Optimization for Machine Learning in Practice II

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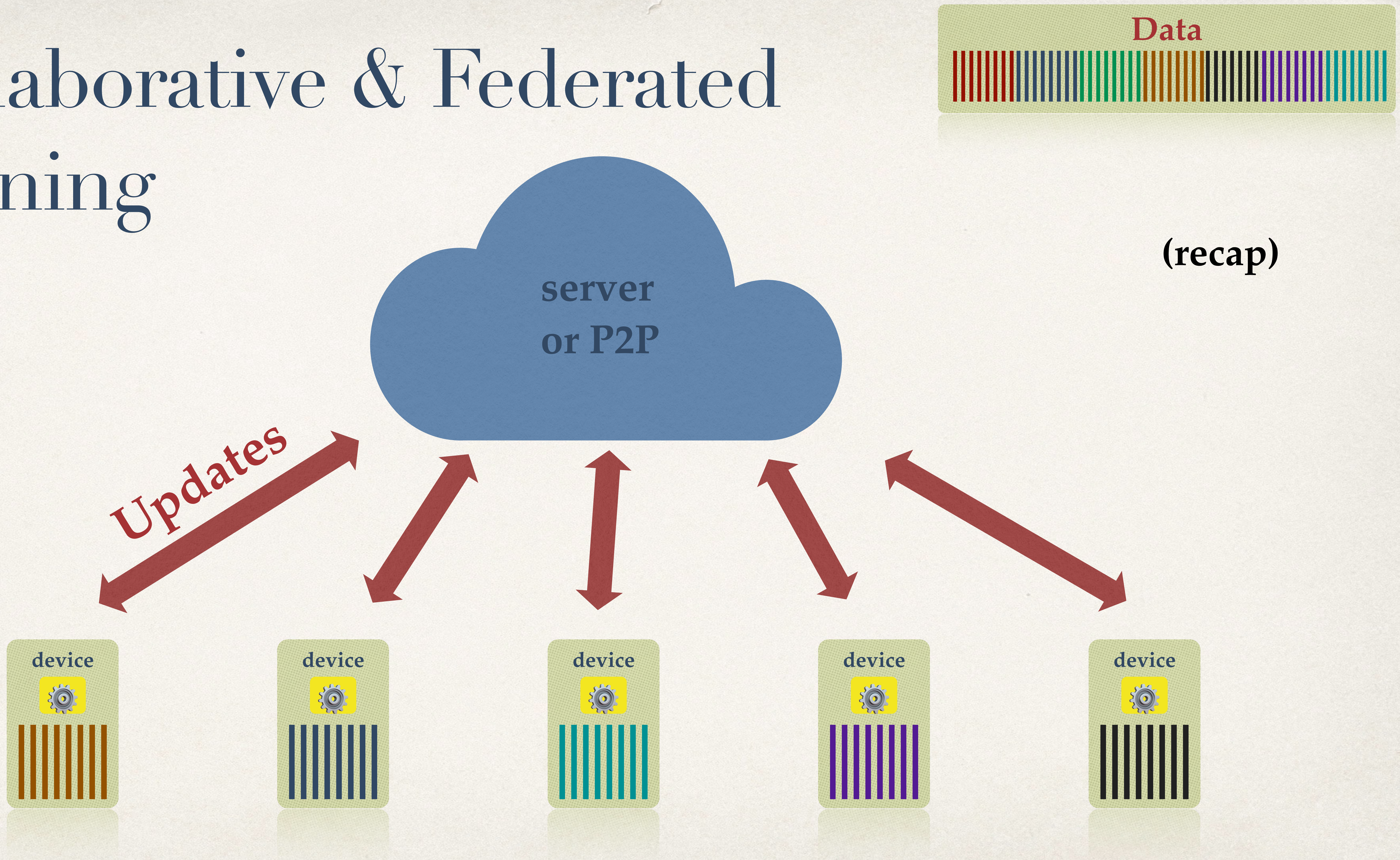
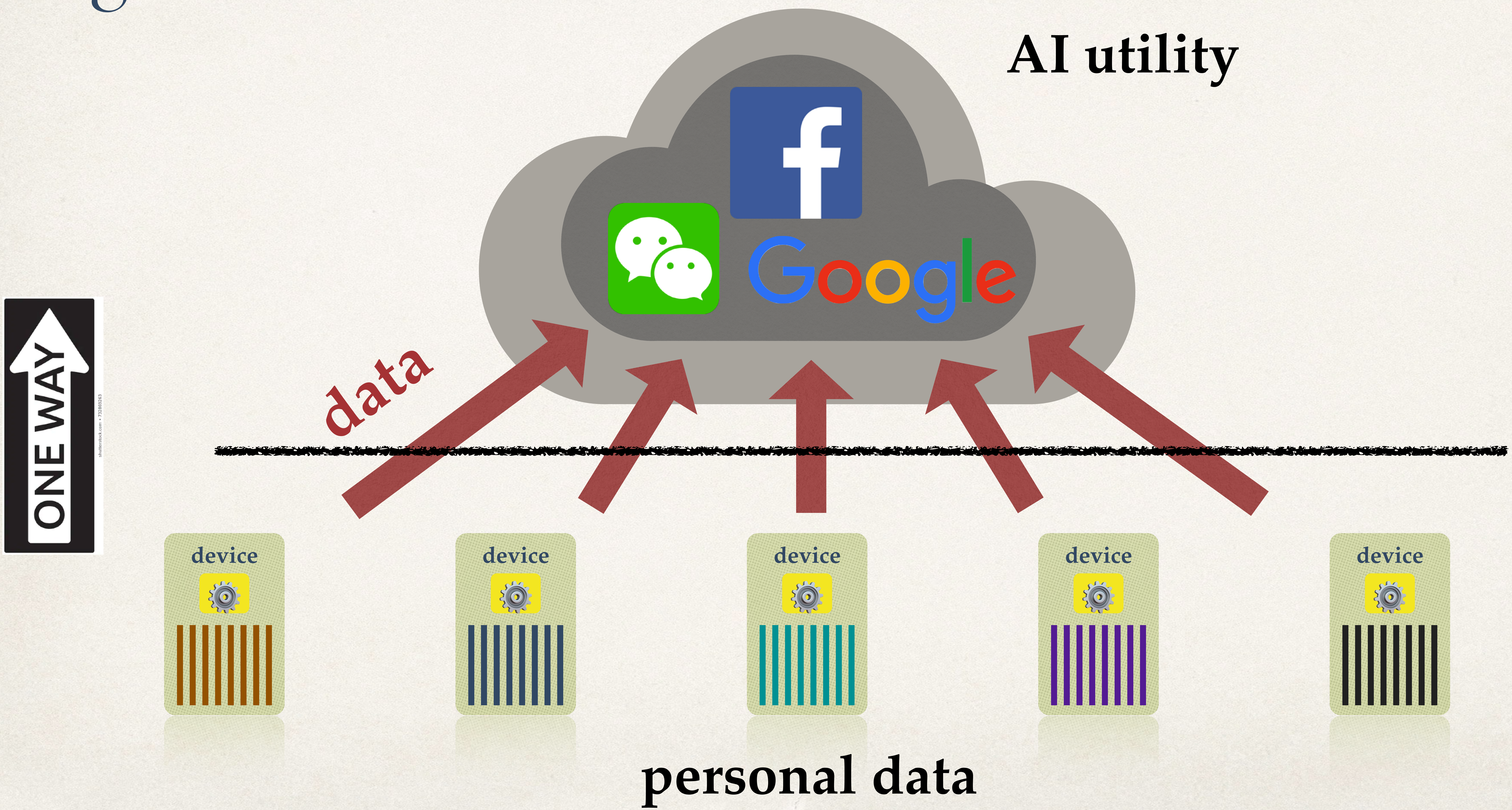
Collaborative Learning

Collaborative & Federated Training

(recap)

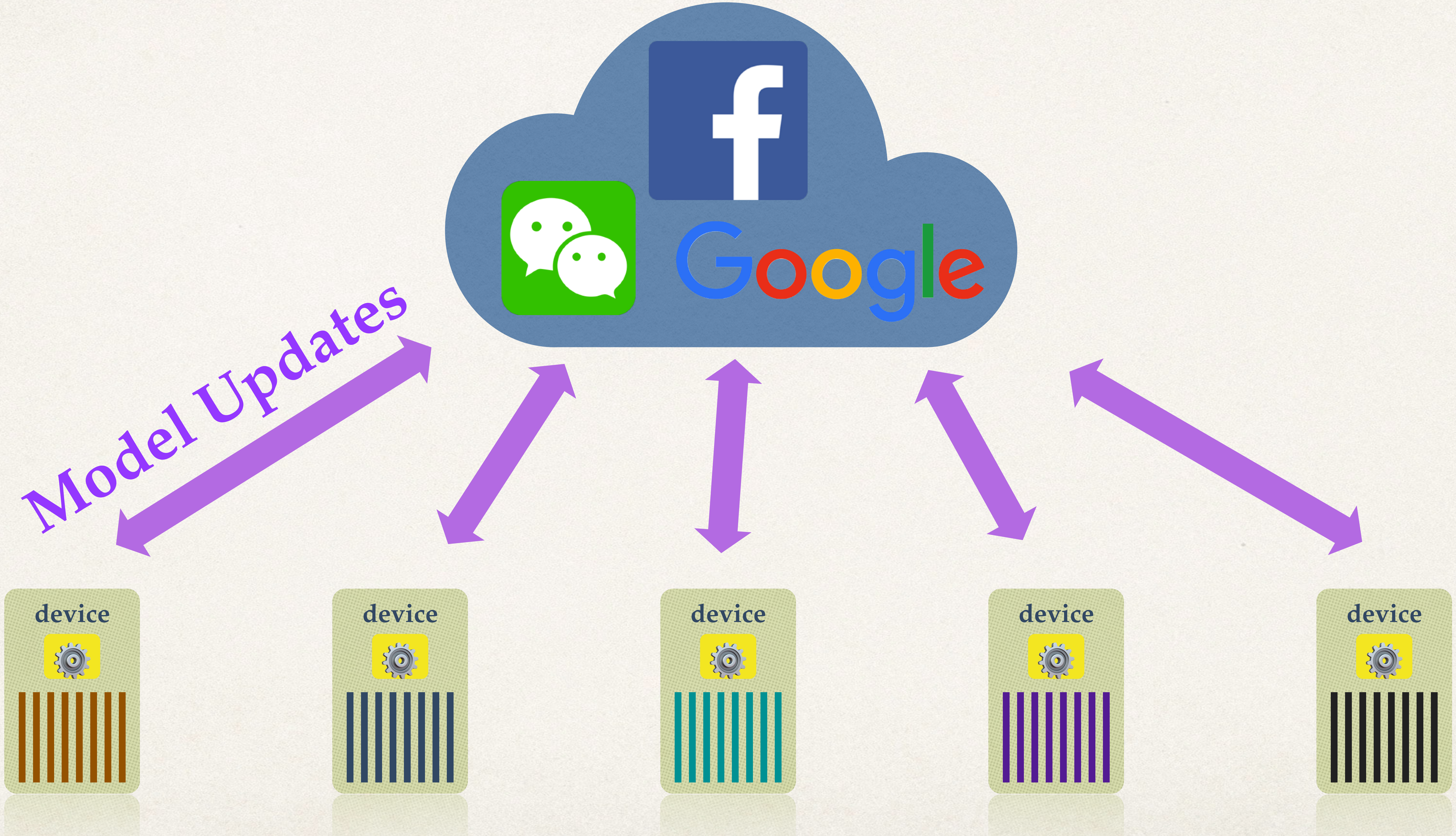


Big Picture


AI utility
Google
data
ONE WAY
device
device
device
device
device
personal data

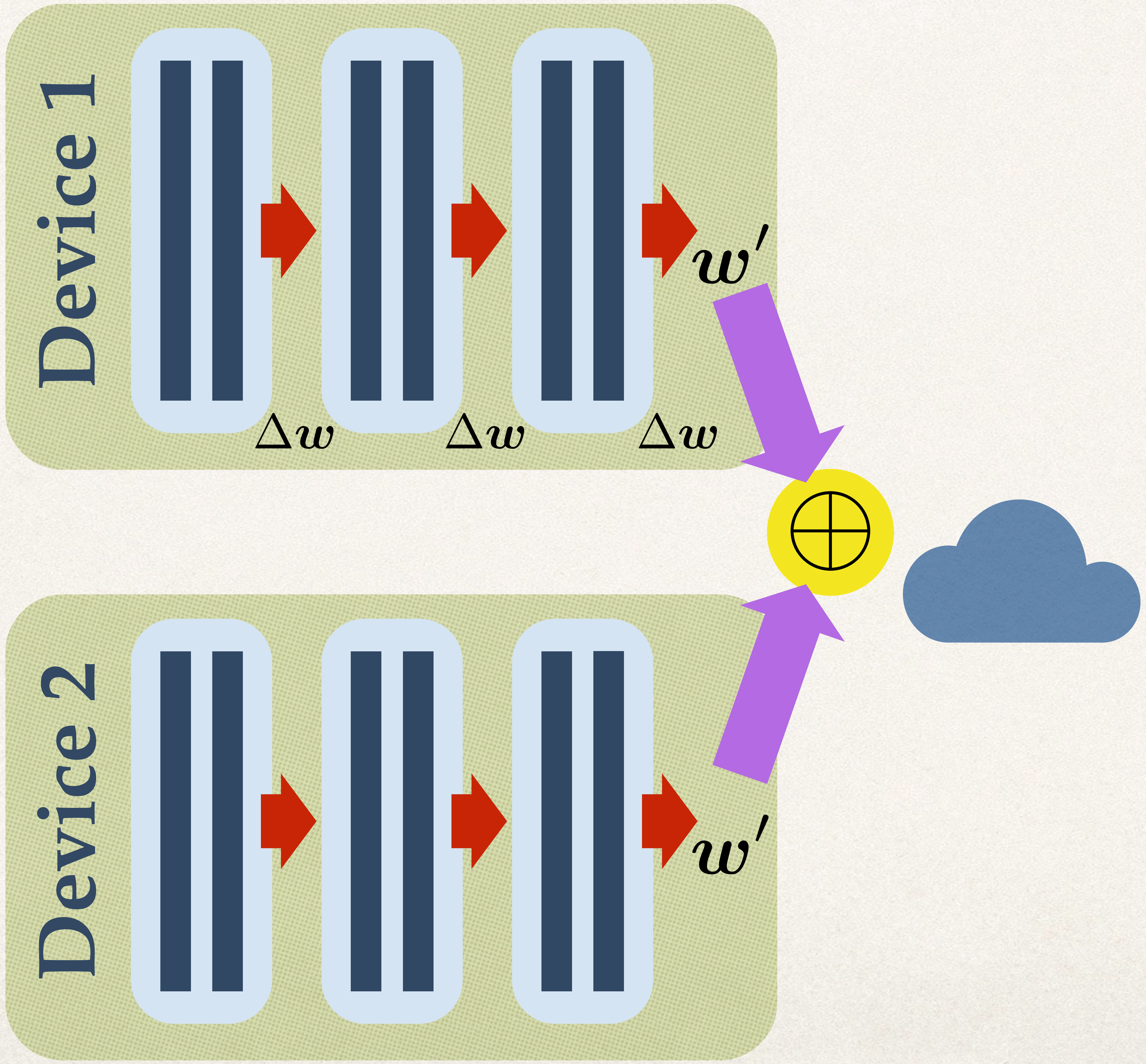
2a

Federated Learning



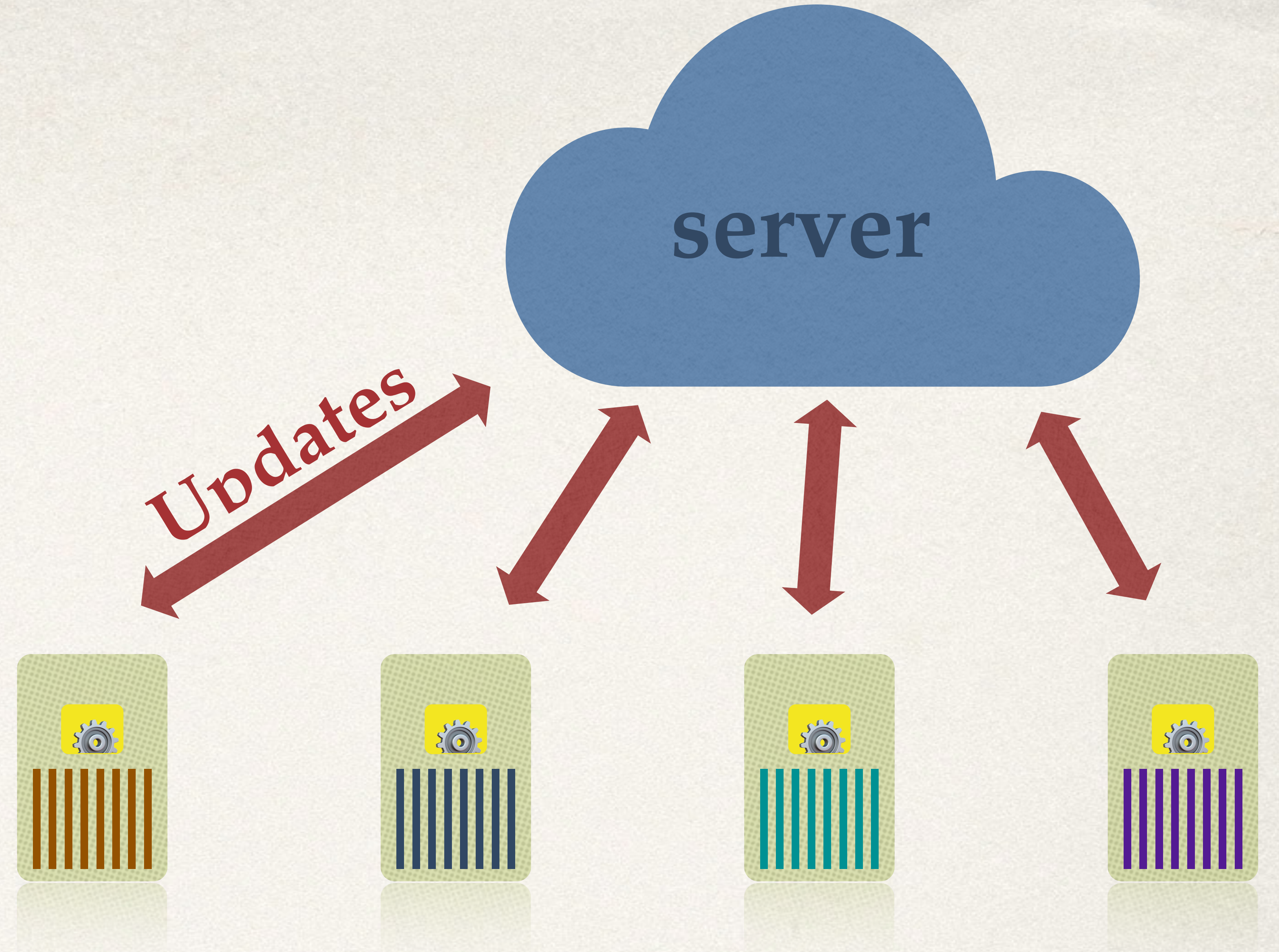
data never leaves device

2a Federated Learning



- Local SGD steps = "Federated averaging"
- Google Android Keyboard

Client drift



- **Federated Learning**

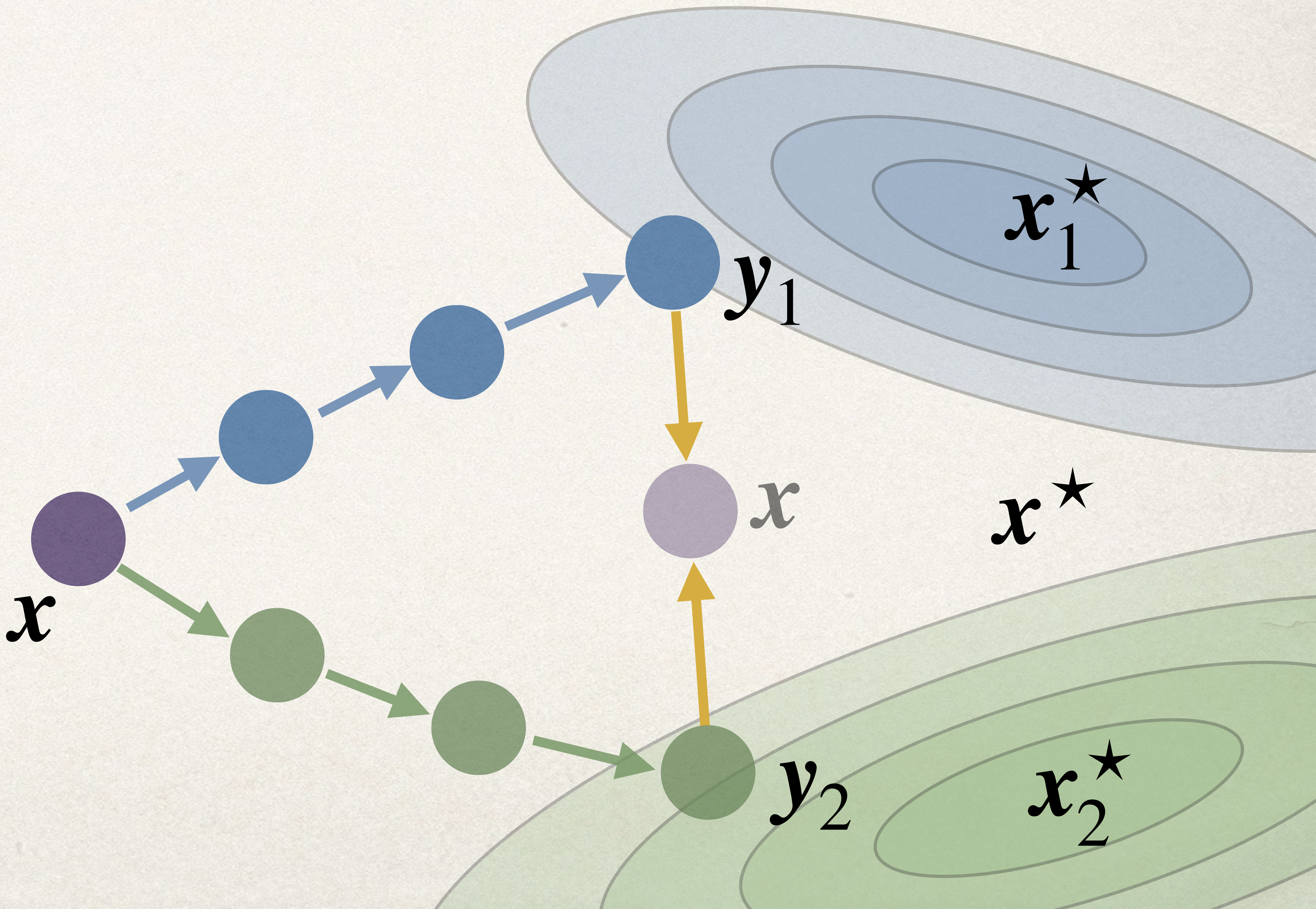
$$\min_{\boldsymbol{x}} \; \frac{1}{n} \sum_{i}^{n} f_i(\boldsymbol{x})$$

- **Fed Avg / Local SGD**

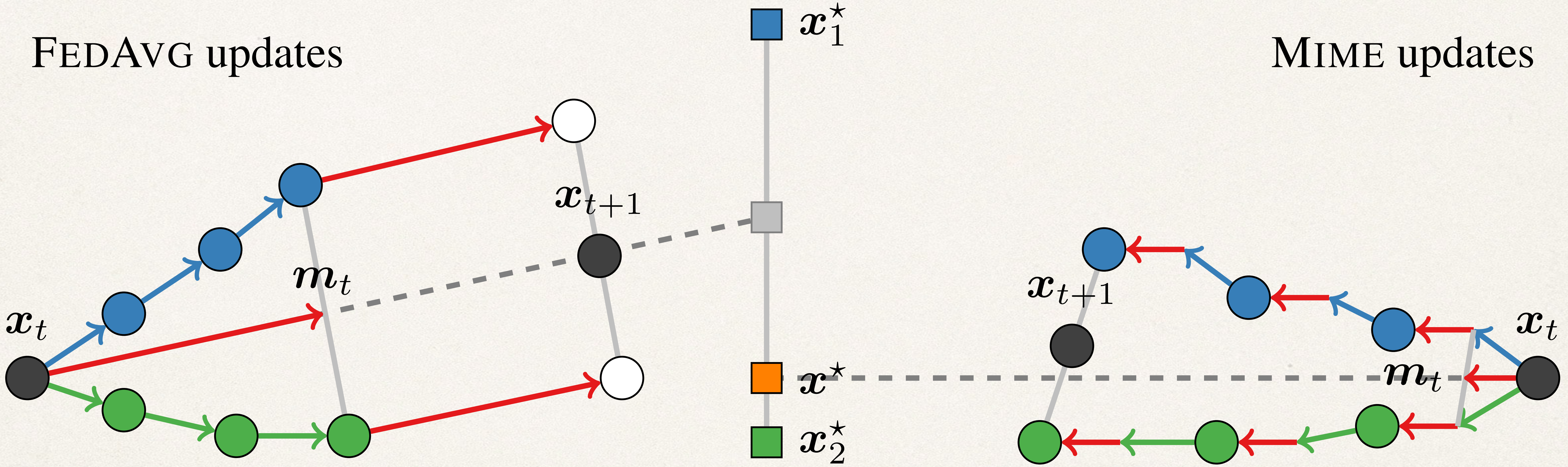
for some local steps

$$\boldsymbol{y}_i := \boldsymbol{y}_i - \eta \nabla f_i(\boldsymbol{y}_i)$$

$$\boldsymbol{x} := \frac{1}{n} \sum_{i=1}^{n} \boldsymbol{y}_i \qquad \textit{(aggregation)}$$



Client drift



Mime algorithm framework

for *some local steps*

$$\boldsymbol{y}_i := \boldsymbol{y}_i - \eta\Big((1-\beta)\nabla f_i(\boldsymbol{y}_i) + \beta\boldsymbol{m}\Big)$$

$$\boldsymbol{m} := (1-\beta)\nabla f_i(\boldsymbol{x}) + \beta\boldsymbol{m}$$

aggregated on server
after each round

2b Federated vs Personalized Learning

- **Federated**

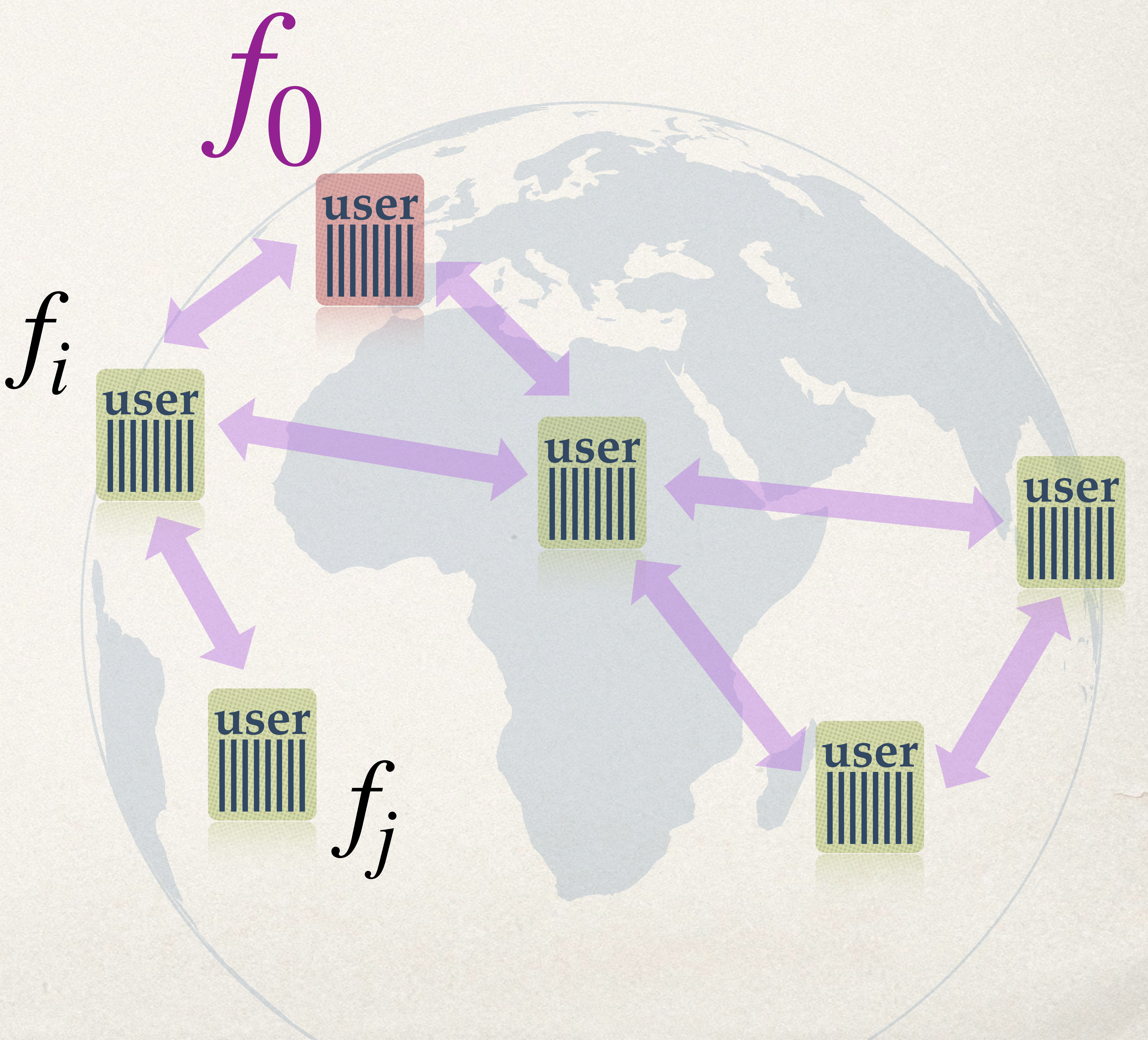
$$\min_{x} \frac{1}{n}\sum_{i}^{n} f_i(x)$$

- **Collaborative / Personalized**

$$\min_{x} f_0(x)$$

$$\min_{x} f_1(x)$$

$$\min_{x} f_n(x)$$



2b Federated vs Personalized Learning

- **Federated**

$$\min_{\boldsymbol{x}} \frac{1}{n} \sum_{i}^{n} f_i(\boldsymbol{x})$$

- **Collaborative / Personalized**

$$\min_{\boldsymbol{x}} f_0(\boldsymbol{x})$$

$$\min_{\boldsymbol{x}} f_1(\boldsymbol{x})$$

$$\min_{\boldsymbol{x}} f_n(\boldsymbol{x})$$

- **Ordering of training**

  Set of active clients evolves (how?)

- **Clients = Tasks**

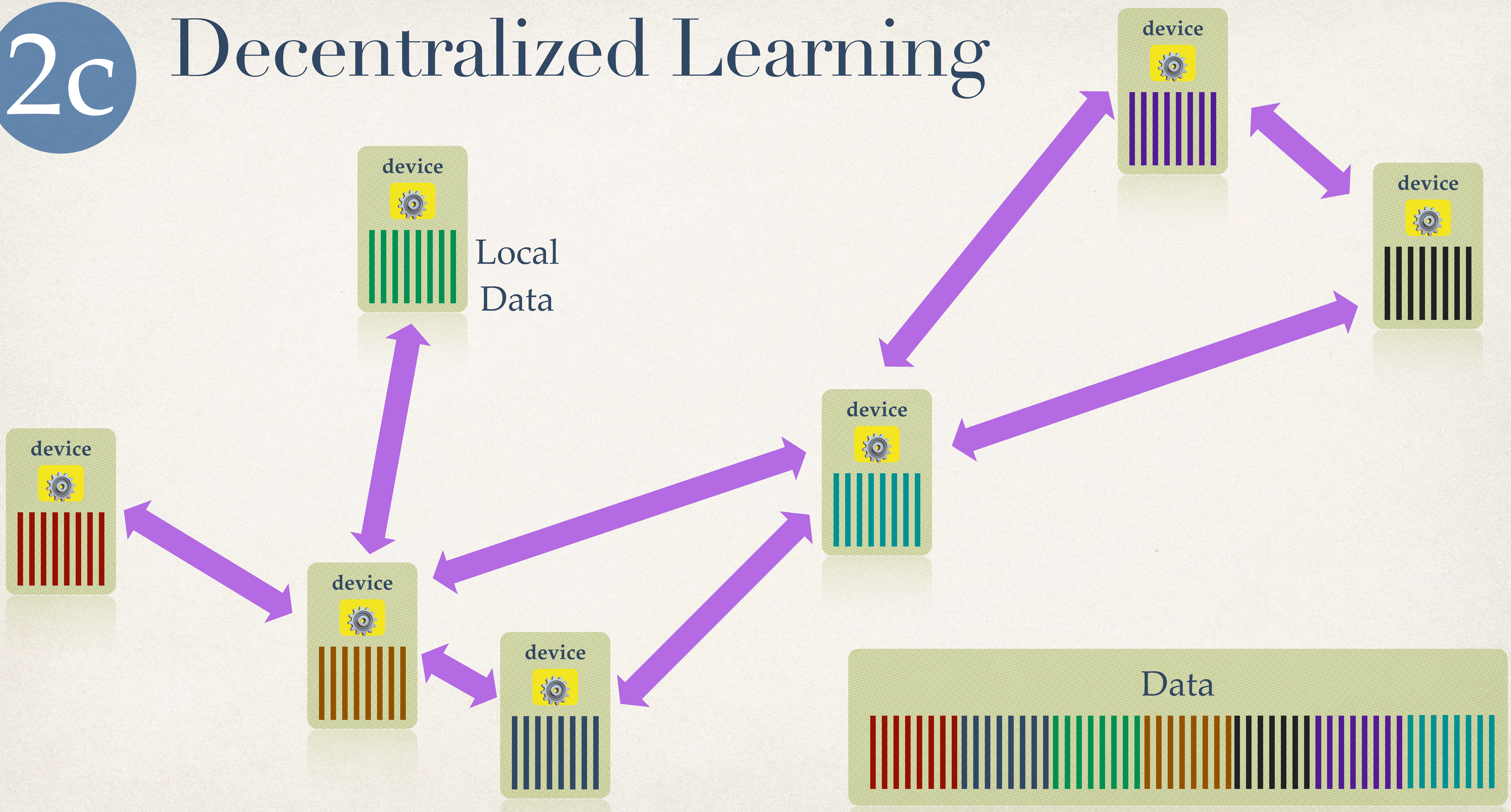
  Sequential fine-tuning

  Transfer learning,

  overparameterized models?

- **Train alone or collaborate?**

2c Decentralized Learning



Motivation

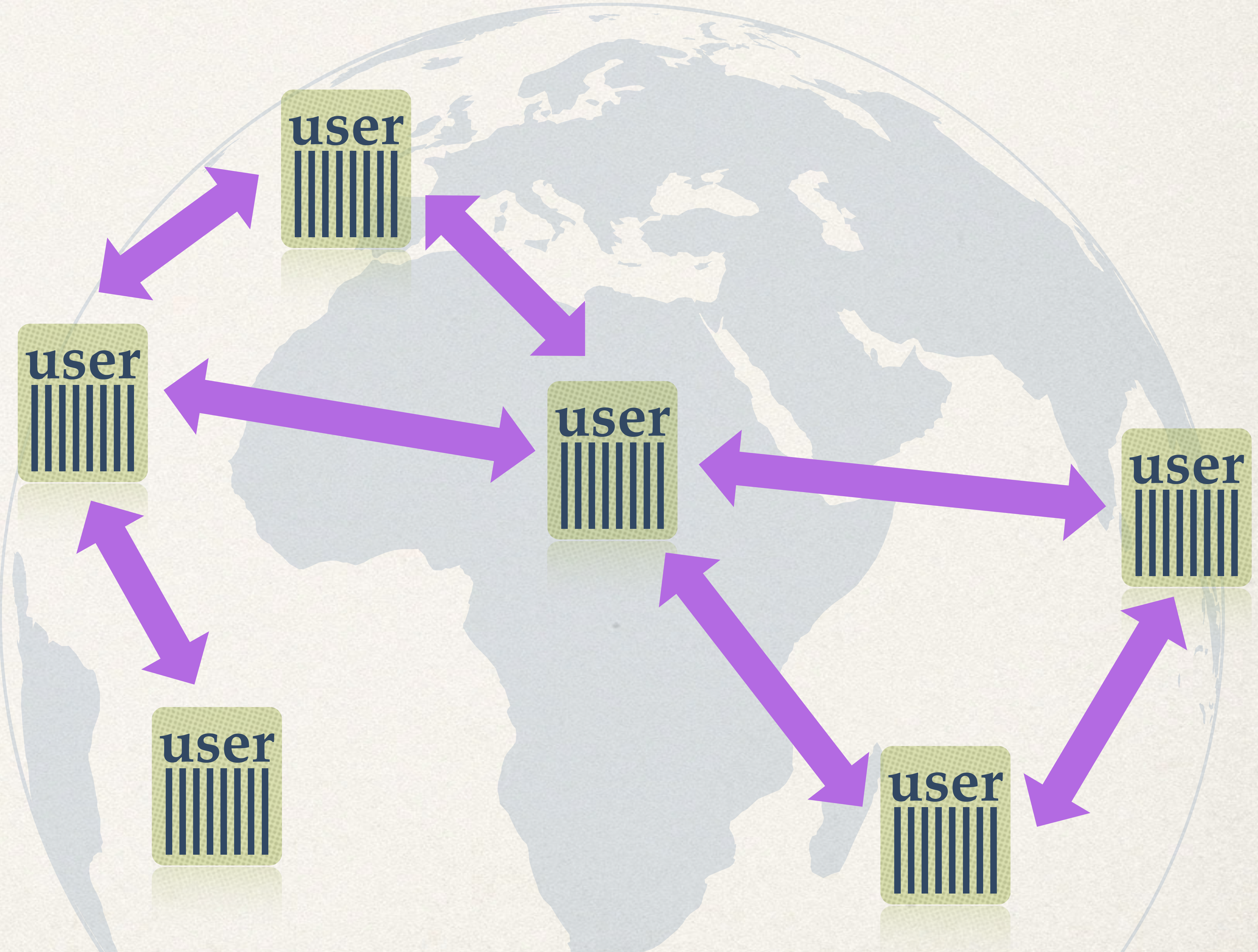
- **Applications:**

  any ML system with user data

  servers, devices, sensors, hospitals, ...

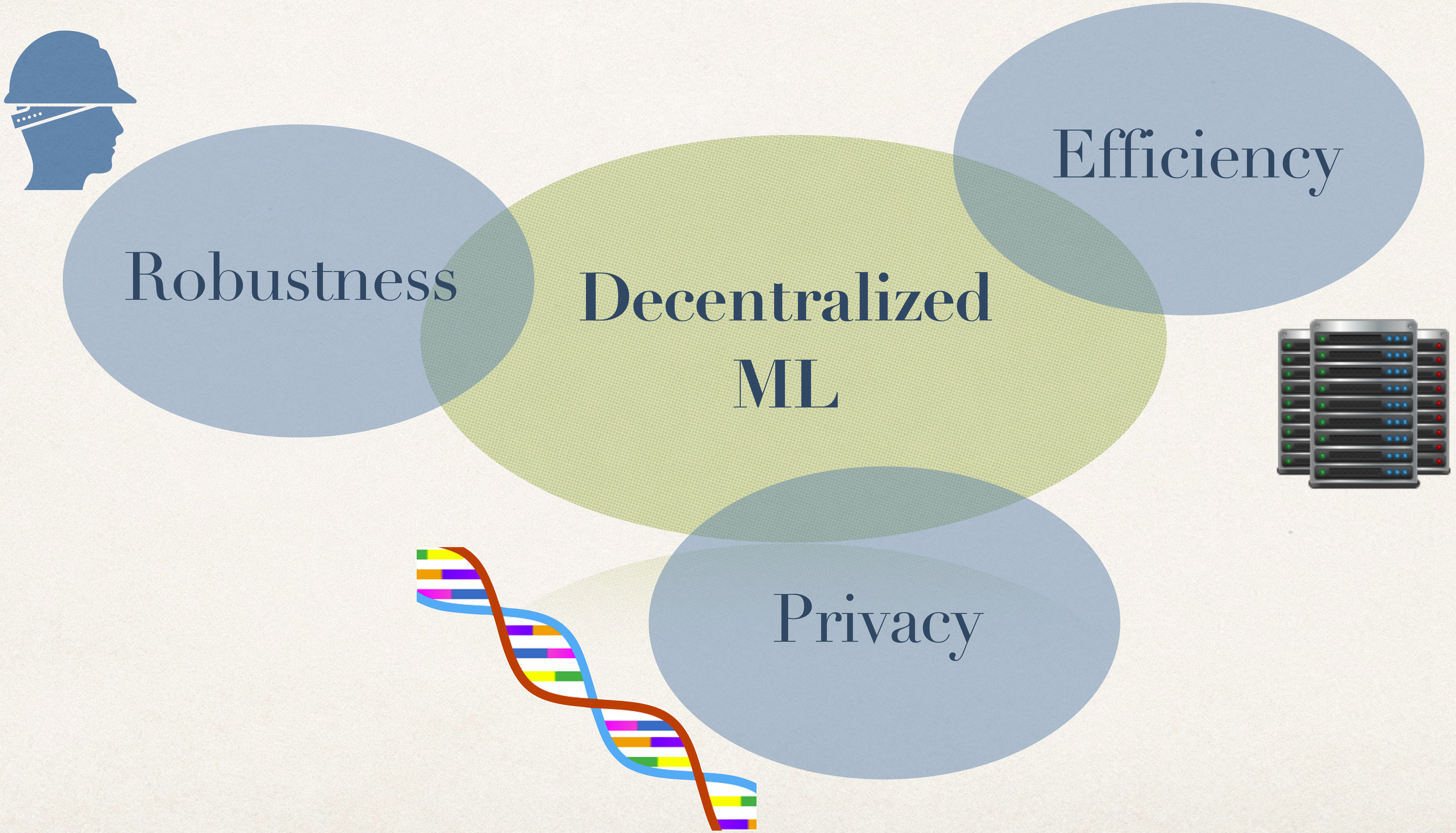
image source

- **Advantages:**

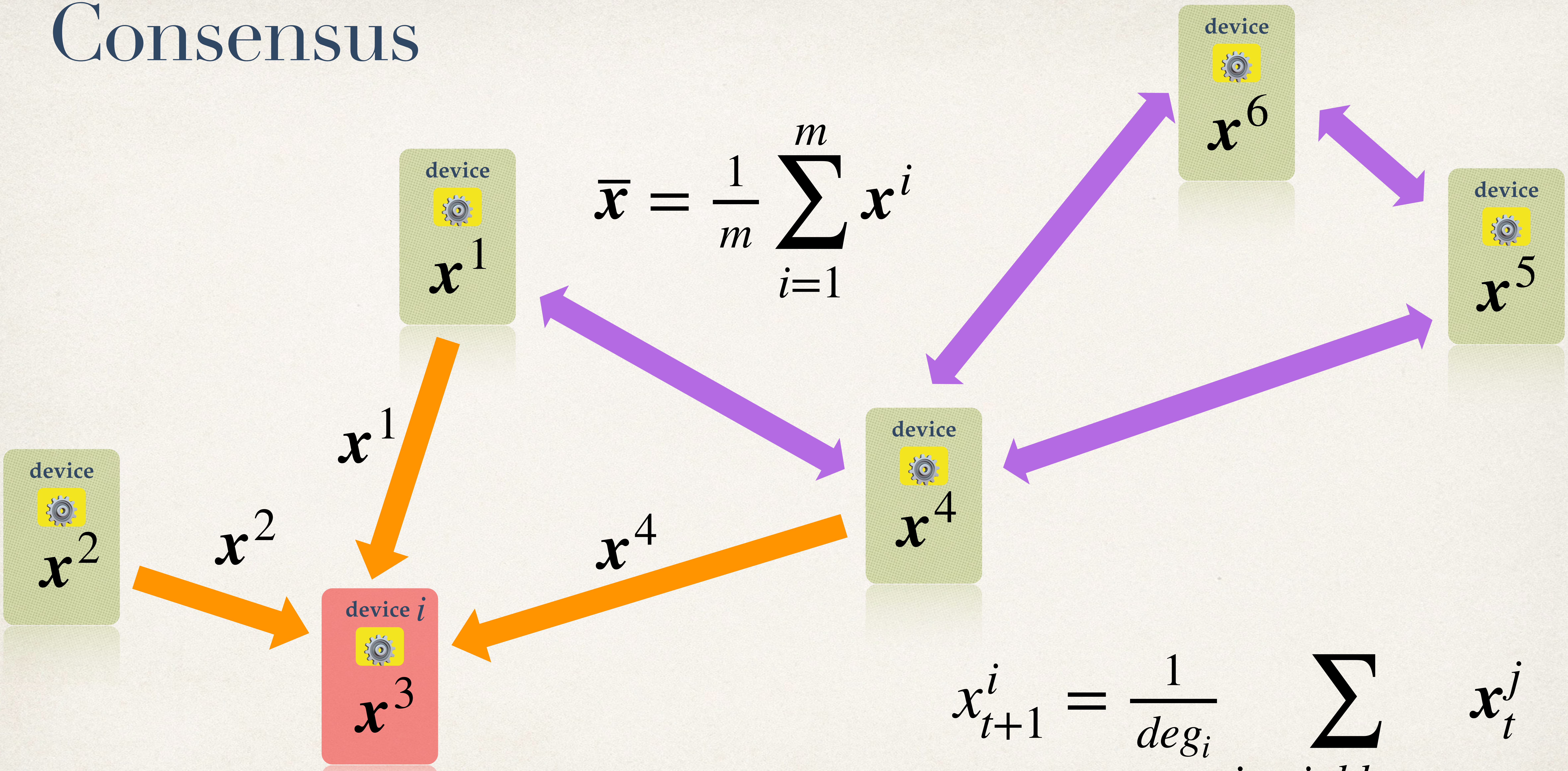


AI utility, control and privacy aligned with data ownership

Required Building Blocks



Consensus



$$\bar{x} = \frac{1}{m} \sum_{i=1}^{m} x^i$$

$$x_{t+1}^i = \frac{1}{deg_i} \sum_{j:neighbours} x_t^j$$

Communication Compression

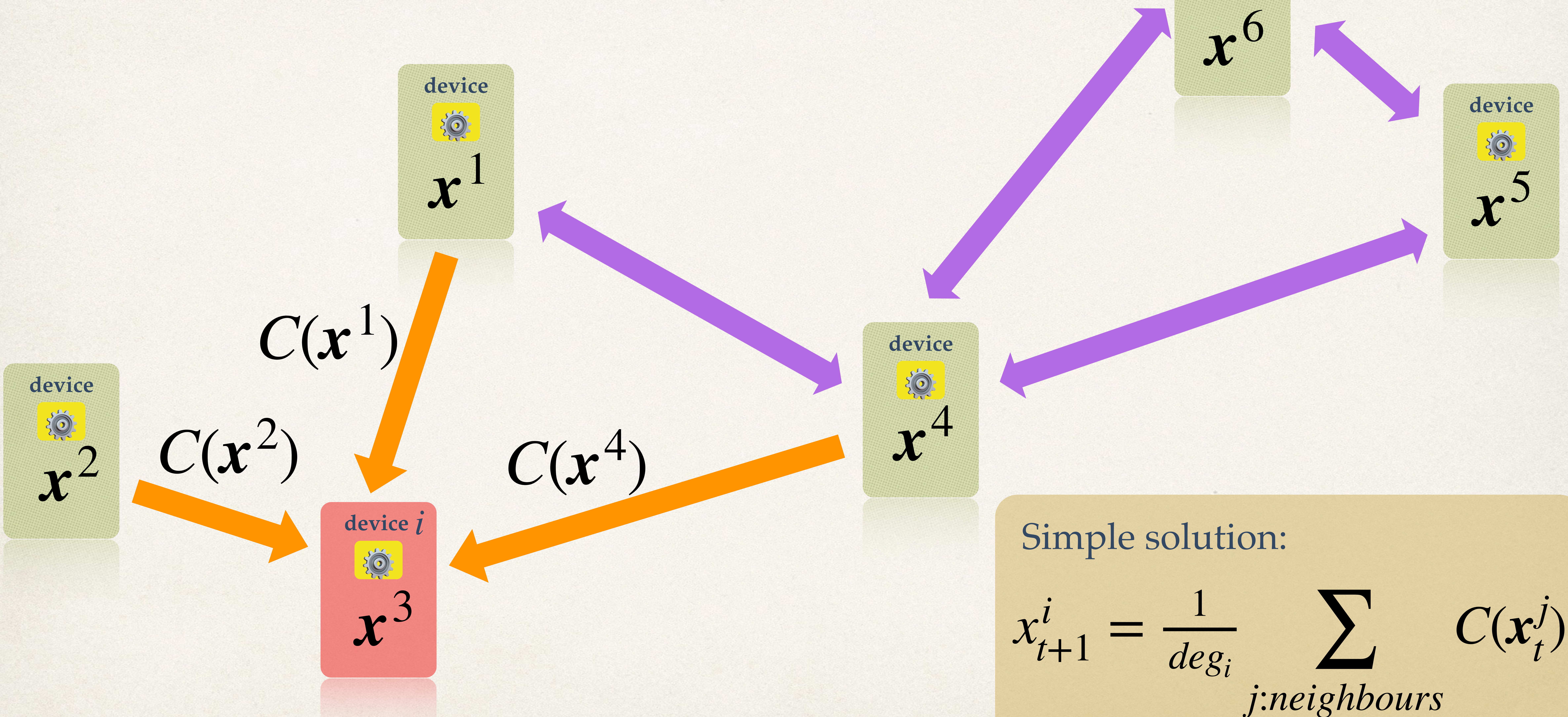
- limited-bit precision vector

e.g. 1-bit per entry reduces communication 32 times

- random/top k% of all the entries

e.g. k=0.1% reduces communication 1000 times

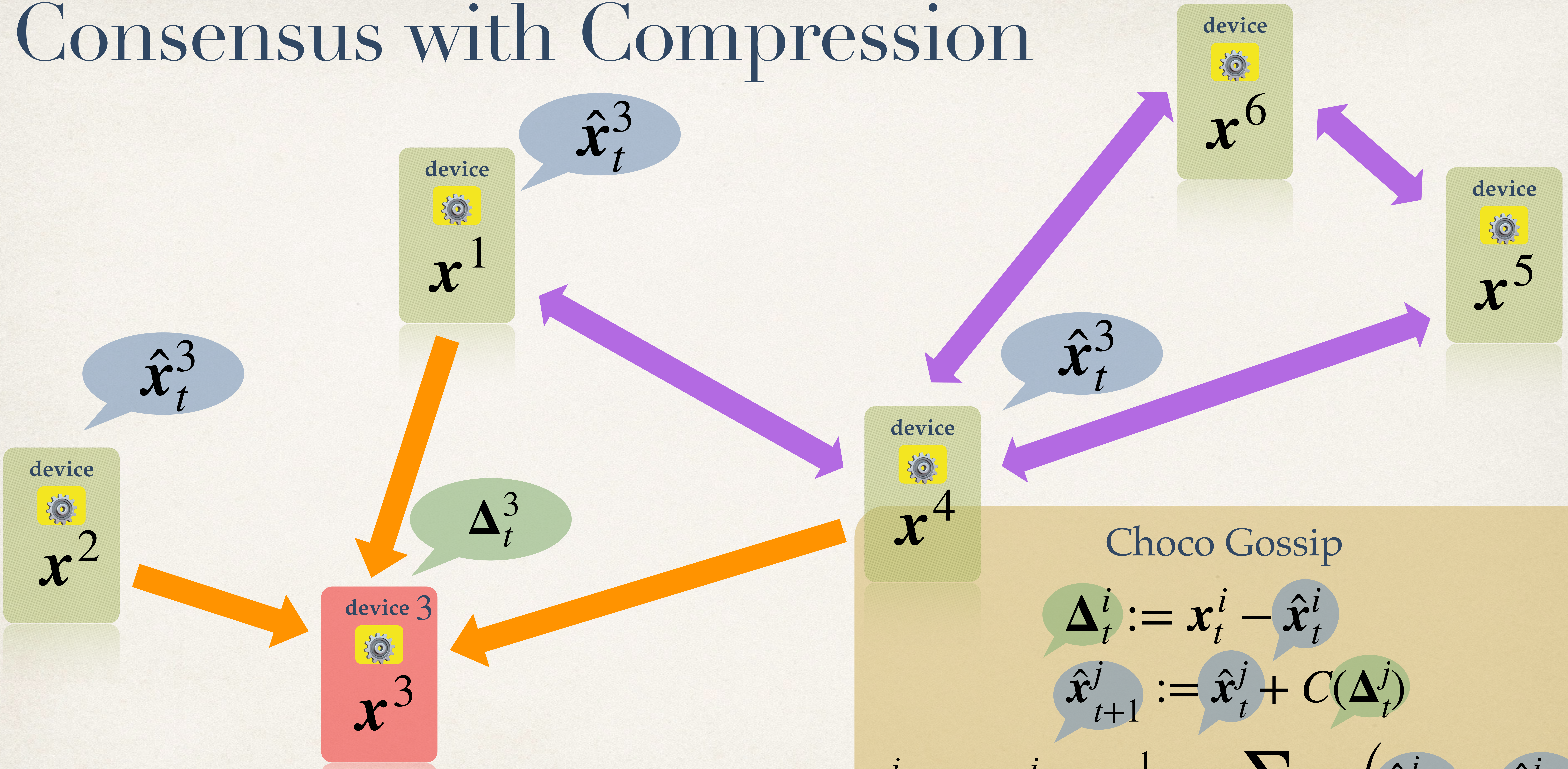
Consensus with Compression



Simple solution:

$$x_{t+1}^i = \frac{1}{deg_i} \sum_{j:neighbours} C(x_t^j)$$

Consensus with Compression



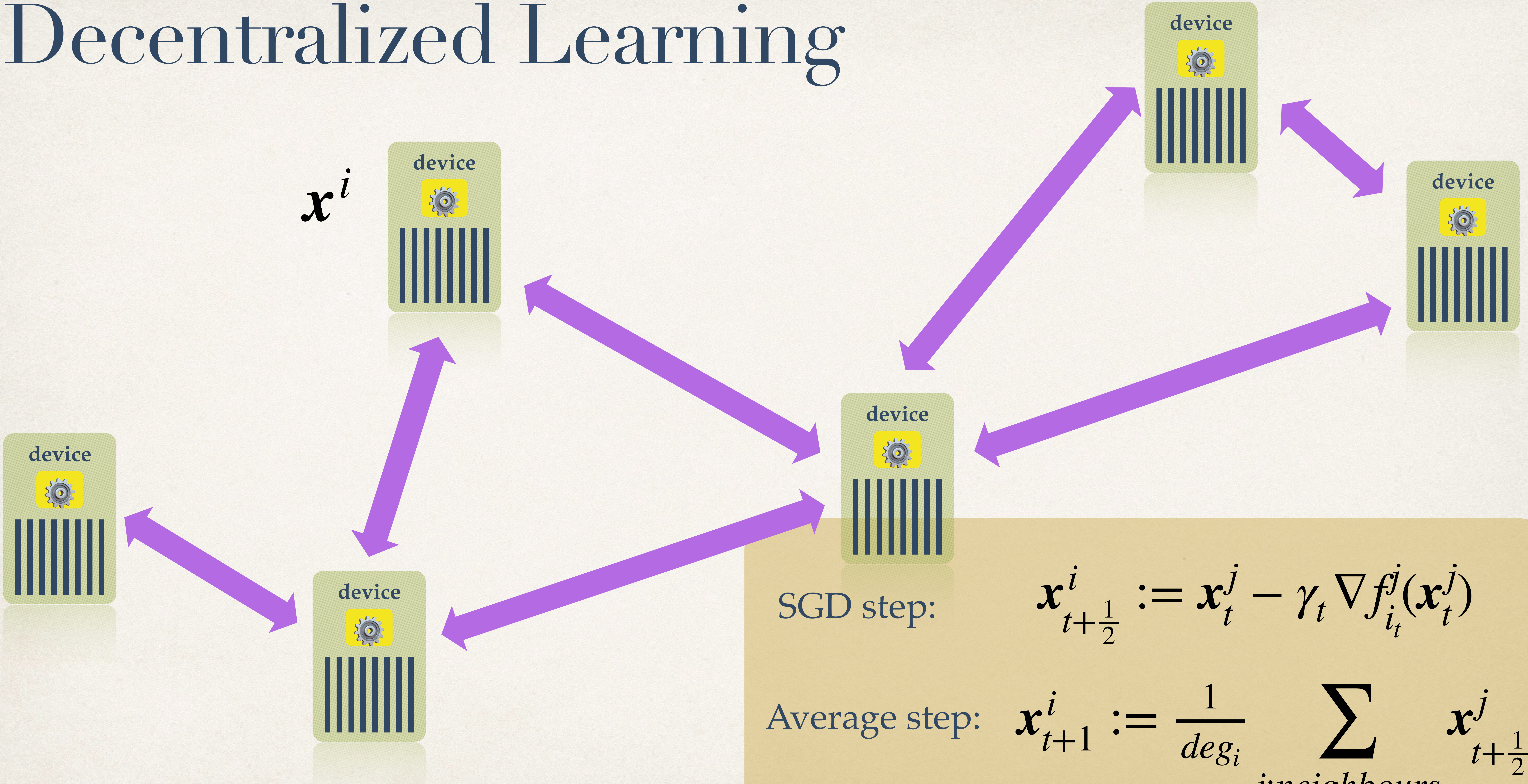
Choco Gossip

$$\boldsymbol{\Delta}_t^i := \boldsymbol{x}_t^i - \hat{\boldsymbol{x}}_t^i$$

$$\hat{\boldsymbol{x}}_{t+1}^j := \hat{\boldsymbol{x}}_t^j + C(\boldsymbol{\Delta}_t^j)$$

$$\boldsymbol{x}_{t+1}^i := \boldsymbol{x}_t^i + \gamma \frac{1}{deg_i} \sum_{j:neighbours} \left(\hat{\boldsymbol{x}}_{t+1}^j - \hat{\boldsymbol{x}}_{t+1}^i \right)$$

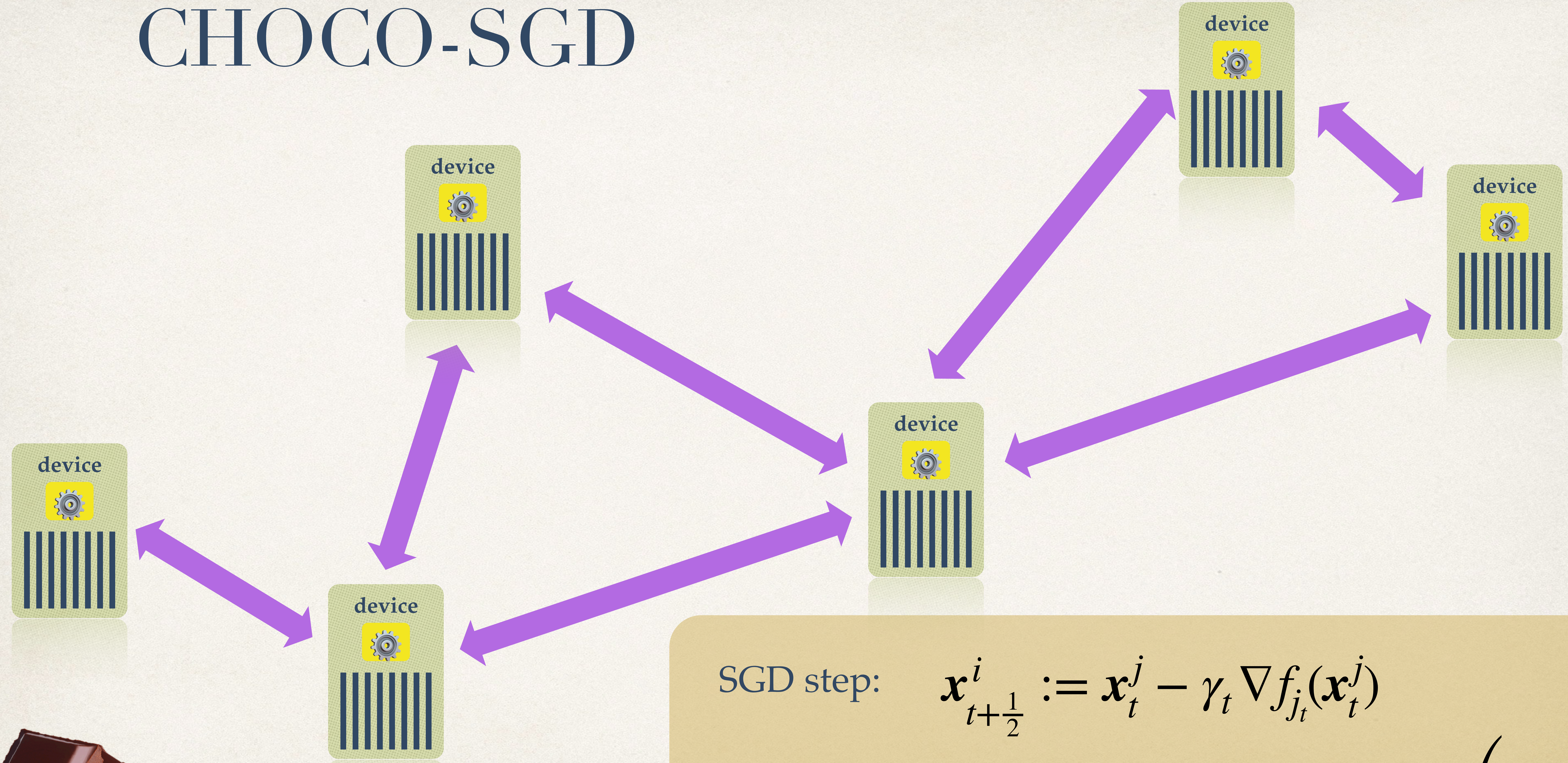
Decentralized Learning



SGD step: $$x^i_{t+\frac{1}{2}} := x^j_t - \gamma_t \nabla f^j_{i_t}(x^j_t)$$

Average step: $$x^i_{t+1} := \frac{1}{deg_i} \sum_{j:neighbours} x^j_{t+\frac{1}{2}}$$

CHOCO-SGD



SGD step: $$\boldsymbol{x}^i_{t+\frac{1}{2}} := \boldsymbol{x}^j_t - \gamma_t \nabla f_{j_t}(\boldsymbol{x}^j_t)$$

$$\boldsymbol{x}^i_{t+1} := consensus\_with\_compression\left(\boldsymbol{x}^j_{t+\frac{1}{2}}\right)$$

Convergence (Non-Convex Case)

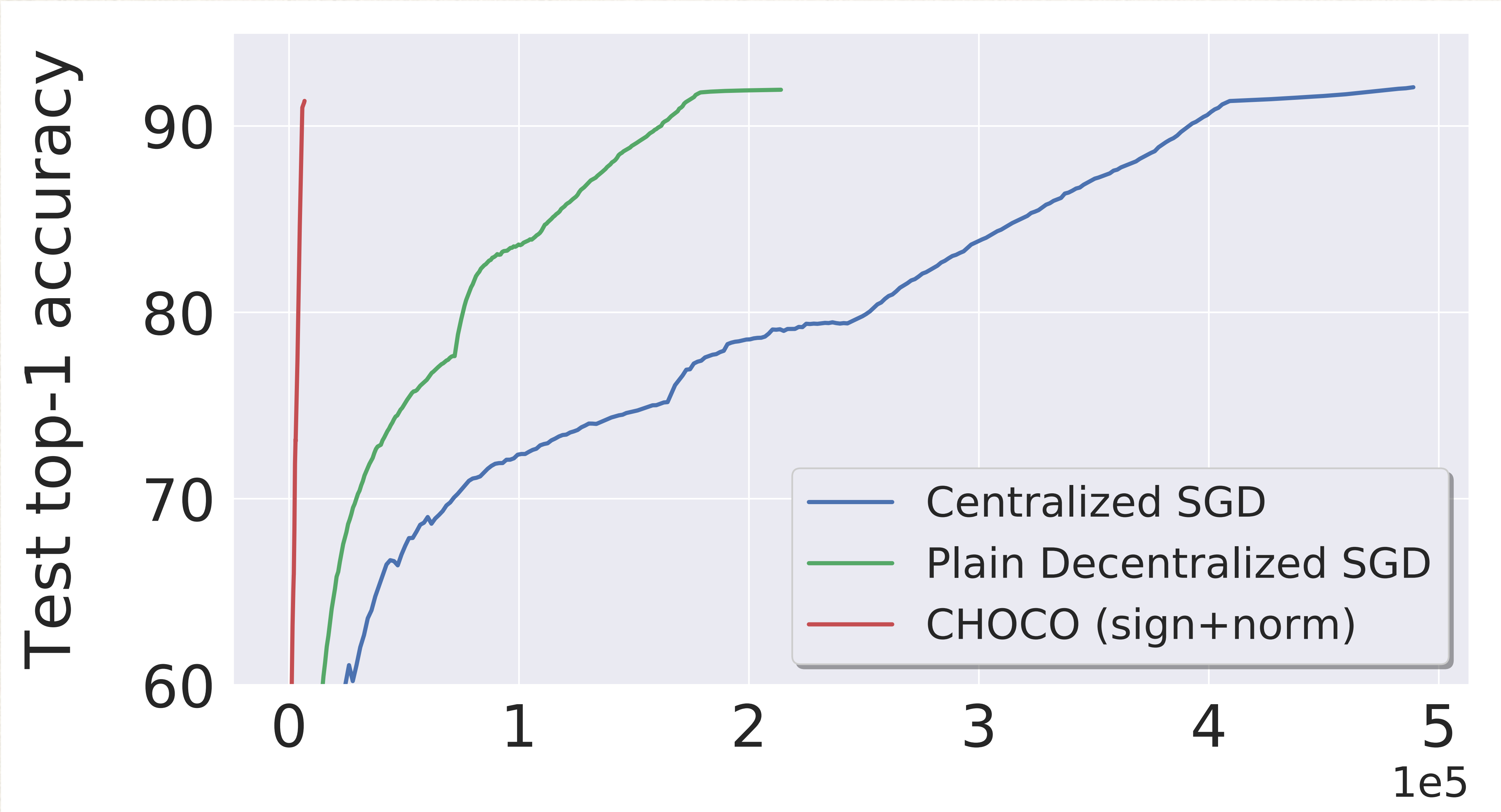
$$\frac{1}{T+1}\sum_{t=0}^{T}\|\nabla f(\bar{x}_t)\|^2 = \mathcal{O}\left(\frac{1}{\sqrt{nT}} + \frac{n}{\delta^2\rho^4 T}\right)$$

δ — compression ratio $\quad \delta \in [0,1], \;\; \delta = 1$ for no compression

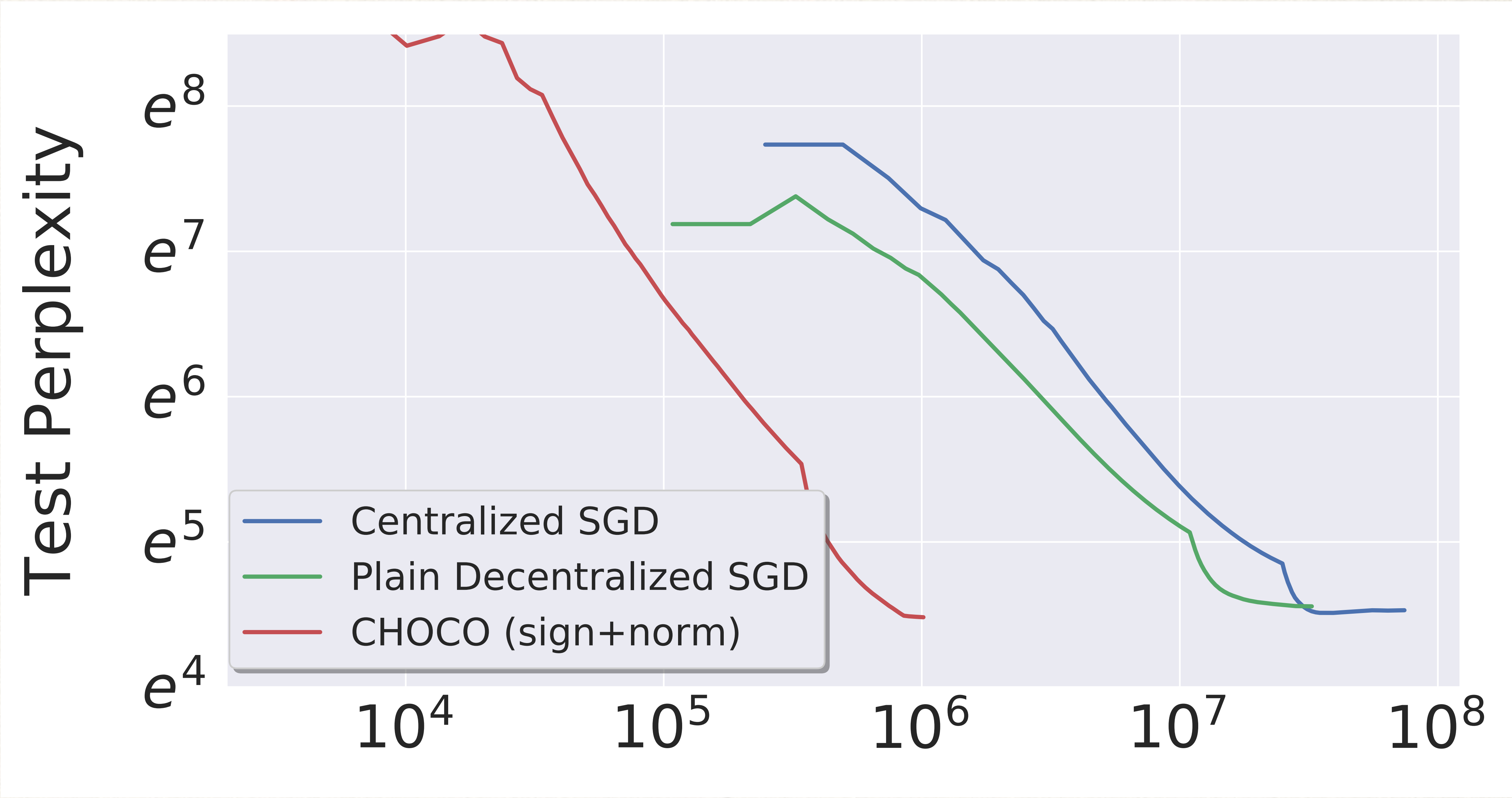
ρ — spectral gap of the graph topology

- linear speedup in the number of workers

Decentralized DL



data transmitted (MB)



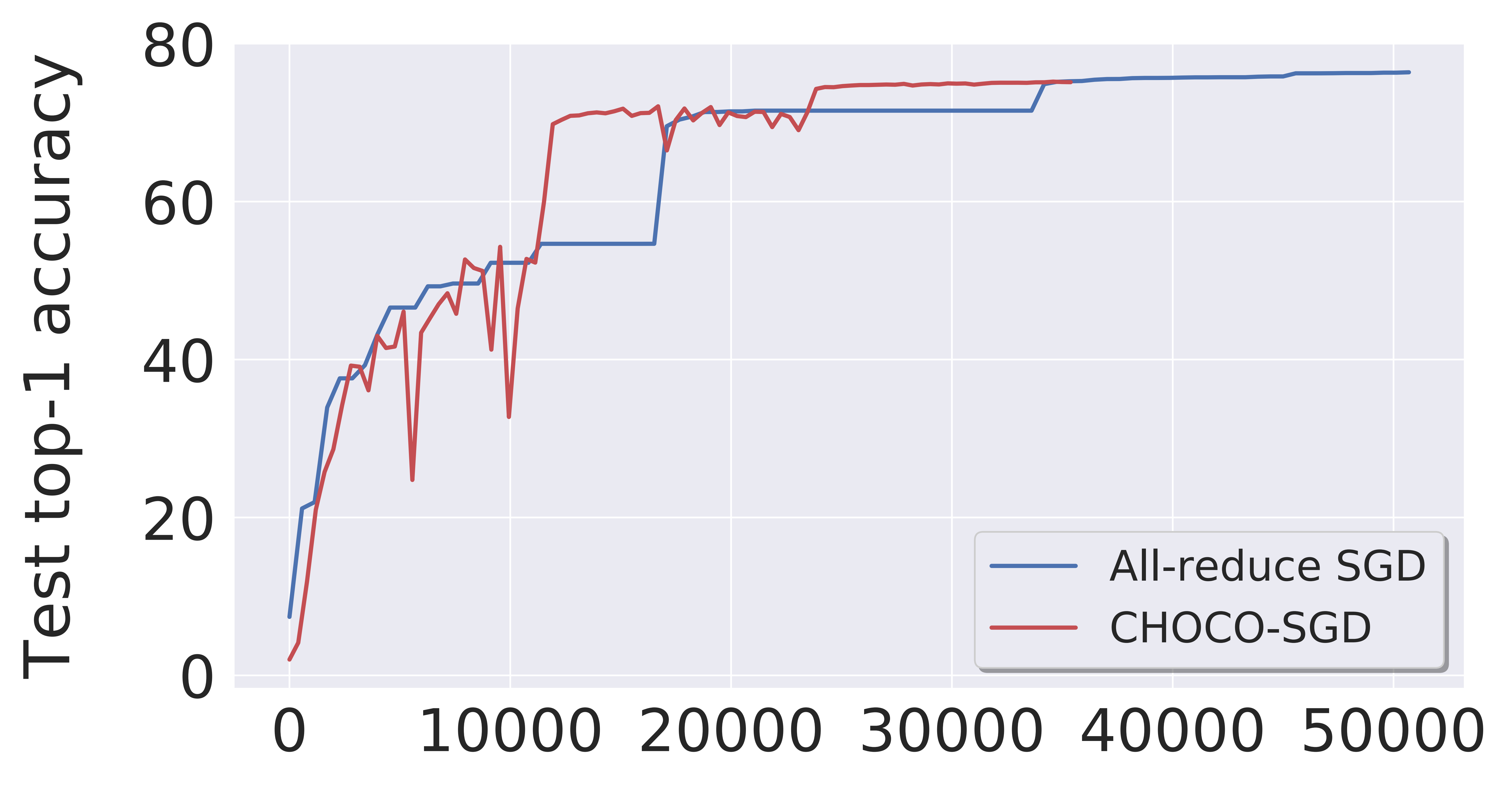
data transmitted (MB)

Resnet20 on Cifar 10

Language model (3-layer LSTM) on WikiText-2

Social Network Topology, 32 nodes of max deg 14
Sign quantization

DL in Datacenter



time

Resnet50 on ImageNet-1k
Ring of 8 nodes, each has 4 P100 GPUs

Conclusions - Choco

- **consensus algorithm** that converges linearly with arbitrary compression
- **decentralized SGD** algorithm that converges with arbitrary compression

Building Blocks for Decentralized ML

- **Efficiency: Communication & Compute**

  on-device learning, Edge AI

  peer-to-peer communication

- **Privacy**

  data locality, leakage?, attacks?

- **Robustness & Incentives**

  tolerate bad players, reward collaboration

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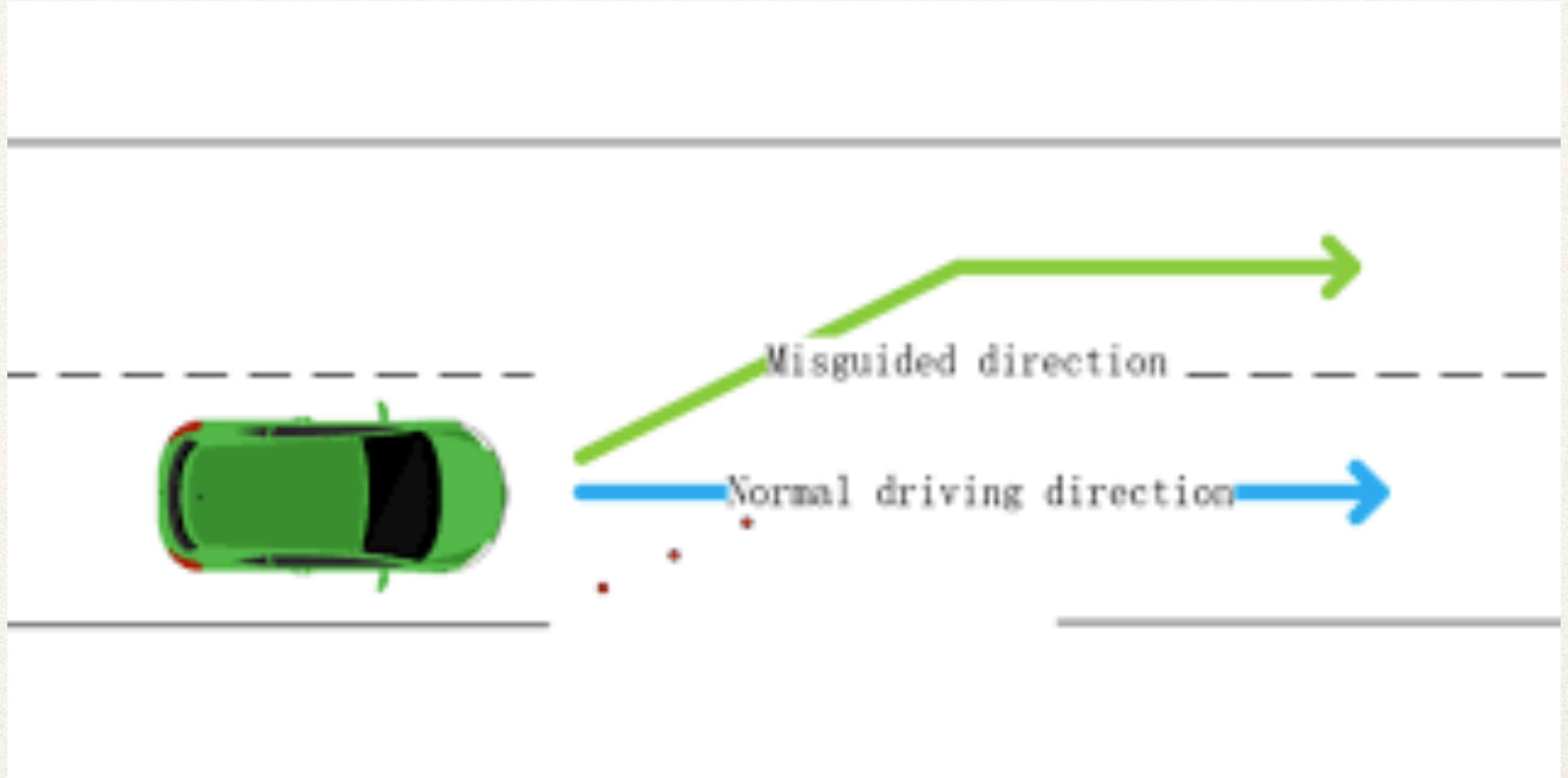
Robustness

During Training and Inference

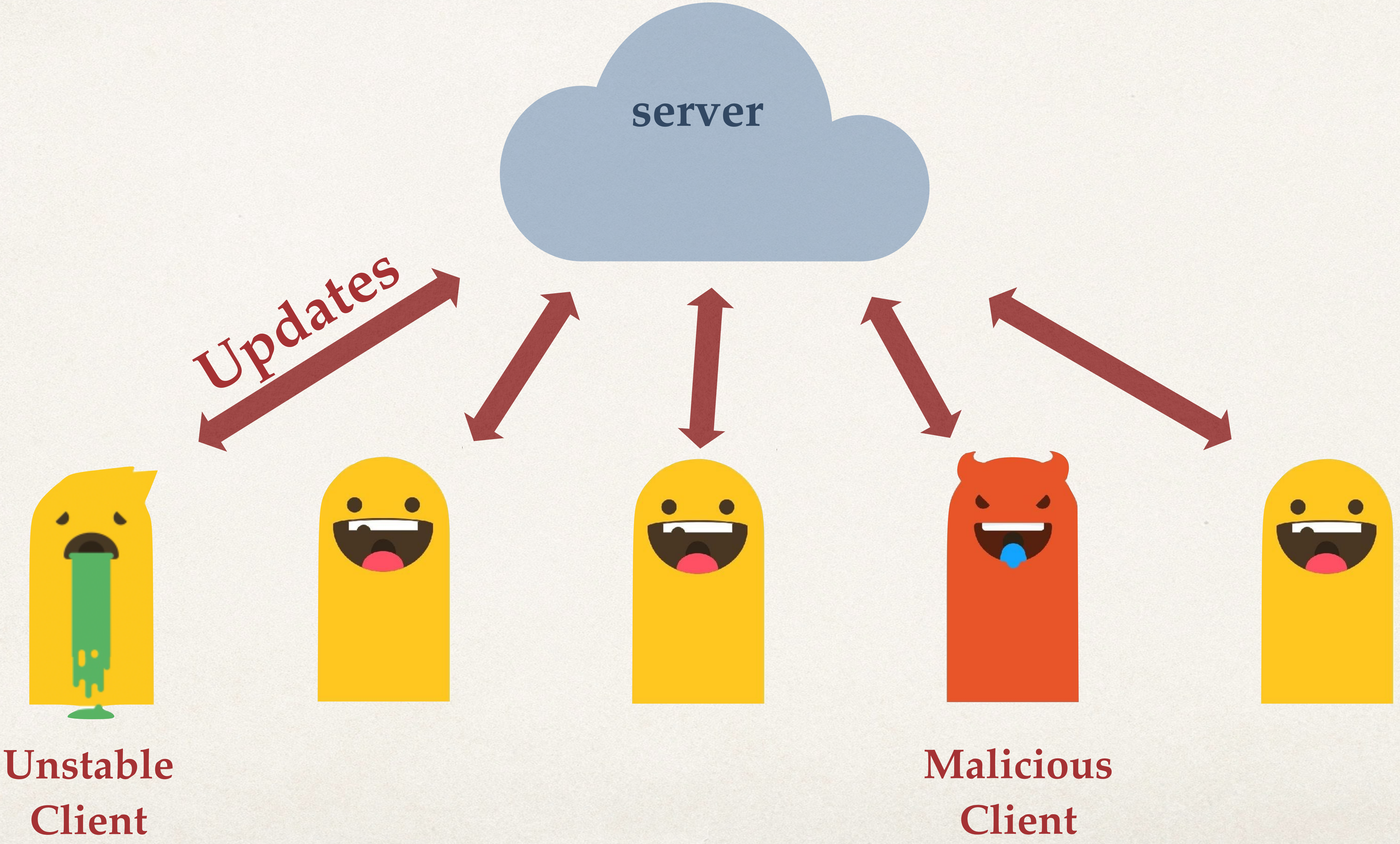


3a

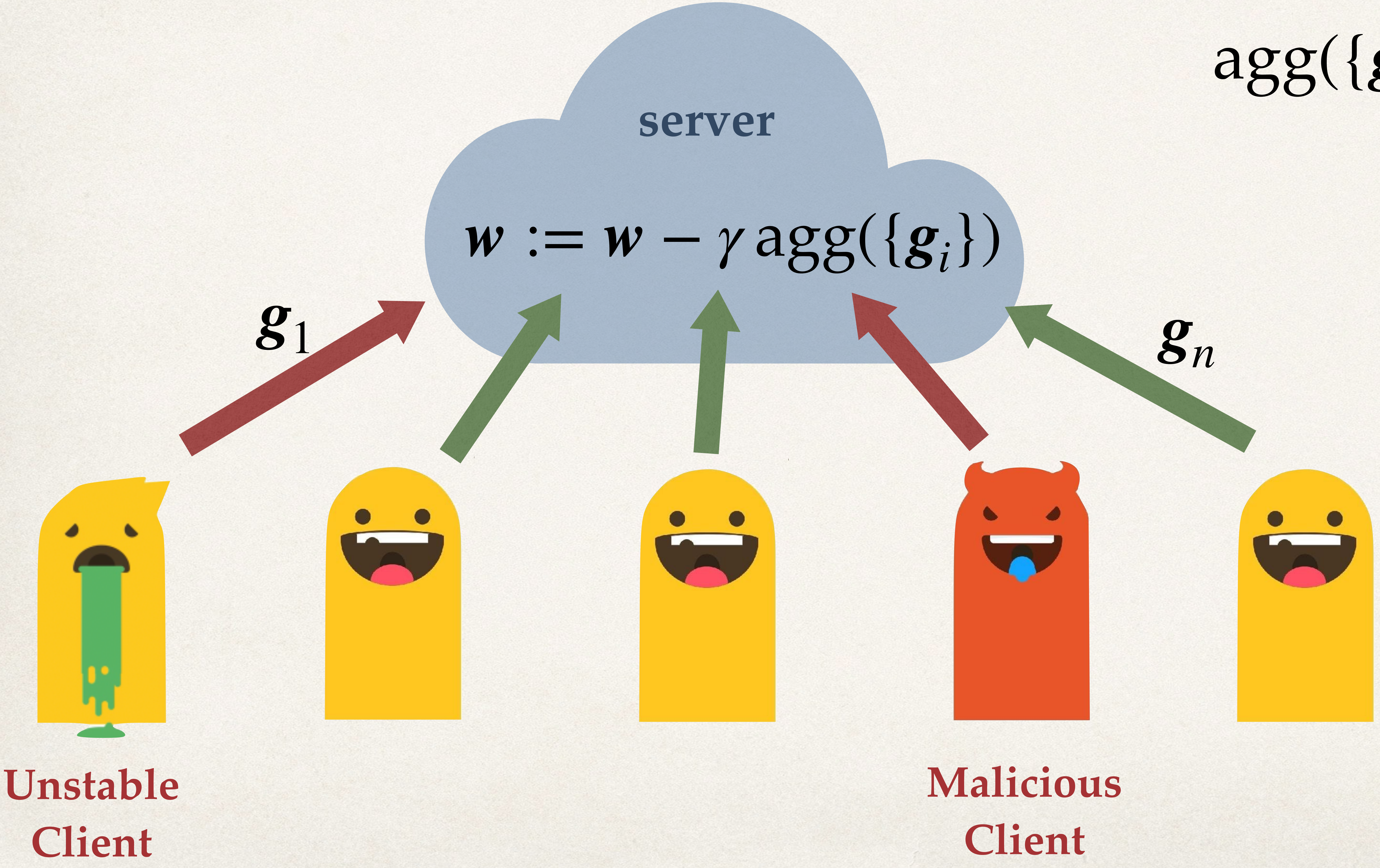
Gradients from faulty/malicious collaborators:

- Byzantine-robust Training

Malicious actors in FL



Byzantine Robust Training



$$\mathrm{agg}(\{\boldsymbol{g}_i\}) := \mathrm{avg}(\{\boldsymbol{g}_i\})$$

$$:= \mathrm{CM}(\{\boldsymbol{g}_i\})$$

Examples:

- Coordinate-wise median [Yin et al. 2017]
- Krum [Blanchard et al. 2018]
- Geometric median / RFA [Pillutla et al. 2019]

Byzantine-robust training

- **Mean vs median**

Zeno: Byzantine-suspicious stochastic gradient descent, 2018, Cong Xie et al.

Negative result

- Robustness of the aggregation rule agg($\{\boldsymbol{g}_i\}$) does **not** imply robust training: *time-coupled attacks - "little is enough"*
- Any aggregation rule which does not use history can **fail** for training (convergence)

Fix: Using history with momentum

- Simply use worker momentum

$$\boldsymbol{m}_i := (1-\beta)\boldsymbol{g}_i + \beta\boldsymbol{m}_i$$

- Effectively averages past gradients, reducing variance

- (Robustly) aggregate worker momentum instead of gradients

$$\boldsymbol{w} := \boldsymbol{w} - \gamma\,\mathrm{agg}(\{\boldsymbol{m}_i\})$$

3b Adversarial Attacks (at inference time)

Image: [Tom B. Brown/Dandelion Mané]

Image: Elsayed ,Papernot et al 2018

Adversarial Attacks (at inference time)

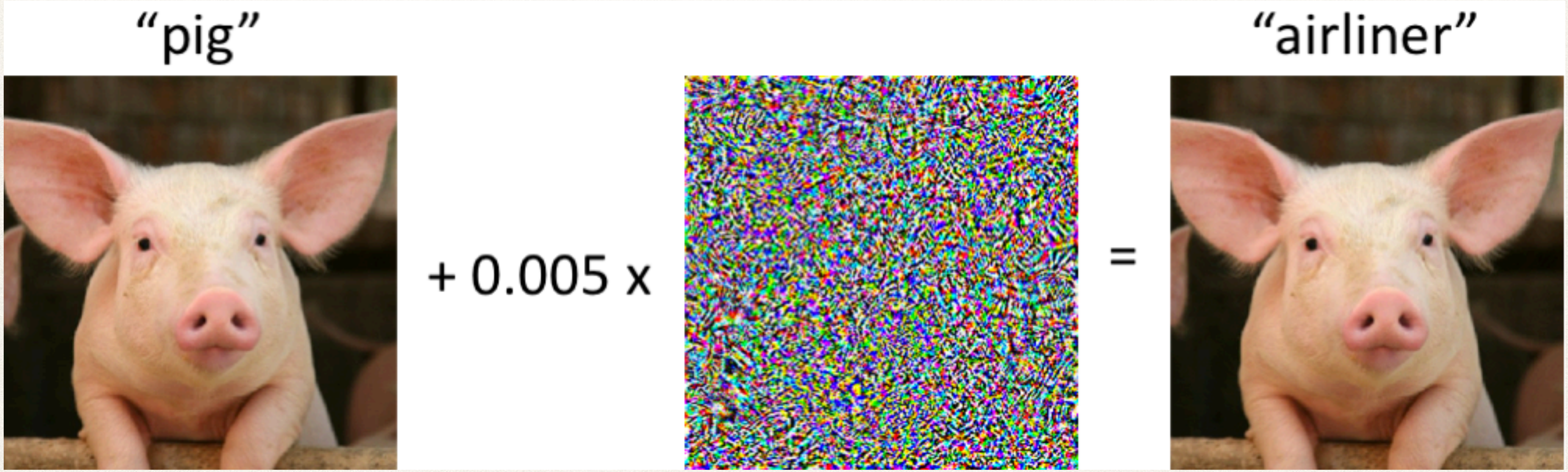


Image: [Mądry, Schmidt]

More info:
http://gradientscience.org/intro_adversarial/

Adversarial Attacks

- Standard **training**

$$\min_{\mathbf{w}} \quad f_{\mathbf{w}}(\mathbf{x}_i)$$

$\nabla_{\boldsymbol{w}} f$

change **model**

- **Attacking**

$$\max_{\mathbf{x} \in R_\infty(\mathbf{x}_i, \varepsilon)} f_{\mathbf{w}}(\mathbf{x}_i)$$

$\nabla_{\boldsymbol{x}_i} f$

change **data**

- by **Projected Gradient Descent!**

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Privacy

- Secure Multiparty Computation
  - secure aggregation
    (private gradients, public model)
- Differential Privacy
- Privacy/inference Attacks

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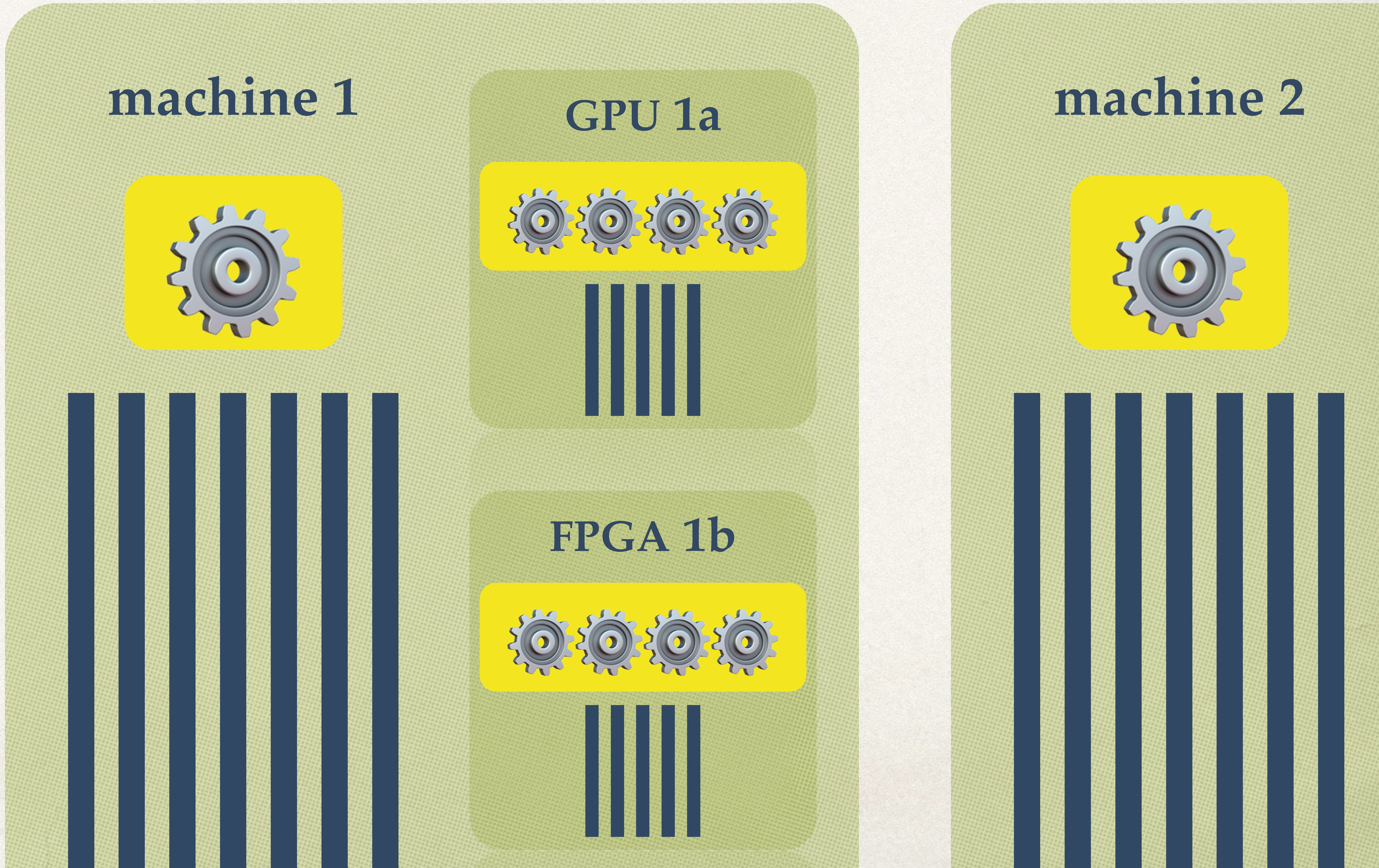
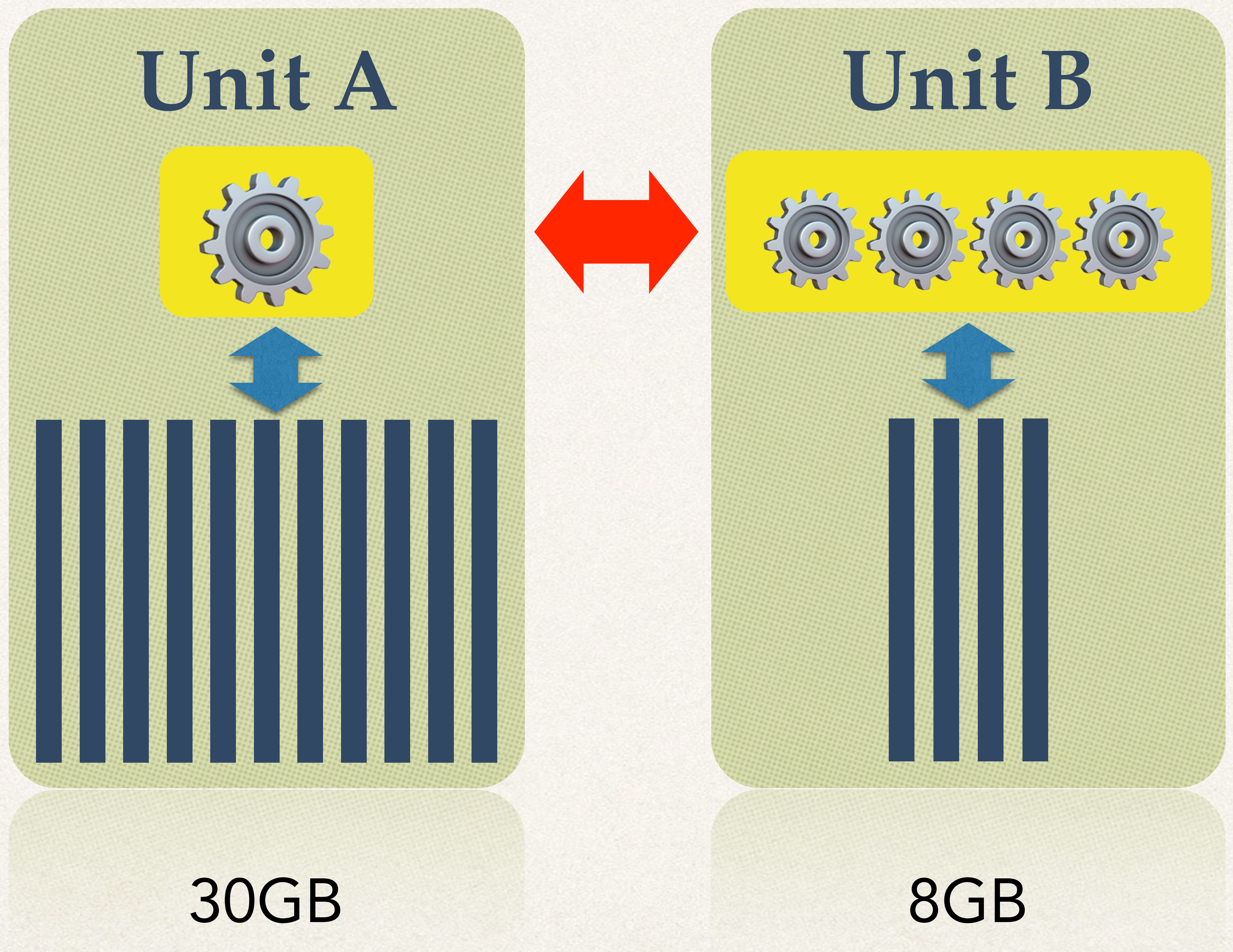
Leveraging Heterogenous Systems

Compute & Memory Hierarchy: Which data to put in which device?



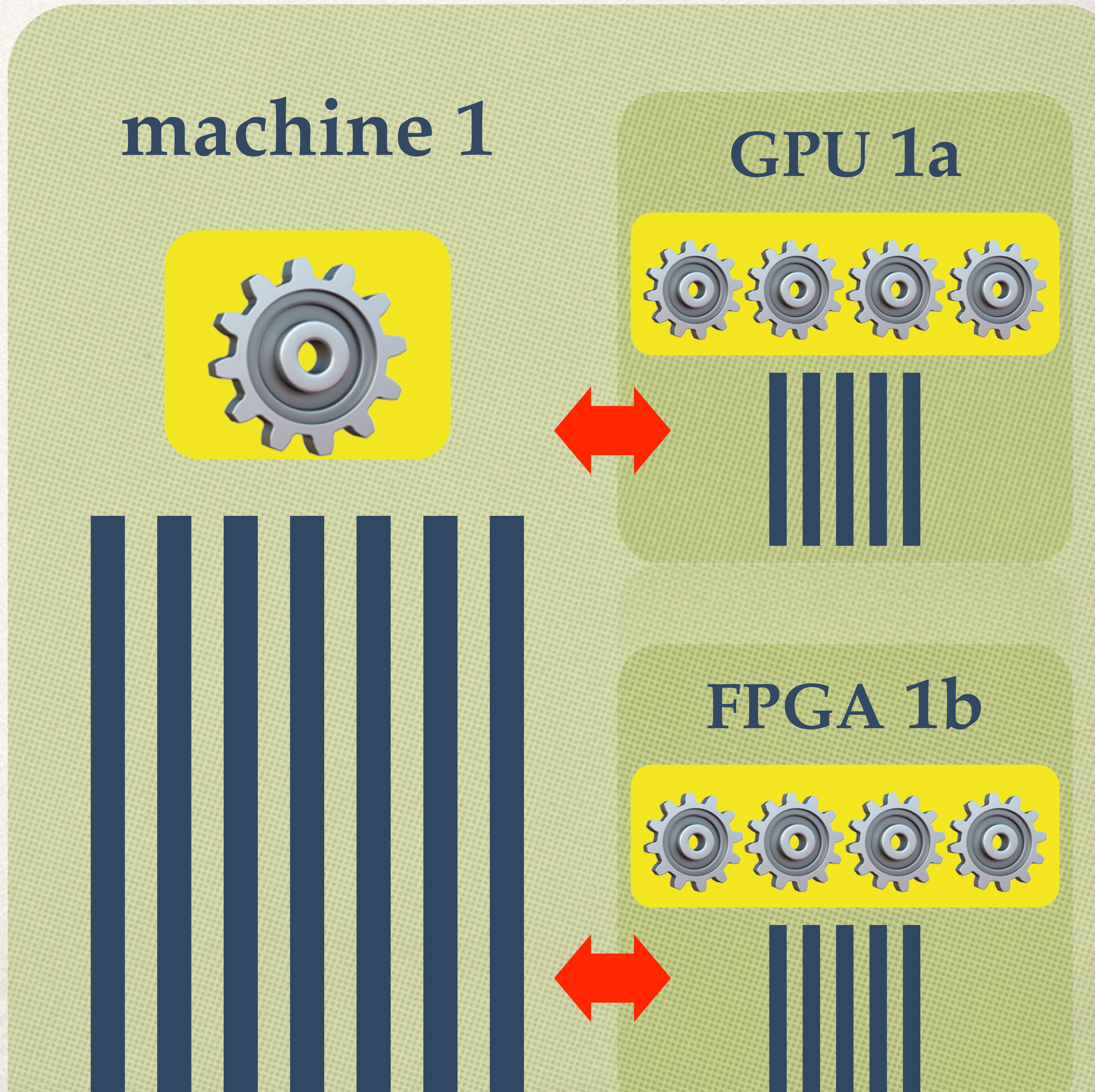
Leveraging Heterogenous Systems



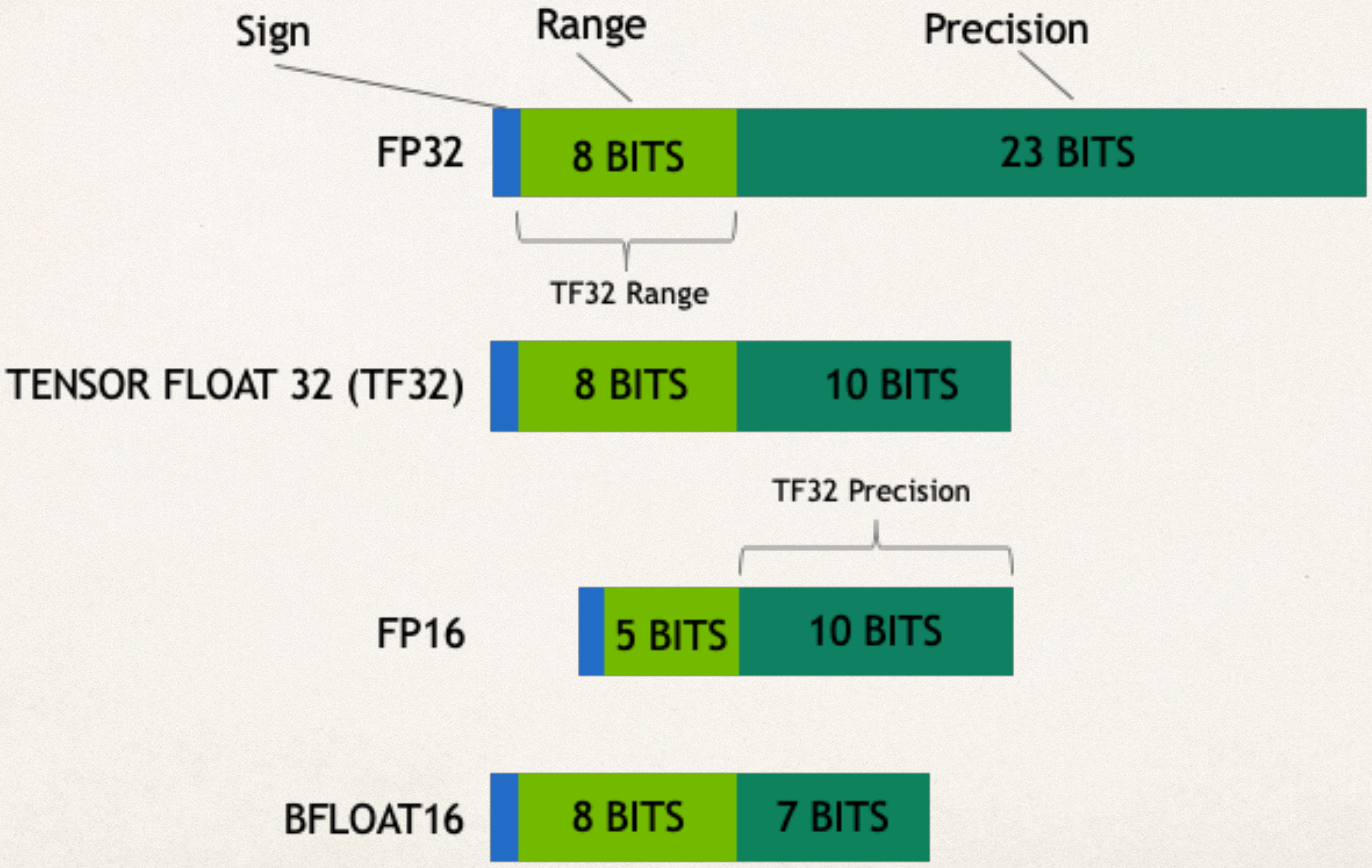
adaptive importance sampling of datapoint
e.g. for general linear models, or word2vec

Trends - Systems

- new **hardware**
  - TPU, GraphCore
  - sparse ops
  - efficient numerics (limited precision), model compression
- **Software** frameworks
  - AutoGrad (Jax, PyTorch, TensorFlow etc)
  - Backends for new hardware

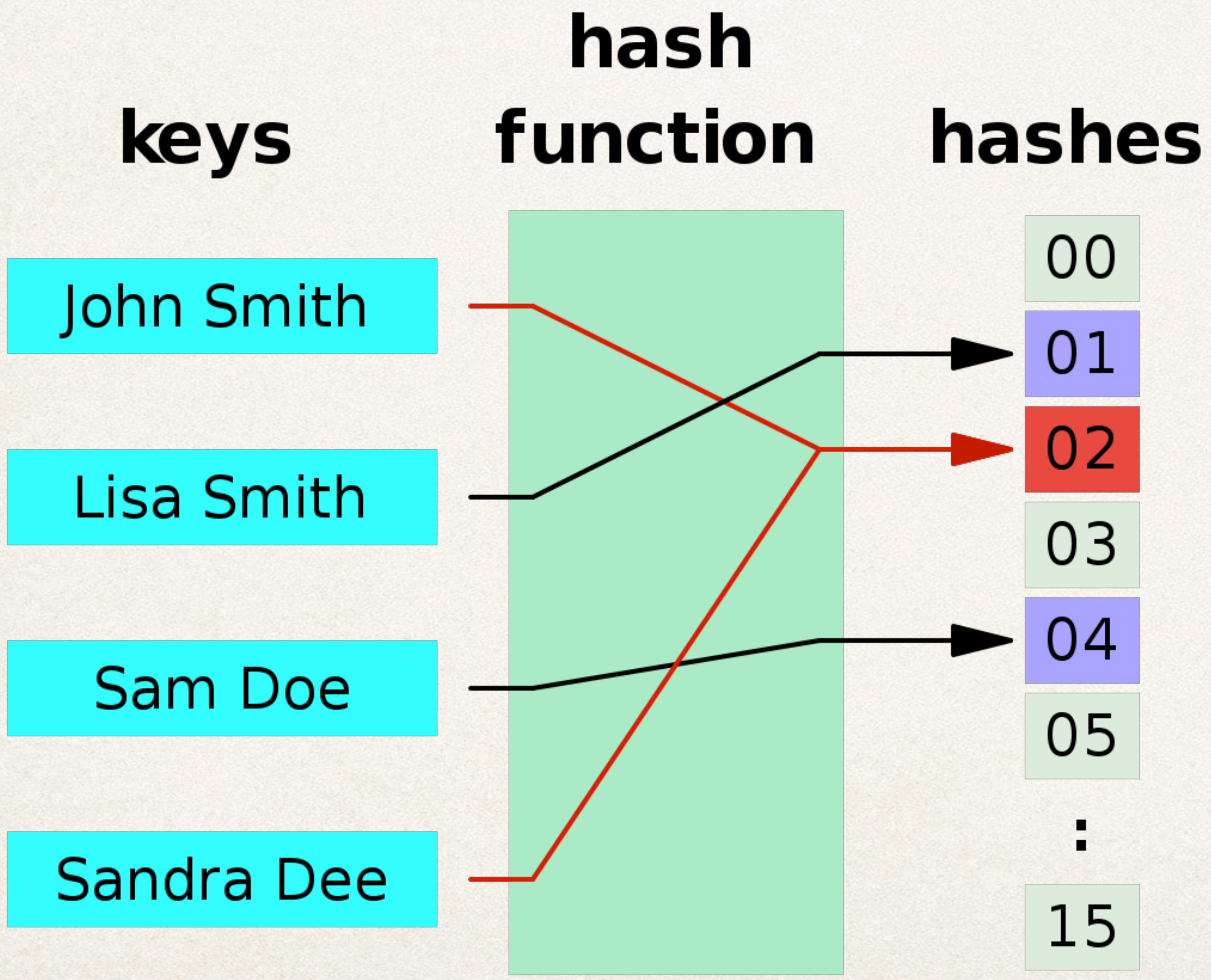


Number formats for DL



Practical tricks

- **feature hashing**



- **limited precision operations**

Auto ML

- **hyper-parameter optimization**
  zero-order methods
- **learning to learn**
  adaptive methods
- **neural architecture search**
  zero-order, warm-start

Thanks!

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