IM-META: Influence Maximization Using Node Metadata in Networks With Unknown Topology

Cong Tran, Won-Yong Shin, Senior Member, IEEE, and Andreas Spitz

Abstract—Since the structure of complex networks is often unknown, we may identify the most influential seed nodes by exploring only a part of the underlying network, given a small budget for node queries. We propose IM-META, a solution to influence maximization (IM) in networks with unknown topology by retrieving information from queries and node metadata. Since using such metadata is not without risk due to the noisy nature of metadata and uncertainties in connectivity inference, we formulate a new IM problem that aims to find both seed nodes and queried nodes. In IM-META, we develop an effective method that iteratively performs three steps: 1) we learn the relationship between collected metadata and edges via a Siamese neural network, 2) we select a number of inferred confident edges to construct a reinforced graph, and 3) we identify the next node to query by maximizing the inferred influence spread using our topology-aware ranking strategy. Through experimental evaluation of IM-META on four real-world datasets, we demonstrate a) the speed of network exploration via node queries, b) the effectiveness of each module, c) the superiority over benchmark methods, d) the robustness to more difficult settings, e) the hyperparameter sensitivity, and f) the scalability.

Index Terms—Influence maximization, network inference, node metadata, node query, Siamese neural network, topologically unknown network.

A. Background and Motivation

SOCIAL networks that encode the relationships and interactions of individuals play a vital role as a medium for facilitating the sharing of ideas, thoughts, and information through the building of virtual networks and communities. Well-known applications of such social networks include viral marketing—for example, a company would like to hire the most influential opinion leaders to advertise a new product. To this end, the so-called influence maximization (IM) problem that aims at identifying a set of seed nodes, leading to the maximum influence spread under given influence diffusion models, was introduced as a formalization [1]. In addition to (viral) marketing in social networks, efficient solutions to the IM problem stand to benefit applications in numerous domains such as microfinance [2] and healthcare [3].

In the original formulation of the IM problem, the topological structure of the underlying network in question is assumed to be fully known [1]. In practice and despite the growing popularity of studies on IM, however, this assumption tends to be overly simplistic as the underlying network cannot be fully observed in many real-world applications of network analyses [4], [5]. Although one could, in principle, invest further efforts into uncovering the complete network prior to the application of existing IM algorithms, the accumulation of a complete network structure is often prohibitively expensive, labor-intensive, or entirely impractical [4]. Even with the increasing availability of (social) network data from social media platforms, this source of information is not without limitations, not least due to privacy concerns [6]. Consequently, when working with graph data, one should assume that none or only a part of the network structure is available in practice [7], [8], [9], [10].

When confronted with the need to perform IM on networks that have such an unknown or partially known topology, a naturally arising question is therefore how one can identify a set of seed nodes, necessitating the network structure. Recent studies have addressed this question by allowing a small budget for node queries to surgically discover parts of the underlying network, while simultaneously aiming to identify a set of seed nodes from the explored subgraph that is expected to be as influential as the globally optimal seed set [3], [11], [12], [13], [14], [15], [16]. However, node metadata (i.e., node features), which can often be retrieved from various sources such as users’ created content over given (social) networks [17] or even be inferred...
from users’ individual behavior [18], are not fully considered in this problem despite the fact that they are more readily available than the relationship between individuals. Such metadata may then be leveraged to identify relations that are likely to exist. For example, in co-authorship networks, one might take advantage of the keywords in each author’s publications to infer a topical relationship between authors. In the IM problem for HIV awareness in homeless youth [5], metadata such as the individual’s name, age, and familial background among the homeless demographic as well as individuals can be readily gathered due to the mandatory registration process at welfare centers, which is necessitated for the disbursement of monthly allowances. Motivated by the observation that the collection of metadata for nodes is cost-effective, we propose a solution for real-world applications of IM in incomplete (social) network settings where the underlying network $G$ is initially unknown.

B. Main Contributions

In this study, we present IM-META, an end-to-end framework that solves the IM problem in a network $G$ with minimal information about $G$, using node queries aided by node metadata in such attributed networks. To this end, we aim to retrieve information from jointly discovering a sequence of node queries and a set of nodes that maximize the influence spread by formulating an entirely new optimization problem that jointly finds the optimal discovered subgraph and seed set in the sense of maximizing an estimate of the expected influence spread. Naturally, solving this optimization problem poses several practical challenges, namely 1) the difficulty of handling noisy node metadata, 2) the scarcity of training labels due to using a small budget for node queries, and 3) the intractability of jointly identifying two optimal subsets (i.e., the subgraph and the seed nodes) and dynamically updating an estimate of the expected influence spread for every query step. The combination of the first two challenges is particularly difficult since the redundancy of observable yet inherently noisy node features in combination with the small query budget is likely to entail the curse of dimensionality that threatens to degrade the inference accuracy.

To address these challenges, we propose a new design principle with IM-META, which utilizes a two-phase system consisting of a network discovery phase (NDP) and a seed selection phase (SSP). First, network discovery is performed in three iteratively repeated steps. Each iteration starts with the first step, NDP1, in which we infer a set of existence probabilities for yet unexplored edges using both the node metadata and the currently explored subgraph. We utilize a minimally supervised learning architecture that is based on a Siamese neural network model capable of learning the relationship between collected metadata and edge prediction by using the explored small-scale subgraph as training data. By learning embeddings that accurately capture the homophily effect of information diffusion networks (i.e., a node’s tendency to associate with similar other nodes [19]), the Siamese neural network inductively embeds new input data (i.e., unexplored nodes) whose connectivity information to the training data (i.e., explored nodes) is unknown. The learned embedding then acts as a feature extraction module (or a dimensionality reduction module) that captures the latent representation of the collected data. In NDP2, we generate a reinforced weighted graph by combining the edge probabilities inferred in NDP1 with the current explored subgraph. To this end, we select a small number of confident edges based on the intuition that 1) using a large portion of uncertain edges leads to an accumulation of noise in the subsequent steps and phase, and that 2) this edge selection also reduces the computational complexity. In the third step, NDP3, we select one queried node for network discovery. In this step, one of our central contributions is a novel topology-aware ranking strategy for query node selection that balances the degree centrality and the geodesic distance to potential seed nodes. As a result, each node that is selected with this ranking strategy has a high expected influence spread. After the completion of the NDP, we select a set of seed nodes in the SSP, similar to the standard IM problem [1], [20], [21], [22].

Our contributions are four-fold:

- We introduce IM-META, a novel end-to-end framework that solves the IM problem in topologically unknown networks;
- We formalize IM on unknown networks as an optimization problem that aims to find both a set of seed nodes and another set of nodes to query by making use of node metadata;
- We design an effective approach for network discovery that iteratively performs three steps, namely network inference, reinforced weighted graph generation, and query node selection;
- Through extensive experiments on real-world datasets with node features across several domains, we validate (a) the fast subgraph exploration, (b) the achievability of the upper bound performance via querying only 5% of nodes, (c) the effectiveness of Siamese neural network-based network inference and topology-aware ranking-based query node selection modules, (d) the superiority of IM-META over benchmark IM methods, (e) the robustness of our method to incomplete node metadata, and (f) scalability.

To the best of our knowledge, this is the first proposed solution to the IM problem in attributed networks with unknown topology.

C. Organization

The remainder of this paper is organized as follows. In Section II, we present prior studies related to our work. In Section III, we explain the methodology of our study, including the problem formulation and an overview of our IM-META method. Section IV describes technical details of the proposed method and analyzes its computational complexity. Experimental results are shown in Section V. Finally, we provide a summary and concluding remarks in Section VI.

II. RELATED WORK

The method that we proposed in this study is related to the following four broad research lines.

IM in topologically known networks: Kempe et al. [1] originally introduced the problem formulation of IM when the network structure is initially known and proposed a greedy approach to solve it. Besides heuristic solutions scalable to
large-scale networks [26], [27], [28], [29], subsequent studies focused mostly on reducing the computational complexity of greedy algorithms, such as CELF/CELF++ [20], [30], TIM/TIM+ [22], IMM [21], SSA/D-SSA [31], RS [32], and CFDI [33], while providing approximate solutions with performance guarantees.

**IM in topologically unknown networks:** More recently, researchers have paid attention to a more challenging IM problem, in which the structure of the underlying network is initially unknown. Following the concept of active learning for classification [34], [35], dynamic IM over a series of rounds in which information on edges is collected after each round has been studied [23]. To aid the network discovery process, exploratory IM (EIM) methods exploit topological information such as the community structure [13]. Recently, EIM methods tend to rely on complementary data such as a set of similar graphs [14], [15], [16]. However, such data are scarcely available under the topology-unaware setting of many real-world networks. As follow-up studies on EIM, CHANGE [11] utilized the friendship paradox, while DQN [14], CLAIM [15], and RL4IM [16] learned patterns from a set of similar graphs to effectively select a set of query nodes. Another attempt to solve the IM problem in unknown networks involves learning an influence function based on observed cascades [24]. Although some attempts have been made to exploit node metadata [3], [25], they rely on handcrafted metadata, thereby incurring significant annotation efforts by domain experts that lack scalability since such work is infeasible on large network datasets. Moreover, a theoretical analysis on the performance of IM was carried out in settings where a subgraph is retrieved via random node sampling [36], [37]. Table I summarizes the aforementioned IM methods utilizing different types of side information in topologically unknown networks.

**IM in temporal/dynamic networks:** Recently, there have been several studies that explore the IM problem for temporal and dynamic networks with different settings. Assuming that the past and current snapshots of the underlying network are known, the authors attempted to forecast its evolution using non-negative matrix factorization and graph neural networks [38]. In another setting, under the assumption that the network changes over time, it was studied that such changes can be obtained by probing nodes and updating the topology [39]. In a similar probing context, a divide-and-conquer strategy was used in [40] to minimize the variance between the observed topology and the ground truth network across diverse representative communities.

**Link prediction using metadata:** When the network structure is partially observable, a matrix factorization-aided approach [41] was proposed to leverage node features for link prediction. Our study is related to the inductive link prediction problem, the so-called cold-start link prediction, in which no initial topological information is available. To achieve satisfactory prediction performance, deep learning-based techniques such as G2G [42] and DEAL [43] have been proposed, where they use a deep encoder that embeds each node in a given network as Gaussian distributions and aligns both structure and feature embeddings, respectively.

**Discussion:** Despite numerous contributions to IM in unknown networks, our method is the first to exploit the collected node metadata to automatically aid the process of discovering influential seed nodes. Unlike prior studies that perform inductive link prediction in a supervised manner (e.g., graph neural network-based methods), our solution tackles the lack of explored edges that can be used as labels in training when only a small portion of the underlying network is observable via node queries.

### III. IM IN NETWORKS WITH UNKNOWN TOPOLOGY

As a basis for the proposed IM-META method in Section IV, we first describe our network and influence diffusion models with basic assumptions. We then formulate a new problem using these models.

#### A. System Model

1) **Network Model:** Let us denote an underlying network with a-priori unknown topology as $G = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ is the set of $n$ nodes and $\mathcal{E}$ is the set of $m$ edges. We assume $G$ to be an undirected unweighted network without self-loops or repeated edges and to have collectible node metadata (i.e., node features) $\mathcal{X}$ for all $n$ nodes. The metadata in $\mathcal{X}$ associated with each node $v_i \in \mathcal{V}$ are assumed to be given in a vector form of $d$ features, denoted as $x_i \in \mathbb{R}^d$.

Following the definition by Kamarthi et al. [14], an induced subgraph $G_0$ is assumed to be observable at a very early stage. When $G_0$ is not initially available, such a subgraph can be obtained by querying a few nodes at random. To retrieve additional structural information from the underlying network $G$, we are allowed to perform $T$ node queries. Specifically, when we query a single node, we are capable of discovering neighbors of the

| Methods       | Required side information |
|---------------|---------------------------|
| IMUG [23]     | ✓                         |
| ARISEN [13]   | ✓                         |
| NeuGreedy [24]| ✓                         |
| DQN [14], CLAIM [15], RL4IM [16] | ✓ |
| DOSIM [25], HEALER [3]     | ✓ ✓ ✓ ✓ ✓ |
| IM-META       | ✓ ✓ ✓ ✓ ✓ |
We consider two models of results in different network realizations. In our study, based is used as input of the IM process, \( \bar{E} \). Finding a \( v \) in the subgraph \( \bar{V} \) and \( \bar{E} \), given \( v \) is chosen to diffuse the influence. For more, \( \sigma_{t}(\cdot) \) that maps a seed set \( S \subseteq V \) given an uncertain edge \( \{u,v\} \) is present, the so-called edge probability. The subgraph \( G_{t} \) and the set of \( \theta_{uv}(t) \)'s for all uncertain edges are fed into the generator function of a weighted graph, denoted as \( G_{gen}^{(t)} \), having all \( n \) nodes. By integrating the connectivity information of both.

1) Influence Diffusion Model: We consider two models of influence diffusion, namely the independent cascade (IC) and weighted cascade (WC) models [1], [26], [36]. In the IC model, each edge is associated with a uniform diffusion probability. In the WC model, this probability is modulated by the in-degree of the node being influenced.

2) Influence Diffusion Model: We consider two models of influence diffusion, namely the independent cascade (IC) and weighted cascade (WC) models [1], [26], [36]. In the IC model, each edge is associated with a uniform diffusion probability. In the WC model, this probability is modulated by the in-degree of the node being influenced.

B. Problem Formulation

In this subsection, we formulate a new IM problem for attributed networks whose topology is unknown and node features are available. In a given diffusion model, we define a function \( I(S) : 2^{V_{t}} \rightarrow [0,1] \) that maps a seed set \( S \) to the number of influenced nodes in the underlying graph \( G \) at the end of the diffusion process, which is a random variable since the same set \( S \) results in different network realizations. In our study, based on the concept of active learning [34], we aim to maximize the expected influence spread \( \sigma(S) = E(I(S)) \) by jointly finding a sequence of queries \( \{v_{0}, v_{1}, \ldots, v_{T-1}\} \) that leads to the finally discovered subgraph \( G_{T} \), as well as a seed set \( S \subseteq V_{T} \), given a query budget \( T \) and a seed budget \( k \). This is also referred to as an IM problem with exploration in the literature [13], [14]. In contrast to the conventional setting of IM [1], since the influence spread \( \sigma(\cdot) \) cannot be computed accurately from \( G \) due to the uncertainty of the unexplored part of \( G \), our problem is ill-defined. Thus, we need to compute an estimate of \( \sigma(\cdot) \) based on the available information.

To this end, we first gradually infer the connections between two nodes in the unexplored part based on both the explored graph and the set of node features, \( X \), by repeatedly querying a single node in each step, which corresponds to network inference in our study. An edge \( \langle u,v \rangle \notin E_{t} \) that is incident to nodes \( u \) and \( v \) that have not yet been queried is referred to as an uncertain edge. We note that there are three types of such uncertain edges, including i) the edges connecting two nodes in \( V_{t} \), ii) the edges connecting one node in \( V_{t} \) and another node in \( V_{t} \), and iii) the edges connecting two nodes in \( V_{t} \), where \( V_{t} \) is the set of unexplored nodes at the \( t \)-th query step such that \( V = V_{t} \cup \bar{V}_{t} \) for two disjoint sets \( V_{t} \) and \( \bar{V}_{t} \). Intuitively, during the \( t \)-th node query, we are capable of learning a generative model of edges, which approximates the distribution of all connections in \( G \) given the set of node features in \( V_{t} \) and the subgraph \( G_{t} \) discovered after \( t \) queries as training samples. Using this learned model, we then predict the probability \( \theta_{uv}(t) \in [0,1] \) that an uncertain edge \( \langle u,v \rangle \) is present, the so-called edge probability. The subgraph \( G_{t} \) and the set of \( \theta_{uv}(t) \)'s for all uncertain edges are fed into the generator function of a weighted graph, denoted as \( G_{gen}^{(t)} \), having all \( n \) nodes. By integrating the connectivity information of both.

---

Fig. 1. Schematic overview of our proposed IM-META method for \( T = 1 \) node query and \( k = 2 \) seed nodes. Here, after adding seven inferred edges to obtain \( G_{gen-prun}^{(0)} \), node \( v_{2} \) (a filled-in yellow circle) is selected. Then, the seed set of two nodes \( v_{1} \) and \( v_{3} \) (filled-in red circles) is chosen from \( V_{1} \) in the subgraph \( G_{1} \).
observable and predicted edges via the generator function, we are capable of creating $G_{\text{gen}}^{(t)}$ whose adjacency matrix $A_{\text{gen}}^{(t)}$ is given by

$$a_{ij} = \begin{cases} 1, & \text{if } (i, j) \in E_t \\ 0, & \text{if } (i, j) \notin E_t \text{ and } i, j \notin Q_t \\ \hat{a}_{ij}^{(t)}, & \text{otherwise} \end{cases}$$

(1)

where $Q_t$ is the set of all queried nodes until $t$ queries and $a_{ij}$ denotes the $(i, j)$-th element of $A_{\text{gen}}^{(t)}$ for $i \neq j$.

Next, using the generated weighted graph $G_{\text{gen}}^{(t)}$, we turn to explaining how to compute an estimate of the expected influence spread of $\sigma(\cdot)$, denoted as $\hat{\sigma}(\cdot)$. Let $E_{u,v}$ denote the event that there exists an edge between nodes $u$ and $v$. Then, it follows that $p(E_{u,v}) = \theta_{u,v}^{(t)}$. Let us denote $A_{u,v}$ as the event that a node $u$ successfully activates another node $v$ in the diffusion process. From the fact that the event $A_{u,v}$ is valid only when an incident edge $(u, v)$ is present, the activation probability that models $\sigma(\cdot)$, while fixing an estimated $\sigma^{(t)}$, is the set of all queried nodes until $t$ since $\sigma(\cdot)$ and $\sigma^{(t)}$ should be optimally that has been discovered denoted as $\mathcal{S}^*(\cdot)$, by taking the expectation over all edges $(u, v)$ in $G_{\text{gen}}^{(t)}$, via Monte-Carlo simulations. Finally, we are ready to formulate our new problem that aims at finding the optimal discovered subgraph and seed set $(G_T^*, \mathcal{S}^*)$ in the sense of maximizing $\hat{\sigma}(\cdot)$ as follows:

$$(G_T^*, \mathcal{S}^*) = \arg \max_{G_T, \mathcal{S} \subseteq \mathcal{V}_T, |\mathcal{S}| = k} \hat{\sigma}(\mathcal{S}).$$

(2)

Intuitively, the discovered subgraph $G_T^*$ should be optimally found in the sense of containing as many optimal seed nodes as possible. Thus, it would be optimal in case all optimal seed nodes $S^*$ are included in the subgraph $G_T^*$ that has been discovered before the seed set selection, i.e., $S^* \subseteq \mathcal{V}_T^*$ in $G_T^*$. However, we note that the inference accuracy of $\hat{\sigma}(\cdot)$ plays an important role in determining the influence (i.e., the number of activated nodes) in the network $G$ since $\hat{\sigma}(\cdot)$ is just an estimate of the actual expected spread. Thus, the designed method should consolidate an accurate estimate of $\sigma(S)$.

In our study, we tackle two practical challenges as follows: 1) we consider a realistic setting in which the number of queries that can be used to obtain training data for the generative model is strictly limited and 2) the problem of solving (2) is NP-hard with an exponential complexity in searching for the two sets $G_T$ and $S$.\footnote{Since our problem maps to the original IM problem when $G_T \equiv G$, the proof of NP-hardness similarly follows that of the original problem [1].} This motivates us to present an accurate and low-complexity solution to this problem in (2).

IV. IM-META METHOD

In this section, we present IM-META, an end-to-end solution to the problem of IM in a topologically unknown attributed network. Our main idea is to solve two subproblems: first update $G_T$ while fixing an estimated $S^*$, then optimizing $S$ with fixed $G_T$. In particular, due to the interdependence of the seed set $S$ on the explored subgraph $G_T$, where $S$ is chosen from vertices within $G_T$, we can represent $S$ as a function of $G_T$ and vice versa, denoted as $S = f(G_T)$ and $G_T = g(S)$. Consequently, our objectives encompass addressing the following two iterative subproblems: 1) when presented with $G_T$, our aim is to identify the optimal $S$; and 2) when provided with an estimated $S^*$, we proceed to optimize $G_T$. The overall procedure of our method is described in Algorithm 1. The algorithm starts with the NDP consisting of the following three functions: 1) NetInference for network inference using metadata (refer to line 3); 2) GraphGen for reinforced weighted graph generation (refer to line 4); and 3) QNodeSelect for query node selection (refer to line 5). After querying $T$ nodes by iteratively invoking the above three functions, we turn to the SSP along with a modified greedy IM function, dubbed ModifiedGreedy, which is invoked to obtain the set of influential seed nodes, $S$, from the reinforced weighted graph $G_{gen-prun}^{(T)}$ (refer to line 9).

Example 1: A schematic overview of our IM-META method is visualized in Fig. 1, where we show one round of exploration from an unknown attributed network $G$ consisting of six nodes. As output of the network inference (NDP1) and the reinforced weighted graph generation (NDP2), we acquire a network $G_{gen-prun}^{(0)}$ by adding seven inferred edges. Based on $G_{gen-prun}^{(0)}$, node $v_2$ (a filled-in yellow circle) is selected via query node selection (NDP3). Afterwards, we similarly obtain $G_{gen-prun}^{(1)}$, which completes the NDP. Under a given budget of $k = 2$ seed nodes, the seed set of two nodes $v_1$ and $v_3$ (filled-in red circles) is chosen from $V_1$, in the subgraph $G_1$ since the seed set maximizes the influence spread over the reinforced graph $G_{gen-prun}^{(1)}$ by employing our own greedy IM algorithm.

A. Network Discovery

The technical details of three steps in the NDP are described in the following.

1) Network Inference Using Node Metadata (NDP1): We elaborate on how to infer a set of uncertain edge probabilities, denoted as $\Theta^{(t)}$, at each query step $t \in \{1, \ldots, T\}$ using node metadata. Such network inference, treated as inductive link prediction, entails several practical challenges. First, not all
collected features in the set $\mathcal{X}$ are useful for the inference process due to redundancy and computational inefficiency. Second, a limited budget for node queries results in a small-size explored subgraph. Since none of the incident edges of each unexplored node in the subgraph are visible, we need to inductively infer $\Theta^{(t)}$ based solely on the node metadata $\mathcal{X}$.

We tackle the aforementioned challenges by adopting a Siamese neural network model, which was originally introduced in image matching [44]. In our work, we take advantage of the “homophily principle” in social networks, the tendency of an individual node to associate with similar others [19], and adopt the Siamese neural network model with the primary role of dimensionality reduction. To this end, we learn embeddings that accurately capture the homophily effect of information diffusion networks. Since a trained Siamese neural network inductively maps new input data (i.e., unexplored nodes) whose connectivity information to the training data (i.e., explored nodes) is unknown, it can easily be applied to our problem. Our Siamese neural network consists of twin multilayer perceptron (MLP) networks to which two feature vectors $x_u$ and $x_v$ associated with nodes $u$ and $v$, respectively, are fed separately. The MLPs act as encoders that compute embedding vectors, denoted as $e_u$ and $e_v$ for nodes $u$ and $v$, respectively. Finally, similarly as in [45], we compute the Hadamard product of two embedding vectors and then utilize a sigmoid output layer to infer $\theta_{uv}^{(t)}$ from the product. That is, $\theta_{uv}^{(t)} = \sigma(e_u \odot e_v)$, where $\sigma$ denotes the Hadamard product.

2) Reinforced Weighted Graph Generation (NDP2): We now explain how to seamlessly generate a reinforced weighted graph. From the step NDP1 (i.e., network inference), we obtain edge probabilities $\Theta^{(t)}$ at each query step $t$. However, a large portion of these uncertain edges do not truly exist since real-world graphs are usually sparse. Thus, using non-existent edges certainly leads to an accumulation of noise in the subsequent processes. This motivates us to select edges that are predicted with high confidence to reduce noise while simultaneously reducing the computational complexity. To this end, we aim to select confident edges whose inferred probabilities $\Theta^{(t)}$ are greater than a given threshold as follows.

Definition 1: Suppose that the set $\Theta^{(t)}$ indicating the probability of uncertain edges is inferred at the $t$-th query step, then an edge $(u,v) \in \Theta^{(t)}$ is called a confident edge if $\theta_{uv}^{(t)} \geq \epsilon$, where $\epsilon > 0$ is a predefined threshold.

Let $H \in \{0, 1, \ldots, |\Theta^{(t)}|\}$ denote the cardinality of the set of selected confident edges. After selecting the top $H$ confident edges in the ranked list of $\Theta^{(t)}$ in descending order, we transform the weighted graph $G_{\text{gen}}$ into a reinforced weighted graph $G_{\text{gen-prun}}^{(t)}$ via our edge pruning strategy. Then, we recompute the diffusion probabilities for all edges in $G_{\text{gen-prun}}^{(t)}$. Specifically, we compute the joint probability distribution based on each diffusion model as follows. For the IC model, we have $Pr(A_{u,v} \mid E_{u,v}) = \theta_{uv}^{(t)} \sim U(0, 1)$. Thus, from Bayes’ rule, it follows that $Pr(E_{u,v} \mid A_{u,v}) = \theta_{uv}^{(t)} \pi_{uv}$. For the WC model, we have $Pr(A_{u,v} \mid E_{u,v}) = \frac{1}{2}$, which is however unknown since $d_v$, representing the degree of node $v$ can only be computed from the fully observed network structure. To overcome this problem, we estimate the node degree at step $t$ as $\hat{d}_v^t := \sum_{u \in \mathcal{N}_v} \theta_{uv}^{(t)}$, where $\mathcal{N}_v$ is the set of all neighbors of $v$ in $G_{\text{gen-prun}}^{(t)}$ and $\theta_{uv}^{(t)} = 1$ if $(u, v) \in E_t$. Then, we have $Pr(E_{u,v} \mid A_{u,v}) = \frac{1}{d_v^t} \theta_{uv}^{(t)}$ for the WC model.

Example 2: An example of the reinforced weighted graph generation can be seen in Fig. 2, where $\epsilon = 0.5$ and two reinforced weighted graphs $G_{\text{gen-prun}}^{(t)}$ are constructed based on both IC and WC models. For the IC model, assuming that $\pi_{uv} = 0.1$, the diffusion probability in $G_{\text{gen-prun}}^{(t)}$ can be simply computed as in the right-top of Fig. 2. For the WC model, we compute the diffusion probabilities of associated edges in $G_{\text{gen-prun}}^{(t)}$ by using an estimate of the node degree, $\hat{d}_v$ (see the right-bottom of Fig. 2). For example, $\hat{d}_v^t$ is given by $1 + \theta_{uv}^{(t)} = 1 + 0.6 = 1.6$; thus, the diffusion probabilities associated with two edges $(v_2, v_1)$ and $(v_1, v_1)$ are $\frac{0.6}{1.6}$ and $\frac{0.6}{1.6}$, respectively.

3) Query Node Selection (NDP3): As the last step of network discovery, we describe our query node selection module. As in prior studies [13, 14], it is natural to select a query node that has a high degree centrality since it enables the resulting explored subgraph to grow fast. In our work, selecting a high-degree node to query would be beneficial in providing more samples to train our Siamese neural network. Instead, we pay attention to the residual degree of a node at each query step $t$, defined as $r_{u,v}^{(t)} = \hat{d}_u^t - d_u^t$, rather than the estimated degree $d_v^t$ itself, where $d_v^t$ denotes the degree of an observable node at the $t$-th query step. This is because obviously, the residual degree $r_v$ represents a better capability to explore more nodes when the inference accuracy is sufficiently high since the observable nodes in the explored subgraph no longer contribute to its growth.

However, such a selection strategy that chooses nodes whose residual degrees are high may not always be beneficial as depicted in Fig. 3. In this example, given an initial subgraph, querying node $v_1$ ($r_1^{(0)} = 2$) leads to an explored subgraph consisting of four nodes and three edges, while choosing node $v_2$ ($r_2^{(0)} = 1$) to query only discovers node $v_3$ and one edge incident
to \( v_2 \). Since it is certain that \( v_2 \) is the most influential node, it should be contained in the explored graph for the seed node selection process. This observation motivates us to make use of the geodesic distance to potentially influential nodes, which represents the length in terms of the number of edges on the shortest path between two vertices, as a vital factor in the query node selection process. For example, in Fig. 3, if we choose one of two nodes \( v_1 \) and \( v_2 \) such that the shortest path to \( v_2 \) yields a shorter geodesic distance as a queried node, then \( v_2 \) should be selected.

In this context, we want to query each node by taking into account both 1) the residual degree (as high as possible) and 2) the sum of the shortest paths to potentially influential nodes (as low as possible). To this end, starting from the reinforced weighted graph \( G^{(t)}_{\text{gen-prun}} \), we first execute an IM algorithm to find the set of \( k \) potentially influential nodes at the \( t \)-th query step, denoted as \( S(t) \subseteq V \). Then, if a node \( v \in S(t) \) belongs to the current explored subgraph (i.e., \( v \in V_t \)), then it is excluded from \( S(t) \) (i.e., \( S(t) \leftarrow S(t) \setminus \{v\} \)) so that only the potentially influential nodes in the unexplored part are possible candidates to be queried. Using the set \( S(t) \), we now propose our own topology-aware ranking strategy by defining a ranking measure:

\[
\text{rank}^{(t)}(u) = r^{(t)}(u) - \alpha \sum_{v \in S^{(t)}} \text{GD}^{(t)}(u, v),
\]

where \( \text{GD}^{(t)}(u, v) \) indicates the geodesic distance between two nodes \( u \) and \( v \), and \( \alpha \geq 0 \) is a hyperparameter balancing two terms in (3). The impact of \( \alpha \) is empirically validated in Section V-D. The node whose \( \text{rank}^{(t)}(u) \) is the highest among \( u \in V_t \) is finally chosen as the queried node in each query step. Intuitively, the potentially influential nodes serve as anchors providing a guidance on choosing the query node \( u \) in the sense of minimizing the sum of geodesic distances between \( u \) and nodes in \( S^{(t)} \), \( \sum_{v \in S^{(t)}} \text{GD}^{(t)}(u, v) \) in (3). It is worth noting that the number of seed nodes, \( k \), is used not only in the SSP but also in the NDP.

We shall empirically validate the effectiveness of our query node selection using the topology-aware ranking strategy in Section V.

B. Seed Set Selection

We now turn to stating the SSP, which can be viewed as a generalization of the greedy IM algorithm [1] and is described

![Fig. 3. Example illustrating that querying a high degree node is not always beneficial given an initial subgraph \( G_0 \) when \( T = k = 1 \) and \( G^{(0)}_{\text{gen-prun}} \) correctly reflects the underlying graph \( G \).](image)

Algorithm 2: ModifiedGreedy

| Line | Code |
|------|------|
| 1    | \( S \leftarrow \phi \) |
| 2    | for \( i \) from 0 to \( k \) do |
| 3    | for each \( v \in V_T \setminus S \) do |
| 4    | \( s_v \leftarrow \hat{\sigma}(S \cup \{v\}) \) |
| 5    | \( S \leftarrow S \cup \arg \max_{v \in V_T \setminus \{v\}} \{s_v\} \) |
| 6    | return \( S \) |

in Algorithm 2. First, the seed set \( S \) is empty (see line 2). Then, we gradually find and add one node maximizing the so-called “marginal expected spread” to \( S \), under the constraint that seed nodes can only be selected from the set of explored nodes, \( V_T \) in the graph \( G^{(T)}_{\text{gen-prun}} \) (see lines 3–6). For each candidate node \( s_v \), we compute the marginal expected spread \( \hat{\sigma}(S \cup \{v\}) \) based on \( G^{(T)}_{\text{gen-prun}} \) (see line 5). We note that \( \hat{\sigma}(\cdot) \) can be approximated via many approaches such as Monte-Carlo simulations, lazy update [20], or reverse reachable sets [21]. The node \( s_v \) is added to \( S \) if its corresponding \( \hat{\sigma}(\cdot) \) is the largest (see line 6).

C. Theoretical Analyses

First, we analyze the computational complexity of our IM-META method as follows.

Theorem 1: The computational complexity of the proposed IM-META method is no higher than that of the greedy IM algorithm.

It is not difficult to show that the complexity for the NDP is dominated by the network inference step, whose complexity is given by \( O(n^2) \), where \( n \) is the number of nodes in \( V \), conditioned that the size of model parameters in MLPs does not scale with \( n \). Of course, the computational complexity for this phase can be greatly reduced when parallelization is applied. Thus, the bottleneck of IM-META is the greedy IM algorithm in the SSP, whose complexity is bounded by \( O((Rknm)\{21\}) \) (refer to [20] for more details), where \( R \) represents the number of Monte-Carlo simulations to estimate the expected influence spread and \( m \) is the number of edges in \( E \). As \( R \) and \( k \) are regarded as constants and \( n < m \), the total complexity of IM-META is given by \( O(nm) \), which lies in the same line as that of the greedy IM algorithm on the underlying graph \( G \).

Next, we theoretically analyze the performance of our IM-META method. More specifically, we show performance guarantees within the factor of \( 1 - \frac{1}{e} \) of the optimum since a modified greedy algorithm is employed in the SSP of IM-META.

Theorem 2: Suppose that the NDP is completed, thus leading to the discovered subgraph \( G_T \). Then, the proposed IM-META method, employing a greedy seed selection approach, achieves a \( (1 - \frac{1}{e}) \)-approximation of the optimal solution with the optimal seed set \( S^* \).

Proof: Let us recall an estimate of the expected influence spread, \( \hat{\sigma}(S) \), used for the objective function in (2). Then, it is not difficult to show that the objective function \( \hat{\sigma}(S) \) is monotone and sub-modular with respect to the seed set \( S \) as

3In our work, degree discount heuristics [26] are adopted to find \( \hat{S}^{(t)} \) for computational efficiency.
long as the SSP is only concerned after the NDP is completed. Hence, following [46], given the function \( \hat{d}(\cdot) \), the greedy seed selection algorithm give a \( (1 - \frac{1}{2}) \)-approximation to the optimal solution with \( S^* \) under our setting with network uncertainty. This completes the proof of Theorem 2.

V. EXPERIMENTAL EVALUATION

A. Benchmark Methods

In this subsection, we present two baseline methods and one state-of-the-art IM approach against which we compare IM-META.

Random (Rand): We randomly select a node to query for each round of exploration. Then, after \( T \) query rounds, the greedy IM algorithm in [1] is used to obtain \( k \) seed nodes from the explored graph \( G_T \) without network inference.

Depth-first search (DFS): We randomly select a node to query out of all neighbors of the queried node in the previous round. Similarly as in Rand, the greedy IM algorithm is used to obtain \( k \) seed nodes from the explored graph \( G_T \).

CHANGE: To facilitate an effective HIV intervention campaign, a state-of-art method was recently proposed in [11]. This model was inspired by the friendship paradox, which states that the expected degree of a random node’s neighbor(s) is larger than that of the random node itself [47]. In this context, a random neighbor of a node in \( G_t \) is selected to query at each query step \( t \) in the NDP. The greedy IM algorithm is also used after \( T \) query rounds. Although CHANGE deals with an end-to-end IM procedure, we still term the friendship paradox sampling as CHANGE for consistency with prior studies [14], [15], [16].

Furthermore, for comparison with the fundamental limit of IM in our setting, we evaluate the performance of another case, termed Upper-Greedy, using the greedy IM algorithm when the underlying graph \( G \) is assumed to be fully available.

B. Datasets

Four real-world datasets across several domains (e.g., social and co-authorship networks with node metadata) commonly adopted in the literature are used as the underlying graph \( G \), namely Coauthorship-CS (CS), Coauthorship-Physics (Physics), Douban, and Ego-Facebook (Ego-FB) [48]. The four datasets are intentionally chosen from our empirical study to display different behaviors of IM-META and benchmark methods under various settings.

We also make use of the associated node features provided in these datasets as the collected node metadata \( \mathcal{X} \). For all experiments, we treat graphs as undirected. The statistics of each dataset, including the number of nodes and the number of edges, and the number of node features, are described in Table II. Note that all metadata presented in these datasets are anonymized as binary values for privacy preservation.

| Name            | \( n \)  | \( m \)  | \( |\mathcal{X}| \) |
|-----------------|--------|--------|----------------|
| Coauthor-CS     | 18,333 | 34,493 | 6,805          |
| Coauthor-Physics| 168,788| 495,924| 8,415          |
| Douban          | 3,906  | 8,164  | 538            |
| Ego-Facebook    | 534    | 4,813  | 262            |

C. Experimental Setup

In our experiments, the induced subgraph \( G_0 \) with four nodes is initialized, similarly as in [14]. For each evaluation, we run experiments over 10 different initialization of \( G_0 \) to compute the average score. The diffusion probability for the IC model is set to 0.1, which is the typical value from the literature (see [1], [20] and references therein). As for the function NetInference, the dimension of embedding vectors is set to 256, and the Siamese neural network model is trained via the Adam optimizer [49] with a learning rate of 0.1 and a batch size of 16 for all datasets.

For each dataset, we randomly split the set of nodes into training/validation sets with a ratio of 90/10%. The parameter \( \alpha \) in (3) for designing our topology-aware ranking strategy and the threshold \( \epsilon \) in the reinforced weighted graph generation are set to 1 and 0.5, respectively, unless otherwise stated. For the function ModifiedGreedy, we employ the CELF algorithm [20] to ensure the correctness of our validation due to its theoretical performance guarantee, in which the number of Monte-Carlo simulations is set to 20,000. However, since the results of all competing methods would take too long to acquire when performing experiments on two large datasets, including Coauthor-CS and Coauthor-Physics, when using CELF, we down-sample the size of both networks to 3,000 nodes using forest fire sampling unless otherwise stated, which is capable of preserving the degree distribution of the original graph [50]. We note that the original CS and Physics datasets without sampling are used to validate the scalability of IM-META in Section V-D6.

All experiments are carried out with Intel (R) 12-Core (TM) i7-10700F CPUs @ 2.90 GHz and 16 GB RAM.

D. Experimental Results

Our empirical study in this subsection is designed to answer the following key research questions (RQs):

- **RQ1**: What is the growth of subgraphs in the query process of IM-META in comparison to the benchmarks?
- **RQ2**: What is the performance contribution of the network inference and query node selection modules?
- **RQ3**: How much does the IM-META method improve the performance of IM in terms of the expected influence spread over the benchmark methods?
- **RQ4**: How robust is IM-META in more challenging settings where a portion of node metadata are missing?
- **RQ5**: What is the effect of model parameters on the performance of IM-META?

---

4 The two co-authorship networks are publicly available online (https://github.com/shchur/gnn-benchmark/tree/master/data).
5 The dataset is publicly available online (https://github.com/maffia92/FINAL-network-alignment-KDD16).
- **RQ6**: How scalable is IM-META with growing size of the networks?

1) **Growth of Explored Subgraphs (RQ1)**: Given a small budget of node queries, it would be desirable to acquire explored subgraphs that are as large as possible since the size of subgraphs primarily determines the performance of IM. To comprehensively understand the query process, we are interested in examining how the explored subgraph $G_t$ scales with the number of queried nodes, $t$, on the four real-world datasets. To this end, we empirically assess the growth of $G_t$ resulting from four methods including IM-META, Rand, DFS, and CHANGE for all datasets, where the number of seed nodes, $k$, is set to 5 and the IC model is applied. Following the results in Fig. 4, our findings can be summarized as follows:

- The size of each subgraph $G_t$ in the CS, Physics, and Douban datasets is relatively small compared to that of the underlying network $G$. For example, from Table II and Fig. 4(c), it is evident that $|V_t| < 0.1|V|$ for the Douban dataset when $t = 60$.

- On the other hand, the Ego-FB network behaves differently from the other three datasets in such a way that $|V_t|$ obtained by all methods is close to $|V|$ even with querying only 60 nodes, which accounts for about 11.2% of the total number of nodes in the Ego-FB network. This is due to the fact that the diameter of ego-networks (created via breadth-first search (BFS) sampling) is inherently small; thus, it is capable of exploring a large number of neighbors by querying even a randomly selected node.

- For the CS and Physics datasets, the subgraph growth rate of IM-META is much faster than that of the other methods. This implies that the accuracy of network inference is sufficiently high due to the rich feature information of these two datasets (refer to Table II).

- In contrast, no such tendency is observed for the Douban and Ego-FB datasets. For the Douban dataset, the relatively low accuracy of network inference achieved by IM-META stems from the fact that node features are heavily anonymized. For the Ego-FB dataset, there is only a negligible gap in the subgraph size $|V_t|$ among the four methods since querying only a small number of nodes leads to a sizeable exploration of subgraphs.

2) **Effectiveness of Each Component (RQ2)**: In order to discover what role each component plays in the success of the proposed IM-META method, we compare the performance of the original IM-META with its four variants.

- IM-META(LR), IM-META(GCN), and IM-META(Transformer): For network inference, the Siamese neural network model is replaced by either logistic regression (LR), a graph convolutional network (GCN) [51], or a graph transformer block (Transformer) [52]. Specifically, for IM–META(LR), we adopt a simple MLP architecture in the hidden layer of size 512. For IM–META(GCN) and IM–META(Transformer), we employ a single GCN layer and a graph transformer block to train on a graph constructed from the explored subgraph $G_t$ and all other unexplored nodes, respectively.

- IM–META(Katz) and IM–META(degree): For query node selection, the topology-aware ranking strategy is replaced by the ranking based on two centrality measures including the Katz centrality and the degree centrality. Precisely, we compute the two centrality measures of all nodes in $V_t$ using the inferred topology in $G_t^{gen-pruned}$. Then, all nodes are ranked in descending order of the centrality measure. The node with the highest rank is finally chosen as the queried node in each query step.

The performance of IM-META and its above-mentioned variants is summarized in Table III, in which we only show the results for the CS dataset when $k = 5$ and the IC model is employed since the results for other datasets exhibit similar trends. Our findings are as follows:

- The original IM-META method always exhibits substantial gains over its variants, which demonstrates that each of our network inference and query node selection modules plays a crucial role in IM.

- The performance of both IM–META(GCN) and IM–META(Transformer) is rather inferior to that of IM–META(LR) when the number of queried nodes is low due to a large number of unexplored edges. This implies that the deep learning-based models used for network inference exhibit overfitting and do not effectively deal with the highly uncertain network structure.

- The centrality measures are not effective for node queries since they do not take the strength of influence into account.

### Table III

| Method                          | Number of queried nodes |
|--------------------------------|-------------------------|
| IM-META                        | 10 20 40 60             |
| IM-META(LR)                    | 45.1 47.1 50.9 61.5     |
| IM-META(GCN)                   | 39.9 41.8 42.3 47.4     |
| IM-META(Transformer)           | 38.6 41.3 42.5 48.8     |
| IM-META(Katz)                  | 38.4 41.2 42.2 48.5     |
| IM-META(degree)                | 42.6 46.2 48.9 55.5     |
| IM-META(gen)                   | 41.9 46.3 48.8 59.2     |

Here, the best performers are highlighted by bold fonts.
3) Comparison With Benchmark Methods (RQ3): To comprehensively compare the performance of IM-META to the benchmark methods and Upper-Greedy, we consider the expected influence spread $\sigma(S)$ for a set of selected seed nodes, $S$, using all four real-world datasets.\(^6\) Figs. 5–8 illustrate $\sigma$ versus the number of node queries, $T$, where $k = \{5, 10\}$ and both IC and WC models are employed. We make the following insightful observations:

\[^6\]To simplify notations, $\sigma(S)$ will be written as $\sigma$ unless otherwise specified.

- IM-META consistently and remarkably outperforms all benchmark methods except for the Ego-FB dataset.
- For the Ego-FB dataset, all methods achieve comparable performance to that of Upper-Greedy even with a very small number of node queries, e.g., $T = 10$. This is not surprising due to the enormous size of explored subgraphs as discussed in Section V-D1, which results in the inclusion of (almost) all influential nodes in any explored subgraph.
- In comparing the IC and WC models, it is likely that, for the WC model, the performance gap between the IM-META and other methods is higher. This is because IM-META is capable of estimating the expected degree of nodes; thus, the diffusion probability can be more precisely represented in the WC model by employing such methods that make use of node features.
- The performance of IM-META tends to be closer to that of Upper-Greedy when the number of seed nodes, $k$, is relatively smaller. As an example, in the Physics dataset, IM-META achieves about 93% of the expected influence spread resulting from Upper-Greedy by querying only 60 nodes, which accounts for 5% of the total number of nodes in the given network, when $k = 5$ and the IC model is applied (see Fig. 5(b)).

Overall, IM-META best approaches the upper bound of the greedy IM algorithm (which has access to the entire network).

4) Robustness to the Degree of Available Node Metadata (RQ4): We now evaluate the performance of IM-META in a more difficult situation that often occurs in real environments, where only a portion of node metadata in the set $X$ are collectible (available). To this end, we randomly remove $\{20, 40, 60, 80\}$% of node features associated with each node in a given dataset. In these experiments, we show only the results for the setting where $T$ and $k$ are set to 60 and 5, respectively. We omit results for the WC model since they follow similar trends.

The performance comparison between IM-META and the three benchmark methods for all datasets is presented in Fig. 9. One can see that the performance of IM-META gradually degrades when more node features are removed from $X$. Our findings for the CS and Physics datasets demonstrate that, in fringe scenarios, e.g., the case where 80% of node features are removed, IM-META still exhibits clear gains over all benchmark methods. This implies that, even under the circumstance where a number of node features are missing, the IM-META method is capable of correctly adding inferred edges in the subgraph.
exploration process, which enables us to better select the set of influential seed nodes. For the Douban dataset with 80% removal of node features, IM-META is slightly inferior to CHANGE yet still reveals gains over other two methods. On the other hand, for the Ego-FB dataset, all methods achieve the performance of Upper-Greedy, meaning that the degree of available node metadata does not affect any performance degradation.

5) Hyperparameter Sensitivity (RQ5): In addition to four key RQs that we answered, another important question concerns the importance of tuning hyperparameters. To answer the question, we carry out experiments as follows.

In Fig. 10, we investigate the impact of hyperparameters $\alpha$ and $\epsilon$ on the performance of IM-META when $T = 60$ and $k = 5$. Recall that $\alpha$ adjusts the balance between two terms for the query node selection in (3), i.e., the residual degree and the sum of the shortest paths to potentially influential nodes, and $\epsilon$ is the threshold controlling the number of confident edges for the reinforced weighted graph generation. When a hyperparameter ($\alpha$ or $\epsilon$) varies so that its effect is clearly revealed, the other parameter is set to the pivot values $\alpha = 1$ and $\epsilon = 0.5$. In these experiments, we only show the results from the IC model since those from the WC model follow a similar trend. Moreover, experimental results for the Ego-FB dataset are excluded since all combinations of hyperparameters return the same performance on this dataset. We observe the following:

- The values of $\alpha$ and $\epsilon$ for which the highest $\sigma$ is achieved tend to be almost identical for all datasets. Specifically, we find that the case of $(\alpha, \epsilon) = (1, 0.5)$ exhibits the best performance almost consistently.
- We investigate the case of $\alpha = 0$ where the residual degree is only taken into account in our topology-aware ranking strategy. In this case, the lowest performance is achieved over all $\alpha$’s regardless of datasets. This finding validates the necessity of the shortest path to potentially influential nodes in judiciously choosing queried nodes by setting the value of $\alpha$ appropriately.
- We next examine the impact of $\epsilon$ on the performance. Setting $\epsilon$ to a high value (e.g., $\alpha = 0.9$) leads to relatively low performance for all datasets. This setting is indeed undesirable since it makes our reinforced weighted graph $G'_{\text{gen-prun}}$ very sparse with only a small number of edges.

Hence, it is crucial to suitably determine the value of $\epsilon$ in guaranteeing satisfactory performance.

Overall, the results of our parameter sensitivity tests are as expected. The importance of the topology-aware ranking strategy, leveraging the residual degree and path information, for IM is clear from our empirical findings; and appropriately deciding the density of the generated weighted graphs is beneficial for the selection of seed nodes.

6) Scalability (RQ6): To empirically validate the computational complexity of IM-META shown in Section 4.3, we conduct experiments using a set of graphs synthetically generated from the Erdős–Rényi graph model [48], where $(n, m) = \{(50, 200), (50, 400), (50, 600), (100, 400), (100, 500), (100, 600), (100, 700), (200, 400)\}$. The metadata associated with each node are generated as a 10-dimensional all-ones vector. The number of Monte-Carlo simulations, the number of seed nodes, and the number of queries are set to 20,000, 5, and 10, respectively. We also set the number of edges to be inferred identically to the number of edges in the underlying network. In Fig. 11, we show the measured runtime complexity of IM-META (in seconds) with respect to different network size products $nm$.

Furthermore, to verify that IM-META is applicable in real-world networks whose sizes are typically large, we measure its runtime complexity using the original Coauthor-CS and original Coauthor-Physics datasets without sampling. For the function ModifiedGreedy, we employ the SSA algorithm [31] for computational efficiency. It is worth noting that we can also replace SSA with any heuristics for much faster runtime as the seed node selection is model-agnostic. Table IV shows the measured runtime of the NDP and SSP each in IM-META as well as IM-META itself (in seconds) with respect to the number of node queries, $T$, where $k$ is set to 10 and the IC model is employed. Empirical evidence reveals that the runtime
TABLE IV
Runtime Complexity of the NDP and SSP Each in IM-META as Well as IM-META Itself With Respect to the Number of Node Queries, T, for k = 10 on Two Large-Scale Networks

| Runtime (s) | Number of queried nodes |
|-------------|-------------------------|
|             | 100                     | 200 | 300 | 400 |
| NDP in IM-META | 144 | 221 | 233 | 245 |
| SSP in IM-META | 1,454 | 1,454 | 1,454 | 1,454 |
| IM-META (Total) | 1,598 | 1,675 | 1,687 | 1,699 |

of the NDP is far smaller than that of the SSP. Moreover, the computational complexity of the SSP, which is the bottleneck, does not scale in proportion to $T$, leading to a gradual rise in the runtime of IM-META.

VI. CONCLUDING REMARKS

In this paper, we investigated the impact and benefits of node metadata in aiding solutions to the IM problem in topologically unknown networks, which was an open and challenging problem due to the noisy nature of metadata and uncertainties in connectivity inference. To tackle this challenge, we introduced IM-META, a novel end-to-end solution that aims to find both a set of seed nodes and another set of nodes to query by making full use of the node metadata. Specifically, we developed the NDP that iteratively performs three steps: 1) learning the relationship between collected metadata and edges via a Siamese neural network model, 2) constructing a reinforced weighted graph by selecting only a limited number of confident edges, and 3) discovering the next node to query using the proposed topology-aware ranking strategy balancing between degree centrality of a target node and its geodesic distance to potential seeds. We then employed a modified IM algorithm to find the seed set, given the ultimately explored subgraph. Using four real-world datasets, we demonstrated that, for almost all cases, the proposed IM-META method consistently outperforms benchmark IM methods in terms of the expected influence spread. The results of our evaluation showed that IM-META achieves up to 93% of the performance of an upper-bound approach that has access to the full network, while IM-META queried only 5% of the underlying network. We also found that IM-META is robust to a lack of available node metadata (e.g., the performance even in extreme settings in which 80% of metadata are missing) and various hyperparameter settings. Overall, our results showed that even very limited access to node metadata and restricted queries to the network structure are sufficient to perform effective influence maximization.

Potential avenues of future research include the design of self-supervised learning models to further enhance the accuracy of network inference based on the node metadata of unexplored nodes. Alternatively, reinforcement learning could be incorporated into the framework for query node selection to further boost the performance. It could also be of interest to theoretically analyzing the gap between the upper bound performance and our achievability as a function of the number of queried nodes. Furthermore, it is worth noting that previous endeavors addressing IM in temporal or dynamic networks have not focused on the effective exploration of subgraphs. Consequently, our IM-META can be accommodated as a possible extension, facilitating enhanced subgraph exploration in temporal or dynamic network scenarios.

REFERENCES

[1] D. Kempe, J. Kleinberg, and É. Tardos, “Maximizing the spread of influence through a social network,” in Proc. 9th ACM SIGKDD Int. Conf. Knowl. Discov. Data Mining, 2003, pp. 137–146.
[2] A. Banerjee, A. G. Chandrasekhar, E. Duflo, and M. O. Jackson, “The diffusion of microfinance,” Science, vol. 341, no. 6144, pp. 1–9, Jul. 2013.
[3] A. Yadav, H. Chan, A. X. Jiang, H. Xu, E. Rice, and M. Tambe, “Using social networks to aid homeless shelters: Dynamic influence maximization under uncertainty,” in Proc. Int. Conf. Auton. Agents Multi-Agent Syst., 2016, vol. 16, pp. 740–748.
[4] T. W. Valente and P. Pumpluan, “Identifying opinion leaders to promote behavior change,” Health Educ. Behav., vol. 34, no. 6, pp. 881–896, Jun. 2007.
[5] E. Rice, E. Tulbert, J. Cederbaum, A. B. Adhikari, and N. G. Milburn, “Maximizing homeless youth for HIV prevention: A social network analysis of the acceptability of a face-to-face and online social networking intervention,” Health Educ. Res., vol. 27, no. 2, pp. 226–236, Jan. 2012.
[6] F. B. Abdesslem, I. Parris, and T. Henderson, “Reliable online social network data collection,” in Computational Social Networks Mining and Visualization, Berlin, Germany: Springer, 2012, pp. 183–210.
[7] Y. Hsu, C. Tran, and W.-Y. Shin, “META-CODE: Community detection via exploratory learning in topologically unknown networks,” in Proc. 31st ACM Int. Conf. Inf. Knowl. Manag., 2022, pp. 4034–4038.
[8] M. Kim and J. Leskovec, “The network completion problem: Inferring missing nodes and edges in networks,” in Proc. 11th SIAM Int. Conf. Data Mining, 2011, pp. 47–58.
[9] C. Tran, W.-Y. Shin, A. Spitz, and M. Gertz, “DeepNC: Deep generative network completion,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 44, no. 4, pp. 1837–1852, Apr. 2022.
[10] C. Tran, W.-Y. Shin, and A. Spitz, “Community detection in partially observable social networks,” ACM Trans. Knowl. Discov. Data, vol. 16, no. 2, pp. 1–24, 2021.
[11] B. Wilder et al., “End-to-end influence maximization in the field,” in Proc. Int. Conf. Auton. Agents Multi-Agent Syst., 2018, vol. 18, pp. 1414–1422.
[12] A. Yadav et al., “Bridging the gap between theory and practice in influence maximization: Raising awareness about HIV among homeless youth,” in Proc. Int. Joint Conf. Artif. Intell., 2018, pp. 5399–5403.
[13] B. Wilder, N. Immorlica, E. Rice, and M. Tambe, “Maximizing influence in an unknown social network,” in Proc. 32th Int. Conf. Artif. Intell., 2018, pp. 1–8.
[14] H. Kamarthi, P. Vijayan, B. Wilder, B. Ravindran, and M. Tambe, “Influence maximization in unknown social networks: Learning policies for effective graph sampling,” in Proc. Int. Conf. Auton. Agents Multi-Agent Syst., 2020, pp. 575–583.
[15] H. Chen, W. Qui, H.-C. Ou, B. An, and M. Tambe, “Contingency-aware influence maximization: A reinforcement learning approach,” in Proc. Conf. Uncertainty Artif. Intell., 2021, vol. 161, pp. 1535–1545.
[16] D. Li, M. Lowalekar, and P. Varakantham, “CLAIM: Curriculum learning policy for influence maximization in unknown social networks,” in Proc. Conf. Uncertainty Artif. Intell., 2021, vol. 161, pp. 1455–1465.
[17] V. Leroy, B. B. Cambazoglu, and F. Bonchi, “Cold start link prediction,” in Proc. 6th ACM Int. Conf. Web Search Data Mining, 2013, pp. 53–62.
[18] M. Kosinski, D. Stillwell, and T. Graepel, “Private traits and attributes are predictable from digital records of human behavior,” Proc. Nat. Acad. Sci., vol. 110, no. 15, pp. 5802–5805, 2013.
[19] J. Tang, H. Gao, X. Hu, and H. Liu, “Exploiting homophily effect for trust prediction,” in Proc. 6th ACM Int. Conf. Web Search Data Mining, 2013, pp. 1413–1422.
[20] J. Leskovec, A. Krause, C. Guestrin, C. Faloutsos, J. VanBriesen, and N. Glance, “Cost-effective outbreak detection in networks,” in Proc. 13th Int. Conf. Knowl. Discov. Data Mining, 2007, pp. 420–429.
[21] Y. Tang, Y. Shi, and X. Xiao, “Influence maximization in near-linear time: A martingale approach,” in Proc. Int. Conf. Manage. Data, 2015, pp. 1539–1554.
IEEE TRANSACTIONS ON NETWORK SCIENCE AND ENGINEERING, VOL. 11, NO. 3, MAY/JUNE 2024

[22] Y. Tang, X. Xiao, and Y. Shi, “Influence maximization: Near-optimal time complexity meets practical efficiency,” in Proc. Int. Conf. Manage. Data, Snowbird, UT, USA, 2014, pp. 75–86.

[23] S. Mihara, S. Tsugawa, and H. Ohsaki, “Influence maximization problem for unknown social networks,” in Proc. Int. Conf. Adv. Social Netw. Anal. Mining, 2015, pp. 1539–1546.

[24] B. Yan, K. Song, J. Liu, F. Meng, Y. Liu, and H. Su, “On the maximization of influence over an unknown social network,” in Proc. Int. Conf. Auton. Agents Multi-Agent Syst., 2019, pp. 2279–2281.

[25] B. Wilder, A. Yadav, N. Immorlica, E. Rice, and M. Tambe, “Uncharted but not uninfluenced: Influence maximization with an uncertain net- work,” in Proc. Int. Conf. Auton. Agents Multi-Agent Syst., 2017, vol. 17, pp. 1305–1313.

[26] W. Chen, Y. Wang, and S. Yang, “Efficient influence maximization in social networks,” in Proc. 15th Int. Conf. Knowl. Discov. Data Mining, 2009, vol. 17, pp. 199–208.

[27] K. Jung, W. Heo, and W. Chen, “IRIE: Scalable and robust influence maximization in social networks,” in Proc. Int. Conf. Manage. Data, 2012, pp. 918–923.

[28] A. M. Samir, S. Rady, and T. F. Gharib, “LKG: A fast scalable community-based approach for influence maximization in social networks,” Physica A: Stat. Mechanics Appl., vol. 582, 2021, Art. no. 126258.

[29] J. Tang, R. Zhang, P. Wang, Z. Zhao, L. Fan, and X. Liu, “A discrete shuffled frog-leaping algorithm to identify influential nodes for influence maximization in social networks,” Knowl.-Based Syst., vol. 187, 2020, Art. no. 104833.

[30] A. Goyal, W. Lu, and L. V. Lakshmanan, “Cellf: Optimizing the greedy algorithm for influence maximization in social networks,” in Proc. 20th Int. Conf. World Wide Web, 2011, pp. 47–48.

[31] H. T. Nguyen, M. T. Thai, and T. N. Dinh, “Stop-and-stare: Optimal sampling algorithms for viral marketing in billion-scale networks,” in Proc. Int. Conf. Manage. Data, 2016, pp. 695–710.

[32] G. Tong, R. Wang, and Z. Dong, “On multi-scale cascade influence maximiza- tion: Model, hardness and algorithmic framework,” IEEE Trans. Netw. Sci. Eng., vol. 8, no. 2, pp. 1600–1613, Apr.–Jun. 2021.

[33] X. Qin, C. Zhong, and Q. Yang, “An influence maximization algorithm based on community-topic features for dynamic social networks,” IEEE Trans. Netw. Sci. Eng., vol. 9, no. 2, pp. 608–621, Mar.–Apr. 2022.

[34] B. Settles, “Active learning literature survey,” Computer Sciences Techni- cal Report #1648, U. Wisconsin-Madison, 2009.

[35] A. J. Joshi, F. Porikli, and N. P. Papanikolopoulos, “Scalable active learning for multiclass image classification,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 34, no. 11, pp. 2259–2273, Nov. 2012.

[36] S. Eshghi, S. Maghsudi, V. Restocchi, S. Stein, and L. Tasssialas, “Efficient influence maximization under network uncertainty,” in Proc. IEEE Conf. Comput. Commun. Workshop, 2019, pp. 365–371.

[37] D. Eckles, H. Esfandiari, E. Mossel, and M. A. Rahimian, “Seeding with costly network information,” in Proc. Conf. Econ. Comput., 2019, pp. 421–422.

[38] E. Yanchenko, T. Murata, and P. Holme, “Link prediction for ex ante influence maximization on temporal networks,” Appl. Netw. Sci., vol. 8, pp. 1–23, 2023.

[39] H. Zhuang, Y. Sun, J. Tang, J. Zhang, and X. Sun, “Influence maximization in dynamic social networks,” in Proc. 15th Int. Conf. Data Mining, 2013, pp. 1313–1318.

[40] M. Han, M. Yan, Z. Cai, Y. Li, X. Cai, and J. Yu, “Influence maximization by probing partial communities in dynamic online social networks,” Trans. Emerg. Telecommun. Technol., vol. 28, no. 4, 2017, Art. no. e3054.

[41] Z. Wang, J. Liang, R. Li, and Y. Qian, “An approach to cold-start link prediction: Establishing connections between non-topological and topological information,” IEEE Trans. Knowl. Data Eng., vol. 28, no. 11, pp. 2857–2870, Aug. 2016.

[42] A. Bojchevski and S. Günnemann, “Deep Gaussian embedding of graphs: Unsupervised inductive learning via ranking,” in Proc. Int. Conf. Learn. Representations, 2018, pp. 2279–2281.

[43] Y. Hao, X. Cao, Y. Fang, X. Xie, and S. Wang, “Inductive link prediction for networks having only attribute information,” in Proc. Int. Joint Conf. Artif. Intell., 2021, pp. 1209–1215.

[44] J. Bromley et al., “Signature verification using a “Siamese” time delay neural network,” Int. J. Pattern Recognit. Artif. Intell., vol. 7, no. 4, pp. 669–688, Aug. 1993.

[45] Z. Wang, C. Chen, and W. Li, “Predictive network representation learning for link prediction,” in Proc. 40th Int. Conf. Res. Des. Inf. Retrieval, Tokyo, Japan, 2017, pp. 969–972.

[46] G. L. Nemhauser, L. A. Wolsey, and M. L. Fisher, “An analysis of approximations for maximizing submodular set functions I,” Math. Program., vol. 14, no. 1, pp. 265–294, 1978.

[47] S. L. Feld, “Why your friends have more friends than you do,” Amer. J. Sociol., vol. 96, no. 6, pp. 1464–1477, 1991.

[48] J. Leskovec and A. Krevl, “SNAP datasets: Stanford large network dataset collection,” Jun. 2014. [Online]. Available: http://snap.stanford.edu/data

[49] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” in Proc. Int. Conf. Learn. Representations, 2015, pp. 1–15.

[50] J. Leskovec and C. Faloutsos, “Sampling from large graphs,” in Proc. 12th Int. Conf. Knowl. Discov. Data Mining, 2006, pp. 631–636.

[51] T. N. Kipf and M. Welling, “Semi-supervised classification with graph convolutional networks,” in Proc. 5th Int. Conf. Learn. Representations, 2017, pp. 1–14.

[52] Y. Shi, Z. Huang, S. Feng, H. Zhong, W. Wang, and Y. Sun, “Masked label prediction: Unified message passing model for semi-supervised classifi- cation,” in Proc. 13th Int. Joint Conf. Artif. Intell., 2021, pp. 1548–1554.

Cong Tran received the B.Sc. degree in network and communication and the M.Sc. degree in computer science from Vietnam National University, Hanoi, Viet- nam, in 2009 and 2014, respectively, and the Doctoral degree in computer science from Dankook University, Yongin, South Korea, in 2021. Since 2021, he has been with the Faculty of Information Technology, Posts & Telecommunication Institute of Technology, Hanoi, Vietnam, as a Lecturer. His research interests include social network analysis, data mining, and machine learning.

Won-Yong Shin (Senior Member, IEEE) received the B.S. degree in electrical engineering from Yonsei University, Seoul, South Korea, in 2002, and the M.S. and Ph.D. degrees in electrical engineering and computer science from the Korea Advanced Institute of Science and Technology (KAIST), Daejeon, South Korea, in 2004 and 2008, respectively. In May 2009, he joined the School of Engineering and Applied Sciences, Harvard University, Cambridge, MA, USA, as a Postdoctoral Fellow and was promoted to a Research Associate in 2011. From 2012 to 2019, he was a Faculty Member (with tenure) of the Department of Computer Science and Engineering, Dankook University, Yongin, South Korea. Since 2019, he has been with the School of Mathematics and Computing (Computational Science and Engineering), Yonsei University, Seoul, South Korea, where he is currently a Full Professor. His research interests include information theory, mobile computing, data mining, and machine learning. From 2014 to 2018, Dr. Shin was an Associate Editor for the IEICE Transactions on Fundamentals of Electronics, Communications and Computer Sciences. He was an Associate Editor for the ICT Express. He also was an Organizing Committee Member for the 2015 IEEE Information Theory Workshop and the 2023/2024 IEEE Consumer Communications & Networking. He was the recipient of the Bronze Prize of the Samsung Humantech Paper Contest in both 2008 and 2022, KICS Haedong Young Scholar Award in 2016, and the ICT Express Best Guest Editor Award in 2021.

Andreas Spitz received the B.Sc. and M.Sc. degrees in computer science from Heidelberg University, Hei- delberg, Germany, in 2012 and 2014, respectively, and the Doctoral degree in computer science from Heidelberg University, in 2019, for his work on im- plicit network representations of unstructured textual data. He is currently an Assistant Professor with the University of Konstanz, Konstanz, Germany, and the Head of the Data and Information Mining Lab. Prior to joining the University of Konstanz in 2021, he was a Postdoctoral Researcher with the Data Science Lab at the École polytechnique fédérale de Lausanne (EPFL), Switzerland. His research interests include information retrieval, natural language processing, complex network analysis, and computational social science.