Distributed TensorFlow

CSE545 - Spring 2020

Stony Brook University

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Big Data Analytics, The Class

Goal: Generalizations
A *model* or *summarization* of the data.

Data Frameworks

- Hadoop File System ✓
- Spark ✓
- Streaming ✓
- MapReduce ✓
- Tensorflow

Algorithms and Analyses

- Similarity Search
- Hypothesis Testing
- Graph Analysis
- Recommendation Systems
- Deep Learning

Limitations of Spark

Spark is fast for being so flexible

- Fast: RDDs in memory + Lazy evaluation: optimized chain of operations.
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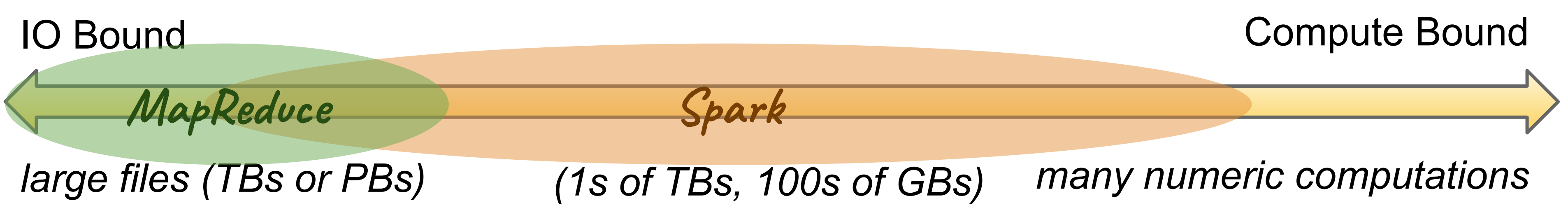

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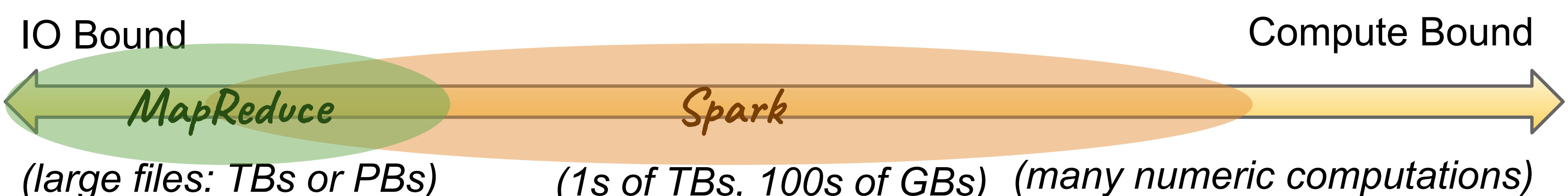

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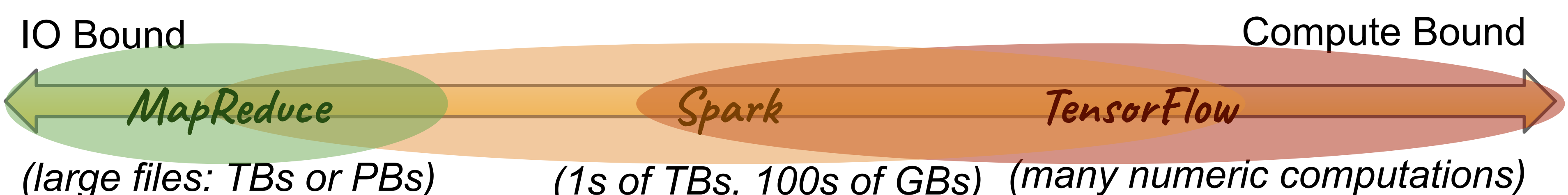

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Learning Objectives

- Understand TensorFlow as a data workflow system.
  - Know the key components of TensorFlow.
  - Understand the key concepts of *distributed* TensorFlow.
- Execute basic distributed tensorflow program.
- Establish a foundation to distribute deep learning models:
  - Convolutional Neural Networks
  - Recurrent Neural Network (or LSTM, GRU)

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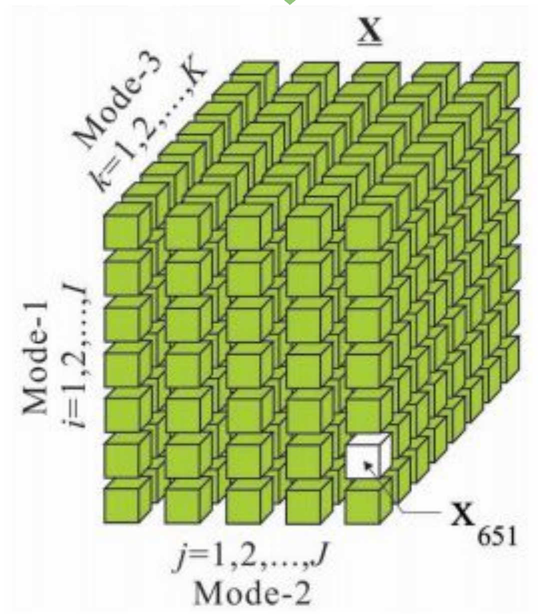

A multi-dimensional matrix

(i.stack.imgur.com)

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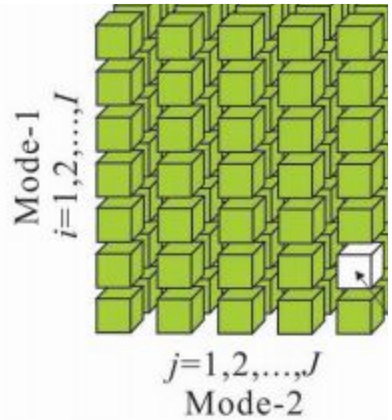

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A 2-d tensor is just a matrix.

- 1-d: vector
- 0-d: a constant / scalar

Note: Linguistic ambiguity:
Dimensions of a Tensor =/= Dimensions of a Matrix

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Examples > 2-d :
Image definitions in terms of RGB per pixel
    Image[*row*][*column*][*rgb*]

Subject, Verb, Object representation of language:
    Counts[verb][subject][object]

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One view: Like Spark, but uses *tensors* instead of *RDDs*.

Technically, less abstract than *RDDs* which could hold tensors as well as many other data structures (dictionaries/HashMaps, Trees, ...etc…).

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Efficient, high-level built-in **linear algebra** and **machine learning optimization** *operations* (i.e. transformations).

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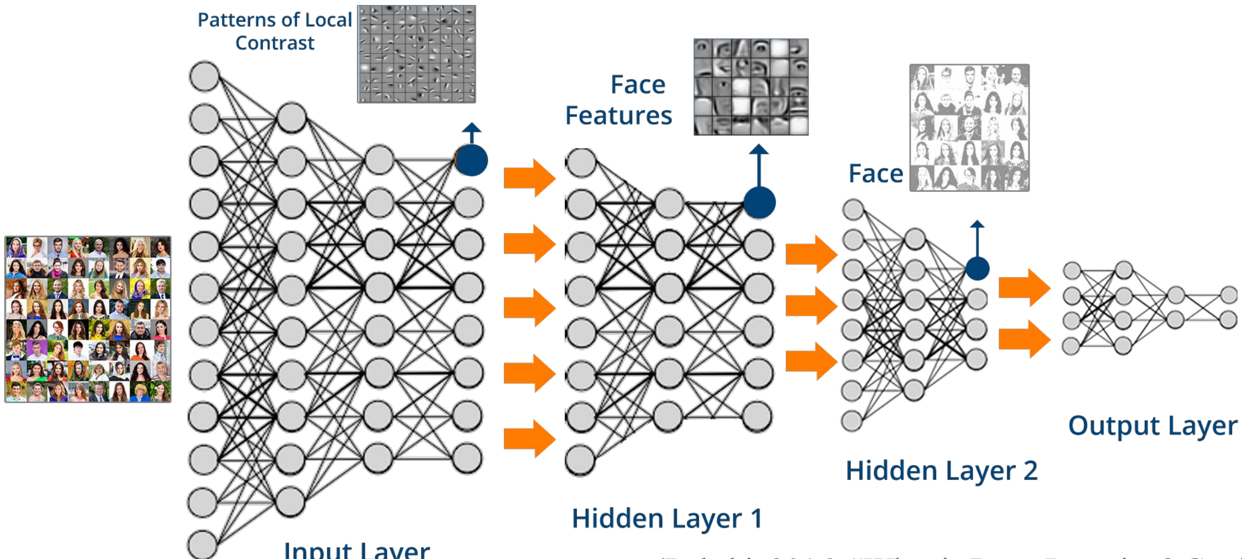

(Bakshi, 2016, "What is Deep Learning? Getting Started With Deep Learning")

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```
import tensorflow as tf

b = tf.Variable(tf.zeros([100]))                   # 100-d vector, init to zeroes
W = tf.Variable(tf.random_uniform([784,100],-1,1)) # 784x100 matrix w/rnd vals
x = tf.placeholder(name="x")                       # Placeholder for input
relu = tf.nn.relu(tf.matmul(W, x) + b)             # Relu(Wx+b)
C = [...]                                          # Cost computed as a function
                                                   # of Relu

s = tf.Session()
for step in xrange(0, 10):
  input = ...construct 100-D input array ...       # Create 100-d vector for input
  result = s.run(C, feed_dict={x: input})          # Fetch cost, feeding x=input
  print step, result
```

(Abadi, M., Agarwal, A., Barham, P., Brevdo, E., Chen, Z., Citro, C., ... & Ghemawat, S. (2016). Tensorflow: Large-scale machine learning on heterogeneous distributed systems. *arXiv preprint arXiv:1603.04467*.)

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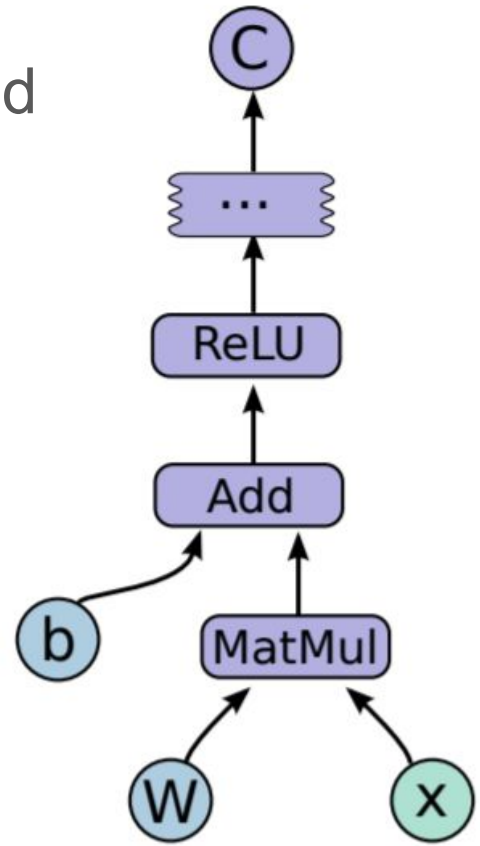

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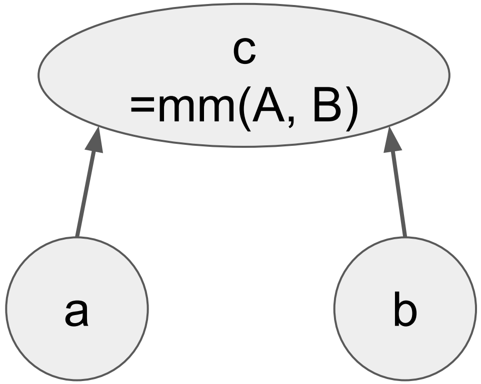
A simpler example:

c = tensorflow.matmul(a, b)



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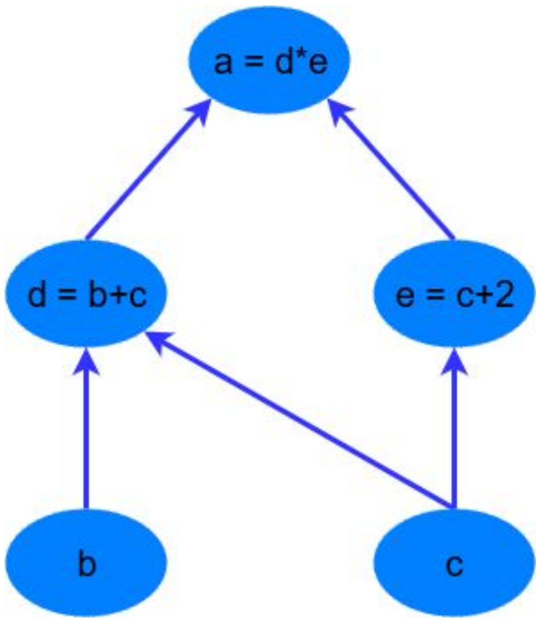
example:

d=b+c
e=c+2
a=d$*$e



(Adventures in Machine Learning. *Python TensorFlow Tutorial*, 2017)

Ingredients of a TensorFlow

tensors*
variables - persistent mutable tensors
constants - constant
placeholders - from data

operations
an abstract computation (e.g. matrix multiply, add) executed by device *kernels*

* technically, still *operations*

graph

session
defines the environment in which operations *run*. (like a Spark context)

devices
the specific devices (cpus or gpus) on which to run the session.

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- tf.Variable(initial_value, name)
- tf.constant(value, type, name)
- tf.placeholder(type, shape, name)

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Category	**Examples**
Element-wise mathematical operations	Add, Sub, Mul, Div, Exp, Log, Greater, Less, Equal, ...
Array operations	Concat, Slice, Split, Constant, Rank, Shape, Shuffle, ...
Matrix operations	MatMul, MatrixInverse, MatrixDeterminant, ...
Stateful operations	Variable, Assign, AssignAdd, ...
Neural-net building blocks	SoftMax, Sigmoid, ReLU, Convolution2D, MaxPool, ...
Checkpointing operations	Save, Restore
Queue and synchronization operations	Enqueue, Dequeue, MutexAcquire, MutexRelease, ...
Control flow operations	Merge, Switch, Enter, Leave, NextIteration

Ingredients of a TensorFlow

- Places operations on devices
- Stores the values of variables (when not distributed)
- Carries out execution: eval() or run()

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Distributed TensorFlow

Typical use-case: (Supervised Machine Learning)

Determine weights, $\mathcal{W}$, of a function, f, such that ε is minimized: $f(\mathcal{X} | \mathcal{W}) = \mathcal{Y} + \varepsilon$

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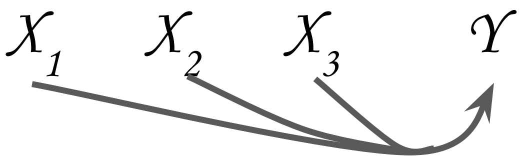

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$X_1 \quad X_2 \quad X_3 \qquad Y$

$X_1 \quad X_2 \quad X_3 \quad X_4 \quad X_5 \quad X_6$

$X_7 \quad X_8 \quad X_9 \quad X_{10} \quad X_{11} \quad X_{12} \qquad\qquad Y$

$X_{13} \quad X_{14} \quad X_{15} \quad \ldots \quad X_m$

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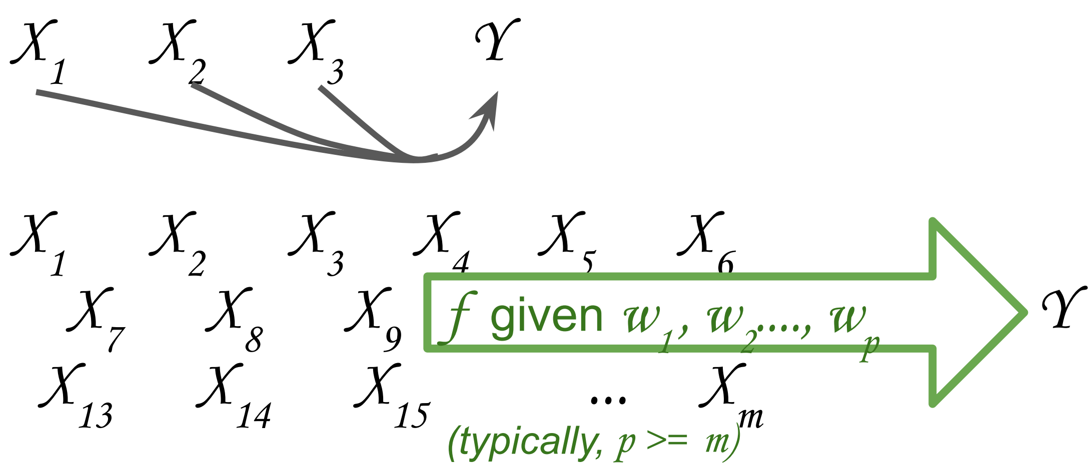

Distributed TensorFlow

Typical use-case:

Determine weights, W, of a function, f, such that $|\varepsilon|$ is minimized:

$$f(X|W) = \hat{Y}$$
$$Y = (X|W) + \varepsilon$$
$$Y = \hat{Y} + \varepsilon$$
$$\varepsilon = \hat{Y} - Y$$

$X_1 \quad X_2 \quad X_3 \quad \rightarrow \quad Y$

$X_1 \quad X_2 \quad X_3 \quad X_4 \quad X_5 \quad X_6$
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Typically, very complex!

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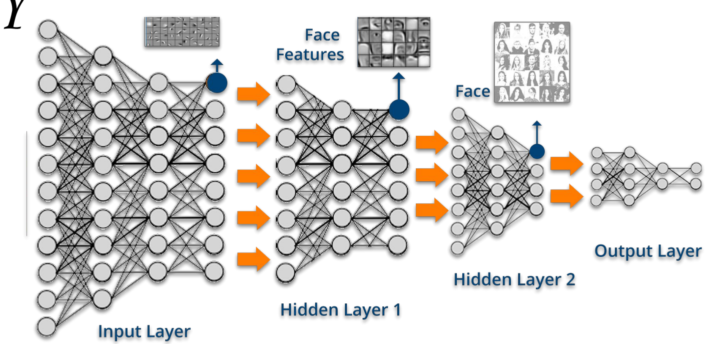

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back propagating error across the network that defines f.

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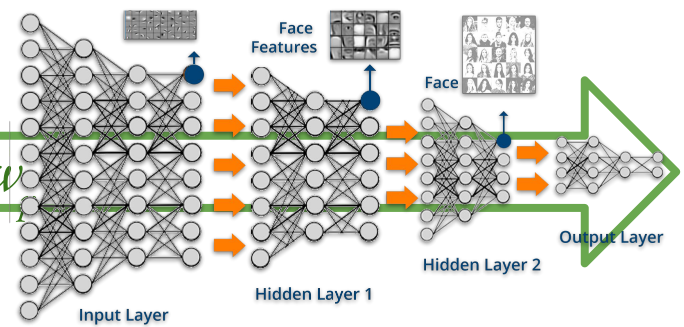

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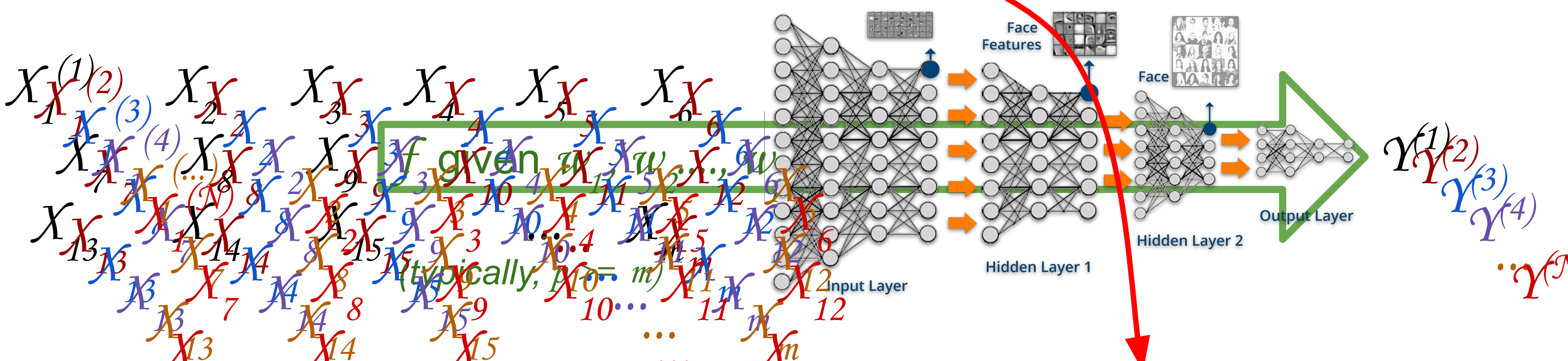
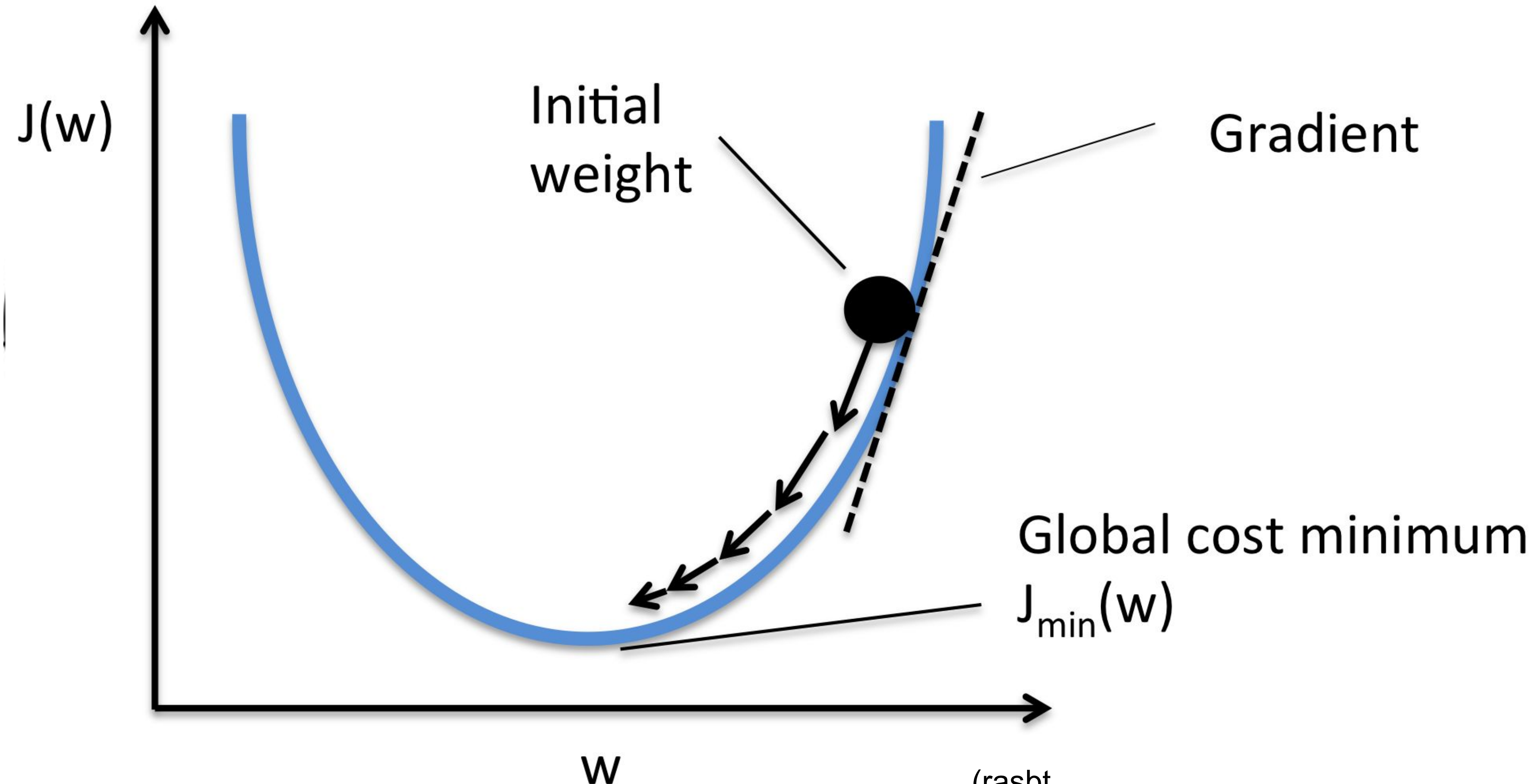


minimizes ε on ***N*** training examples

Weights Derived from Gradients



(rasbt,

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In standard linear equation:

$$y = mx + b$$

$$\text{let } x' = x + [1, 1, ..., 1]_N^T$$

$$\text{then, } y = mx'$$

(if we add a column of 1s, mx + b is just matmul(m, x))

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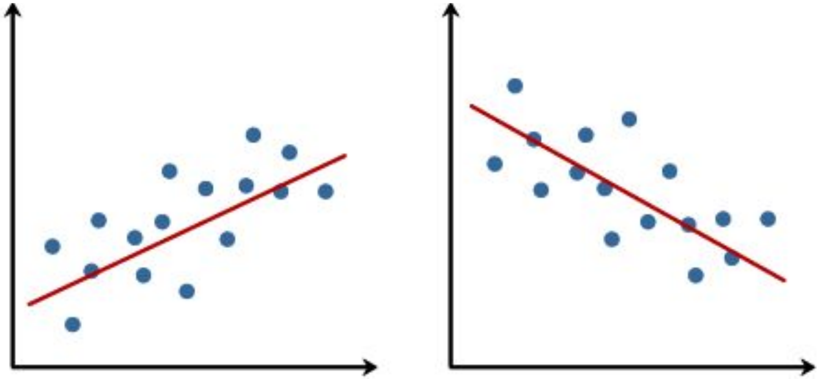

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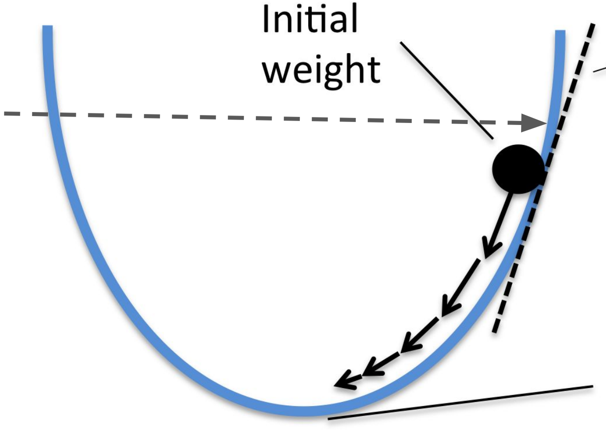
(for gradient descent) "learning rate"



Weights Derived from Gradients

Ridge Regression (L2 Penalized linear regression, $\lambda||\beta||_2^2$)

$$\hat{\beta}^{ridge} = argmin_{\beta}\{\sum_{i=1}^{N}(y_i - \sum_{j=1}^{m} x_{ij}\beta_j)^2 + \lambda \sum_{j=1}^{m} \beta_j^2\}$$

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(Mirrors many parameter optimization problems.)

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tf.gradients(cost, [params])
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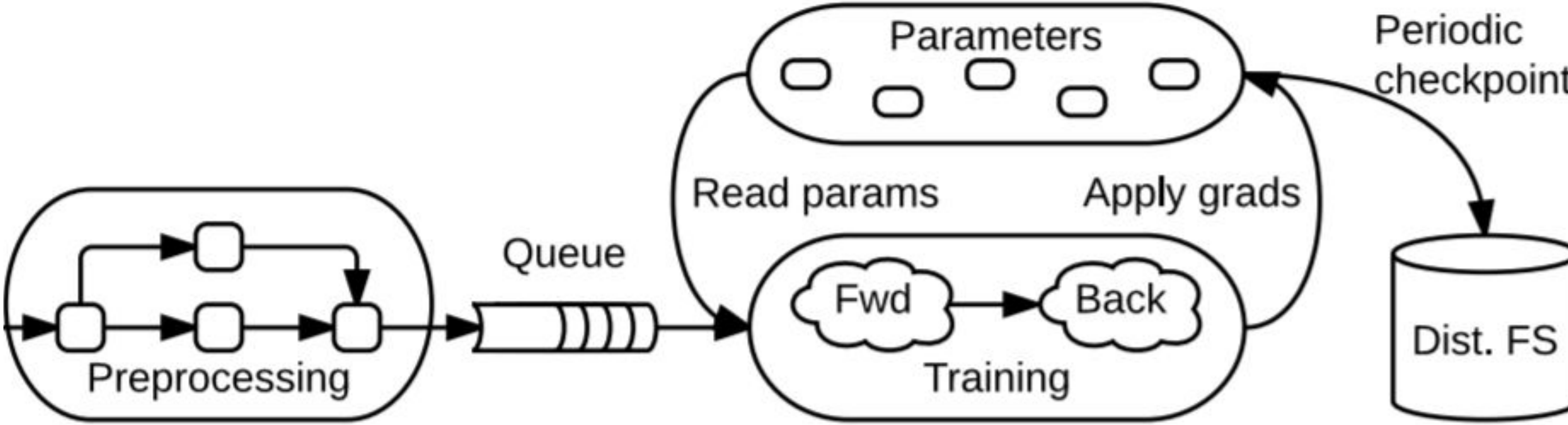

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    Model Parellelism

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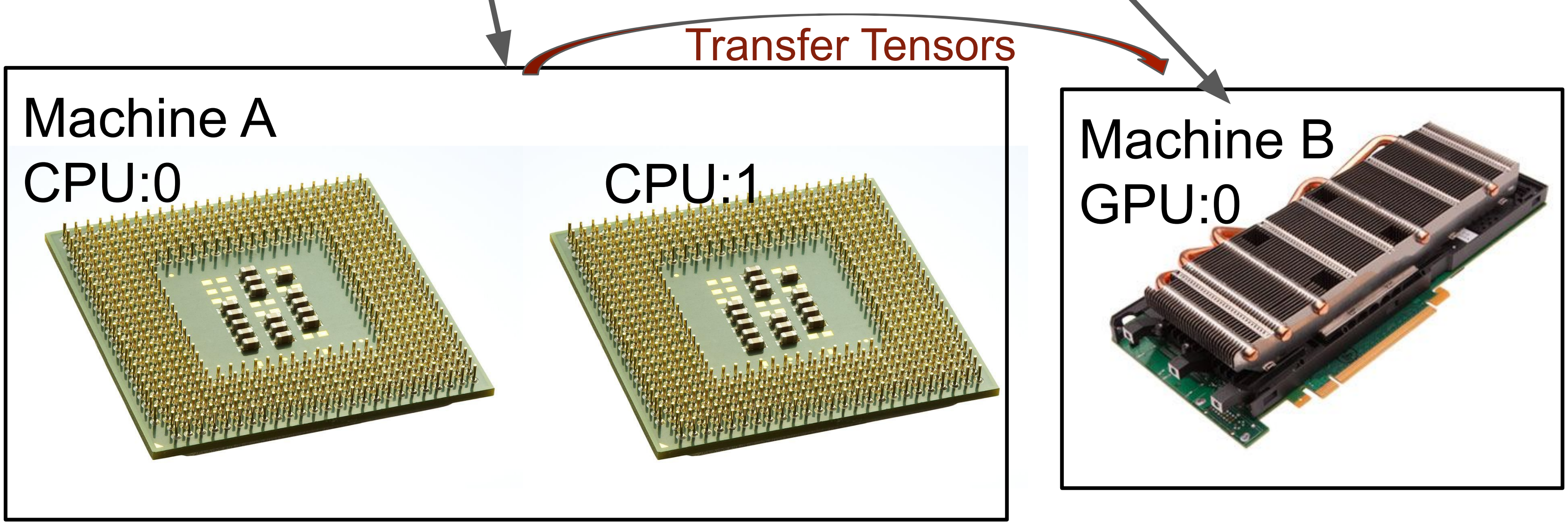
Model Parallelism

Multiple devices on multiple machines

```
with tf.device("/cpu:1")
   beta=tf.Variable(...)
```

```
with tf.device("/gpu:0")
   y_pred=tf.matmul(beta,X)
```



<u>Data</u> Parallelism

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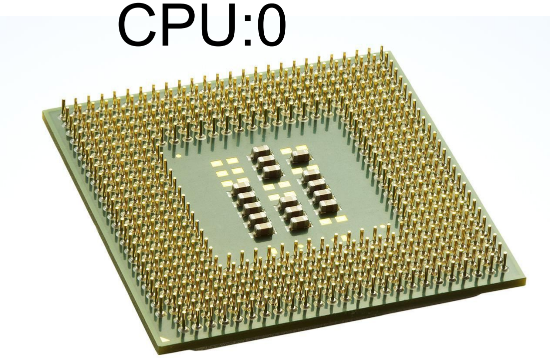
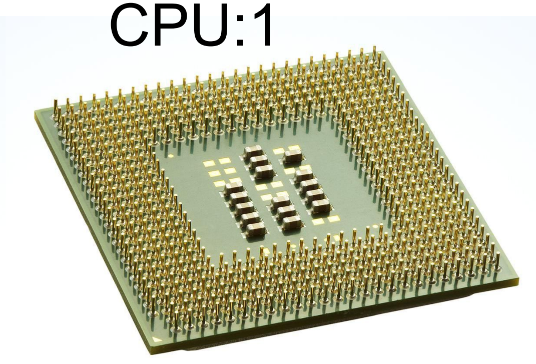
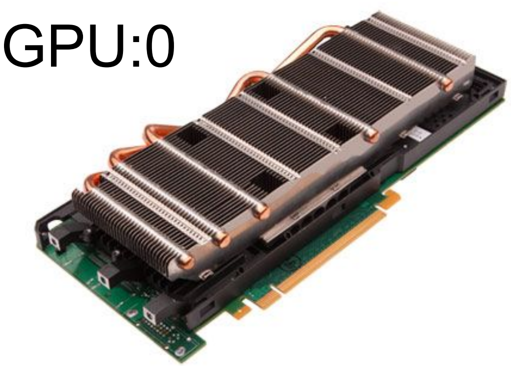
CPU:0



CPU:1



GPU:0



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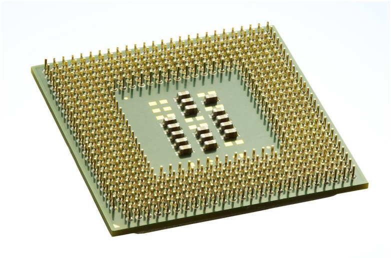
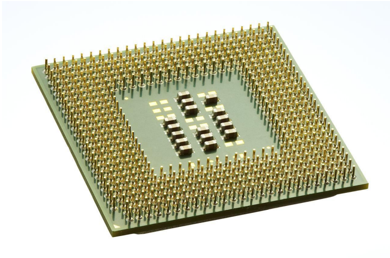
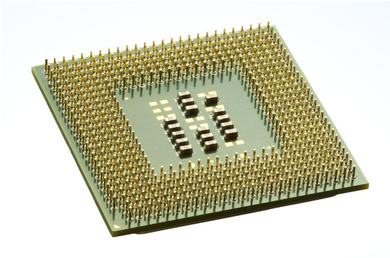


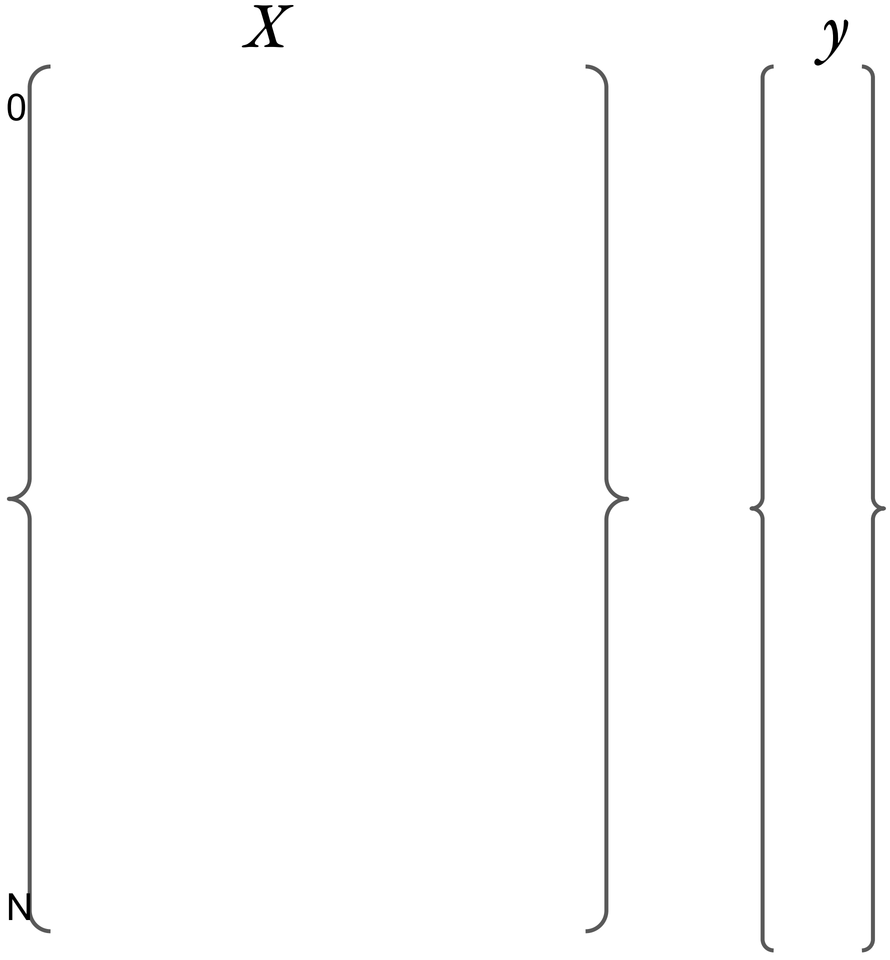
worker:1



worker:2



Distributing Data



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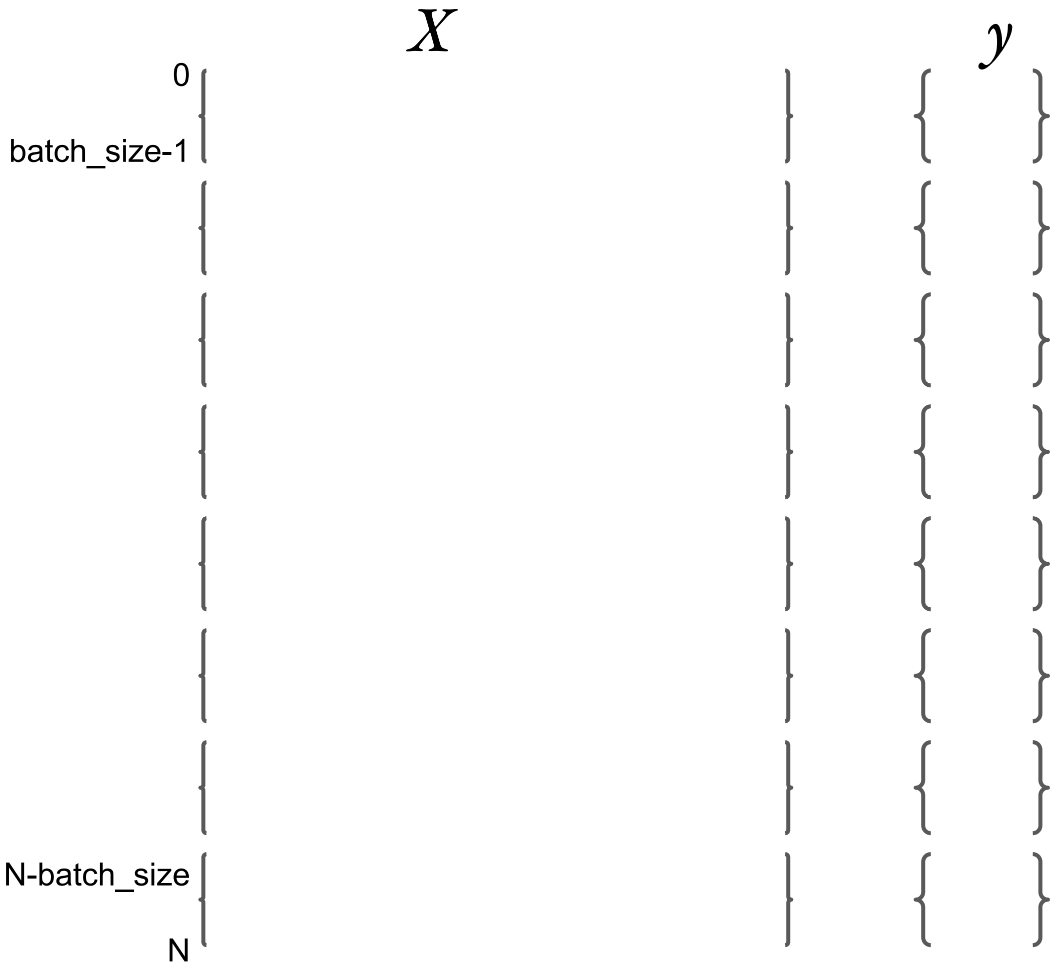

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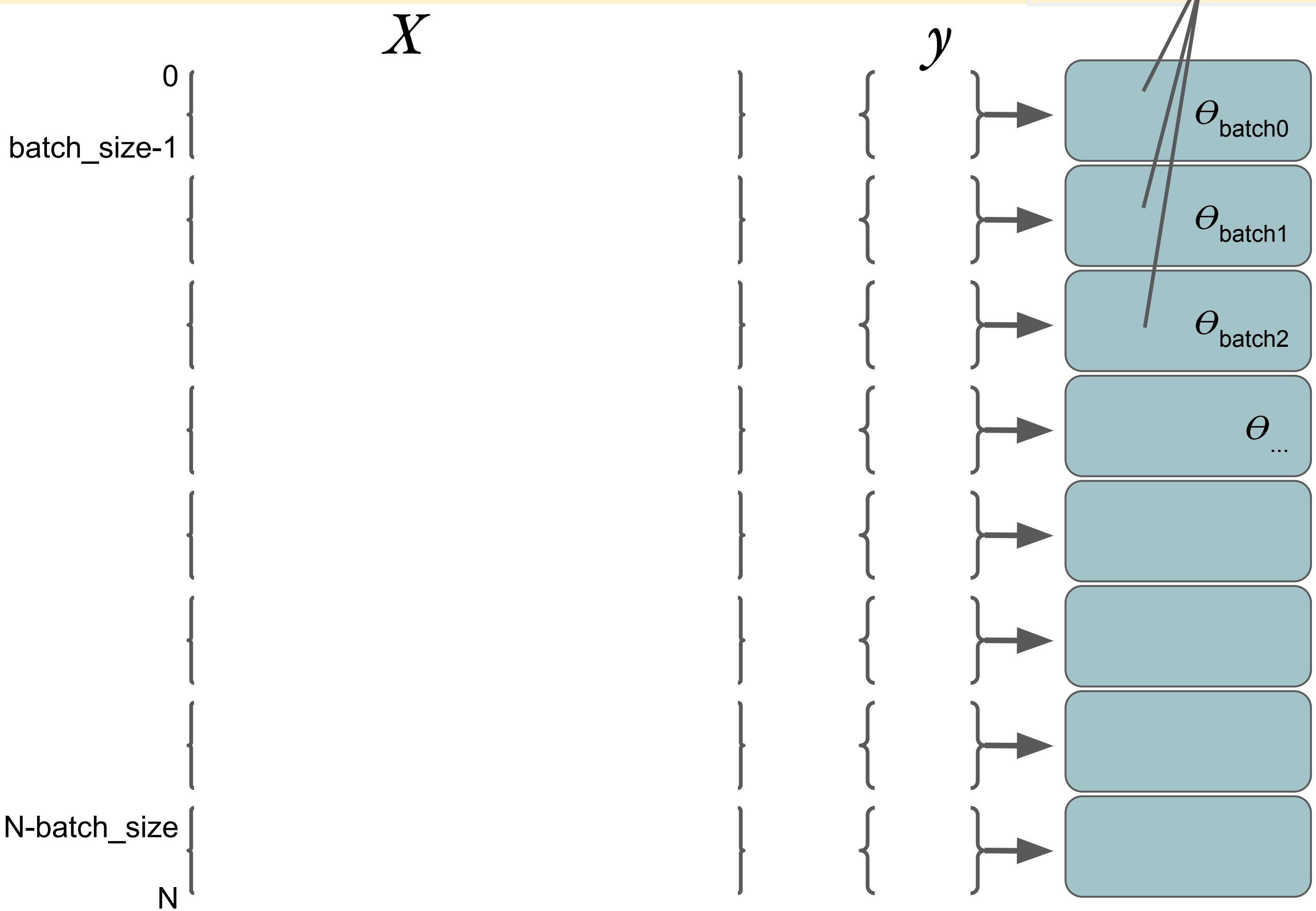

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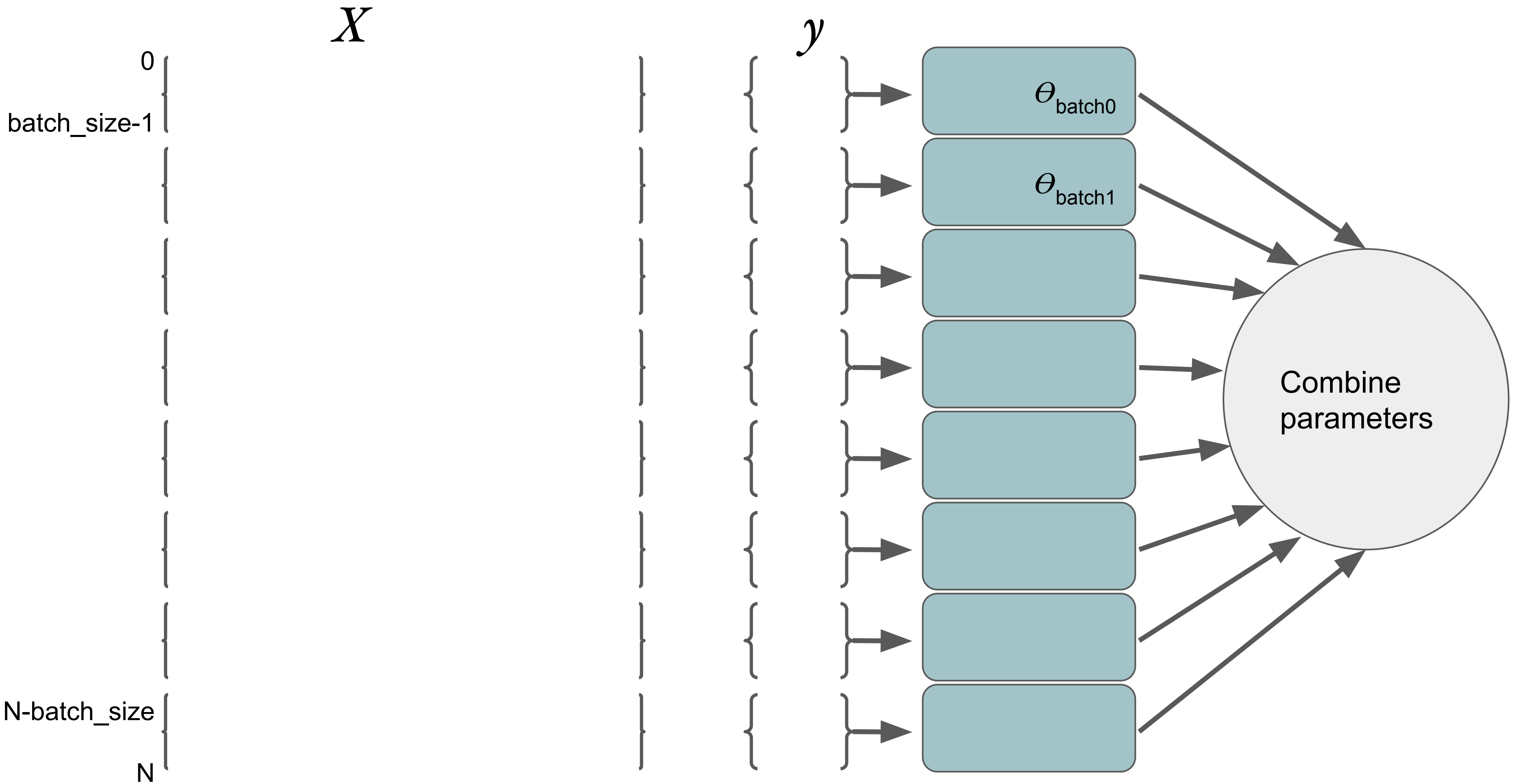

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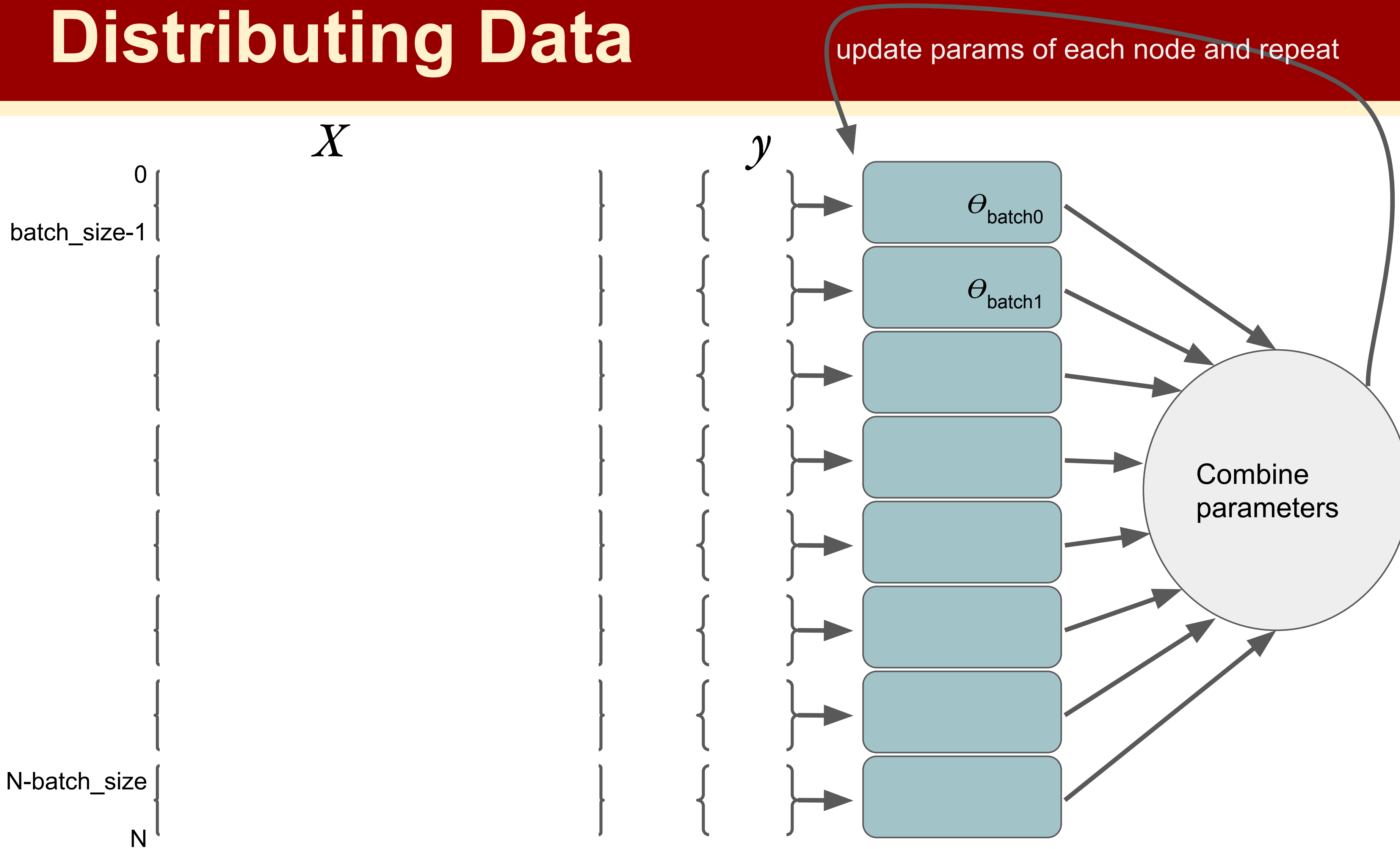
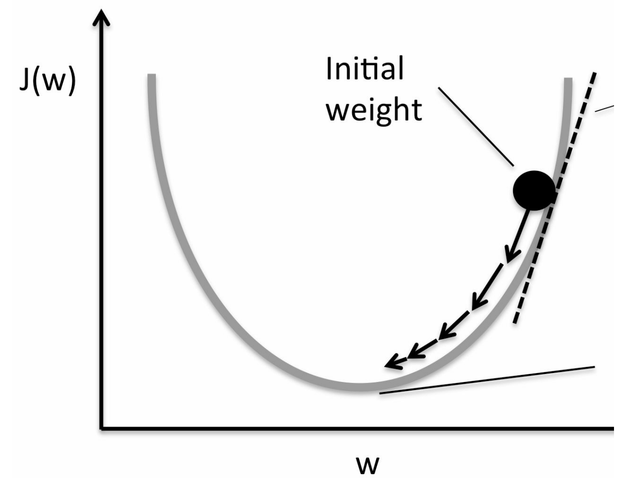


Gradient Descent for Linear Regression



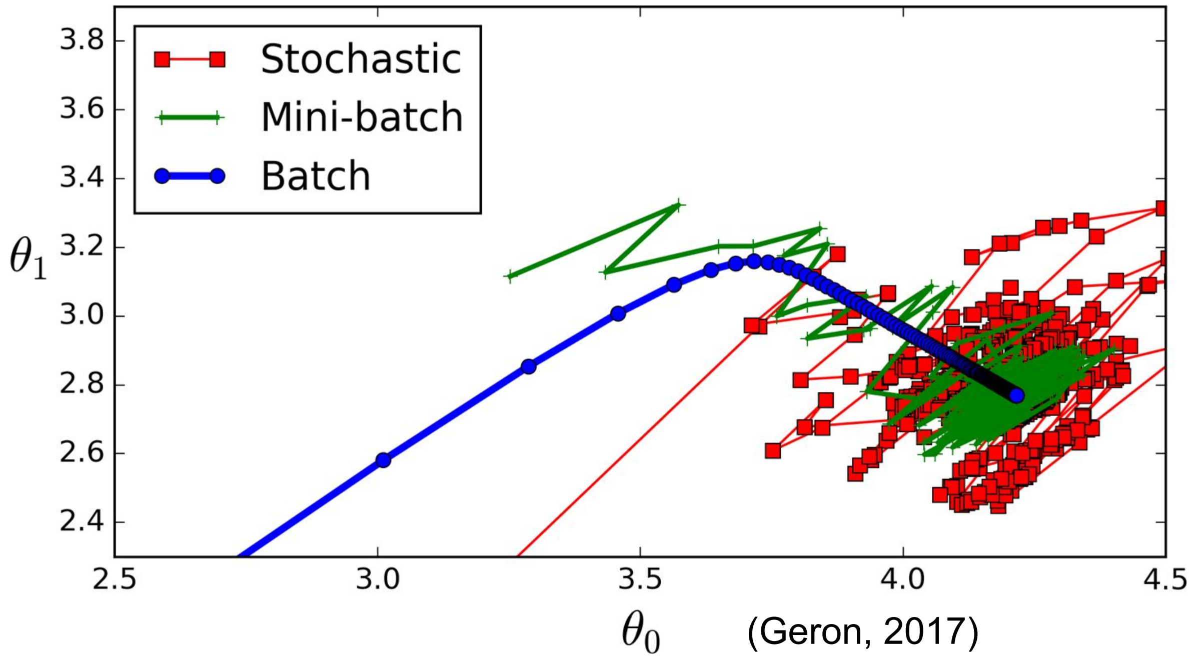
(Geron, 2017)

Gradient Descent for Linear Regression

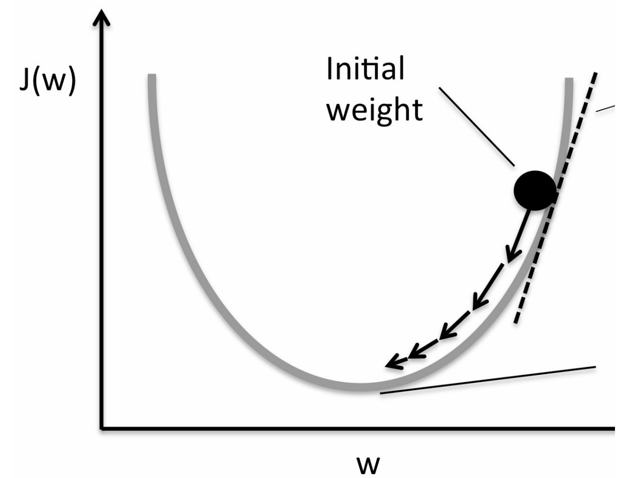
Batch Gradient Descent

Stochastic Gradient Descent: One example at a time

Mini-batch Gradient Descent: k examples at a time.



(Geron, 2017)



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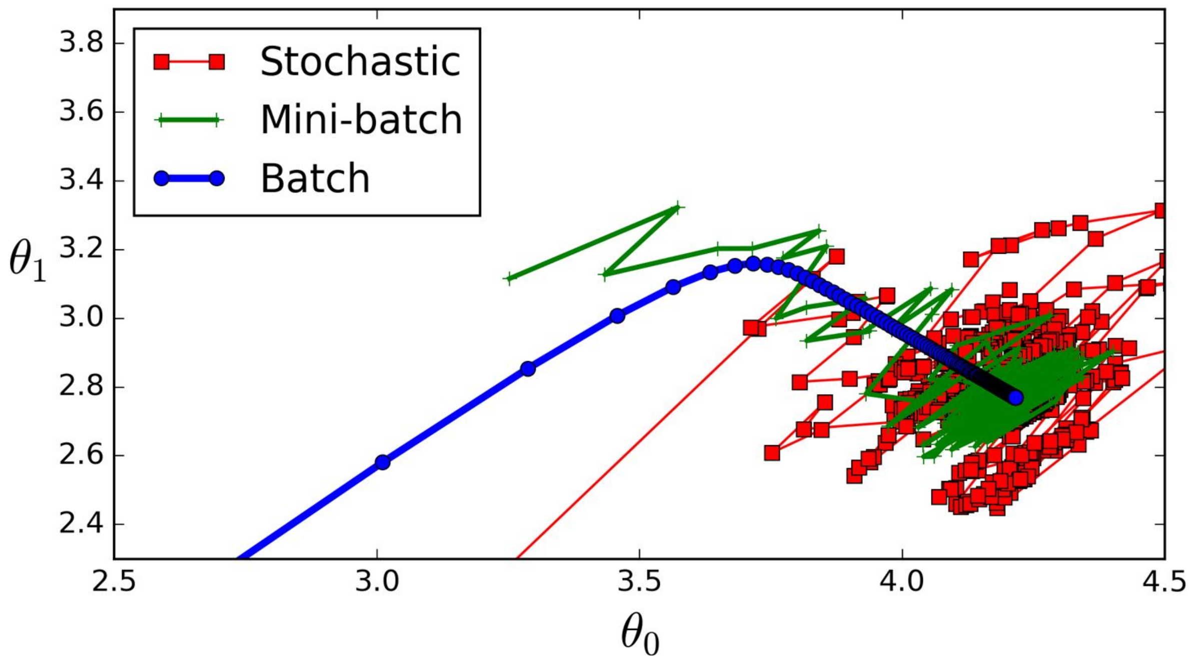
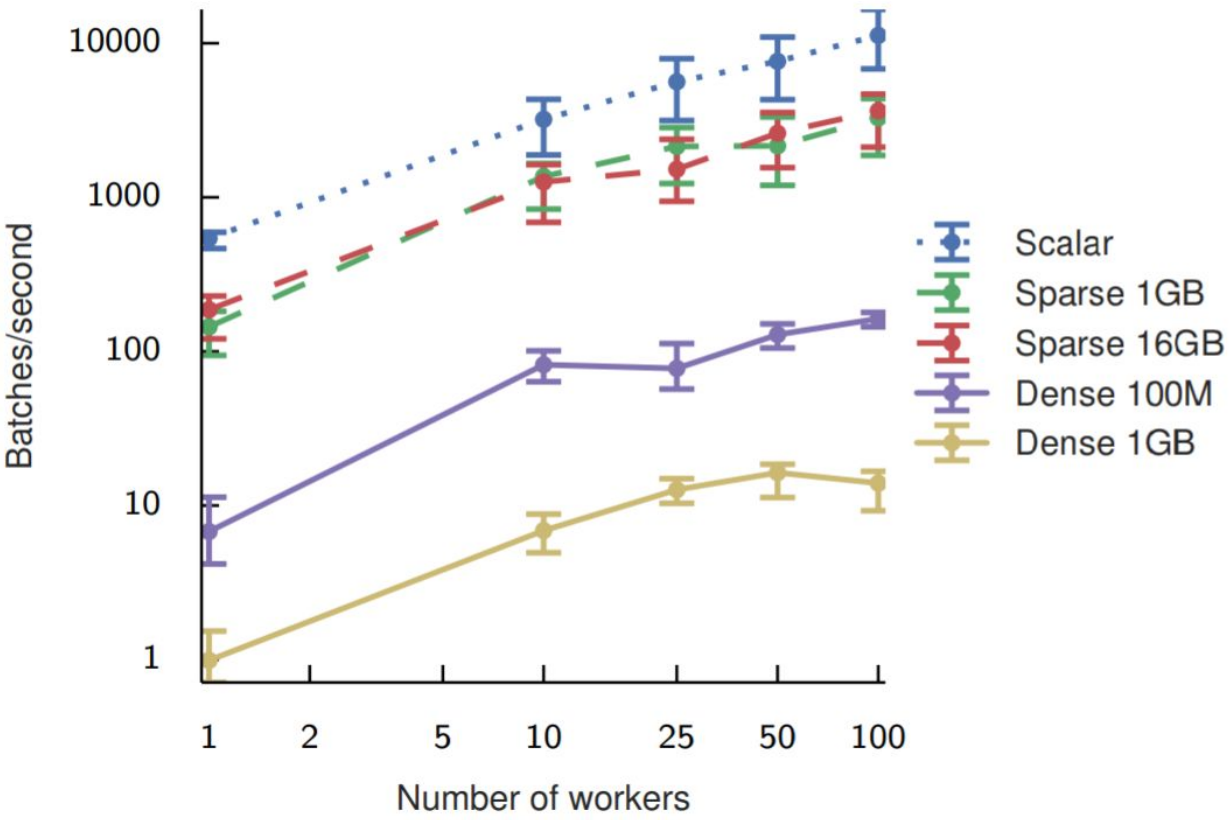


(Geron, 2017)

Distributed TensorFlow



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Distributed:

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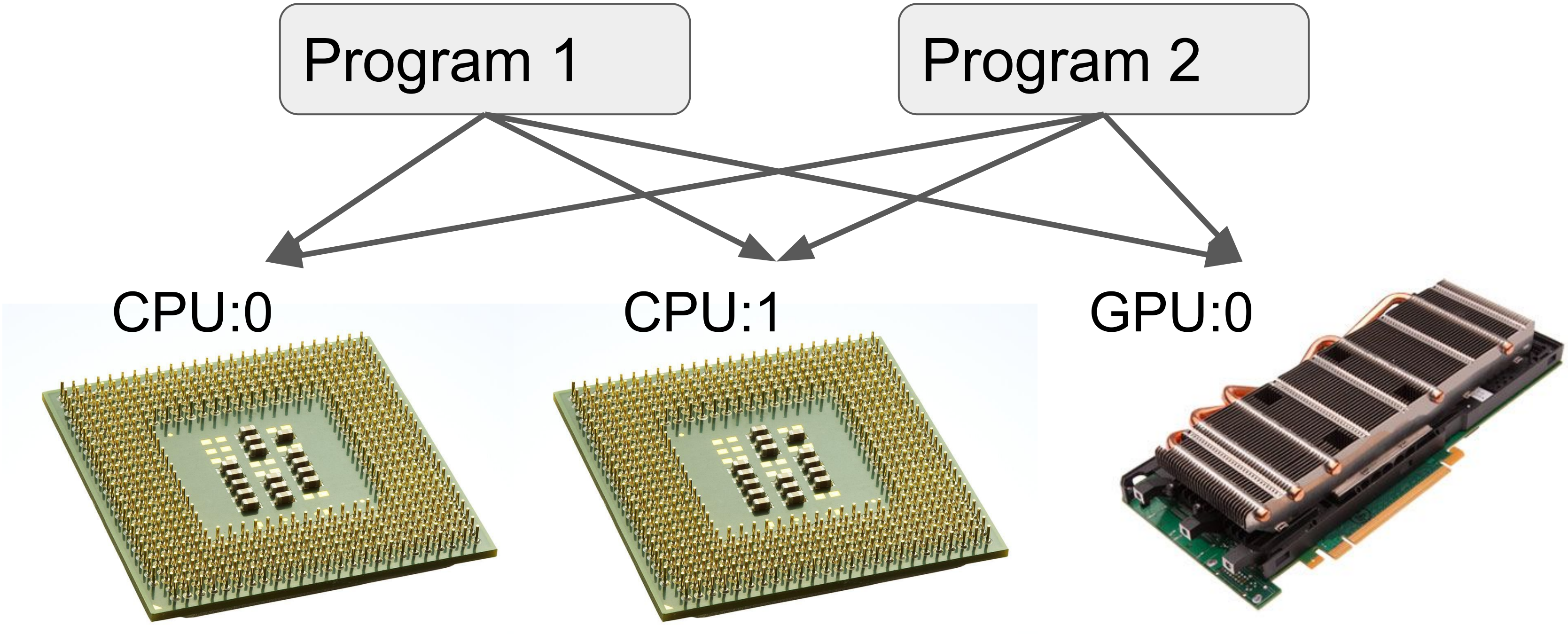
Multiple devices on single machine



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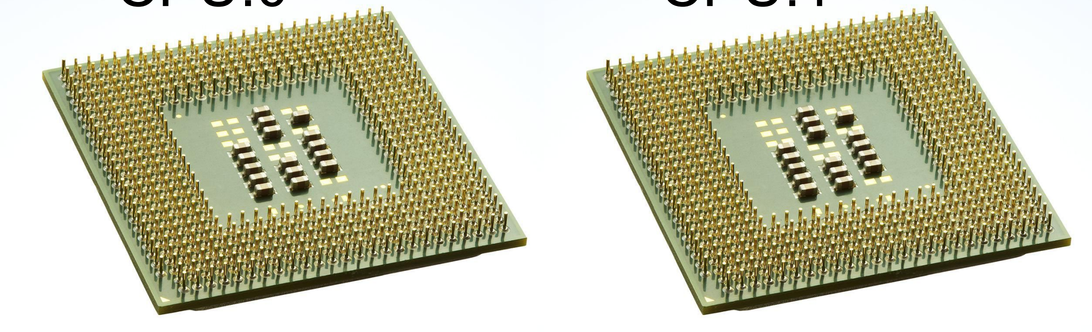

GPU:0

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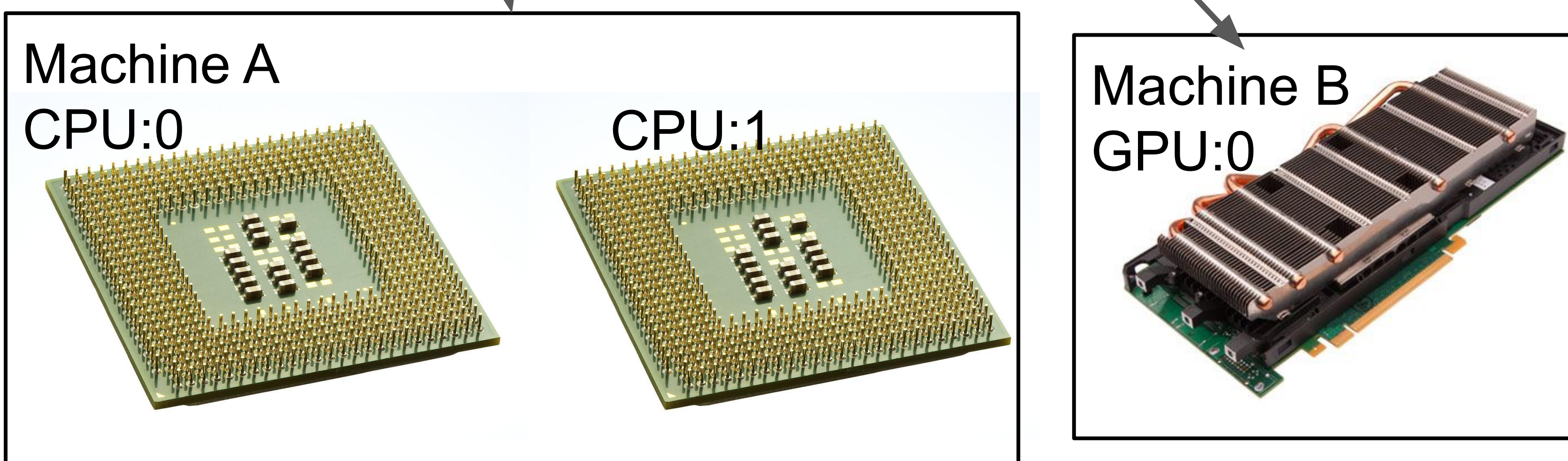

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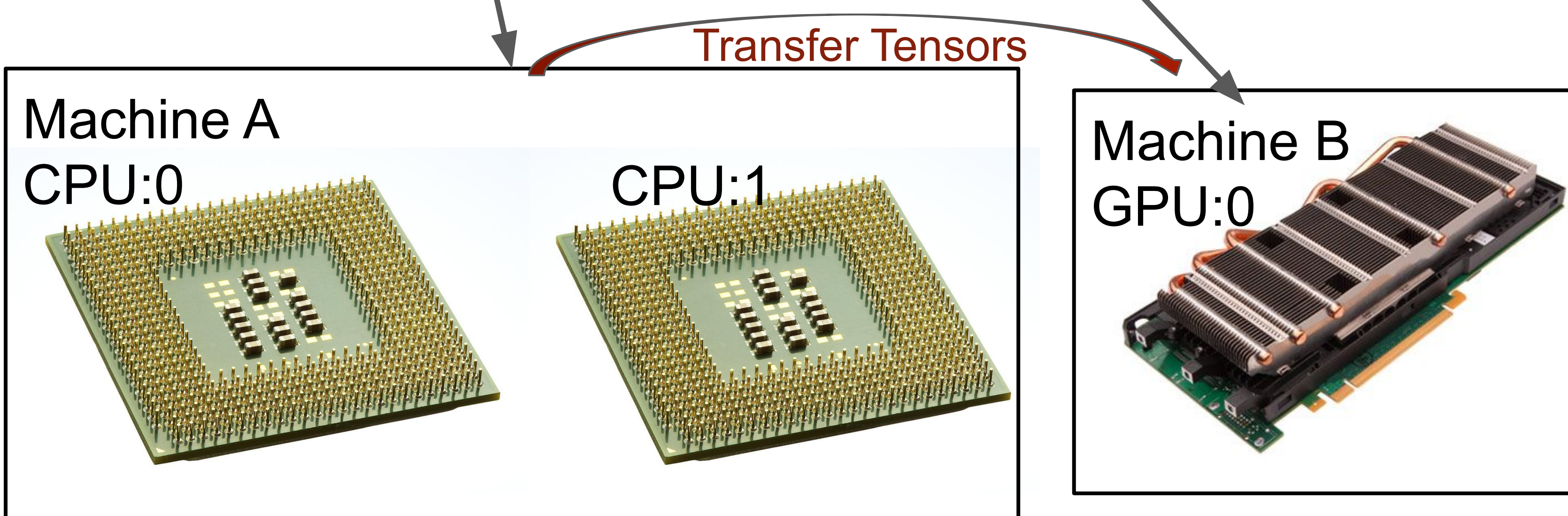

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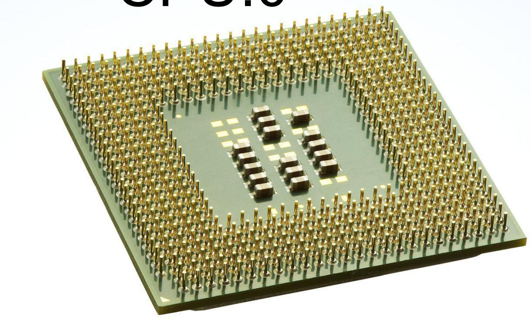
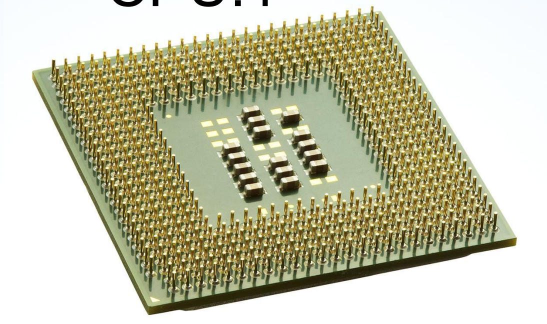


CPU:1



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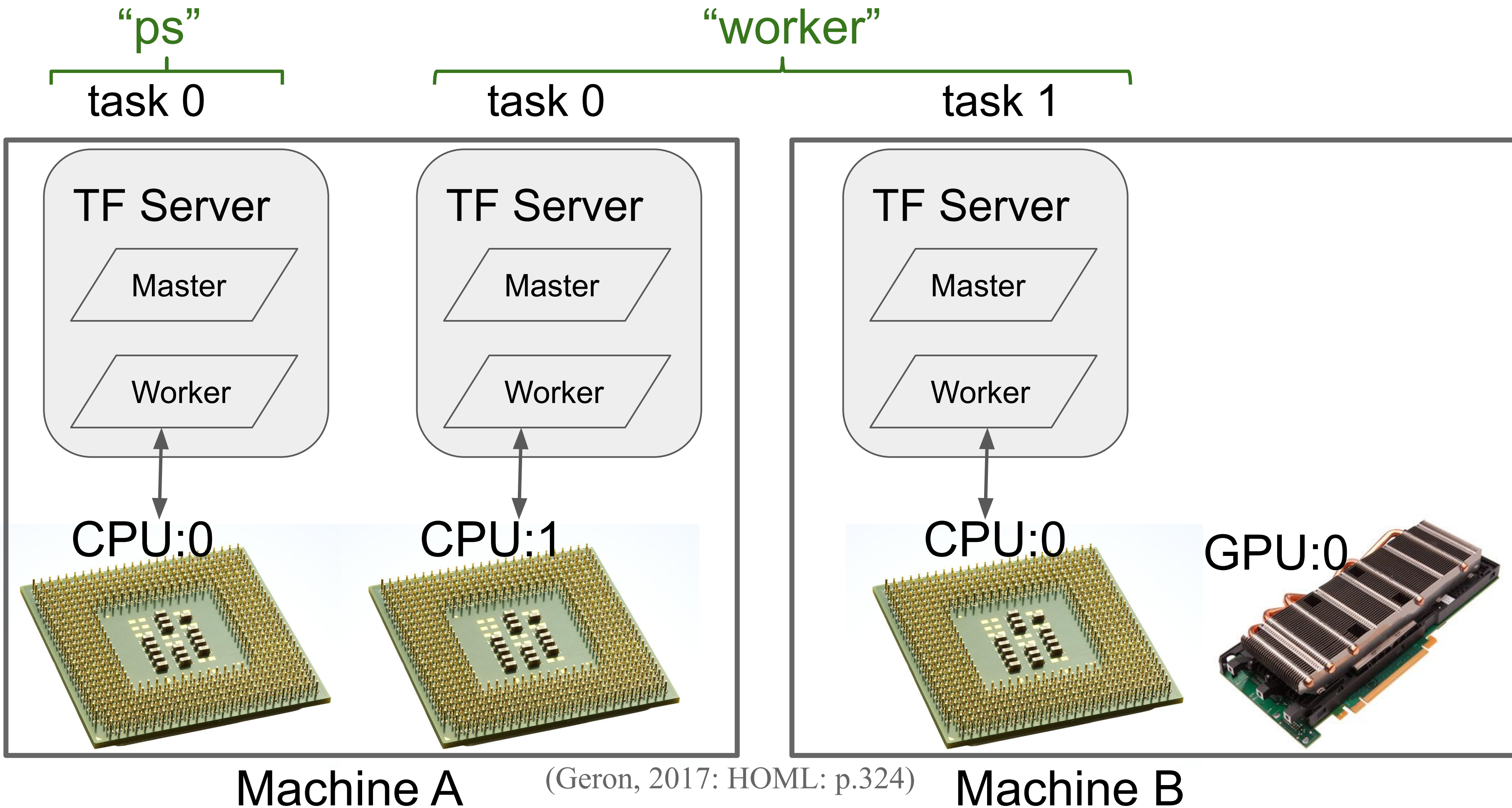
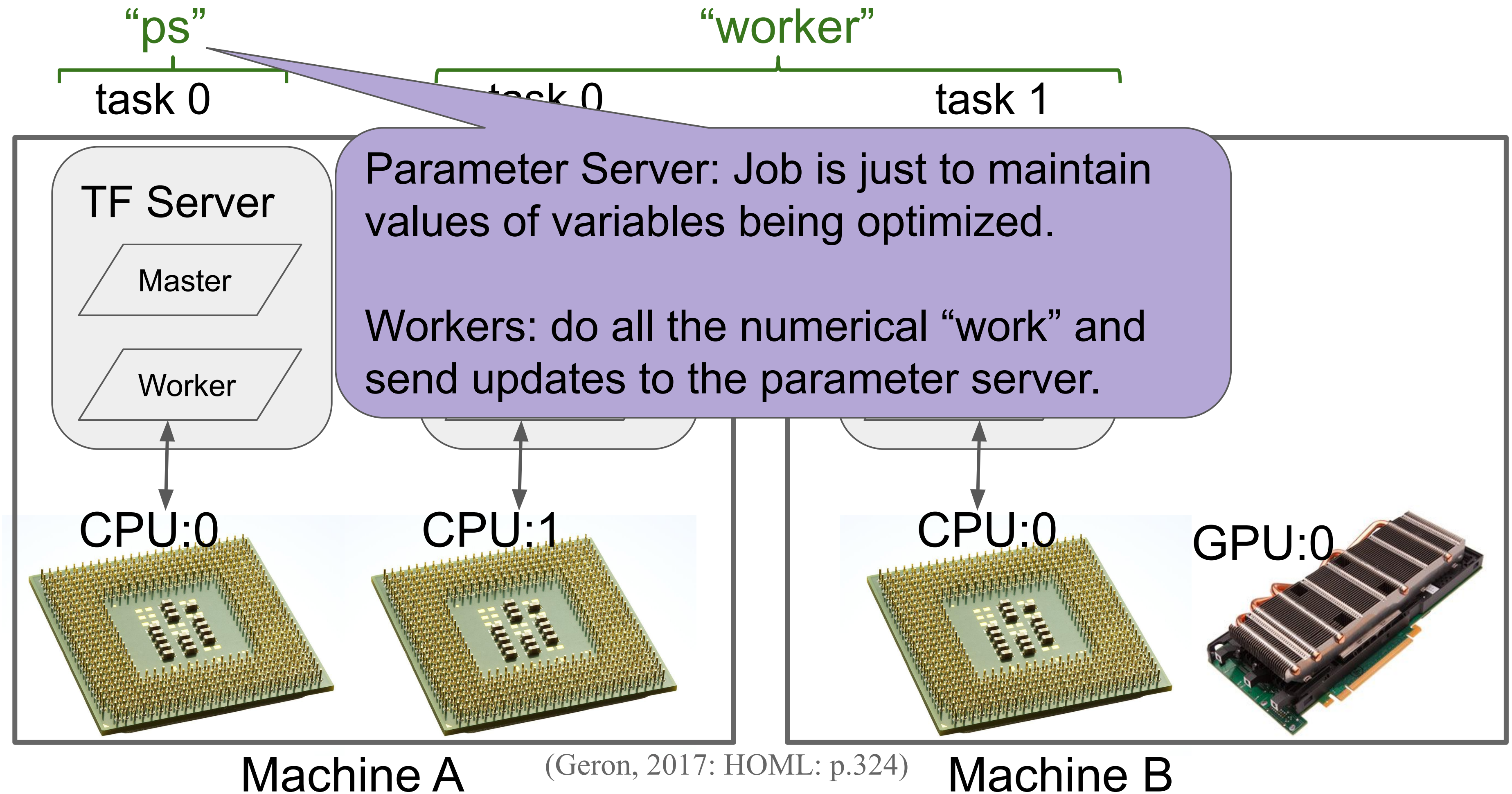


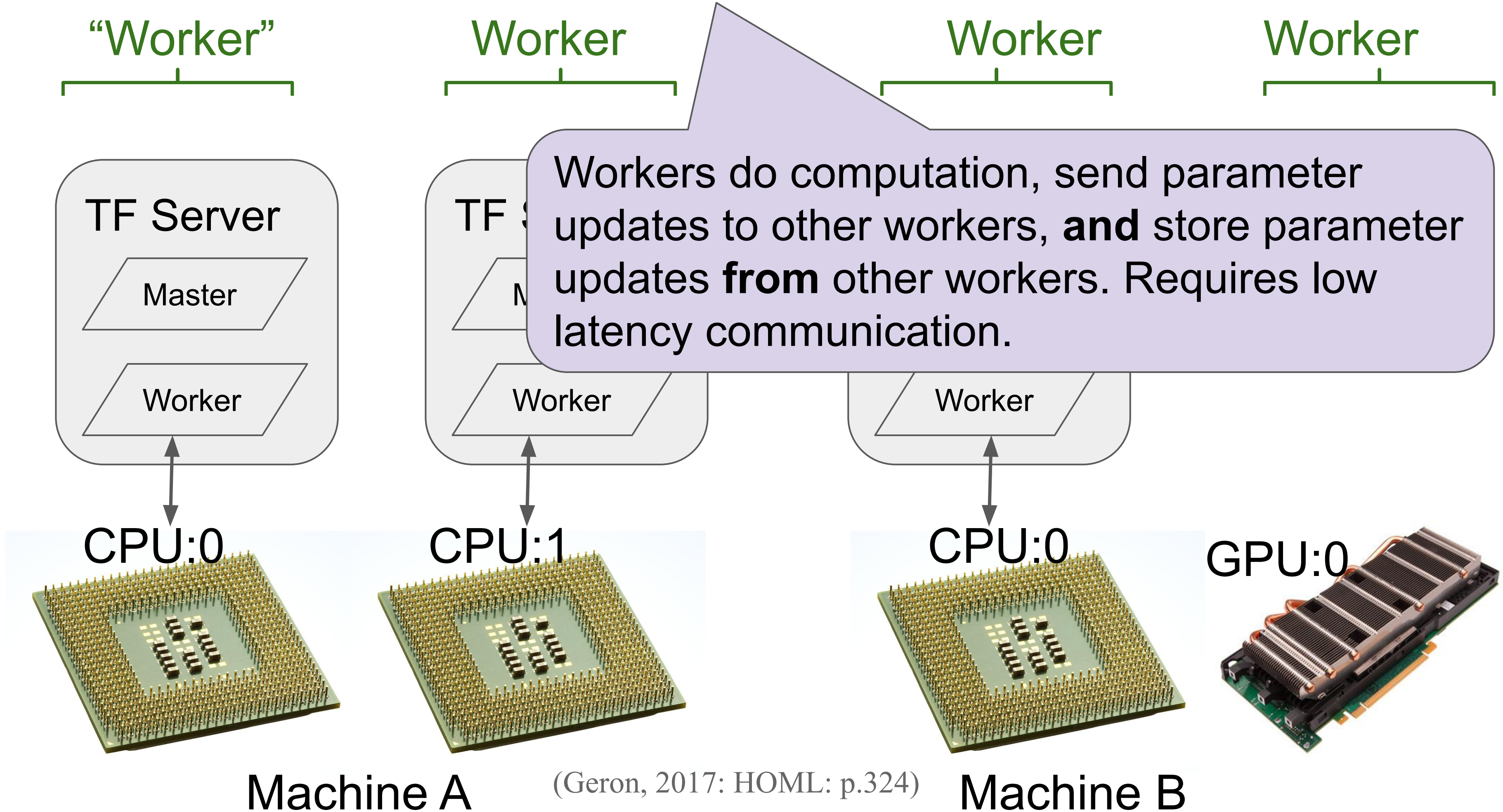
(Geron, 2017: HOML: p.324)

Asynchronous Parameter Server



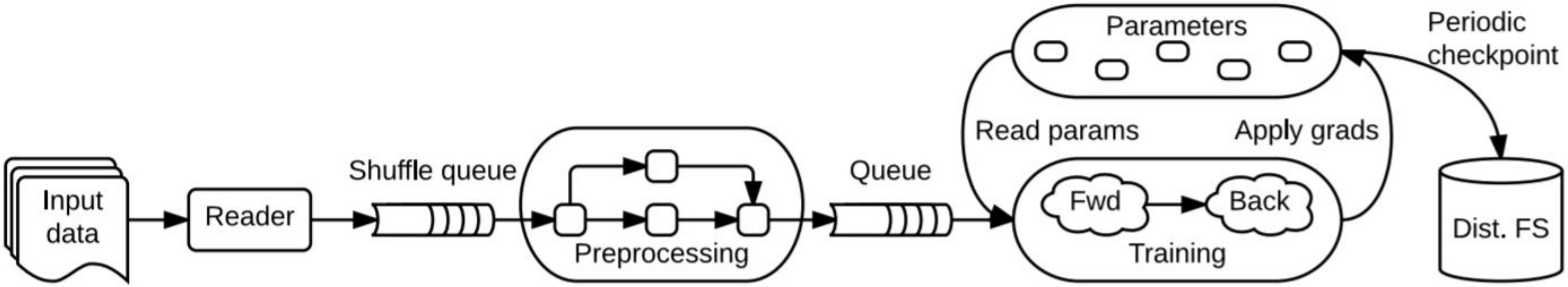
(Geron, 2017: HOML: p.324)

Synchronous All Reduce



(Geron, 2017: HOML: p.324)

Distributed TF: Full Pipeline



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Summary

- TF is a workflow system, where records are always tensors
  - *operations* applied to tensors (as either Variables, constants, or placeholder)
- Optimized for numerical / linear algebra
  - automatically finds gradients
  - custom kernels for given devices
- “Easily” distributes
  - Within a single machine (local: many devices))
  - Across a cluster (many machines and devices)
  - Jobs broken up as parameter servers / workers makes coordination of data efficient