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Deep Learning for Computer Vision with TensorFlow

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Preliminary

- Machine Learning
- Deep Learning
- Linear Algebra
- Python (numpy)

Throughout the Slides

- Please put following codes to run our sample codes.

```
import numpy as np
import tensorflow as tf
```

- All codes are written in python 3.x and TensorFlow 1.x.
- We tested codes in Jupyter Notebook.

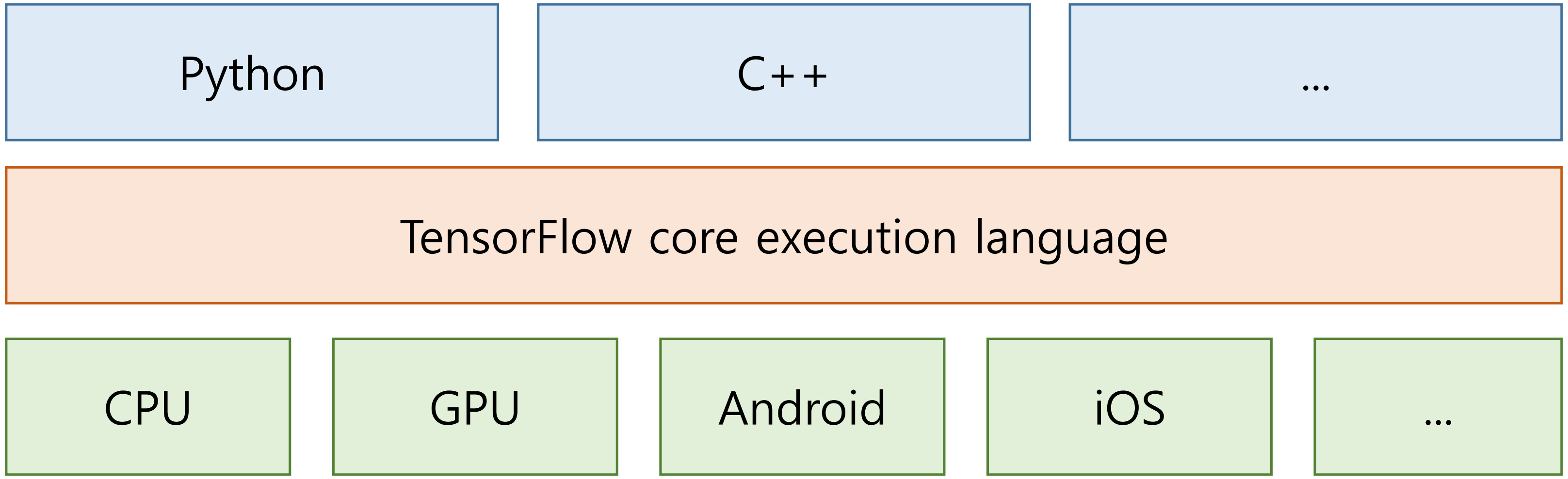
What is TensorFlow?

What is TensorFlow?

- TensorFlow was originally developed by researchers and engineers working on the **Google Brain Team**.
- TensorFlow is an open source software library for numerical computation using **data flow graphs**.
- It deploys computation to one or more **CPUs or GPUs** in a desktop, server, or mobile device with a single API.

TensorFlow Architecture

- Core in C++
  - Very low overhead
- Different front ends for specifying/driving the computation
  - Python and C++ today, easy to add more

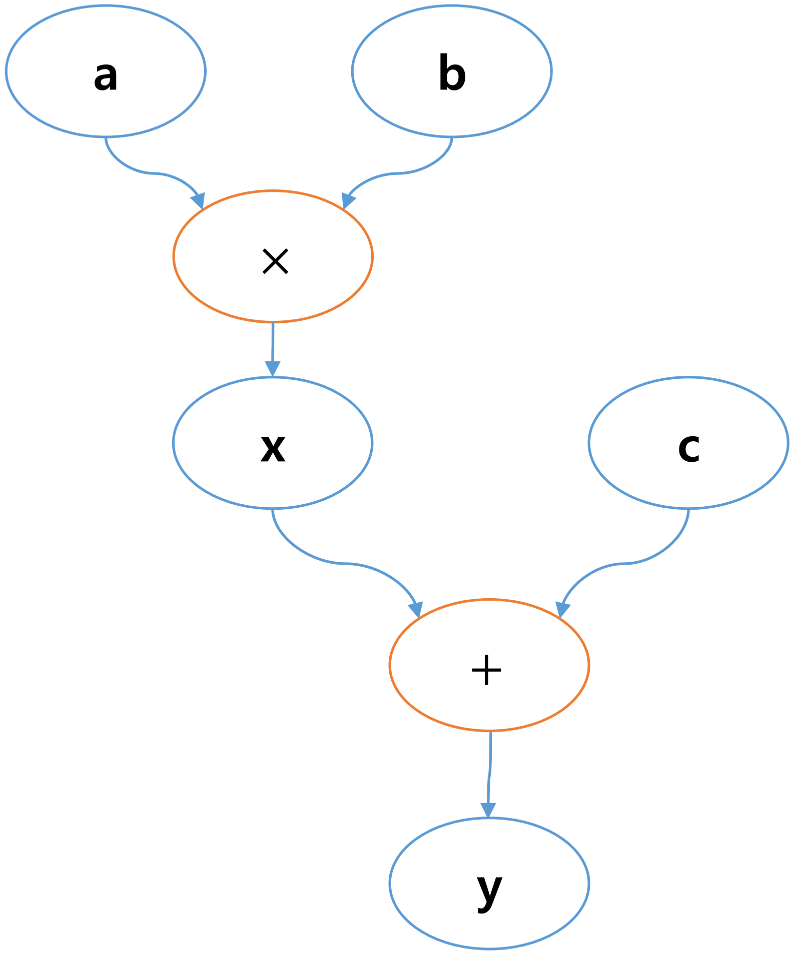


https://www.slideshare.net/JenAman/large-scale-deep-learning-with-tensorflow

Graphs in TensorFlow

- Computation is a **dataflow graph**.
- A variable is defined as a **symbol**.

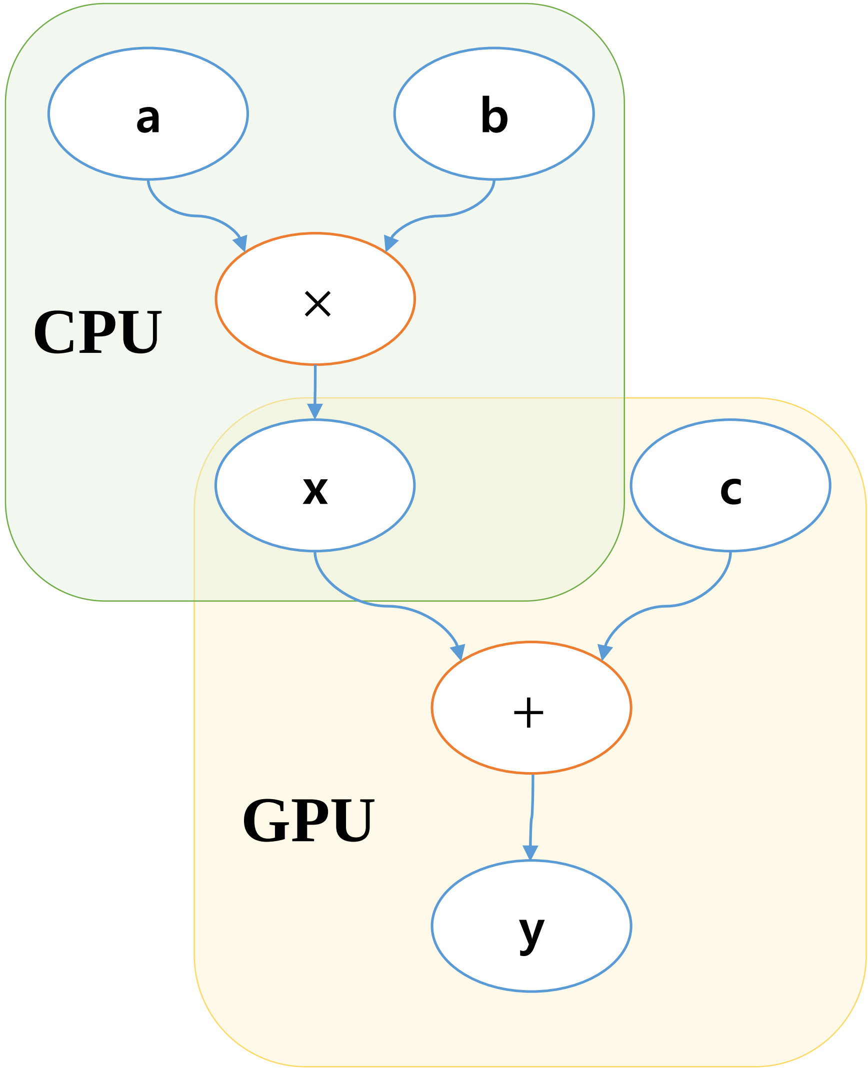
$$
\begin{aligned}
a &= \text{tf.Variable}(3)\\
b &= \text{tf.Variable}(2)\\
c &= \text{tf.Variable}(1)\\
x &= a*b\\
y &= x + c
\end{aligned}
$$



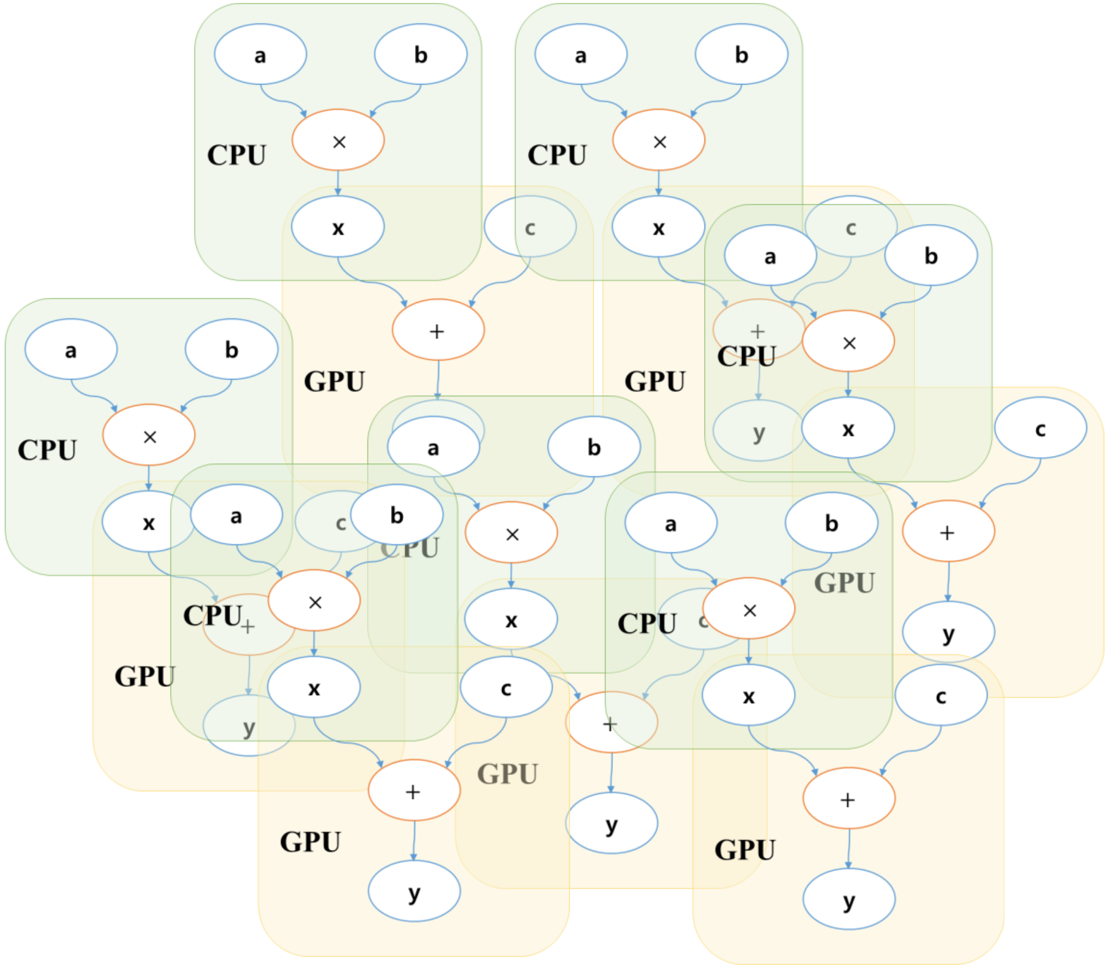
Device Placement

- A variable or operator can be pinned to a **particular device**.

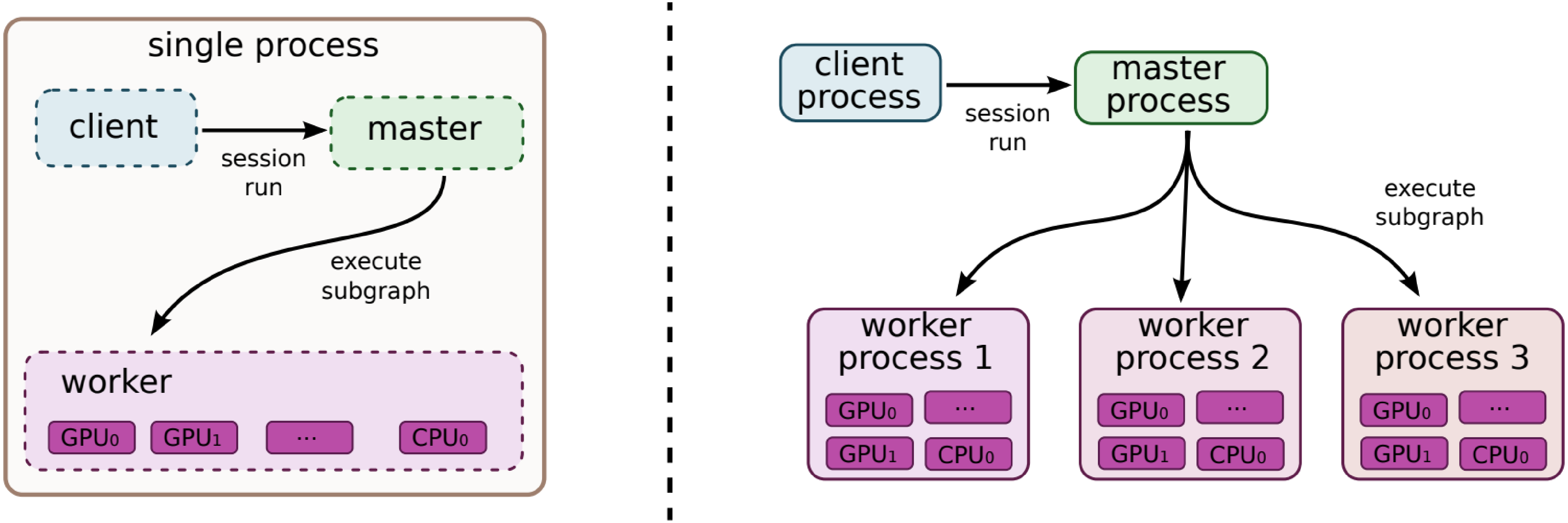
```
# Pin a variable to CPU.
with tf.device("/cpu:0"):
    a = tf.Variable(3)
    b = tf.Variable(2)
    x = a*b

# Pin a variable to GPU.
with tf.device("/gpu:0"):
    c = tf.Variable(1)
    y = x + c
```



Distributed Systems of GPUs and CPUs

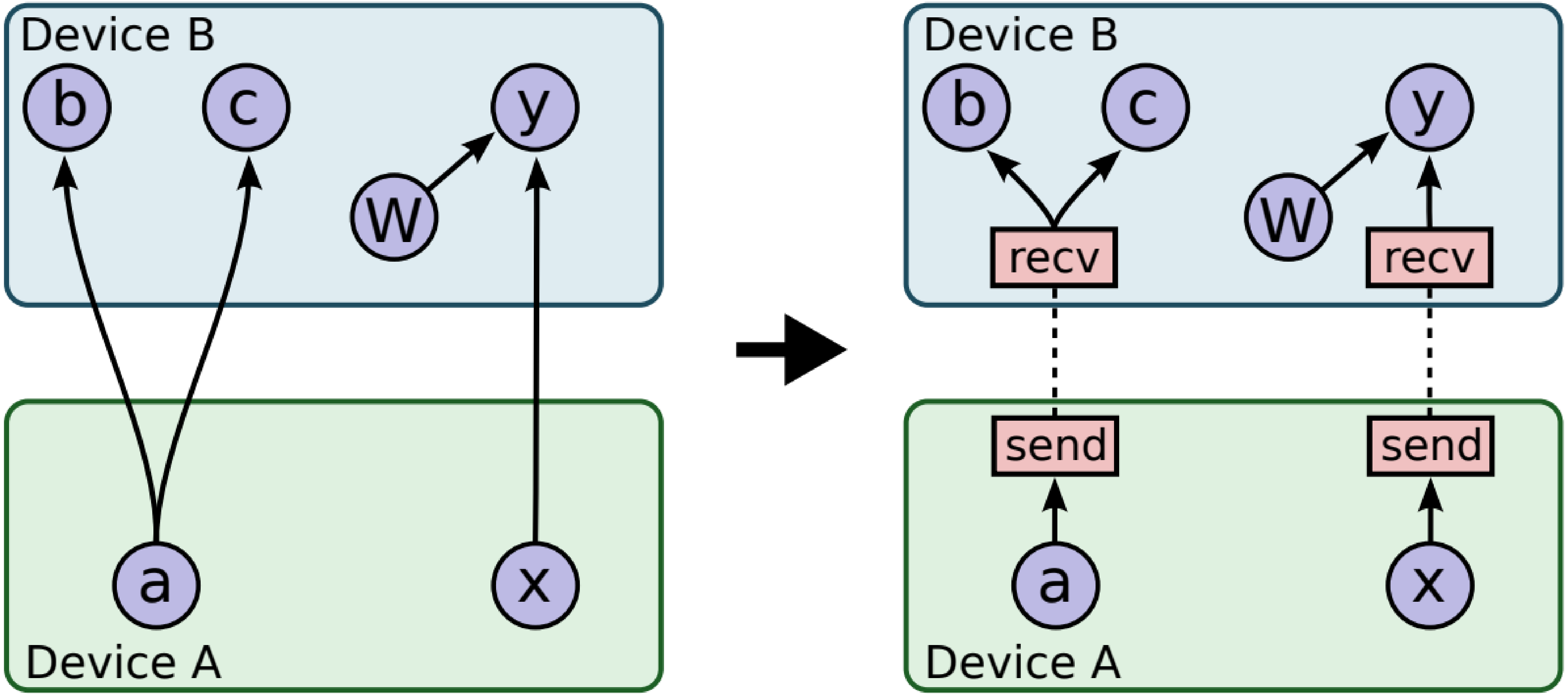


TensorFlow in Distributed Systems



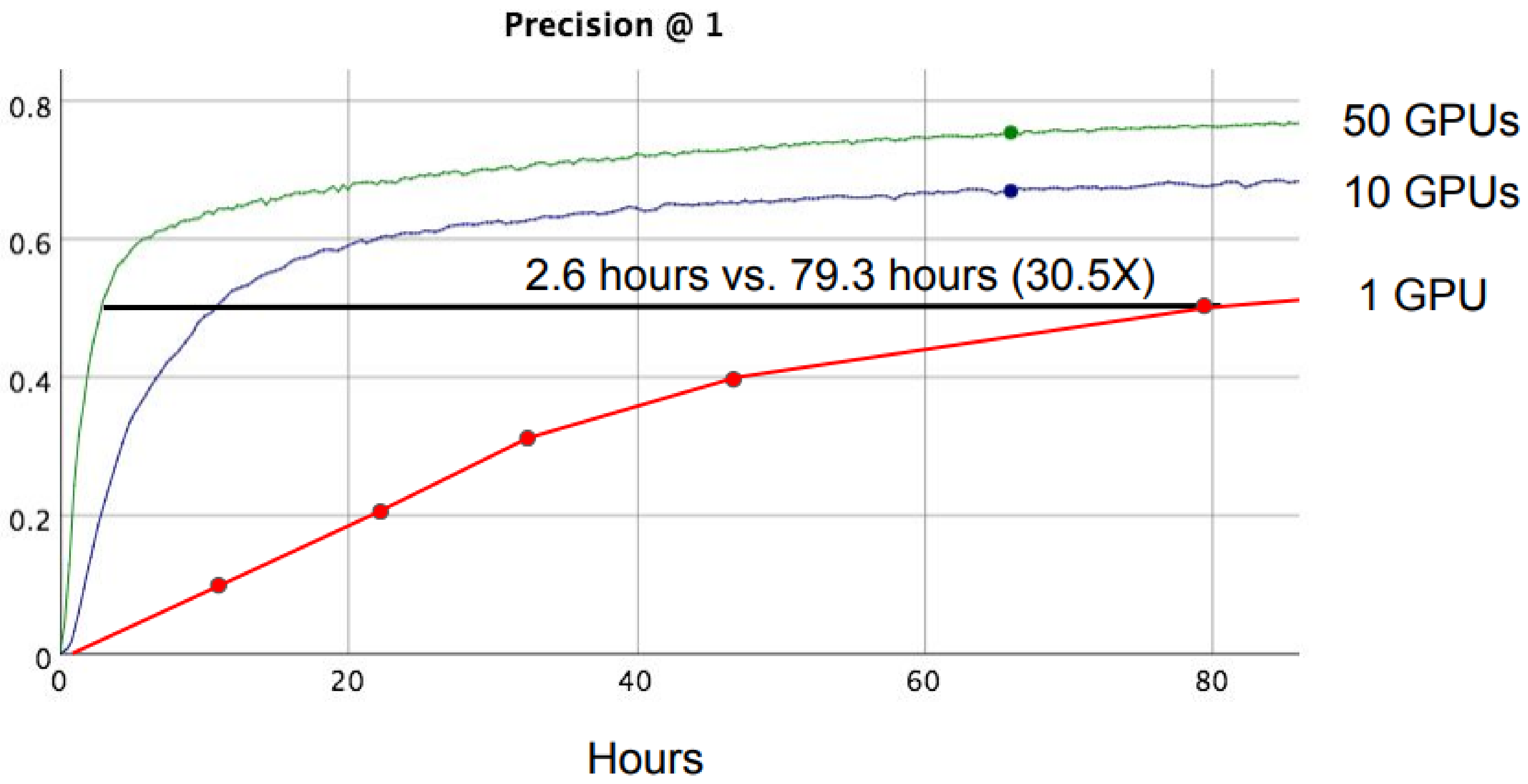
http://download.tensorflow.org/paper/whitepaper2015.pdf

TensorFlow in Distributed Systems cont.



http://download.tensorflow.org/paper/whitepaper2015.pdf

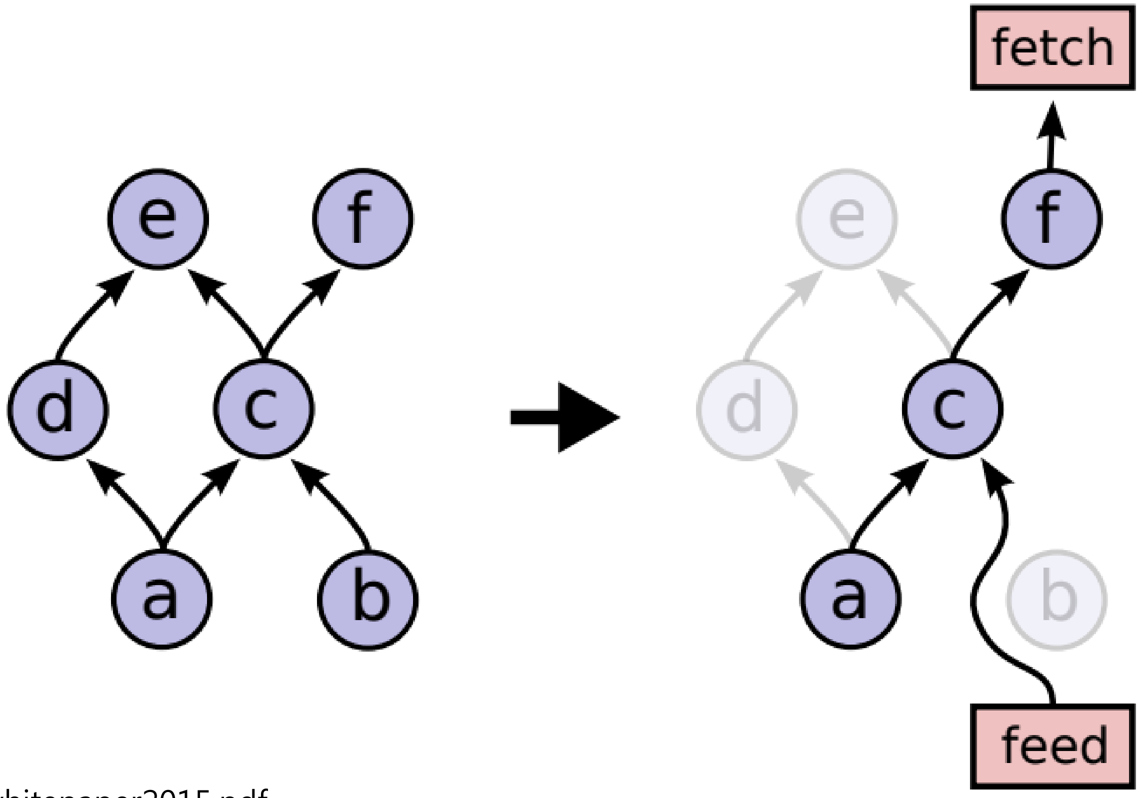
Image Model Training Time



https://www.slideshare.net/JenAman/large-scale-deep-learning-with-tensorflow

Partial Flow

- TensorFlow executes a **subgraph** of the whole graph.
- We do not need “e” and “d” to compute “f”.



http://download.tensorflow.org/paper/whitepaper2015.pdf

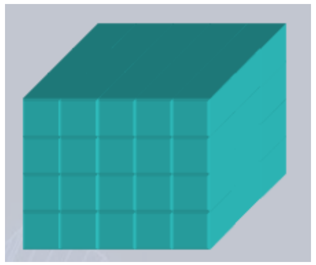
Graph Optimizations

- Common Subexpression Elimination
- Controlling Data Communication and Memory Usage
- Asynchronous Kernels
- Optimized Libraries for Kernel Implementations
  - BLAS, cuBLAS, GPU, cuda-convnet, cuDNN
- Lossy Compression
  - 32 → 16 → 32bit conversion

What is Tensor?

Tensor

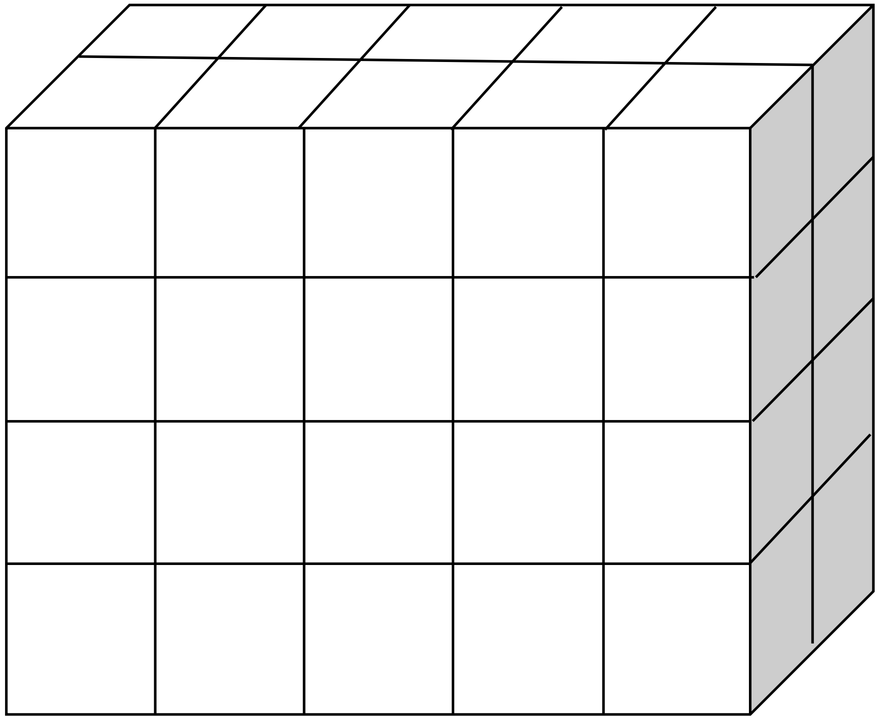
- A tensor is a **multidimensional data array**.

Order	0	1	2	3
	Scalar	**Vector**	**Matrix**	**Cube?**
	100	$[5, 3, 7, \ldots, 10]$	$\begin{bmatrix} 1 & 2 \\ 3 & 1 \end{bmatrix}$	

Shape of Tensor

- **List of dimensions** for each order.
- Shape = [4, 5, 2]

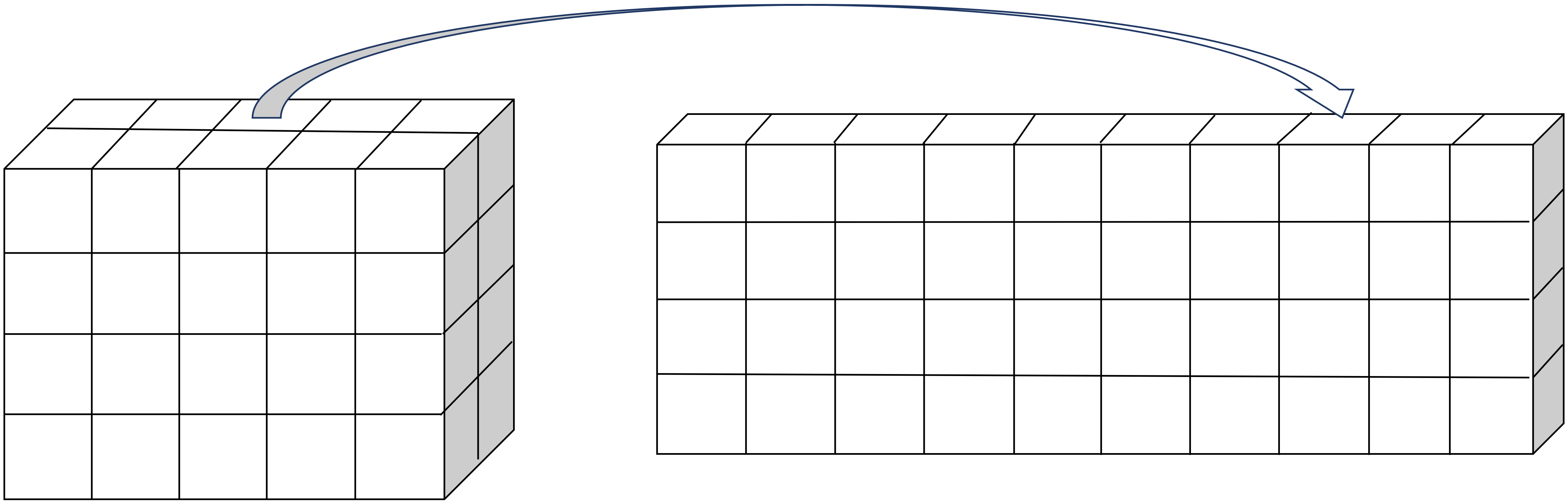
```
V = tf.Variable(tf.zeros([4, 5, 2]))
```



Reshape

- Reshapes the tensor.

```
V = tf.Variable(tf.zeros([4, 5, 2]))
W = tf.reshape(V, [4, 10])
```



Transpose

- Transposes tensors.
- Permutes the dimensions.

tf.transpose

```
transpose(
    a,
    perm=None,
    name='transpose'
)
```

```
a = np.arange(2*3*4)
x = tf.Variable(a)
x = tf.reshape(x, [2, 3, 4])

y1 = tf.transpose(x, [0, 2, 1])
y2 = tf.transpose(x, [2, 0, 1])
y3 = tf.transpose(x, [1, 2, 0])

print(y1.get_shape()) # (2,4,3)
print(y2.get_shape()) # (4,2,3)
print(y3.get_shape()) # (3,4,2)
```

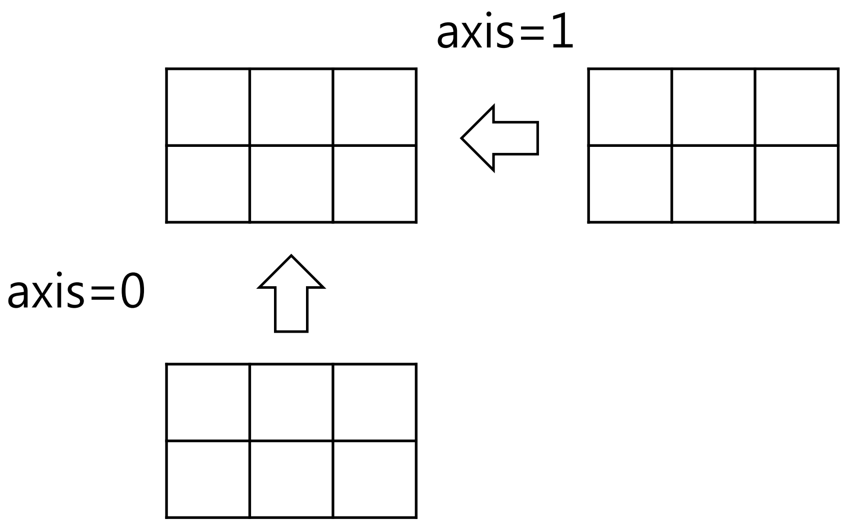
Concatenation

- Concatenate two or more tensors.

tf.concat

```
concat(
    values,
    axis,
    name='concat'
)
```

```
# tensor t1 with shape [2, 3]
# tensor t2 with shape [2, 3]
t3 = tf.concat([t1, t2], 0) # ==> [4, 3]
t4 = tf.concat([t1, t2], 1) # ==> [2, 6]
```



Reduce Operations

- Computes an operation over elements across dimensions of a tensor.
  - tf.reduce_sum(...), tf.reduce_prod(...), tf.reduce_max(...), tf.reduce_min(...)

tf.reduce_sum

```
reduce_sum(
    input_tensor,
    axis=None,
    keep_dims=False,
    name=None,
    reduction_indices=None
)
```

```
# 'x' is [[1, 1, 1]
#         [1, 1, 1]]
tf.reduce_sum(x) # ==> 6
tf.reduce_sum(x, 0) # ==> [2, 2, 2]
tf.reduce_sum(x, 1) # ==> [3, 3]
tf.reduce_sum(x, 1, keep_dims=True) # ==> [[3], [3]]
tf.reduce_sum(x, [0, 1]) # ==> 6
```

Matrix Multiplication

- Matrix multiplication with two tensors of order 2.

```
# 2-D tensor `a`
a = tf.constant([1, 2, 3, 4, 5, 6], shape=[2, 3]) # => [[1. 2. 3.]
                                                      [4. 5. 6.]]
# 2-D tensor `b`
b = tf.constant([7, 8, 9, 10, 11, 12], shape=[3, 2]) # => [[7. 8.]
                                                          [9. 10.]
                                                          [11. 12.]]
c = tf.matmul(a, b) # => [[58 64]
                          [139 154]]
```

Broadcasting

- Broadcasting is the process of making arrays with different shapes have compatible shapes for arithmetic operations.
  - This is similar to that of numpy
- Adding a vector to a matrix.

```
|1 2 3| + |7 8 9|
|4 5 6|
```

```
|1 2 3| + |7 8 9| = |8  10 12|
|4 5 6|   |7 8 9|   |11 13 15|
```

- Adding a scalar to a matrix

```
|1 2 3| + 7 = |8   9   10|
|4 5 6|       |11  12  13|
```

Gradients

- Constructs symbolic partial derivatives.

```
# Build a graph.
x = tf.placeholder(tf.float32, shape=())
y = x*x + tf.sin(x)
g = tf.gradients(y, x) # 2*x + cos(x)

# Launch the graph in a session.
sess = tf.Session()

# Evaluate the tensor `g`.
print(sess.run(g, {x:0.0})) # 1.0
print(sess.run(g, {x:np.pi})) # 5.2831855
```

Variables, Graph, and Session

Variables

- Variables are in-memory buffers containing tensors.
- All variables have names.
  - If you do not give a name, then unique name will be automatically assigned.

```
# Various ways to create variables.
x = tf.Variable(tf.zeros([200]), name="x")
y = tf.Variable([[1, 0], [0, 1]]) # identity matrix
z = tf.constant(6.0) # this is also a variable that does not change!
learning_rate = tf.Variable(0.01, trainable=False) # not trainable!
```

Initialization of Variables and Session

- Variables initializer must be called before other ops in your model can be run.
- A session encapsulates the control and state of the TensorFlow runtime.
- A graph is created and allocated in memory when the session is created.

```
...
# Add an op to initialize the variables.
init_op = tf.global_variables_initializer()

# Later, when launching the model
with tf.Session() as sess:
  # Run the init operation.
  sess.run(init_op)

  # Use the model
  ...
```

sess.run()

- Runs operations and evaluates tensors.
- You may feed values to specific variables in the graph.

```
# Build a graph.
a = tf.constant(5.0)
b = tf.constant(6.0)
c = a * b

# Launch the graph in a session.
sess = tf.Session()

# Evaluate the tensor `c`.
print(sess.run(c)) # 30.0
print(sess.run(c, {b:3.0})) # 15.0
print(sess.run(c, {a:1.0, b:2.0})) # 2.0
print(sess.run(c, {c:100.0})) # 100.0
```

Placeholders

- Inserts a placeholder for a variable that will be always fed.
- Pass type and shape for the placeholders.

```
# Build a graph.
a = tf.placeholder(tf.float32, shape=()) # scalar tensor
b = tf.constant(6.0)
c = a * b

# Launch the graph in a session.
sess = tf.Session()

# Evaluate the tensor `c`.
print(sess.run(c)) # error !
print(sess.run(c, {b:3.0})) # error !
print(sess.run(c, {a:2.0})) # 12.0
```

Variable Update

- Variables can be updated through assign(...) function.

```
# Build a graph.
x = tf.Variable(100)
assign_op = x.assign(x - 1)

# Launch the graph in a session.
sess = tf.Session()

# Run assign_op
sess.run(tf.global_variables_initializer())
print(sess.run(assign_op)) # 99
print(sess.run(assign_op)) # 98
print(sess.run(assign_op)) # 97
```

Problems with Variables

- Sometimes we want to reuse same set of variables.
- Whenever Variable is called it only creates new variable.
- How can we reuse same variable?

```
# define function
def f(x):
  b = tf.Variable(tf.random_normal([10], stddev=1.0))
  return x + b


...
y1 = f(x1)
y2 = f(x2) # it use different 'b' variable
```

Sharing Variables: tf.get_variable()

- The function tf.get_variable() is used to get or create a variable instead of a direct call to tf.Variable.

```
# define function
def f(x):
    b = tf.get_variable('b', [10], initializer=tf.random_normal_initializer())
    return x + b

...
with tf.variable_scope("bias") as scope:
   y1 = f(x1)
   scope.reuse_variables()
   y2 = f(x2) # it use same 'b' variable
```

How Does Variable Scope Work?

- Variable scope wraps variables with a namespace.
- Reusing variables is only valid within the scope.

```
with tf.variable_scope("foo"):
    v = tf.get_variable("v", [1])
assert v.name == "foo/v:0"
```

```
with tf.variable_scope("foo"):
    v = tf.get_variable("v", [1])
with tf.variable_scope("foo", reuse=True):
    v1 = tf.get_variable("v", [1])
assert v1 is v
```

```python
with tf.variable_scope("root"):
    # At start, the scope is not reusing.
    assert tf.get_variable_scope().reuse == False
    with tf.variable_scope("foo"):
        # Opened a sub-scope, still not reusing.
        assert tf.get_variable_scope().reuse == False
    with tf.variable_scope("foo", reuse=True):
        # Explicitly opened a reusing scope.
        assert tf.get_variable_scope().reuse == True
        with tf.variable_scope("bar"):
            # Now sub-scope inherits the reuse flag.
            assert tf.get_variable_scope().reuse == True
    # Exited the reusing scope, back to a non-reusing one.
    assert tf.get_variable_scope().reuse == False
```

Caution: Name Duplication

- Calling tf.get_variable() twice with same name when reuse is off, invokes error.

```
b1 = tf.get_variable('b', [10], initializer=tf.random_normal_initializer())
b2 = tf.get_variable('b', [10], initializer=tf.random_normal_initializer()) # error!
```

```
ValueError: Variable b already exists, disallowed.
Did you mean to set reuse=True in VarScope?
Originally defined at:
```

Saving Variables

- Call tf.train.Saver() to manage all variables in the model.

```
...
# Add an op to initialize the variables.
init_op = tf.global_variables_initializer()

# Add ops to save and restore all the variables.
saver = tf.train.Saver()

# Later, launch the model, initialize the variables, do some work, save the
# variables to disk.
with tf.Session() as sess:
  sess.run(init_op)
  # Do some work with the model.
  ..
  # Save the variables to disk.
  save_path = saver.save(sess, "/tmp/model.ckpt")
  print("Model saved in file: %s" % save_path)
```

Restoring Variables

- The same Saver object is used to restore variables.

```
...
# Add ops to save and restore all the variables.
saver = tf.train.Saver()

# Later, launch the model, use the saver to restore variables from disk, and
# do some work with the model.
with tf.Session() as sess:
  # Restore variables from disk.
  saver.restore(sess, "/tmp/model.ckpt")
  print("Model restored.")
  # Do some work with the model
  ...
```

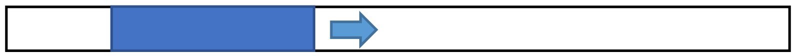
Convolutional Neural Network in TensorFlow

Four Main Components in Machine Learning

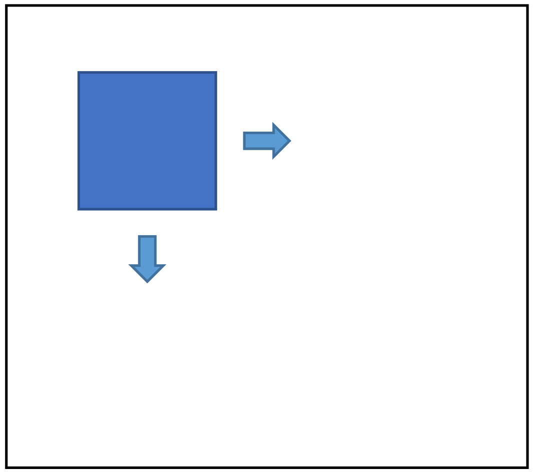
- Hypothesis space
- Objective function
- Optimization algorithm
- Data

Convolution Operations: conv1d, 2d, 3d

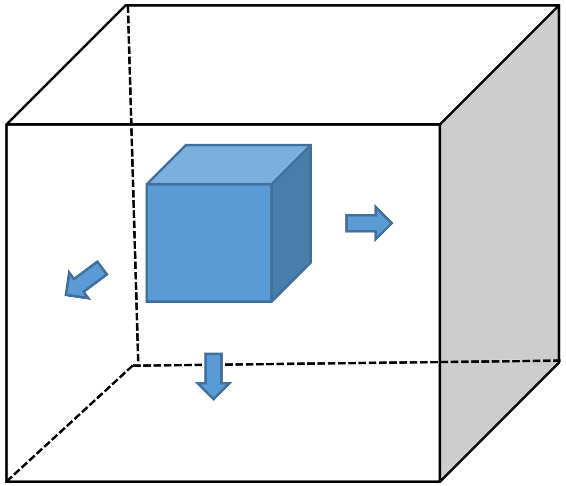
- TensorFlow provides convolution operations.



conv1d



conv2d



conv3d

tf.nn.conv2d()

- Computes a 2-D convolution given 4-D input and filter tensors.
- Input is 4-D tensor.
  - shape=(batch_size, height, width, channels)
- Filter is 4-D tensor.
  - shape=(filter_height, filter_width, in_channels, out_channels)
- Stride is a size of the sliding window for each dimension of input.

tf.nn.conv2d

```
conv2d(
    input,
    filter,
    strides,
    padding,
    use_cudnn_on_gpu=None,
    data_format=None,
    name=None
)
```

tf.nn.conv2d() Padding

- padding = "VALID"
  - Do not use zero padding.
  - Size of filter map shrinks.
  - out_height = ceil((in_height - filter_height + 1) / strides[1])
  - out_width = ceil((in_width - filter_width + 1) / strides[2])
- padding = "SAME"
  - Tries to pad zeros evenly left and right to preserve width and height.
  - If the amount of columns to be added is odd, it will add the extra column to the right.
  - out_height = ceil(in_height / strides[1])
  - out_width = ceil(in_width / strides[2])

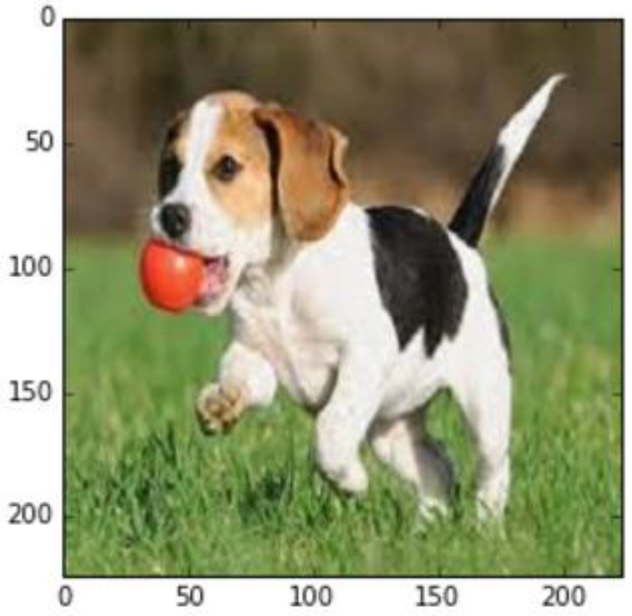
tf.nn.conv2d() Example

```
import tensorflow as tf
import numpy as np
from PIL import Image
import matplotlib.pyplot as plt
%matplotlib inline


# constants
batch_size = 1
img_height = 224
img_width = 224
img_channel = 3

# Build a graph.
x = tf.placeholder(tf.float32, [batch_size, img_height, img_width, img_channel])
w = tf.Variable(tf.random_normal([5, 5, 3, 64], stddev=0.35))
output = tf.nn.conv2d(x, w, strides=[1, 2, 2, 1], padding='SAME')
```

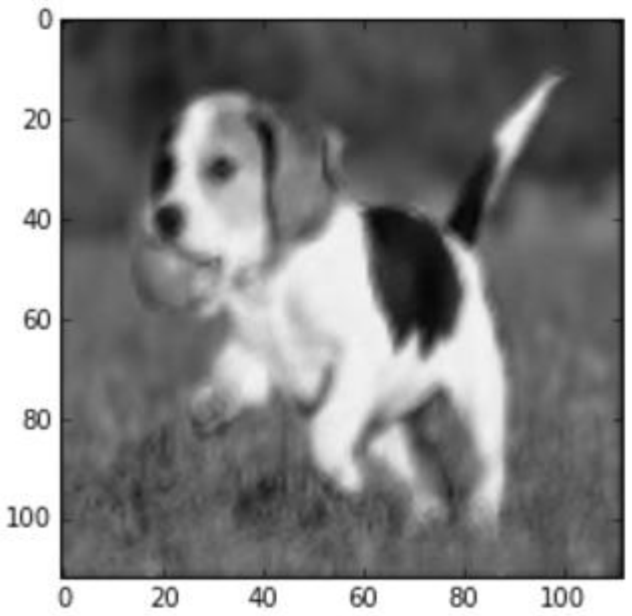
tf.nn.conv2d() Example cont.

```
# Launch the graph in a session.
sess = tf.Session()


with tf.Session() as sess:
    tf.global_variables_initializer().run()

    img = np.array(Image.open('test.jpg'))
    plt.imshow(img)
    plt.show()
    img = img.reshape([1, img_height, img_width, img_channel])

    _out = sess.run(output, {x:img})
    print(_out.shape)

    plt.imshow(_out[0, :, :, 0], cmap='gray')
    plt.show()
```

Original image



(1, 112, 112, 64)



Gray image from the first channel of the output

Adding Bias After tf.nn.conv2d()

- To enhance representation power of CNN, it is nice to add bias to the output.

```
# Build a graph.
x = tf.placeholder(tf.float32, [batch_size, img_height, img_width, img_channel])
w = tf.Variable(tf.random_normal([5, 5, 3, 64], stddev=0.35))
b = tf.Variable(tf.random_normal([64], stddev=0.35))
output = tf.nn.conv2d(x, w, strides=[1, 2, 2, 1], padding='SAME') + b
```

Broadcasting addition

Max Pooling

- Performs the max pooling on the input.
- 'ksize'
  - The size of the window for each dimension of the input tensor.
  - For 2 x 2 pooling, ksize = [1, 2, 2, 1]
- 'strides' and 'padding' are same as those in the tf.nn.conv2d().
- We can use convolution of stride 2, instead of using max pooling without significant loss of performance.
  - Check "Springenberg, J. T. et al., (2014)."

tf.nn.max_pool

```
max_pool(
    value,
    ksize,
    strides,
    padding,
    data_format='NHWC',
    name=None
)
```

Max Pooling Example

- Example of 2 x 2 max pooling.

```
# Build a graph.
x = tf.placeholder(tf.float32, [batch_size, img_height, img_width, img_channel])
w = tf.Variable(tf.random_normal([5, 5, 3, 64], stddev=0.35))
b = tf.Variable(tf.random_normal([64], stddev=0.35))
c = tf.nn.conv2d(x, w, strides=[1, 1, 1, 1], padding='SAME') + b
output = tf.nn.max_pool(c, [1, 2, 2, 1], strides=[1, 2, 2, 1], padding='SAME')
```

Activation Functions

- TensorFlow provides most of the popular activation functions.
  - tf.nn.relu, tf.nn.softmax, tf.nn.sigmoid, tf.nn.elu, …
- Example of using rectified linear function.

```
# Build a graph.
x = tf.placeholder(tf.float32, [batch_size, img_height, img_width, img_channel])
w = tf.Variable(tf.random_normal([5, 5, 3, 64], stddev=0.35))
b = tf.Variable(tf.random_normal([64], stddev=0.35))
c = tf.nn.conv2d(x, w, strides=[1, 1, 1, 1], padding='SAME') + b
c = tf.nn.relu(c)
output = tf.nn.max_pool(c, [1, 2, 2, 1], strides=[1, 2, 2, 1], padding='SAME')
```

Fully Connected (Dense) Layer

- Fully connected (fc) layer can be implemented by calling tf.matmul() function.
  - y = tf.matmul(x, W)
- To compute fc layer after convolution operation, we need to reshape 4-D tensor to 2-D tensor.
  - [batch_size, height, width, channel]

    → [batch_size, height*width*channel]

Fully Connected Layer Example

```
# Build a graph.
x = tf.placeholder(tf.float32, [batch_size, img_height, img_width, img_channel])
w = tf.Variable(tf.random_normal([5, 5, 3, 8], stddev=0.35))
b = tf.Variable(tf.random_normal([8], stddev=0.35))
c = tf.nn.conv2d(x, w, strides=[1, 1, 1, 1], padding='SAME') + b
c = tf.nn.relu(c)
h = tf.nn.max_pool(c, [1, 2, 2, 1], strides=[1, 2, 2, 1], padding='SAME')

h = tf.reshape(h, [batch_size, -1])
fc_w = tf.Variable(tf.random_normal([int(h.get_shape()[1]), 10], stddev=0.35))
fc_b = tf.Variable(tf.random_normal([10], stddev=0.35))
output = tf.matmul(h, fc_w) + fc_b
output = tf.nn.softmax(output)
```

TF Layers: High-level API

- The TensorFlow layers module provides a high-level API that makes it easy to construct a neural network.
- No explicit weight (filter) variable creation.
- Includes activation function in one API.

```
# Convolutional Layer #1
conv1 = tf.layers.conv2d(
    inputs=input_layer,
    filters=32,
    kernel_size=[5, 5],
    padding="same",
    activation=tf.nn.relu)

# Pooling Layer #1
pool1 = tf.layers.max_pooling2d(inputs=conv1, pool_size=[2, 2], strides=2)
```

Other High-level API

- TF Slim
- TF Learn
- Keras (with TensorFlow backend)
- Tensor2Tensor

Loss Functions

- TensorFlow provides various loss functions.
  - tf.nn.softmax_cross_entropy_with_logits, tf.nn.l2_loss, …
- TF Layers also provides similar functions starting with tf.losses.
- Example of tf.losses.softmax_cross_entropy.

```
onehot_labels = tf.one_hot(indices=tf.cast(labels, tf.int32), depth=10)
loss = tf.losses.softmax_cross_entropy(
    onehot_labels=onehot_labels, logits=logits)
```

- Full codes are in https://www.tensorflow.org/tutorials/layers

Optimizers

- TensorFlow provides popular optimizers.
  - Adam, AdaGrad, RMSProp, SGD, …
- Example of plain gradient descent optimizer.
- Parameters are updated when sess.run(train_op, …) is called.

```
# optimizer
learning_rate = 0.01
optimizer = tf.train.GradientDescentOptimizer(learning_rate)
train_op = optimizer.minimize(loss)
…
sess.run(train_op, {x: batch_x, y: batch_y})
```

Review of the Batch Normalization

- Normalize the activations of the previous layer.
- Advantages
  - Allows much higher learning rates.
  - Can be less careful about initialization.
  - Faster learning.
  - No need for Dropout.

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1\ldots m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_\mathcal{B} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma_\mathcal{B}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_\mathcal{B})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_\mathcal{B}}{\sqrt{\sigma_\mathcal{B}^2 + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma\widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Batch Normalization

- tf.nn.batch_normalization() needs bunch of variables and does not support moving statistics, nor inference mode.
- Use tf.layers.batch_normalization()
  - Put **training**=False, when inference mode.
  - It supports moving statistics of the mean and variance.
  - ‘**momentum**’ determines forget rate of the moving statistics.

tf.layers.batch_normalization

```
batch_normalization(
    inputs,
    axis=-1,
    momentum=0.99,
    epsilon=0.001,
    center=True,
    scale=True,
    beta_initializer=tf.zeros_initializer(),
    gamma_initializer=tf.ones_initializer(),
    moving_mean_initializer=tf.zeros_initializer(),
    moving_variance_initializer=tf.ones_initializer(),
    beta_regularizer=None,
    gamma_regularizer=None,
    training=False,
    trainable=True,
    name=None,
    reuse=None,
    renorm=False,
    renorm_clipping=None,
    renorm_momentum=0.99
)
```

tf.layers.batch_normalization

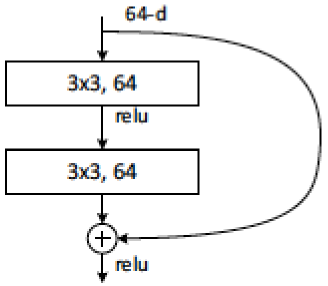
```
import tensorflow as tf
import numpy as np

x = tf.placeholder(tf.float32, shape=(3, 1), name='x')
tr = tf.placeholder(tf.bool, shape=())

y = tf.layers.batch_normalization(x, axis=1, momentum=0.9, training=tr)
update_ops = tf.get_collection(tf.GraphKeys.UPDATE_OPS)

with tf.Session() as sess:
    tf.global_variables_initializer().run()

    batch_x = np.arange(3).reshape([3, 1]).astype(np.float32)

    for i in range(10):
        [_y, _] = sess.run([y, update_ops], {x:batch_x, tr:True})
        if i == 0:
            print(_y.flatten())
            print('='*50)

        _y = sess.run(y, {x:batch_x, tr:False})
        print(_y.flatten())
```

- 'update_ops' should be called to update statistics of batch normalization.
- In inference mode, the values are normalized by moving statistics.

```
[-1.22382736  0.          1.22382736]
==================================================
[-0.10165697  0.91491264  1.93148232]
[-0.19621371  0.83649004  1.86919379]
[-0.28398117  0.76391983  1.81182086]
[-0.36527961  0.69688851  1.75905657]
[-0.44043604  0.63508356  1.71060312]
[-0.50978124  0.57819533  1.66617191]
[-0.57364696  0.5259189   1.6254847 ]
[-0.63236326  0.477956    1.58827519]
[-0.68625563  0.43401629  1.55428815]
[-0.73564309  0.39381903  1.5232811 ]
```

Residual Connection

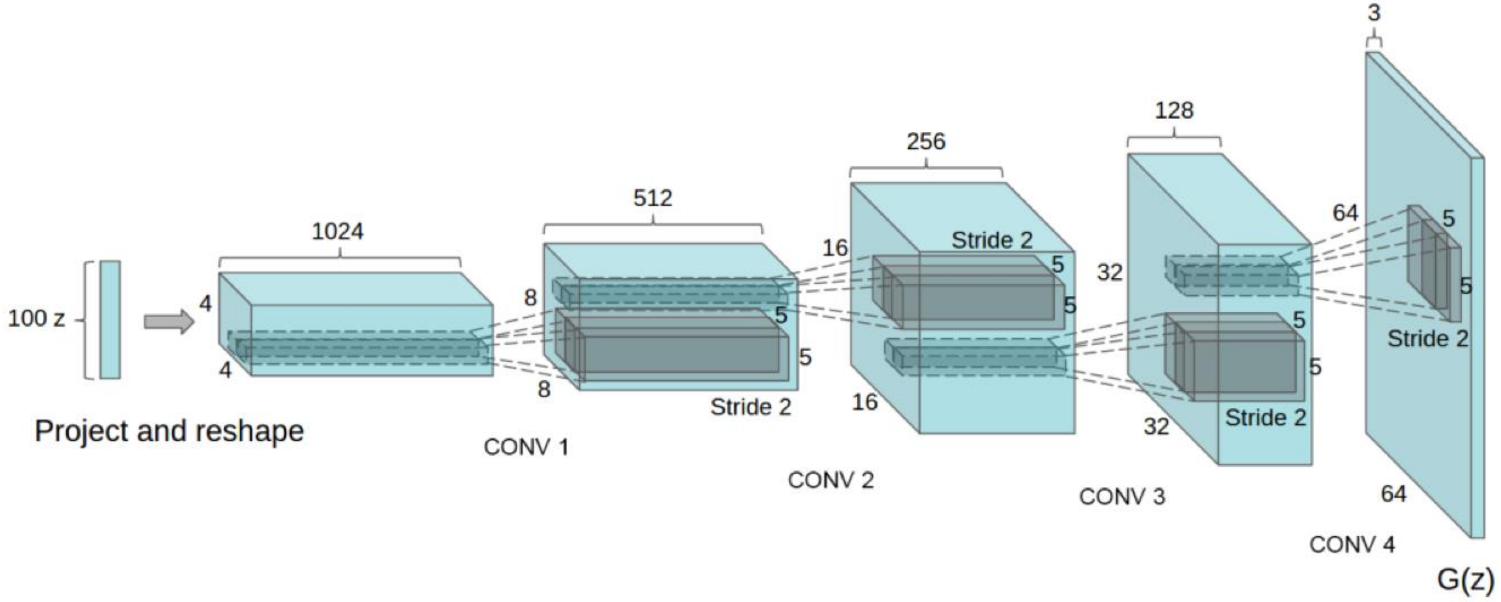
- A Residual Network is a neural network architecture which solves the problem of vanishing gradients.
  - Residual connection: $y = f(x) + x$




```
x = tf.placeholder(tf.float32, [batch_size, img_height, img_width, img_channel])
h = tf.layers.conv2d(x, filters=64, kernel_size=[11, 11], strides=[4, 4], padding="SAME")

# Residual connection
h2 = tf.layers.conv2d(h, filters=64, kernel_size=[3, 3], strides=[1, 1], padding="SAME")
h3 = tf.layers.conv2d(h2, filters=64, kernel_size=[3, 3], strides=[1, 1], padding="SAME")
y = h3 + h
```

Transposed Convolution (Deconvolution)

- The need for transposed convolutions generally arises from the desire to use a transformation going in the opposite direction of a normal convolution.
- tf.layers.conv2d_transpose()



Load Pre-trained Models

- There are popular network architectures in TF Slim
  - https://github.com/tensorflow/models/tree/master/slim
  - Inception V1-V4
  - Inception-ResNet-v2
  - ResNet 50/101/152
  - VGG 16/19
  - MobileNet

Thank You

References

- https://www.tensorflow.org
- https://www.slideshare.net/JenAman/large-scale-deep-learning-with-tensorflow
- https://www.slideshare.net/AndrewBabiy2/tensorflow-example-for-ai-ukraine2016
- http://download.tensorflow.org/paper/whitepaper2015.pdf