Safe Policy Search for Lifelong Reinforcement Learning with Sublinear Regret

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Abstract
Lifelong reinforcement learning provides a promising framework for developing versatile agents that can accumulate knowledge over a lifetime of experience and rapidly learn new tasks by building upon prior knowledge. However, current lifelong learning methods exhibit non-vanishing regret as the amount of experience increases, and include limitations that can lead to suboptimal or unsafe control policies. To address these issues, we develop a lifelong policy gradient learner that operates in an adversarial setting to learn multiple tasks online while enforcing safety constraints on the learned policies. We demonstrate, for the first time, sublinear regret for lifelong policy search, and validate our algorithm on several benchmark dynamical systems and an application to quadrotor control.

1. Introduction
Reinforcement learning (RL) (Busoniu et al., 2010; Sutton & Barto, 1998) often requires substantial experience before achieving acceptable performance on individual control problems. One major contributor to this issue is the tabula-rasa assumption of typical RL methods, which learn from scratch on each new task. In these settings, learning performance is directly correlated with the quality of the acquired samples. Unfortunately, the amount of experience necessary for high-quality performance increases exponentially with the tasks’ degrees of freedom, inhibiting the application of RL to high-dimensional control problems.

When data is in limited supply, transfer learning can significantly improve model performance on new tasks by reusing previous learned knowledge during training (Taylor & Stone, 2009; Gheshlaghi Azar et al., 2013; Lazaric, 2011; Ferrante et al., 2008; Bou Ammar et al., 2012). Multi-task learning (MTL) explores another notion of knowledge transfer, in which task models are trained simultane-
2. Background

2.1. Reinforcement Learning

An RL agent sequentially chooses actions to minimize its expected cost. Such problems are formalized as Markov decision processes (MDPs) \( \langle X, U, P, c, \gamma \rangle \), where \( X \subseteq \mathbb{R}^d \) is the (potentially infinite) state space, \( U \subseteq \mathbb{R}^d \) is the set of all possible actions, \( P : X \times U \times X \rightarrow [0, 1] \) is a state transition probability describing the system’s dynamics, \( c : X \times U \times X \rightarrow \mathbb{R} \) is the cost function measuring the agent’s performance, and \( \gamma \in [0, 1] \) is a discount factor. At each time step \( m \), the agent is in state \( x_m \in X \) and must choose an action \( u_m \in U \), transitioning it to a new state \( x_{m+1} \sim P(x_{m+1} | x_m, u_m) \) and yielding a cost \( c_{m+1} = c(x_{m+1}, u_m, x_m) \). The sequence of state-action pairs forms a trajectory \( \tau = [x_k, M = 1, u_0, M = 1] \) over a (possibly infinite) horizon \( M \). A policy \( \pi : X \times U \rightarrow [0, 1] \) specifies a probability distribution over state-action pairs, where \( \pi(u|x) \) represents the probability of selecting an action \( u \) in state \( x \). The goal of RL is to find an optimal policy \( \pi^* \) that minimizes the total expected cost.

Policy search methods have shown success in solving high-dimensional problems, such as robotic control (Kober & Peters, 2011; Peters & Schaal, 2008a; Sutton et al., 2000). These methods represent the policy \( \pi(u|x) \) using a vector \( \alpha \in \mathbb{R}^d \) of control parameters. The optimal policy \( \pi^* \) is found by determining the parameters \( \alpha^* \) that minimize the expected average cost:

\[
l(\alpha) = \sum_{k=1}^{n} p_\alpha(\tau^{(k)}) C(\tau^{(k)}) ,
\]

where \( n \) is the total number of trajectories, and \( p_\alpha(\tau^{(k)}) \) and \( C(\tau^{(k)}) \) are the probability and cost of trajectory \( \tau^{(k)} \):

\[
p_\alpha(\tau^{(k)}) = P_0(x_0^{(k)}) \prod_{m=0}^{M-1} P(x_{m+1}^{(k)} | x_m^{(k)}, u_m^{(k)}) \times \pi_\alpha(u_{m}^{(k)}) x_{m}^{(k)}
\]

\[
C(\tau^{(k)}) = \frac{1}{M} \sum_{m=0}^{M-1} c(x_{m+1}^{(k)}, u_{m}^{(k)}, x_{m}^{(k)})
\]

with an initial state distribution \( P_0 : X \rightarrow [0, 1] \). We handle a constrained version of policy search, in which optimality not only corresponds to minimizing the total expected cost, but also to ensuring that the policy satisfies safety constraints. These constraints vary between applications, for example corresponding to maximum joint torque or prohibited physical positions.

2.2. Online Learning & Regret Analysis

In this paper, we employ a special form of regret minimization games, which we briefly review here. A regret minimization game is a triple \( (K, F, R) \), where \( K \) is a non-empty decision set, \( F \) is the set of moves of the adversary which contains bounded convex functions from \( \mathbb{R}^n \) to \( \mathbb{R} \), and \( R \) is the total number of rounds. The game proceeds in rounds, where at each round \( j = 1, \ldots, R \), the agent chooses a prediction \( \theta_j \in K \) and the environment (i.e., the adversary) chooses a loss function \( l_j \in F \). At the end of the round, the loss function \( l_j \) is revealed to the agent and the decision \( \theta_j \) is revealed to the environment. In this paper, we handle the full-information case, where the agent may observe the entire loss function \( l_j \) as its feedback and can exploit this in making decisions. The goal is to minimize the cumulative regret \( \sum_{j=1}^{R} l_j(\theta_j) - \inf_{\theta \in K} \sum_{j=1}^{R} l_j(\theta) \).

When analyzing the regret of our methods, we use a variant of this definition to handle the lifelong RL case:

\[
\mathcal{R}_R = \sum_{j=1}^{R} l_j(\theta_j) - \inf_{\theta \in K} \sum_{j=1}^{R} l_j(\theta) ,
\]

where \( l_j(\cdot) \) denotes the loss of task \( t \) at round \( j \).

For our framework, we adopt a variant of regret minimization called “Follow the Regularized Leader,” which minimizes regret in two steps. First, the unconstrained solution \( \tilde{\theta} \) is determined (see Sect. 4.1) by solving an unconstrained optimization over the accumulated losses observed so far. Given \( \tilde{\theta} \), the constrained solution is then determined by learning a projection into the constraint set via Bregman projections (see Abbasi-Yadkori et al. (2013)).

3. Safe Lifelong Policy Search

We adopt a lifelong learning framework in which the agent learns multiple RL tasks consecutively, providing it the opportunity to transfer knowledge between tasks to improve learning. Let \( T \) denote the set of tasks, each element of which is an MDP. At any time, the learner may face any previously seen task, and so must strive to maximize its performance across all tasks. The goal is to learn optimal policies \( \pi_1^*, \ldots, \pi_T^* \) for all tasks, where policy \( \pi_t^* \) for task \( t \) is parameterized by \( \alpha_t ^* \in \mathbb{R}^d \). In addition, each task is equipped with safety constraints to ensure acceptable policy behavior: \( A_t \alpha_t \leq b_t \), with \( A_t \in \mathbb{R}^{d \times d} \) and \( b_t \in \mathbb{R}^d \) representing the allowed policy combinations. The precise form of these constraints depends on the application domain, but this formulation supports constraints on (e.g.) joint torque, acceleration, position, etc.

At each round \( j \), the learner observes a set of \( n_t \) trajectories \( \{ \tau_{t,j}^{(1)}, \ldots, \tau_{t,j}^{(n_t)} \} \) from a task \( t_j \in T \), where each trajectory has length \( M_{t,j} \). To support knowledge transfer between tasks, we assume that each task’s policy parameters \( \alpha_t \in \mathbb{R}^d \) at round \( j \) can be written as a linear combination of a shared latent basis \( L \in \mathbb{R}^{d \times k} \) with coefficient vectors \( s_t \in \mathbb{R}^k \); therefore, \( \alpha_t = L s_t \). Each column of \( L \) represents a chunk of transferrable knowledge; this task construction has been used successfully in previous
Therefore, our goal is to minimize the following objective:

$$
\min_{L,S} \sum_{j=1}^{r} \left[ \eta_j l_j \left( L s_{t_j} \right) \right] + \mu_1 \|S\|_F^2 + \mu_2 \|L\|_F^2
$$

subject to:

- $A_{t_j} \alpha_{t_j} \leq b_{t_j}$ for all $t_j \in I_r$
- $\lambda_{\min} \left( LL^T \right) \geq p$ and $\lambda_{\max} \left( LL^T \right) \leq q$

where $p$ and $q$ are the constraints on $\|L\|_F$, $\eta_j \in \mathbb{R}$ are design weighting parameters, $I_r = \{t_1, \ldots, t_r\}$ denotes the set of all tasks observed so far through round $r$, and $S$ is the collection of all coefficients $S(:,h) = \begin{cases} s_{th} & \text{if } t_h \in I_r \\ 0 & \text{otherwise} \end{cases}$ for all $h \in \{1, \ldots, |T|\}$.

The loss function $l_j(\alpha_{t_j})$ in Eq. (4) corresponds to a policy gradient learner for task $t_j$, as defined in Eq. (1). Typical policy gradient methods (Kober & Peters, 2011; Sutton et al., 2000) maximize a lower bound of the expected cost $l_j(\alpha_{t_j})$, which can be derived by taking the logarithm and applying Jensen’s inequality:

$$
\log \left[ l_j(\alpha_{t_j}) \right] = \log \left[ \sum_{k=1}^{n_{t_j}} \pi_{\alpha_{t_j}}(t_{j}^{(k)}) C(t_{j}^{(k)}) \left( \tau_{j}^{(k)} \right) \right] \tag{5}
$$

$$
\geq \log \left[ \eta_j \right] + E \left[ \sum_{k=1}^{M_{t_j} - 1} \log \left[ \pi_{\alpha_{t_j}} \left( u_{m(t_{j})} | x_{m(t_{j})} \right) \right] \right] + \text{const}
$$

Therefore, our goal is to minimize the following objective:

$$
\mathcal{E}_r = \sum_{j=1}^{r} \left[ \frac{\eta_j}{n_{t_j}} \sum_{k=1}^{M_{t_j} - 1} \sum_{m=0}^{n_{t_j}} \log \left[ \pi_{\alpha_{t_j}} \left( u_{m(t_{j})} | x_{m(t_{j})} \right) \right] \right] + \mu_1 \|S\|_F^2 + \mu_2 \|L\|_F^2
$$

subject to:

- $A_{t_j} \alpha_{t_j} \leq b_{t_j}$ for all $t_j \in I_r$
- $\lambda_{\min} \left( LL^T \right) \geq p$ and $\lambda_{\max} \left( LL^T \right) \leq q$

### 3.1. Online Formulation

The optimization problem above can be mapped to the standard online learning framework by unrolling $L$ and $S$ into a vector $\theta = [\text{vec}(L) \text{ vec}(S)]^T$, Choosing $\Omega_0(\theta) = \mu_2 \sum_{i=1}^{d+k+|T|} \theta_i^2 + \mu_1 \sum_{i=d+k+|T|+l} \theta_i^2$, and $\Omega_1(\theta) = \Omega_{t+1}(\theta) + \eta_j l_j(\theta)$, we can write the safe lifelong policy search problem (Eq. (6)) as:

$$
\theta_{t+1} = \arg \min_{\theta \in K} \Omega_{t+1}(\theta), \tag{7}
$$

where $K \subseteq \mathbb{R}^{d+k+|T|}$ is the set of allowable policies under the given safety constraints. Note that the loss for task $t_j$

3We describe later how to set the $\eta$’s later in Sect. 5 to obtain regret bounds, and leave them as variables now for generality.

can be written as a bilinear product in $\theta$:

$$
l_j(\theta) = -\frac{1}{n_{t_j}} \sum_{k=1}^{M_{t_j} - 1} \sum_{m=0}^{n_{t_j}} \log \left[ \pi_{\theta_{t_j}}(u_{m(t_{j})} | x_{m(t_{j})}) \right] + \text{const}
$$

$$
\Theta_L = \begin{bmatrix} \theta_1 & \ldots & \theta_{d(k-1)+1} \\
\vdots & \ddots & \vdots \\
\theta_d & \ldots & \theta_{dk} \end{bmatrix}, \quad \Theta_{st_j} = \begin{bmatrix} \theta_{dk+1} \\
\vdots \end{bmatrix}.
$$

We see that the problem in Eq. (7) is equivalent to Eq. (6) by noting that at $r$ rounds, $\Omega_r = \sum_{j=1}^{r} \eta_j l_j(\theta) + \Omega_0(\theta)$.

### 4. Online Learning Method

We solve Eq. (7) in two steps. First, we determine the unconstrained solution $\hat{\theta}_{r+1}$ where $K = \mathbb{R}^{d+k+|T|}$ (see Sect. 4.1). Given $\hat{\theta}_{r+1}$, we derive the constrained solution $\overline{\theta}_{r+1}$ by learning a projection $\text{Proj}_{\Omega_{r+1}}(\hat{\theta}_{r+1})$ to the constraint set $K \subseteq \mathbb{R}^{d+k+|T|}$, which amounts to minimizing the Bregman divergence over $\Omega_{r+1}(\theta)$ (see Sect. 4.2). The complete approach is given in Algorithm 1 and is available as a software implementation on the authors’ websites.

#### 4.1. Unconstrained Policy Solution

Although Eq. (6) is not jointly convex in both $L$ and $S$, it is separably convex (for log-concave policy distributions). Consequently, we follow an alternating optimization approach, first computing $L$ while holding $S$ fixed, and then updating $S$ given the acquired $L$. We detail this process for two popular PG learners, eREINFORCE (Williams, 1992) and eNAC (Peters & Schaal, 2008b). The derivations of the update rules below can be found in Appendix A.

These updates are governed by learning rates $\beta$ and $\lambda$ that decay over time; $\beta$ and $\lambda$ can be chosen using line-search methods as discussed by Boyd & Vandenberghe (2004). In our experiments, we adopt a simple yet effective strategy, where $\beta = c\beta - 1$ and $\lambda = c\lambda - 1$, with $0 < c < 1$.

#### Step 1: Updating $L$

Holding $S$ fixed, the latent repository can be updated according to:

$$
L_{\beta+1} = L_{\beta} - \eta_{L} \nabla_{L} e_r(L, S), \quad \text{eREINFORCE}
$$

$$
L_{\beta+1} = L_{\beta} - \eta_{L} G^{-1}(L_{\beta}, S_{\beta}) \nabla_{L} e_r(L, S), \quad \text{eNAC}
$$

with learning rate $\eta_{L} \in \mathbb{R}$, and $G^{-1}(L, S)$ as the inverse of the Fisher information matrix (Peters & Schaal, 2008b).

In the special case of Gaussian policies, the update for $L$...
can be derived in a closed form as $L_{j+1} = Z_L^{-1}v_L$, where

$$Z_L = 2\mu_2 I_{dk \times dk} + \sum_{j=1}^r \eta_t j n_t \sigma_{tj}^{-1} \sum_{k=1}^{M_t-1} \text{vec} \left( \Phi s_{tj}^T \right) \left( \Phi^T \otimes s_{tj}^T \right)$$

$$v_L = \sum_{j} \eta_t j n_t \sigma_{tj}^{-1} \sum_{k=1}^{M_t-1} \text{vec} \left( u_{m,()}^j \phi s_{tj}^T \right) ,$$

$\sigma_{tj}^2$ is the covariance of the Gaussian policy for a task $j$, and $\Phi = \Phi \left( x_{m,()} \right)$ denotes the state features.

**Step 2: Updating $S$** Given the fixed basis $L$, the coefficient matrix $S$ is updated column-wise for all $j$ in $\mathcal{I}_r$:

$$s_{\lambda+1}^{(tj)} = s_{\lambda+1}^{(tj)} - \eta_t \nabla_{s_{tj}} c_r(L, S) \quad \text{(eREINFORCE)}$$

$$s_{\lambda+1}^{(tj)} = s_{\lambda+1}^{(tj)} - \eta_t \nabla_{s_{tj}} c_r(L, S) \quad \text{(eNAC)}$$

with learning rate $\eta_t \in \mathbb{R}$. For Gaussian policies, the closed-form of the update is $s_{tj} = Z_{\lambda+1} s_{tj}$, where

$$Z_{s_{tj}} = 2\mu_1 I_{dk \times dk} + \sum_{i=1}^r \eta_t j n_t \sigma_{tj}^{-1} \sum_{k=1}^{M_t-1} L^T \Phi \Phi^T L$$

$$u_{tj} = \sum_{i=1}^r \eta_t j n_t \sigma_{tj}^{-1} \sum_{k=1}^{M_t-1} u_{m,()}^j L^T \Phi .$$

### 4.2. Constrained Policy Solution

Once we have obtained the unconstrained solution $\tilde{\theta}_{r+1}$ (which satisfies Eq. (7), but can lead to policy parameters in unsafe regions), we then derive the constrained solution to ensure safe policies. We learn a projection

$$\text{Proj}_{\Omega,\mathcal{K}} \left( \tilde{\theta}_{r+1} \right)$$

from $\tilde{\theta}_{r+1}$ to the constraint set:

$$\hat{\theta}_{r+1} = \arg \min_{\theta \in \mathcal{K}} B_{\Omega,\mathcal{K}} \left( \theta, \tilde{\theta}_{r+1} \right) , \quad \text{(8)}$$

where $\Omega_{\mathcal{K}}$ is the Bregman divergence over $\mathcal{K}$:

$$\Omega_{\mathcal{K}}(\theta, \tilde{\theta}_{r+1}) = \Omega_r(\theta) - \Omega_r(\tilde{\theta}_{r+1})$$

$$\text{trace} \left( \nabla_\theta \Omega_r(\tilde{\theta}_{r+1}) (\theta - \tilde{\theta}_{r+1}) \right) .$$

Solving Eq. (8) is computationally expensive since $\Omega_{\mathcal{K}}(\theta)$ includes the sum back to the original round. To remedy this problem, ensure the stability of our approach, and guarantee that the constrained solution for all observed tasks lie within a bounded region, we linearize the current-round loss function $\ell_{t_r}(\theta)$ around the constrained solution of the previous round $\tilde{\theta}_{r}$:

$$\ell_{t_r}(\tilde{\theta}) = \hat{f}_{t_r}(\tilde{\theta})^T \tilde{\theta} , \quad \text{(9)}$$

where

$$\hat{f}_{t_r}(\tilde{\theta}) = \nabla \ell_{t_r}(\tilde{\theta}) \left|_{\tilde{\theta}} \right. - \nabla \ell_{t_r}(\tilde{\theta}) \left|_{\tilde{\theta}} \right. .$$

Given the above linear form, we can rewrite the optimization problem in Eq. (8) as:

$$\hat{\theta}_{r+1} = \arg \min_{\theta \in \mathcal{K}} B_{\Omega,\mathcal{K}}(\theta, \tilde{\theta}_{r+1}) . \quad \text{(10)}$$

Consequently, determining safe policies for lifelong policy search reinforcement learning amounts to solving:

$$\min_{L,S} \mu_1 ||S||^2 + \mu_2 ||L||^2$$

$$+ 2\mu_1 \text{trace} \left( S^T \left|_{\tilde{\theta}_{r+1}} \right. S \right) + 2\mu_2 \text{trace} \left( L^T \left|_{\tilde{\theta}_{r+1}} \right. L \right)$$

s.t. $A_{t_j} L s_{t_j} \leq b_{t_j}$ \forall $t_j \in \mathcal{I}_r$

$$L L^T \leq p I$$ and $L L^T \geq q I .$$

To solve the optimization problem above, we start by converting the inequality constraints to equality constraints by introducing slack variables $c_{t_j} \geq 0$. We also guarantee that these slack variables are bounded by incorporating $||c_{t_j}|| \leq c_{max}$, \forall $t_j \in \{1, \ldots, |\mathcal{T}|\}$:

$$\min_{L,S,C} \mu_1 ||S||^2 + \mu_2 ||L||^2$$

$$+ 2\mu_1 \text{trace} \left( \left|_{\tilde{\theta}_{r+1}} \right. S \right) + 2\mu_2 \text{trace} \left( \left|_{\tilde{\theta}_{r+1}} \right. L \right)$$

s.t. $A_{t_j} L s_{t_j} = b_{t_j} - c_{t_j}$ \forall $t_j \in \mathcal{I}_r$

$c_{t_j} > 0$ and $||c_{t_j}|| \leq c_{max}$ \forall $t_j \in \mathcal{I}_r$

$L L^T \leq p I$ and $L L^T \geq q I .$

With this formulation, learning $\text{Proj}_{\Omega,\mathcal{K}}(\hat{\theta}_{r+1})$ amounts to solving second-order cone and semi-definite programs.

### 4.2.1. Semi-Definite Program for Learning $L$

This section determines the constrained projection of the shared basis $L$ given fixed $S$ and $C$. We show that $L$ can be acquired efficiently, since this step can be relaxed to solving a semi-definite program in $L L^T$ (Boyd & Vandenberghe, 2004). To formulate the semi-definite program, note that

$$\text{trace} \left( \left|_{\tilde{\theta}_{r+1}} \right. L \right) = \sum_{i=1}^k \left| \ell_{r+1}^T \right| \left|_{\tilde{\theta}_{r+1}} \right. l_i .$$

From the constraint set, we recognize:

$$s_{t_j}^T L^T = (b_{t_j} - c_{t_j}) \left( A_{t_j}^T \right)^T$$

$$\implies s_{t_j}^T L^T L s_{t_j} = a_{t_j}^T L s_{t_j} \quad \text{with} \quad a_{t_j} = A_{t_j} \left( b_{t_j} - c_{t_j} \right) .$$
Algorithm 1 Safe Online Lifelong Policy Search

1: **Inputs:** Total number of rounds \( R \), weighting factor \( \eta = \frac{1}{\sqrt{R}} \), regularization parameters \( \mu_1 \) and \( \mu_2 \), constraints \( p \) and \( q \), number of latent basis vectors \( k \).
2: \( S = \text{zeros}(k, |T|) \), \( L = \text{diag}_k(\zeta) \) with \( p \leq \zeta^2 \leq q \)
3: for \( j = 1 \) to \( R \) do
4: \( t_j \leftarrow \text{sampleTask()} \), and update \( I_j \)
5: Compute unconstrained solution \( \hat{\theta}_{j+1} \) (Sect. 4.1)
6: Fix \( S \) and \( C \), and update \( L \) (Sect. 4.2.1)
7: Use updated \( L \) to derive \( S \) and \( C \) (Sect. 4.2.2)
8: end for
9: **Output:** Safety-constrained \( L \) and \( S \)

Since spectrum \((LL^T) = \text{spectum}(L^TL)\), we can write:
\[
\min_{X \in S_{++}} \mu_2 \text{trace}(X) + 2\mu_2 \left\| L \right\|_{\hat{\theta}_{j+1}} \sqrt{\text{trace}(X)} \\
\text{s.t.} s^T j X s_j = a^T j a_j \quad \forall t_j \in I_r \\
\quad X \leq pI \quad \text{and} \quad X \geq qI \quad , \quad \text{with} \quad X = L^TL.
\]

4.2.2. Second-Order Cone Program for Learning Task Projections

Having determined \( L \), we can acquire \( S \) and update \( C \) by solving a second-order cone program (Boyd & Vandenberghe, 2004) of the following form:
\[
\min_{s_1, \ldots, s_j, c_1, \ldots, c_j} \mu_1 \sum_{j=1}^r \left\| s_j \right\|_2^2 + 2\mu_1 \sum_{j=1}^r a^T j s_j \\
\text{s.t.} \quad A^T j L s_j \leq b_j - c_j \\
\quad c_j > 0 \quad \left\| c_j \right\|_2^2 \leq c^2 \quad \forall t_j \in I_r.
\]

5. Theoretical Guarantees

This section quantifies the performance of our approach by providing formal analysis of the regret after \( R \) rounds. We show that the safe lifelong reinforcement learner exhibits sublinear regret in the total number of rounds. Formally, we prove the following theorem:

**Theorem 1** (Sublinear Regret). After \( R \) rounds and choosing \( \forall t_j \in I_R \), \( \eta_j = \eta = \frac{1}{\sqrt{R}} \), \( L \hat{\theta}_i = \text{diag}_k(\zeta) \), with \( \text{diag}_k(\cdot) \) being a diagonal matrix among the \( k \) columns of \( L \), \( p \leq \zeta^2 \leq q \), and \( S \hat{\theta}_i = 0_{k \times |T|} \), the safe lifelong reinforcement learner exhibits sublinear regret of the form:
\[
\sum_{j=1}^R l_j \left( \hat{\theta}_j \right) - l_j \left( \hat{\theta}_j \right) = O \left( \sqrt{R} \right) \quad \text{for any} \quad \theta \in K.
\]

**Proof Roadmap:** The remainder of this section completes our proof of Theorem 1; further details are given in Appendix B. We assume linear losses for all tasks in the constrained case in accordance with Sect. 4.2. Although linear losses for policy search RL are too restrictive given a single operating point, as discussed previously, we remedy this problem by generalizing to the case of piece-wise linear losses, where the linearization operating point is a resultant of the optimization problem. To bound the regret, we need to bound the dual Euclidean norm (which is the same as the Euclidean norm) of the gradient of the loss function, then prove Theorem 1 by bounding: (1) task \( t_j \)'s gradient loss (Sect. 5.1), and (2) linearized losses with respect to \( L \) and \( S \) (Sect. 5.2).

5.1. Bounding \( t_j \)'s Gradient Loss

We start by stating essential lemmas for Theorem 1; due to space constraints, proofs for all lemmas are available in the supplementary material. Here, we bound the gradient of a loss function \( l_j(\theta) \) at round \( r \) under Gaussian policies.

**Assumption 1.** We assume that the policy for a task \( t_j \) is Gaussian, the action set \( U \) is bounded by \( u_{\text{max}} \), and the feature set is upper-bounded by \( \Phi_{\text{max}} \).

**Lemma 1.** Assume task \( t_j \)'s policy at round \( r \) is given by \( \pi_{\theta_j}(u_{m,t}(k,t_j), x_{m,t}(k,t_j)) \) at \( \theta_j \), \( \Phi \), \( \sigma_j \).

for states \( x_{m,t}(k,t_j) \in X_j \) and actions \( u_{m,t}(k,t_j) \in U_j \). For
\[
l_j(\theta_j) = -\sum_{k=1}^n \sum_{m=0}^{M-1} \log \left( \pi_{\theta_j}(u_{m,t}(k,t_j)|x_{m,t}(k,t_j)) \right),
\]
the gradient \( \nabla_{\theta_j} l_j(\theta_j) \) satisfies
\[
\left\| \nabla_{\theta_j} l_j(\theta_j) \right\|_2 \leq \left\| M_{l_j} \left( u_{\text{max}} + \max_{t\in I_{j-1}} \{ \left\| A_{k,t} \right\|_2 (\left\| b_{k,t} \right\|_2 + c_{\text{max}}) \right) \Phi_{\text{max}} \right) \Phi_{\text{max}} \right. \]

for all trajectories and all tasks, with \( u_{\text{max}} = \max_{k,m} \{ u_{m,t}(k,t_j) \} \) and \( \Phi_{\text{max}} = \Phi_{\text{max}} \).

5.2. Bounding Linearized Losses

As discussed previously, we linearize the loss of task \( t_r \) around the constraint solution of the previous round \( \hat{\theta} \). To acquire the regret bounds in Theorem 1, the next step is to bound the dual norm, \( \left\| f_{t_r} \right\|_2 \). It can be easily seen

\[
\left\| f_{t_r} \right\|_2 \leq \left\| \hat{\theta}_r \right\|_2 + \left\| \nabla \theta l_{t_r}(\theta) \right\|_2 + \left\| \nabla \theta l_{t_r}(\theta) \right\|_2 \times \left\| \hat{\theta}_r \right\|_2
\]

Lemma 2

Lemma 3

\( \dagger \)Please note that derivations for other forms of log-concave policy distributions could be derived in similar manner. In this work, we focus on Gaussian policies since they cover a broad spectrum of real-world applications.
Lemma 3. The norm of the gradient of the loss function evaluated at \( \theta \) satisfies

\[
\left\| \nabla_{\theta} l_r(\theta) \right\|_2 \leq \left\| \nabla_{\alpha_r} l_r(\theta) \right\|_2 \left( q \times d + \max_{t_k \in \mathcal{I}_{r-1}} \left\{ \left\| A_{t_k}^l \right\|_2 \left( \left\| b_{t_k} \right\|_2 + c_{\max}^2 \right) + 1 \right\} \right).
\]

To finalize the bound of \( \left\| \hat{f}_r \right\|_2 \) as needed for deriving the regret, we must derive an upper-bound for \( \left\| \hat{\theta}_r \right\|_2 \):

Lemma 3. The \( L_2 \) norm of the constraint solution at round \( r-1 \), \( \left\| \hat{\theta}_r \right\|_2 \) is bounded by

\[
\left\| \hat{\theta}_r \right\|_2 \leq q \times d \left[ 1 + |\mathcal{I}_{r-1}| \frac{1}{p^2} \max_{t_k \in \mathcal{I}_{r-1}} \left\{ \left\| A_{t_k}^l \right\|_2 \left( \left\| b_{t_k} \right\|_2 + c_{\max}^2 \right) \right\} \right],
\]

where \( |\mathcal{I}_{r-1}| \) is the number of unique tasks observed so far.

Given the previous two lemmas, we can prove the bound for \( \left\| \hat{f}_r \right\|_2 \):

Lemma 4. The \( L_2 \) norm of the linearizing term of \( l_r(\theta) \) around \( \hat{\theta}_r \), \( \left\| \hat{f}_r \right\|_2 \), is bounded by

\[
\left\| \hat{f}_r \right\|_2 \leq \left\| \nabla_{\theta} l_r(\theta) \right\|_2 \left( 1 + \left\| \hat{\theta}_r \right\|_2 \right) + l_r(\theta) \left\| \hat{\theta}_r \right\|_2 \right) = \gamma_1(r) \left( 1 + \gamma_2(r) \right) + \delta_{t_r},
\]

where \( \delta_{t_r} \) is the constant upper-bound on \( l_r(\theta) \left\| \hat{\theta}_r \right\|_2 \), and

\[
\gamma_1(r) = \frac{1}{n_t} \frac{d^2}{\sigma_{t_r}^2} \left[ u_{\max} + \max_{t_k \in \mathcal{I}_{r-1}} \left\{ \left\| A_{t_k}^l \right\|_2 \left( \left\| b_{t_k} \right\|_2 + c_{\max}^2 \right) \right\} \Phi_{\max} \right] \times \left( \frac{d}{p} \sqrt{2q} \max_{t_k \in \mathcal{I}_{r-1}} \left\{ \left\| A_{t_k}^l \right\|_2 \left( \left\| b_{t_k} \right\|_2 + c_{\max}^2 + \sqrt{qd} \right) \right\} \gamma_2(r) \leq \sqrt{q \times d} + \sqrt{|\mathcal{I}_{r-1}|} \max_{t_k \in \mathcal{I}_{r-1}} \left\{ \left\| A_{t_k}^l \right\|_2 \left( \left\| b_{t_k} \right\|_2 + c_{\max}^2 \right) \right\}.
\]

5.3. Completing the Proof of Sublinear Regret

Given the lemmas in the previous section, we now can derive the sublinear regret bound given in Theorem 1. Using results developed by Abbasi-Yadkori et al. (2013), it is easy to see that

\[
\nabla_{\theta} \Omega_0(\hat{\theta}_j) - \nabla_{\theta} \Omega_0(\hat{\theta}_{j+1}) = \eta_j \hat{f}_j \left\| \hat{\theta}_j \right\|_2.
\]

From the convexity of the regularizer, we obtain:

\[
\Omega_0(\hat{\theta}_j) \geq \Omega_0(\hat{\theta}_{j+1}) + \left\langle \nabla \Omega_0(\hat{\theta}_{j+1}), \hat{\theta}_j - \hat{\theta}_{j+1} \right\rangle + \frac{1}{2} \left\| \hat{\theta}_j - \hat{\theta}_{j+1} \right\|_2.
\]

We have:

\[
\left\| \hat{\theta}_j - \hat{\theta}_{j+1} \right\|_2 \leq \eta_j \left\| \hat{f}_j \right\|_2.
\]

Therefore, for any \( u \in K \)

\[
\sum_{j=1}^{r} \eta_j \left( l_j(\hat{\theta}_j) - l_j(u) \right) \leq \sum_{j=1}^{r} \left\| \hat{f}_j \right\|_2 \left\| \hat{\theta}_j \right\|_2 + \frac{1}{\eta} \left( \Omega_0(u) - \Omega_0(\hat{\theta}_1) \right).
\]

Assuming that \( \forall t_j \eta_j = \eta \), we can derive:

\[
\sum_{j=1}^{r} \left( l_j(\hat{\theta}_j) - l_j(u) \right) \leq \sum_{j=1}^{r} \left\| \hat{f}_j \right\|_2 \left\| \hat{\theta}_j \right\|_2 + \frac{1}{\eta} \left( \Omega_0(u) - \Omega_0(\hat{\theta}_1) \right).
\]

The following lemma finalizes the proof of Theorem 1:

Lemma 5. After \( R \) rounds with \( \forall t_j \eta_t = \eta = \frac{1}{\sqrt{R}} \), for any \( u \in K \) we have that \( \sum_{j=1}^{R} l_j(\hat{\theta}_j) - l_j(u) \leq O \left( \sqrt{R} \right) \).

Proof. From Eq. (12), it follows that

\[
\left\| \hat{f}_j \right\|_2 \leq \gamma_3(R) + 4 \gamma_1^2(R) \gamma_2^2(R) \leq \gamma_3(R) + 8 \frac{d}{p^2} \gamma_1^2(R) q \left( 1 + |\mathcal{I}_{R-1}| \right) + \frac{1}{\eta} \left( \Omega_0(u) - \Omega_0(\hat{\theta}_1) \right).
\]

with \( \gamma_3(R) = 4 \gamma_1^2(R) + 2 \max_{t_k \in \mathcal{I}_{R-1}} \delta_{t_k}^2 \). Since \( |\mathcal{I}_{R-1}| \leq |T| \), we have that \( \left\| \hat{f}_j \right\|_2 \leq \gamma_5(R) |T| \) with \( \gamma_5 = 8d/p^2 q \gamma_1^2(R) \max_{t_k \in \mathcal{I}_{R-1}} \left\{ \left\| A_{t_k}^l \right\|_2 \left( \left\| b_{t_k} \right\|_2 + c_{\max}^2 \right) \right\} \). Given that \( \Omega_0(u) \leq q d + \gamma_5(R) |T| \), with \( \gamma_5(R) \) being a constant, we have:

\[
\sum_{j=1}^{r} \left( l_j(\hat{\theta}_j) - l_j(u) \right) \leq \eta \sum_{j=1}^{r} \gamma_5(R) |T| \leq \frac{1}{\eta} \left( q d + \gamma_5(R) |T| - \Omega_0(\hat{\theta}_1) \right).
\]

Initializing \( L \) and \( S \): We initialize \( L \left\| \hat{\theta}_i \right\| = \text{diag}_k(\zeta) \), with \( p \leq \zeta^2 \leq q \) and \( S \left\| \hat{\theta}_i \right\| = \mathbf{0}_{k \times |T|} \) to ensure the invertibility...
of $L$ and that the constraints are met. This leads to
\[ \sum_{j=1}^{r} (l_j \langle \theta_j, \theta \rangle - l_j(u)) \leq \eta \sum_{j=1}^{r} \gamma_5(R) |T| \\
+ \frac{1}{\sqrt{R}} (qd + \gamma_5(R) |T| - \mu_2 k \zeta) . \]
Choosing $\forall j \eta_{l_j} = \eta = 1/\sqrt{R}$, we acquire sublinear regret, finalizing the statement of Theorem 1:
\[ \sum_{j=1}^{r} (l_j \langle \theta_j, \theta \rangle - l_j(u)) \leq 1/\sqrt{R} \gamma_5(R) |T| \\
+ \sqrt{R} (qd + \gamma_5(R) |T| - \mu_2 k \zeta) \\
\leq \sqrt{R} \left( \gamma_5(R) |T| + qd \gamma_5(R) |T| - \mu_2 k \zeta \right) \\
\leq \mathcal{O} \left( \sqrt{R} \right). \]

6. Experimental Validation

To validate the empirical performance of our method, we applied our safe online PG algorithm to learn multiple consecutive control tasks on three dynamical systems (Figure 1). To generate multiple tasks, we varied the parameterization of each system, yielding a set of control tasks from each domain with varying dynamics. The optimal control policies for these systems vary widely with only minor changes in the system parameters, providing substantial diversity among the tasks within a single domain.

Figure 1. Dynamical systems used in the experiments: a) simple mass system (left), b) cart-pole (middle), and c) quadrotor unmanned aerial vehicle (right).

Simple Mass Spring Damper: The simple mass (SM) system is characterized by three parameters: the spring constant $k$ in N/m, the damping constant $d$ in Ns/m and the mass $m$ in kg. The system’s state is given by the position $x$ and velocity $\dot{x}$ of the mass, which varies according to a linear force $F$. The goal is to train a policy for controlling the mass in a specific state $g_{ref} = (x_{ref}, \dot{x}_{ref})$.

Cart Pole: The cart-pole (CP) has been used extensively as a benchmark for evaluating RL methods (Busoniu et al., 2010). CP dynamics are characterized by the cart’s mass $m_c$ in kg, the pole’s mass $m_p$ in kg, the pole’s length in meters, and a damping parameter $d$ in Ns/m. The state is given by the cart’s position $x$ and velocity $\dot{x}$, as well as the pole’s angle $\theta$ and angular velocity $\dot{\theta}$. The goal is to train a policy that controls the pole in an upright position.

6.1. Experimental Protocol

We generated 10 tasks for each domain by varying the system parameters to ensure a variety of tasks with diverse optimal policies, including those with highly chaotic dynamics that are difficult to control. We ran each experiment for a total of $R$ rounds, varying from 150 for the simple mass to 10,000 for the quadrotor to train $L$ and $S$, as well as for updating the PG-ELLA and PG models. At each round $j$, the learner observed a task $t_j$ through 50 trajectories of 150 steps and updated $L$ and $s_{t_j}$. The dimensionality $k$ of the latent space was chosen independently for each domain via cross-validation over 3 tasks, and the learning step size for each task domain was determined by a line search after gathering 10 trajectories of length 150. We used eNAC, a standard PG algorithm, as the base learner.

We compared our approach to both standard PG (i.e., eNAC) and PG-ELLA (Bou Ammar et al., 2014), examining both the constrained and unconstrained variants of our algorithm. We also varied the number of iterations in our alternating optimization from 10 to 100 to evaluate the effect of these inner iterations on the performance, as shown in Figures 2 and 3. For the two MTL algorithms (our approach and PG-ELLA), the policy parameters for each task $t_j$ were initialized using the learned basis (i.e., $\alpha_{t_j} = Ls_{t_j}$). We configured PG-ELLA as described by Bou Ammar et al. (2014), ensuring a fair comparison. For the standard PG learner, we provided additional trajectories in order to ensure a fair comparison, as described below.

For the experiments with policy constraints, we generated a set of constraints $(A_t, b_t)$ for each task that restricted the policy parameters to pre-specified “safe” regions, as shown in Figures 2(c) and 2(d). We also tested different values for the constraints on $L$, varying $p$ and $q$ between 0.1 to 10; our approach showed robustness against this broad range, yielding similar average cost performance.

6.2. Results on Benchmark Systems

Figure 2 reports our results on the benchmark simple mass and cart-pole systems. Figures 2(a) and 2(b) depict the performance of the learned policy in a lifelong learning setting over consecutive unconstrained tasks, averaged over all 10 systems over 100 different initial conditions. These results demonstrate that our approach is capable of outperforming both standard PG (which was provided with 50 additional trajectories per iteration to ensure a more fair comparison) and PG-ELLA, both in terms of initial performance and learning speed. These figures also show that the performance of our method increases as it is given more alternating iterations per-round for fitting $L$ and $S$.

We evaluated the ability of these methods to respect safety constraints, as shown in Figures 2(c) and 2(d). The thicker black lines in each figure depict the allowable “safe” region of the policy space. To enable online learning per-task, the same task $t_j$ was observed on each round and the shared basis $L$ and coefficients $s_{t_j}$ were updated using alternating optimization. We then plotted the change in the policy pa-
parameter vectors per iterations (i.e., $\alpha_{t_j} = Ls_{t_j}$) for each method, demonstrating that our approach abides by the safety constraints, while standard PG and PG-ELLA can violate them (since they only solve an unconstrained optimization problem). In addition, these figures show that increasing the number of alternating iterations in our method causes it to take a more direct path to the optimal solution.

### 6.3. Application to Quadrotor Control

We also applied our approach to the more challenging domain of quadrotor control. The dynamics of the quadrotor system (Figure 1) are influenced by inertial constants around $e_{1,B}$, $e_{2,B}$, and $e_{3,B}$, thrust factors influencing how the rotor’s speed affects the overall variation of the system’s state, and the lengths of the rods supporting the rotors. Although the overall state of the system can be described by a 12-dimensional vector, we focus on stability and consider only six of these state-variables. The quadrotor system has a high-dimensional action space, where the goal is to control the four rotational velocities $\{w_i\}_{i=1}^4$ of the rotors to stabilize the system. To ensure realistic dynamics, we used the simulated model described by (Bouabdallah, 2007; Voos & Bou Ammar, 2010), which has been verified and used in the control of physical quadrotors.

We generated 10 different quadrotor systems by varying the inertia around the $x$, $y$ and $z$-axes. We used a linear quadratic regulator, as described by Bouabdallah (2007), to initialize the policies in both the learning and testing phases. We followed a similar experimental procedure to that discussed above to update the models.

Figure 3 shows the performance of the unconstrained solution as compared to standard PG and PG-ELLA. Again, our approach clearly outperforms standard PG and PG-ELLA in both the initial performance and learning speed. We also evaluated constrained tasks in a similar manner, again showing that our approach is capable of respecting constraints. Since the policy space is higher dimensional, we cannot visualize it as well as the benchmark systems, and so instead report the number of iterations it takes our approach to project the policy into the safe region. Figure 4 shows that our approach requires only one observation of the task to acquire safe policies, which is substantially lower than standard PG or PG-ELLA (e.g., which require 545 and 510 observations, respectively, in the quadrotor scenario).

### 7. Conclusion

We described the first lifelong PG learner that provides sub-linear regret $O(\sqrt{T})$ with $R$ total rounds. In addition, our approach supports safety constraints on the learned policy, which are essential for robust learning in real applications. Our framework formalizes lifelong learning as online MTL with limited resources, and enables safe transfer by sharing policy parameters through a latent knowledge base that is efficiently updated over time.
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A. Update Equations Derivation

In this appendix, we derive the update equations for $L$ and $S$ in the special case of Gaussian policies. Please note that these derivations can be easily extended to other policy forms in higher dimensional action spaces.

For a task $t_j$, the policy $\pi^{(t_j)}(u_m^{(k,t_j)}|x_m^{(k,t_j)})$ is given by:

$$\pi^{(t_j)}(u_m^{(k,t_j)}|x_m^{(k,t_j)}) = \frac{1}{\sqrt{2\pi\sigma_n^2}} \exp \left( -\frac{1}{2\sigma_n^2} (u_m^{(k,t_j)} - (LS_{t_j})^T \Phi(x_m^{(k,t_j)}))^2 \right).$$

Therefore, the safe lifelong reinforcement learning optimization objective can be written as:

$$e_r(L,S) = \sum_{j=1}^{r} \eta_j \sum_{k=1}^{n_j} \sum_{t=0}^{M_{t_j}-1} (u_m^{(k,t_j)} - (LS_{t_j})^T \Phi(x_m^{(k,t_j)}))^2 + \mu_1||S||_F^2 + \mu_2||L||_F^2.$$  \hspace{1cm} (13)

To arrive at the update equations, we need to derive Eq. (13) with respect to each $L$ and $S$.

A.1. Update Equations for $L$

Starting with the derivative of $e_r(L,S)$ with respect to the shared repository $L$, we can write:

$$\nabla_L e_r(L,S) = \nabla_L \left[ \sum_{j=1}^{r} \eta_j \sum_{k=1}^{n_j} \sum_{t=0}^{M_{t_j}-1} (u_m^{(k,t_j)} - (LS_{t_j})^T \Phi(x_m^{(k,t_j)}))^2 \Phi(x_m^{(k,t_j)}) s_{t_j}^T + 2\mu_2 L \right] = - \sum_{j=1}^{r} \left[ \eta_j \sum_{k=1}^{n_j} \sum_{t=0}^{M_{t_j}-1} (u_m^{(k,t_j)} - (LS_{t_j})^T \Phi(x_m^{(k,t_j)})) \Phi(x_m^{(k,t_j)}) s_{t_j}^T \right] + 2\mu_2 L.$$

To acquire the minimum, we set the above to zero:

$$\sum_{j=1}^{r} \left[ \eta_j \sum_{k=1}^{n_j} \sum_{t=0}^{M_{t_j}-1} (u_m^{(k,t_j)} - (LS_{t_j})^T \Phi(x_m^{(k,t_j)})) \Phi(x_m^{(k,t_j)}) s_{t_j}^T \right] + 2\mu_2 L = 0$$

$$\sum_{j=1}^{r} \left[ \eta_j \sum_{k=1}^{n_j} \sum_{t=0}^{M_{t_j}-1} s_{t_j}^T L^T \Phi(x_m^{(k,t_j)}) \Phi(x_m^{(k,t_j)}) s_{t_j}^T \right] + 2\mu_2 L = \sum_{j=1}^{r} \eta_j \sum_{k=1}^{n_j} \sum_{t=0}^{M_{t_j}-1} u_m^{(k,t_j)} \Phi(x_m^{(k,t_j)}) s_{t_j}^T.$$

Noting that $s_{t_j}^T L^T \Phi(x_m^{(k,t_j)}) \in \mathbb{R}$, we can write:

$$\sum_{j=1}^{r} \left[ \eta_j \sum_{k=1}^{n_j} \sum_{t=0}^{M_{t_j}-1} \Phi(x_m^{(k,t_j)}) s_{t_j}^T L s_{t_j} \right] + 2\mu_2 L = \sum_{j=1}^{r} \eta_j \sum_{k=1}^{n_j} \sum_{t=0}^{M_{t_j}-1} u_m^{(k,t_j)} \Phi(x_m^{(k,t_j)}) s_{t_j}^T.$$  \hspace{1cm} (14)

To solve Eq. (14), we introduce the standard vec($\cdot$) operator leading to:

$$\text{vec} \left( \sum_{j=1}^{r} \left[ \eta_j \sum_{k=1}^{n_j} \sum_{t=0}^{M_{t_j}-1} \Phi(x_m^{(k,t_j)}) s_{t_j}^T \Phi(x_m^{(k,t_j)}) L s_{t_j} \right] + 2\mu_2 L \right)$$

$$= \text{vec} \left( \sum_{j=1}^{r} \left[ \eta_j \sum_{k=1}^{n_j} \sum_{t=0}^{M_{t_j}-1} u_m^{(k,t_j)} \Phi(x_m^{(k,t_j)}) s_{t_j}^T \right] \right)$$

$$= \sum_{j=1}^{r} \frac{\eta_j}{\sigma_{t_j}^2} \sum_{k=1}^{n_j} \sum_{t=0}^{M_{t_j}-1} \text{vec} \left( \Phi(x_m^{(k,t_j)}) s_{t_j}^T \right) \text{vec} \left( \Phi(x_m^{(k,t_j)}) L s_{t_j} \right) + 2\mu_2 \text{vec}(L)$$

$$= \sum_{j=1}^{r} \frac{\eta_j}{\sigma_{t_j}^2} \sum_{k=1}^{n_j} \sum_{t=0}^{M_{t_j}-1} \text{vec} \left( u_m^{(k,t_j)} \Phi(x_m^{(k,t_j)}) s_{t_j}^T \right).$$
Knowing that for a given set of matrices $A$, $B$, and $X$, $\text{vec}(AXB) = (B^T \otimes A) \text{vec}(X)$, we can write

$$
\sum_{j=1}^{r} \frac{\eta_{t_j}}{\sigma_{t_j}^2} \sum_{k=1}^{n_{t_j}} \sum_{m=0}^{M_{t_j} - 1} \text{vec} \left( \Phi \left( x_{(k,t_j)}^m \right) s_{t_j}^T \right) \left( s_{t_j}^T \otimes \Phi^T \left( x_{(k,t_j)}^m \right) \right) \text{vec}(L) + 2\mu_2 \text{vec}(L) = \sum_{j=1}^{r} \frac{\eta_{t_j}}{\sigma_{t_j}^2} \sum_{k=1}^{n_{t_j}} \sum_{m=0}^{M_{t_j} - 1} \text{vec} \left( u_{(m,t_j)} \Phi \left( x_{(k,t_j)}^m \right) s_{t_j}^T \right).
$$

By choosing $Z_L = 2\mu_2 I_{dk \times dk} + \sum_{j=1}^{r} \frac{\eta_{t_j}}{\sigma_{t_j}^2} \sum_{k=1}^{n_{t_j}} \sum_{m=0}^{M_{t_j} - 1} \text{vec} \left( \Phi \left( x_{(k,t_j)}^m \right) s_{t_j}^T \right) \left( \Phi \left( x_{(k,t_j)}^m \right) \otimes s_{t_j}^T \right)$, and $v_L = \sum_{j=1}^{r} \frac{\eta_{t_j}}{\sigma_{t_j}^2} \sum_{k=1}^{n_{t_j}} \sum_{m=0}^{M_{t_j} - 1} \text{vec} \left( u_{(m,t_j)} \Phi \left( x_{(k,t_j)}^m \right) s_{t_j}^T \right)$, we can update $L = Z_L^{-1} v_L$.

### A.2. Update Equations for $S$

To derive the update equations with respect to $S$, similar approach to that of $L$ can be followed. The derivative of $e_r(L, S)$ with respect to $S$ can be computed column-wise for all tasks observed so far:

$$
\nabla_{s_{t_j}} e_r(L, S) = \nabla_{s_{t_j}} \left[ \sum_{j=1}^{r} \frac{\eta_{t_j}}{\sigma_{t_j}^2} \sum_{k=1}^{n_{t_j}} \sum_{m=0}^{M_{t_j} - 1} \left( u_{(m,t_j)} - (Ls_{t_j})^T \Phi \left( x_{(k,t_j)}^m \right) \right)^2 + \mu_1||S||_F^2 + \mu_2||L||_F^2 \right] = -\sum_{t_k=t_j}^{t_r} \left[ \frac{\eta_{t_k}}{\sigma_{t_k}^2} \sum_{k=1}^{n_{t_k}} \sum_{m=0}^{M_{t_k} - 1} \left( u_{(m,t_k)} - (Ls_{t_k})^T \Phi \left( x_{(k,t_k)}^m \right) \right) L^T \Phi \left( x_{(k,t_k)}^m \right) \right] + 2\mu_2 s_{t_j}.
$$

Using a similar analysis to the previous section, choosing

$$
Z_{a_{t_j}} = 2\mu_1 I_{dk \times dk} + \sum_{t_k=t_j}^{t_r} \frac{\eta_{t_k}}{\sigma_{t_k}^2} \sum_{k=1}^{n_{t_k}} \sum_{m=0}^{M_{t_k} - 1} \left( u_{(m,t_k)} - (Ls_{t_k})^T \Phi \left( x_{(k,t_k)}^m \right) \right) L^T \Phi \left( x_{(k,t_k)}^m \right) L,
$$

we can update $s_{t_j} = Z_{s_{t_j}}^{-1} v_{s_{t_j}}$.

### B. Proofs of Theoretical Guarantees

In this appendix, we prove the claims and lemmas from the main paper, leading to sublinear regret (Theorem 1).

**Lemma 1.** Assume the policy for a task $t_j$ at a round $r$ to be given by $\pi_{(t_j)}(u_{(m,t_j)} | x_{(k,t_j)}^m)$, for $x_{(k,t_j)}^m \in X_{t_j}$ and $u_{(m,t_j)} \in U_{t_j}$ with $X_{t_j}$ and $U_{t_j}$ representing the state and action spaces, respectively. The gradient $\nabla_{\alpha_{t_j}} l_{t_j}(\alpha_{t_j})$ for $l_{t_j}(\alpha_{t_j}) = -1/n_{t_j} \sum_{k=1}^{n_{t_j}} \sum_{m=0}^{M_{t_j} - 1} \log \left[ \pi_{(t_j)}(u_{(m,t_j)} | x_{(k,t_j)}^m) \right]$ satisfies

$$
\left\| \nabla_{\alpha_{t_j}} l_{t_j}(\alpha_{t_j}) \right\|_2 \leq \frac{M_t}{\sigma_{t_j}} \left[ \left\| u_{\text{max}} + \frac{\text{max}_{t_k \in T_{r-j}} \left\{ \left\| A_{t_k} \right\|_2 \left\| b_{t_k} \right\|_2 + c_{\text{max}} \right\} \Phi_{\text{max}} \right\| \Phi_{\text{max}} \right] \right.,
$$

with $u_{\text{max}} = \text{max}_{k,m} \left\{ \left\| u_{(m,t_j)} \right\|_2 \right\}$ and $\Phi_{\text{max}} = \text{max}_{k,m} \left\{ \left\| \Phi \left( x_{(k,t_j)}^m \right) \right\|_2 \right\}$ for all trajectories and all tasks.

**Proof.** The proof of the above lemma will be provided as a collection of claims. We start with the following claims.

**Claim:** Given $\pi_{(t_j)}(u_{(k,t_j)} | x_{(k,t_j)}^m)$, for $x_{(k,t_j)}^m \in X_{t_j}$ and $u_{(k,t_j)} \in U_{t_j}$, and $l_{t_j}(\alpha_{t_j}) = -1/n_{t_j} \sum_{k=1}^{n_{t_j}} \sum_{m=0}^{M_{t_j} - 1} \log \left[ \pi_{(t_j)}(u_{(m,t_j)} | x_{(k,t_j)}^m) \right]$,$\nabla_{\alpha_{t_j}} l_{t_j}(\alpha_{t_j})$ satisfies

$$
\left\| \nabla_{\alpha_{t_j}} l_{t_j}(\alpha_{t_j}) \right\|_2 \leq \frac{M_t}{\sigma_{t_j}} \left[ \left\| u_{\text{max}} + \left\| \alpha_{t_j} \right\|_2 \Phi_{\text{max}} \right\| \Phi_{\text{max}} \right].
$$

(15)
Proof: Since $\pi_{x_j}^{(t_j)} \left( u_m^{(k_j, t_j)} | x_m^{(k_j, t_j)} \right)$ $|_{\theta_r} = \mathcal{N} \left( \alpha^{T}_{t_j} |_{\theta_r}, \Phi \left( x_m^{(k_j, t_j)} \right), \sigma_{t_j} \right)$, we can write

$$\log \left[ \frac{\pi_{x_j}^{(t_j)} \left( u_m^{(k_j, t_j)} | x_m^{(k_j, t_j)} \right)}{\pi_{x_j}^{(t_j)}} \right] = - \log \left[ 2 \pi \sigma_{t_j}^2 \right] - \frac{1}{2 \sigma_{t_j}^2} \left( u_m^{(k_j, t_j)} - \alpha^{T}_{t_j} |_{\theta_r}, \Phi \left( x_m^{(k_j, t_j)} \right) \right)^2 .$$

Therefore:

$$\nabla_{\alpha_j} l_j \left( \alpha_{t_j} \right) |_{\theta_r} = - \frac{M_{\alpha_j}}{\sigma_{t_j}^2} \left( \sum_{k=1}^{n_{t_j}} \sum_{m=0}^{M_{\alpha_j} - 1} \frac{1}{\sigma_{t_j}} \left( u_m^{(k_j, t_j)} - \alpha^{T}_{t_j} |_{\theta_r}, \Phi \left( x_m^{(k_j, t_j)} \right) \right) \Phi \left( x_m^{(k_j, t_j)} \right) \right) \left\| \nabla_{\alpha_j} l_j \left( \alpha_{t_j} \right) \right\|_2 \leq \frac{M_{\alpha_j}}{\sigma_{t_j}^2} \left[ \max_{k, m} \left\{ \left\| u_m^{(k_j, t_j)} \right\| \times \left\| \Phi \left( x_m^{(k_j, t_j)} \right) \right\|_2 \right\} \right] \leq \frac{M_{\alpha_j}}{\sigma_{t_j}^2} \left[ \max_{k, m} \left\{ \left\| u_m^{(k_j, t_j)} \right\| \times \left\| \Phi \left( x_m^{(k_j, t_j)} \right) \right\|_2 \right\} \right] .$$

Denoting $\max_{k, m} \left\{ \left\| u_m^{(k_j, t_j)} \right\| \right\} = u_{\text{max}}$ and $\max_{k, m} \left\{ \left\| \Phi \left( x_m^{(k_j, t_j)} \right) \right\|_2 \right\} = \Phi_{\text{max}}$ for all trajectories and all tasks, we can write

$$\left\| \nabla_{\alpha_j} l_j \left( \alpha_{t_j} \right) \right\|_2 \leq \frac{M_{\alpha_j}}{\sigma_{t_j}^2} \left[ \left( u_{\text{max}} + \max_{k, m} \left\{ \left\| \alpha_j \right\|_2 \right\} \Phi_{\text{max}} \right) \Phi_{\text{max}} \right] .$$

Using the Cauchy-Shwarz inequality (Horn & Mathias, 1990), we can upper bound $\max_{k, m} \left\{ \left\| \alpha_j \right\|_2 \right\}$ as

$$\max_{k, m} \left\{ \left\| \alpha_j \right\|_2 \right\} \leq \max_{k, m} \left\{ \left\| \alpha_j \right\|_2 \right\} \leq \max_{k, m} \left\{ \left\| \alpha_j \right\|_2 \right\} \Phi_{\text{max}} \leq \left\| \alpha_j \right\|_2 \Phi_{\text{max}} .$$

Finalizing the statement of the claim, the overall bound on the norm of the gradient of $l_j \left( \alpha_{t_j} \right)$ can be written as

$$\left\| \nabla_{\alpha_j} l_j \left( \alpha_{t_j} \right) \right\|_2 \leq \frac{M_{\alpha_j}}{\sigma_{t_j}^2} \left[ \left( u_{\text{max}} + \max_{k, m} \left\{ \left\| \alpha_j \right\|_2 \right\} \Phi_{\text{max}} \right) \Phi_{\text{max}} \right] . \quad (16)$$

Claim: The norm of the gradient of the loss function satisfies:

$$\left\| \nabla_{\alpha_j} l_j \left( \alpha_{t_j} \right) \right\|_2 \leq \frac{M_{\alpha_j}}{\sigma_{t_j}^2} \left[ \left( u_{\text{max}} + \max_{t_k \in \mathbb{I}_{\text{r-1}}} \left\{ \left\| A_{t_k}^+ \right\|_2 \left( \left\| b_{t_k} \right\|_2 + c_{\text{max}} \right) \right\} \Phi_{\text{max}} \right) \Phi_{\text{max}} \right] .$$

Proof: As mentioned previously, we consider the linearization of the loss function $l_j$ around the constraint solution of the previous round, $\theta_r$. Since $\theta_r$ satisfies $A_{t_k} \alpha_{t_k} = b_{t_k} - c_{t_k}, \forall t_k \in \mathbb{I}_{\text{r-1}}$. Hence, we can write

$$A_{t_k} \alpha_{t_k} + c_{t_k} = b_{t_k} \forall t_k \in \mathbb{I}_{\text{r-1}} \Rightarrow \alpha_{t_k} = A_{t_k}^+ \left( b_{t_k} - c_{t_k} \right) \text{ with } A_{t_k}^+ = \left( A_{t_k}^T A_{t_k} \right)^{-1} A_{t_k}^T \text{ being the left pseudo-inverse.}$$

Therefore

$$\left\| \alpha_{t_k} \right\|_2 \leq \left\| A_{t_k}^+ \right\|_2 \left( \left\| b_{t_k} \right\|_2 + c_{\text{max}} \right) \leq \left\| A_{t_k}^+ \right\|_2 \left( \left\| b_{t_k} \right\|_2 + c_{\text{max}} \right) .$$
Lemma 2. The norm of the gradient of the loss function evaluated at $\theta_r$ satisfies

$$\left\| \nabla_{\theta_r} l_j (\theta) \right\|_2^2 \leq \left\| \nabla_{\theta_r} l_j (\theta) \right\|_2^2 \left( q \times d \left( 2d/p^2 \max_{t_k \in T_{r-1}} \{ \left\| A_{t_k}^+ \right\|_2 \left( \left\| b_{t_k} \right\|_2 + c_{max} \right) \} + 1 \right) \right) .$$

Proof. The derivative of $l_j (\theta) \bigg|_{\theta_r}$ can be written as

$$\nabla_{\theta_r} l_j (\theta) \bigg|_{\theta_r} = \begin{bmatrix} \frac{\partial \alpha_{t_j}^{(1)}}{\partial \theta_r} & \frac{\partial \alpha_{t_j}^{(2)}}{\partial \theta_r} & \cdots & \frac{\partial \alpha_{t_j}^{(d)}}{\partial \theta_r} \end{bmatrix} \begin{bmatrix} \frac{\partial \alpha_{t_j}^{(1)}}{\partial \theta_r} & \frac{\partial \alpha_{t_j}^{(2)}}{\partial \theta_r} & \cdots & \frac{\partial \alpha_{t_j}^{(d)}}{\partial \theta_r} \end{bmatrix}^T.$$

The results of Lemma 1 bound $\left\| \nabla_{\theta_r} l_j (\theta) \right\|_2^2$.

Now, we target to bound each of $\left\| s_{t_j} \right\|_{\theta_r}^2$ and $\left\| L \right\|_{\theta_r}^2$.

Bounding $\left\| s_{t_j} \right\|_{\theta_r}^2$ and $\left\| L \right\|_{\theta_r}^2$: Considering the constraint $A_{t_j} L s_{t_j} + c_{t_j} = b_{t_j}$ for a task $t_j$, we realize that $s_{t_j} = L^+ \left( A_{t_j}^+ (b_{t_j} - c_{t_j}) \right)$. Therefore,

$$\left\| s_{t_j} \right\|_{\theta_r}^2 \leq \left\| L^+ \left( A_{t_j}^+ (b_{t_j} - c_{t_j}) \right) \right\|_2 \leq \left\| L^+ \right\|_2 \left\| A_{t_j}^+ \right\|_2 \left( \left\| b_{t_j} \right\|_2 + \left\| c_{t_j} \right\|_2 \right) .$$

(17)

Noting that

$$\left\| L^+ \right\|_2 = \left\| (L^T L)^{-1} L^T \right\|_2 \leq \left\| (L^T L)^{-1} \right\|_2 \left\| L^T \right\|_2 \leq \left\| (L^T L)^{-1} \right\|_2 \left\| L^T \right\|_F$$

$$= \left\| (L^T L)^{-1} \right\|_2 \left\| L \right\|_F .$$
To relate $\|L^+\|_2$ to $\|L\|_F$, we need to bound $\left\| \left( L^T L \right)^{-1} \right\|_2$ in terms of $\|L\|_F$. Denoting the spectrum of $L^T L$ as $\text{spec}(L^T L) = \{\lambda_1, \ldots, \lambda_k\}$ such that $0 < \lambda_1 \leq \cdots \leq \lambda_k$, then $\text{spec} \left( \left( L^T L \right)^{-1} \right) = \{1/\lambda_1, \ldots, 1/\lambda_k\}$ such that $1/\lambda_k \leq \cdots \leq 1/\lambda_1$. Hence, $\left\| \left( L^T L \right)^{-1} \right\|_2 = \max \{ \text{spec} \left( \left( L^T L \right)^{-1} \right) \} = 1/\lambda_1 = 1/\lambda_{\min} \left(L^T L\right)$. Noticing that $\text{spec}(L^T L) = \text{spec}(LL^T)$, we recognize $\left\| \left( L^T L \right)^{-1} \right\|_2 = 1/\lambda_{\max} (LL^T) \leq 1/p$. Therefore

$$\left\| L^+ \right\|_2 \leq \frac{1}{p} \|L\|_F .$$

Plugging the results of Eq. (18) into Eq. (17), we arrive at

$$\left\| s_r \right\|_{\theta_r}^2 \leq \frac{1}{p^2} \left\| L \right\|_{\theta_r}^2 \left\{ \left\| A^T_i \right\|_2 \left( \left\| b_{t_k}\right\|_2 + c_{\max} \right) \right\} .$$

Finally, since $\hat{\theta}_r$ satisfies the constraints, we note that

$$\left\| L \right\|_{\hat{\theta}_r}^2 \leq q \times d. \quad \text{Consequently,}$$

$$\left\| \nabla \theta_i \left( \theta \right) \right\|_{\hat{\theta}_r}^2 \leq \left\| \nabla \alpha_j \left( l_i \left( \theta \right) \right) \right\|_{\hat{\theta}_r}^2 \left( q \times d \left( \frac{2d}{p^2} \max_{t_k \in \mathcal{I}_{r-1}} \left\{ \left\| A^T_i \right\|_2 \left( \left\| b_{t_k}\right\|_2 + c_{\max} \right) \right\} + 1 \right) \right) .$$

\[\square\]

Lemma 3. The $L_2$ norm of the constraint solution at round $r-1$, $\|\hat{\theta}_r\|^2_2$ is bounded by

$$\|\hat{\theta}_r\|^2_2 \leq q \times d \left[ 1 + |\mathcal{I}_{r-1}| \frac{1}{p^2} \max_{t_k \in \mathcal{I}_{r-1}} \left\{ \left\| A^T_i \right\|_2 \left( \left\| b_{t_k}\right\|_2 + c_{\max} \right) \right\} \right] ,$$

with $|\mathcal{I}_{r-1}|$ being the cardinality of $\mathcal{I}_{r-1}$ representing the number of different tasks observed so-far.

Proof. Noting that $\hat{\theta}_r = \left[ \theta_1, \ldots, \theta_{dk}, \theta_{dk+1}, \ldots, \theta_{dk+kT} \right]^T$, it is easy to see

$$\|\hat{\theta}_r\|^2_2 \leq \left\| L \right\|_{\hat{\theta}_r}^2 + |\mathcal{I}_{r-1}| \frac{1}{p^2} \max_{t_k \in \mathcal{I}_{r-1}} \left\{ \left\| s_{t_k} \right\|_{\hat{\theta}_r}^2 \right\}$$

$$\leq q \times d + |\mathcal{I}_{r-1}| \frac{1}{p^2} \max_{t_k \in \mathcal{I}_{r-1}} \left\{ \left\| A^T_i \right\|_2 \left( \left\| b_{t_k}\right\|_2 + c_{\max} \right) \right\}$$

$$\leq q \times d \left[ 1 + |\mathcal{I}_{r-1}| \frac{1}{p^2} \max_{t_k \in \mathcal{I}_{r-1}} \left\{ \left\| A^T_i \right\|_2 \left( \left\| b_{t_k}\right\|_2 + c_{\max} \right) \right\} \right] .$$

\[\square\]

Lemma 4. The $L_2$ norm of the linearizing term of $l_i \left( \theta \right)$ around $\hat{\theta}_r$, $\left\| \hat{\theta}_r \right\|_{\hat{\theta}_r}^2$, is bounded by

$$\left\| \hat{\theta}_r \right\|_{\hat{\theta}_r}^2 \leq \left\| \nabla \theta_i \left( \theta \right) \right\|_{\hat{\theta}_r}^2 \left( 1 + \left\| \hat{\theta}_r \right\|_2 \right) + \left\| l_i \left( \theta \right) \right\|_{\hat{\theta}_r}^2 \leq \gamma_1(r) \left( 1 + \gamma_2(r) \right) + \delta_{l_i}$,

with $\delta_{l_i}$ being the constant upper-bound on $\left\| l_i \left( \theta \right) \right\|_{\hat{\theta}_r}$, and

$$\gamma_1(r) = \frac{1}{n_i \sigma_{l_i}} \left[ \left( u_{\max} \max_{t_k \in \mathcal{I}_{r-1}} \left\{ \left\| A^T_i \right\|_2 \left( \left\| b_{t_k}\right\|_2 + c_{\max} \right) \right\} \Phi_{\max} \right) \Phi_{\max} \right]$$

$$\times \left( \frac{d}{p^2} \sqrt{2q} \max_{t_k \in \mathcal{I}_{r-1}} \left\{ \left\| A^T_i \right\|_2 \left( \left\| b_{t_k}\right\|_2 + c_{\max} \right) \right\} + \sqrt{qd} \right) .$$

$$\gamma_2(r) \leq \sqrt{q \times d} + \sqrt{|\mathcal{I}_{r-1}|} \left[ 1 + \frac{1}{p^2} \max_{t_k \in \mathcal{I}_{r-1}} \left\{ \left\| A^T_i \right\|_2 \left( \left\| b_{t_k}\right\|_2 + c_{\max} \right) \right\} \right] .$$
Proof. We have previously shown that \( \| f_t \|_2 \leq \| \nabla \theta_t(\theta) \|_2 + \| l_t \|_2 \times \| \theta \|_2 \). Using the previously derived lemmas we can upper-bound \( \| f_t \|_2 \) as follows

\[
\| \nabla \theta_t(\theta) \|_2^2 \leq \| \nabla \alpha_t(l_t(\theta)) \|_2^2 \leq \left( q \times d \left( \frac{2d}{p^2} \max_{t_k \in I_{t-1}} \left\{ \| A^t_k \|_2^2 \left( \| b_{t_k} \|_2 + c_{\max} \right) \right\} + 1 \right) \right)
\]

\[
\| \nabla \theta_t(\theta) \|_2 \leq \sum_{k \in I_{t-1}} \left( 1 + \frac{1}{p^2} \max_{t_k \in I_{t-1}} \left\{ \| A^t_k \|_2^2 \left( \| b_{t_k} \|_2 + c_{\max} \right) \right\} \right)
\]

\[
\| \theta \|_2 \leq \sqrt{q \times d} + \sqrt{\max_{t_k \in I_{t-1}} \left\{ \| A^t_k \|_2^2 \left( \| b_{t_k} \|_2 + c_{\max} \right) \right\} \}
\]

Further,

\[
\| \theta \|_2 \leq \sqrt{q \times d} + \sqrt{\max_{t_k \in I_{t-1}} \left\{ \| A^t_k \|_2^2 \left( \| b_{t_k} \|_2 + c_{\max} \right) \right\} \}
\]

Therefore

\[
\| f_t \|_2 \leq \sum_{k \in I_{t-1}} \left( 1 + \| \theta \|_2 \right) + \| l_t \|_2 \leq \gamma_1(r) (1 + \gamma_2(r)) + \delta_{ij},
\]

with \( \delta_{ij} \) being the constant upper-bound on \( \| l_t \|_2 \) and

\[
\gamma_1(r) = \frac{1}{n_t \sigma_t^2} \left( u_{\max} + \max_{t_k \in I_{t-1}} \left\{ \| A^t_k \|_2^2 \left( \| b_{t_k} \|_2 + c_{\max} \right) \right\} \right)
\]

\[
\times \left( d/p \sqrt{q \times d} \max_{t_k \in I_{t-1}} \left\{ \| A^t_k \|_2^2 \left( \| b_{t_k} \|_2 + c_{\max} \right) \right\} + \sqrt{q \times d} \right).
\]

\[
\gamma_2(r) \leq \sqrt{q \times d} + \sqrt{\max_{t_k \in I_{t-1}} \left\{ \| A^t_k \|_2^2 \left( \| b_{t_k} \|_2 + c_{\max} \right) \right\} \}
\]

Theorem 1 (Sublinear Regret; restated from the main paper). After \( R \) rounds and choosing \( \eta_t = \cdots = \eta_j = \eta = \frac{1}{\sqrt{R}} \), \( L \mid_\theta = \text{diag}_k(\zeta) \), with \( \text{diag}_k(\cdot) \) being a diagonal matrix among the \( k \) columns of \( L \), \( p \leq \zeta^2 \leq q \), and \( S \mid_\theta = 0_{k \times |T|} \), for any \( u \in K \) our algorithm exhibits a sublinear regret of the form

\[
\sum_{j=1}^R l_t \left( \theta_j \right) - l_t \left( u \right) = O \left( \sqrt{R} \right).
\]

Proof. Given the ingredients of the previous section, next we derive the sublinear regret results which finalize the statement of the theorem. First, it is easy to see that

\[
\nabla \theta_t(\theta_j) = \nabla \theta_t(\theta_j) - \nabla \theta_t(\theta_j) = \eta_t \left( f_t \right) \mid_{\theta_j}.
\]

Further, from strong convexity of the regularizer we obtain:

\[
\Omega_0 \left( \theta_j \right) \geq \Omega_0 \left( \theta_{j+1} \right) + \left( \nabla \theta_t(\theta_j), \theta_j - \theta_{j+1} \right) + \frac{1}{2} \left\| \theta_j - \theta_{j+1} \right\|^2_2.
\]

It can be seen that

\[
\left\| \theta_j - \theta_{j+1} \right\|_2 \leq \eta_t \left( f_t \right) \mid_{\theta_j}.
\]
Finally, for any \( u \in \mathcal{K} \), we have:
\[
\sum_{j=1}^{r} \eta_{t_j} \left( l_{t_j} \left( \hat{\theta}_j \right) - l_{t_j} \left( u \right) \right) \leq \sum_{j=1}^{r} \left[ \eta_{t_j} \left( \left\| f_{t_j} \right\| \_2 \right) ^2 \right] + \Omega_0 \left( u \right) - \Omega_0 \left( \hat{\theta}_1 \right).
\]
Assuming \( \eta_{t_1} = \cdots = \eta_{t_j} = \eta \), we can derive
\[
\sum_{j=1}^{r} \left( l_{t_j} \left( \hat{\theta}_j \right) - l_{t_j} \left( u \right) \right) \leq \eta \sum_{j=1}^{r} \left( \left\| f_{t_j} \right\| \_2 \right) ^2 + 1/\eta \left( \Omega_0 \left( u \right) - \Omega_0 \left( \hat{\theta}_1 \right) \right).
\]

The following lemma finalizes the statement of the theorem:

**Lemma 5.** After \( T \) rounds and for \( \eta_{t_1} = \cdots = \eta_{t_j} = \eta = \frac{1}{\sqrt{R}} \), our algorithm exhibits, for any \( u \in \mathcal{K} \), a sublinear regret of the form
\[
\sum_{j=1}^{R} l_{t_j} \left( \hat{\theta}_j \right) - l_{t_j} \left( u \right) \leq O \left( \sqrt{R} \right).
\]

**Proof.** It is then easy to see
\[
\left\| f_{t_j} \right\| \_2 \leq \gamma_3 \left( R \right) + 4 \gamma_1^2 \left( R \right) \gamma_5 \left( R \right), \quad \text{with} \quad \gamma_3 \left( R \right) = 4 \gamma_1^2 \left( R \right) + 2 \max_{t_j \in \mathcal{I}_{R-1}} \delta_{t_j}
\]
\[
\leq \gamma_3 \left( R \right) + 8 d \left( \gamma_1^2 \left( R \right) q \delta \right) + \frac{1}{p^2} \gamma_1^2 \left( R \right) q \delta \left| \mathcal{I}_{R-1} \right| \max_{t_k \in \mathcal{I}_{R-1}} \left\{ \left\| A_{t_k} \right\| _2 \left( \left\| b_{t_k} \right\| _2 + c_{\max} \right) \right\}.
\]

Since \( \left| \mathcal{I}_{R-1} \right| \leq \left| \mathcal{T} \right| \) with \( \left| \mathcal{T} \right| \) being the total number of tasks available, then we can write
\[
\left\| f_{t_j} \right\| \_2 \leq \gamma_5 \left( R \right) \left| \mathcal{T} \right|,
\]
with \( \gamma_5 = 8 d/p^2 q \gamma_1^2 \left( R \right) \max_{t_k \in \mathcal{I}_{R-1}} \left\{ \left\| A_{t_k} \right\| _2 \left( \left\| b_{t_k} \right\| _2 + c_{\max} \right) \right\} \). Further, it is easy to see that \( \Omega_0 \left( u \right) \leq q \delta + \gamma_5 \left( R \right) \left| \mathcal{T} \right| \) with \( \gamma_5 \left( R \right) \) being a constant, which leads to
\[
\sum_{j=1}^{r} \left( l_{t_j} \left( \hat{\theta}_j \right) - l_{t_j} \left( u \right) \right) \leq \eta \sum_{j=1}^{r} \gamma_5 \left( R \right) \left| \mathcal{T} \right| + 1/\eta \left( q \delta + \gamma_5 \left( R \right) \left| \mathcal{T} \right| - \Omega_0 \left( \hat{\theta}_1 \right) \right).
\]

**Initialzing \( L \) and \( S \):** We initialize \( L \bigg|_{\hat{\theta}_1} = \text{diag}_k(\zeta) \), with \( \rho \leq \zeta^2 \leq q \) and \( S \bigg|_{\hat{\theta}_1} = 0_{k \times \left| \mathcal{T} \right|} \) ensures the invertability of \( L \) and that the constraints are met. This leads us to
\[
\sum_{j=1}^{r} \left( l_{t_j} \left( \hat{\theta}_j \right) - l_{t_j} \left( u \right) \right) \leq \eta \sum_{j=1}^{r} \gamma_5 \left( R \right) \left| \mathcal{T} \right| + 1/\eta \left( q \delta + \gamma_5 \left( R \right) \left| \mathcal{T} \right| - \mu_2 k \zeta \right).
\]
Choosing \( \eta_{t_1} = \cdots = \eta_{t_j} = \eta = 1/\sqrt{R} \), we acquire sublinear regret, finalizing the statement of the theorem:
\[
\sum_{j=1}^{r} \left( l_{t_j} \left( \hat{\theta}_j \right) - l_{t_j} \left( u \right) \right) \leq 1/\sqrt{R} \gamma_5 \left( R \right) \left| \mathcal{T} \right| R + \sqrt{R} \left( q \delta + \gamma_5 \left( R \right) \left| \mathcal{T} \right| - \mu_2 k \zeta \right)
\]
\[
\leq \sqrt{R} \left( \gamma_5 \left( R \right) \left| \mathcal{T} \right| + q \delta \gamma_5 \left( R \right) \left| \mathcal{T} \right| - \mu_2 k \zeta \right) \leq O \left( \sqrt{R} \right),
\]
with \( \gamma_5 \left( R \right) \) being a constant.