ProtoCF: Prototypical Collaborative Filtering for Few-shot Recommendation

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ABSTRACT

In recent times, deep learning methods have supplanted conventional collaborative filtering approaches as the backbone of modern recommender systems. However, their gains are skewed towards popular items with a drastic performance drop for the vast collection of *long-tail* items with sparse interactions. Moreover, we empirically show that prior neural recommenders lack the resolution power to accurately rank relevant items within the long-tail.

In this paper, we formulate long-tail item recommendations as a *few-shot learning* problem of *learning-to-recommend* few-shot items with very few interactions. We propose a novel *meta-learning* framework ProtoCF that learns-to-compose robust prototype representations for few-shot items. ProtoCF utilizes episodic few-shot learning to extract meta-knowledge across a collection of diverse meta-training tasks designed to mimic item ranking within the tail. To further enhance discriminative power, we propose a novel architecture-agnostic technique based on knowledge distillation to *extract, relate, and transfer* knowledge from neural base recom-

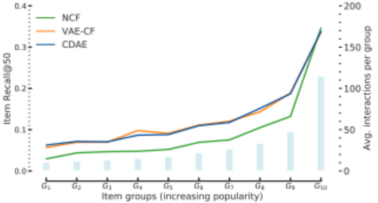

Figure 1: Item Recall@50 of three neural recommenders for item-groups (increasing popularity) in Epinions. Model performance is considerably lower for *long-tail* items.

are critical to diverse e-commerce applications. However, a close examination of neural recommenders' performance reveals a *paradox*:

Source: ProtoCF

Motivation

Strong bias of NCF methods towards popular items

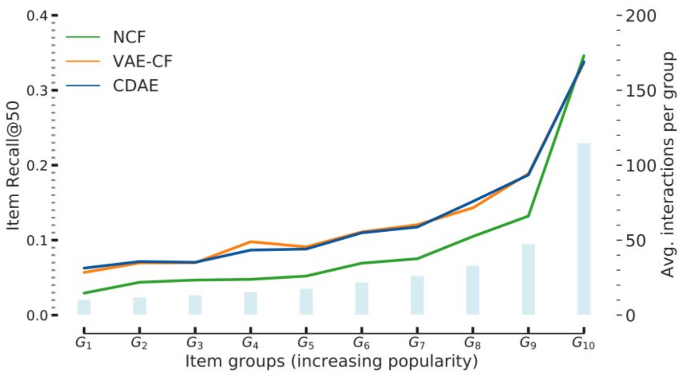

Figure 1: Item Recall@50 of three neural recommenders for item-groups (increasing popularity) in Epinions. Model performance is considerably lower for *long-tail* items.

Motivation

Lack of resolution power to accurately rank long-tail items

Item Subset	Top 50% Items		Bottom 50% Items	
Metric	N@50	R@50	N@50	R@50
NCF [12]	0.0906	0.1874	0.0352	0.0973
VAE-CF [24]	0.1055	0.2106	0.0457	0.1125
CDAE [51]	0.1050	0.2102	0.0471	0.1149

Table 1: Recommendation performance within top-50% *head* and bottom-50% *tail* items by item popularity on Epinions. R@50 and N@50 denote Recall@50 and NDCG@50 metrics. We observe poor ranking *resolution* within the long-tail.

Problems with Long-Tail Items

- sparsity and heterogeneity - tail items have few interactions, but belong to diverse item categories
- distribution mismatch - overall interaction distribution is biased towards head items

Proposed solution

- Few-shot learning to eliminate distribution mismatch
- Composition of discriminative prototypes for tail items
- Architecture-agnostic knowledge transfer from neural base recommender to enhance item prototypes

Neural Base Recommender

A neural base recommender $\mathbf{R}_B$ is trained to learn high-quality user representations and infer item-item relationships.

- X - interactions
- ϕ - model parameters

- $h_u = F_U(u, X \mid \phi)$ - user preference vector
- $h_i = F_I(i, X \mid \phi)$ - item preference vector
- $\hat{y}_b(u, i) = F_{INT}(h_u, h_i)$ - user-item relevance score
- $L_B = l(\hat{y}_b(u, i), y_{ui})$ - training objective obtained from a pointwise or pairwise loss function

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F_{INT} is usually modelled using inner product, however for the purposes of few-shot training cosine similarity is used.

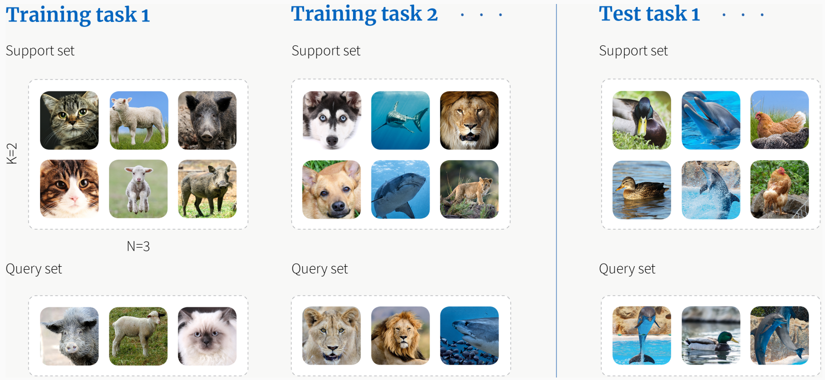
Neural Base Recommender

The authors considered three neural CF methods as base recommenders $\mathbf{R}_B$:

- Matrix Factorization (BPR)
- Variational AutoEncoder (VAE-CF)
- Denoising AutoEncoders (CDAE)

Few-Shot Learning

An example of an *N-way, K-shot* classification problem



Source: Borealis.ai

Collection of meta-training tasks $\{\mathcal{T}_1, \mathcal{T}_2, \dots\}$.

A *K-shot*, *N-item* training task $\mathcal{T} = \{\mathcal{I}_{\mathcal{T},N}, \mathcal{S}, \mathcal{Q}\}$ consists of:

- $\mathcal{I}_{\mathcal{T},N} \subset \mathcal{I}$ - a subset of items chosen for $\mathcal{T}$
- $\mathcal{S} = \{\mathcal{S}_i : i \in \mathcal{I}_{\mathcal{T},N}\}$ - a set of support user sets
- $\mathcal{Q} = \{\mathcal{Q}_i : i \in \mathcal{I}_{\mathcal{T},N}\}$ - a set of query user sets
- $\mathcal{S}_i = \{u_{i,1}, \dots, u_{i,K}\}$ - K users who interacted with item i
- $\mathcal{Q}_i = \{u'_{i,1}, \dots, u'_{i,K'}\}$ - K' users who interacted with item i

Typically $K \approx 5$ to 20

Learn-to-Recommend

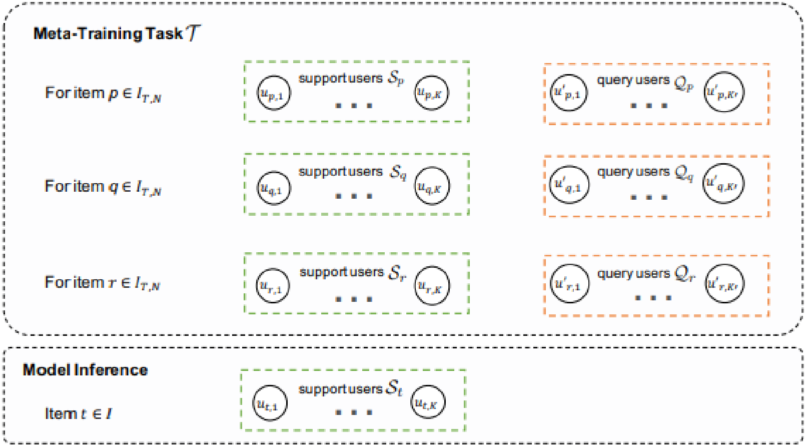


Figure 2: Episodic few-shot learning with meta-training task $\mathcal{T}$ and item embedding inference at meta-testing.

Learn-to-recommend

- $\mathcal{T} = \{\mathcal{I}_{\mathcal{T},N}, \mathcal{S}, \mathcal{Q}\}$ - few-shot task
- $\mathcal{I}_{\mathcal{T},N} \subset \mathcal{I}$ - items in $\mathcal{T}$
- $\mathcal{S}$ - set of support users in $\mathcal{T}$
- $\mathcal{Q}$ - set of query users in $\mathcal{T}$

The *few-shot recommender* $\mathbf{R}_F$ takes as input the support users $\mathcal{S}$ to *learn-to-compose* representations for items $i \in \mathcal{I}_{\mathcal{T},\mathcal{N}}$

$\mathbf{R}_F$ is trained by matching the item recommendations it generates for query users $\mathcal{Q}$ with their corresponding ground-truth interactions over $\mathcal{I}_{\mathcal{T},N}$

Initial Item Prototype

- $\mathcal{T}$ - few-shot task
- $\mathcal{I}_{\mathcal{T},N}$ - items in $\mathcal{T}$
- X_H - interactions in $\mathcal{T}$

We want $\mathbf{R}_F$ to learn a shared metric space of users and items

- $F_U(\cdot \,|\, \phi)$ - pre-trained user encoder of base recommender $\mathbf{R}_B$, parametrized with ϕ
- $G_U(\cdot \,|\, \theta)$ - few-shot user encoder, with parameters initialized from $F_U(\cdot \,|\, \phi)$, but parametrized with learnable parameters θ
- $\mathbf{p}_i = \frac{1}{\mathcal{S}_i} \sum_{u_{i,k} \in \mathcal{S}_i} G_U(u_{i,k}, X_H \,|\, \theta)$ - prototype for item $i \in \mathcal{I}_{\mathcal{T},N}$

Initial Item Prototype

Challenges in handling long-tail items:

- due to sparse support sets, the prototypes are noisy and sensitive to outliers
- due to diversity of tail items, averaging may lack the resolution to discriminate across them

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Challenges in handling long-tail items:

- due to sparse support sets, the prototypes are noisy and sensitive to outliers
- due to diversity of tail items, averaging may lack the resolution to discriminate across them

For these reasons, the few-shot recommender $\mathbf{R}_F$ needs a strong *inductive bias* during prototype learning.
Thus, *item-item* relationship knowledge acquired by base recommender $\mathbf{R}_B$ is used to enhance item prototypes.

Head-Tail Meta Knowledge Transfer

- R_B - base recommender
- h_i - item embedding in $\mathbf{R}_B$

Item-item proximity $sim_b(\cdot)$ in the latent space of $\mathbf{R}_B$ is denoted by:

$$p_B(i,j) \propto sim_b(h_i, h_j) = cos(h_i, h_j) \qquad\qquad i,j \in \mathcal{I}$$

The goal is to extract knowledge from items most related to i. However, dynamically identifying related items during prototype construction is not scalable. Thus, a compact representation of *item-item proximity* knowledge is required.

Group-Enhanced Item Prototype Learning

A set of M ($M \ll |\mathcal{I}|$) group embeddings $\mathcal{Z}_M$ is learned to serve as a *basis vectors* modeling *item-item proximity* in the latent space of $\mathbf{R}_B$.

$$\mathcal{Z}_M = \{z_m \in \mathbb{R}^D : m \in \{1, \ldots, M\}\}$$

To enhance prototype of item $i \in \mathcal{I}_{\mathcal{T},N}$, a *group-enhanced prototype* $\mathbf{g}_i \in \mathbb{R}^D$ is synthesized as a mixture over the M group embeddings.

Group-Enhanced Item Prototype Learning

The mixture coefficients of a *group-enhanced prototype* $\mathbf{g}_i$ are estimated by a learnable attention mechanism.

$$\mathbf{g}_i = \sum_{m=1}^{M} \alpha_{im} z_m \qquad \alpha_{im} = \frac{\exp(\mathbf{W}_q \mathbf{p}_i \cdot \mathbf{k}_m)}{\sum_{m'=1}^{M} \exp(\mathbf{W}_q \mathbf{p}_i \cdot \mathbf{k}_{m'})}$$

Where $\mathcal{K}_M = \{\mathbf{k}_m \in \mathbb{R}^D : m \in \{1, \ldots, M\}\}$ is an auxiliary set of trainable keys to index the group embeddings, and $\mathbf{W}_q \in \mathbb{R}^{DxD}$ projects the prototype $\mathbf{p}_i$ into a query to index the centroids.

Task-level Stochastic Knowledge Distillation

In order to learn *group embeddings* $\mathcal{Z}_M$ that capture *item-item relationships* in $\mathbf{R}_B$, a *knowledge distillation* strategy is used.

A compact *student* model (group embeddings $\mathcal{Z}_M$) is encouraged to emulate predictions of the teacher (item proximity distribution in $\mathbf{R}_B$).

Since operating directly on all items in $\mathcal{I}$ is not scalable, student model is trained at the granularity of each meta-training task $\mathcal{T}$.

Task-level Stochastic Knowledge Distillation

- $\mathcal{T} = \{\mathcal{I}_{\mathcal{T},N}, \mathcal{S}, \mathcal{Q}\}$ - few-shot task
- $\mathcal{I}_{\mathcal{T},N} \subset \mathcal{I}$ - items in $\mathcal{T}$
- $p_B(i,j)$ - proximity of $i,j \in \mathcal{I}$ in $\mathbf{R}_B$
- $\mathbf{g}_i$ - group enhanced item prototype

For each item $i \in \mathcal{I}_{\mathcal{T},N}$,
a soft probability distribution
$p_B(j \mid i, \mathbf{R}_B)$ over other items $j \in \mathcal{I}_{\mathcal{T},N}$ is calculated.
$T > 0$ is a temperature scaling hyper-parameter.

$$p_B(j \mid i, \mathbf{R}_B) = \frac{\exp(p_B(i,j)/T)}{\sum_{k \in \mathcal{I}_{\mathcal{T},N}} \exp(p_B(i,k)/T)} \qquad i,j \in \mathcal{I}_{\mathcal{T},N}$$

Analogously, item similarity distribution $p_F(j \mid i, \mathbf{Z}_M)$ for the student model $\mathcal{Z}_B$ is defined.

$$p_F(j \mid i, \mathcal{Z}_M) = \frac{\exp(\mathrm{sim}_m(\mathbf{g}_i, \mathbf{g}_j))}{\sum_{k \in \mathcal{I}_{\mathcal{T},N}} \exp(\mathrm{sim}_m(\mathbf{g}_i, \mathbf{g}_k)}) \qquad i,j \in \mathcal{I}_{\mathcal{T},N}$$

Task-level Stochastic Knowledge Distillation

- $p_B(j \mid i, \mathbf{R}_B)$ - item similarity distribution for base recommender
- $p_F(j \mid i, \mathcal{Z}_M)$ - item similarity distribution for group-enhanced prototypes

The two distributions are aligned by minimizing cross-entropy between their task-level similarities. Since each item is typically only related to very few items within task T, the distillation loss L_G minimizes distribution divergence over the top-n related items ($n \approx 10$).

$$L_G = -\frac{1}{nN} \sum_{i \in \mathcal{I}_{\mathcal{T},N}} \sum_{j \in \pi_{B,n}(i)} p_B(j \mid i, \mathbf{R}_B) \log p_F(j \mid i, \mathcal{Z}_M)$$

$\pi_{B,n}(i)$ denotes the top-n most related items to i within $\mathcal{I}_{\mathcal{T},N}$ based on teacher $\mathbf{R}_B$. The loss is trained jointly with the rest of the framework.

Item Prototype Fusion via Neural Gating

The initial prototype $\mathbf{p}_i$ for item $i \in \mathcal{I}_{\mathcal{T},N}$ directly encodes its support users $\mathcal{S}_i$, while the group-enhanced prototype $\mathbf{g}_i$ captures the knowledge transferred from related items.

Final *gated item prototype* $\mathbf{e}_i \in \mathbb{R}^D$ is created by merging $\mathbf{p}_i$ and $\mathbf{g}_i$ using a neural gating layer.

$$\begin{aligned} \mathbf{gate} &= \sigma(\mathbf{W}_{g1}\mathbf{p}_i + \mathbf{W}_{g2}\mathbf{g}_i + \mathbf{b}_g) \qquad i \in \mathcal{I}_{\mathcal{T},N} \\ \mathbf{e}_i &= \mathbf{gate} \odot \mathbf{p}_i + (1 - \mathbf{gate}) \odot \mathbf{g}_i \end{aligned}$$

$\mathbf{W}_{g_1} \in \mathbb{R}^{D \times D}, \mathbf{W}_{g_2} \in \mathbb{R}^{D \times D}$, and $\mathbf{b}_g \in \mathbb{R}^D$ are learnable parameters, $\odot$ denotes element-wise product operation, and σ is the sigmoid non-linearity.

Few-shot Recommender Training

Each task $\mathcal{T}$ minimizes a negative log-likelihood L_P between the few-shot recommendations for query users $\mathcal{Q}$ and their ground-truth interactions in $\mathcal{T}$.

$$L_P = -\frac{1}{KN} \sum_{i \in \mathcal{I}_{\mathcal{T},N}} \sum_{u'_{i,k'} \in \mathcal{Q}_i} \log p_F(i \mid u'_{i,k'}, \theta)$$

$p_F(i \mid u'_{i,k'}, \theta)$ is computed based on cosine similarity and the choice of likelihood function for few-shot training.

Few-shot Likelihood Choices

$$L_P = -\frac{1}{KN} \sum_{i \in \mathcal{I}_{\mathcal{T},N}} \sum_{u'_{i,k'} \in \mathcal{Q}_i} \log p_F(i \mid u'_{i,k'}, \theta)$$

The authors considered the following likelihood functions for few-shot training:

- **Multinomial log-likelihood:**

$$p_F(i \mid u', \theta) = \frac{\exp(\text{sim}_m(\mathbf{e}_{u'}, \mathbf{e}_i))}{\sum_{j \in \mathcal{I}_{\mathcal{T},N}} \exp(\text{sim}_m(\mathbf{e}_{u'}, \mathbf{e}_j))}) \qquad u' \in \mathcal{Q}_i$$

- **Logistic log-likelihood:**

$$\log p_F(i \mid u', \theta) = \beta \log \sigma(\hat{y}_{u'i}) + \sum_{j \in \mathcal{I}_{\mathcal{T},N}, u' \notin N_j} \log(1 - \sigma(\hat{y}_{u'j}))$$

Few-shot Recommender Training

The overall loss is composed of the few-shot recommendation loss L_P and the knowledge distillation loss L_G:

$$L = L_P + \lambda L_G$$

where λ is a tunable hyper-parameter.

Model inference

The gated prototype $\mathbf{e}_i$ is inferred for each item $i \in \mathcal{I}$ by sub-sampling K interactions as the support set.

Item recommendations for each user $u \in \mathcal{U}$ are given by:

$$\hat{y}_f(u, i) = \mathrm{sim}_m(\mathbf{e}_u, \mathbf{e}_i) \qquad i \in \mathcal{I} \qquad \mathbf{e}_u = G_U(u, X \mid \theta)$$

The final recommendation is given by ensembling predictions from $\mathbf{R}_F$ and $\mathbf{R}_B$.

$$\hat{y}(u, i) = (1 - \eta) \cdot \hat{y}_b(u, i) + \eta \cdot \hat{y}_f(u, i) \qquad \eta \in (0, 1)$$

Architecture overview

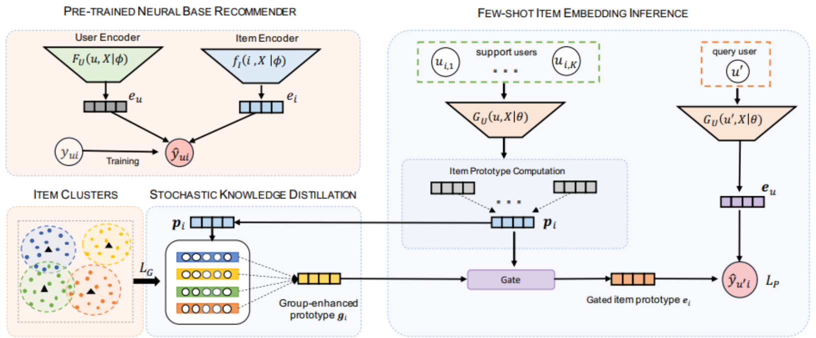

Figure 3: Architecture diagram of PROTOCF depicting the different model components: pre-trained neural base recommender R_B (top left), group embedding learning via stochastic knowledge distillation L_G (bottom left), initial item prototype construction via support set averaging followed by group-enrichment and adaptive gating to construct gated item prototype e_i (right).

Experiments

(RQ1) Does ProtoCF beat state-of-the-art NCF and sparsity-aware methods on *overall* recommendation performance?

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Experiments

(RQ1) Does ProtoCF beat state-of-the-art NCF and sparsity-aware methods on *overall* recommendation performance?

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(RQ3) How do the different *architectural* choices impact the few-shot and overall performance of ProtoCF?

Experiments

(RQ1) Does ProtoCF beat state-of-the-art NCF and sparsity-aware methods on *overall* recommendation performance?

(RQ2) What is the impact of item *interaction sparsity* on the *few-shot* recommendation performance of ProtoCF?

(RQ3) How do the different *architectural* choices impact the few-shot and overall performance of ProtoCF?

(RQ4) How do the *hyper-parameters* (distillation loss balance factor λ and meta-training task size N) affect ProtoCF?

Datasets

- Epinions - product ratings for an e-commerce platform
- Yelp - user ratings on local businesses located in the state of Arizona
- Weeplaces - check-ins for businesses of different categories, like Nightlife, Outdoors, or Entertainment
- Gowalla - restaurant check-ins by users across different cities in United States

Baselines

- Neural Base Recommenders (BPR, VAE-CF, CDAE)
- Neural Collaborative Filtering
- Neural Graph Collaborative Filtering
- Cofactor
- EFM
- DropoutNet
- MetaRec-LWA
- MetaRec-NLBA

Overall Recommendation Results (RQ$_1$)

Dataset	Epinions		Yelp		Weeplaces		Gowalla	
Metric	**N@50**	**R@50**	**N@50**	**R@50**	**N@50**	**R@50**	**N@50**	**R@50**
			STANDARD NEURAL COLLABORATIVE FILTERING METHODS					
BPR [34]	0.0860	0.1666	0.0749	0.1416	0.2537	0.3778	0.1661	0.2703
NCF [12]	0.0878	0.1694	0.0752	0.1429	0.2462	0.3694	0.1702	0.2745
NGCF [48]	0.0913	0.1725	0.0826	0.1579	0.2533	0.3764	0.1696	0.2758
VAE-CF [24]	0.0938	0.1778	0.0854	0.1602	0.2482	0.3730	0.1710	0.2769
CDAE [51]	0.0927	0.1774	0.0870	0.1611	0.2570	0.3760	0.1634	0.2644
			SPARSITY-AWARE LONG-TAIL ITEM RECOMMENDATION METHODS					
DropoutNet [45]	0.0881	0.1697	0.0761	0.1435	0.2516	0.3751	0.1697	0.2768
Cofactor [23]	0.0845	0.1639	0.0734	0.1402	0.2342	0.3539	0.1596	0.2642
EFM [4]	0.0742	0.1534	0.0741	0.1403	0.2306	0.3429	0.1532	0.2584
MetaRec-NLBA [43]	0.0453	0.0937	0.0381	0.0875	0.1698	0.2889	0.0753	0.1384
MetaRec-LWA [43]	0.0467	0.0943	0.0392	0.1425	0.1702	0.2997	0.0722	0.1391
			PROTOTYPICAL COLLABORATIVE FILTERING RECOMMENDERS (PROTOCF)					
PROTOCF + BPR	0.0964	0.1812	0.0815	0.1533	0.2576	0.3879	0.1737	0.2800
PROTOCF + VAE	**0.0977**	**0.1830**	0.0857	0.1605	**0.2725**	**0.4035**	**0.1899**	**0.3004**
PROTOCF + CDAE	0.0972	0.1824	**0.0883**	**0.1623**	0.2697	0.4011	0.1786	0.2875
Percentage Gains	4.16%	2.92%	1.50%	0.75%	6.03%	6.80%	11.05%	8.49%

Table 4: Overall item recommendation results on four datasets, R@K and N@K denote Recall@K and NDCG@K metrics at $K = 50$. **Sparsity-aware models are generally outperformed by standard NCF methods on overall item recommendation; PROTOCF achieves *overall* NDCG@50 gains of 6% and Recall@50 gains of 4% (over the best baseline) across all datasets.**

Overall Recommendation Results (RQ$_1$)

Key observations:

- Models based on autoencoders (VAE-CF, CDAE) and graph neural networks (NGCF) outperform other latent-factor models (NCF, BPR)
- Model regularization strategies using item co-occurence information (CoFactor, EFM) for improving long-tail recommendations are worse than BPR in overall performance
- Sparsity-aware meta-learning models (MetaRec) perform poorly in overall item rankings
- ProtoCF outperforms state-of-the-art baselines on overall item rankings

Few-Shot Recommendation Results (RQ$_2$)

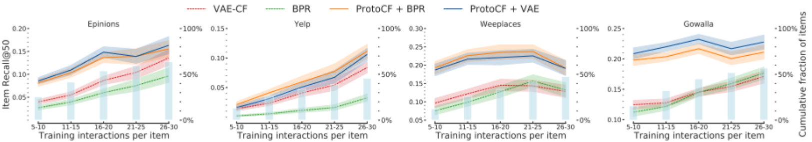

Figure 4: Few-shot item recommendation results: Performance comparison for long-tail items with varying number of training interactions K (5 to 30); lines denote model performance (Recall@50) and background histograms indicate the cumulative fraction of the item inventory covered by tail items with $\leq K$ impressions. Overall performance generally increases with K for all models; ProtoCF achieves notably stronger gains (over baselines) for items with few training interactions (small K).

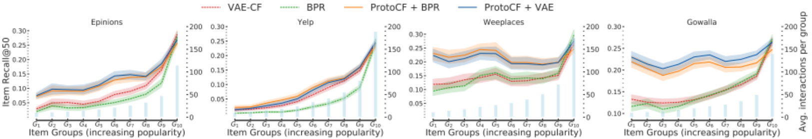

Figure 5: Impact of item interaction sparsity: Performance comparison for item-groups sorted in increasing order by their average training interaction counts; lines denote model performance (Recall@50) and background histograms indicate the average number of interactions in each item-group. ProtoCF has significant performance gains (over baselines) on the tail items (item-groups G_1 to G_8) while maintaining comparable performance on the head items (item-groups G_9 to G_{10}).

Model Ablation Study (RQ_3)

Dataset	Epinions		Gowalla	
Metric	Overall R@50	Few-shot R@50	Overall R@50	Few-shot R@50
ProtoCF	0.1830	0.1070	0.3004	0.2195
w/o Prototype Gating	0.1823	0.0948	0.2992	0.2082
w/o Knowledge Distillation	0.1805	0.0869	0.2923	0.1983
ProtoCF-Avg	0.1801	0.0712	0.2898	0.1696
ProtoCF-logistic	0.1804	0.0896	0.2853	0.1843
VAE-CF [24]	0.1778	0.0549	0.2769	0.1316
MetaRec-LWA [43]	0.0943	0.0898	0.1391	0.1804

Table 5: Model ablation study of ProtoCF; few-shot performance is reported for tail items (less than 20 training interactions). Knowledge transfer and prototype gating contribute 10-19% and 5-11% to few-shot gains respectively.

Parameter Sensitivity (RQ_4)

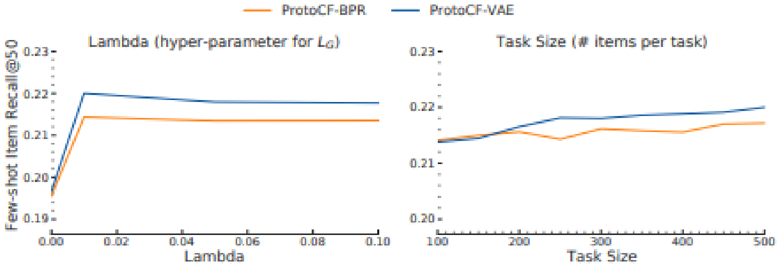

Figure 6: Few-shot performance on Gowalla (for tail items with less than 20 training interactions) is higher for larger meta-training tasks; the empirically optimal value of balance factor $\lambda = 0.01$ also transfers across all datasets.

Reproducibility

set the latent embedding dimension to 128 for consistency. Our implementation of ProtoCF and datasets are publicly available[4].

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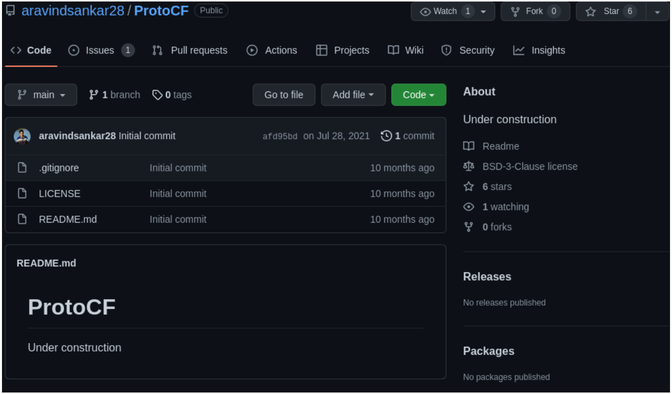

Conclusion

- A sophisticated solution for a specific problem
- Research orthogonal to mainstream advances in recommender systems
- Architecture-agnostic method for improving neural recommenders