# Ringmaster ASGD: The First Asynchronous SGD with Optimal Time Complexity

Artavazd Maranjyan

Peking University

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جامعة الملك عبدالله
للعلوم والتقنية
King Abdullah University of
Science and Technology

# 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)

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

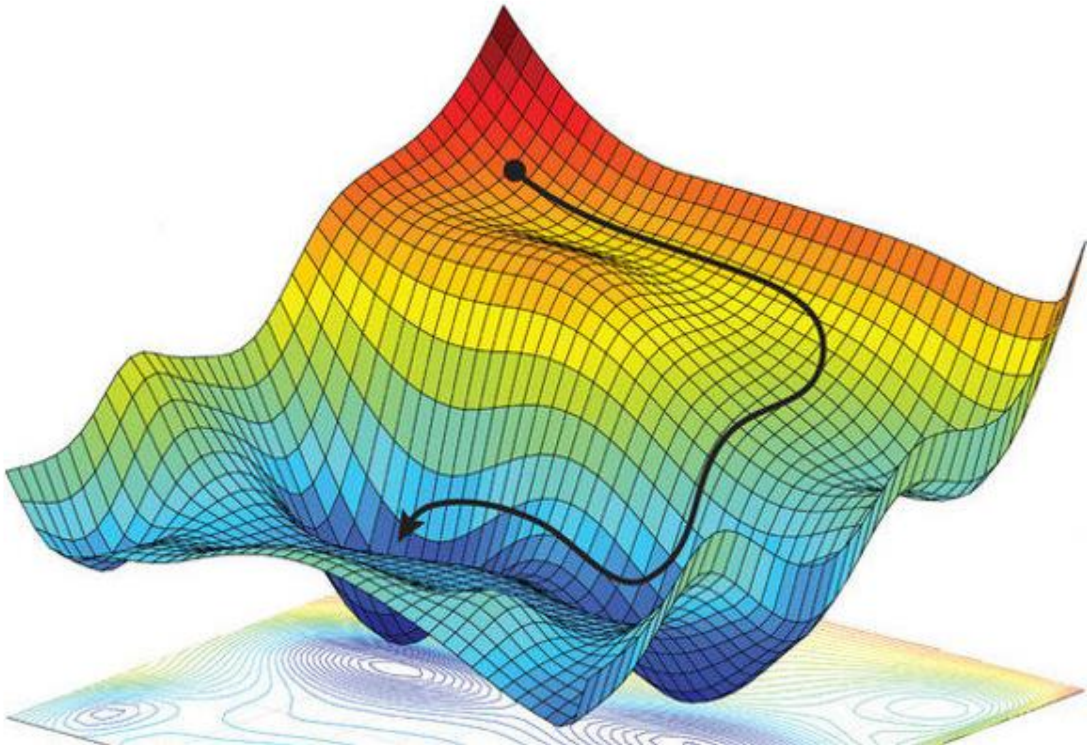
Loss of a data sample $\xi$

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)



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

Stepsize / Learning rate

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?

$\nabla f(x;\xi)$

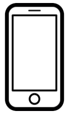
Compute time = $\tau_1$

$\tau_1$

$\nabla f(x;\xi)$

Compute time = $\tau_2$

$\tau_2$



$\nabla f(x;\xi)$

Compute time = $\tau_3$

$\tau_3$

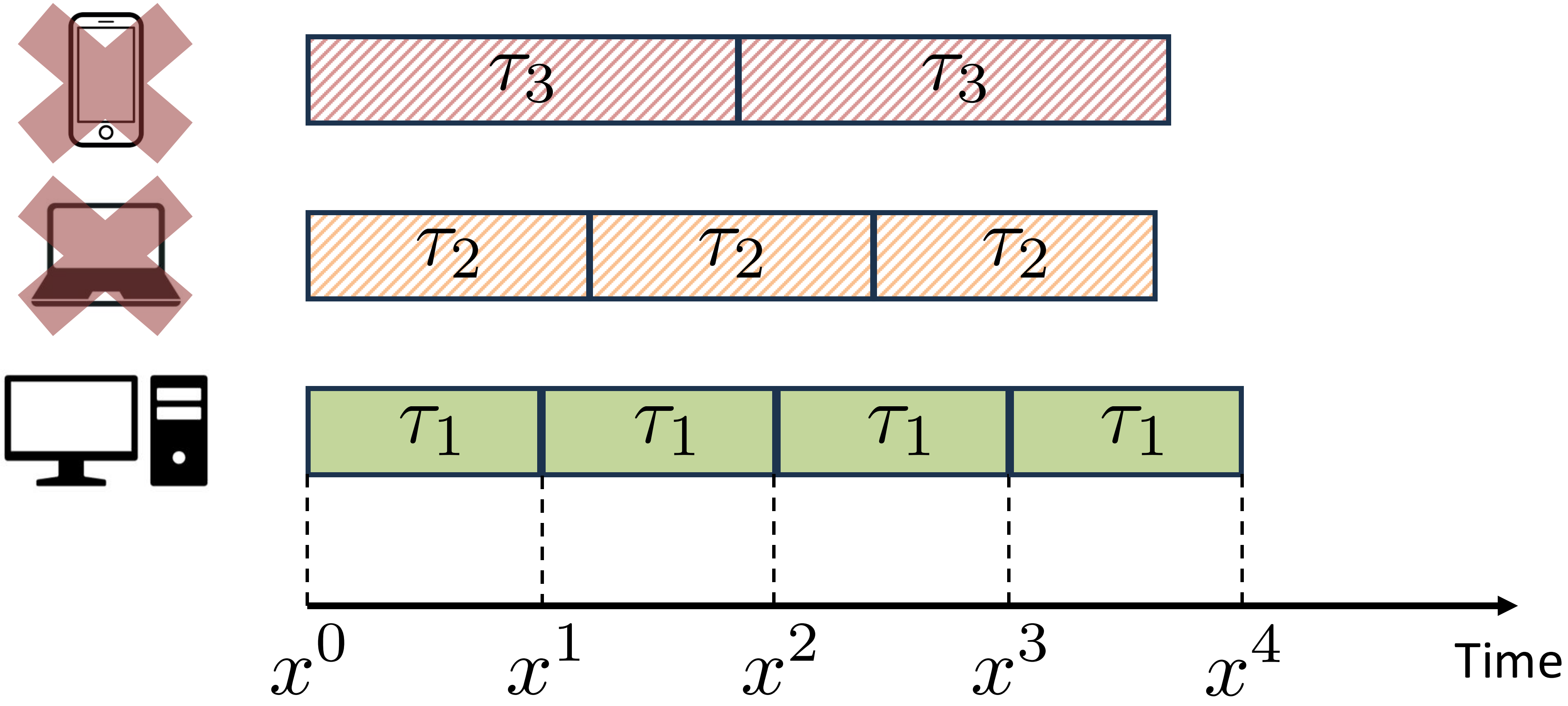
$$\mathbb{E}[g(x^k)] = \nabla f(x^k)$$

**Server**

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

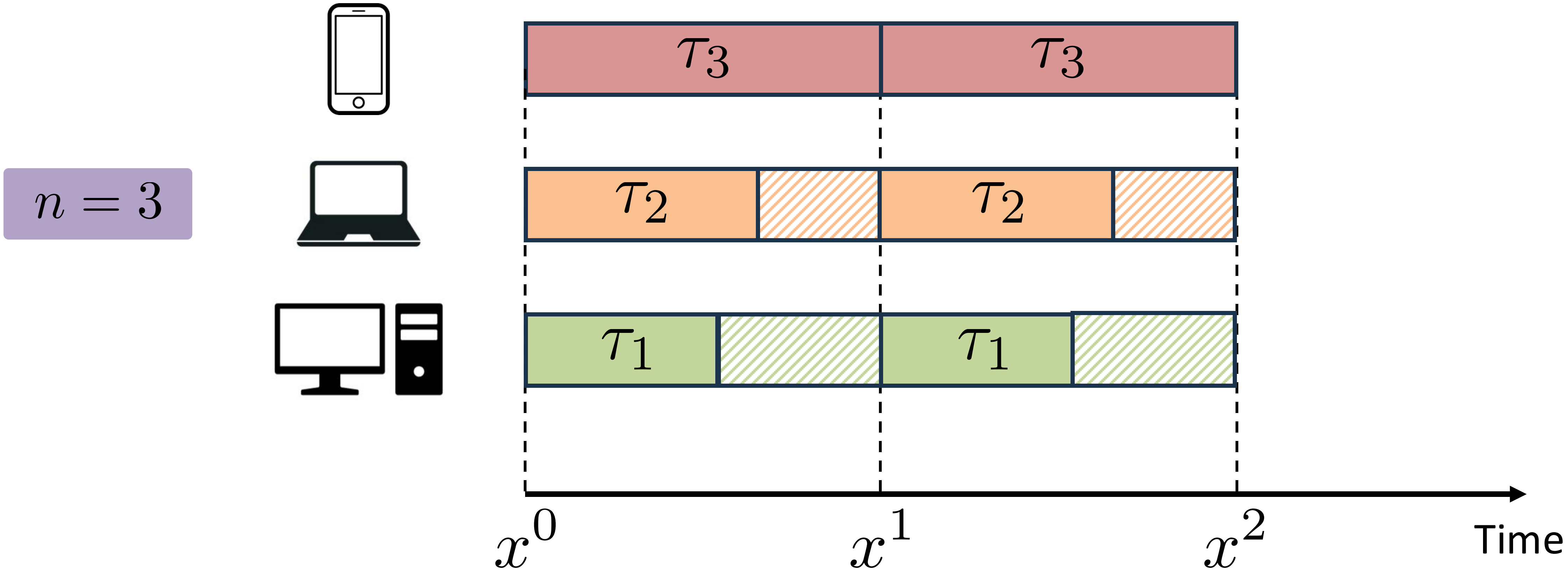
How to construct?

# Hero SGD:
# The fastest worker does it all



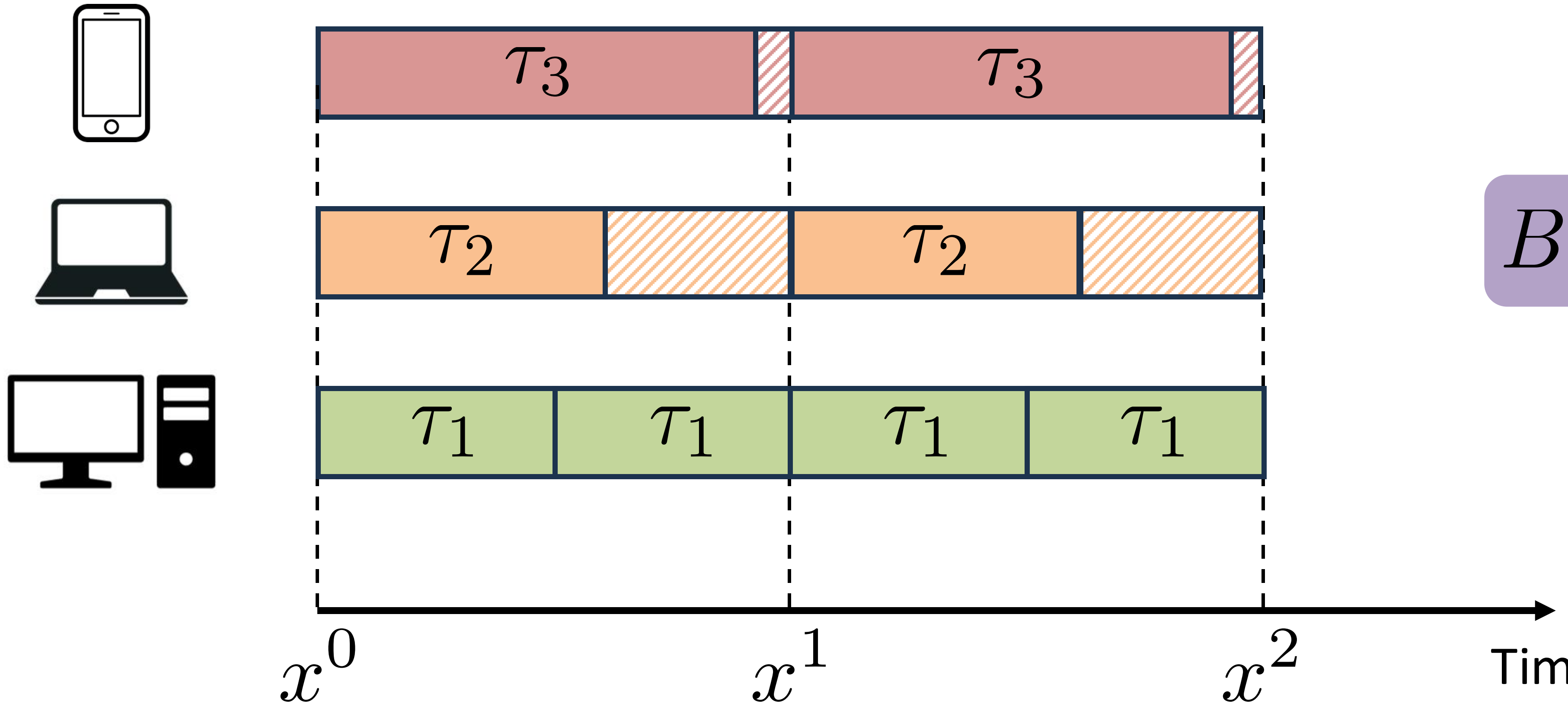

$$x^{k+1} = x^k - \gamma \boxed{\nabla f(x^k; \xi^k)}$$

# 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

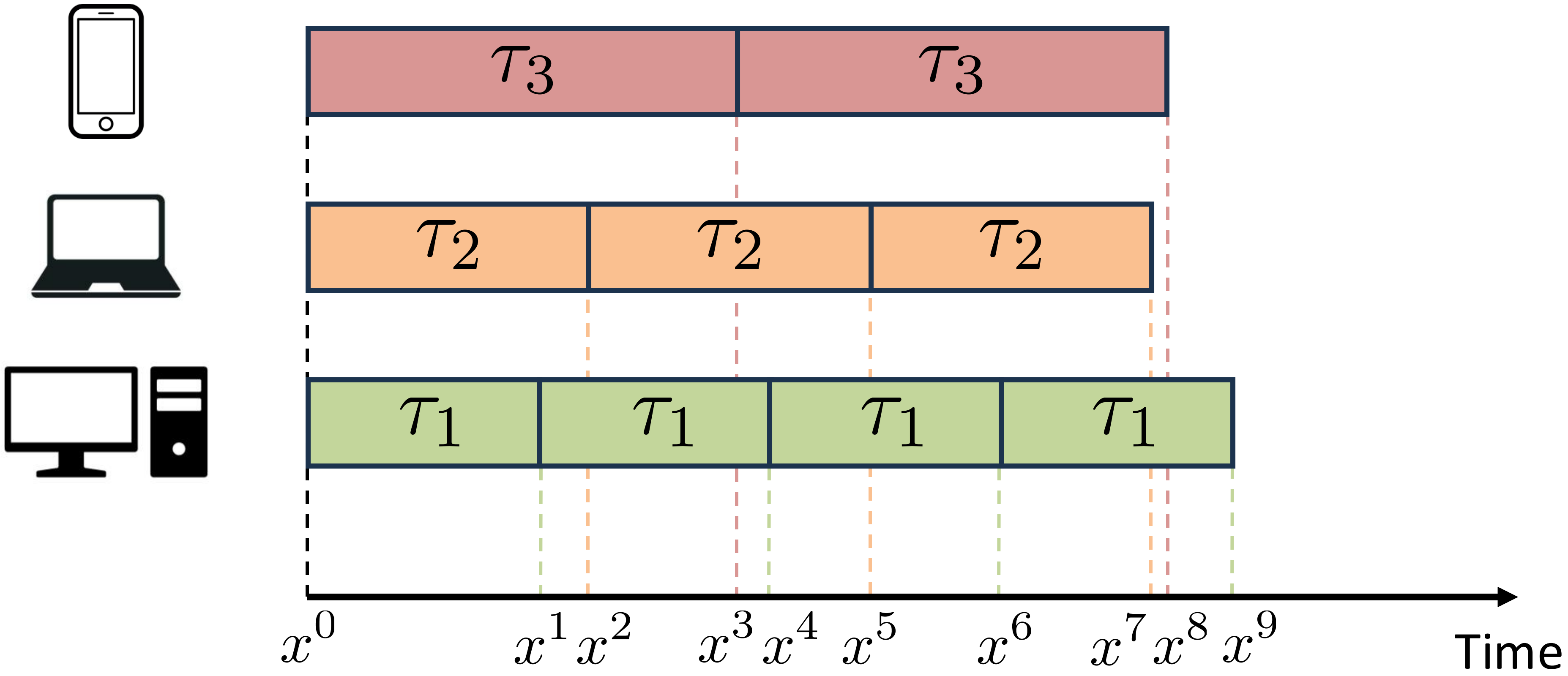



$B = 4$

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

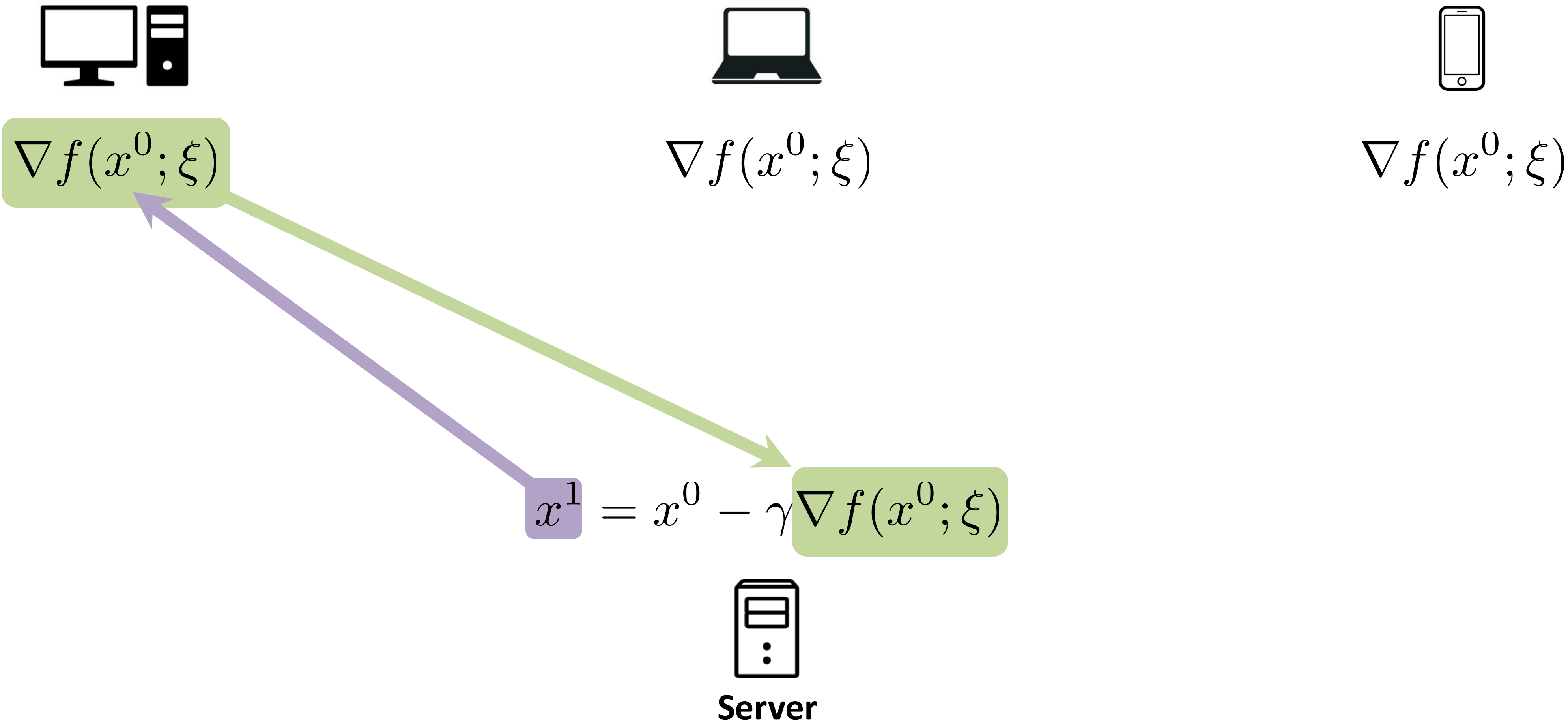
Tyurin and Richtárik (2024)

# Asynchronous SGD
# Remove the synchronization




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

# Updates of Asynchronous SGD has delayed stochastic gradients



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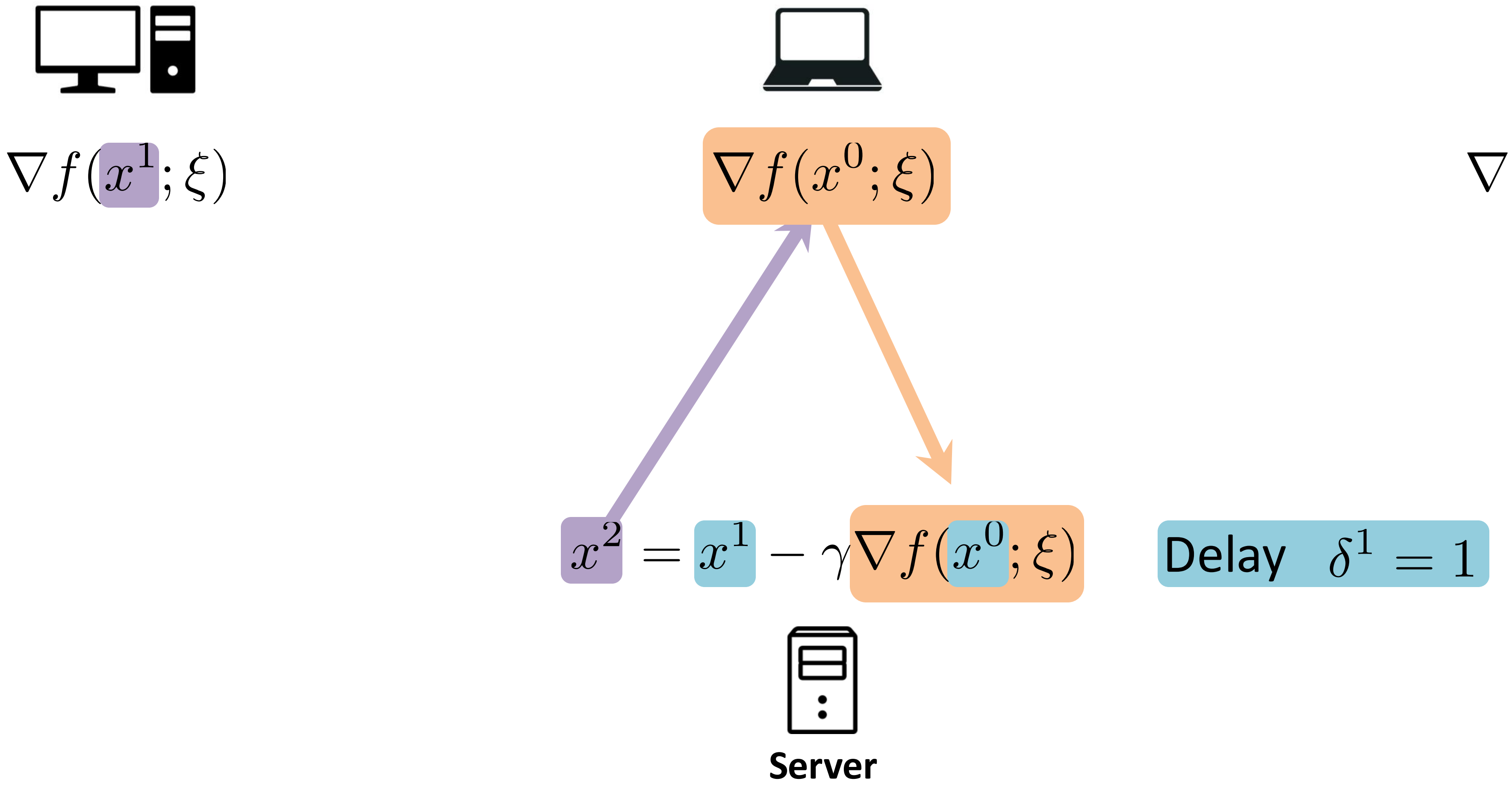
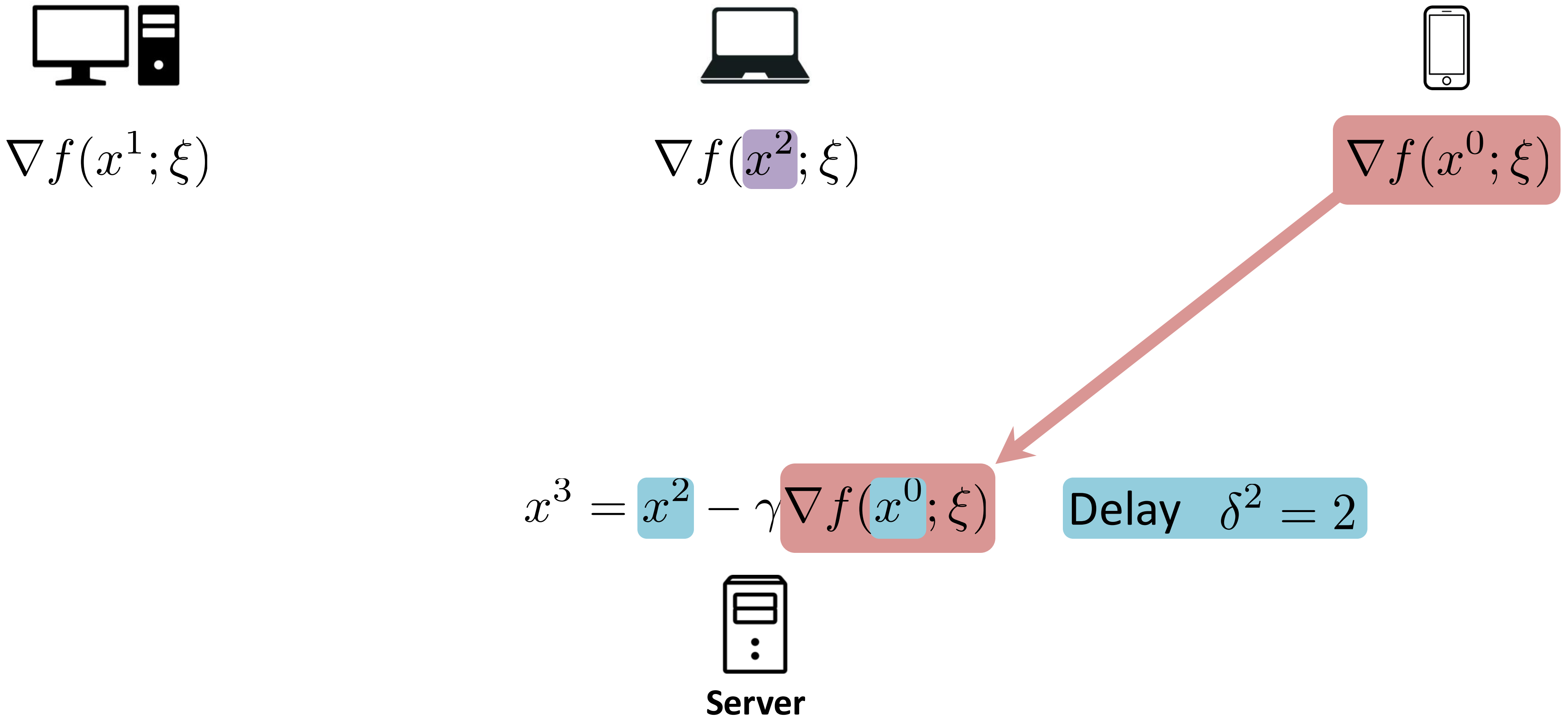


# Updates of Asynchronous SGD has delayed stochastic gradients



# Updates of Asynchronous SGD has delayed stochastic gradients

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

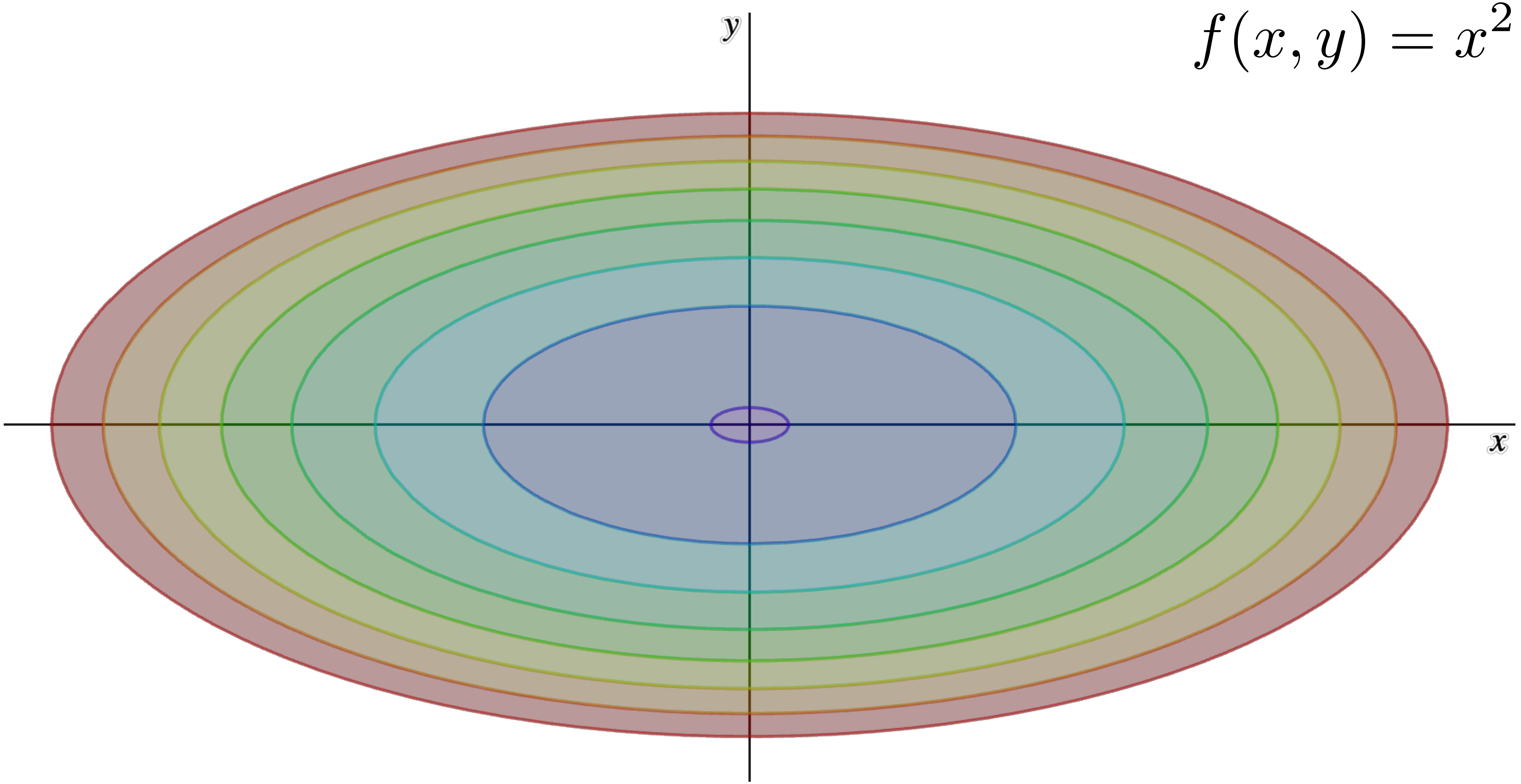
Delay $\delta^k$

**Server**


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

# Asynchronous SGD can get wild: delays can degrade performance

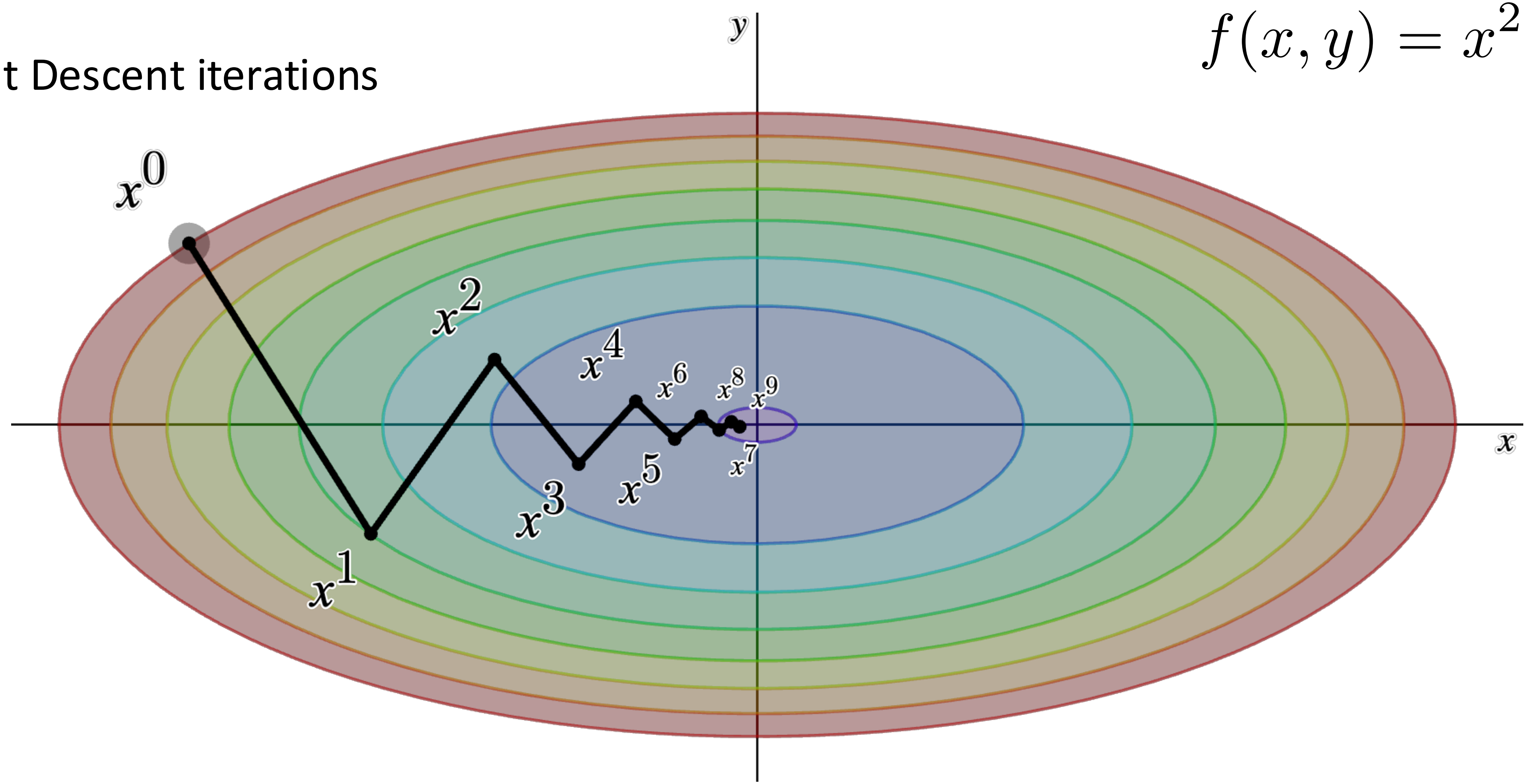
$$f(x, y) = x^2 + 5y^2$$



# Asynchronous SGD can get wild: delays can degrade performance

Gradient Descent iterations

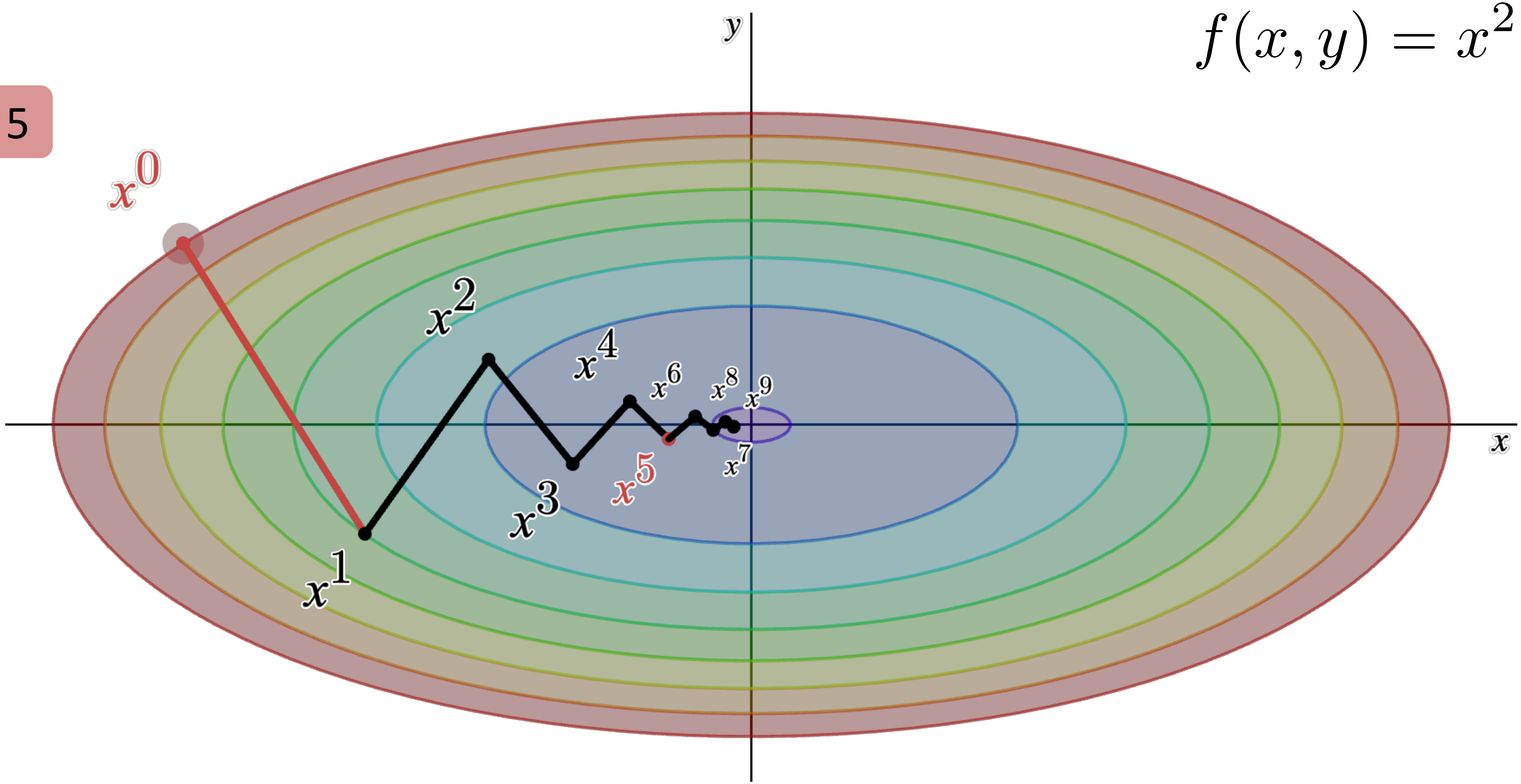
$$f(x, y) = x^2 + 5y^2$$



# Asynchronous SGD can get wild: delays can degrade performance

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

Delay = 5



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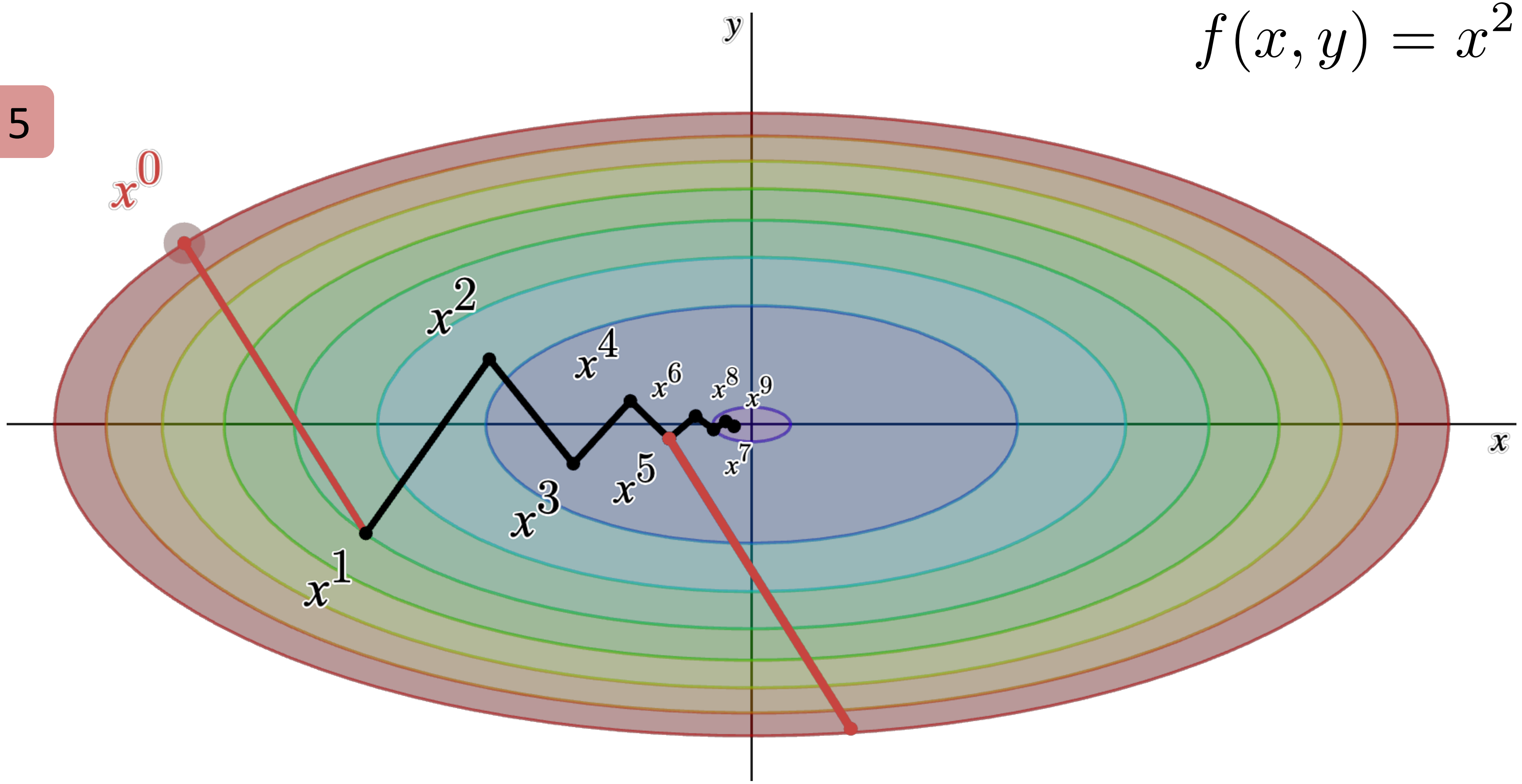
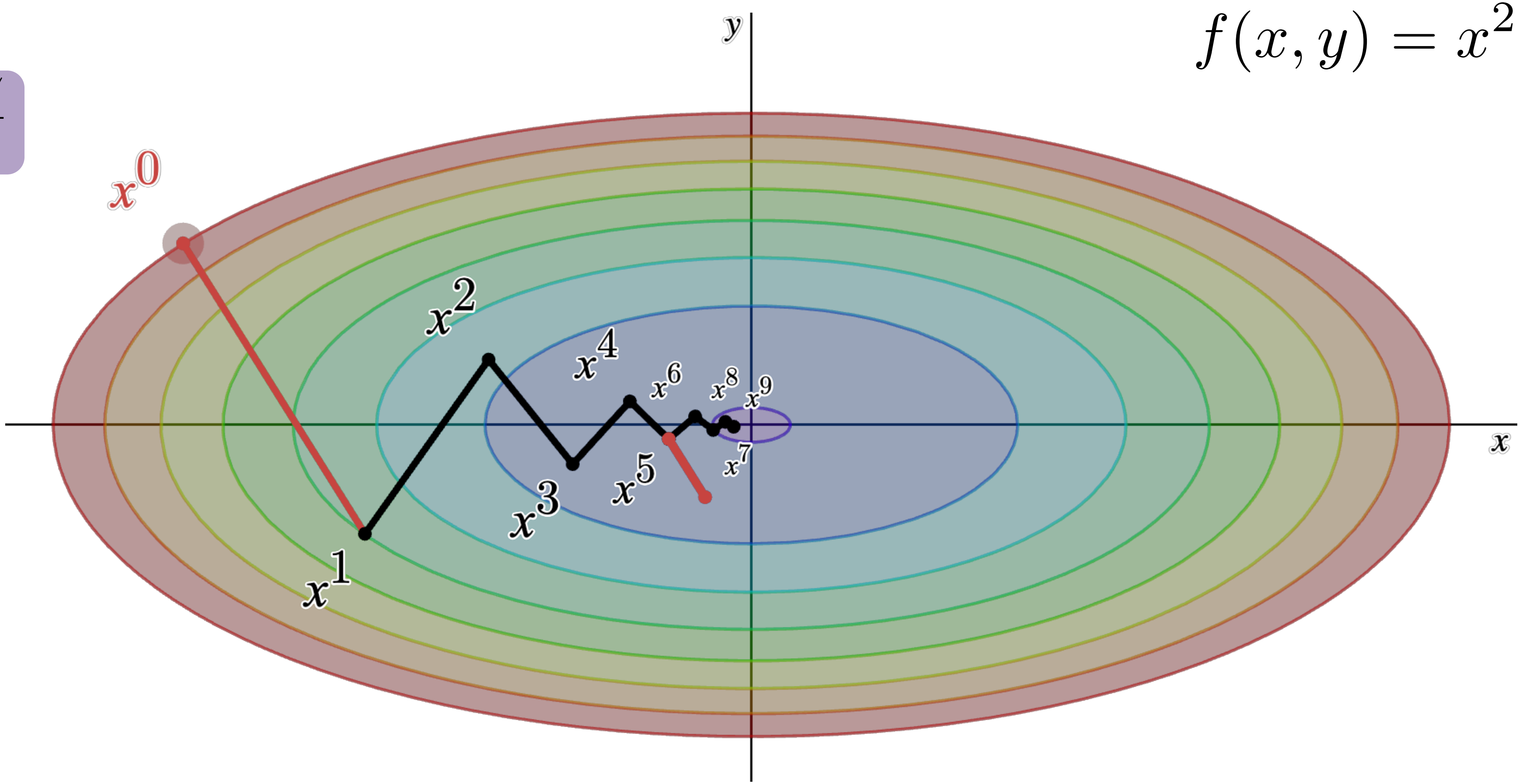


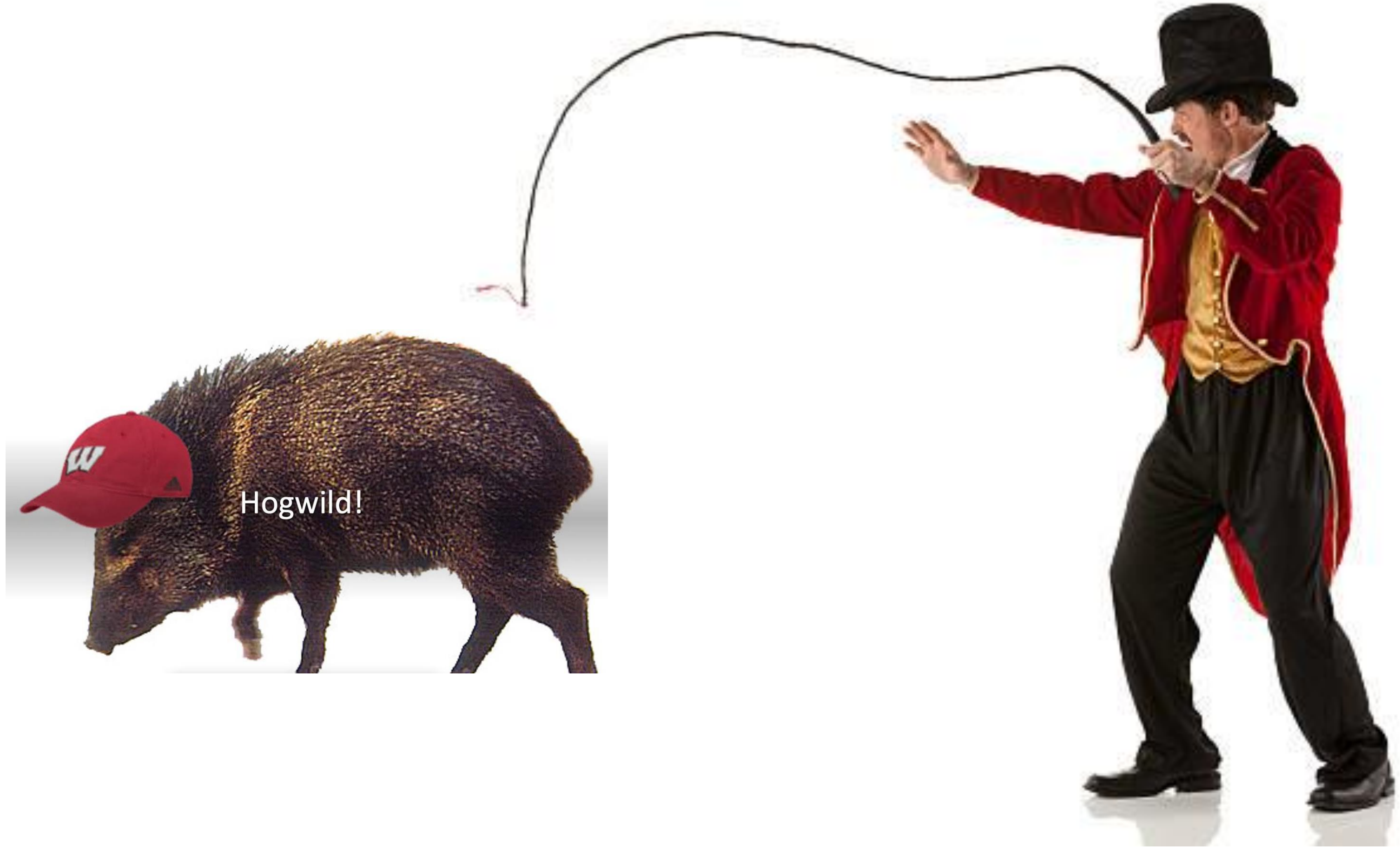
# How to fix this?
# Make the stepsize smaller

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

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



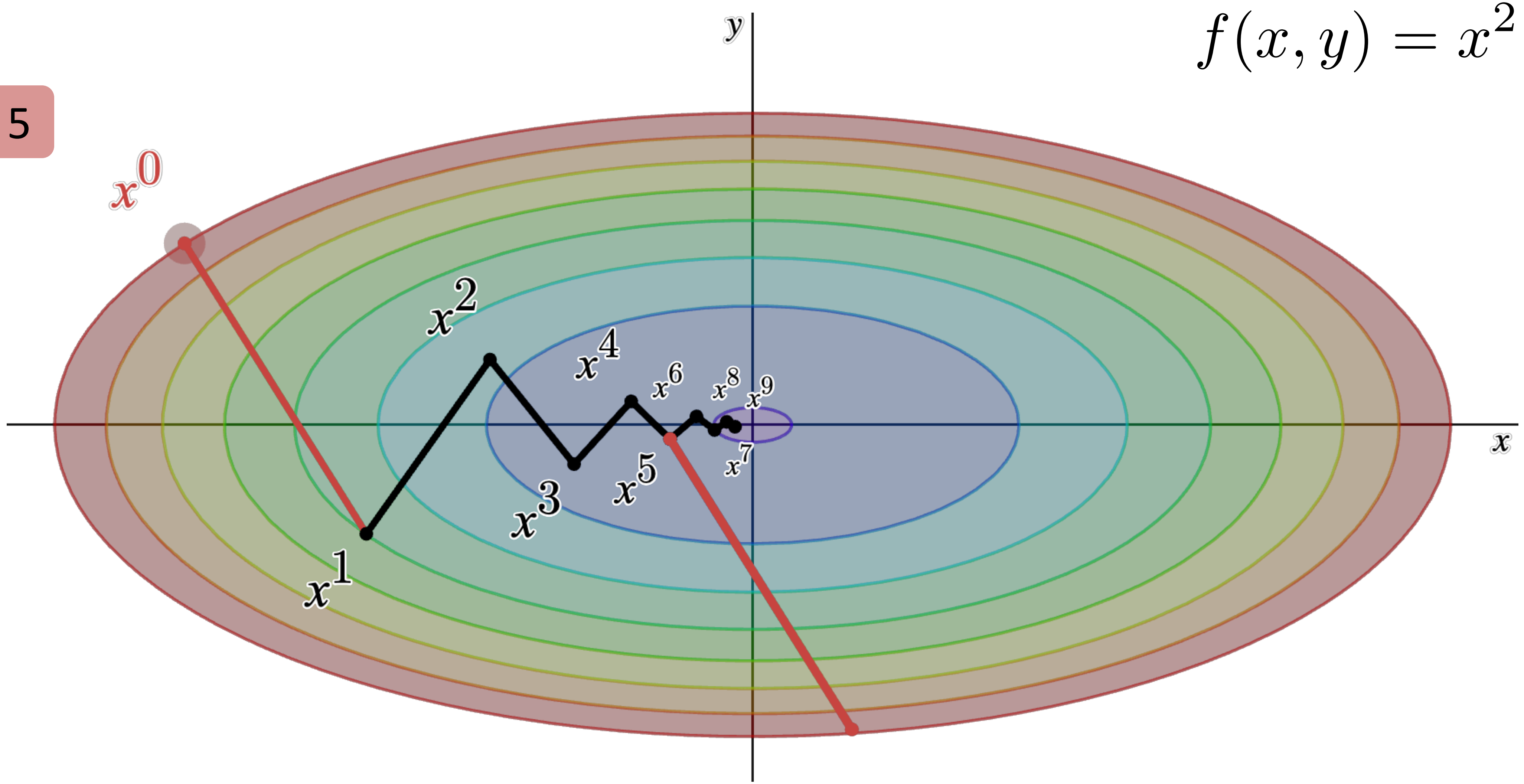
# Asynchronous SGD is too wild:
# Ringmaster ASGD ***tames*** it



# The smaller the delay, the better the gradient

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

Delay = 5



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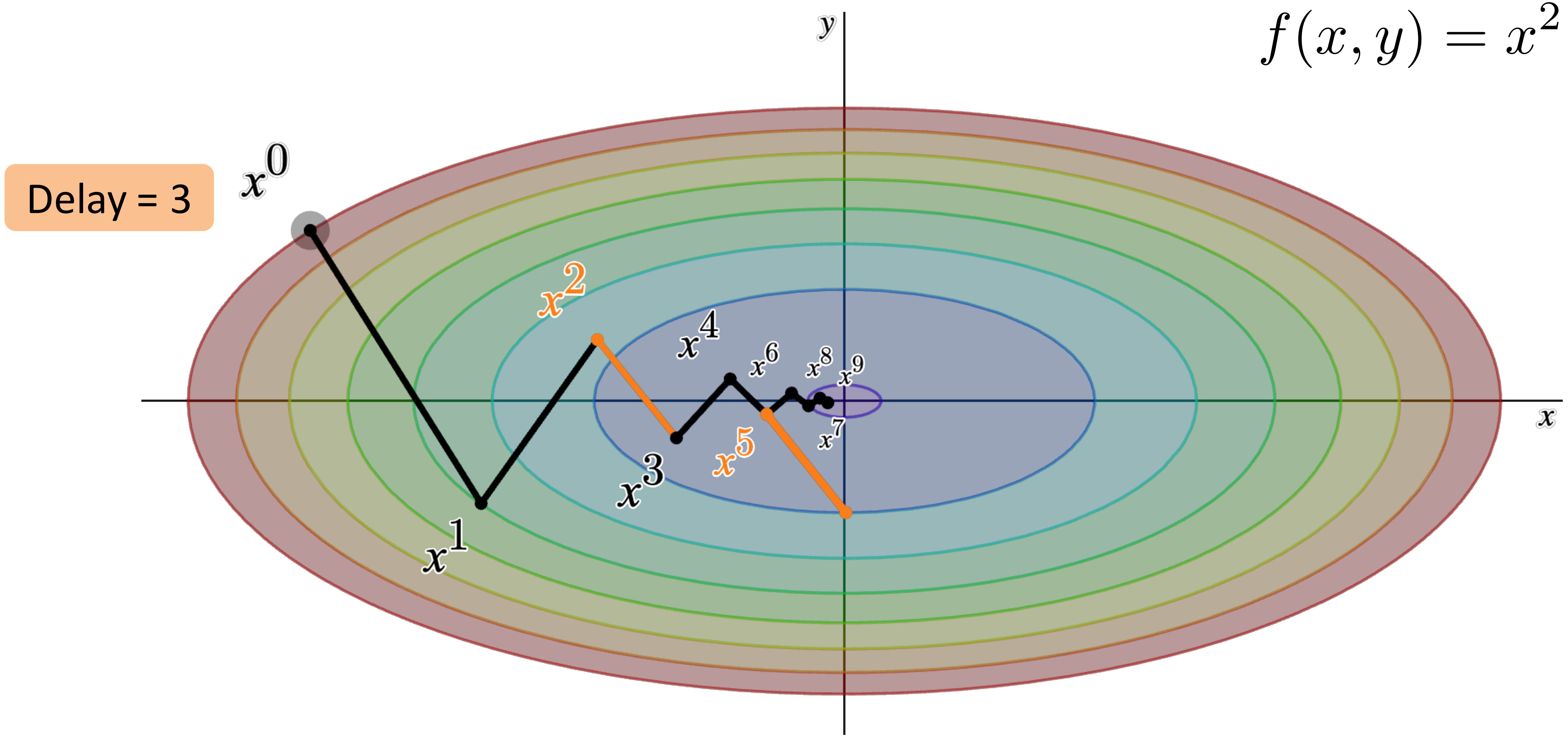


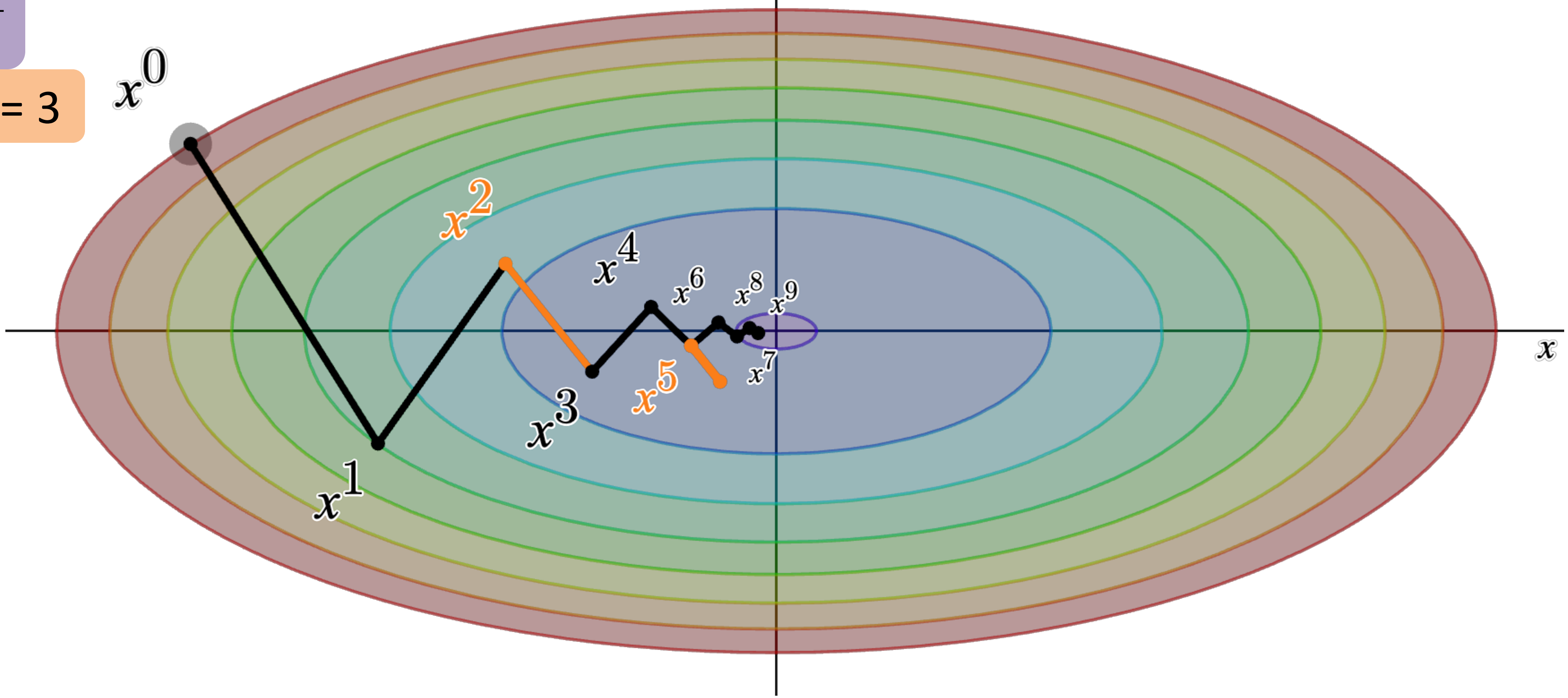
# The smaller the delay, the better the gradient

How can we reduce the delay?

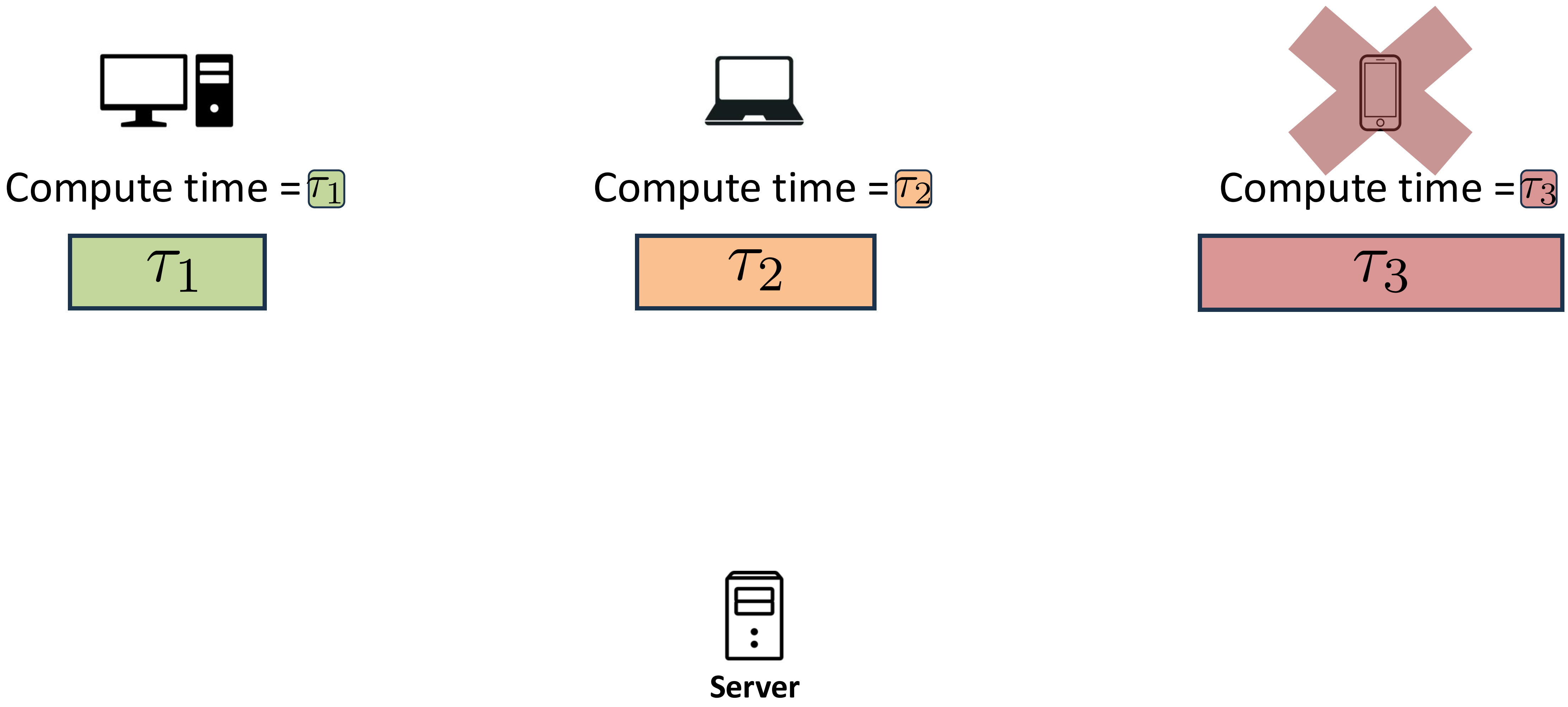
$$f(x,y) = x^2 + 5y^2$$

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

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: $\tau_i$-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

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

Number of iterations

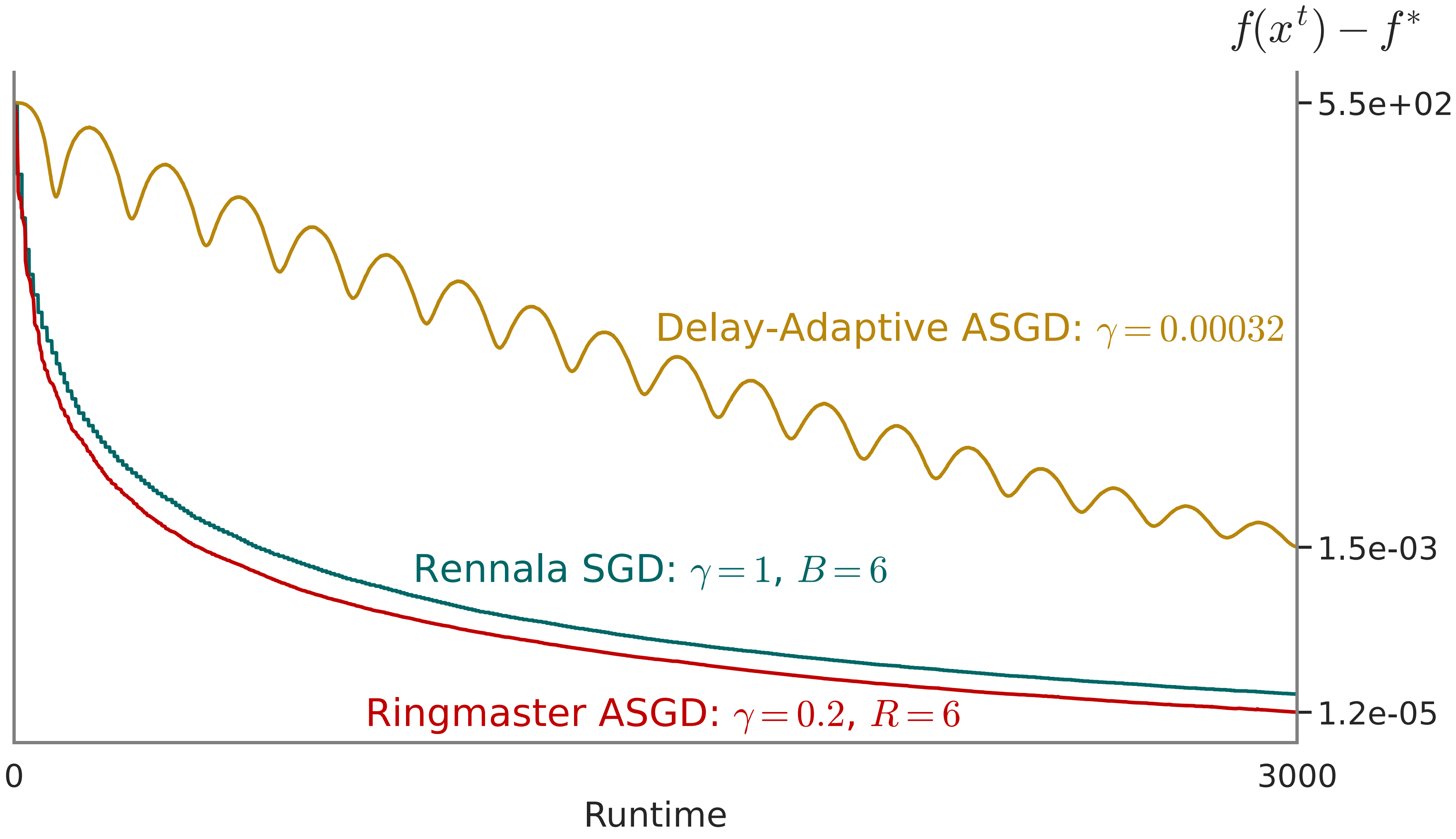
$$\mathcal{O}\left(\min_{m\in[n]}\left[\boxed{\left(\frac{1}{m}\sum_{i=1}^{m}\frac{1}{\tau_i}\right)^{-1}}\left(\frac{1}{\varepsilon}+\boxed{\frac{\sigma^2}{m\varepsilon^2}}\right)\right]\right)$$

Time complexity

non-decreasing

decreasing

# Ringmaster ASGD outperforms existing baselines



# Recap of what we have covered

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

| | | |
|---|---|---|
| $\nabla f(x;\xi)$ | $\nabla f(x;\xi)$ | $\nabla f(x;\xi)$ |
| Compute time = $\tau_1$ | Compute time = $\tau_2$ | Compute time = $\tau_3$ |
| $\tau_1$ | $\tau_2$ | $\tau_3$ |

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

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- Optimization objective
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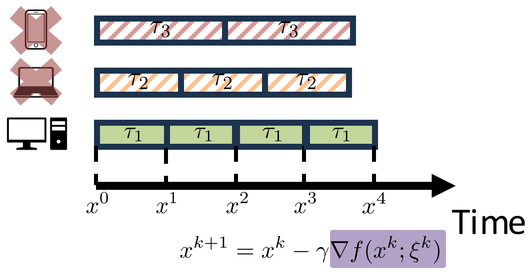


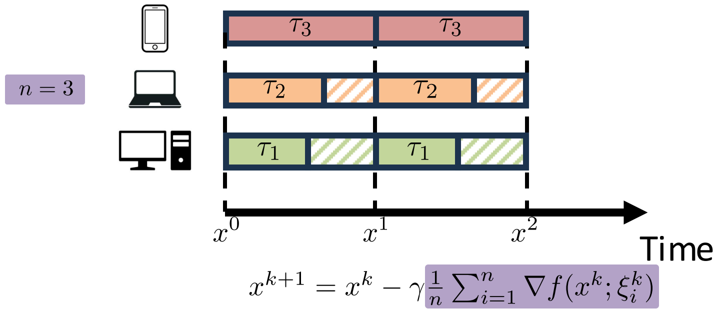


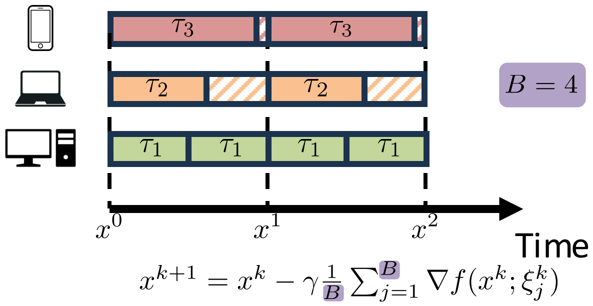


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Different ways of parallelizing SGD

- Synchronized approaches

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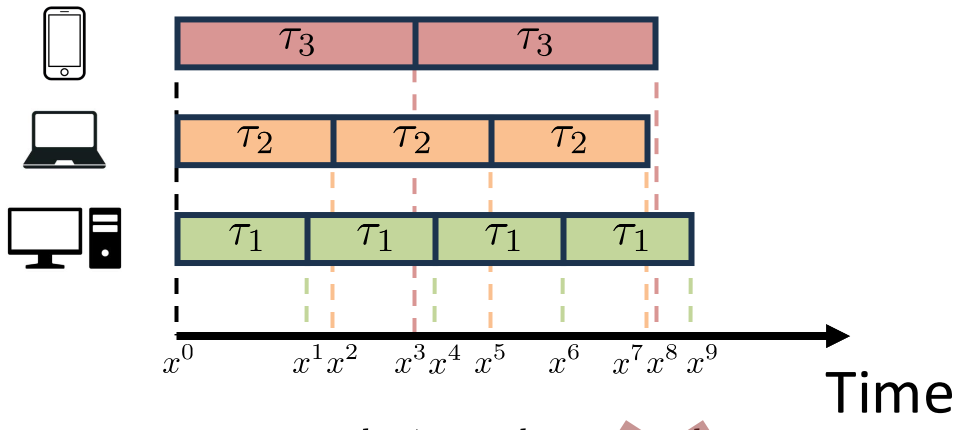


$$x^{k+1} = x^k - \cancel{\gamma g(x^k)}$$


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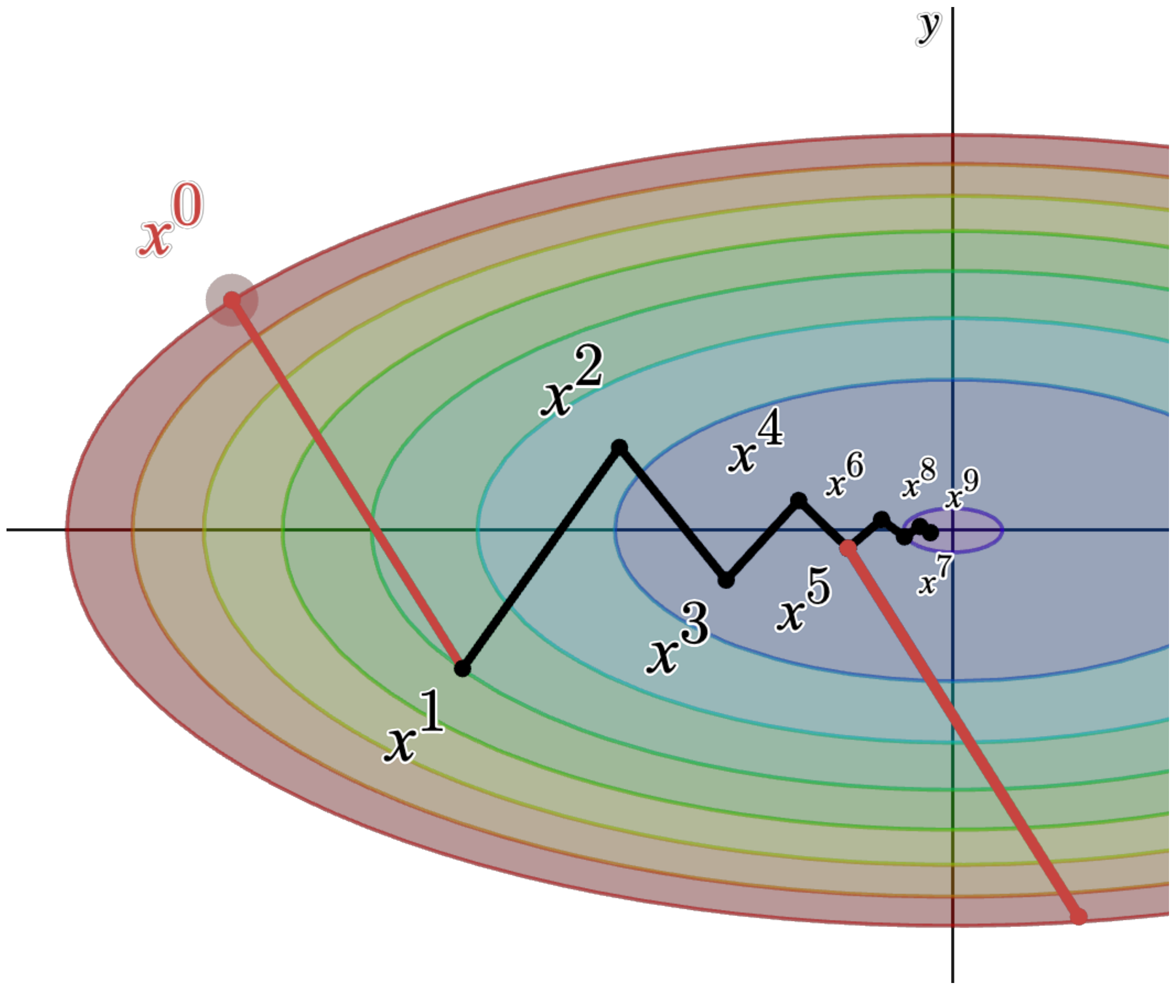


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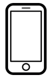

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**Server**

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Different ways of parallelizing SGD

- Synchronized approaches
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Problems of ASGD

Ringmaster ASGD

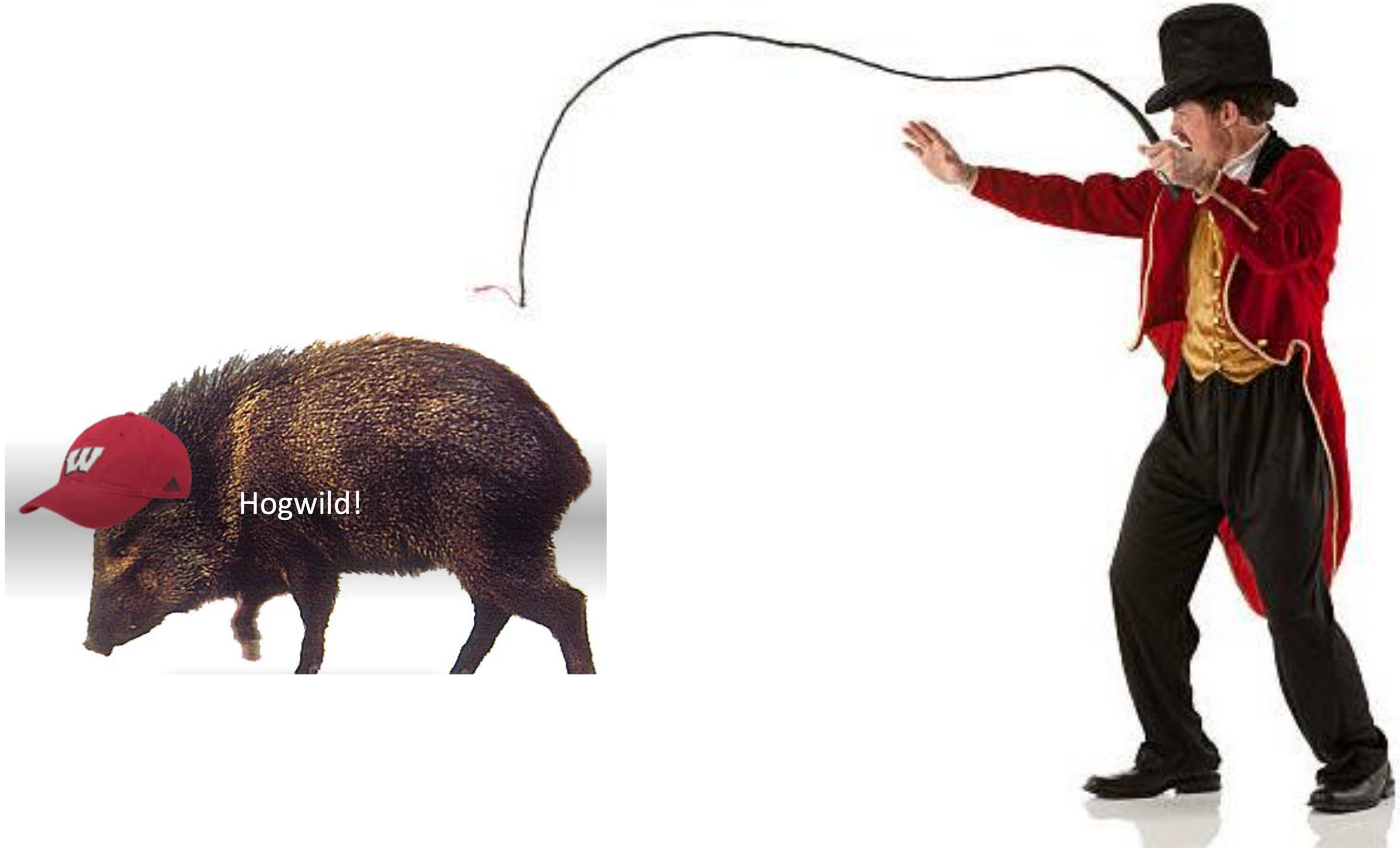

Alexander Tyurin
Skoltech

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!