Against the Echo Chamber: A Unified Framework for Tracing Evolving Political Ideologies on Social Media

Anonymous Author(s)*

Abstract

Social media platforms have evolved as crucial conduits for political discourse. Yet, as internet applications increasingly employ tailored information flow recommendations, users risk becoming ensnared in 'information cocoons', a phenomenon exemplified by the well-known echo effect. Consequently, monitoring users' political inclinations on social media becomes imperative, though fraught with challenges due to temporal dynamics and intricate social interconnections. To this end, this paper introduces a unified framework TSN4PI (Temporal Social Networks for Political Ideologies), melding Natural Language Processing (NLP) with Temporal Graph Neural Networks (TGNNs) to precisely discern political shifts at the user tier. Our integrative multi-task learning framework not only detects a user's political bias from a post but also gauges its potency concurrently. Leveraging BERT-based pre-trained models and our pioneering use of TGNNs, we effectively track evolving political stances. Through the integration of datasets from Allsides.com, vast data from X (formally known as Twitter) pertaining to the U.S. presidential elections, and observations from Truth Social, our experiments chronicle nuanced political evolutions. Conclusively, our approach's effectiveness is substantiated via case studies, signifying a pivotal leap in forecasting political ideologies in digital arenas and proffering vital insights for ensuing scholarly exploration and policy making.

CCS Concepts

• **Human-centered computing** → **Social network analysis**; • **Information systems** → *Social networks*; • **Computing methodologies** → *Temporal reasoning*.

Keywords

Political Ideology Detection and Prediction, Natural Language Processing, Temporal Graph Neural Networks, Multi-task Learning, Unsupervised Domain Adaptation

ACM Reference Format:

Anonymous Author(s). 2018. Against the Echo Chamber: A Unified Framework for Tracing Evolving Political Ideologies on Social Media. In *Proceedings of Make sure to enter the correct conference title from your rights confirmation emai (Conference acronym 'XX)*. ACM, New York, NY, USA, 10 pages. https://doi.org/XXXXXXX.XXXXXXX

Conference acronym 'XX, June 03–05, 2018, Woodstock, NY

ACM ISBN 978-1-4503-XXXX-X/18/06…$15.00
https://doi.org/XXXXXXX.XXXXXXX

1 INTRODUCTION

With the growth of online platforms, driven by the rapid expansion of the Internet and multimedia technologies, there's been a significant change in how people share views and participate in political discussions. Users' political beliefs both reflect and shape the wider sociopolitical trends in this digital environment. [14] In particular, issues like echo chambers and political polarization, which are especially evident on social media platforms, have received growing focus. For instance, *Gilbert et al.* [15] and *Quattrociocchi et al.* [34] have pointed out the phenomenon of echo chambers on Facebook and blogs, respectively. Furthermore, [12] delved into the political polarization observed during the 2016 and 2020 US presidential elections in X (formally known as Twitter). These studies highlight the need to understand true political beliefs from the vast array of online material. At the same time, there has been doubt and caution regarding the echo chambers issue, with some suggesting that such issues might not even exist, and even if they do, their effect on user communities might not be as impactful as previously thought.[17]

This brings the need to delve into political ideologies in the United States, particularly differentiating between the left and right in the current political ecology. The terms "left" and "right" predominantly allude to the Democratic Party and the Republican Party, respectively. A Pew Research Center study unveils that Republicans often stress the importance of "freedom" in both personal and political terms, while Democrats frequently emphasize physical and mental health, often intertwining their well-being with broader societal concerns such as the COVID-19 pandemic. [6] This phenomenon significantly influences political engagement, especially in voting and social media activism, accentuating the importance of exploring these ideological distinctions to better understand the U.S. political landscape. [5]

While current research has examined the impact of Echo Chambers and Political Polarization on users from multiple perspectives and across multiple social media outlets, several challenges persist: 1) Datasets Accessibility: Platforms like Twitter limit data collection, and the lack of suitable datasets elsewhere makes in-depth research difficult. Most available datasets do not match current research needs in size and focus. 2) Annotation Difficulties: The large number of posts makes manual annotation hard. When trying to figure out a user's political beliefs from their posts, the biases of those doing the annotation can change the results. 3) Irrelevant Content: Many posts about everyday life do not contain political information. Mistaking these for political content can make predictions less accurate. Additionally, many methods are not able to consider that people might not always be politically active and miss the subtle differences in political ideologies among users.

Given the vast amount of digital content and the unique blend of text and graph nature inherent to social media, it is essential to

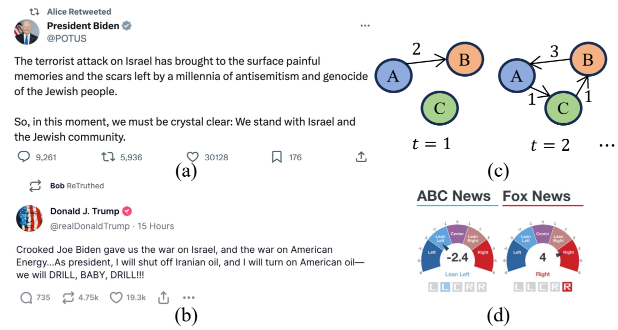

Figure 1: Dynamics of Political Ideology Conflict. Fig. (a) and (b) depict the contrasting stances taken by two party leaders regarding the same specific issue. Fig. (c) presents the temporal graph structure inherent to social networks. Fig. (d) showcases the media ideology scores on allsides.com, offering insights into media biases and perspectives.

transcend traditional manual feature extraction methods. The potential of leveraging advanced techniques becomes evident, especially when addressing the intricacies of textual data and inherent social network structures. Furthermore, the temporal nature of social network graph data, resulting from users' actions over time, coupled with the recent advancements in Temporal Graph Neural Networks (TGNN) for better performance in various tasks.

In this light, we initially decompose the problem into two parts: Political Ideology Detection (PID) and Political Ideology Prediction (PIP). PID focuses on identifying political ideologies in past and present states, while PIP is concerned with predicting political ideologies in future scenarios. our research emphasizes a method that integrates Large Language Models (LLMs) for style transfer with Unsupervised Domain Adaptation (UDA). We aim to flawlessly blend the structured textual format of politically driven news articles with unannotated social media datasets. The core objective is to bridge the gap between the structured world of news articles and the dynamic, free-form nature of authentic social media interactions. In conjunction with multi-task learning, our methodology is geared towards not only detecting if a user has a political ideology but also quantifying its intensity. Further, we exploit the capabilities of Temporal Graph Neural Networks in concert with various downstream tasks for PIP. Our investigative lens focuses on datasets from two prevalent social media platforms: X (formerly known as Twitter) and Truth Social. While X provides a glimpse into mainstream conversations, Truth Social, recognized for its distinct user demographic, offers a contrasting lens.

In summation, our primary contributions are:

- To collect and open-source two datasets: one capturing spectrums of news-political ideology scores from AllSides and a user-level tweet archive with over 77 million entries.
- The use of LLMs for text style transfer combined with UDA to seamlessly bridge the stylistic distribution shift between diverse content forms.
- Making the first attempt to propose a unified framework TSN4PI that synergizes multi-task learning with Temporal Graph Neural Networks to concurrently ascertain the presence of political ideology in users and its specific intensity.
- Detailed case studies spanning two distinct social media platforms: X (formerly known as Twitter) and Truth Social, capturing a holistic spectrum of political dialogues.

Exploring online political discourse, this study examines the presence and extent of Echo Chambers and the Political Polarization phenomenon on social media platforms. We aim to provide a clear methodological framework and key insights to support better policy-making in digital political discussions.

2 RELATED WORK

This section will overview works addressing user-centric ideology detection, echo chambers, and influential technological strides, etc.

2.1 User-centric Political Ideology Detection

User-centric Political Ideology Detection, traditionally reliant on surveys and manual assessments [1], has seen a transformative shift. Recent data influxes from social media, news channels, and personal communications, bolstered by advancements in machine learning, have pivoted the research to data-driven methodologies. These newer strategies have often proven superior, especially within social media analytics. *Conover et al.* employed Twitter datasets to study user political leanings [9], and *Xiao et al.* devised TIMME, a graph-based multi-relational embedding for similar predictions [45]. Nonetheless, challenges persist. For example, *Baly et al.*'s dataset, with 1,066 media entities, poses representativeness concerns [2]. Many annotations rely heavily on manual or heuristic methods, each with its limitations. Furthermore, an overemphasis on singular data modalities, be it text [9] or graph [20, 45], may overlook vital information. And often, basic categorizations like agreement/disagreement [30, 40] can mask nuanced political details.

2.2 Echo Chambers Amplification and Political Polarization on Social Media Platforms

"Echo Chambers" describes the tendency of social media users to engage with like-minded content, reducing exposure to diverse opinions. This, combined with Political Polarization—the growing divide in political beliefs—can be exacerbated by platform algorithms that group users by ideology. This limits content diversity and reinforces existing beliefs. Key studies have explored the role of social media platforms [7], recommendation systems [28], and the effects of making users aware of their echo chamber positioning [16]. Contrarily, some argue against the perceived prevalence and impact of these phenomena. For example, *Lees et al.* [26] suggests people might exaggerate political differences, and some research indicates social media might decrease polarization [3, 4]. However, much of the research has been conducted on a particular snapshot state of the Social Network Platforms and focusing on broad community dynamics while neglecting individual-level trends in echo chambers and political polarization.

2.3 Nature Language Processing for Semantic Understanding

Extracting accurate linguistic and semantic information from vast amounts of textual content, especially user-generated content, remains a pivotal challenge. Initial efforts utilized RNNs and word2vec for partisan predictions in Congressional debates [19]. With the introduction of transformer-based models like BERT [10], there was a significant improvement in understanding sentence structures. *Voita et al.* [43] highlighted that BERT's deep architecture and bidirectional capabilities are instrumental in understanding text details, particularly helpful for breaking down complex political content. Hence, many researchers now use BERT and its variations, including RoBERTa [29], SBERT [36] for sentence embeddings, BERTweet [32] for social network scenarios, TWHIN-BERT [47] for combining BERT with the need of embedding the Twitter Heterogeneous Information Network, aiding tasks like semantic recognition [48], detection [33], information search [31], and harmful content prevention [27]. This presents an optimistic direction for detecting political ideologies from the aspect of texts.

2.4 Style Transfer for Text Contents

Style Transfer involves altering a content's style while retaining its original meaning. Formally, given X from distribution D, the goal is to derive Y from the same distribution, realizing a function $f : X \to Y$. Initially rooted in Computer Vision, a landmark work is CycleGAN [50], which employs a cyclic structure for content reversibility. Transferring this concept to text is challenging due to modality differences and the abstract nature of text. Traditional methods like variational autoencoders face issues in deep text generative models [21], and the absence of high-quality parallel text datasets complicates consistent transfers. Large Language Models (LLMs) present a potential solution. Ref. [35] leverages LLMs, treating Style Transfer as sentence rewriting, enabling zero-shot text style transfer, and signifying a notable progression in the domain.

2.5 Temporal Graph Neural Networks for Political Ideology Prediction

Recently, Graph Neural Networks (GNNs) have become the standard approach for deep learning on graphs and achieved superior performances [24]. Representative GNNs are generally classified as spectral domain-based approaches, represented by GCN, and spatial domain-based approaches, such as GAT [42] and GraphSAGE [18], to name a few. Traditional GNNs can only handle static graphs, leaving learning node representations that evolve over time unexplored. To tackle this challenge, Temporal Graph Neural Networks (TGNNs) are proposed, which aim at the representation learning on graphs that evolve over time. Targeting dynamic user-item interaction, JODIE [25] proposes a coupled recurrent neural network model that learns the embedding trajectories of users and items. TGAT [46] extends GAT [42] by adding a time encoding block based on Bochner's theorem to integrate the time dimension. Similarly, DySAT [39] proposes a neural architecture that learns node representations to capture dynamic graph structural evolution based on the graph attention mechanism. To improve the efficiency of TGNNs, *Rossi et al.* [37] propose a generic framework TGN for deep learning on dynamic graphs represented as sequences of timed events. For scalable temporal graph neural networks, APAN [44] decouples model inference and graph computation to speed up model inference by eliminating the heavy graph query operations. Very recently, GraphMixer [8] noticed that the prevailing Recurrent neural network and self-attention mechanism in existing TGNs are not necessary and instead proposes a simple multi-layer perceptrons-based graph encoder.

Tweet Info	Interact Counts	Interact Target	Contents
ID User Time Convo. ID	Retweets Quotes Likes	RTweet ID QTweet ID Reply ID Reply User Mentions	Text Hashtags

Table 1: Attributes of tweets in the X Dataset.

3 DATA

In this section, we elucidate the datasets exploited for the purpose of this research. Specifically, we have scraped data from allsides.com for discerning media bias in political ideology, a dataset from X(formally known as Twitter) concerning the presidential election, and a dataset from Truth Social[1] for case studies.

Data Privacy Given the sensitivity of Political Ideology, privacy is paramount in our research. For our news dataset, we extracted only public data from media websites, ensuring ethical compliance. In the Social Media Datasets, we rigorously anonymized data. Specifically, for X (formerly Twitter) and Truth Social, personal details, like names and user handles, were replaced with unique numerical IDs. Our focus remained strictly on public content, ensuring private data remained untouched.

3.1 X (Twitter) Dataset

We introduced a large-scale X (formerly known as Twitter) Dataset, collected using the `snscrape` library. Initially, a keyword search for "presidential election" was performed, yielding approximately 10,000 tweets. From these, we extracted a unique user pool of 4,950 and scraped all tweets posted by these users, accumulating around 70 billion tweets from 2011 to 2022.

X has emerged as a pivotal platform for political discourse, allowing direct communication between politicians and the public. Its features like @mentions, retweets, replies, and #hashtags facilitate two-way engagement, making it a favored venue for political interactions. The platform is significantly utilized by politicians, political journalists, and strategists, marking it a critical part of the public political discourse. These aspects underscore X's importance for political communication, justifying its inclusion in our research to examine political ideology and discourse. The X (Twitter) Dataset is expected to provide insightful information for analyzing political ideology in the digital realm.

The dataset's granularity is evident in the variety of attributes accompanying each tweet. As one tweet is illustrated in Table. 1 (a), the following attributes are included in our dataset as follows:

Such intricate data facets not only enhance the depth of our analysis but also provide diverse avenues for exploring political discourse dynamics.

Data Preprocessing We employed the `fasttext-langdetect` library [22, 23] to perform accelerated language identification on the large-scale dataset. Tweets from non-English speaking users were

[1] truthsocial.com

filtered out, aligning with our focus on English-language articles from the Political Ideology Dataset in U.S. scenarios.

3.2 Political Ideology Dataset

Sourced from allsides.com, our Political Ideology Dataset aims to represent media biases linked to articles' media affiliations. Recognizing media's inherent biases, this categorization becomes crucial for grasping the wider political discourse.

allsides.com employs a multi-partisan analysis, offering a comprehensive view across the political spectrum. Political ideologies are mapped onto a numerical spectrum from -6 to 6, categorized further as: -6 to -3 for "Left," -3 to -1 as "Lean Left," -1 to 1 as "Center," 1 to 3 as "Lean Right," and 3 to 6 as "Right." This thoroughness results from methods like Editorial Review, Blind Bias Surveys, Independent Review and Community Feedback.

Using the `requests` and `Newspaper3k` libraries, we extracted a list of rated outlets and scraped approximately 230,000 articles from their main pages. Each article was assigned its outlet's bias rating, ensuring a balanced dataset representation across biases.

Data Preprocessing Same with the X (Twitter) Dataset, we focused on English-language articles, ensuring dataset coherence. Furthermore, we normalized the political ideology scores. Specifically, for a given article N, with an original political ideology score S_{raw} ranging from $[-6, 6]$, the adjusted score S_{adjusted} is computed as:

$$S_{\text{adjusted}}(N) = \frac{S_{\text{raw}} + 6}{12}, \tag{1}$$

This normalization procedure aids in maintaining scale uniformity throughout the dataset.

Style Transfer with Large Language Models Using news article text to predict Political Ideologies, we identified distribution shifts between news and social media texts. We employed Large Language Models, noted for their language prowess, to shift from style transfer to guided text generation. Moreover, to enrich our dataset and enhance the model's discernment capabilities, we integrated a Twitter Dataset replete with daily life content. This fusion not only aids in determining the presence or absence of political ideology in a given content but also gauges the intensity of the said ideology, if it is indeed present.

3.3 Truth Social Dataset

We also incorporated a dataset from Truth Social [13], launched in February 2022 following the suspension of former United States President Donald Trump from multiple platforms, including Twitter (now known as X), Facebook, and others. From 1 (a) and (b), Truth Social was designed to closely mirror X in terms of functionality, with almost identical features. For instance, X's "Retweet" functionality is analogous to "ReTruth" on Truth Social. Supporters of Trump predominantly frequent this platform and generally exhibit a right-leaning political bias. Our aim with this dataset is to delve into the dissemination of information and trace the evolution of user political ideologies within a social network that carries an inherent political bias from the outset.

Structurally, Truth Social bears similarities to X(Twitter). In contrast to X(Twitter)'s "tweets," posts on this platform are referred to as "Truths," and reposts are termed "ReTruths." The dataset comprises over 454,000 users and exceeds 823,000 "Truths." Additionally, it includes the complete post history of the 65,536 most active users. Subtables within this dataset, such as "Truths" and "Users," serve as primary resources for our exploration.

Data Preprocessing Preliminary cleaning and preprocessing were applied to the raw dataset. Given that some "Truths" had missing or misaligned timestamps, we utilized web scraping tools to supplement and correct the timestamps for these accessible "Truths."

4 METHODS

This section covers all the methods of our proposed framework and consists of both NLP and TGNN.

4.1 Political Ideology Detection

Our methodology commences with formulating a model designed to assign labels to individual posts, whether tweets or truths. Each post's textual content undergoes rigorous analysis to discern its political inclination. Posts without a discernible political direction are excluded from further bias scoring. Conversely, politically inclined posts are attributed a score between 0 and 1, representing the magnitude and direction of the bias. The dataset reflecting political bias incorporates news articles post-LLM style transfer.

Multi-Task Learning We develop our scoring model within a multi-task learning framework. Instead of relying solely on the traditional BERT, we employ a variety of pre-trained BERT models, each fine-tuned using different strategies across multiple tasks. This diversified pre-training approach enhances the robustness and generalizability of our feature extraction process. Subsequently, we utilize a combination of a classification head C and a regression head R to discern and quantify a post's political ideology, respectively. If a post exhibits political bias, the regression head ascertains the strength of this bias.

Mathematically, for a given post P, a BERT-based transformer T produces an embedding $E = T(P)$. This embedding subsequently bifurcates into two heads: the classification head C and the regression head R. The classification mechanism identifies the presence or absence of political bias, i.e., $C(E) \in \{0, 1\}$. If $C(E) = 1$, the regression head determines the bias score, i.e., $R(E) \in [0, 1]$. The final multi-task loss $loss_{MT}$ is formulated as follows:

$$loss_{MT} = \lambda \cdot loss_c + (1 - \lambda) \cdot loss_r, \tag{2}$$

where $\lambda \in [0, 1]$ is a hyperparameter balancing the significance of the two tasks, while $loss_c$ and $loss_r$ represent the loss of the classification and regression task, respectively.

Unsupervised Domain Adaptation The employed BERT models were predominantly fine-tuned on tweet data. Despite the style transfer of news articles via LLM, a palpable disparity remains between transformed and genuine posts. Given our lack of genuine post-specific political bias information, we implement Unsupervised Domain Adaptation, aligning features across diverse social media platforms using Maximum Mean Discrepancy (MMD).

MMD serves as a powerful statistical measure that captures the distance between the embeddings of the two distributions in a

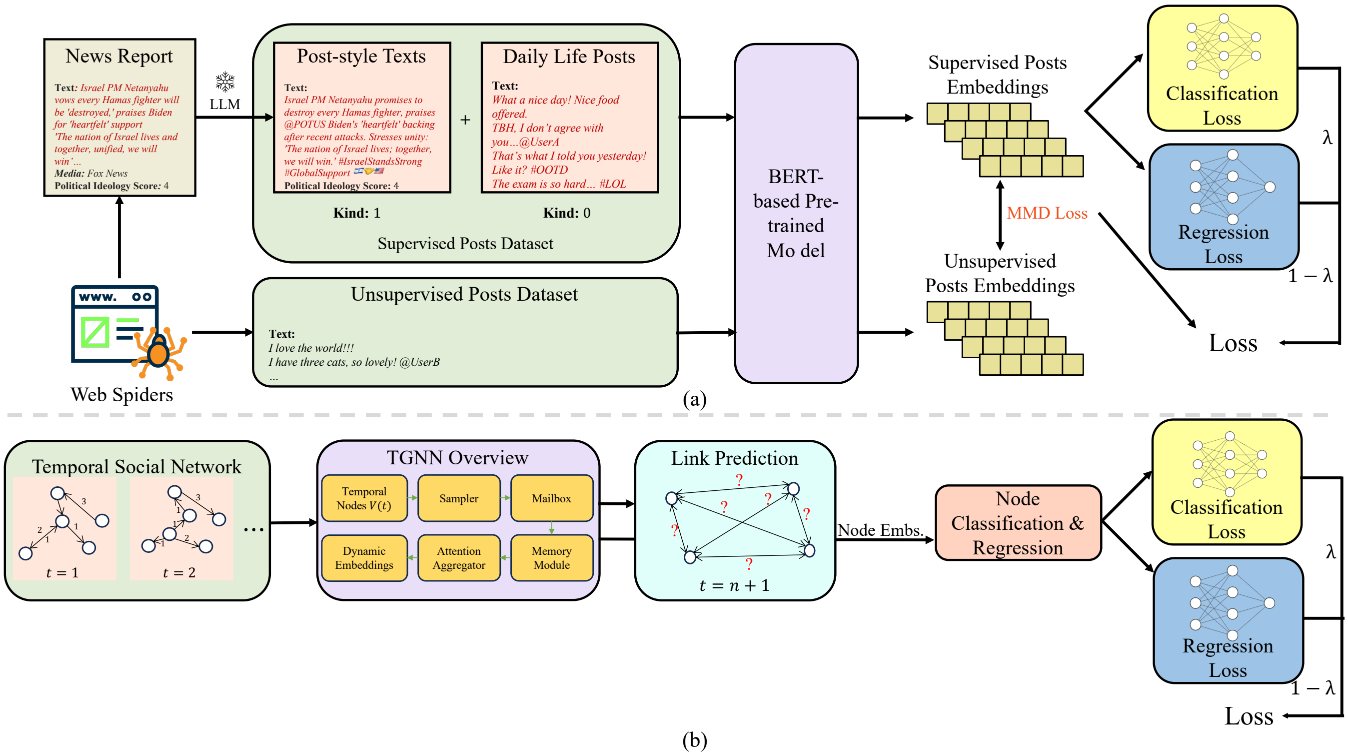

Figure 2: The overview of our proposed framework: TSN4PI. Fig (a) represents the method for Political Ideology Detection, while Fig (b) represents the method for Political Ideology Prediction.

high-dimensional feature space. By minimizing the MMD, we ensure that the features of both domains become indistinguishable, allowing for better transferability and generalization. One notable advantage of MMD is that it does not require paired samples or even samples of the same size from both domains, providing flexibility in its application. Given two distributions X (set of style-transferred posts) and Y (set of authentic posts)(refer to Fig. 2 for Supervised Posts Dataset and Unsupervised Posts Datasets), the MMD loss $loss_{MMD}$ is computed using a Gaussian kernel matrix:

$$loss^2_{MMD}(X,Y) = \mathbb{E}[k(x,x')] + \mathbb{E}[k(y,y')] - 2\mathbb{E}[k(x,y)], \quad (3)$$

where x, x' are samples from X, y, y' are samples from Y, and k is a Gaussian Radial Basis Function (RBF) kernel, which is

$$k(x,y) = \exp\left(-\frac{||x-y||^2}{2\sigma^2}\right). \quad (4)$$

Thus, the cumulative loss for our task is computed as follows:

$$loss = loss_{MT} + loss_{MMD}. \quad (5)$$

After backpropagation of the loss, We hope to use $loss_{MT}$ and $loss_{MMD}$ to allow the model to enhance robustness while being able to simultaneously distinguish whether or not there is Political Ideology and the specific score if there is.

4.2 Political Ideology Prediction

In this subsection, we delve into the intricacies of employing Temporal Graphs. Our objective is to adeptly model the ever-evolving dynamics of political ideology at the user node level. We aim to refine and enhance our predictions of political ideology, capturing the subtle shifts and trends in the future.

Graph Modeling Our graph is formally defined as $G = (V, E, t)$, where V represents users, E corresponds to the posts, and t denotes the timestamp associated with each post. Each post is conceptualized as an edge in the graph. To derive the text embedding serving as the weight of each edge, we employ BERT-based pre-trained models to texts belonging to the post. For posts originated by User A, edges are directed from A to themselves. Conversely, if User A re-posts a post from User B, an edge is drawn from A to B with a weight identical to that of the original post. The reason for choosing re-post as the edge for both users is that this is common across different social media and the other interactions for tweets in Twitter is currently unavailable.

Temporal and Causal Properties In our configuration, all edges (or post updates) are chronologically ordered. During the execution of downstream tasks, all training data precede validation and test datasets in time. For example, given a sequence of graphs G_1, G_2, …, G_{t-1}, the model aims to predict G_t. We argue that this temporal setup is coherent and pragmatically applicable in real-world scenarios, where historical data informs future predictions. Consider a practical example: possessing all posts and interactions from a user spanning from the first to the fifth year, the model aims to forecast the their political ideology in the sixth year.

Link Prediction Our first downstream task involves Link Prediction within the Temporal Graph. Link prediction stands as a quintessential task in graph analysis, serving to unveil implicit relationships and interactions within the network, thereby forecasting the potential future structure of the graph. This task holds paramount significance across diverse domains, such as social network analysis, recommendation systems, and bioinformatics, to enumerate a few. The underlying reason is its capability to intuit potential connections between nodes.

Given a graph $G = (V, E)$ where V represents the set of nodes, and E represents the set of existing edges, and the link prediction task seeks to identify potential links E' that might form in the future. Mathematically, the problem can be stated as:

$$\hat{E}' = f(V, E), \tag{6}$$

where f is the link prediction function that takes in the current nodes and edges and predicts the set of potential future edges $\hat{E}'$.

In our context, a key advantage of Link Prediction is its freedom from explicit post labeling. User interactions, which form potential graph links, can be easily extracted without detailed annotation. This sidesteps issues related to label instability that can yield unreliable predictions. Essentially, the task's strength lies in its reliance on observable interactions, undistorted by label concerns.

We employ a time-aware strategy for our temporal graph link prediction. Data from the last two months is used for training, aiming to predict user interactions in the following two months. This temporal split ensures the model is trained on fresh data, which is crucial for forecasting imminent network links. Using past interactions, the model predicts future links, hinting at subsequent shifts in users' political ideologies. This approach enhances the model's ability to grasp temporal user dynamics, showcasing the practicality of user modeling and shedding light to the future direction of political ideologies and network structures.

Node Classification and Regression The node classification and regression task is imperative for modeling the temporal variations in political ideology at the user node level. Whereas the assignment of political ideology and corresponding scores to individual posts primarily leverages Natural Language Processing (NLP) techniques, it is noteworthy that these techniques presuppose the availability of posts. In real-world scenarios, we often encounter data voids. For illustration, consider having access to posts and interactions from a group of users for five years. One would assign scores to these posts using NLP models and incorporate interactions for graph-level modeling. However, when predicting political ideology for the sixth year (future), the absence of posts renders the prediction challenging, underscoring the indispensable role of temporal graph modeling.

We utilize the political ideology assignment and scores for each post, as elucidated earlier. Initially, we define the political ideology $K(n)_t$ of a user n belonging to set N at time t as:

$$K(n)_t = \text{mode}(K(P_n)), \tag{7}$$

where P_n denotes the set of posts disseminated by user n, K represents the political ideology of the posts ($\in \{0, 1\}$), and mode returns the mode. The political ideology of a user at time t is inferred from the mode of the political ideologies of all posts shared by the user up to time t. Technically, this step could be accelerated by calculating the sum of the kind list to check whether it exceeds half of the list length or notm due to vectorization.

Subsequently, the political ideology score $S(n)_t$ of a user n at time t is defined as:

$$S(n)_t = \text{avg}(S(P_n)), \quad \forall n = 1, 2, \cdots, \text{ s.t. } K(n) = 1, \tag{8}$$

where avg calculates the average. The political ideology score of a user at time t is determined by averaging the scores of all politically oriented posts shared by the user up to time t. These two values collectively represent the node value for each user.

Upon establishing the predicted values at the node level, we proceed with node classification and regression. Although conventional temporal graph neural networks predominantly rely on node classification, we posit that a nuanced prediction of long-term political ideology necessitates a granular scoring system. Mirroring the framework delineated earlier for assigning scores to posts, we first extract temporal embeddings for nodes using various temporal graph frameworks generated in link prediction, which is a general approach in TGNN. [38, 46] Subsequently, these embeddings are fed into classification and regression heads for multi-task learning. The resultant multi-task loss $loss_{MT}$ for the node-level tasks is analogous to that defined earlier:

$$loss_{MT} = \lambda \cdot loss_C + (1 - \lambda) \cdot loss_R, \tag{9}$$

where $\lambda \in [0, 1]$ is a hyperparameter that arbitrates between the two tasks, and $loss_C$ and $loss_R$ denote the losses for the classification and regression tasks, respectively. Notably, the regression loss is computed only for posts with political ideology. We exclude those without any political ideology since the scores for these posts are meaningless by directly block the corresponding backpropagation.

5 Experiments

This section will introduce the experiments to validate the framework's efficacy in detecting and predicting political ideologies.

5.1 Political Ideology Detection

Text Style Transfer We deployed a text generation service on eight machines using the *vllm* framework. Each machine is equipped with 8 *Nvidia A40* GPUs, boasting 48GB of VRAM on each machine, with sets of four cards interconnected via NVlink for faster inter-GPU connectivity. On the software front, each machine runs on *Ubuntu 22.04* and employs *Python 3.11*.

Our choice of the Large Language Model is the pre-trained model *garage-bAInd/Platypus2-30B* from Huggingface, an instruction-tuned model grounded on LLaMA-30B. We favored this model because 1) it ranks high on the Huggingface Open LLM Leaderboard [2] within similar models, showcasing superior instruction comprehension and text generation abilities. 2) This model's size perfectly fits four GPUs, allowing simultaneous operation of two models on a single machine, striking a balance between performance and efficiency. In terms of model parameters, we employed the default temperature setting of 0.8 to ensure a blend of creativity and adherence to text style transfer instructions.

[2] https://huggingface.co/spaces/HuggingFaceH4/open_llm_leaderboard

For deployment, we equally divided all data into 16 portions (8 machines × 2 each) and initiated inference on all machines concurrently. The inference prompt is as follows, where *news_text* is variable for every news report:

Examples of prompt used in LLM for Text Style Transfer

Below is an instruction that describes a task, paired with an input that provides further context. Write a response that appropriately completes the request.
Instruction:
Convert the following news report into a tweet encapsulating its essence. Here are some guidelines for Twitter's language style:

1. **Concise Language**: Maintain brevity.
2. **Abbreviations**: Employ abbreviations like 'IDK' for 'I don't know', 'IMO' for 'in my opinion', and 'ICYMI' for 'in case you missed it' when apt.
3. **Hashtags**: Use hashtags for emphasis or categorization, e.g., *#BreakingNews* or *#TechUpdate*.
4. **Mentions**: Reference other accounts using the '@' symbol, like @OpenAI.

Ensure the tweet stays within the 280-character limit.
Input:
{*news_text*}
Response:
<s>

This prompt has two salient features: 1) it strictly adheres to the LLaMA [41]'s required template, and 2) it briefly introduces the style transfer task and concisely describes the linguistic nuances of platform X (formerly known as Twitter). We opted for the older name due to X's recent rebranding and similarities in linguistic style between Truth Social and Twitter. After reviewing approximately 1,000 generated tweets, we deemed the quality reliable.

Political Ideology Detection After acquiring datasets for Style Transfer-derived social media (Generated) and Political Ideology scores, we labeled all entries within this dataset as "Politically Biased" (Kind 1). We then supplemented this with an equal amount of daily life tweet dataset A, designating their Political Ideology Kind and Score as 0. Additionally, we incorporated another daily tweet dataset, B, ensuring both datasets were mutually exclusive. We employed BERT-based Pre-trained Models to extract text features and performed Unsupervised Domain Adaptation using MMD Loss and daily tweet dataset B to improve the model's proficiency at discerning tweet political bias. Our choice was TwHIN-BERT for two main reasons: 1) its source is a large volume of proprietary tweets, facilitating superior capture of tweet text characteristics, and 2) it is trained using text-based self-supervision and a social objective derived from the rich engagements within a Twitter heterogeneous information network (TwHIN) [11], which ensures its understanding of social engagements. We implemented classification and regression heads after feature extractions. The former determines the presence of political ideology, and the latter evaluates the exact score if the post has political ideologies. Classification utilizes a linear layer coupled with a sigmoid function, while the Score layer is constructed from a linear layer. The decision to predict is contingent on the presence of political bias.

Dataset	Model	AP(%)	AUC(%)	Acc.(%)	MSE
Truth Social	APAN	97.56	97.24	65.14	**0.036**
	JODIE	**99.73**	**99.69**	66.28	0.039
	TGN	99.25	99.14	**72.42**	**0.036**
X (Twitter)	APAN	98.78	98.65	99.98	0.0564
	JODIE	97.83	97.72	99.98	0.0564
	TGN	**98.82**	**98.70**	**99.99**	**0.0560**

Table 3: Experiment results across datasets and models. AP means Test Average Precision, AUC stands for Test Area Under Curve; Acc. is short for classification accuracy, while MSE represents regression Mean Squared Error.

5.2 Political Ideology Prediction

We utilize Temporal Graph Neural Networks (TGNNs) for Political Ideology Predictions, which focus on temporal aspects more than traditional static Graph Neural Networks (GNNs). We compared several models across different tasks.

For our experiments, we employed the TGL framework, optimized for efficient TGNN training on extensive graphs [49]. TGL efficiently manages billion-scale dynamic graphs, merging the capabilities of TGNN with the velocity of contemporary hardware. This framework, enriched with a temporal sampler and a node memory module, offers an ideal foundation for our Political Ideology Prediction explorations on real-world dynamic networks.

Link Prediction assesses the potential future connection between two nodes, essential for understanding user clustering. Understanding the link predictions among users in future scenarios could be beneficial for studying echo chambers and political polarization and be vital for policy-making and observation.

Node Classification and Node Regression are paramount in our setup, necessitating the determination of a social media post's political bias and its associated bias score if existent. Different TGNNs were used to generate node embeddings for each user (node) in the link prediction task, which, after processing through various heads, cater to node classification and regression downstream tasks.

Table 3 shows the results for different models on two diverse datasets. The Node Classification task across two datasets exhibited significant differences in accuracy. A pivotal factor contributing to this deviation is the nature of users selected in the X (Twitter) dataset. Specifically, these users had previously tweeted about "Presidential Election," implying that their likelihood of manifesting a Political Ideology at various times could be substantially higher.

While marginal performance differences were noticed across different models, especially for datasets of diverse magnitudes and tasks of link prediction, JODIE demonstrated superior performance on the Truth Social dataset, whereas TGN was optimal for the X (Twitter) dataset. Overall, TGN emerges as a superior choice due to its simple yet flexibly interchangeable module design.

Conventional Graph Neural Networks (GNNs) like GCN [24] are proficient at processing static graphs but encounter challenges with dynamic or evolving graph scenarios. Considering our datasets and scenarios capture temporally fluctuating interactions, Temporal Graph Neural Networks (TGNNs) stand out as a more suitable choice for our research objectives and could act as the key component of Political Ideology Prediction.

6 RESULTS AND FINDINGS

This section consolidates prior methodologies and experiments, leading to novel findings on social media platforms.

6.1 Political Ideology Detection and Prediction

Our NLP-based Political Ideology Detection and TGNN-based Political Ideology Prediction on two datasets were triumphant. The methodologies exhibited commendable outcomes on our annotated dataset, underscoring the reliability of using social media post content for Political Ideology Detection. We attribute this to the text information's capability to faithfully represent the author's emotional sentiment and Political Ideology. Furthermore, various BERT-based pre-trained models can adeptly extract features from posts of diverse themes, facilitating Political Ideology Detection. For Political Ideology Prediction, different TGNN models have good results, reflecting the strong strength compared to Static GNN, which is a powerful help for our subsequent analysis.

6.2 Findings about Echo Chambers and Political Polarization

We engaged in comprehensive data visualization of social media post content across various levels and objectives. Our ambition was to unearth distinct strata of Political Ideology transformations across different social media platforms while also uncovering intriguing insights about Echo Chambers and Political Polarization:

1) Different Social Media Platforms exhibit distinct overarching Political Ideologies. Our prior Political Ideology Detection on Twitter and Truth Social datasets aimed to chart the political spectrum of both platforms.

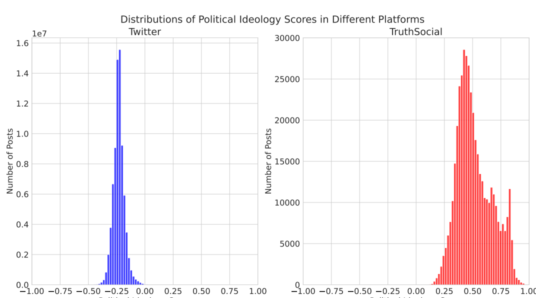

Figure 3: Political spectrum of two social media platforms. Values closer to -1 lean left, while those nearing 1 lean right.

Fig 3 delineates our findings. Despite variations in dataset sizes, our Political Ideology Detection aligns with prevailing perceptions: Twitter exhibits a slight leftward inclination, whereas Truth Social leans more to the right. This not only corresponds with the real-world scenario, given that Twitter is perceived as a more universal platform and the internet-using American citizens tend to exhibit a slight leftward political ideology but also Truth Social, being established at the behest of the former US Republican President, Donald J. Trump, inevitably sees its user base lean considerably more to the right. Moreover, we hypothesize that this dichotomy in Truth Social arises from the amalgamation of influential right-leaning influencers and a broader user community with a mild rightward tilt.

2) Does Echo Chambers and Political Polarization exist on online social media platforms? We analyzed the temporal fluctuations in the average user Political Ideology. Specifically, we employed a moving time window technique to capture short-term shifts in political ideology for two distinct datasets. Given the varied time spans of these datasets, we adopted different window sizes for each. For the X (Twitter) dataset, a window of 14 days was chosen, whereas for the Truth Social dataset, we utilized a 3-day window. Within these windows, the mean was calculated to represent short-term changes in Political Ideology. We subsequently illustrated the political ideology scores for the ten users with the highest standard deviations.

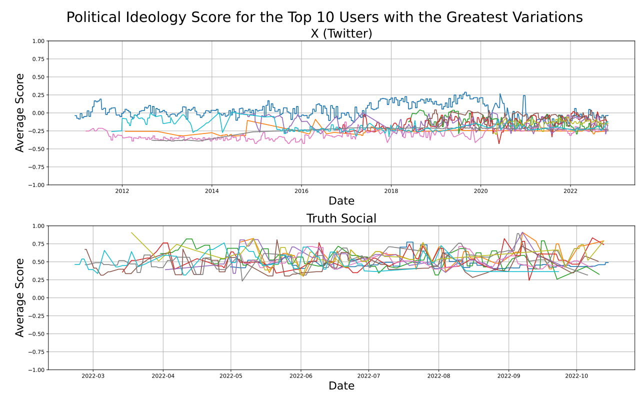

Figure 4: User Political Ideology Score over time.

Fig. 4 showcases this evolving trend. Contrary to our expectations, the Political Ideology scores of the ten users with the most pronounced shifts gradually converged towards an average, indicating a homogenization effect. This observation stands in stark contrast to our initial hypothesis. Traditional Political Polarization theories suggest that in social networks, individuals with left-leaning ideologies would become more left-oriented, while those with right-leaning stances would incline further to the right, which contradicts the evidence presented.

7 Conclusion

This research melds natural language processing with temporal graph neural networks, offering a fresh perspective on tracking political ideologies on social media. Validated over expansive datasets from X (Twitter) and Truth Social, our model adeptly classifies political orientations, bridges the linguistic divide between news and social content, and accurately reflects dynamic user interactions. Contrary to prevailing beliefs about online echo chambers, our findings suggest a convergence in users' political ideologies, challenging accepted arguments of rising digital polarization. As a seminal contribution, this study not only deepens the academic discussion on online political dynamics but also charts a course for future endeavors targeting reduced polarization and enhanced democratic engagement. We anticipate it to foster further interdisciplinary explorations in the political and AI realms.

References

[1] Christopher H. Achen. 1975. Mass Political Attitudes and the Survey Response. *American Political Science Review* 69, 4 (1975), 1218–1231. https://doi.org/10.2307/1955282

[2] Ramy Baly, Georgi Karadzhov, Abdelrhman Saleh, James Glass, and Preslav Nakov. 2019. Multi-Task Ordinal Regression for Jointly Predicting the Trustworthiness and the Leading Political Ideology of News Media. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*. Association for Computational Linguistics, Minneapolis, Minnesota, 2109–2116. https://doi.org/10.18653/v1/N19-1216

[3] Pablo Barberá. 2014. How social media reduces mass political polarization. Evidence from Germany, Spain, and the US. *Job Market Paper, New York University* 46 (2014), 1–46.

[4] Michael A Beam, Myiah J Hutchens, and Jay D Hmielowski. 2018. Facebook news and (de) polarization: Reinforcing spirals in the 2016 US election. *Information, Communication & Society* 21, 7 (2018), 940–958.

[5] Pew Research Center. 2014. *Political Polarization in the American Public.* https://www.pewresearch.org/politics/2014/06/12/political-polarization-in-the-american-public/

[6] Pew Research Center. 2021. *Both Republicans and Democrats prioritize family, but they differ over other sources of meaning in life.* https://www.pewresearch.org/short-reads/2021/11/22/both-republicans-and-democrats-prioritize-family-but-they-differ-over-other-sources-of-meaning-in-life/

[7] Matteo Cinelli, Gianmarco De Francisci Morales, Alessandro Galeazzi, Walter Quattrociocchi, and Michele Starnini. 2021. The echo chamber effect on social media. *Proceedings of the National Academy of Sciences* 118, 9 (2021), e2023301118. https://doi.org/10.1073/pnas.2023301118 arXiv:https://www.pnas.org/doi/pdf/10.1073/pnas.2023301118

[8] Weilin Cong, Si Zhang, Jian Kang, Baichuan Yuan, Hao Wu, Xin Zhou, Hanghang Tong, and Mehrdad Mahdavi. 2023. Do We Really Need Complicated Model Architectures For Temporal Networks? *arXiv preprint arXiv:2302.11636* (2023).

[9] Michael D. Conover, Bruno Goncalves, Jacob Ratkiewicz, Alessandro Flammini, and Filippo Menczer. 2011. Predicting the Political Alignment of Twitter Users. In *2011 IEEE Third International Conference on Privacy, Security, Risk and Trust and 2011 IEEE Third International Conference on Social Computing*. 192–199. https://doi.org/10.1109/PASSAT/SocialCom.2011.34

[10] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805* (2018).

[11] Ahmed El-Kishky, Thomas Markovich, Serim Park, Chetan Verma, Baekjin Kim, Ramy Eskander, Yury Malkov, Frank Portman, Sofía Samaniego, Ying Xiao, et al. 2022. Twhin: Embedding the twitter heterogeneous information network for personalized recommendation. In *Proceedings of the 28th ACM SIGKDD conference on knowledge discovery and data mining*. 2842–2850.

[12] James Flamino, Alessandro Galeazzi, Stuart Feldman, Michael W Macy, Brendan Cross, Zhenkun Zhou, Matteo Serafino, Alexandre Bovet, Hernán A Makse, and Boleslaw K Szymanski. 2023. Political polarization of news media and influencers on Twitter in the 2016 and 2020 US presidential elections. *Nature Human Behaviour* (2023), 1–13.

[13] Patrick Gerard, Nicholas Botzer, and Tim Weninger. 2023. Truth Social Dataset. arXiv:2303.11240 [cs.SI]

[14] Homero Gil de Zúñiga, Nakwon Jung, and Sebastián Valenzuela. 2012. Social Media Use for News and Individuals' Social Capital, Civic Engagement and Political Participation. *Journal of Computer-Mediated Communication* 17, 3 (04 2012), 319–336. https://doi.org/10.1111/j.1083-6101.2012.01574.x arXiv:https://academic.oup.com/jcmc/article-pdf/17/3/319/19492627/jjcmcom0319.pdf

[15] Eric Gilbert, Tony Bergstrom, and Karrie Karahalios. 2009. Blogs are echo chambers: Blogs are echo chambers. In *2009 42nd Hawaii international conference on system sciences*. IEEE, 1–10.

[16] Nabeel Gillani, Ann Yuan, Martin Saveski, Soroush Vosoughi, and Deb Roy. 2018. Me, My Echo Chamber, and I: Introspection on Social Media Polarization. In *Proceedings of the 2018 World Wide Web Conference* (Lyon, France) *(WWW '18)*. International World Wide Web Conferences Steering Committee, Republic and Canton of Geneva, CHE, 823–831. https://doi.org/10.1145/3178876.3186130

[17] Andrew Guess, Brendan Nyhan, Benjamin Lyons, and Jason Reifler. 2018. Avoiding the echo chamber about echo chambers. *Knight Foundation* 2, 1 (2018), 1–25.

[18] William L. Hamilton, Zhitao Ying, and Jure Leskovec. 2017. Inductive Representation Learning on Large Graphs. In *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA*. 1024–1034.

[19] Mohit Iyyer, Peter Enns, Jordan Boyd-Graber, and Philip Resnik. 2014. Political Ideology Detection Using Recursive Neural Networks. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Association for Computational Linguistics, Baltimore, Maryland, 1113–1122. https://doi.org/10.3115/v1/P14-1105

[20] Julie Jiang, Xiang Ren, and Emilio Ferrara. 2023. Retweet-BERT: political leaning detection using language features and information diffusion on social networks. In *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 17. 459–469.

[21] Vineet John, Lili Mou, Hareesh Bahuleyan, and Olga Vechtomova. 2019. Disentangled Representation Learning for Non-Parallel Text Style Transfer. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*. Association for Computational Linguistics, Florence, Italy, 424–434. https://doi.org/10.18653/v1/P19-1041

[22] Armand Joulin, Edouard Grave, Piotr Bojanowski, Matthijs Douze, Hérve Jégou, and Tomas Mikolov. 2016. FastText.zip: Compressing text classification models. *arXiv preprint arXiv:1612.03651* (2016).

[23] Armand Joulin, Edouard Grave, Piotr Bojanowski, and Tomas Mikolov. 2016. Bag of Tricks for Efficient Text Classification. *arXiv preprint arXiv:1607.01759* (2016).

[24] Thomas N. Kipf and Max Welling. 2017. Semi-Supervised Classification with Graph Convolutional Networks. In *5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings*. OpenReview.net.

[25] Srijan Kumar, Xikun Zhang, and Jure Leskovec. 2019. Predicting Dynamic Embedding Trajectory in Temporal Interaction Networks. In *Proceedings of the 25th ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM.

[26] Jeffrey Lees and Mina Cikara. 2020. Inaccurate group meta-perceptions drive negative out-group attributions in competitive contexts. *Nature human behaviour* 4, 3 (2020), 279–286.

[27] Song Liao, Ebuka Okpala, Long Cheng, Mingqi Li, Nishant Vishwamitra, Hongxin Hu, Feng Luo, and Matthew Costello. 2023. Analysis of COVID-19 Offensive Tweets and Their Targets. In *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining* (Long Beach, CA, USA) *(KDD '23)*. Association for Computing Machinery, New York, NY, USA, 4473–4484. https://doi.org/10.1145/3580305.3599773

[28] Ping Liu, Karthik Shivaram, Aron Culotta, Matthew A. Shapiro, and Mustafa Bilgic. 2021. The Interaction between Political Typology and Filter Bubbles in News Recommendation Algorithms. In *Proceedings of the Web Conference 2021* (Ljubljana, Slovenia) *(WWW '21)*. Association for Computing Machinery, New York, NY, USA, 3791–3801. https://doi.org/10.1145/3442381.3450113

[29] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692* (2019).

[30] Kuan-Chieh Lo, Shih-Chieh Dai, Aiping Xiong, Jing Jiang, and Lun-Wei Ku. 2021. Escape from An Echo Chamber. In *Companion Proceedings of the Web Conference 2021* (Ljubljana, Slovenia) *(WWW '21)*. Association for Computing Machinery, New York, NY, USA, 713–716. https://doi.org/10.1145/3442442.3458613

[31] Wenhao Lu, Jian Jiao, and Ruofei Zhang. 2020. TwinBERT: Distilling Knowledge to Twin-Structured Compressed BERT Models for Large-Scale Retrieval. In *Proceedings of the 29th ACM International Conference on Information & Knowledge Management* (Virtual Event, Ireland) *(CIKM '20)*. Association for Computing Machinery, New York, NY, USA, 2645–2652. https://doi.org/10.1145/3340531.3412747

[32] Dat Quoc Nguyen, Thanh Vu, and Anh Tuan Nguyen. 2020. BERTweet: A pre-trained language model for English Tweets. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*. 9–14.

[33] Nicole Peinelt, Dong Nguyen, and Maria Liakata. 2020. tBERT: Topic Models and BERT Joining Forces for Semantic Similarity Detection. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. Association for Computational Linguistics, Online, 7047–7055. https://doi.org/10.18653/v1/2020.acl-main.630

[34] Walter Quattrociocchi, Antonio Scala, and Cass R Sunstein. 2016. Echo chambers on Facebook. *Available at SSRN 2795110* (2016).

[35] Emily Reif, Daphne Ippolito, Ann Yuan, Andy Coenen, Chris Callison-Burch, and Jason Wei. 2022. A Recipe For Arbitrary Text Style Transfer with Large Language Models. arXiv:2109.03910 [cs.CL]

[36] Nils Reimers and Iryna Gurevych. 2019. Sentence-bert: Sentence embeddings using siamese bert-networks. *arXiv preprint arXiv:1908.10084* (2019).

[37] Emanuele Rossi, Ben Chamberlain, Fabrizio Frasca, Davide Eynard, Federico Monti, and Michael Bronstein. 2020. Temporal Graph Networks for Deep Learning on Dynamic Graphs. In *ICML 2020 Workshop on Graph Representation Learning*.

[38] Emanuele Rossi, Ben Chamberlain, Fabrizio Frasca, Davide Eynard, Federico Monti, and Michael Bronstein. 2020. Temporal graph networks for deep learning on dynamic graphs. *arXiv preprint arXiv:2006.10637* (2020).

[39] Aravind Sankar, Yanhong Wu, Liang Gou, Wei Zhang, and Hao Yang. 2020. Dysat: Deep neural representation learning on dynamic graphs via self-attention networks. In *Proceedings of the 13th international conference on web search and data mining*. 519–527.

[40] Eitan Sapiro-Gheiler. 2019. Examining political trustworthiness through text-based measures of ideology. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 33. 10029–10030.

[41] Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurelien Rodriguez, Armand Joulin, Edouard Grave, and Guillaume Lample. 2023. LLaMA: Open and Efficient Foundation Language Models. arXiv:2302.13971 [cs.CL]

[42] Petar Velickovic, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Liò, and Yoshua Bengio. 2018. Graph Attention Networks. In *6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 - May 3, 2018, Conference Track Proceedings*. OpenReview.net.

[43] Elena Voita, David Talbot, Fedor Moiseev, Rico Sennrich, and Ivan Titov. 2019. Analyzing Multi-Head Self-Attention: Specialized Heads Do the Heavy Lifting, the Rest Can Be Pruned. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*. Association for Computational Linguistics, Florence, Italy, 5797–5808. https://www.aclweb.org/anthology/P19-1580

[44] Xuhong Wang, Ding Lyu, Mengjian Li, Yang Xia, Qi Yang, Xinwen Wang, Xinguang Wang, Ping Cui, Yupu Yang, Bowen Sun, et al. 2021. Apan: Asynchronous propagation attention network for real-time temporal graph embedding. In *Proceedings of the 2021 international conference on management of data*. 2628–2638.

[45] Zhiping Xiao, Weiping Song, Haoyan Xu, Zhicheng Ren, and Yizhou Sun. 2020. TIMME: Twitter ideology-detection via multi-task multi-relational embedding. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 2258–2268.

[46] Da Xu, Chuanwei Ruan, Evren Korpeoglu, Sushant Kumar, and Kannan Achan. 2020. Inductive representation learning on temporal graphs. *arXiv preprint arXiv:2002.07962* (2020).

[47] Xinyang Zhang, Yury Malkov, Omar Florez, Serim Park, Brian McWilliams, Jiawei Han, and Ahmed El-Kishky. 2023. TwHIN-BERT: A Socially-Enriched Pre-trained Language Model for Multilingual Tweet Representations at Twitter. In *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*. 5597–5607.

[48] Zhuosheng Zhang, Yuwei Wu, Hai Zhao, Zuchao Li, Shuailiang Zhang, Xi Zhou, and Xiang Zhou. 2020. Semantics-aware BERT for language understanding. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 34. 9628–9635.

[49] Hongkuan Zhou, Da Zheng, Israt Nisa, Vasileios Ioannidis, Xiang Song, and George Karypis. 2022. Tgl: A general framework for temporal gnn training on billion-scale graphs. *arXiv preprint arXiv:2203.14883* (2022).

[50] Jun-Yan Zhu, Taesung Park, Phillip Isola, and Alexei A Efros. 2017. Unpaired image-to-image translation using cycle-consistent adversarial networks. In *Proceedings of the IEEE international conference on computer vision*. 2223–2232.

Received 20 February 2007; revised 12 March 2009; accepted 5 June 2009