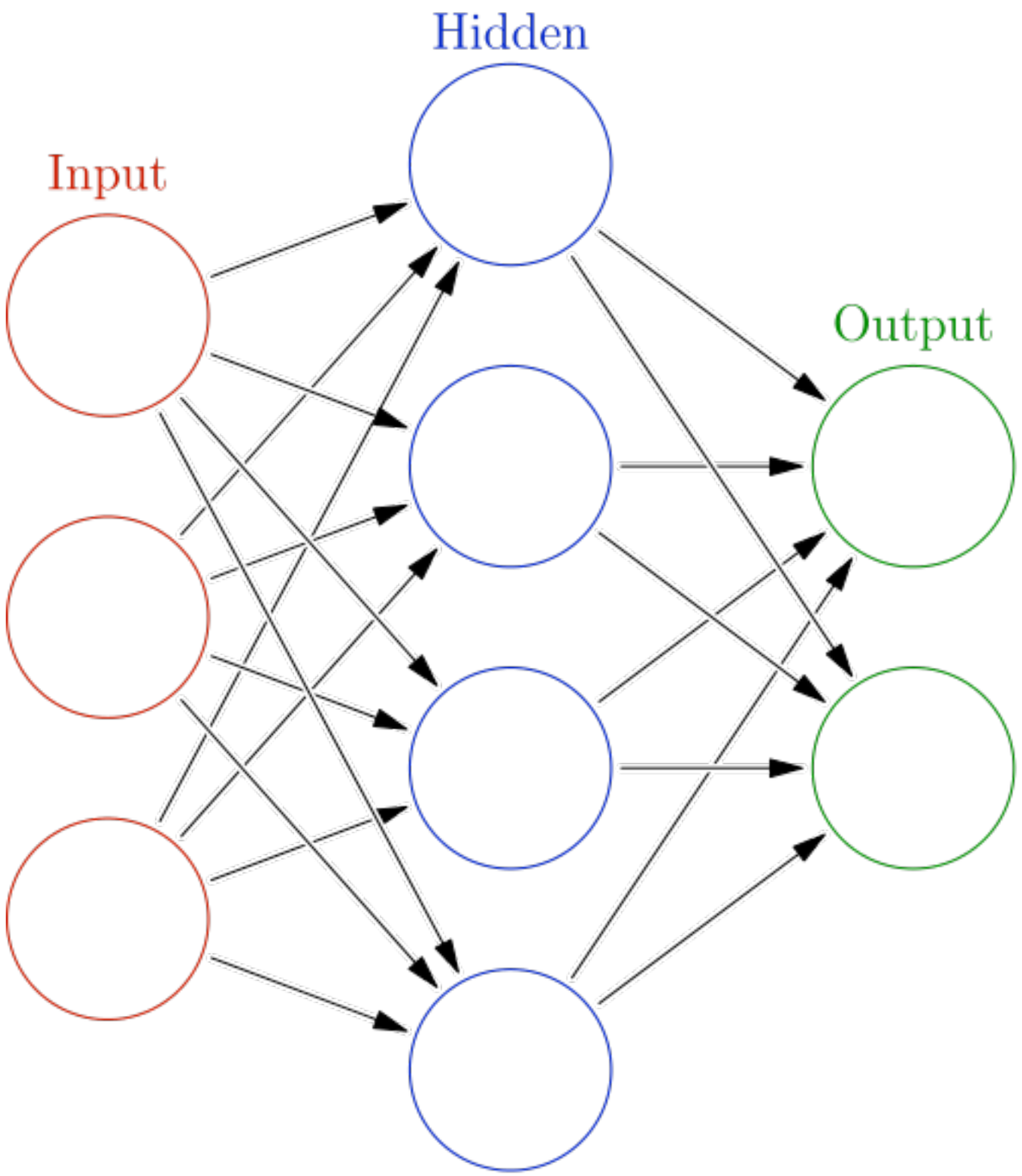
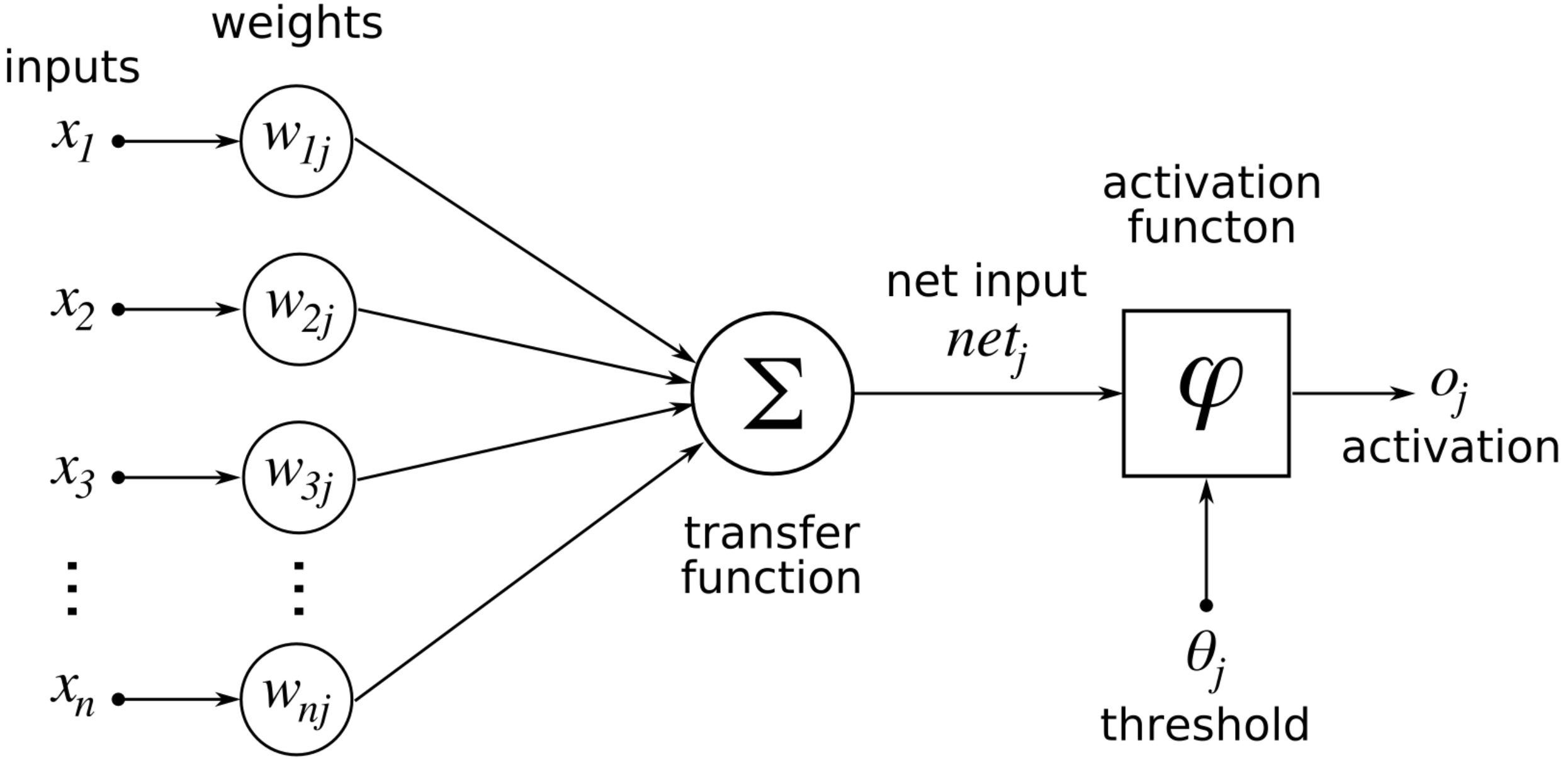
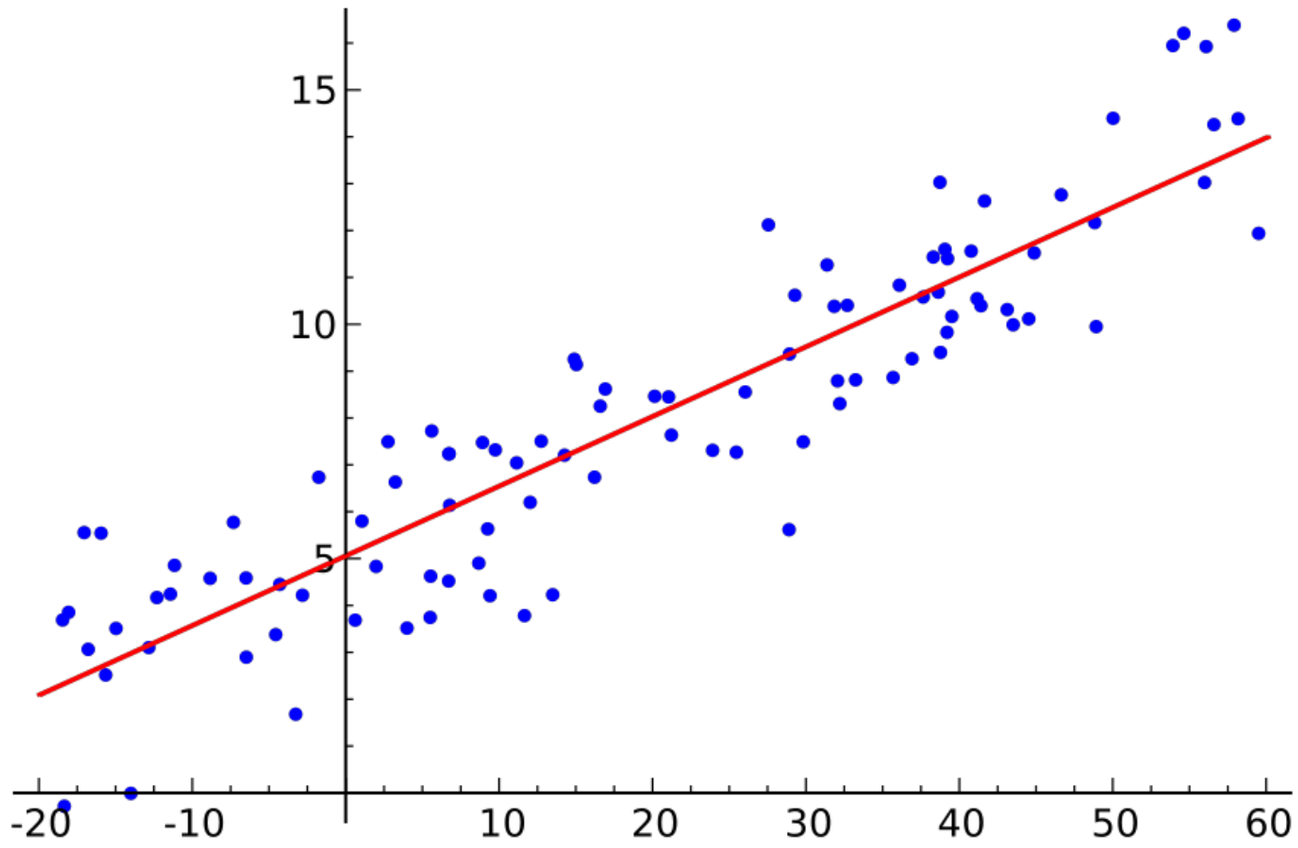
Building Brains - Parallelisation Strategies of Large-Scale Deep Learning Neural Networks on Parallel Scale Out Architectures Like Apache Spark

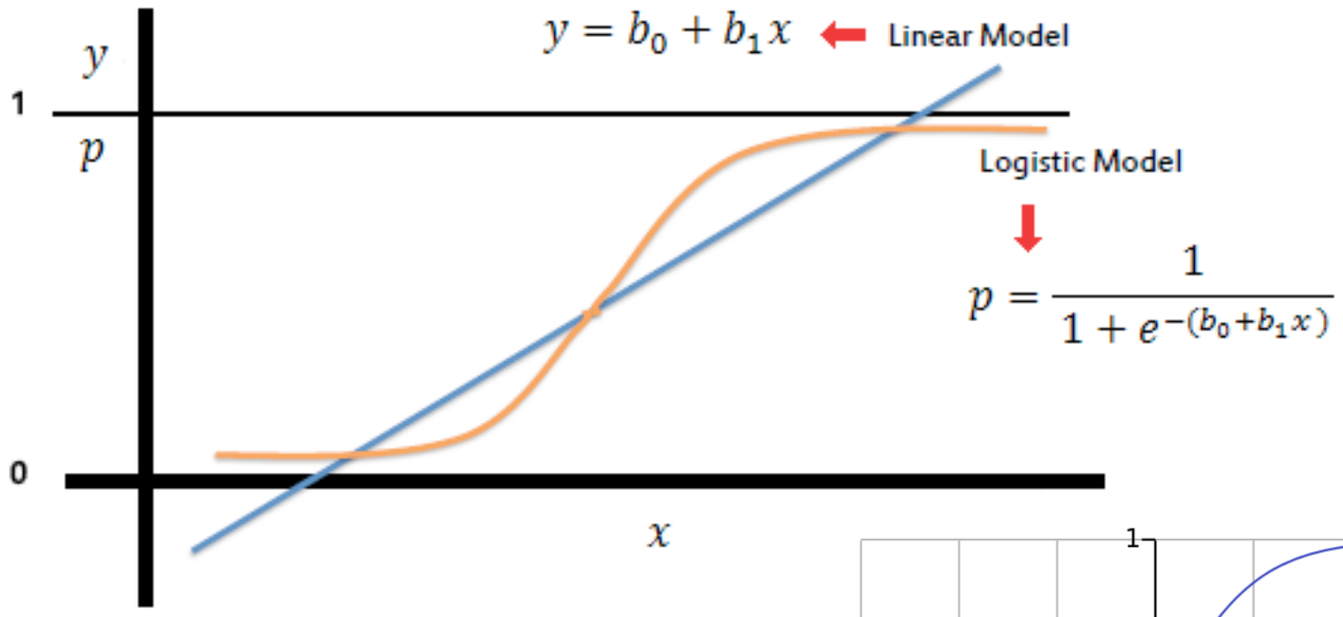
Romeo Kienzler, IBM Watson IoT


Hidden
Input
Output

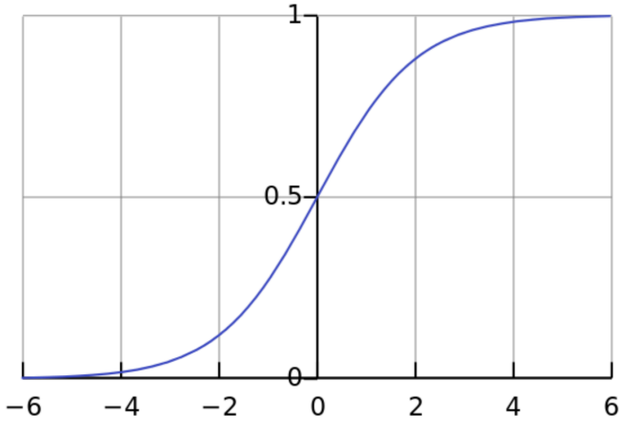

weights
inputs
x_1
w_{1j}
x_2
w_{2j}
x_3
w_{3j}
x_n
w_{nj}
$\sum$
transfer
function
net input
net_j
activation
functon
φ
o_j
activation
θ_j
threshold



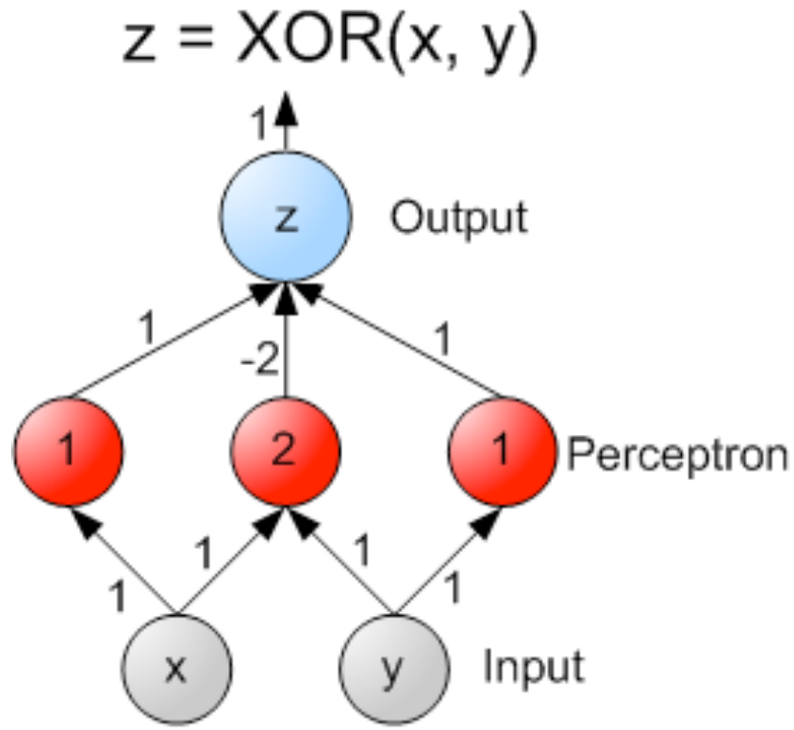
$$y_i = \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \varepsilon_i = \mathbf{x}_i^{\mathrm{T}} \boldsymbol{\beta} + \varepsilon_i, \qquad i = 1, \ldots, n$$


$y = b_0 + b_1 x$
Linear Model
y
1
p
Logistic Model
$p = \frac{1}{1 + e^{-(b_0 + b_1 x)}}$
0
x

$$S(t) = \frac{1}{1 + e^{-t}}$$


1
0.5
0
−6
−4
−2
0
2
4
6

the forward pass



$$o = f(\sum_{k=1}^{n} i_k W_k)$$

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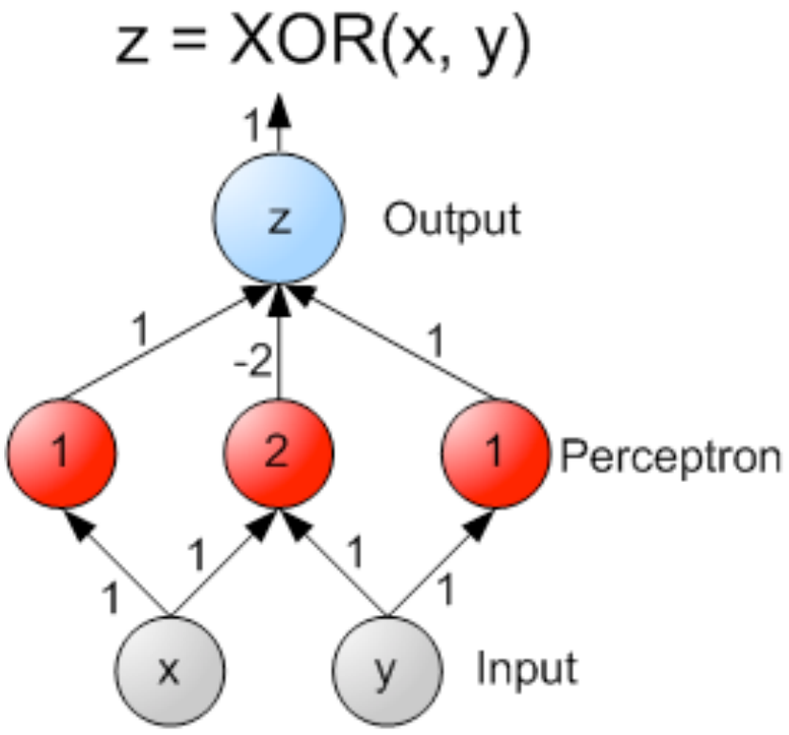
back propagation



$$z^{(2)} = XW^{(1)} \quad (1)$$

$$a^{(2)} = f(z^{(2)}) \quad (2)$$

$$z^{(3)} = a^{(2)}W^{(2)} \quad (3)$$

$$\hat{y} = f(z^{(3)}) \quad (4)$$

$$J = \sum \frac{1}{2}(y - \hat{y})^2 \quad (5)$$

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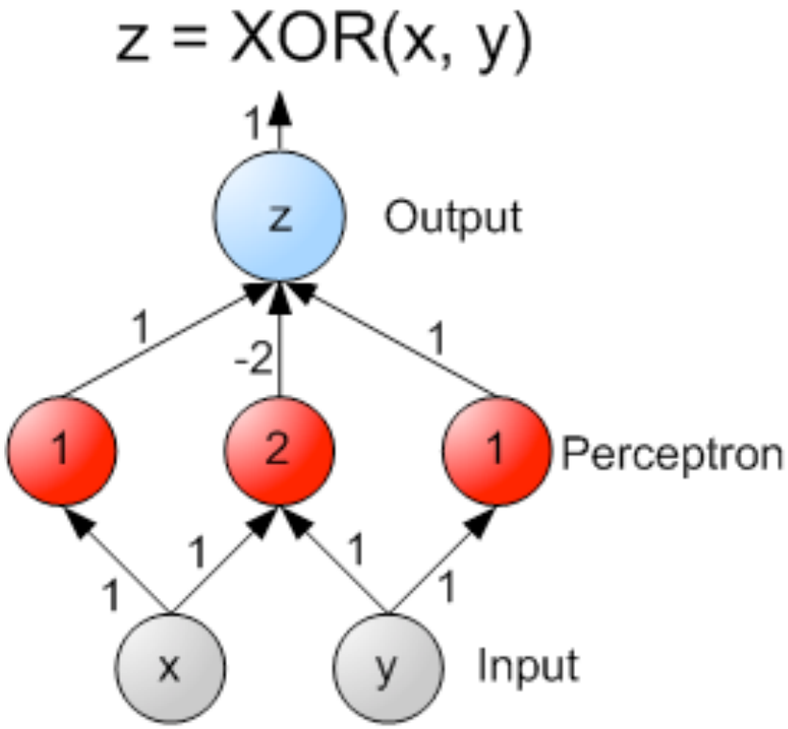
back propagation



$$J = \sum \frac{1}{2}(y - f(\, f(\, XW^{(1)}\,)\, W^{(2)}\,)\,)^2$$

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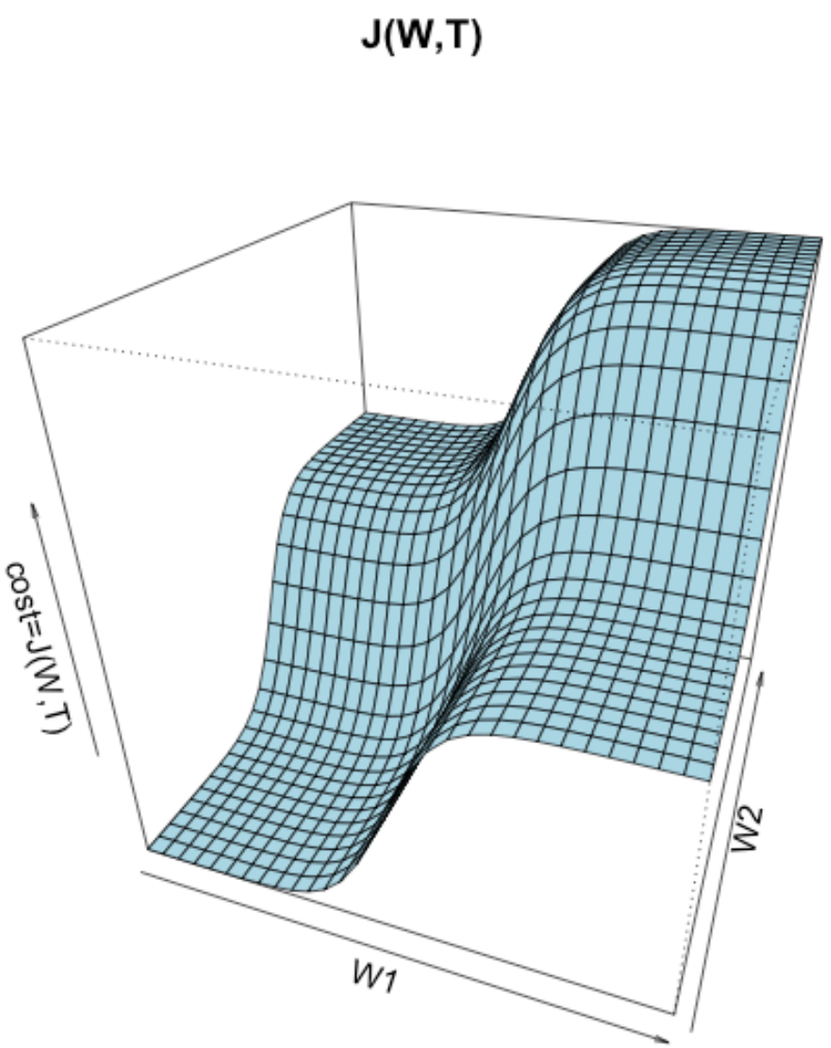
gradient descent



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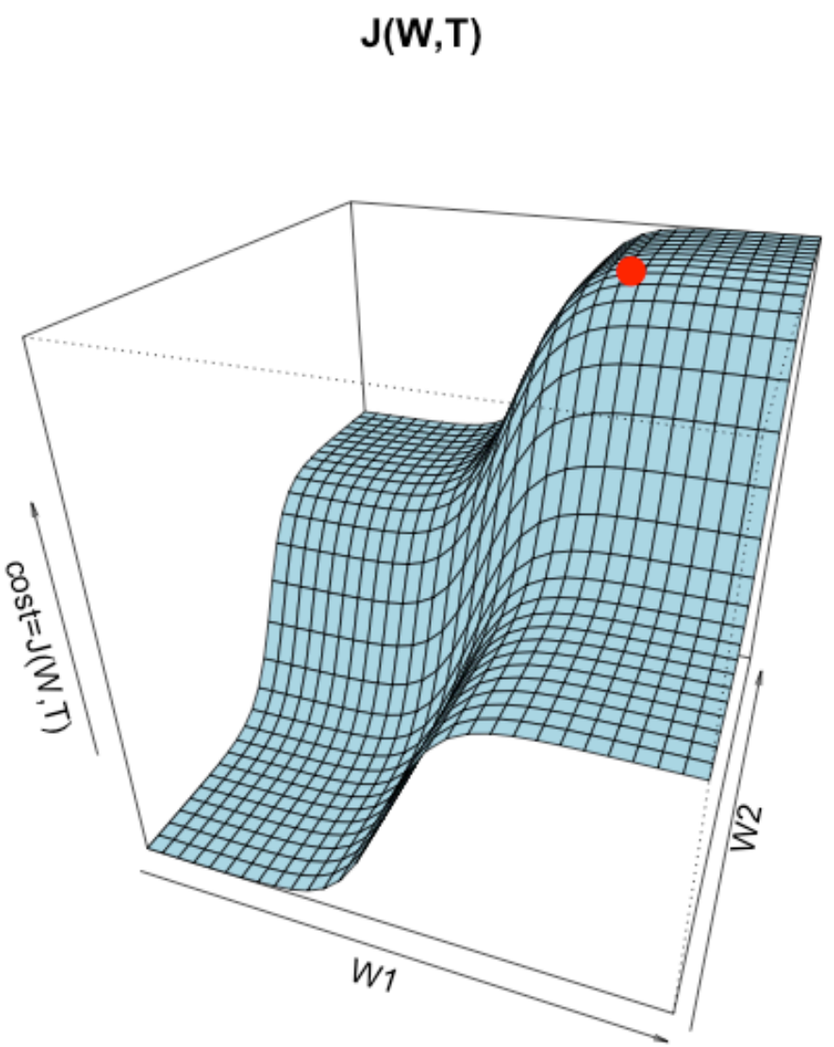
gradient descent



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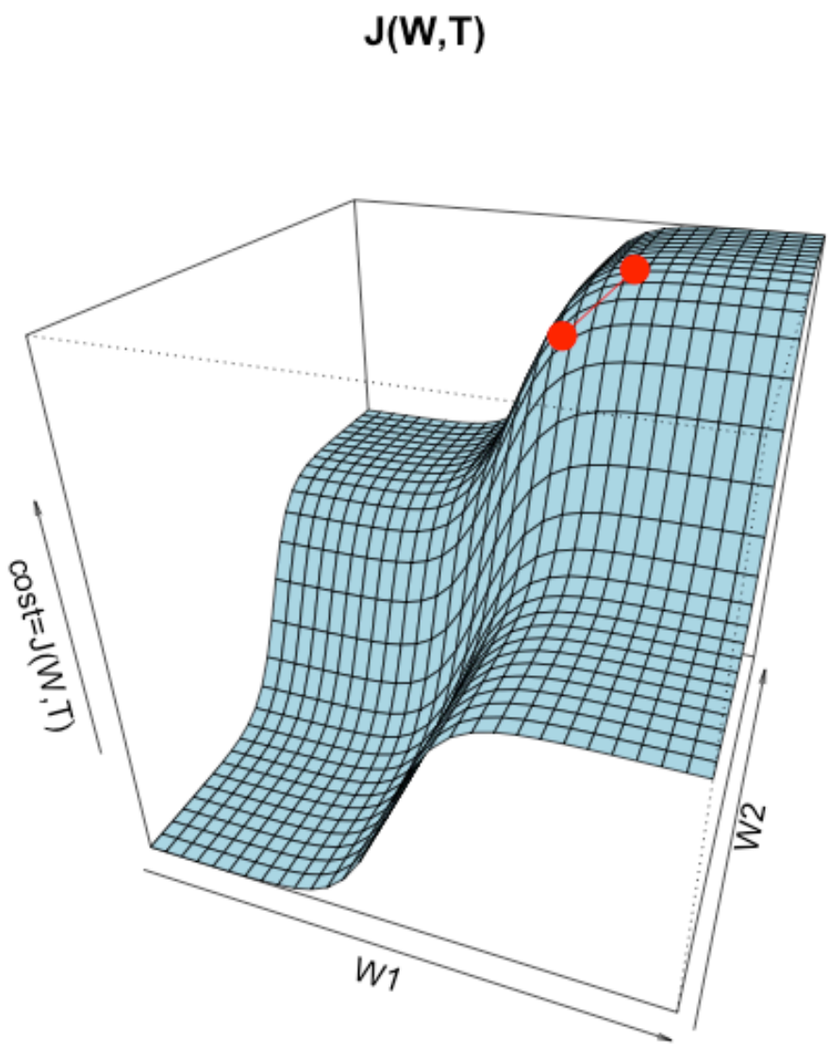
gradient descent



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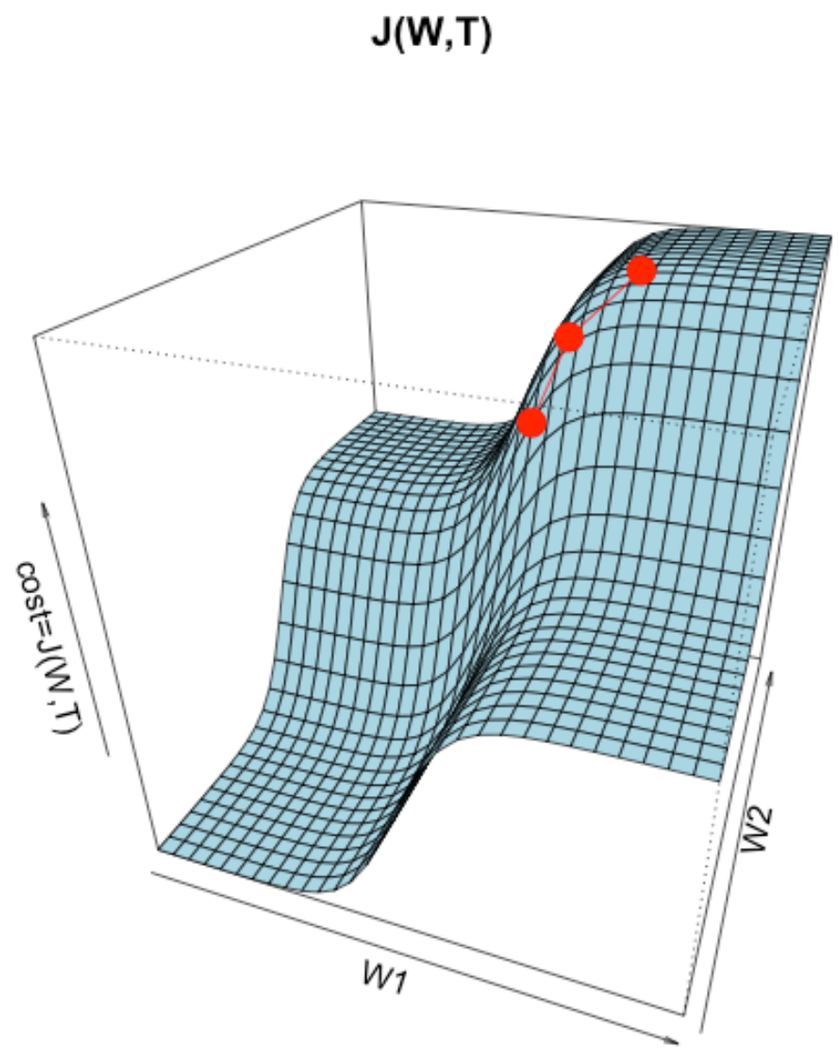
gradient descent



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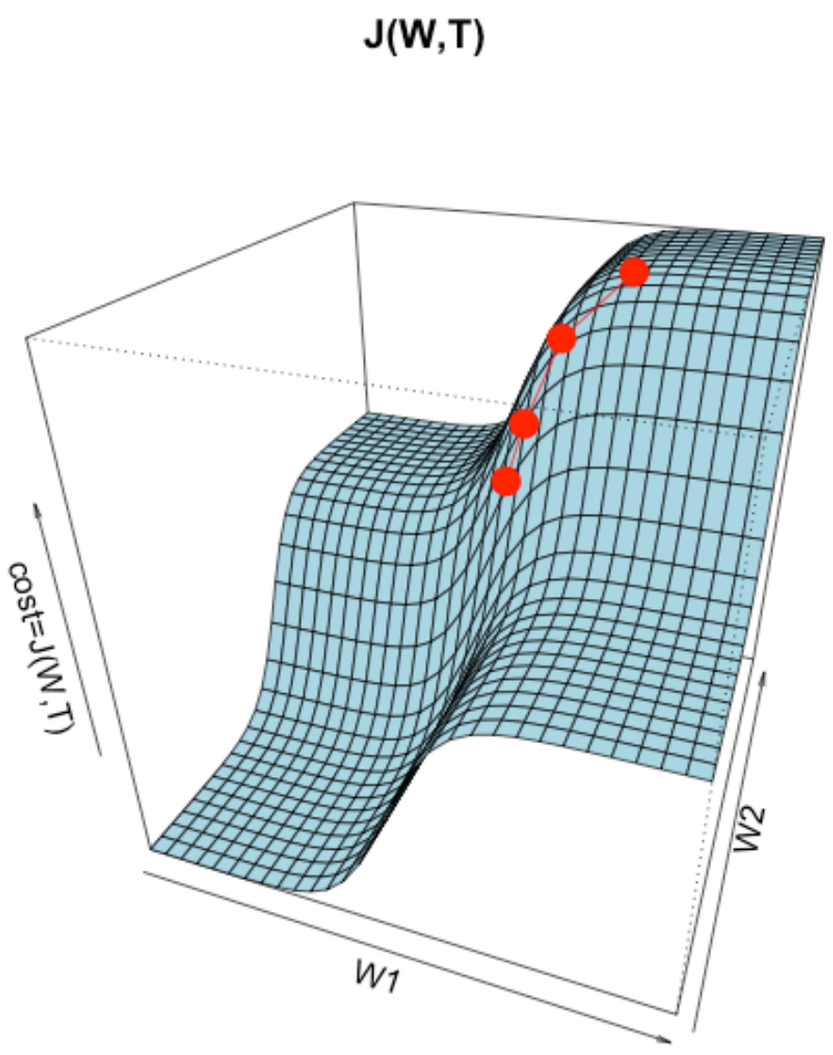
gradient descent



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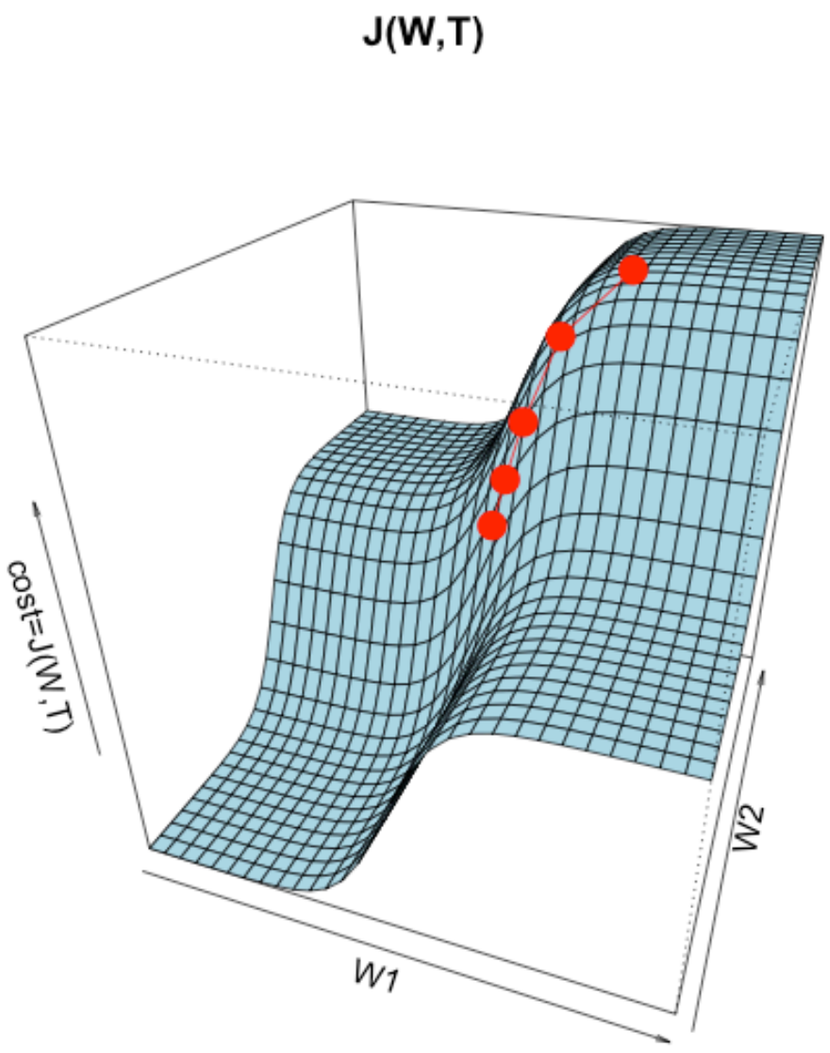
gradient descent



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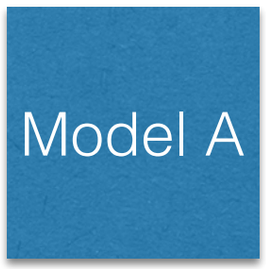
parallelisation

- inter-model parallelism
- data parallelism
- intra-model parallelism
- pipelined parallelism

inter-model parallelism

aka. hyper parameter space exploration / tuning



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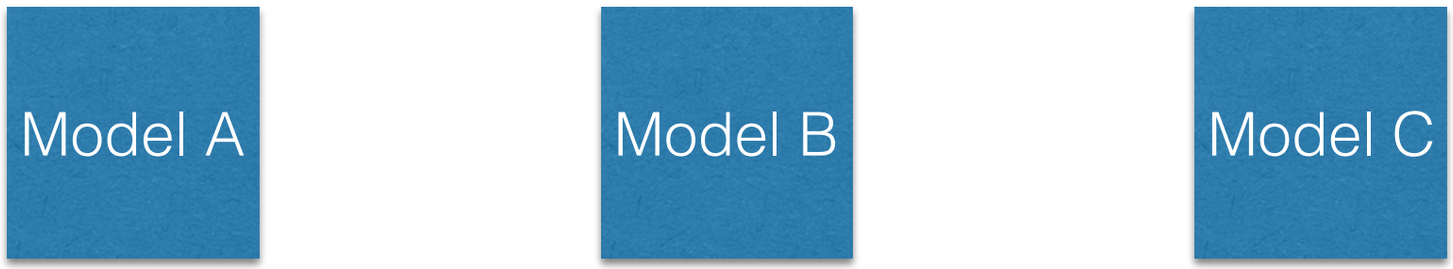

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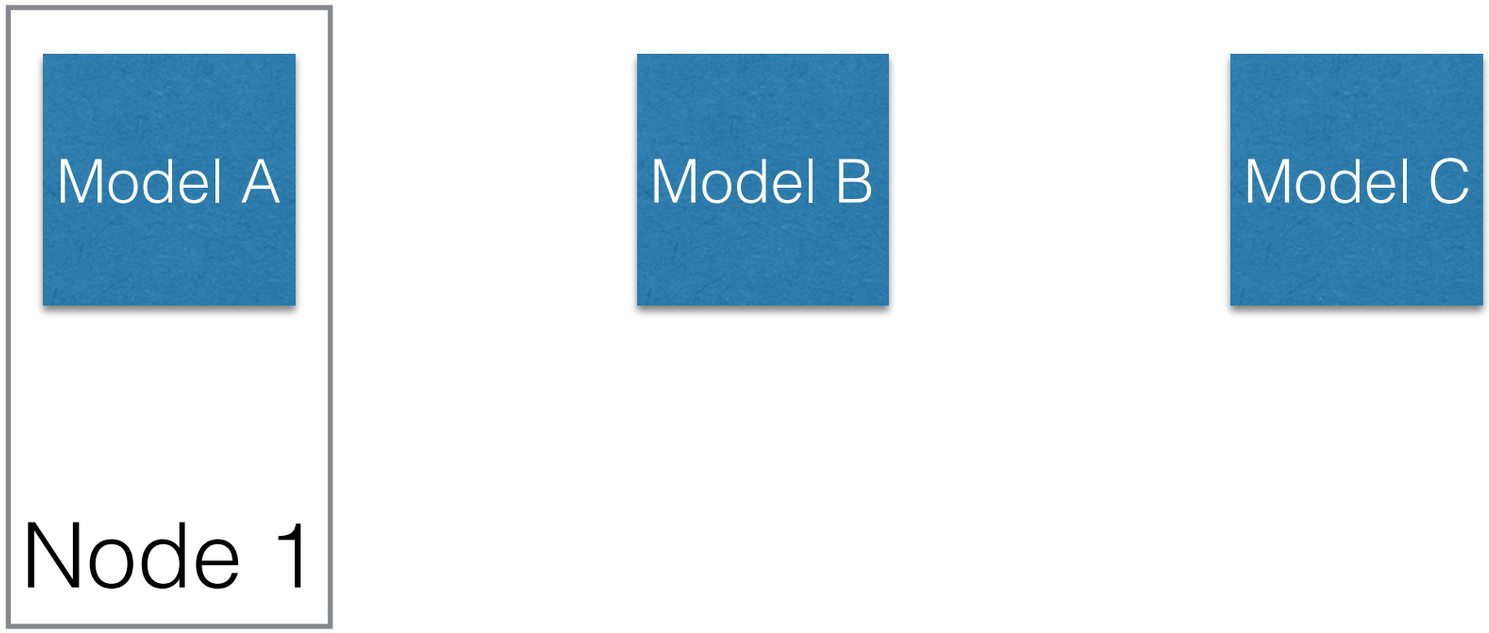

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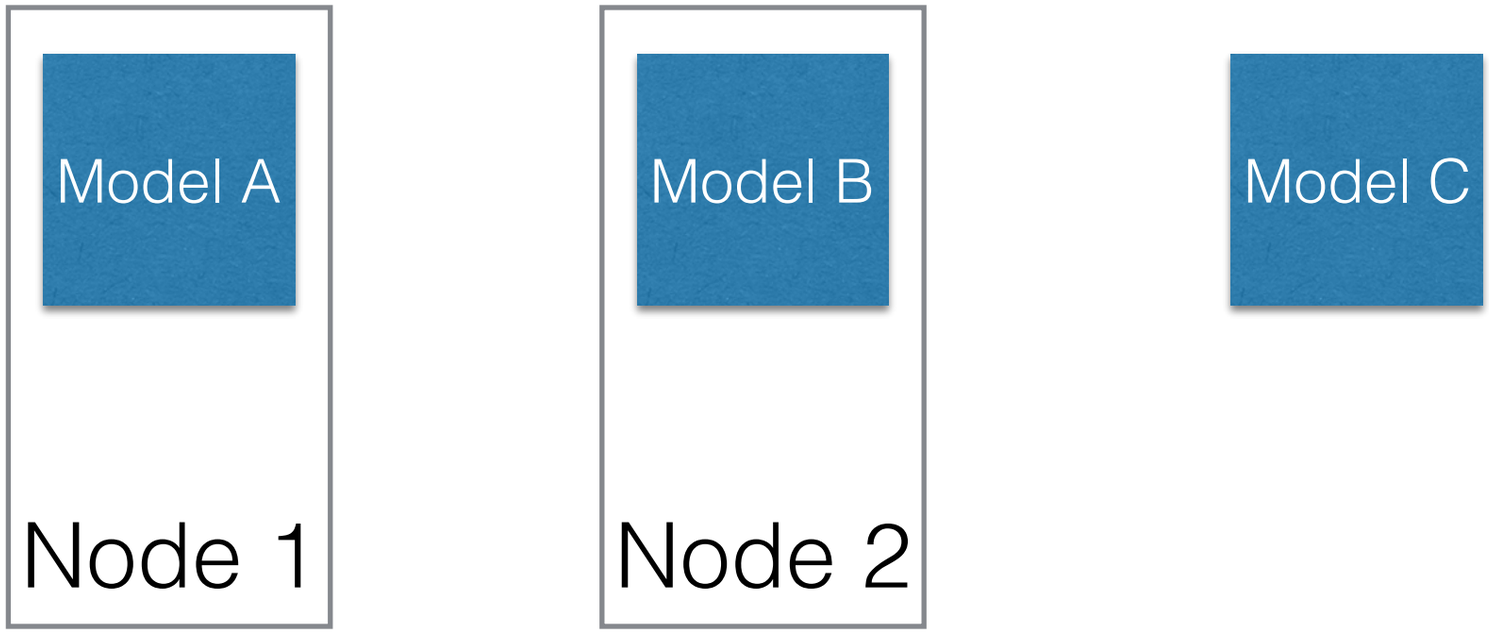

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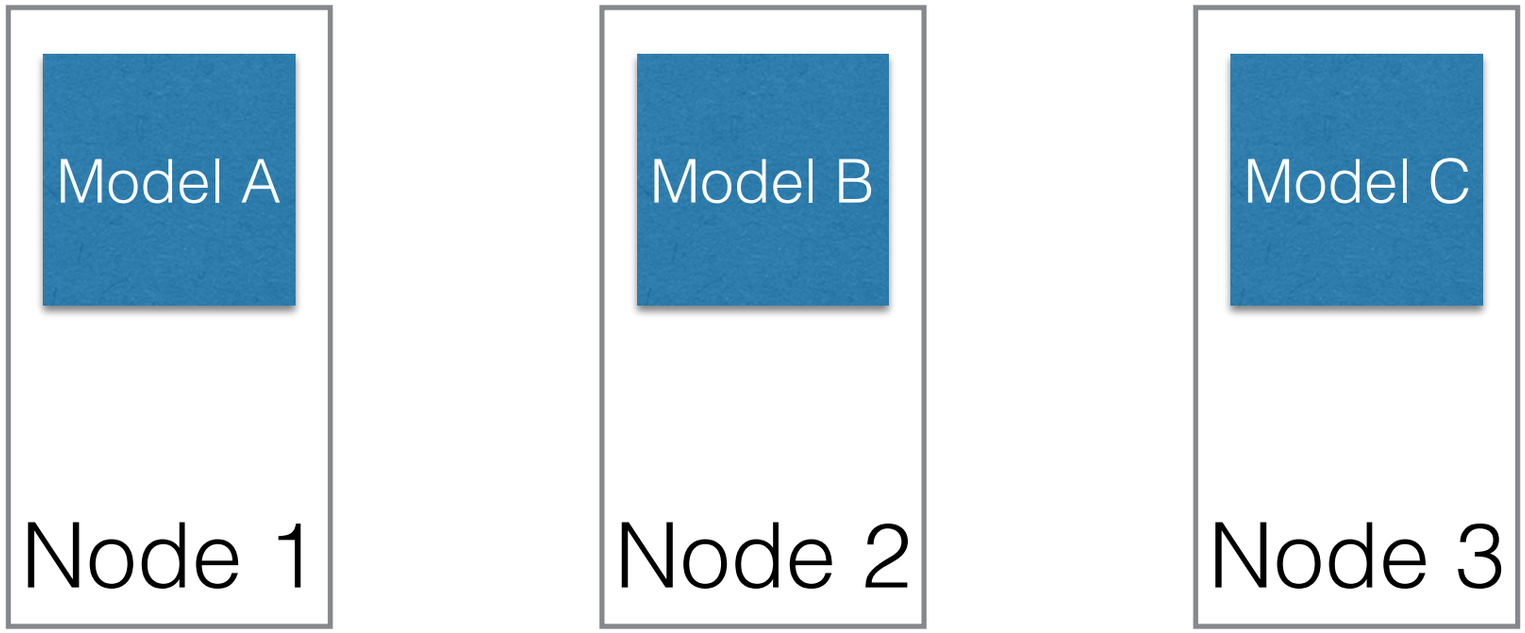

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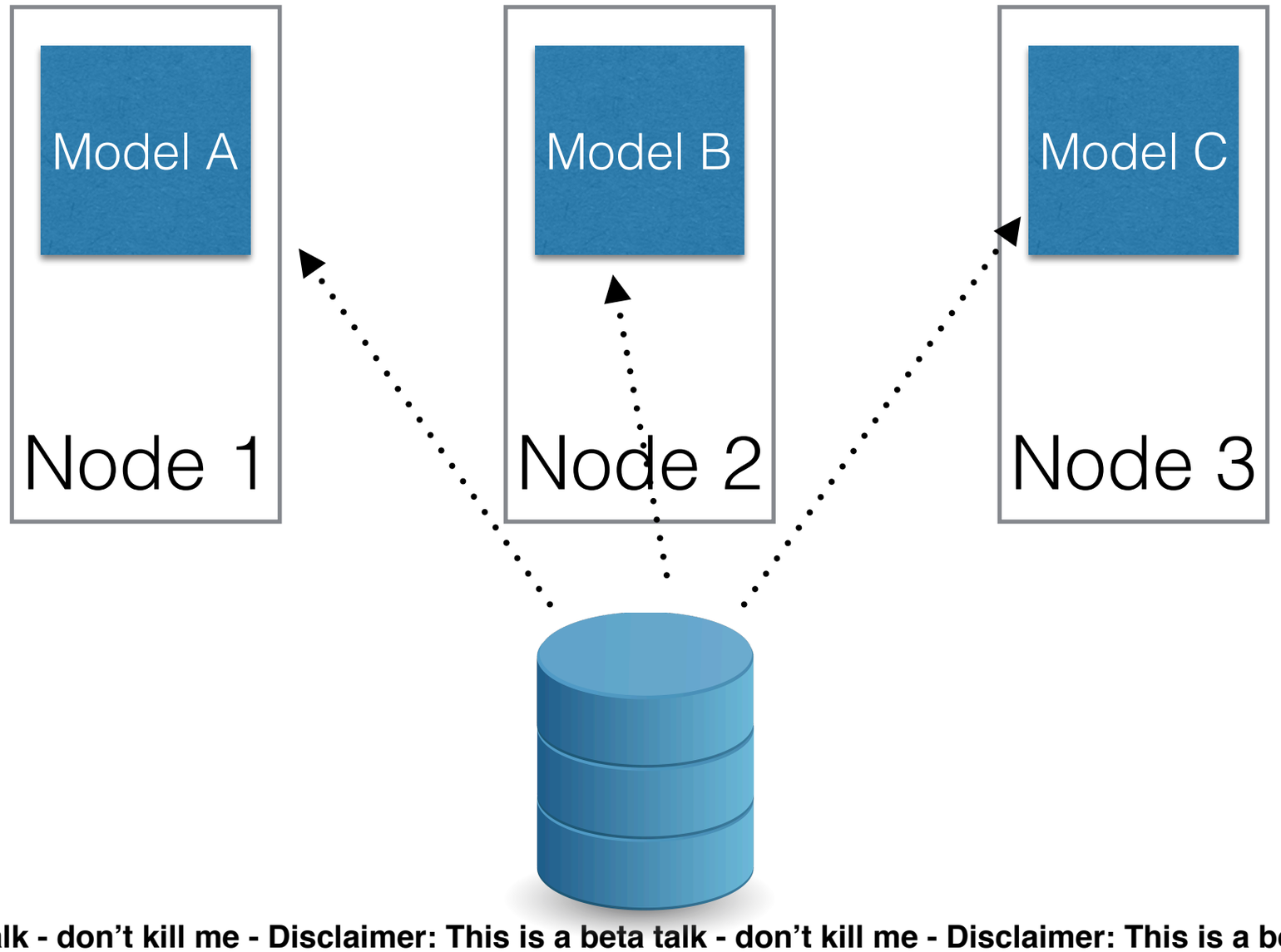

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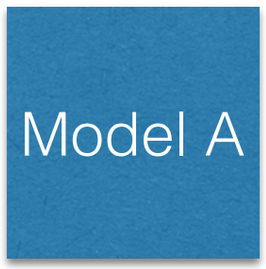
data parallelism

aka. “Jeff Dean style” parameter averaging



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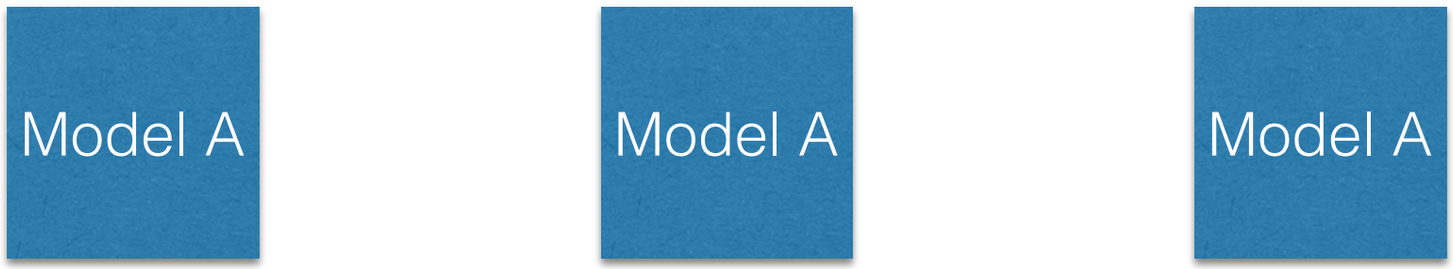

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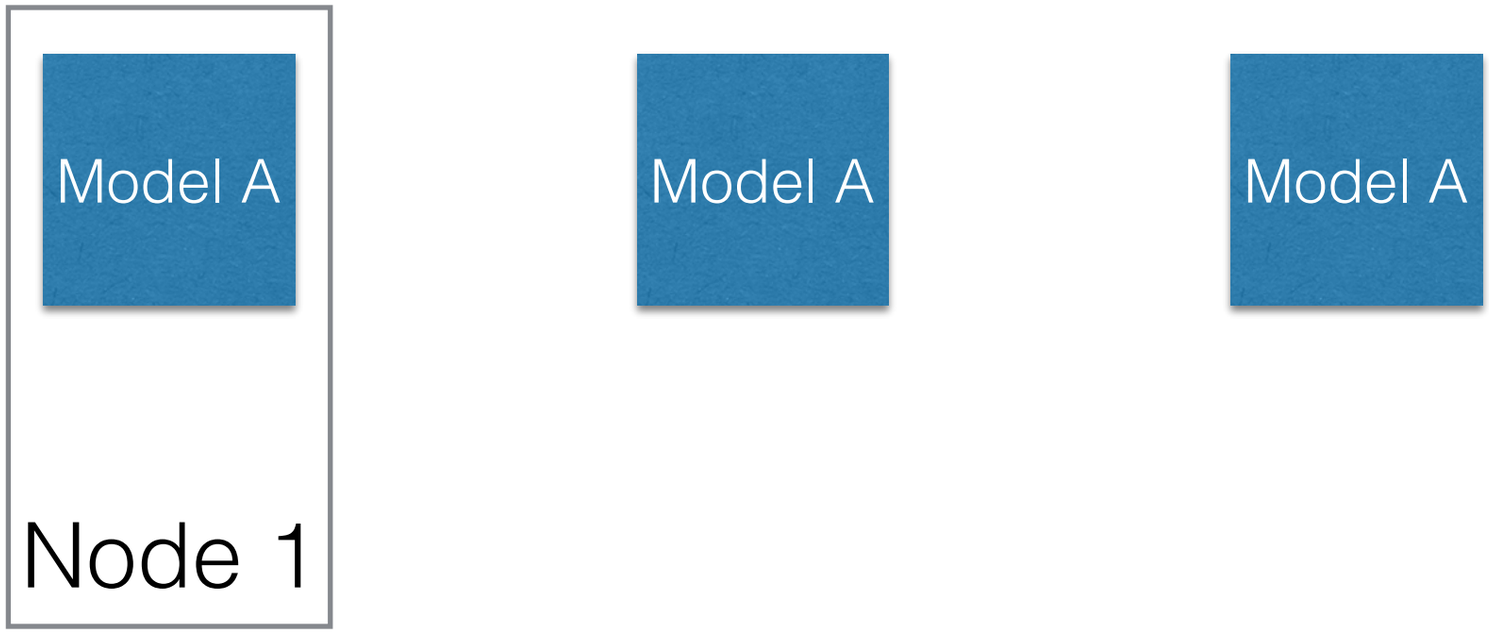

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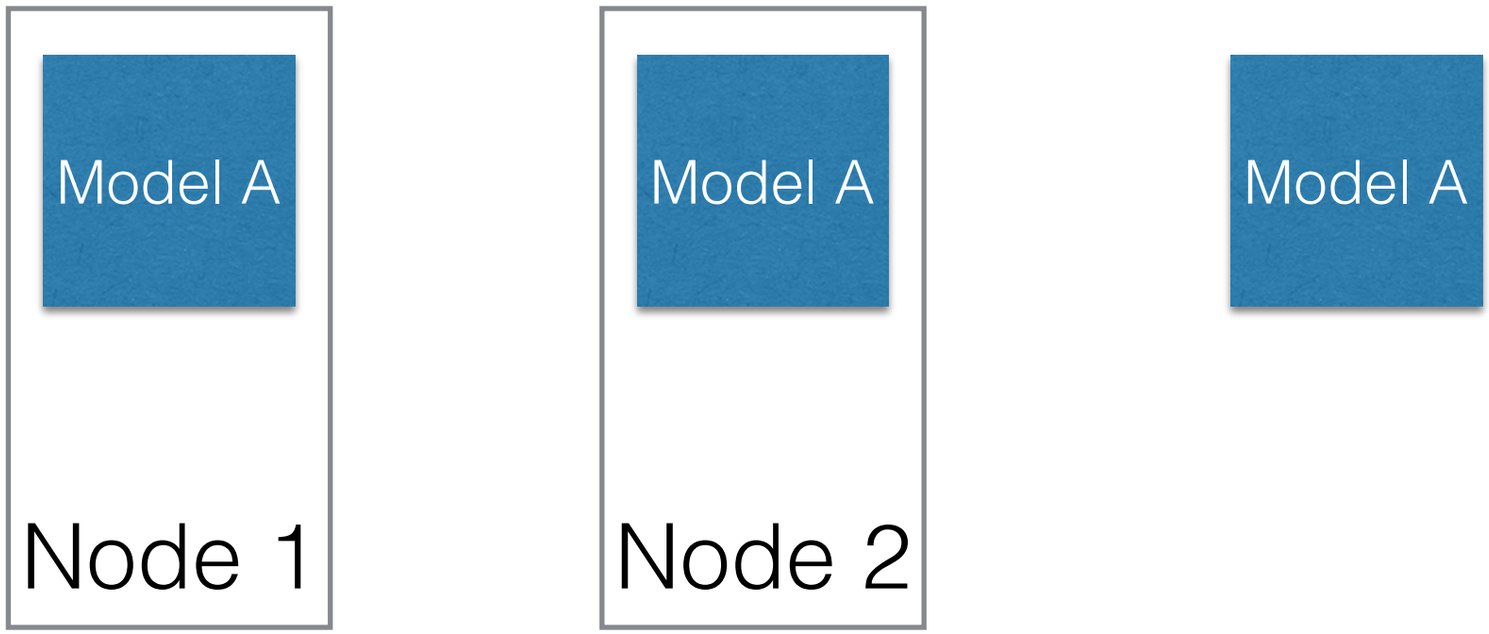

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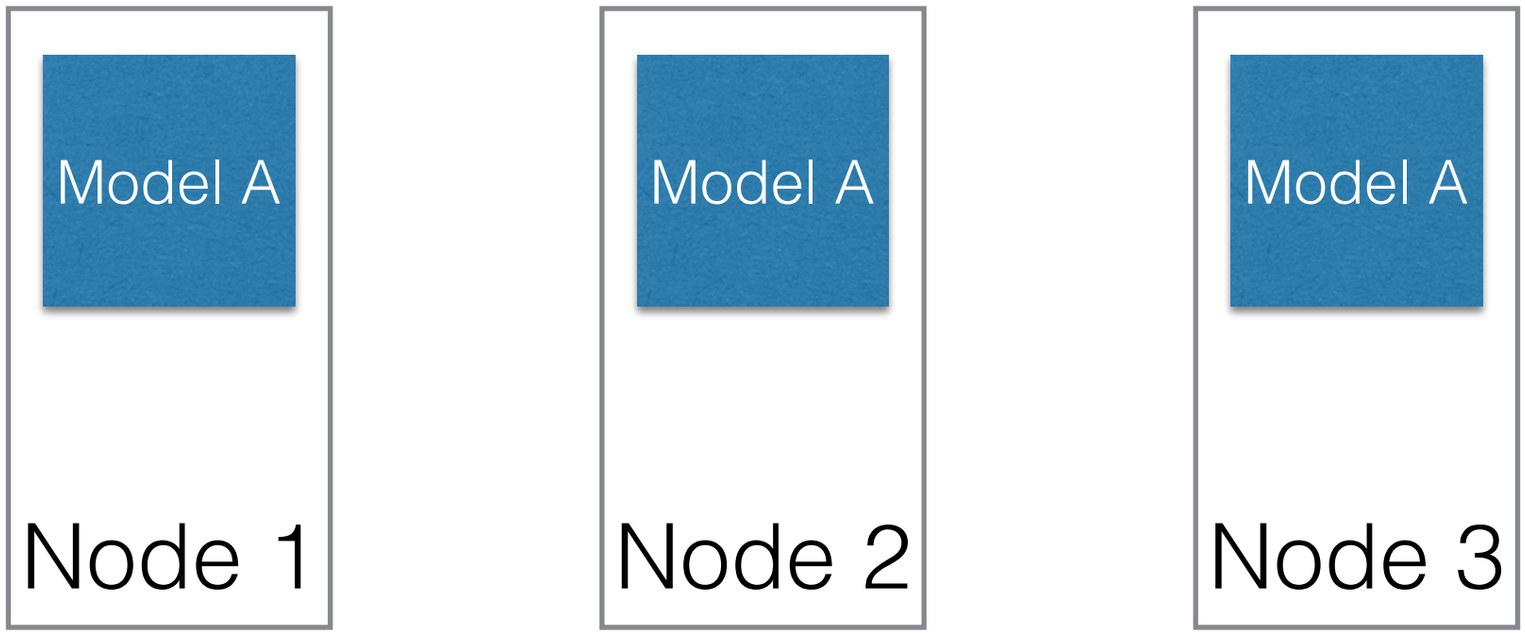

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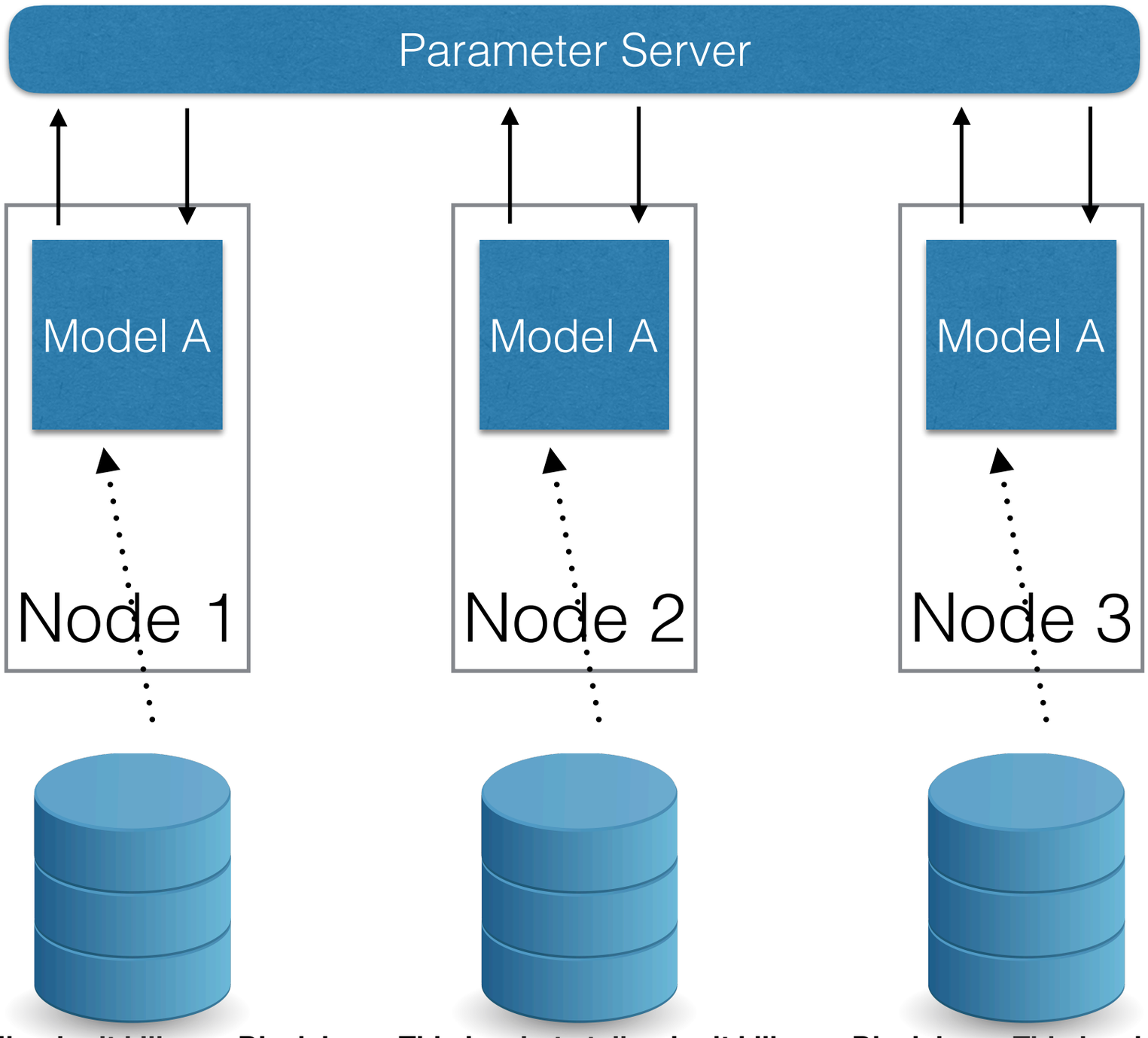
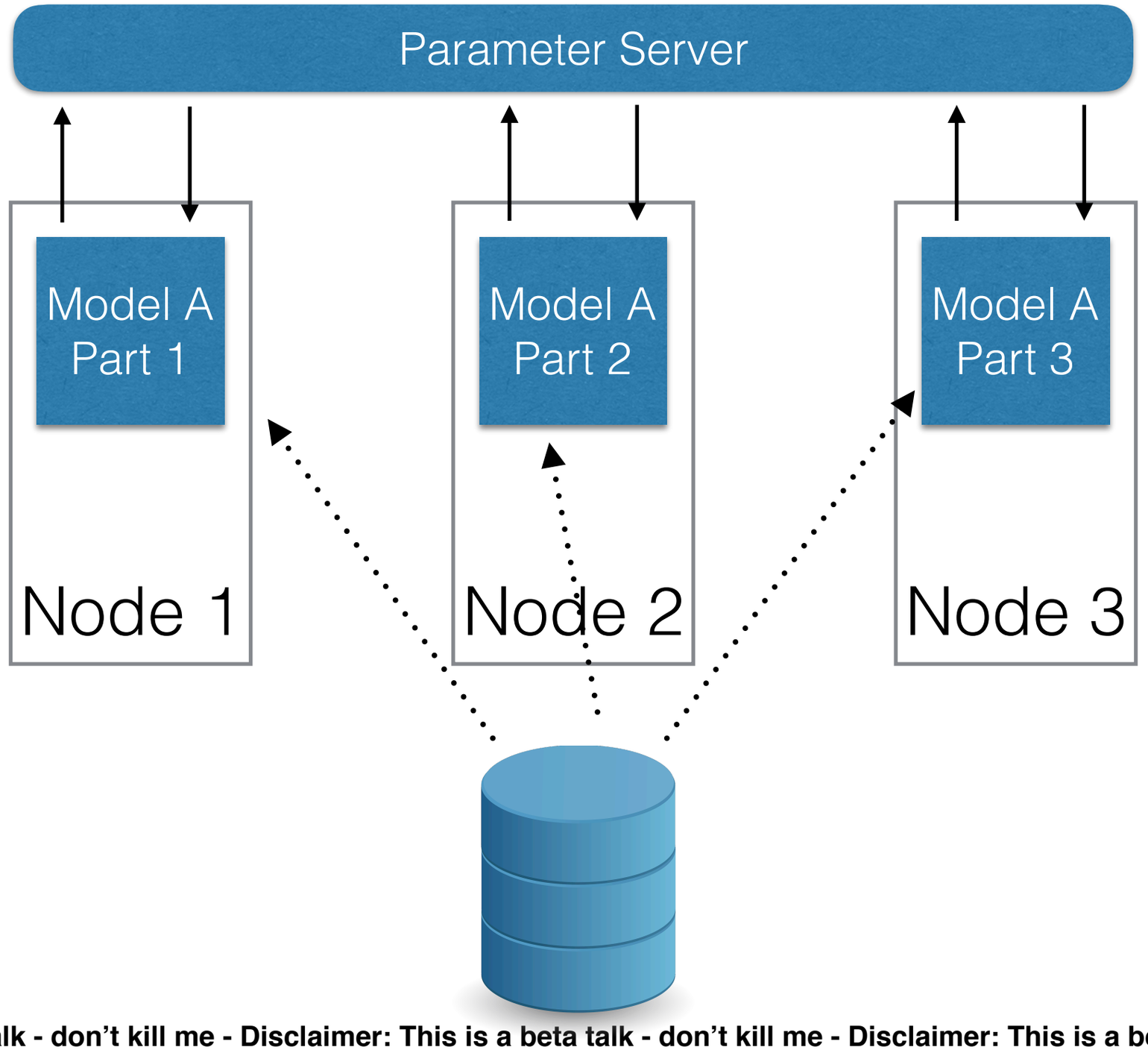


intra-model parallelism



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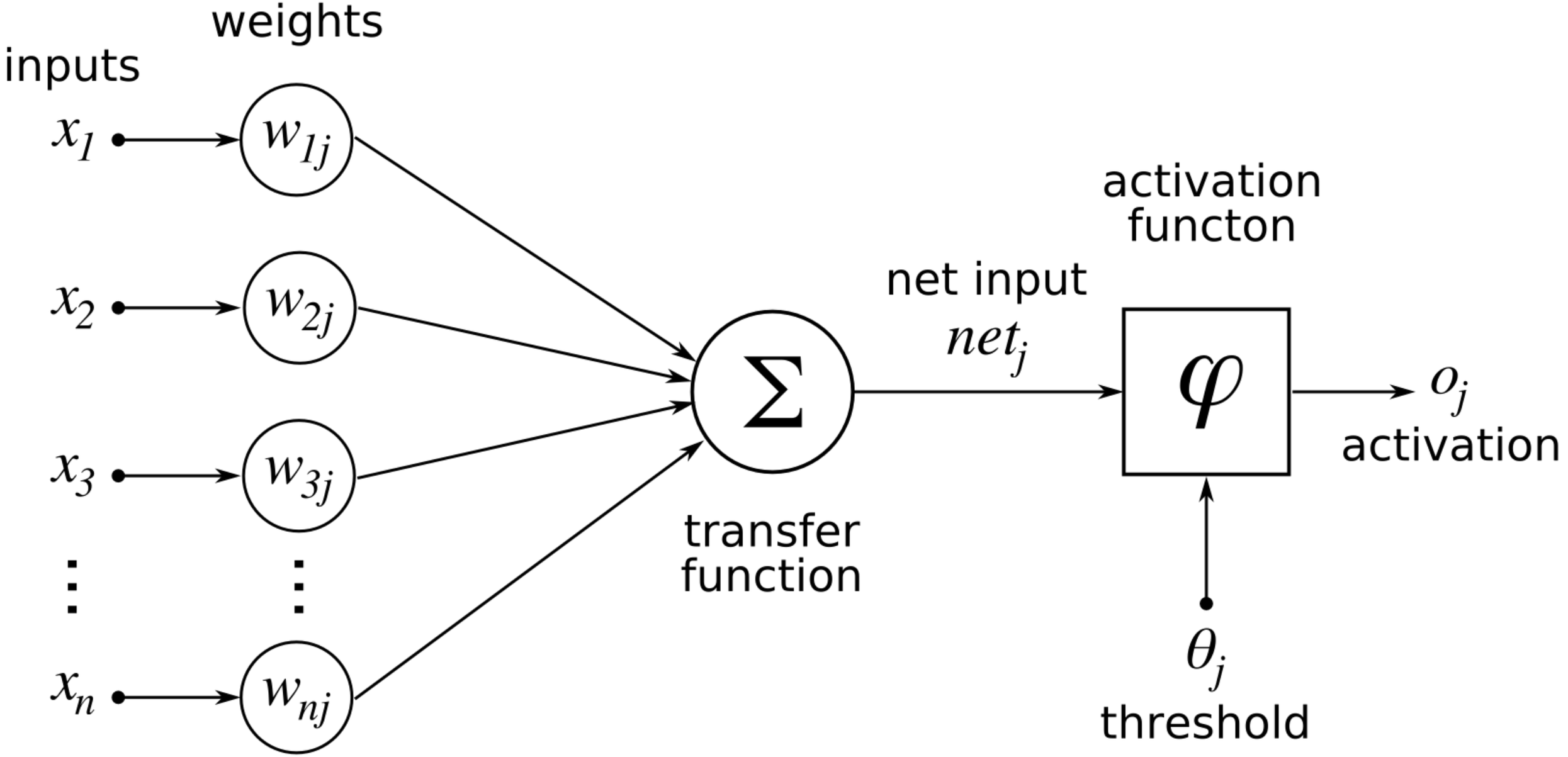
intra-model parallelism



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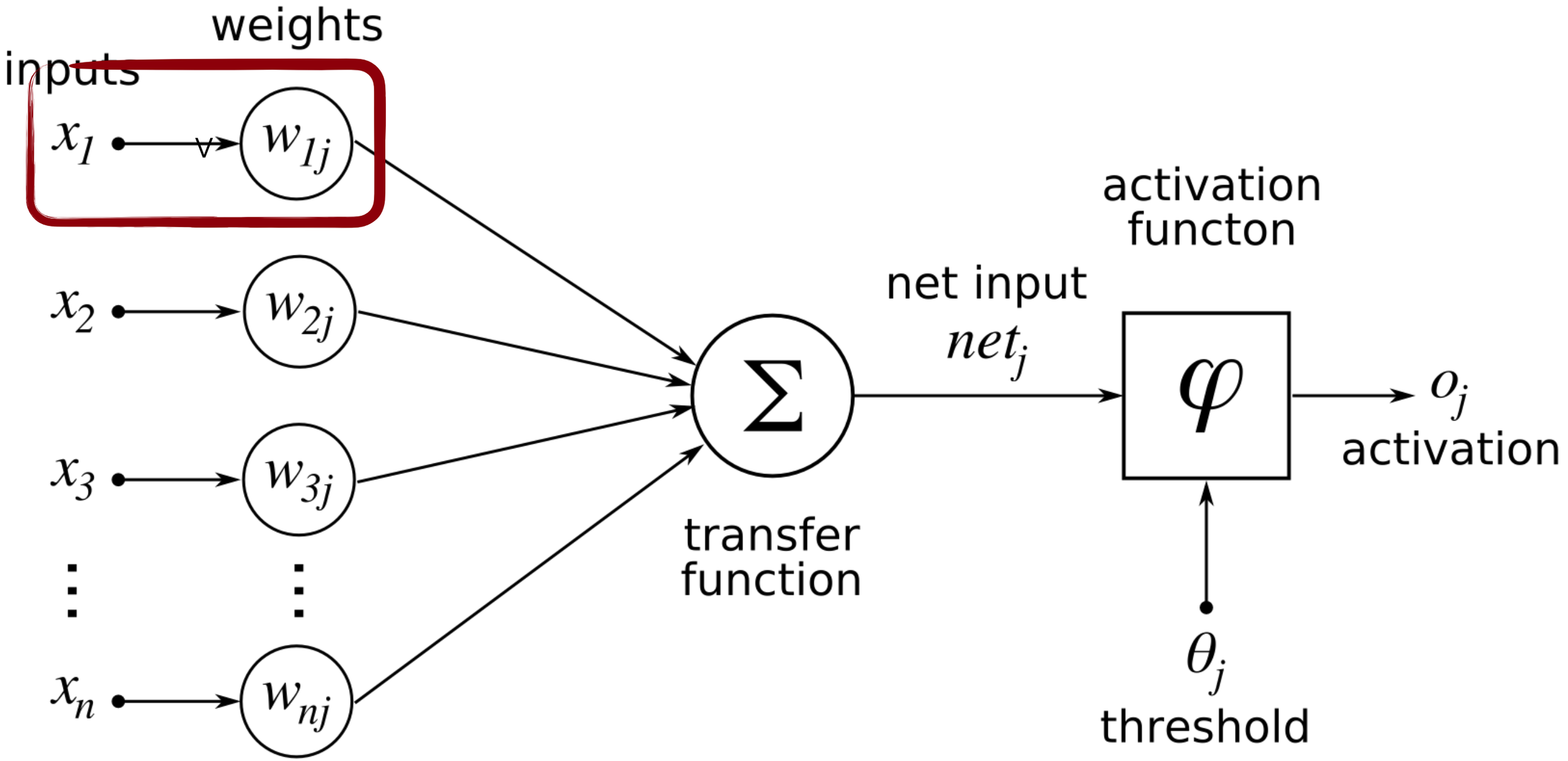

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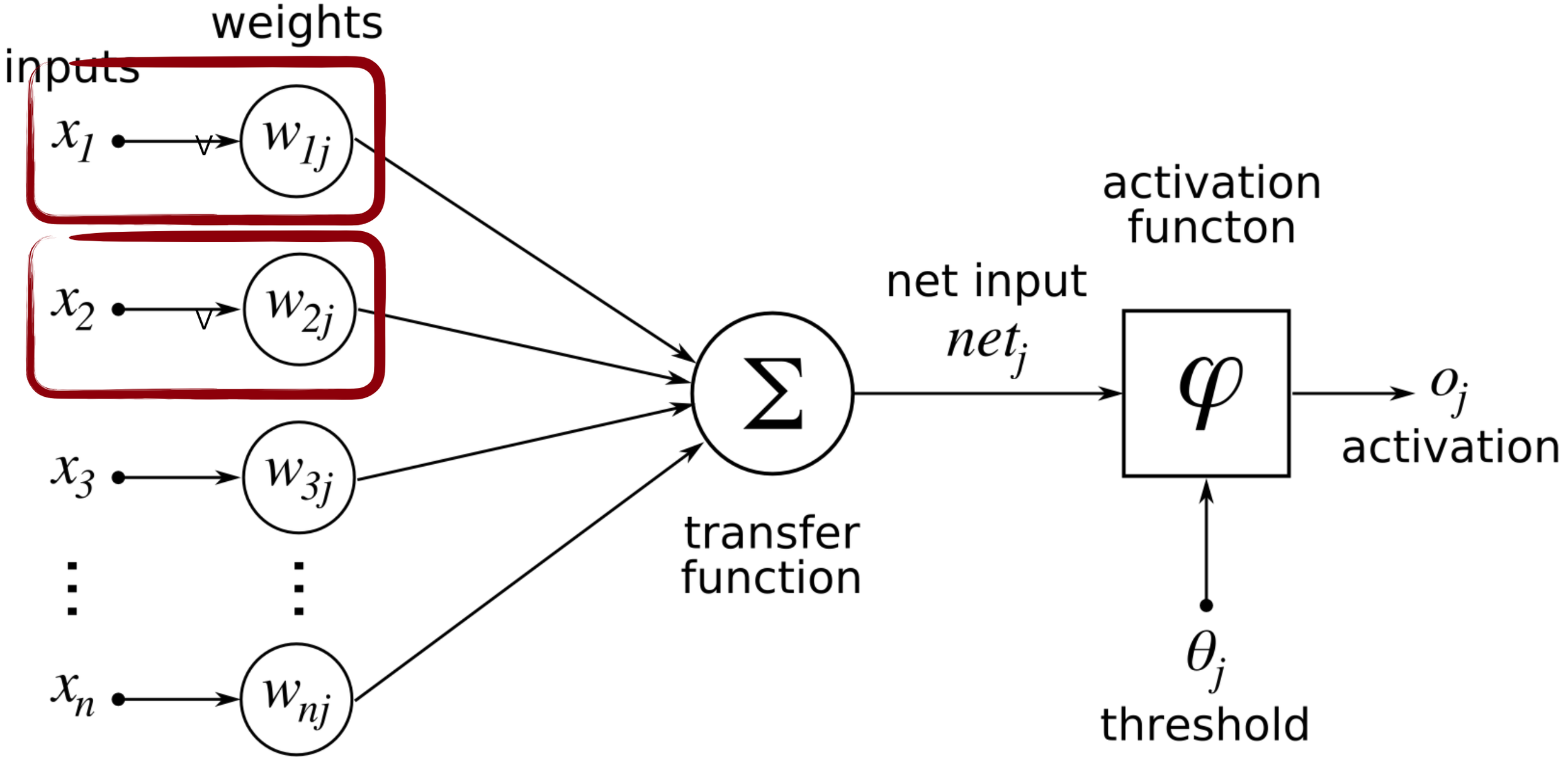

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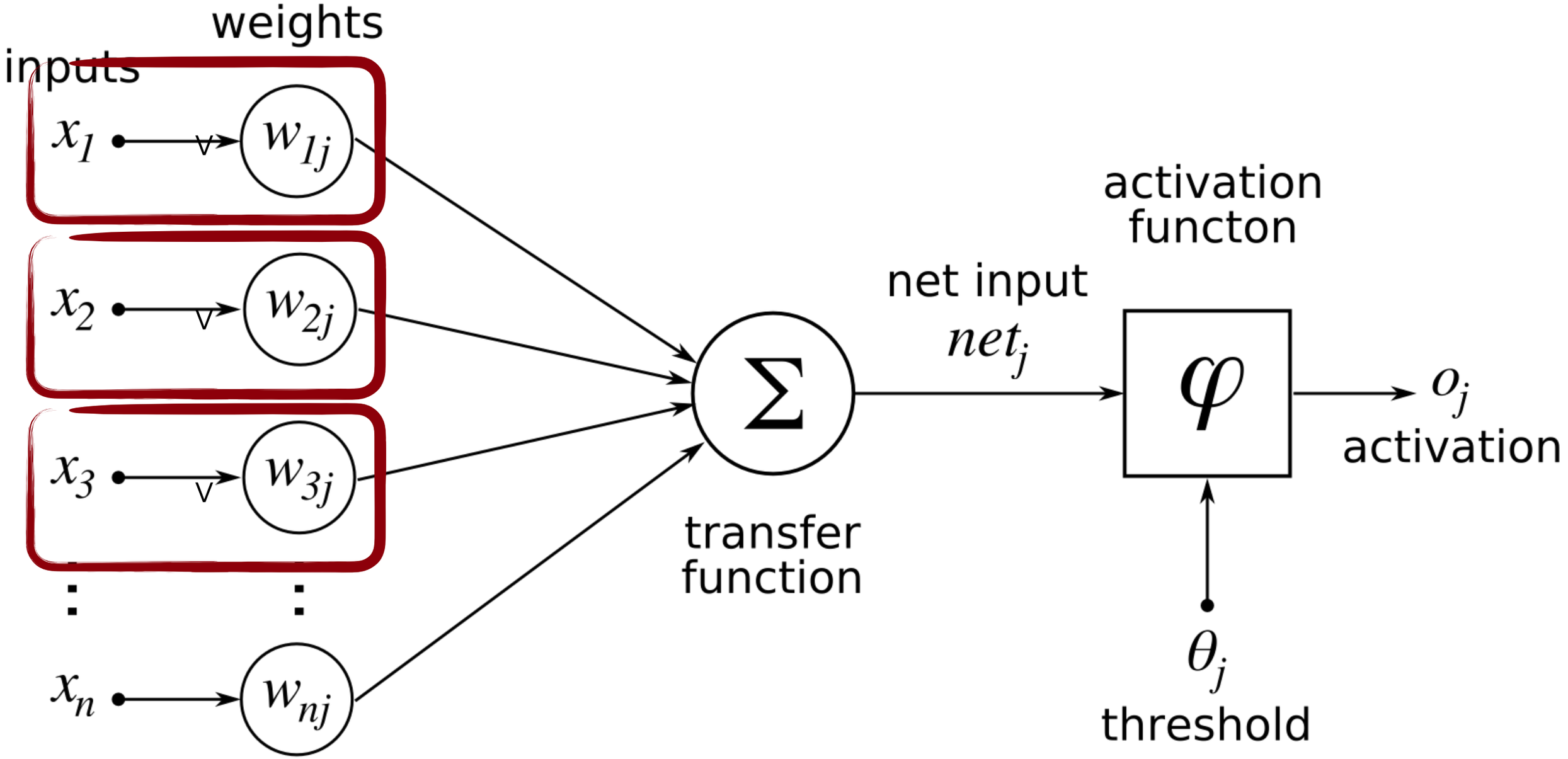

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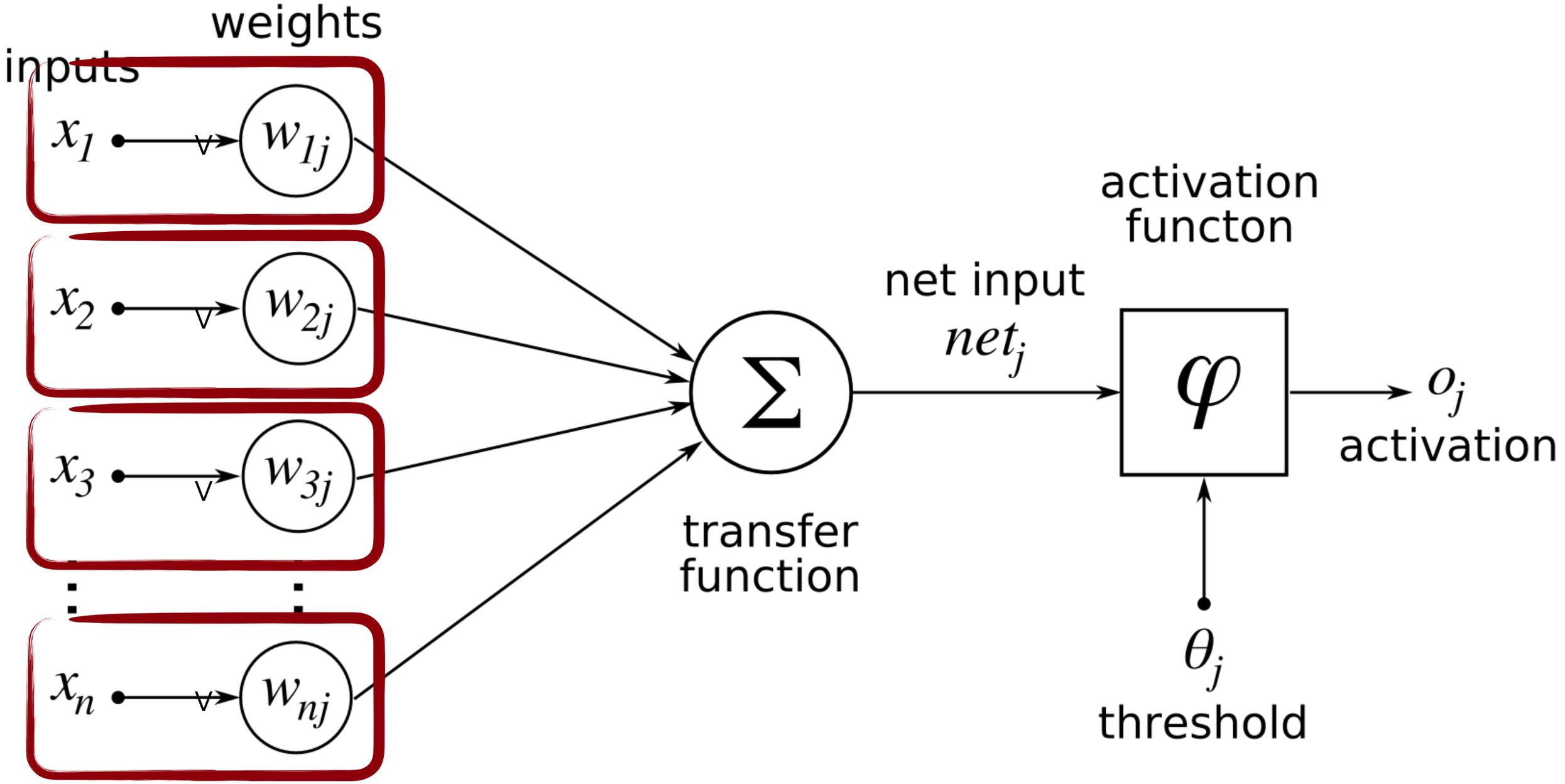

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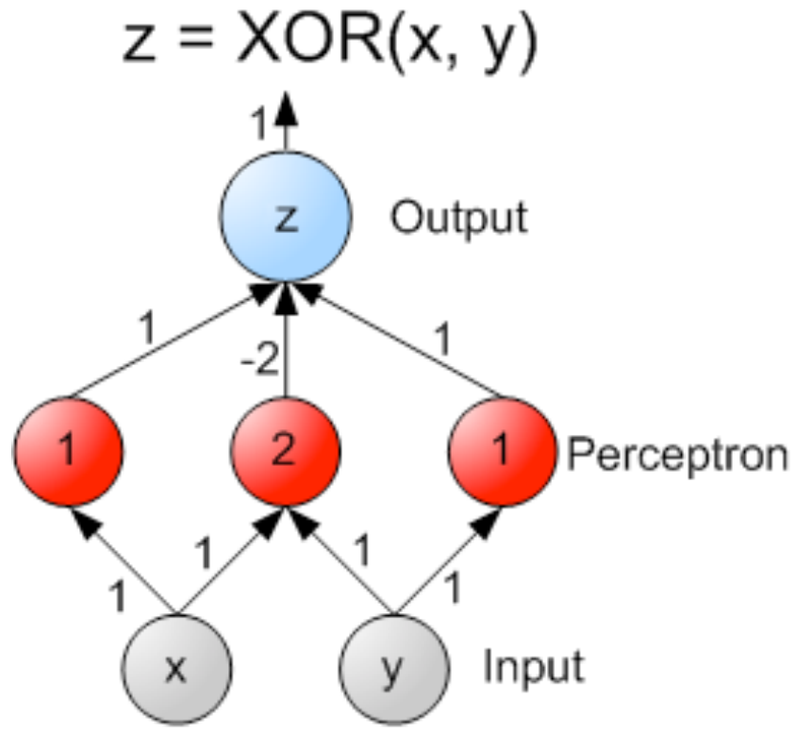
pipelined parallelism



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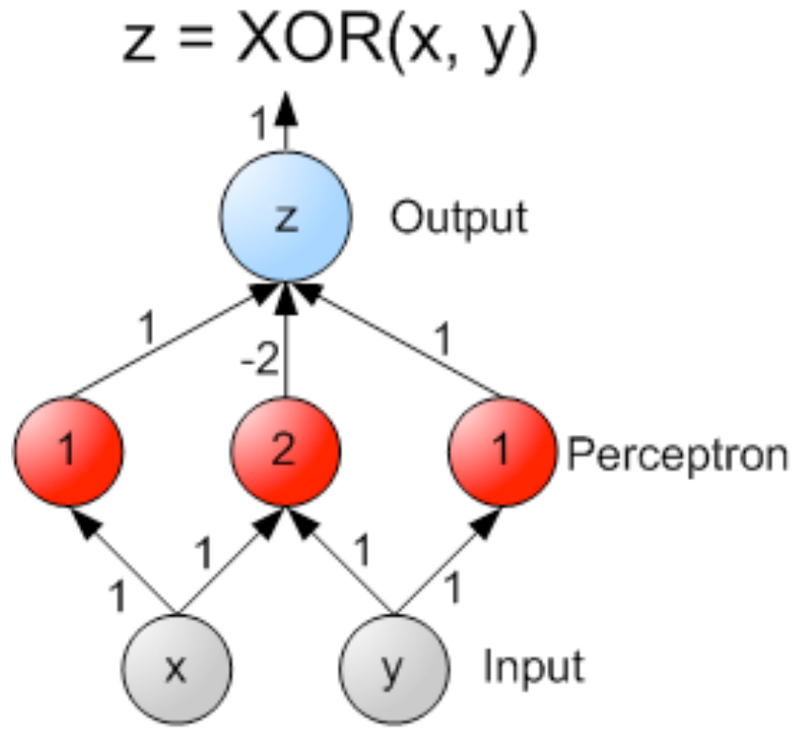
pipelined parallelism



0 0
0 1
1 0
1 1

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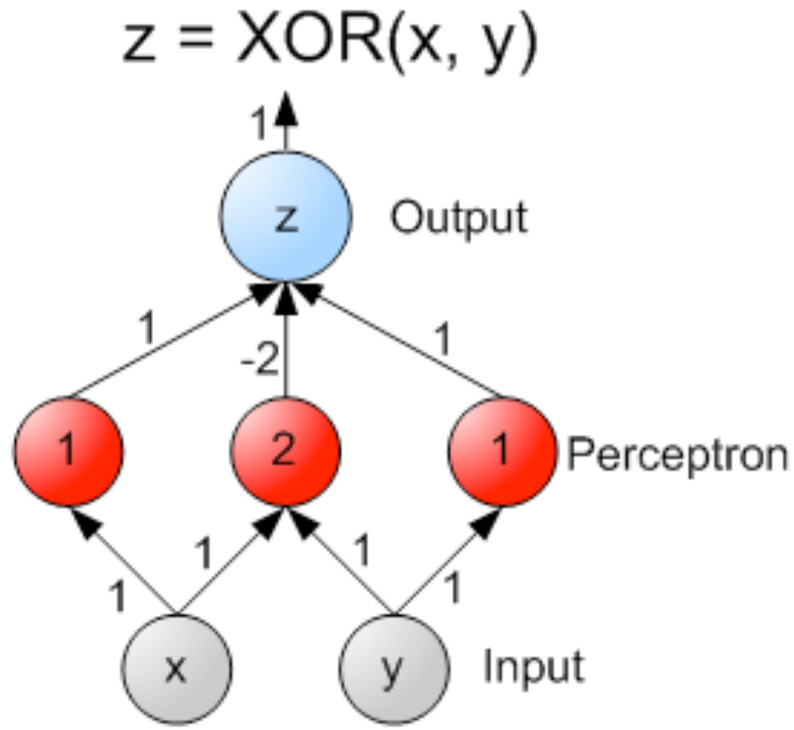
pipelined parallelism



0 0

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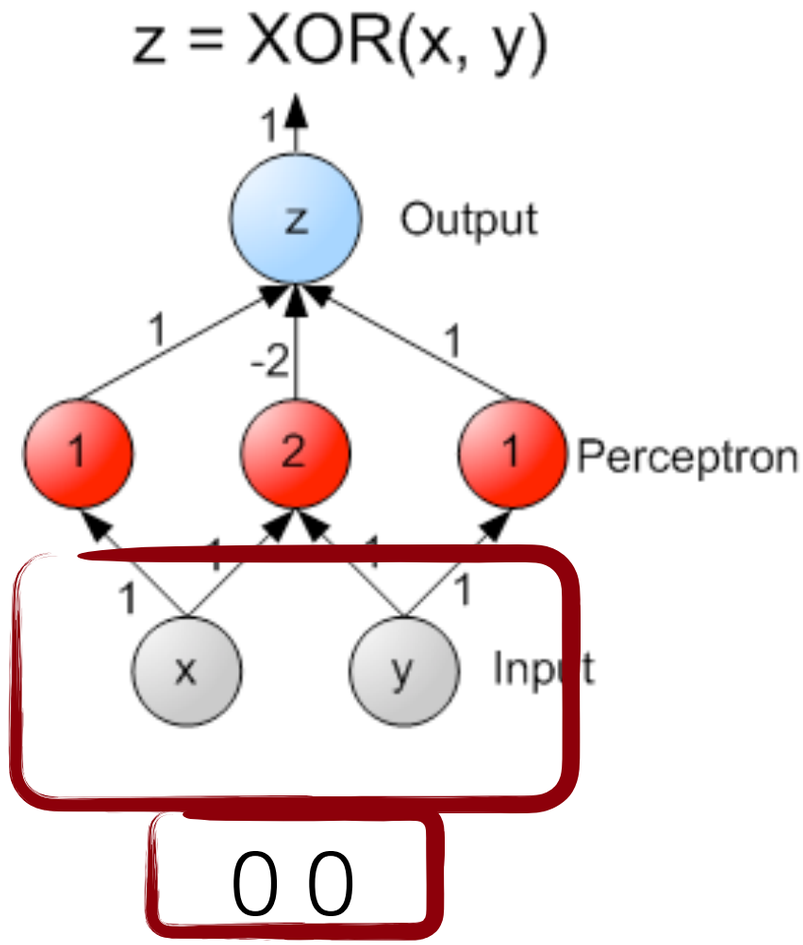

0 0

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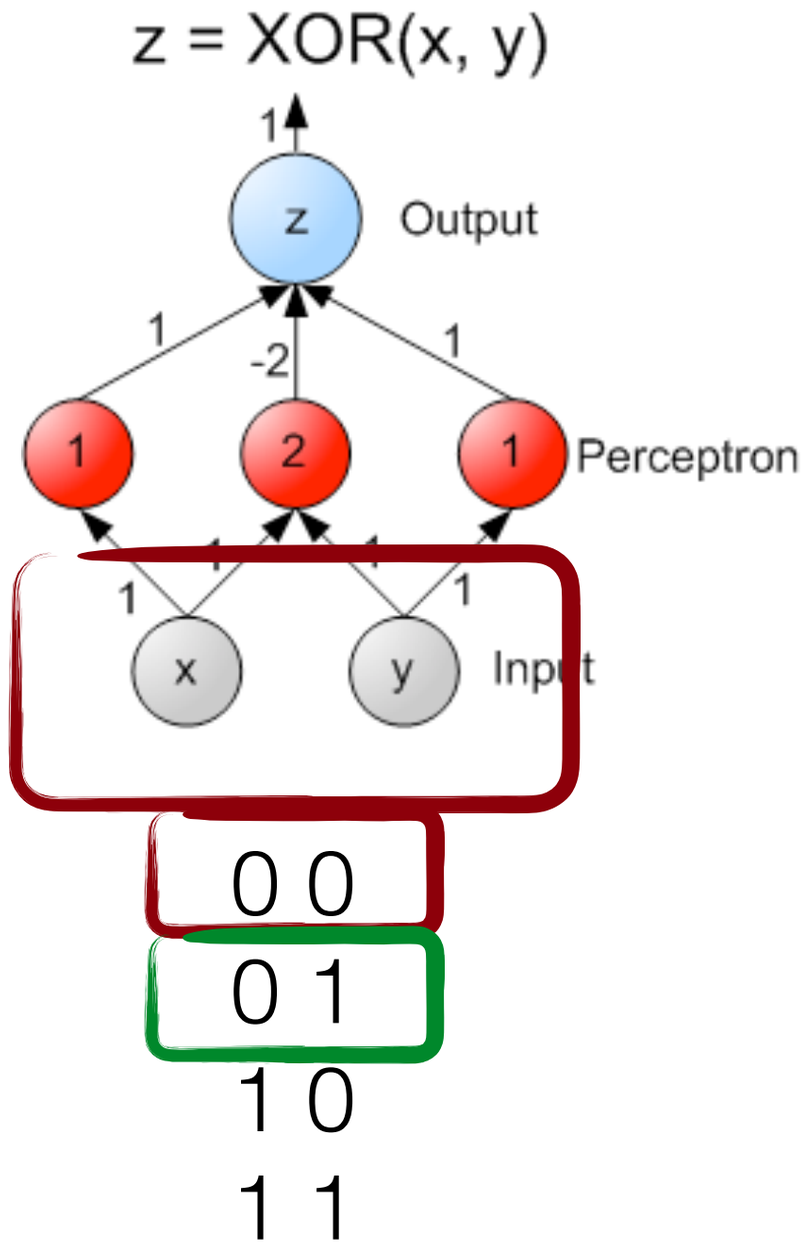

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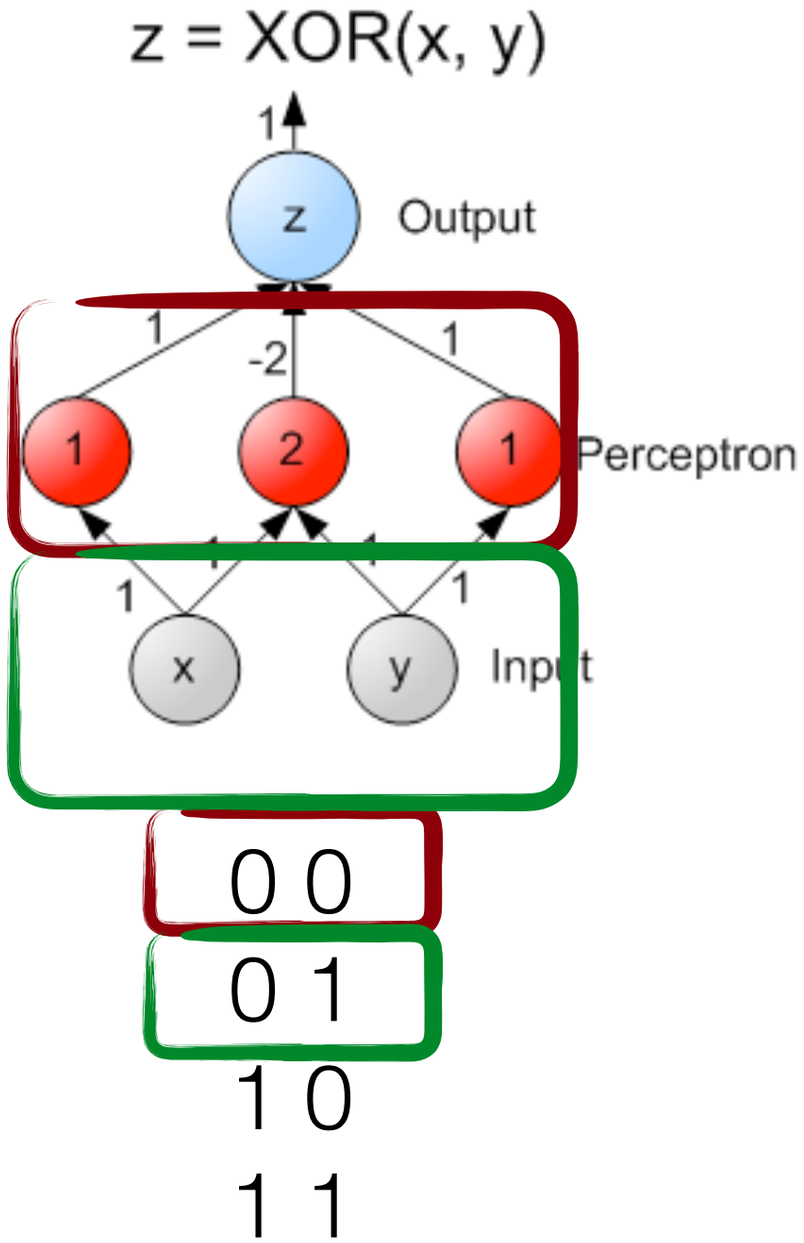

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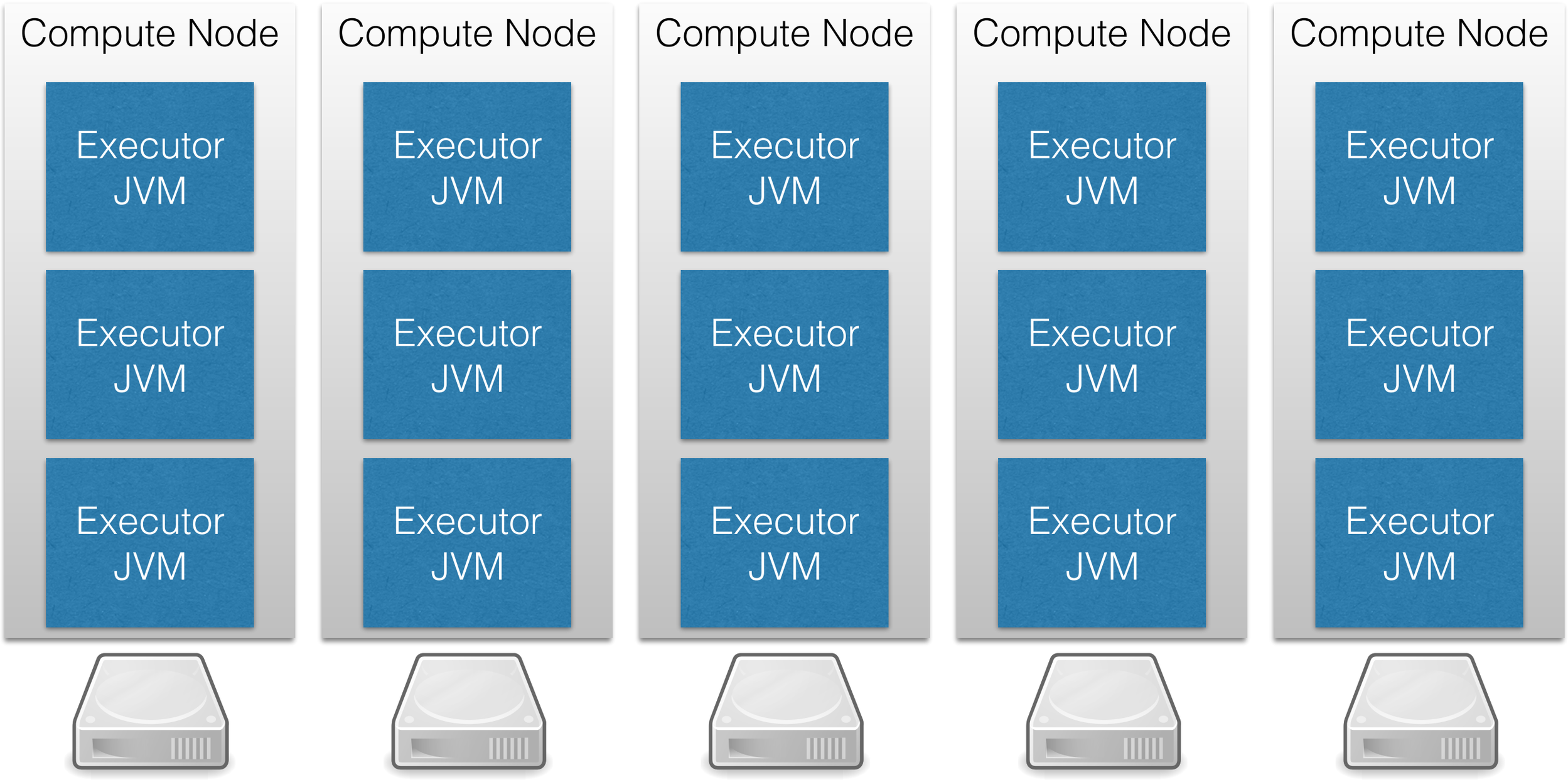
Driver JVM

Apache Spark



DeepLearning4J

```
new MultiLayerNetwork(conf);
```

VS.

```
new SparkDl4jMultiLayer(sc, conf, tm);
```

```
TrainingMaster tm = new ParameterAveragingTrainingMaster.Builder(int dataSetObjectSize)
        ... (your configuration here)
        .build();
```

DeepLearning4J

```
new MultiLayerNetwork(conf);
```

VS.

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```

data parallelism

```
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```

ND4J (DeepLearning4J)

- Tensor support (Linear Buffer + Stride)
- Multiple implementations, one interface
  - vectorized c++ code (JavaCPP), off-heap data storage, BLAS (OpenBLAS, Intel MKL, cuBLAS)
  - GPU (CUDA 8)

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Apache SystemML

- Custom machine learning algorithms
- Declarative ML
- Transparent distribution on data-parallel framework
  - Scale-up
  - Scale-out
- Cost-based optimiser generates low level execution plans

2007-2008: Multiple projects at IBM Research – Almaden involving machine learning on Hadoop.

2009: We form a **dedicated team** for scalable ML

2009-2010: Through engagements with customers, we observe how data scientists create **ML solutions**.

2007 2008 2009 2010

Research

2011 2012 2013 2014

June 2015: IBM Announces open-source SystemML

September 2015: Code available on Github

November 2015: SystemML enters Apache incubation

February 2016: First release (0.9) of Apache SystemML

June 2016: Second Apache release (0.10)

2015

2016

Apache SystemML

```
U = rand(nrow(X), r, min = -1.0, max = 1.0);
V = rand(r, ncol(X), min = -1.0, max = 1.0);
while(i < mi) {
   i = i + 1; ii = 1;
   if (is_U)
      G = (W * (U %*% V - X)) %*% t(V) + lambda * U;
   else
      G = t(U) %*% (W * (U %*% V - X)) + lambda * V;
   norm_G2 = sum(G ^ 2); norm_R2 = norm_G2;
   R = -G; S = R;
   while(norm_R2 > 10E-9 * norm_G2 & ii <= mii) {
     if (is_U) {
       HS = (W * (S %*% V)) %*% t(V) + lambda * S;
       alpha = norm_R2 / sum (S * HS);
       U = U + alpha * S;
     } else {
       HS = t(U) %*% (W * (U %*% S)) + lambda * S;
       alpha = norm_R2 / sum (S * HS);
       V = V + alpha * S;
     }
     R = R - alpha * HS;
     old_norm_R2 = norm_R2; norm_R2 = sum(R ^ 2);
     S = R + (norm_R2 / old_norm_R2) * S;
     ii = ii + 1;
   }
   is_U = ! is_U;
}
```

Apache SystemML

```
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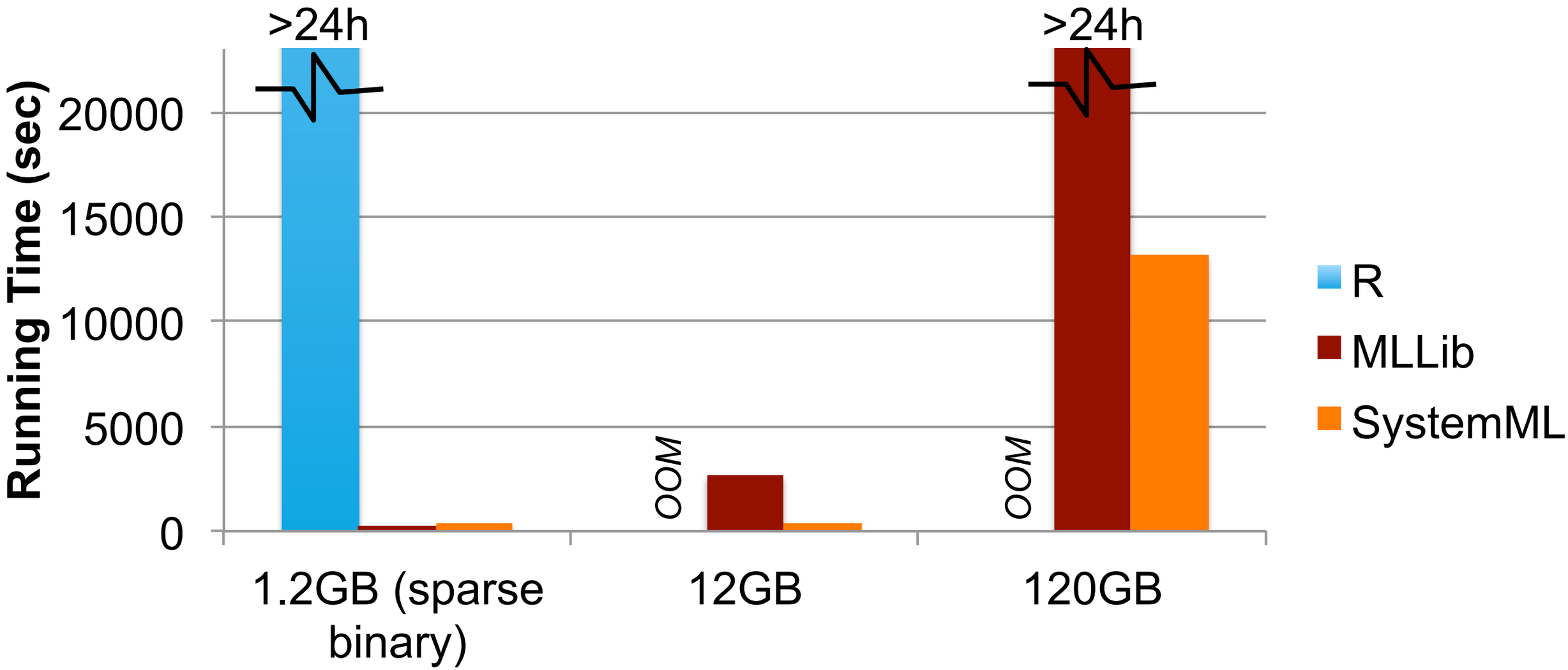
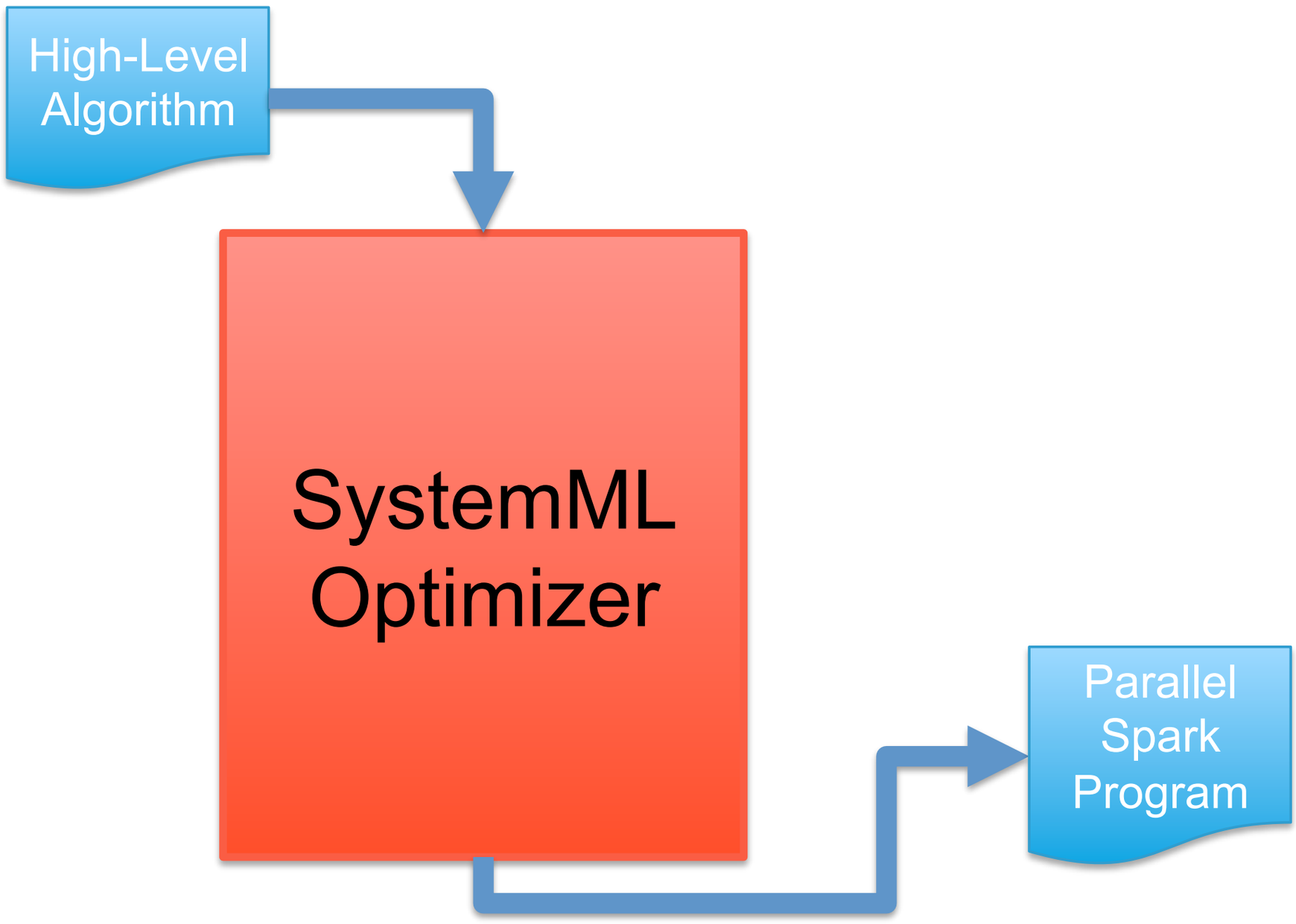
     if (is_U) {
       HS = (W * (S %*% V)) %*% t(V) + lambda * S;
       alpha = norm_R2 / sum (S * HS);
       U = U + alpha * S;
     } else {
       HS = t(U) %*% (W * (U %*% S)) + lambda * S;
       alpha = norm_R2 / sum (S * HS);
       V = V + alpha * S;
     }
     R = R - alpha * HS;
     old_norm_R2 = norm_R2; norm_R2 = sum(R ^ 2);
     S = R + (norm_R2 / old_norm_R2) * S;
     ii = ii + 1;
   }
   is_U = ! is_U;
}
```

SystemML:
compile and run at scale
no performance code needed!


>24h
>24h
Running Time (sec)
20000
15000
10000
5000
0
OOM
OOM
1.2GB (sparse binary)
12GB
120GB
R
MLLib
SystemML

Architecture



Architecture

High-level language front-ends

Cost Based Optimizer

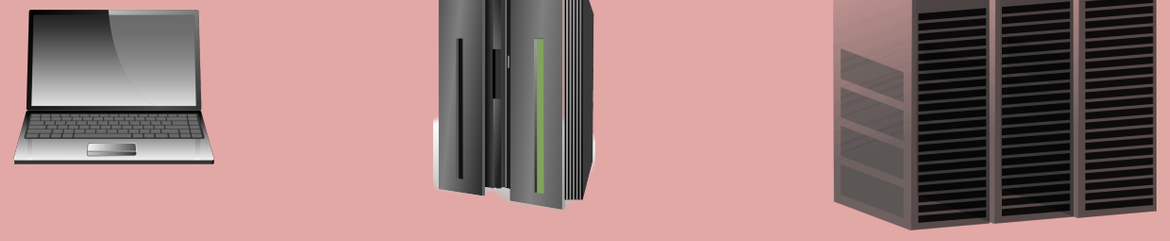
High-Level Operations (HOPs)

General representation of statements in the data analysis language

Low-Level Operations (LOPs)

General representation of operations in the runtime framework

Multiple execution environments



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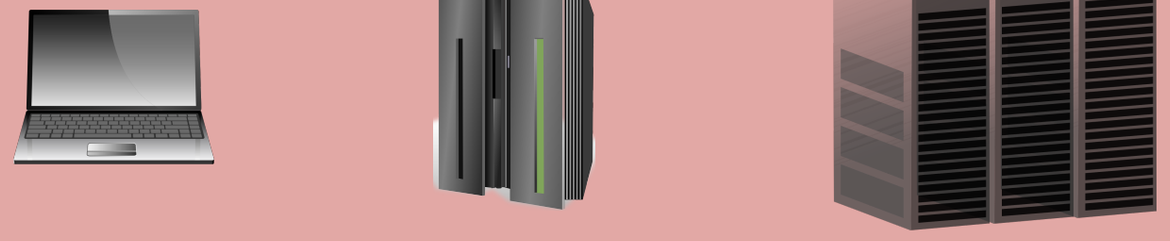
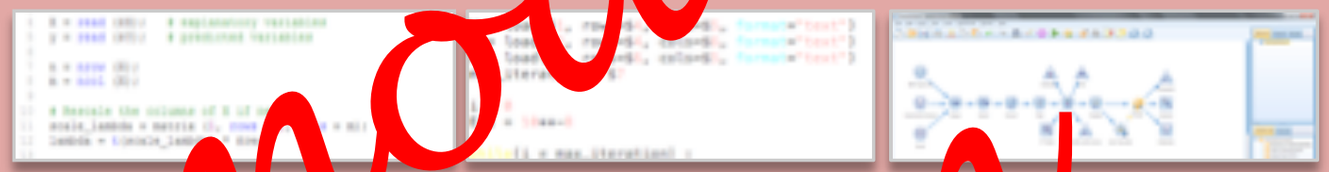


data parallelism

Architecture

High-level language front-ends



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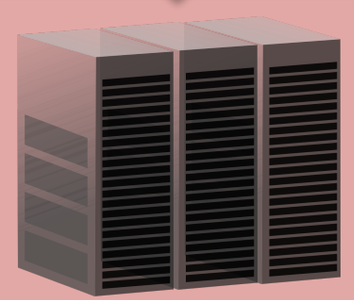
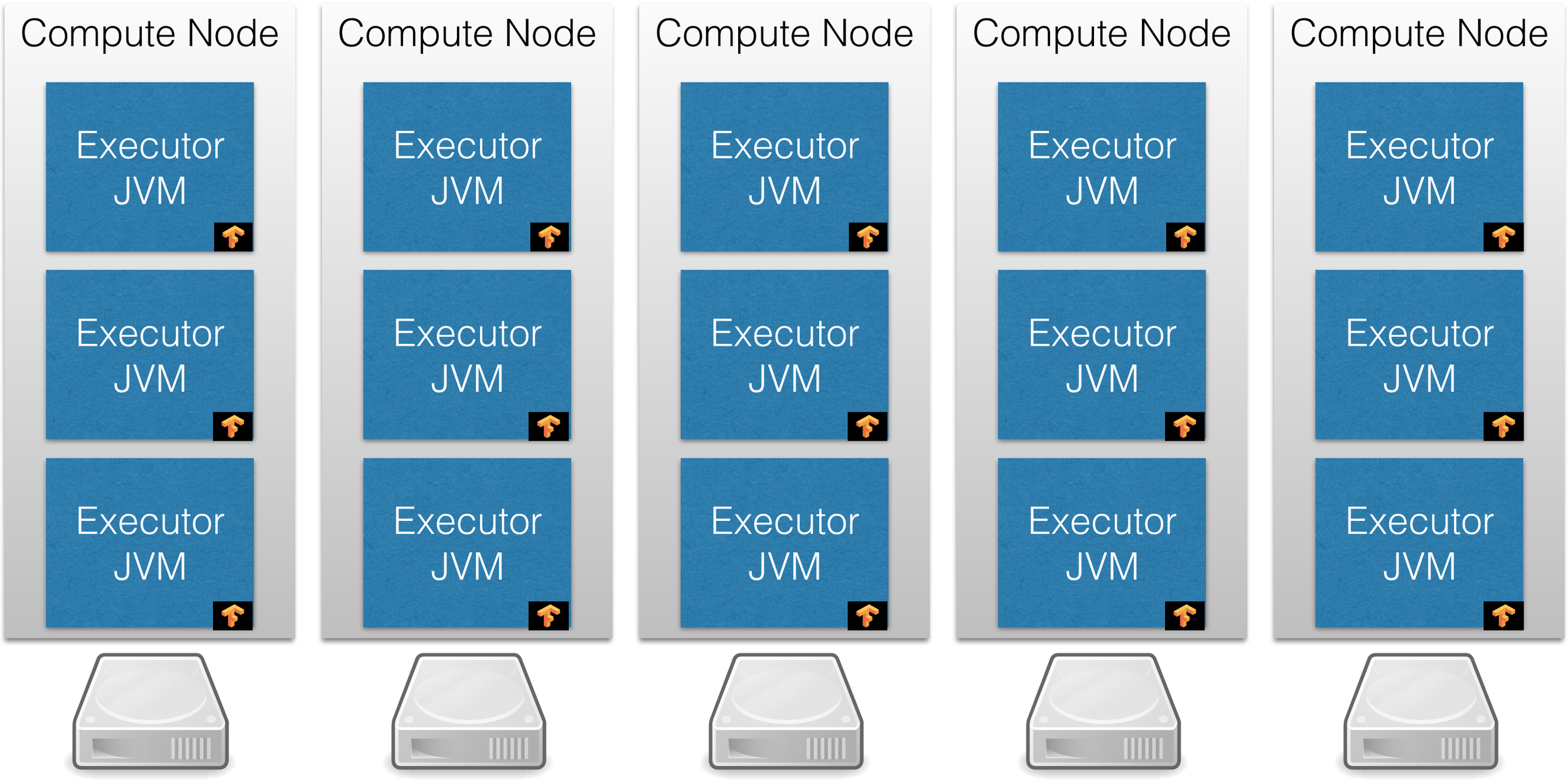


TensorFrames



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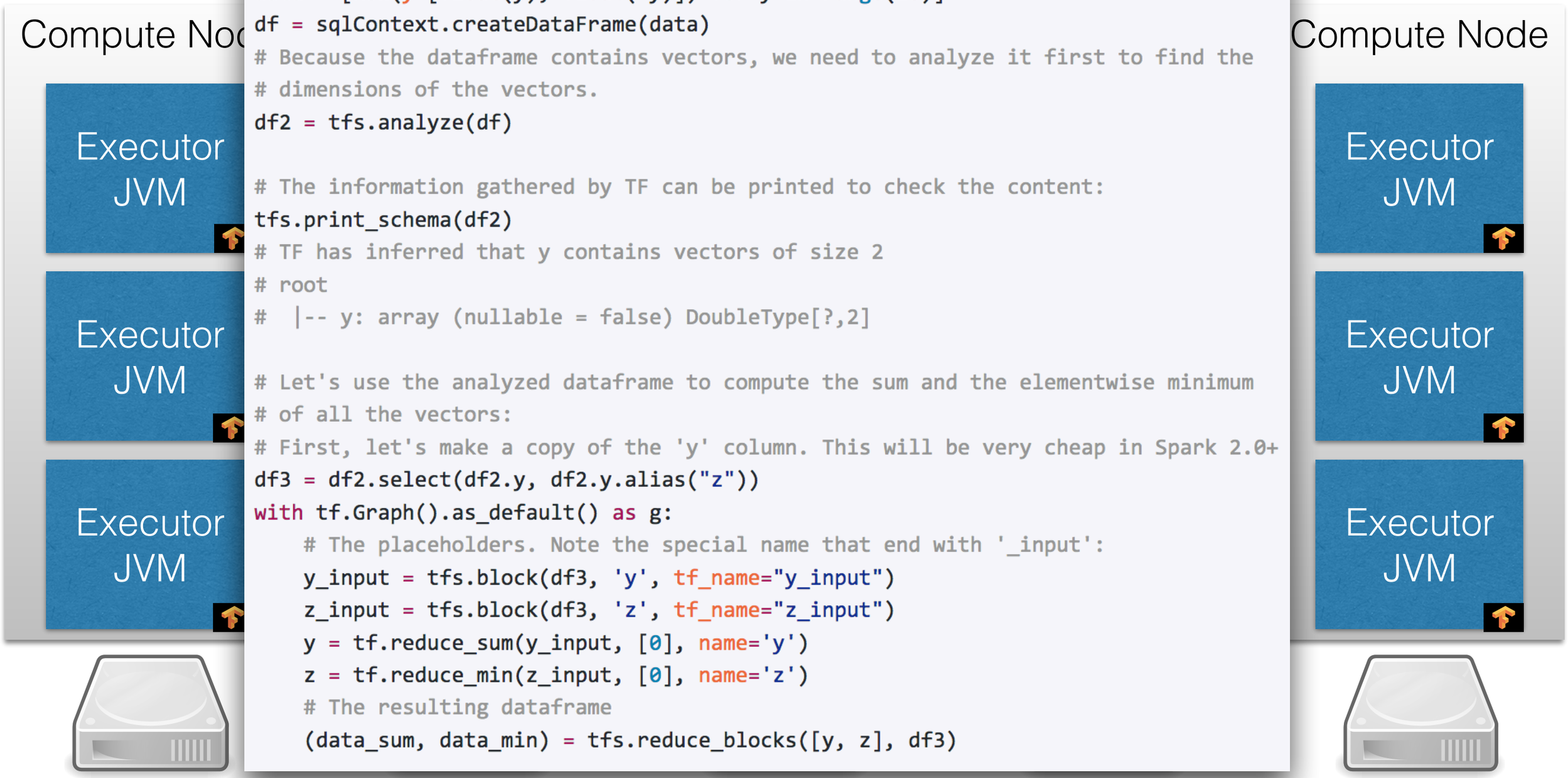


```
# Build a DataFrame of vectors
data = [Row(y=[float(y), float(-y)]) for y in range(10)]
df = sqlContext.createDataFrame(data)
# Because the dataframe contains vectors, we need to analyze it first to find the
# dimensions of the vectors.
df2 = tfs.analyze(df)

# The information gathered by TF can be printed to check the content:
tfs.print_schema(df2)
# TF has inferred that y contains vectors of size 2
# root
#  |-- y: array (nullable = false) DoubleType[?,2]

# Let's use the analyzed dataframe to compute the sum and the elementwise minimum
# of all the vectors:
# First, let's make a copy of the 'y' column. This will be very cheap in Spark 2.0+
df3 = df2.select(df2.y, df2.y.alias("z"))
with tf.Graph().as_default() as g:
    # The placeholders. Note the special name that end with '_input':
    y_input = tfs.block(df3, 'y', tf_name="y_input")
    z_input = tfs.block(df3, 'z', tf_name="z_input")
    y = tf.reduce_sum(y_input, [0], name='y')
    z = tf.reduce_min(z_input, [0], name='z')
    # The resulting dataframe
    (data_sum, data_min) = tfs.reduce_blocks([y, z], df3)
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TensorFrames

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Compute Node

Executor JVM

Executor JVM

Executor JVM

Executor JVM

Compute Node

Executor JVM

Executor JVM

Executor JVM

inter-node parallelism

Romeo Kienzler

Parameter Server on Driver

TensorSpark

Compute Node

Executor JVM

Executor JVM

Compute Node

Executor JVM

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Compute Node

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Compute Node

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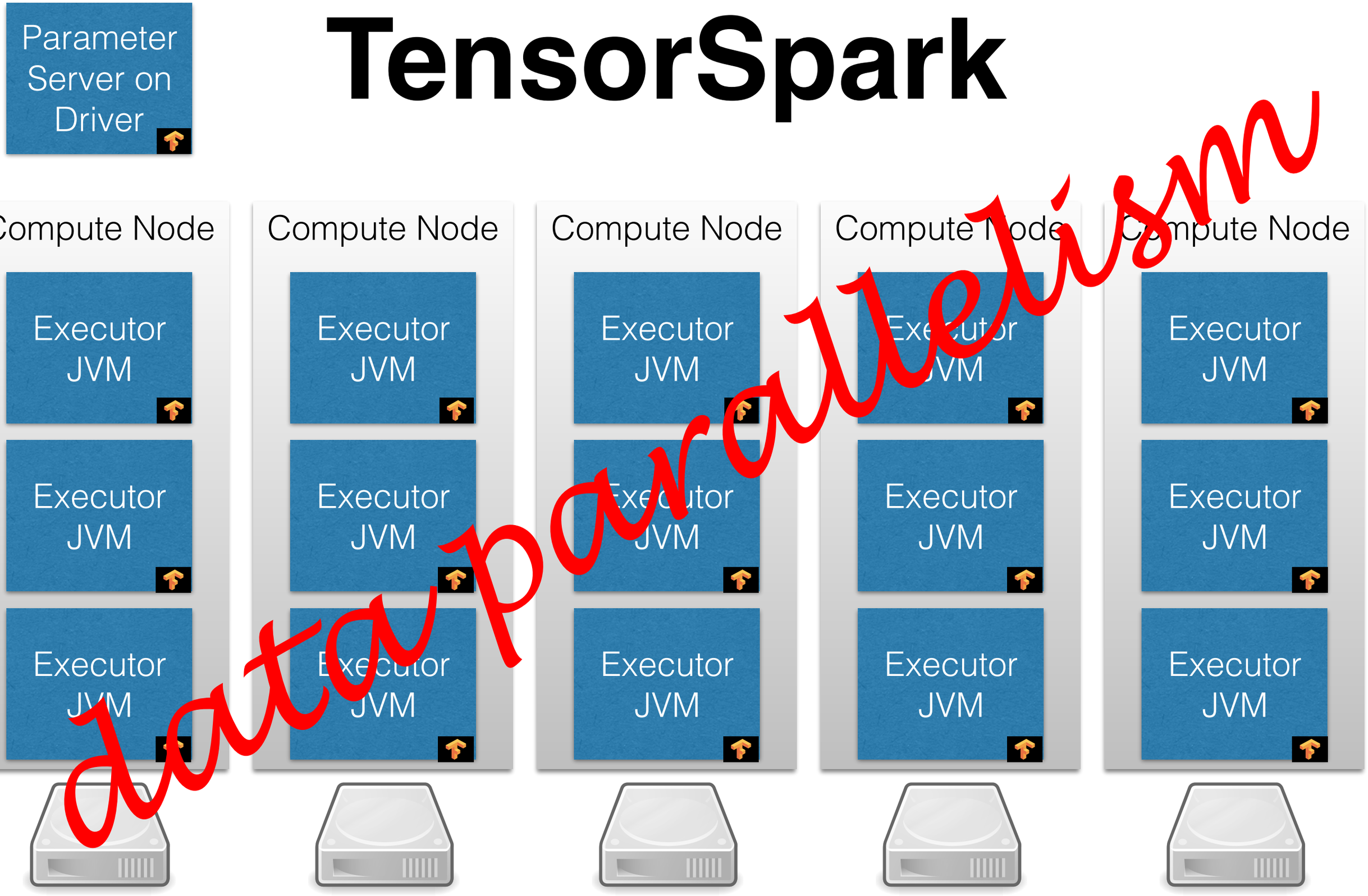
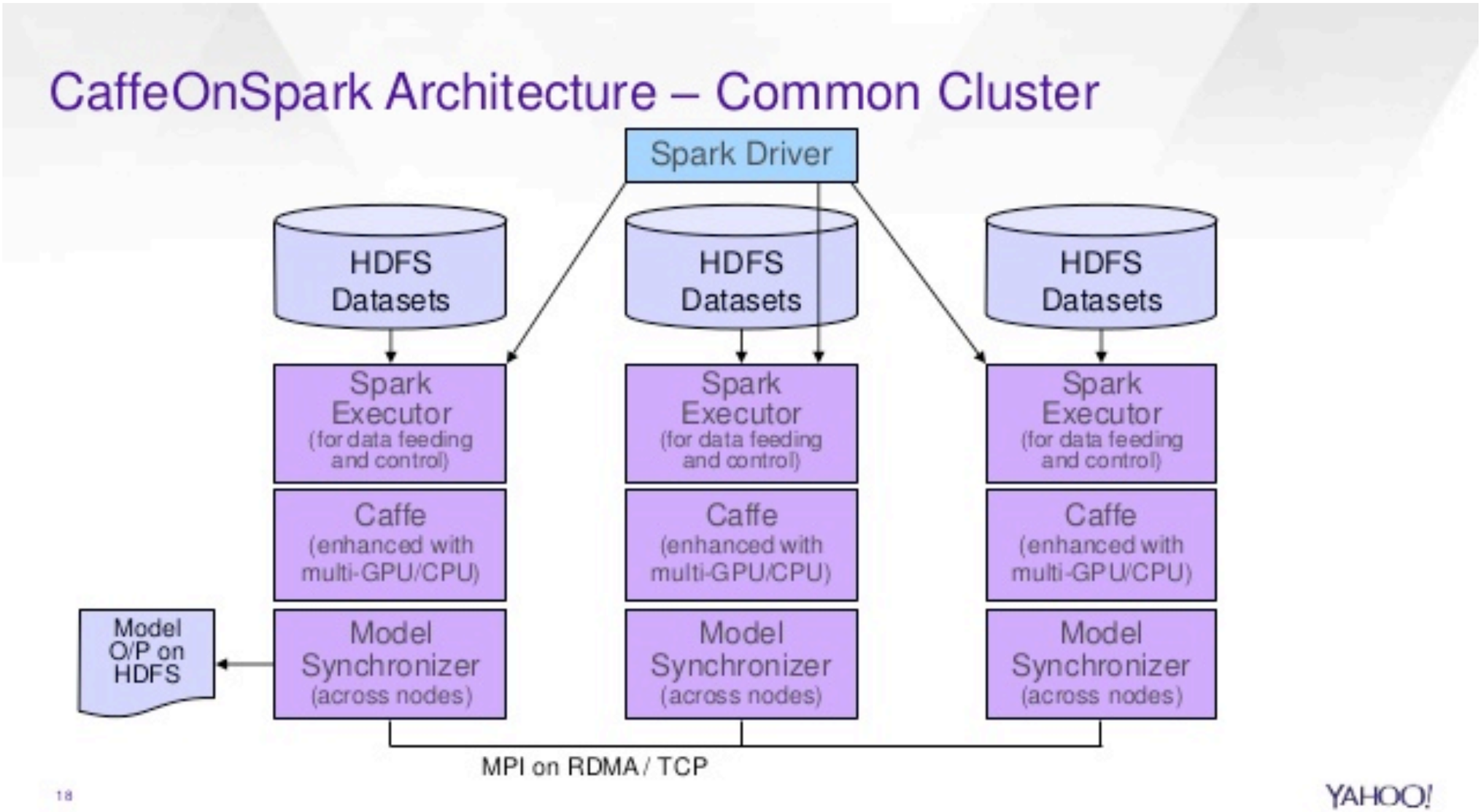
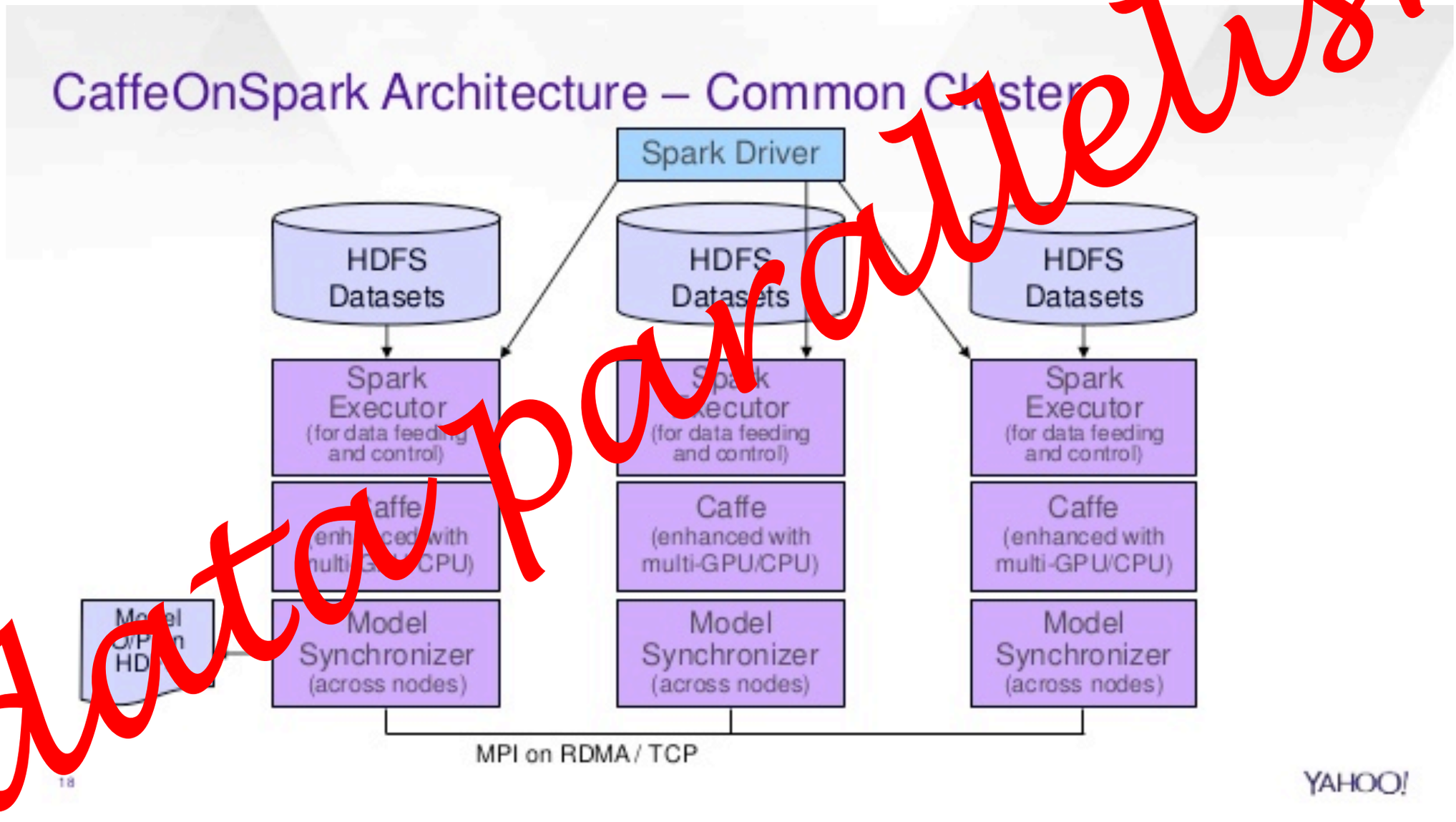
TensorSpark



CaffeOnSpark



CaffeOnSpark



data parallelism

?