Ringmaster ASGD: The First Asynchronous SGD with Optimal Time Complexity

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Ringmaster ASGD: The First Asynchronous SGD with Optimal Time Complexity

- Problem setup
  - Optimization objective
  - Heterogenous system
  - Method (SGD)
- Different ways of parallelizing SGD
  - Synchronized approaches
  - Asynchronous SGD
- Problems of ASGD
- Ringmaster ASGD

The core optimization problem in Machine Learning (and beyond)

$$\min_{x \in \mathbb{R}^d} \left\{ f(x) := \mathbb{E}_{\xi \sim \mathcal{D}} \left[f(x;\xi) \right] \right\}$$

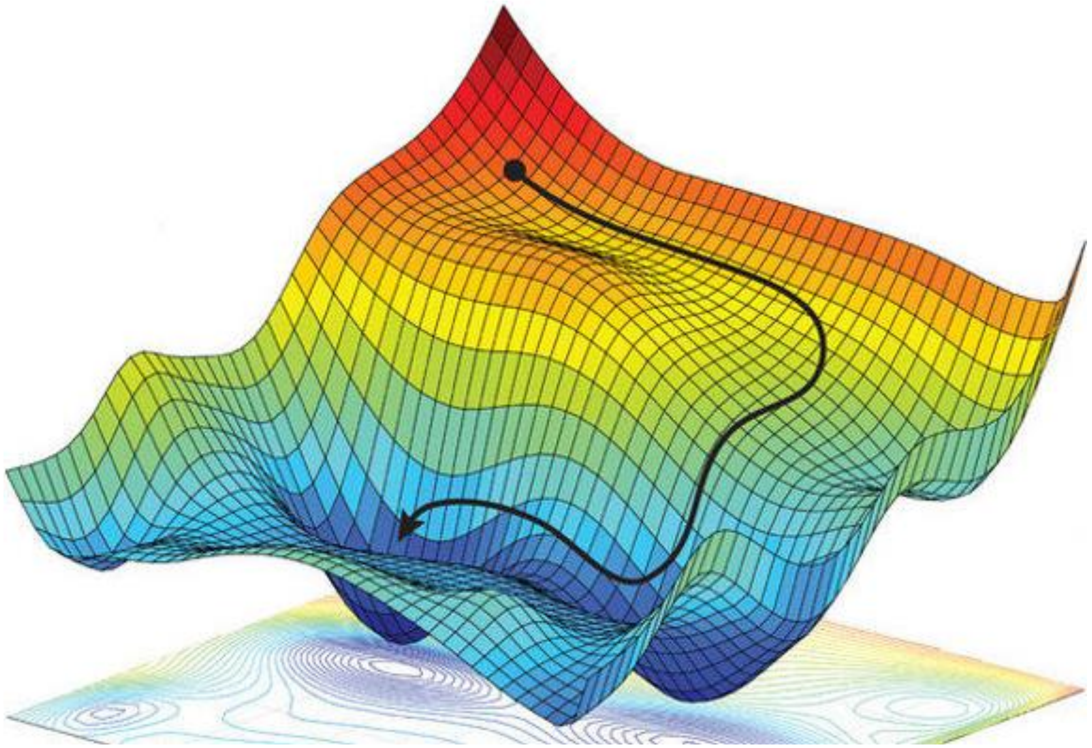
Loss of a data sample ξ

The distribution of the training dataset

$\mathcal{D} = \mathrm{Uniform}([m])$

$$\frac{1}{m} \sum_{i=1}^{m} f(x;\xi_i)$$

A common method in ML is Stochastic Gradient Descent (SGD)



Stepsize / Learning rate

$$x^{k+1} = x^k - \gamma g(x^k)$$

Unbiased gradient estimator, e.g.,

$$\nabla f(x^k; \xi^k)$$

$$\frac{1}{B} \sum_{i=1}^{B} \nabla f(x^k; \xi_i^k)$$

How to parallelize SGD in heterogeneous systems?

$\nabla f(x;\xi)$

Compute time = τ_1

τ_1

$\nabla f(x;\xi)$

Compute time = τ_2

τ_2

$\nabla f(x;\xi)$

Compute time = τ_3

τ_3

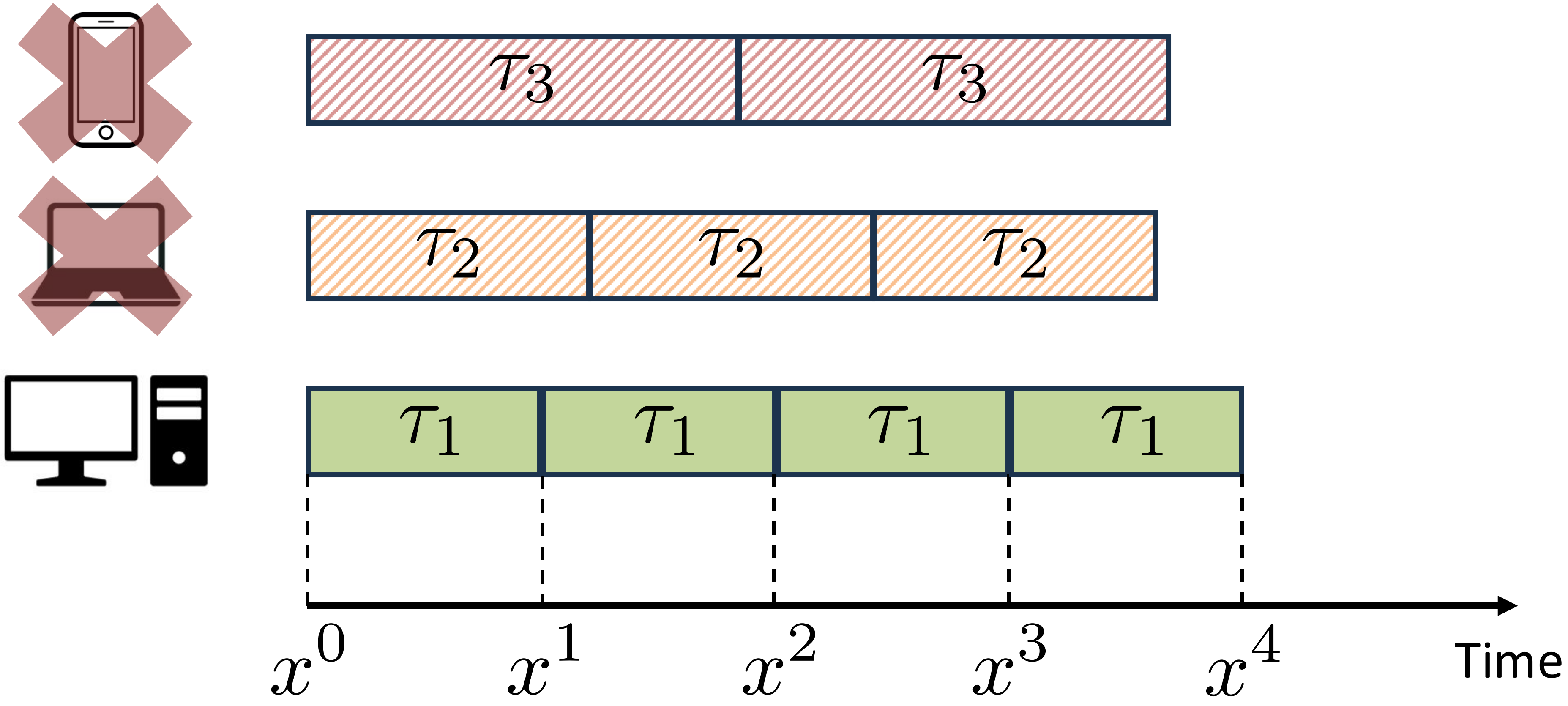
$$\mathbb{E}[g(x^k)] = \nabla f(x^k)$$

Server

$$x^{k+1} = x^k - \gamma \boxed{g(x^k)}$$

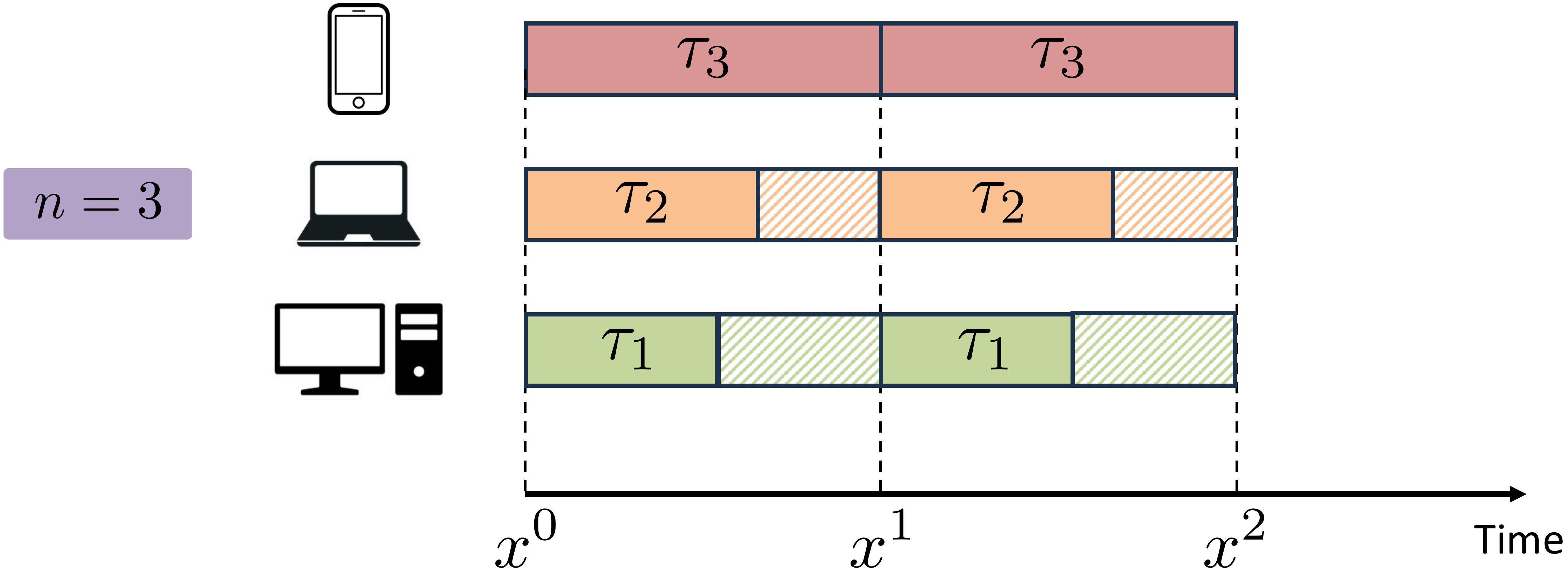
How to construct?

Hero SGD:
The fastest worker does it all



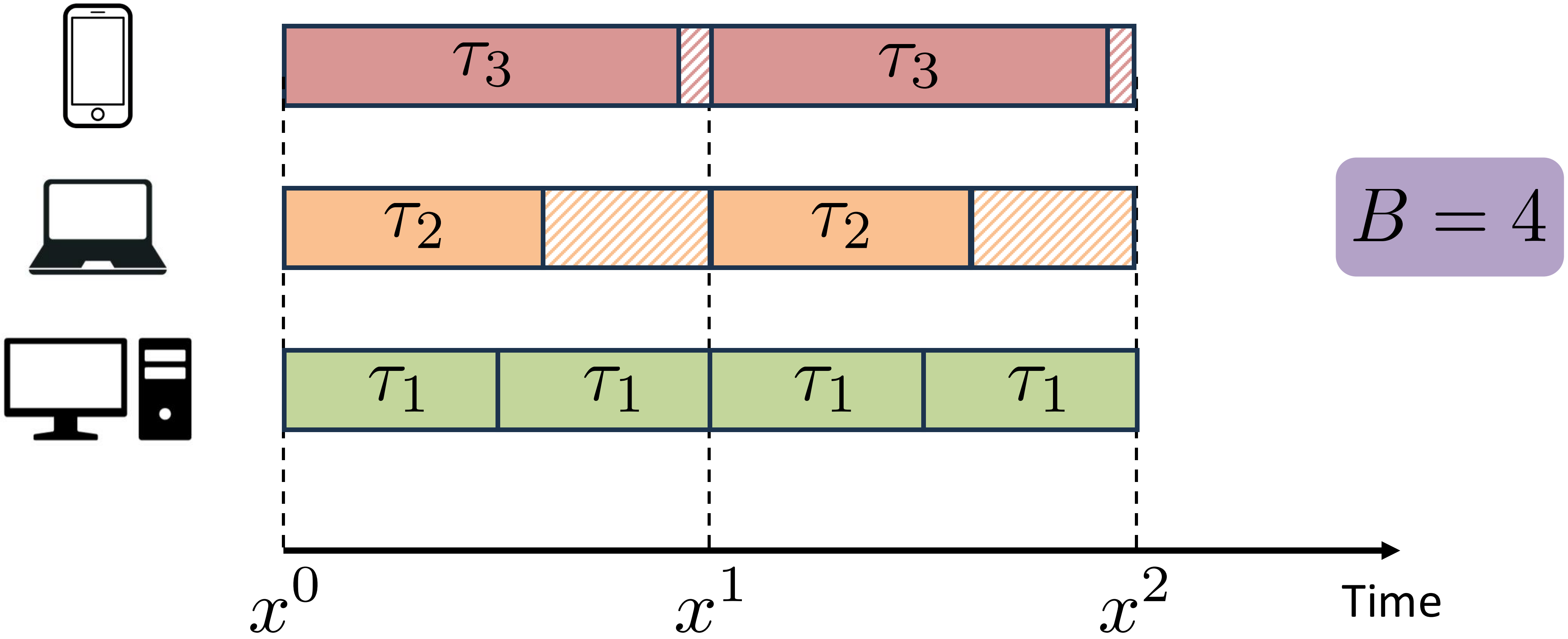
$$x^{k+1} = x^k - \gamma \nabla f(x^k; \xi^k)$$

Minibatch SGD:
Each worker does one job only



$$x^{k+1} = x^k - \gamma \frac{1}{n} \sum_{i=1}^{n} \nabla f(x^k; \xi_i^k)$$

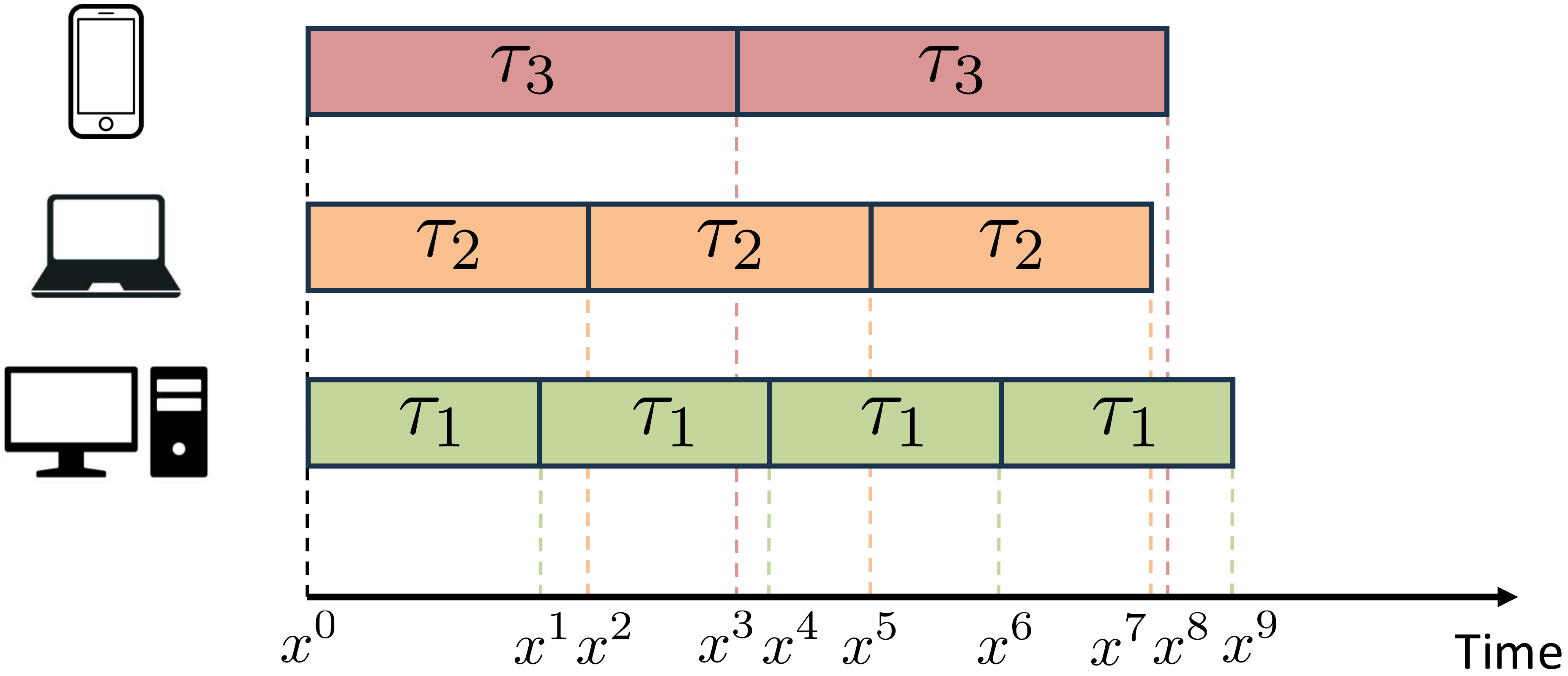
Rennala SGD: Asynchronous batch collection



$$x^{k+1} = x^k - \gamma \frac{1}{B} \sum_{j=1}^{B} \nabla f(x^k; \xi_j^k)$$

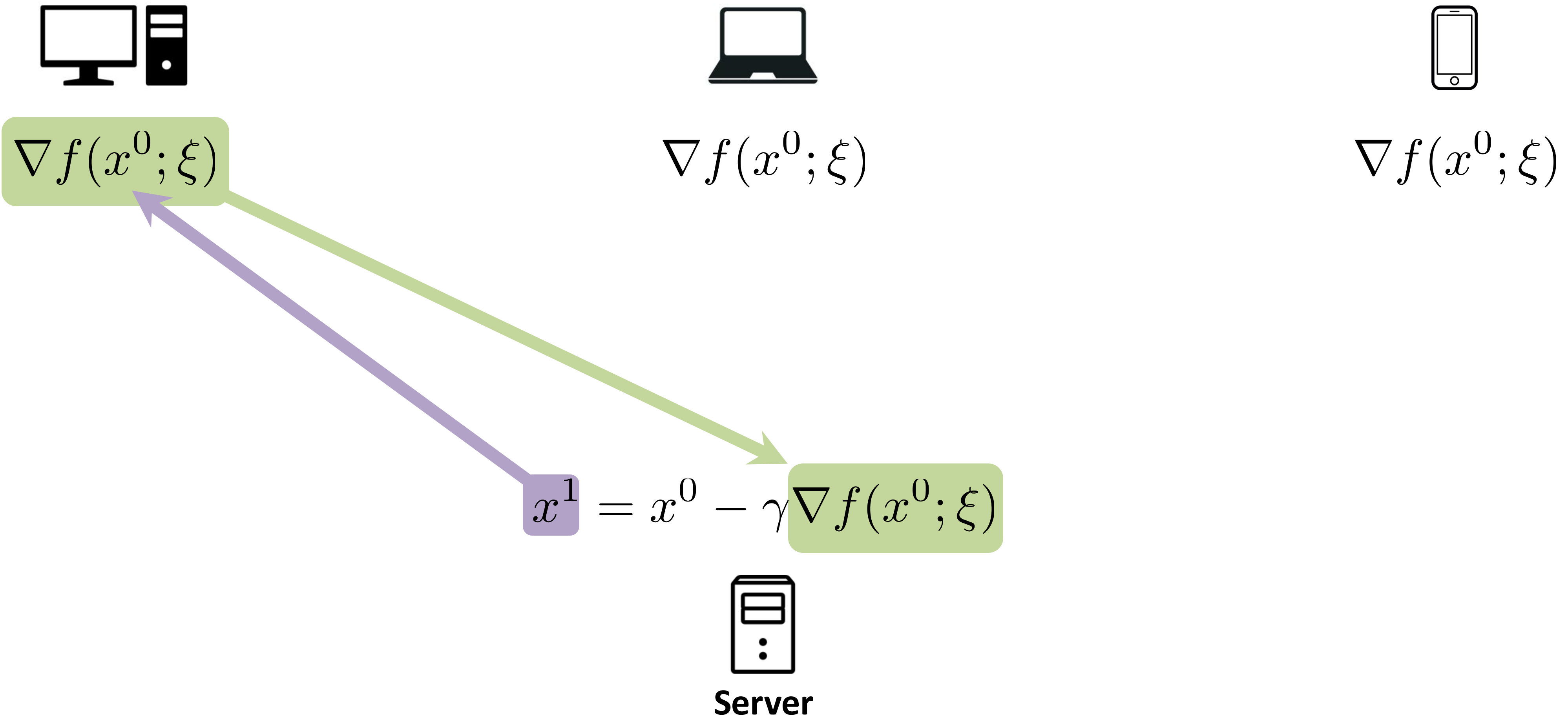
Tyurin and Richtárik (2024)

Asynchronous SGD
Remove the synchronization

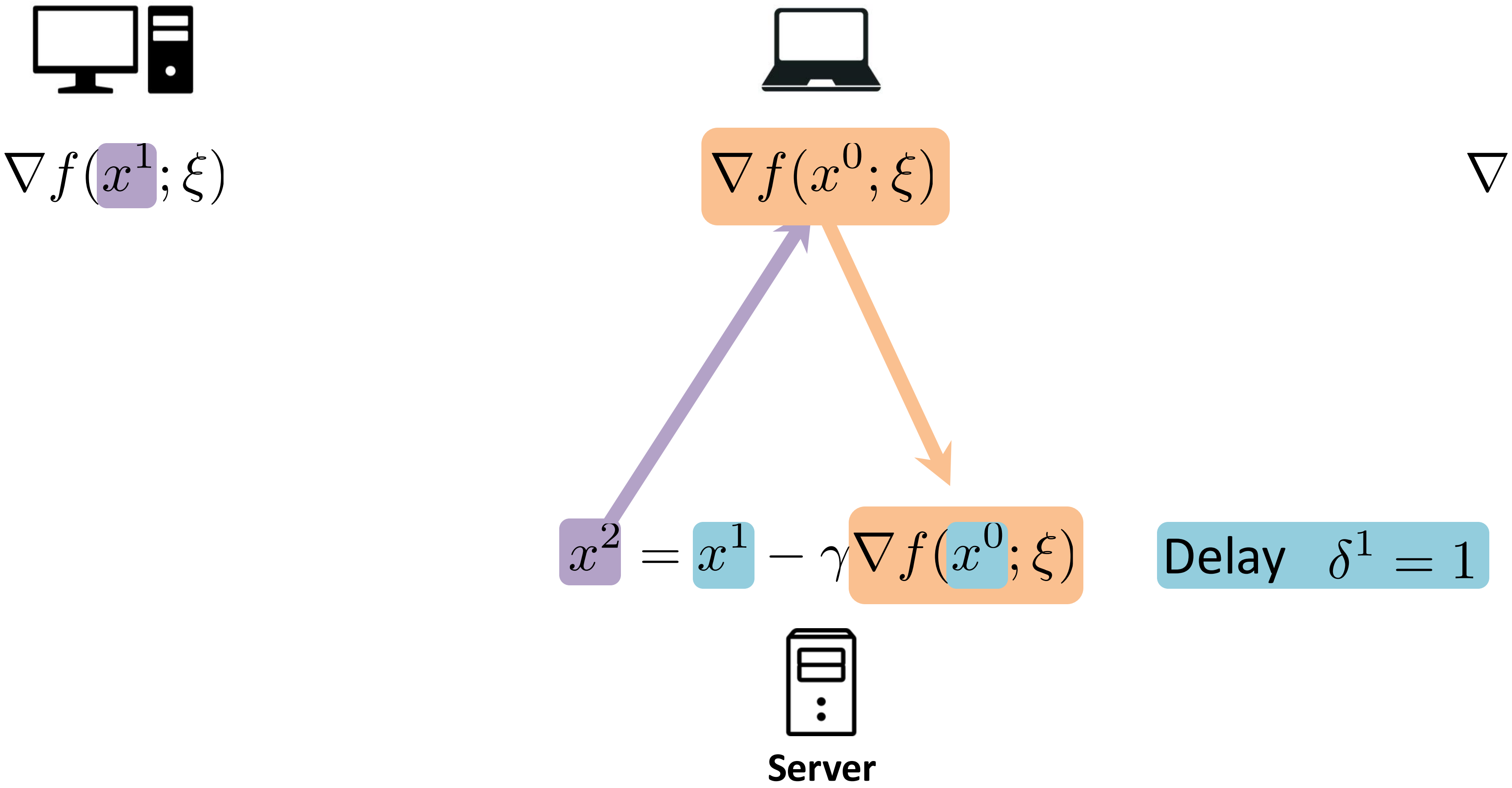


$$x^{k+1} = x^k - \gamma \cancel{g(x^k)}$$

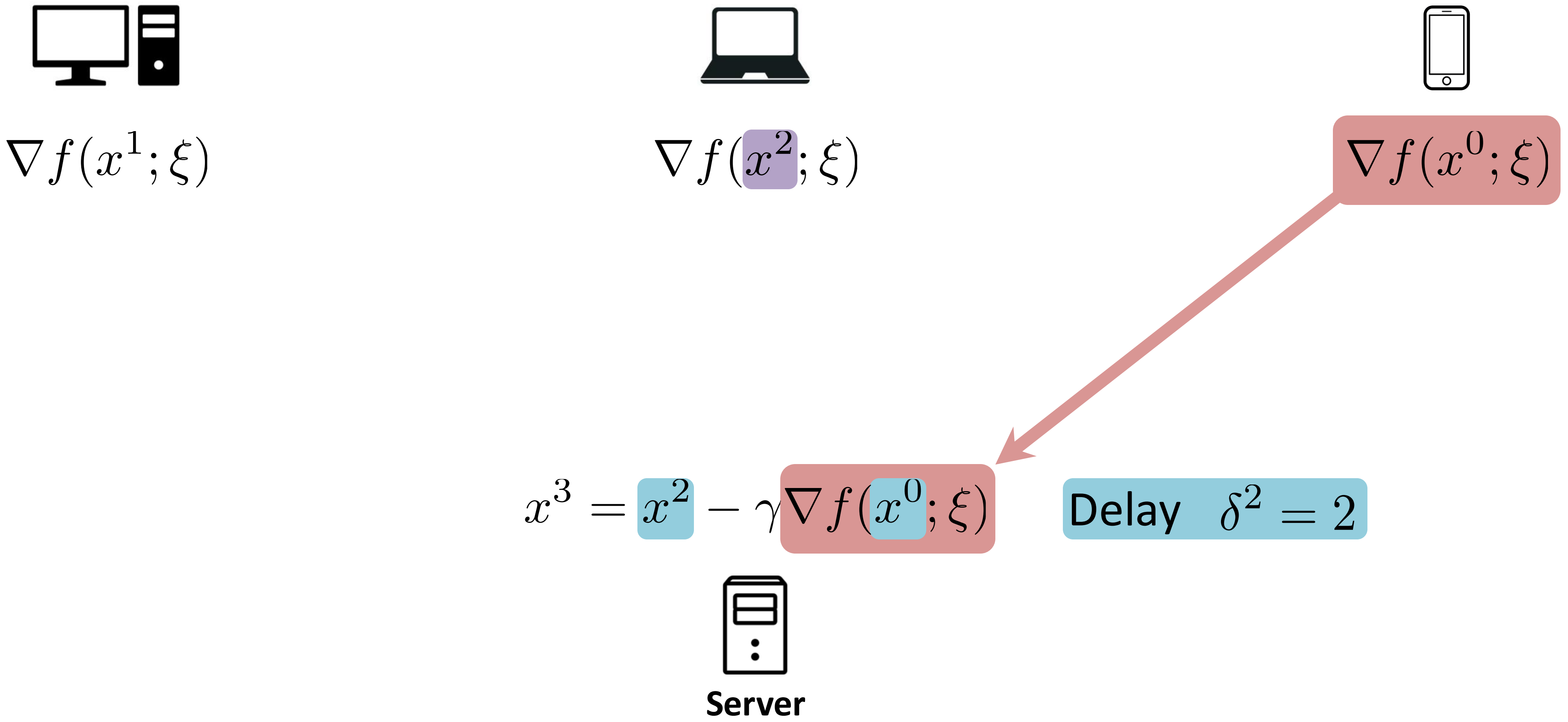
Updates of Asynchronous SGD has delayed stochastic gradients



Updates of Asynchronous SGD has delayed stochastic gradients



Updates of Asynchronous SGD has delayed stochastic gradients



Updates of Asynchronous SGD has delayed stochastic gradients

$$x^{k+1} = x^k - \gamma \nabla f(x^{k-\delta^k}; \xi)$$

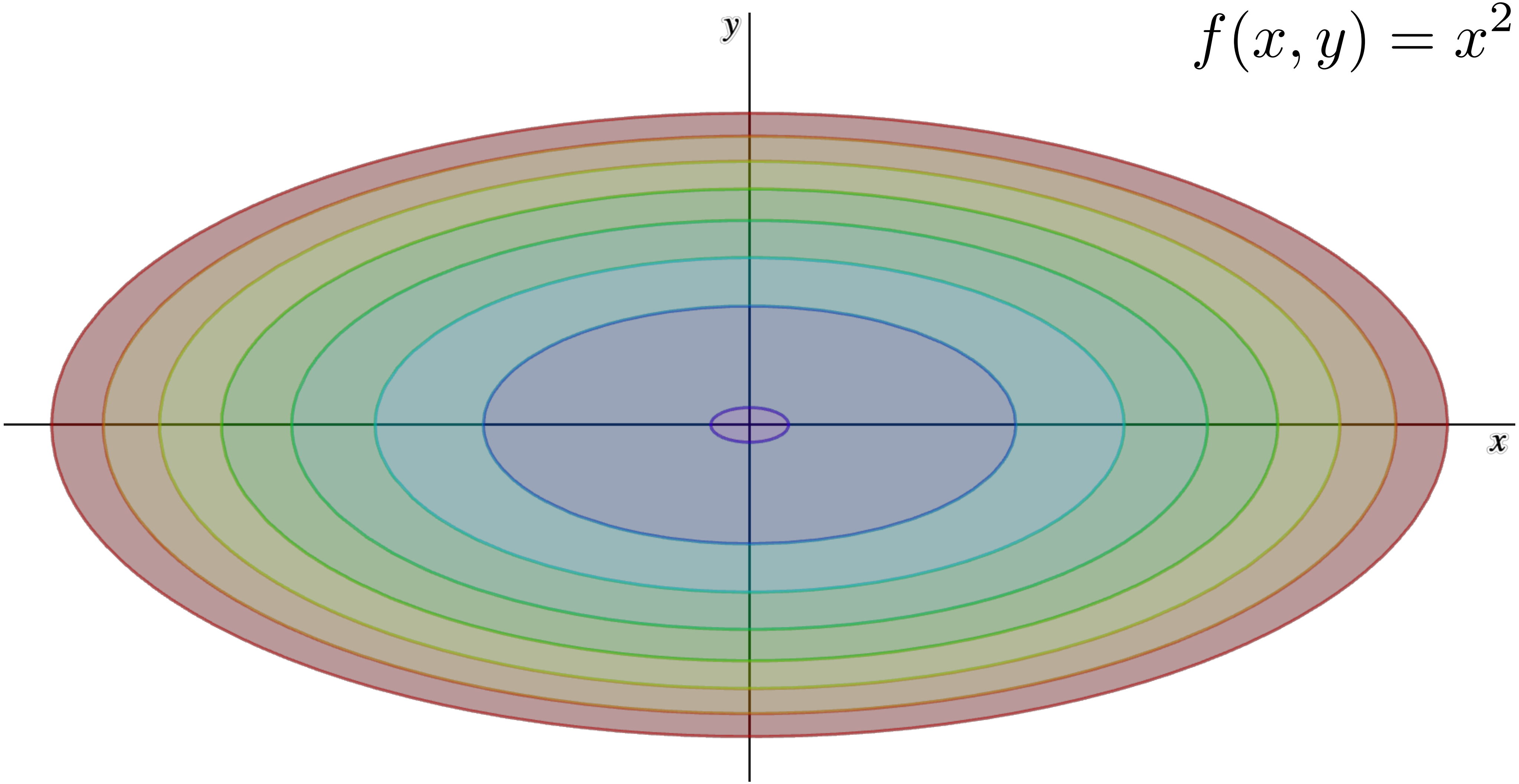
Delay δ^k

Server

Niu, et al. (2011).
HOGWILD!: A lock-free approach to parallelizing stochastic gradient descent.

Asynchronous SGD can get wild: delays can degrade performance

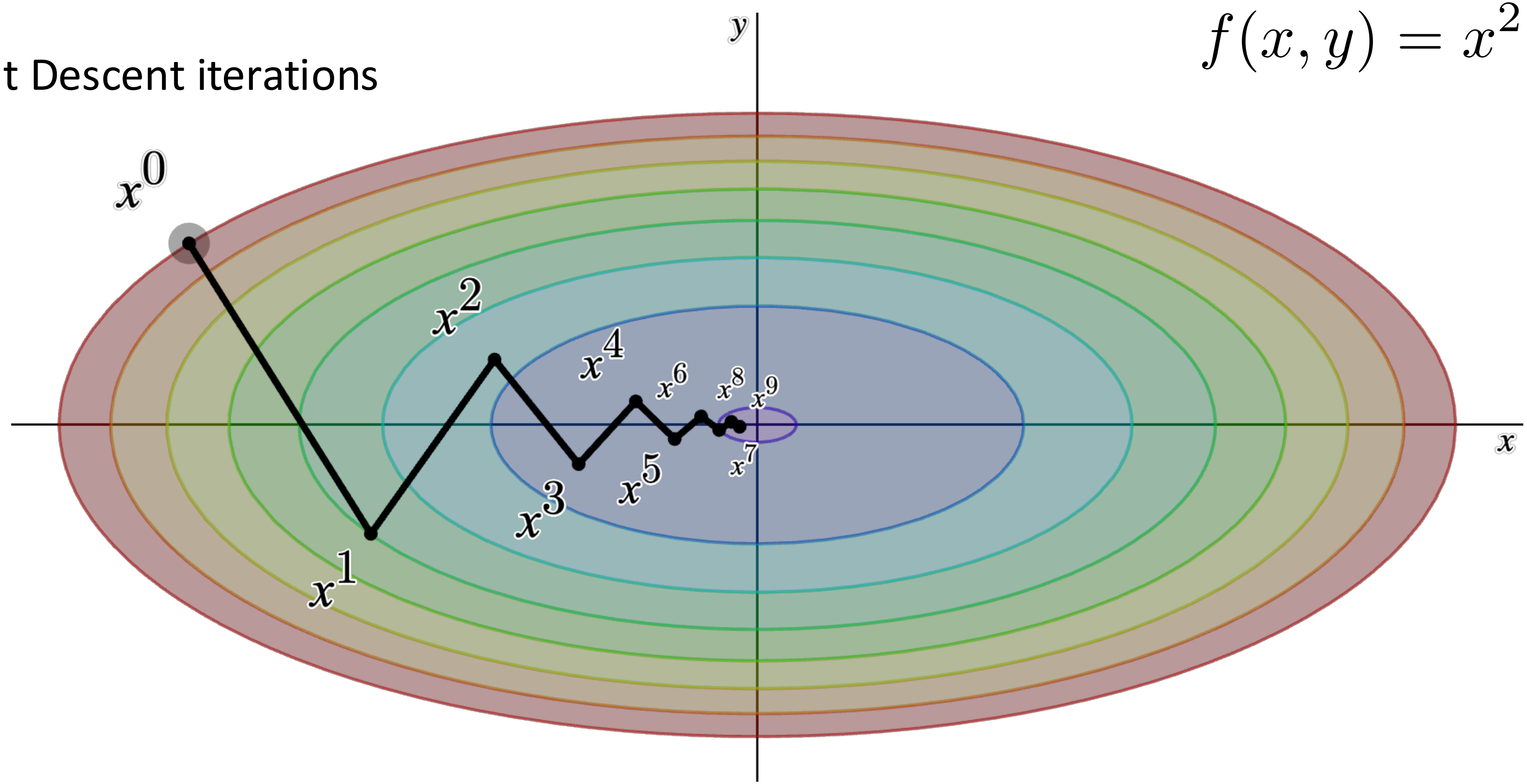
$$f(x, y) = x^2 + 5y^2$$



Asynchronous SGD can get wild: delays can degrade performance

Gradient Descent iterations

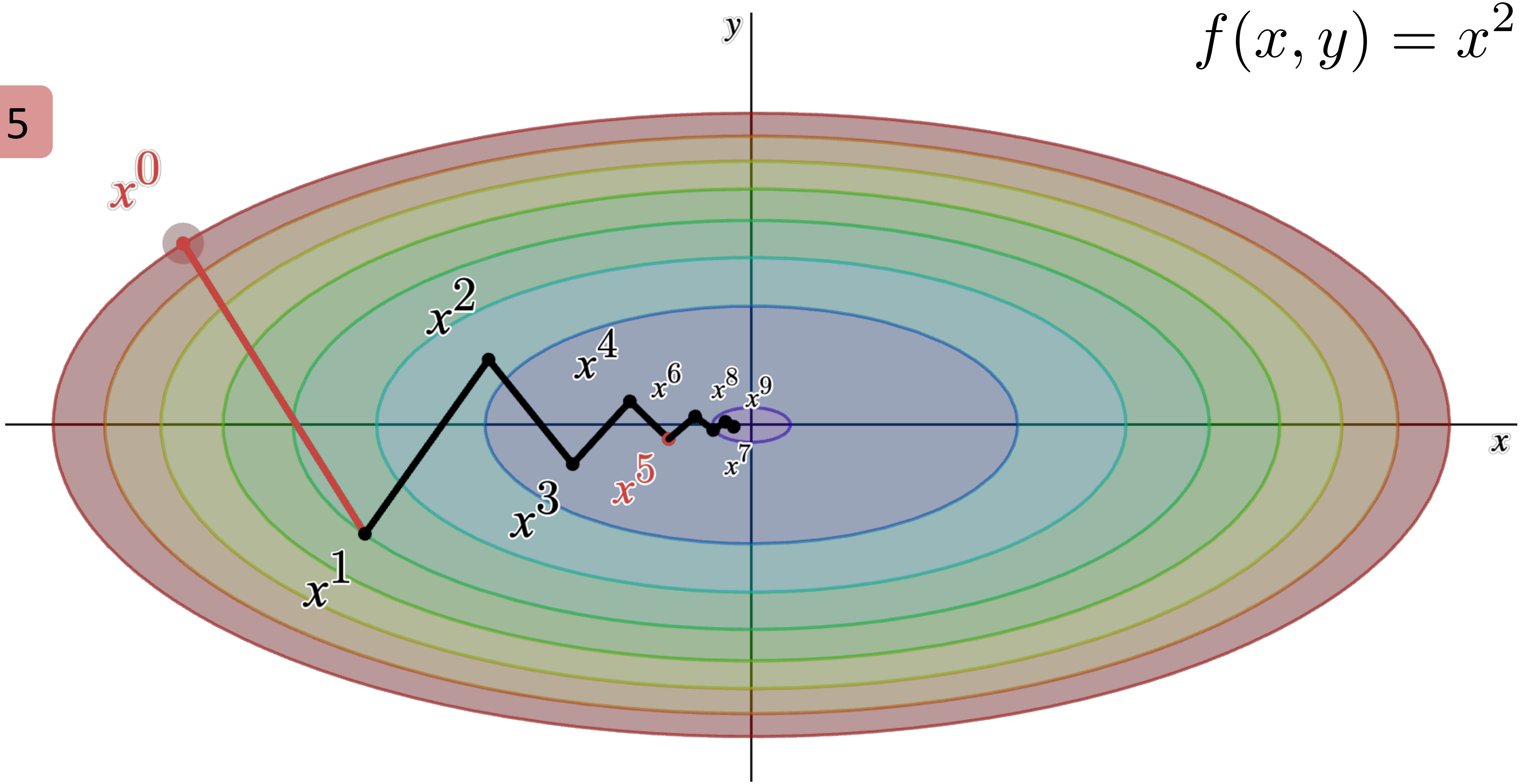
$$f(x, y) = x^2 + 5y^2$$



Asynchronous SGD can get wild: delays can degrade performance

$$f(x,y) = x^2 + 5y^2$$

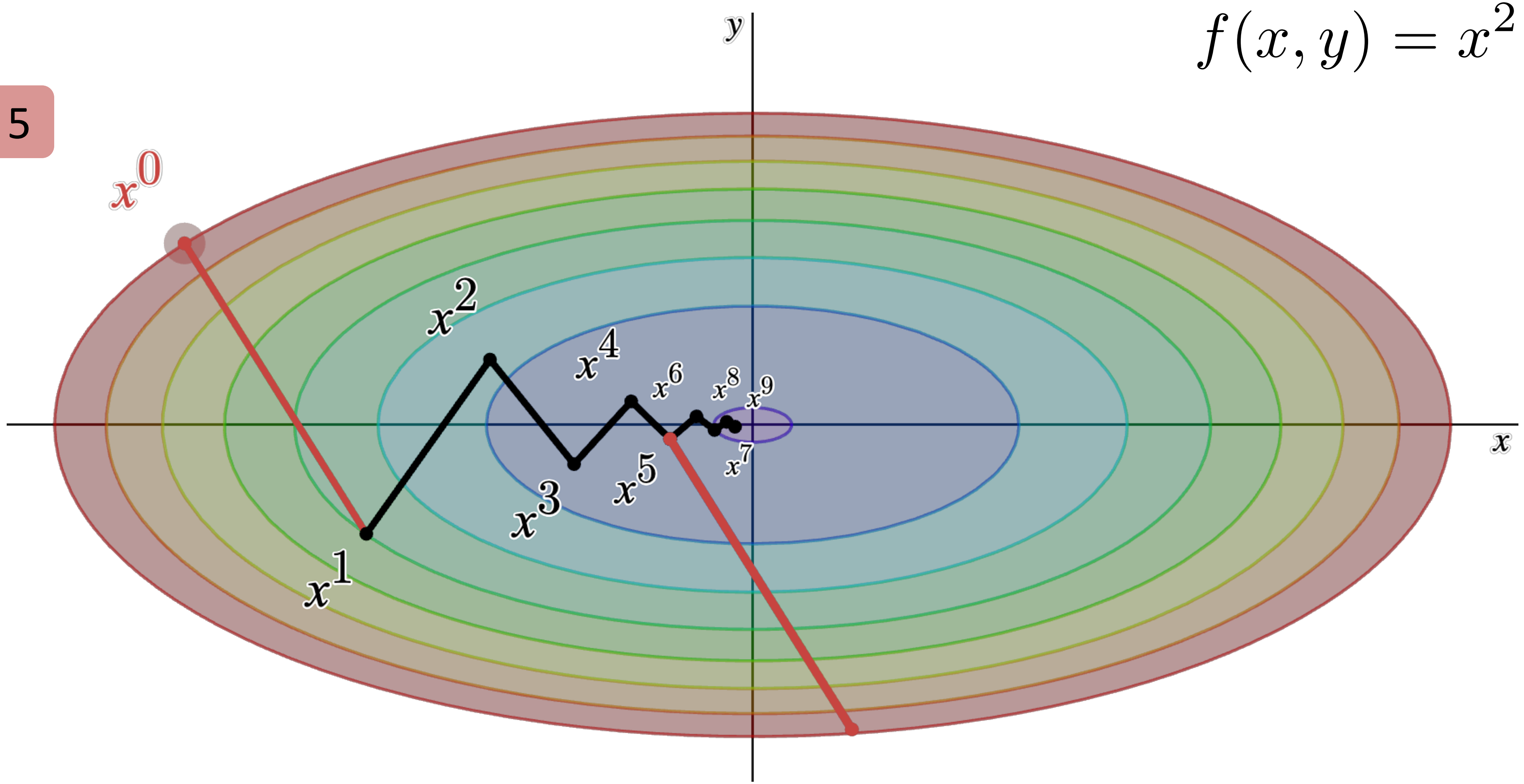
Delay = 5



Asynchronous SGD can get wild: delays can degrade performance

Delay = 5

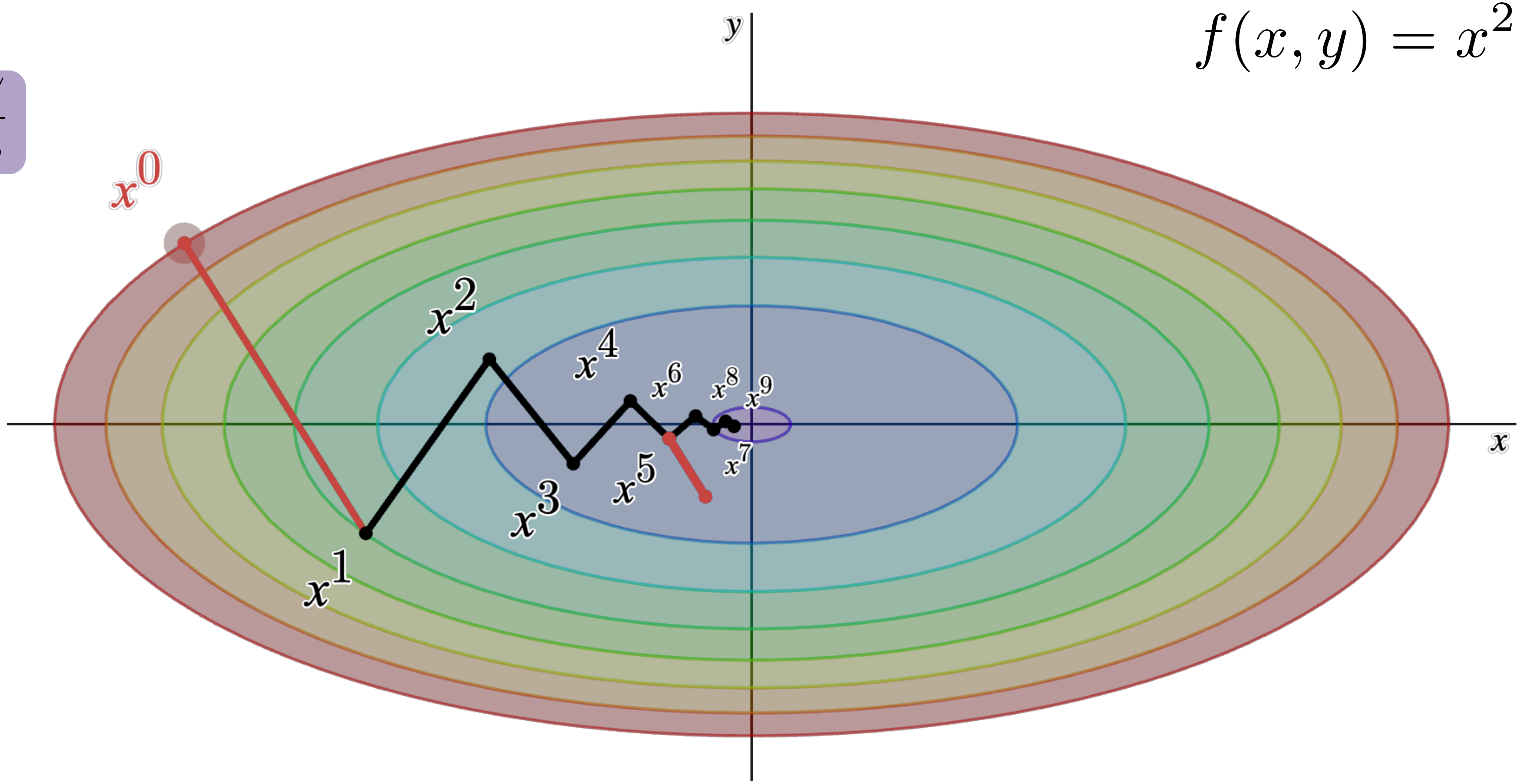
$$f(x, y) = x^2 + 5y^2$$



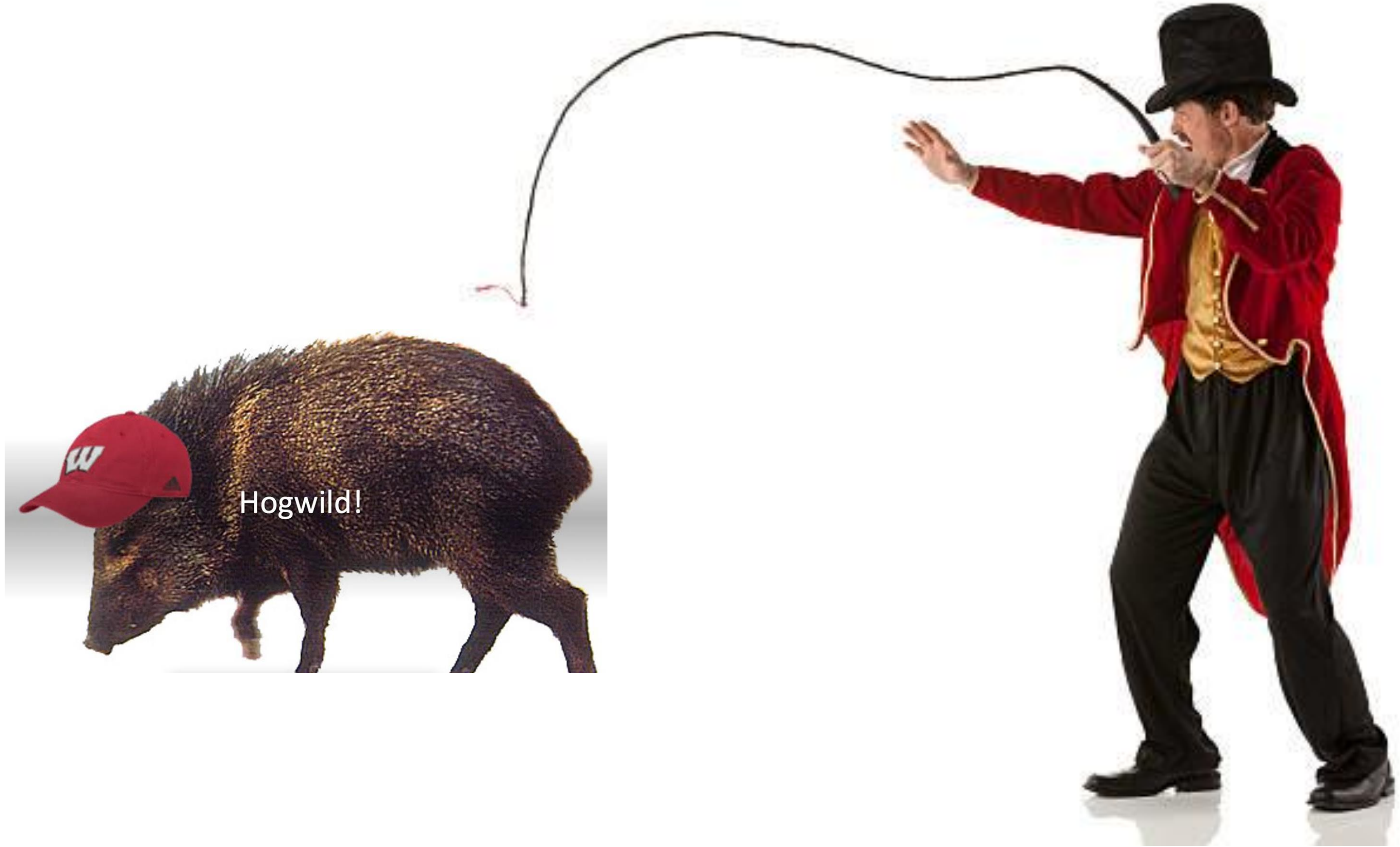
How to fix this?
Make the stepsize smaller

$$f(x, y) = x^2 + 5y^2$$

$$\gamma = \frac{\gamma}{5}$$



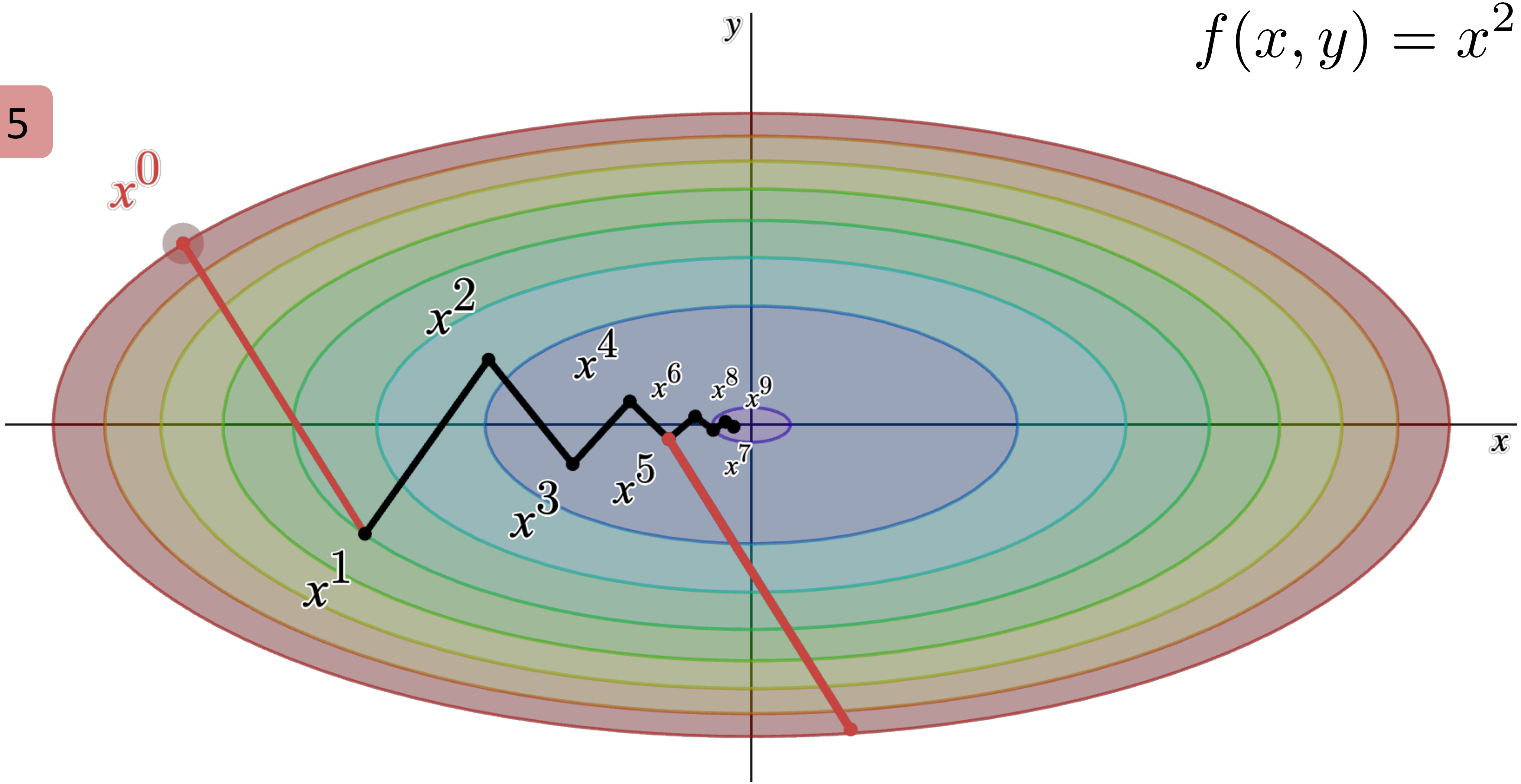
Asynchronous SGD is too wild: Ringmaster ASGD ***tames*** it



The smaller the delay, the better the gradient

Delay = 5

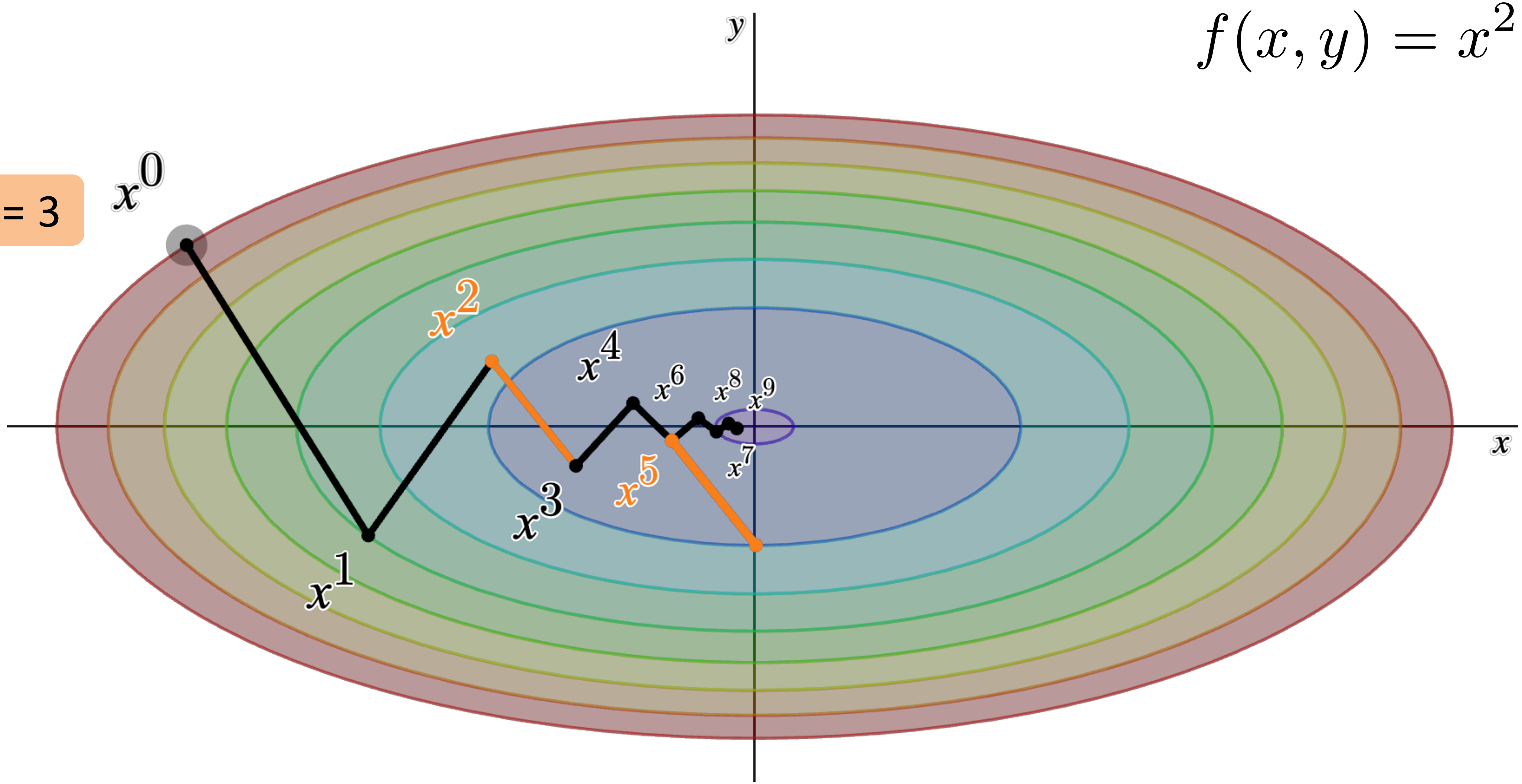
$$f(x, y) = x^2 + 5y^2$$



The smaller the delay, the better the gradient

$$f(x, y) = x^2 + 5y^2$$

Delay = 3



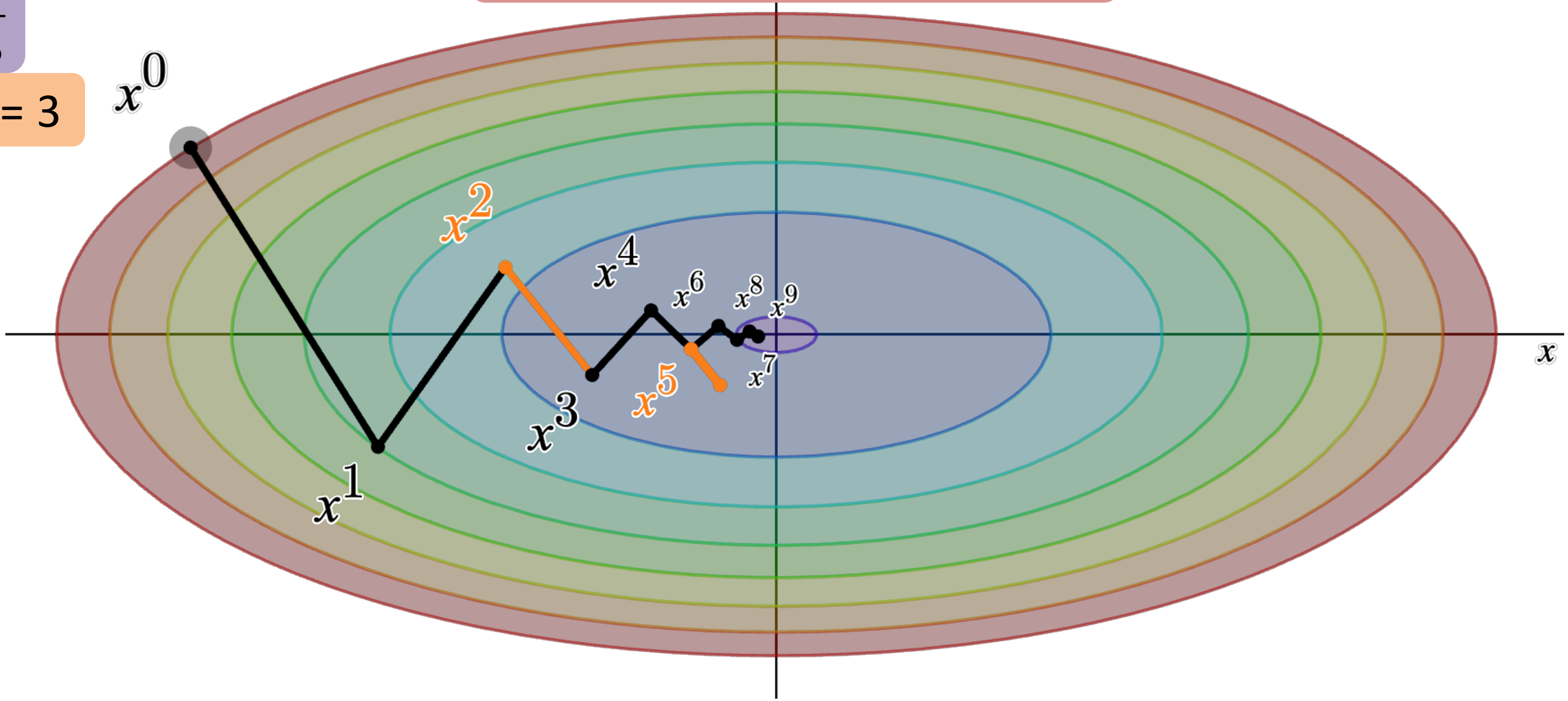
The smaller the delay, the better the gradient

How can we reduce the delay?

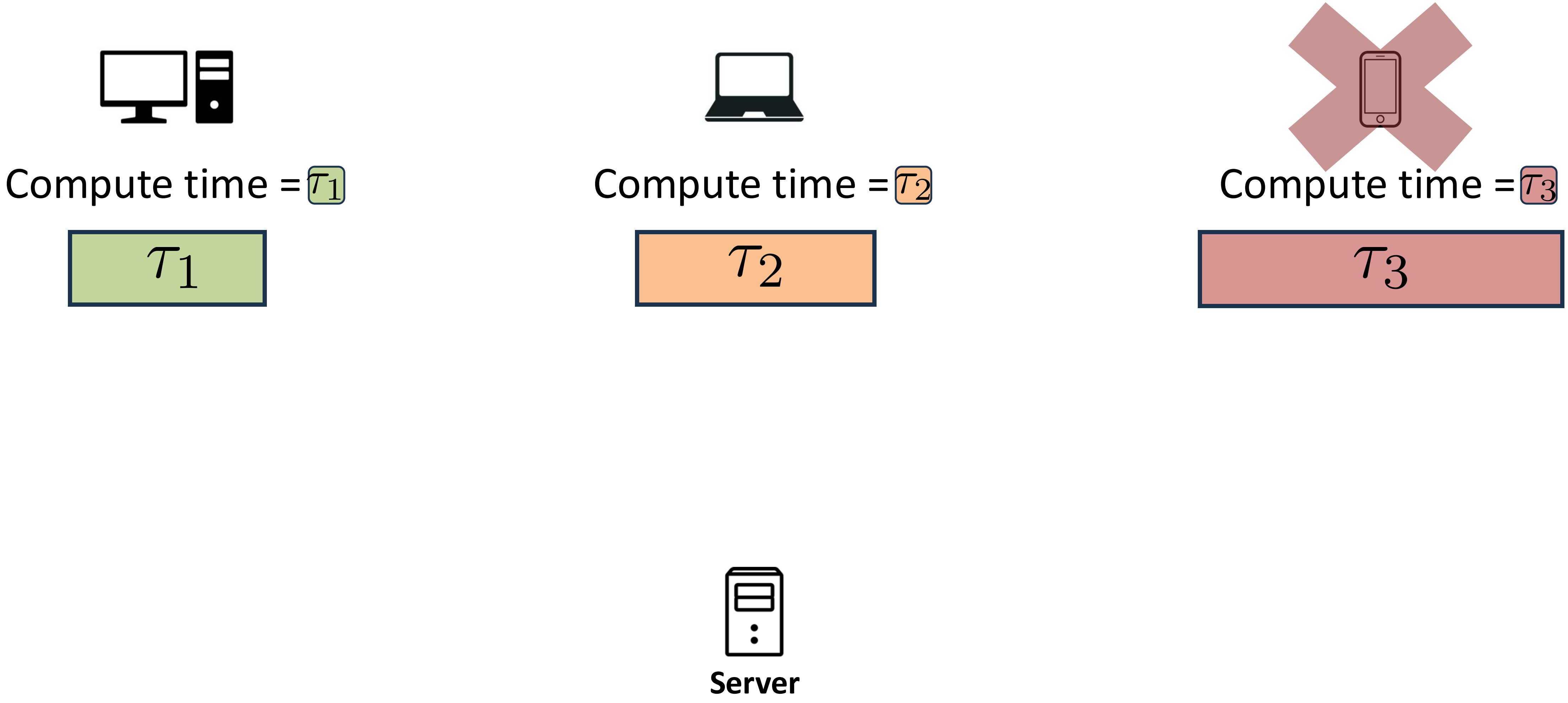
$$f(x, y) = x^2 + 5y^2$$

$\gamma = \frac{\gamma}{3}$

Delay = 3



Naive approach:
Remove slow workers



Naive approach: Remove slow workers

$$\mathbb{E}\left[\|\nabla f(x;\xi) - \nabla f(x)\|^2\right] \leq \sigma^2$$

Use only the first $m_\star = \arg\min_{m \in [n]} \left\{ \left(\frac{1}{m} \sum_{i=1}^{m} \frac{1}{\tau_i} \right)^{-1} \left(1 + \frac{\sigma^2}{m\varepsilon} \right) \right\}$ fastest workers

$$\mathbb{E}\left[\|\nabla f(x)\|^2\right] \leq \varepsilon$$

Problem: τ_i-s may be unknown and dynamic

Ringmaster ASGD: Have a threshold on delays

$$\nabla f\left(x^{k-\delta^k}; \xi_i^{k-\delta^k}\right)$$

If: $\delta^k < R$

$$x^{k+1} = x^k - \gamma \nabla f\left(x^{k-\delta^k}; \xi_i^{k-\delta^k}\right)$$

Else: Ignore the gradient and send the current point x^k to the worker

Server

Ringmaster ASGD: Have a threshold on delays

$\nabla f\left(x^k; \xi_i^k\right)$

How to choose the delay threshold R

If: $\delta^k < R$

$$x^{k+1} = x^k - \gamma \nabla f\left(x^{k-\delta^k}; \xi_i^{k-\delta^k}\right)$$

Else: Ignore the gradient and send the current point x^k to the worker

Server

Certain threshold choices in Ringmaster ASGD recover previous methods

$$R = \max\left\{1, \left\lceil \frac{\sigma^2}{\varepsilon} \right\rceil \right\}$$

$R = 1$
Hero SGD

Sweet spot

$R = \infty$
HOGWILD!

Theoretical results validate our intuition

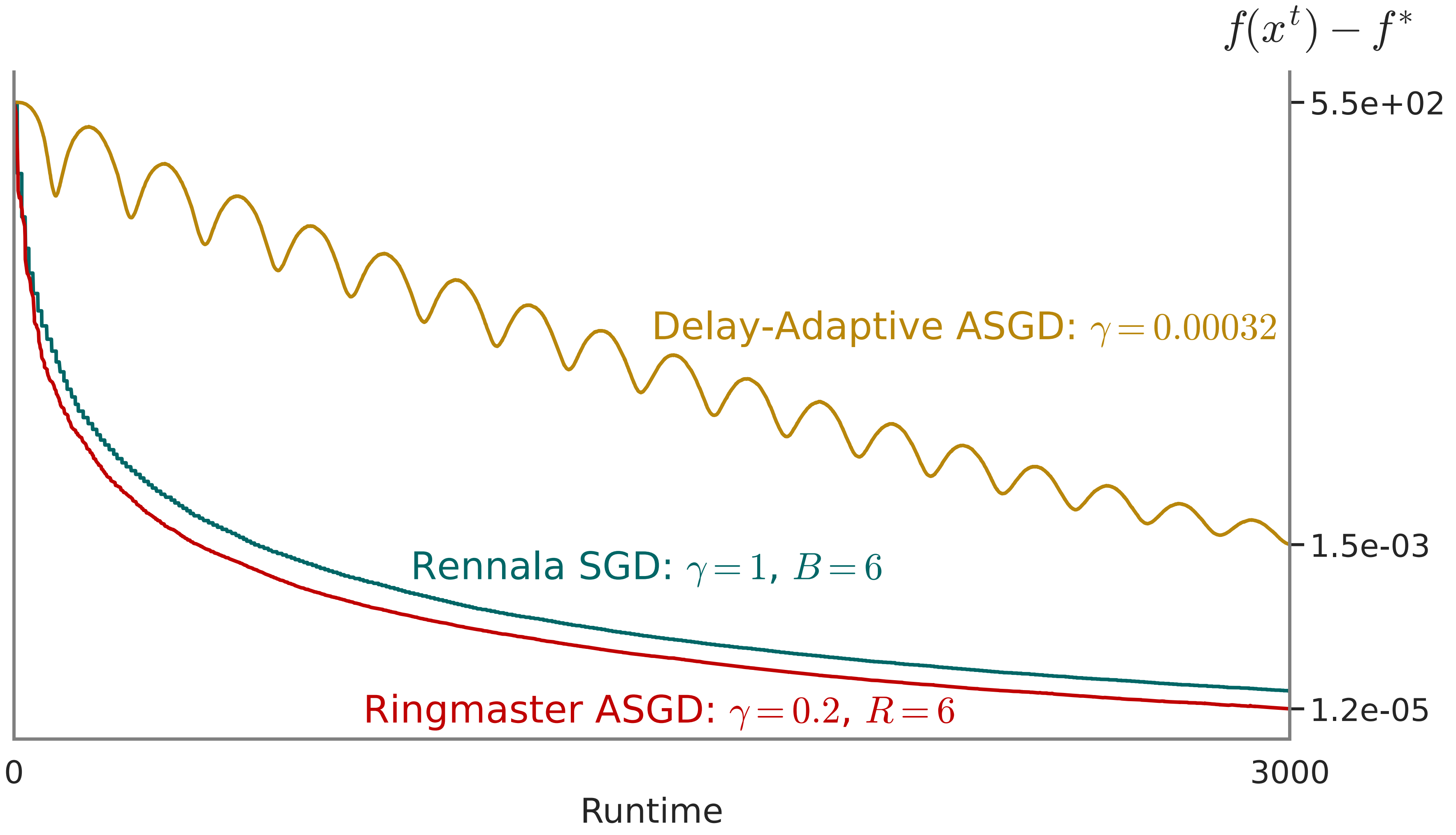
$$\mathcal{O}\left(\boxed{R}\frac{}{\varepsilon} + \frac{\sigma^2}{\varepsilon^2}\right)$$

Number of iterations

$$\mathcal{O}\left(\min_{m\in[n]}\left[\underbrace{\left(\frac{1}{m}\sum_{i=1}^{m}\frac{1}{\tau_i}\right)^{-1}}_{\text{non-decreasing}}\left(\frac{1}{\varepsilon}+\underbrace{\frac{\sigma^2}{m\varepsilon^2}}_{\text{decreasing}}\right)\right]\right)$$

Time complexity

Ringmaster ASGD outperforms existing baselines



Recap of what we have covered

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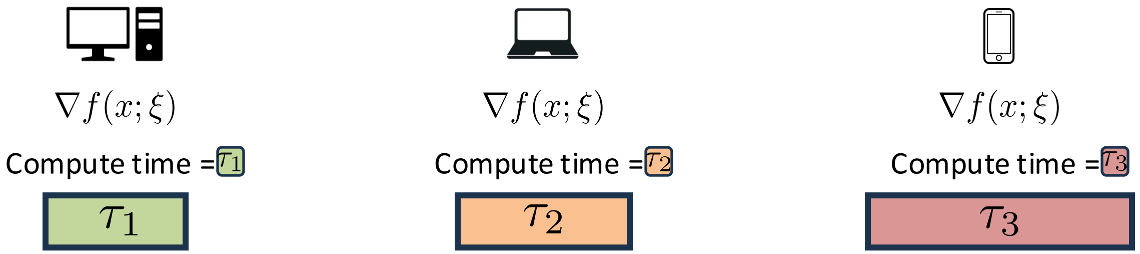

$$x^{k+1} = x^k - \gamma g(x^k)$$

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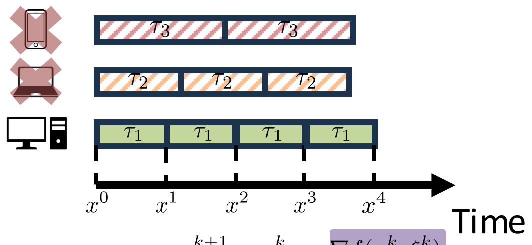

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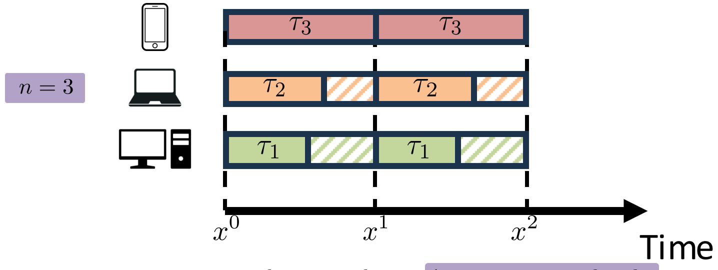
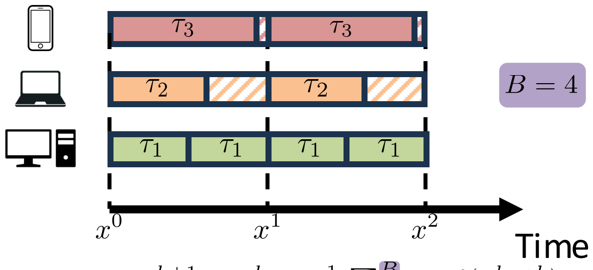


$$x^{k+1} = x^k - \gamma \frac{1}{n} \sum_{i=1}^{n} \nabla f(x^k; \xi_i^k)$$



$$x^{k+1} = x^k - \gamma \frac{1}{B} \sum_{j=1}^{B} \nabla f(x^k; \xi_j^k)$$

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Different ways of parallelizing SGD

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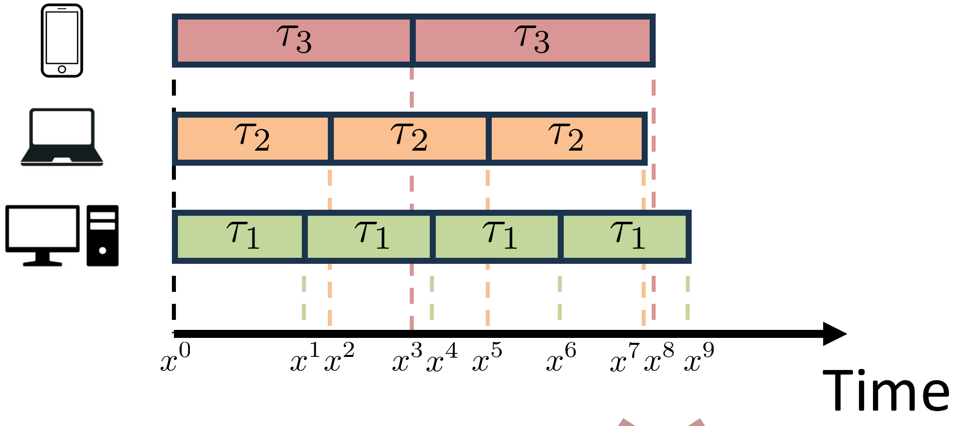

$$x^{k+1} = x^k - \gamma \cancel{g(x^k)}$$

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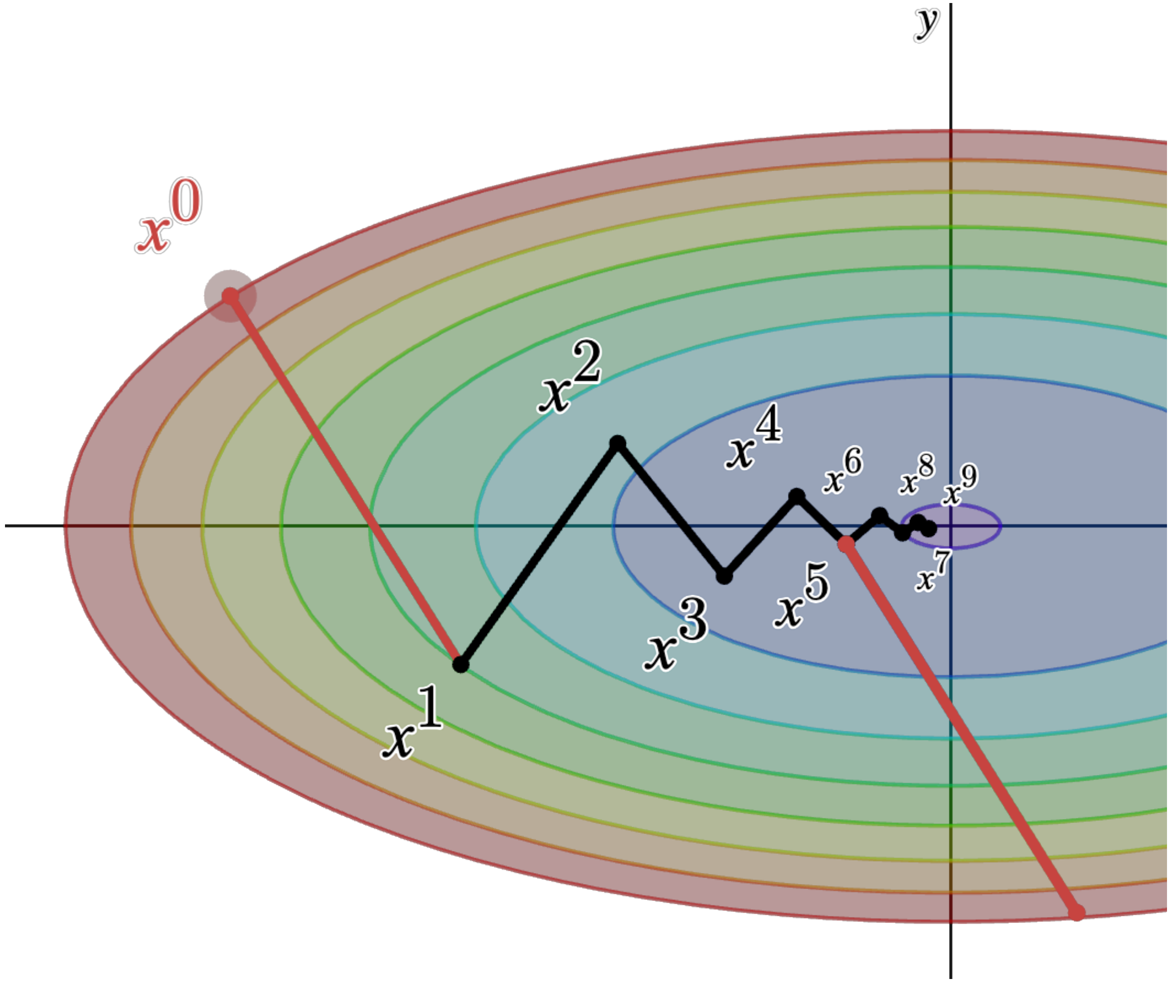

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Problems of ASGD

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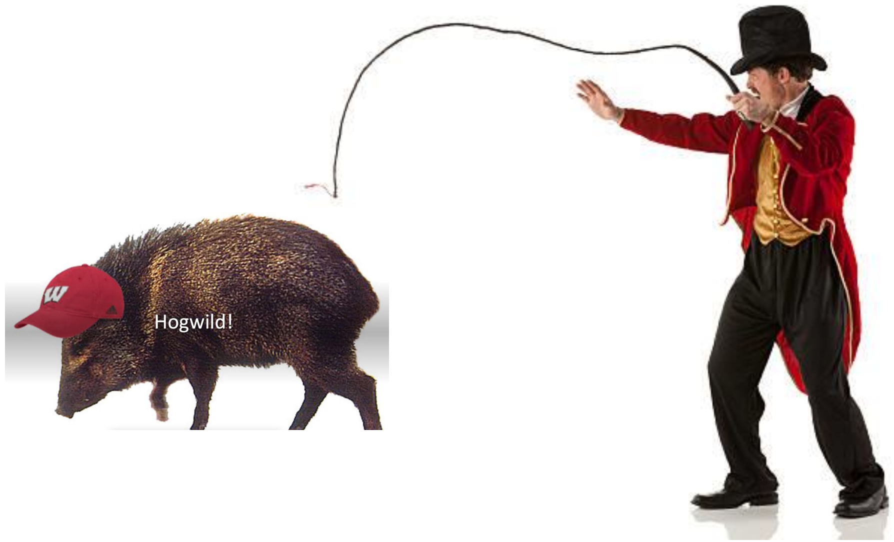

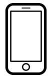

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Problems of ASGD

Ringmaster ASGD

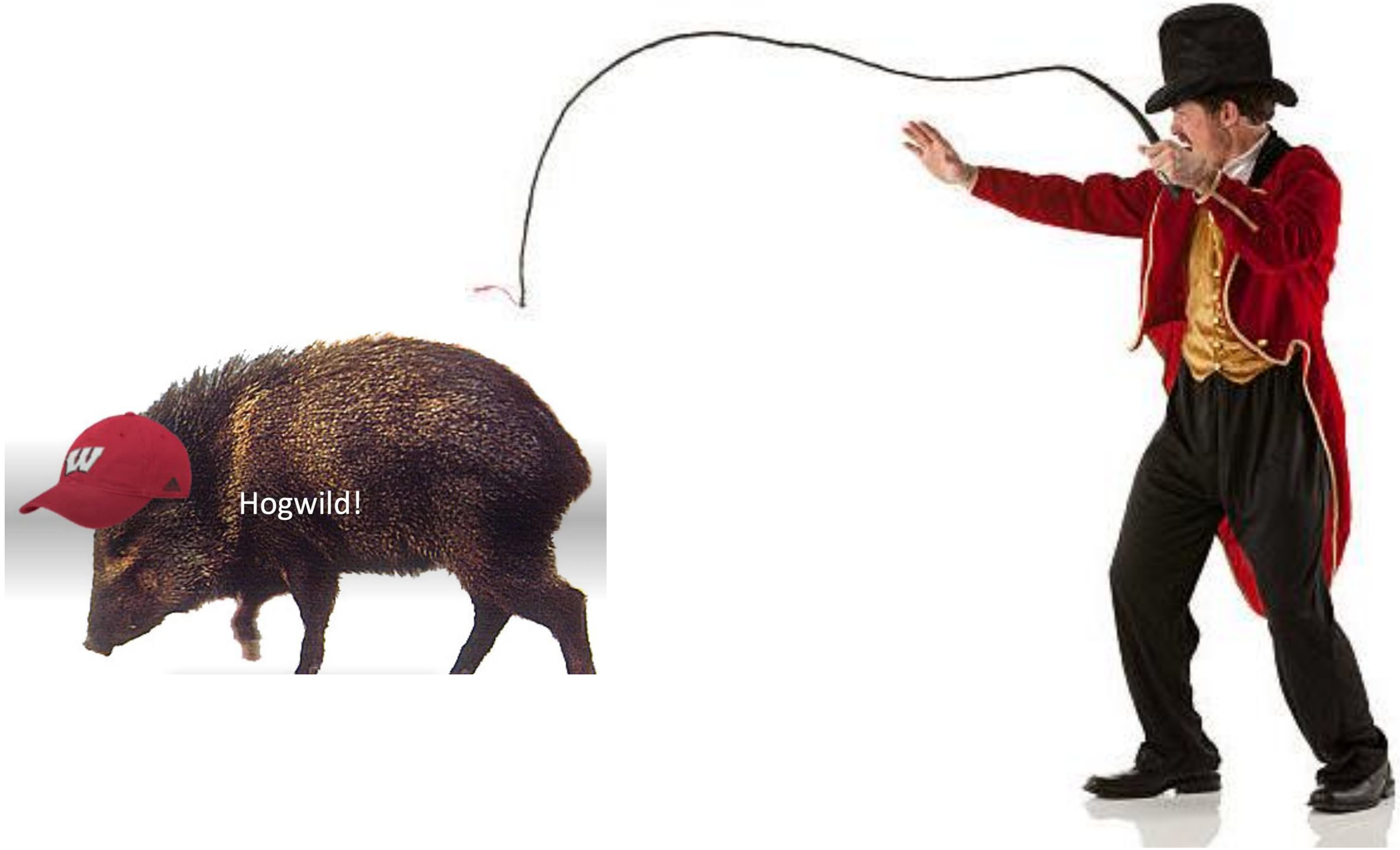
Alexander Tyurin
Skoltech

Peter Richtárik
KAUST

Closely related papers

Artavazd Maranjyan, Omar Shaikh Omar, Peter Richtárik (2024)
MindFlayer: Efficient asynchronous parallel SGD in the presence of heterogeneous and random worker compute times

Artavazd Maranjyan, El Mehdi Saad, Peter Richtarik, and Francesco Orabona (2025)
ATA: Adaptive Task Allocation for Efficient Resource Management in Distributed Machine Learning


Hogwild!