

▼ Classification Using Keras and Tensorflow

Richard Kuo, 20180701, ver. 0.1.0

Code borrowed from:

- [Cifar-10 Classification using Keras Tutorial](#)
- [Object Recognition with Convolutional Neural Networks in the Keras Deep Learning Library](#)
- [Convolutional Neural Networks \(CNN\) for CIFAR-10 Dataset](#)
- [Deep-math-machine-learning.ai code](#)
- [Keras code example](#)

▼ Import libraries

```
import time
import sys
import os

from __future__ import print_function

# sys.path.insert(0, 'drive/cifar10')
# os.chdir("drive/cifar10")

import keras
from keras.models import Sequential
from keras.layers import Dense, Dropout, Activation, Flatten
from keras.layers import Conv2D, MaxPooling2D
from keras.layers.normalization import BatchNormalization

from keras.optimizers import SGD
from keras.utils import print_summary, to_categorical, np_utils

from keras.constraints import maxnorm

# Set backend,
# For the difference of "tf" and "th"
# see https://stackoverflow.com/questions/39547279/loading-weights-in-th-format
from keras import backend as K
if K.backend()=='tensorflow':
    K.set_image_dim_ordering("th")

# Import Tensorflow with multiprocessing
import tensorflow as tf
import multiprocessing as mp

# Loading the CIFAR-10 datasets
from keras.datasets import cifar10

# Plot
import matplotlib.pyplot as plt
% matplotlib inline
from scipy.misc import toimage

import numpy as np
np.random.seed(2018)
```

▼ Define constants

This will make code more flexible.

```
# Declare variables

batch_size = 32 # 32 examples in a mini-batch, smaller batch size means more
nbr_classes = 10
# epochs = 100 # repeat 100 times
```

▼ Load and display dataset

After data loading, to verify and better understand the dataset; sample some them. For more complicate dataset, plot, explore the contents.

- shapes
- sizes
- sample values

```
# load data, instead of using the built-in function, this can be done with pyth
(X_train, Y_train), (X_test, Y_test) = cifar10.load_data()

X_train # tensor type
Y_train
print('X_train shape:', X_train.shape)
print('Y_train shape:', Y_train.shape)
print(X_train.shape[0], ' train samples')
print(X_test.shape[0], ' test samples')

print("Value of the first element of X_train:")
print(X_train[0])
print("Value of the first element of Y_train:")
print(Y_train[0])

# create a grid of 3x3 images
print("X can be converted back to original images via utility function:")
for i in range(0, 9):
    plt.subplot(330 + 1 + i)
    plt.imshow(toimage(X_train[i]))
# show the plot
plt.show(.,)
```



```

X_train shape: (50000, 3, 32, 32)
Y_train shape: (50000, 1)
50000 train samples
10000 test samples
Value of the first element of X_train:
[[ 59  43  50 ... 158 152 148]
 [ 16   0  18 ... 123 119 122]
 [ 25  16  49 ... 118 120 109]
 ...
 [208 201 198 ... 160  56  53]
 [180 173 186 ... 184  97  83]
 [177 168 179 ... 216 151 123]]

[[ 62  46  48 ... 132 125 124]
 [ 20   0   8 ...  88  83  87]
 [ 24   7  27 ...  84  84  73]
 ...
 [170 153 161 ... 133  31  34]
 [139 123 144 ... 148  62  53]
 [144 129 142 ... 184 118  92]]

[[ 63  45  43 ... 108 102 103]
 [ 20   0   0 ...  55  50  57]
 [ 21   0   8 ...  50  50  42]
 ...
 [ 96  34  26 ...  70   7  20]
 [ 96  42  30 ...  94  34  34]
 [116  94  87 ... 140  84  72]]]
Value of the first element of Y_train:
[6]

```

Y can be converted back to original images via utility function.

There are three different sets/formats: python, Matlab and binary. Binary format has broke the dataset into smaller size so we can do batch process.

For python version:

data -- a 10000x3072 numpy array of uint8s. Each row of the array stores a 32x32 (=1024) colour image. The first 1024 entries contain the red channel values, the next 1024 the green, and the final 1024 the blue. The image is stored in row-major order, so that the first 32 entries of the array are the red channel values of the first row of the image, [59 43 50 ... 158 152 148].

The color of the first pixel of the image is R = 59, G= 62, B = 63.

Each image is represented by 3 X 32 X 32 (colors, width and height) tensor. The first diamension is for Red, the next sheet is for Blue, then the next sheet is for Green; like 3 sheets of paper, which are size 32 by 32 grids. Each grid records the values of the color, RBG, of image values (0–255). There are 50000 images for X_train.

Tensor is data structure, for example,

```

1D  [1,2,3,4]          # one row
2D  [                  # one sheet with two rows
      [1,2,3,4],
      [5,6,7,8]]
3D  [                  # three sheets, each sheet represents some
type of measurement

```

```
[
    # for example, people's height, or
    intensity of color red
    [1,2,3,4],
    [5,6,7,8]],
[
    # for example, people's weight, or
    intensity of color blue, we only have two colors.
    [7,2,3,4],
    [6,6,7,8]]]
```

labels -- a list of 10000 numbers in the range 0-9. The number at index i indicates the label of the i th image in the array data. For example, `label_names[0] == "airplane"`, `label_names[1] == "automobile"`, etc.

`label_names = ['airplane','automobile','bird','cat','deer', 'dog','frog','horse','ship','truck']`

`Y_train` and `Y_test` are a vector (1D tensor). `Y_train[0] = [6]` means the label of the first element is a frog.

`X_train` and `X_test` are 3D tensor, which can be converted back to image.



See [toronto data repo](#) for more details.

► Pre-process Data

The data may need to be pre-processed to fit ML library we want to use.

Normalize

RGB value is range from 0-255. It would be easier to work from 0-1.

↳ 9 cells hidden

▼ Tensorflow

We will try to develop the solution with two different frameworks: Tensorflow and Keras, do Tensorflow first. The architecture looks like

[input (X)] -> [convolution (C1)] -> [pooling (P1)] -> [convolution (C2)] -> [pooling (P2)] -> [convolution (C3)] -> [pooling (P3)] -> [FC] -> [softmax] -> [output (Y predict)]

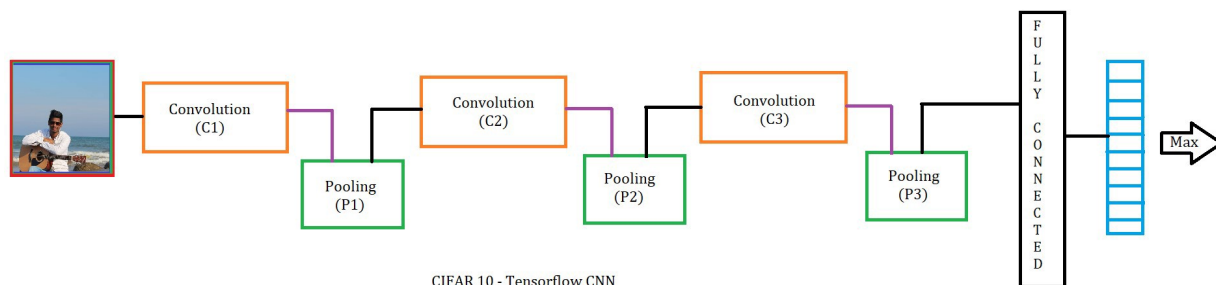


Figure from <https://medium.com/deep-math-machine-learning-ai/chapter-8-1-code-for-convolutional-neural-networks-tensorflow-and-keras-theano-33bef285dd93>

▼ Model

▼ placeholder

Inserts a placeholder for a tensor that will be always fed, see [doc].

(https://www.tensorflow.org/api_docs/python/tf/placeholder)

```
tf.placeholder(  
    dtype,  
    shape=None,  
    name=None  
)
```

Args:

- dtype: The type of elements in the tensor to be fed.
- shape: The shape of the tensor to be fed (optional). If the shape is not specified, you can feed a tensor of any shape.
- name: A name for the operation (optional).

The difference is that with `tf.Variable` you have to provide an initial value when you declare it. With `tf.placeholder` you don't have to provide an initial value and you can specify it at run time with the `feed_dict` argument inside `Session.run`

```
import tensorflow as tf  
  
X = tf.placeholder("float", [None, 32, 32, 3])  
Y = tf.placeholder("float", [None, 10])
```

Weight

define a function to populate specific shape of tensor initially with random numbers.

`tf.random_normal` returns a tensor of specific shape with random number, see [doc](#)

```
tf.random_normal(  
    shape,  
    mean=0.0,  
    stddev=1.0,  
    dtype=tf.float32,  
    seed=None,  
    name=None  
)
```

Args:

- shape: A 1-D integer Tensor or Python array. The shape of the output tensor.

- mean: A 0-D Tensor or Python value of type dtype. The mean of the normal distribution.
- stddev: A 0-D Tensor or Python value of type dtype. The standard deviation of the normal distribution.
- dtype: The type of the output.
- seed: A Python integer. Used to create a random seed for the distribution. See `tf.set_random_seed` for behavior.
- name: A name for the operation (optional).

▼ Layer

tf's Layers (contrib) package

- provide ops that take care of creating variables that are used internally in a consistent way,
- provide the building blocks for many common machine learning algorithms.

```
def init_weights(shape):
    return tf.Variable(tf.random_normal(shape, stddev=0.01))

W_C1 = init_weights([3,3,3,32])      # 3x3x3 conv, 32 outputs
W_C2 = init_weights([3,3,32,64])     # 3x3x32 conv, 64 outputs
W_C3 = init_weights([3, 3, 64, 128]) # 3x3x64 conv, 128 outputs

W_FC = init_weights([128 * 4 * 4, 625]) # FC 128 * 4 * 4 inputs, 625 outputs
W_O  = init_weights([625, 10])        # FC 625 inputs, 10 outputs (labels)

p_keep_conv = tf.placeholder("float") #for dropouts as percentage
p_keep_hidden = tf.placeholder("float")
```

Convolution

tf's Neural Network (nn) API supports (partially excerpt here):

- Convolution ops sweep a 2-D filter over a batch of images, applying the filter to each window of each image of the appropriate size.
- Activation Function ops provide various types of nonlinearities for use in neural networks.
- Pooling ops sweep a rectangular window over the input tensor, computing a reduction operation for each window (average, max, or max with argmax). ... for details see [nn](#)

`tf.nn.conv2d` computes a 2-D convolution given 4-D input and filter tensors, see [tf.conv2d](#) for details.

```
tf.nn.conv2d(
    input,
    filter,
    strides,
    padding,
    use_cudnn_on_gpu=True,
    data_format='NHWC',
    dilations=[1, 1, 1, 1],
    name=None
)
```

Activation

ReLU is one of activation function supported in tf. `tf.nn.relu` takes a tensor (type options: float32, float64, int32, uint8, int16, int8, int64, bfloat16, uint16, half, uint32, uint64.) as input, rectifies it, and returns a tensor with the same type as input.

```
tf.nn.relu(  
    features,  
    name=None  
)
```

Pooling

tf supports several different pooling ops:

- `tf.nn.avg_pool`
- `tf.nn.max_pool`
- `tf.nn.max_pool_with_argmax`
- `tf.nn.avg_pool3d`
- `tf.nn.max_pool3d`
- `tf.nn.fractional_avg_pool`
- `tf.nn.fractional_max_pool`
- `tf.nn.pool`

Max_pooling is a very popular pooling.

```
tf.nn.max_pool(  
    value,  
    ksize,  
    strides,  
    padding,  
    data_format='NHWC',  
    name=None  
)
```

Args:

- `value`: A 4-D Tensor of the format specified by `data_format`.
- `ksize`: A 1-D int Tensor of 4 elements. The size of the window for each dimension of the input tensor.
- `strides`: A 1-D int Tensor of 4 elements. The stride of the sliding window for each dimension of the input tensor.
- `padding`: A string, either 'VALID' or 'SAME'. The padding algorithm. See the comment here
- `data_format`: A string. 'NHWC', 'NCHW' and 'NCHW_VECT_C' are supported.
- `name`: Optional name for the operation.

Returns: A Tensor of format specified by `data_format`. The max pooled output tensor.

▼ Dropout

`tf.nn.dropout` computes dropout. The dropout is used to prevent overfitting. Some % of neurons will be randomly dropped out (don't get computed).

With probability `keep_prob`, outputs the input element scaled up by $1 / \text{keep_prob}$, otherwise outputs 0. The scaling is so that the expected sum is unchanged, for details see [dropout](#).

```
tf.nn.dropout(
    x,
    keep_prob,
    noise_shape=None,
    seed=None,
    name=None
)
```

```
def model(X, W_C1, W_C2, W_C3, W_FC, W_O, p_keep_conv, p_keep_hidden):

    C1 = tf.nn.relu(tf.nn.conv2d(X, W_C1, strides=[1,1,1,1], padding = "SAME"))
    P1 = tf.nn.max_pool(C1, ksize=[1,2,2,1], strides=[1,2,2,1], padding = "SAME")
    D1 = tf.nn.dropout(P1, p_keep_conv) # 1st dropout at conv

    C2 = tf.nn.relu(tf.nn.conv2d(D1, W_C2, strides=[1,1,1,1], padding = "SAME"))
    P2 = tf.nn.max_pool(C2, ksize=[1,2,2,1], strides=[1,2,2,1], padding = "SAME")
    D2 = tf.nn.dropout(P2, p_keep_conv) # 2nd dropout at conv

    C3 = tf.nn.relu(tf.nn.conv2d(D2, W_C3, strides=[1,1,1,1], padding = "SAME"))
    P3 = tf.nn.max_pool(C3, ksize=[1,2,2,1], strides=[1,2,2,1], padding = "SAME")

    P3 = tf.reshape(P3, [-1, W_FC.get_shape().as_list()[0]]) # reshape to (?)
    D3 = tf.nn.dropout(P3, p_keep_conv) # 3rd dropout at conv

    FC = tf.nn.relu(tf.matmul(D3, W_FC))
    FC = tf.nn.dropout(FC, p_keep_hidden) # dropout at fc

    output = tf.matmul(FC, W_O)

    return output
```

▼ Cost function, Optimizer and Predicted function.

todo - read [Neural Network Optimization Algorithms](#)

```
Y_pred = model(X, W_C1, W_C2, W_C3, W_FC, W_O, p_keep_conv, p_keep_hidden) #
cost = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits_v2(logits = Y_pre
optimizer = tf.train.RMSPropOptimizer(0.001, 0.9).minimize(cost)
predict_op = tf.argmax(Y_pred, 1)
```

▼ Session

To run TensorFlow model, we need to create a session and feed the real data.

```
# reshape input data per tf
X_train = X_train.reshape(-1, 32, 32, 3)
```



```
X_test = X_test.reshape(-1,32,32,3)
```

```
epochs = 50
import numpy as np
with tf.Session() as sess:
    # you need to initialize all variables
    sess.run(tf.global_variables_initializer())

    for epoch in range(epochs):

        for start, end in zip(range(0, len(X_train), 128), range(128, len(X_train), 128)):
            sess.run(optimizer, feed_dict={X : X_train[start:end] , Y : Y_train[start:end] ,
                                           p_keep_conv: 0.8, p_keep_hidden: 0.5})

        if epoch % 10 == 0:
            accuracy= np.mean(np.argmax(Y_test, axis=1) ==
                               sess.run(predict_op, feed_dict={X: X_test, p_keep_conv: 0.8, p_keep_hidden: 0.5}))

            print("epoch : {} and accuracy : {}".format(epoch, accuracy))

            print("testing labels for test data")
            print(sess.run(predict_op, feed_dict={X: X_test, p_keep_conv: 1.0, p_keep_hidden: 0.5}))

        print("Final accuracy : {}".format(np.mean(np.argmax(Y_test, axis=1) ==
                                                    sess.run(predict_op, feed_dict={X: X_test, p_keep_conv: 1.0, p_keep_hidden: 0.5}))))
```

```
↳ epoch : 0 and accuracy : 0.2969
testing labels for test data
[5 8 8 ... 5 1 7]
epoch : 10 and accuracy : 0.5843
testing labels for test data
[6 8 8 ... 5 1 7]
epoch : 20 and accuracy : 0.6202
testing labels for test data
[6 8 8 ... 5 1 7]
epoch : 30 and accuracy : 0.6298
testing labels for test data
[3 8 8 ... 5 1 7]
epoch : 40 and accuracy : 0.6416
testing labels for test data
[3 8 8 ... 5 1 7]
Final accuracy : 0.6405
```

