From Static Policies to Adaptive Priors in Offline Reinforcement Learning

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Abstract

Offline reinforcement learning (RL) has traditionally focused on learning policies for direct deployment under conservative objectives, where uncertainty outside the offline dataset is treated pessimistically to ensure robustness. We argue that this formulation becomes incomplete when an offline-trained policy is subsequently updated through online interaction, as increasingly occurs in modern intelligent systems through test-time adaptation and online fine-tuning. This position paper argues that, in such settings, the objective of offline RL should extend beyond immediate deployment and instead prioritize learning *adaptive policy priors*: policies that preserve the capacity to improve during subsequent interaction through memory, exploration, and self-correction. We formalize this perspective as *adaptive offline reinforcement learning* (AORL), distinguish it from offline-to-online RL, and explain why adaptability becomes important under distributional shift, limited dataset coverage, and changing test-time conditions. We further discuss Bayesian offline RL as one principled direction for constructing adaptive policy priors by preserving epistemic uncertainty over plausible environments. Finally, we outline connections, open challenges, and research directions for treating offline RL as preparation for future experience rather than as a static deployment problem.

1 Introduction

Offline reinforcement learning (RL) studies how to optimize a policy using a static dataset of trajectories, without relying on online interaction during training[1]. In its classical formulation (Levine et al., 2020), the objective is to learn a policy for *direct deployment*: the offline-learned policy is treated as a static, final decision rule whose performance is expected to derive entirely from offline data rather than from subsequent interaction. This makes distributional shift particularly challenging (Kumar et al., 2019): out-of-dataset actions compound errors over time with no mechanism for correction.

As a result, the dominant design principle of offline RL has been *conservatism*: uncertainty about out-of-dataset actions is treated pessimistically so that learned policies remain safe and robust under limited support. This principle is realized through various objectives and constraints (Kumar et al., 2020; Yu et al., 2020; Fujimoto & Gu, 2021), and has driven much of the progress in offline RL (Reed et al., 2022; Lee et al., 2022a; Kumar et al., 2023; Park et al., 2025b).

A fundamental limitation is that this leaves little room for improvement after offline learning, even though modern systems routinely continue learning after deployment through in-context learning (Brown et al., 2020; Wei et al., 2022), planning (Yao et al., 2023; Snell et al., 2025), or online RL fine-tuning (Guo et al., 2025a,b). In the *era of experience* (Silver & Sutton, 2025), agent capability depends not only on static data but on acquiring new information through interaction (Hadsell et al.,

[1]We refer to "training" as parameter updates in the policy, in contrast to in-context learning (Brown et al., 2020).

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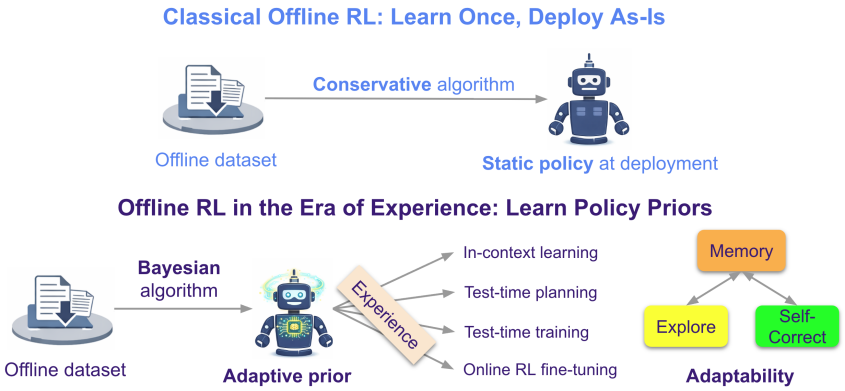

Figure 1: Top: **Classical offline RL** learns a static policy from a static dataset under conservative objectives. Bottom: **Adaptive offline RL** learns a policy prior that remains improvable through subsequent experience, including in-context learning, planning, or online fine-tuning. Here, **adaptability** arises from the interaction between memory, exploration, and self-correction. Bayesian perspective is highlighted as one principled direction for constructing such adaptive priors.

2020; Hughes et al., 2024), yet excessive conservatism makes this difficult by suppressing actions that interaction would reveal to be beneficial.

In this position paper, we use the term *adaptive offline reinforcement learning* (AORL) to refer to settings where offline RL should prioritize adaptability beyond direct deployment. **Our position is that when policies will continue improving through interaction, offline RL should learn adaptive policy priors rather than static policies.** Under this view, offline learning should not eliminate uncertainty solely for immediate robustness, but preserve sufficient behavioral flexibility for later adaptation. Such adaptability requires three ingredients: *memory*, so that decisions depend on online history; *exploration*, so that uncertain but potentially valuable actions remain reachable; and *self-correction*, so that new evidence can revise early mistakes during interaction. Actions outside the dataset are therefore not inherently undesirable; rather, they reflect epistemic uncertainty that can later be resolved through in-context learning, planning, or fine-tuning. Fig. 1 summarizes this shift from static policies to adaptive policy priors.

One principled direction for AORL arises from Bayesian perspectives (Ghosh et al., 2022; Ni et al., 2025). In this view, offline RL is cast as an epistemic POMDP (Ghosh et al., 2021): limited dataset coverage induces a posterior distribution over plausible MDPs that agree on observed data while differing beyond dataset support. The resulting optimal policy is naturally *adaptive in context*: by conditioning on online history, it can first explore uncertain but potentially good actions, then exploit the most promising ones. Bayesian offline learning therefore offers a concrete interpretation of adaptive policy priors whose value emerges through test-time interaction rather than as static behavior at deployment.

2 Formulation of Adaptive Offline Reinforcement Learning

We consider the standard offline RL setting (Levine et al., 2020) for a discrete-time, infinite-horizon, discounted-reward MDP defined by the tuple $\mathcal{M}^* = (\mathcal{S}, \mathcal{A}, \rho^*, P^*, R^*, \gamma)$. Here, the state space $\mathcal{S}$, the action space $\mathcal{A}$, and the discount factor $\gamma \in (0, 1)$ are assumed known, while the environment components, including the initial state distribution $\rho^* \in \Delta(\mathcal{S})$, the transition function $P^* : \mathcal{S} \times \mathcal{A} \to \Delta(\mathcal{S})$, and reward function $R^* : \mathcal{S} \times \mathcal{A} \to \Delta(\mathbb{R})$, are *unknown*.

Instead of interacting with $\mathcal{M}^*$ during training, the offline learner receives a static offline dataset $\mathcal{D} = \{\tau^i\}_{i=1}^N$ of trajectories collected by an unknown behavior policy β. Each trajectory $\tau = (s_0, a_0, r_1, s_1, a_1, r_2, \dots)$ is generated by $s_0 \sim \rho^*, a_t \sim \beta(h_t), s_{t+1} \sim P^*(s_t, a_t), r_{t+1} \sim R^*(s_t, a_t), \forall t \geq 0$, where the behavior policy may depend on the interaction history. We define the *history* at time t as $h_t := (s_0, a_0, r_1, s_1, \dots, a_{t-1}, r_t, s_t)$, with $h_t \in \mathcal{H}_t$ and $\mathcal{H}_t$ denoting the corresponding history space. The *ideal goal* for offline RL is to find a policy that maximizes expected discounted return under the true environment: $\max_\pi J(\pi; \mathcal{M}^*) := \mathbb{E}_\tau \left[\sum_{t=1}^\infty \gamma^{t-1} r_t \,\middle|\, \pi, \mathcal{M}^*\right]$. In the most general form, this policy may depend on interaction history, denoted as $\pi : \mathcal{H}_t \to \Delta(\mathcal{A})$.

Because $\mathcal{M}^*$ is inaccessible during offline optimization, this objective cannot be optimized directly. The key difficulty is epistemic uncertainty in state-action regions poorly covered by $\mathcal{D}$. We define the **behavioral support** of a state s within $\mathcal{D}$ as $\text{supp}_\mathcal{D}(s) = \{a \mid \Pr_\mathcal{D}(a \mid s) > \epsilon\} \subseteq \mathcal{A}$, where $\Pr_\mathcal{D}(\cdot \mid s)$ denotes the empirical action distribution in $\mathcal{D}$ and $\epsilon > 0$ is a small threshold. For states

s not observed in the dataset, $\text{supp}_{\mathcal{D}}(s) = \emptyset$. Epistemic uncertainty therefore remains substantial over actions in $\mathcal{A} \setminus \text{supp}_{\mathcal{D}}(s)$ for each $s \in \mathcal{S}$. Different treatments of this uncertainty give rise to different algorithmic principles, including conservative offline RL (Levine et al., 2020), Bayesian offline RL (Ghosh et al., 2022), and optimistic offline RL (Agarwal et al., 2020).

2.1 Core Components of Adaptive Policy Priors

Table 1: Comparison between classical offline RL and adaptive offline RL.

Property	Classical Offline RL	Adaptive Offline RL
Decision rule	Markovian	History-dependent
Uncertainty treatment	Within offline support	Preserve flexibility
Design focus	Offline stage	Offline + test-time stages
Core capabilities	Safety, robustness	Memory, exploration, self-correction

History dependence in decision making (memory). Classical offline RL typically assumes a Markovian decision rule, where actions are selected solely from the current state through a policy $\pi : \mathcal{S} \to \Delta(\mathcal{A})$ (Levine et al., 2020). The offline-learned Markovian policy remains fixed during deployment. In adaptive offline RL (AORL), by contrast, effective decision making should depend on online interaction history, because limited offline coverage leaves uncertainty about environment dynamics. This dependence can be implemented *explicitly* through a history-dependent policy $\pi : \mathcal{H}_t \to \Delta(\mathcal{A})$ (Chen et al., 2021b), or *implicitly* through online adaptation of latent variables (Ghosh et al., 2022; Liu et al., 2023), plans (Janner et al., 2022), or even policy parameters (Xu et al., 2025).

Behavioral flexibility (exploration and self-correction). Classical offline RL typically restricts learned actions to the behavioral support $\text{supp}_{\mathcal{D}}(s)$ or heavily penalizes actions outside it (Levine et al., 2020). In AORL, by contrast, out-of-support actions are not treated as intrinsically undesirable: some may be potentially useful but remain unresolved under offline data alone because of epistemic uncertainty rather than evidence of poor value. Preserving non-negligible probability on such actions allows the policy to explore uncertain behaviors during interaction. Equally importantly, because these actions may fail, the policy should be able to self-correct by using online feedback to revise future decisions rather than committing to early mistakes (Wang et al., 2024; Kumar et al., 2025).

These components define the basic requirements for an **adaptive policy prior**: the policy should retain memory from interaction history while preserving sufficient flexibility to explore uncertain behaviors and correct them online. Table 1 summarizes the key differences.

Forms of adaptation. Adaptation mechanisms differ in whether policy parameters are updated and how much online data they require. Common forms are summarized in Table 2.

Table 2: Common forms of adaptation after offline optimization. See Sec. A for details.

Form of Adaptation	Online Data	Parameter Update?	Mechanism
Test-time in-context learning	Limited	No	Implicit inference
Test-time planning	Limited	No	Explicit inference
Test-time training	Limited	Yes	Temporary update
Online RL fine-tuning	Extended	Yes	Persistent update

3 Why Offline RL Needs Adaptive Policy Priors?

The previous section defined adaptive policy priors through memory and behavioral flexibility. We now ask why these properties are needed beyond the classical offline RL objective. The key reason is that uncertainty often persists beyond offline optimization, appearing in online environments through distributional shift, limited data coverage, exploration bottlenecks, or changing conditions.

Inevitable distributional shift. Classical offline RL reduces risk by keeping actions within behavioral support, yet out-of-distribution (OOD) states may still arise during deployment because small errors accumulate over time. This is well known in imitation learning, where compounding errors induce *covariate shift* (Ross & Bagnell, 2010), and remains a practical bottleneck in offline RL (Park et al., 2024a). Since such OOD states are rarely trained explicitly under conservative objectives, the learned policy may become brittle when uncertainty matters most. Adaptability helps address this by preparing the offline-learned policy to use memory and online feedback to **self-correct** once OOD states are encountered.

Limited high-quality coverage. Classical offline RL effectively bounds policy improvement by the quality of behaviors represented in the dataset (Jin et al., 2021; Uehara & Sun, 2022). This

limitation becomes pronounced when high-quality actions are absent or underrepresented (Ni et al., 2025). In practice, collecting high-quality trajectories is expensive, and in open-ended domains even carefully curated datasets may remain incomplete. Adaptability mitigates this limitation by preserving behavioral flexibility, allowing subsequent interaction to **explore** uncertain actions and reinforce those that prove beneficial.

Exploration bottleneck in online RL fine-tuning. A standard way to overcome the limited adaptability of offline RL is to continue learning through online RL fine-tuning (Nair et al., 2020). However, in classical offline-to-online RL, online improvement is often slow and incremental (Luo et al., 2023; Zhao et al., 2023). In foundation model post-training, recent evidence further suggests that RL often mainly reweights behaviors already present in the policy prior rather than reliably discovering new ones (Yue et al., 2025; Zhao et al., 2025). As a result, behavioral support may contract further during fine-tuning, as illustrated in Fig. 2, making underrepresented but potentially good actions increasingly difficult to recover. Although prolonged fine-tuning can alleviate this effect (Liu et al., 2025), a complementary and often cheaper solution is to prepare a **behaviorally flexible** policy prior that already preserves diverse modes beyond well-supported actions in the offline dataset.

Test-time condition change. Standard offline RL typically assumes that the deployment environment matches the one that generated the offline dataset (i.e., $\mathcal{M}^*$). In realistic open-ended domains, dynamics, rewards, or task structure may shift after offline data collection, so actions that were optimal under the offline dataset may no longer remain optimal at test time. Prior work has shown that offline-learned policies can become brittle under such mismatches, including settings where variation is specified through environment parameters (Liang et al., 2023), external data sources (Lyu et al., 2024), natural-language instructions (Karthikeyan & Pant, 2025), or left unspecified (Mediratta et al., 2024).

4 A Bayesian Perspective for Adaptive Policy Priors

A natural question is whether adaptive policy priors admit a principled computational interpretation. One promising direction arises from Bayesian principles in offline RL (Ghosh et al., 2022), building on Bayes-adaptive MDPs (Duff, 2002), whose practical potential has recently been demonstrated (Chen et al., 2021b; Choi et al., 2024; Ni et al., 2025). Rather than collapsing uncertainty conservatively or treating unseen actions optimistically, Bayesian offline RL maintains multiple plausible environment hypotheses consistent with the offline dataset, as illustrated in Fig. 3.

Bayesian formulation of offline RL. In Bayesian model-based offline RL, the agent maintains epistemic uncertainty over environments consistent with the offline dataset $\mathcal{D}$. A prior distribution $\Pr(\mathcal{M})$ over MDPs induces a posterior $\Pr(\mathcal{M} \mid \mathcal{D})$ after observing the dataset, where each MDP $\mathcal{M}$ is specified by environment parameters (ρ, P, R). The offline objective becomes $\max_\pi \mathbb{E}_{\mathcal{M}\sim\Pr(\mathcal{M}|\mathcal{D})}[J(\pi;\mathcal{M})]$. Because each sampled MDP $\mathcal{M}$ is unknown to the agent, decision making becomes a partially observable problem over environment hypotheses, often called an *epistemic POMDP* (Ghosh et al., 2021, 2022). The optimal policy is therefore naturally history-dependent: it maintains Bellman consistency under the posterior over plausible MDPs. By contrast, model-free offline RL may assign unreliable values to out-of-support actions without an explicit mechanism for Bellman consistency.

Connection to adaptive policy priors. This formulation directly explains the ingredients of adaptive policy priors. Online history h_t provides *memory* about the environment; uncertain actions induce *exploration*; and newly observed evidence supports *self-correction*. Formally, online interaction further updates the environment posterior: $\Pr(\mathcal{M} \mid \mathcal{D}, h_t) \propto \Pr(\mathcal{M} \mid \mathcal{D}) \Pr(h_t \mid \mathcal{M}, \mathcal{D})$, where the offline posterior $\Pr(\mathcal{M} \mid \mathcal{D})$ serves as the effective *prior* for online interaction. Adaptability is thus a direct consequence of preserving epistemic uncertainty during offline optimization. Moreover, test-time condition shift is naturally handled by reweighting the posterior toward the test-time MDP $\mathcal{M}'$, provided that $\mathcal{M}'$ falls within the support of $\Pr(\mathcal{M} \mid \mathcal{D})$.

5 Conclusion

We argue that offline RL should prioritize learning *adaptive policy priors* that preserve memory, exploration, and self-correction for subsequent interaction, rather than static policies optimized for immediate deployment. Bayesian offline RL provides one principled direction, though many algorithmic and theoretical questions remain open (see Sec. B). Alternative views are discussed in Sec. C and connections to related RL areas are in Sec. D. More broadly, offline RL should move beyond a supervised-learning view shaped by data scaling laws (Kaplan et al., 2020), toward a continual-learning view aligned with the emerging era of experience (Silver & Sutton, 2025).

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Appendix

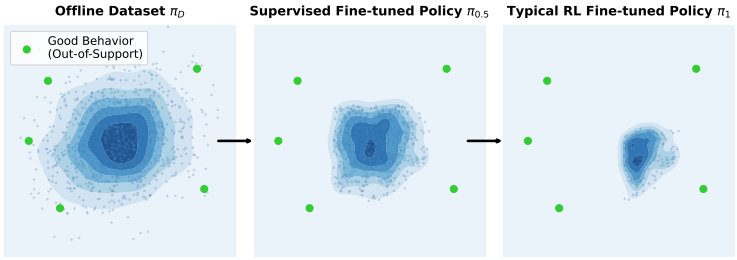

Figure 2: Behavioral support may shrink across offline (here, SFT) and online fine-tuning stages, making underrepresented but possibly good actions increasingly difficult to recover (Yue et al., 2025).

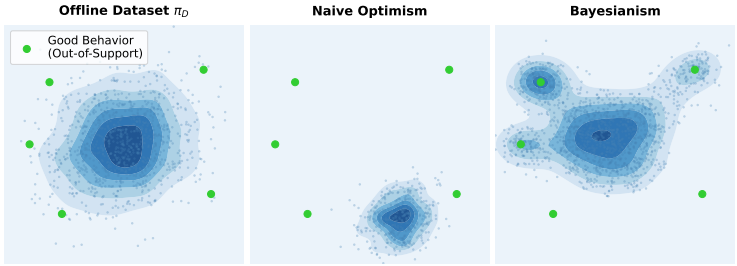

Figure 3: Bayesian offline RL treats unseen actions as uncertain rather than inherently bad or reliably good. In contrast, naive optimism in model-free off-policy RL may assign unreliable values to out-of-support actions due to extrapolation error (Fujimoto et al., 2019).

A Forms of Adaptation in Details

Test-time in-context learning. The simplest form of adaptation occurs when decision making is history-dependent, so that behavior changes directly through interaction history without modifying policy parameters or performing additional optimization. This mechanism is commonly referred to as *in-context learning* (Brown et al., 2020; Moeini et al., 2025), and has often been interpreted as implicit Bayesian inference over latent tasks (Xie et al., 2022). It differs from *in-weight learning*, where adaptation occurs through parameter updates. A special case of in-context learning is *self-improvement* (Shinn et al., 2023), where explicit reward signals may be unavailable at test time, yet the agent can still improve through informative observations that reduce uncertainty about the environment. Self-improvement includes settings where the uncertainty lies in transition dynamics rather than reward function (Packer et al., 2018), as well as settings where feedback is conveyed through language observations (Cheng et al., 2024; Klissarov et al., 2026).

Test-time planning. In-context learning relies primarily on the generalization ability of the offline-learned policy, which may be insufficient when the true environment $\mathcal{M}^*$ differs substantially from what is specified by $\mathcal{D}$. Test-time planning addresses this limitation by improving policy decisions with online search over future trajectories, often using learned world models (Argenson & Dulac-Arnold, 2020; Zhou et al., 2025; Wei et al., 2025). Recent planning approaches further enable trajectory optimization through probabilistic inference (e.g., diffusion-based denoising) without requiring an explicit world model (Janner et al., 2022; Ajay et al., 2023).

Test-time training. Adaptation may also occur through parameter updates using a limited amount of online data collected at test time (Finn et al., 2017; Sun et al., 2020). Unlike in-context learning or planning, test-time training modifies the policy itself, often through maximizing Q-value on test-time states without reward signals (Park et al., 2024a; Xu et al., 2025). Although this lies outside the classical offline RL formulation, it is relevant under AORL because the offline-learned policy is viewed as a prior that should support efficient improvement from limited online experience.

Online RL fine-tuning. A more extended form of adaptation is online RL fine-tuning, where the offline-learned policy serves as an initialization for continued RL with substantial online interaction.

This includes offline-to-online RL (Nair et al., 2020; Lee et al., 2022b) and RL post-training of foundation models (Guo et al., 2025a). Compared with test-time training, the focus is not rapid local adaptation, but sustained policy improvement through accumulating experience.

B Open Challenges and Research Directions

Benchmarks and evaluation for adaptability. Existing offline RL benchmarks evaluate many important settings, including high-dimensional observations (Gulcehre et al., 2020; Lu et al., 2023), sparse rewards and stitching (Fu et al., 2020; Park et al., 2025a), stochasticity (Qin et al., 2022), and safety (Liu et al., 2024). However, they rarely evaluate whether an offline-learned policy can *improve through subsequent interaction*. Prior work on adaptability has so far focused either on bandit-like settings (Ghosh et al., 2022; Ni et al., 2025) or illustrative task modifications (Liang et al., 2023; Zhou et al., 2025; Karthikeyan & Pant, 2025). Two notable exceptions are the off-dynamics RL benchmark (Lyu et al., 2024) and the generalization benchmark (Mediratta et al., 2024). In Lyu et al. (2024), test-time condition changes are specified through externally provided datasets, whereas in Mediratta et al. (2024), changes are conveyed either through text instructions in WebShop or remain unspecified in Procgen. If AORL is to become a meaningful research direction, progress will require more benchmarks that explicitly measure the capability for test-time adaptation.

On the offline side, dataset design should include at least two cases: *underrepresented but valuable actions*, where useful behaviors appear only sparsely in the data, and *unseen but plausible actions*, where beneficial behaviors are absent altogether and must be discovered through later interaction. On the online side, evaluation should go beyond a single fixed test environment and instead consider *a distribution of environments*: (1) environments fully aligned with the offline data, and (2) environments with test-time condition changes under varying degrees of specification.

More broadly, AORL benchmarks should treat *multi-episode interaction* as the basic unit of training and evaluation, akin to meta-RL setups (Duan et al., 2016), in order to capture the improvable capacity of adaptive agents. Evaluation should measure not only final returns, but also *how* improvement unfolds through interaction, including adaptation speed, robustness to early mistakes, recovery after failed exploration, and sensitivity to test-time horizon length (Sentenac et al., 2025).

Theory of adaptive offline RL. Classical offline RL theory typically relies on coverage assumptions over good actions and Markovian policies. Extending these guarantees to history-dependent policies that can discover unseen but valuable actions through online interaction remains largely open. Key questions include which class of offline datasets favors adaptive priors over static policies, when in-context learning suffices versus when parameter updates are necessary, and how guarantees should change under test-time condition shift.

Overcoming value overestimation. A major challenge in AORL is that classical *value overestimation* re-emerges once explicit conservatism is relaxed (Fujimoto et al., 2019; Kumar et al., 2019; Sims et al., 2024). Because adaptive priors must preserve uncertain actions for later exploration, avoiding overestimation *without* collapsing back to conservative behavior becomes a central algorithmic difficulty. Recent evidence from Bayesian offline RL suggests that sufficiently long-horizon rollouts can mitigate this problem (Ni et al., 2025). This points to a broader direction: scaling long-horizon planning in model-based offline RL, potentially informed by recent progress in long-horizon world modeling (Li et al., 2025a; Lin et al., 2026).

Scalable Bayesian inference. A practical bottleneck of the Bayesian direction in Sec. 4 is that exact posterior inference over MDPs is typically intractable. In practice, uncertainty is often approximated through model ensembles, where disagreement serves as a proxy for epistemic uncertainty (Yu et al., 2020). Improving the scalability of such approximations, while achieving more reliable uncertainty quantification (He et al., 2026), remains an important direction for AORL.

Memory-based RL. Memory remains underexplored in offline RL, with the most notable progress such as the Decision Transformer family (Chen et al., 2021a), which still operate under conservative objectives. We believe that advances in understanding memory (Ni et al., 2023; Cherepanov et al., 2026), learning history representations (Lambrechts et al., 2024; Ni et al., 2024; Sinha & Mahajan, 2024), and scaling memory-based RL (Grigsby et al., 2024; Luo et al., 2024) in online POMDPs can help AORL by understanding how in-context learning emerges from offline-trained policies.

Beyond Bayesian model-based direction. Although we emphasize the Bayesian model-based direction in Sec. 4 because it offers a principled interpretation of adaptive policy priors, simpler alternatives may also achieve adaptive behavior. These include model-free approaches (Hu et al., 2024; Wagenmaker et al., 2025) as well as non-Bayesian approaches (Touati et al., 2023). Understanding when such methods recover similar adaptive mechanisms, and when they fundamentally differ from model-based formulations, remains an important open direction.

Foundation models for AORL. World foundation models offer an intriguing answer to the *prior* specification problem in Sec. 4: rather than constructing $\Pr(\mathcal{M})$ from scratch, one can specify the MDP prior from a foundation model pretrained on broad dynamics data. Pretrained history-dependent policies, including large language models and vision-language-action models, may further serve as strong initial policies that efficiently explore beyond offline dataset support.

AORL for foundation models. Recent progress in foundation models already highlights the importance of test-time adaptation and continual learning (Wei et al., 2025; Snell et al., 2025). Yet offline post-training remains dominated by supervised fine-tuning (SFT) (Ouyang et al., 2022), which may narrow behavioral support and hinder later test-time adaptation or online RL fine-tuning (Zhang et al., 2026a). Bayesian directions may therefore offer a useful path for AORL in foundation models: model-based formulations can preserve broader support through synthetic on-policy rollouts (Chen et al., 2025), while Bayesian formulations can promote in-context adaptation (Zhang et al., 2026b).

C Alternative Views

Conservatism as the first principle. A dominant alternative view in offline RL is that conservatism should remain the primary design principle, motivated mainly by a technical concern: offline value estimation is prone to extrapolation error and value overestimation (Fujimoto et al., 2019; Kumar et al., 2019). Conservative objectives therefore restrict policy improvement toward in-distribution behavior to stabilize learning; in high-stakes deployment settings, this also aligns naturally with safety requirements. Our position differs when an offline-learned policy is expected to continue improving online. In this setting, uncertainty need not be fully eliminated offline, and excessive conservatism may suppress behaviors needed for later adaptation. Recent evidence suggests that value overestimation can also be controlled through alternative mechanisms such as long-horizon planning (Ni et al., 2025), weakening the case for conservatism as the default first principle. Importantly, *adaptability does not rule out moderate conservatism*: some degree of conservatism may still be necessary (Wendl et al., 2026), and can even be adjusted at test time (Swazinna et al., 2023). What matters is preserving enough memory and behavioral flexibility for the policy to revise decisions through interaction. The key distinction is whether offline learning aims to produce a static, final policy or an improvable prior.

Adaptation should be left to online RL, not offline RL. Another alternative view is that offline RL need not itself produce an adaptive prior; its role is simply to provide a stable initialization for subsequent online RL, while adaptation is delegated to downstream fine-tuning. Under this perspective, one may even blur the distinction between offline and online learning by directly training online RL from scratch with offline data (Song et al., 2023; Ball et al., 2023). This is reasonable in settings where online interaction is abundant, but incomplete when online experience is limited or costly. If offline training collapses the policy too narrowly—for example through behavioral cloning or strongly conservative objectives—online RL may inherit a restricted search space and struggle to recover underrepresented but valuable behaviors (Yue et al., 2025). Finally, when offline learning is intended to produce *reusable* priors rather than task-specific warm starts, its objective should therefore extend beyond fast initialization to preserving behavioral flexibility for later adaptation.

Adaptability already appears in many offline RL methods. Another alternative view is that offline RL already contains mechanisms associated with adaptation, making an explicit shift in objective unnecessary. Common history-dependent policies with sequence modeling (Chen et al., 2021a) use past context during action generation, yet typically remain constrained by patterns learned from the offline dataset. Test-time planning methods (Argenson & Dulac-Arnold, 2020; Janner et al., 2022) improve decisions through online search, but the candidate trajectories they consider are usually still constrained by offline support. Similarly, *stitching* (Fu et al., 2020) enables compositional generalization from offline data, but this remains a passive recombination of in-distribution behaviors rather than adaptation driven by new online evidence. These examples suggest

that adaptive ingredients are increasingly present in offline RL, but common formulations still do not explicitly preserve exploration and self-correction under later interaction.

D Connections Beyond Offline RL

Adaptive offline RL connects naturally to neighboring research areas that study adaptation and generalization under different assumptions.

Offline-to-online RL. Although offline RL is defined by the absence of online data collection during training, the learned policy is still evaluated through interaction with the true environment $\mathcal{M}^*$ at test (deployment) time. This creates a temporal separation between the offline stage, where parameters are optimized from a fixed dataset, and the online stage, where decisions are generated under the true environment. This distinction also separates offline RL (including AORL) from offline-to-online RL (Nair et al., 2020), where the policy (persistently) updates its parameters in the online stage.

Meta-RL. The Bayesian perspective in Sec. 4 is closely related to contextual MDPs (Hallak et al., 2015) and meta-RL (Duan et al., 2016; Wang et al., 2017; Beck et al., 2025), where policies are trained across a distribution of tasks so that adaptation emerges at test time. The key difference is that in meta-RL the task distribution is pre-specified before training, whereas in Bayesian offline RL the distribution over environments must be self-constructed from offline data. Nevertheless, both settings give rise to similar adaptive behavior at test time, including online exploration and self-correction under uncertainty.

Plasticity in continual RL. The ability to improve from subsequent experience is closely related to *plasticity* in continual RL (Abbas et al., 2023; Klein et al., 2024) and offline-to-online RL (Li et al., 2025b). AORL differs in that adaptation often occurs without parameter updates at deployment time, also known as *in-context plasticity* (Klissarov et al., 2026). Still, the central concern is similar: whether prior learning preserves the capacity to improve when new experience becomes available.

Behavior foundation models. A recent line of work trains behavior foundation models (BFMs) from *reward-free* offline datasets, aiming to produce policies that generalize zero-shot to arbitrary downstream reward functions (Touati et al., 2023; Park et al., 2024b; Frans et al., 2024). The key idea is to learn representations that decouple dynamics from reward, so that a new task is solved by simple computation on a few externally-provided reward-labeled samples without further training. Once the task embedding is inferred, the policy is static and memoryless; dynamics are typically assumed fixed.

BFMs are therefore complementary to, rather than a substitute for, AORL. Their reward generalizability could be incorporated into adaptive policy priors to handle the *reward specification* problem at test time. This also sharpens what "adaptation" means in AORL: unlike the passive task inference of BFMs from externally provided data, AORL requires *active* generalization in which the agent generates its own experience to resolve uncertainty.