DUET: Dual Model Co-Training for Entire Space CTR Prediction

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Abstract

The pre-ranking stage plays a pivotal role in large-scale recommender systems but faces an intrinsic trade-off between model expressiveness and computational efficiency. Owing to the massive candidate pool and strict latency constraints, industry systems often rely on lightweight two-tower architectures, which are computationally efficient yet limited in estimation capability. As a result, they struggle to capture the complex synergistic and suppressive relationships among candidate items, which are essential for producing contextually coherent and diverse recommendation lists. Moreover, this simplicity further amplifies the Sample Selection Bias (SSB) problem, as coarse-grained models trained on biased exposure data must generalize to a much larger candidate space with distinct distributions.

To address these issues, we propose DUET (**DU**al Model Co-Training for **E**ntire Space C**T**R Prediction), a set-wise pre-ranking framework that achieves expressive modeling under tight computational budgets. Instead of scoring items independently, DUET performs set-level prediction over the entire candidate subset in a single forward pass, enabling information-aware interactions among candidates while amortizing the computational cost across the set. Moreover, a dual model co-training mechanism extends supervision to unexposed items via mutual pseudo-label refinement, effectively mitigating SSB. Validated through extensive offline experiments and online A/B testing, DUET consistently outperforms state-of-the-art baselines and achieves improvements across multiple core business metrics. At present, DUET has been fully deployed in Kuaishou and Kuaishou Lite Apps, serving the main traffic for hundreds of millions of users.

CCS Concepts

• **Information systems** → **Recommender systems**;

Keywords

Recommender Systems, Click-Through Rate Estimation, Sample Selection Bias, Candidate Set

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1 Introduction

In industrial recommender systems, the pre-ranking stage must process thousands of candidates under millisecond-level latency. As a result, this stage heavily relies on simple two-tower architectures, which offer low inference cost but suffer from limited estimation capability [2, 11, 20, 47, 48]. The computational constraint prevents adopting sophisticated deep models, making pre-ranking the bottleneck of the entire recommendation cascade [39, 53, 61]. Consequently, the model's simplicity not only limits prediction accuracy but also gives rise to two closely coupled challenges that are particularly pronounced at the pre-ranking stage. [7, 12, 60].

Figure 1: The left and middle panels contrast a point-wise model, which overlooks item synergy, with a set-wise model that captures it. The right panel shows the cascading architecture, where multi-stage filtering creates severe SSB.

Firstly, candidate items often exhibit complex synergistic and suppressive relationships, requiring models to capture inter-item dependencies. In practice, pre-ranking models commonly employ inner-product–based two-tower architectures to cope with time constraints, yet this design sacrifices expressive power and aggravates the limitations of point-wise scoring [17, 44, 62]. As illustrated in Figure 1, a point-wise prediction model would assign an exceptionally high score to a timely and universally relevant news item (e.g., "Timely News: Beijing Heating to Start Tomorrow"). In contrast, a commercial item such as "Ad:New Down Jacket," which belongs to the long-tail category, would likely receive a relatively modest score and thus be filtered out. Yet, from a set-level perspective, presenting the advertisement immediately after the heating news creates a strong synergy effect: the news stimulates user awareness of warmth needs, and the ad provides a precise solution. This context–product combination not only improves CTR but also enhances user value and commercial revenue.

Secondly, the Sample Selection Bias (SSB) problem is even more severe in pre-ranking [16, 28, 29, 52, 58]. This is because pre-ranking operates at the largest candidate scale yet relies on the simplest model form. As illustrated in Figure 1, industrial recommender systems employ a cascading architecture that progressively filters a vast item pool through multiple ranking stages, with only a few items ultimately displayed to users. The feedback used for model training is therefore collected exclusively from this final, heavily filtered exposure set, representing only a minute fraction of the initial candidate space. In contrast, the pre-ranking model must evaluate the entire upstream candidate set—often thousands of items per request—where the vast majority are unexposed and lack labels. This creates a much larger distributional gap between training and inference compared with later stages [4, 5, 19]. Moreover, the lightweight two-tower models in pre-ranking lack sufficient expressiveness to infer reliable signals for unseen items, thereby exacerbating bias accumulation across cascaded stages.

Critically, these two challenges are not independent. The point-wise paradigm, by isolating item scoring, reinforces users' inherent preferences and traps them in information cocoons, thereby intensifying SSB. Existing studies remain confined to this paradigm, and both major categories of SSB methods still suffer from fundamental limitations. The first category is grounded in causal inference, such as Inverse Propensity Scoring (IPS) [33, 43, 55] and Doubly Robust

(DR) methods [14, 23, 24], aiming to obtain unbiased estimates from exposed samples. However, their scope is strictly limited to the exposed space, overlooking the abundant signals contained in the vast unexposed data. The second category seeks to exploit unexposed samples by generating pseudo-labels through techniques such as knowledge distillation and domain adaptation [26, 53, 56]. Nevertheless, these methods typically depend on a single model to generate labels, which not only introduces substantial noise but also lacks effective error-correction mechanisms.

To address the aforementioned challenges, we propose **DUET** (**DU**al Model Co-Training for **E**ntire Space C**T**R Prediction), a novel and practical framework that collaboratively tackles these two fundamental issues. Our model introduces two key innovations: (i) Our framework departs from conventional two-tower designs and employs a set-wise scoring mechanism that simultaneously captures intra-candidate dependencies and alleviates the computational burden. (ii) We introduce a dual model co-training mechanism that extends the supervisory signal to unexposed samples by interactively generating and correcting pseudo labels across the entire candidate set, thereby mitigating Sample Selection Bias.

Extensive offline experiments and online A/B tests show that DUET consistently surpasses SOTA baselines and improves key business metrics at Kuaishou. It is now fully deployed in both the Kuaishou and Kuaishou Lite apps, serving hundreds of millions of users. To summarize, we highlight the key contributions of this paper as follows:

- **Framework:** We propose DUET, a practical pre-ranking framework that adopts a set-wise scoring paradigm to achieve intra-candidate awareness under strict latency budgets, jointly tackles the intertwined challenges of set-level context modeling and SSB.
- **Methodology:** We develop an efficient and stable set-level interaction module to model item dependencies, enabling list-wise optimization under strict latency constraints. And introduce a dual model co-training mechanism to mitigate SSB by extending supervision to unexposed data with robust pseudo-labels.
- **Experiment:** Extensive offline and online A/B experiments validate DUET consistently outperforming SOTA methods and improving key business metrics. The framework has been fully deployed in both kuaishou and kuaishou lite app, supporting core traffic for hundreds of millions of users.

2 Preliminary

In this section, we will briefly introduce the problem definition used in this paper, in order to aid in the reader's understanding.

2.1 Problem Formulation

For a given user u, we consider a candidate set $C_u = \{i_1, i_2, \ldots, i_m\}$ returned from the retrieval stage, together with a user behavior sequence $S_u = \{j_1, j_2, \ldots, j_n\}$. In conventional point-wise CTR prediction models such as DIN [64], each candidate item $i \in C_u$ is treated independently. The prediction score, i.e., the click-through probability, is computed based on the user-side features f_u (e.g., user ID, age, gender), item-side features f_i (e.g., item ID, category, author ID), cross features f_{ui}, and the user behavior sequence $\{f_j\}_{j \in S_u}$:

$$\hat{p}_{u,i} = \text{DIN}(f_u, f_i, f_{ui}, \{f_j\}_{j \in S_u}), \quad i \in C_u. \tag{1}$$

This independent scoring overlooks the interactions among items when presented together, whereas an effective recommendation list should form a coherent "content ecosystem" rather than a mere collection of high-scoring items. To this end, we adopt a candidate-set level modeling paradigm: the entire candidate set $\{(f_i, f_{ui})\}_{i \in C_u}$, user features f_u, and behavior sequence $\{f_j\}_{j \in S_u}$ are jointly fed into the model, which outputs all click probabilities in a single forward pass:

$$\hat{\boldsymbol{p}}_u = \sigma\Big(\mathcal{M}(f_u, \{(f_i, f_{ui})\}_{i \in C_u}, \{f_j\}_{j \in S_u}; \Theta)\Big) \in (0,1)^{|C_u|}, \tag{2}$$

where $\mathcal{M}(\cdot)$ denotes the prediction model parameterized by Θ, $\sigma(\cdot)$ is the element-wise sigmoid function, and $\hat{\boldsymbol{p}}_u$ is the predicted probability vector for the candidate set, with its i-th component $\hat{p}_{u,i}$ representing the click probability of item $i \in C_u$.

3 Framework

To address the intertwined challenges of inadequate intra-candidate relationship modeling and severe Sample Selection Bias (SSB) that prevail in the pre-ranking stage of large-scale recommender systems, we propose a novel framework, DUET. As depicted in Figure 2, the DUET architecture is composed of two core components: a set-level modeling module to capture item interactions, and a dual model co-training mechanism to mitigate SSB. We will elaborate on each component in the following sections.

3.1 Set-Level Modeling

In large-scale recommender systems, traditional ranking models typically adopt a point-wise paradigm, where each candidate item is independently modeled to predict its click-through rate (CTR). However, this approach ignores the potential dependencies among items within the candidate set, often resulting in a recommendation list that is a simple stack of high-score items, lacking global consistency and diversity. To address this issue, we propose a set-level modeling approach, which simultaneously captures user–candidate interactions as well as intra-candidate relations to enhance the overall quality of recommendation results.

Feature Representation. For a given user u, the inputs consist of their profile features $\mathbf{f}_u$, a candidate set $C_u = \{i_1, \ldots, i_m\}$ of m items, and a historical behavior sequence $\mathcal{S}_u = \{j_1, \ldots, j_n\}$ of length n. We first map all high-dimensional sparse categorical features into low-dimensional dense vector representations via an embedding layer. This process yields four key feature matrices for subsequent interaction modeling:

- **Candidate Embedding Matrix** $\mathbf{F}_{\text{can}} \in \mathbb{R}^{m \times d}$: Stacked embeddings of the m candidate items.
- **Sequence Embedding Matrix** $\mathbf{F}_{\text{seq}} \in \mathbb{R}^{n \times d}$: Stacked embeddings of the n historical behavior items.
- **User Profile Embedding Matrix** $\mathbf{F}_u \in \mathbb{R}^{m \times d_u}$: The user profile vector $\mathbf{f}_u$ tiled m times to match the candidate set dimension.
- **Cross Feature Embedding Matrix** $\mathbf{F}_{\text{cro}} \in \mathbb{R}^{m \times d_c}$: Embeddings of user-item cross features for each candidate.

User-Candidate Interaction Modeling. To accurately capture the alignment between a user's dynamic interests and the candidate items, we must model the deep interactions between the candidate set $\mathbf{F}_{\text{can}}$ and the user's long behavior sequence $\mathbf{F}_{\text{seq}}$. A standard attention mechanism, with $\mathbf{F}_{\text{can}}$ as the Query and $\mathbf{F}_{\text{seq}}$ as the Key and Value, would incur a computational complexity of $O(mn)$. This is computationally prohibitive in industrial scenarios where both m and n can be in the thousands or larger.

To achieve efficient full-sequence interaction, we incorporate the Linear Attention mechanism [22]. By replacing the softmax function with a kernel function $\phi(\cdot)$ and leveraging the associative property of matrix multiplication, the computation order can be rearranged from $(\phi(\mathbf{F}_{\text{can}})\phi(\mathbf{F}_{\text{seq}})^\top)\mathbf{F}_{\text{seq}}$ to $\phi(\mathbf{F}_{\text{can}})(\phi(\mathbf{F}_{\text{seq}})^\top\mathbf{F}_{\text{seq}})$. This transformation reduces the complexity from quadratic, $O(mn)$, to linear, $O(m+n)$. The representation $\mathbf{F}_{\text{c-s}}$ is defined as:

$$\mathbf{F}_{\text{c-s}} = \text{LinearAttn}(\mathbf{F}_{\text{can}}, \mathbf{F}_{\text{seq}}, \mathbf{F}_{\text{seq}}) \in \mathbb{R}^{m \times d}, \tag{3}$$

where each row in $\mathbf{F}_{\text{c-s}}$ aggregates the interest representation for the corresponding candidate item, distilled from the user's history.

Intra-Candidate Relation Modeling. Beyond user-item matching, a high-quality recommendation list must account for the intrinsic relationships among items. For instance, a news item followed by a contextually relevant advertisement can create a synergistic effect, whereas presenting multiple homogeneous items may lead to user fatigue. To capture these contextual dependencies, we design a second attention stream that performs self-attention within the candidate set. We again employ Linear Attention to ensure computational efficiency. This process is formalized as:

$$\mathbf{F}_{\text{c-c}} = \text{LinearAttn}(\mathbf{F}_{\text{can}}, \mathbf{F}_{\text{can}}, \mathbf{F}_{\text{can}}) \in \mathbb{R}^{m \times d}. \tag{4}$$

The matrix $\mathbf{F}_{\text{c-c}}$ encodes the contextual information of each item within the current candidate "ecosystem," enabling the model to perceive collaborative and competitive relationships.

Fusion and Prediction. Finally, we concatenate the outputs from the two attention modules, $\mathbf{F}_{\text{c-s}}$ and $\mathbf{F}_{\text{c-c}}$, with the user profile embeddings $\mathbf{F}_u$ and cross feature embeddings $\mathbf{F}_{\text{cro}}$. This forms a final comprehensive feature representation matrix $\mathbf{F}_{\text{final}}$:

$$\mathbf{F}_{\text{final}} = \text{Concat}(\mathbf{F}_{\text{c-s}}, \mathbf{F}_{\text{c-c}}, \mathbf{F}_u, \mathbf{F}_{\text{cro}}) \in \mathbb{R}^{m \times d_{\text{final}}}. \tag{5}$$

This matrix is then fed into a Multi-Layer Perceptron (MLP) for non-linear transformation. A final Sigmoid activation function is applied to produce the predicted click-through rates (pCTR) for all m candidate items simultaneously.

$$\hat{\mathbf{y}} = \sigma(\text{MLP}(\mathbf{F}_{\text{final}})) \in \mathbb{R}^{m \times 1} \tag{6}$$
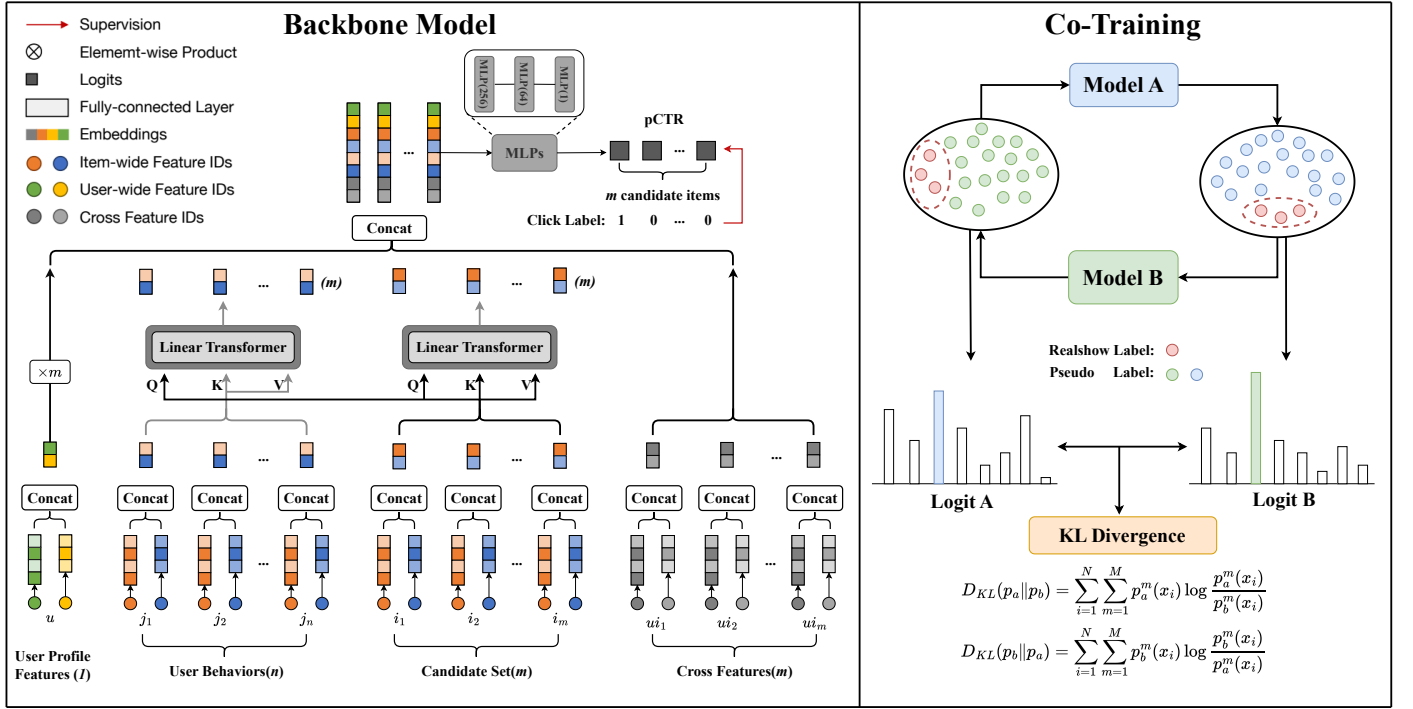
Figure 2: An overview illustration of the DUET architecture.

Through this set-wise modeling approach, our model not only predicts the individual relevance of each item but also optimizes the global utility of the entire recommendation list.

Degree Normalization. While Linear Attention offers significant efficiency gains, the removal of the softmax function also eliminates its inherent normalization property. This can lead to numerical explosion during the aggregation process, causing training instability.

To address this issue, we draw inspiration from the normalization strategy employed in Graph Convolutional Networks (GCNs) [57]. GCNs normalize aggregated features by the node degree to prevent features from high-degree nodes from dominating. Analogously, we can conceptualize the sum of similarities between a query and all keys as its "attention degree."

We introduce a degree normalization term to stabilize the training process. Specifically, the Linear Attention computation in Equation 3 is reformulated as:

$$\mathbf{E} = \mathbf{D}^{-1}\phi(\mathbf{Q})(\phi(\mathbf{K})^{\top}\mathbf{V}), \tag{7}$$

where $\mathbf{Q} = \mathbf{F}_{can}$, and $\mathbf{K} = \mathbf{V} = \mathbf{F}_{seq}$. Here, $\mathbf{D}$ is a diagonal matrix whose i-th diagonal element is the sum of similarities between the i-th query and all keys, defined as $\mathbf{D} = \text{diag}(\phi(\mathbf{Q})\phi(\mathbf{K})^{\top}\mathbf{1})$, with $\mathbf{1}$ being a column vector of ones. This degree normalization effectively regularizes the aggregation, ensuring training stability while preserving the linear complexity benefits.

3.2 Co-Training

To effectively mitigate the severe Sample Selection Bias (SSB) problem arising from training solely on exposed feedback, we introduce

a dual model co-training mechanism. The core of this mechanism lies in utilizing two independent models to extend the supervisory signal from the sparse exposed space to the entire unexposed candidate space through interactive pseudo-labeling.

Specifically, the framework comprises two models with identical architectures but independently initialized parameters, denoted as $M_A(\cdot; \theta_A)$ and $M_B(\cdot; \theta_B)$. For any given batch of candidates $\mathcal{D}$, we partition it into two subsets: the exposed set $\mathcal{D}_{obs}$, which contains ground-truth labels $\{y_i\}$, and the unexposed set $\mathcal{D}_{unobs}$, which lacks labels. The co-training mechanism operates as follows:

Interactive Pseudo-Labeling. For samples x_i in the unexposed set $\mathcal{D}_{unobs}$, the two models act as mutual teachers to provide supervisory signals. Specifically, the learning target for model M_A (i.e., the pseudo-label) is given by the prediction of model M_B, and vice versa. This process is formalized as:

$$\tilde{y}_i^A = M_B(x_i; \theta_B) \quad \text{and} \quad \tilde{y}_i^B = M_A(x_i; \theta_A), \quad \forall x_i \in \mathcal{D}_{unobs} \tag{8}$$

where $\tilde{y}_i^A$ and $\tilde{y}_i^B$ are the soft pseudo-labels used to train M_A and M_B, respectively. Since the models learn from different initial states, they capture distinct aspects and biases of the data, forming complementary "views". This view diversity enables one model to correct potential errors made by the other in its pseudo-label generation, establishing a dynamic and adaptive error-correction loop that effectively suppresses the confirmation bias common in single-model pseudo-labeling approaches.

Consistency Regularization. While view diversity is crucial for the error-correction mechanism, excessive divergence can lead to noisy pseudo-labels and destabilize the training process. To strike

a balance between diversity and consensus, we introduce a consistency regularization term that penalizes discrepancies between the predictive distributions of the two models. We treat the model outputs as parameters of a Bernoulli distribution and employ the symmetric Kullback-Leibler (KL) divergence to measure the difference between these two distributions, P_A and P_B:

$$\mathcal{L}_{\text{con}} = \mathbb{E}_{x \in \mathcal{D}} \left[\text{KL}(P_A(\cdot|x)||P_B(\cdot|x)) + \text{KL}(P_B(\cdot|x)||P_A(\cdot|x)) \right]. \quad (9)$$

3.3 Optimization

For model $M_A(\cdot; \theta_A)$, its objective is composed of two main components. The first is the supervised loss, $\mathcal{L}_{\text{sup}}^A$, which employs the BCE loss function. The source of supervision for this loss depends on the sample's origin. For samples in the exposed set $\mathcal{D}_{obs}$, we use the ground-truth label y_i. Conversely, for samples in the unexposed set $\mathcal{D}_{unobs}$, we use the soft pseudo-label $\hat{y}_i^B = \sigma(M_B(x_i; \theta_B))$ generated by model M_B, where $\sigma(\cdot)$ is the Sigmoid activation function. We define this conditional loss as follows:

$$\mathcal{L}_{\text{sup}}^A = -\mathbb{E}_{x_i \in \mathcal{D}} \left[\begin{cases} \mathcal{L}_{\text{BCE}}(y_i, \hat{y}_i^A) & \text{if } x_i \in \mathcal{D}_{obs} \\ \mathcal{L}_{\text{BCE}}(\hat{y}_i^B, \hat{y}_i^A) & \text{if } x_i \in \mathcal{D}_{unobs} \end{cases} \right]. \quad (10)$$

The second part is the consistency regularization term, $\mathcal{L}_{\text{consist}}$, as defined previously, which aims to align the predictive distributions of the two models. Combining these two parts, the final optimization objective for model M_A, denoted as $\mathcal{L}_A$, is defined as:

$$\mathcal{L}_A(\theta_A, \theta_B) = \mathcal{L}_{\text{sup}}^A + \lambda \mathcal{L}_{\text{con}}, \quad (11)$$

where λ is a hyperparameter that balances the importance of fitting the supervisory signals against maintaining inter-model consistency. The optimization objective for model M_B, $\mathcal{L}_B(\theta_A, \theta_B)$, is defined in a perfectly symmetric manner.

3.4 Deployment of DUET

DUET is deployed in Kuaishou's production recommender system, serving hundreds of millions of users. As shown in Figure 3, the deployment consists of two main components: the Online Serving Architecture and the Offline Training Pipeline.

Online Serving Architecture. Industrial recommender systems typically employ a multi-stage cascaded architecture to reconcile the trade-off between recommendation quality and system latency. Our framework DUET is deployed at the pre-ranking stage. Positioned after retrieval, this stage is tasked with efficiently refining an initial candidate pool of 4,500 items into a higher-value subset of 600. This curated subset is then passed to subsequent modules for the final ranking presented to the user.

Offline Training Pipeline. The offline training pipeline of DUET operates as an automated cyclical process with the following stages:

(1) **Log Processing:** The process commences with a log processing module that collects real-time user interactions (e.g., clicks, watch time) with exposed items. These interactions form the basis for generating labeled training samples.

(2) **Entire Space Co-Training:** To mitigate the severe Sample Selection Bias (SSB) from training only on exposed items, we incorporate unexposed data. The framework's dual models, Alice and Bob, perform corrective co-training by interactively generating and refining pseudo-labels for each other on these samples.

This mutual supervision enhances model generalization across the entire candidate space.

(3) **Model Update and Deployment:** Upon completion of the training cycle, the superior performing model is deployed to the online serving environment, replacing the previous pre-ranking model. Notably, only one model is deployed to preserve efficiency and avoid redundant serving cost.
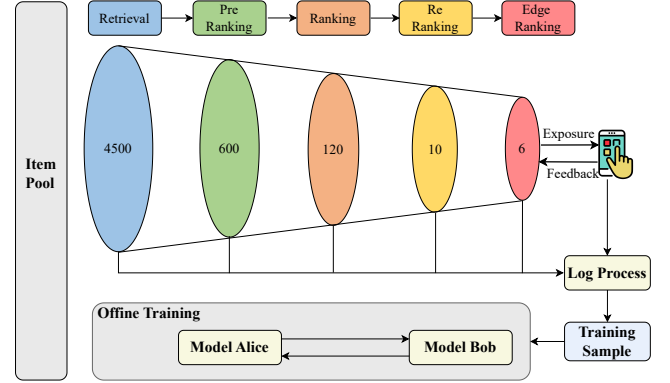

Figure 3: The deployment of DUET at Kuaishou.

4 Experiments

To validate the performance of our DUET framework, we design and conduct comprehensive experimental studies. In this section, we present our experimental setup and results analysis. Specifically, our experiments aim to investigate the following research questions:

- **RQ1**: How does DUET perform in offline experiments on real-world datasets compared to baseline models?
- **RQ2**: How does each proposed module contribute to the performance?
- **RQ3**: How do hyper-parameters influence the performance of DUET?
- **RQ4**: How does DUET perform in real online CTR Prediction?

4.1 Experimental Setup

4.1.1 Datasets. We validate our approach on the Recflow dataset and further evaluate it using streaming data from Kuaishou's production environment, demonstrating robustness in both academic and industrial contexts. Detailed statistics are provided in Table 1.

Public Dataset: Since this study requires datasets that include candidate sets across the entire recommendation pipeline, to the best of our knowledge, RecFlow [30] is the only publicly available dataset that meets this requirement. RecFlow provides comprehensive coverage of exposed and unexposed samples across all stages of the recommendation pipeline. Following prior work [44, 45], we adopt the leave-one-out strategy to partition each user's interactions into training, validation, and test sets.

Private Dataset: To further validate the effectiveness of our model in real-world industrial settings, we train and evaluate the model directly on streaming data from Kuaishou's online recommendation system to assess its performance in large-scale industrial environments. The dataset is collected from the real-time data

streams of Kuaishou's online recommendation system. It continuously receives exposure and click feedback from real users and covers the entire recommendation pipeline, ranging from candidate retrieval to final exposure.

Table 1: The statistics of datasets (M: million, B: billion).

Dataset	User	Item	Sample	Request	Impression	Click
Recflow	42471	5M	524M	1.1M	4.8M	2.1M
Industrial	144M	71M	75B	300M	980M	608M

4.1.2 Evaluation Metrics. To evaluate model performance, we use AUC (Area Under the Curve) and UAUC (User-level AUC) as the primary performance metrics. Following [64], we adopt the *Relative Improvement* (RelaImpr) metric to evaluate model performance improvements. Considering a random guesser yields an AUC of 0.5, RelaImpr is defined as:

$$\text{RelaImpr} = \left(\frac{\text{AUC(measured model)} - 0.5}{\text{AUC(base model)} - 0.5} - 1 \right) \times 100\%. \quad (12)$$

4.1.3 Baselines. To ensure a thorough assessment, the baselines are organized into two distinct categories.
First, Causal Methods. The first group of methods aims to mitigate sample selection bias by integrating causal inference.

- **Multi-DR** [59]: This method leverages multi-task learning to combine causal modeling and error imputation, thereby ensuring robustness to propensity misspecification.
- **Multi-IPS** [59]: This method employs inverse propensity weighting within a multi-task learning framework to produce unbiased conversion rate estimates given accurate propensities.
- **DR-JL** [51]: This method introduces a principled doubly robust approach to alleviate bias from inaccurate imputations and variance from propensity estimation.
- **MRDR** [18]: This method integrates theoretical variance reduction with empirical joint learning to achieve stable and reliable debiasing under missing not at random conditions.
- **DCMT** [65]: This method formulates conversion prediction as a causal multi-task problem and directly incorporates counterfactual samples to correct hidden negative biases.
- **DDPO** [46]: This method combines causality-based optimization with dynamic soft-labeling, thereby enhancing generalization and robustness across both observed and unobserved samples.

Second, Empirical Methods. This group of methods mitigates exposure bias by generating pseudo-labels for unexposed samples.

- **UKD** [56]: This method formulates conversion prediction as a knowledge distillation task, explicitly incorporating unclicked samples with uncertainty modeling to enhance robustness.
- **SIDA** [53]: This method adopts a domain adaptation module that generates exposure-independent pseudo labels to enhance robustness against exposure bias.
- **UECF** [26]: This method generates reliable pseudo-labels for unexposed samples through feature-level disentanglement, thereby mitigating exposure bias.

4.1.4 Implementation Details. We select the optimal hyperparameters based on the AUC metric evaluated on the validation set. The maximum sequence length is fixed at 200, and the embedding dimension is uniformly set to 64 across both datasets. The AdamW optimizer is employed, with the learning rate chosen from {1e−3, 5e−3, 1e−4, 5e−4, 1e−5, 5e−5} . All other hyperparameters are kept consistent with the original configurations reported in their respective studies. We adopt the widely used DIN model as the base CTR prediction framework [54, 62]. All experiments are implemented in TensorFlow and executed on a computing environment equipped with 25 Intel Xeon CPU cores (2.10 GHz) and two NVIDIA RTX A10 GPUs, providing sufficient computational resources for large-scale training and hyperparameter optimization.

4.2 Overall Performance (RQ1)

Table 2 reports the comprehensive performance of all the compared baselines across Recflow and Industrial datasets. Based on the results, the main observations are as follows:

- Compared with baseline methods in the category of causal inference approaches (e.g., Multi-IPS, DR-JL, MRDR), DUET demonstrates significant and consistent improvements across all evaluation metrics. While these causal estimators aim to achieve unbiased learning from observed exposure data, their core design is restricted to bias correction within the observed sample space, thereby failing to exploit the rich signals inherent in unexposed data. Although recent methods such as DCMT and DDPO attempt to incorporate unobserved samples, they still derive propensity scores solely from observed data and neglect the necessity of separately modeling the unobserved space. As a result, residual bias is introduced, ultimately limiting their effectiveness.
- Within the family of empirical baselines, DUET consistently demonstrates superior performance. While these empirical methods attempt to leverage unexposed samples, they typically rely on a single model to generate pseudo labels. This paradigm suffers from inherent limitations: it is prone to introducing substantial noise, resulting in pseudo labels of uneven quality, and lacks effective error-correction mechanisms to ensure the generation of high quality pseudo-labels. In contrast, the Co-Training framework of DUET establishes a dynamic error-correction loop through mutual supervision and information exchange between two models, thereby producing pseudo labels that are both higher in quality and more robust.
- DUET's consistently superior performance across diverse datasets demonstrates its robust generalization and industrial applicability. This robustness stems from systematically addressing two intertwined challenges: SSB and the absence of intra-candidate interaction modeling. DUET's dual model co-training mechanism enables mutual supervision between models, generating high-quality pseudo-labels for unexposed samples. Additionally, its set-level modeling explicitly captures synergistic or suppressive relationships among candidates, which are overlooked by traditional point-wise methods. By capturing these interactions, DUET enhances recommendation lists' global coherence and diversity, proving particularly critical in industrial scenarios with large-scale, complex candidate sets.

Table 2: The overall performance evaluation results of the proposed method and compared methods on two benchmark datasets. Results are grouped into heuristic and trainable methods. Within each group, the best and second-best performances are highlighted in bold and borderline, respectively. Numbers with an asterisk (*) indicate statistically significant improvements over the best trainable baseline (t-test with p-value < 0.05).

Model	Recflow		Industrial			
	AUC	RelaImpr	AUC	RelaImpr	UAUC	RelaImpr
BaseModel	0.6127	NA	0.6730	NA	0.6675	NA
Causal Estimation Scenario						
Multi-IPS	0.6141	1.24%	0.6755	1.47%	0.6679	0.27%
Multi-DR	0.6133	0.53%	0.6751	1.24%	0.6677	0.12%
DR-JL	0.6189	5.50%	0.6769	2.28%	0.6687	0.74%
MRDR	0.6160	2.92%	0.6788	3.36%	0.6693	1.09%
DCMT	0.6173	4.08%	0.6801	4.15%	0.6715	2.43%
DDPO	0.6179	4.61%	0.6826	5.56%	0.6718	2.61%
OURS	**0.6322***	**17.31%**	**0.6881***	**8.73%**	**0.6787***	**6.69%**
Empirical Estimation Scenario						
UKD	0.6171	3.91%	0.6812	4.76%	0.6694	1.19%
SIDA	0.6235	9.58%	0.6824	5.44%	0.6731	3.36%
UECF	0.6273	12.96%	0.6836	6.12%	0.6756	4.83%
OURS	**0.6322***	**17.31%**	**0.6881***	**8.73%**	**0.6787***	**6.69%**

4.3 Ablation Study (RQ2)

To evaluate the effectiveness of the proposed DUET framework, we conducted a series of ablation studies by removing three key components: the set-level interaction module (DUET w/o Set), the dual model co-training mechanism (DUET w/o Co), and the distribution alignment regularizer (DUET w/o KL). Table 3 presents our results, from which we derive the following important conclusions.

- Among all ablations, removing the dual model co-training mechanism (w/o Co) leads to the most pronounced performance degradation. This highlights the pivotal role of co-training in addressing the SSB problem. Without this mechanism, the framework degenerates into a single model pseudo labeling paradigm, which is highly susceptible to confirmation bias and thus fails to generate reliable and high quality labels. By contrast, DUET leverages a dual model architecture in which two independently parameterized models mutually supervise each other, forming a dynamic error correction loop. The design guarantees the reliability and robustness of the generated pseudo labels, thereby strengthening the model's generalization across the entire data space.
- Removing the set-level interaction module (w/o Set) also causes a notable decline in performance. This finding underscores the necessity of explicitly modeling the complex dependencies among items within a candidate set during the pre-ranking phase. Traditional point-wise methods evaluate candidates in isolation, overlooking the synergistic or suppressive effects that arise when items are jointly presented. In contrast, DUET's set-level module

leverages a self-attention mechanism to capture such contextual information, transforming the prediction task from independent item scoring into a holistic list-wise optimization problem. This enables the model to generate more coherent and diverse recommendations that better align with user preferences.
- Ablating the distribution alignment regularization term (w/o KL) impairs model performance. The essence of co-training lies in leveraging the complementary perspectives of two independent models for mutual correction and reinforcement. However, this view discrepancy is a double-edged sword. On one hand, it generates diverse supervisory signals, preventing either model from converging to a local optimum. On the other hand, if left unconstrained, it can exacerbate predictive divergence between the models, leading to conflicting pseudo-labels and ultimately disrupting the collaborative mechanism. To balance this trade-off, We introduce KL divergence as a soft constraint not to eliminate these model discrepancies, but to guide them.

Table 3: Performance of design variants on two datasets. Bold numbers denote the largest performance changes.

Model	Recflow		Industrial			
	AUC	RelaImpr	AUC	RelaImpr	UAUC	RelaImpr
DUET	0.6322	0.00%	0.6881	0.00%	0.6787	0.00%
w/o Set	0.6279	-3.36%	0.6813	-3.75%	0.6732	-3.16%
w/o Co	**0.6257**	**-5.17%**	**0.6792**	**-4.97%**	**0.6703**	**-4.93%**
w/o KL	0.6306	-1.22%	0.6834	-2.56%	0.6749	-2.17%

4.4 In-depth Analysis (RQ3)

The regularization coefficient λ governs the essential trade-off between view diversity and prediction consensus in the dual model. We conduct a sensitivity analysis to examine its impact, and the results are shown in Figure 4.

We observe a clear unimodal relationship between λ and model performance, validating the underlying rationale of our design. When λ is too small, the weak constraint allows excessive divergence between the two models. Their predictions drift apart, producing inconsistent pseudo-labels that undermine the co-training mechanism. Conversely, an overly large λ forces the models into homogenization. Although this ensures consistency, it suppresses the diversity needed for mutual correction and causes the paradigm to degenerate into self-training. for mutual correction and causes.
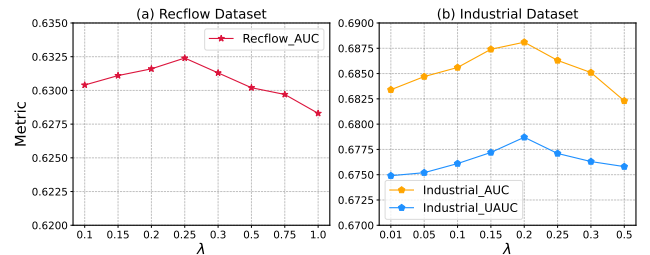

Figure 4: The impact of the regularization strength λ.

4.5 Online Result (RQ4)

To evaluate the performance of the DUET framework in a real-world industrial environment, we deployed a two-week online A/B test on both the Kuaishou and Kuaishou Lite applications. As detailed in Table 4, the experimental results clearly demonstrate that our proposed model surpasses the baseline across multiple core business metrics, achieving statistically significant improvements.

Specifically, DUET delivered significant growth in user engagement and retention. On the Kuaishou app, for instance, Total Watch Time and Avg. App Usage Time increased by +0.195% and +0.147%, respectively. This indicates that by generating more accurate predictions over the entire candidate space and modeling item synergies, DUET produces more compelling recommendation lists, thereby effectively enhancing user retention and consumption depth.

Furthermore, DUET fosters a healthier content ecosystem and drives long-term value. This is evidenced by significant uplifts in diversity-oriented metrics, including Avg. Novel Cluster (+0.173%) and Avg. Surprise Cluster Exposure (+0.165%). These results underscore DUET's capacity to surface novel content, thereby mitigating the risk of filter bubbles and broadening user interest boundaries. These improvements in content ecology, together with the retention gains, demonstrate that the model delivers tangible and multifaceted value in a large-scale production environment.

Table 4: A/B test performance on Kuaishou and Kuaishou Lite across engagement metrics. The Improvement column reports the relative percentage uplift of the treatment over the control. The Confidence Interval (CI) provides a range of plausible values for the true uplift. A CI that does not contain 0 indicates that the result is statistically significant.

Scenario	Metric	Improv.	CI
Kuaishou	Avg. App Usage Time	+0.147%	[0.07%, 0.22%]
	Total Watch Time	+0.195%	[0.09%, 0.30%]
	Video Watch Time	+0.125%	[0.00%, 0.25%]
	Avg. Suprise Cluster	+0.165%	[0.09%, 0.24%]
	Avg. Novel Cluster	+0.173%	[0.11%, 0.24%]
	Avg. Long-Term Cluster Exp.	+0.100%	[0.03%, 0.17%]
	Avg. Accurately Interest	+0.149%	[0.05%, 0.24%]
Kuaishou Lite	Avg. App Usage Time	+0.049%	[0.01%, 0.09%]
	Total Watch Time	+0.061%	[0.01%, 0.11%]
	Video Watch Time	+0.056%	[0.01%, 0.10%]
	Number of Novel Interests	+0.058%	[0.01%, 0.11%]
	Avg. Long-Term Interest Exp.	+0.041%	[0.01%, 0.08%]
	Avg. Cluster Exp.	+0.051%	[0.02%, 0.08%]
	Avg. Effectively Clusters	+0.050%	[0.01%, 0.08%]

5 Related Work

In this section, we review two relevant prior works: Click-through rate model and sample selection bias.

5.1 Click-Through-Rate Prediction

Research on CTR prediction progressed from linear and shallow factorization models, including Logistic Regression (LR) [32], Factorization Machines (FM) [41], and Field-aware Factorization Machines

(FFM) [21], to deep architectures that combine memorization and generalization. Wide & Deep [13], DeepFM [17], and DCN [49, 50] enable end-to-end learning of higher-order feature interactions. To model evolving interests, the DIN family adopts behavior-sequence modeling and advances from relevance attention to interest evolution, short-term preference modeling, and unified treatment of short and long terms [10, 15, 63, 64]. Leveraging extended user histories is also crucial: HPMN [40] and MIMN [35] use external memory networks to preserve persistent preferences. To reduce the inconsistency between short and long terms, retrieval then modeling frameworks first retrieve salient subsequences and then apply specialized modeling. SIM [36] and UBR4CTR [37, 38] follow this design; ETA [9] and SDIM [3] improve retrieval precision with locality-sensitive hashing and signature mechanisms. TWIN-V2 [44] scales historical modeling to 10^6 behaviors using hierarchical clustering with cluster-aware attention, enabling long range retrieval with real time efficiency.

5.2 Sample Selection Bias

Sample Selection Bias (SSB) is a critical challenge in recommender systems and online advertising, arising because models are trained on biased data from observed user feedback but must perform inference on the entire, unbiased data space [5, 6, 27, 31, 34]. Causal inference is a primary approach to mitigate Sample Selection Bias (SSB). Initial work employed methods like Inverse Propensity Scoring (IPS) [1, 8, 31, 55] and Doubly Robust (DR) estimators [25, 42, 45, 66], as demonstrated in the doubly robust joint learning approach for recommendation. These have been enhanced in frameworks like MRDR [18] to reduce variance, and in Multi-IPW/Multi-DR [59] to combat data sparsity via multi-task learning. Advanced methods extend this by leveraging the entire data space, often by generating pseudo-labels for unobserved samples. This is achieved through techniques such as the dual propensity networks in DDPO [46], the counterfactual framework in DCMT [65], and the uncertainty-regularized knowledge distillation in UKD [56]. Specifically for the challenging pre-ranking stage, comprehensive frameworks like SIDA [53] combine sample selection with unbiased distillation, while UECF [26] introduces an unbiased causal framework with automatic sample filtering to ensure theoretical unbiasedness.

6 Conclusion

This paper addresses the critical, intertwined challenges of Sample Selection Bias (SSB) and point-wise scoring limitations in the pre-ranking stage of recommender systems. We proposed DUET, a novel framework that integrates a dual model co-training mechanism with an efficient set-level interaction module. The co-training paradigm effectively mitigates SSB by extending supervision to the entire candidate space via interactive pseudo-label generation and error correction. Simultaneously, the set-level module captures complex inter-item dependencies, enabling holistic list-wise optimization. Extensive offline experiments and large-scale online A/B tests have validated DUET's significant superiority over state-of-the-art baselines. Its successful deployment in Kuaishou, serving hundreds of millions of users and improving key business metrics, demonstrates its profound practical value and industrial impact.

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