

From Lyapunov Analysis to Algorithm Design in two-sided PL Minimax Optimization

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Minmax optimization

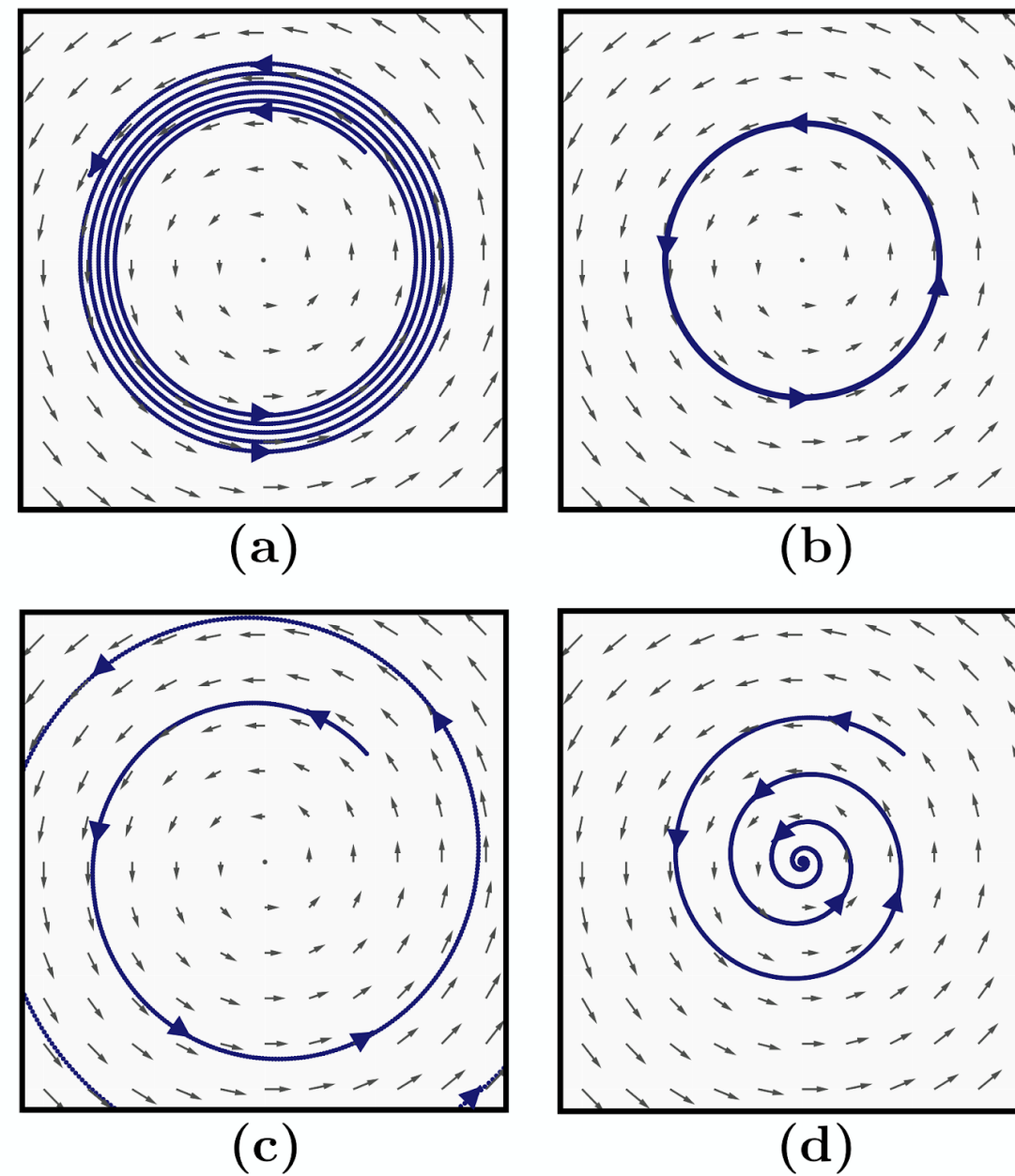
$$\min_{\mathbf{x}} \max_{\mathbf{y}} f(\mathbf{x}, \mathbf{y})$$

Goal: Find \mathbf{x}_k and \mathbf{y}_k such that

$$\max_{\mathbf{y}} f(\mathbf{x}_k, \mathbf{y}) - \min_{\mathbf{x}} f(\mathbf{x}, \mathbf{y}_k) \leq \epsilon$$

- **Examples: GANs, Robust optimization, constrained optimization**

Minmax optimization



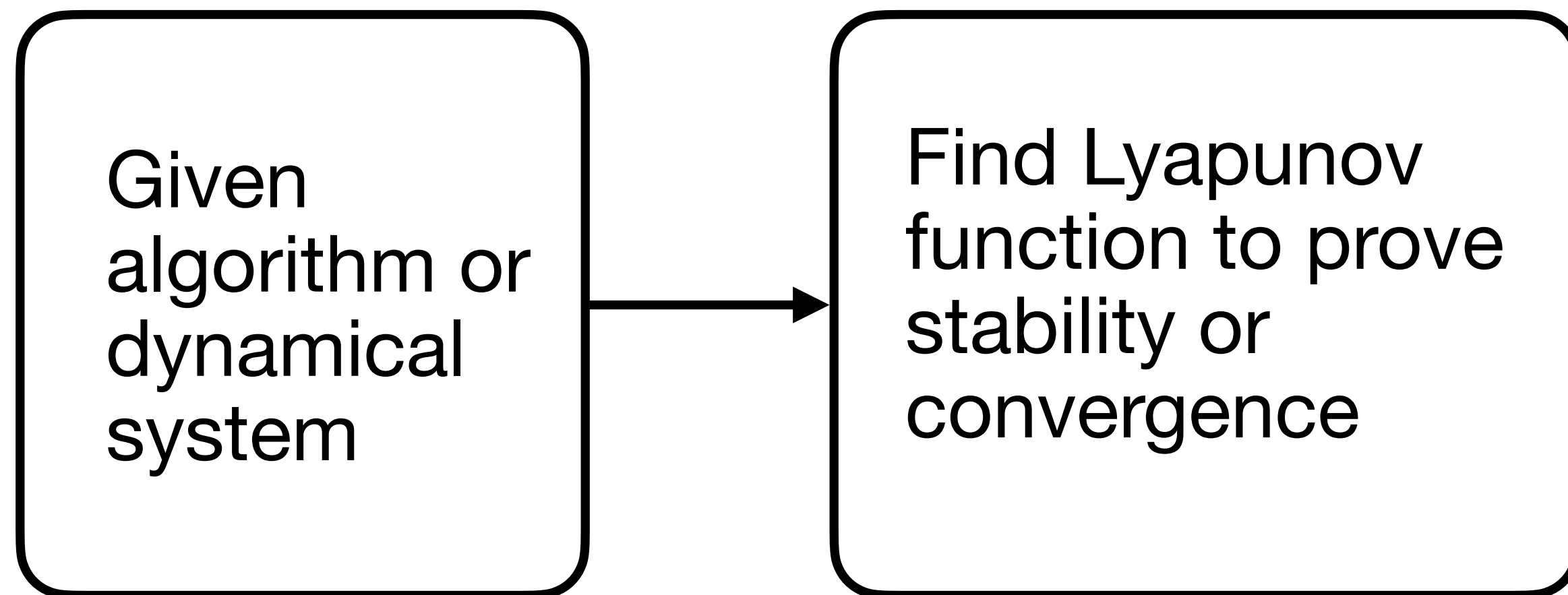
(a) Simultaneous GDA, (b) Alternating GDA
(c) Alternating GDA + momentum, (d) Negative momentum

- **Complicated dynamics:** convergence in min-max demand non-intuitive updates, and intuitive updates often diverge.
- **The Challenge:** Principled framework for algorithm design in Min-Max

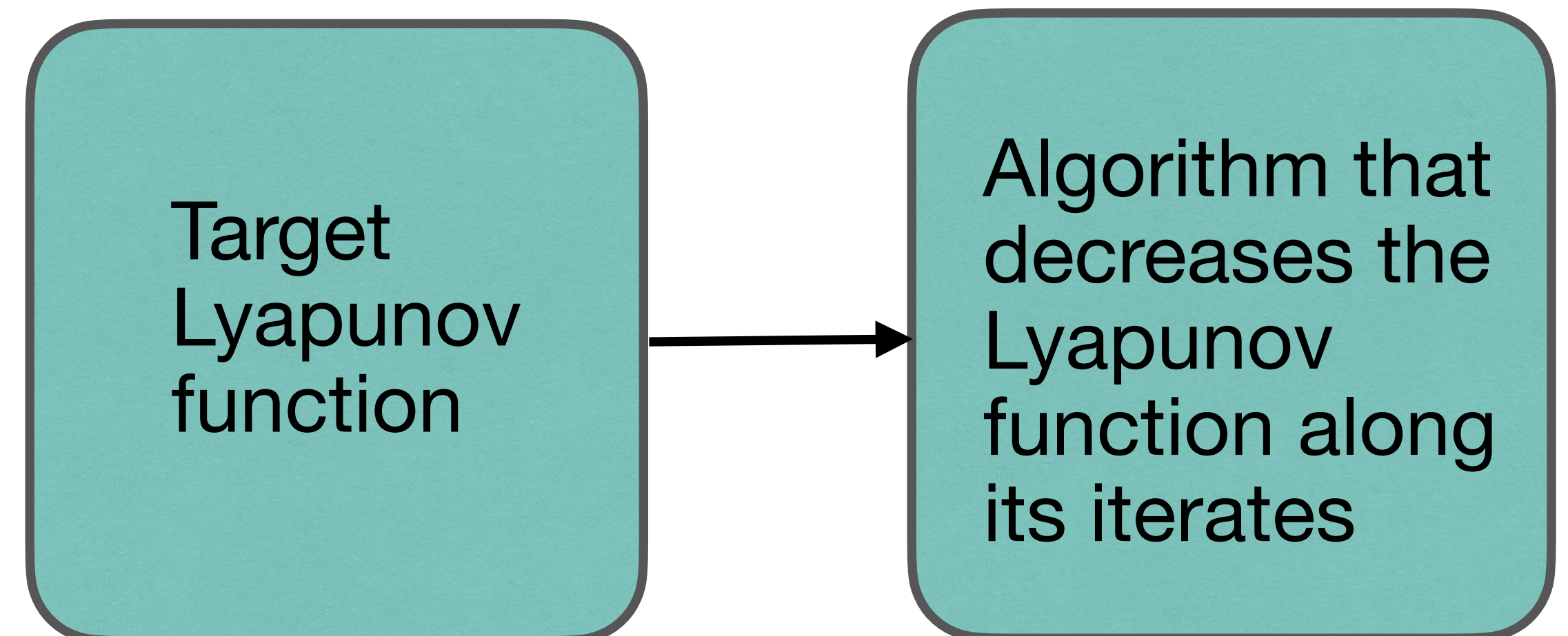
Lyapunov functions

- Lyapunov functions: Generalized energy for dynamical systems.

Lyapunov function to analyze stability and convergence



Our approach



Idealized Lyapunov function for minimax problems

$$V^{Exact}(\mathbf{x}_k, \mathbf{y}_k) = \overbrace{\max_{\mathbf{y}} f(\mathbf{x}_k, \mathbf{y}) - \min_{\mathbf{x}} f(\mathbf{x}, \mathbf{y}_k)}^{\text{primal-dual gap}}$$

- Not exactly computable

Assumption: Two-sided Polyak-Lojaseiwicz (PL) inequality

$$f(\mathbf{x}, \mathbf{y}) - \min_{\mathbf{x}} f(\mathbf{x}, \mathbf{y}) \leq \frac{1}{2\mu} \|\nabla_{\mathbf{x}} f(\mathbf{x}, \mathbf{y})\|^2$$

$$\max_{\mathbf{y}} f(\mathbf{x}, \mathbf{y}) - f(\mathbf{x}, \mathbf{y}) \leq \frac{1}{2\mu} \|\nabla_{\mathbf{y}} f(\mathbf{x}, \mathbf{y})\|^2$$

Computable Lyapunov function

- Using two-sided PL inequality, we have

$$0 \leq V^{Exact}(\mathbf{x}, \mathbf{y}) \leq V(\mathbf{x}, \mathbf{y}, \tilde{\mathbf{x}}, \tilde{\mathbf{y}})$$

where

$$V(\mathbf{x}, \mathbf{y}, \tilde{\mathbf{x}}, \tilde{\mathbf{y}}) = f(\mathbf{x}, \tilde{\mathbf{y}}) - f(\tilde{\mathbf{x}}, \mathbf{y}) + \frac{1}{2\mu} \|\nabla_{\mathbf{x}} f(\tilde{\mathbf{x}}, \mathbf{y})\|^2 + \frac{1}{2\mu} \|\nabla_{\mathbf{y}} f(\mathbf{x}, \tilde{\mathbf{y}})\|^2$$

- Introduce two new variables $\tilde{\mathbf{x}}$ and $\tilde{\mathbf{y}}$

If $\tilde{\mathbf{x}} = \underset{\mathbf{x}}{\operatorname{argmin}} f(\mathbf{x}, \mathbf{y})$ and $\tilde{\mathbf{y}} = \underset{\mathbf{y}}{\operatorname{argmax}} f(\mathbf{x}, \mathbf{y})$, then $V(\mathbf{x}, \mathbf{y}, \tilde{\mathbf{x}}, \tilde{\mathbf{y}}) = V^{Exact}(\mathbf{x}, \mathbf{y})$

Algorithm design

• Goal is to find updates for \mathbf{x}_{k+1} , \mathbf{y}_{k+1} , $\tilde{\mathbf{x}}_{k+1}$, and $\tilde{\mathbf{y}}_{k+1}$, such that

$$V(\mathbf{x}_{k+1}, \mathbf{y}_{k+1}, \tilde{\mathbf{x}}_{k+1}, \tilde{\mathbf{y}}_{k+1}) \leq (1 - r)V(\mathbf{x}_k, \mathbf{y}_k, \tilde{\mathbf{x}}_k, \tilde{\mathbf{y}}_k) + \text{some negative terms}$$

for some rate $r \in (0, 1)$

Algorithm: TALDA-Tri Action Lyapunov Descent Ascent

- **Single loop algorithm**, thanks to Lyapunov approach

Gradient step to approximate the min/max

$$\tilde{\mathbf{x}}_{k+1} = \tilde{\mathbf{x}}_k - \frac{1}{L_f} \nabla_{\mathbf{x}} f(\tilde{\mathbf{x}}_k, \mathbf{y}_k) \quad \tilde{\mathbf{y}}_{k+1} = \tilde{\mathbf{y}}_k + \frac{1}{L_f} \nabla_{\mathbf{y}} f(\mathbf{x}_k, \tilde{\mathbf{y}}_k)$$

Yes: Keep the
GD update

$V_{k+1} \leq (1 - r)V_k$
How do we satisfy this?

Yes: Keep
the Swap

Action: Take gradient step on $\mathbf{x}_k, \mathbf{y}_k$

Is the condition satisfied?

No

Action: Swap $\mathbf{x}_k, \mathbf{y}_k$ and $\tilde{\mathbf{x}}_{k+1}, \tilde{\mathbf{y}}_{k+1}$

Is the condition satisfied?

No

Action: If both fail, do
nothing to $\mathbf{x}_k, \mathbf{y}_k$

Comparison

Alternating gradient descent ascent:

$$T = \kappa_x \kappa_y^2 \log(\epsilon^{-1})$$

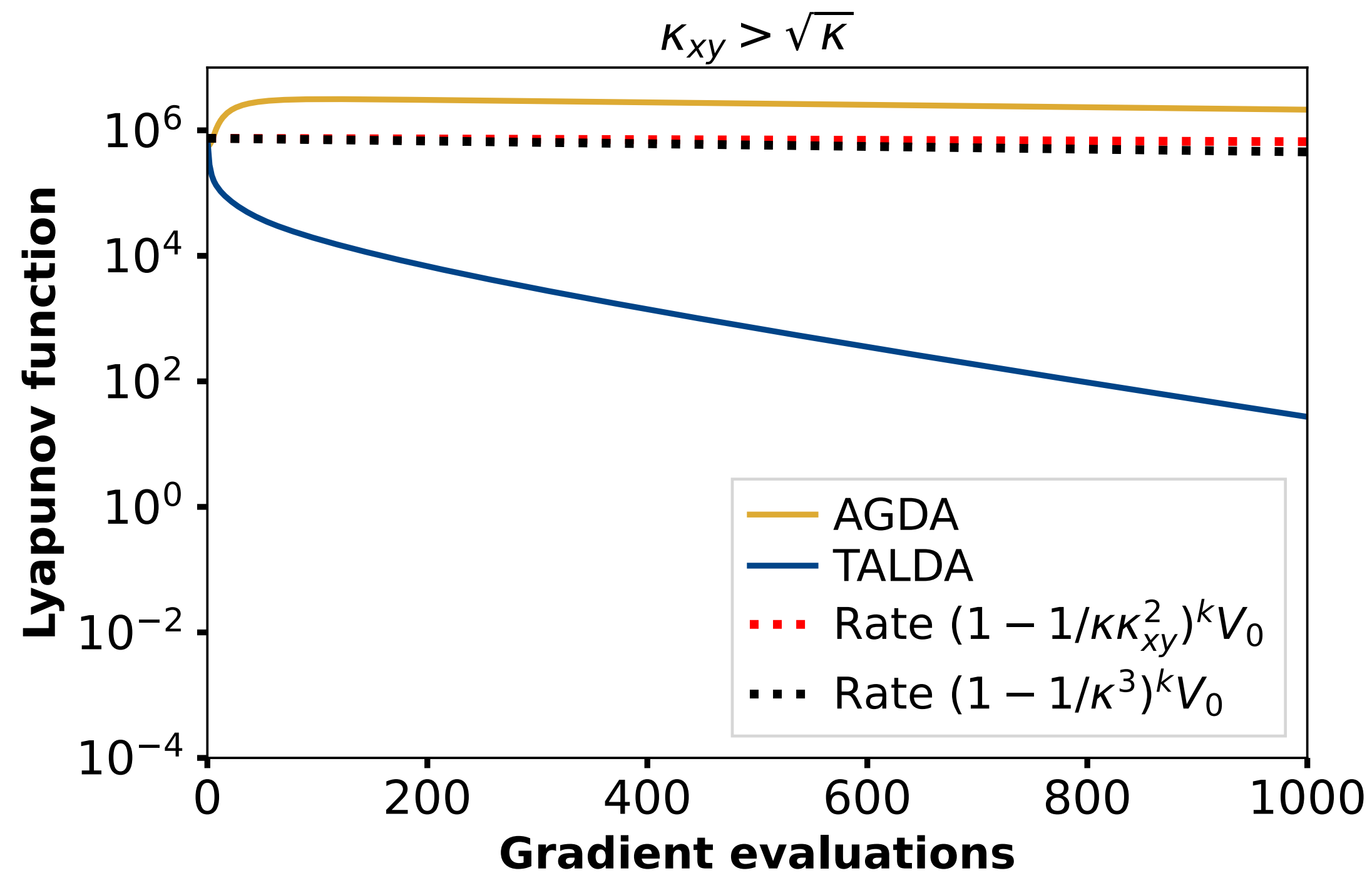
TALDA:

$$T = O(\kappa_f(\kappa_f + \kappa_{xy}^2) \log^2(\epsilon^{-1}))$$

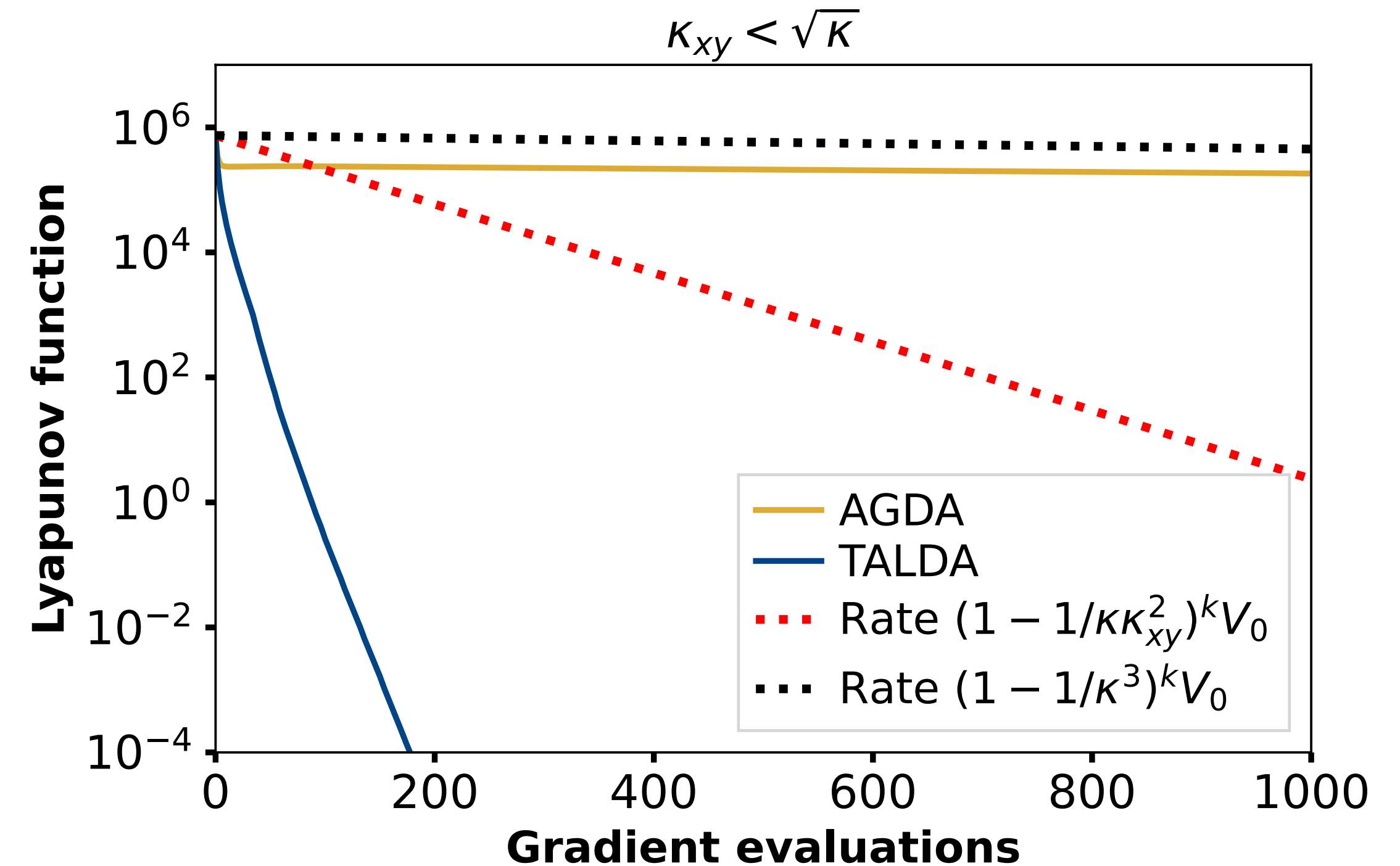
TALDA is better than AGDA

$$\text{when } \kappa_{xy} \leq \sqrt{\kappa_f}$$

Numerical experiments (Synthetic)



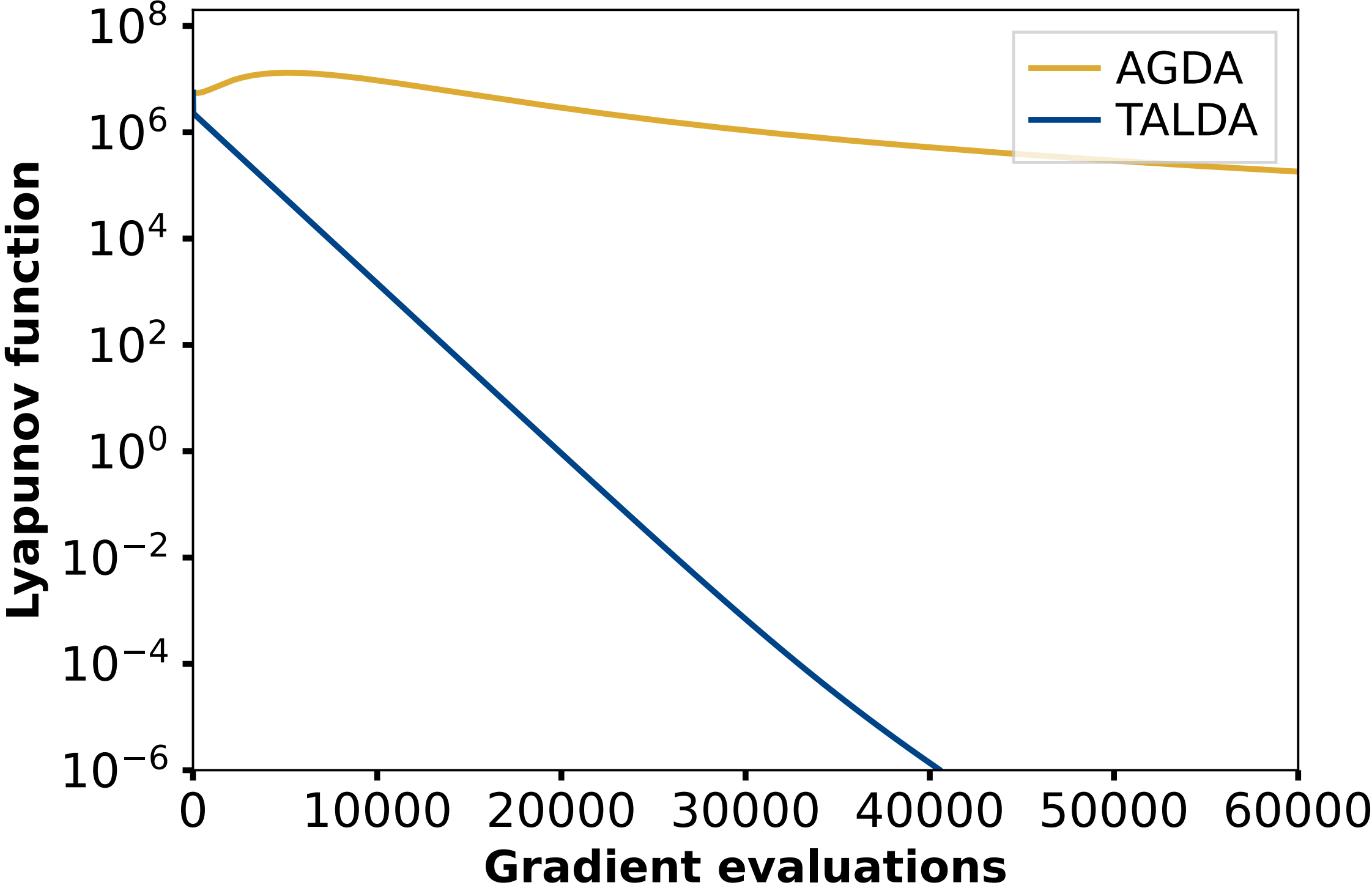
(a)



(b)

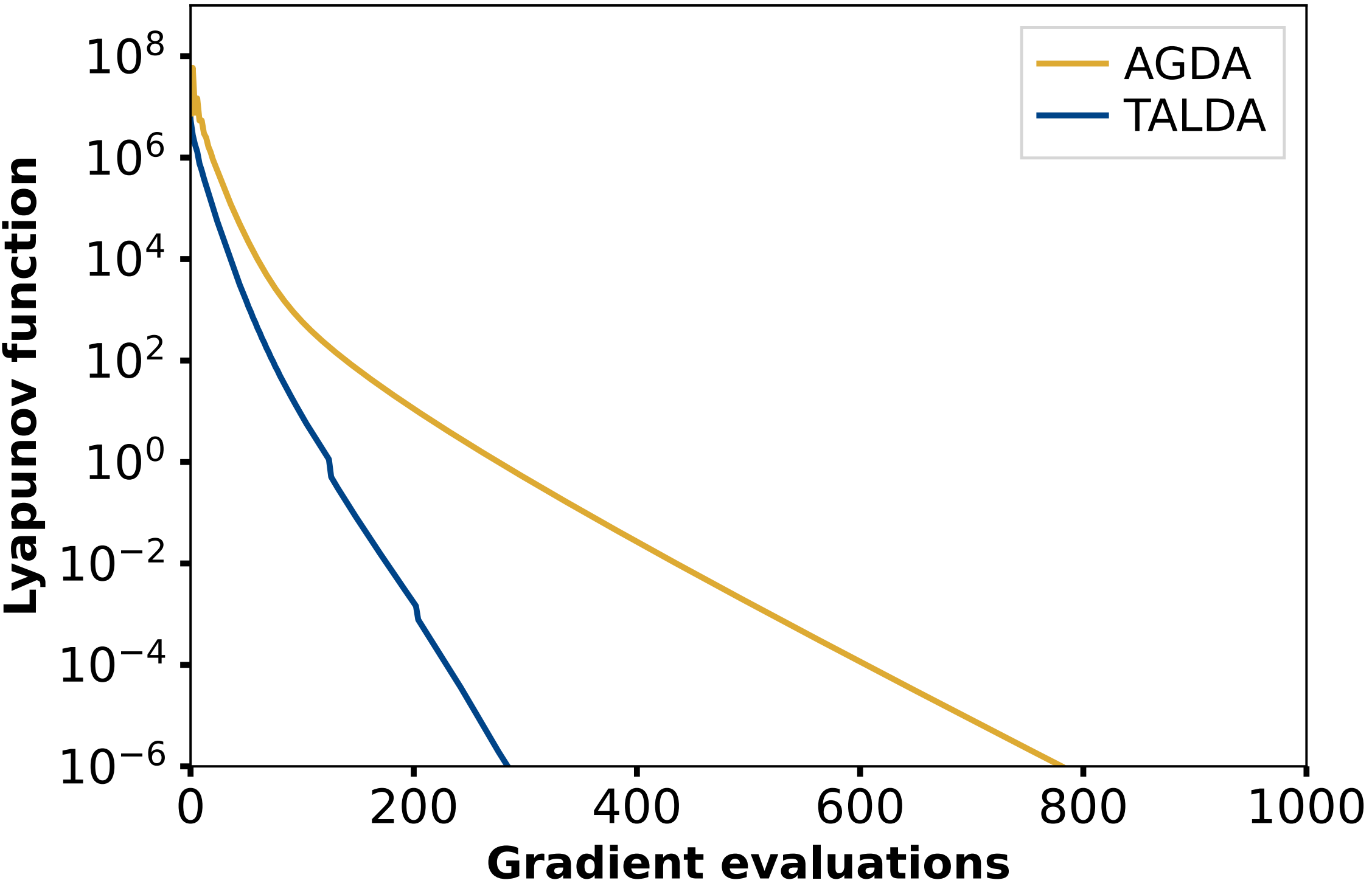
$$\min_{\mathbf{x}} \max_{\mathbf{y}} \frac{1}{2} \mathbf{x}^T \mathbf{A} \mathbf{x} + \mathbf{y}^T \mathbf{B} \mathbf{x} - \frac{1}{2} \mathbf{y}^T \mathbf{C} \mathbf{y} + \mathbf{d}^T \mathbf{x} - \mathbf{e}^T \mathbf{y}$$

Numerical experiments (Robust Least Squares)



(a)

Theoretical learning rates



(b)

Finetuned learning rates

$$\min_{\mathbf{x}} \max_{\mathbf{y}} \|\mathbf{A}\mathbf{x} - \mathbf{y}\|_M^2 - \lambda \|\mathbf{y} - \mathbf{y}_0\|_M^2$$

Key Takeaways

- **Lyapunov functions as a design tool.**
- **TALDA:** Single loop first order method with linear convergence under smooth two sided PL setting.
- **Swap procedure** as a result of using Lyapunov functions as design tool.
- **Coupling matters:** Rate scales with cross-smoothness not worst case condition number.

Please check out our paper and visit our poster on July 8th 2:30 pm - 4:15 pm