Deep Learning with TensorFlow

Deep Learning — Units 7 & 8

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Slides available at `jonkrohn.com/talks`

March 24th, 2018

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Outline

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Assessing

Your Deep Learning Project III

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Where are you at with respect to the following?

1. Splitting your data
   - training set (80% — for optimizing parameters)
   - validation set (10% — for hyperparameters)
   - test set (10% — don't touch yet!)
2. Building and assessing architecture
   - get above chance (simplifying problem, if necessary)
   - do existing performance benchmarks exist?
   - if not, use a simple architecture as benchmark

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Leading DL Libraries

	Caffe	Torch	MXNet	TensorFlow
Language	Python, Matlab	Lua, C	Python, R, C++ Julia, Matlab JavaScript, Go Scala, Perl	Python, R, C++ C, Java, Go
Programming Style	Symbolic	Imperative	Imperative	Symbolic
Parallel GPUs: Data	Yes	Yes	Yes	Yes
Parallel GPUs: Model		Yes	Yes	Yes
Pre-Trained Models	Model Zoo	ModelZoo	Model Zoo	github.com/tensorflow/models
For RNNs				Best
High-Level APIs		PyTorch	in-built	Keras, TFLearn

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TensorFlow Graphs

1. build graph
2. initialize session
3. fetch and feed data

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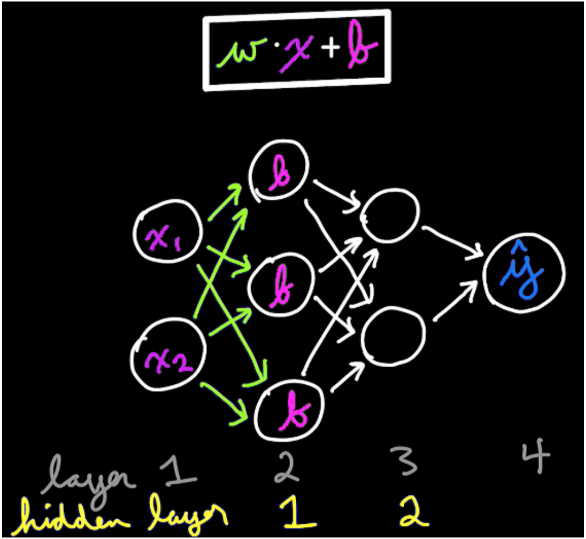
A Familiar Equation



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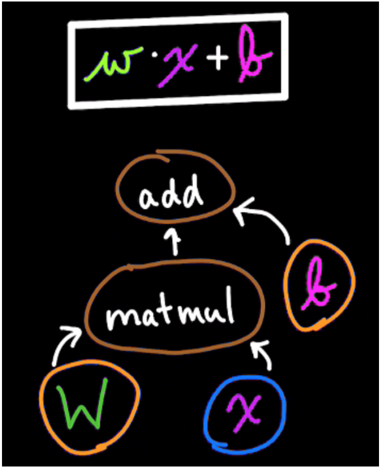

Outline

TensorFlow Graph
Programming

[*first TensorFlow graphs* notebook]

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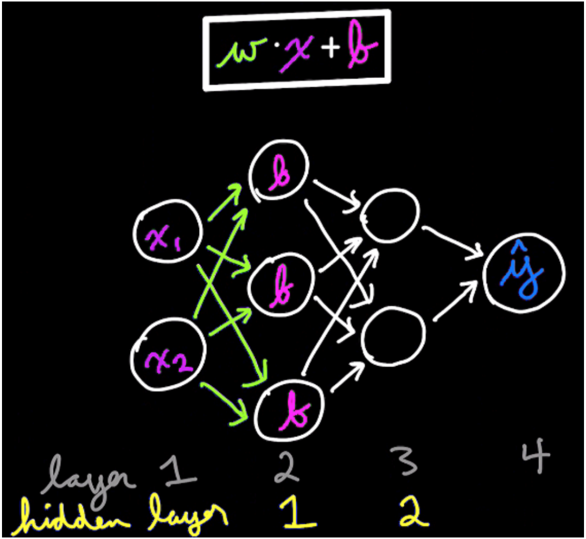

Neurons in TensorFlow

Programming

[*first TensorFlow neurons* notebook]

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Fitting Eight Points

[*point by point intro to TensorFlow* notebook]

Fitting Eight Points

with Tensors

[*tensor-fied intro to TensorFlow* notebook]

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Fitting Eight Million Points

[*intro to TensorFlow times a million* notebook]

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Dense Nets

[*intermediate net in TensorFlow* notebook]

Dense Nets

[*deep net in TensorFlow* notebook]

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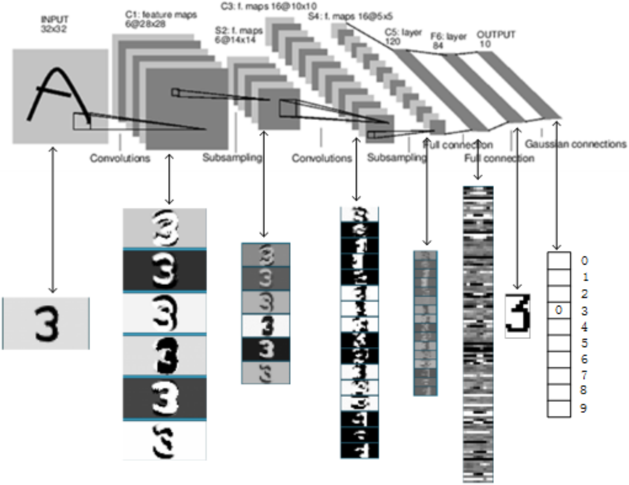
LeNet-5

LeCun et al. (1998)



LeNet-5

LeCun et al. (1998)

[*LeNet in TensorFlow* notebook]

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3. Improving performance & tuning hyperparameters in ten steps...

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1. Initialization

…in `lenet_in_tensorflow.ipynb`:

Set neural network hyperparameters

```
epochs = 20
batch_size = 128
display_progress = 40 # after this many batches, output progress to screen
wt_init = tf.contrib.layers.xavier_initializer() # weight initializer
```

```
weight_dict = {
    'W_c1': tf.get_variable('W_c1',
                            [k_conv_1, k_conv_1, 1, n_conv_1], initializer=wt_init),
    'W_c2': tf.get_variable('W_c2',
                            [k_conv_2, k_conv_2, n_conv_1, n_conv_2], initializer=wt_init),
    'W_d1': tf.get_variable('W_d1',
                            [dense_inputs, n_dense], initializer=wt_init),
    'W_out': tf.get_variable('W_out',
                             [n_dense, n_classes], initializer=wt_init)
}
```

2. Get Above Chance

If your accuracy is below chance, try:

- simplifying the problem
- simplifying the network architecture
- reducing your training set size (to iterate more quickly)

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3. Layers

Experiment with varying:

- number of layers
- type of layers
- layer width (by powers of two)

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4. Cost

…in `lenet_in_keras.ipynb`:

Configure model

```
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
```

…in `lenet_in_tensorflow.ipynb`:

Define model's loss and its optimizer

```
cost = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits=predictions, labels=y))
optimizer = tf.train.AdamOptimizer().minimize(cost)
```

5. Avoid Overfitting

If validation cost begins to increase or validation accuracy begins to decrease, consider:

- stopping training earlier
- dropout

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...in `lenet_in_keras.ipynb`:

```
model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(28, 28, 1)))
model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(n_classes, activation='softmax'))
```

...in `lenet_in_tensorflow.ipynb`:

```
# max pooling layer:
pool_size = 2
mp_layer_dropout = 0.25

# dense layer:
n_dense = 128
dense_layer_dropout = 0.5
```

```
# convolutional and max-pooling layers:
conv_1 = conv2d(square_x, weights['W_c1'], biases['b_c1'])
conv_2 = conv2d(conv_1, weights['W_c2'], biases['b_c2'])
pool_1 = maxpooling2d(conv_2, mp_psize)
pool_1 = tf.nn.dropout(pool_1, 1-mp_dropout)

# dense layer:
flat = tf.reshape(pool_1, [-1, weights['W_d1'].get_shape().as_list()[0]])
dense_1 = dense(flat, weights['W_d1'], biases['b_d1'])
dense_1 = tf.nn.dropout(dense_1, 1-dense_dropout)
```

6. Learning Rate

...in `lenet_in_keras.ipynb`:

Configure model

```
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
```

...in `lenet_in_tensorflow.ipynb`:

Define model's loss and its optimizer

```
cost = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits=predictions, labels=y))
optimizer = tf.train.AdamOptimizer().minimize(cost)
```

7. Epochs

...in `lenet_in_keras.ipynb`:

Train!

```
model.fit(X_train, y_train, batch_size=128, epochs=20, verbose=1, validation_data=(X_test, y_test))
```

...in `lenet_in_tensorflow.ipynb`:

Set neural network hyperparameters

```
epochs = 20
batch_size = 128
display_progress = 40 # after this many batches, output progress to screen
wt_init = tf.contrib.layers.xavier_initializer() # weight initializer
```

```
with tf.Session() as session:
    session.run(initializer_op)

    print("Training for", epochs, "epochs.")

    # loop over epochs:
    for epoch in range(epochs):
```

8. Regularization λ

If using L1 or L2 regularization, consider:

- adjusting λ by orders of magnitude

9. Batch Size

...in `lenet_in_keras.ipynb`:

Train!

```
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y_test))
```

...in `lenet_in_tensorflow.ipynb`:

Set neural network hyperparameters

```
epochs = 20
batch_size = 128
display_progress = 40 # after this i
wt_init = tf.contrib.layers.xavier_i
```

```
# loop over all batches of the epoch:
n_batches = int(mnist.train.num_examples / batch_size
for i in range(n_batches):

    # to reassure you something's happening!
    if i % display_progress == 0:
        print("Step ", i+1, " of ", n_batches, " in epoch ", epoch+1, ".", sep='')

    batch_x, batch_y = mnist.train.next_batch(batch_size
```

10. Automation

For grid search of hyperparameters, consider:

- sampling values instead of looping over fixed values
- using [Spearmint]

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All together now...

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4. Cost
5. Avoid Overfitting
6. Learning Rate
7. Epochs
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Generative Adversarial Networks

April 7th —*In a Fortnight!*

Reinforcement Learning

April 7th —*In a Fortnight!*