Predicting Information Pathways Across Online Communities

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ABSTRACT

The problem of *community-level information pathway prediction* (CLIPP) aims at predicting the transmission trajectory of content across online communities. A successful solution to CLIPP holds significance as it facilitates the distribution of valuable information to a larger audience and prevents the proliferation of misinformation. Notably, solving CLIPP is non-trivial as inter-community relationships and influence are unknown, information spread is multi-modal, and new content and new communities appear over time. In this work, we address CLIPP by collecting large-scale, multi-modal datasets to examine the diffusion of online YouTube videos on Reddit. We analyze these datasets to construct community influence graphs (CIGs) and develop a novel dynamic graph framework, INPAC (**In**formation **P**athway **A**cross Online **C**ommunities), which incorporates CIGs to capture the temporal variability and multi-modal nature of video propagation across communities. Experimental results in both warm-start and cold-start scenarios show that INPAC outperforms seven baselines in CLIPP.

CCS CONCEPTS

• **Information systems → Content ranking**; *Data mining*; *Collaborative and social computing systems and tools.*

KEYWORDS

graph neural networks, information pathway, information diffusion

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1 INTRODUCTION

Background. Social media users form communities based on their interests, beliefs, ethnicity, and geographical location [51, 54]. These communities are prevalent on popular social platforms such as Reddit, WhatsApp, and Telegram, enabling users to connect with like-minded individuals as well as consume and disseminate information in an interactive manner. As communities grow in size, they become hubs of information flow, facilitating the exchange of information across communities. Existing research has shown that online communities interact with and influence one another [14, 33, 36, 70, 74].

As information spreads from one community to the other, it can rapidly reach all members in the new community. While individual posts and hyperlinks may propagate in varying patterns, the underlying pathways on which information propagates remain relatively stable [18, 59]. Their stability is partially due to the behavior of common users who repeatedly spread information among the same communities, creating a reinforcing effect of the underlying information pathways.

The fast-paced evolution of social media has accelerated the spread of information, including a variety of content types ranging from news articles, commercial advertisements, to harmful content such as online rumors, fake news, hate speech, and political bias [65, 66, 80]. The unmoderated spread of these contents can cause adverse social impacts. For example, the COVID-19 pandemic has led to the formation and growth of multiple online communities, such as subreddits r/CoronavirusUS, r/COVID-19Positive, and r/COVID19, where users discuss various topics related to the pandemic. These communities are inter-connected, with similar topics and user groups, thus having a significant influence on each other. Sometimes misinformation proliferates in online communities, such as the unfounded claim that 5G technology can spread the virus [1, 69]. Despite a lack of scientific evidence, this conspiracy theory gained traction in several online communities, including r/conspiracy, r/5G, r/CoronavirusUS, and r/COVID19, causing unwarranted fear and concern among the public.

The Community-Level Information Pathway Prediction (CLIPP) problem seeks to predict the transmission trajectory of information among online communities. CLIPP is of significant importance as it enables prediction of communities where information, including problematic content, is likely to emerge and spread. Such capability can provide numerous benefits across a wide range of applications. Efficient prediction of misinformation spread with CLIPP can guide intervention strategies, while for advertising, CLIPP can refine strategies and maximize the efficacy of marketing campaigns, increasing the visibility of information and providing insights into the communities where their target audience is most active.

Challenges. Solving CLIPP is challenging. First, community-to-community influence is usually unknown [18, 61], and the mechanisms of interactions between communities and how they impact users remains hidden [36]. Different communities may have different norms, values, and communication patterns that influence the temporal patterns of information diffusion [84]. In this case, we only observe where new content is propagated to the new communities and when it takes place. The underlying community influence, *i.e.*, who influences the propagation, remains unknown. Most existing works focus on predicting information diffusion at the user level (*i.e.*, microscopic influence) [39, 59, 81]. Meanwhile, existing datasets [48, 49, 72, 93] only contain limited information about community structures, making it difficult to study cross-community information spread.

Second, the spread of information is characterized by a complex and dynamic diffusion environment [45]. Posts contain multi-modal

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Table 1: Examples of cross-community information flow in our datasets. A video is usually shared on a set of semantically similar subreddits. "→" indicates the temporal order of the sharing.

Title of the Video	Subreddits on Which the Video Appears
Canadian Trudeau Investigation	Liberate_Canada → conspiracy → TheNewRight → PeoplesPartyofCanada → Canada_First
Reviews: Super Dragon Ball Heroes Episode 19	promote → AnimeReviews → anime_manga → YouTubeAnimeCommunity → Anime_and_Manga
Warcraft 3 Reforged Cutscene Only	WC3 → pcgaming → warcraft3 → gaming → legaladviceofftopic
Practical Greeting Phrases for Chinese New Year	learnchinese → learnmandarin → learnmandarinchinese
Accepting what is. (Realize Instant Freedom)	AnxietyDepression → Soulnexus → SpiritualAwakening → Meditation → spirituality → awakened → inspiration
Covid-19 Explained with Data Science	Python → CoronavirusUS → CanadaCoronavirus → CoronaVirus_2019_nCoV → CoronavirusUK
Implement RNN-LSTM for Music Genre Classification	learnmachinelearning → Python → tensorflow → musictheory

signals, such as text, images, and videos [4, 8, 28]. Diffusion patterns vary across content types. For example, misleading news and inflammatory microblogs spread faster and wider than true information [20, 29, 73]. Niche content is only be shared within few narrow-interest communities, while broad-interest content creates far-reaching cascades and reach several disparate communities [58, 74, 75]. Understanding these propagation patterns is essential to accurately predict information spread across communities.

Our Work. In this work, we investigate the dynamics of community-level information flow while jointly addressing the challenges of complex diffusion environment and the continuously evolving information ecosystem.

We choose Reddit as the platform for studying community-level information diffusion since it provides numerous communities, named "subreddits," that are dedicated to specific topics or interests. Towards this goal, we collect two large-scale and multi-modal datasets that enable us to study the community-level diffusion of visual contents for information pathway prediction. Based on that, we identify distinct temporal patterns of information sharing using inter-activity time distribution, infer macroscopic community-to-community influence, and construct novel community influence graphs (CIGs).

We design INPAC, or **In**formation **P**athway **A**cross Online **C**ommunities, a dynamic graph-based method to predict community-level information pathways using CIGs and content's multi-modal information (visual features and channel metadata). INPAC integrates structure, content semantics, and temporal information by utilizing Continuous-Time Dynamic Graphs (CTDGs) to model the time-aware propagation patterns of videos. In INPAC, nodes and edges are continuously introduced to the graph, incorporating both visual features and channel metadata of the content.

Contributions. Our main contributions are as follows:

- **Novel Multi-modal Datasets and Analysis**: We collect two large-scale, multi-modal datasets to study community-level diffusion of visual contents for information pathway prediction. We identify distinct temporal content sharing patterns that are used to infer community-to-community influence graphs.

Table 2: Statistics of our datasets.

	Large	Small
#Videos	183,596	6,802
#Subreddits	57,894	7,319
#Users	291,047	8,752
#Shares	1,323,714	36,118
Density	7.96E-05	6.11E-04
%Cold-start Videos	11.0 %	36.6 %

- **Information Pathway Prediction Framework**: To solve CLIPP, we propose INPAC, a dynamic graph framework based on CIGs that learns from multimodal data and the dynamics of the interactions between users and communities.
- **Experimental Evaluation**: We demonstrate the effectiveness of INPAC framework and its design choices through experiments in various scenarios, *e.g.*, prediction of cold/warm-start videos on communities with various popularity. INPAC reaches performance improvements of up to 19.4% on MRR, 13.6% on NDCG@5, and 6.3% on Rec@5.

Our code is available at Anonymous GitHub[1]. We plan to release all the datasets and code upon the acceptance of this work.

2 DATASET AND PROBLEM

2.1 Dataset Description

In this study, we aim to study the spread of visual content across communities on social media. To this end, we collect massive visual contents on YouTube and long-term community activity on Reddit. The reasons for selecting these two platforms in this study as follows:

- **YouTube** is one of the most widely used video-sharing platforms that contains over 2.56 billion users[2] and provides a venue for users to upload, share, and view videos.

[1] https://anonymous.4open.science/r/KDD2023-F803/
[2] https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/

- **Reddit** is one of the largest social platforms for content creation, rating, and sharing. It allows users to interact in a variety of communities (*i.e.*, subreddits). Reddit is an ideal platform for studying the propagation of online visual contents such as YouTube videos because of its vast and diverse user base as well as its open-source nature and community structures.

As the first step, we collected 54 months of historical Reddit posts from January 2018 to June 2022 via PushShift[3], in which 133,996,300 posts contain URLs. After that, we removed any posts that did not contain valid URLs, resulting in 133,996,300 posts. We retain URLs associated with valid YouTube videos, resulting in 5,723,910 posts and 3,737,191 associated videos. We use python-youtube[4] to retrieve video metadata, including the titles, descriptions, topics, tags, channels, duration, publish time, default languages, and thumbnail images of the YouTube videos, as well as related statistics such as the number of views, likes, and comments of videos. Table 2 shows the statistics of the two datasets we construct. The large dataset covers 54 months of video propagation history from January 2018 to June 2022, while the small dataset covers a 3-month period from January to March 2020. Table 2 reveals that both datasets contain a considerable number of cold-start videos with only one interaction in a subreddit, which reflects the real-world distribution and the challenges associated with information pathway prediction.

2.2 Problem Formulation

We formulate the CLIPP problem as follows: Given a video and a sequence of subreddits in which it has been posted, predict the next community the video will be posted in at a given time. Formally, we define a posting of a video as a video link appearing on a subreddit, either as a standalone post or as part of a longer post. A *posting instance* is represented as a 4-tuple $p_{ij} = (v_i, s_j, u_j, t_j)$, where v_i is a video posted by a user u_j in an online community s_j at time t_j. The *posting sequence* for v_i is defined as a list of posting instances $P_i = \{(v_i, s_j, u_j, t_j)\}_{j=1}^{N}$, which indicates the dissemination trajectory with length N across communities for the video v_i. Then, our problem can be defined as follows:

> **Problem 1 (Information Pathway Prediction).** *Given a video v_i, its posting sequence $P_i = \{(v_i, s_j, u_j, t_j)\}_{j=1}^{N}$ with length N, and a target timestamp $t_{j'}$, our model outputs a ranked list of communities $\{s_k\}$ indicating the most likely communities that v_i will appear at time $t_{j'}$.*

Table 3 summarizes a list of notations used in this paper.

3 THE PROPOSED FRAMEWORK: INPAC

3.1 Overview

In this work, we aim to study the propagation of online visual content on social media. To this end, we propose a dynamic graph framework INPAC based on Community Influence Graphs (CIGs) that learns the dynamics of cross-community information flow and accurately predicts information pathways. As shown in Figure 1, INPAC consists of three key modules: (1) community influence modeling; (2) video content modeling; and (3) dynamic modeling.

[3] https://pushshift.io/

[4] https://github.com/sns-sdks/python-youtube.git

Table 3: Notations used in this paper.

Notation	Description
V, S	Set of videos and communities
v_i, s_j, u_k	Video, community, user
S^u	Historical interaction sequence for user u
P_i	Posting sequence of video v_i
$\mathcal{G}_i^S$	Community-community influence graph for v_i
$\mathcal{G}^D$	Dynamic graph
n	Maximum sequence length
e_{jk}	Edge weights
α	Teleport probability for APPNP
λ_1, λ_2	Hyperparameters
$\Delta_t^{\text{Same}}, \Delta_t^{\text{Diff}}$	Time intervals for same / different users
$f_\theta(\cdot, \cdot)$	Message function for dynamic modeling

3.2 Community Influence Modeling

Given a community (*e.g.*, a subreddit), INPAC learns its embedding such that the embedding preserves its influence on other communities during information propagation. We infer the influence relationships between communities using content sharing patterns in those communities. Specifically, a video is usually shared in communities that have similar topics. For example, in Table 1, the video "Practical Greeting Phrases for Chinese New Year" is shared within a set of subreddits related to language learning, such as `r/learnchinese` and `r/learnmandarin`. To model this, we create a novel influence network by leveraging the video's temporal interaction patterns.

Influence Graph Construction. In the context of CLIPP, community-level influence is defined as the presence of causal relationships between posting of a video in two different communities. This can happen when two communities share a common group of users. To infer the influence exerted by one community on another, we employ a sequence of communities $\{s_1, s_2, \ldots\}$, in which a video v_i is posted.

Assuming that users require a certain amount of time to engage in online content, the interval between the appearance of a video v_i in two communities s_1 and s_2 serves as an indicator of the influence of s_1 on the appearance of the video in s_2. If a video is shared by two users within a very short time interval, it suggests that the shares occur simultaneously and are not influenced by one another. Based on this assumption, we model a posting sequence P_i of v_i among communities as a directed graph $\mathcal{G}_i^S$ consisting of community nodes s_j involved in the propagation of a video v_i.

To model the propagation sequence of a video, we first identify its concurrent sharing events, where the propagation of the video takes place within a brief time period, referred to as a session, in the same or different communities. To this end, one needs to decide whether two shares are within the same session. A straightforward approach is to set a threshold time limit, such as one hour or one day, as is common in session-based recommender systems [7, 19, 43, 47, 83]

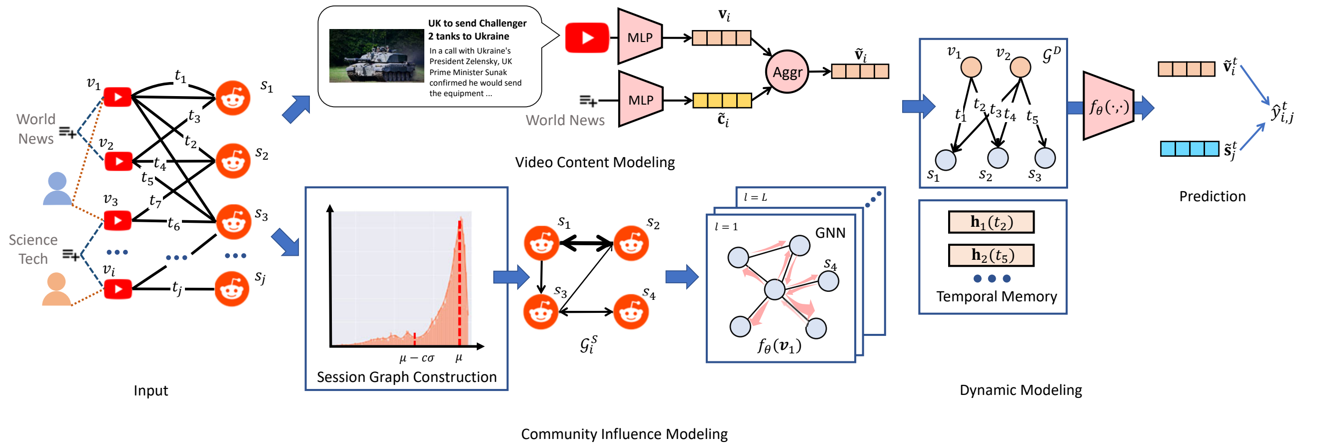

Figure 1: The overview of our proposed INPAC framework, which consists of static modeling, including video content and community influence modeling, as well as dynamic modeling.

However, this ad-hoc use of the time limit is insufficient as it can vary across datasets, videos, and platforms [27, 53, 63].

We note that consecutive sharing of a video can occur due to the same user or different users, resulting in differing sharing patterns and motivations. Therefore, we create two distributions of time difference between consecutive shares of each video v_i: (1) Δt^{Same}, representing the time intervals between consecutive shares of v_i by the *same user*; (2) Δt^{Diff}, representing the time intervals between the first share of v_i by *different users*. Figure 2 illustrates an example of a video's consecutive sharing on several communities over time by three users. From Figure 2, we can observe how the two time intervals $\Delta t_1^{\text{same}}, \Delta t_2^{\text{same}}$ for the same user u_1 as well as the two intervals $\Delta t_1^{\text{diff}}, \Delta t_2^{\text{diff}}$ for different users u_1, u_2, u_3 are computed.

For Δt^{Same}, it is important to consider that a user's multiple postings of the same video in different communities should not be viewed as one community influencing another. This is because users usually post the same content in various venues to enhance its visibility and attract more "likes" [15, 30, 87]. This is not indicative of natural flow of content from one community to another.

Thus, we only utilize Δt^{Diff} to identify community-level influence. Specifically, we plot the distribution of Δt^{Diff} across sharing events of all videos, as shown in Figure 3, where the x-axis represents the time interval in seconds with a logarithmic scale of base 10, and the y-axis indicates the percentage. Then, we fit a Gaussian distribution to Δt^{Diff} and found that the distribution has a mean of 6.844 and a standard deviation of 0.823 on the logarithmic scale. Based on this finding, we determine the cutoff time for partitioning sessions using $\Delta t^{\text{Thres}} = \mu - c\sigma$, where c is a hyperparameter that represents the confidence level for determining concurrent shares. When the time difference between two postings exceeds Δt^{Thres}, the later posting is considered to be influenced by the former.

Now, we construct the community influence graph (CIG) $\mathcal{G}_i^S$ with respect to v_i based on the threshold Δt^{Thres}. Each node in $\mathcal{G}_i^S$ indicates a community s_j and a directed edge from s_j to s_k indicates s_k is influenced by s_j. Specifically, if two shares of v_i from different users occur within Δt^{Thres}, they are considered concurrent postings

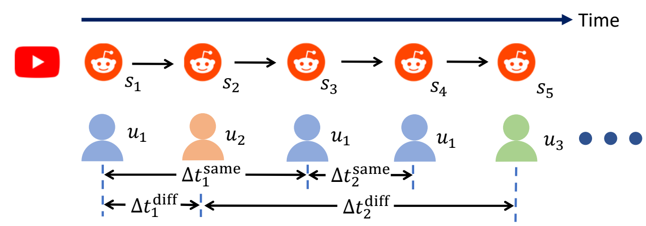

Figure 2: Illustration of how Δt^{Same} and Δt^{Diff} are calculated.

in the same session and not influenced by each other. Otherwise, a directed edge is added from s_j to s_k for $t_j < t_k$ in $\mathcal{G}_i^S$. Furthermore, when v_i is simultaneously shared by the same user in two different communities s_j and s_k, a bi-directional edge is added between these communities to reflect their mutual influence as a result of overlapping users.

Message Aggregation. After the construction of $\mathcal{G}_i^S$, the graph is transformed from a multigraph to a weighted graph by merging multiple edges with the same source and destination nodes. Let $\mathcal{E}_{jk}$ denote the set of edges between s_j and s_k. The new edge weight e_{jk} is calculated using the logarithmic value

$$e_{jk} = \ln(1 + |\mathcal{E}_{jk}|). \tag{1}$$

As $\mathcal{G}_i^S$ consists of a number of periphery nodes, such as inactive online communities with few propagations, long-range dependencies should be considered to learn distinct node representation. To this end, we leverage the propagation scheme of APPNP [16] based on the personalized PageRank algorithm [2]. APPNP adds a probability of teleporting back to the root node, which ensures that the PageRank score encodes the local neighborhood for every node and mitigates the oversmoothing issues.

Then, we obtain the embedding matrix $\mathrm{S}_i^{(l)}$ at layer l for communities involved in the i-th propagation sequence P_i:

$$\mathrm{S}_i^{(l)} = (1-\alpha)\hat{\mathrm{D}}_i^{-1/2}\hat{\mathrm{A}}_i\hat{\mathrm{D}}_i^{-1/2}\mathrm{S}_i^{(l-1)} + \alpha\mathrm{S}_i^{(0)}, \tag{2}$$

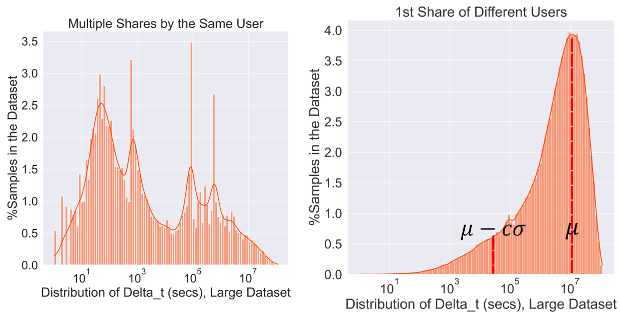

Figure 3: Distribution of $\Delta t^{\mathbf{Same}}$ (Left) and $\Delta t^{\mathbf{Diff}}$ (Right) for videos on the Large dataset.

where $\mathrm{S}_i^{(0)} = [\mathbf{s}_1 || \dots || \mathbf{s}_{|\mathcal{G}_i^S|}]$ is the initial embedding matrix for all $s_i \in \mathcal{G}_i^S$. $\hat{\mathbf{A}}_i$ and $\hat{\mathbf{D}}_i$ are the adjacency matrix and the diagonal degree matrix, respectively. $\alpha \in [0, 1)$ is the teleport probability.

During training, we derive a probability distribution over all communities $\mathbb{P}(s_{N+1}|v_i, \mathcal{G}_i^S)$, which indicates the most likely community for the next share of v_i. This requires both the current status of the sharing and the global information about $\mathcal{G}_i^S$. The current status can be represented using the latest posting event encoded in $\mathbf{s}_{|\mathcal{G}_i^S|}$. For global information, we leverage soft-attention to derive β_i, the importance of each community in the posting sequence

$$\beta_i = \mathbf{w}_1^\top \sigma \left(\text{Linear} \left(\mathbf{s}_{|\mathcal{G}_i^S|} \right) + \left(\text{Linear} \left(\mathbf{s}_i \right) \right) \right), \tag{3}$$

where $\mathbf{w}_1 \in \mathbb{R}^d$ is trainable parameter. $\sigma(\cdot)$ is the sigmoid activation function.

Finally, we compute the probability by taking linear transformation over the concatenation:

$$\mathbb{P}(s_{N+1}|v_i, \mathcal{G}_i^S) = \text{Softmax}(\text{MLP}(\left[\mathbf{s}_{|\mathcal{G}_i^S|} || \sum_{i=1}^{n} \beta_i \mathbf{s}_i \right]) \mathrm{S}_i), \tag{4}$$

where $||$ is the concatenation operand. $\mathrm{S}_i = \left[\mathbf{s}_1 || \mathbf{s}_2 || \dots || \mathbf{s}_{|\mathcal{G}_i^S|} \right]$ is the concatenation of all community embeddings in the sessions.

3.3 Video Content Modeling

Given a video, INPAC encodes its visual content into a low-dimensional feature vector. The content modeling component of INPAC can utilize a diverse range of encoders. Here, we note that online visual content is highly diverse in terms of topics, languages, and subject matter. Therefore, the titles, descriptions, and metadata of these videos such as channel information, can provide valuable insights into their content. These additional data sources can be leveraged to better categorize and understand the content of videos. We thus utilize the titles, descriptions, and channel information as the static features for each video. Specifically, inspired by the success of pre-trained language models in natural language understanding [9, 46], we encode the title and descriptions of each video v_i into a feature vector $\mathbf{v}_i \in \mathbb{R}^D$ based on a multilingual version of MiniLM [76]. Similarly, we encode each video's channel $c_{\rho(i)}$ into a feature vector $\mathbf{c}_{\rho(i)}$, where $\rho(\cdot) : V \rightarrow C$ maps each video to the channel that posts v_i. Then, the two feature vectors are aggregated into a joint representation

$$\tilde{\mathbf{v}}_i = \text{Aggr}(\mathbf{v}_i, \mathbf{c}_{\rho(i)}). \tag{5}$$

Here, a wide variety of aggregation schemes can be applied, including addition, concatenation, and element-wise multiplication, to obtain the joint representation. In Section 4.3, we investigate the impact of using different aggregation schemes for $\mathbf{v}_i$ and $\mathbf{c}_{\rho(i)}$.

3.4 Dynamic Modeling

In the dynamic modeling component, INPAC models the temporal variability of each video's propagation on communities, obtaining temporal embedding of videos and communities. Here, we note that a video can be shared multiple times within a short amount of time [42]. Inspired by continuous-time dynamic graph (CTDG) [62], we design a dynamic modeling module to provide a robust representation of the video sharing process and better handles the bursty nature of information sharing.

First, we leverage temporal graph network (TGN) [62] and represent our dynamic network as a pair $(\mathcal{G}_0^D, E)$ where $\mathcal{G}_0^D$ is the initial state of the dynamic network represented as a static graph. E is a set of graph events with timestamps. In INPAC, we consider two types of graph events, including node additions (*i.e.*, the emergence of new videos and communities) and edge additions (*i.e.*, a video is posted in an online community).

Input Encoding. The input embeddings $\mathbf{x}_i(t)$ and $\mathbf{x}_j(t)$ are raw feature representations for each video v_i and community s_j, respectively. We leverage the embeddings derived from Section 3.2-3.3 as the raw node embeddings. Namely, $\mathbf{x}_i(t) = \tilde{\mathbf{v}}_i$ for video v_i and $\mathbf{x}_j(t) = \mathbf{s}_j^{(L)}$ for community s_j, where $\mathbf{s}_j^{(L)}$ is the representation of s_j at the final layer in Equation 2.

Time Encoding. Similar to [62, 67, 85], the time encoding function $\phi(\cdot) : \mathbb{R} \rightarrow \mathbb{R}^d$ maps a continuous timestamp to the d-dimensional vector space:

$$\phi(t) = \cos \left(t\mathbf{w}_2 + \mathbf{b}_1 \right), \tag{6}$$

where $\mathbf{w}_2, \mathbf{b}_1 \in \mathbb{R}^d$ are learnable parameters.

Temporal Memory. As in [62], to track the propagation state for each node, v_i or s_j, at any timestamp, there exists a memory vector, $\mathbf{h}_i(t)$ or $\mathbf{h}_j(t)$, to store history interactive memory in a compressed format. The memory of each node is initialized to zero and updated after each graph event. Given a node addition event of v_i, v_i's message $\mathbf{m}_i^{node}(t)$ at time t is computed as the concatenation of i's raw features and memory:

$$\mathbf{m}_i^{node}(t) = \text{MLP} \left(\left[\mathbf{h}_i(t') || \mathbf{x}_i(t) || \phi(t) \right] \right), \tag{7}$$

where $\mathbf{h}_i(t')$ is v_i's memory from time t', *i.e.*, the time of the previous interaction involving v_i. In the same manner, we obtain each community s_j's message $\mathbf{m}_j(t)$ at t given s_j's event.

For an edge addition event involving v_i and s_j, the edge's message $\mathbf{m}_i^{edge}(t)$ with respect to v_i at t is computed as:

$$\mathbf{m}_i^{edge}(t) = \text{MLP} \left(\left[\mathbf{h}_i(t') || \mathbf{h}_j(t') || \mathbf{x}_i(t) || \mathbf{x}_j(t) || \phi(t) \right] \right). \tag{8}$$

Similarly, we can obtain the edge's message $\mathbf{m}_j^{edge}(t)$ with respect to s_j at t.

During batch training, multiple events in the same batch can be associated with the same nodes. Therefore, we aggregate multiple messages of video v_i and community s_j from t_1 to t_B through mean pooling, thus obtaining $\overline{\mathbf{m}}_i(t)$ and $\overline{\mathbf{m}}_j(t)$ as in [62].

Based on these messages, the memory embeddings of v_i and s_j are updated upon each event involving v_i and s_j, respectively:

$$\mathbf{h}_i(t) = \text{GRU}\left(\overline{\mathbf{m}}_i(t), \mathbf{h}_i(t')\right), \tag{9}$$

$$\mathbf{h}_j(t) = \text{GRU}\left(\overline{\mathbf{m}}_j(t), \mathbf{h}_j(t')\right). \tag{10}$$

During prediction, we pass the representation $\mathbf{h}_i(t), \mathbf{h}_j(t)$ through multiple GNN layers to aggregate the features of each node from its neighbors on G^D

$$\tilde{\mathbf{v}}_i^t = f_\theta(\mathbf{h}_i(t), \mathcal{G}^D), \quad \tilde{\mathbf{s}}_j^t = f_\theta(\mathbf{h}_j(t), \mathcal{G}^D), \tag{11}$$

where $\tilde{\mathbf{v}}_i^t, \tilde{\mathbf{s}}_j^t$ are the transformed representation of v_i, s_j. The aggregation function $f_\theta(\cdot,\cdot)$ can be chosen from a wide range of GNN operators, such as GCN [35], GraphSAGE [21], TransformerConv [64], and GIN [86]. In practice, we employ a 2-layer Graph Attention Network (GAT) [71].

3.5 Training

We employ element-wise multiplication to calculate the score between each video v_i and each community s_j at time t:

$$\hat{y}_{ij}^t = \text{MLP}(\tilde{\mathbf{v}}_i^t \odot \text{MLP}(\tilde{\mathbf{s}}_j^t)), \tag{12}$$

where $\hat{y}_{ij}^t$ is the predicted score between v_i and s_j. We train our model using the Bayesian Personalized Ranking (BPR) [60] loss, which encourages the prediction of an observed interaction to be greater than an unobserved one:

$$\mathcal{L}_{\text{BPR}} = \sum_{(i,j^+,j^-,t)} -\ln(\text{sigmoid}(\hat{y}_{ij^+}^t - \hat{y}_{ij^-}^t)), \tag{13}$$

where (i, j^+, j^-, t) denotes an example in the pairwise training data. j^+ indicates that one sharing of v_i is observed in community s_{j^+}, and j^- indicates an unobserved one.

Furthermore, for the training of the community influence graph, we use the next item prediction objective. Given each $\mathcal{G}_i^S$, the loss function $\mathcal{L}_{\text{CE}}^i$ is defined as the cross-entropy of the predicted and ground-truth community that will propagate v_i at the next timestamp:

$$\mathcal{L}_{\text{CE}}^i = \text{CrossEntropy}(\mathbb{P}(s_{N+1}|v_i, P_i), \mathbf{y}_{N+1}), \tag{14}$$

where $\mathbf{y}_{N+1} \in \mathbb{R}^{|\mathcal{S}|}$ is a one-hot vector that encodes the ground-truth community interacted at the next timestamp.

The overall optimization objective is defined as follows:

$$\mathcal{L} = \mathcal{L}_{\text{BPR}} + \lambda_1 \sum_{i \in \mathcal{V}} \mathcal{L}_{\text{CE}}^i + \lambda_2 \|\Theta\|_2, \tag{15}$$

where Θ denotes all trainable model parameters. λ_1 and λ_2 are hyperparameters in INPAC.

4 EVALUATION

In this section, we conduct experiments to answer the following evaluation questions (EQs):

- **(EQ1)** Does INPAC outperform the baseline models for the task of community-level information pathway prediction (Section 4.2.1)?
- **(EQ2)** Does INPAC provide excellent inductive reasoning for cold-start videos (Section 4.2.2)?
- **(EQ3)** What is the contribution of each component in INPAC (Section 4.3)?
- **(EQ4)** Do community influence graphs (CIGs) constructed by INPAC manifest macroscopic influences (Section 4.4)?

4.1 Experimental Setup

4.1.1 Datasets. We construct two multi-modal datasets that provide the diffusion of YouTube videos on Reddit. Details can be found in Section 2.1. Table 2 provides an overview of their statistics. To partition the datasets into train/validation/test sets, we used a 70/15/15 ratio based on the timestamps in a sequential manner. To ensure validity, we constructed the community influence graphs (CIGs) exclusively using the interactions from the training set to prevent any potential information leakage.

4.1.2 Baselines. To evaluate the effectiveness of INPAC, we compare INPAC with seven baselines. We categorize them into four folds: (1) *Matrix Factorization*, including MF [60]; (2) *Graph-based Recommendation*, including NGCF [77], LightGCN [23], and SVD-GCN [57]; (3) *Sequential Recommendation*, including TiSASRec [44]; (4) *Representation Learning on Temporal Graphs*, including TGAT [85], and TGN [62].

4.1.3 Metrics. We measure the models' performances using three widely adopted metrics in the field of ranking systems: (1) recall@K, which measures the proportion of relevant items (*i.e.*, ground truth) that are retrieved among the top-K items; (2) normalized discounted cumulative gain (NDCG)@K, which evaluates the ranking quality of the top-K items, with a score of 1 assigned to the ideal ranking; (3) mean reciprocal rank (MRR), which computes the average reciprocal rank of the top-ranked relevant item. In this paper, we set K to 5 and 10. Our evaluation procedure follows the established method [12, 24, 44] by randomly selecting 100 communities with no observed propagations of the video and ranking the test item among the 100 items. Additionally, we exclude any existing interactions in the training set from the test set.

4.1.4 Implementation Details. We implemented INPAC in PyTorch [56] and PyG [13]. For a fair comparison, we set the embedding size to 64 in all methods including INPAC and perform Xavier initialization [17] on the model parameters. We use Adam optimizer [34] with a batch size of 256. For the baseline models, the hyperparameters are set to the optimal values as reported in the original paper. For all models, we search the learning rate within the range of $[1e-4, 3e-4, 1e-3, 3e-3, 1e-2]$ and select the best setting. We set $\alpha = 0.1$, $c = 3$, $\lambda_1 = 1$, and $\lambda_2 = 1e-3$, respectively. L, the number of GNN layers in Community Influence Modeling (Section 3.2) is set to 4.

4.2 Overall Performances

We conducted comparative experiments on 2 datasets to demonstrate the superiority of INPAC over the 7 baselines. To this end, we grouped the videos into warm-start and cold-start videos, as discussed in Section 4.1.1. We define warm-start videos as videos with $\geq$ 2 postings, and cold-start videos as videos with only one posting. Furthermore, the number of videos posted in communities creates an imbalanced distribution. For instance, in the small dataset, more than 20% of videos were posted on the *two* most

Table 4: Performances of INPAC and 7 competitors for warm-start videos. Values in bold and underline represent the best and 2nd best performance in each column, respectively. "Impr" denotes the performance improvement of INPAC compared to the best baseline.

(a) Large Dataset

	Popular Communities					Non-Popular Communities				
	NDCG@5	Rec@5	NDCG@10	Rec@10	MRR	NDCG@5	Rec@5	NDCG@10	Rec@10	MRR
MF	0.5216	0.7194	0.6002	0.8469	0.4734	0.1346	0.2205	0.1820	0.3595	0.1513
NGCF	0.5291	0.7307	0.5597	0.8477	0.5246	0.1399	0.2213	0.1845	0.3680	0.1581
LightGCN	0.5468	0.7349	0.5675	0.8505	0.5215	0.1537	0.2426	0.1987	0.3832	0.1691
SVD-GCN	0.5677	0.7572	0.6002	0.8514	0.5379	0.1609	0.2539	0.2065	0.3960	0.1739
TiSASRec	0.5696	0.7593	0.6029	0.8534	0.5354	0.1668	0.2586	0.2078	0.3956	0.1770
TGAT	0.5679	0.7603	0.6130	0.8530	0.5354	0.1684	0.2590	0.2121	0.3969	0.1775
TGN	0.5723	0.7604	0.6140	0.8569	0.5576	0.1687	0.2596	0.2138	0.3970	0.1818
INPAC	**0.6013**	**0.7816**	**0.6383**	**0.8793**	**0.5822**	**0.1798**	**0.2741**	**0.2263**	**0.4182**	**0.1923**
Impr	**5.1%**	**2.8%**	**4.0%**	**3.0%**	**4.4%**	**6.6%**	**5.6%**	**5.9%**	**5.3%**	**5.8%**

(b) Small Dataset

	Popular Communities					Non-Popular Communities				
	NDCG@5	Rec@5	NDCG@10	Rec@10	MRR	NDCG@5	Rec@5	NDCG@10	Rec@10	MRR
MF	0.3594	0.5211	0.4017	0.6585	0.3356	0.0764	0.1203	0.0991	0.1958	0.0803
NGCF	0.3641	0.5282	0.4100	0.6620	0.3411	0.0807	0.1250	0.1000	0.1816	0.0887
LightGCN	0.3789	0.5493	0.4167	0.6796	0.3448	0.0852	0.1321	0.1172	0.2241	0.0967
SVD-GCN	0.3893	0.5634	0.4235	0.6839	0.3621	0.0947	0.1415	0.1204	0.2311	0.1011
TiSASRec	0.3907	0.5617	0.4287	0.6840	0.3642	0.0948	0.1439	0.1233	0.2335	0.1061
TGAT	0.3922	0.5669	0.4276	0.6845	0.3676	0.0953	0.1445	0.1256	0.2321	0.1095
TGN	0.4037	0.5728	0.4324	0.6849	0.3753	0.0981	0.1462	0.1302	0.2358	0.1156
INPAC	**0.4377**	**0.6092**	**0.4613**	**0.7031**	**0.4026**	**0.1115**	**0.1533**	**0.1428**	**0.2524**	**0.1380**
Impr.	**8.4%**	**6.3%**	**6.7%**	**2.7%**	**7.3%**	**13.6%**	**4.8%**	**9.7%**	**7.0%**	**19.4%**

popular subreddits. Since it can be easier to make predictions for such popular subreddits, we split subreddits into popular (top 25 percentile subreddits where YouTube videos are posted most frequently) and non-popular (the rest of the subreddits). The results are partitioned with respect to whether the target community is a popular subreddit or a non-popular subreddit.

4.2.1 Warm-Start Prediction. Tables 4(a)-(b) show the results for warm-start prediction on the large and small datasets, respectively. We observe that INPAC consistently and significantly outperforms all baselines on both datasets for both groups of subreddits. On the large dataset, INPAC outperforms the best baseline by 5.1% on NDCG@5 and 4.4% on MRR for the popular communities, as well as 6.6% on NDCG@5 and 5.8% on MRR for non-popular communities, respectively. On the small dataset, INPAC outperforms the best competitor by 8.4% and 7.3% on the two metrics for popular communities, and 13.6% and 19.4% for popular communities, respectively. Our results demonstrate the effectiveness of INPAC in the task of CLIPP. Moreover, we observe that representation learning methods on temporal graphs (*i.e.*, TGAT and TGN) outperform all other baselines. This observation underscores the importance of considering temporal information in predicting information pathways.

4.2.2 Cold-Start Prediction. As the content sharing network evolves, the emergence and spread of new content to a diverse range of communities presents considerable challenges for CLIPP, particularly in cold-start scenarios where historical propagation of videos is absent. Thus, the prediction problem becomes: *given a video that has only 1 propagation, how can we predict its second propagation?* Tables 5(a)-(b) show the performances of seven baselines and INPAC for the large and small datasets, respectively. We observe that INPAC is able to achieve even greater performance improvements in the cold-start scenario through its inductive reasoning capability, consistently outperforming all competitors on both datasets for both groups of subreddits. Moreover, from Tables 5(a) and (b), we observed that when the cold-start videos are propagated to popular communities, predicting these flows is relatively straightforward for all the models, including INPAC. On the other hand, the results in Tables 5-(a) and (b) show that predicting the flow of cold-start videos to less popular communities is a more challenging task. Despite this, INPAC still shows the best performance. These results encourage further investigation into such flows, which we consider to be a potential area of future work.

4.3 Ablation Studies

In this section, we validate the effectiveness of the design choices in INPAC: (1) aggregation schemes; (2) community influence graphs.

Aggregation Schemes. In Section 3.3, we aggregated two feature vectors, *i.e.*, video and channel, to obtain the embeddings of videos. To compare the impact of using different aggregation schemes, we

Table 5: Performances of INPAC and 7 competitors for cold-start videos.

(a) Large Dataset

	Popular Communities					Non-Popular Communities				
	NDCG@5	Rec@5	NDCG@10	Rec@10	MRR	NDCG@5	Rec@5	NDCG@10	Rec@10	MRR
MF	0.5291	0.7361	0.5669	0.8411	0.4824	0.1069	0.1593	0.1390	0.2600	0.1245
NGCF	0.5632	0.7485	0.5862	0.8380	0.5118	0.1371	0.2285	0.1834	0.3732	0.1508
LightGCN	0.5768	0.7534	0.6005	0.8373	0.5247	0.1426	0.2515	0.1942	0.3926	0.1576
SVD-GCN	0.5808	0.7633	0.6033	0.8398	0.5344	0.1484	0.2532	0.1944	0.3972	0.1696
TiSASRec	0.5853	0.7604	0.6023	0.8380	0.5326	0.1516	0.2538	0.1990	0.3973	0.1705
TGAT	0.5896	0.7638	0.6104	0.8435	0.5497	0.1586	0.2549	0.2067	0.4009	0.1760
TGN	0.5872	0.7636	0.6102	0.8404	0.5452	0.1623	0.2552	0.2080	0.4019	0.1732
INPAC	**0.6174**	**0.7855**	**0.6397**	**0.8677**	**0.5776**	**0.1764**	**0.2705**	**0.2205**	**0.4238**	**0.1873**
Impr.	**4.7%**	**2.8%**	**4.8%**	**2.9%**	**5.1%**	**8.6%**	**6.0%**	**6.0%**	**5.5%**	**6.4%**

(b) Small Dataset

	Popular Communities					Non-Popular Communities				
	NDCG@5	Rec@5	NDCG@10	Rec@10	MRR	NDCG@5	Rec@5	NDCG@10	Rec@10	MRR
MF	0.3524	0.5785	0.4167	0.8508	0.2922	0.0730	0.1134	0.1077	0.2150	0.0961
NGCF	0.3631	0.5864	0.4332	0.8351	0.3194	0.0816	0.1237	0.1099	0.2320	0.0991
LightGCN	0.3958	0.5890	0.4421	0.8639	0.3221	0.0825	0.1289	0.1107	0.2262	0.0984
SVD-GCN	0.4034	0.6073	0.4515	0.8743	0.3283	0.0800	0.1289	0.1136	0.2268	0.1011
TiSASRec	0.4172	0.6466	0.4682	0.8807	0.3643	0.0849	0.1366	0.1142	0.2320	0.1071
TGAT	0.4244	0.6709	0.4779	0.8814	0.3664	0.0839	0.1392	0.1149	0.2371	0.1073
TGN	0.4273	0.6753	0.4797	0.8831	0.3696	0.0883	0.1443	0.1157	0.2396	0.1094
INPAC	**0.4646**	**0.7155**	**0.5083**	**0.9110**	**0.3847**	**0.1008**	**0.1526**	**0.1272**	**0.2506**	**0.1180**
Impr.	**8.7%**	**5.9%**	**5.9%**	**3.1%**	**4.1%**	**14.2%**	**5.8%**	**10.0%**	**4.6%**	**7.9%**

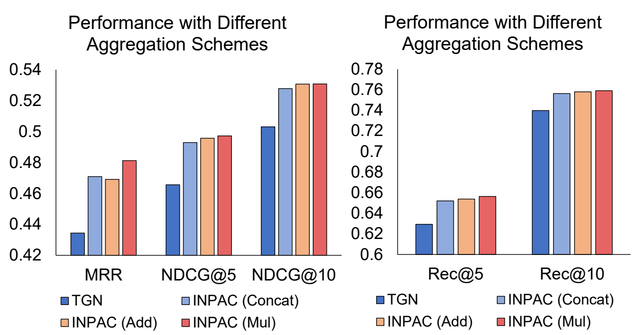

Figure 4: Performances of different aggregation methods for video and channel embeddings on the Large dataset.

made three variants of INPAC, *i.e.*, INPAC (Concat), INPAC (Add), and INPAC (Mul), each of which uses concatenation, addition, or multiplication as the aggregation schemes. Figure 4 shows the results, where x-axis indicates the metrics and y-axis indicates the performances. From Figure 4, we observe that INPAC (Mul) outperforms other variants of INPAC, with the greatest performance improvement on MRR. The results also demonstrate that all the variants of INPAC outperform the strongest baseline TGN.

Community Influence Graphs (CIGs). In Section 3.2, we designed a way to construct community influence graphs (CIGs) by considering the time that videos were propagated in communities.

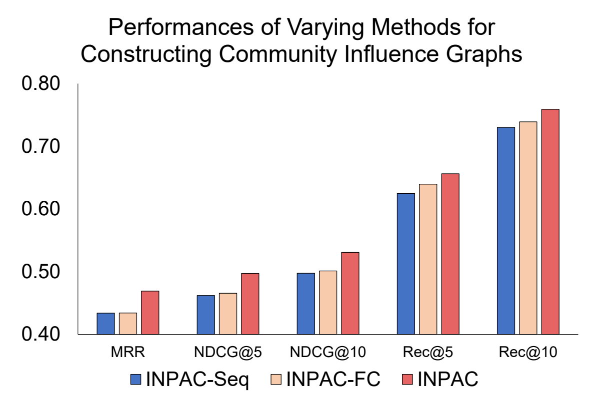

Figure 5: Performances of different methods for constructing the community influence graph on the Small dataset.

To evaluate the effectiveness of our design, we made two variants of INPAC: The first variant, INPAC-Seq, connects the community nodes sequentially, *i.e.*, we create a directed edge from s_j to s_k if they are adjacent in the corresponding propagation sequence P_i. The second variant, INPAC-FC, establishes connections in a fully-connected manner, meaning that an edge is created between s_j and s_k if s_j precedes s_k in P_i. From Figure 5, we observe that INPAC-Seq exhibits the lowest performances. This result can be attributed to the limitations of the sequential connection method, which fails to capture the underlying influencing relationships between communities as manifested by the sharing events. On the other hand, INPAC-FC performs better than INPAC-Seq in terms of Rec@5 and Rec@10. However, the fully-connected method can potentially lead to spurious correlations. Overall, the method employed by INPAC achieves the best performances, demonstrating the effectiveness of our graph construction approach.

4.4 Analysis of CIG

In Figure 6, we visualize the Community Influence Graphs (CIGs) (Section 3.2) for 4 videos that differ in terms of topics. Each video was propagated in exactly 20 communities. The node colors and sizes in the graphs depict the node degrees, while edge colors indicate the edge weights. Our analysis demonstrates that the graphs generated from different videos demonstrate diverse connectivities and structures. For instance, the CIG for the video "How Wildlife Trade is Linked to Coronavirus" (Figure 6(a)) exhibits weaker connectivity. It is worth noting that the 5-clique in the figure comprises five subreddits that are topically similar: r/Vegan, r/VeganActivism, r/PlantBasedDiet, r/AnimalRights, and r/animalwelfare. This implies that the video was initially propagated within one community and was then spread by users to multiple semantically similar communities due to overlapping users. On the other hand, the CIG for the viral music video "ME!" by Taylor Swift (Figure 6-(d)) exhibits strong connectivity and encompasses a more diverse range of subreddits, including r/TaylorSwift and r/WorshipTaylorSwift, as well as more semantically distant communities such as r/french and r/terracehouse. This reveals that the video is likely to have rapidly spread across multiple communities in a short time frame. In conclusion, our proposed CIG effectively captures the semantic similarity and potential influence among the communities, and provides unique insights into the popularity and propagation patterns of each video.

5 RELATED WORKS

5.1 Information Diffusion

Modeling the spread of information in online social networks has been a challenging task. Previous works have investigated information diffusion on social media [11, 18], prediction of popularity [3], social influence [39, 59], and topological analysis of follower networks [38, 68] for information sharing. While these studies cover a broad spectrum of social interactions in online communities, they generally focus on user-level influence and interactions. Research has shown that the dissemination of information within a community is different from that at the individual level [6, 50, 55, 55, 91]. In this sense, diffusion models have been used to understand the spread of ideas, information and influence on social and information networks [41, 52]. Our study differs from the prior studies in its methodology as it endeavors to delve into the intricacies of community-level interactions.

5.2 Graph Neural Networks

Graph Neural Networks (GNNs) [21, 35, 92] have received increased attention in recent years due to their exceptional capacity to model complex, non-Euclidean graph structures. Recently, GNNs have

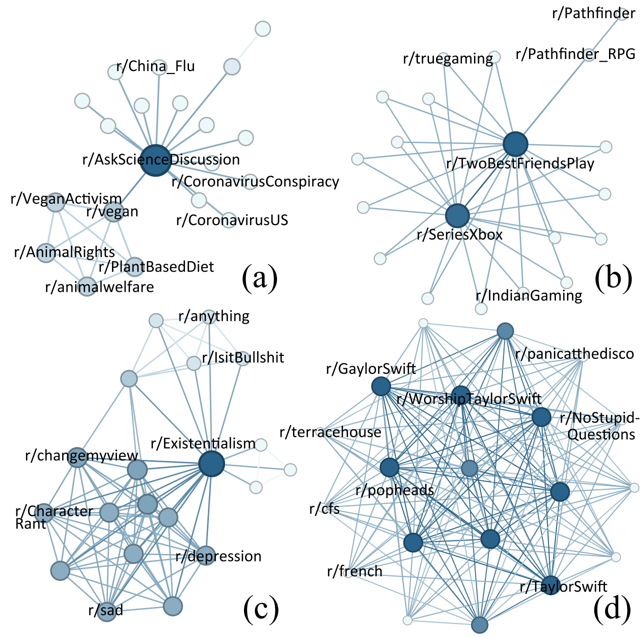

Figure 6: Community Influence Graphs (CIGs) of 4 different videos, all of which were propagated in exactly 20 communities. (a) "How Wildlife Trade is Linked to Coronavirus"; (b) "Black Myth: Wukong - Official 13 Minutes Gameplay Trailer"; (c) Thought experiment "BRAIN IN A VAT"; (d) "Taylor Swift - ME!" Node sizes and colors indicate the node degrees. Edge colors indicate the edge weights.

achieved state-of-the-art performances in various applications, including recommendation [5, 10, 22, 40, 78, 89], user modeling [25, 81], and social influence estimation [39, 59, 90]. These methods typically structure events into interaction graphs and leverage high-order relationships to derive node/edge attributes [26, 31, 57, 82, 88]. Recently, dynamic graph models [32, 37, 79, 85] have emerged as powerful tools for various tasks, such as node classification, link prediction, representation learning, and event forecasting. The problem of CLIPP (Problem 1) can be modeled using dynamic networks in which time-dependent representations of videos and communities are learned to infer future interactions.

6 DISCUSSION AND CONCLUSION

Inference of community-to-community influence pathways can provide important information about the structure and dynamics of online platforms and the resulting information flow in the platform. This work created and utilized this influence graph in a dynamic graph framework INPAC to predict the flow of YouTube videos across Reddit communities (subreddits). Some shortcomings of this work include: (i) studying only YouTube-Reddit data and (ii) difficulty in the validation of the inferred influence graph. Future work includes alternate approaches to generate and validate influence graphs, creation of new dynamic graph models to predict information flow, and using multi-platform data.

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A APPENDIX

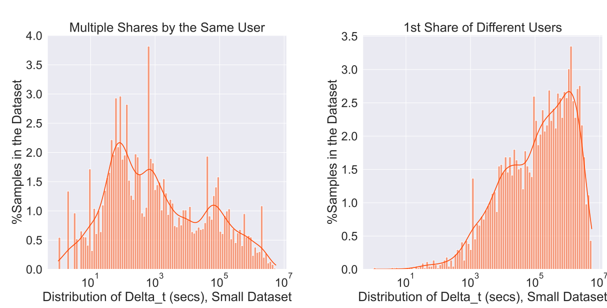

Figure 7: Distribution of Δt^{Same} (Left) and Δt^{Diff} (Right) for videos on the Small dataset.

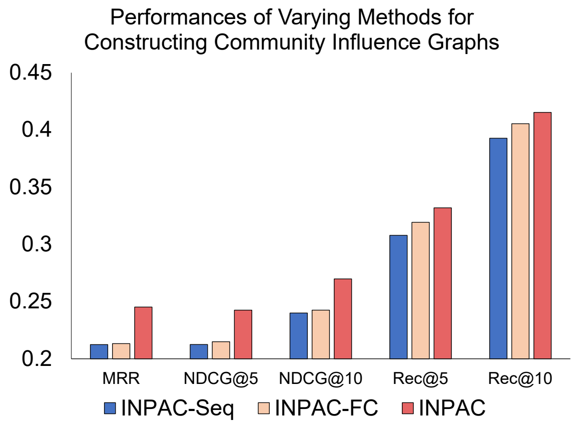

Figure 8: Performances of different methods for constructing the community influence graph on the Small dataset.