What are the Key Predictors of Democratic Erosion?

Sanittawan Nikki Tan *

26 May 2019

Abstract

Democratic erosion (or democratic backsliding) is an emerging concept in regime change literature in comparative politics. Certain scholars define it as a deliberate elimination or weakening of the political institutions which results in a decline in the quality of democracy. This article probes key predictors of such phenomena by utilizing gradient boosted trees which is a non-parametric statistical learning model and leveraging indices of democratic quality collected by the Varieties of Democracy project and the Freedom House. Important predictors of democratic erosion appear to be indicators on the independence of an election management body, education quality, an indicator on executive corruption and bribery, an indicator on the quality of public administration, the level of political participation, and the duration of democracy. The result from a predictive model contributes to the current literature on the subject by pointing scholars to important factors that could be examined using a causal inference framework to test the causal relationship between these indicators and democratic erosion.

1 Introduction

The phenomenon of democratic erosion has been gaining more scholarly attention since the rise of various right-wing populist parties in Europe, the election of U.S. president Don-

*Masters in Computational Social Science, The University of Chicago

ald Trump in 2016, recent political developments in Turkey, and a consecutive decline in the global freedom score reported by the Freedom House. Democratic erosion differs from tradition regime breakdowns and authoritarian reversions in a way that it is a gradual "...deterioration of qualities associated with democratic governance, within any regime" (Waldner and Lust 2018). In the past, countries experienced a more abrupt regime breakdown through illegal means such as coups d'état or self-coups. Democratic erosion results in a poorer quality of democracy which involves weakened checks and balances and, frequently, stronger executive power.

Although we have developed more understanding about what democratic erosion looks like and its symptoms, the predictors of this phenomenon seem to be under speculation, rather than systematically analyzed. Some literature point to the rise of populists (Kendall-Taylor and Frantz 2016) and polarization (Levitsky and Ziblatt 2018). Since democratic erosion is often associated with the decline in the quality of democratic institutions, this article takes the advantage of the extant indicators on the quality of main political institutions from the Varieties of Democracy project (V-DEM) and attempts to identify key predictors of such phenomena using gradient boosted trees model. The contribution of this article is twofold. Firstly, it aims to increase our understanding about the predictors of democratic erosion. Secondly, it aims to propose a systematic alternative to classifying cases of democratic erosion. To date, there is yet to be an academic consensus on how to measure or classify cases of democratic erosion. This article utilizes the Freedom House's country and territory statuses for achieving this task. A larger goal in play here is to identify overlapping and non-overlapping cases of democratic erosion classified by different methods including the decline in V-DEM and Polity IV scores which were used in other scholarly works (Gottlieb et al. 2018; Gibler and Randazzo 2011). Admittedly, none of the existing approaches maps very well onto the conceptualization of democratic erosion.

This article begins with a review of the body of work on democratic erosion which details its definition. The third section describes the data set used for the analysis of this article. The fourth section explains the gradient boosted trees model and important methods for overcoming challenges of the data set. The fifth section reports the result of the model. Finally, the article concludes with a brief summary of the findings and propose an avenue for future research.

2 Existing Theories on Democratic Erosion

This article mainly speaks to research on regime change in comparative politics. This section takes readers through a brief review of the concept of democratic erosion, differentiates it from conventional regime breakdown, and explores several explanations of possible associations or even causal mechanisms that lead to democratic erosion.

Democratic erosion (or democratic backsliding) is a rather new concept that is emerging in regime change literature in comparative politics. In their annual review article, Waldner and Lust (2018) define it as follows: "[Democratic] [b]acksliding entails a deterioration of qualities associated with democratic governance, within any regime." They focus on backsliding within democracies and argue that backsliding occurs through "a discontinuous series of incremental actions." Bermeo (2016) offers a similar definition: "the state-led debilitation or elimination of any of the political institutions that sustain an existing democracy." These two definitions clearly highlight a slow and incremental process that constitutes an erosion, rather than an abrupt breakdown or a regime change.

However, another distinct characteristic of democratic erosion is that in many cases the means to weaken or eliminate democratic institutions are perfectly legal. Bermeo (2016) points to at least two of them. First, democratic institutions are deliberately weakened by the executive branch, a process she coins "executive aggrandizement." One outstanding example is Turkey under Recep Tayyip Erdoğan. Erdoğan gradually undermined the checks and balance of the Constitutional Court by securing the ability to appoint 14 out of 17 Constitutional Court judges. His government revised laws to allow criminal prosecution of journalists and created a series of defamation laws in an attempt to silence critics (10-11).

Second, elections are strategically manipulated much in advance. Bermeo argues that manipulations include suppressing media access, preventing opposition candidates from running an election, and changing electoral rules to favor the incumbent government (13).

This article agrees with the definition of democratic erosion provided by Waldner and Lust and Bermeo. However, I would like to underscore that countries that can experience democratic erosion has to be a democracy in the first place and they have to show signs of erosion through at least one of the means that Bermeo mentions.

Where do scholars draw the line between democratic erosion and democratic breakdown? The answer is still being contested but for a good reason. Democratic erosion is more difficult to detect and classify because it slowly occurs. Democratic breakdown, on the other hand, is easier to witness since it involves an abrupt regime change. One of the traditional ways that democracy breaks down is via coup d'état. Other types of breakdown include intervention by foreign forces.

There are three major schools of thought that explain democratic breakdown. The first is the elite-driven models which include those who argued that transitions are a result of intra-elite conflicts. Haggard and Kaufman (2012) note that, in some cases, the military or factions within the military stage a coup against an incumbent government or economic elites may mobilize the mass, the military, or militia to topple office holders (508). The second is the redistributive models of democracy (e.g. Acemoglu and Robinson, 2001, 2006). Acemoglu and Robinson (2006) posit that the relationship between income inequality and the probability of democratization is an inverted U shape, democracy is likely to break down when income inequality is high—but not too high—because elites are fearful of extreme redistribution and will resort to coup d'état if the cost of coups is not high. Therefore, redistributive pressure leads to a democratic breakdown. The final explanation emphasizes the role of international factors in aiding or hindering democratic transitions (e.g. Poast and Urpenlainen 2015).

Bermeo (2016) argues that a regime change through "promissory coups," which occurs when the military stages a coup, promises to hold an election and restores democracy as soon as possible, is a variety of democratic erosion. I argue that promissory coups more closely resemble traditional democratic breakdown since there is a disruption in the regime. Hence, this paper only treats cases where there is an attempt to gradually weaken checks and balances, accountability, and participation as democratic erosion.

Waldner and Lust (2018) imply that democratic erosion is under theorized since it is a new research frontier. This is reflected through the current stage of the literature on democratic erosion which appears to be an amalgam. Some focus on describing the process (Varol 2015; Levitsky and Ziblatt 2018; Ginsburg and Huq 2018) while others seek to evaluate particular country cases (Lieberman et al. 2018; Norris 2017). The closest to theory building is a group of work that attempts to draw causal links between democratic backsliding and other concurrently observed events or characteristics of a democracy such as political polarization and a decline in press freedom.

Lieberman et al. (2018) argue in their article that erosion of democracy in America is caused by polarized two-party presidentialism, exclusion of certain groups from civic membership such as groups divided by race and economic status, and erosion of democratic norms. McCoy et al. (2018) propose a causal chain that links political polarization to democratic erosion. They argue that elites adopt and spread polarizing discourse. Polarization reduces collective action and, once polarized, the opposing groups adopt a zero-sum perception. The resulting perception leads to a willingness of the polarized camps to engage in conflict and to tolerate authoritarian-leaning leaders at the expense of liberal democracy (25-26). Slater (2018) also recalls experiences of Southeast Asian countries and attributes democratic erosion to a reduction in press freedom. As Bermeo (2016) points out, one of the means to erode democracy is media buyout which undermines checks and reduces the transparency of a regime.

In sum, there appears to be a variety of causes of democratic erosion. However, none of the mentioned causes are linked to the quality of democratic institutions. This article will demonstrate that indicators related to the quality of democratic institutions are also a good predictor of such phenomena.

The next section first discusses the challenges around measuring and classifying countries which are experiencing or have experienced democratic erosion. It then explains the data collection process and the final data set that is used for the analysis in this paper.

3 Data

Although there is no scholarly consensus on how to measure or classify countries that are experiencing democratic erosion yet, existing literature shows that there are two common approaches, both employing proxies or indices. The first approach is to use a reduction in the Polity IV scores (Gibler and Randazzo 2011). The second approach is to classify countries based on the reduction in the Varieties of Democracy (V-DEM) scores. In the second approach, Gottlieb et al. (2018) classify countries which are suspected to be experiencing democratic erosion if a country's liberal democracy index as measured by V-DEM at time t is lower than that of time $t-1$. Specifically, a country is classified as "democratic erosion" if its liberal democracy index's score has declined between 2015 and 2017.

Both approaches are problematic because, firstly, they do not distinguish between democracies and non-democracies. This begs an important question to the literature: can non-democracies experience democratic backsliding? My answer is no. I argue that countries that can experience democratic erosion should be considered democracies in the first place. This leads to the question of what constitutes a democracy. This paper agrees with the definition and coding of Boix, Miller, and Rosato (2013) (hereafter "BMR"). Inspired by Robert Dahl, Boix et al. consider a country to be democratic if it satisfies both contestation and participation criteria. They argue "...democracies feature political leaders chosen through free and fair elections and satisfy a threshold value of suffrage." Secondly, as both indices are composite, they do not differentiate how countries "backslide." In fact, the cases selected into the universe by the two approaches could be false positives since some could be unconsolidated democracies. Symptoms that appear to be similar to countries that are experiencing democratic erosion may, in fact, be symptoms of weak and unconsolidated democratic regimes.

In addition, as discussed in the previous section, there is still a major gap between theoretical ground and the current measurement of democratic erosion. Put differently, the current measurement of democratic backsliding does not necessarily comport with its theory. In fact, measurement is particularly challenging since democratic erosion is more difficult to observe and its invisibility affects the coding and analysis of the cases. In addition, there are various ways that a country can backslide. Researchers may encounter measurement error which could jeopardize the credibility of the findings. Lueders and Lust (2018) found that there is little agreement among political scientists when conceptualizing and measuring regime changes (i.e. democracy, autocracy, or hybrid regimes) which spills over to conceptualizing democratic erosion. The measurement debate is by no means the scope of this paper; however, it is crucial to point to the current debate in the field.

As other scholars have employed Polity IV and V-DEM scores as proxies for selecting democratic erosion cases, this paper aims to contribute to the debate by employing an alternative measure: Freedom House's country ratings as proxies for classifying regimes and selecting cases of democratic erosion. A larger goal in play is to eventually test the discrepancies across sets of cases that were selected using different measurement which is a future project. This paper classifies a country-year case as democratic backsliding according to the following rules:

- Country-year cases are first classified as democracies and non-democracies according to BMR's coding rule.
- For the year 2000, every case in the data set is coded as non-erosion (is_erosion takes on the value of 0).
- If a country-case was not a democracy in 2000, it is deemed a young democracy and is_erosion receives a value of 0 throughout (This rules intend to rule out false positives of weak democracies).
- For subsequent years, if a country's status is "Free" (F) at $t-1$ but was classified as "Partly Free" (PF) or "Not Free" (NF) at t, is_erosion takes on the value of 1.
- If a country was PF at $t-1$ and PF at t, if Political Rights or Civil Liberties scores at t is more than or equal to $t-1$[1], is_erosion takes on the value of 1.
- If a county was PF at $t-1$ and NF at t, is_erosion takes on the value of 1.
- For all other cases, is_erosion takes on the value of 0.

The Freedom House states in their methodology section that "The average of a country or territory's political rights and civil liberties ratings is called the Freedom Rating,

1. According to the Freedom House, the Political Rights and Civil Liberties scores range from 1 (best) to 7 (worst).

and it is this figure that determines the status of Free (1.0 to 2.5), Partly Free (3.0 to 5.0), or Not Free (5.5 to 7.0)" The overall score is obtained by combining political rights and civil liberties scores which range from 1 to 7. I argue that the Freedom House's rating may be a fair proxy for indicating democratic erosion because in order to obtain the overall scores in the middle range, it is more likely that the country was rated in the middle range (3-5) for both political rights and civil liberties. It is less likely that a country that receives a rating of 6 or 7 in political rights (which means a country is ruled by authoritarian regime or with severe government oppression will receive a score of 1 or 2 in civil liberties which means a country enjoys a wide range of civil liberties and freedom, hence receiving an overall score of 3.5 to 4). Lueders and Lust were partially correct when criticizing the Freedom House's aggregation (738). They state that there is a "multitude of logically possible combinations of individual scores [that] may yield the same rating on the Political Rights [or Civil Liberties] at the question level..." However, they may have overlooked the fact that the political rights and civil liberties scores are fairly correlated. Thus, the actual possible combinations for arriving at a certain level of ratings may be lower than what they expected.

When the Freedom House classifies a country case as partly free, it implies that such country case is not yet a full-blown authoritarian, but its democracy is highly flawed. This implication is consistent with most literature on democratic erosion including Waldner and Lust (2018) and Bermeo (2016). In addition, Bermeo (2016) and Varol (2015) observe that, in some cases, erosion (or stealth authoritarianism in Varol's conceptualization) was initiated by the executive branch. Regardless of how erosion occurs, Lust and Waldner and Bermeo tend to agree that the result is weakened political institutions which are supposed to serve as checks and balances against the government. Thus, this paper's hypothesis is that deterioration in the quality of political institutions should correlate with or be a good predictor of democratic erosion.

The coding rules for classifying democratic backsliding cases in this paper is by no means “the best” approach. However, the advantage of my method is mainly to minimize false positives. Since democratic erosion is a fairly recent phenomenon, I believe that beginning the data set in 2000 is appropriate. Many countries transitioned to democracy at end of the Cold War which increases our risk to classify countries with weak democratic regimes as democratic erosion. Thus, leaving ten years gap should be sufficient for new democracies to consolidate. As long as these regimes do not experience an abrupt breakdown via traditional approaches such as coups d’état, I am more confident to suspect them as having experienced democratic erosion if their quality of democracy suddenly declines.

In order to test the hypothesis about democratic backsliding, I constructed a data set that combines three following data sources.

- Freedom House country and territory ratings and statuses (1973-2018)
- Boix-Miller-Rosato Dichotomous Coding of Democracy (1800-2015)
- V-Dem Country-Year Dataset v9 (Full 450 V-Dem indicators and 59 other indicators)

The dependent variable of interest is whether or not the country is experiencing or has experienced democratic erosion. Regarding independent variables, I carefully selected a wide range of indicators from BMR and V-DEM. Variables “democracy breakdowns” which records a country’s number of democratic breakdowns and “democracy duration” which records the number of consecutive years of current regime type are selected from BMR. I also selected 65 V-DEM indicators from 12 categories including those that entail the quality of the executive, the legislature, and the judiciary. Appendix 1 records for a full list of selected indicators.

In terms of the organization of the data set, I follow the tradition of scholarly work in regime change literature by coding longitudinal country-year data set. In other words, each country and year is treated as independent case or observation in the data set. The final

Table 1: Freedom House's Country Statuses Proportion

Category	Number of Cases
Not Free (0)	853
Partly Free (1)	1,043
Free (2)	1,582

Table 2: Proportions of Cases of Democratic Erosion

Category	Number of Cases
No Democratic Erosion (0)	3,081
Democratic Erosion (1)	397

data set which is used for the analysis in the subsequent section has 76 columns (including identifies such as year and country) and 3,478 country-year observations. The number of columns increases from 67 because some of the independent variables are categorical and have to be one-hot encoded. The breakdown of country-year cases are shown in table 1 and 2.[2] Table 1 and Table 2 show the breakdown of the country statuses classified by the Freedom House and the cases of erosion and non-erosion classified by my coding rule. The data set includes 195 unique states or countries from 2000 to 2017. It should be noted that some countries may appear fewer than 18 times in the data set because they came to be a country after 2000 such as Serbia.

The data set presents various challenges due to its nature which I will address in the next section.

2. The full data set can be found in the `data` directory with the name `democracy.csv`.

4 Model and Methods

4.1 Predictive Model: Gradient Boosted Trees

As the data section describes, fitting a functional form to this high dimensional data set becomes a classification problem since the dependent variable of interest is a dichotomous variable. This article argues that a gradient boosted decision tree algorithm which is a supervised ensemble method is suitable for this task because the method treats missing data values as its own category unlike other statistical learning models that require users to drop rows with missing values or impute them.[3] The main difference between gradient boosted trees and the random forest model is that the former grows trees (learners) sequentially with the aim to minimize the errors generated by previous trees.

The objective function which will be optimized is defined as:

$$\sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t)}) + \sum_{i=1}^{t} \Omega(f_i) \tag{1}$$

The objective function contains two components: the training loss and the regularization term. Since it is a classification problem, logistic loss function is used:

$$L(\theta) = \sum_{i} [y_i \ln(1 + e^{-\hat{y}_i}) + (1 - y_i) \ln(1 + e^{\hat{y}_i})] \tag{2}$$

θ denotes the model's parameters.

The `XGBoost` implementation learns function f_i using an additive strategy. The general simplified objective function is:

3. This paper uses `XGBoost` implementation of gradient boosted trees as proposed by Chen and Guestrin (2016).

$$\sum_{i=1}^{n}[l(y_i, \hat{y}_i^{(t-1)}) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)] + \Omega(f_t) \tag{3}$$

where $g_i = \partial_{\hat{y}_i^{(t-1)}} l(y_i, \hat{y}_i^{(t-1)})$ and $h_i = \partial^2_{\hat{y}_i^{(t-1)}} l(y_i, \hat{y}_i^{(t-1)})$

To make sure that my final model has a good bias-variance trade-off, I implemented a hyperparameter tuning via randomized search. Randomized search is selected over exhaustive grid search to reduce the training time. I varied standard hyperparameters including maximum tree depth, learning rate, number of trees, ratio of sub-sample for training, L1 regularization, and L2 regularization.[4] I also followed XGBoost's suggestion for handling imbalanced data set by balancing positive and negative weights. The final model is selected if it maximizes the 5-fold cross-validated accuracy rate.

4.2 Challenges of the Data Set

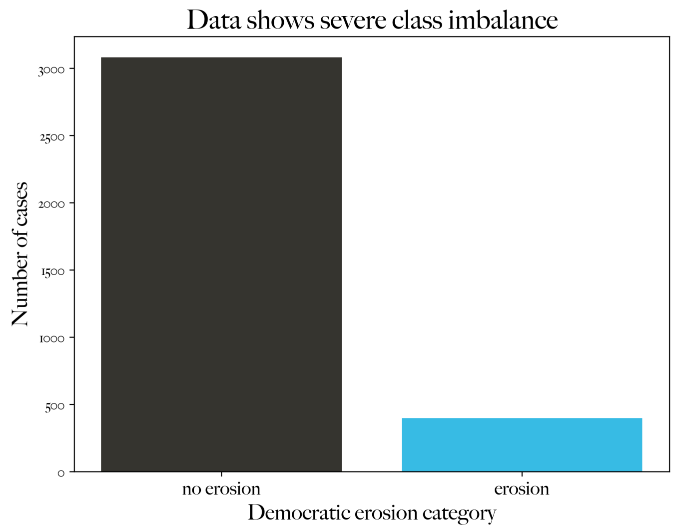
The data set presents three challenges for implementing a non-parametric statistical learning model like gradient boosted trees.

Firstly, as shown in Table 2, the cases of democratic erosion are rarer than the cases of non-erosion. Figure 1 further illustrates this point.

There are various ways imbalanced classes can be handled; however, I choose to implement stratified sampling to split between the train and the test sets. The method preserves the same class proportion of approximately 0.3 in both the training set and the test set. Hence, when the model is trained on a training set, it sees the same proportion of cases of democratic erosion and non-democratic erosion. Since the sampling is randomized and the resulting sets are not in chronological order as in our original data set, I sort them

4. The code is available in `analysis.ipynb`

Figure 1: Class Imbalance

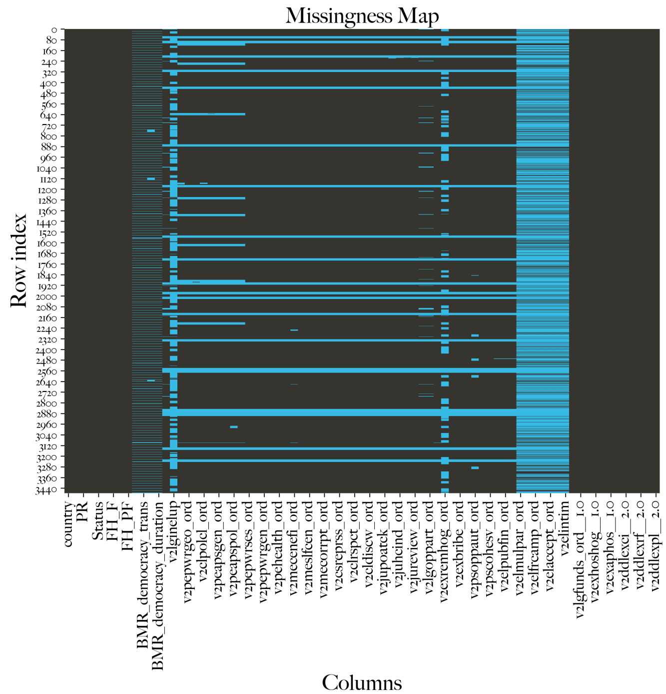


to preserve the chronological order.

Secondly, certain columns in the original data set includes a large number of missing values, some of which are *not* missing at random. To diagnose the problem, I create a missingness map to identify the proportion of missing values per row and column. Figure 2 which illustrates a missingness map showing precisely the issue with certain columns.

Since some columns such as vote buying in elections, whether elections are free and fair, and whether election losers accept the results contain a large number of missing data, I dropped them before training the model. The alternative to dropping these values is imputation. However, some of the columns contain categorical values which prove to be more difficult as mode or mean imputation may not yield the best result. In addition, these data points pertain to specific countries and years. Imputing using values from individual countries which have only a maximum of 18 observations may not be sufficient. It is possible to group similar countries for imputation. Nevertheless, imputation is not essential in this case because gradient boosted trees via the implementation of XGBoost treats missing data as its own category.

Figure 2: Missingness Map



Finally, because the data set is longitudinal, it presents a cross validation challenge to conventional cross validation methods which randomly select observations into folds. Longitudinal data implies temporal dependencies which may not be meaningful for model evaluation if the chronological relationship is broken in the cross validation process. To address this issue, I implement a rolling cross validation set where the next "fold" contains data from the previous "fold."[5]

4.3 Interpreting the Model with Feature Importance Approach

Unlike linear regression models, gradient boosted trees do not lend itself well for interpretation. To get a glimpse of what happens inside the model, I adopt a model-agnostic

5. The Python implementation of this method is readily available through the `TimeSeriesSplit` class in the `scikit learn` package.

interpreting method for machine learning models as proposed by Fisher, Rudin, and Dominici (2018). According to Molnar (2019), feature importance works by permuting or shuffling the values of each feature in the data set at a time. Then, the approach calculates the increase in the model's prediction error. If the model's prediction error significantly increases after permuting that feature, it means that the model relies on it to make a good prediction, hence an important feature. The approach repeats the permutation and the calculation for each feature and ranks them based on which permuted features result in the highest increase in the model's prediction error.

The advantage of this approach is that it is intuitive and is not too complicated to implement. However, the main disadvantages are (i) it can create an unrealistic data set and (ii) it has high variance. To the first point, permuting the data set breaks any association between the feature and the true outcome. Since the values are permuted, it is possible that, for example, the U.S. ends up with a low score on education equality for men and high score for women which is unrealistic since the two features should be positively correlated in the actual data set. To the second point, shuffling data involves some randomness and the features that are identified as important can vary each time the approach is applied. To ameliorate this issue, I implement 100 iterations of feature importance approach and count the number of times a feature appears in the top ten most important feature list. My final output is the frequency of all features that appear in the top ten most important list per iteration. Implementing this improves the reliability of the result since it does not depend on a single execution.

5 Results

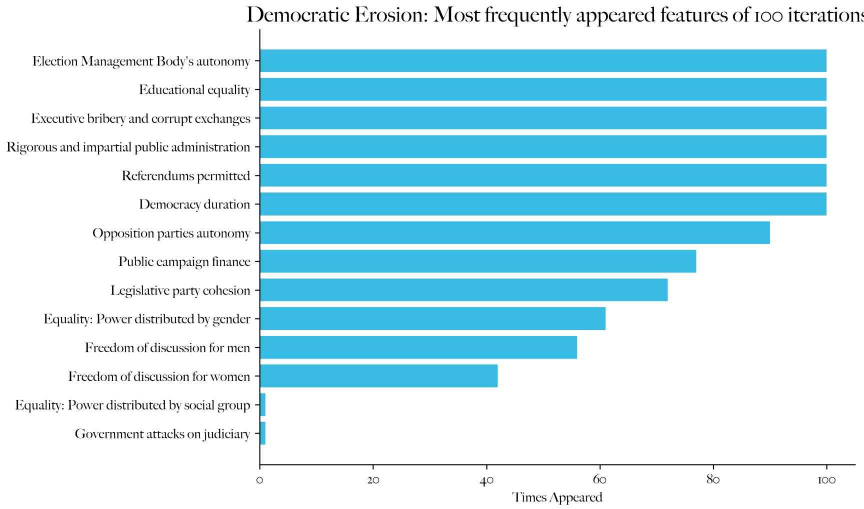
The tuned gradient boosted trees model achieves a cross-validated accuracy rate of 96.3 percent on the training set. It, unfortunately, achieves 80.4 percent accuracy rate in the test set, which implies overfitting. I believe there are several ways to improve the test set accuracy rate. Firstly, on top of stratified sampling to split the training and test sets, deliberate undersampling of the majority class and oversampling the minority class can be implemented on the training set. According to Raschka and Mirjalili (2017), statistical learning models tend to be biased toward the majority class because the cost function is computed as a sum over the entire training set. Another way to improve the test set's accuracy (and avoid overfitting) is to implement a nested cross validation where the training set contains the first half of the time series of individual countries (e.g. 2000-2008) and the validation set contains the second half of the time series of individual countries (2009-2017).

Although accuracy is important, interpreting the model is also as significant for this paper since I would like to learn about the predictors of democratic erosion. As mentioned in the previous section, I chose a feature importance approach with 100 iterations to reduce the variance of the result. Figure 3 shows the frequency counts of each independent variable which appears on the top ten most important features per iteration. For instance, election management body's autonomy appears 100 times among the top ten most important features of our model whereas freedom of discussion for women appears slightly more than 40 times per 100 iterations.

Based on the model, important predictors of democratic erosion appear to be indicators on the independence of an election management body, education quality, an indicator on executive corruption and bribery, an indicator on the quality of public administration, the level of political participation, and the duration of democracy. These six predictors consistently appear in every iteration. The interpretation is that the model relies heavily on these features to make predictions. However, it should be noted that this does not imply causation.

Feature importance yields an interesting insight. The identified important predic-

Figure 3: Importance Features



tors are broader than the quality of the formal political institutions such the legislature or the court. Education quality and the duration of democracy seem to be good predictors of democratic erosion. This suggests that scholars should not only look at political but also socioeconomic factors to gain more understanding of what could be driving such phenomena. Secondly, scholars can use this result as a starting point to study the causal relationship between these predictors and democratic erosion.

6 Conclusion

This article leverages gradient boosted trees which is a non-parametric statistical learning model coupled with feature importance which is a model-agnostic interpretation approach to understand the key predictors of democratic erosion. The model suggests that the important predictors appear to be indicators on the independence of an election management body, education quality, an indicator on executive corruption and bribery, an indicator on the quality of public administration, the level of political participation, and the duration of democracy. This result contributes to the current burgeoning literature on democratic erosion by identifying potential predictors that may have causal relationship with democratic erosion. The predictors identified from the model can be a stepping stone for scholars who are interested in answering causal questions, especially to explain what causes such phenomena.

A fruitful avenue for future research is precisely this issue. It is possible that being a good predictor does not necessarily imply that it causes democratic erosion. Scholars should investigate further if any of the identified predictors cause democratic erosion.

References

Acemoglu, Daron, and James A. Robinson. 2001. "A Theory of Political Transitions." *The American Economic Review* 91 (4): 938. ISSN: 00028282. `http://proxy.uchicago.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=edsjsr&AN=edsjsr.2677820&site=eds-live&scope=site`.

———. 2006. *Economic origins of dictatorship and democracy.* Cambridge Univ. Press. ISBN: 0521855268.

Bermeo, Nancy. 2016. "On Democratic Backsliding." *Journal of Democracy,* no. 1: 5–19.

Boix, Carles, Michael Miller, and Sebastian Rosato. 2013. "A Complete Data Set of Political Regimes, 1800–2007." *Comparative Political Studies* 46 (12): 1523–1554. doi:10.1177/0010414012463905. eprint: https://doi.org/10.1177/0010414012463905. https://doi.org/10.1177/0010414012463905.

Bonica, Adam, Howard Rosenthal, and David J Rothman. 2014. "The Political Polarization of Physicians in the United States: An Analysis of Campaign Contributions to Federal Elections, 1991 Through 2012." *JAMA internal medicine (Print),* no. 8: 1308. ISSN: 2168-6106. http://proxy.uchicago.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=edscal&AN=edscal.28772317&site=eds-live&scope=site.

Chen, Tianqi, and Carlos Guestrin. 2016. "XGBoost: A Scalable Tree Boosting System." http://proxy.uchicago.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=edsarx&AN=edsarx.1603.02754&site=eds-live&scope=site.

Cochrane, Courtney. 2018. *Time Series Nested Cross-Validation.* https://towardsdatascience.com/time-series-nested-cross-validation-76adba623eb9.

Coppedge, Michael, John Gerring, Carl Henrik Knutsen, Staffan I. Lindberg, Jan Teorell, David Altman, Michael Bernhard, et al. 2019. *V-Dem Country-Year Dataset v9.* Varieties of Democracy (V-Dem) Project. https://doi.org/10.23696/vdemcy19.

Delia, Baldassarri, and Andrew Gelman. 2007. "Partisans Without Constraint: Political Polarization and Trends in American Public Opinion." http://proxy.uchicago.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=edsbas&AN=edsbas.71C14458&site=eds-live&scope=site.

Douglas M., Gibler, and Kirk A. Randazzo. 2011. "Testing the Effects of Independent Judiciaries on the Likelihood of Democratic Backsliding." *American Journal of Political Science* 55 (3): 696. ISSN: 00925853. http://proxy.uchicago.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=edsjsr&AN=edsjsr.23024945&site=eds-live&scope=site.

Fisher, Aaron, Cynthia Rudin, and Francesca Dominici. 2018. *All Models are Wrong but many are Useful: Variable Importance for Black-Box, Proprietary, or Misspecified Prediction Models, using Model Class Reliance.* eprint: `arXiv:1801.01489`.

Freedom House. 2018. *Freedom in the World Country and Territory Ratings and Statuses, 1973-2018.* `https://freedomhouse.org/content/freedom-world-data-and-resources`.

Ginsberg, Tom, and Aziz Huq. 2018. *How to Save a Constitutional Democracy.* The University of Chicago Press.

Gottlieb, Jessica, Rob A. Blair, Aries Arugay, Cameron Ballard-Rosa, Hannah Baron, Guy Grossman, Shelby Grossman, et al. 2018. *Democratic Erosion Event Dataset v.2.* Democratic Erosion Project: A Cross-University Collaboration. `http://democratic-erosion.com/event-dataset/raw-data/`.

Haggard, Stephan, and Robert R. Kaufman. 2012. "Inequality and Regime Change: Democratic Transitions and the Stability of Democratic Rule." *The American Political Science Review* 106 (3): 495. ISSN: 00030554. `http://proxy.uchicago.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=edsjsr&AN=edsjsr.23275430&site=eds-live&scope=site`.

Hanna, Alexander, Chris Wells, Peter Maurer, Lew Friedland, Dhavan Shah, and Matthes. 2013. "Partisan alignments and political polarization online." *Conference on Information Knowledge Management:* 15. `http://proxy.uchicago.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=edb&AN=103019507&site=eds-live&scope=site`.

Kendall-Taylor, Andrea, and Erica Frantz. 2016. *How Democracies Fall Apart.* `https://www.foreignaffairs.com/articles/2016-12-05/how-democracies-fall-apart`.

LeBas, Adrienne. 2018. "Can Polarization Be Positive? Conflict and Institutional Development in Africa." *American Behavioral Scientist* 62 (1): 59–74. ISSN: 00027642. http://proxy.uchicago.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=edswss&AN=000429623800004&site=eds-live&scope=site.

Levitsky, Steven, and Daniel Ziblatt. 2018. *How Democracies Die.* Crown.

Lieberman, Robert C., Suzanne Mettler, Thomas B. Pepinsky, Kenneth M. Roberts, and Richard Valelly. 2018. "The Trump Presidency and American Democracy: A Historical and Comparative Analysis." *Perspectives on Politics:* 1–10. doi:10.1017/S1537592718003286.

Lueders, Hans, and Ellen Lust. 2018. "Multiple Measurements, Elusive Agreement, and Unstable Outcomes in the Study of Regime Change." *The Journal of Politics* 80 (2): 736–741. doi:10.1086/696864. eprint: https://doi.org/10.1086/696864. https://doi.org/10.1086/696864.

McCoy, Jennifer, Tahmina Rahman, and Murat Somer. 2018. "Polarization and the Global Crisis of Democracy: Common Patterns, Dynamics, and Pernicious Consequences for Democratic Polities." *American Behavioral Scientist* 62 (1): 16–42. ISSN: 00027642. http://proxy.uchicago.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=hch&AN=128683062&site=eds-live&scope=site.

Molnar, Christopher. 2019. *Interpretable Machine Learning.* 1st ed. Christoph Molnar. ISBN: 9780244768522.

Norris, Pippa. 2017. "Is Western Democracy Backsliding? Diagnosing the Risks." https://research.hks.harvard.edu/publications/getFile.aspx?Id=1514.

Poast, Paul, and Johannes Urpelainen. 2015. "How International Organizations Support Democratization: Preventing Authoritarian Reversals or Promoting consolidation?" *World Politics* 67 (1): 72–113. doi:10.1017/S0043887114000343.

"Political polarization in social media: Analysis of the "Twitter political field" in Japan." 2017. *2017 IEEE International Conference on Big Data (Big Data), Big Data (Big Data), 2017 IEEE International Conference on:* 3143. ISSN: 978-1-5386-2715-0. http://proxy.uchicago.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=edseee&AN=edseee.8258291&site=eds-live&scope=site.

Przeworski, Adam, Michael Alvarez, Jose Antonio Cheibub, and Fernando Limongi. 2000. *Democracy and development: political institutions and well-being in the world, 1950-1990.* Cambridge studies in the theory of democracy. Cambridge Univ. Press. ISBN: 978-0-521-79032-1.

Raschka, Sebastian, and Vahid Mirjalili. 2017. *Python Machine Learning.* 2nd ed. Birmingham, UK: Packt. ISBN: 9781787125933.

Shanto, Iyengar, and Sean J. Westwood. 2015. "Fear and Loathing across Party Lines: New Evidence on Group Polarization." *American Journal of Political Science* 59 (3): 690. ISSN: 00925853. http://proxy.uchicago.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=edsjsr&AN=edsjsr.24583091&site=eds-live&scope=site.

Slater, Dan. 2018. *After Democracy.* https://www.foreignaffairs.com/articles/2018-11-06/after-democracy.

Varol, Ozan. 2015. "Stealth Authoritarianism." *Iowa Law Review* 100 (4): 1673–1742. ISSN: 00210552. http://proxy.uchicago.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=a9h&AN=102648598&site=eds-live&scope=site.

Waldner, David, and Ellen Lust. 2018. "Unwelcome Change: Coming to Terms with Democratic Backsliding." *Annual Review of Political Science* 21:93–113. ISSN: 10942939. http://proxy.uchicago.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=edswss&AN=000433417100006&site=eds-live&scope=site.