Fisher-Weighted Merge of Contrastive Learning Models in Sequential Recommendation

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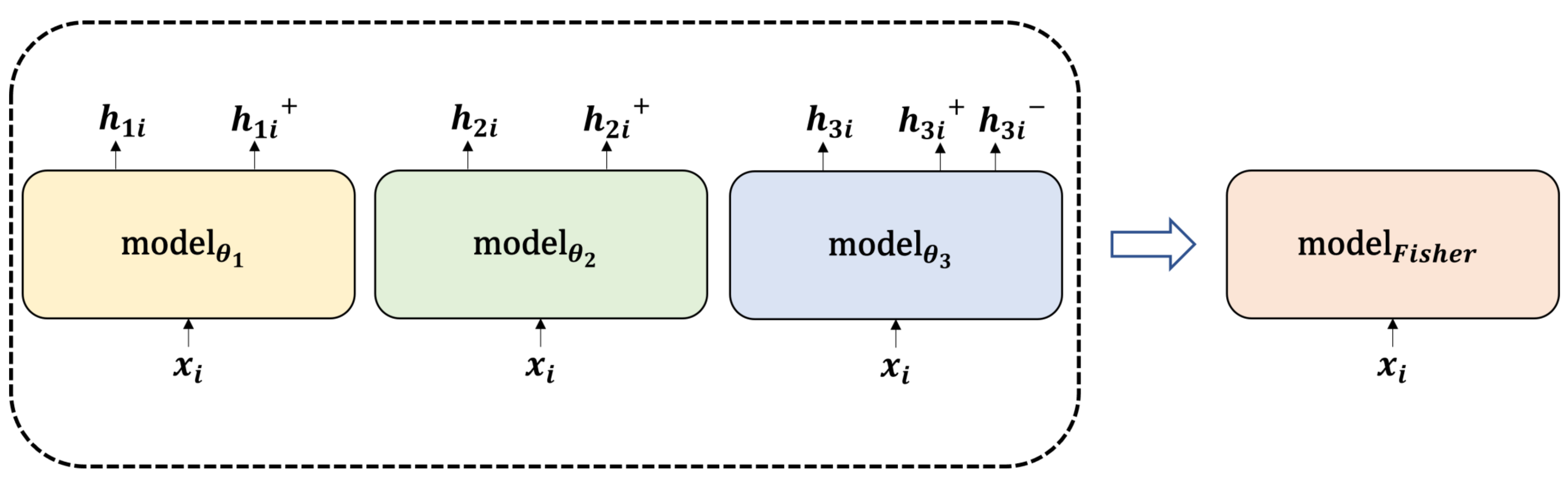
Summary

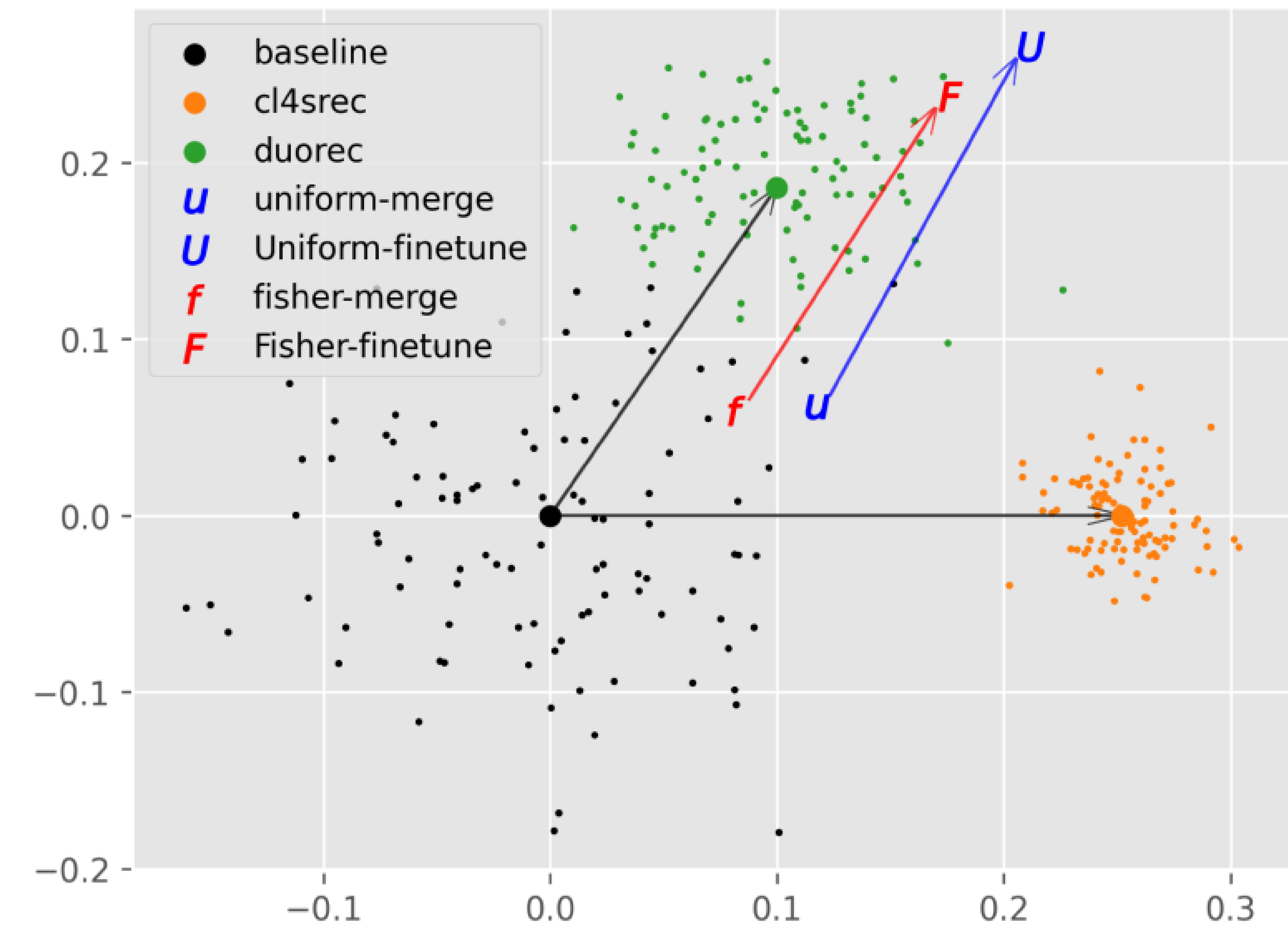
We introduce a novel **ensemble technique for sequential models by applying Fisher merging in sequential recommendation systems.**

This approach ensures robust fine-tuning by merging the parameters of multiple models, resulting in improved overall performance.

Parameter Merging



Visual Result



Background

Task Sequential recommendation aims to capture evolving user preferences over time. For user $u_i \in \mathcal{U}$ and item $v_i \in \mathcal{V}$, consider a chronological order of user-item interaction $s_i = \left[v_1^{u_i}, v_2^{u_i}, \cdots, v_t^{u_i}, \cdots, v_{n_{u_i}}^{u_i}\right]$. Our task is to predict the item with which user is interact in the next time step; $p(v_{n_{u_i}+1}^{u_i} = v \mid s_i)$.

Preliminaries Perform model ensemble based on different types of loss.

Interpret the process of finding θ^* as maximizing the joint likelihood of the posteriors; $\sum_{\mathrm{m}} \log p(\theta|\theta_{\mathrm{m}})$.

(1) Assuming $p(\theta|\theta_{\mathrm{m}})$ follows Gaussian distribution $\mathcal{N}(\hat{\theta}_{\mathrm{m}}, I)$,

$$\theta^* = \operatorname{argmax}_\theta \sum_m \lambda_m \log p(\theta|\theta_m, I) = \frac{1}{M}\sum_m \theta_m.$$

(2) Assume $p(\theta|\theta_{\mathrm{m}})$ follow a Gaussian distribution $\mathcal{N}(\hat{\theta}_{\mathrm{m}}, H^{-1})$, where H corresponds to Hessian matrix of θ_{m} obtained through the second-order Taylor expansion at the mode of the posterior(Fisher Matrix).

$$\theta^* = \operatorname{argmax}_\theta \sum_m \lambda_m \log p(\theta|\theta_m, F_{\mathrm{m}})$$

where $F_m = E_x E_{y\sim p_\theta(y|x)} \nabla_\theta \log p_\theta(v|s_i)\, \nabla_\theta \log p_\theta(v|s_i)^T$.

(closed form) $\theta^{*(j)} = \dfrac{\sum_m \lambda_m F_m^{(j)} \theta_m^{(j)}}{\sum_m \lambda_m F_m^{(j)}}$

Method

Applying Model Ensemble

$$\mathbb{E}_{s_i}\mathbb{E}_{v\sim p_\theta(v|s_i)}(\nabla_\theta \log p_\theta(v|s_i))^2$$
$$= \frac{1}{|\mathcal{U}|}\sum_i^{|\mathcal{U}|}\sum_j^{|\mathcal{V}|} p_\theta(v_j|s_i)\,(\nabla_\theta \log p_\theta(v_j|s_i))^2$$

To alleviate the computational burden, we employ batch-wise and sampling-based approach within the methodology.

Batch-wise Computation $\frac{1}{\mathrm{BS}_k}\sum_j^{|\mathcal{V}|}\left(\sum_i^{\mathrm{BS}_k} p_\theta(v_j|s_i)\right)\left(\nabla_\theta \sum_i^{\mathrm{BS}_k} \log p_\theta(v_j|s_i)\right)^2$

How to Sample Items

- ✓ Random Sampling : Randomly sample j from the total number of items.
- ✓ Top-k Sampling : Selected a set of n items that are most likely to be of interest to the corresponding user, i.e., $p_\theta(v_j|s_i)$.

$$\sum_j^{\text{top}-k} p_\theta(v_j|\mathrm{s})\,(\nabla_\theta \log p_\theta(v_j|\mathrm{s}))^2$$

- ✓ Model-based Sampling : Randomly sample a subset of items v_j based on the conditional probability $p_\theta(v_j|s_i)$.

$$\frac{1}{N}\sum_{v_j\sim p_\theta(v_j|s)}^{N} (\nabla_\theta \log p_\theta(v_j|\mathrm{s}))^2$$

- ✓ Calculate with target item : Compute Fisher matrix based on the target item, disregarding other items with direct relevance.

$$p_\theta(v_j^*|\mathrm{s})\,(\nabla_\theta \log p_\theta(v_j^*|\mathrm{s}))^2$$

Experimental Result

	Sample Size	Full NDCG10	Full NDCG20	Random NDCG10	Random NDCG20	Popular NDCG10	Popular NDCG20
Baseline		0.135	0.1601	0.5573	0.5786	0.0426	0.0706
CL4SRec		0.0585	0.0751	0.0513	0.043	**0.0466**	0.0701
DuoRec (sup.)		0.1346	0.1591	0.5547	0.58	0.0454	0.068
DuoRec (unsup.)		0.1358	0.1609	0.5594	0.5782	0.0445	0.0742
DuoRec (sup.&unsup.)		0.1351	0.1599	0.554	0.5732	0.0423	0.0724
Random Sampling	10	0.1379	<u>0.1638</u>	0.5606	<u>0.5825</u>	0.0457	0.0691
	30	0.1366	0.1624	0.5584	0.58	0.0477	**0.0726**
	50	<u>0.1386</u>	0.1636	0.5598	0.5813	0.0419	0.0419
Top-k Sampling	10	0.1364	0.1624	0.5602	0.5817	0.0446	0.0689
	30	0.1373	0.1616	**0.5637**	**0.5835**	0.0457	0.0708
	50	**0.1387**	0.1635	0.5592	0.5807	0.0424	0.0672
Model-based Sampling	10	0.1358	0.1619	0.5564	0.5782	0.044	0.0696
	30	0.1385	**0.1646**	0.5579	0.5784	0.0446	0.0689
	50	0.138	0.1632	0.5605	0.5814	<u>0.0465</u>	0.0719
Calculate on target item	1	<u>0.1386</u>	0.1628	<u>0.5618</u>	0.5806	0.0428	<u>0.0725</u>