

## Motivations



Superhuman Poker AI



Adversarial Training

- ♦ Alternation: a numerical trick that greatly improved performance
- ♦ Question: whether alternation *provably* helps performance

## Preliminaries

- ♦ Bilinear saddle point problems (SPPs):

$$\min_{x \in \mathcal{X}} \max_{y \in \mathcal{Y}} y^\top A x$$

- $\mathcal{X} \subseteq \mathbb{R}^n$  and  $\mathcal{Y} \subseteq \mathbb{R}^m$  are compact convex sets
- $A$  is an  $n \times m$  matrix

- ♦ Bilinear two-player zero-sum games (matrix games):

$$\min_{x \in \Delta_n} \max_{y \in \Delta_m} y^\top A x$$

- $\Delta_n = \{x \in \mathbb{R}_+^n \mid \sum_{i=1}^n x_i = 1\}$
- $\Delta_m = \{y \in \mathbb{R}_+^m \mid \sum_{j=1}^m y_j = 1\}$

- ♦ Nash equilibrium (NE):  $(x^*, y^*) \in \Delta_n \times \Delta_m$  satisfying

$$y^\top A x^* \leq (y^*)^\top A x^* \leq (y^*)^\top A x \quad \forall x \in \Delta_n, y \in \Delta_m$$

- ❖ Simultaneous Gradient Descent-Ascent (SimGDA)

$$\begin{aligned} x^{t+1} &= \Pi_{\mathcal{X}}(x^t - \eta A^\top y^t) \\ y^{t+1} &= \Pi_{\mathcal{Y}}(y^t + \eta A x^t) \end{aligned}$$

- ❖ Alternating Gradient Descent-Ascent (AltGDA)

$$\begin{aligned} x^{t+1} &= \Pi_{\mathcal{X}}(x^t - \eta A^\top y^t) \\ y^{t+1} &= \Pi_{\mathcal{Y}}(y^t + \eta A x^{t+1}) \end{aligned}$$

## Performance Estimation Programming (PEP)

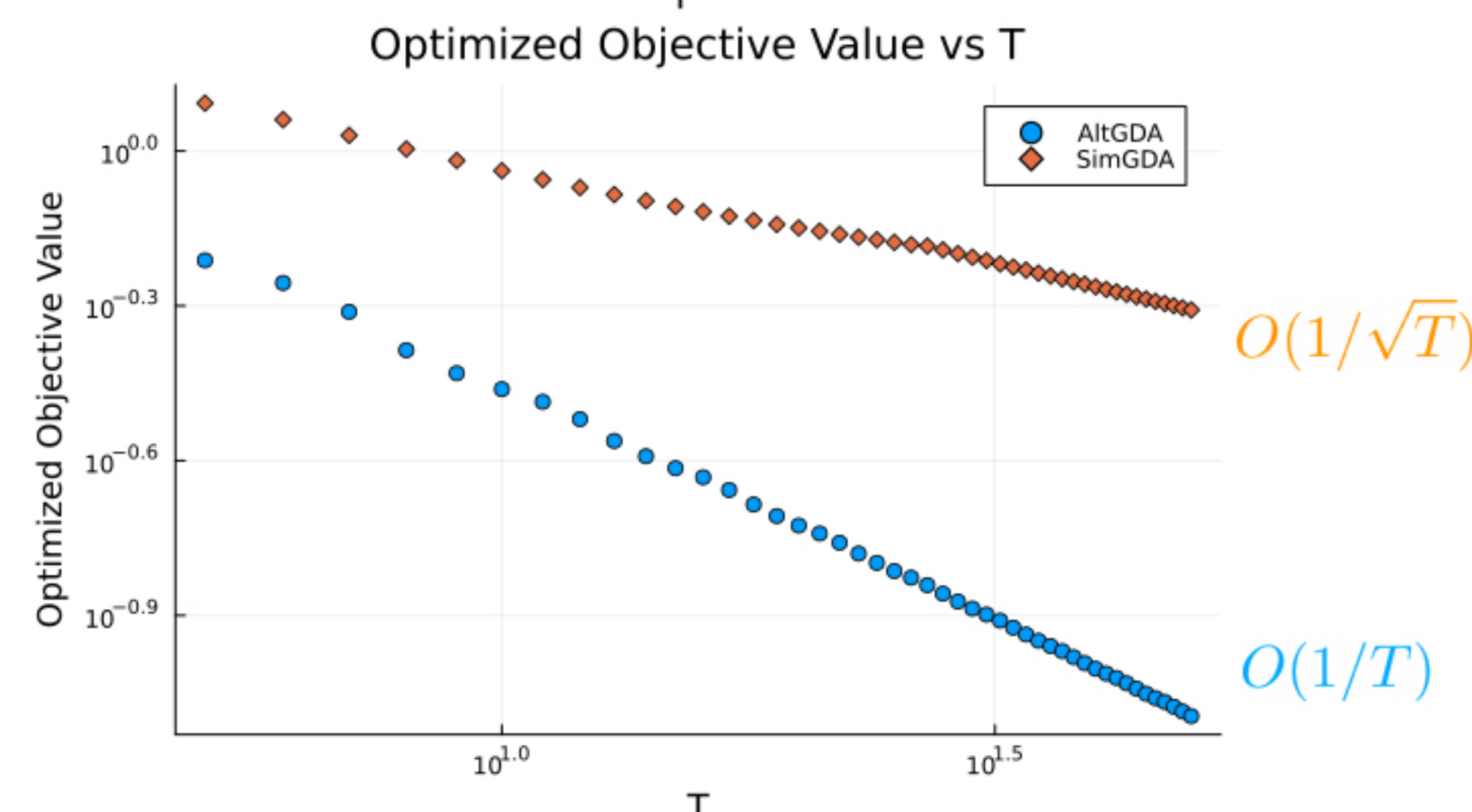
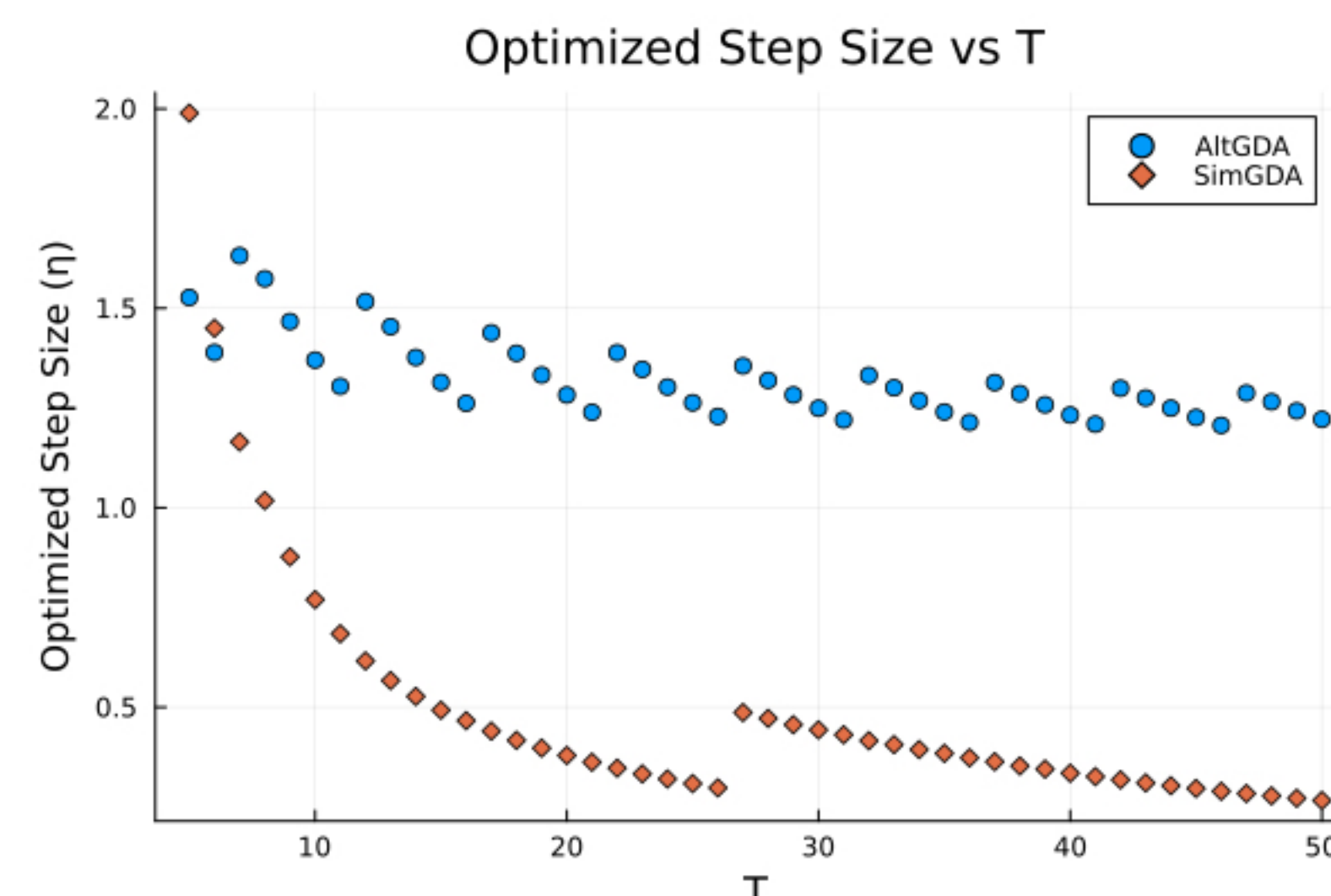
- ⊗ The worst-case performance measure over *all* bilinear saddle point problems can be computed by solving the following optimization problem, for any fixed iteration budget  $T$  and fixed step-size  $\eta$

$$\mathcal{P}_T(\eta) :=$$

$$\begin{aligned} & \text{maximize} && \frac{1}{T} \sum_{t=1}^T (y^\top A x^t - (y^t)^\top A x) \\ & \text{subject to} && x, y, \{(x^t, y^t)\}_{0 \leq t \leq T}, \mathcal{X}, \mathcal{Y}, A, m, n \\ & && \mathcal{X} \text{ is a convex compact set in } \mathbb{R}^n \text{ with radius 1,} \\ & && \mathcal{Y} \text{ is a convex compact set in } \mathbb{R}^m \text{ with radius 1,} \\ & && \sigma_{\max}(A) \leq 1, \\ & && \{(x^t, y^t)\}_{1 \leq t \leq T} = \text{AltGDA}(\eta, x^0, y^0), \\ & && (x^0, y^0), (x, y) \in \mathcal{X} \times \mathcal{Y}. \end{aligned}$$

- ⊗ This program can be reduced to a finite-dimensional SDP
- ⊗ For a fixed  $T$ , the best convergence rate of AltGDA can be found by solving

$$\mathcal{P}_T^* = \text{minimize}_{\eta} \mathcal{P}_T(\eta)$$



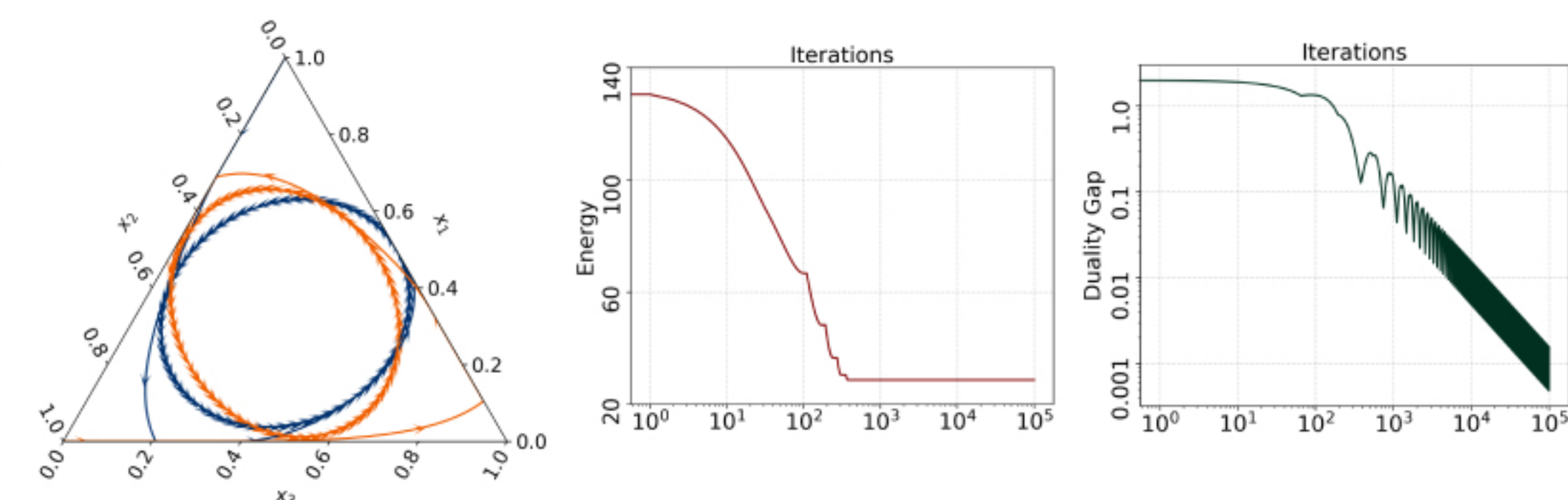
## $O(1/T)$ Convergence Rates

- ♦ We prove that AltGDA can achieve an  $O(1/T)$  convergence rate in bilinear games: if the game admits an interior Nash equilibrium, the duality gap of the averaged iterates of AltGDA with a constant step-size independent of  $T$  converges at an  $O(1/T)$  rate

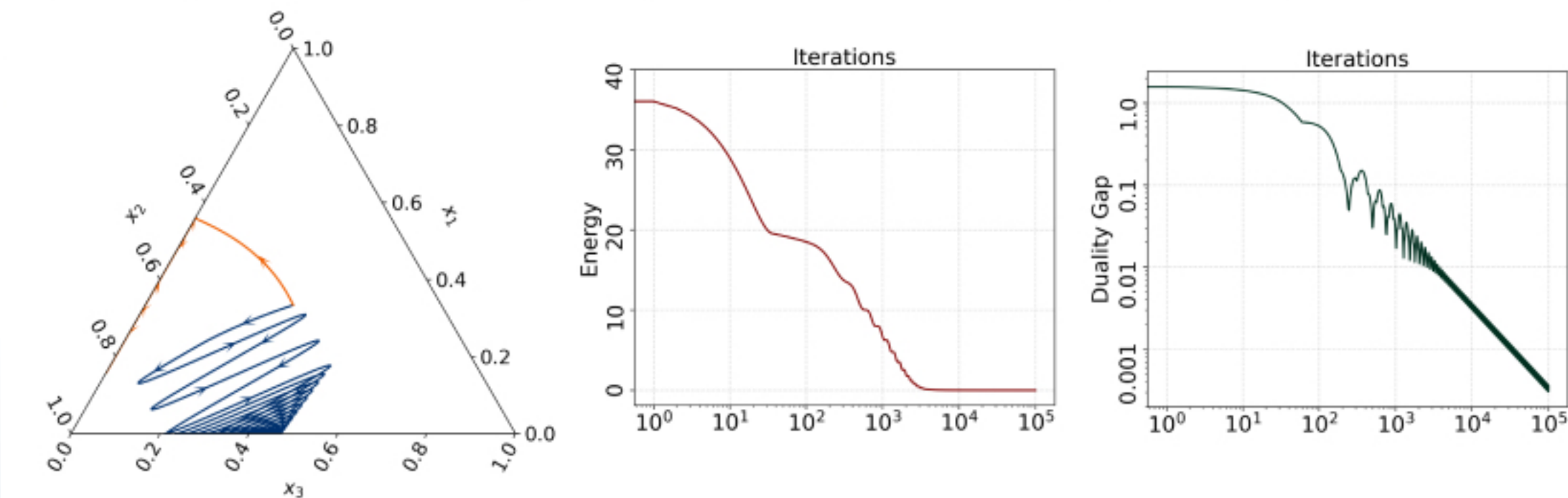
- ♦ The proof leverages the following observations and connections in AltGDA's two-phase behaviors

### Summary for bilinear games with an interior NE

| Phase 1                               | Phase 2                                  |
|---------------------------------------|------------------------------------------|
| Trajectory collides with the boundary | Trajectory is in the interior            |
| Energy function decays                | Energy function remains constant         |
| Duality gap decreases slowly          | Duality gap decreases with $O(1/T)$ rate |



- ♦ For general bilinear games, we show a local  $O(1/T)$  convergence rate



## Numerical Performances

- ⊗ Numerical performance comparisons between SimGDA and AltGDA on larger instances:  $60 \times 120$  matrix games with various value distributions

