SOCIAL RECOMMENDATION OVERVIEW

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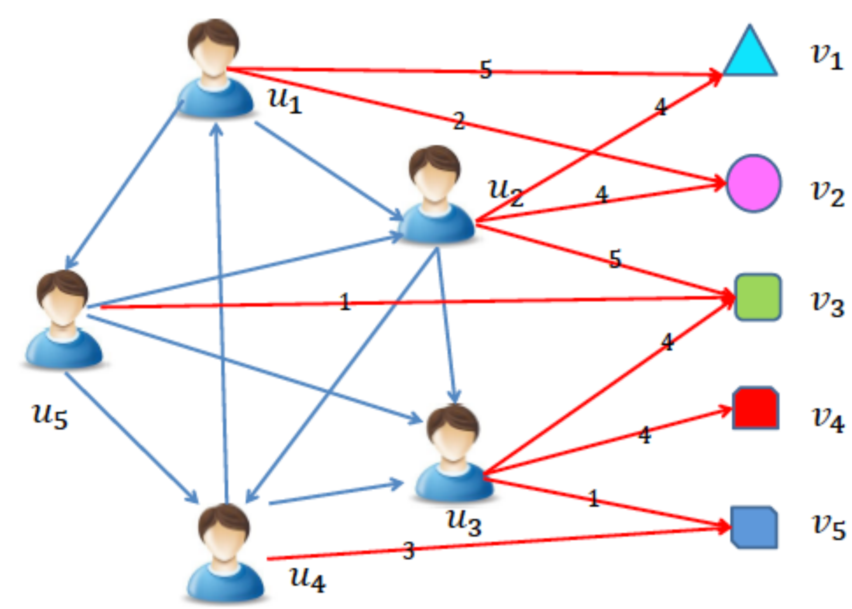
MOTIVATION

➤ Social Recommendation:

	v_1	v_2	v_3	v_4	v_5
u_1	5	?	2	?	?
u_2	4	4	5	?	?
u_3	?	?	4	4	1
u_4	?	?	?	?	3
u_5	?	?	1	?	?

Rating matrix



Social Network

➤ Online users are connected via *friendship* and *trust* relations.

➤ Social Homophily and Temporal Influence.

MOTIVATION

- Benefits:
  - Facilitates "more" personalized recommendations, by constraining the space of recommended items.
  - Cold-start users: New users with few ratings.
  - Increase item coverage via interest propagation through social network.
- Trust Networks : Assumes similar tastes with other users they trust.
  - Epinions: network of trust (and distrust) relationships between users.
- Social Networks: Friends may not share item preferences.
  - Facebook, Twitter, Douban, etc.

OUTLINE

- Neighborhood models.
- Model-based models.
  - Co-factorization approaches.
  - Ensemble methods.
  - Regularization methods.
  - Neural regularization methods.

- Implicit Feedback.

NEIGHBORHOOD MODEL REVIEW

- User-User based neighborhood models

$$\hat{r}_{ui} = b_{ui} + \frac{\sum_{v \in N^+(i;u)} s_{uv}(r_{vi} - b_{vi})}{\lambda + \sum_{v \in N^+(i;u)} s_{uv}}$$

- s_{uv}: User-user similarity. $N^+(u;i)$: Users who rated item i.
- Prediction based on ratings of similar users on the same item.
- Correlated users N^+: Use both ratings and social network.
- How to identify *similar* users in the social network?

TRUSTWALKER

- Random walk to explore the network.
- Trade-off between precision and coverage.
- Ratings of strongly trusted friends on similar items are more reliable than ratings of weakly trusted neighbors on the exact target item.

- User Neighborhood: Direct and indirect friends’ ratings for the target item as well as similar items.
- Biased Random walk:
  - Either stop at node and choose item most similar to target item.
  - Continue exploration to neighbor.

MATRIX FACTORIZATION REVIEW

- Draw latent factors: $u_i \sim N(0, \lambda_U^{-1} I)$; $v_j \sim N(0, \lambda_V^{-1} I)$
- Draw rating: $r_{ij} \sim N(u_i^T v_j, \epsilon^2)$ for rating by user u_i on item v_j.
- Assume ratings in [0, 1].
- $$L(R, U, V) = \sum_{i=1}^{N} \sum_{j=1}^{M} I_{ij}^R (r_{ij} - g(U_i^t V_j))^2 + \frac{\lambda_U}{2} \|U\|_F^2 + \frac{\lambda_V}{2} \|V\|_F^2$$
- I_{ij}^R : Indicator to denote whether user u_i rated item v_j.
- $g(x) = 1/(1 + exp(-x))$, to bound $U_i^T V_j$ in the range [0, 1].
- How do we incorporate social network?

CO-FACTORIZATION (SOREC)

- Consider social network as a matrix $S \in R^{N \times N}$.
- User u_i has the same preference vector U_i in the interest space (rating information) and the social space (trust information).
- Co-factorization of rating and social network matrices.
-
$$L(R,S,U,V,Z) = \sum_{i=1}^{N}\sum_{j=1}^{M} I_{ij}^{R}(r_{ij} - g(U_i^t V_j))^2 + \boxed{\frac{\lambda_S}{2}\sum_{i=1}^{N}\sum_{k=1}^{N} I_{ik}^{S}(s_{ij} - g(U_i^t Z_k))^2}$$
$$+ \frac{\lambda_U}{2}\|U\|_F^2 + \frac{\lambda_V}{2}\|V\|_F^2 + \frac{\lambda_Z}{2}\|Z\|_F^2$$

Social matrix factorization

- What are potential limitations of this approach?

ENSEMBLE (STE)

- Users and their trusted friends have similar ratings on items.
- Predict rating for user u as a linear combination (ensemble) of ratings from u and her trusted friends N_u.
- $$\hat{r}_{ij} = g\left(\alpha U_i^T V_j + (1-\alpha) \sum_{k \in N_i} S_{ik} U_k^T V_j\right)$$
- α: hyper-parameter to balance own tastes and trusted friends'.

$$L(R,S,U,V) = \sum_{i=1}^{N} \sum_{j=1}^{M} I_{ij}^{R} \left(r_{ij} - g\left(\alpha U_i^T V_j + (1-\alpha) \sum_{k \in N_i} S_{ik} U_k^T V_j\right)\right)^2$$

- $$+ \frac{\lambda_U}{2} \|U\|_F^2 + \frac{\lambda_V}{2} \|V\|_F^2$$
- Trust may not imply same rating. Fixed α across all users.

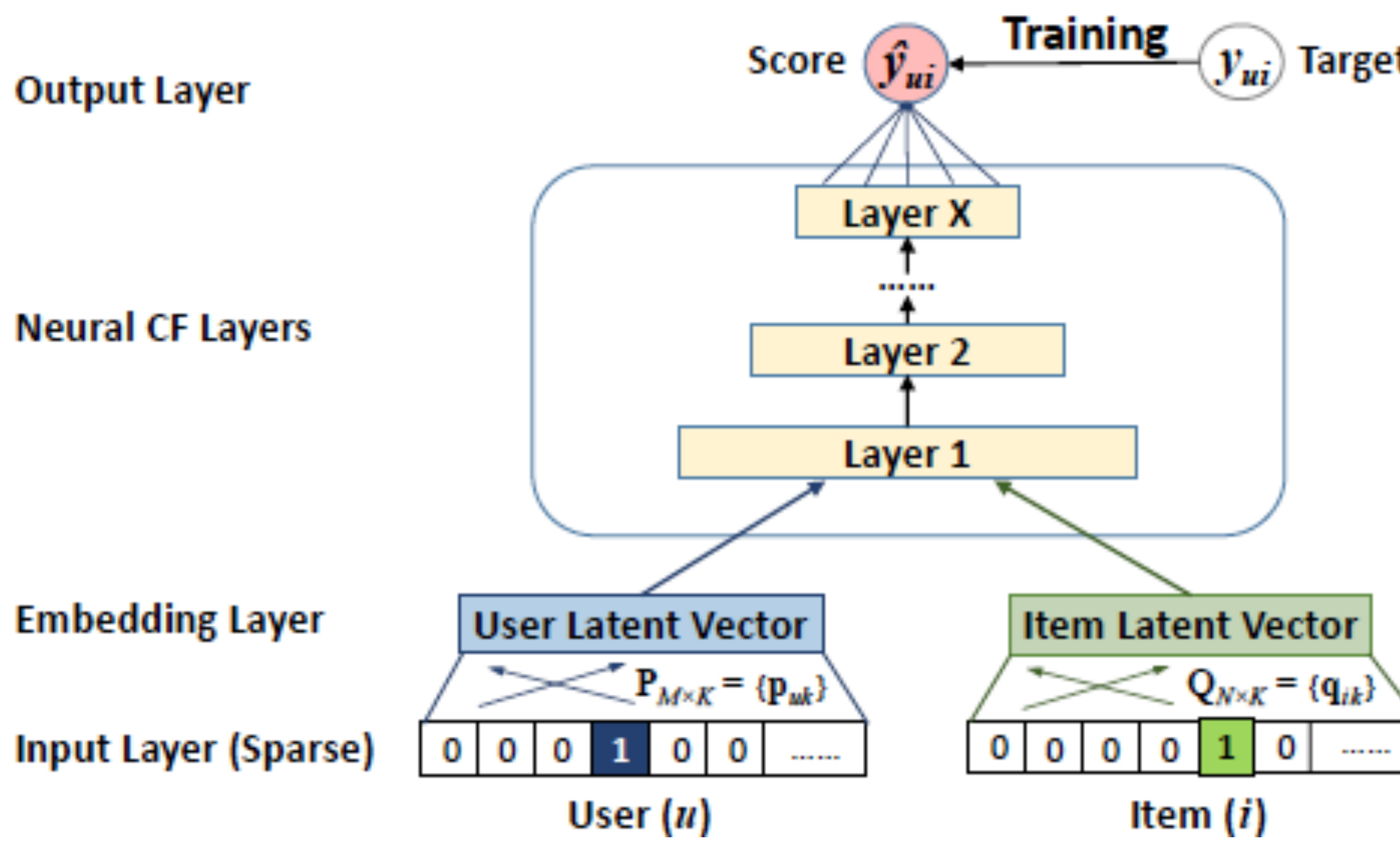
REGULARIZATION (SOCIALMF)

- User's preferences should be similar to that of her trust network.
- Trust propagation from friends to learn latent factors.
- Forces the latent vector of a user to be closer to the average preference of the user's trust neighbors.
- Tighter coupling between interest and social space.
- $$L(R,S,U,V) = L_{MF} + \frac{\lambda_S}{2}\sum_{i=1}^{N}\Big(U_i - \sum_{k\in N_i}(U_i - T_{ik}U_i)^T(U_i - \sum_{k\in N_i} T_{ik}U_i)\Big)$$
- Average cannot distinguish diverse preferences of friends.

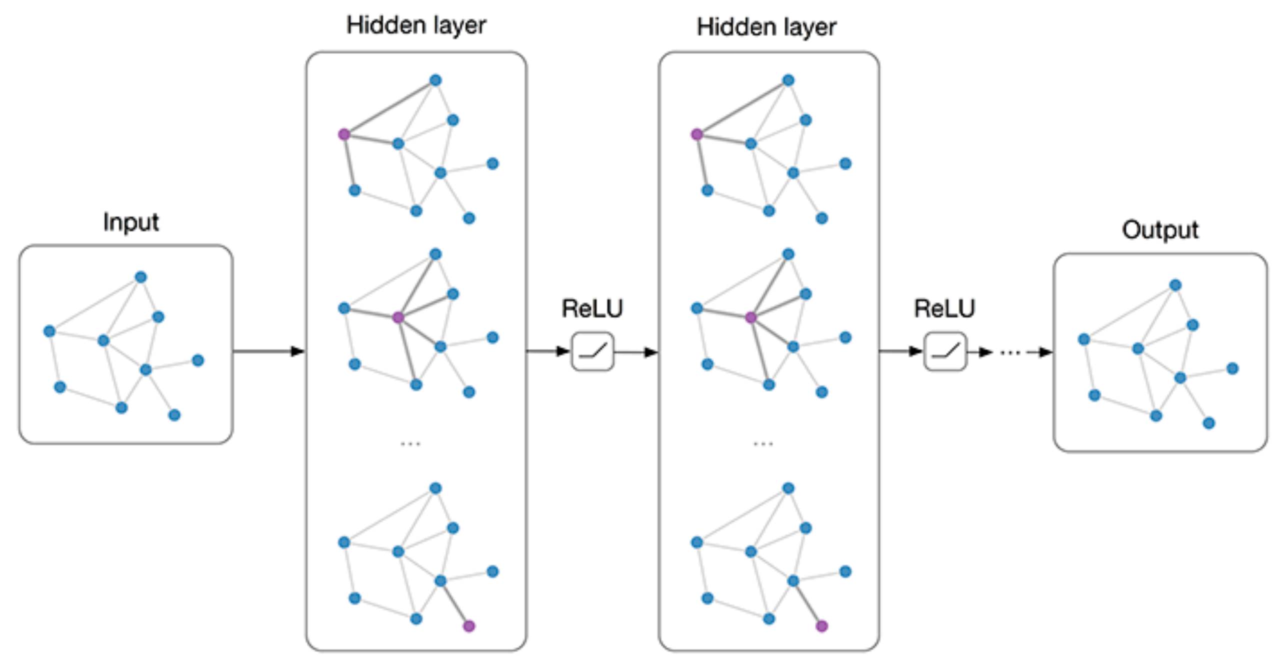
SIMILARITY-DRIVEN REGULARIZATION

- Explicitly account for differing impacts of friends.
- Pair-wise similarity-driven regularization:
- $$L(R, S, U, V) = L_{MF} + \sum_{i=1}^{N} \sum_{k \in N_i} sim_{ik} \| U_i - U_k \|^2$$
- sim_{ij}: preference closeness of two users u_i and u_j (Pearson correlation).
- This formulation is the most expressive matrix factorization based objective, for social recommendation.

NEURAL COLLABORATIVE FILTERING

- Inner product can limit the expressiveness of MF.
- Multi-layer perceptron (MLP) to learn the user-item interaction function.
- 

NEURAL SOCIAL RECOMMENDATION



- User-Item Matrix:
  - Neural CF.
  - Auto-encoders.
- Social Network:
  - Graph Convolutional Networks.
- Key Objectives:
  - Interest-driven social neighborhood aggregation.
  - Flexibly prioritize relevant social connections.

IMPLICIT FEEDBACK

- Binary user-item interaction (or click) matrix X.
- $x_{ui} = \begin{cases} 1 & \text{if interaction } (u, i) \text{ is observed} \\ 0, & \text{otherwise} \end{cases}$
- $\hat{x}_{ui}$: personalized score for user u on item i.
- If we use MSE (mean squared error) to predict x_{ui} for all entries, what happens?
- Cannot treat all unobserved entries as negatives.
- Ranking objectives:
  - Positive sample: (u, i) where $x_{ui} = 1$; Negative: (u,j) where $x_{uj} = 0$

RANKING METRICS

- I_u: Set of held-out items for user u.
- $rel(k)$: indicator equaling 1 if item at rank k is relevant.
- Recall@K (also called HitRate): Fraction of relevant items retrieved correctly within top-k ranks.
- NDCG@K (normalized discounted cumulative gain): Discount factor to emphasize the importance of higher ranks.
- NDCG= DCG/IDCG, where IDCG is ideal discounted cumulative gain.
- $\text{Recall@}K(u) = \dfrac{\sum_{k=1}^{K} rel(k)}{min(K, |I_u|)}$ $\qquad \text{DCG@}K(u) = \sum_{k=1}^{K} \dfrac{rel(k)}{\log_2(k+1)}$

PROJECT DETAILS

- Implicit feedback recommendation on Yelp.
- Inputs:
  - Social network of users.
  - Item categories: Can induce a social network of items.
- **Goal**: Develop a social recommender that outperforms BPR.

- **Tips**: Deep Learning libraries such as Tensorflow, PyTorch, enable fast prototyping of neural recommendation models.

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