Legislative Voting Dynamics in Ukraine

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Abstract. Current work in roll call modeling focuses on the legislative decision process and does not take advantage of the dynamic nature of legislation. Some political systems, such as Ukraine's Verkovna Rada, are inherently dynamic, and should be modeled as such. In the model proposed, the entire legislative body is modeled together and bills are viewed as a dynamic process. This model requires no contextual information about individual legislators and predicts the amount of favorable votes a bill will receive within 6.2%, on average. Additionally, we find differences in behavior of bills proposed by the President and those proposed by parliament members or the Cabinet. This work only uses a simple differential model, opening the door to the use of more complex models capable of leveraging contextual information in the future.

Keywords: Differential modeling · Roll call prediction

1 Introduction

The legislative process in the Ukrainian Parliament, the Verkovna Rada, is inherently dynamic. Each bill is voted on several times before being passed or rejected. Current work in roll call modeling focuses on the legislative decision process and does not take advantage of the dynamic nature of legislation. This work seeks to answer the question: can a simple model that takes advantage of bill dynamics be used to predict future legislative outcomes? To answer this question, we propose a new model for dynamic legislation, in which the entire legislative body is modeled together and bills are viewed as a dynamic process. First, background information on the Verkovna Rada is provided. Then, a review of previous voting models is discussed. Following, the model, the procedure for its use, and the results are shown. Finally we discuss the implications of the models vis-a-vis avenues for future work.

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2 Voting in the Verkovna Rada

The Verkovna Rada, Ukraine's parliament, consists of 440 members. Bills may be sponsored by one of three subjects: a parliament member, the Government of Ukraine (the Cabinet), or the President. Additionally, bills from any subject may be tied to a committee. It is believed that bills sponsored by the President are passed quicker than those sponsored by others. The legislative procedure in the Verkovna Rada requires multiple votes on a bill before it is put into law. Technically a bill passes after 3 separate votes with at least 225 legislators voting "for" it. This leads to bills going through many iterations, sometimes as many as 9, before the bill is passed or given up on. This work uses bills from the most recent convocation, which began on November 27, 2014 and will continue until November 27, 2019.

3 Voting Models

Many strategies for modeling roll call voting have been employed in the past. Early work focused on accurately representing individual legislator's decision process using as much contextual information as possible [4,6]. Part of this contextual analysis relies on political dimensions of the legislation. Early work by MacRae showed the presence of political dimensions in legislation from the United States Congress [5]. Clausen, among others, used these dimensions as the basis for legislative decision making [1]. Most recently, the dynamics of political systems have been leveraged through game theory [2,3]. In contrast to previous work which focused on modeling legislative decision making, we focus on the group dynamic process behind roll call voting.

4 The Data

In total 78 bills were analyzed. Note that the model needs 2 vote iterations before prediction can begin, so the "predictable points" are the following vote iterations. As such, bills with less than 3 iterations would have no predictable points, so they were not used. Each bill has a sponsoring subject, and committee. The votes on each bill iteration are collapsed into a single number, percentage of votes in favor, in order to model the legislative body as a whole, rather than predicting member's individual votes. The summary statistics for the data are shown in Table 1.

Since the percentage of votes for a bill is changing dynamically in time, it can be viewed in phase-space. The phase space diagram shown in Fig. 1. This diagram shows votes spiraling in towards an equilibrium point on the x-axis, indicating that it can be modeled using a differential equation.

Table 1. Bill summary statistics by subject

Subject	Bills	Max iterations	Predictable points	Committees	Mean	Std. Dev.	Min	Max	Median
Parliament	71	9	359	21	45.454	10.681	10.090	71.760	48.813
Government	4	8	21	4	44.640	10.476	22.421	56.502	48.380
President	3	5	12	1	47.160	12.897	26.233	74.664	48.318

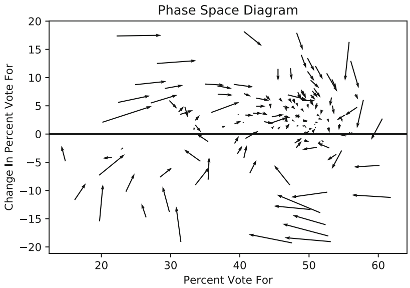


Fig. 1. Percentage of votes for, viewed in phase space.

5 Methodology

5.1 The Model

The goal of the work is to find a model equation, $v(t)$ that approximates the percentage of favorable votes that it receives at time t. Since bills are voted on at discrete intervals, i, we say that votes occur during regular intervals proportionate to the bill iteration:

$$t_i = \alpha * i \ . \tag{1}$$

Based on the structure seen in the phase diagram, Fig. 1, it seems appropriate to use a differential model. This work's model equation follows the form of a second order linear homogeneous differential equation:

$$A * \frac{d^2 v}{dt^2} + B * \frac{dv}{dt} + C * v = 0, \tag{2}$$

where A, B, C, and D are constants that can be fit to the data. This model was selected for its simplicity; higher order and/or non-homogeneous models are left for future work. The discrete nature of the bill data also makes estimating derivatives challenging. At least 3 data points are needed to calculate the second derivative. The best estimate of the first derivative at the center point is the average of the change before and the change after. Thus, only bills with 3 or more votes could be used to fit the model. The advantage of having the simple model in Eq. 2 is its analytic solutions. With an analytic solution, the first two iterations of a bill can be fit exactly, instead of relying on the poor estimate of the derivative at point 2, as would be needed for numerical integration.

Following this, $\frac{d^2v}{dt^2}$ and $\frac{dv}{dt}$ will be referred to as v'' and v', respectively. When calculating derivatives from the raw data, the unknown factor α must also be accounted for, thus, the model equation becomes:

$$\frac{A}{\alpha^2}v'' + \frac{B}{\alpha}v' + C * v = 0. \tag{3}$$

Finally, the model will be solved analytically, and will be written in terms of bill iteration (instead of t). Based on the phase portrait, real eigenvalues are expected. In this case, the solution will be of the form:

$$v(i) = C_1 e^{\lambda_1 i} + C_2 e^{\lambda_2 i}. \tag{4}$$

5.2 Fitting Parameters

For each possible vote iteration, the derivatives were calculated, resulting in N data points, each having a value for v, v', and v''. Note that consecutive data points may or may not belong to the same bill. For example, a bill with 4 iterations will become two data points: $[v_2,v_2',v_2'']$ and $[v_3,v_3',v_3'']$. The data does not follow the model exactly, so an objective function was defined:

$$F = \sum_{b=1}^{N}(v_b'' + C_{v'}\alpha v_b' + C_v \alpha^2 v_b)^2. \tag{5}$$

This function is simply Eq. 3 set equal to zero with the v'' coefficient normalized to one, squared, and summed over the whole dataset. Squaring the values is used in place of an absolute value sign, making differentiation smooth. The objective function was minimized using SciPy's implementation of Nelder and Mead's simplex method for minimization [7].

Once the parameters for Eq. 4 are found, bills can be predicted. First, the coefficients C_1 and C_2 are calculated:

$$\begin{bmatrix} C_1 \\ C_2 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ e^{\lambda_1} & e^{\lambda_2} \end{bmatrix}^{-1} \begin{bmatrix} V_0 \\ V_1 \end{bmatrix}. \tag{6}$$

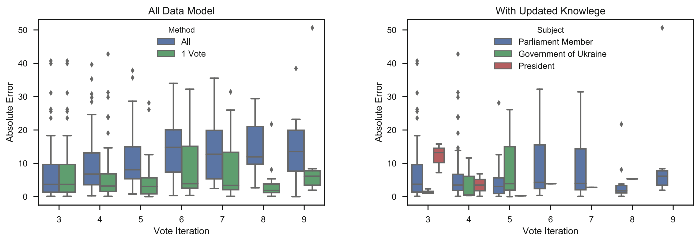
From here, the model was used in two ways. First, Eq. 4 was evaluated at all desired times. Second, the model equation was updated after every iteration by refitting Eq. 6 to the incoming data. The updated knowledge method is more accurate but less powerful as only one iteration is predicted at a time.

6 Results

6.1 All Data

First, the bills sponsoring subject and committee were ignored, and a model was fit to the entire dataset. The resulting model from Eq. 4 has the values

$\lambda_1 = -0.424$ and $\lambda_2 = -0.008$. The negative exponents indicate that the model is indeed following the sink behavior observed in the phase diagram. The average absolute difference between prediction and actual percentage vote for the entire data set is 6.2% using this model. Figure 2 shows the models absolute error by vote iteration. The non-updated prediction performs worse on later iterations. While average error is low, the upper bound on error is very high. Figure 2 also shows that the overall model performs differently based on the initial subject.



(a) (b)

Fig. 2. Predictions using updated knowledge are in a. Updated knowledge model error by subject are in b.

6.2 Bill Subject

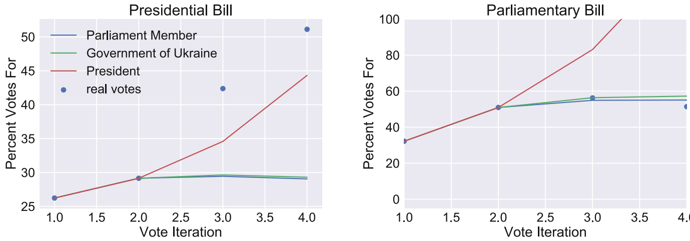
After seeing the difference in model performance by subject, each subject was modeled separately. The parameters λ_1 and λ_2 in Eq. 4 are $(-0.284, -0.005)$, $(-0.494, -0.012)$, and $(0.478, -0.026)$ for bills from parliament, government, and the President, respectively. It is noteworthy that while the parliamentary and government models have two negative coefficients, the presidential model has one positive and one negative. The first two models are sinks, while the last is a saddle. Thus, presidential bill behavior is quantitatively different. See Sect. 7.

On average, the absolute difference was 6.25%, 3.78%, and 2.97% for Parliament, Government, and President respectfully. The subject modeling improved the average accuracy for every subject. The presidential and government models had no instances of greater than 12%. About 25% of parliamentary votes are poorly predicted, >10% absolute error.

Since all the bills with greater than 10% error are from Parliamentary Members, the Bill Committee analysis was performed on only the parliamentary bills. Fitting models based on committee does improve overall error, but there is still many instances of >20% error.

7 Discussion

While fitting a single model for all bills achieves an average error of nearly 6%, modeling initial bill subjects separately increases accuracy and shows that presidential bill have different behavior than those of other subjects. This gives evidence to the hypothesis that presidential bills tend to have different trajectories than bills from other sources. Parliamentary and government bills are modeled to stabilize quickly, while presidential bills continue to increase or decrease based on what happened in the initial two iterations.



(a) (b)

Fig. 3. Predictions and votes for a presidential bill (a) and a parliamentary bill (b).

The difference in model behavior is visualized in Fig. 3. There are two reasons that the presidential model increases rapidly for the parliamentary bill. First, the presidential data has less bills with many iterations, and only a max iteration of 5, so the model is fit mostly to predict iteration 3. Second, the presidential bills all changed slowly first, with a maximum increase of only 5% from the first iteration to the second.

While modeling parliamentary bills separately based on their committee increased the overall accuracy, there were still several instances of >20%, and these errors were spread across many committees. Thus, fitting for committee and fitting for subject cannot completely explain why some iterations of bills are poorly predicted. It is also noteworthy that the parliamentary model has a mean error of 3.5% for the "Committee on Legal Policy and Justice," and a maximum error of 12%. This is the only committee sponsoring presidential bills, indicating that the difference in models cannot be just explained by the committee.

8 Conclusion

This work takes advantage of the dynamic nature of legislative voting in the Verkhovna Rada to build predictive models for future legislative votes. Without considering the initial subject of a bill, the model predicted the percentage of votes in favor of bills within 6.2% on average. Validation on 600 unlabeled bills from convocation 8 resulted in similar accuracy. Modeling by initial subject improved prediction for bills initiated by the President and by the Cabinet to 3.0% and 3.8% respectively. The models imply that presidential bills change significantly after the first two votes, while other bills stabilize quickly.

About 20–25% of parliamentary votes are predicted with over 10% error. Accounting for committee did not resolve this error, so it seems that some votes simply do not follow the model equation. Still, given how little information the model uses, its success shows the potential of dynamic modeling. Future work may use more complex models to better predict the remaining bills.

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