The Role of Economic and Political Features in Classification of Countries-in-Transition by Human Development Index

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Typical classification research of the United Nations' Human Development Index, HDI, has focused on its direct underlying sub-indices, i.e., Gross National Income, GNI, Education and Health. In this paper, economic and political systems within which the elements of HDI are created are under study. We use Bertelsmann Foundation's qualitative data from period 2008-2016 on 124 countries-in-transition including features of market economy, democracy and governance. The purpose is to identify the most important economic and political features predicting the level of HDI and to compare the classification performances of the applied models: an artificial neural network, ANN, and a logistic regression. The multi-method approach is complemented by multiple correspondence analysis for descriptive analysis purposes. The main results and original contributions include proving the effectiveness of the ANN over the logistic regression and showing that the higher levels and specific individual factors of marked economy, governance and democracy, the higher the HDI.
Keywords: *Artificial Neural Network, Democracy, Governance, Human Development Index, Logistic Regression Multiple Correspondence Analysis, Market Economy*

1 Introduction

The real wealth of a nation arises from its population and the its productive actions taking place in an economic system, which is based on institutions and rules affected by political system with governing decision-makers.The goal of economic development is to create an environment that will provide people with a long life and a good living standard and to improve peoples' lives[1, 2]. Individuals have subjective expectations in terms of better life [3] and they pursue to it through exchange in market-economy system [4]. Growth and human development ensure the quality of life and they are interdependent and complementary [5, 6].Therefore, using the outcomes of economic growth to increase the level of sustainable human development calls for special attention [7]. The 2011 Human Development Report [8] shows that the global challenges of sustainable development and economic growth need to be considered together, and governments have to cooperate with the business community to provide better living standards. Economic freedom is a feature of market economy. It means encouraging entrepreneurial activities, protecting property rights, freedom of exchange, reducing the size of governments, and lowering government expences. The relationship between economic freedom and human development is clear, when we look at the Economic Freedom Index and the Gross National Income (GNI) per capita: the more economic freedom, the higher the economic performance [9, 10]. Using GNI per capita, as an indicator of economic performance is argued being more appropriate than using GDP per capita [11,12].

The United Nations' Human Development Index (HDI) takes into account several dimensions to qualify a country as strong, medium or poorly developed [13]. HDI has three main dimensions of human development: (1) a long and healthy life, measured by life expectancy at birth; (2) knowledge: measured by the adult literacy rate and by enrollment in primary, secondary and tertiary education; (3) a decent living standard: represented by GNI per capita. HDI is a standardized measure of well-being, used to determine whether a country is developed, developing or underdeveloped, as

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well as, to measure the impact of economic policies on quality of life. Its purpose has been to work as a reference framework for both economic and social development. Analysis of the HDI highlights the existence of economic and social disparities between developed and developing countries and allows the identification, definition and implementation of government policies needed to reduce the gaps [14].

HDI covers limited areas, which are not necessarily related and complementary. For example, a high level of literacy and enrolment in education does not necessarily mean a high value of GNI. For comparison, the Economic Freedom Index (EFI) covers broader areas. EFI measures freedom as a precondition for development, while HDI focuses on human development as the ultimate goal, regardless of the factors contributing to it [15, 16]. The high scores for some of the indexes that make up it are consistent with a high degree of government intervention [17] and, for example, the countries with high scores on the education index have the highest shares of GNI spent on education. It is obvious that the components (1)-(3) of HDI are its very good predictors, but national income level (3) has been found the most important one followed by education level (2) and life-expectancy, in this order [18].

Using the direct component of HDI, neural network modelling has shown over 95% accuracy in predicting the level of HDI, while classical linear regression has reached an accuracy level of 90% [19]. In general, the prediction capability of neural networks has been shown superior over other methods in several studies and application environments [20, 21, 22, 23, 24]. Some recent research has focused on HDI, for example, Connoly et al. [25] apply the logistic regression to study the predictors that lead to a probability of high HDI: GDP per capita, the number of schooling years and life expectancy. Their investigation shows that an increase in the expected years in education most likely will contribute to a very high level of HDI. Saboo et al [26] compare ANNs and multilinear regression accuracy in predicting HDI based on four predictors: mean years of schooling, average years of schooling, GNI per capita and life expectancy at birth. The experiment showed that ANNs accuracy was better, 95%.

HDI has its limitations as an indicator of development, but it is widely used and factors affecting it are of major interest for policy makers [18]. Market-economy system based on free exchange requires rules and they are affected by political systems within which decision-makers govern. In this paper, the purpose is to take into account these perspectives ranging from the status and characteristics of existing market-economy system, level of democracy, and the capability of decision-makers in their difficult environment, and their impact on HDI.

In section 2, the used data variables are described and discussed. Section 3 applies the chosen methods, firstly in 3.1, the HDI categories of the 124 countries-in-transition are described by using multiple correspondence analysis, MCA, to analyze the correlations of categorical aggregate-level indices built on the features of market economy, democracy, governance quality and difficulty. To broaden the picture, we include also factors determining the difficulty level, i.e., the UN's education index and gross national income index, the two direct underlying factors of HDI. In section 3.2, an artificial neural networks approach is used to find out the most important factors predicting HDI categories. Section 3.3 uses logistic regression to withdraw another perspective to the relation of economic and political features and HDI. The predictive power of the models and other results are discussed in comparison in the concluding section 4.

2 Data

Bertelsmann Foundation's most recent data from 2018 [27] depicting the situation as of January 2017 is used together with United Nation's human development index, HDI, for the period 2008-2016 [13] (table 1). The Bertelsmann variables evaluate three aspects: political, economic, and governance quality.

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Table 1. Description of variables

Variable	**Criteria**
***Aggregate indicators* for MCA**	
ME - Market economy	ME averages the factors of political system, V6-V12.
DEM - Democracy	DEM averages the factors of political system, V1-V5.
BTI - Bertelsmann Index	The Bertelsmann transformation index averages the underlying political, V1-V5, and economic, V6-12, indicators. BTI is a combination of ME and DEM. [27]
GOV – Governance Index	The governance index weighs the quality indicators, V14-V17, by difficulty levels underlying V13. [27]
DIF – Difficulty Index	DIF measures the difficulty of the operating environment [27].
GNI - Income Index	The UN's gross national income of its production less the cost of used factors of owned by others. Atlas scaled index. [27]
EDU - Education Index	The UN's rescaled education index [27]
HDI, human development index	United Nation's composite index measuring human development by the three dimensions: 1) life expectancy, 2) education and 3) standard of living (GNI). The dependent variable is divided into categories: *high, medium*, *low* and *very low* [13]
Political features	
V1 - Stateness	Clarity of state's existence with established structures.
V2 - Political Participation	Extent of general, free and fair elections and political liberties.
V3 - Rule of Law	Extent of separation of powers and civil rights.
V4 - Stability of Democratic Institutions	Capability and acceptance of existing democratic institutions.
V5 - Political and Social Integration	Level of representative meditation between society and the state.
Economic features	
V6 - Level of Socio-economic Development	Level of lack of poverty and inequality, which exclude people from society and don't permit freedom of choice for all citizens.
V7 - Organization of the Market and Competition	Level of clear rules for stable market-based competition.
V8 - Currency and Price Stability	Extent of institutional precautions to control inflation sustainably with appropriate monetary and fiscal policies.
V9 - Private Property	Extent of property rights to support a functional private sector.
V10 - Welfare Regime	Extent of equal opportunities and social safety nets to compensate for social risk of unemployment, poverty and illness.
V11 - Economic Performance	Level of economic performance based on quantitative measures such as GDP, inflation, unemployment, FDI, public debt, etc.
V12 - Sustainability	Level of sustainable growth based on education, research and development, and environmentally sustainable policies.
Governance features	
V13 - Steering Capability	Capability of governance to prioritize and implement policies.
V14 - Resource Efficiency	Efficient use of resources in anti-corruption policy environment.
V15 - Consensus-Building	Level of governance's consensus-building within society.
V16 - International Co-operation	Level of governance's ability to co-operate with external actors.

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Table 1 describes first the aggregate-level variables, which are mainly used for descriptive purposes. They are built on the following variables, V1-V16, except the dependent variable, HDI.

1) the political indicators measure the state of political transformation in terms of five criteria, V1-V5, based on expert assessment of 18 underlying questions (excluded here). Each five criteria have further underlying variables of which are weighted by averaging. V1, Stateness, measures specifically state's monopoly on the use of force and is viewed as a precondition to democracy, V2 deals with general political liberties, V3 focuses on the separation of powers, V4 deals with general quality and acceptance of exiting political institutions, while V5 measures representativeness of the institutions;

2) the economic indicators measure the state of transformation towards market economy in terms of seven criteria, V6-V12, which are further built on 14 underlying indicators (not included here although some are pointed out for their importance of later interpretations of results). These take into account the freedom of choice not limited by poverty, V6, rules of competition, V7, stability of monetary and fiscal policies, V8, property rights, V9, equal opportunity based on safety nets, V10, economic performance, V11, sustainable growth, V12;

3) the governance indicators, V13-V16, are further built on individual indicators. Bertelsmann data also uses difficulty level (DIF in table 1) as a governance indicator as weight for governance quality measured by V14-V17 to get the Bertelsmann's governance index, BTI. Data for the difficulty include structural difficulties, traditions and conflicts in society all based on expert evaluations, but it further includes comparable measures for education and GNI, the UN's education index., and also rule of law. We use these difficulty-related variables only for descriptive purposes and exclude them from neural network and logistic regressions as they have direct underlying variables of HDI, while our goal is to focus on the political and economic features, which allow development measured by income, education and health. V13 measures the capability of policymakers, V14 the efficiency in the use of resources, and V15 the co-operation in decision-making within a country, while V17 reflects the co-operation with foreign actors.

3 Methods and Analysis

3.1 Description of HDI Classes and Multiple Correspondence Analysis (MCA)

Following [28], the multiple correspondence analysis is conducted with R software to find the related high-level factors characterizing countries and to reveal their importance in explaining the variations in the data. MCA is a principal component method applicable to qualitative, categorical, data. Dimensions represent principal components, which are ordered so that the first and second ones (Dim1 and Dim2 in figures 1 and 2) explain most of the variation of the data. In MCA, the indicator matrix is used and associations between variables are uncovered by calculating distances between the variable categories, as well as, between countries. The associations are visualized and interpreted. We use categorical data based on Bertelsmann's classification ("aggregate" variables in Table 1) for market economy (ME based on V6-V12), democracy (DEM based on V1-V5), their combination (BTI combining DEM & ME based on V1-V12 and corresponding the actual Bertelsmann Transformation Index), governance (GOV based on V14-V16), the level of environmental difficulty to govern (DIF based on V13), and the four categories of the UN's human development (HDI) and national income index (GNI, Atlas-scaled) and UN's education index (EDU).

The United Nations [13] classifies countries in four categories according to four intervals of HDI: low (0-0.499), medium (0.500-0.799), high (0.800-0.899) or very high (greater than 0.900). Here, instead classify countries into following four classes: very low (0-0.520), low (0.521-0.678), medium (0.679-0.768), and high (greater than 0.769) based on the calculated quartile levels from our sample. As our sample of 124 consists of countries-in-transition, we do not have countries belonging

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to the UN's very high class except Singapore with its HDI of 0.91 (cf. tables 2-5).

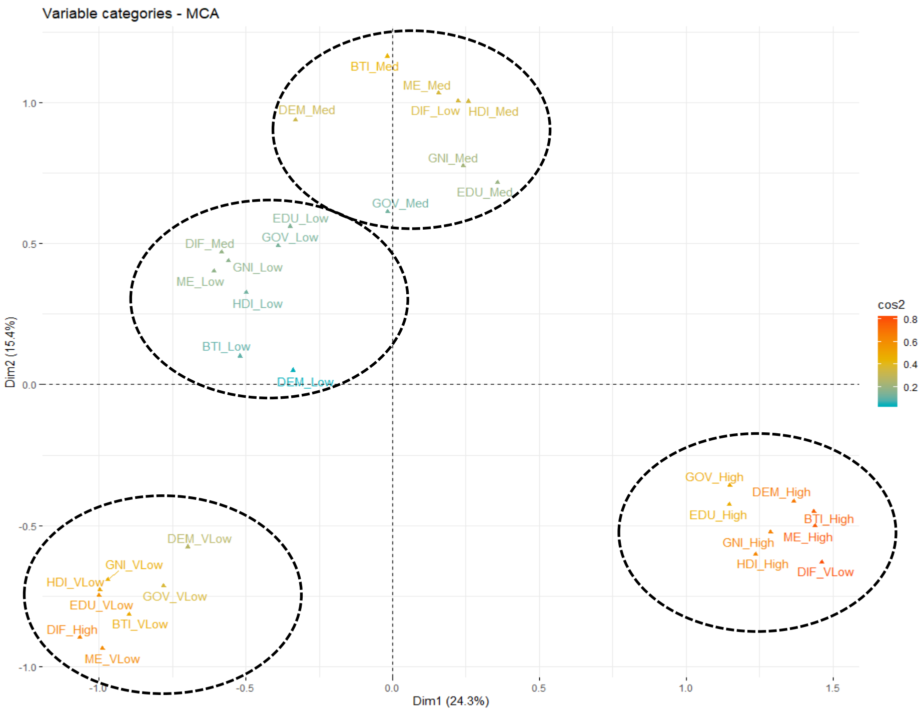

Fig. 1. MCA and aggregate variable classes: HDI, ME, DEM, BTI, GOV, DIF, EDU and GNI

Figure 1 shows all the classes of the aggregate variables HDI (range 0-1), ME, DEM, BTI (DE&ME), GOV (all ranging from 0 to 10), DIF, GNI, and EDU (ranging from 0 to 10, but in *reversed order,* i.e., the lower the index value, the better). The largest contributions (measured by their correlation, cos2, with the two dimensions) are depicted from largest (red) to lowest (blue). The variable classes are clustered together very clearly. Without exceptions, *high* classes of HDI, ME, DEM, BTI, GOV, DIF, GNI and EDU are clustered together with *very low* DIF, and the same applies to *medium, low* and *very low* categories (the difficulty level rising, when other variables get lower). The horizontal axis of figure 1 measures the variables' contribution to the first component (Dim1) of MCA, which explains 24.3% of total variability of the X variables (which have Y-Z classes each), while the vertical axis measures the contribution to the second most important component (Dim2) explaining 15.4% of the total variability.In Figure 2, countries are positioned on the same two dimensions. It is seen that the largest correlations (cos2) with the dimensions are found on the bottom-right corresponding the *high-class* countries with the lowest difficulty level, on the top corresponding to *medium*-class countries, on the bottom-left corresponding to very *low-class* countries with the highest difficulty level. The countries seen in figure 2 are *related* to the variable classes positioned similarly in the two-dimensional space (Figure 1), so, they are close to each other; the variable classes can be seen as features describing the countries grouped close to each other.

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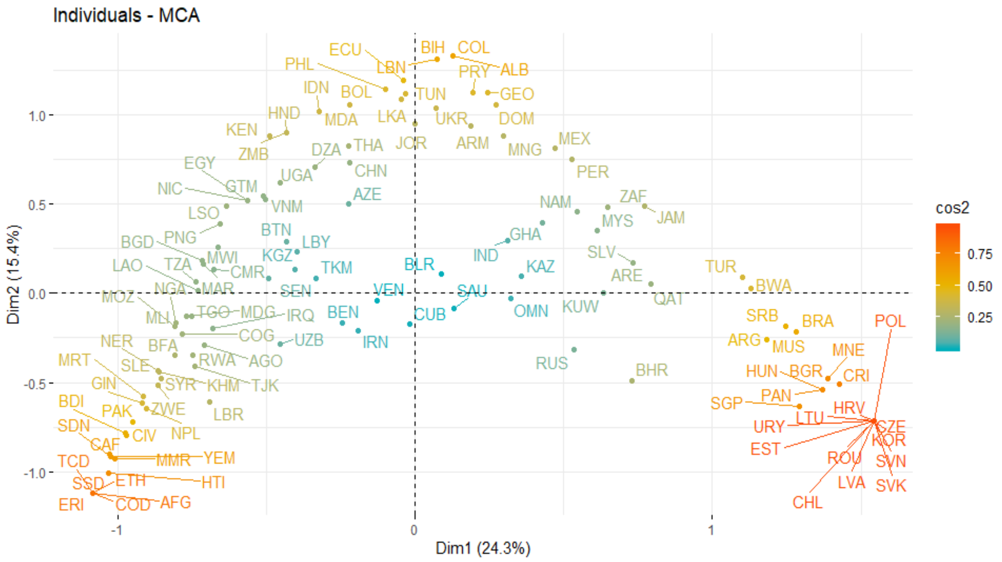

Fig. 2. MCA and the 124 countries-in-transition

The countries in the four HDI groups are described using the aggregate variable classes. *The high-level group* dominated by the bottom-right quadrant is related to *highly advanced democracy and market economy* (the highest class of the Bertelsmann index, BTI) with *negligible difficulty* of the acting environment (related to difficulties to govern, traditions in society, and social, ethnic and religious conflicts). The 31 countries belonging to this group are shown in table 2 ordered by HDI values. The average HDI is 0.82; The average market economy and democracy combination, BTI, is 7.1 (ME: 7.5, DEM: 6.8), and the average of governance quality, GOV, is 5.6. The mean difficulty index, DIF, is very low (3.0) supported by high GNI (avg: 2.1) and high education (avg: 1.7).

Table 2. Countries with *High* HDI category

Country	ID	HDI	Country	ID	HDI
Singapore	SGP	0,91	Bahrain	BHR	0,81
South Korea	KOR	0,89	Oman	OMN	0,80
Slovenia	SVN	0,88	Romania	ROU	0,80
Czech Republic	CZE	0,87	Montenegro	MNE	0,80
Estonia	EST	0,86	Belarus	BLR	0,80
United Arab Emirates	ARE	0,85	Kuwait	KUW	0,80
Qatar	QAT	0,84	Russia	RUS	0,79
Poland	POL	0,84	Bulgaria	BGR	0,79
Lithuania	LTU	0,84	Uruguay	URY	0,79
Slovakia	SVK	0,84	Malaysia	MYS	0,78
Latvia	LVA	0,83	Kazakhstan	KAZ	0,78
Saudi Arabia	SAU	0,83	Cuba	CUB	0,77
Hungary	HUN	0,83	Iran	IRN	0,77
Chile	CHL	0,82	Panama	PAN	0,77
Croatia	HRV	0,82	Costa Rica	CRI	0,77
Argentina	ARG	0,81	Average		0,82

The medium-level group is dominated by countries mainly contributing to the second dimension (Dim2). The 31 countries belonging to this group and their HDI values are seen in table 3. They are all related to *advanced democracy and market economy* and mostly to *high national income (GNI) and high HDI.* The average HDI of the group is 0.73; The average BTI is 6.0 (based on the levels of avg. ME: 6.0 and DEM: 5.9). Average governance quality (GOV: 4.9). is lower than in the first group. The difficulty level, DIF, is higher than in the first group averaging 4.8 and the income and education levels are lower (GNI: 5.1; EDU: 2.8).

Table 3. Countries with *Medium* HDI category

Country	ID	HDI	Country	ID	HDI
Serbia	SRB	0,77	Peru	PER	0,73
Venezuela	VEN	0,77	Thailand	THA	0,73
Mauritius	MUS	0,76	Ecuador	ECU	0,73
Albania	ALB	0,76	Libya	LBY	0,73
Mexico	MEX	0,76	Colombia	COL	0,73
Sri Lanka	LKA	0,75	Jamaica	JAM	0,72
Turkey	TUR	0,75	China	CHN	0,72
Lebanon	LBN	0,75	Tunisia	TUN	0,72
Georgia	GEO	0,75	Mongolia	MNG	0,72
Azerbaijan	AZE	0,74	Dominican Republic	DOM	0,71
Ukraine	UKR	0,74	Turkmenistan	TKM	0,69
Bosnia and Herzegovina	BIH	0,74	Paraguay	PRY	0,68
Brazil	BRA	0,74	Moldova	MDA	0,68
Armenia	ARM	0,74	Uzbekistan	UZB	0,68
Algeria	DZA	0,74	Botswana	BWA	0,68
Jordan	JOR	0,73	Average		0,73

The low-level group of countries and their features also mainly contribute to the second component (Dim2). The 31 countries and the HDI values in this group seen table 4. They are characterized by *market economy with functional flaws* and *defective democracy.* They have less able *governances*, which face *serious difficulties.* The average of HDI is 0.60; BTI is 5.1 (ME: 5.0; DEM: 5.3); GOV: 4.6. The difficulty (DIF: 6.2) is much higher than in the first two groups, while average income (GNI: 7.5) and education (EDU: 6.0) levels are far lower (reminding that the GNI and EDU indices are in reversed order compared to other aggregate indices).

Table 4. Countries with *Low* HDI category

Country	ID	HDI	Country	ID	HDI
Philippines	PHL	0,68	India	IND	0,60
Egypt	EGY	0,68	Bhutan	BTN	0,58
Indonesia	IDN	0,67	Congo Republic	COG	0,57
El Salvador	SLV	0,67	Ghana	GHA	0,57
Vietnam	VNM	0,67	Laos	LAO	0,57
South Africa	ZAF	0,67	Bangladesh	BGD	0,56
Bolivia	BOL	0,66	Zambia	ZMB	0,56
Iraq	IRQ	0,66	Kenya	KEN	0,56
Kyrgyzstan	KGZ	0,65	Cambodia	KHM	0,55
Tajikistan	TJK	0,64	Myanmar	MMR	0,55

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Country	ID	HDI	Country	ID	HDI
Nicaragua	NIC	0,63	Nepal	NPL	0,54
Morocco	MAR	0,63	Angola	AGO	0,54
Guatemala	GTM	0,62	Pakistan	PAK	0,54
Namibia	NAM	0,61	Papua New Guinea	PNG	0,53
Syria	SYR	0,60	Cameroon	CMR	0,52
Honduras	HND	0,60	Average		0,60

The very low -level group of countries and variable classes are seen on the top-left quadrant of figure 2. These 31 countries with their HDI values are shown in table 5. Their most important characteristic is *failed democracy and market economy* (BTI). They are also described by *failed governance* with *massive difficulties.* Further, *rudimentary market economy* and *very low human development*, *income* and *education* levels are related classes. The averages of the bottom group are: HDI: 0.45; BTI: 4.4 (ME: 4.0; DEM: 4.8); GOV 4.4; DIF: 7.5; GNI: 9.2; and EDU: 8.7.

Table 5. Countries with *Very Low* HDI category

Country	ID	HDI	Country	ID	HDI
Madagascar	MDG	0,51	Malawi	MWI	0,45
Nigeria	NGA	0,51	Ethiopia	ETH	0,43
Tanzania	TZA	0,50	Guinea	GIN	0,42
Lesotho	LSO	0,50	Eritrea	ERI	0,42
Mauritania	MRT	0,50	Congo Democratic Republic	COD	0,42
Rwanda	RWA	0,49	Liberia	LBR	0,42
Zimbabwe	ZWE	0,49	Mozambique	MOZ	0,41
Uganda	UGA	0,49	Mali	MLI	0,41
Yemen	YEM	0,49	Burundi	BDI	0,40
Benin	BEN	0,49	Sierra Leone	SLE	0,40
Sudan	SDN	0,48	South Sudan	SSD	0,40
Haiti	HTI	0,48	Burkina Faso	BFA	0,39
Afghanistan	AFG	0,47	Chad	TCD	0,38
Senegal	SEN	0,47	Central African Republic	CAF	0,35
Togo	TGO	0,47	Niger	NER	0,33
Côte d'Ivoire	CIV	0,46	Average		0,45

3.2 Multilayer Artificial Neural Network

The multilayer perceptron (MLP) neural network (NN) built using IBM SPSS v 20 as the statistical software. We have chosen the approach based on its proven predictive ability over several classifiers, e.g., in evaluating country risk ratings [20] and in predicting student learning performance, several authors [21, 22, 23] ascertained the superiority of NNs over other algorithms.

The dataset of 124 countries-in-transition (total of 617 valid cases over the period 2008-2016) was divided into two subsets: the train set contains 70.7% of the observations, and the test set contains 29.3% (Table 6).

Table 6. Case Processing Summary

		N	Percent
Sample	Training	436	70.7%
	Testing	181	29.3%

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Valid	617	100.0%
Excluded	0	
Total	617	

We used the back-propagation algorithm based on the scaled conjugated gradient and one hidden layer. The hidden layer's activation function is the hyperbolic tangent, $f:\mathrm{R}\to(-1,1), f(c)=\dfrac{e^{c}-e^{-c}}{e^{c}+e^{-c}}$, and the output layer activation function is softmax,

$$\sigma: R^{K}\to(0,1), P_j=\sigma(z)_j=\frac{e^{z_j}}{\sum_{k=1}^{K}e^{z_k}}, for\ j=1,...,K\ and\ z=(z_1,...,z_K)\in R^{K}$$

K is the number of output neurons, four in this case. The weights are updated at each step with the goal of minimizing the error function. The error function is here the cross-entropy error due to the use of softmax-activation function. The sum of the output activations equals 1, therefore we can interpret the softmax layer as a probability distribution and the values P_j as the estimated probabilities of the inputs' classification [21]. For the output node j, its predicted value P_j and the real target value t_j, the cross-entropy error is $E=\sum_{j=1}^{K}t_j\ln P_j$.

The independent variables, V1-V16, are shown in Table 1 and the dependent variable is HDI. Figure 3 shows the number of neurons in every layer, the 16 independent variables in the input layer and the four HDI categories in the output layer. We chose one hidden layer MLP and the automatic architecture selected seven neurons and the bias.

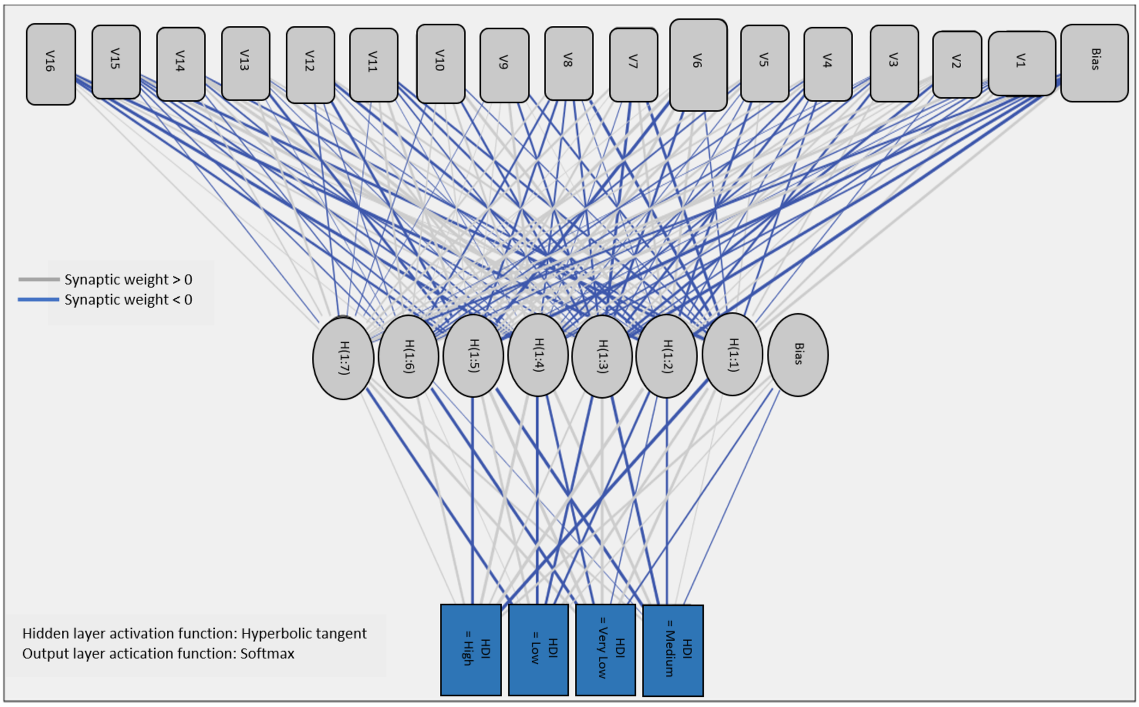

Fig. 3. The applied neural network architecture

From Figure 4, it is seen that the level of socioeconomic development (V6, particularly, socio-economic barriers), welfare regime, (V10, particularly, equal opportunities and safety nets), sustainability (V12), rule of law (V3), political and social integration (V5) and resource efficiency (V14) have the greatest effect on how MLP classifies the countries in terms of HDI categories. Other determinants of MLP predictive power are the currency and

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price stability (V8) and organization of the market and competition (V7).

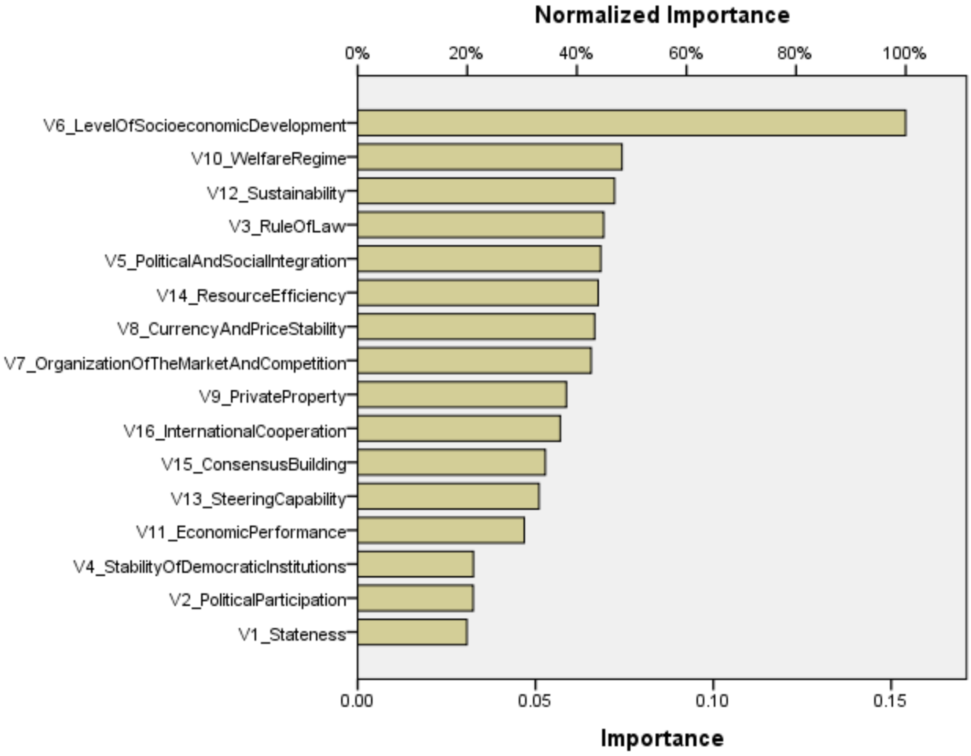

Fig. 4. The importance of factors on HDI

The model summary in Table 7 gives information about the MLP performance on the train set and the test set. The overall percentage of correct predictions of the train set and test set are 83.5% and, respectively, 85.1%. MLP correctly classified.

Table 7. Classification

Sample	Observed	Predicted				
		Very Low	Low	Medium	High	Percent Correct
Training	High	0	1	10	110	90.9%
	Medium	0	10	84	11	80.0%
	Low	14	88	12	0	77.2%
	Very Low	82	13	1	0	85.4%
	Overall Percent	22.0%	25.7%	24.5%	27.8%	**83.5%**
Testing	High	0	0	9	47	83.9%
	Medium	0	4	35	3	83.3%
	Low	4	39	3	0	84.8%
	Very Low	33	4	0	0	89.2%
	Overall Percent	20.4%	26.0%	26.0%	27.6%	**85.1%**

Each predicted value is the probability that a country belongs to a class. One notices from table 7 that for wrongly predicted cases, MPL predicts a category very close to the real one, all the wrongly predicted categories in the test set have been predicted as the neighboring category or the actual one.

3.3 Multinomial Logistic Regression

The model uses HDI as a class variable. HDI was conceived as a composite index combining three dimensions: education, health and income factors. Multinomial logistic regression measures the extent to which the class variable HDI depends on the set of explanatory variables, V1-V16. Each class of the dependent variable HDI leads to a probability of success. The reference class is the *very low* level of HDI.

Table 8. Model Fitting Information

Model	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC	BIC	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	1709.856	1723.130	1703.856			
Final	761.162	986.831	659.162	1044.693	48	.000

Table 8 is the likelihood ratio test of this model called Final model against the model with all parameter coefficients null called Null model. The Chi-Square statistic is 1044.663, computed as the difference between the -2 log-likelihoods of the Null and Final models. The significance level is less than 0.05, therefore the Final model outperforms the Null model.

Table 9. Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	1112.710	1800	1.000
Deviance	659.162	1800	1.000

Table 9 shows two tests of the null hypothesis according to which the model fits the data. If the null hypothesis is true, then the Pearson and deviance statistics have chi-square distributions with the degrees of freedom displayed in Table 9. The significance level equals 1, greater than 0.05, meaning that the model fits the data.

Table 10. Pseudo R-Square

Cox and Snell	.816
Nagelkerke	.871
McFadden	.613

The three models from Table 10 are used to measure the coefficient of determination pseudo R-square. Nagelkerke's R^2 is the largest of all, 0.871, so this model is the most appropriate: 87.1% is the proportion of variance in HDI associated with the predictors.

Table 11. Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	731.176	72.014	3	**.000**

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V1	662.137	2.974	3	.396
V2	665.763	6.600	3	.086
V3	666.225	7.062	3	.070
V4	661.830	2.667	3	.446
V5	665.476	6.314	3	.097
V6	870.765	211.603	3	**.000**
V7	674.764	15.601	3	**.001**
V8	678.208	19.045	3	**.000**
V9	670.849	11.687	3	**.009**
V10	669.649	10.487	3	**.015**
V11	686.472	27.310	3	**.000**
V12	669.147	9.985	3	**.019**
V13	665.879	6.717	3	.081
V14	668.518	9.356	3	**.025**
V15	668.868	9.706	3	**.021**
V16	677.520	18.357	3	**.000**

As seen in table 11, the significance value (Sig.) of the Chi-square test should be small than 0.05, so one can conclude that significant factors om HDI are the level of socioeconomic development (V6), organization of the market and competition (V7), currency and price stability (V8), private property (V9), welfare regime (V10), economic performance (V11), sustainability (V12), V14 resource efficiency (V14), V15 consensus building (V15) and international co-operation (V16).

Table 12. Classification

Observed	Predicted				
	Very Low	Low	Medium	High	Percent Correct
High	0	2	19	156	88.1%
Medium	0	21	103	23	70.1%
Low	22	120	18	0	75.0%
Very Low	107	26	0	0	80.5%
Overall Percentage	20.9%	27.4%	22.7%	29.0%	78.8%

We note that under the logistic regression model all the features of the political system (V1-V5), which together make up the democracy index, are insignificant (V3, rule of law, would be significant at 10% level, though) together with governance's steering capability (V13), while the governance quality (V14-V16) are significant together with all features of the economic system (V6-V12).

Table 12 contains the classification results, with an overall percentage of 78.8% correct classification. The model predicts very well the countries in the top (*high*) and bottom (*very low*) HDI categories, 88.1% and 80.5%, respectively, while the middle (*medium* and *low*) categories the accuracy is lower, 70.1% and 75.0%, respectively.

4. Conclusions

This paper took a multi-method approach to study the impact of features of political and economic system on human development index, HDI over the period of 2008-2016. The purpose was to compare the effectiveness of neural network (MPL) and logistic regression in predicting the HDI classes (*very low, low, medium, high*) for 124 countries-in-transition and to identify the most important features

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contributing to HDI and the related aggregate-level qualitative characteristics of countries using multiple correspondence analysis, MCA.
The MCA was run, firstly, for all countries with aggregated categorized variables of HDI, market economy, democracy, their combination, BTI, governance quality, difficulty level and GNI and education indices. The last two were included for two reasons: they are direct underlying variables in HDI and Bertelsmann use them also in their difficulty index. For the same reason, we excluded the difficulty level as it can distort the effects of political and economic features on HDI this being the main research subject. MCA suggested that higher levels of market economy, democracy and governance quality go hand-in-hand and the higher they are, the more developed the countries tend to be measured by HDI, GNI or education level.
The research literature showed in wide range of application areas that neural network can provide more accurate predictions than the more traditional statistical methods, including logistic regression models. We trained the neural network model to predict the development levels of countries-in-transition. The model had a very high rate of accuracy, 85.1%. The corresponding accuracy of the logistic regression was 78.8%. The identified most powerful predictors of HDI class were level of socioeconomic development (V6 reflecting socio-economic barriers), welfare regime, (V10, reflecting equal opportunities and safety nets), sustainability (V12), rule of law (V3), political and social integration (V5) and resource efficiency (V14), currency and price stability (V8) and organization of the market and competition (V7), in this order. Logistic regression gave support to the results from the NN, but rule of law was found insignificant. The most interestingly, logistic regression didn't find any political features, V1-V5 statistically significant undermining the significance of democracy index. Regardless of the statistical insignificance in the individual political factors, the aggregate democracy level was clearly positively related to high HDI levels aside with market economy and governance quality, the latter also on the individual variable level.

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