Hierarchical Multi-agent Meta-Reinforcement Learning for Cross-channel Bidding

Shenghong He, Chao Yu*, Qian Lin, Shangqin Mao, Bo Tang,
Qianlong Xie, Xingxing Wang

Abstract—**Real-time bidding (RTB) plays a pivotal role in online advertising ecosystems. Advertisers employ strategic bidding to optimize their advertising impact while adhering to various financial constraints, such as the return-on-investment (ROI) and cost-per-click (CPC). Primarily focusing on bidding with fixed budget constraints, traditional approaches cannot effectively manage the dynamic budget allocation problem where the goal is to achieve global optimization of bidding performance across multiple channels with a shared budget. In this paper, we propose a hierarchical multi-agent reinforcement learning framework for multi-channel bidding optimization. In this framework, the top-level strategy applies a CPC constrained diffusion model to dynamically allocate budgets among the channels according to their distinct features and complex interdependencies, while the bottom-level strategy adopts a state-action decoupled actor-critic method to address the problem of extrapolation errors in offline learning caused by out-of-distribution actions and a context-based meta-channel knowledge learning method to improve the state representation capability of the policy based on the shared knowledge among different channels. Comprehensive experiments conducted on a large scale real-world industrial dataset from the Meituan ad bidding platform demonstrate that our method achieves a state-of-the-art performance.**

Index Terms—**Multi-channel Bidding; Hierarchical Learning; Reinforcement Learning; Multi-agent Learning; Diffusion Models; Meta Learning**

I. INTRODUCTION

Real-Time Bidding (RTB) [1], [2] is a programmatic advertising mechanism where advertisers participate in bidding through automated platforms when a user visits a webpage, securing the opportunity to display ads on the page through either a first-price auction [3] or a second-price auction [4]. In RTB, advertising platforms formulate a bid request for every individual impression (i.e., display page) in real-time, and then advertisers submit bids for this impression utilizing their bidding algorithms. The bidding algorithms commonly assist in bid determination by considering factors in the users' preferences, requirement information, and other relevant issues, aiming to improve the revenue of the advertising platform (typically linked to user clicks) while at the same time adhering to constraints such as budget, cost-per-click (CPC) and return on investment (ROI), where CPC reflects the cost

Shenghong He, Chao Yu and Qian Lin are with the School of Computer Science and Engineering, Sun Yat-sen University, Guangzhou 510006, China (e-mail: yuchao3@mail.sysu.edu.cn)

Bo Tang is with the School of Artificial Intelligence and Data Science, University of Science and Technology of China. Hefei 340101, China

Shangqin Mao, Qianlong Xie, and Xingxing Wang are with Meituan, Beijing 100102, China.

per ad click, and ROI is a measure of return on advertising investment.

An increasing number of advertising platforms have introduced automated bidding services in various ad settings, including recommendation ads (i.e., ads suggesting products to potential users) [5], [6], search ads (i.e., ads presented in response to user search queries) [7], [8], and others [7], [9]. These ad settings typically involve multiple advertising channels, each of which corresponds to a specific medium or user-customized service for ad delivery. However, most existing studies only focus on **single-channel settings** where the bidding strategy is applied to a single channel to improve bidding performance therein [10]–[12]. Unlike single-channel bidding, in cross-channel bidding, advertisers can bid on multiple advertising channels at the same time, which requires the bidding algorithm to take into account diversities in user characteristics and behaviors of different channels, and calls for more complex budget allocation and management strategies to ensure efficient and effective budget utilization across different channels. Some studies [13], [14] have attempted to address the cross-channel bidding problem using single-channel methods. However, they have not considered the issues of channel budget allocation or interconnections between channels, which are critical in determining the final performance. In this paper, we focus on **cross-channel bidding settings** where the goal is to achieve global optimization of bidding performance across multiple channels with a shared budget (i.e., the objective is to maximize the benefits for advertisers and advertising platforms while enhancing the user's overall client experience).

In this setting, there exist two main challenges to be addressed. The first is **the dynamic allocation of budgets among different bidding channels**. A straightforward solution to this challenge is to share the total budget as a whole across different channels or allocate budgets to each channel based on a preset ratio. However, as the optimal pairing between channels and advertisers can evolve over time, such a static allocation scheme may yield myopic budget allocations and thus lead to suboptimal performance. Therefore, a better solution is to allocate the total budget dynamically to different channels based on the real-time information of channels and markets. The second challenge is **the utilization of cross-channel interrelationships for efficient bidding decision making within each channel**. In the cross-channel setting, an effective bidding strategy should not only consider the characteristic of each channel but also incorporate bidding information from other channels to achieve global maximiza-

tion of bidding performance. By harnessing their inherent relationships and knowledge sharing across various channels, it is capable of learning more efficient bidding strategies, particularly for those channels with only low customer traffic and thus limit data for training.

To tackle the above challenges, we propose a novel reinforcement learning (RL) approach called **H**ierarchical **M**ulti-agent **M**eta-reinforcement Learning for **C**ross-channel **B**idding (HMMCB) to solving the cross-channel bidding problem under a hierarchical RL framework. In HMMCB, the top-level strategy focuses on dynamically allocating budgets to each channel, while the bottom-level strategy centers on making bidding decisions by utilizing cross-channel interrelationships under the given budget constraint. In specific, **at the top level**, budget allocation to multiple channels is determined by solving an optimization problem that maximizes user clicks at the bottom level while satisfying the CPC constraint provided by users. However, accurate budget allocation based on channel characteristics is a difficult problem for the top-level strategy, particularly when dealing with complex channel distributions (i.e., the customer traffic varies in different channels at different times). To this end, a CPC-constrained diffusion budget allocation model is proposed by incorporating an additional CPC-based loss into the optimization objective of diffusion regularization methods, in order to satisfy the CPC constraint during the budget allocation learning process. The CPC-constrained diffusion model offers several advantages: (1) it can capture the multi-modal distribution of budget allocations in dynamic environments, particularly in RTB, where advertiser budgets, market conditions, and customer traffic fluctuate significantly over time; and (2) it can incorporate value function maximization and CPC constraints at each reverse diffusion step to enable more effective budget allocation.

At the bottom level, we first propose a novel offline RL approach, namely the state-action decoupled actor-critic method, which learns a state policy to predict the optimal next state and an action policy to infer the action given the predicted next state. In this way, we can decompose the state-action learning in the original task into state learning and action learning, and conduct these two learning processes independently in a supervised manner, thereby avoiding the extrapolation error problem caused by out-of-distribution actions in traditional offline RL. Moreover, to leverage cross-channel information to improve bidding strategies and mitigate the potential data scarcity problem, we propose a context-based meta-channel knowledge learning method by introducing a channel-shared meta learning objective that extracts the shared knowledge from different channels to learn a more generalizable channel representation. Finally, formulating the bidding strategies for different channels as a multi-agent RL problem, we utilize a central value function based on the observations from all channels to achieve global maximization of bidding performance. The main contributions of this paper are as follows:

- We provide a formal RL formulation for the problem of cross-channel bidding with a shared budget, and propose a novel solution HMMCB to optimize cross-channel bidding decisions with dynamic budget allocations from

a hierarchical and multi-agent perspective.
- We propose a state-action decoupled actor-critic method in offline RL and a knowledge-sharing context-based learning method in meta RL, in order to utilize the cross-channel interrelationships for efficient bidding decision making within each channel.
- Empirical results from offline evaluation and online A/B tests on a large scale realistic ad bidding platform prove the superiority of HMMCB over state-of-the-art methods.

II. RELATED WORK

A. Bidding Optimization in RTB

The objective of bidding optimization is to determine the appropriate bid price for each impression presented in the auction to achieve total revenue maximization. Perlich et al. [15] first introduce a linear bidding strategy based on ad impression evaluation, which has been widely adopted in real-world applications. Zhang et al. [16] and Wang et al. [17] propose bidding optimization approaches based on the nonlinear relationships between optimal bids and ad impression evaluation. In addition, many works model bidding optimization from a sequence decision perspective and solve it using RL methods [10], [18]–[20]. Cai et al. [10] utilize an MDP framework to sequentially allocate budget based on real-time impressions. Wang et al. [12] develop a course-guided Bayesian reinforcement learning (CBRL) framework to adaptively balance the multiple constraints in a non-stationary advertising market. Tunuguntla et al. [19] propose a multi-period dynamic programming model to provide advertisers with the optimal combination of generic and brand bids for search ads.

Most existing studies concentrate on bidding optimization under single-channel setting and cannot be directly applied on scenarios where there are multiple ad channels with significant quality differences. On this basis, some studies [13], [14], [21]–[23] have developed methods for allocating budgets across multiple advertising channels under total budget constraints via model-base RL or influencer probabilistic modeling. However, these methods require an accurate distribution estimation of bidding results, such as the expected number of clicks, and overlook the interconnections between different channels, which restricts their applicability. Moreover, Jin et al. [23] address bidding optimization across various channels through multi-agent reinforcement learning. However, they adopt a budget allocation scheme that shares the total budget as a whole across different channels, which can lead to a greedy budget allocation and thus globally suboptimal performance. While wen et al. [13] investigate the competition and cooperation relation among auto-bidding agents and propose a temperature-regularized credit assignment to establish a mixed cooperative-competitive paradigm, they did not consider the issue of channel budget allocation. Wang et al. [14] employ λ-generalization to adapt to budget changes across different channels, treating each channel as an independent agent and aiming to achieve global optimality through individual optimal values. However, the assumption that channels will not affect each other does not hold in multi-channel advertising bid

setting, thus limiting its performance. Unlike previous works, we utilize each channel's characteristics and interrelationship information across multiple bidding channels to achieve dynamic budget allocation and optimal bidding decisions.

B. RL

Offline RL allows for the learning of effective policies solely from pre-existing data, thus avoiding potential risks induced by online interactions. However, offline RL encounters well-known distribution shift challenges [24], which is typically attributed to evaluation of actions that do not exist in the offline dataset (i.e., out-of-distribution actions) during policy learning. To mitigate this problem, recent studies have proposed several policy regularization methods that force the learned policy to stay close to the behavior policy by equipping policy optimization objective with various regularizers, including different divergence penalties [25]–[27], implicitly weighted behavior cloning [28], [29], or reconstruction loss of the generative policy model [30], [31]. In contrast to directly regularizing the learned policies, an alternative approach is to incorporate behavioral regularization into value estimation objective, encouraging adherence to the behavioral distribution through a conservative value estimate towards unseen state-action pairs [32], [33].

The above methods require the setting of complex regularization terms to ensure the effectiveness of strategy learning, which becomes challenging for cross-channel advertising bidding platforms with diverse distribution changes (i.e., customer traffic, ad format and advertising request time). Our method is a simpler regularization method that decouples the process of learning behavior policy into state learning and action learning, which adopts an imitation-style manner to train the state policy and action policy. By doing so, our method can model state-state correlation, rather than state-action correlation in previous work, which avoids the extrapolation errors of evaluating out-of-distribution actions.

Meta RL equips agents with the capability to quickly adapt to novel tasks through training on a diverse task distribution. Optimization-driven methods [34], [35] are one type of the most widely-studied approaches to achieve this goal, which formalizes the task adaptation process by employing policy gradients over a limited set of few-shot samples, thereby acquiring an optimal policy initialization. In addition, context-based Meta RL methods [36], [37] model the meta-learning problem as a partially observable Markov decision process (POMDP), where the task information is viewed as hidden components of states and extracted from historical trajectories.

The above methods focus on the distribution mismatch between offline data and online exploration data, and require additional online exploration. Unlike them, we consider using entirely offline data to learn channel common knowledge representation and leverage this common knowledge to enhance the learning effectiveness of the strategy.

III. PRELIMINARY

A. Reinforcement Learning

A reinforcement learning (RL) problem is a sequential decision-making problem, which is generally modeled as
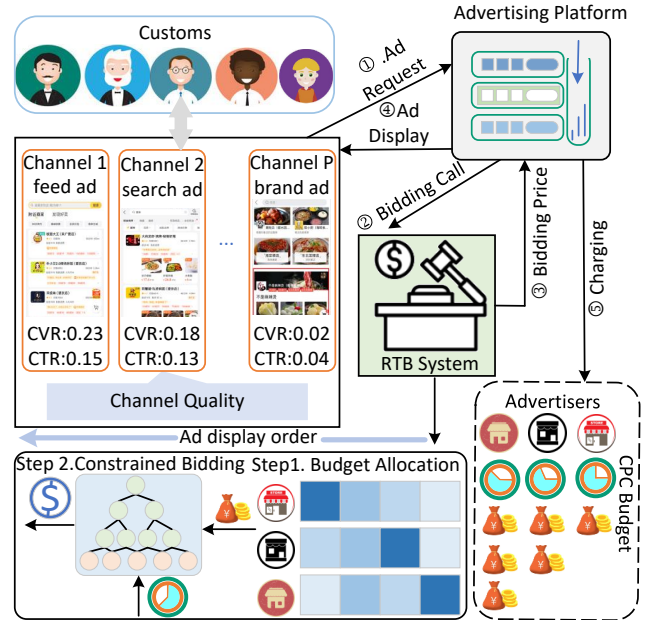

Fig. 1. An overview of the Meituan advertising system. Advertising platforms need to bid on different channels based on the budget and constraints of merchants. CTR and CVR represent average click-through rate and conversion rate respectively.

a Markov Decision Process (MDP) represented by a tuple $(S, A, \mathcal{P}, R)$, where S is the state space of the environment with each state $s \in S$ representing a unique situation within the environment, A denotes the set of all actions that an agent can take within the environment, $R : S \times A \to \mathbb{R}$ is the numerical reward obtained as a result of a particular action taken within a specific state, and $\mathcal{P} : S \times A \to [0, 1]$ is the probabilistic transition function that captures the impact of an action on the future state, where $s_{t+1} \in S$ is the next state that is observed after taking action $a_t \in A$ in a given state $s_t \in S$ at a time step t. The agent takes actions according to a policy $\pi : S \times A \to [0, 1]$, which maps the states to a probability distribution over actions. The goal of RL is to learn a policy π that maximizes the expected total reward in the environment:

$$\max_{\pi} J(\pi) = \max_{\pi} \mathbb{E}_{\mathcal{P}, \pi} \left[\sum_t R(s_t, a_t) \right] \qquad (1)$$

In the offline RL setting where online interactions are inaccessible [25], [27], [32], the goal is to maximize the expected total reward using only the offline dataset $D = \{(s_t, a_t, s_{t+1}, r_t)\}_{t=1}^{T}$ collected by a behavior policy. Training a policy that outperforms the behavior policy using historical data often entails querying the value function of the actions that were not seen in the dataset (i.e., out-of-distribution actions). These actions can be viewed as adversarial examples for the Q function [38], leading to an extrapolation error of value estimation.
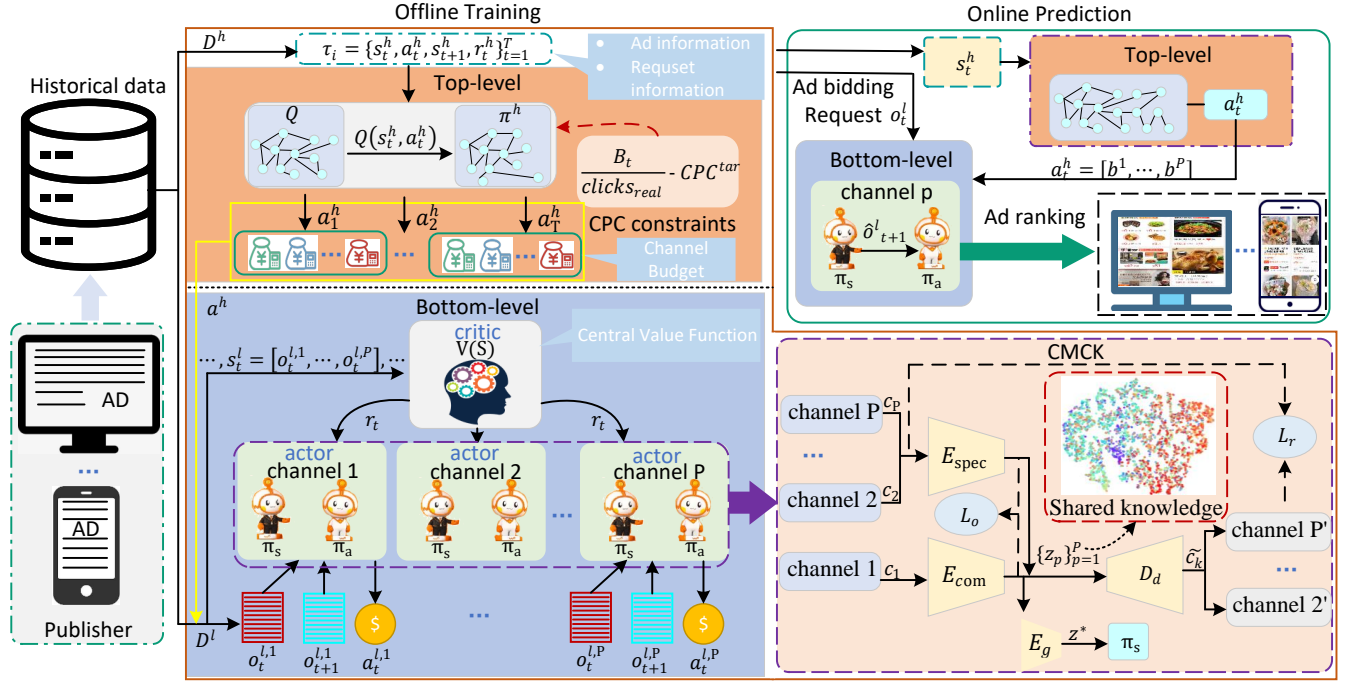
Fig. 2. The HMMCB framework.

B. Meituan Cross-channel Budget Sharing Ad System

Boasting over 400 million users and 66 million merchants, Meituan[1] is one of China's largest ad bidding platforms for online services including food delivery, hotel and travel et al., which handles an average of more than 100 million impression requests every day. The overall process of Meituan advertising system is shown in Fig. 1. When receiving an advertising impression request, the advertising platform sends a bidding call to the RTB system. The RTB system then supports advertisers in determining a bidding price for this impression based on the real-time information of each channel as well as the budgets and bidding constraints specified by advertisers. After that, the advertising platform shows ads from the winning bidding groups and deducts the respective bid amounts from their budgets (i.e., the displayed advertiser will be charged the price of the second highest bid in this ad auction). Finally, this advertiser will receive revenue if a consumer clicks on the ad and makes a purchase.

A significant feature of the Meituan ad system is that advertisers can place ads on one or more channels with a shared total budget that is updated every day. Because ad requests arrive at different times for each channel, the channel that receives the earliest ad request will send the ad bid. With a sufficient budget, advertisers often bid above the actual bidding price to get the ad slot, particularly for recommended and brand ads that do not require user activation. However, this may result in advertisers not having enough funds to invest in other channels (e.g., the search ad channel) later in the day, causing them to miss out potential users and ultimately reducing the revenue. While allocating a budget for each individual channel can address this issue, the complexity

arises from varying budget requirements based on channel characteristics and the need for different budget amounts at different times due to the fluctuating customer traffic.

In addition, making optimal bidding decisions in cross-channel bidding requires considering information from multiple channels. For example, consider two advertisers, A and B, bidding on two channels, C_1 and C_2. Assume that A can successfully bid on both channels, while B can only succeed on C_2 when A is not bidding, and the advertising revenue for A from C_1 significantly outweighs that from C_2. In a scenario where C_1 and C_2 initiate ad bidding simultaneously, if A wins bids on both channels, B loses the opportunity to display ads on C_2, resulting in decreased revenue. Conversely, if A bids only on C_1 and B on C_2, both A and B can obtain corresponding revenues. Thus, effective bidding strategies should consider not only the characteristics of each channel but also the combined bidding information of multiple channels in order to achieve optimal decisions.

C. Optimization Objective

In this paper, our overall objective is to maximize total ad clicks while satisfying all advertisers' set budgets and CPC constraints, ensuring that the platform's revenue remains within an acceptable range. As shown in Fig. 2, our approach is divided into a top-level strategy and a bottom-level strategy. The goal of top-level strategy is to allocate budget to each channel while meeting the advertisers's total budget. Consider a scenario where M advertisers are served by a top-level strategy that allocates the budget of each advertiser to P channels. Each advertiser m provides a budget $\mathcal{B}_m$ to the advertising platform once a day, and then the top-level strategy allocates this budget to different channels to constrain the

bidding decisions therein. Formally, the objective of the top-level strategy can be expressed as follows:

$$\max_{b^p_{m,t}} \sum_{m=1}^{M} \sum_{P=1}^{P} \sum_{j=1}^{\mathbb{T}} \text{click}(b^p_{m,j})$$

$$\text{subject} \quad \text{to}: \sum_{p=1}^{P} \sum_{j=1}^{\mathbb{T}} b^p_{m,j} \leq \mathcal{B}_m, \forall m \in \{1, 2, \cdots, M\} \quad (2)$$

$$\text{and} \quad CPC^{real}_m \leqslant CPC^{tar}_m,$$

where $b^p_{m,j}$ denotes the allocated budget on channel p for advertiser m at time j, $\text{click}(b^p_{m,j})$ represents the number of clicks given the budget $b^p_{m,j}$ at time j, while CPC^{real} and CPC^{tar}_m represent the actual CPC realized by the advertiser m and the CPC target set by the advertiser m, respectively. To avoid the abuse of symbols, we use b_j to represent the budget of an advertiser at time j across all channels. Table I shows a more detailed description of the symbols.

After receiving the budget allocation b from the top-level strategy, the bottom-level strategy then maximizes the number of clicks while satisfying the budget. Assume there are T ad requests on channel p during the time interval, the objective of the bottom-level strategy can be expressed as follows:

$$\max_{a^p_t} \sum_{p=1}^{P} \sum_{t=1}^{T} click(a^p_t)$$

$$subject \quad to: \sum_{t=1}^{T} cost(a^p_t) \leq b^p, \quad \forall p \in \{1, \cdots, P\}, \quad (3)$$

where $cost(a^p_t)$ denotes the actual cost, $b^p \in b$ represents the budget of channel p, and $click(a^p_t)$ indicates whether the user has clicked the ad after giving a bidding price a^p_t. Note that, at the bottom-level, we take the number of ad requests as $\mathbb{T}$. Hence, t represents both the number of ad requests and the time instance for the bottom-level strategy.

IV. METHOD

The overall framework of HMMCB is shown in Fig. 2. During **the offline training process**, the top-level strategy applies the *CPC-constrained diffusion budget allocation method* to achieve dynamic budget allocation among the channels while satisfying the CPC constraint, and the bottom-level strategy utilizes the *state-action decoupled actor-critic method*, *context-based meta-channel knowledge learning method* and *multi-agent RL training scheme* for offline RL, cross-channel knowledge sharing and cross-channel bidding decision making, respectively.

During **the online prediction process**, the top-level strategy allocates the total budgets to each channel based on the global information from all channels. Meanwhile, the bottom-level strategy for a specific channel makes bidding decisions based on the allocated budgets and real-time channel information. Finally, the ads of the successful bidders will be displayed in the ad space of that channel.

TABLE I
IMPORTANT SYMBOLS AND EXPLANATIONS IN THIS PAPER

Notation	Explanation
M,m	total number, index of advertisers
P,p	total number, index of channel
$\mathbb{T}$,j	total number, index of time step
T,t	total number, index of ad request
ROI, CPC	return-on-investment, cost-per-click
D^h, D^l	top-level and bottom-level datasets
$s,\hat{s}$	top-level and bottom-level global observation (state)
$\mathcal{O},b,g$	local observation (state), action, reward of time j in top-level MDP
O,a,r	local observation (state), action and reward of ad request t in bottom-level MDP
B	total budget
Q_ϕ, π_θ	top-level Q network and policy network
V_ϕ, π_s, π_a	bottom-level V network, state and action policy network

A. Top-level Strategy for Dynamic Budget Allocation

1) MDP formulation for budget allocation. The top-level MDP for each advertiser m is formulated as a tuple $(\mathbb{S}, \mathbb{B}, \mathbb{P}, \mathbb{R}, \gamma)$, where $\mathbb{S}$ is the state space, $\mathbb{B}$ denotes the action space, $\mathbb{P}$ indicates the state transition function, $\mathbb{R}$ represents the reward function, and γ is the discount factor.

- **State** $\mathbb{S}$: the $s \in \mathbb{S} = \{\mathcal{O}^1, \cdots, \mathcal{O}^P\}$ contains the state of each channel, where $\mathcal{O}^p$ denotes the state space of the p-th channel, which comprises the advertiser allocated budget and historical statistics (e.g., the user-preferences, average click-through rate (CTR) and conversion rate (CVR)). Note that an advertiser might engage in bidding activities exclusively in specific channels, with some channels lacking information related to this advertiser. To maintain data consistency and training stability, we employ zero tensors of identical dimensionality to supplement s.
- **Action** $\mathbb{B}$: the $b \in \mathbb{B}$ encompasses the budget for each individual channel, where b^p represents the budget allocated to channel p. We discretize the action using the percentage of the budget and mask invalid actions that exceed the total budget.
- **Reward** $\mathbb{R}$: the reward $g \in \mathbb{R}$ is calculated as the sum of the number of user clicks across all channels within a given time interval.

According to the above formulation, we obtain offline data $D^h = [\tau_1, \tau_2, \cdots, \tau_N]$ from the bidding log, where $\tau_i = \{s_j, b_j, g_j\}_{j=1}^T$ [2] denotes an offline trajectory.

2) CPC-constrained diffusion model for dynamic budget allocation. Multi-channel advertising bidding is a dynamic environment with tens of thousands of advertisers and customers participating at every moment. In this scenario, the policy must be expressive and accurately capture the multi-modal distribution [31] to dynamically allocate an appropriate budget for each channel. To achieve this, we employ a policy regularization method that utilizes a diffusion model in the action space, forming a conditional diffusion model

---

[2]We set $T = 7$ in compliance with the Meituan system, corresponding to a week of advertising bidding activities

conditioned on states [31], [39], [40]. In specific, the top-level strategy is expressed through the inverse process of a conditional diffusion model, denoted as:

$$\pi_\theta(b|s) = p_\theta(b^{0:\mathcal{I}}|s)$$
$$= \mathcal{N}(b^{\mathcal{I}}; 0, I)\Pi_{i=1}^{\mathcal{I}} p_\theta(b^{i-1}|b^i, s), \quad (4)$$

where the end sample of the reverse chain (i.e., $b = b^0$) is the action used for RL, $i \in \{0, \cdots, \mathcal{I}\}$ denotes the diffusion timestep, and $\mathcal{N}$ represents Gaussian distribution. To train the conditional model, we follow the simplified objective set by DDPM [40] and Diffusion-QL [31] as follows:

$$L_{simple}(\theta) := \mathbb{E}_{i\sim\mu,\epsilon\sim\mathcal{N}(0,1),(s,b)\sim D}[||\epsilon-$$
$$\epsilon_\theta(\sqrt{\bar{\alpha}_t}b + \sqrt{1 - \bar{\alpha}_i}\epsilon, s, i)||^2]. \quad (5)$$

Thus,

$$\pi^h = \underset{\pi_\theta}{argmax}\, \mathcal{L}(\theta)$$
$$= L_{simple} - \alpha \cdot \mathbb{E}_{s\sim D^h, b^0\sim\pi_\theta}[Q_\phi(s, b^0)], \quad (6)$$

where ϵ is a random variable, α is a hyperparameter, and Q is the Q-value network for policy evaluation.

While maximizing returns (clicks) may expand the potential customer groups, there is a risk of running out the advertising budget rapidly if the CPC becomes excessively high. By setting a CPC constraint, advertisers can better control their advertising budget, ensuring the sustainability of their advertising bidding. However, although the use of hard constraints [41] can force the policy to stay within the CPC constraints set by the advertiser, it may also encounter the problem that no feasible policies can be found to meet the constraints, thus impacting the final learning efficiency and performance. To avoid this challenge, we transform the CPC constraint into a variance loss and incorporate a reverse diffusion chain during the training phase. Assuming that all bottom-level strategies are fully capable of conducting bidding activities in accordance with the budget allocated by the top-level strategy, the actual CPC^{real} can be expressed as:

$$CPC^{real} = \frac{\sum_{p=0}^P (b^p)}{g}. \quad (7)$$

If we consider CPC^{real} as the output label and CPC^{tar} as the target label, the *CPC* constraint problem can be simplified into a linear regression problem and thus be optimized using the mean square errors of CPC^{tar} and CPC^{real} as:

$$L_{\text{CPC}} = \frac{\sum_{m=1}^M (CPC^{tar} - CPC^{real})^2}{M}. \quad (8)$$

Equation (8) can be approximated as a soft constraint [42], which ensures that the diffusion policy can maximize the exploration around the CPC^{tar} by minimizing the variance of the advertiser's CPC constraint. Finally, the ultimate policy-learning objective comprises a linear combination of policy regularization, CPC constraint and policy enhancement components, as follows:

$$\pi^h = \underset{\pi_\theta}{argmax}\, \mathcal{L}(\theta)$$
$$= L_{simple} + L_{\text{CPC}} - \alpha \cdot \mathbb{E}_{s\sim D^h, b^0\sim\pi_\theta}[Q_\phi(s, b^0)]. \quad (9)$$

The procedure for offline training of the top-level algorithm is delineated in Appendix II.

B. Bottom-level Strategy for Cross-channel Bidding

1) Bottom-level MDP for cross-channel constrained bidding. Since each request t only affects the cost of a specific channel p, we model each channel separately and represent it as a tuple(S, A, P, R, γ).

- **State** O: the $o \in O$ state contains the allocated budgets b^h, bidding requests, and advertiser information, where the bidding request comprises the request time and current advertising status (e.g., the budget consumption rate and the ratio of financial constraint satisfaction), while the advertiser information is identical to the state of the top-level strategy ($\mathcal{O}$).
- **Action** A : the $a \in A$ is a bidding ratio, and the final bidding price is calculated using $a_t \times CPC_m^{tar}$. Note that $a \in [\xi_{min}, \xi_{max}]$, while ξ_{min} and ξ_{max} have various values in different channels.
- **Reward** R: the $r \in R$ represents the number of user clicks on the ad. For each request t, if the bidding is successful and the user finally clicks the ad, the reward $r_t \in \{0, 1\}$ is set to 1. However, because using clicks as a reward may lead to costs exceeding a budget of the channel, we introduce a budget constraint

$$c_t = cost(a_t) - b^p, \quad (10)$$

which ensures to maximize ad clicks while keeping the costs within predefined budget limits. Finally, the bottom-level reward is defined as follows:

$$r_t = click(a_t) - c_t. \quad (11)$$

According to the above formulation, we obtain offline data $D^l = [\tau_1, \tau_2, \cdots, \tau_N]$ from the bidding log, where $\tau_i = \{o_t, \cdots, o_t^P, a_t, \cdots, a_t^P, r_t, \cdots, r_t^P\}_{t=1}^T$ [3] denotes an offline trajectory for bottom level strategy learning.

2) State-action decoupled actor-critic for bidding strategy learning. In advertising bidding systems where users can freely participate and exit, existing works face challenges in addressing the problem of out-of-distribution actions because the data distribution of bidding logs cannot cover the true bidding data distribution. We propose the state-action decoupled actor-critic method to overcome this problem by training a state value function, denoted as $V(o) : O \to \mathbb{R}$, that only uses the samples without information of actions, i.e., (o_t, o_{t+1}), to evaluate and predict the optimal next state, and an action policy, denoted as $\pi_a(o_t, o_{t+1}) : O \times O \to [\xi_{min}, \xi_{max}]$, to infer the action given the predicted next state.

In order to approximate the optimal value function, we use the asymmetric least squares method from recent research [43], [44], which involves applying an l_2 loss with a different weight using expectile regression, resulting in the following asymmetric l_2 loss function:

---

[3] T represents the total number of ad requests from the start to the end of a day's bidding, which varies from day to day

$$\max_{\phi} \mathbb{E}_{(o_t, r, o_{t+1}) \sim D}[L_2^{\varrho}(r + \gamma V'(o_{t+1}) - V(o_t)],$$
$$where \quad L_2^{\varrho}(\mu) = |\varrho - \mathbb{1}(\mu \leq 0)|\mu^2. \tag{12}$$

When $\varrho = 0.5$, the operator simplifies to the Bellman expectation operator, whereas when $\varrho = 1$, the operator increasingly resembles the Bellman optimality operator. Note that our learning objectives are similar to IQL [43], but our goal is to learn the state value function, which avoids evaluating state−action pairs that are not present in the dataset (i.e., extrapolation errors).

Simply maximizing the state policy π_s with respect to V can lead to the state policy overlooking the logical coherence between pairs of states (i.e., it is not possible to reach the next state from the current state), which can hinder the action policy π_a from making correct decisions. To mitigate this potential issue, a behavior cloning term is incorporated into the learning objective of the π_s as follows:

$$\max_{\omega} \mathbb{E}_{(o_t, o_{t+1} \sim D^l)}[log \pi_s(o_{t+1}|o_t) + \lambda \cdot V(\pi_s(o_t))], \tag{13}$$

where λ is a hyperparameter for balancing behavior cloning and value guidance, while ω is the network parameter of π_s.

During the training phase, the action policy π_a performs supervised learning by maximizing the likelihood of the actions given the states and next states, yielding the following objective:

$$\max_{\theta} \mathbb{E}_{(o_t, a_t, o_{t+1}) \sim D^l}[\log \pi_a(a_t|o_t, o_{t+1})], \tag{14}$$

where θ represents the network parameter of π_a. During the evaluation phase, the state policy π_s generates an optimal next state based on the current state, and π_a takes action based on the current and next state as:

$$a_t = \arg\max_{a_t} \pi_a(a_t|o_t, \pi_s(o_t)). \tag{15}$$

3) Context-based meta-channel knowledge learning for cross-channel bidding. Within the framework of the multi-channel advertising bidding system, each channel exhibits unique characteristics such as different customer types, various advertisement formats (e.g., video and text ads), and distinct ROI metrics. Provided there is sufficient training data, we can learn effective bidding strategies directly based on the information of each channel. However, the historical data distribution of channels with sparse customer traffic could greatly differ from the real data distribution (i.e., the data scarcity problem), which causes the policy to converge towards the local rather than the global optimal. To solve this problem, we propose a context-based meta-channel knowledge learning method (the **CMCK** component shown in the right corner of Fig. 2), which uses the context-based meta-RL to learn generalizable representations of different channels while transferring common knowledge across channels to facilitate the learning efficiency in each channel.

Specifically, CMCK comprises a **task-infer module** and a **policy learning module** that are trained in two phases. First, the task inference module is trained to encode shared knowledge across channels using two distinct encoders, namely common encoder E_{com} and specific encoder E_{spec}. The encoder

E_{com} is used to encode the information that is shared across the channels, while E_{spec} is employed to encode the information of the task within the specific channel. Subsequently, the data are reconstructed by a decoder D_d to ensure the integrity of the shared knowledge. Then, in the policy learning module, the pre-trained encoder E_{spec} is employed to extract the latent features of the data, and an aggregator E_g is used to aggregate all features to facilitate the learning of the state policy.

Assuming that the bidding data of p channels follow the distribution $\rho(\mathcal{T})$, we sample the batch context c_p (i.e., c_p represents bidding data at different times) of the current channel data $\mathcal{T}_p$ and another context c_k sampled from the other k channels $\mathcal{T}_k \in \mathcal{T} \setminus \{\mathcal{T}_p\}$. The task-infer module is comprised of $\tilde{c}_k = D(E_{com}(c_p) + E_{spec}(c_k))$ and $z = E_{com}(c_p)$, where $\tilde{c}_k$ represents the reconstruction of inputs c_p and c_k, while z symbolizes the shared knowledge. Let z_p and z_k denote the matrices of the features of c_p and c_k, respectively. The soft subspace orthogonality loss is used to facilitate the formation of distinct representations by the common and specific encoders within the latent space z as follows:

$$L_o = \|z_p^T z_k\|_F^2, \tag{16}$$

where $\| * \|_F^2$ represents the squared Frobenius norm. In addition, the reconstruction loss L_r is used to guarantee that the shared knowledge z_p is transferred between different channels:

$$L_r = \sum_{p=0}^{P} L_{smse}(c_k, \tilde{c}_k), \tag{17}$$

$$L_{smse}(c, \tilde{c}) = \frac{1}{n}\|c - \tilde{c}\|_2^2 - \frac{1}{n^2}((c - \tilde{c}) \cdot 1_n)^2, \tag{18}$$

where $\| * \|_2^2$ denotes the squared L_2-norm, n is the number of element in input c, and 1_n is the vector of ones of length n. The objective of the CMCK training process is to minimize the following loss concerning the parameters $\Theta = \{\theta_{com}, \theta_{spec}, \theta_d\}$:

$$L = L_o + \eta \cdot L_r, \tag{19}$$

where η is a weight hyperparameter.

When the state policy π_s is updated, CMCK expands the state s by potentially representing z^*, which improves the adaptability of policy π_s to effectively respond to changes across different channels.

4) Multi-agent training for cross-channel bidding. Training each channel strategy independently without considering their interconnections can lead to suboptimal results. To this end, we model the bottom-level strategy as a co-operative multi-agent to alleviate the local optimal problem of independent training channel strategy. Specifically, the bottom channel bidding can be viewed as a Partially Observable Markov Decision Process (POMDP) [45], [46] $\mathcal{G} = <N, \hat{S}, \hat{A}, \{R_i\}_{i \in P}, \mathcal{P}>$, where P represents the number of channels, $\hat{S} = [o^1, \cdots, o^P]$ denotes the joint state space, $\hat{A} = [a^1, \cdots, a^P]$ indicates the joint action space, $\mathcal{P} : S \times A \rightarrow S$ represents the transition function, and R_i

is the reward functions for channel strategy i. Our learning objective is:

$$\max_{\pi_{ent}} \mathbb{E}[\sum_{t=0}^{T} \gamma^t (R(o_t, a_t) - \mathcal{K}f(\pi_{ent}(a_t|o_t), \pi_{ent}^*(a_t|o_t)))], \tag{20}$$

where $\mathcal{K}$ is a scale parameter, π_{ent} is the joint learning policy, π_{ent}^* denotes joint behavior policy, and $f(\cdot)$ represents the function that captures the divergence between π_{ent} and π_{ent}^*. However, the state-action space of multi-channel scenario is enormous, making it difficult to directly compute the regularization term between the global policy π_{tot} and the global behavior policy π_{tot}^*. Although existing works [47]–[49] use local regularization instead of global regularization by decomposing the function f, local regularization cannot be effectively applied to other channels due to the huge gap in state features (e.g., user traffic and ad types) between each channel.

To this end, we use central value functions to guide the learning of each strategy (i.e., global value functions guide local regularization), which aligns with the centralized training with decentralized execution (CTDE) framework [50]. Simply put, each channel is considered an agent, and the training process requires all P learning agents to participate in jointly improving the policy network parameters θ and value network parameters ϕ. At time t and $t + 1$, the value function gathers observations from all agents, denoted as $\hat{s}_t = [o_t^1, \cdots, o_t^P]$ and $\hat{s}_{t+1} = [o_{t+1}^1, \cdots, o_{t+1}^P]$, respectively. The reward r_t is the sum of rewards from all channels, represented as $\hat{r}_t = r_t^1 + \cdots + r_t^P$. Thus, Eq. (12) can be rewritten as:

$$\begin{aligned} \max_{\phi} \mathbb{E}_{(s_t, \hat{r}, s_{t+1}) \sim D^l} &[L_2^\varrho(\hat{r}_t + \gamma \sum_{p=0}^{P} V'(o_{t+1}^p)) - \sum_{p=0}^{P} V(o_t)] \\ = \max_{\phi} \mathbb{E}_{(s_t, \hat{r}, s_{t+1}) \sim D^l} &[L_2^\varrho(\hat{r}_t + \gamma V'(\hat{s}_{t+1}^p)) - V(\hat{s}_t)]. \end{aligned} \tag{21}$$

In the absence of ad requests at time t for channel p, the state remains unchanged (i.e., $o_t = o_{t-1}$), and the reward is set to zero (i.e., $r_t^p = 0$). Unlike value functions, the bidding policy (i.e., state policy and action policy) can only make actions based on local observations o_t specific to their channel (e.g., customer traffic, bidding, and the budget for that channel), which can be denoted as:

$$\max_{\omega} \mathbb{E}_{(o_t^p, o_{t+1}^p) \sim D^l}[\sum_{p=0}^{P} \log \pi_{s,p}(o_{t+1}^p|o_t^p) + \lambda \cdot V(\pi_s(\hat{s}_t))], \tag{22}$$

$$\max_{\theta} \mathbb{E}_{(o_t^p, a_t^p, o_{t+1}^p) \sim D^l}[\sum_{p=0}^{P} \log \pi_{a,p}(a_t^p|o_t^p, o_{t+1}^p)]. \tag{23}$$

The offline training process of the bottom-level strategy is shown in Appendix II.

Finally, after offline model evaluation, HMMCB can be deployed to the online system for online predictions. For each ad request t, HMMCB obtains advertiser-level features and request-level features (i.e., s^l) from the ad platform. Then, the top-level strategy takes advertiser-level information and user-preferences (i.e, s^h) as input to allocate budget

TABLE II
FEATURES DESCRIPTION

Notation	Explaination
ctr	Click-through-rate
histctr	Historical CRT
final_charge	Final transaction price
cpc	Cost-per-click
aimcpc	Target cost-per-click
impr	Ad impression
revenue	Ad revenue
clicks	User clicks on advertisements
order_num	Orders number
mt_butie	Meituan subsidies
budget	Advertiser's Budget
user_id	user ID
request_time	Ad bidding request time
dt	Log creation time
pvid	Channel ID
impr_before1week	Impression from a week ago
click_before1week	User clicks from a week ago
cpc_before1week	CPC from a week ago
order_num_before1week	User orders from a week ago
...	...
order_num_before4week	...
user_pref	User preferences

$b = [b^1, \cdots, b^P]$. After getting the budget of each channel, the bottom-level strategy gives the final bidding actions according to Eq. 15. To ensure model optimality, HMMCB continuously optimizes and updates the model based on online data and user feedback, with the implementation details outlined in Experiment V-B2.

V. EXPERIMENT

In this section, we conduct a series of offline and online experiments to assess the performance of HMMCB. We first describe the primary setup, and then compare HMMCB with representative learning models to validate its effectiveness. Finally, ablation studies are conducted to verify the efficacy of each key component and hyperparameter in HMMCB.

A. Experiment Setup

1) Dataset: We use log data from the Meituan real-time advertising system for offline training and performance evaluation. These data are a mixture of expert, medium and random data, where expert data consists of bids achieving an advertising ROI exceeding the expected ROI while satisfying CPC constraints through an automated bidding strategy, medium data includes bids that either meet CPC constraints or surpass the expected ROI, and random data is bids generated through exploration with a random strategy. Specifically, these data span 35 days of bidding logs collected from four channels: feed ad, search ad, brand ad, and recommendation ad, with an average sampling of 80 million ad requests from 72,351 advertisers across four channels each day and Table II describing the important features in the logs. The dataset is divided into two segments for training and evaluation: 28 days of bidding data for training and 7 days for evaluation.

2) Simulated offline evaluation system: Implementing a predictive model into an operational system without comprehensively evaluating its potential implications has inherent

risks (i.e., financial losses). To mitigate this issue, we have developed an offline evaluation system for simulating the realistic cross-channel bidding process. This system comprises two modules: an advertising system simulator and a user feedback predictor. The former simulates the Meituan online advertising platform, including retrieval, bidding, ranking, and pricing, while the latter predicts the user feedbacks on ads and evaluates the results.

3) Compared methods: We compare the recent methods that can or can be adapted to handle multi-channel constraints, categorized into three lines of works: (1) single-channel slot-wise approximation methods PID [51] and CEM [52]; (2) soft combination (RL-based) methods MCQ [53], CBRL [12] and HiBid [14]; and (3) a hierarchical offline method OPAL [54].

- **PID** is a classical feedback controller, known for its effective performance in unknown environments. We utilize it to maintain the advertiser's current CPC close to the target CPC, ensuring compliance with the advertiser's cross-channel CPC constraint.
- **CEM** is a gradient-free stochastic optimization technique widely employed in the industry, which strives to optimize a greedy sub-problem within each time slot, striking a balance between exploration and exploitation. We formulate the multi-channel bidding problem as an optimization challenge to maximize the click count within the specified total budget and CPC constraint.
- **MCQ** effectively mitigates the value overestimation effect that arises in out-of-distribution actions by proactively training and adjusting their Q values, which is currently considered a state-of-the-art method in the field of offline DRL. We use MCQ to model each channel and set clicks as rewards, thus encouraging the strategy to make bidding decisions that maximize the click count.
- **CBRL** is a recognized state-of-the-art approach in the context of ROI-restricted single-channel bidding, which combines Bayesian techniques with an indicator-augmented reward function designed to dynamically manage the trade-off between constraints and objectives. To ensure a fair comparison, we adapt CBRL to the multi-channel ad bidding setting by substituting the ROI constraint with a CPC constraint while keeping its original training process.
- **OPAL** is a hierarchical offline algorithm, where the top-level agent is trained using unsupervised learning to provide a temporal abstraction for the bottom-level agent to improve the final policy optimization. OPAL and HMMCB are configured with identical hierarchical settings, i.e., the top-level agent allocates the budget, while the bottom-level agent makes advertising bidding decisions.
- **HiBid** is a novel algorithm for bid budget allocation that incorporates an auxiliary loss function to mitigate the risk of over-allocation to specific channels. The algorithm employs λ-parametric generalization to adapt to variations in budgetary constraints, and integrates a CPC guided action selection mechanism to satisfy cross-channel CPC constraints.

TABLE III
CONFIGURATIONS AND PERPARAMETERS IN HMMCB.

	Parameters		
	top-level strategy	bottom-level strategy	CMCK
batch size	7084	1024	2048
learing rates	1e-5	1e-5	2e-4
discounted factors	0.99	0.99	-
decision interval	1 day	each request	-
repetion times	25	8	-
action range	[0,1]	[0.5,1.5]	-

The hyperparameters of the above methods follow the default settings in previous works. Table III shows the main hyperparameters of HMMCB, and the remaining hyperparameters are discussed in Appendix III.

4) Evaluation metrics: To assess the performance of HMMCB, we incorporate four metrics for a comprehensive evaluation of multi-channel bidding scenarios, including total *impressions* (**IMPR**), total *clicks* (**CLICKS**), average *cost per click* (**CPC**) and average *return on investment* (**ROI**) across all advertisers. Simply put, IMPR, representing the number of times an advertisement is displayed, indicates the level of activity among customers for that ad slot. CLICKS represents the number of times that customers click on an advertisement, reflecting the level of interest in the advertised product. CPC is the cost paid by advertisers for each click on an ad, and a small CPC means a low advertising cost for advertisers. ROI represents the percentage of value that advertisers recoup from ad placements relative to the cost of advertising, and a large ROI represents a higher return on investment. Note that ROI is the important comparison metric in all experiments.

In offline evaluation, in order to accurately evaluate the effectiveness of various methods and mitigate the influence of specific application scenarios, we employ a normalized scoring approach based on the statistical results obtained from the log data and use the offline evaluation system for testing. In online evaluation, we use the A/B testing [55] for each metric. Specifically, we employ 1% of the whole customer traffic to independently conduct a two-week online experiment across four ad channels. Note that each channel has an average of approximately 35,000 ad requests daily.

B. Performance Comparison

1) Offline performance comparison: In the offline setting, HMMCB is compared with PID, CEM, OPAL, CBRL and MCQ. Results in Table IV indicate that HMMCB excels in maximizing both the ROI and IMPR, and effectively reduces the CPC, thereby enhancing the overall cost-effectiveness of the system. Although CBRL can progressively adapt its bidding strategy to meet constraints through the learning process, its performance still falls short of HMMCB, which can be attributed to the inability to allocate the budget accurately. MCQ uses a conservative strategy to prevent overestimation of errors in out-of-distribution actions, but it suppresses the generalization of the value function and hinders performance improvement, resulting in a 1.91% increase in CPC. OPAL demonstrates a 1.20% improvement in IMPR, but a decrease in CLICKS, which can be attributed to the fact that the
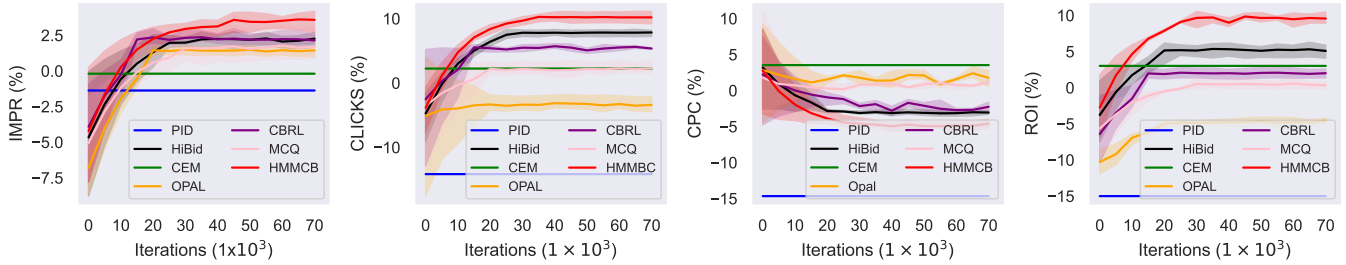
Fig. 3. Offline convergence process of the six methods. The vertical axis of each subplot represents different evaluation metrics, while the horizontal axis denotes the number of training steps. Each method is executed with 10 randomly selected seeds.
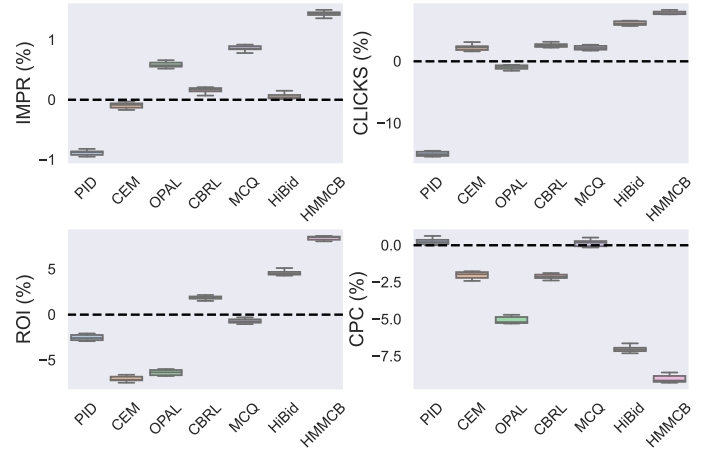
TABLE IV
RESULTS OF OFFLINE EVALUATION IN TERMS OF A RELATIVE IMPROVEMENT COMPARED TO THE ORIGINAL METHOD APPLIED IN THE MEITUAN BIDDING SYSTEM. ∗ DENOTES THE PRIMARY METRIC FOR COMPARISON.

methods	IMPR	CLICKS	CPC	ROI*
PID	-1.30%	-15%	**-14.91%**	-15.0%
CEM	-0.21%	3.02%	3.59%	2.45%
OPAL	1.20%	-4.12%	3.41%	-5.01%
CBRL	2.11%	4.50%	-3.12%	2.45%
MCQ	2.05%	2.90%	1.91%	0.35%
HiBid	2.15%	7.93%	-2.91%	5.35%
HMMCB	**3.97%**	**9.35%**	-3.40%	**9.80%**

(a) Online A/B Testing on the Meituan online advertising bidding system. Each boxplot shows the average and median results of 30 independent repeated runs.

(b) 99.9% request completion time for six methods. The system's response warning time is 50 milliseconds.

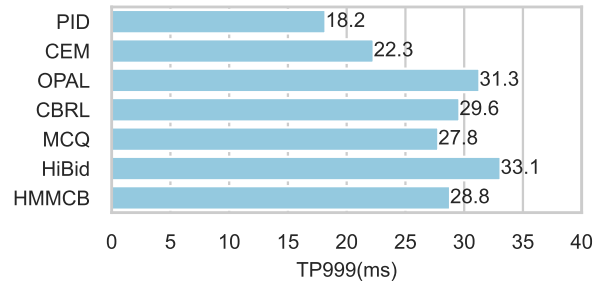Fig. 4. Results of online experiments with seven methods

budget allocation strategy learned through supervised learning lacks appropriate adjustments in unfavorable situations. Due to limitations in policy representation capability, CEM struggles to effectively accommodate advertisers' requirements, resulting in a significant increase in CPC to 3.59%. While dynamically adjusting bidding prices based on the current CPC, PID fails to consider the variability in average CPC across different channels, leading to a 14.91% improvement in CPC, but decrease in all other metrics. HiBid introduces auxiliary losses to prevent channel-specific over-allocation and uses λ-generalization to adapt to budget changes, but it ignores the internal connections between individual channels, resulting in only a 5.35% ROI improvement.

Compared with these models, HMMCB uses a diffusion strategy with CPC constraints to dynamically allocate budgets according to the characteristics of each channel, and uses the state action decoupled actor-critic method to avoid overestimation of out-of-distribution actions. In addition, HMMCB is trained using the CMCK and central value function, allowing it not only to consider the specific attributes of each channel but also to coordinate all channels to achieve a global optimal performance. As a result, HMMCB achieves the highest ROI while ensuring superiority in other metrics. A comprehensive depiction of the training convergence process is presented in Fig. 3. Compared with other single-channel methods, HMMCB requires simultaneous learning of the characteristics of different channels to provide the best overall bidding solution, hence it requires multiple iterations to reach convergence.

2) Online A/B testing on the Meituan advertising platform: HMMCB and all other five baselines are validated using the Meituan advertising platform across four channels: feed

ad, search ad, brand ad, and recommendation ad, with each method running a total test time of two weeks. As depicted in Fig. 4a, HMMCB surpasses all other baseline methods in all metrics, achieving an increase of at least 1.15% in IMPR, 8.30% in CLICKS, 8.65% in ROI, and a decrease of 8.83% in CPC. Fig. 4b displays the TP999 (i.e., completion time for 99.9% requests) for each model. While the HMMCB method takes into account the characteristics of different channels during training, each channel's strategy is executed independently during the evaluation, therefore it can still respond to requests in a relatively short amount of time.

In addition, we show that HMMCB can continually improve its performance by swiftly adapting to the evolving environment. To this end, we conduct the following iterated training

TABLE V
FINE-TUNE THE TEST RESULTS OF THE MODEL. HMMCB0 REPRESENTS
THE MODEL THAT HAS NOT BEEN FINE-TUNED, AND
HMMCB1−HMMCB3 REPRESENT THE MODELS THAT HAVE BEEN
FINE-TUNED BASED ON THE PREVIOUS CYCLE MODEL.

	IMPR	CLICKS	CPC	ROI*
HMMCB0	1.15%	8.30%	-8.83%	8.65%
HMMCB1	2.97%	8.36%	-8.88%	9.35%
HMMCB2	3.99%	8.44%	-8.90%	9.68%
HMMCB3	**4.11%**	**8.62%**	**-8.95%**	**9.89%**

TABLE VI
THE DATA IN THE TABLE IS AN OFFLINE EVALUATION OF THE BRAND AD
CHANNEL.

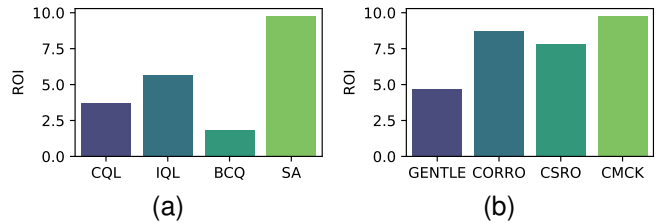|	IMPR	CLICKS	CPC	ROI*
PID	0.12%	-6.53%	0.95%	-1.23%
CEM	-1.49%	-2.36%	0.47%	0.31%
OPAL	-8.33%	-1.49%	2.15%	-8.33%
CBRL	2.13%	-1.45%	0.56%	-8.76%
MCQ	-3.42%	-7.83%	2.63%	-2.34%
HiBid	-1.31%	0.23%	-1.39%	-2.78%
HMMCB	**1.73%**	**6.43%**	**-5.39%**	**2.01%**

Fig. 5. Comparison results of HMMBC with existing methods. The experimental results are based on running the experiment 5 times with a random seed, and the y-axis represents the ROI. SA denotes the state-action decoupled actor-critic method.

TABLE VII
COMPARISON RESULTS OF OFFLINE MULTI-AGENT METHODS

	IMPR	CLICKS	CPC	ROI*
MAAB	0.63%	1.22%	2.98%	0.78%
ICQ	0.13%	-5.45%	5.32%	-5.76%
OMAR	-1.42%	-6.23%	3.63%	-1.94%
OMIGA	-0.31%	0.33%	-0.59%	-1.78%
HMMCB	**3.97%**	**9.53%**	**-3.40%**	**9.80%**

process: (1) Daily bidding logs are automatically processed and stored in the server; (2) After one cycle, HMMCB is fine-tuned using the aforementioned offline data; and (3) After offline training, the new HMMCB model is synchronized to the RTB system for online bidding services. We train four versions of HMMCB with a 5-day fine-tuning cycle and still use A/B testing for online experimental evaluation. Table V indicates that HMMCB can achieve improvements in each evaluation metric after continuous fine-tuning and updating.

3) Effects of shared knowledge learning: We adjust the data portion of the brand ad channel in the offline dataset against the other three channels as 1:50:50:50 and use this dataset to train PID, CEM, MCQ, CBRL, OPAL, HiBid, and HMMCB. Table VI shows the impact of data scarcity on strategy learning. The bidding performance of PID, CEM, MCQ, CBRL, OPAL, and HiBid algorithms drops significantly due to insufficient data for learning the characteristics of the brand channel. HMMCB achieves superior results by leveraging CMCK to learn the shared knowledge of different channels and using this shared knowledge to enhance policy learning for the characteristics of the brand ad channel.

C. Further Study

In this section, we explore the comparison of the state-action decoupled actor-critic method and the context-based knowledge sharing approach (CMCK) with several existing works. Specifically, we replace the state-action decoupled actor-critic method with mainstream offline RL methods CQL [53], IQL [43], and BCQ [56], respectively. Similarly, we substitute the context-based knowledge-sharing approach with offline meta-RL methods, including GENTLE [57], CORRO [58], and CSRO [59]. Fig. 5a shows that the state-action decoupled actor-critic method consistently outperforms the CQL, IQL, and BCQ methods. CQL and BCQ prioritize learning policies that are very similar to behavioral policies, which limits their ability to leverage non-expert data to enhance policy performance. IQL reduces extrapolation errors in the policy

improvement process by avoiding the direct evaluation of actions that are not present in the dataset. However, IQL employs advantage-weighted behavior cloning to learn a policy, which may be inadequate for capturing the optimal policy distribution in a bidding dataset containing a significant proportion of non-expert data. Fig. 5b shows the comparison results between CMCK and Meta-RL methods, indicating that CMCK achieves the highest ROI, while GENTLE results in the lowest ROI. GENTLE increases channel data by reconstructing state transitions and rewards, which may bring larger distribution errors, causing the learned policy to deviate from the actual data distribution.

Additionally, HMMCB is compared with existing multi-agent methods to highlight its practicality in multi-channel bidding scenarios. Specifically, we compare the bidding multi-agent algorithm MAAB [13], which uses the temperature-regularized credit assignment to handle bidding relationships between different channels. The original MAAB algorithm does not meet the requirements of existing bidding environments, as it does not consider channel budgets and is designed for settings where channels exhibit cooperative-competitive relationships. We modify the MAAB to align with the cooperative environment settings and allocate budgets proportionally according to the historical revenue ratios of each channel. Moreover, we also consider representative offline MARL algorithms, ICQ [47], OMAR [48], and OMIGA [49], with the core idea of replacing global regularization with local regularization to learn the optimal joint policy. The results in Table VII indicate that HMMCB consistently outperforms the MAAB, ICQ, OMAR, and OMIGA methods. This superior performance arises not only from HMMCB's effective resolution of the out-of-distribution (OOD) problem but also from its dynamic budget allocation and efficient handling of different channel characteristics. In contrast, the ICQ, OMAR and OMIGA algorithms focus on solving the offline multi-agent OOD problem, which makes them unable to obtain satisfactory performance in complex and stochastic bidding

TABLE VIII
ABLATION STUDY.

method	IMPR	CLICKS	CPC	ROI*
HMMC	**3.97**%	9.35%	**-3.40**%	**9.80**%
without CPC	1.27%	6.25%	1.34%	2.34%
without Diffusion	3.74%	0.36%	6.23%	-2.34%
without CMCK	3.03%	4.54%	3.25%	-1.34%
without Central	3.73%	**9.54**%	8.25%	-7.34%

scenarios because different channel budgets and customer traffic can affect bidding.

D. Ablation Study

In this section, we modify each component within HMMCB to demonstrate their individual effectiveness, with the results given in Table VIII. First, we evaluate the influence of top-level strategies by comparing bidding policies with and without CPC constraints. Without a CPC constraint, HMMCB can disregard the overall CPC to maximize clicks, leading to a 6.25% surge in clicks while also causing a 1.34% rise in CPC. Second, we examine the influence of policy regularization capability, specifically focusing on whether employing diffusion model as a top-level strategy can enhance the effectiveness of our bidding model. Results show employing a traditional MLP as a top-level strategy degrades the overall model performance, due to its incapability in accurately capturing the data distribution across multiple channels. Finally, we explore the impact of CMCK and central value function on the final performance. In scenarios where the state policy is not learned using CMCK, independently trained state policies struggle to effectively generalize the optimal next state for each channel. Hence, it incurs a reduction of 1.34% in ROI and an increase of 3.25% in CPC. When each bottom-level strategy undergoes independent training without reliance on a central value function, there is a notable 7.43% decrease in ROI, despite a 9.54% increase in clicks. This discrepancy can be attributed to the fact that each policy solely focuses on maximizing its own returns without considering the interrelationships among different channels, leading to a local optimum in overall performance.

In addition, we use SNE [60] to visualize the feature distribution of $\pi_s(s_t)$ and s_{t+1} to illustrate how the state strategy guides the action strategy in bidding decisions. The results are shown in Fig. 6, where the left image illustrates the distribution of the state, while the right image represents the reward value for each state. We can see that the state distribution of π_s follows the distribution of the original data and achieves higher returns, which is crucial in guiding the action policy to make better decisions through accumulating and propagating high return through multiple time steps.

VI. CONCLUSION

In this paper, we conduct in-depth analysis of the cross-channel bidding problem and propose a hierarchical optimization architecture HMMCB to solve it. HMMCB enables the dynamic allocation of channel budgets by implementing a CPC-constrained diffusion model, and uses a state-action decoupled actor-critic method and a context-based meta-channel
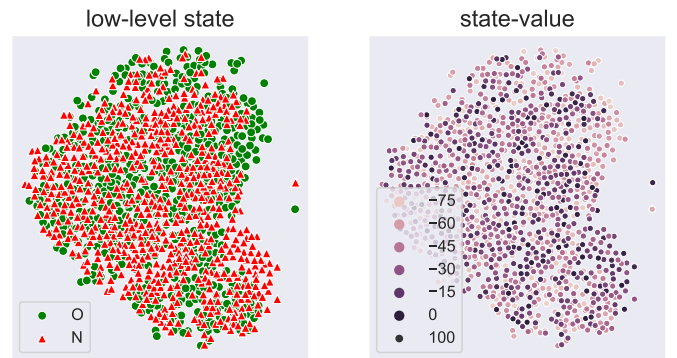

Fig. 6. In the left, O (green dot) represents the original state distribution, while N (red △) represents the states generated by the state policy. The right displays state reward values, with darker colors indicating higher values.

knowledge learning method to utilize the cross-channel interrelationships for efficient bidding decision making within each channel. Both offline and online experiments based on industry data from the Meituan ad bidding platform validate the superiority of HMMCB against some traditional or state-of-the-art methods.

REFERENCES

[1] A. Goldfarb and C. Tucker, "Online display advertising: Targeting and obtrusiveness," *Mark. Sci.*, vol. 30, no. 3, pp. 389–404, 2011.

[2] J. Wang, W. Zhang, and S. Yuan, "Display advertising with real-time bidding (RTB) and behavioural targeting," *Found. Trends Inf. Retr.*, vol. 11, no. 4-5, pp. 297–435, 2017.

[3] S. Despotakis, R. Ravi, and A. Sayedi, "First-price auctions in online display advertising," *Journal of Marketing Research*, vol. 58, no. 5, pp. 888–907, 2021.

[4] S. Yuan, J. Wang, and X. Zhao, "Real-time bidding for online advertising: measurement and analysis," in *KDD*. ACM, 2013, pp. 3:1–3:8.

[5] M. Gao, J. Li, C. Chen, Y. Li, J. Zhang, and Z. Zhan, "Enhanced multi-task learning and knowledge graph-based recommender system," *IEEE Trans. Knowl. Data Eng.*, pp. 10 281–10 294, 2023.

[6] M. Zhang, S. Wu, X. Yu, Q. Liu, and L. Wang, "Dynamic graph neural networks for sequential recommendation," *IEEE Trans. Knowl. Data Eng.*, pp. 4741–4753, 2023.

[7] J. Yu, H. Yin, X. Xia, T. Chen, J. Li, and Z. Huang, "Self-supervised learning for recommender systems: A survey," *IEEE Trans. Knowl. Data Eng.*, pp. 335–355, 2024.

[8] A. Koenecke, E. Giannella, R. Willer, and S. Goel, "Popular support for balancing equity and efficiency in resource allocation: A case study in online advertising to increase welfare program awareness," in *AAAI*, vol. 17, 2023, pp. 494–506.

[9] P. R. Padghan, A. D. Samuel, and R. Pitchaimuthu, "Aggregator-induced demand response and bidding strategy for electricity market environment based on ethereum smart contracts," *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, vol. 45, no. 1, pp. 299–318, 2023.

[10] H. Cai, K. Ren, W. Zhang, K. Malialis, J. Wang, Y. Yu, and D. Guo, "Real-time bidding by reinforcement learning in display advertising," in *WSDM*. ACM, 2017, pp. 661–670.

[11] Y. He, X. Chen, D. Wu, J. Pan, Q. Tan, C. Yu, J. Xu, and X. Zhu, "A unified solution to constrained bidding in online display advertising," in *KDD*. ACM, 2021.

[12] H. Wang, C. Du, P. Fang, S. Yuan, X. He, L. Wang, and B. Zheng, "Roi-constrained bidding via curriculum-guided bayesian reinforcement learning," in *KDD*. ACM, 2022, pp. 4021–4031.

[13] C. Wen, M. Xu, Z. Zhang, Z. Zheng, Y. Wang, X. Liu, Y. Rong, D. Xie, X. Tan, C. Yu, J. Xu, F. Wu, G. Chen, X. Zhu, and B. Zheng, "A cooperative-competitive multi-agent framework for auto-bidding in online advertising," in *WSDM*. ACM, 2022, pp. 1129–1139.

[14] H. Wang, B. Tang, C. H. Liu, S. Mao, J. Zhou, Z. Dai, Y. Sun, Q. Xie, X. Wang, and D. Wang, "Hibid: A cross-channel constrained bidding system with budget allocation by hierarchical offline deep reinforcement learning," *IEEE Trans. Computers*, vol. 73, no. 3, pp. 815–828, 2024.

[15] C. Perlich, B. Dalessandro, R. Hook, O. Stitelman, T. Raeder, and F. J. Provost, "Bid optimizing and inventory scoring in targeted online advertising," in *KDD*. ACM, 2012, pp. 804–812.

[16] W. Zhang, S. Yuan, and J. Wang, "Optimal real-time bidding for display advertising," in *KDD*. ACM, 2014, pp. 1077–1086.

[17] T. Wang, H. Yang, H. Yu, W. Zhou, Y. Liu, and H. Song, "A revenue-maximizing bidding strategy for demand-side platforms," *IEEE Access*, vol. 7, pp. 68 692–68 706, 2019.

[18] Z. Jiang, K. Zhou, M. Zhang, R. Chen, X. Hu, and S. Choi, "Adaptive riskaware bidding with budget constraint in display advertising," *ACM SIGKDD Explorations Newsletter*, vol. 25, no. 1, pp. 73–82, 2023.

[19] V. Tunuguntla, K. Rakshit, and P. Basu, "Bidding for an optimal portfolio of keywords in sponsored search advertising: From generic to branded keywords," *European Journal of Operational Research*, vol. 307, no. 3, pp. 1424–1440, 2023.

[20] D. Wu, X. Chen, X. Yang, H. Wang, Q. Tan, X. Zhang, J. Xu, and K. Gai, "Budget constrained bidding by model-free reinforcement learning in display advertising," in *CIKM*. ACM, 2018, pp. 1443–1451.

[21] S. Xiao, L. Guo, Z. Jiang, L. Lv, Y. Chen, J. Zhu, and S. Yang, "Model-based constrained MDP for budget allocation in sequential incentive marketing," in *CIKM*. ACM, 2019, pp. 971–980.

[22] N. Alon, I. Gamzu, and M. Tennenholtz, "Optimizing budget allocation among channels and influencers," in *WWW*. ACM, 2012, pp. 381–388.

[23] J. Jin, C. Song, H. Li, K. Gai, J. Wang, and W. Zhang, "Real-time bidding with multi-agent reinforcement learning in display advertising," in *CIKM*. ACM, 2018, pp. 2193–2201.

[24] S. Levine, A. Kumar, G. Tucker, and J. Fu, "Offline reinforcement learning: Tutorial, review," *and Perspectives on Open Problems*, vol. 5, 2020.

[25] Y. Wu, G. Tucker, and O. Nachum, "Behavior regularized offline reinforcement learning," *CoRR*, vol. abs/1911.11361, 2019.

[26] A. Kumar, J. Fu, M. Soh, G. Tucker, and S. Levine, "Stabilizing off-policy q-learning via bootstrapping error reduction," in *NeurIPS*, 2019, pp. 11 761–11 771.

[27] S. Fujimoto and S. S. Gu, "A minimalist approach to offline reinforce-ment learning," in *NeurIPS*, 2021, pp. 20 132–20 145.

[28] Z. Wang, A. Novikov, K. Zolna, J. Merel, J. T. Springenberg, S. E. Reed, B. Shahriari, N. Y. Siegel, Ç. Gülçehre, N. Heess, and N. de Freitas, "Critic regularized regression," in *NeurIPS*, 2020.

[29] X. B. Peng, A. Kumar, G. Zhang, and S. Levine, "Advantage-weighted regression: Simple and scalable off-policy reinforcement learning," *CoRR*, vol. abs/1910.00177, 2019.

[30] S. Fujimoto, H. van Hoof, and D. Meger, "Addressing function ap-proximation error in actor-critic methods," in *ICML*, ser. Proceedings of Machine Learning Research, vol. 80. PMLR, 2018, pp. 1582–1591.

[31] Z. Wang, J. J. Hunt, and M. Zhou, "Diffusion policies as an expressive policy class for offline reinforcement learning," in *ICLR*. OpenRe-view.net, 2023.

[32] O. Nachum, B. Dai, I. Kostrikov, Y. Chow, L. Li, and D. Schuurmans, "Algaedice: Policy gradient from arbitrary experience," *CoRR*, vol. abs/1912.02074, 2019.

[33] H. Xu, X. Zhan, and X. Zhu, "Constraints penalized q-learning for safe offline reinforcement learning," in *AAAI*. AAAI Press, 2022, pp. 8753–8760.

[34] J. N. Foerster, G. Farquhar, M. Al-Shedivat, T. Rocktäschel, E. P. Xing, and S. Whiteson, "Dice: The infinitely differentiable monte-carlo estimator," in *ICLR*. OpenReview.net, 2018.

[35] R. Houthooft, Y. Chen, P. Isola, B. C. Stadie, F. Wolski, J. Ho, and P. Abbeel, "Evolved policy gradients," in *NeurIPS*, 2018, pp. 5405–5414.

[36] L. M. Zintgraf, K. Shiarlis, M. Igl, S. Schulze, Y. Gal, K. Hofmann, and S. Whiteson, "Varibad: A very good method for bayes-adaptive deep RL via meta-learning," in *ICLR*. OpenReview.net, 2020.

[37] R. Fakoor, P. Chaudhari, S. Soatto, and A. J. Smola, "Meta-q-learning," in *ICLR*. OpenReview.net, 2020.

[38] A. Kumar, A. Zhou, G. Tucker, and S. Levine, "Conservative q-learning for offline reinforcement learning," in *NeurIPS*, 2020.

[39] Y. Song and S. Ermon, "Generative modeling by estimating gradients of the data distribution," in *NeurIPS*, 2019, pp. 11 895–11 907.

[40] J. Ho, A. Jain, and P. Abbeel, "Denoising diffusion probabilistic models," in *NeurIPS*, 2020.

[41] J. Garcıa and F. Fernández, "A comprehensive survey on safe reinforce-ment learning," *Journal of Machine Learning Research*, vol. 16, no. 1, pp. 1437–1480, 2015.

[42] J. Huang, Y. Pang, Y. Liu, and H. Yan, "Posterior regularized bayesian neural network incorporating soft and hard knowledge constraints," *Knowledge-Based Systems*, vol. 259, p. 110043, 2023.

[43] I. Kostrikov, A. Nair, and S. Levine, "Offline reinforcement learning with implicit q-learning," in *ICLR*. OpenReview.net, 2022.

[44] X. Ma, Y. Yang, H. Hu, J. Yang, C. Zhang, Q. Zhao, B. Liang, and Q. Liu, "Offline reinforcement learning with value-based episodic memory," in *ICLR*. OpenReview.net, 2022.

[45] D. S. Bernstein, S. Zilberstein, and N. Immerman, "The complexity of decentralized control of markov decision processes," *CoRR*, vol. abs/1301.3836, 2013.

[46] J. Chen, T. Lan, and C. Joe-Wong, "Rgmcomm: Return gap minimization via discrete communications in multi-agent reinforcement learning," in *AAAI*. AAAI Press, 2024, pp. 17 327–17 336.

[47] Y. Yang, X. Ma, C. Li, Z. Zheng, Q. Zhang, G. Huang, J. Yang, and Q. Zhao, "Believe what you see: Implicit constraint approach for offline multi-agent reinforcement learning," in *NeurIPS*, 2021, pp. 10 299–10 312.

[48] L. Pan, L. Huang, T. Ma, and H. Xu, "Plan better amid conservatism: Offline multi-agent reinforcement learning with actor rectification," in *International Conference on Machine Learning, ICML 2022, 17-23 July 2022, Baltimore, Maryland, USA*, vol. 162. PMLR, 2022, pp. 17 221–17 237.

[49] X. Wang, H. Xu, Y. Zheng, and X. Zhan, "Offline multi-agent rein-forcement learning with implicit global-to-local value regularization," in *NeurIPS*, 2023.

[50] R. Lowe, Y. Wu, A. Tamar, J. Harb, P. Abbeel, and I. Mordatch, "Multi-agent actor-critic for mixed cooperative-competitive environments," in *NeurIPS*, 2017, pp. 6379–6390.

[51] K. H. Ang, G. Chong, and Y. Li, "PID control system analysis, design, and technology," *IEEE Trans. Control. Syst. Technol.*, vol. 13, no. 4, pp. 559–576, 2005.

[52] P. de Boer, D. P. Kroese, S. Mannor, and R. Y. Rubinstein, "A tutorial on the cross-entropy method," *Ann. Oper. Res.*, vol. 134, no. 1, pp. 19–67, 2005.

[53] J. Lyu, X. Ma, X. Li, and Z. Lu, "Mildly conservative q-learning for offline reinforcement learning," in *NeurIPS*, 2022.

[54] A. Ajay, A. Kumar, P. Agrawal, S. Levine, and O. Nachum, "OPAL: of-fline primitive discovery for accelerating offline reinforcement learning," in *ICLR*. OpenReview.net, 2021.

[55] Y. Zhang, B. Tang, Q. Yang, D. An, H. Tang, C. Xi, X. Li, and F. Xiong, "Bcorle(λ): An offline reinforcement learning and evaluation framework for coupons allocation in e-commerce market," in *NeurIPS*, 2021, pp. 20 410–20 422.

[56] S. Fujimoto, D. Meger, and D. Precup, "Off-policy deep reinforcement learning without exploration," in *ICML*, vol. 97. PMLR, 2019, pp. 2052–2062.

[57] R. Zhou, C.-X. Gao, Z. Zhang, and Y. Yu, "Generalizable task represen-tation learning for offline meta-reinforcement learning with data limita-tions," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 38, no. 15, 2024, pp. 17 132–17 140.

[58] H. Yuan and Z. Lu, "Robust task representations for offline meta-reinforcement learning via contrastive learning," in *ICML*, ser. Proceed-ings of Machine Learning Research, K. Chaudhuri, S. Jegelka, L. Song, C. Szepesvári, G. Niu, and S. Sabato, Eds., vol. 162. PMLR, 2022, pp. 25 747–25 759.

[59] Y. Gao, R. Zhang, J. Guo, F. Wu, Q. Yi, S. Peng, S. Lan, R. Chen, Z. Du, X. Hu, Q. Guo, L. Li, and Y. Chen, "Context shift reduction for offline meta-reinforcement learning," in *NeurIPS*, 2023.

[60] G. E. Hinton and S. T. Roweis, "Stochastic neighbor embedding," in *NIPS*. MIT Press, 2002, pp. 833–840.

Shenghong He is currently a PhD student under the supervision of Prof. Chao Yu in the School of Computer Science and Engineering, Sun Yat-sen University, China. He has published a few works at IEEE TDSC, and is now working on the problem of offline learning and security with deep reinforcement learning.

Qianlong Xie received his M.S. degree from Beijing University of Posts and Telecommunications in Beijing, China in 2013. He is currently employed as a machine learning scientist at Meituan. He has published several works at prestigious conferences such as ICML, WWW, and DASFAA. His primary research interests include image generation, machine learning, and data mining.

Chao Yu received the Ph.D. degree in computer science from the University of Wollongong, Australia, in 2014. He is currently an Associate Professor with the School of Computer Science and Technology, Dalian University of Technology, Dalian, China, and a Visiting Professor with the Department of Computer Science, Hong Kong Baptist University, Hong Kong. He has published more than 50 papers in prestigious journals, such as the IEEE TNNLS, IEEE TCYB, and IEEE TVT. His research interests include multi-agent systems, reinforcement learning, and their wide applications in autonomous driving, smart grid, robotic control, and intelligent healthcare.

Xingxing Wang earned his M.S. degree from the Computer Network Information Center at the Chinese Academy of Sciences in Beijing, China in 2013. He is currently employed as a machine learning scientist at Meituan. He has published several works at prestigious conferences such as ICML, WWW, AAAI, CIKM, and DASFAA. His primary research interests include recommender systems, machine learning, and data mining.

Qian Lin , a Master's student in Sun Yat-sen University, China, supervised by Professor Chao Yu. He mainly focuses on reinforcement learning (RL), especially under various settings, including offline, safe, and multi-objective scenarios. He has published several research in top venues, including ICML, AAMAS and ICLR.

Shangqin Mao received his Ph.D. degree from Huazhong University of Science and Technology in Hubei, China in 2013. He currently works as a data scientist at Meituan. His current research interests include auction theory and reinforcement learning.

Bo Tang is currently a PhD student under the supervision of Prof. Jingrun Chen in the School of Artificial Intelligence and Data Science, University of Science and Technology of China. He has published several works at major conferences such as ICML, NeurIPS, WWW, and CIKM, and is now focusing on the problem of advertising bidding using deep reinforcement learning.