Concentration Inequalities for System Identification

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CDC 2019 Tutorial

Problem statement

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- Want **bounds** on estimators $(\hat{A}, \hat{B})$ of the form:

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- Here, either ε or δ will be a function of (A, B, ε, T).

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- Basic least-squares estimator:

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- Has closed-form solution:

$$(\hat{A}, \hat{B}) = \left(\sum_{i=0}^{t-1} x_{i+1} z_i^\top \right) \left(\sum_{i=0}^{t-1} z_i z_i^\top \right)^{-1}, \quad z_i = \begin{bmatrix} x_i \\ u_i \end{bmatrix}.$$

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- For simplicity, let us assume scalar autonomous system:
$$x_{t+1} = ax_t + w_t$$
- Then (dating back to Mann and Wald 1943), we have a CLT:
$$\sqrt{T}(\hat{a}_T - a) \xrightarrow{d} \mathcal{N}(0, 1 - a^2) \text{ if } |a| < 1,$$
$$|a|^T(\hat{a}_T - a) \xrightarrow{d} (a^2 - 1)\Psi \text{ if } |a| > 1$$

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    - (Ψ is standard Cauchy.)

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- Therefore, as a becomes more “explosive”, estimation becomes easier!

Beyond asymptotics

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- Can we generalize to the **vector** case?

Roadmap

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- Discuss why vector case is a non-trivial extension.

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- Discuss why vector case is a non-trivial extension.
- Discuss state-of-the-art results in the vector case.

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- Error is therefore:

$$e_t := a_t - a = \frac{\sum_{i=0}^{t-1} x_i w_i}{\sum_{i=0}^{t-1} x_i^2}.$$

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- Define the filtration $\mathcal{F}_t := \sigma(w_0, \ldots, w_{t-1})$.
  - $(x_0, \ldots, x_t, M_t)$ are $\mathcal{F}_t$-measurable.
- Furthermore, M_t is a martingale since:

$$\mathbb{E}[M_{t+1} \,|\, \mathcal{F}_t] = \mathbb{E}[M_t \,|\, \mathcal{F}_t] + \mathbb{E}[x_t w_t \,|\, \mathcal{F}_t] = M_t.$$

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- Next, we define the **quadratic variation** $\langle M \rangle_t$ as:

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- Therefore, we can write:

$$e_t = \frac{\sum_{i=0}^{t-1} x_i w_i}{\sum_{i=0}^{t-1} x_i^2} = \sigma^2 \frac{M_t}{\langle M \rangle_t}.$$

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- Is often referred to as a **self-normalized** process.
- A rich body of concentration inequalities to draw from that are of the form:

$$\mathbb{P}(M_t \geq \alpha \langle M \rangle_t) \leq \ldots$$

Self-normalized inequality

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- One concrete result from [Bercu and Touati 08]:

$$\mathbb{P}(M_n \geq \alpha \langle M \rangle_n) \leq \inf_{p \geq 1} \left(\mathbb{E} \left[\exp \left(-(p-1) \frac{\alpha^2}{2} \langle M \rangle_n \right) \right] \right)^{1/p}.$$

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- Observe that if $M_n = \sum_{i=1}^{n} w_i$ with $w_i \sim \mathcal{N}(0, \sigma^2)$, then this reduces to $\mathbb{P}\left(\sum_{i=1}^{n} w_i \geq t \right) \leq \exp(-t^2/(2n\sigma^2))$.

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- By tower property of expectations:

$$\mathbb{E}\left[\exp\left(\theta\sum_{i=0}^{T-2}x_i^2\right)\mathbb{E}[\exp\left(\theta x_{T-1}^2\right)\mid\mathcal{F}_{T-2}]\right]$$

$$=\mathbb{E}\left[\exp\left(\theta\sum_{i=0}^{T-2}x_i^2\right)\mathbb{E}[\exp\left(\theta(ax_{T-2}+w_{T-1})^2\right)\mid\mathcal{F}_{T-2}]\right]$$

An elementary MGF bound

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- An elementary result states that for $\theta < 0$ and μ fixed,
$$\mathbb{E}\exp(\theta(\mu + w)^2) \leq \frac{1}{\sqrt{1 - 2\sigma^2\theta}}, \ w \sim \mathcal{N}(0,\sigma^2).$$

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$$\mathbb{E}\exp(\theta(\mu + w)^2) \le \frac{1}{\sqrt{1 - 2\sigma^2\theta}}, \; w \sim \mathcal{N}(0, \sigma^2).$$

- Therefore:

$$\begin{aligned}
\mathbb{E}\left[\exp\left(\theta \sum_{i=0}^{T-2} x_i^2\right) \mathbb{E}[\exp\left(\theta x_{T-1}^2\right) \mid \mathcal{F}_{T-2}]\right] &= \mathbb{E}\left[\exp\left(\theta \sum_{i=0}^{T-2} x_i^2\right) \mathbb{E}[\exp\left(\theta(a x_{T-2} + w_{T-1})^2\right) \mid \mathcal{F}_{T-2}]\right] \\
&\le \mathbb{E}\exp\left(\theta \sum_{i=0}^{T-2} x_i^2\right) \frac{1}{\sqrt{1 - 2\sigma^2\theta}} \\
&\le \dots \\
&\le \frac{1}{(1 - 2\sigma^2\theta)^{T/2}}
\end{aligned}$$

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- Recall the inequality from [Bercu and Touati 08]:

$$\mathbb{P}(e_T \geq v) \leq \inf_{p \geq 1} \left(\mathbb{E}\left[\exp\left(-(p-1)\frac{v^2}{2\sigma^2} \sum_{i=0}^{T-1} x_i^2 \right) \right] \right)^{1/p}.$$

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- Now setting $\theta = -(p-1)v^2/(2\sigma^2)$,

$$\mathbb{P}(e_T \geq v) \leq \inf_{p \geq 1} \left[\frac{1}{1+(p-1)v^2} \right]^{T/2p} \leq \left[\frac{1}{1+v^2} \right]^{T/4}.$$

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- Repeating the same argument for $-e_T$, we obtain our first concentration inequality by a union bound:

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$$\mathbb{P}(|e_T| \geq v) \leq 2 \left[\frac{1}{1+v^2}\right]^{T/4}.$$

- Inverting this bound for large T, this states that with probability at least $1-\delta$, we have roughly:

$$|e_T| \lesssim \sqrt{\frac{1}{T}\log(1/\delta)}.$$

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- First, consider stable $|a| < 1$. From CLT we know that $\sqrt{T}e_T \xrightarrow{d} \mathcal{N}(0,1-a^2)$. Hence a more correct bound would have the form $|e_T| \asymp \sqrt{\dfrac{1-a^2}{T}}$.

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- First, consider stable $|a| < 1$. From CLT we know that $\sqrt{T}e_T \xrightarrow{d} \mathcal{N}(0,1-a^2)$. Hence a more correct bound would have the form $|e_T| \asymp \sqrt{\dfrac{1-a^2}{T}}$.
- Situation is even worse for unstable $|a| > 1$, where we expect exponential rates: $|e_T| \asymp \dfrac{a^2-1}{|a|^T}$.

Sharpening the scalar bound

- The bound can be sharpened by a more refined MGF analysis— see [Simchowitz et al. 19].

Difficulties of vector case

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- We consider the following decomposition:

$$\|E_T\| \leq \frac{\left\| \left(\sum_{i=0}^{T-1} w_i x_i^\top \right) \left(\sum_{i=0}^{T-1} x_i x_i^\top \right)^{-1/2} \right\|}{\sqrt{\lambda_{\min} \left(\sum_{i=0}^{T-1} x_i x_i^\top \right)}}.$$

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- The term $\left\| \left(\sum_{i=0}^{T-1} w_i x_i^\top \right) \left(\sum_{i=0}^{T-1} x_i x_i^\top \right)^{-1/2} \right\|$ is a vector-valued **self-normalized** martingale. For stable A, also not too difficult to bound [Abbasi-Yadkori et al. 11].

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- The tricky part is lower bounding $\lambda_{\min}\left(\sum_{i=0}^{T-1} x_i x_i^\top \right)$.

Attempt 1: Matrix Chernoff

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- Define $\Sigma_T := \sum_{i=0}^{T-1} x_i x_i^\top$. For $\theta > 0$:

$$
\begin{aligned}
\mathbb{P}\left(\lambda_{\min}(\Sigma_T) \le v\right) &= \mathbb{P}(-\theta\lambda_{\min}(\Sigma_T) \ge -\theta v) \\
&= \mathbb{P}(\exp(-\theta\lambda_{\min}(\Sigma_T)) \ge \exp(-\theta v)) \\
&\le \exp(\theta v)\mathbb{E}\exp(-\theta\lambda_{\min}(\Sigma_T)) \\
&= \exp(\theta v)\mathbb{E}\exp(\lambda_{\max}(-\theta\Sigma_T)) \\
&= \exp(\theta v)\mathbb{E}\lambda_{\max}(\exp(-\theta\Sigma_T)) \\
&\le \exp(\theta v)\mathbb{E}\operatorname{tr}\exp(-\theta\Sigma_T)
\end{aligned}
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&= \exp(\theta v)\mathbb{E}\exp(\lambda_{\max}(-\theta\Sigma_T)) \\
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&\le \exp(\theta v)\mathbb{E}\operatorname{tr}\exp(-\theta\Sigma_T)
\end{aligned}
.
$$

- Therefore:

$$
\mathbb{P}(\lambda_{\min}(\Sigma_T) \le v) \le \inf_{\theta<0} \exp(-\theta v)\mathbb{E}\operatorname{tr}\exp(\theta\Sigma_T).
$$

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- The matrix version is to bound $\mathbb{E}\,\mathrm{tr}\exp(\theta\Sigma_T)$.
- The difficulty is that $\exp(A + B) \neq \exp(A)\exp(B)$ for matrices, so the scalar proof does not go through.

Attempt 2: Scalar projections

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- We can then use scalar analysis to lower bound $\sum_{i=0}^{T-1} \langle v, x_i \rangle^2$ for each fixed v.
- But $\lambda_{\min}(\sum_{i=0}^{T-1} x_i x_i^\top) = \inf_{\|v\|=1} \sum_{i=0}^{T-1} \langle v, x_i \rangle^2$. How do you pass to uniformly on $\mathcal{S}^{n-1}$?

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- Naive covering argument:

$$\lambda_{\min}\left(\sum_{i=0}^{T-1} x_i x_i^\top\right) = \inf_{\|v\|=1} \sum_{i=0}^{T-1} \langle v, x_i \rangle^2$$

$$\geq \min_{v \in N(\varepsilon)} \sum_{i=0}^{T-1} \langle v, x_i \rangle^2 - 2\varepsilon \left\| \sum_{i=0}^{T-1} x_i x_i^\top \right\| .$$

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- But this requires upper bound on $\| \sum_{i=0}^{T-1} x_i x_i^\top \|$, which is very unsatisfying! (nevertheless this does work in the stable case).

State of the art vector results

Stable case

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- [Simchowitz et al. 19]: If $\rho(A) < 1$, then with probability at least $1 - \delta$:

$$\|\hat{A}_T - A\| \lesssim \sqrt{\frac{n \log(n/\delta)}{T\lambda_{\min}(\Sigma_\infty)}}.$$

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- Here, Σ_∞ is the stationary covariance:

$$A \Sigma_\infty A^\top - \Sigma_\infty + \sigma^2 I = 0.$$

Marginally stable case

Marginally stable case

- [Simchowitz et al. 19]: In the special case when $A = O$ with O orthogonal, then with probability $1 - \delta$:
$$\|\hat{A}_T - A\| \lesssim \frac{n \log(n/\delta)}{T}.$$

"Explosive" case

- [Sarkar and Rakhlin 19]: If $|\lambda_i| > 1$ for all i, then with probability at least $1 - \delta$:
$$\|\hat{A}_T - A\| \lesssim \|A^{-T}\|/\delta.$$

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