

ADSC Case 8 Report

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Introduction

This report provides an analysis to (1) identify key factors influencing an individual's salary and (2) draw meaningful conclusions about how these factors impact salaries using regression modeling techniques. The Wages dataset has ten explanatory variables and one dependent variable, salary. The methodology section outlines the steps taken to build the regression models, including selecting relevant variables and handling potential multicollinearity. The results section presents the outcomes of the regression models and the findings from the diagnostic tests. Finally, the conclusion section provides insights into how salaries are influenced by these variables, highlights which variables significantly impact salary, and explains the potential interaction effects among these variables.

Methodology

[TO-DO]: Write out the beginning section of the Methodology. Include the following points:

1. The metric we look at to determine this is the best-fitting regression model (Adjusted R-squared, P-value)
2. Whatever else you feel appropriate for this section – feel free to write and include in this
3. *Model development process – Mint - done*

Our initial model with all numeric variables aim to observe their effects and assess the adjusted R-squared. The **Model 1 results** show an overall p-value of 2.2e-16, which is significantly less than 0.05, and an adjusted R-squared of 99%. This extremely high R-squared indicates that the included variables are highly effective at explaining an individual's salary. However, the p-value is mainly driven by the variable Salary.5, which is overpowering the other predictors and potentially causing the lack of statistical significance for other variables. As a result, we decided to remove Salary.5 from our next model.

Model 1 Results

```
##
## Call:
## lm(formula = Salary ~ Salary.5 + FatherEducation + MotherEducation +
##     GPA + Age + Experience + Education, data = Wages)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -5.886 -1.529 -0.193  1.230 34.722
##
## Coefficients:
```

```
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept)    9.788205   2.844657   3.441  0.00066 ***
## Salary.5       0.992074   0.006335 156.594 < 2e-16 ***
## FatherEducation -0.262894   0.163080  -1.612  0.10798
## MotherEducation 0.272293   0.141860   1.919  0.05586 .
## GPA            -0.076393   0.436517  -0.175  0.86119
## Age            0.061761   0.078806   0.784  0.43382
## Experience     -0.075763   0.078486  -0.965  0.33515
## Education      0.002663   0.087803   0.030  0.97582
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.855 on 306 degrees of freedom
## Multiple R-squared:  0.9922, Adjusted R-squared:  0.992
## F-statistic: 5530 on 7 and 306 DF, p-value: < 2.2e-16
```

Additionally, we were interested to examine potential multicollinearity among Salary.5 and the other variables. The **Model 1 Variance Inflation Factor (VIF) test** reveals a strong correlation between the variables Age and Experience, with both having VIF values greater than the threshold of 5, indicating a high degree of multicollinearity with other predictors. To address this, we chose to remove Age from our next model.

Model 1 VIF Test

```
##           Salary.5 FatherEducation MotherEducation      GPA      Age
##           1.585746      4.136541      4.101660      1.007316 10.241068
##           Experience      Education
##           10.718555      1.059702
```

After testing various combinations of variables and interaction terms, we finalized a model (**Model 2**) that includes *Experience*, *Education*, and three interaction terms: *Job*Province*, *Job*Experience*, and *Province*Experience*. These variables were selected because they significantly contribute to explaining salary variations, and their inclusion results in a higher adjusted R-squared, indicating a better fit for the model.

Results

[TO-DO]: Interpret the Model 2 results in details. Mention the coefficient estimates, their p-values and whatever details you feel appropriate/helpful

Model 2 Results

```
##
## Call:
## lm(formula = Salary ~ Experience + Education + Job * Province +
##       Job * Experience + Province * Experience, data = Wages)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -36.336  -8.406  -0.312   7.699  35.120
##
## Coefficients:
##                                     Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept) -25.3131 7.7259 -3.276 0.00118 **
## Experience 2.4202 0.2275 10.638 < 2e-16 ***
## Education 2.3650 0.3841 6.157 2.39e-09 ***
## JobData Scientist 48.1453 6.2230 7.737 1.58e-13 ***
## JobTeacher 37.3222 6.6140 5.643 3.88e-08 ***
## ProvinceBC 25.6867 6.4012 4.013 7.59e-05 ***
## ProvinceOntario -5.3855 6.1146 -0.881 0.37916
## JobData Scientist:ProvinceBC -45.4000 4.2798 -10.608 < 2e-16 ***
## JobTeacher:ProvinceBC -60.8748 4.3549 -13.979 < 2e-16 ***
## JobData Scientist:ProvinceOntario 22.4922 4.1392 5.434 1.14e-07 ***
## JobTeacher:ProvinceOntario -23.5570 4.6047 -5.116 5.59e-07 ***
## Experience:JobData Scientist -1.3974 0.2515 -5.556 6.11e-08 ***
## Experience:JobTeacher -1.3224 0.2702 -4.893 1.62e-06 ***
## Experience:ProvinceBC 1.6769 0.2669 6.282 1.18e-09 ***
## Experience:ProvinceOntario 1.2601 0.2506 5.029 8.53e-07 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 12.57 on 299 degrees of freedom
## Multiple R-squared: 0.8516, Adjusted R-squared: 0.8446
## F-statistic: 122.5 on 14 and 299 DF, p-value: < 2.2e-16
```

Conclusions

[TO-DO]: Sum up the results – provides insights into how salaries are influenced by these variables, highlights which variables significantly impact salary, and explains the potential interaction effects among these variables.

Appendix

```
#import data

Wages <- read.csv("Wages.csv")

#data cleaning, change categorical variables into factors

Wages$Job <- factor(Wages$Job)
levels(Wages$Job) #three type of jobs: Biologist, Data Scientist, Teacher

Wages$Location <- factor(Wages$Location)
levels(Wages$Location) #two locations: Metro, Rural

Wages$Province <- factor(Wages$Province)
levels(Wages$Province) #three provinces: Alberta, BC, Ontario
head(Wages)

library(dplyr)
library(car)
library(knitr)
```

```

all_num_model <- lm(Salary ~ Salary.5 + FatherEducation + MotherEducation + GPA + Age + Experience + Education, data = Wages)
summary(all_num_model)

vif(all_num_model) #thresholds of 5 -- age, experience

#add interactions (job*province + job*experience + province*experience)
model_8 <- lm(Salary ~ Experience + Education + Job*Province + Job*Experience + Province*Experience, data = Wages)
summary(model_8) #up to 84%, almost everything is significant

#all numeric variables

library(car)

all_num_model <- lm(Salary ~ Salary.5 + FatherEducation + MotherEducation + GPA + Age + Experience + Education, data = Wages)
summary(all_num_model)
vif(all_num_model) #thresholds of 5 -- age, experience

#Age: VIF = 10.24 - This is relatively high, suggesting that Age might be highly correlated with other variables
#Experience: VIF = 10.72 - Similar to Age, this suggests that Experience is highly correlated with other variables

all_num_model_excl_age <- lm(Salary ~ Salary.5 + FatherEducation + MotherEducation + GPA + Experience + Education, data = Wages)
summary(all_num_model_excl_age)
vif(all_num_model_excl_age)

##Multicollinearity: Since Salary.5 is such a strong predictor, it might be causing the lack of statistical significance for other variables

#salary and 5 other numeric variables (excluding Salary.5)
model_1 <- lm(Salary ~ FatherEducation + MotherEducation + GPA + Experience + Education, data = Wages)
summary(model_1) #only 35% explanatory power, momedu, dadedu, gpa aren't significant
vif(model_1) #removing age, because multicorrelation with experience

#experience and education only
model_2 <- lm(Salary ~ Experience + Education, data = Wages)
summary(model_2) #down to 31%
vif(model_2)

#numeric (exp, edu on salary) add job in
model_3 <- lm(Salary ~ Experience + Education + Job, data = Wages)
summary(model_3) #up 46%
vif(model_3)

#numeric (exp, edu on salary) add job and location in -- no change
model_4 <- lm(Salary ~ Experience + Education + Job + relevel(Location, "Metro"), data = Wages)
summary(model_4) #up 46%
vif(model_4)

#numeric (exp, edu on salary) add job in, no location, add province
model_5 <- lm(Salary ~ Experience + Education + Job + Province, data = Wages)
summary(model_5) #up 60%, all significant
vif(model_5)

```

```

#add interactions
model_6<- lm(Salary ~ Experience + Education + Job + Province + Job*Province, data = Wages)
summary(model_6) #up to 80%, almost everything is significant

#add interactions (job*province + job*experience)
model_7 <- lm(Salary ~ Experience + Education + Job + Province + Job*Province + Job*Experience, data = Wages)
summary(model_7) #up to 82%, almost everything is significant

#add interactions (job*province + job*experience + province*experience)
model_8 <- lm(Salary ~ Experience + Education + Job + Province + Job*Province + Job*Experience + Province*Experience, data = Wages)
summary(model_8) #up to 84%, almost everything is significant

```

```

#all numeric variables

library(car)

all_num_model <- lm(Salary ~ Salary.5 + FatherEducation + MotherEducation + GPA + Age + Experience + Education, data = Wages)
summary(all_num_model)

```

```

##
## Call:
## lm(formula = Salary ~ Salary.5 + FatherEducation + MotherEducation + GPA + Age + Experience + Education, data = Wages)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -5.886 -1.529 -0.193  1.230 34.722
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    9.788205   2.844657   3.441  0.00066 ***
## Salary.5        0.992074   0.006335 156.594 < 2e-16 ***
## FatherEducation -0.262894   0.163080  -1.612  0.10798
## MotherEducation  0.272293   0.141860   1.919  0.05586 .
## GPA             -0.076393   0.436517  -0.175  0.86119
## Age              0.061761   0.078806   0.784  0.43382
## Experience      -0.075763   0.078486  -0.965  0.33515
## Education        0.002663   0.087803   0.030  0.97582
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.855 on 306 degrees of freedom
## Multiple R-squared:  0.9922, Adjusted R-squared:  0.992
## F-statistic: 5530 on 7 and 306 DF, p-value: < 2.2e-16

```

```

vif(all_num_model) #thresholds of 5 -- age, experience

```

```

##      Salary.5 FatherEducation MotherEducation      GPA      Age
##      1.585746      4.136541      4.101660      1.007316     10.241068
##      Experience      Education
##      10.718555      1.059702

```

#Age: VIF = 10.24 - This is relatively high, suggesting that Age might be highly correlated with other variables
#Experience: VIF = 10.72 - Similar to Age, this suggests that Experience is highly correlated with other variables

```
all_num_model_excl_age <- lm(Salary ~ Salary.5 + FatherEducation + MotherEducation + GPA + Experience + Education, data = Wages)
summary(all_num_model_excl_age)
```

```
##
## Call:
## lm(formula = Salary ~ Salary.5 + FatherEducation + MotherEducation + GPA + Experience + Education, data = Wages)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -6.102  -1.504  -0.121   1.181  34.717
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   11.1401313   2.2605131    4.928 1.36e-06 ***
## Salary.5       0.9921119   0.0063311  156.703 < 2e-16 ***
## FatherEducation -0.2649528   0.1629565   -1.626  0.1050
## MotherEducation 0.2746646   0.1417381    1.938  0.0536 .
## GPA           -0.0767821   0.4362424   -0.176  0.8604
## Experience     -0.0186643   0.0291681   -0.640  0.5227
## Education       0.0004256   0.0877015    0.005  0.9961
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.853 on 307 degrees of freedom
## Multiple R-squared:  0.9921, Adjusted R-squared:  0.992
## F-statistic: 6460 on 6 and 307 DF, p-value: < 2.2e-16
```

```
vif(all_num_model_excl_age)
```

```
##      Salary.5 FatherEducation MotherEducation      GPA      Experience
##      1.585652      4.135467      4.099793      1.007315      1.482231
##      Education
##      1.058581
```

##Multicollinearity: Since Salary.5 is such a strong predictor, it might be causing the lack of statistical significance for other variables

#salary and 5 other numeric variables (excluding Salary.5)

```
model_1 <- lm(Salary ~ FatherEducation + MotherEducation + GPA + Experience + Education, data = Wages)
summary(model_1) #only 35% explanatory power, momedu, dadedu, gpa aren't significant
```

```
##
## Call:
## lm(formula = Salary ~ FatherEducation + MotherEducation + GPA + Experience + Education, data = Wages)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -46.357  -19.226   -5.267   20.784   89.673
```

```
##
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -60.3988    19.8914  -3.036 0.002599 **
## FatherEducation   2.7195     1.4541   1.870 0.062391 .
## MotherEducation   0.7091     1.2732   0.557 0.577991
## GPA              1.9648     3.9177   0.502 0.616366
## Experience       2.5449     0.2170  11.730 < 2e-16 ***
## Education       2.5811     0.7739   3.335 0.000957 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 25.64 on 308 degrees of freedom
## Multiple R-squared:  0.3636, Adjusted R-squared:  0.3532
## F-statistic: 35.19 on 5 and 308 DF, p-value: < 2.2e-16
```

```
vif(model_1) #removing age, because multicorrelation with experience
```

```
## FatherEducation MotherEducation          GPA      Experience      Education
##           4.078978           4.098224       1.006417       1.015966       1.021254
```

```
#experience and education only
```

```
model_2 <- lm(Salary ~ Experience + Education, data = Wages)
summary(model_2) #down to 31%
```

```
##
## Call:
## lm(formula = Salary ~ Experience + Education, data = Wages)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -47.996 -19.902  -5.492  19.290  89.813
##
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -1.3078    12.4049  -0.105  0.91611
## Experience     2.4980     0.2233  11.186 < 2e-16 ***
## Education     2.4693     0.7945   3.108 0.00206 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 26.46 on 311 degrees of freedom
## Multiple R-squared:  0.3156, Adjusted R-squared:  0.3112
## F-statistic: 71.7 on 2 and 311 DF, p-value: < 2.2e-16
```

```
vif(model_2)
```

```
## Experience Education
##      1.010562    1.010562
```

```
#numeric (exp, edu on salary) add job in
model_3 <- lm(Salary ~ Experience + Education + Job, data = Wages)
summary(model_3) #up 46%
```

```
##
## Call:
## lm(formula = Salary ~ Experience + Education + Job, data = Wages)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -56.596 -15.342  -1.243   13.769   89.123
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)      5.8319    10.9687   0.532 0.595329
## Experience        2.3739     0.1973  12.030 < 2e-16 ***
## Education         2.2979     0.7053   3.258 0.001245 **
## JobData Scientist 10.6608     3.1457   3.389 0.000792 ***
## JobTeacher       -20.5361     3.3370  -6.154 2.34e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 23.32 on 309 degrees of freedom
## Multiple R-squared:  0.4718, Adjusted R-squared:  0.465
## F-statistic:    69 on 4 and 309 DF,  p-value: < 2.2e-16
```

```
vif(model_3)
```

```
##              GVIF Df GVIF^(1/(2*Df))
## Experience 1.015799  1      1.007868
## Education  1.025062  1      1.012453
## Job        1.020830  2      1.005167
```

```
#numeric (exp, edu on salary) add job and location in -- no change
model_4 <- lm(Salary ~ Experience + Education + Job + relevel(Location, "Metro"), data = Wages)
summary(model_4) #up 46%
```

```
##
## Call:
## lm(formula = Salary ~ Experience + Education + Job + relevel(Location,
##      "Metro"), data = Wages)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -57.175 -15.270  -1.348   13.434   89.966
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)      4.9661    11.1092   0.447 0.655173
## Experience        2.3663     0.1981  11.945 < 2e-16 ***
## Education         2.3195     0.7073   3.279 0.001160 **
## JobData Scientist 10.6935     3.1501   3.395 0.000777 ***
```



```
## JobTeacher          -20.4438      3.3457  -6.110    3e-09 ***
## relevel(Location, "Metro")Rural  1.3680      2.6511   0.516  0.606203
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 23.34 on 308 degrees of freedom
## Multiple R-squared:  0.4722, Adjusted R-squared:  0.4637
## F-statistic: 55.12 on 5 and 308 DF,  p-value: < 2.2e-16
```

```
vif(model_4)
```

```
##              GVIF Df GVIF^(1/(2*Df))
## Experience      1.021392  1      1.010640
## Education       1.028633  1      1.014215
## Job             1.023806  2      1.005899
## relevel(Location, "Metro") 1.011738  1      1.005852
```

```
#numeric (exp, edu on salary) add job in, no location, add province
model_5 <- lm(Salary ~ Experience + Education + Job + Province, data = Wages)
summary(model_5) #up 60%, all significant
```

```
##
## Call:
## lm(formula = Salary ~ Experience + Education + Job + Province,
##     data = Wages)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -51.042 -14.069  -2.611   13.605   79.889
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -12.9905     9.7149  -1.337  0.182156
## Experience       2.4108     0.1716  14.050 < 2e-16 ***
## Education       2.3181     0.6133   3.780  0.000188 ***
## JobData Scientist 12.0062     2.7390   4.383  1.61e-05 ***
## JobTeacher     -18.8827     2.9133  -6.482  3.61e-10 ***
## ProvinceBC      26.5397     2.8192   9.414 < 2e-16 ***
## ProvinceOntario 22.6319     2.8383   7.974  3.06e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 20.27 on 307 degrees of freedom
## Multiple R-squared:  0.6035, Adjusted R-squared:  0.5957
## F-statistic: 77.88 on 6 and 307 DF,  p-value: < 2.2e-16
```

```
vif(model_5)
```

```
##              GVIF Df GVIF^(1/(2*Df))
## Experience 1.016636  1      1.008284
## Education  1.025887  1      1.012861
## Job        1.036786  2      1.009072
## Province   1.018069  2      1.004487
```

```
#add interactions
model_6<- lm(Salary ~ Experience + Education + Job + Province + Job*Province, data = Wages)
summary(model_6) #up to 80%, almost everything is significant
```

```
##
## Call:
## lm(formula = Salary ~ Experience + Education + Job + Province +
##      Job * Province, data = Wages)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -40.469  -8.570  -0.399   8.822  57.950
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -26.5247     7.1756  -3.697 0.000259 ***
## Experience         2.4040     0.1207  19.916 < 2e-16 ***
## Education         2.4713     0.4345   5.687 3.04e-08 ***
## JobData Scientist  18.2811     3.4769   5.258 2.76e-07 ***
## JobTeacher         9.2548     3.6192   2.557 0.011041 *
## ProvinceBC        60.2515     3.4564  17.432 < 2e-16 ***
## ProvinceOntario   20.5843     3.4563   5.956 7.18e-09 ***
## JobData Scientist:ProvinceBC -43.9220     4.8297  -9.094 < 2e-16 ***
## JobTeacher:ProvinceBC -60.4098     4.9075 -12.310 < 2e-16 ***
## JobData Scientist:ProvinceOntario 23.3342     4.6790   4.987 1.03e-06 ***
## JobTeacher:ProvinceOntario -22.8935     5.2082  -4.396 1.53e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 14.22 on 303 degrees of freedom
## Multiple R-squared:  0.8073, Adjusted R-squared:  0.8009
## F-statistic: 126.9 on 10 and 303 DF, p-value: < 2.2e-16
```

```
#add interactions (job*province + job*experience)
model_7 <- lm(Salary ~ Experience + Education + Job + Province + Job*Province + Job*Experience, data = Wages)
summary(model_7) #up to 82%, almost everything is significant
```

```
##
## Call:
## lm(formula = Salary ~ Experience + Education + Job + Province +
##      Job * Province + Job * Experience, data = Wages)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -35.079  -8.332   0.111   8.206  45.279
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -46.5380     7.5392  -6.173 2.17e-09 ***
## Experience         3.3473     0.1922  17.417 < 2e-16 ***
## Education         2.4425     0.4113   5.939 7.91e-09 ***
## JobData Scientist  50.5031     6.6488   7.596 3.89e-13 ***
```

```
## JobTeacher          39.4177      7.0485   5.592 5.03e-08 ***
## ProvinceBC          61.2399      3.2748  18.700 < 2e-16 ***
## ProvinceOntario     21.5735      3.2748   6.588 1.99e-10 ***
## JobData Scientist:ProvinceBC -44.3220    4.5726  -9.693 < 2e-16 ***
## JobTeacher:ProvinceBC -62.1183    4.6600 -13.330 < 2e-16 ***
## JobData Scientist:ProvinceOntario 22.7086    4.4298   5.126 5.30e-07 ***
## JobTeacher:ProvinceOntario -23.7159    4.9306  -4.810 2.39e-06 ***
## Experience:JobData Scientist -1.4950    0.2686  -5.566 5.77e-08 ***
## Experience:JobTeacher -1.4018    0.2877  -4.872 1.79e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 13.46 on 301 degrees of freedom
## Multiple R-squared:  0.8286, Adjusted R-squared:  0.8217
## F-statistic: 121.2 on 12 and 301 DF,  p-value: < 2.2e-16
```

```
#add interactions (job*province + job*experience + province*experience)
model_8 <- lm(Salary ~ Experience + Education + Job + Province + Job*Province + Job*Experience + Province*Experience, data = Wages)
summary(model_8) #up to 84%, almost everything is significant
```

```
##
## Call:
## lm(formula = Salary ~ Experience + Education + Job + Province +
##      Job * Province + Job * Experience + Province * Experience,
##      data = Wages)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -36.336  -8.406  -0.312   7.699  35.120
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -25.3131     7.7259  -3.276  0.00118 **
## Experience         2.4202     0.2275  10.638 < 2e-16 ***
## Education         2.3650     0.3841   6.157 2.39e-09 ***
## JobData Scientist  48.1453     6.2230   7.737 1.58e-13 ***
## JobTeacher       37.3222     6.6140   5.643 3.88e-08 ***
## ProvinceBC       25.6867     6.4012   4.013 7.59e-05 ***
## ProvinceOntario  -5.3855     6.1146  -0.881  0.37916
## JobData Scientist:ProvinceBC -45.4000     4.2798 -10.608 < 2e-16 ***
## JobTeacher:ProvinceBC -60.8748     4.3549 -13.979 < 2e-16 ***
## JobData Scientist:ProvinceOntario 22.4922     4.1392   5.434 1.14e-07 ***
## JobTeacher:ProvinceOntario -23.5570     4.6047  -5.116 5.59e-07 ***
## Experience:JobData Scientist -1.3974     0.2515  -5.556 6.11e-08 ***
## Experience:JobTeacher -1.3224     0.2702  -4.893 1.62e-06 ***
## Experience:ProvinceBC  1.6769     0.2669   6.282 1.18e-09 ***
## Experience:ProvinceOntario  1.2601     0.2506   5.029 8.53e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 12.57 on 299 degrees of freedom
## Multiple R-squared:  0.8516, Adjusted R-squared:  0.8446
## F-statistic: 122.5 on 14 and 299 DF,  p-value: < 2.2e-16
```