Modeling Personalized Item Frequency Information for Next-basket Recommendation

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August 12, 2022

1 Main Contribution

1. The authors analyze two patterns associated with PIF and the target basket. The collaborative purchase pattern that PIF can contribute to the NBR in a collaborative way is discovered.

2. The authors discover the difficulty of RNNs in learning vector addition in recommendation setting. To their best knowledge, they are the first to present and analyze this phenomenon.

3. The authors propose a simple and effective kNN based method to directly capture the two useful patterns associated with PIF. The temporal dynamics is also considered in the proposed method.

4. The authors perform experiments on four real-world data sets to demonstrate the effectiveness of the proposed method.

2 Methodology

2.1 Integrating Temporal Dynamics

Generally, the authors observe that recent purchases have more impact to trigger a repeated purchase than the behavior long time ago. Thus, they propose to assign decayed weights to the same item appearing at different time steps. The earlier the item appears, the smaller weight the item contributes to the final frequency.

2.2 Nearest Neighbors based Method

At first the authors propose to aggregate the historical records into one vector which is easy for similarity calculation. The direct way to aggregate the historical records is to sum them up. But this way has a limitation shown in the last section.

Thus, the authors make the items bought recently contribute more in the similarity calculation than the items bought long time ago. However, a single time decayed weight is not flexible to model another property of temporal dynamics that consecutive steps have small changes while steps far from each others have large changes.

To capture both temporal dynamics, the authors propose to use hierarchical time decayed weights. The process is as follows:

1. All baskets are divided into several groups.

2. All vectors in each group are multiplied by the corresponding time-decayed weight within the group, and then all are added together as the vectors of the group.

3. All group vectors are multiplied by the time-decayed weight across the group, and all are added together as the final result.

In fact, compared to the single time decayed weight, the generation of the hierarchical time decayed weights is divided into two steps, so that the change of adjacent vectors is not too steep.

The prediction is a combination of following two parts:

1. Repeated purchase component: Denote the user representation of the target user as u_t. It is corresponding to repeated purchase pattern.

2. Collaborative purchase component: Denote the set of target user's nearest neighbors vector representations as $U_{neighbor}$. Denote the average vector of all vectors belong to $U_{neighbor}$ as u_n. u_n is corresponding to collaborative purchase pattern.

The final prediction is:

$$P = \alpha \cdot u_t + (1\alpha) \cdot u_n$$

where the α is a hyper-parameter to balance two parts. The s items corresponding to the largest s entries in P are recommended.

3 Experiments

The paper experiments with two benchmark datasets: Dunnhumby, Val- uedShoppe, Instacart and TaFeng. The baselines include TopFreq, PersonTopFreq, userKNN, RepeatNet, FPMC, DREAM, SHAN, Sets2Sets and TIFU-KNN. The results are as follows:

Data	Metric	(a) TopFreq	(b) PersonTopFreq	(c) userKNN	(d) RepeatNet	(e) FPMC	(f) DREAM	(g) SHAN	(h) Sets2Sets	(i) TIFU-KNN	improvement vs. (a)-(b)	improvement vs. (c)-(h)
ValuedShopper	recall@10	0.0982	**0.2109**	0.0988	0.1031	0.0951	0.0991	0.0847	0.1259	0.2162	2.5%	71.7%
	recall@20	0.0904	**0.2969**	0.1329	0.1485	0.1391	0.1448	0.1220	0.1774	0.3028	2.7%	70.6%
	NDCG@10	0.0779	**0.2128**	0.1415	0.1439	0.1188	0.1231	0.1032	0.1626	0.2171	2.1%	33.5%
	NDCG@20	0.0904	**0.2544**	0.1662	0.1693	0.1253	0.1287	0.1074	0.1884	0.2589	1.7%	37.4%
Instacart	recall@10	0.0724	**0.3426**	0.0720	0.2107	0.0763	0.0866	0.0902	0.3021	0.3952	15.3%	30.8%
	recall@20	0.1025	**0.4652**	0.1260	0.2637	0.1073	0.1128	0.1246	0.3654	0.4875	4.8%	33.4%
	NDCG@10	0.0641	**0.3618**	0.1020	0.2285	0.0946	0.1063	0.1152	0.3487	0.3825	5.7%	9.6%
	NDCG@20	0.0689	**0.4155**	0.1394	0.2513	0.0992	0.1157	0.1212	0.3626	0.4384	5.5%	20.9%
Dunnhumby	recall@10	0.0819	**0.1853**	0.1135	0.1324	0.0919	0.0915	0.1007	0.2068	0.2087	12.6%	0.9%
	recall@20	0.1077	**0.2366**	0.1648	0.1989	0.1186	0.1087	0.1201	0.2653	0.2692	13.7%	1.4%
	NDCG@10	0.0601	**0.1771**	0.1707	0.1545	0.1025	0.1009	0.1149	0.2134	0.1983	11.9%	-7.0%
	NDCG@20	0.0609	**0.2016**	0.2052	0.1732	0.1057	0.1022	0.1167	0.2385	0.2302	14.1%	-3.5%
TaFeng	recall@10	**0.0773**	0.0704	0.1089	0.0645	0.0868	0.0902	0.0878	0.1190	0.1301	33.7%	9.3%
	recall@20	0.1151	**0.1203**	0.1278	0.0919	0.1056	0.1149	0.1065	0.1767	0.1810	50.4%	2.4%
	NDCG@10	0.0519	**0.0766**	0.0832	0.0592	0.0667	0.0763	0.0813	0.0844	0.1011	31.9%	8.4%
	NDCG@20	0.0608	**0.0896**	0.1064	0.0679	0.0743	0.0841	0.0892	0.1071	0.1206	34.5%	12.6%

Figure 1: Performance

1. The simple top-n frequent baseline achieves reasonable performance compared to other existing methods in recall.

2. Personalized top-n frequent method achieves competitive performance across all data sets.

3. The existing NBR methods (excluding Sets2Sets) is surpassed by the baseline personalized top-n frequent method in ValuedShopper, Instacart, and Dunnhumby data sets by a large margin.

4. The tweaked top-n recommendation method userKNN and session-based recommnedation method RepeatNet are worse than the state-of-the-art method Sets2Sets.

5. the proposed TIFU-KNN is better than other methods in ValuedShopper, Instacart and TaFeng data sets, which verifies the superiority of the proposed method.

4 Future Work

1. A direct extension is whether there are other commonly-used functions which are hard to be learned by existing widely-used deep models. This direction can help us better understand how to apply deep learning based methods in recommendation systems as we observe that recent publications show a worry about the unclear progress in sequential/session-based recommendation.

2. Another direct extension is to investigate if there are other patterns associated with PIF or other patterns that are associated with different types of item frequency, e.g., global item frequency, local item frequency (the item frequency associated with a small group of users or a small group of items), and inverse item frequency.

5 My Idea

In this paper, the authors introduce a simple kNN-based method. It is amazingly simple but actually outperforms the state-of-the art deep learning based methods. In future study, we can use this method instead of RNN or MC for its good performance. And because of its simplicity, it can be more easily combined with other methods like knowledge graph.