A Two-stage Ranking Framework for Multilingual Recommendation(Team:AIDA)

Shijie Liu, Chenliang Zhang, Xutao Han, Wen Wu, Wei Zhang*

East China Normal University, Zhejiang University

Overall architecture

Our method follows a two-stage paradigm commonly used in recommender systems,

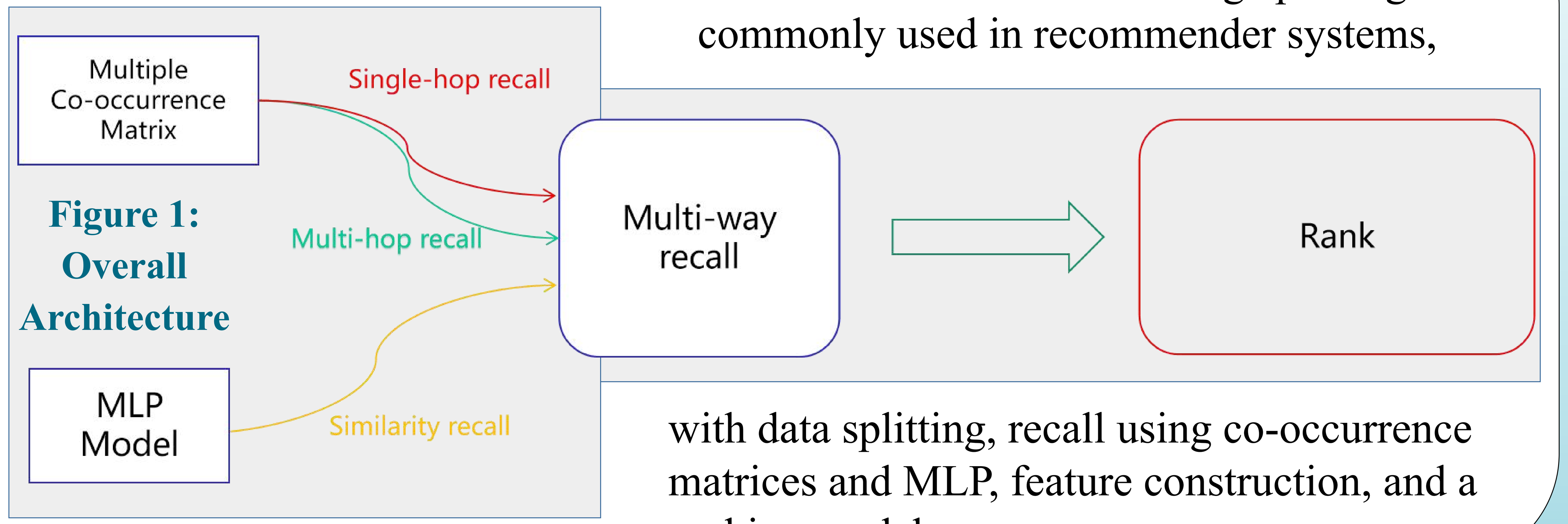

Figure 1: Overall Architecture

with data splitting, recall using co-occurrence matrices and MLP, feature construction, and a ranking model.

Co-occurrence Matrix

A simple but effective co-occurrence matrix construction method: assuming $P\ (a,b)$ represents the co-occurrence count of a and b, whenever $[x_i, x_{i+1}]$ appears once in session, $P\ (x_i, x_{i+1})$ is incremented by 1, and $P\ (x_{i+1}, x_i)$ is incremented by 0.5.

Recall

Co-occurrence Matrix Recall

$$\arg\max_{y} \sum_{i=1}^{n} W_{n-i} \cdot P(x_i, y)$$

$$P_{l-hop}(i,j) = \sum_{k \in I} \frac{P_{(l-1)-hop}(i,k) \cdot P(k,j)}{\sum_{t \in I} P(k,t)}$$

MLP Model Recall

Find the item embedding that is most similar to the session embedding, forming a candidate set.

MLP Model

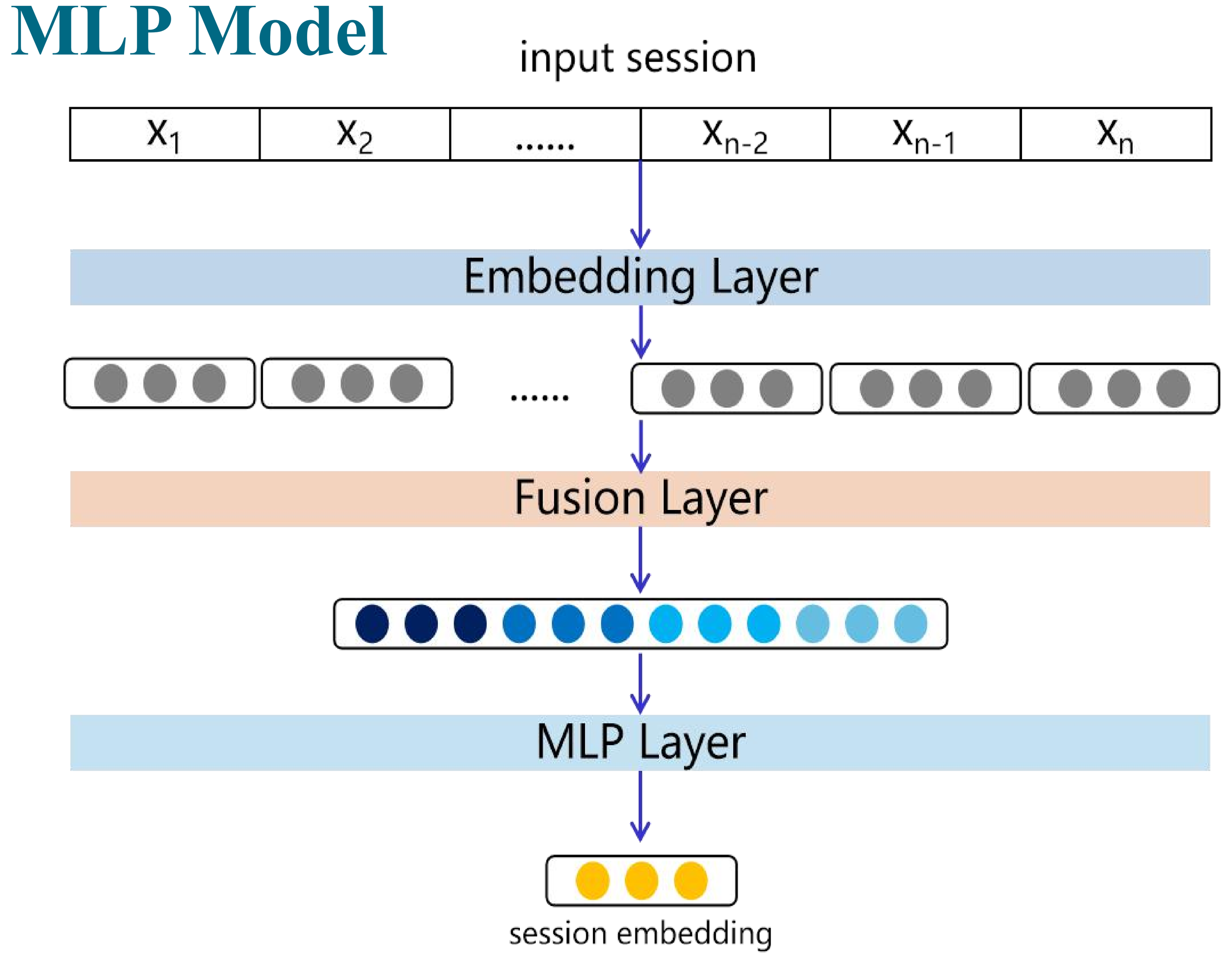

Figure 2: The architecture proposed in this paper to obtain session embedding.

Our proposed method consists of two modules, session encoder and target encoder. The structure of the session encoder is shown in **Figure 2.**

Where x_i represents the k-dimensional embedding of the i-th item in the input session, and $[\cdot]$ represents the concat operation.

Fusion Layer can be described as:

$$U = [\sum_{0<i<n-3} \frac{x_i}{n-4}, \frac{x_{n-3} + x_{n-2}}{2}, x_{n-1}, x_n]$$

Our final optimization target is:

$$\mathcal{L} = -log \frac{e^{cos(U_i, Y_i^+)/\tau}}{\sum_{j=1}^{N} e^{cos(U_i, Y_j^-)/\tau}}$$

which makes the session embedding and label item embedding as similar as possible.

Ranking Feature

1.Item-CF

$$sim(x,y) = \frac{1}{\sqrt{|U_i||U_j|}} \sum_{u \in U_i \cap U_j} \frac{\alpha^{|l_i - l_j| - 1}}{log(1 + |I_u|)},$$

$$\alpha = \begin{cases} 0.8, l_i < l_j \\ 0.7, l_i > l_j \end{cases}$$

2.Co-occurrence Matrix Feature

$$score_i(x,y) = \frac{P_i(x,y)}{max(1, \sum_{k \in I} P(x,k))}$$

3.Attribute Feature

4.MLP Model Feature

5. Transfer Co-occurrence Matrix Feature For Task 2

Ranking Model And Tips

XGBoost

We tested the objectives of "rank" and "binary" and found that learning classification tasks can achieve higher scores.

In addition, we found that lowering the score of goods that did not appear in the test set can significantly improve the final score.