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Measuring Multi-dimensional Vulnerability to Poverty: A Study Through Construction of Index and Decomposition of Influences with the Help of Fuzzy Logic and Artificial Intelligence

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The traditional multi-dimensional measures have failed to properly estimate the vulnerability of households towards poverty. The reasons behind this inability are the failure of the existing measures to recognise the graduality inside the concept of poverty and the ex-post consideration of the idea of poverty. So this work wants to develop a measure to estimate the vulnerability in an ex-ante multidimensional perspective with the help of fuzzy logic and artificial intelligence. To estimate and to decompose the vulnerability an integrated mathematical framework is developed. The constructed index is tested and the dimensional influences are compared under different socio-economic clusters.

Like the previous works this work has also described vulnerability on the basis of poverty and risk. But the current work differs on the grounds of determination of thresholds and quantification of risk. The idea of poverty suffers from vagueness and naturally cannot be defined through a well defined cut-off. The graduality within a vague concept can best be represented through fuzzy logic. So here the membership function has been used to forecast the extent of risk. On the other hand, decomposition of this index is executed through Shapley Value Decomposition with the help of Machine Learning. SHapley Additive exPlanation (SHAP) executes this through Local Interpretable Machine-agnostic Explanation (LIME) algorithms. Finally, the constructed index is tested over a sample of 320 households. To construct the index the indicators as accepted by the 2018 Global Multidimensional Poverty Index have been used. Further the sample is clustered through machine learning to understand the influence of different dimensions under different socio-economic perspectives. Thus the specific objectives of this study are:

- Estimating the vulnerability to become poor multi-dimentionaly in ex-ante perspectives through fuzzy logic.
- Development of machine learning process to examine the dimensional influences.
- Understanding the influences of dimensions on vulnerability of different socio-economic clusters.

Let there are i households where i=1,2,.n and j dimensions where j=1,2,…k. The performance of n households in k dimensions can be expressed through n×k real valued non-negative matrix. Here each row vector $y_i = \{y_{ij}\}$ interprets the performance of ith household. The grade of membership to the poor set of the ith household in jth dimension is expressed through the membership function μ_p(ij). A household is definitely poor if his performance in dimension j is from 0 upto y'_j. On the other hand if achievement is above y''_j then the individual is not poor on dimension j. For achievement between y'_j and y''_j the membership function thakes on values in [0,1]. More clearly it can be interpreted that if

- μ_p(ij) = 0 if the ith household is certainly not poor in the jth dimension.
- μ_p(ij) = 1 if the ith household completely belongs to the poor set corresponding to jth dimension.
- 0 < μ_p(ij) < 1 if the ith household shows a partial membership to the poor set p of jth dimension.

The grade of membership of the ith household to the multi-dimensional poor set can be defined as

$$\mu_M(i) = \frac{\sum_{j=1}^{k} \mu_p(ij)}{k}$$

Then social vulnerability is

$$\lambda = \frac{\sum_{ji=1}^{n} \mu_M(i)}{n}$$

When the desired value of λ is 0, the difference between desired and observed vulnerability is λ. To decompose λ Shapley value decomposition has been used. Thus the total no of combinations without the jth dimension is –

$$^{(K-1)}C_1 + {}^{(K-1)}C_2 + {}^{(K-1)}C_3 + {}^{(K-1)}C_4 + \ldots + {}^{(K-1)}C_{K-1}$$

$$= \sum_{\square=1}^{K-1} (k-1)_{C_\square}$$

$$= \theta$$

If j^{th} dimension is added to each of θ combinations we would get θ marginal contributions of j. Let, the marginal contribution of j^{th} dimension from s^{th} combination is φ_s. Then the set of marginal contributions of the j^{th} dimension is-

$$H_j = (\varphi_1{}^j, \varphi_2{}^j, \ldots, \varphi_\theta^j)$$

Then average of marginal contribution of the jth dimension is

$$CON_{\mathrm{j}} = \frac{1}{\theta}\sum_{s=1}^{\theta}\varphi_{\mathrm{s}}{}^{\mathrm{j}}$$

The polinomial form of sth combination under the jth dimension can be chosen from the set of ψ alternative polinomials ψ^{sj}. Learning from the successive errors within ψ^{sj} the machine learning process chooses that polinomial from ψ^{sj} which minimises the error. In this way θ^{j} functional forms are determined. From these θ functions θ^{j} incremental influences are estimated.

This estimation of dimensional contributions is executed through Local Interpretable Machine-agnostic Explanation (LIME) algorithms. LIME deliberately perturbs a combination by accepting input variables from the neighbourhood and counts the effect of that perturbation on the output. Finally the relevance of the particular input is determined through the average of deviation in the output due to the perturbations. Technically here LIME initiates the process to locate

$$\min E_{\pi_{sj}} = \min[\mathrm{g}(F_u) - \mathrm{f}(F_v)]_{\pi_{sj}} \rightarrow F_{sj}^{*} \rightarrow \varphi_{s}^{j}$$

where u≠ v and u,v=1,2…..ψ. π_s is the neighbourhood of sth functional form under jth dimension. g(F_u) is the expected value and f(F_v) is the observed value of the multi-dimensional poverty from a particular polinomial related to π_{sj}. F_{sj}^{*} is the chosen polynomial from ψ^{sj}. This process is used for all the combinations under θ^{j} to find θ^{j} incremental influences. Finally the average of the θ^{j} incremental incluences determines

$$CON_{\mathrm{j}} = \frac{1}{\theta}\sum_{s=1}^{\theta}\varphi_{\mathrm{s}}{}^{\mathrm{j}}$$

The application of the constructed index on our dataset finds that rural dwellers, female headed households, senior citizens, indigenous people, religious minorities and academically backward households are more vulnerable to multidimensional poverty in comparison to their counterparts. Decomposition of the index finds that the dimensional influences varied significantly under different socio-economic groups. The relative influence of health on vulnerability has been found to be highest in comparison to other dimensions for the female headed households, senior citizens and indigenous communities. The relative influence of education on vulnerability is highest within the set of dimensions for the religious minorities and the academically backward households. Interestingly it is also observed that the relative influence of health on the composite vulnerability also very high for the academically backwards. The relative influence of standard of living on composite vulnerability has been found to be highest for the rural dwellers.