Primal-dual Learning for the Model-free Risk-constrained Linear Quadratic Regulator

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Abstract

Risk-aware control, though with promise to tackle unexpected events, requires a known exact dynamical model. In this work, we propose a model-free framework to learn a risk-aware controller of a linear system. We formulate it as a discrete-time infinite-horizon LQR problem with a state predictive variance constraint. Since its optimal policy is known as an affine feedback, i.e., $u^*(x) = -Kx + l$, we alternatively optimize the gain pair $(K, l)$ by designing a primal-dual learning algorithm. First, we observe that the Lagrangian function enjoys an important local gradient dominance property. Based on it, we then show that there is no duality gap despite the non-convex optimization landscape. Furthermore, we propose a primal-dual algorithm with global convergence to learn the optimal policy-multiplier pair. Finally, we validate our results via simulations.

Keywords: Risk-aware control; Policy optimization; Reinforcement learning; Optimal control; Constrained Markov decision process.

1. Introduction

Stochastic optimal control (Åström, 2012) is a well-studied framework that deals with inherent random noises in the dynamical system. Its classical formulation targets to minimize an expected long-term cost, which is risk-neutral as it only optimize the expectation without explicit considerations on the variability of the state. Thus, the system behaviours may be easily influenced by less probable but large noises, leading to catastrophic consequences for the safety-critical systems. In decades, the risk-aware controllers have been proposed to tackle the extreme noises with a slight sacrifice of average performance (Sopasakis et al., 2019; Jacobson, 1973; Moore et al., 1997; Bäuerle and Rieder, 2014; Roulet et al., 2020). For example, the risk is typically addressed by replacing the cost with its exponentiation (Speyer et al., 1992; Moore et al., 1997) or optimizing the risk measure (Chapman et al., 2019) e.g., Conditional Value-at-Risk (CVaR) (Rockafellar et al., 2000). However, most of them are model-based (Chapman et al., 2019; Moore et al., 1997; Speyer et al., 1992) and hence not directly applicable when the exact dynamical model is unknown.

Model-free reinforcement learning (RL) (Sutton et al., 1998; Bertsekas, 2019) has achieved tremendous progress recently in the continuous control field (Mnih et al., 2015; Lillicrap et al., 2016). Instead of identifying the underlying dynamical model first, it approaches the control problem by directly searching for an optimal policy that minimizes the estimated cost function. Under the RL framework, the prevalent risk-averse methods (Wen and Topcu, 2018; Prashanth L and Fu, 2018; Borkar and Jain, 2014) take the risk into consideration by, e.g., adding a risk-related cumulative cost constraint to the Markov decision process (MDP) (Paternain et al., 2019; Chow et al., 2017; Yu et al., 2019; Tessler et al., 2018), or formulating the risk as an adversary (Pan et al., 2019).
Though empirically successful on the continuous control benchmarks (Pan et al., 2019; Tessler et al., 2018), they typically lack strong theoretical guarantees, hampering their physical-world applications.

Recent advances in the context of policy optimization (PO) for the linear quadratic regulator (LQR) (Bertsekas, 1995), including policy gradient (Fazel et al., 2018; Bu et al., 2019; Zhang et al., 2019, 2020) and random search methods (Malik et al., 2019; Mohammadi et al., 2020), have been shown to enjoy the global convergence in spite of the non-convex nature of the optimization landscape. Some works focus on the LQR variants e.g., robust control with multiplicative noises (Gravel et al., 2020), distributed LQR (Li et al., 2019) and Markov jump linear systems(Jansch-Porto et al., 2020). In particular, the PO for $H_2$ linear control with $H_\infty$ robustness guarantees is analyzed in Zhang et al. (2020) for a risk-sensitive linear exponential quadratic Gaussian (LEQG) (Whittle, 1981) instance. However, to the best of our knowledge, there is no such analysis for the risk-aware formulation with a risk constraint explicitly concerned.

In this paper, we consider the learning problem for the model-free risk-aware controller. Inspired by Tsiamis et al. (2020), we formulate it as a discrete-time infinite-horizon LQR problem with a one-step predicted state variability constraint. By Zhao et al. (2021a), the solution to it is an affine state feedback policy. Thus, we can alternatively optimize over the stabilizing affine policy set. Nevertheless, in contrast to LQR, three challenges exist in our setting. Firstly, the constraint optimization problem is non-convex in that the objective function, the risk constraint and the stabilizing policy set are all non-convex. Moreover, the optimization variable in LQR is a single feedback gain (Fazel et al., 2018), while in our case it is a gain pair and hence the optimization landscape is not clear yet. Finally, the first-order optimization methods cannot be used since the dynamical model is unknown.

This work proposes a primal-dual learning framework to solve the risk-constrained LQR problem. Alongside, we take an initial step towards understanding the theoretical aspects of PO for the constrained LQR. Our contributions are summarized below. Firstly, in spite of the constrained non-convex optimization nature, we show that the strong duality holds. Secondly, we study the optimization landscape of the Lagrangian function over the stabilizing affine policy set. In particular, we find that it enjoys two favourable properties, i.e., the local gradient dominance and Lipschitz property. Thirdly, we propose a primal-dual algorithm to learn the optimal policy-multiplier pair and show its global convergence.

2. Problem Formulation

In the standard setup of LQR, we consider a time-invariant discrete linear stochastic system with full state observations,

$$x_{t+1} = Ax_t + Bu_t + w_t,$$

where the next state $x_{t+1}$ is a linear combination of the current state $x_t \in \mathbb{R}^n$, the control $u_t \in \mathbb{R}^m$, and the random noise $w_t \in \mathbb{R}^d$. The model parameters are denoted as $A \in \mathbb{R}^{n \times n}$ and $B \in \mathbb{R}^{n \times m}$.

The goal of infinite-horizon LQR is to find a control policy $\pi$ which minimizes an average long-term cost, i.e.,

$$\text{minimize } \lim_{T \to \infty} \frac{1}{T} \mathbb{E} \sum_{t=0}^{T-1} (x_t^\top Q x_t + u_t^\top R u_t)$$

(2)
where \( u_t = \pi(h_t) \) with the history trajectory \( h_t = \{x_0, u_0, \cdots, x_{t-1}, u_{t-1}\} \) and the expectation is taken with respect to the random noise \( w_t \). Throughout the paper, we make the following assumption standard in the control theory (Bertsekas, 1995).

**Assumption 1** \( Q \) is positive semi-definite and \( R \) is positive definite. The pair \((A, B)\) is stabilizable and \((A, Q^{1/2})\) is observable.

Under Assumption 1, solving (2) yields a unique linear state feedback policy \( u_t = -K x_t \) when \( w_t \) has zero mean. Clearly, the classical LQR is risk-neutral as it aims to minimize only the expected cost. Thus, the state may be largely influenced by the low-probability but large noises, especially those with heavy-tailed distributions.

In this paper, we study the infinite-horizon risk-constrained LQR in Zhao et al. (2021a) and solve it in a model-free approach. That is, a user-defined risk tolerance constant. In contrast to standard LQR (2), we do not require the noise \( w_t \) to be zero-mean. Instead, we only assume a finite 4th-order moment of \( w_t \) (Tsiamis et al., 2020).

In our recent work Zhao et al. (2021a), we have shown that the optimal policy to (3) is an affine state feedback, i.e., \( u^*(x) = -K^* x + l^* \), which is also able to stabilize the system. Exploiting this affine structure, we can alternatively optimize the gain pair \((K, l)\). Define the mean \( \bar{w} = \mathbb{E}[w_t] \), the covariance \( W = \mathbb{E}[(w_t - \bar{w})(w_t - \bar{w})^\top] > 0 \), higher-order weighted statistics \( M_3 = \mathbb{E}[(w_t - \bar{w})(w_t - \bar{w})^\top Q(w_t - \bar{w})] \) and \( M_4 = \mathbb{E}[(w_t - \bar{w})^\top Q(w_t - \bar{w}) - \text{tr}(WQ)]^2 \) of the noise \( w_t \). Given that \( w_t \) has a finite 4-th order moment, (3) can be reformulated by Zhao et al. (2021a) as

\[
\begin{align*}
\text{minimize} & \quad J(K, l) = \lim_{T \to \infty} \frac{1}{T} \mathbb{E} \sum_{t=0}^{T-1} (x_t^\top Q x_t + u_t^\top R u_t) \\
\text{subject to} & \quad J_c(K, l) = \lim_{T \to \infty} \frac{1}{T} \mathbb{E} \sum_{t=0}^{T-1} (4 x_t^\top Q W Q x_t + 4 x_t^\top Q M_3) \leq \bar{\rho}
\end{align*}
\]

with \( u_t = -K x_t + l \) and \( \bar{\rho} = \rho - m_4 + 4 \text{tr}((WQ)^2) \). In (4), \((K, l)\) is the optimization variable.

The direct PO for the risk-neutral formulation (2) has been well studied and typically enjoys the convergence guarantee, including random search and policy gradient methods Fazel et al. (2018). However, (4) is not only a non-convex constrained optimization problem, but also differs from (2) in that the optimization variable is a gain pair \((K, l)\). In this paper, we study the analytical property of the constrained optimization problem (4). Furthermore, we propose a convergent primal-dual algorithm to solve it exactly by solely using data.

### 3. Primal-dual Optimization for Risk-constrained LQR

In this section, we introduce the primal-dual method for solving the risk-constrained LQR problem in (4). In contrast to Fazel et al. (2018), its Lagrangian function is only locally gradient dominated.
and locally Lipschitz with respect to the policy. Moreover, we establish the strong duality for the non-convex constrained optimization problem (4).

3.1. Primal-dual method

In the rest of the paper, we use the augmented matrix $X = [K \ I]$ to denote the optimization variable. Define $\mathcal{S} = \{X = [K \ I] | \rho(A - BK) < 1, K \in \mathbb{R}^{n \times m}, I \in \mathbb{R}^n \}$, where $\rho(\cdot)$ denotes the spectral radius. Clearly, we have $J(X) < +\infty$ and $J_c(X) < +\infty$ if and only if $X \in \mathcal{S}$. Let $\mu \geq 0$ denote the Lagrange multiplier and $Q_\mu = Q + 4\mu Q W Q$ and $S = 2\mu Q M_3$. We define the Lagrangian function of (4) as

$$\mathcal{L}(X, \mu) = J(X) + \mu(J_c(X) - \bar{\rho}) = \lim_{T \to \infty} \frac{1}{T} \mathbb{E} \sum_{t=0}^{T-1} c_\mu(x_t, u_t),$$

(5)

where $c_\mu(x_t, u_t) = x_t^\top Q_\mu x_t + 2x_t^\top S + u_t^\top R u_t - \mu \bar{\rho}$, which is a reshaped cost with a risk weight $\mu$ that balances the objective and the risk. Accordingly, we define the dual function $D(\mu) = \min_X \mathcal{L}(X, \mu)$ and the dual problem

$$\max_{\mu \geq 0} D(\mu) = \max_{\mu \geq 0} \min_{X \in \mathcal{S}} \mathcal{L}(X, \mu).$$

(6)

Our primal-dual method is iteratively given as

$$X_j \in \arg \min_{X \in \mathcal{S}} \mathcal{L}(X, \mu_j),$$

(7)

$$\mu_{j+1} = [\mu_j + \xi_j \cdot \omega(\mu_j)]_+,$$

(8)

where the stepsize $\xi_j > 0$, $\omega(\mu_j)$ is a subgradient of $D(\mu)$ at $\mu_j$ and $[x]_+ = \max\{0, x\}$ for any $x \in \mathbb{R}$.

To guarantee the global convergence of the primal-dual method, the strong duality between the primal problem and dual problem is essential. However, the constrained optimization problem (4) is non-convex and, therefore, the strong duality does not trivially follow. Moreover, the primal-dual method requires to solve (7) under a fixed multiplier $\mu$. Though for LQR problems some model-free algorithms are guaranteed to find an optimal gain $K$ (Fazel et al., 2018; Malik et al., 2019; Mohammadi et al., 2020), they cannot be directly applied as our optimization variable is a gain pair $(K, l)$. In particular, these algorithms exploit favourable properties of the objective function such as gradient dominance (Fazel et al., 2018) and Lipschitz continuity (Malik et al., 2019), which are unclear for $\mathcal{L}(K, l, \mu)$. In what follows, we work towards addressing these problems.

3.2. Closed-form of the Lagrangian Function and its Gradient

We first derive the closed-form of $\mathcal{L}(X, \mu)$. It follows from (5) that $\mathcal{L}(X, \mu)$ is finite if and only if $X \in \mathcal{S}$. For a stabilizing policy $X \in \mathcal{S}$, the state has a stationary distribution, the mean $\bar{x}_{K,l}$ of which satisfies $\bar{x}_{K,l} = (A - BK)\bar{x}_{K,l} + Bl + \bar{w}$, and its correlation matrix can be solved through a Lyapunov equation

$$\Sigma_K = W + (A - BK)\Sigma_K(A - BK)^\top.$$

(9)

Suppose that $P_K \geq 0$ is the solution of the Lyapunov equation

$$P_K = Q_\mu + K^\top RK + (A - BK)^\top P_K(A - BK)$$

and let $E_K = (R + B^\top P_K B)K - B^\top P_K A$ and $V = (I - (A - BK))^{-1}$.
Proposition 1 (Closed-form expression) The Lagrangian function \( \mathcal{L}(X, \mu) \) is given by
\[
\mathcal{L}(K, l, \mu) = \text{tr}\{P_K(W + (Bl + \bar{w})(Bl + \bar{w})^T)\} + g_{K,l}^\top(Bl + \bar{w}) + l^\top Rl - \mu\bar{\rho}.
\]  
where \( g_{K,l}^\top = 2(-l^\top E_K + S^\top + \bar{w}^\top P_K(A - BK))V \) and \( z_{K,l} \) is a constant.

Proposition 2 (Policy gradient expression) The gradient of \( \mathcal{L}(X, \mu) \) with respect to \( X \) is given by \( \nabla \mathcal{L}(X, \mu) = 2[E_K \ G_{K,l}] \Phi_{K,l} \), where \( G_{K,l} = (R + B^\top P_K B)l + B^\top P_K \bar{w} + \frac{1}{2}B^\top g_{K,l} \) and \( \Phi_{K,l} \) is the correlation matrix
\[
\Phi_{K,l} = \lim_{T \to \infty} \frac{1}{T} \mathbb{E} \sum_{t=0}^{T-1} \begin{bmatrix} x_t \\ -1 \end{bmatrix} \begin{bmatrix} x_t \\ -1 \end{bmatrix}^\top = \begin{bmatrix} \Sigma_{K} + \bar{x}_{K,l} \bar{x}_{K,l}^\top & -\bar{x}_{K,l}^\top \\ -\bar{x}_{K,l} & 1 \end{bmatrix} > 0.
\]

Since \( \Phi_{K,l} \) is positive definite, the stationary point of \( \mathcal{L}(X, \mu) \) can be uniquely solved by setting the gradients to zero as \( X^*(\mu) = [K^*(\mu) \ l^*(\mu)] \) with
\[
K^*(\mu) = (R + B^\top P_K^*\mu B)^{-1}B^\top P_K^*\mu A,
\]
\[
l^*(\mu) = -(R + B^\top P_K^*\mu B)^{-1}B^\top V^\top (P_K^*\mu \bar{w} + S).
\]

3.3. Properties of the Lagrangian Function

The minimization on \( \mathcal{L}(X, \mu) \) in (10) is a non-convex optimization problem, in that both the objective function and the stabilizing policy set \( S \) are non-convex, which poses challenges in solving (7) with standard policy gradient-based methods. In the PO for classical LQR problems (2) (Fazel et al., 2018), this is alleviated by observing that the objective function is globally gradient dominated. For a differentiable function \( f(x) : \mathbb{R}^n \to \mathbb{R} \) with a finite global minimum \( f^* \), it is globally gradient dominated if
\[
f(x) - f^* \leq \lambda \|\nabla f(x)\|^2, \quad \forall x \in \text{dom}(f) \subseteq \mathbb{R}^n
\]
where \( \lambda \geq 0 \) is a gradient dominance constant. Clearly, it implies that a stationary point must be the global minimizer. Hence, if \( f(z) \) is also Lipschitz smooth, one would expect that the gradient-based algorithms converge at a linear rate to the global minimum (Malik et al., 2019).

We show that \( \mathcal{L}(X, \mu) \) enjoys a local gradient dominance property, which is weaker than the more common global one in the sense that it only holds locally over a compact set. Before formalizing it, we note that the compact set can be constructed by observing that \( \mathcal{L}(X, \mu) \) is coercive.

Lemma 3 (Coercivity) Under a fixed \( \mu > 0 \), the Lagrangian \( \mathcal{L}(X, \mu) \) is coercive in \( X \) in the sense that \( \lim_{X \to \partial S} \mathcal{L}(X, \mu) = +\infty \), where \( \partial S \) denotes the boundary of \( S \). Moreover, it has a compact \( \alpha \)-sublevel set
\[
S_\alpha = \{ X \in \mathbb{R}^{m \times (n+1)} | \mathcal{L}(X, \mu) \leq \alpha \}.
\]

Then, we obtain the local gradient dominance property of \( \mathcal{L}(X, \mu) \) over \( S_\alpha \).

Lemma 4 (Local Gradient Dominance) \( \mathcal{L}(X, \mu) \) is gradient dominated locally over the compact set \( S_\alpha \) in (14), namely,
\[
\mathcal{L}(X, \mu) - \mathcal{L}(X^*(\mu), \mu) \leq \lambda_\alpha \text{tr}\{\nabla \mathcal{L}^\top \nabla \mathcal{L}\},
\]
where \( \lambda_\alpha = \frac{\|\Phi^*\|_{\text{min}(R)} \phi_\alpha}{4\sigma_{\min}(R) \phi_\alpha} > 0 \) is a constant related to \( S_\alpha \) and \( \phi_\alpha = \min_{X \in S_\alpha} \sigma_{\min}(\Phi_{K,l}) > 0 \).
By the local gradient dominance and the coercivity, we can determine the global minimizer of the Lagrangian.

**Theorem 5** The critical point $X^*(\mu)$ in (12) is the unique global minimizer of $\mathcal{L}(X, \mu)$.

Finally, we show that both $\mathcal{L}(X, \mu)$ and its gradient $\nabla \mathcal{L}$ are locally Lipschitz.

**Lemma 6 (Locally Lipschitz)** There exist positive scalars $(\zeta_X, \beta_X, \gamma_X)$ that depend on the current policy $X$, such that for all policies $X' \in \mathcal{S}$ satisfying $\|X' - X\| \leq \gamma_X$, we have

\[
|\mathcal{L}(X', \mu) - \mathcal{L}(X, \mu)| \leq \zeta_X \|X' - X\| \quad \text{and} \\
\|\nabla \mathcal{L}(X', \mu) - \nabla \mathcal{L}(X, \mu)\| \leq \beta_X \|X' - X\|.
\]

Note that the scalars $\zeta_X, \beta_X, \gamma_X$ in Lemma 6 are functions of $X$ as well as the problem parameters e.g., $(A, B, Q, R)$.

**3.4. Strong Duality**

The duality analysis is generally difficult for a non-convex constrained optimization problem. Nevertheless, we show that the strong duality between the primal problem (4) and dual problem (6) indeed holds, by leveraging the established properties of the Lagrangian.

**Theorem 7** Suppose that the Slater’s condition in (4) holds, i.e., there exists a policy $\tilde{X} \in \mathcal{S}$ such that $J_c(\tilde{X}) < \bar{\rho}$, then there is no duality gap for the primal problem (4) and the dual problem (6).

**4. Primal-dual Learning Algorithm for the Risk-constrained LQR**

In the model-free setting, $(A, B)$ is unknown and the gradient $\nabla \mathcal{L}(X, \mu)$ cannot be computed directly. Thus, we estimate the gradient via noisy samples of the Lagrangian. By focusing on a sublevel set, we can leverage the gradient dominance and smoothness to develop a random search method to solve (7). Moreover, we propose a primal-dual algorithm to find an optimal pair $(X^*, \mu^*)$ where an estimation of the subgradient is also used for the dual ascent in (8).

**4.1. Random Search for (7)**

Assume that we have a cost oracle, which returns a noisy evaluation of $\mathcal{L}(X, \mu)$ and $J_c(X)$ as

\[
\hat{\mathcal{L}}(X, \mu) = \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} c_\mu(x_t, u_t) \quad \text{and} \quad \hat{J}_c(X) = \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} (4x_t^\top QWQx_t + 4x_t^\top QM_3),
\]

respectively. In practice, $T$ is selected to be sufficiently large since the estimation error in the cost decreases quickly as $T \to \infty$ (Malik et al., 2019). Clearly, the oracle is weaker than the commonly assumed state-input trajectories in the model-free setting.

We develop a stochastic zero-order algorithm to solve (7) in Algorithm 1. The difficulties in the convergence analysis of Algorithm 1 hinge on that (a) both the objective function $\mathcal{L}(X, \mu)$ and its feasible set $\mathcal{S}$ are non-convex; (b) unlike in Fazel et al. (2018), the gradient dominance property does not hold globally; (c) $\mathcal{L}(X, \mu)$ is infinite for $X \not\in \mathcal{S}$ therefore the step size $\eta$ must be chosen
Theorem 8 Suppose that the step-size and smoothing radius are chosen such that the probability in Theorem 8 can be improved to a gradient norm bound for the average cost setting. In view of Furieri et al. (2020), the convergence probability in Theorem 8 can be improved to $1 - \delta$ for any $0 < \delta < 1$ by working on $S_\delta = \{X \mid \mathcal{L}(X, \mu) - \mathcal{L}(X_0, \mu) \leq 10\delta^{-1}\Delta_0\} \subset S$. For simplicity, we adopt the methodology in Malik et al. (2019).
Algorithm 2: Primal-dual learning algorithm for the risk-constrained LQR

**Input:** Initial multiplier $\mu_1$, step size $\xi_j$, $j \in \{1, 2, \ldots \}$.

for $j = 1, 2, \ldots$ do

**Step 1: learning the dual function**
Learn a policy $X_j \in \text{argmin}_{X \in S} \mathcal{L}(X, \mu_j)$ by Algorithm 1;

**Step 2: dual ascent**
Obtain a noisy sample $\hat{J}_c(X_j)$ from the oracle;
Estimate the subgradient $\hat{\omega}(\mu_j)$ by (19);
Update the dual variable by $\mu_{j+1} = [\mu_j + \xi_j \hat{\omega}(\mu_j)]_+$;
end

4.2. Primal-dual Algorithm

By dual theory (Nesterov, 2013; Nedić and Ozdaglar, 2009), the subgradient of $D(\mu)$ is given as

$$
\omega(\mu) = J_c(X^*(\mu)) - \bar{\rho},
$$

(18)

However, $J_c(X^*(\mu))$ cannot be computed directly as we do not have a dynamical model. To this end, we estimate it by a noisy sample from the oracle. The subgradient $\omega(\mu)$ is approximated as

$$
\hat{\omega}(\mu) = \hat{J}_c(X^*(\mu)) - \bar{\rho}
$$

(19)

We present our complete primal-dual algorithm in Algorithm 2. In general, there is no guarantee that a primal variable sequence will converge to the optimal solution unless the subdifferential at the dual variables is a singleton (Bertsekas, 1997; Boyd et al., 2004). Fortunately, this is indeed the case for (4) as minimizing the Lagrangian function yields a unique solution, which implies that the subgradient in (18) is actually a gradient. Furthermore, we analyze its convergence by leveraging the boundedness of the gradient norm $||\hat{\omega}(\mu)||$, which is evidenced by the fact that a stabilizing policy $X^*(\mu)$ yields a finite cost.

**Theorem 9** Let $\mathbb{E}[|\hat{\omega}(\mu_j)|| \leq b$ and $\mathbb{E}[|\mu_j|| \leq e$ with $b, e > 0$. Define $\bar{\mu}_j = \frac{1}{j} \sum_{i=1}^{j} \mu_i$. Then, by selecting a diminishing step size $\xi_j = \frac{1}{be} \sqrt{j}$, Algorithm 2 satisfies

$$
D^* - \mathbb{E}[D(\bar{\mu}_j)] \leq \frac{3be}{\sqrt{j}}.
$$

5. Simulation Results

In the experiment, we consider an unmanned aerial vehicle (UAV) that operates in a 2-D x-y plane. The discrete-time dynamical model is given by a double integrator as

$$
x_{k+1} = \begin{bmatrix} 1 & 0.5 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0.5 \\ 0 & 0 & 0 & 1 \end{bmatrix} x_k + \begin{bmatrix} 0.125 & 0 \\ 0.5 & 0 \\ 0 & 0.125 \\ 0 & 0.5 \end{bmatrix} (u_k + w_k),
$$

(20)
where \((x_{k,1}, x_{k,3})\) and \((x_{k,2}, x_{k,4})\) denote the position and velocity, respectively, \(u_k\) represents the acceleration and \(w_k\) is the input disturbance from the wind. Suppose that the gust \(w_{k,1}\) in the direction of \(x_{k,1}\) is subject to a mixed Gaussian distribution of \(\mathcal{N}(3, 30)\) and \(\mathcal{N}(8, 60)\) with weights 0.2 and 0.8, respectively. In contrast, the gust \(w_{k,2}\) in the orthogonal direction satisfies \(w_{k,2} \sim \mathcal{N}(0, 0.01)\). We set the penalty matrix in (4) as \(Q = \text{diag}(1, 0.1, 0.2)\) and \(R = \text{diag}(1, 1)\).

We verify the convergence of the proposed primal-dual learning method by examining the optimality gap and the risk constraint violation. Since the system (20) is open-loop unstable, we select an initial policy

\[
K_0 = \begin{bmatrix}
0.5 & 0.5 & 0 & 0 \\
0 & 0 & 0.5 & 0.5
\end{bmatrix}
\quad \text{and} \quad
l_0 = \begin{bmatrix}
-6 \\
0
\end{bmatrix},
\]

which is readily stabilizing. The risk tolerance in (4) is set as \(\bar{\rho} = 15\).

We first perform the random search in Algorithm 1 to solve (7). We set the initial multiplier as \(\mu_1 = 0\), the smoothing radius as \(r = 0.2\) and the sample horizon of the oracle as \(T = 100\). We empirically select the step size \(\eta = 1 \times 10^{-5}\) to yield a good performance, which is common in the policy optimization of LQR problems. We perform 20 independent trials and display the relative
Lagrangian error when $\mu = 2$ in Fig. 1. Clearly, Algorithm 1 converges to relative error 3% within $3 \times 10^5$ iterations and exhibits small variance.

Then, we conduct our primal-dual learning method in Algorithm 2 with 20 independent trials. The horizon of the risk oracle is set as $T = 10^4$ to reduce the variance of subgradient. Denote the optimal value of (4) as $J(X^*)$. Since there is an inevitable error in the Lagrangian (around 3%) per iteration, the optimality gap and constraint violation finally converge to 5%, see Fig. 2. The variance of them originates from the primal iteration and the subgradient estimation.

6. Conclusion

In this paper, we have proposed a primal-dual learning framework for the model-free risk-constrained LQR. In particular, we have shown that the Lagrangian function is both locally gradient dominated and Lipschitz, based on which the strong duality is established. Furthermore, we have shown the global convergence of the proposed primal-dual learning algorithm.

This work only considers the gradient descent method in a stochastic form. However, the optimization landscape of natural gradient and Gauss-Newton method for the risk-constrained LQR, even in the model-based setting, is still unclear. We have considered the policy gradient primal-dual method in the model-based setting in Zhao et al. (2021b). Also note that there is only one constraint in our optimization problem. It is also interesting to study the PO for LQR with multiple constraints, which will be our future work.

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1. **Proof in Section 3.2**

In this section, we establish the closed-form expression for the Lagrangian function $\mathcal{L}(X, \mu)$ and its gradient.

We define the value function with the reshaped cost $c_\mu(x_t, u_t)$ as

$$V_{K,l}(x) = \mathbb{E} \sum_{t=0}^{\infty} [c_\mu(x_t, u_t) - \mathcal{L}(K, l, \mu)|x_0 = x],$$  \hspace{1cm} (21)

which differs from its classical definition in that it accumulates the relative cost with respect to the average cost $\mathcal{L}(K, l, \mu)$. This definition is to ensure that for a stabilizing policy the value function is finite. Suppose that $P_K \geq 0$ is the solution of the algebraic Riccati equation

$$P_K = Q_\mu + K^\top RK + (A - BK)^\top P_K(A - BK)$$

and let $E_K = (R + B^\top P_K B)K - B^\top P_K A$ and $V = (I - (A - BK))^{-1}$. In the following proposition, we show that $V_{K,l}(x)$ is quadratic in $x$, by the derivation of which the closed-form of $\mathcal{L}(K, l, \mu)$ can be obtained.

**Proposition 10 (Closed-form expression)** The value function in (21) for a stabilizing policy $X \in \mathcal{S}$ is given by

$$V_{K,l}(x) = x^\top P_K x + g_{K,l}^\top x + z_{K,l},$$  \hspace{1cm} (22)

where $g_{K,l}^\top = 2(-l^\top E_K + S^\top + \bar{w}^\top P_K(A - BK))V$ and $z_{K,l}$ is a constant. Moreover, the Lagrangian function $\mathcal{L}(K, l, \mu)$ can be expressed with $P_K$ and $g_{K,l}$ as

$$\mathcal{L}(K, l, \mu) = \text{tr}\{P_K(W + (Bl + \bar{w})(Bl + \bar{w})^\top)\} + g_{K,l}^\top (Bl + \bar{w}) + l^\top Rl - \mu \bar{\rho}.$$  \hspace{1cm} (23)
1.1. Proof of Proposition 10

Inserting $u_t = -Kx_t + l$ into $V_{K,t}(x)$ in (21), it follows that

$$V_{K,t}(x) = \sum_{t=0}^{\infty} \mathbb{E}[x_t^T (Q + K^T R K)x_t + (2S^T - 2l^T R K)x_t + l^T R l - \mu \bar{\rho}] - \mathcal{L}(K, l, \mu).$$

Due to the linear dynamical model (20), it follows immediately from the dynamic programming theory (Bertsekas, 1995) that $V_{K,t}(x)$ has a quadratic form, i.e.,

$$V_{K,t}(x) = x^T P_K x + g_{K,t}^T x + z_{K,t},$$

where $P_K, g_{K,t}, z_{K,t}$ are parameters to be determined. Clearly, $V_{K,t}(x)$ satisfies the Bellman equation

$$V_{K,t}(x_t) = x_t^T (Q + K^T R K)x_t + (2S^T - 2l^T R K)x_t + l^T R l - \mathcal{L}(K, l, \mu) + \mathbb{E}[V_{K,t}(x_{t+1})].$$

Thus, it follows that

$$x_t^T P_K x_t + g_{K,t}^T x_t + z_{K,t}$$

$$= x_t^T (Q + K^T R K)x_t + (2S^T - 2l^T R K)x_t + l^T R l - \mathcal{L}(K, l, \mu) - \mu \bar{\rho}$$

$$+ \mathbb{E}[(A - BK)x_t + Bl + w_t]^T P_K [(A - BK)x_t + Bl + w_t] + \mathbb{E}[g_{K,t}^T x_t] + z_{K,t}$$

$$= x_t^T [Q + K^T R K + (A - BK)^T P_K (A - BK)]x_t + 2 [-l^T E_K + S^T + \bar{w}^T P_K (A - BK)]x_t$$

$$+ \text{tr}[P_K (W + (Bl + \bar{w})(Bl + \bar{w})^T)] + g_{K,t}^T (Bl + \bar{w}) + l^T R l - \mathcal{L}(K, l, \mu) - \mu \bar{\rho} + z_{K,t},$$

which holds for all $x_t \in \mathbb{R}^n$. Hence, we can solve the parameters

$$P_K = Q_K + (A - BK)^T P_K (A - BK),$$

$$g_{K,t} = 2 [-l^T E_K + S^T + \bar{w}^T P_K (A - BK)]V,$$

and obtain

$$\mathcal{L}(K, l, \mu) = \text{tr}\{P_K (W + (Bl + \bar{w})(Bl + \bar{w})^T)\} + g_{K,t}^T (Bl + \bar{w}) + l^T R l - \mu \bar{\rho}.$$

1.2. Proof of Proposition 2

Before deriving the gradient expression $\nabla \mathcal{L}(X, \mu)$, we first present the following lemma.

Lemma 11 Define $Q_K = Q + K^T R K$. The Lagrangian function and its gradient can also be expressed as

$$\mathcal{L}(K, l, \mu) = \text{tr}\{Q_K (\Sigma_K + \bar{x}_{K,t} \Sigma_{K,t}^T)\} + (2S^T - 2l^T R K)\bar{x}_{K,t} + l^T R l - \mu \bar{\rho}$$

$$\nabla_K \mathcal{L}(K, l, \mu) = 2 E_K \Sigma_K - \nabla_1 \mathcal{L}(K, l, \mu) \Sigma_{K,t}^T$$

$$\nabla_1 \mathcal{L}(K, l, \mu) = 2 B^T V^T (Q_K \bar{x}_{K,t} - K^T R l + S) - 2 R (K \bar{x}_{K,t} - l).$$
**Proof** Recall the definition of $\mathcal{L}(K, l, \mu)$

$$
\mathcal{L}(K, l, \mu) = \lim_{T \to \infty} \frac{1}{T} \mathbb{E} \sum_{t=0}^{T-1} (x_t^T Q_{\mu} x_t + 2 x_t^T S + u_t^T R u_t - \mu \bar{p})
$$

$$
= \mathbb{E}_\tau(x_t^T Q_{\mu} x_t + 2 x_t^T S + (-K x_t + l)^T R(-K x_t + l) - \mu \bar{p}),
$$

where $\tau$ denotes the stationary distribution of the steady state.

Combining the definition of $\bar{x}_{K,l}$ and $\Sigma_K$, we obtain

$$
\mathcal{L}(K, l, \mu) = \text{tr}\{Q_K(\Sigma_K + \bar{x}_{K,l}\bar{x}_{K,l}^T)\} + (2S^T - 2l^T RK)\bar{x}_{K,l} + l^T R l - \mu \bar{p}. \tag{24}
$$

Then, we derive the gradient with respect to $K$ and $l$, respectively. It follows from (24) that

$$
\nabla_K \mathcal{L} = 2RK(\Sigma_K + \bar{x}_{K,l}\bar{x}_{K,l}^T) + \nabla_K \text{tr}\{Q_K(\Sigma_K + \bar{x}_{K,l}\bar{x}_{K,l}^T)\}|_{Q_K=Q_{\mu}+K^T RK} + \nabla_K \{2S^T - 2l^T RK\}\bar{x}_{K,l}
$$

$$
= 2RK(\Sigma_K + \bar{x}_{K,l}\bar{x}_{K,l}^T) - 2B^T P_K(A - BK)\Sigma_K - 2B^T V^T(Q_{\mu} + K^T RK)\bar{x}_{K,l}\bar{x}_{K,l}^T
$$

$$
- 2Rl\bar{x}_{K,l} - 2B^T V^T(S - K^T R l)\bar{x}_{K,l}^T
$$

$$
= 2E_K\Sigma_K + 2R(K\bar{x}_{K,l} - l)\bar{x}_{K,l}^T - 2B^T V^T((Q_{\mu} + K^T RK)\bar{x}_{K,l} - K^T R l + S)\bar{x}_{K,l}^T,
$$

and

$$
\nabla_l \mathcal{L}(K, l, \mu) = \nabla_l \text{tr}\{(Q_{\mu} + K^T RK)\bar{x}_{K,l}\bar{x}_{K,l}^T\} + \nabla_l \{2S^T - 2l^T RK\}\bar{x}_{K,l} + 2Rl
$$

$$
= 2B^T V^T(Q_{\mu} + K^T RK)\bar{x}_{K,l} + 2B^T V^T(S - K^T R l) - 2RK(\bar{x}_{K,l} - l).
$$

Hence, it can be easily observed that

$$
\nabla_K \mathcal{L}(K, l, \mu) = 2E_K\Sigma_K - \nabla_l \mathcal{L}(K, l, \mu)\bar{x}_{K,l}^T.
$$

In view of Proposition 10, $\mathcal{L}(K, l, \mu)$ is a quadratic function of $l$, thus $\nabla_l \mathcal{L}(K, l, \mu)$ can be derived in another way, i.e.,

$$
\nabla_l \mathcal{L}(K, l, \mu) = \nabla_l \text{tr}\{P_K(W + (Bl + \bar{w})(Bl + \bar{w})^T)\} + \nabla_l \{g_{K,l}(Bl + \bar{w})\} + 2Rl
$$

$$
= 2B^T P_K(Bl + \bar{w}) + (2B^T PA - 2(B^T PB + R)K)\bar{x}_{K,l} + B^T g_{K,l}
$$

$$
= 2G_{K,l} - 2E_K\bar{x}_{K,l}.
$$

Hence, it follows that

$$
\nabla_K \mathcal{L}(K, l, \mu) = 2E_K\Sigma_K - \nabla_l \mathcal{L}(K, l, \mu)\bar{x}_{K,l}^T
$$

$$
= 2E_K(\Sigma_K + \bar{x}_{K,l}\bar{x}_{K,l}^T) - 2G_{K,l}\bar{x}_{K,l}^T.
$$

Noting that $\nabla_X \mathcal{L}(X, \mu) = [\nabla_K \mathcal{L} \quad \nabla_l \mathcal{L}]$, the proof is completed.
2. Proof of Lemma 4

As in Fazel et al. (2018), the gradient dominance property can be derived by analysing the advantage function. We begin by a definition.

**Definition 12** Define the T-truncated value function

\[
V_{K,l}^T(x) = \mathbb{E} \sum_{t=0}^{T-1} [c_\mu(x_t, u_t) - \mathcal{L}(K, l, \mu)|x_0 = x],
\]

and the T-truncated action-dependent value function

\[
Q_{K,l}^T(x, u) = c_\mu(x, u) - \mathcal{L}(K, l, \mu) + \mathbb{E}V_{K,l}^{T-1}(Ax + Bu + w).
\] (25)

The T-truncated advantage value function is given by

\[
A_{K,l}^T(x, u) = Q_{K,l}^T(x, u) - V_{K,l}^T(x).
\]

With the T-truncated value function description, we are able to compute the Lagrangian cost difference of two policies \((K, l)\) and \((K', l')\).

**Lemma 13** Suppose that both \((K, l)\) and \((K', l')\) are stabilizing. Let \(\{x'_t\}\) and \(\{u'_t\}\) be sequences generated by following \((K', l')\). Then

\[
\mathcal{L}(K', l', \mu) - \mathcal{L}(K, l, \mu) = \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} A_{K,l}^T(x'_t, u'_t).
\]

**Proof** It follows from the definition of \(V_{K,l}^T(x)\) that

\[
\mathcal{L}(K', l', \mu) - \mathcal{L}(K, l, \mu) = \lim_{T \to \infty} \frac{1}{T} \mathbb{E} \sum_{t=0}^{T-1} (c_\mu(x'_t, u'_t) - c_\mu(x_t, u_t))
\]

\[
= \lim_{T \to \infty} \frac{1}{T} \mathbb{E} \left[ \sum_{t=0}^{T-1} (c_\mu(x'_t, u'_t)) - V_{K,l}^T(x'_t) - T \cdot \mathcal{L}(K, l, \mu) \right]
\]

\[
= \lim_{T \to \infty} \frac{1}{T} \mathbb{E} \left[ \sum_{t=0}^{T-1} (c_\mu(x'_t, u'_t) + V_{K,l}^T(x'_t) - V_{K,l}^T(x'_t)) - V_{K,l}^T(x'_t) - T \cdot \mathcal{L}(K, l, \mu) \right]
\]

\[
= \lim_{T \to \infty} \frac{1}{T} \mathbb{E} \sum_{t=0}^{T-1} (c_\mu(x'_t, u'_t) - \mathcal{L}(K, l, \mu) + V_{K,l}^T(x'_{t+1}) - V_{K,l}^T(x'_t))
\]

\[
= \lim_{T \to \infty} \frac{1}{T} \mathbb{E} \sum_{t=0}^{T-1} (Q_{K,l}^T(x'_t, u'_t) - V_{K,l}^T(x'_t))
\]

\[
= \lim_{T \to \infty} \frac{1}{T} \mathbb{E} \sum_{t=0}^{T-1} A_{K,l}^T(x'_t, u'_t)
\]

Then, we show that the advantage value function has a closed-form.
Lemma 14  The advantage value function $A_{K,l}(x,u) = \lim_{T \to \infty} A_{K,l}^T(x,u)$ under policy $(K',l')$ is given as

$$A_{K,l}(x,u) = Q_{K,l}(x,u) - V_{K,l}(x)$$

$$= \lim_{T \to \infty} Q_{K,l}^T(x,u) - V_{K,l}^T(x)$$

$$= 2x^T (K' - K)^\top E_K x + x^T (K' - K)^\top (R + B^\top P_K B) (K' - K) x$$

$$- 2G_{K,l}^T(K' - K)x - 2(l' - l)^\top (R + B^\top P_K B)(K' - K)x$$

$$- 2(l' - l)^\top E_K x + 2(l' - l)^\top G_{K,l} + (l' - l)^\top (R + B^\top P_K B)(l' - l)$$

Proof  By Definition 12, it follows that

$$A_{K,l}(x,u) = Q_{K,l}(x,u) - V_{K,l}(x)$$

$$= \lim_{T \to \infty} Q_{K,l}^T(x,u) - V_{K,l}^T(x)$$

$$= x^T Q_\mu x + 2S^\top x + (-K'x + l')^\top R(-K'x + l') - \mathcal{L}(K,l,\mu)$$

$$+ \mathbb{E}_w V_{K,l}((A - BK')x + Bl' + w) - V_{K,l}(x)$$

$$= x^T (Q_\mu + (K')^\top RK')x + x^T (A - BK')^\top P_K (A - BK')$$

$$+ (2S^\top - 2(l')^\top RK')x + 2(Bl' + \bar{w})^\top P_K (A - BK')x + g_{K,l}^T(A - BK')x$$

$$+ tr\{P_K(W + (Bl' + \bar{w})(Bl' + \bar{w})^\top)\} + g_{K,l}^T(Bl' + \bar{w}) + (l')^\top Rl' - \mathcal{L}(K,l,\mu) - V_{K,l}(x)$$

$$= x^T (Q_\mu + (K')^\top RK')x + x^T (A - BK')^\top P_K (A - BK')$$

$$- x^T (Q_\mu + (K')^\top RK')x - x^T (A - BK')^\top P_K (A - BK')$$

$$+ (2S^\top - 2(l')^\top RK')x + 2(Bl' + \bar{w})^\top P_K (A - BK')x + g_{K,l}^T(A - BK')x$$

$$- (2S^\top - 2(l')^\top RK')x - 2(Bl + \bar{w})^\top P_K (A - BK) x - g_{K,l}^T(A - BK) x$$

$$+ tr\{P_K(W + (Bl + \bar{w})(Bl + \bar{w})^\top)\} + g_{K,l}^T(Bl + \bar{w}) + (l')^\top Rl'$$

$$- tr\{P_K(W + (Bl + \bar{w})(Bl + \bar{w})^\top)\} - g_{K,l}^T(Bl + \bar{w}) - l^\top Rl$$

By reorganizing the terms and using the definition of $G_{K,l}$, the proof is completed.

We are now ready to establish the key lemma that leads to the local gradient dominance.

Lemma 15  For a stabilizing policy $X \in S$, it holds that

$$\mathcal{L}(K,l,\mu) - \mathcal{L}(K^*,l^*,\mu) \leq \frac{\|\Phi^*\|}{4\sigma_{\min}(R)\sigma^2_{\min}(\Phi_{K,l})} tr \left\{ [\nabla_K \mathcal{L} \nabla_l \mathcal{L}]^\top [\nabla_K \mathcal{L} \nabla_l \mathcal{L}] \right\}$$

Proof  Note that $A_{K,l}(x,u)$ can be further reorganized as

$$A_{K,l}(x,u) = [(K' - K)x - (l' - l) + (R + B^\top P_K B)^{-1}(E_K x - G_{K,l})]^\top (R + B^\top P_K B)$$

$$\times [(K' - K)x - (l' - l) + (R + B^\top P_K B)^{-1}(E_K x - G_{K,l})]$$

$$- (E_K x - G_{K,l})^\top (R + B^\top P_K B)^{-1}(E_K x - G_{K,l})$$

$$\geq -(E_K x - G_{K,l})^\top (R + B^\top P_K B)^{-1}(E_K x - G_{K,l}).$$
Let \( \{x^*_t\} \) and \( \{u^*_t\} \) be sequences generated by following the optimal policy \((K^*, l^*)\) and \(\Phi^*\) be the correlation matrix \(\Phi_{K^*, l^*}\). Then, it follows that

\[
\mathcal{L}(K, l, \mu) - \mathcal{L}(K^*, l^*, \mu) \\
= - \lim_{T \to \infty} \frac{1}{T} \mathbb{E} \sum_{t=0}^{T-1} A^T_{K,l}(x^*_t, u^*_t) \\
\leq \lim_{T \to \infty} \frac{1}{T} \mathbb{E} \sum_{t=0}^{T-1} \text{tr} \left\{ (E_K x^*_t - G_{K,l})^\top (R + B^\top P_K B)^{-1} (E_K x^*_t - G_{K,l}) \right\} \\
= \lim_{T \to \infty} \frac{1}{T} \mathbb{E} \sum_{t=0}^{T-1} \left\{ \left[ \begin{array}{c} x^*_t \\ 1 \end{array} \right] \left[ \begin{array}{c} x^*_t \\ 1 \end{array} \right]^\top \left[ \begin{array}{c} E_K \\ G_{K,l} \end{array} \right]^\top (R + B^\top P_K B)^{-1} [E_K \\ G_{K,l}] \right\} \\
= \text{tr} \left\{ \Phi^*[E_K \\ G_{K,l}]^\top (R + B^\top P_K B)^{-1} [E_K \\ G_{K,l}] \right\} \\
\leq \|\Phi^*\| \text{tr} \left\{ [E_K \\ G_{K,l}]^\top (R + B^\top P_K B)^{-1} [E_K \\ G_{K,l}] \right\} \\
= \|\Phi^*\| \text{tr} \left\{ (R + B^\top P_K B)^{-1} [E_K \\ G_{K,l}][E_K \\ G_{K,l}]^\top \right\} \\
\leq \|\Phi^*\| \|R + B^\top P_K B\|^{-1} \text{tr} \left\{ [E_K \\ G_{K,l}][E_K \\ G_{K,l}]^\top \right\} \\
\leq \frac{\|\Phi^*\|}{\sigma_{\text{min}}(R)} \text{tr} \left\{ [E_K \\ G_{K,l}][E_K \\ G_{K,l}]^\top \right\}
\]

To make the connections between the policy gradients and the cost difference clear, recall that

\[
\text{tr} \left\{ [\nabla_K \mathcal{L} \ \nabla_l \mathcal{L}]^\top [\nabla_K \mathcal{L} \ \nabla_l \mathcal{L}] \right\} = 4 \text{tr} \left\{ \Phi_{K,l} \Phi_{K,l}^\top [E_K \\ G_{K,l}]^\top [E_K \\ G_{K,l}] \right\}
\]

Thus, the gap \(\mathcal{L}(K, l, \mu) - \mathcal{L}(K^*, l^*, \mu)\) can be further bounded by the gradient, i.e.,

\[
\mathcal{L}(K, l, \mu) - \mathcal{L}(K^*, l^*, \mu) \\
\leq \frac{\|\Phi^*\|}{\sigma_{\text{min}}(R)} \text{tr} \left\{ [E_K \\ G_{K,l}][E_K \\ G_{K,l}]^\top \right\} \\
= \frac{\|\Phi^*\|}{4\sigma_{\text{min}}(R)} \text{tr} \left\{ (\Phi_{K,l} \Phi_{K,l}^\top)^{-1} \text{tr} \left\{ [\nabla_K \mathcal{L} \ \nabla_l \mathcal{L}]^\top [\nabla_K \mathcal{L} \ \nabla_l \mathcal{L}] \right\} \right\} \\
\leq \frac{\|\Phi^*\|}{4\sigma_{\text{min}}(R)\sigma_{\text{min}}(\Phi_{K,l})^2} \text{tr} \left\{ [\nabla_K \mathcal{L} \ \nabla_l \mathcal{L}]^\top [\nabla_K \mathcal{L} \ \nabla_l \mathcal{L}] \right\}
\]

Since the lower bound of \(\sigma_{\text{min}}(\Phi_{K,l})\) is zero, we cannot find a uniform gradient dominance constant. However, we notice that the positive definite correlation matrix \(\Phi_{K,l}\) (11) is continuous with respect to \(K\) and \(l\). Thus, if we restrict the policy \(X\) in a compact set, its minimal eigenvalue must be positive. The proof is completed by considering the compact sub-level set in (14).
3. Proof of Lemma 6

In this section, we show the Lipschitz continuity for the Lagrangian function and its gradient, respectively.

3.1. Proof of Lipschitz continuity of the Lagrangian Function

We introduce an auxiliary cost function to facilitate the analysis.

**Lemma 16** Define \( C(K) = \text{tr}(P_K W) \), then it follows that

\[
C(K) = \text{tr}[(Q_\mu + K^T R K) \Sigma_K] \leq \mathcal{L}(K, l) + S^T Q_\mu^{-1} S.
\]

**Proof** Comparing the definition of \( \mathcal{L}(K, l, \mu) \) and \( C(K) \), we obtain that

\[
\mathcal{L}(K, l, \mu) = \text{tr}[(Q_\mu + K^T R K)(\Sigma_K + \bar{x}_{K,l} \bar{x}_{K,l}^\top)] + (2S^T - 2l^T R K)\bar{x}_{K,l} + l^T R l
\]

\[
= \text{tr}[(Q_\mu + K^T R K)\Sigma_K] + (Q_\mu \bar{x}_{K,l} + S)^T Q_\mu^{-1} (Q_\mu \bar{x}_{K,l} + S) - S^T Q_\mu^{-1} S + (K\bar{x}_{K,l} - l)^T R (K\bar{x}_{K,l} - l)
\]

\[
\geq C(K) - S^T Q_\mu^{-1} S.
\]

In fact, \( C(K) \) is the cost function of the classical LQR formulation, see Fazel et al. (2018); Bu et al. (2019). By introducing it, we build a connection between \( \mathcal{L}(K, l, \mu) \) and \( C(K) \). Thus, some results in Fazel et al. (2018) can be utilized for our analysis.

We now present some technical lemmas.

**Lemma 17** Suppose that \( K \) is stabilizing, i.e., \( \rho(A - BK) < 1 \). Then we have following results.

(a) \[
\|\Sigma_K\| \leq \frac{C(K)}{\sigma_{\min}(Q_\mu)}, \quad \|P_K\| \leq \frac{C(K)}{\sigma_{\min}(W)}.
\]

(b) If \[
\|K' - K\| \leq \min \left( \frac{\sigma_{\min}(Q_\mu)\sigma_{\min}(W)}{4C(K)\|B\|\|A - BK\| + 1}, \|K\| \right),
\]

then it follows that

\[
\|P_{K'} - P_K\| \leq 6\|K\|\|R\| \left( \frac{C(K)}{\sigma_{\min}(Q_\mu)\sigma_{\min}(W)} \right)^2 \left(\|K\|\|B\|\|A - BK\| + \|K\|\|B\| + 1\right)\|K - K'\|.
\]

(c) The norm \( \|K\| \) can be bounded by

\[
\|K\| \leq \frac{1}{\sigma_{\min}(R)} \left( \sqrt{\|R + B^T P_K B\|} \frac{(C(K) - C(K^*))}{\mu} + \|B^T P_K A\| \right)
\]

(d) \[
\text{tr} \left( \Sigma_K \right) \geq \frac{\sigma_{\min}(W)}{2(1 - \rho(A - BK))}.
\]
As a consequence, \(\frac{1}{1-\rho(A-BK)}\) is bounded, i.e.,

\[
\frac{1}{1-\rho(A-BK)} \leq \frac{2n\|\Sigma_K\|}{\sigma_{\min}(W)} \leq \frac{2nC(K)}{\sigma_{\min}(W)\sigma_{\min}(Q_\mu)}.
\]

**Proof** The proof follows the results of Fazel et al. (2018).

**Lemma 18** Define \(V_K = (I-(A-BK))^{-1}\). Suppose that \(\|K' - K\| \leq \frac{1-\rho(A-BK)}{2\|B\|}\), it follows that

\[
\|V_{K'} - V_K\| \leq \frac{2\|B\|\|K' - K\|}{1-\rho(A-BK)}
\]

**Proof** The proof follows immediately from matrix inverse perturbation theorem (Horn and Johnson, 2012).

**Lemma 19** \(\text{tr}(E_K^T E_K)\) can be bounded as

\[
\text{tr}(E_K^T E_K) \leq \text{tr}\{[E_K G_{K,l}]^T[E_K G_{K,l}]\} \leq \frac{\|R + B^T P_K B\|}{\phi_\alpha} (\mathcal{L}(K,l) - \mathcal{L}(K^*,l')) \tag{25}
\]

where \(\phi_\alpha\) is defined in Lemma 4.

**Proof** Let \(X' = X - (R + B^T P_K B)^{-1} [E_K G_{K,l}]\), we have

\[
\mathcal{L}(K,l) - \mathcal{L}(K^*,l') \geq \mathcal{L}(K,l) - \mathcal{L}(K',l')
\]

\[
= \text{tr}\{[E_K G_{K,l}]^T (R + B^T P_K B)^{-1} [E_K G_{K,l}]\Phi_{K',l'}\}
\]

\[
\geq \frac{\sigma_{\min}(\Phi_{K',l'})}{\|R + B^T P_K B\|} \text{tr}\{[E_K G_{K,l}]^T[E_K G_{K,l}]\}
\]

\[
\geq \frac{\phi_\alpha}{\|R + B^T P_K B\|} \text{tr}\{[E_K G_{K,l}]^T[E_K G_{K,l}]\}.
\]

The last inequality is obtained by choosing a sufficiently large \(\alpha\).

**Lemma 20** For all \(K'\) such that

\[
\|K' - K\| \leq \min\left(\frac{\sigma_{\min}(Q_\mu)\sigma_{\min}(W)}{4C(K)\|B\|(\|A-BK\|+1)},\|K\|,\frac{1-\rho(A-BK)}{2\|B\|}\right),
\]

it follows that,

\[
\|g_{K',l} - g_{K,l}\| \leq c_{K_1}\|K' - K\|.
\]
Proof It follows from the definition of $g_{K,l}$ that
\[
g_{K',l} - g_{K,l} = 2([-l^T E_{K'} + S^T + \bar{w}^T P_{K'}(A - BK')]V_{K'} - 2[-l^T E_{K} + S^T + \bar{w}^T P_{K}(A - BK)]V_{K} = 2([-l^T (E_{K'} - E_K) + \bar{w}^T P_{K'}(A - BK') - \bar{w}^T P_{K}(A - BK)]V_{K'} + 2[-l^T E_{K} + S^T + \bar{w}^T P_{K}(A - BK)](V_{K'} - V_{K})
\]
By lemma 18, we have
\[
\|V_{K'} - V_{K}\| \leq \frac{2\|B\|\|K' - K\|}{1 - \rho(A - BK)}
\]
Further,
\[
\|V_{K'}\| = \|V_{K'} - V_{K} + V_{K}\| \leq \|V_{K'} - V_{K}\| + \|V_{K}\| = \frac{1 + 2\|B\|\|K' - K\|}{1 - \rho(A - BK)}.
\]
By lemma 19,
\[
\|E_{K}\| \leq \sqrt{\frac{\|R + B^T P_{K}B\|}{\phi_{\alpha}}} (\mathcal{L}(K,l) - \mathcal{L}(K^*,l^*))
\]
Also note that
\[
\|P_{K'}(A - BK') - P_{K}(A - BK)\| \leq \|P_{K'} - P_{K}\|\|A - BK'\| + \|P_{K}\|\|B\|\|K' - K\|.
\]
By using the assumptions on $\|K' - K\|$ and the bounds in lemma 17, we finally obtain that
\[
\|g_{K',l} - g_{K,l}\| \leq c_1(K,l)\|K' - K\|,
\]
where $c_1(K,l)$ is polynomial in $C(K), \|A\|, \|B\|, \frac{1}{\sigma_{\min}(W)}, \frac{1}{\sigma_{\min}(Q_{\mu})}, \frac{1}{\sigma_{\min}(R)}, \|l\|, \|\bar{w}\|$.  

Equipped with the above lemmas, we are now ready to find the Lipschitz constants of $\mathcal{L}(K,l,\mu)$ with respect to $K$ and $l$, respectively.

Lemma 21 Suppose that
\[
\|K' - K\| \leq \min\left(\frac{\sigma_{\min}(Q_{\mu})\sigma_{\min}(W)}{4C(K)\|B\|\|A - BK\| + 1}, \|K\|, \frac{1 - \rho(A - BK)}{2\|B\|}\right),
\]
then
\[
\mathcal{L}(K',l) - \mathcal{L}(K,l) \leq c_2(K,l)\|K' - K\|
\]
Proof Note that
\[
\mathcal{L}(K',l) - \mathcal{L}(K,l) = \text{tr}[(P_{K'} - P_{K})(W + (Bl + \bar{w})(Bl + \bar{w})^T)] + (g_{K',l} - g_{K,l})^T (Bl + \bar{w}).
\]
Using the bounds built in above lemmas, we can find $c_2(K,l)$ as a polynomial in $C(K), \|A\|, \|B\|, \frac{1}{\sigma_{\min}(W)}, \frac{1}{\sigma_{\min}(Q_{\mu})}, \frac{1}{\sigma_{\min}(R)}, \|l\|, \|\bar{w}\|, \|W\|$.  

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Lemma 22  Suppose that $||l' - l|| \leq ||l|| + \bar{w}$, then

$$||L(K, l') - L(K, l)|| \leq c_3(K, l)||l' - l||.$$  

Proof  Since $L(K, l)$ is quadratic in $l$, the analysis is much simpler. We have

$$L(K, l') - L(K, l) = l'^T(R + B^T P_K B)l' - l^T(R + B^T P_K B)l + 2\bar{w}^T P_K (l' - l)$$
$$+ g_l^T (Bl' + \bar{w}) - g_l^T (Bl + \bar{w})$$
$$= (l' - l)^T(R + B^T P_K B)l' + l^T(R + B^T P_K B)(l' - l)$$
$$+ 2\bar{w}^T P_K (l' - l) + g_l^T (l' - l) + (g_l'^T - g_l^T)(Bl + \bar{w}).$$

Since

$$||g_l'^T - g_l^T|| \leq 2||l' - l|| ||E_K|| ||V_K||,$$

it follows that

$$||gL|| \leq ||gL|| + ||g_l'^T - g_l^T|| \leq 2(2||l|| + ||\bar{w}||)||E_K|| ||V_K|| + 2||l^T E_K + S^T + \bar{w}^T P_K (A - BK)|| ||V_K||.$$  

Also using the technical lemmas, we obtain

$$||L(K, l') - L(K, l)|| \leq c_3(K, l)||l' - l||,$$

where $c_3(K, l)$ is polynomial in $C(K), ||R||, ||A||, ||B||, \frac{1}{\sigma_{\min}(W)}, \frac{1}{\sigma_{\min}(Q_c)}, \frac{1}{\sigma_{\min}(K)}, ||l||, ||\bar{w}||$.  

Combining Lemma 21 and Lemma 22, the Lipschitz constant can be found.

Lemma 23 (The cost is locally Lipschitz.)  There exist positive scalars $(L_1, \gamma_1)$ that depends on the current policy $X = [K \ l]$, such that for all policies $X'$ satisfying $||X' - X|| \leq \gamma_1$, the cost difference is Lipschitz bounded, namely,

$$||L(X', \mu) - L(X, \mu)|| \leq L_1 ||X' - X||.$$  

Proof  By choosing $\gamma_1$ such that the assumptions in Lemma 21 and Lemma 22 hold for all $X' \in \{X' ||X' - X|| \leq \gamma_1\}$, if follows that

$$||L(K', l') - L(K, l)|| = ||L(K', l') - L(K', l) + L(K', l) - L(K, l)||$$
$$\leq ||L(K', l') - L(K', l)|| + ||L(K', l) - L(K, l)||$$
$$\leq c_3(K', l)||l' - l|| + c_2(K, l)||K' - K||$$
$$\leq L_1 ||X' - X||.$$  

$$\blacksquare$$
3.2. Proof of the Lipschitz Continuity of the Gradient

Analogy to the above derivation, we first establish the Lipschitz property for the gradient $\nabla_K \mathcal{L}$ and $\nabla_{\ell} \mathcal{L}$ and then combine them.

Lemma 24 Suppose that

$$
\| K' - K \| \leq \min \left( \frac{\sigma_{\min}(Q_\mu)\sigma_{\min}(W)}{4C(K)\|B\|(\|A - BK\| + 1)}, \|K\|, \frac{1 - \rho(A - BK)}{2\|B\|} \right),
$$

then it follows that

$$
\| \Phi_{K',\ell} - \Phi_{K,\ell} \| \leq c_4(K, \ell)\| K' - K \|.
$$

Proof Note that

$$
\| \Phi_{K',\ell} - \Phi_{K,\ell} \| \leq \text{tr}(\Phi_{K',\ell} - \Phi_{K,\ell})
\leq n\|\Sigma_{K'} - \Sigma_K\| + \|\bar{x}_{K'}\bar{x}_{K'}^T - \bar{x}_K\bar{x}_K^T\|.  \tag{28}
$$

It has been shown in Fazel et al. (2018) that

$$
\|\Sigma_{K'} - \Sigma_K\| \leq 4 \left( \frac{C(K)}{\sigma_{\min}(Q_\mu)} \right)^2 \|B\|(\|A - BK\| + 1) \| K - K' \|. 
$$

For the second term in (28)

$$
\|\bar{x}_{K'}\bar{x}_{K'}^T - \bar{x}_K\bar{x}_K^T\| = \|(\bar{x}_{K'} - \bar{x}_K)\bar{x}_{K'} + \bar{x}_K(\bar{x}_{K'} - \bar{x}_K)\|,
$$

we have

$$
\|\bar{x}_{K'} - \bar{x}_K\| = \|(V_{K'} - V_K)(Bl + \bar{w})\| \leq \frac{2\|B\||Bl + \bar{w}|\|K' - K\|}{1 - \rho(A - BK)}
$$

and

$$
\|\bar{x}_{K'}\| \leq \|\bar{x}_K\| + \|\bar{x}_{K'} - \bar{x}_K\|
\leq \frac{2\|B\||K' - K\| + 1\|Bl + \bar{w}\|}{1 - \rho(A - BK)}.
$$

Thus,

$$
\|\bar{x}_{K'}\bar{x}_{K'}^T - \bar{x}_K\bar{x}_K^T\| \leq 2 \left( \frac{\|Bl + \bar{w}\|}{1 - \rho(A - BK)} \right)^2 \|B\|(2 + 2\|B\||K' - K\|)\|K' - K\|
\leq 6 \left( \frac{\|Bl + \bar{w}\|}{1 - \rho(A - BK)} \right)^2 \|B\|\|K' - K\|.  \tag{29}
$$

Combining (28) and (29), we can find $c_4(K, \ell)$ as a polynomial in $C(K), \|R\|, \|A\|, \|B\|, \frac{1}{\sigma_{\min}(Q_\mu)}, \frac{1}{\sigma_{\min}(R)}, \|l\|, \|\bar{w}\|, n.$

Lemma 25 Suppose that

$$
\| K' - K \| \leq \min \left( \frac{\sigma_{\min}(Q_\mu)\sigma_{\min}(W)}{4C(K)\|B\|(\|A - BK\| + 1)}, \|K\|, \frac{1 - \rho(A - BK)}{2\|B\|} \right),
$$

it follows that

$$
\| \nabla_{K',\ell} \mathcal{L} - \nabla_{K,\ell} \mathcal{L} \| \leq c_5(K, \ell)\| K' - K \|.
$$
Proof Suppose that \( l \) is fixed, then we have

\[
\|\nabla_{K,l} \mathcal{L} - \nabla_{K,l} \mathcal{L}\| = 2 \| [E_{K'} G_{K,l}] \Phi_{K',l} - [E_K G_{K,l}] \Phi_{K,l}\|
\]

\[
\leq 2 \| [E_{K'} - E_K G_{K,l} - G_{K,l}] \Phi_{K',l} + [E_K G_{K,l}] (\Phi_{K',l} - \Phi_{K,l})\|.
\]

\( \|\Phi_{K,l}\| \) can be bounded as

\[
\|\Phi_{K,l}\| \leq 1 + tr(\Sigma_K + \bar{x}_K \bar{x}_K^T)
\]

\[
\leq 1 + n\|\Sigma_K\| + \|\bar{x}_K\|^2
\]

\[
\leq 1 + n \frac{C(K)}{\sigma_{\min}(Q)} \left( \frac{\|Bl + \bar{w}\|}{1 - \rho(A - BK)} \right)^2.
\]

Further, using the conditions on \( K \), it follows that

\[
\|\Phi_{K',l}\| \leq \|\Phi_{K,l}\| + \|\Phi_{K',l} - \Phi_{K,l}\|
\]

\[
\leq 1 + \frac{5nC(K)}{\sigma_{\min}(Q)} \left( \frac{\|Bl + \bar{w}\|}{1 - \rho(A - BK)} \right)^2 + \frac{3n\|Bl + \bar{w}\|^2}{1 - \rho(A - BK)}.
\]

Also,

\[
\|G_{K',l} - G_{K,l}\| = \|B^T (P_{K'} - P_K) Bl + B^T (P_{K'} - P_K) \bar{w} + \frac{1}{2} B^T (g_{K',l} - g_{K,l})\|
\]

can be bounded by \( \|K' - K\| \). From lemma 19, we obtain

\[
\|\Phi_{K',l}\| = \sqrt{\frac{\|R + B^T P_K B\|}{\|\Phi_{K',l}\|} \left( \mathcal{L}(K, l) - \mathcal{L}(K^*, l^*) \right)}.
\]

Combining the above inequalities, we conclude that

\[
\|\nabla_{K,l} \mathcal{L} - \nabla_{K,l} \mathcal{L}\| \leq c_5(K, l) \|K' - K\|,
\]

where \( c_5(K, l) \) is polynomial in \( C(K), \|R\|, \|A\|, \|B\|, \frac{1}{\sigma_{\min}(W)}, \frac{1}{\sigma_{\min}(Q)}, \frac{1}{\sigma_{\min}(R)}, \|l\|, \|\bar{w}\|, n \).

\[\Box\]

Lemma 26 Suppose that \( \|l' - l\| \leq \|l\| \), then we have

\[
\|\nabla_{K,l} \mathcal{L} - \nabla_{K,l} \mathcal{L}\| \leq c_6(K, l) \|l' - l\|,
\]

where \( c_6(K, l) \) is polynomial in \( C(K), \|R\|, \|A\|, \|B\|, \frac{1}{\sigma_{\min}(W)}, \frac{1}{\sigma_{\min}(Q)}, \frac{1}{\sigma_{\min}(R)}, \|l\|, \|\bar{w}\|, n \).

Proof Note that

\[
\|\nabla_{K,l} \mathcal{L} - \nabla_{K,l} \mathcal{L}\| = 2 \| [E_K G_{K,l}] \Phi_{K',l} - [E_K G_{K,l}] \Phi_{K,l}\|
\]

\[
= 2 \| [0 \ G_{K',l} - G_{K,l}] \Phi_{K',l} + [E_K G_{K,l}] (\Phi_{K',l} - \Phi_{K,l})\|,
\]

Then, combining

\[
\|G_{K',l} - G_{K,l}\| = \frac{1}{2} \|B\| \|g_{K',l} - g_{K,l}\| \leq \|B\| \|E_K\| \|V_K\| \|l' - l\|,
\]
and
\[
\|\Phi_{K',l} - \Phi_{K,l}\| \leq \text{tr}(\Phi_{K',l} - \Phi_{K,l}) \\
= \|\bar{x}_l^T \bar{x}_l' - \bar{x}_l \bar{x}_l^T\| \\
= \|\bar{x}_l - \bar{x}_l'\| \|\bar{x}_l - \bar{x}_l'\| \\
\leq 2\|Bl + \bar{w}\| + \|B\|\|ll\| \|V_{K}\| \|ll' - l\|,
\]
the proof is completed.

Lemma 27 (The gradient is locally Lipschitz.) There exist positive scalars \((L_2, \gamma_2)\) that depends on the current policy \(X = [K\ l]\), such that for all policies \(X'\) satisfying \(\|X' - X\| \leq \gamma_2\), the gradient difference is Lipschitz bounded, namely,
\[
\|\nabla_{X'}L - \nabla_XL\| \leq L_2\|X' - X\|.
\]

Proof By choosing \(\gamma_2\) such that the assumptions in Lemma 21 and Lemma 22 hold for all \(X'\) satisfying \(\|X' - X\| \leq \gamma_2\), it follows that
\[
\|\nabla_{X'}L - \nabla_XL\| = \|\nabla_{K',l}L - \nabla_{K,l}L + \nabla_{K',l}L - \nabla_{K,l}L\| \\
\leq \|\nabla_{K',l}L - \nabla_{K,l}L\| + \|\nabla_{K',l}L - \nabla_{K,l}L\| \\
\leq c_6(K', l)\|ll' - l\| + c_5(K, l)\|K' - K\| \\
\leq L_2\|X' - X\|.
\]

Setting \(\gamma_X = \min\{\gamma_1, \gamma_2\}\) and \(\zeta_X = L_1, \beta_X = L_2\), Lemma 6 is proved.

4. Proof of Theorem 7

The following lemma from the duality theory (Nesterov, 2013; Nedić and Ozdaglar, 2009) provides a sufficient and necessary condition for the absence of duality gap.

Lemma 28 Suppose that \((X^*, \mu^*)\) is a feasible pair of the Lagrangian function \(\mathcal{L}(X, \mu)\) with \(X^* \in \mathcal{S}\) and \(\mu^* > 0\), then the following three statements are equivalent:

(a) \((X^*, \mu^*)\) is a saddle point for the Lagrangian function \(\mathcal{L}(X, \mu)\).

(b) \(X^*\) and \(\mu^*\) are optimal solutions to the primal and dual problems, respectively, with zero duality gap, i.e., \(D^* = P^*\).

(c) The following conditions hold, i.e.,
\[
\mathcal{L}(X^*, \mu^*) = \min_{X \in \mathcal{S}} \mathcal{L}(X, \mu^*), \\
J_c(X^*) \leq \tilde{\rho}, \\
\mu^*(J_c(X^*) - \tilde{\rho}) = 0.
\]

In the sequel, we prove Theorem 7 by examining the conditions in (30).

Define
\[
\mu^* \triangleq \inf \{\mu \geq 0 : J_c(X^*(\mu)) \leq \tilde{\rho}\}.
\]
We will show that when $\mu^*$ is finite, then the policy-multiplier pair $(X^*(\mu^*), \mu^*)$ satisfies the conditions in (30). And it is indeed the case if the Slater’s condition holds.

Suppose that the Slater’s condition is satisfied, i.e., there exists a feasible policy $X' \in \mathcal{S}$ such that $J_c(X') < \bar{\rho}$. We first show $\mu^*$ defined in (31) is finite.

Clearly, $J(X') < \infty$ since $X' \in \mathcal{S}$. By the definition of $D(\mu)$, for all $\mu \geq 0$ we have

$$D(\mu) \leq J(X') + \mu(J_c(X') - \bar{\rho}).$$

Suppose that for any $\mu \geq 0$, $J_c(X^*(\mu)) > \bar{\rho}$. Then, it follows that

$$J(X') \geq \sup_{\mu \geq 0} D(\mu) - \mu(J_c(X') - \bar{\rho})$$

$$= \sup_{\mu \geq 0} J(X^*(\mu)) + \mu(J_c(X^*(\mu)) - \bar{\rho}) - \mu(J_c(X') - \bar{\rho})$$

$$= \sup_{\mu \geq 0} J(X^*(\mu)) + \mu(J_c(X^*(\mu)) - J_c(X'))$$

$$= \infty,$$

which contradicts with $J(X') < \infty$. Thus, $\mu^*$ must be finite.

To show that the complementary slackness $\mu^*(J_c(X^*(\mu^*)) - \bar{\rho}) = 0$ is satisfied, we discuss two cases. If $\mu^* = 0$, then the complementary slackness trivially holds; or $\mu^* > 0$, then we must have $J_c(X^*(\mu^*)) = 0$. Thus, it suffices to consider the second case, i.e., $\mu^* > 0$. By assumption, it follows that $J_c(X^*(0)) \geq \bar{\rho}$. Since $J_c(X^*(\mu))$ is decreasing with $\mu > 0$, there exists a multiplier $\mu'$ such that $J_c(X^*(\mu')) < \bar{\rho}$. We notice that $X^*(\mu)$ is continuous with respect to $\mu$ as all matrix inverses in (12) are continuous. Combining with the smoothness of $J_c(X)$, it follows that we can only have $J_c(X^*(\mu^*)) = \bar{\rho}$.

Now, the conditions in (30) hold and there is zero duality gap.

5. Convergence Analysis

In this section, we provide the convergence analysis of the proposed algorithms.

5.1. Proof of Theorem 8

We prove it by applying a result in the zero-order optimization (Malik et al., 2019, Theorem 1). To guarantee the convergence of random search, it requires (a) the gradient dominance, (b) the locally Lipschitz property and (c) the boundedness of gradient norm $G_\infty$ and $G_2$. To this end, we only need to establish (c) by leveraging the uniform boundedness of $\|w_t\|$. Since $G_2 \leq G_\infty^2$, it suffices to bound $G_\infty$.

We first show that $\hat{L}(X, \mu)$ is bounded for $X \in \mathcal{S}_{10}$. By the linear dynamics (1), for $X \in \mathcal{S}$ the state $x_t$ can be written as a function of $x_0$ and $\{w_0, w_1, \ldots\}$, i.e.,

$$x_t = (A - BK)^t x_0 + \sum_{k=0}^{t-1} (A - BK)^{t-1-k} (Bl + w_t).$$
For a bounded noise sequence \( w = \{ w_0, w_1, \ldots \} \), we have

\[
\hat{L}(X, \mu) = \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T} x_t^\top (Q_\mu + K^\top R K) x_t \\
+ 2(S - 2K^\top R l)_t^\top x_t + l^\top R l \\
\leq \max_w \lim_{t \to \infty} x_t^\top (Q_\mu + K^\top R K) x_t \\
+ 2(S - 2K^\top R l)_t^\top x_t + l^\top R l
\]

Noting that \( \lim_{t \to \infty} (A - BK)^t x_0 = 0 \), we have

\[
\hat{L}(X, \mu) \leq \max_w \left( \sum_{k=0}^{\infty} (A - BK)^k (Bl + w_t) \right)^\top \\
\times (Q_\mu + K^\top R K) \left( \sum_{k=0}^{\infty} (A - BK)^k (Bl + w_t) \right) \\
+ 2 \left( \sum_{k=0}^{\infty} (A - BK)^k (Bl + w_t) \right)^\top (S - K^\top R l) + l^\top R l \\
\leq \left( \sum_{k=0}^{\infty} \|A - BK\|^k \right) \left( \|Bl\| + \|v\| \right) \|Q_\mu + K^\top R K\| \\
+ 2 \left( \sum_{k=0}^{\infty} \|A - BK\|^k \right) \left( \|Bl\| + \|v\| \right) \|S - K^\top R l\| + l^\top R l \\
\leq \frac{1}{(1 - \rho(A - BK))^2} (\|Bl\| + \|v\|)^2 \|P_K\| + l^\top R l \\
+ \frac{2}{1 - \rho(A - BK)} (\|Bl\| + \|v\|) (\|S\| - \|K\| \|R\| \|l\|),
\]

where \( \|P_K\|, \|K\|, \|l\|, \rho(A - BK) \) are uniformly bounded over \( X \in S \). Thus, \( \hat{L}(X, \mu) \) is bounded.

Similarly, it follows from the Lipschitz property that

\[
\| \hat{L}(X + rU, \mu) - L(X + rU, \mu) \| \leq F
\]

with \( F > 0 \).

For a given radius \( r < \gamma_0 \) and a unit perturbation \( U \in S \), the gradient estimate is bounded as

\[
\| \hat{\nabla} L \|_2 = \frac{n}{r^2} \| \hat{L}(X + rU, \mu) \| \\
= \frac{n}{r^2} (\| L(X + rU, \mu) \| + F) \\
\leq \frac{n}{r^2} (\| L(X, \mu) \| + r\xi_0 + F) \\
\leq \frac{n}{r^2} (\| 10 L(X_0, \mu) \| + \gamma_0 \xi_0 + F).
\]

Now, the proof follows directly from (Malik et al., 2019, Theorem 1).
5.2. Proof of Theorem 9

By the definition of projection and the subgradient, it follows that

\[ \mathbb{E}[\|\mu_{i+1} - \mu^*\|^2] \leq \mathbb{E}[\|\mu_i - \mu^* + \xi_i \cdot \hat{w}_i\|^2] \]
\[ = \mathbb{E}[\|\mu_i - \mu^*\|^2 + 2\xi_i \hat{w}_i(\mu_i - \mu^*) + (\xi_i)^2\|\hat{w}_i\|^2] \]
\[ \leq \mathbb{E}[\|\mu_i - \mu^*\|^2] + 2\xi_i \mathbb{E}[D(\mu_i) - D^*] + (\xi_i)^2 b^2. \]

Then, rearranging it yields that

\[ \mathbb{E}[D^* - D(\mu_i)] \leq \frac{\mathbb{E}[\|\mu_i - \mu^*\|^2]}{2\xi_i} - \frac{\mathbb{E}[\|\mu_{i+1} - \mu^*\|^2]}{2\xi_i} + \frac{\xi_i b^2}{2}. \]

Summing up from \( i = 1 \) to \( k \) and noting \( \xi_i \geq \xi_{i+1} \), it follows that

\[ \mathbb{E}[\sum_{i=1}^{k}(D^* - D(\mu_i))] \leq -\frac{1}{2\xi_{j+1}} \mathbb{E}[\|\mu_{j+1} - \mu^*\|] + \frac{b^2}{2} \sum_{i=1}^{j} \xi_i \]
\[ + \frac{1}{2\xi_1} \mathbb{E}[\|\mu_1 - \mu^*\|^2] + \frac{1}{2} \sum_{i=1}^{j} \left( \frac{1}{\xi_{i+1}} - \frac{1}{\xi_i} \right) \mathbb{E}[\|\mu_{i+1} - \mu^*\|^2] \]
\[ \leq \frac{2}{\xi_j} e^2 + \frac{b^2}{2} \sum_{i=1}^{j} \xi_i. \]

By Jenson’s inequality, one can easily obtain that

\[ \mathbb{E}[D^* - D(\bar{\mu}_j)] \leq \frac{2}{j\xi_j} e^2 + \frac{b^2}{2j} \sum_{i=1}^{j} \xi_i. \]

The proof follows by noting that \( \xi_i = \frac{1}{be} \sqrt{\frac{2}{7}} \).