How to build & run your first deep learning network in TensorFlow

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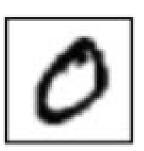


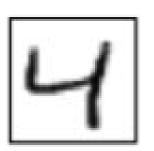
DAY 3

Single Layer Neural Network in TensorFlow

- MNIST Data-set : "Hello World"
 - set of black and white images containing hand-written digits, containing more than 60.000 examples for training a model, and 10.000 for testing it.
 - The images have been normalized into 20x20 pixel images, preserving the aspect ratio. After that, the images are centered in 28x28 pixel frames
 - The images are labeled with the digit they represent.
 - The images are like:







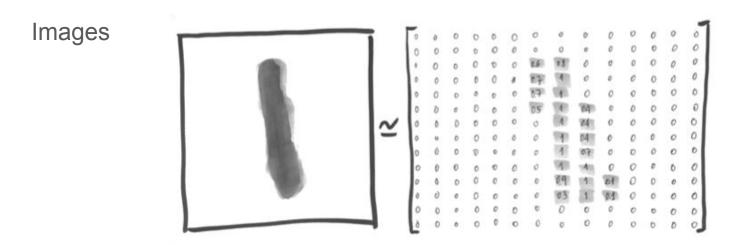


- MNIST Data-set : "Hello World"
 - To download easily the data, you can use the script input_data.py
 - From your application you only need to import and use in the following way:

```
import input_data
mnist = input_data.read_data_sets("MNIST_data/", one_hot=True)
```

- MNIST Data-set : "Hello World"
 - After executing these two instructions you will have
 - the full training data-set in mnist.train and
 - the test data-set in mnist.test.
 - each element is composed by an image, referenced as "xs", and its corresponding label "ys"

MNIST Data-set : "Hello World"



Where each position indicates the level of lackness of each pixel between 0 and 1. This matrix can be represented as an array of $28 \times 28 = 784$ numbers. Actually, the image has been transformed in a bunch of points in a vectorial space of 784 dimensions.

An easy example to start: Softmax

The *softmax* function has two main steps:

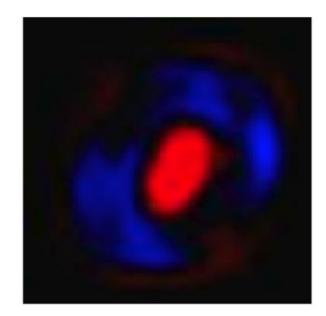
1. Compute the "evidences" for an image belonging to a certain label

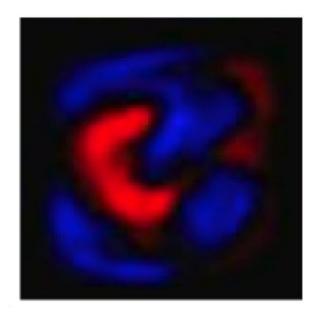
2. Convert the evidences into probabilities for each possible label

Softmax(x):=
$$\frac{\exp(x_i)}{\underset{j}{\neq} \exp(x_j)} = \frac{e^{x_i}}{\underset{j}{\neq} \exp(x_j)}$$

1. Compute the "evidences" for an image belonging to a certain label are

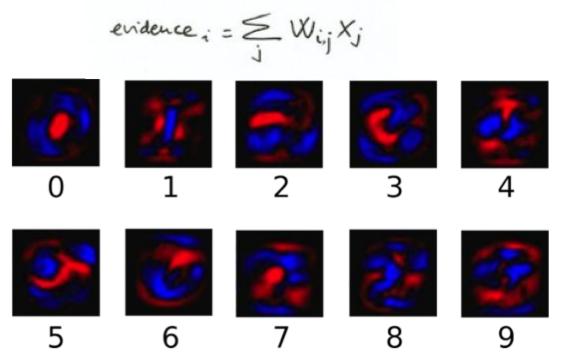
- a usual approximation is to compute the weighted sum of pixel intensities.
- That weight is negative when a pixel with high intensity happens to not to be in a given class,
- o and positive if the pixel is frequent in that class.





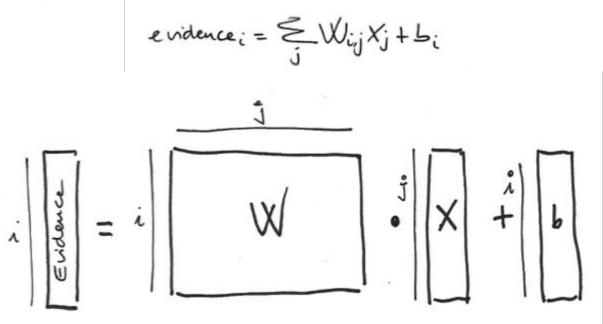
1. Compute the "evidences" for an image belonging to a certain label are

In a more formal way, we can say that the evidence for a class i given an input x is expressed
 as:



1. Compute the "evidences" for an image belonging to a certain label are

 The model also include an extra parameter representing the bias (adding some base uncertainty)

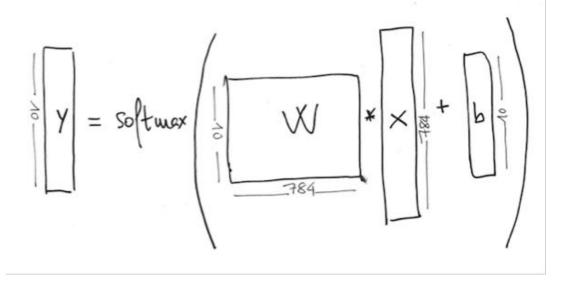


2. Convert the evidences into probabilities for each possible label.

Softmax(x); =
$$\frac{\exp(x_i)}{\underset{j}{\leq} \exp(x_j)} = \frac{e^{x_i}}{\underset{j}{\leq} e^{x_j}}$$

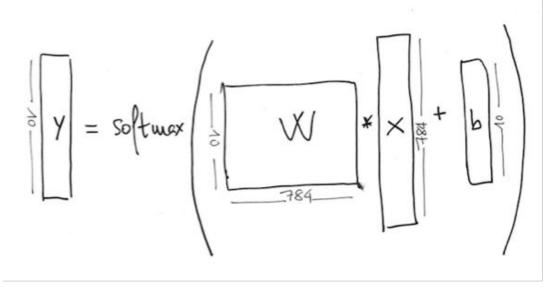
The interesting fact of such function is that a good prediction will have one output with a value near 1, while all the other outputs will be near zero; and in a weak prediction, some labels may show similar support.

Data structure:



Two variable are created using the tf. Variable function

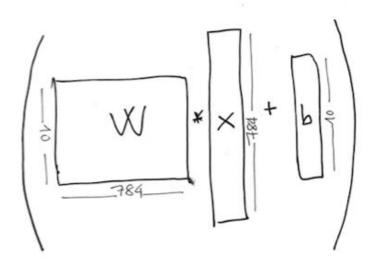
```
W = tf.Variable(tf.zeros([784,10]))
b = tf.Variable(tf.zeros([10]))
```



We create a tensor of two dimensions to keep the information of the x points (used to store the MNIST images as a vector of 784 floating point values (*)).

```
x = tf.placeholder("float", [None, 784])
```

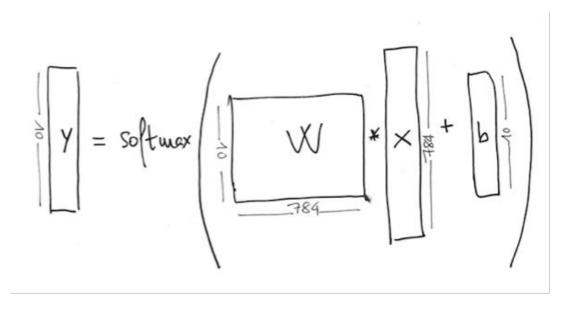
(*) None indicates that the dimension can be any size



tf.matmul(x,W) + b

implementing the previously described softmax function:

$$y = tf.nn.softmax(tf.matmul(x, W) + b)$$



 Once specified the model implementation, we can specify the necessary code to obtain the weights for W and bias b using an iterative training algorithm

 For each iteration, the training algorithm gets the training data, applies the neural network and compares the obtained result with the expected one.

• As a cost function : *cross entropy error*

$$- \leq y'_i \log(y_i)$$

To implement the cross-entropy measurement we need:

```
y_ = tf.placeholder("float", [None, 10])
cross_entropy = -tf.reduce_sum(y_*tf.log(y))
```

• As a iterative minimization process: backpropagation with gradient descent method using the cross-entropy cost function.

```
train_step = tf.train.GradientDescentOptimizer(0.01).minimize
(cross_entropy)
```

Start the computation by instantiating tf.Session():

```
sess = tf.Session()
sess.run(tf.initialize_all_variables())

for i in range(1000):
   batch_xs, batch_ys = mnist.train.next_batch(100)
sess.run(train_step, feed_dict={x: batch_xs, y_: batch_ys})
For each iteration, a bundle of 100 inputs of data, randomly sampled from the training data-set, are picked.
```

The returning parameter for *train_step*, when executed, will apply the gradient descent to the involved parameters. So training the model can be achieved by repeating the *train_step* execution.

- A model must be evaluated after training to see how much "good" is!
 - For example, we can compute the percentage of hits and misses in our prediction, seeing which examples were correctly predicted

```
correct_prediction = tf.equal(tf.argmax(y,1), tf.argmax(y_,1))
accuracy = tf.reduce_mean(tf.cast(correct_prediction, "float"))
print sess.run(accuracy, feed_dict={x: mnist.test.images, y_:
mnist.test.labels})
```

```
correct_prediction = tf.equal(tf.argmax(y,1), tf.argmax(y_,1))
```

the tf.argmax(y, 1) function returns the index of the highest value of a tensor according a given axis. In effect, tf.argmax(y, 1) is the label in our model with higher probability for each input, while $tf.argmax(y_1, 1)$ is the correct label.

```
accuracy = tf.reduce_mean(tf.cast(correct_prediction, "float"))
```

Using *tf.equal* method we can compare if our prediction coincides with the correct label.

For example, [True, False, True, True] will turn into [1,0,1,1] and the average will be 0.75 representing the percentage of accuracy. Now we can ask for the accuracy of our test data-set using the mnist.test as the feed_dict argument:

Using *tf.equal* method we can compare if our prediction coincides with the correct label:

```
correct_prediction = tf.equal(tf.argmax(y,1), tf.argmax(y_,1))
```

This instruction returns a list of Booleans. To determine which fractions of predictions are correct, we can cast the values to numeric variables (floating point) and do the following operation:

```
accuracy = tf.reduce_mean(tf.cast(correct_prediction, "float"))
```

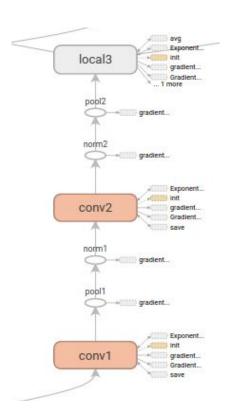
For example, [True, False, True, True] will turn into [1,0,1,1] and the average will be 0.75 representing the percentage of accuracy. Now we can ask for the accuracy of our test data-set using the mnist.test as the feed_dict argument:

print sess.run(accuracy, feed_dict={x: mnist.test.images, y_: mnist.test.labels})

Class hands-on (or Homework)

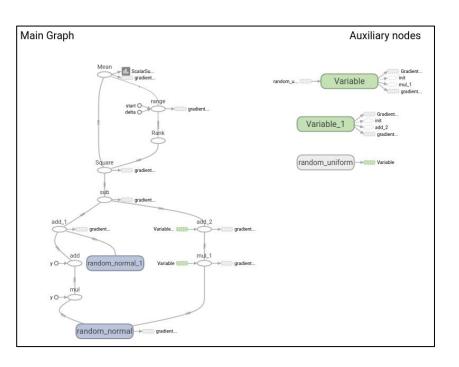
 Download the code SingleLayerNeuralNetwork.py from github and indicates the obtained value.

- Built-in graph visualization tool
- Can help you better understand the model
- Show and plot quantitative metrics about your graph
- Requires some extra work on the original code
- Some links for reference:
 - TensorBoard: Visualizing Learning
 - o TensorBoard: Graph Visualization
 - Running demo (code)
 - TensorBoard README



- Some useful functions
 - tf.name_scope('name') → used to define a hierarchy of the nodes in the graph.
 - Summary Operations (<u>Python API</u>)
 - tf.scalar_summary('name', values) → summary for scalar values
 - tf.histogram_summary('name', values) → summary with a histogram of the values
 - tf.merge_all_summaries() → merges all summaries collected in the graph
 - Adding Summaries to Event Files (<u>Python API</u>)
 - tf.train.SummaryWriter('logdir', sess.graph) → creates event file in the given directory
 - add_summary(summary, step) → adds summary to the event file
- Most functions have a name parameter, use it for better graph organization
- You can organize different runs and compare them modifying 'logdir'

- Step 1: Name variables and make use of scopes for organizing your graph
- Step 2: Place summaries for those values you want to keep track
- Step 3: Let TF manage all summaries with tf.merge_all_summaries()
- Step 4: Create a writer pointing to the desired directory
- Step 5: Add the merged summaries to the writer
- Step 6: Launch TensorBoard



```
import tensorflow as tf
tf.set_random_seed(1234)
x = tf.random_normal([100], mean=0.0, stddev=0.9)
y = x * 0.1 + 0.3 + tf.random_normal([100], mean=0.0, stddev=0.05)
W = tf.Variable(tf.random_uniform([], minval=-1.0, maxval=1.0))
b = tf.Variable(tf.zeros([]))
y_hat = W * x + b
loss = tf.reduce_mean(tf.square(y - y_hat))
train = tf.train.GradientDescentOptimizer(0.05).minimize(loss)
init = tf.initialize_all_variables()
sess = tf.Session()
writer = tf.train.SummaryWriter('/tmp/regression/', sess.graph)
sess.run(init)
for step in range(1, 101):
    _, slope, intercept, error = sess.run([train, W, b, loss])
    if step % 10 == 0:
        print('Step %.3d; W = %.5f; b = %.5f; loss = %.5f' %
             (step, slope, intercept, error))
```

Step 1: Name variables and make use of scopes for organizing your graph

```
with tf.name_scope('data'):
    with tf.name_scope('x'):
        x = tf.random_normal([100], mean=0.0, stddev=0.9, name='rand_x')
    with tf.name_scope('y'):
        y_{true} = x * tf.costant(0.1, name='real_slope') + tf.constant(0.3, name='bias') +
                 tf.random_normal([100], mean=0.0, stddev=0.05, name='rand_y')
with tf.name_scope('W'):
    W = tf.Variable(tf.random_uniform([], minval=-1.0, maxval=1.0))
with tf.name_scope('b'):
    b = tf.Variable(tf.zeros([]))
with tf.name_scope('function'):
    v \text{ pred} = W * x + b
with tf.name_scope('error'):
    loss = tf.reduce_mean(tf.square(y_pred - y_true))
```

Step 2: Place summaries for those values you want to keep track

```
with tf.name_scope('W'):
    W = tf.Variable(tf.random_uniform([], minval=-1.0, maxval=1.0))
    tf.scalar_summary('function/W', W)

with tf.name_scope('b'):
    b = tf.Variable(tf.zeros([]))
    tf.scalar_summary('function/b', b)

with tf.name_scope('error'):
    loss = tf.reduce_mean(tf.square(y_pred - y_true))
    tf.scalar_summary('error', loss)
```

Step 3: Let TF manage all summaries with tf.merge_all_summaries()

```
merged = tf.merge_all_summaries()
```

- Step 4: Create a writer pointing to the desired directory
 - Use different paths for each run to compare the performance when modifying hyperparameters

```
writer = tf.train.SummaryWriter('/tmp/regression/run1', sess.graph)
```

- Step 5: Add the merged summaries to the writer
 - Specify a global step (iteration, etc.) to be added to the summary

```
summary_str = sess.run(merged)
writer.add_summary(summary_str, step)
```

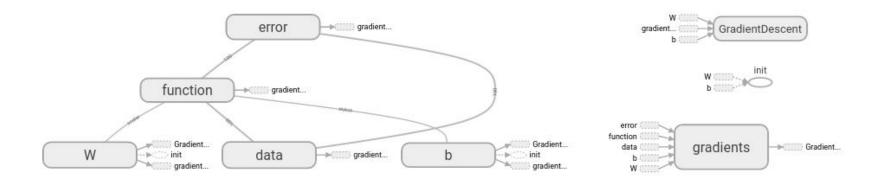
Step 6: Launch TensorBoard

Use the command → \$ tensorboard --logdir=/tmp/regression/

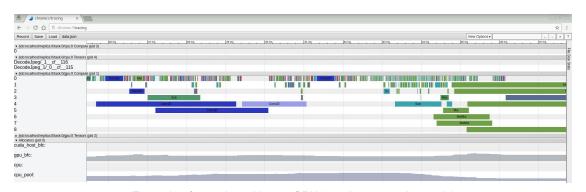
Then browse → http://localhost:6006/

If using Docker you may need to add the parameter -p 6006:6006

Main Graph Auxiliary nodes



- Some runtime statistics in TensorBoard
 - See and run regression_tb_md.py for basic changes
 - Also available in <u>Running demo</u> (<u>code</u>)
- More advanced CPU and GPU tracing
 - Steps to follow to enable it → <u>Link</u>
 - Also, lines commented in regression_tb_md.py
 - Go to chrome://tracing and load the json file obtained



- Homework:
 - Build a TB version of the simple network build today
 - Make use of tf.histogram_summary('name', values) for non-scalar variables