Fast Rates for Offline Contextual Bandits with Forward-KL Regularization under Single-Policy Concentrability

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Abstract

Kullback-Leibler (KL) regularization is ubiquitous in reinforcement learning algorithms in the form of *reverse* or *forward* KL. Recent studies have demonstrated ϵ^{-1}-type fast rates for decision making under reverse KL regularization, in contrast to the standard ϵ^{-2}-type sample complexity. However, for forward-KL-regularized objectives, existing statistical analyses are either not applicable or result in $\widetilde{O}(\epsilon^{-2})$ slow rates. We take the first step towards addressing this problem via a streamlined analysis of forward-KL-regularized offline CBs. We give the first $\widetilde{O}(\epsilon^{-1})$ upper bounds in tabular and general function approximation settings, both under notions of *single-policy concentrability*. In particular, our convex-analytical pipeline unifies these settings by exploiting the pessimism principle in a novel way and completely bypasses the proof routines in previous works based on the mean value theorem, which might be of independent interest. Moreover, we provide rate-optimal lower bounds, manifesting the tightness of our upper bounds in terms of statistical rates. Our lower bounds also demonstrate that the forward-KL-regularized sample complexity recovers the unregularized slow rate in the low-regularization regime, similarly to the reverse-KL regularization.

1 Introduction

KL-regularized objectives in the form of $J \coloneqq \mathbb{E}[r] - \eta^{-1}\mathsf{KL}$ have recently become a pivotal prototype for algorithm design in decision making such as robotics (Levine and Koltun, 2013; Schulman, 2015; Haarnoja et al., 2018), and foundation model finetuning (Ouyang et al., 2022; Rafailov et al., 2023; Ji et al., 2023; Wang et al., 2023; Guo et al., 2025; Shan et al., 2025). Here, r stands for variants of reward or advantage functions, η^{-1} is the regularization intensity; and KL is typically either $\mathsf{KL}\left(\pi \| \pi^{\mathsf{ref}}\right)$ or $\mathsf{KL}\left(\pi^{\mathsf{ref}} \| \pi\right)$, where π^{ref} is the reference policy. The reverse KL regularizer $\mathsf{KL}\left(\pi \| \pi^{\mathsf{ref}}\right)$ has been arguably more popular in algorithmic formulations, which has rich connections with Gibbs distributions and entropy regularization in machine learning (Williams, 1992; McAllester, 1999; Ziebart et al., 2008; Zhang, 2023). But there are also emerging lines of works that formulate their RL fine-tuning algorithms via the forward KL regularizer $\mathsf{KL}\left(\pi^{\mathsf{ref}} \| \pi\right)$ (Ji et al., 2023; Wang et al., 2023; Shan et al., 2025), or *effectively* employ this forward counterpart at the implementation level (Guo et al., 2025; Tang and Munos, 2025; Shah et al., 2025).

There has been a line of efforts motivated by the practical relevance of KL-regularized objectives towards understanding the *data efficiency* of learning with respect to *KL-regularized performance metrics*, which dates back to at least Tiapkin et al. (2023); Xie et al. (2024); Xiong et al. (2024). In the case of reverse KL, sharpest rates in previous works have been $\mathrm{polylog}(T)$ regret (Zhao et al., 2025b; Ji et al., 2026; Nayak et al., 2025) and $\widetilde{\Theta}(\epsilon^{-1})$ sample complexity (Tiapkin et al., 2023; Zhao et al., 2025a, 2026; Foster et al., 2025; Zhang et al., 2026) in offline, online, and hybrid settings for contextual bandits (CBs) or Markov decision processes (MDPs). The analysis of the forward KL

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Table 1: Comparison of regret or sample complexity upper and lower bounds for forward KL-regularized CBs. In this table, ϵ is the target suboptimality gap, and η is the inverse regularization intensity. Under function approximation, $\mathcal{G}$ is the function class, whose covering number is $N_{\mathcal{G}}$, and $D^2_{\pi^*}$ is the D^2-type single policy concentrability. In the tabular setting, $\mathcal{S}$ is the context set and $\mathcal{A}$ is the action set, and $|\mathcal{S}|$ and $|\mathcal{A}|$ denotes the corresponding cardinality. Furthermore, $C_{\varepsilon_{\text{FKL}}}$ is the density-ratio-based local forward KL-ball coverage coefficient, and C^{π^*} is the density-ratio-based single-policy concentrability. $\widetilde{O}(\cdot)$ hides logarithmic factors except $\log(N_{\mathcal{G}})$.

Type	Algorithm	Setting	Sample Complexity
Upper Bound	Forward KL-Regularized RLHF (Aminian et al., 2025)	Function Approximation	$\widetilde{O}\big(\log N_{\mathcal{G}} C_{\varepsilon_{\text{FKL}}}/\epsilon^2\big)$
	FKL-PCB (This Work)	Function Approximation	$\widetilde{O}\big(\eta C^{\pi^*} D^2_{\pi^*} \log N_{\mathcal{G}}/\epsilon\big)$
	FKL-PCB (This Work)	Tabular	$\widetilde{O}\big(\eta (C^{\pi^*})^2 \lvert\mathcal{S}\rvert\lvert\mathcal{A}\rvert/\epsilon\big)$
Lower Bound	This Work	Tabular	$\Omega(\eta \lvert\mathcal{S}\rvert\lvert\mathcal{A}\rvert/\epsilon)$

counterparts is significantly less explored. Zhao et al. (2026) derives $\widetilde{\Theta}(\epsilon^{-1})$ bounds for general f-divergence-regularized suboptimality for offline CBs, but they need f to be strongly convex, and is thus inapplicable to forward KL because forward KL is f-divergence with $f(x) = -\log x$, which is only strictly convex. Lee et al. (2026) derives a logarithmic regularized regret upper bound with general regularizers in a self-play setting, but the bound directly scales inversely with the minimal eigenvalue of the expected feature covariance matrix, and their regularizer needs to be strongly convex, which may not be the case for forward KL unless the sample complexity is allowed to inversely scale with the minimal mass $\min_{s,a} \pi^{\text{ref}}(a|s)$ of the reference policy.[2] Aminian et al. (2025) gives the first $\widetilde{O}(\epsilon^{-2})$ upper bound for offline CBs with forward-KL regularization, where no lower bounds are known by far. Therefore, the following problem remains open **even for learning from pure** i.i.d. **data**:

What is the statistical rate of decision making with respect to forward-KL-regularized objectives?

Any meaningful progress regarding this problem in the offline setting is likely to confront the distributional shift between the i.i.d. data and the optimal policy. On one hand, *single-policy concentrability*, where the behavioral policy π^{ref} only covers the optimal policy, is shown to be a sufficient notion that permits the near-optimal $\widetilde{\Theta}(1/\epsilon)$ sample complexity in many **reverse**-KL-regularized settings where the contexts and actions are acquired offline (Zhao et al., 2026; Foster and Rakhlin, 2023). On the other hand, classic wisdom implies that the forward-KL regularizer and its reverse counterpart adapt π to the modes of π^{ref} in distinct ways (Bishop and Nasrabadi, 2006; Ji et al., 2023; GX-Chen et al., 2025): in short, (in certain parametrized cases) reverse KL is believed to be mode-seeking, which heavily penalizes $\pi > 0$ where $\pi^{\text{ref}} \approx 0$; while forward KL appears to be mass-covering, which mainly penalizes $\pi \to 0$ where $\pi^{\text{ref}} > 0$. The following problem then arises **on top of the statistical rate problem** above:

Is single-policy concentrability *also sufficient for rate-optimal offline learning with forward-KL regularization*?

We solve these problems for offline CBs concretely by the $\widetilde{\Theta}(\epsilon^{-1})$ sample complexity characterization[3], which is achieved under single-policy concentrability assumptions for the first time. At the core of our achievability results is a novel suboptimality decomposition for forward-KL-regularized objectives, overcoming the limitation of the traditional synergy of Taylor expansion and the mean value theorem (Zhao et al., 2025a, 2026, 2025b; Nayak et al., 2025; Ji et al., 2026) for analyzing the divergence-regularized sample complexity of bonus-based RL algorithms, which leads to a streamlined analysis of ***F**orward **KL**-Regularized **P**essimistic **C**ontextual **B**andits* (FKL-PCB) algorithms without any standalone dependency on $\min_{s,a} \pi^{\text{ref}}(a|s)$. Our hardness results further demonstrate the fundamental rate limits in both the high- and low-regularization regimes.

Notation. The calligraphic $\mathcal{S}$ and $\mathcal{A}$ denote finite sets throughout this paper. $\Delta(\mathcal{A})$ is the set of probability distributions on $\mathcal{A}$ and $\Delta(\mathcal{A}|\mathcal{S})$ is the family of probability kernels from $\mathcal{S}$ to $\mathcal{A}$. For $P, Q \in \Delta(\mathcal{A})$ with $P \ll Q$, the KL divergence from P to Q is denoted by $\mathsf{KL}(P\|Q) :=$

[2] See Lemma 5.1 for the concrete exposition.

[3] We omit the dependencies on quantities other than ϵ here for presentation clarity.

$\int \log(\mathrm{d}P/\mathrm{d}Q)\,\mathrm{d}P$, and $\mathrm{supp}(P)$ denotes the support set of P. For any subset E of a Euclidean space, $\mathrm{ri}(E)$ denotes its *relative interior*. For any extended real-valued convex function f, its *domain* is $\mathrm{dom}(f) \coloneqq \{\pi : f(\pi) < +\infty\}$. Any closed convex function $\ell : \mathbb{R}^d \to \mathbb{R} \cup +\infty$ induces a Bregman divergence $\mathsf{B}_\ell(\mathbf{x}, \mathbf{y}) \coloneqq \ell(\mathbf{x}) - \ell(\mathbf{y}) - \langle \nabla\ell(\mathbf{y}), \mathbf{x} - \mathbf{y}\rangle$ for $\mathbf{x}, \mathbf{y} \in \mathbb{R}^d$. Given $f, g : \mathcal{A} \to \mathbb{R} \cup \{+\infty\}$, $\langle f, g\rangle$ denotes the summation $\sum_{a\in\mathcal{A}} f(a)g(a)$. We use standard asymptotic notations including $O(\cdot)$, $\Omega(\cdot)$, and $\Theta(\cdot)$; for which $\widetilde{O}(\cdot), \widetilde{\Omega}(\cdot), \widetilde{\Theta}(\cdot)$ further hide $\mathrm{polylog}$ factors.

1.1 Key Related Works

We survey recent sharp sample complexity analyses of decision making with respect to regularized objectives and defer other related works on pessimism and forward KL regularization to Appendix A.

Fast Rates for Regularized Decision Making. The practical relevance of regularized objectives has motivated a broad line of sharper analyses of the statistical efficiency of decision-making under such formulations. The pioneering work of Tiapkin et al. (2023) first established an ϵ^{-1}-type fast sample complexity in the pure-exploration setting, followed by a series of works (Zhao et al., 2025b; Ji et al., 2026) that focused on regret minimization. A parallel line of research focuses on the offline or hybrid setting, starting from Zhao et al. (2025a) that obtained a $\widetilde{\Theta}(\epsilon^{-1})$ rate under concentrability of all policies. This requirement was relaxed in subsequent works (Foster et al., 2025; Kim et al., 2026; Zhao et al., 2026), in the context of adaptive reward-query, batched online learning, and pure offline learning, respectively. Similar fast convergence has also been shown in online (Nayak et al., 2025) and offline (Zhang et al., 2026) multi-agent RL, and self-play CBs with generalized bilinear function approximation (Lee et al., 2026). Despite these advances, the literature has largely focused on reverse KL or regularizers with certain strong-convexity-type properties, leaving a wide range of regularizers, such as forward KL, comparatively underexplored. Notably, Aminian et al. (2025) gave the first algorithm analysis for offline contextual dueling bandits with multiple reference models under forward-KL regularization; which, however, yields an $\widetilde{O}(\epsilon^{-2})$ slow rate.

2 Preliminaries

Consider offline CBs with context space $\mathcal{S}$, action space $\mathcal{A}$, mean reward function $r : \mathcal{S} \times \mathcal{A} \to [0, 1]$, context distribution $\rho \in \Delta(\mathcal{S})$, and reference policy $\pi^{\mathsf{ref}} \in \Delta(\mathcal{A}|\mathcal{S})$. The agent only learns from an i.i.d. dataset $\mathcal{D} = \{s_i, a_i, r_i\}_{i=1}^n$, where $s_i \sim \rho$, $a_i \sim \pi^{\mathsf{ref}}(\cdot|s_i)$, and $r_i = r(s_i, a_i) + \varepsilon_i$ for each i. Here, each ε_i is conditionally mean-zero and 1-subgaussian given (s_i, a_i), and π^{ref} *serves as the behavioral policy*. In particular, the class of interest satisfying all constraints above is denoted by $\mathrm{CB}(\mathcal{S}, \mathcal{A}, r, \rho, \pi^{\mathsf{ref}})$.[4] Given the inverse regularization intensity $\eta > 0$, let the forward-KL-regularized objective be

$$J_{\mathrm{FKL}}(\pi) \coloneqq J_{\mathrm{FKL}}(\pi; r) \coloneqq \langle r, \pi\rangle - \eta^{-1}\mathsf{KL}\left(\pi^{\mathsf{ref}} \| \pi\right), \tag{2.1}$$

where we overload $\langle r, \pi\rangle \coloneqq \mathbb{E}_{s\sim\rho}\langle r(s, \cdot), \pi(\cdot|s)\rangle$ and $\mathsf{KL}\left(\pi^{\mathsf{ref}} \| \pi\right) \coloneqq \mathbb{E}_{s\sim\rho}\mathsf{KL}\left(\pi^{\mathsf{ref}}(\cdot|s) \| \pi(\cdot|s)\right)$. The learning objective is $\max_{\pi\in\Delta(\mathcal{A}|\mathcal{S})} J_{\mathrm{FKL}}(\pi)$. We assume π^{ref} has full support to ensure learnability over $\Delta(\mathcal{A}|\mathcal{S})$ and simplify the presentation.

Assumption 2.1. $\min_{s,a\in\mathcal{S}\times\mathcal{A}} \pi^{\mathsf{ref}}(a|s) > 0$.

If $\mathrm{supp}(\pi^{\mathsf{ref}}(\cdot|s)) \subsetneq \mathcal{A}$, $\mathcal{D}$ never contains actions outside $\mathcal{A}_s^{\mathrm{eff}} \coloneqq \mathrm{supp}(\pi^{\mathsf{ref}}(\cdot|s))$. Unlike reverse KL (which evaluates to $+\infty$ outside $\mathcal{A}_s^{\mathrm{eff}}$), $\mathsf{KL}\left(\pi^{\mathsf{ref}}(\cdot|s) \| \pi(\cdot|s)\right)$ remains finite when $\pi(\cdot|s)$ places mass outside $\mathcal{A}_s^{\mathrm{eff}}$, so unrestricted optimization over $\Delta(\mathcal{A}|\mathcal{S})$ can be unidentifiable from offline data (specifically whenever $\eta > 1$) without cross-action structural assumptions; whereas optimizing over the support-restricted class $\Pi_{\mathrm{eff}} \coloneqq \{\pi \in \Delta(\mathcal{A}|\mathcal{S}) : \mathrm{supp}(\pi(\cdot|s)) \subseteq \mathcal{A}_s^{\mathrm{eff}}, \forall s \in \mathcal{S}\}$ reduces the action set to $\mathcal{A}_s^{\mathrm{eff}}$, where π^{ref} has full support by definition (see Appendix E.2). Thus, the central statistical question is whether the sample complexity blows up as $\min_{s,a\in\mathcal{A}_s^{\mathrm{eff}}} \pi^{\mathsf{ref}}(a|s) \to 0$. Assumption 2.1 has also been used in Huang et al. (2024, Lemma F.4) to derive a closed-form solution of a regularized optimal policy, and in the analyses of Wang et al. (2023); Aminian et al. (2025) implicitly in a similar way. It does *not* impose a quantitative gap between $\min_{s,a} \pi^{\mathsf{ref}}(a|s)$ and 0, which is also not needed in our analysis. The following closed-form of the forward-KL-regularized optimal policy follows from the classic KKT theory (See, e.g., Beck (2017, Appendix A) and Wang et al., 2023; Aminian et al., 2025). We provide its proof in Appendix E for completeness.

[4] In single-context or context-wise derivations with fixed $s \in \mathcal{S}$, we write $r(a)$ as shorthand for $r(s, a)$.

Lemma 2.2. Under Assumption 2.1, $\forall s \in \mathcal{S}$, there exists a unique $\lambda_s > \max_{a\in\mathcal{A}} r(s,a)$ such that

$$\pi^*_{\mathrm{FKL}}(\cdot|s) := \frac{\eta^{-1}\pi^{\mathsf{ref}}(\cdot|s)}{\lambda_s - r(s,\cdot)} \tag{2.2}$$

is the unique solution to $\max_{\pi\in\Delta(\mathcal{A}|\mathcal{S})} J_{\mathrm{FKL}}(\pi)$.

We then define the sub-optimality gap *regularized by forward KL* as

$$\mathrm{SubOpt}_{\mathrm{FKL}}(\cdot) := \mathrm{SubOpt}_{\mathrm{FKL}}(\cdot;\mathcal{S},\mathcal{A},r,\rho,\pi^{\mathsf{ref}}) = J_{\mathrm{FKL}}(\pi^*_{\mathrm{FKL}}) - J_{\mathrm{FKL}}(\cdot), \tag{2.3}$$

under which, the agent aims to find the *ϵ-optimal policy* $\widehat{\pi}$ with $\mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}) \le \epsilon$. For simplicity, we use π^* interchangeably with π^*_{FKL} to avoid notation clutter unless otherwise specified.

Concentrability. In offline learning and decision making, how the dataset $\mathcal{D}$ collected by π^{ref} covers a target distribution or a collection of potential target distributions largely shapes the learnability of the problem. This coverage is typically characterized by *the* concentrability in offline RL, which quantifies the ability of the behavior policy to generate diverse actions. We first introduce the density-ratio-based concentrability (Chen and Jiang, 2019; Xie et al., 2021a; Rashidinejad et al., 2021; Li et al., 2024) as follows, which characterizes how each pair of $(s,a) \in \mathcal{S}\times\mathcal{A}$ is covered by the behavior policy.

Definition 2.3 (*Density-ratio-based* concentrability)**.** Given some policy class Π and some reference policy π^{ref}, the density-ratio-based all-policy concentrability C^{Π} is defined by $C^{\Pi} := \sup_{\pi\in\Pi, s\in\mathcal{S}, a\in\mathcal{A}} \pi(a|s)/\pi^{\mathsf{ref}}(a|s)$, whose single-policy counterpart under the optimal policy π^* is $C^{\pi^*} := \sup_{s\in\mathcal{S},a\in\mathcal{A}} \pi^*(a|s)/\pi^{\mathsf{ref}}(a|s)$.

When the optimal policy π^* is contained within the policy class Π, the relationship $C^{\pi^*} \le C^{\Pi}$ necessarily holds. Consequently, an analytical dependency on the single-policy concentrability coefficient C^{π^*} is strictly weaker, and thus more general, than a dependency on the all-policy coefficient C^{Π}. In this work, we demonstrate that this more relaxed single-policy concentrability is sufficient for learning forward-KL-regularized bandits. This result stands in contrast to the more restrictive requirement of all-policy concentrability typically invoked in previous literature (Zhao et al., 2025a; Wu et al., 2025; Aminian et al., 2025).

2.1 Function Approximation

While the tabular setting serves as the minimal decision making formalization without additional structures, algorithms designed directly for this setting become computationally intensive or even intractable in most real-world applications due to the curse of dimensionality. To address this issue, it is generally assumed that the learner has access to some class of functions that incorporate the ground truth reward (Jin et al., 2021; Xiong et al., 2022; Di et al., 2023). In this paper, we also consider the scenarios that the reward lies in some known function class $\mathcal{G}$, as formalized by the following realizable assumption.

Assumption 2.4. For this known function class $\mathcal{G} \subseteq (\mathcal{S}\times\mathcal{A}\to[0,1])$, $\exists g^* \in \mathcal{G}$ with $g^* = r$.

To characterize the complexity measure of the reward function class, we adopt the standard notion of covering number (Wainwright, 2019, Definition 5.1).

Definition 2.5 (ϵ-net and covering number)**.** Given a function class $\mathcal{G} \subset (\mathcal{S}\times\mathcal{A}\to\mathbb{R})$, a finite set $\mathcal{G}(\epsilon) \subset \mathcal{G}$ is an ϵ-net of $\mathcal{G}$ w.r.t. $\|\cdot\|_\infty$, if for any $g \in \mathcal{G}$, there exists $g' \in \mathcal{G}(\epsilon)$ such that $\|g - g'\|_\infty \le \epsilon$. The ϵ-covering number is the smallest cardinality $N_{\mathcal{G}}(\epsilon)$ of such $\mathcal{G}(\epsilon)$.

Assumption 2.6. For any $\epsilon_c > 0$, the ϵ_c-covering number $N_{\mathcal{G}}(\epsilon_c)$ of $\mathcal{G}$ is $\mathrm{poly}(\epsilon_c^{-1})$.

Assumption 2.6 allowing $\log N_{\mathcal{G}}(\epsilon)$ to be roughly negligible is arguably mild. For example, when $\mathcal{G}$ is the class of linear functions of dimension d and radius R, the covering number is $N_{\mathcal{G}}(\epsilon) = O((1+R\epsilon^{-1})^d)$ (Jin et al., 2020, Lemma D.6), which satisfies Assumption 2.6.

In the presence of function approximation, the density-ratio-based concentrability in Definition 2.3 does not precisely capture the quality of the offline dataset due to the absence of the function approximation structure in its definition. For example, a particular context-action pair $(s,a) \in \mathcal{S}\times\mathcal{A}$ might be frequently visited by π^* but seldom by π^{ref}, leading to very large C^{π^*}. However, if there

Algorithm 1 FKL-PCB for Tabular Setting

Require: regularization η, reference policy π^{ref}, offline dataset $\mathcal{D}$

Set $N(s,a) = \sum_{i=1}^{n} \mathbb{1}\{(s_i,a_i) = (s,a)\}$ for all $a \in \mathcal{A}$, $s \in \mathcal{S}$

for $s \in \mathcal{S}$, $a \in \mathcal{A}$ **do**

  if $N(s,a) = 0$ **then**

    Set the empirical reward $\bar{g}(s,a) \leftarrow 0$, penalty $b(s,a) \leftarrow 1$

  else

    Compute the empirical reward $\bar{g}(s,a) \leftarrow \sum_{i=1}^{n} r_i \mathbb{1}\{(s_i,a_i) = (s,a)\}/N(s,a)$

    Compute the penalty to be

$$b(s,a) \leftarrow \sqrt{4\log(2|\mathcal{S}||\mathcal{A}|/\delta)/N(s,a)}, \tag{3.1}$$

  end if

  Set $\widehat{g}(s,a) \leftarrow \max\{\bar{g}(s,a) - b(s,a), 0\}$

end for

Ensure: $\widehat{\pi} = \operatorname{argmax}_{\pi \in \Delta(\mathcal{A}|\mathcal{S})} \langle \widehat{g}, \pi \rangle - \eta^{-1} \mathsf{KL}\left(\pi^{\mathsf{ref}} \| \pi\right)$

is some $(s',a') \in \mathcal{S} \times \mathcal{A}$ frequently appearing in the dataset $\mathcal{D}$ such that $g(s,a) \approx g(s',a')$ for all $g \in \mathcal{G}$, then the reward of (s,a) is still well estimated, since feature representation associated with (s,a) is frequently visited by visiting (s',a'). To capture this dependency, we introduce the following D^2-type concentrability (Gentile et al., 2022; Agarwal et al., 2023; Zhao et al., 2025a) in function approximation, which characterize the coverage of the behavior policy on the feature space.

Definition 2.7. Given function class $\mathcal{G} \subset (\mathcal{S} \times \mathcal{A} \to \mathbb{R})$ and policy π, their D^2-divergence is

$$D^2_{\mathcal{G}}((s,a);\pi) := \sup_{g,h \in \mathcal{G}} \frac{\big(g(s,a) - h(s,a)\big)^2}{\mathbb{E}_{(s',a') \sim \rho \times \pi}[(g(s',a') - h(s',a'))^2]}, \forall (s,a) \in \mathcal{S} \times \mathcal{A}.$$

We are now ready to define the D^2-type single policy concentrability.

Assumption 2.8 (Single-policy concentrability)**.** $D^2_{\pi^*} := \mathbb{E}_{(s,a) \sim \rho \times \pi^*} D^2_{\mathcal{G}}((s,a);\pi^{\mathsf{ref}}) < \infty$.

Assumption 2.8 indicates that the errors on the context-action distributions $\rho \times \pi^*$ can be bounded by the error on the samples from $\rho \times \pi^{\mathsf{ref}}$ up to some constant. Similar to the density-ratio-based concentrabilities, here it is also true that the single-policy concentrability assumption is strictly weaker than the all-policy concentrability assumption (e.g., Zhao et al. 2026, Assumption 2.7). Remarkably, the two quantities characterizing single-policy concentrability C^{π^*} and $D^2_{\pi^*}$ cannot be bounded by each other up to constant factors in general. We provide a detailed discussion of the relation between C^{π^*} and $D^2_{\pi^*}$ in Appendix B.

3 Algorithms and Sample Complexity Upper Bounds

In this section, we present the algorithm, FKL-PCB, for learning forward-KL-regularized CBs. For ease of presentation, we present its adaptations for both tabular setting and reward function approximation respectively, in Section 3.1 and Section 3.2.

3.1 Algorithm for Tabular Setting

We first tackle the most vanilla tabular setting, where the reward function can be any map in $\mathcal{S} \times \mathcal{A} \to [0,1]$, as summarized in Algorithm 1. At a high level, the algorithm follows previous pessimism-based algorithms (Rashidinejad et al., 2021) for regularized objectives (Zhao et al., 2026). In particular, Algorithm 1 first employs a least-squares estimator to estimate the reward function. Then following Zhao et al. (2026), we subtract a penalty term to prevent over-estimation, leading to a pessimistic reward estimate. In the tabular case, we adopt the standard tabular confidence bound (Xie et al., 2021b), leading to the penalty given by (3.1). The following results show that $\widehat{g}$ is indeed a pessimistic estimate with high probability and the number of samples $N(s,a)$ does not deviate too much from its expectation $\rho(s)\pi^{\mathsf{ref}}(a|s)$.

Lemma 3.1. Given $\delta \in (0,1)$, let $\bar{g}(s,a)$ and $b(s,a)$ be as defined in Algorithm 1, and let $\mathcal{E}_{\mathrm{tab}}(\delta)$ denote the event that the reward estimation error is uniformly controlled:

$$\mathcal{E}_{\mathrm{tab}}(\delta) := \Big\{ \big|\bar{g}(s,a) - g^*(s,a)\big| \le b(s,a), \text{ for all } (s,a) \in \mathcal{S} \times \mathcal{A} \Big\}. \tag{3.2}$$

Algorithm 2 FKL-PCB for Function Approximation

Require: regularization η, reference policy π^{ref}, offline dataset $\mathcal{D}$, function class $\mathcal{G}$

1: Reward estimation via least squares: $\bar{g} \in \operatorname{argmin}_{g\in\mathcal{G}} \sum_{(s_i,a_i,r_i)\in\mathcal{D}} \big(g(s_i,a_i) - r_i\big)^2$

2: Compute the pessimism penalty with $\beta = \widetilde{O}\Big(\sqrt{\log\big(2N_{\mathcal{G}}(\epsilon)/\delta\big)/n + \epsilon}\Big)$

$$\Gamma_n(s,a) = \beta D_{\mathcal{G}}\big((s,a), \pi^{\mathsf{ref}}\big), \forall (s,a) \in \mathcal{S}\times\mathcal{A} \tag{3.3}$$

3: Compute the pessimistic reward function $\widehat{g}(s,a) \leftarrow \max\{\bar{g}(s,a) - \Gamma_n(s,a), 0\}, \forall (s,a) \in \mathcal{S}\times\mathcal{A}$

Ensure: $\widehat{\pi} = \operatorname{argmax}_{\pi\in\Delta(\mathcal{A}|\mathcal{S})} \langle \widehat{g}, \pi\rangle - \eta^{-1}\mathsf{KL}\left(\pi^{\mathsf{ref}} \| \pi\right)$

We further use $\mathcal{E}_{\mathrm{bin}}(\delta)$ to denote the event under which $N(s,a)$ does not deviate too much from the expectation, that is

$$\mathcal{E}_{\mathrm{bin}}(\delta) := \left\{ \frac{1}{N(s,a)\vee 1} \le \frac{8\log(2|\mathcal{S}||\mathcal{A}|/\delta)}{n\rho(s)\pi^{\mathsf{ref}}(a|s)} \text{ for all } (s,a)\in\mathcal{S}\times\mathcal{A} \right\}.$$

Then the event $\mathcal{E}_{\mathrm{tab}}(\delta) \cap \mathcal{E}_{\mathrm{bin}}(\delta)$ holds with probability at least $1-\delta$.

Finally, we construct the output policy to be the regularized maximizer under the clipped pessimistic reward $\widehat{g}$. The following theorem provides the sample complexity guarantee of Algorithm 1; the proofs of Lemma 3.1 and theorem 3.2 are deferred to Appendix C.

Theorem 3.2. For sufficiently small $\epsilon \in (0,1)$, with probability at least $1-\delta$, $\widetilde{O}\big(\eta(C^{\pi^*})^2|\mathcal{S}||\mathcal{A}|\epsilon^{-1}\big)$ samples suffice to guarantee the learned policy $\widehat{\pi}$ of Algorithm 1 to be ϵ-optimal.

3.2 Algorithm for Function Approximation

While the algorithm follows the same backbone as Algorithm 1, access to the function class $\mathcal{G}$ allows us to perform least-squares estimation within $\mathcal{G}$. After the estimation, we construct the pessimism penalty as in (3.3), following Di et al. (2023); Zhao et al. (2026). For simplicity, Algorithm 2 uses the population disagreement width $D_{\mathcal{G}}((s,a);\pi^{\mathsf{ref}})$ and assumes oracle access to least-squares regression and bonus evaluation over $\mathcal{G}$ (while $\widehat{\pi}$ admits the context-wise closed form in Lemma 2.2). When ρ is unknown, replacing $D_{\mathcal{G}}$ with a sample-split regularized empirical disagreement width preserves the guarantee of Theorem 3.4 up to universal constants and logarithmic factors; see Appendix E.3 for the explicit construction, oracle model, and tractable linear/tabular instantiations. Since $g^* \in [0,1]$, this penalty ensures $0 \le \widehat{g} = \max\{\bar{g} - \Gamma_n, 0\} \le g^*$ with high probability. Formally, we define the event $\mathcal{E}_{\mathrm{gfa}}(\delta)$ given $\delta > 0$ as

$$\mathcal{E}_{\mathrm{gfa}}(\delta) := \left\{ \sup_{(s,a)\in\mathcal{S}\times\mathcal{A}} \Big[\big|\bar{g} - g^*\big| - \Gamma_n\Big](s,a) \le 0 \right\}. \tag{3.4}$$

The following lemma indicates that $\mathcal{E}_{\mathrm{gfa}}(\delta)$ holds with probability at least $1-\delta$.

Lemma 3.3 (Lemma 2.9, Zhao et al. 2026)**.** $\forall \delta \in (0,1)$, $\mathcal{E}_{\mathrm{gfa}}(\delta)$ holds with probability at least $1-\delta$.

Finally, we construct the output policy as the maximizer of the pessimistic reward $\widehat{g}$ under the regularized objective. The following theorem provides the sample complexity guarantee of Algorithm 2 (proved in Appendix C).

Theorem 3.4. For sufficiently small $\epsilon \in (0,1)$, $\widetilde{O}\big(\eta C^{\pi^*} D^2_{\pi^*}\epsilon^{-1}\log N_{\mathcal{G}}(\epsilon)\big)$ samples suffice to guarantee the learned policy $\widehat{\pi}$ of Algorithm 2 to be ϵ-optimal with probability at least $1-\delta$.

Remark 3.5. Previously, Aminian et al. (2025) obtained a $\widetilde{O}\big(\log N_{\mathcal{G}} C_{\varepsilon_{\mathrm{FKL}}}/\epsilon^2\big)$ sample complexity guarantee for offline learning with forward-KL-regularized objective. In contrast, both Theorem 3.2 and Theorem 3.4 establish an ϵ^{-1}-fast rate, improving upon the previous ϵ^{-2} dependency. Moreover, the sample complexity in both Theorem 3.2 and Theorem 3.4 only relies on the notion of single policy concentrability, thereby relaxing the stronger all-policy concentrability assumption required in Aminian et al. (2025).[5] It is also worth noting that this combination of an ϵ^{-1} fast rate and relaxed concentrability requirements has recently been shown to be both necessary and sufficient for reverse-KL-regularized CBs (Zhao et al., 2026).

[5]Technically, the $C_{\varepsilon_{\mathrm{FKL}}}$ in Aminian et al. (2025) requires the behavioral policy to cover every policy with a local forward-KL-ball of the reference policy well.

4 Minimax Lower Bounds

In this section, we present worst-case hardness results in the tabular setting, whose proofs are deferred to Appendix D.

Theorem 4.1. Let $\widehat{\pi} \in \Delta(\mathcal{A}|\mathcal{S})$ be any estimator (with full support) from n context-action-reward pairs, then for any even $A \geq 2$, $S \geq 1$, $\eta > 0$, and $n > 16SA \vee 4\eta^2 SA$,

$$\sup_{\mathrm{CB}(\mathcal{S},\mathcal{A},r,\rho,\pi^{\mathsf{ref}}):|\mathcal{S}|=S,|\mathcal{A}|=A} \mathbb{E}_{\mathcal{D}\sim P_{\pi^{\mathsf{ref}},r}} \mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}; \mathcal{S}, \mathcal{A}, r, \rho, \pi^{\mathsf{ref}}) \gtrsim \frac{\eta SA}{n}.$$

Theorem 4.1 implies a minimax sample complexity lower bound of $\Omega(\eta SA\epsilon^{-1})$ for learning an ϵ-optimal policy in the tabular setting whenever $\epsilon \lesssim \eta \wedge \eta^{-1}$,[6] matching Theorem 3.2 in the statistical rate ϵ^{-1} as well as the linear dependencies on η, S, and A under uniform coverage ($C^{\pi^*} = \Theta(1)$). Because our hard instances employ $\pi^{\mathsf{ref}} = \mathsf{Uniform}(\mathcal{A})$, characterizing the minimax optimal dependencies on the coverage coefficients—specifically $(C^{\pi^*})^2$ in Theorem 3.2 and $C^{\pi^*} D^2_{\pi^*}$ in Theorem 3.4—and deriving fast-rate lower bounds with function-class complexity under general function approximation remain open directions.

The regime with large η. Both our fast-rate upper and lower bounds scale linearly with η, mirroring *reverse* KL (Zhao et al., 2025a, 2026). Note that Theorem 4.1 applies to the *high-regularization* regime $\eta^2 \lesssim n/(SA)$. As η grows large, the regularization vanishes and the problem enters a *low-regularization* regime, where reverse-KL offline (Zhao et al., 2026) and online (Ji et al., 2026) CBs transition to an η-free $\Omega(\epsilon^{-2})$ slow rate. In Appendix D.2 (Theorem D.3), we prove an analogous $\Omega(\eta n^{-1} \wedge n^{-1/2})$ phase-transition lower bound for two-armed forward-KL bandits. Complementarily, FKL-PCB simultaneously enjoys an η-independent $\widetilde{O}(\epsilon^{-2})$ upper bound on the same high-probability event (see Appendix E.4), though matching the exact transition threshold of η across all problem parameters (C^{π^*}, S, A, $D^2_{\pi^*}$) is left for future work.

5 Technical Overview

We use $|\mathcal{S}| = 1$ (offline bandits) as the working example to outline the limitations (or inapplicability) of previous works and highlight the key technique for our algorithm analysis.

5.1 Limitations of Traditional Routines

In the first statistical analysis *specialized for* $\mathrm{SubOpt}_{\mathrm{FKL}}(\cdot)$, Aminian et al. (2025, Theorem 6.3) treat all terms involving forward KL with a gross bound depending on an all-policy-type concentrability coefficient $C_{\varepsilon_{\mathrm{FKL}}}$ to reduce the suboptimality to its *unregularized* counterpart, which unavoidably exhibits at least the fundamental limit of estimation, i.e., $\widetilde{O}(\epsilon^{-2})$. Another conjugate-based routine (Zhao et al., 2026) gives $\widetilde{\Theta}(\epsilon^{-1})$ sample complexity offline CBs under general f-divergence-regularized objectives with strongly convex f, which excludes $\mathsf{KL}\left(\pi^{\mathsf{ref}} \| \pi\right)$. Recently, Lee et al. (2026) consider regularized objectives in an online setting for strongly convex regularizers in a unified manner, which is, however, not ideal for forward KL in the offline case because: although $\pi \mapsto \mathsf{KL}\left(\pi \| \pi^{\mathsf{ref}}\right)$ is $\Theta(1)$-strongly-convex with respect to the L^1 distance (Polyanskiy and Wu, 2025; Zhao et al., 2026), the modulus of strong convexity for $\pi \mapsto \mathsf{KL}\left(\pi^{\mathsf{ref}} \| \pi\right)$ may depend on the condition of π^{ref} as manifested in the following lemma, whose proof is deferred to Appendix E.

Lemma 5.1. Under Assumption 2.1, if $\min_{a\in\mathcal{A}} \pi^{\mathsf{ref}}(a) = \alpha$, $\pi \mapsto \mathsf{KL}\left(\pi^{\mathsf{ref}} \| \pi\right)$ is $\Theta(\alpha)$-strongly-convex with respect to the L^1 distance as a map from $\mathrm{ri}\left(\Delta(\mathcal{A})\right)$ to $\mathbb{R}_+$.

Consequently, techniques following Lee et al. (2026) for analyzing offline algorithms may yield sample complexity bounds *proportional to* α^{-1}, which translates to the undesirable (density-ratio-based) *all*-policy concentrabilty even in multi-armed bandits.

5.1.1 The Limitation of Techniques Tailored to *Reverse* KL

Existing results under relatively weak concentrability conditions for *reverse*-KL-regularized objectives either heavily relies on specific log-linear parametric forms (Foster et al., 2025) or hinges on a

[6] Note that $n > 16SA \vee 4\eta^2 SA$ is an applicability condition of Theorem 4.1 rather than an additional sample cost: when $\epsilon \lesssim \eta \wedge \eta^{-1}$, setting $n_0 = \lfloor 16SA \vee 4\eta^2 SA \rfloor + 1$ gives $\eta SA/n_0 \gtrsim \epsilon$, so by sample-discarding monotonicity no estimator with $n \leq n_0$ achieves expected suboptimality ϵ, whence $n \gtrsim \eta SA\epsilon^{-1}$.

curious pessimism-induced monotonic property in a Taylor-type argument based on the mean value theorem (Zhao et al., 2026). In particular, we expose here the limitation in this latter mid-point-based routine, rendering it not sharp enough for forward KL. A faithful adaptation of the spirit in Zhao et al. (2026, Section 2.4) to the nature of $\mathsf{KL}\left(\pi^{\mathsf{ref}}\|\pi\right)$ and π^*_{FKL} yields (5.1) and (5.2) in Lemma 5.2, whose proof is detailed in Appendix E.

Lemma 5.2. If $\widehat{\pi} \in \operatorname{argmax}_{\pi\in\Delta(\mathcal{A})} J_{\mathrm{FKL}}(\pi;\widehat{r})$, where $\widehat{r}:\mathcal{A}\to[0,1]$; then $\exists \bar{u}\in[0,1]$ such that under Assumption 2.1, $\mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}) =$

$$\frac{\eta}{2}\left(\mathbb{E}_{a\sim\pi_{\bar{u}}}\left[\left(\frac{\pi_{\bar{u}}}{\pi^{\mathsf{ref}}}(r-\widehat{r})^2\right)(a)\right] - \left(\sum_a \left(\frac{\pi^2_{\bar{u}}}{\pi^{\mathsf{ref}}}(r-\widehat{r})\right)(a)\right)^2 \Big/ \sum_a \frac{\pi^2_{\bar{u}}}{\pi^{\mathsf{ref}}}(a)\right), \tag{5.1}$$

where $\pi_{\bar{u}} \in \operatorname{argmax}_{\pi\in\Delta(\mathcal{A})} J_{\mathrm{FKL}}(\pi;r_{\bar{u}})$ with $r_{\bar{u}} \coloneqq (1-\bar{u})r + \bar{u}\widehat{r}$. (5.1) directly implies

$$\mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}) \le \frac{\eta}{2}\mathbb{E}_{a\sim\pi_{\bar{u}}}\left[\left(\frac{\pi_{\bar{u}}}{\pi^{\mathsf{ref}}}(r-\widehat{r})^2\right)(a)\right]. \tag{5.2}$$

The pillar behind the proof of Zhao et al. (2026, Theorem 2.10) is that the counterpart of (5.1) or (5.2) for *reverse* KL is *non-increasing* in $\bar{u}$ on $[0,1]$ under *the premise of pessimism* (i.e., $r\ge\widehat{r}$), so that the maximizer of the corresponding RHS is $\bar{u}=0$, which helps replace the troublemaker $\pi_{\bar{u}}$ with π^*; and thus lets the RHS depend on the single-policy concentrability that only covers π^*. Unfortunately, the calculations (deferred to Appendix E) in Lemma 5.3 deny such a belief for forward KL.

Lemma 5.3. Let $F(\bar{u}) \coloneqq$ RHS of (5.1), $w_u(a) \coloneqq \frac{\pi_u(a)}{\pi^{\mathsf{ref}}(a)}$, $Z_u \coloneqq \sum_a \frac{\pi^2_u(a)}{\pi^{\mathsf{ref}}(a)}$, and the probability distribution $\mu_u(a) \coloneqq \frac{\pi^2_u(a)}{\pi^{\mathsf{ref}}(a)}/Z_u$, and $g \coloneqq r-\widehat{r}$, then $\forall u\in(0,1)$,

$$F'(u) = -\eta^2 Z_u \cdot \mathbb{E}_{a\sim\mu_u}\left[w_u(a)\big(g(a)-\mathbb{E}_{a\sim\mu_u}g(a)\big)^3\right]. \tag{5.3}$$

The sign of (5.3) may be hard to determine in general for $u\in(0,1)$ even if $g\ge 0$ uniformly because it is a tilted skewness of a *centered* random variable, which is strong evidence that the mean-value-type approach might not work for analyzing bandit learning under forward KL regularization.

Remark 5.4. Sharp readers may wonder whether it is possible to disregard the second term in (5.1) and take derivative of just (5.2). However, since (5.2) is a part of (5.1), the calculations in Lemma 5.3 already imply that $\widetilde{F}'(u) = -\eta^2 Z_u \mathbb{E}_{a\sim\mu_u}\left[w_u(a)g(a)^2\big(g(a)-\mathbb{E}_{a\sim\mu_u}[g(a)]\big)\right]$ for RHS of (5.2)$=:\widetilde{F}(\bar{u})$. Since $\widetilde{F}'(u)$ turns out to be at best a *plausible* tilted covariance between g^2 and a *centered* $g-\mathbb{E}_{\mu_u}g$, its sign may still be indefinite even conditioned on $g\ge 0$.

5.2 Our Key Technique

Note that (5.1) is already an *identity*, which, together with the limitations we outline, suggests that it may not be suitable to tweak this mean-value argument based on Taylor expansion further. Instead, we prepare another identity (5.7) based on a *general* characterization (Lemma F.4) of *regularized objectives* via the dual perspective of convex conjugate (over the simplex), which is *fully detached from any specific design* of bonus terms; and craft a neat self-bounding argument (5.9) on top of it to utilize the pessimism principle *directly* in (5.10) without resorting to the aforementioned monotinicity mechanism. This suite of key techniques is elaborated in the proof of Lemma 5.5 as follows.

Lemma 5.5. Following the notation in (2.1), if $\widehat{\pi} \in \operatorname{argmax}_{\pi\in\Delta(\mathcal{A})} J_{\mathrm{FKL}}(\pi;\widehat{r})$, where $\widehat{r}:\mathcal{A}\to[0,1]$, and $r\ge\widehat{r}$ uniformly; then under Assumption 2.1,

$$\mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}) = J_{\mathrm{FKL}}(\pi^*_{\mathrm{FKL}};r) - J_{\mathrm{FKL}}(\widehat{\pi};r) \le 2\eta \sum_{a\in\mathcal{A}} \left(\frac{{\pi^*_{\mathrm{FKL}}}^2}{\pi^{\mathsf{ref}}}(r-\widehat{r})^2\right)(a). \tag{5.4}$$

Proof. Let $h(\cdot) \coloneqq \eta^{-1}\mathsf{KL}\left(\pi^{\mathsf{ref}}\|\cdot\right)$. Then h is strictly convex by Lemma 5.1, obviously continuously differentiable on $\mathrm{ri}(\Delta(\mathcal{A}))$, $\mathrm{dom}(h) \coloneqq \{\pi\in\Delta(\mathcal{A}) : h(\pi)<\infty\} = \mathrm{ri}(\Delta(\mathcal{A}))$; and the uniqueness of π_u as well as $\pi_u\in\mathrm{ri}(\Delta(\mathcal{A}))$ is guaranteed by Lemma 2.2 and Assumption 2.1. Thus, Lemmas F.3 and F.4 are applicable; under the notations of which: $\pi^*_{\mathrm{FKL}} = \pi_r$ and $\widehat{\pi} = \pi_{\widehat{r}}$; $J_{\mathrm{FKL}}(\pi^*_{\mathrm{FKL}};r) = h^*(r)$ and $J_{\mathrm{FKL}}(\widehat{\pi};\widehat{r}) = h^*(\widehat{r})$ are their constrained convex conjugate, respectively.[7] Therefore,

[7] Appendix F.2 review concepts related to convex conjugate.

(5.5), which is inspired by Zhao et al. (2026, Appendix E.1), holds by definition; and $\nabla h^*(\widehat{r}) = \widehat{\pi}$ follows from Lemma F.3. In detail,

$$\begin{aligned}
\mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}) &= h^*(r) - h^*(\widehat{r}) - \langle r, \widehat{\pi}\rangle + \langle \widehat{r}, \widehat{\pi}\rangle && (5.5)\\
&= \mathsf{B}_{h^*}(r, \widehat{r}) = \mathsf{B}_h(\widehat{\pi}, \pi^*) && (5.6)\\
&= \eta^{-1}\left\langle \pi^{\mathsf{ref}}, \log\frac{\pi^{\mathsf{ref}}}{\widehat{\pi}}\right\rangle - \eta^{-1}\left\langle \pi^{\mathsf{ref}}, \log\frac{\pi^{\mathsf{ref}}}{\pi^*}\right\rangle - \langle \nabla h(\pi^*), \widehat{\pi} - \pi^*\rangle\\
&= \eta^{-1}\sum_{a\in\mathcal{A}} \pi^{\mathsf{ref}}(a)\Big[\frac{\widehat{\pi}(a)}{\pi^*(a)} - 1 - \log\Big(1 - \big(1 - \frac{\widehat{\pi}(a)}{\pi^*(a)}\big)\Big)\Big]\\
&= \eta^{-1}\sum_{a\in\mathcal{A}} \pi^{\mathsf{ref}}(a)\big[-y_a - \log(1-y_a)\big] = \eta^{-1}\sum_{a\in\mathcal{A}} \pi^{\mathsf{ref}}(a)\phi(y_a), && (5.7)
\end{aligned}$$

where the first equality in (5.6) is a combination of the definition of Bregman divergence and $\nabla h^*(\widehat{r}) = \widehat{\pi}$; and the second equality in (5.6) is by applying Lemma F.4 to h; $y_a := 1 - \widehat{\pi}(a)/\pi^*(a), \forall a \in \mathcal{A}$; and $\phi(y) := -y - \log(1-y), \forall y < 1$. On the other hand, the definition of $\widehat{\pi}$ alone already implies

$$\begin{aligned}
\mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}) = J(\pi^*; r) - J(\widehat{\pi}; r) &\le J(\pi^*; r) - J(\pi^*; \widehat{r}) + J(\widehat{\pi}; \widehat{r}) - J(\widehat{\pi}; r)\\
&= \langle r - \widehat{r}, \pi^*\rangle + \langle \widehat{r} - r, \widehat{\pi}\rangle\\
&= \langle r - \widehat{r}, \pi^* - \widehat{\pi}\rangle = \sum_{a\in\mathcal{A}} \pi^*(a) g(a) y_a, && (5.8)
\end{aligned}$$

where $g := r - \widehat{r}$. We thus define $z_a := 2\eta\pi^*(a)g(a)/\pi^{\mathsf{ref}}(a)$ to deduce from (5.8) that

$$\begin{aligned}
2\cdot\mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}) &\le \eta^{-1}\sum_{a\in\mathcal{A}} \pi^{\mathsf{ref}}(a) z_a y_a\\
&\le \eta^{-1}\sum_{a\in\mathcal{A}} \pi^{\mathsf{ref}}(a)\big[\phi(y_a) + \phi^*(z_a)\big]\\
&= \mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}) + \eta^{-1}\sum_{a\in\mathcal{A}} \pi^{\mathsf{ref}}(a)\big(z_a - \log(1+z_a)\big), && (5.9)
\end{aligned}$$

where the second inequality is due to the Fenchel-Young inequality, the last equality is due to Fact F.10; and the pessimism $r \ge \widehat{r}$ ensures $z_a \ge 0 > -1$, which in turn ensures the well-posedness of the constrained convex conjugate $\phi^*(z_a)$. Rearranging (5.9) yields

$$\begin{aligned}
\mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}) &\le \eta^{-1}\sum_{a\in\mathcal{A}} \pi^{\mathsf{ref}}(a)\big(z_a - \log(1+z_a)\big)\\
&\le \eta^{-1}\sum_{a\in\mathcal{A}} \pi^{\mathsf{ref}}(a)\frac{z_a^2}{2} && (5.10)\\
&= 2\eta\sum_{a\in\mathcal{A}} \pi^{\mathsf{ref}}(a)\left(\frac{\pi^*(a)}{\pi^{\mathsf{ref}}(a)} g(a)\right)^2,
\end{aligned}$$

where the second inequality (5.10) is due to $z_a \ge 0$ (i.e., pessimism) together with the fact that $\forall z \ge 0, z - \log(1+z) \le z^2/2$; and the equality follows from the definition of z_a. □

Again, since the $\mathrm{SubOpt}_{\mathrm{FKL}}(\cdot)$ on general $\mathcal{S}$ with $|\mathcal{S}| \ge 1$ is the expectation of the bandit suboptimality over $s \sim \rho$, the sample complexity in Theorems 3.2 and 3.4 follow from the conjunction of a context-wise application of Lemma 5.5 and the corresponding concentration arguments conditioned on the pessimism events, respectively; as detailed in Appendix C. To see why Lemma 5.5 helps bypass the need of all-policy concentrability, we observe that the RHS of (5.4) is bounded from above in the tabular setting by $2\eta(C^{\pi^*})^2\mathbb{E}_{\pi^{\mathsf{ref}}}(r - \widehat{r})^2$, where the squared loss admits a $\widetilde{O}(n^{-1})$ concentration with high probability; the reasoning is similar under general function approximation.

6 Conclusion, Limitations, and Future Work

We initiate the study of forward-KL regularization as a performance metric for data efficiency in offline decision making. For offline CBs, we certify the sufficiency of single-policy concentrability

for achieving $\widetilde{O}(\epsilon^{-1})$ forward-KL-regularized sample complexity via FKL-PCB in both the tabular and realizable function-approximation settings (while simultaneously retaining η-independent $\widetilde{O}(\epsilon^{-2})$ slow rates; see Appendix E.4). Our lower bounds confirm rate-optimality in ϵ and η (as well as S and A in the tabular setting) and demonstrate a fast-to-slow rate phase transition as regularization weakens.

Technically, while the simplex conjugate-Bregman identity (Lemma F.4) behind Lemma 5.5 holds for general strictly convex regularizers, achieving ϵ^{-1} fast rates relies on a decoupling property specific to $f(t) = -\log t$ and its synergy with offline pessimism; as we detail in Appendix E.5, general strictly convex f-divergences need not admit quadratic dual growth, and online optimism reverses the dual sign condition. Regarding **limitations** and open problems: (i) while dependence on C^{π^*} is natural under distribution shift, tightening the coverage dependencies, viz., $(C^{\pi^*})^2$ in Theorem 3.2 and $C^{\pi^*} D^2_{\pi^*}$ in Theorem 3.4, and deriving fast-rate lower bounds under general function approximation remain open; (ii) closing the parameter gap in the phase-transition threshold of η beyond two-armed bandits (Theorem D.3) is unsettled; and (iii) extending our guarantees beyond exact realizability (Assumption 2.4) and one-step CBs to misspecified reward models and multi-step MDPs (Jin et al., 2020; Zhao et al., 2025b; Lee et al., 2026) is an important direction for future work.

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Additional Notations in Appendix

Boldface capital letters are reserved for matrices. Boldface lowercase letters denote vectors in Euclidean spaces or vector-valued functions. For two probability distributions P and Q, the total variation (TV) distance is denoted by $\mathsf{TV}\left(P\|Q\right) \coloneqq 0.5 \int |\,\mathrm{d}P - \mathrm{d}Q|$. $\forall n \in \mathbb{N}_{++}$, $\overline{[n]} \coloneqq \{0, 1, .., n-1\}$. For dimension-compatible vectors $\mathbf{x}, \mathbf{y}$, $\mathbf{x} \odot \mathbf{y}$ denotes their element-wise product.

A Additional Related Works

Pessimism in Offline RL. Classical analyses of batch value and policy iteration (Farahmand et al., 2010; Scherrer, 2014; Chen and Jiang, 2019; Xie and Jiang, 2021) establish sample complexity guarantees under all-policy (uniform) concentrability, requiring the data distribution to cover all candidate policies or value functions so as to prevent out-of-distribution overestimation by greedy updates. To relax this uniform coverage condition, a substantial line of work incorporates pessimism in the face of uncertainty, penalizing uncertain state-action values or optimizing over conservative confidence sets so that coverage is required only with respect to a single comparator policy π^*. Existing guarantees can be grouped into tabular and function-approximation regimes. In tabular offline CBs and MDPs, lower-confidence-bound (LCB) penalties in value iteration, Q-learning, and model-based planning attain minimax-optimal $\widetilde{O}(\epsilon^{-2})$ sample complexity under density-ratio single-policy concentrability C^{π^*} (Rashidinejad et al., 2021; Shi et al., 2022; Li et al., 2024), alongside variance- and gap-dependent refinements (Yin and Wang, 2021; Wang et al., 2022). Under linear and general function approximation, explicit pointwise LCB bonuses (Jin et al., 2021; Xiong et al., 2022; Li et al., 2022; Di et al., 2023) as well as Bellman-consistent and model-based pessimistic formulations (Zanette et al., 2021; Xie et al., 2021a; Uehara and Sun, 2021; Zhan et al., 2022)—and their counterparts in offline preference-based alignment (Zhu et al., 2023; Zhan et al., 2023)—replace tabular density ratios with feature-covariance or Bellman-evaluation concentrability coefficients while retaining $\widetilde{O}(\epsilon^{-2})$ worst-case rates for unregularized objectives. For reverse-KL-regularized offline learning, plug-in estimators without pessimism achieve $\widetilde{O}(\epsilon^{-1})$ fast rates either under all-policy concentrability (Zhao et al., 2025a) or with $\exp(O(\eta))$ dependence under reference-policy coverage (Wu et al., 2025). While strongly convex f-divergences admit coverage-free $\widetilde{O}(\epsilon^{-1})$ rates via plug-in estimation and dual-Bregman smoothness, Zhao et al. (2026) combine LCB reward estimation with a mean-value monotonicity argument to attain polynomial-in-η, $\widetilde{O}(\epsilon^{-1})$ sample complexity under single-policy concentrability for reverse KL. Because forward KL ($f(x) = -\log x$) lacks uniform strong convexity on $\Delta(\mathcal{A})$ and invalidates this mean-value monotonicity (Lemmas 5.1 and 5.3), our analysis invokes pessimism directly to guarantee non-negativity of the dual argument in a constrained Fenchel–Young self-bounding inequality (Lemma 5.5), yielding $\widetilde{O}(\epsilon^{-1})$ sample complexity under single-policy concentrability.

Forward-KL Regularization in RL. Forward-KL regularization has been recently utilized in variants of Direct Preference Optimization (DPO) (Rafailov et al., 2023). Wang et al. (2023) generalized DPO to f-divergence penalties, which encompasses forward KL; while other specific alignment algorithms formulated via forward-KL regularization have also been developed for large language models (LLMs) (Ji et al., 2023) and diffusion models (Shan et al., 2025). Another line of research investigates how practical gradient estimation of KL divergence in RL implicitly induces forward-KL regularization. Tang and Munos (2025) and Shah et al. (2025) theoretically and empirically demonstrated that auto-differentiating certain variance-reduced Monte Carlo estimators of reverse KL in some famous KL-regularized RL fine-tuning algorithms actually produces gradients of the forward KL in expectation. Furthermore, Zhang and Ba (2026) introduced an policy gradient framework that incorporates top-k forward-KL regularization to stabilize LLM fine-tuning. A traditional viewpoint on the distinct divergence properties of forward and reverse KL, which has usually been respectively characterized as mass-covering and mode-seeking, is systematically ablated by GX-Chen et al. (2025), who claim that diversity collapse can be an inherent consequence of the regularized RL objective itself regardless of the KL direction. On the theoretical front, the sample complexity of forward-KL-regularized RL is largely unclear. Recently, Aminian et al. (2025) provided the first $\widetilde{O}(\epsilon^{-2})$ slow-rate upper bound for offline contextual dueling bandits with multiple reference models under forward-KL regularization, leaving the achievability of ϵ^{-1}-type fast rates as an open question.

B Relation between Coverage Notions

In this section, we provide more illustrations on the relation between two coverage measures, $D^2_{\pi^*}$ and C^{π^*}, in the context of forward-KL regularized bandits. In particular, we provide two cases under linear function approximation, in one of which $D^2_{\pi^*} = \Omega(dC^{\pi^*})$ and in the other we have $D^2_{\pi^*} \ll C^{\pi^*}$, where d is the dimension of the function class. We summarized them as two propositions.

Proposition B.1. For any $C > 1$, $d \geq 3$ being odd, and $\eta \geq 2$, there exist a forward-KL-regularized linear bandit instance, such that $C^{\pi^*} = O(C)$ and $D^2_{\pi^*} = \Omega(Cd)$, leading to $D^2_{\pi^*} = \Omega(dC^{\pi^*})$.

Proof. We construct the instance as follows. Let $d = 2A + 1$ be some odd number and consider an $2A + 1$-armed bandit, such that the feature vector of the i-th arm, $\boldsymbol{\phi}(a_i) = \mathbf{e}_i \in \mathbb{R}^d$, which has 1 on its i-th entry and 0 on all other entries. The reference policy $\pi^{\mathsf{ref}}(a_i) = (2AC)^{-1}$ for $i \in [2A]$ and $\pi^{\mathsf{ref}}(a_{2A+1}) = (C-1)/C$, where $C \geq 1$ and $\eta \geq 2$. The ground truth reward function $\boldsymbol{\theta}^* = \sum_{i \leq A} \mathbf{e}_i$ and the function class is given by all $\|\boldsymbol{\theta}\|_\infty \leq 1$. By construction, we know that $\pi^*(a_i) \geq \pi^{\mathsf{ref}}(a_i)$ if and only if $i \in [A]$ and its closed form is given by

$$\pi^*(a_i) = \frac{1}{A} \frac{\sqrt{(\eta-1)^2C^2 + 2\eta C} + (\eta-1)C}{2\eta C} \leq \frac{2}{A}$$

which gives $C^{\pi^*} = O(C)$. Now we compute the $D^2_{\pi^*}$ of this instance. For all $i \in [A]$, we know that

$$D^2(a_i) = \sup_{\|\boldsymbol{\theta}\|_\infty \leq 2} \frac{\langle \boldsymbol{\theta}, \mathbf{e}_i \rangle^2}{\mathbb{E}_{\pi^{\mathsf{ref}}} \langle \boldsymbol{\theta}, \mathbf{e}_j \rangle^2} = 2CA = \Theta(Cd),$$

where the second equation holds with $\boldsymbol{\theta} = \mathbf{e}_i$. Taking expectation over π^*, we have

$$D^2_{\pi^*} \geq \frac{1}{2A} \sum_{i \in [A]} D^2(a_i) = \Theta(C^{\pi^*} d),$$

which concludes the proof. □

The following proposition provides another instance on which $D^2_{\pi^*} \ll C^{\pi^*}$.

Proposition B.2. For any $C \geq 2$ and $\eta \geq 2$, there exists a KL-regularized linear bandit instance, such that $C^{\pi^*} = C/2$ and $D^2_{\pi^*} = \Theta(1)$.

Proof. We consider the function class of $\boldsymbol{\theta} \in \mathbb{R}^2$ and $\|\boldsymbol{\theta}\| \leq \sqrt{2}$. The instance consists of three arms, where $\boldsymbol{\phi}(a_1) = (1, 0)$, $\boldsymbol{\phi}(a_2) = (0, 1)$, and $\boldsymbol{\phi}(a_3) = (1, 1)$. The ground truth parameter $\boldsymbol{\theta}^* = (1, 1)$. The reference policy is given by $\pi^{\mathsf{ref}}(a_1) = \pi^{\mathsf{ref}}(a_2) = 1/2 - 1/2C$ and $\pi^{\mathsf{ref}}(a_3) = 1/C$, where $C \geq 2$. We further fix any $\eta \geq 2$. A direct computation yields that

$$\pi^*(a_3) = \frac{(\eta-1) + \sqrt{(\eta-1)^2 + 4\eta C^{-1}}}{2\eta} \geq \frac{\eta-1}{\eta},$$

which results in $C^{\pi^*} \geq C/2$. On the other hand, we know that for $i = 1, 2$, we have $D^2(a_i) \leq \pi^{\mathsf{ref}}(a_i)^{-1} \leq 4$. As for a_3, since we have $\langle \boldsymbol{\theta}, \phi(a_3) \rangle^2 = \langle \boldsymbol{\theta}, \phi(a_1) + \phi(a_2) \rangle^2 \leq 2 \langle \boldsymbol{\theta}, \phi(a_1) \rangle^2 + 2 \langle \boldsymbol{\theta}, \phi(a_2) \rangle$, which gives that $D^2(a_3) \leq 2D^2(a_1) + 2D^2(a_2) \leq 16$. Therefore, taking expectation over π^*, we know that $D^2_{\pi^*} \leq 16$ which is a constant. □

C Missing Proofs in Section 3

C.1 Proof of Lemma 3.1

Proof of Lemma 3.1. Let $S := |\mathcal{S}|$ and $A := |\mathcal{A}|$. We first show that $\mathcal{E}_{\mathrm{tab}}(\delta)$ holds with probability at least $1 - \delta/2$. Fix any $(s, a) \in \mathcal{S} \times \mathcal{A}$ and condition on the realized context-action pairs $\{(s_i, a_i)\}_{i=1}^n$. When $N(s, a) = 0$, Algorithm 1 sets $\bar{g}(s, a) = 0$ and $b(s, a) = 1$; since $g^*(s, a) \in [0, 1]$, $\left|\bar{g}(s, a) - g^*(s, a)\right| = g^*(s, a) \leq 1 = b(s, a)$ holds deterministically. When $N(s, a) = m \geq 1$, we have $\bar{g}(s, a) - g^*(s, a) = \frac{1}{m} \sum_{i:(s_i,a_i)=(s,a)} \varepsilon_i$; conditioned on $\{(s_i, a_i)\}_{i=1}^n$, the noises $\{\varepsilon_i : (s_i, a_i) = (s, a)\}$ are mutually independent, mean-zero, and 1-subgaussian. Applying the subgaussian Hoeffding inequality (Lemma F.12) conditioned on $\{(s_i, a_i)\}_{i=1}^n$ gives

$$\mathbb{P}\Big(\left|\bar{g}(s, a) - g^*(s, a)\right| > b(s, a) \,\Big|\, \{(s_i, a_i)\}_{i=1}^n\Big) \leq 2 \exp\Big(-\frac{mb(s, a)^2}{2}\Big) = 2\Big(\frac{\delta}{2SA}\Big)^2 \leq \frac{\delta}{2SA},$$

where the last inequality uses $\delta \in (0, 1)$ and $SA \geq 1$. Taking expectation over $\{(s_i, a_i)\}_{i=1}^n$ and applying a union bound over all $(s, a) \in \mathcal{S} \times \mathcal{A}$, we obtain $\mathbb{P}\big(\mathcal{E}_{\mathrm{tab}}(\delta)\big) \geq 1 - \delta/2$. Next, by Lemma F.11, for each fixed $(s, a) \in \mathcal{S} \times \mathcal{A}$, with probability at least $1 - \delta/(2SA)$,

$$\frac{1}{N(s, a) \vee 1} \leq \frac{8 \log(2SA/\delta)}{n\rho(s)\pi^{\mathsf{ref}}(a|s)}.$$

Taking a union bound over all $(s, a) \in \mathcal{S} \times \mathcal{A}$ shows $\mathbb{P}\big(\mathcal{E}_{\mathrm{bin}}(\delta)\big) \geq 1 - \delta/2$. A final union bound over $\mathcal{E}_{\mathrm{tab}}(\delta)$ and $\mathcal{E}_{\mathrm{bin}}(\delta)$ completes the proof. □

C.2 Proof of Theorem 3.4

Proof of Theorem 3.4. On event $\mathcal{E}_{\mathrm{gfa}}(\delta)$, we have $|\bar{g}(s,a)-g^*(s,a)| \le \Gamma_n(s,a)$ for all $(s,a) \in \mathcal{S}\times\mathcal{A}$. Since $g^*(s,a) \in [0,1]$ and $\widehat{g}(s,a) = \max\{\bar{g}(s,a)-\Gamma_n(s,a), 0\}$, it holds for all $(s,a)\in\mathcal{S}\times\mathcal{A}$ that $\widehat{g}(s,a)\in[0,1]$ and

$$0 \le g^*(s,a) - \widehat{g}(s,a) \le g^*(s,a) - \big(\bar{g}(s,a)-\Gamma_n(s,a)\big) \le 2\Gamma_n(s,a).$$

Therefore, invoking Lemma 5.5 context-wise and taking expectation over $s\sim\rho$ gives

$$\begin{aligned}
\mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}) &\le 2\eta\mathbb{E}_{s\sim\rho}\left[\sum_{a\in\mathcal{A}}\left(\frac{{\pi^*_{\mathrm{FKL}}}^2(a|s)}{\pi^{\mathsf{ref}}(a|s)}(g^*(s,a)-\widehat{g}(s,a))^2\right)\right] \\
&= 2\eta\mathbb{E}_{s\sim\rho}\left[\sum_{a\in\mathcal{A}}\left[\left(\frac{\pi^*_{\mathrm{FKL}}(a|s)}{\pi^{\mathsf{ref}}(a|s)}\right)\pi^*_{\mathrm{FKL}}(a|s)(g^*(s,a)-\widehat{g}(s,a))^2\right]\right] \\
&\le 8\eta C^{\pi^*}\mathbb{E}_{(s,a)\sim\rho\times\pi^*_{\mathrm{FKL}}}\left[\Gamma_n^2(s,a)\right] \\
&= 8\eta C^{\pi^*}\beta^2 D^2_{\pi^*},
\end{aligned}$$

where the second inequality uses $\pi^*_{\mathrm{FKL}}(a|s)/\pi^{\mathsf{ref}}(a|s) \le C^{\pi^*}$ and $g^*-\widehat{g}\le 2\Gamma_n$, and the last equality uses (3.3) and Assumption 2.8. Setting the covering scale in β to $\epsilon_c \asymp n^{-1}$ under Assumption 2.6 yields $\mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}) \le \widetilde{O}\big(\eta C^{\pi^*} D^2_{\pi^*} n^{-1}\log(N_{\mathcal{G}}(n^{-1})/\delta)\big)$, which translates to the stated sample complexity. Finally, by Lemma 3.3, $\mathcal{E}_{\mathrm{gfa}}(\delta)$ holds with probability at least $1-\delta$. □

C.3 Proof of Theorem 3.2

Proof of Theorem 3.2. On event $\mathcal{E}_{\mathrm{tab}}(\delta)\cap\mathcal{E}_{\mathrm{bin}}(\delta)$, fix any $(s,a)\in\mathcal{S}\times\mathcal{A}$. When $N(s,a)\ge 1$, $|\bar{g}(s,a)-g^*(s,a)|\le b(s,a)$ and $g^*(s,a)\in[0,1]$ imply $\widehat{g}(s,a)=\max\{\bar{g}(s,a)-b(s,a),0\}\in[0,1]$ and $0\le g^*(s,a)-\widehat{g}(s,a)\le 2b(s,a)$, whence $(g^*(s,a)-\widehat{g}(s,a))^2 \le 4b(s,a)^2 \le \frac{128\log^2(2|\mathcal{S}||\mathcal{A}|/\delta)}{n\rho(s)\pi^{\mathsf{ref}}(a|s)}$ by $\mathcal{E}_{\mathrm{bin}}(\delta)$. When $N(s,a)=0$, Algorithm 1 sets $\widehat{g}(s,a)=0\in[0,1]$, so $0\le g^*(s,a)-\widehat{g}(s,a) = g^*(s,a)\le 1$, and $\mathcal{E}_{\mathrm{bin}}(\delta)$ yields $(g^*(s,a)-\widehat{g}(s,a))^2 \le \frac{1}{N(s,a)\vee 1} \le \frac{8\log(2|\mathcal{S}||\mathcal{A}|/\delta)}{n\rho(s)\pi^{\mathsf{ref}}(a|s)}$. Consequently, $\widehat{g}(s,a)\in[0,1]$ and $0\le g^*(s,a)-\widehat{g}(s,a)$ hold uniformly on $\mathcal{S}\times\mathcal{A}$, and invoking Lemma 5.5 context-wise gives

$$\begin{aligned}
\mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}) &\le 2\eta\mathbb{E}_{s\sim\rho}\left[\sum_{a\in\mathcal{A}}\left(\frac{{\pi^*_{\mathrm{FKL}}}^2(a|s)}{\pi^{\mathsf{ref}}(a|s)}(g^*(s,a)-\widehat{g}(s,a))^2\right)\right] \\
&= 2\eta\mathbb{E}_{s\sim\rho}\left[\sum_{a\in\mathcal{A}}\left[\left(\frac{\pi^*_{\mathrm{FKL}}(a|s)}{\pi^{\mathsf{ref}}(a|s)}\right)^2\pi^{\mathsf{ref}}(a|s)(g^*(s,a)-\widehat{g}(s,a))^2\right]\right] \\
&\le 2\eta(C^{\pi^*})^2\mathbb{E}_{(s,a)\sim\rho\times\pi^{\mathsf{ref}}}\left[\big(g^*(s,a)-\widehat{g}(s,a)\big)^2\right] \\
&\le 2\eta(C^{\pi^*})^2\sum_{s\in\mathcal{S}}\rho(s)\sum_{a\in\mathcal{A}}\pi^{\mathsf{ref}}(a|s)\frac{128\log^2(2|\mathcal{S}||\mathcal{A}|/\delta)}{n\rho(s)\pi^{\mathsf{ref}}(a|s)} \\
&= \widetilde{O}\big(\eta(C^{\pi^*})^2|\mathcal{S}||\mathcal{A}|n^{-1}\big),
\end{aligned}$$

where the second inequality holds by $\pi^*_{\mathrm{FKL}}(a|s)/\pi^{\mathsf{ref}}(a|s)\le C^{\pi^*}$. By Lemma 3.1, $\mathcal{E}_{\mathrm{tab}}(\delta)\cap\mathcal{E}_{\mathrm{bin}}(\delta)$ holds with probability at least $1-\delta$, which finishes the proof. □

D Missing Proofs in Section 4

We first present (for each given context) a suboptimality decomposition lemma applicable for general learners.[8]

Lemma D.1. Let $\widehat{\pi}\in\Delta(\mathcal{A})$ be *any* distribution with $\mathrm{supp}(\widehat{\pi})=\mathcal{A}$, then under Assumption 2.1,

$$\mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}) = \eta^{-1}\mathbb{E}_{a\sim\pi^{\mathsf{ref}}}\left[\psi\Big(\frac{\widehat{\pi}(a)}{\pi^*_{\mathrm{FKL}}(a)}\Big)\right], \tag{D.1}$$

where $\psi(x) := x-1-\log x$.

[8] We drop the dependency on context in Lemma D.1 as the suboptimality gaps on each $s\in\mathcal{S}$ are purely additive.

Proof of Lemma D.1. Lemma 2.2 implies that $\forall a \in \mathcal{A}$,

$$r(a) = \lambda - \eta^{-1} \frac{\pi^{\mathsf{ref}}(a)}{\pi^*(a)},$$

which, substituted into $\mathrm{SubOpt}(\cdot)$, yields

$$\begin{aligned}
\mathrm{LHS} &\coloneqq J(\pi^*; r) - J(\widehat{\pi}; r) \\
&= \langle r, \pi^* - \widehat{\pi} \rangle + \eta^{-1} \sum_{a \in \mathcal{A}} \pi^{\mathsf{ref}}(a) \log \frac{\pi^{\mathsf{ref}}(a)}{\widehat{\pi}(a)} - \eta^{-1} \sum_{a \in \mathcal{A}} \pi^{\mathsf{ref}}(a) \log \frac{\pi^{\mathsf{ref}}(a)}{\pi^*(a)} \\
&= \langle \lambda \mathbf{1} - \eta^{-1} \frac{\pi^{\mathsf{ref}}}{\pi^*}, \pi^* - \widehat{\pi} \rangle - \eta^{-1} \sum_{a \in \mathcal{A}} \pi^{\mathsf{ref}}(a) \log \frac{\widehat{\pi}(a)}{\pi^*(a)} \\
&= -\eta^{-1} \sum_{a \in \mathcal{A}} \pi^{\mathsf{ref}}(a) \Big(1 - \frac{\widehat{\pi}(a)}{\pi^*(a)}\Big) - \eta^{-1} \sum_{a \in \mathcal{A}} \pi^{\mathsf{ref}}(a) \log \frac{\widehat{\pi}(a)}{\pi^*(a)} \\
&= \eta^{-1} \mathbb{E}_{a \sim \pi^{\mathsf{ref}}} \left[\frac{\widehat{\pi}(a)}{\pi^*(a)} - 1 - \log \frac{\widehat{\pi}(a)}{\pi^*(a)} \right],
\end{aligned}$$

where the penultimate equality is because both π^* and $\widehat{\pi}$ are probability distributions. □

Remark D.2. Although the *pattern* of Lemma D.1 fits into (5.6) exactly, their applicable scopes are different because the first equality of (5.6) is a specialization of Lemma F.4 to forward KL, which only needs mild regularity conditions of the regularizer h but requires $\widehat{\pi}$ to be the maximizer of $J_{\mathrm{FKL}}(\cdot; \widehat{r})$. On the other hand, Lemma D.1 is tailored to forward KL but $\widehat{\pi}$ here can be essentially an arbitrary probability distribution.

D.1 The Fast Rate Lower Bound

Proof of Theorem 4.1. Let $K \coloneqq A/2$. We consider MABs with context set $\mathcal{S} = \overline{[S]}$ and action set $\mathcal{A} = \overline{[A]}$. We fix $\rho = \mathsf{Uniform}(\mathcal{S})$ $\pi^{\mathsf{ref}} = \mathsf{Uniform}(\mathcal{A})$, where every reward follows a Bernoulli distribution. We consider the subset of instances with the following parameterization. Let $\mathcal{V} = \{\pm 1\}^{S \times K}$ and we use $v_{s,k}$ to denote its (s,k)-th entry given any $v \in \mathcal{V}$. The reward distribution given $v \in \mathcal{V}$ is given as follows:

$$r_v(s, 2k) = 0.5 - v_k c, \; r_v(s, 2k+1) = 0.5 + v_k c; \quad \forall\, (s,k) \in \overline{[S]} \times \overline{[K]},$$

where $c \in (0, 0.25)$ is to be specified.

We now compute the optimal policy π_v for each instance parameterized by $v \in \mathcal{V}$. Fix any s, we know by Lemma 2.2 that $\pi_v^*(\cdot|s) = (\eta A)^{-1}/(\lambda - r_v(s, \cdot))$; and thus all instances share the same λ over all the contexts $s \in \mathcal{S}$ and λ is determined by

$$\sum_{k=0}^{K-1} \Big(\frac{(\eta A)^{-1}}{\lambda - 0.5 - c} + \frac{(\eta A)^{-1}}{\lambda - 0.5 + c} \Big) = 1 \Longrightarrow \lambda - 0.5 = \frac{1 + \sqrt{1 + 4\eta^2 c^2}}{2\eta},$$

which is because $\lambda > \max_{v,a} r_v(a)$. Let $\iota = \lambda - 0.5$, then $\iota = \eta(\iota^2 - c^2)$, and thus we set $\kappa_{v,s,a} \coloneqq (-1)^{a - 2\lfloor a/2 \rfloor} \cdot v_{s, \lfloor a/2 \rfloor}$ and $\omega \coloneqq c/\iota = 2\eta c / \big(1 + \sqrt{1 + 4\eta^2 c^2}\big)$ to obtain

$$\begin{aligned}
\pi_v^*(a|s) &= \frac{1}{\eta A} \cdot \frac{1}{\iota + (-1)^{a - 2\lfloor a/2 \rfloor} \cdot v_{s, \lfloor a/2 \rfloor} \cdot c} \\
&= \frac{\iota - \kappa_{v,s,a} c}{\eta A (\iota^2 - c^2)} \\
&= A^{-1}(1 - \kappa_{v,s,a} c/\iota) \\
&= \frac{1 - \kappa_{v,s,a} \omega}{A}.
\end{aligned}$$

Note that Lemma D.1 implies

$$\mathrm{SubOpt}(\widehat{\pi}; r_v) = \sum_{s=0}^{S-1} \sum_{k=0}^{K-1} \frac{1}{\eta S A} \left[\psi\Big(\frac{\widehat{\pi}(2k|s)}{\pi_v^*(2k|s)} \Big) + \psi\Big(\frac{\widehat{\pi}(2k+1|s)}{\pi_v^*(2k+1|s)} \Big) \right]$$

$$= \sum_{s=0}^{S-1} \sum_{k=0}^{K-1} \underbrace{\frac{1}{\eta SA}\left[\psi\Big(\frac{A\widehat{\pi}(2k|s)}{1-v_k\omega}\Big) + \psi\Big(\frac{A\widehat{\pi}(2k+1|s)}{1+v_k\omega}\Big)\right]}_{=:\Psi_{s,k}(\widehat{\pi};v)}.$$

Then for $v \sim_{s,j} v'$ (i.e., $v, v' \in \{\pm 1\}^{S\times K}$ differ only in the (s,j)-th coordinate),

$$\begin{aligned}
&\Psi_{s,j}(\widehat{\pi}; v) + \Psi_{s,j}(\widehat{\pi}; v') \\
&\quad = \frac{1}{\eta SA}\left(\psi\Big(\frac{A\widehat{\pi}(2j|s)}{1-\omega}\Big) + \psi\Big(\frac{A\widehat{\pi}(2j|s)}{1+\omega}\Big) + \psi\Big(\frac{A\widehat{\pi}(2j+1|s)}{1-\omega}\Big) + \psi\Big(\frac{A\widehat{\pi}(2j+1|s)}{1+\omega}\Big)\right).
\end{aligned} \tag{D.2}$$

Now we specify $c = \sqrt{SA/n}$, which is less than 0.25 by design. Recall that $\psi(x) = x - 1 - \log x$, elementary calculus shows that $o \mapsto \psi\big(o/(1+\omega)\big) + \psi\big(o/(1-\omega)\big)$ is minimized at $o = 1-\omega^2$, and thus

$$\begin{aligned}
\text{(D.2)} &\geq \frac{2}{\eta SA}\log\frac{1}{1-\omega^2} \\
&= \frac{2}{\eta SA}\cdot\log\frac{1+\sqrt{1+4\eta^2c^2}}{2} \\
&\geq \frac{2}{\eta SA}\cdot\frac{\sqrt{1+4\eta^2c^2}-1}{4} \\
&= \frac{\sqrt{1+4\eta^2c^2}-1}{2\eta SA} \\
&\geq \frac{2\eta c^2}{SA(1+\sqrt{17})} \\
&= \Omega(\eta n^{-1}),
\end{aligned} \tag{D.3}$$

where the second inequality is because $\eta^{-1} > c/2$ and $\log(1+x) \geq x/2$ for $x \in [0,2]$, and the last inequality is again due to $\eta^{-1} > c/2$.

Now, given any reward function r, let $\mathbb{P}_{\pi^{\mathsf{ref}},\mathtt{r}}$ be the distribution of $(a,\mathtt{r})$ for $(s,a) \sim \rho \times \pi^{\mathsf{ref}}$ and $\mathtt{r} \sim \mathsf{Bernoulli}(r(a))$. We further use $\mathbb{P}_{\pi^{\mathsf{ref}},v}$ for $v \in \mathcal{V}$ to denote $\mathbb{P}_{\pi^{\mathsf{ref}},r}$ if r is parameterized by $v \in \mathcal{V}$. The divergence decomposition lemma (Lattimore and Szepesvári, 2020, Lemma 15.1) then implies that for any $(s,j) \in \overline{[S]} \times \overline{[K]}$ and $v \sim_{s,j} v'$,

$$\begin{aligned}
\mathsf{KL}\left(\mathbb{P}^{\otimes n}_{\pi^{\mathsf{ref}},v} \| \mathbb{P}^{\otimes n}_{\pi^{\mathsf{ref}},v'}\right) &= \frac{n}{SA}\mathsf{KL}\left(\mathrm{Bern}(r_v(2j)) \| \mathrm{Bern}(r_{v'}(2j))\right) \\
&\quad + \frac{n}{SA}\mathsf{KL}\left(\mathrm{Bern}(r_v(2j+1)) \| \mathrm{Bern}(r_{v'}(2j+1))\right)
\end{aligned} \tag{D.4}$$

$$\leq \frac{128}{3}\frac{nc^2}{SA} = \frac{128}{3}, \tag{D.5}$$

where we utilize $\mathsf{KL}\left(\mathrm{Bern}(p) \| \mathrm{Bern}(q)\right) \leq (p-q)^2/[q(1-q)]$ and $c \in [0, 0.25]$. By Lemma F.15, (D.3) and (D.5) together imply the desired lower bound. □

D.2 Lower Bound for Two-Armed Bandits: Phase Transition

Theorem D.3. Let $\widehat{\pi} \in \Delta(\mathcal{A})$ be any estimator from n action-reward pairs, then for any $n > 16$ and $\eta > 0$,

$$\sup_{(\mathcal{A},r,\pi^{\mathsf{ref}}) \in \mathrm{MAB}_2} \mathbb{E}_{\mathcal{D}\sim P_{\pi^{\mathsf{ref}},r}} \mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}; \mathcal{A}, r, \pi^{\mathsf{ref}}) \gtrsim \eta n^{-1} \wedge n^{-1/2}. \tag{D.6}$$

Proof. We construct two MABs sharing $\mathcal{A} = \{0,1\}$ and $\pi^{\mathsf{ref}} = \mathsf{Uniform}(\mathcal{A})$,[9] where the rewards follow Bernoulli distribution with means specified as

$$\acute{r} = (0.5 + c, 0.5 - c), \grave{r} = (0.5 - c, 0.5 + c). \tag{D.7}$$

[9] In this proof, we drop notations that are clear in the context to make the presentation less heavy.

Here, $c \in (0, 0.25)$ will be specified later. By Lemma 2.2, $\pi^*(\cdot) = (2\eta)^{-1}\big(\lambda - r(\cdot)\big)^{-1}$, which means the two instances $\acute{r}$ and $\grave{r}$ share the same λ, i.e., the λ in both cases satisfies

$$(\lambda - 0.5 - c)(\lambda - 0.5 + c) = \frac{2\lambda - 1}{2\eta}. \tag{D.8}$$

To get an eligible distribution π^*, we require $\lambda > 0.5 + c$ according to (2.2), which means (D.8) yields

$$2\lambda - 1 = \eta^{-1} + \sqrt{\eta^{-2} + 4c^2}. \tag{D.9}$$

Thus, for any estimator $\widehat{\pi} \in \Delta(\{0, 1\})$,

$$\begin{aligned}
\mathrm{SubOpt}(\widehat{\pi}; \acute{r}) + \mathrm{SubOpt}(\widehat{\pi}; \grave{r}) &= \langle \acute{r}, \acute{\pi}^* \rangle + \langle \grave{r}, \grave{\pi}^* \rangle - \overbrace{\langle \acute{r} + \grave{r}, \widehat{\pi} \rangle}^{=1} + \overbrace{2\eta^{-1}\mathsf{KL}\left(\pi^{\mathsf{ref}} \| \widehat{\pi}\right)}^{\geq 0} \\
&\quad - \eta^{-1}\mathsf{KL}\left(\pi^{\mathsf{ref}} \| \acute{\pi}^*\right) - \eta^{-1}\mathsf{KL}\left(\pi^{\mathsf{ref}} \| \grave{\pi}^*\right) \\
&\geq 2\langle \acute{r}, \acute{\pi}^* \rangle - 1 - 2\eta^{-1}\mathsf{KL}\left(\pi^{\mathsf{ref}} \| \acute{\pi}^*\right) \\
&= 2\Big((0.5 + c)\acute{\pi}^*(0) + (0.5 - c)\acute{\pi}^*(1)\Big) - 1 \\
&\quad - \eta^{-1}\Big(\log \eta(\lambda - 0.5 - c) + \log \eta(\lambda - 0.5 + c)\Big) \\
&= \frac{c\eta^{-1}}{\eta(\lambda - 0.5 - c)} - \frac{c\eta^{-1}}{\eta(\lambda - 0.5 + c)} \\
&\quad - \eta^{-1}\Big(\log \eta(\lambda - 0.5 - c) + \log \eta(\lambda - 0.5 + c)\Big) \\
&= \frac{4c^2}{2\lambda - 1} - \eta^{-1} \log \frac{\eta(2\lambda - 1)}{2} \qquad \text{(D.10)} \\
&= \frac{4c^2}{\eta^{-1} + \sqrt{\eta^{-2} + 4c^2}} - \eta^{-1} \log \Big(1 + \frac{\sqrt{1 + 4c^2\eta^2} - 1}{2}\Big). \qquad \text{(D.11)}
\end{aligned}$$

where (D.10) is due to (D.8) and (D.11) follows from (D.9). Given any mean function r, let $P_{\pi^{\mathsf{ref}}, r}$ be the distribution of $(a, \mathtt{r})$ for $a \sim \pi^{\mathsf{ref}}$ and $\mathtt{r} \sim \mathsf{Bernoulli}(r(a))$. The tensorization property of KL (Polyanskiy and Wu, 2025, Chapter 2) then implies

$$\mathsf{KL}\left(P_{\pi^{\mathsf{ref}}, \acute{r}}^{\otimes n} \| P_{\pi^{\mathsf{ref}}, \grave{r}}^{\otimes n}\right) = n\mathsf{KL}\left(P_{\pi^{\mathsf{ref}}, \acute{r}} \| P_{\pi^{\mathsf{ref}}, \grave{r}}\right) = 2nc \log \frac{1 + 2c}{1 - 2c} \leq 16nc^2, \tag{D.12}$$

where the inequality follows from the requirement $c \in (0, 0.25)$. Since $n > 16$. we can set $c = n^{-1/2}$.

Case $\eta^{-1} \leq c/2 = 0.5n^{-1/2}$. Using standard $\sqrt{x + y} \leq \sqrt{x} + \sqrt{y}$ and $\log(1 + x) \leq x$ for $x, y \geq 0$,

$$\text{(D.11)} \geq \frac{4c^2}{2\eta^{-1} + 2c} - \eta^{-1} \log(1 + c\eta) \geq \frac{2c^2}{\eta^{-1} + c} - c \geq c/3,$$

which, combined with Lemma F.14 and (D.12), yields

$$\text{LHS of (D.6)} \gtrsim n^{-1/2}.$$

Case $\eta^{-1} > c/2 = 0.5n^{-1/2}$. Using $1 = \sup_{x>0} x^{-1} \log(1 + x)$,

$$\begin{aligned}
\text{(D.11)} &= \frac{2}{1 + \sqrt{1 + 4c^2\eta^2}} \left(2\eta c^2 - \eta c^2 \cdot \frac{\log\left(1 + \frac{\sqrt{1+4c^2\eta^2}-1}{2}\right)}{\frac{\sqrt{1+4c^2\eta^2}-1}{2}}\right) \\
&\geq \frac{2}{1 + \sqrt{17}}(2\eta c^2 - \eta c^2) \geq \eta c^2/3,
\end{aligned}$$

which, combined with Lemma F.14 and (D.12), yields

$$\text{LHS of (D.6)} \gtrsim \eta n^{-1}.$$

□

E Other Missing Proofs

E.1 Missing Proofs of Supporting Lemmas

Proof of Lemma 2.2. Under Assumption 2.1, consider the primal problem[10]

$$\begin{aligned} \min_{\pi} \; & -\langle r, \pi \rangle + \eta^{-1} \mathsf{KL}\left(\pi^{\mathsf{ref}} \| \pi\right) \\ \text{s.t. } & \langle \mathbf{1}, \pi \rangle = 1, -\pi \le \mathbf{0}; \end{aligned} \tag{P}$$

whose Lagrangian with dual variables (ν, λ) is

$$\mathcal{L}(\pi, \nu, \lambda) \coloneqq -\langle r, \pi \rangle + \eta^{-1} \mathsf{KL}\left(\pi^{\mathsf{ref}} \| \pi\right) + \lambda(\langle \mathbf{1}, \pi \rangle - 1) - \langle \nu, \pi \rangle.$$

Since $\pi^{\mathsf{ref}}(a) > 0$ for all $a \in \mathcal{A}$, any feasible π with finite objective must satisfy $\pi(a) > 0$ for all $a \in \mathcal{A}$. Moreover, since the constraints in (P) are affine, Slater's condition holds, implying strong duality. The KKT conditions at an optimal primal-dual tuple (π, ν, λ) read

$$\nabla_\pi \mathcal{L}(\pi, \nu, \lambda) = \mathbf{0}, \tag{E.1}$$

$$\pi \ge \mathbf{0}, \langle \mathbf{1}, \pi \rangle = 1, \tag{E.2}$$

$$\nu \ge \mathbf{0}, \pi \odot \nu = \mathbf{0}. \tag{E.3}$$

Because $\pi(a) > 0$ for all $a \in \mathcal{A}$, complementary slackness in (E.3) forces $\nu = \mathbf{0}$. (E.1) then yields

$$\forall a \in \mathcal{A}, \quad \pi(a) = \frac{\eta^{-1} \pi^{\mathsf{ref}}(a)}{\lambda - r(a)},$$

which requires $\lambda > \max_{a \in \mathcal{A}} r(a)$ and that λ solves

$$\sum_{a \in \mathcal{A}} \frac{\eta^{-1} \pi^{\mathsf{ref}}(a)}{\lambda - r(a)} = 1. \tag{E.4}$$

Since $\lambda \mapsto \sum_{a \in \mathcal{A}} \eta^{-1} \pi^{\mathsf{ref}}(a) / \big(\lambda - r(a)\big)$ is strictly decreasing and continuous on $(\max_{a \in \mathcal{A}} r(a), +\infty)$ with range $(0, +\infty)$, the root λ of (E.4) exists and is unique. By Lemma 5.1, (P) is strictly convex on $\mathrm{ri}(\Delta(\mathcal{A}))$, so π^*_{FKL} is the unique global solution. □

Proof of Lemma 5.1. Pick an arbitrary $\pi \in \mathrm{ri}\left(\Delta(\mathcal{A})\right)$, let $F(\cdot) = \mathsf{KL}\left(\pi^{\mathsf{ref}} \| \cdot\right)$. Then

$$\nabla F(\pi) = -\frac{\pi^{\mathsf{ref}}}{\pi} \Rightarrow \nabla^2 F(\pi) = \mathrm{diag}\Big\{\frac{\pi^{\mathsf{ref}}}{\pi^2}\Big\}. \tag{E.5}$$

Here, both divisions are element-wise. $\forall \mu, \nu \in \Delta(\mathcal{A})$,

$$\begin{aligned} (\mu - \nu)^\top \nabla^2 F(\pi)(\mu - \nu) &= \sum_{a \in \mathcal{A}} \frac{\pi^{\mathsf{ref}}(a)\big(\mu(a) - \nu(a)\big)^2}{\big(\pi(a)\big)^2} \\ &\ge \alpha \sum_{a \in \mathcal{A}} \frac{\big(\mu(a) - \nu(a)\big)^2}{\big(\pi(a)\big)^2} \\ &\ge \alpha \frac{\Big(\sum_{a \in \mathcal{A}} |\mu(a) - \nu(a)|\Big)^2}{\sum_{a \in \mathcal{A}} \big(\pi(a)\big)^2} \\ &\ge 4\alpha \cdot \big(\mathsf{TV}\left(\mu \| \nu\right)\big)^2, \end{aligned}$$

where the second inequality follows from Cauchy–Schwarz.[11] Here, we recall that TV is equivalent to the L^1 distance up to a multiplicative constant 2, and thus the conclusion follows. □

[10] We drop the context $s \in \mathcal{S}$ and its conditioning in this proof since the optimal solution for each context is fully decoupled.

[11] Technically, $\dim \Delta(\mathcal{A}) = A - 1 < A$; and thus by $\nabla F(\pi)$ (resp. $\nabla^2 F(\pi)$) for $\pi \in \mathrm{ri}(\Delta(\mathcal{A}))$ in this proof, we actually mean the Euclidean gradient (resp. Hessian) of the analytical continuation of F defined as $F_{\mathrm{ext}}(\mu) \coloneqq \langle \pi^{\mathsf{ref}}, \log \frac{\pi^{\mathsf{ref}}}{\mu} \rangle$ for $\mu \in \mathbb{R}^{\mathcal{A}}_{++}$ and $+\infty$ otherwise. A similar convention follows in the proof of Lemma 2.2.

Proof of Lemma 5.2. For $u \in [0,1]$, $r_u \coloneqq (1-u)r + u\widehat{r}$, and $\pi_u = \operatorname{argmax}_{\pi \in \Delta(\mathcal{A})} J_{\mathrm{FKL}}(\pi; r_u)$, the latter of which exists and is unique by Lemma 2.2. Let

$$V(u) \coloneqq J_{\mathrm{FKL}}(\pi_u; r_u), \quad \Phi(u) \coloneqq J_{\mathrm{FKL}}(\pi_u; r).$$

Lemma 2.2 and the definition of J_{FKL} guarantee that both $V(\cdot)$ and $u \mapsto J_{\mathrm{FKL}}(\pi, r_u)$ is differentiable given any $\pi \in \Delta(\mathcal{A})$. Therefore, by Lemma F.2, $\forall u \in (0,1)$,

$$V'(u) = \left\langle \frac{\mathrm{d}}{\mathrm{d}u} r_u, \pi_u \right\rangle = \langle \widehat{r} - r, \pi_u \rangle,$$

which, substituted to $\Phi(u) = V(u) + \langle r - r_u, \pi_u \rangle = V(u) + u\langle \widehat{r} - r, \pi_u \rangle$, yields

$$\begin{aligned} \forall u \in (0,1), \Phi'(u) &= V'(u) + \frac{\mathrm{d}}{\mathrm{d}u}\Big(u\langle r - \widehat{r}, \pi_u \rangle\Big) \\ &= \langle \widehat{r} - r, \pi_u \rangle + \langle r - \widehat{r}, \pi_u \rangle + u\Big\langle r - \widehat{r}, \frac{\mathrm{d}}{\mathrm{d}u}\pi_u \Big\rangle = u\Big\langle r - \widehat{r}, \frac{\mathrm{d}}{\mathrm{d}u}\pi_u \Big\rangle. \end{aligned} \tag{E.6}$$

By definition,

$$\text{LHS of (5.1)} = \Phi(0) - \Phi(1) = -\int_0^1 \Phi'(u)\,\mathrm{d}u = \int_0^1 u\Big\langle \widehat{r} - r, \frac{\mathrm{d}}{\mathrm{d}u}\pi_u \Big\rangle \,\mathrm{d}u. \tag{E.7}$$

Let $h(\cdot) \coloneqq \eta^{-1}\mathsf{KL}\left(\pi^{\mathsf{ref}} \| \cdot\right)$. Since h is strictly convex and continuously differentiable on $\mathrm{ri}(\Delta(\mathcal{A}))$, $\mathrm{dom}(h) \coloneqq \{\pi \in \Delta(\mathcal{A}) : h(\pi) < \infty\} = \mathrm{ri}(\Delta(\mathcal{A}))$, and the uniqueness of π_u is guaranteed by Lemma 2.2, applying Lemma F.3 to h yields that $\forall u \in (0,1)$, $\pi_u = \nabla h^*(r_u)$, where the notation h^* is consistent with Lemma F.3. Consequently,

$$\frac{\mathrm{d}}{\mathrm{d}u}\pi_u = \frac{\mathrm{d}}{\mathrm{d}u}\nabla h^*(r_u) = \left[\nabla^2 h^*(r_u)\right] \cdot \frac{\mathrm{d}}{\mathrm{d}u} r_u = \left[\nabla^2 h^*(r_u)\right](\widehat{r} - r), \tag{E.8}$$

where $\widehat{r} - r$ is again viewed as a vector. Substituting (E.8) into (E.7) yields

$$\begin{aligned} \text{LHS of (5.1)} &= \int_0^1 u(\widehat{r} - r)^\top \left[\nabla^2 h^*(r_u)\right](\widehat{r} - r)\,\mathrm{d}u \\ &= \int_0^1 u(r - \widehat{r})^\top \left[\nabla^2 h(\pi_u)\right]^{-1}(r - \widehat{r})\,\mathrm{d}u - \int_0^1 u \frac{\left(\mathbf{1}^\top \left[\nabla^2 h(\pi_u)\right]^{-1}(r - \widehat{r})\right)^2}{\mathbf{1}^\top \left[\nabla^2 h(\pi_u)\right]^{-1}\mathbf{1}}\,\mathrm{d}u \\ &= \eta \int_0^1 \left(\sum_a \left(\frac{\pi_u^2}{\pi^{\mathsf{ref}}}(r - \widehat{r})^2\right)(a) - \frac{\left(\sum_a \left(\frac{\pi_u^2}{\pi^{\mathsf{ref}}}(r - \widehat{r})\right)(a)\right)^2}{\sum_a \frac{\pi_u^2}{\pi^{\mathsf{ref}}}(a)} \right) u\,\mathrm{d}u, \end{aligned}$$

where $\frac{\pi_u^2}{\pi^{\mathsf{ref}}}(r - \widehat{r})^2$ is viewed as a function, the second equality follows from Lemma F.7 and Assumption 2.1 and the last equality follows from direct calculations detailed in (E.5). The final result thus follows from the *second* mean value theorem for definite integrals.

□

Proof of Lemma 5.3. Recall that $F(\bar{u})$ denotes (5.1), $\widetilde{F}(\bar{u})$ denotes (5.2); $w_u(a) \coloneqq \frac{\pi_u(a)}{\pi^{\mathsf{ref}}(a)}$, $Z_u \coloneqq \sum_a \frac{\pi_u^2(a)}{\pi^{\mathsf{ref}}(a)}$, and $\mu_u(a) \coloneqq \frac{\pi_u^2(a)}{\pi^{\mathsf{ref}}(a)}/Z_u$, and $g \coloneqq r - \widehat{r}$. First, the chain rule directly gives

$$\widetilde{F}'(u) = \eta \left\langle g \odot w_u, g \odot \frac{\mathrm{d}}{\mathrm{d}u}\pi_u \right\rangle. \tag{E.9}$$

We follow the same pipeline as that in the proof of Lemma 5.2 to calculate $\frac{\mathrm{d}}{\mathrm{d}u}\pi_u$. Specifically, we again substitute $\left[\nabla^2 h(\pi_u)\right]^{-1} = \eta \cdot \mathrm{diag}(\pi_u^2/\pi^{\mathsf{ref}})$ into Lemma F.7, and then substitute the result into (E.8) to obtain

$$\eta^{-1}\frac{\mathrm{d}}{\mathrm{d}u}\pi_u = Z_u\big(-\mu_u \odot g + \langle \mu_u, g \rangle\, \mu_u\big). \tag{E.10}$$

We set $X(a) \coloneqq -w_u(a) \cdot g(a)$ and substitute (E.10) into (E.9) to obtain

$$\eta^{-2}\widetilde{F}'(u) = \mathbb{E}_{a \sim \pi^{\mathsf{ref}}} X(a)^3 - \Big(\mathbb{E}_{a \sim \pi_u} X(a)^2\Big)\mathbb{E}_{a \sim \pi_u} X(a)/Z_u. \tag{E.11}$$

Another application of the chain rule yields that $\widetilde{F}'(u) - F'(u)$

$$= \frac{\mathrm{d}}{\mathrm{d}u}\left(\frac{\eta Z_u}{2} \cdot \langle \mu_u(a), g(a)\rangle^2\right)$$
$$= -\frac{2\eta \mathbb{E}_{a\sim\pi_u} X(a)}{Z_u}\left\langle w_u, g \odot \frac{\mathrm{d}}{\mathrm{d}u}\pi_u\right\rangle - \frac{\eta}{Z_u^2}\left(\mathbb{E}_{a\sim\pi_u} X(a)\right)^2 \left\langle w_u, \frac{\mathrm{d}}{\mathrm{d}u}\pi_u\right\rangle. \tag{E.12}$$

Substituting (E.10) into (E.12) yields

$$\eta^{-2}\cdot(\text{E.12}) = \frac{\mathbb{E}_{a\sim\pi_u} X(a)}{Z_u}\cdot\left(\mathbb{E}_{a\sim\pi_u} X(a)^2 - \mathbb{E}_{a\sim\mu_u} X(a)\mathbb{E}_{a\sim\pi_u} X(a)\right)$$
$$- \left(\mathbb{E}_{a\sim\pi_u} X(a)/Z_u\right)^2 \cdot \left(Z_u \cdot \mathbb{E}_{a\sim\mu_u} X(a) - \langle w_u, \mu_u\rangle \cdot \mathbb{E}_{a\sim\pi_u} X(a)\right),$$

which, added to (E.11), yields

$$\eta^{-2} F'(u) = \mathbb{E}_{a\sim\pi^{\mathsf{ref}}} X(a)^3 - \frac{3}{Z_u}\mathbb{E}_{a\sim\pi_u} X(a)^2 \mathbb{E}_{a\sim\pi_u} X(a)$$
$$+ \frac{3}{Z_u}\left(\mathbb{E}_{a\sim\pi_u} X(a)\right)^2 \mathbb{E}_{a\sim\mu_u} X(a) - \left(\frac{\mathbb{E}_{a\sim\pi_u} X(a)}{Z_u}\right)^3 \cdot \langle w_u, \mu_u\rangle Z_u. \tag{E.13}$$

$\eta^2 \cdot$ (E.13) is exactly $-\eta^2 Z_u \cdot \mathbb{E}_{a\sim\mu_u}\left[w_u(a)\cdot\left(g(a) - \mathbb{E}_{a\sim\mu_u} g(a)\right)^3\right]$.

□

E.2 Discussion on Assumption 2.1 and Non-Full-Support Reference Policies

We elaborate on how the forward-KL-regularized offline bandit problem behaves when $\mathrm{supp}(\pi^{\mathsf{ref}}(\cdot|s)) \subsetneq \mathcal{A}$ for some context $s \in \mathcal{S}$. Unlike the reverse KL divergence $\mathsf{KL}\left(\pi(\cdot|s)\|\pi^{\mathsf{ref}}(\cdot|s)\right)$—which evaluates to $+\infty$ whenever $\mathrm{supp}(\pi(\cdot|s)) \not\subseteq \mathrm{supp}(\pi^{\mathsf{ref}}(\cdot|s))$ and thus automatically confines any finite-value policy to $\mathcal{A}_s^{\mathrm{eff}} := \mathrm{supp}(\pi^{\mathsf{ref}}(\cdot|s))$—the forward KL divergence $\mathsf{KL}\left(\pi^{\mathsf{ref}}(\cdot|s)\|\pi(\cdot|s)\right) = \sum_{a\in\mathcal{A}_s^{\mathrm{eff}}} \pi^{\mathsf{ref}}(a|s)\log\frac{\pi^{\mathsf{ref}}(a|s)}{\pi(a|s)}$ imposes only a finite normalization penalty on unsupported mass: writing $\pi(\cdot|s) = (1-q)\mu + q\nu$ with $\mu \in \Delta(\mathcal{A}_s^{\mathrm{eff}})$, $\nu \in \Delta(\mathcal{A}\setminus\mathcal{A}_s^{\mathrm{eff}})$, and $q \in [0,1)$, one has $\mathsf{KL}\left(\pi^{\mathsf{ref}}(\cdot|s)\|\pi(\cdot|s)\right) = \mathsf{KL}\left(\pi^{\mathsf{ref}}(\cdot|s)\|\mu\right) - \log(1-q)$.

For rewards in $[0,1]$ and strong regularization $\eta \le 1$, this normalization cost dominates any reward gain ($J_{\mathrm{FKL}}(\pi;r) - J_{\mathrm{FKL}}(\mu;r) \le q + \eta^{-1}\log(1-q) < 0$ for all $q \in (0,1)$), so $q^* = 0$ still holds. Whenever $\eta > 1$, however, unrestricted optimization becomes unidentifiable from offline data. Concretely, consider a single-context two-action instance with $\mathcal{A} = \{a_1, a_2\}$, $\pi^{\mathsf{ref}} = (1,0)$, and mean reward $r = (0,1)$: parameterizing $\pi \in \Delta(\mathcal{A})$ by $q := \pi(a_2) \in [0,1)$ gives $J_{\mathrm{FKL}}(\pi;r) = q + \eta^{-1}\log(1-q)$, whose unique maximizer for $\eta > 1$ is $q^* = 1 - \eta^{-1} > 0$, placing strictly positive mass on $a_2 \notin \mathrm{supp}(\pi^{\mathsf{ref}})$. Meanwhile, under $\pi^{\mathsf{ref}} = (1,0)$, the dataset $\mathcal{D}$ consists exclusively of pulls of a_1, so $\mathbb{P}_{\pi^{\mathsf{ref}},r}^{\otimes n}$ is identical under $r = (0,1)$ ($q^* = 1-\eta^{-1}$) and under $r' = (0,0)$ ($q^* = 0$). Thus, without cross-action structural assumptions, unrestricted optimization over $\Delta(\mathcal{A}|\mathcal{S})$ is unidentifiable in general when π^{ref} lacks full support.

Conversely, if one formulates the offline policy optimization problem over the support-restricted policy class

$$\Pi_{\mathrm{eff}} := \left\{\pi \in \Delta(\mathcal{A}|\mathcal{S}) : \mathrm{supp}(\pi(\cdot|s)) \subseteq \mathcal{A}_s^{\mathrm{eff}},\ \forall s \in \mathcal{S}\right\},$$

then for each context $s \in \mathcal{S}$ the optimization reduces to the admissible action set $\mathcal{A}_s^{\mathrm{eff}}$, on which $\pi^{\mathsf{ref}}(\cdot|s)$ satisfies Assumption 2.1 by definition. All upper bounds in Section 3 apply directly to $\max_{\pi\in\Pi_{\mathrm{eff}}} J_{\mathrm{FKL}}(\pi)$ upon replacing $\mathcal{A}$ by $\mathcal{A}_s^{\mathrm{eff}}$, with no quantitative dependence on $\min_{s\in\mathcal{S}, a\in\mathcal{A}_s^{\mathrm{eff}}} \pi^{\mathsf{ref}}(a|s)$.

E.3 Unknown Context Distribution and Empirical Disagreement Bonus

In Section 3.2, Algorithm 2 uses the population disagreement width $D_{\mathcal{G}}((s,a);\pi^{\mathsf{ref}})$, whose denominator takes expectation over $\nu := \rho \times \pi^{\mathsf{ref}}$. Here we show that when ρ is unknown, a sample-split regularized empirical disagreement width (Zhu et al., 2023; Di et al., 2023) preserves the statistical rate of Theorem 3.4 up to universal constants and logarithmic factors.

Sample-split construction and oracle model. Assume $n \geq 2$, write $X_i := (s_i, a_i)$ for the i-th sample in $\mathcal{D}$ and $x := (s, a) \in \mathcal{S} \times \mathcal{A}$, and define $\|f\|_\nu^2 := \mathbb{E}_{X\sim\nu}[f(X)^2]$ so that $D_{\pi^*}^2 = \mathbb{E}_{X\sim\rho\times\pi^*_{\mathrm{FKL}}}[D_{\mathcal{G}}^2(X;\pi^{\mathsf{ref}})]$. After a uniform random permutation of indices, split $\mathcal{D}$ into $I_{\mathrm{geo}} := \{1,\dots,m_0\}$ and $I_{\mathrm{reg}} := \{m_0+1,\dots,n\}$, where $m_0 := \lfloor n/2 \rfloor$ and $m_1 := n - m_0 = \lceil n/2 \rceil$ are independent halves with $m_1 \geq m_0 \geq n/3$. Define the empirical semi-norm on I_{geo} by $\|f\|_{\widehat{\nu}_0}^2 := m_0^{-1}\sum_{i\in I_{\mathrm{geo}}} f(X_i)^2$, and compute the least-squares estimator on I_{reg} via

$$\bar{g} \in \operatorname*{argmin}_{g\in\mathcal{G}} \sum_{i\in I_{\mathrm{reg}}} \big(g(X_i) - r_i\big)^2. \tag{E.14}$$

Set $\epsilon_0 := m_1^{-1}$, $L_n := 2\log N_{\mathcal{G}}(\epsilon_0) + \log(8/\delta)$, and $\lambda_n := \frac{5L_n}{3m_0} + 10\epsilon_0$. Define the empirical disagreement width, empirical bonus, and clipped pessimistic reward for each $x \in \mathcal{S}\times\mathcal{A}$ by

$$\begin{aligned} \widehat{D}^2_{\mathcal{G},\lambda_n}(x) &:= \sup_{g,h\in\mathcal{G}} \frac{\big(g(x)-h(x)\big)^2}{\|g-h\|^2_{\widehat{\nu}_0} + \lambda_n}, \\ \widehat{\Gamma}_n(x) &:= \sqrt{54\lambda_n}\,\widehat{D}_{\mathcal{G},\lambda_n}(x), \qquad \widehat{g}(x) := \max\big\{\bar{g}(x) - \widehat{\Gamma}_n(x), 0\big\}, \end{aligned} \tag{E.15}$$

and output $\widehat{\pi} = \operatorname{argmax}_{\pi\in\Delta(\mathcal{A}|\mathcal{S})} J_{\mathrm{FKL}}(\pi;\widehat{g})$. Computationally, for a general class $\mathcal{G}$, this procedure assumes access to (i) a least-squares ERM oracle solving (E.14) and (ii) an empirical disagreement oracle evaluating $\widehat{D}^2_{\mathcal{G},\lambda_n}(x)$ in (E.15), while the policy update reduces to one-dimensional root-finding per context via Lemma 2.2.

Proposition E.1. Under Assumptions 2.1, 2.4, 2.6 and 2.8, for any $\delta \in (0,1)$ and $n \geq 2$, with probability at least $1-\delta$, the sample-split estimator $\widehat{\pi}$ defined via (E.14) and (E.15) satisfies

$$\mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}) \leq O\left(\frac{\eta C^{\pi^*} D_{\pi^*}^2}{n}\big(\log N_{\mathcal{G}}(n^{-1}) + \log(1/\delta)\big)\right),$$

and hence achieves $\mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}) \leq \epsilon$ using $n = \widetilde{O}\big(\eta C^{\pi^*} D_{\pi^*}^2 \epsilon^{-1} \log N_{\mathcal{G}}(\epsilon)\big)$ samples.

Proof. We first establish a two-sided uniform norm comparison on I_{geo}. Let $\mathcal{G}(\epsilon_0) \subset \mathcal{G}$ be a minimal ϵ_0-net of $\mathcal{G}$ in $\|\cdot\|_\infty$ with $|\mathcal{G}(\epsilon_0)| = N_{\mathcal{G}}(\epsilon_0)$, and define $\mathcal{F}_0 := \{\widetilde{g} - \widetilde{h} : \widetilde{g}, \widetilde{h} \in \mathcal{G}(\epsilon_0)\}$, which satisfies $|\mathcal{F}_0| \leq N_{\mathcal{G}}(\epsilon_0)^2$. Fix any $\widetilde{f} \in \mathcal{F}_0$. Since $\mathcal{G} \subseteq (\mathcal{S}\times\mathcal{A} \to [0,1])$, we have $|\widetilde{f}(X)| \leq 1$, $\widetilde{f}(X)^2 \in [0,1]$, and $\mathrm{Var}_{X\sim\nu}\big(\widetilde{f}(X)^2\big) \leq \mathbb{E}_{X\sim\nu}[\widetilde{f}(X)^4] \leq \|\widetilde{f}\|_\nu^2$. Applying Bernstein's inequality (Lemma F.13) to $\{\widetilde{f}(X_i)^2\}_{i\in I_{\mathrm{geo}}}$ and taking a union bound over $\mathcal{F}_0$ yields that, with probability at least $1 - 2|\mathcal{F}_0|e^{-L_n} \geq 1 - \delta/4$, simultaneously for all $\widetilde{f} \in \mathcal{F}_0$,

$$\big|\|\widetilde{f}\|^2_{\widehat{\nu}_0} - \|\widetilde{f}\|^2_\nu\big| \leq \sqrt{\frac{2L_n\|\widetilde{f}\|^2_\nu}{m_0}} + \frac{2L_n}{3m_0} \leq \frac{1}{2}\|\widetilde{f}\|^2_\nu + \frac{5L_n}{3m_0}, \tag{E.16}$$

where the second inequality follows from $2ab \leq \frac{1}{2}a^2 + 2b^2$. Now take arbitrary $g, h \in \mathcal{G}$ and set $f := g - h$. Choose $\widetilde{g}, \widetilde{h} \in \mathcal{G}(\epsilon_0)$ with $\|g-\widetilde{g}\|_\infty \leq \epsilon_0$ and $\|h-\widetilde{h}\|_\infty \leq \epsilon_0$, and set $\widetilde{f} := \widetilde{g} - \widetilde{h} \in \mathcal{F}_0$. Then $\|f - \widetilde{f}\|_\infty \leq 2\epsilon_0$ and $|f(x) + \widetilde{f}(x)| \leq 2$, so $\|f^2 - \widetilde{f}^2\|_\infty \leq 4\epsilon_0$, which implies $\big|\|f\|_\mu^2 - \|\widetilde{f}\|_\mu^2\big| \leq 4\epsilon_0$ for both $\mu \in \{\nu, \widehat{\nu}_0\}$. Combining this perturbation bound with both directions of (E.16) gives, for all $g, h \in \mathcal{G}$,

$$\frac{1}{2}\|g-h\|_\nu^2 - \lambda_n \leq \|g-h\|^2_{\widehat{\nu}_0} \leq 2\|g-h\|_\nu^2 + \lambda_n, \tag{E.17}$$

since $\frac{3}{2}(\|f\|_\nu^2 + 4\epsilon_0) + \frac{5L_n}{3m_0} + 4\epsilon_0 \leq 2\|f\|_\nu^2 + \lambda_n$ and $\frac{1}{2}(\|f\|_\nu^2 - 4\epsilon_0) - \frac{5L_n}{3m_0} - 4\epsilon_0 \geq \frac{1}{2}\|f\|_\nu^2 - \lambda_n$. Independently on I_{reg}, the standard covering-number least-squares bound (Zhao et al., 2026, Eq. (D.2)) guarantees that with probability at least $1 - \delta/2$,

$$\|\bar{g} - g^*\|_\nu^2 \leq \frac{128}{3m_1}\log\left(\frac{4N_{\mathcal{G}}(\epsilon_0)}{\delta}\right) + 18\epsilon_0 \leq \frac{128L_n}{3m_0} + 18\epsilon_0 \leq 26\lambda_n, \tag{E.18}$$

where we used $m_1 \geq m_0$ and $\log(4N_{\mathcal{G}}(\epsilon_0)/\delta) \leq L_n$. Let $\mathcal{E}_{\mathrm{emp}}(\delta)$ denote the intersection event on which both (E.17) and (E.18) hold; by a union bound, $\mathbb{P}(\mathcal{E}_{\mathrm{emp}}(\delta)) \geq 1 - \delta$. On $\mathcal{E}_{\mathrm{emp}}(\delta)$, the

upper bound in (E.17) and (E.18) yield $\|\bar{g} - g^*\|^2_{\widehat{\nu}_0} + \lambda_n \le 2\|\bar{g} - g^*\|^2_{\nu} + 2\lambda_n \le 54\lambda_n$. By the definition of $\widehat{D}_{\mathcal{G},\lambda_n}$ in (E.15), $|\bar{g}(x) - g^*(x)| \le \sqrt{54\lambda_n}\,\widehat{D}_{\mathcal{G},\lambda_n}(x) = \widehat{\Gamma}_n(x)$ for all $x \in \mathcal{S} \times \mathcal{A}$, whence $\widehat{g}(x) \in [0,1]$ and $0 \le g^*(x) - \widehat{g}(x) \le 2\widehat{\Gamma}_n(x)$. Meanwhile, the lower bound in (E.17) gives $\|g - h\|^2_{\widehat{\nu}_0} + \lambda_n \ge \frac{1}{2}\|g - h\|^2_{\nu}$ for all $g, h \in \mathcal{G}$, so $\widehat{D}^2_{\mathcal{G},\lambda_n}(x) \le 2D^2_{\mathcal{G}}(x;\pi^{\mathsf{ref}})$ pointwise and thus $\mathbb{E}_{X\sim\rho\times\pi^*_{\mathrm{FKL}}}[\widehat{D}^2_{\mathcal{G},\lambda_n}(X)] \le 2D^2_{\pi^*}$. Invoking Lemma 5.5 context-wise on $\mathcal{E}_{\mathrm{emp}}(\delta)$ gives

$$\begin{aligned}\mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}) &\le 2\eta C^{\pi^*}\mathbb{E}_{X\sim\rho\times\pi^*_{\mathrm{FKL}}}\big[4\widehat{\Gamma}_n(X)^2\big] \\ &= 432\eta C^{\pi^*}\lambda_n\mathbb{E}_{X\sim\rho\times\pi^*_{\mathrm{FKL}}}\big[\widehat{D}^2_{\mathcal{G},\lambda_n}(X)\big] \le 864\eta C^{\pi^*}D^2_{\pi^*}\lambda_n.\end{aligned}$$

Noting $m_0, m_1 = \Theta(n)$ and converting from statistical error to sample complexity under Assumption 2.6 completes the proof. □

Remark E.2 (Tractable instantiations)**.** In structured classes, $\widehat{D}^2_{\mathcal{G},\lambda}(x)$ admits closed-form expressions without calling a generic supremum oracle. In the tabular case $\mathcal{G} = (\mathcal{S}\times\mathcal{A} \to [0,1])$, $\widehat{D}^2_{\mathcal{G},\lambda}(s,a) = \big(m_0^{-1}N_{\mathrm{geo}}(s,a) + \lambda\big)^{-1} \asymp m_0/(N_{\mathrm{geo}}(s,a) \vee 1)$ for $\lambda \asymp m_0^{-1}$, recovering the count-based bonus in Algorithm 1. In the bounded linear class $\mathcal{G} = \{x \mapsto \langle \boldsymbol{\phi}(x), \boldsymbol{\theta}\rangle : \boldsymbol{\theta} \in \boldsymbol{\Theta} \subset \mathbb{R}^d\}$ where $\boldsymbol{\Theta}$ is bounded and $\boldsymbol{\Theta} - \boldsymbol{\Theta}$ contains a Euclidean ball of constant radius around the origin, we have $D^2_{\mathcal{G}}(x;\pi^{\mathsf{ref}}) \asymp \boldsymbol{\phi}(x)^\top\boldsymbol{\Sigma}^\dagger\boldsymbol{\phi}(x)$ with $\boldsymbol{\Sigma} := \mathbb{E}_{X\sim\nu}[\boldsymbol{\phi}(X)\boldsymbol{\phi}(X)^\top]$, while its empirical counterpart satisfies $\widehat{D}^2_{\mathcal{G},\lambda}(x) \asymp \boldsymbol{\phi}(x)^\top\bar{\boldsymbol{\Sigma}}_\lambda^{-1}\boldsymbol{\phi}(x) = m_0\boldsymbol{\phi}(x)^\top\widehat{\boldsymbol{\Sigma}}_{m_0\lambda}^{-1}\boldsymbol{\phi}(x)$ with $\bar{\boldsymbol{\Sigma}}_\lambda := m_0^{-1}\sum_{i\in I_{\mathrm{geo}}}\boldsymbol{\phi}(X_i)\boldsymbol{\phi}(X_i)^\top + \lambda\mathbf{I}_d$ and unnormalized ridge Gram matrix $\widehat{\boldsymbol{\Sigma}}_{m_0\lambda} := \sum_{i\in I_{\mathrm{geo}}}\boldsymbol{\phi}(X_i)\boldsymbol{\phi}(X_i)^\top + m_0\lambda\mathbf{I}_d$ (so $\widehat{\Gamma}_n(x) \asymp \sqrt{m_0\lambda_n}\,\|\boldsymbol{\phi}(x)\|_{\widehat{\boldsymbol{\Sigma}}^{-1}_{m_0\lambda_n}}$), matching standard elliptical confidence bounds (Jin et al., 2020; Zhu et al., 2023).

E.4 Simultaneous η-Independent Slow-Rate Upper Bounds

Although Theorems 3.2 and 3.4 focus on the $\widetilde{O}(\epsilon^{-1})$ fast rate, the exact same output policies $\widehat{\pi}$ of Algorithms 1 and 2 simultaneously enjoy η-independent $\widetilde{O}(\epsilon^{-2})$ slow-rate guarantees on the same high-probability events.

Proposition E.3. Under Assumption 2.1, for any $\eta > 0$ and $\delta \in (0,1)$:

1. On $\mathcal{E}_{\mathrm{tab}}(\delta) \cap \mathcal{E}_{\mathrm{bin}}(\delta)$, the output $\widehat{\pi}$ of Algorithm 1 simultaneously satisfies
$$\mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}) \le \widetilde{O}\left(\frac{\eta(C^{\pi^*})^2|\mathcal{S}||\mathcal{A}|}{n} \wedge \sqrt{\frac{C^{\pi^*}|\mathcal{S}||\mathcal{A}|}{n}}\right).$$
2. Under Assumptions 2.4, 2.6 and 2.8 with $\epsilon_c = n^{-1}$ in (3.3), on $\mathcal{E}_{\mathrm{gfa}}(\delta)$, the output $\widehat{\pi}$ of Algorithm 2 simultaneously satisfies
$$\mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}) \le \widetilde{O}\left(\frac{\eta C^{\pi^*}D^2_{\pi^*}\log N_{\mathcal{G}}(n^{-1})}{n} \wedge D_{\pi^*}\sqrt{\frac{\log N_{\mathcal{G}}(n^{-1})}{n}}\right).$$

Proof. Since $\widehat{\pi} \in \mathrm{argmax}_{\pi\in\Delta(\mathcal{A}|\mathcal{S})} J_{\mathrm{FKL}}(\pi;\widehat{g})$ satisfies $J_{\mathrm{FKL}}(\widehat{\pi};\widehat{g}) \ge J_{\mathrm{FKL}}(\pi^*_{\mathrm{FKL}};\widehat{g})$, the linear decomposition in (5.8) holds context-wise for every $\eta > 0$. On the respective pessimism events, $g^*(s,a) - \widehat{g}(s,a) \ge 0$ for all $(s,a) \in \mathcal{S}\times\mathcal{A}$, and hence dropping the non-positive term $-\langle g^* - \widehat{g}, \widehat{\pi}\rangle \le 0$ yields

$$\mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}) \le \langle g^* - \widehat{g}, \pi^*_{\mathrm{FKL}} - \widehat{\pi}\rangle \le \mathbb{E}_{(s,a)\sim\rho\times\pi^*_{\mathrm{FKL}}}\big[g^*(s,a) - \widehat{g}(s,a)\big]. \tag{E.19}$$

In the tabular setting, on $\mathcal{E}_{\mathrm{tab}}(\delta) \cap \mathcal{E}_{\mathrm{bin}}(\delta)$, the proof of Theorem 3.2 shows $(g^*(s,a) - \widehat{g}(s,a))^2 \le \frac{128\log^2(2|\mathcal{S}||\mathcal{A}|/\delta)}{n\rho(s)\pi^{\mathsf{ref}}(a|s)}$ for all $(s,a) \in \mathcal{S}\times\mathcal{A}$. Applying Cauchy–Schwarz to (E.19) gives

$$\begin{aligned}\mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}) &\le \frac{8\sqrt{2}\log(2|\mathcal{S}||\mathcal{A}|/\delta)}{\sqrt{n}}\sum_{s\in\mathcal{S},a\in\mathcal{A}}\sqrt{\rho(s)\pi^*_{\mathrm{FKL}}(a|s)\frac{\pi^*_{\mathrm{FKL}}(a|s)}{\pi^{\mathsf{ref}}(a|s)}} \\ &\le 8\sqrt{2}\log(2|\mathcal{S}||\mathcal{A}|/\delta)\sqrt{\frac{|\mathcal{S}||\mathcal{A}|}{n}\sum_{s\in\mathcal{S},a\in\mathcal{A}}\rho(s)\pi^*_{\mathrm{FKL}}(a|s)\frac{\pi^*_{\mathrm{FKL}}(a|s)}{\pi^{\mathsf{ref}}(a|s)}}\end{aligned}$$

$$= \widetilde{O}\left(\sqrt{\frac{C^{\pi^*}|\mathcal{S}||\mathcal{A}|}{n}}\right).$$

Under function approximation, on $\mathcal{E}_{\mathrm{gfa}}(\delta)$, we have $0 \le g^*(s,a) - \widehat{g}(s,a) \le 2\beta D_{\mathcal{G}}((s,a);\pi^{\mathsf{ref}})$. Applying Jensen's inequality to (E.19) yields $\mathrm{SubOpt}_{\mathrm{FKL}}(\widehat{\pi}) \le 2\beta \mathbb{E}_{(s,a)\sim\rho\times\pi^*_{\mathrm{FKL}}}[D_{\mathcal{G}}((s,a);\pi^{\mathsf{ref}})] \le 2\beta D_{\pi^*}$. Combining these η-free bounds with the fast-rate bounds in Theorems 3.2 and 3.4 completes the proof. □

Proposition E.3 implies simultaneous sample complexity bounds of $\widetilde{O}\big(\eta(C^{\pi^*})^2|\mathcal{S}||\mathcal{A}|\epsilon^{-1} \wedge C^{\pi^*}|\mathcal{S}||\mathcal{A}|\epsilon^{-2}\big)$ in the tabular setting and $\widetilde{O}\big(\eta C^{\pi^*} D^2_{\pi^*}\epsilon^{-1}\log N_{\mathcal{G}}(\epsilon) \wedge D^2_{\pi^*}\epsilon^{-2}\log N_{\mathcal{G}}(\epsilon^2)\big)$ under function approximation. In the tabular setting, this upper bound transitions at $\eta \asymp (C^{\pi^*}\epsilon)^{-1}$ (or $\eta \asymp \sqrt{n/((C^{\pi^*})^3|\mathcal{S}||\mathcal{A}|)}$ in sample size n), whereas our two-armed lower bound in Theorem D.3 transitions at $\eta \asymp \sqrt{n}$; reconciling these transition thresholds across general $|\mathcal{S}|$, $|\mathcal{A}|$, and C^{π^*} remains an open problem.

E.5 Scope of the Convex-Conjugate Pipeline Beyond Forward KL and Offline Settings

We examine why the specific generator of forward KL and offline pessimism are pivotal for achieving the ϵ^{-1} fast rate in Lemma 5.5, and identify the exact technical barriers that arise for general strictly convex regularizers and online regret minimization.

General strictly convex f-divergences. Consider a single-context f-divergence regularizer $h(\pi) := \eta^{-1}D_f(\pi\|\pi^{\mathsf{ref}}) = \eta^{-1}\sum_{a\in\mathcal{A}}\pi^{\mathsf{ref}}(a)f\big(\pi(a)/\pi^{\mathsf{ref}}(a)\big)$, where $f : (0,+\infty) \to \mathbb{R}$ is twice continuously differentiable and strictly convex with $f(1) = 0$. Note that forward KL corresponds to $D_f(\pi\|\pi^{\mathsf{ref}})$ with $f(t) = -\log t$. Assuming $\pi^* = \pi_r \in \mathrm{ri}(\Delta(\mathcal{A}))$ and $\widehat{\pi} = \pi_{\widehat{r}} \in \mathrm{ri}(\Delta(\mathcal{A}))$, Lemmas F.3 and F.4 still yield $\mathrm{SubOpt}_{D_f}(\widehat{\pi}) = \mathsf{B}_{h^*}(r,\widehat{r}) = \mathsf{B}_h(\widehat{\pi},\pi^*)$. Writing $x_a := \pi^*(a)/\pi^{\mathsf{ref}}(a) > 0$ and $y_a := 1 - \widehat{\pi}(a)/\pi^*(a) < 1$ so that $\widehat{\pi}(a)/\pi^{\mathsf{ref}}(a) = x_a(1-y_a)$, a direct expansion of the Bregman divergence gives the analogue of (5.7):

$$\mathrm{SubOpt}_{D_f}(\widehat{\pi}) = \eta^{-1}\sum_{a\in\mathcal{A}}\pi^{\mathsf{ref}}(a)\phi_{x_a}(y_a), \quad \text{where } \phi_x(y) := f\big(x(1-y)\big) - f(x) + xf'(x)y.$$

Combining this identity with $\mathrm{SubOpt}_{D_f}(\widehat{\pi}) \le \sum_{a\in\mathcal{A}}\pi^*(a)(r(a)-\widehat{r}(a))y_a$ and applying the Fenchel–Young inequality action-wise with $z_a := 2\eta\frac{\pi^*(a)}{\pi^{\mathsf{ref}}(a)}(r(a)-\widehat{r}(a))$ yields

$$\mathrm{SubOpt}_{D_f}(\widehat{\pi}) \le \eta^{-1}\sum_{a\in\mathcal{A}}\pi^{\mathsf{ref}}(a)\phi^*_{x_a}(z_a), \quad \text{where } \phi^*_x(z) := \sup_{y<1}\big\{yz - \phi_x(y)\big\}. \tag{E.20}$$

For $f(t) = -\log t$, logarithmic homogeneity yields $\phi_x(y) = -\log(1-y) - y$, which decouples completely from $x_a = \pi^*(a)/\pi^{\mathsf{ref}}(a)$ and satisfies $\phi''(0) = 1 > 0$, so its conjugate $\phi^*(z) = z - \log(1+z)$ enjoys the quadratic bound $\phi^*(z) \le z^2/2$ for all $z \ge 0$. For a general strictly convex generator f lacking strong convexity, ϕ_{x_a} depends on x_a and can have vanishing second derivative $\phi''_x(0) = x^2f''(x) = 0$, destroying the $O(z^2)$ dual bound needed to obtain an ϵ^{-1} fast rate via (E.20). For example, take the strictly convex generator $f(t) = (t-1)^4$. At any action with $x_a = \pi^*(a)/\pi^{\mathsf{ref}}(a) = 1$, we have $\phi_1(y) = y^4$, whose constrained conjugate over $y \le 1$ evaluates to $\phi^*_1(z) = 3\cdot 4^{-4/3}z^{4/3}$ for $z \in [0,4]$. Since $\phi^*_1(z) = \Theta(z^{4/3})$ rather than $O(z^2)$ as $z \downarrow 0$, (E.20) yields only an $O(n^{-2/3})$ rate (i.e., $O(\epsilon^{-3/2})$ sample complexity) rather than an $O(\epsilon^{-1})$ fast rate.

Obstacles in online regret minimization. While our lower bounds in Section 4 extend naturally to online forward-KL-regularized regret (Ji et al., 2026), extending our upper-bound pipeline in Lemma 5.5 to online optimism is nontrivial even for multi-armed bandits unless one allows an explicit $(\min_a \pi^{\mathsf{ref}}(a))^{-1}$ factor via Lemma 5.1. Specifically, in (5.9) and (5.10), pessimism ($r \ge \widehat{r}$) guarantees $z_a \ge 0$, keeping z_a bounded away from the singularity $z = -1$ of $\phi^*(z) = z - \log(1+z)$ and enabling $\phi^*(z_a) \le z_a^2/2$. Under online optimism ($\widehat{r} \ge r$), however, $z_a \le 0$, so $\phi^*(z_a)$ blows up as $z_a \downarrow -1$ (and becomes $+\infty$ whenever $z_a \le -1$), precluding a direct application of Lemma 5.5 without new algorithmic mechanisms.

F Technical Tools

F.1 Differentiating maximal functions

We adapt simplified versions of Bertsekas et al. (2003, Proposition 4.5.1) and Milgrom and Segal (2002, Theorem 1) as follows.

Lemma F.1 (Danskin's Theorem, Bertsekas et al. 2003)**.** Let $\Pi \subset \mathbb{R}^m$ be compact, $G : \mathbb{R}^n \times \Pi \to \mathbb{R}$ be continuous, and $\forall \pi \in \Pi, r \mapsto G(r, \pi)$ be convex. For $g(\cdot) \coloneqq \max_{\pi \in \Pi} G(\cdot, \pi)$, if $\operatorname{argmax}_{\pi \in \Pi} G(\widetilde{r}, \pi) = \{\widetilde{\pi}\}$ is a singleton and $r \mapsto G(r, \widetilde{\pi})$ is differentiable at $r = \widetilde{r}$, then $\nabla g(\widetilde{r})$ exists and $\nabla g(\widetilde{r}) = \nabla_1 G(\widetilde{r}, \widetilde{\pi})$, where ∇_1 is the gradient with respect to the first input.

Lemma F.2 (The Envelope Theorem, Milgrom and Segal 2002)**.** Let Π be a set and $J : \Pi \times [0, 1] \to \mathbb{R}$ be a function. Let $V(\cdot) \coloneqq \sup_{\pi \in \Pi} J(\pi, \cdot)$. For any $u \in (0, 1)$ and $\widetilde{\pi} \in \Pi$, if $J(\widetilde{\pi}, u) = V(u)$, $V'(u)$ exists, and $\partial_u J(\widetilde{\pi}, u)$ exists; then $V'(u) = \partial_u J(\widetilde{\pi}, u)$.

F.2 Properties of convex conjugate over the simplex

The *convex conjugate*, whose supremum is taken over the entire Euclidean space, has been a well-established notion (Rockafellar, 1997); it has various handy properties for the analysis of bandit learning (see, e.g., Lattimore and Szepesvári (2020, Chapter 26)). We adapt some of them to the case where the supremum is taken over the probability simplex $\Delta(\mathcal{A})$ for the sake of rigorousness.

Lemma F.3. Suppose a closed convex function $h : \Delta(\mathcal{A}) \to \mathbb{R} \cup \{+\infty\}$ is continuously differentiable and strictly convex on $\operatorname{ri}(\Delta(\mathcal{A}))$, and $\operatorname{dom}(h) \supset \operatorname{ri}(\Delta(\mathcal{A}))$. Suppose for any $r \in \mathbb{R}^{\mathcal{A}}$, $\pi_r \in \operatorname{ri}(\Delta(\mathcal{A}))$ exists, where $\pi_r \coloneqq \operatorname{argmax}_{\pi \in \Delta(\mathcal{A})} \langle r, \pi \rangle - h(\pi)$. Then $h^*(\cdot) \coloneqq \max_{\pi \in \Delta(\mathcal{A})} \langle \cdot, \pi \rangle - h(\pi)$ is differentiable and $\nabla h^*(r) = \pi_r$.

Proof of Lemma F.3. First, note that π_r in the relative interior is uniquely well-defined by the existence assumption and strict convexity. Also, h induces another proper, closed, and convex function $\widetilde{h} : \mathbb{R}^{\mathcal{A}} \to (-\infty, +\infty]$ defined as

$$\widetilde{h}(\pi) \coloneqq \begin{cases} h(\pi), & \pi \in \Delta(\mathcal{A}); \\ +\infty, & \text{otherwise}; \end{cases}$$

which is also bounded from below (Beck, 2017, Theorem 2.12). Here, the (unconstrained) conjugate of $\widetilde{h}$ evaluates to h^* because

$$\widetilde{h}^*(r) = \sup_{\pi \in \mathbb{R}^{\mathcal{A}}} \langle r, \pi \rangle - \widetilde{h}(\pi) = \max_{\pi \in \Delta(\mathcal{A})} \langle r, \pi \rangle - h(\pi) = h^*(r),$$

which, together with the compactness of $\Delta(\mathcal{A})$, implies that h^* is finite everywhere. Also, since $h^* = \widetilde{h}^*$ implies that h^* is convex (Beck, 2017, Theorem 4.3). Therefore, the (assumed) uniqueness of $\pi_r = \operatorname{argmax}_{\mu \in \mathbb{R}^{\mathcal{A}}} \langle r, \mu \rangle - \widetilde{h}(\mu)$ applying to the conjugate subgradient theorem (Beck, 2017, Theorem 4.20) yields that

$$\pi_r \in \partial \widetilde{h}^*(r) = \partial h^*(r) = \{\pi_r\}. \tag{F.1}$$

Since we already shown h^* is finite everywhere, applying Beck (2017, Theorem 3.33) to (F.1) yields that h^* is differentiable and $\nabla h^*(r) = \pi_r$. □

Lemma F.4. Under the conditions (and following the notation) in Lemma F.3, $\forall r, r' \in \mathbb{R}^{\mathcal{A}}$,

$$\mathsf{B}_{h^*}(r, r') = \mathsf{B}_h(\pi_{r'}, \pi_r),$$

where the Bregman divergence induced by h is defined as $\mathsf{B}_h(\pi_{r'}, \pi_r) \coloneqq h(\pi_{r'}) - h(\pi_r) - \langle \nabla h(\pi_r), \pi_{r'} - \pi_r \rangle$ and similarly for h^*.

Proof. Direct calculates yield

$$\begin{aligned} \text{LHS} &= h^*(r) - h^*(r') - \langle \nabla h^*(r'), r - r' \rangle \\ &= h^*(r) - h^*(r') - \langle \pi_{r'}, r - r' \rangle \\ &= \big(\langle r, \pi_r \rangle - h(\pi_r)\big) - \big(\langle r', \pi_{r'} \rangle - h(\pi_{r'})\big) - \langle \pi_{r'}, r \rangle + \langle \pi_{r'}, r' \rangle \\ &= h(\pi_{r'}) - h(\pi_r) - \langle r, \pi_{r'} - \pi_r \rangle, \end{aligned} \tag{F.2}$$

where the second and third equalities follow from Lemma F.3. Because $\pi_r \in \operatorname{ri}(\Delta(\mathcal{A}))$ maximizes $\langle r, \cdot \rangle - h(\cdot)$ over $\Delta(\mathcal{A})$, the first-order optimality condition (of the Lagrangian) under the normalization constraint (i.e., probabilities sum to one) implies that $\exists \lambda \in \mathbb{R}$ such that

$$\forall a \in \mathcal{A}, r(a) - \frac{\partial h}{\partial \pi(a)}(\pi_r) = \lambda,$$

where we note that there is no Lagrangian multiplier (dual variable) for the non-negativity constraint due to complementary slackness and the assumption that $\pi_r \in \mathrm{ri}(\Delta(\mathcal{A}))$. Thus, $r - \nabla h(\pi_r) \in \mathrm{span}(\mathbf{1})$.[12] This relation implies $\langle r, \pi_{r'} - \pi_r \rangle = \langle \nabla h(\pi_r), \pi_{r'} - \pi_r \rangle$ and in turn implies

$$(\text{F.2}) = h(\pi_{r'}) - h(\pi_r) - \langle \nabla h(\pi_r), \pi_{r'} - \pi_r \rangle = \text{RHS}.$$

□

Remark F.5. To be conceptually minimal (without the introduction any convex-analytical definitions of *gradient* for functions defined on low-dimensional convex subsets), we understand the "continuous differentiability" for h in Lemmas F.3 and F.4 as: h admits a *continuation* $h_{\mathrm{ext}} : \mathbb{R}_+^{\mathcal{A}} \to (-\infty, +\infty]$ such that the *Euclidean gradient* $\mu \mapsto \nabla h_{\mathrm{ext}}(\mu)$ is continuous. The continuation h_{ext} is not necessarily unique, but this non-uniqueness does not hurt in the proof of either Lemma F.3 or Lemma F.4 because if there are two different valid continuations $h_{\mathrm{ext}}^{(1)}$ and $h_{\mathrm{ext}}^{(2)}$, they must agree on $\Delta(\mathcal{A})$, viz., their directional derivatives along any path strictly inside $\Delta(\mathcal{A})$ must be equal, i.e., $\forall \pi \in \mathrm{ri}(\Delta(\mathcal{A}))$, $\langle \nabla h_{\mathrm{ext}}^{(1)}(\pi), \mathbf{t} \rangle = \langle \nabla h_{\mathrm{ext}}^{(2)}(\pi), \mathbf{t} \rangle$ as long as the tangent direction $\mathbf{t}$ satisfies $\langle \mathbf{t}, \mathbf{1} \rangle = 0$; in which case $\nabla h_{\mathrm{ext}}^{(1)}(\pi) - \nabla h_{\mathrm{ext}}^{(2)}(\pi) \in \mathrm{span}(\mathbf{1})$, and thus the first-order quantity $\langle \nabla h_{\mathrm{ext}}(\pi), \pi' - \pi \rangle$ between any two probability vectors π' and π does NOT vary with the choice of continuation. We thus only write ∇h in place of ∇h_{ext} in these lemma statements and proofs.

Remark F.6. The $\mathrm{dom}(h) \supset \mathrm{ri}(\Delta(\mathcal{A}))$ in Lemma F.3 implies that we allow h to blow up on the boundary of $\Delta(\mathcal{A})$, which is the case for forward KL $h(\cdot) = \eta^{-1}\mathsf{KL}\left(\pi^{\mathsf{ref}} \| \cdot\right)$ even under Assumption 2.1. This is the reason that prevents us from using Danskin's theorem (Lemma F.1) to directly prove Lemma F.3.

Lemma F.7. Under the conditions (and following the notation) in Lemma F.3, if h is also twice continuously differentiable on $\mathrm{ri}(\Delta(\mathcal{A}))$ and there is an $r_\flat \in \mathbb{R}^{\mathcal{A}}$ such that the Hessian matrix $\nabla^2 h(\pi_{r_\flat}) \succ \mathbf{0}_{A \times A}$, then h^* is twice continuously differentiable in a neighborhood of $r_\flat$ and

$$\left[\nabla^2 h^*(r_\flat)\right] = \left[\nabla^2 h(\pi_{r_\flat})\right]^{-1} - \frac{\left[\nabla^2 h(\pi_{r_\flat})\right]^{-1} \mathbf{1}\mathbf{1}^\top \left[\nabla^2 h(\pi_{r_\flat})\right]^{-1}}{\mathbf{1}^\top \left[\nabla^2 h(\pi_{r_\flat})\right]^{-1} \mathbf{1}}, \tag{F.3}$$

where $\mathbf{1} \in \mathbb{R}^{\mathcal{A}}$ is the all-one vector. Consequently, let $\mathbf{P} \coloneqq \mathbf{I} - A^{-1}\mathbf{1}\mathbf{1}^\top$,[13] (F.3) implies

$$\left[\nabla^2 h^*(r_\flat)\right] \cdot \left[\nabla^2 h(\pi_{r_\flat})\right] \cdot \mathbf{P} = \mathbf{P}.$$

Proof. Let $\mathbf{H} \coloneqq \left[\nabla^2 h(\pi_{r_\flat})\right]$. Then $\mathbf{H} \succ \mathbf{0}_{A \times A}$ by assumption. By Lemma F.3, h^* is a closed convex function that is differentiable everywhere and $\nabla h^*(r) = \pi_r$, and thus Lemma F.9 implies that $r \mapsto \nabla h^*(r)$ is continuous on $\mathbb{R}^{\mathcal{A}}$. Since $\pi_{r_\flat} \in \mathrm{ri}\left(\Delta(\mathcal{A})\right)$, there is an open neighborhood $\mathcal{U} \subset \mathbb{R}^{\mathcal{A}}$ of $r_\flat$ such that $\forall r \in \mathcal{U}$, $\pi_r \in \mathrm{ri}\left(\Delta(\mathcal{A})\right)$ and the non-negativity constraint is inactive due to complementary slackness. And thus the first-order optimality condition and the primal feasibility $\mathbf{1}^\top \pi = 1$ are necessary and sufficient for characterizing the maximizer π_r (unique by assumption) for every $r \in \mathcal{U}$, i.e., there exists a unique Lagrangian multiplier λ_r for each $r \in \mathcal{U}$ such that

$$\begin{cases} \nabla h(\pi_r) - r - \lambda_r \mathbf{1} & = \mathbf{0}, \\ \langle \mathbf{1}, \pi_r \rangle - 1 & = 0. \end{cases}$$

Let the mapping $\mathbf{f} : \mathbb{R}^A \times \mathbb{R} \times \mathbb{R}^A \to \mathbb{R}^{A+1}$ be

$$\mathbf{f}(\pi, \lambda, r) \coloneqq \begin{bmatrix} \nabla h(\pi) - r - \lambda \mathbf{1} \\ \langle \mathbf{1}, \pi \rangle - 1. \end{bmatrix}$$

Then $\mathbf{f}(\pi_{r_\flat}, \lambda_{r_\flat}, r_\flat) = \mathbf{0}_{A+1}$. The Jacobian matrix $\mathbf{J}_\flat$ of $\mathbf{f}$ with respect to the variables (π, λ) (i.e., excluding the explicit dependency of r) evaluated at $(\pi_{r_\flat}, \lambda_{r_\flat}, r_\flat)$ is thus

$$\mathbf{J}_\flat = \begin{bmatrix} \mathbf{H} & -\mathbf{1}_A \\ \mathbf{1}_A^\top & 0 \end{bmatrix}.$$

[12] Recall that this $\mathrm{span}(\mathbf{1})$ is inherent, as elaborated in Remark F.5.

[13] $\mathbf{P}$ is the the orthogonal projection matrix onto the tangent space of $\Delta(\mathcal{A})$ at any $\pi \in \Delta(\mathcal{A})$.

To verify that $\mathbf{J}_\flat$ is non-singular, suppose $\mathbf{J}_\flat[\mathbf{a}^\top\ b]^\top = \mathbf{0}_{A+1}$ for some $\mathbf{a} \in \mathbb{R}^A$ and $b \in \mathbb{R}$, which is equivalent to $\mathbf{H}\mathbf{a} - b\mathbf{1}_A = \mathbf{0}_A$ and $\mathbf{1}_A^\top \mathbf{a} = 0$. Since $\mathbf{H} \succ \mathbf{0}_{A\times A}$ is invertible with $\mathbf{H}^{-1} \succ \mathbf{0}_{A\times A}$, left-multiplying $\mathbf{H}\mathbf{a} = b\mathbf{1}_A$ by $\mathbf{1}_A^\top \mathbf{H}^{-1}$ yields $0 = \mathbf{1}_A^\top \mathbf{a} = b(\mathbf{1}_A^\top \mathbf{H}^{-1}\mathbf{1}_A)$. Because $\mathbf{1}_A \neq \mathbf{0}_A$ and $\mathbf{H}^{-1} \succ \mathbf{0}_{A\times A}$, we have $\mathbf{1}_A^\top \mathbf{H}^{-1}\mathbf{1}_A > 0$, which forces $b = 0$ and in turn $\mathbf{H}\mathbf{a} = \mathbf{0}_A \implies \mathbf{a} = \mathbf{0}_A$. Thus $\mathbf{J}_\flat$ has trivial kernel and is non-singular; applying the implicit function theorem on which gives that $r \mapsto (\pi_r, \lambda_r)$ is continuously differentiable in an open neighborhood $\widetilde{\mathcal{U}} \subset \mathbb{R}^{\mathcal{A}}$ of $r_\flat$. Recall that $\nabla h^*(r) = \pi_r$, we further obtain that $r \mapsto \nabla h^*(r)$ is continuously differentiable locally, viz., h^* is twice continuously differentiable at $r_\flat$. Therefore, it is legal to calculate $\nabla^2 h^*(r_\flat)$. Recall that for $r \in \mathcal{U}$, $\mathbf{f}(\pi_r, \lambda_r, r) \equiv \mathbf{0}_{A+1}$, we use the chain rule for taking the derivative on both sides of $\mathbf{f}(\pi_r, \lambda_r, r) = \mathbf{0}_{A+1}$ with respect to r and evaluate the derivative at $r = r_\flat$ to obtain

$$\begin{bmatrix} \mathbf{H} & -\mathbf{1} \\ \mathbf{1}^\top & 0 \end{bmatrix} \begin{bmatrix} \nabla_r \pi_{r_\flat} \\ \nabla_r \lambda_{r_\flat} \end{bmatrix} + \begin{bmatrix} -\mathbf{I}_{A\times A} \\ \mathbf{0}_A^\top \end{bmatrix} = \mathbf{0}_{(A+1)\times A},$$

which implies $\mathbf{1}^\top \nabla_r \pi_{r_\flat} = \mathbf{0}_A^\top$ and $\mathbf{H}\nabla_r \pi_{r_\flat} - \mathbf{1}\nabla_r \lambda_{r_\flat} = \mathbf{I}_{A\times A}$.[14] Thus, $\nabla_r \pi_{r_\flat} = \mathbf{H}^{-1} + \mathbf{H}^{-1}\mathbf{1}\nabla_r \lambda_{r_\flat}$, substituting which into $\mathbf{1}^\top \nabla_r \pi_{r_\flat} = \mathbf{0}^\top$ yields

$$\mathbf{0}_A = \mathbf{1}^\top \left(\mathbf{H}^{-1} + \mathbf{H}^{-1}\mathbf{1}\nabla_r \lambda_{r_\flat}\right) \Longrightarrow \nabla_r \lambda_{r_\flat} = -\frac{\mathbf{1}^\top \mathbf{H}^{-1}}{\mathbf{1}^\top \mathbf{H}^{-1}\mathbf{1}}.$$

Finally,

$$\nabla^2 h^*(r_\flat) = \nabla_r \pi_{r_\flat} = \mathbf{H}^{-1} + \mathbf{H}^{-1}\mathbf{1}\nabla_r \lambda_{r_\flat} = \mathbf{H}^{-1} - \frac{\mathbf{H}^{-1}\mathbf{1}\mathbf{1}^\top \mathbf{H}^{-1}}{\mathbf{1}^\top \mathbf{H}^{-1}\mathbf{1}}.$$

□

Remark F.8. Lemma F.7 is a fine-grained version of Zhao et al. (2026, Lemma E.4), which is used in the current paper only to demonstrate why the mean-value-type argument fails to achieve single-policy concentrability under forward-KL regularization, but can be of independent interest. The counterpart of Lemma F.4 for *unconstrained* convex conjugate has been established before (see, e.g., Lattimore and Szepesvári (2020, Lemma 26.4)).

F.3 Miscellanies

Lemma F.9 (Rockafellar 1997, Corollary 25.5.1)**.** Suppose h is a proper convex function that is finite and differentiable on an open convex set C, then h is continuously differentiable on C.

Fact F.10. $\phi(y) = -y - \log(1-y)$ is convex on $(-\infty, 1)$, whose (constrained) convex conjugate is

$$\phi^*(z) \coloneqq \sup_{y<1} yz - \phi(y) = \begin{cases} z - \log(1+z), & z > -1; \\ +\infty, & z \leq -1. \end{cases}$$

And the Fenchel-Young inequality $yz \leq \phi(y) + \phi^*(z)$ holds for any $y < 1$ and $z \in \mathbb{R}$.

Proof. Direct calculation gives that $\phi'(y) = -1 + (1-y)^{-1}$, thus $\phi''(y) = (1-y)^{-2} > 0$ for all $y < 1$, concluding that ϕ is convex. Now fix any $z > -1$, let $\phi_z(y) = yz - \phi(y)$ for $y < 1$, then

$$\phi_z'(y) = 1 + z - \frac{1}{1-y}.$$

Therefore ϕ_z takes maximum at $z(1+z)^{-1}$. Plugging in this value of y gives that $\phi^*(z) = z - \log(1+z)$. Finally, for any $y < 1$ and $z \geq 0$, $\phi^*(z) \geq yz - \phi(y)$, resulting in $yz \leq \phi(y) + \phi^*(z)$. □

Lemma F.11 (Lemma A.1, Xie et al. 2021b)**.** Suppose $N \sim \mathsf{Bin}(n, p)$ where $n \geq 1$ and $p > 0$, then

$$\mathbb{P}\left[N \geq \frac{np}{2}\right] \geq 1 - \exp(-np/8).$$

Equivalently, with probability at least $1 - \delta$,

$$\frac{p}{N \vee 1} \leq \frac{8\log(1/\delta)}{n}.$$

[14] In this equation we use the row-layout for notational simplicity, i.e., $\nabla_r \lambda_{r_\flat} \in \mathbb{R}^{1\times A}$.

Lemma F.12 (Subgaussian Hoeffding inequality, Wainwright 2019, Proposition 2.5)**.** Let $\varepsilon_1, \ldots, \varepsilon_m$ be independent mean-zero σ-subgaussian random variables, i.e., $\mathbb{E}[\exp(\lambda \varepsilon_j)] \le \exp(\lambda^2 \sigma^2/2)$ for all $\lambda \in \mathbb{R}$ and $j \in [m]$. Then for every $t \ge 0$,

$$\mathbb{P}\left(\left| \frac{1}{m} \sum_{j=1}^{m} \varepsilon_j \right| \ge t \right) \le 2 \exp\left(- \frac{m t^2}{2\sigma^2} \right).$$

Lemma F.13 (Bernstein's inequality, Wainwright 2019, Proposition 2.10)**.** Let $Y_1, \ldots, Y_m$ be i.i.d. random variables taking values in $[0,1]$ with $\sigma^2 := \mathrm{Var}(Y_1)$. Then for every $t > 0$, with probability at least $1 - 2e^{-t}$,

$$\left| \frac{1}{m} \sum_{i=1}^{m} Y_i - \mathbb{E}[Y_1] \right| \le \sqrt{\frac{2\sigma^2 t}{m}} + \frac{2t}{3m}.$$

Lemma F.14 (Le Cam's two-point method, Le Cam 1973; Yu 1997)**.** Let $\mathcal{R}$ be the set of instances, Π be the set of estimators, and $L : \Pi \times \mathcal{R} \to \mathbb{R}_+$ be a loss function. For $\acute{r}, \grave{r} \in \mathcal{R}$, suppose $\exists c > 0$ such that

$$\inf_{\pi \in \Pi} L(\pi, \acute{r}) + L(\pi, \grave{r}) \ge c,$$

then

$$\inf_{\pi \in \Pi} \sup_{r \in \mathcal{R}} \mathbb{E}_{\mathcal{D} \sim P_r} L\big(\pi(\mathcal{D}), r\big) \ge \frac{c}{4} \cdot \exp\left(- \mathsf{KL}\left(P_{\acute{r}} \| P_{\grave{r}}\right) \right),$$

where the trajectory distribution of π interacting with instance r is denoted by P_r.

Lemma F.15 (Assouad's Lemma, Yu 1997; Chen et al. 2024)**.** Let $\mathcal{R}$ be the set of instances, Π be the set of estimators, $\Theta := \{\pm 1\}^S$ for some $S > 0$, and $\{L_j\}_{j=1}^S$ be S functions from $\Pi \times \mathcal{R}$ to $\mathbb{R}_+$. Suppose $\{r_\theta\}_{\theta \in \Theta} \subset \mathcal{R}$ and the loss function is

$$L(\pi, r) := \sum_{j=1}^{S} L_j(\pi, r), \forall (\pi, r) \in \Pi \times \mathcal{R}.$$

We denote $\theta \sim_j \theta'$ if they differ only in the j-th coordinate. Further assume that

$$\theta \sim_j \theta' \Rightarrow \inf_{\pi \in \Pi} L_j(\pi, r_\theta) + L_j(\pi, r_{\theta'}) \ge c \tag{F.4}$$

for some $c > 0$, then

$$\inf_{\pi \in \Pi} \sup_{r \in \mathcal{R}} \mathbb{E}_{\mathcal{D} \sim P_r} L\big(\pi(\mathcal{D}), r\big) \ge S \cdot \frac{c}{4} \min_{\exists j : \theta \sim_j \theta'} \exp\left(- \mathsf{KL}\left(P_{r_\theta} \| P_{r_{\theta'}}\right) \right),$$

where the trajectory distribution of π interacting with instance $r \in \mathcal{R}$ is denoted by P_r.

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