INTRODUCTION TO CONVOLUTIONAL NETWORKS USING TENSORFLOW

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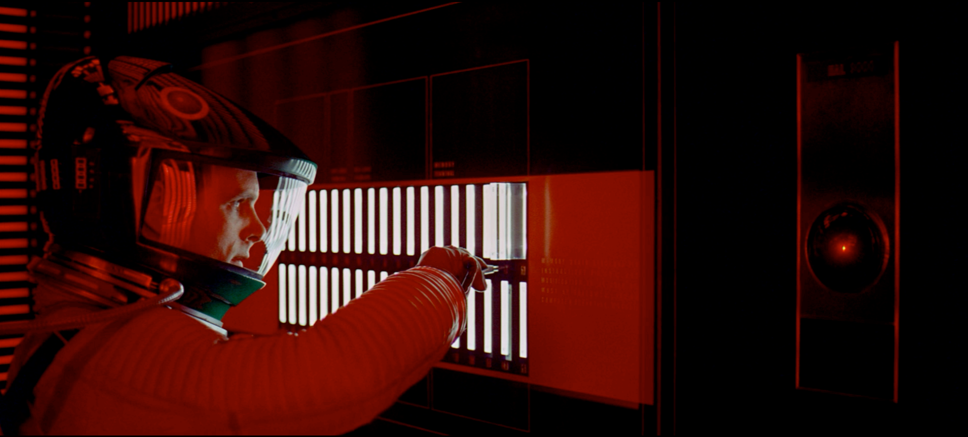
INSTALL INSTRUCTIONS



INSTALL INSTRUCTIONS

- Create a virtual environment with anaconda (it takes some time)

  ```
  $ conda update conda
  $ conda create -n tensorflow python=2.7 anaconda
  ```

  (tensorflow is the name of the environment, it can be whatever we want)

- Activate our new environment, prompt changes to (tensorflow)$

  ```
  $ source activate tensorflow
  ```

- To deactivate the environment you have to write (do it at the end of the session)

  ```
  $ source deactivate
  ```

- Install tensorflow but only in the new environment (also takes time)

  Ubuntu/Linux 64-bit, CPU only:

  ```
  $ pip install --upgrade
   https://storage.googleapis.com/tensorflow/linux/
   cpu/tensorflow-0.5.0-cp27-none-linux_x86_64.whl
  ```

  Ubuntu/Linux 64-bit, GPU enabled:

  ```
  $ pip install --upgrade
   https://storage.googleapis.com/tensorflow/linux/
   gpu/tensorflow-0.5.0-cp27-none-linux_x86_64.whl
  ```

  Mac OS X, CPU only:

  ```
  $ pip install --upgrade
   https://storage.googleapis.com/tensorflow/mac/
   tensorflow-0.5.0-py2-none-any.whl
  ```

Test the new instalation

```
(tensorflow)$ python

>>> import tensorflow as tf
>>> hello = tf.constant('Hello, TensorFlow!')
>>> sess = tf.Session()
>>> print sess.run(hello)
Hello, TensorFlow!
>>> a = tf.constant(10)
>>> b = tf.constant(32)
>>> print sess.run(a + b)
42
>>>
```

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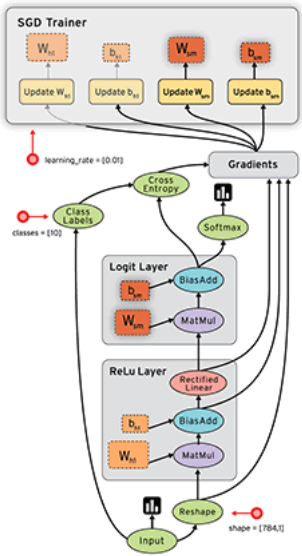
Developed by **Google Brain Team** and **Google's Machine Intelligence** research organization.

- Interface for expressing machine learning algorithms, and an implementation for executing them.
- Deep Flexibility: If you can write a computation graph.
- True Portability.
- Connect Research and Production.
- Auto-Differentiation.
- Language Options: Python, C++.
- Maximize Performance.

- In *tensorflow* computation represented using **Graphs**.
  - Each node is an **operation (op)**.
- Data is represented a **Tensors**.
  - **Op** takes **Tensors** and returns **Tensors**.
- Variables maintain state across executions of the graph.
- Two phases in the program:
  - Construct the computation **graph**.
  - Executes a **graph** in the context of a **Session**.
- Feed/fetch data to/from the graph.

EXAMPLE OF COMPUTATION GRAPH



CONSTRUCTION OF COMPUTATION GRAPH

Always the same 3-steps pattern:

1. inference() - Builds the graph as far as is required for running the network forward to make predictions.
2. loss() - Adds to the inference graph the ops required to generate loss.
3. training() - Adds to the loss graph the ops required to compute and apply gradients.

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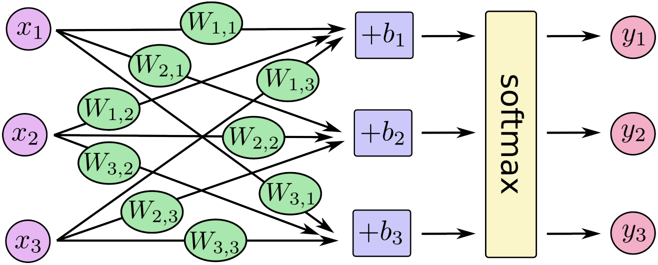
Each image is 28 pixels by 28 pixels.
55,000 data points of training data (mnist.train)
10,000 points of test data (mnist.test)
5,000 points of validation data (mnist.validation).

Use `tensorflow.googlesource.com/tensorflow/+/master/tensorflow/examples/tutorials/mnist/input_data.py` to download the data.

$$y = \text{softmax}(Wx + b)$$

$$\text{softmax}(x)_i = \frac{\exp x_i}{\sum_j \exp x_j}$$



mnist_ softmax.py

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

Fichero descarga de datos:

`tensorflow.googlesource.com/tensorflow/+/master/tensorflow/examples/tutorials/mnist/input_data.py`

mnist_ softmax.py: Variable declaration

```
x = tf.placeholder(tf.float32, [None, 784])
y_ = tf.placeholder(tf.float32, [None, 10])

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

ASSEMBLE COMPUTATION GRAPH

- Inference

mnist_ softmax.py: Inference

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

- Loss

mnist_ softmax.py: Loos computation

```
cross_entropy = -tf.reduce_sum(y_*tf.log(y))
```

- Training

mnist_ softmax.py : Training

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

TensorFlow also provides many other **optimization algorithms**: using one is as simple as tweaking one line:

class tf.train.AdagradOptimizer

class tf.train.MomentumOptimizer

class tf.train.AdamOptimizer

EVALUATION

How well we are predicting the correct label?

mnist_ softmax.py: Evaluation

```
correct_prediction = tf.equal(tf.argmax(y,1), tf.argmax(y_,1))
accuracy = tf.reduce_mean(tf.cast(correct_prediction, "float"))
```

EXECUTE THE COMPUTATION GRAPH

mnist_ softmax.py: Initialize all the variables

```
init = tf.initialize_all_variables()
```

mnist_softmax.py: Start a new session

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

# Let's train -- we'll run the training step 1000 times!
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})
print sess.run(accuracy, feed_dict={x: mnist.test.images,
                                    y_: mnist.test.labels})
```

Result around 91 %: **VERY BAD for MNIST**

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- State-of-the-art of Image Recognition.
- Traditional Approach: **Handmade features**.

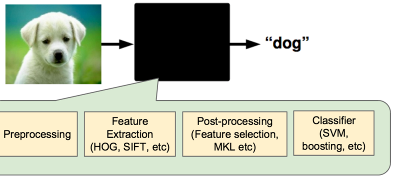

Figura 1: `http://www.cs.umd.edu/~djacobs`

- ¿Can we learn the features+classifier?

  Complex non-linear map from pixels to labels.

  Do it in several *simple* layers: Function composition.

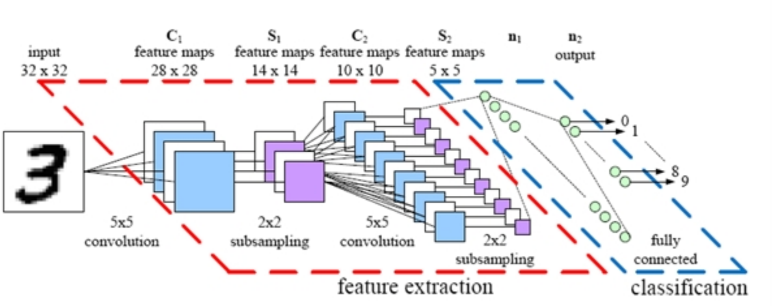

Figura 2: `http://parse.ele.tue.nl/`

Explanation of each layer.

Train using **Backpropagation**.

This works very well. Why?

Rick Baraniuk "opinion": **A Probabilistic Theory of Deep Learning.**

Reuse the data loading part of mnist_softmax.py.

mnist_cnn.py

```
import tensorflow as tf
import input_data
mnist = input_data.read_data_sets('MNIST_data', one_hot=True)

x = tf.placeholder("float", shape=[None, 784])
y_ = tf.placeholder("float", shape=[None, 10])
```

We will have to initialize a lot of weights.

mnist_cnn.py: weight initialization

```
def weight_variable(shape):
  initial = tf.truncated_normal(shape, stddev=0.1)
  return tf.Variable(initial)

def bias_variable(shape):
  initial = tf.constant(0.1, shape=shape)
  return tf.Variable(initial)
```

Convolution and pooling operations. We will use them in different layers.

mnist_cnn.py: Convolution and pooling

```
def conv2d(x, W):
  return tf.nn.conv2d(x, W, strides=[1, 1, 1, 1], padding='SAME')

def max_pool_2x2(x):
  return tf.nn.max_pool(x, ksize=[1, 2, 2, 1],
                        strides=[1, 2, 2, 1], padding='SAME')
```

First layer: From input data to second layer

mnist_cnn.py: First Convolutional Layer

```
W_conv1 = weight_variable([5, 5, 1, 32])
b_conv1 = bias_variable([32])

x_image = tf.reshape(x, [-1, 28, 28, 1])

h_conv1 = tf.nn.relu(conv2d(x_image, W_conv1) + b_conv1)
h_pool1 = max_pool_2x2(h_conv1)
```

Second layer: From ouput of first layer to FC layer

mnist_cnn.py: Second Convolutional Layer

```
W_conv2 = weight_variable([5, 5, 32, 64])
b_conv2 = bias_variable([64])

h_conv2 = tf.nn.relu(conv2d(h_pool1, W_conv2) + b_conv2)
h_pool2 = max_pool_2x2(h_conv2)
```

mnist_cnn.py: Fully Connected layer

```
# Densely connected layer
W_fc1 = weight_variable([7 * 7 * 64, 1024])
b_fc1 = bias_variable([1024])

h_pool2_flat = tf.reshape(h_pool2, [-1, 7*7*64])
h_fc1 = tf.nn.relu(tf.matmul(h_pool2_flat, W_fc1) + b_fc1)
```

Dropout trick and output layer.

mnist_cnn.py: Dropout

```
# Add dropout
keep_prob = tf.placeholder("float")
h_fc1_drop = tf.nn.dropout(h_fc1, keep_prob)
```

mnist_cnn.py: Readout layer

```
# Readout layer
W_fc2 = weight_variable([1024, 10])
b_fc2 = bias_variable([10])

y_conv = tf.nn.softmax(tf.matmul(h_fc1_drop, W_fc2) + b_fc2)
```

mnist_cnn.py: Train and Evaluate

```
cross_entropy = -tf.reduce_sum(y_*tf.log(y_conv))
train_step = tf.train.AdamOptimizer(1e-4).minimize(cross_entropy)
correct_prediction = tf.equal(tf.argmax(y_conv,1), tf.argmax(y_,1))
accuracy = tf.reduce_mean(tf.cast(correct_prediction, "float"))
```

mnist_cnn.py: Execute

```
init = tf.initialize_all_variables()
sess = tf.InteractiveSession()
sess.run(init)
for i in range(20000):
  batch = mnist.train.next_batch(50)
  if i%100 == 0:
    train_accuracy = accuracy.eval(feed_dict={
        x:batch[0], y_: batch[1], keep_prob: 1.0})
    print "step %d, training accuracy %g"%(i, train_accuracy)
  train_step.run(feed_dict={x: batch[0], y_: batch[1], keep_prob: 0.5})

print "test accuracy %g"%accuracy.eval(feed_dict={
    x: mnist.test.images, y_: mnist.test.labels, keep_prob: 1.0})
```

Go back to work while it finishes: Accuracy $\approx 99{,}2\,\%$.

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WHAT ELSE?

- Tensorboard.
  `https://www.tensorflow.org/versions/0.6.0/how_tos/summaries_and_tensorboard/index.html`

- Vector Representation of Words (word2vec).
- Recurrent Neural Networks (Long short-term memory Networks, seq2seq models).
- General Mathematics (Mandelbrot Set, Partial Differential Equations)

- **Udacity free online course**