Relation-Aware Graph Convolutional Networks for Agent-Initiated Social E-Commerce Recommendation

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ABSTRACT

Recent years have witnessed a phenomenal success of agent-initiated social e-commerce models, which encourage users to become selling agents to promote items through their social connections. The complex interactions in this type of social e-commerce can be formulated as *Heterogeneous Information Networks* (HIN), where there are numerous types of relations between three types of nodes, i.e., users, selling agents and items. Learning high quality node embeddings is of key interest, and *Graph Convolutional Networks* (GCNs) have recently been established as the latest state-of-the-art methods in representation learning. However, prior GCN models have fundamental limitations in both modeling heterogeneous relations and efficiently sampling relevant receptive field from vast neighborhood. To address these problems, we propose *RecoGCN*, which stands for a REIation-aware CO-attentive GCN model, to effectively aggregate heterogeneous features in a HIN. It makes up current GCN's limitation in modelling heterogeneous relations with a relation-aware aggregator, and leverages the semantic-aware meta-paths to carve out concise and relevant receptive fields for each node. To effectively fuse the embeddings learned from different meta-paths, we further develop a co-attentive mechanism to dynamically assign importance weights to different meta-paths by attending the three-way interactions among users, selling agents and items. Extensive experiments on a real-world dataset demonstrate RecoGCN is able to learn meaningful node embeddings in HIN, and consistently outperforms baseline methods in recommendation tasks.

CCS CONCEPTS

• **Human-centered computing** → **Social recommendation**; • **Information systems** → **Recommender systems**; • **Computing methodologies** → **Neural networks**;

KEYWORDS

Social E-commerce; Recommender System; Heterogeneous Information Network; Graph Convolutional Network

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1 INTRODUCTION

Understanding how social influence affects economic behavior in e-commerce has been a long-standing research problem in both academia and industry [3, 31]. Numerous attempts have been made to promote the e-commerce platforms with social features, including adding user review functions (e.g., Amazon), facilitating group buying (e.g., Groupon), and integrating e-commerce with social media (e.g., F-commerce on Facebook and T-commerce on Twitter). Particularly, the recently emerged agent-initiated social e-commerce platforms turn out to be an immediate success (e.g., Pinduoduo[1], Beidian[2]) [1, 26]. These platforms differ from previous attempts in using commission fees to motivate the users to share items with their intimate friends. Driven by financial rewards, the motivated users are likely to exert direct influences on their social networks, and hence are referred to as *selling agents* in our study.

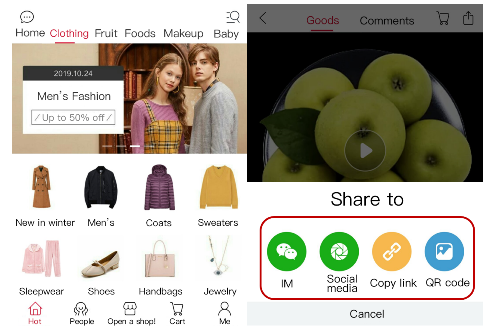
Besides the huge business success, the agent-initiated social e-commerce platforms also present unique challenges to the design of recommender system. It requires the platforms to recommend items to the selling agents that they can sell to certain users with high probability, which relies on modeling the purchase intentions that are closely intertwined with social influence. Specifically, the challenge can be broken down into three parts: First, besides interactions with items, there are various types of features that are important to model user's purchase feedback, such as the structure of social network and user attributes. It requires the recommendation models to effectively handle these heterogeneous features. Second, in terms of the social network structure, there are two types of nodes in the network denoting selling agents and users. Intuitively, different types of nodes exert different influences on the social network, hence the recommendation models should be able to capture the semantics of different relations in the heterogeneous network. Third, user's purchase decisions are likely driven by complex motivations, including preference over items and social

[1]https://www.pinduoduo.com
[2]https://www.beidian.com

influence [31], e.g., social proof and authority. Therefore, to properly model the interaction feedback, we need to differentiate the underlying motivations in each purchase.

A natural choice is to model the social e-commerce interactions with a *Heterogeneous Information Network* (HIN) [20], which is a well established framework to analyze networks with multiple types of nodes and relations. *Graph Convolutional Networks* (GCNs) have recently set a series of new state-of-the-art benchmarks in wide range of network representation learning tasks [7, 22], including recommendations [24, 27]. The core building block of GCN is a powerful spatial invariant aggregator function that learns how to aggregate information from each node's neighbourhood to generate node embeddings. Although it might model the node types as certain feature of the nodes, it is fundamentally limited in characterizing heterogeneous relations since it applies identical aggregator function on various types of edges. On the other hand, another important limitation is the exponential growth of the neighbourhood size as the layers stacked up. In addition to the expensive computation overhead [27], researchers empirically show that the performance of GCN quickly degenerates when the number of layers is deep, since the informative neighbours will diminish in large amount irrelevant neighbours [14]. Attempts have been made to address this problem with attention based neighbourhood sampler [14] and meta-path based neighbourhood sampler [23]. However, these approaches either fell short in modeling the heterogeneous relations [14] or simply sample the target node connected by meta-paths while leave out the important context information, i.e., the concrete instances of meta-paths [23]. Such feature has been proven vital in the recommendation tasks on HINs [9]. Finally, current models result in static node embeddings, which hinder their ability to reason the complex and potentially dynamic motivations for purchasing items in agent-initiated social e-commerce. For example, some purchases are result from user's preference, while some may be triggered by the social influence of the selling agents.

Motivated by the limitations of current GCN models, we design a novel Relation-aware Co-attentive Graph Convolutional Networks (RecoGCN) for representation based recommendation on HINs. It consists of three key components. First, the elementary building block of RecoGCN is a relation-aware aggregator, which fundamentally makes up current GCN's limitations in modelling heterogeneous relations by allowing RecoGCN to share aggregators relation-wise instead of layer-wise. Specifically, the relation-aware aggregator first discriminates the neighbors based on their relation with the target nodes (i.e., the type of connecting edges), and implements an attention mechanism to aggregate weighted information from each type of neighbors. It allows RecoGCN to explicitly model the semantic of various relations by learning specific aggregator functions for them. Second, we design a meta-path defined receptive field sampler to address the problem of rapidly growing receptive field, i.e. multiple-hop neighborhood of each node. The underlying intuition is to leverage the semantic-aware meta-paths to guide the RecoGCN to carve out concise and relevant receptive field by sampling specific type of neighbours hop by hop. It effectively allows the RecoGCN to control the size of receptive field, and aggregate the context information from the semantic-aware receptive field, which makes up the shortcomings of both attention based sampler [14] and meta-path based sampler [23]. Third, we further design a parallel co-attentive mechanism to dynamically fuse the embeddings learned from different meta-paths with attention weights. The key idea is to use the interactions among the elements in each purchase (i.e., user, selling agent and item) to infer the primary reasons of the purchase decision, i.e., assigning higher attention weights to more relevant meta-paths.



(a) Service interface (b) Product sharing

Figure 1: Service interfaces in Beidian platform.

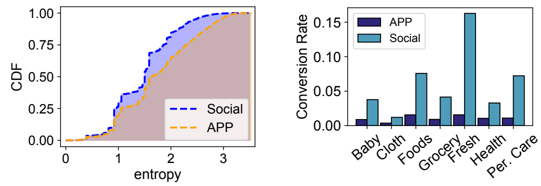
The contributions of this work can be summarized as follows:

- We conduct an in-depth analysis on user behaviors on the agent-initiated social e-commerce platform, i.e., Beidian. The comparison study presents clear behavioral difference between social e-commerce and conventional e-commerce scenarios.
- we formulate the recommendation problem in agent-initiated social e-commerce with HIN framework and propose a relation-aware co-attentive GCN model, RecoGCN, which is able to explicitly model the different semantics of the heterogeneous relations in this novel scenario.
- We design a meta-path defined receptive field sampler. It carves out concise and semantically relevant receptive field from vast multiple-hop neighborhoods. Morever, we design a co-attentive mechanism to dynamically fuse the node embeddings learned from different meta-paths. It reasons the primary motivations behind each purchase decision and model the interaction feedback more accurately.
- We conduct extensive experiments to demonstrate the effectiveness of our proposed models and meanwhile provide some analysis of the quality of learned representations in the HIN.

2 A FIRST LOOK AT AGENT-INITIATED SOCIAL E-COMMERCE

2.1 Background

We introduce the background of agent-initiated social e-commerce with the case study of a leading platform, i.e., Beidian[2]. Since its launch in August 2017, Beidian rapidly accumulates over 13.29 million monthly active users within 2 years. To demonstrate its core business model, we show the service interface in Figure 1. Specifically, users can browse, add to cart and purchase various types of items on this app (see Figure 1(a)). In addition to these conventional functions, more importantly, it also facilitates users to share the URL links of items via instant messages, social media and



(a) Entropy on item categories (b) Conversion rate per click

Figure 2: Comparisons on the purchase behavior patterns.

Table 1: Performance of matrix factorization model.

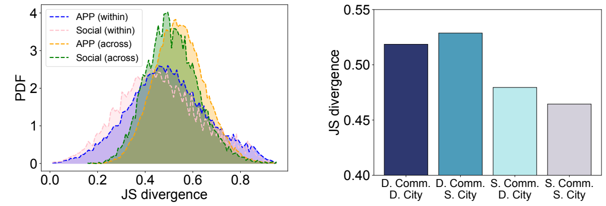
	MRR@30	NDCG@30	HR@1	HR@3
BMF (Social only)	0.2326	0.3795	0.1454	0.2305
BMF (Social+APP)	0.2105	0.3621	0.1181	0.2106

quick respond codes (QR codes) to their friends (see Figure 1(b)). By clicking the links, users will directly access the web pages of purchasing the shared items. The platform motivates users to share links with the commission fees on the purchases made via their links. We refer to the link sharing scenario as social e-commerce in our study, since it mainly propagates via user's social network.

2.2 What Makes Social E-commerce Different?

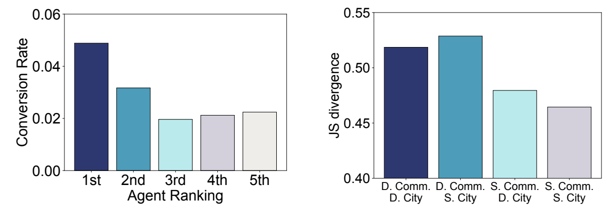
We first conduct a comparison study on user's purchase behavioral patterns to understand how social e-commerce differs from conventional scenario. The mobile app interface this platform (not through social networks) is close to conventional e-commerce platforms, and hence it is suitable to serve as the comparison baseline. Figure 2(a) shows the cumulative distribution function of the entropy on the categories of purchased items. We can observe that users tend to have **a relative smaller entropy in social e-commerce**, which indicates user's preference is more concentrated on fewer categories. Moreover, Figure 2(b) demonstrates that **there is a striking difference in user's purchase conversion rate per clicks between two scenario**. Comparing to conventional e-commerce, the purchase conversion rate is 3.09 to 10.37 times higher in social e-commerce across all categories of products. To further explore how these differences impact on recommender systems, we empirically test the classic matrix factorization models, i.e., biased matrix factorization [11], on the purchase interactions in social e-commerce and applications. Table 1 shows that the performance of social e-commerce recommendation surprisingly goes down when we combine the interactions in app. It indicates user's interactions in conventional e-commerce platforms cannot be directly transferred to social e-commerce, which motivates us have a more in-depth analysis on the underlying reasons of the behavioral difference.

The most prominent variable in social e-commerce is the social relation intertwined with the purchase process. Researchers have long converged on the impact of social homophily [17] and direct social influence [3] on user's economic behavior. Following this line of research, we investigate the social influence from the following two aspects.



(a) Divergence on item categories (b) Correlation with user demographic

Figure 3: The social homophily in the preference of users.



(a) Clicks per user (b) Conversion rate per user

Figure 4: Differentiating selling agent's influences on users.

Social homophily in user preference: We first cluster users into small communities based on their shared selling agents, and then examine the preference similarity among the user pairs within the same community and across different communities, which is measured by the JS-divergence [13] of users' purchase frequency on different categories. Specifically, the smaller JS-divergence indicates the user pair has more similar preference. Figure 3(a) shows the probability distribution function (PDF) of JS-divergences of all user pairs. We can observe that the social homophily effect indeed exists since users within the same community tend to have smaller JS-divergence compared to users across different communities. In addition, it is more prominent in social e-commerce scenario. Researchers often attribute such homophily effect to the similar demographic within social communities [17]. Therefore, we further examine its correlation with user demographic. Figure 3(b) shows that users from different social communities have more different preference when they are from same cities. However, completely opposite conclusion is drawn for users from same communities, where social homophily effect indeed is more prominent among users from same cities. These results indicate that the social homophily effect has a complex mechanism, and cannot be solely attributes to the demographic of users.

Social influence on purchase decision: We investigate this problem by differentiating user's responses to different selling agents' recommendations. We first characterize selling agents' roles to each user as their rankings based on the number of successfully recommended items to that user. For example, a user's top 1 selling agent is the selling agent he/she has purchased most items from. Figure 4(a) shows the average clicks per user significantly biased towards the top 1 selling agents, where they enjoy 14.05 clicks per user compared to 6.01 clicks per user on the second selling agents. In addition, Figure 4(b) shows the purchase conversion rate on the top 1 agents is 0.085, which is also significantly higher than the other selling agents. These results demonstrate that users indeed respond very differently to the recommendations made by different selling agents.

These empirical observations suggest the social factors in terms of social network structure, user demographic and social tie strength play an important role in user's purchase decision in social e-commerce. Therefore, instead of only considering user's interactions with items, the recommender system should also take these heterogeneous features reside in social network into account.

3 PROBLEM DEFINITION

The interactions in social e-commerce can be abstracted as a heterogeneous network with three types of entities: selling agents, users and items. To properly formalize the social e-commerce recommendation problem, we model the network with a well-established framework, i.e., HIN [20]. We first briefly introduce the definition of HIN, and then formally define the social e-commerce network and the problem of corresponding recommendation.

Definition 3.1. **HIN** [20]. A HIN is defined as a directed graph $G = (V, E)$ with an node type mapping function $\phi(v) : V \rightarrow \mathcal{T}, \forall\, v \in V$ and a relation mapping function $\psi(e) : E \rightarrow \mathcal{R}, \forall\, e \in E$, where the types of node $|\mathcal{T}| > 1$ or types of relations $|\mathcal{R}| > 1$.

Social e-commerce network can be considered as a type of generalized HIN. Specifically, we define four types of nodes corresponding to selling agents, users, items via link sharing and items in mobile app, and six types of edges denoting various types of relations between them. Note that items via link sharing and items in mobile app refer to same entities, but user's interactions with them have different implications, i.e., under or not under the influence of selling agents. Therefore, we separate them into two virtual types of nodes for clarity. The schema of social e-commerce network is displayed in Figure 5, which is formally defined as follow.

Definition 3.2. **Social E-commerce Network.** The social e-commerce network G_{SE} in our work is a generalized HIN, containing four types of nodes: selling agents $\{v_s|\, \phi(v_s) = t_S\}$, users $\{v_u|\, \phi(v_u) = t_U\}$, items via link sharing $\{v_i|\, \phi(v_i) = t_I\}$ and items in application $\{v_a|\, \phi(v_a) = t_A\}$, where S, U, I and A denote the corresponding node types respectively. Edges exist between v_s and v_u denoting *recommend to* r_{su} or *recommended by* r_{us} relations, between v_u and v_i denoting *purchase with recommendation* r_{ui} or *purchased by with recommendation* r_{iu} relations, between v_u and v_a denoting *purchase without recommendation* r_{ua} or *purchased by without recommendation* r_{au} relations. There is a node feature mapping function that maps each type of nodes to their feature vectors $\xi(v) : v_s \rightarrow \mathcal{X}_S,\ v_u \rightarrow \mathcal{X}_U,\ v_i \rightarrow \mathcal{X}_I,\ v_a \rightarrow \mathcal{X}_A$.

In the scenario of social e-commerce, items are eventually recommended to users by the selling agents. However, due to lack of experience or information, such recommendations are often inefficient. Therefore, it is of great important to identify whether a given user will buy the items under selling agents' recommendation. That is finding the most probable items given the pairs of selling agents and users. Given the above preliminaries, we are ready to formally define the problem of social e-commerce recommendation.

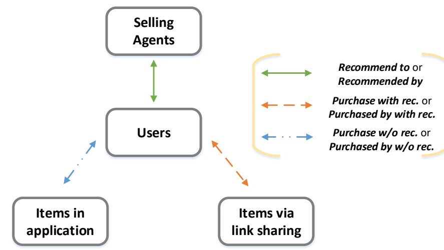


Figure 5: The schema of social e-commerce network.

Problem 1. ***Social E-commerce Recommendation.*** *Given a social e-commerce network G_{SE} with user's purchase records dataset $\mathcal{D} = \{< v_u, v_s, v_i >\}$, for each user and selling agent pair $< v_u, v_s >$, we aim to recommend a ranked list of items according the likelihood that the user v_u will purchase them with the recommendation of selling agent v_s.*

Specifically, we aim to accomplish the recommendation task by learning effective node embeddings, which is of key interest in social e-commerce scenario since significant amount of informative features are heterogeneous and reside in network. High quality node embeddings are able to benefit wide range of applications in recommendation, including item recall and improving the performance of scorer models.

4 METHOD

In this section, we describe our designed GCN based recommendation model, RecoGCN, to generate effective node embeddings for recommendation purpose. The key idea behind our model is to learn how to aggregate heterogeneous features from each node's local neighbourhood. Specifically, we first present a novel relation-aware aggregator that is able to discern the heterogeneous relations on HIN. Then, we design mechanisms to carve out concise and semantic-aware receptive fields in HIN, and further enhance the node embeddings via co-attending to the interactions in each purchase.

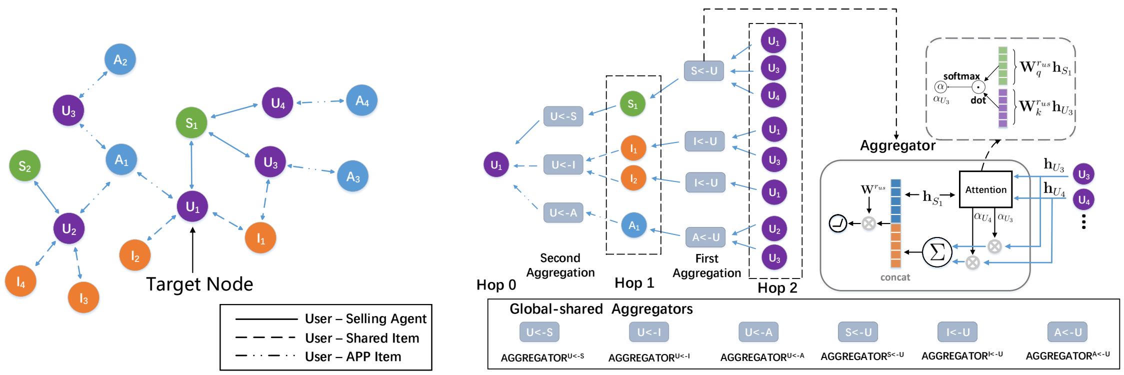
4.1 Graph Convolutional Network on HIN

Most existing GCN models cannot effectively model the heterogeneous relations in HIN due to their fundamental *spatial invariant* assumption [10]. As for the social e-commerce network shown in Figure 6(a), spatial invariant aggregators will apply identical functions when aggregating information from item I_1 to user U_3 and from user U_1 to selling agent S_1, disregarding their completely different implications. Therefore, we are motivated to design a novel GCN model that built on the top of relation-aware aggregators.

We first propose the r-**neighborhood** notion that allows us to consider relation type when searching node's local neighborhood:

Definition 4.1. r-**neighborhood** $\mathcal{N}_r(v)$. Given $G_{SE} = (V, E)$, for a node v, its r-neighborhood $\mathcal{N}_r(v)$ is defined as the set of nodes that connect to v with edges of type r, i.e., $\{w|\ e_{w,v} \in E,\ \psi(e_{w,v}) = r\}$.

Algorithm 1 describes the elementary building block of our RecoGCN model, i.e., relation-aware aggregator. The underlying intuition is to share the aggregator function relation-wise instead of



(a) An example of social e-commerce network (b) Illustration of the mechanisms in AGGREGATOR^r

Figure 6: The computation process of aggregating heterogeneous features with AGGREGATOR^r

Algorithm 1 : AGGREGATOR^r for edges of relation r

Require: embedding $\mathbf{h}_v$ of node v, embedding of nodes in its r-neighborhood $\{\mathbf{h}_w | \forall\, w \in \mathcal{N}_r(v)\}$;

Ensure: Updated embedding $\mathbf{h}'_v$ of node v

1: $\alpha_{vw} \leftarrow \text{softmax}_w(\mathbf{W}^r_q\mathbf{h}_v \cdot \mathbf{W}^r_k\mathbf{h}_w)\ \forall\, w \in \mathcal{N}_r(v)$

2: $\mathbf{h}_c \leftarrow \sum_{\forall w \in \mathcal{N}_r(v)} \alpha_{vw}\mathbf{h}_w$

3: $\mathbf{h}'_v \leftarrow \text{ReLU}\left(\mathbf{W}^r \text{concat}(\mathbf{h}_v,\ \mathbf{h}_c) + \mathbf{b}^r\right)$

layer-wise. That is to learn a specific aggregator function for each type of relation to explicitly model the semantics, which is shown in Figure 6(b). The input of Algorithm 1 is the current embedding $\mathbf{h}_v$ of target node v and the embedding of nodes in its r-neighbourhood $\{\mathbf{h}_w | \forall\, w \in \mathcal{N}_r(v)\}$. The relation-aware aggregator employs attention mechanism to aggregate the information to node v as context embedding $\mathbf{h}_c$ from its neighbourhood, which has been proven effective to prioritize neighbors based on their importance [22], e.g., assigning higher weights to user's top 1 selling agents. The embeddings of target node and its neighbors are first transformed into query vector and key vectors with separate trainable weights $\mathbf{W}^r_q$ and $\mathbf{W}^r_k$, respectively. Then, the attention coefficients α_{vw} are computed as the softmax normalized inner product of the query vector and the key vectors. After that, we feed the concatenated vector of $\mathbf{h}_v$ and $\mathbf{h}_c$ through a fully connected layer $\mathbf{W}^r$ biased with $\mathbf{b}^r$, and activate the output with ReLU function to generate the updated node embedding $\mathbf{h}'_v$. Note that the node embeddings are originally initiated as the feature vectors of nodes, and iteratively updated with the output of the aggregators. By recursively apply l according relation-aware aggregators, the model can effectively aggregate the features of nodes within l-hops neighborhoods from the target nodes.

4.2 Meta-path Defined Receptive Field Sampler

Another important limitation of current GCN models is the receptive field, i.e., the set of neighbours the model aggregates feature from, grows exponentially with the number of layers. Such inconvenient property not only results in expensive computation overhead, but also empirically leads to rapidly degenerating performance as the network goes deeper [14]. On the other hand, previous research also demonstrated that random walk based sampling on HIN will likely lead to low quality samples due to the significant bias to the dominant node types and highly visible nodes [9]. To address these problems, we design a novel receptive field sampler on HIN by leveraging the power of semantic-aware meta-paths [20].

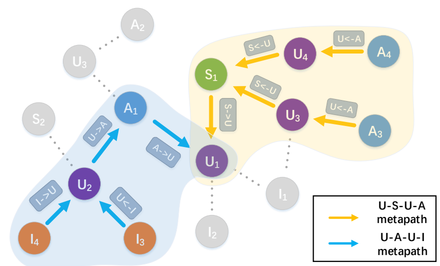


Figure 7: An example of meta-path defined receptive fields.

Definition 4.2. **Meta-path** [20]. A meta-path ρ is defined as a path in HIN in the form of $t_1 \xrightarrow{r_1} t_2 \xrightarrow{r_2} \cdots \xrightarrow{r_l} t_{l+1}$, where there is a composite relation $R = r_1 \circ r_2 \circ \cdots \circ r_l$ between node type t_1 and t_{l+1}. We denote meta-path ρ as $t_1 - t_2 \cdots - t_{l+1}$ for short.

Definition 4.3. **Meta-path defined receptive field.** Given a social e-commerce network $G_{SE} = (V, E)$, for a node v and a meta-path ρ of length l, a meta-path defined receptive field $F^\rho_v = (f^\rho_v(0), f^\rho_v(1), \cdots, f^\rho_v(l))$ is defined as the set of nodes that can be travelled to or passed by from node v via the meta-path ρ, where $f^\rho_v(k)$ denotes the set of nodes reached by k jumps on ρ.

The key idea behind meta-path defined receptive field sampler is to carve out high quality and semantic-aware receptive fields with the guidance of carefully designed meta-paths, which is demonstrated in Figure 7. In the illustrated example, we sample two receptive fields for node U_1 based on the meta-paths $U - S - U - A$ and $U - A - U - I$, which are marked with yellow area and blue area respectively. We can observe that the number of nodes per receptive field decrease to 5 compared with the 15 nodes in the conventional 3-hops receptive field. In addition, two receptive fields contain nodes of semantic relevance and distinct implications. The $U-S-U-A$ receptive field sample out the nodes characterizing the homophily effect in social e-commerce, i.e., what items have been purchased by the users with same selling agents. On the other hand, the $U-A-U-I$ receptive field mainly captures the "collaborative filtering" feature, i.e., what other items have been purchased by the users who bought same items with target user in application.

By integrating the **meta-path defined receptive field** sampler into our model, we derive the node embedding generation algorithm in Algorithm 2. Given a target node w and a meta-path ρ, it first iteratively samples out the receptive field $F_v^\rho = (f_v^\rho(0), f_v^\rho(1), \cdots, f_v^\rho(l))$. Then, the algorithm aggregates the feature from the end of the meta-path back to the target node w in a hop-by-hop manner with the corresponding relation-aware aggregator in each hop.

Algorithm 2 : Embedding generation algorithm

Require: social e-commerce graph $G_{SE} = (V, E)$, target node w, node features $\{\mathbf{x}_v, \forall v \in V\}$, meta-path $\rho = (r_1, r_2, \cdots, r_l)$, relation-based aggregator function $\text{AGGREGATOR}^{\text{r}}$
Ensure: vector representation $\mathbf{h}_w^\rho$ for node w

```
/*Sampling meta-path defined receptive field */
f_w^ρ(0) ← w
for i = 1 to l do
    f_w^ρ(i) ← ∪ {N_{r_i}(v) | ∀ v ∈ f_w^ρ(i − 1)}
end for
/*Generating embeddings */
h_v ← x_v, ∀v ∈ f_w^ρ(l)
for i = l to 1 do
    for v ∈ f_w^ρ(i − 1) do
        h_v ← AGGREGATOR^{r_i}(x_v, {h_j | ∀j ∈ N_{r_i}(v)})
    end for
end for
h_w^ρ ← h_w
```

4.3 Differentiating Purchase Motivations via Co-Attention Mechanism

In social e-commerce, users are often driven by different motivations when they make purchase decision. For example, a user may purchase a cloth based on her preference or based on the recommendation of friends. To account for different motivations in purchase decisions, a fusing mechanism is needed to dynamically integrate the embeddings derived from different meta-paths. A straightforward solution is apply average pooling operation on the embeddings,

$$\mathbf{y}_v = \frac{1}{|\mathcal{M}_{\phi(v)}|} \sum_{\rho \in \mathcal{M}_{\phi(v)}} \mathbf{h}_v^\rho, \tag{1}$$

where $\mathcal{M}_{\phi(v)}$ denotes the set of meta-path designed for the types of node v and $\mathbf{y}_v$ is the fused embedding of node v. However, the average operation cannot be personalized to each user or item. In addition, the primary motivations often vary per purchase, hence we aim to design a dynamic fusing mechanism that is able to adapt to each purchase event.

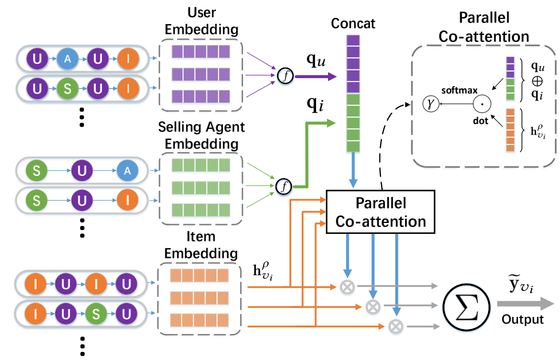


Figure 8: The architecture of the co-attentive embeddings fusing mechanism, taking item embedding as an example.

Intuitively, for a given user, the primary motivations to purchase or not are influenced by the interactions with other elements in the purchase event. That is given a specific purchase event $< v_u, v_s, v_i >$ the embedding fusing function of v_u should be conditioned on v_s, v_i. Based on this intuition, we propose a three-way co-attention mechanism to learn the embedding fusing function for each element in the purchase event by attending to other elements. Figure 8 demonstrates the architecture of the co-attentive mechanism, which is illustrated by the example of learning fusion function of items. Specifically, we first transformed the embeddings of user, selling agent and item into respective query vectors $\mathbf{q}_\star$:

$$\mathbf{q}_\star = f\big(\mathbf{W}_q^\star \sum_\rho \beta_{\star,\rho}\, \mathbf{h}_{v_\star}^\rho\big), \tag{2}$$

where $\mathbf{W}_q^\star$, $\beta_{\star,\rho}$ denotes trainable weight matrix and coefficient, and $f(\cdot)$ denote a nonlinear activation function, which is set to the ReLU function.

We then concatenate the user query vector and selling agent query vector, and compute the attention coefficient $\gamma_{\rho,u,s}^i$ for items on meta-path ρ as the softmax normalized inner product between the embedding $\mathbf{h}_{v_i}^\rho$ and the concatenated query vector.

$$\gamma_{\rho,u,s}^i = \text{softmax}_\rho\big((\mathbf{q}_u \oplus \mathbf{q}_s) \cdot \mathbf{h}_{v_i}^\rho\big). \tag{3}$$

The fused embedding of item $\widetilde{\mathbf{y}}_{v_i}$ is computed as the attention coefficient weighted sum over the embeddings derive from different meta-path defined receptive fields.

$$\widetilde{\mathbf{y}}_{v_i} = \sum_\rho \gamma_{\rho,u,s}^i \mathbf{h}_{v_i}^\rho. \tag{4}$$

Similar attention mechanism is applied in parallel to fuse the embeddings of users and selling agents into the fused embeddings $\widetilde{\mathbf{y}}_{v_u}, \widetilde{\mathbf{y}}_{v_s}$ by attending to the other two elements in each purchase.

4.4 Training and Learning

In order to learn effective and expressive representations for recommendation, we train RecoGCN in a supervised learning way with the purchase interaction feedback dataset $\mathcal{D} = \{< v_u, v_s, v_i >\}$, where v_u, v_s and v_i denote the users, selling agents and items in successful purchase. Specifically, we first compute the predicted likelihood of purchase as follows:

$$z(v_u, v_s, v_i) = \sigma\big((\widetilde{\mathbf{y}}_{v_u} \oplus \widetilde{\mathbf{y}}_{v_s})\mathbf{W_b}\widetilde{\mathbf{y}}_{v_i}\big), \tag{5}$$

where $\mathbf{W_b}$ is a fully connected weight matrix that projects the concatenated vectors of the embeddings of user and selling agents to the space of item embeddings. The predictive likelihood is computed as the inner product of projected user-agent pair embeddings and item embedings, and activated with sigmoid function $\sigma(\cdot)$.

Then, for each positive feedback in $\mathcal{D}$, we sample a pre-defined number of negative items v_n according to $P_n(v_i)$ distribution to construct negative feedback. Specifically, $P_n(v_i)$ is set to the frequency of items v_i being purchase. We adopt a max-margin based ranking loss function to train the parameters in RecoGCN.

$$J_{\mathcal{G}}(v_u, v_s, v_i) = \mathbb{E}_{v_n \sim P_n(v)} \max\{0,\ z(v_u, v_s, v_n) - z(v_u, v_s, v_i) + \Delta\}, \tag{6}$$

where Δ denotes the hyper-parameter of pre-defined margin. The intuition of this loss function is to train the model to predict the positive samples with a higher likelihood by a pre-defined margin.

5 EXPERIMENTS

5.1 Dataset

We evaluate our proposed RecoGCN based on a large-scale real-world dataset collected from a leading platform, i.e., Beidian. The dataset covers all types of interactions in the platform from Aug. 1th, to Nov. 27th, 2018. To avoid the data sparsity issues, we filter out the active users and items with more than 5 purchase records to derive a more concise dataset. The basic statistics and categories of utilized feature are reported in Table 2. From this complete dataset, we further filter out a subset that only consists of the interactions in social e-commerce scenario, which is referred to as social-only dataset and denoted with "(-)" in the evaluation. We compare the performance of models on the complete and social-only datasets to evaluate their ability to transfer user's interactions in conventional e-commerce to social e-commerce recommendation. We also report the selected meta-paths for each type of nodes in in Table 3. To avoid noisy semantics introduced by the meaningless long meta-paths [20], we only select the concise and semantic clear meta-paths. For example, we leverage the "U-I-U-I" path to aggregate the information from the items that are purchased by the users sharing similar preference with the target users, which captures the features of "collaborative filtering" effect [9]. Similarly, we use the "U-S-U-I" path the aggregate the feature of social homophily [17], the "U-I" path to establish a preference profile, and so on.

5.2 Experimental Setup

Comparison baselines. We compare our model with representation based recommendation methods instead of scorer models, e.g., NCF [8]. Without loss of generality, the learned node embeddings of RecoGCN can be fed into any downstream scorer models to improve recommendation performance. Specifically, we compare with two categories of baselines: matrix factorization based methods (BMF, DNN, Metapath MF) and GCN-based methods (PinSage [27], GAT [22], HAN [23], DiffNet [24]). We also report the performance of two variants of our model (ReGCN, ReGCN$_{MP}$) to show the effectiveness of the components.

Table 2: The basic statistics of evaluation dataset.

Node types	#Node	Avg. Inter. (Social)	Avg. Inter. (APP)
User	87105	6.36	26.15
Item	77982	7.10	29.21
Selling Agent	13057	40.99	-

Table 3: The selected meta-paths for each type of node.

	Meta-paths
Users	U-I, U-A, U-S-U-I, U-A-U-I, U-I-U-I
Selling Agents	S-U, S-U-I, S-U-A
Items	I-U, I-U-I-U, I-U-S-U, I-U-A-U

- BMF: Classic biased matrix factorization model.
- DNN: Content-boosted deep learning recommendation model, which concatenates the identity embeddings with feature embeddings fed through two layer MLP.
- Metapath MF: Extended interaction matrices are constructed based on the meta-paths in Table 3, and then it performs matrix factorization on each matrix. The learned embeddings are averaged with learnable weights to output final representations.
- PinSage [27]: The state-of-the-art GCN recommender system with GraphSage [7] as the backbone GCN model. Note that we choose PinSage over the classic GCN model introduced in [10], since it is able to scale to real-world social e-commerce network with the "sample and aggregate" technique and empirically provides superior performance. We adopt the optimal implementation released in [27].
- GAT [22]: The state-of-the-art attention-based GCN model. We adopt the optimal implementation released in [22].
- HAN [23]: The state-of-the-art GCN-based network embedding model for HINs. Note that HAN is chosen over the other deep heterogeneous network embedding models (e.g., metapath2vec [2], metagraph2vec [28]), because it has superior performance and also is a GCN-based model. We adopt the optimal implementation released in [23].
- DiffNet [24]: The state-of-the-art GCN model that considers the social influence diffusion in recommendation problem. We adopt the optimal implementation released in [24].
- ReGCN: It is a variant of RecoGCN, which only employs the r-Aggregators-based GCN to social e-commerce network.
- ReGCN$_{MP}$: It is a variant RecoGCN, which integrates meta-path defined receptive field sampler into ReGCN.
- RecoGCN: It is our complete model.

Evaluation Metrics. We adopt three performance metrics: *Mean Reciprocal Rank at Rank K* (MRR@K), *Normalized Discounted Cumulative Gain at Rank K* (NDCG@K), *Hit Ratio at Rank K* (HR@K) [8, 27]. Intuitively, MRR@K and NDCG@K measure the ranking positions of test items, while HR@K accounts for whether test items are present in top-k list. Note that it is undesirable for the selling agents to spam their friends with large amount of item recommendations in social e-commerce scenario. Therefore, it requires the

Table 4: Performance comparison with baseline models, where (∗∗) indicates p<0.01 significance over best baseline.

Method	MRR@30	NDCG@30	HR@1	HR@3
BMF(-)	0.2326	0.3795	0.1454	0.2305
BMF	0.2105	0.3621	0.1181	0.2106
DNN(-)	0.2348	0.3814	0.1472	0.2336
DNN	0.1895	0.3445	0.0991	0.1863
Metapath MF(-)	0.2226	0.3710	0.1394	0.2152
Metapath MF	0.2207	0.3691	0.1390	0.2118
PinSage(-)	0.2533	0.4015	0.1448	0.2611
PinSage	0.2493	0.3988	0.1348	0.2637
GAT(-)	0.2536	0.4020	0.1439	0.2637
GAT	0.2339	0.3867	0.1191	0.2429
DiffNet	0.2254	0.3721	0.1449	0.2204
HAN	0.2571	0.4037	0.1542	0.2621
ReGCN	0.2553	0.4033	0.1463	0.2628
ReGCN$_{MP}$	0.2593	0.4061	0.1526	0.2663
RecoGCN(-)	0.2619	0.4073	**0.1596**∗∗	0.2675
RecoGCN	**0.2632**∗∗	**0.4086**∗∗	**0.1592**∗∗	**0.2708**∗∗

recommender system to make precise and concise recommendations. Specifically, we evaluate the HR@1 and HR@3 to examine accuracy in the first few recommendations, while we use MRR@30 and NDCG@30 to examine the overall rankings.

Reproducibility. For the baseline models, we adopt the implementations released by the authors and change the loss function into margin-based ranking loss for recommendation purpose. In addition, we fix the dimensions of output embeddings for all evaluated models at 128, and tune the learning rate and regularization parameters to optimal for each model by grid searching. Specifically, we adopt the ADAM optimizer to train the models. Since it is inefficient to rank the test items with all entire item set, for each test item we randomly sample 100 negative items based on the popularity to train and evaluate the models. The implementation code of our model is available at https://github.com/xfl15/RecoGCN.

All the evaluated models are implemented with tensorflow, and trained on a server with two CPUs (Intel Xeon E5-2650 * 2) and eight GPUs (NVIDIA GTX 1080 * 8). Empirically, we observe the RecoGCN can be effectively trained in less than 3 hours on single GPU. We expect the model can be further accelerated to full-scale deployment with several implementation improvements, such as generating the embeddings of different meta-paths in parallel on different GPUs.

5.3 Overall Performance Analysis

The experiment results are reported in Table 4. We have the following observations and conclusions.

1) In both complete and social-only datasets, the proposed RecoGCN model significantly outperforms the baselines on all four evaluation metrics. Specifically, it provides the relative performance gain of 2.4% (p<0.01), 1.2% (p<0.01), 3.2% (p<0.01) and 3.3% (p<0.01) in MRR@30, NDCG@30, HR@1 and HR@3 over the best baselines respectively. These results demonstrate that the RecoGCN model is able to successfully aggregate information in heterogeneous social e-commerce network and generate high quality node embeddings for recommendation.

2) Among all the variants of RecoGCN, we observe the consistent performance order on different metrics as: RecoGCN > ReGCN$_{MP}$ > ReGCN. It leads us to the following conclusions: First, ReGCN is able to outperform all the baselines without meta-paths but is weakest variant, which indicates that simply apply r-Aggregator cannot fully address the challenges of recommendation in HINs. As a GCN model without meta-path assistance, it surpasses its rivals, i.e., PinSage and GAT. Second, a performance gain is received by incorporating meta-path defined receptive field into ReGCN. The ReGCN$_{MP}$ also outperforms the GCN baseline with meta-path assistance, i.e., HAN. It implies the proposed receptive field sampler can indeed address the noisy information challenge in HIN and improve the node embeddings. These high quality node embeddings are prime for item recall applications. Third, the co-attentive embedding fusing mechanism leads to further significant performance improvement. It indicates that the dynamically fused node embeddings are better fit for recommendation tasks, which can be fed into downstream scorer models to improve the overall performance. The RecoGCN model exceeds all the baselines models.

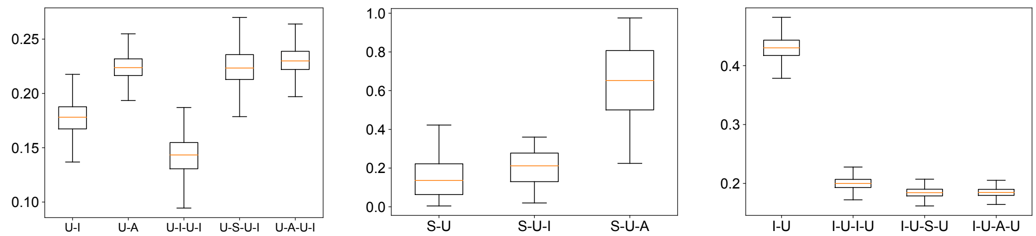
3) By comparing the results on the complete dataset and social-only dataset, we observe the BMF, DNN and GAT experience surprisingly significant performance degeneration when applying on complete dataset, while Metapath MF, PinSage and HAN output comparable results in both datasets. These results suggest that users exhibit very different behavioral patterns in the two scenario, and the baseline models cannot effectively transfer user's interactions in conventional scenario. On the other hand, RecoGCN shows performance gain by incorporating the interactions in conventional scenario, which indicates it can discern the semantic of user's interactions with items in different scenario and effectively leverage user's interactions in other scenario as side information.

4) In general, the GCN based models produce preferable results compared with matrix factorization based models. It shows that GCN is a powerful model for recommendation tasks, which can leverage network structure information and node features simultaneously.

5.4 In-depth Performance Analysis

To better understand the performance of RecoGCN, we take a peek under its hood by conducting a series of in-depth analysis.

Differentiating the importance of meta-paths: It is an interesting and important research question to examine which meta-paths play important roles in predicting user's purchase decisions. In order to investigate it, we show the boxplots of the attention weights among various meta-paths in Figure 9. From the results, We observe that the RecoGCN assigns highest weight to "U-A-U-I" and "U-A", while the classic collaborative path "U-I-U-I" surprisingly has the lowest weight. One plausible explanation is that user's interactions with items in social e-commerce do not fully represent their preferences, but are also affected by other factors, e.g. social influences. On the other hand, user's interactions in conventional e-commerce are more representative of their preference. As a result, "U-A-U-I" and "U-A" will be more effective to model user's preference over items. In addition, the "U-S-U-I" path also receives



(a) attention weights of user (b) attention weights of agent (c) attention weights of item

Figure 9: The co-attention weights on different meta-paths and the performance change when gradually add in meta-paths.

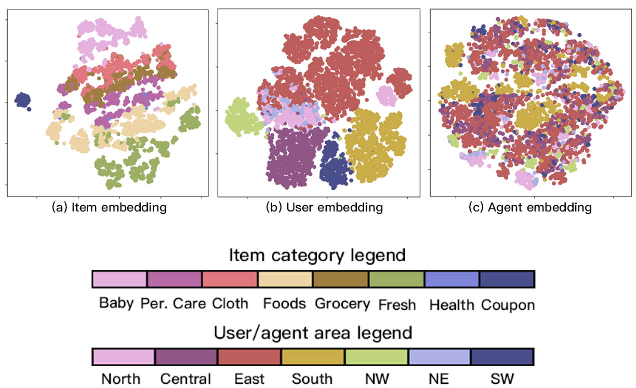


Figure 10: t-SNE plot of node embeddings in 2 dimensions.

high attention weights, which indicates the social homophily factor also plays an important role in social e-commerce. As for the selling agents, the model assigns highest weight to the "S-U-A" path, that is what your users will buy without your recommendation. This finding is consistent with user's attention distribution, which both indicate knowing what users will purchase in conventional e-commerce scenario is informative for selling agent's strategy. Finally, figure 9(c) shows the "I-U" path has dominant weight in item's meta-paths. It suggests item's embeddings can be learned with more concise paths.

Visualization of the learned embeddings: We conduct a qualitative study on the node embeddings learned by ReGCN$_{MP}$, the variant without co-attentive mechanism. Specifically, we first project the node embeddings to 2-D space with t-SNE algorithm [16], and present distribution of nodes in Figure 10, where items are denoted with different color based on categories while users and selling agents are based on regions in China. We can observe that the distribution of items is closely correlated with the categories, where the items belong to the same categories are likely to cluster with each other. In addition, there is an outlier cluster denoted with dark blue color representing a special type of items, i.e., the coupons. Moreover, the categories with close semantic links are also distribute closer, e.g., the food category locates next to fresh fruit and vegetable category.

On the other hand, the embeddings of users are also nicely clustered according to their regions, which is probably because users from different regions are likely to have different preference, e.g. purchasing local food. Another plausible reason is that users within same regions are more likely form relations, and hence has more similar behavior due to social homophily. In addition, the regions of more users, e.g., eastern china, can be easily classified into more sub-clusters, representing more fine-grained preference groups. However, Figure 10(c) shows the clustering phenomenon is less prominent in selling agents. One plausible reason is that each selling agent can reach to many users due to the convenience of social network, and therefore they exhibit more similar traits. To conclude, the visualization shows that RecoGCN can effectively learned semantic-aware representations for social e-commerce network.

6 RELATED WORK

Social factors in recommender systems: Social networks have shown to be promising and useful for enhancing recommender systems [21]. [15] modeled the social network feature as a regularization term. TrustSVD proposed to incorporate the social regularization into classic collaborative filtering framework, and showed notable performance gain [6]. SBPR model integrate social information into bayesian personalized framework by assuming users will assign high rating to the items preferred by their friends [29]. A recently proposed DiffNet [24] leverages GCNs to model the social regularization as influence diffusion in social network. Different from prior efforts in social recommendation, we consider a novel scenario, i.e., agent-initiated social e-commerce, where selling agents will directly influence user's purchase decisions.

Representation learning for recommender system: The surging representation learning techniques show promising performance in profiling user's latent preference and interest in recommender systems [30]. Specifically, numerous deep representation learning frameworks have been proposed to learn user profile via embedding techniques, and show notable performance gains in news recommendation [12], search ranking [4] and session-based recommendations [25]. One branch of closely related previous works are the network representation learning methods like deepwalk [18] and node2vec [5], which aim to learn node embeddings from network structure. However, these network embedding models are not suitable for recommender systems since they are unsupervised and cannot model node feature.

Graph convolutional networks: The recent development of GCNs has established a series of new state-of-the-art benchmarks in wide range of network learning tasks, including node classification [22], link prediction [19] and community detection [7]. Researchers also show consistent performance gains in recommender system by leveraging GCNs to model user's interactions with items [27], social homophily in user preference [24] and transitions in recommendation sessions [25]. However, these research efforts focus on designing GCN methods to model homogeneous graph, and cannot properly exploit the rich information in HINs. Our work fills in this gap by extending the paradigm of GCN-based recommender systems to HINs with relation-aware aggregators. In addition, combining with the receptive field sampler and co-attentive embeddings fusing mechanisms, the proposed RecoGCN model achieves notable performance improvement in social e-commerce recommendations.

7 CONCLUSION

In this paper, we study the recommender system design in an emerging scenario, i.e., social e-commerce. We propose a relation-aware co-attentive GCN based recommendation model, RecoGCN, to effectively collect the heterogeneous features in HIN to generate node embeddings for recommendation. The RecoGCN addresses the challenges with three novel components: 1) a relation-aware aggregator that explicitly model the semantic of heterogeneous relations; 2) a meta-path defined receptive field sampler that efficiently carve out concise and semantic relevant receptive fields; 3) a co-attentive embeddings fusing mechanism that allows for dynamically reasoning the complex motivations behind purchases. Extensive experiments show the proposed RecoGCN can learned meaningful node embeddings in social e-commerce network, and consistently outperforms all baseline method by significant margin. Important future works will be to identify the implication of RecoGCN on downstream scorer functions in recommender systems and explore the feasibility of automatically searching for optimal meta-paths.

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