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Graph Learning of Multifaceted Motivations for Online Engagement Prediction in Counter-party Social Networks

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Abstract

Social media has emerged as an essential venue to invigorate online political engagement. However, political engagement is multifaceted and impacted by both individuals' self-motivation and social influence from peers and remains challenging to model in a counter-party network. Therefore, we propose a counter-party graph representation learning model to study individuals' intrinsic and extrinsic motivations for online political engagement. Firstly, we capture users' intrinsic political interests providing self-motivation from a user-topic network. Then, we encode how users cast influence on others from the inner-/counter-party through a user-user network. With the learned embedding of intrinsic and extrinsic motivations, we model the interactions between these two facets and utilize the dependency by deep sequential model decoding. Finally, extensive experiments using Twitter data related to the 2020 U.S. presidential election and the 2019 HK protests validate the model's predictive power. This study has implications for online political engagement, political participation, and political polarization.

Keywords: Graph Learning, Online Political Engagement, Social Network, Multifaceted Graph

Introduction

Online political engagement refers to various Internet-based political activities depending on the specific type of online platforms used (Ekman and Amnå 2012). With a low cost and high efficiency of information diffusion, social media has emerged as one of the most popular platforms for users to spread political attitudes, construct affiliations, and call attention to the shortcomings of their counter-party competitors by leveraging user-generated content (Anderson et al. 2018; Gil de Zúñiga et al. 2012) , which facilitate collective action and political movement (Eltantawy and Wiest 2011; Enli 2017). The social impact of online political engagement is boosted by its influence on offline political participation as well as social interaction patterns (Dahlgren 2000; Kim et al. 2017). Empirical evidence indicates that political engagement is multifaceted and influenced by inherent user interests and external social interactions (Bond et al. 2012; Kahne and Bowyer 2018). Due to the impact of social media activities on political incidents, the need for new methodology and theoretical insights into online political engagement has been argued (Gibson and Cantijoch 2013). Compared with offline interactions, social media users are exposed to diverse information from multiple sources (Kane et al. 2014; Shore et al. 2016), which may involve counter-party interactions. It has been noticed that counter-party dialogues extensively appeared in social media discussions during the U.S. presidential election, which led to polarized ideological camps among Twitter users (Conover et al. 2011). The impact of counter-party interactions among users with different ideological leanings and political interests on subsequent political activities is significant and different from inner-party interactions but remains less examined (Bail et al. 2018).

The existing online engagement prediction models, which do not focus on the political context, ignore the necessity of considering the user's party affiliation and an angle for studying counter-party interactions in social networks. These studies only consider attribute information (Anelli et al. 2020; Liu et al. 2019) or social interaction among users in the same party (Fan et al. 2019; Liu et al. 2019; Tang et al. 2020). Little attention has been paid to the importance of the topology of a counter-party network and the corresponding high-dimensional latent factors in online political engagement.

The growth of social media communities provides tremendous user-generated data for researchers to examine user behaviors, such as online engagement (Nguyen et al. 2020). Meanwhile, Artificial Intelligence technologies in graph representation learning provide new opportunities for exploring the dynamics of online political engagement (Chen et al. 2020). However, due to the multifaceted dependencies on intrinsic interest and extrinsic persuasion, it remains a challenging task to model the political engagement dynamics in a counter-party interactive network with conflicting political attitudes. To this end, we propose a multifaceted and multi-objective graph representation learning model for online political engagement prediction. By benchmarking against the state-of-the-art graph representation models, we validate the importance of extending the graph learning framework in a counter-party interactive network.

Our graph learning framework embeds users' intrinsic interest and extrinsic persuasion for online political engagement prediction. The graph attention mechanism is utilized to learn users' intrinsic interests as they actively engage in topics related to political events. We also learn the extrinsic political persuasion that users receive from inner-party users of the same political affiliations and counter-party users of conflicting political attitudes by embedding the user network structural role with GraphWave. With learned user intrinsic and extrinsic embedding, we apply a transformer decoder to capture the temporal dependency and the interaction between the two facets. Finally, extensive experiments using real data from user-generated content related to the 2020 U.S. presidential election and the 2019 Hong Kong protests on Twitter demonstrate the effectiveness of our political engagement predictor.

Research Background

In this section, we draw on the motivation theory to guide the design of a graph learning model to conceptualize the mechanisms underlying the dynamics of political engagement in a counter-party social network. We first review the theoretical background and methodological development of online political engagement and then propose a graph learning framework to model the joint forces of users' intrinsic and extrinsic motivations.

Theoretical Background

Researchers have applied social science theories such as selective exposure (Brundidge and Rice 2008) and echo chamber (Dubois and Blank 2018) to explain the dynamics of online political engagement, suggesting that individuals are easily persuaded by others holding the same political standpoint. However, they lack a global perspective of the complicated motivating mechanisms of online political engagement as social actions, including both inherent personal interest and external influence from social networks (Bond et al. 2012; Lilleker and Koc-Michalska 2018). To explore the mechanism of online political engagement from a big picture, we draw on the Motivation Theory of user engagement (Deci and Ryan 2013; Ryan and Deci 2000) for a better understanding of the impact of users' intrinsic *ideology* and extrinsic *persuasion* on engagement motivations, and further consider the specific counter-party interactive patterns in this context.

Intrinsic and Extrinsic Motivations for Online Political Engagement

The Motivation Theory suggests that user behavior is induced by both intrinsic and extrinsic motivations (Ryan and Deci 2000). Specifically, intrinsic motivation refers to the inherent desire to conduct a certain activity due to the utility of such activity itself, while extrinsic motivation refers to the external incentives which motivate certain actions (i.e., potential rewards or punishments) (Deci and Ryan 2013; Goes et al. 2016). Intrinsic and extrinsic motivations are closely related and influence each other, and their joint forces explain the likelihood of an action (Ryan and Deci 2000). Extended to the political context, the reason for individuals' engagement has also been explained in terms of intrinsic and extrinsic motivations.

Intrinsic motivation for online political engagement

In political science, users' intrinsic motivations have been widely studied. For instance, political efficacy, defined as the perceived competence for acting in the political sphere and influencing the government (Campbell et al. 1954; Levy and Akiva 2019), has strong positive effects on various forms of political participation (Pei et al. 2018). Also, it is found that political interest (i.e., individuals' willingness to pay attention to political issues) is significantly related to political engagement, both directly and indirectly through political efficacy (Schulz 2005). Moreover, personal interest and political ideology also have an impact on online political engagement (Brundidge and Rice 2008; Kahne and Bowyer 2018; Levy and Akiva 2019). Social media users are attracted to engaging in discussions on varied topics according to their personalized interests and exhibit consistent preferences (Anderson et al. 2018). This holds true for online political engagement as well, where users' attention to specific topics can effectively reflect their intrinsic motivations.

Extrinsic motivation for online political engagement

It has been emphasized that political engagement is not a personal action, but rather a social activity motivated by persuasive communication from social interactions (Lilleker and Koc-Michalska 2018). Although much less examined, extrinsic motivations have a strong explanatory and predictive power for online political participation (Lilleker and Koc-Michalska 2018). On the one hand, based on the motivation theory, extrinsic incentives may crowd in the intrinsic ones as perceived self-efficacy and sense of autonomy are undermined, meaning that individuals are less influenced by intrinsic motivations with the existence of extrinsic ones (Ryan and Deci 2000). On the other hand, social media enables various new means for engaging in politics, which significantly improve the efficiency and power of persuasive communication for user interactions, leading to a greater impact of extrinsic motivations on online political engagement (Koc-Michalska and Lilleker 2016). Early studies explain online political engagement from the perspectives of selective exposure (Brundidge and Rice 2008) and echo chamber (Dubois and Blank 2018), indicating that users are more likely to receive and accept like-minded information, highlighting the social influence of inner-party interactions. However, in contrast to the homophily-shaped offline political engagement, social media platform enables users to encounter more diverse opinions, especially opposing ones from counter-party individuals, in addition to the confirmatory information (Kane et al. 2014; Shore et al. 2016).

Counter-party persuasion

Although proposing mixed findings and arguments, existing studies indicate a great impact of exposure to opposing opinions on subsequent political engagement behaviors, which should be differentiated from inner-party interactions and not be ignored. On the one hand, some studies argue that counter-party interactions with diversified viewpoints would challenge the stereotypes and induce deliberation, thus leading to more moderate political attitudes and political compromise (Huckfeldt et al. 2004; Pettigrew and Tropp 2006). On the other hand, recently, researchers found that conflicting information from counter-party individuals may even exacerbate political polarization due to the backfire effects (Bail et al. 2018), which suggests that people exposed to such opinions tend to counterargue them through motivated reasoning, which in turn reinforces their commitment to preexisting beliefs (Lord et al. 1979; Nyhan and Reifler 2010). Considering the significant influence of counter-party communication, we believe that introducing counter-party social network analysis and differentiating inner-/counter-party interactions is beneficial to this literature stream.

Due to the complicated motivating mechanism of online political engagement, which is induced by the joint forces of intrinsic and extrinsic motivations in a counter-party interactive network with conflicting arguments, a multifaceted and multi-objective graph representation learning model is desired to capture the overall framework and improve prediction power.

Methodological Development

Before proposing a joint learning framework capturing intrinsic and extrinsic motivations based on the motivation theory, we first review the existing prediction methodologies, including feature-based models and graph learning framework for social network modeling, which may not be designed for the specific online political engagement context but can be applied to this task.

Feature-based Prediction Models

Traditional feature-based social network models are designed to capture observed statistical features of nodes, edges, and subgraph statistics for profiling social network activities (Chen and Saad 2010), ignoring different implicit motivations behind user activities. Specifically, node centralities based on degree, closeness, betweenness, and eigenvector (Borgatti et al. 2009) have been proposed to measure the importance of a node in a network for engagement prediction (Bródka et al. 2011). Also, diffusion models measuring patterns over time combined with neighborhood social influence in the network have been proposed to predict general engagement (Kawale et al. 2009; Shang et al. 2012).

More recently, statistical relational learning (Rossi et al. 2012) and machine learning models (Wang et al. 2022) are developed to extract unobserved network information from node relationships that cannot be obtained from explicit or implicit descriptions of the network. These machine learning algorithms leverage social network features for a variety of applications, including but unlimited to node/link/community detection (e.g., feature-based models for top persuader detection (Fang and Hu 2018) and link detection (Glenski and Weninger 2017)) and online engagement (Hu et al. 2015; Wang et al. 2022). For example, the topical interest of users is statistically modeled to predict online user engagement with real-world events (Hu et al. 2015). Also, existing research studied observed user's clicking, browsing, and voting behaviors on Reddit and applied machine-learning models to predict engagement (Glenski and Weninger 2017), ignoring the unobserved motivations behind the users' activities. Another example is the deep neural network fusion with an embedding-based deep neural network (FEBDNN), which integrates user features and social influence indicators for within-group interactions to predict social media retweeting behavior (Wang et al. 2022). While these studies combine user features with machine learning algorithms for online engagement prediction, they typically ignore the underlying motivations behind user activities in social networks and the fine-grained information of user dyadic interactions within/between different groups, especially groups with conflicting attitudes.

Graph Learning Framework for Social Network Modeling

The development of graph representation learning, which integrates node information with network topological structure, can complement the traditional feature-based statistical and machine learning methods for social network modeling (Chen et al. 2020). While these graph learning models do not focus on the theoretical explanations of online engagement, they indirectly explore users' inherent characteristics (Qiu et al. 2018) or external social influence (Fan et al. 2019) for engagement prediction. Specifically, they incorporated both network structures and user-specific features into convolutional neural and attention networks for social representation learning, which significantly outperforms conventional feature-based prediction approaches (Qiu et al. 2018). From the perspective of information source, existing methods consider the information about friendships within the user-user social graph (Fan et al. 2019; Wang et al. 2020a) and user actions within the user-item graph (Wang et al. 2020b) to make predictions of user engagement. Combining such information together, a tensor-based graph neural network with mixed attention mechanisms to predict user engagement in a friendship network has been proposed (Tang et al. 2020).

Despite the outstanding performance in social network modeling, existing graph representation techniques mainly focus on general online engagement for content creators to reach their intended audience, and for consumers to be directed to the most pertinent content (Anelli et al. 2020). The engagement prediction among people and objects is vital, which only requires the modeling of single-community persuasion (Fan et al. 2019; Tang et al. 2020), homophily (Liu et al. 2019), and social influence from friends to predict user engagement behavior (Wang et al. 2020a). However, unlike general online engagement, political engagement is closely related to user intrinsic interest and extrinsic influence induced by political topics, discussions, arguments, and debates with inner-/counter-party users. It is important to consider the network structures of user-topic (for intrinsic motivations) and user-user (for extrinsic motivations) graph representations in a counter-party social network for online political engagement prediction. However, to the best of our knowledge, little attention has been paid to extending the existing graph-learning algorithms with the lens of different types of motivations behind user activities for political engagement prediction in counter-party social networks.

Concerning the multifaceted nature of online political engagement in a counter-party social network, this study follows the design science paradigm and draws on the Motivation Theory to guide the design of a multifaceted graph representation learning framework to model the joint forces of intrinsic and extrinsic motivations for online political engagement prediction in a counter-party interactive network. Different from the traditional studies of online engagement that only consider attribute information (Liu et al. 2019) and single-community interaction (Fan et al. 2019; Liu et al. 2019; Tang et al. 2020) while lacking a global view of the motivation mechanism and ignoring the great influence of within/counter-party persuasion, we extend the graph representation models by combining the influence of users' intrinsic interest in political topics and political persuasions from both within-party and counter-party users. The proposed method provides a deep learning research framework to explore the mechanisms of online political engagement, which significantly complements the statistical and feature-based social network models.

Problem Statement

In this section, we define some preliminaries used throughout this paper and formulate the problem of online engagement prediction in a counter-party social network.

Definition 1 (Online Engagement)**.** *We follow the "E-expressive" concept of online political engagement (Gibson and Cantijoch 2013) (i.e., posting, forwarding, or commenting on political content) and define user u's online engagement in period t as a binary indicator (Qiu et al. 2018), with value 1 indicating the content generated by user u in period t is related to a focal topic and 0 otherwise. A list of relevant topics is predefined by a dictionary of keywords. For example, #senator and #turn Texas blue were two hot topics that attracted social media users to discuss about the 2020 U.S. election during the study period.*

Definition 2 (User-Topic Intrinsic Network)**.** *We define the intrinsic user-topic network as a complete bipartite graph, $\mathcal{G}_{in}^t = (\mathcal{V}^t, \mathcal{T}_{in}^t, \mathcal{E}_{in}^t)$, where $\mathcal{V}^t$ represents the set of user nodes and $\mathcal{T}_{in}^t$ represents the set of topic nodes in period t. The edge e_{uj} in the edge set $\mathcal{E}_{in}$ is defined as the similarity between a user node u and a topic j, indicating the probability of u's intrinsic interest in topic j. We learn users' intrinsic interest in different topics from their historical topic engagements, as seen in Figure 1. For the same political topic, social media users with different partisan affiliations (e.g., republicans or democrats) can engage in expressing their attitudes, calling for others' attention, or persuading others to join discussions and debates. The number of topics and topic popularity would vary in different periods, and more users with interest can be motivated to engage in topic discussions.*

Definition 3 (User-User Extrinsic Network)**.** *We define the user-user extrinsic network in period t as an undirected counter-party graph $\mathcal{G}_{ex}^t = (\mathcal{V}^t, \mathcal{E}_{ex}^t)$, where $\mathcal{V}^t$ is the same set of social media users connected to others by the edge set $\mathcal{E}_{ex}^t$. Each edge in the extrinsic network represents the frequency of social interactions (e.g., commenting and retweeting) between a pair of user nodes. Different from the general social network,*

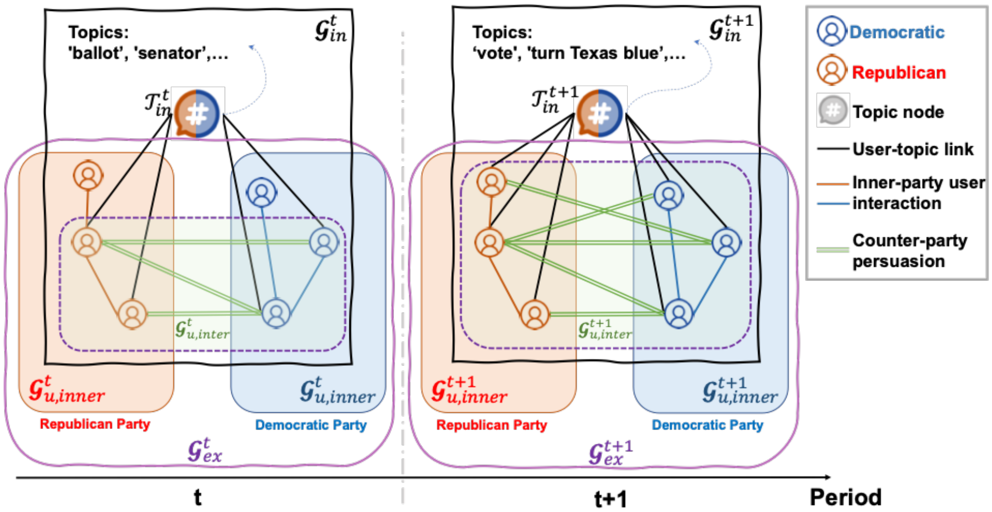


Figure 1. A Motivating Example of Graph Representation of Online Political Engagement

the counter-party social network has two sub-networks with conflicting contents. We identify participants' political affiliations to classify users into Republicans ($u \in \mathcal{V}_R$) and Democrats ($u \in \mathcal{V}_D$) using the pre-defined model (Pennacchiotti and Popescu 2011).

Figure 1 presents a motivating example of counter-party interactions between Republicans and Democrats. For each user u, the extrinsic network is segmented into two sub-graphs: inner-community extrinsic network and inter-community extrinsic network. The inner-community extrinsic network $G^t_{u,inner}$ focused on user u contains the interactions of users with the same political affiliation, while the inter-community extrinsic network $G^t_{u,inter}$ contains the interactions with the counter-party of a different political affiliation. Extrinsic persuasions, either from friends in the same party or opponents in the counter-party, would engage more users in topic discussion.

Problem Statement. Given the historical user engagement observed in the intrinsic user-topic network $\mathcal{G}^{\tau}_{in}$ and the extrinsic user-user interactions in the counter-party social networks $\mathcal{G}^{\tau}_{ex}$ observed in period τ, the problem of online engagement prediction is to model the probability of a user u's future engagement in period $t+1$ based on the observations up to time t:

$$P(y_u^{t+1} = 1 | \{\mathcal{G}^{\tau}_{in}, \mathcal{G}^{\tau}_{ex}\}_{\tau \le t}) \tag{1}$$

Methodology

We propose a graph representation learning framework to explore the joint forces of intrinsic *interest* and extrinsic *persuasion* on users' online political engagement. The framework is presented in Figure 2, which illustrates the details of an intrinsic interest module, an extrinsic persuasion module, and a joint learning module. The intrinsic module models users' historical engagement in certain political topics to extract their interest in political topics, indicating their intrinsic motivation for political engagement. The extrinsic module models user interactions in a counter-party network to incorporate the social influence of political persuasion on political engagement. The joint learning module integrates both intrinsic interest and extrinsic persuasion for future engagement prediction.

Intrinsic Interest Encoding

To learn the latent representation of users' intrinsic motivations to engage in different topics, we propose a user-topic attention graph to model users' intrinsic interest in political topics and their corresponding topic engagements.

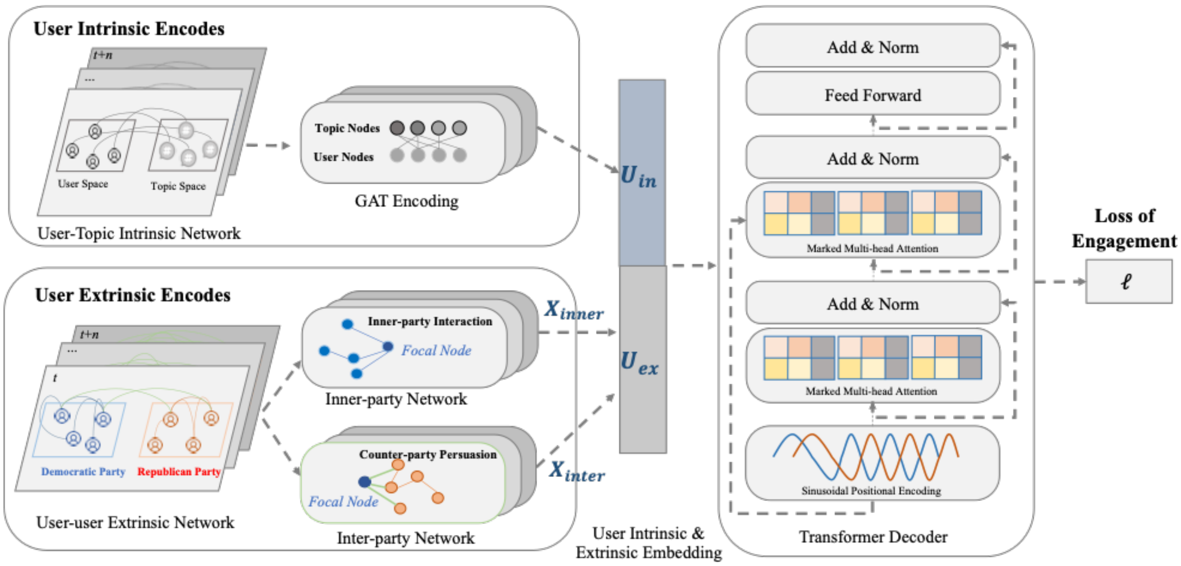


Figure 2. Framework Overview of the Graph Representation Learning Model

Figure 3 presents the process of intrinsic topic learning and representation for social media users. Given the user-topic intrinsic network $\mathcal{G}_{in}^t$ with n user nodes and m topic nodes, we first define the user and topic intrinsic embedding matrices, $V \in \mathbb{R}^{n\times F}$ and $T_{in} \in \mathbb{R}^{m\times F}$, where F is the number of dimensions of the latent features[1], to model the relationship between a user and a topic. For each $(u, j) \in \mathcal{E}_{in}$, let e_{uj} denote the similarity between a user $u \in \mathcal{V}$ and a topic $j \in \mathcal{T}_{in}$:

$$e_{uj} = f(\mathbf{h}_u, \mathbf{h}_j) \tag{2}$$

where $\mathbf{h}_u \in \mathbb{R}^F$ and $\mathbf{h}_j \in \mathbb{R}^F$ are feature vectors of a user node and a topic node, respectively. We consider that higher similarity between a user node and a topic node is associated with a higher probability (or frequency) of user engagement. The score e_{uj} is thus proportional to the similarity of the two node features. In order to learn a better representation of a user's intrinsic topic interest, we apply the linear transformation of node features and take their inner products to calculate the similarity score, formally expressed as:

$$e_{uj} = \frac{exp\{(W_i\mathbf{h}_u)^T(W_j\mathbf{h}_j)\}}{\sum_{k\in\mathcal{T}_{in}} exp\{(W_u\mathbf{h}_u)^T(W_k\mathbf{h}_k)\}} \tag{3}$$

Loss function of intrinsic engagement. With the user and topic representation from the graph attention network, we use the user-topic similarity score to approximate the probability that user u engages in topic j. We then learn the user's intrinsic engagement by minimizing the intrinsic loss function (i.e., minimizing the difference between the user's actual engagement and the similarity approximation):

$$\ell_{in} = \frac{1}{nm} \sum_{u\in\mathcal{V}, j\in\mathcal{T}_{in}} (E_{uj} - e_{uj})^2 \tag{4}$$

where E_{uj} is the frequency of user u engaging in topic j, normalized by a softmax function.

Leveraging the attention passed from all topic nodes to the user nodes, we compute the aggregated representation U_{in}, which is used for subsequent engagement modeling. Formally, for each user u in the aggregated representation, we have:

$$v_u = \sum_{j\in\mathcal{T}_{in}} e_{uj} w_j h_j \tag{5}$$

[1] We first formulate a latent feature space from political topics, each of which is represented by multiple features. Then, keywords in user-generated content are mapped to the same feature space for user-topic similarity score calculation.

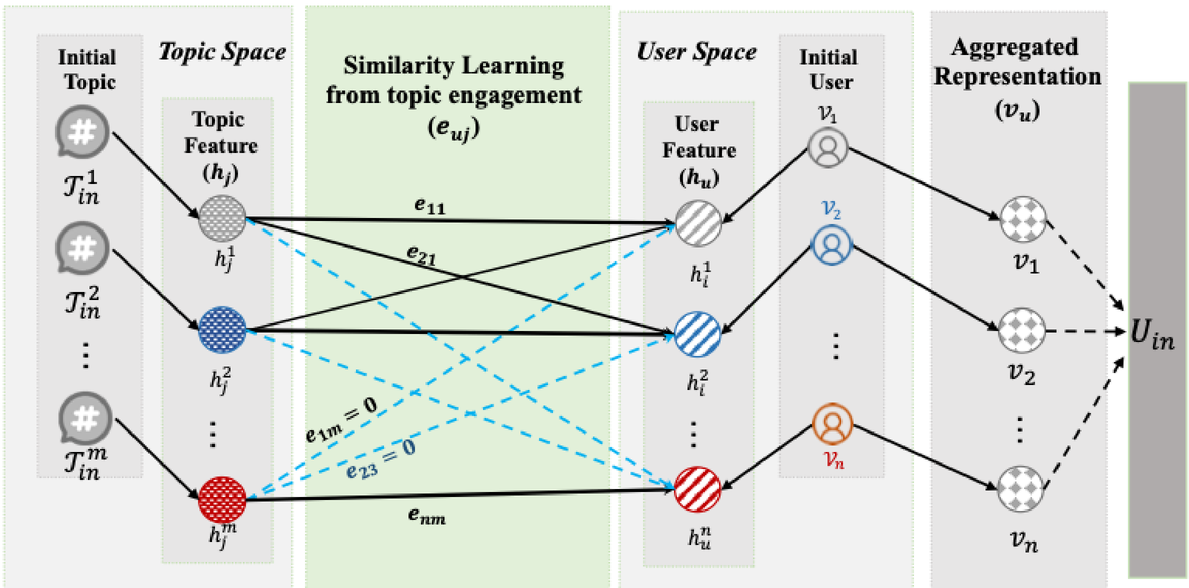


Figure 3. The Attention Mechanism for Intrinsic Topic Interest Encoding

Extrinsic Persuasion Encoding

A user's structural role in the network reflects how the user receives political persuasion or interacts with neighboring participants, either with members from the same party or with counter-party members of conflicting attitudes. By relating a focal user's engagement to their interactions with neighbors, we model user-user interactions as extrinsic motivation using GraphWave (Donnat et al. 2018), which encodes the structural role of node u in their inner-community network $G^t_{u,inner}$ and inter-community network $G^t_{u,inter}$, respectively.

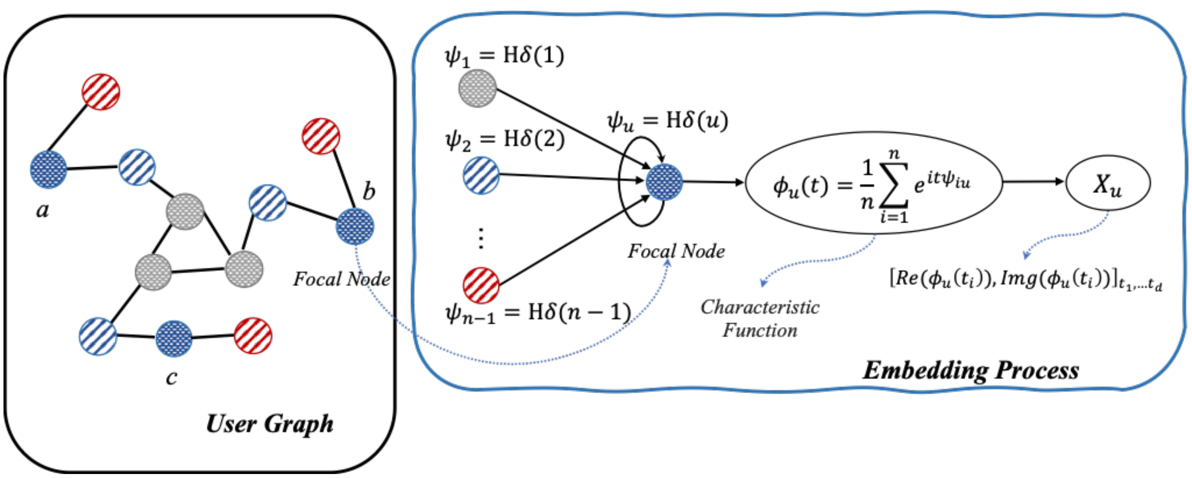


Figure 4. Extrinsic Persuasion Encoding for the Structural Role of the User-user Network

GraphWave embeds the structural information into node representation by capturing how a spectral graph wavelet diffuses around a focal node. The intuition is that GraphWave simulates the process where a focal node sends a unit of the stimulator (e.g., information, heat) to the rest of the graph and receives responses from the graph. As seen in Figure 4, nodes a, b, c, residing in different parts of the subgraphs, have similar structural roles in their local network topology (i.e., having connections with the red/blue slashed nodes). Thus, by treating the wavelets as probability distributions over the graph, GraphWave can learn the structural embedding of nodes with similar structures based on the diffusion of spectrogram wavelets centered around these nodes. Specifically, it defines a Dirac vector $\delta(u) \in \mathbb{R}^{n \times 1}$ on the focal node u. Then, the algorithm formulates the spectral graph wavelet

$$\Psi = H\delta(u) \tag{6}$$

where $H = Qe^{-\tau\Lambda}Q^\top$ is the heat kernel of the graph. Q is the eigenvector matrix and Λ is the diagonal eigenvalue matrix of the graph Laplacian. τ is the continuous time variable of the simulated diffusion process.

The algorithm further considers the empirical characteristic function of the quantity of simulator from a given node u:

$$\phi_u(t) = \frac{1}{n}\sum_{i=1}^{n} e^{it\Psi_{iu}} \tag{7}$$

where Ψ_{iu} is the u-th column vector element of Ψ and stands for the spectral graph wavelet for a heat kernel centered at node u, and Ψ is an $n \times n$ matrix of the graph wavelet that represents the diffusion pattern from each node.

The characteristic function above fully characterizes the probability distribution of the graph wavelet Ψ by all the moments. Then, the algorithm forms the GraphWave embedding for every node from the real and the imagined parts of this empirical characteristic function

$$X_u = [Re(\phi_u(t_i)), Img(\phi_u(t_i))]_{t_1,\cdots,t_d} \tag{8}$$

where $t_1, \cdots, t_d$ is d evenly spaced points.

Finally, we concatenate the GraphWave embedding of a focal user u's inner-community and inter-community extrinsic networks by using concatenated embedding U_{ex}, which forms the user's extrinsic representation.

Multi-Objective Learning

The influence of intrinsic and extrinsic motivations on user behavior is often intertwined and correlated (Ryan and Deci 2000). To capture the joint forces of these motivations, we first formulate a comprehensive user embedding by concatenating both the intrinsic and extrinsic embeddings by applying the motivation modeling mentioned:

$$U = [U_{in}, U_{ex}] \tag{9}$$

Online political engagement is motivated continuously by the heterogeneous accumulated effects of intrinsic interest and extrinsic persuasion from all previous and current periods. The representation of the learned U could be different, and directly using a feed-forward network may not extract information sufficiently. We employ the Transformer (Vaswani et al. 2017) as a deep sequential decoder to take in this encoded user embedding matrix and output the predicted engagement for user u, and eventually, we can utilize the decoder of the Transformer to extract important information from the representation of U:

$$y_u = f(U) \tag{10}$$

where the function f is the Transformer decoder. We learn this function by optimizing against the following objective function (i.e., minimizing the differences between actual engagement behavior and the predicted engagement):

$$\ell(\hat{\mathbf{y}}, \mathbf{y}) = \frac{1}{n}\sum_{u\in\mathcal{V}^t} y_u^t \log(\hat{y}_u^t) + (1 - y_u^t)\log(1 - \hat{y}_u^t) \tag{11}$$

where y_u^t is the true engagement for user u.

Experimental Results

To validate the effectiveness of the proposed model, extensive experiments are performed on the real-world Twitter data from the 2020 U.S. presidential election[2] and the 2019 Hong Kong protests[3]. The two datasets

[2]https://en.wikipedia.org/wiki/2020_United_States_presidential_election
[3]https://en.wikipedia.org/wiki/2019-2020_Hong_Kong_protests

were scraped in the periods from September 30 to October 31 2020, and from May 01 to October 01 2019, respectively. 56,510 users following the 115^{th} and 116^{th} congressmen and 11,438 users who posted or commented on the 2019 Hong Kong protests on Twitter were randomly selected as our focal users. We apply the LDA model (Blei et al. 2003) to automatically extract hashtags to identify key topics from the scraped corpus. The two datasets contain 906 election-related topics and 306 HK protest-related topics. Table 1 summarizes the statistics of the two datasets and the corresponding social networks, including the network properties of the user-topic intrinsic graph and the user-user extrinsic network constructed in a 3-day time window.

Data Source		US Election	HK Protest
Time Span		Sep $\sim$ Oct. 2020	May $\sim$ Oct 2019
Social Media Raw Data	# of Users	56,510	11,438
	# Posts	86,117	11,142
	# Comments	925,102	35,287
	# Unique topics	906	306
Intrinsic User-topic Network	# Topic/user(std)	3.331(1.582)	2.168(1.132)
	# User/topic(std)	22.884(4.455)	16.063(5.663)
	Density(std)	0.071(0.031)	0.062(0.046)
Extrinsic User-user Network	# Node(std)	11,835(8,629)	4,051(1,325)
	# Edges(std)	23,357(21,229)	6,012(1,073)
	Degree(std)	3.505(0.610)	2.996(0.705)

Table 1. Summary Statistics and Average Network Properties of the Research Data

Baselines and Evaluation Metrics

We use a sliding window of 3-day observation with a 1-day time interval to capture the graph representations of online political activities. A rolling prediction and validation procedure is applied to evaluate the model performance. Specifically, the model is trained using data from the first K time windows, and the trained model is used to predict user engagement in the following 3 days. Then, the model is trained using data from the first $K+1$ windows. The process continues in a rolling manner. We use the first 20 days for training initialization and the rest for testing. The metrics we adopt to evaluate the model performance include the AUC score, the Cohen Kappa (Kappa) score, and the F1 score. The Kappa score (McHugh 2012) ranges between -1 and 1 and measures inter-rater reliability. It is generally considered more robust than a simple percentage agreement calculation. We compare the performance of the proposed model with the following three baseline models, including classic feature-based machine learning methods, state-of-the-art graph representation learning methods, alternative graph attention networks, and reduced model for ablation test. All experiments are conducted on a GPU server with a 2X 10-core Intel Xeon Gold 5215 Processor and 1 TB RAM.

- **Feature-based machine learning methods.** The feature-based methods first extract factors influencing Twitter engagement from user-generated content (Mohammed and Ferraris 2021) and social networks (Chen and Pirolli 2012), including the number of different forms of posts and interactions, the number of event-related topics, the number of activities of following influencers, etc. These influential factors are then fed into machine learning methods to predict future engagement, including Logistic Regression (**LogReg**), XGBoost (**XGB**), and Ensemble Learning (**EL**).
- **Graph representation methods.** The graph representation methods utilize users' past interests and user-user interactions in social networks to predict future engagements, assuming interest and engagement can spill over among friends and followers. This class of methods has been widely applied to make predictions for engagement in non-political settings, where conflicting attitudes or interests are absent. Benchmark methods include the Who-Likes-What system (WLWS) for user interest prediction (Bhattacharya et al. 2014), FATE for friends' persuasion engagement (Tang et al. 2020), and GraphRec considering both user-user social graph and user-item graph (Fan et al. 2019).

- **Alternative Graph Attention Networks and Network Embeddings.** We use a graph attention network with Monte-Carlo Tree Search (MCTS) (Xiao et al. 2019) to utilize the structural information of the interactive network. MCTS is used to sample nodes in the interactive network and apply the graph attention network to model how a focal node receives and casts influence. Network embedding techniques that can effectively represent the structural information of the focal node are used as alternatives for graph modeling, including node embedding from Role2Vec (Ahmed et al. 2019) and whole graph embedding from FeatherGraph (FG) (Rozemberczki and Sarkar 2020) and GeoScattering (GS) (Gao et al. 2019).
- **Reduced Model for Ablation Study.** Three reduced models with different modules removed from the proposed model are evaluated to verify the effectiveness of the architecture design. The intrinsicality-ablated and extrinsicality-ablated models remove a user's intrinsic and extrinsic representation, respectively. The model with single-party persuasion keeps both representations but uses a single community label without discriminating against counter-party arguments.

Performance Evaluation

The overall performance comparisons for online political prediction using the U.S. presidential election dataset between the proposed model and the baselines are summarized in Table 2. It is seen that the proposed model consistently outperforms all baseline models, with an AUC of 0.771, a Kappa of 0.751, and an F1 of 0.793.

Model Class	Methods	AUC	Kappa	F1
Feature-based Machine Learning	LogReg	0.584(0.051)	0.483(0.079)	0.611(0.06)
	Ensemble Learning	0.628(0.056)	0.536(0.052)	0.659(0.056)
	XGBoost	0.652(0.041)	0.550(0.082)	0.707(0.048)
Graph Representation Learning	WLWS	0.681(0.031)	0.588(0.072)	0.692(0.043)
	FATE	0.730(0.061)	0.608(0.114)	0.730(0.076)
	GraphRec	0.753(0.045)	0.664(0.073)	0.777(0.052)
Alternative Modules	GAT with MCTS	0.741(0.071)	0.676(0.089)	0.753(0.076)
	FeatherGraph	0.749(0.071)	0.666(0.066)	0.779(0.086)
	GeoScattering	0.745(0.068)	0.688(0.057)	0.748(0.077)
Proposed Model	Intrinsicality Ablated	0.721(0.054)	0.644(0.062)	0.723(0.049)
	Extrinsicality Ablated	0.657(0.047)	0.593(0.104)	0.680(0.060)
	Single-party Persuasion	0.742(0.066)	0.647(0.076)	0.740(0.071)
	Full Model	**0.771**(0.081)	**0.715**(0.081)	**0.793**(0.086)

Table 2. Results of Political Engagement Prediction for US Election

The proposed method significantly outperforms the feature-based machine learning methods. Compared with XGBoost, the best feature-based machine learning method in our test, the proposed model achieves an 18.52% improvement of AUC, a 30.00% improvement of Kappa, and a 12.16% improvement of F1. The performance comparison demonstrates that network structure should not be neglected for online political engagement prediction. Although the aggregated features can provide a summary of users' intrinsic interests and neighbors' persuasions, it is more desirable to utilize the network structure at the individual level for fine-grained modeling.

The benchmark graph representation learning algorithms also achieve an outstanding performance even though these methods only consider user interaction in a single-party framework. For instance, GraphRec, which considers both user-user social graphs and user-item graphs, outperforms the reduced models that are either intrinsicality-ablated or extrinsicality-ablated. However, by integrating counter-party interactions into our graph representation learning, the proposed model achieves a 2.39% improvement of AUC, a 7.68% improvement of Kappa, and a 2.06% improvement of F1. This performance comparison indicates the superiority of the proposed method with a counter-party model design. In addition, the models with alternative graph attention networks have a comparable performance with the benchmark graph learning algorithms and the proposed model, indicating the effectiveness of graph attention modeling in online political engagement prediction.

Finally, the ablation test is conducted to verify the effectiveness of the architecture design. It is seen that neither the solo intrinsic embedding nor the solo extrinsic embedding can provide an outstanding performance compared to the full model with a unified architecture. The model without being optimized against the user-user extrinsic persuasion experiences a significant degradation in performance, demonstrating the necessity of modeling user persuasion in online political engagement. In addition, the benchmark against the reduced model with single-party persuasion indicates the importance of counter-party arguments to engaging individual users in political topics.

We further verify the performance using data from the 2019 Hong Kong Protests. As shown in Table 3 the observations are similar to those using data from the 2020 U.S. Presidential Election; that is, the proposed full model outperforms all other baseline methods, including the state-of-the-art graph representation learning methods and the reduced models.

Model Class	**Methods**	**AUC**	**Kappa**	**F1**
Feature-based Machine Learning	LogReg	0.567(0.062)	0.469(0.077)	0.616(0.082)
	Ensemble Learning	0.575(0.069)	0.520(0.077)	0.655(0.095)
	XGBoost	0.645(0.092)	0.590(0.094)	0.668(0.065)
Graph Representation Learning	WLWS	0.635(0.102)	0.594(0.076)	0.699(0.103)
	FATE	0.721(0.06)	0.609(0.152)	0.750(0.081)
	GraphRec	0.739(0.074)	0.680(0.106)	0.734(0.102)
Alternative Modules	GAT with MCTS	0.753(0.087)	0.640(0.124)	0.752(0.072)
	FeatherGraph	0.724(0.082)	0.684(0.098)	0.756(0.072)
	GeoScattering	0.743(0.092)	0.681(0.078)	0.764(0.084)
Proposed Model	Intrinsicality Ablated	0.744(0.057)	0.649(0.101)	0.744(0.056)
	Extrinsicality Ablated	0.714(0.083)	0.591(0.093)	0.732(0.086)
	Single-party Persuasion	0.757(0.057)	0.646(0.092)	0.754(0.067)
	Full Model	**0.765**(0.070)	**0.685**(0.086)	**0.772**(0.063)

Table 3. Results of Political Engagement Prediction for HK Protest

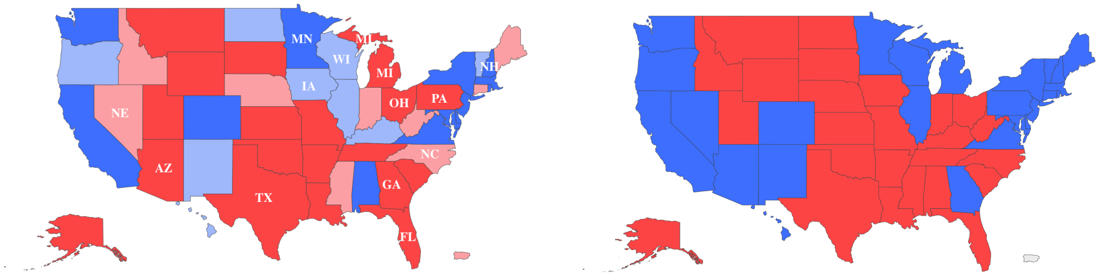
Implications from Online Political Engagement Prediction

Online political engagements can directly reflect and influence individuals' political attitudes and voting behavior (Bond et al. 2012), intensify political conflicts (Dahlgren 2000), and complement or reinforce offline political activities (Kim et al. 2017). We present the practical implications of our model of online political engagement prediction by evaluating the relationship between online and offline engagement. In addition, we present the time trend of political conflicts by implementing the engagement predictor on polarization forecasting.

Offline Engagement

Using the trained model, we perform the last-period prediction from 29 October 2020 to 31 October 2020 to empirically assess whether the predicted online engagement can reflect voting patterns in the offline presidential election, which was held on November 3, 2020 right after our study period. To alleviate the bias that the user group of Democrats outnumbers that of Republicans on Twitter, we group the users by state and ideological affiliation, then normalize the number of predicted online political engagements within each ideology group (Barberá and Rivero 2015). The difference between the normalized number of online political participants from that of the counter-party is used to study offline voting patterns at the state level.

Figure 5(a) shows the geographical distribution of the normalized differences between the predicted online political engagements of Republicans and Democrats. Red represents a different value in the Republican direction (more Republican engagement) larger than 0.6 and light red represents a difference value between 0 and 0.6. Blue represents a different value in the Democrat direction (more Democrat engagement) smaller than -0.6 and light blue represents a difference value between -0.6 and 0. The winning party in each state in terms of online political engagement is generally consistent with the true result of the presidential election as shown in Figure 5(b), and the inconsistency mainly appears in swing states. These states have split



(a) Predicted winning party. (b) 2020 U.S. Presidential Election result

Figure 5. Distribution of the Winning Parties in the 2020 U.S. Presidential Election

support for Democratic and Republican candidates and they are labeled with abbreviated names in Figure 5(a). It is notable that several swing states have shown premature signs of swinging in terms of predicted online political engagement - for instance, in Nevada, Iowa, Wisconsin, and North Carolina, neither party can significantly overpower the other on social media engagement. Traditionally, people identify swing states before presidential elections by survey data, which are labor-intensive and costly to collect. Our study provides an alternative way to identify swing states from social media data with a half-month lead before the election ballot.

Political Polarization

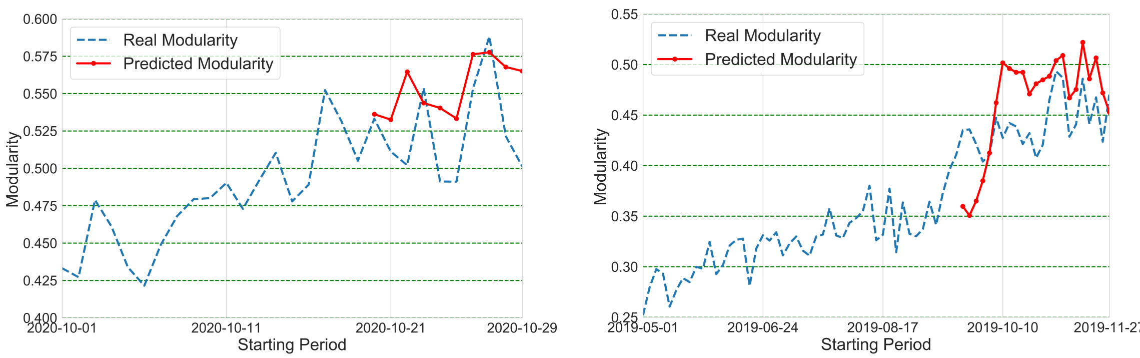
Political polarization refers to the divergence of political attitudes away from the center towards ideological extremes (Bail et al. 2018). Politicians have been using social media platforms for propagating their political views, and for persuading followers to support or engage in debates with other politicians. Twitter, as the most pivotal online platform for political engagement, has been used to facilitate direct communication and exchange of ideas between political entities and introduce different political attitudes. Even for platforms without obvious political orientation, polarization can gradually form and intensify, especially when users are exposed to information from those with opposing political attitudes. The debates and arguments between counter-party users on social media can thus increase political polarization (Bail et al. 2018).

The polarization of a network is traditionally measured by modularity, the extent to which a network is modularized compared to a random network. Networks with high modularity have dense connections among nodes within modules but sparse connections between those in different modules. Given a graph $G(V, E)$ of m nodes and the adjacency matrix A, the modularity of the network is defined by

$$Q_t = \frac{1}{2m} \sum_{i \in \mathcal{V}^t, j \in \mathcal{V}^t} y_i^t y_j^t [A_{i,j} - \frac{k_i k_j}{2m}] \frac{s_i s_j + 1}{2} \tag{12}$$

where y_i^t is the predicted engagement of user i, k_i and k_j are the degrees of nodes i and j, respectively. The product of the state variable $s_i s_j$ equals 1 if nodes i and j are in the same community and -1 otherwise. In other words, only connections between nodes in the same community contribute to the modularity score. In addition, $\frac{k_i k_j}{2m}$ is an approximation of the expected number of edges among nodes in a random network in which each node has the same degree.

Based on the prediction of user engagement, we evaluate the modularity of the Twitter social network in the next time period. Figures 6(a) and 6(b) present the modularities of the US and HK datasets, respectively. The red line is the predicted modularity during the testing period, and the dashed blue line shows the real modularity calculated using our datasets. It is seen that the proposed graph representation learning can provide an accurate estimation of political polarization. For the 2020 U.S. presidential election, the modularity has an average value of 0.493. It is already very stable 10 days before the election with an estimated value of 0.554, compared to the actual value of 0.525. The modularity of the 2019 HK protest data increases monotonically as time passes by during the study period. It starts at 0.252 in the period of 2019-05-01 to 2019-05-03 and reaches a maximum of 0.493 in the period of 2019-11-03 to 2019-11-05. The estimated



(a) 2020 U.S. Presidential Election Discussion Network.

(b) 2019 HK Protest Discussion Network.

Figure 6. Modularity Prediction for Political Polarization

average modularity during the testing period is 0.463, compared to the actual average of 0.441.

Conclusion

Online social engagement, although with great social impact, remains a challenging task for prediction due to its complicated motivating mechanisms from both intrinsic interest and extrinsic influence. Such a prediction task has not been well addressed by existing methods, which ignore the nature and great influence of inner/counter-party interaction patterns in the context of online political engagement. Therefore, this paper draws on the Motivation Theory to develop a multifaceted graph representation learning model by embedding individuals' intrinsic political interest and extrinsic political persuasion in a counter-party interactive network for online political engagement prediction. On the one hand, the user-topic intrinsic network designed as a bipartite graph can learn the similarities between political topics and users from their historical topic engagement, which are aggregated to represent users' intrinsic interest in political topics. On the other hand, the user-user extrinsic network transformed by the GraphWave algorithm can learn the impact of political persuasion from both inner-party friends and inter-party opponents. We conducted experiments using real social network data on the U.S. 2020 election and the 2019 HK protests from Twitter and demonstrated the advantages of the proposed model over the state-of-the-art benchmarks. Moreover, the proposed model also presents potential implications for offline political engagement and online political polarization.

Besides, we believe our approach is not limited to political domains but can be applied to other counter-party contexts with conflicting opinions and arguments, which is quite common, especially on social media platforms. As intrinsic interest can also be represented by related topics in other contexts, the design science framework can be generalized to many other contexts with intrinsic/extrinsic joint force, without the limitation of political topics.

This work has certain limitations, which open opportunities for future research. Our graph representation learning approach allows us to have an accurate prediction of online political engagement. Still, it does not point to the causal relationship between intrinsic/extrinsic motivation and political engagement. In addition, although the ablation study shows that extrinsic persuasion is more important for improving prediction accuracy, it does not statistically differentiate between the significance of intrinsic interest and extrinsic persuasion for political engagement. A followup empirical study or explainable graph representation learning is more desired. Also, we admit that the current modeling cannot entirely capture the latent nature of motivations. And it's also more desirable to validate the results from the affiliation detection model and LDA model before using them as a pillar of the following analyses. Besides, some recently emerging methods such as natural language processing methods, expansive language models, and salient graph learning methods need to be further considered for future improvements or as potential benchmarks.

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