AN ALTERNATIVE CLASSIFICATION FOR HUMAN DEVELOPMENT OF ASIAN COUNTRIES BY USING WARD'S CLUSTERING ALGORITHM

Tugba Altintas,
Faculty of Business Administration, Istanbul Aydin University, Istanbul, Turkey.

ABSTRACT

In this study, Asian countries have been classified to obtain development clusters UNDP's Human Development Index indicators have been used as independent variables. Ward's clustering algorithm as a hierarchical clustering method has been applied for classification. The main goal of this research is to compare clusters and memberships of ward's method to the development groups based on HDI rankings. In this way, it has been tested whether cluster memberships of Asian countries changed or not. It has been seen that some countries could relocate due to the applied clustering algorithm. Then, the study represents another quantitative choice to classify countries.

Keywords: Welfare and social development, human development index, Ward's Clustering, development classification, Asian countries.

INTRODUCTION

The Human Development Index (HDI) has been reported in theUnited Nations DevelopmentProgramme's (UNDP) Human Development Reports (HDRs) was created in 1990 (Böhringer and Jochem, 2007; Wilsonet al., 2007). The UNDP has published a series of annual HDRs in which the human development index (HDI) is computed for each country (Sagar, 1998). Depending on the deficiency of income (GDP) used for measuring human development, HDI consisting of new indicators as well as income,was created as a new concept(Aguna, andKovacevic, 2010).The first HDR correctly recognizes that "development is much more than just the expansion of income and wealth" and defines human development as "the process of enlarging people's choices" (UNDP, 1990).Today, the HDI examines three basic dimensions to determine a country's growth and achievements in human development.The first is health, which is measured by life expectancy at birth. Those with higher life expectancies rank higher than those with lower life expectancies. The second dimension measures a country's overall knowledge level via the literacy rate among adults over 25 years combined with the gross enrolment ratio of students from primary school through university. The third and final dimension is a country's standard of living, measured as the gross domestic product per capita in purchasing power parity terms, based on the United States dollar (Hou et al., 2014).

The breakthrough for the HDI was the creation of a single statistic which was to serve as a frame of reference for both social and economic development and to allow cross-country comparison (OPHI, 2011).The HDI was created for each dimension by setting each indicator on a scale of 0–1 using maximum and minimum scaling values. Since the variables included in the HDI have different units,scaling and normalization of values are required. Life expectancy is in years, adult literacy rate is in percentages, and the GDP per capita is in PPP$. Then, normalization removes the heterogeneity of units by converting them into pure numbers(Hou et al., 2014).

Starting with the 2010 Human Development Report the HDI combines three dimensions(UNDP, 2013):

A long and healthy life: Life expectancy at birth
Education index: Mean years of schooling and Expected years of schooling
A decent standard of living: GNI per capita (PPP US$)

1. Life Expectancy Index (*LEI*) = $\frac{LE-20}{85-20}$

2. Education Index *(EI)*= $\frac{MYSI-EYSI}{2}$

   2.1 Mean Years of Schooling Index (*MYSI*) = $\frac{MYS}{15}$

   2.2 Expected Years of Schooling Index (*EYSI*) = $\frac{EYS}{18}$

3. Income Index*(II)* = $\frac{\ln(GNI_{pc})-\ln(100)}{\ln(75000)-\ln(100)}$

Finally, the HDI is the geometric mean of the previous three normalized indices:

$$HDI = \sqrt[3]{LEI \cdot EI \cdot II}$$

LE: Life expectancy at birth, **MYS:**Mean years of schooling (Years that a 25-year-old person or older has spent in schools), **EYS:**Expected years of schooling (Years that a 5-year-old child will spend with his education in his whole life), **GNIpc:**Gross national income at purchasing power parity per capita

Based on the above calculation, the Asian countries have been grouped as "very high human development (HDI=0.900)", "high human development (0.800<=HDI<0.900)", "medium human development (0.500<=HDI<0.800)", and "low human development (HDI<0.500)" countries(Ferrer, 2009).Table I shows development classesof Asian countries according to the UNDP 2012 ranking (UNDP, 2012).

Table I. Development Groups of Countries

Development Level	Country
Very High	Brunei Darussalam, Hong Kong, South Korea, Singapore
High	Armenia, Azerbaijan, Georgia, Malaysia, Palau, Sri Lanka, Kazakhstan, Turkey
Medium	Bhutan, Cambodia, China, Fiji, India, Indonesia, Kiribati, Kyrgyzstan, Laos, Maldives, Micronesia, Mongolia, Philippines, Samoa, Tajikistan, Thailand, Timor Leste, Tonga, Turkmenistan, Uzbekistan, Vanuatu, Vietnam
Low	Afghanistan, Bangladesh, Burma, Nepal, Pakistan, Papua New Guinea, Solomon

The HDI indicators - life expectancyat birth, mean years of schooling, expected years of schooling, and GNI per capita-could also be thought as independent variables for some multivariate statistical methods focused on classification. Since the main goal of this paper is to evaluate the Asian countries' development classesbased on HDI rankings, Ward's

Clustering Method asa multivariate statistical analysiswas chosen to compare development groups in terms of memberships.

Similar comparative studies could be found in the literature on human development index. Aguna,andKovacevicstudied uncertainty and sensitivity of HDI (Aguna, and Kovacevic, 2010). Guillermo et al. studied on explanation of HD components by using multivariate statistical analysis (Guillermo et al., 2007). Vázquez, andSumner used cluster analysis and obtained five development clusters (Vázquez, and Sumner,2012). Vázquez, andSumneralsousedclusteranalysistobuild a multidimensionaltaxonomy of developingcountries(Vázquez, andSumner,2013).

MATERIAL AND METHOD

Clustering is a popular techniqueused in manydifferentdisciplinesandthereareseries of multivariatemethodsthat is usedtofindtruegroups of data. Perhap some of them ostinteresting features is when unexpected groups are found, as the sereveal some unknown information about the data. In clustering the object sare grouped so that similar objects fall into the same class. Objects in one cluster should be homogeneous, with respect to some characteristics describing the within clusterproperties, and well separated from the elements in other clusters (Danielsson, 1999).

Ward’s clustering is one of the hierarchical clustering methods. Hierarchical clustering is a widely used data analysis tool. The idea is to build a binary tree of the data that successivelymerges similar groups of points. Visualizing this tree provides a useful summary of the data (Blei, 2008).

Ward's clustering method is also known as the minimum variance method (Hervada and Jarauta, 2004). It tends produce homogeneous clusters and the clusters are more balanced in size and tests have shown that Ward’s Methodis good at recovering the cluster structure. In general, Ward’s method almost performs the best in most situations, with the exception of situations where the data contain one or two very large groups and a few other very small groups and the method has also the highest accuracy in most situations (Ferreira, andHitchcock, 2009). Ward's minimum variance technique was superior, in the sense of giving a larger amount of correct classified observations, to most other methods (Sharma, 1996). Due to these advantages, it has been chosen as a clustering method for counties’ classification.

Ward'shierarchicalalgorithm starts with all the data points as a separatecluster. Each step of thealgorithminvolvesmergingtwoclustersthatarethe most similar. Aftereachmerge, the total number of clustersdecreasesbyone. Thesesteps can be repeated until the desired number of clustersis obtainedorthedistancebetweentwoclosestclusters is above a certain threshold distance(Karypis et al., 1999).

In order for the clusteringalgorithmtowork,the squared Euclidean distance measure was used, which is one of the most commonly adopted measures (Fovell et al., 1993). It is also a metric faster than clustering with the regular Euclidean Distance and an efficient tool for clustering databases(Mouffron et al., 2008).

The squared Euclidean Distance Measure is;

$$d^2(x,y) = (x_{MYS} - y_{MYS})^2 + (x_{EYS} - y_{EYS})^2 + (x_{GNI} - y_{GNI})^2 + (x_{LE} - y_{LE})^2$$

where:

x =country x; y =country y; MYS = mean years of schooling; EYS = expected years of schooling; GNI = gross national income; LE = life expectancy.

To determine the number of clusters there are several techniques without priorknowledge of the number of clusters or any other information about their composition (Fraley and Adrian, 1998).In this study, number of clusters was taken as four because there are four categoriesfor development levelsaccording to the HDI. All variables were standardized as z scoresto eliminatedifferent measuring units. Data for indicators; life expectancy at birth, mean years of schooling, expected years of schooling and GDP, were obtained from World Data Bank belong to the year 2012, and attached in Appendix A.

RESULTS AND CONCLUSION

By using Ward's Clustering Algorithm, four country clusters were obtained. Agglomeration schedule in Table II and dendrogram in Figure I displaythecasescombined at eachstage, thedistancesbetweenthecasesbeingcombined, andthelastclusterlevel at which a casejoinedthecluster.

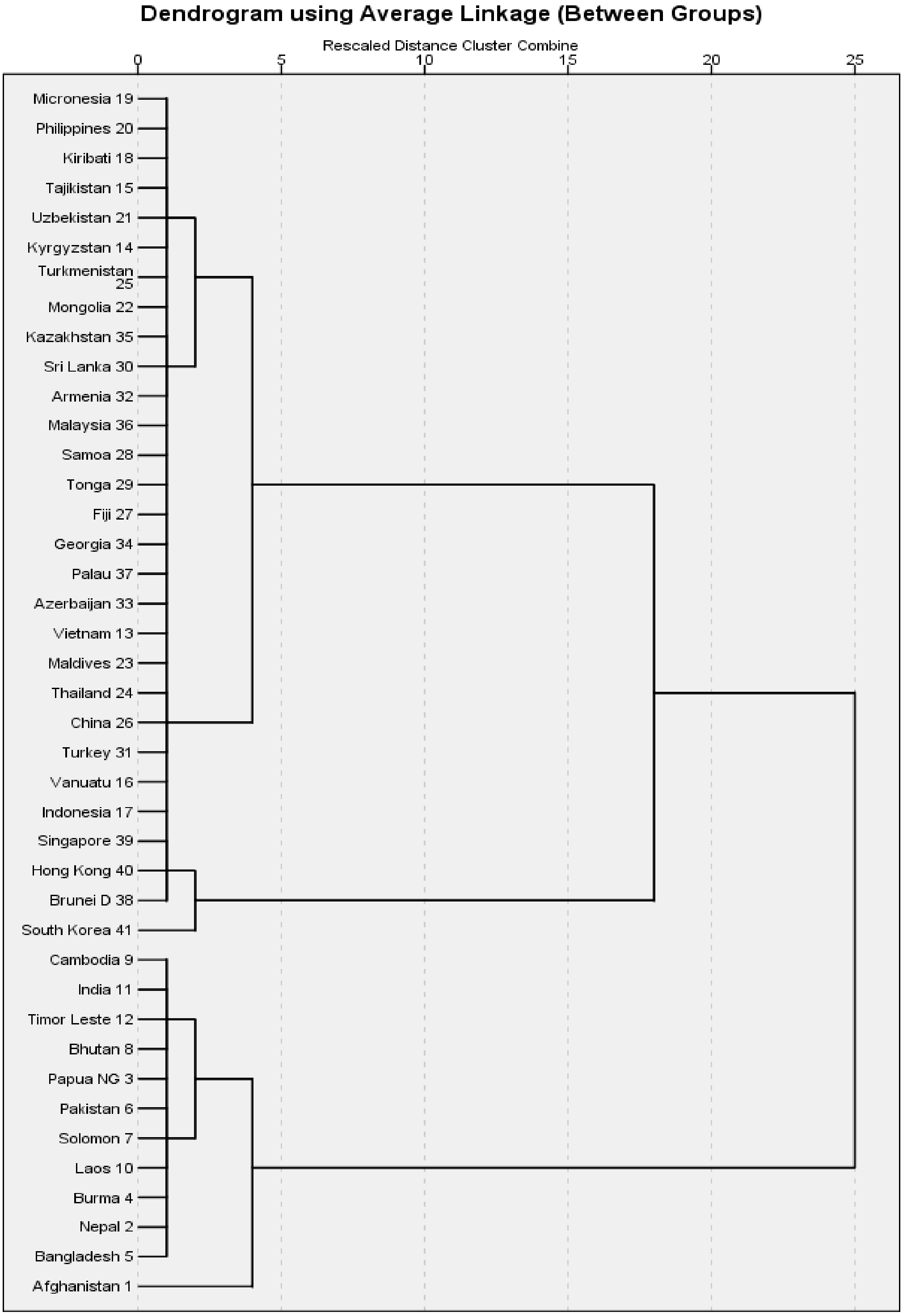
Table II. Agglomeration Schedule

	Cluster Combined			Stage Cluster First Appears		
Stage	Cluster 1	Cluster 2	Coefficients	Cluster 1	Cluster 2	NextStage

1	19	20	,010	0	0	6
2	15	21	,027	0	0	10
3	28	29	,074	0	0	14
4	7	10	,138	0	0	7
5	24	26	,228	0	0	15
6	18	19	,356	0	1	17
7	4	7	,504	0	4	21
8	13	23	,654	0	0	25
9	30	32	,825	0	0	19
10	14	15	,997	0	2	17
11	9	11	1,197	0	0	16
12	34	37	1,408	0	0	24
13	2	5	1,630	0	0	21
14	27	28	1,878	0	3	28
15	24	31	2,160	5	0	25
16	9	12	2,450	11	0	31
17	14	18	2,763	10	6	26
18	39	40	3,090	0	0	23
19	30	36	3,428	9	0	30
20	3	6	3,801	0	0	32
21	2	4	4,224	13	7	32
22	22	35	4,750	0	0	33
23	38	39	5,284	0	18	34
24	33	34	5,831	0	12	28
25	13	24	6,387	8	15	29
26	14	25	6,963	17	0	36
27	16	17	7,548	0	0	29
28	27	33	8,239	14	24	30
29	13	16	9,250	25	27	38
30	27	30	10,324	28	19	33
31	8	9	11,509	0	16	35
32	2	3	13,898	21	20	35
33	22	27	16,376	22	30	36
34	38	41	19,430	23	0	39
35	2	8	23,880	32	31	37
36	14	22	28,492	26	33	38

37	1	2	36,730	0	35	40
38	13	14	47,008	29	36	39
39	13	38	93,720	38	34	40
40	1	13	160,000	37	39	0

FigureI. Dendrogram



The cluster of low human development countries is on the bottomof dendrogramand their HDI values are within 0.37and 0.58.The cluster of high human development countries is on the top and their HDI values are within 0.62and 0.79.The cluster of medium development countries is on the upper middle side and their HDI values are within 0,69 and 0,72. On the lower middle side very high development countries occurs and their HDI values are within 0.86 and 0.91. It has been thought that the clusters and HD groups include almost same countries. Only a few medium human development countries' memberships are inconsistent according to the HDI groups. Clusters and memberships obtained from Ward's Method have been listed in Table III.

Table III. Ward's Cluster Memberships

Development Level	Country
Very High	Brunei Darussalam, Hong Kong, South Korea, Singapore
High	Armenia, Azerbaijan, Georgia, Malaysia, Palau, Sri Lanka, Kazakhstan, Fiji, Kiribati, Kyrgyzstan, Micronesia, Mongolia, Philippines, Samoa, Tajikistan, Tonga, Turkmenistan, Uzbekistan
Medium	China, Indonesia, Maldives, Thailand, Vanuatu, Vietnam, Turkey
Low	Afghanistan, Bangladesh, Burma, Nepal, Pakistan, Papua New Guinea, Solomon, Bhutan, Cambodia, India, Laos, Timor Leste

If we compare very high developed countries, HDI list and Ward's consist of same countries. Brunei, Hong Kong, Korea, Singapore.

Ward's Methodconsists more high developed countries than HDI list. These are additionally Fiji, Kiribati, Kyrgyzstan, Micronesia, Mongolia, Philippines, Samoa, Tajikistan,Tonga,Turkmenistan andUzbekistanwhich are the medium developed countries in HDI list.

If we look at themedium developed countries,there arelesscountries in the Ward's cluster than HDI list. These are China, Indonesia, Maldives, Thailand, Vanuatu, Vietnam and also Turkey. The Ward's Clustering Method made change either by relocating from medium to low or from medium to high. But, only Turkey changed membership from high to medium class.For each variable, Turkey was compared to the high developed countries' mean values. Except "mean years of schooling", there has not been a statistically significant difference between them with 5% level of significance. Then, mean years of schooling in Turkey issignificantly lower than the high developed countries. This could be the reason why Turkey's membership has been changed.

Low developed countries Afghanistan, Bangladesh, Burma, Nepal, Pakistan, Papua, Solomon are commonfor both Ward's Method and HDI. But according to the Ward's,Bhutan, Cambodia, India, Laos and TimorLesteare clustered in the low developed group.

This paper aimed at studying how would development classes be in case of using cluster analysis instead of UN's HDI ranking. It was compared thatthe Asian countries' development groups accordingto HDI distribution to anaturalclassification based on cluster analysis.The component indicators (variables) without any additional variables were used in the analysis. In order to obtain development groups Ward's Hierarchical Clustering Analysis was applied. All variables were standardized as z scores to eliminate the effect of outliers and variables' different measuring units. The Squared Euclidean Distance Measure waschosen as a dissimilarity measure. It was found that the classification into four groups is very stable.Very high developed countries didn't change, but the low, middle and high developedcountrieswere regrouped.According to the HDI list, most of the countries were in the medium developed class when Ward's method separates them relatively in a more balanced way. That means, geometric mean used for HDI calculation rates all medium developed countries with similar scores, when Ward's Method move some of them to another cluster because of the algorithm even if same indicators are used.

Overall, the results have shown that the clustering analysis could also be used as a robust choice to group countries in terms of HD indicators.In addition, it is hoped that this study would contribute to the future studies about development and could be of use for both individuals and organizations in selection of countries to invest.

References

1. **Böhringer, C.,Jochem, P.E.P., (2007)**Measuringtheimmeasurable—a survey of sustainabilityindices. Ecol. Econ. 63 (1), 1–8.
2. **Wilson, J.,Tyedmers, P., Pelot, R., (2007)**Contrastingandcomparingsustainabledevelopmentindicatormetrics. Ecol. Indicat. 7 (2), 299–314.
3. **Sagar., A.N., (1998)** "Thehumandevelopmentindex: a criticalreview." *Ecologicaleconomics*, 25.3, p. 249-264.
4. **Aguna, C.,Kovacevic M., (2010)** "Uncertaintyandsensitivityanalysis of thehumandevelopmentindex." *Human Development ResearchPaper*, p.11.
5. **UNDP (1990)**, Human Development Report, United Nations DevelopmentProgramme.
6. **Hou, J.,Walsh, P. P., &Zhang, J. (2014)**Thedynamics of Human Development Index. TheSocialScienceJournal.
7. **OPHI, (2011)** http://www.ophi.org.uk/wp-content/uploads/OPHI-RP-29a.pdf?0a8fd7
8. **UNDP, (2013)** "Human Development Report 2013, *Technical Notes*, Retrieved 28 November, 2013 fromhttp://hdr.undp.org/sites/default/files/hdr_2013_en_technotes.pdf
9. **Ferrer, E., (2009)** "ICT policyandperspectives of humandevelopment in Latin America: thePeruvianexperience." *Journal of technologymanagement&innovation*4.4, p. 161-170.
10. **UNDP, (2013)***Human Development Index (HDI) - 2012 Rankings*, Retrieved 14 January, 2014 from http://hdr.undp.org/en/statistics/
11. **Guillermo, P.,Cartea, M.E., Ordás, A., (2007)** "Comparison of severalclusteringmethods in grouping kale landraces." *Journal of theAmericanSocietyforHorticulturalScience*132.3, p. 387-395.
12. **Vázquez, S.T.,Sumner, A., (2012)** "Beyond LowandMiddleIncomeCountries: WhatifThereWereFiveClusters of DevelopingCountries?." *IDS WorkingPapers* 2012.404, p. 1-40.
13. **Vázquez, S.T.,Sumner, A., (2013)** "RevisitingtheMeaning of Development: A MultidimensionalTaxonomy of DevelopingCountries." *Journal of Development Studies* 49.12, p. 1728-1745.

14. **Danielsson, Åsa, et al.(1999)** "Spatialclustering of metals in thesediments of theSkagerrak/Kattegat." *AppliedGeochemistry*14.6: 689-706.
15. **Blei, David M. (2008)** "Hierarchicalclustering." LectureSlides, February
16. **Hervada-Sala, C.,&Jarauta-Bragulat, E. (2004)** A program toperformWard'sclusteringmethod on severalregionalizedvariables. Computers&geosciences, 30(8), 881-886.
17. **Ferreira, L., Hitchcock, D.B., (2009)** "A Comparison of Hierarchical Methods For Clustering Functional Data", *Communications in Statistics—SimulationandComputation*, 38.9, p. 1925-1949.
18. **S. Sharma, S., (1996)***AppliedMultivariateTechniques*, John WileyandSons, New York.
19. **Karypis, G.,Eui-Hong, H., Vipin, K., (1999)** "Chameleon: Hierarchicalclusteringusingdynamicmodeling." *Computer*32.8, p. 68-75.
20. **Fovell, R. G.,andFovell M.Y.C. (1993)**ClimateZones of theConterminous United StatesDefined Using Cluster Analysis. J.Climate, 6, 2103-2135.
21. **Mouffron, M.,Frederic R., Huafei Z., (2008)** "SecureTwo-PartyComputation of SquaredEuclideanDistances in the Presence of MaliciousAdversaries." *Information Security andCryptology*. Springer Berlin Heidelberg.
22. **Fraley, Chris, andAdrian E. Raftery. (1998)** "How manyclusters? Whichclusteringmethod? Answersvia model-basedclusteranalysis." Thecomputerjournal41.8: 578-588.