

Graph Neural Networks for Friend Ranking in Large-scale Social Platforms

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ABSTRACT

Graph Neural Networks (GNNs) have recently enabled substantial advances in graph learning. Despite their rich representational capacity, GNNs remain relatively under-explored for large-scale social modeling applications. One such industrially ubiquitous application in online social platforms is friend suggestion: platforms recommend their users other candidate users to befriend, to improve user connectivity, retention and engagement. However, modeling such user-user interactions on large-scale social platforms poses unique challenges: such graphs often have heavy-tailed degree distributions, where a significant fraction of users are inactive and have limited structural and engagement information. Moreover, users interact with different functionalities, communicate with diverse groups, and have multifaceted interaction patterns.

We study the application of GNNs for friend suggestion, providing the first investigation of GNN design for this task, to our knowledge. To leverage the rich knowledge of heterogeneous in-platform user actions, we formulate friend suggestion as *multi-faceted friend ranking* with multi-modal user features and link communication features. We present a neural architecture, GRAFRANK, which is carefully designed to learn expressive user representations from multiple user feature modalities and user-user interactions. Specifically, GRAFRANK handles heterogeneity in modality homophily via *modality-specific* neighbor aggregators, and learns non-linear modality correlations through *cross-modality attention*. We conduct experiments on two multi-million user social network datasets from Snapchat, a leading and widely popular mobile social platform, where GRAFRANK outperforms several state-of-the-art approaches on candidate retrieval (by 30% MRR) and ranking (by 20% MRR) tasks. Moreover, our qualitative analysis suggests notable gains for critical populations of less-active and low-degree users.

KEYWORDS

Graph Neural Network, Social Network, Recommendation System

1 INTRODUCTION

Learning latent user representations has become increasingly important in advancing user understanding, and has seen widespread adoption in various industrial settings, e.g., video recommendations on YouTube [10], related pin recommendations on Pinterest [42] etc. The user representations learned using deep models are *effective* at complementing, or even replacing conventional collaborative filtering methods [21], and are *versatile*, e.g., the learned user embeddings can be used to suggest new friendships and also to infer profile attributes (e.g., age, gender) in social networks.

Learning latent representations of nodes in graphs has prominent applications in multiple *academic* settings, such as link prediction [45], community detection [8], and *industrial* recommender

systems, including e-commerce [37, 38], content discovery [41, 42], and food delivery [23]. Graph Neural Networks (GNNs) [40] have emerged as a popular paradigm for graph representation learning due to their ability to learn representations combining graph structure and node/link attributes, without relying on expensive feature engineering. GNNs can be formulated as a *message passing* framework where node representations are learned by propagating features from local graph neighborhoods via trainable aggregators. Recently, GNNs have demonstrated promising results in a few industrial systems designed for item recommendations in bipartite [42] or multipartite [41] user-to-item interaction graphs.

Despite their rich representational ability, GNNs have been relatively unexplored in large-scale *user-user social interaction* modeling applications, like friend suggestion. Recommending new potential friends to encourage users to expand their networks, is a cornerstone of social networking, and plays an important role towards user retention, and promoting engagement within the platform.

Prior efforts typically formulate friend suggestion as link prediction (or matrix completion) with a rich literature of graph-based heuristics [29] to quantify user-user affinity, e.g., two users are more likely to connect if they have many common friends. A few GNN models target link prediction in academic settings, learn aggregators over enclosing subgraphs around each candidate link [44–46]; such models do not scale to industry-scale social graphs with over millions of nodes and billions of edges. Still, GNNs have enormous potential for learning expressive user representations in social networks, due to their intuitive message-passing paradigm that enables attention to social influence from friends in their ego-network.

Yet, designing GNNs for friend recommendations in large-scale social media poses unique challenges. First, social networks are characterized by *heavy-tailed* degree distributions, e.g., many networks approximately follow power-law distributions [3]. This poses a key challenge of *limited structural information* for a significant proportion of users with very few friends. A related challenge is *activity sparsity* where a very small fraction of users actively form new friendships at any given time. Secondly, contemporary social networking platforms offer a multitude of avenues for users to interact, e.g., users can communicate with friends either by *directly* exchanging messages, pictures, and videos, or *indirectly* through a variety of social actions, including liking, sharing, and commenting on posts. Extracting knowledge from such *heterogeneous* in-platform user actions is challenging, yet extremely *valuable* to address sparsity challenges for a vast majority of inactive users.

Present Work: In this work, we overcome structural and interactional sparsity by exploiting the rich knowledge of heterogeneous in-platform actions. We formulate friend recommendation on social networks as *multi-faceted friend ranking* on an *evolving* friendship graph, with multi-modal user features and link communication

features (Figure 1). We represent users with heterogeneous feature sets spanning multiple *modalities*, that include a collection of *static* profile attributes (e.g., demographic information) and *time-sensitive* in-platform activities (e.g., content interests and interactions). We also leverage pairwise link features on existing friendships, which capture recent communication activities across multiple direct (e.g., messages) and indirect (e.g., stories) channels within the platform.

To understand the complexity of user interactions and gain insights into various factors impacting friendship formation, we conduct an empirical analysis to investigate *attribute homophily* with respect to different user feature modalities. Our analysis reveals *diverse homophily distributions* across modalities and users, and indicates non-trivial *cross-modality* correlations. Motivated by these observations, we design an end-to-end GNN architecture, GRAFRANK (Graph Attentional Friend Ranker) for multi-faceted friend ranking.

GRAFRANK generates user representations by *modality-specific* neighbor aggregation and *cross-modality* attention. We handle heterogeneity in modality homophily by learning modality-specific message-passing aggregators to compute a set of latent representations for each user. Specifically, the neighbor aggregator is driven by a friendship attention mechanism that captures the influence of individual features and pairwise communications. We introduce a *cross-modality* attention module to compute the effective user representation by attending over the different modality-specific representations for each user, thereby learning non-linear correlations across modalities. We summarize our key contributions below:

- **Graph-Neural Friend Ranking:** To our knowledge, ours is the first work to investigate *graph neural network* usage and design for social user-user interaction modeling applications. Unlike prior work that typically view friend recommendation as structural link prediction, we present a novel formulation with multi-modal user features and link features, to leverage knowledge of rich heterogeneous user activities in social networking platforms.
- **GRAFRANK Model:** Motivated by our empirical analysis that reveals heterogeneity in modality homophily and cross-modality correlations, we design a novel GNN architecture, GRAFRANK, to learn *multi-faceted* user representations. Distinct from conventional GNNs that operate on a single homogeneous feature space, GRAFRANK encapsulates information from multiple correlated feature modalities and user-user interactions.
- **Robust Experimental Results:** Our extensive experiments on two large-scale datasets from a popular social networking platform Snapchat, indicate significant gains for GRAFRANK over state-of-the-art baselines on friend candidate retrieval (relative MRR gains of 30%) and ranking (relative MRR gains of 20%) tasks. Our qualitative analysis indicates stronger gains for a large, but especially crucial population of *less-active* and *low-degree* users.

2 RELATED WORK

We briefly review a few related lines of work on friend recommendations, graph neural networks, and multi-modal learning.

Friend Recommendation: The earliest methods were carefully designed *graph-based heuristics* of user-user proximity in social networks [29], e.g., path-based Katz centrality [25] or common neighbor-based Adamic/Adar [1]. Supervised learning techniques exploited a collection of such extracted pairwise features to train

classifiers and ranking models [12, 32]. However, computing pairwise heuristics *on-the-fly* for every potential link, is *infeasible* in large-scale evolving social networks.

More recently, *graph embedding* methods to learn latent node representations in graphs that capture the structural properties of a node and its neighborhoods, gained popularity owing to the scalability and efficacy of skip-gram models [11]. In particular, graph embedding models like node2vec [15] and Deepwalk [33] learn unsupervised node embeddings to maximize the likelihood of co-occurrence in fixed-length random walks, with applications in downstream tasks such as node classification and link prediction.

Graph embedding methods cannot directly incorporate node/link features, and more importantly learn latent embeddings for each node; this implies that number of *model parameters* scales linearly with the *size of the graph*, which is *prohibitive* for large-scale social networks with over multiple millions of users.

Graph Neural Networks: GNNs learn node representations by recursively propagating features (i.e., message passing) from local neighborhoods through the use of aggregation and activation functions [40]. A key feature of GNNs is their ability to learn node representations combining graph topology and node/link attributes. Graph Convolutional Networks (GCNs) [27] learn degree-weighted neighborhood aggregators by operating on the graph Laplacian. Many models generalize GCN with a wide range of learnable aggregators, e.g., self-attentions [36], mean and max pooling functions [16, 17]; these approaches have consistently outperformed embedding techniques based upon random walks [15, 33]. In contrast to most GNN models that store the entire graph in GPU memory, GraphSAGE [16] is an inductive variant that reduces memory footprint by sampling a fixed-size set of neighbors in each GNN layer. A few scalable extensions include minibatch training with variance reduction [6, 22], subgraph sampling [43], and graph clustering [9].

Despite the successes of GNNs in diverse applications, *very few* industrial systems have developed large-scale GNN implementations. One recent system, PinSage [42] extends GraphSAGE for Pinterest recommendation on a user-item bipartite graph. MultiSage [41] extends PinSage to multipartite user-item graphs.

However, GNNs remain unexplored for large-scale *user-user* social modeling applications where users exhibit multifaceted behaviors by interacting with different functionalities on social platforms. In our work, we design GNNs for the important application of *friend suggestion*, through a *novel multi-faceted friend ranking* formulation with *multi-modal user features* and *link communication features*.

Multi-Modal Learning: Deep learning techniques for multi-modal feature fusion over diverse modalities such as text, images, video, and graphs, have diverse applications [13, 24]. Specifically, multi-modal extensions of GNNs have recently been explored in micro-video recommendation [39] and urban computing [14] applications. In contrast to prior work that regard modalities as largely *independent* data sources, user feature modalities in social networks tend to be correlated. In this work, we propose a novel *cross-modality attention* layer that captures non-linear modality correlations, to learn *multi-faceted* user representations.

3 PRELIMINARIES

We first formulate the problem of *multi-faceted friend ranking* in large-scale social platforms (Section 3) and then briefly introduce relevant background on *graph neural networks* (Section 3.2).

3.1 Problem Formulation

In this section, we introduce the different information sources in a social networking platform, that are relevant to friend recommendation. Each registered individual in the platform is denoted by a *user* u or v and a pair of users (u, v) may be connected by a *friendship*, which is an undirected relationship, *i.e.*, if u is a friend of v , v is also a friend of u . We assume that the social network has a set of N users \mathcal{V} introduced until our latest observation time of the platform. The friendship graph \mathcal{G} evolves when new friendships form and when new users join the platform. In this work, we only consider the emerging of new users and friendships while leaving the removal of existing users and edges as future work.

Prior work typically represent a dynamic network as a sequence of static snapshots, primarily due to scaling concerns. However, graph snapshots are coarse approximations of the actual continuous-time network and rely on a user-specified discrete time interval for snapshot creation [34, 35]. We also assume multiple time-aware user-level features (across modalities) and link(edge)-level features capturing pairwise user-user communications. In industrial settings, such features are commonly extracted by routine batch jobs and populated in an upstream database at regular time intervals (*e.g.*, daily batch inference jobs), to facilitate efficient model training.

Thus, we adopt a hybrid data model that achieves the best of both worlds. We formulate the *friendship graph* as a continuous-time dynamic graph (CTDG) with the expressivity to record friendships at the finest possible temporal granularity; and represent *features* as a sequence of daily snapshots where the time-sensitive features (*e.g.*, engagement activity) are recorded at different time scales.

Friendship Graph: Let us consider an observation time window (t_s, t_e) such that friendships created in this window specify the training data for the friend ranking model. We divide this window (t_s, t_e) into a sequence of S daily snapshots, denoted by $1, 2, \dots, S$. Formally, we model the friendship graph \mathcal{G} as a timed sequence of friend creation events over the entire time range $(0, t_e)$, defined as:

Definition 3.1 (Friendship Graph). Given a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{T})$, let \mathcal{V} be the set of users, $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V} \times \mathbb{R}$ be the set of friendship links between users in \mathcal{G} . At the finest granularity, each link $e = (u, v, t) \in \mathcal{E}$ is assigned a unique timestamp $t \in \mathbb{R}^+$; $0 < t < t_e$ that denotes the link creation time, and $\mathcal{T} : \mathbb{R}^+ \mapsto [0, S]$ is a function that maps each timestamp t to a corresponding snapshot.

Note that the time window (t_s, t_e) corresponds to snapshots $[1, S]$, and snapshot 0 is a placeholder for any $t < t_s$. However, friendship graph \mathcal{G} includes the entire set of friendships created with all time-stamped links in $(0, t_e)$. The set of temporal neighbors of user v at time t includes all friends created before t , defined as $N_t(v) = \{w : e = (v, w, t') \in \mathcal{E} \wedge t' < t\}$.

Multi-Modal Evolving User Features: In a social network, users typically use multiple features, such as posting videos, exchanging messages or pictures with friends, or liking and sharing posts and articles, which can be indicative of both their stable traits

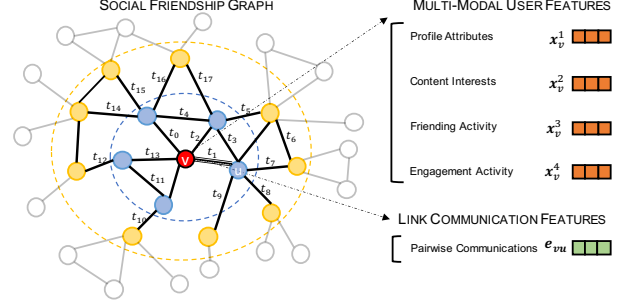


Figure 1: Desiderata for Multi-faceted Friend Ranking: temporally evolving friendship graph with multi-modal user features and pairwise link communication features.

and mutable interests. Since users with shared interests tend to form social connections due to homophily [31], we extract user attributes spanning a total of $K = 4$ modalities, which include profile attributes, in-app interests, friend creation activities, and user engagement activities, described in detail below:

- **Profile Attributes:** a set of (mostly) static demographic features describing the user, including age, gender, recent locations, languages, etc., that are listed or inferred from their profile.
- **Content Interests:** a real-valued feature vector describing the textual content (*e.g.*, posts, news) interacted by the user within the platform, *e.g.*, topics of posts liked by the user on Facebook.
- **Friending Activity:** this feature modality records the aggregated number of friend requests sent/received, reciprocated friendships, and viewed suggestions made by the user in different time ranges (*e.g.*, daily, weekly, and monthly).
- **Engagement Activity:** this modality records the aggregated number of in-app direct and indirect engagements made by the user (*e.g.*, direct messages, pictures, and comments on posts) with other friends in different time ranges.

The user feature modalities include a combination of *static* and *time-sensitive* features, *i.e.*, the profile attributes are static while the rest of the modalities are time-sensitive and often evolve at different scales across users, *e.g.*, a long-time active user may frequently communicate with a stable set of friends, while a new user is more likely to quickly add new friends before communicating.

The feature vector of a user $u \in \mathcal{V}$ in snapshot $s \in [1, S]$ is defined by $\mathbf{x}_u^s = [\mathbf{x}_u^{s,1}, \dots, \mathbf{x}_u^{s,K}]$ where $\mathbf{x}_u^{s,k} \in \mathbb{R}_k^D$ is the k -th user feature modality and $[\cdot]$ denotes row-wise concatenation.

Pairwise Link Communication Features: Social networks evolve centering around communication artifacts, with two predominant types of online communication channels: *conversations* and *social actions*. Conversations can include exchanges of text messages, pictures, and video content with friends, which indicate direct user-user interactions via communication. In contrast, social actions facilitate indirect user interactions through a variety of actions, *e.g.*, posting a Snapchat Story (image or video content) or liking a Facebook post, results in a passive broadcast to friends.

For conversational channels, we extract bidirectional edge features between users and their friends reflecting the number of communications sent and received by each pair of users. We capture indirect social actions by recording the number of user actions associated with each friend. Similar to user features, we extract edge

features per snapshot by aggregating communications at different time intervals. The link feature vector for a pair of users (u, v) at time t (who became friends before t), is denoted by $\mathbf{e}_{uv}^s \in \mathbb{R}^F$ where $s = \mathcal{T}(t)$ is the snapshot corresponding to timestamp t , and E is the total number of extracted link communication features.

We now formally define the problem of *multi-faceted friend ranking* in large-scale social platforms, over friendship graph \mathcal{G} with multi-modal user features and pairwise link features, as follows:

PROBLEM (MULTI-FACETED FRIEND RANKING). *Our objective is to leverage the multi-modal user features $\{\mathbf{x}_v^s : v \in \mathcal{V}, 1 \leq s \leq S\}$, link communication features $\{\mathbf{e}_{uv}^s : s = \mathcal{T}(t), (u, v, t) \in \mathcal{E}\}$ and the structure of the friendship graph \mathcal{G} , to generate temporal user representations $\{\mathbf{h}_v(t) \in \mathbb{R}^D : v \in \mathcal{V}\}$ at time t , that can be used for friend ranking, e.g., via nearest-neighbor lookup for candidate retrieval, or friend candidate re-ranking.*

3.2 Background on GNNs

We briefly introduce a generic formulation of a graph neural network layer with message-passing for neighborhood aggregation.

GNNs use multiple layers to learn node representations. At each layer $l > 0$ ($l = 0$ is the input layer), GNNs compute a representation for node v by aggregating features from its neighborhood, through a learnable aggregator $F_{\theta,l}$ per layer. Stacking k layers allows the k -hop neighborhood of a node to influence its representation.

$$\mathbf{h}_{v,l} = F_{\theta,l}(\mathbf{h}_{v,l-1}, \{\mathbf{h}_{u,l-1}\}), \quad u \in N(v) \quad (1)$$

Equation (1) indicates that the node embedding $\mathbf{h}_{v,l} \in \mathbb{R}^D$ for node v at the l -th layer is a non-linear aggregation $F_{\theta,l}$ of the embeddings from layer $l - 1$ of node v and the embeddings of immediate network neighbors $u \in N(v)$ of node v . The function $F_{\theta,l}$ defines the message passing function at layer l and can be instantiated using a variety of aggregator architectures, including graph convolution [27], graph attention [36], and pooling [16]. The node representation for v at the input layer is $\mathbf{h}_{v,0}$, where $\mathbf{h}_{v,0} = \mathbf{x}_v$ and $\mathbf{x}_v \in \mathbb{R}^D$. The representation of node v at the final GNN layer is typically trained using a supervised training objective.

The above formulation (Equation 1) operates under the setting of a static graph and assumes a single static input feature vector for each node. In contrast, our social network has a time-evolving friendship graph \mathcal{G} with pairwise link features and multi-modal node (user features), which poses unique modeling challenges.

4 GRAPH NEURAL FRIEND RANKING

In this section, we present our approach to inductively learn user representations in a dynamic friendship graph with pairwise link features and time-sensitive multi-modal node features.

We first conduct an empirical analysis on user feature modalities, to gain insights into various factors impacting friendship formation (Section 4.1). We then formulate the design choices of our model GRAFRANK for friend ranking grounded on our acquired insights (Section 4.2), followed by model training details (Section 4.3)

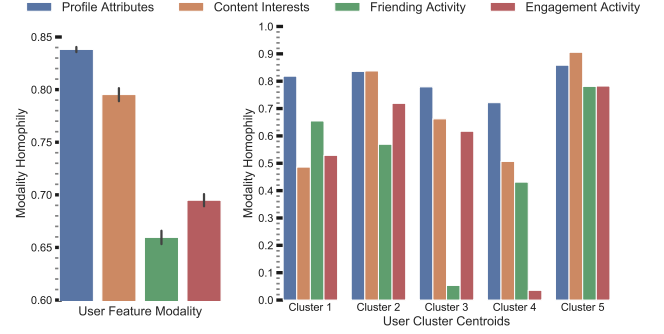


Figure 2: Users exhibit different extents of homophily across feature modalities. (a) Overall modality homophily scores, with 95% confidence interval bands (b) five representative cluster centroids identified by clustering users based on their homophily distributions over the K modalities.

4.1 Motivating Insight: Modality Analysis

We conduct an empirical study that helps us formulate the design choices in our model. We aim to validate the existence and understand the extent and variance of attribute homophily with respect to the different user feature modalities. We begin by analyzing users' ego-networks to characterize *modality homophily*, both overall and broken-down across different user segments. The definition of *modality homophily* echoes the standard definition of attribute homophily [31], but generalized to include a modality of attributes, i.e., the tendency of users in a social graph to associate with others who are *similar* to them along attributes of a certain modality.

We define a homophily measure \mathbf{m}_{vu}^k between a user v and her friend u on modality k by the standard cosine similarity [2], which is a normalized metric that accounts for heterogeneous activity across users. We compute a modality homophily score \mathbf{m}_u^k for user v on modality k by the mean over all her neighbors, defined by:

$$\mathbf{m}_v^k = \frac{1}{|N_v|} \sum_{u \in N_v} \mathbf{m}_{vu}^k \quad \mathbf{m}_{vu}^k = \cos(\mathbf{x}_u^k, \mathbf{x}_v^k) \quad (2)$$

Note that, we omit the snapshot s above since the discussion is restricted to a single feature snapshot. Figure 2 (a) shows the overall modality homophily scores (averaged across all users), for each of the K modalities. We observe differing extents of attribute homophily across modalities, with higher variance for the time-sensitive modalities (e.g., friending and engagement activities).

We further extend our analysis to examine the *homophily distribution* over modalities at the granularity of individual users, to understand if modality homophily varies across different users. To study this, we first represent each user u by a K -dimensional *modality vector* $\mathbf{m}_u = [\mathbf{m}_u^1, \dots, \mathbf{m}_u^K]$ that describes the homophily distribution over the K feature modalities. We then use k -means [18] to cluster the set of all users based on their computed modality vectors; Figure 2 (b) shows the centroid vectors of five representative clusters identified by k -means. We observe stark differences in the modality vector centroids across the five clusters, indicating the existence of user segments with diverse homophily distributions over the K modalities. This motivates our first key observation:

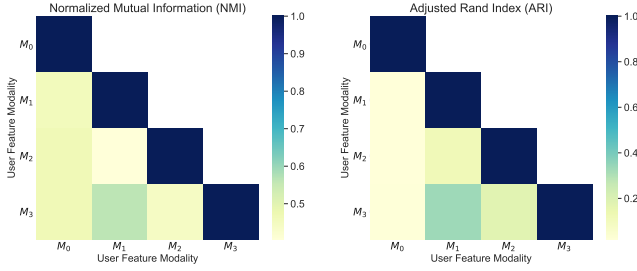


Figure 3: Cross-modality Correlation Study: NMI (a) and ARI (b) metrics for each pair of modalities, quantifying pairwise correlation by consensus in ego-clustering assignments (obtained independently with respect to each modality). We observe substantial correlations across pairs of modalities.

OBSERVATION 1 (HETEROGENEITY IN MODALITY HOMOPHILY). *Users exhibit different extents of homophily across feature modalities, and the homophily distribution over modalities varies significantly across diverse user segments.*

Each modality enables identification of a subset of friends that exhibit modality homophily. However, this poses a question: do the K modalities induce the same (or disparate) subsets of homophilous friends, or are the friends that exhibit homophily in each modality, correlated? We investigate this relationship in this section.

For every feature modality k , we cluster the ego-network (set of direct friends) $N(v)$ of each user $v \in \mathcal{V}$ by representing it as a set of modality-specific feature vectors $\{\mathbf{x}_u^k \in \mathbb{R}^{D_k} : u \in N(v)\}$; this results in ego-clustering assignments for each modality k . To quantify *cross-modality correlations*, we compute a *correlation score* for each pair of modalities, measured by the *consensus* between their corresponding ego-clustering assignments.

We use two standard measures: Normalized Mutual Information (NMI) and Adjusted Rand Index (ARI) to evaluate consensus between clusterings [4]. NMI measures the statistical correlation between two clustering assignments; however, NMI increases with the number of distinct clusters. ARI measures the percentage of correct pairwise assignments, and is chance-corrected with an expected value of zero. Note that NMI and ARI are symmetric metrics.

Figure 3 depicts average NMI and ARI scores for each pair of feature modalities. We observe substantial correlation in cluster assignments across a few modalities (e.g., time-sensitive modalities M_1 and M_3) while some (e.g., static modality M_0) are quite distinct from the rest. Our key takeaway regarding modality correlation is:

OBSERVATION 2 (CROSS-MODALITY CORRELATION). *There exist non-trivial correlations between pairs of feature modalities, indicated by the consensus in their induced ego-network clustering of users.*

4.2 GRAFRANK: Multi-Faceted Friend Ranking

In this section, we first introduce the key components of our model GRAFRANK (Graph Attention Friend Ranker) for friend ranking. Our modeling choices in designing a multi-modal GNN, directly follow from our observations. GRAFRANK has three modules (Figure 5):

- Modality-specific neighbor aggregation.
- Cross-modality attention layer.
- Pairwise ranking objective for model training.

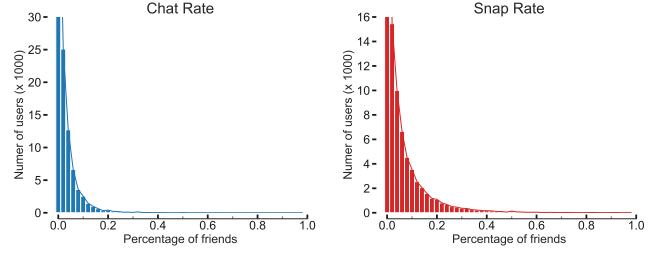


Figure 4: Friend communication rate in two direct channels (Chat, Snap) on Snapchat. Most users communicate frequently only with a subset ($\leq 20\%$) of their friends, making influence modeling critical during neighbor aggregation.

Below, we present a detailed description of each module.

4.2.1 Modality-specific Neighbor Aggregation. Since the feature modalities vary in the extent of induced homophily (Observation 1), we treat each modality individually as opposed to the popular choice of directly combining multi-modal user features by concatenation. Thus, our objective is to learn a modality-specific representation $\mathbf{z}_v^k(t) \in \mathbb{R}^D$ for each user $v \in \mathcal{V}$ at time $t \in \mathbb{R}^+$, that encapsulates information exclusively from modality k . We endow each user v with the expressivity to flexibly prioritize different friends in her temporal neighborhood $N_t(v)$, hence accounting for the variance in homophily distribution across user segments.

To achieve this, we design a *modality-specific neighbor aggregation* module to compute K representations $\{\mathbf{z}_v^1(t), \dots, \mathbf{z}_v^K(t)\}$, $\mathbf{z}_v^k(t) \in \mathbb{R}^D$ for each user v at time $t \in \mathbb{R}^+$, where each $\mathbf{z}_v^k(t)$ is obtained using an independent and unique message-passing function per modality. We begin by describing a single layer, which consists of two major operations: *message propagation* and *message aggregation*. We then discuss generalization to multiple successive layers.

Message Propagation: We define the message-passing mechanism to aggregate information from the ego-network $N_t(v)$ of user v at time t . Specifically, the propagation step for modality k aggregates the k -th modality features $\{\mathbf{x}_u^{s,k} : u \in N_t(v), s = \mathcal{T}(t)\}$ from the corresponding snapshot $s = \mathcal{T}(t)$ of temporal neighbors $N_t(v)$. To quantify the importance of each friend u in the ego-network, we propose a friendship attention [36] which takes embeddings $\mathbf{x}_u^{s,k}$ and $\mathbf{x}_v^{s,k}$ as input, and computes an attentional coefficient $\alpha^k(v, u, t)$ to control the influence of friend u on v at time t .

$$\alpha^k(v, u, t) = \text{LeakyReLU}\left(\mathbf{a}_k^T (\mathbf{W}_1^k \mathbf{x}_v^{s,k} \parallel \mathbf{W}_1^k \mathbf{x}_u^{s,k})\right) \quad s = \mathcal{T}(t) \quad (3)$$

where $\mathbf{W}_1^k \in \mathbb{R}^{D_k \times D}$ is a shared linear transformation applied to each user, \parallel is the concatenation operation, and the friendship attention is modeled as a single feed-forward layer parameterized by weight vector $\mathbf{a}_k \in \mathbb{R}^{2D}$ followed by the LeakyReLU nonlinearity. We then normalize the attentional coefficients across all friends connected with v at time t by adopting the softmax function:

$$\alpha^k(v, u, t) = \frac{\exp(\alpha^k(v, u, t))}{\sum_{w \in N_t(v)} \exp(\alpha^k(v, w, t))} \quad (4)$$

We now define an ego-network representation $\mathbf{z}_v^k(t, N_v(t)) \in \mathbb{R}^{D_k}$ for user v in modality k that captures messages propagated

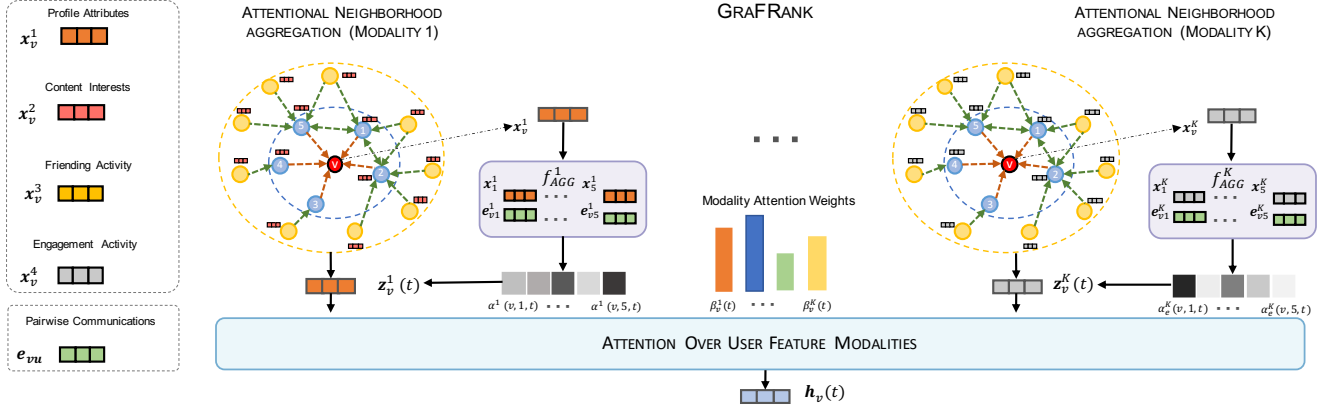


Figure 5: Overall framework of GRAFRANK: a set of K modality-specific neighbor aggregators (parameterized by individual modality-specific user features and link communication features) to compute K intermediate user representations; cross-modality attention layer to compute final user representations by capturing discriminative facets of each modality.

from first-order neighbors in the ego-network $N_v(t)$. The message $\mathbf{m}_{v \leftarrow u}^k \in \mathbb{R}^D$ propagated from friend u to user v at time t is defined as the transformed friend embedding, i.e., $\mathbf{m}_{v \leftarrow u}^k = \mathbf{W}_1^k \mathbf{x}_u^{s,k}$. We then compute $\mathbf{z}_v^k(t, N_v(t))$ through a weighted average of message embeddings from each friend $u \in N_v(t)$ and guided by normalized friendship weights $\alpha^k(u, v, t)$, which is defined as:

$$\mathbf{z}_v^k(t, N_v(t)) = \sum_{u \in N_v(t)} \alpha^k(v, u, t) \mathbf{m}_{v \leftarrow u}^k \quad (5)$$

While the above equation specifies different contributions to friends, these weights are learnt merely based on the connectivity structure of the ego-network. In reality, most users only have a few close friends, and users with many friends only frequently communicate with a few of them. To empirically validate this hypothesis, we compute the *friend communication rate* of all users, defined by the percentage of friends that a user has directly communicated with at least once (directly sent a Chat/Snap with on Snapchat) in a one-month window. From Figure 4, we find that a vast majority of users communicate primarily with a small percentage (10-20%) of their friends; thus, we posit that *friendship activeness* is critical to precisely model user affinity.

Towards this goal, we incorporate *pairwise link communication* features to parameterize both the attentional coefficients and the message aggregated from friends in the ego-network. Specifically, we formulate the message $\mathbf{m}_{v \leftarrow u}^k \in \mathbb{R}^D$ from friend u to user v at time t as a function of both friend feature $\mathbf{x}_u^{s,k}$ and link feature \mathbf{e}_{vu}^s .

$$\mathbf{m}_{v \leftarrow u}^k = \mathbf{W}_2^k \mathbf{x}_u^{s,k} + \mathbf{W}_e^k \mathbf{e}_{vu}^s + \mathbf{b} \quad s = \mathcal{T}(t) \quad (6)$$

where $\mathbf{W}_2^k \in \mathbb{R}^{D_k \times D}$, $\mathbf{W}_e^k \in \mathbb{R}^{E \times D}$ are trainable weight matrices operating on the user and link features respectively, and $\mathbf{b} \in \mathbb{R}^D$ is a learnable bias vector. The attentional co-efficient $\alpha^k(v, u, t)$ is then computed as a function of user feature $\mathbf{x}_v^{s,k}$ and message embedding $\mathbf{m}_{v \leftarrow u}^k \in \mathbb{R}^D$ from friend u to user v , defined by:

$$\alpha^k(v, u, t) = \sigma \left(\mathbf{a}_k^T \left(\mathbf{W}_1^k \mathbf{x}_v^{s,k} \parallel \mathbf{m}_{v \leftarrow u}^k \right) \right) \quad s = \mathcal{T}(t) \quad (7)$$

where σ is a non-linearity such as LeakyRELU. We similarly normalize the attentional coefficients $\alpha^k(v, u, t)$ using Equation 4 and compute the ego-network representation $\mathbf{z}_v^k(t, N_v(t))$ for user v on modality k using Equation 5 with the message embedding $\mathbf{m}_{v \leftarrow u}^k$ from Equation 6 conditioned on link features.

Distinct from conventional graph convolution and attention networks [16, 27, 36, 42] that only consider user $\mathbf{x}_v^{s,k}$ and friend $\mathbf{x}_u^{s,k}$ features to parameterize the neighbor aggregation, we additionally encode the link communication features \mathbf{e}_{vu}^s into the attentional co-efficient $\alpha^k(v, u, t)$ (Equation 7) and the message $\mathbf{m}_{v \leftarrow u}^k$ (Equation 6) passed from friend u ; this encourages the aggregation to be cognizant of the pairwise communications with friends, e.g., passing more messages from the active friendships. In addition, we observe a boost in friend ranking performance (Section 5.4) owing to our novel communication-aware message passing strategy.

Message Aggregation: We refine the latent representation for user v by aggregating the messages propagated from friends in $N_v(t)$. In addition to the messages from $N_v(t)$, we additionally consider the self-connection of v , i.e., $\mathbf{m}_{v \leftarrow v}^k = \mathbf{W}_1^k \mathbf{x}_v^{s,k}$ to preserve knowledge of the original features (\mathbf{W}_1 is the same transformation used in Equation 3). Specifically, we concatenate the ego-network and self-representations of user v , and further transform the concatenated embedding through a dense layer F_θ^k , defined by:

$$\mathbf{z}_v^k(t) = F_\theta^k \left(\mathbf{m}_{v \leftarrow v}^k, \mathbf{z}_v^k(t, N_v(t)) \right) \quad (8)$$

$$= \sigma \left(\mathbf{W}_a^k \left(\mathbf{z}_v^k(t, N_v(t)) \parallel \mathbf{m}_{v \leftarrow v}^k \right) + \mathbf{b}_a \right) \quad (9)$$

where $\mathbf{W}_a^k \in \mathbb{R}^{D \times D}$, $\mathbf{b}_a \in \mathbb{R}^D$ are trainable weight parameters of the message aggregator, and σ denotes the ELU activation function, which allows messages to encode both positive and small negative signals. Empirically we observe significant performance gains owing to retaining knowledge of self-representation via concatenation, instead of directly using the propagated ego-network representation from the neighborhood, as in GCN [27], and GAT [36].

Higher-order Propagation: We stack multiple neighbor aggregation layers to model high-order connectivity information, i.e.,

propagate features from l -hop neighbors. The inputs to layer l depend on the user representations output from layer $(l-1)$ where the initial (i.e., “layer 0”) representations are set to the input user features in modality k . By stacking l layers, we recursively formulate the representation $\mathbf{z}_{v,l}^k$ of user v at the end of layer l by:

$$\mathbf{z}_{v,l}^k = F_{\theta,l}^k(\mathbf{m}_{v \leftarrow v,l-1}^k, \mathbf{z}_{v,l-1}^k(t, N_v(t))) \quad \mathbf{m}_{v \leftarrow v,l-1}^k = \mathbf{z}_{v,l-1}^k \quad (10)$$

where $\mathbf{z}_{v,l-1}^k$ is the representation of user v in modality k after $(l-1)$ layers and $\mathbf{z}_{v,l-1}^k(t, N_v(t))$ denotes the $(l-1)$ -ego-network representation of user v . We apply L neighbor aggregation layers to generate the layer- L representation $\mathbf{z}_{v,L}^k$ of user v in modality k .

4.2.2 Cross Modality Attention. To learn complex non-linear correlations between different feature modalities, we design a *cross-modality attention* mechanism. Specifically, we learn modality attention weights $\beta_v^k(t)$ to distinguish the influence of each modality k using a two-layer Multi-Layer Perceptron, defined by:

$$\beta_v^k(t) = \frac{\exp(\mathbf{a}_m^T \mathbf{W}_m \mathbf{z}_{v,L}^k + b_m)}{\sum_{k'=1}^K \exp(\mathbf{a}_m^T \mathbf{W}_m \mathbf{z}_{v,L}^{k'} + b_m)} \quad (11)$$

with weights $\mathbf{W}_m \in \mathbb{R}^{D \times D}$, $\mathbf{a}_m \in \mathbb{R}^D$ and scalar bias b_m . The final representation $\mathbf{h}_v(t) \in \mathbb{R}^D$ of user v is computed by a weighted aggregation of the layer- L modality-specific user representations $\{\mathbf{z}_{v,L}^1, \dots, \mathbf{z}_{v,L}^K\}$, guided by modality weights $\beta_v^k(t)$, defined by:

$$\mathbf{h}_v(t) = \sum_{k=1}^K \beta_v^k(t) \mathbf{W}_m \mathbf{z}_{v,L}^k \quad (12)$$

4.3 Model Training

We train GRAFRANK using a supervised pairwise ranking objective to differentiate *positive* and *negative* neighborhoods. We assume access to training data described by a set of timestamped links \mathcal{L} created in a time span (t_s, t_e) , where $(v, u, t) \in \mathcal{L}$ indicates a bi-directional friendship link between *source* user u and *target* friend v formed at time $t \in (t_s, t_e)$. To train the parameters of GRAFRANK, we define a triplet like objective based on max-margin ranking.

4.3.1 Pairwise Ranking Objective. We define a time-sensitive ranking loss over the final user embeddings $(\mathbf{h}_v(t))$ for user v at time t to rank the inner product of positive links $(v, u, t) \in \mathcal{L}$, higher than sampled negatives (v, n, t) by a margin factor Δ , as:

$$L = \sum_{(u,v,t) \in \mathcal{L}} \mathbb{E}_{n \sim P_n(v)} \max\{0, \mathbf{h}_v(t) \cdot \mathbf{h}_n(t) - \mathbf{h}_v(t) \cdot \mathbf{h}_u(t) + \Delta\} \quad (13)$$

where Δ is a margin hyper-parameter and $P_n(v)$ is the negative sampling distribution for user v . This generic contrastive learning formulation enables usage of the same framework to learn user embeddings for different recommendation tasks such as candidate retrieval and ranking, with diverse negative sampling distributions.

4.3.2 Friend Candidate Retrieval and Ranking Tasks. We learn user embeddings towards two key use-cases in friend ranking: *candidate retrieval* and *candidate ranking*. Candidate retrieval aims to generate a list of top- N (e.g., $N = 100$) potential friend suggestions

Dataset	Region 1	Region 2
# users	3.1 M	17.1 M
# links	286 M	2.36 B
# user features	79	79
# link features	6	6
# test set friend requests	46K	340K

Table 1: Dataset statistics

out of a very large candidate pool (over millions of users), while candidate ranking involves fine-grained re-ranking within a much smaller pool of the generated candidates, to determine the top- n (e.g., $n = 10$) suggestions shown to end users in the platform. We define different negative sampling distributions $P_n(v)$ for each task owing to their different ranking granularities, as follows:

- **Candidate Retrieval:** For the *coarse-grained* task of candidate retrieval, we uniformly sample five *random negative* users for each positive link, from the entire user set \mathcal{V} . Generating random negatives is efficient and effective at quickly training the model to identify potential friend candidates for each user. However, random negatives are often too *easy* to distinguish and may not provide the requisite resolution for the model to learn *fine-grained distinctions* necessary for candidate friend ranking.
- **Candidate Ranking:** To enhance model resolution for candidate ranking, we also consider *hard negative* examples for each positive pair (u, v) that are related to the source u , but not as relevant as the target friend v . For each user u , we generate five hard negatives based on graph proximity. Specifically, users in k -hop ($3 \leq k \leq 4$) graph neighborhoods of u (that are not within the 2-hop neighborhood), are randomly sampled as hard negatives. In practice, we pre-compute a set of hard negatives for each user, to facilitate efficient negative sampling during model training. We adopt a *two-phase* learning approach for candidate ranking. We pre-train the model on random negatives (as in candidate retrieval), to identify good model initialization points, followed by fine-tuning on hard negatives. Ranking hard negatives is more challenging, hence encouraging the model to progressively learn friend distinctions at a finer granularity. We empirically show notable gains on candidate ranking due to our two-phase strategy, compared to training individually on random or hard negatives.

4.3.3 Temporal Neighborhood Sampling. We learn a temporal user representation $\mathbf{h}_v(t)$ for user v at time t by selecting a fixed number of friends from $N_v(t)$ for neighbor aggregation at each layer; this controls the memory footprint during training [16].

To efficiently identify and sample neighbors of v at any time t , we represent the time-evolving friendship graph \mathcal{G} as a *temporal adjacency list* at its latest time t_s where each user v has a list of (friend, time) tuples sorted by link creation times. This data representation enables $O(\log d)$ neighbor lookup at an arbitrary timestamp t via binary search where d is the average user degree in the graph.

4.3.4 Multi-GPU Minibatch Training. We train GRAFRANK with minibatches of links from \mathcal{L} using multiple GPUs on a single shared memory machine. The temporal adjacency list of \mathcal{G} and feature matrices \mathbf{X}, \mathbf{E} are placed in shared CPU memory to enable fast parallel neighborhood sampling and feature lookup. We adopt a *producer-consumer* architecture [42] that alternates between CPUs

Dataset	Region 1					Region 2				
	N@5	N@50	HR@5	HR@50	MRR	N@5	N@50	HR@5	HR@50	MRR
LogReg	0.1752	0.2460	0.2452	0.5262	0.1751	0.0761	0.1367	0.1134	0.3654	0.0831
MLP	0.1923	0.2679	0.2721	0.5726	0.1903	0.0973	0.1720	0.1466	0.4541	0.1046
XGBoost	0.2099	0.2865	0.2932	0.5957	0.2071	0.1366	0.2097	0.1936	0.4921	0.1409
GCN	0.0934	0.1836	0.1490	0.5154	0.1034	0.1651	0.2634	0.2503	0.6427	0.1678
GAT	0.0851	0.1813	0.1424	0.5352	0.0960	0.1797	0.2794	0.2698	0.6663	0.1812
SAGE + Max	0.1790	0.2736	0.2695	0.6409	0.1797	0.1520	0.2505	0.2315	0.6269	0.1566
SAGE + Mean	0.2378	0.3240	0.3338	0.6757	0.2333	0.2870	0.3805	0.4005	0.7655	0.2790
GRAFRANK	0.3152	0.3983	0.4318	0.7533	0.3035	0.4166	0.4950	0.5386	0.8395	0.4012
Percentage Gains	32.55 %	22.93 %	29.36 %	11.48 %	30.09 %	45.16 %	30.09 %	34.48 %	9.67 %	43.8 %

Table 2: GRAFRANK outperforms feature-based models and GNNs (relative gains of 30-43 % MRR with respect to the best baseline) on candidate retrieval in Regions 1 and 2. HR@K and N@K denote Hit-Rate@K and NDCG@K metrics for $K = 5, 50$.

and GPUs for model training. A CPU-bound producer constructs friend neighborhoods, looks up user and link features, and generates negative samples for the links of a minibatch. We then partition each minibatch across multiple GPUs, to compute forward passes and gradients with a PyTorch model over dynamically constructed computation graphs. The gradients from different GPUs are synchronized using PyTorch’s Distributed Data Parallel [28] construct.

5 EXPERIMENTS

To analyze the quality of user representations learned by GRAFRANK, we propose five research questions to guide our experiments:

- (RQ₁) Can GRAFRANK outperform feature-based models and state-of-the-art GNNs on candidate *retrieval* and *ranking* tasks?
- (RQ₂) How does GRAFRANK compare to prior work under alternative metrics of *reciprocated* and *communicated* friendships?
- (RQ₃) How do the different *architectural* design choices and *training* strategies in GRAFRANK impact performance?
- (RQ₄) How do training strategies and hyper-parameters impact convergence and performance of GRAFRANK?
- (RQ₅) How do the learned user embeddings in GRAFRANK perform across diverse user cohorts?

5.1 Experiment Setup

We now present our experimental setup with a brief description of datasets, evaluation metrics, and model training details.

5.1.1 Datasets. We evaluate the user representations learned by GRAFRANK for friend recommendations, on two large-scale datasets from Snapchat. Each dataset is constructed from the interactions among users belonging to a specific country (obscured for privacy reasons). We collect 79 user features spanning four modalities and six pairwise link communication features, as described in Section 3. All features are standardized by zero-mean and unit-variance normalization before model training. We define the set \mathcal{L} of positive training examples (Equation 13) using all timestamped friendships created in a span of one week. Since our objective is to evaluate the quality of friendship recommendations, the test set comprises all *friend add requests* generated by users over the next four days. We use 10% of the labeled examples for hyper-parameter tuning. Table 1 shows the statistics of the two datasets.

5.1.2 Evaluation Metrics. We experiment on two friend recommendation tasks: candidate retrieval and candidate ranking, as outlined in Section 4.3. To evaluate friend recommendation, we use standard ranking metrics Hit-Rate (HR@K), Normalized Discounted Cumulative Gain (NDCG@K) and Mean Reciprocal Rank (MRR). We adopt the standard negative-sample evaluation [20] to generate N negative samples per positive pair of users (u, v) in the test set (user u has sent a friend request to user v). We then compute ranking metrics for each test pair (u, v) by ranking v among the N negative samples via inner products in the latent space.

To evaluate candidate retrieval, we use $N = 10000$ *randomly sampled negative users* for each positive test pair, to emulate retrieval from a large candidate pool. Ideally, candidate ranking should operate over a shortlisted list of potential friends identified by the retrieval system. However, we aim to provide a fair benchmark comparison of different models for candidate ranking that is agnostic to the biases of the upstream retrieval system. Thus, we instead generate $N = 500$ *hard negatives samples* per test pair based on K -hop neighborhoods (Section 4.3), to ensure an unbiased comparison.

5.1.3 Training Details. We train GRAFRANK using $L = 2$ message passing layers per feature modality with a hidden dimension size of 64 and output embedding dimension $D = 32$. In each layer, we sample 15 first-order neighbors and 15 second-order neighbors for each sampled first-order neighbor; each user receives messages propagated from upto 225 friends. During model training, we apply dropout with rate of 0.3 in the two aggregation layers. The model is trained for a maximum of 30 epochs with a batch size of 256 positive pairs (apart from 5 random/hard negatives per pair) and learning rate of 0.001 using Adam optimizer. We benchmark our experiments using a machine with 32 cores, 200 GB shared CPU memory, and a single Nvidia Tesla P100 GPU with PyTorch [28] implementations on the Linux platform.

5.2 Baselines

We compare the performance of GRAFRANK on friend ranking against strong feature-based machine learning models, and state-of-the-art graph neural networks that learn user representations.

- **LogReg** [19]: Logistic regression classifier for link prediction. The input feature for each pair of users, is a concatenation of source and target features across the K user feature modalities.

Dataset	Region 1					Region 2				
	N@5	N@10	HR@5	HR@10	MRR	N@5	N@10	HR@5	HR@10	MRR
LogReg	0.1521	0.1795	0.2268	0.3116	0.1523	0.1398	0.1711	0.2136	0.3106	0.1449
MLP	0.1873	0.2190	0.2663	0.3644	0.1915	0.1927	0.2241	0.2721	0.3695	0.1967
XGBoost	0.1714	0.2002	0.2394	0.3287	0.1779	0.1844	0.2174	0.2605	0.363	0.1911
GCN	0.1345	0.1698	0.2039	0.3136	0.1462	0.1758	0.2147	0.2619	0.3826	0.1831
GAT	0.1416	0.1776	0.2197	0.3313	0.1503	0.2028	0.2445	0.2984	0.4276	0.2077
SAGE + Max	0.2063	0.2441	0.2980	0.4151	0.2094	0.2426	0.2818	0.3443	0.4654	0.2426
SAGE + Mean	0.2232	0.2607	0.3165	0.4330	0.2255	0.2766	0.3164	0.3835	0.5064	0.2744
GRAFRANK	0.2684	0.3098	0.3772	0.5051	0.2669	0.3342	0.3767	0.4529	0.5841	0.3282
Percentage Gains	20.25 %	18.83 %	19.18 %	16.65 %	18.36 %	20.82 %	19.06 %	18.1 %	15.34 %	19.61 %

Table 3: GRAFRANK achieves significant improvements (relative gains of 18-20% MRR with respect to the best baseline) over both feature-based models and prior GNNs in all ranking metrics on friend candidate ranking in both Region 1 and Region 2.

- **XGBoost** [7]: Tree boosting model for pairwise learning to rank, trained using the same input features as LogReg. It is currently deployed at Snapchat for quick-add friend suggestions.
- **MLP** [19]: Two-layer Multi-Layer Perceptron with fully-connected layers and ReLU activations to learn user representations. We train MLP using the same ranking loss as our model (Equation 13).
- **GCN** [27]: Graph convolutional networks with degree-weighted neighbor aggregation and neighborhood sampling for scalable training. For each user, we concatenate features across the K user feature modalities into a new nodal feature vector.
- **GAT** [36]: Graph attention networks with self-attentional aggregation and neighborhood sampling for scalable training.
- **SAGE + Max** [16]: Element-wise max pooling for neighbor aggregation and self-embedding concatenation at each layer.
- **SAGE + Mean** [16]: Same as SAGE + Max with element-wise mean pooling function for neighbor aggregation.

Note that neural graph autoencoders [26] and graph convolutional matrix completion models [5] are not comparable because they cannot scale to our large-scale social network datasets.

For each baseline, we train separate models for candidate retrieval and ranking tasks. We use random negatives for retrieval model training while resorting to hard negatives for ranking; we empirically find training separate models to be vastly superior to a training a single model using a mixture of random and hard negatives, or even a curriculum training scheme [42].

5.3 Experimental Results

We first present our main results comparing GRAFRANK with competing baselines on candidate retrieval and ranking tasks, followed by comparisons with alternative measures of friendship quality.

5.3.1 Friend Candidate Retrieval and Ranking (RQ₁). We compare friend recommendation performance (based on add requests) of various approaches on retrieval and ranking in Tables 2 and 3 respectively. Interestingly, we find that SAGE based models variants often outperform popular GNN models GCN and GAT. A possible explanation is the impact of feature space heterogeneity in social networks and stochastic neighbor sampling; this results in noisy user representations for GNN models (GCN, GAT) that

recursively aggregate neighbor features without emphasizing self-connections. Preserving knowledge of the original user features by explicitly concatenating the self-embedding in each layer results in noticeable gains (SAGE variants).

GRAFRANK significantly outperforms state-of-the-art approaches with over 20-30% relative MRR gains. In contrast to singular aggregation over the entire feature space by prior GNNs, GRAFRANK handles variance in homophily across different modalities through modality-specific communication-aware neighbor aggregation. Further, the final user representations are learnt by a correlation-aware attention layer to capture discriminative facets of each modality.

5.3.2 Alternative Friendship Quality Indicators (RQ₂). In addition to evaluating friend suggestion based on the generated friend addition requests, we consider other metrics to quantify friendship quality, e.g., social platforms often want to incentivize friendships that result in greater downstream engagement. We therefore define friendship *reciprocation* and future bi-directional *communication* as two alternative measures of friendship quality. We present comparisons to evaluate *reciprocated* and *communicated* friend recommendation performance on the retrieval task in Table 4.

We observe consistently high gains for GRAFRANK on the reciprocated and communicated friend retrieval tasks; this also demonstrates the generality of our pairwise friend ranking objective (Equation 13) in learning user representations that promote downstream engagement. Designing multi-criteria ranking objectives to balance different quality measures is worth exploring in the future.

5.4 Ablation Study (RQ₃)

In this section, we present an ablation study to analyze the *architectural modeling* choices and *training strategies* in GRAFRANK.

5.4.1 Model Architecture. We design three variants to study the utilities of *communication-aware* and *modality-specific aggregation*.

- **GraFRank_{UM} (User-Modality):** We analyze the contribution of link features by parameterizing the k -th modality aggregator with *just* the k -th modality user features (Equation 3). Note that link features are excluded during neighbor aggregation.

Dataset	Add		Reciprocate		Communicate	
Metric	HR@50	MRR	HR@50	MRR	HR@50	MRR
LogReg	0.5262	0.1751	0.5582	0.2029	0.5495	0.1811
MLP	0.5726	0.1903	0.6006	0.2165	0.6001	0.1979
XGBoost	0.5957	0.2071	0.6286	0.2322	0.6407	0.2274
GCN	0.5154	0.1034	0.5329	0.1113	0.5273	0.1038
GAT	0.5352	0.0960	0.5596	0.1045	0.5654	0.0971
SAGE + Max	0.6409	0.1797	0.6653	0.2043	0.6670	0.1834
SAGE + Mean	0.6757	0.2333	0.6984	0.2609	0.7056	0.2446
GraFrank	0.7533	0.3035	0.7756	0.3367	0.7942	0.3152
Percent Gains	11.48 %	30.09%	11.05%	29.05%	12.56%	28.86 %

Table 4: Comparison of all models on *add*, *reciprocate* and *communicate* friendship retrieval tasks (reported on Region 1). GRAFRANK has consistent gains across all tasks.

Dataset	Retrieval		Ranking	
Metric	HR@50	MRR	HR@10	MRR
(a) GRAFRANK _U	0.6968	0.2346	0.4255	0.2164
(b) GRAFRANK _{UL}	0.7069	0.2423	0.4450	0.2301
(c) GRAFRANK _{UM}	0.7239	0.2823	0.4887	0.2480
GRAFRANK	0.7533	0.3035	0.5051	0.2669

Table 5: Model architecture ablation study of GRAFRANK. Removing (c) link communication features, (b) modality-specific aggregation, or (a) both, hurt model performance.

- **GraFRank_{UL} (User-Link):** To study the effectiveness of learning *modality-specific* aggregators, we define a *single modality-agnostic* aggregator over user feature vectors obtained by concatenation across the K modalities and link features.
- **GraFRank_U (User):** We remove link features from the aggregator in GraFRank_{UL} to further test the standalone benefits of link features in parameterizing a single neighbor aggregator.

The performance of all architectural variations are reported in Table 5. GRAFRANK_{UL} performs much worse than GRAFRANK highlighting the benefits of learning multiple modality-specific aggregators to account for varying extents of modality homophily.

Communication-aware neighbor aggregation is effective at identifying actively engaged friends during neighbor aggregation; this is evidenced by the gains of GRAFRANK over GRAFRANK_{UM} (modality-aware user feature aggregation). We find noticeable gains from parameterizing the aggregator with link features, even in the absence of modality-specific aggregation, from the comparison between GRAFRANK_{UL} and GRAFRANK_U (single user feature aggregator).

5.4.2 Training Strategy. We examine different training strategies to learn GNN models for friend recommendation. We train GRAFRANK with random negatives for candidate retrieval, but adopt two-phase hard negative fine-tuning (with random negative pre-training) for candidate ranking. To validate our choices, we examine three model training settings: (a) random negative training, (b) hard negative training, and (c) fine-tuning (after pretraining on random negatives), for two GNN models: SAGE + Mean, and GRAFRANK, across both candidate retrieval and ranking tasks. Note that training with combination of random and hard negatives, as proposed in [42], is excluded since it consistently performs worse than the above three strategies on both retrieval and ranking tasks.

Dataset	Retrieval		Ranking	
Metric	HR@50	MRR	HR@10	MRR
SAGE + Mean (random)	0.6757	0.2333	0.3943	0.1923
SAGE + Mean (hard)	0.3275	0.0766	0.4330	0.2255
SAGE + Mean (fine-tune)	0.3978	0.0965	0.4561	0.2372
GRAFRANK (random)	0.7533	0.3035	0.4655	0.2254
GRAFRANK (hard)	0.4542	0.1461	0.4823	0.2594
GRAFRANK (fine-tune)	0.5283	0.1871	0.5051	0.2669

Table 6: Training strategy comparison of two GNNs across retrieval and ranking tasks. Random negative training achieves best results for retrieval. Random negative pre-training with hard negative fine-tuning benefits ranking.

We make three consistent observations from the performance comparison (Table 6) across all of the compared GNN models:

- Random negative training achieves best results for retrieval, but performs poorly on ranking; such models lack the *resolution* to discriminate amongst potential candidates for re-ranking.
- Training on hard negatives improves candidate ranking as expected, yet results in poor retrieval performance. Learning fine profile-oriented distinctions among graph-based neighbors, is actually detrimental to the coarse-grained task of retrieval.
- Random negative pretraining yields good parameter initialization points that are more conducive for effective fine-tuning on hard negatives. Fine-tuning improves results for all GNNs over direct hard negative training on ranking, but is ineffective for retrieval.

5.5 Training and Sensitivity Analysis (RQ₄)

In this section, we quantitatively analyze model *convergence* and model *sensitivity* to sampled *neighborhood sizes* in GNN models.

5.5.1 Model Training Analysis. We investigate the relative abilities of different models to optimize the pairwise friend ranking objective (Equation 13). We compare the convergence rates of base-lines MLP, SAGE + Mean, and our model GRAFRANK under both random and hard negative training settings, by examining the average training loss per epoch in Figures 6 (a) and (b) respectively.

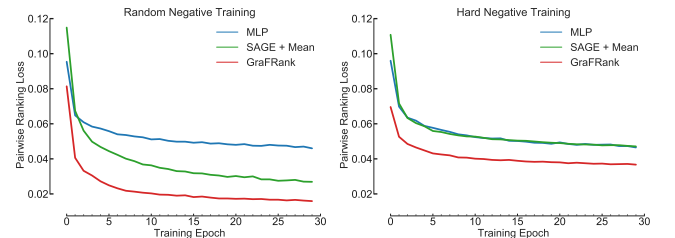


Figure 6: GRAFRANK converges faster to better optimization minima in *random* and *hard* negative settings, which translates to notable gains on both retrieval and ranking tasks.

As expected, all models converge to a lower training loss against random negatives (Figure 6 (a)) when compared to hard negatives (Figure 6 (b)). Interestingly, SAGE + Mean shows similar training convergence as MLP in Figure 6 (b), but achieves better test results; this indicates better generalization for GNNs over feature-based

models. Compared to baselines, GRAFRANK converges to a better optimization minimum, under both random and hard negative settings, that also generalizes to better test results (Tables 2 and 3).

5.5.2 Runtime and Sensitivity Analysis. A key trade-off in training scalable GNN models lies in choosing the size of sampled neighborhoods T in each message-passing layer. In our experiments, we train two-layer GNN models for friend ranking. Figure 8 shows the runtime and performance of SAGE + Mean and GRAFRANK for different sizes of sampled neighborhoods T from 5 to 20.

Model training time generally increases linearly with T , but a greater slope after $T = 15$. We also observe diminishing returns in model performance (MRR) with increase in the size of sampled neighborhood T after $T = 15$. Thus, we select a two-layer GNN model with layer-wise neighborhood size of 15, to provide an effective trade-off between computational cost and performance.

Compared to SAGE + Mean, GRAFRANK has marginally higher training times, yet achieves significant performance gains (20% MRR), justifying the added cost of modality-specific aggregation.

5.6 User Cohort Analysis (RQ₅)

In this section, we present multiple *qualitative* analyses to examine model performance across user segments with varied node *degree* and friending *activity* levels, and compare *t-SNE visualizations* of user representations learned by different neural models.

5.6.1 Impact of degree and activity. We examine friend recommendation performance, across users with different node degrees and friending activities. Specifically, for each test user, *degree* is the number of friends, and *activity* is the number of friend requests sent/received in the past 30 days. We divide the test users into groups, independently based on their degree and activity levels. We compare GRAFRANK with feature-based models MLP, XGBoost and the best GNN baseline SAGE + Mean. Figures 9(a) and (b) depict friend candidate retrieval performance HR@50 across user segments with different degrees and activities respectively.

From Figure 9(a), overall model performance generally increases with node degree, due to the availability of more structural information. GRAFRANK has significant improvements across all user segments, with notably higher gains for *low-to-medium* degree users (relative gains of 20%). GRAFRANK prioritizes active friendships by communication-aware message-passing, which compensates for the lack of sufficient local connectivities in the ego-network.

The performance variation across users with different *activity* levels in Figure 9(b), exhibits more distinctive trends with clear gains for GNN models over feature-based MLP and XGBoost for less-active users. Significantly, GRAFRANK has much stronger gains over SAGE + Mean, in *less-active user segments*, owing to its *multi-faceted modeling* of heterogeneous in-platform user actions. GRAFRANK effectively overcomes sparsity concerns for less-active users, through modality-specific neighbor aggregation over multi-modal user features to learn expressive user representations for friend ranking.

5.6.2 Visualization. To analyze the *versatility* of learned user embeddings, we present a qualitative visualization to compare different models on their expressivity to capture geographical user proximity. We randomly select users from three different cities within Region 1 and use t-SNE [30] to transform their learned embeddings

into two-dimensional vectors. Figure 7 compares the visualization results from different neural models. Evidently, the visualization learned by MLP does not capture geographical proximity, while the GNN models are capable of grouping users located within the same city. Compared to SAGE + Mean, GRAFRANK forms even more well-segmented groups with minimal inter-cluster overlap.

6 CONCLUSION

This paper investigates graph neural network usage and design for friend suggestion in large-scale social platforms. We formulate friend suggestion as a multi-faceted friend ranking with multi-modal user features and link communication features. Motivated by our insights from an empirical analysis on user feature modalities, we design a neural architecture GRAFRANK that handles heterogeneity in modality homophily via modality-specific neighbor aggregators, and learns non-linear modality correlations through cross-modality attention. Our experiments on two multi-million social network datasets from Snapchat reveal significant performance gains in friend candidate retrieval (30% MRR gains) and ranking (20% MRR gains). Further, our qualitative analysis indicates stronger gains for a crucial population of less-active and low-degree users.

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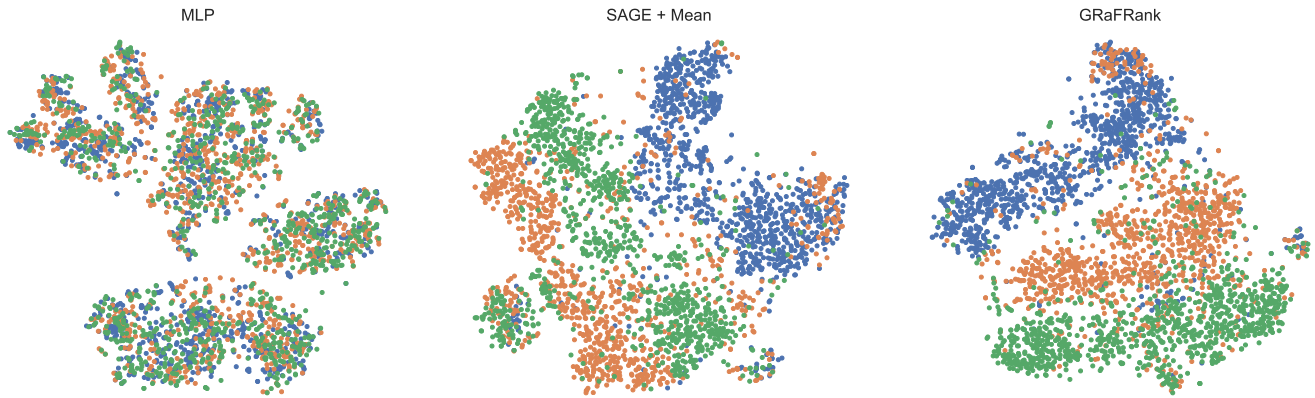


Figure 7: Visualization of two-dimensional t-SNE transformed user representations from feature-based MLP, and GNN models: SAGE + Mean, and GRAFRANK. Users with the same color belong to the same city. Compared to MLP and SAGE + Mean, the friendship relationships learnt by GRAFRANK result in well-separated user clusters capturing geographical proximity.

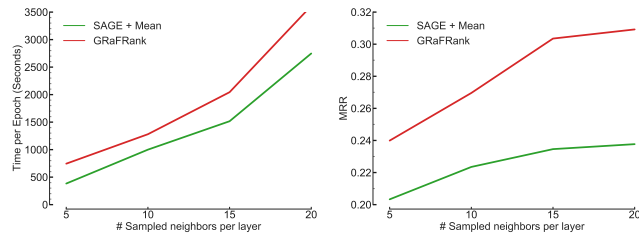


Figure 8: We observe diminishing returns in MRR after neighborhood size $T = 15$; GRAFRANK has significant gains over SAGE + Mean, with marginally higher training times.

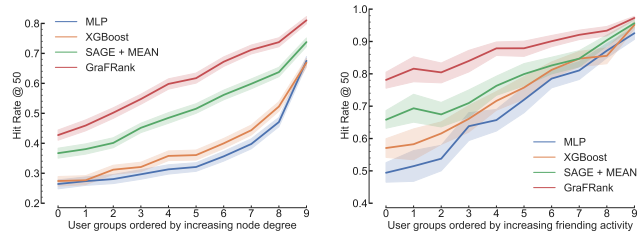


Figure 9: GRAFRANK has significant improvements across all user segments, with notably larger gains for low-to-medium degree users (a), and less-active users (b).

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