Distributed TensorFlow

Stony Brook University

CSE545, Spring 2019

Goals

- 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 workflow system catered to numerical computation.

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

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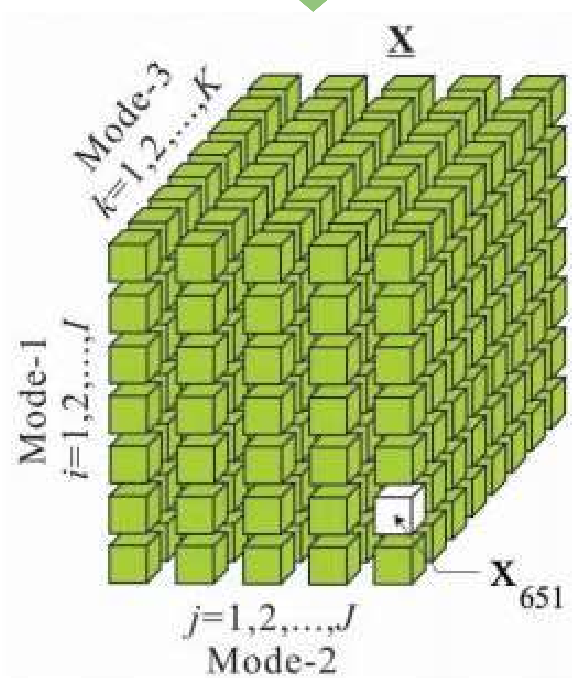

A multi-dimensional matrix

(i.stack.imgur.com)

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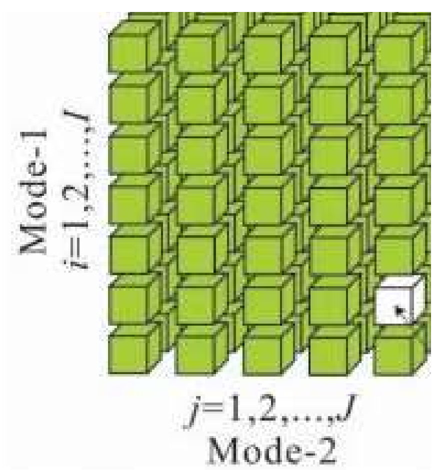

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A 2-d tensor is just a matrix.

- 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]

TensorFlow

A workflow system catered to numerical computation.

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…).

Then, why TensorFlow?

TensorFlow

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

enables complex models, like deep learning

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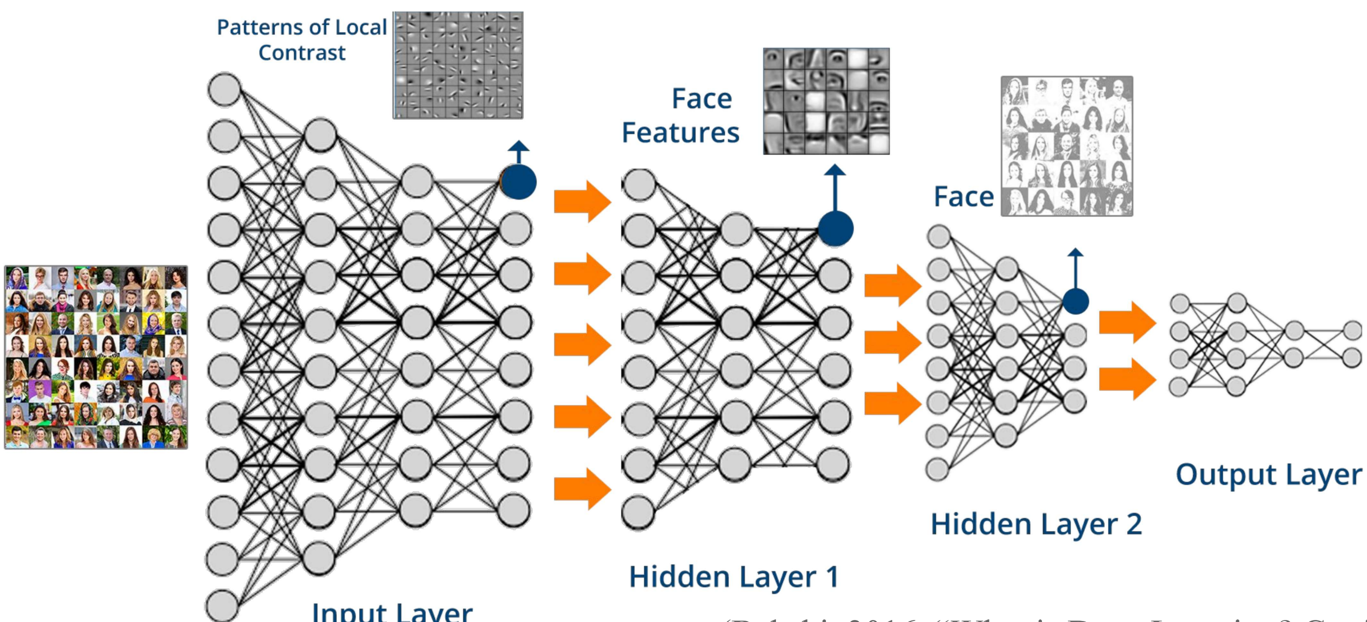

(Bakshi, 2016, "What is Deep Learning? Getting Started With Deep Learning")

TensorFlow

Efficient, high-level built-in **linear algebra** and **machine learning** *operations*.

```
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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Operations on tensors are often conceptualized as **graphs**:

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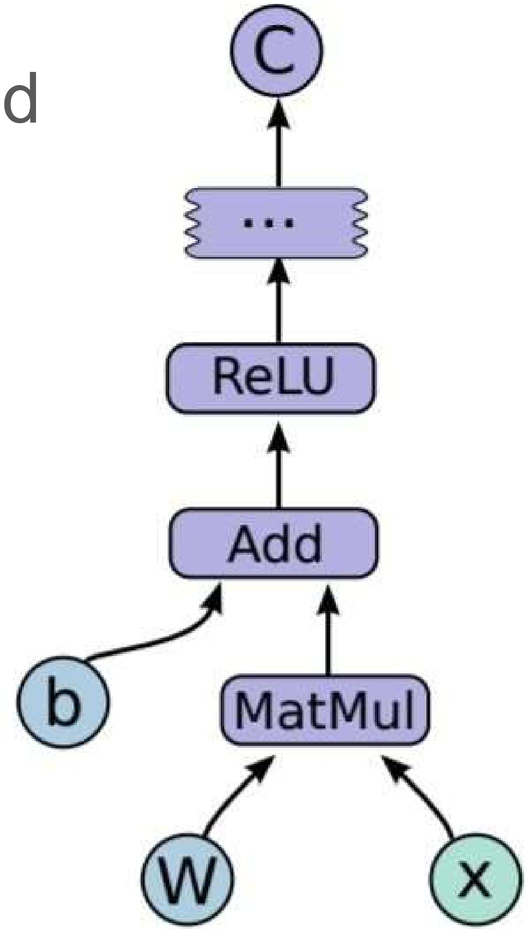

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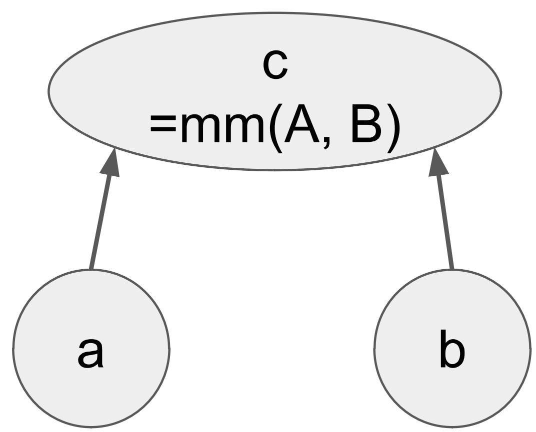
A simpler example:

c = tensorflow.matmul(a, b)



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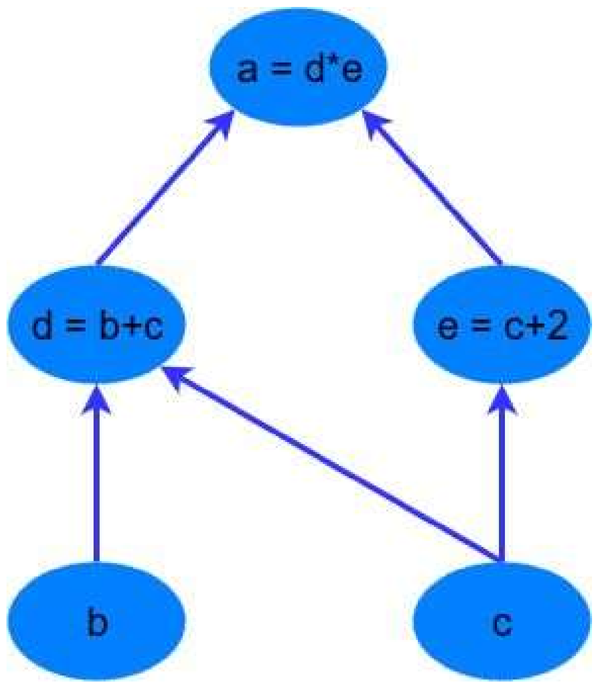
example:

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



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

* technically, *operations* that work with tensors.

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*

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defines the environment in which operations *run*.
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- tf.Variable(initial_value, name)
- tf.constant(value, type, name)
- tf.placeholder(type, shape, name)

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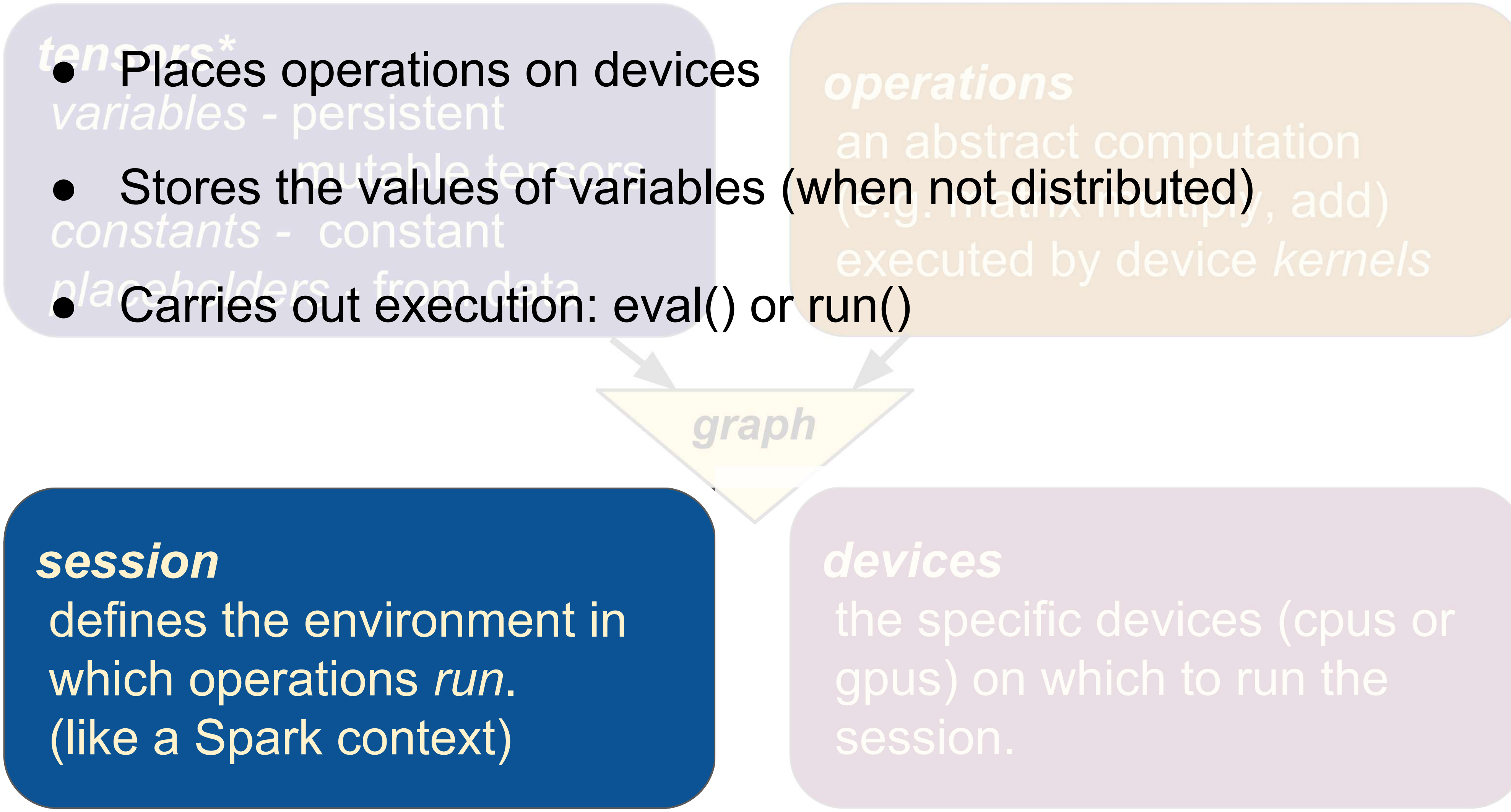
Category	**Examples**
Element-wise mathematical operations	Add, Sub, Mul, Div, Exp, Log, Greater, Less, Equal, ...
Array operations	Concat, Slice, Split, Constant, Rank, Shape, Shuffle, ...
Matrix operations	MatMul, MatrixInverse, MatrixDeterminant, ...
Stateful operations	Variable, Assign, AssignAdd, ...
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

Sessions

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



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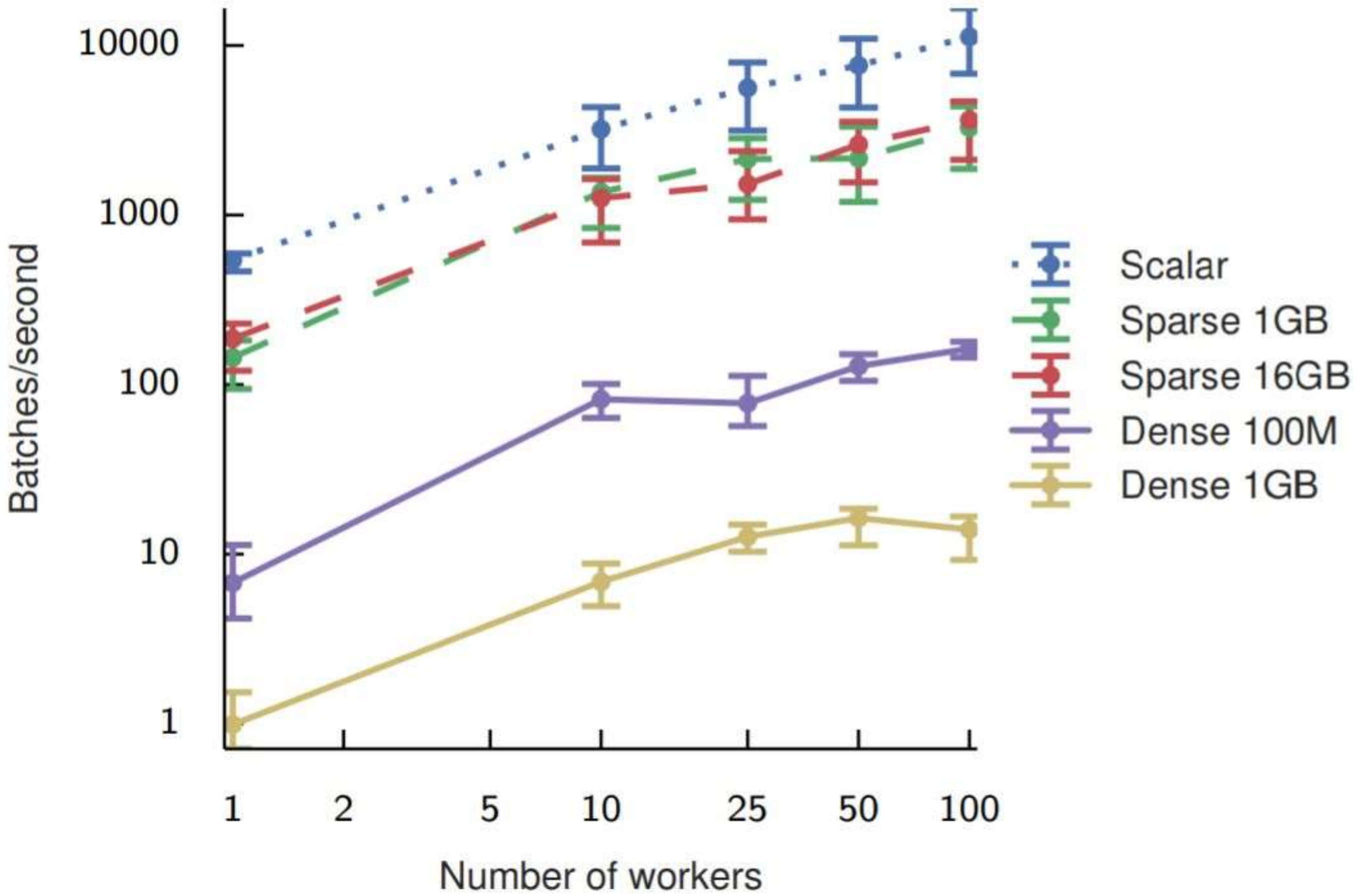

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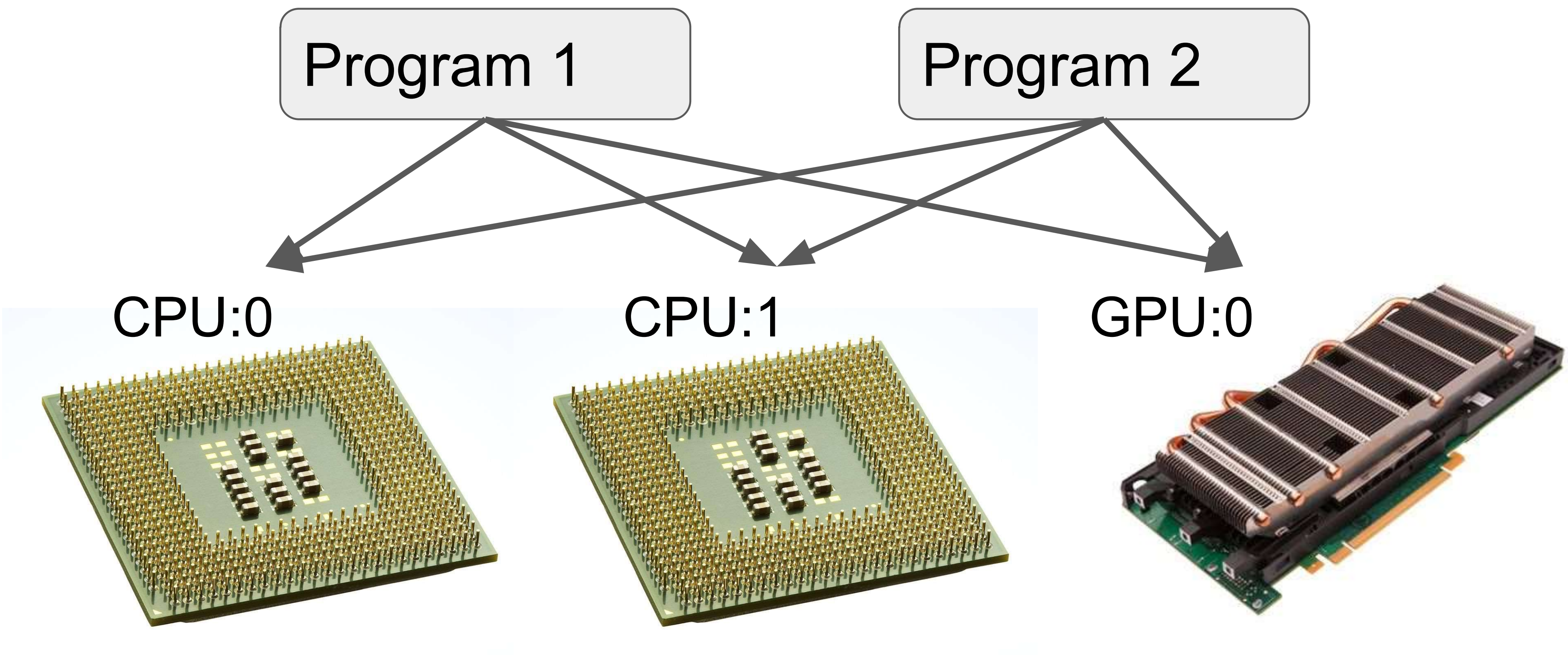
Multiple devices on single machine



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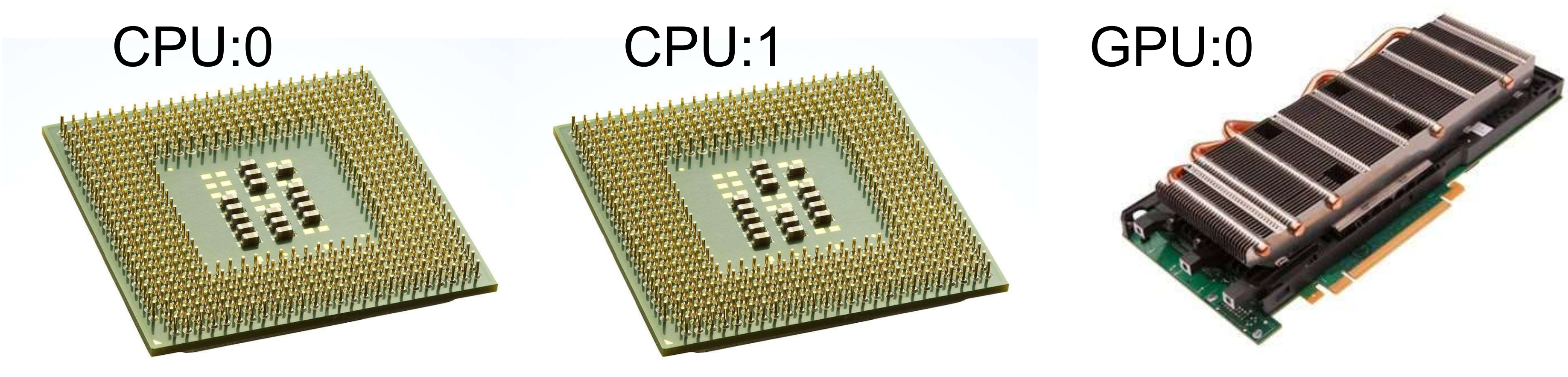

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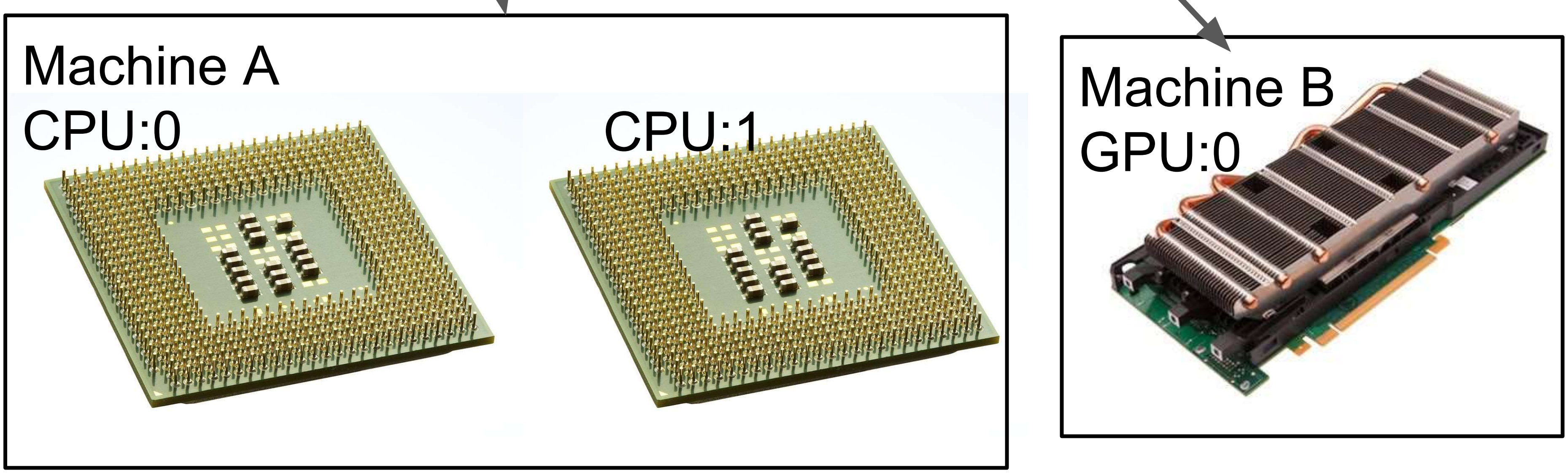

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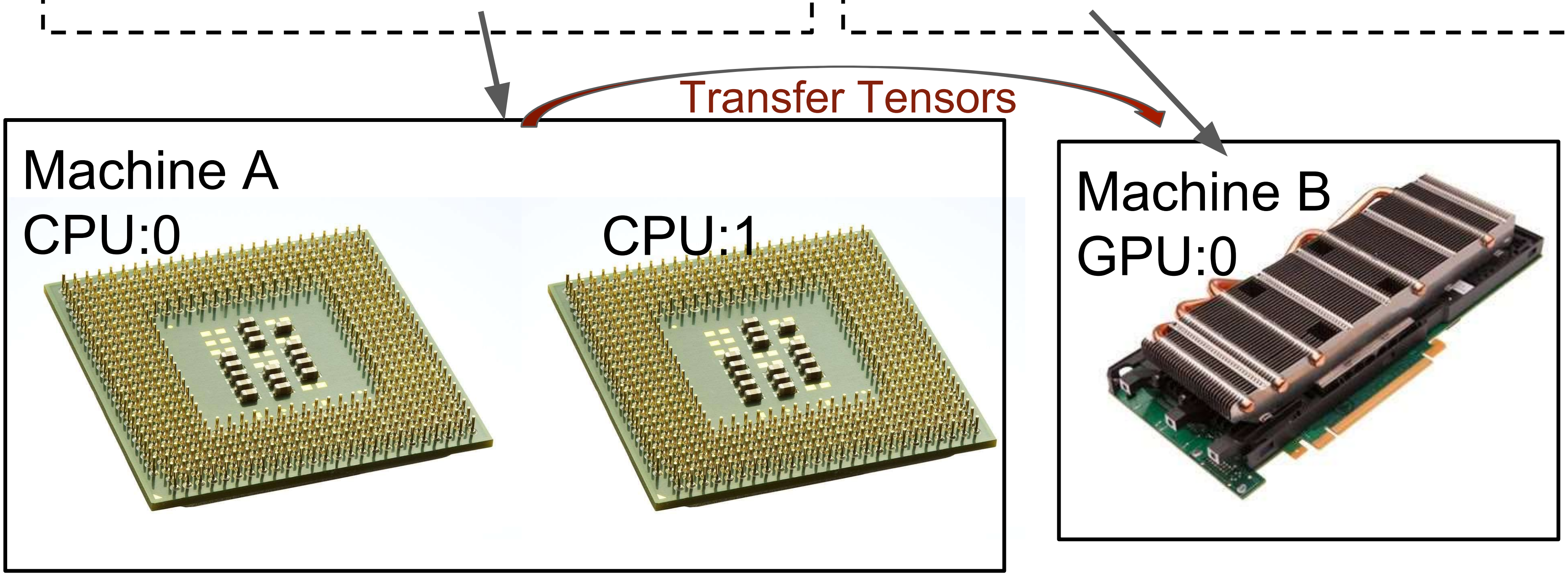

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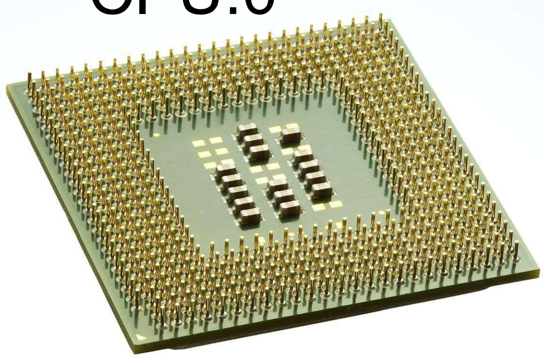
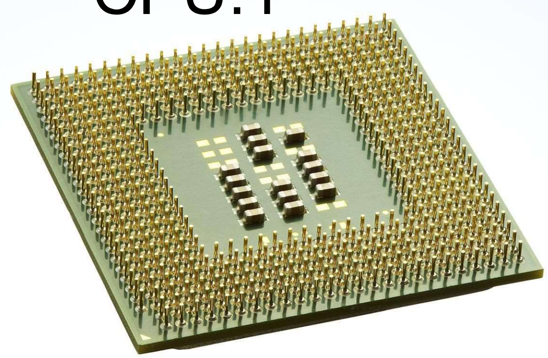
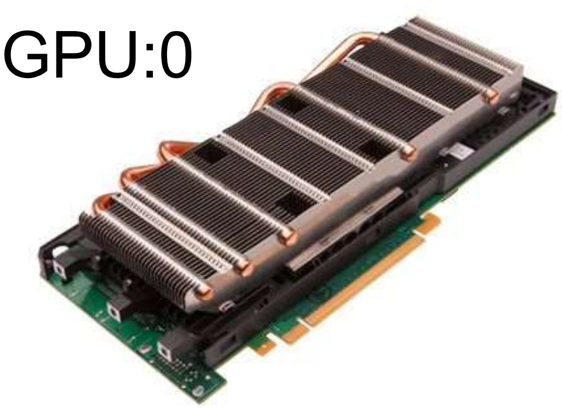


CPU:1



GPU:0



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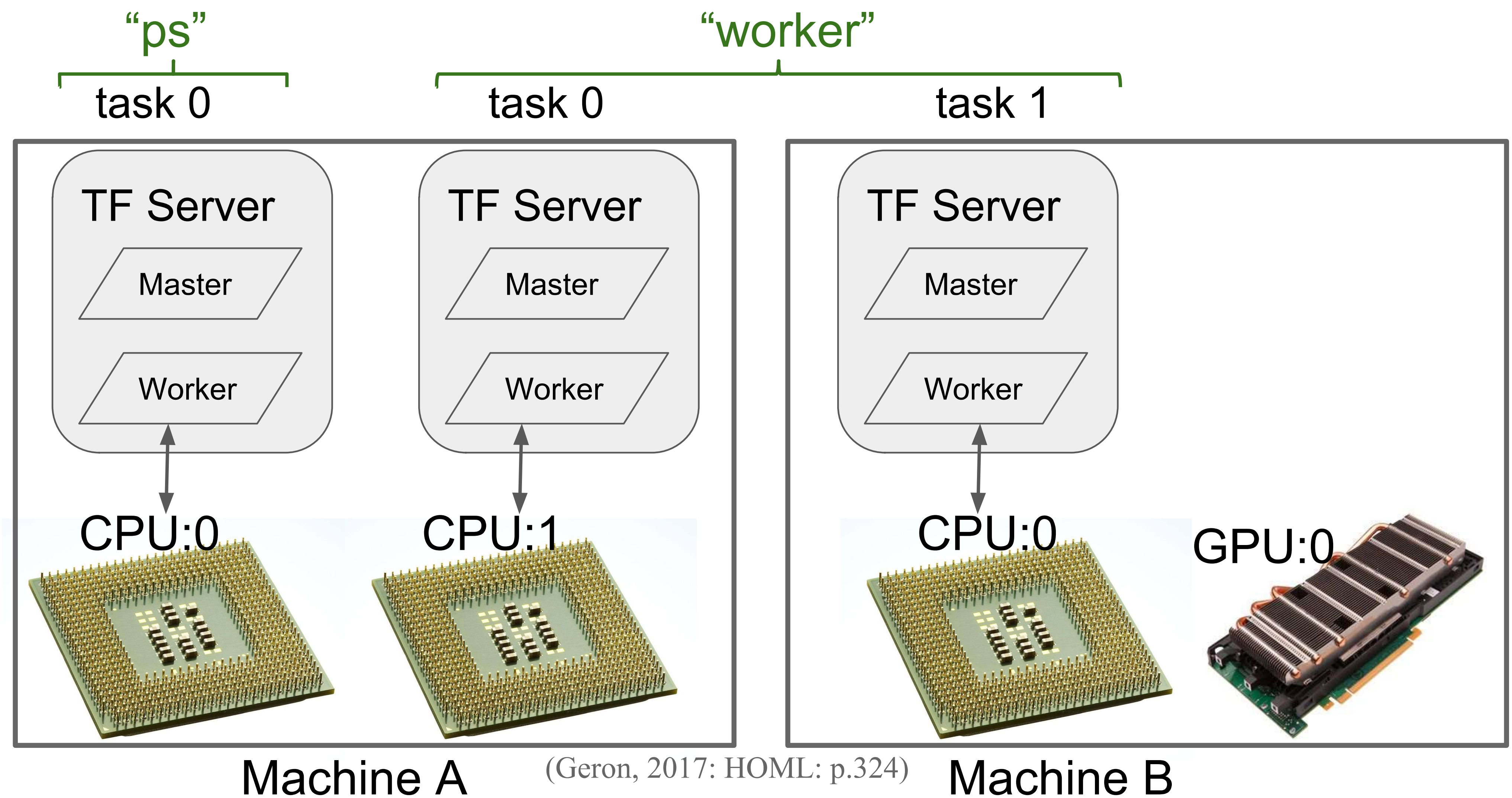

(Geron, 2017: HOML: p.324)

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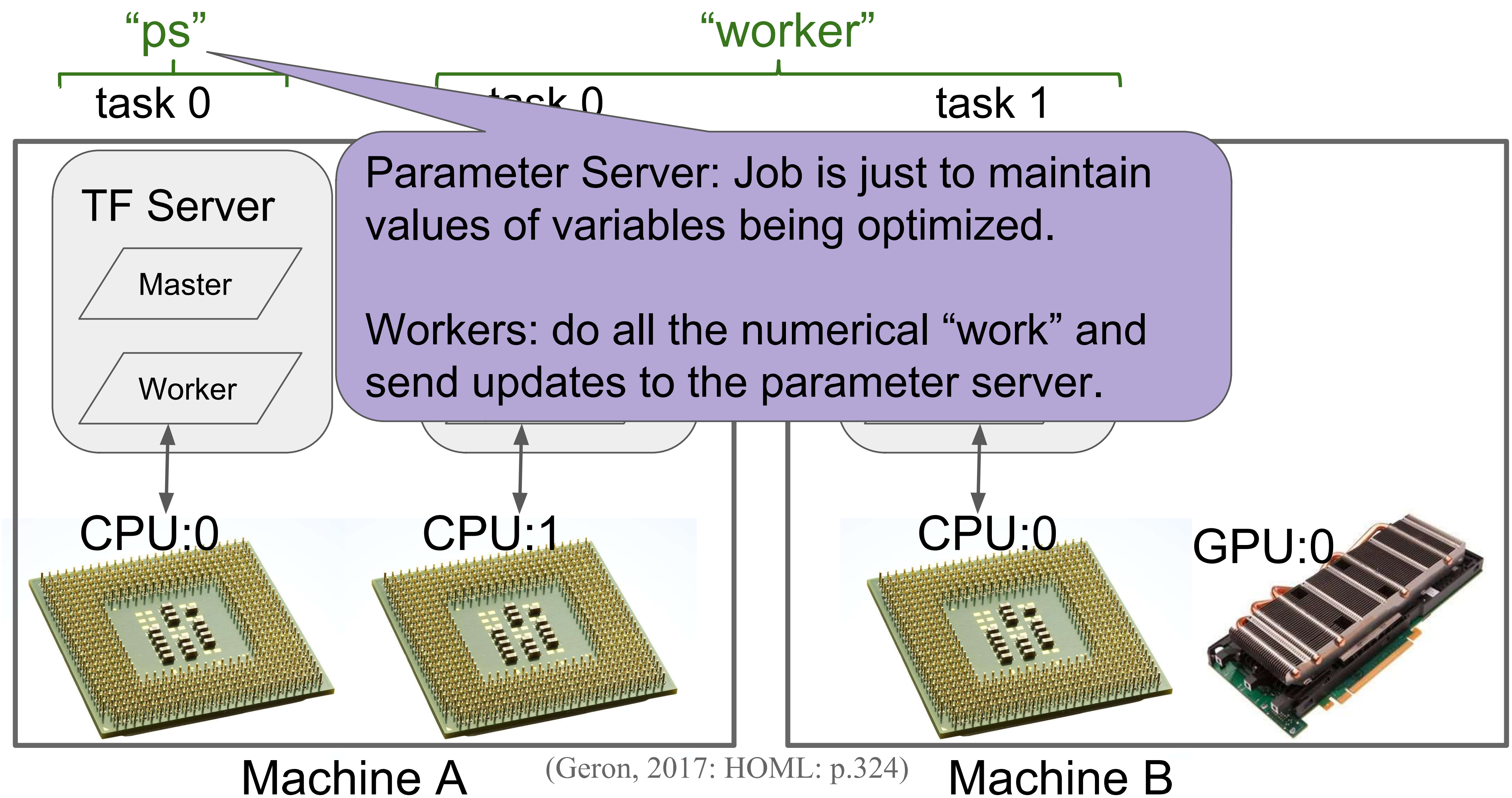

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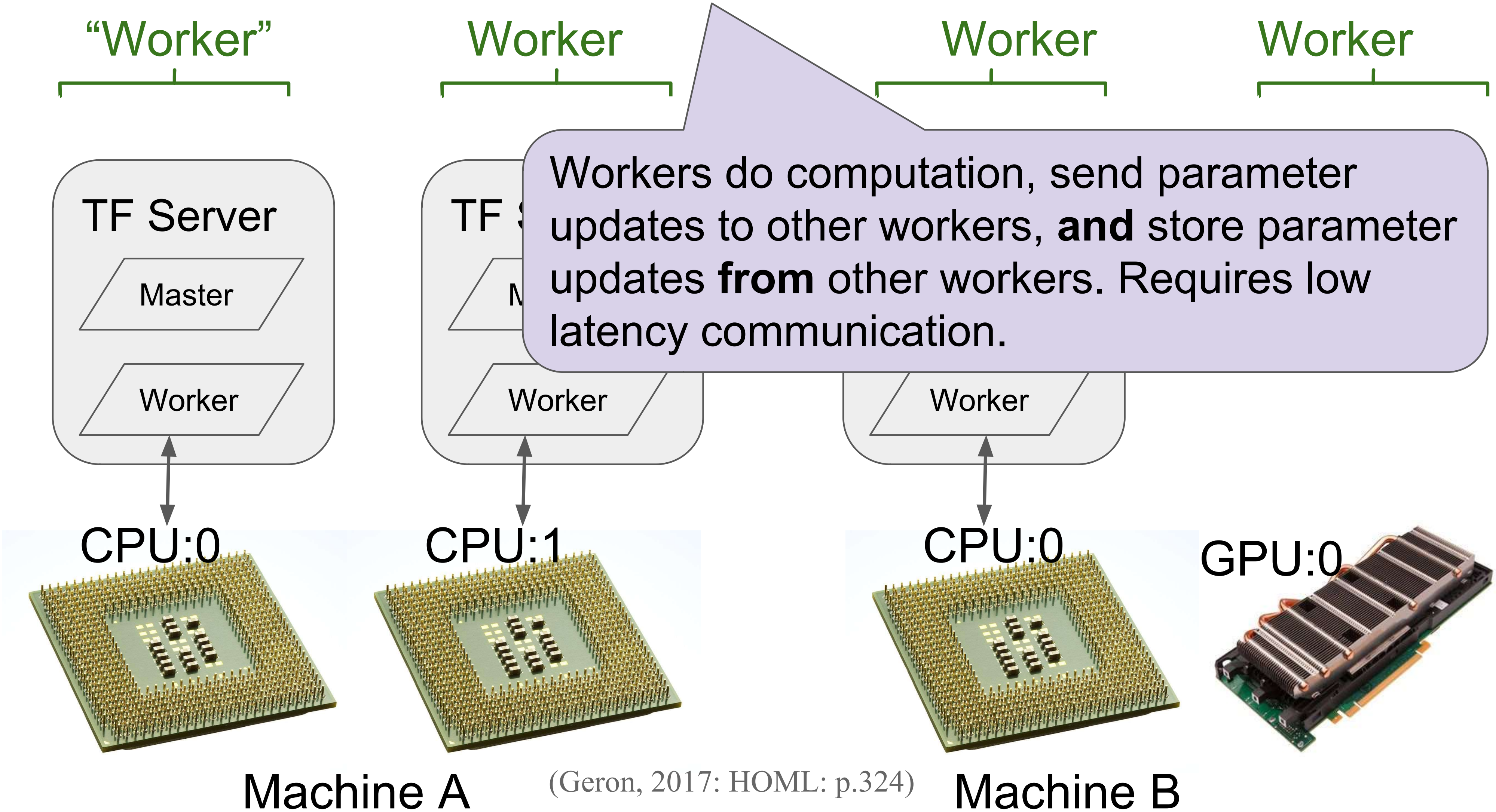
Synchronous AllReduce



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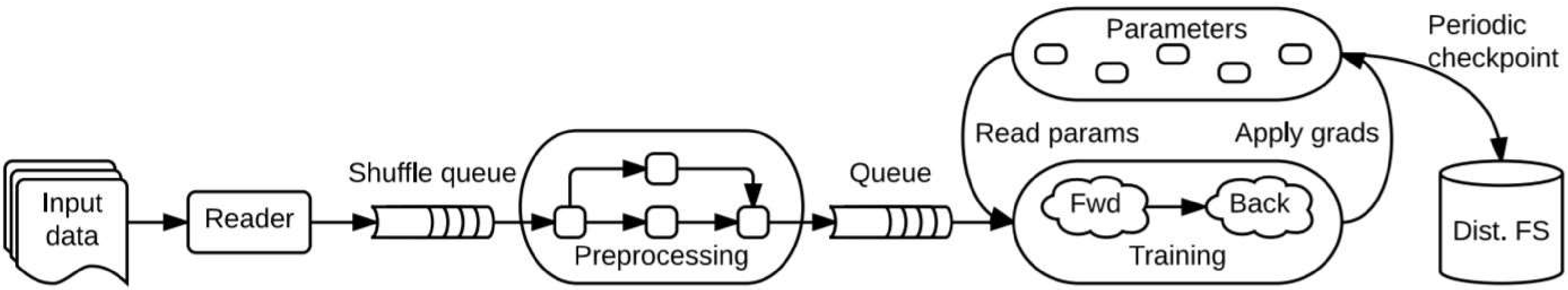
Distributed TensorFlow: Full Pipeline



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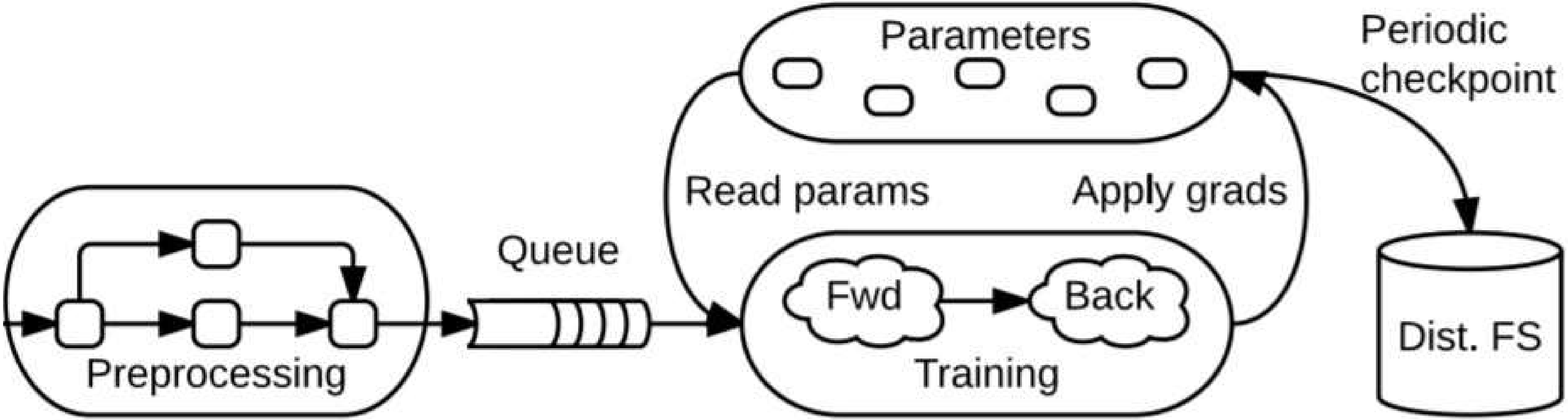
Parameters -- derived from **gradients**



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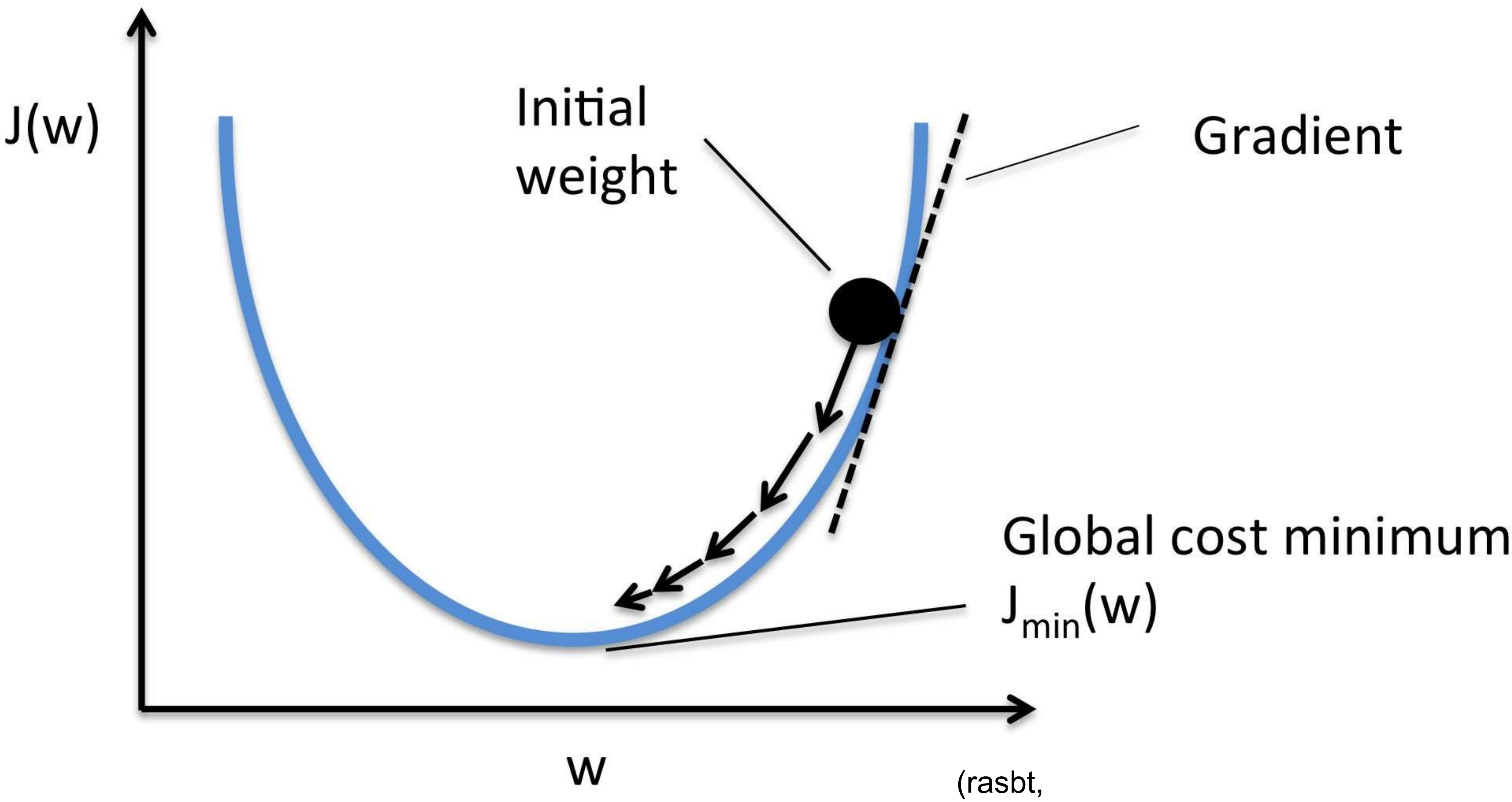

(rasbt,

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$$\hat{y}_i = X_i\beta$$

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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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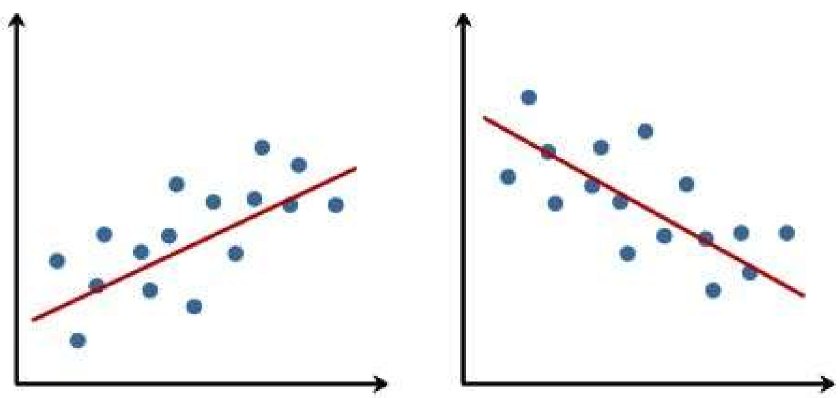

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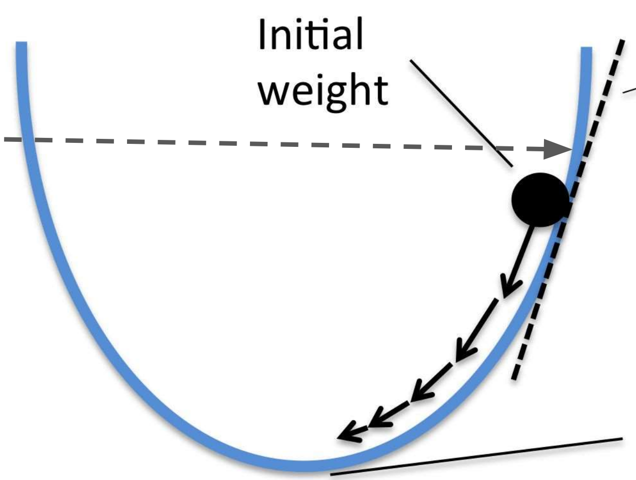
(for gradient descent) "learning rate"



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

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

1. Matrix Solution:

$$\hat{\beta}^{ridge} = (X^T X + \lambda I)^{-1} X^T y$$

Demo

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2. Gradient descent solution
(Mirrors many parameter optimization problems.)

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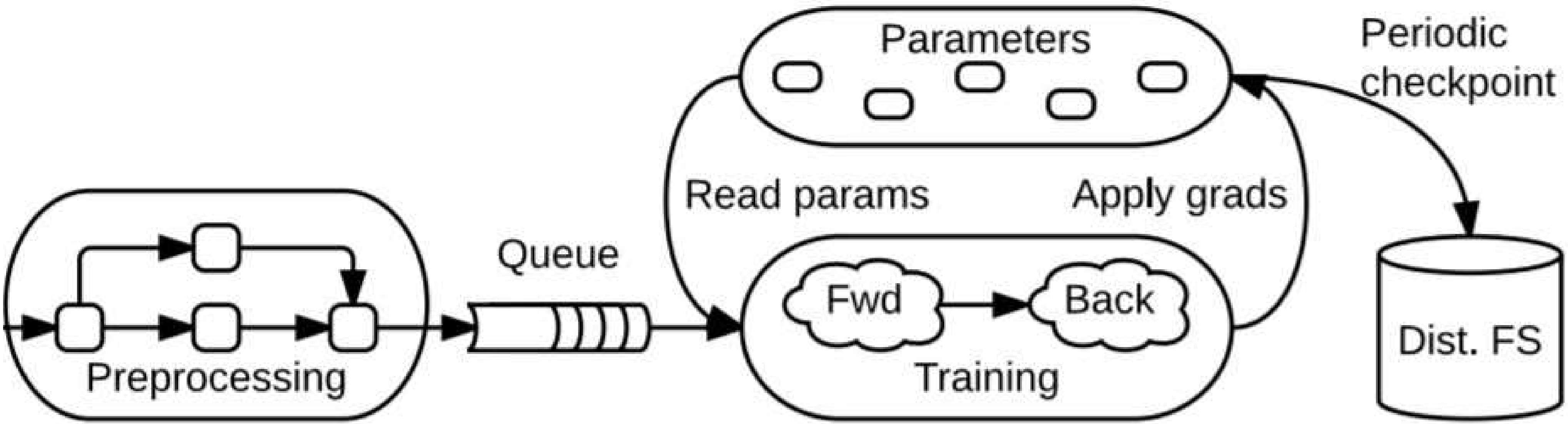

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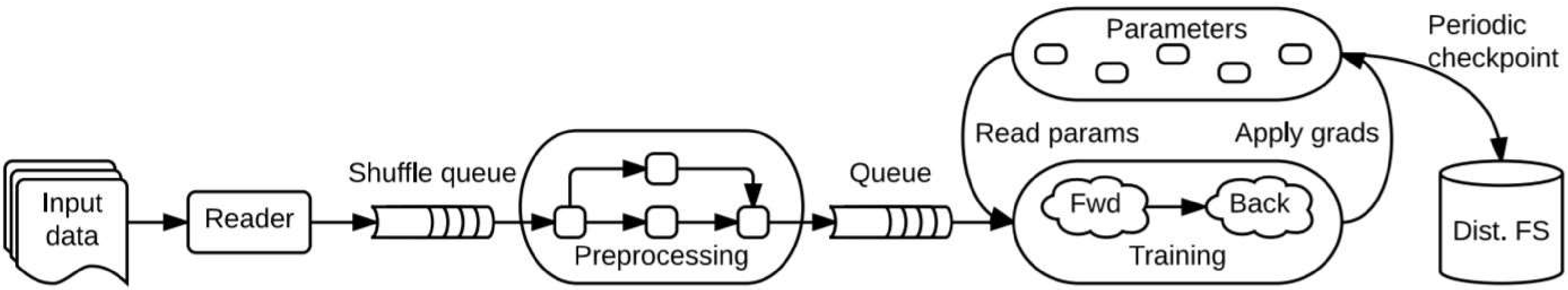

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