STEM: Unleashing the Power of Embeddings for Multi-task Recommendation

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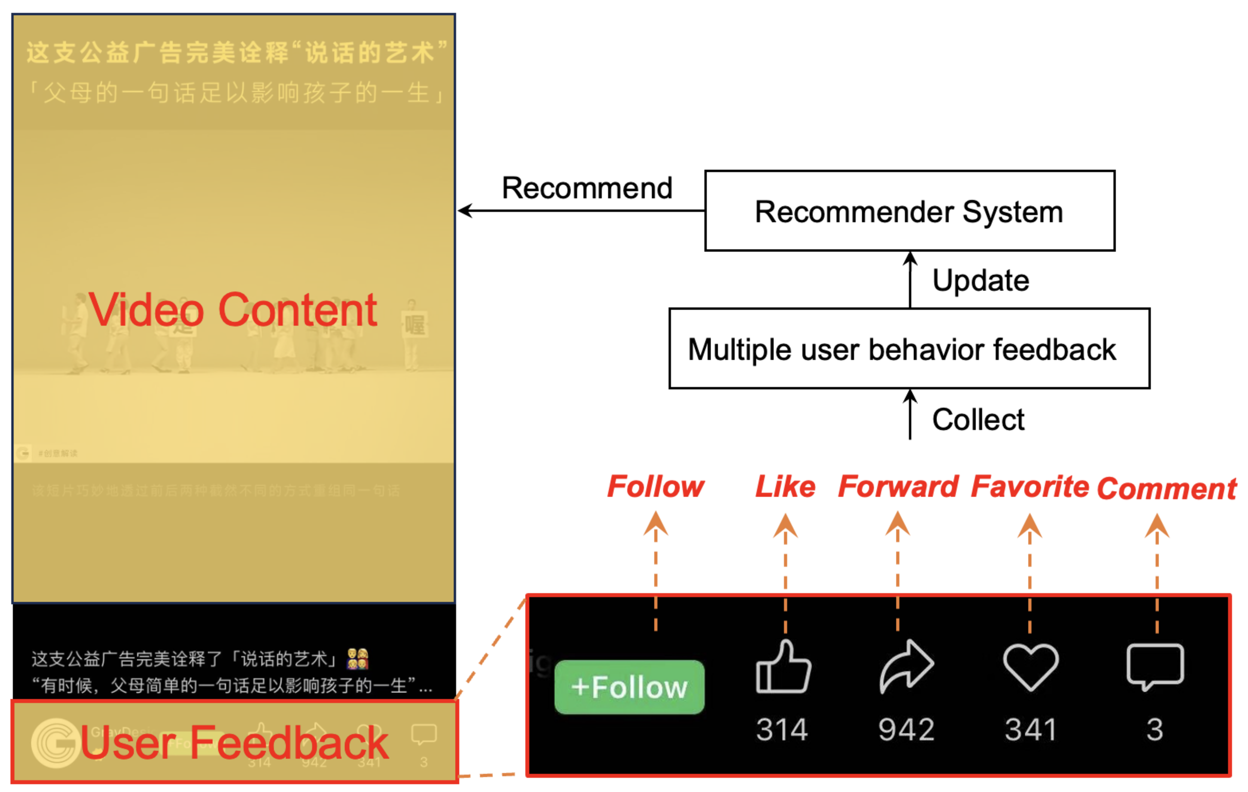
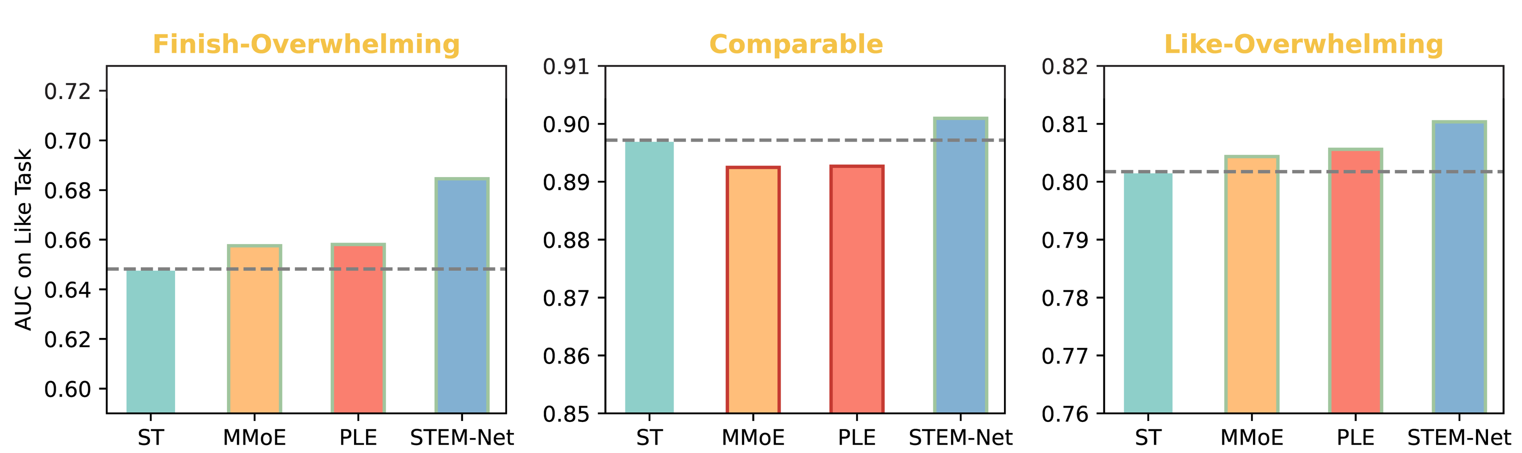
Background



In order to adequately model user interests, industrial recommendation systems typically optimize multiple user behavior feedback (e.g., Follow, Like). However, prior works have identified *negative transfer*, whereby multi-task learning models may not always outperform single-task models.

Rethinking: Where negative transfer occurs?



- `Finish`**-Overwhelming** consists of samples with overwhelming positive feedback from task `Finish`.
- **Comparable** consists of samples with comparable positive feedback from both tasks.
- `Like`**-Overwhelming** consists of samples with overwhelming positive feedback from task `Like`.

Finding. Negative transfer is more likely to occur on the Comparable sub-dataset, where samples receive comparable positive feedback from both tasks.

Limitation. Existing MTL methods, including MMoE and PLE, all follow a *shared-embedding paradigm*. That is, they learn a universal embedding for each user and item, shared across tasks. Such a paradigm is only able to capture a single preference of users, hindering the ability to capture the preference divergence across tasks.

The STEM Paradigm

We introduce a Shared and Task-specific EMbeddings (STEM) paradigm, which *incorporates both shared and task-specific embeddings* to learn common and task-specific user preference. For a given feature x_i, we get the task-specific embeddings $\{\boldsymbol{v}_i^t\}$ for task t as well as the shared embedding $\boldsymbol{v}_i^S$.

The STEM-Net Model

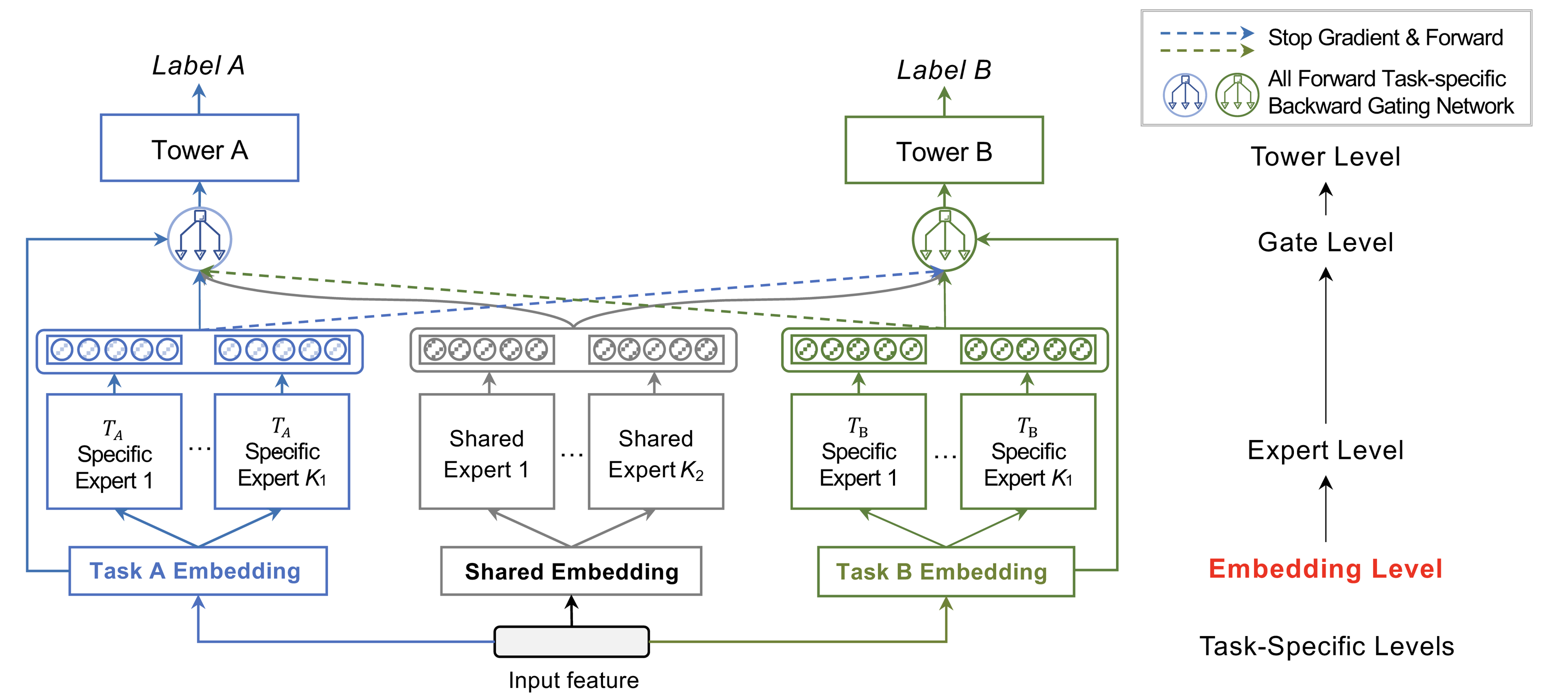


Figure 1. The architecture of STEM-Net.

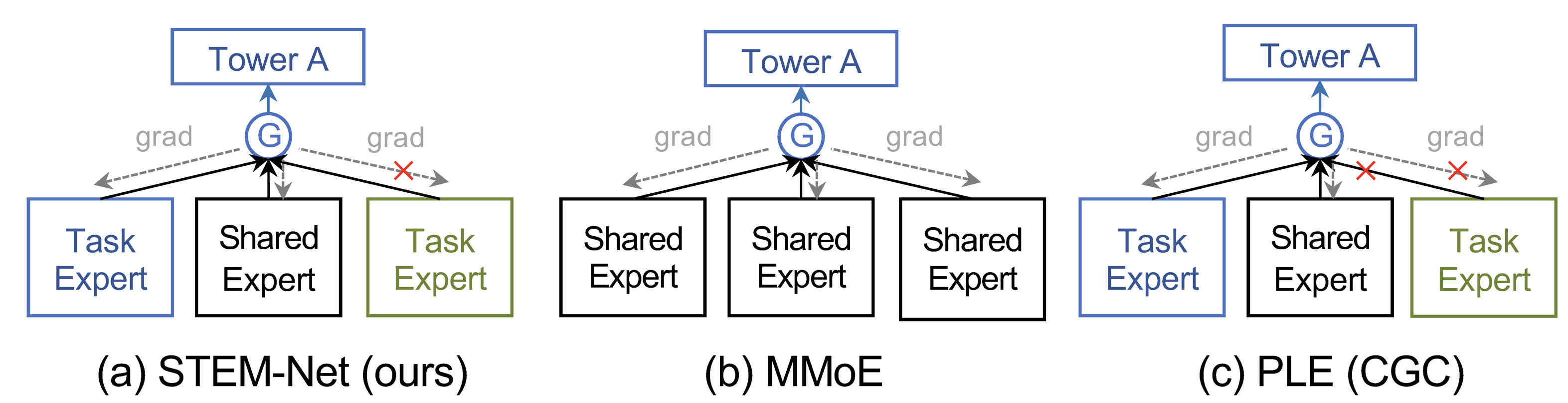
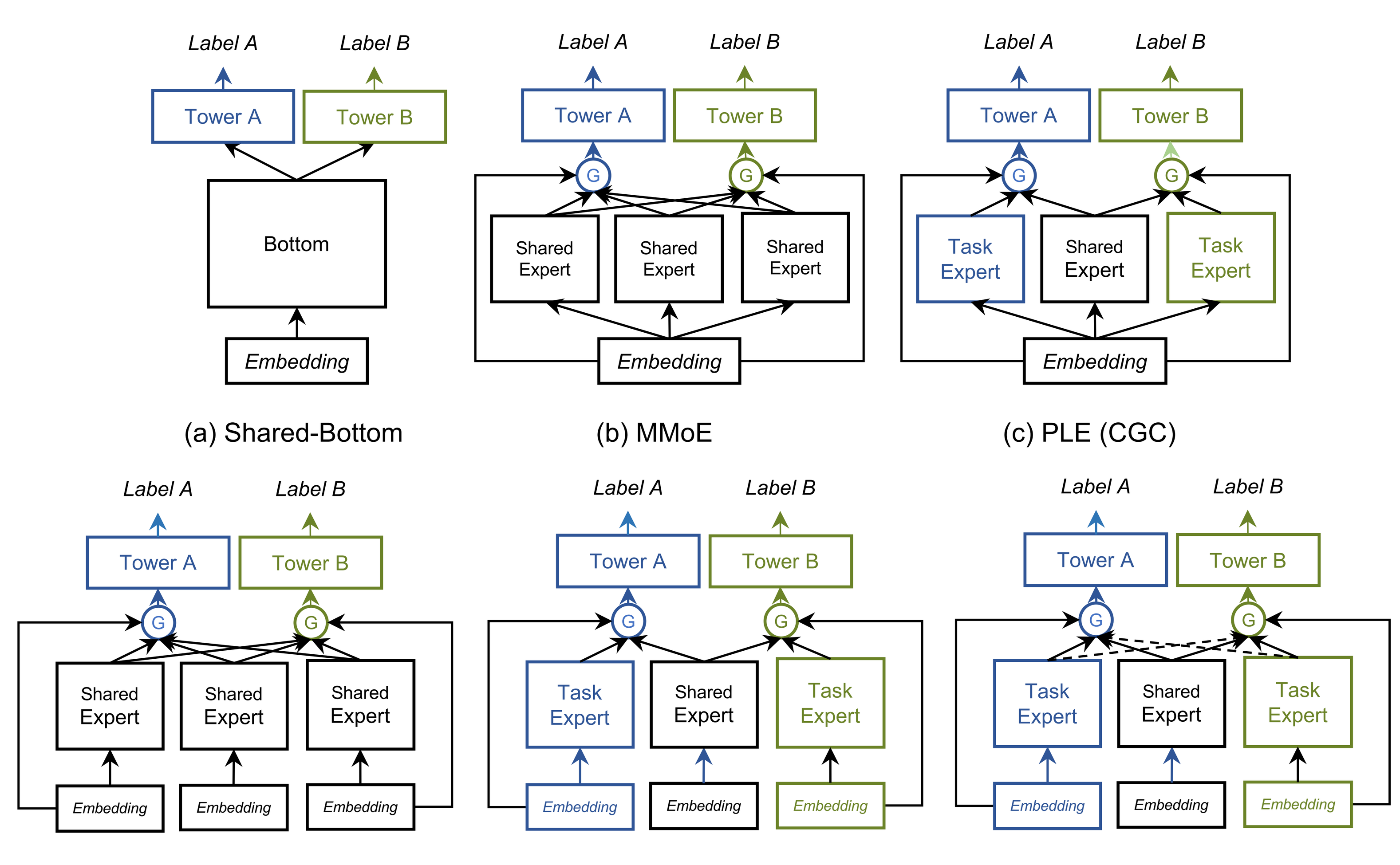


Figure 2. Comparison of gating networks of MMoE (All Forward All Backward), PLE (Task-specific Forward Task-specific Backward) and our STEM-Net (All Forward Task-specific Backward).

Model Comparison



Contradictory User Preference Analysis

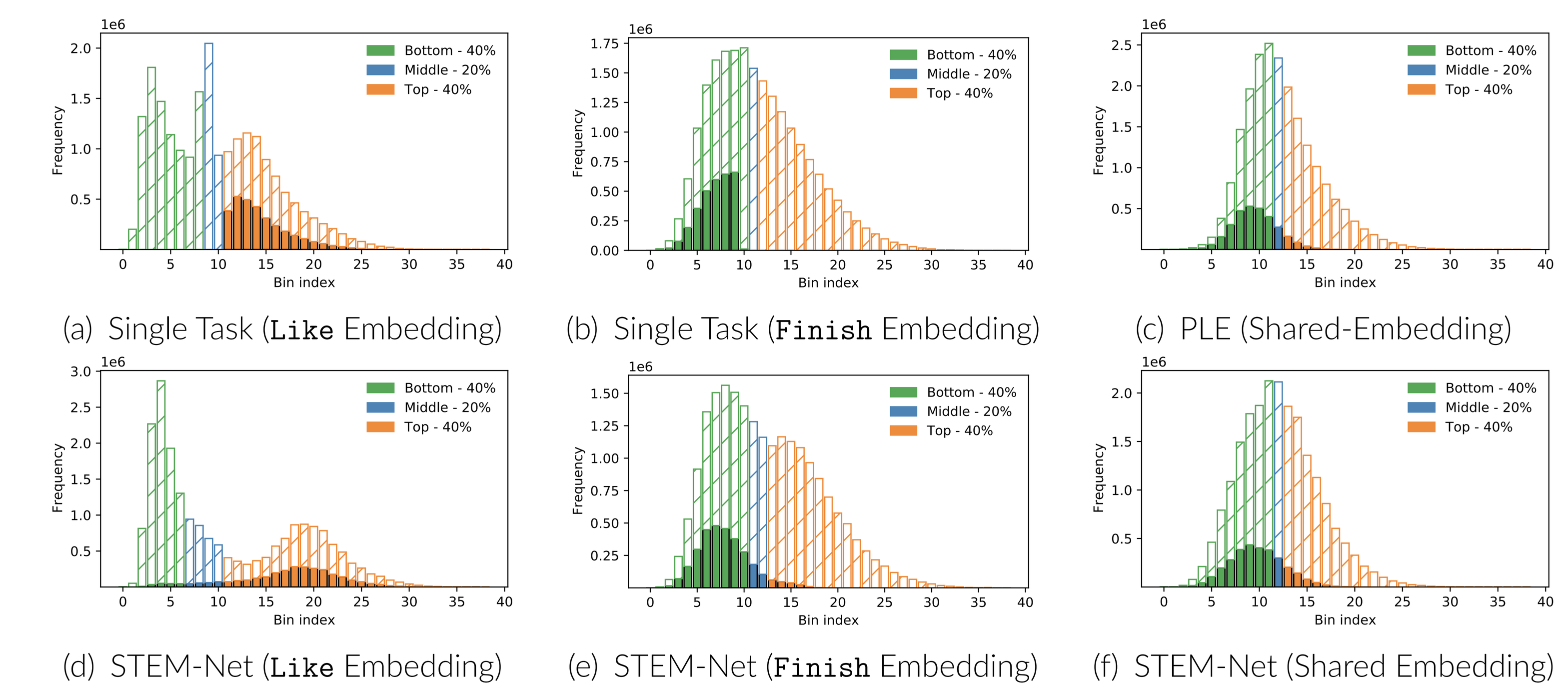


Figure 4. The distance distribution of the contradictory user item pair set S (with solid color) as well as the whole user item pair set (with slash lines) regarding: the single task `Like` (a) and `Finish` embedding (b), the PLE embedding (c), and the `Like` (d) and `Finish`-specific (e) embedding and shared embedding (f) in STEM-Net.

Overall Performance

Model	`Finish`		`Like`		Average
	Logloss↓	AUC ↑	Logloss↓	AUC↑	AUC ↑
Single-Task	0.5111	0.7505	0.0558	0.9058	0.8281
Shared-Bottom	0.5112	0.7504	0.0560	0.9022	0.8263
OMoE	**0.5103**	**0.7516**	0.0559	0.9029	0.8273
MMoE	0.5105	0.7511	0.0560	0.9018	0.8265
PLE	0.5105	0.7511	0.0560	0.9016	0.8264
ESMM	0.5111	0.7503	0.0564	0.9012	0.8258
AITM	0.5109	0.7506	0.0560	0.9026	0.8266
ME-MMoE	0.5114	0.7502	0.0557	0.9045	0.8274
ME-PLE	0.5120	0.7492	0.0560	0.9058	0.8275
STEM-Net	0.5104	0.7513	**0.0553**	**0.9095**	**0.8304**

Table 1. Overall performance on TikTok.

Model	`Click`		`Like`		Average
	Logloss↓	AUC ↑	Logloss↓	AUC↑	AUC ↑
Single-Task	0.2826	0.9234	0.0378	0.9400	0.9317
Shared-Bottom	0.2857	0.9235	0.0380	0.9389	0.9312
OMoE	0.2826	0.9238	**0.0373**	0.9394	0.9316
MMoE	0.2813	0.9238	0.0379	0.9401	0.9319
PLE	0.2832	0.9238	0.0375	0.9399	0.9318
ESMM	0.2847	0.9208	0.0378	0.9368	0.9288
AITM	0.2836	0.9237	0.0386	0.9398	0.9318
ME-MMoE	0.2815	**0.9239**	0.0375	0.9407	0.9323
ME-PLE	0.2818	0.9238	0.0374	0.9410	0.9324
STEM-Net	0.2816	0.9237	0.0381	**0.9426**	**0.9331**

Table 2. Overall performance on QK-Video.

Scenario	Follow	Activation	Fulfill Sheet	Pay	Avg.
Scenario 1	+0.29%	+0.33%	+0.29%	+0.35%	+0.32%
Scenario 2	+0.13%	+0.22%	+0.33%	+0.27%	+0.24%
Scenario 3	+0.47%	+0.39%	+0.28%	+0.78%	+0.48%

Table 3. AUC Lift of Online A/B Test