Asynchronous Parallel Learning for Neural Networks and Structured Models with Dense Features

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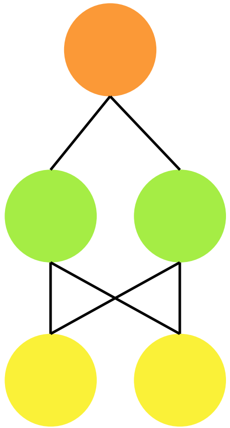
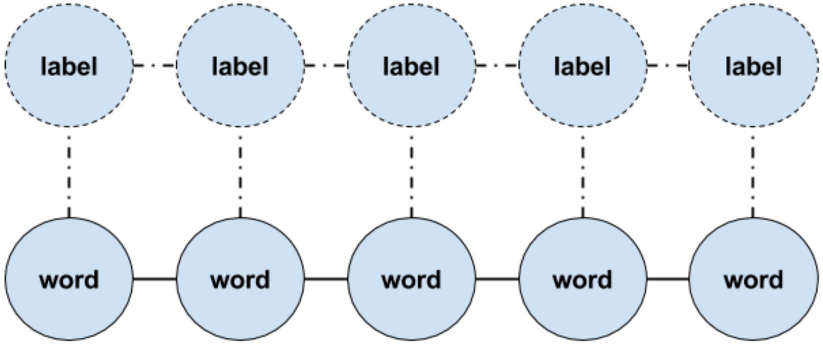
Motivation

- **Neural networks** **->** **Good Performance**
  - CNN, RNN, LSTM...
  - Sequence labelling, parsing, machine translation...



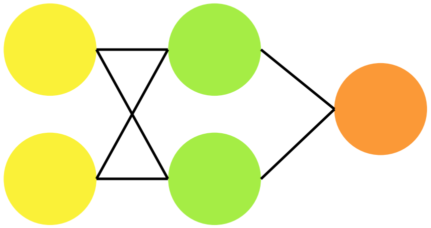
- **Neural networks** **->** **Slow Training**
  - Large parameter space
  - Dense feature
  - Complex computation



- **Faster Training ?** **->** **Parallel Training**
  - Synchronous
  - Asynchronous -> AsynGrad

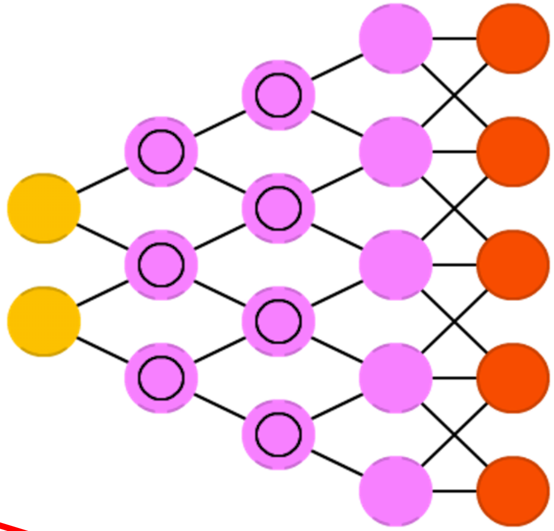
Neural Networks

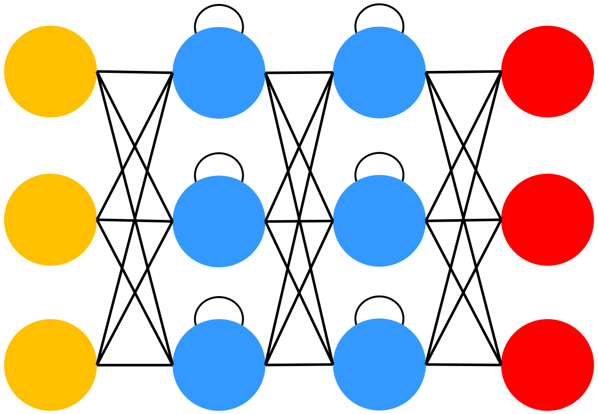
- **Many kinds**



- Feed Forward Neural Networks
  - logistic regression

- Convolutional Neural Networks
  - image processing





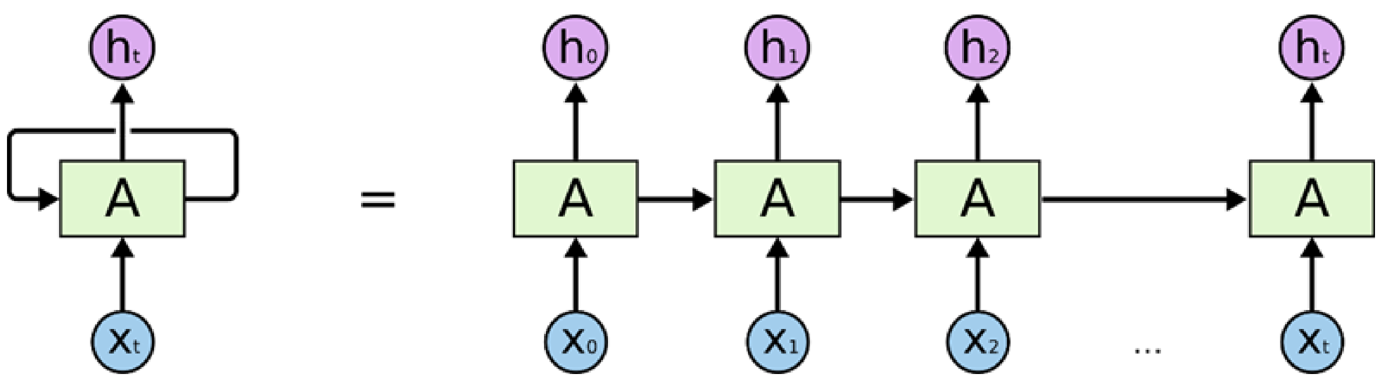
- Recurrent Neural Networks
  - RNN, LSTM, GRU…
  - structured prediction

Recurrent Neural Network (RNN)

- **Recurrent neural network** (Elman, Cognitive Science 1990)
  - Model time series
  - Predict linear-chain structures
  - Conditioned on all previous input

$$h_t = f(Uh_{t-1} + Wx_t)$$

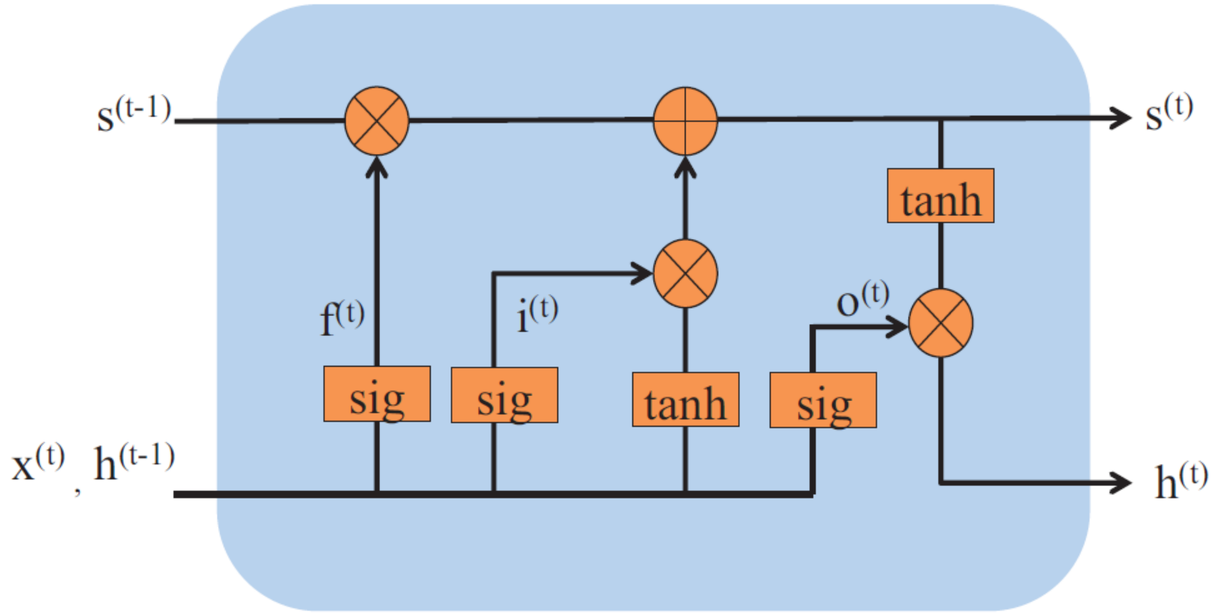
$$\hat{y}_t = softmax(W^{(s)}h_t)$$



Picture from Christopher Olah

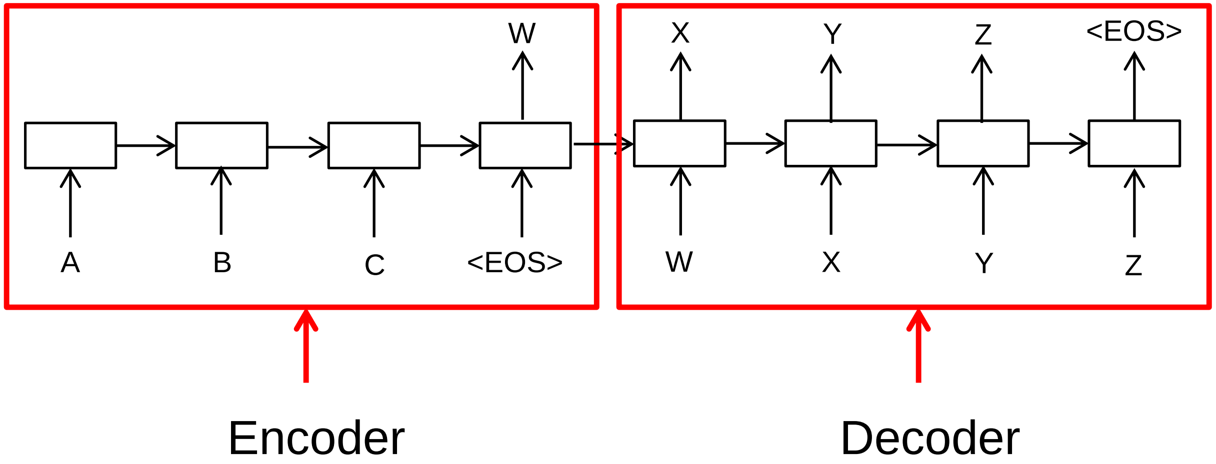
Long Short-term Memory (LSTM)

- **Long short-term memory** (Hochreiter and Schmidhuber 1997)
  - A lasting linear memory
    - Capture long distance dependency
  - Three gates: input, forget and output gates
    - Control modification to the memory



Sequence-to-Sequence Model

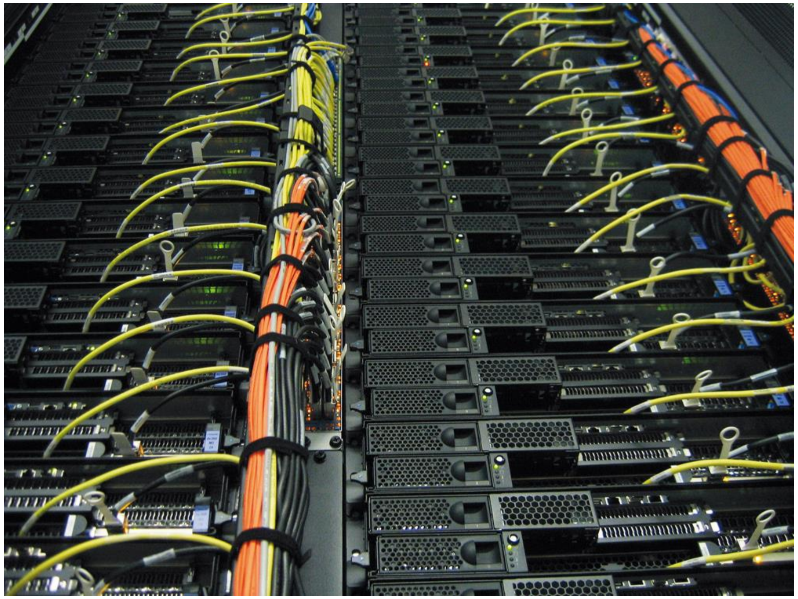
- **Sequence to sequence neural network** (Sutskever et al., NIPS 2014)
  - Encoder & Decoder
  - The encoder information is stored in a fixed-length vector



- **Popular for high-level task**
  - Machine Translation
  - Summarization
  - …

For Large-Scale Structured Prediction

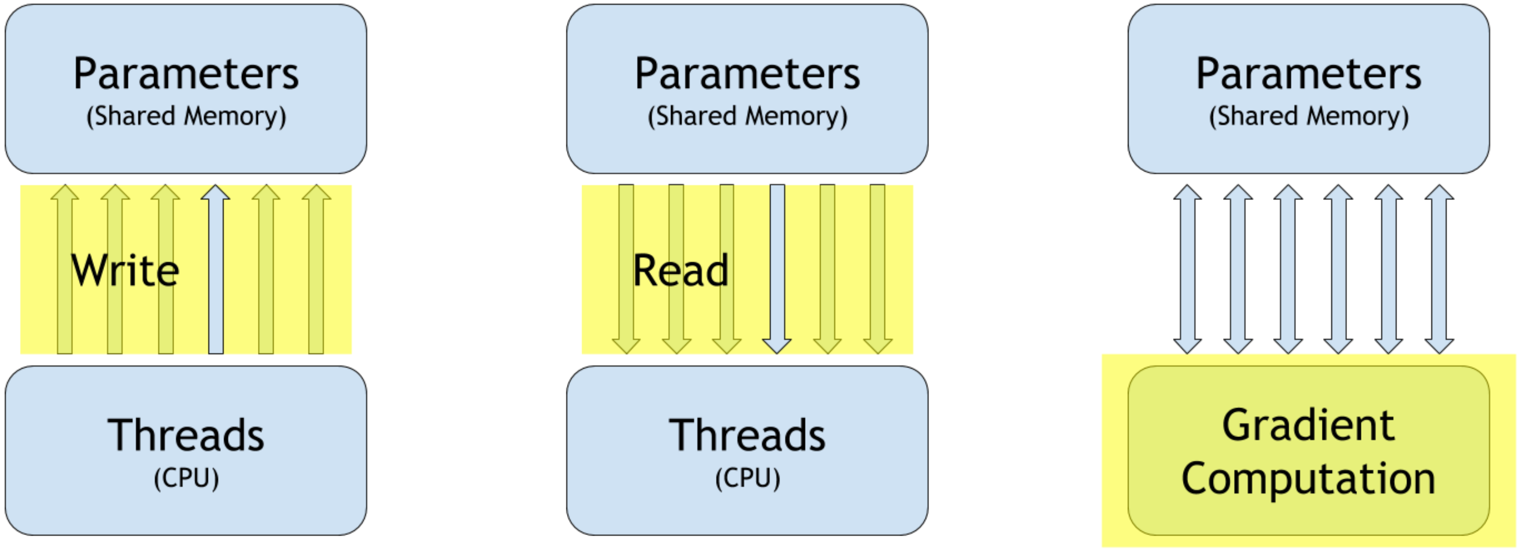
- **Training large-scale neural networks is costly**
  - Numerous parameters
  - Dense Feature
  - Time-consuming



- **For example**
  - A NMT model may take weeks to train
  - Days, even if with GPU clusters
- **How to accelerate training speed?**
  - Parallel training
  - Especially, asynchronous (lock-free) parallel training

Problem Analysis

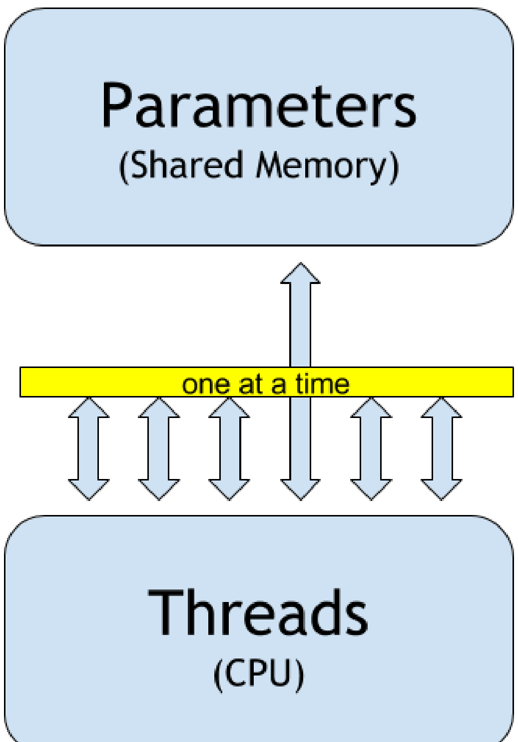
- **Basic operations in parallel training**



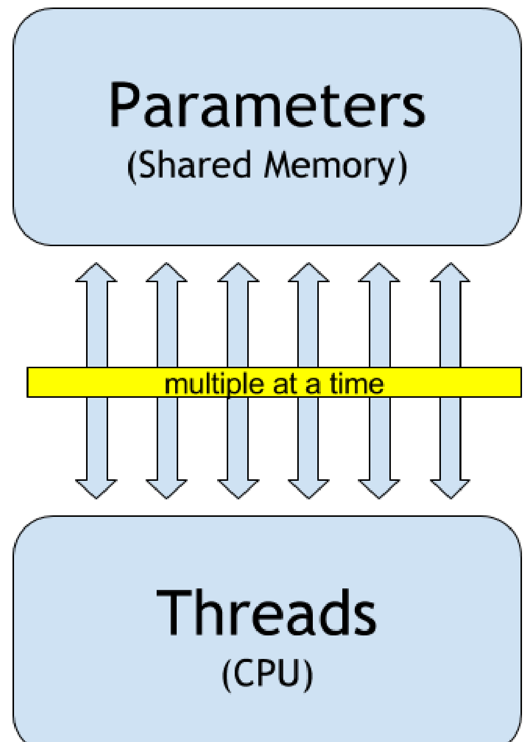
- **Problem differs in**
  - Online vs. Mini-batch vs. Batch
  - Synchronous parallel vs. Asynchronous parallel
  - Dense feature model vs. Sparse feature model

Parallel Training

- **Synchronous (locked)**
  - Multiple threads
  - Only one can modify model parameters at the same time

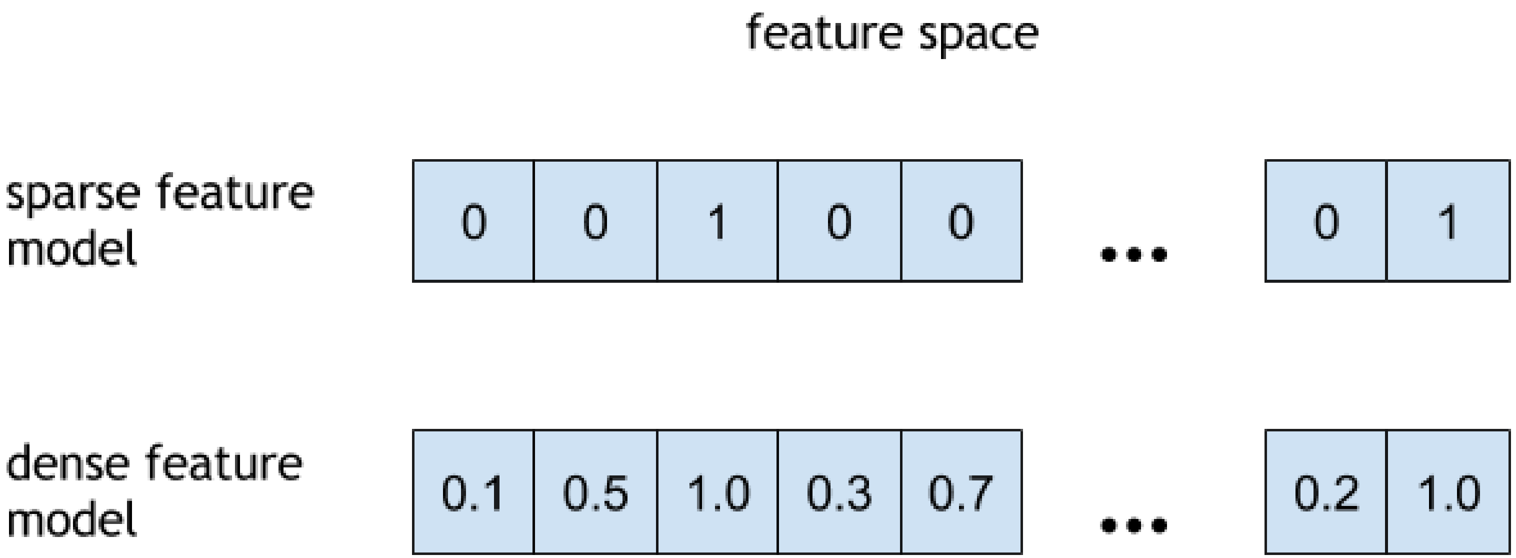


- **Asynchronous (lock-free)**
  - Multiple threads
  - Each one can modify model parameters at the same time



Model Types

- **Sparse feature model**
  - e.g. HMM, CRF, Perceptron, MILA…
  - features are sparse
  - less read & write time
- **Dense feature model**
  - e.g. RNN, LSTM, Sequence-to-Sequence…
  - features are dense
  - more read & write time



Problem Analysis

- How threads interact with each other?

	Sparse	Dense
Sync.	?	?
Async.	?	?

Problem Analysis

- How threads interact with each other?

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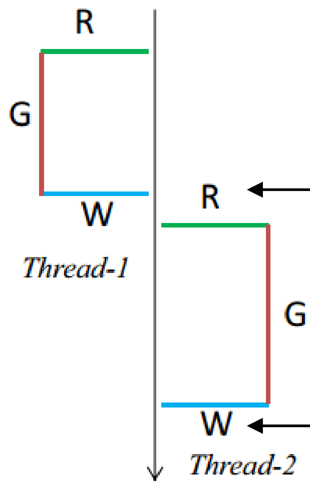
Synchronous Online Parallel Training

- **Correctness**

No problem at all!

1. Simple case



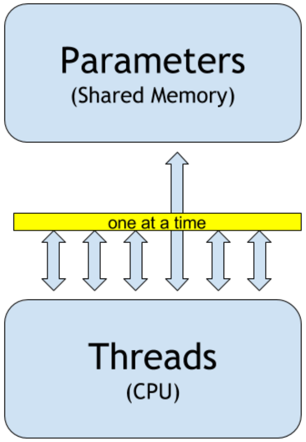
Reading parameters from shared memory

Computing **G**radients

Writing parameters to shared memory

(a) Simple case

- **Current approach: DSGD (round-robin)**
  - Langford et al, NIPS 2009
  - Stochastic parallel learning by locking memory



Synchronous Online Parallel Training

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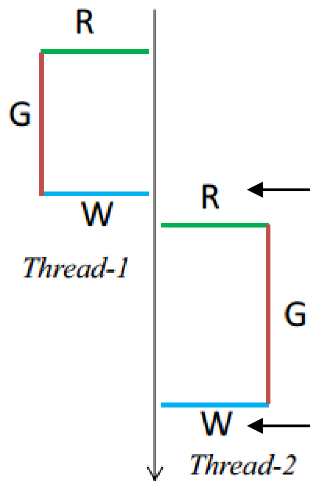


Reading parameters from shared memory

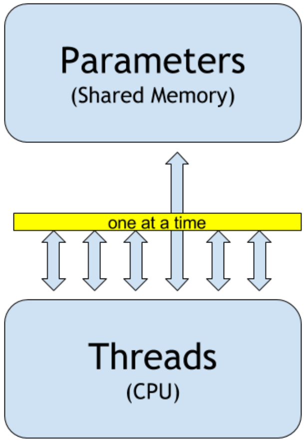
Computing **G**radients

Writing parameters to shared memory

(a) Simple case

Current approach:

- mini-batch based method
- Computing gradients in parallel
  - such as: parallel matrix operations via GPU



Problem Analysis

- How threads interact with each other?

	Sparse	Dense
Sync.	✔	✔
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Problem Analysis

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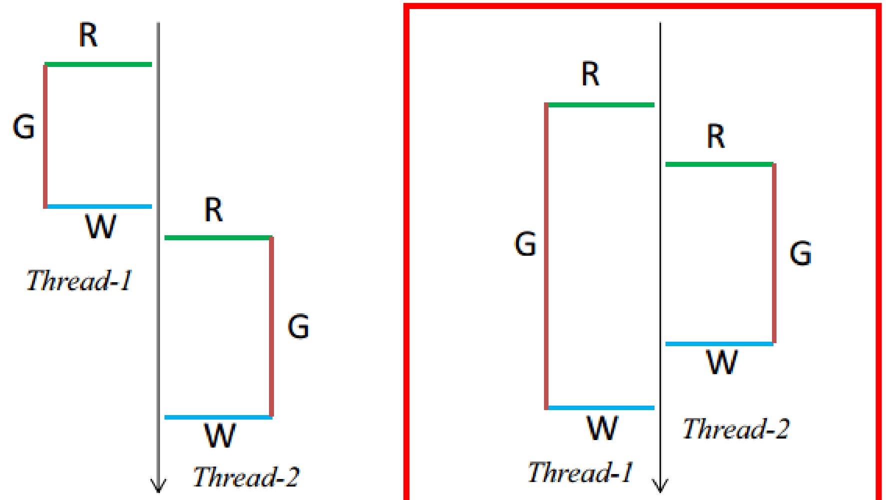
Asynchronous Online Parallel Training

- **Asynchronous parallel learning is very popular for traditional sparse feature models**

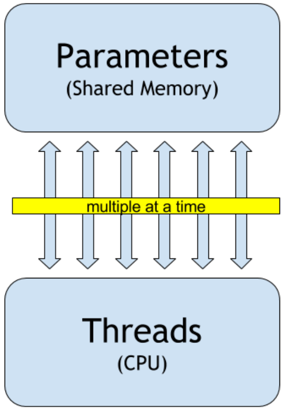


(a) Simple case

(b) Grad delay case

2. This case is called Gradient Delay case

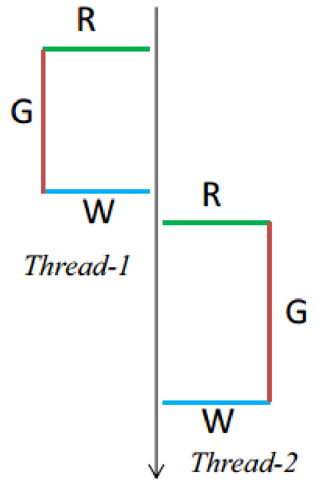
→ More complicated, but problem solved for sparse feature models (Niu et al. NIPS 2011)



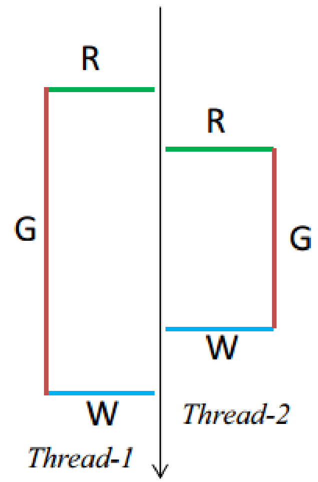
Asynchronous Online Parallel Training

- **Current approach: HogWild! and variants**
  - Multiple threads updating parameters at the same time
  - For sparse feature models
- **Advantage**
  - Actual parallel training
  - Fast training speed with no performance loss

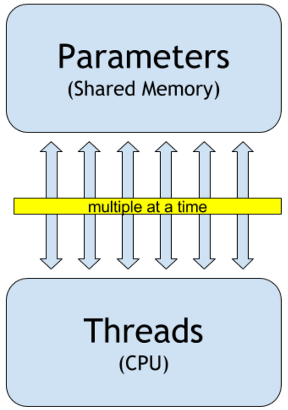
Problem also solved (for sparse feature models)!



(a) Simple case



(b) Grad delay case



Problem Analysis

- How threads interact with each other?

	Sparse	Dense
Sync.	✓	✓
Async.	✓	?

Problem Analysis

- How threads interact with each other?

	Sparse	Dense
Sync.	✓	✓
Async.	✓	?

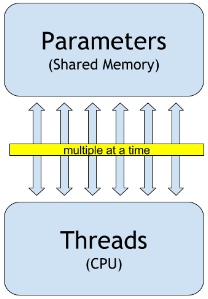
Problem Analysis

- **How threads interact with each other?**

	Sparse	Dense
Sync.	✓	✓
Async.	✓	?

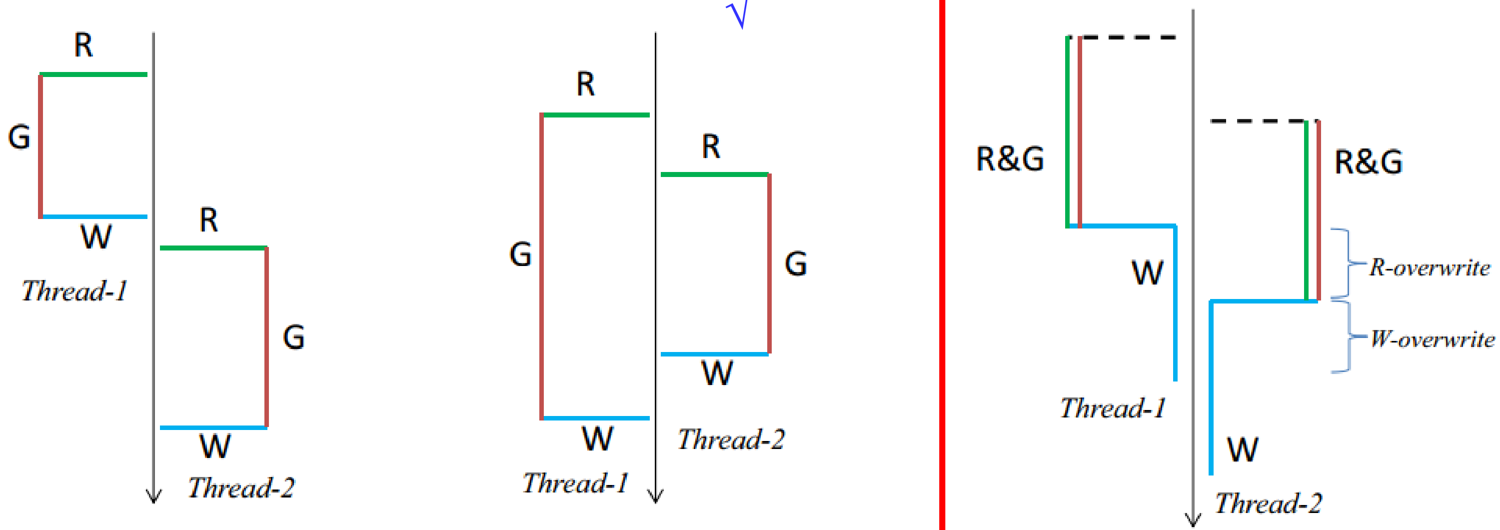
Asynchronous Online Parallel Learning

- **3. Even more difficult case: Gradient Error Case**
  - Happens for dense feature models, like neural networks
    - Actions (R, G & W) are time-consuming
  - Read-overwrite and write-overwrite problems



→Not well studied before, how to deal with this problem?

√



(a) Simple case (b) Grad delay case (c) Grad error case

Problem Analysis

- How threads interact with each other?

	Sparse	Dense
Sync.	✓	✓
Async.	✓	?

Problem Analysis

- **How threads interact with each other?**

	Sparse	Dense
Sync.	✓	✓
Async.	✓	AsynGrad

AsynGrad aims to solve gradient error case

Problem Analysis

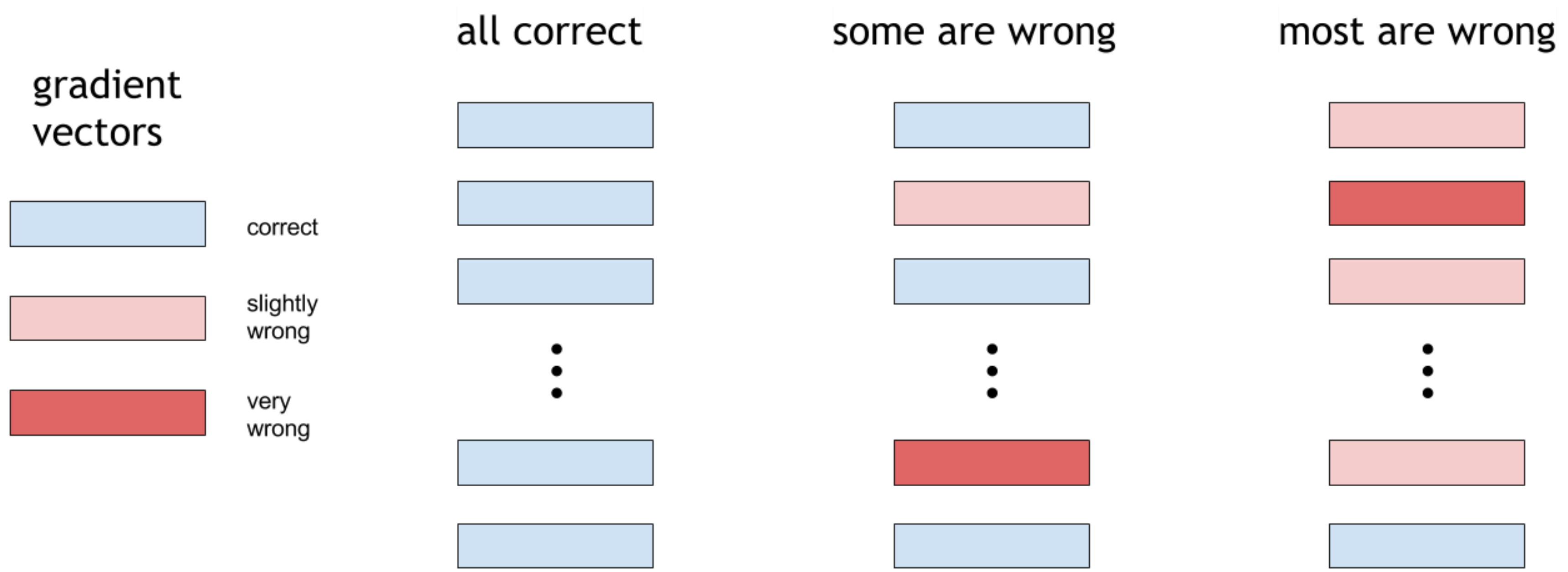
- **How threads interact with each other?**

	Sparse	Dense
Sync.	✓	✓
Async.	✓	AsynGrad

This is our proposal

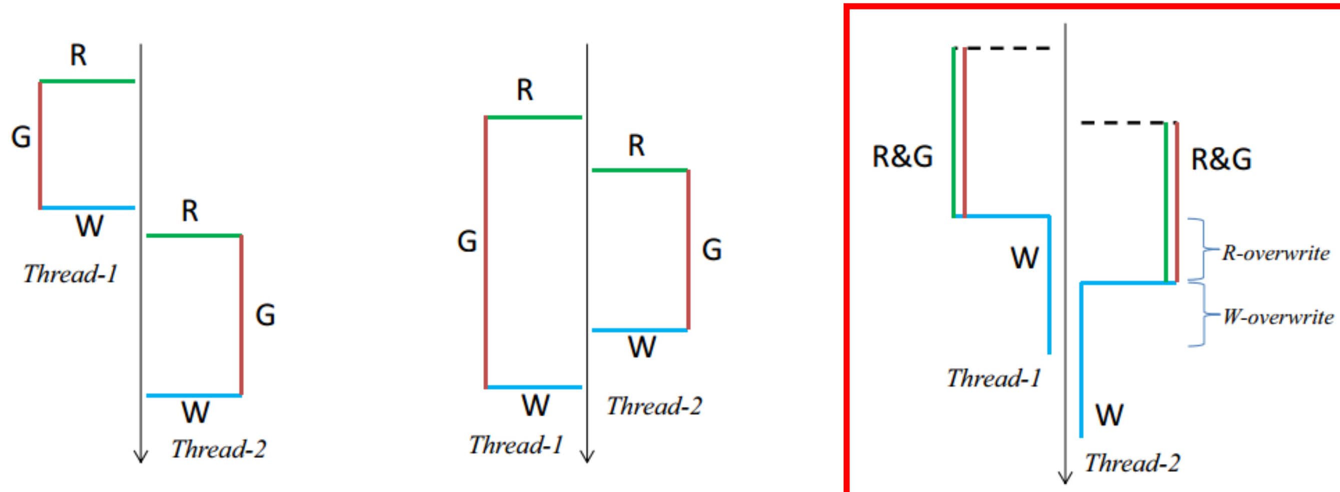
Review of Gradient Error Case

- **Gradient error has two aspects**
  - How many of the gradients are wrong?
  - How wrong are they?

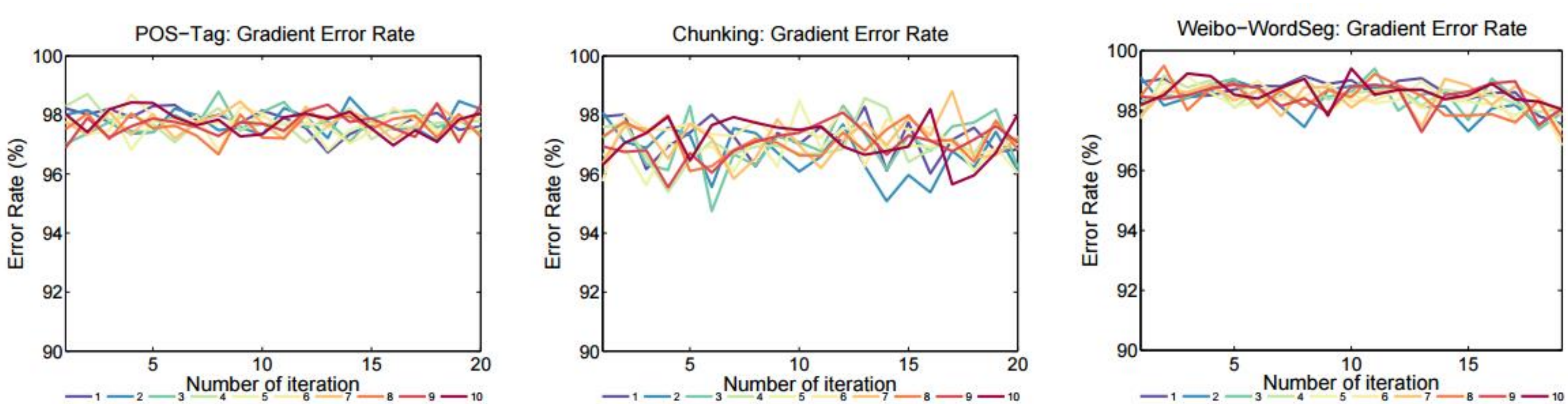


Experimental Observations

- **Gradient error is very common in asynchronous training of neural networks** in real-world tasks

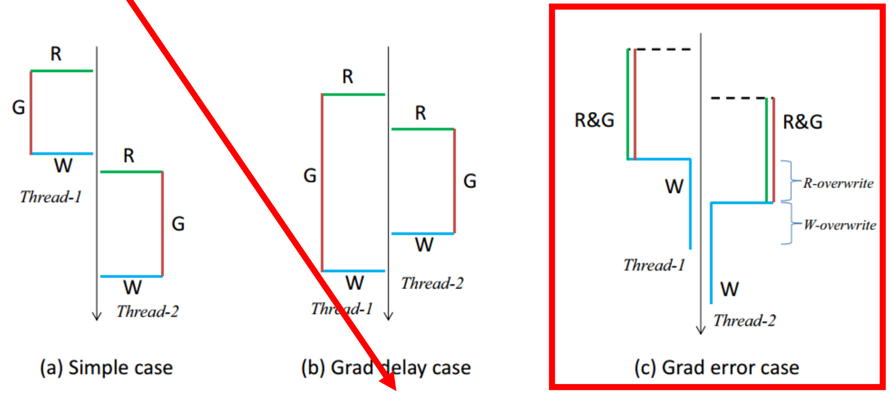


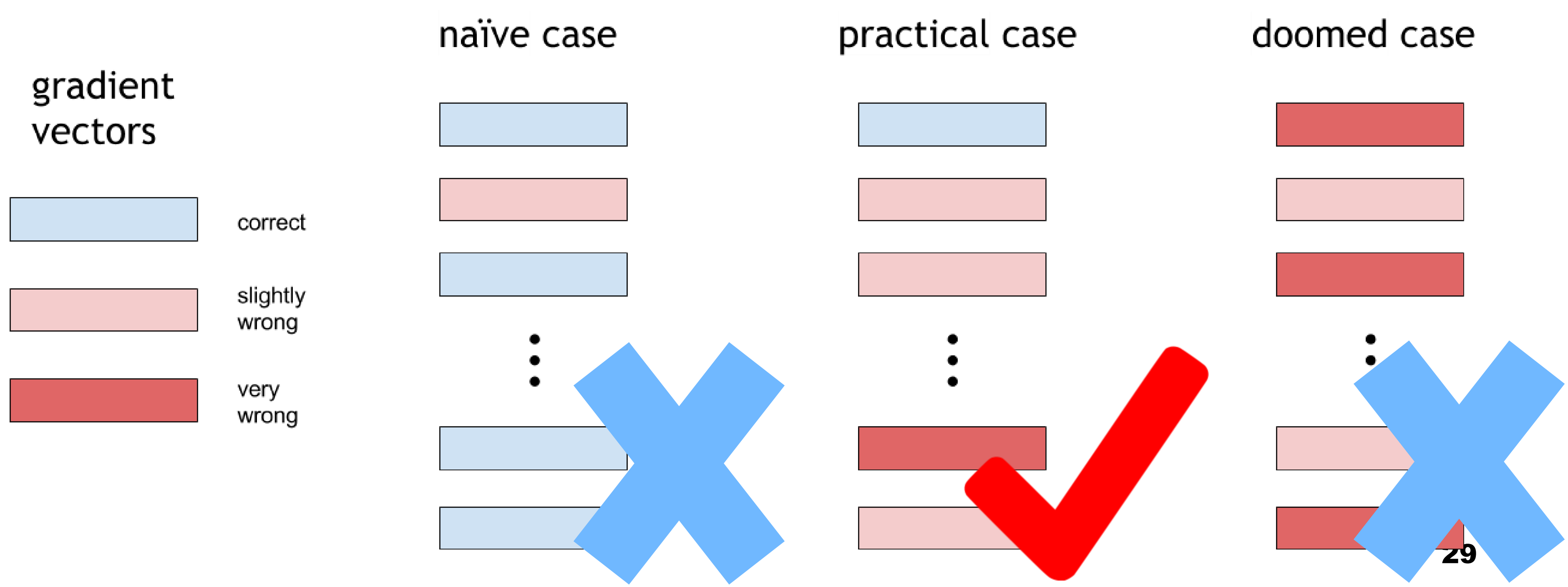
(a) Simple case (b) Grad delay case (c) Grad error case



Experimental Observations

- **Gradient error is moderate in asynchronous training of neural networks** in real-world tasks





Our Theoretical Analysis

- Can training still converge with gradient errors?

Theorem 1 (*AsynGrad* convergence and convergence rate). *With the conditions (4), (5), (6), (7), let $\epsilon > 0$ be a targe… …imum). Let τ denote …*

Even though there are gradient errors, training still converges towards the optimum, when the gradient errors are bounded.

(8)

where $\boldsymbol{w}$ … $\boldsymbol{z}$ such that $\boldsymbol{s}(\boldsymbol{w}) = \mathbb{E}_{\boldsymbol{z}}[\boldsymbol{s}_{\boldsymbol{z}}(\boldsymbol{w})]$. Let γ be a learning rate as

$$\gamma = \frac{c\epsilon - 2\tau q}{\beta q \kappa^2} \tag{9}$$

where we can set β as any value as far as $\beta \geq 1$. Let t be the number of updates as follows

$$t \doteq \frac{\beta q \kappa^2 \log(q a_0/\epsilon)}{c(c\epsilon - 2\tau q)} \tag{10}$$

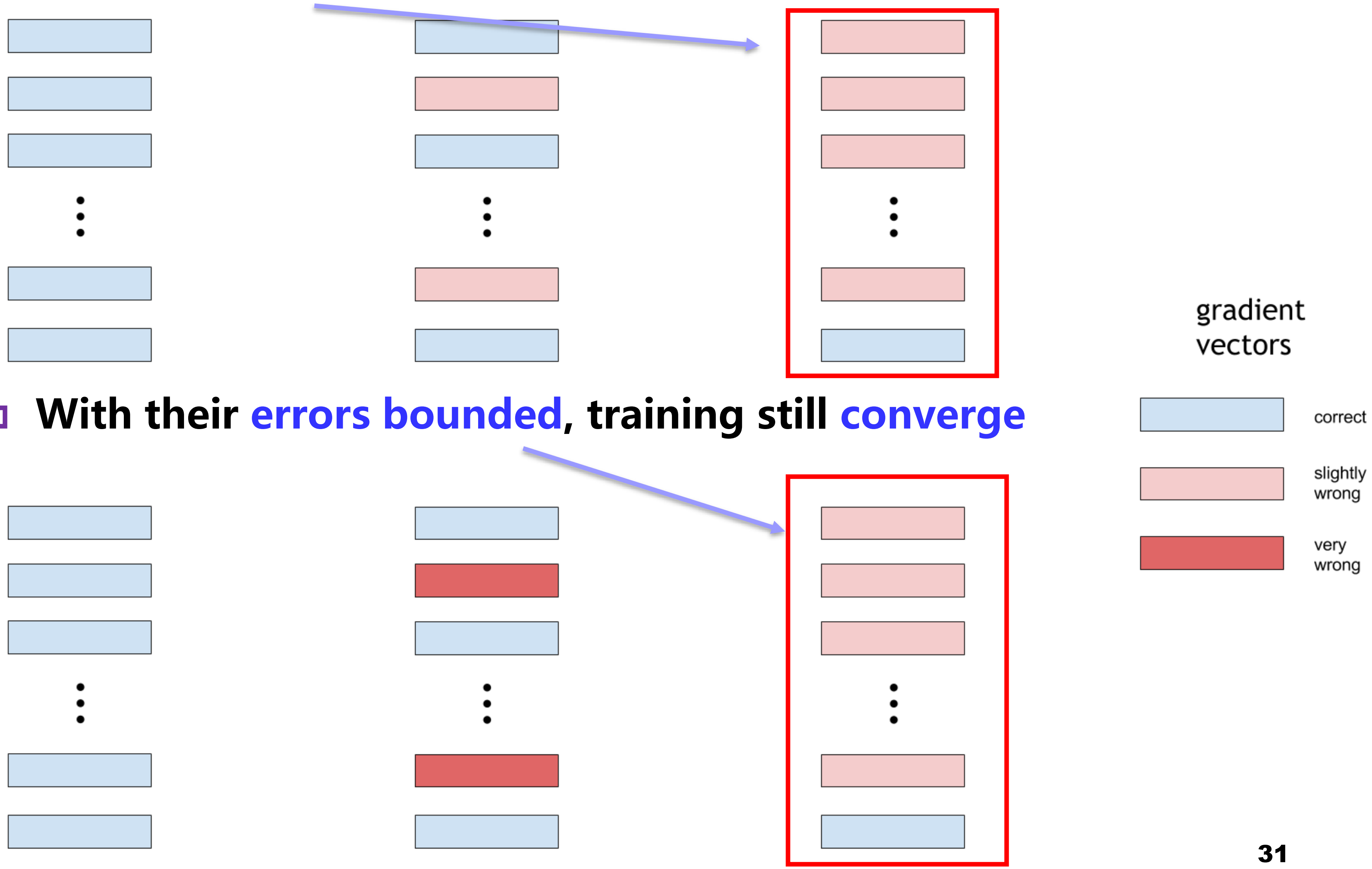
where $\doteq$ means ceil-rounding of a real value to an integer, and a_0 is the initial distance such that $a_0 = ||\boldsymbol{w}_0 - \boldsymbol{w}^*||^2$. Then, after t updates of $\boldsymbol{w}$, AsynGrad *converges towards the optimum such that $\mathbb{E}[f(\boldsymbol{w}_t) - f(\boldsymbol{w}^*)] \leq \epsilon$, as far as the gradient errors are bounded such that*

bounded gradient errors

$$\boxed{\tau \leq \frac{c\epsilon}{2q}} \tag{11}$$

Our Theoretical Analysis

- Even if most of the gradients are wrong
- With their errors bounded, training still converge



AsynGrad

- **An asynchronous parallel learning solution for fast training of neural networks**
  - Asynchronous Parallel Learning with Gradient Error (AsynGrad)
- **Algorithm**

Algorithm 1 *AsynGrad*: Asynchronous Parallel Learning with Gradient Error

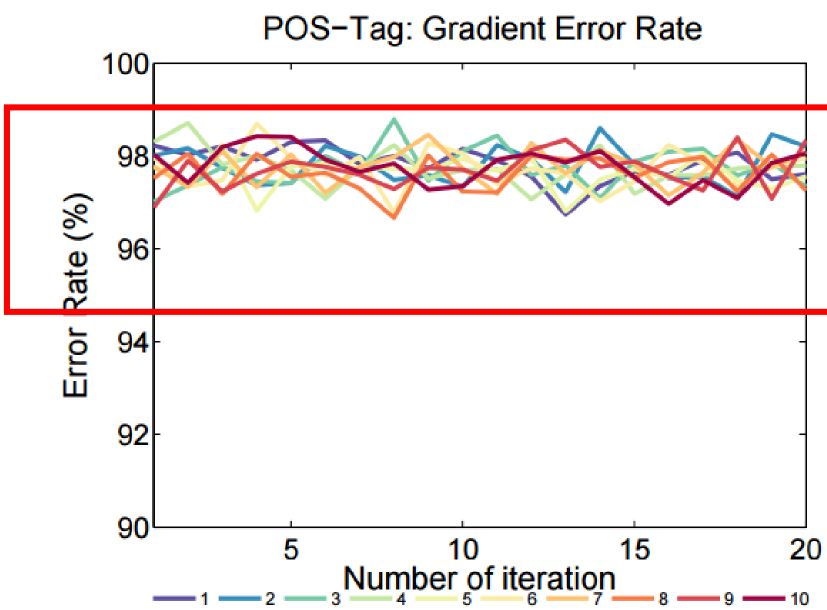
---

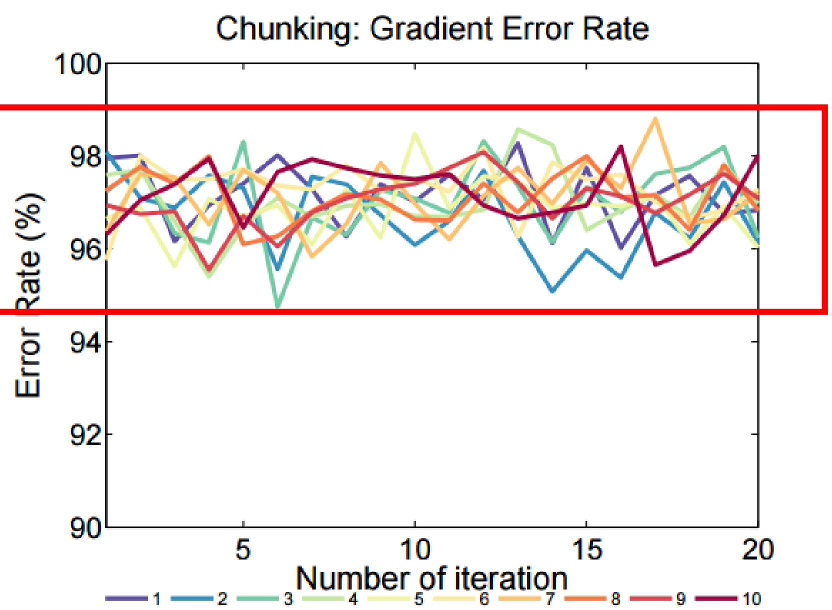
Input: model weights $\boldsymbol{w}$, training set S of m samples
Run k threads in parallel with share memory, and procedure of each thread is as follows:
repeat
    Get a sample $\boldsymbol{z}$ uniformly at random from S
    Get the update term $\boldsymbol{s_z}(\boldsymbol{w})$, which is computed as $\nabla f_{\boldsymbol{z}}(\boldsymbol{w})$ but usually contains error
    Update $\boldsymbol{w}$ such that $\boldsymbol{w} \leftarrow \boldsymbol{w} - \gamma \boldsymbol{s_z}(\boldsymbol{w})$
until Convergence
return $\boldsymbol{w}$

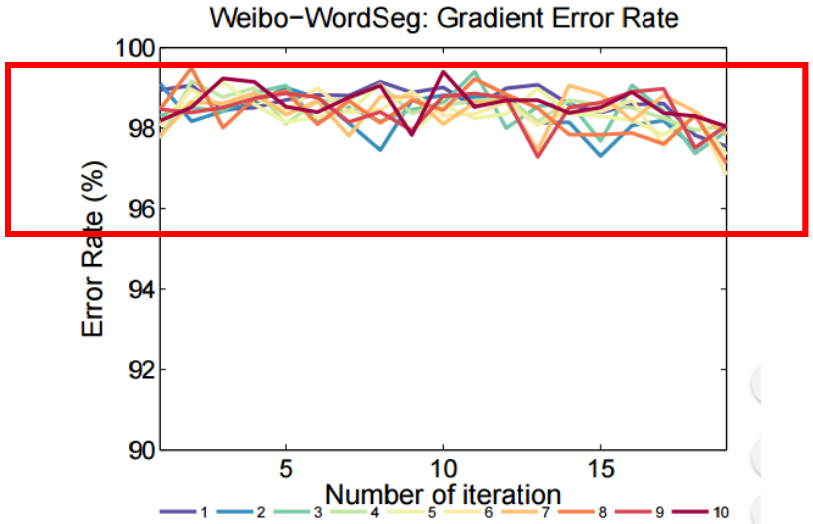
X. Sun. Asynchronous Parallel Learning for Neural Networks and Structured Models with Dense Features. COLING 2016.

Experiments on LSTM

Experiments show a high gradient error rate

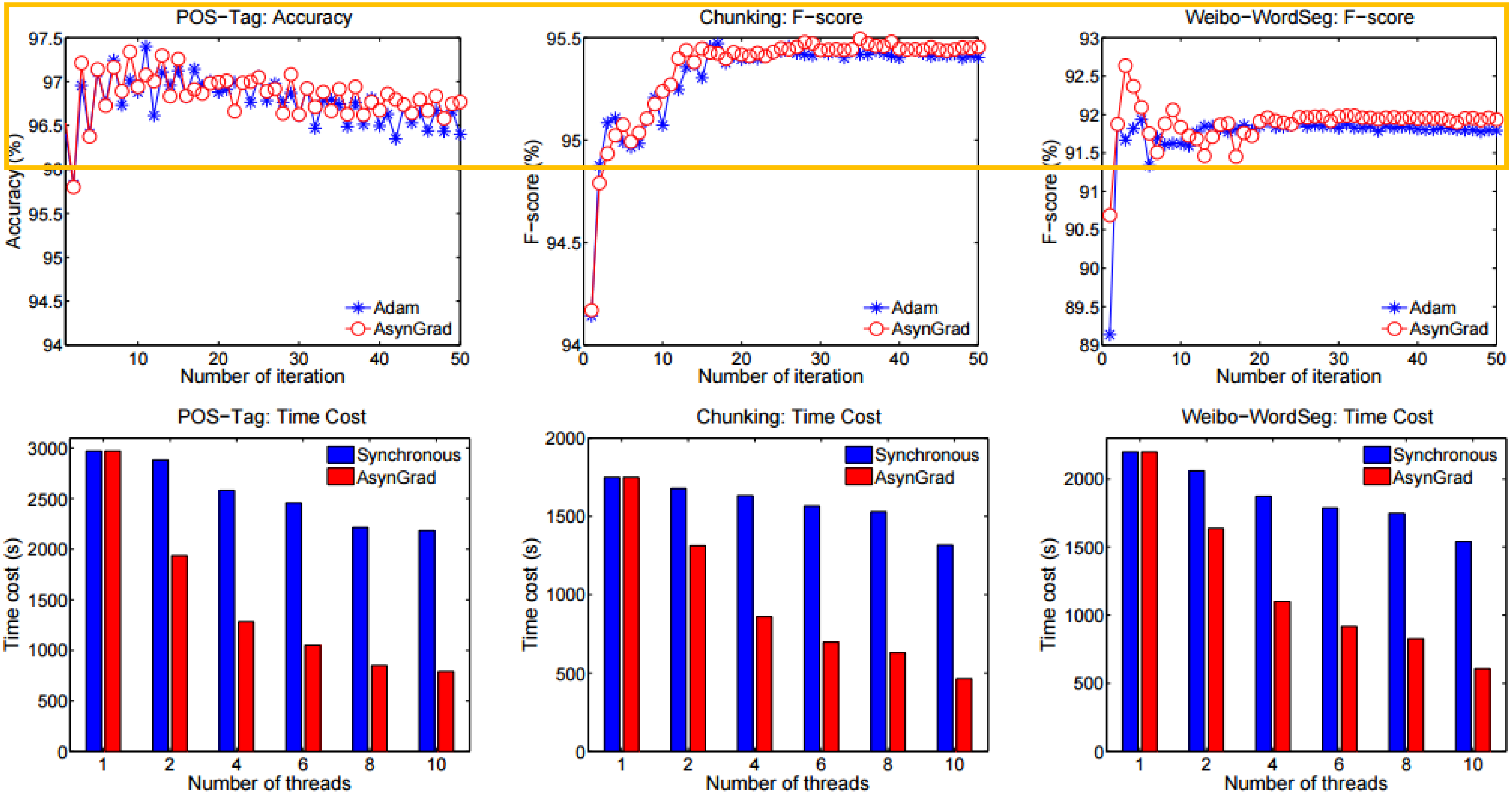






Experiments on LSTM

Experiments show that AsynGrad still converge even with a high gradient error rate

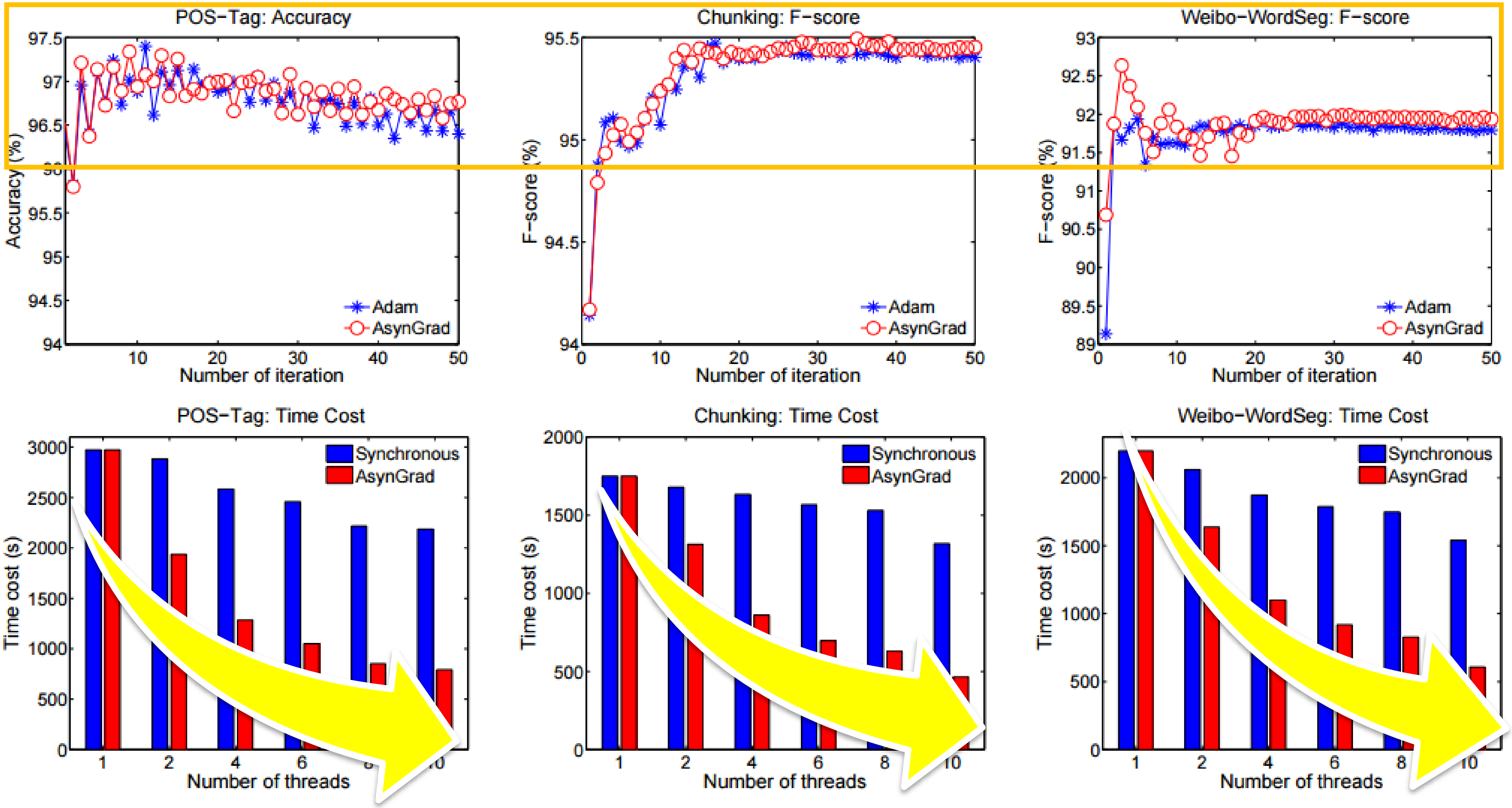


Experiments on LSTM

- No loss on accuracy/F-score

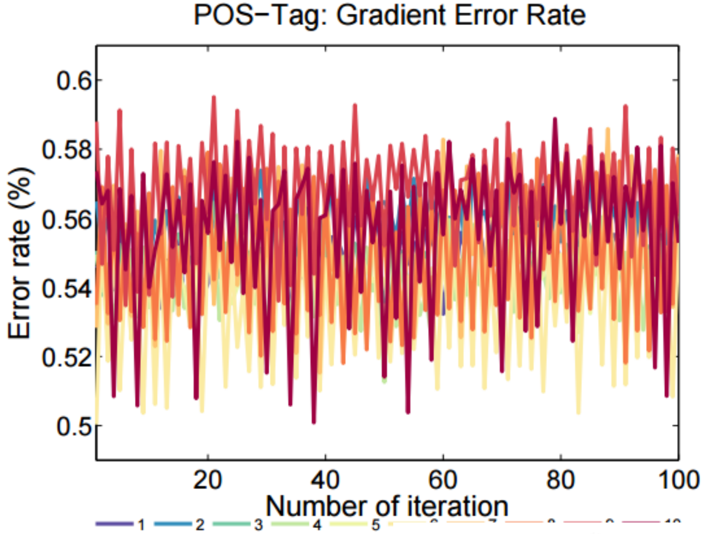
AsynGrad

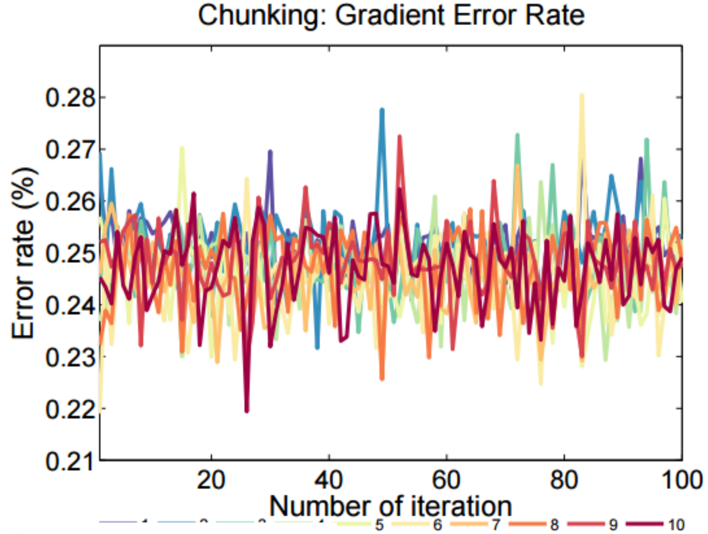
- With substantially faster training speed

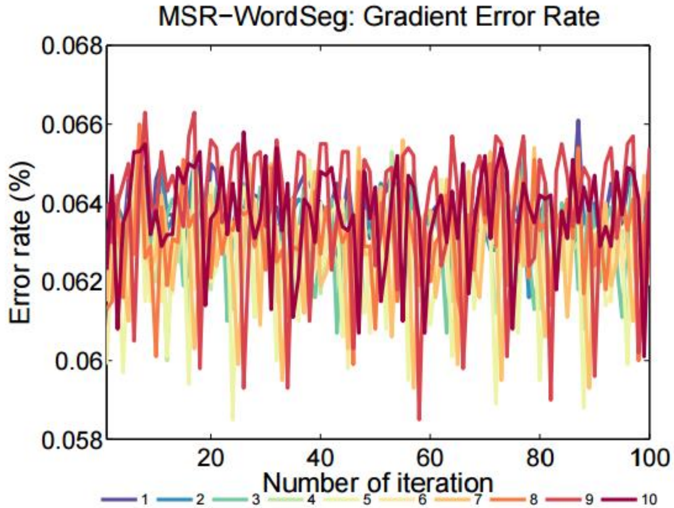


AsynGrad: A General-Purpose Solution

- **Also suitable for other dense feature models**
  - Dense CRF -> moderate error rate



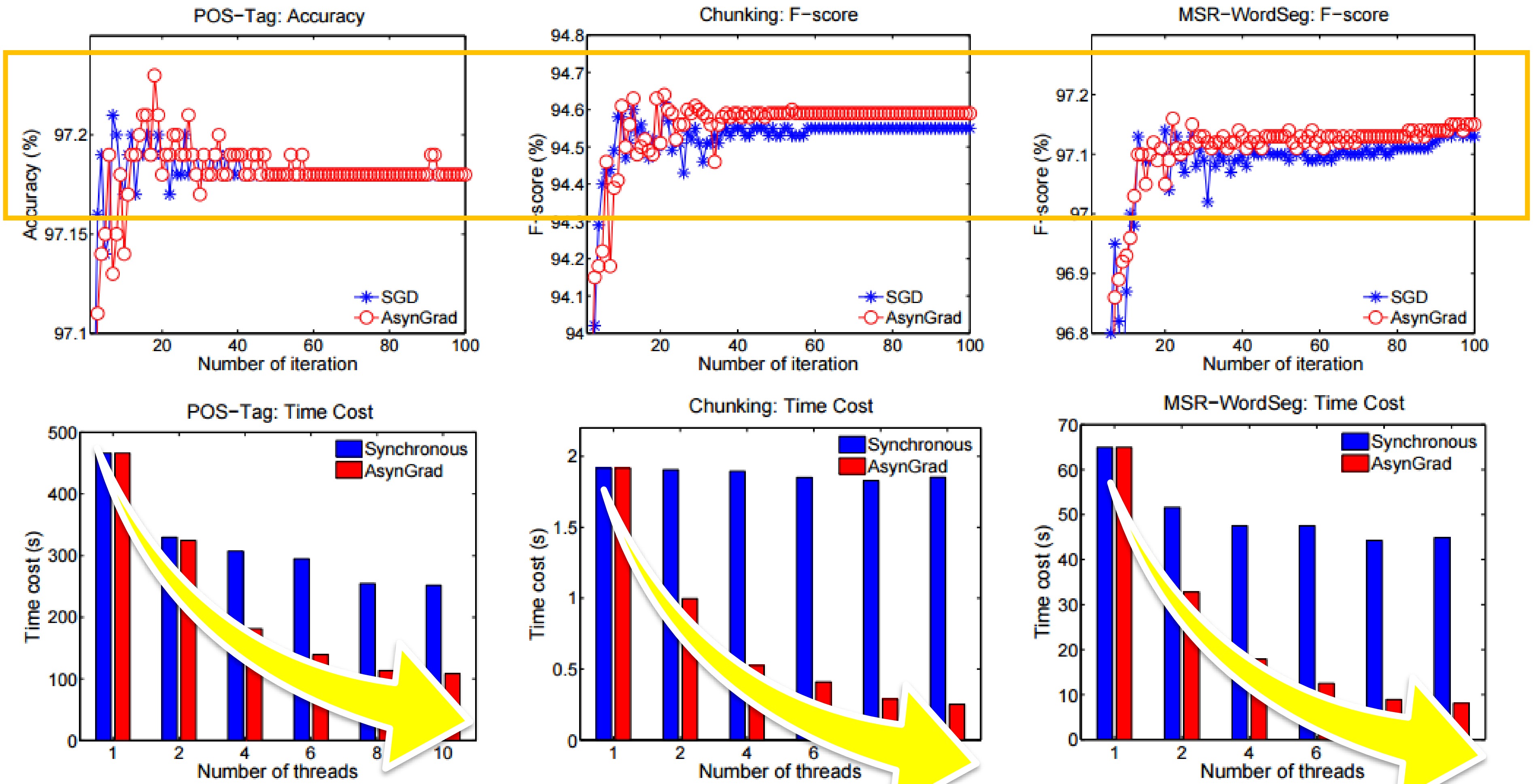




Experiments on Dense-CRF

- No loss on accuracy/F-score
- With substantially faster training speed

AsynGrad



POS−Tag: Accuracy with SR

Chunking: F−score with SR

MSR−WordSeg: F−score with SR

Problem Analysis

- How threads interact with each other?

	Sparse	Dense
Sync.	✓	✓
Async.	✓	✓

AsynGrad

- **Gradient errors are common and inevitable in asynchronous training of dense feature models**
  - Such as neural networks

- **AsynGrad survives with gradient errors**
  - With substantial faster training speed
  - No loss at all on test accuracy
  - Theoretical justification

Thanks!