Machine Learning System Stack

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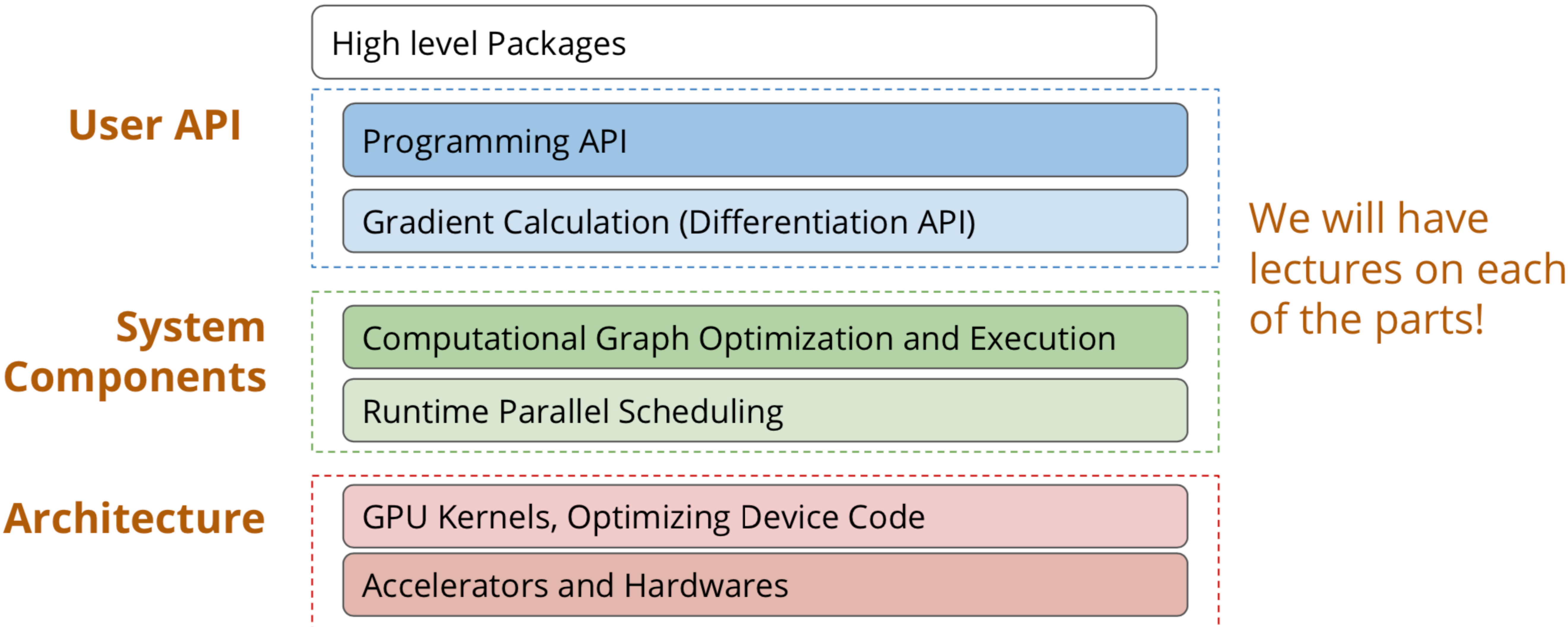
[The slides are mainly based on UW Systems for ML Course]

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



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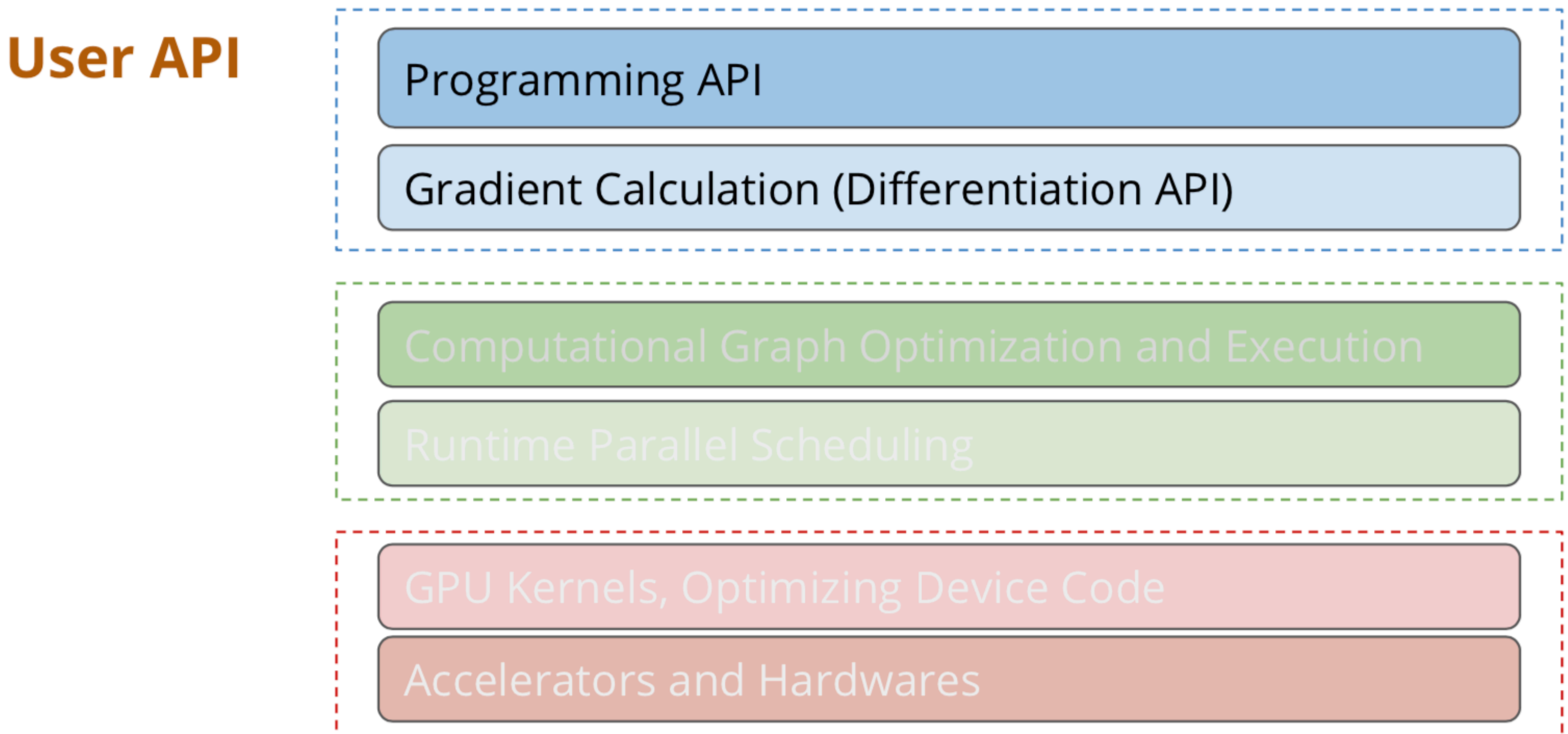


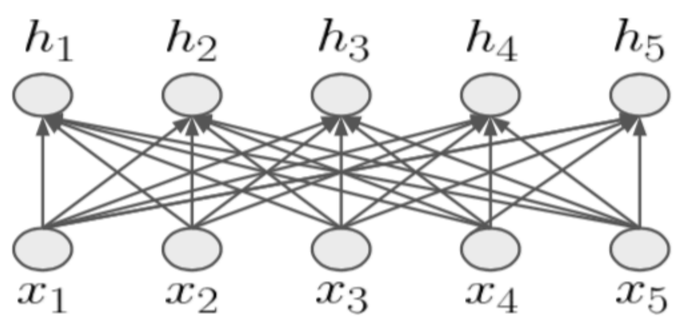
Example: Logistic Regression

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

```python
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)

Forward Computation **Declaration**

```
import tinyflow as tf
from tinyflow.datasets import get_mnist
# Create the model
x = tf.placeholder(tf.float32, [None, 784])
W = tf.Variable(tf.zeros([784, 10]))
y = tf.nn.softmax(tf.matmul(x, W))
# 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
learning_rate = 0.5
W_grad = tf.gradients(cross_entropy, [W])[0]
train_step = tf.assign(W, W - learning_rate * W_grad)
# Training Loop
sess = tf.Session()
sess.run(tf.initialize_all_variables())
mnist = get_mnist(flatten=True, onehot=True)
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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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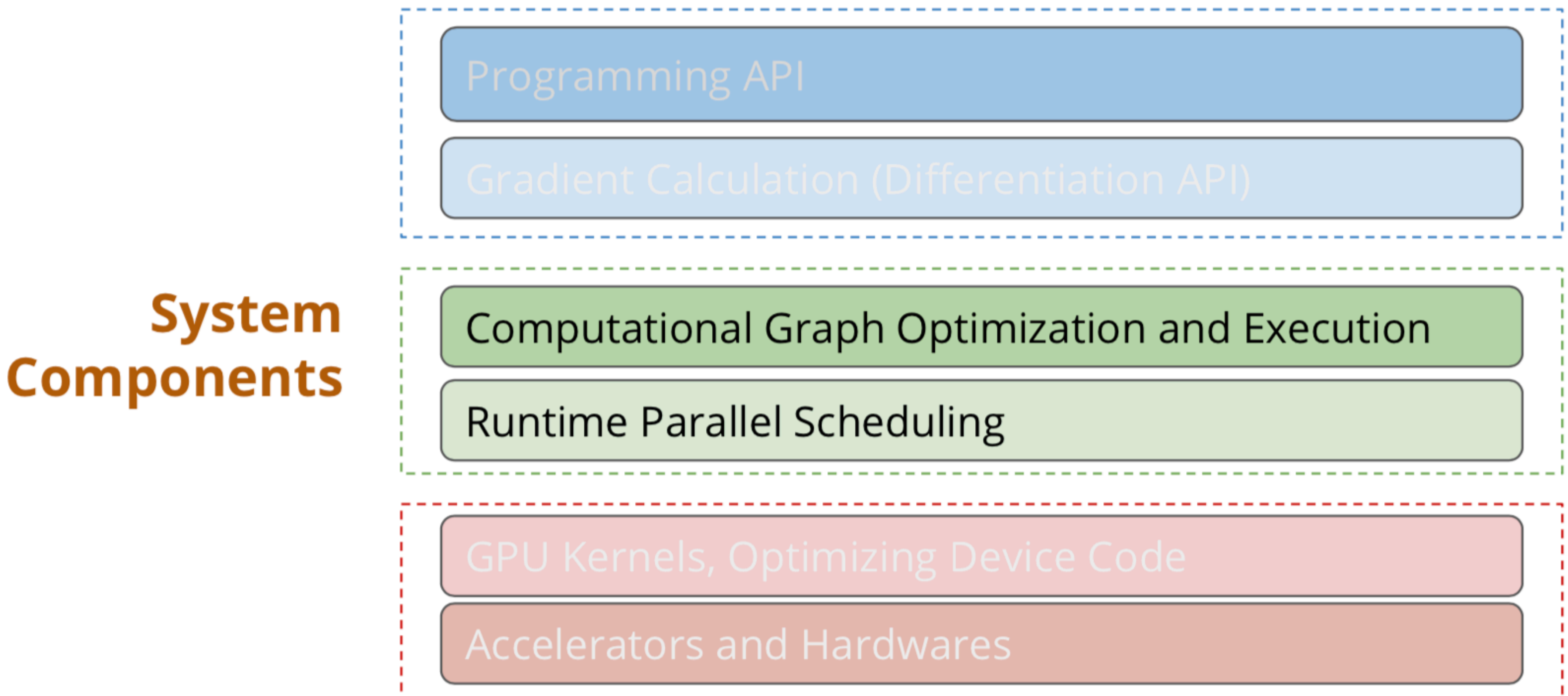
```

Real execution happens here!

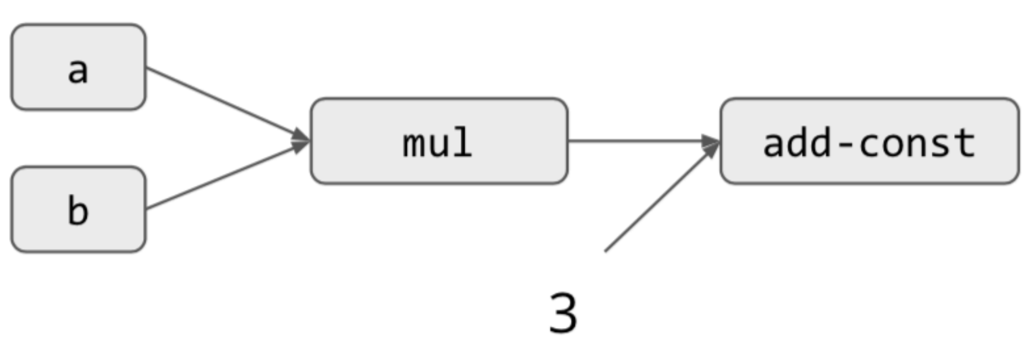
Typical Deep Learning System Stack



The Declarative Language: Computation Graph

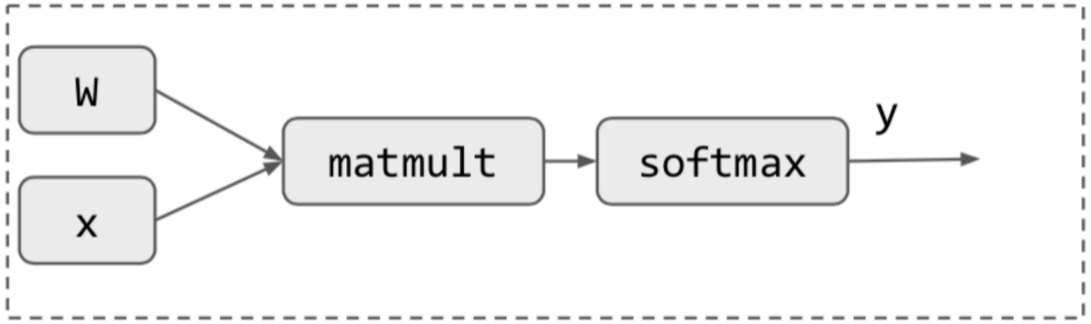
- Nodes represents the computation (operation)
- Edge represents the data dependency between operations

Computational Graph for `a * b +3`



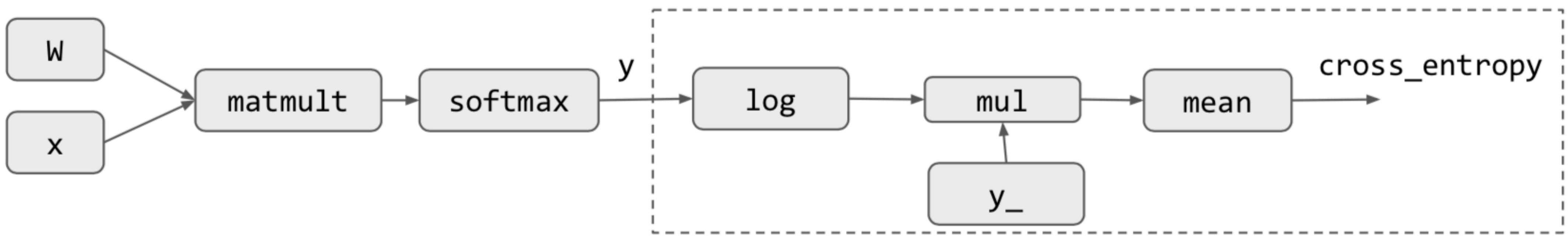
Computational Graph Construction by Step

```
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

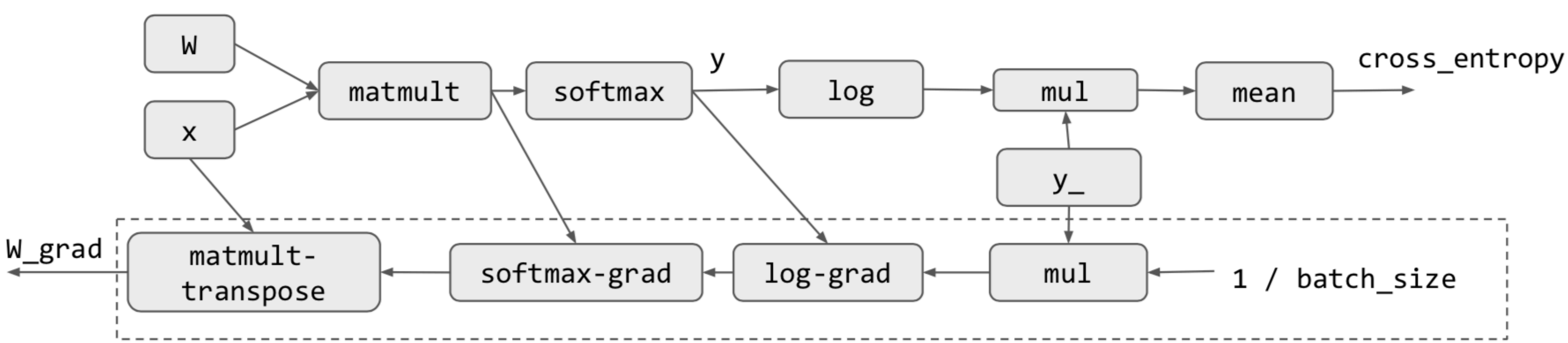
```
y_ = tf.placeholder(tf.float32, [None, 10])
cross_entropy = tf.reduce_mean(-tf.reduce_sum(y_ * tf.log(y), reduction_indices=[1]))
```



Computational Graph Construction by Step

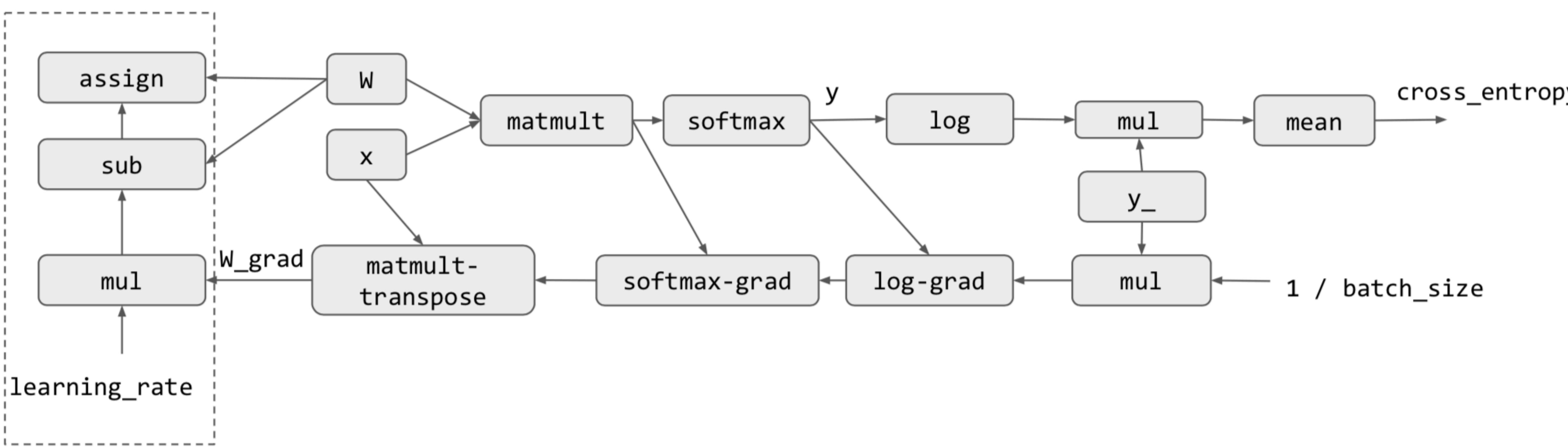
```
W_grad = tf.gradients(cross_entropy, [W])[0]
```

Automatic Differentiation, detail in next lecture!



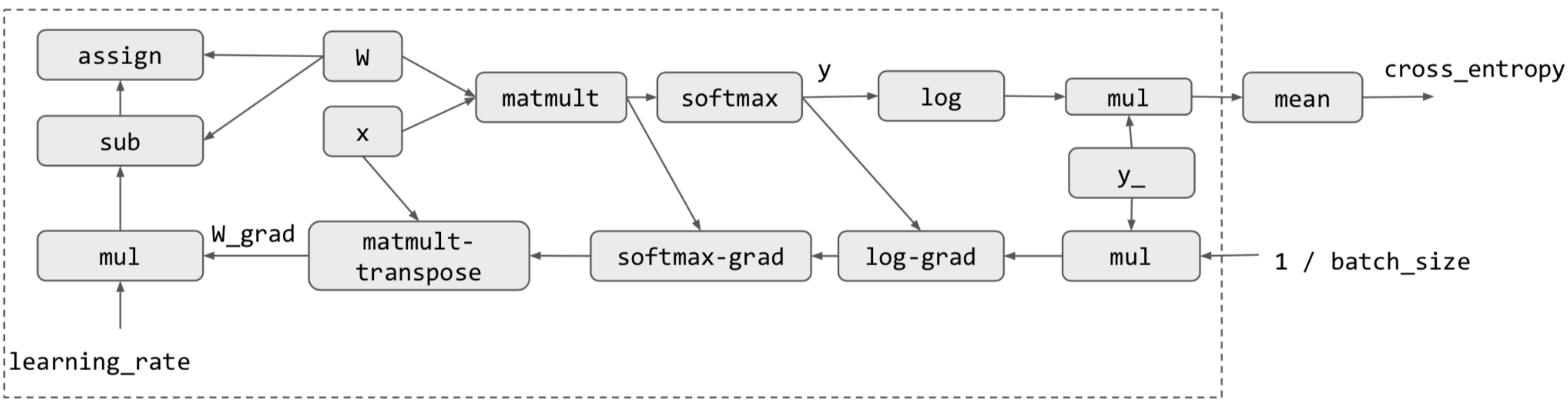
Computational Graph Construction by Step

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



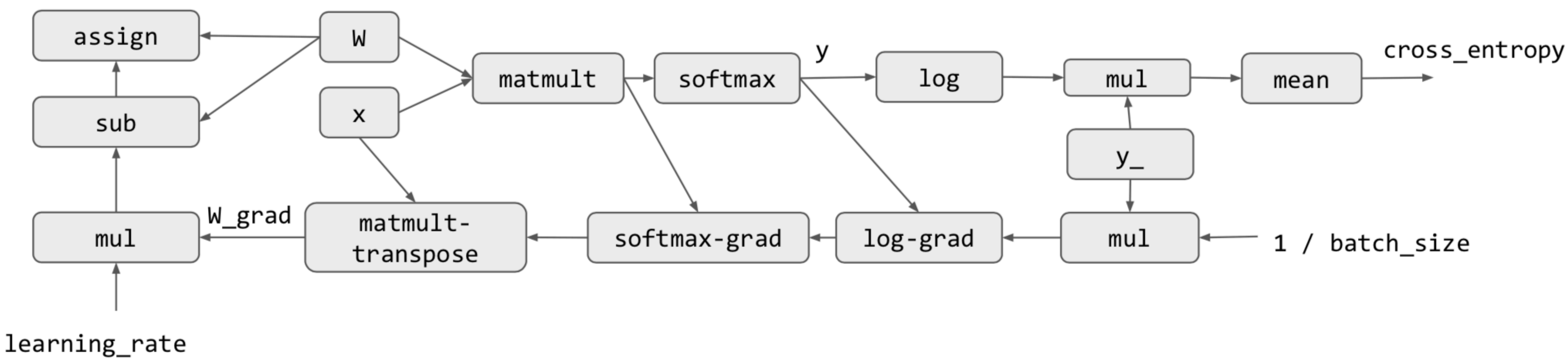
Execution only Touches the Needed Subgraph

```
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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```
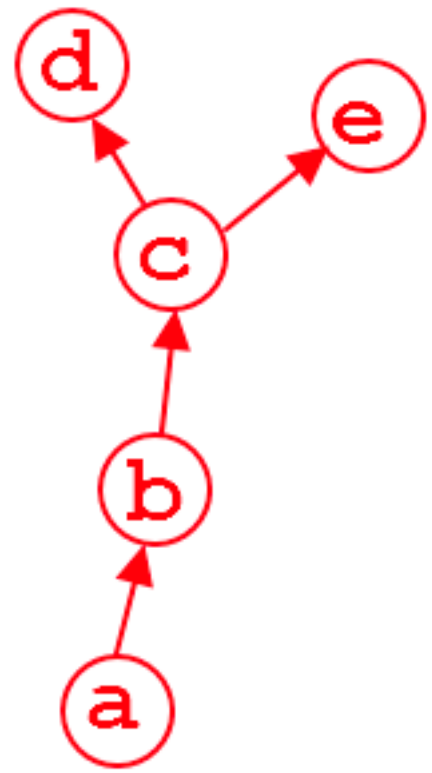
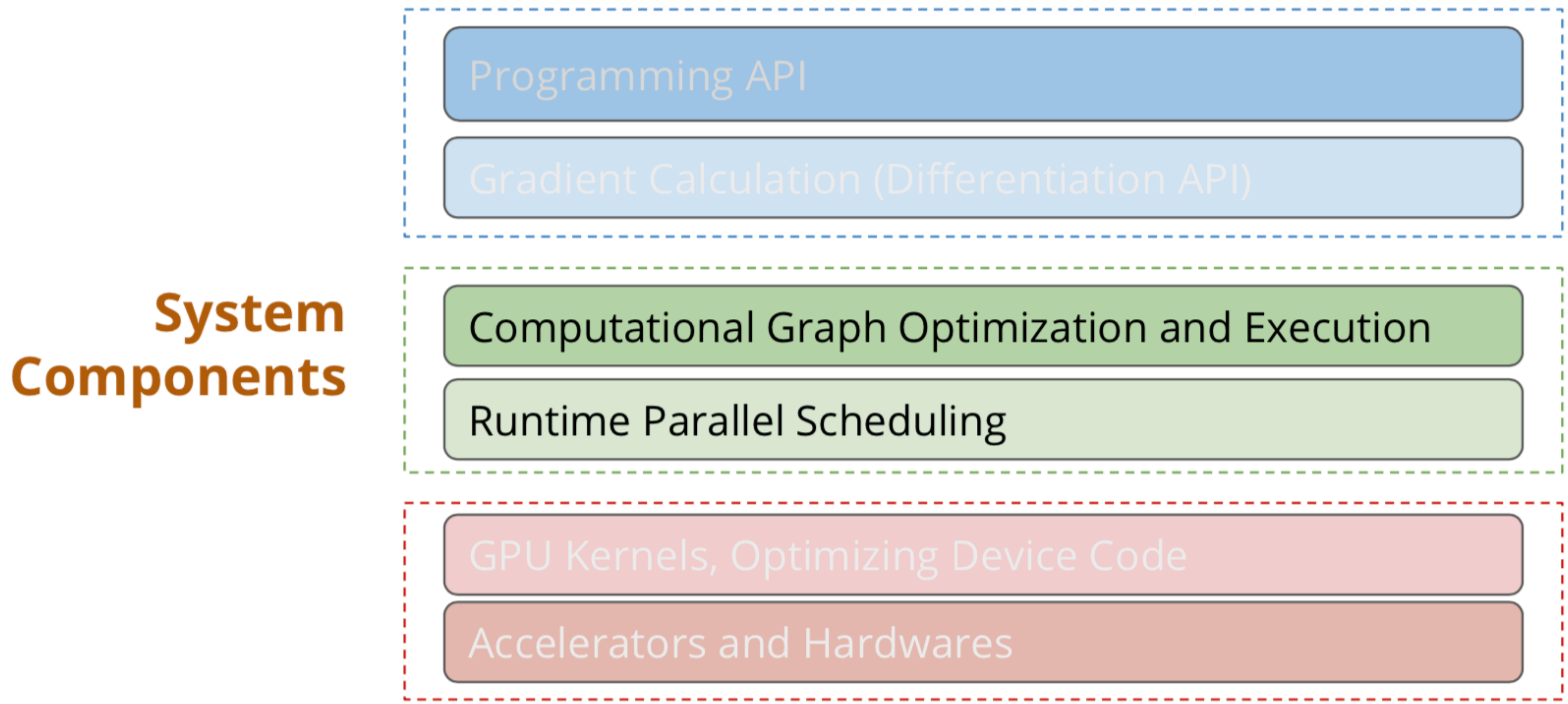

Computational graphs in other frameworks: PyTorch



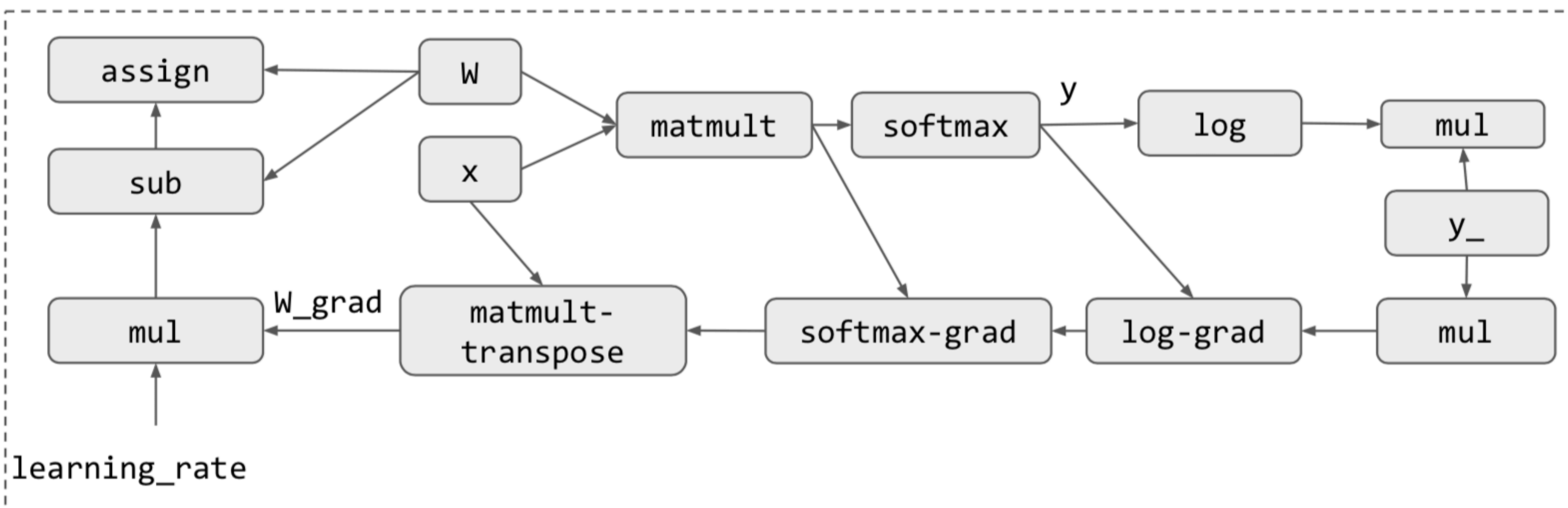

```
import torch
from torch.autograd import Variable
a = Variable(torch.rand(1, 4), requires_grad=True)
b = a**2
c = b*2
d = c.mean()
e = c.sum()
```

Typical Deep Learning System Stack



Computation Graph Optimization

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

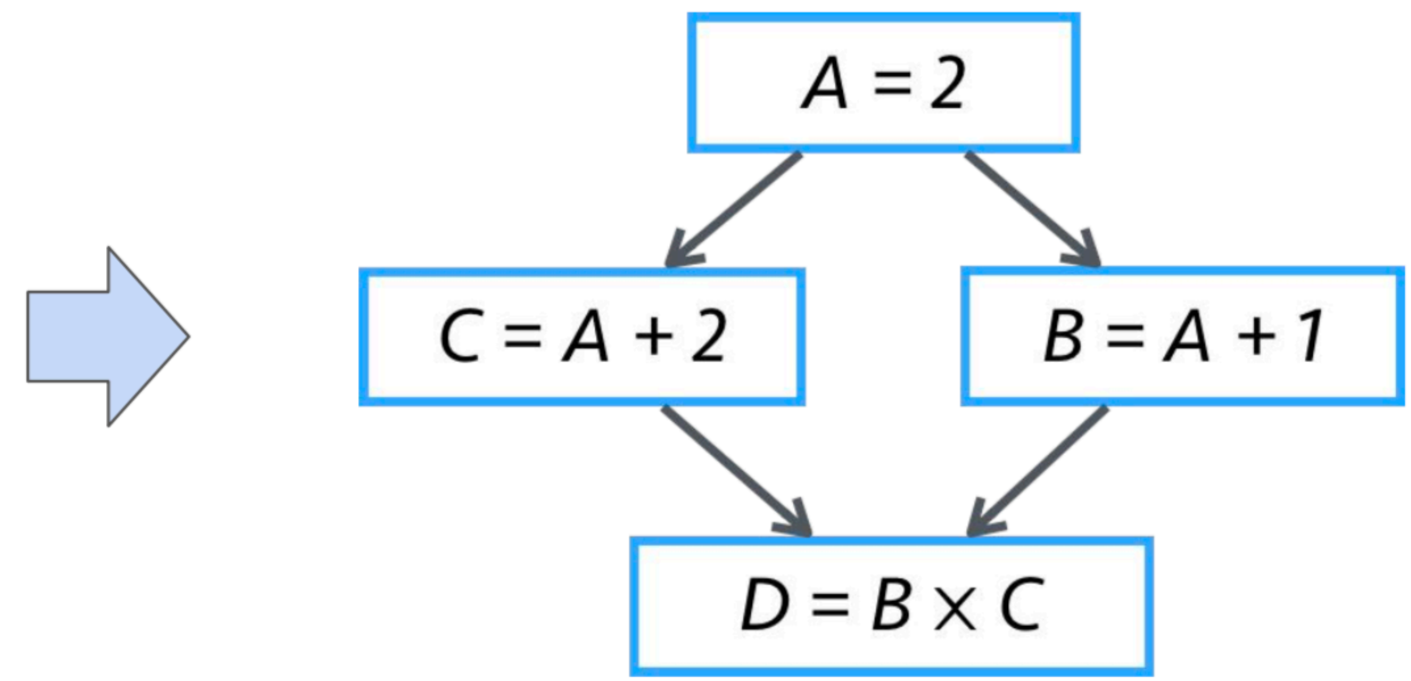


Parallel Scheduling

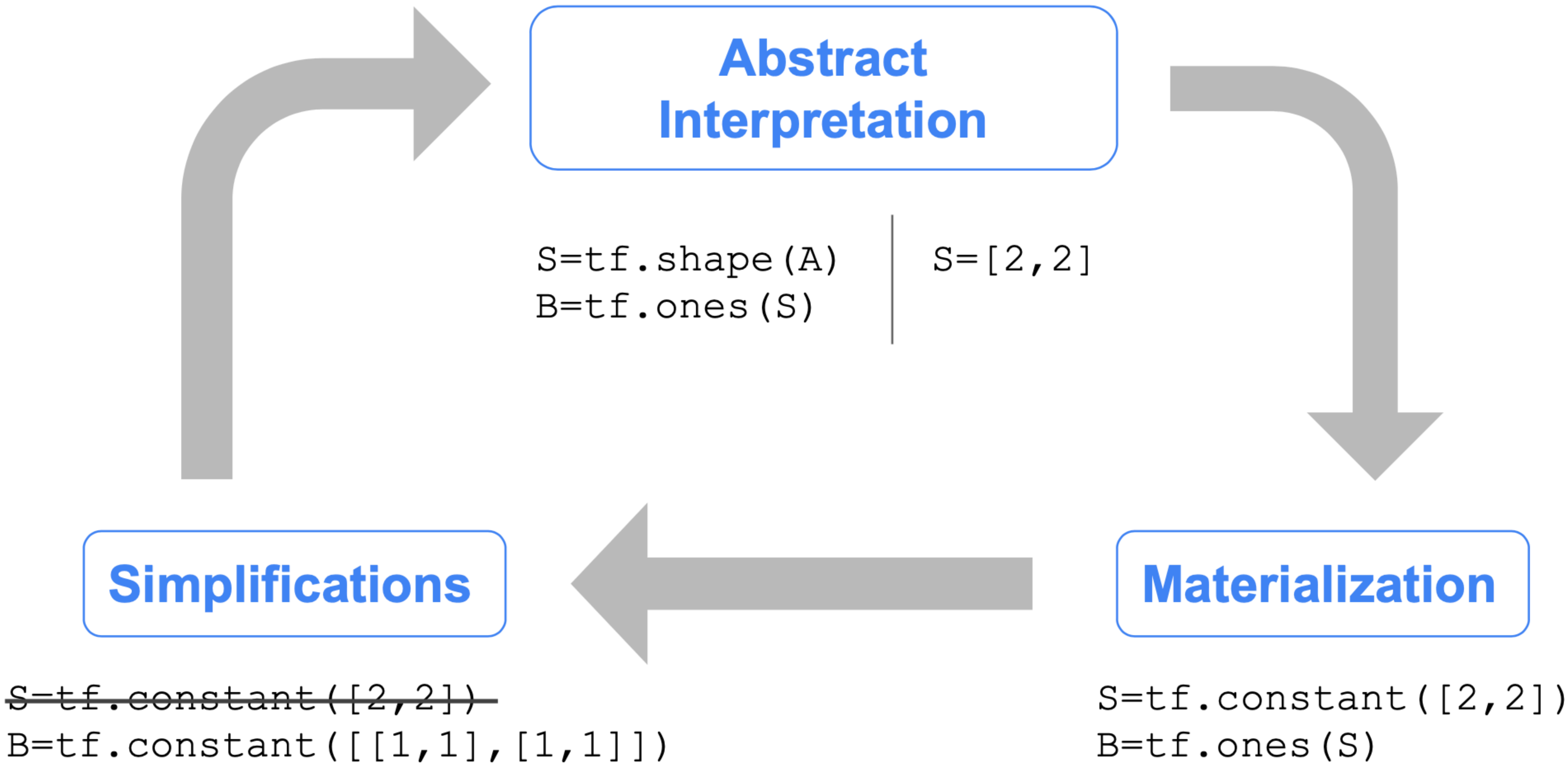
- Code need to run parallel on multiple devices and worker threads
- Detect and schedule parallelizable patterns
- Detail lecture on later

MXNet Example

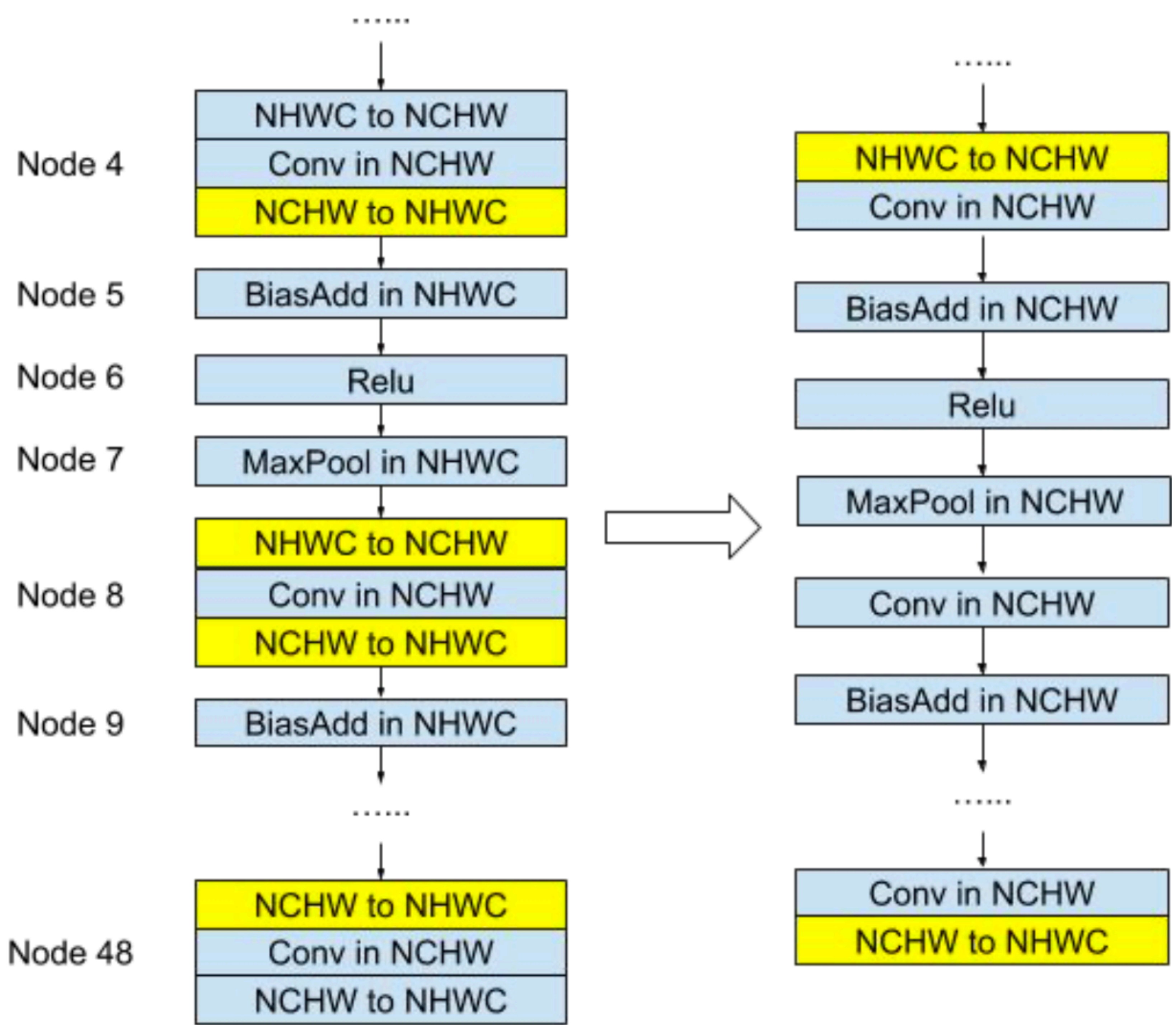
```
>>> import mxnet as mx
>>> A = mx.nd.ones((2,2)) *2
>>> C = A + 2
>>> B = A + 1
>>> D = B * C
```



Graph Simplifications

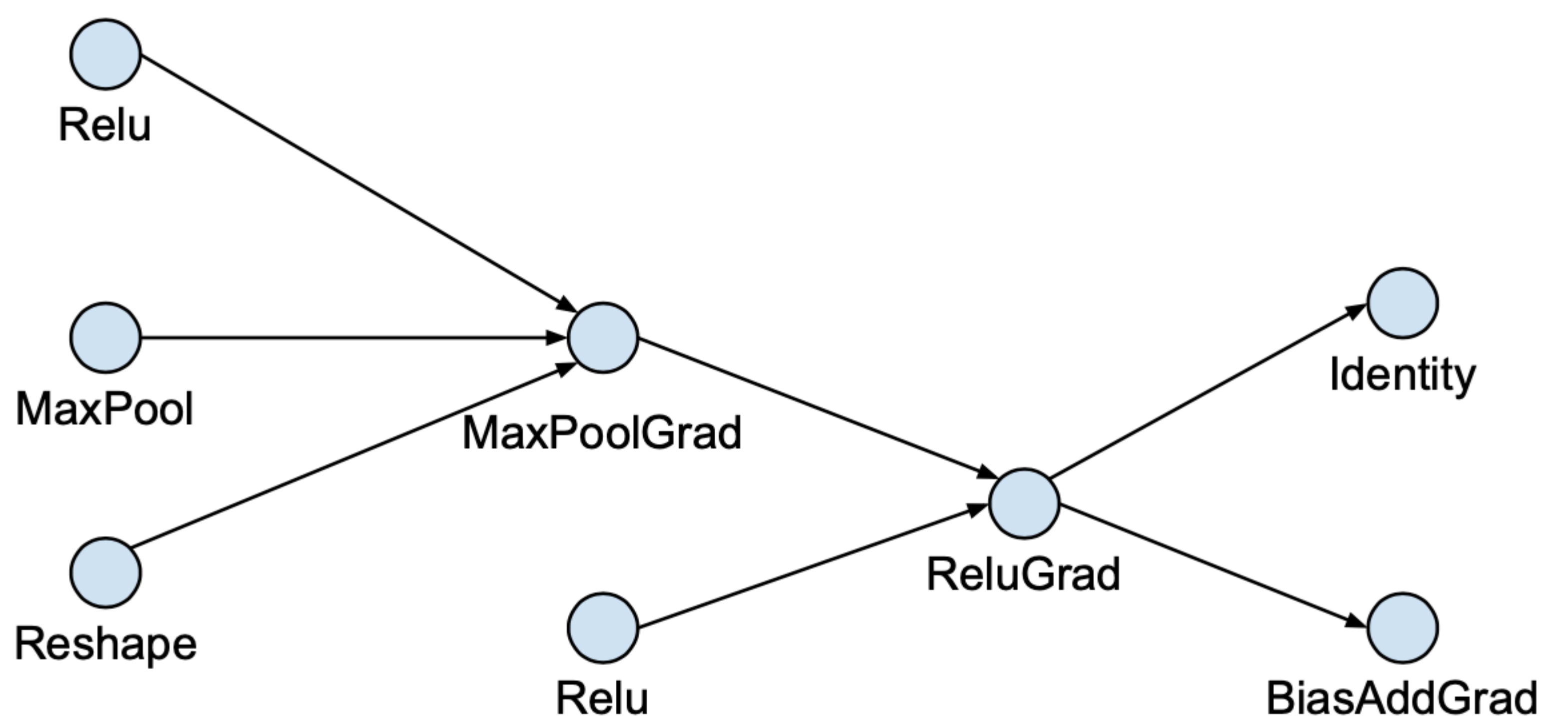


Layout Optimization



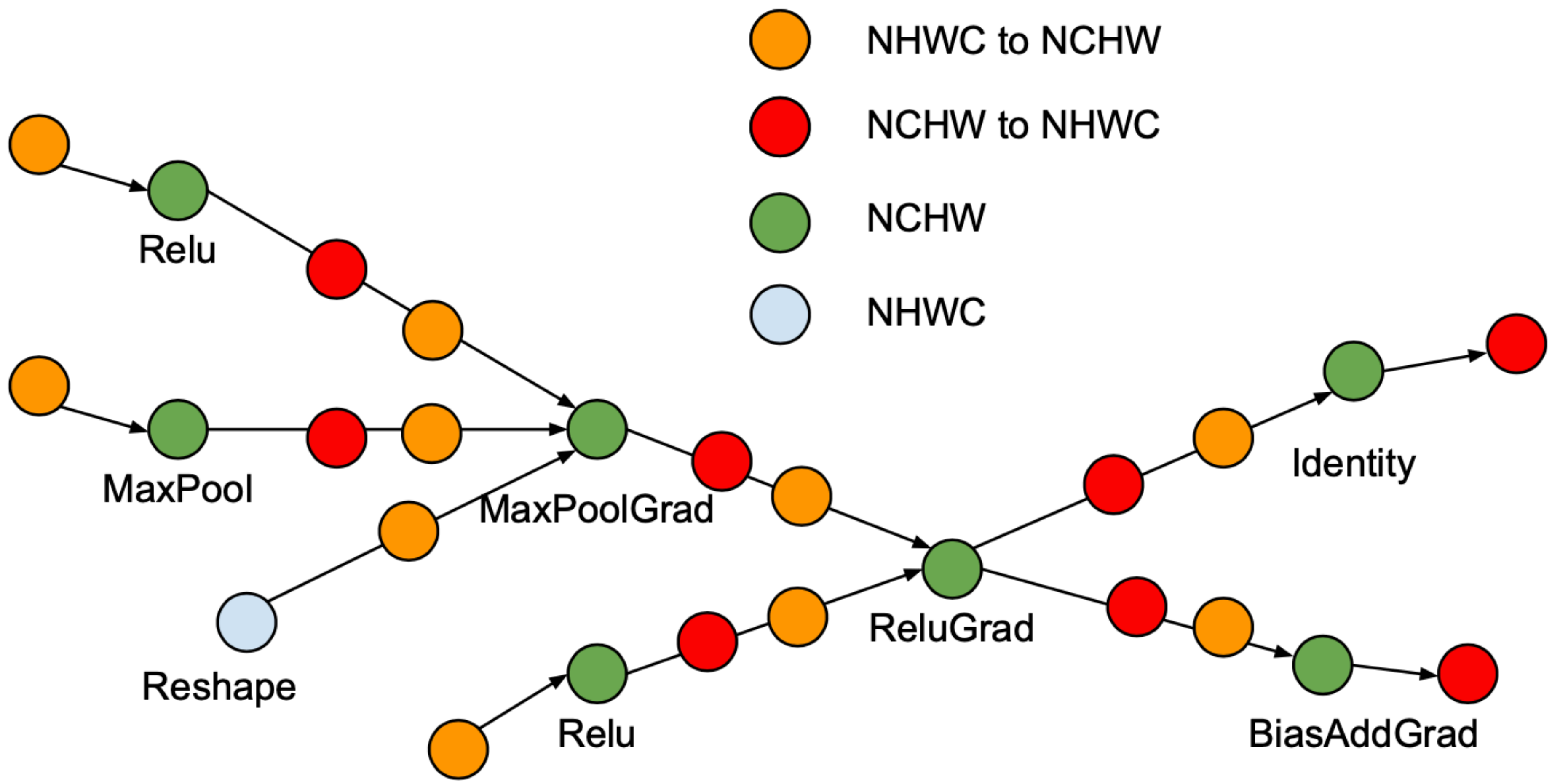
Layout Optimization

Example: Original graph with all ops in NHWC format



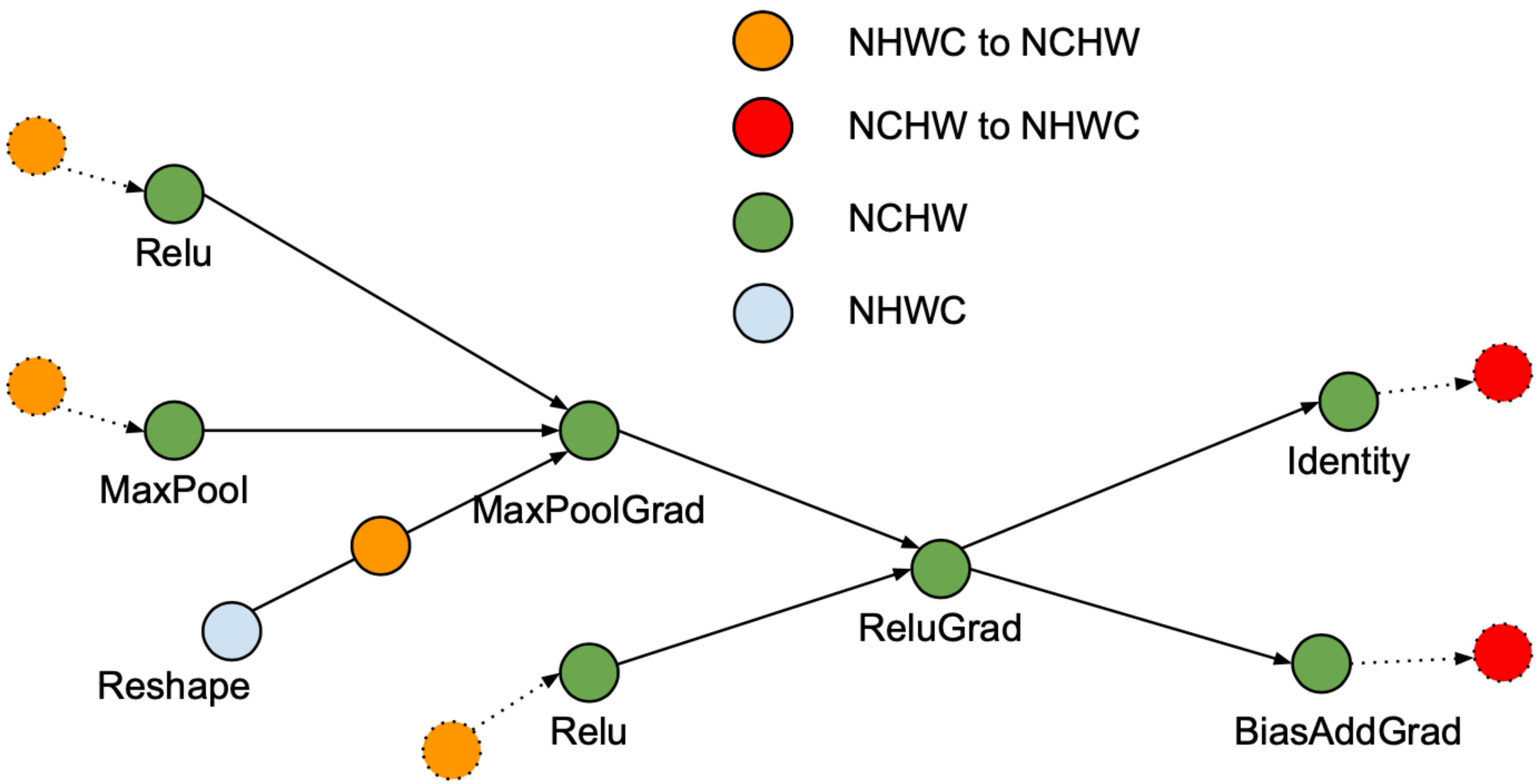
Layout Optimization

Phase 1: Expand by inserting conversion pairs

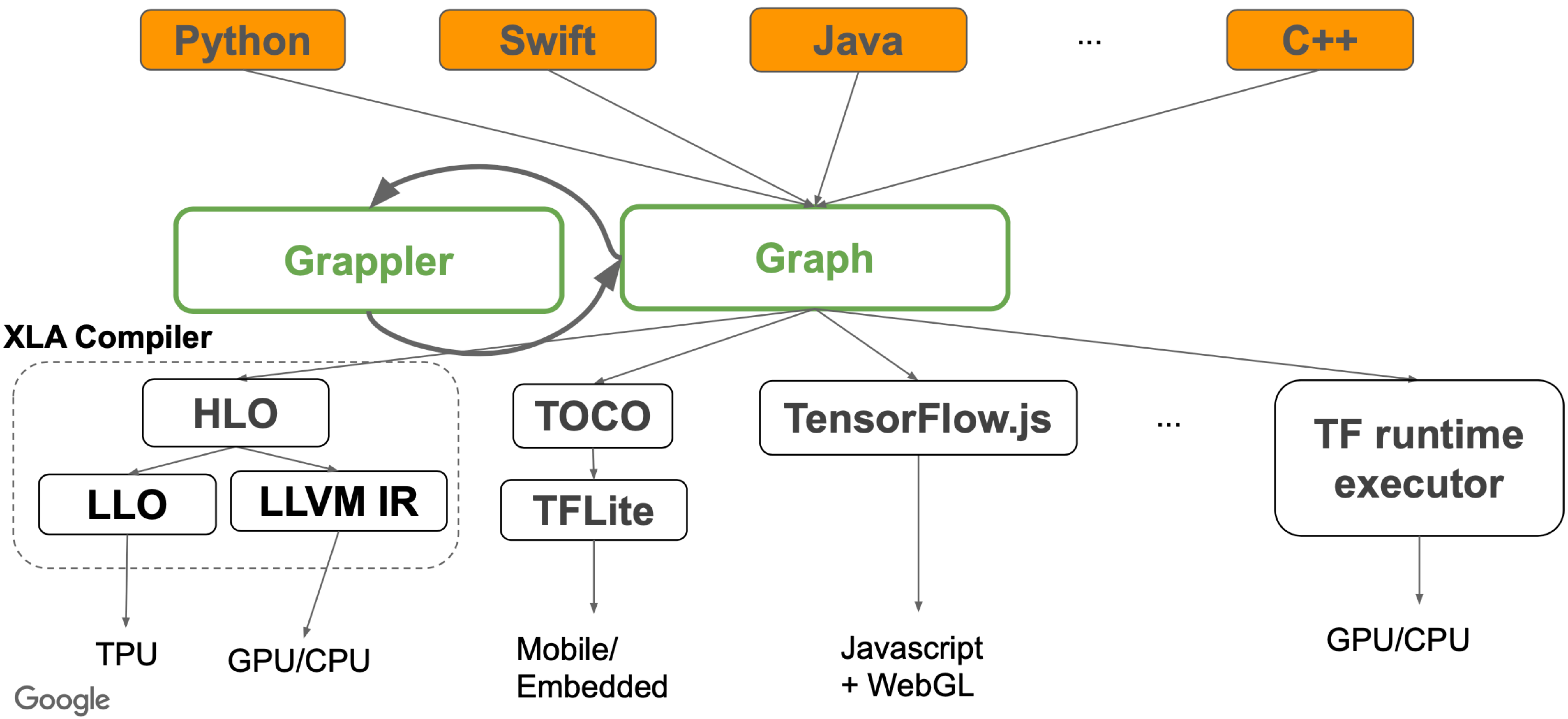


Layout Optimization

Phase 2: Collapse adjacent conversion pairs



Computation Graph Optimization



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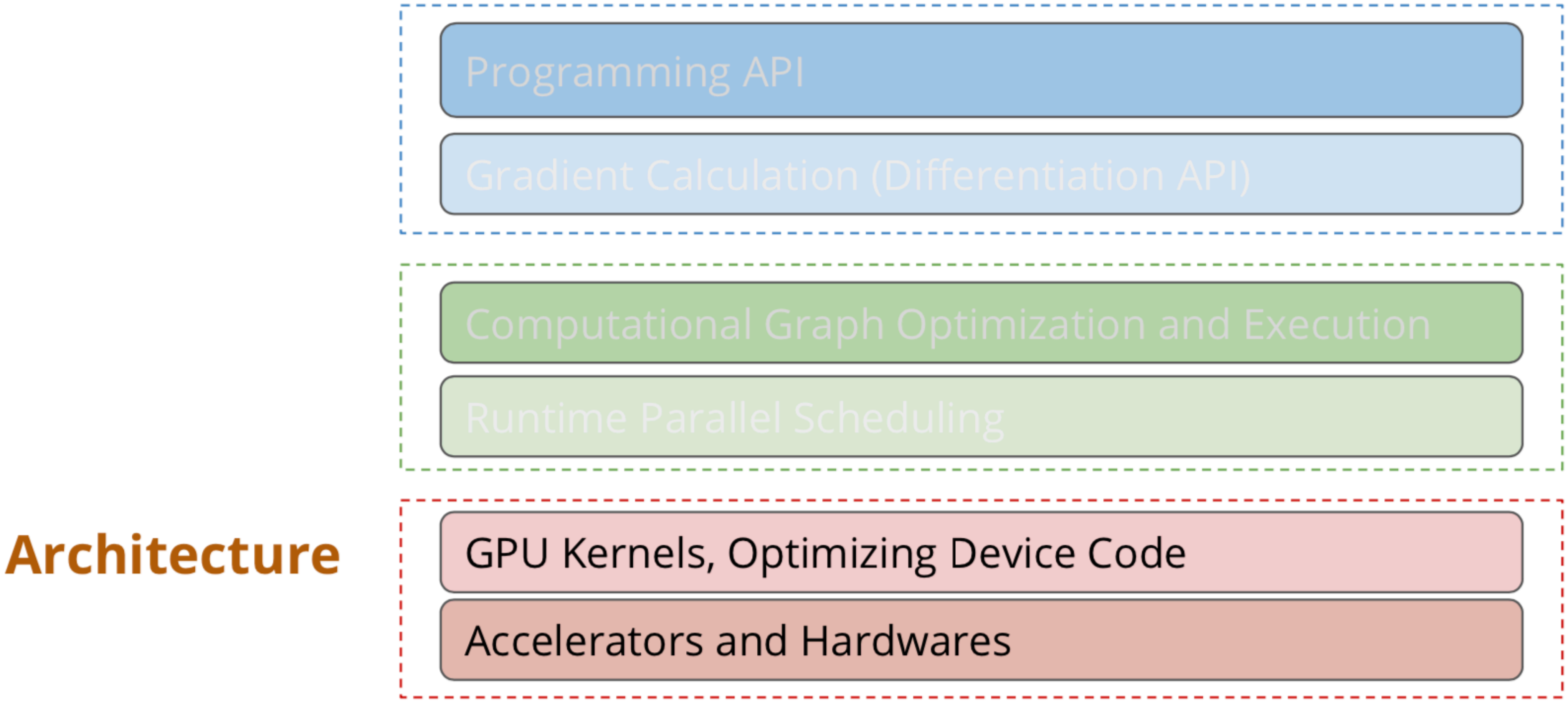


GPU Acceleration

- 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)

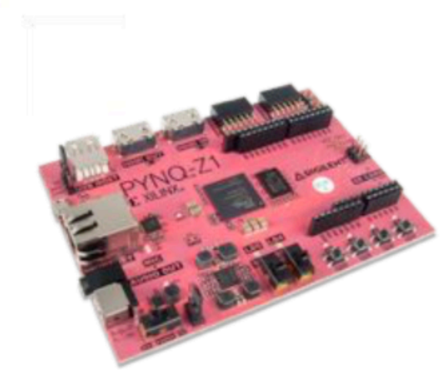
System Components

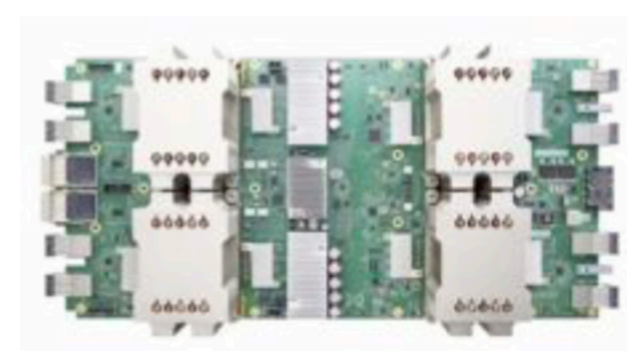
- Computational Graph Optimization and Execution
- Runtime Parallel Scheduling

Architecture

- GPU Kernels, Optimizing Device Code
- Accelerators and Hardwares

Supporting More Hardware backends





Each Hardware backend requires a software stack

Programming API

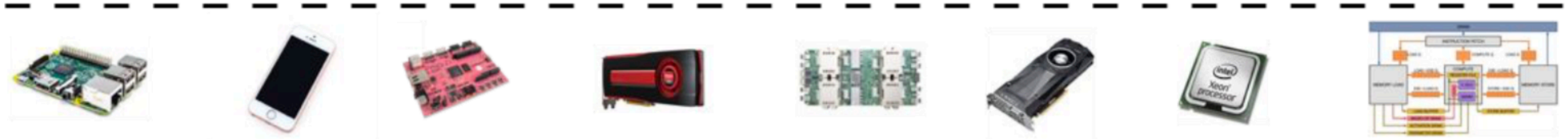
Gradient Calculation (Differentiation API)

Computational Graph Optimization and Execution

Runtime Parallel Scheduling

CUDA Library | MKL Library | TPU Library | ARM Library | JS Library

Hardware



New Trend: Compiler based Approach