Predictive Modeling on Hourly Wages

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GitHub Repo: https://github.com/Iandrewburg/Assignment_1

This analysis looks at the CPS-Earnings dataset with the purpose of generating predictive modeling of hourly wages, and determining which variables best predict hourly wages. The dataset was filtered to specifically look at Medical Practitioners, and thus, the occupation codes from 3000 through 3540 were analyzed. Furthermore, the data was cleaned by replacing missing values with “Missing”, but this did not seem to impact the data at all.

The variables that were selected for building the predictive model include: age, gender, children present, marital status, working status, and level of education. Gender and marital status were selected on the premise of possible wage discrimination based on gender, with the justification that if an employer learns you are married, they may want to pay you less because your time will be allocated outside of work to your family. Similarly, how in the United States, pregnant women face discrimination from employers, the number of children an individual has could be associated with wage differences. Furthermore, working status and level of education have a more direct associated with the daily work of the individual, and could be associated with wages stronger. Finally, age tends to have an association with wages, because the older an individual gets, the more experience they accumulate. These are all very important variables for individuals working in the medical profession, as employment and employees are looked at very closely to determine their wages since it is an extremely important industry.

Dummy variables were created for each of the categorical variables, isolating the different levels of each variable. Furthermore, wages underwent a log transformation to display the relative differences. Lowess plots were created to visualize each variable with respect to log wages. These can be found in the index.

Four regression models were created, each incrementally becoming more complex. Each categorical variable has a dummy variable dropped. The following were not included in the regression models for the purpose of creating baseline categories: never married, 0 children, master’s degree, and male. The final model includes interaction variables between age and education level, as age and education level visually seemed to have a more significant alteration association in hourly wages in the lowess plot; however, the regression table shows that when these variables are interacted, they do not have a significant correlation with log wages.

Of the four models, Model 4 has the highest R-Squared (16.1%), lowest BIC (15595.33), and lowest RSME (0.56); this does not mean it is the best model. This is because the difference between the RSME, BIC, and R-Squared in Model 4 and Model 3 is very miniscule. As Model 3 has much larger R-Squared than Models 1 and 2, Model 3 would be the best model to go with as it has less variables than Model 4 and is therefore less complex and easier to interpret.

The K-Fold Cross Validation of the RSME was performed to analyze the performance of the data on a more granulated level for the purpose of machine learning applicability. The results show that Model 3 and 4 have the lowest values. They are very close in value, so Model 3 is the best model here since it has the lower number of variables included in its model.

Prediction models were created for Model 1 and Model 3 for the purpose of comparison. The first prediction table represents the 95% prediction interval (PI) and shows that the predicted log hourly wage value from Model 1 is 3.229 and 3.454 for Model 3. This represents the expected log hourly wages according to each model, and Model 3 shows a higher value since there are more variables included in the model. For Model 1, the low PI suggests that there is a 95% confidence that the log hourly wage will not fall below 2.055, and for Model 3, it will not fall below 2.361. The high PI for Model 1 suggests that the log hourly wage will not exceed 4.403, and for Model 3 will not exceed 4.548. Model 3 continues to give higher values in the prediction modeling.

In the 80% prediction interval table, Model 3 performs similarly as it did in the 95% prediction interval table. Model 3 has consistently larger values than Model 1. Furthermore, the range between the high and low PI of Model 3 is smaller than Model 1, suggesting that Model 3 more accurately predicts log wages.

Overall, with consideration of the correlation coefficients and their significance levels, the best variables for predictive modeling out of Model 3 include: age, gender, marital status, number of children, and level of education. Level of education, and having one child, were found to have the highest correlation coefficient values at the 5% statistical significance threshold. These variables should be analyzed more in depth in future research for predictive modeling of hourly wages.

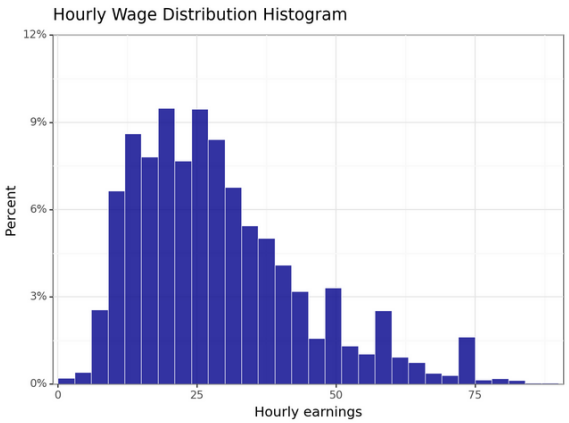
Appendix

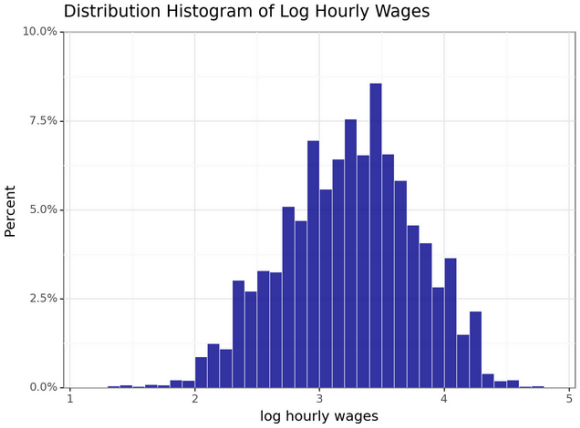
Regression table for log hourly wages

	Dependent variable: log hourly wages			
	(1)	(2)	(3)	(4)
Constant	2.788***	1.932***	1.779***	1.743***
	(0.023)	(0.103)	(0.098)	(0.102)
Age	0.011***	0.056***	0.044***	0.045***
	(0.001)	(0.005)	(0.004)	(0.004)
Age^2		-0.001***	-0.000***	-0.000***
		(0.000)	(0.000)	(0.000)
Age × University				-0.001
				(0.001)
Age × Prof Degree				0.003
				(0.003)
Age × PhD				0.003
				(0.002)
Female		-0.137***	-0.068***	-0.066***
		(0.016)	(0.016)	(0.016)
Working		-0.002	-0.006	-0.006
		(0.044)	(0.043)	(0.043)
Married		0.081***	0.045***	0.044***
		(0.013)	(0.012)	(0.012)
Divorced		-0.000***	-0.000***	0.000***
		(0.000)	(0.000)	(0.000)
Widowed		-0.050	-0.035	-0.034
		(0.050)	(0.048)	(0.048)
1 Child		0.164***	0.116***	0.116***
		(0.026)	(0.025)	(0.025)
2 Children		0.017	0.013	0.012
		(0.031)	(0.028)	(0.028)
3 Children		0.029	0.033*	0.032
		(0.020)	(0.020)	(0.020)
4+ Children		0.035**	0.039**	0.038**
		(0.017)	(0.016)	(0.016)
University			0.389***	0.445***
			(0.014)	(0.048)
Prof Degree			0.233***	0.120
			(0.031)	(0.112)
PhD			0.274***	0.158
			(0.028)	(0.100)
Observations	9208	9208	9208	9208
R^2	0.040	0.076	0.160	0.161
Adjusted R^2	0.040	0.075	0.159	0.159
Residual Std. Error	0.599 (df=9206)	0.588 (df=9197)	0.561 (df=9194)	0.561 (df=9191)

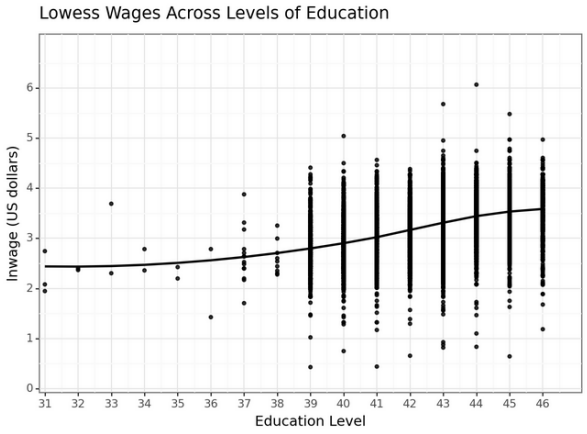
F Statistic	362.512*** (df=1; 9206)	87.954*** (df=10; 9197)	152.317*** (df=13; 9194)	130.950*** (df=16; 9191)
RSME	0.599	0.588	0.56	0.56
BIC	16713.16	16449.69	15595.33	15619.09
Note:				*p<0.1; **p<0.05; ***p<0.01

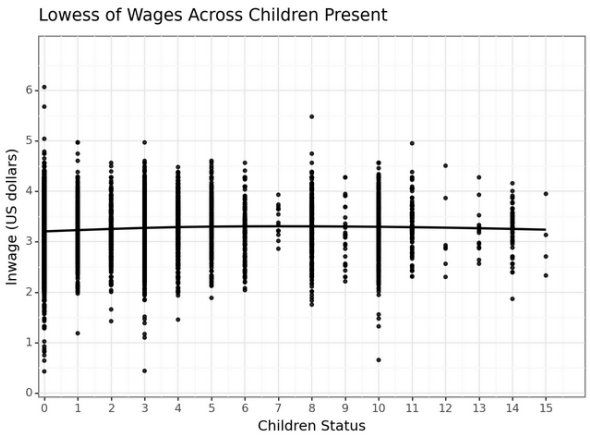
Distribution Histograms

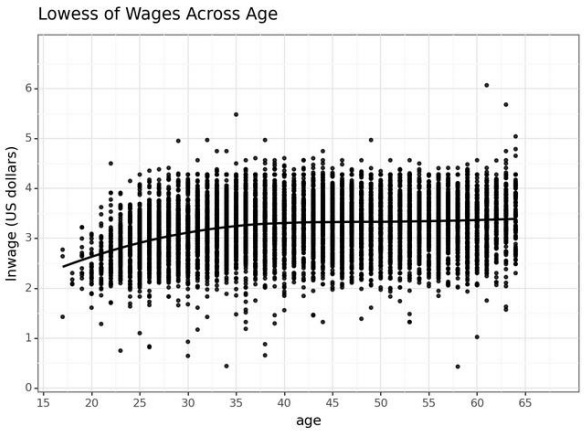




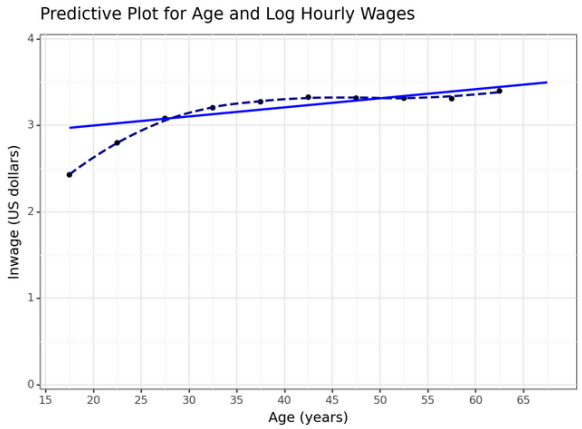
Lowess Plots







Predictive Plot



Prediction Interval Tables

	Model1	Model3
Predicted	3.229	3.454
PI_low(95%)	2.055	2.361
PI_high(95%)	4.403	4.548

	Model1	Model3
Predicted	3.229	3.454
PI_low(80%)	2.461	2.740
PI_high(80%)	3.997	4.169