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Vibe Check: Social Resonance Learning for Enhanced Recommendation

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***Abstract*—Social Resonance is a common socio-behavioral phenomenon in which users are more influenced by opinions that have similar vibes. That is, opinions from two different groups of users can *mutually reinforce* (or resonate with) each other to have an even stronger impact on the user. In this paper, we explore the powerful social resonance effect between social connections and other users in an eCommerce platform to improve recommendation. Specifically, we first formulate an item-aware user influence network that connects users who rate the same item. With the social network and item-aware user influence network, a novel graph-based mutual learning framework is proposed, which captures the resonance influence from both user local correlations and global connections. We then fuse these influence paths to predict the resonance-enhanced user preference towards items. Experiments on public benchmarks show the proposed approach outperforms state-of-the-art social recommendation methods.**

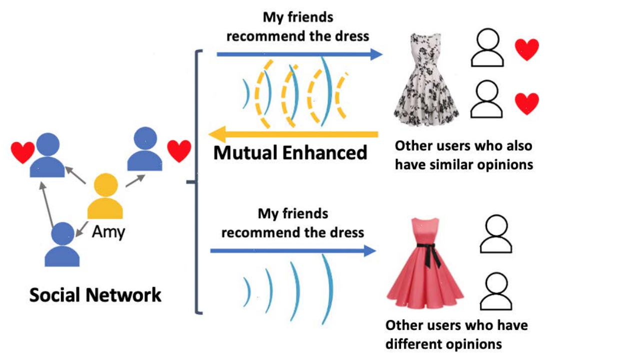

Fig. 1. Social resonance example: When Amy sees both her social friends and other users in the eCommerce platform recommend the same items, the similar "vibe" can reinforce its influence on Amy's preference towards the top dress (in contrast to the bottom dress that lacks this resonance).

I. Introduction

Social Resonance is a common socio-behavioral phenomenon in which users are more influenced by opinions that have similar vibes [1, 2]. That is, opinions from two different groups of users can *mutually reinforce* (or resonate with) each other to have an *even stronger* impact on the user. One of the unique properties for resonance is that it can expand in intensity with mutual re-enforcement between different sources, leading to more powerful influence on user intentions and actions. This social resonance effect has been widely studied in many areas such as marketing [1, 3, 4], communication [2, 5], and human behavior [6]. These studies further show social resonance can heavily influence a user's attitude towards items, impact a user's propensity to buy, and also provoke other desired actions.

For example, as shown in Figure 1, compared with the dress that is only recommended by Amy's friends, when *both* Amy's friends and other users in an eCommerce platform strongly recommend the same dress, the similar mutual "vibe" (or resonance) can potentially strengthen Amy's intensity of her preference towards the dress (e.g., leading to a higher chance of purchase). The resonance effect is especially *manifest* in eCommerce platforms like Epinions and Ciao [7], where users can make friends to help them discuss and choose items [8]. The resonance also widely impacts engagement with online media (e.g., resonating between a user's friends on Facebook and other users on a platform like YouTube) and apps (e.g., resonating between communities of reddit users and other users on the Google Play Store), among others.

However, there is little if any work on *explicitly* exploring the powerful social resonance effect on user preference towards items in recommendation. Most existing social-aware recommendation methods mainly focus on the *intrinsic internal* properties of the social network (e.g., social homophily [9, 10] or social influence diffusion [11]), ignoring the close *mutual interactions* with users on the eCommerce platform and the reinforced resonating influence effect. This gap between the user-user social network and the user-item interactions on an eCommerce platform may limit the learning capacity of social effects on user preferences towards items.

In this work, we propose the first investigation of the powerful social resonance effect to improve recommendation. To do so, it poses two key challenges: (i) There is high heterogeneity between the social network and the eCommerce platform: the social network captures user-user connections, while the eCommerce platform exhibits user-item interactions. How can we model the mutual interactions of the social resonance effect across these fundamentally different perspectives? (ii) Social resonance captures the similar mutual vibe between two groups of users. Therefore, different from traditional user influence that typically focuses on how one user impacts on a single target user, the resonance effect measures the correlation

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between two groups of users. Hence, an important question is how to model the *correlation influence* of social resonance on user preference towards items?

With these challenges in mind, we propose a social Resonance Recommendation approach called ResRec that builds a novel graph-based mutual learning framework to learn social resonance for improved recommendation. As *one of the first works* to explicitly explore the social resonance effect in eCommerce recommendation, this paper finds that ResRec consistently outperforms state-of-the-art social recommendation methods.

II. Related Work

Social-aware recommendation is based on the common assumption that users can be influenced through their social connections to have similar preferences [12, 13]. Many studies further explore different social effects in a social network to enhance the learning of social influence [9, 14, 15]. However, most of those methods mainly focus on the internal properties of the social network (e.g., social homophily), ignoring the mutual social resonance effect and its reinforced influence on user preference towards items.

Recently, many studies have shown that users who have rated or reviewed an item could heavily influence the preferences of other users towards the item [16, 17]. For example, Amazon users may refer to the previous ratings and reviews of an item to help make a purchase decision. We refer to such an influence network for each item as the item-aware user influence network [17]. However, few of these works consider the connections between the item-aware user latent influence and the user social network, which we find especially helpful to bridge the gap between user-user social connection and user-item interactions to estimate user preference.

III. Problem Formulation

In this section, we first introduce the problem setting. Suppose we have n users $U = \{u_1, u_2, ...u_n\}$ and m items $P = \{p_1, p_2, ...p_m\}$. Users can rate and review items to show their preferences and opinions towards those items [12]. Let $\mathbf{R} \in R^{n\times m}$ denote the rating matrix, where $r_{ai} \in \mathbf{R}$ is user u_a's rating of item p_i. Our goal is to predict a user's unknown preference for items, i.e., the missing ratings in $\mathbf{R}$.

To model social resonance, we first model the social network and users in the eCommerce platform as follows:

Social Network G^S. First, we assume there is a trust social network $G^S = (U, E^S)$. In G^S, the nodes are users U and the edges $E^S \in R^{n\times n}$ are based on the social connections: if u_a trusts (or follows) u_b, then $e_{ab} = 1$, otherwise it is 0. The connections mean u_a could be influenced by u_b.

Item-Aware User Influence Network $G^P(p_i)$. For the eCommerce platform, similar as [17], users who rate p_i could potentially form a latent influence network, which we denote as the *item-aware user influence network* $G^P(p_i) = (U(p_i), E^P(p_i))$ for each p_i. The nodes $U(p_i)$ are the users who rate p_i, and the edges $E^P(p_i)$ connect users who rate *before* the target user. That is, to give a recommendation for a target user u_a, u_a is connected to users $G^P(p_i, u_a) = \{u_b \in U(p_i) | \exists\ r_{ai}$ and r_{bi}, and $(t(u_b, p_i) < t(u_a, p_i))\}$, where $t(u_b, p_i)$ is the time u_b rates p_i, since a user $u_a \in U(p_i)$ could only be influenced by other users who rate the item *before* u_a. Then, similar as [17], we can use models (e.g. attention mechanisms) to estimate the user actual influence in $G^P(p_i)$.

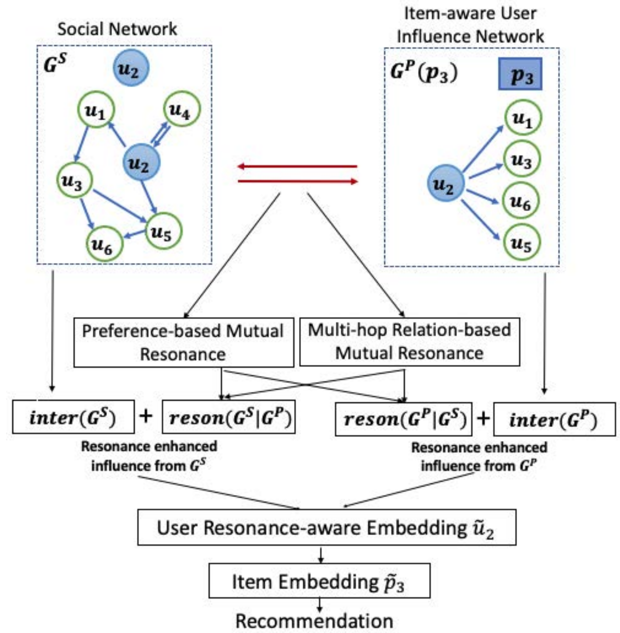

Fig. 2. ResRec Framework: By taking the user-item pair (u_2, p_3) as an input example. ResRec explores the mutual resonance effect between users in social network G^S and users (u_1, u_3, u_6, u_5) who have purchased p_3 through both preference-based and multi-hop relation-based resonance (the connections between u_1, u_3, u_6, u_5 in $G^P(p_3)$ are omitted here for simplicity.).

Based on these two perspectives, **social resonance in recommendation** can be defined as: Given user u_a social network G^S and users who have rated item p_i, the social resonance effect for a user u_a towards item p_i (i.e. a user-item pair (u_a, p_i)) is the mutual correlation between users in user u_a's social network (G^S) and users who have rated the item p_i ($G^P(p_i, u_a)$), which influences u_a's preference towards items.

IV. Proposed Approach: ResRec

In this section, we propose a novel graph-based mutual learning framework called ResRec that learns the reinforced resonance effect between G^S and G^P for improved recommendation, as shown in Figure 2.

A. *Preference-based Resonance*

First, the social resonance often occurs when users express similar opinions [4]. In our context of item recommendation, if users who rate an item express similar preferences as my friends, then I am more likely to be influenced. This preference-based resonance captures the preference correlations between a user's friends (in G^S) and other users in the eCommerce platform (in G^P).

We begin by examining the preference-based resonance between a user's friends (i.e. G^S) and the group of users who

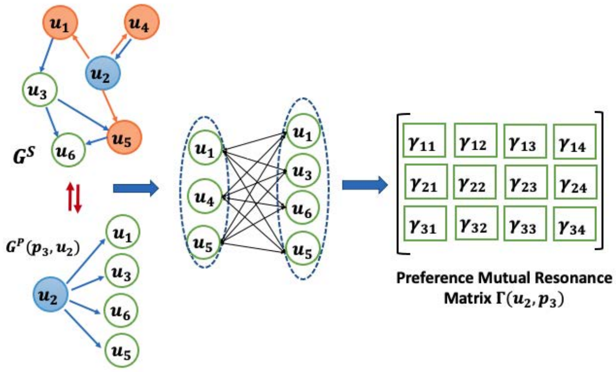

Fig. 3. Preference-based resonance effect for user u_2 towards item p_3. We explore the preference similarities between a user's friends (in orange) and users who have rated the same item.

have rated the item p_i (i.e. $G^P(p_i, u_a)$). To do so, in this section, we introduce a preference mutual learning module that utilizes the user embeddings to match user preference correlations based on the local graph structure of G^S and $G^P(p_i, u_a)$, as shown in Figure 3.

Concretely, we first apply a user embedding lookup layer to describe the user u_a as an embedding vector $\mathbf{u}_a$ that represents the user's personal preferences. Similarly, item p_i is represented by an embedding vector $\mathbf{p}_i$. With the user embedding, to capture the preference connections, we define a cross correlation scoring function $\gamma^{relation}(\cdot,\cdot)$ that exploits the Euclidean distance to learn the correlation between user preference expressed in both the social network G^S and the item-aware influence network $G^P(p_i)$: $\gamma^{relation}(\mathbf{u}_s, \mathbf{u}_p) = \frac{1}{1+|\mathbf{u}_s - \mathbf{u}_p|}$, $\forall u_s \in G^S(u_a), u_p \in G^P(p_i, u_a)$, where $\mathbf{u}_s$ is u_a's friends and $\mathbf{u}_p$ is a user who has rated item p_i before u_a. With the correlation scoring function, the preference mutual resonance matrix $\Gamma(u_a, p_i)$ for user u_a towards item p_i can be formed by her social-oriented and item-aware connections as: $\Gamma(u_a, p_i) = \gamma^{relation}(G^S(u_a), G^P(p_i, u_a))$. Each element in $\Gamma(u_a, p_i) \in R^{|G^S(u_a)| \times |G^P(p_i, u_a)|}$ denotes the preference correlation between u_a's friends and a user who rates p_i.

Specifically, each row $\Gamma(u_a, p_i)[s, :]$ represents the preference similarity between the user's s_{th} friend and users who potentially influence the user at the item-level. Each column $\Gamma(u_a, p_i)[:, p]$ indicates the similarity between the p_{th} user in $G^P(p_i, u_a)$ and user u_a's social connections. Therefore, the preference resonance scores $z^S(u_b|u_a, p_i)$ of user $u_b^S \in G^S(u_a)$ to user u_a, and the resonance scores $z^P(u_c|u_a, p_i)$ of $u_p \in G^P(p_i, u_a)$ to user u_a is:

$$z^S(u_s|u_a, p_i) = \sum \Gamma(u_a, p_i)[s, :],$$
$$z^P(u_p|u_a, p_i) = \sum \Gamma(u_a, p_i)[:, p]. \tag{1}$$

Equation (1) shows: to predict the preference resonance effect of her friend $u_s \in G^S$ to u_a, ResRec measures the preference similarities between u_s and all the users who rate item p_i, denoted as $z^S(u_s|u_a, p_i)$; mutually, to predict the resonance effect of $u_p \in G^P(p_i, u_a)$ to u_a, ResRec measures the preference similarities between u_p and all the user u_a's friends to find whether u_p has similar opinions as u_a's friends, denoted as $z^P(u_p|u_a, p_i)$.

TABLE I
SUMMARY OF THE THREE DATASETS.

	Epinions	Ciao
# Users	22,164	2,248
# Items	296,277	16,861
# Item Interaction	922,267	36,065
# Social Connection	355,800	57,544
Rating Density	0.014%	0.095%
Link Density	0.072%	1.139%

B. Multi-hop Relation-based Resonance

The preference-based resonance uncovers the preference similarities between a user's directly-connected friends and users who rate item p_i. Besides that, other users beyond those directly connected to our target user could also wield influence on her preferences, e.g., through information diffusion. Hence, in this section, we further explore the connections between G^S and G^P from the perspective of these multi-hop relations. Different from the preference-based resonance which learns the preference correlations between users in the local graph structure, this relation-based resonance explores the multi-hop relation influence of resonance effect based on the global graph structure (via node positions [18] in the global graph).

To do so, we first gather all the users who have rated the item p_i before u_a, i.e. the nodes in $G^P(p_i, u_a)$ to build the mutual anchor set S_{mutual} for user social graph G^S: $S_{mutual} = \{u_p | u_p \in G^P(p_i, u_a) \text{ and } u_p \in G^S\}$. We then compute the t-hop shortest path based on [18]:

$$d^t(u_a, u_p|G^S) = \begin{cases} d(u_a, u_p|G^S) & \text{if } d(u_a, u_p|G^S) \leq t, \\ \infty & \text{otherwise,} \end{cases}$$

where $d(u_a, u_p|G^S)$ is the shortest path distance between user u_p to user u_a in G^S.The t-hop shortest path makes ResRec easy to scale.

With the relative distance, we can build the message passing from users in S_{mutual} to u_a, to learn the relation-based resonance influence in G^P based on the graph structure in G^S: $m^P(u_p|u_a, G^S) = \frac{1}{d^t(u_a, u_p|G^S)+1}$, where $m^P(u_p|u_a, G^S)$ is the message transformation weight from u_p to u_a.

Integrated Resonances Effect. We finally aggregate the two types of resonance to represent the joint resonance effect between graph G^P and G^S:

$$reson(G^P|G^S) = AGG(z^P(u_p|u_a, p_i), m^P(u_p|u_a, G^S))\mathbf{u}_p,$$
$$reson(G^S|G^P) = AGG(z^S(u_s|u_a, p_i), m^S(u_s|u_a, G^P))\mathbf{u}_s,$$

where AGG is an aggregation function such as MEAN, MAX, SUM, which is permutation invariant. We find using a simple SUM aggregation function experimentally provides good results.

By capturing the resonance effect, ResRec can be applied to different recommendation methods to learn item embeddings and thus recommend items that resonate with users. Here

TABLE II

PERFORMANCE COMPARISON OF RESREC WITH OTHER METHODS. THE NUMBERS IN THE PARENTHESES SHOW THE RELATIVE IMPROVEMENTS OF RESREC COMPARING WITH THE CORRESPONDING BASELINES. THE '**' INDICATES THAT THE IMPROVEMENTS OVER ALL BASELINES PASS THE SIGNIFICANCE TEST WITH P-VALUE < 0.001. RESREC SIGNIFICANTLY OUTPERFORMS THE OTHER METHODS IN TERMS OF BOTH MAE AND RMSE.

			Social Network			
		PMF	TrustSVD	GraphRec	DANSER	ResRec
Epinions	MAE	0.8764 (10.01%)	0.8104 (2.75%)	0.8374 (6.18%)	0.7980 (1.18%)	**0.7887****
	RMSE	1.1427 (8.33%)	1.0775 (2.86%)	1.0653 (1.70%)	1.0596 (1.16%)	**1.0475****
Ciao	MAE	0.7844 (11.68%)	0.7291 (5.24%)	0.7212 (4.10%)	0.7134 (2.97%)	**0.6928****
	RMSE	1.0276 (10.50%)	0.9607 (4.46%)	0.9399 (2.19%)	0.9321 (1.35%)	**0.9197****

we use the commonly applied method in [9] as the item embedding to better evaluate the effect of mutual resonance for recommendation. Then with the user and item embedding, the dot product [19] is used to estimate the user preference towards items.

V. EVALUATION

We use two real world datasets, as shown in Table I. We use the most recent rating for each item to construct the test dataset, the one rating before the most recent as the validation set, and all the other ratings for training. For evaluation metrics, we use MAE (Mean Absolute Error) and RMSE (Root Mean Square Error). *Note here, as indicated by [12], a small decrease of MAE and RMSE can bring a significant impact on the quality of top-k recommendation.*

We select representative and state-of-the-art social recommendation methods as the baselines: PMF [19], TrustSVD [20], GraphRec [12] and DANSER [9]. The latent dimensions d for all methods are fixed to be 10. Model hyperparameters are decided by grid search.

A. Overall Comparison

We investigate the overall performance of ResRec as shown in Table II. The '**' indicates that the improvements over all baselines pass the significance test with p-value < 0.001. In Table II, the numbers in the parentheses show the improvements of ResRec comparing with the corresponding baselines. Overall, ResRec consistently outperforms all the baselines in all datasets. Concretely:

First, TrustSVD achieves better performance than PMF. The improvement confirms that social networks can help improve item recommendation, since all those methods are based on matrix factorization.

Second, comparing with the MF-based methods, graph neural network-based models (GraphRec and DANSER) generally give a better performance. The results demonstrate the power of graph neural networks in modeling the social network for ratings prediction, since the GNN-based methods can naturally capture the topological structure of the social network.

Third, ResRec significantly outperforms the other methods, especially the state-of-the-art methods GraphRec and DANSER. Since all of these methods use graph neural networks, the improvement of ResRec verifies that the modeled social resonance indeed can help improve the prediction of user preference towards items. Moreover, through the resonance mutual learning layer, ResRec can simultaneously utilize the two networks to enhance the learning of each influence.

VI. CONCLUSION

We have explored the potential of social resonance to enhance the learning of user preference towards items. The proposed ResRec framework comprehensively learns resonance from preference and multi-hop relation-based aspects. Extensive experimental results show that ResRec significantly improves upon state-of-the-art social recommenders. In our continuing work, we are exploring additional sources of resonance, e.g., from user reviews.

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