1. Tensorflow Basic Part I

August 10, 2018

1 Tensorflow

```
In [1]: import tensorflow as tf
```

2 Our first tensorflow program: Hello world

```
In [2]: h = tf.constant("Hello")
        w = tf.constant(" world")
        hw = h + w
```

```
In [3]: with tf.Session() as sess:
            ans = sess.run(hw)

        print ans
```

```
Hello world
```

3 Key concepts of Tensorflow

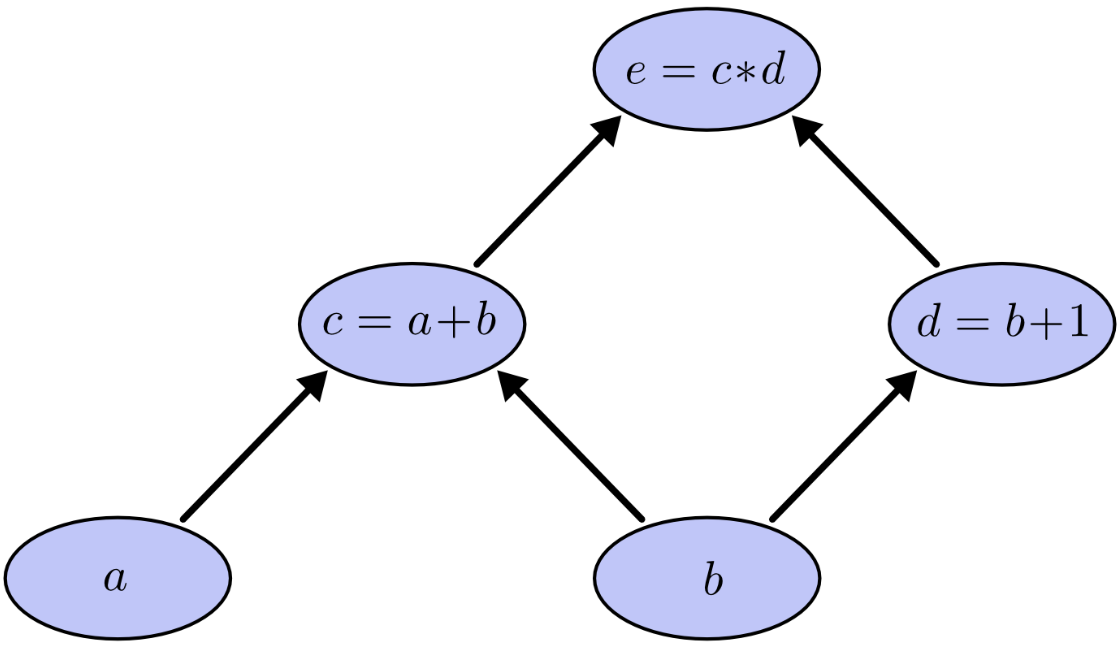
- Computation graph
- Execution

4 Computation graph

- Nodes & Edges
- Operations
- Benefits of graph computation

```
In [4]: from IPython.display import Image
        Image(filename='Computation graph.png')
```

Out[4]:



- We create 5 nodes assigned to arbitrarily named variables, a ~ e
- The contents of these variables should be regarded as the output of the operation, not operation themselves
- But for now we refer to both the output of the operation and operation themselves with the names of corresponding variables.

```
In [5]: a = tf.constant(5)
        b = tf.constant(2)
        c = a + b
        d = b + 1
        e = tf.multiply(c, d)
```

5 Execution

- Sessions
- Fetches

```
In [6]: sess = tf.Session()     # session object
        outs = sess.run(e)      # the session object compute the operation, e. Arguments to run,
        sess.close()
        print "out = {}".format(outs)

out = 21
```

```
In [7]: with tf.Session() as sess:
            print "out = {}".format(sess.run(e))
```

```
out = 21
```

6 Creating a computation graph

- Right after we import tensorflow, a specific empty default graph is formed.
- All the nodes we create are automatically associated with the default graph

```
In [8]: g1 = tf.get_default_graph()   # get default graph
        g2 = tf.Graph()               # generate new graph

        print g1
        print g2
```

```
<tensorflow.python.framework.ops.Graph object at 0x7fc853e21d50>
<tensorflow.python.framework.ops.Graph object at 0x7fc853e21450>
```

```
In [9]: print a.graph is g1    # checks which graph owns the operation, a
        print a.graph is g2
```

```
True
False
```

7 What is Session?

- Tensorflow's computation system runs on GPUs which have independent memory system and calculators.
- So, we need to associate python objects and data on our end with the computation system
- Session object is a Tensorflow object for the association

```
In [10]: sess = tf.Session()
```

8 Execution

- Tensorflow.Session().run()
- From the requested outputs, works backward, computing nodes that must be executed according to the set of dependencies

```
In [11]: sess.run(e)  # we want to compute e, then from e, figure out dependencies between nodes
```

```
Out[11]: 21
```

```
In [12]: sess.run([e, d, c, b, a]) # multiple fetches, notice that the order of results = the or
```

```
Out[12]: [21, 3, 7, 2, 5]
```

```
In [13]: sess.close() # strongly recommended for resource management purpose
```

9 Flowing Tensors

- Node = Operation
- Edge = Tensor

```
In [14]: f = tf.add(e, d) # This operation creates actual operation instance, but do not produce
                          # but rather references its to-be-computed result as a handle that can
                          # these handles are tensor objects
```

```
In [15]: print f    # not actual value, handle for the result(not yet computed) of the correspon
```

```
Tensor("Add:0", shape=(), dtype=int32)
```

9.0.1 Setting attributes for tensor and operations

- name, shape, dtype, ...

```
In [16]: f = tf.add(e, d, name='Addition_E_D') # shape and dtype of operation are automatically
         print f
```

```
Tensor("Addition_E_D:0", shape=(), dtype=int32)
```

```
In [17]: h = tf.constant([1,2,3], name='const_3', dtype=tf.float32)
         print h
```

```
Tensor("const_3:0", shape=(3,), dtype=float32)
```

10 Tensor

10.0.2 1) is the name of an object used in the python api as a handle for the result of an operation in the graph.

10.0.3 2) is also a mathematical term for n-dimensional arrays

- 1 x 1 tensor = scalar
- 1 x n tensor = vector
- n x n tensor = matrix
- n x n x n tensor = 3-dimensional array
- ...

11 Tensor array initialization

```
In [18]: # Random number generation
         i = tf.Variable(tf.random_normal(shape=[10,10]), name='random_norm')
```

```
In [19]: sess = tf.Session()
         sess.run(tf.global_variables_initializer())
         print i
```

```
<tf.Variable 'random_norm:0' shape=(10, 10) dtype=float32_ref>
```

```
In [20]: print sess.run(i)
```

```
[[ 1.76543212e+00  4.32564497e-01  9.72211838e-01 -6.43687248e-01
  -1.21464290e-01 -1.37247026e+00 -9.36417758e-01 -2.39865974e-01
   1.73359960e-01 -6.15796089e-01]
 [ 7.17706203e-01 -5.83130158e-02  1.15591094e-01 -3.63293588e-01
  -1.18528628e+00  2.03466088e-01 -3.18020761e-01  1.49252906e-01
   1.21068084e+00  1.61724448e+00]
 [-7.96645939e-01  1.15474725e+00 -3.21333706e-01  4.43559319e-01
  -1.09148395e+00 -2.77464855e-02  1.81540108e+00  1.20130491e+00
   1.10164726e+00  2.74230289e+00]
 [ 4.90358502e-01 -1.33525416e-01  9.21714127e-01  1.12049091e+00
  -1.29760131e-01 -8.67207408e-01 -1.14448212e-01  3.10444742e-01
   8.16107243e-02  9.44006979e-01]
 [ 1.01526690e+00  1.08581746e+00  8.32218349e-01  1.82956329e-03
  -3.36233109e-01  3.51894170e-01  7.28676736e-01 -8.15776706e-01
  -1.43610269e-01 -1.38183042e-01]
 [-1.16303575e+00  4.76424277e-01  1.41872239e+00  1.52177882e+00
   1.02745295e+00  1.01564348e+00 -6.14714861e-01 -1.20882176e-01
  -1.25554070e-01  6.62051439e-01]
 [ 1.29020202e+00  7.94911265e-01 -2.20984554e+00 -6.28462374e-01
   1.62653613e+00  1.07774532e+00  1.22504130e-01 -9.88793135e-01
   1.09768569e+00  2.23159885e+00]
 [-2.16830397e+00  2.13437811e-01  8.74156415e-01 -8.31503868e-01
  -1.46399423e-01 -3.94881815e-01 -6.10830784e-01 -1.63033593e+00
   1.47092268e-01  3.29295099e-01]
 [-9.28258672e-02  2.19273281e+00  6.02474272e-01 -6.27267063e-01
   2.68810183e-01  6.56095505e-01  6.71676517e-01 -3.88856083e-01
   1.70886266e+00  1.19880855e+00]
 [ 4.84252013e-02 -1.14467263e+00 -1.84157118e-01  9.44752216e-01
   3.68006974e-01  4.93237674e-02  1.95067003e-01  1.30749047e+00
   4.89180952e-01 -1.39254892e+00]]
```

```
In [21]: sess.close()
```

12 Matrix multiplication

- Matrix A: [M x N]
- Matrix B: [N x K]
- A x B : [M x K]

```
In [22]: M = 10
         N = 5
         K = 8

         A = tf.Variable(tf.random_normal(shape=[M, N], dtype=tf.float32), name='Matrix_A')
         B = tf.Variable(tf.random_normal(shape=[N, K], dtype=tf.float32), name='Matrix_B')
         C = tf.matmul(A, B)

         sess = tf.InteractiveSession()
         sess.run(tf.global_variables_initializer())

         print 'Matmul(A,B) :', C.eval()
         print 'Shape :', C.get_shape()
```

```
Matmul(A,B) : [[ 4.9575895e-01  1.8628086e+00  1.2861952e+00  1.9142175e-01
  -3.4036922e+00  2.2414093e+00  1.3109031e+00  8.8190734e-01]
 [ 1.8711339e+00  6.1970348e+00  2.0674398e+00  1.6390033e+00
  -4.5526347e+00  3.0976284e+00  7.0880127e-01  1.9912920e+00]
 [ 1.5207050e+00 -5.9241042e+00 -1.2662030e+00  2.0578046e+00
   3.6490829e+00 -4.1264000e+00  2.9452741e-03  4.6974498e-01]
 [ 4.1289916e+00 -4.1741815e+00  1.2581675e+00  3.9573221e+00
   1.2221881e+00 -2.4298873e+00 -4.4353664e-01  1.9756210e+00]
 [ 9.9584901e-01 -6.0096874e+00  2.5057626e-01  8.3295602e-01
   2.4992800e+00 -2.5919039e+00 -1.4965640e+00 -1.4311445e-01]
 [ 1.8129790e+00 -7.6873016e-01  2.3317926e-01  8.1023496e-01
   2.6163244e+00  2.6019347e-01  1.0044088e+00 -4.8376638e-01]
 [-6.8796176e-01 -7.1675926e-01 -3.2295951e-01 -1.1125695e+00
   7.6810992e-01  6.2310338e-01  8.6187714e-01 -9.5701081e-01]
 [ 2.5271626e+00 -1.1329877e+00  5.3780955e-01  5.5750966e-02
   5.6522226e+00  1.5583522e+00  1.6926724e+00 -2.1207931e+00]
 [ 3.8287621e+00 -3.2631305e-01  2.4302430e+00  1.8408196e+00
   1.9938418e+00  1.5550959e+00 -1.0094592e-01 -1.2188792e-02]
 [-1.8440151e-01 -2.1451929e+00 -2.8432384e+00  4.6494055e-01
   5.7310820e+00 -3.6488147e+00 -1.3869411e-01 -1.0000851e+00]]
Shape : (10, 8)
```

```
In [23]: sess.close()
```

13 Tensor object name

- Note that Tensor objects residing in the same graph cannot have the same name
- Automatically followed by the index of tensor in the outputs of the operation that produced it

```
In [24]: A1 = tf.Variable(tf.random_normal(shape=[M, N], dtype=tf.float32), name='Matrix_A')
         A2 = tf.Variable(tf.random_normal(shape=[M, N], dtype=tf.float32), name='Matrix_A')
```

```
print A1.name
print A2.name
```

```
Matrix_A_1:0
Matrix_A_2:0
```

14 Name scope

- heirachical grouping of object names
- very useful when dealing with a large, complicated graph

```
In [25]: k1 = tf.constant(1., name='k')
         with tf.name_scope('prefix_name'):
             k2 = tf.constant(1., name='k')
             k3 = tf.constant(1., name='k')

         print k1.name
         print k2.name
         print k3.name
```

```
k:0
prefix_name/k:0
prefix_name/k_1:0
```

15 Variables & Placeholder

```
In [26]: var_a = tf.Variable(tf.random_normal(shape=[1, 100], dtype=tf.float32), name='var')
         print var_a
         with tf.Session() as sess:
             sess.run(tf.global_variables_initializer())
             print sess.run(var_a)
```

```
<tf.Variable 'var:0' shape=(1, 100) dtype=float32_ref>
[[ 0.6653831   1.3791506  -0.10195301 -1.6813173   0.8751185   0.01129055
  -1.4622062   0.6074679   1.262346    1.8850379  -0.01946986 -0.16157788
  -0.7027838  -0.6554051  -0.01522055 -1.52461    -1.2823409   0.44614947
  -0.836785   -0.27211922  0.57041836 -2.2181041  -1.646425    0.30064288
  -1.5148413  -1.9163382  -0.07588363 -0.14843263  0.38889936 -0.58876044
   0.5916117  -1.1125816  -0.8171849  -0.3992469   0.90365696  0.06570981
   0.7231378  -1.0638485   1.9087532  -0.7204932   0.6351097   0.5846274
   1.5521302   0.15776552  0.42325106  0.57951707  0.8122477  -0.6274473
   1.8899337  -0.17532238 -0.5597155   0.27203158  0.5363315  -0.6394399
  -1.4160008   0.02431237 -0.53705275 -0.58560103  0.5444054  -1.2710557
  -0.6148214   0.37262687 -0.70824623  0.16020577 -0.88495815  0.7797979
  -0.12483959  1.4959303   0.69797415  0.13797398 -1.9859734  -1.0090563
```

```
  -1.0378356  -0.63841     1.3049648  -1.0237182  -1.1568127  -0.13480233
   0.472      -0.7348273   0.39346412  0.1185667   0.6244066  -0.3493913
  -0.15730108 -0.7738369   1.4978056  -3.9548302  -2.2351487  -1.6785712
   1.0263594  -2.1334944   1.4782141   0.2443358   0.32686797  0.10157384
  -0.85684025 -0.15669419 -0.5749858  -1.5986487 ]]
```

```
In [27]: import numpy as np
```

```
In [28]: val1 = np.random.randn(10, 5)
         val2 = np.random.randn(5, 10)

         ph1 = tf.placeholder(dtype=tf.float32, shape=[10, 5])
         ph2 = tf.placeholder(dtype=tf.float32, shape=[5, 10])
         rst = tf.matmul(ph1, ph2)

         with tf.Session() as sess:
             sess.run(tf.global_variables_initializer())
             print sess.run(rst, feed_dict={ph1:val1, ph2:val2}) # feed placeholders at the exec
```

```
[[ 6.7704554  -4.2027783   0.6966889  -4.504948   -4.071384    1.6463145
  -0.21468985  0.3670642  -8.154308    4.197429  ]
 [-1.1280397   3.2678237   1.7171372  -1.5603057   1.619727    2.0589895
   3.198231   -2.7798543  -3.8069863   2.1170576 ]
 [ 3.5722914  -2.2203355  -1.6268415  -2.5500612  -1.3810587   1.2549694
   0.50319207 -1.4301254  -2.8254564   1.5731803 ]
 [ 1.7295699  -4.0300446  -2.283965    1.634112   -1.9618982  -2.5137799
  -3.389064    3.262247    3.814848   -2.3493514 ]
 [-5.6625667   2.3533108   3.1471574   0.8724818   3.3446507  -0.9331237
   3.5602293  -1.37436    -3.361684    1.01857   ]
 [ 2.208654   -3.7521296  -2.4315162   1.4578652  -1.9096482  -2.698502
  -2.529924    3.4339898   2.5193563  -2.118298  ]
 [-1.0124531   1.7834175   3.238422   -2.535202    0.57820004  3.096833
   1.4275998  -3.2354555  -3.9572163   3.272065  ]
 [ 1.6402011   2.3444574  -3.6304994   1.4234297  -0.5777743   1.8519924
  -3.6916685  -0.3501258  10.145537   -3.5752437 ]
 [ 3.1029468  -2.9242594  -2.8232224   1.8584743  -2.6310258  -2.0179238
  -4.2034597   3.9961987   5.3556104  -2.97404   ]
 [ 9.363311    2.6019008  -2.663109   -6.719274   -2.8997283   7.8664184
   0.9050351  -5.4741774  -3.1946158   3.850216  ]]
```

16 Optimization

16.0.4 Linear regression

- y: target variable
- x: feature vector

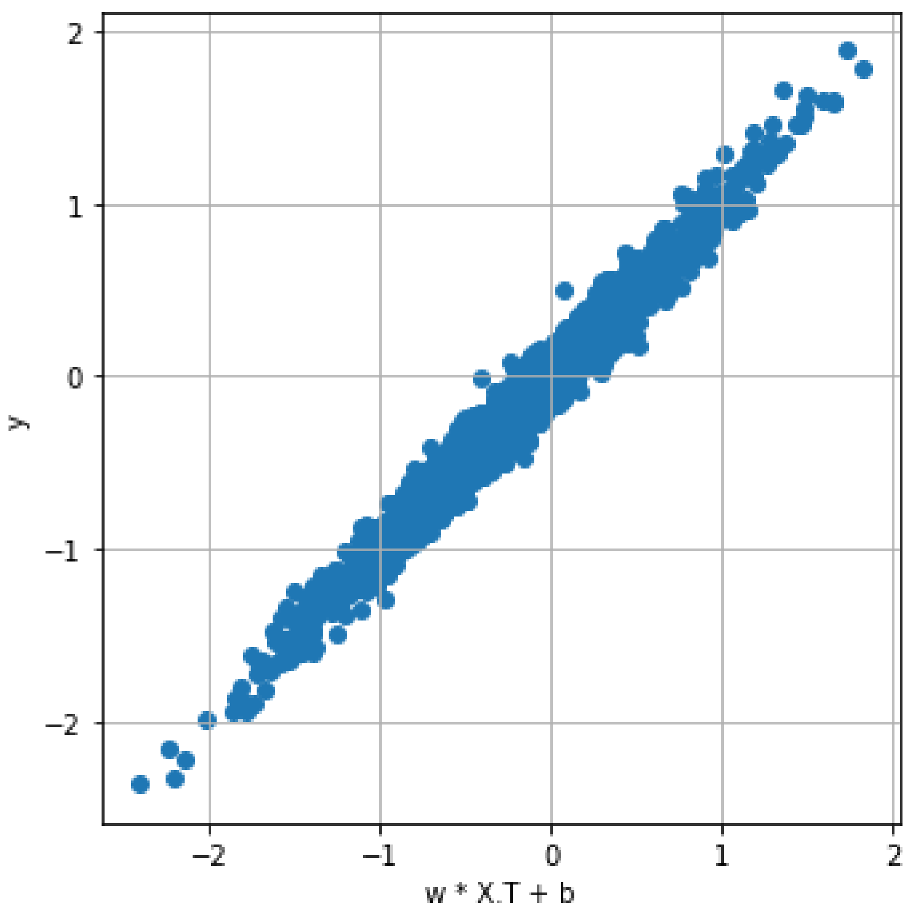
- y = x * W + b

```
In [35]: x_data = np.random.randn(2000, 3)
         w_real = [0.3, 0.5, 0.1]
         b_real = -0.2
         noise = np.random.randn(1, 2000) * 0.1

         temp = np.matmul(w_real, x_data.T) + b_real
         y_data = temp + noise
```

```
In [36]: import matplotlib.pylab as plt
```

```
In [38]: plt.figure(figsize=[5,5])
         plt.xlabel('w * X.T + b')
         plt.ylabel('y')
         plt.scatter(temp, y_data)
         plt.grid(True)
         plt.tight_layout()
         plt.show()
```



16.0.5 Optimization goal

- Given x_data and y_data, we want to find w_real and b_real

```
In [35]: # training to predict
         NUM_STEPS = 10

         x = tf.placeholder(dtype=tf.float32, shape=[None, 3])
         y_true = tf.placeholder(dtype=tf.float32, shape=None)

         with tf.name_scope('inference') as scope:
             w = tf.Variable([[0,0,0]],dtype=tf.float32, name='weights')
             b = tf.Variable(0, dtype=tf.float32, name='bias')
             y_pred = tf.matmul(w, tf.transpose(x)) + b
```

16.0.6 Loss function

- Mean squared error
- Cross entropy

```
In [36]: with tf.name_scope('mse') as scope:
             mse_loss = tf.reduce_mean(tf.square(y_true - y_pred))

In [37]: with tf.name_scope('cross_entropy') as scope:
             cross_entropy_loss = tf.reduce_mean(tf.nn.sigmoid_cross_entropy_with_logits(labels=
```

16.0.7 Training

```
In [38]: with tf.name_scope('train') as scope:
             learning_rate = 0.5
             optimizer = tf.train.GradientDescentOptimizer(learning_rate)
             train = optimizer.minimize(mse_loss)

In [39]: with tf.Session() as sess:
             sess.run(tf.global_variables_initializer())
             for step in range(NUM_STEPS):
                 sess.run(train, feed_dict={x:x_data, y_true:y_data})
                 if step % 5 == 0:
                     print step, sess.run([w, b])

             print 10, sess.run([w, b])

0 [array([[0.3105729 , 0.49970657, 0.08790597]], dtype=float32), -0.21092714]
5 [array([[0.29926383, 0.49876568, 0.09481297]], dtype=float32), -0.1982763]
10 [array([[0.29926383, 0.49876568, 0.09481298]], dtype=float32), -0.1982763]
```

17 Optimization

17.0.8 logistic regression

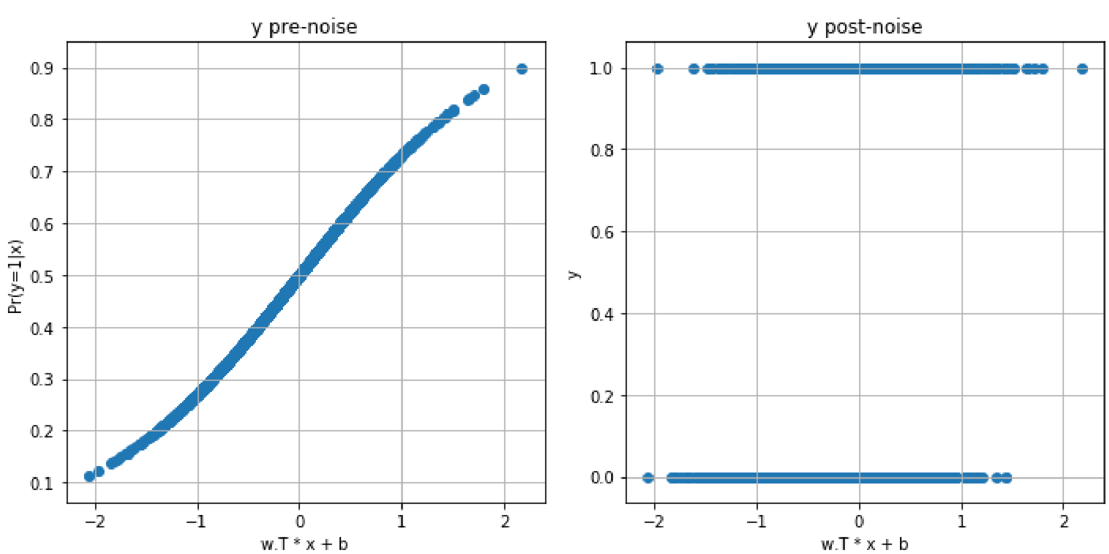
```
In [40]: def sigmoid(x):
             return 1 / (1 + np.exp(-x))
```

```
In [41]: N = 2000
         x_data = np.random.randn(N, 3)
         w_real = [0.3, 0.5, 0.1]
         b_real = -0.2
         wxb = np.matmul(w_real, x_data.T) + b_real

         y_data_pre_noise = sigmoid(wxb)
         y_data = np.random.binomial(1, y_data_pre_noise)
```

```
In [42]: plt.figure(figsize=[10,5])
         plt.subplot(1,2,1)
         plt.title('y pre-noise')
         plt.xlabel('w.T * x + b')
         plt.ylabel('Pr(y=1|x)')
         plt.scatter(wxb, y_data_pre_noise)
         plt.grid(True)

         plt.subplot(1,2,2)
         plt.title('y post-noise')
         plt.xlabel('w.T * x + b')
         plt.ylabel('y')
         plt.scatter(wxb, y_data)
         plt.grid(True)
         plt.tight_layout()
         plt.show()
```



In [45]:
```python
NUM_STEPS = 50

x = tf.placeholder(dtype=tf.float32, shape=[None, 3])
y_true = tf.placeholder(dtype=tf.float32, shape=None)

with tf.name_scope('inference') as scope:
    w = tf.Variable([[0,0,0]],dtype=tf.float32, name='weights')
    b = tf.Variable(0, dtype=tf.float32, name='bias')
    y_pred = tf.matmul(w, tf.transpose(x)) + b

with tf.name_scope('loss'):
    loss = tf.nn.sigmoid_cross_entropy_with_logits(labels=y_true, logits=y_pred)
    loss = tf.reduce_mean(loss)

with tf.name_scope('train') as scope:
    learning_rate = 0.5
    optimizer = tf.train.GradientDescentOptimizer(learning_rate)
    train = optimizer.minimize(loss)

init = tf.global_variables_initializer()
with tf.Session() as sess:
    sess.run(init)
    for step in range(NUM_STEPS):
        sess.run(train, {x:x_data, y_true:y_data})
        if step % 5 == 0:
            print (step, sess.run([w, b]))

    print (50, sess.run([w, b]))
```

```
(0, [array([[0.03531037, 0.05989414, 0.00871425]], dtype=float32), -0.02725])
(5, [array([[0.15451796, 0.26329753, 0.03964205]], dtype=float32), -0.12354487])
(10, [array([[0.21670775, 0.3705548 , 0.05726023]], dtype=float32), -0.17757638])
(15, [array([[0.2507458 , 0.42986125, 0.06770609]], dtype=float32), -0.20892145])
(20, [array([[0.2699842 , 0.4637024 , 0.07404341]], dtype=float32), -0.2274949])
(25, [array([[0.28107464, 0.48338377, 0.0779311 ]], dtype=float32), -0.23863155])
(30, [array([[0.28754628, 0.49496192, 0.08032685]], dtype=float32), -0.24535105])
(35, [array([[0.29135165, 0.5018208 , 0.08180471]], dtype=float32), -0.24941792])
(40, [array([[0.29360032, 0.5059016 , 0.08271566]], dtype=float32), -0.25188252])
(45, [array([[0.29493356, 0.508336  , 0.08327626]], dtype=float32), -0.25337657])
(50, [array([[0.29559845, 0.5095565 , 0.08356448]], dtype=float32), -0.25413534])
```