CONSTRANDED REINFORCEMENT LEARNING FOR SHORT VIDEO RECOMMENDATION

Qingpeng Cai, Ruohan Zhan, Chi Zhang, Jie Zheng, Guangwei Ding, Pinghua Gong, Dong Zheng, Peng Jiang
Kuaishou Technology
Beijing, China
{caiqingpeng,zhanruohan,zhangchi08,zhengjie,dingguangwei03,gongpinghua,zhengdong,jiangpeng}@kuaishou.com

ABSTRACT

The wide popularity of short videos on social media poses new opportunities and challenges to optimize recommender systems on the video-sharing platforms. Users provide complex and multifaceted responses towards recommendations, including watch time and various types of interactions with videos. As a result, established recommendation algorithms that concern a single objective are not adequate to meet this new demand of optimizing comprehensive user experiences. In this paper, we formulate the problem of short video recommendation as a constrained Markov Decision Process (MDP), where platforms want to optimize the main goal of user watch time in long term, with the constraint of accommodating the auxiliary responses of user interactions such as sharing/downloading videos.

To solve the constrained MDP, we propose a two-stage reinforcement learning approach based on actor-critic framework. At stage one, we learn individual policies to optimize each auxiliary response. At stage two, we learn a policy to (i) optimize the main response and (ii) stay close to policies learned at the first stage, which effectively guarantees the performance of this main policy on the auxiliaries. Through extensive simulations, we demonstrate effectiveness of our approach over alternatives in both optimizing the main goal as well as balancing the others. We further show the advantage of our approach in live experiments of short video recommendations, where it significantly outperforms other baselines in terms of watch time and interactions from video views. Our approach has been fully launched in the production system to optimize user experiences on the platform.

1 Introduction

The surging popularity of short videos has been changing the status quo of social media. As of 2021, the monthly active users on TikTok have reached one billion worldwide TikTok [n.d.]. Such prevalence of short video consumption has brought in huge business opportunities for organizations. As a result, there has been an increasing interest in optimizing recommendation strategies for short video platforms, where user feedback is multifaceted. Potential responses from a user after consuming a video include WatchTime (the time spent on watching the video), and several types of interactions: Share (sharing this video with his/her friends), Download (downloading the video), Comment (providing comments on the video), etc. Thereby, established recommender systems that exclusively optimize a single objective (such as gross merchandise volume for e-commerce platforms Pi et al. [2020]) is no longer sufficient—the applied systems should take all aspects of responses into consideration to optimize user experiences.

In this paper, we present our solution in the context of constrained optimization. As opposed to Pareto optimality that is often applied to study multi-objective strategies Sener and Kolun [2018], Chen et al. [2021], preferences on different objectives are often pre-specified in real applications. Notably, one main goal for short video platforms is to increase the watch time, which is observed from each video view and widely concerns all users. Besides, watch time reflects user attention, which is the scarce resource that companies compete for. Conversely, other responses such as Share/Comment are not mutually exclusive among platforms and thus could be sacrificed mildly. On the other hand, platforms have been focusing on optimizing user long-term engagement, which directly drives daily active users (DAU)
and thereby the revenue growth. Recently, a growing literature has focused on applying reinforcement learning (RL) to recommender systems, due to its ability to improve cumulative reward Nemati et al. [2016], Zhao et al. [2017, 2018], Chen et al. [2018], Zou et al. [2019], Liu and Yang [2019], Chen et al. [2019b], Xian et al. [2019], Ma et al. [2020], Afsar et al. [2021], Ge et al. [2021]. In particular, watch time, as the dense response, can be effectively cumulatively maximized to increase user spent time across multiple requests with RL approaches Chen et al. [2019a]. Thereby, we propose to learn an RL-based agent that optimizes the main goal (WatchTime), with the constraint of compensating other auxiliary responses (Share, Download, and Comment) with reasonable levels.

The problem of this constrained policy learning is much more challenging as compared to its unconstrained counterpart. A natural idea would be learning a value-based or policy-based model that maximizes the Lagrangian with pre-specified multipliers. However, such method is often difficult to be realized in practice via standard RL methods for the following two reasons.

First, it is not sufficient to use a single policy evaluation model to estimate the Lagrangian dual objective. As discussed, the agent may receive different types of responses from the user. A straightforward approach is to combine them into a single weighted sum using pre-specified multipliers, and learn a value-based model such as Q-learning Mnih et al. [2013] to optimize it, as proposed in Stamenkovic et al. [2021]. Such response combination is not adequate, particularly for responses with their own discount factors—the formulation of temporal difference error in value-based models only allows for a single discount value. In scenarios where one discount factor suffices, it can still be difficult for a single value model to evaluate the policy accurately, especially when different responses are observed at various frequencies, as typical for short video recommendations. The WatchTime response is dense and observed from each video view, while the interaction-signal such as Share/Comment is much more sparse and may not be provided within dozens of views. Signal from the sparse responses will be weakened by the dense responses when naively summing them up together. To address this multi-response evaluation difficulty, we separately evaluate each response via its own value model, which allows for response-specific discount factors and mitigates the interference on evaluation from one response on another, similar to the procedure conducted in Chen et al. [2021], Tajmajer [2018], Hessel et al. [2019]. As an example, we evaluate the behavior policy on a popular short video platform using data collected real time and find that such separate evaluation improves learning on WatchTime and interaction-signal by 0.191% and 0.143% respectively1; Appendix A elaborates the experimental detail.

Second, it is hard for a single policy to balance both dense responses and sparse responses. Learning a sparse response itself is well-known to be problematic—it may take the agent undesirably long to learn something meaningful Florensa et al. [2017], Riedmiller et al. [2018]. Coexistence of both dense and sparse responses exacerbates the learning difficulty. In most time, the agent only learns to optimize the policy in the direction of optimizing dense responses, which may negatively affect its learning for sparse responses. On account of this, we propose to firstly learn a policy to optimize each auxiliary response and then “softly” regularize the policy of the main response to be in the neighborhood of others. We demonstrate empirically that our approach can better balance different responses in both simulated data and live experiments.

Together, we summarize our contributions as below:

- **Constrained Optimization in Short Video Recommendations**: We formalize the problem of constrained policy learning in short video recommendations, where different aspects of responses may be observed at various frequencies, and the agent learns to optimize one with the constraint of balancing others.

- **Multi-Critic Policy Estimation**: To better evaluate policy on multiple responses that may differ in discount factors and observation frequencies, we propose to separately learn a value model to evaluate each response.

- **Two-Stage Actor-Critic Learning**: We propose a two-stage actor-critic framework which firstly learns a policy to optimize each auxiliary response and secondly regularizes the policy of the main response to be not far from others, which we demonstrate to be a more effective way in constrained optimization as compared with other alternatives.

- **Gains in Live Experiments**: We demonstrate the effectiveness of our approach in live experiments, showing the ability of our approach in optimizing the main response of WatchTime as well as balancing other interaction ones.

---

1. In real applications for video recommendations, an improvement around 0.1% on value estimation is already significant to be reflected in production performance.
2 Related Work

Constrained Reinforcement Learning Our work is also closely related to the literature of constrained reinforcement learning, where the sequential decision making problem is formulated into a constrained Markov Decision Process (CMDP) [Sutton and Barto, 2018], and the policy learning procedure is expected to respect the constraints. There are mainly two categories of constraints: cumulative ones (sum of a given signal should be limited into certain region) and instantaneous ones (constraints should be satisfied at each step) [Liu et al., 2021; Perkins and Barto, 2002; Garcia and Fernández, 2015]. To deal with cumulative constraints, there is a large body of literature focusing on Lagrangian relaxation [Chow et al., 2017, 2019; Tessler et al., 2018; Dalal et al., 2018]. As an example, Tessler et al. [2018] propose to update the policy and the Lagrangian multiplier alternatively and prove the convergence of their algorithm to a fix point. This approach however does not deal with the difficulty of policy learning on rewards with different observation frequencies and thus is difficult to achieve a good balance among multiple responses. In contrast, for each cumulative reward, we learn a policy to maximize it specifically, then we “softly” regularize the main policy to be in the neighborhood of others. We show empirically that this is a more effective way for constrained policy learning when dealing with both sparse and dense rewards. Different from Nair et al. [2020] that studies in offline RL and regularizes the learned policy to be in the neighborhood of one behavior policy, we softly restrict the policy within other policies maximizing other auxiliary responses and we do not limit to offline settings.

Multi-objective Optimization We also discuss a relevant line on multi-objective optimization. To trade off different objectives, methods in this field can be broadly categorized into two classes: the Pareto optimization and the joint optimization with pre-specified weights. The goal of Pareto optimization is to find a solution such that no other solutions can concurrently improve all objectives, named as Pareto optimality [Nguyen et al., 2020; Sener and Koltun, 2018; Chen et al., 2021]. However, a Pareto optimal solution may not prioritize the objective that is most valued in applications. The second method combines different objectives together into a single one via pre-specify the weights [White et al., 1980; Mossalam et al., 2016]. However, it is difficult to quantify these weights that can accurately reflect preferences in real applications [Tessler et al., 2018].

3 Preliminaries

3.1 Constrained Markov Decision Process

We start by formulating the problem of short video recommendation on mobile app services. When a user \( u \) opens the app, a new session starts. A session consists of multiple requests. At each request \( t \) when the user slides down the app, the recommender system (agent) takes an action \( a_t \) that recommends the user a video based on the user current state, characterized by his/her demographics, historical interactions, etc. Then the user provides multi-faceted responses (such as WatchTime, Share, Download, Comment) on the shown video, which are received by the agent as vector-valued reward signal and used for future planning; let \( m \) be the number of types of responses. The goal of the recommender system is to optimize cumulative reward of the main response \( e.g., \text{WatchTime} \), with the constraint of not sacrificing others much.

We model the above procedure as a Constrained Markov Decision Process (CMDP) [Sutton and Barto, 2018] \((S, A, P, R, C, \rho_0, \Gamma)\), where \( S \) is the state space of user current representation \( s_t \), \( A \) is the action space (and each action \( a_t \) corresponds to a recommended video for one request), \( P : S \times A \rightarrow \Delta(S) \) captures the state transition, \( R : S \times A \rightarrow \mathbb{R}^m \) defines the vector-valued reward function that yields \( m \) different rewards \( r(s_t, a_t) = (r_1(s_t, a_t), \ldots, r_m(s_t, a_t)) \), \( \rho_0 \) is the initial state distribution, \( \Gamma = (\gamma_1, \ldots, \gamma_m) \in (0,1)^m \) denotes the vector of discount factor for reward of each response, and \( C \) specifies the constraints on the auxiliary responses.

Define the vector-valued discounted cumulative reward \( R_t \) as \( R_t = \sum_{t'=1}^{T} \gamma^{t'-t} \cdot r(s_{t'}, a_{t'}) \), where \( T \) is the session length (i.e., the number of requests), \( \Gamma^b = (\gamma_1^b, \ldots, \gamma_m^b) \), and \( \times \cdot y \) denotes the pointwise product. Let \( V_\pi^\gamma(s) = (V_1^\gamma(s), \ldots, V_m^\gamma(s)) \) be the state value \( E_\pi[R_t|s_t = s] \) under actions sampled in accordance with policy \( \pi \) and \( Q(s, a) = (Q_1(s, a), \ldots, Q_m(s, a)) \) be its state-action value \( E_\pi[R_t|s_t = s, a_t = a] \). Denote \( \rho_\pi \) as the state distribution induced by policy \( \pi \). Without loss of generality, we set the first response as our main response. The goal is to learn a recommendation policy \( \pi(\cdot|s) \) over the action space to solve the following optimization problem:

\[
\max_{\pi} \quad E_{\rho_\pi}[V_1^\pi(s)] \\
\text{s.t.} \quad E_{\rho_\pi}[V_i^\pi(s)] \geq C_i, \quad i = 2, \ldots, m
\]

where \( C_i \) is constraint on the auxiliary response \( i \).
4 Two-Stage Constrained Actor Critic

In this section, we propose our two-stage constrained policy learning based on actor-critic framework, addressing the learning challenges in the context of dense and sparse rewards:

**Stage One** For each auxiliary response, we learn a policy to optimize its cumulative reward.

**Stage Two** For the main response, we learn a policy to optimize its cumulative reward, while limiting it to be close to other policies that are learned to optimize the auxiliary.

We first elaborate our framework in the settings of online learning with stochastic policies (such as A2C and A3C Williams [1992], Mnih et al. [2016]) in Sections 4.1 and 4.2 (the procedure is summarized in Appendix C). We then discuss its extensions to deterministic policies (such as DDPG and TD3 Lillicrap et al. [2015], Fujimoto et al. [2018]). For offline setting, please refer to Appendix D.

4.1 Stage One: Policy Learning for Auxiliary Responses

At this stage, we learn policies to optimize the cumulative reward of each auxiliary response separately. For completeness, we write out our procedure following the standard advantage actor critic approach Williams [1992]. Considering response $i$, let the learned actor and the critic be parameterized by $\pi_{\theta_i}$ and $V_{\phi_i}$ respectively. At iteration $k$, we observe sample $(s, a, s')$ collected by $\pi_{\theta_i}$, i.e., $s \sim \pi_{\theta_i}, a \sim \pi_{\theta_i}(\cdot | s)$ and $s' \sim P(\cdot | s, a)$. We update the critic to minimize the Bellman equation:

$$\phi^{(k+1)}_i \leftarrow \arg\min_{\phi} E_{\pi_{\theta_i}} \left[ (r_i(s, a) + \gamma_i V_{\phi_i}(s') - V_{\phi_i}(s))^2 \right].$$

We update the actor to maximize the advantage:

$$\theta^{(k+1)}_i \leftarrow \arg\max_{\theta} E_{\pi_{\theta_i}} \left[ A_i^{(k)} \log (\pi_{\theta}(a|s)) \right]$$

where $A_i^{(k)} = r_i(s, a) + \gamma_i V_{\phi_i}(s') - V_{\phi_i}(s)$.

4.2 Stage Two: Constrained Optimization of the Main Response

After pretraining the policies $\pi_{\theta_2}, \ldots, \pi_{\theta_m}$ that optimize the auxiliary responses, we now move onto the second stage of learning the policy to optimize the main response. We propose a new constrained advantage actor critic approach. Let the actor and the critic be $\pi_{\theta_1}$ and $V_{\phi_1}$ respectively. At iteration $k$, we similarly update the critic to minimize the Bellman equation:

$$\phi^{(k+1)}_1 \leftarrow \arg\min_{\phi} E_{\pi_{\theta_1}} \left[ (r_1(s, a) + \gamma_1 V_{\phi_1}(s') - V_{\phi_1}(s))^2 \right].$$

The principle of updating the actor is two-fold: (i) maximizing the advantage; (ii) restricting the policy to the domain that is not far from other policies. The optimization is formalized below:

$$\max_{\pi} \quad E_{\pi}[A_1^{(k)}]$$

s.t. $D_{KL}(\pi || \pi_{\theta_i}) \leq \epsilon_i, \quad i = 2, \ldots, m,$

where $A_1^{(k)} = r_1(s, a) + \gamma_1 V_{\phi_1}(s') - V_{\phi_1}(s)$.

Equation (5) has the closed form solution

$$\pi^*(a|s) \propto \prod_{i=2}^{m} (\pi_{\theta_i}(a|s))^{\frac{\lambda_i}{\sum_{j=2}^{m} \lambda_j}} \exp \left( \frac{A_1^{(k)}}{\sum_{j=2}^{m} \lambda_j} \right),$$

where $\lambda_i$ with $i = 2, \ldots, m$ are Lagrangian multipliers for constraints in (5), and the value of $\lambda_i$ controls the degree of constraint.

Given data collected by $\pi_{\theta_1}$, we learn the policy $\pi_{\theta_1}$ by minimizing its KL divergence from the optimal policy $\pi^*$:

$$\theta^{(k+1)}_1 \leftarrow \arg\min_{\theta} E_{\pi_{\theta_1}} \left[ D_{KL}(\pi^*(\cdot | s) || \pi_{\theta}(\cdot | s)) \right]$$

$$= \arg\max_{\theta} \prod_{i=2}^{m} \left( \frac{\pi_{\theta_i}(a|s)}{\pi_{\theta_1}(a|s)} \right)^{\frac{\lambda_i}{\sum_{j=2}^{m} \lambda_j}} \exp \left( \frac{A_1^{(k)}}{\sum_{j=2}^{m} \lambda_j} \right) \log \pi_{\theta}(a|s)).$$

4
Appendix B contains the derivation details. We here provide some intuition behind actor updating in (7). The ratio $$\frac{\pi_{\theta_i}(a|s)}{\pi_{\theta_j}(a|s)}$$ suggests that the updating direction of policy $$\pi_{\theta_i}$$ will be favored when it’s aligned with the constraint policies $$\pi_{\theta_j}$$, which effectively regularizes the learned policy $$\pi_{\theta_i}$$ to be in the neighborhood of other policies $$\pi_{\theta_j}$$. Small Lagrangian multipliers $$\lambda_i$$ indicate weaker constraints, and when $$\lambda_i = 0$$, we allow the learned policy $$\pi_{\theta_i}$$ to be irrelevant of the constraint policy $$\pi_{\theta_j}$$.

Deterministic Policies We now shed light on adaptation of our framework to deterministic policies such as deep deterministic policy gradient (DDPG) algorithm Lillicrap et al. [2015], inspired by the updating rule for the actor of constrained policy discussed in (7). Similarly, at stage one, for each auxiliary response $$i$$, we learn the actor $$\pi_{\theta_i}(s)$$ and critic $$Q_{\phi_i}(s, a)$$ via DDPG algorithm respectively. At stage two, for the main response, we learn critic $$Q_{\phi_1}(s, a)$$ via temporal learning; and for actor $$\pi_{\theta_1}(s)$$, the updating rule follows the form of

$$\max_{\theta_1} \prod_{i=2}^{m} \frac{h(a, \pi_{\theta_i}(s))}{h(a, \pi_{\theta_1}(s))} \frac{\sum_{j=2}^{m} \lambda_j^i}{\sum_{j=2}^{m} \lambda_j} f \left( \frac{Q_{\phi_1}(s, \pi(s))}{\sum_{j=2}^{m} \lambda_j} \right),$$

(8)

where $$f$$ is an increasing function which pushes the gradient of $$\pi_{\theta_i}$$ towards increasing the policy value; $$h(a_1, a_2)$$ scores high when two actions $$a_1, a_2$$ are close to each other and scores low vice versa; $$\lambda_i \geq 0$$ plays the same role as the constraint Lagrangian multiplier in (7)—larger $$\lambda_i$$ denotes stronger constraint. As a demonstration, one can choose $$f$$ to be the identity function and $$h(a_1, a_2) = \exp \left( - \frac{(a_1-a_2)^2}{2} \right)$$. Section 5 showcases how this construction of softly constrained DDPG algorithm effectively achieves the main goal as well as balancing the auxiliaries.

5 Offline Experiments

In this section, we evaluate our approach on a public dataset via extensive offline learning simulations. We demonstrate the effectiveness of our approach as compared to existing baselines in both achieving the main goal and balancing the auxiliaries.

5.1 Setup

Dataset We consider a hotel-review dataset named TripAdvisor, which is a standard dataset for studying policy optimization in recommender system with multiple responses in Chen et al. [2021]. In this data, customers not only provide an overall rating for hotels but also score hotels in multiple aspects including service, business, cleanliness, check-in, value, rooms, and location Alam et al. [2016]. Reviews provided by the same user are concatenated chronologically to form a trajectory; we filter trajectories with length smaller than 20. In total, we have 20277 customers, 150 hotels, and 257932 reviews.

MDP A trajectory tracks a customer hotel-reviewing history. For each review, we have state $$s_t$$: customer ID and the last three reviewed hotel IDs as well as corresponding multi-aspect review scores; action $$a_t$$: currently reviewed hotel ID; reward $$r_t$$: a vector of eight scores the customer provided for the reviewed hotel in terms of service, business, cleanliness, check-in, value, rooms, location, and overall rating; discount factor $$\gamma$$: 0.99. We set the main goal to be maximizing the cumulative overall rating, and treat others as the auxiliaries.

Evaluation We use the Normalised Capped Importance Sampling ((NCIS) approach to evaluate different policies, which is a standard offline evaluation method in literature Swaminathan and Joachims [2015].

Compared algorithms We compare our approach with a range of recommendation algorithms.

- BC: a supervised behavior-cloning policy $$\pi_\beta$$ to mimic customer reviewing pattern, with input as the user state and output as the reviewed hotel ID.
- Wide&DeepCheng et al. [2016]: a supervised model which utilizes wide and deep layers to balance both memorization and generalization, with input as the user state, output as the reviewed hotel id, and sample weight as the weighted sum of 8 scores for this review.
- A3C Mnih et al. [2016]: an online RL approach with one actor and one critic, where reward is the weighted sum of 8 scores for a given customer-hotel review.

The dataset consists of both the main objective and other responses, which can also be used to evaluate constrained policy optimization in recommender system.
The ultimate goal of recommender systems is to improve online user experience. To demonstrate the effectiveness of our algorithm, we test its real-world performance as well as other alternatives via A/B experiments. Algorithms are embodied in a candidate-ranking system used in production at a popular short video platform, that is, when a user arrives, these algorithms are expected to rank the candidate videos, and the system will recommend the top video to the user.
user. We show that the proposed constrained actor-critic model is able to learn a policy that maximizes the main goal while also effectively balancing the auxiliary goal, and in particular, we set the main one as maximizing the watch time and the auxiliary one as improving the interactions between users and videos.

6.1 Setup

Evaluation metrics We use online metrics to evaluate policy performance. For the main goal, we look at the total amount of time user spend on the videos, referred to as WatchTime. For the auxiliary goal, users can interact with videos through multiple ways, such as sharing the video to friends, downloading it, or providing comments. Here, we focus on the three online metrics associated with the user-video interactions—the total number of Share, Download, Comment interactions.

MDP Following the formulation in Section 3.1, we present the constrained MDP in the context of short video recommendation. A trajectory starts when a user opens the app and ends when the user leaves. At time $t$, we have

- state $s_t$: a vector embedding of user current representation, for which we concatenate embeddings of user historical interactions (encoded by recurrent neural networks) and instantaneous context (such as device and location).
- action $a_t$: a vector embedding of algorithm-predicted user preferences on different video topics, which determines the actual recommendation action—the video to be recommended—via a ranking function described below.
- the ranking function: for each candidate video, this function calculates the dot product between the predicted user preference vector ($a_t$) and the video embedding (representing its topic and quality). The platform then recommends the video that achieves the largest score.
- reward $r_t = (l_t, i_t)$: after each recommendation, the system observes how long the user spent on the video, denoted as $l_t$, and whether the user has interacted with the video (such as sharing/downloading/commenting on it), denoted as $i_t$.
- discount factor: we set $\gamma = 0.95$ for the time reward $l_t$ and $\gamma = 0.0$ for interaction reward $i_t$ if not specified otherwise.3

Compared algorithms We choose A3C Mnih et al. [2016] as the base actor critic model, since algorithms compared are trained online in our live experiment setup, as opposed to the offline learning in Section 5 that uses DDPG as the base actor critic model. Specifically, the action $a_t$ is sampled from a multivariate Gaussian distribution whose mean and variance are output of the actor model. We also complement our evaluation with a supervised learning-to-rank (LTR) baseline, which is the default model run on the platform.

- A3C: We define a combined reward $m_t = l_t + \lambda i_t$ and learn a standard A3C Mnih et al. [2016] policy to maximize cumulative $m_t$ with discount factor 0.95.

3We find that 0.95 is optimal for optimizing Watch time and 0 is optimal for maximizing the interactions in live experiments.
As we can see, both A3C with combined reward and RCPO-A3C with combined advantage learn to improve the interaction and does much better on interaction metric by being restricted to the neighborhood of \( \pi_i \), such that when combining these two responses together—in the form of either reward or advantage—both models cannot effectively balance the interaction well. Performance of the Interaction model is as expected: with signal from only the interaction reward \( d_i \) in the neighborhood of policy \( \pi_i \), with critic update following (4) and actor update following (7).

- **LTR (Baseline)**: The learning-to-rank model? that takes user state embedding and video embedding as input and fits the sum of responses.

**Experimental details** To test different algorithms, we randomly split users on the platform into five buckets with splitting ratio being 80%, 5%, 5%, 5%, 5%. The first bucket runs the baseline LTR model, and the remaining buckets run models A3C, RCPO-A3C, Interaction-A3C, and Constrained-A3C respectively. Models are pre-trained online for a couple of days and then are fixed to concurrently test performance within one day.

## 6.2 Results

Table 2 shows the results of algorithm comparison regarding metrics WatchTime, Share, Download, and Comment. As we can see, both A3C with combined reward and RCPO-A3C with combined advantage learn to improve the WatchTime as compared to the base model; but interaction-signal is too sparse with respect to WatchTime, such that when combining these two responses together— in the form of either reward or advantage—both models cannot effectively balance the interaction well. Performance of the Interaction model is as expected: with signal from only the interaction reward, the model learns to improve the interaction-related metrics (Share, Download, Comment); such interactions between users and videos also improve the user watch time, since more interesting videos with high potential of invoking interactions are recommended, which optimizes user whole experience. Finally, our model achieves the best performance: as compared to A3C and RCPO-A3C, it has slightly better WatchTime and does much better on interaction metrics, thanks to the effective regularization during training that it should not be too far from the Interaction-A3C policy.

To understand how our Constrained-A3C model learns to balance the main and auxiliary goal, Figure 2 plots its online performance—relative to the LTR baseline—during the learning phase on the two live metrics: WatchTime and Share. As shown, the model quickly learns to improve the Share metric by being restricted to the neighborhood of Interaction-A3C policy, demonstrating the effectiveness of our soft constraint. Then gradually, the model learns to improve WatchTime over time.

## 7 Conclusion

In this paper, we propose a constrained RL-based policy learning approach that optimizes the main goal as well as balancing the others for short video platforms. Our approach consists of two learning stages and is developed based on

---

4 Different from Tessler et al. [2018], we here use a fixed Lagrangian multiplier since we found that in practice it is hard to specify the constraint level that is required to update Lagrangian multiplier in Tessler et al. [2018]
the actor-critic framework. At stage one, for each auxiliary response, we learn a policy to optimize its cumulative reward respectively. At stage two, we learn the major policy that optimizes the cumulative main response in the neighborhood of the policies learned at stage one for other responses. We demonstrate the advantages of our approach over existing alternatives via extensive offline simulations as well as live experiments. We show that our approach effectively achieves to optimize the main goal with a good trade-off for the auxiliaries.

References

[n.d.]. Kuaisou Reports $3.2 Billion Total Revenue, Expanded Net Loss in Q3. https://pandaily.com/kuaisou-reports-3-2-billion-total-revenue-expanded-net-loss-in-q3/. Accessed: 2022-02-08.

[n.d.]. TikTok User Statistics (2022). https://backlinko.com/monthly-active-tiktok-users. Accessed: 2022-02-08.

M Mehdi Afsar, Trafford Crump, and Behrouz Far. 2021. Reinforcement learning based recommender systems: A survey. arXiv preprint arXiv:2101.06286 (2021).

Md Hijbul Alam, Woo-Jong Ryu, and SangKeun Lee. 2016. Joint multi-grain topic sentiment: modeling semantic aspects for online reviews. Information Sciences 339 (2016), 206–223.

Rich Caruana. 1997. Multitask learning. Machine learning 28, 1 (1997), 41–75.

Haokun Chen, Xinyi Dai, Han Cai, Weinan Zhang, Xuejian Wang, Ruiming Tang, Yuzhou Zhang, and Yong Yu. 2019b. Large-scale interactive recommendation with tree-structured policy gradient. In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 33. 3312–3320.

Minmin Chen, Alex Beutel, Paul Covington, Sagar Jain, Francois Belletti, and Ed H Chi. 2019a. Top-k off-policy correction for a REINFORCE recommender system. In Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining. 456–464.

Shi-Yong Chen, Yang Yu, Qing Da, Jun Tan, Hai-Kuan Huang, and Hai-Hong Tang. 2018. Stabilizing reinforcement learning in dynamic environment with application to online recommendation. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. 1187–1196.

Xu Chen, Yali Du, Long Xia, and Jun Wang. 2021. Reinforcement Recommendation with User Multi-aspect Preference. In Proceedings of the Web Conference 2021. 425–435.

Heng-Tze Cheng, Levent Koc, Jeremiah Harmsen, Tal Shaked, Tushar Chandra, Hrishi Aradhye, Glen Anderson, Greg Corrado, Wei Chai, Mustafa Isbir, et al. 2016. Wide & deep learning for recommender systems. In Proceedings of the 1st workshop on deep learning for recommender systems. 7–10.

Yinlam Chow, Mohammad Ghavamzadeh, Lucas Janson, and Marco Pavone. 2017. Risk-constrained reinforcement learning with percentile risk criteria. The Journal of Machine Learning Research 18, 1 (2017), 6070–6120.

Yinlam Chow, Ofir Nachum, Aleksandra Faust, Edgar Duenez-Guzman, and Mohammad Ghavamzadeh. 2019. Lyapunov-based safe policy optimization for continuous control. arXiv preprint arXiv:1901.10031 (2019).

Gal Dalal, Krishnamurthy Dvijotham, Matej Vecerik, Todd Hester, Cosmin Paduraru, and Yuval Tassa. 2018. Safe exploration in continuous action spaces. arXiv preprint arXiv:1801.08757 (2018).

Carlos Florensa, David Held, Markus Wulfmeier, Michael Zhang, and Pieter Abbeel. 2017. Reverse curriculum generation for reinforcement learning. In Conference on robot learning. PMLR, 482–495.
Scott Fujimoto, Herke Hoof, and David Meger. 2018. Addressing function approximation error in actor-critic methods. In International conference on machine learning. PMLR, 1587–1596.

Javier García and Fernando Fernández. 2015. A comprehensive survey on safe reinforcement learning. Journal of Machine Learning Research 16, 1 (2015), 1437–1480.

Yingqiang Ge, Shuchang Liu, Ruoyuan Gao, Yikun Xian, Yunqi Li, Xiangyu Zhao, Changhua Pei, Fei Sun, Junfeng Ge, Wenhua Ou, et al. 2021. Towards Long-term Fairness in Recommendation. In Proceedings of the 14th ACM International Conference on Web Search and Data Mining. 445–453.

Huifeng Guo, Ruiming Tang, Yunming Ye, Zhenguo Li, and Xiuzhi He. 2017. DeepFM: a factorization-machine based neural network for CTR prediction. arXiv preprint arXiv:1703.04247 (2017).

Matteo Hessel, Hubert Soyer, Lasse Espeholt, Wojciech Czarnecki, Simon Schmitt, and Hado van Hasselt. 2019. Multi-task deep reinforcement learning with popart. In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 33. 3796–3803.

Timothy P Lillicrap, Jonathan J Hunt, Alexander Pritzel, Nicolas Heess, Tom Erez, Yuval Tassa, David Silver, and Daan Wierstra. 2015. Continuous control with deep reinforcement learning. arXiv preprint arXiv:1509.02971 (2015).

Dong Liu and Chenyang Yang. 2019. A deep reinforcement learning approach to proactive content pushing and recommendation for mobile users. IEEE Access 7 (2019), 83120–83136.

Yongshuai Liu, Avishai Halev, and Xin Liu. 2021. Policy learning with constraints in model-free reinforcement learning: A survey. In Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence.

Jiaqi Ma, Zhe Zhao, Xinyang Yi, Jilin Chen, Lichan Hong, and Ed H Chi. 2018. Modeling task relationships in multi-task learning with multi-gate mixture-of-experts. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. 1930–1939.

Jiaqi Ma, Zhe Zhao, Xinyang Yi, Ji Yang, Minmin Chen, Jiaxi Tang, Lichan Hong, and Ed H Chi. 2020. Off-policy learning in two-stage recommender systems. In Proceedings of The Web Conference 2020. 463–473.

Volodymyr Mnih, Adria Puigdomenech Badia, Mehdi Mirza, Alex Graves, Timothy Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. 2016. Asynchronous methods for deep reinforcement learning. In International conference on machine learning. PMLR, 1928–1937.

Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, and Martin Riedmiller. 2013. Playing atari with deep reinforcement learning. arXiv preprint arXiv:1312.5602 (2013).

Hossam Mossalam, Yannis M Assael, Diederik M Roijers, and Shimon Whiteson. 2016. A multi-objective deep reinforcement learning framework. Engineering Applications of Artificial Intelligence 96 (2020), 103915.

Theodore J Perkins and Andrew G Barto. 2002. Lyapunov design for safe reinforcement learning. Journal of Machine Learning Research 3, Dec (2002), 803–832.

Qi Pi, Guorui Zhou, Yujing Zhang, Zhe Wang, Lejian Ren, Ying Fan, Xiaqiang Zhu, and Kun Gai. 2020. Search-based user interest modeling with lifelong sequential behavior data for click-through rate prediction. In Proceedings of the 29th ACM International Conference on Information & Knowledge Management. 2685–2692.

Doina Precup. 2000. Eligibility traces for off-policy policy evaluation. Computer Science Department Faculty Publication Series (2000), 80.

Doina Precup, Richard S Sutton, and Sanjoy Dasgupta. 2001. Off-policy temporal-difference learning with function approximation. In ICML. 417–424.

Martin Riedmiller, Roland Hafner, Thomas Lampe, Michael Neunert, Jonas Degrave, Tom Wiele, Vlad Mnih, Nicolas Heess, and Jost Tobias Springenberg. 2018. Learning by playing solving sparse reward tasks from scratch. In International Conference on Machine Learning. PMLR, 4344–4353.

Ozan Sener and Vladlen Koltun. 2018. Multi-task learning as multi-objective optimization. arXiv preprint arXiv:1810.04650 (2018).
Dusan Stamenkovic, Alexandros Karatzoglou, Ioannis Arapakis, Xin Xin, and Kleomenis Katevas. 2021. Choosing the Best of Both Worlds: Diverse and Novel Recommendations through Multi-Objective Reinforcement Learning. *arXiv preprint arXiv:2110.15097* (2021).

Richard S Sutton and Andrew G Barto. 2018. *Reinforcement learning: An introduction*. MIT press.

Adith Swaminathan and Thorsten Joachims. 2015. The self-normalized estimator for counterfactual learning. *advances in neural information processing systems* 28 (2015).

Tomasz Tajmajer. 2018. Modular multi-objective deep reinforcement learning with decision values. In *2018 Federated conference on computer science and information systems (FedCSIS)*. IEEE, 85–93.

Chen Tessler, Daniel J Mankowitz, and Shie Mannor. 2018. Reward constrained policy optimization. *arXiv preprint arXiv:1805.11074* (2018).

C Ch White, CC III WHITE, and KIM KW. 1980. Solution procedures for vector criterion Markov decision processes. (1980).

Ronald J Williams. 1992. Simple statistical gradient-following algorithms for connectionist reinforcement learning. *Machine learning* 8, 3 (1992), 229–256.

Yikun Xian, Zuohui Fu, Shan Muthukrishnan, Gerard De Melo, and Yongfeng Zhang. 2019. Reinforcement knowledge graph reasoning for explainable recommendation. In *Proceedings of the 42nd international ACM SIGIR conference on research and development in information retrieval*. 285–294.

Xiangyu Zhao, Liang Zhang, Zhuoye Ding, Long Xia, Jiliang Tang, and Dawei Yin. 2018. Recommendations with negative feedback via pairwise deep reinforcement learning. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 1040–1048.

Xiangyu Zhao, Liang Zhang, Long Xia, Zhuoye Ding, Dawei Yin, and Jiliang Tang. 2017. Deep reinforcement learning for list-wise recommendations. *arXiv preprint arXiv:1801.00209* (2017).

Lixin Zou, Long Xia, Zhuoye Ding, Jiaxing Song, Weidong Liu, and Dawei Yin. 2019. Reinforcement learning to optimize long-term user engagement in recommender systems. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 2810–2818.

### A Evaluation of Default Policy on A Popular Short Video Platform

We showcase the advantage of separate evaluation for each response over a single evaluation of summed response. Specifically, we consider two types of responses from each video view: WatchTime and interaction-signal (which is an indicator function of whether Share/Comment/Download happens during the view).

- For the single evaluation, we learn a value model $V_{\text{single}}$ with reward as a summation of WatchTime and interaction-signal.
- For the separate evaluation, we learn two value models $V_w$ and $V_i$ with reward as WatchTime and interaction-signal respectively. Define the value of separate evaluation as $V_{\text{separate}} = V_w + V_i$.

For fair comparison, we share the same discount factor $0.95$ for all value models and train them on the same data collected from a popular short video platform for one day. To evaluate the extend to which the value model learns the information of WatchTime and interaction-signal, we compute the correlation between model values $V_{\text{single}}$ and $V_{\text{separate}}$ with the Monte Carlo value of the corresponding response. As compared to $V_{\text{single}}$, $V_{\text{separate}}$ is more correlated with WatchTime and interaction-signal by $0.191\%$ and $0.143\%$ respectively, demonstrating that the separate evaluation better learns different reward responses.

### B Derivation of the Constrained Actor-Critic Algorithm

The Lagrangian of the constrained optimization (5) is

$$
\mathcal{L}(\pi, \lambda_2, \ldots, \lambda_m) = -E_\pi[A_1^{(k)}] + \sum_{i=2}^{m} \lambda_i (D_{KL}(\pi||\pi_{\theta_i}) - \epsilon_i),
$$

We focus on the summation of estimated values from $V_w$ and $V_i$, since it will be later used to guide policy learning.
with $\lambda_i \geq 0, i = 2, \ldots, m$ and $\int_a \pi(a|s) = 1$. Compute the gradient of $\mathcal{L}(\pi, \lambda_2, \ldots, \lambda_m)$ with respect to $\pi$, we have

$$\frac{\partial \mathcal{L}}{\partial \pi} = -A^{(k)}_1 + \sum_{i=2}^m \lambda_i (1 + \log(\pi(a|s)) - \log(\pi_0(a|s))).$$

(10)

Setting $\frac{\partial \mathcal{L}}{\partial \pi} = 0$, we have the solution $\pi^*$ satisfies

$$\pi^*(a|s) = \frac{1}{Z(s)} \prod_{i=2}^m \left( \frac{\pi_{\theta_i}(a|s)}{\pi_{\theta_i}(a|s)} \right)^{\frac{\lambda_i}{\sum_{j=2}^m \lambda_j}} \exp \left( \frac{A^{(k)}_1}{\sum_{j=2}^m \lambda_j} \right),$$

(11)

where $Z(s)$ is the partition function to make sure that $\int_a \pi(a|s) = 1$.

To solve parameter $\theta^{(k+1)}_1$ of the main policy with data collected by $\pi_{\theta^{(k)}_1}$, we minimize the KL divergence between $\pi^*$ and $\pi_{\theta^{(k+1)}_1}$:

$$\theta^{(k+1)}_1 \leftarrow \arg \min_{\theta} E_{\pi_{\theta^{(k)}_1}} [D_{KL}(\pi^*(a|s)||\pi_{\theta}(a|s))],$$

$$= \arg \min_{\theta} E_{\pi_{\theta^{(k)}_1}} [E_{\pi^*} [-\log \pi_{\theta}(\cdot|s)]]$$

$$= \arg \max_{\theta} E_{\pi_{\theta^{(k)}_1}} \left[ E_{\pi^*} \left[ -\log \pi_{\theta}(\cdot|s) \right] \right]$$

$$= \arg \max_{\theta} E_{\pi_{\theta^{(k)}_1}} \left[ \prod_{i=2}^m \left( \frac{\pi_{\theta_i}(a|s)}{\pi_{\theta_i}(a|s)} \right)^{\frac{\lambda_i}{\sum_{j=2}^m \lambda_j}} \exp \left( \frac{A^{(k)}_1}{\sum_{j=2}^m \lambda_j} \right) \log \pi_{\theta}(a|s) \right].$$

(12)

### C The Two-Stage Constrained Actor Critic Algorithm

**Algorithm 1: Two-Stage Constrained Actor Critic**

**Stage One:** For each auxiliary response $i = 2, \ldots, m$, learn a policy to optimize the response $i$, with $\pi_{\theta_i}$ denoting actor and $V_{\phi_i}$ for critic.

While not converged, at iteration $k$:

$$\phi^{(k+1)}_i \leftarrow \arg \min_{\phi} E_{\pi_{\theta^{(k)}_1}} \left[ (r_i(s, a) + \gamma_i V_{\phi^{(k)}_i}(s') - V_{\phi}(s))^2 \right],$$

$$\theta^{(k+1)}_i \leftarrow \arg \max_{\theta} E_{\pi_{\theta^{(k)}_1}} \left[ A^{(k)}_1 \log (\pi_{\theta}(a|s)) \right].$$

**Stage Two:** For the main response, learn a policy to both optimize the main response and restrict its domain close to the policies $\{\pi_{\theta_i}\}_{i=2}^m$ of auxiliary responses, with $\pi_{\theta_1}$ denoting actor and $V_{\phi_1}$ for critic.

While not converged, at iteration $k$:

$$\phi^{(k+1)}_1 \leftarrow \arg \min_{\phi} E_{\pi_{\theta^{(k)}_1}} \left[ (r_1(s, a) + \gamma_1 V_{\phi^{(k)}_1}(s') - V_{\phi}(s))^2 \right],$$

$$\theta^{(k+1)}_1 \leftarrow \arg \max_{\theta} E_{\pi_{\theta^{(k)}_1}} \left[ A^{(k)}_1 \log (\pi_{\theta}(a|s)) \right]$$

$$\times \exp \left( \frac{A^{(k)}_1}{\sum_{j=2}^m \lambda_j} \right) \log \pi_{\theta}(a|s) \right].$$

**Output:** the constrained policy $\pi_1$.

### D Offline Learning

We now discuss adapting our constrained actor critic framework to policy learning using offline datasets.

**Multi-Critic Learning** In contrast to online learning that critics evaluating different responses are trained with data under different actor policies, these critics now share the same offline dataset, which can be formulated into a multi-task
learning problem. One can apply off-the-shelf multi-task algorithms to learn the commonalities shared by different tasks and also the differences for the task-specific considerations. As an example, the shared-bottom model architecture proposed in Caruana [1997] is efficient in leveraging sharing attributes and avoiding overfitting, but it may bring in optimization conflict from different tasks for the bottom parameters. One remedy is to learn several expert models and use task-specific gates to generate each model prediction, named as the multi-gate mixture-of-experts (MMOE) method proposed in Ma et al. [2018].

Debiased Actor Learning

The main change when moving from the online actor learning to the offline setup is the bias correction on the policy gradient. The actor is no longer updated on data collected by current policy but by another behavior policy \( \pi_\beta \), which may result in a different data distribution induced by the policy being updated. To address the distribution mismatch when estimating the policy gradient, a common strategy is to apply bias-correction ratio via importance sampling Precup [2000], Precup et al. [2001]. Given a trajectory \( \tau = (s_1, a_1, s_2, a_2, \ldots) \), the bias-correction ratio on the policy gradient for policy \( \pi_\theta \) is

\[
w(s_t, a_t) = \prod_{t'=1}^{t} \frac{\pi_\theta(s_{t'}|a_{t'})}{\pi_\beta(s_{t'}|a_{t'})},
\]

which gives an unbiased estimation, but the variance can be huge. Therefore, we suggest using a first-order approximation of (13), and use the current action-selection ratio when optimizing the actors of auxiliary responses,

\[
\theta_i^{(k+1)} \leftarrow \arg \max_{\theta} \mathbb{E}_{\pi_\theta^{(k)}} \left[ A_i^{(k)} \log(\pi_\theta(a|s)) \right]
\]

\[
\approx \arg \max_{\theta} \mathbb{E}_{\pi_\beta} \left[ \frac{\pi_\theta(a|s)}{\pi_\beta(a|s)} A_i^{(k)} \log(\pi_\theta(a|s)) \right].
\]

Similarly, when updating the actor of the main response, we have

\[
\theta_1^{(k+1)} \leftarrow \arg \max_{\theta} \mathbb{E}_{\pi_\theta^{(k)}} \left[ \prod_{i=2}^{m} \left( \frac{\pi_\theta(a|s)}{\pi_\beta(a|s)} \right)^{\frac{\lambda_i}{\sum_{j=2}^{m} \lambda_j}} A_1^{(k)} \log(\pi_\theta(a|s)) \right] \times \exp \left( \frac{A_1^{(k)}}{\sum_{j=2}^{m} \lambda_j} \right). 
\]

\[
\approx \arg \max_{\theta} \mathbb{E}_{\pi_\beta} \left[ \prod_{i=2}^{m} \left( \frac{\pi_\theta(a|s)}{\pi_\beta(a|s)} \right)^{\frac{\lambda_i}{\sum_{j=2}^{m} \lambda_j}} A_1^{(k)} \log(\pi_\theta(a|s)) \right] \times \exp \left( \frac{A_1^{(k)}}{\sum_{j=2}^{m} \lambda_j} \right).
\]

E Ablation Study

The Effect of the discount factor on the performance

As a critical hyper-parameter in RL methods, the discount factor \( \gamma \) plays a vital role in model performance. To this end, we study the influence of \( \gamma \) and range its value across \([0.5, 0.7, 0.9, 0.99, 0.999]\). We present our model performance on the main response (overall score) and other auxiliary tasks. The results are shown in Figure 3. We can see that as \( \gamma \) increases, our policy progressively delivers improved performance for the main response since the long term reward is further considered, while the performance on the auxiliary task first remains relatively stable and then peaks for \( \gamma = 0.99 \). However, the policy performance may deteriorate when \( \gamma \) is too large. In this dataset, We select \( \gamma = 0.99 \) as an appropriate choice.
Figure 3: Effect of Discount Factor on model performance for all responses. The X-axis denotes the discount factor $\gamma$ and the Y-axis is the score of each response.