Privacy-Preserving Deep Learning

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(UT Austin and Cornell Tech)

Machine Intelligence LANDSCAPE

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Tech 2015: Deep Learning And Machine Intelligence Will Eat The World

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Robert Hof
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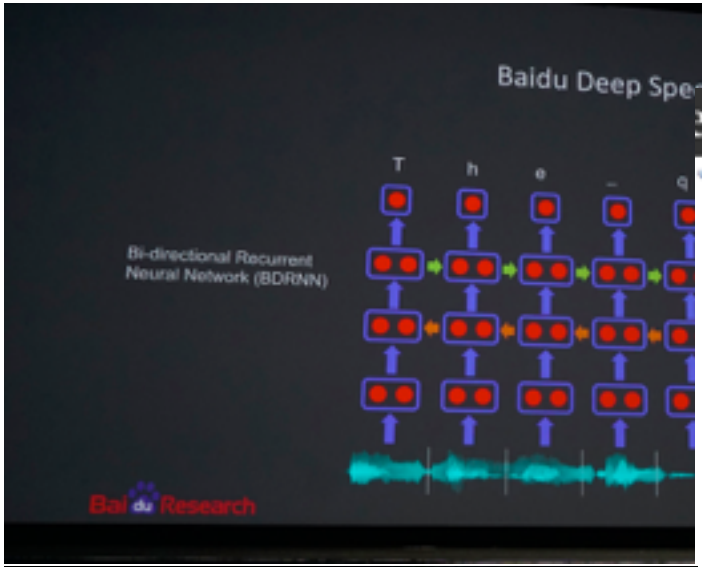

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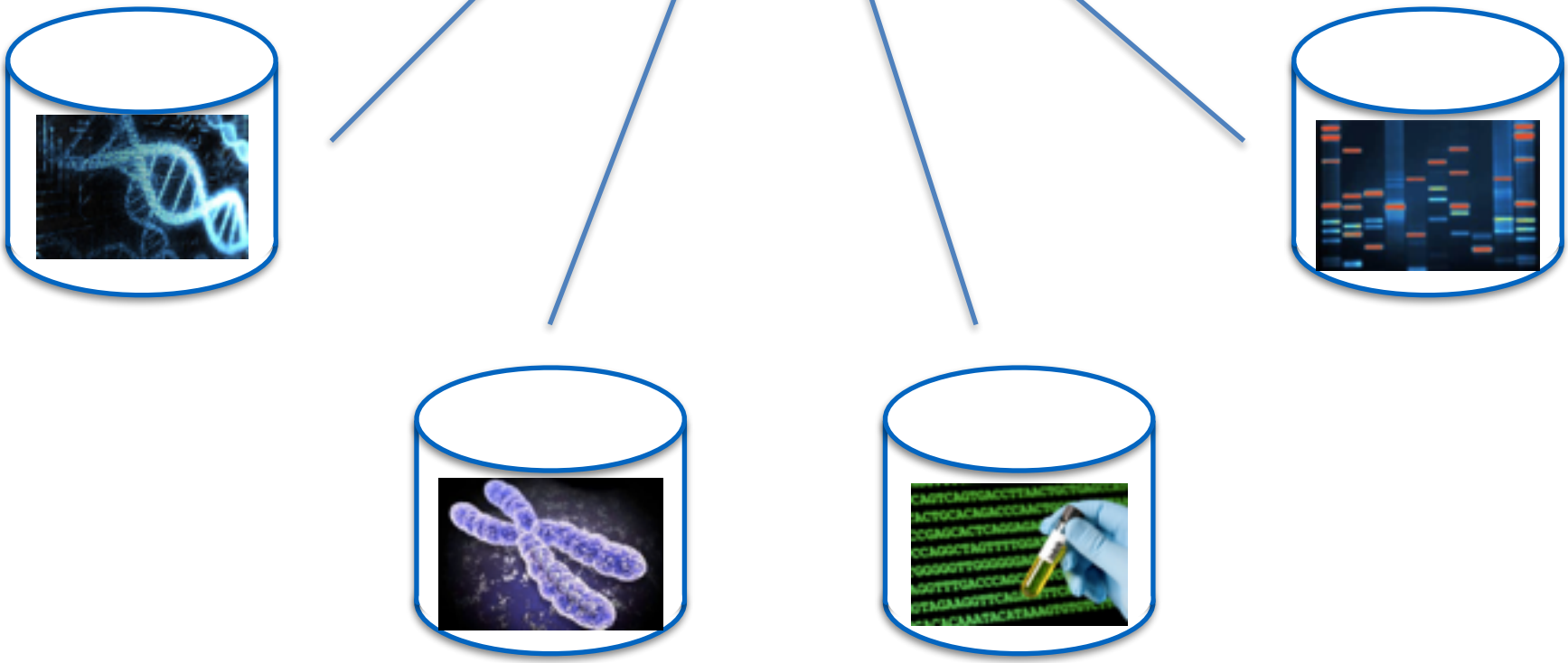
Microsoft's Deep Learning Project Outperforms Humans In Image Recognition

Michael Thomsen
Contributor

Images used to test Microsoft's deep learning AI. Image via Microsoft.

Deep Learning Today



Privacy Concerns

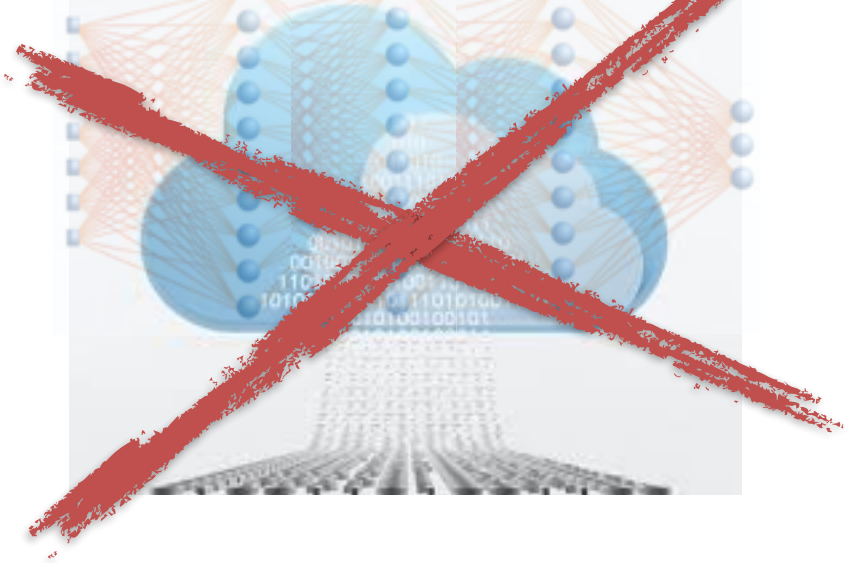
- Training data is very sensitive
  - speech, photo images, written documents, might contain sensitive private information
- Users have no control over the learning objective
- Using trained networks requires users to share their private data with service providers

Possible Consequences

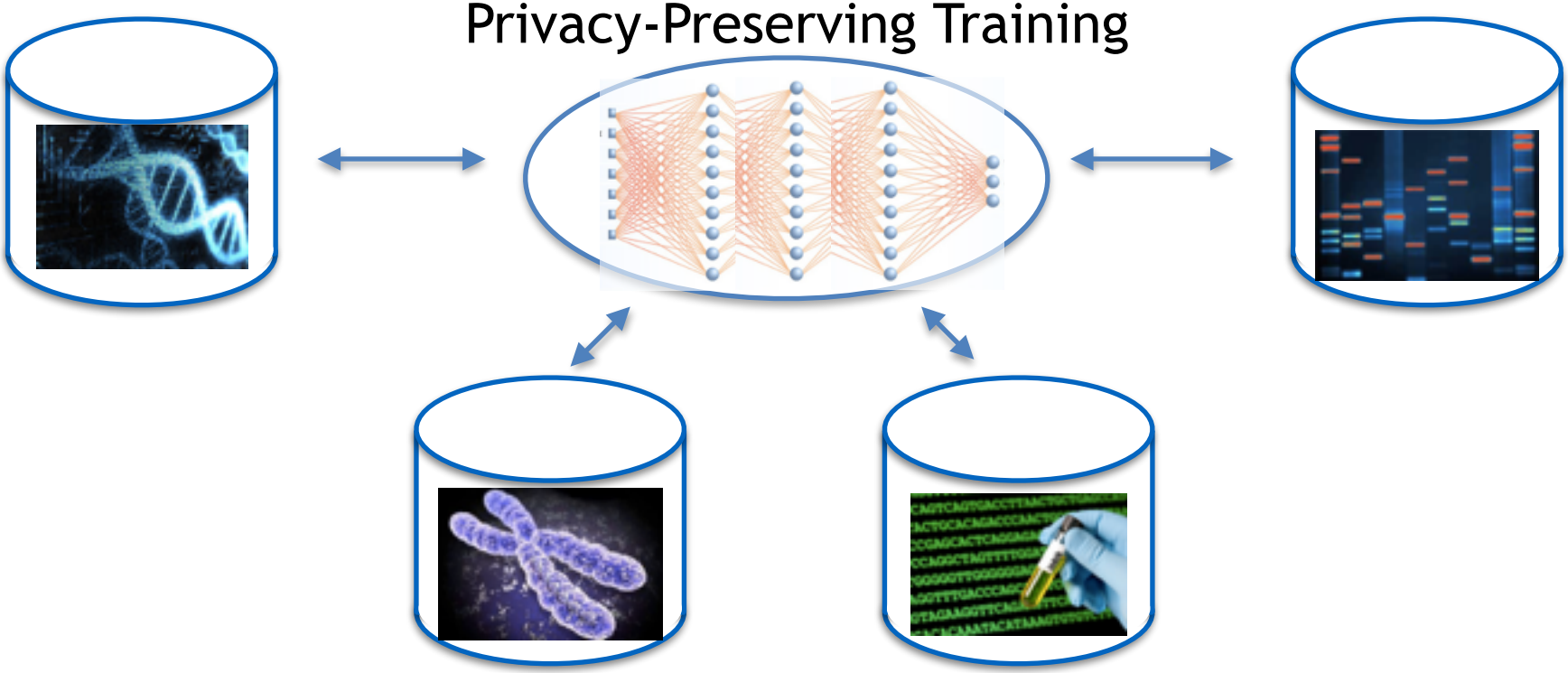
- Users' data might be used in wrong context
  - Compromises and data breaches
  - Inference of sensitive information
  - Training of intrusive models

- Holders of sensitive data cannot benefit from large-scale deep learning because they may not share their datasets for training
  - Biomedical researchers?
  - Social scientists?

Our Objective



Privacy-Preserving Training

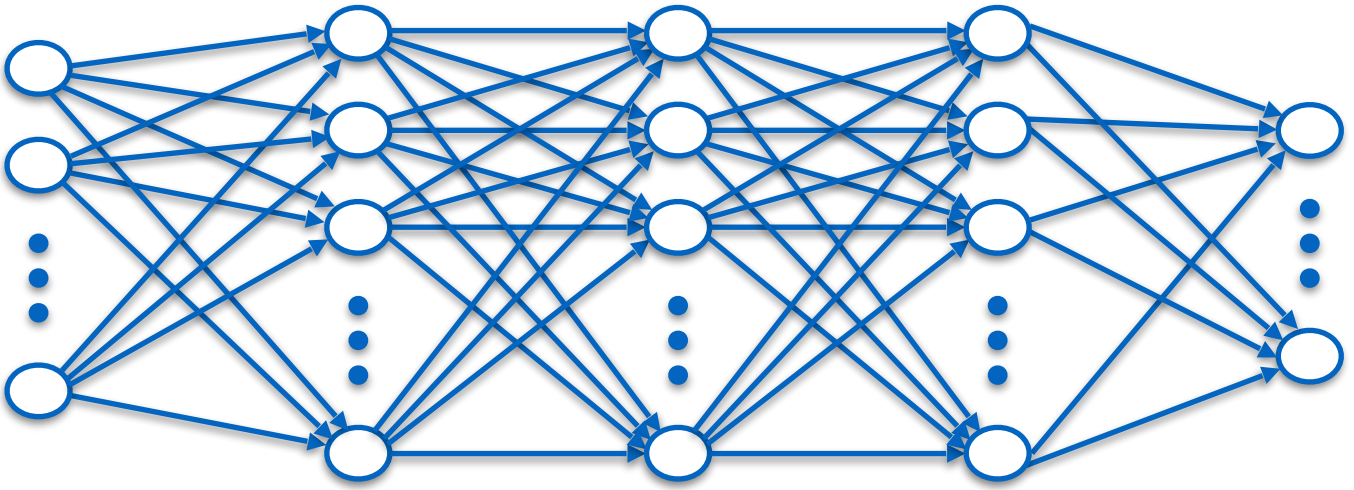


Private data remain private

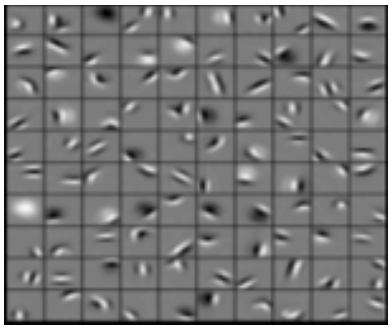
Background

Deep Neural Networks

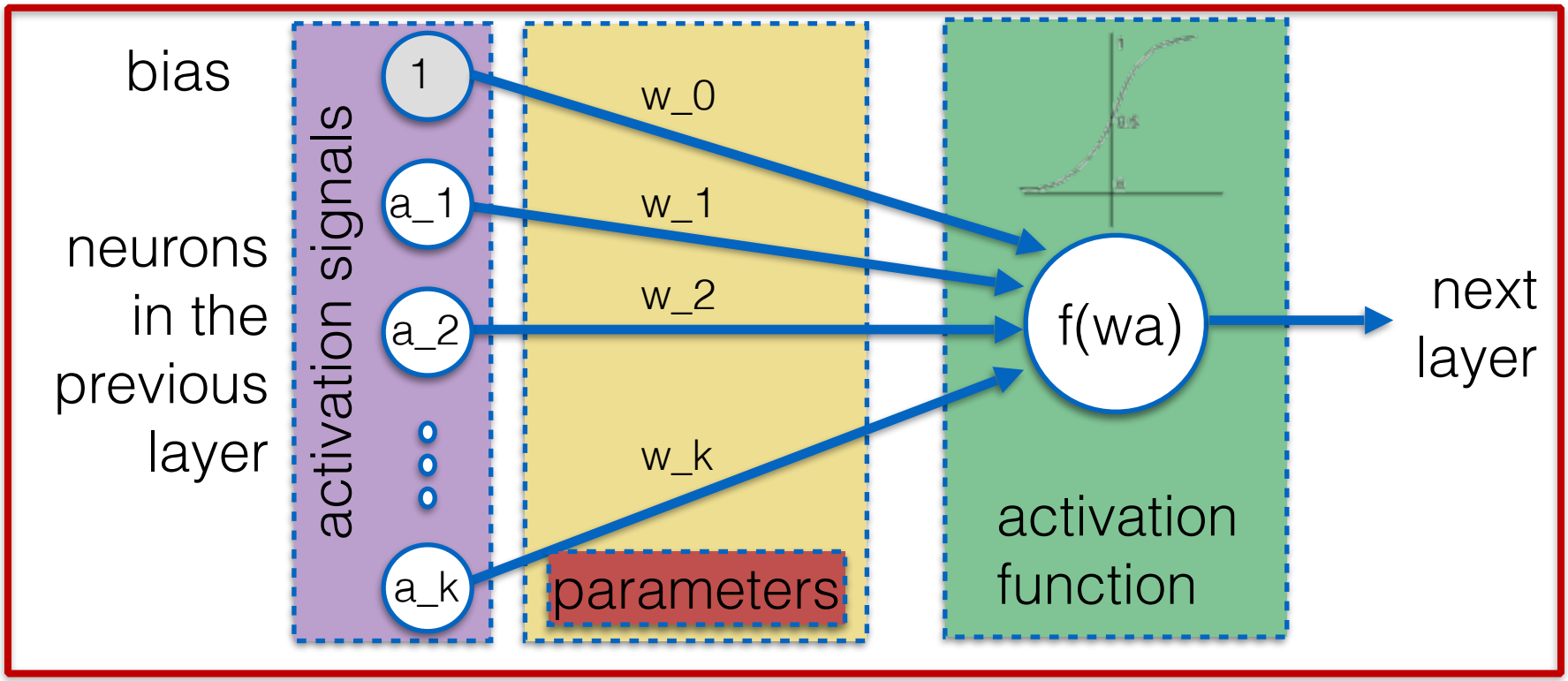
input



output

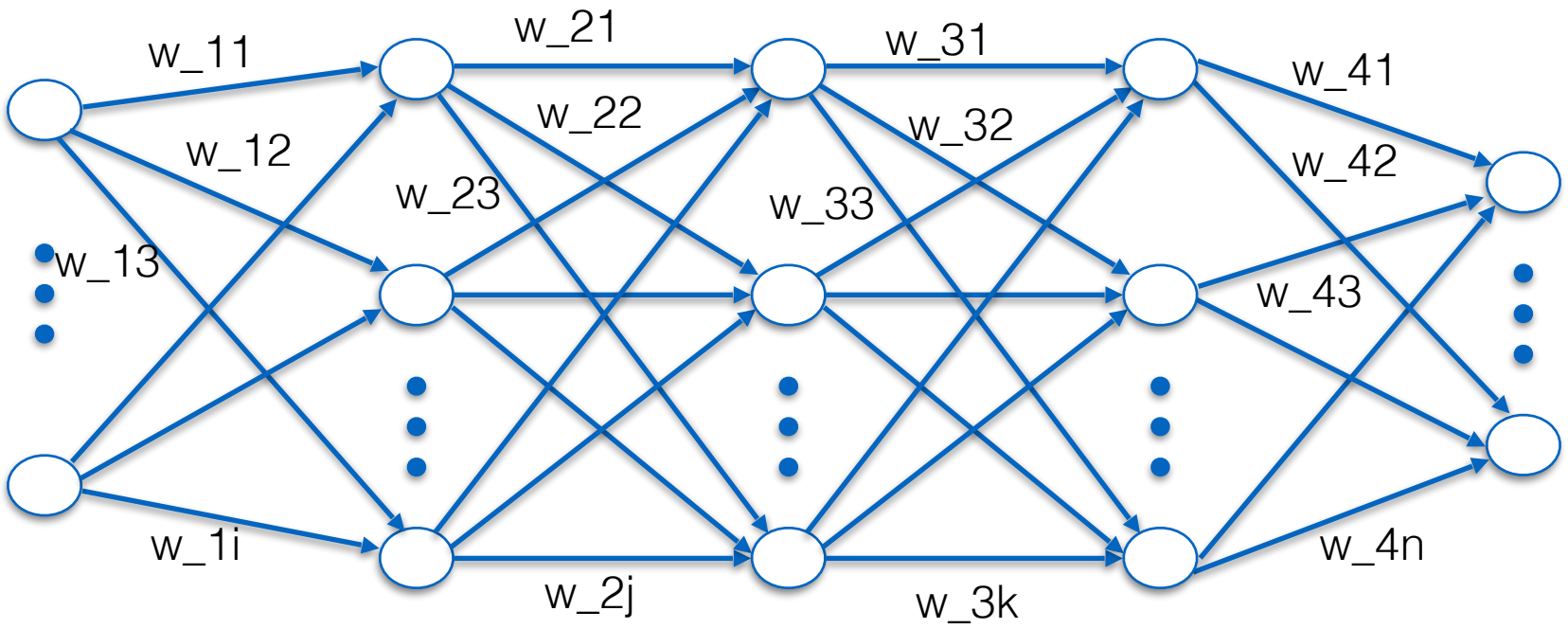


Deep Neural Networks



Learn parameters using
Stochastic Gradient Descent (SGD) algorithm

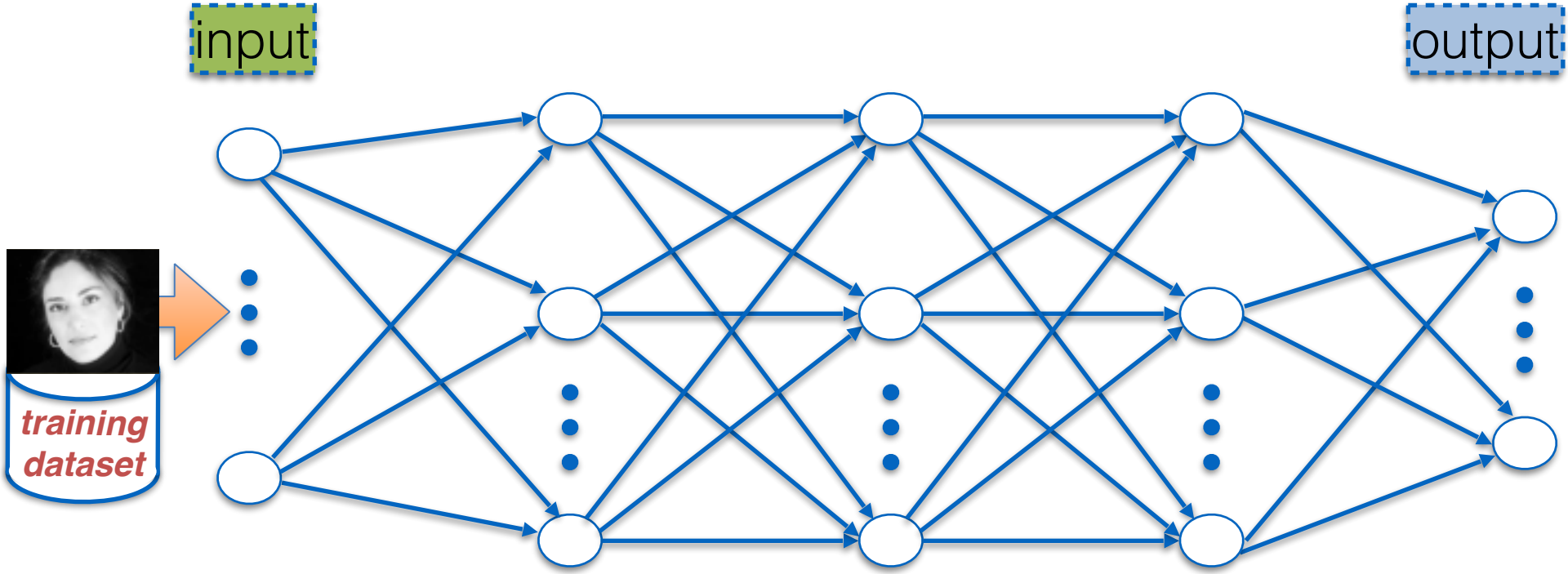
Parameter Training using SGD



- Find parameters that minimize the classification error

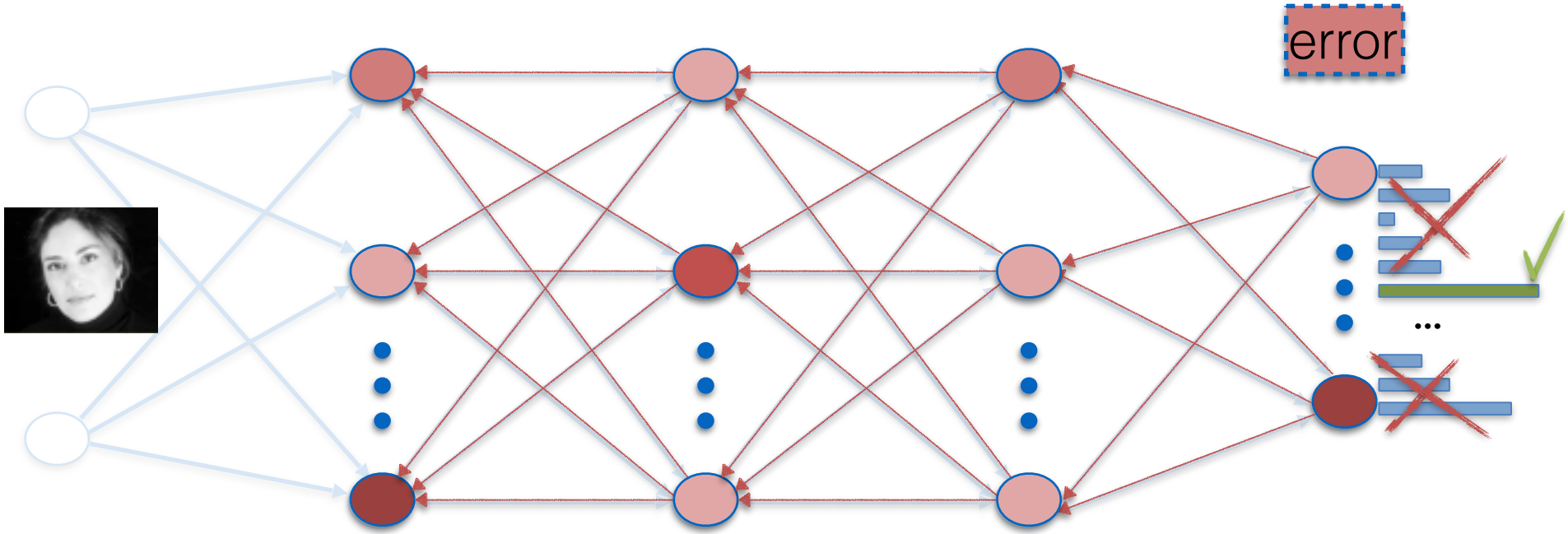
Parameter Training using SGD

1) Feed-Forward

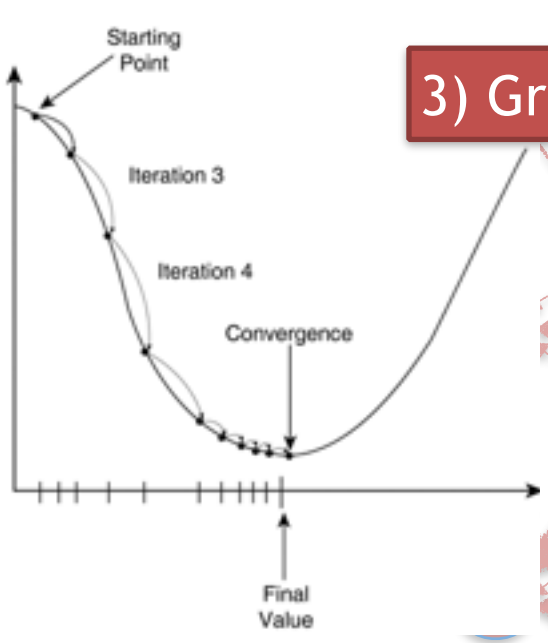


Parameter Training using SGD

2) Back-propagation



Parameter Training using SGD



3) Gradient Descent

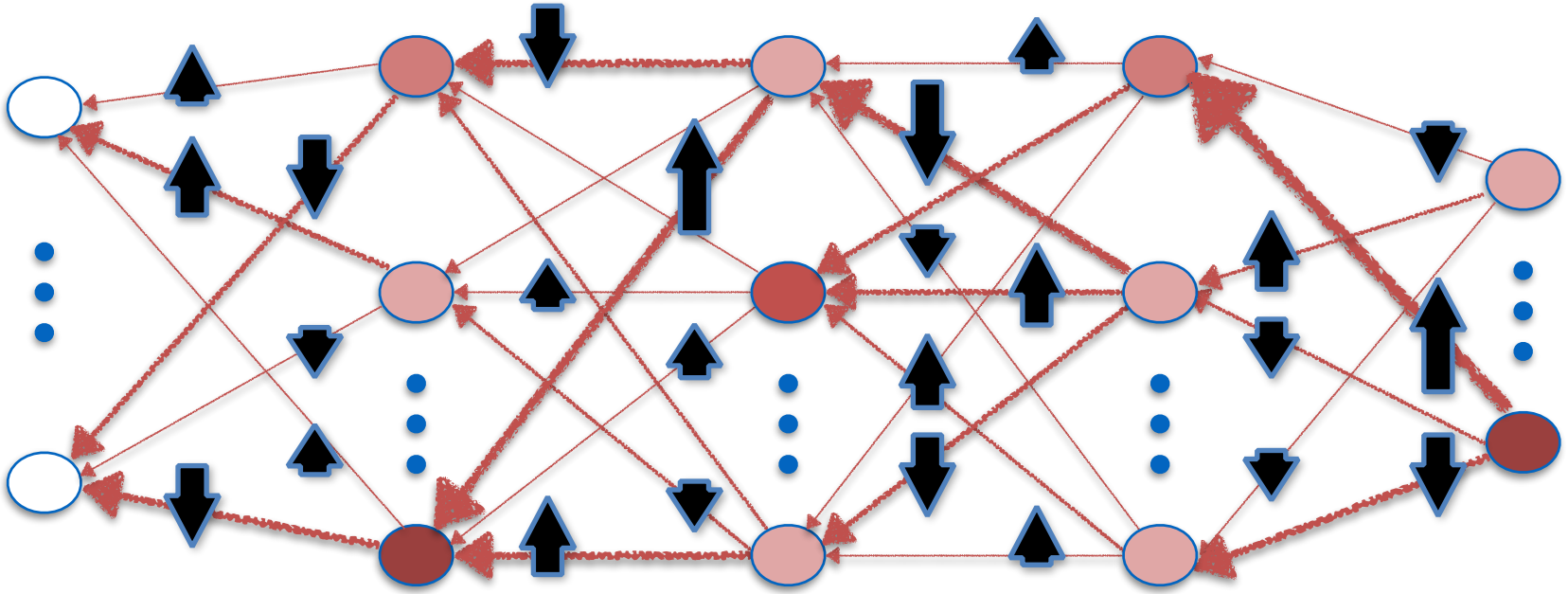
$$w_j := w_j - \alpha \frac{\partial E}{\partial w_j}$$

error E

$$\frac{\partial E}{\partial w_j}$$

Parameter Training using SGD

Parameter Update

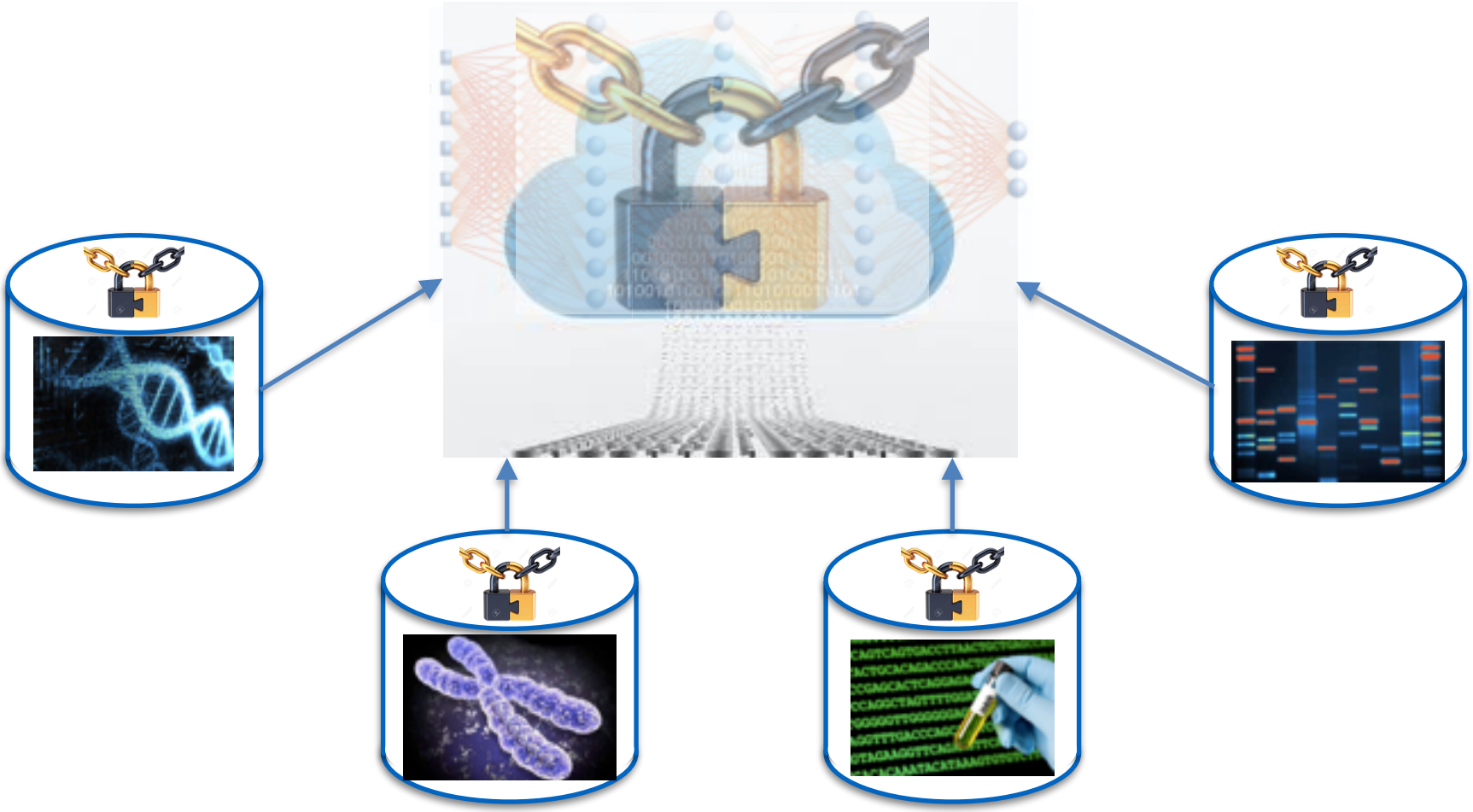


Repeat for new batches of training data

Privacy-Preserving Deep Learning

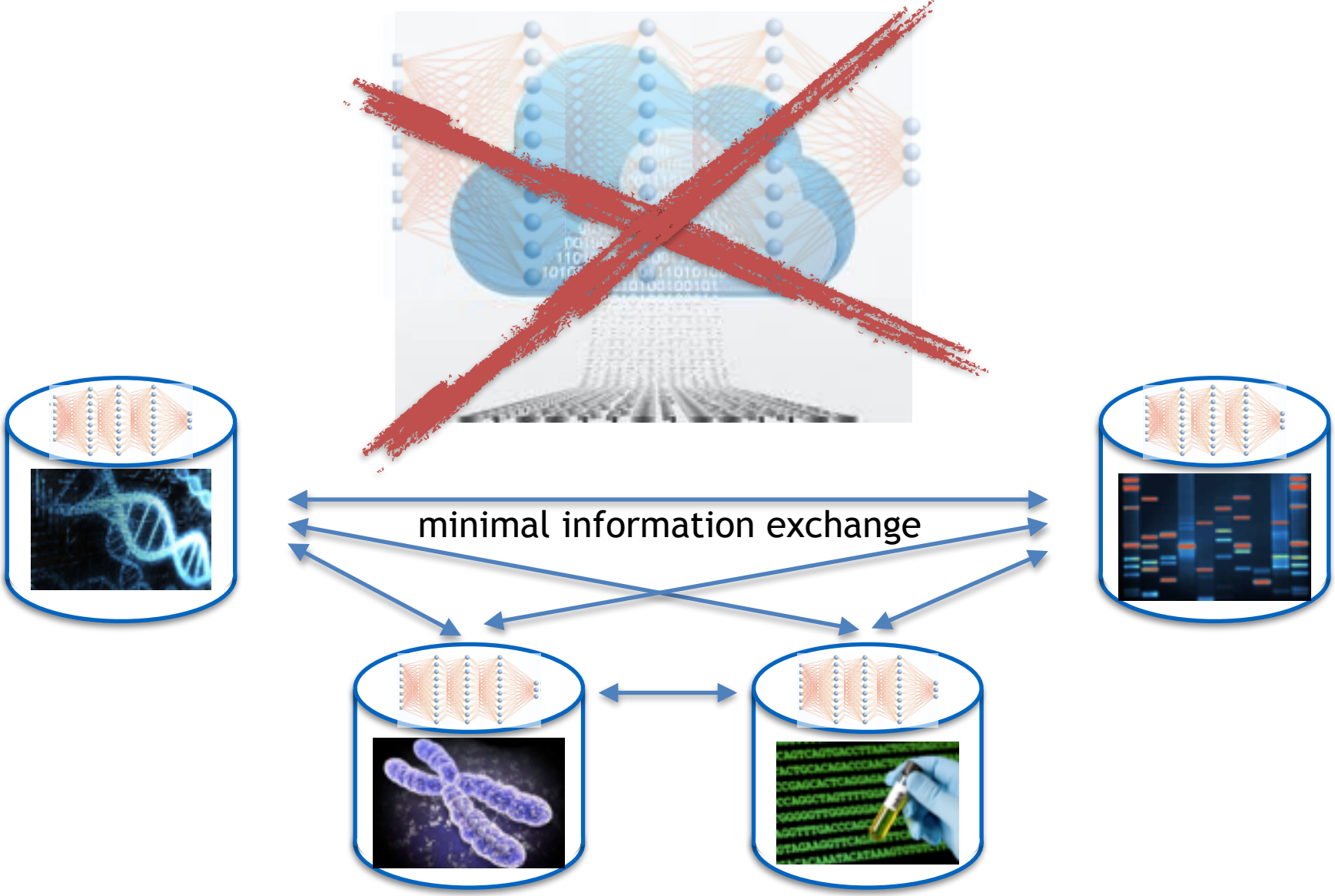
Prior Work

Secure multi-party computation



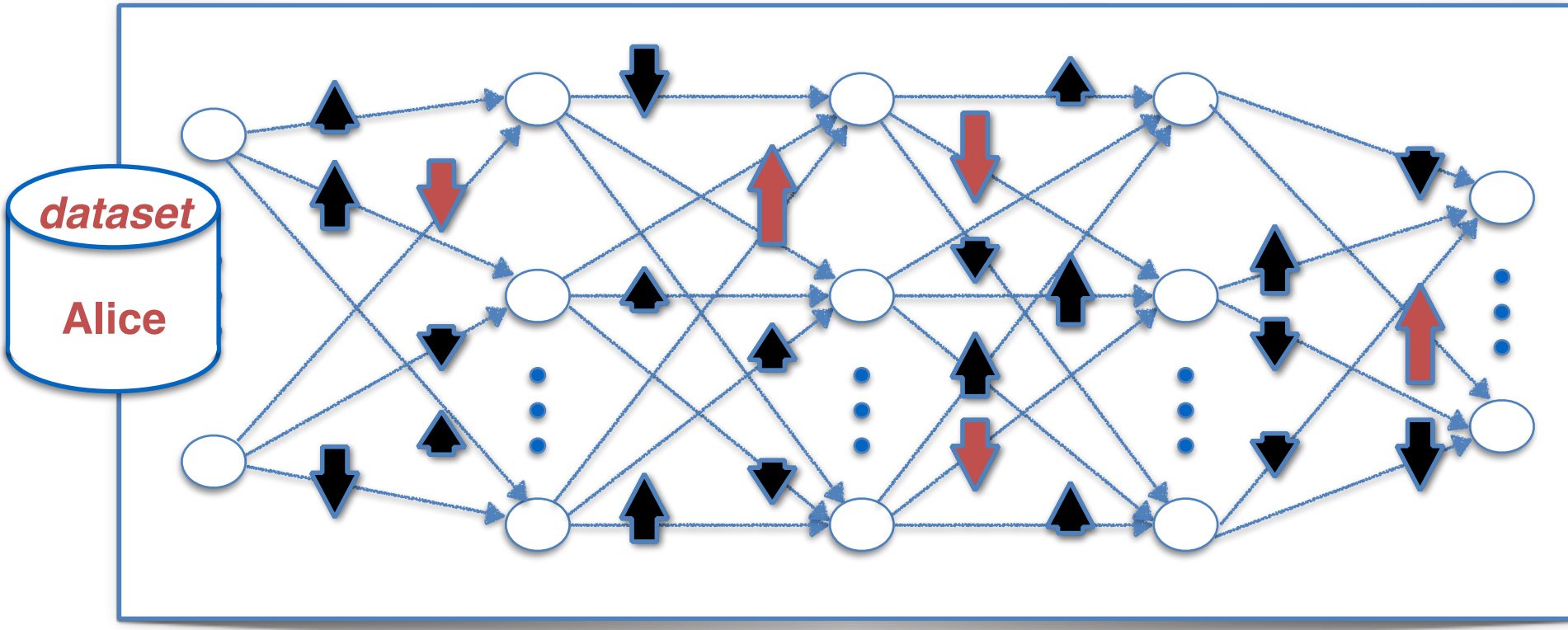
J. Yuan, S. Yu, "Privacy Preserving Back-Propagation Neural Network Learning Made Practical with Cloud Computing", IEEE TPDS, 2014.

A. Bansal, T. Chen, S. Zhong, "Privacy preserving Back-propagation neural network learning over arbitrarily partitioned data", Neural Computing and Applications, 2011



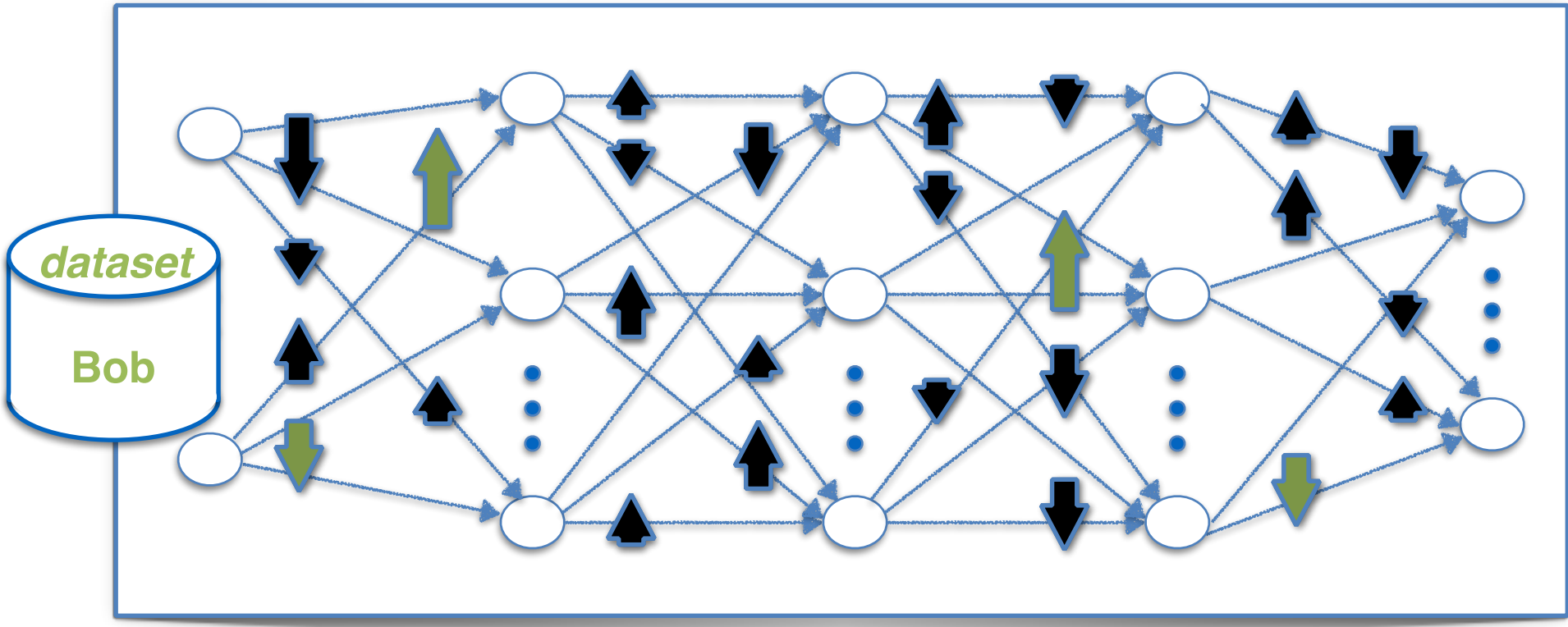
Distributed Selective SGD (DSSGD)

Selective SGD

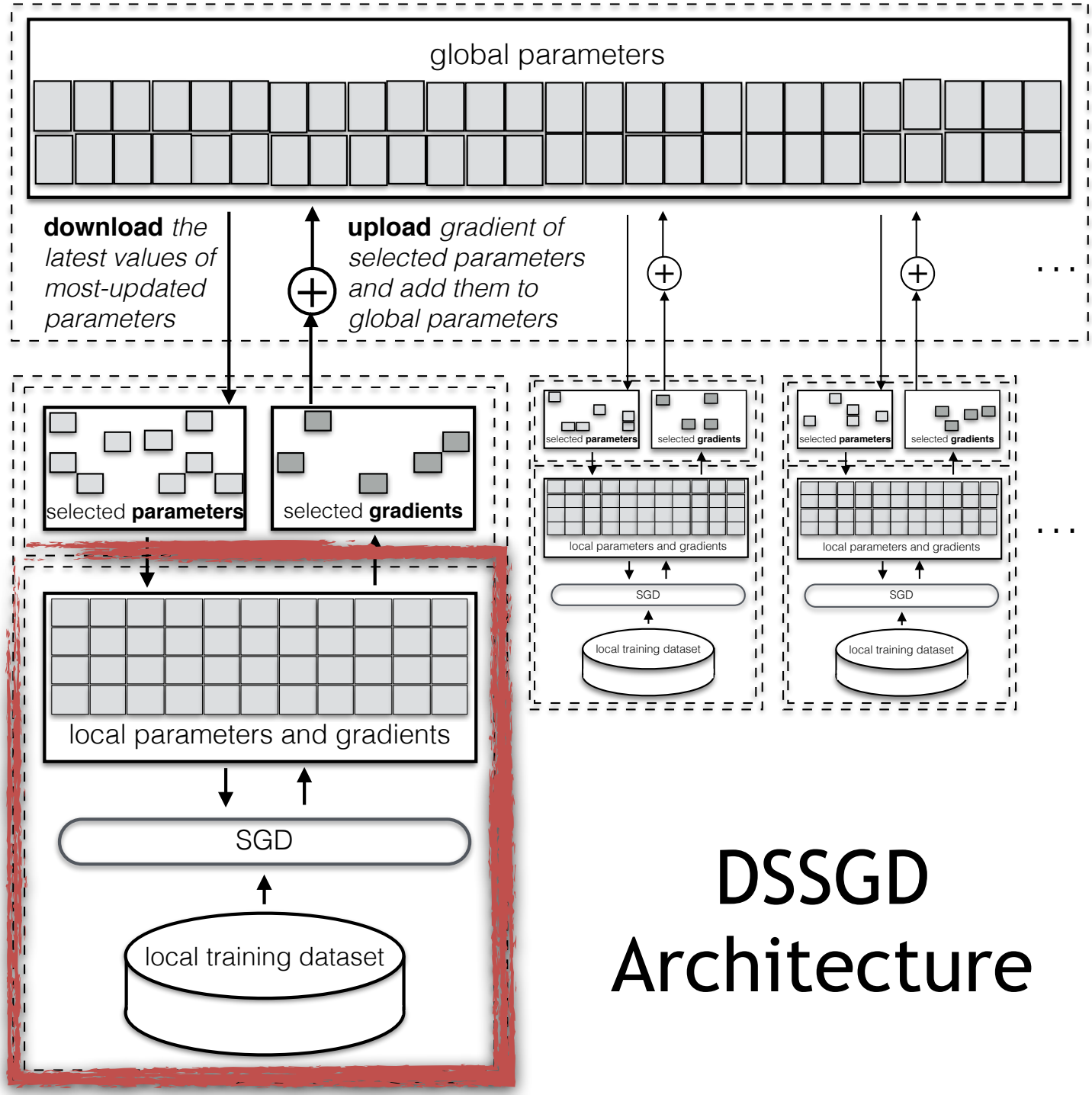


Share with others

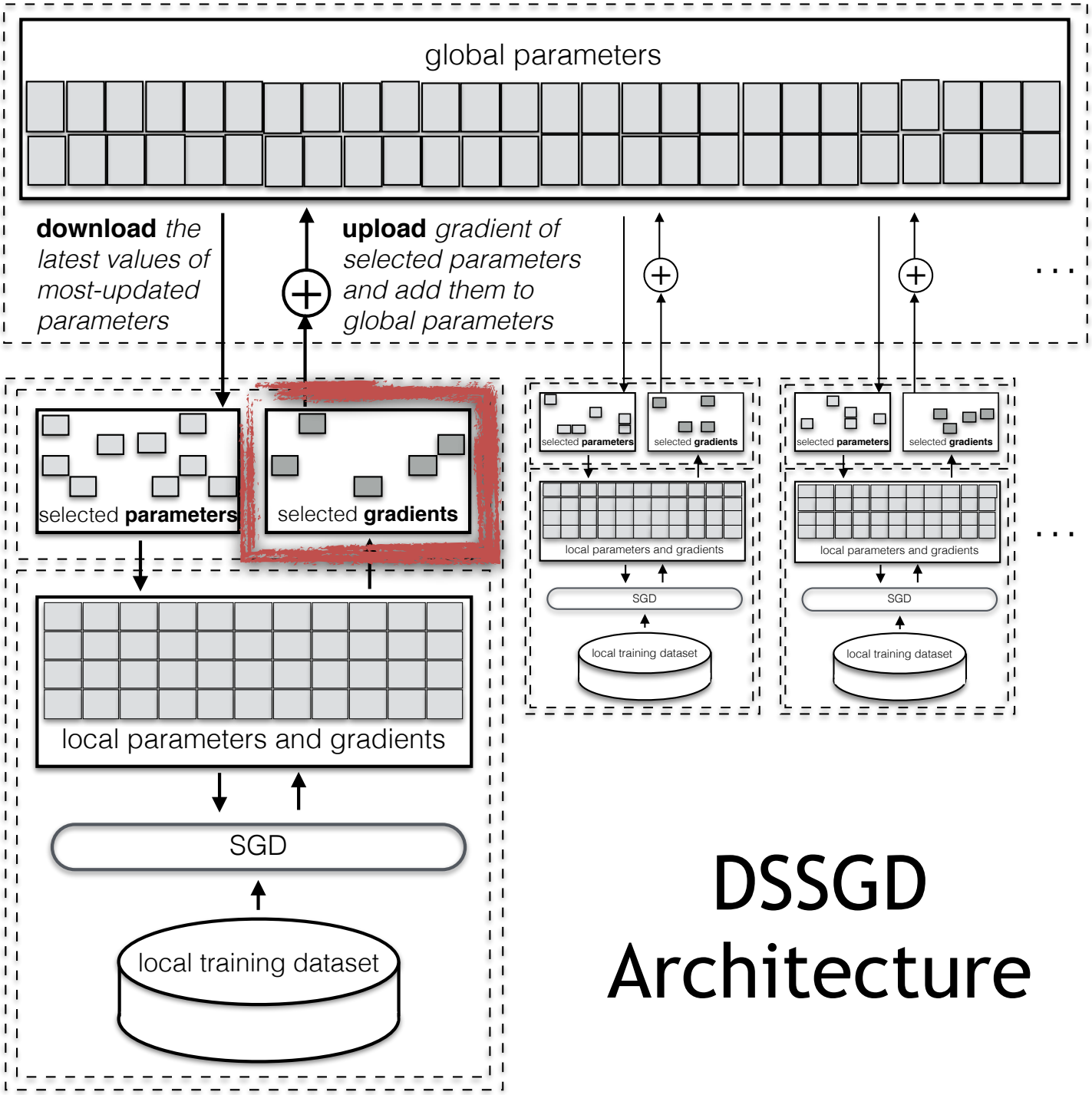
Selective SGD



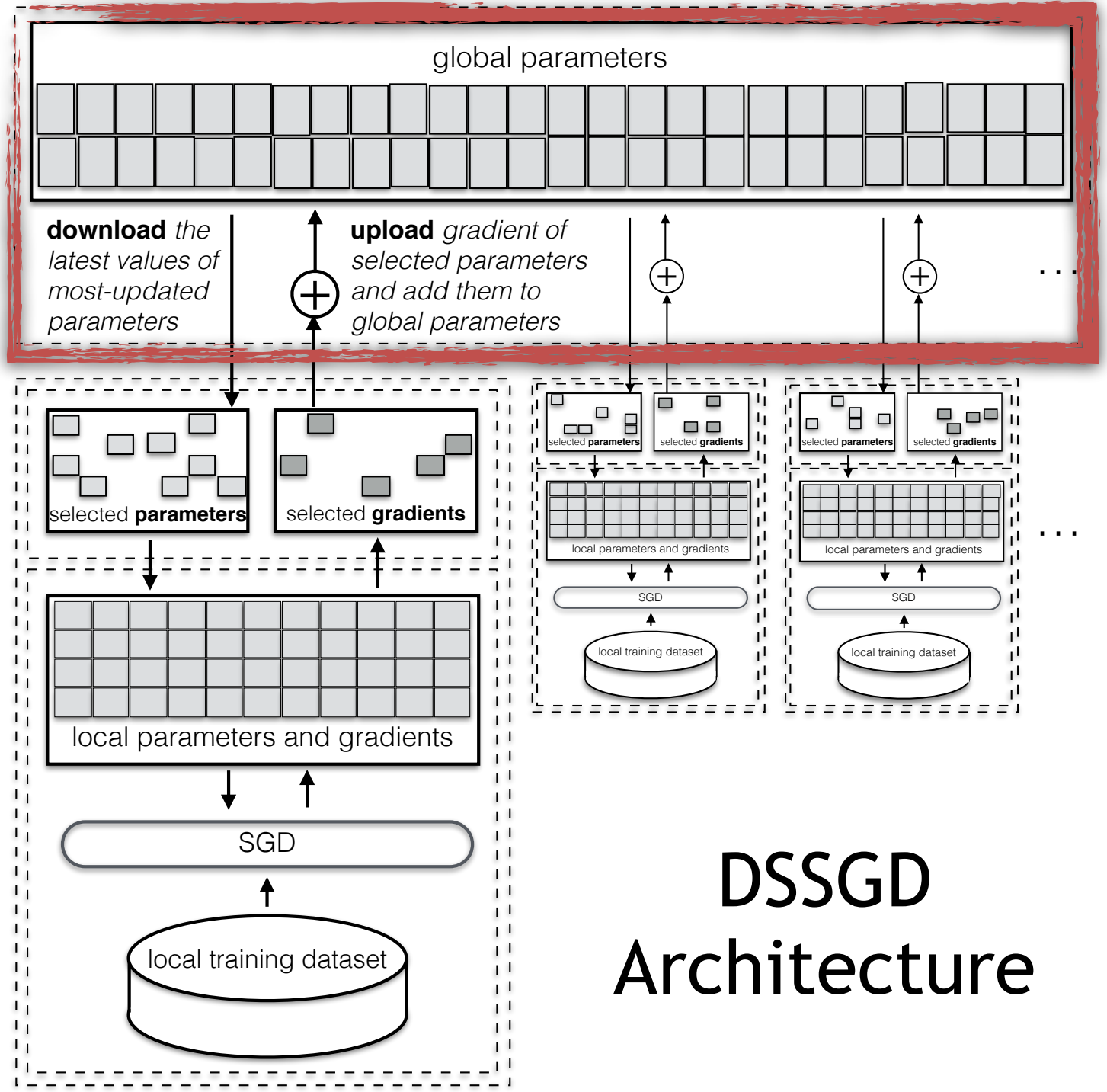
Share with others



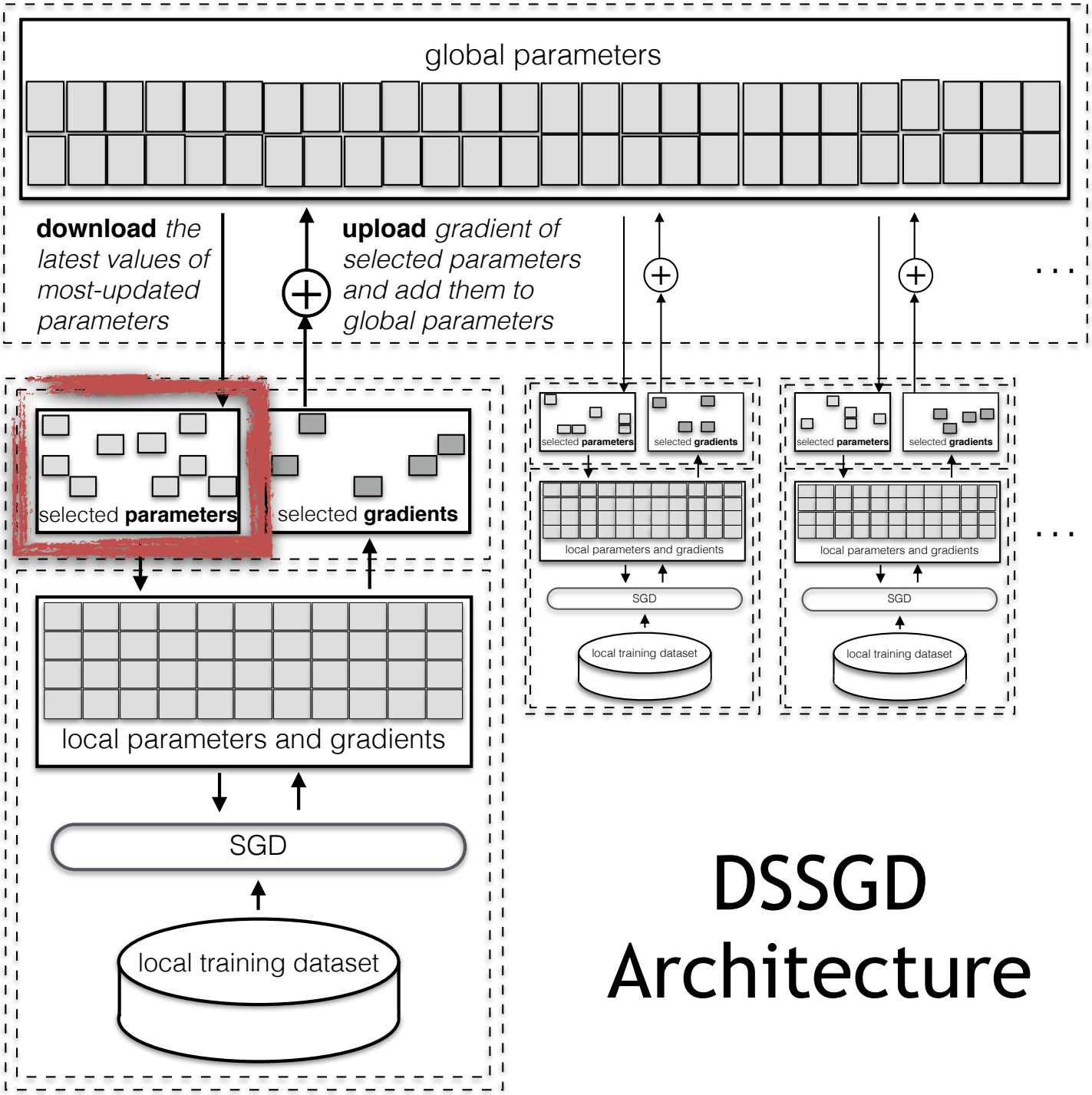
DSSGD Architecture



DSSGD Architecture



DSSGD Architecture



DSSGD Architecture

Distributed Selective SGD

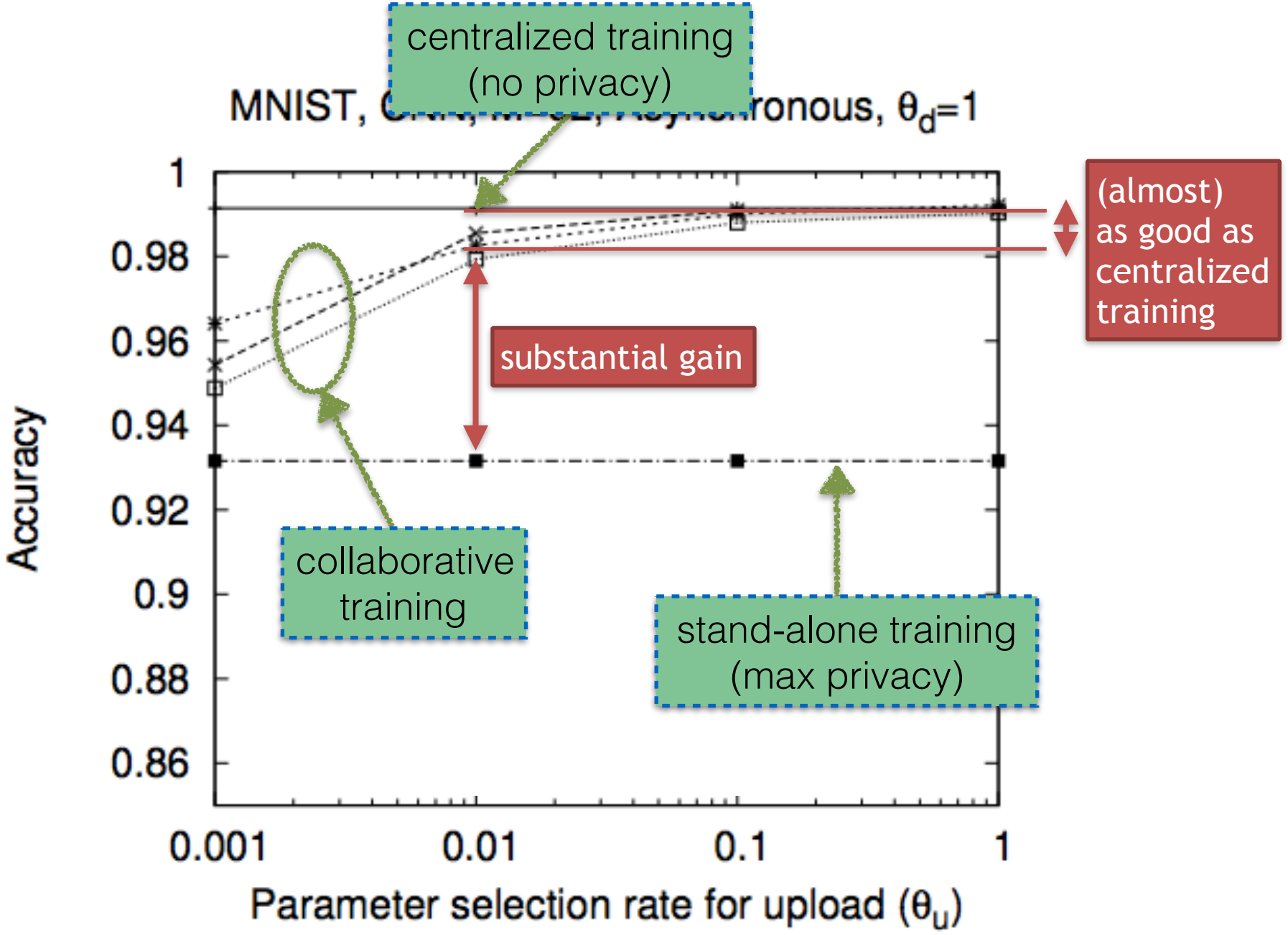
- Local training, Global convergence
- High training stochasticity
- Less overfitting

Evaluation Datasets

MNIST

SVHN

Task: Find the digit in the image (classify into one of 10 classes)

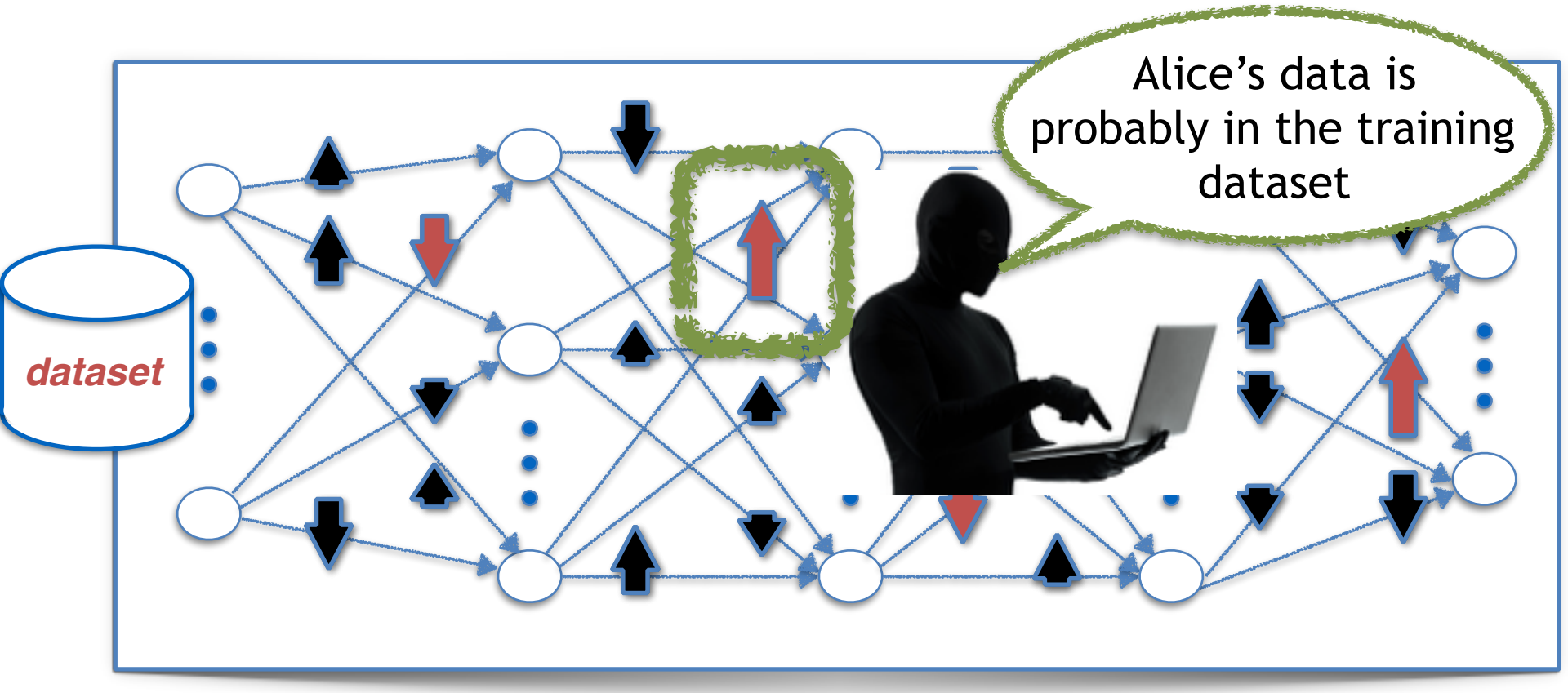

centralized training
(no privacy)
MNIST, ronous, θ_d=1
(almost)
as good as
centralized
training
substantial gain
collaborative
training
stand-alone training
(max privacy)
Accuracy
1
0.98
0.96
0.94
0.92
0.9
0.88
0.86
0.001
0.01
0.1
1
Parameter selection rate for upload (θ_u)

Privacy Properties

- Participants' datasets remain private
- Full control over parameter selection
- Known learning objective
- Resulting model available to all parties

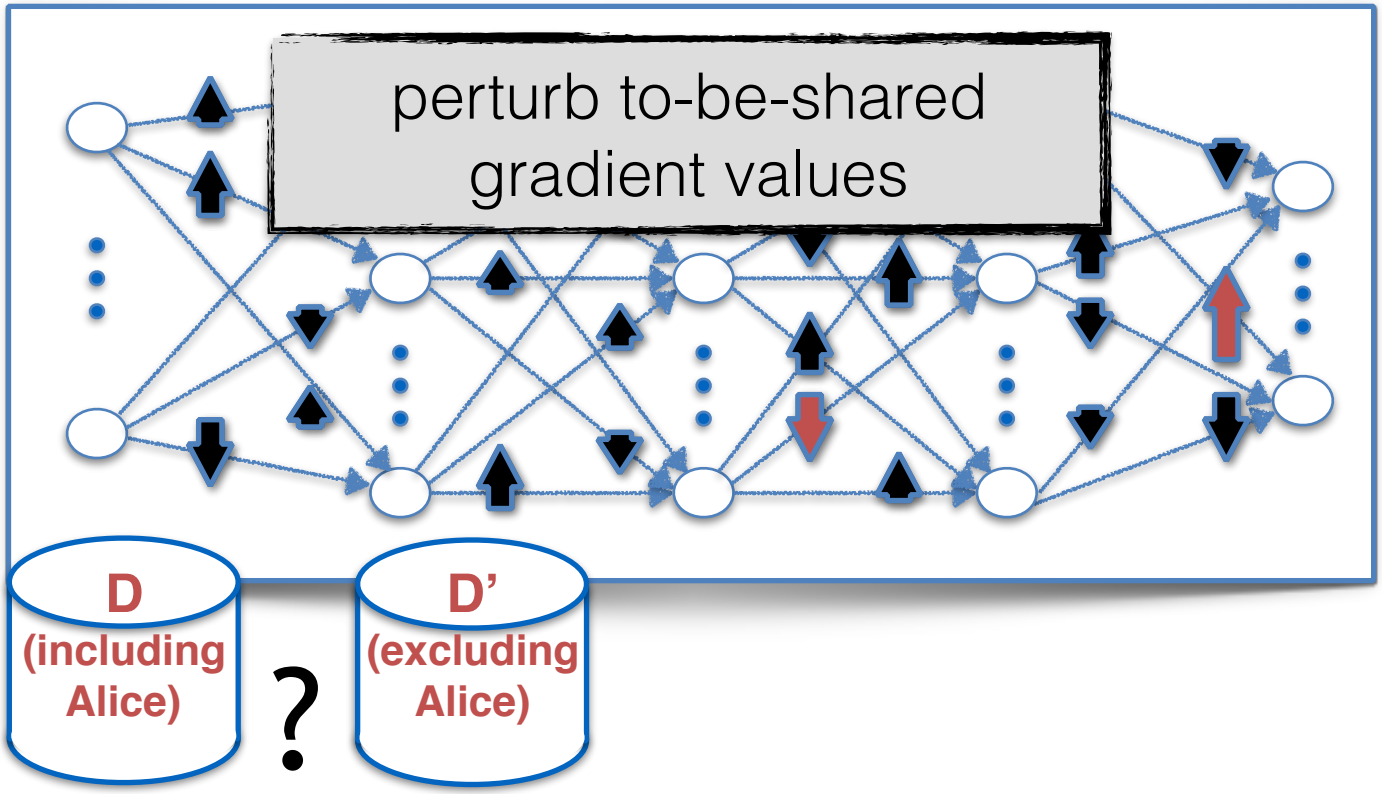
Indirect Information Leakage

through gradient sharing



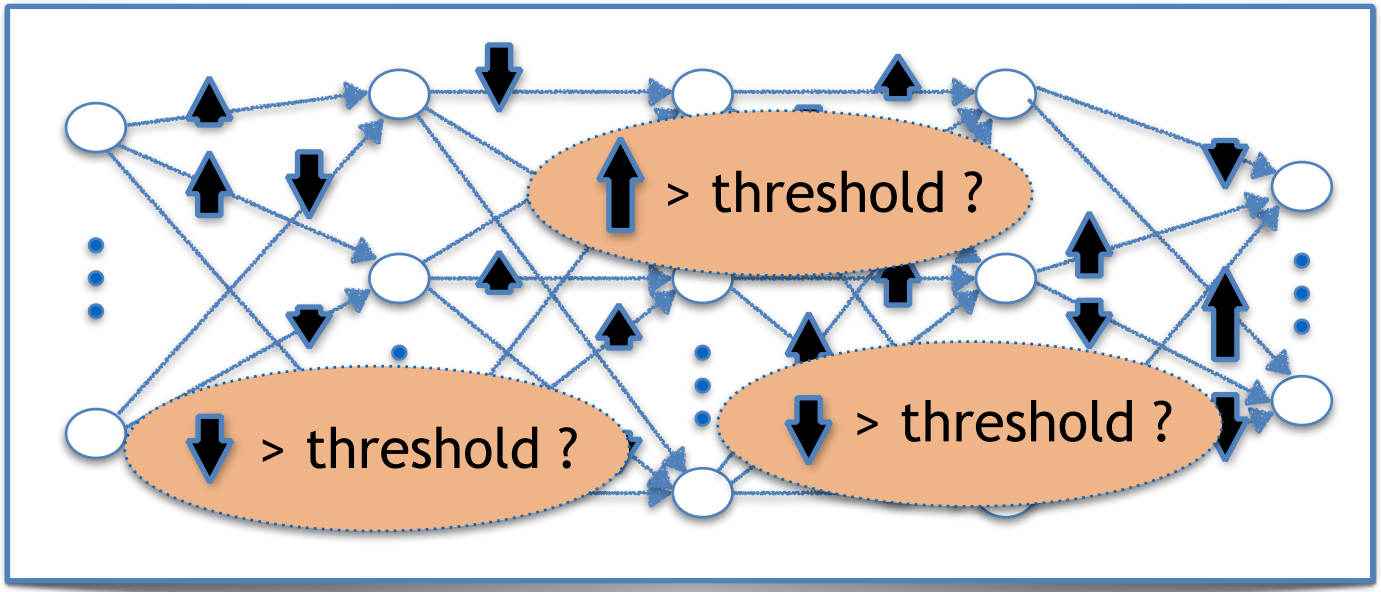
Limit Indirect Info. Leakage

- *Differentially Private* parameter selection and gradient sharing



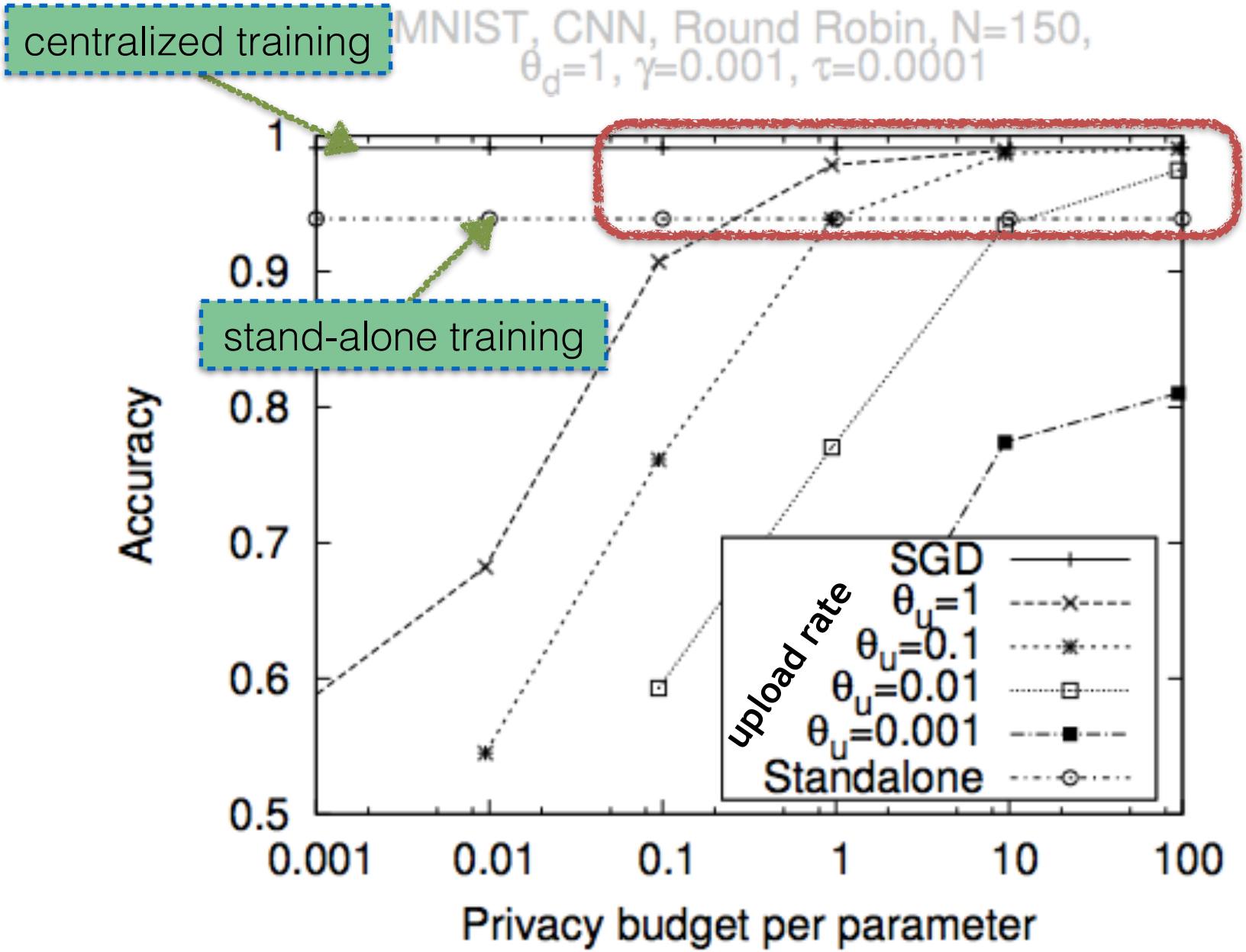
Sparse Vector Technique

- Select a small fraction of (perturbed) gradients that are above a given (perturbed) threshold



C. Dwork and A. Roth. The algorithmic foundations of differential privacy. *Theoretical Computer Science*, 9(3-4):211–407, 2013.

differentially-private comparison


centralized training
stand-alone training
MNIST, CNN, Round Robin, N=150,
θd=1, γ=0.001, τ=0.0001
Accuracy
Privacy budget per parameter
1
0.9
0.8
0.7
0.6
0.5
0.001
0.01
0.1
1
10
100
upload rate
SGD
θu=1
θu=0.1
θu=0.01
θu=0.001
Standalone

Conclusions

- Massive data collection required for deep learning presents substantial privacy risks
- We design privacy-preserving deep learning system
  - Holders of sensitive data collaborate to build powerful models without sharing their data
- Differentially-private information exchange protocol
  - Prevents indirect leakage about participants' private datasets
- Accuracy of our system
  - is substantially better than that of standalone learning
  - is very close to accuracy of centralized SGD