Estimating Armenian household poverty with Econometric and Machine Learning techniques

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Հայ տնային տնտեսությունների աղքատության գնահատում էկոնոմետրիկ և մեքենայական ուսուցման մեթոդների միջոցով

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Ամփոփում. Հոդվածի նպատակն է օգտագործել էկոնոմետրիկ վերլուծությունը և մեքենայական ուսուցման մոդելավորումը `բացատրելու համար Հայաստանի տնային տնտեսության աղքատության բազմաչափ բնույթը: Բազմանդամ լոգիստիկ ռեգրեսիայի արդյունքները ցույց են տալիս, որ կան աղքատության վրա ազդող դրամավարկային և սոցիալ-տնտեսական փոփոխականներ: Դրամի, սննդի և ոչ պարենային ապրանքների հետ կապված գնումները, տնային տնտեսության անդամները, բնակավայրը, որն ընդգրկում է Երևանը, քաղաքային և գյուղական այլ քաղաքներ, դրսից ստացված եկամուտները, տնային տնտեսության ղեկավարի կրթական մակարդակը և մի քանի այլ փոփոխականներ էականորեն ազդում են աղքատության կարգավիճակի վրա: Ուղղակի փոփոխական ազդեցությունը չափելուց հետո կառուցվում է նեյրոնային ցանց: Թե՛ լոգիստիկ ռեգրեսիան, և թե՛ նեյրոնային ցանցի մոդելները կառուցվում են միևնույն ուսումնական տվյալների վրա, և հետագայում գնահատվում են նույն փորձարկման տվյալների վրա ` պարզելու համար, թե որքանով են նրանք կատարում աղքատ և շատ աղքատ տնային տնտեսությունների դասակարգման առաջադրանքը: Սկզբնական տվյալներից, երկու տոկոսից պակաս մասը բաժին է ընկնում շատ աղքատ դասակարգին, ուստի այս դասի ճիշտ արդյունքները առավել առաջնային են: Նեյրոնային ցանցի մոդելը ավելի լավ արդյունքներ է տալիս ` թեստավորման տվյալներից աղքատ և շատ աղքատ տնային տնտեսությունները ճիշտ դասակարգելու առումով, չնայած որ կա մեկնաբանելիության զգալի փոխզիջում: Մենք ընտրում ենք F1 հաշիվը `որպես մեր դասակարգման հիմնական չափանիշ:
Վճռորոշ բառեր` տնային տնտեսությունների աղքատություն, բազմանդամ լոգիստիկ ռեգրեսիա, նեյրոնային ցանցեր

Оценка бедности Армянских домохозяйств с помощью эконометрических методов и машинного обучения

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Аннотация. В статье используется сочетание эконометрического анализа и моделирования машинного обучения для объяснения многомерной природы бедности армянских домохозяйств. Результаты полиномиальной логистической регрессии показывают, что существуют денежные и социально-экономические переменные, влияющие на бедность. Покупки продуктов питания и непродовольственных товаров в драмах, члены домохозяйства, поселение, которое включает Ереван, другие городские и сельские города, доход, полученный из-за границы, уровень образования главы домохозяйства и некоторые другие переменные имеют значительное влияние о статусе бедности. После измерения прямого переменного воздействия строится нейронная сеть. И логистическая регрессия, и нейросетевые модели подходят для одних и тех же обучающих данных, а затем оцениваются на одних и тех же данных тестирования, чтобы выяснить, насколько хорошо они выполняют задачу классификации бедных и очень бедных домохозяйств. Из исходных данных менее двух процентов наблюдений попадают в категорию очень плохих, поэтому правильные результаты для этого класса имеют наибольший приоритет. Модель нейронной сети обеспечивает лучшие результаты с точки зрения правильной классификации бедных и очень бедных домохозяйств на основе данных тестирования, хотя существует значительный компромисс интерпретируемости. Мы выбираем оценку F1 в качестве основного показателя классификации.
Ключевые слова: бедность домохозяйств, полиномиальная логистическая регрессия, нейронные сети.

Introduction

In the recent literature relating to socio-economic issues, poverty reduction has been a key policy debate. The elaboration of policies for poverty relief requires a thorough knowledge of this phenomenon. In 2016, the poverty rate in Armenia was 29.4% compared to the 27.6% recorded in 2008 and the share of extremely poor was 1.8% compared to 1.6% recorded in 2008. Armenia's administrative division consists of 10 marzes (regions) and the capital of Yerevan. The results of 2016 show that the poverty indicators in Shirak, Lori, Kotayk, Tavush, and Armavir provinces are higher than the country average, and the highest poverty rate is in Shirak Region, where 46% of the population is below the poverty line ('Poverty Profile'). According to the same report, however, 62.4% of the poor in Armenia are urban residents. We find it important to estimate the factors affecting the poverty status in Armenia using linear and non-linear models. The estimation of the models is based on the Armenian household survey data from 2015-2017. The data is divided into training and testing sets. The former is used for model construction and the latter for model evaluation. The methodology starts with the multiclass logistic regression analysis, fit on the training data, and includes coefficient interpretation for the significant variables from the perspective of econometrics. The obtained model is used to fit the testing data and the classifications metrics such as Recall, Precision, F1 score, along confusion matrix results are presented. The same training and testing data are used for building the neural network model, which is later compared to the logistic regression model. The use of machine learning methodology in combination with econometric interpretation will be a contribution to the existing literature.

Literature Review

Poverty is a mixture of economic and social aspects (Patlagean,1977, as cited in Jmaii, 2016) which must be studied simultaneously to find the most efficient reduction policy. Poverty is determined by multiple factors operating at micro (household) as well as macro (national) levels (Rahman, 2013). According to the existing literature, we can distinguish two main forms of poverty. The first form is monetary poverty, which results from a lack of resources and leads to insufficient consumption. This approach is related to the economy of welfare since the monetary indicators define poverty according to an income deficiency or a low consumption which reflects a low standard of living (Townsend,1985, as cited in Jmaii, 2016). It is a widely used concept of classifying individuals according to their monetary resources and is usually referred to as a unidimensional index. The poor are those individuals or households whose income or consumption is below a given threshold (Ravallion,1998). This threshold is then defined by measuring the consumption of a basket of goods and services which allows to achieve a minimum standard of living. The second concept of poverty mostly referred to as poverty of living conditions initiated by Townsend (1979) is determined through a multidimensional index. This index is usually constructed by getting information not only about consumption but also from non-monetary factors such as education or working conditions about a family by household surveys. The aim is to get an overall view of the living conditions to better capture the phenomena of poverty. This approach corresponds to the logic of Sen (1985) with his concept on individual capacities, and it supports the idea that poverty reflects a lack of basic functional capabilities.

Sikander's and Ahmed's (2008) study on Pakistan finds a high dependency of the size of the household having a positive impact on the household's probability of being poor. It has been demonstrated that the household size and the dependency ratio have a significant positive correlation with the household's probability of being poor while the educational level of the households, age of the household head, and landholding negatively affect the probability of being poor (Rahman, 2013). In their studies, Bógale and Korf (2009) find that an increase in household size by one adult equivalently increases the probability of being extremely poor and moderately poor by 3.13 and 5.16 percent respectively and it lowers the likelihood that a household will fall under the category of slightly poor and slightly non-poor by 0.49 and 7.79 percent, respectively. Rahman (2013) demonstrates that households headed by younger persons are less likely to be poor than households headed by older persons. Female-headed households are more likely to live in poverty than male-headed households and larger households are more likely to live in poverty. (Alkire et al., 2015) have demonstrated that an increase of one year of education decreases the odds of being poor by 49%, ceteris paribus, whereas having a female household head increases the odds of being poor by 28%, ceteris paribus. Similarly, the odds of a household being poor decrease by 57% for households living in urban areas, ceteris paribus, and increase by 10% for each additional household member. Increasing household size by one unit increases the probability of falling into chronic poverty by 3 percent while the probability of never being poor decreases by 2 percent. Living in a rural area increases the probability of being chronically poor by 3 percent and if the head of the household is a woman the probability of the household being chronically poor increases while the probability of never being poor decreases.

Background information and Data Description

The data is comprised of 18144 observations of Armenian Household Survey Data from the years 2015 to 2017. The initial dataset includes 60 variables. The important independent variables after collinearity check (De Veaux & Ungar) and significance check for both logistic regression models are identified and the descriptive statistics for these variables in the training data is presented.

The variables are:

- Non-food purchased of household per month in dram
- Non-monetary income of household per month in dram
- Food in small amount of household per month in dram
- Food purchases of household per month in dram
- Present members of the household
- Income from abroad- money received from relatives, living out of Armenia
- Income from savings
- Educational level of the head of the household: no primary, illiterate, no primary literate, primary, general, secondary, preliminary vocational, middle vocational, higher, postgraduate
- Settlement- Yerevan, Other Urban, Rural

The correlation matrix shows that no high correlation is present in the dataset between the variables. The highest correlation is between the present members of the household and food purchased in small amounts per month and it is 59.5%. The next highest correlation is between present members of the household and the food purchases variable. However, as they do not exceed the 70% threshold, these variables are included in the model building. The dependent variable is Poverty. 71% of the observations belong to the Non-Poor category, around 27.1% to the Poor category, and around 1.72% to the Very-Poor category. The results are provided in the table. For the neural network model, alongside the variables presented above, five other variables are also included. The observations for the network are normalized using the Min-Max scaling method. The data is divided into training and testing sets, which we use for model building and validation. 75% of the observations are used for training the models, 25% for testing the models.

Models and Methodology

To study the relationship between the multiclass dependent categorical variable and the independent variables, we construct logistic regression and neural network models. The goal is to explain the variables with their unit impact using logistic regression then find out the most optimal model in terms of the classification metrics using both logistic regression and a neural network. We will start the analysis with a multinomial logistic regression. For this analysis, we do not assume the independent variables are normally distributed and homoscedasticity is also not required. The independent variables linearly predict a logit transformation of the dependent variable while the equation in terms of probabilities is nonlinear. We will present the results in the logit form for interpretability. Probability (P) varies from 0 to 1, while the range of logit is from minus to plus infinity (‘Logistic Regression’). Multinomial logistic regression, in other terms referred to as Softmax Regression, is used when the target variable has multiple classes. It gives the probability that the response variable takes on each of the possible classes.

$$Pr\left(Y^i = K \middle| x^i; \beta\right) = \frac{exp\left(\beta^{(k)T} x^{(i)}\right)}{\sum_{j=1}^{K} \exp\left(\beta^{(j)T} x^{(i)}\right)}$$

where K is the distinct number of possible target variable outcomes and K-1 is the number of independent binary logistic regression models built. The model provided in the table is a regularized multinomial logistic regression model presented in the logit form, fit with an L1 regularization and with a 0.1 alpha term, which is the weight for the L1 penalty. As our dependent variable has three categories, Poor, Non-Poor, and Very-Poor, there will be two regression equations built (‘Logistic Regression’). Non-Poor is the base class, and the results are presented in two linear models.

$$\ln\left(\frac{P_{(Poor)}}{P_{(Non\ Poor)}}\right) = \beta_{0Poor} + \beta_{Poor1}X_{1,i} + \beta_{2Poor}X_{2,i} + \cdots + \beta_{mPoor}X_{m,i}$$

$$\ln\left(\frac{p_{(Very\ Poor)}}{p_{(Non\ Poor)}}\right) = \beta_{0Very\ Poor} + \beta_{1Very\ Poor}X_{1,i} + \beta_{2\ VeryPoor}X_{2,i} + \cdots + \beta_{m\ Very\ Poor}X_{m,i}$$

Table 1: *Logistic Regression Model*

Model: MNLogit Method: MLE Observations: 13608			Log-Likelihood: -3692.5 Pseudo R^2: 0.5354 LLR p-value: 0.000		
	Logit Coef.	**Std. Err.**	**Z**	**P> |z|**	**Odds Ratio Coef.**
const	0.1146	0.147	0.779	0.436	1.121453
Non-Food Purchases	-9.516e-05	2.8e-06	-33.983	0.000***	0.999905
Non-Monetary Income	-6.674e-05	2.85e-06	-23.455	0.000***	0.999933
Food in Small Amount Per Month	-0.0001	3.34e-05	-4.364	0.000***	0.999854
Food Purchases	-3.013e-05	1.9e-06	-15.856	0.000***	0.999970
Present members of Household	1.7594	0.045	39.018	0.000***	5.809121
Income received from abroad	-3.59e-06	7.77e-07	-4.618	0.000***	0.999996
Income from savings	1.622e-05	2.88e-06	-5.677	0.000***	0.999984
Education Level of HH Head	-0.0864	0.021	-4.161	0.000***	0.917265
Settlement	-0.4286	0.045	-9.489	0.000***	0.651443
Poverty= Very-Poor **Variable**	**Logit Coef.**	**Std. Err.**	**Z**	**P> |z|**	**Odds Ratio Coef.**
const	-0.0897	0.396	-0.226	0.821	0.914166
Non-Food Purchases	-0.0002	7.8e-06	-23.851	0.000***	0.999814
Non-Monetary Income	-0.0001	9.06e-06	-14.552	0.000***	0.999868
Food in Small Amount Per Month	-0.0006	0.000	-5.494	0.000***	0.999420
Food Purchases	-7.147e-05	5.48e-06	-13.050	0.000***	0.999929
Present members of Household	2.6771	0.081	33.051	0.000***	14.542962
Income received from abroad	-6.47e-06	3.24e-06	-1.996	0.046**	0.999994
Income from savings	-3.004e-	9.49e-06	-3.165	0.002***	0.999970
Education Level of HH Head	-0.3339	0.066	-5.032	0.000***	0.716154
Settlement	-0.2952	0.144	-2.047	0.041**	0.744351

For explaining each variable coefficient, we need to consider the ceteris paribus effect. The results show that if we increase non-food purchases of households by 1 unit, which is 1 dram, the odds of being poor will change by 0.999905, or go down by 0.0095% and the odds of very poor will change by 0.999814 or decrease by 0.0186%, ceteris paribus. The impact of the variables is quite small because the unit is represented in one Armenian dram. Instead, we can consider the Δchange in variables to be 1000 drams. Increasing the non-monetary income of the household by 1000 drams will decrease the odds of being poor by 6.7% and the odds of being very poor by 13.2%. This means a person will be less likely to be poor by 6.7% and 13.2% less likely to be very poor. The same logic applies to the rest of the variables. If we increase the food purchased in small amounts of the household by 1000 drams, the odds of being poor will decrease by 14.6% and the odds of being very poor will decrease by 58%. If we increase the food purchased per household per month in 1000 drams, the odds of being poor go down by 3%, and the odds of being very poor go down by 7.1%. It is visible that the variables which are related to money and purchasing have a bigger impact on the very poor category. Income received from relatives living outside of Armenia has the following interpretation. Increasing income received from abroad by 1000 drams, decreases the odds of being poor by 0.4% and the odds of being very poor by 0.6%. The variable which overall has the biggest impact is the number of present members in the family. Increasing the present number of household members by 1 person increases the odds of being poor by 5.81 or by 481% and the odds of being very poor by 14.54 or by 1354%. The model also suggests that if income from savings goes up, a person is less likely to be poor by 1.6% and likely to be very poor by 3% less. Finally, if the education of the head of the family increases by one level, the odds of being poor decrease by 8.27%, and the odds of being very poor decreases by 28.38%. The model also says that the chance of a person who lives in an urban area rather than Yerevan is less likely to be poor by 34.86% and very poor by 25.56% and a person who lives in a rural area is less likely to be poor by 69.72% and very poor by 51.12%. Although most of the results provided by logistic regression are intuitive, in certain cases, such as for settlement, we see that according to the model, people living in Yerevan are more likely to be poor. A possible explanation is that the variable distribution is more complex, which we are not able to capture with a linear model.

Table 2: *Logistic Regression Classification Metrics Report*

	Classification Report				**Confusion Matrix**		
					Predicted Class		
	Precision	Recall	F1	Support	Non-Poor	Poor	Very-Poor
Non-Poor	0.91	0.95	0.93	3524	0.95 (3361)	0.046(163)	0 (0)
Poor	0.75	0.65	0.7	958	0.35 (333)	0.65(622)	0.0031(3)
Very-Poor	0.75	0.17	0.27	54	0 (0)	0.83 (45)	0.17 (9)
AVG Accuracy/Total	0.88	0.89	0.88	4536			

Table 3: *Neural Networks Classification Metrics Report*

	Classification Report				**Confusion Matrix**		
					Predicted Class		
	Precision	Recall	F1	Support	Non-Poor	Poor	Very-Poor
Non-Poor	0.93	0.95	0.94	3524	0.95(3336)	0.053 (187)	0.00028 (1)
Poor	0.77	0.69	0.73	958	0.27 (259)	0.69 (661)	0.04 (38)
Very-Poor	0.49	0.70	0.58	54	0 (0)	0.3 (16)	0.7 (38)
AVG Accuracy/Total	0.89	0.89	0.89	4536			

The classification report of the model enables us to assess the overall goodness of fit and the predictive power of the model and will be a common base for comparing the Logistic Regression, and the Neural Network models. The confusion matrix allows us to see how many observations from each category have been correctly classified and misclassified using different metrics. F1 score is defined as the harmonic mean between precision and recall. We see that 17% of the households that belonged to the Very-Poor category have been classified as Very-Poor by our model. 65% of the households which belonged to the Poor category have been classified as Poor and 95% of the households which belonged to the Non-Poor category have been classified as Non-Poor. We see that the model is highly accurate on the Non-Poor observations and below 20% accurate for the Very-Poor category. This happens because out of 4536 testing observations, only 54 belong to the Very-Poor class, making the task of the model to correctly classify difficult. From the Precision results, we also see that for the Very-Poor category, from all existing observations classified as Very-Poor, 75% were Very-Poor, out of all observations classified as Poor, 75% were Poor, and similarly, 91% classified as Non-Poor were Non-Poor. After fitting the logistic regression model and obtaining the classification results, we move on to build a neural network model, with four layers; one input, two hidden, and 1 output layer. The trained neural network, which is comprised of neurons at each layer, has 14 input variables, five more than our logistic regression model. A neuron is a unit that takes the inputs and gives an output by a certain function. The function that does the following mapping is called an activation function ('Multi-Layer Neural Network').

$$h_{W,b} = f(W^T x) = f(\sum_{i=1}^{n} W_i X_i + b)$$

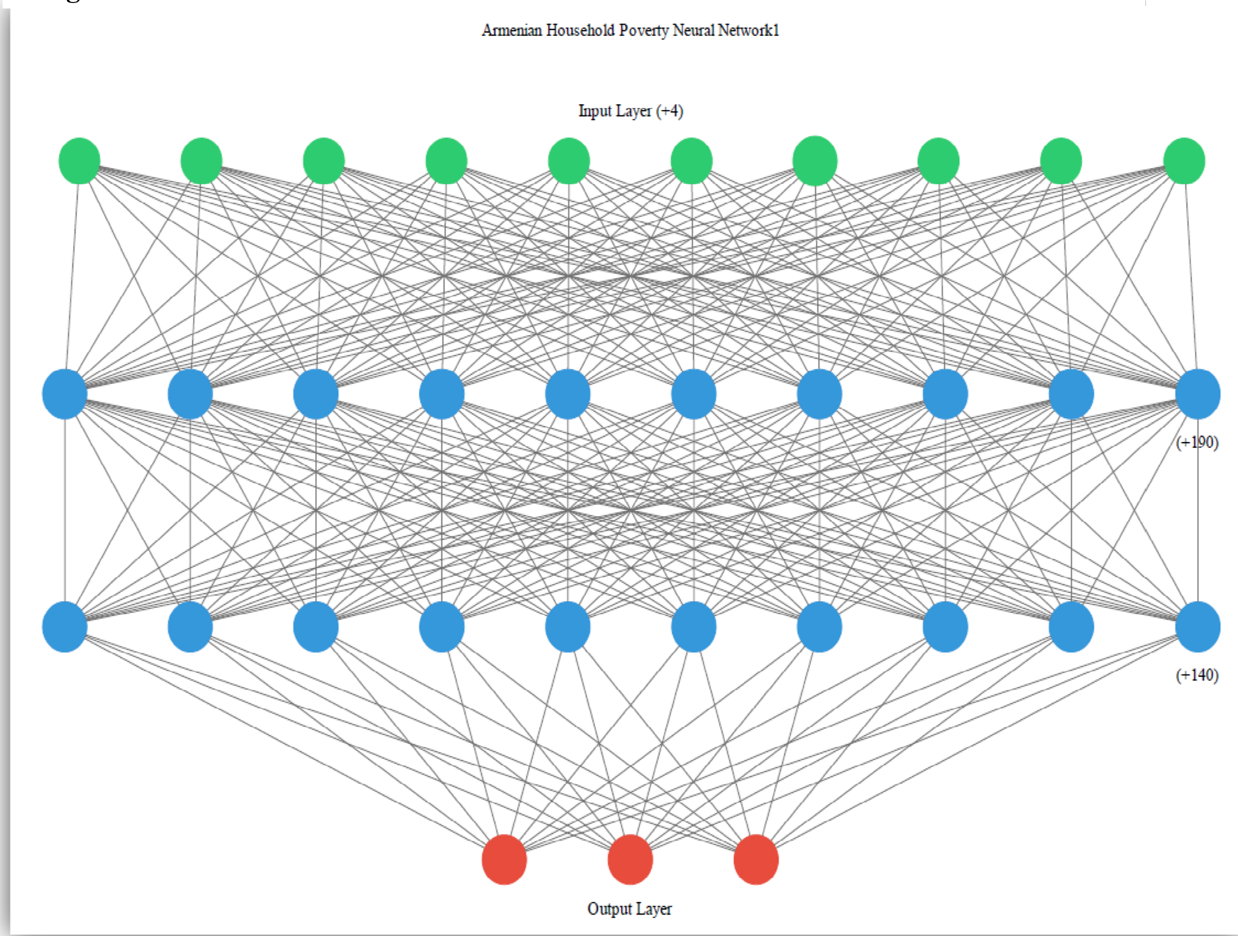
The first hidden layer of the network contains 200 neurons, the second one 150 neurons, and rectified linear activation function (Relu) is used for these layers. Relu is given by:

$$f(z) = \max(0, z)$$

where z is the weighted sum of inputs including the bias term. Softmax activation, introduced for logistic regression, is used as the activation function for the output layer. The model is minimizing a sparse categorical cross-entropy loss function, the same loss function used for logistic regression, with 50 epochs and 100 batch size. The graph of the fitted neural network is presented in Figure 1.

For the Neural Networks model, the Recall results are the following. Given that a person belongs to a Very-Poor category, the model correctly classified 70% of them as Very-Poor, for the Poor category the percentage of correctly classified observations was 69% and for the Non-Poor category, 95% of the observations who were Non-Poor were correctly classified as Non-Poor. These results can also be found from the top to bottom diagonal results of the confusion matrix. The Precision (specificity) shows that out of all observations that were classified as Very-Poor 49% belonged to the Very-Poor category, out of all observations classified as Poor 77% were Poor, and from all Non-Poor classified observations 93% were Non-Poor.

Figure 1 : Visualized Neural Network



In terms of classifying the Very-Poor category, the Neural Network model is highly outperforming the Logistic Regression classifier. To compare the overall predictive power of the models, we can look at the F1 score which incorporates both Recall and Precision. The neural network model has the highest measures for all three categories and thus outperforms Logistic Regression. The score for the Very-Poor category is of the highest interest.

Discussion

The findings presented in the paper can be valuable in terms of policy development. We saw that besides the monetary and income variables, settlement, number of household members and head of the education turned out to be very significant. The educational level of the household head had the biggest role in reducing household poverty, so the governments of Armenia should initiate policies or legislative changes to make education more accessible. The results demonstrate that larger households have a higher chance of being poor. A policy solution could be to start educational trainings to inform families about the advantages of keeping the households small to avoid poverty risks. We believe doing the analysis on a dataset including pre-2015 observations would provide more insight, so this can be a future task to impellent. In terms of models, there is a tradeoff. Logistic regression provides results that can be intuitively interpreted, allowing to measure the direct impact of the variable on poverty, however, is not very accurate during the prediction phase, while the neural network does a better job of correctly classifying a household as poor or very poor, and for the Very-Poor category, it does it with much higher accuracy. If one is not much interested in model interpretation rather in a model providing the most accurate results in terms of categories, the neural networks may be a much better choice.

Conclusion

This paper, using 2015-2017 household data, aimed to find out the factors contributing towards the multidimensional poverty in Armenia and compare the predictive powers of logistic regression, and neural networks using classification metrics. The results from logistic regression show that poverty status depends on both monetary and non-monetary factors. Increasing non-food related purchases, food-related purchases, the non-monetary income of households per month in dram and income from savings decreases the odds of being poor and very poor. The settlement variable is quite significant. Though a little surprising, the results show that outside of Yerevan a person has less chance of being poor or very poor. Income received from relatives living outside of Armenia though small but has an impact on the poverty status. Increasing income received from abroad by 1000 drams, decreases the odds of being poor by 0.4% and the odds of being very poor by 0.6%. Increasing the present number of household members by 1 person significantly increases the odds of being poor and very poor. If the education of the head of the family increases by one level, the odds of being poor decrease by 8.27%, and the odds of being very poor decrease by 28.38%. We are mostly interested in the models' predictive ability on the Poor and Very-Poor categories. By looking at the F1 scores for the Poor and Very-Poor categories, which is a balanced measure between precision and recall, we see that the neural network model provides the best results. Logistic Regression provides a lower F1 score for the Very-Poor category (0.27) compared to Neural Network's (0.58) scores for the same category. We should also note that despite the significant difference in the predictive power, the neural network model contained more variables during the model training, which may partially be responsible for the difference in the final accuracy.

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