Spatial Autoregressive Coding for Graph Neural Recommendation

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ABSTRACT

Graph embedding methods including traditional shallow models and deep Graph Neural Networks (GNNs) have led to promising applications in recommendation. Nevertheless, shallow models especially random-walk-based algorithms fail to adequately exploit neighbor proximity in sampled subgraphs or sequences due to their optimization paradigm. GNN-based algorithms suffer from the insufficient utilization of high-order information and easily cause over-smoothing problems when stacking too much layers, which may deteriorate the recommendations of low-degree (long-tail) items, limiting the expressiveness and scalability.

In this paper, we propose a novel framework SAC, namely Spatial Autoregressive Coding, to solve the above problems in a unified way. To adequately leverage neighbor proximity and high-order information, we design a novel spatial autoregressive paradigm. Specifically, we first randomly mask multi-hop neighbors and embed the target node by integrating all other surrounding neighbors with an explicit multi-hop attention. Then we reinforce the model to learn a neighbor-predictive coding for the target node by contrasting the coding and the masked neighbors’ embedding, equipped with a new hard negative sampling strategy. To learn the minimal sufficient representation for the target-to-neighbor prediction task and remove the redundancy of neighbors, we devise Neighbor Information Bottleneck by maximizing the mutual information between target predictive coding and the masked neighbors’ embedding, and simultaneously constraining those between the coding and surrounding neighbors’ embedding. Experimental results on both public recommendation datasets and a real scenario web-scale dataset Douyin-Friend-Recommendation demonstrate the superiority of SAC compared with state-of-the-art methods.

CCS CONCEPTS

• Theory of computation → Graph algorithms analysis; • Information systems → Recommender systems.

KEYWORDS

Graph Embedding, Graph Neural Network, Contrastive Learning, Autoregressive, Recommendation

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1 INTRODUCTION

Embedding-based methods are fundamental to modern recommender systems, which vectorize entities such as users and items based on historical interactions. Collaborative Filtering (CF) is one of the most representative techniques that use low-dimensional vectors to characterize users and items by reconstructing the similarity between them. With the development of neural networks, deep learning methods are adopted in many areas [9, 22, 29, 45], in addition to abundant works based on CF, many deep learning methods have been proposed for recommendation, covering the shortage of traditional models [10, 13, 16, 34, 39].

Recently, it has been shown that applying graph structure to model the interactions in recommender systems can obtain great benefits [6, 23, 27, 31, 33, 36]. The most common paradigm of graph-based recommendation is introducing representations for nodes with graph embedding techniques. Traditional shallow models mostly utilize matrix factorization or random walk process to construct local context to preserve the adjacency similarity or structural similarity in the low-dimensional space [6, 23, 26, 27]. Many
works based on shallow graph embedding models for recommendation have achieved good results [32, 42, 49]. Recent years, many deep models for graph embedding emerged, among which Graph Neural Networks (GNNs) received special attention because of their superior ability in learning graph-structured data. The main idea of these GNN-based methods is to iteratively aggregate feature information from neighbors and integrate it with the current central node representation [1, 8, 15, 30, 40, 43, 47, 48]. Numerous GNN-based methods been proposed for recommendation, and the performances of these methods far surpass traditional algorithms [11, 37, 38, 48]. Despite their effectiveness in recommendation, we argue that both traditional shallow and deep models are not sufficient to learn good enough representations especially when scaling them up to large scale graph with sparse connections. We go deep into their characteristics and point out their limitations as the following:

- Shallow models mainly rely on matrix decomposition or random walk. Matrix decomposition usually has high time complexity and cannot be extended to large-scale graphs. Most random-walk-based shallow models have limited capacity to model the neighbor proximity because only a small part of neighbors are sampled as described in Figure 1, and they are prone to be affected by sampling bias.
- Some deep models only exploit deep encoders and model the context in a similar way to random walk, still limited in capability [2, 31]. While other GNN-based models conduct feature propagation across hops iteratively, which causes over-smoothing problems when stacking too many layers, limiting the ability for integrating high-order information. This limitation also amplifies the influence of high degree nodes, causing long-tail nodes cannot capture sufficient information. In addition, loading the whole graph Laplacian matrix into memory is impossible for large-scale graphs, at which point most GNN models [11, 15, 30, 37] fail to work.

Present work. We propose SAC, Spatial Autoregressive Coding, a novel and effective framework to address aforementioned problems in a unified way, as illustrated in Figure 1. Specifically, we first use node-wise sampling to sample multi-hop neighbors for target node. Then we perform random masking on neighbors at each hop and flatten all other surrounding neighbors along with the target node to a single Transformer-based encoder, which directly integrates the

![Figure 1: Schematic comparisons between our proposed SAC and previous methods in graph embedding process. SAC learns the embedding of target node (in red) by predicting the masked neighbor (in blue) in a spatial autoregressive way.](image)

multi-hop neighbors context into target node representation while alleviating over-smoothing caused by layer-by-layer aggregation. After getting the update target, we apply an autoregressive model to reinforce the target node to approximate the masked neighbors in a contrastive manner. The whole masking-and-predicting process induces the latent space to capture information that is maximally useful to predict neighbor nodes and preserve structural proximity and high-order information in a unified way. To improve the robustness of the model, we equip the contrastive loss with a novel hard negative sampling strategy, which helps to better understand the boundary between positive and negative samples. It is noted that we also devise Neighbor Information Bottleneck (NIB) to remove the information redundancy in neighbor aggregation process and thus learn a minimal sufficient representation for prediction task. NIB is realized by maximizing the mutual information between target coding and the masked neighbors and applying constraint on the mutual information between target coding and surrounding neighbors. Empirical experiments are conducted on datasets of multiple scales to prove the effectiveness and scalability of SAC.

To summarize, our paper makes the following contributions:

- To the best of our knowledge, we firstly propose Spatial Autoregressive Coding (SAC) for recommendation, to learn a neighbor-predictive coding for target node by adequately utilizing neighbor proximity in a spatial autoregressive paradigm, which effectively maximizes the mutual information of target-neighbor pairs in latent space.
- We are the first to propose Multi-Hop Neighbor Modeling to explicitly integrate complete neighbor context into target node with long-range attention, and approximate multi-hop neighbors simultaneously, which better models high-order information and alleviates the long-tail problems.
- We propose a negative sampling strategy for graph-based contrastive learning, using random walks and distance-based similarity metrics to generate hard negatives, helping distinguish between positive and negative samples better.
- To remove the information redundancy in neighbor propagation process, we propose Neighbor Information Bottleneck to learn the minimal sufficient representation for target node. It discourages the representation from acquiring additional information from the surrounding neighbors that is irrelevant for predicting the neighbor (minimal).
- We conduct experiments on three public large-scale datasets while most of the previous methods choose smaller ones. We also verify SAC on a web-scale dataset Douyin-Friend-Recommendation to evaluate the model in a real scenario. Experimental results show SAC outperforms previous methods by a significant margin. We also conduct ablation studies to demonstrate the effectiveness of SAC.

2 RELATED WORK

We briefly review existing studies on graph neural recommendation related to our work: traditional CF-based methods, graph embedding methods including shallow and deep models.

*Traditional CF-based methods for recommendation.* Collaborative Filtering (CF) is a representative embedding based technique.
Matrix factorization (MF) [17] constructed embedding indexed by the unique ID of users or items and performed inner product between them to represent their interactions. Later on, to enrich the content of the embedding, information such as users’ historical actions, social relations was adopted [16, 34]. Deep learning techniques are also widely used to make up for the shortcomings of shallow models [10, 13, 39]. Neural Factorization Machine [10] combines second-order linear features extracted by FM [25] with the high-order nonlinear features extracted by neural network. [13] exploit metric learning to enhance the CF model. [39] further using auto-encoders to achieve a better result for top-n recommendation.

Graph embedding methods for recommendation. Most graph embedding methods can be divided into two categories: shallow models and deep models. Traditional shallow models mainly exploit matrix factorization or random walk. Random-walk-based methods utilize random walk process to sample nodes and some of them rely on the Skip-Gram language model [20], which aim to capture the pointwise similarity [18]. There are abundant random-walk-based works for recommendation. HOP-Rec [42] combines the embedding-based MF methods with random walks to enrich user’s context. [32] also trains the embedding by combining random walks and Skip-Gram model [20] to generate nodes’ rich context for click through rate (CTR) prediction. GEPS [49] exploits DeepWalk [23] and Node2Vec [6] to integrate neighbors’ information. In recent years, many works introduce deep models into graph embedding [44]. For example, auto-encoder is introduced with random walk for recommendation [2, 31]. From the perspective of user’s historical behavior and time series modeling [46], Transformer is also applied for sequential recommendation [14, 41]. Among those, GNNs achieve great success. GCN [15] approximates the first-order eigen-decomposition of the graph Laplacian to iteratively aggregate information from neighbors. Graph Attention Network (GAT) [30] further proposed attention-based neighbor aggregation. GraphSage [8] samples a fixed size of neighbors for each node, aims at learning the aggregating function. GNN-based graph embedding methods has made great improvements in many tasks, leading to a surge of works that applying GNNs to recommender systems. PinSage [48] combines efficient random walks and graph convolutions to generate embeddings of nodes (i.e. items) that incorporate both graph structure as well as node feature information, it also proposed a hard negative sampling method. LightGCN [11] learns user and item embeddings by linearly propagating them on interaction graph, and uses the weighted sum of the embeddings learned at all layers as the final embedding. SGL [37] proposed a self-supervised framework, using data augmentation to produce multi-views for nodes and their context, then GCN is adopted to generate the embedding. GIN [19] adopts multi-layered graph diffusion to enrich user behaviors for solving the behavior sparsity problem.

However, these works have very limited scalability, and cannot fully model the neighbor proximity while effectively integrating higher-order information, that’s what we’re trying to solve.

3 PRELIMINARY

We introduce the common paradigm of GNN-based recommendation methods. Let \( \mathcal{U} \) and \( \mathcal{I} \) be the set of users and items respectively, for predicting how likely user \( u \in \mathcal{U} \) would adopt item \( i \in \mathcal{I} \), we produce representation \( n_u \) and \( n_i \) by aggregating neighbors iteratively with an L-layers GNN on bipartite graph \( \mathcal{G} = (\mathcal{V}, \mathcal{E}) \), in which \( \mathcal{V} = \mathcal{U} \cup \mathcal{I} \) and \( \mathcal{E} \) contains all the interactions:

\[
    n_u^{(l)} = \text{COMBINE}(n_u^{(l-1)}, \text{AGG}((n_j^{(l-1)} | j \in N_u))),
\]

where \( N_u \) denotes the neighbors of \( u \), \( \text{COMBINE} \) and \( \text{AGG} \) denotes the combing function and aggregating function respectively. A readout function is optional to generate the final \( n_u \) by combing \( n_u^{(L)} \), \( j = 1, 2, ..., L \). Commonly, we predict the preference score of \( u \) on item \( i \) by computing the inner product of their representations, i.e. \( \text{score}_{ui} = n_u^T n_i \). In different scenarios, items are different types of things, such as friends, goods, etc. To better distinguish between different node types in the graph, in the following, we denote the target user as \( n_{target} \), the multi-hop neighbors of the target user as \( n_1, n_2, ..., n_k \). The neighbors are composed of both similar users and items. Unless otherwise specified, the bold character represents the embedding of the corresponding node symbolized by that character.
4 SPATIAL AUTOREGRESSIVE CODING

In this section, we introduce our proposed algorithm in detail. Subsection 4.1 introduces vanilla Spatial Autoregressive Coding (SAC) including new Spatial Autoressive Paradigm for graph embedding, powered by Multi-Hop Neighbor Modeling. Subsection 4.2 introduces the Neighbor Information Bottleneck for enhancing the SAC and provides theoretical analyses. Subsection 4.3 introduces a new negative sampling method for training and give the final optimization objective for SAC.

4.1 Spatial Autoregressive Paradigm

4.1.1 Neighbor Predictive Learning. The main intuition of our Spatial Autoregressive Paradigm is that embedding all the shared neighbor proximity into the node representations among the subgraph. We convert the previous graph embedding task into a neighbor prediction task since in high-dimensional graph-structured data modeling, using neighbor prediction is able to adequately exploit the local smoothness and neighbour contexts of the target node. When predicting higher order of neighbor, the amount of shared information becomes much lower, and the model needs to capture high order proximity. For example, in the recommender systems, the graph structure is usually user-item bipartite graph with extremely low sparsity. Therefore, capturing high order proximity is also non-trivial to improve the performance of recommendation, which presents a way to find underlying possible interests for users. Figure 2 shows the architecture of spatial autoregressive coding algorithms. We select a target node \( n_{\text{target}} \) and sample N-hop neighbors of \( n_{\text{target}} \) to form a subgraph, denoted by \((G, n_1, \ldots, n_k)_c\). Then we integrate target node \( n_{\text{target}} \) with all other surrounding neighbors to predict a randomly masked neighbor node \( n_i \). Thus the problem is to estimate the likelihood:

\[
Pr(n|n_{\text{target}}, n_1, \cdots, n_i-1, n_{i+1}, \cdots, n_k) \tag{2}
\]

where \( n \) represents the trainable node embedding and \( i \) is the index of the masked neighbor. The spatial autoregressive process expects the model to learn a neighbor-predictive coding to maximize the likelihood function. To achieve this, we aim to learn a neighbor predictive coding to predict the masked neighbor:

\[
c_p = f_p(n_{\text{target}} + \mu_{\text{target}}, n_1 + p_1, \cdots,
         n_{i-1} + p_{i-1}, n_{i+1} + p_{i+1}, \cdots, n_k + p_k) \tag{3}
\]

where \( p \) represents the hop-indexed position embedding and \( c_p \) is the predictive coding that aggregates the surrounding neighbors with target node. \( f_p \) is the normal Transformer encoder. The process enables target node to capture attentional context based on local proximity that is helpful to predict the masked neighbor. To obtain the compact predictive \( c_p \), our model needs to meet the following two characteristics: 1. predicting the representation of masked neighbor node; 2. distinguishing the representation from other noisy neighbors. Thus in a subgraph batch, for each target node, we treat \( c_p \) and the masked neighbor node \( n_i \) in the same subgraph as a positive pair, and treat nodes beyond the subgraph as negative samples of \( c_p \), denoted by \( B^- \), and let \( B^+ = B^- \cup \{ n_i \} \). Thus our SAC uses a target-to-neighbor learning objective by adopting contrastive loss InfoNCE [7] to maximize the agreement of \( c_p \) and \( n_i \) while minimizing that of negative pairs:

\[
\mathcal{L}_{\text{Vanilla-SAC}} = -\log \frac{\exp(c_p^T n_i / \tau)}{\sum_{n' \in V^-} \exp(c_p^T n' / \tau)} \tag{4}
\]

where \( \tau \) is the temperature parameter. Such learning objective optimizes both the target and masked neighbor embeddings.

4.1.2 Multi-Hop Neighbor Modeling. In recommender systems especially in large-scale ones, there usually exist a number of sparsely-connected entities, i.e. long tail phenomenon. Thus nodes of low degrees need high-order information to embedding the structural proximity. Although existing methods have made efforts to embed the multi-hop information into node representation, the way conduct is implicit and usually in a cascade way, which would lead to underutilization of partial useful high-order information. Therefore, we propose the Multi-Hop Neighbor Modeling to enhance the multi-hop information processing. Specifically, for a same target node, we simultaneously mask the neighbors of multiple hops and add the relative position embedding to the rest neighbors according to the hop index. In the prediction procedure, we predict the masked neighbors all at once which reinforces the target node to explicitly and simultaneously acquire the multi-hop information. The procedure makes the neighbor predictive coding \( c_p \) reconstruct multi-hop local structure around \( n_{\text{target}} \). We reformulate the loss function (4) as the following:

\[
\mathcal{L}_{\text{Vanilla-SAC}} = \sum_{h=1}^{N} -\log \frac{\exp(c_p^T n_{i,h} / \tau)}{\sum_{n' \in V} \exp(c_p^T n' / \tau)} \tag{5}
\]

where \( n_{i,h} \) denotes the \( i \)-th neighbour which is masked at hop \( h \), there are a total of \( N \)-hop neighbors. The loss function \( \mathcal{L}_{\text{Vanilla-SAC}} \) takes the multi-hop optimization into account and explicitly utilizes high-order information.

4.2 Neighbor Information Bottleneck

Although vanilla SAC performs well, it deteriorates the performance when encountering complex graphs which consists of diverse neighbors and complicated local topology structures. Therefore, when predicting the different masked neighbors, we should only extract the minimal sufficient information and filter the irrelevant information from the surrounding neighbors. To achieve this goal, we propose Neighbor Information Bottleneck (NIB), an information-theoretic principle inherited from Information Bottleneck [29]. NIB is designed for learning informative and predictive coding for node representation in graphs. Specifically, after we obtain the neighbor-predictive context coding \( c_p \), NIB maximizes the mutual information between the \( c_p \) and the masked neighbor \( n_i \), and simultaneously constrain the mutual information between the \( c_p \) and the input nodes (including target node and surrounding neighbours), \( x_{in} = \{ n_{\text{target}}, n_1, \cdots, n_{i-1}, n_{i+1}, \cdots, n_k \} \). Based on this formulation, the objective can be summarized as:

\[
\max_{\theta} \quad I(c_p, n_i; \theta) - \beta I(c_p, x_{in}; \theta) \tag{6}
\]

where \( \beta \) is the Lagrange multiplier attached to the constrained meaningful information. \( \theta \) is the parameters of the Transformer encoder and we will remove it for simplicity. The first term in the formula expects the \( c_p \) to contain more informative information for predicting \( n_i \), and the second term wants \( c_p \) to remove the useless information from \( x_{in} \).
Objective (6) contains two terms about estimating mutual information. However, the mutual information is hard to estimate and we should transform it to another way. Take \( I(p, n) \) for example:

\[
I(p, n) = \int_{c=p}^{n} p(n, c) \log \frac{p(n, c)}{p(n)p(c)} \, dc \, dn
\]

\[
= \int_{c=p}^{n} p(n, c) \log \frac{p(n/c)}{p(n)} \, dc \, dn \quad (7)
\]

\[
KL(p(c,n)||p(c)p(n)) \propto JS(p(c,n)||p(c)p(n)).
\]

Note that the distributions of the nodes are hard to estimate and thus we refer to [21, 28, 29] for an alternative way to transform the objective (6) and derive the NIB loss \( L_{NIB} \) as following:

\[
L_{NIB} = \sum_{h=1}^{N} -\log(\sigma(c_P^T W_{n,h} n)) + \beta \sum_{n \in x_{in}} \log(\sigma(c_P^T W_{n,j} n)).
\]

where \( N \) is the number total hops and \( k \) is the number of nodes (excluding masked neighbor) in subgraph, \( \sigma \) denotes the non-linear activation function, \( W_1 \) and \( W_2 \) is linear transformation matrices for bilinear fusion of \( e_i \) and \( n_{i,hop} \). NIB focuses on optimizing the efficacy of local aggregation while Objective (5) aims to discriminate the representations in a global space.

### 4.3 Model Optimization

#### Negative Sampling Strategy

The summation item in loss function (5) need to be estimated by designing a negative sampling strategy. Instead of simply sampling negative examples from the entire set of items (i.e. easy negatives), choosing those that are closer to the positive samples as negatives (i.e. hard negatives) can help the model better distinguish between positive and negative samples [48]. In graph structure, the distance of two nodes can reflect the similarity between them to a certain extent. With this in mind, for mining hard negative samples, we propose a random-walk-based method. Specifically, for target node \( n_{target} \), we perform 2nd order random walk [6] starting from \( n_{target} \). The unnormalized transition probability \( \alpha_{pq}(t, x) \) is defined as:

\[
\alpha_{pq}(t, x) = \begin{cases} 
\frac{1}{p^d}, & d_{tx} = 0 \\
1, & d_{tx} = 1 \\
\frac{1}{q^d}, & d_{tx} = 2
\end{cases}
\]

where the random walk just traversed edge \((t, v)\) and now at node \( v \), \( x \) denotes the nodes connected to \( v \). Let’s roughly estimate the depth (i.e. the longest distance to the target node) of random walk. If choose \( x \) with \( d_{tx} <= 1 \), such random walk approximate BFS behavior, only when \( d_{tx} = 2 \) achieve DFS-like behavior. If whenever choosing \( d_{tx} = 2 \), the shortest distance between the target node and \( x \) strictly increases, we can approximate that this process follows a binomial distribution with \( p = \frac{p}{p+q} \). Thus, the upper bound on the expectation of walk depth \( D \) from target node is:

\[
D \approx Lp = L \cdot \frac{p}{p+q+q},
\]

\( L \) denotes the length of random walk. Intuitively, nodes farther from the target have less similarities with it, thus we sample N-hop neighbors and choose an appropriate value \( L \) such that \( D \) is slightly larger than \( N \), and take the last element from random walk sequence as hard negative, as described in Figure 4. Finally, we combine hard negatives with easy ones.

**Total Objective Function.** Objective (5) discriminates the target embedding in global latent space and objective (8) removes the information redundancy in local feature aggregation procedure. They are both critical and thus we add them to derive the final objective function of our SAC:

\[
L_SAC = L_{vanilla-SAC} + \eta L_{NIB}.
\]

where \( \eta \) is the weight factor of NIB loss. Equipped with NIB, our SAC is able to learn more useful representations that optimally balance expressiveness and robustness of nodes in graphs, which is proved by extensive experimental results in next section.

### 4.4 Relation with Existing Works

With the success of Masked Language Modeling (MLM) [3] in natural language processing area, many related efforts have been made in other areas including recommender systems. In a recent work [41], a BERT-like framework, UPRec, is proposed. Similar to MLM, it devises a Mask Item Prediction (MIP) task to embed the user by predicting the masked item from the historical user-item interactions sequence. First of all, MIP focuses on temporal domain modeling by only using first-order interactions, while SAC on spatial. In addition, although SAC and MLM both build a prediction task for target embedding, the differences between them are still significant (also depicted in Fig.3):

- MLM-based methods mainly focus on optimizing the encoder network by masking and reconstructing the masked neighbor, which is an implicit and indirect way to optimize the embedding for target node. On the contrary, our SAC explicitly optimizes the target node embedding by minimizing
We verify SAC on three public benchmark datasets as well as a web-scale dataset. We select the latest 20% reviews for test, which are timestamped later than September 1, 2018, there are a total of 14682436 training samples and 4671632 testing samples. We hold out 10% interactions from the training set as validation set for all of these three datasets. See Table 1 for statistics of these three datasets.

**Douyin Dataset.** We conduct extra experiments on Douyin-Friend-Recommendation to answer RQ3. Douyin is a short-form-video-focused social networking service owned by Chinese company ByteDance Ltd. We extract users’ social relationships and the historical friend recommendation data to build a social graph, and produce representations for users with SAC then add to downstream friend recommendation models. We build the graph by collecting users’ social relationships and historical behaviors earlier than July 31st, 2021 from the database, including users’ historical follow records, social relations. The graph is composed of 1.5 billion users and 250 billion edges. We use historical recommendation data between August 14, 2021 and August 24, 2021 for evaluation. On average, there are 0.65 billion samples per day. All of the used information including the user’s ID and basic attributes, as well as the user’s historical behavior records, have been strictly desensitized: all user IDs are hashed, and all attribute values are anonymized, the user’s relationship information does not contain any sensitive information.

### 5 EXPERIMENTS

We verify SAC on three public benchmark datasets as well as a web-scale dataset Douyin-Friend-Recommendation. We seek to answer the following research questions:

- **RQ1**: How does SAC perform compared with state-of-the-art methods especially GNN-based methods on public datasets?
- **RQ2**: How different hyper-parameter settings and different parts of SAC influence the performance?
- **RQ3**: Is there any improvement in practical application scenarios, especially for long-tail user?

#### 5.1 Experimental Setup

**Datasets.** We use three public benchmark datasets Yelp¹, User-Behavior² and Book-Crossing⁴ [50] to answer RQ1 and RQ2. For Yelp and Book-Crossing, we directly generate the user-item bipartite graphs from the raw data¹. For User-Behavior, in order to reproduce the baselines using public code as much as possible while avoiding memory overflow, we randomly select about 22% items from the whole 4162024 items, and delete the users that have no interactions with any of these selected items. For Yelp, we select the latest 20% reviews for test, which are timestamped later than September 1, 2018, there are a total of 6620865 training samples and 221391 testing samples. For Book-Crossing, we select 20% interactions for each user to build test set, there are a total of 928389 training samples and 221391 testing samples. For User-Behavior, we leave the interactions later than December 2, 2017, 12:00:00 for testing, there are a total of 14682436 training samples and 4671632 testing samples. We hold out 10% interactions from the training set as validation set for all of these three datasets. See Table 1 for statistics of these three datasets.

**Douyin Dataset.** We conduct extra experiments on Douyin-Friend-Recommendation to answer RQ3. Douyin is a short-form-video-focused social networking service owned by Chinese company ByteDance Ltd. We extract users’ social relationships and the historical friend recommendation data to build a social graph, and produce representations for users with SAC then add to downstream friend recommendation models. We build the graph by collecting users’ social relationships and historical behaviors earlier than July 31st, 2021 from the database, including users’ historical follow records, social relations. The graph is composed of 1.5 billion users and 250 billion edges. We use historical recommendation data between August 14, 2021 and August 24, 2021 for evaluation. On average, there are 0.65 billion samples per day. All of the used information including the user’s ID and basic attributes, as well as the user’s historical behavior records, have been strictly desensitized: all user IDs are hashed, and all attribute values are anonymized, the user’s relationship information does not contain any sensitive information.

#### 5.2 Implementation Details

To make our model scalable to any scale, we implement SAC by TensorFlow and deploy it on the distributed architecture PS-Worker². We also use the graph engine Euler³ to build a real-time neighbor sampling service for performing neighbor query operation high efficiently. We implement all baseline models based on publicly available code. For LINE, HOP-Rec and PinSage, we directly implement the code in Tensorflow and deploy it on PS-Worker Architecture. For NGCF⁷, LightGCN⁸, GCC⁹, we reimplement the code (we modify the data processing code to avoid memory overflow) based on their public PyTorch version and run experiments on Linux servers with 256 RAM and NVIDIA RTX 3090 GPU. For SGL, we reimplement it with their public TensorFlow-based code¹⁰.

#### 5.3 Settings

To optimize the objective (11), following most existing works, for each positive pair, we sample 4096 easy negative nodes from $B^{-}$ (defined in 4.1.1), and choose 16 hard negatives by performing 2nd random walk with $p = 1, q = 0.5$, and select the last elements in each walk. We tune the length of walk within {8, 10, 12, 14}. We choose Adagrad [4] as the optimizer with learning rate $\eta = 0.001$. All of the parameters are initialized with the Xavier [5]. The batch size is fixed to 1024, the embedding size(also the hidden size) is 128 for Book-Crossing, and 256 for others, we tune the Transformer encoder layers within the range of {1, 2, 3, 4, 5, 6}, We tune the weight factor $\eta, \beta, \tau$ in loss (8) and (11) within [0, 1, 2, 3, 4, 5, 6].
which can better verify the scalability of SAC.

In addition, we directly use the raw data of Yelp and Book-Crossing without pruning. Datasets with larger preference scores on all items by computing the dot product of the target user’s representation is not sufficient enough. Performance of both GCC and SGL proves that self-supervised paradigm for local structure reconstruction is a better choice for large-scale sparse graph embedding learning.

SAC consistently yields the best performance over all of the three datasets. Specifically, for Recall@20, the improvement of SAC over SGL is 7.99%, 9.04%, 12.10% in Book-Crossing, User-Behavior, Yelp respectively, for NDCG@20, the improvement is 9.36%, 9.93%, 18.37%. There are similarities between GCC/SGL and SAC, both self-supervising and auto-regressive paradigm aims at learning local topology by constructing subgraphs. The improvements of SAC over GCC/SGL shows the benefits of directly aggregating multi-hop neighbors. The improvements are more significant on User-Behavior and Yelp, which have sparser connections between users and items, implies multi-hop masking bring benefits for large-scale recommendation. In addition, the improvements over traditional GNNS means SAC can efficiently select useful signals among a large number of neighbor information containing noise.

5.3 Model Analysis (RQ2)

In this section, we study how different components and hyper-parameter settings affect the performance of SAC.

5.1.5 Baselines. We compare our proposed SAC, with the following methods:

- **LINE** [27]: A classic large-scale graph embedding algorithm which consider both local and global similarity. We directly use the generated embedding for evaluation. We directly train LINE on the user-item bipartite graph.

- **HOP-Rec** [42]: It combines MF and Graph-based models. Based on the original MF method, different types of positive samples are sampled with a certain probability through random walk on graph.

- **MLM**: Following Mask Item Prediction (MIP) proposed in UPRec [41], we devise an MLM-based model, which uses the BERT as encoder and multi-hop neighbors as context, and produces the users’ embedding by employing max-pooling operation on final hidden representations.

- **PinSage** [48]: As an variant of GraphSage [8], it generates node’s context by random walk and proposes a hard negative sampling methods. It is the first work that deployed GCN to web-scale recommender systems.

- **NGCF** [35]: This is a CF method which performs message-passing progress over user-item bipartite graph to explicitly model the high-order connectivity.

- **LightGCN** [11]: It proposed that the linear transformation and non-linear activation in GCN do not have much effect on collaborative filtering, and even have side effects on the performance of recommendation. So LightGCN is only composed of neighborhood aggregation.

- **GCC** [24]: A graph self-supervised pre-training framework. It performs random walk and node anonymization to generate subgraphs and optimizes InfoNCE to learn transferable structural representations. We get the similarity between user and item by computing the dot product of embedding.

- **SGL** [37]: Similar to GCC, this work also introduces self-supervised learning on graph. It uses node dropout, edge dropout and random walk to generate different views for nodes and maximizes the agreement between different views of the same node compared to that of other nodes.

It is worth noting that different from most existing works that verified their models on small-sized datasets which is a small subset of the original ones, we select larger and sparser ones. For example, the scale of datasets used in [11, 12] is ten or even hundred times smaller than ours. In addition, we directly use the raw data of Yelp and Book-Crossing without pruning. Datasets with larger scale and sparser connections are more in line with real scenario, which can better verify the scalability of SAC.

5.2 Performance Comparison (RQ1)

We compare the performance of SAC with all baseline methods. The evaluation results of different methods are shown in Table 2, from the top half and the last row of which we have several observations:

- All of the neural-based methods consistently outperform LINE in three datasets, proving that merely using first-order information is not sufficient to capture the complex similarity between items and users.

- Hop-Rec and MLM performs better than LINE, but there is still a significant gap compared with other GNNS, the performance of MLM implies that indirectly optimizing the target user’s representation is not sufficient enough.

- PinSage outperforms NGCF and LightGCN in User-Behavior and Yelp, while underperforms these two in Book-Crossing. Book-Crossing is much smaller that the other two. That implies transductive GNNS will be less effective on large-scale graphs compared with on smaller ones. LightGCN performs better than NGCF, verifying the non-linear transformation and weight matrix is useless in CF-based recommendation.

- GCC and SGL exploit self-supervising to enhance the representation learned by GNNS. We find GCC performs closely to LightGCN in Book-Crossing and outperforms LightGCN in User-Behavior and Yelp. SGL consistently achieves the best result along all baselines on all datasets. The performance of both GCC and SGL proves that self-supervised paradigm for local structure reconstruction is a better choice for large-scale sparse graph embedding learning.

It is worth noting that different from most existing works that verified their models on small-sized datasets which is a small subset of the original ones, we select larger and sparser ones. For example, the scale of datasets used in [11, 12] is ten or even hundred times smaller than ours. In addition, we directly use the raw data of Yelp and Book-Crossing without pruning. Datasets with larger scale and sparser connections are more in line with real scenario, which can better verify the scalability of SAC.

5.1.5 Evaluation Metrics. For each user, we treated all items have no interaction with him as negative samples. We get the user’s preference scores on all items by computing the dot product of the embeddings between them. For RQ1 and RQ2, We adopt two commonly used metrics Recall@k and NDCG@k (k = 20 by default). In addition, instead of estimating metrics by sampling, we rank all items for each user to generate a top-k list. For real scenario friend recommendation task, we use AUC (Area Under the receiver operating characteristic Curve) and UAUC (User grouped AUC) for evaluation, we will describe more details in section 5.4.
there are three key components of SAC: (1) Multi-Hop Neighbor Modeling mechanism. (2) Neighbor Information Bottleneck (NIB). (3) Hard negative sampling strategy. To assess the impact of these modules, we compare different ablation variants of SAC: In SAC (base), we remove all of the three key components (by removing (1), we only mask one-hop neighbors; by removing (2), we replace the loss function with the vanilla one; by removing (3), we only sample easy negatives). SAC (base)+mhop, SAC (base)+NIB, SAC (base)+hn represent equipping SAC (base) with Multi-Hop Neighbor Modeling, NIB, hard negative sampling strategy respectively. The lower part of Table 2 shows the experimental results, from which we have the following observations:

- SAC (base) outperforms SGL and all other GNN-based methods, also including the MLM model equipped with Transformer, proving the efficiency of spatial-autoregressive paradigm over GNNs. Combining spatial-autoregressive paradigm with the Transformer, we equip the model with powerful global interaction capabilities, helps better capture local topology and high order proximity.

- All of the three components have a positive effect and combining them reaches a better result. By introducing multi-hop masking, we force SAC to model the high-order proximity, which is similar to augmenting the interactions between users and items, mitigates the negative effects of sparse interactions. We also find it has the greatest influence on User-Behavior, which is the sparsest one, meaning the importance of modeling high-order proximity delicately. NIB having the greatest on both Book-Crossing and Yelp, and it is also very significant on User-Behavior. The second part of loss (8) strictly limits the mutual information between predictive coding and neighbors, forcing the model to extract useful information. The improvement of equipping hard negative sampling demonstrates the model can better distinguish between positive and negative samples.

3.5.3 Impact of Neighbor Sampling Parameters. We study how do neighbor aggregating parameters influence the model’s performance. There are two key parameters for generating the subgraph: (1) hop: How many hops will be considered to generate the subgraph. (2) Si: How many number of nodes will be sampled at hop i. we conduct ablation study by setting hop and Si to different values respectively. We search hop in the range of {1, 2, 3, 4, 5}, Si in {4, 8, 16, 32, 64, 128}. For Si, we set i = 1. The experimental results are shown in Figure 5 and 6(a), we observe that: (1) Only using one hop neighbors degrades the performance compared with hop = 2 and 3. Intuitively, it is equal to merely use the observed interactions, totally ignoring useful high-order information. When hop ≥ 3, the performance begins to decline. Recap that we sample a fixed number of nodes at each hop, the number of noises grows fast with the size of the subgraph, bringing more biases. (2) Figure 6(a) shows a similar result. The running time of each step grows rapidly with the number of sampled nodes at each hop, which do not always achieve improvement of performance. An appropriate neighbor size (i.e. 16 to 32 in our experimental results) is important to achieve better generalization performance.

3.5.3 Impact of the number of Transformer layers. We use Transformer to produce neighbor predictive coding \( e_p \). We study the influence of the Transformer layers on the performance. From Figure 6(b), we find that only a single encoder layer is not sufficient to model high-order proximity. However, stacking too much layers (greater than 2) will not significantly improve the model’s performance, even have negative effect, while forward propagation time of each step increases roughly linearly with the number of

| Methods         | Book-Crossing |          |          |          |          |          |          |          |          |          |          |          |
|-----------------|---------------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
|                 | Recall        | NDCG     | Recall   | NDCG     | Recall   | NDCG     | Recall   | NDCG     | Recall   | NDCG     | Recall   | NDCG     |
| SAC (base)      | 0.0425 (+2.91%) | 0.0246 (+4.68%) | 0.0193 (+2.66%) | 0.0144 (+2.13%) | 0.0131 (+5.65%) | 0.0052 (+6.12%) |
| SAC (base) + mhop | 0.0433 (+3.84%) | 0.0251 (+6.81%) | 0.0201 (+6.91%) | 0.0152 (+7.30%) | 0.0134 (+8.06%) | 0.0054 (+10.20%) |
| SAC (base) + NIB | 0.0439 (+6.30%) | 0.0234 (+8.09%) | 0.0198 (+5.32%) | 0.0149 (+5.67%) | 0.0135 (+8.87%) | 0.0056 (+14.29%) |
| SAC (base) + hn  | 0.0431 (+4.36%) | 0.0249 (+5.96%) | 0.0196 (+4.26%) | 0.0146 (+3.55%) | 0.0131 (+5.65%) | 0.0053 (+8.16%) |
| SAC              | 0.0446 (+7.99%) | 0.0257 (+9.36%) | 0.0205 (+9.04%) | 0.0155 (+9.93%) | 0.0139 (+12.10%) | 0.0058 (+18.37%) |

Figure 5: Performance of SAC w.r.t different number of hops for generating the context on Yelp.

| Methods | Book-Crossing | User-Behavior | Yelp |          |          |          |          |          |          |          |          |          |
|---------|---------------|---------------|------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
|         | Recall        | NDCG          |      | Recall   | NDCG     | Recall   | NDCG     | Recall   | NDCG     | Recall   | NDCG     | Recall   | NDCG     |
| SAC     | 0.0446 (+7.99%) | 0.0257 (+9.36%) | 0.0205 (+9.04%) | 0.0155 (+9.93%) | 0.0139 (+12.10%) | 0.0058 (+18.37%) |

Table 2: Overall Performance Comparison. The percentage in brackets denote the relative performance improvement over SGL.
layers. For graph structure, the relative position to the target node can describe most of the structural information, which is different from natural language. Thus stacking too much layers is useless.

5.3.4 Training Curves Analysis. We study the training process of SAC compared with some baselines. Figure 7 shows the training curves of these models on Book-Crossing, the performance on the other two datasets are similar. We find self-supervising and autoregressive paradigms (i.e. SGL and SAC) achieve faster converge speed compared with the other two models, and SAC converges faster than SGL. We attribute the speedups to the following highlights: (1) Our spatial autoregressive paradigm is similar to masked language model, which has proved its superiority in natural language processing. But different from simply masking a node and predicting it, we exploit spatial autoregressive to generate the predictive embedding from target node and predict multi-hop neighbors at once, which enables the model to learn more information once. (2) Multi-hop masking make the target node interact with more nodes (e.g. items, users), which alleviates connection sparsity, thus implicitly alleviate overfitting caused by sparse interaction.

5.4 Evaluation on Online Recommendation Task (RQ3)

To further verify the effectiveness of SAC in practical, we train it on a large-scale dataset Douyin-Friend-Recommendation, in which the social graph is composed of 1.5 billion nodes, and evaluate the quality of representation by adding it to the downstream recommendation model, which recommend other users for target users in their feed, that is similar to product recommendation.

Experiment Setup. We conduct experiments with several competitors: (i) Base: Two-tower-based model. (ii) Base+LINE: Base model with embedding features generated by LINE. (iii) Base+PinSage: Base model with embedding features generated by PinSage. (iv) Base+SAC: Base model with embedding features generated by SAC. We focus on the following two practical metrics: (i) AUC: we treat (user, recommended user) pairs which have real interactions as positive samples. (ii) UAUC: Different from AUC which sorts all samples according to the predicted value to calculate the AUC, UAUC is obtained by calculating the AUC of each user respectively, and takes the average of them. The UAUC can better reflect the quality of recommendation from user’s perspective.

Improvement for Friend Recommendation. Figure 8 shows the evaluation result of daily recommendation between August 14, 2021 and August 24, 2021. We find adding the embedding to downstream recommendation model can gain a positive growth of AUC and UAUC; SAC achieves more impressive results than LINE and PinSage. SAC increase the AUC by more than 1 thousandths on average. In real scenarios, 1 thousandths increment is already a significant improvement. For UAUC, we can see a more significant improvement. Replacing LINE and PinSage with SAC can amplify the improvement, up to about 7%. On average, the improvement of SAC compared with LINE is more than 1%, which means the quality of recommendation in user’s feed has improved a lot.

Long-tail User Recommendation. At last, we study the effectiveness of SAC for long-tail users. We split all users into three groups based on the number of friends, fewer friends means the user has sparser social interactions, recommendation quality for this group of users reflects the capability for modeling long-tail users. From Table 3, we find about 40% of users have less than 60 friends, which once again confirms the long tail phenomenon. The evaluation results demonstrate that compared with LINE and PinSage, SAC significantly improves the recommendation performance on long-tail user. From both Figure 8 and Table 3, we can conclude that the improvement using SAC is mostly attributed to the improvement of recommendation performance on long-tail user.
6 CONCLUSION

In this work, we propose Spatial Autoregressive Coding (SAC), a unified novel framework for graph neural recommendation. Different from conventional multi-pass graph signal propagation which is sensitive to over-smoothing problems, SAC straightly aggregates the high-order node context via spatial autoregressive paradigm, and then approximates diverse masked neighbors in a contrastive fashion to make full use of the connectivity information. In addition, a negative sampling strategy is specially designed to boost the model's capability of distinguishing between positive and negative samples. We also introduce a Neighbor Information Bottleneck which suppresses redundancy and potentially adverse noise to optimize the reliability of compact graph substructure representations.

Through performing quantitative and qualitative analyses on both medium- and large-scale benchmarks as well as Douyin online dataset, we probe the effectiveness of our proposed SAC, and set forth the applicability of autoregressive paradigm in practical graph-based recommendation systems.

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