Team Project 1

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Summary

Through this report we try to analyze the impact of a training program by gauging its effect on the real annual earnings and through its likeliness to help the participants earn a non-zero wage. To do so, we use linear and logitic regression models respectively. We use a dataset from the National Supported Work (NSW) Demonstration (1975-1978) for the same and build models using the AIC/BIC criterion based on the statistical significance and reasonableness. We then find out that ..... have significant association with annual incomes suggesting that taking the training might be an important factor associated with increase in wages. Also, We find that non-zero wages are associated with ..... suggesting that training is not a very significant factor associated with non-zero wages. Thus, it can be understood that training program as a factor does not seem to have a very strong association with improvement in wages or by providing a source of earning.

For detailed information on this research, please check the following papers.

- Paper 1
- Paper 2

Introduction

In the 1970s, researchers in the United States ran several randomized experiments to evaluate public policy programs. One of the most famous experiments is the National Supported Work (NSW) Demonstration, in which researchers wanted to assess whether or not job training for disadvantaged workers had an effect on their wages. Based on a subset of the investigation, in order to undersatnd the impact of the training program we need to look at two main questions:

Part I: Is there evidence that workers who receive job training tend to earn higher wages than workers who do not receive job training?

To address this question we need to look at quantify the effect of the treatment, that is, receiving job training, on real annual earnings and understanding the likely range for the effect of training. We also need to check if there is any evidence that the effects differ by demographic groups and if there are other interesting associations with wages.

Part II: Is there evidence that workers who receive job training tend to be more likely to have positive (non-zero) wages than workers who do not receive job training?

To understand this question we need to quantify the effect of the treatment, that is, receiving job training, on the odds of having non-zero wages and what would be the likely range for the effect of training. We also need to see if there is any evidence that the effects differ by demographic groups and also if there are other interesting associations with positive wages.

These questions would help us understand the potential association of the impact of the training program on the wages. To answer these questions the report uses a linear regression on the differences in wages and a logistic regression model on the odds of getting a non-zero wage after the training. It begins with an EDA of the data, tries building a model by exploring models built with the help of AIC and BIC criteria using

forward and stepwise model building and chooses the most suitable model on the basis of accuracy and plausibility to answer the above questions.

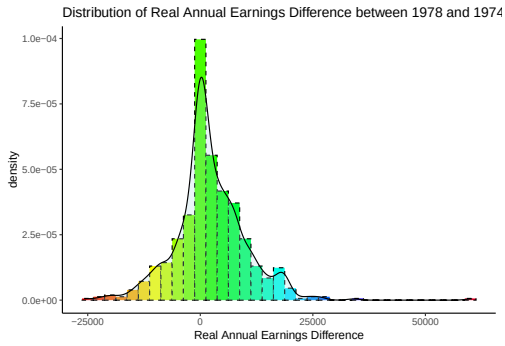
PART I

DATA

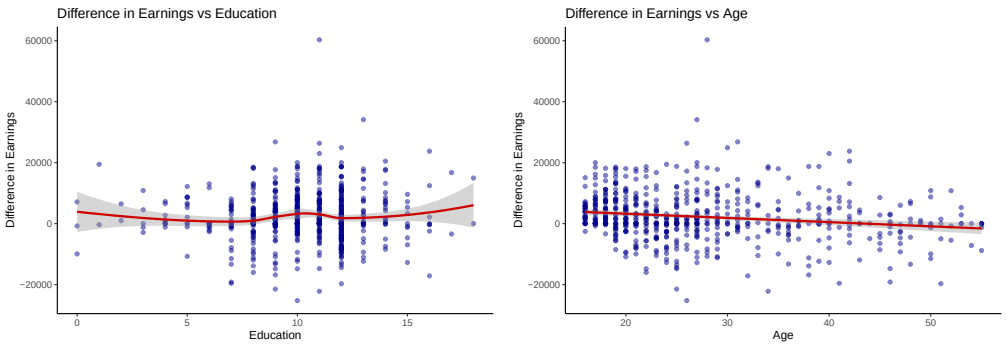
The data we have considered for the analysis consists of 614 observations and 11 variables viz. X (Participant ID), treat, age, educ (education level), black, hispan (Hispan), married, nodegree, re74 (real earnings in 1974), re75 (real earnings in 1975), and re78 (real earnings in 1978). Further, the dataset contains 185 male participants that have attended the training program and 429 male participants that have not attended the training program. There are 243 black and 72 hispanic participants. We converted treat, black, hispan, married, nodegree into binary factor variables, educ to a discrete variable and age as a continuous variable. The columns X and re75 will not be used in this analysis. We will not use re75 as it cannot be considered as a constant baseline among the participants.

Exploratory Data Analysis

We initially noticed that re78 was not normally distributed so that could not be used as the response variable. The difference between re78 and re74 seemed to portray more characteristics of normal distribution hence we have taken this difference as the model's response variable.

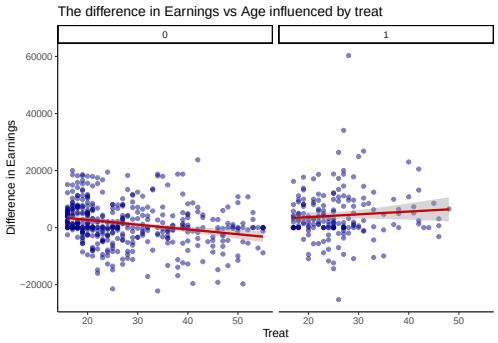


It is observed the variable age shows a slightly decreasing linear relationship with the wage differences, while variable education shows a non-linear trend. Further, we also see that categorical variables treat, black, hispan and married seem to show some differences based on the categories. We then look into the interactions and find that the association between wage differences and treat seems to differ by age; while one has an increasing trend the other has a decreasing trend. The trend between the two also shows differences by races , educ and married. We also find that trends between the wage differences and education differ by married. This is also found so for the age variable to differ by married.



Unlike the relationship between age and 'treat' (Right), the relationship between education(left) and 'treat' is not linear. It indicates that there is some non-linear transformation should be performed on education.

After evaluation, we decide to use the square to transform the variable.



The plot above illustrates the interaction between age and treat with the response variable. The annual earnings trend with the increase of age is different according to treat. Further investigation of this interaction would be exerted in the model fitting step.

Model

Model selection

Based on these, we try building a model using the AIC forward/ BIC and selecting the model.

Null Model contained only the treat variable while the full model contained all the predictors along with its interactions. The null model has an AIC value of 12771.89 while the full model has an AIC value of 12764.68.

The output of Forward AIC model is:

diff ~ treat + agec + married + educc2 + treat:agec + agec:married

Where agec - age centered variable and educc - education centered variable.

The AIC model contains the variables, treat, agec, married, educc2 (squared term of educ) along with the interaction between treat & agec and agec & married.

On comparing the model to the Null Model and Full Model, we find that the above model is more statistically significant (p-value: 6.668e-07 (null) and p-value:0.3817 (full)). Further, we test excluding and including some variables and found this to indeed be the most statistically significant one. However, we add the variables black and hispan as is required for analysing the question of interest. We also add the variable educc as we retain its second order term [ˆShows a significant p-value for the dataset.]

Interaction between "married" and "age" was found in this step. It's p-Value is slightly above 0.05, but it small than 0.1. The ANOVA test also indicates that it would improve our model significantly. Hence it was preserved in our final model.

Intuitively, education duration has a strong correlation with a high school degree. In this dataset, the correlation of the two variables is -0.7 which suggests that we could not include both of them in our model. After evaluation, education duration was preserved since it can provide more information than the high school degree variable.

Final model

$$diff_i = \beta_0 + \beta_1 * black_i + \beta_2 * hispan_i + \beta_3 * agec_i + \beta_4 * married_i + \beta_5 * treat_i : agec_i +$$
$$\beta_6 * educc_i + \beta_7 * educc_i^2 + \beta_8 agec : married_i + \varepsilon_i; \varepsilon \overset{iid}{\sim} \mathcal{N}(\mu, \sigma^2)$$

Model Summary & CI

From the above, we find that ..... Are strongly associated with the differences in wages. Further at a level of significance, it can be observed that .... Increase or decrease . with ..... Keeping other variables

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1743.6676	655.9077	2.66	0.0081
treat1	3254.1008	884.7055	3.68	0.0003
black1	-698.6038	853.5575	-0.82	0.4134
hispan1	623.2948	1047.1434	0.60	0.5519
agec	-220.0966	52.3925	-4.20	0.0000
married1	-1879.6013	727.0043	-2.59	0.0100
educc	151.2465	131.5212	1.15	0.2506
educc2	55.4840	26.6443	2.08	0.0377
treat1:agec	300.3163	89.6793	3.35	0.0009
agec:married1	137.9935	71.1252	1.94	0.0528

Table 1: Coefficient-Level Estimates

	pValue	RSquare
value	7.25e-09	0.09

Table 2: Evaluationl

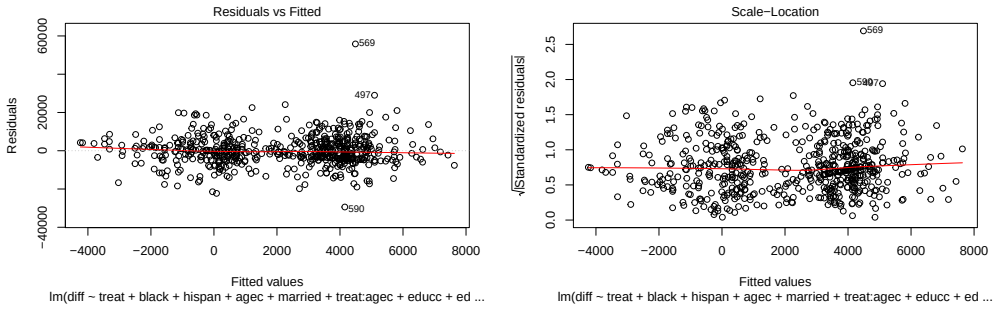
constant.

From the above, we find that treat is significant at level ..... And the likely range of wage difference is ..... This suggests that training does have an association with higher wages.

With demographic factors. ....

Model Verification

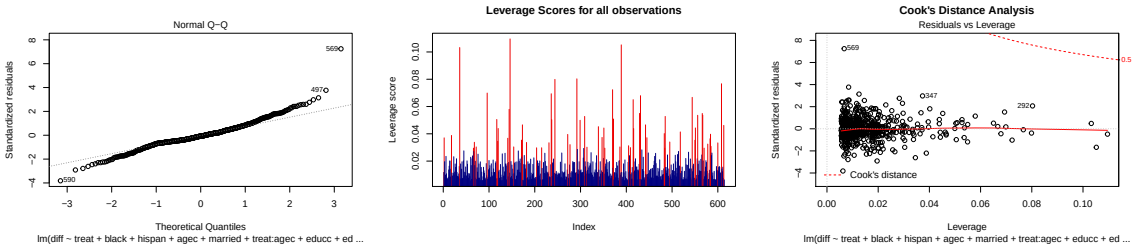
Residuals



- The residuals are scattered randomly; there is no apparent trend in the plots.
- The error is no correlation of error terms in the plot.
- The variance of the error is constant, there is no apparent change along the x-axis.

Summary: According to residual analysis, there is no obvious evidence indicate the assumptions of linear regression were broken.

Outliers and High Leverage



- There are a few outliers under this model.
- There are some high leverage points.
- According to cook's distance, there is no high influence points (> 0.5).

Summary: There are some outliers and high leverage points; however, there are not high influence data. Hence, these data points can be preserved in the model without worry.

Colineary

	names	x
1	treat1	1.69
2	black1	1.79
3	hispan1	1.17
4	agec	2.75
5	married1	1.32
6	educc	1.23
7	educc2	1.26
8	treat1:agec	1.31
9	agec:married1	2.25

Table 3: VIF

- According to VIF table, there is obvious colineary problem in this model.

Conclusion

1. Tread has positive effects on workers' annual salary because its p-value is significant. Controlling other factors, taking job training would increase $3254 on annual salary on average. It's 95% CI is (1516, 4991)
2. The effect varies by age. The interaction of treat and age is significant in our model. Workers who received training would receive $124 per year for per 1-year increase in age, while the no-training workers' salary would decrease by $322 per year for per 1-year increase in age.
3. Other interesting associations with wages:

- Marriage would significantly bring down workers' annual salary by $1879 (95% CI is 452, 3307)
- Education duration would increase workers' salaries. For 1 unit increase for its square, the annual salary would increase by $55 (95% CI: 3, 108)
- Age and married have weak interaction. Controlled other factors, for the married workers, while the old ones would receive more salary. One year increase on age would raise the workers' salary by $137 per year (95% CI: -2, 278)

Deficiency

1. The final model's R-squared is only 0.088, which is relatively low.
2. Some outliers deserve further investigation.

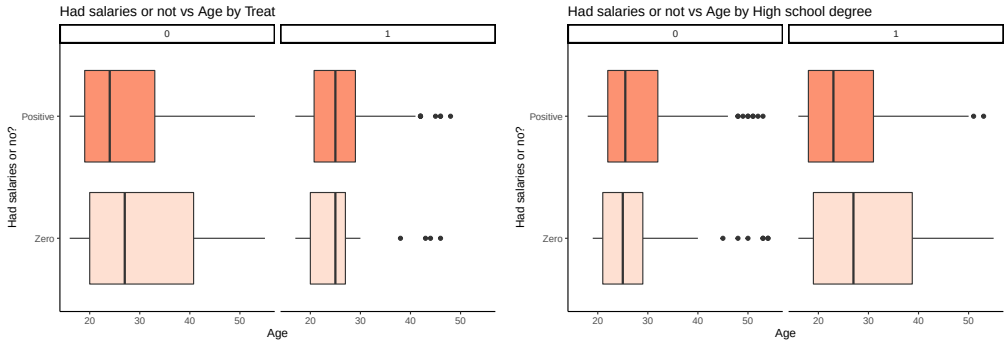
Part II

DATA

To answer the questions of interest, we converted the re78 variable into a binary response variable. A 0 value of the variable was taken to indicate that the participant made no earnings in 1978 while a 1 to indicate some (non-zero) monetary earnings in 1978. In other words, the variable is an indicator of the employment status of the participants in 1978 and is made our response variable. The variable re74 (real earnings in 1974) has also been removed from the analysis as the main aim was to look at the impact of training on positive wages (employment status). The other variables have been retained as was also mentioned in Part 1.

EDA

We then look at some of the trends between the other variables and the response variable. On some analysis, we find that this employment variable seems to show relation with age.



As reported by the first plot (left), the relation between age and employment in 1978 is different based on whether or not the employee took the training program. The second plot points out that the relation between employment and age is also influenced by whether or not the worker has a high school degree

	0	1
Zero	0.26	0.21
Positive	0.74	0.79

Table 4: Employed rate with marital status - Non Hispanic

	0	1
Zero	0.08	0.28
Positive	0.92	0.72

Table 5: Employed rate with marital status - Hispanic

We also observe through the two tables shown that there are some differences in the relationship between marital status and positive wages according to race. For the Hispanic participants, the unmarried workers' unemployment rate seems to be lower than single workers of other races (8% vs. 26%). At the same time, this advantage disappears in the married Hispanic workers. The married Hispanic workers' unemployment rate

is 28%, while Non-Hispanic races' married unemployment rate is 21%. This interesting sign of interaction would be further investigated in the model fitting.[1]

Model

Model selection

Based on the above trends, we build a logistic regression model using the AIC forward model selection method. For doing so we construct our Null Model as:

$$logit(\pi_i) = \beta_0 + \beta_1 * treat_i + \beta_2 * black_i + \beta_3 * agec_i + \beta_4 * agec_i^2 + \varepsilon_i$$

Full Model as:

$$logit(\pi_i) = \beta_0 + (\beta_1 agec_i + \beta_2 educc_i + \beta_3 treat_i + \beta_4 black_i + \beta_5 hispan_i + \beta_6 married_i + \beta_7 nodegree_i)^2 + \beta_8 * age_i c^2 + \varepsilon_i$$

Using the AIC forward model, we find that the square transform of "age" is significant in the model. After verification with ANOVA test, we decide to keep this transformation in the final model

As shown in the model output, the interactions between "age" &"nodegree" and "hispan" & "married" seems to be statistically significant, with a p value of 0.03 and 0.01 respectively. Interestingly, even though the interaction between treat and age is weakly significant (p-value=0.09), the ANOVA test confirmed its significance and hence we have included this in the final model. As the variable treat is statistically not significant (p-value=0.4), we preserve it in our final model as it is used to answer the questions of interest.

Final model

$$logit(\pi_i) = \beta_0 + \beta_1 * treat_i + \beta_2 * black_i + \beta_3 * agec_i + \beta_4 * agec_i^2 + \beta_5 * nodegree_i + \beta_6 * hispan_i + \beta_7 * married_i + \beta_8 * agec_i : nodegree_i + \beta_9 * hispan_i : married_i + \beta_{10} * agec_i : treat_i + \varepsilon_i$$

Model Summary

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	1.4481	0.2641	5.48	0.0000
treat1	0.2360	0.2845	0.83	0.4069
black1	-0.5399	0.2648	-2.04	0.0415
agec	0.0138	0.0245	0.56	0.5734
agec2	-0.0021	0.0011	-1.93	0.0536
nodegree1	-0.0157	0.2147	-0.07	0.9417
hispan1	1.1998	0.6436	1.86	0.0623
married1	0.3621	0.2629	1.38	0.1683
agec:nodegree1	-0.0447	0.0210	-2.13	0.0330
hispan1:married1	-1.8004	0.7703	-2.34	0.0194
treat1:agec	0.0456	0.0276	1.65	0.0990

Table 6: Coefficients

The baseline values taken in the intercept is treat=0 and black=0, nodegree=0, hispan=0, age=27, and married=0. Keeping all predictors at 0, the birth weight of the newborn would be 46.39 ounces (does not make any sense as centering is not done). Keeping other variables constant, 1. The odds ratio of a black employee having earnings in 1978 decreases by 0.417 times when compared to a non-black employee. 2. The odds ratio of a hispanic employee having earnings in 1978 increases by 3.32 times when compared to a non-hispanic employee.

[1]The Chi-square tests for independence are not significant. The variables are explored later.

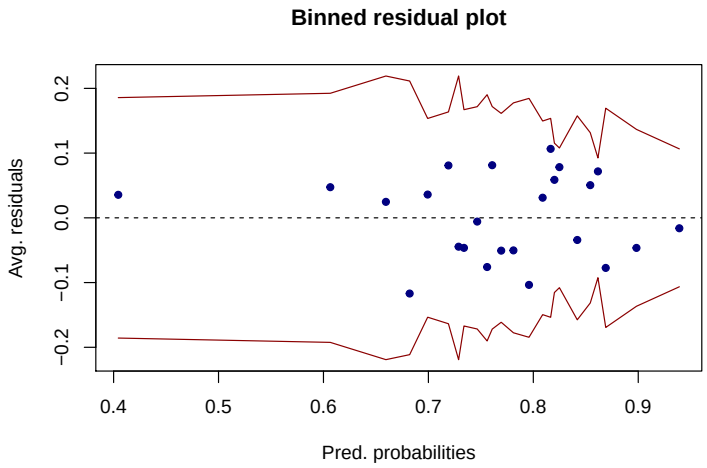
	2.5 %	97.5 %
(Intercept)	0.94	1.98
treat1	-0.32	0.80
black1	-1.06	-0.02
agec	-0.03	0.06
agec2	-0.00	0.00
nodegree1	-0.44	0.40
hispan1	0.08	2.68
married1	-0.15	0.88
agec:nodegree1	-0.09	-0.00
hispan1:married1	-3.47	-0.37
treat1:agec	-0.01	0.10

Table 7: Confidence Interval

	NULL_deviance	Residual_deviance
1	666.50	627.54

Table 8: Deviance

Model Verification



Residuals

The binned plot above illustrates the average residuals vs predicted probabilities. As shown, more than 95% of points reside inside the red band (within 95% confidence intervals) and no distinct pattern is observed. The binned plots for average residuals vs individual variables have been plotted and these plots also do not violate the above rules. This concludes a strong justification for the model's efficiency.

Null model deviance : 666.5 Final model deviance : 627.54 The decrease of deviance indicates that the model is valid.

Colineary According to the table, most of the VIF values for the predictors are below 5, indicating moderately correlated. However, age centered seems to have a VIF value of 6.8, indicating high correlation.

	names	x
1	treat1	1.82
2	black1	1.79
3	agec	6.83
4	agec2	3.06
5	nodegree1	1.09
6	hispan1	3.35
7	married1	1.69
8	agec:nodegree1	3.54
9	hispan1:married1	3.44
10	treat1:agec	1.38

Table 9: VIF

Summary Various indicators point out that the final model is valid and can be used to answer the questions about the dataset.

Model Assessment

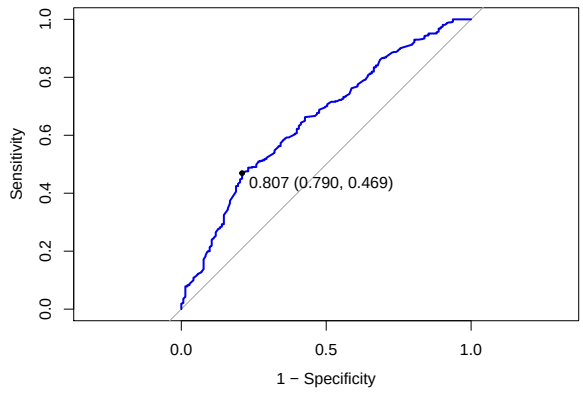
	0	1
0	91	192
1	52	279

Table 10: Confusion Matrix

The Sensitivity value, also known as true positive rate $\frac{TP}{TP+FN}$ of the model is 0.59.

The Specificity value, also known as true negative rate $\frac{TN}{FP+TN}$ of the model is 0.64

The Accuracy $\frac{TP+TN}{TP+TN+FP+FN}$ of the model is 0.60, 60%.



The ROC curve above has a AUC value of 0.65 and a cut-off value of 0.81.

Discussion

1. Is there evidence that workers who receive job training tend to be more likely to have positive (non-zero) wages than workers who do not receive job training? Quantify the effect of the treatment, that is, receiving job training, on the odds of having non-zero wages.LIMITS

According to the model, the variable treat is not statistically significant as it has a p value greater than 0.05. Hence receiving job training would not directly influence the odds of these worker's positive wages and

cannot quantify the effect of treatment on the odds of having non-zero wages. However, the interaction item "treat1:agec" is relatively significant.

3) Is there any evidence that the effects differ by demographic groups?

Yes. In the logistic regression model, black and hispan are statistically significant. For a black worker, his odds of getting a job are 41% lower than a non-black worker under the same other conditions. The odds ratio of a hispanic employee having positive earnings in 1978 increases by 3.32 times when compared to a non-hispanic employee.

4) Are there other interesting associations with positive wages that are worth mentioning?

Race of Hispanic and marital status. Controlling other factors, a Hispanic workers odd to be employed is 231% higher than others. However, the effect would bring down by being married. A married Hispanic worker's odds of getting a job are 45% lower than others under the same conditions.

Age. Age is a complex factor in our model. Generally speaking, aging would increase these workers' odds of being jobless. Taking the job training may slow down the trends.

Conclusion

To understand the impact of job training on positive wages, we built a logistic regression model. We confirmed the model using AIC forward selection and ANOVA tests. The assessment of the model was done using binned residual plots and identifying specificity, sensitivity, accuracy, and area under the ROC. We noticed that the variable treat is not statistically significant, inferring that job training would not directly influence the odds of these worker's positive wages. Race and Age seemed to be statistically significant when predicting the positive wages. Three interactions, Age & treat, hispan & married, age & "no degree" are also statistically significant as determined by p value less than 0.05. The effect of age is hard to interpret because it involves square transformation and interaction with treat.

Limitation

Sensitivity and accuracy are relatively low. Data on the long term effect of training is missing in this dataset. Intuitively, job training would exert its influence on people's work in the long run. However, it can not be verified in this analysis. There is an imbalance in The number of participants who joined the training program The ratio of hispanics to non-hispanics

Appendix I (Part1 R Code)

```
###### Clear environment and load libraries
rm(list = ls())
library(ggplot2)
library(rms)
library(MASS)
library(arm)
library(gganimate)
library(gifski)
library(av)
library(dplyr)
theme_set(theme_bw())

###### Load the data
lalondedata <-
  read.table(
    "lalondedata.txt",
    header = TRUE,
    sep = ",",
    colClasses = c(
      "factor",
      "factor",
      "numeric",
      "numeric",
      "factor",
      "factor",
      "factor",
      "factor",
      "numeric",
      "numeric",
      "numeric"
    )
  )

subrace <- lalondedata[c("black", "hispan")]
lalondedata$race <- apply(subrace, 1, function(x) {
  ifelse(x[1] == 1 & x[2] == 0, 1,
         ifelse(x[1] == 0 & x[2] == 1, 2, 0))
})
lalondedata$race <-
  factor(
    lalondedata$race,
    levels = c(0, 1, 2),
    labels = c("Otherwise", "Black", "Hispanic")
  )
lalondedata$diff <- lalondedata$re78 - lalondedata$re74
dim(lalondedata)
str(lalondedata)
summary(lalondedata)

###### EDA
# hist(lalondedata$re78 - lalondedata$re74, breaks = 20)
df1 <- data.frame(x=lalondedata$re78, time = 1)
```

```
df2 <- data.frame(x=lalondedata$diff, time = 2)
df <- cbind(df1, df2)

ggplot(df, aes(x = x)) +
  geom_histogram(
    aes(y = ..density..),
    color = "black",
    linetype = "dashed",
    fill = rainbow(25),
    binwidth = 2500
  ) +
  geom_density(alpha = .25, fill = "lightblue") +
  scale_fill_brewer(palette = "Blues") +
  labs(title = "Distribution of Real Annual Earnings in 1978",
       x = "Real Annual Earnings Difference") +
  theme_classic() + theme(legend.position = "none") +
  transition_states(time) +
  shadow_mark()

ggplot(lalondedata, aes(x = diff)) +
  geom_histogram(
    aes(y = ..density..),
    color = "black",
    linetype = "dashed",
    fill = rainbow(35),
    binwidth = 2500
  ) +
  geom_density(alpha = .25, fill = "lightblue") +
  scale_fill_brewer(palette = "Blues") +
  labs(title = "Distribution of Real Annual Earnings Difference between 1978 and 1974",
       x = "Real Annual Earnings Difference") +
  theme_classic() + theme(legend.position = "none")

# relationship b/w diff & each predictor
# age
ggplot(lalondedata, aes(x = age, y = diff)) +
  geom_point(alpha = .5, colour = "blue4") +
  geom_smooth(method = "lm", col = "red3") +
  theme_classic() +
  labs(title = "Difference in Earnings vs Age", x = "Age",
       y = "Difference in Earnings")

# educ
ggplot(lalondedata, aes(x = educ, y = diff)) +
  geom_point(alpha = .5, colour = "blue4") +
  geom_smooth(col = "red3") +
  theme_classic() +
  labs(title = "Difference in Earnings vs Education", x = "Education",
       y = "Difference in Earnings")

# treat
ggplot(lalondedata, aes(x = treat, y = diff, fill = treat)) +
  geom_boxplot() + #coord_flip() +
  scale_fill_brewer(palette = "Blues") +
```

```
  labs(title = "Difference in Earnings vs Received Job Training", x = "Received Job Training",
       y = "Difference in Earnings") +
  theme_classic() + theme(legend.position = "none")

# race
ggplot(lalondedata, aes(x = race, y = diff, fill = race)) +
  geom_boxplot() + #coord_flip() +
  scale_fill_brewer(palette = "Blues") +
  labs(title = "Difference in Earnings vs Races", x = "Races",
       y = "Difference in Earnings") +
  theme_classic() + theme(legend.position = "none")

# married
ggplot(lalondedata, aes(x = married, y = diff, fill = married)) +
  geom_boxplot() + #coord_flip() +
  scale_fill_brewer(palette = "Blues") +
  labs(title = "Difference in Earnings vs Marital Status", x = "Marital Status",
       y = "Difference in Earnings") +
  theme_classic() + theme(legend.position = "none")

# nodegree
ggplot(lalondedata, aes(x = nodegree, y = diff, fill = nodegree)) +
  geom_boxplot() + #coord_flip() +
  scale_fill_brewer(palette = "Blues") +
  labs(title = "Difference in Earnings vs No High School Degree", x = "No High School Degree",
       y = "Difference in Earnings") +
  theme_classic() + theme(legend.position = "none")

# interactions with age
ggplot(lalondedata, aes(x = age, y = diff)) +
  geom_point(alpha = .5, colour = "blue4") +
  geom_smooth(method = "lm", col = "red3") +
  theme_classic() +
  labs(title = "Difference in Earnings vs Age", x = "Age",
       y = "Difference in Earnings") +
  facet_wrap( ~ treat)

ggplot(lalondedata, aes(x = age, y = diff)) +
  geom_point(alpha = .5, colour = "blue4") +
  geom_smooth(method = "lm", col = "red3") +
  theme_classic() +
  labs(title = "Difference in Earnings vs Age", x = "Age",
       y = "Difference in Earnings") +
  facet_wrap( ~ race)

ggplot(lalondedata, aes(x = age, y = diff)) +
  geom_point(alpha = .5, colour = "blue4") +
  geom_smooth(method = "lm", col = "red3") +
  theme_classic() +
  labs(title = "Difference in Earnings vs Age", x = "Age",
       y = "Difference in Earnings") +
  facet_wrap( ~ married)

ggplot(lalondedata, aes(x = age, y = diff)) +
```

```
  geom_point(alpha = .5, colour = "blue4") +
  geom_smooth(method = "lm", col = "red3") +
  theme_classic() +
  labs(title = "Difference in Earnings vs Age", x = "Age",
       y = "Difference in Earnings") +
  facet_wrap( ~ nodegree)

# interactions with educ
ggplot(lalondedata, aes(x = educ, y = diff)) +
  geom_point(alpha = .5, colour = "blue4") +
  geom_smooth(method = "lm", col = "red3") +
  theme_classic() +
  labs(title = "Difference in Earnings vs Education", x = "Education",
       y = "Difference in Earnings") +
  facet_wrap( ~ treat)

ggplot(lalondedata, aes(x = educ, y = diff)) +
  geom_point(alpha = .5, colour = "blue4") +
  geom_smooth(method = "lm", col = "red3") +
  theme_classic() +
  labs(title = "Difference in Earnings vs Education", x = "Education",
       y = "Difference in Earnings") +
  facet_wrap( ~ race)

ggplot(lalondedata, aes(x = educ, y = diff)) +
  geom_point(alpha = .5, colour = "blue4") +
  geom_smooth(method = "lm", col = "red3") +
  theme_classic() +
  labs(title = "Difference in Earnings vs Education", x = "Education",
       y = "Difference in Earnings") +
  facet_wrap( ~ married)

ggplot(lalondedata, aes(x = educ, y = diff)) +
  geom_point(alpha = .5, colour = "blue4") +
  geom_smooth(method = "lm", col = "red3") +
  theme_classic() +
  labs(title = "Difference in Earnings vs Education", x = "Education",
       y = "Difference in Earnings") +
  facet_wrap( ~ nodegree)

# interactions with treat
ggplot(lalondedata, aes(x = treat, y = diff, fill = treat)) +
  geom_boxplot() + #coord_flip() +
  scale_fill_brewer(palette = "Blues") +
  labs(title = "Difference in Earnings vs Received Job Training", x = "Received Job Training",
       y = "Difference in Earnings") +
  theme_classic() + theme(legend.position = "none") +
  facet_wrap( ~ race)

ggplot(lalondedata, aes(x = treat, y = diff, fill = treat)) +
  geom_boxplot() + #coord_flip() +
  scale_fill_brewer(palette = "Blues") +
  labs(title = "Difference in Earnings vs Received Job Training", x = "Received Job Training",
       y = "Difference in Earnings") +
```

```
  theme_classic() + theme(legend.position = "none") +
  facet_wrap( ~ married)

ggplot(lalondedata, aes(x = treat, y = diff, fill = treat)) +
  geom_boxplot() + #coord_flip() +
  scale_fill_brewer(palette = "Blues") +
  labs(title = "Difference in Earnings vs Received Job Training", x = "Received Job Training",
       y = "Difference in Earnings") +
  theme_classic() + theme(legend.position = "none") +
  facet_wrap( ~ nodegree)

# interactions with race
ggplot(lalondedata, aes(x = race, y = diff, fill = race)) +
  geom_boxplot() + #coord_flip() +
  scale_fill_brewer(palette = "Blues") +
  labs(title = "Difference in Earnings vs Races", x = "Races",
       y = "Difference in Earnings") +
  theme_classic() + theme(legend.position = "none") +
  facet_wrap( ~ married)

ggplot(lalondedata, aes(x = race, y = diff, fill = race)) +
  geom_boxplot() + #coord_flip() +
  scale_fill_brewer(palette = "Blues") +
  labs(title = "Difference in Earnings vs Races", x = "Races",
       y = "Difference in Earnings") +
  theme_classic() + theme(legend.position = "none") +
  facet_wrap( ~ nodegree)

# interactions with married
ggplot(lalondedata, aes(x = married, y = diff, fill = married)) +
  geom_boxplot() + #coord_flip() +
  scale_fill_brewer(palette = "Blues") +
  labs(title = "Difference in Earnings vs Marital Status", x = "Marital Status",
       y = "Difference in Earnings") +
  theme_classic() + theme(legend.position = "none") +
  facet_wrap( ~ nodegree)

###### Modeling Fitting
# mean center the numerical predictors
lalondedata$agec <- c(scale(lalondedata$age, scale = F))
lalondedata$educc <- c(scale(lalondedata$educ, scale = F))
lalondedata$educc2 <- lalondedata$educc ^ 2

# Null Model
Model_Null <- lm(diff ~ treat * race, data = lalondedata)
summary(Model_Null)

# Full Model
Model_Full <-
  lm(diff ~ (agec + educc + treat + race + married + nodegree) ^ 2 + educc2,
     data = lalondedata)
summary(Model_Full)

# Stepwise
```

```
Model_stepwise_aic <-
  step(Model_Null,
       scope = Model_Full,
       direction = "both",
       trace = 0)
summary(Model_stepwise_aic)

Model_forward_aic <-
  step(Model_Null,
       scope = Model_Full,
       direction = "forward",
       trace = 0)
summary(Model_forward_aic)

Model_backward_aic <-
  step(Model_Null,
       scope = Model_Full,
       direction = "backward",
       trace = 0)
summary(Model_backward_aic)


## Final model is Model2
Model2 <-
  lm(
    diff ~ treat + black + hispan + agec + married + treat:agec + educc + educc2
    + agec:married,
    data = lalondedata
  )

summary(Model2)

confint(Model2, level = 0.95)

##### Model Assesment
vif(Model2)

# Assumptions
plot(Model2, which = 1:5, col = c("blue4"))

ggplot(lalondedata, aes(x = agec, y = Model2$residuals)) +
  geom_point(alpha = .7) + geom_hline(yintercept = 0, col = "red3") + theme_classic() +
  labs(title = "Residuals vs Age (Centered)", x = "Age (Centered)", y =
         "Residuals")
ggplot(lalondedata, aes(x = educc, y = Model2$residuals)) +
  geom_point(alpha = .7) + geom_hline(yintercept = 0, col = "red3") + theme_classic() +
  labs(title = "Residuals vs Education (Centered)", x = "Education (Centered)", y =
         "Residuals")
```

Appendix II (Part2 R Code)

```
###### Clear environment and load libraries
rm(list = ls())
library(ggplot2)
library(rms)
library(MASS)
library(arm)
library(pROC)
library(e1071)
library(caret)
library(dplyr)
library(tidyr)
require(gridExtra)

###### Load the data
lalondedata <-
  read.table(
    "lalondedata.txt",
    header = TRUE,
    sep = ",",
    colClasses = c(
      "factor",
      "factor",
      "numeric",
      "numeric",
      "factor",
      "factor",
      "factor",
      "factor",
      "numeric",
      "numeric",
      "numeric"
    )
  )

lalondedata$earn <- ifelse(lalondedata$re78 > 0, 1, 0)

lalondedata$earnf <-
  factor(
    ifelse(lalondedata$re78 > 0, 1, 0),
    levels = c(0, 1),
    labels = c("Zero", "Positive")
  )

###### Exploratory data analysis
# earn vs age
ggplot(lalondedata, aes(x = earnf, y = age, fill = earnf)) +
  geom_boxplot() + coord_flip() +
  scale_fill_brewer(palette = "Reds") +
  labs(title = "Had salaries or not vs Age",
       x = "Had salaries or no?", y = "Age") +
  theme_classic() + theme(legend.position = "none")
```

```
# earn vs age by treat
ggplot(lalondedata, aes(x = earnf, y = age, fill = earnf)) +
  geom_boxplot() + coord_flip() +
  scale_fill_brewer(palette = "Reds") +
  labs(title = "Had salaries or not vs Age by Treat",
       x = "Had salaries or no?", y = "Age") +
  theme_classic() + theme(legend.position = "none") +
  facet_wrap(~ treat)

# earn vs age by black
ggplot(lalondedata, aes(x = earnf, y = age, fill = earnf)) +
  geom_boxplot() + coord_flip() +
  scale_fill_brewer(palette = "Reds") +
  labs(title = "Had salaries or not vs Age by Black Race",
       x = "Had salaries or no?", y = "Age") +
  theme_classic() + theme(legend.position = "none") +
  facet_wrap(~ black)

# earn vs age by hispan
ggplot(lalondedata, aes(x = earnf, y = age, fill = earnf)) +
  geom_boxplot() + coord_flip() +
  scale_fill_brewer(palette = "Reds") +
  labs(title = "Had salaries or not vs Age by Hispanic Ethinicity",
       x = "Had salaries or no?", y = "Age") +
  theme_classic() + theme(legend.position = "none") +
  facet_wrap(~ hispan)

# earn vs age by married
ggplot(lalondedata, aes(x = earnf, y = age, fill = earnf)) +
  geom_boxplot() + coord_flip() +
  scale_fill_brewer(palette = "Reds") +
  labs(title = "Had salaries or not vs Age by Marital Status",
       x = "Had salaries or no?", y = "Age") +
  theme_classic() + theme(legend.position = "none") +
  facet_wrap(~ married)

# earn vs age by nodegree
ggplot(lalondedata, aes(x = earnf, y = age, fill = earnf)) +
  geom_boxplot() + coord_flip() +
  scale_fill_brewer(palette = "Reds") +
  labs(title = "Had salaries or not vs Age by High school degree",
       x = "Had salaries or no?", y = "Age") +
  theme_classic() + theme(legend.position = "none") +
  facet_wrap(~ nodegree)

# earn vs educ
ggplot(lalondedata, aes(x = earnf, y = educ, fill = earnf)) +
  geom_boxplot() + coord_flip() +
  scale_fill_brewer(palette = "Reds") +
  labs(title = "Had salaries or not vs Education",
       x = "Had salaries or no?", y = "Education") +
  theme_classic() + theme(legend.position = "none")

# earn vs educ by treat
```

```
ggplot(lalondedata, aes(x = earnf, y = educ, fill = earnf)) +
  geom_boxplot() + coord_flip() +
  scale_fill_brewer(palette = "Reds") +
  labs(title = "Had salaries or not vs Education by Treat",
       x = "Had salaries or no?", y = "Education") +
  theme_classic() + theme(legend.position = "none") +
  facet_wrap(~ treat)

# earn vs educ by black
ggplot(lalondedata, aes(x = earnf, y = educ, fill = earnf)) +
  geom_boxplot() + coord_flip() +
  scale_fill_brewer(palette = "Reds") +
  labs(title = "Had salaries or not vs Education by Black Race",
       x = "Had salaries or no?", y = "Education") +
  theme_classic() + theme(legend.position = "none") +
  facet_wrap(~ black)

# earn vs educ by hispan
ggplot(lalondedata, aes(x = earnf, y = educ, fill = earnf)) +
  geom_boxplot() + coord_flip() +
  scale_fill_brewer(palette = "Reds") +
  labs(title = "Had salaries or not vs Education by Hispanic Ethinicity",
       x = "Had salaries or no?", y = "Education") +
  theme_classic() + theme(legend.position = "none") +
  facet_wrap(~ hispan)

# earn vs educ by married
ggplot(lalondedata, aes(x = earnf, y = educ, fill = earnf)) +
  geom_boxplot() + coord_flip() +
  scale_fill_brewer(palette = "Reds") +
  labs(title = "Had salaries or not vs Education by Marital Status",
       x = "Had salaries or no?", y = "Education") +
  theme_classic() + theme(legend.position = "none") +
  facet_wrap(~ married)

# earn vs educ by nodegree
ggplot(lalondedata, aes(x = earnf, y = educ, fill = earnf)) +
  geom_boxplot() + coord_flip() +
  scale_fill_brewer(palette = "Reds") +
  labs(title = "Had salaries or not vs Education by High school degree",
       x = "Had salaries or no?", y = "Education") +
  theme_classic() + theme(legend.position = "none") +
  facet_wrap(~ nodegree)

# earn vs treat
t1 <-
  round(apply(table(lalondedata[, c("earnf", "treat")]) /
                sum(table(lalondedata[, c("earnf", "treat")])),
              2, function(x)
                x / sum(x)), 4)
t2 <-
  round(apply(table(lalondedata[, c("earnf", "black")]) /
                sum(table(lalondedata[, c("earnf", "black")])),
              2, function(x)
```

```
                x / sum(x)), 4)
t3 <-
  round(apply(table(lalondedata[, c("earnf", "hispan")]) /
                sum(table(lalondedata[, c("earnf", "hispan")])),
              2, function(x)
                x / sum(x)), 4)
t4 <-
  round(apply(table(lalondedata[, c("earnf", "married")]) /
                sum(table(lalondedata[, c("earnf", "married")])),
              2, function(x)
                x / sum(x)), 4)
t5 <-
  round(apply(table(lalondedata[, c("earnf", "nodegree")]) /
                sum(table(lalondedata[, c("earnf", "nodegree")])),
              2, function(x)
                x / sum(x)), 4)

chitest1 <- chisq.test(table(lalondedata[, c("earnf", "treat")]))
chitest2 <- chisq.test(table(lalondedata[, c("earnf", "black")]))
chitest3 <- chisq.test(table(lalondedata[, c("earnf", "hispan")]))
chitest4 <- chisq.test(table(lalondedata[, c("earnf", "married")]))
chitest5 <- chisq.test(table(lalondedata[, c("earnf", "nodegree")]))

black0 <- lalondedata %>%
  filter(black == 0)
black1 <- lalondedata %>%
  filter(black == 1)
apply(table(black0[, c("earnf", "treat")]) / sum(table(black0[, c("earnf", "treat")])),
      2, function(x)
        x / sum(x))
apply(table(black1[, c("earnf", "treat")]) / sum(table(black1[, c("earnf", "treat")])),
      2, function(x)
        x / sum(x))
# + black:treat

hispan0 <- lalondedata %>%
  filter(hispan == 0)
hispan1 <- lalondedata %>%
  filter(hispan == 1)
apply(table(hispan0[, c("earnf", "treat")]) / sum(table(hispan0[, c("earnf", "treat")])),
      2, function(x)
        x / sum(x))
apply(table(hispan1[, c("earnf", "treat")]) / sum(table(hispan1[, c("earnf", "treat")])),
      2, function(x)
        x / sum(x))
# + treat:hispan

married0 <- lalondedata %>%
  filter(married == 0)
married1 <- lalondedata %>%
  filter(married == 1)
apply(table(married0[, c("earnf", "treat")]) / sum(table(married0[, c("earnf", "treat")])),
      2, function(x)
        x / sum(x))
```

```
apply(table(married1[, c("earnf", "treat")]) / sum(table(married1[, c("earnf", "treat")])),
      2, function(x)
        x / sum(x))
# ~ treat:married

nodegree0 <- lalondedata %>%
  filter(nodegree == 0)
nodegree1 <- lalondedata %>%
  filter(nodegree == 1)
apply(table(nodegree0[, c("earnf", "treat")]) / sum(table(nodegree0[, c("earnf", "treat")])),
      2, function(x)
        x / sum(x))
apply(table(nodegree1[, c("earnf", "treat")]) / sum(table(nodegree1[, c("earnf", "treat")])),
      2, function(x)
        x / sum(x))
# - treat:nodegree

black0 <- lalondedata %>%
  filter(black == 0)
black1 <- lalondedata %>%
  filter(black == 1)
apply(table(black0[, c("earnf", "married")]) / sum(table(black0[, c("earnf", "married")])),
      2, function(x)
        x / sum(x))
apply(table(black1[, c("earnf", "married")]) / sum(table(black1[, c("earnf", "married")])),
      2, function(x)
        x / sum(x))
# + married:black

black0 <- lalondedata %>%
  filter(black == 0)
black1 <- lalondedata %>%
  filter(black == 1)
apply(table(black0[, c("earnf", "nodegree")]) / sum(table(black0[, c("earnf", "nodegree")])),
      2, function(x)
        x / sum(x))
apply(table(black1[, c("earnf", "nodegree")]) / sum(table(black1[, c("earnf", "nodegree")])),
      2, function(x)
        x / sum(x))
# + nodegree:black

hispan0 <- lalondedata %>%
  filter(hispan == 0)
hispan1 <- lalondedata %>%
  filter(hispan == 1)
apply(table(hispan0[, c("earnf", "nodegree")]) / sum(table(hispan0[, c("earnf", "nodegree")])),
      2, function(x)
        x / sum(x))
apply(table(hispan1[, c("earnf", "nodegree")]) / sum(table(hispan1[, c("earnf", "nodegree")])),
      2, function(x)
        x / sum(x))
# + nodegree:hispan

hispan0 <- lalondedata %>%
```

```
  filter(hispan == 0)
hispan1 <- lalondedata %>%
  filter(hispan == 1)
apply(table(hispan0[, c("earnf", "married")]) / sum(table(hispan0[, c("earnf", "married")])),
      2, function(x)
        x / sum(x))
apply(table(hispan1[, c("earnf", "married")]) / sum(table(hispan1[, c("earnf", "married")])),
      2, function(x)
        x / sum(x))
# + hispan:married

nodegree0 <- lalondedata %>%
  filter(nodegree == 0)
nodegree1 <- lalondedata %>%
  filter(nodegree == 1)
apply(table(nodegree0[, c("earnf", "married")]) / sum(table(nodegree0[, c("earnf", "married")])),
      2, function(x)
        x / sum(x))
apply(table(nodegree1[, c("earnf", "married")]) / sum(table(nodegree1[, c("earnf", "married")])),
      2, function(x)
        x / sum(x))
# + nodegree:married

#binned plots
par(mfcol = c(1, 1))
binnedplot(
  x = lalondedata$age,
  y = lalondedata$earn,
  xlab = "Age",
  ylim = c(0, 1),
  col.pts = "navy",
  ylab = "Had salaries or not ",
  main = "Binned Plot for Had salaries or not  w.r.t \nAge",
  col.int = "white"
)

binnedplot(
  x = lalondedata$educ,
  y = lalondedata$earn,
  xlab = "Education",
  ylim = c(0, 1),
  col.pts = "navy",
  ylab = "Had salaries or not ",
  main = "Binned Plot for Had salaries or not  w.r.t \nEducation",
  col.int = "white"
)

###### Model fitting
lalondedata$agec <- lalondedata$age - mean(lalondedata$age)
lalondedata$agec2 <- lalondedata$agec ^ 2
lalondedata$educc <- lalondedata$educ - mean(lalondedata$educ)

ModelNull <-
  glm(earn ~ treat + black + agec + agec2,
```

```
      data = lalondedata,
      family = binomial)
summary(ModelNull)

ModelFull <-
  glm(
    earn ~ (agec + educ + treat + black + hispan + married + nodegree) ^ 2 + agec2,
    data = lalondedata,
    family = binomial
  )
summary(ModelFull)

Model_stepwise_aic <- step(ModelNull,
                           scope = ModelFull,
                           direction = "both",
                           trace = 0)
summary(Model_stepwise_aic)

Model_forward_aic <- step(ModelNull,
                          scope = ModelFull,
                          direction = "forward",
                          trace = 0)
summary(Model_forward_aic)

Model_backward_aic <- step(ModelNull,
                           scope = ModelFull,
                           direction = "backward",
                           trace = 0)
summary(Model_backward_aic)

Model1 <-
  glm(earn ~ treat + black + agec + agec2 + agec:treat,
      data = lalondedata,
      family = binomial)
summary(Model1)
anova(ModelNull, Model1, test = "Chisq")

Model2 <-
  glm(
    earn ~ treat + black + agec + agec2 + agec:treat + educ + educ:black,
    data = lalondedata,
    family = binomial
  )
summary(Model2)
anova(Model1, Model2, test = "Chisq")

Model3 <-
  glm(
    earn ~ treat + black + agec + agec2 + agec:treat + hispan + hispan:educ,
    data = lalondedata,
    family = binomial
  )
summary(Model3)
anova(Model1, Model3, test = "Chisq")
```

```
Model4 <-
  glm(
    earn ~ treat + black + agec + agec2 + agec:treat +  married + married:educc,
    data = lalondedata,
    family = binomial
  )
summary(Model4)
anova(Model1, Model4, test = "Chisq")

Model5 <-
  glm(
    earn ~ treat + black + agec + agec2 + agec:treat +  nodegree + nodegree:agec,
    data = lalondedata,
    family = binomial
  )
summary(Model5)
anova(Model1, Model5, test = "Chisq")

Model6 <-
  glm(
    earn ~ treat + black + agec + agec2 + agec:treat +  nodegree + nodegree:agec + nodegree:educ,
    data = lalondedata,
    family = binomial
  )
summary(Model6)
anova(Model1, Model6, test = "Chisq")

Model7 <-
  glm(
    earn ~ earn ~ treat + black + agec + agec2 + agec:treat +  nodegree + nodegree:agec +
      treat:black + treat:hispan + treat:married + treat:nodegree +
      black:hispan + black:married + black:nodegree +
      hispan:married + hispan:nodegree +
      nodegree:married + hispan + married,
    data = lalondedata,
    family = binomial
  )
summary(Model7)
anova(Model6, Model7, test = "Chisq")

Model8 <- step(Model5,
               scope = Model7,
               direction = "both",
               trace = 0)
summary(Model8)

Model9 <- step(Model5,
               scope = Model7,
               direction = "forward",
               trace = 0)
summary(Model9)

Model10 <- step(Model5,
```

```
                scope = Model7,
                direction = "backward",
                trace = 0)
summary(Model10)

Model11 <-
  glm(
    earn ~ treat + black + agec + agec2 + agec:treat +  nodegree + nodegree:agec +
      hispan + married + hispan:married,
    data = lalondedata,
    family = binomial
  )
summary(Model11)
anova(Model5, Model11, test = "Chisq")

Model12 <-
  glm(
    earn ~ treat + black + agec + agec2 + agec:treat +
      hispan + married + hispan:married,
    data = lalondedata,
    family = binomial
  )
summary(Model12)
anova(Model12, Model11, test = "Chisq")

FinalModel <- Model11
summary(FinalModel)

Model13 <-  glm(
  earn ~ treat + race + agec + agec2 + agec:treat++married + race:married,
  data = lalondedata,
  family = binomial
)
summary(Model13)

Model14 <- glm(
  earn ~ treat + black + agec + agec2 + hispan + married + agec:treat +
    nodegree + nodegree:agec + hispan:married + black:treat,
  data = lalondedata,
  family = binomial
)
summary(Model14)
anova(Model11, Model14, test = "Chisq")
# - black:treat

Model15 <- glm(
  earn ~ treat + black + agec + agec2 + hispan + married + agec:treat +
    nodegree + nodegree:agec + hispan:married + treat:hispan,
  data = lalondedata,
  family = binomial
)
summary(Model15)
anova(Model11, Model15, test = "Chisq")
# + treat:hispan
```

```
Model16 <- glm(
  earn ~ treat + black + agec + agec2 + hispan + married + agec:treat +
    nodegree + nodegree:agec + hispan:married  + treat:hispan + treat:married,
  data = lalondedata,
  family = binomial
)
summary(Model16)
anova(Model15, Model16, test = "Chisq")

Model17 <- glm(
  earn ~ treat + black + agec + agec2 + hispan + married + agec:treat +
    nodegree + nodegree:agec + hispan:married  + treat:hispan + married:black,
  data = lalondedata,
  family = binomial
)
summary(Model17)
anova(Model15, Model17, test = "Chisq")

Model18 <- glm(
  earn ~ treat + black + agec + agec2 + hispan + married + agec:treat +
    nodegree + nodegree:agec + hispan:married  + treat:hispan + nodegree:black,
  data = lalondedata,
  family = binomial
)
summary(Model18)
anova(Model15, Model18, test = "Chisq")

Model19 <- glm(
  earn ~ treat + black + agec + agec2 + hispan + married + agec:treat +
    nodegree + nodegree:agec + hispan:married  + treat:hispan + nodegree:hispan,
  data = lalondedata,
  family = binomial
)
summary(Model19)
anova(Model15, Model19, test = "Chisq")

Model20 <- glm(
  earn ~ treat + black + agec + agec2 + hispan + married + agec:treat +
    nodegree + nodegree:agec + hispan:married  + treat:hispan + nodegree:married,
  data = lalondedata,
  family = binomial
)
summary(Model20)
anova(Model15, Model20, test = "Chisq")

anova(Model11, Model15, test = "Chisq")

Model21 <- step(Model11,
                scope = Model15,
                direction = "both",
                trace = 0)
summary(Model21)
# Model21 = Model11
```

```
FinalModel <- Model11
summary(FinalModel)


###### Model fitting
rawresid <- residuals(FinalModel, "resp")

#binned residual plots
par(mfrow = c(1, 1))
binnedplot(
  x = fitted(FinalModel),
  y = rawresid,
  xlab = "Pred. probabilities",
  col.int = "red4",
  ylab = "Avg. residuals",
  main = "Binned residual plot",
  col.pts = "navy"
)

binnedplot(
  x = lalondedata$agec,
  y = rawresid,
  xlab = "Age (Centered)",
  col.int = "red4",
  ylab = "Avg. residuals",
  main = "Binned residual plot",
  col.pts = "navy"
)

binnedplot(
  x = lalondedata$educc,
  y = rawresid,
  xlab = "Education (Centered)",
  col.int = "red4",
  ylab = "Avg. residuals",
  main = "Binned residual plot",
  col.pts = "navy"
)


######## Model Validation
Conf_mat <-
  confusionMatrix(as.factor(ifelse(
    fitted(FinalModel) >= mean(lalondedata$earn), "1", "0"
  )),
  as.factor(lalondedata$earn), positive = "1")
Conf_mat$table
Conf_mat$overall["Accuracy"]
Conf_mat$byClass[c("Sensitivity", "Specificity")]

roc(
  lalondedata$earn,
  fitted(FinalModel),
```

```
  plot = T,
  print.thres = "best",
  legacy.axes = T,
  print.auc = T,
  col = "red3",
  quiet = TRUE
)

###### Confidence Interval
confint(FinalModel)
```