Lecture 3: Overview of Deep Learning System

CSE599G1: Spring 2017

The Deep Learning Systems Juggle

dmlc mxnet

TensorFlow

Microsoft CNTK

Chainer

theano

Caffe

torch

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)

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GPU Kernels, Optimizing Device Code

Accelerators and Hardwares

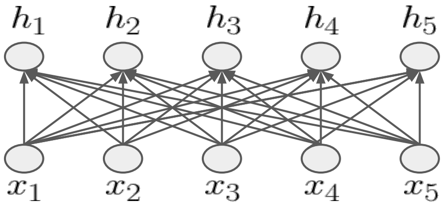
Example: Logistic Regression

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.

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```

Weight Update via SGD

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

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OF COMPUTER SCIENCE & ENGINEERING

Discussion: Numpy based Program

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from tinyflow.datasets import get_mnist
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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)

```python
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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Forward Computation **Declaration**

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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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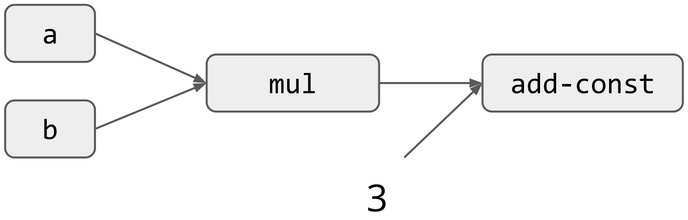
```

Real execution happens here!

The Declarative Language: Computation Graph

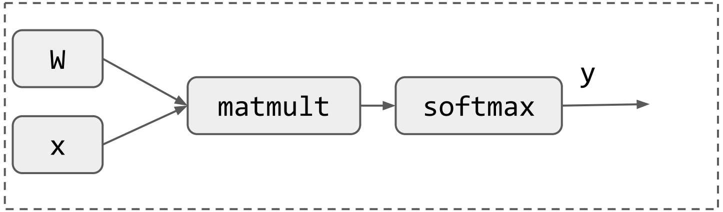
- Nodes represents the computation (operation)
- Edge represents the data dependency between operations

Computational Graph for `a * b +3`



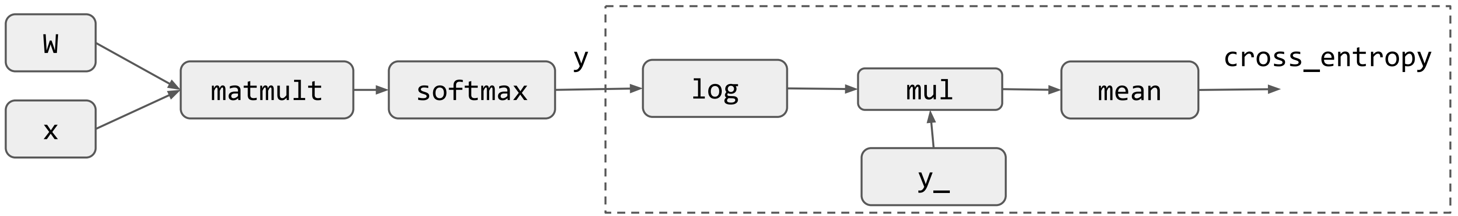
Computational Graph Construction by Step

```
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

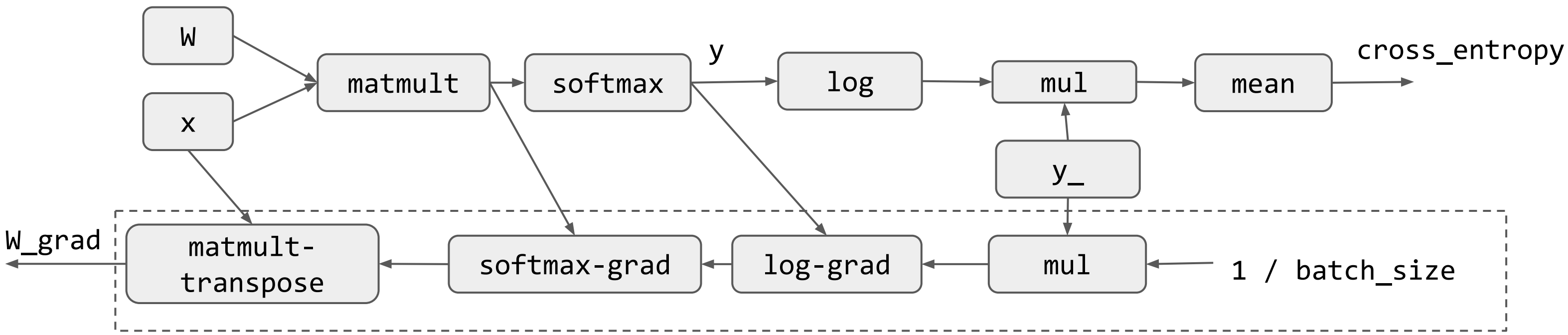
```
y_ = tf.placeholder(tf.float32, [None, 10])
cross_entropy = tf.reduce_mean(-tf.reduce_sum(y_ * tf.log(y), reduction_indices=[1]))
```



Computational Graph Construction by Step

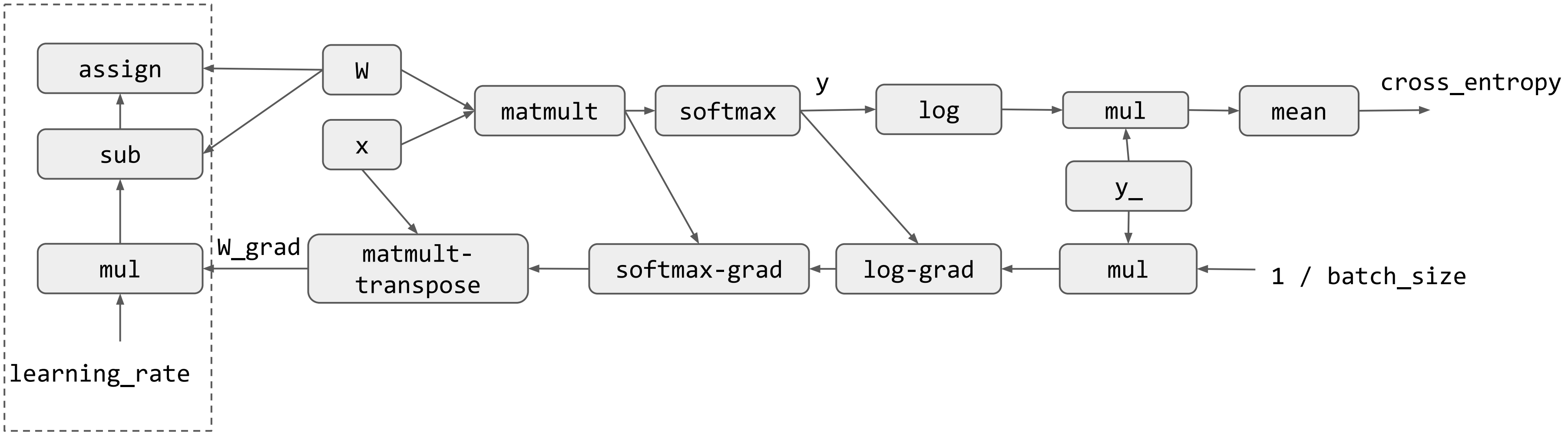
```
W_grad = tf.gradients(cross_entropy, [W])[0]
```

Automatic Differentiation, detail in next lecture!



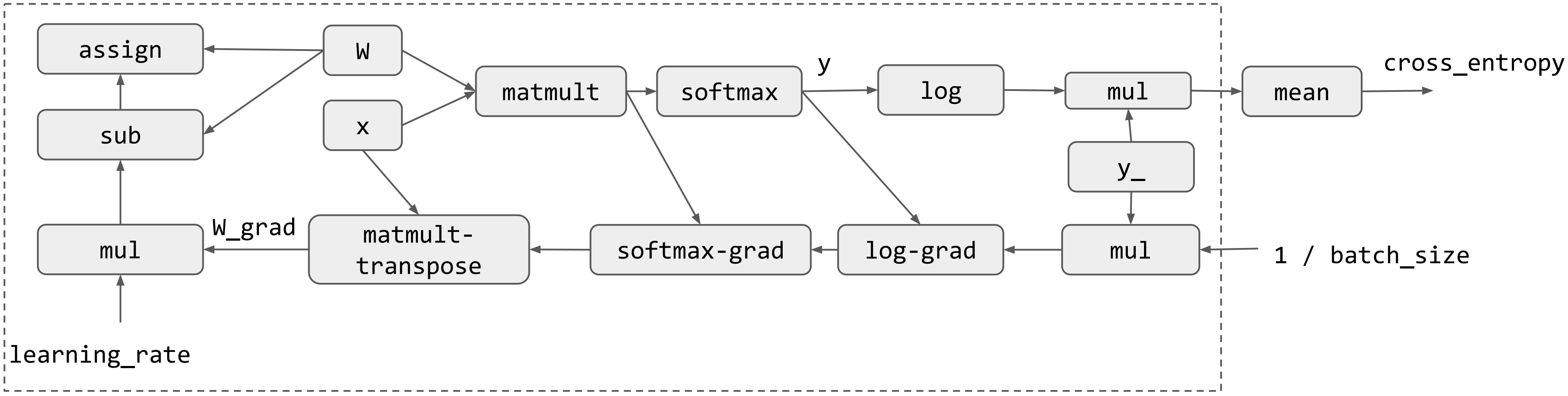
Computational Graph Construction by Step

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



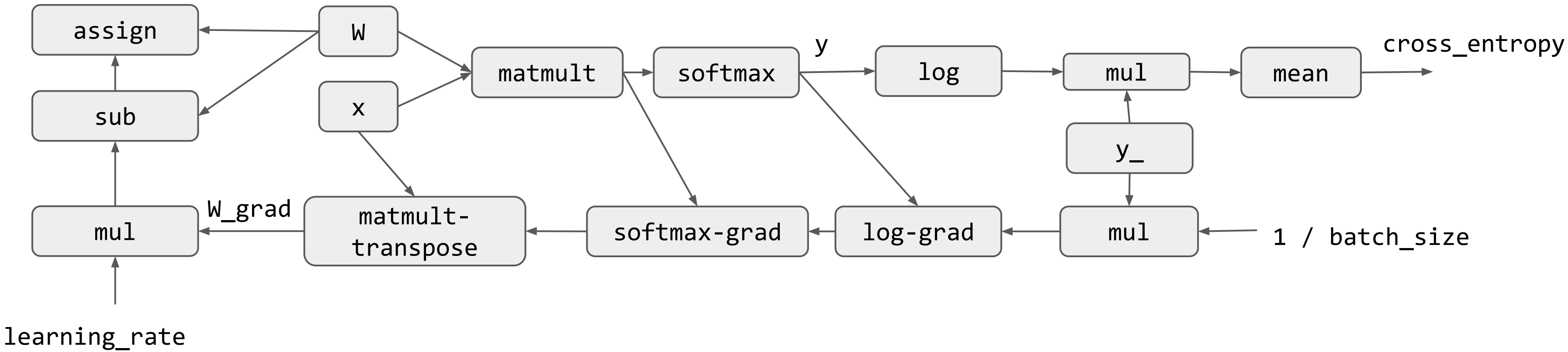
Execution only Touches the Needed Subgraph

```
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 TinyFlow Program

What is the benefit/drawback of the TinyFlow 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

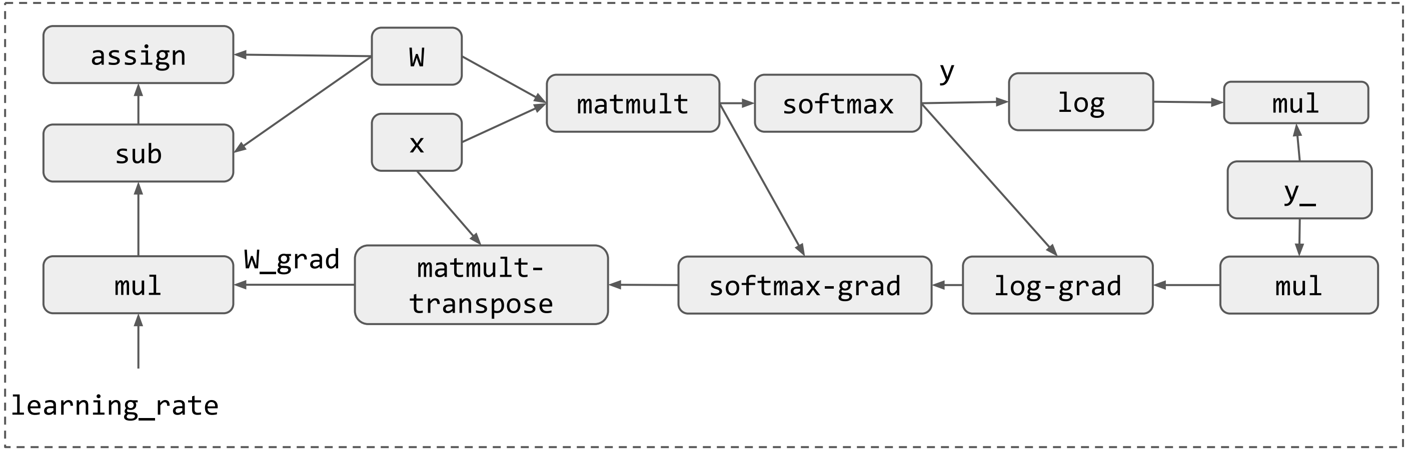
Runtime Parallel Scheduling

GPU Kernels, Optimizing Device Code

Accelerators and Hardwares

Computation Graph Optimization

- E.g. Deadcode elimination
- Memory planning and optimization (lecture on Apr 18th)
- What other possible optimization can we do given a computational graph?

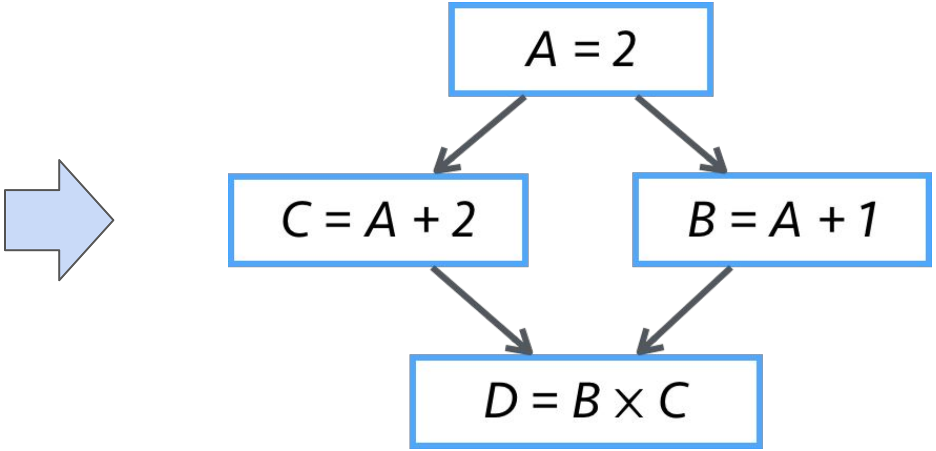


Parallel Scheduling

- Code need to run parallel on multiple devices and worker threads
- Detect and schedule parallelizable patterns
- Detail lecture on Apr 25th

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

Custom Hardwares are coming

- Joint Session with CSE 548 on ASIC and FPGA
  - Different date as normal hour
  - Checkout the schedule page for details

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
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- Runtime Parallel Scheduling

Architecture
- GPU Kernels, Optimizing Device Code
- Accelerators and Hardwares

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