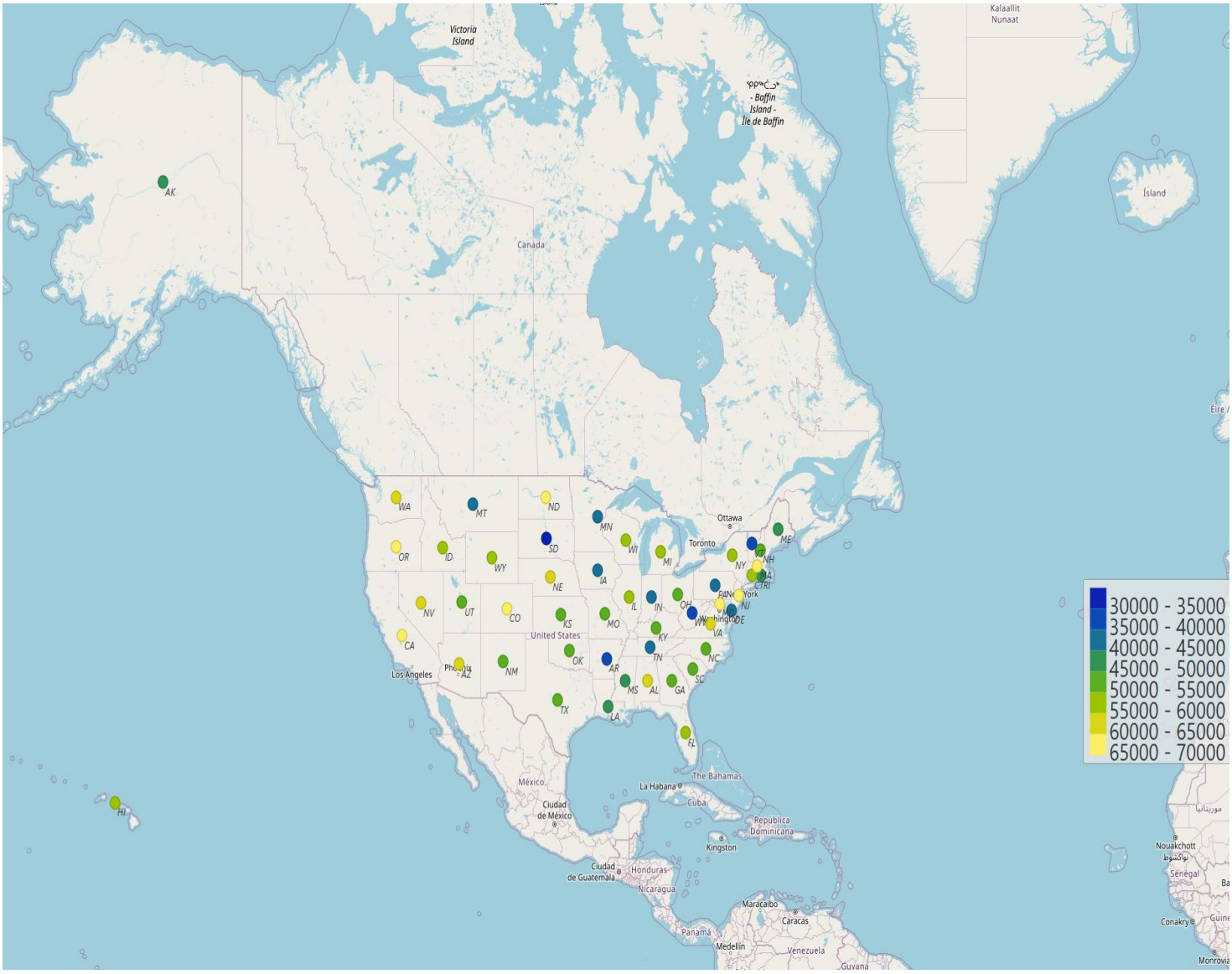



*Figure 30 Income level mapped*

- Years of education by State

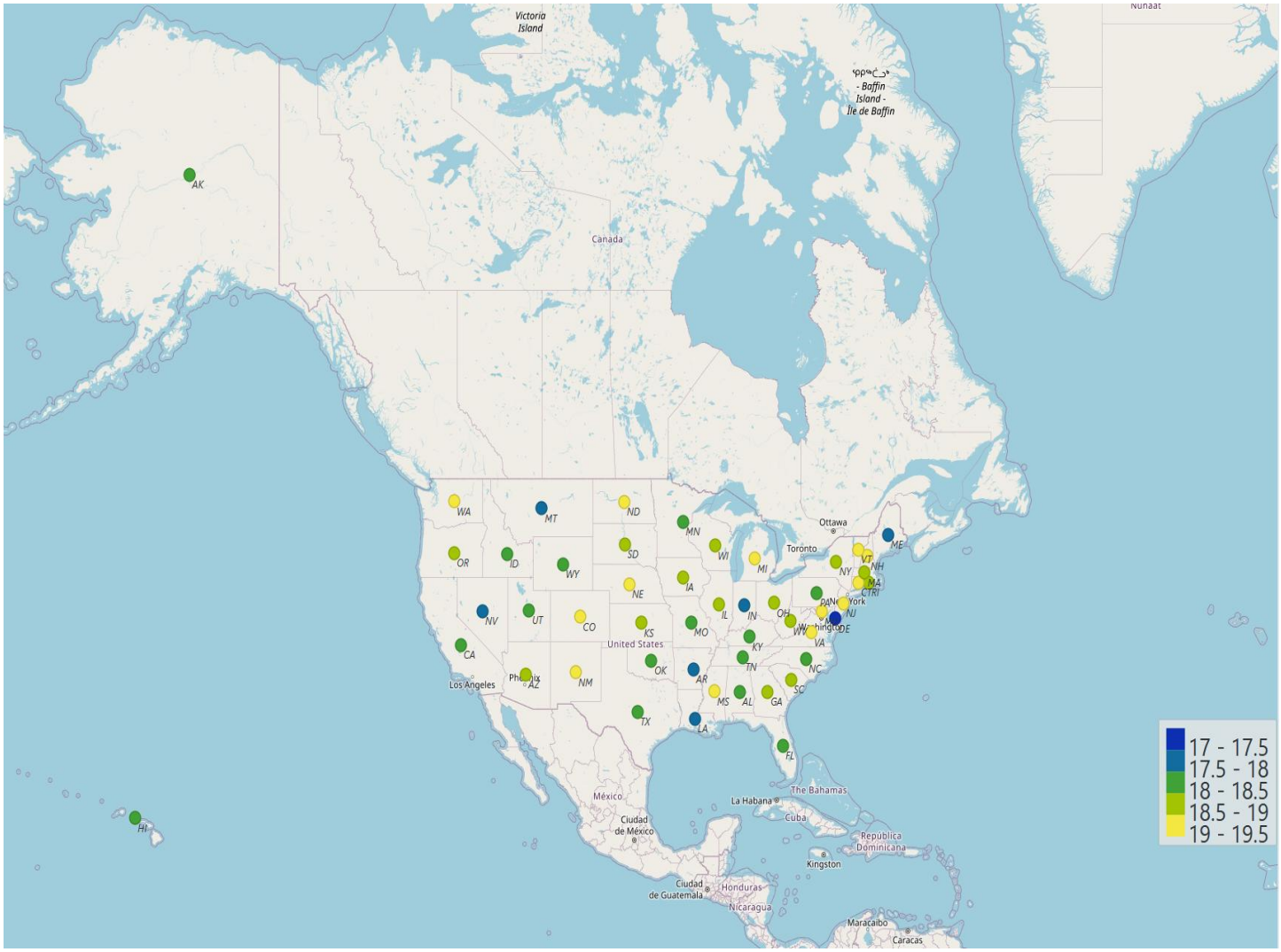



*Figure 31 Average years in education mapped*

- Combined graph showing winner, income (by size of dot) and years of education

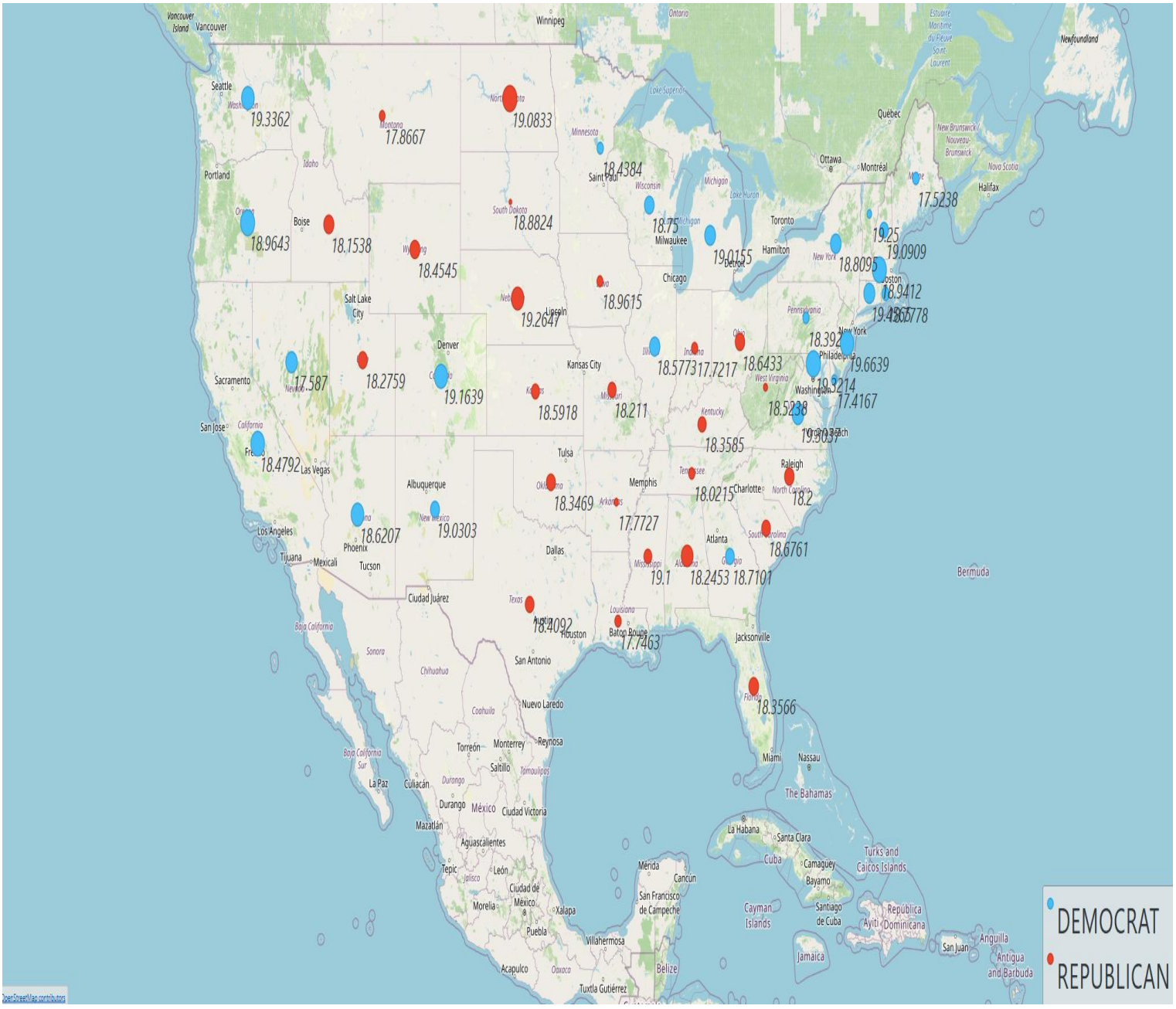



*Figure 32 Map of multiple variables*

## Comment on the visual comparisons of the maps

- Regional results map: Southern America and the Midwest are more likely to vote for Trump whilst the North-eastern and West-coast states are likely to vote for Biden
- Income map: More urban and coastal states generally tend to have higher incomes
- Education levels map: More urban states appear to have higher educational attainment
- Combined map: There appears to be a correlation between education levels and income levels. Both these factors visually appear to correlate positively with voting for Biden, although more complex analysis might be required to establish that.

## Test the 2 following hypothesis:

- *Low-income states voted for Trump*
- *States with high educational attainment voted for Biden*

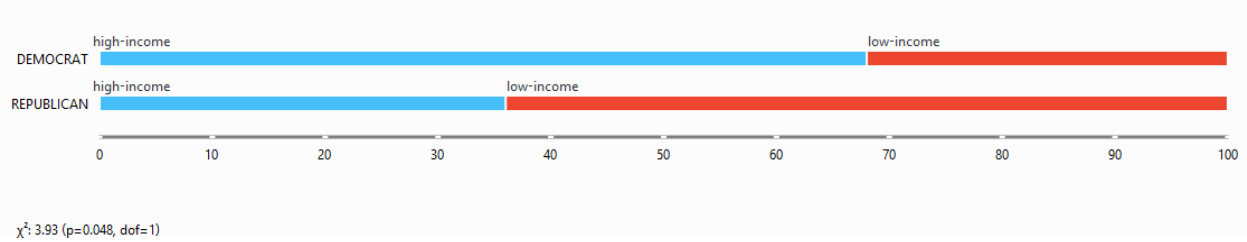



*Figure 33 state_vote by state_income_level*

The above box plot graph shows the election results of states based on their income levels. 65% of high-income states voted for the Democratic Party (Biden) whilst 67% of low-income states voted for the Republican Party (Trump).

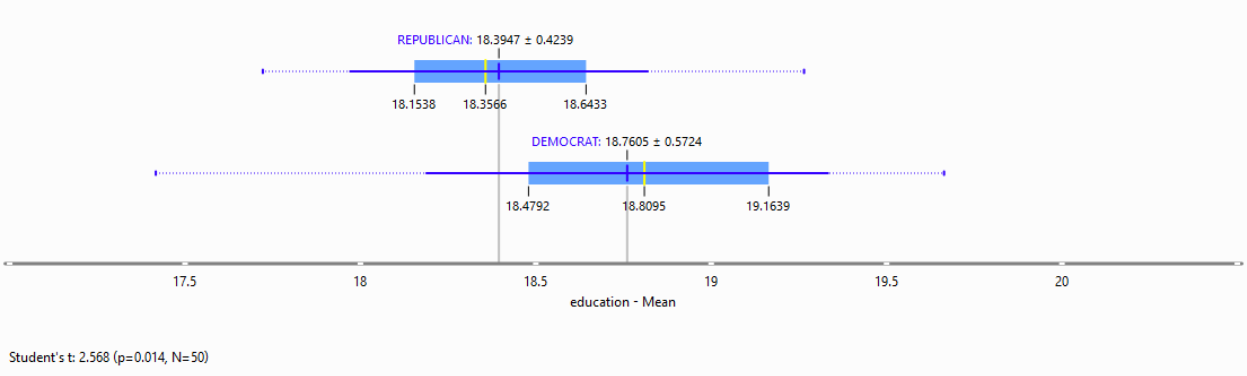



*Figure 34 T-test results by Party*

The above box plot shows the t-test results for each winning party by the distribution of years in education. The p-value (0.014) indicates that there is a statistically significant difference in mean education levels between the chosen political party. The spread of data for those who voted for Biden indicated a higher variability in education levels. The hypothesis is supported as Republic states have a lower mean education level (18.3947) vs Democrat winning states (18.8095).

Testing hypotheses using logistic regression:

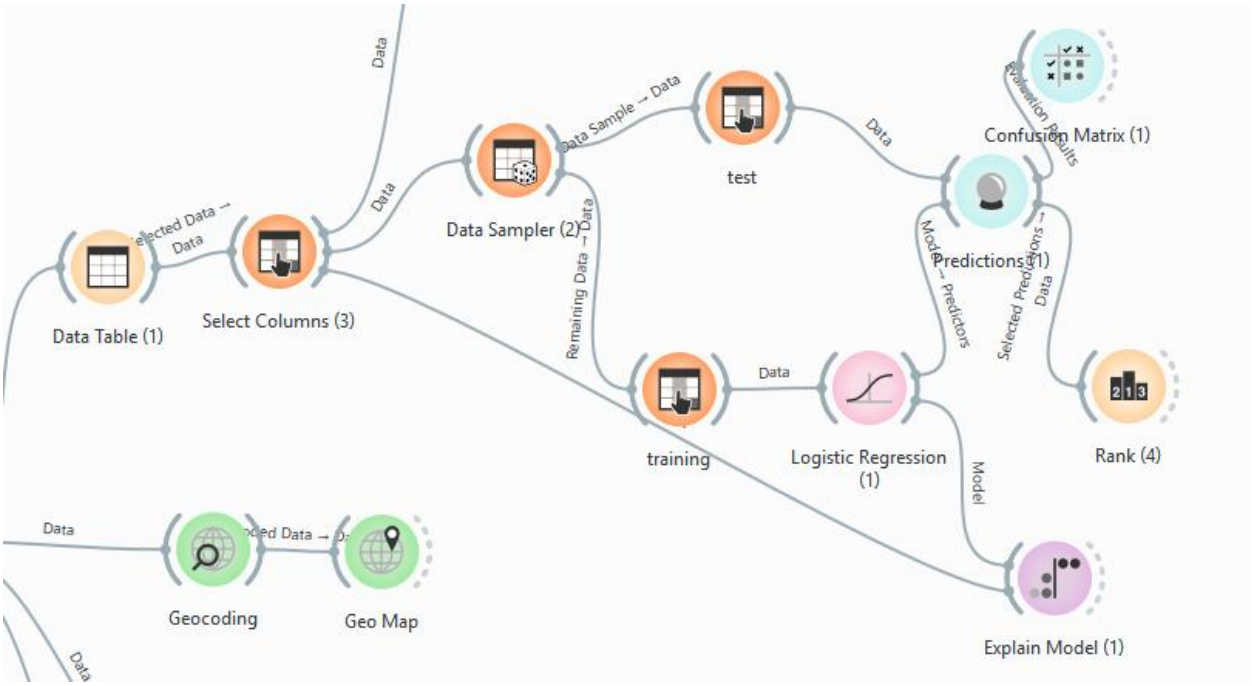



*Figure 35 Logitic regression node setup*

The state income level was set as target, and the data was sampled and ran through a Logistic Regression model to perform a regression analysis and analyze the impact of different variables.

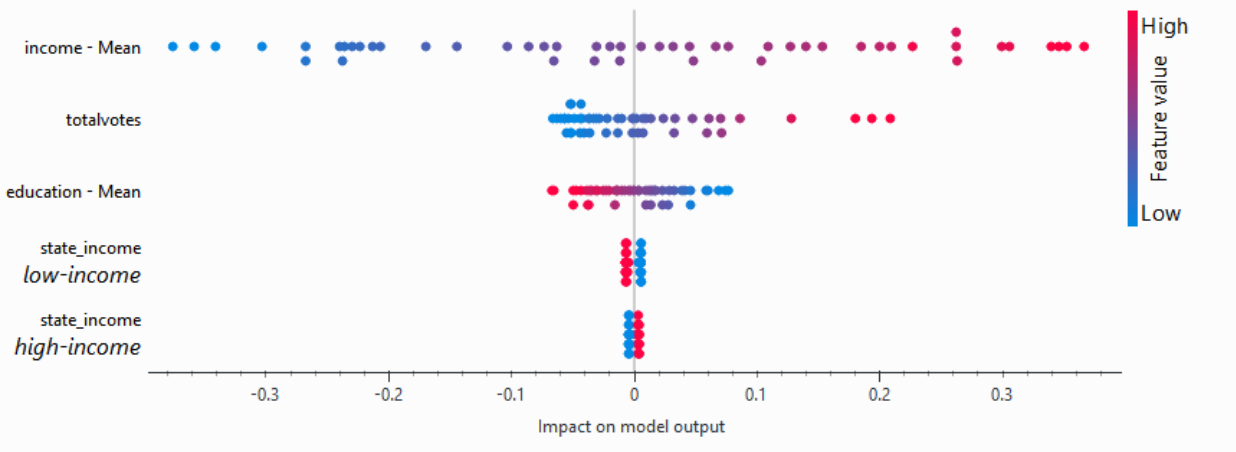



*Figure 36 Democrat results*

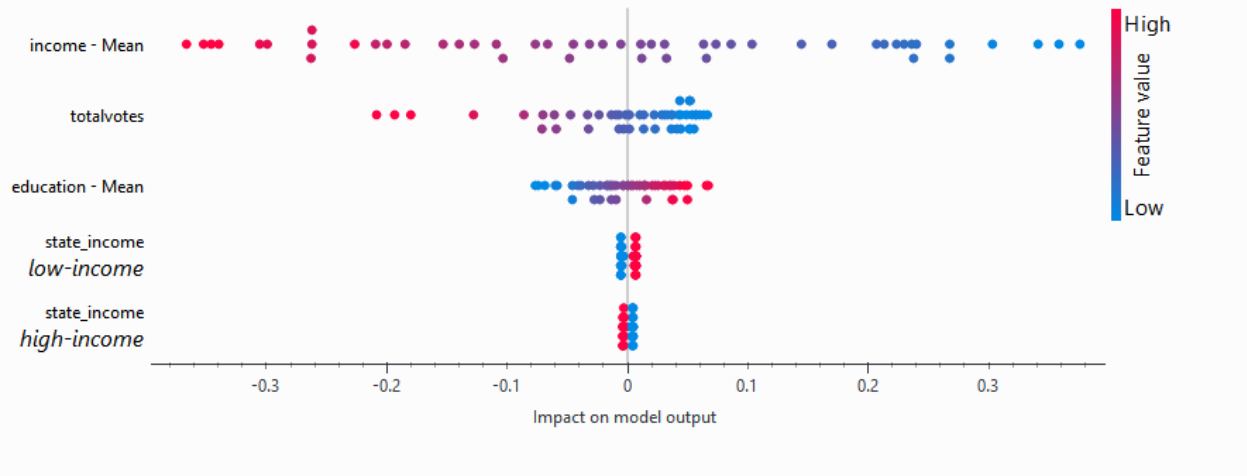



*Figure 37 Republican results*

By targeting the class “Democrats”, high-income states show a positive correlation with mean-income. A positive correlation is also observed with mean-education. For “Republicans” a positive correlation is show with lower mean-income and mean-education. In both instances the mean-income results are more spread than the mean-education results, indicating that there is more diversity in income levels which might be influenced by type of industry, hours worked, and different costs-of-living associated with a State.

In summation, based on the statistical analysis and visualizations both hypotheses are supported.

# Part 5. Your own data mining

## *Hypothesis: The impact of weekly working hours on income is moderated by the type of occupation*

### *Exploratory analysis*

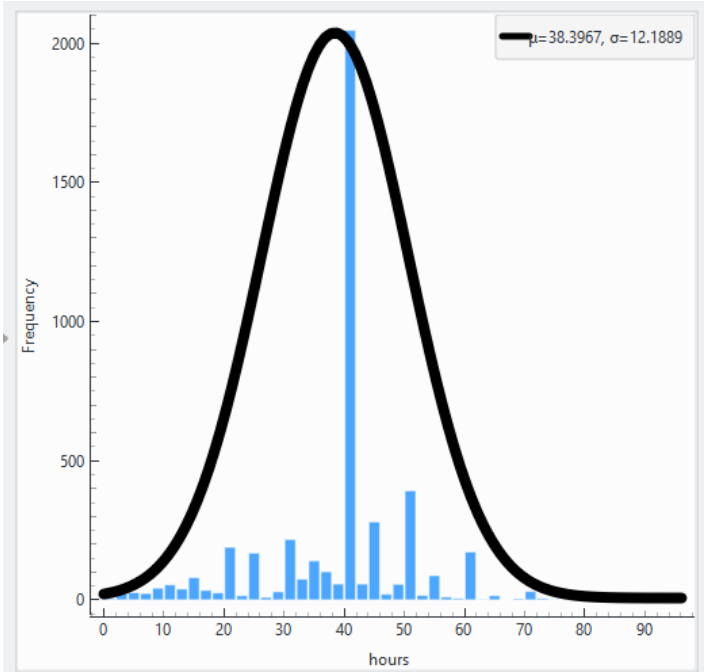



*Figure 38 hours vs frequency graph*

Figure 38 shows the distribution of weekly worked hours across the data set. The following graphs show the distribution of hours by industry, log(income) as well as the hourly rate data spread by each industry.

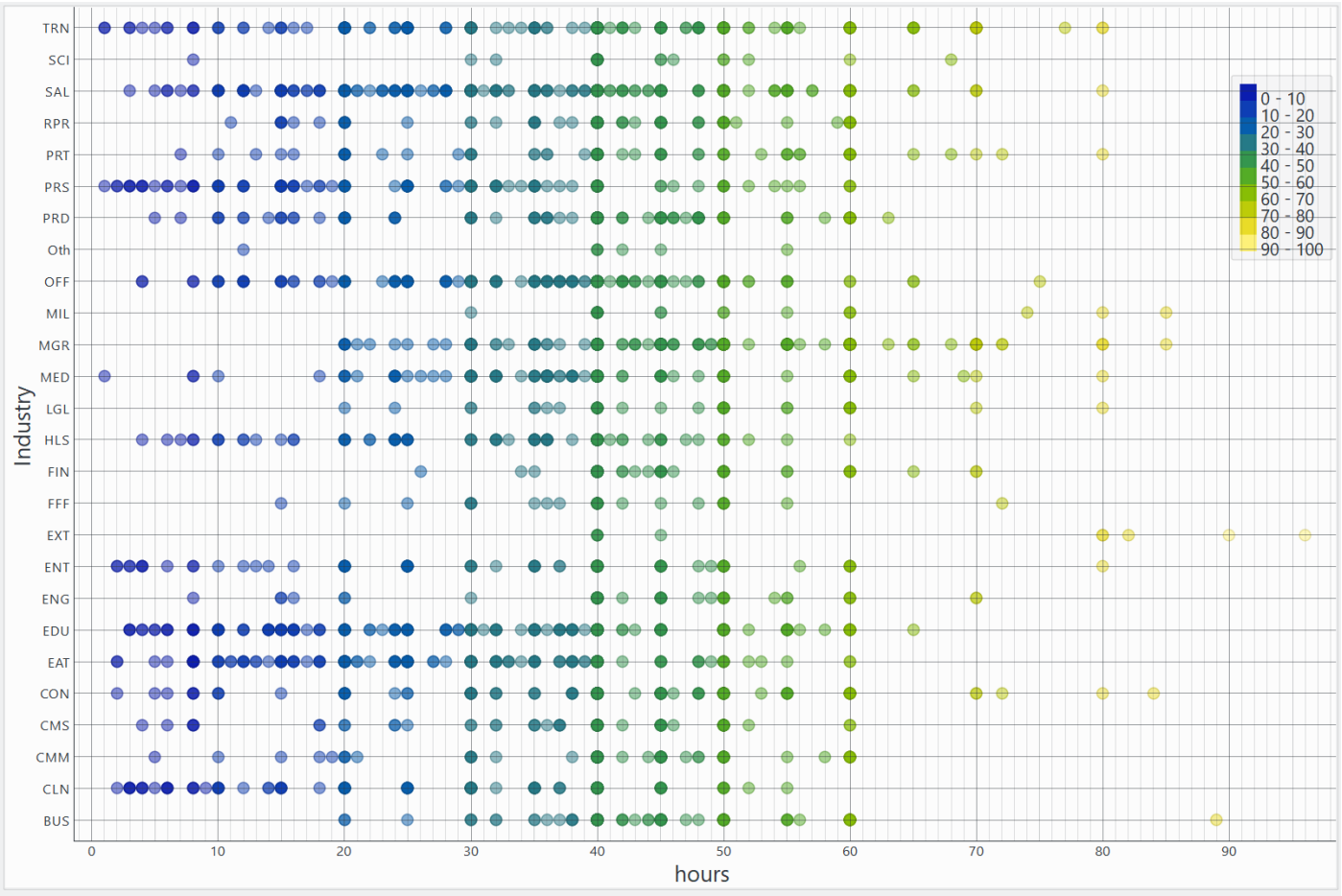



*Figure 39 Weekly hours by industry Scatter Plot*

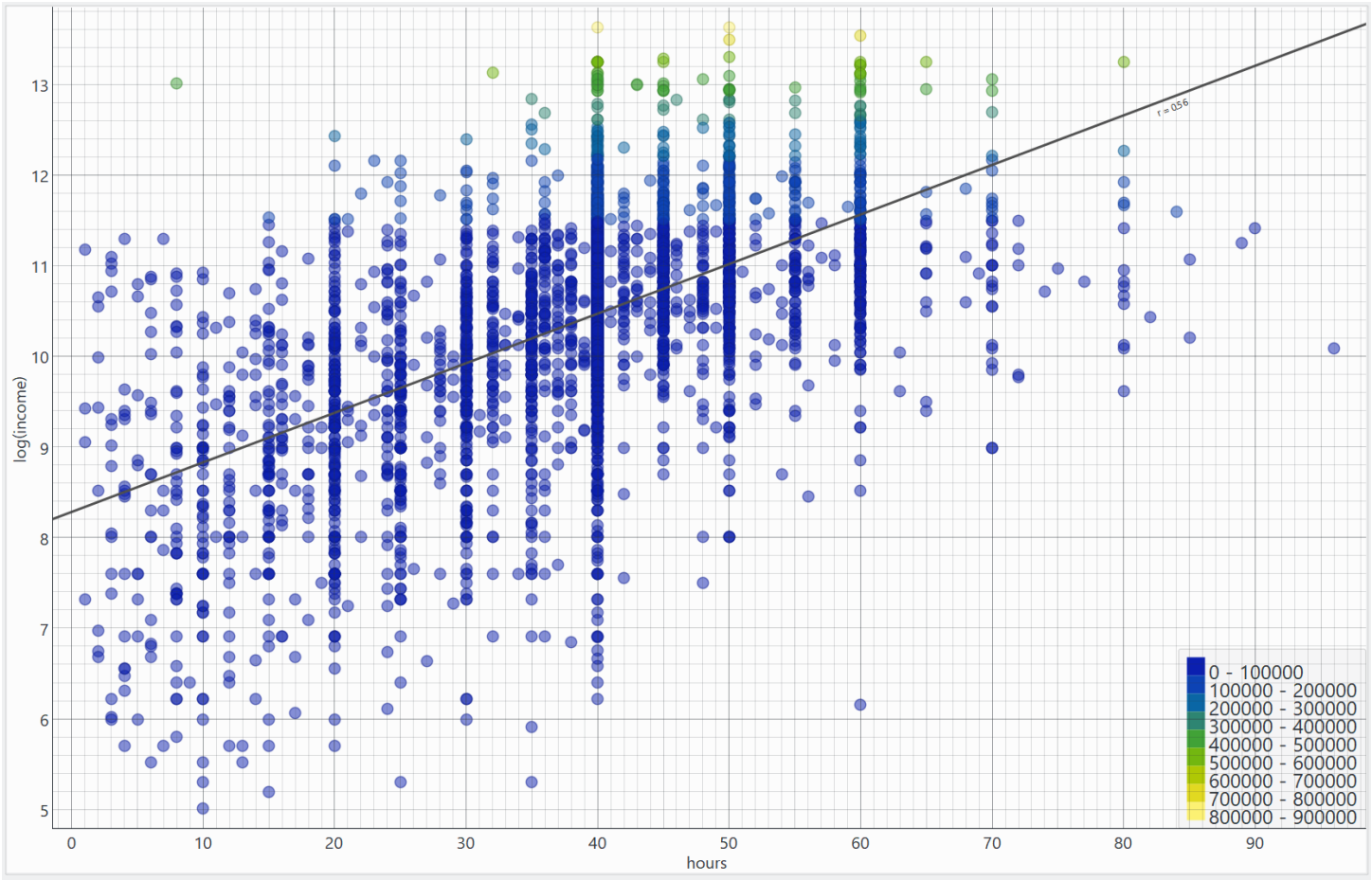



*Figure 40 Weekly hours by log(income) Scatter Plot*

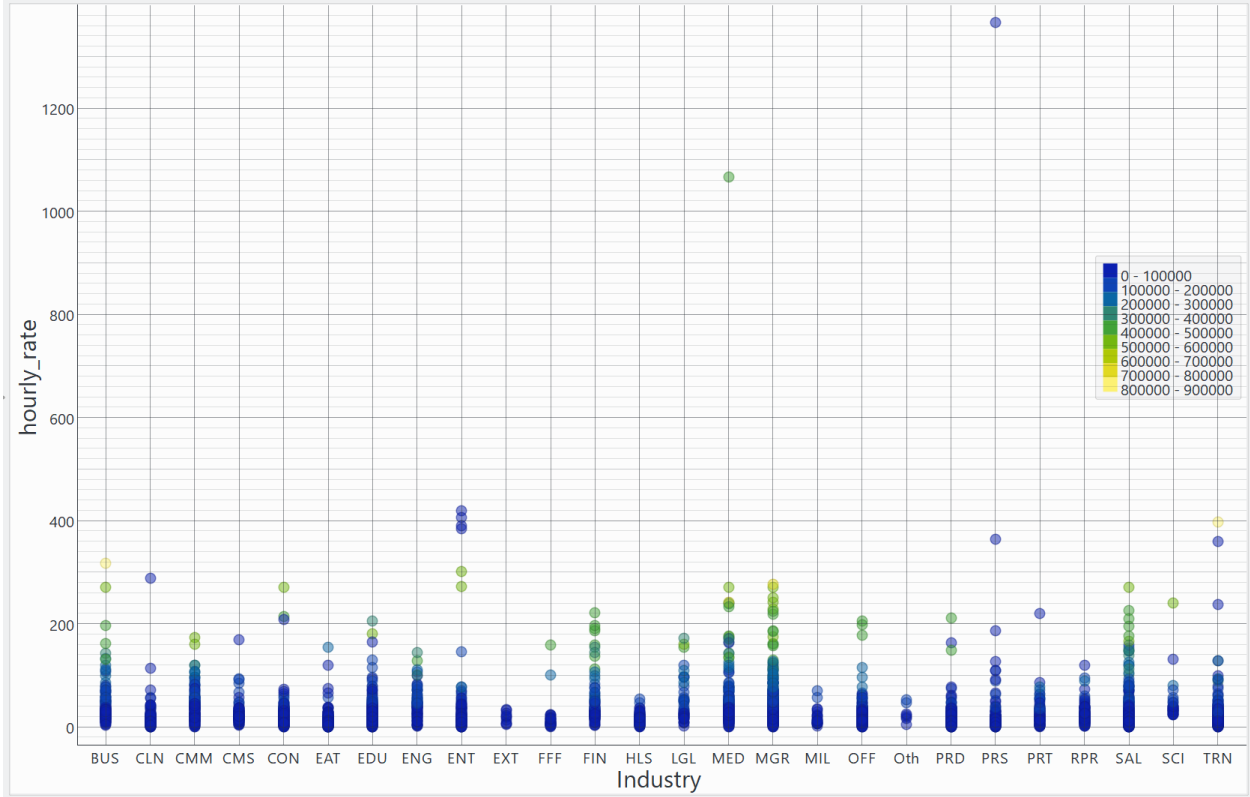



*Figure 41 Hourly rate by Industry Scatter Plot*

The t-test results (figure 42) show that industry type is statistically significant in determining the number of weekly hours worked as the p-value is 0.00.

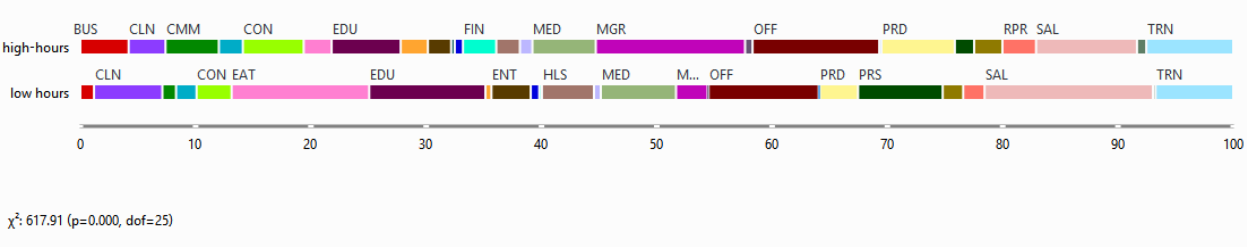



*Figure 42 Box plot of Industry by number of hours*

The summary statistics of the variables Hourly rate, hours and income are tabulated below:

| | Hourly Rate | Hours | Income |
|---|---|---|---|
| **Mean** | 28.1031 | 38.3967 | 56519.8 |
| **Mode** | 19.1781 | 40 | 50000 |
| **Median** | 19.1781 | 40 | 39300 |
| **Dispersion** | 1.50456 | 0.317445 | 1.26636 |
| **Min** | 0.109589 | 1 | 150 |
| **Max** | 1365.48 | 96 | 830000 |

*Table 10*

A new categorical category (hours_type) is created based off the median number of weekly hours worked to categorize the data into high and low-hours. Different classifier models were used to determine the hours_type. Those models are shown in Figure 43 and their results are displayed below.

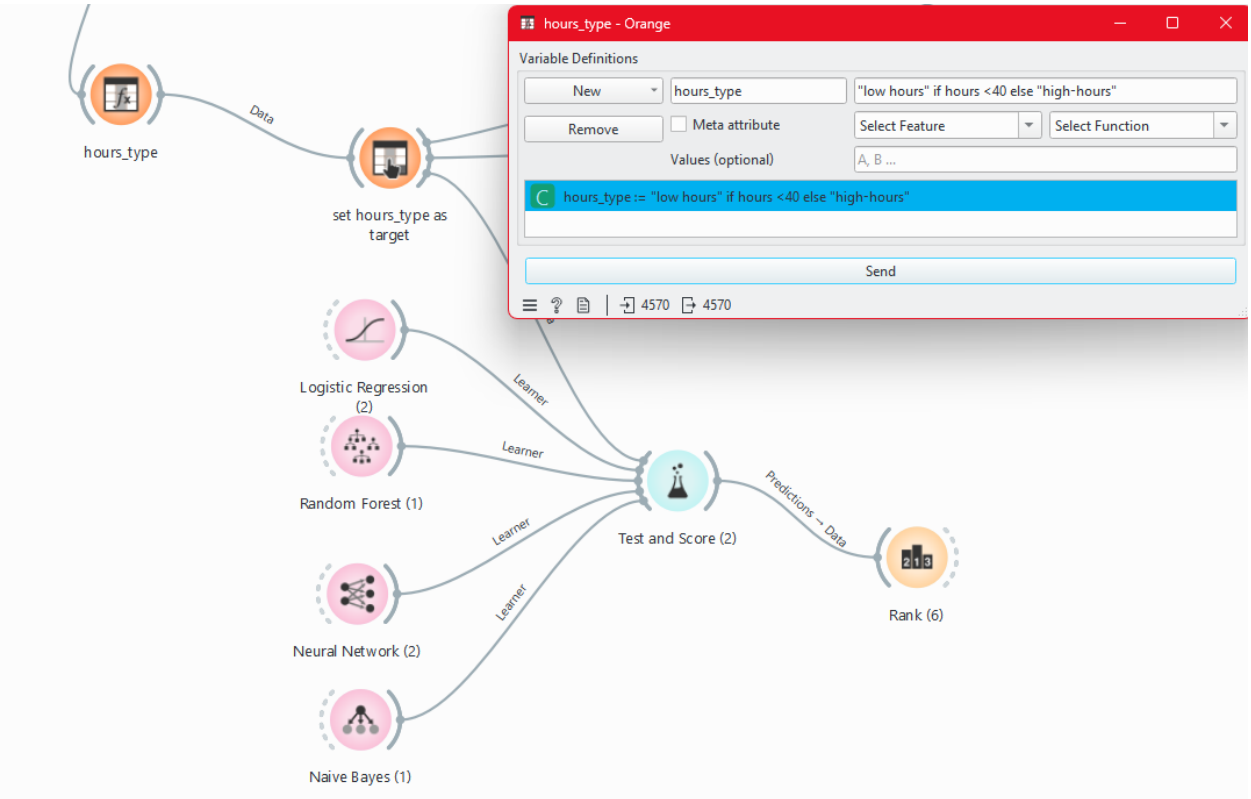



*Figure 43 Orange setup showing models used*

Evaluation results for target (None, show average over classes)

| Model | AUC | CA | F1 | Prec | Recall | MCC |
|---|---|---|---|---|---|---|
| Logistic Regression (2) | 1.000 | 0.995 | 0.995 | 0.995 | 0.995 | 0.987 |
| Random Forest (1) | 0.891 | 0.850 | 0.845 | 0.847 | 0.850 | 0.625 |
| Neural Network (2) | 0.951 | 0.903 | 0.902 | 0.902 | 0.903 | 0.763 |
| Naive Bayes (1) | 0.800 | 0.764 | 0.766 | 0.770 | 0.764 | 0.445 |

Compare models by: Area under ROC curve  Negligible diff.: 0.1

| | Logistic Regression (2) | Random Forest (1) | Neural Network (2) | Naive Bayes (1) |
|---|---|---|---|---|
| Logistic Regression (2) | | 1.000 | 1.000 | 1.000 |
| Random Forest (1) | 0.000 | | 0.002 | 0.999 |
| Neural Network (2) | 0.000 | 0.998 | | 1.000 |
| Naive Bayes (1) | 0.000 | 0.001 | 0.000 | |

*Figure 44 Test and Score results*

Out of all the models, Logistic Regression performed best in the side-by-side comparison and by having the best scores across all parameters. This model was applied to training data and the results are displayed:

| | | Predicted | | |
|---|---|---|---|---|
| | | high-hours | low hours | Σ |
| Actual | high-hours | 100.0 % | 0.0 % | 1031 |
| | low hours | 0.9 % | 99.1 % | 432 |
| | Σ | 1035 | 428 | 1463 |

A rank node is attached to show the impact of each variables on weekly hours worked and an explain model is attached to the classifier.

| | # | Inf...ain | Gain ratio | $\chi^2$ |
|---|---|---|---|---|
| N income | | 0.175 | 0.087 | 241.212 |
| C Industry | 26 | 0.105 | 0.025 | 2.414 |
| N occupation | | 0.060 | 0.030 | 1.263 |
| N hourly_rate | | 0.057 | 0.029 | 65.813 |
| N age | | 0.042 | 0.021 | 12.569 |
| C sex | 2 | 0.027 | 0.027 | 28.449 |
| C education_lvl | 8 | 0.017 | 0.006 | 19.756 |
| C marital | 5 | 0.016 | 0.010 | 63.634 |
| N education | | 0.012 | 0.006 | 14.141 |
| C CoW | 5 | 0.000 | 0.000 | 1.001 |
| C race | 2 | 0.000 | 0.000 | 0.462 |
| C PoB | 2 | 0.000 | 0.000 | 0.428 |

*Figure 45 Rank node results*

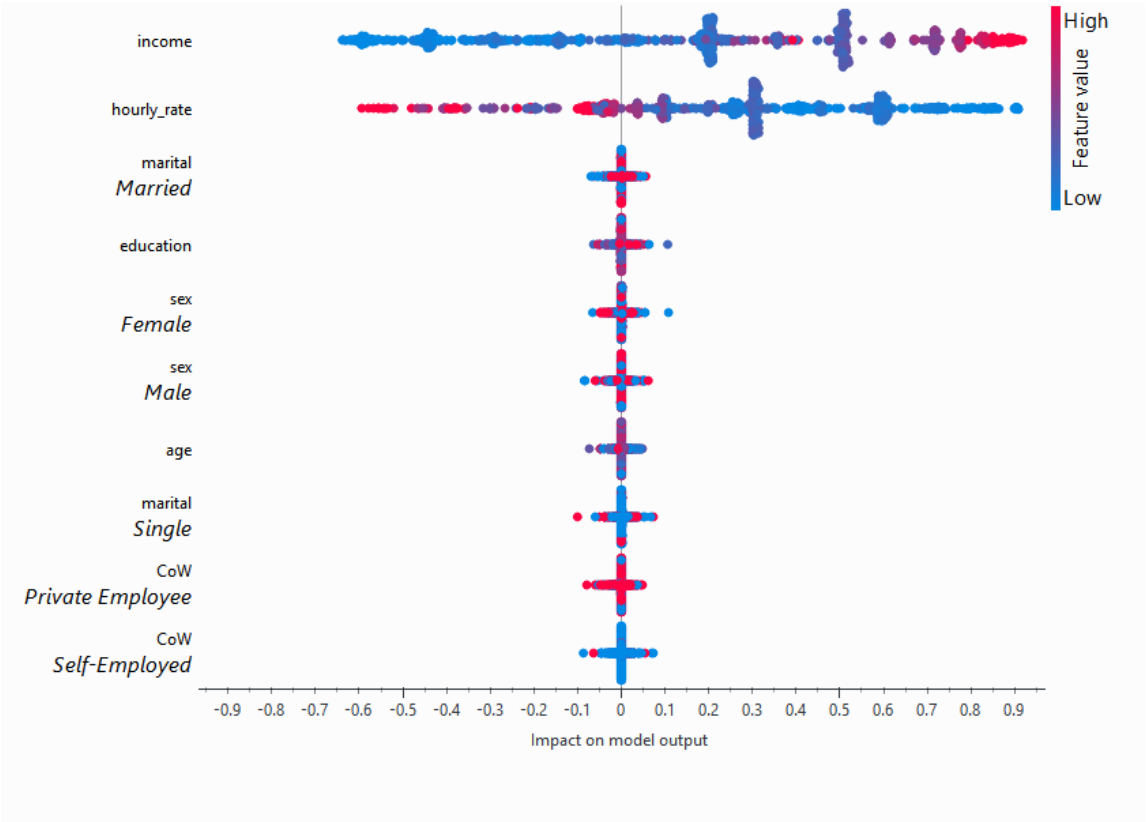



*Figure 46 Explain Model node results*

## Results Analysis

The exploratory analysis shows a positive correlation between hours worked with income with a diverse variation across different types of industries. This suggests that the type of industry have a statisically siginifcant impact on the number of weekly worked hours. The final Rank node and Explain model results establish that occupation type does moderate the number weekly hours worked supporting the hypothesis. However, due to the information gain, gain ratio and chi-square results, income has a higher influence on weekly hours over the type of industry.

# Appendix

## Part 1. Orange Nodes

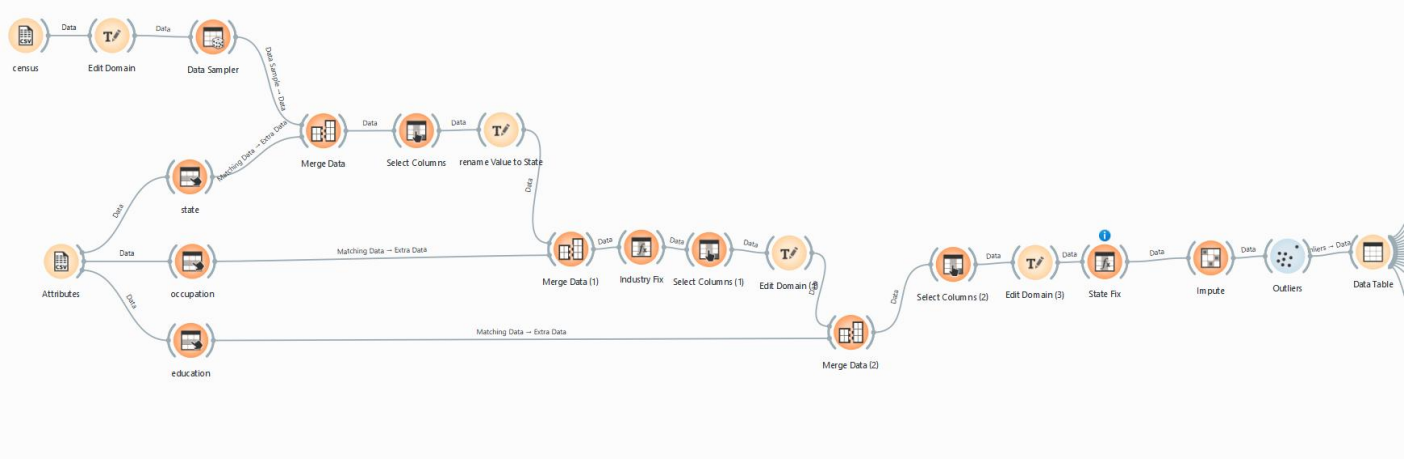



*Figure 47 Part 1*

## Part 2. Orange Nodes

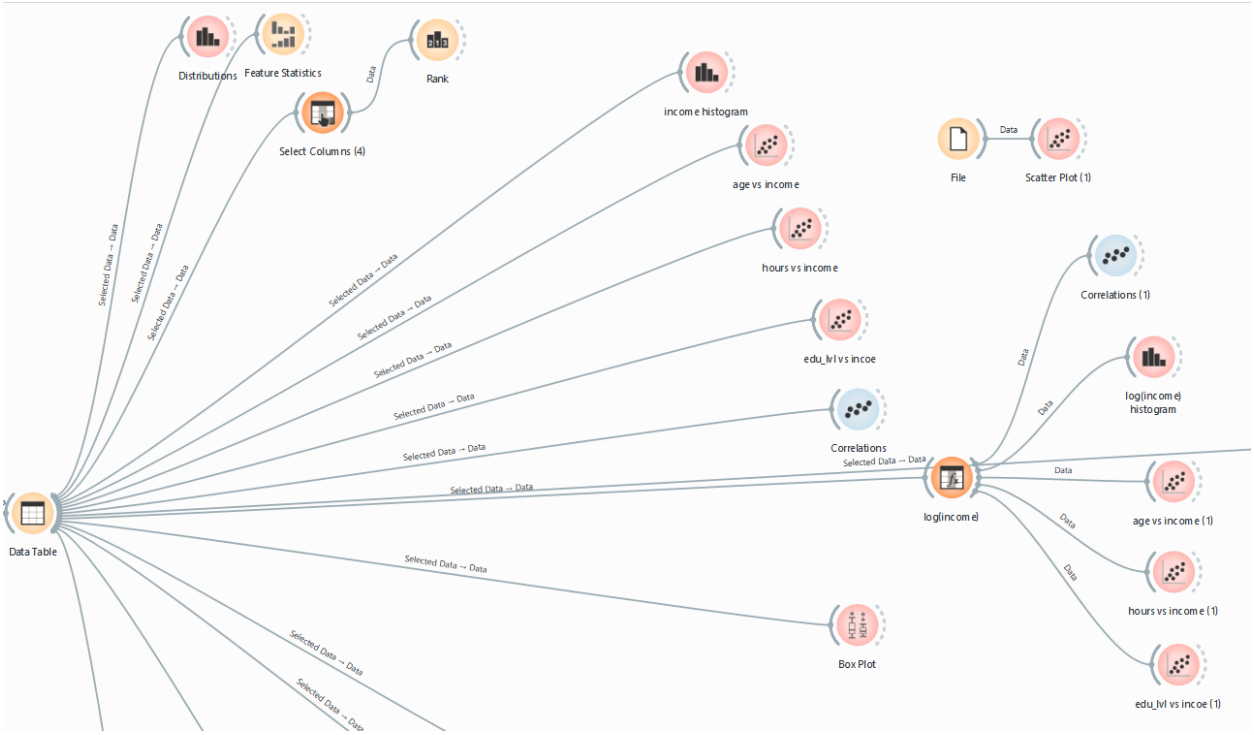



*Figure 48 Part 2*

## Part 3. Orange Nodes

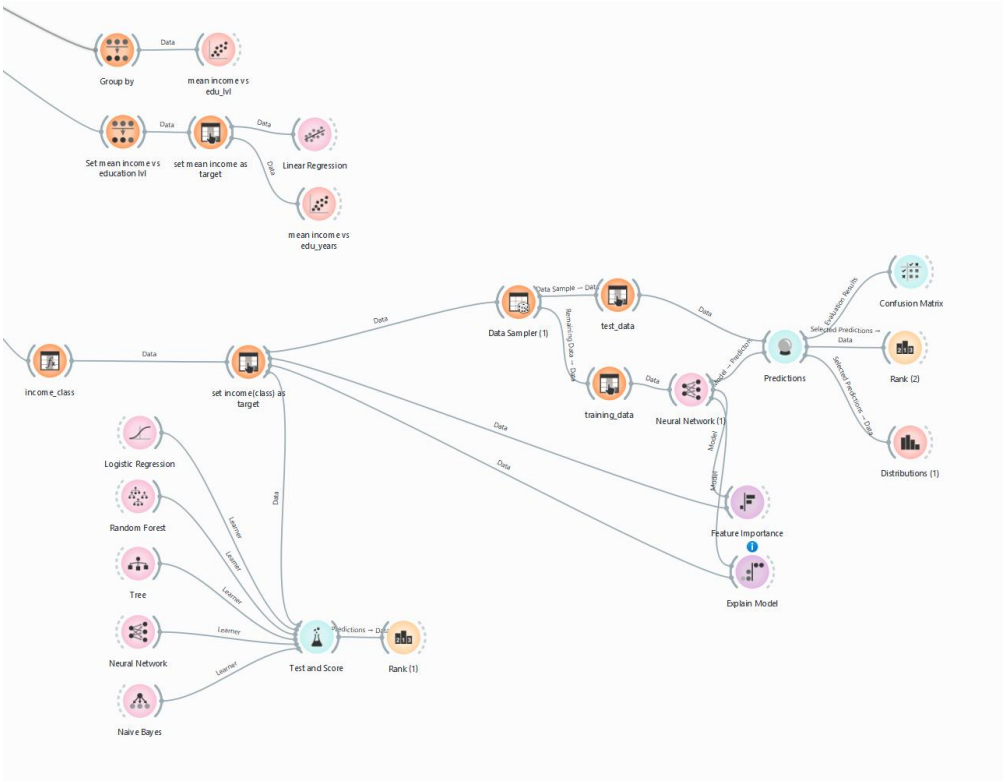



*Figure 49 Part 3*

## Part 4. Orange Nodes

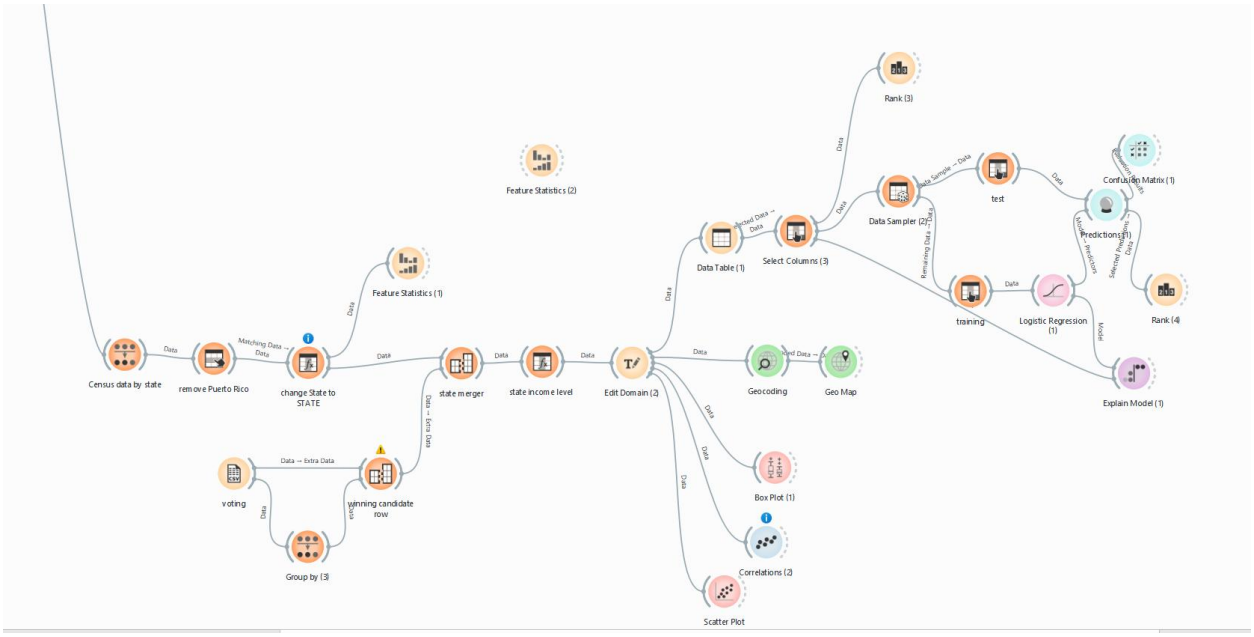



*Figure 50 Part 4*

## Part 5. Orange Nodes

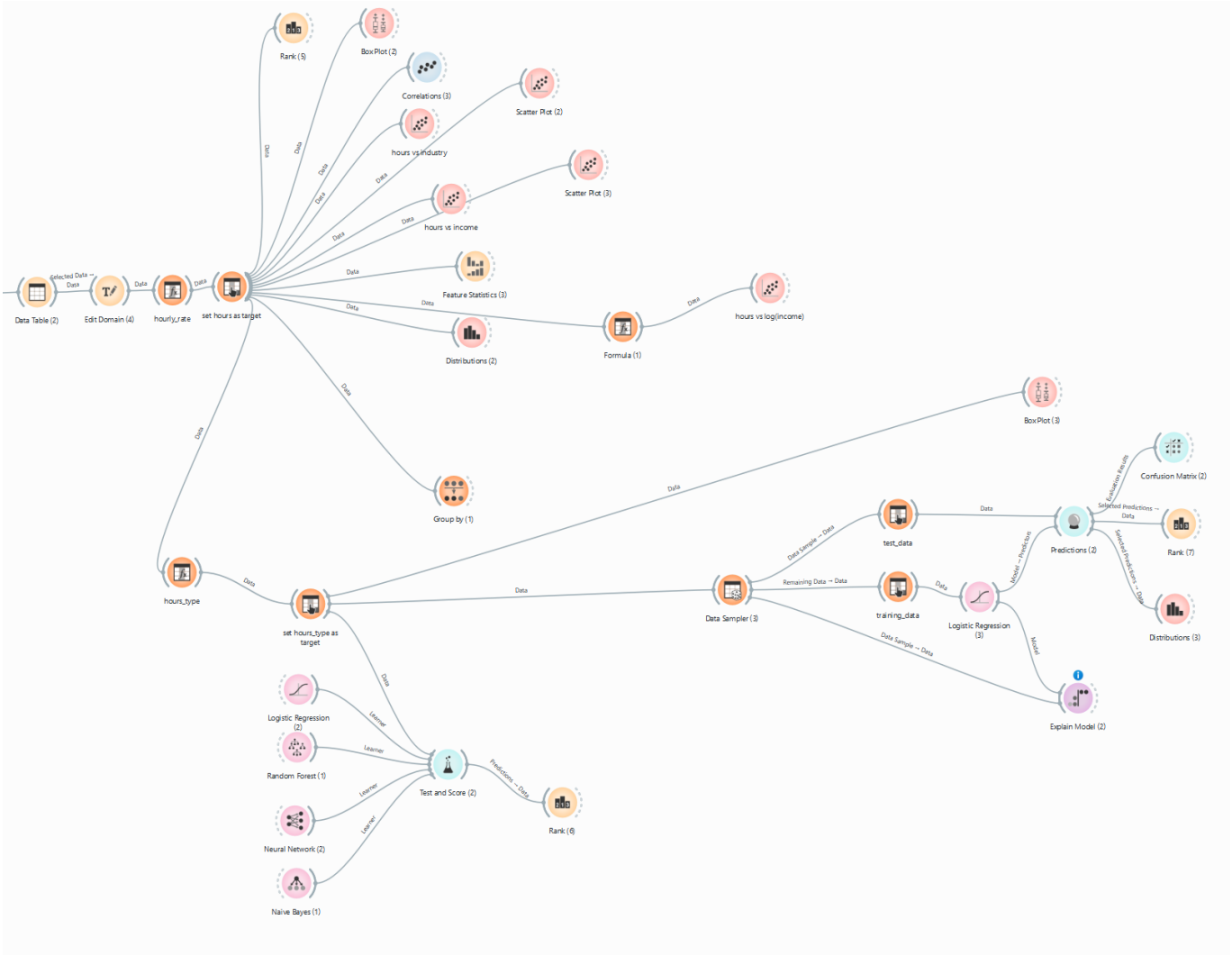



*Figure 51 Part 5*