Economic and Political Determinants of a Nation's Well-Being

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Abstract

Economic development varies dramatically across countries, with some nations achieving high prosperity while others struggle with poverty. We investigated which factors most strongly influence a country's well-being using data on GDP, political voice, military spending, and regional characteristics from over 150 countries. Three machine learning models revealed that the relationship between development factors and well-being is complex and non-linear, with countries at different development stages benefiting differently from improvements in areas like education or governance. Our models showed that interconnected features working together matter more than any single factor in isolation. These findings suggest policymakers should prioritize developing multiple complementary areas simultaneously, tailoring strategies to their country's current development level.

Introduction

Problem Statement and Motivation

Global economic development remains dramatically uneven, with countries experiencing vastly different levels of well-being despite similar geopolitical contexts. While some nations have achieved high prosperity and quality of life, others continue to struggle with poverty and limited political voice. Understanding the relationships between economic, political, and geographic factors can help to identify patterns that inform evidence-based policy decisions with practical implications for governments, international development organizations, and policymakers seeking to improve outcomes for their populations.

Key Questions of Interest

This study addresses two fundamental questions about national development. First, *how do economic factors of a country impact its population's well-being*? We investigate whether higher GDP per capita directly translates to better quality of life, and how economic prosperity and political freedom interact to influence overall well-being. Second, *how do political factors affect a country's economy*? We examine the relationship between governance quality, political voice, and accountability, as well as their impact on economic outcomes, including the relationship between government spending and both financial and political development.

Data Description

Our Data pipeline:

1. Pull data from the World Bank API to get the raw data
2. Clean the data to prepare the data frame for visualization and analysis
3. Visualize using plotting libraries, such as Seaborn, Plotly, and Matplotlib
4. Analyze using Machine Learning methodologies.

Our data was acquired from the World Bank developer API. The data was sourced from two query systems: the indicator query and the country data query systems. We reformatted the data, then filed it into a dataframe indexed by the country's two-letter identification code, as follows:

	SP.POP.TOTL	NY.GNP.PCAP.CD	SI.POV.DDAY	SI.POV.GINI	MS.MIL.XPND.GD.ZS	VA.EST	region	incomeLevel
AW	107359.0	30120.0	NaN	NaN	NaN	1.019175	Latin America & Caribbean	High income
AF	41454761.0	370.0	NaN	NaN	NaN	-1.852901	Middle East, North Africa, Afghanistan & Pakistan	Low income
AO	36749906.0	2130.0	NaN	NaN	1.332529	-0.737252	Sub-Saharan Africa	Lower middle income
AL	2745972.0	7680.0	NaN	NaN	1.743992	0.168997	Europe & Central Asia	Upper middle income
AD	80856.0	47920.0	NaN	NaN	NaN	0.996940	Europe & Central Asia	High income
AE	10483751.0	49020.0	NaN	NaN	NaN	-1.094941	Middle East, North Africa, Afghanistan & Pakistan	High income
AR	45538401.0	12890.0	1.2	42.4	0.472747	0.533922	Latin America & Caribbean	Upper middle income
AM	2964300.0	6840.0	1.9	27.2	5.450925	0.076708	Europe & Central Asia	Upper middle income
AS	47521.0	NaN	NaN	NaN	NaN	NaN	East Asia & Pacific	High income
AG	93316.0	19880.0	NaN	NaN	NaN	0.741840	Latin America & Caribbean	High income
AU	26652777.0	63160.0	NaN	NaN	1.922199	1.506602	East Asia & Pacific	High income
AT	9131761.0	55220.0	0.5	31.2	0.844275	1.411248	Europe & Central Asia	High income
AZ	10153958.0	6670.0	NaN	NaN	4.602103	-1.411534	Europe & Central Asia	Upper middle income
BI	13689450.0	220.0	NaN	NaN	3.658928	-1.366918	Sub-Saharan Africa	Low income
BE	11787423.0	55020.0	0.1	26.8	1.214616	1.325729	Europe & Central Asia	High income
BJ	14111034.0	1390.0	NaN	NaN	0.711202	-0.218987	Sub-Saharan Africa	Lower middle income
BF	23025776.0	860.0	NaN	NaN	4.005327	-0.809887	Sub-Saharan Africa	Low income
BD	171466990.0	2880.0	NaN	NaN	1.022818	-0.753886	South Asia	Lower middle income
BG	6446596.0	14270.0	1.0	39.5	1.847373	0.388988	Europe & Central Asia	High income
BH	1577059.0	28460.0	NaN	NaN	3.108460	-1.377833	Middle East, North Africa, Afghanistan & Pakistan	High income

We then cleaned the data for use by our methods by removing unnecessary data labels (in this case, the ‘SI.POV.DDAY’ and ‘SI.POV.GINI’ labels had too many missing values to be usable), and filtering out countries still missing one or more data point. This yielded our cleaned baseline data for use in the Machine Learning models.

	SP.POP.TOTL	NY.GNP.PCAP.CD	MS.MIL.XPND.GD.ZS	VA.EST	region	incomeLevel
AO	36749906.0	2130.0	1.332529	-0.737252	Sub-Saharan Africa	Lower middle income
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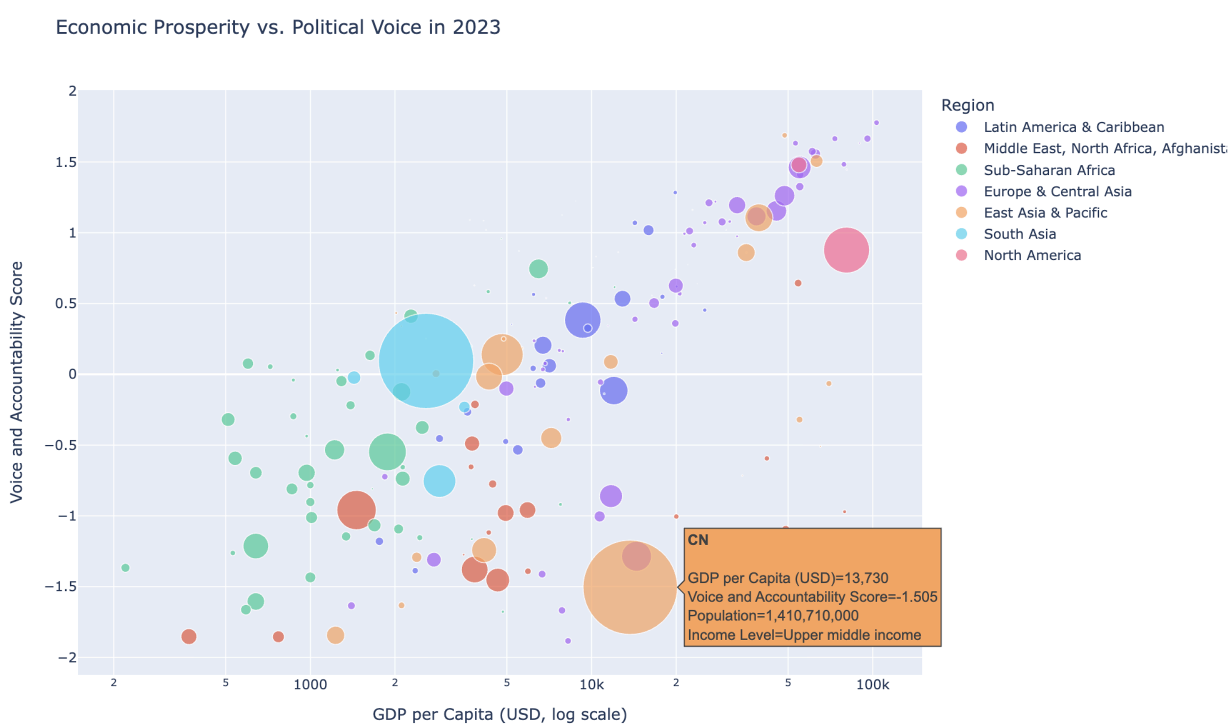
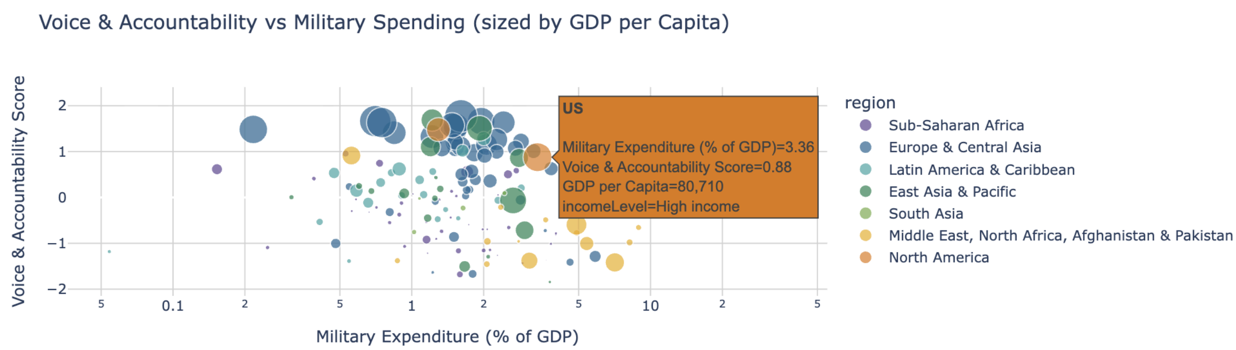
Next, we performed a minor data analysis by constructing graphs of the data. This gave us a sense of the general trends we would like to analyze.



This graph shows the relationship between GDP per Capita and the Voice & Accountability Score. We can see the relationship between countries' income per person and their people's perception of their ability to participate in government elections, have free media, and various freedoms of expression. We can see a strong positive correlation. This tells us that as GDP per capita increases, so does people's perception of freedom.



This graph shows us the Military Expenditure compared to the Voice & Accountability Score. It gives us a look into the correlation between countries with stricter and more centralized control of governance spending and how much their military spending is. The distribution is pretty similar, but it is interesting to note that higher income countries tend to have higher VA scores, and most of those countries are predominantly in the Europe and Central Asian region. There are a few outliers with military spending, the largest being Ukraine.

Methods

In order to address our problem motivation as well as our final and more generalized research question of "How strongly do World Bank development indicators influence a country's well-being and prosperity?", we selected and implemented three total machine learning algorithms. Our analysis was centered around the idea of predicting one of the indicators, "Voice and Accountability" (VA.EST) scores, as a proxy for national well-being. We based this on other economic and geographical indicators such as total population (SP.POP.TOTL), GDP per capita (NY.GNP.PCAP.CD) , and Military expenditure (% of GDP), (MS.MIL.XPND.GD.ZS). By examining how well these World Bank development indicators collectively predicted governance quality through our several models, we aimed to understand how strongly economic and geographical indicators shaped a country's prosperity.

Multiple Linear Regression

Our first machine learning model was a multiple linear regression model, which tests whether there's a straightforward, linear relationship between our predictors and the Voice and Accountability score, aiming to get a clear sense of how much each development indicator actually contributes to the outcome. In our case, we looked at GDP per capita, population size, and military spending, and used the model to see how each of those factors relates to governance quality.

To make sure the model was working the way it should, we reviewed several diagnostic plots. Namely, the independence of observations, linearity between predictors and the response, constant variance of residuals (homoscedasticity), and normally distributed errors. To evaluate performance, we relied on Mean Squared Error (MSE) to measure how accurate the predictions were and R^2 to see how much of the variation in Voice and Accountability the model could actually explain.

Polynomial Regression

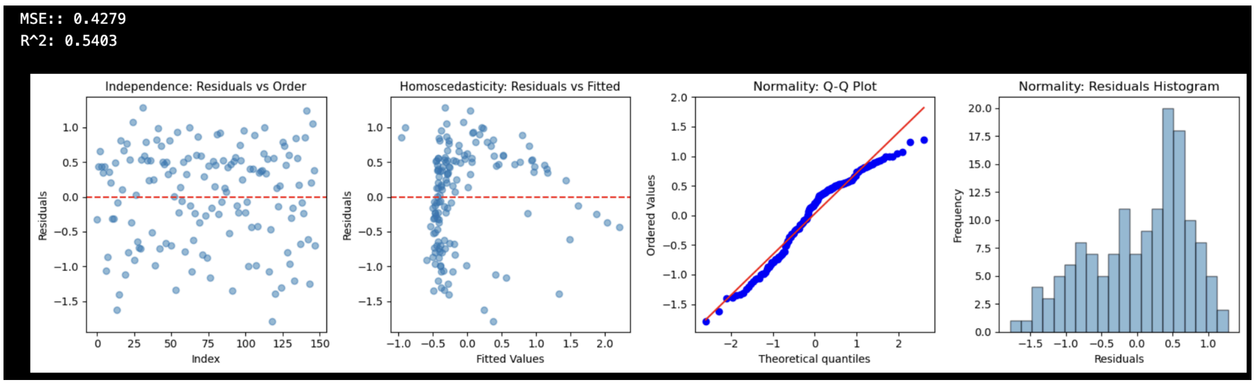
To address potential non-linear relationships between our predictor indicators and the Voice & Accountability indicator, we also implemented polynomial regression as our second ML model. We used degree-2 features to create quadratic terms (ex: GDP^2, $population^2$) and interaction effects (ex: GDP × military spending), introducing more complexity to capture how variables might work together to influence governance. This approach of polynomial regression can be used to model scenarios where relationships may be nonlinear. An example of this is how the overall influence of GDP per capita on governance may increase or plateau at different income levels. Even so, this model performed worse compared to our previous multiple linear regression model. The polynomial regression model yielded an MSE of 0.6310 and an R^2 of 0.39, suggesting potential overfitting and a weak overall relationship. It also demonstrates a low likelihood of any significant non-linear relationships between our predictors indicators and Voice & Accountability scores.

K-Nearest Neighbors

We also studied whether the region associated with the country had an impact on its economic and political factors. To find a possible correlation, we constructed a kNN model attempting to predict the region based on our economic indicators - total population, GDP per capita, Military expenditure, and Political Voice. If the model is capable of accurately predicting the region associated with the country, this indicates that there is some relationship between the region and indicators, and a likely causal relationship.

Results

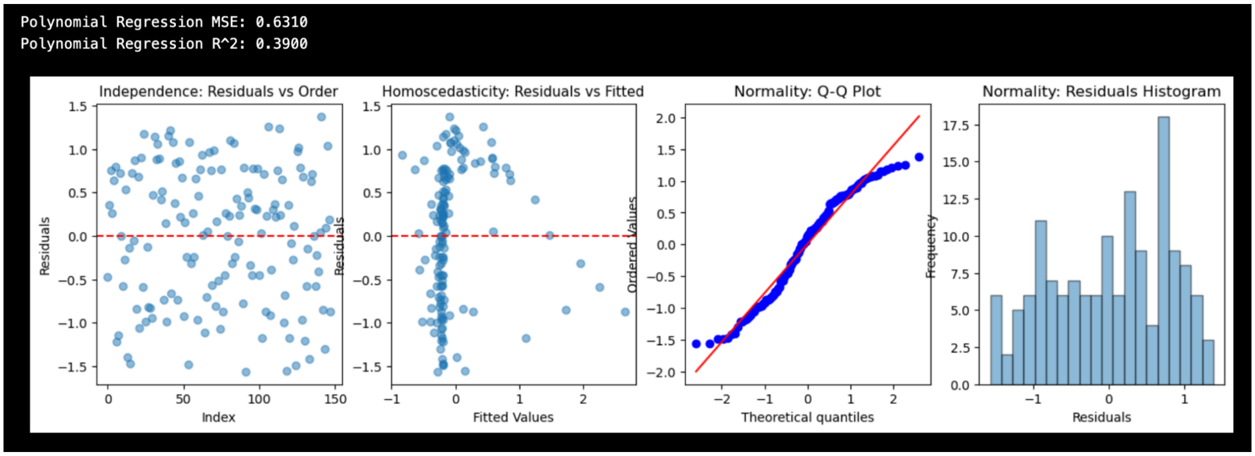
Multiple Linear Regression



The multiple linear regression model yielded an MSE of 0.4279 and an R^2 of 0.5403, indicating that it explains a little over half of the variation in Voice and Accountability scores. That tells us that the economic and geographic indicators we selected definitely influence governance quality, but not in a way that fully determines it. Most of the model assumptions look fine, the independence check is clean, and the Q-Q plot and histogram show the residuals are pretty close to normal. So from a structural standpoint, the linear model behaves how we'd expect and gives us a solid baseline for understanding the overall trends in the data.

The one real issue shows up in the Residuals-vs-Fitted plot, where we see the variance widen for fitted values above roughly 0.5. That funnel shape points to heteroscedasticity, which in this case means that the model gets less consistent as countries become more democratic. Whereas it performs much more reliably for countries in the low to mid range of Voice and Accountability. Even with that limitation, the model still helps us see how these indicators work together, even if it struggles to capture the full complexity at the high end of the distribution.

Polynomial Regression



As mentioned before, our polynomial regression model performed worse quantitatively. It yielded an MSE of 0.6310, which is 47.46% greater than the MSE of our multiple linear regression model. The R^2 of 0.39 is 27.82% lower than the R^2 of our multiple linear regression model. This demonstrates that the polynomial terms may have introduced multicollinearity or overall instability rather than capturing any actual non-linear patterns. Despite this, the plots for this polynomial regression model show improvements compared to those of the multiple linear regression model. Specifically, the Residuals vs Fitted plot shows superior homoscedasticity, with a more consistent variance across fitted values. Additionally, although both independence and normality assumptions were satisfied, the performance metrics indicate that this may have come at the cost of our predictive accuracy.

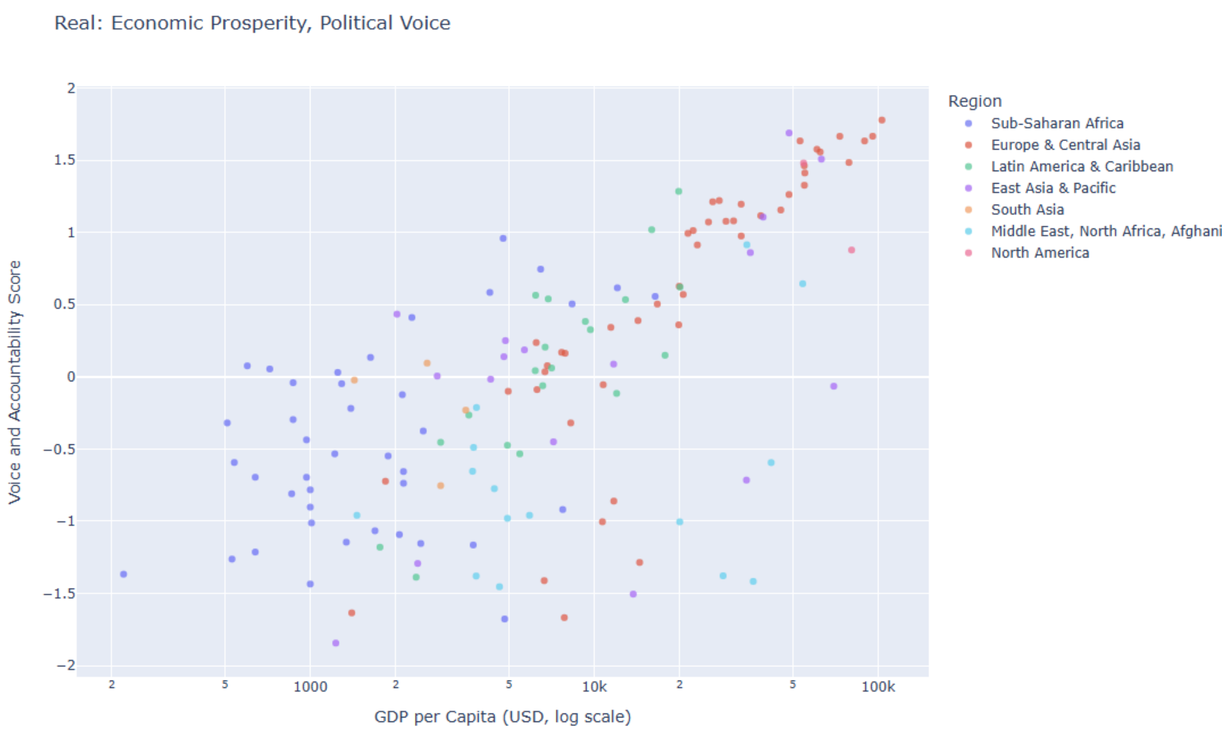
K-Nearest Neighbors

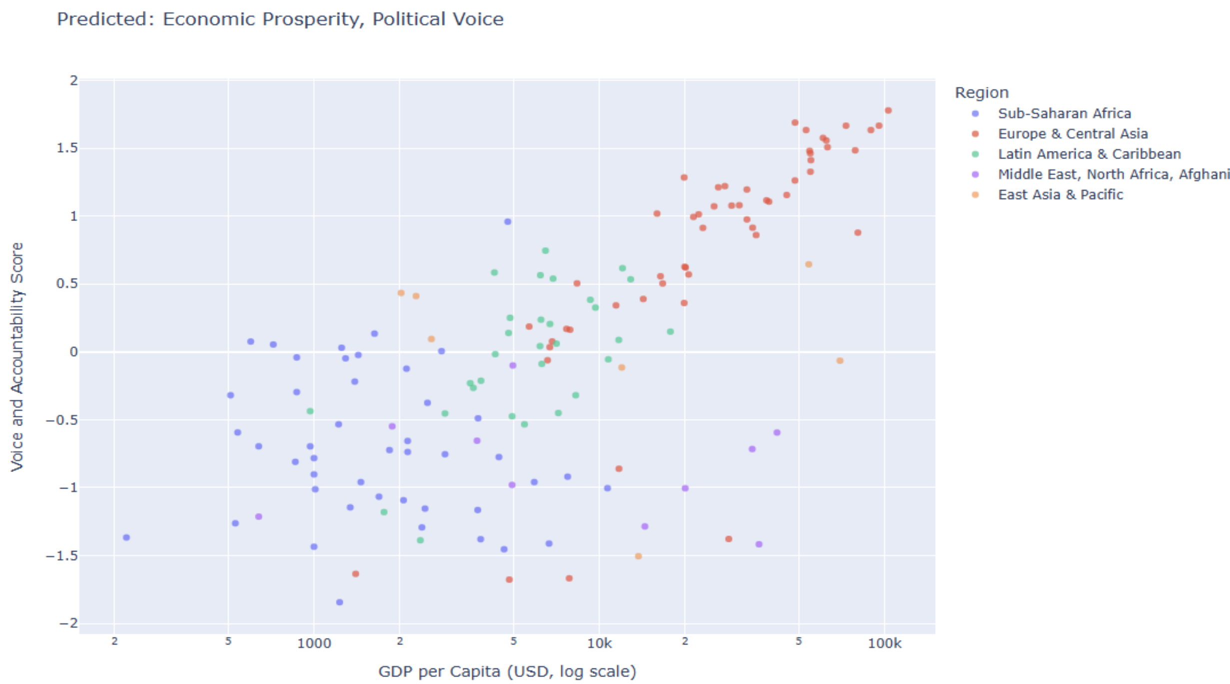
The first few rows of our data table, with prediction and accuracy included.

	SP.POP.TOTL	NY.GNP.PCAP.CD	SI.POV.DDAY	SI.POV.GINI	MS.MIL.XPND.GD.ZS	VA.EST	region	incomeLevel	predicted	correct
AO	36749906.0	2130.0	NaN	NaN	1.332529	-0.737252	Sub-Saharan Africa	Lower middle income	Sub-Saharan Africa	True
AL	2745972.0	7680.0	NaN	NaN	1.743992	0.168997	Europe & Central Asia	Upper middle income	Europe & Central Asia	True
AR	45538401.0	12890.0	1.2	42.4	0.472747	0.533922	Latin America & Caribbean	Upper middle income	Latin America & Caribbean	True
AM	2964300.0	6840.0	1.9	27.2	5.450925	0.076708	Europe & Central Asia	Upper middle income	Europe & Central Asia	True
AU	26652777.0	63160.0	NaN	NaN	1.922199	1.506602	East Asia & Pacific	High income	Europe & Central Asia	False

Our kNN model was fairly accurate, correctly matching 91 out of 145 countries, or 0.6276 accuracy. Since there are 8 possible regions, a random guess would have an accuracy of 0.125, which is significantly lower than our model's accuracy. This seems to indicate that such a relationship exists.

Graphing a couple of the indicators and associated labels seems to support this conclusion. The indicators seem to be loosely divided into groups by region, which are mostly mirrored by the predicted values. Weirdly enough, the kNN seems to have 'lost' two region tags. This makes sense when we consider that two North America and four South Asia countries in our data set, and they aren't clustered enough to be predicted by a 5NN model.





- Trying to see whether region impacts factors by finding a possible correlation
- Trying to see whether a correlation exists by predicting region with factors

Discussion

The results of the three machine learning models highlight the complexity in understanding a nation's development and well-being using macro indicators. The Multiple Linear Regression model performed the best quantitatively, but every model showed the limitations of economic, political, and geographic features shape governance. The Polynomial Regression and KNN model show important results that help us understand the causal relationship between features.

The Multiple Linear Regression offered the clearest baseline across all the models. The R^2 value (0.5403) indicates that over half of the variation in Voice & Accountability scores can be explained by GDP per capita, population, military spending, and region. Our indicators do clearly influence governance quality; however, the model was heteroskedastic showing uneven performance across the development tiers. This pattern reveals an interesting idea: improvements in socioeconomic indicators do not translate uniformly with our same political well-being. In low-income countries, increasing income or spending may have a stronger effect on governance than in high-income countries where institutions are already set.

The Polynomial Regression model, performed substantially worse with variance and overfitting clouding meaningful conclusions. Its low R^2 and higher MSE suggests that adding non-linear terms was not able to better capture meaningful patterns, but instead created noise and multicollinearity. This gap in performance serves as a reminder that even though a pattern is non-linear, a simple polynomial expansion may not effectively close the gap. The interactions between governance, economic indicators, and regional context requires a flexible, high-dimensional approach.

The K-Nearest-Neighbor offers this contrasting perspective by shifting from prediction of governance to a prediction of region based on economic and political features. It was the most accurate model (0.6276), showing that regional patterns play a substantial role in shaping a country's development outcomes. Regions have strong relationships between their indicators that help shape their development outcomes. This model adds a contextual dimension that is important in understanding development patterns, and how geography, history, and culture can influence national trajectories.

Identifying the most important factor is not as straightforward as finding the highest weighted variable within a regression. The models collectively show a non-linear effect where features could be intertwined. The stronger performance of multiple linear regression or the more meaningful performance of the KNN show the complex relationship between the indicators and a country's development. These findings can be used in future research, policy making, and more.

Future steps could include:

- Exploring more flexible models (e.g., random forests or neutral network). The complex models can account for the higher-dimensional interactions between indicators.

- Using this data to find indicators that are most important at different stages. The elasticity shows us that countries at different stages will require different approaches to future development.
- Incorporating indicators of historic trends, evidence of colonialism or poor institutions that set up a poor development trajectory.

These models come together to show a complex relationship between the development of countries and their well-being. In our world, there is a large gap in development, with people experiencing extreme wealth and poverty, sometimes within the same country. While we must be aware of the complexity within development of a country, seeing how various countries are able to achieve their levels of development and well-being will give us a broader understanding of the importance of specific variables. Our findings show that improvement in one area alone isn't enough. There is not one indicator that can move a country's development. Policy makers should be multi-factor strategies to improve development. Governments can use these models to benchmark themselves against similarly developed countries. With these findings, countries can help countries to maximize well-being and ensure a better tomorrow.