Machine Learning Systems

Lecture 7: Machine Learning System Stack

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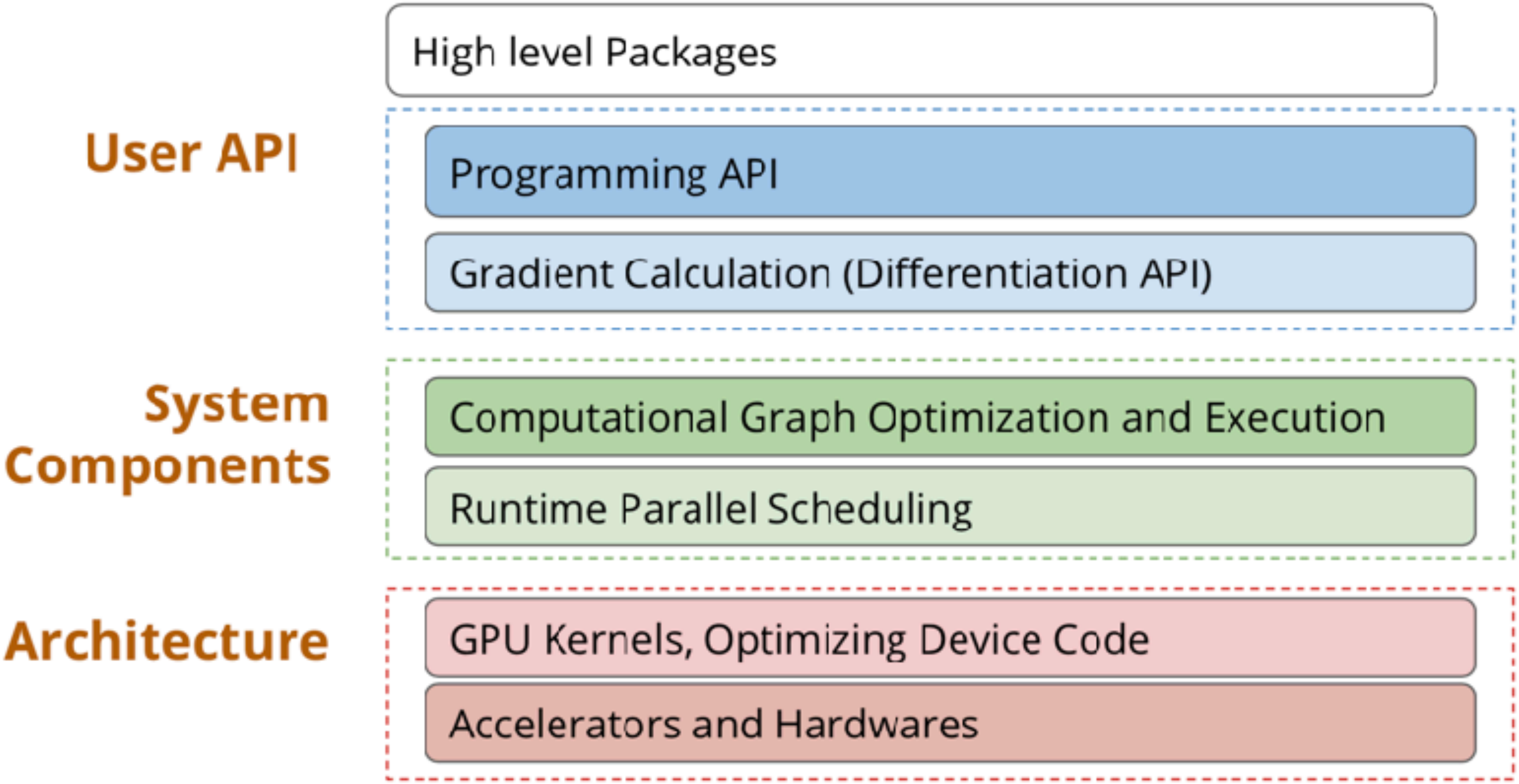
UofSC™

Machine Learning Systems Juggle

We won’t focus on a specific one, but will discuss the common and useful elements of these systems

Typical Machine Learning System Stack



High level Packages

User API

Programming API

Gradient Calculation (Differentiation API)

System Components

Computational Graph Optimization and Execution

Runtime Parallel Scheduling

Architecture

GPU Kernels, Optimizing Device Code

Accelerators and Hardwares

We will have lectures on each of the parts!

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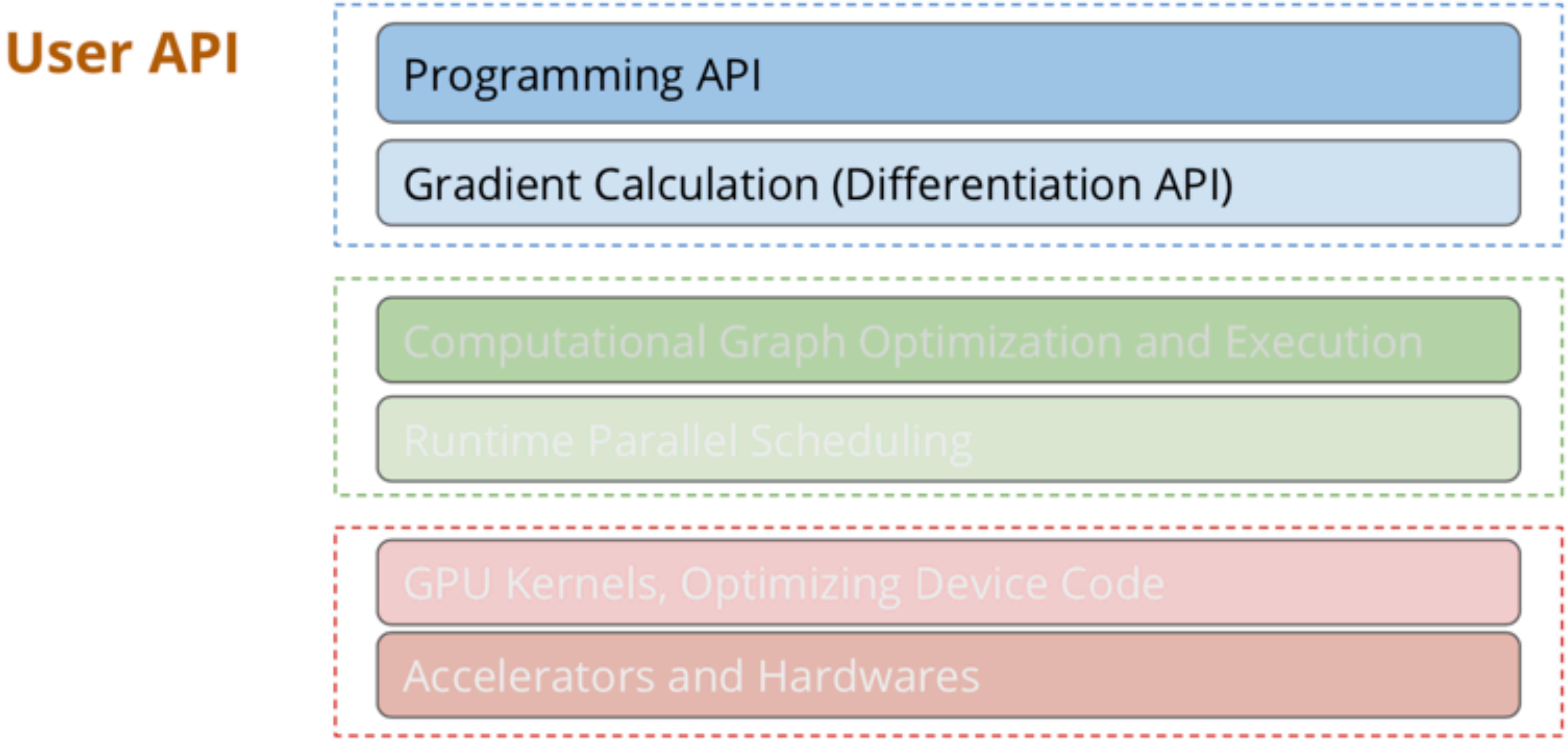


User API

Programming API

Gradient Calculation (Differentiation API)

Computational Graph Optimization and Execution

Runtime Parallel Scheduling

GPU Kernels, Optimizing Device Code

Accelerators and Hardwares

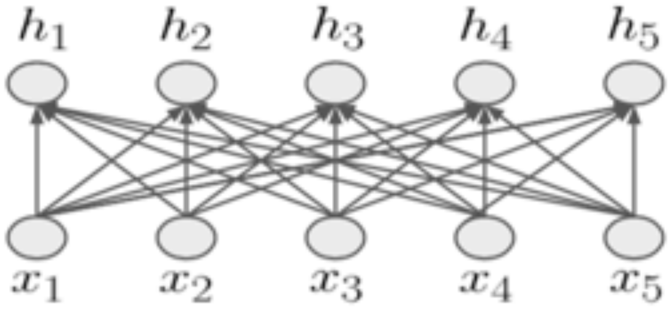
Example: Logistic Regression

Data

$$x_i = \begin{bmatrix} \text{pixel}_1 \\ \text{pixel}_2 \\ \cdots \\ \text{pixel}_m \end{bmatrix}$$

Fully Connected Layer

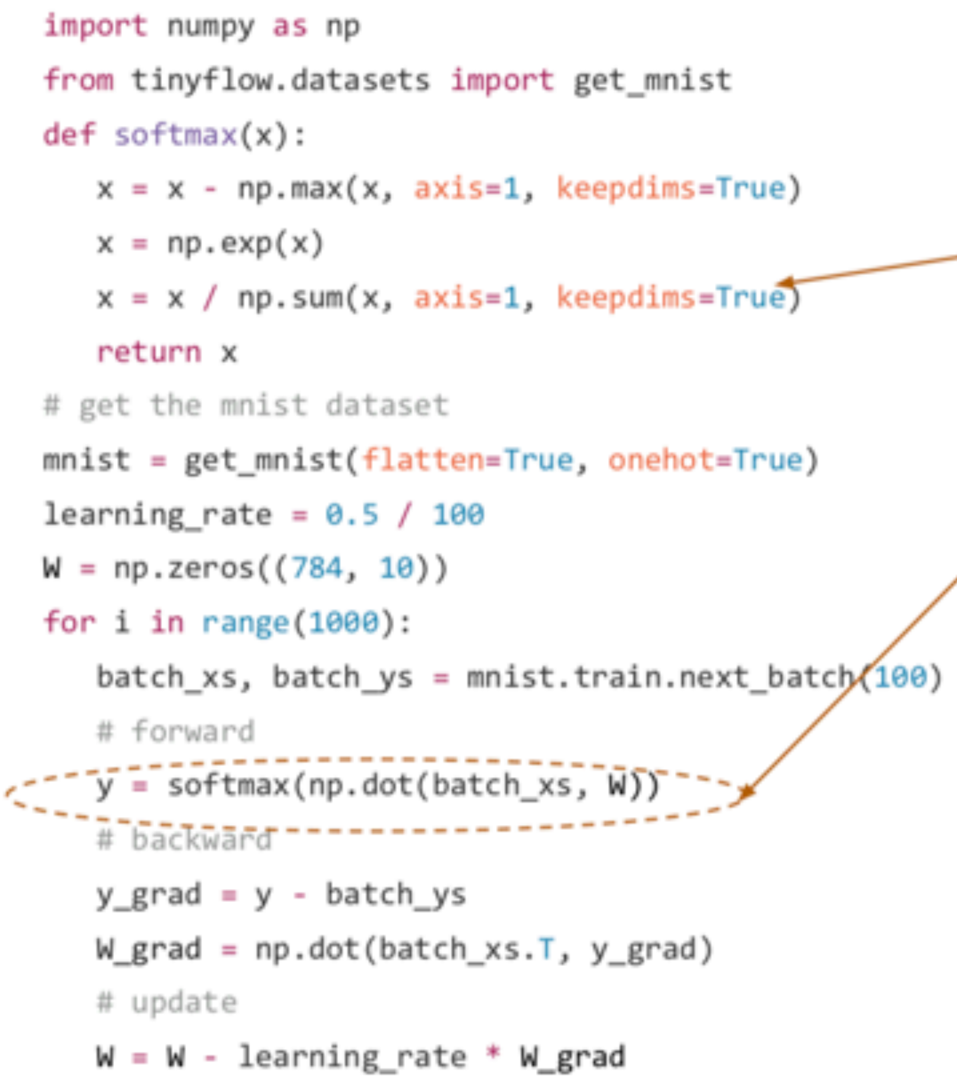
$$h_k = w_k^T x_i$$



Softmax

$$P(y_i = k | x_i) = \frac{\exp(h_k)}{\sum_{j=1}^{10} \exp(h_i)}$$

Logistic Regression in Numpy

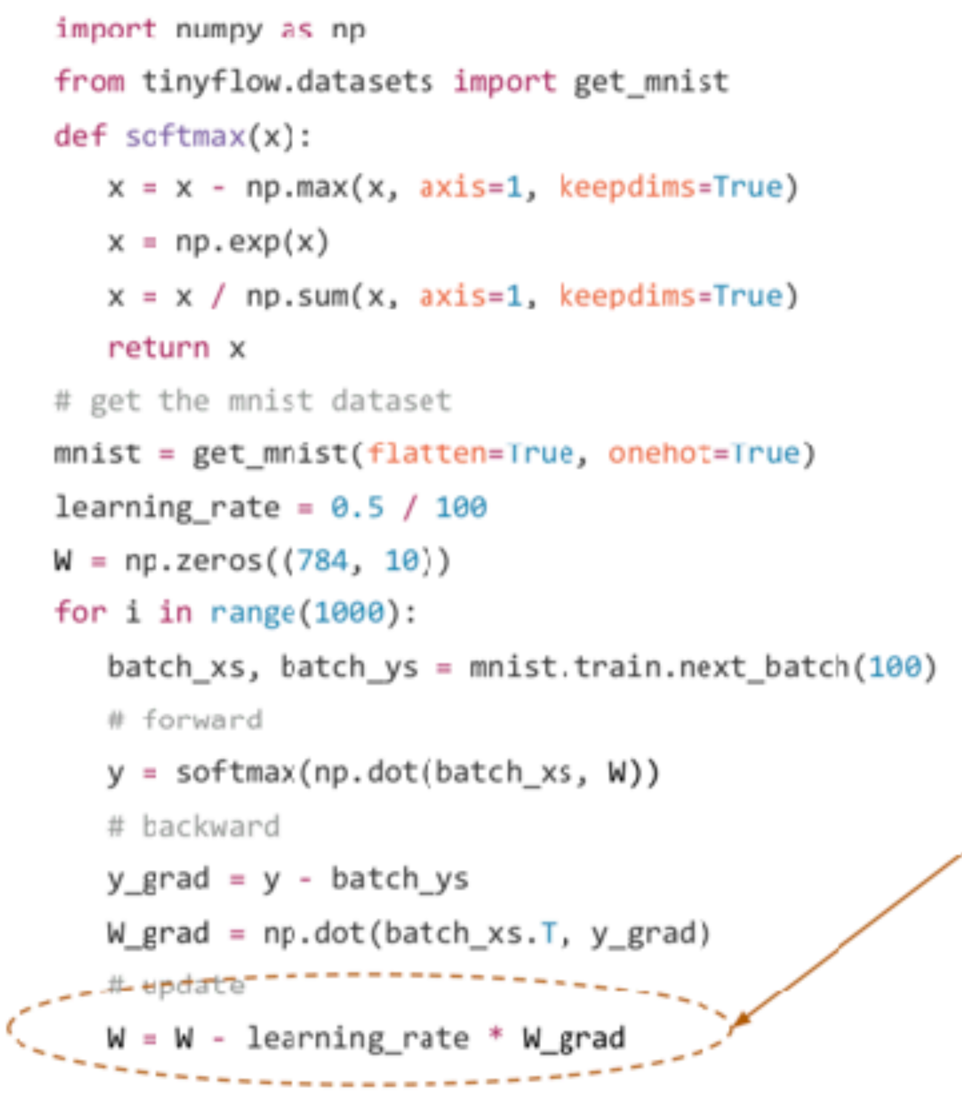


```
import numpy as np
from tinyflow.datasets import get_mnist
def softmax(x):
   x = x - np.max(x, axis=1, keepdims=True)
   x = np.exp(x)
   x = x / np.sum(x, axis=1, keepdims=True)
   return x
# get the mnist dataset
mnist = get_mnist(flatten=True, onehot=True)
learning_rate = 0.5 / 100
W = np.zeros((784, 10))
for i in range(1000):
   batch_xs, batch_ys = mnist.train.next_batch(100)
   # forward
   y = softmax(np.dot(batch_xs, W))
   # backward
   y_grad = y - batch_ys
   W_grad = np.dot(batch_xs.T, y_grad)
   # update
   W = W - learning_rate * W_grad
```

Forward computation:
Compute probability of each class y given input

- Matrix multiplication
    - `np.dot(batch_xs, W)`
- Softmax transform the result
    - `softmax(np.dot(batch_xs, W))`

Logistic Regression in Numpy



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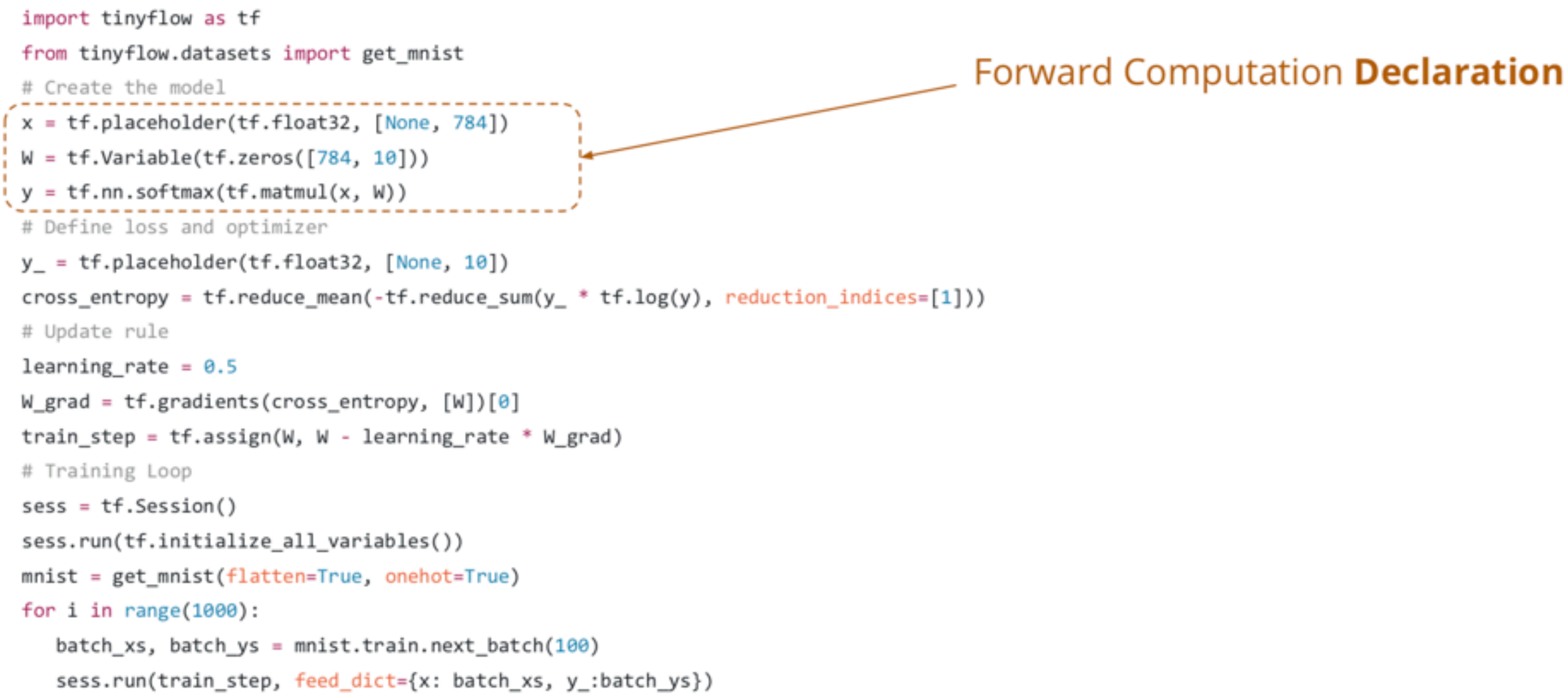
```

Weight Update via SGD

$$w \leftarrow w - \eta \nabla_w L(w)$$

Logistic Regression in TinyFlow (TensorFlow like API)



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# Define loss and optimizer
y_ = tf.placeholder(tf.float32, [None, 10])
cross_entropy = tf.reduce_mean(-tf.reduce_sum(y_ * tf.log(y), reduction_indices=[1]))
# Update rule
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```
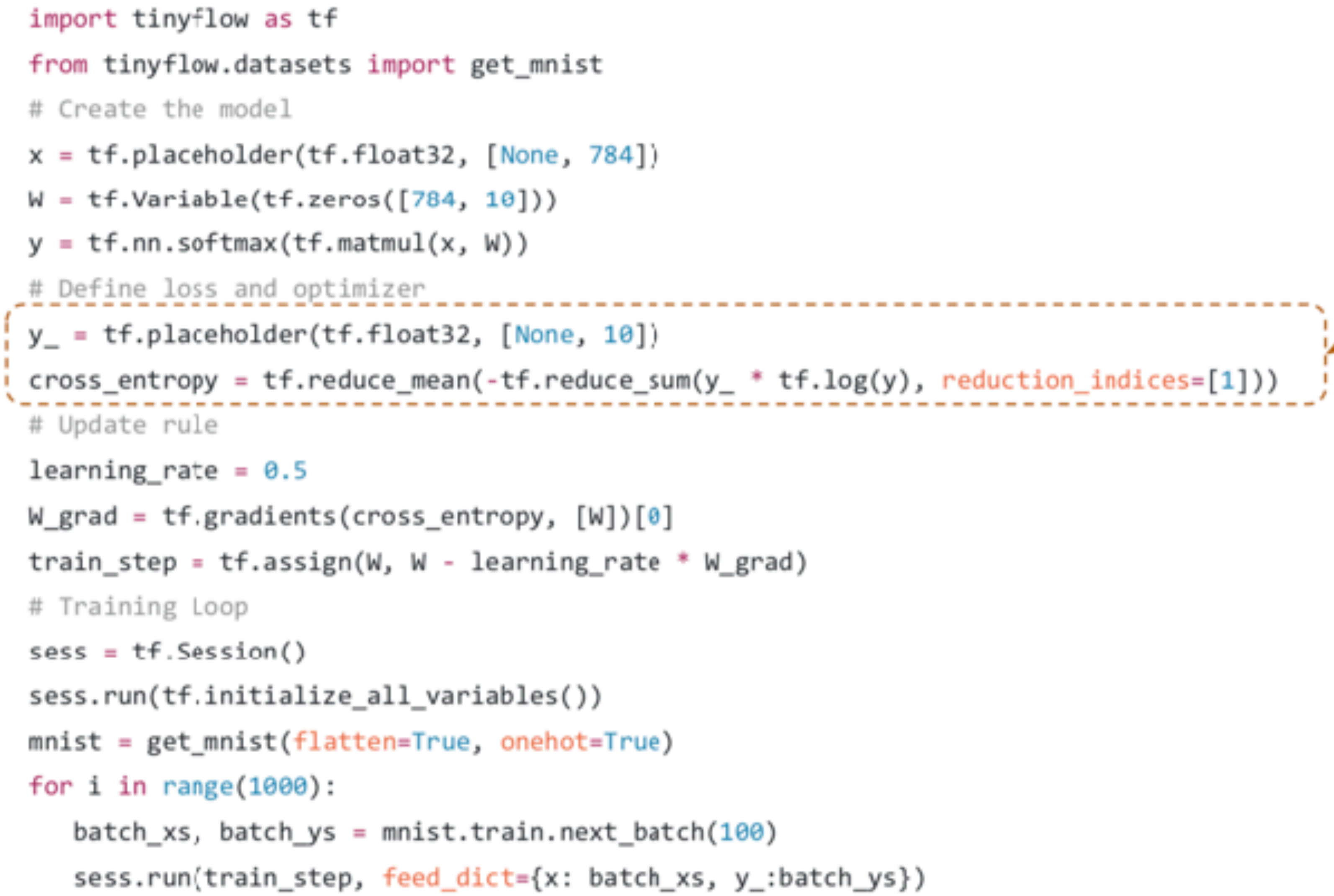

Forward Computation **Declaration**

Logistic Regression in TinyFlow



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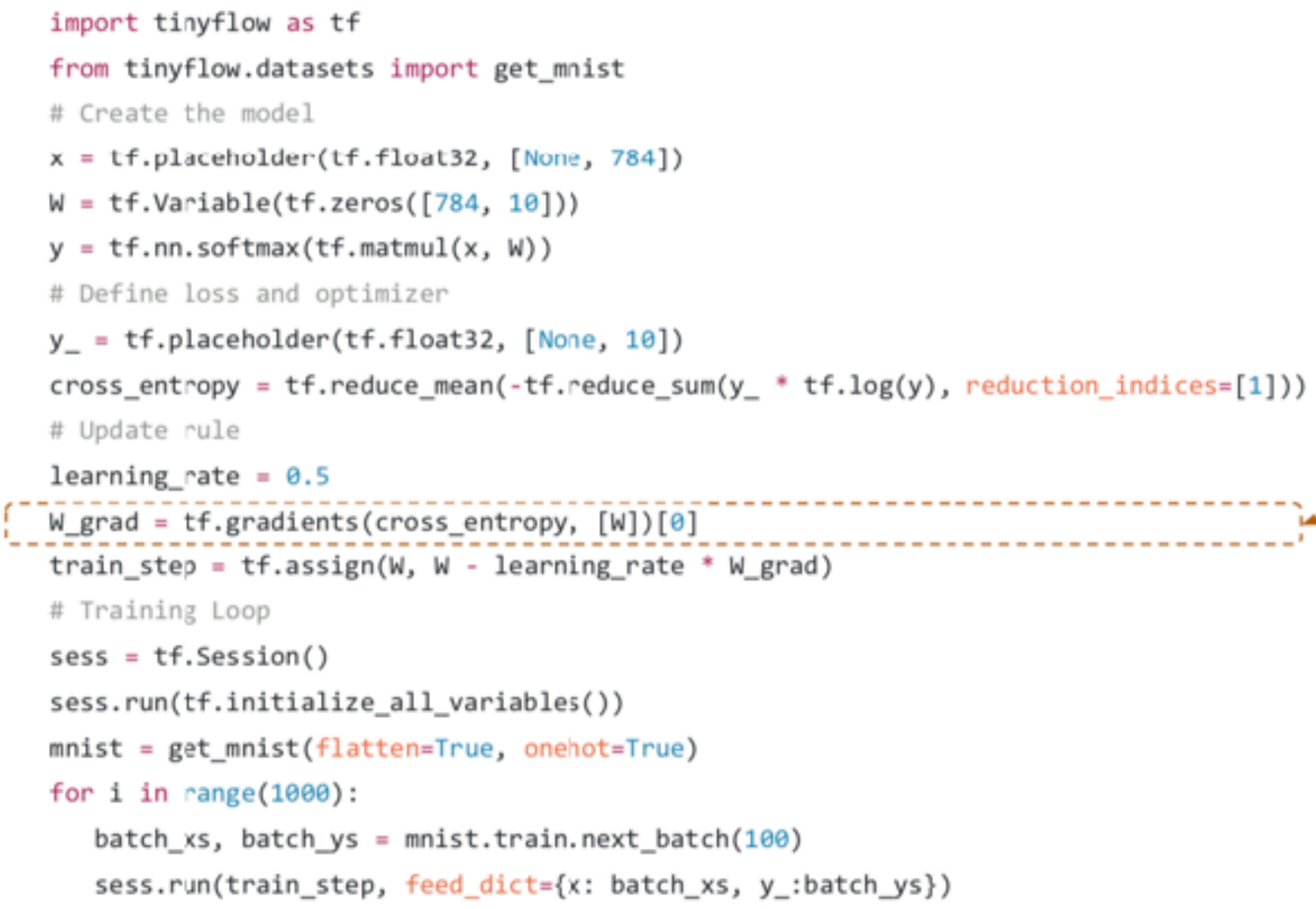
```

Loss function **Declaration**

$$P(\text{label} = k) = y_k$$

$$L(y) = \sum_{k=1}^{10} I(\text{label} = k) \log(y_i)$$

Logistic Regression in TinyFlow



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```
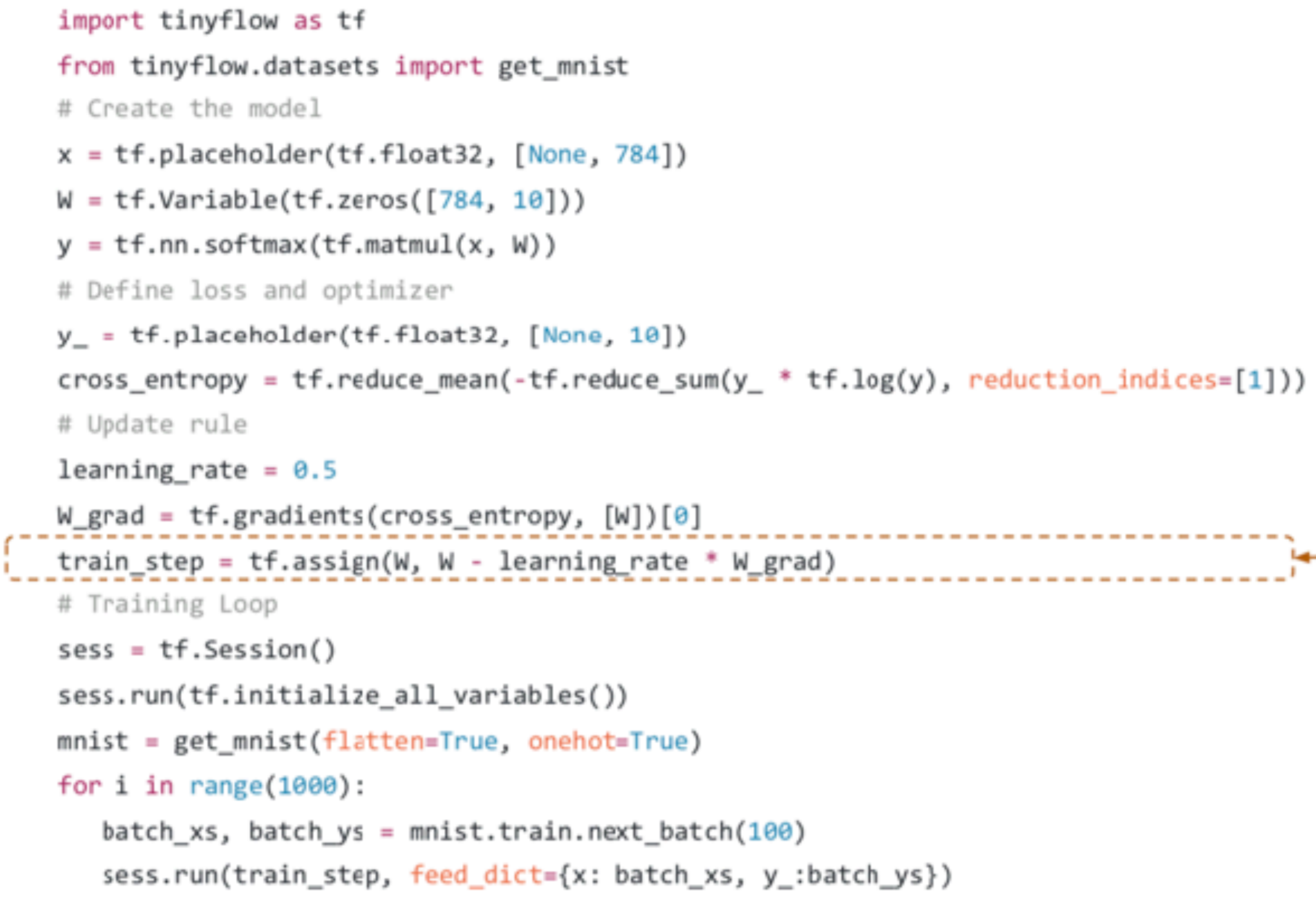

Automatic Differentiation: Details in next lecture!

Logistic Regression in TinyFlow



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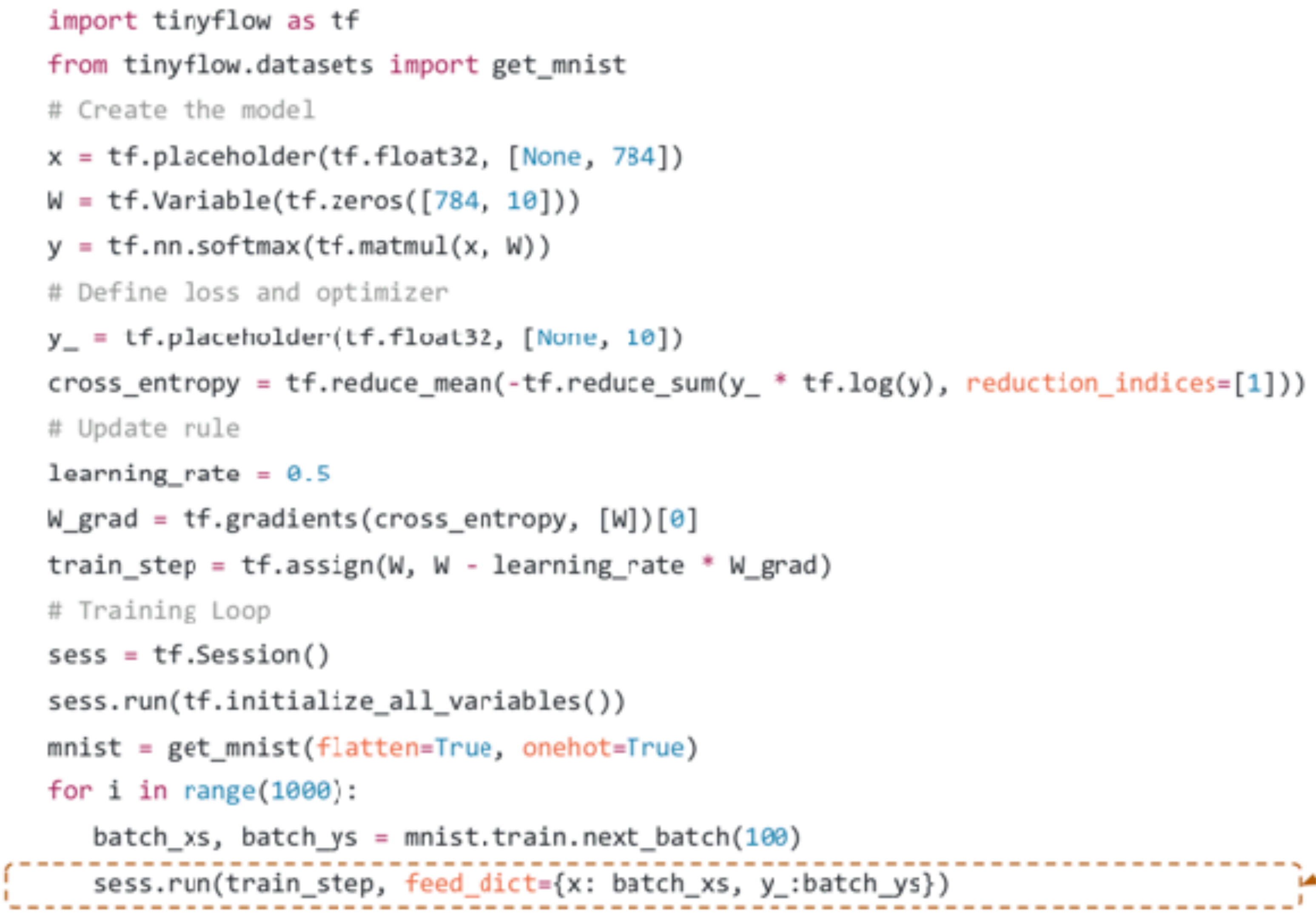
```

SGD update rule

Logistic Regression in TinyFlow



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```
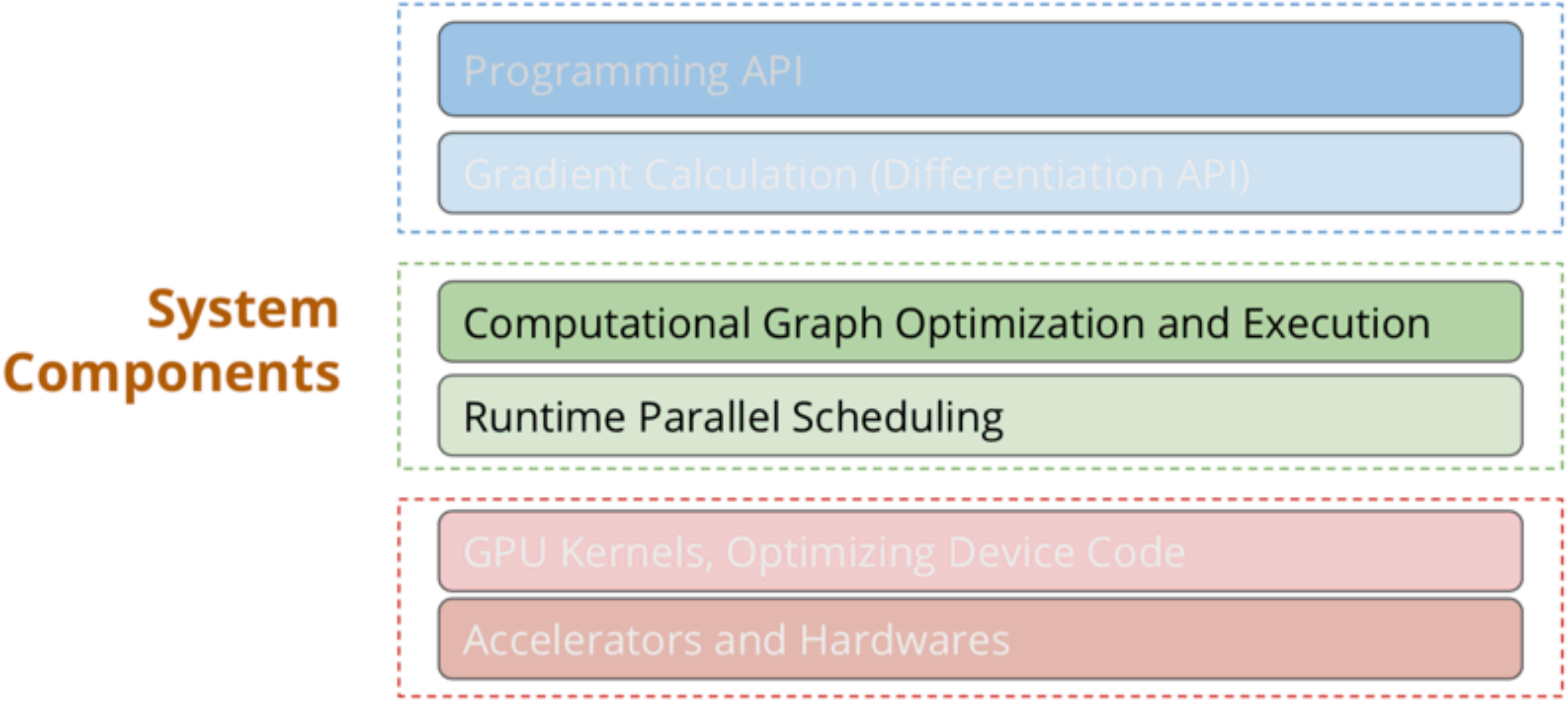

Real execution happens here!

Typical Deep Learning System Stack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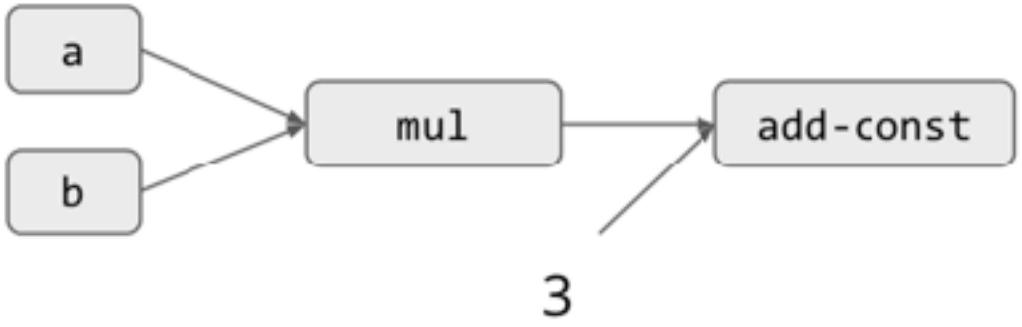
The Declarative Language: Computation Graph

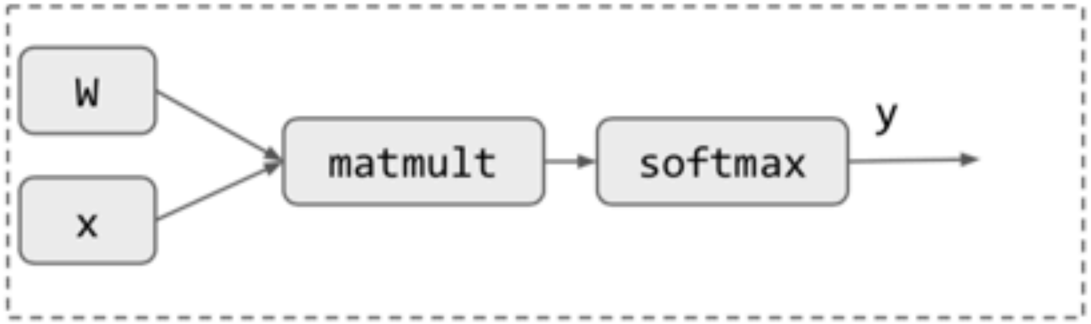
- Nodes represents the computation (operation)
- Edge represents the data dependency between operations

Computational Graph for `a * b +3`

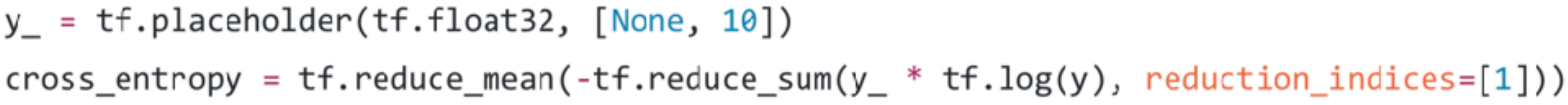


Computational Graph Construction by Step

```
x = tf.placeholder(tf.float32, [None, 784])
W = tf.Variable(tf.zeros([784, 10]))
y = tf.nn.softmax(tf.matmul(x, W))
```



Computational Graph Construction by Step



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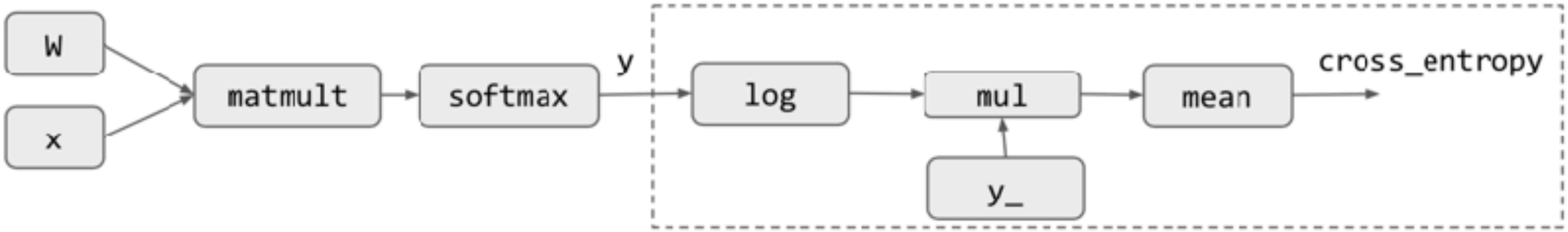
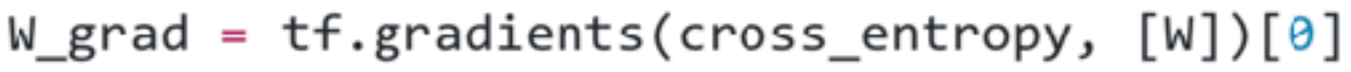
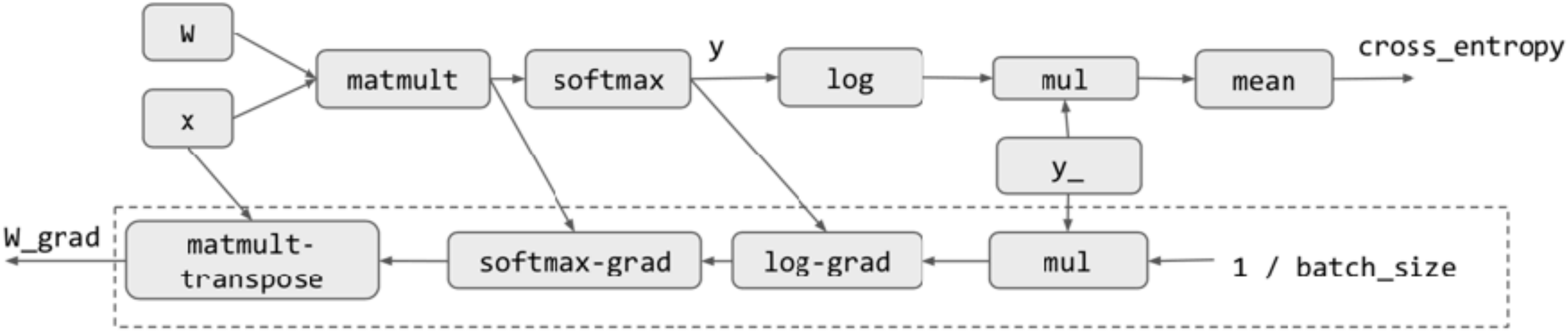


Computational Graph Construction by Step

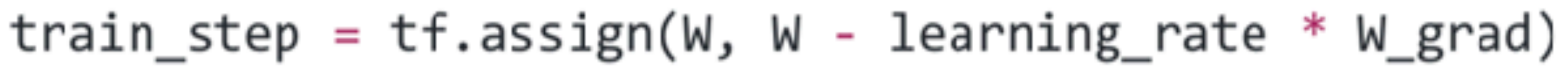


```
W_grad = tf.gradients(cross_entropy, [W])[0]
```

Automatic Differentiation,
detail in next lecture!



Computational Graph Construction by Step



```
train_step = tf.assign(W, W - learning_rate * W_grad)
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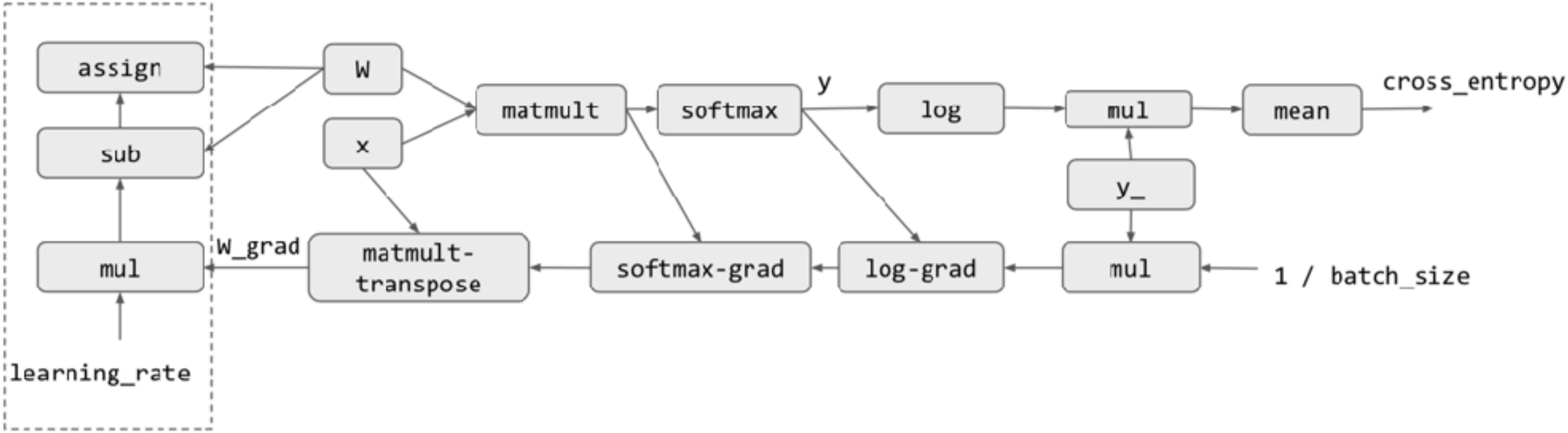
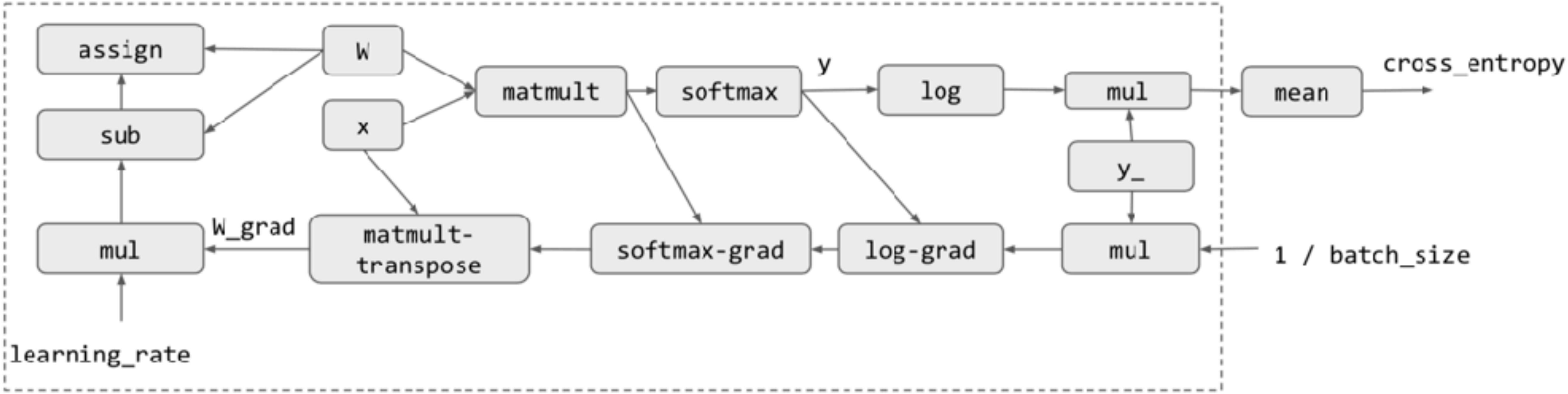


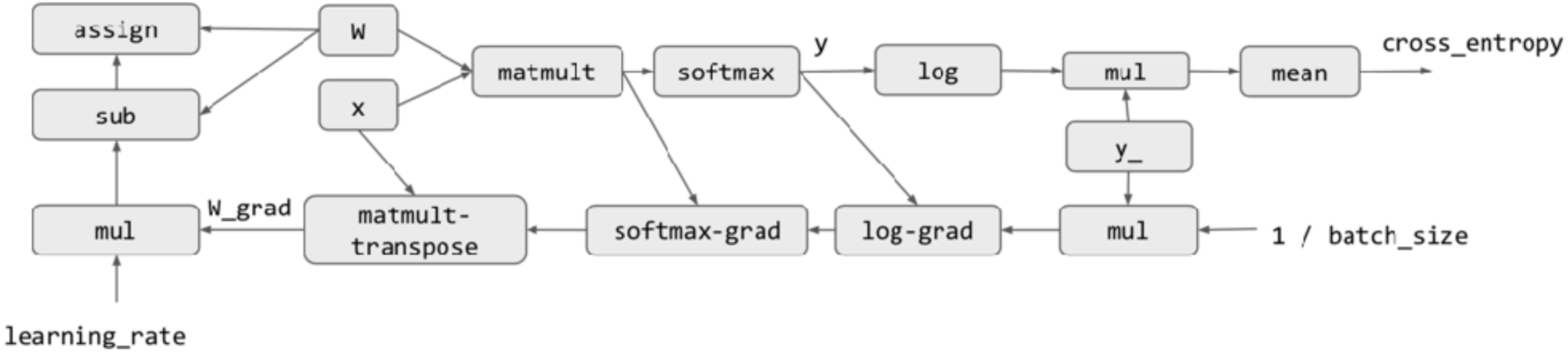
Execution only Touches the Needed Subgraph

```
sess.run(train_step, feed_dict={x: batch_xs, y_:batch_ys})
```



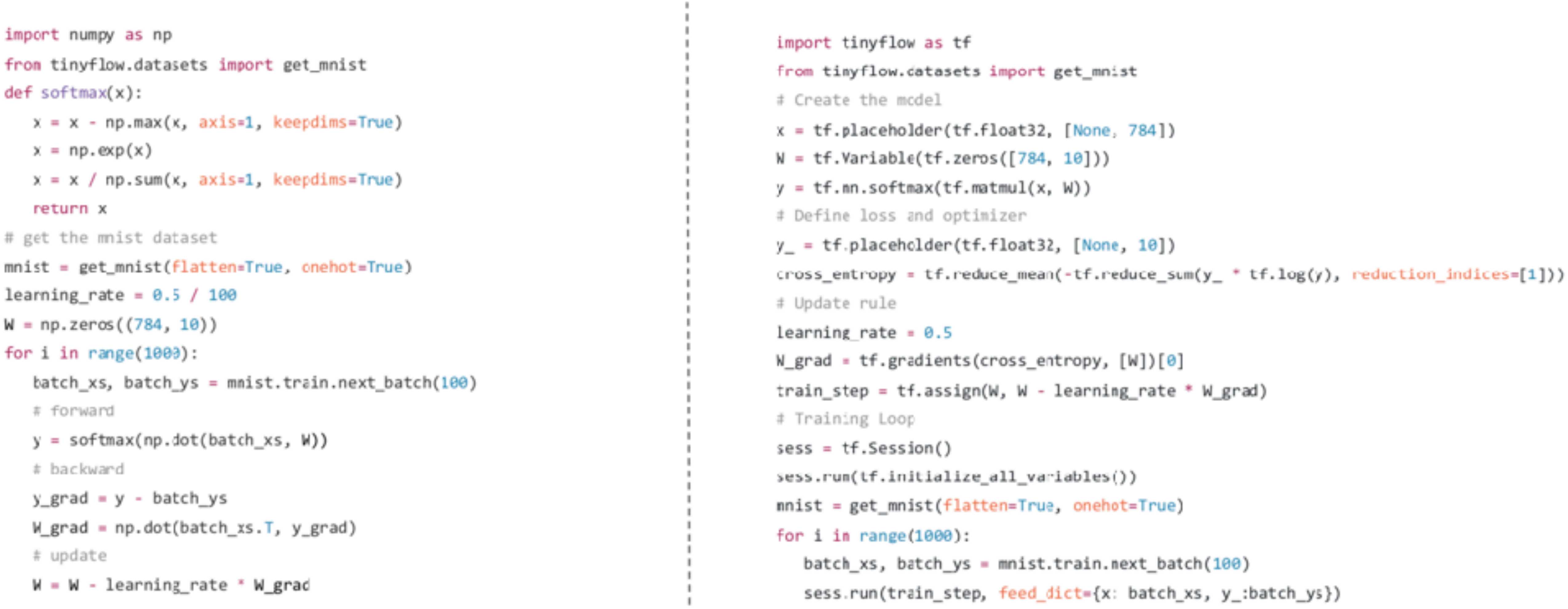
Discussion: Computational Graph

- What is the benefit of computational graph?
- How can we deploy the model to mobile devices?



Discussion:
Numpy vs TF Program

What is the benefit/drawback of the TF model vs Numpy Model



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```
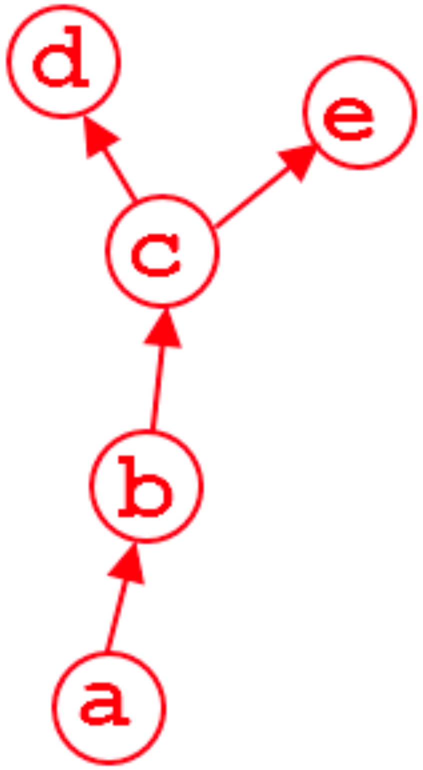
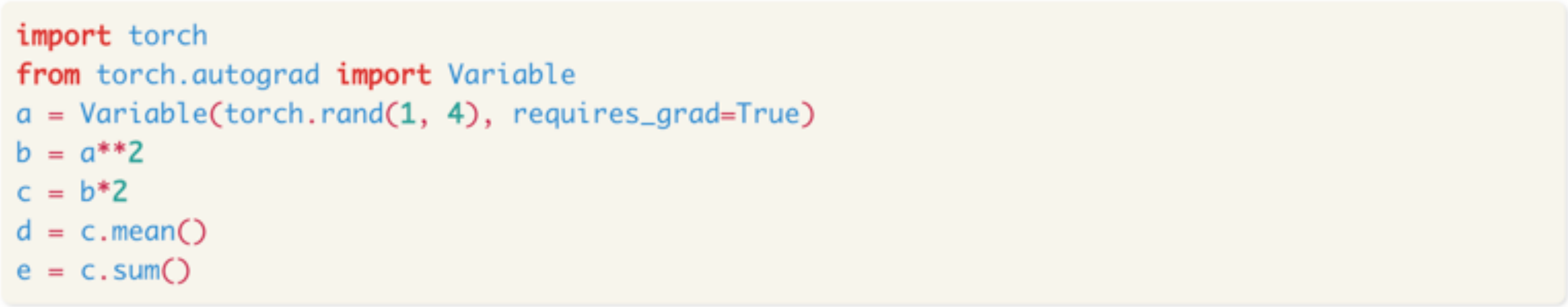
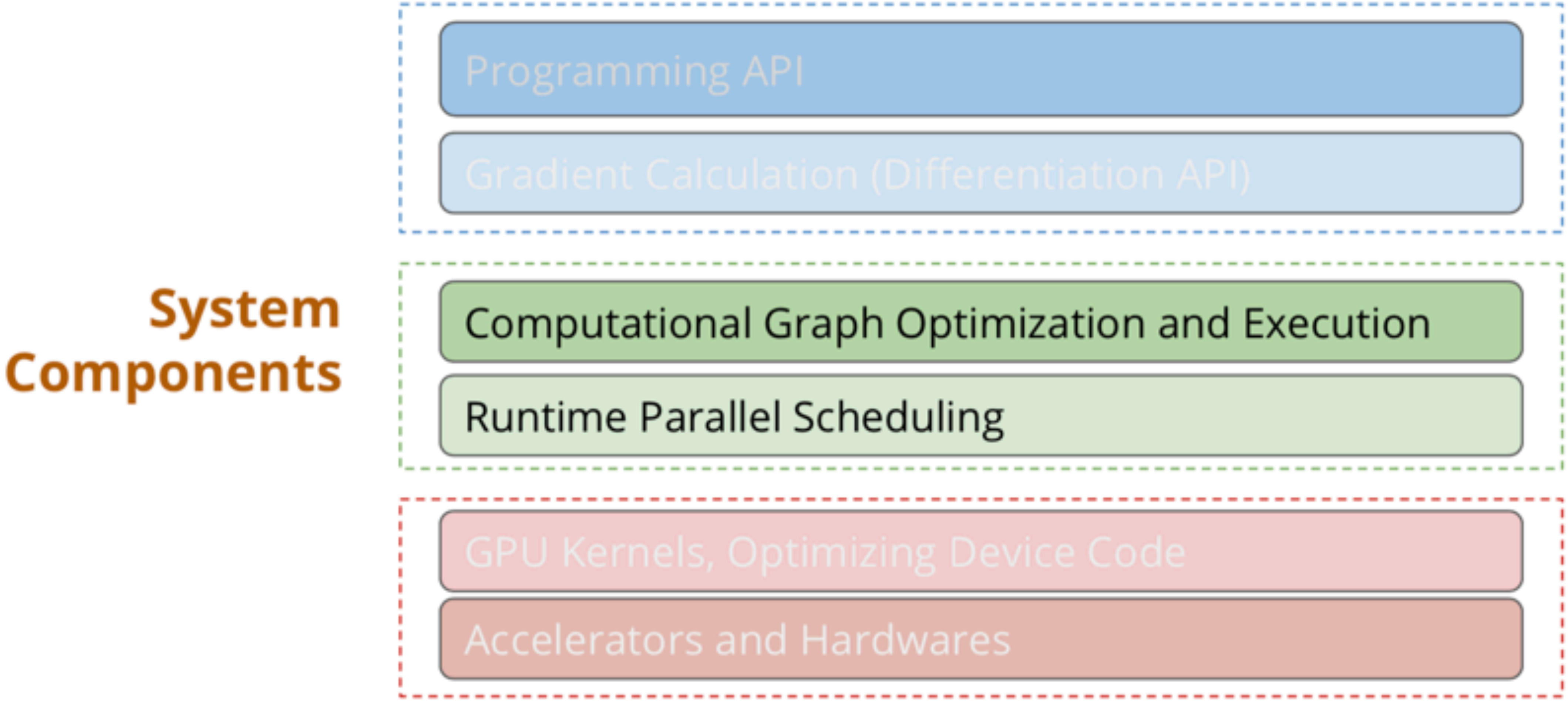

Computational graphs in other frameworks: PyTorch





```
import torch
from torch.autograd import Variable
a = Variable(torch.rand(1, 4), requires_grad=True)
b = a**2
c = b*2
d = c.mean()
e = c.sum()
```

Typical Deep Learning System Stack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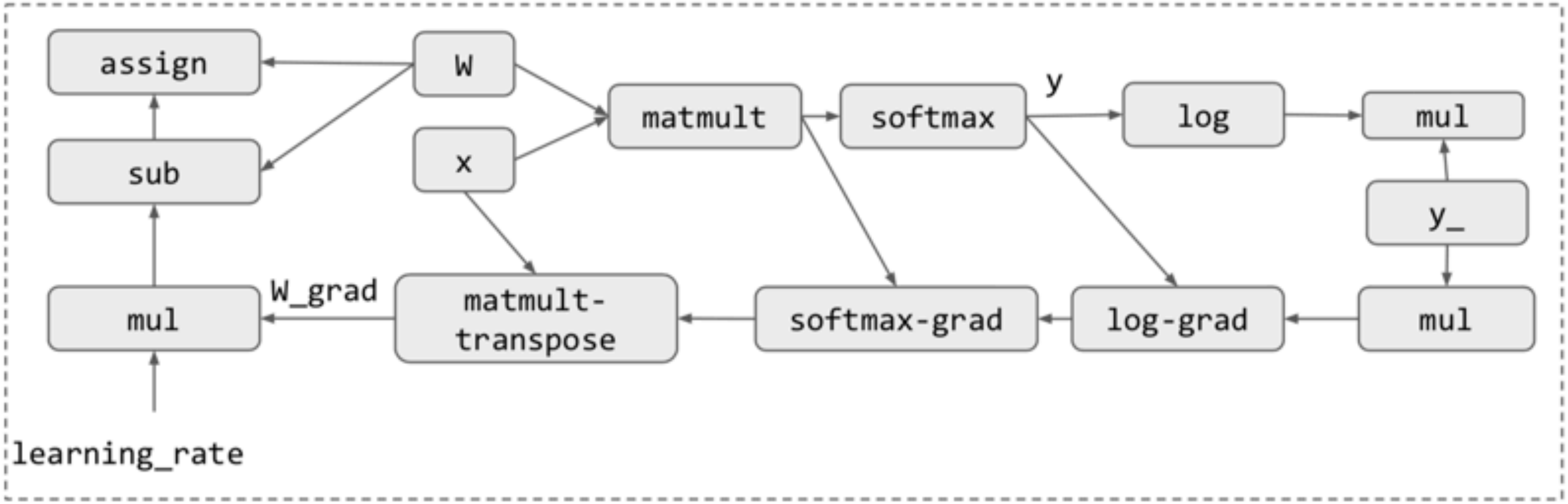
Computation Graph Optimization

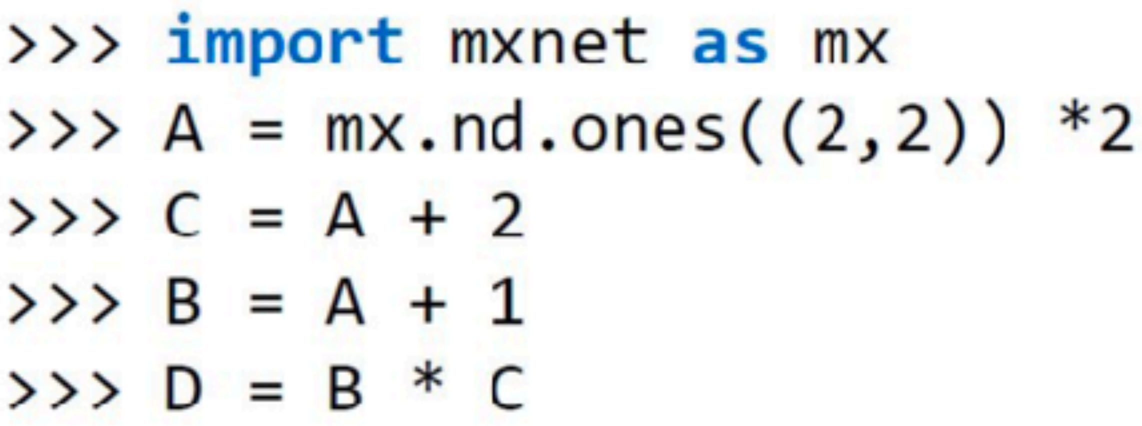
- E.g. Deadcode elimination
- Memory planning and optimization
- What other possible optimization can we do given a computational graph?



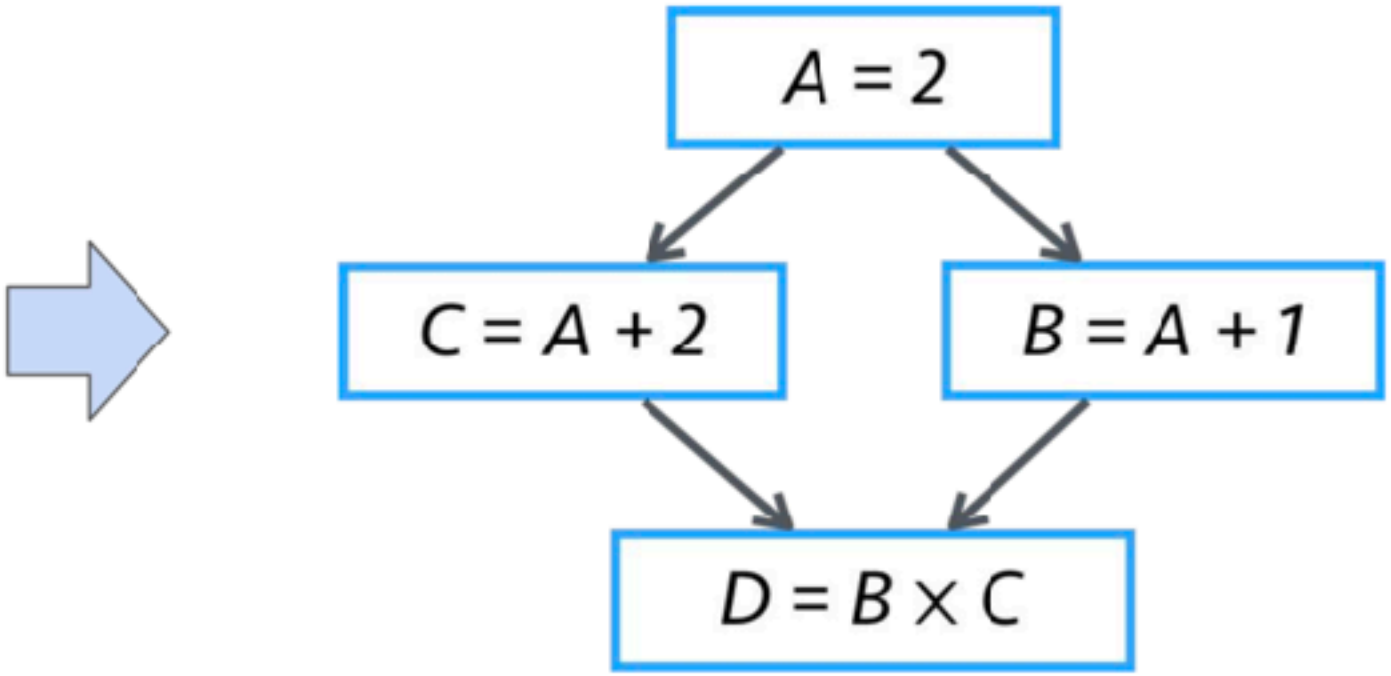
Parallel Scheduling

- Code need to run parallel on multiple devices and worker threads
- Detect and schedule parallelizable patterns
- Detail lecture on later

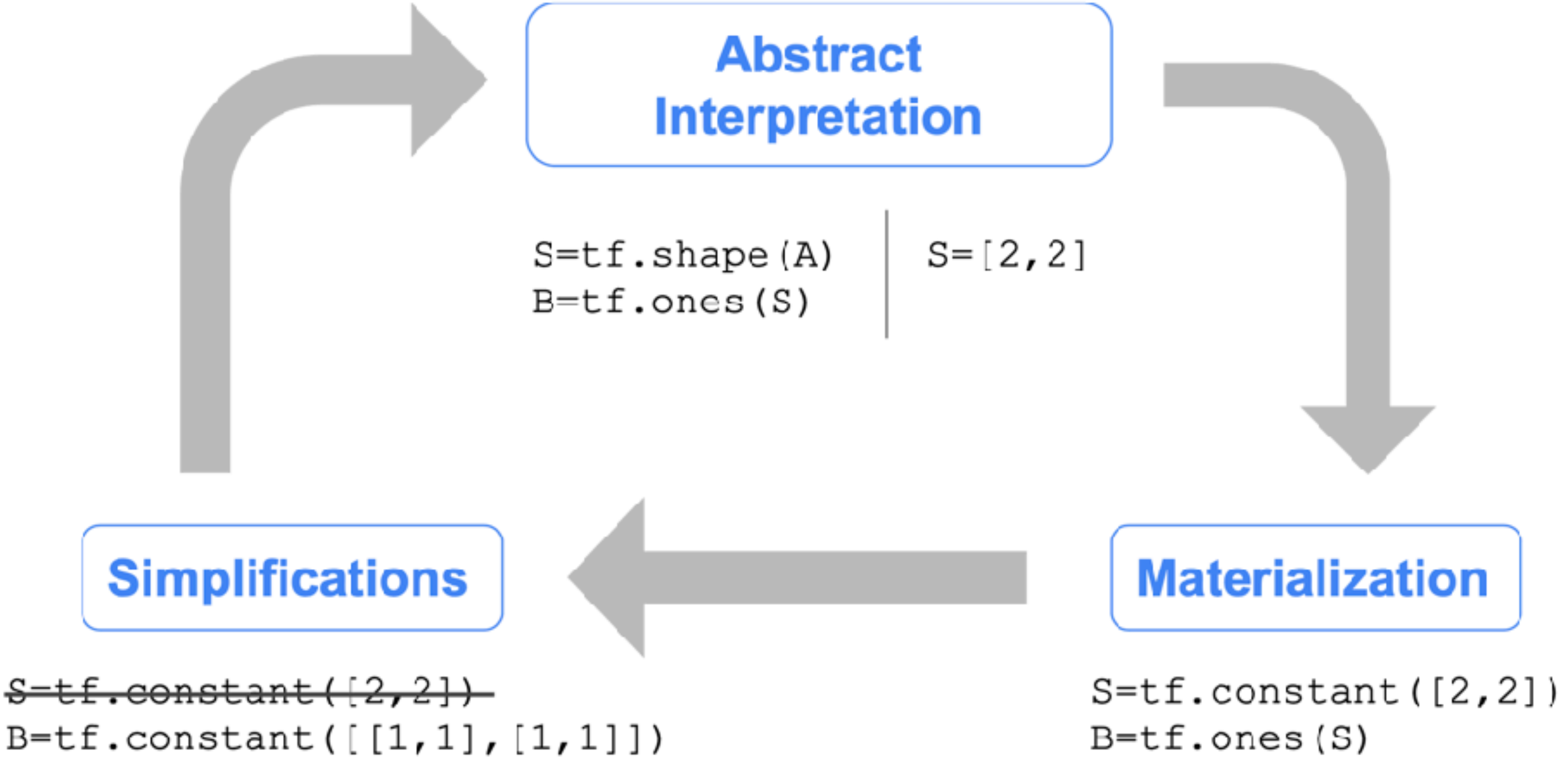
MXNet Example



```
>>> import mxnet as mx
>>> A = mx.nd.ones((2,2)) *2
>>> C = A + 2
>>> B = A + 1
>>> D = B * C
```



Graph Simplifications



Abstract Interpretation

```
S=tf.shape(A)    S=[2,2]
B=tf.ones(S)
```

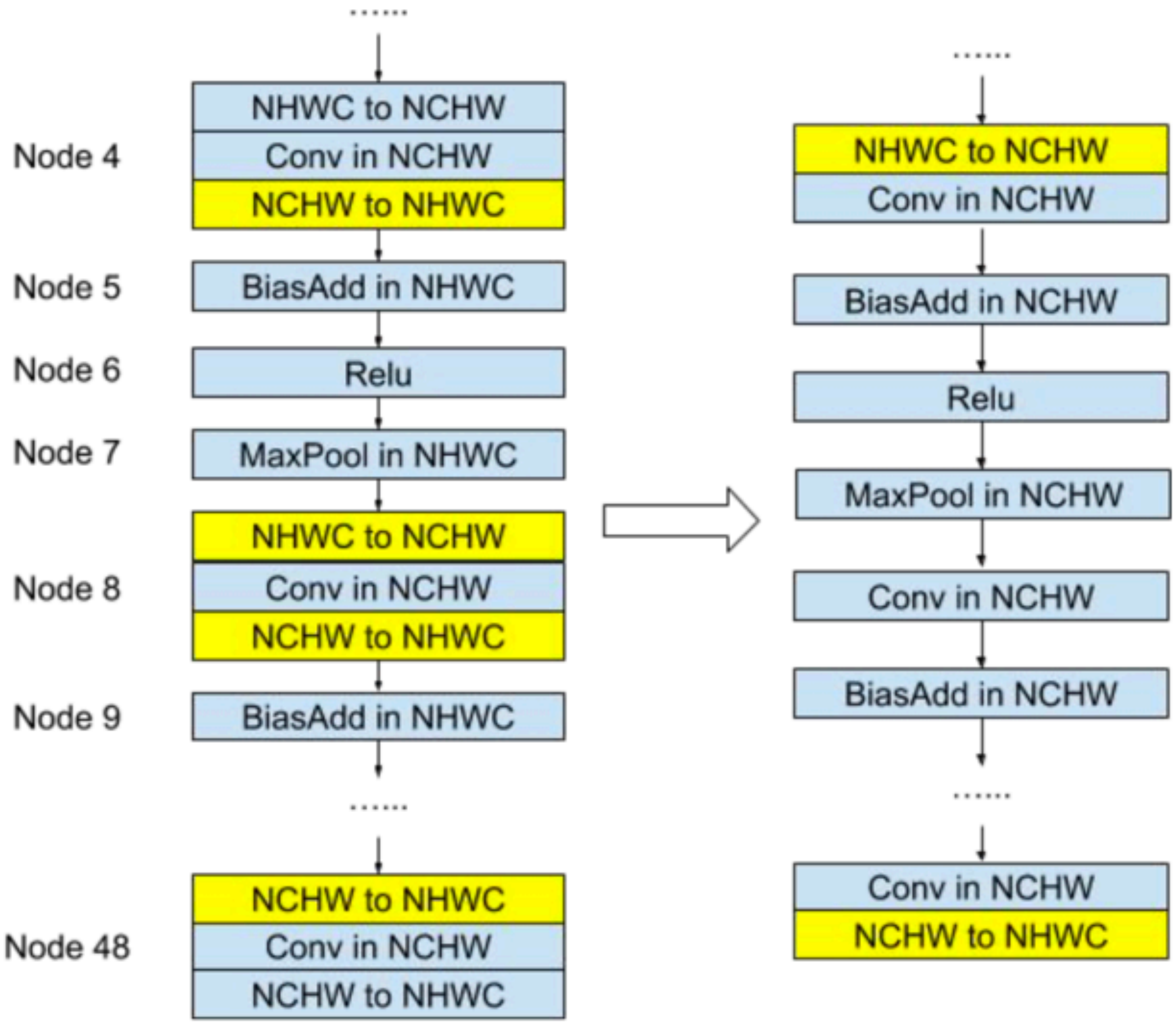
Materialization

```
S=tf.constant([2,2])
B=tf.ones(S)
```

Simplifications

~~S=tf.constant([2,2])~~
B=tf.constant([[1,1],[1,1]])

Layout Optimization



Node 4

NHWC to NCHW

Conv in NCHW

NCHW to NHWC

Node 5

BiasAdd in NHWC

Node 6

Relu

Node 7

MaxPool in NHWC

Node 8

NHWC to NCHW

Conv in NCHW

NCHW to NHWC

Node 9

BiasAdd in NHWC

Node 48

NCHW to NHWC

Conv in NCHW

NCHW to NHWC

NHWC to NCHW

Conv in NCHW

BiasAdd in NCHW

Relu

MaxPool in NCHW

Conv in NCHW

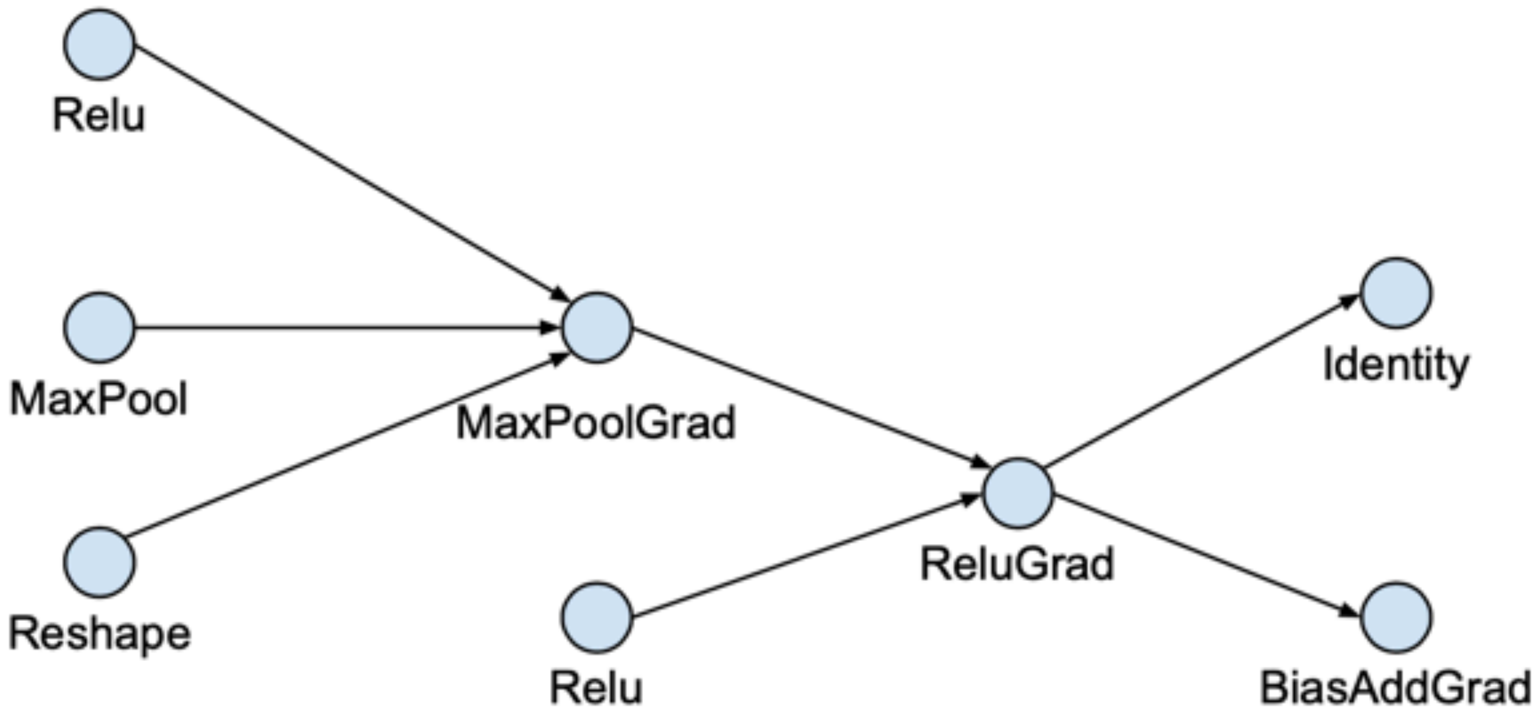
BiasAdd in NCHW

Conv in NCHW

NCHW to NHWC

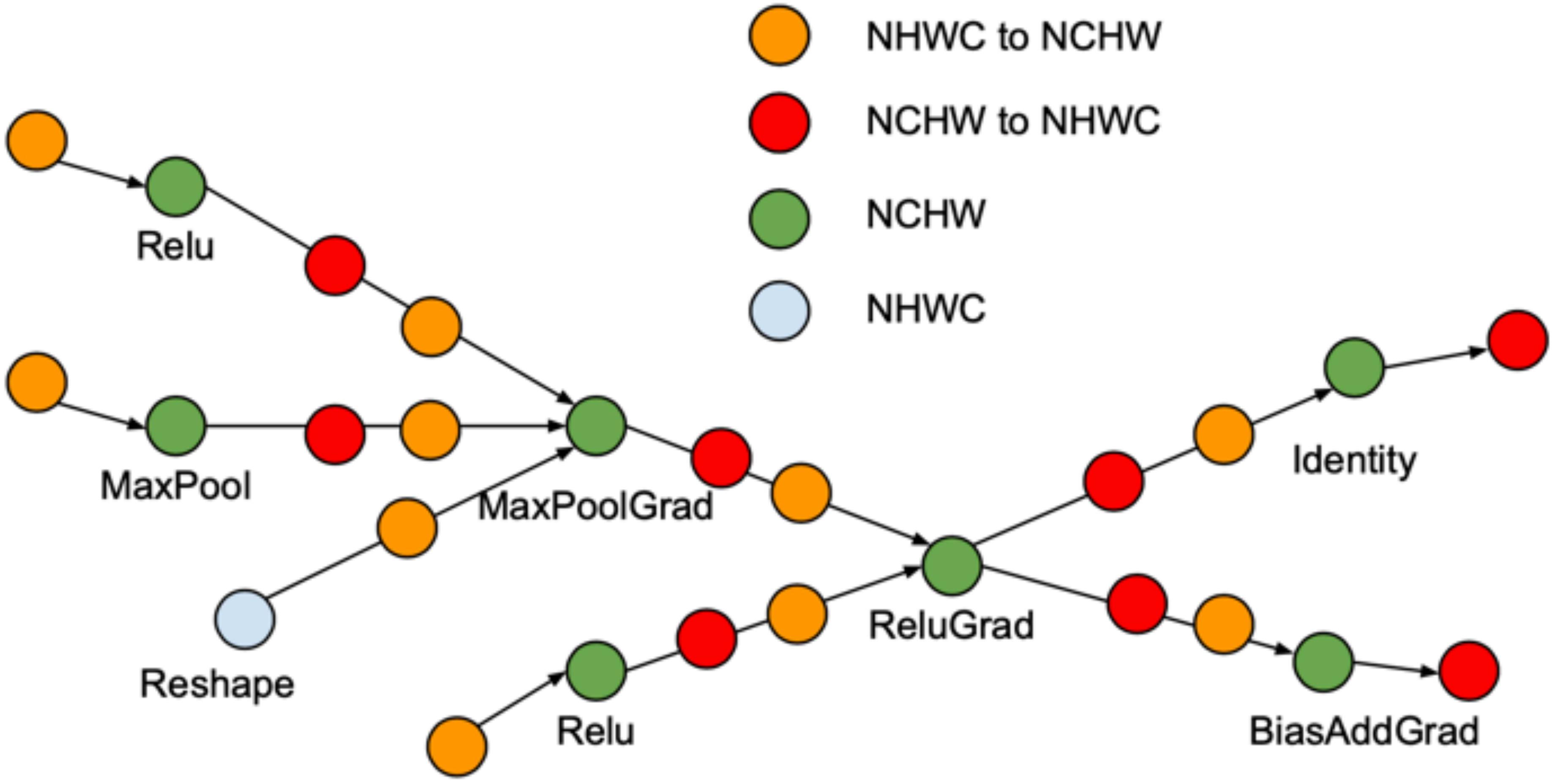
Layout Optimization

Example: Original graph with all ops in NHWC format



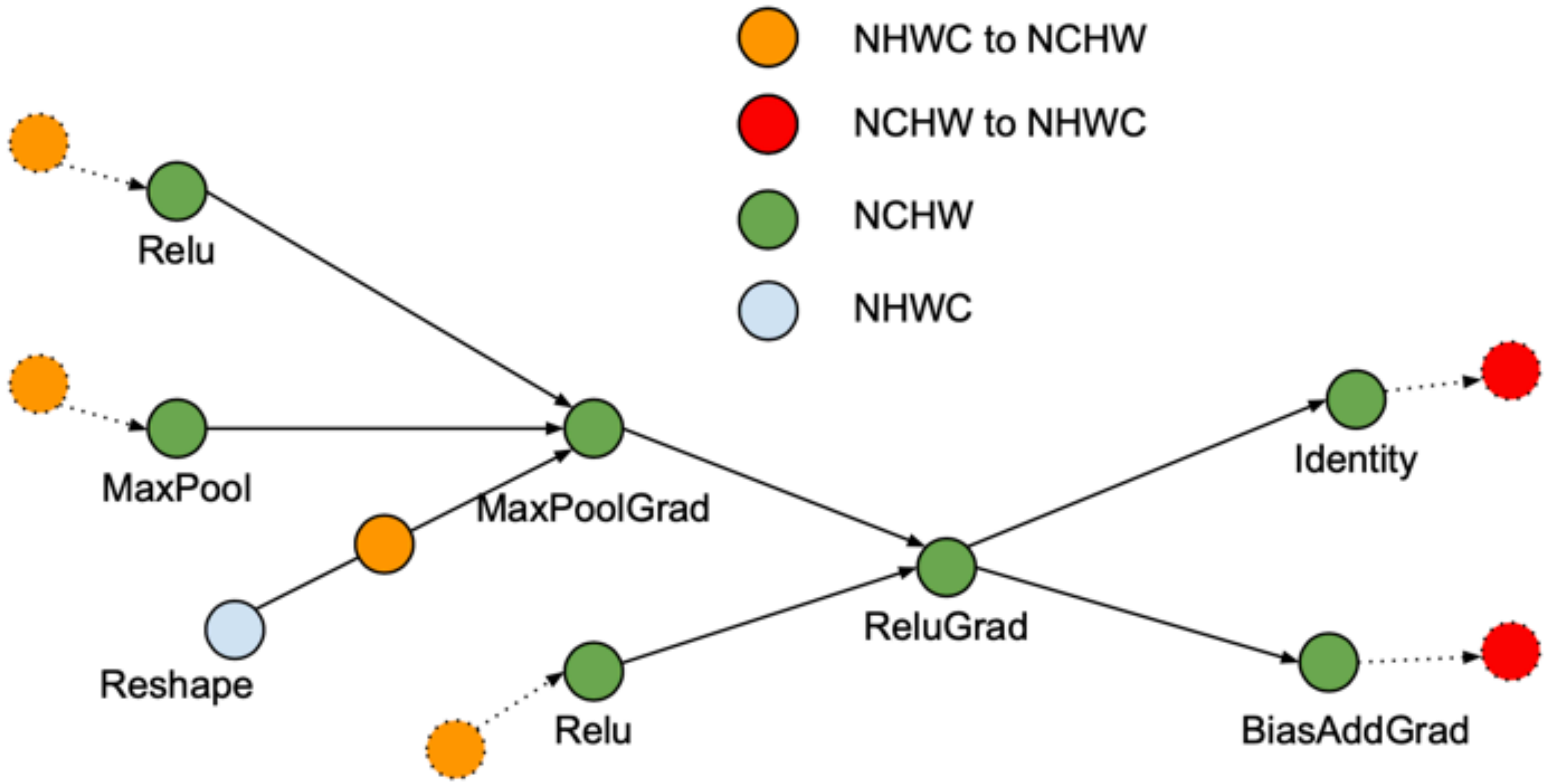
Layout Optimization

Phase 1: Expand by inserting conversion pairs

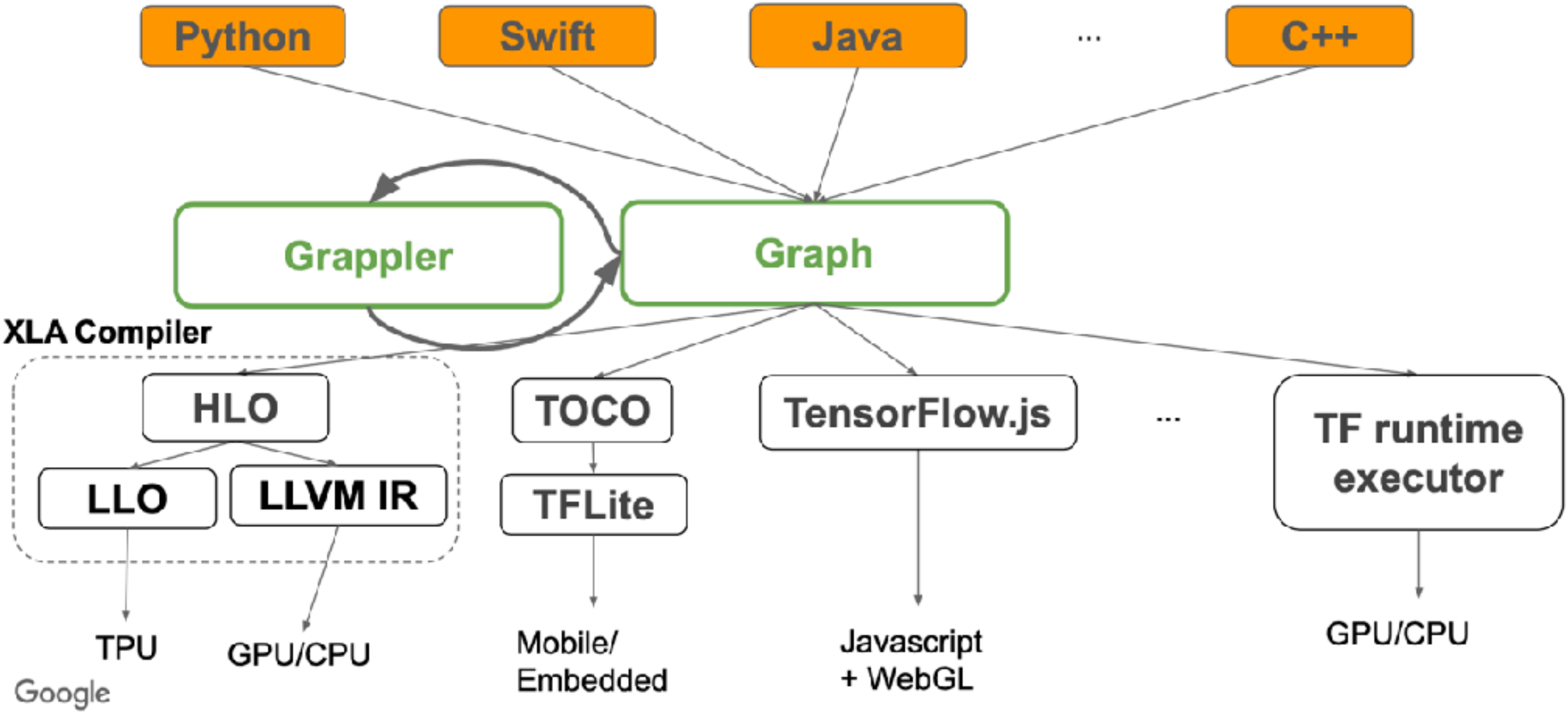


Layout Optimization

Phase 2: Collapse adjacent conversion pairs



Computation Graph Optimization



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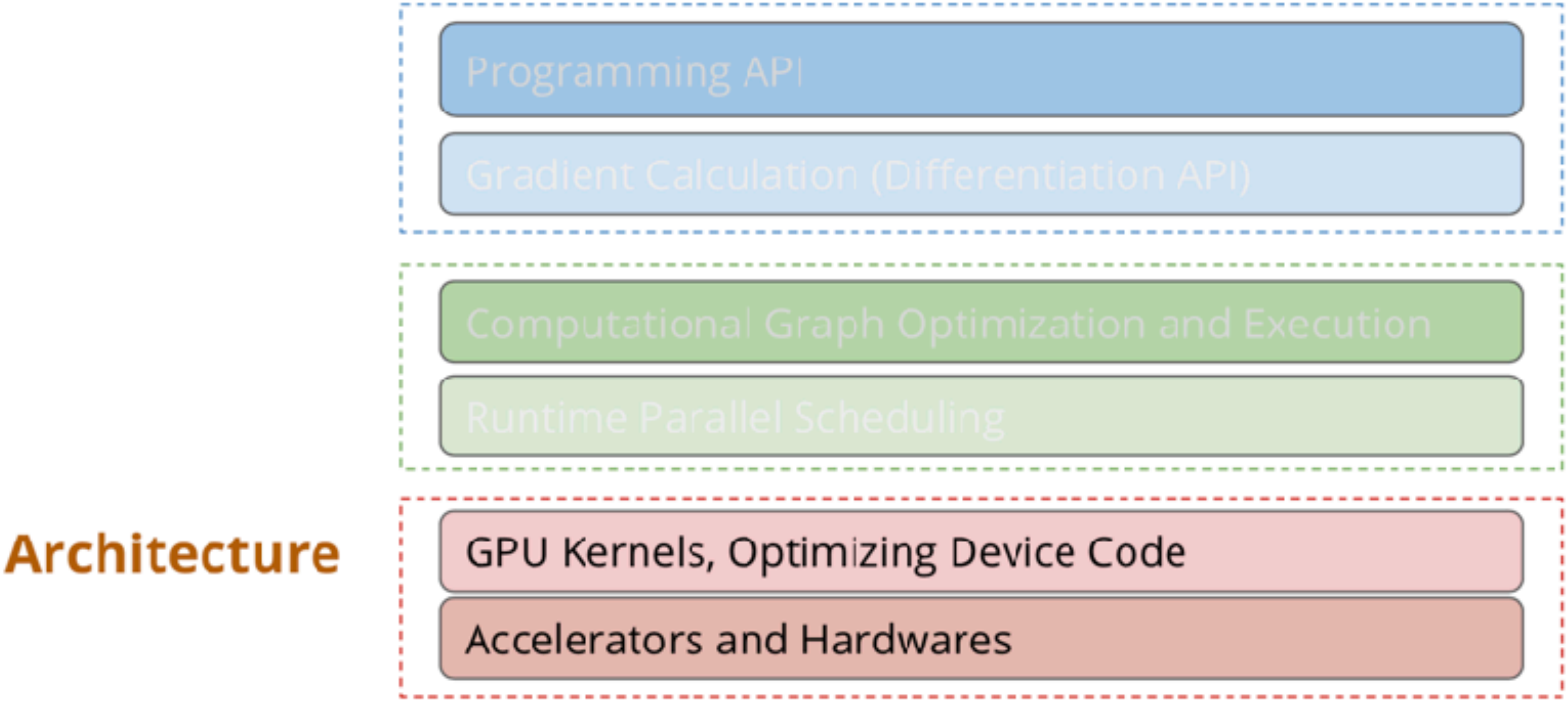
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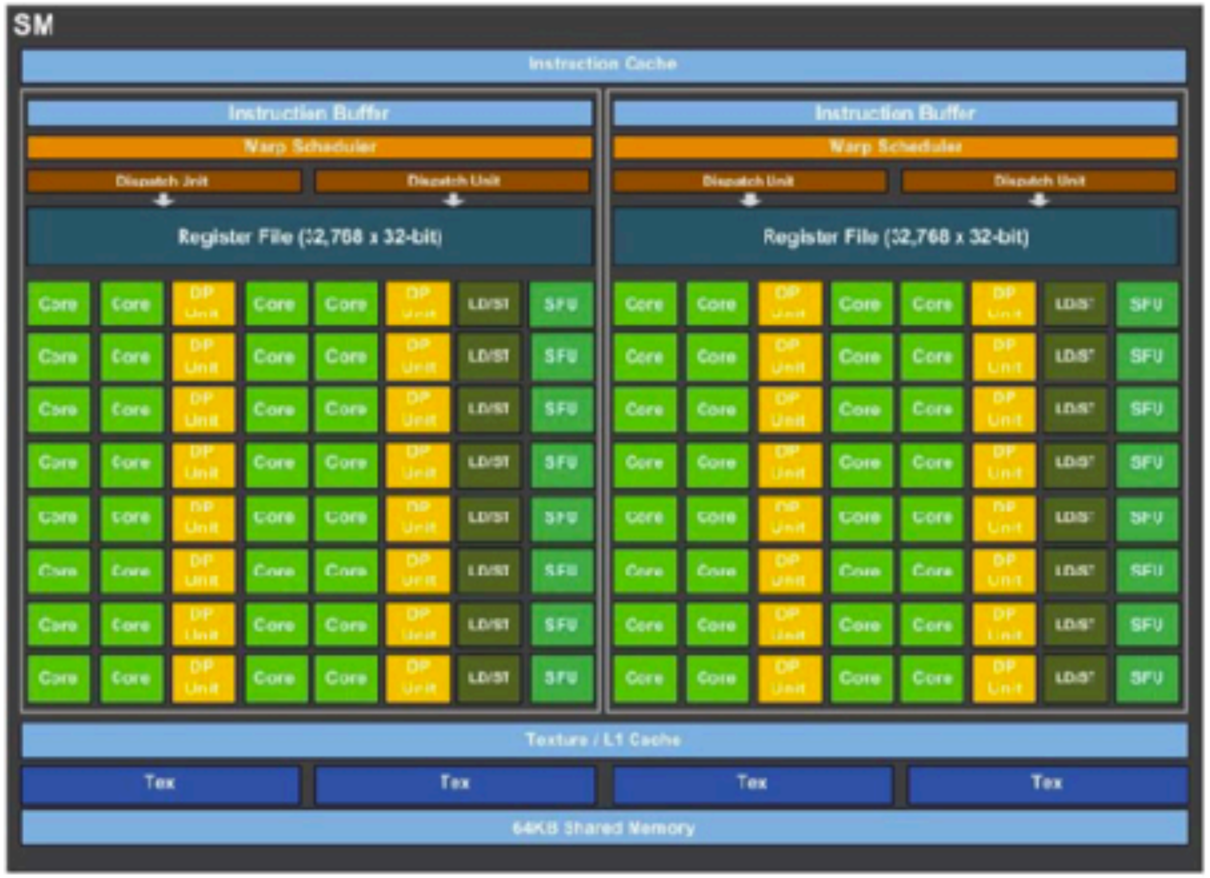
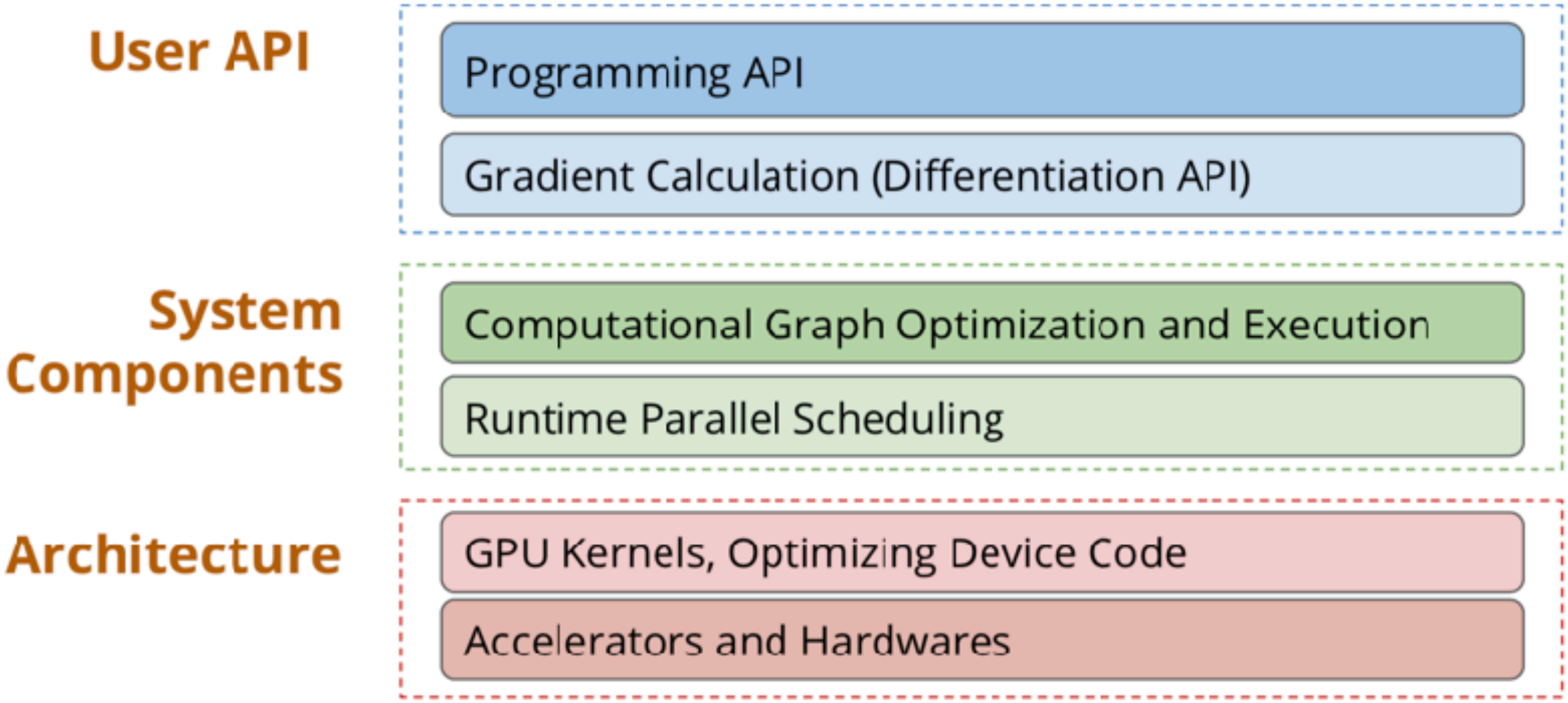
GPU Acceleration

- Most existing deep learning programs runs on GPUs
- Modern GPU have Teraflops of computing power



Typical Deep Learning System Stack

Not a comprehensive list of elements
The systems are still rapidly evolving :)



User API

Programming API

Gradient Calculation (Differentiation API)

System Components

Computational Graph Optimization and Execution

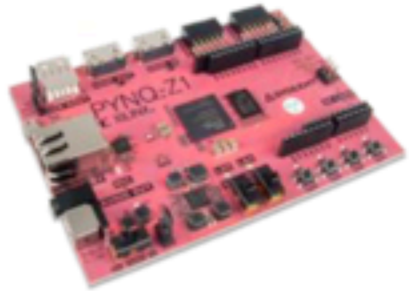
Runtime Parallel Scheduling

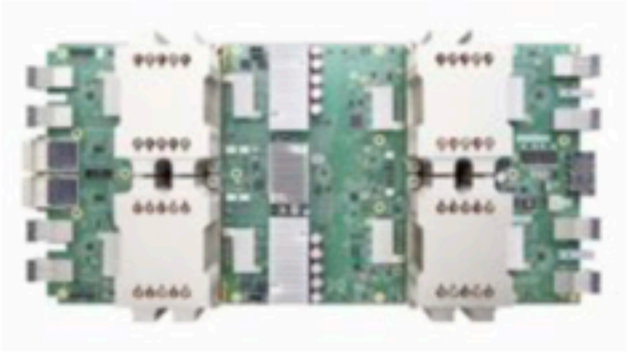
Architecture

GPU Kernels, Optimizing Device Code

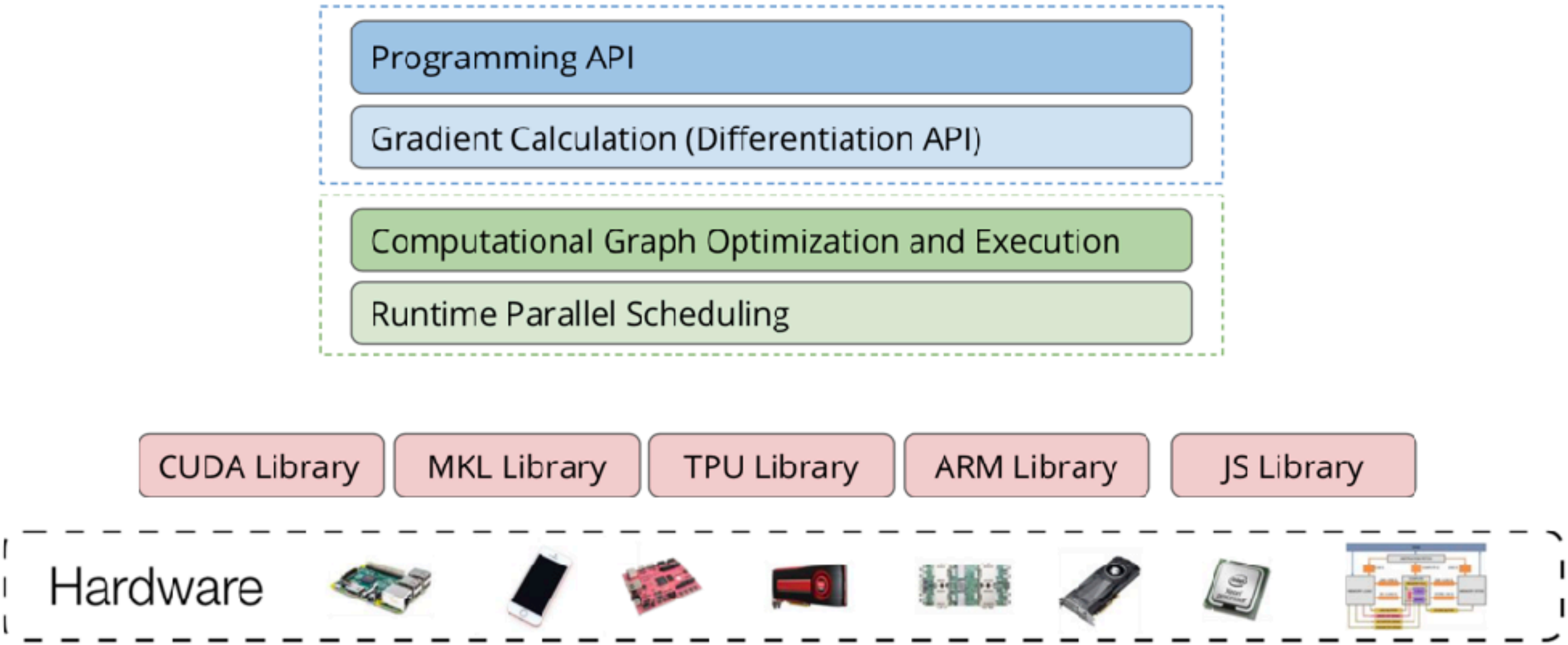
Accelerators and Hardwares

Supporting More Hardware backends





Each Hardware backend requires a software stack



Programming API

Gradient Calculation (Differentiation API)

Computational Graph Optimization and Execution

Runtime Parallel Scheduling

CUDA Library

MKL Library

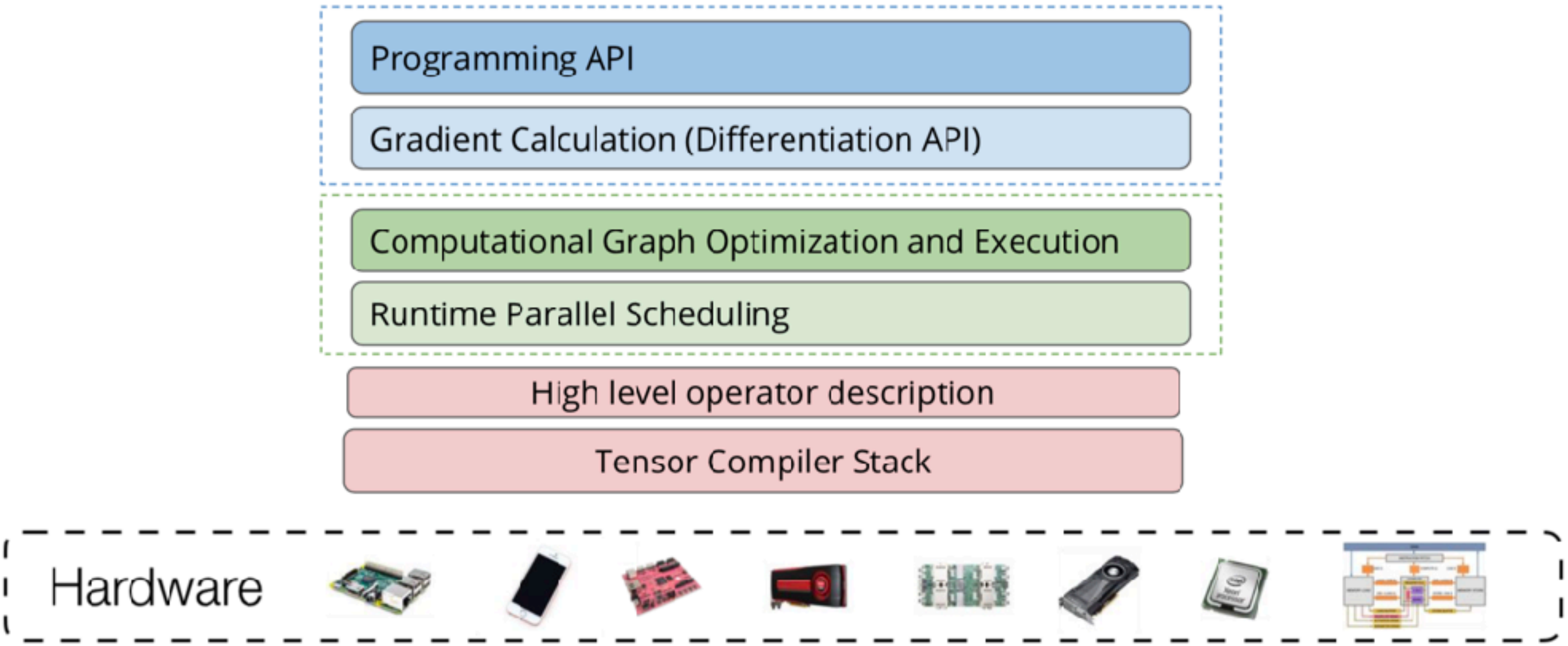
TPU Library

ARM Library

JS Library

Hardware

New Trend: Compiler based Approach



Programming API

Gradient Calculation (Differentiation API)

Computational Graph Optimization and Execution

Runtime Parallel Scheduling

High level operator description

Tensor Compiler Stack

Hardware