Lecture 3: Overview of Deep Learning System

CSE599W: Spring 2018

The Deep Learning Systems Juggle

mxnet TensorFlow Microsoft CNTK Chainer theano

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

Typical Deep 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!

Typical Deep Learning System Stack

User API

Programming API

Gradient Calculation (Differentiation API)

Computational Graph Optimization and Execution

Runtime Parallel Scheduling

GPU Kernels, Optimizing Device Code

Accelerators and Hardwares

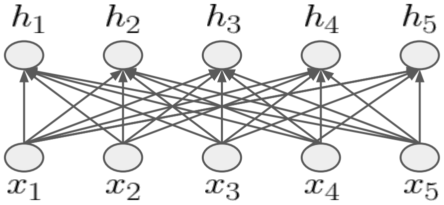
Example: Logistic Regression

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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```

Manually calculate the gradient of weight with respect to the log-likelihood loss.

Exercise: Try to derive the gradient rule by yourself.

y: 100*784 784*10 = 100*10
W_grad: 784*100 100*10 784*10

Logistic Regression in Numpy

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```

Weight Update via SGD

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

Discussion: Numpy based Program

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```

- Talk to your neighbors 2-3 person:)
- What do we need to do to support deeper neural networks
- What are the complications

Logistic Regression in Numpy

- Computation in Tensor Algebra
  - `softmax(np.dot(batch_xs, W))`

- Manually calculate the gradient
  - `y_grad = y - batch_ys`
  - `W_grad = np.dot(batch_xs.T, y_grad)`

- SGD Update Rule
  - `W = W - learning_rate * W_grad`

Logistic Regression in TinyFlow (TensorFlow like API)

```
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)
for i in range(1000):
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   sess.run(train_step, feed_dict={x: batch_xs, y_:batch_ys})
```

Forward Computation **Declaration**

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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

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```
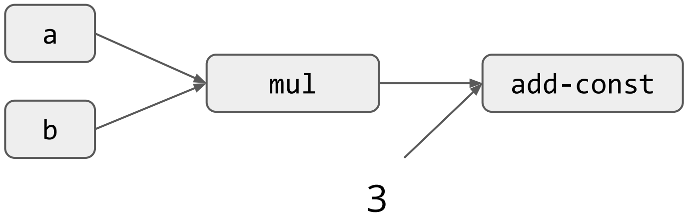

Real execution happens here!

The Declarative Language: Computation Graph

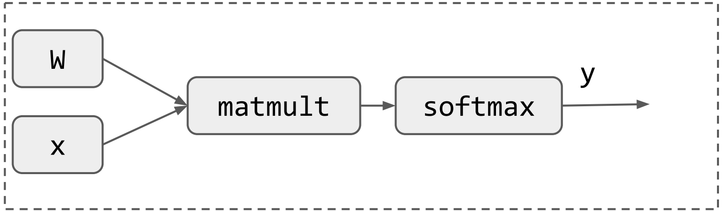
- Nodes represents the computation (operation)
- Edge represents the data dependency between operations

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 by Steps

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cross_entropy = tf.reduce_mean(-tf.reduce_sum(y_ * tf.log(y), reduction_indices=[1]))
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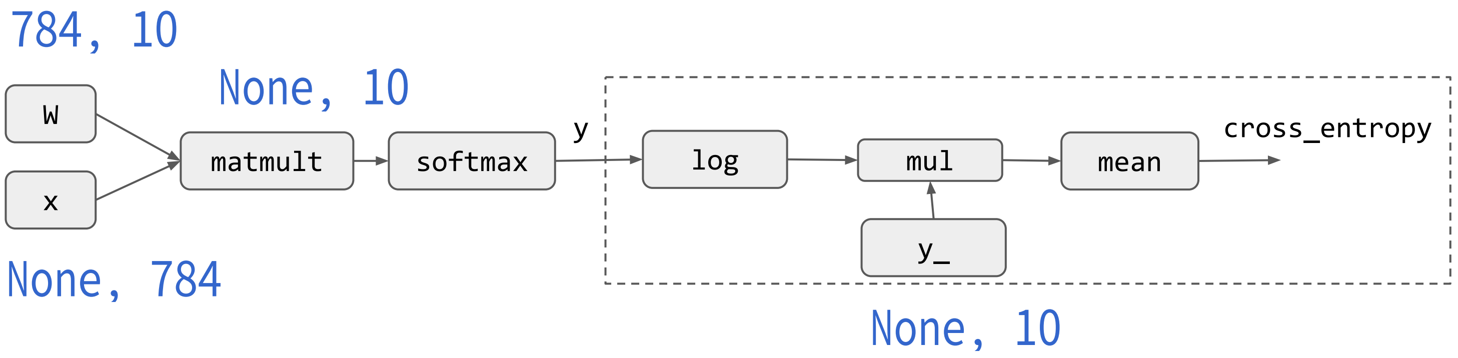
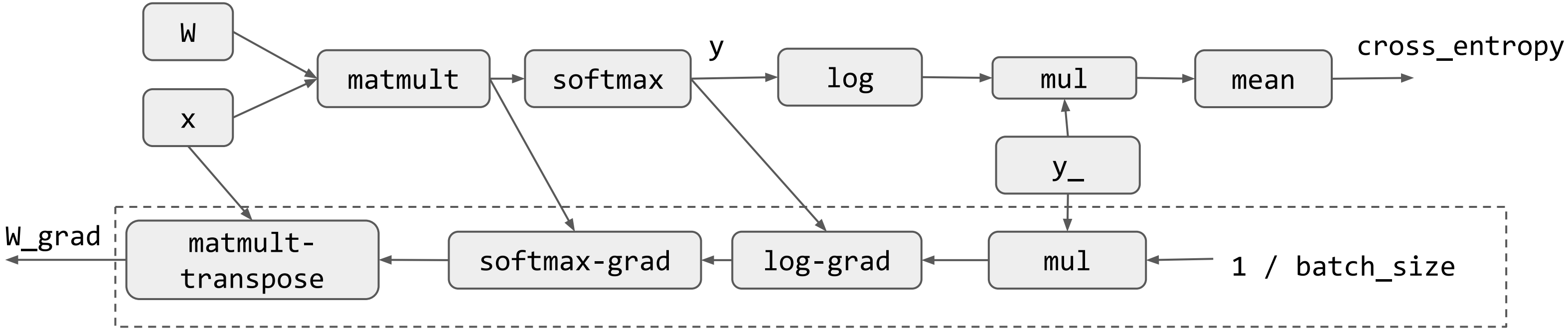


Computational Graph Construction by Step

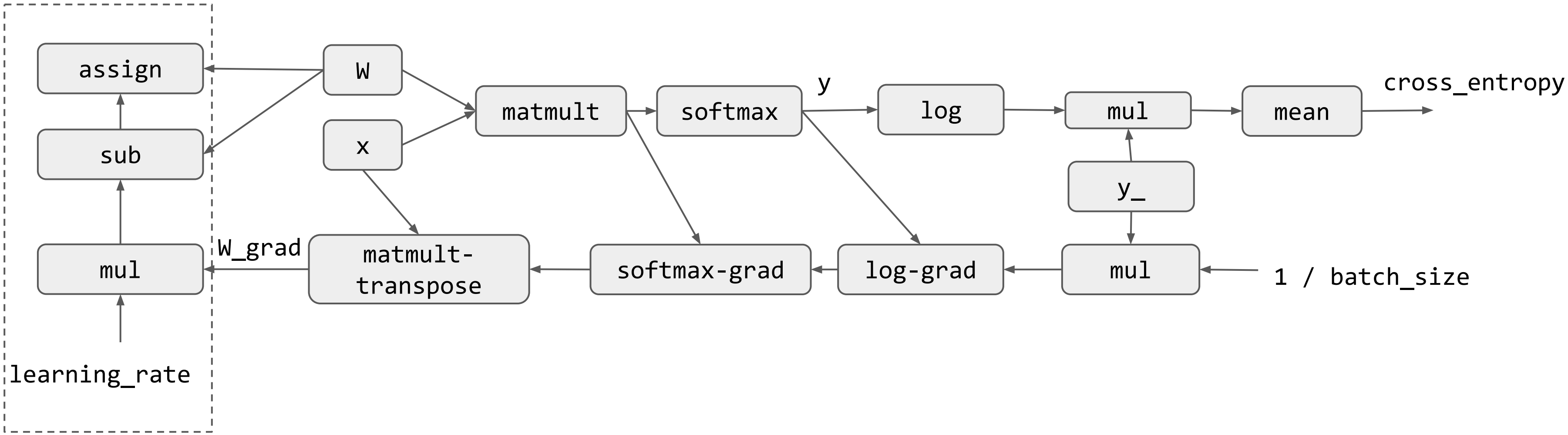
```
W_grad = tf.gradients(cross_entropy, [W])[0]
```

Automatic Differentiation, detail in next lecture!



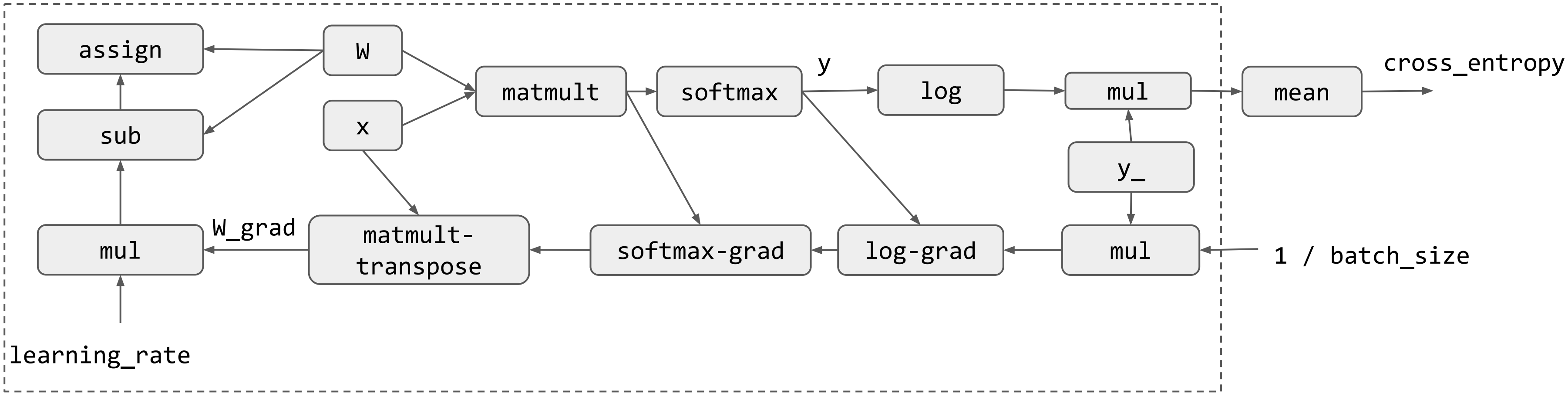
Computational Graph Construction by Step

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



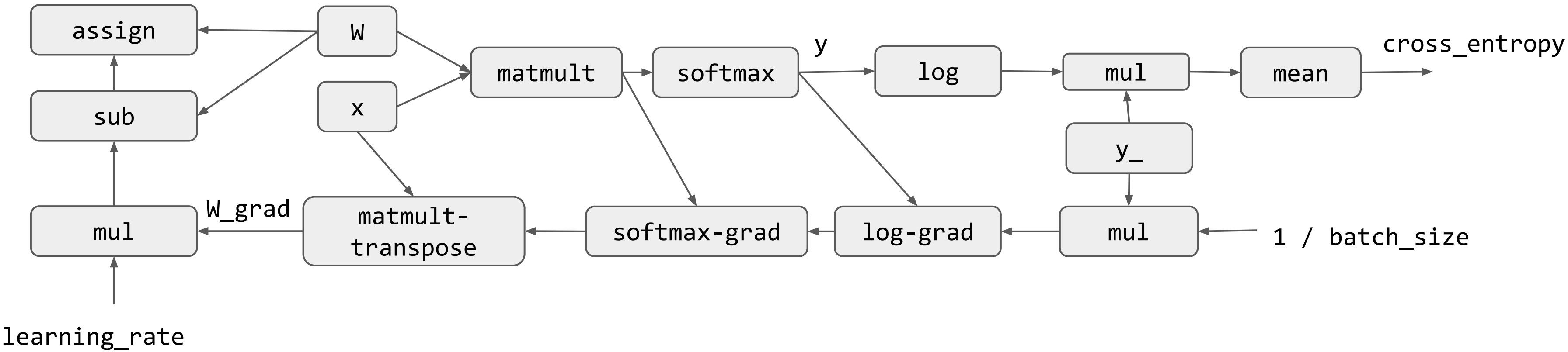
Execution only Touches the Needed Subgraph

```
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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Typical Deep Learning System Stack

Programming API

Gradient Calculation (Differentiation API)

System Components

Computational Graph Optimization and Execution

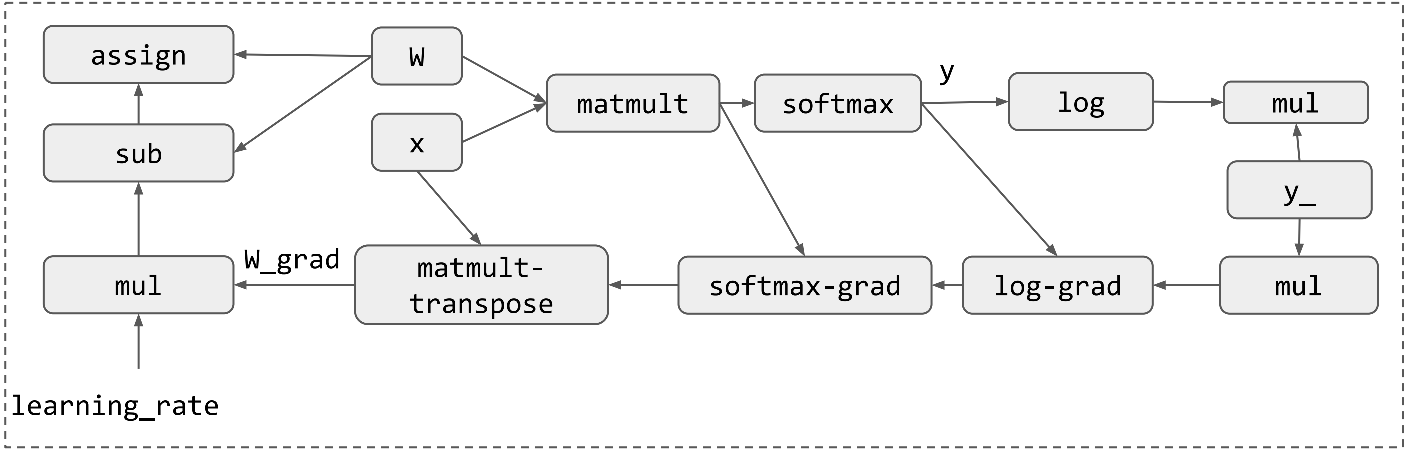
Runtime Parallel Scheduling

GPU Kernels, Optimizing Device Code

Accelerators and Hardwares

Computation Graph Optimization

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

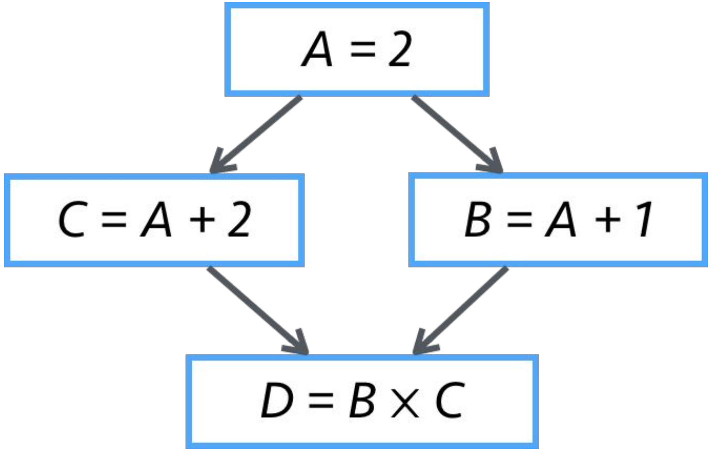


Parallel Scheduling

- 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
```



Typical Deep Learning System Stack

Programming API

Gradient Calculation (Differentiation API)

Computational Graph Optimization and Execution

Runtime Parallel Scheduling

Architecture

GPU Kernels, Optimizing Device Code

Accelerators and Hardwares

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
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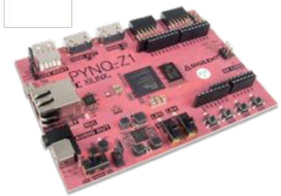
Supporting More Hardware backends



Each Hardware backend requires a software stack

Programming API

Gradient Calculation (Differentiation API)

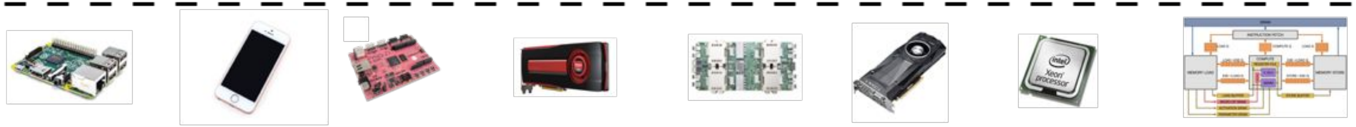
Computational Graph Optimization and Execution

Runtime Parallel Scheduling

The fastest and most-used math library for Intel®-based systems1. Accelerate math processing routines, increase application performance, and reduce development time

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

Hardware



New Trend: Compiler based Approach

Programming API

Gradient Calculation (Differentiation API)

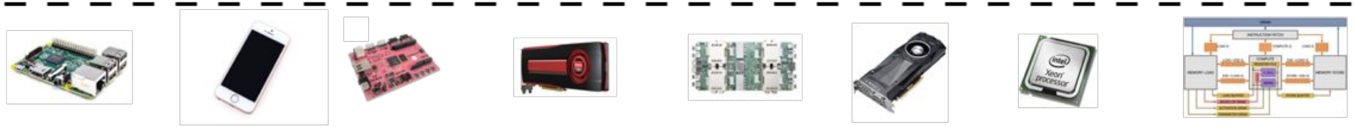
Computational Graph Optimization and Execution

Runtime Parallel Scheduling

High level operator description

Tensor Compiler Stack

Hardware



Links

- TinyFlow: 2K lines of code to build a TensorFlow like API
  - https://github.com/dlsys-course/tinyflow
- The source code used in the slide
  - https://github.com/dlsys-course/examples/tree/master/lecture3