

AlexNet

March 21, 2019

1 AlexNet

1.1 TensorFlow model

Following is an AlexNet model implementation with some of the hyperparameter changes.

AlexNet model implementation is given in paper krizhevsky et al. 2012 ImageNet Classification with Deep Convolutional Neural Networks

```
In [23]: import math
import numpy as np
import h5py
import matplotlib.pyplot as plt
import scipy
from PIL import Image
from scipy import ndimage
import tensorflow as tf
from tensorflow.python.framework import ops
from cnn_utils import *

%matplotlib inline
np.random.seed(1)
```

Run the next cell to load the “SIGNS” dataset you are going to use.

```
In [24]: # Loading the data (signs)
X_train_orig, Y_train_orig, X_test_orig, Y_test_orig, classes = load_dataas

In [25]: X_train = X_train_orig/255.
X_test = X_test_orig/255.
Y_train = convert_to_one_hot(Y_train_orig, 6).T
Y_test = convert_to_one_hot(Y_test_orig, 6).T
print ("number of training examples = " + str(X_train.shape[0]))
print ("number of test examples = " + str(X_test.shape[0]))
print ("X_train shape: " + str(X_train.shape))
print ("Y_train shape: " + str(Y_train.shape))
print ("X_test shape: " + str(X_test.shape))
print ("Y_test shape: " + str(Y_test.shape))
conv_layers = {}
```

```

number of training examples = 1080
number of test examples = 120
X_train shape: (1080, 64, 64, 3)
Y_train shape: (1080, 6)
X_test shape: (120, 64, 64, 3)
Y_test shape: (120, 6)

```

```
In [26]: # GRADED FUNCTION: create_placeholders
```

```

def create_placeholders(n_H0, n_W0, n_C0, n_y):
    """
    Creates the placeholders for the tensorflow session.

    Arguments:
    n_H0 -- scalar, height of an input image
    n_W0 -- scalar, width of an input image
    n_C0 -- scalar, number of channels of the input
    n_y -- scalar, number of classes

    Returns:
    X -- placeholder for the data input, of shape [None, n_H0, n_W0, n_C0]
    Y -- placeholder for the input labels, of shape [None, n_y] and dtype
    """

    ### START CODE HERE ### (≈2 lines)
    X = tf.placeholder(tf.float32, shape = (None, n_H0, n_W0, n_C0) )
    Y = tf.placeholder(tf.float32, shape = (None, n_y) )
    ### END CODE HERE ###

    return X, Y

```

```

In [27]: X, Y = create_placeholders(64, 64, 3, 6)
print ("X = " + str(X))
print ("Y = " + str(Y))

```

```

X = Tensor("Placeholder_2:0", shape=(?, 64, 64, 3), dtype=float32)
Y = Tensor("Placeholder_3:0", shape=(?, 6), dtype=float32)

```

Expected Output

```

X = Tensor("Placeholder:0", shape=(?, 64, 64, 3), dtype=float32)
Y = Tensor("Placeholder_1:0", shape=(?, 6), dtype=float32)

```

```
In [28]: # GRADED FUNCTION: initialize_parameters
```

```

def initialize_parameters():
    """
    Initializes weight parameters to build a neural network with tensorflow

```

```

        W1 : [4, 4, 3, 8]
        W2 : [2, 2, 8, 16]

Returns:
parameters -- a dictionary of tensors containing W1, W2
"""

tf.set_random_seed(1)                                # so that your "ran

### START CODE HERE ### (approx. 2 lines of code)
W1 = tf.get_variable("W1", [4,4,3,96], initializer = tf.contrib.layers
W2 = tf.get_variable("W2", [5,5,96,256], initializer = tf.contrib.laye
W3 = tf.get_variable("W3", [3,3,256,384], initializer = tf.contrib.lay
W4 = tf.get_variable("W4", [3,3,384,384], initializer = tf.contrib.lay
W5 = tf.get_variable("W5", [3,3,384,256], initializer = tf.contrib.lay
### END CODE HERE ###

parameters = {"W1": W1,
              "W2": W2,
              "W3": W3,
              "W4": W4,
              "W5": W5}

return parameters

In [29]: tf.reset_default_graph()
        with tf.Session() as sess_test:
            parameters = initialize_parameters()
            init = tf.global_variables_initializer()
            sess_test.run(init)
            print("W1 = " + str(parameters["W1"].eval()[1,1,1]))
            print("W2 = " + str(parameters["W2"].eval()[1,1,1]))
            print("W3 = " + str(parameters["W3"].eval()[1,1,1]))
            print("W4 = " + str(parameters["W4"].eval()[1,1,1]))
            print("W5 = " + str(parameters["W5"].eval()[1,1,1]))

W1 = [ 0.01671694  0.06110588 -0.03386452  0.05938012  0.0145212  -0.04832294
 -0.0015871  -0.05174213 -0.0278542  -0.05713523  0.04564724 -0.0372206
  0.05195162 -0.05525731  0.01492433  0.05662248  0.04479869 -0.03715155
 -0.05752828 -0.00128394 -0.03468554  0.0339203  -0.03956766  0.02586722
  0.060818    0.04539385 -0.04254989  0.02562458 -0.04011025 -0.03983246
 -0.02190537  0.00698699 -0.03841595 -0.01560952 -0.04289921  0.0344194
  0.00680743 -0.03082583 -0.02350465 -0.0006859  -0.04149082  0.04848495
 -0.01811537  0.06091134  0.04603212  0.00425005  0.0264094  -0.0155791
  0.01267537  0.03423977  0.04724856 -0.02301043 -0.06008575 -0.04107204
  0.05599377  0.01036631 -0.02794269 -0.01615478  0.0023118  -0.0564984
 -0.04331018  0.01856513 -0.01615087 -0.00593869 -0.05587354  0.00578145
  0.03594472  0.00681745  0.0383089  -0.01609302  0.04841047 -0.01697941
  0.04661693 -0.05066967  0.02465578  0.00763012  0.01949468 -0.03252451]

```

```

0.02658572  0.05321065  0.03188632 -0.0090435   0.02677608  0.02768232
0.02984896  0.00816341 -0.04608572 -0.0448757   0.01875175 -0.01630981
0.01755036 -0.05491311  0.05647813 -0.00041866  0.05029892  0.02728762]
W2 = [ -2.28116140e-02  1.56503953e-02 -2.09522806e-02 -1.05351806e-02
-2.86834314e-03 -2.60384977e-02 -2.04855613e-02 -8.38680193e-04
-2.48638541e-03 -1.70377977e-02  2.28094310e-02  1.25329942e-02
 1.93224326e-02  6.72557205e-03 -1.94250420e-02 -6.17854297e-03
-4.96730953e-03  1.85426772e-02 -1.10777393e-02  4.52413410e-03
-2.20224708e-02  2.78520212e-03 -1.19479336e-02  1.21424980e-02
 7.11625442e-04 -1.36418492e-02  1.93708539e-02  2.07001567e-02
 2.27590576e-02  1.32034197e-02 -1.09712146e-02 -1.31583456e-02
-2.20609996e-02 -1.40878754e-02 -1.73405558e-02 -1.96183659e-03
-1.73670147e-02  7.14662671e-03 -1.68680847e-02 -2.08857115e-02
 2.41937712e-02 -7.04086199e-03 -1.85305607e-02 -1.55747551e-02
-2.23334022e-02 -2.12480240e-02 -7.87477382e-03  1.71285793e-02
 1.89388357e-02  8.92788544e-03 -9.75785218e-03  1.98293477e-03
 1.07878745e-02  1.58816054e-02  2.02306844e-02 -1.16106309e-03
-1.27728060e-02  4.86495532e-03  1.25059485e-02  1.42796338e-02
-1.88271068e-02  1.23864189e-02 -2.73988768e-03  2.11786665e-02
-1.19657815e-03  4.15571034e-04 -8.56810249e-03 -1.58635937e-02
 3.33899260e-03  1.38684697e-02  2.09810026e-03 -8.75842758e-03
-1.79842599e-02  2.01283991e-02 -7.38026388e-03 -6.75064698e-03
-1.13674486e-02  8.60524178e-03 -3.83711234e-03 -4.21114080e-03
-9.25161317e-03 -6.26409985e-03  1.49438307e-02 -1.48791363e-02
 2.16972493e-02 -9.37076285e-03  1.26143992e-02  1.74523219e-02
-2.16881596e-02 -5.96321560e-03 -8.06864910e-03  2.40674727e-02
-1.41511885e-02 -2.20954772e-02 -1.07581774e-02 -1.57033987e-02
 2.75510922e-03 -1.84299871e-02  2.17168033e-02  2.49045417e-02
-9.32989269e-03  3.71674076e-04  1.67023726e-02  1.95019022e-02
 2.26771422e-02 -2.31597256e-02 -2.28918120e-02  1.42620578e-02
 1.53184123e-02 -2.53770817e-02 -1.14697032e-02  2.60040164e-02
-1.37862926e-02  8.81697983e-03  2.50400938e-02 -2.37854384e-02
 2.08353847e-02  2.60140114e-02  1.88717730e-02  2.25756541e-02
 1.75004900e-02  2.56490931e-02  7.05140084e-03 -1.10510755e-02
-1.61550343e-02 -2.59027630e-02  2.04093754e-03 -1.62372421e-02
 1.43824518e-02  1.53250061e-02  2.18021683e-02 -2.10200027e-02
 2.47574635e-02  4.44566272e-03 -4.96343151e-03 -8.17756355e-03
-1.07720112e-02  5.96679375e-03 -2.42185593e-02  1.25457421e-02
 1.68355443e-02  1.49464346e-02 -1.97378285e-02  1.01043098e-03
-1.70328468e-03 -1.21614309e-02  6.31091744e-03  1.33283585e-02
-8.03607702e-03  1.70042999e-02 -1.28471637e-02  2.48464383e-02
 1.28031373e-02  1.71082467e-02  1.12551861e-02  4.56025451e-03
 3.12375091e-03  1.60355233e-02  2.50408873e-02  1.10869221e-02
-1.58079304e-02 -1.46511588e-02 -1.56884901e-02 -2.24675238e-03
-9.51839983e-03 -2.44935341e-02  4.31986898e-03  1.74547248e-02
 5.31339645e-03 -1.78105459e-02 -1.24370214e-02 -5.58655336e-03
 2.43464857e-02 -2.26440672e-02  2.15265639e-02  1.44334696e-02
 2.30001807e-02  1.32468604e-02 -1.18725486e-02 -2.20355187e-02

```

-8.28113221e-03	2.86033750e-03	-2.37379763e-02	-1.69697218e-02
1.15917027e-02	1.92906074e-02	-4.10260633e-04	2.02245899e-02
8.64890963e-03	1.86929144e-02	9.22200456e-03	-1.81243606e-02
6.22365996e-03	4.87270020e-03	-1.29485643e-02	2.06260085e-02
-3.23323347e-03	-7.11390004e-03	-3.64359282e-03	2.25017220e-02
9.93504748e-03	-2.47857533e-02	1.22857429e-02	1.23111717e-02
4.86853532e-03	1.09994113e-02	1.29152276e-02	-1.08455587e-02
2.18650140e-03	2.59937420e-02	-1.76716726e-02	-1.47688575e-02
-3.64778377e-03	1.72021687e-02	-2.27755494e-02	-1.39360540e-02
1.36064552e-03	-3.25546414e-03	2.79416703e-03	-2.06871256e-02
1.67099275e-02	-9.58685577e-03	-2.28858851e-02	-9.30551253e-03
1.64918229e-02	-2.30539367e-02	1.15740746e-02	1.55139714e-05
-4.50919941e-03	2.07831524e-02	-2.08854321e-02	1.12305321e-02
-8.55347142e-04	2.47392729e-02	8.80973414e-03	1.98072568e-02
6.22695312e-03	7.62192532e-03	1.62524395e-02	2.53255852e-02
1.14379339e-02	1.71308517e-02	-1.30487457e-02	-1.57330576e-02
-3.31781246e-03	1.87824517e-02	9.50602815e-04	-1.97389740e-02
2.04719156e-02	-2.17265654e-02	-2.56286785e-02	-7.98400119e-03
-1.89660490e-03	-1.71508845e-02	-1.82185266e-02	-2.42804158e-02]
W3 = [-2.52654366e-02	9.48805362e-03	-1.86284631e-02	-3.21126431e-02
8.69024917e-03	6.01965934e-04	-1.96405984e-02	1.84573904e-02
7.76708126e-03	3.16396765e-02	-2.72833239e-02	-2.28701457e-02
-3.22012603e-03	-7.60075636e-03	-8.93948786e-03	2.40180120e-02
-1.99917424e-02	-1.12908501e-02	-3.05692498e-02	-1.46081485e-02
1.35720633e-02	9.17029753e-03	2.10062861e-02	-4.75275517e-03
3.18480320e-02	-2.20453329e-02	7.89177045e-03	3.67438048e-03
1.63373463e-02	7.88483024e-03	-1.14708208e-03	-1.53476689e-02
1.04521103e-02	2.30432637e-02	2.09836662e-03	-9.64063406e-03
-2.86115687e-02	3.09754573e-02	-7.88081251e-03	9.62344557e-03
-1.63701177e-02	-1.33356843e-02	-2.22635008e-02	-3.05798072e-02
-8.23901221e-03	-6.94086216e-03	-1.71542615e-02	-1.60118490e-02
2.45709233e-02	1.24289393e-02	-2.90630981e-02	1.99617259e-02
3.12704220e-03	2.77591310e-02	1.92498043e-02	-4.47371416e-03
2.88650170e-02	-1.48755852e-02	3.13170962e-02	2.67066956e-02
2.58136690e-02	-5.47687896e-03	-9.07146372e-03	2.64718570e-02
1.43976621e-02	8.66010785e-04	-8.58764537e-03	1.82803459e-02
-1.03779882e-03	-2.12974325e-02	7.14082271e-03	4.84588742e-03
1.51312426e-02	1.37211010e-02	-1.79184452e-02	1.48426890e-02
-3.53084691e-03	-1.13312714e-02	-9.14226472e-03	-1.12383794e-02
1.31572783e-02	1.59223489e-02	-1.93343647e-02	-1.51769351e-02
-2.77663339e-02	-1.77864991e-02	2.43163444e-02	-2.99473852e-02
2.84502916e-02	-2.93214321e-02	-3.08156386e-03	5.17319143e-03
-1.21186320e-02	-3.11755557e-02	-1.42795444e-02	9.06738639e-03
-2.99577806e-02	1.26180798e-03	-2.53256503e-02	3.19252573e-02
-1.58906858e-02	-1.60747245e-02	8.89611244e-03	1.41575336e-02
-2.95532886e-02	-4.33970243e-04	-2.02652588e-02	2.15807594e-02
7.97616690e-03	-5.87994792e-03	-2.89721601e-03	2.04581246e-02
-7.87183642e-04	1.17731467e-03	-7.31881335e-03	-2.61217430e-02

-2.82618254e-02	-7.79837742e-03	-8.37631524e-04	-1.99464336e-02
1.82352960e-05	2.96582542e-02	2.97308788e-02	2.36910582e-03
-8.32738727e-03	-1.35082211e-02	-3.18604819e-02	-2.61129625e-03
8.76035914e-03	-5.81083074e-03	-3.15470211e-02	-2.07581967e-02
7.81723112e-03	1.40576139e-02	-1.84134357e-02	-3.16274799e-02
2.10222863e-02	2.88765579e-02	-1.55311618e-02	2.35224739e-02
-2.04435103e-02	1.73229724e-03	-5.04173338e-04	9.37767327e-05
-2.02058218e-02	2.04105377e-02	-8.73883627e-03	-1.16048642e-02
1.38149932e-02	3.00846994e-02	-3.08130793e-02	-2.73738001e-02
-1.27821509e-02	-2.79430859e-02	-1.27585120e-02	2.65248567e-02
1.03123002e-02	-3.19578387e-02	-6.58590347e-03	-4.78730537e-03
1.35402158e-02	-1.84784736e-02	2.08281875e-02	-3.04682180e-03
-2.86676399e-02	2.99472213e-02	-1.12949982e-02	-1.77997202e-02
-3.20704691e-02	3.00224796e-02	2.71638669e-02	1.16583072e-02
-1.74432825e-02	-3.17719989e-02	5.58549166e-03	-2.17913538e-02
2.95937024e-02	-2.81560831e-02	-5.01029752e-03	1.97515637e-03
2.83542499e-02	-5.76616265e-03	-1.64092220e-02	-6.69310056e-03
3.17269526e-02	-1.18017327e-02	1.42288022e-02	1.71669424e-02
1.02547742e-02	1.04069114e-02	-1.09344590e-02	-3.02985497e-03
3.67402658e-03	-2.78475769e-02	3.20602022e-02	-2.09702980e-02
2.91639268e-02	1.36400796e-02	-2.96610482e-02	1.21603012e-02
2.22789831e-02	1.77013092e-02	-2.07042620e-02	1.21951178e-02
1.84795037e-02	-1.03297997e-02	-7.20819086e-03	1.16985105e-02
-1.01767015e-02	-1.63314119e-03	2.63395719e-02	2.38251686e-03
-2.88248174e-02	2.67854780e-02	-1.16053335e-02	2.31085718e-02
8.10972229e-03	1.67791657e-02	-2.81229094e-02	9.21143591e-03
2.20419541e-02	2.78143361e-02	-1.33951735e-02	4.52110916e-03
-3.35382670e-03	8.79030675e-03	-1.04315430e-02	9.38742608e-03
2.73697078e-03	1.85816325e-02	1.20667852e-02	1.00556836e-02
-3.14987190e-02	-8.44261236e-03	-3.14451307e-02	3.01005840e-02
1.44591294e-02	1.65085718e-02	-2.63085682e-02	-2.90829353e-02
-2.69476548e-02	1.89783424e-02	-8.19619000e-03	2.98139602e-02
-2.39140987e-02	-2.84877867e-02	-5.56484796e-03	2.26782262e-02
-2.18301676e-02	-2.83756498e-02	1.94959193e-02	-1.27526708e-02
-1.26247499e-02	-2.19299868e-02	1.23868920e-02	-1.47584993e-02
9.02951136e-03	1.96096115e-02	1.15674287e-02	1.53777190e-02
-2.97047868e-02	-3.06967162e-02	2.02891827e-02	-2.19811499e-02
-1.04892161e-02	1.46604516e-02	2.36157589e-02	-2.34402772e-02
2.21064463e-02	-1.96184218e-02	-3.90041992e-03	-1.53082106e-02
1.85879432e-02	2.99208760e-02	3.11652943e-03	-2.35038362e-02
-2.50062644e-02	-2.82088928e-02	8.94382223e-03	-1.95155647e-02
2.19933987e-02	-3.13628204e-02	3.02137360e-02	-1.74973160e-04
-2.75591947e-02	-1.22428276e-02	-1.78473033e-02	-1.36919990e-02
2.02232450e-02	5.57336956e-04	-2.99807452e-03	-1.51637457e-02
-1.85195878e-02	-2.78642513e-02	5.31440973e-03	6.85732812e-04
2.19102576e-02	2.47329399e-02	2.88912095e-02	6.72215596e-03
2.32652947e-03	-2.47483384e-02	2.41762586e-02	7.58368149e-03
-1.12736207e-02	1.14830062e-02	-2.54772399e-02	6.33840263e-03

4.50205430e-03	-1.28488429e-02	-2.93681175e-02	-2.16162950e-02
2.43331641e-02	1.19332597e-02	-1.76074468e-02	-1.30328964e-02
4.70712408e-03	4.93161753e-03	-2.81401686e-02	1.92249119e-02
-2.50384677e-02	6.46509975e-03	2.75478065e-02	-1.62562560e-02
2.65124477e-02	-2.89820321e-02	2.46308595e-02	2.62328275e-02
-7.33321160e-03	4.69728187e-03	-6.25040382e-03	-1.54863708e-02
-6.36629015e-03	-1.06993262e-02	-1.26027353e-02	1.77243948e-02
-7.51685910e-03	-2.75672209e-02	2.11036839e-02	2.63386630e-02
-3.74324247e-03	-2.22334433e-02	-1.58813279e-02	-1.63184237e-02
2.50214152e-02	-2.38050707e-02	-2.30590552e-02	-6.44195825e-04
-3.00810989e-02	-1.70257092e-02	2.72374153e-02	3.15164439e-02
-1.44076720e-03	-2.72787604e-02	-3.20438892e-02	-1.56763960e-02
8.75578821e-03	-6.98973238e-03	5.97841293e-03	-1.34601891e-02
-1.28397923e-02	1.49974674e-02	2.77152546e-02	1.52868032e-03
-2.68319398e-02	6.22936711e-03	-8.37869942e-04	-1.32319257e-02
1.69289783e-02	1.13459006e-02	-9.98224318e-03	-1.42330285e-02
1.99795067e-02	-1.52655412e-02	1.07876323e-02	-2.38478705e-02
-8.78676027e-03	-6.86823763e-03	1.53603964e-02	1.52571462e-02
-1.70840994e-02	-2.87272688e-02	-9.01207514e-03	-2.97464542e-02]
W4 = [-4.89076972e-03	-2.91089248e-02	2.25343537e-02	-1.62415691e-02
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-2.07652189e-02	-2.92120092e-02	-2.63499357e-02	1.73448753e-02
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6.52522407e-03	-2.57320628e-02	7.09596463e-03	-2.85090841e-02
2.66359579e-02	-2.86701545e-02	-9.97641124e-03	-1.17212292e-02
2.76828576e-02	1.05945934e-02	5.35250269e-03	2.18085777e-02
-2.93732285e-02	7.24026933e-04	4.01734747e-03	1.67196337e-02
1.24212354e-03	2.39806939e-02	-7.38351047e-03	-2.63811313e-02
-4.57471795e-03	1.89058669e-03	-4.49907780e-03	3.65865417e-03
-3.88938934e-04	-1.89946517e-02	1.25014577e-02	-2.05800254e-02
9.33294930e-03	1.84220280e-02	2.90899780e-02	-9.39756632e-03
2.82955337e-02	-5.90318628e-03	1.47771481e-02	-7.59123079e-03
2.03307625e-02	-1.37071311e-02	-2.31697410e-03	-9.64168832e-03
7.67331757e-03	-1.94885284e-02	-1.31968316e-02	-2.09946167e-02
-8.99825431e-03	-1.17791519e-02	2.61277314e-02	2.89409067e-02
6.62823953e-03	-3.38429399e-03	-7.40532763e-03	2.60269456e-03
-2.67013144e-02	-1.94629226e-02	-9.18764807e-03	2.06070151e-02
4.81856428e-03	2.88231988e-02	-1.98557172e-02	1.42271314e-02
-1.17137972e-02	-1.66150331e-02	2.77652200e-02	-1.35200564e-02
1.62001383e-02	1.16430596e-03	-8.62583704e-03	-1.99205615e-02
2.13208552e-02	-5.03392890e-03	-1.75483394e-02	2.36127526e-04
-2.02017780e-02	-2.77884789e-02	5.39316051e-03	-1.64439585e-02
2.33250502e-02	2.02515032e-02	1.56586077e-02	-4.60171327e-03
7.36508518e-05	1.05681624e-02	1.10908728e-02	-1.65428072e-02
-1.09365396e-03	-1.26323234e-02	-6.16871752e-03	-2.37983093e-02
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8.10554251e-04	3.46785598e-03	-4.88059036e-03	6.12413324e-03
-1.78131536e-02	-1.66686848e-02	1.69964600e-02	-2.52321176e-03

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2.55674589e-02	1.27443727e-02	6.31717965e-04	-1.87002122e-03
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5.62367402e-03	-1.39481556e-02	2.04696786e-02	2.84778606e-02
1.65169146e-02	-1.23725086e-02	1.09592471e-02	-4.19420935e-03
-2.86516100e-02	-1.39074977e-02	-8.17440450e-05	-2.87534297e-02
2.11314168e-02	8.10145400e-03	-4.52022813e-03	2.34010126e-02
-2.66654752e-02	2.50673238e-02	1.75902192e-02	2.11156625e-02
5.66243567e-03	1.23136733e-02	1.75234675e-03	1.16527062e-02
-8.84109549e-03	-7.05795363e-03	1.76740754e-02	-3.47647630e-03
2.73754653e-02	-1.48626603e-03	-1.46226399e-03	-5.35931438e-04
-2.40378436e-02	-1.56417973e-02	-1.39538310e-02	1.97659936e-02
-9.29832458e-03	-1.67754367e-02	-8.72808509e-03	-2.79385224e-03
-9.74237919e-04	2.17257533e-02	2.60607731e-02	2.22415868e-02
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-1.79185085e-02	1.66895259e-02	2.75237318e-02	2.01491509e-02
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-2.28597969e-02	-8.67331587e-03	-1.87239274e-02	-1.00585632e-03
-4.94880602e-04	3.73067148e-03	1.90931279e-02	-1.43646291e-02
-1.71081163e-03	-2.13225894e-02	1.81576628e-02	2.25261990e-02
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1.29772257e-02	1.84867177e-02	-2.32727863e-02	1.30072236e-03
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6.42335601e-03	-1.43020274e-02	-1.52600389e-02	1.06902812e-02
-1.94338560e-02	2.28215065e-02	-2.11002007e-02	2.76649650e-02
-2.86598578e-02	1.20120291e-02	-1.44523010e-03	9.83663835e-03
2.26780195e-02	-6.86174631e-03	2.17739735e-02	-1.48475617e-02
-1.70812048e-02	2.37910543e-02	-1.21577457e-03	1.06347594e-02
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-6.38691150e-03	-2.66829655e-02	-5.51449135e-04	-1.34142041e-02
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2.51508448e-02	-1.24410260e-02	-8.39685276e-03	-2.38021947e-02
-1.23174302e-02	1.60309132e-02	-1.13261938e-02	6.98613003e-04

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-2.77890544e-02	1.59263182e-02	-1.22619085e-02	-2.65075509e-02
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-1.38831083e-02	1.66508928e-03	3.46855260e-03	1.21306833e-02
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2.90413294e-02	-2.55340151e-02	1.40729528e-02	9.06254910e-03
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-1.53782470e-02	2.06340421e-02	-1.09641515e-02	2.49069761e-02
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2.73082796e-02	1.33823138e-02	-1.96659938e-03	2.02569179e-03
2.59946678e-02	2.82173920e-02	-1.23807788e-03	2.64149737e-02
-8.96634907e-03	-5.26448712e-04	2.78111380e-02	2.54497696e-02
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W5 = [1.92275271e-02	7.53147900e-03	-2.91527994e-02	9.72753391e-03
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3.84243205e-03	-3.11368126e-02	2.78578252e-02	-1.86226759e-02
2.87191980e-02	2.71252692e-02	2.52398290e-02	-1.79977641e-02
-2.09563170e-02	-2.88551580e-02	-2.94115786e-02	-2.77974643e-03
-3.09810899e-02	9.76259261e-03	-3.21706794e-02	-2.47014910e-02
-3.11596729e-02	2.32211426e-02	2.68629342e-02	6.60672411e-03
2.27521136e-02	-5.23351133e-03	-4.20087576e-03	2.00313255e-02
-1.50813479e-02	-2.79840473e-02	2.01260895e-02	-2.74006333e-02
1.86673142e-02	-2.46787220e-02	-1.10475291e-02	-3.00861858e-02
-1.95201896e-02	2.09020302e-02	-1.21839456e-02	-2.57611591e-02
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-1.19520724e-03	2.41987593e-02	-2.62665469e-02	1.72586367e-02
1.11584961e-02	-1.17990840e-02	-1.64970830e-02	3.81037965e-03
2.31272317e-02	2.33251154e-02	-2.08918750e-03	-1.10982768e-02
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-1.25867072e-02	-1.30001158e-02	-1.48793869e-02	2.75516883e-03
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2.94772238e-02	-2.24150047e-02	2.43558660e-02	3.50125134e-03
-2.19724160e-02	1.99813396e-04	-5.12155145e-03	-1.54592227e-02
-1.94635466e-02	-1.96376815e-03	1.74782574e-02	5.60801476e-03
-8.50153901e-03	5.83323091e-03	3.47994268e-04	2.82813162e-02
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1.83587335e-02	-7.91140087e-03	-1.57474596e-02	-1.89100821e-02
-2.52654366e-02	9.48805362e-03	-1.86284631e-02	-3.21126431e-02
8.69024917e-03	6.01965934e-04	-1.96405984e-02	1.84573904e-02
7.76708126e-03	3.16396765e-02	-2.72833239e-02	-2.28701457e-02
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-1.99917424e-02	-1.12908501e-02	-3.05692498e-02	-1.46081485e-02
1.35720633e-02	9.17029753e-03	2.10062861e-02	-4.75275517e-03
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-2.86115687e-02	3.09754573e-02	-7.88081251e-03	9.62344557e-03
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2.45709233e-02	1.24289393e-02	-2.90630981e-02	1.99617259e-02
3.12704220e-03	2.77591310e-02	1.92498043e-02	-4.47371416e-03
2.88650170e-02	-1.48755852e-02	3.13170962e-02	2.67066956e-02
2.58136690e-02	-5.47687896e-03	-9.07146372e-03	2.64718570e-02
1.43976621e-02	8.66010785e-04	-8.58764537e-03	1.82803459e-02
-1.03779882e-03	-2.12974325e-02	7.14082271e-03	4.84588742e-03
1.51312426e-02	1.37211010e-02	-1.79184452e-02	1.48426890e-02
-3.53084691e-03	-1.13312714e-02	-9.14226472e-03	-1.12383794e-02
1.31572783e-02	1.59223489e-02	-1.93343647e-02	-1.51769351e-02
-2.77663339e-02	-1.77864991e-02	2.43163444e-02	-2.99473852e-02
2.84502916e-02	-2.93214321e-02	-3.08156386e-03	5.17319143e-03
-1.21186320e-02	-3.11755557e-02	-1.42795444e-02	9.06738639e-03
-2.99577806e-02	1.26180798e-03	-2.53256503e-02	3.19252573e-02
-1.58906858e-02	-1.60747245e-02	8.89611244e-03	1.41575336e-02
-2.95532886e-02	-4.33970243e-04	-2.02652588e-02	2.15807594e-02
7.97616690e-03	-5.87994792e-03	-2.89721601e-03	2.04581246e-02
-7.87183642e-04	1.17731467e-03	-7.31881335e-03	-2.61217430e-02
-2.82618254e-02	-7.79837742e-03	-8.37631524e-04	-1.99464336e-02
1.82352960e-05	2.96582542e-02	2.97308788e-02	2.36910582e-03
-8.32738727e-03	-1.35082211e-02	-3.18604819e-02	-2.61129625e-03]

**** Expected Output:****

<tr>

<td>

W1 =

</td>

<td>

[0.00131723 0.14176141 -0.04434952 0.09197326 0.14984085 -0.03514394 -0.06847463 0.05245192]

<tr>

<td>

```
W2 =
</td>
<td>
```

```
[-0.08566415 0.17750949 0.11974221 0.16773748 -0.0830943 -0.08058 -0.00577033 -0.14643836
0.24162132 -0.05857408 -0.19055021 0.1345228 -0.22779644 -0.1601823 -0.16117483 -0.10286498]
```

```
In [30]: # GRADED FUNCTION: forward_propagation
```

```
def forward_propagation(X, parameters):
    """
    Implements the forward propagation for the model:
    CONV2D -> RELU -> MAXPOOL -> CONV2D -> RELU -> MAXPOOL -> FLATTEN -> LINEAR

    Arguments:
    X -- input dataset placeholder, of shape (input size, number of examples, depth, height, width)
    parameters -- python dictionary containing your parameters "W1", "W2"
                  the shapes are given in initialize_parameters

    Returns:
    Z3 -- the output of the last LINEAR unit
    """

    # Retrieve the parameters from the dictionary "parameters"
    W1 = parameters['W1']
    W2 = parameters['W2']
    W3 = parameters['W3']
    W4 = parameters['W4']
    W5 = parameters['W5']

    ### START CODE HERE ###
    # CONV2D: stride of 1, padding 'VALID'
    Z1 = tf.nn.conv2d(X, W1, strides = [1,1,1,1], padding = 'VALID')
    # ?? have not taken b1 parameter
    # RELU
    A1 = tf.nn.relu(Z1)
    # MAXPOOL: window 3x3, stride 2, padding 'VALID'
    P1 = tf.nn.max_pool(A1, ksize = [1,3,3,1], strides = [1,2,2,1], padding = 'VALID')
    # CONV2D: filters W2, stride 1, padding 'SAME'
    Z2 = tf.nn.conv2d(P1, W2, strides = [1,1,1,1], padding = 'SAME')
    # RELU
    A2 = tf.nn.relu(Z2)
    # MAXPOOL: window 2x2, stride 1, padding 'VALID'
    P2 = tf.nn.max_pool(A2, ksize = [1,2,2,1], strides = [1,1,1,1], padding = 'VALID')
    # CONV2D: filters W3, stride 1, padding 'SAME'
    Z3 = tf.nn.conv2d(P2, W3, strides = [1,1,1,1], padding = 'SAME')
    # RELU
    A3 = tf.nn.relu(Z3)
```

```

# CONV2D: filters W4, stride 1, padding 'SAME'
Z4 = tf.nn.conv2d(A3,W4, strides = [1,1,1,1], padding = 'SAME')
# RELU
A4 = tf.nn.relu(Z4)
# CONV2D: filters W5, stride 1, padding 'SAME'
Z5 = tf.nn.conv2d(A4,W5, strides = [1,1,1,1], padding = 'SAME')
# RELU
A5 = tf.nn.relu(Z5)
# MAXPOOL: window 3x3, stride 2, padding 'VALID'
P3 = tf.nn.max_pool(A5, ksize = [1,3,3,1], strides = [1,2,2,1], padding = 'VALID')
# FLATTEN
P3 = tf.contrib.layers.flatten(P3)
# FULLY-CONNECTED with non-linear activation function.
A6 = tf.contrib.layers.fully_connected(P3, 4096)
A7 = tf.contrib.layers.fully_connected(A6, 4096)
# FULLY-CONNECTED without non-linear activation function (not not called)
# 6 neurons in output layer. Hint: one of the arguments should be "activation_fn=None"
Z8 = tf.contrib.layers.fully_connected(A7, 6, activation_fn=None)
### END CODE HERE ###

return Z8

```

```
In [31]: tf.reset_default_graph()
```

```

with tf.Session() as sess:
    np.random.seed(1)
    X, Y = create_placeholders(64, 64, 3, 6)
    parameters = initialize_parameters()
    Z8 = forward_propagation(X, parameters)
    init = tf.global_variables_initializer()
    sess.run(init)
    a = sess.run(Z8, {X: np.random.randn(2,64,64,3), Y: np.random.randn(2,64,64,3)})
    print("Z8 = " + str(a))

```

```

Z8 = [[-0.00572854 -0.10159744  0.19650701  0.0035533  0.02199078  0.00088809]
      [ 0.00432064 -0.09484988  0.18270491  0.02251715  0.09731591 -0.02702793]]

```

Expected Output:

```

Z3 =
[[-0.44670227 -1.57208765 -1.53049231 -2.31013036 -1.29104376  0.46852064] [-0.17601591 -
1.57972014 -1.4737016 -2.61672091 -1.00810647  0.5747785 ]]

```

```
In [43]: # GRADED FUNCTION: compute_cost
```

```

def compute_cost(Z8, Y):
    """
    Computes the cost

```

```

Arguments:
Z3 -- output of forward propagation (output of the last LINEAR unit),
Y -- "true" labels vector placeholder, same shape as Z3

Returns:
cost - Tensor of the cost function
"""

### START CODE HERE ### (1 line of code)
cost = tf.reduce_mean( tf.nn.softmax_cross_entropy_with_logits(logits
### END CODE HERE ###

return cost

```

```
In [44]: tf.reset_default_graph()
```

```

with tf.Session() as sess:
    np.random.seed(1)
    X, Y = create_placeholders(64, 64, 3, 6)
    parameters = initialize_parameters()
    Z8 = forward_propagation(X, parameters)
    cost = compute_cost(Z8, Y)
    init = tf.global_variables_initializer()
    sess.run(init)
    a = sess.run(cost, {X: np.random.randn(4, 64, 64, 3), Y: np.random.randn(
print("cost = " + str(a))

```

```
cost = 1.02641
```

Expected Output:

```
cost =
```

```

<td>
2.91034
</td>

```

```
In [45]: # GRADED FUNCTION: model
```

```

def model(X_train, Y_train, X_test, Y_test, learning_rate = 0.009,
          num_epochs = 100, minibatch_size = 64, print_cost = True):
    """
    Implements a three-layer ConvNet in Tensorflow:
    CONV2D -> RELU -> MAXPOOL -> CONV2D -> RELU -> MAXPOOL -> FLATTEN -> FC

    Arguments:
    X_train -- training set, of shape (None, 64, 64, 3)
    Y_train -- test set, of shape (None, n_y = 6)
    X_test -- training set, of shape (None, 64, 64, 3)

```

```

Y_test -- test set, of shape (None, n_y = 6)
learning_rate -- learning rate of the optimization
num_epochs -- number of epochs of the optimization loop
minibatch_size -- size of a minibatch
print_cost -- True to print the cost every 100 epochs

Returns:
train_accuracy -- real number, accuracy on the train set (X_train)
test_accuracy -- real number, testing accuracy on the test set (X_test)
parameters -- parameters learnt by the model. They can then be used to
"""

ops.reset_default_graph() # to be able to rerun
tf.set_random_seed(1) # to keep results consistent
seed = 3 # to keep results consistent
(m, n_H0, n_W0, n_C0) = X_train.shape
n_y = Y_train.shape[1]
costs = [] # To keep track of costs

# Create Placeholders of the correct shape
### START CODE HERE ### (1 line)
X, Y = create_placeholders(n_H0, n_W0, n_C0, n_y)
### END CODE HERE ###

# Initialize parameters
### START CODE HERE ### (1 line)
parameters = initialize_parameters()
### END CODE HERE ###

# Forward propagation: Build the forward propagation in the tensorflow graph
### START CODE HERE ### (1 line)
Z8 = forward_propagation(X, parameters)
### END CODE HERE ###

# Cost function: Add cost function to tensorflow graph
### START CODE HERE ### (1 line)
cost = compute_cost(Z8, Y)
### END CODE HERE ###

# Backpropagation: Define the tensorflow optimizer. Use an AdamOptimizer
### START CODE HERE ### (1 line)
optimizer = tf.train.AdamOptimizer(learning_rate = learning_rate).minimize(cost)
### END CODE HERE ###

# Initialize all the variables globally
init = tf.global_variables_initializer()

# Start the session to compute the tensorflow graph

```

```

with tf.Session() as sess:

    # Run the initialization
    sess.run(init)

    # Do the training loop
    for epoch in range(num_epochs):

        minibatch_cost = 0.
        num_minibatches = int(m / minibatch_size) # number of minibatches
        seed = seed + 1
        minibatches = random_mini_batches(X_train, Y_train, minibatch_size, seed)

        for minibatch in minibatches:

            # Select a minibatch
            (minibatch_X, minibatch_Y) = minibatch
            # IMPORTANT: The line that runs the graph on a minibatch.
            # Run the session to execute the optimizer and the cost, to get the
            ### START CODE HERE ### (1 line)
            _, temp_cost = sess.run([optimizer, cost], feed_dict = {X: minibatch_X, Y: minibatch_Y})
            ### END CODE HERE ###

            minibatch_cost += temp_cost / num_minibatches

        # Print the cost every epoch
        if print_cost == True and epoch % 5 == 0:
            print ("Cost after epoch %i: %f" % (epoch, minibatch_cost))
        if print_cost == True and epoch % 1 == 0:
            costs.append(minibatch_cost)

    # plot the cost
    plt.plot(np.squeeze(costs))
    plt.ylabel('cost')
    plt.xlabel('iterations (per tens)')
    plt.title("Learning rate =" + str(learning_rate))
    plt.show()

    # Calculate the correct predictions
    predict_op = tf.argmax(Z3, 1)
    correct_prediction = tf.equal(predict_op, tf.argmax(Y, 1))

    # Calculate accuracy on the test set
    accuracy = tf.reduce_mean(tf.cast(correct_prediction, "float"))
    print (accuracy)
    train_accuracy = accuracy.eval({X: X_train, Y: Y_train})

```

```

test_accuracy = accuracy.eval({X: X_test, Y: Y_test})
print("Train Accuracy:", train_accuracy)
print("Test Accuracy:", test_accuracy)

return train_accuracy, test_accuracy, parameters

```

Run the following cell to train your model for 100 epochs. Check if your cost after epoch 0 and 5 matches our output. If not, stop the cell and go back to your code!

```
In [ ]: _, _, parameters = model(X_train, Y_train, X_test, Y_test)
```

Expected output: although it may not match perfectly, your expected output should be close to ours and your cost value should decrease.

Cost after epoch 0 =

```

<td>
1.917929
</td>

```

Cost after epoch 5 =

```

<td>
1.506757
</td>

```

Train Accuracy =

```

<td>
0.940741
</td>

```

Test Accuracy =

```

<td>
0.783333
</td>

```