cnn_cifar

May 15, 2018

ECE 194N: Homework 2
Topics: CNN Problem
Due: May 14

0.0.1 (a) Visualize one sample image for each of the 10 classes

```
In [36]: %matplotlib inline
         import matplotlib.pyplot as plt
         import numpy as np
         import math
         import matplotlib.pyplot as plt
         from matplotlib import cm
         from mpl_toolkits.mplot3d import Axes3D

         from data import get_data_set
```

```
In [70]: train_x, train_y = get_data_set("train")
         test_x, test_y = get_data_set("test")
         class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse
         print("Classes:", "")
         print("- Training-set:\t\t{}".format(len(train_y)))
         print("- Test-set:\t\t{}".format(len(test_y)))

         def plot_images(images, cls_true, cls_pred=None, smooth=True):

             assert len(images) == len(cls_true) == 9

             # Create figure with sub-plots.
             fig, axes = plt.subplots(3, 3)

             # Adjust vertical spacing if we need to print ensemble and best-net.
             if cls_pred is None:
                 hspace = 0.3
             else:
                 hspace = 0.6
             fig.subplots_adjust(hspace=hspace, wspace=0.3)
```

```
    for i, ax in enumerate(axes.flat):
        # Interpolation type.
        if smooth:
            interpolation = 'spline16'
        else:
            interpolation = 'nearest'
        #print(images.shape)
        # Plot image.
        ax.imshow(images[i, :, :, :],
                  interpolation=interpolation)

        # Name of the true class.
        cls_true_name = class_names[cls_true[i]]

        # Show true and predicted classes.
        if cls_pred is None:
            xlabel = "True: {0}".format(cls_true_name)
        else:
            # Name of the predicted class.
            cls_pred_name = class_names[cls_pred[i]]

            xlabel = "True: {0}\nPred: {1}".format(cls_true_name, cls_pred_name)

        # Show the classes as the label on the x-axis.
        ax.set_xlabel(xlabel)

        # Remove ticks from the plot.
        ax.set_xticks([])
        ax.set_yticks([])

    # Ensure the plot is shown correctly with multiple plots
    # in a single Notebook cell.
    plt.show()

count = 0
ref_idx = []
for i in range(200):
    idx = np.argmax(test_y[i])
    if(count == idx):
        #print(test_y[i],' -> ',test_y[i])
        ref_idx.append(i)
        count = count + 1
    if(count == 9):
        break;

# Get the images from the test-set.
images = np.zeros(shape=[9, 32, 32, 3], dtype=float)
```

```python
cls_true = np.zeros(shape=[9], dtype=int)
count = 0
for ids in ref_idx:
    images[count] = test_x[ids].reshape(32,32,3)
    # Get the true classes for those images.
    cls_true[count] = np.argmax(test_y[ids])
    count = count + 1

print('Reading ',len(images),' Image Ids: ',ref_idx)
print('Class True: ',cls_true)
# Plot the images and labels using our helper-function above.
plot_images(images=images, cls_true=cls_true, smooth=False)
```

```
Classes:
- Training-set:                 50000
- Test-set:                 10000
Reading  9  Image Ids:  [3, 6, 25, 46, 58, 85, 93, 99, 108]
Class True:  [0 1 2 3 4 5 6 7 8]
```

0.0.2 (b) Design a model to classify these 10 classes. Choose parameters of your model architecture such as number of layers, number of neurons and the loss function. Comment on these choices. Implement this model in Tensorflow and train the model weights using the training set. Plot the training and testing loss and accuracy over time and observe the network's improvement with every iteration.

In [38]:
```
import tensorflow as tf
from time import time
import math

def model():
    _IMAGE_SIZE = 32
    _IMAGE_CHANNELS = 3
    _NUM_CLASSES = 10
    tf.reset_default_graph()
    with tf.name_scope('main_params'):
        x = tf.placeholder(tf.float32, shape=[None, _IMAGE_SIZE * _IMAGE_SIZE * _IMAGE
        y = tf.placeholder(tf.float32, shape=[None, _NUM_CLASSES], name='Output')
        x_image = tf.reshape(x, [-1, _IMAGE_SIZE, _IMAGE_SIZE, _IMAGE_CHANNELS], name=

        global_step = tf.Variable(initial_value=0, trainable=False, name='global_step
        learning_rate = tf.placeholder(tf.float32, shape=[], name='learning_rate')

    with tf.variable_scope('conv1') as scope:
        conv = tf.layers.conv2d(
            inputs=x_image,
            filters=32,
            kernel_size=[3, 3],
            padding='SAME',
            activation=tf.nn.relu
        )
        conv = tf.layers.conv2d(
            inputs=conv,
            filters=64,
            kernel_size=[3, 3],
            padding='SAME',
            activation=tf.nn.relu
        )
        pool = tf.layers.max_pooling2d(conv, pool_size=[2, 2], strides=2, padding='SAM
        drop = tf.layers.dropout(pool, rate=0.25, name=scope.name)

    with tf.variable_scope('conv2') as scope:
        conv = tf.layers.conv2d(
            inputs=drop,
            filters=128,
            kernel_size=[3, 3],
            padding='SAME',
            activation=tf.nn.relu
```

```
            )
            pool = tf.layers.max_pooling2d(conv, pool_size=[2, 2], strides=2, padding='SAM
            conv = tf.layers.conv2d(
                inputs=pool,
                filters=128,
                kernel_size=[2, 2],
                padding='SAME',
                activation=tf.nn.relu
            )
            pool = tf.layers.max_pooling2d(conv, pool_size=[2, 2], strides=2, padding='SAM
            drop = tf.layers.dropout(pool, rate=0.25, name=scope.name)

        with tf.variable_scope('fully_connected') as scope:
            flat = tf.reshape(drop, [-1, 4 * 4 * 128])

            fc = tf.layers.dense(inputs=flat, units=1500, activation=tf.nn.relu)
            drop = tf.layers.dropout(fc, rate=0.5)
            softmax = tf.layers.dense(inputs=drop, units=_NUM_CLASSES, activation=tf.nn.so

        y_pred_cls = tf.argmax(softmax, axis=1)

        return x, y, softmax, y_pred_cls, global_step, learning_rate


    def lr(epoch):
        learning_rate = 1e-3
        if epoch > 80:
            learning_rate *= 0.5e-3
        elif epoch > 60:
            learning_rate *= 1e-3
        elif epoch > 40:
            learning_rate *= 1e-2
        elif epoch > 20:
            learning_rate *= 1e-1
        return learning_rate
```

In [40]:
```
x, y, output, y_pred_cls, global_step, learning_rate = model()
global_accuracy = 0


# PARAMS
_BATCH_SIZE = 128
_EPOCH = 5
_SAVE_PATH = "tensorboard/cifar-10-v1.0.0/"


# LOSS AND OPTIMIZER
loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits_v2(logits=output, labels
```

```
optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate,
                                   beta1=0.9,
                                   beta2=0.999,
                                   epsilon=1e-08).minimize(loss, global_step=global_s

# PREDICTION AND ACCURACY CALCULATION
correct_prediction = tf.equal(y_pred_cls, tf.argmax(y, axis=1))
accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))

# SAVER
merged = tf.summary.merge_all()
saver = tf.train.Saver()
sess = tf.Session()
train_writer = tf.summary.FileWriter(_SAVE_PATH, sess.graph)

try:
    print("\nTrying to restore last checkpoint ...")
    last_chk_path = tf.train.latest_checkpoint(checkpoint_dir=_SAVE_PATH)
    saver.restore(sess, save_path=last_chk_path)
    print("Restored checkpoint from:", last_chk_path)
except ValueError:
    print("\nFailed to restore checkpoint. Initializing variables instead.")
    sess.run(tf.global_variables_initializer())


def train(epoch):
    batch_size = int(math.ceil(len(train_x) / _BATCH_SIZE))
    i_global = 0

    for s in range(batch_size):
        batch_xs = train_x[s*_BATCH_SIZE: (s+1)*_BATCH_SIZE]
        batch_ys = train_y[s*_BATCH_SIZE: (s+1)*_BATCH_SIZE]

        start_time = time()
        i_global, _, batch_loss, batch_acc = sess.run(
            [global_step, optimizer, loss, accuracy],
            feed_dict={x: batch_xs, y: batch_ys, learning_rate: lr(epoch)})
        duration = time() - start_time

        if s % 50 == 0:
            percentage = int(round((s/batch_size)*100))

            bar_len = 29
            filled_len = int((bar_len*int(percentage))/100)
            bar = '=' * filled_len + '>' + '-' * (bar_len - filled_len)

            msg = "Global step: {:>5} - [{}] {:>3}% - acc: {:.4f} - loss: {:.4f} - {:
            print(msg.format(i_global, bar, percentage, batch_acc, batch_loss, _BATCH_
```

```
    test_and_save(i_global, epoch)


def test_and_save(_global_step, epoch):
    global global_accuracy

    i = 0
    predicted_class = np.zeros(shape=len(test_x), dtype=np.int)
    while i < len(test_x):
        j = min(i + _BATCH_SIZE, len(test_x))
        batch_xs = test_x[i:j, :]
        batch_ys = test_y[i:j, :]
        predicted_class[i:j] = sess.run(
            y_pred_cls,
            feed_dict={x: batch_xs, y: batch_ys, learning_rate: lr(epoch)}
        )
        i = j

    correct = (np.argmax(test_y, axis=1) == predicted_class)
    acc = correct.mean()*100
    correct_numbers = correct.sum()

    mes = "\nEpoch {} - accuracy: {:.2f}% ({}/{})"
    print(mes.format((epoch+1), acc, correct_numbers, len(test_x)))

    if global_accuracy != 0 and global_accuracy < acc:

        summary = tf.Summary(value=[
            tf.Summary.Value(tag="Accuracy/test", simple_value=acc),
        ])
        train_writer.add_summary(summary, _global_step)

        saver.save(sess, save_path=_SAVE_PATH, global_step=_global_step)

        mes = "This epoch receive better accuracy: {:.2f} > {:.2f}. Saving session..."
        print(mes.format(acc, global_accuracy))
        global_accuracy = acc

    elif global_accuracy == 0:
        global_accuracy = acc

    print("###########################################################################
```

```
Trying to restore last checkpoint ...
INFO:tensorflow:Restoring parameters from tensorboard/cifar-10-v1.0.0/-1173
Restored checkpoint from: tensorboard/cifar-10-v1.0.0/-1173
```

```
In [41]: for i in range(_EPOCH):
             print("\nEpoch: {0}/{1}\n".format((i+1), _EPOCH))
             train(i)
```

```
Epoch: 1/5

Global step:  1174 - [>-----------------------------]   0% - acc: 0.6562 - loss: 1.7873 - 134.
Global step:  1224 - [===>--------------------------]  13% - acc: 0.6484 - loss: 1.8177 - 133.
Global step:  1274 - [=======>----------------------]  26% - acc: 0.6328 - loss: 1.8171 - 135.
Global step:  1324 - [===========>------------------]  38% - acc: 0.6797 - loss: 1.7582 - 138.
Global step:  1374 - [==============>---------------]  51% - acc: 0.6484 - loss: 1.8109 - 142.
Global step:  1424 - [==================>-----------]  64% - acc: 0.6641 - loss: 1.7929 - 141.
Global step:  1474 - [======================>-------]  77% - acc: 0.6797 - loss: 1.7782 - 140.
Global step:  1524 - [==========================>---]  90% - acc: 0.5938 - loss: 1.8742 - 135.

Epoch 1 - accuracy: 67.28% (6728/10000)
################################################################################################

Epoch: 2/5

Global step:  1565 - [>-----------------------------]   0% - acc: 0.7578 - loss: 1.7070 - 140.
Global step:  1615 - [===>--------------------------]  13% - acc: 0.7109 - loss: 1.7537 - 136.
Global step:  1665 - [=======>----------------------]  26% - acc: 0.7266 - loss: 1.7396 - 119.
Global step:  1715 - [===========>------------------]  38% - acc: 0.7500 - loss: 1.7068 - 121.
Global step:  1765 - [==============>---------------]  51% - acc: 0.6406 - loss: 1.8265 - 94.7
Global step:  1815 - [==================>-----------]  64% - acc: 0.7188 - loss: 1.7593 - 137.
Global step:  1865 - [======================>-------]  77% - acc: 0.7891 - loss: 1.6766 - 128.
Global step:  1915 - [==========================>---]  90% - acc: 0.7109 - loss: 1.7587 - 124.

Epoch 2 - accuracy: 69.74% (6974/10000)
This epoch receive better accuracy: 69.74 > 67.28. Saving session...
################################################################################################

Epoch: 3/5

Global step:  1956 - [>-----------------------------]   0% - acc: 0.7109 - loss: 1.7347 - 136.
Global step:  2006 - [===>--------------------------]  13% - acc: 0.7031 - loss: 1.7464 - 91.6
Global step:  2056 - [=======>----------------------]  26% - acc: 0.7734 - loss: 1.7004 - 102.
Global step:  2106 - [===========>------------------]  38% - acc: 0.7422 - loss: 1.7154 - 145.
Global step:  2156 - [==============>---------------]  51% - acc: 0.6328 - loss: 1.8136 - 114.
Global step:  2206 - [==================>-----------]  64% - acc: 0.7188 - loss: 1.7405 - 142.
Global step:  2256 - [======================>-------]  77% - acc: 0.7734 - loss: 1.6813 - 103.
Global step:  2306 - [==========================>---]  90% - acc: 0.7031 - loss: 1.7757 - 137.

Epoch 3 - accuracy: 70.68% (7068/10000)
```

```
This epoch receive better accuracy: 70.68 > 69.74. Saving session...
##########################################################################################

Epoch: 4/5

Global step:  2347 - [>-----------------------------]   0% - acc: 0.7812 - loss: 1.6802 - 126.3
Global step:  2397 - [===>--------------------------]  13% - acc: 0.7734 - loss: 1.6851 - 135.3
Global step:  2447 - [=======>----------------------]  26% - acc: 0.7812 - loss: 1.6782 - 140.7
Global step:  2497 - [===========>------------------]  38% - acc: 0.7578 - loss: 1.7085 - 125.6
Global step:  2547 - [==============>---------------]  51% - acc: 0.7031 - loss: 1.7590 - 117.4
Global step:  2597 - [==================>-----------]  64% - acc: 0.7500 - loss: 1.7288 - 94.2
Global step:  2647 - [======================>-------]  77% - acc: 0.7656 - loss: 1.6979 - 129.5
Global step:  2697 - [==========================>---]  90% - acc: 0.7344 - loss: 1.7375 - 138.8

Epoch 4 - accuracy: 70.03% (7003/10000)
##########################################################################################

Epoch: 5/5

Global step:  2738 - [>-----------------------------]   0% - acc: 0.7969 - loss: 1.6671 - 136.3
Global step:  2788 - [===>--------------------------]  13% - acc: 0.7578 - loss: 1.7062 - 135.8
Global step:  2838 - [=======>----------------------]  26% - acc: 0.7734 - loss: 1.6899 - 126.6
Global step:  2888 - [===========>------------------]  38% - acc: 0.8125 - loss: 1.6561 - 130.7
Global step:  2938 - [==============>---------------]  51% - acc: 0.7344 - loss: 1.7218 - 127.7
Global step:  2988 - [==================>-----------]  64% - acc: 0.7266 - loss: 1.7308 - 138.9
Global step:  3038 - [======================>-------]  77% - acc: 0.8047 - loss: 1.6592 - 110.2
Global step:  3088 - [==========================>---]  90% - acc: 0.7031 - loss: 1.7550 - 125.0

Epoch 5 - accuracy: 72.33% (7233/10000)
This epoch receive better accuracy: 72.33 > 70.68. Saving session...
##########################################################################################
```

0.0.3 Accuracy plot based on the partial run that I did here

(c) Calculate the total number of free, trainable parameters

- We have Conv1 and Conv2 layers followed by a Fully connected layer
- Each Conv layer has 2 Conv2D operation with a 3x3 kernel
- Relu is used for the final activation

```
In [64]: def testMisclassification(epoch):
             i = 0
             predicted_class = np.zeros(shape=len(test_x), dtype=np.int)
             while i < len(test_x):
                 j = min(i + _BATCH_SIZE, len(test_x))
                 batch_xs = test_x[i:j, :]
                 batch_ys = test_y[i:j, :]
                 predicted_class[i:j] = sess.run(
```

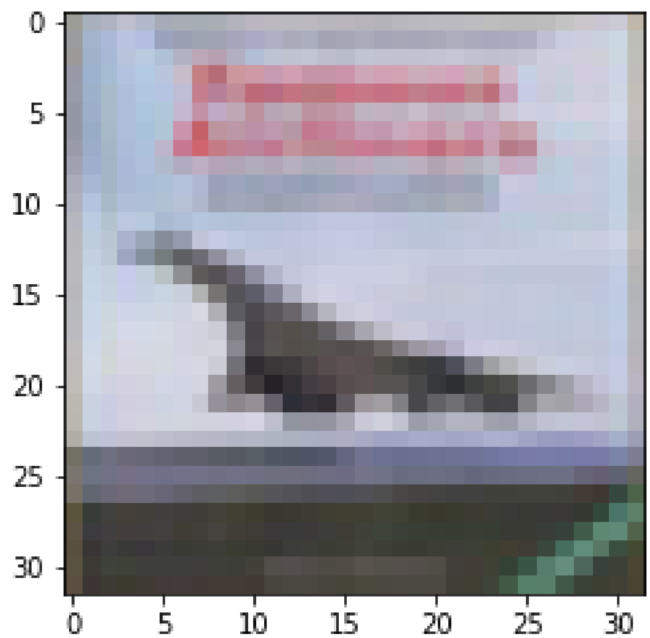
```
                y_pred_cls,
                feed_dict={x: batch_xs, y: batch_ys, learning_rate: lr(epoch)}
            )
            i = j
        misclassification = (np.argmax(test_y, axis=1) != predicted_class)
        misclassification_numbers = misclassification.sum()
        print('Misclassification Id:',misclassification[0:20])
        print('Misclassification count:',misclassification_numbers)

        mis_id = np.argmax(misclassification)
        print(mis_id)
        print('Expected: ',test_y[mis_id],' => Predicted:',predicted_class[mis_id])
        img = test_x[mis_id].reshape(32,32,3)
        print('Image Shape:',img.shape)
        imgplot = plt.imshow(img)
        print('--------')
        count = 0
        missed = np.array(np.where(misclassification == True))
        print(missed)
        updates_mis = []
        for i in range(misclassification_numbers):
            mis_id = missed[0][i]
            y_pred = predicted_class[mis_id]
            #print(mis_id, ' ', y_pred)
            if(y_pred == count):
                count = count + 1
                print('Expected: ',test_y[mis_id],' => Predicted:',predicted_class[mis_id
                updates_mis.append(mis_id)
            if(count==9):
                break;
        print('--------')
        return updates_mis, predicted_class


    missed_ids, predicted_class = testMisclassification(20)
    print('Missed: ', missed_ids)
```

```
Misclassification Id: [False False False  True False False False  True False False False False
  True False False False False  True False False]
Misclassification count: 2767
3
Expected:  [1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]  => Predicted: 8
Image Shape: (32, 32, 3)
--------
[[   3    7   12 ... 9987 9989 9995]]
Expected:  [0. 0. 0. 0. 1. 0. 0. 0. 0. 0.]  => Predicted: 0
Expected:  [0. 0. 0. 0. 0. 0. 0. 0. 0. 1.]  => Predicted: 1
Expected:  [0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]  => Predicted: 2
```

```
Expected:  [0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]  => Predicted: 3
Expected:  [0. 0. 0. 0. 0. 0. 0. 1. 0. 0.]  => Predicted: 4
Expected:  [0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]  => Predicted: 5
Expected:  [1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]  => Predicted: 6
Expected:  [0. 0. 0. 0. 1. 0. 0. 0. 0. 0.]  => Predicted: 7
Expected:  [1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]  => Predicted: 8
--------
Missed:  [40, 259, 275, 321, 355, 384, 428, 466, 477]
```



0.0.4 (d) Visualize one wrongly-classified sample from each of the 10 classes.

In [76]:
```python
def plot_images_missed(images, cls_true, cls_pred=None, smooth=True):

    assert len(images) == len(cls_true) == 9

    # Create figure with sub-plots.
    fig, axes = plt.subplots(3, 3)

    # Adjust vertical spacing if we need to print ensemble and best-net.
    if cls_pred is None:
        hspace = 0.3
    else:
        hspace = 0.6
    fig.subplots_adjust(hspace=hspace, wspace=0.3)
```

```
    for i, ax in enumerate(axes.flat):
        # Interpolation type.
        if smooth:
            interpolation = 'spline16'
        else:
            interpolation = 'nearest'

        # Plot image.
        image = images[i].reshape(32,32,3)
        ax.imshow(image,
                  interpolation=interpolation)

        # Name of the true class.
        cls_true_name = class_names[np.argmax(cls_true[i])]

        # Show true and predicted classes.
        if cls_pred is None:
            xlabel = "True: {0}".format(cls_true_name)
        else:
            # Name of the predicted class.
            cls_pred_name = class_names[cls_pred[i]]

            xlabel = "True: {0}\nPred: {1}".format(cls_true_name, cls_pred_name)

        # Show the classes as the label on the x-axis.
        ax.set_xlabel(xlabel)

        # Remove ticks from the plot.
        ax.set_xticks([])
        ax.set_yticks([])

    # Ensure the plot is shown correctly with multiple plots
    # in a single Notebook cell.
    plt.show()

#for ids in ref_idx:
#    images[count] = test_x[ids].reshape(32,32,3)

plot_images_missed(images=test_x[missed_ids], cls_true=test_y[missed_ids], cls_pred=p
```

0.0.5 Final epoch receive better accuracy: 72.33 > 70.68.