A Dynamic Recurrent Model for Next Basket Recommendation

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1 Main Contribution

1. The authors investigate the dynamic representation of each user and the global sequential behaviors of item-purchase history.
2. Experiments on two datasets are conducted to validate the effectiveness of DREAM model.
3. DREAM is the first approach that attempts to incorporate dynamic representation and global sequential behaviors for enhancing the performance of next basket recommendation.

2 Model

2.1 Framework

The framework Beacon consists of three main components:

1. Pooling layer: it takes all of the item vectors in the basket as input and then use maximum or average pooling to aggregate the item vectors into a basket vector.
2. RNN: it takes all of the basket vectors as input and generate Dynamic representation of a user as output. The network is as follow:

$$\boldsymbol{h}_{t_i}^u = f\left(\boldsymbol{X}\boldsymbol{b}_{t_i}^u + \boldsymbol{R}\boldsymbol{h}_{t_{i-1}}^u\right)$$

3. Scoring: it takes Dynamic representation of a user as input and generate score as output:

$$\boldsymbol{o}_{u,t_i} = \boldsymbol{N}^T\boldsymbol{h}_{t_i}^u$$

where N is the item matrix.

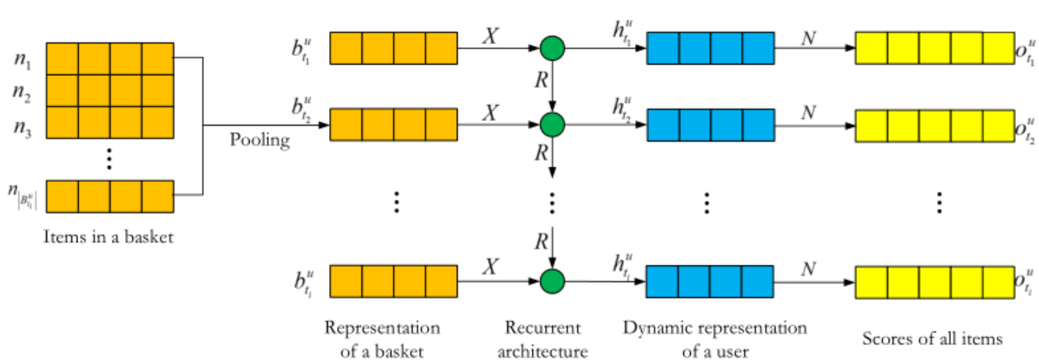


Figure 1: Structure

2.2 Objective Function

In the learning process of DREAM, the authors adopt Bayesian Personalized Ranking (BPR). The basic assumption is that a user prefers an item in basket at a specific time than a negative item sample. In this way, they need to maximize the following probability:

$$p\left(u, t, v \succ v'\right) = \sigma\left(o_{u,t,v} - o_{u,t,v'}\right)$$

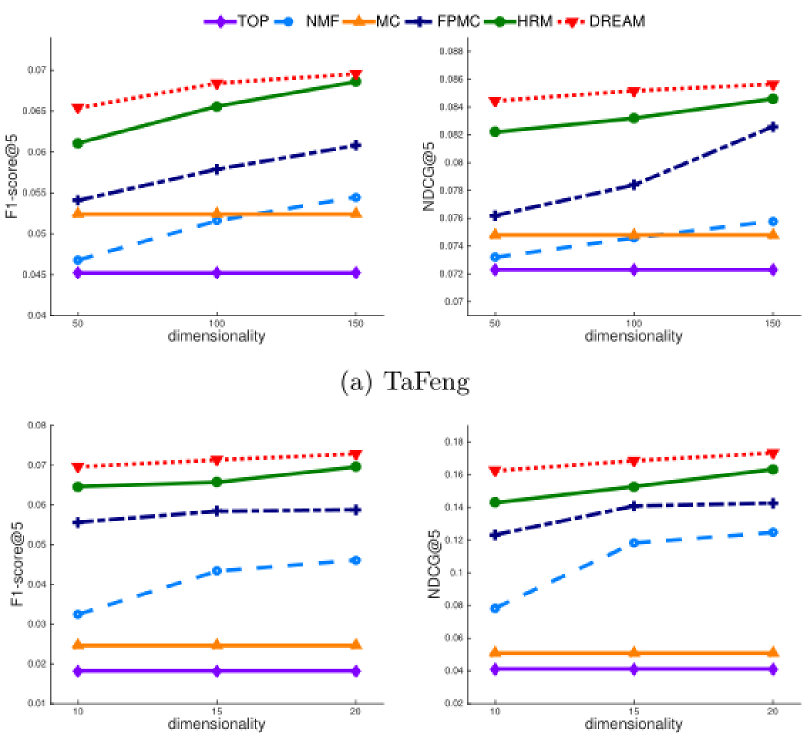
Adding up all the log likelihood and the regularization term, the objective function can be written as follows:

$$J = \sum \ln\left(1 + e^{-\left(o_{u,t,v} - o_{u,t,v'}\right)}\right) + \frac{\lambda}{2}\|\Theta\|^2$$

After that, the authors use Back Propagation Through Time (BPTT) to obtain the gradients of all the parameters and then update parameters utilizing Stochastic Gradient Descent (SGD) until converge.

3 Experiments

The paper experiments with two benchmark datasets: **Ta-Feng, T-mall**. The baselines include **TOP, MC, NMF, FPMC, HRM**. The results are as follows:



(a) TaFeng

(b) Tmall

Figure 2: Performance

In general, the performance ranking of next basket recommendation methods is as follows, DREAM, HRM, FPMC, NMF, MC and TOP.

4 My Idea

In this paper, the authors propose a model named DREAM that utilizes RNN to do the next basket recommendation. Compared to the MC method, it can utilize the information in all of the history but not only the adjacent one. It is really novel at that time, but nowadays it is just a famous baseline. But because of its simplicity we can combine it with our methods easily.