Using Artificial Neural Networks to Visualize Poverty

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Abstract

From 69,130 households that were covered by a comprehensive community-based monitoring survey conducted in one of the cities that comprise Metro-Manila, in the Philippines, a neural network technique is used to identify the "absolute poor". Households are considered to be among the "absolute poor" when the per capita income is less that 1USD per day, which is based on the UNESCO definition of absolute poverty. Based on this definition, 10% or 6,998 households are considered poor. A backpropagation neural network is trained to distinguish households as either poor or not. We achieve an accuracy of about 61% on both the train and test sets. Further rule-extraction on the trained network is done in order to understand, in terms of the features used for training, which features contribute to the positive identification of households that are poor by UNESCO definition. To complement the extracted rules, the poverty dataset is also used to train a Self-Organizing Map (SOM), which is then used to allow for an intuitive visualization of various facets of poverty. From the trained SOM, three distinct "poverty" clusters were identified.

Keywords : backpropagation, rule extraction, self-organizing maps, visualization, poverty

1. *Data Mining Tools to Visualize and Understand Poverty*

Data mining and data visualization tools have been used in numerous applications and for all types of data [6][13][14]. We demonstrate a data mining technique and procedure in a socially relevant area, which is the analysis and visualization of ***poverty*** in the city of Pasay in Metro-Manila, Philippines.

The data on poverty have been collected through the Angelo King Institute of De La Salle University, as part of the Community-Based Monitoring System (CBMS) of the global Partnership for Economic Policy (PEP) project - a multi-country, multi-continent study funded by the International Development Research Centre (IDRC) of Canada. The poverty dataset was collected from several provinces in the Philippines, covering a huge segment of the Philippine archipelago. These datasets contain in-depth information about individual households, clustered into small social and political units or districts, referred to locally as "barangay". Each barangay has from a few hundreds to a few thousand households. As of January 24, 2012, extensive poverty-related data have been collected from **66** provinces (**34** of which have been province-wide), **776** municipalities and **51** cities. So far, this has covered a total of **20, 671** "barangays".[1]

The CBMS Poverty dataset [12] is comprehensive and includes information that capture in great detail the various living conditions as well as demographic profile of the members of each household. The poverty dataset pertaining to individual households has numerous data fields and are encoded into two separate subfiles. The first file contains information referring to the various poverty-related information concerning the entire household, such as access to clean water, type of toilet facilities, type of materials used for walls and roof, and various other household information. The other subfile would refer to demographic information of each member of the household, i.e. head of household, spouse, children, grandparents, in-laws, relatives, etc.

[1] Information on the PEP and CBMS projects are described in greater detail in http://www.pep-net.org/programs/cbms/about-cbms/

Note that "poverty" is not a single-faceted concept. More and more, poverty is expressed as a multi-dimensional phenomenon. For example, a household may not be poor in terms of salaries and income, but may be poor because of the prevalence of crime and violence that has directly affected the household ("security poor"). Another example is the inaccessibility of basic utilities and sanitation facilities that would expose the household to health issues, especially the children. In this case, the household may be classified as "health poor". For the purpose of this research, households have been classified as "poor" or "not poor", based on the annual per capita income. This was computed based on the annual income of the entire household divided by the number of members in the household. A household is considered "poor" when the per capita annual income is at most 1 USD / day X 365 days. This is based on the UNESCO standard definition of "absolute poverty" [19].

2. *Data preparation and pre-processing*

The subfiles were merged so that data about members of a given household were assembled together with the rest of the household information. The merging of files had to deal with some errors in the encoding of the household identification number or key. Some other issues with inconsistencies and missing data, typical in live datasets, have had to be dealt with. Once merged, cleaned, and pre-processed, the data fields were uniformly encoded based on the elaborate coding scheme adopted by the survey instrument.

For the experiments discussed in this paper, we have chosen to retain only a small fraction of the data fields – concentrating only on a) the physical attributes of the house or dwelling, such as the materials used for the walls and roof, b) various community-related condition of a household that may be generally associated with poverty, such as access to clean drinking water, access to proper toilet facilities, and garbage collection; and 3) various indicators affecting the household such as being hit by a calamity (e.g. typhoon, flood, fire) in the past 12 months or having had no food to eat for at least one instance during the last 3 months.

Non-poverty-related fields, such as those that refer to the demographic profile of specific members of the household, e.g. gender of the head of the household, marital status of the couple living in the household, age and religion of individual household members, etc. have been partially retained, but had not been used in training the neural networks. Table I provides the list of 39 features used for training the neural networks.

3. Understanding using Neural Network Rule Extraction

As a first attempt at understanding what features allow for the automatic categorization of households into “poor” and “not poor” households, we used a backpropagation neural network (BNN) to learn how to distinguish the two types of households using a training set that had accompanying information (using the annual per capita income as basis for a poor/not-poor tag) to train the BNN [7][8]. Subsequently, the trained network was used to try to classify a test set, composed of households that have not been part of the training set. Five percent of the available data samples were selected randomly to form the training set. The remaining 95% of the samples formed the test set. The total number of samples in the two sets were 3407 and 65674, respectively.

Table I. List of features used in determining if a node is “poor” and “not poor”

f1	DeathIndicator	f21	water_dist_4 (don't know)
f2	CalamityIndicator	f22	toilet_1 (Water sealed flush to sewerage system/septic tank - own use)
f3	FoodShortageIndicator	f23	toilet_2 (Water sealed flush to sewerage system/septic tank - shared with other households)
f4	Garbage	f24	toilet_3 (Closed pit)
f5	water_1 (Community water system - own use)	f25	toilet_4 (Open pit)
f6	water_2 (Community water system - shared with other households)	f26	toilet_5 (No toilet)
f7	water_3 (Artesian deep well - own use)	f27	toilet_6 (Others)
f8	water_4 (Artesian deep well - shared with other)	f28	wall_1 (Strong materials)
f9	water_5 (Artesian shallow well - own use)	f29	wall_2 (Light materials)
f10	water_6 (Artesian shallow well - shared with other households)	f30	wall_3 (Salvaged/Makeshift materials)
f11	water_7 (Dug/shallow well - own use)	f31	wall_4 (Mixed but predominantly strong materials)
f12	water_8 (Dug/shallow well - shared with other households)	f32	wall_5 (Mixed but predominantly light materials)
f13	water_9 (River, stream, lake, spring and other bodies of water)	f33	wall_6 (Mixed but predominantly salvaged materials)
f14	water_10 (Bottled water/Purified/Distilled water)	f34	roof_1 (Strong Materials)
f15	water_11 (Tanker truck/Peddler)	f35	roof_2 (Light Materials)
f16	water_12 (others)	f36	roof_3 (Salvaged/Makeshift Materials)
f17	water_dist_0 (unknown)	f37	roof_4 (Mixed but predominantly strong materials)
f18	water_dist_1 (Within premises)	f38	roof_5 (Mixed but predominantly light materials)
f19	water_dist_2 (Outside premises but 250 meters or less)	f39	roof_6 (Mixed but predominantly salvaged materials)
f20	water_dist_3 (251 meters or more)		

Twenty neural networks were trained. The number of hidden units in the networks was set to 4. Network training was terminated when a minimum of the error function was reached. The pruning process to remove redundant connections and network units then began. Hidden units, input units and individual network connections were removed as long as the network accuracy on the training set was above 60%. The twenty pruned networks had test set accuracy that ranged from 59.66% to 60.70%. The number of hidden units left was either just one or at most two, while the number of connections ranged from 11 to 24.

One of the networks with the fewest number of connections was selected for rule extraction. It had a total of 11 connections, 7 connections from the input units to the only remaining hidden unit, 2 connections from this hidden unit to the two output units plus 2 bias weights at the output units. The 7 relevant inputs correspond to the following features:

1. f5: water_1 (Community water system - own use)
2. f6: water_2 (Community water system - shared with other households)
3. f19: water_dist_2 (Outside premises but 250 meters or less)
4. f27: toilet_6 (Others)
5. f28: wall_1 (Strong materials)
6. f29: wall_2 (Light materials)
7. f34: roof_1 (Strong Materials)

Since the network structure is very simple, it is rather straightforward to obtain a set of rules to give an indication as to what the data mining tool was able to automatically deduce as to the most important features for categorizing households as either poor or not poor, based on the UNESCO definition of *absolute poverty*. The accuracy of the extracted rules below on the training and test data sets are 60.52% and 60.67%, respectively.

A household is considered poor if it meets one of the following rule conditions:

- [water_dist_2 (Outside premises but 250 meters or less) = YES]
- [water_2 (Community water system - shared with other households) = YES] and [wall_2 (Light materials) = NO]

- [wall_1 (Strong materials) = NO] and [wall_2 (Light materials) = NO] and [roof_1 (Strong Materials) = NO]
- [water_1 (Community water system - own use)=YES] and [wall_2 (Light materials) = NO] and [roof_1 (Strong Materials) = NO]
- [water_1 (Community water system - own use)=YES] and [wall_1 (Strong materials)=NO] and [[wall_2 (Light materials) = NO]
- [toilet_6 (Others) = YES]

4. Visualizing Poverty Using Self-Organizing Maps (SOM)

A second data mining tool is used to elucidate further the kind of poverty that can be found among the "poor" households in the city that was surveyed. This second data mining approach is the Self-Organizing Map (SOM) [13][16][17][18], which is a computational intelligence technique that allows for the clustering and visualization of the data attributes and classes of a given dataset.

A SOM is usually a regular rectangular grid (some are hexagonal grids) of cells or nodes, each of which is represented as a vector of so called "weights". One weight is assigned to each feature in the training set. Initially the SOM is initialized with random weights. These randomly assigned weights will then be continuously adapted and refined as learning or training progresses. During training, unlike in the case of BNN, the data items of each household does not have accompanying information as to whether the household is of category "poor" or "not poor"[1][3][4]. Thus, as opposed to the supervised training method of BNN, the SOM method is considered unsupervised. The SOM method is essentially is a clustering technique [5] that allows for a simultaneous visualization of the various clusters formed – in particular, the SOM would tend to assign similar clusters into locations in the map that are likewise spatially near each other.

The SOM learning algorithm iteratively takes a randomly selected data item from the dataset and compares it to every node in the map using some distance or similarity measure, usually the Euclidean distance measure D, as defined in 1 below. As shown, V is the vector of attribute values of the selected input data item. $\boldsymbol{W_k}$ is the vector of weights associated with node ***k***. The total number of features or attributes used for training the SOM is denoted by ***n***.

$$Dk = \sqrt{\sum_{i=0}^{i=n} (V_i - Wk_i)^2} \tag{1}$$

The node m that has the smallest distance $\boldsymbol{D_m}$ with respect to the current input data item is referred to as the *best matching unit* (BMU). Once the BMU is determined, the weights of the nodes in the *winning neighborhood* of the BMU (including those of the BMU itself) will be updated and adapted, following the Grossberg learning rule defined in 2 below [9][10].

$$W_{t+1} = W_t + \alpha(V_t - W_t) \tag{2}$$

In the weight update rule above, $\boldsymbol{\alpha}$ is the learning rate, such that 0 < $\boldsymbol{\alpha}$ < 1, which decreases linearly from the first iteration to the maximum number of iterations of SOM learning. As for the so-called *winning neighborhood*, this is defined by a “radius” such that all nodes within a given radius from the BMU would be considered to be part of the winning neighborhood. The neighborhood radius also decreases as training progresses until it gets fixed to the value 1, in which case all nodes directly adjacent to the BMU would be part of the winning neighborhood.

The training process continuous until the user-defined maximum number of iterations is reached. Once trained, each node of the map would need to be labeled. Each node k is labeled as P (for Poor) or N (for Not poor), which is determined as follows:

1. compute the distance of each data item (household) to the node; we use the Euclidean distance measure
2. sort the data items from the closest to the farthest, in terms of the Euclidean distances computed, and retain the first M data items closest to the node;
3. assign the label P or N depending on which of the two has the majority among the M data items associated to the node.

Note that during training, the SOM, being completely unsupervised, is not being given any information as to the actual label or category of the individual data items that are being presented for training. The labeling, however, is a supervised process in that a labeled dataset is used to assign a distinct category label to each node in the trained map.

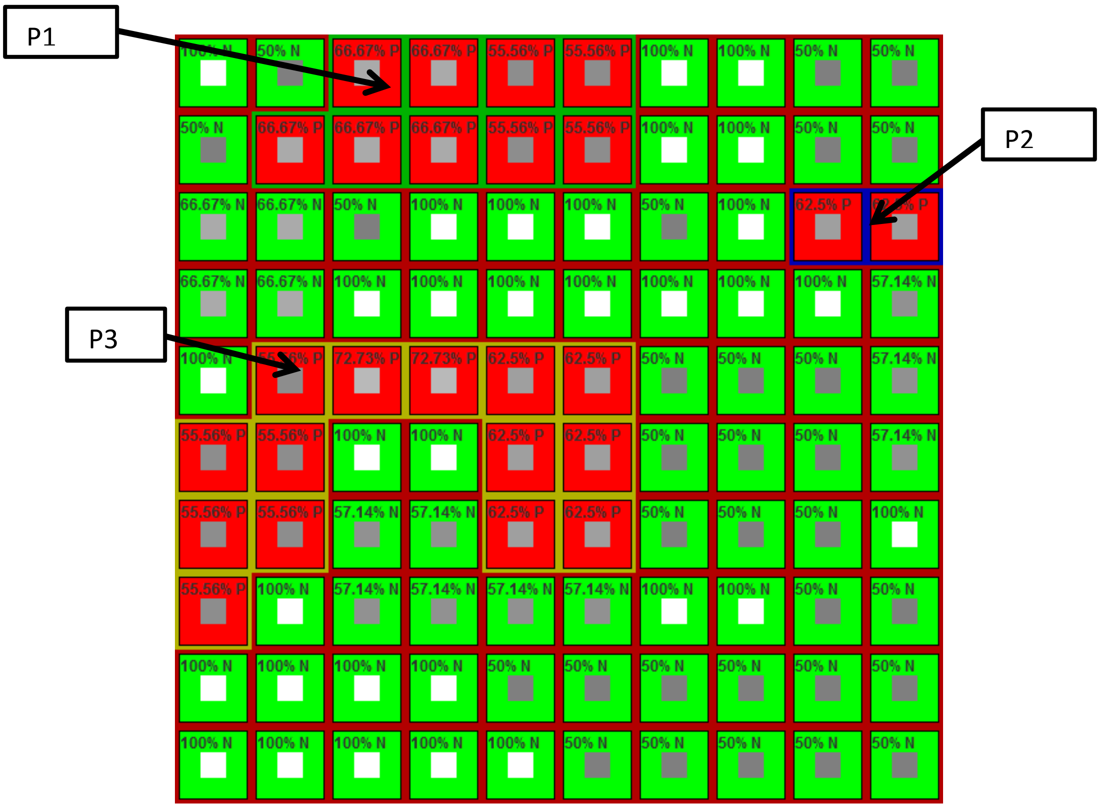


Figure 1. Trained SOM showing three clusters of nodes labeled as P "poor" (red boxes). The grey boxes inside each node reflect the degree by which the top nodes associated to a given node are of the same tag (P or N). White denotes that 100% of the items associated to the node are either all P or all N.

The binarized data were used to train a 10 x 10 Self-Organized Map that appears in Figure 1. Nodes associated to "poor" households, based on the labeling process described above, have boxes colored red. There are only about 10% of the households surveyed (6,998 out of 69,130) that are classified as "poor". This is why in the trained SOM, significantly less nodes are labeled P (red) as compared to those labeled N (green). This is one characteristic of Self-Organizing Maps, where it renders visually the relative proportion of the data belonging to the various categories.

5. Second level SOM Visualization

Notice from Figure 1 that there are three different distinct clusters of “poor” households. We refer to these three poor clusters as P1, P2, and P3. As a second level visualization of the poverty dataset, it would be interesting to see whether there are specific features used in the training set that have generally high values among poor households and low values among “not poor” households, or vice versa. And whether there are features that have high values only for one poverty cluster (e.g. P2) and not for the “not poor nodes” nor for any of the other poverty clusters (e.g. P1 and P3).

The SOM interface that we developed allows us to “peel” the SOM one “component plane” at a time [2], in order to visualize the distribution of the values of the individual features among the weight vectors of the nodes of the trained SOM. The component planes simply render in grey scale values (black is low value, white is high value) the weight of each node for the specific target feature. Once these component planes are laid on top of the labeled map, it becomes easy to spot the “prominent” features that have quite distinct values (relatively high or relatively low) between those households that are poor from those that are not poor. The component planes will at the same time also help in visualizing the difference between and among the three poverty clusters P1, P2, and P3. The notion of “prominent” features will be discussed in a more rigorous manner in the next section.

Most component planes do not reveal any interesting findings, such as the component planes shown in Figure 2. In these component planes, the values of the weights for the corresponding feature (or the component) do not differ much whether the nodes are mostly red (poor) or mostly green (not poor). Either they are mostly black or mostly white in most parts of the map.

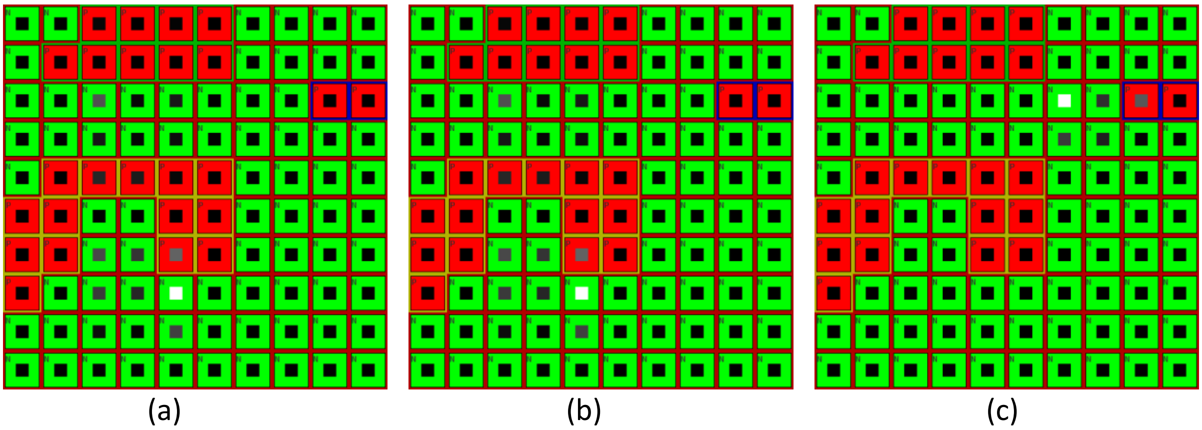


Figure 2. Regular component planes for some of the features (f10, f11, f12) used to train the SOM. Note that the values of the weight vectors corresponding to the specific components or features do not differ much between those nodes labeled “poor” (red) to those nodes labeled “not poor” (green).

A few of the more interesting component planes are shown in Figures 3 to 7. Note that the green nodes in the lower half of the map have white component values for the components/features that correspond to toilet facilities for private use by the members of the household (f22) and to use of strong wall material (f28). As per the common notion of “poverty”, these “prominent” features are generally associated with dwellings that are “not poor”.

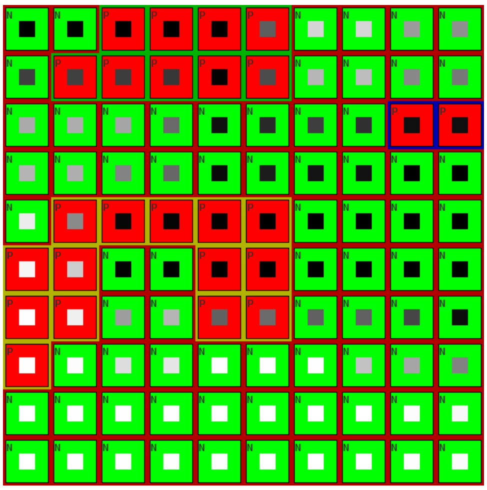


Figure 3. Trained SOM showing component plane for whether there are proper toilet facilities (f22) for private use by the members of the household. Note that the green (N) nodes at the bottom of the map mostly have white component values, meaning these nodes are associated with households that have proper toilet facilities for private use. As

can be seen in the figure, the top red cluster and the right red cluster are black this means that they do not have good toilet facility.

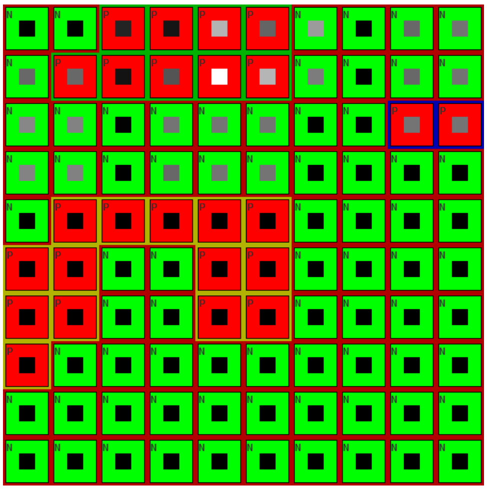


Figure 4. Trained SOM showing component plane for whether the toilets used by the households are closed pits (f24). Seen in the figure is some gray component values for the the P1 and P2 clusters, but not the P3 cluster. It shows that they do not have good toilet facilities as compared to the households in P3.

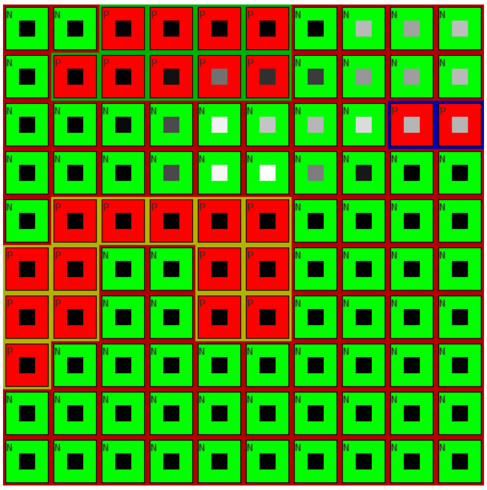


Figure 5. Trained SOM showing the component plane for no toilet at all (f26) which is gray only for the P2 cluster, but not for P1 and P3.

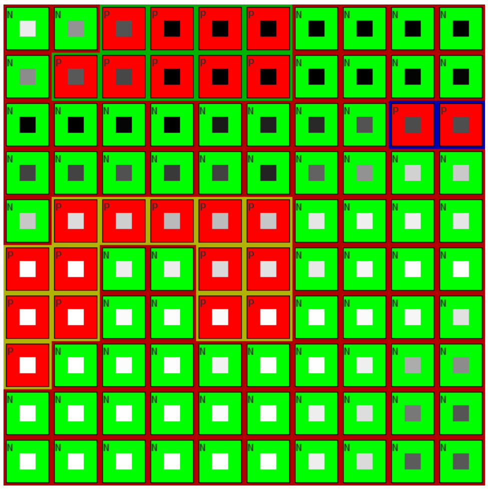
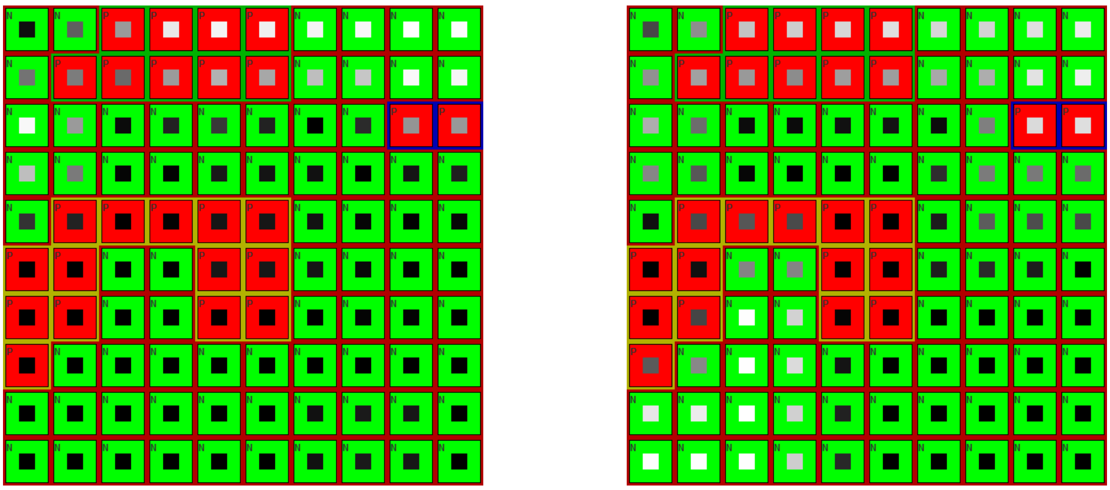


Figure 6. Trained SOM showing the component plane for whether strong materials were used to build the walls of the house (f28). Note that the green (N) nodes at the bottom of the map mostly have white component values, meaning these nodes are associated with households that have strong materials used for the wall, such as concrete hollow blocks. Here, the P3 cluster defers from P1 and P2.



(a) (b)

Figure 7. Two poverty clusters 1 and 2 have relatively higher values for features f31 and f37, referring to the type of material used for the walls and roof (mixed materials).

6. Third level SOM Visualization

It is possible to find the *prominent* features in a more systematic manner. Finding the prominent features of a given cluster is done by computing the mean of the values of a given feature among all nodes in one type of nodes (in-cluster mean), and to do the same among nodes outside the given cluster (out-cluster mean). If the in-cluster mean deviates from the out-cluster mean by more than one standard deviation, then the specific feature is said to be "prominent" for the cluster under consideration. This technique for finding prominent features is based on earlier work [1][2][3][4].

The net difference between the in-cluster mean and the out-cluster mean is tallied for all features, and for every given cluster. The prominent features of a given cluster are then used to "characterize" each cluster, as summarized in Figure 8. Table II shows the list of prominent features for the Poverty 1 cluster. The prominent features include the Death Indicator, which means that the households associated to this cluster tend to have significantly (in a statistical sense) more instances of having at least one member of the household who died in the last 12 months. In addition, there are relatively more households in this cluster that have "closed pits" (dug hole in the ground) as toilet facility, instead of a regular, sanitary toilet with the proper septic tank facility or a community based sewage system. The other prominent features of this cluster indicate that they have relatively less use of strong materials for roof and walls, and instead use "mixed materials", although these are predominantly strong materials. It is presumed that because of poverty, the households belonging to this cluster have resorted to whatever material they can use for roof and wall, even if these materials tend to be the "strong type", like hollow blocks and concrete.

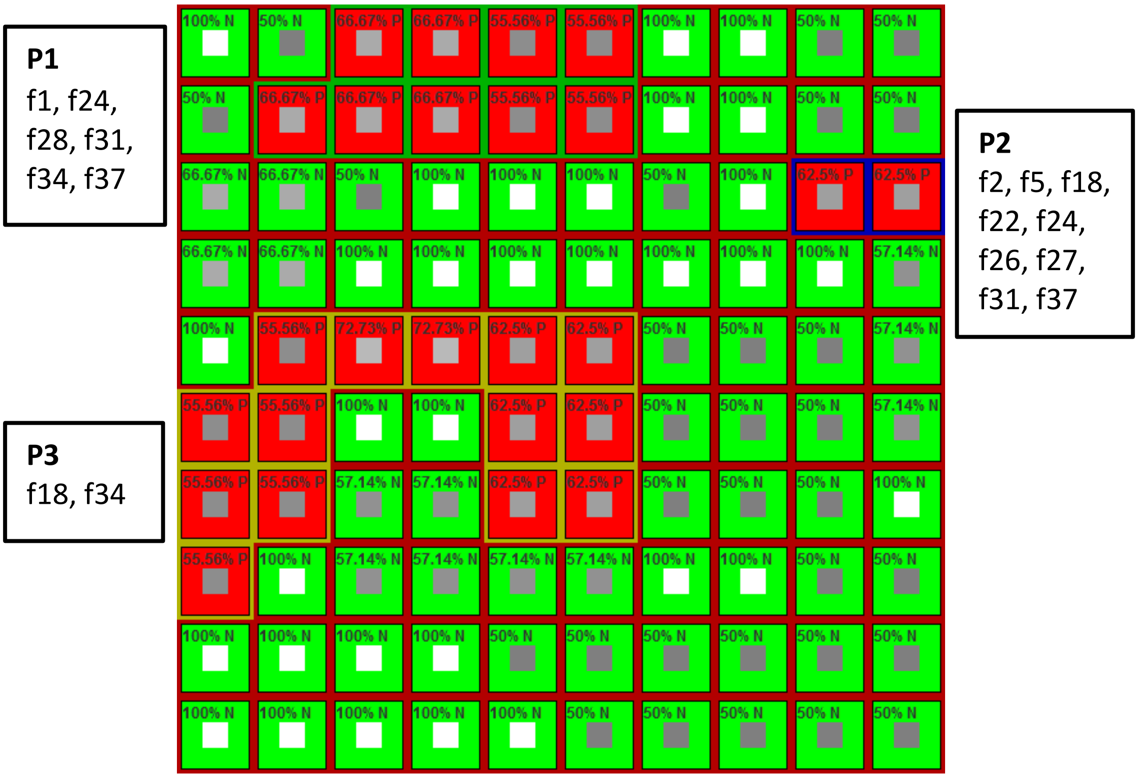


Figure 8. Poverty clusters 1, 2 and 3 with their prominent features as seen in Tables II to IV.

Table II. The prominent features of the Poverty 1 cluster of nodes. A feature is prominent for a cluster if the mean value of the weights among nodes in the cluster deviates by more than 1 standard deviation of the weights of all nodes outside the cluster

Feature	in-cluster mean	out-cluster mean	net difference	std dev
F1-DeathIndicator	0.06	0.01	0.05	0.0315
F24-toilet_3 (Closed pit)	0.08	0.02	0.06	0.0448
F28-wall_1 (Strong materials)	0.11	0.67	0.56	0.3957
F31-wall_4 (Mixed but predominantly strong materials)	0.68	0.16	0.52	0.3194
F34-roof_1 (Strong materials)	0.04	0.46	0.42	0.3758
F37-roof_4 (Mixed but predominantly strong materials)	0.7	0.33	0.37	0.3631

The prominent features for poverty cluster 2 are shown in Table III. In the case of this cluster, the prominent features includes the calamity indicator. This cluster is relatively low for this feature, meaning that most households have not been affected by calamities compared to other households. Other prominent features are related to toilet facilities. For this cluster, the toilet features that are generally associated to non-hygienic facilities (i.e. closed pit, no toilet, others) have relatively higher weights, indicating that relatively more households associated with this cluster have these kinds of toilet conditions. Finally, relatively more households associated to this poverty cluster have mixed materials for both walls and roof.

Table III. The prominent features of the Poverty 2 cluster of nodes.

Feature	in-cluster mean	out-cluster mean	net difference	std dev
F2-Calamity Indicator	0.02	0.16	0.14	0.1259
F5-water_1 (Community water system – own use)	0.86	0.32	0.54	0.0319
F18-water_distance_1 (Water is within premises)	0.95	0.39	0.56	0.4319
F22-toilet_1 (water sealed flushed to sewerage f24-system/septic tank – own use)	0.06	0.51	0.45	0.4048
F24-toilet_3 (Closed pit)	0.09	0.02	0.07	0.0448
F26-toilet_5 (No toilet)	0.09	0.02	0.07	0.0362
F27-toilet_6 (Others)	0.21	0.07	0.15	0.1264
F31-wall_4 (Mixed but predominantly Strong Materials)	0.58	0.2	0.38	0.3194
F37-roof_4 (Mixed but predominantly strong materials)	0.86	0.36	0.5	0.3631

As for poverty cluster 3 which is the big cluster of red nodes somewhere in the middle of the SOM map, the prominent features are “distance to water source” and the “roof material” used. Significantly more households associated to this cluster, than households associated to the other clusters, have access to clean water within their premises and use strong materials for the roof. There are other features in cluster 3 where the difference between the in-cluster mean and the out-cluster mean are high but not high enough to surpass the standard deviation. These are the features that are generally associated with poverty, which may explain why the cluster is a poverty cluster, even if the *prominent* features are both generally associated with non-poor households.

Table IV. The prominent features of the Poverty 3 cluster of nodes.

Feature	in-cluster mean	out-cluster mean	net difference	std dev
F18-water_distance_1 (Water is within premises)	0.0	0.46	0.46	0.4319
F34-roof_1 (Strong Materials)	0.8	0.36	0.44	0.3758
*F28-wall_1 (Strong Materials)	0.9	0.58	0.32	0.3957
*F19-water_dist_2 (Outside premises but 250 meters or less)	0.62	0.32	0.3	0.4064
*F31-roof_4 (Mixed but predominantly strong materials)	0.12	0.41	0.29	0.3631
*F37-wall_4 (Mixed but predominantly Strong Materials)	0.04	0.24	0.2	0.3194
*F23-toilet_2 (Water sealed flush to sewerage system/septic tank - shared with other households)	0.54	0.35	0.19	0.3813
*F5-water_1 (Community water system - own use)	0.2	0.36	0.16	0.3716
*F14-water_10 (Bottled water/Purified/Distilled water)	0.37	0.21	0.16	0.3900
*F17-water_dist_0 (unknown)	0.37	0.21	0.16	0.3900

*features with relatively high net difference, however, they are not higher than the standard deviation.

Conclusion

It is very difficult to correctly classify households as either poor or not poor, based simply on various attributes about the way the house has been built, access to clean water, and access to proper toilet facilities. Even if we add features about whether the household has experienced some calamity, whether there was death in the family or whether the family has experienced hunger in the past months, automatic classification continues to be very difficult. This is partly explained by the fact that the basis for absolute poverty, which is the annual per capita income, is a continuous range of values and therefore would yield households that are technically not "poor" by UNESCO standards, but have nonetheless the same kind of poverty conditions in terms of the physical attributes of the house or dwelling, or in terms of access to clean water and proper toilet facilities.

The Self-Organizing Map (SOM) approach is a good alternative for probing deeper into what constitutes poverty. The trained SOM produced three distinct poverty clusters and by using a methodical way of identifying the prominent features that would characterize each poverty cluster, a clearer notion of the conditions of poverty emerges.

References

[1] A. Azcarraga, M.H. Hsieh, S.L. Pan and R. Setiono. Improved SOM Labeling Methodology for Data Mining Applications. In Soft Computing for Knowledge Discovery and Data Mining. (O. Maimon and L. Rokach, Eds.), pp 45-75, Springer, 2008.

[2] A. Azcarraga, M.H. Hsieh, S.L. Pan and R. Setiono. Extracting salient dimensions for automatic SOM labeling, IEEE Transactions on Systems, Man, and Cybernetics, Part C, Vol. 35, No. 4, pages 595-600, 2005.

[3] A. Azcarraga, M.H. Hsieh and R. Setiono. Visualizing Globalization: A SOM Approach to Customer Profiling. 24th International Conference on Information Systems (ICIS), Seattle, Washington, December 2003.

[4] A. Seret, T. Verbraken, S. Verailles and B. Baesens. A new SOM-based method for profile generation: Theory and an application in direct marketing. European Journal of Operational Research. 2012.

[5] B. Everitt. Cluster analysis, Heinemann Educational Books, London. 1974.

[6] C. Soares et al. Applications of Data Mining in E-Business Finance: Introduction. Proceedings of the 2008 conference on Applications of Data Mining in E-Business and Finance. 2008.

[7] D. E. Rumelhart, G.E. Hinton, and R.J. Williams, D.E. Rumelhart and J. L. McClelland. Learning internal representations by error propagation, *Parallel and Distributed Processing*, vol. 1, pp.318 -362 1986 :MIT Press

[8] D.E. Rumelhart and D.Zipser, D.E. Rumelhart and J.L. McClelland. Feature discovery by competitive learning, *Parallel Distributed Process.*, vol. 1, pp.151 -193 1986 :MIT Press

[9] D.M. Clark and K. Ravishankar. A Convergence Theorem for Grossberg Learning. Neural Networks 3(1): 97-92. 1990.

[10] G.A. Carpenter and S. Grossberg. *Pattern-Recognition by Self-Organizing Neural Networks*, 1991 :MIT Press

[11] G. Deboeck and T. Kohonen. Visual Explorations in Finance with Self-organizing Maps. London: Springer-Verlag. 1998.

[12] J. Bancolita and M.N. Alvarado. Developing Composite Indicators using CBMS: *Amalgamating the Dimensions of Poverty*. 4th CBMS Network Conference. November 2006.

[13] M.Y. Kiang and A. Kumar. An evaluation of self-organizing map networks as a robust alternative to factor analysis in data mining applications, Information Systems Research 12: 177-194. 2001.

[14] P.Berka et al. Data Mining and Medical Knowledge Management: Cases and Applications. 2009.

[15] S. Haykin. *Neural Networks: A Comprehensive Foundation*, 1999 :Prentice-Hall

[16] T. Kohonen. Self-Organizing Maps. Springer-Verlag, Berlin. 1995.

[17] T. Kohonen. Kohonen Maps, Elsevier, New York. 1999

[18] T. Kohonen. Self-organization of a massive document collection, IEEE Transactions in Neural Networks 11(3): 574-585. 2000.

[19] UNESCO. Poverty. http://www.unesco.org/education/poverty/index.shtml