Legislator Representation Learning with Social Context and Expert Knowledge

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Abstract

Modeling the ideological perspectives of political actors is an essential task in computational political science with applications in many downstream tasks. Existing approaches are generally limited to textual data and voting records, while they neglect the rich social context and valuable expert knowledge for holistic evaluation. In this paper, we propose a representation learning framework of political actors that jointly leverages social context and expert knowledge. Specifically, we retrieve and extract factual statements about legislators to leverage social context information. We then construct a heterogeneous information network to incorporate social context and use relational graph neural networks to learn legislator representations. Finally, we train our model with three objectives to align representation learning with expert knowledge, model ideological stance consistency, and simulate the echo chamber phenomenon. Extensive experiments demonstrate that our learned representations successfully advance the state-of-the-art in three downstream tasks. Further analysis proves the correlation between learned legislator representations and various socio-political factors, as well as bearing out the necessity of social context and expert knowledge in modeling political actors.

1 Introduction

Modeling the perspectives of political actors has applications in various downstream tasks such as roll call vote prediction [Mou et al., 2021] and political perspective detection [Feng et al., 2021]. Existing approaches generally focus on voting records or textual information of political actors to induce their stances. Ideal point model [Clinton et al., 2004] is one of the most widely used approach for vote-based analysis, while later works enhance the ideal point model [Kraft et al., 2016; Gu et al., 2014; Gerrish and Blei, 2011] and yield promising results on the task of roll call vote prediction. For text-based methods, text analysis techniques are combined with textual information in social media posts [Li and Goldwasser, 2019], Wikipedia pages [Feng et al., 2021], legislative text [Mou et al., 2021] and news articles [Li and Goldwasser, 2021] to enrich the perspective analysis process.

However, existing methods fail to incorporate the rich social context and valuable expert knowledge. As illustrated in Figure 1, social context information such as state and party affiliation serves as background knowledge and helps connect different political actors [Yang et al., 2021]. These social context facts about political actors also differentiate them and indicate their ideological stances. In addition, expert knowledge from political think tanks provides valuable insights and helps to anchor the perspective analysis process. As a result, political actor representation learning should be guided by domain expertise to facilitate downstream tasks in computational political science. That being said, social context and expert knowledge should be incorporated in modeling legislators to ensure a holistic evaluation process.

In light of these challenges, we propose a legislator representation learning framework that jointly leverages social context and expert knowledge. We firstly collect a dataset of political actors by retrieving and extracting social context information from their Wikipedia homepages and adapting expert knowledge from two political think tanks AFL-CIO\(^1\) and Heritage Action\(^2\). After that, we construct a heterogeneous information network to model social context information and adopt relational graph neural networks for representation learning. Finally, we train the framework with three training objectives to leverage expert knowledge, model social and political phenomena, and learn representations of pol-

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\(^1\)https://aflcio.org/
\(^2\)https://heritageaction.com/
Our main contributions are summarized as follows:

- To the best of our knowledge, this is the first work to jointly leverage social context and expert knowledge to learn representations of political actors.
- We propose a heterogeneous graph-based approach to learn legislator representations with three training objectives, which aligns social context with expert knowledge, ensures stance consistency, and models the echo chamber phenomenon in socio-economic systems.
- Extensive experiments demonstrate that our proposed approach outperforms the state-of-the-art in three related downstream tasks. Further studies suggest our learned legislator representations reflect various socio-political factors and prove the necessity of social context and expert knowledge in our proposed approach.

## 2 Related Work

The ideological perspectives of political actors play an essential role in their individual behaviour and add up to influence the overall legislative process. Political scientists first explored to quantitatively model political actors based on their voting behaviour. Ideal point model [Clinton et al., 2004] is one of the earliest approach to leverage voting records to analyze their perspectives. It projects political actors and legislation onto one-dimensional spaces and measure distances. Many works later extended the ideal point model. Gerrish and Blei [2011] leverages bill content to infer legislator perspectives. Gu et al. [2014] introduces topic factorization to model voting behaviour on different issues to establish a fine-grained approach. Kraft et al. [2016] models legislators with multidimensional ideal vectors to analyze voting records.

In addition to voting, various forms of textual data such as speeches and public statements are also leveraged to model the perspectives of political actors. Li and Goldwasser [2019] proposes to analyze social media posts to better understand the stances of political content. Feng et al. [2021] introduces textual information on Wikipedia and constructs a knowledge graph to facilitate perspective detection. Mou et al. [2021] proposes to leverage tweets, hashtags and legislative text to grasp the full picture of the political discourse. Li and Goldwasser [2021] focuses on analyzing the political perspectives of news articles and their mentioned political entities. In this paper, we explore to leverage social context and expert knowledge for legislator representation learning.

## 3 Methodology

Figure 2 presents an overview of our political actor representation learning framework. We firstly collect data of political actors from Wikipedia and political think tanks. We then construct a heterogeneous information network to jointly model political actors, their social context and expert knowledge. After that, we learn graph representations with gated relational graph convolutional networks (gated R-GCN) and train the proposed framework with three different objectives.

### 3.1 Data Collection

We collect a dataset about political actors in the United States that were active in the past decade while our proposed approach is applicable for all nations and time ranges. For social context information, we retrieve the list of senators and congresspersons from the 114th congress to the 117th congress.³ We then retrieve their Wikipedia pages⁴ and extract these named entities: presidents, senators, congresspersons, governors, states, political parties, supreme court justices, government institutions, and office terms (117th congress etc.). In this way, we obtain 1,069 social and political entities. Based these entities, we identify five types of relations: party affiliation, home state, political office, term in office, and ap-

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³https://www.congress.gov/
⁴https://github.com/goldsmith/Wikipedia
point relationships. In this way, we obtain 9,248 heterogeneous edges. For expert knowledge, we make use of the legislator scoreboards at AFL-CIO and Heritage Action, two political think tanks that lie in opposite ends of the ideological spectrum. Specifically, we retrieve the scoreboard content and extract each legislator’s score in each office term. In this way, we obtain 777 scores from AFL-CIO and 679 scores from Heritage Action. We consolidate the collected social context and expert knowledge to serve as the data set in our experiments, which is available as supplementary material.

3.2 Graph Construction

To better model the interactions between political entities and their shared social context, we propose to construct a heterogeneous information network (HIN) from the dataset. For initial node features, we use pre-trained RoBERTa [Liu et al., 2019] to encode the first paragraph of Wikipedia homepage.

Heterogeneous Nodes

Based on the collected dataset, we select diversified entities that are essential factors in modeling the political process. Specifically, we use eight types of nodes to represent political actors and diversified social context entities.

N1: Office Terms We use four nodes to represent the 114th, 115th, 116th, 117th congress spanning from 2015 to 2021. We use these nodes to model the change in politics through time and could be similarly extended to other time periods.

N2: Legislators We retrieve senators and congresspersons from the 114th to the 117th and use one node to represent each distinct legislator.

N3: Presidents The presidency is the highest elected office in the United States. We use three nodes to represent President Biden, Trump and Obama to match with legislators.

N4: Governors State and local politics are also essential in analyzing the political process. We use one node to represent each distinct governor of 50 states.

N5: States The home state of political actors is often an important indicator and helps connect different individuals. We use one node to represent each state in the United States.

N6: Government Institutions We use four nodes to represent the white house, senate, house of representatives and supreme court. These nodes enable our constructed HIN to separate different political actors based on the office they hold.

N7: Supreme Court Justices Supreme court justices are nominated by presidents and approved by senators, which helps connect different types of political actors. We use one node to represent each supreme court justice.

N8: Political Parties We use two nodes to represent the two major political parties in the United States: the Republican Party and the Democratic Party.

Heterogeneous Relations

Based on N1 to N8, we extract five types of informative interactions between entities to complete the HIN structure. Specifically, we use five types of heterogeneous relations to connect different nodes and construct our political actor HIN.

R1: Party Affiliation We connect political actors and their affiliated political party with R1:

\[ R1 = (N2 \cup N3 \cup N4) \times 8 \]  

R2: Home State We connect political actors with their home states with R2:

\[ R2 = (N2 \cup N3 \cup N4 \cup N7) \times N4 \]  

R3: Hold Office We connect political actors with the political office they hold with R3:

\[ R3 = (N2 \cup N3 \cup N4 \cup N7) \times N6 \]  

R4: Time in Office If a political actor holds office during one of the time stamps in N1, we connect them with R4:

\[ R4 = (N2 \cup N3 \cup N4 \cup N7) \times N1 \]  

R5: Appoint Besides from being elected, certain political actors are appointed by others. We denote this relation with R5:

\[ R5 = (N3 \times N7) \cup (N4 \times N2) \]  

3.3 Representation Learning

Since nodes represent political actors, we learn node-level representations with gated R-GCN to jointly leverage social context and external expert knowledge. Let \( E = \{ e_1, \ldots, e_n \} \) be n entities and \( v_i \) be the initial features of entity \( e_i \). Let \( R \) be the heterogeneous relation set and \( N_r(e_i) \) be entity \( e_i \)'s neighborhood under relation type \( r \). We firstly transform \( v \) to serve as the input of graph neural networks,

\[ x_i^{(0)} = \phi(W_1 \cdot v_i + b_1) \]  

where \( \phi \) is leaky-relu, \( W_1 \) and \( b_1 \) are learnable parameters. We then propagate entity messages and aggregate them with gated R-GCN. For the \( l \)-th layer,

\[ u_i^{(l)} = \sum_{r \in R} \frac{1}{|N_r(e_i)|} \sum_{j \in N_r(e_i)} f_r(x_j^{(l-1)}) + f_s(x_i^{(l-1)}) \]  

where \( f_s \) and \( f_r \) are parameterized linear layers for self loops and edges of relation \( r \), \( u_i^{(l)} \) is the hidden representation for entity \( e_i \) at layer \( l \). We then calculate gate levels,

\[ g_i^{(l)} = \sigma(W_G \cdot [u_i^{(l)}, x_i^{(l-1)}] + b_G) \]  

where \( W_G \) and \( b_G \) are learnable parameters, \( \sigma(\cdot) \) denotes the sigmoid function and \([\cdot, \cdot]\) denotes the concatenation operation. We then apply the gate mechanism to \( u_i^{(l)} \) and \( x_i^{(l-1)} \),

\[ x_i^{(l)} = tanh(u_i^{(l)}) \odot g_i^{(l)} + x_i^{(l-1)} \odot (1 - g_i^{(l)}) \]  

where \( \odot \) is the Hadamard product operation. After \( L \) layer(s) of gated R-GCN, we obtain node representations \( \{ x_1^{(L)}, \ldots, x_n^{(L)} \} \) and the nodes representing political actors are extracted as learned representations.

3.4 Model Training

We propose to train our framework with a combination of supervised, self-supervised and unsupervised tasks, which aligns social context with expert knowledge, ensures stance consistency and simulates the echo chamber phenomenon. The overall loss function of our model is as follows:

\[ L = \lambda_1 L_1 + \lambda_2 L_2 + \lambda_3 L_3 + \lambda_4 \sum_{w \in \theta} w^2 \]  

where \( \lambda_i \) is the weight of loss \( L_i \) and \( \theta \) are all learnable parameters in the model. We then present the motivation and details of each loss function \( L_1, L_2 \) and \( L_3 \).
The stance consistency task is motivated by the echo chamber phenomenon that is common in real-world socio-economic systems.

4 Experiments

4.1 Experiment Settings

We train our representation learning framework with the proposed loss function $L$ in Equ (10) and evaluate the learned representations of political actors on three downstream tasks: political perspective detection, roll call vote prediction, and entity stance prediction. We submit our data, implemented codes, hyperparameter settings and other experiment details as supplementary material to facilitate reproduction.

Political Perspective Detection

Political perspective detection aims to detect stances in text such as public statements and news articles, which generally mention many political actors to provide context and present arguments. Feng et al. [2021] proposes to leverage TransE [Bordes et al., 2013] to learn representations of political actors and augment the argument mining process. To examine the quality of our representation learning, we replace TransE in Feng et al. [2021] with our learned representations and conduct political perspective detection. We adopt the same datasets [Kiesel et al., 2019; Li and Goldwasser, 2019] and settings so that the results are directly comparable.
Roll Call Vote Prediction

Roll call vote prediction aims to predict the voting behavior of legislators given different pieces of legislation, which is essential in the political process and involves analyzing political actors. To examine our representations’ effectiveness in vote prediction, we concatenate our learned representations with RoBERTa [Liu et al., 2019] encoding of legislation texts and conduct vote prediction with two fully connected layers. We adopt the same dataset and experiment settings as Mou et al. [2021] so that the results are directly comparable.

Expert Knowledge Prediction

To the best of our knowledge, this is the first work to leverage expert knowledge from political think tanks in modeling political perspectives. To examine whether our learned representations correlate well with expert knowledge, we compare with various text [Pedregosa et al., 2011; Horne et al., 2018; Pennington et al., 2014; Liu et al., 2019; Beltagy et al., 2020] and graph [Kipf and Welling, 2016; Veličković et al., 2017; Hamilton et al., 2017; Shi et al., 2020; Bresson and Laurent, 2017] analysis baselines on the expert knowledge task.

4.2 Results

Political Perspective Detection

Table 1 presents model performance on two political perspective detection datasets. We run our approach five times and report the average performance. It is demonstrated that our approach consistently outperforms all state-of-the-art approaches on both benchmarks, which indicates that our learned representations of political actors could serve as external knowledge in the task of political perspective detection to help augment the argument mining process.

Roll Call Vote Prediction

Figure 3 presents model performance on roll call vote prediction. We run ours five times and report the average results. It is demonstrated that our approach outperforms existing base-

| Method          | Text | Graph | Acc  | MaF  | MiF  |
|-----------------|------|-------|------|------|------|
| Linear BoW      | ✓    |       | 68.49| 40.00| 68.53|
| Bias Features   | ✓    |       | 47.26| 20.08| 47.10|
| Glove           | ✓    |       | 52.05| 26.94| 52.01|
| RoBERTa         | ✓    |       | 71.92| 49.70| 71.87|
| LongFormer      | ✓    |       | 68.49| 42.27| 68.56|
| GCN             | ✓    | ✓     | 74.66| 54.16| 74.46|
| GAT             | ✓    | ✓     | 78.08| 55.82| 78.17|
| GraphSAGE       | ✓    | ✓     | 75.34| 51.39| 75.43|
| TransformerConv | ✓    | ✓     | 77.40| 55.63| 77.48|
| ResGatedConv    | ✓    | ✓     | 76.03| 54.31| 75.97|
| Ours            | ✓    | ✓     | 80.82| 60.37| 80.89|

Table 2: Our model’s performance on the expert knowledge prediction task compared to various text and graph analysis baselines. Acc, MaF and MiF denote accuracy, macro and micro averaged F1-score.
whether we have achieved this end, we adopt t-sne [Maaten and Hinton, 2008] to illustrate our learned representations of political actors in Figure 4.

Social Context

Figure 4 (a) and (b) illustrate the correlation between learned representations and social context. The DBI scores [Davies and Bouldin, 1979] quantitatively indicate great collocation among different social context groups.

Congressional Caucuses

Figure 4 (c) and (d) demonstrate the correlation between learned representations and major congressional caucuses in both parties. Both the illustration and the DBI scores suggest little collocation among caucuses, which could be attributed to the fact that inter-party differences outweigh intra-party differences in contemporary U.S. politics.

Voting Records

Figure 4 (e), (f), (g) and (h) illustrate how legislators vote with or against the sitting president. We retrieve this information from FiveThirtyEight and illustrate voting records with color gradients. As a result, our learned representations of legislators in the 115th and 116th congress correlate well with their voting records, while the 117th congress might have not hold enough votes for an accurate categorization.

4.4 Ablation Study

Our framework aims to learn representations of political actors with the help of social context and expert knowledge as well as three training objectives. We conduct ablation study to examine their effect in the representation learning process and report performance on the expert knowledge prediction.

Social Context

We use five types of heterogeneous relations $R_1$ to $R_5$ to connect different entities based on their social context. We gradually remove five types of social context edges in the constructed HIN and report model performance in Figure 5. It is illustrated that all relations but $R_4$ (Time in Office) significantly contributes to the overall performance. Besides, Figure 5 illustrates a great gap between 90% and 100% edges, suggesting the importance of a complete HIN structure.

5 Conclusion

In this paper, we present a framework to learn representations of political actors with social context and expert knowledge. We retrieve context information from Wikipedia and expert knowledge from political think tanks: AFL-CIO and Heritage Action. We retrieve their evaluation of political actors and construct a supervised task to train our framework. To examine the effect of these expert knowledge in our proposed approach, we gradually remove expert knowledge labels in $L_1$ and report model performance in Figure 6. It is illustrated that our performance drops with partial expert knowledge from either AFL-CIO or Heritage Action. As a result, expert knowledge is essential in our model’s representation learning process.

Expert Knowledge

We learn legislator representations with the help of two political think tanks: AFL-CIO and Heritage Action. We retrieve their evaluation of political actors and construct a supervised task to train our framework. To examine the effect of these expert knowledge in our proposed approach, we gradually remove expert knowledge labels in $L_1$ and report model performance in Figure 6. It is illustrated that our performance drops with partial expert knowledge from either AFL-CIO or Heritage Action. As a result, expert knowledge is essential in our model’s representation learning process.

Training Objectives

We propose to train our framework with three objectives. To examine their effect, we train our method with different combinations of $L_1$, $L_2$ and $L_3$ and report performance in Table 3. Our model performs best with all three training objectives, proving the effectiveness of our loss function design.

Table 3: Ablation study of three training objectives.

| Loss Function(s) | Acc | MaF | MiF |
|------------------|-----|-----|-----|
| $L_1$ only       | 78.08 | 56.43 | 78.17 |
| $L_1$ and $L_2$  | 79.45 | 55.97 | 79.52 |
| $L_1$ and $L_3$  | 76.03 | 51.91 | 76.11 |
| $L_1$, $L_2$, and $L_3$ | **80.82** | **60.37** | **80.89** |

3https://fivethirtyeight.com/
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Table 4: Model performance with different GNN operators. Our approach adopts gated R-GCN and achieves the best performance. Het. denotes whether the method supports heterogeneous graphs.

| GNN operator | Het. | Acc | MaF | MiF |
|--------------|------|-----|-----|-----|
| GCN          | X    | 76.03 | 58.31 | 78.08 |
| GAT          | X    | 77.40 | 59.01 | 78.85 |
| SAGE         | ✓    | 78.77 | 58.04 | 78.81 |
| R-GCN        | ✓    | 78.08 | 55.61 | 78.15 |
| Gated R-GCN  | ✓    | 80.82 | 60.37 | 80.89 |

Table 5: Model performance with one to five gated R-GCN layers.

| L  | 0    | 1   | 2   | 3   | 4   |
|----|------|-----|-----|-----|-----|
| Acc| 69.18| 74.66| 80.82| 78.08| 78.08|
| MaF| 42.00| 52.87| 60.37| 57.66| 62.33|
| MiF| 69.26| 74.74| 80.89| 76.80| 78.08|

Figure 7: Model performance with different loss weights.

A Supplementary Studies

To better understand the effectiveness of our propose framework, we present additional studies that do not fit in the main paper. We report model performance on the expert knowledge prediction task in supplementary studies.

A.1 Graph Learning Study

We construct a HIN to model social context and adopt gated R-GCNs for representation learning, thus we further study the effect of these graph-related elements.

GNN Operator

We adopt five heterogeneous relations R1 to R5 to connect eight types of entities N1 to N8, thus our constructed graph is heterogeneous. To examine whether the graph heterogeneity contributes to model performance, we substitute gated R-GCNs with homogeneous GNNs such as GCN, GAT and GraphSAGE. Table 4 shows that our model performs best with gated R-GCNs, proving the necessity of heterogeneous relations to represent diversified social context.

GNN Layers

Two or three GNN layers are typically adopted for node-level representation learning in similar tasks. To examine the effect of GNN layers in our proposed approach, we learn node representations with one to five layers of gated R-GCNs. Table 5 illustrates that two layers of gated R-GCNs perform best, thus we adhere to this setting in other experiments.

A.2 Training Objective Study

We propose to train the representation learning framework with three objectives: expert knowledge, stance consistency, and the echo chamber phenomenon. We further study the effect of these training objectives in model performance.

Loss Weight

We fix $\lambda_1 = 1$ and $\lambda_4 = 10^{-5}$, present model performance under different settings of loss weights for auxiliary tasks $\lambda_2$ and $\lambda_3$ in Figure 7. It is illustrated that $0.2 \leq \lambda_2 \leq 0.3$ and $0.01 \leq \lambda_3 \leq 0.1$ would generally lead to an effective balance of differently supervised loss functions.

Negative Sample

For the echo chamber objective, we randomly select nodes from $N_e$ to serve as negative samples and balance $L_3$ with $Q$. We study the effect of negative sample amount and their weight $Q$ in the model’s performance and present them in Figure 8. It is illustrated that 2 negative samples and $Q = 0.1$ or 0.2 performs best, which indicates that the echo chamber objective contributes to overall performance, while too many negative samples and large $Q$s might overshadow the overall representation learning process.

B Experiment Details

In this section, we provide additional details to facilitate reproducing our results and findings. We submit data and code as supplementary material and commit to make them publicly available upon acceptance.

B.1 Hyperparameters

We present the hyperparameter settings of our proposed approach in Table 6. We follow these settings throughout the paper unless stated otherwise.

B.2 Implementation

We use pytorch [Paszke et al., 2019], pytorch lightning [Falcon, 2019], torch geometric [Fey and Lenssen, 2019] and the transformers library [Wolf et al., 2020] for an efficient implementation of our proposed framework. All implemented codes are available as supplementary material.
| Hyperparameter     | Value | Hyperparameter     | Value |
|--------------------|-------|--------------------|-------|
| RoBERTa size       | 768   | GNN size           | 512   |
| optimizer          | Adam  | learning rate      | $1e-3$|
| batch size         | 64    | max epochs         | 100   |
| $L$                | 2     | $\phi$            | ReLU  |
| $Q$                | −0.1  | #negative sample   | 2     |
| $\lambda_1$       | 0.01  | $\lambda_2$       | 0.2   |
| $\lambda_3$       | 1     | $\lambda_4$       | $1e-5$|

Table 6: Hyperparameters of our proposed approach.

Figure 8: Model performance with different number of negative samples and weight $Q$.

B.3 Experiment Details

Political Perspective Detection

We replace TransE in Feng et al. [2021] with our learned representations of political actors. We use the GRGCN setting in Feng et al. [2021] as backbone. We maintain the same evaluation settings to ensure a fair comparison and highlight the effectiveness of our learned representations.

Roll Call Vote Prediction

We make our best effort to maintain the same experiment settings as Mou et al. [2021] while their might be minor differences. For random, we conduct roll call vote prediction for legislators in the 114th and 115th congress and average the results. We follow the same 6:2:2 split for each setting. For time-based, we use the 114th congress as training and validation set and the 115th congress as test set.

Expert Knowledge Prediction

We collect expert knowledge about legislators from two political think tanks, which assigns a continuous score $s$ from 0 to 1 to indicate how liberal or conservative a legislator is. We construct a classification task from expert knowledge by creating five discrete labels: strongly favor ($0.9 \leq s \leq 1$), favor ($0.75 \leq s \leq 0.9$), neutral ($0.25 \leq s \leq 0.75$), oppose ($0.1 \leq s \leq 0.25$), and strongly oppose ($0 \leq s \leq 0.1$). In this way, we adapt from expert knowledge to derive liberal and conservative labels for legislators. We use 7:2:1 to partition them into training, validation and test sets. We calculate evaluation metrics on the liberal and conservative set separately, and present the harmonic mean of two sets. In this way, the presented results accurately and comprehensively reflect how our proposed approach and existing baselines perform on both political think tanks. For text-based baselines, we encode Wikipedia summaries of entities with these methods and predict their stances with two fully connected layers. For graph-based baselines, we train them with the constructed HIN and the expert knowledge training objective.