

Predicting democratic backsliding with Machine learning

Model comparison

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Abstract

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Quod idem licet transferre in voluptatem, ut postea variari voluptas distinguere possit, augeri amplificarique non possit. At etiam Athenis, ut e patre audiebam facete et urbane Stoicos irridente, statua est in quo a nobis philosophia defensa et.

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1. Motivation and Context

With the rise in populist parties and the postfactual time we live in a lot of problems are accounted to this authoritarian perspective. one of them is Corruption. Due to the advancements that have been made in Machine learning we have decided to analyse further the interplay between political corruption and the potential predictors for that. In the sphere of political science there are multiple datasets that measure corruption and the possible predictors. Although most of them don't combine as nicely with the other predictors that we want to analyse. Therefore we have decided on using the Vdem dataset as our entry point to the data analysis. In short Vdem is an aggregated dataset that uses multiple sources to combine in one dataset, the dataset is composed of multiple indices, that measure the state of different states around the world. In this Final report we want to limit some of the data as we will show in Section 3.

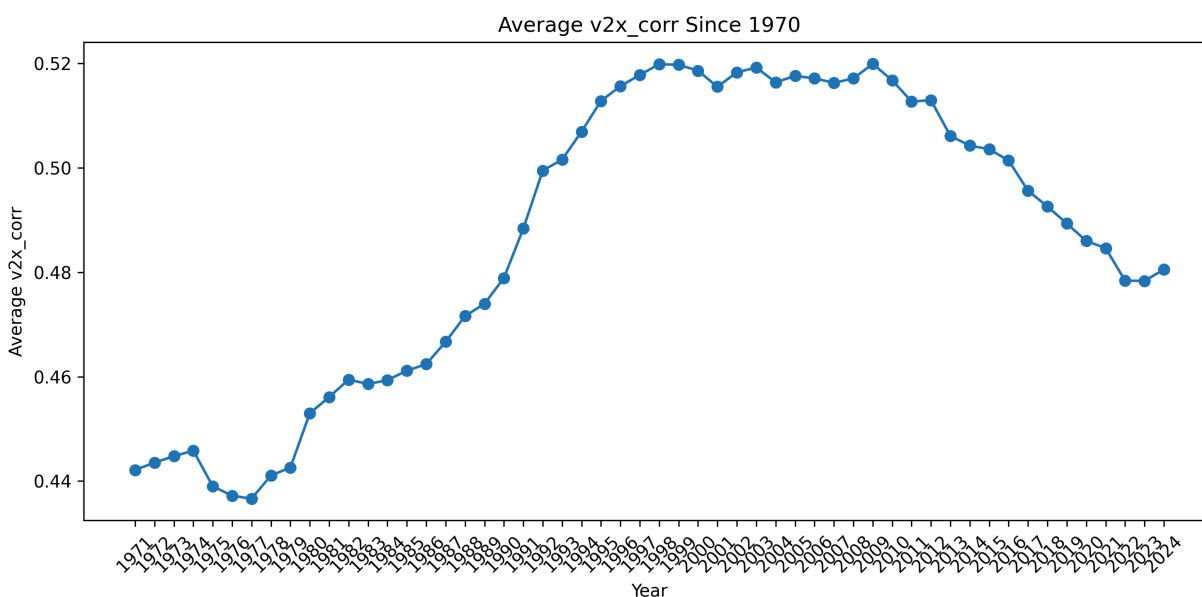


Figure 1: average of political corruption over time

2. Our Hypothesis

Vdem on its own already delivers a properly constructed corruption index, that takes into account multiple different points of resources. The Index is split into multiple sub indices such as Public and political corruption. see the figure down below for a dependence tree of the dataset.

We argue that with the help of machine learning models we can successfully predict the corruption level of a country based on factors that are not included within the current indicators for corruption. The claim lies in the assumption that political partaking as well as the ability to partake correlates highly with multiple other datapoints that are already provided and with widely available data such as the GDP of a country.

We argue that especially the social issues can be used as strong predictors for the level of corruption in the Vdem dataset.

3. Assumptions and limits

We feel the need to explain the steps that we will take in the further analysis of the dataset as they are not self explanatory in the further cleaning of the data.

1. **We Subset for liberal western Democracies:** We argue that a subsetting of the dataset might not seem to be essential in the context of corruption, but under the inherently different design of States in the sense of authoritarian perspective, it is essential for the model success to not only build an environment in which the data, as is, is comparable but also the states behind it. Therefore we have subset the data for Liberal western democracies, as we assume them to be high trust societies where corruption is not inherent in their state structure as it would be with rent seeking states as shown by Ross (2001) in “Does Oil hinder democracies”. The full list of Countries can be found in Appendix B.
2. **Limiting of the Time:** We see the need to limit the data, not only to fill NA values but to keep a comparable time frame of the different countries, such as the deeper integration of the European union as the difference in justiciable account of corruption has been normalized among the member states, it would make sense to set the limit lower than the 1980s to train a model that can also predict that data but under the lens of non isolated development in political interaction with that topic we choose not to pursue that.

On the matter of *normal* problems in the dataset we need to highlight the non availability of different indices, that stems from the fact that the dataset introduced multiple variables in a progressive manner. Due to that we have decided to limit the number of variables that we will use for the prediction. Another point that we have taken into account is the dependencies of the data. Vdem gives an overview of the dataset and how the different indices are constructed at Coppedge *et al.* (2025) but that information is not mapped into data, thus the result of this project report is also a comprehensive mapping of the Vdem Dataset, made available as a github gist and included in this repository.

4. Reproduceability

To make this analysis reproducible within the means of it we organized this analysis

5. Subset and EDA

To make t

5.1. Subset

To properly use the model to predict the Target it was necessary to filter the dataset further, for that we implemented a filtering to only keep the bare variables of the dataset without any additional operations as they are included by the authors of vdem.¹ In the next step we filtered for non numeric features and removed as pointed out in the missing values.

5.2. EDA

To get a first overview of the data and potential cross dependencies that we havent captured yet with our dependence mapping a correlation matrix was created² This correlation matrix directly pointed out more highspots that after a manual correction have been removed. The

¹To make this process reproduceable we organised the dataset subsetting process in a pipeline that can be run from the root of the project dir on github, manual or with a makefile

²Script: `./src/corr_matrix_plot.py`

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Bibliography

Coppedge, M. *et al.* (2025) “V-Dem Codebook V15.”

Ross, M.L. (2001) “Does Oil Hinder Democracy?,” *World Politics*, 53(3), pp. 325–361. Available at: <http://www.jstor.org/stable/25054153> (Accessed: May 5, 2025).

A Tables and Data

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B List of Countries

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- Belgium
- Bulgaria
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- Cyprus
- Czech Republic
- Denmark
- Estonia
- Finland
- France
- Germany
- Greece
- Hungary
- Ireland
- Italy
- Latvia
- Lithuania
- Luxembourg
- Malta
- Netherlands
- Poland
- Portugal
- Romania
- Slovakia
- Slovenia
- Spain
- Sweden
- United States of America
- United Kingdom