First-Explore, then Exploit: Meta-Learning Intelligent Exploration

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Abstract

Standard reinforcement learning (RL) agents never intelligently explore like a human (i.e. by taking into account complex domain priors and previous explorations). Even the most basic intelligent exploration strategies such as exhaustive search are only inefficiently or poorly approximated by approaches such as novelty search or intrinsic motivation, let alone more complicated strategies like learning new skills, climbing stairs, opening doors, or conducting experiments. This lack of intelligent exploration limits sample efficiency and prevents solving hard exploration domains. We argue a core barrier prohibiting many RL approaches from learning intelligent exploration is that the methods attempt to explore and exploit simultaneously, which harms both exploration and exploitation as the goals often conflict. We propose a novel meta-RL framework (First-Explore) with two policies: one policy learns to only explore and one policy learns to only exploit. Once trained, we can then explore with the explore policy, for as long as desired, and then exploit based on all the information gained during exploration. This approach avoids the conflict of trying to do both exploration and exploitation at once. We demonstrate that First-Explore can learn intelligent exploration strategies such as exhaustive search and more, and that it outperforms dominant standard RL and meta-RL approaches on domains where exploration requires sacrificing reward. First-Explore is a significant step towards creating meta-RL algorithms capable of learning human-level exploration which is essential to solve challenging unseen hard-exploration domains¹

1 Introduction

Reinforcement learning (RL) is seeing successful application to a range of challenging tasks from plasma control [1], molecule design [2], game playing [3], and to the control of robots [4]. Despite this promise, standard RL is *very* sample inefficient. It can take an agent hundreds of thousands of episodes of play to learn a task that humans could learn in a few tries [5].

This sample inefficiency has several causes. First, standard RL cannot condition on a complex prior such as a human's common sense or general experience [6]. For example, a human gamer has intuitions when *first encountering* a 2D game with a character, platforms, ladders, keys and doors (e.g., Montezuma's Revenge). They think they can probably control the character with the game actions, and that the character might be able to jump, climb ladders, collect keys, and use keys to open doors. It has been shown that much of the sample efficiency of humans comes from such priors

¹Code is available at https://github.com/btnorman/First-Explore.

[7]. Second, standard RL is limited in how it adapts as it relies on reinforcing existing behaviours over multiple episodes rather than being able to tailor each exploration to be maximally informative. For example, upon finding and reading a treasure map in one episode, a human might navigate to the treasure location in the next episode, or upon losing to a strategy in a symmetric game (e.g. in chess losing against a particular opening), they might mimic and attempt to master that strategy in subsequent play. This lack of human-like adaption further harms sample efficiency. Third, standard RL and standard meta reinforcement learning (meta-RL) both use the same policy to explore (gather data to improve the policy) and to exploit (achieve high episode reward) [8, 9]. Standard meta-RL [9–12] does not enable intelligent exploration (exploration and good exploitation are different, e.g., when exploring requires sacrificing episode reward, using the same policy to both explore and to exploit can cause terrible sample inefficiency and potentially prevent learning (detailed in section 2.1.3).

We present *First-Explore*, a simple framework for meta-RL that overcomes these limitations by learning a pair of policies: an explore policy that can *intelligently* explore, and an exploit policy that can *intelligently* exploit. First-Explore enables the potential of learning policies that exhibit meta-RL's human-level-in-context-sample-efficient learning on unseen hard-exploration domains including hostile ones that require sacrificing reward to properly explore.

2 Preliminaries and Related Work

2.1 Problems with Standard RL Exploration

2.1.1 Exploring by Exploiting

In standard RL, the same policy is generally used for two different purposes: i) Exploring: gathering data to improve the policy and ii) Exploiting: using the gathered data to specify a highly performant policy [13]. Standard RL algorithms (such as PPO [8]) rely on exploring by sampling the small area of policy space covered by a noisy policy centered on exploitation, e.g., by ensuring the exploit policy has high entropy [14] or by epsilon-greedy sampling of the policy [5].

Exploring by relying on such *noisy exploiting* will never solve some tasks. For example, imagine an environment with two long paths, one orange and one blue. While the orange path is straightforward, and leads to a medium reward, the blue path is blocked by a locked door that requires great lock-picking skills to open. However, behind the door is a vast treasure (with significantly higher reward). During an episode an agent does not have time to reach the end of both paths. We shall call this the locked path environment (Figure 1).

The standard-RL approach of exploring by (noisily) exploiting will not enable learning the best strategy (reaching the blue path reward). This dynamic occurs because while the agent is unskilled at lock picking the blue path gives zero reward, which is lower than the medium reward of the orange path. Hence, an agent attempting to exploit each episode will solely travel the orange path.

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Figure 1: Locked Path Environment. The high reward blue path requires complex behavior.

Finally, because the blue path is never travelled, there is no chance to learn lock picking. The best strategy is not learnt because travelling the orange path is a local optima.

Because of this local optima, getting the maximum reward in the locked path environment requires effective exploring (learning to travel the blue path and unlock the lock) which requires sacrificing episode reward during exploration (by not getting the orange path reward). This is a general principle we now define:

• *Sacrificial* exploration: exploration that is *not* exploitative is *sacrificial* as one is 'sacrificing' episode reward for information gain.

Examples: paying for information or tutoring, doing practice drills, practicing ones weaknesses, attempting to solve a task in an unfamiliar way when one can already solve it in a familiar way.

• *Coincidental* exploration: exploitation that happens by coincidence when *noisily exploiting* (exploiting with noise potentially added or encouraged).

Relying on *coincidental* exploration is the standard RL approach, and is vulnerable to local optima.

Examples: practicing one's strengths, playing normal matches, attempting to solve a task in a familiar way, attempting something new when nothing is working.

Standard RL never intentionally *sacrificially* explores because each episode is spent trying to maximize reward. This inability prevents standard RL from optimally exploring, and so causes greater sample inefficiency, making solving hostile tasks (where exploration requires sacrificing reward) infeasible.

2.1.2 Memory-less Exploration

People often exhaustively explore. For example, an explorer, searching for new lands, has little interest in places they have already visited. In standard RL, an agent has no knowledge or memory of previous episodes, and so (while noisily exploiting) it will do approximately the same 'exploration' repeatedly. This lack of memory can make the standard RL exploration hugely sample inefficient. While the agent's policy may change due to updates to the policy's weights, the policy change is slow, and unlikely to allow human-level adaption, wherein people change their policy substantially and appropriately based on a single episode of experience.

2.1.3 No Prior on Exploration

Effective and efficient exploration *requires* a prior on how to explore in the environment. When a human sees a level of Montezuma's Revenge, they have an intuition that keys open rooms, and hence collecting them is important for exploration. Having such intuition is core to efficient exploration.

Furthermore, a good exploration prior is often different from a good exploitation prior because optimal exploration often requires sacrificing episode reward, e.g. to experiment with new strategies. Imagine playing an adventure game where one explores a strange and unfamiliar dungeon. When one is purely exploiting each episode, one acts as though one only has a single life and it is wise to only perform actions one knows are safe, e.g. not open any doors to previously unexplored rooms. However, when purely exploring, one would play as though one has infinite lives with the only concern regarding dying being the opportunity cost of wasting subsequent exploration that one could have done were one still alive in that episode, e.g. open all the unexplored dungeon rooms, but with the safest seeming rooms opened first. Both ways of playing correspond to a complex prior on how the player should act, however the prior for exploitation actively prohibits effective exploration (no new rooms are explored).

2.2 Meta-RL

Meta-RL attempts to address many of standard-RL's issues by learning a reinforcement learning algorithm. This reinforcement learning algorithm can be realized as a mapping from a context of rollouts c in an environment m to a peformant policy $\pi_{\theta,c}$ specialized to that environment, whether by a transformer [9], recurrent neural network [10] or other method capable of processing long-sequences or memory. To train meta-RL, one specifies a distribution of environments \mathcal{M} . Giving the agent multiple interactions with a sampled environment then enables the policy to learn to adapt to the specifics of the environment m it is in, and also make use of and learn the prior that the environment comes from the training distribution, $m \sim \mathcal{M}$.

Once trained, the learnt RL algorithm can be very sample efficient [9, 10]. For example, when trained to find a reward location in mazes, a learnt RL algorithm can remember the areas of the maze it has already visited, and know not to visit those areas again [10] (unless worth it to reach other unseen areas). This capability allows an unseen maze to be solved in a few tries, which is fewer episode rollouts than are needed for a single batched gradient update of standard RL [10].

Despite these benefits, the standard approach to meta-RL is still limited in that it learns a single policy (the learnt RL algorithm) and uses it for two different purposes: to a) get information about the current environment, and b) get maximum reward in the current environment. Thus these meta-RL approaches would still fail the locked path environment described in section 2.1.1 because in this case intelligent exploration and intelligent exploitation are very different, meaning that modelling

both at once is not possible. First-Explore solves this problem by instead learning two policies: one to *intelligently* explore and one to *intelligently* exploit.

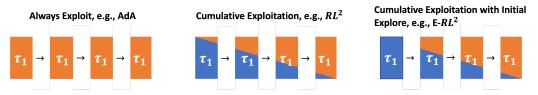


Figure 2: Different meta-RL training approaches. Here, arrows depict the flow of context, with episodes having as context all episodes preceding in the chain of arrows. The proportion of *sacrificial* exploration is depicted in blue, the proportion of pure exploitation is depicted in orange. (Left) Always-Exploit training incentizes each episode to be exploitative conditioned on the previous context, and hence learns no *sacrificial* exploration. (Middle) Cumulative exploitation trains to maximize summed reward across episodes and hence can learn to sacrifice early rewards for later payoffs. (Right) Tweaking cumulative exploitation to ignore the reward of the first k episodes allows a burn-in period of *sacrificial* exploration.

We will first consider two existing works of meta-RL, and detail how they suffer from the problem of exploring by exploiting. The first is AdA [9]. The authors note that their trained model always attempts to maximize individual episode reward conditional on the context of previous episodes (Fig. 2, left). AdA then demonstrates very efficient exploitation that can learn and adapt from previous episodes. However, because the agent is always exploiting, all exploration comes from *coincidental* exploration. This restriction prohibits the method working in domains that require *sacrificial* exploration. With minor modifications, AdA could learn to perform sacrificial exploration, such as if the reward function is the reward gained in the final episode only; then it might learn to sacrificially explore in early episodes and exploit in the last episode.

The second work we consider is RL^2 [10] (concurrently invented in [11]). RL^2 maximizes cumulative reward (Fig. 2, middle). This incentive means it learns a changing explore exploit trade-off, where initial episodes can be slightly *sacrificially* exploratory. However, maximizing cumulative reward prohibits pure sacrificial exploration with arbitrarily negative rewards, because the initial exploration could be so costly as to make the overall sum negative. RL^2 is also inflexible as it links the explore exploit trade-off to the size of the context, and hence one cannot exploit early, or continue exploring indefinitely.

Another work, Stadie et al. [15] presents $E-RL^2$, which is a modification of RL^2 that still maximizes cumulative reward but ignores the reward of the first k episodes. This modification makes the first k episodes exploratory on a new task, and allows initial sacrificial exploration on those first k episodes (Fig. 2, right). Despite this improvement, it is limited for several reasons. First, the method introduces an across-episode value assignment problem of assigning credit to which of the k exploratory episodes contributed to the explore context. It is also inflexible in that a) only the final episode is purely exploitative and b) the number of zero reward episodes is set as a hyperparameter and the same for all tasks (both at training and at inference). This constraint can be inefficient and counter productive if at inference one wants to continually explore until a satisfactory policy quality is reached.

2.3 Other Works Addressing Exploration

There is a rich literature on non-meta-RL exploration approaches. One relevant approach is Intrinsic Motivation (IM), which replaces the environment reward with an intrinsic motivation reward such as novelty [16]. Despite the success of IM at enabling *sacrificial* exploration, these methods are limited by being slow to adapt due to lacking a memory not encoded via weights (section 2.1.2) and not having a complex learnt prior on exploration (section 2.1.3). Another deeper problem is that many of these methods enable *sacrificial* exploration by entirely ignoring the reward signal, leading to pathologies such as the noisy TV problem [17, 18], where an agent looking for new states will find a TV showing white noise to be endlessly captivating. There is also work on combining such (IM) methods with meta-RL such as Liu et al. [19] which has the insight of decoupling exploration from exploitation, however, they do so at the cost of making the exploration un-grounded in ultimate reward, introducing the pathologies just mentioned. Another method, Go-Explore [20], decouples exploration and exploitation, but lacks complex priors. There are also approaches within the multi-armed bandit literature, and regret-based learning [18].

Despite the benefits of all these approaches, they all have pathologies, and only meta-RL is both a) computationally tractable and b) capable of human-level sample efficiency in high dimensional state spaces. As discussed above our method is an improvement on top of meta-RL learning by allowing sacrificial exploration.

3 First-Explore Framework

First-Explore is a framework that overcomes the outlined standard RL and meta-RL limitations by recognizing that RL is composed of two tasks. The task of a) gathering informative environment rollouts and b) mapping those to an effective policy. By separating exploration and exploitation we can learn sample-efficient and intelligent pure-exploration and pure-exploitation policies that are not hampered by attempting to do both at once.

First-explore learns a pair of policies. An explore policy $\pi_{explore,\theta,c}$ that explores and provides information (context) for itself and for exploitation, and an exploit policy $\pi_{exploit,\theta,c}$ that exploits after every explore providing feedback to train the explore policy. The policies may share or have separate parameters, e.g., for policies with separate parameters, one could write $\theta = (\theta_{explore}, \theta_{exploit})$ with each policy only dependent on its own subset of θ . This framework is visualized in Figure 3.

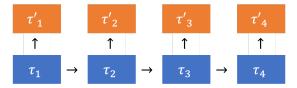


Figure 3: The **First-Explore Framework**. The explore episodes τ_1, \ldots, τ_4 in blue are sampled using the explore policy $\pi_{\text{explore},\theta,c}$ and the context of previous explore episodes, e.g. for $\tau_t, c = \{\tau_1, \ldots, \tau_{t-1}\}$. These explore episodes are purely exploratory and are able to *sacrificially* explore. The exploit episodes τ'_1, \ldots, τ'_4 in orange are sampled using the exploit policy $\pi_{\text{exploit},\theta,c}$ and the context of all preceding explore episodes. They are purely exploitative.

- The explore policy $\pi_{\text{explore},\theta,c}$ gathers informative environment rollouts based on the current context *c* (all previous explores) and parameters θ .
- The exploit policy $\pi_{\text{exploit},\theta,c}$ exploits (maximizes episode return) based on the current context *c* (all previous explores) and parameters θ .

Here the notation $\pi_{\text{explore},\theta,c}$ refers to the explore policy conditioned on the context $\pi_{\text{explore},\theta,c} = \pi_{\text{explore},\theta}|c$ and similarly for $\pi_{\text{exploit},\theta,c}$. Notably, each policy is limited by the quality of the other as if there is no useful context then an excellent exploit policy will do no better than a mediocre one, and if the exploit policy is poor then mediocre and excellent context will be similarly indistinguishable. Thus, for complex tasks, the policies need to be learnt together.

A central idea of First-Explore is that the exploratory value v_{explore} of an explore episode τ_{explore} given a context of past episodes $\{\tau_1, \ldots, \tau_n\}$ is the increase in expected reward of a subsequent exploit when the explore episode is added to the context to create new context $\{\tau_1, \ldots, \tau_n, \tau_{\text{explore}}\}$.

 $v_{\text{explore}}(\tau_{\text{explore}})|\{\tau_1,\ldots,\tau_n\} = \mathbb{E}(\tau_{\text{exploit}}|\{\tau_1,\ldots,\tau_n,\tau_{\text{explore}}\}) - \mathbb{E}(\tau_{\text{exploit}}|\{\tau_1,\ldots,\tau_n\})$

where $\tau_{\text{exploit}} | c$ denotes a rollout from $\pi_{\text{exploit},\theta,c}$.

As the last term does not depend on the explore episode τ_{explore} , it is possible to discard the last term $\mathbb{E}(\tau_{\text{exploit}} | \{\tau_1, \ldots, \tau_n\})$ when learning the optimal exploration policy. The reward function for the explore policy is thus the reward of the following exploit.

To train, one then iterates building a context exclusively from exploration, each time determining the value of each exploration by a subsequent exploit. Evaluating and crediting each explore in this way allows First-Explore to avoid the value assignment problem of $E-RL^2$. First-explore can be combined with different meta-RL approaches and losses. Algorithm 2 gives an example of a training update for a simple loss function l such as policy gradient [13].

Once the two policies have been trained, to adapt to an environment, one performs iterated rollouts in the environment using the explore policy to sample-efficiently explore, with each explore rollout added to the context potentially improving the context-conditioned exploit policy. This process is the analogue of sample-efficiently training a standard RL policy where accumulation of informative context replaces standard RL-training, and exploit rollouts replace standard RL evaluation rollouts.

One approach would be to explore in the environment until a preset desired exploit quality is reached (similarly to training in standard RL until an environment is solved). Algorithm 1 gives an example of this method. One could also simply do a set number of rollouts (similarly to training standard RL for a set number of epochs).

```
# rollout conducts an episode when provided with an environment and policy
# and returns all the episode infomation.
def calc_loss(\theta):
    """A basic First-Explore training step."""
    # sample an environment, and initalize context c and loss value
    m = sample(\mathcal{M}); c = set(); loss = 0
    for i in range(k): # do k iterated rollouts
        	au_{explore} = rollout(m, \pi_{explore, \theta, c}) # explore given context c
        	au_{explore} = rollout(m, \pi_{exploit, \theta, c} \cup {\tau_{explore}}) # exploit given c \cup {\tau_{explore}}}
    r = final_reward(	au_{exploit}) # get the exploit reward
        # add \pi_{explore}'s loss using the exploit reward and pre-explore context
        # and \pi_{exploit}'s loss using the exploit reward and post-explore context
        loss = loss+l(r, \pi_{explore, \theta, c}, \tau_{explore, c_1}) + l(r, \pi_{exploit, \theta, c} \cup {\tau_{explore}})
        c = c \cup {\tau_{explore}} # update the context for the next explore
        return loss
```

 $\theta = \theta - \text{learning_rate} \times \nabla \text{calc_loss}(\theta) \ \# \ training \ update$

Algorithm 1: Example meta-RL training update using First-Explore framework for a simple loss l such as policy gradient. First-Explore is a framework for meta-RL training, not a specific algorithm.

Algorithm 2: Example of using the trained First-Explore policies to in-context learn on a new environment until a desired exploit reward is reached.

4 Results

For each domain, the architecture is a standard GPT-2 style transformer architecture [21]. For simplicity, the parameters are shared between the two policies, differing only by a final linear-layer head. As a control, we modified the same algorithm used to train the First-Explore policies to instead learn to always-exploit. We use a novel loss based on predicting the sequence of future actions conditional on the episode having high reward, which preliminary experiments showed improved training stability. While an innovation, it is not core to the framework, and other standard losses (e.g. PPO) should work as replacements. Full architecture, training details and hyperparameters are given in the supplementary materials (SI).

Because the environments differ in how difficult and rewarding they are, a single evaluation of the policies involves sampling a batch of environments (10,000 for the bandit domain, and 1,000 for the treasure-room one), performing iterated rollouts in *each* environment (allowing the policy to in-context adapt to each environment) and calculating the average statistics across the batch (e.g., the average first episode exploit reward).

To ensure non-spurious results, First-Explore and the always-exploit control were both trained ten times with ten different random seeds. Furthermore, the in-context learning of each training run was evaluated ten times each on an independently sampled batch of environments (for a total of 100 evaluations). Each treatment is then visualized by a line showing the mean over the evaluations and training runs. The darker-shaded area shows one standard deviation from the mean, and the lighter-shaded area shows the minimum and maximum value (across evaluations and seeds). If the light area shaded around one line (e.g. the First-Explore exploit reward) is above the light shaded area around another (e.g. the always-exploit reward) then, in all 100 evaluations, one treatment beats the other, which (as the runs are independent) is statistically significant ($p \le 2^{-10}$). All lines have these shaded areas, however the deviation between evaluations can be so small that the shaded areas can be hard to see.

4.1 Gaussian Multi-armed Bandit

The first problem setting is a multi-armed Gaussian Bandit with k arms specified by k arms means $\mu_{\{1,...k\}} \in \mathbb{R}$. At each time step t the agent chooses an arm a_t and receives as reward r_t equal to the arm mean plus a normally distributed noise term, $r_t = N(\mu_{a_t}, \frac{1}{2})$. In our meta-RL approach, the agent observes its previous actions and their rewards, and can adapt based on that. Each environment's arm means are normally distributed, $\mu_{\{1,...,k\}} \sim N(\mathbf{0}, \mathbf{I})$.

In this domain, First-Explore learns intelligent exploration, learning a policy that exhaustively searches (Fig. 4, right blue line) in the first ten actions and then significantly and appropriately changes to sampling high reward arms (Fig. 4, left blue line). This series of average episode rewards show how the learnt policy is grounded in reward (by focusing on high reward arms at times), while also able to *sacrificially* explore (by getting low expected reward for the first ten pulls). The First-Explore exploit policy has the highest reward (Fig. 4, left orange line), and also matches optimal hand-coded exploitation when the hand-coded exploitation function is provided with the context produced by the First-Explore explore policy (Fig. 5, left). Further, First-Explore exploration exceeds random play exploration, iterated exploitation, and even hand-coded exhaust search at informing optimal exploitation (Fig. 5, right).

Interestingly, after the First-Explore exploration policy changes to sampling the high reward arms, the explore episode reward steadily trends downward and eventually becomes negative. This behavior is consistent across all training runs, and all evaluations. We believe this phenomenon occurs because, once the agent has gained sufficient information about the high-payoff arms, the only useful behavior left is to check if the low expected value arms truly are low value, and were not just unlucky when previously sampled.

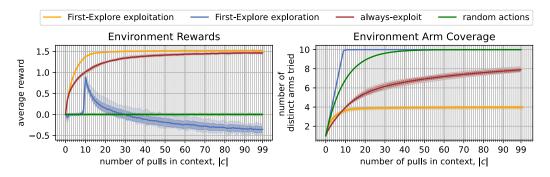


Figure 4: Gaussian Armed Bandit Results. Left: Rewards of different policies. First-Explore exploitation (orange) shows the average reward of the exploit policy when provided the context produced by previous First-Explore explores (blue). The First-Explore exploration (blue) reward is the average reward obtained by the explore policy provided a context of previous explores. Always-exploit (red) attempts to always exploit given the context of its previous explore). Notably, a) First-Explore exploit has significantly higher reward than always-exploit and b) the explore policy gets close to zero average reward for the first ten pulls, and then transitions sharply to prioritizing sampling the high rewarding arms, evidencing intelligent exploration (blue) exhaustively searches all arms until each has been tried once. Notably, the First-Explore exploit (orange) coverage is the worst of all. The First-Explore explore policy having the best coverage and the First-Explore exploit policy having the worst coverage highlights how different exploring are, and how it is beneficial to have a separate policy for each.

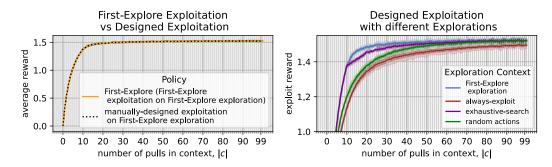


Figure 5: Gaussian Armed Bandit Additional Analysis. Left: Comparison of a manually designed exploit policy (black dots) that selects the arm with highest expected reward (including not-yet-pulled arms) vs the learnt First-Explore exploit policy (orange). When evaluated on the First-Explore explore context, First-Explore is effectively identical to manually designed exploitation. This result shows the effectiveness of the First-Explore exploit policy provided with different explore explore context. Right: A manually designed exploit policy provided with different exploration contexts. Notably, a) always-exploiting (brown) provides worse exploration information than random action selection (green) and b) First-Explore's exploration (blue) matches and then *outperforms* cycling through arms in order (purple). This success shows both the structure and complexity of even such a simple learnt explore policy, further shown in Figure 4, left.

4.2 Dark Treasure-Room

The second problem setting is the Dark Treasure-Room (based on the Darkroom in Laskin et al. [22]). Dark Treasure-Rooms are $w \times h$ grids full of treasure. The agent navigates (up, left, down, or right) to find treasure, and cannot see its surroundings. It receives only its current coordinates (x, y) as observation, with a meta-RL agent also observing past rewards and actions. When the agent encounters a treasure it consumes it, and receives an associated reward (positive or negative). The lack of sight means each individual room is a separate training challenge for a standard RL agent,

with the agent having to memorise the locations of rewards and how to reach them in the agent's parameters, e.g. in the neural network weights. A meta-RL agent has access to a context of all past environment interactions, and so can instead in-context adapt to newly sampled environments, rather than needing to be trained anew.

The training distribution was 9×9 Dark Treasure-Rooms, each having 8 treasure locations. The rewards associated with these locations are uniformly distributed in the range -4 to 2 (i.e., $r_i \sim U[-4, 2]$). The locations of the treasures are randomly sampled uniformly, with overlapping treasure locations having their reward values stack. Importantly, the average value of any location is negative, meaning that visiting a location not in memory gives a negative expected reward. The negative expected reward for visiting new states makes the environment distribution hostile to *coincidental* exploration, thus requiring *sacrificial* exploration.

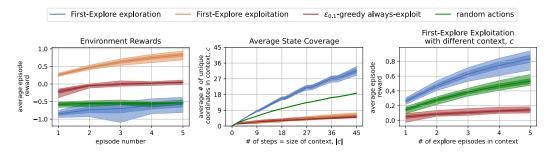


Figure 6: Dark Treasure-Room Results. Left: Average episode rewards. Epsilon-greedy sampled always-exploit (red) learns to avoid negative reward, but not to find positive rewards. First-Explore's exploration policy (blue) and random actions (green) obtain negative reward. Only First-Explore exploitation (orange) finds significant positive reward. Middle: State coverage for different policies. In this environment the average reward of a previously *unseen* location is negative, hence a good always-exploit policy (red) mostly stays still, with the minimal exploration it performs coming via epsilon greedy sampling. First-Explore exploration (blue) covers the space better than random play (green), and noisy always-exploiting (red) catastrophically fails to explore. The First-Explore exploitation coverage (orange) shows how the First-Explore exploit policy repeatedly returns to the same states (the high reward ones found using the First-Explore explore policy). **Right**: How well different contexts inform the learnt exploitation policy. How well a policy covers the state space (middle plot) corresponds to how good that policy is at informing exploitation and producing higher reward.

On this distribution, always-exploiting (even with epsilon-greedy sampling to provide extra exploration, as is common in standard RL) only learns to avoid negative reward (Fig. 6, left green), while First-Explore in-context adapts over multiple explorations to exploit and achieve increasing positive reward with the number of explorations (Fig. 6, left orange). The increased reward with additional explorations demonstrates First-Explore succeeding at learning in an environment where *sacrificial* exploration is needed, and where always-exploiting fails. The failure of always-exploiting can be understood by considering how the policy explores the state space. As each unseen location has negative reward in expectation, the always-exploiting policy learns to avoid entering locations not already in the context, resulting in very poor state space coverage. In contrast, First-Explore exploration does not experience this issue (Fig. 6, middle blue). This difference is because always-exploiting actively avoids *sacrificial* exploration, while First-Explore embraces it. Figure 6, right visualizes the correspondence between coverage and how context informs exploitation. See SI for visualizations of iterated rollouts in these environments and how successive explorations inform exploitation.

These highly consistent First-Explore results across training runs (e.g., the coverage of First-Explore exploration, Fig. 6 middle blue) suggest that the same systematic behaviour is being learnt regardless of the network initialisation and random seed used for training (which determines both the sampled training environments and the action selection). This consistency suggests that First-Explore is learning something fundamental to the domain, and is promising as it potentially means First-Explore might learn a consistent algorithm or heuristic for general exploration if paired with a sufficiently-complex task-distribution.

5 Limitations and Future Work

One limitation with First-Explore is that reward during training can matter. Imagine a chef robot learning a new recipe in a physical home. In this scenario, it is vital the robot behaves safely and does not endanger humans or damage the kitchen while learning; however, it is fine if it cooks poorly, or makes a poor-tasting meal. First-Explore being willing to *sacrifice* reward could be dangerous, as it might ignore a safety reward penalty in order to master the recipe. One potential solution is to infinitely penalize endangerment or damage while training both the explore and exploit policy. This proposed version of First-Explore could actually result in far safer training (via in-context adaption) than attempting to use standard-RL, as the meta-RL policies would have learnt a strong prior of avoiding potentially endangering actions. However, it could be that such a strong penalty could prohibit effective training too. As such, it seems an open question, worth further investigation.

This initial version of First-Explore is also limited in that the explore policy $\pi_{explore,\theta}$ is optimized to provide the single best episode of exploration that will increase the expected reward of the exploit policy $\pi_{exploit,\theta}$ by the greatest amount. Unfortunately, iterated optimal myopic exploration does not necessarily produce an optimal sequence of explorations (Fig. 7). One potential solution is to reward exploration episodes with weighted sums of the rewards of all subsequent exploitations.

A final problem is the challenge of long sequence modelling, with certain environments requiring a very large context. However, it seems likely the rapid progress in context lengths, and the research on more effectively using context, will continue.[9, 22–25]. We also expect improvements in stably training transformers for RL.

6 Discussion

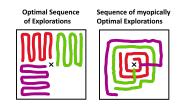


Figure 7: A visualization of wellplanned sequential exploration (left) and myopic exploration (right) of a plane from the origin over multiple episodes. The initial explore (red) is equally good, but myopic exploration hinders the second explore (green) as it must revisit previously seen locations, and more so for the third (purple).

Given that First-Explore uses RL algorithms to train the meta-RL policy, how could it solve hardexploration domains that standard-RL can not? For example, how might First-Explore learn to pick the lock in the locked path environment? The answer is that it is possible if there are always some tasks in the training distribution suitable for the current agent (e.g., a curriculum that leads to learning to pick locks). Initially, the agent does not know how to explore at all and must learn to exploit based on random noise. Once it has learnt rudimentary exploitation, the agent can learn rudimentary exploration. Then it can learn better exploitation, then better exploration, and so on, each time relying on there being tasks within a 'goldilocks zone' of being not too hard and not too easy, see Wang et al. [26]. Learning via this process essentially corresponds to how standard RL can use domain randomization to aid exploration (see Baker et al. [27] for an example of how domain randomization can solve a seemingly hard exploration task). The advantage of First-Explore is that we spend our compute on domain randomization upfront to learn intelligent exploration. Once trained, however, the explore policy can be *very* sample efficient at learning a new task.

Additionally, one might wonder how significant a limitation exploring by exploiting is, given that standard-RL seems to succeed despite it. We argue that it is when one attempts to explore and exploit *intelligently* with human-level adaption on complex tasks that the difference becomes especially significant. In both problem domains, the results show how optimal exploiting and exploring significantly differ, both in how they cover the state or action space, and in how and whether they help achieve high reward, and how this difference matters in order to achieve efficient in-context learning.

7 Conclusion

We identify the problem of attempting to explore by exploiting, and demonstrate that the novel meta-RL framework, First-Explore, solves this problem via the simple modification of learning two policies (one to first explore, another to then exploit). This paradigm of learned, intelligent exploration informing learned exploitation significantly improves meta-RL performance. First-

Explore performs better on even simple domains such as the multi-armed Gaussian-bandit, and massively improves performance on domains that require *sacrificial* exploration, such as the Dark Treasure Room environment (when it has negative average expected treasure value). The results in this paper show First-Explore allows learning basic intelligent exploration strategies, such as exhaustive search for the first ten actions, followed by prioritizing sampling actions with high reward.

We believe combining First-Explore with a curriculum, such as the AdA [9] curriculum, could be a step towards creating algorithms able to exhibit human-level performance on unseen hard-exploration domains, which is one of the core challenges of creating artificial general intelligence (AGI). Provided we can adequately address the real and significant safety concerns associated with developing AGI, such developments would allow us to reap AGI's tremendous potential benefits.

8 Acknowledgments and Disclosure of Funding

Resources used in preparing this research were provided, in part, by the Province of Ontario, the Government of Canada through CIFAR, and companies sponsoring the Vector institute www.vectorinstitute.ai/#partners. This work was further supported by an NSERC Discovery Grant, and a generous donation from Rafael Cosman.

Thanks to Michiel van de Panne, Mark Schmidt and Ken Stanley for discussions, and to Yuni Fuchioka and Ryan Fayyazi for feedback on the writing. We also thank Aaron Dharna, Shengran Hu, and Jenny Zhang (sorted alphabetically) in our lab at the University of British Columbia for discussions and feedback.

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Supplementary Material

A Replicability

For full transparency, replicability, and to make it easier for future scientists to build on our work, we are releasing the training code, visualization code, the code to generate the significance plots, and the environment code. We are also releasing the weights of a trained model for each domain for both First-Explore, and the always-exploit control. Each model contains both the explore and exploit policies as separate heads on the shared trunk. The code is available at https://github.com/btnorman/First-Explore.

B Compute

Each training run commanded a single GPU, specifically a Nvidia T4. Table 1 gives the approximate walltime of each run.

Table 1. Compute Osage Fer Training Kun		
Run	Runtime	
Bandit Always Exploit Bandit First-Explore Dark Treasure-Room Always-Exploit Dark Treasure-Room First-Explore	6 hours 18.5 hours 64 hours 122 hours	

Table 1: Compute Usage Per Training Run

Evaluation (sampling the multiple evaluation environments and performing iterated First-Explore and comparison rollouts) was with a single GPU, and took minutes.

C Training Details

Full training code to replicate the results is provided. The architecture for both domains is a GPT-2 transformer architecture [21] specifically the Jax framework [28] implementation provided by Hugging Face [29], with the code being modified so that token embeddings could be passed rather than token IDs. The different Hyperparameters for the two domains are given in Table 2.

For both domains each token embedding is the sum of a linear embedding of an action, a linear embedding of the observations that followed that action, a linear embedding of the reward that followed that action, a positional encoding of the current timestep, and a positional encoding of the episode number. See the provided code for details. For the dark treasure-room environments a reset

Table 2: Model Hyperparameters				
Hyperparameter	Bandit	Dark		
Hidden Size	128	128		
Number of Heads	4	4		
Number of Layers	3	4		

token was added between episodes that contained the initial observations of the environment, and a unique action embedding corresponding to a non-action. The bandit domain had no such reset token.

For training we use AdamW [30] with a piece-wise linear warm up schedule that interpolates linearly from an initial rate of 0 to the full learning rate in the first 10% training steps, and then interpolates linearly back to zero in the remaining 90% of training steps. Table 3 gives the optimization hyperparameters.

Table 3: Optimization Hyperparameter				
	Hyperparameter	Value		
	Batch Size	128		
	Optimizer	Adam		
	Weight Decay	1e-4		
	Learning Rate	3e-4		

Hyperparameters were chosen based on a relatively modest amount of preliminary experimentation. Finally, for efficiency, all episode rollouts and training was done on GPU using the Jax framework [28].

C.1 Optimization Loss

The First-Explore policies are trained by a novel optimization approach. To learn to exploit we learn the distribution of actions that lead to 'maximal' exploit episodes. Here we define an exploit episode as maximal if it a) has higher or equal reward to the best reward found in all of the previous First-Explore explore and exploit episodes in the current environment, and b) also exceeds a set baseline reward (hyperparameter) for the domain, see Algorithm 3. To learn to *explore* we learn the distribution of actions that lead to 'informative' explore episodes. Informative episodes are those that when added to the context lead to a subsequent exploit episode that a) exceeds the best reward of previous First-Explore explore and exploit episodes and b) has higher reward than the environment baseline. This explore criterion is slightly different from the exploit 'maximal' criterion, as it requires an improvement in reward, see Algorithm 3. The baseline reward is there such that the first First-Explore explore episodes have an incentive to be respectively exploitative and exploratory.

Because in the dark treasure-room each episode is composed of multiple actions, the probability of an initial action leading to any outcome is potentially dependent on the distribution of future actions (e.g., imagine requiring two up actions to reach a reward; the first up action is no better than the first down action if the policy always moves down in the second step). Hence, one must learn the distribution conditional on a rollout policy. This expression is shown in Equation 1 for the case of the exploit distribution. Here "episode is maximal" refers to an exploit episode having higher reward than the baseline reward and the previous First-Explore explores and exploits (see previous paragraph). a_t refers to the current action, and $[a]_{i>t} \sim \pi$ expresses how subsequent actions are taken under the rollout policy.

$$\mathbf{P}(\text{episode is maximal}|a_t, [a]_{i>t} \sim \pi) \tag{1}$$

To learn this distribution, the predicted likelyhoods of actions being 'maximal' or 'informative' are compared to the action distributions of the rollouts that are 'maximal' or 'informative.' The predictions are improved by minimizing a cross entropy loss between the actions observed in the

maximal and informative episodes, and the calculated probability of those actions being selected. This loss is detailed in Algorithm 3 as well as the provided code.

Once learned, the explore and exploit distributions combined with a sampling temperature each then specify a policy that with high probability selects actions likely to lead to good exploitation or good exploration. To ensure that all actions are sampled and to provide more exploration during training (of both the explore and exploit policy), we add a small probability ϵ chance of selecting a random action instead of one sampled from the unmodified explore or exploit policy. This probability is then a hyperparameter that can be tuned. Learning the distributions then allows iteratively updating the rollout policies by each time taking the new rollout policies and learning the new distributions of maximal and informative actions under the rollout policy. The frequency of such updates is then a hyperparameter. The hyperparameters used are given in Table 4.

While preliminary experiments found this meta-RL training method performed best, we believe the First Explore meta-RL framework will work for general approaches too, such as using policy gradient with actor critic, or Muesli [31] which was used in AdA [9].

Table 4: Training Rollout Hyperparameters			
Hyperparameter	Bandit	Darkroom	
Exploit Sampling Temperature	1	1	
Explore Sampling Temperature	1	1	
Policy Update Frequency	every training step	every 10,000 training steps	
ϵ chance of random action selection	0.05	0	
Baseline Reward	0	0	
Training Updates	200,000	1,000,000	

For evaluation, we then sample by taking the argmax over actions, and do not add the ϵ -noise.

```
# rollout conducts an episode when provided with an environment and policy
# and returns all the episode infomation
def model_conditional_actions(\theta, \pi, baseline_reward):
     # sample an environment, and initalize context c and loss values
     m = \text{sample}(\mathcal{M}); c = \text{set}(); \text{loss} = 0
     best_reward_seen = baseline_reward
     for i in range(k): # do k iterated rollouts
          \tau_{\text{explore}} = \text{rollout}(m, \pi_{\text{explore}, c}) \# \text{ explore given context } c
          \tau_{\text{exploit}} = \texttt{rollout}(m, \pi_{\text{exploit}, c \ \cup \ \{\tau_{\text{explore}}\}}) \texttt{ # exploit given } c \ \cup \ \{\tau_{\text{explore}}, \}
          r = \text{final\_reward}(\tau_{\text{exploit}}) \# \text{get the exploit reward}
          # calculate a weight on the episodes
          # non-increasing episodes have zero weight
          # and increasing episodes have weight proportional to reward improvment
          explore_weight = 1_{r>best_reward_seen} * (1 + r - best_reward_seen)
          exploit_weight = 1_{r>best reward seen} * (1 + r - best_reward_seen)
          explore_loss = cross_ent(\pi and \theta predicted probability, \tau_{explore} actions)
          exploit_loss = cross_ent(\pi and \theta predicted probability, \tau_{exploit} actions)
          # update the loss, conditional on the episodes being improvements
          loss = loss + explore_weight * explore_loss
          loss = loss + exploit_weight * exploit_loss
          c = c \cup \{\tau_{\text{explore}}\} # update the context for the next explore
          # update the best reward seen
          best_reward_seen = max(best_reward_seen, final_reward(\tau_{explore})), final_reward(\tau_{explore}))
     return loss
```

Algorithm 3: Training to model conditionally increasing exploits with First-Explore rollouts.

D Dark Treasure-Room Visualizations

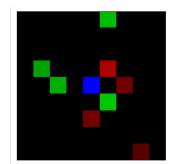


Figure 8: A visualization of the dark treasure-room. The agent's position is visualized by the blue square, positive rewards are in green, and negative rewards are in red, with the magnitude of reward being visualized by the colour intensity. When the agent enters a reward location it consumes the reward, and for that timestep is visualized as having the additive mixture of the two colours.

Here are example iterated First-Explore rollouts of the two trained policies, $\pi_{explore}$, $\pi_{exploit}$, visualized for a single sampled darkroom.

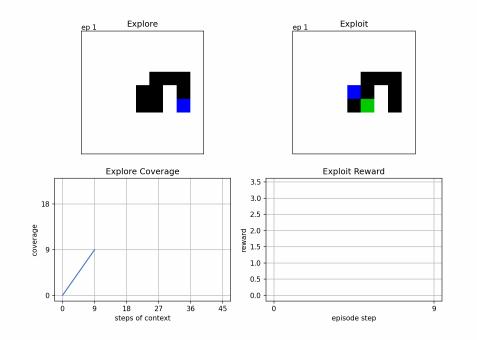


Figure 9: The first (First-Explore) explore episode. **Top left** visualizes the last step of a First-Explore explore episode, with the locations that are not in the cumulative context being coloured white, as the agent is blind to them (having no observations or memory of those locations). This figure plots the end of the first exploration, and shows a reward has been found. **Bottom left** visualizes the coverage of the cumulative context by plotting the total number of unique locations visited by the exploration against the cumulative episode step count. In this explore, the agent never doubled back on itself, which is good as it is optimal to have as many unique locations visited as possible. **Top right** visualizes a step in a First-Explore exploit episode, with the locations that are in context visualized. The agent can effectively 'see' those locations in its memory. **Bottom right** plots the exploit episode, the agent has yet to move and encounter rewards, but will have done so in the subsequent visualizations.

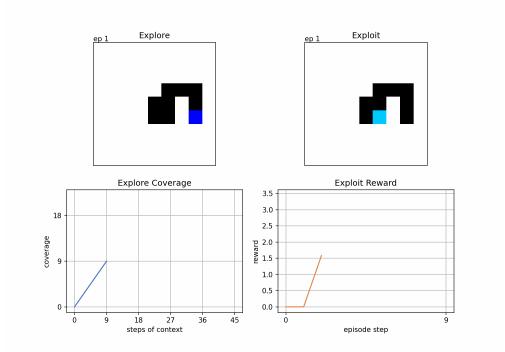


Figure 10: The first (First-Explore) exploit episode. This figure uses the same visualization design as Figure 9. **Left top and bottom** are the same as in Figure 9, and of the explore context, not the current exploit episode. **Right top**, the agent (the light blue square) has found the reward in the first two steps. Consuming the reward is visualized by the agent color and the reward color being combined. **Right bottom**, the associated episode reward is shown.

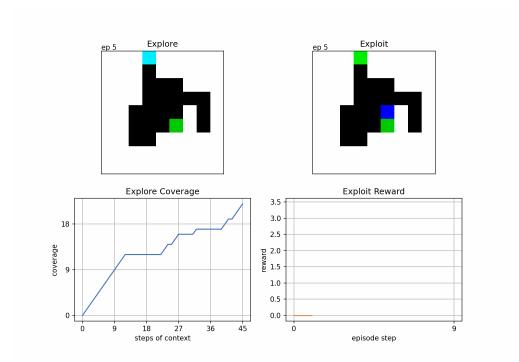


Figure 11: The fifth (First-Explore) explore episode. At the end of the 5th explore episode the agent has discovered a new positive reward at the top of the room, and can now 'see' it in memory. The new information presents an opportunity for the exploit policy to obtain both rewards, but it only has exactly enough time-steps in an episode to navigate to do so, and thus cannot make a mistake navigating.

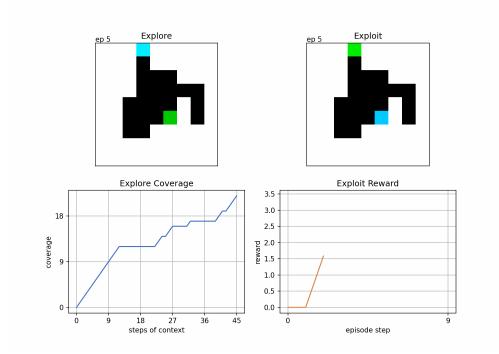


Figure 12: The first reward of the fifth (First-Explore) exploit episode. Two steps into the episode the agent (in consuming, light blue) has consumed the nearby reward.

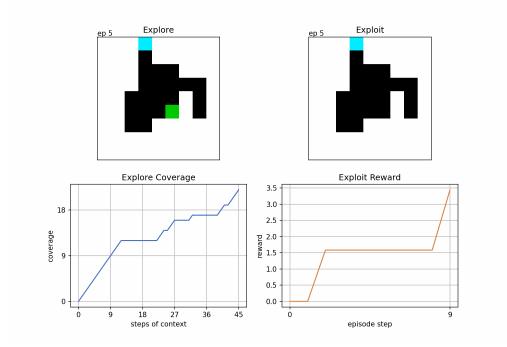


Figure 13: The end of the fifth (First-Explore) exploit episode. After consuming the nearby reward the agent has reached the newly discovered reward at the top of the room and consumed it. This success required making no mistakes and pathing first to the nearby reward then to the top one on the first try. This inference is possible because the quickest the agent can reach both rewards is exactly the length of the episode (9 steps). The pathing in this episode is an example of intelligent exploitation, as after the information reveal (the reward at the top) of a single episode the agent appropriately changes its policy based on the context and using the learnt environment prior (e.g., how to navigate), produces a highly structured behaviour (pathing with no mistakes).