Angelo Leogrande[1]*°
*LUM University Giuseppe Degennaro, Casamassima, Bari, Puglia, Italy, EU
°LUM Enterprise s.r.l., Casamassima, Bari, Puglia, Italy, EU

Ranking of Countries by Value of Corruption Control

Between 2013 and 2021, the ability of countries to control corruption grew by an average of 7.20%

Corruption Control captures perceptions of the extent to which public power is exercised for private gain, including both small and large forms of corruption, as well as the "capture" of the state by the elite and private interests. The estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, ie ranging from approximately -2.5 to 2.5.

Ranking of countries by value of corruption control. In first place is Denmark with a corruption check value of 2.37, Finland with a value of 2.27, New Zealand with a value of 2.20, Singapore with a value of 2.17, Norway with a value of 2.14. In the middle of the table are Vietnam with -0.28, followed by India with a value of -0.29, Malawi and Belize with a value of -0.30, Lesotho with -0.31, Sri Lanka with -0 ,33. In last place are South Korea and Venezuela with an amount of -1.60, Yemen with an amount of -1.65, Somalia and the Syrian Arab Republic with -1.78, and South Sudan with -1, 82.

Ranking of countries by the value of the percentage change in the control of corruption between 2013 and 2021. Considering the value of the percentage change in the control of corruption between 2013 and 2021 it appears that the Marshall Islands are in first place with a value of 7,224.92 , followed by Saudi Arabia with the amount of 1,227.73%, Kiribati with the amount of 1,180.77%, Italy with the amount of 663.11%, Micronesia Fed. Sts 412.81. In the middle of the table are Rwanda with a value of -4.14%, followed by Sweden with -4.87%, Japan with -5.03%, Israel with a value of -5.55%, New Zealand with -5 .67%, Iceland with a value of -5.99%. The ranking is closed with Lesotho with a model -212.74%, followed by Brazil with -389.07%, Tunisia with -455.08%, Turkey with -520.48%, North Macedonia with -525.59%, Belize -1,519.39%.

Machine learning and predictions. A machine learning analysis using eight different algorithms is presented below. The algorithms are optimized by maximizing the R-squared and minimizing the statistical errors. An ordering of algorithms is thus identified as follows:

- Linear Regression with a value of 4;
- Polynomial Regression with a payoff value of 8;
- Gradient Boosted Trees with a payoff value of 13;
- Simple Regression Tree with a payoff value of 18;
- Tree Ensemble with a payoff value of 20;
- ANN-Artificial Neural Network with a payoff value of 21;
- Random Forest with a payoff value of 28;
- PNN with a payoff value of 32.

[1]Professor of Economics at LUM University Giuseppe Degennaro and Researcher at LUM Enterprise s.r.l. Email: leogrande.cultore@lum.it, Strada Statale 100 km 18, Casamassima, Bari, Puglia, Italia.

Therefore by applying the Linear Regression algorithm it is possible to identify the following predictions, namely:

- Syrian Arab Republic with 246.76%;
- Venezuela with 29.33%;
- Haiti with a value of 22.73%;
- Nicaragua with a value of 19.42%;
- Belize with a value of 10.19%;
- Oman with a value of 10.00%;
- Solomon Islands with a value of 9.25%;
- Croatia with a value of 6.37%;
- Zambia with a value of 5.9%;
- Antingua and Barbuda with 5.39%;
- Slovenia with a value of 3.75%;
- Mozambique with a value of 3.57%;
- Cyprus with a value of 2.75%;
- St. Vincent and the Grenadines with a value of 1.44%;
- St. Lucia with a value of 1.23%;
- Bhutan with a value of 0.76%;
- Philippines with a value of 0.67%;
- Serbia with a value of 0.2%;
- Singapore with a value of -0.87%;
- Kuwait with a value of -1.19%;
- Mauritius with a value of -1.67%;
- Japan with a value of -1.76%;
- Georgia with a value of -3.06%;
- Senegal with a value of -3.42%;
- Lao PDR with a value of -4.98%;
- Madagascar with a value of -5.08%;
- Burkina Faso with a value of -6.07%;
- Seychelles with a value of -7.05%;
- Cameroon with a value of -7.14%;
- Moldova with a value of -7.99%;
- China with a value of -8.22%;
- Guinea-Bissau with a value of -8.35%;
- Malawi with a value of -8.91%;
- Egypt Arab Rep with a value of -10.21%;
- Congo Rep with a value of -12.29%;
- Sudan with a value of -26.44%
- South Korea with a value of -26.88%;
- Angola with a value of -27.24%;
- Afghanistan with a value of -47.96%.

Conclusions. If we look at the map of countries by value of corruption control, we can see that they are essentially "*Western*" countries. At the top are the Scandinavian countries, the countries of Central Europe, the Anglo-Saxon countries and Japan. On the African continent, the only country with a medium-high level of corruption control is Botswana. While in Latin America Chile and Uruguay are the only two countries to have a high average value of control of corruption. The vast majority of

non-Western countries are characterized by high levels of corruption. At the top are the countries of Central Africa and also Algeria, Venezuela, Syria, Yemen. The growing countries in terms of GDP or the BRICS-Brazil, Russia, India, China all have medium-high levels of corruption. It must be considered that the quality of institutions is an essential element for economic development and economic growth. Certainly having corrupt or "*extractive*" institutions reduces the likelihood of countries following an economic growth path that is sustained at high levels. Above all, the new Asian giants appear to have very high levels of corruption, and in the Asian world only Japan, South Korea and Australia have the opportunity to be able to count on efficient institutions. If countries with growing per capita incomes want to stay on the path of economic growth, they should improve their institutions by reducing corruption. In fact, corruption prevents the smooth running of business, can lead to the growth of production costs causing companies to go bankrupt, and can also reduce investor confidence in a certain country.

Declarations

Data Availability Statement. The data presented in this study are available on request from the corresponding author.

Funding. The author received no financial support for the research, authorship, and/or publication of this article.

Declaration of Competing Interest. The author declares that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication.

Software. The author has used the following software: Gretl for the econometric models, Orange for clusterization and network analysis, and KNIME for machine learning and predictions. They are all free version without licenses.

Acknowledgements. I am grateful to the teaching staff of the LUM University "Giuseppe Degennaro" and to the management of the LUM Enterprise s.r.l. for the constant inspiration to continue our scientific research work undeterred.

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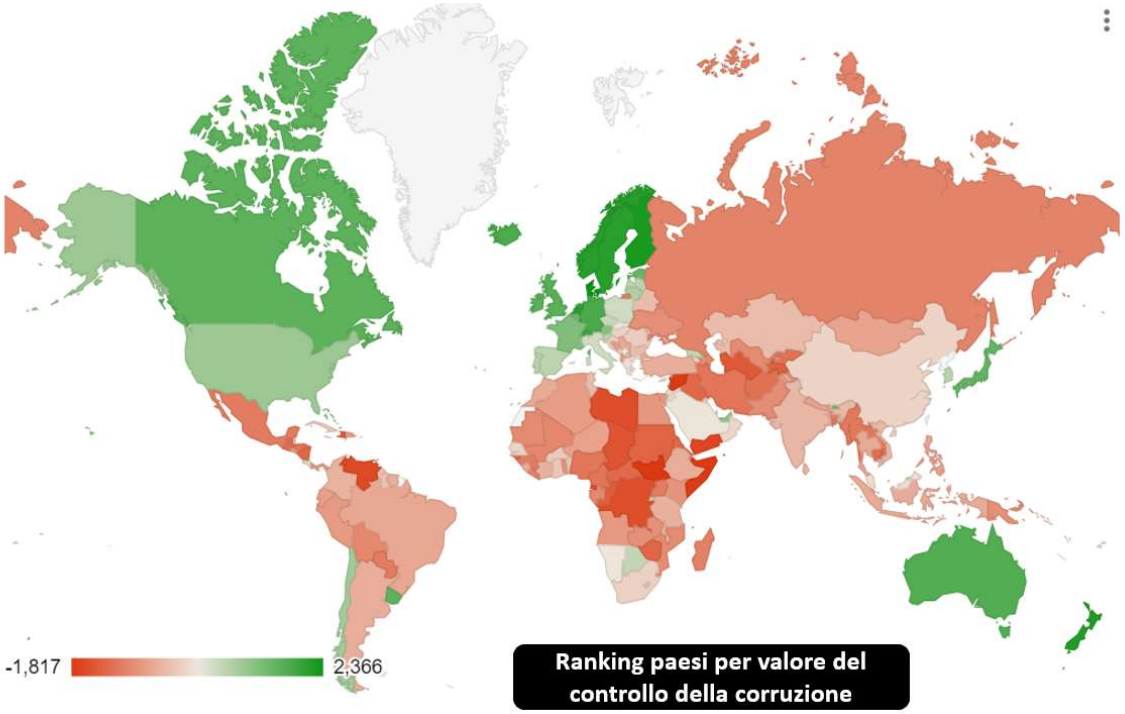
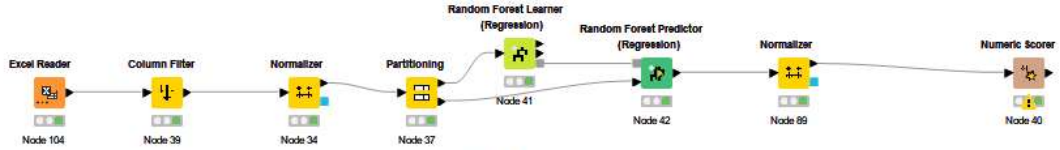
Appendix



	ANN	PNN	Simple Regression Tree	Gradient Boosted Trees
R^2	0,948865202	0,875611439	0,951650582	0,953015157
mean absolute error	0,046859119	0,076743836	0,049534968	0,047988754
mean squared error	0,003699721	0,008999801	0,003498193	0,003399463
root mean squared error	0,060825335	0,094867282	0,059145521	0,05830491
	Random Forest Regression	**Tree Ensemble**	**Linear Regression**	**Polynomial Regression**
R^2	0,938150865	0,94888068	0,979143911	0,975254896
mean absolute error	0,055024064	0,049150481	0,027052766	0,029313307
mean squared error	0,004474929	0,003698601	0,001257652	0,001711438
root mean squared error	0,066894907	0,060816129	0,035463391	0,041369536

	R^2	mean absolute error	mean squared error	root mean squared error	sum
Linear Regression	1	1	1	1	4
Polynomial Regression	2	2	2	2	8
Gradient Boosted Trees	3	4	3	3	13
Simple Regression Tree	4	6	4	4	18
Tree Ensemble	5	5	5	5	20
ANN	6	3	6	6	21
Random Forest Regression	7	7	7	7	28
PNN	8	8	8	8	32


Random Forest Learner (Regression)
Random Forest Predictor (Regression)
Excel Reader
Column Filter
Normalizer
Partitioning
Normalizer
Numeric Scorer
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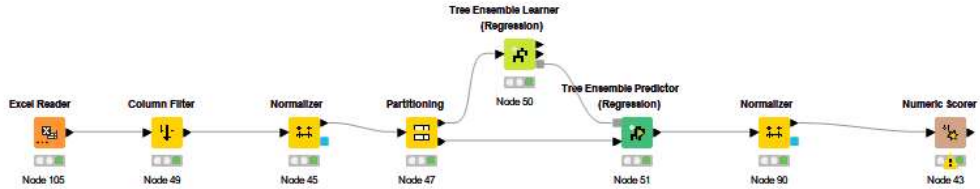
Node 39
Node 34
Node 37
Node 41
Node 42
Node 89
Node 40


Tree Ensemble Learner (Regression)
Tree Ensemble Predictor (Regression)
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Partitioning
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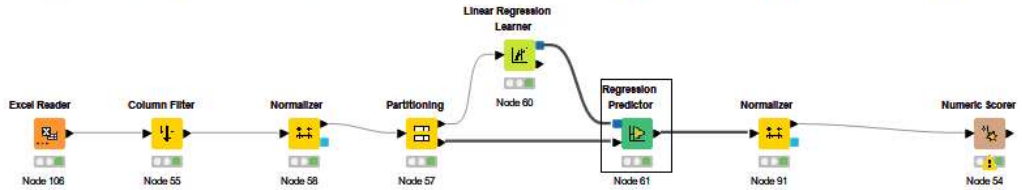
Numeric Scorer
Node 105
Node 49
Node 45
Node 47
Node 50
Node 51
Node 90
Node 43


Linear Regression Learner
Regression Predictor
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Numeric Scorer
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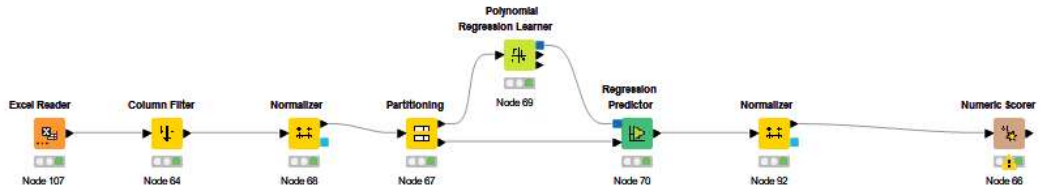
Node 55
Node 58
Node 57
Node 60
Node 61
Node 91
Node 54


Polynomial Regression Learner
Regression Predictor
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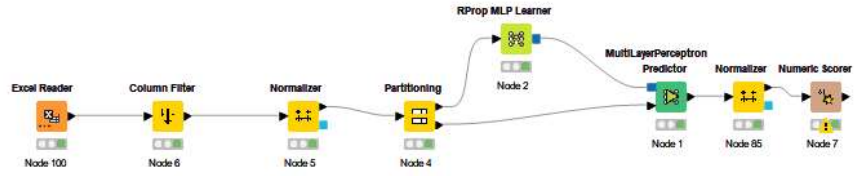
Node 64
Node 68
Node 67
Node 69
Node 70
Node 92
Node 66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MultiLayerPerceptron Predictor
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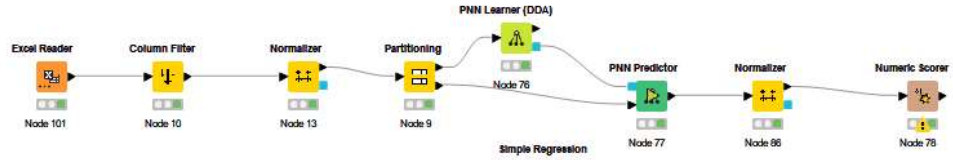
Node 6
Node 5
Node 4
Node 2
Node 1
Node 85
Node 7


PNN Learner (DDA)
PNN Predictor
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Partitioning
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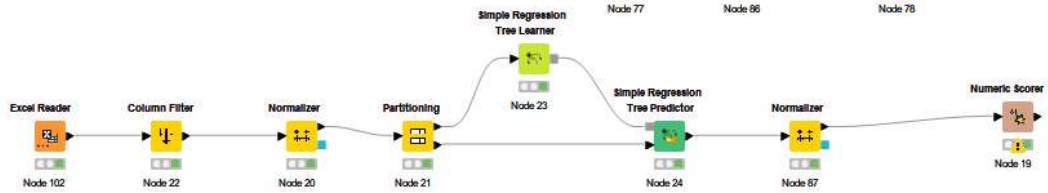
Node 10
Node 13
Node 9
Node 76
Node 77
Node 86
Node 78


Simple Regression Tree Learner
Simple Regression Tree Predictor
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Partitioning
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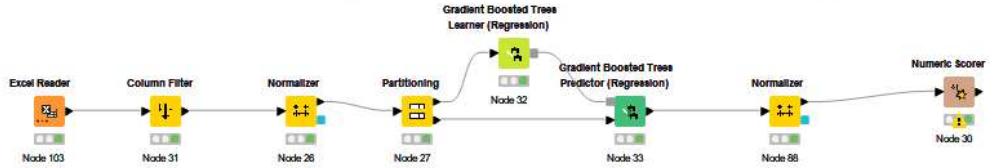
Node 102
Node 22
Node 20
Node 21
Node 23
Node 24
Node 87
Node 19


Gradient Boosted Trees Learner (Regression)
Gradient Boosted Trees Predictor (Regression)
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Node 103
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Node 26
Node 27
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Node 33
Node 88
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