Personalized Inter-Task Contrastive Learning for CTR&CVR Joint Estimation

Zihan Lin†, Xuanhua Yang‡, Shaoguo Liu†, Xiaoyu Peng‡, Wayne Xin Zhao‡, Liang Wang‡, Bo Zheng‡

1School of Information, Renmin University of China
2Alibaba Group
3Gaoling School of Artificial Intelligence, Renmin University of China
4Beijing Key Laboratory of Big Data Management and Analysis Methods
zhlin@ruc.edu.cn, {xuanhua.yxh,shaoguo.lsg,pengxiaoyu.pxy}@alibaba-inc.com,
batmanfly@gmail.com, {liangbo.wl,bozheng}@alibaba-inc.com

Abstract

In most of advertising and recommendation systems, multi-task learning (MTL) paradigm is widely employed to model diverse user behaviors (e.g., click, view, and purchase). Existing MTL models typically use task-shared networks with shared parameters or a routing mechanism to learn the commonalities between tasks while applying task-specific networks to learn the unique characteristics of each task. However, the potential relevance within task-specific networks is ignored, which is intuitively crucial for overall performance. In light of the fact that relevance is both task-complex and instance-specific, we present a novel learning paradigm to address these issues. In this paper, we propose Personalized Inter-task COntastive Learning (PICO) framework, which can effectively model the inter-task relationship and is utilized to jointly estimate the click-through rate (CTR) and post-click conversion rate (CVR) in advertising systems. PICO utilizes contrastive learning to integrate inter-task knowledge implicitly from the task representations in task-specific networks. In addition, we introduce an auxiliary network to capture the inter-task relevance at instance-level and transform it into personalized temperature parameters for contrastive learning. With this method, fine-grained knowledge can be transferred to improve MTL performance without incurring additional inference costs. Both offline and online experiments show that PICO outperforms previous multi-task models significantly.

1 Introduction

As a result of the explosion of information on the Internet, recommender and advertising systems become increasingly important for uncovering customer interest and providing a personalized experience (Yuan et al. 2014). They attempt to track and predict a variety of user feedbacks (click, purchase et al.), aiming to deliver more tailored services. In the past, researchers have paid the most attention to estimating click-through rate (CTR) and post-click conversion rate (CVR) (Ma et al. 2018b; Wei et al. 2021), which are two fundamental techniques to grasp customer preference.

To jointly model the pattern of multiple user behaviors, Multi-Task Learning (MTL) (Caruana 1997) has been investigated and developed to capture the complicated relationship between the task of prediction on each behavior (Wei et al. 2021; Tang et al. 2020; Misra et al. 2016). Most of their work is typically structured on the basic task-shared and task-specific networks paradigm, in which some parameters are shared in a hard or soft way and others are independent of each task. Previous studies have mostly concentrated on carefully designing or exploring the complex structures of task-shared networks (Ma et al. 2018a; Tang et al. 2020 (shown in Fig. 1(a)(b)). However, the task-specific networks, which make predictions directly for each task, are equally crucial. Intuitively, it may be sub-optimal to focus purely on capturing the common knowledge with explicitly shared parameters while ignoring the implicit relationship between individual networks (shown in Fig. 1(c)). Besides, it could be costly to manually search optimum shared architectures for different tasks (Bai et al. 2022).

To model the relationship within the task-specific networks, an empirical way is to manually conduct regularization or integration between tasks in either layer- or parameter-level. As an illustration, AutoHERI (Wei et al. 2021) automatically learns optimal connections between the layers in task-specific networks to model the task relationship. However, it is not efficient on computation and memory during both training and inference. So far, few works have been devoted to capturing the inter-task relationship in an efficient and effective manner.

To achieve better effectiveness, there are two critical is-
sues: (1) The relationship is **task-complex**. There is no doubt that relations vary dramatically between different tasks. Determining the degree of similarity between two tasks is very challenging. Although we can describe how similar two tasks are with enough expert knowledge, it could not be transferable to a new task with a distinct behavior. Furthermore, It’s also worth noting that there is no universally accepted criterion for measuring similarities. (2) The relationship is **instance-specific**. Data in a real-world industrial setting is extremely large, making it difficult to establish a universal relationship between tasks that works well in all instances. If we merely train a model with pre-defined coarse-grained task relations, different instances may run the risk of having noise, and their performance may degrade.

For alleviating the above intractable issues, the representation learning for each task can be enhanced with unsupervised learning paradigm to explicitly capture and utilize the relation between tasks. Contrastive learning recently has proved to have very promising results in unsupervised representation learning (Lin et al. 2022). The objective of contrastive learning is to make all sample representations uniformly distributed while aligning the representations of similar samples (Wang and Liu 2021). To learning informative representations, the positive and negative samples for each task are constructed based on the underlying meaning. Motivated by these aspects, we suggest modeling the task relationship in a contrastive learning paradigm.

In this paper, we propose a novel **Personalized Inter-task Contrastive Learning (PICO)** framework which conducts contrastive learning between two tasks using in-batch negative samples and learnable instance-level temperatures. To solve the first challenge, we employ contrastive learning which leverages the representation of one task as positive samples of another task to contrast. In order to automatically learn the similarities across tasks, we draw the negative instances from representations of others that in the same batch. To learn the relevance of tasks at instance level, we introduce an auxiliary network for each pair of tasks during training but remove it during inference. This allows the model to automatically capture the instance-specific relationships when facing with various types of data, which is helpful to tackle the second challenge. Creatively, we use the learned task relevance as the temperature parameter of InfoNCE (Oord, Li, and Vinyals 2018) loss to make the contrastive learning personalized for each data instance.

We apply PICO on large-scale datasets where CTR and CVR are two key tasks that are estimated jointly. As mentioned above, PICO is architecture-agnostic and can automate the process of modeling inter-task relationship in an efficient and effective way. Thus, PICO is easily expandable to other tasks with complex behaviors. Our contributions can be summarized as follows:

- To the best of our knowledge, it is the first study that introduces contrastive learning in MTL to facilitate knowledge transfer between tasks.
- We propose a novel personalized inter-task contrastive learning framework which learns the relevance of tasks at instance-level and use it as temperature personally.
- Both offline and online experiments demonstrate that PICO significantly outperforms baseline models. This indicates that PICO can capture inter-task relationship, enhancing the multi-task learning paradigm.

## 2 Related works

In this section, we briefly review related works in three aspects: CTR/CVR estimation, multi-task learning and contrastive learning.

**CTR/CVR Estimation.** In online recommender system and advertising systems, click-through rate (CTR) and post-click conversion rate (CVR) are core indicators of service (Wang 2020). From the traditional linear regression (Richardson, Dominowska, and Ragni 2007) to the latest neural-based models (Zhang et al. 2021), plenty of architectures were designed to either make in-depth feature interactions (Guo et al. 2017; Li et al. 2019) or incorporate representative data patterns (Zhou et al. 2019; Qin et al. 2020). Most previous studies leverage complex networks or technologies to improve the model’s performance on a single task. For example, FiGNN (Li et al. 2019) introduces graph neural networks to model feature interaction between different fields. Despite their effectiveness, those models may be sub-optimal since they omit the potential relation between different tasks. For instance, it has been proved that optimizing the two tasks of CTR and CVR estimation jointly can boost overall performance (Wei et al. 2021).

**Multi-Task Learning.** For similar tasks, multi-task learning aims to jointly train a unified model with shared parameters or knowledge (Collobert and Weston 2008). It has attracted more and more attention in the field of recommender and advertising systems (Yang et al. 2022; Wei et al. 2021; Pan et al. 2019). Some of these researches build the relations among tasks with business expertise (Ma et al. 2018b), knowledge distillation (Yang et al. 2022) or automatic architecture search (Wei et al. 2021). In another line of research, well-designed architectures were designed to conduct knowledge sharing further (Ma et al. 2018a; Tang et al. 2020; Hazimeh et al. 2021). For example, Ma et al. (2018a) originally took multiple expert networks with learnable gates as the shared architecture. And Tang et al. (2020) further separated the gates into shared and specific ones.

Different from these works, in our method, contrastive learning is conducted to model the inter-task relationship. Instead of designing complex architectures, we just employ simple contrastive objectives to transfer the shared knowledge. In addition, our paradigm is model-agnostic and can be combined with most of existing MTL architectures.

**Contrastive Learning.** In light of the success of contrastive learning (He et al. 2020), researchers have devoted themselves to exploring its enormous potential in natural language processing (Gao, Yao, and Chen 2021), graph mining (Zhu et al. 2020) and recommendation (Lin et al. 2022). Apart from the large-scale applications of contrastive learning, there are also several insightful works that analyse the underlying principles (Wang and Liu 2021; Robinson et al. 2021). Among them, an impressive summary is that align-
ment and uniformity are two vital characteristics that captured by contrastive learning \cite{Wang2020}. These principles are also helpful in multi-task learning where the representation learning is performed for different tasks by separate structures. Therefore, we try to transfer the paradigm of contrastive learning to multi-task CTR/CVR estimation and further upgrade it with instance-specific temperature for personalized modeling \cite{Zhang2021a}.

3 Methodology

This section provides a thorough introduction to the proposed framework. Without loss of generality, the method is applied on tasks of CTR and CVR estimation, while it can be easily extendable to other more tasks. The overall framework of PICO is shown in Figure 2. PICO consists of two essential parts as follows. First, we describe the formulation and the backbone architecture\cite{Zhang2021b}. Then, we emphatically introduce the contrastive learning mechanism along with the learnable temperature parameter\cite{Zhang2021c, Zhang2021d}. Finally, we present the optimization strategy and complexity discussion\cite{Zhang2021e, Zhang2021f}.

3.1 Task Formulation and Model Backbone

CTR estimation is the effort of predicting whether or not a user would click on a certain advertisement or item, and CVR estimation is the task of predicting the probability of post-click conversion (e.g., view, purchase). An impression data usually consists of a list of features and user feedbacks. The user features, item features and other context features make up the feature set, which is often converted into various one-hot encoding vectors. The user feedbacks indicate whether or not the user has performed actions like clicking, viewing, or purchasing \emph{et al.} Consider an impression instance $(x, y_{ctr}, y_{cvr})$, where $x$, $y_{ctr} \in \{0, 1\}$ and $y_{cvr} \in \{0, 1\}$ denotes feature vectors, click label and post-click conversion label respectively. The multi-task CTR/CVR estimation, aiming at learning a unified model that can predict both click and conversion labels, is denoted as follows:

$$y_{ctr}, y_{cvr} = f(x|\Theta).$$

where $\Theta$ represents the parameters that need to be learned.

The backbone of MTL usually contains task-shared layers at bottom and several task-specific layers at top. For the scenario of CTR/CVR estimation, we can specifically split the model into the paradigm as $y_{ctr} = f_{ctr}(f_{sh}(\cdot))$ and $y_{cvr} = f_{cvr}(f_{sh}(\cdot))$, where $f_{ctr}(\cdot)$, $f_{cvr}(\cdot)$ and $f_{sh}(\cdot)$ represents the CTR-specific layers, CVR-specific layers and task-shared layers respectively. As illustrated in Fig. 2, the original one-hot encoding features are transformed into dense vectors through looking up a shared embedding table, and then the dense vectors are concatenated (presented as $e(x)$) as the input of task-shared projection. There are two main fashions of task-shared projection: hard or soft sharing. For hard sharing methods, the outputs ($x^{ctr}$ and $x^{cvr}$) of $f_{sh}(\cdot)$ are the same, denoted as:

$$x^{cvr} = x^{ctr} = f_{sh}(e(x))$$

For soft sharing methods, the outputs of $f_{sh}(\cdot)$ vary from different tasks through some task-aware gating mechanism \cite{Ma2018a, Tang2020}, simply denoted as follows:

$$x^{ctr} = f_{sh}^{ctr}(e(x)), \quad x^{cvr} = f_{sh}^{cvr}(e(x)).$$

After task-shared projection, the CTR-specific layers take the feature representation $x^{ctr}$ as input and produces the CTR prediction after multiple layers and an activation function: $y_{ctr} = f_{ctr}(x^{ctr})$. CVR estimation has the similar architecture and procedure: $y_{cvr} = f_{cvr}(x^{cvr})$. Previous methods learn all the parameters with supervised binary cross-entropy loss and regularization function. However, in our framework, we will propose that sufficient knowledge be transferred between $f_{ctr}(\cdot)$ and $f_{cvr}(\cdot)$.

3.2 Inter-Task Contrastive Learning

Formally, the representations for CTR and CVR estimation tasks are produced by $f_{ctr}(\cdot)$ and $f_{cvr}(\cdot)$, which consists of several nonlinear projection layers. The parameters of these layers are optimized only with the cross-entropy loss which would discard the explicit knowledge from other tasks. An early solution is to regularize the L2 distance between the parameters in two networks \cite{Ruder2019}. However, the carrying capacity of the network is severely limited with the regularization as it performs hard constraint regardless of the inputs. From another aspect, we can refer to the optimization on the intermediate in these networks which can be considered as the task representations. A straightforward way is to minimize the dot product between the representations of CTR and CVR task:

$$L_{reg} = h^{ctr}_{x} \cdot h^{cvr}_{x},$$

where $h^{ctr}_{x}$ represents the hidden vectors of middle layers in $f_{ctr}(\cdot)$ for instance $x$. Although $L_{reg}$ could achieve the knowledge communication by forcing the representations of tasks to be close, model performance heavily relies on the manual selection of coefficient between the cross-entropy loss and regularization loss. If the weight of $L_{reg}$ is too small, the knowledge integration is insufficient. Correspondingly, overlarge weight would erase the individuality of task. Moreover, when more tasks are incorporated, the number of coefficients grows exponentially, which limits the applicability on complex multi-task scenarios.

To tackle this problem, a key idea is to learn representations with the help of task relations instead of hard regularization. Inspired by the paradigm of contrastive learning \cite{He2020}, we introduce negative samples to guide the integration. For the instance $x$, the representations for CTR and CVR are treated as positive pairs and the representations of another instance $z$ are served as negative samples. The regularization loss can be conducted pair-wisely:

$$L_{reg}^{BPR} = -\log(h^{ctr}_{x} \cdot h^{cvr}_{x} - h^{ctr}_{z} \cdot h^{cvr}_{z}).$$

Here we use $h^{cvr}_{z}$ as negative samples instead of $h^{ctr}_{z}$ to ensure the same representation space. In this loss, the similarity between task representations is optimized and knowledge integration can be achieved between representations softly.
Considering the efficiency, we introduce more in-batch negative samples and update Eq. (5) into the following contrastive learning paradigm:

$$\mathcal{L}_{cl} = - \sum_{x \in \mathcal{X}} \log \frac{\exp(h_{x}^{ctr} \cdot h_{x}^{cvr} / \tau)}{\sum_{x \in \mathcal{B}} \exp(h_{x}^{ctr} \cdot h_{z}^{cvr} / \tau)},$$

where $\mathcal{B}$ represents a batch of data and $\tau$ is the temperature parameter that controls the strength to contrast (Wang and Isola 2020). Usually smaller $\tau$ indicates more strict constraint. It is practical to find a proper and fixed $\tau$ outputs of task-shared layers as inputs: blue blocks in Figure 2). The relevance network takes the relevance between the CTR and CVR tasks (illustrated by light blue blocks in Figure 3). The relevance network is also optimized with a similar way, the relevance network is also optimized with labels that guide the training of the relevance network. In a similar way, the relevance network is also optimized with binary cross-entropy loss as:

$$\mathcal{L}_{ce}^{rel} = -y_{rel} \log(\hat{y}_{rel}) - (1 - y_{rel}) \log(\hat{y}_{rel}),$$

where $\odot$ represents element-wise product. Then, the interacted representations $x^{rel}$ will be transformed by several MLP layers and a sigmoid function to generate the predicted output:

$$\hat{y}_{rel} = \sigma(\text{MLP}(x^{rel})).$$

The supervision signal of relevance network is determined by the labels of CTR and CVR tasks. Intuitively, the more instances that two tasks have the same labels (both 1 or 0), the more relevant they are to each other. Therefore, we propose to use the Xor operator on each instance to generate labels that guide the training of the relevance network. In a similar way, the relevance network is also optimized with binary cross-entropy loss as:

$$\mathcal{L}_{ce}^{rel} = -y_{rel} \log(\hat{y}_{rel}) - (1 - y_{rel}) \log(\hat{y}_{rel}),$$

where $y_{rel} = y_{ctr} \oplus y_{cvr}$ and $\oplus$ indicates the Xor operator.

After obtaining the predicted task relevance, we turn it to the temperature parameter $\tau$ of contrastive learning to control the strength of representation integration. Here we consider using linear projection to control the temperature in an appropriate range:

$$\tau = (\tau^{l} - \tau^{u}) \cdot \hat{y}_{rel} + \tau^{u},$$

where $\tau^{u}$ and $\tau^{l}$ are hyper-parameters that indicate the upper-bound and lower-bound of temperature.

Finally, we update the inter-task contrative objective with the learned temperature to make it personalized across data.
instances as the follow equation:

$$L_{cl} = - \sum_{x \in \mathcal{X}} \log \frac{\exp(h_x^{\text{ctr}} \cdot h_x^{\text{cvr}} / \tau_x)}{\sum_{z \in \mathcal{B}} \exp(h_x^{\text{ctr}} \cdot h_z^{\text{cvr}} / \tau_x)},$$

where $\tau_x$ is generated by equation (10) for the instance $x$.

### 3.4 Model Optimization

The whole framework can be optimized in an end-to-end way, which is useful for training efficiency and practicality in online services. Meanwhile, to isolate the learning of task relevance and task representations, we cut off the gradient from contrastive loss to the parameters in the relevance network. The overall objective is the weighted sum of the traditional cross-entropy loss on each task, the additional loss for task relevance and the proposed personalized contrastive learning loss:

$$L = L_{ce}^{\text{ctr}} + L_{ce}^{\text{cvr}} + \alpha L_{ce}^{\text{rel}} + \beta L_{cl} + \lambda ||\Theta||_2,$$

where $\alpha$, $\beta$ and $\lambda$ are the hyper-parameters to rescale the loss of task relevance, proposed contrastive objective and the regularization term, respectively. We adopt L2 normalization on all the model parameters $\Theta$ to alleviate overfitting.

### 3.5 Discussion on Complexity

PICO only incorporates an additional auxiliary network to learn the task relevance, which is merely used for model training. In this way, high efficiency is guaranteed without incurring any extra memory cost during the inference stage. In terms of time complexity, most of the additional computation comes from the proposed inter-task contrastive objective. Suppose the training batch size is set to $B$ then the time complexity of the contrastive learning can be roughly estimated as $O(B^2d)$, where $d$ is the dimension of embedding vector. As $B$ is usually small (1024 or less), the additional time cost is affordable at training. By the way, the additional computational cost is also eliminated at inference.

### 4 Experiments

To evaluate the effectiveness of the proposed PICO, we conduct extensive experiments on both public dataset and industrial dataset. Then, we further deploy it on real advertising system to conduct A/B test.

#### 4.1 Datasets

We conduct the offline experiments on two industrial datasets. The first one is Ali-CCP (Ma et al. 2018b) which is a public dataset with 23 categorical features. We follow the original training/test splitting. The second dataset, Ecomm-Ads, is collected from a large-scale advertising system for online shopping. We collect the users’ feedbacks for 8 days and the model is trained on the data of first seven days and tested on the data of last day. The dataset contains over one hundred categorical features and three behaviors (e.g., click, view and conversion). The statistics of two experimental datasets are listed in Table 1.

| Dataset   | #impression | #click | #view | #conversion |
|-----------|-------------|--------|-------|-------------|
| Ali-CCP   | 85 M        | 3.3 M  | -     | 18 K        |
| Ecomm-Ads | 0.7 B       | 20 M   | 8.7 M | 1.1 M       |

### 4.2 Evaluation Metrics

We adopt two widely used metrics, Area Under ROC Curve (AUC) and group AUC (GAUC) (He and McAuley 2016), for all the offline experiments. AUC indicates the probability of ranking positive samples higher than negative samples. GAUC is the extended metric of AUC for recommendation or advertising where the samples are grouped based on user and the final score is the weighted average of the AUC scores on each user. It is defined as:

$$GAUC = \frac{\sum_{u} w_u \ast AUC_u}{\sum_{u} w_u},$$

where $AUC_u$ is the AUC score over the samples of user $u$ and $w_u$ is the weight for user $u$. We set all the weights to 1 in our experiments.

### 4.3 Compared Methods

We compare the proposed PICO with several state-of-the-art multi-task learning methods: (1) Single-DNN (Covington and Emre 2016) uses separate networks for different tasks. (2) Shared-Bottom (Caruana 1997) makes the embedding table and bottom MLP layers shared for multiple tasks and the upper MLP layers are individual. (3) Cross-stitch (Misra et al. 2016) introduces learnable weights between different networks to fuse the knowledge of each task. (4) MMoE (Ma et al. 2018a) utilizes several shared experts as the bottom layers and learns an attention gate for each task to guide the feature routing. (5) PLE (Tang et al. 2020) additionally divides the experts into both shared ones and independent ones to better retain the individuality of tasks. (6) AutoHERI introduces automated hierarchical representation integration between the individual networks.

### 4.4 Experimental Details

To ensure fair comparison, we fix the feature embedding size to 8 and $\lambda$ to 1 for all the methods. The network for each task is a three-layered MLP and we set the hidden sizes as [128, 64, 32] on Ecomm-Ads dataset and [64, 32, 16] on Ali-CCP dataset due to their different data scales. The number of experts is set to three for those expert-based methods and the first MLP layer is shared for other models. We use Adam optimizer with the batch size of 1024 and set the learning rate to 0.0005 consistently. For PICO, based on the performance, we adopt shared-bottom and MMoE as the backbone for Ali-CCP and Ecomm-Ads respectively. The hyper-parameter $\alpha$ and $\beta$ are set to 1 and 0.01 based on grid search. The lower and upper bound of $\tau$ is set to 0.05 and 1. And we use the output of first MLP layer as the task representations to contrast. All the models are trained for three times repeatedly and the average results are reported.

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3 GAUC is only reported on Ecomm-Ads dataset as it performs much similar as AUC on Ali-CCP dataset.
4.5 Overall Performance
The performance comparison of the proposed PICO and other baseline methods on two datasets is shown in Table 2. We find several insightful observations:

(1) Compared to Single-DNN that is trained with independent network for each task, all other multi-task learning methods gain some improvements on Conversion task. While the performance of Click task decreases slightly on both datasets. This situation is mainly due to the peculiarity of label skew (Ma et al. 2018b) in real-world advertising scenarios. The positive instances of Conversion task are extremely sparse compared to Click task (e.g., 183:1 on Ali-CCP dataset and 18:1 on Ecomm-Ads dataset). Therefore, the networks for Click task can be learned adequately and the introduction of Conversion task is meaningless. Generally speaking, the task with sparser data (e.g., Conversion) can obtain more benefits from the additional knowledge that introduced by other tasks. In this way, the effectiveness of multi-task learning is validated as Conversion is usually the final target in most of industrial scenarios (Wei et al. 2021).

(2) Among the multi-task learning baselines, we find that MMoE performs best on Ecomm-Ads dataset which shows the effectiveness of expert routing mechanism in controlling the feature integration for multiple tasks. However, Shared-Bottom and Cross-stitch perform better on Ali-CCP dataset. A possible reason is that those expert-sharing methods have complex parameters to control the routing, which can not be well optimized with limited data. Especially in PLE, the CVR-specific experts and gates can not be well-trained as the supervised signals of Conversion task are deficient.

(3) Finally, as for PICO, we can observe comparable results on Click task and significant improvements on Conversion task compared to baseline methods (increasing over 0.1 is significant for advertising). The superiority of PICO is consistent over two datasets. The advantage is mainly brought by the inter-task contrastive learning paradigm, which explicitly captures the potential shared knowledge across tasks to help the representation learning for the task of Conversion. Furthermore, the learnable temperature parameters make the contrastive representation integration personalized at instance-level, which reduce the noise in naive task-level regularization. In addition, our method gains more improvement on sparser dataset (e.g., Ali-CCP) which points out the great potential of contrastive learning in multi-task scenarios.

4.6 Further Study
To give in-depth understanding of the proposed PICO, we conduct a series of detailed experiments to analyse the effectiveness. We only report the results on Ecomm-Ads dataset as it has extensive data and features.

Ablation Study. There are several components in the proposed PICO. To study the effectiveness of each parts, we compare our method with four variants: (1) The variant that removes personalized temperature parameter and fix the $\tau$ to 0.05 for all the instances. (2) The variant that removes learnable temperature parameter and set $\tau$ based on statistical relevance. (3) The variant that removes the negative samples in contrastive learning and only optimize the dot product between positive samples. (4) The variant that removes the contrastive learning completely. Their results are reported in Table 3. Through the comparison, we can find that learning personalized temperature is a significant strategy for inter-task contrastive learning, which distinguishes data instances by the relevance of labels to make fine-grained representation integration. Besides, it has shown that simply optimizing the distance between task representations without negative samples yields a large performance drop, which further validates the effectiveness of contrastive learning paradigm.

Choice of task representation $h$. In the proposed method, the task representations are generated by the individual MLP networks. To study how PICO performs when contrastive learning is conducted on different choices of task representations, based on the model that only shares embedding table, we select the output hidden vector of the first, second and third MLP layer as the task representation to conduct the proposed personalized contrastive learning. The results are shown in Figure 3 which show that the performance on Conversion task drops gradually when we select the outputs of higher layer to contrast. Similarly, the performance on click task is damaged severely when we contrast the outputs of third layer. It is suggested that we should preserve some task-independent parameters to capture the speciality of different tasks and achieve knowledge integration between the bottom layers for more benefits.

Applying PICO with different Backbones. As our method is model-agnostic, we further apply it with different backbones for generalization. The results are reported in Table 4. We can observe that the proposed method can outperform the base model consistently which further indicates the feasibility and applicability of our framework. Moreover, compared to MMoE, the relative improvement on PLE is more significant on Conversion task. The possible reason is that PLE has less shared parameters which can not be well optimized without the proposed contrastive objective.

Performance on More Tasks. To verify the consistency of improvement on more than two tasks, we jointly consider three tasks of Click, View and Conversion on Ecomm-Ads dataset. Based on our experience and experimental results, the contrastive learning is only conducted between Click and other tasks. The experimental results on three tasks are shown in Figure 4. In the figure, we can find that the performance of PICO is consistently better than other baselines.
Table 2: Experimental results on Ali-CCP and Ecomm-Ads datasets where the best one is bolded and the runner-up is underlined. Our proposed method performs best on Conversion task and comparably on the Click task.

| Model        | Click AUC | GAUC AUC | Conversion AUC | GAUC AUC |
|--------------|-----------|----------|----------------|----------|
| PICO         | 83.667    | 78.286   | 87.569         | 83.285   |
| w/o personalized τ | 83.659 | 78.266 | 87.493 | 83.283 |
| w/o learnable τ | 83.637 | 78.221 | 87.381 | 83.083 |
| w/o negative | 83.628 | 78.175 | 87.344 | 82.987 |
| w/o contrastive | 83.670 | 78.249 | 87.326 | 83.034 |
| MMoE         | 83.642    | 78.256   | 87.393         | 83.008   |

Table 3: Performance comparison of different variants. Each component is indispensable in PICO.

| Model        | Click AUC | GAUC AUC | Conversion AUC | GAUC AUC |
|--------------|-----------|----------|----------------|----------|
| Shared-Bottom | 83.622   | 78.219   | 87.354         | 83.027   |
| +PICO        | 83.642    | 78.229   | 87.557         | 83.265   |
| MMoE         | 83.642    | 78.256   | 87.393         | 83.006   |
| +PICO        | 83.667    | 78.286   | 87.569         | 83.285   |
| PLE          | 83.660    | 78.265   | 87.188         | 82.798   |
| +PICO        | 83.652    | 78.255   | 87.515         | 83.329   |

Table 4: Performance comparison w.r.t. different backbones on all the tasks. The task of View has denser labels compared to Conversion, which brings more useful knowledge for Click task. Therefore, we can conclude that PICO can consistently improve the performance when there are more tasks with comparable data scale.

### 4.7 Online A/B Test

We test PICO in our online advertising system for one week. Table 5 reports the relative improvements on CTR, CVR and cost-per-conversion(CPC) compared to the current online model. The superiority of PICO is consistent over all metrics, validating the effectiveness for industrial deployment. Moreover, the improvement on CVR is more significant which discloses the ability of PICO in promoting the performance of difficult task.

| Method | CTR↑ | CVR↑ | CPC↓ |
|--------|------|------|------|
| PICO   | +2.37% | +4.82% | -5.78% |

Table 5: Relative improvements in online A/B test. The lower the CPC, the better the performance.

Figure 4: Performance comparison of PICO, Shared-Bottom (SB for short) and MMoE on three tasks. The results of AUC and GAUC are plotted at upper and lower, respectively.

**5 Conclusion**

In this work, we introduce Personalized Inter-task COntрастive Learning (PICO), a novel contrastive learning framework for multi-task learning that aims to achieve implicit knowledge integration between tasks. We propose that, as opposed to designing hard or soft sharing architecture, the representations in the top task-specific networks can be contrasted. Furthermore, we enhance the basic InfoNCE objective with customized temperatures to capture fine-grained relevance between tasks. It is learned for each instance to regulate the degree of contrastive learning. The effectiveness and applicability of the proposed approach are demonstrated by extensive offline experiments on large-scale datasets and online A/B tests on industrial advertising systems.
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