# Governance, Human Development and Aid:
# Patterns Discovered Using Data Mining Techniques

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By Ruben Canlas Jr.


## Abstract

This paper uses data mining tools to discover patterns at work in governance, human development and aid effectiveness. It reports countries with good governance scores also have high levels of human development, and the top recipients of aid have low governance scores. Based on these findings, it recommends designing policies for strengthening government effectiveness, regulatory quality, rule of law, political stability, and voice and accountability.


## 1. Introduction

A specter is haunting the development community -- lack of good governance has undermined billions of dollars worth of development aid poured into countries with corrupt government structures. The top ten recipients of official development assistance (ODA) all have unimpressive governance ratings, based on World Bank's indicators (World Bank, 2009). This is now being cited as explanation for the failure of aid to trickle down and improve the quality of life of people in the recipient countries.

Kaufmann, one of the pioneers on studying governance, said, "Focusing on the group of countries that are performing very poorly on corruption... may spur further debate about aid effectiveness. This could be healthy (Kaufmann, 2009 18 November)."

Previous works of Kaufmann, et al. demonstrate that good governance leads to good per capita national income (Kaufmann and Kraay, 2002). But does it also mean a better quality of life for people? Some countries, like China and oil-rich states, have high per capita income but score low on the Human Development Index (HDI).

The Philippines lost $48 billion to corruption in the span of twenty years, an amount enough to pay its $40.6 billion foreign debt (ADB, 2009). Yet the country belongs to the top third of ODA recipients and its HDI score falls under the medium class (0.751). It scored below the regional governance average on three out of five governance indicators: control of corruption, rule of law and political stability (Kaufmann, et al., 2009). It scored lower than India and China which are its main competitors in business process outsourcing.

The problem of corruption in the Philippines is so alarming that its Medium Term Development Program devotes one chapter to it: “Corruption distorts access to services for the poor, results in government’s poor performance and, consequently, low public confidence in government. The culture of corruption in the country breeds the vicious cycles of poverty and underdevelopment (NEDA, 2004).”

Change agents need a more systematic approach to analyze governance and its effects on countries. Kaufmann, et al.’s work in developing the governance indicators gave us a data set that allow us to operationalize, quantify and compare among different countries. Development experts are now conducting different kinds of studies on these indicators, finding correlation with different economic measurements by using statistical regression techniques.

This paper takes a fresh approach to the topic. It uses data mining techniques to uncover patterns and trends in the records of governance indicators. It tries to relate governance to human development using the HDI metrics. To my knowledge, no papers have been written about using data mining on governance indicators. Surveying the literature, I only found data mining applied to corporate governance.

## 2. Objectives

This study aims to:

2.1. Apply data mining techniques to find patterns and trends between governance indicators and human development. Which particular governance indicators contribute more to determining HDI?

2.2. Apply the same techniques to analyze aid distribution. What attributes do the top aid recipients share in common?

2.3. Derive rule tables and guidelines based on the data mining models.

2.4. Draw policy recommendations based on these findings.

## 3. Data mining and regression

Data mining employs a methodology that diverges from traditional statistical techniques. It looks for association or correlation among attributes (variables); regression seeks to establish causality. It is exploratory in nature, preferring to start with a large data set and let schemes find the best predictive attributes.

Regression prefers a pared down list of attributes while data mining takes on many attributes and pares them down as the experiments proceed. Data mining starts by playing with different data models and ends up with a hypothesis. Regression starts with a hypothesis and ends up with a model (Shillabeer and Roddick, 2007). While both techniques try to predict a future outcome, regression results to a parametric equation and data mining produces concept descriptions in the form of rules, tables, trees and also equations.

Some data mining models have performed better than parametric equations and this was true in cases involving many variables and whose interactions were not fully understood. In a Texas study on the effect of ground ozone production (the prime ingredient of smog), data mining schemes performed better at predicting smog days than the existing parametric equation used by scientists (Zhang and Fan, 2007). Scientists have found a correlation between ground ozone and smog but are yet to define the chemical process behind the pollutant.

Because of its ability to discover patterns and relationships in large, random attributes, data mining is suitable for unravelling a complex domain such as governance and human development.

Data mining is a recent development compared to regression. Although it is used in market research (Amazon and iTunes use data mining to recommend titles to customers), it has not gained acceptance in other fields. (I tried to do a review of literature but the closest related studies were papers applying data mining on corporate governance).

## 4. Methodology

This study followed four steps common to data mining: understand the data and knowledge domain, gather and prepare data, conduct data mining (also known as modelling), and interpret/evaluate the results.

### 4.1. Understanding the data and knowledge domain.

I used Kaufmann, Kraay, and Zoido-Lobaton's *Governance Matters* (1999) to understand the indicators and their correlation with national income. This has since been updated to *Governance Matters VIII* (2009).

In these works, Kaufmann, et. al provide a conceptual framework for governance -- the power of citizens to choose their governments, the quality and effectiveness of policy and law, and how well citizens respect social institutions. From this framework, Kaufmann, et al. operationalized governance through six metrics:

i. Voice and Accountability (VA08) - freedom of citizens to express and to participate in choosing government.
ii. Political stability and absence of violence (PV08) - probability that a government will be overthrown.
iii. Government effectiveness (GE08) - quality of government services and how independent they are from political pressure.
iv. Regulatory quality (RQ08) - capacity to design and run policies and regulations that foster private enterprise.
v. Rule of law (RL08) - ability to enforce laws through the police and courts.

vi. Control of corruption (CC08) - extent of using public power to advance private interests.

The six indicators themselves are aggregates of 441 variables coming from different sources. Kaufmann's team processed these variables to come up with a standard rating scale of -2.5 to 2.5, with-2.5 being the lowest score. To simplify the study and due to limited time, I chose to focus on one year's worth of data, the 2008 governance indicators provided by the online database (World Bank, 2009).

In *Growth without Governance* (2002), Kaufmann and Kraay assert a causal relationship between per capita Gross Domestic Product (GDPPC) and governance. I am interested to find a relation between governance and the Human Development Index (HDI). The United Nations Development Program (UNDP) developed HDI in response to the lack of national metrics for quality of life. HDI values range from 0 (lowest) to 1 (highest) and incorporates metrics on health, education and national income. The calculations of these indices are beyond the scope of my study, but the details are available in the UNDP website. Based on HDI, we could compare the quality of life among countries and use it as a way to find a relationship between governance and human development.

### 4.2. Gathering and preparing data.

The data set for this study came from three separate sources -- governance and country business indicators from World Bank and HDI. All databases are available online (see references for links). After merging and cleaning, the records consisted of 220 countries with 23 attributes including governance indicators, business indicators (imports, exports), and

HDI scores. As I conducted the experiments, the attributes narrowed down into only the six governance indicators, the HDI classes (explained below), per capita national income (adjusted for purchasing power parity) and official development assistance amounts.

To build the HDI classes, I adapted UNDP's categories to classify the countries by HDI score: VH for very high HDI (countries with a score of 0.9 and above), HI (0.8 to 0.895), MD or medium (0.5 to 0.799) and LO (0.1 to 0.499).

The list, below, describes the attributes used. An excerpt of the raw data set is attached in the appendix.

- GNI_PC_PPP numeric - gross national income per capita, adjusted for purchasing power parity
- VA08 numeric - Voice and accountability
- PV08 numeric - Political stability and absence of violence
- GE08 numeric - Government effectiveness
- RQ08 numeric - Regulatory quality
- RL08 numeric - Rule of law
- CC08 numeric - Control of corruption
- ODA_mn numeric - Official development assistance, in million dollars
- HDI_Class - Human Development Index, converted into classes :LO,HI,MD,VH

Initial examination showed Singapore with the highest governance ratings 2.53 (GE08) along with Finland: 2.34 (CC08). Somalia had the lowest set of indicators -3.28 (PV08), -2.51 (GE08), -2.77 (RQ08), -2.69 (RL08), -2.5 (GI_AVE).

Data problems included mismatched records, missing values, and outliers. Bermuda, Iraq, and Reunion were in the governance database but not in HDI. "Occupied Palestine" had an HDI entry but no governance indicators. Iraq skewed the ODA attribute, receiving a total of $9.11 billion while other countries received only $543 million on average (median was $225 million). Somalia also stood out in governance indicators, getting the lowest average among all the countries.

I also watched out for “overfitting” the data -- a form of double-counting when one attribute is used to compute another. In the governance-HDI data set, this meant removing the World Bank classification (WB_Class), HDI rank and per capita Gross Domestic Product (GDPPC) in some experiments.

To prepare the data set for Weka, I marked missing values with question marks. I used functions in MS Excel and TextWrangler (a free text editor) to automate some merging, grouping and cleaning tasks.

Missing values sometimes confound data mining schemes. Weka allowed me to fill missing data with median and mode values. If results improved, I kept them. If not, I used the alternative set.

### 4.3. Data mining (modelling).

Data mining is also called “machine learning” because it uses learning schemes (software algorithms) to discover patterns in the data set. Like in the real world, the learning process involves training and testing.

Modelling the data involved iterations of testing, evaluating, and removing attributes -- an electronic process of winnowing to get a data set producing correlations. I  used classification (OneR and J48 Decision Trees) schemes to discover interesting trends.

Classification schemes work by sorting data into categories or classes in a methodical process. In the governance data set, we used HDI classes VH, HI, MD and LO. To train OneR, we gave it a set of *classified* examples (the training set) and asked it to infer a set of classification rules. In the testing phase, we gave it a separate data set with the classes hidden (the testing set), and asked it to sort the records. Since we knew the actual classes of the testing set, we could compare the predicted versus actual classes and gauge the accuracy of the model.

## 5. Results and Interpretation

### 5.1. OneR Classification

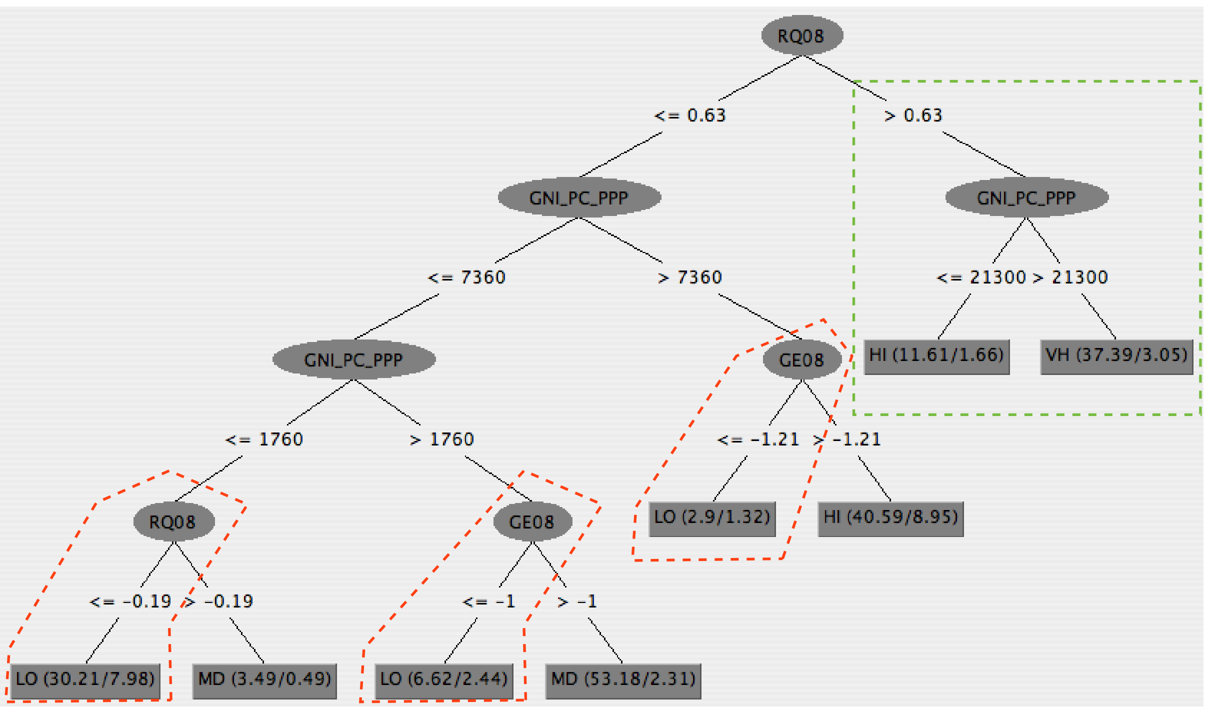
I started exploring the data set with a simple learning scheme: OneR, short for "one rule" because it generates a rule based on one attribute. OneR went through all the country records and looked for the attribute that best predicted the HDI class. The OneR results, below, indicate a correlation between government effectiveness (GE08) and HDI scores, including the threshold scores for government effectiveness for each HDI class. Countries with a score of 0.79 or higher tend to have very high HDI, while those scoring lower than -1.35 have low HDI. Countries with scores between -1.36 and 0.11 have medium HDI and those that score between 0.12 to 0.78 have high HDI.

```
GE08:
    < -1.35   -> LO
    < 0.12    -> MD
    < 0.79    -> HI
    >= 0.79   -> VH
```

**Limitations and Implications.** The OneR scheme was 63.49% accurate when it was applied to the testing set. OneR is limited because it can handle only one attribute. I included its results as a way to introduce the process of data mining and to get an initial impression on the country records. To uncover more contributing attributes and their relation with human development, I used a decision tree classification scheme.

### 5.2. Decision Tree

Like a family tree, the decision tree tells the story of how governance contributes to human development. The decision tree, below (Model D1), demonstrates the role of regulatory quality (RQ08), per capita national income (GNI_PC_PPP), and government effectiveness. Think of the diagram as an inverted picture of a tree -- the top node is the root and the bottom ones are leaves containing the possible HDI classes.




**Model D1.** Decision tree showing how regulatory quality (RQ08), per capita national income (GNI_PC_PPP), and government effectiveness (GE08) contribute to human development.

Using the D1 decision tree as our guide, we can tell the story of a country's governance and human development. If a country's regulatory quality is above 0.63, it moves down along the right-most branch of the tree and tends to have high or very high human development (green dotted box). If its regulatory quality is below -0.19 or government effectiveness is below -1, it moves to the left-most branch and tends to have low human development (red dotted boxes).

Using the decision tree, I found common attributes shared by countries in the same human development class and compiled a character profile of countries summarized, below.

| **Countries with the following HDI class:** | **Share these attributes:** |
|---|---|
| Very High | • Positive regulatory quality, above 0.63<br>• Per capita income of at least $21,300 |
| High | • Positive regulatory quality, above 0.63<br>• Per capita income between $7,360 and $21,300<br>• Government effectiveness above -1.21 |
| Medium | • Regulatory quality between -0.19 and 0.63<br>• Per capita income between $1,760 and $7,360 *and* government effectiveness above -1.<br>• If per capita income is lower than $1,760 but regulatory quality is *above* -0.19, a country may still have medium HDI. |
| Low | • Regulatory quality score of -0.19 or less.<br>• Per capita income of $1,760 or less *and* regulatory quality of -0.19 or less.<br>• If per capita income is above $1,760 but government effectiveness is -1 or less, a country may still have low HDI. |

**D1 Rule Table.** Model D1 found attributes shared by countries that fall under the same on human development class.

**Limitations and Policy Implications.** I used the D1 decision tree on two countries -- Portugal and Ecuador -- to test its strengths and limitations. It correctly predicted Portugal's HDI class, but failed on Ecuador. Portugal has a very high HDI class. Its per capita income is \$22,080, within the threshold of \$21,300. Its regulatory quality score is 1.12, also within the threshold of 0.63. Portugal therefore satisfies D1 Rule Table for a very high HDI country.

Ecuador's per capita income (\$7,769) and government effectiveness (-0.97) meet the threshold for high HDI class, but its regulatory quality score fails at -1.14 (threshold is 0.63). The decision tree failed on account of Ecuador's irregular regulatory quality score. However, we should not throw away the model just because it fails to classify a few countries.

At 80.11% accuracy, Model D1's decision tree is more reliable than OneR and still works on most of the country records. It is still useful as a guide for understanding the relationship between governance and human development. If we knew only the country's governance indicators and per capita income, we can make informed guesses about its quality of life just by consulting the decision tree and rule table. Reversing this: just by looking at HDI scores and the decision tree, we can make inferences about a country's regulatory quality, government effectiveness, and per capita income, which could guide us for making better policies and programs.

Model D1 provides additional support for Kaufmann, et al.'s findings that governance determines national income and growth may only be possible in countries with a good foundation of governance. Change agents -- government leaders, civil society advocates, and global development officers -- could initiate real growth by strengthening governance, starting from government effectiveness and regulatory quality. These may design and implement campaigns and programs to improve government's delivery of basic services, both in quality and coverage. They may push for more equitable laws and regulations to promote growth of private enterprise and not just a handful of private interests.

This brings back the issue of aid effectiveness in the face of corruption and it turns out a decision tree can also discover patterns on our country records, if we add information on official development assistance (ODA).

### 5.3. Governance and Aid

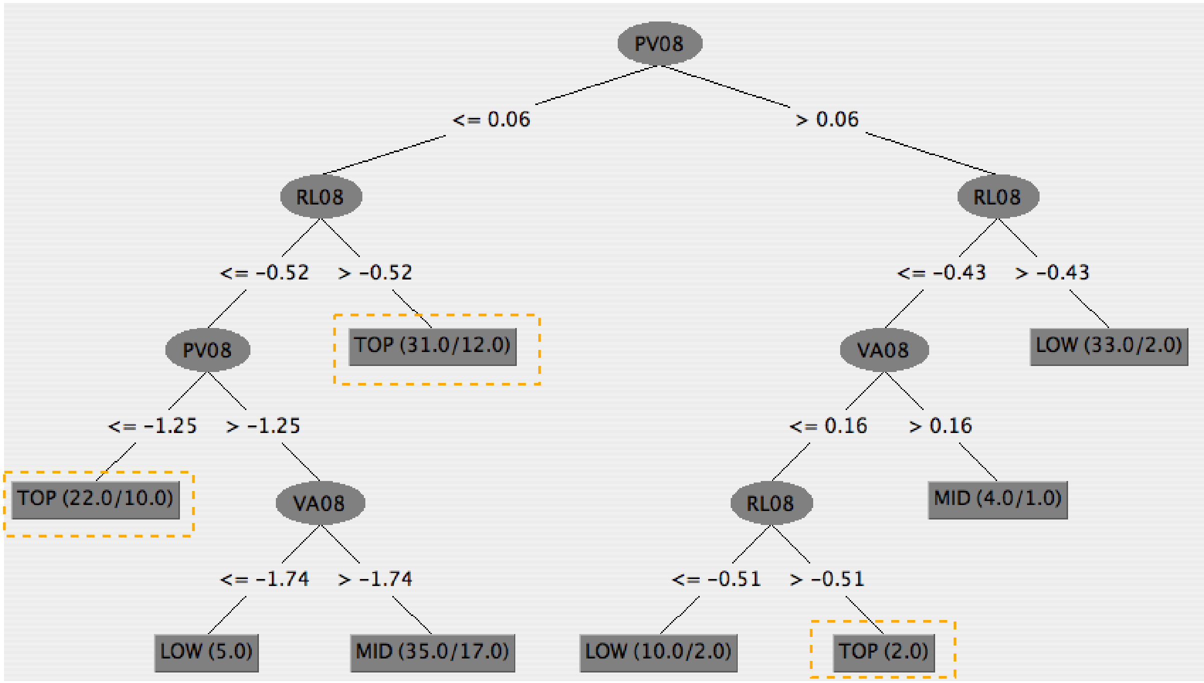
Records show that the biggest amounts of aid were poured into countries with negative governance scores. Iraq has an average governance score of -1.63 (recalling the lowest possible score is -2.5). Its regulatory quality is -1.09 (RQ08) and government effectiveness is -1.41 (GE08). Yet, it has received the biggest chunk of ODA at $9.11 billion. Afghanistan tells the same story: average governance score of -1.74, regulatory quality of -1.58 and government effectiveness of -1.31. The rest of the top ten ODA recipients are listed in the table, below.

| | VA08 | PV08 | **GE08** | **RQ08** | RL08 | CC08 | **GI Ave** | ODA million $ |
|---|---|---|---|---|---|---|---|---|
| Iraq | -1.26 | -2.69 | **-1.41** | **-1.09** | -1.87 | -1.48 | **-1.63** | 9,114.71 |
| Afghanistan | -1.26 | -2.64 | **-1.31** | **-1.58** | -2.01 | -1.64 | **-1.74** | 3,951.08 |
| Tanzania | -0.09 | 0.01 | **-0.45** | **-0.39** | -0.28 | -0.51 | **-0.29** | 2,810.84 |
| VietNam | -1.62 | 0.32 | **-0.31** | **-0.53** | -0.43 | -0.76 | **-0.56** | 2,496.73 |
| Ethiopia | -1.3 | -1.79 | **-0.43** | **-0.86** | -0.6 | -0.66 | **-0.94** | 2,422.48 |
| Pakistan | -1.01 | -2.61 | **-0.73** | **-0.47** | -0.92 | -0.77 | **-1.09** | 2,212.42 |
| Sudan | -1.77 | -2.44 | **-1.41** | **-1.36** | -1.5 | -1.49 | **-1.66** | 2,104.19 |
| Nigeria | -0.6 | -2.01 | **-0.98** | **-0.62** | -1.12 | -0.92 | **-1.04** | 2,042.33 |
| Cameroon | -1.02 | -0.53 | **-0.8** | **-0.66** | -0.99 | -0.9 | **-0.82** | 1,932.60 |
| West Bank & Gaza | -0.94 | -1.76 | **-1.36** | **-1.12** | -0.81 | -1.13 | **-1.19** | 1,868.20 |

**Top ten official development assistance (ODA) recipients.** (Source: World Bank)

The table shows all of the top ten recipients have negative average governance indicator scores (GI). Disaggregating the averages, all countries scored negative in all the governance indicators, with the exception of political stability in Tanzania and VietNam. Using a decision tree, could we find other patterns about governance and the distribution of aid?

The decision tree, Model D2 (below), is our starting point for investigating ODA distribution. To get this decision tree, I translated the ODA amounts into a range of three classes: TOP (countries on the top third of ODA recipients), MID (middle third), and LOW (bottom third). These ODA classes became the leaves at the bottom of the decision tree. The first leaf -- TOP (22.0/10.0) -- means the model classified 22 countries in the TOP class, but made a mistake in ten of them.




**Model D2.** Decision tree showing how governance indicators affect ODA class.

Model D2's structure unfolds the story of governance and inefficient aid distribution over countries with low, even negative, governance scores on political stability, rule of law, and voice and accountability.

Counting the values in the "TOP" leaves (orange dotted boxes) reveals the following shared attributes about top ODA recipients. Twelve of the top recipients scored -0.52 or less on rule of law, and -1.25 or less on political stability (again, the lowest being -2.5). A total of 33 top recipients have rule of law scores less than 0.06. Only two of the top recipients have political stability scores above 0.06.

**Limitations and Policy Implications.** Model D2 is only 47.92% accurate. Even with this accuracy, the tree still gives us a picture of how many countries share the attributes of top ODA recipients. Uncovering only one anomaly like Iraq is enough to investigate aid effectiveness, but the D2 decision tree uncovered 33 top recipients with low governance scores, enough to raise the alarm and rethink aid strategy.

These findings confirm the observations of Kaufmann, et al. Donors are pouring billions of dollars on countries like Iraq, Afghanistan and Sudan whose governance structures are not ready for effective implementation of development programs. Donor agencies need to design and prioritize programs to strengthen political stability, rule of law, and voice and accountability. National leaders and civil society advocates seeking genuine change could take insights from studies about aid effectiveness and governance. Agents of change have always been challenged by basic questions like where to start and what to measure in a field that has offered a vast array of conflicting advice. These findings on governance point the way to more effective, more focused planning and execution.

## 6. Conclusion

Decision tree D1 identify regulatory quality and government effectiveness as key areas for improving human development. Decision tree D2 implies top recipients of aid share weak governance structures in political stability, rule of law, and voice and accountability. The D1 Rule Table in page 12 provides a guide for analysts and change agents on common attributes of countries belonging to the same HDI class. It could be used for developing strategies for change.

The decision trees shift attention away from corruption and into the other aspects of governance. In the past, campaigns on good governance revolved around fighting corruption. Years of slow progress may require a different approach, defocusing from corruption to state capture (Kaufmann, et al., 2002).

State capture refers to the ability of a country's system and structure to resist being influenced by elite private interests. It includes the ability of the elite to purchase their way into shaping laws favorable to them. Kaufmann points to state capture as the more critical factor perpetuating corruption and stunted growth.

Planners and policy makers desiring genuine and effective change can combine the concept of state capture with the lessons of the decision trees to take up the following recommendations:

1. Sponsor policies and programs that strengthen the quality of regulation. These include taking action to protect regulatory processes from the influence of the elite.
2. Promote government effectiveness in delivering basic services to the people. A good way to start on these is by strengthening educational and health institutions.

3. Encourage and protect the freedom of media institutions and civil society organizations. These institutions allow for a stronger environment where people have more voice and public servants are more accountable to citizens.
4. Strengthen the rule of law by supporting and improving law enforcement and court systems. Quality of regulation is meaningless without strict enforcement. In the Philippines, the police and court systems are some of the most neglected institutions. This may also account for why they are perceived to be some of the most corrupt offices in the system. Weakness in enforcing the rule of law also weakens the other governance components.
5. Build and support mechanisms by which people choose and monitor their governments. This is a tricky recommendation because, as Iraq and Afghanistan shows, elections do not necessarily imply democracy. Perhaps, this should be put in last priority.

The limitation of these recommendations is that they work on a narrow interpretation of governance and human development. However, as experience is showing us, it is better to start with a narrow focus than to try to do everything and achieve nothing.

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Appendix: The data set used for data mining (ARFF format).

```
@attribute GNI_PC_PPP numeric
@attribute VA08 numeric
@attribute PV08 numeric
@attribute GE08 numeric
@attribute RQ08 numeric
@attribute RL08 numeric
@attribute CC08 numeric
@attribute ODA_mn numeric
@attribute HDI_Class {LO,HI,MD,VH}


@data
Afghanistan,?,-1.26,-2.64,-1.31,-1.58,-2.01,-1.64,3951,LO
Albania,7950,0.13,0.01,-0.34,0.16,-0.6,-0.45,305,HI
Algeria,7940,-1.05,-1.15,-0.5,-0.79,-0.7,-0.44,390,MD
Andorra,?,1.34,1.4,1.56,1.35,1.22,1.32,?,VH
Angola,5020,-1.07,-0.43,-0.98,-0.94,-1.28,-1.22,241,MD
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Armenia,6310,-0.66,0.01,-0.07,0.32,-0.36,-0.54,352,MD
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Bahamas,?,1.14,0.74,1.1,0.99,1.2,1.38,?,HI
Bahrain,?,-0.82,-0.18,0.47,0.88,0.66,0.44,?,HI
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Congo,290,-1.16,-0.61,-1.34,-1.19,-1.16,-1.16,1217,MD
Congo_Democratic_Republic_of_the,3090,-1.48,-2.34,-1.89,-1.43,-1.68,-1.31,127,LO
Costa_Rica,10950,0.98,0.56,0.39,0.47,0.44,0.48,53,HI
Cote_d_Ivoire,1580,-1.24,-1.91,-1.39,-0.93,-1.52,-1.17,165,LO
Croatia,18420,0.48,0.57,0.52,0.5,0.08,0.12,164,HI
Cuba,?,-1.85,0.04,-0.51,-1.59,-0.85,-0.06,92,HI
Cyprus,?,0.99,0.52,1.25,1.25,1.03,1.04,?,VH
Czech_Republic,22790,1.02,0.93,1.07,1.09,0.85,0.37,?,VH
Denmark,37280,1.48,1,2.19,1.86,1.92,2.32,?,VH
Djibouti,2330,-1.12,-0.13,-0.98,-0.75,-0.54,-0.33,112,MD
Dominica,8300,1.09,0.97,0.72,0.16,0.63,0.67,19,HI
Dominican_Republic,7890,0.14,0.1,-0.4,-0.24,-0.6,-0.62,128,MD
Ecuador,7760,-0.22,-0.83,-0.97,-1.14,-1.23,-0.79,215,HI
Egypt,5460,-1.19,-0.67,-0.37,-0.17,-0.09,-0.67,1083,MD
El_Salvador,6670,0.06,0.09,-0.15,0.31,-0.63,-0.22,88,MD
Equatorial_Guinea,21700,-1.89,-0.09,-1.43,-1.37,-1.31,-1.62,31,MD
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Eritrea,630,-2.2,-0.84,-1.41,-2.13,-1.24,-0.38,155,LO
Estonia,19280,1.03,0.57,1.15,1.47,1.05,0.94,?,HI
Ethiopia,870,-1.3,-1.79,-0.43,-0.86,-0.6,-0.66,2422,LO
Fiji,4270,-0.65,-0.05,-0.95,-0.68,-0.52,-0.31,57,MD
Finland,35660,1.48,1.36,1.95,1.58,1.87,2.34,?,VH
France,34400,1.24,0.58,1.54,1.25,1.4,1.43,?,VH
Gabon,12270,-0.84,0.23,-0.7,-0.65,-0.62,-1.07,48,MD
Gambia,1280,-0.97,0.14,-0.77,-0.44,-0.25,-0.78,72,LO
Georgia,4850,-0.25,-1,0.18,0.59,-0.34,-0.23,382,MD
Germany,35940,1.34,1.08,1.65,1.46,1.72,1.77,?,VH
Ghana,1430,0.48,0.06,-0.08,0.08,-0.1,-0.06,1151,MD
Greece,28470,0.88,0.32,0.56,0.81,0.75,0.1,?,VH
Grenada,8060,0.89,0.67,0.19,0.31,0.16,0.37,23,HI
Guatemala,4690,-0.26,-0.58,-0.49,-0.12,-1.1,-0.72,450,MD
Guinea,1190,-1.32,-1.91,-1.39,-1.15,-1.6,-1.35,224,LO
Guinea-Bissau,530,-0.79,-0.38,-1.26,-1.22,-1.43,-1.16,123,LO
Guyana,2510,0.17,-0.56,-0.17,-0.55,-0.7,-0.47,124,MD
Haiti,1180,-0.71,-1.39,-1.29,-0.89,-1.35,-1.21,701,MD
Honduras,3870,-0.29,-0.36,-0.57,-0.27,-0.89,-0.82,464,MD
Hong_Kong_China_SAR,43960,0.49,1.09,1.83,2,1.56,1.88,?,VH
Hungary,17790,1,0.59,0.66,1.26,0.82,0.55,?,HI
Iceland,25220,1.45,1.22,1.58,1.12,1.91,2.32,?,VH
India,2960,0.45,-0.99,-0.03,-0.21,0.12,-0.37,1298,MD
Indonesia,3830,-0.14,-1,-0.29,-0.27,-0.66,-0.64,796,MD
Iran_Islamic_Republic_of,?,-1.48,-1.06,-0.75,-1.63,-0.8,-0.71,102,MD
Iraq,?,-1.26,-2.69,-1.41,-1.09,-1.87,-1.48,9115,LO
Ireland,37350,1.4,1.16,1.61,1.91,1.74,1.76,?,VH
Israel,27450,0.69,-1.39,1.3,1.2,0.88,0.87,?,VH
Italy,30250,0.96,0.41,0.39,0.95,0.43,0.13,?,VH
Jamaica,7360,0.61,-0.27,0.09,0.36,-0.49,-0.53,26,MD
Japan,35220,0.95,0.94,1.46,1.23,1.4,1.25,?,VH
Jordan,5530,-0.71,-0.32,0.27,0.34,0.49,0.41,504,MD
Kazakhstan,9690,-1.01,0.51,-0.47,-0.37,-0.78,-0.95,202,HI
Kenya,1580,-0.16,-1.25,-0.6,-0.07,-0.98,-1.01,1275,MD
Korea_Republic_of,28120,0.59,0.41,1.26,0.73,0.79,0.45,?,VH
Kuwait,2140,-0.53,0.45,0.11,0.04,0.7,0.5,?,VH
Kyrgyzstan,2040,-0.72,-0.68,-0.7,-0.32,-1.26,-1.06,274,MD
Lao_Peoples_Democratic_Republic,
10308.61961,-1.71,-0.01,-0.84,-1.25,-0.9,-1.23,396,MD
Latvia,16740,0.86,0.4,0.56,1.07,0.73,0.29,?,HI
Lebanon,10880,-0.4,-1.94,-0.64,-0.2,-0.73,-0.83,939,HI
Lesotho,2000,0.04,-0.03,-0.31,-0.63,-0.3,0.04,130,MD
Liberia,300,-0.29,-0.99,-1.36,-1.32,-1.23,-0.6,696,LO
Libyan_Arab_Jamahiriya,15630,-1.9,0.48,-0.84,-0.93,-0.65,-0.81,19,HI
Liechtenstein,?,1.32,1.4,1.86,1.35,1.47,1.26,?,VH
Lithuania,18210,0.85,0.73,0.64,1.14,0.58,0.18,?,HI
Luxembourg,64320,1.5,1.52,1.65,1.71,1.82,2.02,?,VH
Macedonia_the_Former_Yugoslav_Republic_of,
9950,0.16,-0.31,-0.14,0.21,-0.32,-0.11,213,HI
Madagascar,1040,-0.16,-0.42,-0.59,-0.33,-0.46,-0.1,892,MD
Malawi,830,-0.18,0.05,-0.65,-0.39,-0.29,-0.59,735,LO
Malaysia,13740,-0.58,0.13,1.13,0.27,0.49,0.14,200,HI
Maldives,5280,-0.39,-0.1,-0.35,-0.42,-0.24,-0.6,37,MD
Mali,1090,0.28,-0.21,-0.78,-0.33,-0.35,-0.47,1017,LO
Malta,?,1.21,1.3,1.26,1.17,1.59,1.01,?,VH
Mauritania,?,-0.92,-0.93,-0.97,-0.59,-1.01,-0.8,364,MD
Mauritius,12480,0.88,0.84,0.6,0.95,0.88,0.53,75,HI
Mexico,14270,0.08,-0.62,0.18,0.45,-0.64,-0.26,121,HI
Moldova,3210,-0.27,-0.38,-0.76,-0.2,-0.46,-0.64,269,MD
Mongolia,3480,0.24,0.35,-0.68,-0.29,-0.54,-0.62,228,MD
Montenegro,13920,0.25,0.59,0.01,-0.05,-0.09,-0.28,106,HI
Morocco,4330,-0.7,-0.47,-0.09,-0.03,-0.11,-0.26,1090,MD
Mozambique,770,-0.02,0.29,-0.38,-0.47,-0.66,-0.55,1777,LO
Myanmar,?,-2.24,-1.56,-1.68,-2.24,-1.48,-1.69,190,MD
Namibia,6270,0.57,0.96,0.31,0.13,0.36,0.59,205,MD
Nepal,1120,-0.79,-1.69,-0.75,-0.66,-0.76,-0.68,598,MD
Netherlands,41670,1.53,0.95,1.86,1.75,1.76,2.19,?,VH
New_Zealand,25090,1.48,1.16,1.76,1.72,1.85,2.32,?,VH
Nicaragua,2620,-0.14,-0.39,-0.96,-0.36,-0.86,-0.81,834,MD
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Niger,680,-0.41,-0.75,-0.79,-0.52,-0.8,-0.82,542,LO
Nigeria,1940,-0.6,-2.01,-0.98,-0.62,-1.12,-0.92,2042,MD
Norway,58500,1.53,1.33,1.95,1.34,1.96,1.88,?,VH
Oman,?,-1.07,0.95,0.42,0.65,0.82,0.59,-31,HI
Pakistan,2700,-1.01,-2.61,-0.73,-0.47,-0.92,-0.77,2212,MD
Panama,11650,0.59,0.11,0.16,0.63,-0.2,-0.15,-135,HI
Papua_New_Guinea,2000,0.09,-0.55,-0.8,-0.59,-0.94,-1.13,317,MD
Paraguay,4820,-0.33,-0.63,-0.78,-0.49,-1.03,-0.93,108,MD
Peru,7980,0.02,-0.84,-0.3,0.33,-0.74,-0.26,263,HI
Philippines,3900,-0.2,-1.41,0,-0.05,-0.49,-0.75,634,MD
Poland,17310,0.86,0.79,0.48,0.77,0.49,0.38,?,HI
Portugal,22080,1.19,1.05,1.05,1.12,1.02,1.08,?,VH
Qatar,?,-0.77,1.01,0.68,0.66,0.86,1.24,?,VH
Romania,13500,0.48,0.3,-0.14,0.53,-0.05,-0.06,?,HI
Russian_Federation,15630,-0.97,-0.62,-0.32,-0.56,-0.91,-0.98,?,HI
Rwanda,1010,-1.24,-0.14,-0.2,-0.49,-0.5,0.03,713,LO
Saint_Kitts_and_Nevis,15170,1.12,0.85,0.66,0.5,0.75,1,3,HI
Saint_Lucia,9190,1.24,0.66,0.88,0.4,0.83,1.17,24,HI
Saint_Vincent_and_the_Grenadines,8770,1.11,0.81,0.74,0.4,0.87,1,66,MD
Samoa,4340,0.63,1.11,-0.07,-0.43,0.74,0.24,37,MD
Sao_Tome_and_Principe,1780,0.24,0.29,-0.74,-0.72,-0.5,-0.44,36,MD
Saudi_Arabia,?,-1.74,-0.39,0.01,0.17,0.33,0.11,-131,HI
Senegal,1760,-0.16,-0.16,-0.12,-0.29,-0.31,-0.45,843,LO
Serbia,11150,0.19,-0.5,-0.28,-0.21,-0.46,-0.16,834,HI
Seychelles,19770,-0.04,0.91,-0.01,-0.65,0.24,0.23,3,HI
Sierra_Leone,750,-0.28,-0.23,-1.13,-0.86,-1.03,-1.07,535,LO
Singapore,47940,-0.41,1.33,2.53,1.92,1.73,2.34,?,VH
Slovakia,21300,0.89,0.92,0.76,1.14,0.52,0.43,?,HI
Slovenia,26910,1.02,1.07,1.09,0.81,0.91,0.95,?,VH
Solomon_Islands,2580,0.19,0.12,-0.79,-1.31,-0.78,-0.41,248,MD
Somalia,?,-1.85,-3.28,-2.51,-2.77,-2.69,-1.9,384,LO
South_Africa,9780,0.68,-0.04,0.75,0.63,0.12,0.3,794,MD
Spain,31130,1.12,-0.03,0.99,1.27,1.16,1.18,?,VH
Sri_Lanka,4460,-0.44,-2.04,-0.29,-0.28,-0.01,-0.15,589,MD
Sudan,1930,-1.77,-2.44,-1.41,-1.36,-1.5,-1.49,2104,MD
Suriname,7130,0.57,0.15,0,-0.67,-0.33,-0.09,151,MD
Swaziland,5010,-1.2,0.22,-0.66,-0.57,-0.51,-0.38,63,MD
Sweden,38180,1.53,1.13,1.99,1.68,1.9,2.24,?,VH
Switzerland,46460,1.45,1.23,2.06,1.66,1.86,2.15,?,VH
Syrian_Arab_Republic,4350,-1.75,-0.56,-0.67,-1.17,-0.54,-1.07,75,MD
TAIWAN,?,0.7,0.72,0.88,1.07,0.77,0.55,?,HI
Tajikistan,1860,-1.32,-0.74,-0.88,-0.97,-1.12,-0.99,221,MD
Tanzania_United_Republic_of,1230,-0.09,0.01,-0.45,-0.39,-0.28,-0.51,2811,MD
Thailand,5990,-0.56,-1.19,0.11,0.26,-0.03,-0.38,-312,MD
Timor-Leste,4690,0.15,-1.13,-1,-1.4,-1.15,-0.89,278,LO
Togo,820,-1.13,-0.1,-1.43,-1.05,-0.8,-0.98,121,LO
Tonga,3880,-0.08,0.21,-0.41,-0.75,0.13,-0.73,30,MD
Trinidad_and_Tobago,23950,0.53,0.08,0.3,0.62,-0.25,-0.17,18,HI
Tunisia,7070,-1.26,0.29,0.35,0.11,0.24,-0.04,310,MD
Turkey,13770,-0.19,-0.73,0.2,0.22,0.09,0.1,797,HI
Turkmenistan,6210,-2.06,0.23,-1.16,-2.03,-1.3,-1.34,28,MD
Uganda,1140,-0.47,-0.88,-0.51,-0.08,-0.51,-0.79,1728,MD
Ukraine,7210,-0.03,-0.01,-0.6,-0.39,-0.62,-0.72,405,MD
United_Arab_Emirates,?,-0.98,0.74,0.82,0.58,0.75,1.02,?,VH
United_Kingdom,36130,1.33,0.56,1.74,1.79,1.68,1.77,?,VH
United_States,46970,1.12,0.59,1.65,1.58,1.65,1.55,?,VH
Uruguay,12540,1.02,0.83,0.48,0.08,0.5,1.12,34,HI
Uzbekistan,2660,-1.9,-0.91,-0.68,-1.41,-1.18,-1.08,166,MD
Vanuatu,3940,0.62,1.3,-0.36,-0.76,0.46,0.33,57,MD
Venezuela_Bolivarian_Republic_of,12830,-0.62,-1.23,-0.85,-1.44,-1.59,-1.13,71,HI
Viet_Nam,2700,-1.62,0.32,-0.31,-0.53,-0.43,-0.76,2497,MD
West_Bank_and_Gaza,?,-0.94,-1.76,-1.36,-1.12,-0.81,-1.13,1868,LO
Yemen,2210,-1.18,-1.89,-0.99,-0.7,-0.93,-0.73,225,MD
Zambia,1230,-0.09,0.29,-0.66,-0.33,-0.5,-0.48,1045,LO
Zimbabwe,?,-1.52,-1.56,-1.56,-2.18,-1.81,-1.37,465,LO
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