Linear Bandits

Wen Sun

CS 6789: Foundations of Reinforcement Learning

Recap on MAB

Setting:

We have K many arms: $a_1, \ldots, a_K$

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We have K many arms: $a_1, \ldots, a_K$

Each arm has a unknown reward distribution, i.e., $\nu_i \in \Delta([0,1])$,
w/ mean $\mu_i = \mathbb{E}_{r \sim \nu_i}[r]$

Regret

More formally, we have the following learning objective:

$$\mu^\star = \max_{i \in [K]} \mu_i$$

$$\text{Regret}_T = T\mu^\star - \sum_{t=0}^{T-1} \mu_{I_t}$$

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Total expected reward of the arms we pulled over T rounds

Goal: no-regret, i.e., $\text{Regret}_T / T \to 0$, as $T \to \infty$

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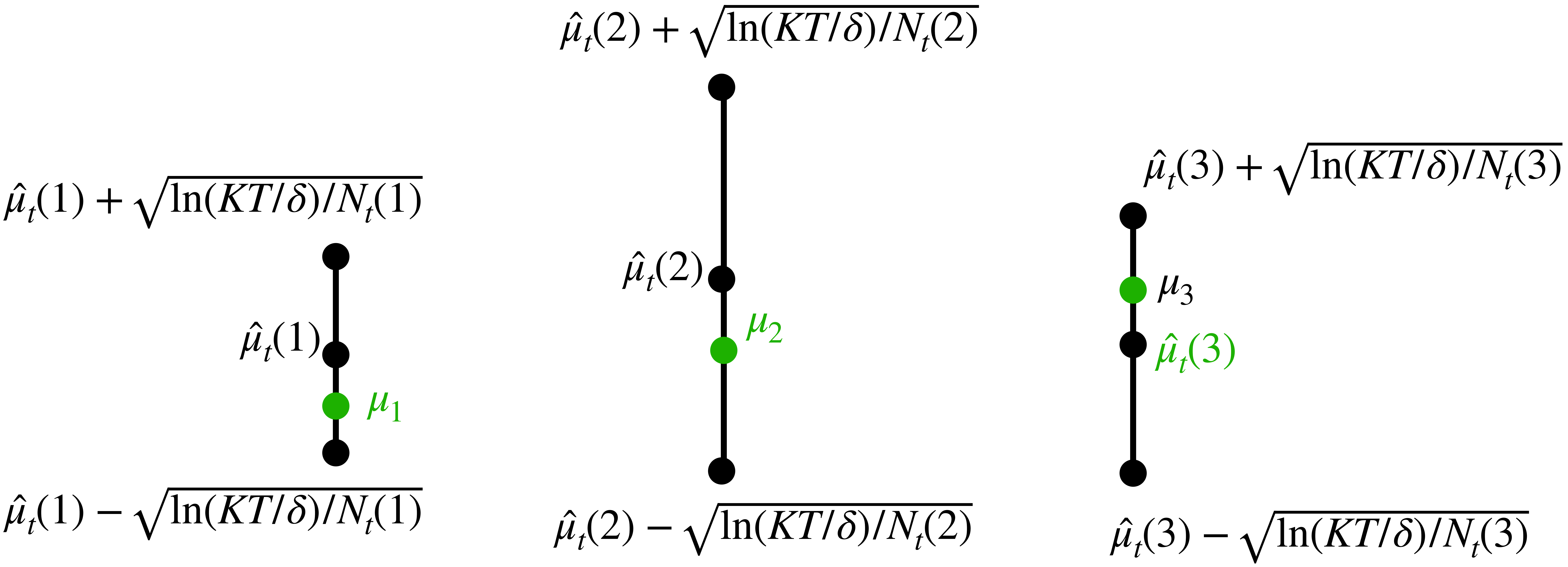

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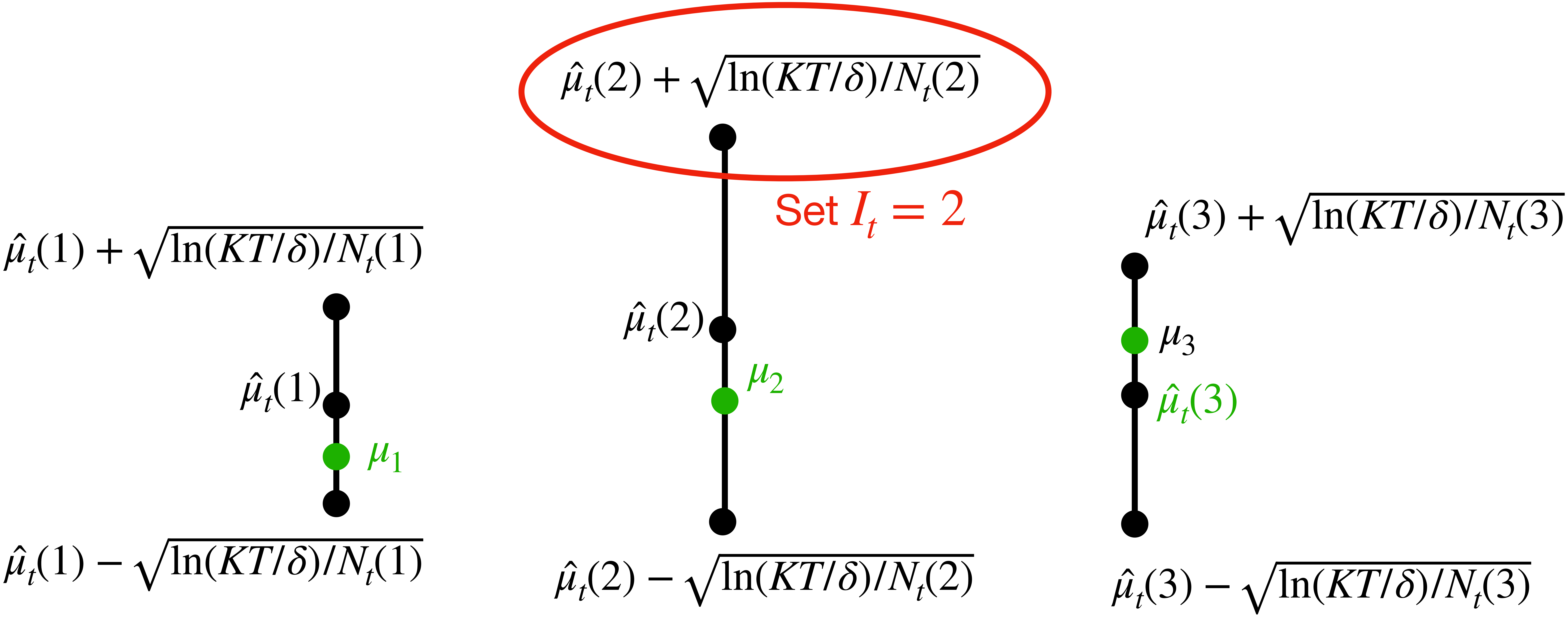

Optimism in the face of uncertainty

Denote the optimal arm $I^\star = \arg\max_{i \in [K]} \mu_i$; recall $I_t = \arg\max_{i \in [K]} \hat{\mu}_t(i) + \sqrt{\frac{\ln(KT/\delta)}{N_t(i)}}$

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Today:

MAB w/ K arms has regret $O(\sqrt{KT})$

What if there are infinitely many actions?

Introducing structures in the reward function

Outline for Today:

1. Linear Bandit Setting

2. Algorithm: LinUCB

3. Regret analysis of LinUCB

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$$x^\star = \arg\max_{x \in D} \mu^\star \cdot x$$

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LinUCB algorithm

Overall idea:

Ridge linear regression for learning $\mu^\star$ + design exploration bonus

LinUCB algorithm

In iteration t:

1. Perform Ridge LR on data $\{x_i, r_i\}_{i=0}^{t-1}$:

Set $\hat{\mu}_t := \arg\min_{\mu} \sum_{i=0}^{t-1} (\mu^\top x_i - r_i)^2 + \lambda \|\mu\|_2^2$

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2: Set exploration bonus: $b_t(x) = \beta \sqrt{x^\top \Sigma_t^{-1} x}$

3: Play optimistically, i.e., $x_t = \arg\max_{x \in D} \hat{\mu}_t^\top x_t + b_t(x)$

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\begin{aligned}
\hat{\mu}_t &= \Sigma_t^{-1} \sum_{i=0}^{t-1} x_i r_i \\
&= \Sigma_t^{-1} \sum_{i=0}^{t-1} x_i (x_i^\top \mu^\star + \eta_i)
\end{aligned}
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Let us look at the training error:

$$\sqrt{(\hat{\mu}_t - \mu^\star)^\top \Sigma_t (\hat{\mu}_t - \mu^\star)}$$

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Self-normalized Martingale bound

Self-normalized Bound for Vector-valued Martingales

Suppose $\{\eta_i\}_{i=0}^{\infty}$ are mean zero random variables, and $|\eta_i| \leq \sigma$;

Let $\{x_i\}_{i=0}^{\infty}$ be any sequence of random vectors with $\|x_i\| \leq 1$, then w/ prob $1-\delta$, for all $t \geq 1$,

$$\left\| \Sigma_t^{-1/2} \sum_{i=0}^{t-1} x_i \eta_i \right\|^2 \leq \sigma^2 d \cdot \left(\ln\left(\frac{t}{\lambda} + 1 \right) + \ln(1/\delta) \right)$$

Analysis of Ridge Linear Regression (Continue)

$$\hat{\mu}_t - \mu^\star = -\lambda \Sigma_t^{-1} \mu^\star + \Sigma_t^{-1} \sum_{i=0}^{t-1} x_i \eta_i$$

Let us look at the training error:

$$\sqrt{(\hat{\mu}_t - \mu^\star)^\top \Sigma_t (\hat{\mu}_t - \mu^\star)} \leq \left\| \lambda \Sigma_t^{-1/2} \mu^\star \right\| + \left\| \Sigma_t^{-1/2} \sum_{i=0}^{t-1} \eta_i x_i \right\|$$

$$\lesssim \sqrt{\lambda} + \sigma \sqrt{d \cdot \ln(T/(\lambda\delta))}$$

Summary for Ridge Linear Regression

$$\hat{\mu}_t - \mu^\star = -\lambda \Sigma_t^{-1} \mu^\star + \Sigma_t^{-1} \sum_{i=0}^{t-1} x_i \eta_i$$

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Optimism

$$\sqrt{(\hat{\mu}_t - \mu^\star)^\top \Sigma_t (\hat{\mu}_t - \mu^\star)} \lesssim \sqrt{\lambda} + \sigma^2 d \ln(T/(\lambda\delta))$$

Let's construct uncertainty quantification for each action $x \in D$

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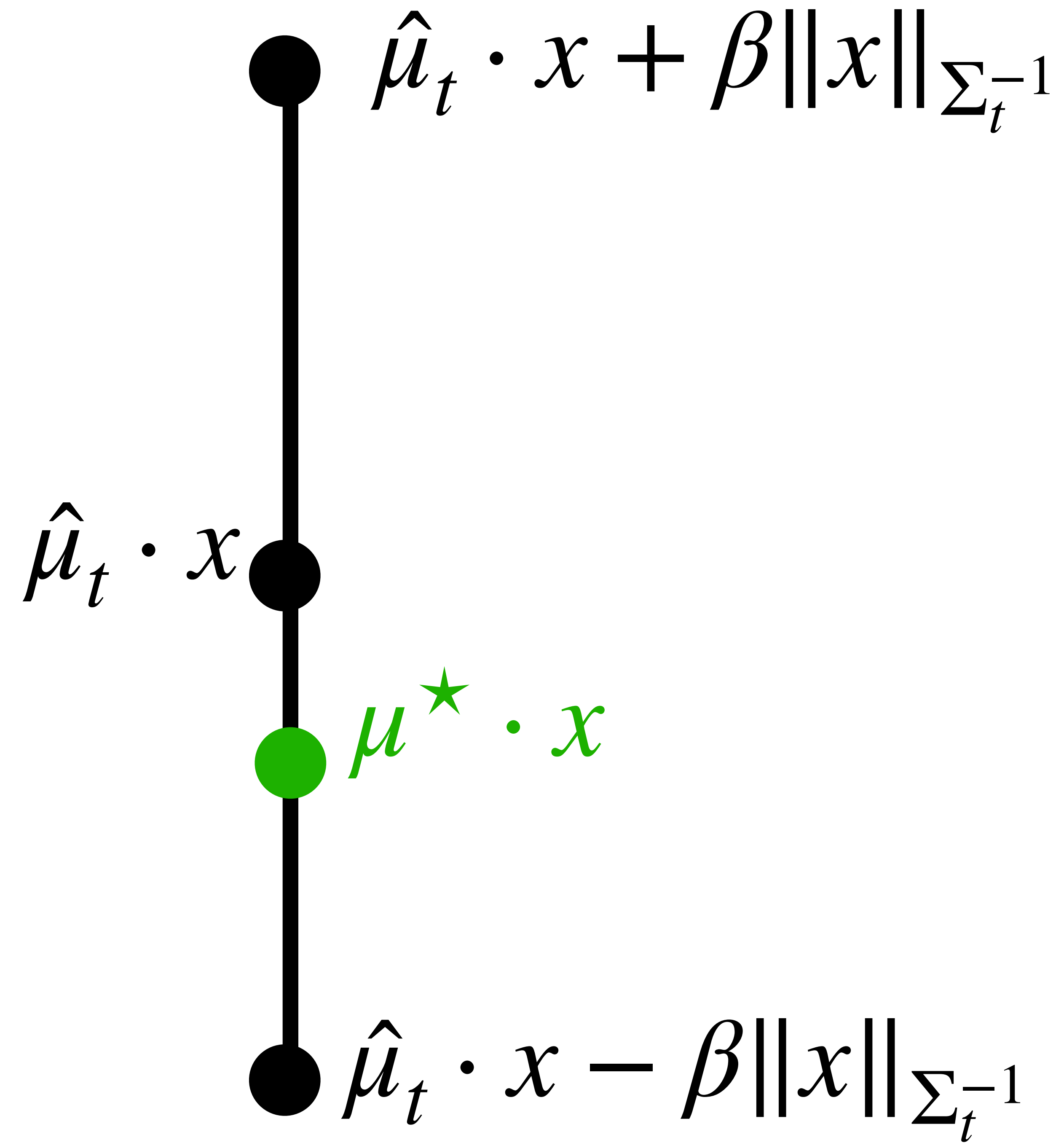

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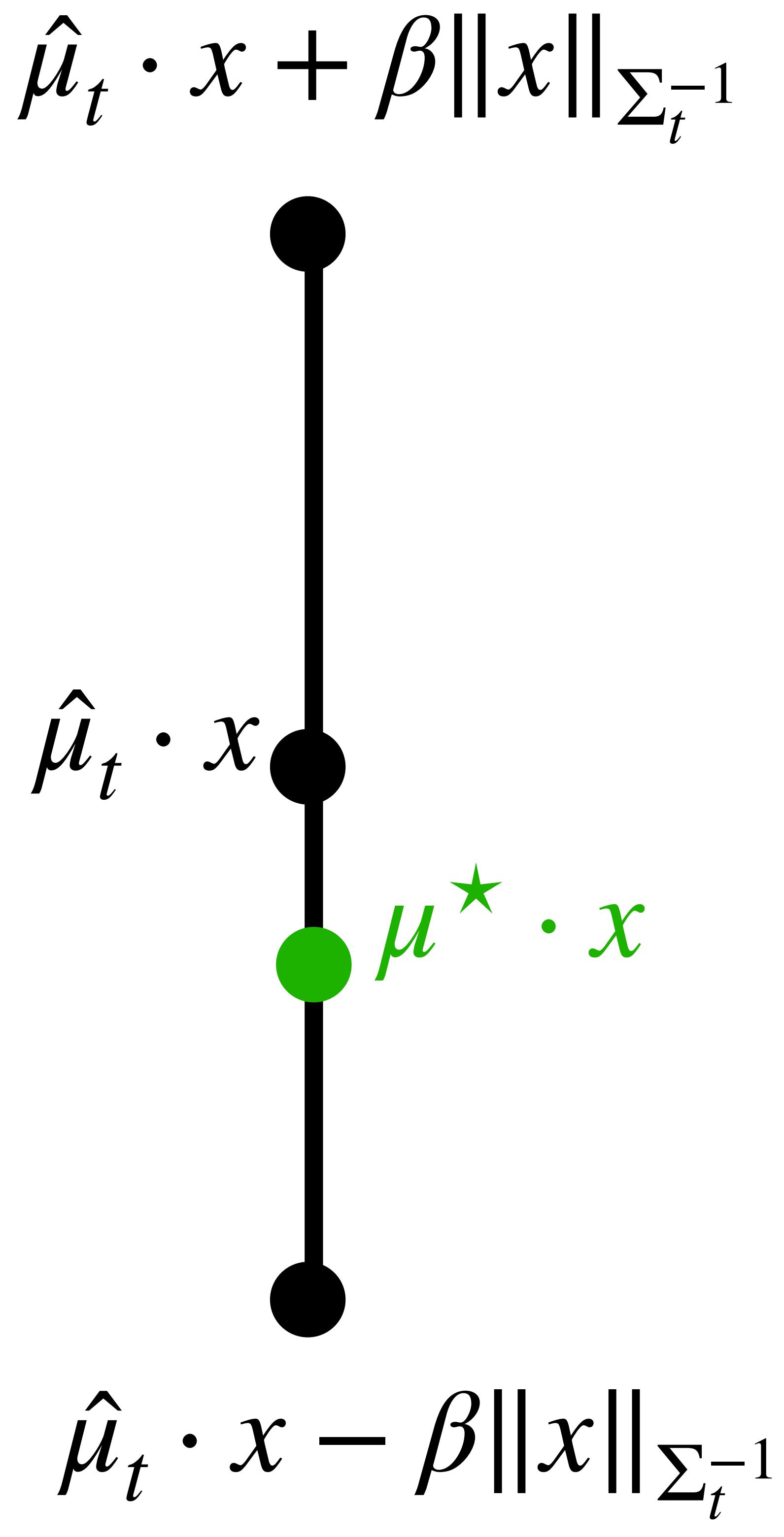
$\forall x \in D$

Proof:



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Case 1: x_t is a bad arm, i.e., $2\beta \|x_t\|_{\Sigma_t^{-1}} \geq \mu^\star \cdot (x^\star - x_t) \geq \delta$

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Then regret at this round is small too, i.e., we exploited!

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Summary

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2. Analysis of Ridge LR gives us bound on on $|(\mu^\star - \hat{\mu}_t)^\top x|$

3. Optimism in the face of uncertainty: $\mu^\star \cdot x^\star \leq \hat{\mu}_t^\top x_t + \beta \|x_t\|_{\Sigma_t^{-1}}$

4. Regret is upper bounded by $\beta \sum_t \|x_t\|_{\Sigma_t} \leq \beta \sqrt{T} \sqrt{\sum_t \|x_t\|^2_{\Sigma_t^{-1}}}$