Learning Recommender Systems with Soft Target: A Decoupled Perspective

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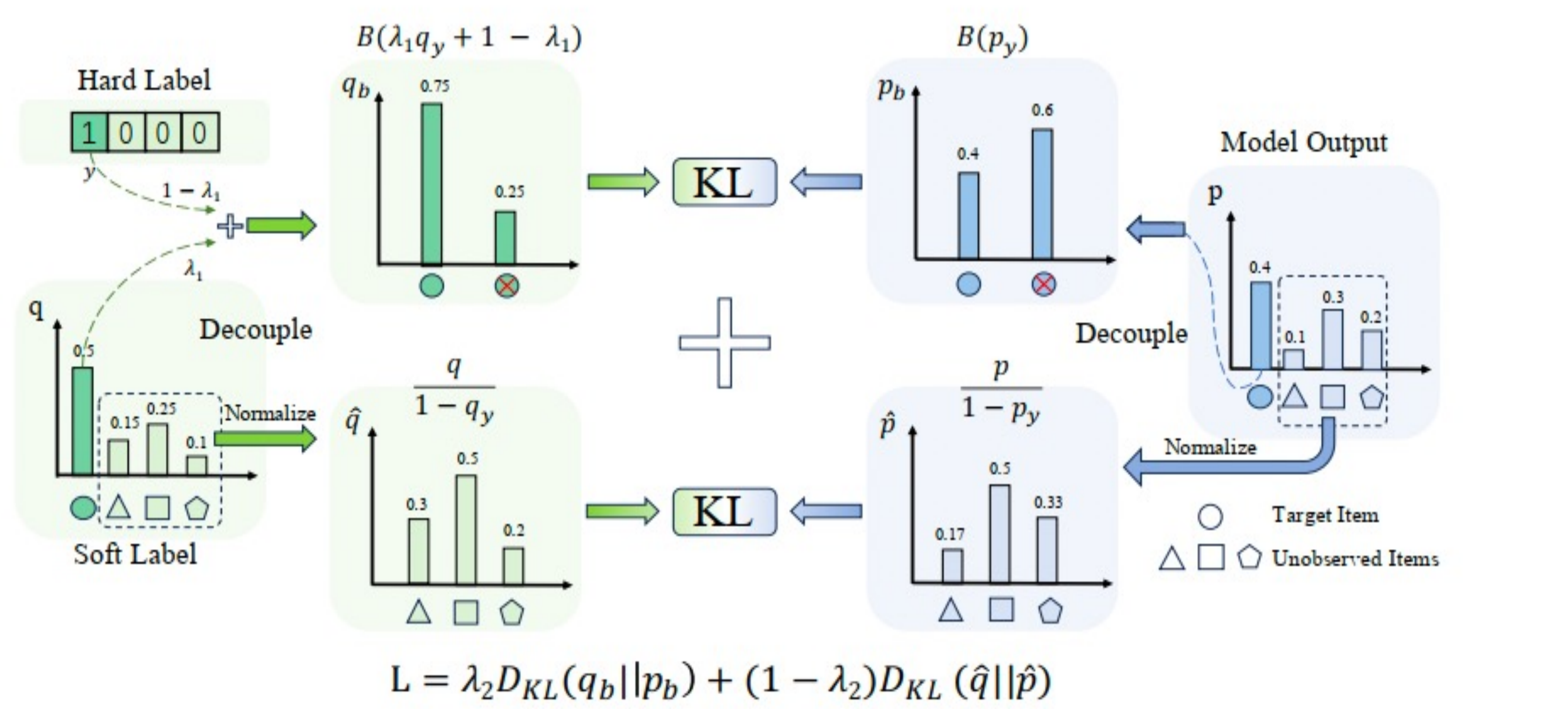
➢Motivation

A common practice for learning deep recommender systems is to treat the recommendation task as a multi-class classification problem, in which Softmax loss is often conducted to optimize the model by combining the one-hot label corresponding to the target item. However, this setting tends to ignore the difference between potential positive feedback and truly negative feedback, ultimately leading model to over-confidence. Although some methods utilizing soft labels have been proposed to mitigate this issue e.g. Label Smoothing, SoftRec, they may still suffer from the following limitations:

- They directly optimize the joint distribution of target item and unobserved feedback items, which imposes inflexibility on model training due to the couple relation between such two kind items, as revealed through our careful theoretical analysis.
- Current methods for constructing soft labels are relatively simple and fail to capture the diverse potential interests of users.

➢Our Proposed Method



A. Decoupled Soft Targets Optimization Framework

Assume the model output after the Softmax operation is $p \in \mathbb{R}^{|I|}$, denote the one-hot label and soft target as $d, q \in \mathbb{R}^{|I|}$, Traditional optimization framework often trade off these two supervisory signals with a controlling parameter $\lambda_1 \in [0,1]$ as:

$$\mathcal{L}(p,q,d) = \lambda_1 \mathcal{D}_{KL}(q||p) + (1-\lambda_1)\mathcal{H}(d,p),$$

where $\mathcal{D}_{KL}$ and $\mathcal{H}$ stands for KL-divergence and cross-entropy. As previously discussed, to provide a novel perspective, we separate the objective into the target item and the remain items by the following transformation. Denote the target item as y, we have:

$$\mathcal{L}(p,q,d) = \mathcal{D}_{KL}(q_b||p_b) + \lambda_1(1-q_y)\mathcal{D}_{KL}(\hat{q}||\hat{p}) + F(q)$$

In which p_b, q_b can be regarded as the binomial distribution related to target item, while $\hat{p} = \frac{p}{1-p_y}, \hat{q} = \frac{q}{1-q_y} \in \mathbb{R}^{|I|-1}$ describes the distribution over unobserved feedback and F(q) is a constant term unrelated to model. According to the above analysis, we can observe that (1) the weight of the second part is constrained by q_y while q_y is often set to the highest value and suggested to be larger than 0.5. (2) It is inflexible to balance these two aspects since λ_1 is also used to control the confidence of the target item $q_b = Bernoulli(\lambda_1 q_y + 1 - \lambda_1)$. Therefore, we propose to decouple the objectives by re-weighting the loss function with λ_2 :

$$\mathcal{L}_{Deso}(p,q,d) = \lambda_2 \mathcal{D}_{KL}(q_b||p_b) + (1-\lambda_2)\mathcal{D}_{KL}(\hat{q}||\hat{p}),$$

B. Soft Target Generation

To maximize the performance of the proposed method, we design an interest-sharing mechanism to explore users' potential positive feedback through their neighbors. We initialize each user u with a one-hot label, And in each label propagation round, all of them will receive distributions from their neighbors to update their current soft targets with the similarity matrix w.

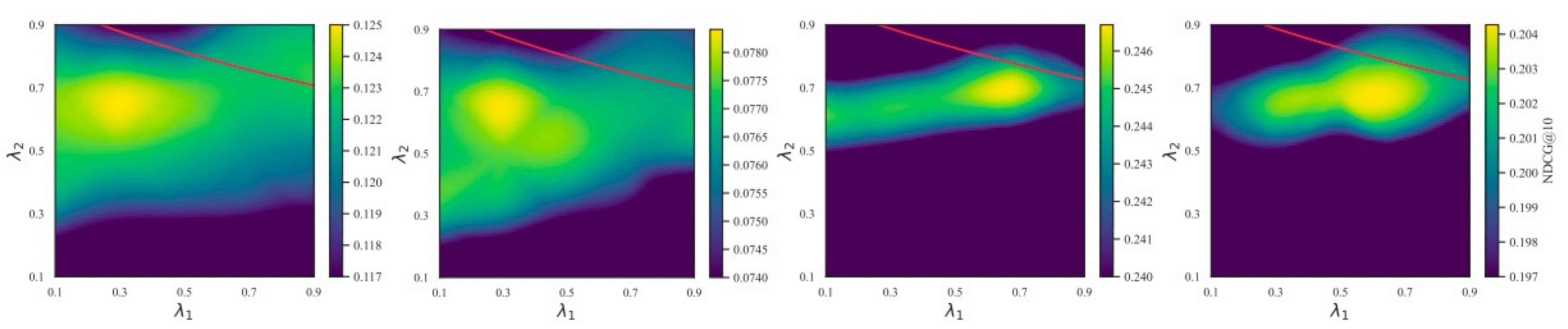
$$q_u^{t+1} = \sum_{v \in N(u)} p(v|u) q_v^t = w_u q^t \qquad q^{t+1} = \frac{1}{2} w q^t + \frac{1}{2} q^0.$$

Then we can get the final soft targets $q^* = q^T$ after T iterations.

➢Experiments

Recommenders	Methods	Diginetica R@20	Diginetica N@20	Diginetica R@10	Diginetica N@10	MovieLens R@20	MovieLens N@20	MovieLens R@10	MovieLens N@10	Last.FM R@20	Last.FM N@20	Last.FM R@10	Last.FM N@10
DeepFM	Base	0.1507	0.0761	0.1124	0.0665	0.2390	0.1099	0.1652	0.0913	0.2738	0.2024	0.2463	0.1955
	LS	0.1508	0.0760	0.1125	0.0663	0.2418	0.1118	0.1679	0.0933	0.2931	0.2142	0.2632	**0.2066**
	POP+	0.1418	0.0724	0.1071	0.0636	0.2450	0.1133	0.1705	0.0945	0.2938	0.2134	0.2629	0.2056
	CSN	0.1500	0.0753	0.1111	0.0655	0.2443	0.1127	0.1691	0.0937	0.2841	0.2041	0.2533	0.1964
	Ours	**0.1581**	**0.0792**	**0.1163**	**0.0686**	**0.2546**	**0.1189**	**0.1778**	**0.0995**	**0.3035**	**0.2150**	**0.2689**	0.2063
YoutubeDNN	Base	0.1350	0.0753	0.1077	0.0684	0.2427	0.1125	0.1689	0.0939	0.2028	0.1590	0.1850	0.1545
	LS	0.1402	0.0819	0.1151	0.0755	0.2473	0.1149	0.1720	0.0961	0.2409	0.1950	0.2232	0.1905
	POP+	0.1334	0.0789	0.1107	0.0732	0.2482	0.1155	0.1729	0.0965	0.2428	0.1962	0.2242	0.1913
	CSN	0.1521	0.0846	0.1213	0.0768	0.2519	0.1177	0.1763	0.0987	0.2465	0.1947	0.2255	0.1894
	Ours	**0.1597**	**0.0870**	**0.1247**	**0.0782**	**0.2578**	**0.1204**	**0.1803**	**0.1009**	**0.2669**	**0.2085**	**0.2442**	**0.2024**
GRU4Rec	Base	0.1066	0.0505	0.0767	0.0430	0.2473	0.1136	0.1705	0.0942	0.2558	0.2024	0.2345	0.1970
	LS	0.1173	0.0557	0.0843	0.0473	0.2488	0.1153	0.1725	0.0942	0.2725	0.2152	0.2499	0.2094
	POP+	0.1197	0.0591	0.0881	0.0511	0.2471	0.1143	0.1714	0.0952	0.2792	0.2177	0.2552	0.2117
	CSN	0.1181	0.0570	0.0853	0.0487	0.2517	0.1160	0.1740	0.0945	0.2668	0.2102	0.2442	0.2045
	Ours	**0.1289**	**0.0623**	**0.0942**	**0.0536**	**0.2586**	**0.1182**	**0.1777**	**0.0978**	**0.2834**	**0.2199**	**0.2578**	**0.2134**
SASRec	Base	0.1766	0.1075	0.1517	0.1012	0.2612	0.1298	0.1905	0.1120	0.3248	0.2608	0.3084	0.2567
	LS	0.1818	0.1088	0.1538	**0.1017**	0.2696	0.1343	0.1969	0.1159	0.3287	0.2626	0.3114	0.2582
	POP+	0.1750	0.1067	0.1501	0.1004	0.2700	0.1340	0.1972	0.1157	0.3156	0.2676	0.3016	0.2641
	CSN	0.1843	0.1073	0.1550	0.0999	0.2651	0.1319	0.1938	0.1140	0.3241	0.2684	0.3082	0.2643
	Ours	**0.1895**	**0.1093**	**0.1562**	0.1009	**0.2733**	**0.1351**	**0.1983**	**0.1162**	**0.3360**	**0.2735**	**0.3157**	**0.2684**

Recommendation performance



(a) Diginetica, R@10 (b) Diginetica, N@10 (c) Last.FM, R@10 (d) Last.FM, N@10

Abaltion of λ_1, λ_2; Red line means the traditional framework

➢Conclusion

This paper introduced a novel decoupled soft target optimization framework for recommendation to flexibly optimize the deep recommender systems. And we further designed an adaptive soft target generation method to maximize the performance of the proposed method. The experimental results also demonstrated the effectiveness and generality of our DesoRec.

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https://github.com/zh-ustc/desorec/)