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CLUSTERING RURAL DEVELOPMENT TYPOLOGY IN EAST JAVA PROVINCE USING LATENT CLASS ANALYSIS

Desy Setiawati, Aji Hamim Wigena, Bagus Sartono
Statistics Department, FMIPA, Institut Pertanian Bogor

Abstract

To deliver the sustained and equitable regional development in Indonesia, the government must understand the characteristics of each region based on its area features, therefore, the classification of rural area must be handled to increase the precision of the development program. Since the rural area has their own specific characteristics that may lead to its rural level, the classification must ensure that the development policy fit in each area.

In this paper, we try to classify the typology of rural development that measured based on the rural potential characteristics, education, and socioeconomic. We select villages in East Java province as a scope of research area since East Java was well-known as a center of agricultural in Java, however, in 2011-2014, according to BPS, the poverty rate put east Java in 15th position in the national poverty rate.

The classification uses latent class analysis, which models the data into particular statistical distribution to identify immeasurable cluster membership between subjects with observed categorical or continuous variables. The method was able to handle overlapping model data by setting different characteristics, and the modeling results can be tested its accuracy level. Expectation Maximization (EM) algorithm is used to estimate parameters of the latent class model. The research uses PODES 2011 dataset which contains characteristics and facilities information of 8502 villages.

The result showed that using latent class analysis generates five clusters of rural area development, while the current classification from Ministry of Home Affairs only uses three typologies of rural development. The research result was able to give more detail additional information of current three classifications by dividing its typology into several detail typology classifications.

Key words: Latent Class Analysis, Maximum Likelihood, Expectation Maximization Algorithm, Rural Development Typology

INTRODUCTION

According to Indonesian long-term development plan 2005-2025 that derived from middle-term development plan 2010-2014, the village development is directed to embody the national development priority. In order to achieve the government program goals in village development, the comprehensive database that explains the village's features to support the program development is needed.

Directorate General of Community Development (Ditjen PMD), Ministry of Home Affairs, Republic of Indonesia, has developed the concept of the village's database as shown in the Regulation of the Minister of Home Affairs No. 12 of 2007 on guidelines for measuring the level of rural development. The village development level indicators that were used are included the local economy, public education, public health, infrastructure, security and order, the political sovereignty of the community, community participation in development, community organizations, the performance of the village administration, coaching and supervision. Based on these indicators, typologies of rural development are classified into:

- *Desa swadaya*, namely territory that almost all people are able to meet their needs by organizing themselves, technology, facilities and infrastructure are still lacking, isolated areas, people tend to be closed and uphold traditional customs.
- *Desa swakarya*, namely areas where people are able to meet their own needs, technology, facilities and infrastructure began to rise, started their interaction with other residents outside the village which resulted in a change of mind and start apart from traditional customs.
- *Desa swasembada*, areas where people, namely more advanced and able to develop all the existing potential optimally, technology, modern and complete infrastructure, people tend to be open and manage a rational relationship in human relations, has been freed from the traditional customs.

We chose East Java Province as a study area, since it's one of the agricultural centers in Indonesia, especially the largest rice producer in Indonesia, however, in 2011-2014, the poverty percentage has ranked 15th largest in the national poverty level. Therefore, the depth study in order to know the typology of rural development, according to the indicators that have been determined previously is needed. According to data from Ditjen PMD, Ministry of Home Affairs, in 2011, there are 50 percent of *Desa swadaya*, 49 percent of Desa Swakarsa, and only 1 percent of *Desa swasembada* in East Java Province.

There are some related researches in typology classification for village clustering. Lastini (2011) have done classification typology based on a community forest identifier in Ciamis with K-Means clustering method. From these studies produced two typologies of villages: potential village and no potential for the development of community forests. Additionally, Resia (2012) have done classification typology developed areas in Sampang with Hierarchical Cluster and produces three types of developed areas, which underdeveloped areas, heading advanced areas, and advanced areas. Both of these studies are advised to consider the use of other influential variables, whether numerical and/or categorical variables.

The purpose of this research is to obtain the best model for rural development typology, The research result is also able to give more detail additional information about the current Ministry of Home Affairs classifications by dividing its typology into several detail typology classifications, in order to obtain accurate data base to support rural development.

RESEARCH METHOD

Method and Material

The research uses PODES 2011 dataset which contains characteristics and facilities information of 8502 villages. Some of the classification variables which have been used as the basis of typology measurement in village development based on Regulation no.12/2007.

Table 1. Indicator and Variable(s) to Classify Rural Development Typology

Indicator(s)	Variable(s)		Scale Type
Village Government	X1	The existence of the village head office location	Nominal
	X2	The highest education completed by village chief	Ordinal
Community Institutions	X3	Number of active non-profit organization type and sport group	Nominal
Community Participation and Political	X4	The existence of residents originating more than one ethnic/tribal and residents environmental activities in past year	Nominal

Sovereignty Society	X5	Number of program types/community empowerment activity within past three years and the existence of village consultative bureau (BPD)	Nominal
Public Health	X6	Access to clinic, village health center, village sub-health center, doctors practice center	Ordinal
	X7	Sources of drinking water and cooking in most village family	Nominal
	X8	The plague of infectious diseases	Ordinal
Public Education	X9	The existence of formal education infrastructure (elementary, junior, senior)	Nominal
	X10	The existence of skills and education facility and public library	Nominal
Public Economy	X11	Number of hotel/lodging type	Ordinal
	X12	Number and type of savings and loans institution and credit facility that received by resident in past a year	Ordinal
	X13	Access to permanent/semi permanent market building and lighting at the main street village	Nominal
Infrastructure	X14	The type of widest main street surface and the ability of road village crossed by four or more wheels of motor vehicle	Nominal
	X15	Cellular Phone Signal and The existence Public Telephone Facility, Internet Cafe	Nominal
	X16	Dispose of waste type that mostly used	Nominal
	X17	The existence of slums	Ordinal
	X18	Proportion of family subscribe the cable-phone	Ordinal
	X19	Family proportion as electric users	Ordinal
	X20	The fuel type to cooking and the existence of kerosene or LPG base	Nominal
Security and Order	X21	The amount of crime type, mass fighting (vandalism), and brothel during the last year	Ordinal

Stages of the analysis conducted in this study are:

1. Establishment of a new variable, which is a combination of several variables. It is intended that the exercise of the assumption of local independence required in latent class analysis.
2. Selection of the best model, by choosing the model with the smallest BIC value.
3. Checking the local independence assumption by bivariate residuals between two variables of all variables that exist.
4. Analysis of the results of parameter estimation with maximum likelihood estimation.
5. Comparison of the results of clustering with classification Ministry of Home Affairs.

Some of the tools used in this study are SPSS 22, R with package poLCA, Latent Gold 4.5, and MS Excel.

Methodology

Latent Class Analysis

Model of latent class analysis is a technique for analyzing the relationship of data categories, namely the relationship among variables were measured with nominal and ordinal scale (McCutcheon 1987). Vermunt and Magidson (2002a) define a model of latent class analysis as a statistical method to identify clusters that are not measurable membership between subjects with observed variables, which is categorical or continuous variables. Latent class analysis models commonly referred to as finite mixture models. The method was able to handle overlapping model data by setting different characteristics, and the modeling results can be tested its accuracy level.

Let say $(x_1, x_2, \ldots, x_h)$ as a vector of h variables measurement, where each variable has a conditional distribution in the exponential family, such as Bernoulli, Poisson, Multinomial, and Normal and x_{ij} is the value of *i* sample of the object/element for variable *j* (*j* = 1,2, ..., *n*). Line vector $x'_j = (x_{1h}, x_{2h}, \ldots, x_{hi})$ which refers to the shape of the response j object(s). In latent class analysis model, vector space is assumed consist of K clusters. For every k clusters associated with π_k which refers to the initial opportunity observations *x* (Moustaki and Papageorgiu 2004). Joint distribution of the observed variables is finite mixture of probability:

$$g(x_j|\theta) = \sum_{k=1}^{K} \pi_k \, f(x_{ih}|\theta_k)$$

where:

$g(x_j|\theta)$ = distribution of x_j is given by the model parameter θ

$f(x_{ih}|\theta_k)$ = x_{ih} distribution given by the parameter θ, *k* cluster

π_k = initial probability latent classes or clusters K on the data *x*, where $\pi_k = \frac{n_k}{N}$

θ_k = probability of an object on a clusters K

K = number of cluster(s) (k=1,2,…,K), where $\sum_{k=1}^{K} \theta_k = 1$ and $\sum_{k=1}^{K} \pi_k = 1$

Nainggolan, B (2009) have done clustering dengue fever and dengue hemorrhagic fever with Latent Class Analysis (LCA), the selection process of the model using maximum likelihood estimation. Clustering results show that the criteria used for each cluster are almost the same as the WHO criteria for determining the group of dengue fever and dengue hemorrhagic fever. Additionally, Riswan (2010) have also been used Latent Class Analysis of Logistics in Indonesian student mathematics achievement grouping. Results grouping can know the background of each group is formed, it can even be done forecasting of an object into the specified group.

Expectation Maximization Algorithm

One method to estimate the parameters of the latent class analysis model is Maximum Likelihood Estimation (MLE). The log-likelihood function that is required on the MLE approach can be derived from the probability density function which defines the model. EM algorithm (Expectation Maximization Algorithm) is a tool for estimating the MLE of the parameters of the latent class analysis model. The likelihood function of the mixture latent class model is:

$$L = \sum_{j=1}^{n} \log f(x_j)$$

$$L(\theta|x) = \sum_{j=1}^{n} log \sum_{k=1}^{K} \pi_k \, f(x_j|\theta_k)$$

The process of estimating the EM algorithm starts with the iteration of the EM. Each circle in the process of the EM algorithm consists of two steps, namely the expectation step (E) and the maximization (M), with stages:

1. Define the initial value $\theta^{(0)} = (\pi^{(0)}, \alpha^{(0)}, \mu^{(0)}, \sigma^{(0)})$
2. Calculate $g(x_j|\theta_k) = \sum_{k=1}^{K} \pi_k\, f(x_{ih}|\theta_k)$
3. Step E: be calculated $\left(\hat{P}(k|x_j)^{(r)};\ j = 1, \dots, n;\ k = 1, \dots, K\right)$ where $\hat{P}(k|x_j)^{(r)}$ is conditional probability that states x_j emerge from K clusters, where:
$$\hat{P}(k|x_j)^{(r)} = \frac{\hat{\pi}_k{}^{(r)} f(x_j, \hat{\theta}_k)^{(r)}}{\sum_{l=1}^{K} \hat{\pi}_l{}^{(r)} f(x_j, \hat{\theta}_l)^{(r)}}$$
4. Step M: The maximum likelihood equation is obtained from the log-likelihood derivatives, in order to obtain a new parameter estimator.
5. Repeat steps 2 and 3 until convergent.

RESULT AND DISCUSSION

The results of the analysis stages in this study as follows:

1. Establishment of a new variable that is a combination of several variables, IE variables X3, X4, X5, X10, X12, X13, X14, X15, and X20.
2. From the results of the value of BIC, BIC smallest value found in 5-clusters model. So that the best model selected is 5-clusters model.
   5 – Cluster Model:
$$g(x_j|\theta) = 0.0869\, f(x_{ih}|\theta_1) + 0.3971\, f(x_{ih}|\theta_2) + 0.1661\, f(x_{ih}|\theta_3) + 0.2598\, f(x_{ih}|\theta_4) + 0.0901\, f(x_{ih}|\theta_5)$$

Table 2. BIC and Log-Likelihood Values of Several Cluster Models

Model	BIC	LL
3 – Clusters Model	257859.7	-127794.3
4 – Clusters Model	256644.5	-126806.7
5 – Clusters Model	256302.7	- 126255.8
6 – Clusters Model	256593.9	- 126021.4
7 – Clusters Model	257306.3	- 125997.6

Table 3. Simultaneous Model for Clusters

Intercept	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Wald	p-value
	0.7107	0.4983	0.0042	-0.5210	-0.6922	892.5114	7.0e-192

Table 4. Partial Model for Clusters

Peubah	Wald	p-value	R^2
X1	200.0946	6.1e-39	0.0870
X2	993.0540	1.1e-213	0.1905
X3	758.6552	7.0e-139	0.0435
X4	428.7282	3.1e-84	0.0339
X5	712.1676	5.9e-138	0.0707
X6	546.0882	7.2e-117	0.1124
X7	1571.4563	1.5e-329	0.1876
X8	80.7778	1.2e-16	0.0171
X9	942.3217	2.2e-180	0.0791
X10	1020.5391	7.2e-211	0.1539
X11	125.0409	4.5e-26	0.0690
X12	150.2795	1.8e-31	0.0273
X13	1104.5217	1.9e-221	0.0901
X14	356.1414	1.4e-58	0.0573
X15	1750.1714	2.7e-345	0.2112

X16	1504.5759	1.4e-319	0.3795
X17	1600.1953	2.7e-345	0.1072
X18	1482.9146	7.2e-320	0.4832
X19	196.5827	2.0e-41	0.0428
X20	1094.5165	7.2e-216	0.2733
X21	46.8482	1.6e-9	0.0094

In overall this model is quite feasible to be used. It can be seen from the p-value model for clusters < $\propto$ (p-value=7.0e-192). R^2 value indicates how well a variable of the model is explained by the model. The biggest variable explained by the model is proportion of families who subscribe to cable-phone (48.32%), further dispose of waste type that mostly used (37.95%). While most low variable can be explained by the model is the amount of crime type, mass fighting (vandalism), and brothel during the last year (0.94%).

3. Checking local freedom disorders can be seen from the bivariate residual value (BVR). Suppose $\propto = 0.01$. If BVR value > ${X^2}_{0.01;db=1}$ (6.63) hence no interference with the freedom of local. Based on the BVR output, it can be concluded that no disruption of local freedom in 5-clusters model using 21 variables.

4. Table 5. The Expectation Value of The Parameter Estimation Results

	class 1	class 2	class 5	swadaya	class 4	swakarya	class 3	swasembada
X1	2.6579	2.9746	2.9934	2.9258	2.9920	2.9248	2.9900	2.9703
X2	5.0101	5.4434	5.2445	5.3074	5.6630	5.5490	6.4113	6.7129
X3	2.2664	4.4120	4.0344	3.1312	5.2312	5.0944	5.0400	7.2773
X4	2.9577	2.8002	3.0761	2.6924	3.3418	3.5079	3.6364	3.9208
X5	4.6864	5.2753	5.6059	5.1969	5.5924	5.4866	4.9071	5.6337
X6	2.7619	3.1885	2.9905	3.0686	3.2478	3.2461	3.4197	3.3168
X7	2.8878	2.9562	2.4654	2.8066	2.9852	3.0477	3.5594	3.4654
X8	4.6060	4.6316	4.3431	4.4760	4.4840	4.5332	4.3086	4.4258
X9	6.6881	5.7119	6.2110	5.6934	6.6559	6.7731	6.9890	7.8713
X10	1.0456	1.1165	1.1923	1.0938	1.6862	1.7196	2.4752	3.4357
X11	1.0001	1.0004	1.0338	1.0090	1.0419	1.0715	1.2799	1.5247
X12	2.3826	1.9575	1.9512	2.0635	2.0987	2.0605	2.3134	2.6931
X13	2.4508	3.6184	2.7801	3.2035	3.2602	3.2810	3.3036	2.7128
X14	7.0839	7.6508	7.4553	7.5087	7.8335	7.8012	7.9889	7.9802
X15	5.2022	6.8326	5.4242	6.2035	8.2836	8.0320	9.4017	9.7030
X16	1.7249	1.9757	1.8124	1.9008	2.0228	2.1460	2.9087	2.7327
X17	2.9932	2.9906	2.9778	2.9851	2.9751	2.9420	2.7459	2.6733
X18	1.0589	1.3531	1.0954	1.2774	1.8172	1.8131	2.7005	2.5547
X19	4.6133	4.9141	4.8635	4.8522	4.9144	4.9015	4.8770	4.8614
X20	3.1245	5.7128	3.5286	4.7433	6.2469	6.0351	6.9779	6.8713
X21	3.9876	3.9714	3.9721	3.9719	3.9271	3.9388	3.9245	3.8911

Based on the output above, the characteristics of the clustering result compared to Ministry of Home Affairs classification are described as follows:

- Cluster 1, 2, and 5 show the characteristics approach to *desa swadaya*, where:
  - Cluster 1, which the administration of the village is quite poor, community institutions are only slight, community participation in supporting rural development is still lacking, access to public health facilities is still relatively difficult, and road infrastructure, telephone, garbage disposal, electricity subscription, and cooking fuel are inadequate.
  - Cluster 2, which the institutions to support the economy in the village are still

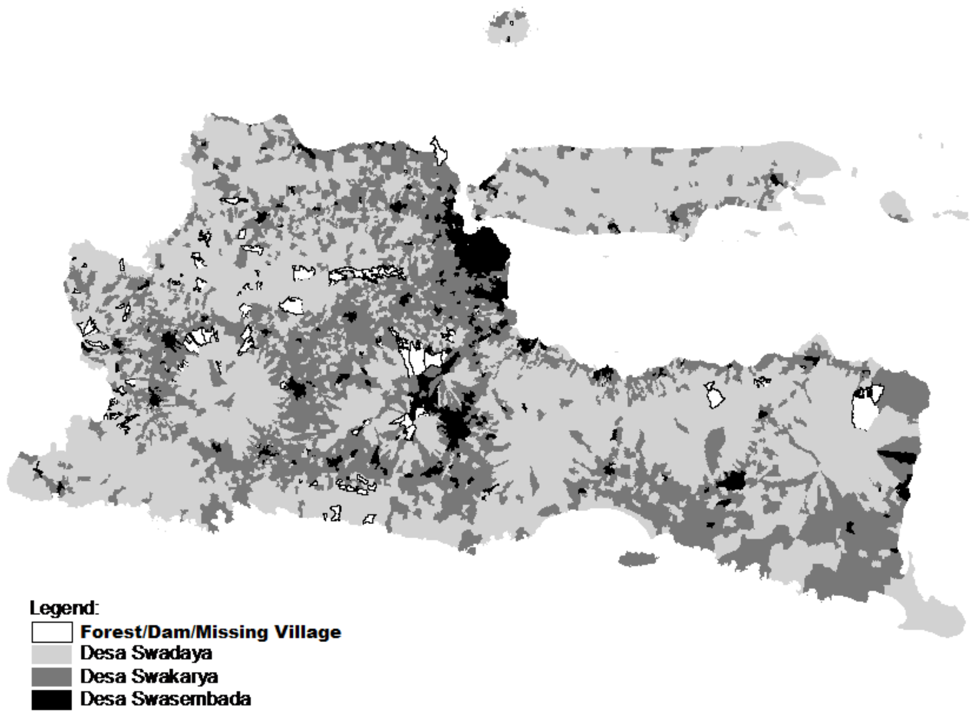
inadequate.

- Cluster 5, which the education of village government officials below the average, poor public health, the economy of the community less developed, and road infrastructure, telephone, garbage disposal, and cooking fuel are inadequate.

- Cluster 4 shows characteristics approaching the *desa swakarya*, especially in terms of the village administration, community institutions, public education, and infrastructure.
- Cluster 3 shows characteristics approaching *desa swasembada*, however, certain characteristics such as civil society and community education approaching to *desa swakarya*.

	Desa Swadaya				Desa Swakarya	Desa Swasembada
	1-cluster	2-cluster	5-cluster	Total		
LCA	748	673	2655	4076	3525	901
Ministry of Home Affairs classification				4236	4165	101

Rural Development Typology Map
In East Java Province, 2011, Using Latent Class Analysis



CONCLUSION AND SUGGESTION

Based on the research result of clustering rural development typology using Latent Class Analysis (LCA), it can be concluded as follows:

1. From the results of rural development typology clustering using LCA has produced five clusters model. Three clusters approach to the characteristics of *desa swadaya*, one cluster approaches to the characteristics of *desa swakarya*, and one cluster approaches to the characteristics of *desa swasembada*. This result was able to give more detail additional information of current three classifications from Ministry of Home Affairs.
2. Suitability level of LCA model for rural development typology clustering with Ministry of

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Home Affairs classification is quite high, therefore, the LCA can be used as a tool for classifying rural development typology.

3. Need for further studies on the best model selection process and the handling of missing information on the model of LCA.

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