Asymmetric On-Policy Distillation Learns In-Context Exploration

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Abstract

Sequential decision-making under partial observability is difficult because agents must explore to infer hidden, task-relevant information before acting effectively. Learning such information-gathering behaviors *tabula rasa* via online reinforcement learning is sample-inefficient, whereas offline imitation fails to learn exploratory behaviors due to insufficient coverage of deployment-time histories. To address this, we develop an online imitation-based method that learns to explore and adapt during deployment. We focus specifically on the setting of asymmetric student-teacher learning in POMDPs using oracle information from clairvoyant experts. Direct imitation learning fails because clairvoyant experts need not demonstrate the information-gathering actions required by students. In this work, we propose ASTEROID , a simple yet surprisingly effective framework for learning exploration from privileged experts. Our method, ASTEROID , is based on the key idea that history-conditioned student policies can learn to explore through online asymmetric distillation: the student first collects on-policy context under partial observability, and the privileged expert then provides action labels conditioned on that context. Iteratively, as the context grows, the student learns to use past observations to infer hidden task information and act according to the inferred latent state, yielding exploration similar to efficient Bayesian posterior sampling. Across a diverse range of ten different simulated environments, including discrete exploration benchmarks, robotic manipulation, navigation, and Procgen environments, ASTEROID achieves $\sim 2\times$ higher returns under fixed exploration budgets and uses up to $\sim 100\times$ fewer interactions than baselines. Finally, ASTEROID transfers policies trained entirely in simulation to vision-denied real-world robot manipulation, exhibiting efficient exploration and improving success by 40% relative to baselines. Overall, ASTEROID provides a simple yet surprisingly effective framework to learn efficient test-time exploration from privileged supervision. [1]

1 Introduction

Sequential decision-making under partial observability remains a central challenge in reinforcement learning (RL) [29, 45]. In many real-world settings, from robotics to embodied AI, agents receive only partial, noisy observations of the environment. Effective behavior, therefore, requires exploration to infer hidden, task-relevant information before acting successfully [26, 69, 36, 65, 39, 62]. For e.g., a household robot searching for an object must use onboard sensing to infer likely object locations, track locations it has already searched, and adapt future exploration based on prior attempts [9, 8, 25]. Such problems are formalized as partially observable Markov decision processes (POMDPs) [29].

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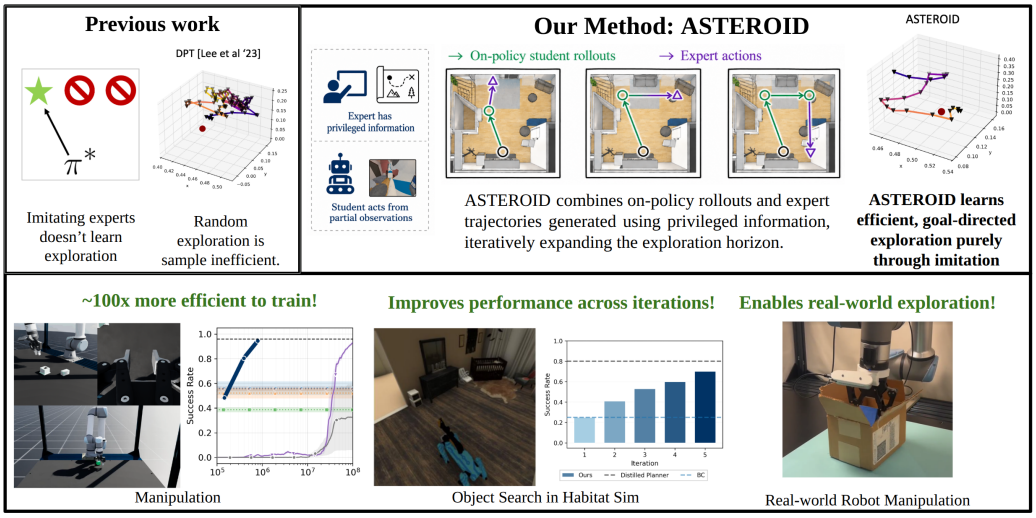


Figure 1: ASTEROID provides a simple, reliable, and performant method for achieving efficient exploration in partially observed domains via on-policy asymmetric student-teacher distillation.

Prior work [23, 43] has shown that history and recurrent models are important for POMDPs. Learning such models tabula rasa via online RL or meta-RL is sample-inefficient [3, 69, 17], as the agent must learn to both gather information and exploit it to solve the task. A natural way to improve sample efficiency is to assume training-time access to a "clairvoyant" oracle that observes the hidden privileged state and acts accordingly. This oracle can teach the learner how to act once the hidden state is known, but it does not teach the learner how to acquire that information [37]. The reason is simple: the privileged expert has no incentive to explore, whereas the deployed student must explore to infer the hidden state. Consequently, naively distilling expert behavior does not teach the student the information-gathering behavior needed for adaptation [61]. Existing approaches to this asymmetric student-teacher setting address the mismatch using expensive online RL [65], unrealistic expert formulations [64], or strong offline coverage assumptions [36].

In this work, we propose ASTEROID (**A**symmetric **S**tudent **Te**acher **R**oll**o**ut **I**n-context **D**istillation), an iterative method for learning efficient exploration from privileged expert labels using supervised policy updates. The key idea is to decouple the source of the history from the source of the supervision. ASTEROID rolls out the current student under partial observability, producing a history of observations, actions, and rewards. It then queries a privileged expert for actions to take from the state reached after that history. The expert does not need to demonstrate exploration itself; instead, it labels histories generated by the unprivileged student. As a result, failed searches, uninformative probes, and partial observations become useful training context: they specify what evidence the student has accumulated, while the expert label specifies the correct next action given the hidden state. This trains the student to infer hidden information in context and adapt its future behavior.

These on-policy contexts with privileged actions induce a supervision signal for exploration, as a partial history represents uncertainty over the hidden state. Returning to the household search example, suppose the object could be in location A, B, or C. If the student searches A and does not find the object, that history rules out the hidden state where the object is at A, but remains consistent with the object being at B or C. A privileged expert observing the true object location would label this kind of partial history with "search B" when the object is at B, and "search C" when the object is at C. The student therefore learns to randomize over the remaining plausible action. After failing at A, it may sample either B or C; after also failing at B, the history eliminates both A and B, making C the remaining plausible continuation. This is different from sampling locations independently at random, as the policy conditions on its history and avoids repeatedly trying hypotheses that its own experience has ruled out. Generally, across many training tasks, histories that alias multiple hidden states receive a distribution of expert labels over plausible expert trajectories. Sampling from this distribution chooses a valid hypothesis, and the resulting observation or reward updates the history, eliminating additional hypotheses in the process. Repeating this process trains an in-context policy to search when the hidden state is uncertain and exploit once the relevant information is revealed.

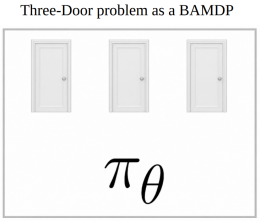
The on-policy nature of this data collection is critical: the student is trained on the belief states (histories) induced by its own behavior, rather than relying on random or offline data to cover all possible exploration contexts [36]. As the student improves, ASTEROID continually relabels the histories that the current student actually visits with privileged expert continuations. We show empirically (Section 5) and theoretically (Appendix H) that ASTEROID converges to Bayesian posterior sampling, a provably efficient exploration strategy [58, 45], while retaining the simplicity and sample efficiency of imitation learning. In summary, we make the following contributions:

1. Present ASTEROID , a simple algorithm for learning to explore and improve on deployment in partially observed decision-making tasks. ASTEROID pairs on-policy student contexts with privileged expert labels to learn in-context exploration through supervised learning.
2. Evaluate ASTEROID across 11 environments over 4 benchmarks, including discrete exploration, procedurally generated navigation, simulated and real-world robotic manipulation, and embodied object search. Across these domains, ASTEROID learns fast in-context adaptation under partial observability, consistently outperforming RL and supervised baselines under fixed exploration budgets while using up to two orders of magnitude fewer training interactions.
3. Show that the learned policies exhibit memory, goal-directed search, and efficient real-world exploration behavior, and provide a theoretical insight showing that, under appropriate assumptions, on-policy asymmetric distillation recovers posterior-sampling behavior with compounding error that scales linearly rather than quadratically in the horizon.

2 Problem Statement

We study decision-making under *partial observability*, modeled as a partially observable Markov decision process (POMDP) [29]. A POMDP is represented by the tuple $(\mathcal{S}, \mathcal{A}, \mathcal{O}, T, R, E, \rho_0, \gamma)$, where $\mathcal{S}$ is the state space, $\mathcal{A}$ is the action space, $\mathcal{O}$ is the observation space and T, R, ρ_0, γ are the transition kernel, reward function, initial state distribution and discount respectively. In a POMDP, the policy does not observe the state s_t but receives partial observations $o_t \sim E(\cdot \mid s_t)$. For simplicity, we also define the Bayes-Adaptive Markov decision process (BAMDP), a special case of POMDPs in which the only hidden variable is a latent parameter, denoted by z, i.e., $s_t = (o_t, z)$. For each interaction, $z \in \mathcal{Z}$ is sampled from a prior $p(z)$ and remains fixed for K episodes (unlike a POMDP, where hidden states may vary at each step). Given a z, BAMDPs are fully observed and can be represented as a collection of MDPs M_z (or tasks).

As a running example, consider the three-door environment in the given figure. This is a BAMDP with latent parameter z denoting the target door. At the start of each interaction, z is sampled uniformly from the three doors and remains fixed across multiple episodes, where the objective is to navigate to the correct door. The agent observes only its current position and must use its interaction history to infer the hidden goal and then exploit that information. A POMDP can be constructed by varying the hidden ground-truth position at each time step.



Since o_t contains partial information, the optimal policy is non-Markovian and depends on the history $h_t = (o_0, a_0, r_0, \ldots, o_t)$, where it must use history to infer hidden information and to exploit it. Let $d_\pi(h)$ denote the distribution over histories for a policy π in the POMDP. Learning information-gathering behavior directly from sparse rewards is highly sample-inefficient, often requiring impractical amounts of experience [3]. To mitigate this sample inefficiency, we study an *asymmetric* training–testing setting in which a privileged teacher $\pi^*(a_t \mid s_t)$ can access s_t during training, while the deployed student $\pi_\theta(a_t \mid h_t)$ acts under partial observability using h_t. We assume that the algorithm can interact with the POMDP during training to collect experience as transition tuples (o_t, a_t, r_t, o'_t), and can query the teacher for $a^*_t \sim \pi^*(\cdot \mid s_t)$. In practice, such teachers can be trained in the fully observed MDP using RL, imitation learning, or hybrid approaches [66, 52, 22, 44]. Our objective is to use these interactions and privileged teacher supervision to learn a history-conditioned student policy $\pi_\theta(\cdot \mid h_t)$ that maximizes the expected return $J(\pi_\theta) = \mathbb{E}_{\pi_\theta}[\sum_{t=0}^{\infty} \gamma^t r_t]$. [2] This asymmetric distillation setting arises naturally in household navigation [18, 28], sim2real robotic manipulation [66, 31], human-in-the-loop learning [32], and knowledge distillation [21].

[2] Since π^* conditions on strictly more information, its performance upper bounds that of any partially observed student.

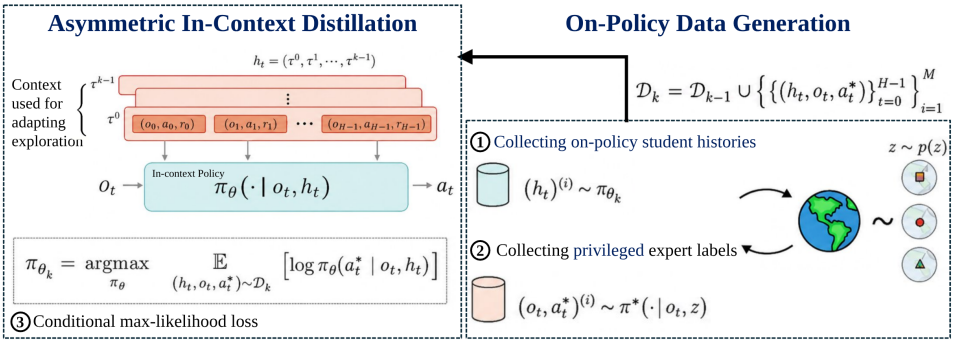


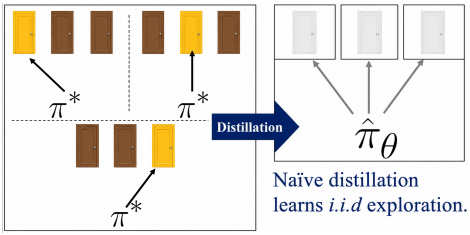
Figure 2: In each iteration, ASTEROID (1) collects on-policy context from the student π_{θ_k} and then (2) expert trajectories from π^*, under the same hidden parameters z. With this dataset, we can (3) train policies that perform in-context exploration.

3 Background: Student-Teacher Distillation

Our work builds on student–teacher distillation [56, 61, 5], meta-learning [17, 69, 53], and in-context reinforcement learning [36, 33, 11]. We defer a full related-work discussion to Appendix A. In the following sections, we focus on the key paradigms for teacher–student distillation under partial observability, discuss why they break down in asymmetric settings, and motivate ASTEROID as an iterative on-policy distillation method for learning in-context exploration.

Naive asymmetric student–teacher distillation cannot learn adaptive exploration. A natural approach to train partially observed student policies is via behavior-cloning trajectories generated solely by a privileged policy [18, 46]. But there is a conflict: the privileged teacher policy $\pi^*(\cdot|s_t)$ solves the task without exploration, whereas the unprivileged student policy π_θ must gather information through exploration before exploiting for task success[23].

Following the three-door example from Section 2, privileged experts observe z, while the student only receives partial observations o_t. At $t = 0$, o_0 is identical for all values of z. Here, a student policy acting on partial observation o_0 cannot distinguish between actions provided for the three goals and learns the marginal expert behavior induced by the training data d_{π^*}, i.e., choosing a door uniformly at random. Thus,



Naive asymmetric distillation from expert trajectories learns *i.i.d* exploration, but fails to exploit environment rewards and feedback.

In-context learning via Decision Pretrained Transformer (DPT) [36] can learn exploration. Recent work [36] has shown that asymmetric student-teacher distillation can learn exploration when the training dataset is constructed with specific design choices. Lee et al. [36] introduce DPT, an in-context learning framework that constructs a dataset of contexts, observations and target actions: $\mathcal{D}^{\text{DPT}} = \{(h_t, o_t, a_t^*)^i\}_{i=1}^N$ for supervised learning, where $d_{\mathcal{D}}$ denotes the empirical distribution of histories and query observations in the dataset $\mathcal{D}$. DPT proposes that the offline dataset of histories is generated under an independent behavior policy. Further, it labels randomly sampled query observations $o_t \in \mathcal{O}$, with the privileged expert $a_t^* \sim \pi * (\cdot|o_t, z)$. The history h_t provides context about the underlying hidden parameter, which the policy learns to use at the query observation o_t to predict actions. DPT trains a recurrent policy maximizing action likelihood over this dataset :

$$\mathcal{L}(\theta) = \mathop{\mathbb{E}}_{(h_t, o_t, a_t^*) \sim \mathcal{D}_k} \left[\sum_{t=0}^{H} -\log \pi_{\theta_k}(a_t^* \mid o_t, h_t) \right]. \tag{1}$$

Under coverage assumptions, π_θ^{DPT} shows that it converges to posterior sampling [45], a provably efficient exploration algorithm: it uses h_t to form an implicit posterior over the latent state, and acts according to the expert policy averaged under this posterior, i.e., $\pi(a_t|h_t) = \int \pi^*(a|s)\ \mathrm{p}(s|h_t)\ ds$.

Let $\mathcal{H}_t = (\mathcal{O} \times \mathcal{A} \times \mathcal{R})^t \times \mathcal{O}$ denote the space of length-t history and observation tuples (h_t, o_t).

The primary limitation of DPT is the reliance on an infinite-coverage assumption: the dataset must cover the combinatorial space of arbitrary contexts and query observations. i.e., we require,

$$\mathrm{supp}(d_{\mathcal{D}}) = \bigcup_{t=0}^{H} \mathcal{H}_t,$$

which scales exponentially with the horizon H.

The above assumption holds in the infinite-data limit, when randomly sampling histories and query observations provides complete coverage (see Figure 3). Under finite data, this quickly becomes impractical in high-dimensional observation and action spaces, where the number of possible histories grows exponentially, and informative feedback is sparse [4]. Consequently, purely offline context datasets do not scale to learning exploration in realistic, large-scale decision-making problems. This has fundamentally limited the applicability of methods like DPT in robotics and other high-dimensional problems.

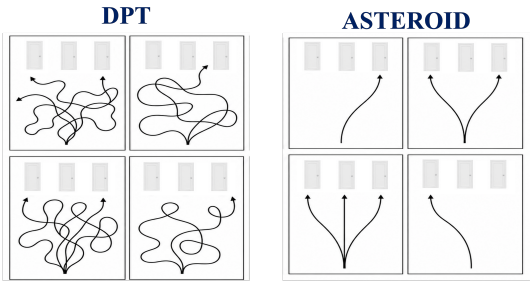


Figure 3: DPT intractably needs infinite-context coverage for training, while ASTEROID generates on-policy rollouts to learn scalable exploration.

4 Asymmetric Student Teacher Rollout In-context Distillation

In Section 3, we identified a central bottleneck in supervised learning for in-context exploration: generating data that covers the histories a partially observed agent will experience at deployment.

Our key insight is that the training dataset $\mathcal{D}$ actually need not cover the entire combinatorial history space $\mathcal{H}_t$; the distribution of trajectories generated by the student itself – the "on-policy" rollouts $h_t \sim d_{\pi_\theta}$ – provides sufficient coverage in the dataset across contexts to learn an adaptive exploration strategy, i.e.

$$\mathrm{supp}(d_{\pi_\theta}) \subseteq \mathrm{supp}(d_{\mathcal{D}})$$

Consequently, this relaxes the excessive assumption of infinite coverage over histories that renders DPT intractable. Our method ASTEROID is an iterative asymmetric distillation procedure that alternates between collecting on-policy histories from the student and training a history-conditioned student policy from privileged expert labels. Collecting supervision on histories induced by the student minimizes the distribution shift between the histories seen during training and those during deployment (similar to Ross et al. [51]). We show both empirically and theoretically that on-policy student rollouts provide sufficient coverage to learn an efficient exploration policy. In Appendix D, we show that our introduced method is distinct from standard interactive imitation learning methods like DAgger. ASTEROID uses environment feedback and context-level supervision for adaptation.

4.1 How does ASTEROID learn in-context exploration?

In this section, we present an outline of our proposed approach. The details are presented in algorithm 2 and Figure 2. Let π_{θ_k} denote the ASTEROID student policy and $\mathcal{D}_k$ denote the dataset of on-policy histories and labels at iteration k. To simplify the explanation, we first instantiate our method in a BAMDP and then present a general solution for POMDPs. In a BAMDP, the latent z is sampled at the start of each interaction and kept consistent, while a policy interacts with the environment for k episodes. ASTEROID works iteratively in two distinct phases:

1. **Data Generation**: For each iteration, we run the following loop:

(i) Sample a task M_z with latent parameter $z \sim p(z)$,

(ii) Roll out the student policy π_{θ_k} under partial observability to generate on-policy history $(\tau^0, \tau^1, \cdots \tau^{k-1})$ over k episodes, where $\tau^j = (o_0, a_0, r_0, \cdots o_{H-1}, a_{H-1}, r_{H-1})$ is the episode j during interaction and H is the episode horizon.

(iii) Query the clairvoyant expert $a^*_t \sim \pi^*(\cdot|o_t, z)$ to generate the expert label $\tau^* = (o^*_0, a^*_0, r^*_0, \ldots o^*_{H-1}, a^*_{H-1}, r^*_{H-1})$.

To simplify, we denote on-policy history $h_t = (\tau^0, \cdots \tau^{k-1})$, query observations $o_t = (o^*_{0:t}, r^*_{0:t-1})$, giving us a dataset: $\{(h_t, o_t, a^*_t)\}_{t=0}^{H-1}$. We run this for M samples of z, and aggregate the dataset across previous iterations, $\mathcal{D}_k \leftarrow \mathcal{D}_{k-1} \cup \{\{(h_t, o_t, a^*_t)\}_{t=0}^{H-1}\}_{i=1}^{M}$. Effectively, we generate context h_t from on-policy student rollouts and query observations with privileged action targets (o_t, a^*_t) from expert rollouts.

2. **Supervised Learning**: Given the dataset, we update π_{θ_k} by training the model to auto-regressively predict the privileged action labels, conditioned on the context history, using the same conditional imitation loss as DPT (Eq. 1). In practice, we encode all transitions across the context and the expert trajectory as inputs to a decision transformer [11], and compute the loss only over expert actions. At iteration k, we get π_{θ_k} performing in-context exploration over k test-time episodes.

Revisiting the three-door problem from Section 2,

Iteration 0. π_{θ_0} learns an *i.i.d.* policy with no in-context learning. It randomly chooses a door every episode, ignoring feedback from previous episodes.

Iteration 1. π_{θ_0} generates an on-policy trajectory, which visits a random door. The reward reveals whether that door is correct: $+1$ if correct, 0 otherwise. The expert label then returns to the same door on success or points to a different door after failure. Thus, π_{θ_1} learns to use the first episode as context for choosing the second. However, π_{θ_1} has context window $= 1$, so it cannot reason over more than one attempt, motivating more iterations to expand the window and learn longer-horizon adaptation.

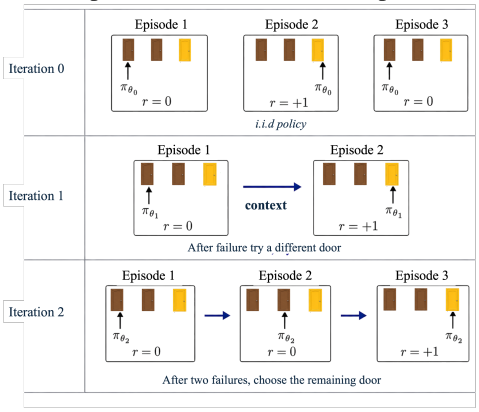


Figure 4: We iteratively learn to adapt exploration using feedback over longer contexts.

Iteration 2. π_{θ_1} now generates two context trajectories: it repeats a successful door, or tests a new door after failure. If both tested doors fail, the expert label points to the remaining door. Thus, π_{θ_2} learns an in-context exploration strategy that identifies the true goal in this partially observed task.

Algorithm 1 ASTEROID

Require: iterations K, tasks per iteration N, horizon H, privileged teacher π^*

Initialize $\mathcal{D}_0 \leftarrow \emptyset$, student π_{θ_0}
for $k = 0, \ldots, K-1$ **do**
  $\mathcal{D}_{k+1} \leftarrow \mathcal{D}_k$
  `// Collect on-policy contexts and privileged labels`
  for $i = 1, \ldots, N$ **do**
    Sample $z \sim p(z)$ and instantiate M_z
    Roll out π_{θ_k} in M_z for k episodes: $h_k^{(i)} = (\tau^0, \ldots, \tau^{k-1})$
    Roll out π^* in M_z for one episode: $\tau^{*,(i)} = (o^*_0, a^*_0, r^*_0, \ldots, o^*_{H-1}, a^*_{H-1}, r^*_{H-1})$
    Add labels $\mathcal{D}_{k+1} \leftarrow \mathcal{D}_{k+1} \cup \{(h_k^{(i)}, o^*_{0:t}, r^*_{0:t-1}, a^*_t)\}_{t=0}^{H-1}$
  end for
  `// Update student by conditional imitation`
  Train $\pi_{\theta_{k+1}}$ on $\mathcal{D}_{k+1}$ using Eq. 1
end for
return π_{θ_K}

To further illustrate ASTEROID , Appendix E provides another dry run showing that the student behavior approaches posterior sampling. We discuss certain practical details of the method below.

4.2 Practical Implementation

Initialization. We initialize $\mathcal{D}_0$ with privileged expert trajectories. The initial policy π_{θ_0} is therefore trained without contextual information and resembles naive student–teacher distillation; see Section 3.

Deployment. At deployment, the policy starts from a null context, $h_0 = \emptyset$. At each step, it observes o_t, samples $a_t \sim \pi_\theta(\cdot \mid h_t, o_t)$, receives reward r_t, and updates $h_{t+1} = (h_t, o_t, a_t, r_t)$. Thus, the policy uses context to infer hidden information and exploit it to solve the task. For evaluations longer than the training context length, we use a sliding window over past context.

Context-length curriculum. At each iteration k, the policy is rolled out for k episodes, inducing a curriculum on rollout horizons. As the horizon expands, the student can eliminate task instances that are inconsistent with its history over a longer horizon, making exploration efficient. This also makes our method more sample efficient, and we present further discussion in Appendix B.3.

4.3 How does ASTEROID work on arbitrary POMDPs?

We described ASTEROID in a BAMDP, where a fixed latent variable z remains fixed across multiple episodes. In a general POMDP, the hidden state evolves within a single episode: each action and observation changes which states remain plausible. For example, in a locally observed maze, the agent does not observe its global position, and this hidden position changes after every move. The policy interacts with the environment at test time for a single episode over a fixed horizon H. As the underlying state changes at each step, the agent faces a branching inference problem: each action and observation changes which hidden states remain plausible. Thus, instead of coverage over repeated episodes for a fixed z, we need coverage over on-policy histories h_t across timesteps $t \in [H]$.

In practice (see Algorithm 3), ASTEROID samples a timestep t, rolls out the student to produce an on-policy history h_t, and queries the privileged expert from the reached state for the next action label a_t^*. The resulting tuples (h_t, o_t, a_t^*) train the policy to map its accumulated history to actions that are optimal for the hidden state implied by that history, i.e., it approximates $\pi(a_t|o_t, h_t) = \int \pi^*(a_t|s_t)p(s_t|o_t, h_t)ds$. For example, in the maze, after each move, the local observations and reward feedback prune some possible positions while keeping others plausible, guiding exploration. Further, we induce a curriculum in the context horizon by iteratively biasing the sampled timestep t toward longer horizons. Thus, we adapt the method to a POMDP: collect the histories the student actually visits, then use privileged labels to teach how those histories should guide future behavior.

5 Experiments

In our experiments, we aim to answer the following questions: (1) Does ASTEROID learn to solve partially observed problems efficiently on deployment? (2) Is ASTEROID sample efficient and simple to train? (3) What kind of exploratory behavior do policies trained with ASTEROID display at test time? (4) Is learning from on-policy contexts necessary? (5) Does ASTEROID learn exploration policies that can be deployed on real-robot hardware?

5.1 Training and Evaluation Details:

We test our hypothesis by comparing all methods across 10 environments over 4 benchmarks, and three seeds [3]. We include the hyperparameters, training, and environment details in Appendix F. Further, we also include ablations over ASTEROID in Appendix B, and qualitative videos on the website. We evaluate the policy's performance and exploration efficiency across multiple test-time episodes. We compare policy performance across training iterations, with a fixed test-time budget.

Tasks. We evaluate our approach on a diverse suite of partially observable decision-making problems across robotic manipulation, discrete exploration, and continuous navigation (Fig. 5), requiring strong elements of exploration, memory, and adaptation under limited sensing.

- **Partially observed gridworlds [12]** are a classic benchmark consisting of discrete search problems, where an agent acts over multiple episodes in a gridworld to reach a goal(s). The agent is in an

[3] We run Habitat on a single seed due to high computational cost and wall-clock time.



Figure 5: Tasks: (left to right) meta-learning gridworld benchmark, partially observed navigation, Procgen maze navigation, embodied object search, simulated robot and real robot manipulation.

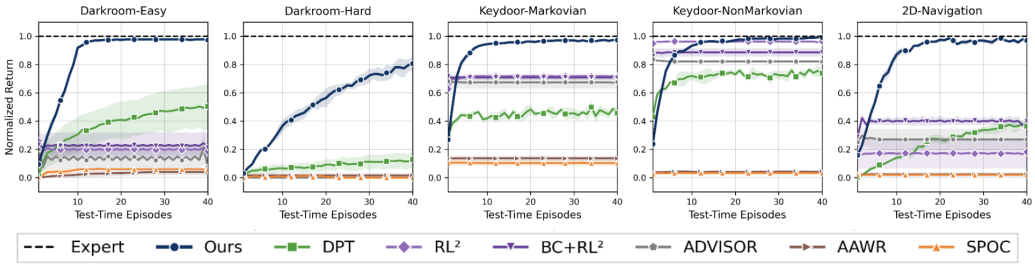


Figure 6: Performance on discrete exploration tasks requiring memory and task inference. We observe that ASTEROID significantly outperforms all the methods in terms of test-time efficiency, and in harder exploration problems, is the only method to learn an effective exploration and converge to the true performance, after inferring the hidden task variables.

$n \times n$ grid and must perform targeted exploration to solve the task, such as finding the hidden goal or sequentially finding the hidden key and the door across multiple episodes.

- **Meta-Learning navigation [49]** is a meta-learning task where an agent must navigate in an environment to a hidden goal. We instantiate (i) Ant Navigation, where the agent is a 8-DOF robot, and (ii) 2D Navigation, which reduces the dynamics to a simple point mass.
- **Procgen Maze Navigation [14]** involves finding the goal in procedurally generated mazes, where the agent receives only a local 3×3 observation and has to infer the maze layout and goal location using the interaction history.
- **Embodied Object Search [48]** involves searching for a household object in a fixed environment in Habitat-Sim. This presents a visually complex domain for a realistic partially observed problem.
- **Simulated Robotic Manipulation [66]** are high-dimensional, continuous-control manipulation tasks under partial observability: Wrist-Camera Peg Insertion and Tactile-Pick. Here, the robot has to use limited sensing to manipulate objects on a tabletop and complete the given task.
- **Real Robot Manipulation** We reconstruct one of the simulated tasks in the real-world, where the robot has to pick up a cube using proprioception from the arm and gripper only. We train policies in simulation with domain-randomization [59, 66] and then transfer them to the real-world.

Baselines. We compare against strong baselines from several frameworks under partial observability:

- **Asymmetric student–teacher: DPT** [36] trains a transformer on an in-context dataset of randomly collected interactions to predict oracle actions; **SPOC** [18] imitates shortest-path trajectories with data augmentation, yielding exploration-like behavior. **AAWR** [25] extends Advantage Weighted Regression [47] to POMDPs, using privileged state during training to learn a stronger critic.
- **Meta-RL: RL^2** [17] trains a recurrent policy to adapt to the hidden parameters purely through interaction, treating the policy's hidden state as an implicit learning algorithm that updates from histories across episodes. **Distilled Planner** [48]. For embodied navigation in Habitat, we train a policy that performs posterior-sampling RL (PSRL) [45] (i.e., upper bound performance).
- **Imitation-informed RL: BC+PPO** [52, 17] accelerates PPO [52] by adding a behavior-cloning loss over privileged actions; for meta-learning tasks, we use an adapted variant (BC+RL^2) that leverages privileged supervision to bootstrap learning. **ADVISOR** [65] dynamically combines IL and online RL objectives during training, resolving the imitation gap adaptively.

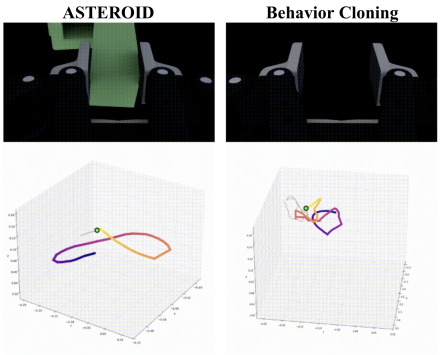


Figure 8: Robot positions during exploration for peg-insertion from wrist-images. ASTEROID adapts via contexts, while BC fails to adapt.

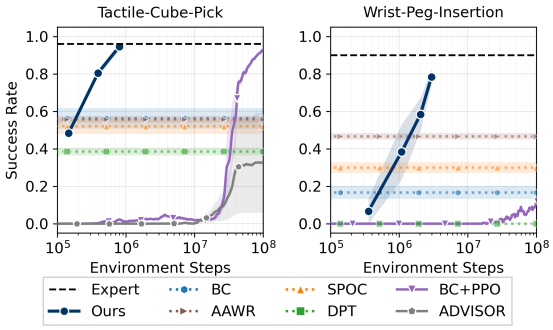


Figure 9: We observe extreme sample efficiency $\sim 100\times$ speed up when using ASTEROID to train policies for robot manipulation under limited sensing.

5.2 Does ASTEROID learn to solve partially observed problems efficiently on deployment?

In Figure 6, we compare the test-time performance of in-context policies learned via ASTEROID against baselines on hard exploration tasks. Given the same test-time exploration budget, ASTEROID achieves substantially higher final performance. Unlike the baselines, it efficiently covers relevant test-time histories and uses the context to infer task-relevant information, leading to higher returns. Figures 9, 10, and 13 show the same trend in partially observed navigation and manipulation. In Procgen Nav (Figure 7), ASTEROID solves procedurally generated mazes by using a history of local observations to maintain an implicit belief over the maze state and goal, guiding exploration toward unexplored regions [30]. This avoids redundant search and enables ASTEROID to achieve higher success rates while taking nearly half as many timesteps as baselines. In contrast, BC achieves non-trivial success through random exploration but does not use context to avoid redundant search, making it highly inefficient. DPT also underperforms because offline datasets provide incomplete coverage over test-time histories.

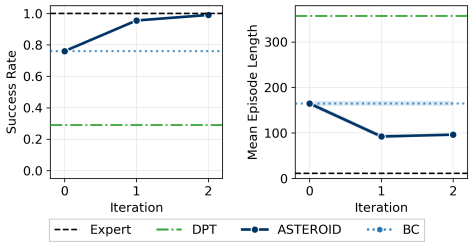


Figure 7: ASTEROID improves success while reducing episode length on Procgen Maze; BC succeeds non-trivially via random exploration but is much less efficient.

5.3 Is ASTEROID sample efficient and simple to train?

In this section, we compare the training-time sample efficiency of ASTEROID against baselines that combine RL with privileged supervision to learn policies under partial observability. Using GPU-parallelized simulation [41], we evaluate manipulation tasks in which the policy has access to limited sensory modalities. In Figure 9, ASTEROID is $\sim 100\times$ more efficient in environment steps than RL baselines, converging to a policy that explores and successfully picks the cube or inserts the peg. In Figure 13b, the student observes only the history of past actions and tactile sensing (no proprioception), and ASTEROID efficiently learns policies with $\sim 92\%$ success rate under this extreme partial observability. The supervised updates in ASTEROID (as compared to expensive RL) make it highly efficient during training, even for high-dimensional tasks. While RL baselines can learn in low-dimensional settings (Appendix B.4), they are significantly sample-inefficient or fail in complex domains such as ant navigation and robot manipulation (Figures 9 and 10).

5.4 What kind of in-context exploratory behavior do policies learned via ASTEROID display?

In Figure 8, we visualize the qualitative exploration learned by ASTEROID . In wrist-camera tasks, the policy actively scans the tabletop to localize both the object and target. In contrast, naive distillation goes out of distribution and degenerates. In Tactile-Pick (Figure 17), the policy probes multiple grasp points, uses tactile feedback from failed attempts to inform its next actions, unlike BC, which treats trials independently and relies on i.i.d. exploration.

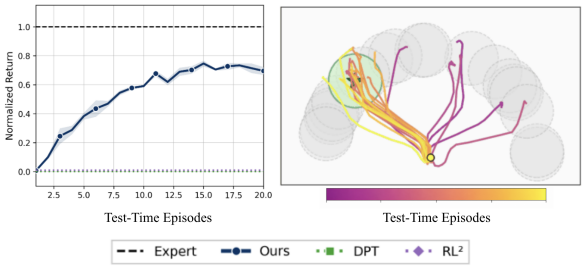
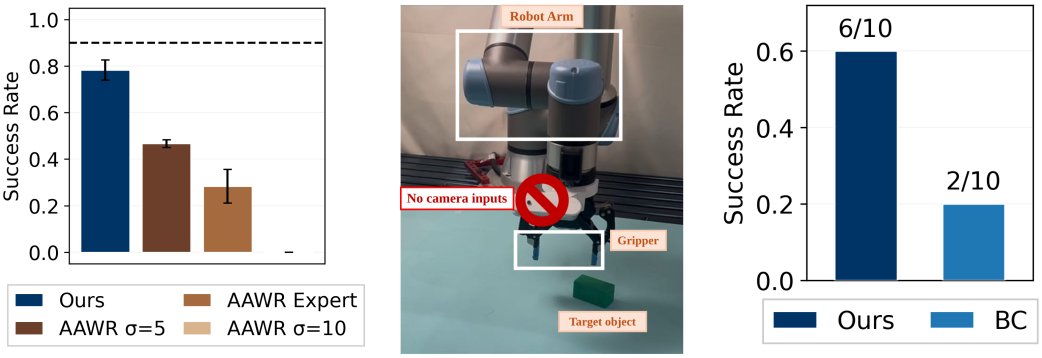


Figure 10: Ant Navigation. ASTEROID performs posterior sampling over goals while controlling the 8-dof robot; RL^2 and DPT fail to learn control and exploration in higher dimensions.

We observe similar goal-directed, memory-based exploration in Habitat and navigation tasks: the policy explores the environment, remembers failed locations through history, and avoids redundant search. See Appendix C and the website for videos. In Figure 10, we empirically observe in the AntNav task that the learned exploration resembles strategies found in prior meta-learning methods [49, 69]. Although RL can learn similar behavior, its sample inefficiency compared to ASTEROID makes it impractical. DPT exhibits inefficient exploration behavior; in continuous-control tasks, it is nearly impossible to construct offline datasets via random exploration that reasonably cover test-time histories, causing a large train-test mismatch.

5.5 Is learning from on-policy contexts necessary?

Across multiple domains, DPT performs poorly because offline random contexts fail to capture the deployment histories. In Figure 11a, we compare ASTEROID against AAWR [25] trained with offline datasets of varying diversity in the peg-insertion task, to highlight the importance of on-policy context collection. AAWR [25], which learns from an offline dataset, is highly sensitive to the dataset quality and diversity. ASTEROID avoids this offline dependence by generating on-policy contexts from the student. This focuses supervision on deployment-relevant contexts, and is robust to imperfect expert labels (see B.2).



(a) (b) (c)

Figure 11: (a.) ASTEROID is online, while AAWR is sensitive to the quality and coverage of offline datasets. (b.) Real robot setup, where the agent must rely solely on proprioception (arm joint positions, gripper distance) to infer the object's location and pick it up successfully. (c.) Comparing performance of sim-to-real distillation via naive BC and our method on the real-robot task. ASTEROID learns an effective exploration policy that achieves higher success rate across 10 random initial positions.

5.6 Does ASTEROID learn exploration policies that can be deployed on real robot hardware?

In Figure 11b, we evaluate ASTEROID on a real robot manipulation task that requires exploration under partial observability. We first train clairvoyant experts in IsaacLab using large-scale reinforcement learning with domain randomization [41, 66, 68]. These experts use privileged state information to pick up a cube. At deployment, however, the real robot observes only proprioceptive signals, such as joint angles and gripper positions. It cannot directly observe the cube location, so we cannot deploy these experts directly. We need to train student policies for real-world transfer that must infer this hidden information by trying different grasp locations and using contact feedback from the gripper.

The standard transfer baseline is to distill the simulation expert into the student policy via behavior cloning. This student policy imitates expert trajectories, but does not learn how to recover from failed attempts. In contrast, ASTEROID trains the policy on on-policy contexts, so the robot learns to adapt

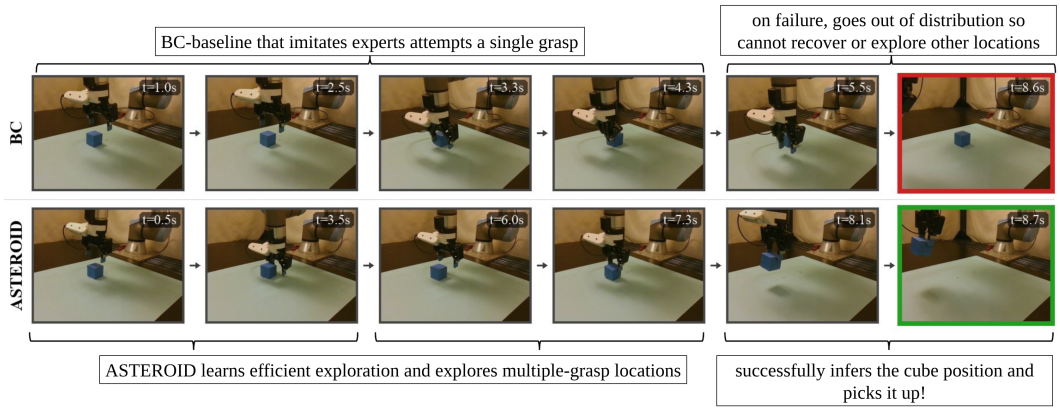


Figure 12: We evaluate sim-to-real transfer of policies learned via ASTEROID and naive behavior cloning on a real-robot task, where the robot cannot use the camera to localize the object and pick it up. Instead, it has to use the proprioception of the arm and the gripper and explore different locations by attempting grasps at different positions. The baseline (first row) is trained to imitate expert data only and goes out of distribution. Meanwhile, ASTEROID (second row) learns a policy that uses its in-context abilities to explore multiple grasp locations and pick up the object successfully.

its next grasp attempt based on the history of previous attempts and gripper feedback. As shown in Figure 11c, ASTEROID achieves a higher success rate than behavior cloning. The qualitative rollouts in Figure 12 show the same behavior: after a failed attempt, the baseline goes out of distribution, while ASTEROID continues searching over potential cube locations using its in-context abilities, completes the grasp, and successfully picks up the cube under partial observability. We further show that as the policy is not reliant on vision, it can successfully solve the task in situations where the partial observability is natural - e.g., rummaging inside a box, in the dark under visual distractors. Finally, we include videos of the real world rollouts on our website.

6 Discussion

In this work, we propose ASTEROID , an iterative *asymmetric* student–teacher distillation framework for learning in-context exploration. The key idea is to train a history-conditioned student policy using supervised targets from a privileged expert, while collecting the in-context histories *on-policy* from the student. This combination directly addresses two bottlenecks for exploration in POMDPs: (i) privileged teachers typically do not demonstrate information-gathering behavior, and (ii) offline or randomly collected contexts may not cover the informative histories the student will encounter at deployment. As a result, our method learns policies with adaptive behavior typically obtained using expensive RL methods, but with the sample complexity of supervised learning.

A limitation of the approach is that it relies on the availability of a strong privileged expert, although it is agnostic to how this expert is generated. An interesting future direction is to remove this reliance and train clairvoyant experts from offline demonstrations. While posterior sampling has bounded regret, it can be inefficient, motivating future extensions that combine our approach with optimistic exploration. Additionally, the student policy is trained to imitate expert actions conditioned on histories, but may produce potentially unsafe exploration. Therefore, an important direction is to enforce safety during on-policy rollouts, e.g., via explicit behavior constraints and safety filters.

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A Related Work

Student–Teacher Distillation Learning from privileged experts arises in settings from self-driving [10, 16, 2] to robotic exploration [13, 28, 5]. In partially observed domains, interactive imitation learning addresses covariate shift and the resulting, compounding errors that drive the learner into unseen states [10, 35] with classic iterative schemes including [15, 51, 50, 55]. Recent results suggest that on-policy imitation is necessary under partial observability [56], and that off-policy cloning [38] can fail in non-realizable settings where information-gathering behavior is required [54, 65]. Our work targets this non-realizable regime: the learner must take information-gathering actions that are not directly recoverable from a fully observed expert [34]. Prior approaches handle this via additional assumptions (e.g., access to confounders at test time [57] or differentiable experts [64]) or by incorporating reinforcement learning to induce exploration [42, 65, 61, 25, 65]. In contrast, we learn information-gathering behavior using iterative distillation conditioned on on-policy histories, which is substantially more stable and sample-efficient than RL-based alternatives.

Meta Learning A common approach to learning in POMDPs is to use recurrent policies that compress the interaction history into a latent belief representation [23, 26]. Meta-RL provides a general framework for learning adaptive exploration across task distributions [17, 69, 49], but often requires extensive online training interaction [63, 3], making it difficult to scale to high-dimensional, sparse-reward domains with long-horizon credit assignment. Our approach replaces this expensive RL-based adaptation with iterative supervised learning, still enabling long-horizon, history-dependent exploration through on-policy context collection. Additionally, unlike prior work [36, 69, 17, 34], our method is not limited to Bayes-Adaptive MDPs [34], where the agent interacts with an environment with a fixed underlying parameter across multiple episodes. We demonstrate that our method scales to POMDPs, in which the policy explores actions within a single episode to estimate the underlying state distribution and achieve task success.

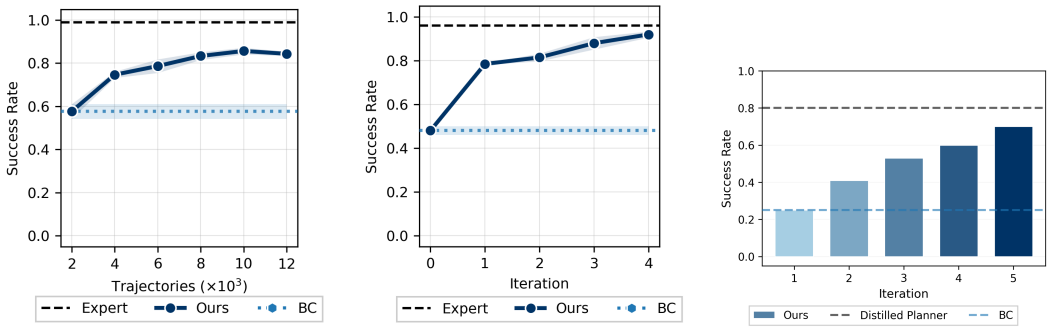
Posterior Sampling Posterior sampling methods [58, 45] drive exploration by implicitly or explicitly maintaining a belief over the environment's underlying hidden parameters, acting optimally under samples from this distribution, and updating the belief based on feedback. Despite strong empirical and theoretical results [7, 45], such approaches typically require maintaining and sampling from an explicit posterior, and solving for policies under the sampled parameters (e.g., PSRL, BOSS) [45, 1], limiting practicality in rich-observation settings. While recent approaches [53, 67] for learning Bayes-optimal policies for POMDPs are applied in discrete settings, posterior sampling yields a simple, scalable solution with provable regret guarantees. ASTEROID does not explicitly optimize a posterior-sampling objective, but in Section 5 we show that posterior-sampling-like behavior emerges naturally from our method through iterative on-policy distillation, even in high-dimensional continuous environments. Further, in Appendix H, we show that theoretically, ASTEROID converges to posterior sampling with linear regret akin to standard online learning methods [51].

In-Context Decision-Making Recent works [27, 6, 60] extensively use transformers as decision-making policies. When trained on a large corpus of sequential data using autoregressive supervised prediction, transformers can exhibit in-context learning [19, 40, 20], i.e., adapting their behavior to new inputs based on interaction histories or input-output examples provided in context. In online decision-making, prior works have used these emergent capabilities to steer policies conditioned on rewards or prior context. For example, Decision Transformer (DT) [11] learns a transformer to autoregressively predict actions conditioned on past interactions and the desired return. Similarly, Algorithm Distillation [33] uses experience traces from a learning method (such as PPO [52]) to adapt and improve policy behavior based on past contexts. More recently, Decision Pretrained Transformer [36] shows that we can learn an in-context policy that performs posterior sampling in certain POMDPs. DPT generates the context using random interactions in the environment and action supervision from oracle experts with privileged information. Such methods assume that these offline datasets provide coverage over all possible histories of interaction, which is intractable and unrealistic in high-dimensional domains. ASTEROID , instead, uses a dataset of on-policy contexts, removing the coverage assumption and scaling to much harder and higher-dimensional problems (see Section 5).

B Ablation Experiments

B.1 Performance of ASTEROID on additional environments.

In Figure 13, we show the performance of our proposed methods across additional partially observed environments. ASTEROID leverages on-policy context accumulation and expert supervision to solve these tasks efficiently. In the Tactile Pick w/o Proprioception task, the objective is to pick a randomly placed cube on the table. The arm is randomly initialized, and the only observation available to the student is tactile forces and the last action. We observe that ASTEROID effectively solves the high-dimensional POMDP task with ($\sim 92\%$ success rate) by implicitly maintaining a belief over the underlying state. We plot the performance over iterations and the resulting behavior in Figure 13b. Note that in the tactile-pick (and some other) tasks, BC is also history-conditioned and achieves non-trivial performance (here, $\sim 48\%$) because certain evaluation reset conditions do not require significant or directed exploration to locate the object.



(a) Fixed Maze Navigation (b) Tactile Pick w/o Proprioception (c) Habitat Object Search

Figure 13: ASTEROID learns to solve POMDPs such as maze navigation, robot manipulation, and Habitat object search, where agents must act under limited fields of view, random resets, and partial sensing.

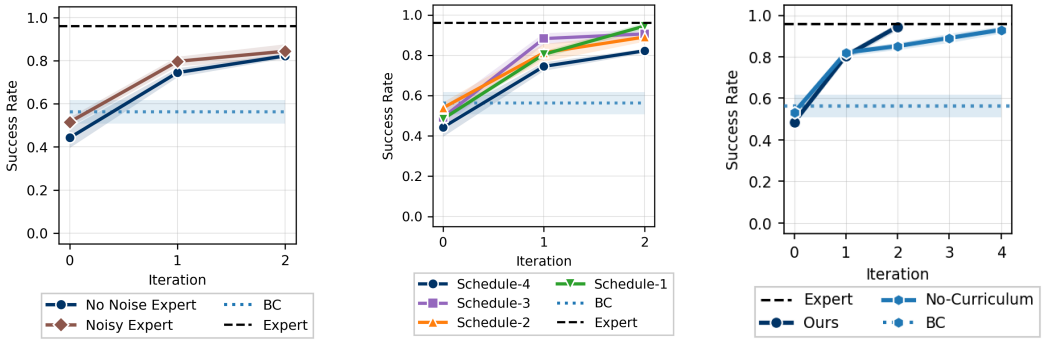


Figure 14: We run ablations on different parts of ASTEROID in the Tactile-Pick task. Left: we run ASTEROID with a noisy expert and observe no performance drop. Middle: we sweep over different curricula with increasing exploration horizons and find minimal sensitivity. Right: we show that adding curriculum improves the efficiency of the ASTEROID by ensuring that as the horizon increases over iterations, the learned policy does not suffer from OOD histories and generate random actions.

B.2 Robustness of ASTEROID to noise in privileged expert supervision

We evaluate the robustness of ASTEROID through an ablation study in which a noisy expert supervises the student. We inject Gaussian noise into the expert actions during training ($\sigma = 0.2$) and find that ASTEROID remains performant under noisy supervision. The slight performance improvement may stem from the regularising effect of learning from noisy targets.

B.3 How does the curriculum of exploration affect ASTEROID during training?

At each iteration $k < K$, the policy interacts with the environment for k episodes, thereby inducing an increasing curriculum on on-policy rollout horizons. As the context window gradually expands, it allows the student to use longer histories to rule out hidden states or task instances inconsistent with its observations and feedback (Appendix B.5). The curriculum also avoids a subtle distribution-shift issue. Suppose the maximum context length is K, and we roll out an intermediate policy π_{θ_k} for more than k episodes. Since π_{θ_k} was only trained on contexts of length at most k, maintaining an in-distribution context would require a sliding window over the most recent k episodes. However, this window can discard early exploration outcomes. If a failed goal is no longer in context, the policy may re-explore it, producing redundant exploration histories that a fully converged policy would not generate. Informally, this reduces the effective number of length-H exploration contexts from $|\mathcal{Z}|^H$ arbitrary failure sequences to at most $\frac{|\mathcal{Z}|!}{(|\mathcal{Z}|-H)!}$ ordered non-redundant histories. This further reduces the effective context space, thereby making ASTEROID sample-efficient.

In Figure 14 (right), we compare the performance of ASTEROID across two different schedules: (i) No-Curriculum: the exploration horizon is sampled from a fixed range across all iterations, and (ii) Curriculum: the exploration horizon is sampled from a range that increases every iteration. We observe that curriculum-based exploration is more efficient than non-curriculum baselines, as it keeps student policy rollouts in distribution and makes on-policy data generation more sample-efficient. Furthermore, in Figure 14 (middle), we compare the robustness of the method across different values of increasing curriculum and observe that it is relatively insensitive to this parameter.

B.4 ASTEROID is significantly more scalable than RL in complex domains.

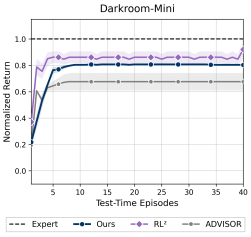


Figure 15: RL is effective over short horizons, but ASTEROID uses supervised updates to be effective across long-horizon tasks as well.

In Figures 6 and 9, we observe that RL-based baselines (RL^2, BC+RL^2, and ADVISOR) severely underperform in some long-horizon sparse reward tasks. To further ablate this, we run the RL baselines and our method in a smaller version of the Darkroom environment, where the grid size is 5x5. We observe that RL baselines learn competitive search policies in these small-scale environments. ASTEROID uses supervised learning to model expert actions while building exploration context via student rollouts, rather than relying on expert supervision and dynamic programming over random contexts to learn how to explore and exploit information. As a result, ASTEROID is more performant in high-dimensional long-horizon settings over RL baselines.

B.5 Does iterative context accumulation actually help ASTEROID ?

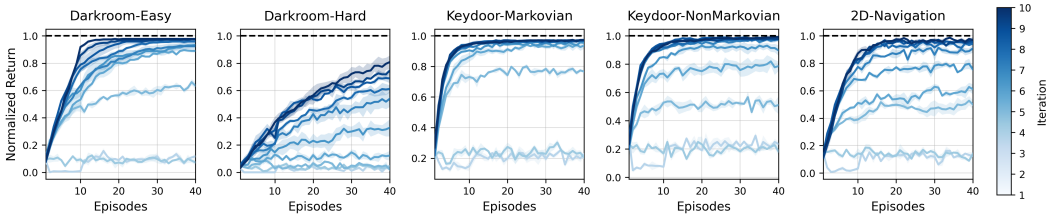


Figure 16: The test-time efficiency of ASTEROID increases significantly with more iterations of asymmetric on-policy distillation, demonstrating that as the context dataset grows, the policy can adapt over longer horizons, making exploration more efficient.

Figure 13c shows exploration performance as a function of the number of in-context exploration iterations on a high-dimensional navigation task. In Habitat Navigation, performance improves steadily as additional exploration steps allow the policy to gather informative observations and refine its behavior, despite the complexity of the observations, converging to the posterior-sampling upper bound. Further, in Figure 16, we observe that the test-time efficiency of ASTEROID improves significantly with more iterations. These results indicate that ASTEROID effectively uses in-context interaction to accumulate task-relevant information, translating additional exploration into improved downstream task performance in realistic, partially observable environments, such as higher success

rates in embodied object search in Habitat and in robot manipulation tasks. In Appendix B.3, we further include ablations showing the benefits and robustness of ASTEROID to the curriculum over exploration horizon across multiple iterations.

C Qualitative Results

C.1 ASTEROID learns efficient exploration in robot manipulation under limited sensing, and Procgen.

In Figure 17, we further compare the qualitative exploration behavior across the tactile and the procgen task. We observe that ASTEROID enables active exploration-like behavior during manipulation, in which the robot arm moves efficiently across the table to locate the cube. Similarly, in the 2D navigation maze task, ASTEROID learns a policy that adaptively searches for the goal in unexplored regions and converges to high reward in subsequent episodes once it can identify the goal region from past trials. We include full videos of the policies on our website: https://sites.google.com/view/icl-exploration, which also includes goal-directed exploration across different rooms in Habitat.

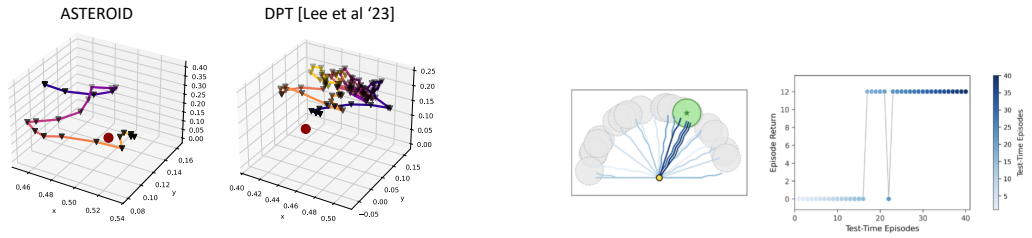
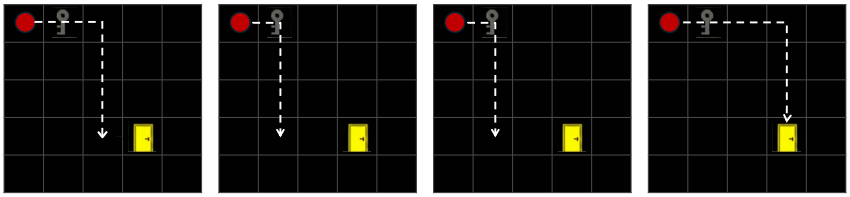
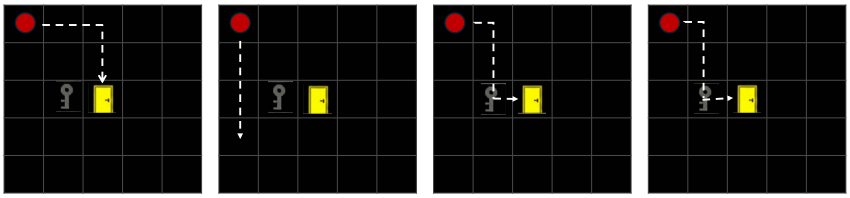


Figure 17: We observe that across the tactile-pick task and the 2D navigation environment, ASTEROID can adapt its exploration based on context, while offline imitation learning learns inefficient, near-random exploration.

C.2 ASTEROID presents emergent in-context properties such as memory as a result of on-policy in-context learning.



(a) The agent finds the key in earlier episodes, can reference it back in its context, and always picks up the key before searching for the door.



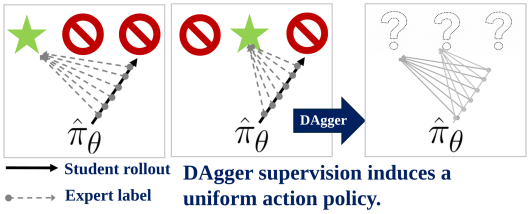
(b) The agent finds the door in the first step but gets no reward. So, in the next episodes, it looks for the key and memorizes the door location. As a result, in episode 3, it finds the key and goes directly to the door (without having to search for it, since it has memory).

Figure 18: In the Key2Door task, the agent explores to find both the key and the door to get +1 reward for each task. ASTEROID learns an effective strategy: if it reaches the key or door first, it uses its context to remember the location, and upon finding the other goal, it can immediately complete the task without additional exploration.

To investigate whether the policy learned with ASTEROID actually attends to context, we construct a variant of the Key-Door environment in which the agent observes two boolean flags in its state whenever it lands on the key or the door during exploration. Policies trained with ASTEROID exhibit

emergent in-context memory. If the agent discovered the key or door in earlier attempts, it can later retrieve that information from context and use it efficiently.

D Per-step interactive imitation learning fails in history-conditioned asymmetric distillation.



An extension to improve naive teacher-student distillation is to apply standard interactive learning methods, such as DAgger [51], on a history-conditioned student policy $\pi_\theta(\cdot|o_t, h_t)$. However, these interactive methods are not feedback-driven, i.e., they aggregate privileged action labels across observation and action histories, while the information needed for exploration often arrives only through rewards. Further, in POMDPs, DAgger surprisingly converges to an exploration strategy that is generally worse than naive distillation. Consider that a policy has to take H steps towards a potential goal to receive a reward and disambiguate between them. Here, $\pi_\theta(\cdot|o_t, h_t)$ cloned on expert behavior would randomly pick a door and generate an H step trajectory. Applying DAgger, an expert provides supervision at each step of the trajectory. In the figure above, we see that under different latent settings, the same student trajectory receives multi-modal action targets at each step. Supervised learning on this aggregated dataset would instead learn a policy that chooses a random goal at each step, which does not correspond to meaningful, effective exploration. Over repeated interactions, the updated policy uniformly explores the environment to find the goal, leading to extremely high exploration budgets. Overall, DAgger underperforms as a baseline in partially observed domains, even more so than naive behavior cloning. Instead, ASTEROID employs trajectory/context-level supervision, i.e., given the history h_t, we supervise either the full interaction trajectory (in BAMDPs) / partial trajectory from the takeover state (in POMDPs). This enforces the policy to execute goal-directed actions over a longer horizon (rather than uniform dithering), resulting in much more efficient exploration, even in high-dimensional continuous action spaces (see Figure 10).

E Didactic Example: ASTEROID learns efficient posterior sampling.

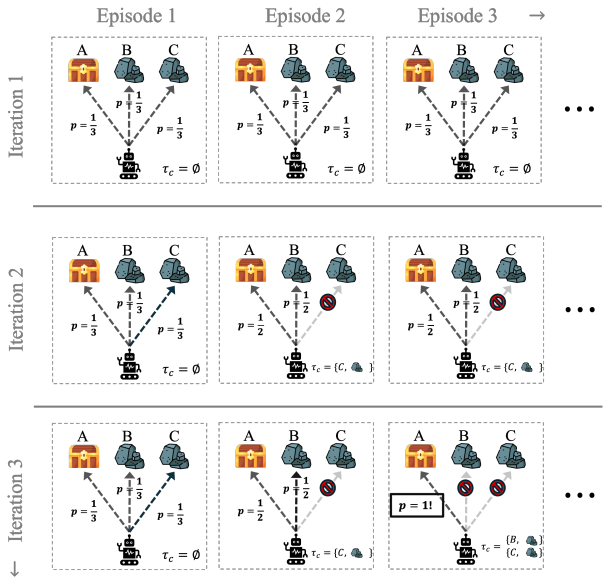


Figure 19: Toy Example demonstrating that ASTEROID learns adaptive in-context behavior, where it effectively explores based on history.

Consider a POMDP with one hidden variable. For each episode, a fixed goal $g \in \{A, B, C\}$ is sampled uniformly. The agent takes actions to move to one of the locations in $\{A, B, C\}$ and receives a reward of 1 if it matches g and 0 otherwise. A privileged teacher observes g and always chooses the correct door, producing expert trajectories: $(A, 1)$, $(B, 1)$, or $(C, 1)$ depending on the goal. If the student is trained only on these expert rollouts with no context (i.e., $\tau^c = \emptyset$), then at deployment it cannot infer g and must choose uniformly, yielding expected reward $1/3$.

Dry run. At iteration $k = 0$, we train on expert-only trajectories with $\tau^c = \emptyset$, so the student has no information about g at decision time. The resulting policy chooses A, B, C uniformly, giving an expected reward of $1/3$.

Now deploy this student and collect on-policy contexts. If the true goal is $g = C$, then across episodes the observed contexts are of the form $(A, 0)$, $(B, 0)$, or $(C, 1)$, depending on which door was tried. At iteration $k = 1$, ASTEROID pairs each such context with a privileged teacher trajectory generated under the same goal. For example, conditioning on $\tau^c = (A, 0)$ rules out $g = A$, so the teacher data for this context consists only of successful choices at the remaining doors, i.e., $(B, 1)$ or $(C, 1)$. After distillation, the updated student still chooses uniformly when $\tau^c = \emptyset$. Still, it adapts after one failed attempt: given $\tau^c = (A, 0)$ it chooses between $\{B, C\}$ uniformly, yielding expected reward $1/2$ on the next episode.

At iteration $k = 2$, the student generates longer contexts such as $(A, 0; B, 0)$, $(A, 0; C, 1)$, etc. A context like $(A, 0; B, 0)$ uniquely identifies $g = C$, so the teacher data for this context concentrates on choosing C. After distillation, the student learns the corresponding rule: once it has observed two failures, it deterministically selects the remaining door and receives a reward of 1. Figure 19 depicts this progression: as τ^c grows with on-policy interaction, the student eliminates inconsistent goals based on context and its behavior approaches posterior sampling over $\{A, B, C\}$.

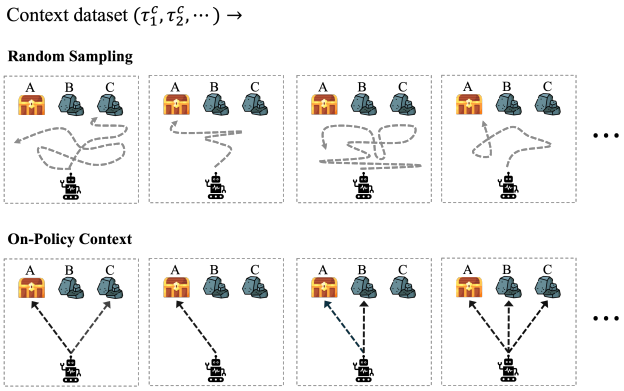


Figure 20: On-policy contexts ensure efficient coverage over relevant histories, while random exploration [36] can generate uninformative contextual information that harms training.

On-policy context enables more efficient learning than random exploration rollouts. In this example, a context τ_c is useful only if it induces a non-trivial posterior over the goal, i.e., it eliminates some candidates in $\{A, B, C\}$ based on observed rewards. Suppose instead that reaching each location requires multiple actions before any reward is revealed. Then a large fraction of randomly generated rollouts will fail to reach any door within the context horizon (row 1 in Figure 20), producing trajectories whose rewards are uninformative and whose posterior over g remains essentially unchanged. By contrast, on-policy contexts produced by the student concentrate on trajectories that actually reach candidate doors, since the student is trained on teacher trajectories that are goal-directed and therefore yield plausible search behavior (row 2 in Figure 20). As a result, the contexts in $\mathcal{D}_k$ more often contain the key feedback events that reduce uncertainty about g, providing a higher-signal training distribution for learning a context-conditioned policy.

F Training and Implementation Details

F.1 Training Details

Asymmetric Sampling of datasets. For the robot manipulation tasks, to avoid overfitting, we skew the sampling ratio of the data collected across iterations to upweight the new data more. This significantly reduced overfitting to past data and enabled better policy learning.

Filtering successful trajectories. As ASTEROID imitates privileged actions conditioned on context, we keep only the successful trajectories while collecting the datasets during each iteration. This ensures that the learned in-context policy samples from a distribution of expert actions that are optimal under the true parameters that could generate the given context.

F.2 Tasks

Wrist-Camera Peg Insertion. [66] A 7-DoF robot must locate a peg on a tabletop and insert it into the corresponding hole using only a wrist-mounted RGB camera and proprioception. This is a single-episode POMDP: the peg and arm are randomly reset at the start of each episode, and the robot must search under a limited camera field of view. We denote the privileged state as $s_t = (q_t, p_{\text{peg}}, p_{\text{hole}})$, where q_t is the robot proprioceptive state and $p_{\text{peg}}, p_{\text{hole}}$ are the peg and hole positions. The student observes $o_t = (I_t^{\text{wrist}}, q_t, a_{t-1})$, where I_t^{wrist} is the wrist-camera RGB image and a_{t-1} is the previous action. The reward indicates successful insertion, and expert trajectories are generated using large-scale RL as described in Yin et al. [66]. An effective exploration strategy must scan the workspace, localize the peg and hole from partial views, and then execute the contact-rich insertion behavior.

Tactile Pick. [66, 24] The robot must locate and pick up a cube using proprioceptive and tactile feedback, without visual observations. This is a single-episode POMDP: the cube pose is randomly reset and hidden, so the agent can only infer it through contact during the episode. We denote the privileged state as $s_t = (q_t, p_{\text{cube}})$, where q_t is the robot proprioceptive state and p_{cube} is the cube position. The student observes $o_t = (q_t, \tau_t, a_{t-1})$, where τ_t is the 2×3-dimensional force feedback from the two fingers of the parallel-jaw gripper. The reward indicates successful pickup, and expert trajectories are generated using large-scale RL as described in Yin et al. [66]. An effective exploration strategy must probe the workspace, use contact events to infer the cube location, and then transition from search to grasping. We also evaluate a harder variant with observations $o_t = (\tau_t, a_{t-1})$, where the robot observes the world only through contact forces and past actions. In this setting, the robot starts from a random configuration and must use its interaction history to maintain a belief over both its own joint configuration and the cube position.

Dark Room. [12, 36] The agent must find a hidden goal in a partially observable gridworld. We use three versions with different grid sizes: Mini (5×5), Easy (10×10), and Hard (25×25). This is a BAMDP: the agent interacts with the environment over multiple test-time episodes, the goal remains fixed across episodes, and the agent is reset to $(0, 0)$ at the start of each episode. We denote the privileged state as $s_t = (p_x, p_y, g_x, g_y)$, where (p_x, p_y) is the agent position and (g_x, g_y) is the hidden goal. The student observes $o_t = (p_x, p_y, r_t)$, where $r_t = 1\{(p_x, p_y) = (g_x, g_y)\}$. The expert is obtained by planning the shortest path to the hidden goal using privileged goal information. An effective exploration strategy must use the interaction history to avoid revisiting locations that already produced zero reward, search new candidate goals, and exploit the goal once it is found. This is exactly the structure induced by ASTEROID : given a student history, if a rewarding position has been observed, the expert labels return to it; otherwise, the expert labels target positions not yet ruled out by the history. We train and evaluate on an 80–20 random split of goal locations.

Key2Door. [12, 36] The agent must first locate a hidden key and then navigate to a door; the key is picked up and the door is opened by moving to their respective positions. This is a BAMDP with non-Markovian observations: the agent interacts across multiple test-time episodes, and optimal behavior depends on remembering which locations have been searched and whether the key has already been acquired. We denote the privileged state as $s_t = (p_x, p_y, k_x, k_y, d_x, d_y, 1\{\text{has key}\})$, where (p_x, p_y) is the agent position, (k_x, k_y) is the key position, (d_x, d_y) is the door position, and the final bit indicates whether the agent has the key. The student observes $o_t = (p_x, p_y, r_t)$. In

the Markovian version, the agent receives a reward of $+1$ at every timestep after acquiring the key, effectively revealing the task stage. This dense reward also leads the RL baselines to get stuck in a local minimum and perform poorly. In the non-Markovian version, the agent receives a reward of $+1$ only at the timestep when it picks up the key, so it must use its history to decide whether to continue searching for the key or switch to searching for the door. In both versions, the agent receives an additional reward of $+1$ upon reaching the door with the key, and the episode ends. An effective exploration strategy must search for the key, remember how to acquire it, and then search for or navigate to the door.

Ant and 2D Navigation. [49, 69] The agent must discover and reach a hidden goal, either in a continuous 2D navigation domain or with a high-dimensional quadruped. These are BAMDPs: the goal remains fixed across multiple episodes within a trajectory, while the agent resets between episodes and must use in-context exploration to identify unvisited candidate goals. We denote the privileged state as $s_t = (x_t, g)$, where x_t is the agent state and g is the hidden goal. The student observes $o_t = (x_t, r_t)$, but not g. The reward is sparse, with $r_t = 1\{\|x_t - g\|_2 \leq \epsilon\}$ for a success threshold ϵ. The expert uses privileged access to g to produce goal-directed behavior. We train and evaluate on an 80–20 split of goal locations. An effective exploration strategy must use history to avoid revisiting unlikely goals, sample unexplored regions, and exploit the goal once discovered.

Habitat Object Navigation. [48] The agent must find a target object in a realistic indoor environment, where the object is placed at one of k possible locations. This is a BAMDP: the agent starts from the same reset state and interacts for a single episode, while the hidden object location remains fixed throughout the episode and must be inferred from experience. We denote the privileged state as $s_t = (\mathcal{M}, x_t, g)$, where $\mathcal{M}$ is the map of the house, x_t is the robot pose, and $g \in \{1, \ldots, k\}$ is the hidden object location. The student observes $o_t = (x_t, I_t, b_t)$, where I_t is the onboard camera observation and $b_t \in \{0, 1\}$ is the output of an object detector applied to the current image. The reward is sparse and indicates whether the target object has been found. The expert is an oracle planner that uses the map and object location to navigate to the target. The student policy must use history to eliminate previously checked locations, search among the remaining candidates, and stop once the detector identifies the object.

Procgen Maze Navigation. The agent must navigate a procedurally generated maze to find a hidden goal. This is a single-episode POMDP: the maze layout, initial position, and goal location are unknown, and the agent observes only a local 3×3 window centered at its current position. We denote the privileged state as $s_t = (\mathcal{M}, p_t, g)$, where $\mathcal{M}$ is the maze layout, p_t is the agent position, and g is the goal location. The student observes $o_t = \mathcal{M}_{3\times3}(p_t)$, the local egocentric crop centered on the agent, but not the global map or the goal. The reward is sparse and indicates whether the agent reaches the goal. The expert plans the shortest path using Q-learning and privileged access to the full maze layout and goal location. An effective exploration strategy must use temporal context to build an implicit belief over the maze, avoid repeatedly visiting uninformative regions, and search until the goal is found. In Fixed Maze Navigation, we evaluate a simplified variant with a fixed maze layout but random initial and goal positions, isolating the challenge of goal-directed exploration under local 3×3 observations from the additional generalization required by procedurally generated layouts.

G Baseline Implementation Details

DPT [36]. We use the official implementation of DPT with the default hyperparameters from Lee et al. [36]. For a fair comparison, we set the dataset size to match the total data collected in the final iteration of ASTEROID .

SPOC [18]. SPOC augments naive distillation with sampled positional embeddings. We implement SPOC within our codebase and train it on the same total amount of data used across all iterations of ASTEROID .

RL baselines. For continuous-control RL baselines, we use high-quality implementations from RSL-RL [41] and Omni-Reset [66], which support large-scale GPU-parallel training. We implement ADVISOR in RSL-RL and tune its α and β parameters over the ranges reported in the original paper. For the meta-RL baselines, we use an adapted RL^2/PPO baseline [17] that incorporates

privileged expert supervision, thereby reducing the computational burden of learning exploration and task execution from sparse rewards alone. For gridworld tasks, we use Stable-Baselines3 PPO implementations with task-specific modifications. On the wrist-camera task, we run the vision-based RL baseline for one seed due to computational cost: 10^8 environment steps take roughly four days on an RTX-enabled GPU. Despite this scale, the learned exploration policy achieves only 10% success.

AAWR [25]. We use an extended version of the original AAWR implementation. To construct the initial offline dataset, we add Gaussian noise to generate broad coverage over possible histories. As shown in Figure 11a, AAWR is sensitive to this initial dataset coverage, whereas ASTEROID avoids this dependence by collecting context on-policy. AAWR and SPOC were not originally designed for BAMDPs, but we include them in both settings for completeness.

Distilled Planner. For Habitat object search, we construct an upper-bound baseline by distilling a posterior-sampling planner. The dataset consists of expert trajectories that visit the possible object locations in a fixed order and terminate upon finding the target. This produces goal-directed exploration behavior, which we distill into a transformer policy. Unlike ASTEROID , however, this baseline assumes access to the full set of possible object locations and the underlying task structure during training, which is unrealistic.

G.1 Pseudocode

Algorithm 2 ASTEROID

Require: iterations K, tasks per iteration N, horizon H, privileged teacher π^*

Initialize $\mathcal{D}_0 \leftarrow \emptyset$, student π_{θ_0}
for $k = 0, \dots, K-1$ **do**
  $\mathcal{D}_{k+1} \leftarrow \mathcal{D}_k$
  `// Collect on-policy contexts and privileged labels`
  for $i = 1, \dots, N$ **do**
    Sample $z \sim p(z)$ and instantiate M_z
    Roll out π_{θ_k} in M_z for k episodes: $h_k^{(i)} = (\tau^0, \dots, \tau^{k-1})$
    Roll out π^* in M_z for one episode: $\tau^{*,(i)} = (o_0^*, a_0^*, r_0^*, \dots, o_{H-1}^*, a_{H-1}^*, r_{H-1}^*)$
    Add labels $\mathcal{D}_{k+1} \leftarrow \mathcal{D}_{k+1} \cup \{(h_k^{(i)}, o_{0:t}^*, r_{0:t-1}^*, a_t^*)\}_{t=0}^{H-1}$
  end for
  `// Update student by conditional imitation`
  Train $\pi_{\theta_{k+1}}$ on $\mathcal{D}_{k+1}$ using Eq. 1
end for
return π_{θ_K}

Algorithm 3 ASTEROID for general POMDPs

Require: iterations K, samples per iteration N, horizon H, privileged teacher π^*

Initialize $\mathcal{D}_0 \leftarrow \emptyset$, student π_{θ_0}
for $k = 0, \dots, K-1$ **do**
  $\mathcal{D}_{k+1} \leftarrow \mathcal{D}_k$
  `// Collect on-policy contexts and privileged labels`
  for $i = 1, \dots, N$ **do**
    Sample T uniformly in $[1, H-1]$
    Roll out π_{θ_k} in POMDP for T steps: $h_k^{(i)} = (o_0, a_0, r_0 \cdots o_{t-1}, a_{t-1}, r_{t-1})$
    Roll out π^* in the same episode from o_T: $\tau^{*,(i)} = (o_T^*, a_T^*, r_T^*, \dots, o_{H-1}^*, a_{H-1}^*, r_{H-1}^*)$
    Add labels $\mathcal{D}_{k+1} \leftarrow \mathcal{D}_{k+1} \cup \{(h_k^{(i)}, o_{0:t}^*, r_{0:t-1}^*, a_t^*)\}_{t=T}^{H-1}$
  end for
  `// Update student by conditional imitation`
  Train $\pi_{\theta_{k+1}}$ on $\mathcal{D}_{k+1}$ using Eq. 1
end for
return π_{θ_K}

Table 1: Hyperparameters for Context Accumulation on Gridworld tasks.

Hyperparameter	**Value**
Training	
Dataset size (per iteration)	1000
ASTEROID iterations	10
Batch size	64
Learning rate	1×10^{-4}
Weight decay	1×10^{-4}
Number of training epochs (per iteration)	100
Warmup ratio	0.03
Gradient clipping	1.0
Optimizer	AdamW
LR scheduler	Warmup + Cosine Decay
Model Architecture (Decision Transformer [11])	
Number of layers	4
Number of attention heads	4
Embedding dimension	256
Dropout	0.1
Max Context length	$H \times K$
Evaluation	
Test-time episodes	40
Episode length	100

Table 2: Hyperparameters for In-Context Exploration on IsaacLab tasks. Sampling ratios are ordered from the oldest to the newest dataset. The exploration horizon denotes the $[\min, \max]$ fraction of the episode during which the exploration policy acts before handing off to the expert.

Hyperparameter	**Value**
Training	
Demonstrations per iteration	8k for Tactile-Pick / 5k for Wrist-Camera Peg
Training steps per iteration	50,000 gradient steps
Intial Learning rate	1×10^{-4}
Fine-tuning learning rate	1×10^{-5}
Optimizer	AdamW
Curriculum Schedule (Ratio of episode length)	
Exploration horizon (iteration 1)	$[0.2, 0.5]$
Exploration horizon (iteration 2)	$[0.3, 0.8]$
Exploration horizon (iteration 3)	$[0.4, 0.9]$
Evaluation	
Evaluation episodes	64
Episode length	240

G.2 Hyperparameters

H Additional Theory

We present a theoretical analysis of some properties of learning in-context exploration from privileged teachers using Methods. Reusing notation from Section 3, h_t denotes the student's history, d_π denotes the history distribution induced by a policy π, $d_\mathcal{D}$ denotes the empirical history distribution in a dataset, $\pi^*(a_t \mid s_t)$ denotes the privileged teacher, and $\pi_\theta(a_t \mid h_t)$ denotes the history-conditioned student.

We present the following claims and proof sketches: (i) privileged labels on compliant histories provide posterior-sampling supervision (which follows from Lee et al. [36]), (ii) because ASTEROID collects on-policy histories, it recovers posterior sampling on the covered history support, and (iii) on-policy context aggregation changes the cumulative latent z-prediction error from a quadratic offline compounding term to a linear approximation term.

H.1 Preliminaries

We define the posterior-sampling policy

$$\pi^{\mathrm{PS}}(a \mid h_k) := \int \pi^\star(a \mid s, z)\, p(z \mid h_k)\, dz.$$

Thus posterior sampling acts according to the posterior over latent variables induced by the history.

For a context length k, let $d_{\pi,k}$ denote the marginal of d_π over histories induced by running π for the first $k-1$ interaction episodes. We measure the student's latent-predictive action error at context length k by

$$e_k(\pi) := \mathbb{E}_{h\sim d_{\pi,k}}\left[\mathrm{TV}\big(\pi(\cdot \mid h), \pi^{\mathrm{PS}}(\cdot \mid h)\big)\right]. \tag{2}$$

This quantity measures whether the student matches the posterior-predictive behavior induced by the latent belief after its own interaction history.

Assumption 1 (Compliance)**.** *The policy used to generate context is unprivileged: at time t, its action depends only on the observed history h_t, not directly on the latent variable z. Similar to Assumption 1 in DPT [36].*

Assumption 2 (On-policy support coverage)**.** *At ASTEROID iteration k, the aggregated dataset covers the support of the histories actually visited by the current rollout policy up to k episodes of context.*

H.2 Privileged Labels Provide Posterior-Sampling Supervision

The key observation is that privileged labels are posterior-sampling labels when conditioned on compliant histories. A history is compliant if it is generated by a policy that does not directly observe the latent variable z. This is similar to the assumptions in prior work on learning a posterior from in-context supervision [36]. Intuitively, compliance ensures that the history reveals information about z only through observations, actions, and rewards available to the student, not through hidden privileged information.

Lemma 1 (Privileged labels equal posterior-sampling labels)**.** *Let h_k be a compliant history. If the privileged teacher label is sampled as*

$$a^\star \sim \pi^\star(\cdot \mid o, z),$$

then

$$\mathbb{P}(a^\star = a \mid h_k) = \pi^{\mathrm{PS}}(a \mid h_k).$$

This lemma says that we do not need to explicitly infer z. If we train on privileged labels conditioned on compliant histories, maximum likelihood directly trains the posterior-predictive policy. This follows from the proof in Lee et al. [36].

Theorem 1 (ASTEROID converges to posterior sampling on covered histories)**.** *Assume realizability, population optimization, and on-policy support coverage. Then, at iteration i, for every history h in the support of the aggregated on-policy dataset,*

$$\pi_i(\cdot \mid h) = \pi^{\mathrm{PS}}(\cdot \mid h).$$

Consequently, as the context horizon reaches the full online interaction horizon, ASTEROID matches posterior sampling on the covered trajectory support.

Proof. The proof is by induction over iterations.

Base case. At iteration 0, ASTEROID trains on null-context. For any history h in the support of that dataset, Lemma 1 implies that the conditional label distribution is exactly $\pi^{\mathrm{PS}}(\cdot \mid h)$. On minimizing cross-entropy over the D_0, we get this conditional distribution, $\pi_0(\cdot \mid h) = \pi^{\mathrm{PS}}(\cdot \mid h)$ over the support of the dataset.

Inductive step. Assume that at iteration k, $\pi_k(\cdot \mid h) = \pi^{\mathrm{PS}}(\cdot \mid h)$ for every rollout history h of depth at most k episodes in support. ASTEROID now rolls out π_{θ_k} to collect on-policy contexts up to k episodes. Since the distributions agree up to that depth, the collected histories are exactly the same histories that posterior sampling would generate up to that horizon. At each such history h, ASTEROID queries the privileged teacher. By Lemma 1, we have the conditional label distribution given h is $\pi^{\mathrm{PS}}(a \mid h) \Rightarrow \pi_{\theta_{k+1}}(\cdot \mid h) = \pi^{\mathrm{PS}}(\cdot \mid h)$. Because the context schedule expands from k to $k+1$ episodes, the agreement extends to the larger support. This proves the inductive claim.

As k increases, the resulting student policy converges to posterior sampling on the support of the dataset D_k. The theorem is intentionally an on-support statement. ASTEROID does not need offline coverage of all possible histories. It constructs the relevant support by rolling out the student and querying the teacher on the histories the student actually visits.

H.3 Offline Latent Error is quadratic in horizon.

We now compare on-policy context aggregation to an offline context learner. Suppose an offline learner is trained on histories from a fixed behavior distribution d_k^{off}, and has small latent-predictive error on that distribution:

$$\mathbb{E}_{h_k \sim d_k^{\mathrm{off}}} \left[\mathrm{TV}\big(\pi(\cdot \mid h_k), \pi^{\mathrm{PS}}(\cdot \mid h_k)\big) \right] \le \epsilon.$$

At deployment, however, the learner is evaluated on its own history distribution d_k^{π}. Therefore,

$$e_k(\pi) \le \epsilon + \mathrm{TV}(d_k^{\pi}, d_k^{\mathrm{off}}).$$

Lemma 2 (Offline history mismatch compounds)**.** *If the offline history distribution is not updated on-policy, then a per-episode latent-predictive error ϵ can induce*

$$\mathrm{TV}(d_k^{\pi}, d_k^{\mathrm{off}}) = O(k\epsilon).$$

Consequently,

$$e_k(\pi) = O(k\epsilon).$$

Proof sketch. Couple a rollout from the offline history distribution with a rollout from the learner. At each earlier online episode, the learner can make a latent-predictive error with probability at most $O(\epsilon)$. Once such an error occurs, the subsequent history may differ from the offline history, since future observations, rewards, and actions are conditioned on the previous trajectory. By a union bound over the first $k-1$ online episodes, the probability that the two histories have diverged by episode k is $O(k\epsilon)$. This upper bounds the total variation distance between the two history distributions. Substituting into the previous inequality gives $e_k(\pi) = O(k\epsilon)$. □

Summing over K online episodes gives the cumulative offline latent error:

$$\sum_{k=1}^{K} e_k(\pi) \le O\left(\epsilon \sum_{k=1}^{K} k \right) = O(\epsilon K^2).$$

Thus, even if the offline learner has small error on its dataset, its error can compound quadratically because the histories it sees at deployment drift away from the histories used for training.

H.4 On-Policy Latent Error is linear in horizon.

ASTEROID avoids this mismatch by training on the student's own histories. Let $\pi_1, \ldots, \pi_K$ be the policies produced during iterative training, and define the on-policy latent-predictive loss

$$\ell_i(\pi) := \mathbb{E}_{h \sim d^{\pi_i}} \left[\mathrm{TV}\big(\pi(\cdot \mid h), \pi^{\mathrm{PS}}(\cdot \mid h)\big) \right].$$

Let $\epsilon_K := \min_{\pi \in \Pi} \frac{1}{K} \sum_{i=1}^{K} \ell_i(\pi)$ be the lowest latent-predictive error, and suppose the supervised learner has online regret γ_N:

$$\frac{1}{K} \sum_{i=1}^{K} \ell_i(\pi_i) \le \epsilon_K + \gamma_K.$$

Lemma 3 (On-policy latent error)**.** *There exists an iterate $\hat{\pi} \in \{\pi_1, \ldots, \pi_K\}$ such that*

$$\mathbb{E}_{h \sim d^{\hat{\pi}}} \left[\mathrm{TV}\big(\hat{\pi}(\cdot \mid h), \pi^{\mathrm{PS}}(\cdot \mid h)\big) \right] \leq \epsilon_K + \gamma_K.$$

Proof. The average on-policy loss of the iterates is at most $\epsilon_K + \gamma_K$. Therefore at least one iterate has loss no larger than this average. □

For this iterate, the cumulative latent-predictive error over K online episodes is

$$\sum_{k=1}^{K} e_k(\hat{\pi}) \leq K(\epsilon_K + \gamma_K).$$

The key difference from the offline case is that there is no additional history-mismatch term $\mathrm{TV}(d_k^{\pi}, d_k^{\mathrm{off}})$: the training distribution is the student's own induced history distribution.

Theorem 2 (On-policy history error is linear in horizon)**.** *Let $\hat{\pi}$ be the iterate from Lemma 3, and write $\epsilon := \epsilon_K + \gamma_K$. Since ASTEROID trains on histories induced by the student itself, the per-episode latent-predictive error satisfies*

$$e_k(\hat{\pi}) = O(\epsilon) \qquad \textit{for all } k \leq K.$$

Consequently,

$$\sum_{k=1}^{K} e_k(\hat{\pi}) = O(\epsilon K).$$

Proof sketch. Unlike the offline learner, ASTEROID does not train on histories from a fixed behavior distribution. At each iteration, the histories in the dataset are generated by the current student policy itself. Therefore, when the learned policy is evaluated on its own histories, there is no additional mismatch term of the form $\mathrm{TV}(d_k^{\hat{\pi}}, d_k^{\mathrm{off}})$. The only remaining error is the supervised latent-predictive error on the student's own induced history distribution. By Lemma 3, there exists an iterate $\hat{\pi}$ whose on-policy latent-predictive error is at most $\epsilon_K + \gamma_K = \epsilon$.

Thus, at each context depth k, the expected deviation from posterior sampling on histories induced by $\hat{\pi}$ is $O(\epsilon)$:

$$e_k(\hat{\pi}) = \mathbb{E}_{h_k \sim d_k^{\hat{\pi}}} \left[\mathrm{TV}\big(\hat{\pi}(\cdot \mid h_k), \pi^{\mathrm{PS}}(\cdot \mid h_k)\big) \right] = O(\epsilon).$$

Summing over the K online episodes gives

$$\sum_{k=1}^{K} e_k(\hat{\pi}) \leq \sum_{k=1}^{K} O(\epsilon) = O(\epsilon K).$$

Thus, on-policy context aggregation removes the extra history-mismatch term that causes the offline error to grow like $O(k\epsilon)$. The cumulative error is therefore linear in the number of online episodes rather than quadratic. Thus, the total regret is the PSRL $\widetilde{O}(HS\sqrt{AK})$ regret, with an extra $O(K)$ approximation error. □

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Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [N/A]

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