Gradient Coding: Mitigating Stragglers in Distributed Gradient Descent.

Alex Dimakis

joint work with
R. Tandon, Q. Lei, UT Austin
N. Karampatziakis, Microsoft

Setup

- Problem: Large-scale learning.

- Given a lot of labeled examples and we want to fit a model, i.e. minimize a function.

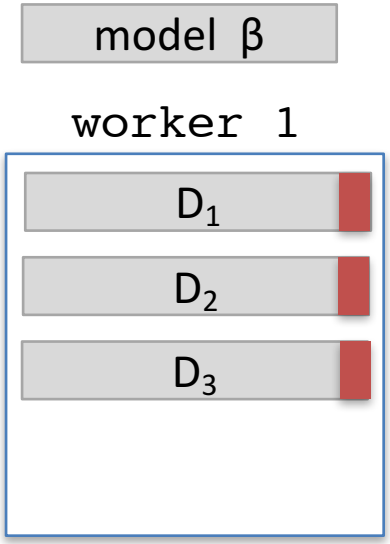
- Modern models are becoming very complex.
- Training takes a very long time

(dozens of hours, days, weeks)

Typical examples:

1. Big logistic regression (Ad prediction)
2. Training a deep neural network model.
   (vision, speech, NLP problems etc)

Gradient descent

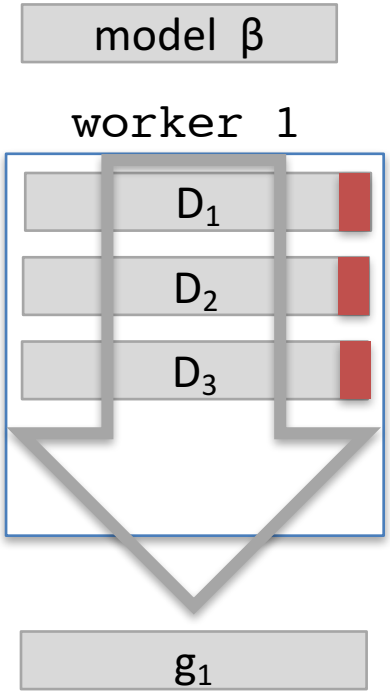


Loss: $L(\beta) = \sum_{i=1}^{d} \ell(\beta; x_i, y_i)$

Gradient descent update step: $\beta^{t+1} = \beta^t - \eta g^t$

Gradient has the form: $g^t = \sum_{i=1}^{d} \nabla \ell(\beta^t; (x_i, y_i))$

Gradient descent

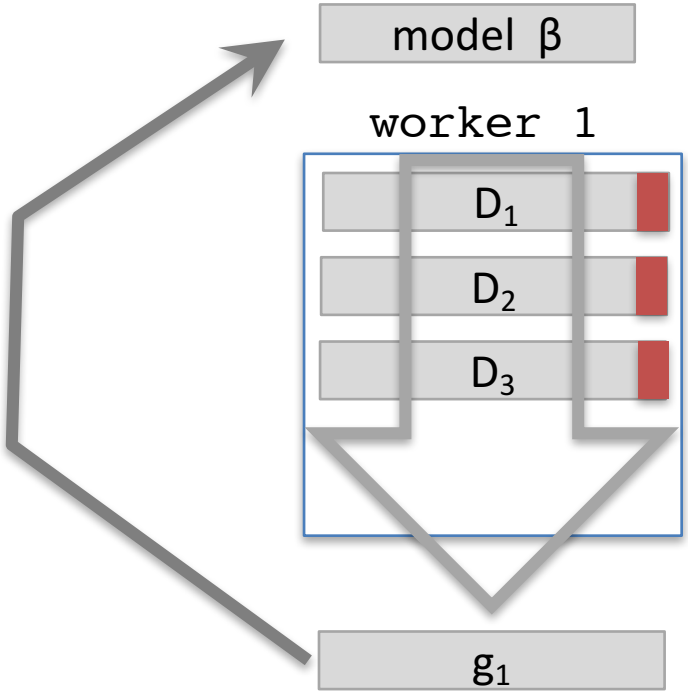


Loss: $L(\beta) = \sum_{i=1}^{d} \ell(\beta; x_i, y_i)$

Gradient descent update step: $\beta^{t+1} = \beta^t - \eta g^t$

Gradient has the form: $g^t = \sum_{i=1}^{d} \nabla \ell(\beta^t; (x_i, y_i))$

Gradient descent

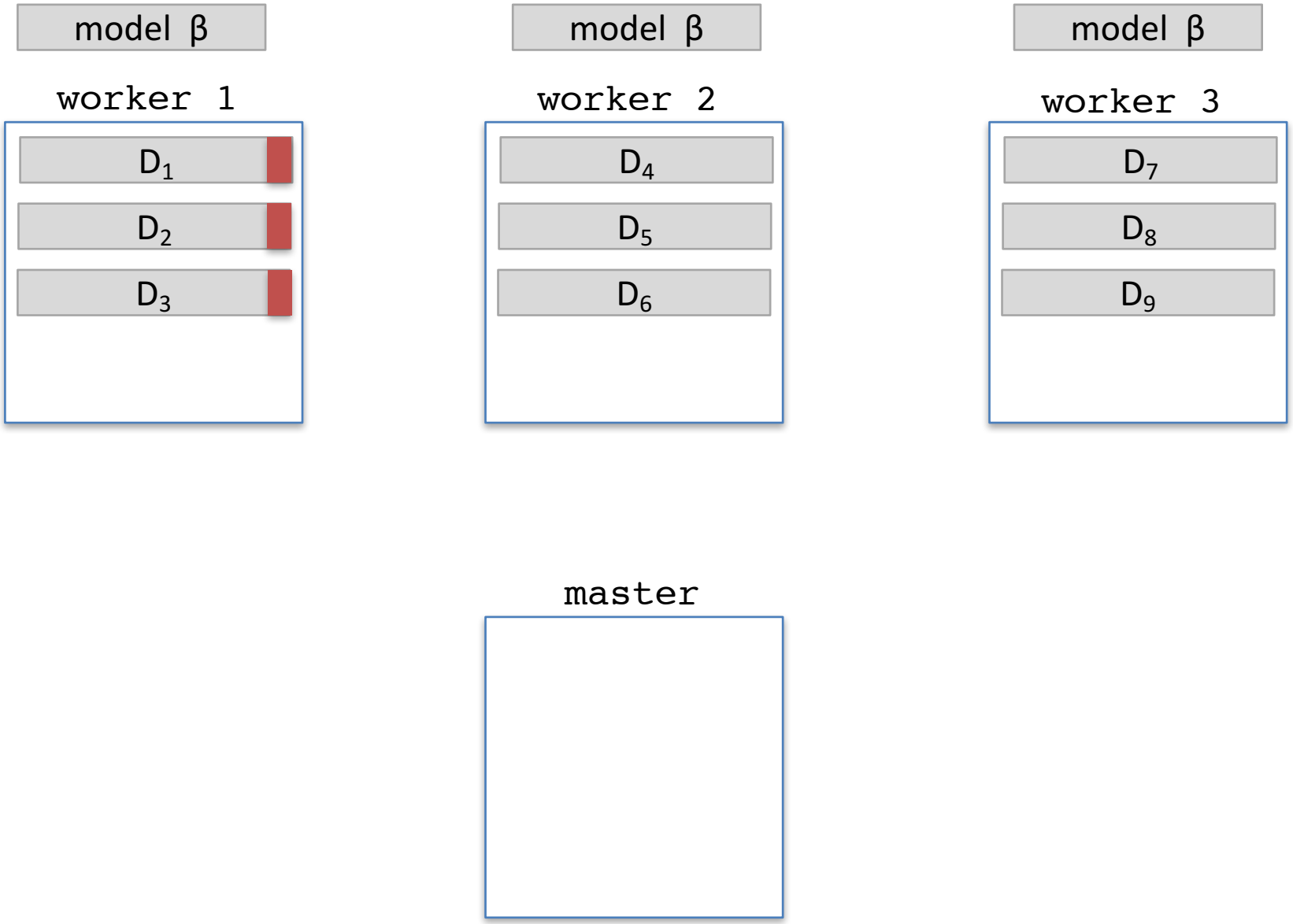


Loss: $L(\beta) = \sum_{i=1}^{d} \ell(\beta; x_i, y_i)$

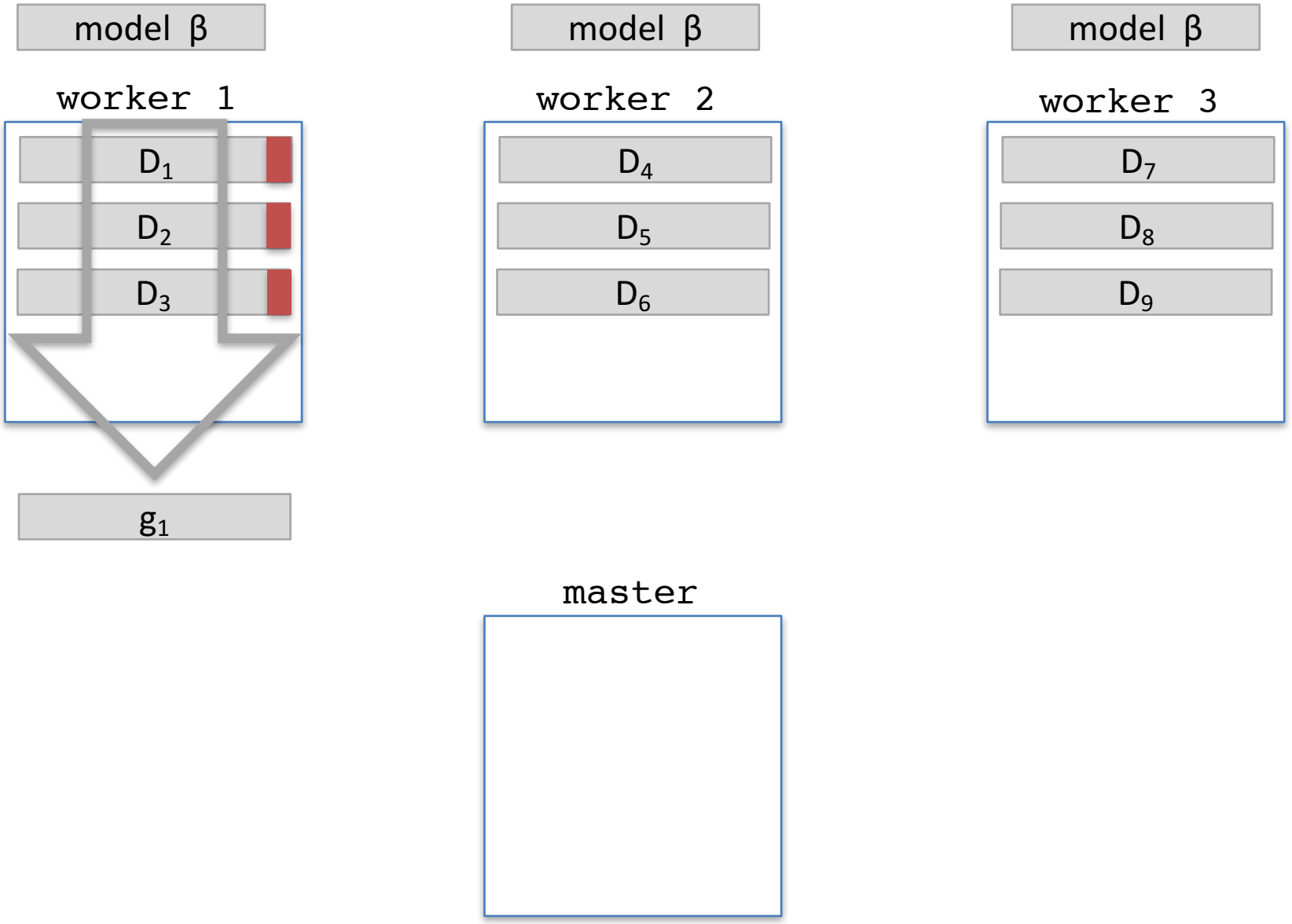
Gradient descent update step: $\beta^{t+1} = \beta^t - \eta g^t$

Gradient has the form: $g^t = \sum_{i=1}^{d} \nabla \ell(\beta^t; (x_i, y_i))$

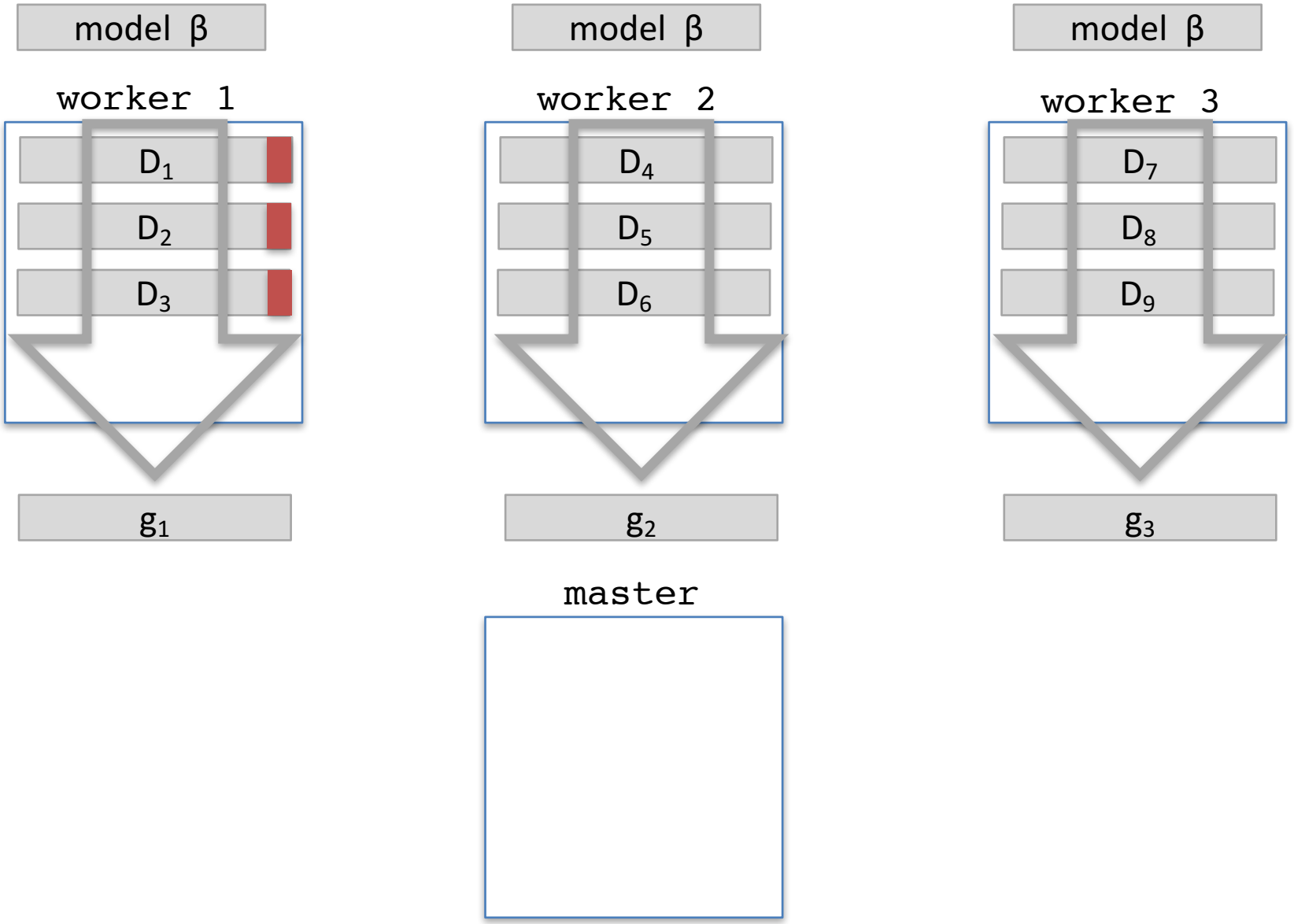
Distributed gradient descent



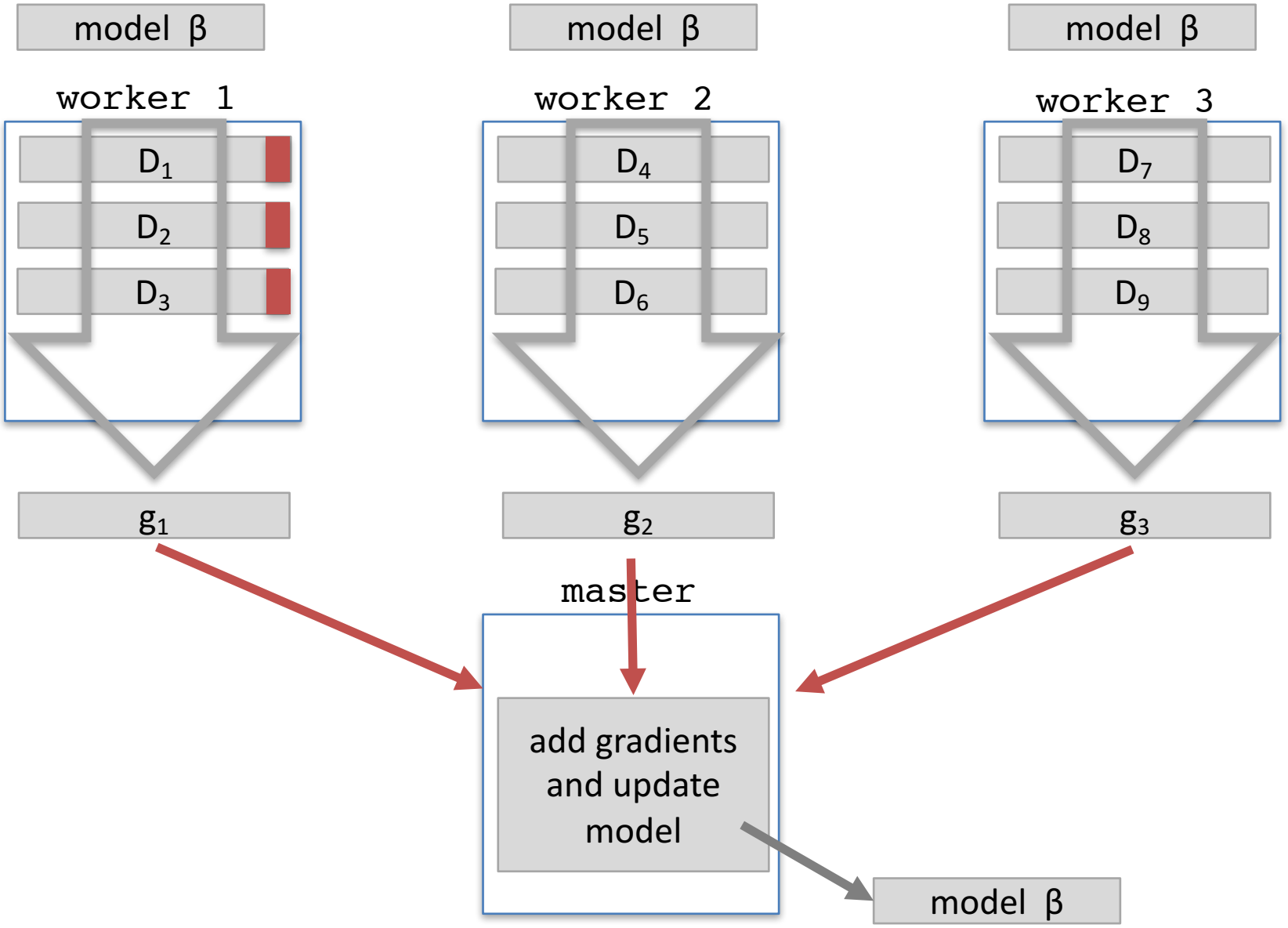
Distributed gradient descent



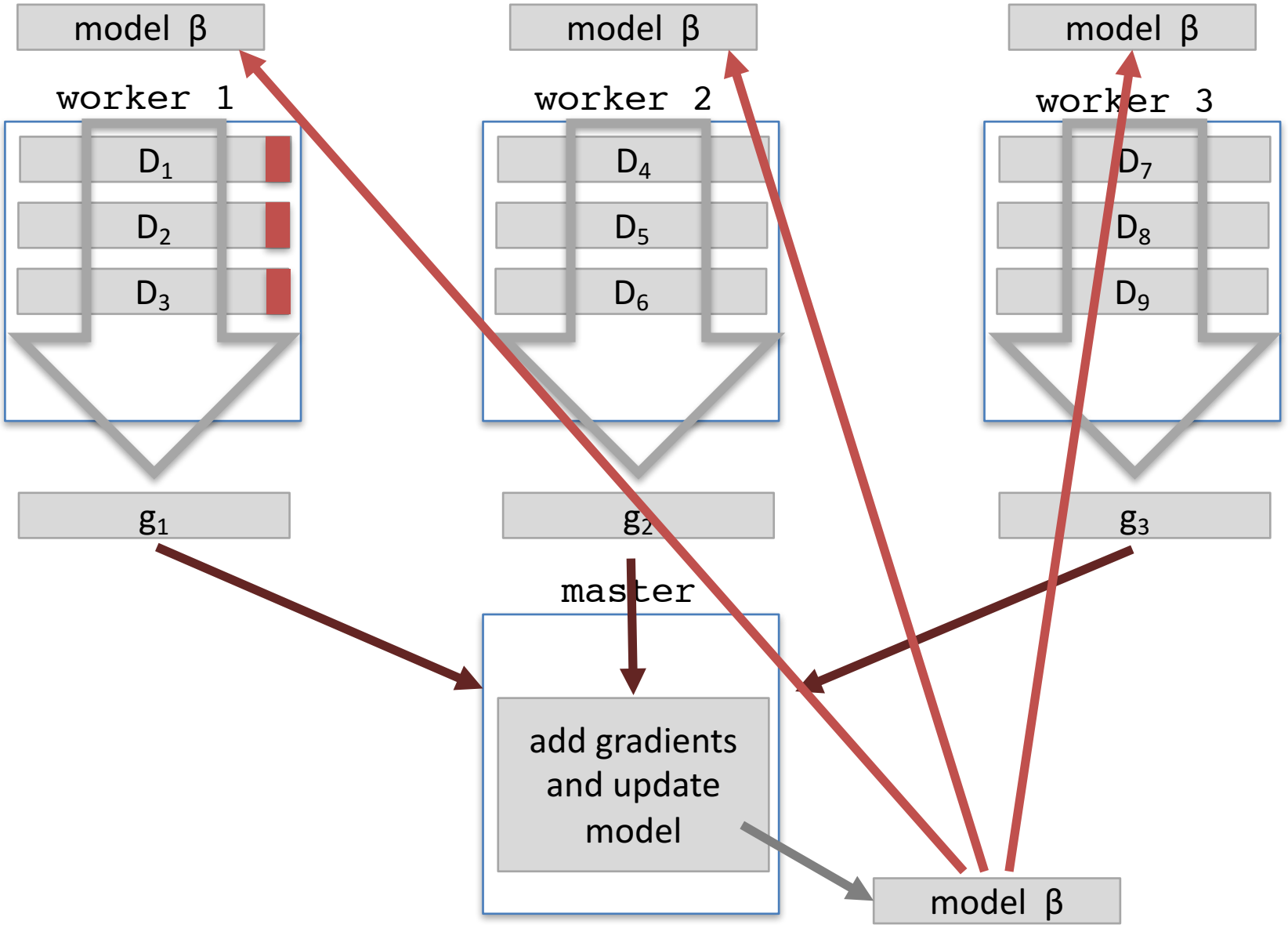
Distributed gradient descent



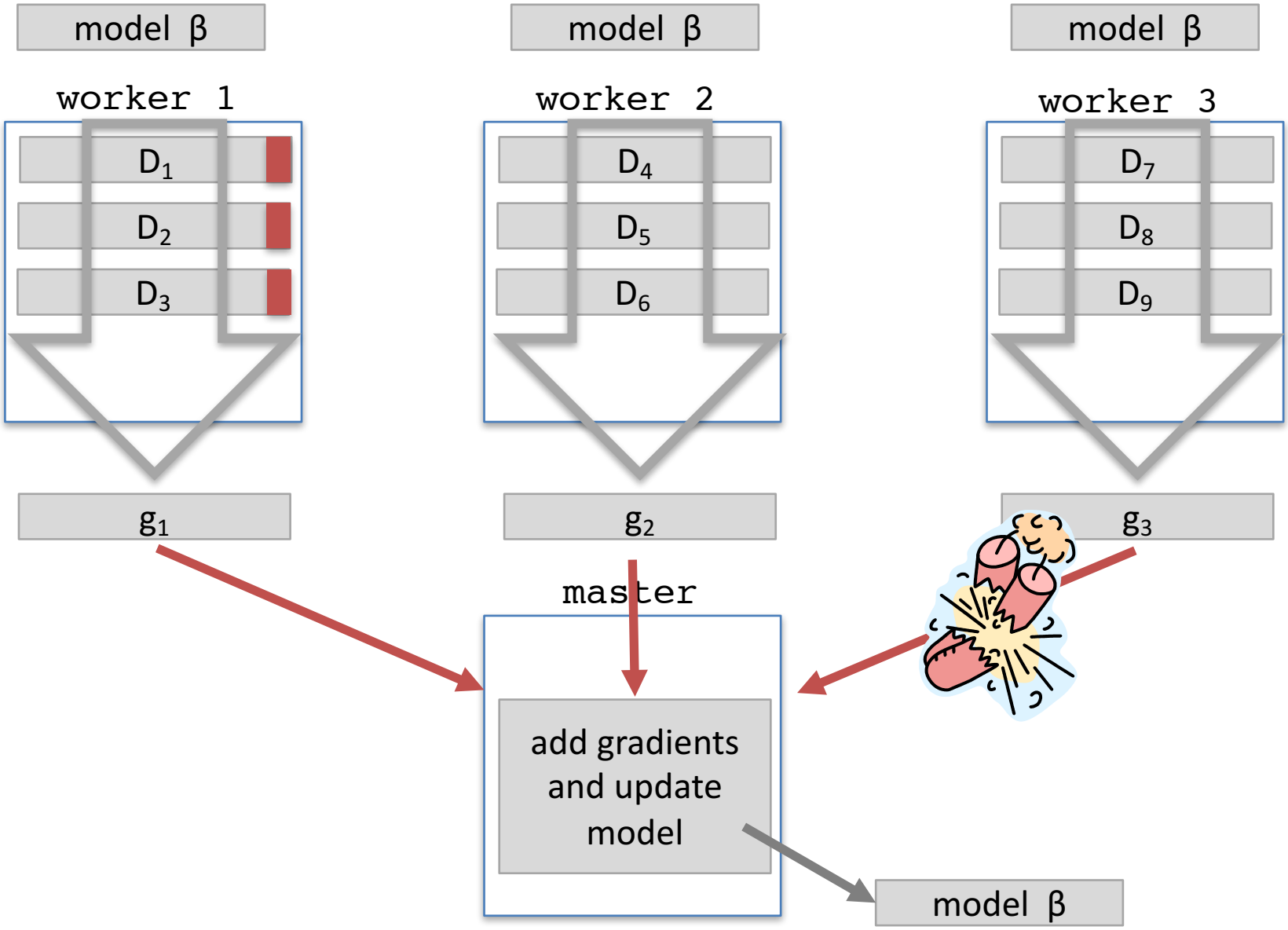
Distributed gradient descent



Distributed gradient descent



Distributed gradient descent



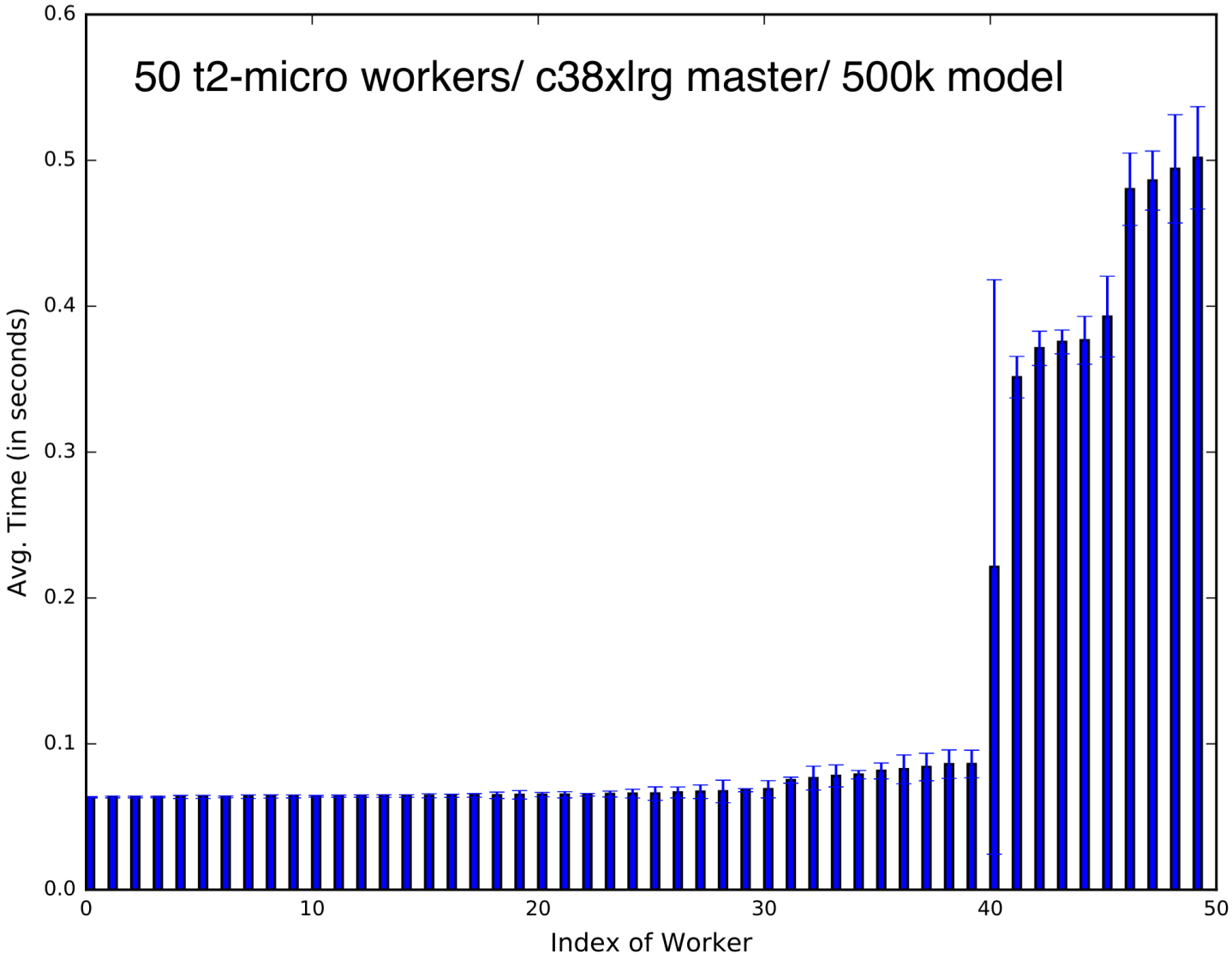
Distributed Synchronous Gradient Descent

- All workers have the model and process different data examples to compute different gradients.
- We simply want to add them all up and update the model
- After we update the model, send it back to the workers to re-compute gradients.
- Repeat this for a number of iterations.

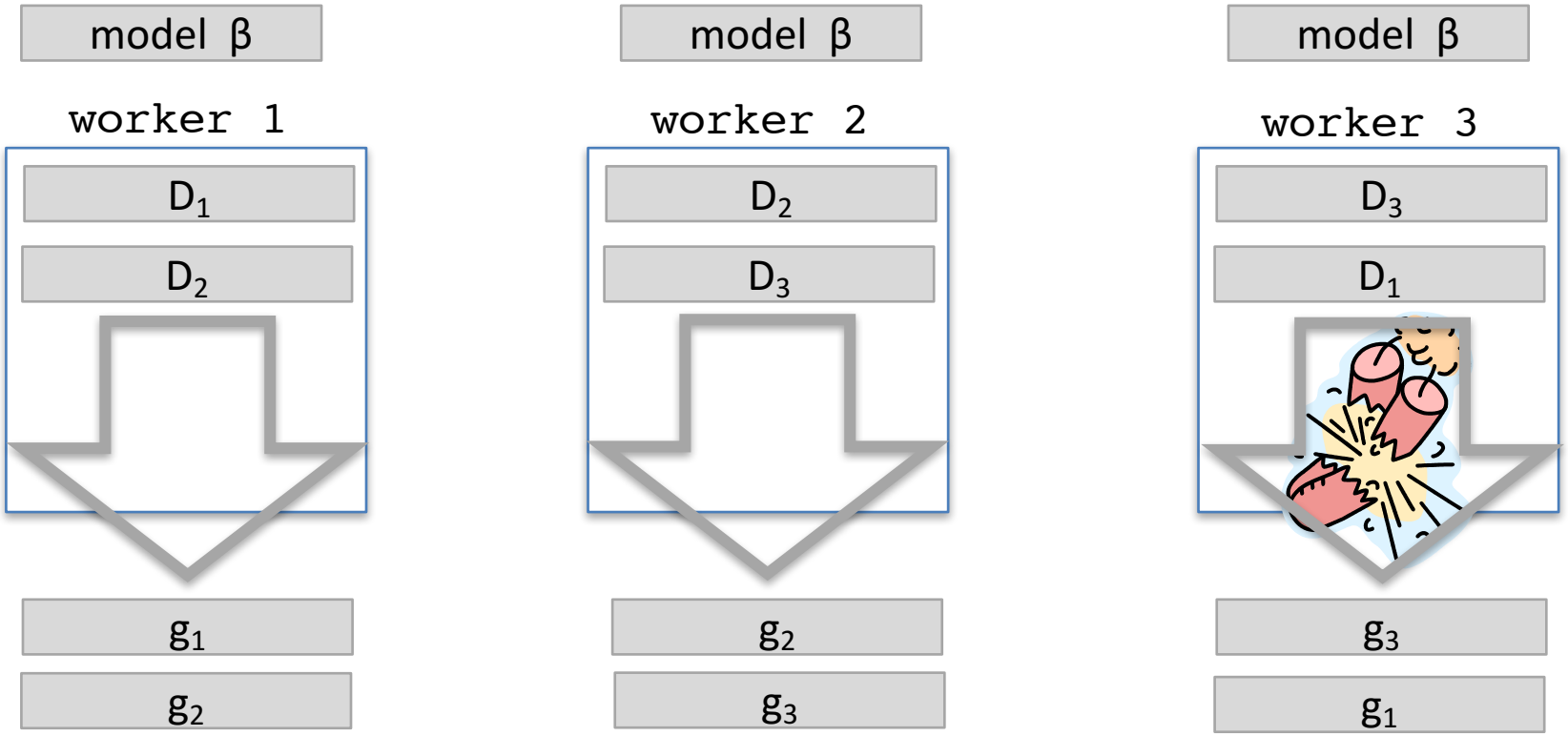
- Problem: **Stragglers**. Some machines take too long to send their gradient.

- **Communication** seems to be the bottleneck

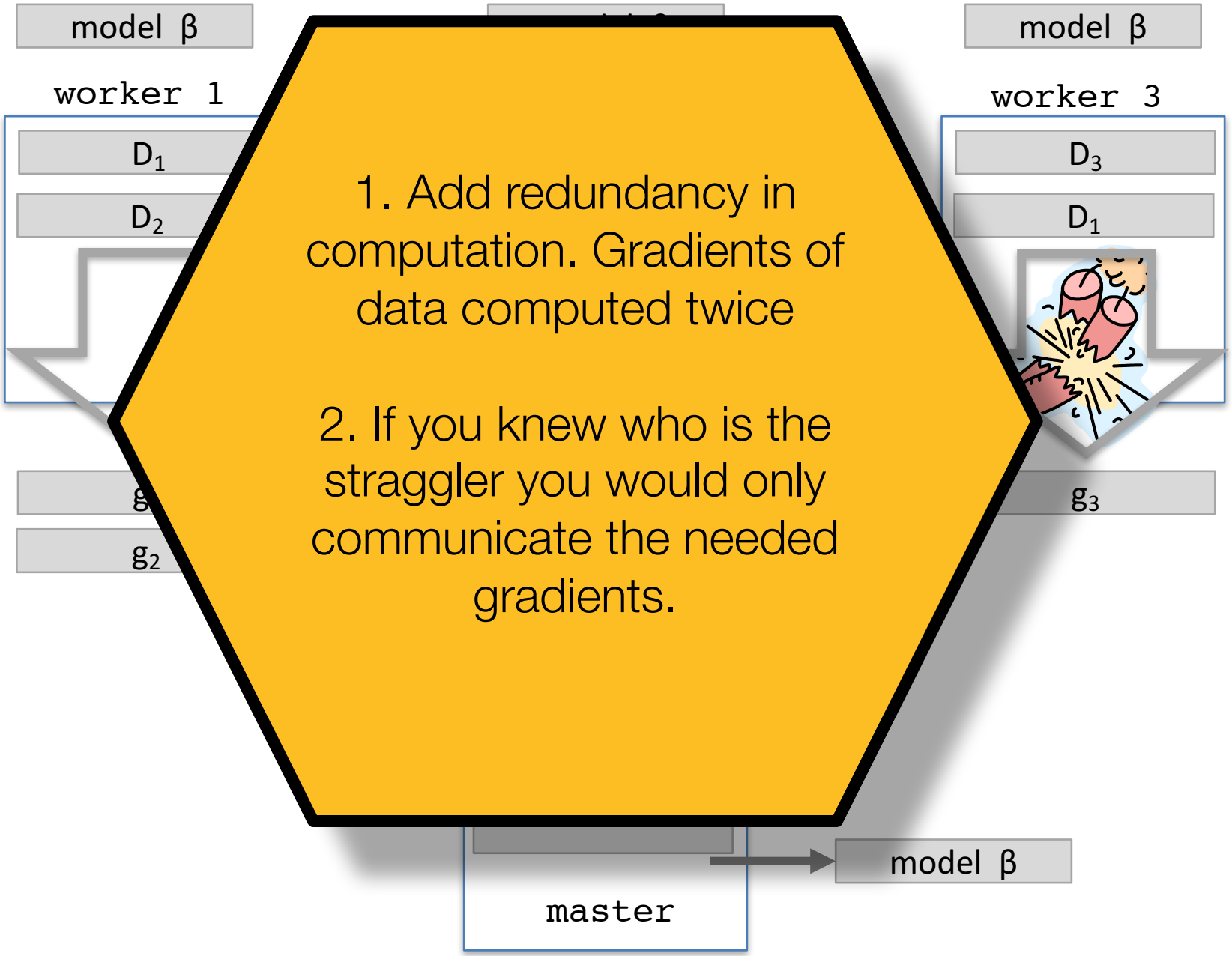
How much Straggling is there?



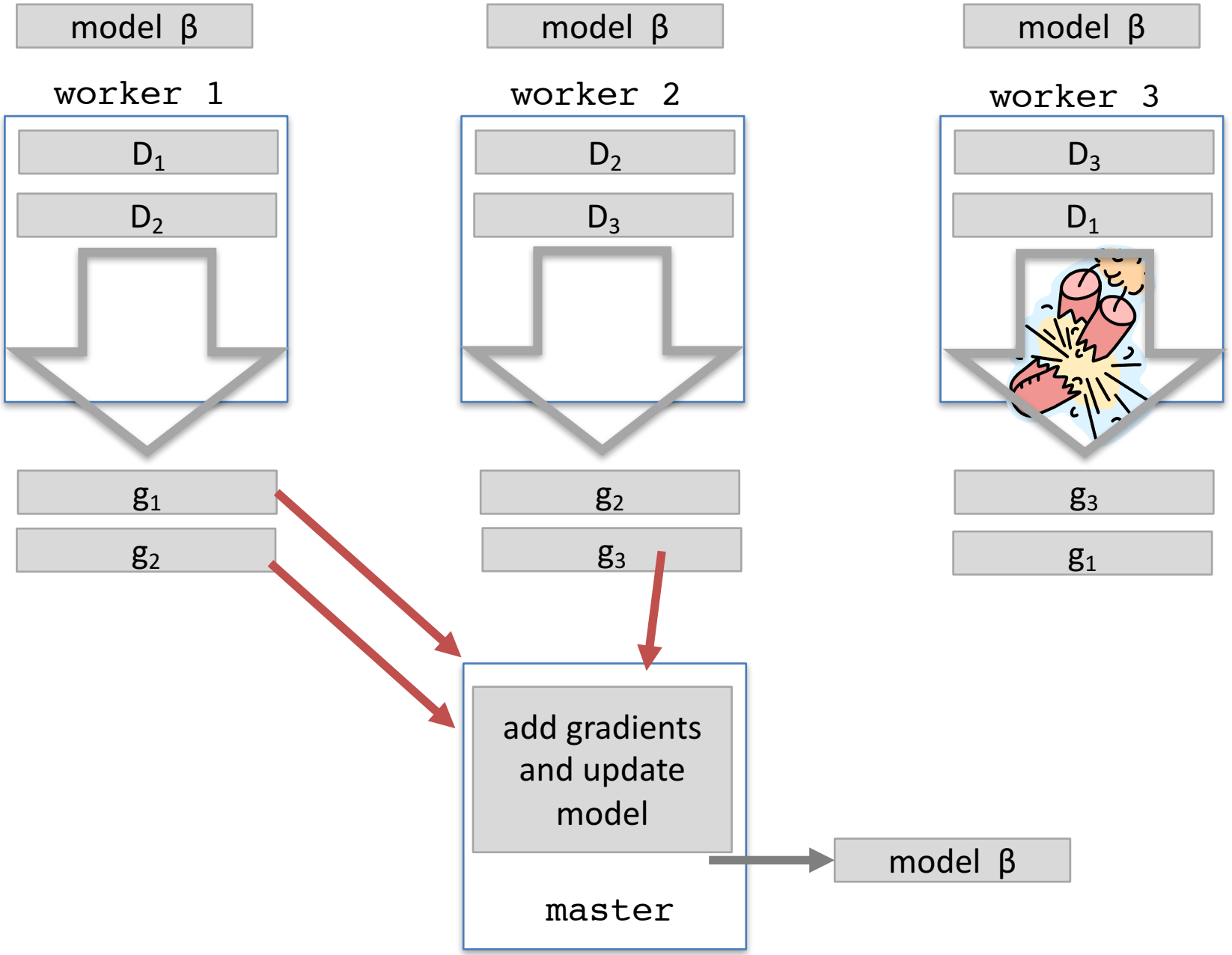
Gradient coding



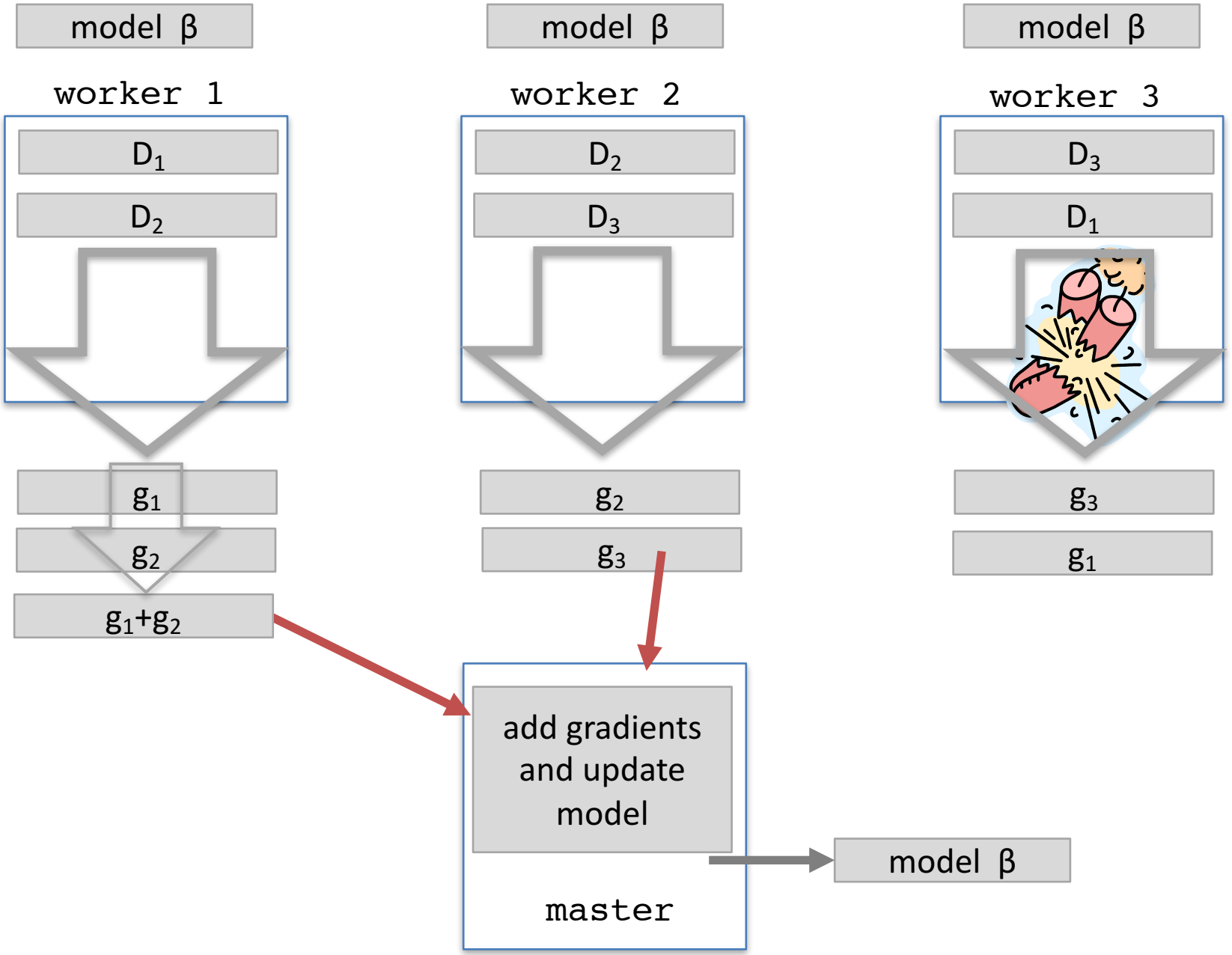
Gradient coding



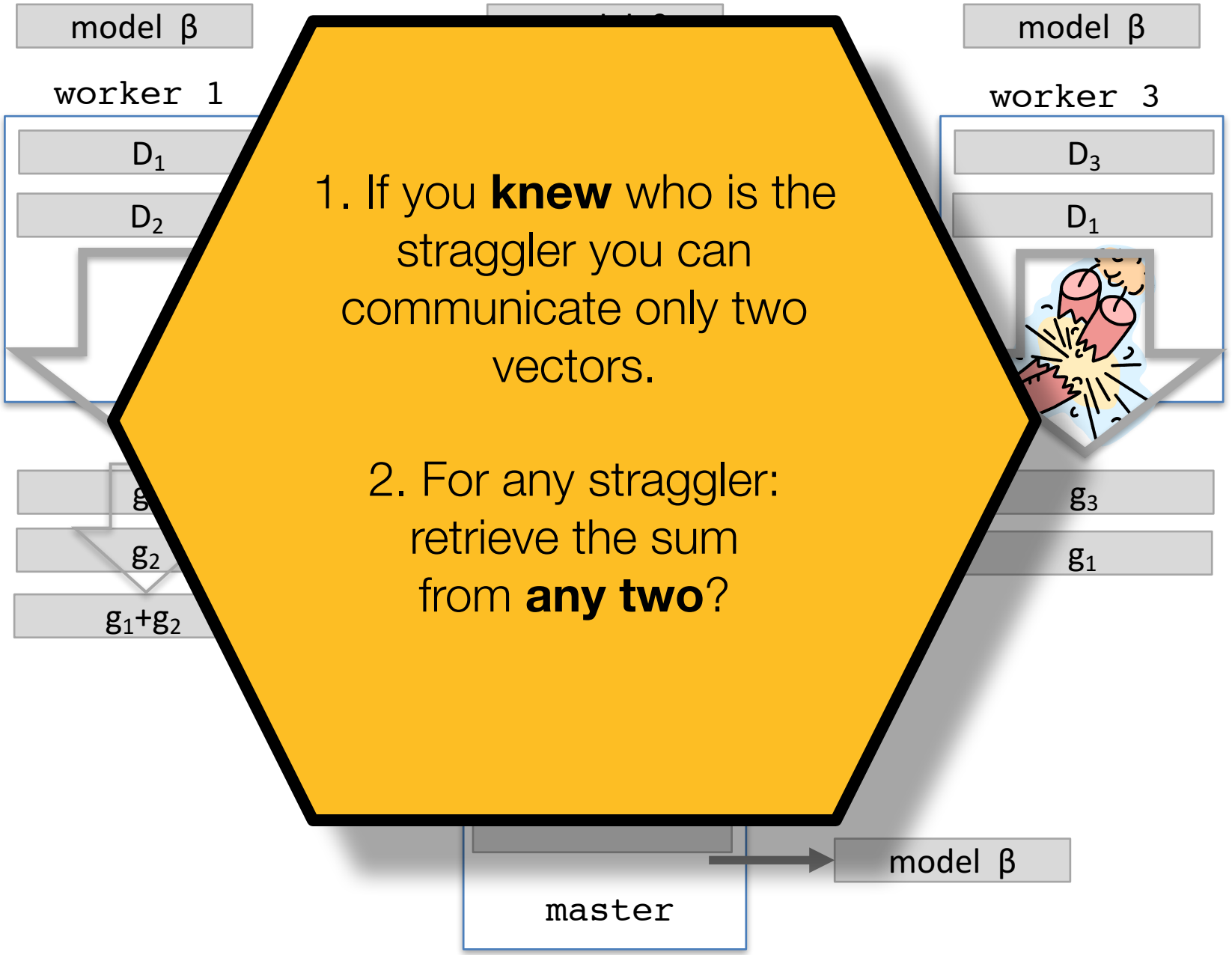
Gradient coding



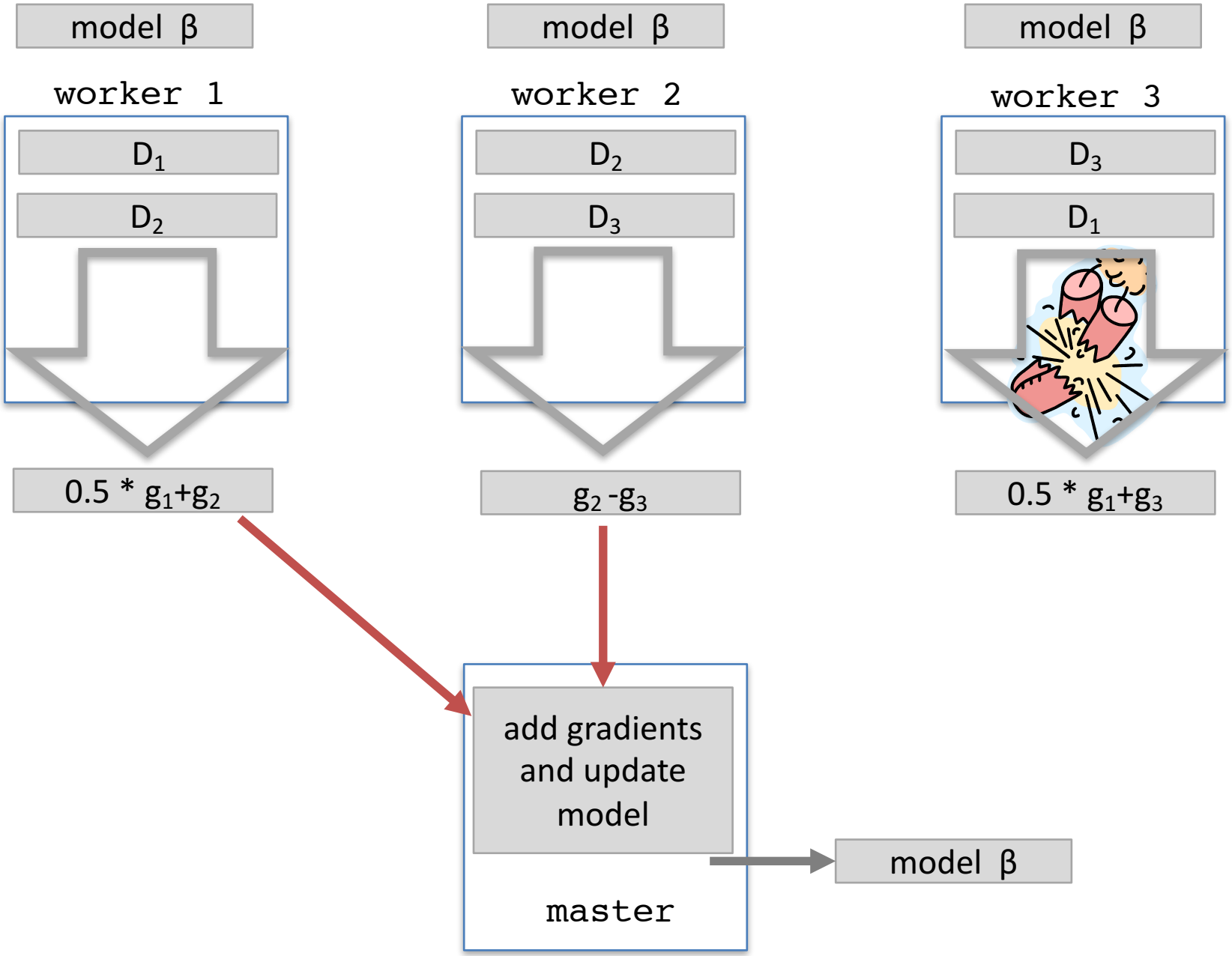
Gradient coding



Gradient coding



Gradient coding



Gradient coding idea

- Design a matrix so that any n-s rows contain [1,1,1] in their span.

$$B = \begin{pmatrix} 1/2 & 1 & 0 \\ 0 & 1 & -1 \\ 1/2 & 0 & 1 \end{pmatrix}$$

- Trivial if B is all ones. Want to minimize the amount of work per machine, i.e. the number of non-zeros per row of B.

Gradient coding lower bound

- Design a matrix so that any n-s rows contain [1,1,1] in their span.

$$B = \begin{pmatrix} 1/2 & 1 & 0 \\ 0 & 1 & -1 \\ 1/2 & 0 & 1 \end{pmatrix}$$

- Trivial if B is all ones. Want to minimize the amount of work per machine, i.e. the number of non-zeros per row of B.

Theorem 1 (Lower Bound on B's density). *Consider any scheme (A, B) robust to **any** s stragglers, given n workers (with $s < n$) and k partitions. Then, if all rows of B have the same number of non-zeros, we must have: $\|b_i\|_0 \geq \frac{k}{n}(s+1)$ for any $i \in [n]$.*

set k=n. Each data row much be processed s+1 times to tolerate any s stragglers.

Gradient coding achievability

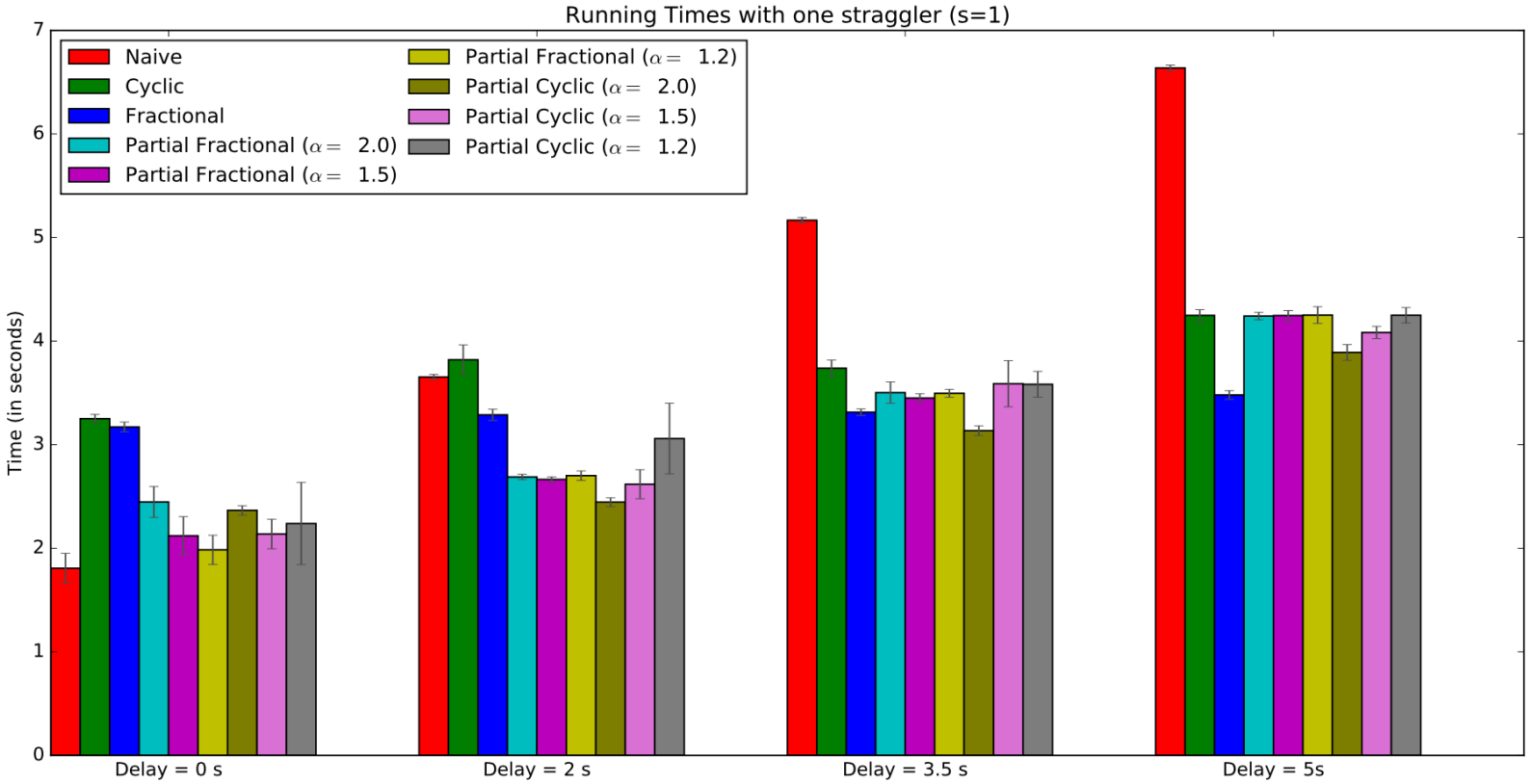
- If n divides (s+1) very simple replication scheme is optimal.

- We have a scheme: Cyclic repetition that is optimal for any n,s.

- Designing codes for partial stragglers: One machine will only compute half of the gradients.

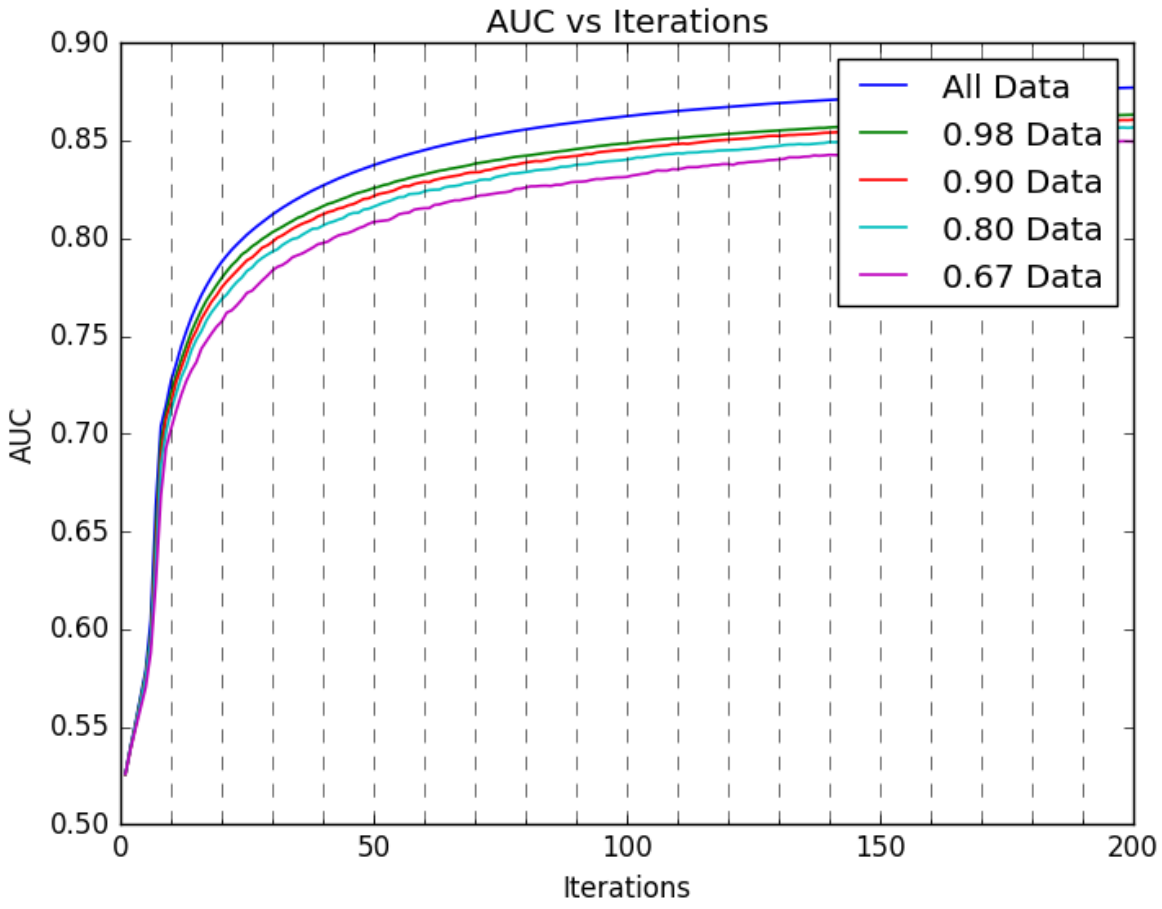
Experiments

- Real ec2 deployment, artificial straggling, n=12 machines.



Real contender: Ignore stragglers

- Just update model when 90% of machines have reported gradients. Used wi(l)dely in practice.



Conclusions and outlook

- Accelerating distributed learning is a real problem.

- Coding techniques can be used in a few different ways
- K. Lee, M. Lam, R. Pedarsani, D.S. Papailiopoulos, and K. Ramchandran
- S. Dutta, V. Cadambe, P. Grover
- S. Li, M. Maddah-Ali, S. Avestimehr

- Gradient coding can be used directly on any model (e.g. nonlinear). Only codes over the gradient vectors.

- Significant work ahead: Understanding bottlenecks for cost/bottleneck on AWS for different instances. Test over Tensorflow and MPI

- Partial Stragglers.

- Approximately containing ones vector in span.

- Better communication schemes (e.g. Trees).

Coded Computation partayyy