DREAM: A Dynamic Relational-Aware Model for Social Recommendation

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About the Speaker

- Senior Algorithm Engineer in Ping An Technology Co., Ltd
- **Major Research Direction:** Deep Learning, Recommendation System, Knowledge Graph

1 Introduction

Challenges

Social connections play a vital role in modeling users' potential preferences and improving the performance of recommendation systems (RS). However, incorporating social information into RS is challenging.

- Both users' personal interests and their friends' influences change over time.
- In real world, social relations are very sparse. Many datasets show that sometimes, real friends could not provide enough useful information.

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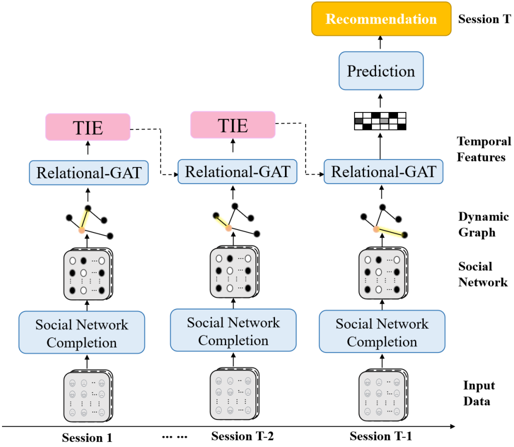
Contributions

Our contributions in this paper are as follows:

- We propose a novel RS approach, which aims to model users' dynamic interests and dynamic influences from their friends. The model encodes the outputs form historical sessions by recursively combining the features encoded by relational-GAT modules and that from last TIE module.
- We design a GloVe-based method to increase the number of friends, and use relational-GAT to aggregate user representations from both completed social network in each session.
- We conduct experiments on real-world recommendation scenarios, and the results prove the efficacy of DREAM over several state-of-the-art baselines.

Framework

The model consists of social network completion, relational-aware graph attention network (relational-GAT) modules, temporal information encoding (TIE) modules and recommendation.



Virtual Friends Definition and Selection

Virtual friend: users having similar consumption habits, and the connection is stronger if they are more similar.

- Utilize GloVe mechanism to learn user representations.
- Calculated the similarity among all users:

$$s^V_{p,q} = \mathrm{softmax}(\langle \boldsymbol{g}_{u_p}, \boldsymbol{g}_{u_q} \rangle) = \frac{\exp(\langle \boldsymbol{g}_{u_p}, \boldsymbol{g}_{u_q} \rangle)}{\sum_{u_l, u_s \in \mathcal{U}} \exp(\langle \boldsymbol{g}_{u_l}, \boldsymbol{g}_{u_s} \rangle)}.$$

- Choose top-k users whose similarity is higher.

Node Representation

Friends' influences always lag, since friends may consumed products first and then influence the user. So in t-th relational-GAT module, friends node representations are calculated in (t-1)-th session. Here, we use users' short-term interests, which are gotten by employing GRU over user u_j's interaction sequence in (t-1)-th session

$$\mathcal{S}_{t-1}^{j} = \{i_{t-1,1}^{j}, i_{t-1,2}^{j}, \ldots, i_{t-1,N_{k,t}}^{j}\},$$

i.e.

$$\boldsymbol{s}_j = \mathrm{GRU}(\mathcal{S}_{t-1}^{j}).$$

- Challenges
- Contributions

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Relational-GAT Module

For target user u with $|\mathcal{N}(u)|$ friends, we rerepresent nodes as $\boldsymbol{h}_u^{(0)} = \widetilde{\boldsymbol{u}}_{t-1}$ and $\{\boldsymbol{h}_j^{(0)} = \boldsymbol{s}_j\}$, where user node representation $\widetilde{\boldsymbol{u}}_{t-1}$ is gotten from last TIE module. The attention score:

$$\alpha_{uk} = \frac{\exp(f_r(\boldsymbol{h}_u^{(0)}, \boldsymbol{P}_r \boldsymbol{h}_k^{(0)}))}{\sum_{u_j \in \mathcal{N}(u) \cup \{u\}} \exp(f_r(\boldsymbol{h}_u^{(0)}, \boldsymbol{P}_r \boldsymbol{h}_j^{(0)}))}, \quad \forall w \in \mathcal{N}(u),$$

where $f_r(\cdot, \cdot)$ is the deep neutral network performing relational attention. Then, we aggregate information from $\mathcal{N}(u)$:

$$\boldsymbol{h}_u = \sigma\left(\sum_{u_j \in \mathcal{N}(u) \cup \{u\}} \alpha_{uj} \boldsymbol{h}_j^{(0)}\right),$$

where σ denotes the activation function. We denote the final representation of user as $\boldsymbol{u}_t = \boldsymbol{h}_u$.

TIE module

To combine relational-GAT encoded features at each time, as well as the target user's dynamic personal interests, we design a GRU-like module, called TIE module.

$$
\begin{aligned}
\boldsymbol{u}_q &= \boldsymbol{W}_q^t \widetilde{\boldsymbol{u}}_{t-1} + \boldsymbol{b}_q^t \\
\boldsymbol{u}_e &= \boldsymbol{W}_e^t \boldsymbol{u}_t + \boldsymbol{b}_e^t \\
\widetilde{\boldsymbol{h}}_t &= \tanh(\boldsymbol{W}_h^t \boldsymbol{u}_t + \boldsymbol{u}_e \circ \boldsymbol{U}_h^t \widetilde{\boldsymbol{u}}_{t-1} + \boldsymbol{b}_h^t) \\
\widetilde{\boldsymbol{u}}_t &= (\boldsymbol{1} - \boldsymbol{u}_q) \circ \widetilde{\boldsymbol{u}}_{t-1} + \boldsymbol{u}_q \circ \widetilde{\boldsymbol{h}}_t,
\end{aligned}
$$

where $\boldsymbol{W}_q^t$, $\boldsymbol{W}_e^t$, $\boldsymbol{W}_h^t$, $\boldsymbol{U}_h^t \in \mathbb{R}^{d \times d}$, $\boldsymbol{b}_q^t$, $\boldsymbol{b}_e^t$, $\boldsymbol{b}_h^t \in \mathbb{R}^d$.

Dataset

To comprehensively study our proposed model DREAM, we conduct experiments on real-world datasets to answer the following questions: Q1: Does DREAM outperform the state-of-the-art baselines? Q2: How is DREAM affected by each component?

Table 1: Descriptive statistics of two datasets

	Epinions	Movie
# Users	15,489	57,496
# Items	255,253	56,858
# Events	500,770	3,007,442
# Social links	355,217	1,758,302
Avg.session/user	2.3778	2.8786
Avg. real friends/user	22.99	15.60

Model Analysis

Table 2: Overall performance. 'Imprv.' denotes percentage improvement of DREAM, with respect to the best baseline.

Model	Epinions			Movie		
	R@10	NDCG	MRR	R@10	NDCG	MRR
BPR	0.00585	0.08396	0.00228	0.01574	0.11265	0.00651
SBPR	0.00658	0.08948	0.00281	0.01642	0.11333	0.00685
GraphRec	0.00880	0.09635	0.00409	0.01787	0.11352	0.00698
GRU	0.00410	0.09229	0.00360	0.01141	0.11380	0.00700
SASRec	0.00410	0.09239	0.00287	0.01723	0.11459	0.00747
DGRec	**0.01176**	**0.09632**	**0.00468**	**0.01901**	**0.11486**	**0.00750**
DREAM	0.01639	0.09787	0.00628	0.02285	0.11669	0.00870
Imprv.	39.37%	1.58%	34.19%	20.20%	1.59%	16.00%

Model Analysis

Table 3: Ablation study comparing the performance of the complete model DREAM with several variations.

Model Components		Epinions		Movie	
		R@10	MRR	R@10	MRR
Inner-Session	DREAM-R	0.00820	0.00325	0.01868	0.00759
	DREAM-V	0.01230	0.00347	0.01873	0.00765
Inter-Session	DREAM-GAT	0.01510	0.00527	0.02109	0.00816
	DREAM-TGRU	0.01530	0.00551	0.02186	0.00837
	DREAM-S1	0.01297	0.00389	0.01931	0.00749
	DREAM-S3	0.01430	0.00486	0.02000	0.00826
DREAM		0.01639	0.00628	0.02285	0.00870

Summary

- In each session, to solve the sparsity of social relations, we design a GloVe-based method to increase the number of friends, and utilize relational-GAT to integrate influences from friends.
- Then we build TIE modules to encode the outputs form historical sessions by recursively combining the features encoded by relational-GAT modules and that from last TIE module.
- In the extensive experiments on the public datasets, DREAM significantly outperforms the state-of-the-art solutions.

Q&A

Thank you for your attention!

If you have any questions, please email to
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