Introduction to Deep Learning with

TensorFlow

Sebastian Raschka

PyData AnnArbor 2017 • August 24, 2016

Slides

Speaker Deck:
https://speakerdeck.com/rasbt/introduction-to-deep-learning-with-tensorflow-at-pydata-ann-arbor

Code snippets

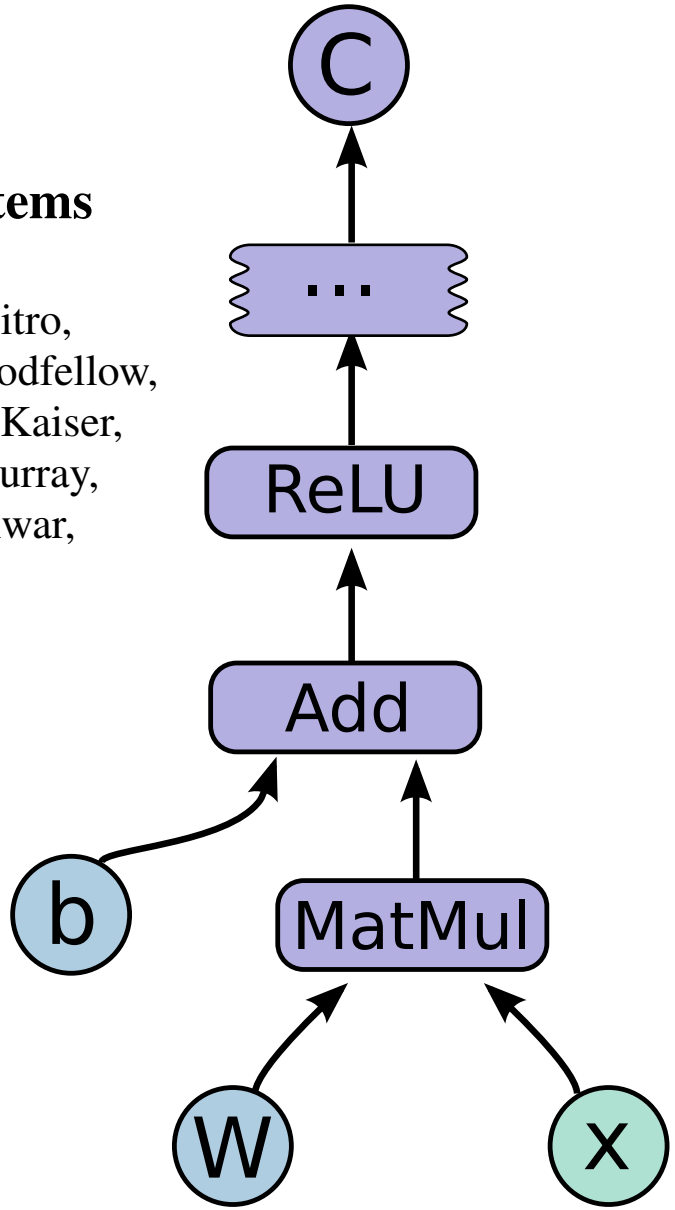
GitHub:
https://github.com/rasbt/pydata-annarbor2017-dl-tutorial

TensorFlow:
Large-Scale Machine Learning on Heterogeneous Distributed Systems

(Preliminary White Paper, November 9, 2015)

Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Ian Goodfellow, Andrew Harp, Geoffrey Irving, Michael Isard, Yangqing Jia, Rafal Jozefowicz, Lukasz Kaiser, Manjunath Kudlur, Josh Levenberg, Dan Mané, Rajat Monga, Sherry Moore, Derek Murray, Chris Olah, Mike Schuster, Jonathon Shlens, Benoit Steiner, Ilya Sutskever, Kunal Talwar, Paul Tucker, Vincent Vanhoucke, Vijay Vasudevan, Fernanda Viégas, Oriol Vinyals, Pete Warden, Martin Wattenberg, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng
Google Research*

https://static.googleusercontent.com/media/research.google.com/en//pubs/archive/45166.pdf



Tensors?

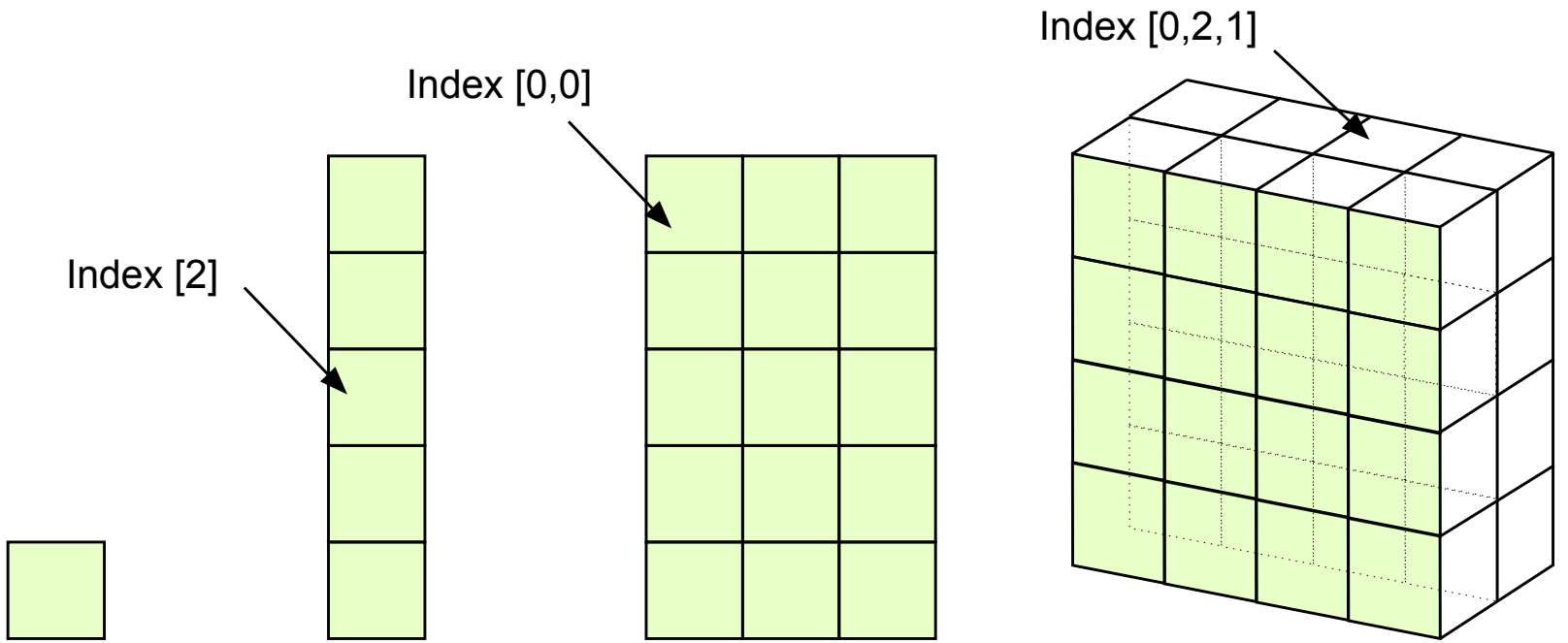
Scalar: $\mathbb{R}$

Vector: $\mathbb{R}^n$

Matrix: $\mathbb{R}^n \times \mathbb{R}^m$

3-Tensor: $\mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^p$

…



https://sebastianraschka.com/pdf/books/dlb/appendix_g_tensorflow.pdf

Installing TensorFlow

pip install tensorflow
pip install tensorflow-gpu

https://www.tensorflow.org/install/

pip install tensorflow
pip install tensorflow-gpu

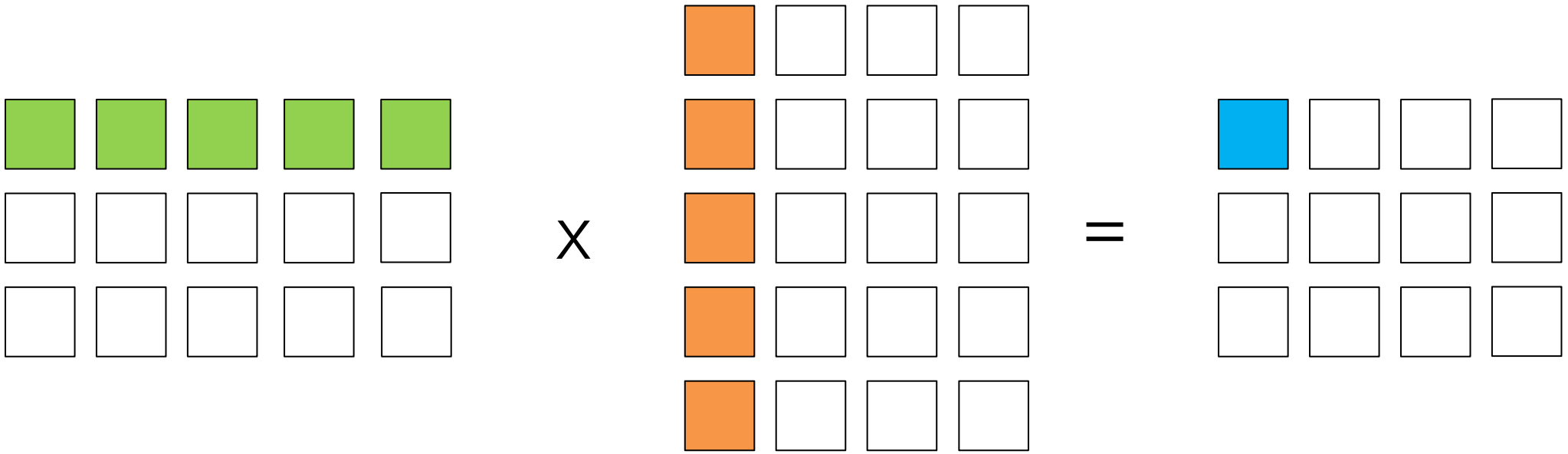
Specifications	Intel® Core™ i7-6900K Processor Extreme Ed.	NVIDIA GeForce® GTX™ 1080 Ti
Base Clock Frequency	3.2 GHz	< 1.5 GHz
Cores	8	3584
Memory Bandwidth	64 GB/s	484 GB/s
Floating-Point Calculations	409 GFLOPS	11300 GFLOPS
Cost	~ $1000.00	~ $700.00

Setup help:

- https://www.tensorflow.org/install/
- https://sebastianraschka.com/pdf/books/dlb/appendix_h_cloud-computing.pdf

Vectorization

```
X = np.random.random((num_train_examles, num_features))
W = np.random.random((num_features, num_hidden))
```



```
logits = np.zeros([num_train_examples, num_hidden])

for i, row in enumerate(X): # row = training_example

    for j, col in enumerate(W.T): # col = features

        vector_dot_product = 0
        for a, b in zip(row, col):
            vector_dot_product += a*b

        logits[i, j] = vector_dot_product

np.allclose(logits, np.dot(X, W))
```

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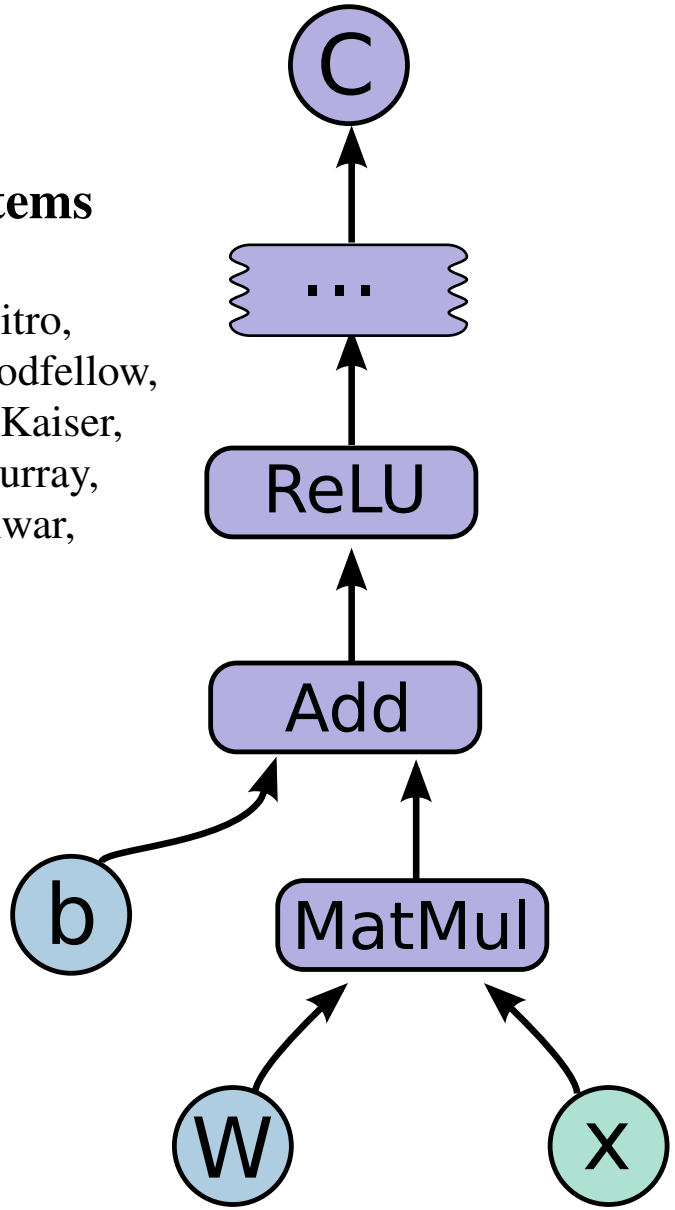
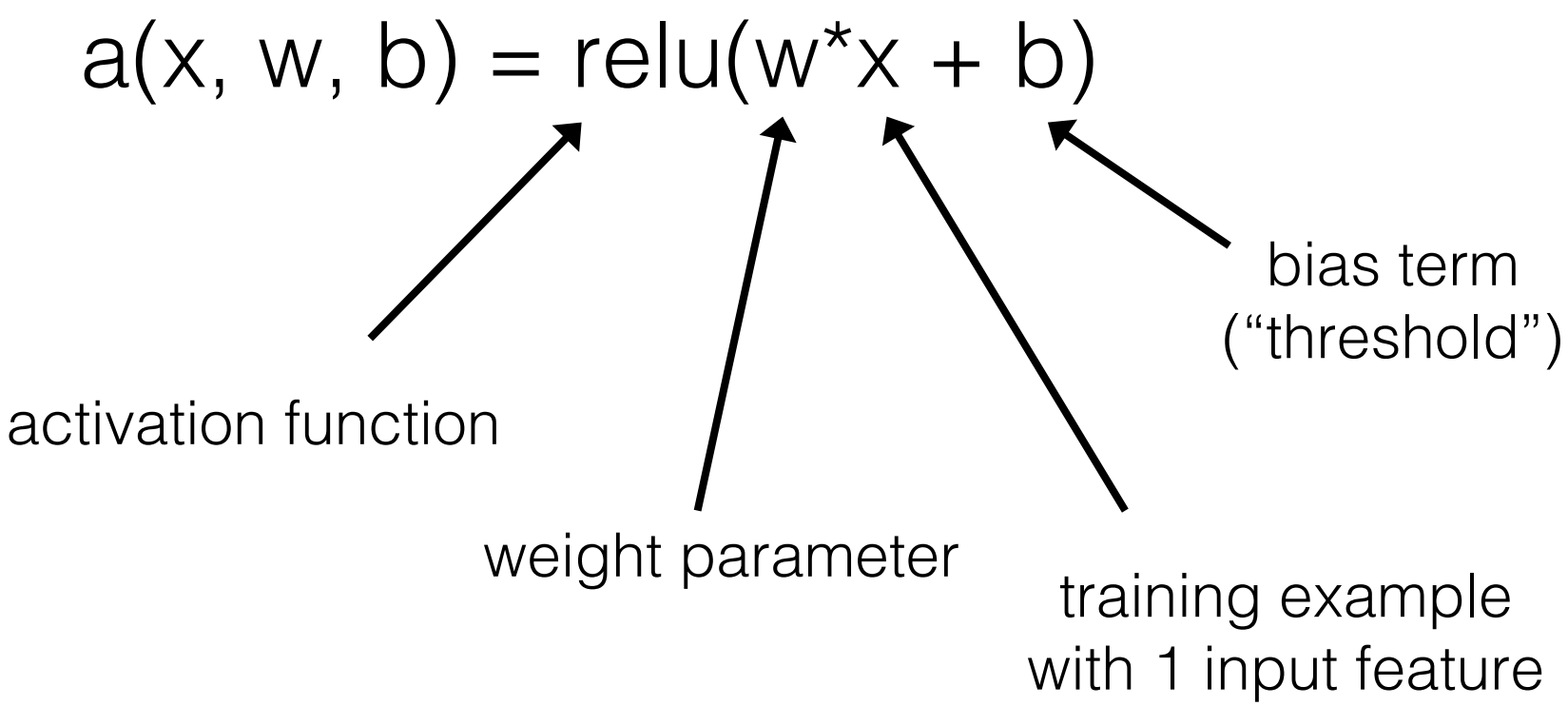


Computation Graphs

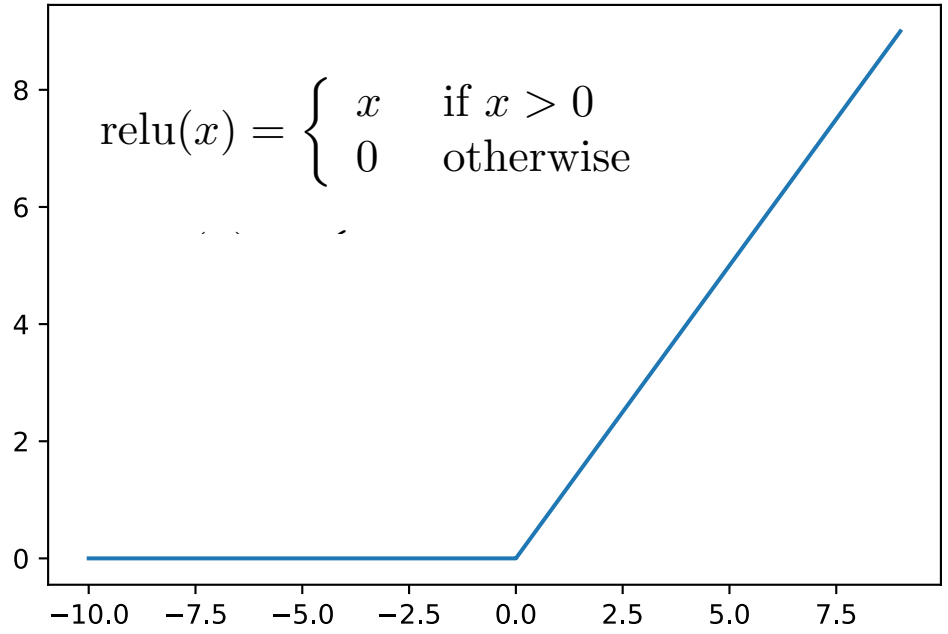


REctified Linear Unit

```python
import matplotlib.pyplot as plt
import numpy as np

def relu(x):
    # max(0, x)
    return x * (x > 0)

x = np.arange(-10, 10)
plt.plot(x, relu(x))
```



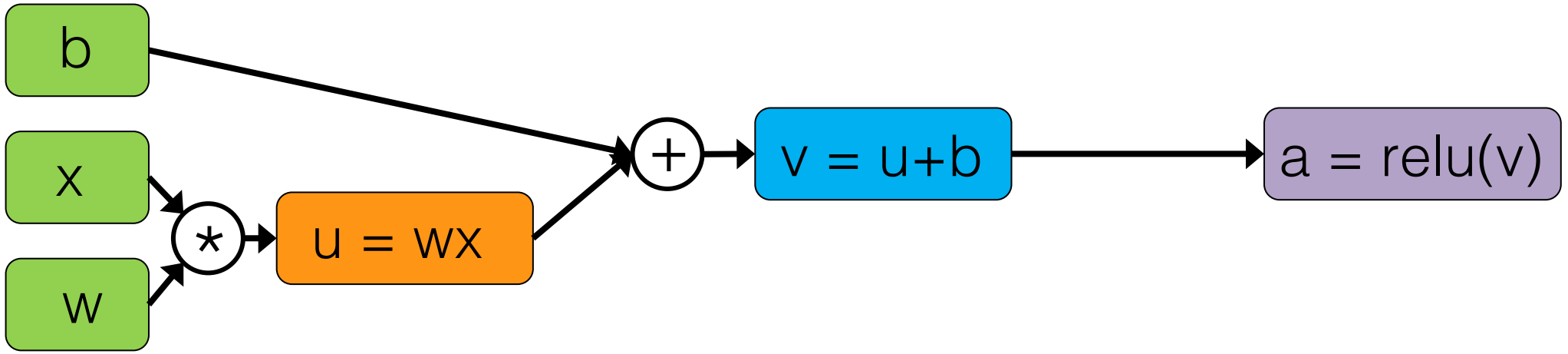
Computation Graphs

$$a(x, w, b) = \text{relu}(\underbrace{w*x}_{u} + b)$$

$$\underbrace{\qquad\qquad}_{v}$$

Computation Graphs

$$a(x, w, b) = \text{relu}(\underbrace{w*x}_{u} + \underbrace{b}_{v})$$



Computation Graphs

```
import tensorflow as tf

g = tf.Graph()
with g.as_default() as g:

    x = tf.placeholder(dtype=tf.float32, shape=None, name='x')
    w = tf.Variable(initial_value=2, dtype=tf.float32, name='w')
    b = tf.Variable(initial_value=1, dtype=tf.float32, name='b')

    u = x * w
    v = u + b
    a = tf.nn.relu(v)

    init_op = tf.global_variables_initializer()

print(x, w, b, u, v, a)
```

$$a(x, w, b) = \text{relu}(\underbrace{w*x}_{u} + \underbrace{b}_{v})$$

Computation Graphs

```
import tensorflow as tf

g = tf.Graph()
with g.as_default() as g:

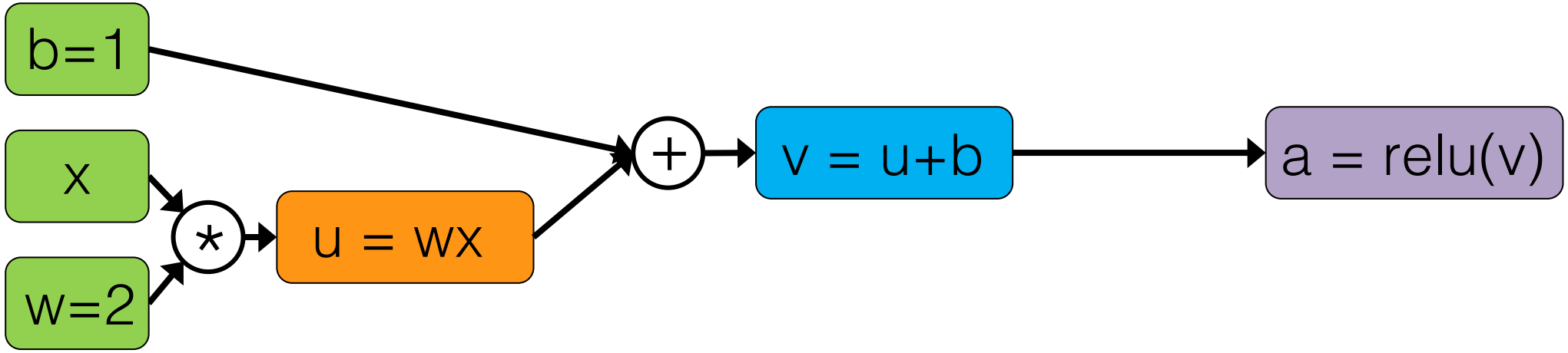
    x = tf.placeholder(dtype=tf.float32, shape=None, name='x')
    w = tf.Variable(initial_value=2, dtype=tf.float32, name='w')
    b = tf.Variable(initial_value=1, dtype=tf.float32, name='b')

    u = x * w
    v = u + b
    a = tf.nn.relu(v)

print(x, w, b, u, v, a)
```

```
Tensor("x:0", dtype=float32) <tf.Variable 'w:0' shape=() dtype=float32_ref> <tf.Variable
'b:0' shape=() dtype=float32_ref> Tensor("mul:0", dtype=float32) Tensor("add:0",
dtype=float32) Tensor("Relu:0", dtype=float32)
```

Computation Graphs




```
with tf.Session(graph=g) as sess:
    sess.run(init_op)
    b_res = sess.run('b:0')

print(b_res)

1.0
```

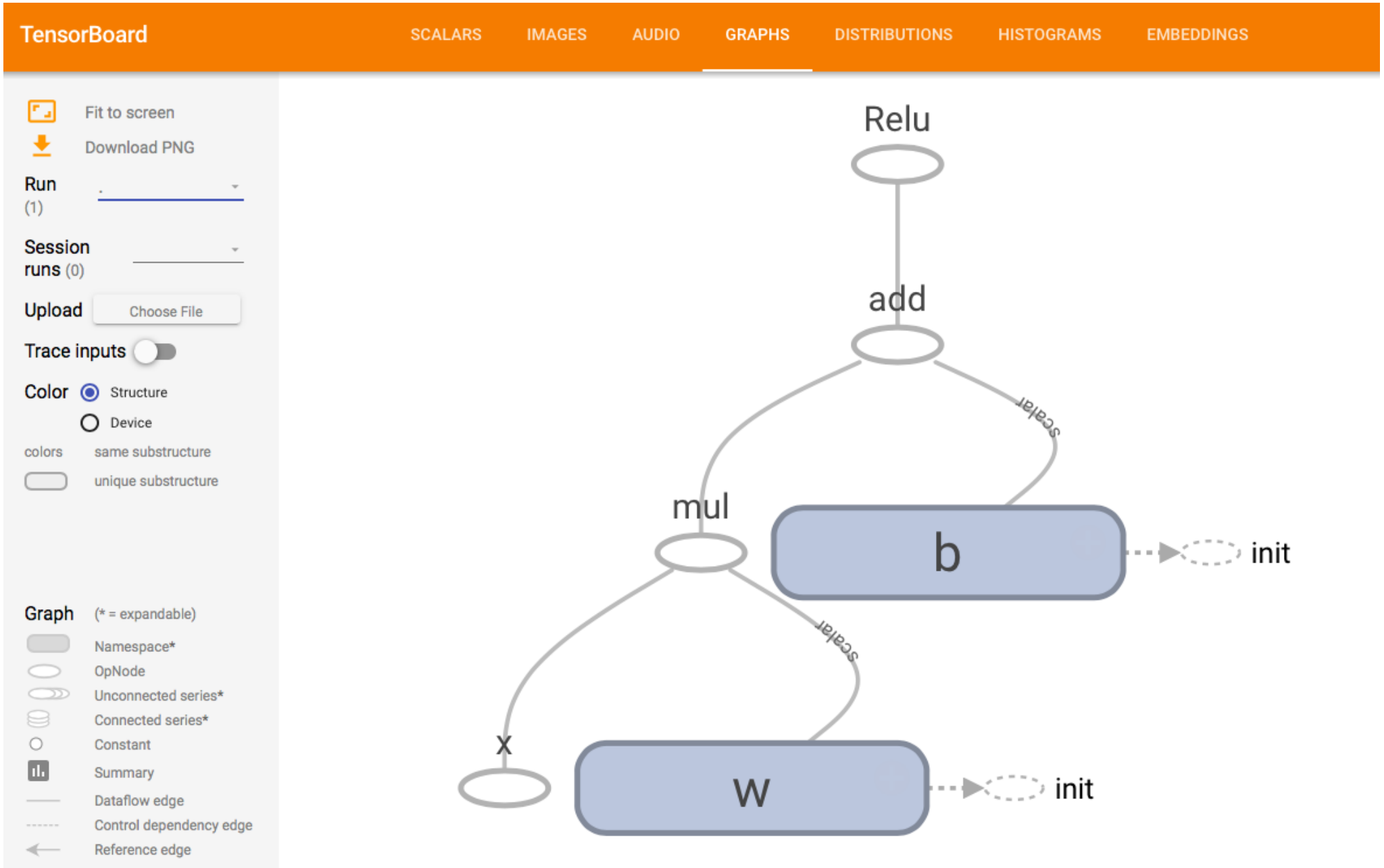
TensorBoard

```
with tf.Session(graph=g) as sess:

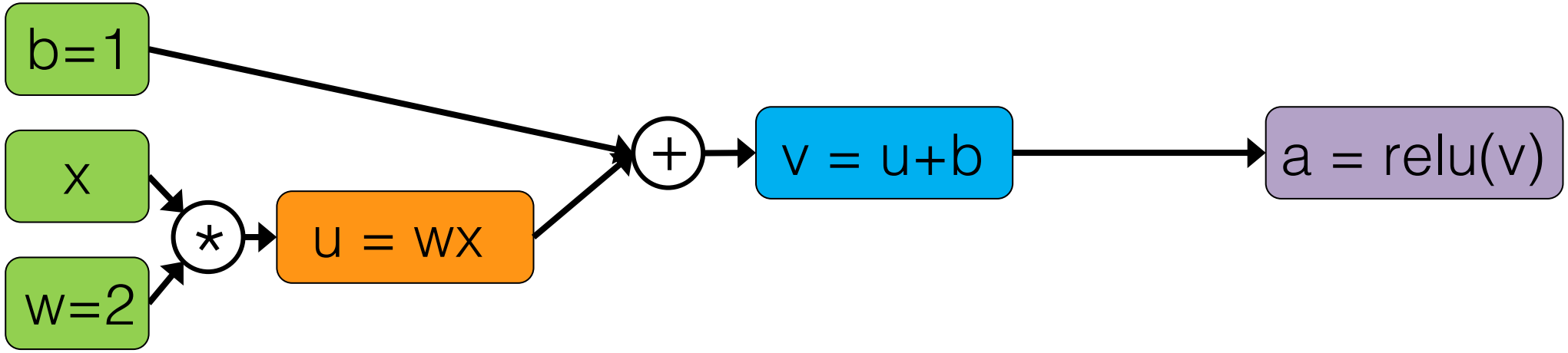
    sess.run(init_op)
    file_writer = tf.summary.FileWriter(logdir='logs/graph-1', graph=g)
```

In your terminal

```
$ pip install tensorboard
$ tensorboard --logdir logs/graph-1
```


TensorBoard
SCALARS
IMAGES
AUDIO
GRAPHS
DISTRIBUTIONS
HISTOGRAMS
EMBEDDINGS
Fit to screen
Download PNG
Run (1)
Session runs (0)
Upload
Choose File
Trace inputs
Color
Structure
Device
colors
same substructure
unique substructure
Graph
(* = expandable)
Namespace*
OpNode
Unconnected series*
Connected series*
Constant
Summary
Dataflow edge
Control dependency edge
Reference edge
Relu
add
mul
b
init
x
w
init
Scalar
Scalar

Computation Graphs

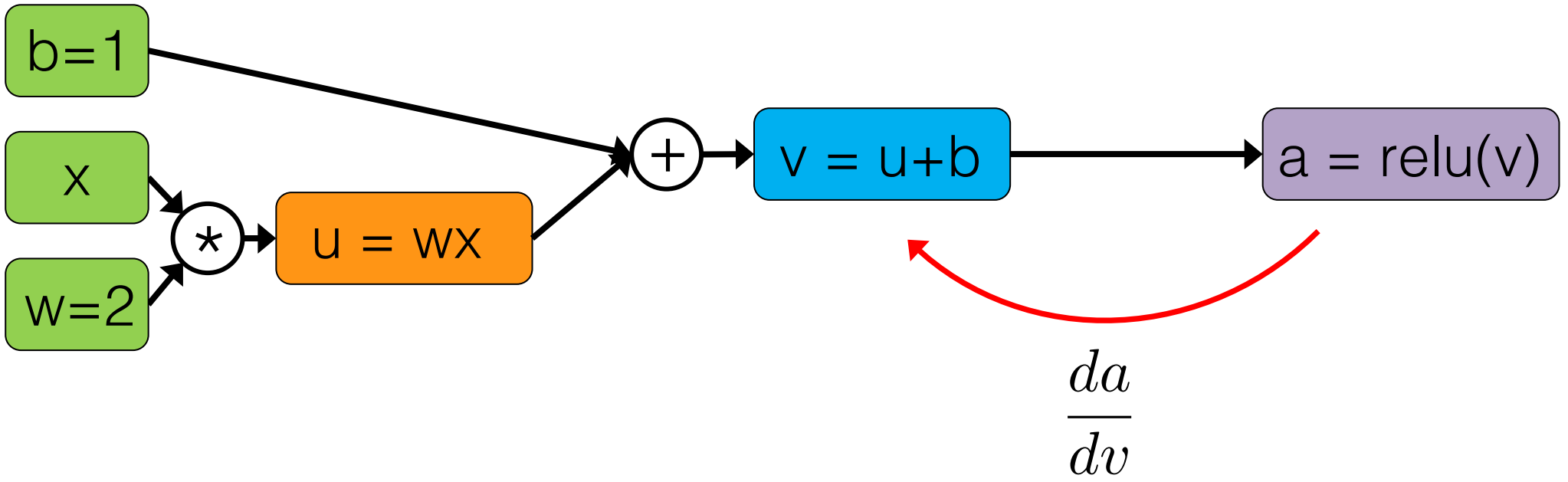



```
with tf.Session(graph=g) as sess:
    sess.run(tf.global_variables_initializer())
    u_res, v_res, a_res = sess.run([u, v, a], feed_dict={'x:0': 3})

print(u_res, v_res, a_res)
```

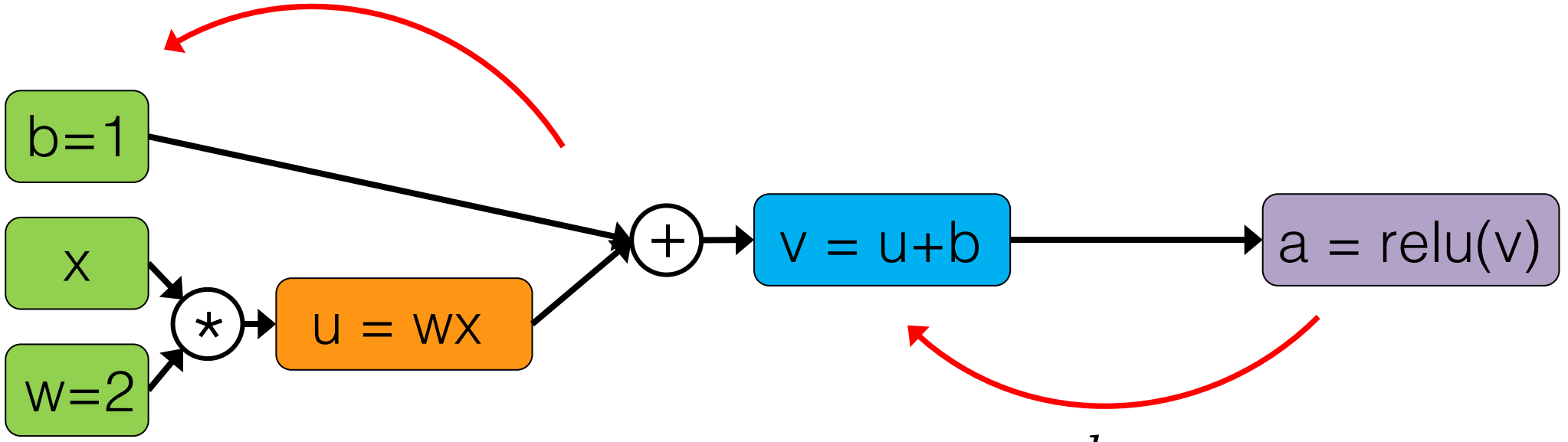
```
6.0, 6.0 7.0
```

Computation Graphs and Derivatives



Calculus refresher:
https://sebastianraschka.com/pdf/books/dlb/appendix_d_calculus.pdf

$$\frac{\partial a}{\partial b} =$$



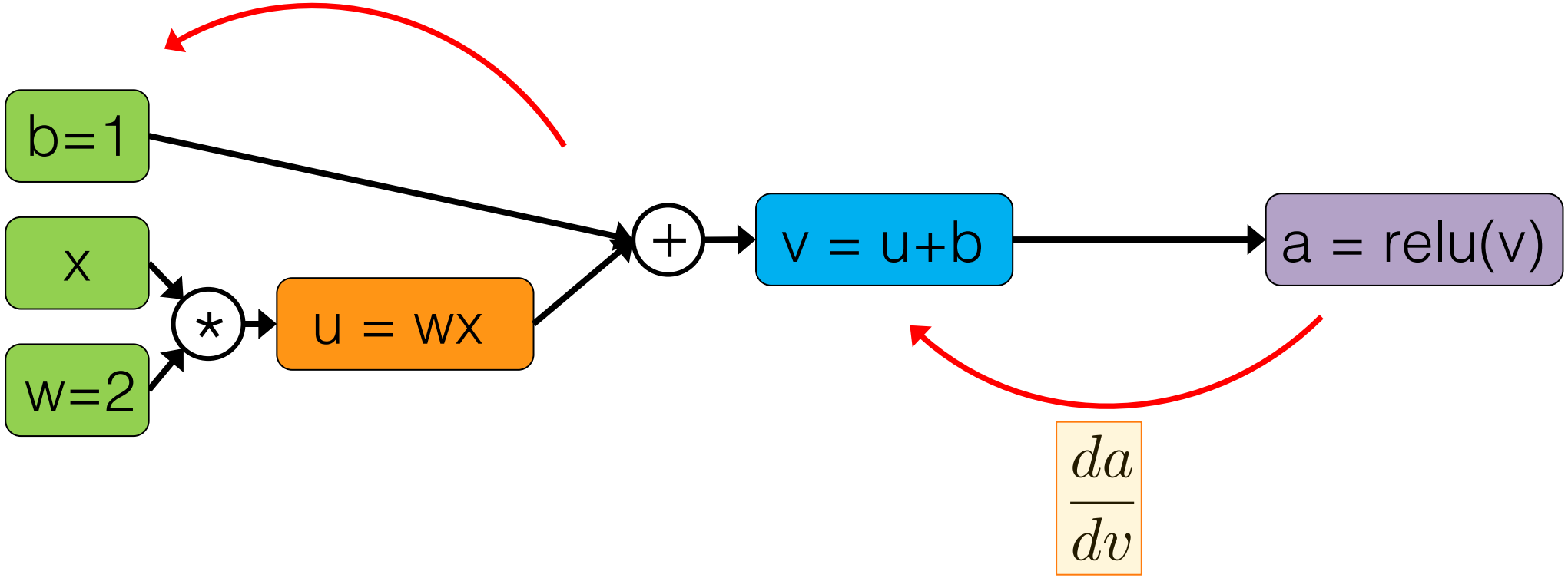
$$\frac{da}{dv}$$

Chain Rule

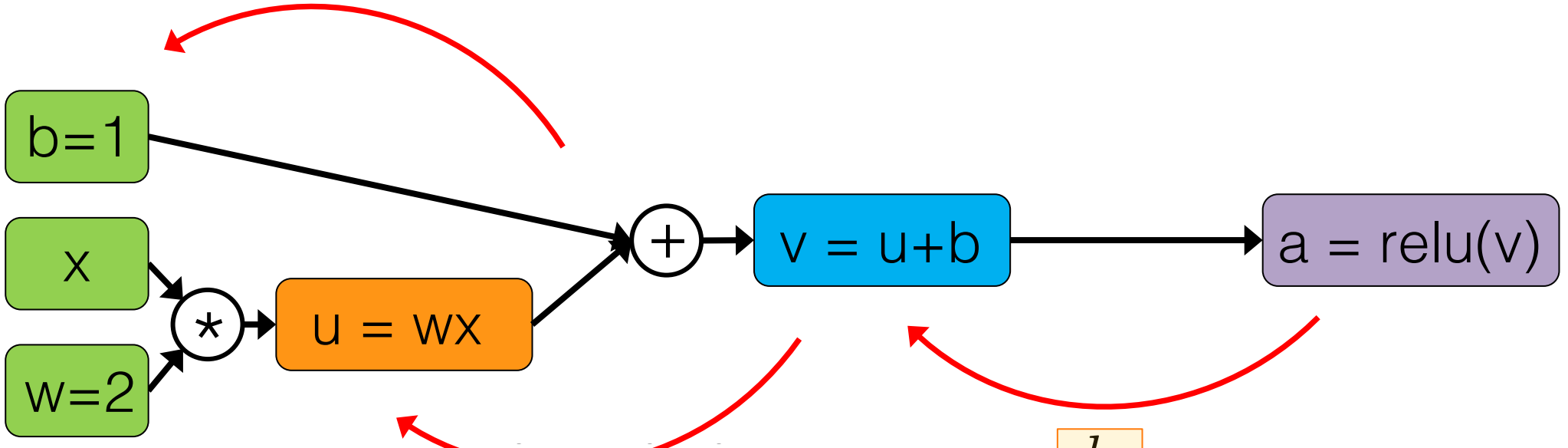
$$f(g(x))$$

$$\frac{d}{dx}\left[f(g(x))\right] = \frac{df}{dg} \cdot \frac{dg}{dx}$$

$$\frac{\partial a}{\partial b} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial b}$$



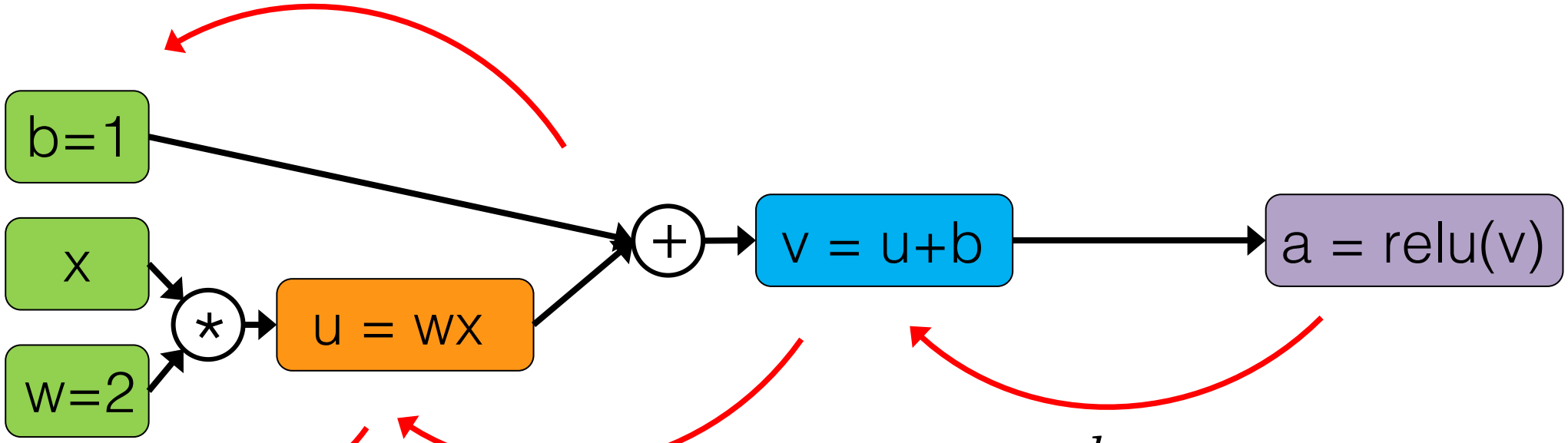
$$\frac{\partial a}{\partial b} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial b}$$



$$\frac{\partial a}{\partial u} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial u}$$

$$\frac{da}{dv}$$

$$\frac{\partial a}{\partial b} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial b}$$

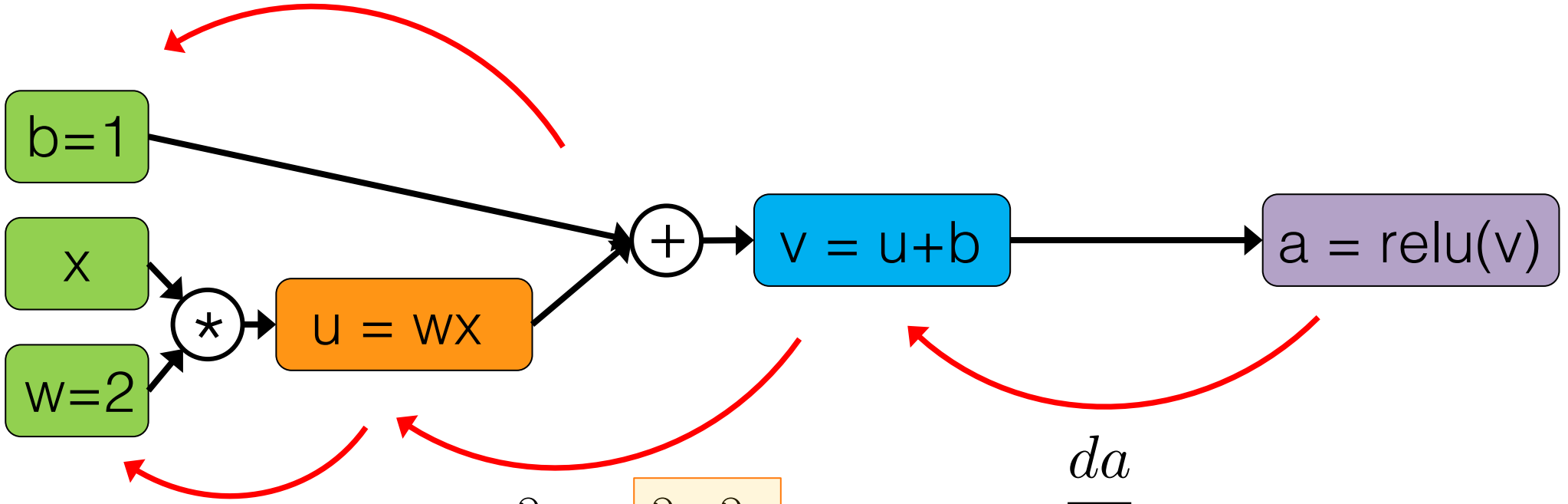


$$\frac{\partial a}{\partial w} = \boxed{\frac{\partial a}{\partial u}}\frac{\partial u}{\partial w}$$

$$\boxed{\frac{\partial a}{\partial u}} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial u}$$

$$\frac{da}{dv}$$

$$\frac{\partial a}{\partial b} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial b}$$



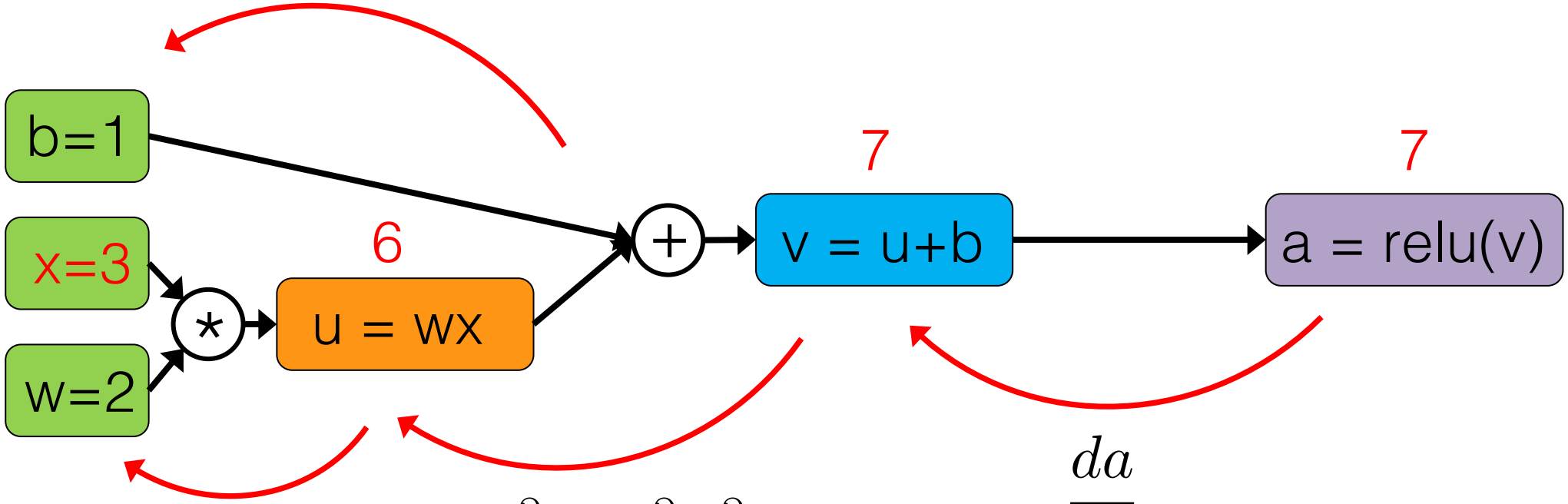
$$\frac{\partial a}{\partial u} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial u}$$

$$\frac{da}{dv}$$

$$\frac{\partial a}{\partial w} = \frac{\partial a}{\partial u}\frac{\partial u}{\partial w}$$

$$= \frac{\partial a}{\partial v}\frac{\partial v}{\partial u}\frac{\partial u}{\partial w}$$

$$\frac{\partial a}{\partial b} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial b}$$

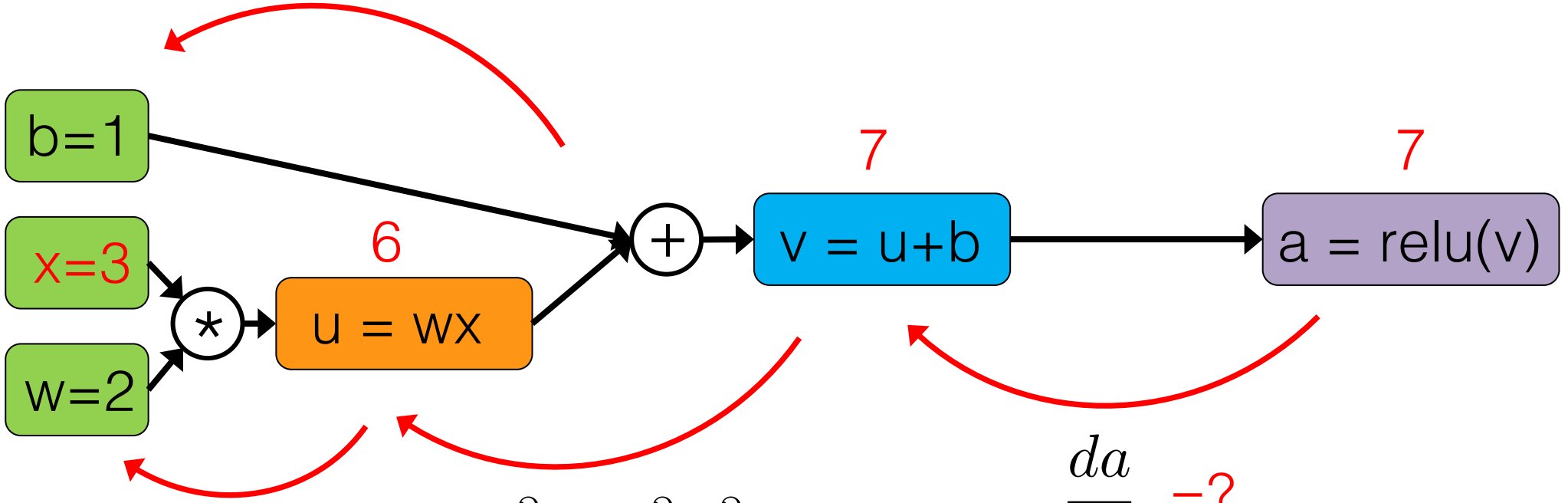


$$\frac{\partial a}{\partial w} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial u}\frac{\partial u}{\partial w}$$

$$\frac{\partial a}{\partial u} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial u}$$

$$\frac{da}{dv}$$

$$\frac{\partial a}{\partial b} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial b}$$

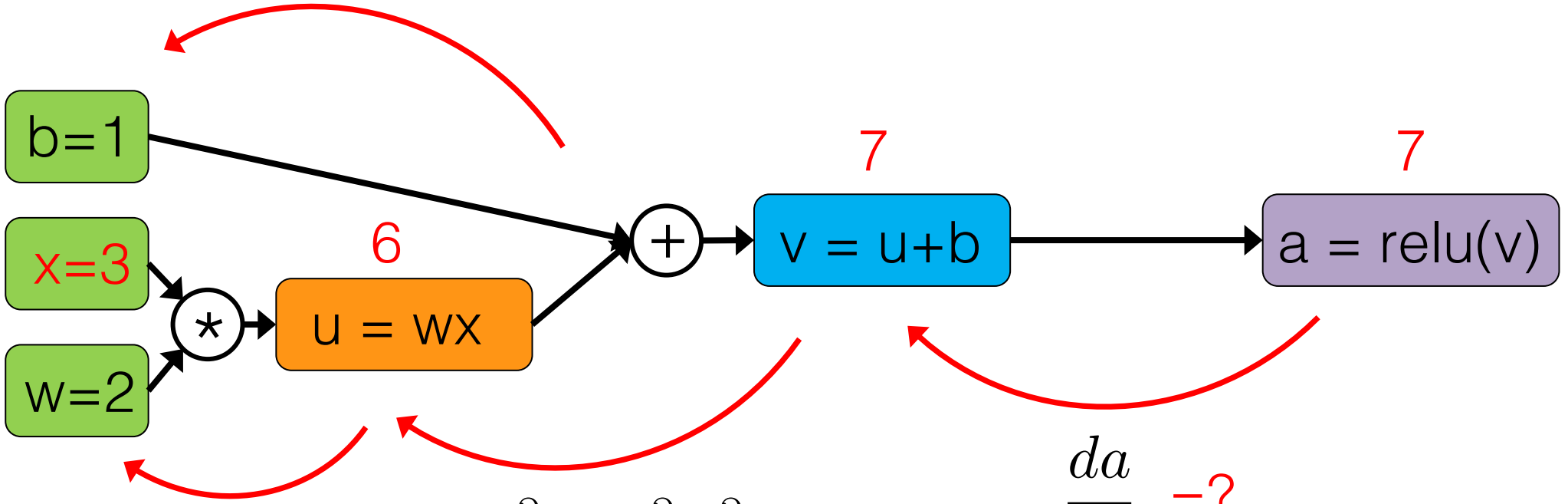


$$\frac{\partial a}{\partial u} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial u}$$

$$\frac{\partial a}{\partial w} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial u}\frac{\partial u}{\partial w}$$

$$\frac{da}{dv} \quad =?$$

$$\frac{\partial a}{\partial b} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial b}$$



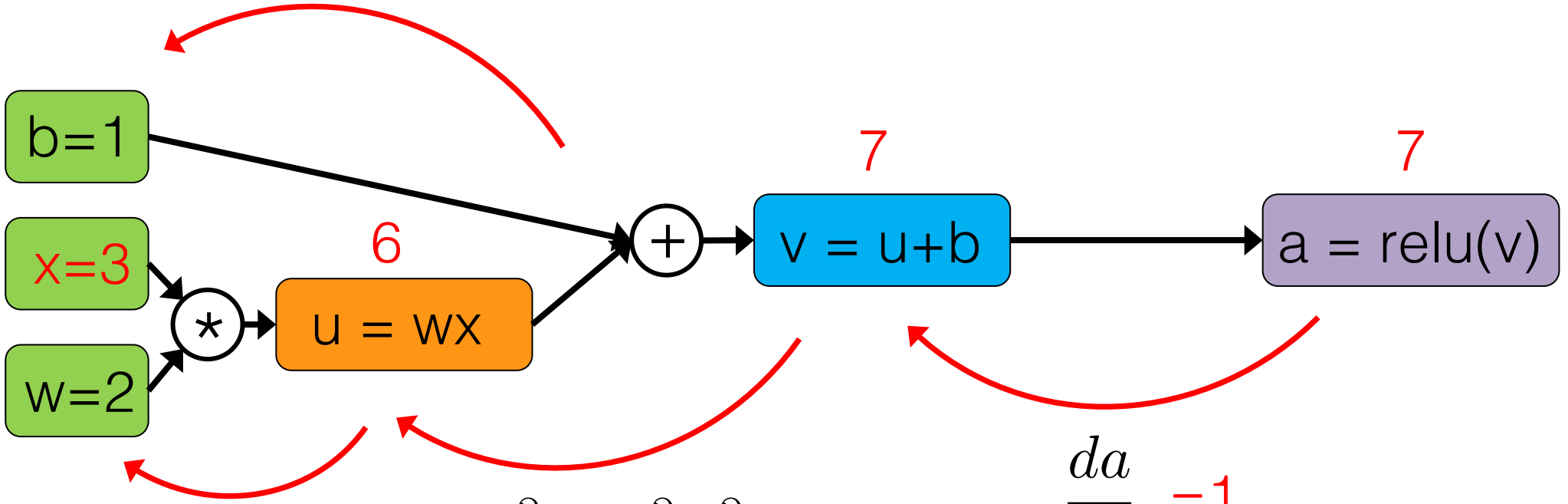
$$\frac{\partial a}{\partial w} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial u}\frac{\partial u}{\partial w}$$

$$\frac{\partial a}{\partial u} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial u}$$

$$\frac{da}{dv} \quad =?$$

$$\text{relu}(x) = \begin{cases} x & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$\frac{\partial a}{\partial b} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial b}$$

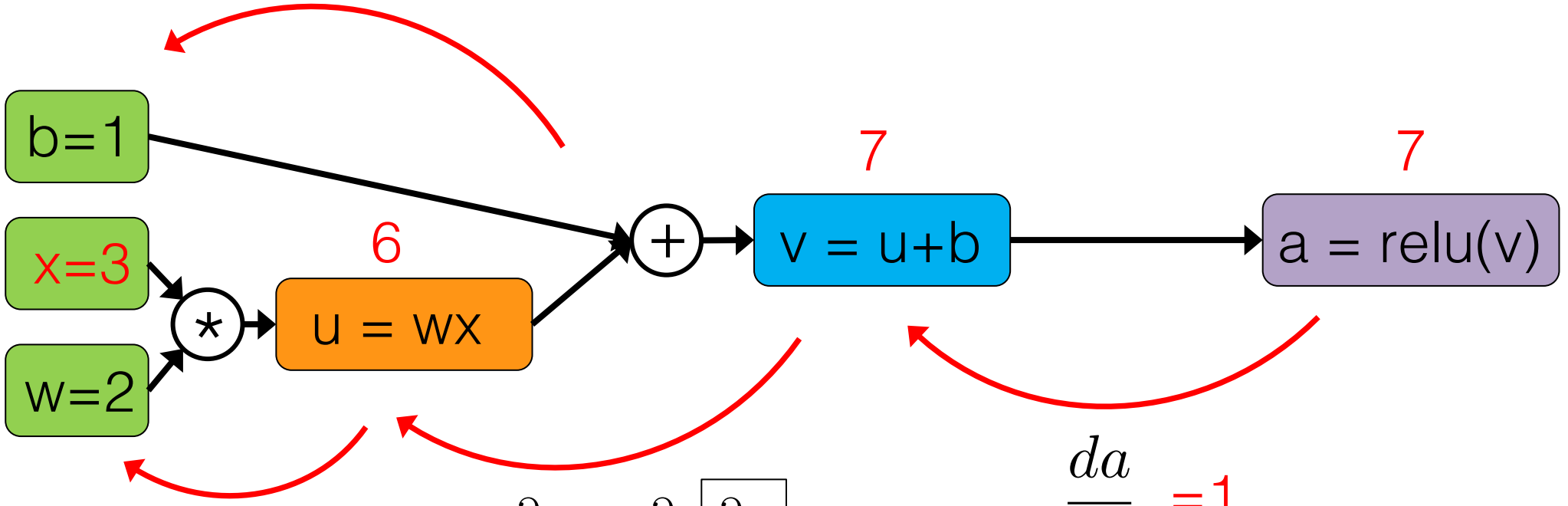


$$\frac{\partial a}{\partial w} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial u}\frac{\partial u}{\partial w}$$

$$\frac{\partial a}{\partial u} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial u} \quad =?$$

$$\frac{da}{dv} \quad =1$$

$$\frac{\partial a}{\partial b} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial b}$$



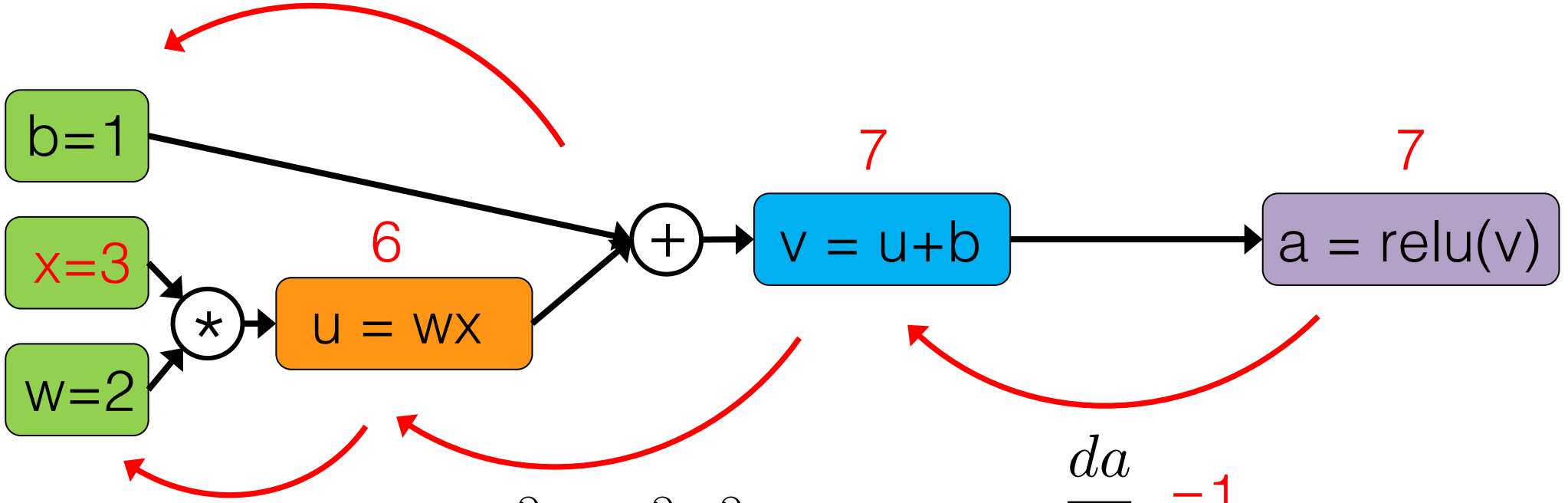
$$\frac{\partial a}{\partial w} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial u}\frac{\partial u}{\partial w}$$

$$\frac{\partial a}{\partial u} = \frac{\partial a}{\partial v}\boxed{\frac{\partial v}{\partial u}} \quad =?$$

$$\frac{da}{dv} \quad =1$$

Function	Derivative
$f(x) + g(x)$	$f'(x) + g'(x)$

$$\frac{\partial a}{\partial b} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial b} \quad =?$$



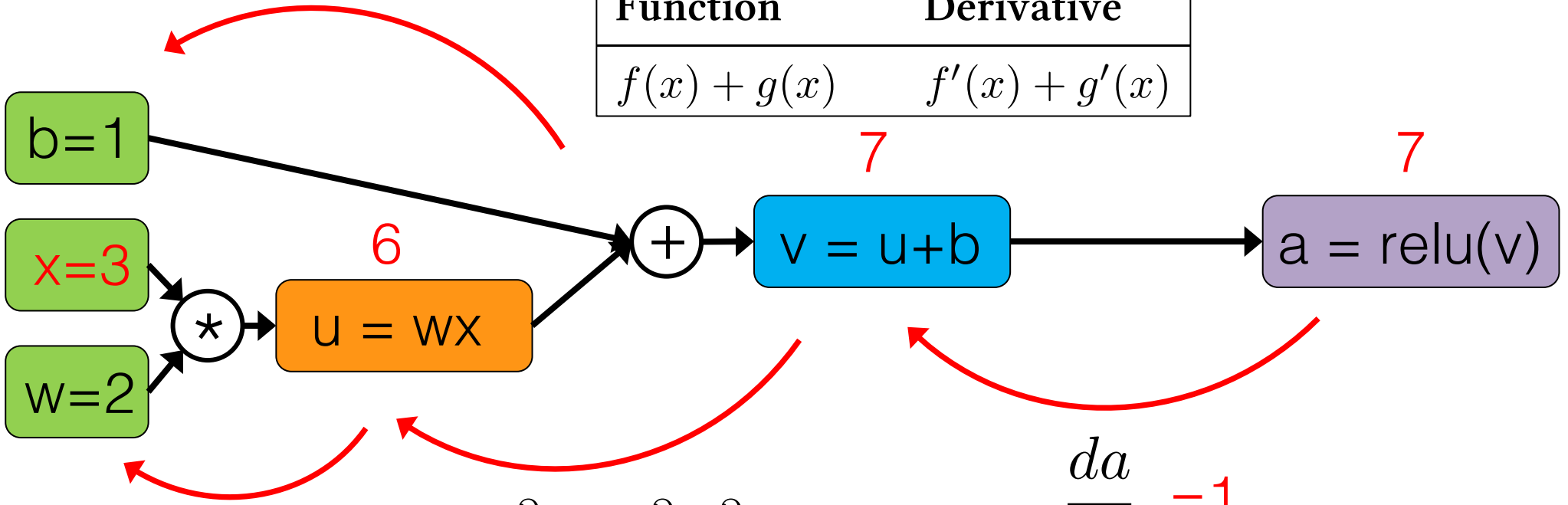
$$\frac{\partial a}{\partial w} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial u}\frac{\partial u}{\partial w}$$

$$\frac{\partial a}{\partial u} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial u} \quad =1*1=1$$

$$\frac{da}{dv} \quad =1$$

$$\frac{\partial a}{\partial b} = \frac{\partial a}{\partial v}\boxed{\frac{\partial v}{\partial b}} \quad =?$$

Function	Derivative
$f(x) + g(x)$	$f'(x) + g'(x)$

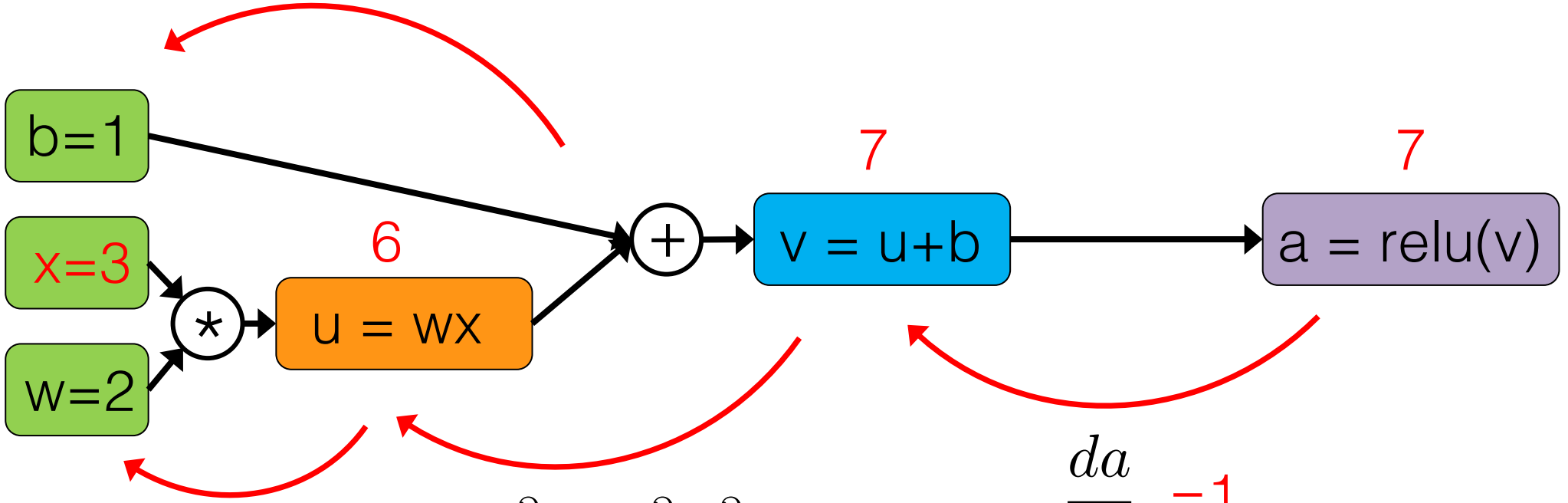


$$\frac{\partial a}{\partial w} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial u}\frac{\partial u}{\partial w}$$

$$\frac{\partial a}{\partial u} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial u} \quad =1*1=1$$

$$\frac{da}{dv} \quad =1$$

$$\frac{\partial a}{\partial b} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial b} \quad =1*1=1$$



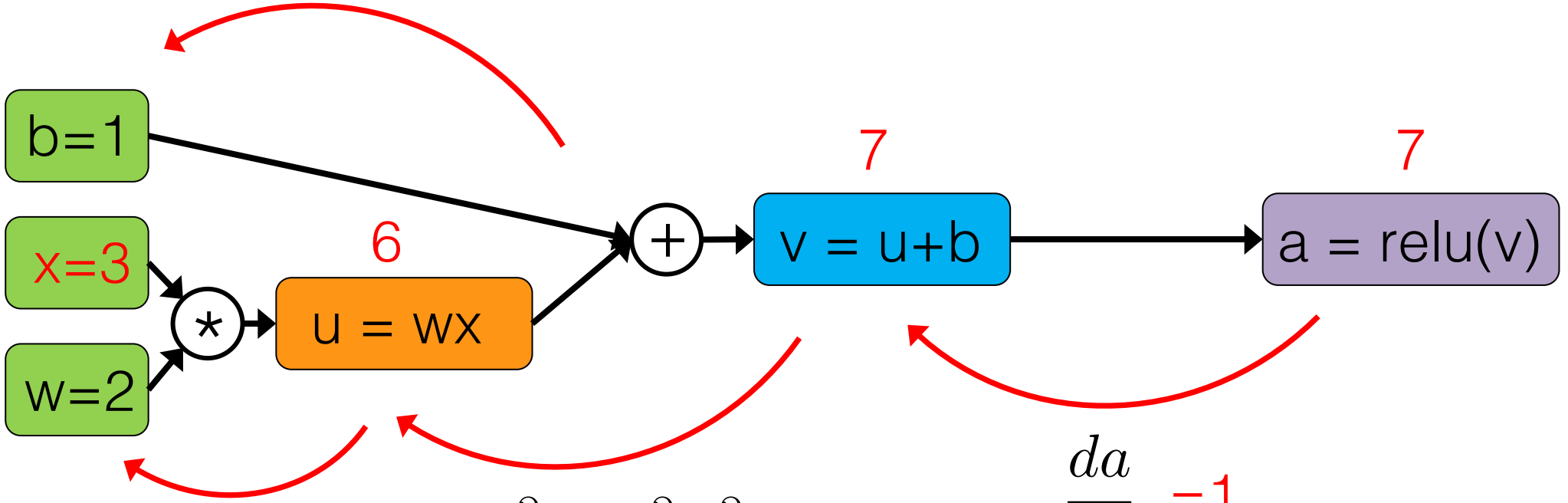
$$\frac{\partial a}{\partial u} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial u} \quad =1*1=1$$

$$\frac{da}{dv} \quad =1$$

$$\frac{\partial a}{\partial w} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial u}\frac{\partial u}{\partial w}$$

=?

$$\frac{\partial a}{\partial b} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial b}$$ =1*1=1



$$\frac{\partial a}{\partial u} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial u}$$ =1*1=1

$$\frac{da}{dv}$$ =1

$$\frac{\partial a}{\partial w} = \frac{\partial a}{\partial v}\frac{\partial v}{\partial u}\frac{\partial u}{\partial w}$$

=1*1*3=3

```
with g.as_default() as g:
    d_a_w = tf.gradients(a, w)
    d_b_w = tf.gradients(a, b)


with tf.Session(graph=g) as sess:
    sess.run(init_op)
    dw, db = sess.run([d_a_w, d_b_w], feed_dict={'x:0': 3})

print(dw, db)
```

[3.0] [1.0]

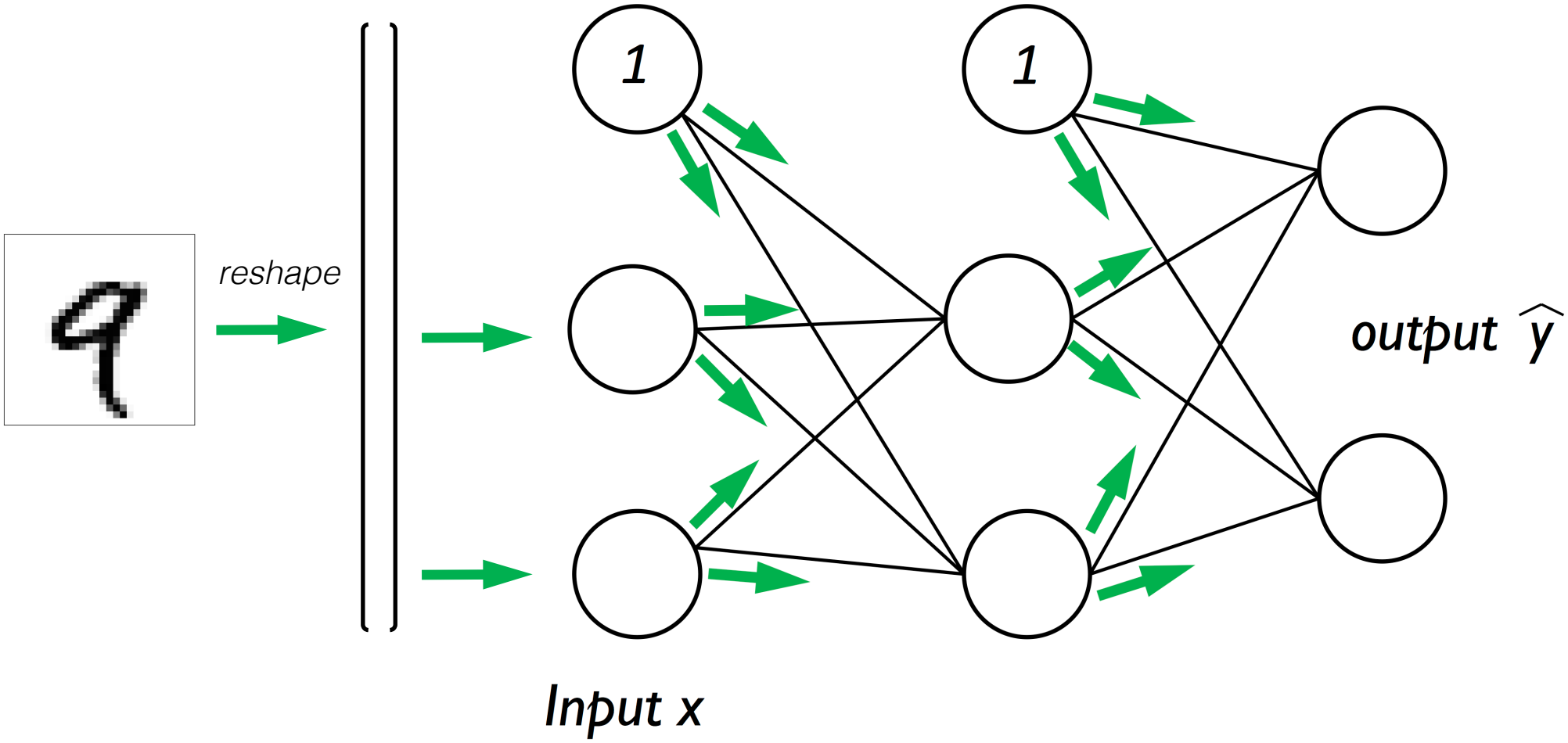
```
g = tf.Graph()
with g.as_default() as g:
    x = tf.placeholder(dtype=tf.float32, shape=None, name='x')
    w = tf.Variable(initial_value=2, dtype=tf.float32, name='w')
    b = tf.Variable(initial_value=1, dtype=tf.float32, name='b')

    u = x * w
    v = u + b
    a = tf.nn.relu(v)

    d_a_w = tf.gradients(a, w)
    d_b_w = tf.gradients(a, b)

with tf.Session(graph=g) as sess:
    sess.run(tf.global_variables_initializer())
    res = sess.run([d_a_w, d_b_w], feed_dict={'x:0': 3})
```

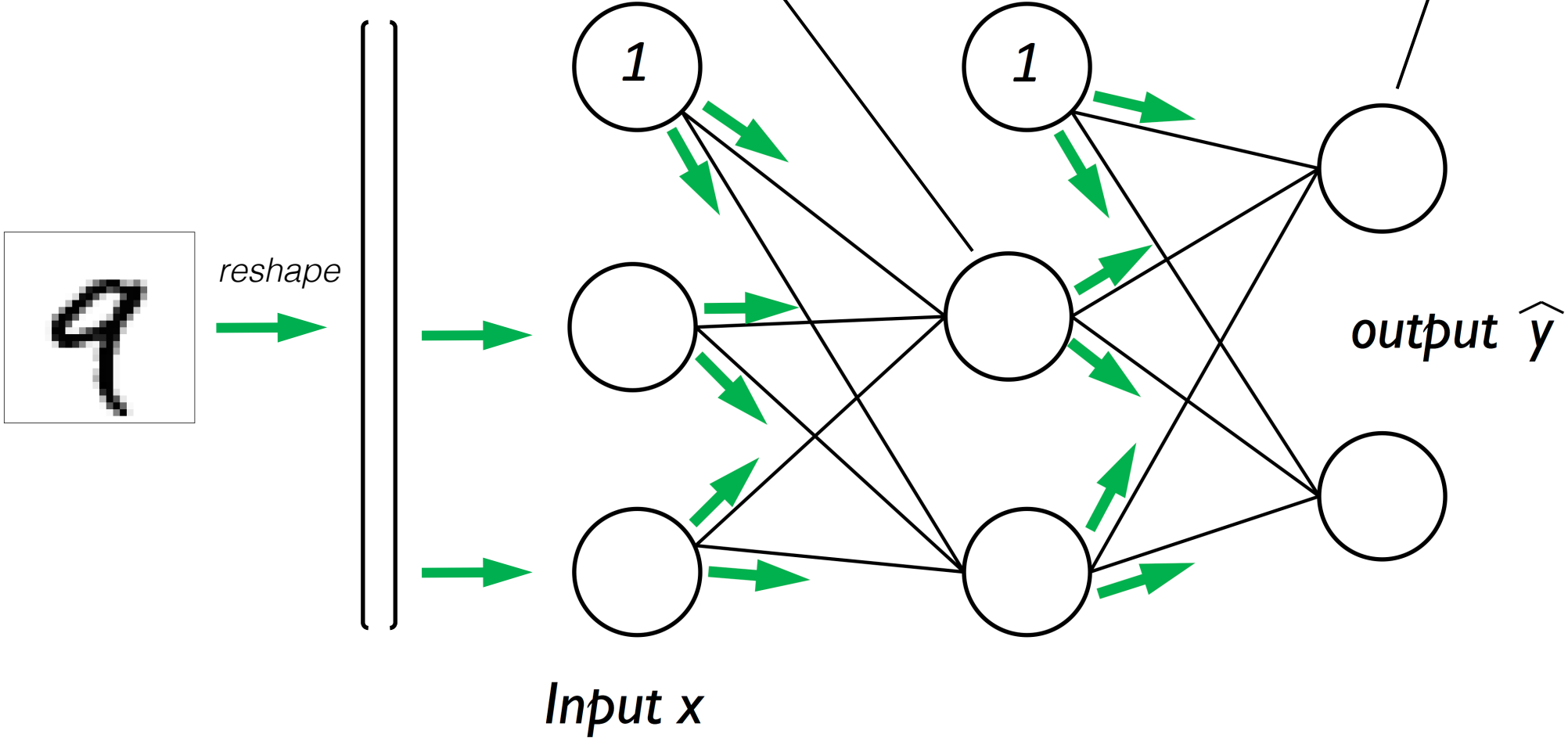
Multilayer Perceptron – Forward Pass



$$z_1^{(h)} = a_0^{(in)} w_{0,1}^{(h)} + a_1^{(in)} w_{1,1}^{(h)} + \cdots + a_m^{(in)} w_{m,1}^{(h)}$$

$$a_1^{(h)} = sigmoid\left(z_1^{(h)}\right)$$

$$a_1^{(o)} = softmax\left(z_1^{(o)}\right)$$



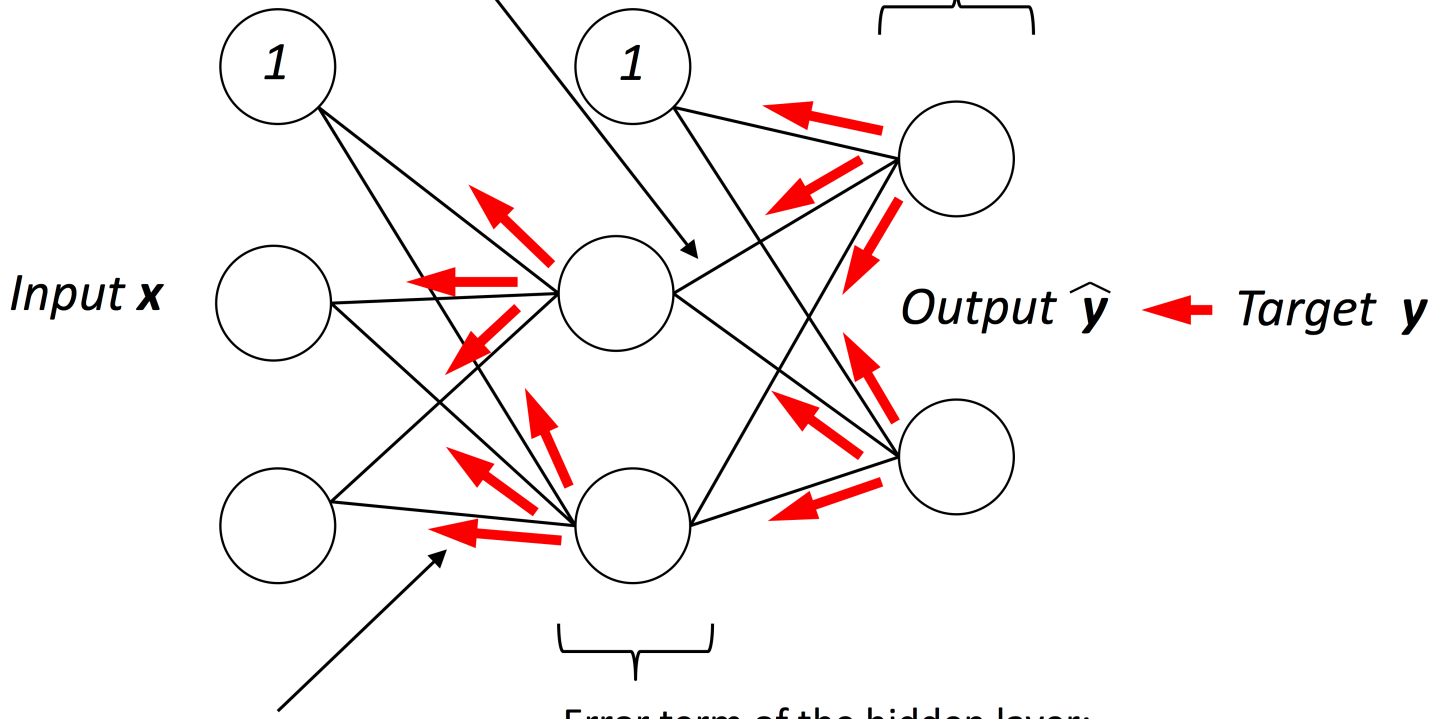
Multilayer Perceptron – Backpropagation

Compute the gradient:

$$\frac{\partial}{\partial w_{i,j}^{(o)}} J(\boldsymbol{W}) = a_j^{(h)} \delta_i^{(o)}$$

Error term of the output layer:

$$\boldsymbol{\delta}^{(o)} = \boldsymbol{a}^{(o)} - \boldsymbol{y}$$



Error term of the hidden layer:

$$\boldsymbol{\delta}^{(h)} = \boldsymbol{\delta}^{(o)} \left(\boldsymbol{W}^{(o)}\right)^T \odot \frac{\partial \phi\left(z^{(h)}\right)}{\partial z^{(h)}}$$

Compute the gradient:

$$\frac{\partial}{\partial w_{i,j}^{(h)}} J(\boldsymbol{W}) = a_j^{(in)} \delta_i^{(h)}$$

As implemented in https://github.com/rasbt/pydata-annarbor2017-dl-tutorial/blob/master/code.ipynb

TensorFlow makes implementing neural nets very convenient!

```
# Loss
loss = tf.nn.softmax_cross_entropy_with_logits(logits=out_z, labels=tf_y)
cost = tf.reduce_mean(loss, name='cost')

# input/output dim: [n_samples, n_classlabels]
sigma_out = (out_act - tf_y) / batch_size

# input/output dim: [n_samples, n_hidden_1]
softmax_derivative_h1 = h1_act * (1. - h1_act)

# input dim: [n_samples, n_classlabels] dot [n_classlabels, n_hidden]
# output dim: [n_samples, n_hidden]
sigma_h = (tf.matmul(sigma_out, tf.transpose(weights['out'])) *
           softmax_derivative_h1)

# input dim: [n_features, n_samples] dot [n_samples, n_hidden]
# output dim: [n_features, n_hidden]
grad_w_h1 = tf.matmul(tf.transpose(tf_x), sigma_h)
grad_b_h1 = tf.reduce_sum(sigma_h, axis=0)

# input dim: [n_hidden, n_samples] dot [n_samples, n_classlabels]
# output dim: [n_hidden, n_classlabels]
grad_w_out = tf.matmul(tf.transpose(h1_act), sigma_out)
grad_b_out = tf.reduce_sum(sigma_out, axis=0)

# Update weights
upd_w_1 = tf.assign(weights['h1'], weights['h1'] - learning_rate * grad_w_h1)
upd_b_1 = tf.assign(biases['b1'], biases['b1'] - learning_rate * grad_b_h1)
upd_w_out = tf.assign(weights['out'], weights['out'] - learning_rate * grad_w_out)
upd_b_out = tf.assign(biases['out'], biases['out'] - learning_rate * grad_b_out)

train = tf.group(upd_w_1, upd_b_1, upd_w_out, upd_b_out, name='train')
```

(very) low-level backprop

```
##########################
### TRAINING & EVALUATION
##########################

with tf.Session(graph=g) as sess:
    sess.run(tf.global_variables_initializer())

    for epoch in range(training_epochs):
       avg_cost = 0.
        total_batch = mnist.train.num_examples // batch_size

        for i in range(total_batch):
            batch_x, batch_y = mnist.train.next_batch(batch_size)
            _, c = sess.run(['train', 'cost:0'], feed_dict={'features:0': batch_x,
                                                            'targets:0': batch_y})
```

low-level backprop

```
# Loss
loss = tf.nn.softmax_cross_entropy_with_logits(logits=out_z, labels=tf_y)
cost = tf.reduce_mean(loss, name='cost')

##################
# Backpropagation
##################

# Get Gradients
dc_dw_out, dc_db_out = tf.gradients(cost, [weights['out'], biases['out']])
dc_dw_1, dc_db_1 = tf.gradients(cost, [weights['h1'], biases['b1']])

# Update Weights
upd_w_1 = tf.assign(weights['h1'], weights['h1'] - learning_rate * dc_dw_1)
upd_b_1 = tf.assign(biases['b1'], biases['b1'] - learning_rate * dc_db_1)
upd_w_out = tf.assign(weights['out'], weights['out'] - learning_rate * dc_dw_out)
upd_b_out = tf.assign(biases['out'], biases['out'] - learning_rate * dc_db_out)

train = tf.group(upd_w_1, upd_b_1, upd_w_out, upd_b_out, name='train')
```

“convenient” backprop

```
# Loss
loss = tf.nn.softmax_cross_entropy_with_logits(logits=out_z, labels=tf_y)
cost = tf.reduce_mean(loss, name='cost')

###################
# Backpropagation
###################

optimizer = tf.train.GradientDescentOptimizer(learning_rate=learning_rate)
train = optimizer.minimize(cost, name='train')
```

```
##########################
### TRAINING & EVALUATION
##########################

with tf.Session(graph=g) as sess:
    sess.run(tf.global_variables_initializer())

    for epoch in range(training_epochs):
       avg_cost = 0.
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        for i in range(total_batch):
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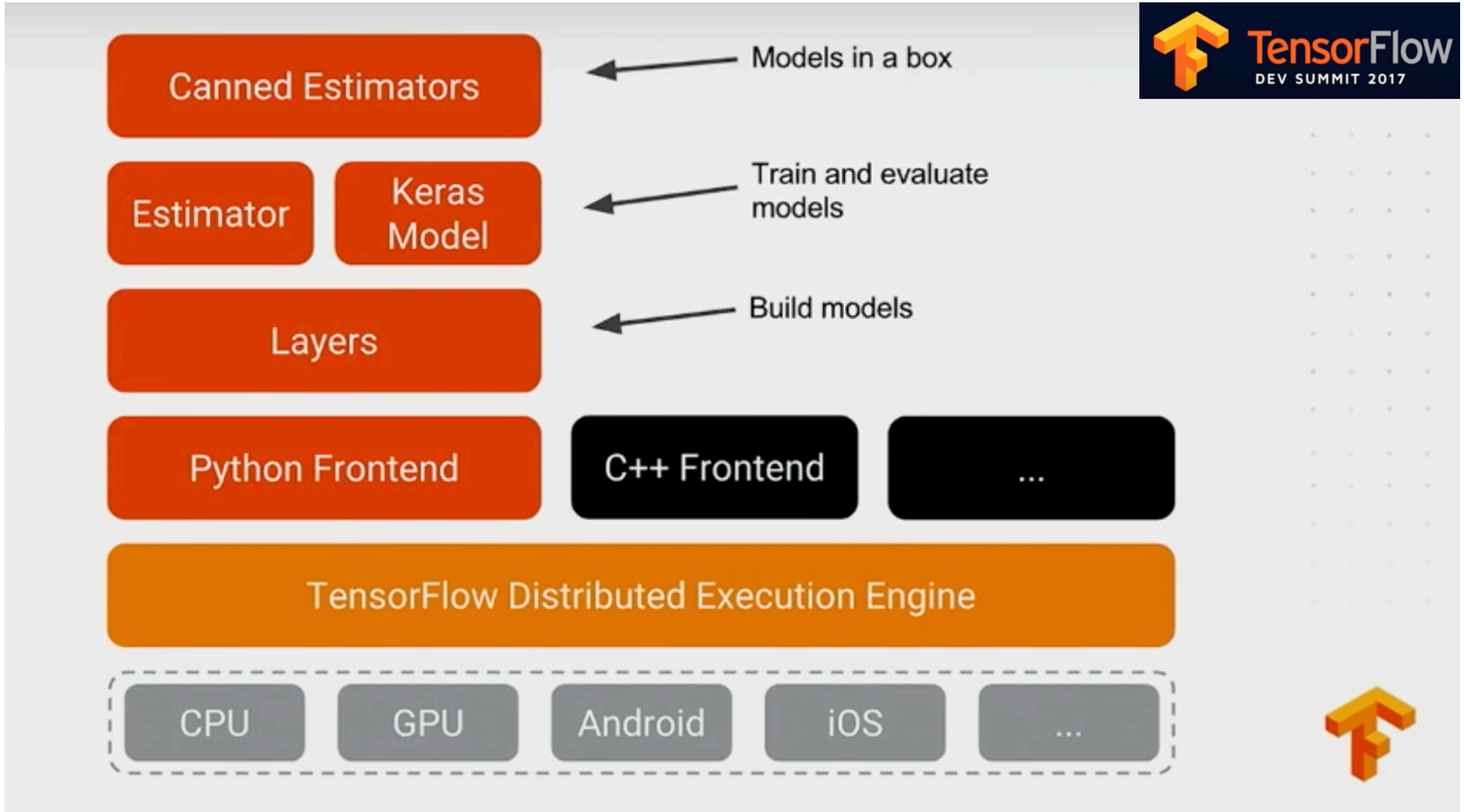
                                                            'targets:0': batch_y})
```

TensorFlow Layers



Link to the talk: https://www.youtube.com/watch?v=t64ortpgS-E
Estimator Documentation: https://www.tensorflow.org/extend/estimators

Defining your wrapper functions manually

```
def fully_connected(input_tensor, output_nodes,
                    activation=None, seed=None,
                    name='fully_connected'):

    with tf.variable_scope(name):
        input_nodes = input_tensor.get_shape().as_list()[1]
        weights = tf.Variable(tf.truncated_normal(shape=(input_nodes,
                                                         output_nodes),
                                                  mean=0.0,
                                                  stddev=0.01,
                                                  dtype=tf.float32,
                                                  seed=seed),
                              name='weights')
        biases = tf.Variable(tf.zeros(shape=[output_nodes]), name='biases')

        act = tf.matmul(input_tensor, weights) + biases
        if activation is not None:
            act = activation(act)
    return act
```

Using tensorflow.layers

```
g = tf.Graph()
with g.as_default():

    # Input data
    tf_x = tf.placeholder(tf.float32, [None, n_input], name='features')
    tf_y = tf.placeholder(tf.float32, [None, n_classes], name='targets')

    # Multilayer perceptron
    layer_1 = tf.layers.dense(tf_x, n_hidden_1,
                              activation=tf.nn.relu,
                              kernel_initializer=tf.truncated_normal_initializer(stddev=0.1))
    layer_2 = tf.layers.dense(layer_1, n_hidden_2,
                              activation=tf.nn.relu,
                              kernel_initializer=tf.truncated_normal_initializer(stddev=0.1))
    out_layer = tf.layers.dense(layer_2, n_classes, activation=None)
```

Feeding Data into the Graph

From Python via placeholders

```
sess.run([…], feed_dict={'x:0': …, 'y:0': …, …})
```

- Python pickle
- NumPy .npz archives (https://github.com/rasbt/deep-learning-book/blob/master/code/model_zoo/image-data-chunking-npz.ipynb)
- HDF5 (https://github.com/rasbt/deep-learning-book/blob/master/code/model_zoo/image-data-chunking-hdf5.ipynb)
- CSV
- …

Using input pipelines and queues

- Reading data from TFRecords files (https://github.com/rasbt/deep-learning-book/blob/master/code/model_zoo/tfrecords.ipynb)
- Queues for loading raw images (https://github.com/rasbt/deep-learning-book/blob/master/code/model_zoo/file-queues.ipynb)

More info: https://www.tensorflow.org/programmers_guide/reading_data

abstract_pydata-meetup_aug2017.txt

PyData Aug 2017

Name: Sebastian Raschka

Title: An Introduction to Deep Learning with TensorFlow

Abstract
==========

In this tutorial, you will learn how to use the open-source TensorFlow library for deep learning. What's so great about TensorFlow is that it allows us to work with multi-dimensional arrays and train deep neural network very efficiently by utilizing GPU resources.

In this introduction to TensorFlow, you will learn how to define computational graphs and how to execute them in a Python runtime environment. After implementing backpropagation for a simple multi-layer perceptron, we will talk about TensorFlow's convenience features for optimization and the new layers API to construct more complex deep learning architectures more compactly. Finally, we will implement a General Adversarial Networks architecture to see how we can access and update variables from different network graphs and scopes -- the entry point for inventing and experimenting with novel architectures in our real-world applications and research.

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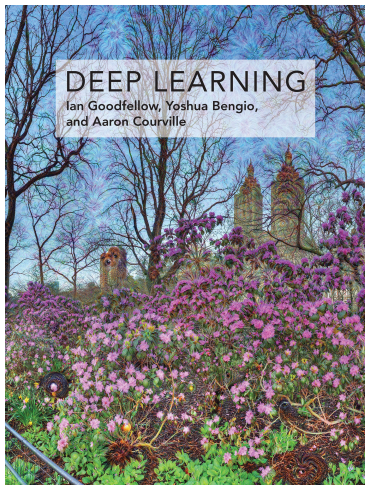
```

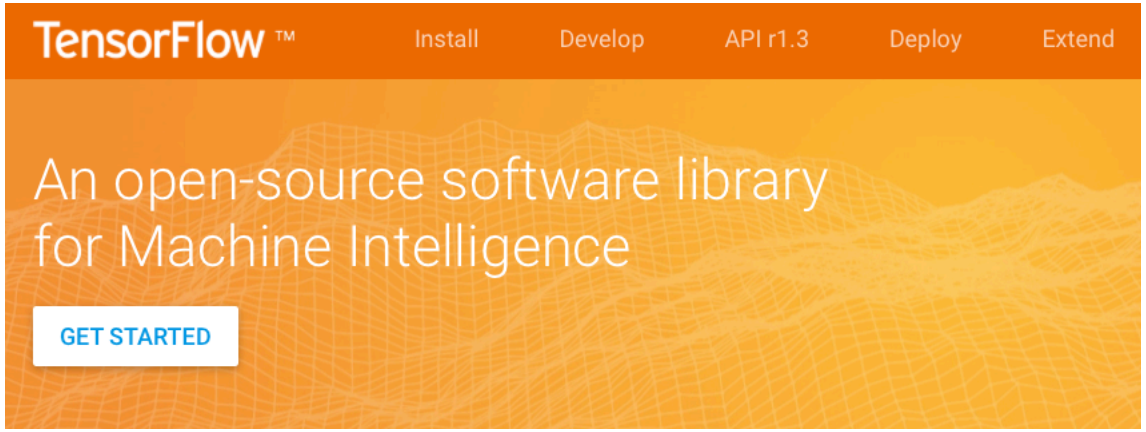
Code snippets

GitHub: https://github.com/rasbt/pydata-annarbor2017-dl-tutorial

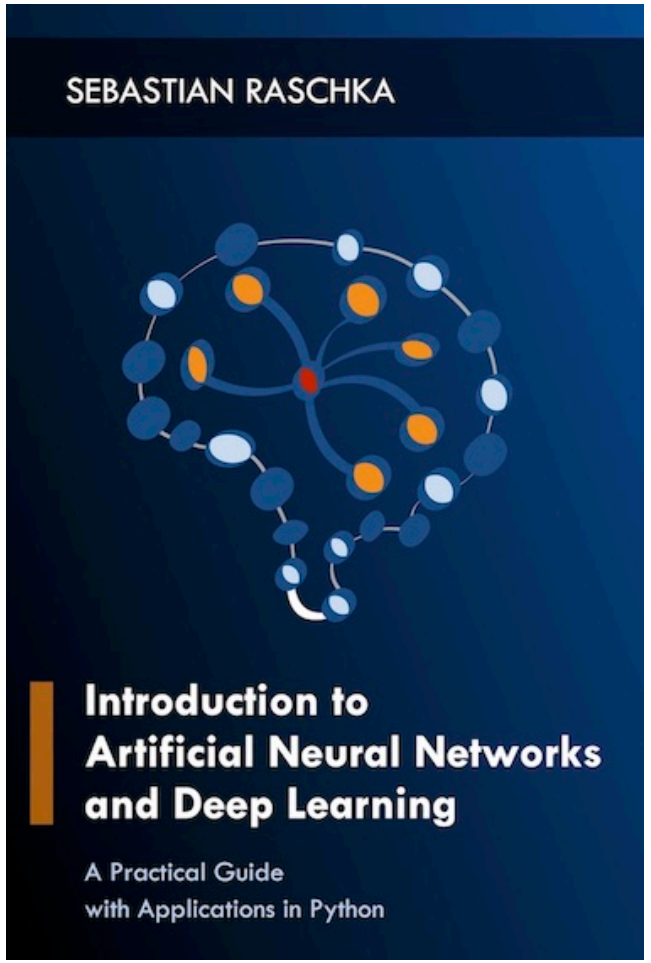
Useful (and Free) Resources



http://www.deeplearningbook.org

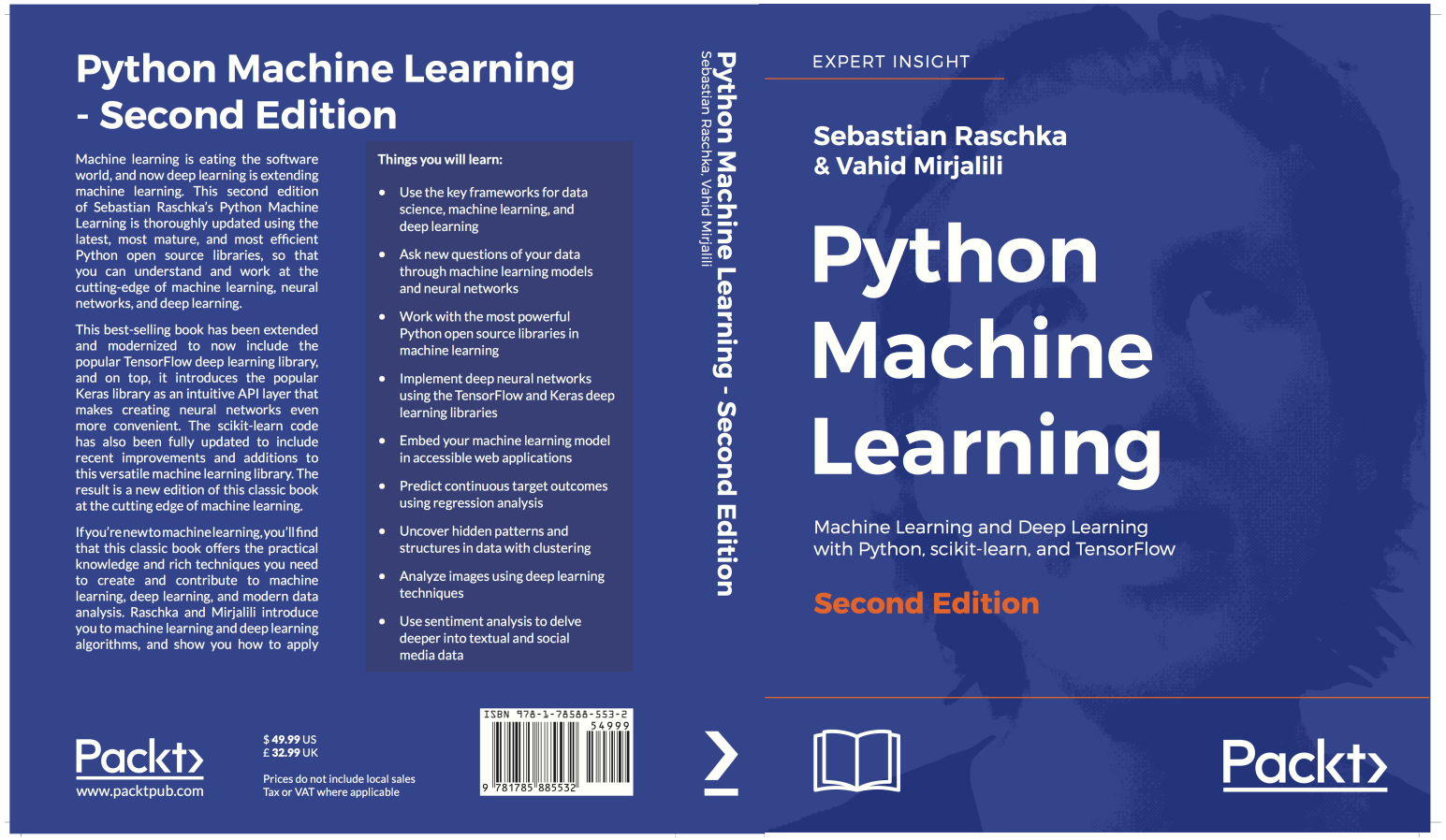


https://www.tensorflow.org



https://github.com/rasbt/deep-learning-book

One More Thing!



https://www.amazon.com/Python-Machine-Learning-scikit-learn-TensorFlow/dp/1787125939/

Thanks for attending!

Slides

Speaker Deck:
https://speakerdeck.com/rasbt/introduction-to-deep-learning-with-tensorflow-at-pydata-ann-arbor

Code snippets

GitHub:
https://github.com/rasbt/pydata-annarbor2017-dl-tutorial

Contact:

- E-mail: mail@sebastianraschka.com
- Website: http://sebastianraschka.com
- Twitter: @rasbt
- GitHub: rasbt

Thanks for attending!

Questions?

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