The Impact of Educational Expenses of New Coders*

The Factors Affecting Education Costs of Beginner Programmers to Learn to Code aside from University Tuition

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1 Introduction

With an increasing interest in computer programming and the growth of coding related jobs, more and more people invest their time and money in taking programming courses (Hughes 2020). In this paper, I examine some of the factors that may affect educational expenses of new coders or entry-level programmers aside from university tuition, mainly focusing on the level of education, the size of city, commuting time, income, and learning time. Approximately 20,000 beginner programmers had participated in the survey (freeCodeCamp 2017).

Firstly, I processed correlation analysis to identify the relationship between each independent variable and dependent variable (education costs) pair and found that all the pairs have a positive linear relationship except for commuting time. Secondly, I used multiple linear regression to determine the statistical significance of the factors. The result of the analysis shows that commuting time is not statistically significant. Interestingly, education background is also not statistically significant associated with educational expenses of beginner programmers. Other variables, such as the size of city, income, and learning time, have a statistical significance on the costs.

This analysis shows that beginner programmers living in small towns and/or low-income households are likely to spend less money on learning to code aside from university tuition than those who live in bigger cities and/or high-income households. It is assumed that there is still a lack of educational resources for new coders living in rural areas and/or low-income households. Free online learning platforms such as freeCodeCamp can be a great resource of education for the coders.

The paper is organized as follows. The Data section describes features of the original survey data and how the data is preprocessed. The Model section explains the multiple linear regression model used to assess the association between each factor and educational costs of beginner programmers, and evaluates the model using its residual standard error, multiple R-squared, and F-statistic. The Results section summarises the results of the regression model and model evaluation processes in the Model section. Lastly, the Discussion section discusses the findings and potential limitations of the paper, and suggests directions for future research related to this data.

2 Data

*https://github.com/bonjwow/new-coders

Table 1: A partial view of the cleaned dataset

Gender	Age	City Population	Commute Time	Income	Months Programming	School Degree	Money For Learning
0	21	2	2	13000	5	0	1000
0	26	1	0	24000	5	1	0
1	29	1	3	40000	12	1	0
1	23	0	0	30000	29	1	700
0	20	0	1	20000	5	2	0
0	18	0	1	10000	3	0	0
0	32	0	3	20000	1	3	0
0	29	1	3	60000	12	3	200
1	46	2	0	76000	14	2	500
0	31	0	3	34000	28	1	500

2.1 Data Collection

The survey was run by `freeCodeCamp`, a non-profit organization that helps people learn to code through their free online courses and build a network for their alumni (Larson 2019). The purpose of the survey was to examine how the users learn to code (Larson 2017). The survey was conducted over the internet, and the survey respondents were limited to those persons with less than 5 years learning programming; all the respondents were asked whether they have already been coding for more than 5 years or not before starting the survey (Larson 2017). The survey is composed of 48 questions and takes about five minutes to complete, and the survey results are under the Open Data Common License, which can be freely distributed through the organization' GitHub repository (Larson 2017).[1]

2.2 Description of Dataset

The original dataset used for this paper is obtained from `freeCodeCamp`'s GitHub page. The format of the dataset is a comma-separated values (CSV) file, which contains 136 columns and 18,175 observations. I selected 8 variables and cleaned the data using the R programming language (R Core Team 2020) and the `tidyverse` package (Wickham et al. 2019) and the `dplyr` package (Wickham et al. 2021). The selected variables are: Age, CityPopulation, CommuteTime, Gender, Income, MoneyForLearning, MonthsProgramming, and SchoolDegree. The CityPopulation is the estimated number of city population of the recipient; the question asked was "About how many people live in your city?", and there are three options to choose: "less than 100,000", "between 100,000 and 1 million", and "more than 1 million". Since these answers were coded as strings, I converted them into numeric variables using the `recode` function of `dplyr` (Wickham et al. 2021). The answers for CommuteTime and SchoolDegree were also coded as strings in the original dataset, so I applied the same data cleaning process to the variables as I did with CityPopulation. Also, I omitted observations which have a missing value. Table 1 is a partial view of the cleaned dataset after the preprocessing.

Table 2 displays descriptive statistics for the cleaned data after the preprocessing. The total number of observations is 7,022 and the data type for all variables are numeric variables. The median age of the respondents is 30 years and the median income of them is about $43,000 in U.S. dollars. The average of the respondents has spent about 2 years and about $1,000 in U.S. dollars learning to code.

[1] https://github.com/freeCodeCamp/2017-new-coder-survey

Table 2: Descriptive statistics for the cleaned dataset

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Gender	7,022	0.174	0.379	0	0	0	1
Age	7,022	29.774	7.684	13	25	33	71
CityPopulation	7,022	1.221	0.777	0	1	2	2
CommuteTime	7,022	2.199	1.451	0	1	3	5
Income	7,022	42,966.890	59,162.290	6,000	17,000	55,000	1,000,000
MonthsProgramming	7,022	23.986	46.496	0	3	26	744
SchoolDegree	7,022	1.676	0.968	0	1	2	4
MoneyForLearning	7,022	1,032.273	4,030.722	0	0	399	170,000

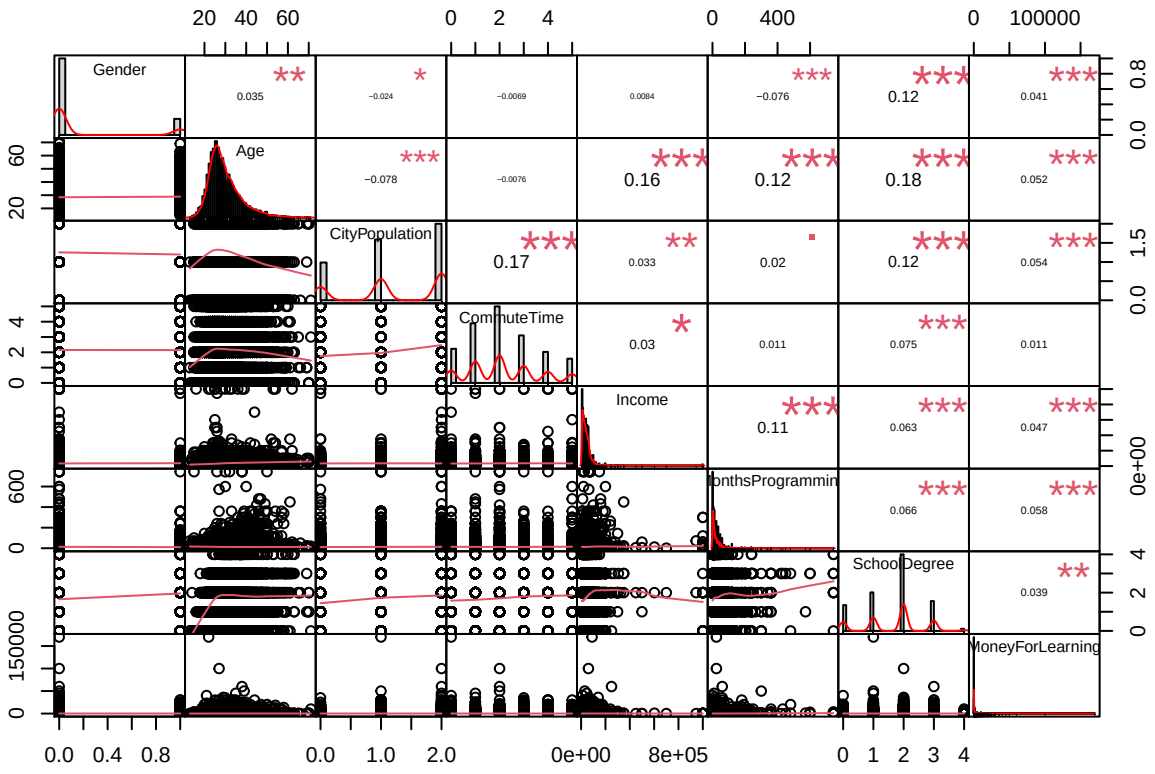
Table 3: Correlation matrix for variables

	1	2	3	4	5	6	7	8
1. Gender	-							
2. Age	0.03**	-						
3. CityPopulation	-0.02*	-0.08***	-					
4. CommuteTime	-0.01	-0.01	0.17***	-				
5. Income	0.01	0.16***	0.03**	0.03*	-			
6. MonthsProgramming	-0.08***	0.12***	0.02	0.01	0.11***	-		
7. SchoolDegree	0.12***	0.18***	0.12***	0.07***	0.06***	0.07***	-	
8. MoneyForLearning	0.04***	0.05***	0.05***	0.01	0.05***	0.06***	0.04**	-

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.3 Correlation Analysis

I ran a correlation matrix to check correlation coefficients between the variables. To create the correlation matrix, I used a custom function written by Stefan Eng (Eng 2018). His function contains the `Hmisc` package's `rcorr` function to calculate the correlations with the p-values and display starts based on the significance level of each cell when the value is lower than a specific level (Harrell Jr, Charles Dupont, and others. 2021). Along with his custom to compute the correlation matrix, I used the `kable` package to print out the result in a table format (Zhu 2020). As can be seen in Table 3, the result of the correlation matrix shows that all independent variables have a positive significant relationship with the dependent variable, MoneyForLearning, except for CommuteTime. This can be interpreted that a commuting time to work does not affect educational expenditure of new coders aside from their post-secondary education cost.



3 Model

3.1 Model formulae

This equation (1) is a model formula for the regression model 1.

$$MoneyForLearning \sim \beta_0 + \beta_1 \times CityPopulation + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \epsilon \tag{1}$$

This equation (2) is a model formula for the regression model 2.

$$MoneyForLearning \sim \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \epsilon \tag{2}$$

This equation (3) is a model formula for the regression model 3.

$$MoneyForLearning \sim \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \epsilon \tag{3}$$

3.2 Model validation with RMSE

Table 4: Result of regression model

	Dependent variable:		
	MoneyForLearning		
	(1)	(2)	(3)
Gender			452.228***
			(127.718)
Age		21.819***	21.376***
		(6.477)	(6.473)
CityPopulation	249.369***	272.157***	279.850***
	(62.105)	(62.427)	(62.414)
Income	0.003***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)
MonthsProgramming	4.469***	4.107***	4.427***
	(1.038)	(1.043)	(1.046)
SchoolDegree	114.783**	83.969*	62.563
	(50.043)	(50.835)	(51.152)
Constant	317.123***	−283.293	−328.825
	(120.613)	(215.155)	(215.362)
Observations	7,022	7,022	7,022
R^2	0.008	0.010	0.012
Adjusted R^2	0.008	0.009	0.011
Residual Std. Error	4,014.821 (df = 7017)	4,011.863 (df = 7016)	4,008.569 (df = 7015)
F Statistic	14.932*** (df = 4; 7017)	14.233*** (df = 5; 7016)	13.970*** (df = 6; 7015)
Note:			*p<0.1; **p<0.05; ***p<0.01

```r
#### RMSE with custom function ####
# Source: https://stackoverflow.com/questions/26237688/rmse-root-mean-square-deviation-calculation-in-r

RMSE <- function(error) {
  sqrt(mean(error^2))
}

RMSE(multiReg1$residuals)
```

```
## [1] 4013.391
```

```r
RMSE(multiReg2$residuals)
```

```
## [1] 4010.149
```

```r
RMSE(multiReg3$residuals)
```

```
## [1] 4006.57
```

```r
# Model3 has the lowest RMSE among the 3 models => Model3 is the best!
```

```r
#### Beta ####
QuantPsyc::lm.beta(multiReg3)
```

```
##            Gender               Age    CityPopulation            Income
##        0.04249842        0.04074859        0.05396766        0.03187444
## MonthsProgramming      SchoolDegree
##        0.05107189        0.01502007
```

```r
#### Check multicollinearity with Variance Inflation Factor (VIF) & Tolerance ####

### VIF
car::vif(multiReg3)
```

```
##            Gender               Age    CityPopulation            Income
##          1.022638          1.080713          1.028395          1.035771
## MonthsProgramming      SchoolDegree
##          1.033779          1.070588
```

```r
### Tolerance
1/car::vif(multiReg3)
```

```
##            Gender               Age    CityPopulation            Income
##         0.9778634         0.9253147         0.9723886         0.9654647
## MonthsProgramming      SchoolDegree
##         0.9673249         0.9340664
```

4 Results

5 Discussion

Appendix

References

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