Residual Multi-Task Learner for Applied Ranking

Based on joint work with Cong Fu et al. Deployed in Shopee Search.

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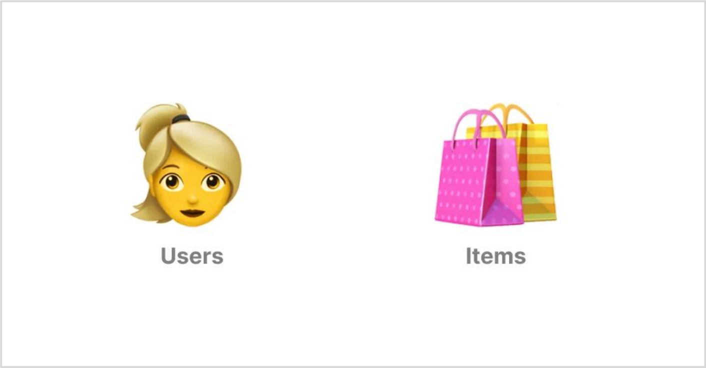
01 Problem

Applied Ranking

Predicting which items users will be more interested in,



(e.g., search, recommendation)

based on user and item features and their interactions.

John	5	1	3	5
Tom	?	?	?	2
Alice	4	?	3	?

Multi-Task in Applied Ranking

When ranking items,

we may **estimate**

the click-through rate (CTR)

the add-to-cart rate (ATCR)

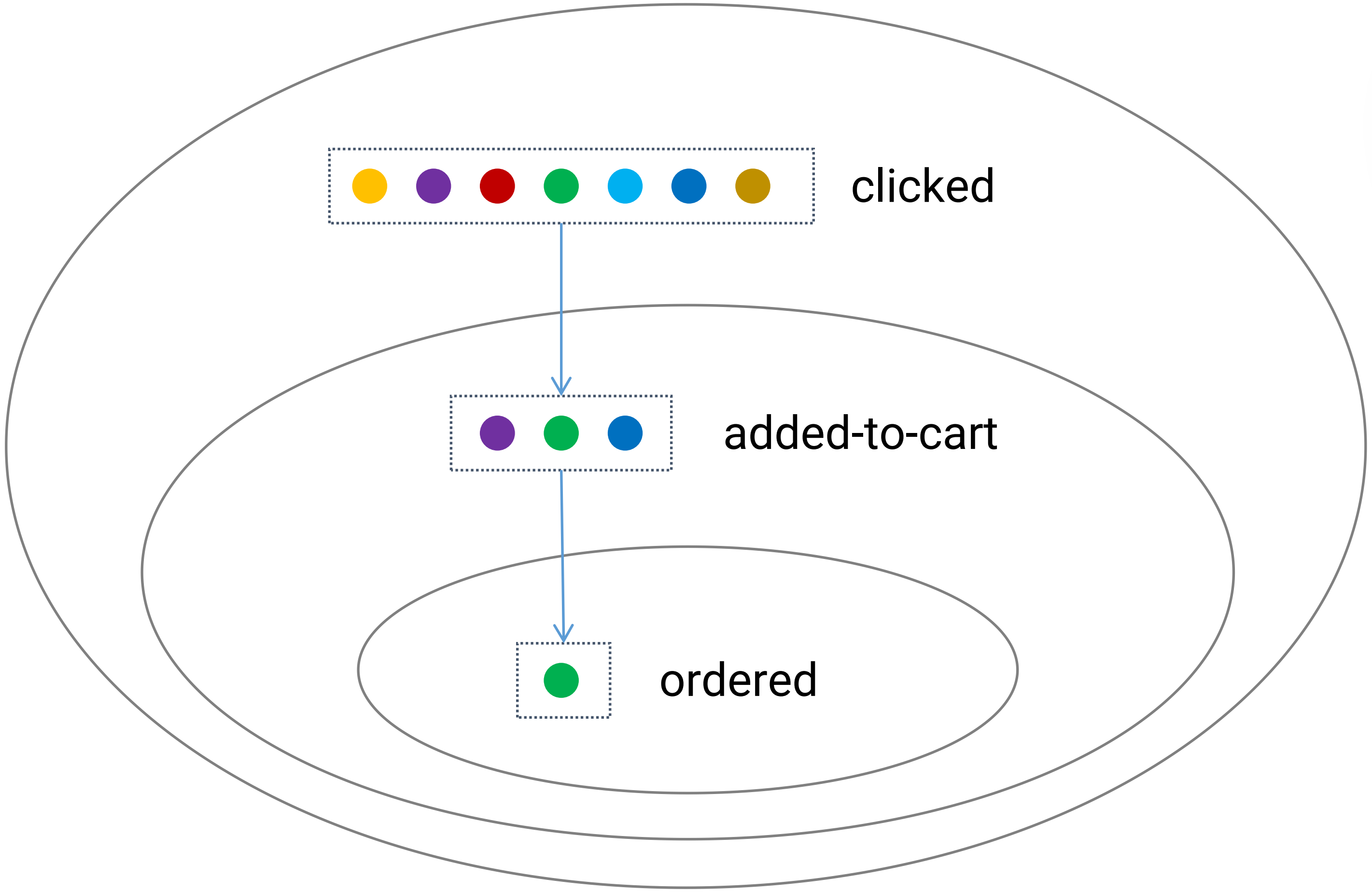
the final conversion rate (CTCVR)

Multi-Task
(same input, different but related outputs)

of a user w.r.t. items,

and jointly consider all these predictions.

Attribute 0 : Sparse Data



latter task, e.g., CTCVR estimation, has significantly sparser data → multi-task learning

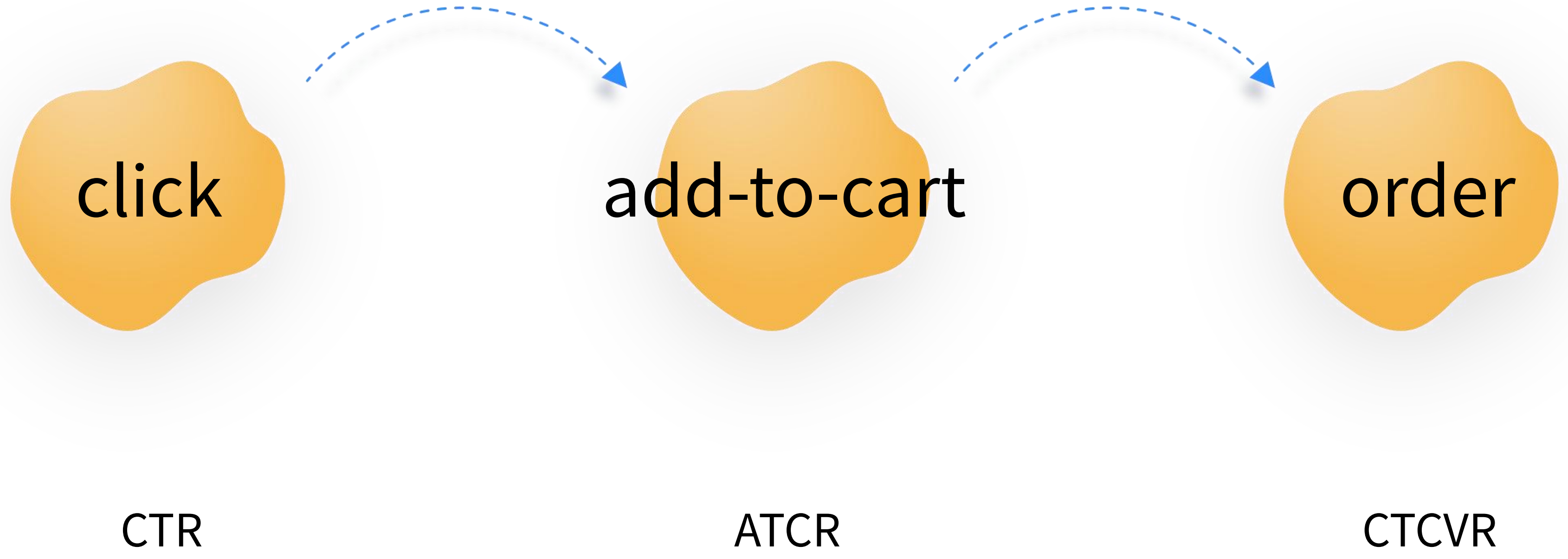
Attribute 1 : Large Scale & Real-Time

Practical application scenario:

- enormous items
- need to response in a second

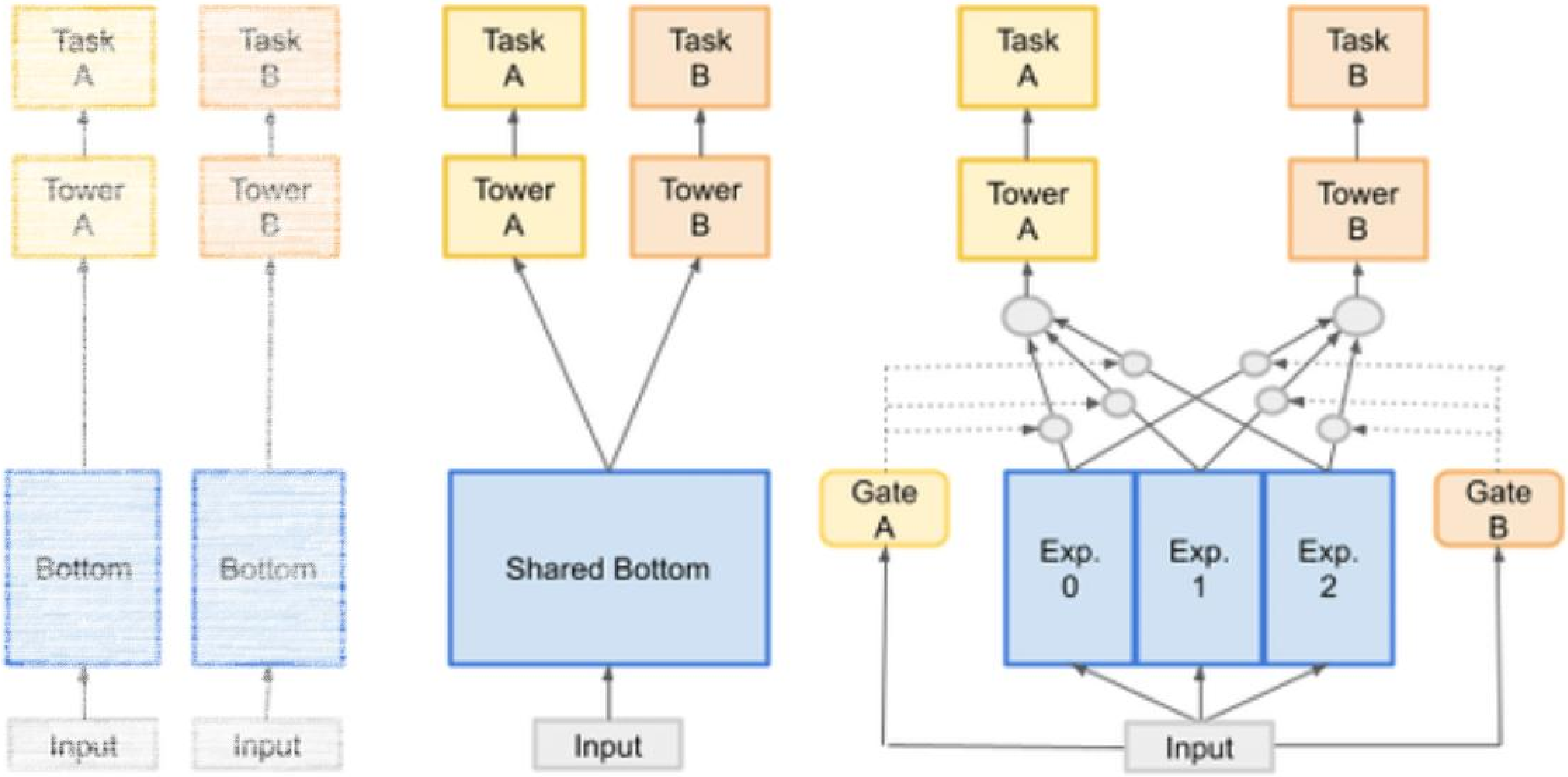
Ranking algorithm **esquires high efficiency**.

Attribute 2 : Sequential Dependency



02 Existing Methods

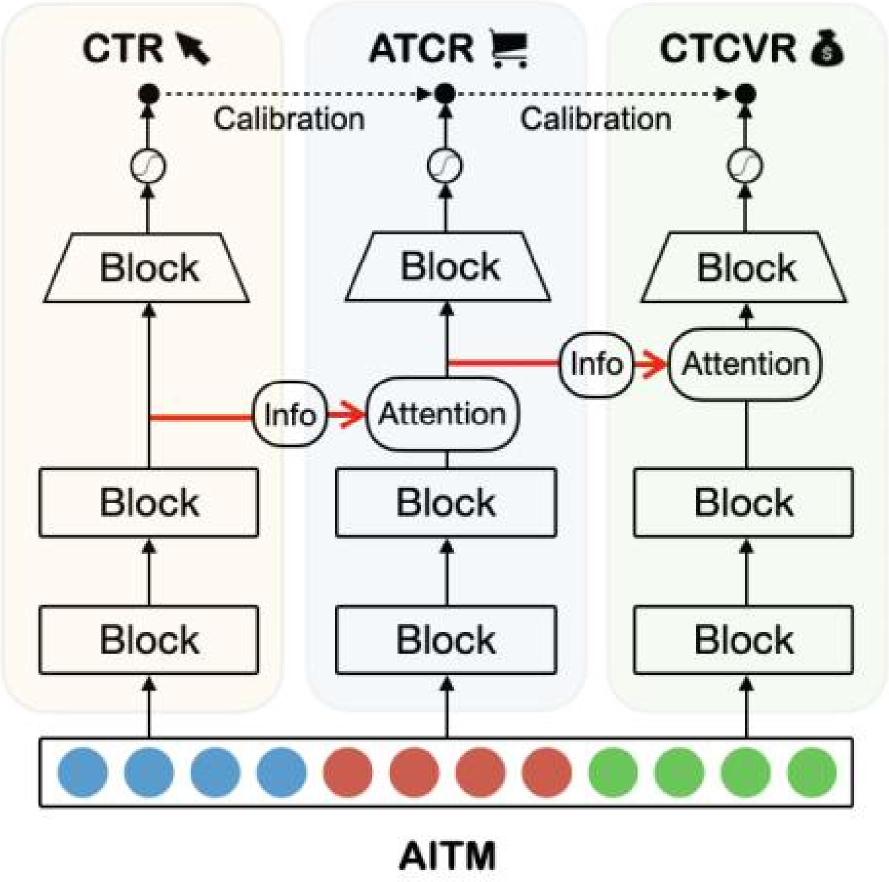
The Shared Bottom Class



(a) (b) (c)

indirect information transfer → inferior performance

Adaptive Information Transfer

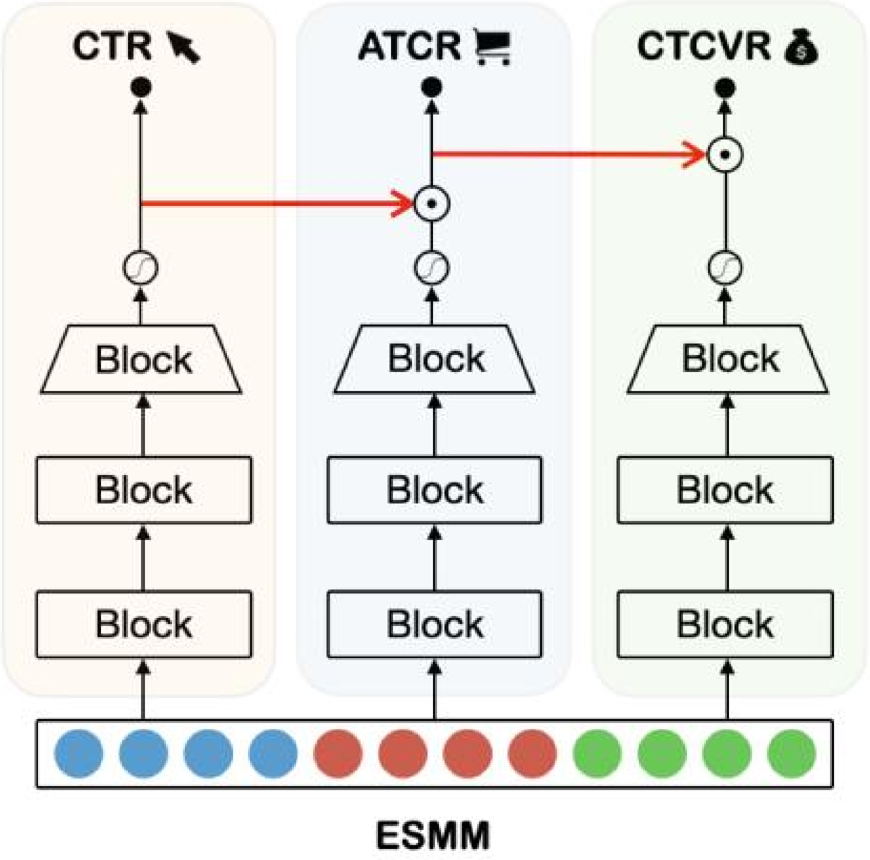


Transferring the last layer feature:

- via an attention-based module

- ☐ Computationally inefficient
- ☐ Inadequate information transfer

Entire Space Multitask Model (ESMM)



Transferring the output probability:

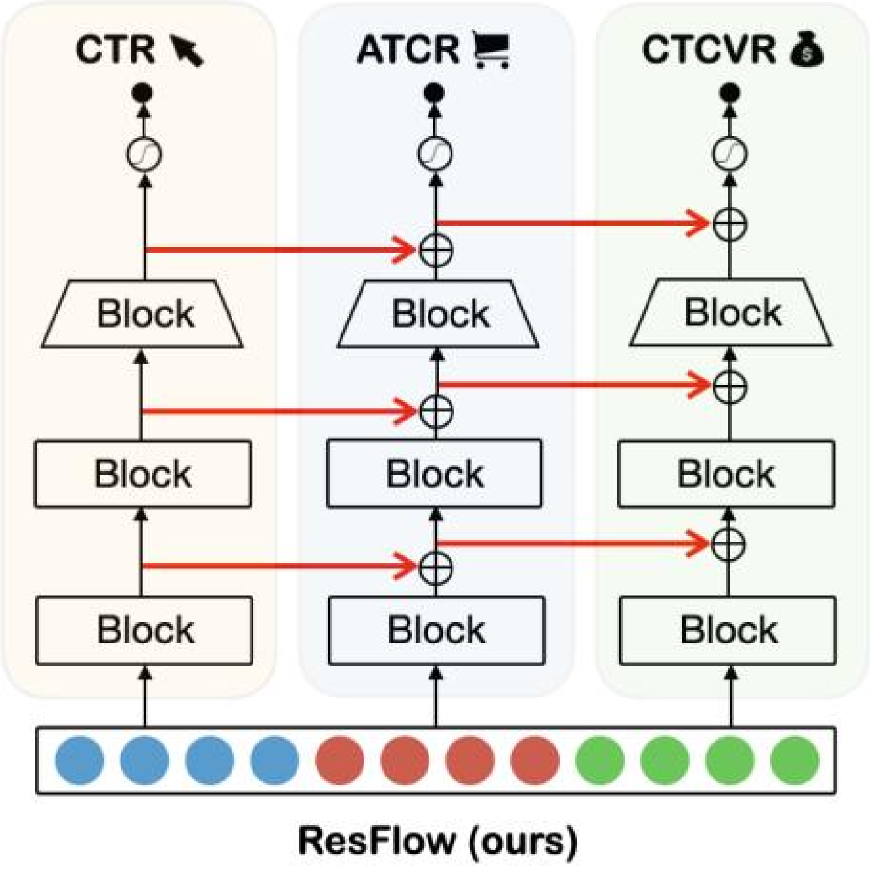
- multiplicatively
- modeling the conditional probability

☐ Light-weight

☐ Inadequate information transfer

03 ResFlow

Residual Multi-Task Learner (ResFlow)



Transferring <u>all features and the final logit</u>

- additively
- via cross-task residual connection

☐ light weight

☐ sufficient & effective information transfer

Results

Table 4: The AUC results of the CTCVR estimation task on offline e-commerce datasets. The best results are presented in bold font, while the second bests are marked with underlines. ResFlow consistently achieves the best.

Dataset	NSE	PLE	AITM	ESMM	ESCM^2-IPW	ESCM^2-DR	DCMT	ResFlow (ours)
S0	0.619±0.001	0.630±0.005	0.636 ± 0.002	0.632 ± 0.001	0.624 ± 0.007	0.622±0.006	<u>0.640 ± 0.001</u>	**0.656 ± 0.001**
S1	0.621±0.002	0.624±0.003	0.623 ± 0.001	0.623 ± 0.003	0.624 ± 0.002	0.623±0.003	<u>0.632 ± 0.002</u>	**0.647 ± 0.002**
S0&S1	0.623±0.002	0.635±0.001	0.637 ± 0.001	0.637 ± 0.003	0.623 ± 0.005	0.623±0.001	<u>0.634 ± 0.002</u>	**0.661 ± 0.001**
AliCCP	0.624±0.002	0.640±0.002	<u>0.644 ± 0.001</u>	0.641 ± 0.003	0.625 ± 0.005	0.627±0.003	0.643 ± 0.002	**0.664 ± 0.002**
AE-ES	0.861±0.002	0.873±0.002	0.876 ± 0.001	0.867 ± 0.003	0.868 ± 0.003	0.871±0.002	<u>0.886 ± 0.003</u>	**0.893 ± 0.001**
AE-FR	0.842±0.002	0.852±0.002	0.856 ± 0.002	0.851 ± 0.001	0.873 ± 0.007	0.870±0.005	<u>0.874 ± 0.003</u>	**0.885 ± 0.001**
AE-NL	0.831±0.003	0.844±0.002	0.843 ± 0.001	0.840 ± 0.002	0.854 ± 0.006	0.854±0.004	<u>0.858 ± 0.001</u>	**0.864 ± 0.001**
AE-US	0.826±0.001	0.851±0.003	0.843 ± 0.002	0.827 ± 0.002	0.843 ± 0.006	0.841±0.003	<u>0.863 ± 0.003</u>	**0.872 ± 0.001**
AE-RU	0.870±0.003	0.886±0.001	0.882 ± 0.002	0.878 ± 0.002	0.882 ± 0.006	0.880±0.006	<u>0.887 ± 0.001</u>	**0.913 ± 0.002**
Shopee-2	0.865±0.001	0.860±0.003	0.855 ± 0.006	<u>0.882 ± 0.001</u>	0.840 ± 0.012	0.812±0.041	0.867 ± 0.001	**0.902 ± 0.001**
Shopee-3	0.877±0.002	0.877±0.003	0.871 ± 0.003	<u>0.893 ± 0.001</u>	/	/	/	**0.910 ± 0.002**

Ablations

Table 5: Ablation results of ResFlow in terms of CTCVR AUC.

Model	AE-RU	Shopee-2
NSE	0.869 ± 0.003	0.865 ± 0.001
NSE + Feature Residual (FR)	0.897 ± 0.001	0.891 ± 0.001
NSE + FR (H1-only)	0.880 ± 0.002	0.868 ± 0.002
NSE + FR (H2-only)	0.898 ± 0.002	0.887 ± 0.001
NSE + Logit Residual (LR)	0.907 ± 0.002	0.896 ± 0.001
ResFlow (NSE + FR + LR)	$\mathbf{0.913 \pm 0.002}$	$\mathbf{0.902 \pm 0.001}$
ESMM	0.878 ± 0.002	0.882 ± 0.001
ESMM + FR	0.899 ± 0.004	0.891 ± 0.002
ESMM + FR + LR	0.896 ± 0.006	0.888 ± 0.001

- ✓ FR (H1-only) < FR (H2-only) < LR
  - higher-level abstraction is more critical
- ✓ ESMM < ESMM + FR < LR
  - additive is better than multiplicative
- ✓ FR (H2-only) < FR (i.e., H1 + H2) < FR + LR
  - residual link in every layer benefits

Extension

Table 6: Performance on KuaiRand-Pure-S1 in terms of AUC. The bests are in bold font. The second bests are underlined.

Target	is_follow	is_forward	is_comment
NSE	0.821 ± 0.005	0.750 ± 0.011	0.779 ± 0.003
AITM	0.785 ± 0.014	<u>0.764 ± 0.012</u>	0.782 ± 0.005
ESMM	<u>0.822 ± 0.007</u>	0.757 ± 0.007	0.782 ± 0.004
$ESCM^2$-IPW	0.817 ± 0.010	0.754 ± 0.008	0.773 ± 0.004
$ESCM^2$-DR	0.821 ± 0.009	0.754 ± 0.008	0.782 ± 0.003
DCMT	0.819 ± 0.007	0.762 ± 0.008	<u>0.783 ± 0.003</u>
ResFlow	**0.826 ± 0.002**	**0.776 ± 0.006**	**0.789 ± 0.003**

- ResFlow generalizes well to non-sequentially dependent tasks.
- Building the task topology according to their sample sparsities is a good choice.

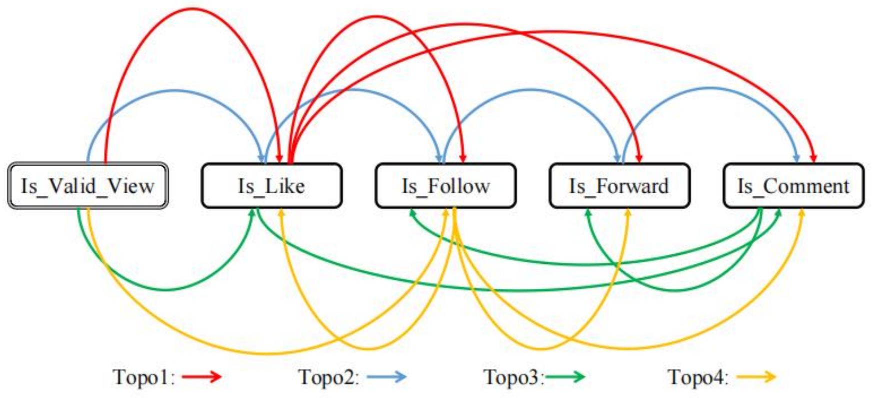


Figure 5: Visualization of different task topologies of KuaiRand-Pure-S1 Multi-Task.

Table 7: Performance on KuaiRand-Pure-S1 in terms of AUC. The bests are in bold font. The second bests are underlined.

Target	is_follow	is_forward	is_comment
ResFlow-topo1	**0.826 ± 0.002**	**0.776 ± 0.006**	**0.789 ± 0.003**
ResFlow-topo2	<u>0.825 ± 0.003</u>	0.756 ± 0.010	0.771 ± 0.002
ResFlow-topo3	0.811 ± 0.007	<u>0.774 ± 0.007</u>	0.778 ± 0.003
ResFlow-topo4	0.820 ± 0.002	0.748 ± 0.009	0.775 ± 0.002
NSE	0.821 ± 0.005	0.750 ± 0.011	<u>0.779 ± 0.003</u>

Extension

Regression (e.g., rating) as Progressive Multi-Task

- Task 0: the likelihood of v being larger than v_0
- Task 1: the likelihood of v being larger than v_1
- …
- Task K: the likelihood of v being larger than v_K

$$v_0 < v_2 < \cdots < v_K$$

Table 8: Regression performances on KuaiRand-Pure-S1 and MovieLens-1M in terms of MSE. Progressive indicates converting the regression into a progressive multi-task problem.

Dataset	KuaiRand-Pure-S1	MovieLens-1M
Traditional	1719.92 ± 3.82	0.906 ± 0.002
Progressive + NSE	1720.12 ± 4.32	0.906 ± 0.002
Progressive + ResFlow	**1658.44 ± 5.21**	**0.894 ± 0.002**

- ResFlow can also be used in regression tasks

04 Online Deployment

Score Fusion

How to fuse the predictions from multiple tasks into a simple ranking indicator:

- traditional, multiplicative: $\boldsymbol{CTR^{\alpha} * CTCVR^{\beta}}$
- proposed, additive: $\boldsymbol{\alpha * CTV + \beta * CTCVR}$

Method & Score Formula	WR@100	List AUC	OPU	CTR	CTCVR	BCR@20
ESMM, $CTR^{0.9} \times CVR^{1.1}$	+0.77%	+0.23%	+0.56%	-0.02%	+0.61%	+0.02%
ESMM, CTR*2+CTCVR*19	+2.7%	+0.09%	+0.75%	+0.12%	+0.67%	-0.01%
ResFlow, CTCVR	+1.41%	+1.82%	+0.45%	-0.15%	+0.40%	-0.02%
ResFlow, $CTR^{-0.2} \times CTCVR$	+3.37%	+1.03%	+1.33%	+0.06%	+1.19%	-0.02%
ResFlow, CTR+CTCVR*20	+4.19%	+0.88%	+2.14%	+0.66%	+2.11%	+0.02%
ResFlow, CTR+CTCVR*20+RL	+4.11%	+0.82%	+2.04%	+0.61%	+1.97%	-2.13%
ResFlow, CTR+CTCVR*20+RS	+0.03%	-0.13%	-0.53%	-0.19%	-0.44%	-2.99%

- Score fusion leads to better online performance than simply using CTCVR.
- Additive fusion leads to better online performance than multiplicative fusion.

Online-Offline Metric Alignment

Online metric OPU (order-per-user) is totally different from what we predict, while online A/B test is costly

- need a surrogate for online metric to more efficiently tune the model and fusion parameters
- it is a long-standing challenge that still remains unresolved

Propose an offline surrogate metric:

$$WR@K = \frac{\sum_{k=0}^{K} W_k}{\sum_{n=0}^{N} W_n},$$

- W_k indicates the number of orders of item k

Table 10: Pearson correlation coefficient (PCC) between offline metric uplift and online metric uplift.

Metrics	2 Targets Uplift PCC	2 Targets Uplift p-value	3 Targets Uplift PCC	3 Targets Uplift p-value
Recall@100	0.0814	0.4425	0.1974	0.0606
NDCG	0.3719	0.0002	0.3825	0.0002
List AUC	0.4353	1.6×10^{-5}	0.1564	0.1386
WR@100	0.7879	1.9×10^{-20}	0.8666	2.5×10^{-42}

- Significantly better than existing surrogates

Online Performance

Compared with the previously deployed:

- OPU: ↑1.29%
- Online CTR: ↑0.25%
- Online CTCVR: ↑1.37%

THANKS FOR YOUR ATTENTION!

Q & A

Based on joint work with Cong Fu et al. Deployed in Shopee Search.

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