ECE472
Deep Learning - Assignment 4

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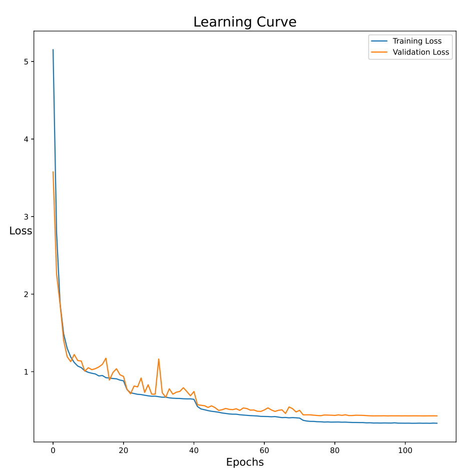
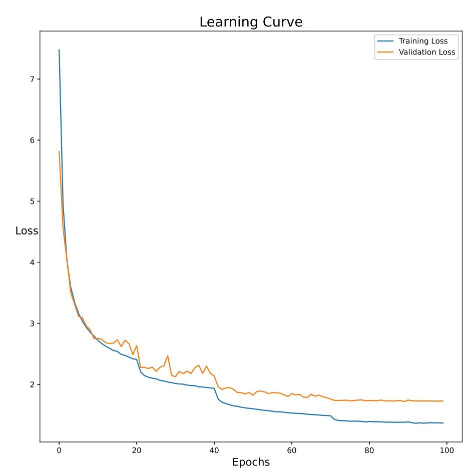
Summary

Cifar-10 and Cifar-100 datasets were downloaded, extracted, and split into training, validation, and test sets. Models were trained for each dataset and fter a lot of trial, error, and reading papers, the models converged to the ones seen in the code attached. The accuracy for the cifar-10 model reached %88, which I claim is around state of the art, while the top-5 accuracy of the cifar-100 model reached %85 percent, exceeding the required %80. The learning curves for the two models chosen can be seen in figures 1a and 1b.



(a) Cifar-10



(b) Cifar-100

Figure 1: Learning Curves for the Final Models for Each of the Datasets

My Various Attempts:

This project took me a lot of different attempts to get to the level I presented. I began by only looking at the cifar-10 ”problem”, as it seemed more complex out of the two to me. I looked and found code that downloads the dataset, and used it to import. From a quick research, I decided to set an early goal of %75 accuracy so I am able to begin training models (which I knew might take a long time).

I wasn’t sure where to start, so I began with the network I made for assignment 3 for the MNIST dataset. This didn’t work whatsoever, and after tweaking and increasing the number of layers, adding more regularization in the form of dropout, and having the network not give meaningful results after hours of training I gave up on this approach.

I decided I needed to ”get inspiration” from papers, because at the pace I was going I was getting nowhere (at this point I was at around %70 accuracy and not happy about it whatsoever). I started with the papers we had to read for this week, and after some lookup online I saw that people were saying that residual units might be a good idea for this type of problem. I liked the approach in the paper ”Identity Mappings in Deep Residual Networks” and also had a look at ”Deep Residual Learning for Image Recognition” to gain some more understanding of these units. I went about trying to program these and failed, getting errors that the layers don’t match in the addition, which meant that I was doing something wrong. After some time trying to fix that I decided to gain more ”inspiration” and proceeded to look for other people’s implementations, which I ended up adapting to make up my network, which finally ran and got an accuracy around %75.

At this point I went back to refine my goal to match ”state-of-the-art”. I came upon a website listing benchmarks for the cifar-10 dataset (which can be found here). I saw networks that achieved over %99 accuracy, which I felt was too high for this project. To find a more reasonable accuracy to aim for, I considered the papers we read for this week and saw that the website listed a residual network that had an accuracy of %93. I knew that I do not have the resources to fully optimize this network, so I set the goal %5 bellow this at %88 accuracy.

I went back to the model and started adjusting parameters, changing the activations to elu, and trying out different types and levels of regularization. This brought me up to around %83 accuracy. The next thing I explored was the scheduling learning rate changes, and that allowed me to increase the accuracy to a bit over %85. The last thing I ended up doing was adding data augmentation, which finally let me surpass my limit for state of the art and reach a validation and eventually test accuracy above %88.

Appendix I- Python Code

```
# -*- coding: utf-8 -*-
"""DeepLearningAssignment4.ipynb

Automatically generated by Colaboratory.

Original file is located at
    https://colab.research.google.com/drive/1fttnv5Q8BGa8iFyPHgbBwzs7N1GbvXc4

**ECE472, Deep Learning - Assignment 4**

Submit by Oct. 1, 10pm

tldr: Classify cifar10. Acheive performance similar to the state of the art. Classify
"""

import numpy as np
import pandas as pd
import numpy.random as npr
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import matplotlib.pyplot as plt
from tensorflow.keras.layers import Add, Conv2D, BatchNormalization, Activation
from tensorflow.keras.layers import MaxPooling2D, Input, Flatten, Dense, Dropout
from tensorflow.keras.regularizers import l1, l2
from keras.callbacks import LearningRateScheduler, ReduceLROnPlateau
from sklearn.model_selection import train_test_split
from tensorflow.keras.metrics import TopKCategoricalAccuracy

import tarfile
import os
import sys
import pickle
from urllib.request import urlretrieve

#Links I looked at and might not have mentioned elsewhere:
'''
https://github.com/ostapstephan/DeepLearning/blob/master/hw4curro/CIFAR10Res.py
https://github.com/Minhtyyufa/Deep_Learning/blob/master/hw_4/hw_4.py
https://github.com/keras-team/keras/blob/
  1a3ee8441933fc007be6b2beb47af67998d50737/examples/cifar10_resnet.py#L140
https://www.reddit.com/r/MachineLearning/comments/7806n6/
  d_why_arent_inceptionstyle_networks_successful_on/
```

```
https://analyticsindiamag.com/why-resnets-are-a-major-breakthrough-in-image-processin
  #:~:text=ResNets%20are%20being%20implemented%20in,negate%20the%20vanishing%20gradie
https://medium.com/@zurister/depth-wise-convolution-and-depth-wise-separable-convolut
https://github.com/facebookarchive/fb.resnet.torch/blob/master/models/resnet.lua
https://towardsdatascience.com/mobilenetv2-inverted-residuals-and-linear-bottlenecks-
https://github.com/hendrycks/init/blob/master/cifar100.py
'''

im_size  = 32
im_channels = 3
train_num = 50_000
test_num = 10_000
SEED = 25

def cifar10(path=None):
    r"""Return (train_images, train_labels, test_images, test_labels).

    Args:
        path (str): Directory containing CIFAR-10. Default is
            /home/USER/data/cifar10 or C:\Users\USER\data\cifar10.
            Create if nonexistant. Download CIFAR-10 if missing.

    Returns:
        Tuple of (train_images, train_labels, test_images, test_labels), each
            a matrix. Rows are examples. Columns of images are pixel values,
            with the order (red -> blue -> green). Columns of labels are a
            onehot encoding of the correct class.


    Found function at:
    https://mattpetersen.github.io/load-cifar10-with-numpy
    """
    url = 'https://www.cs.toronto.edu/~kriz/'
    tar = 'cifar-10-binary.tar.gz'
    files = ['cifar-10-batches-bin/data_batch_1.bin',
             'cifar-10-batches-bin/data_batch_2.bin',
             'cifar-10-batches-bin/data_batch_3.bin',
             'cifar-10-batches-bin/data_batch_4.bin',
             'cifar-10-batches-bin/data_batch_5.bin',
             'cifar-10-batches-bin/test_batch.bin']

    if path is None:
        path = os.path.join(os.path.expanduser('~'), 'data', 'cifar10')
```

```python
# Create path if it doesn't exist
os.makedirs(path, exist_ok=True)

# Download tarfile if missing
if tar not in os.listdir(path):
    urlretrieve(''.join((url, tar)), os.path.join(path, tar))
    print("Downloaded %s to %s" % (tar, path))

# Load data from tarfile
with tarfile.open(os.path.join(path, tar)) as tar_object:
    # Each file contains 10,000 color images and 10,000 labels
    fsize = 10000 * (32 * 32 * 3) + 10000

    # There are 6 files (5 train and 1 test)
    buffr = np.zeros(fsize * 6, dtype='uint8')

    # Get members of tar corresponding to data files
    # -- The tar contains README's and other extraneous stuff
    members = [file for file in tar_object if file.name in files]

    # Sort those members by name
    # -- Ensures we load train data in the proper order
    # -- Ensures that test data is the last file in the list
    members.sort(key=lambda member: member.name)

    # Extract data from members
    for i, member in enumerate(members):
        # Get member as a file object
        f = tar_object.extractfile(member)
        # Read bytes from that file object into buffr
        buffr[i * fsize:(i + 1) * fsize] = np.frombuffer(f.read(), 'B')

# Parse data from buffer
# -- Examples are in chunks of 3,073 bytes
# -- First byte of each chunk is the label
# -- Next 32 * 32 * 3 = 3,072 bytes are its corresponding image

# Labels are the first byte of every chunk
labels = buffr[::3073]

# Pixels are everything remaining after we delete the labels
pixels = np.delete(buffr, np.arange(0, buffr.size, 3073))
images = pixels.reshape(-1, 3072).astype('float32') / 255
```

```
    # Split into train and test
    train_images, test_images = images[:50000], images[50000:]
    train_labels, test_labels = labels[:50000], labels[50000:]

    return train_images, train_labels, test_images, test_labels

train_images, train_labels, test_images, test_labels = cifar10()

plt.imshow(np.transpose(train_images.reshape(-1, 3,32,32), (0, 2, 3, 1))[1])

num_classes  = 10

def shuffle(X, y, seed = SEED):
  npr.seed(seed)
  num_shuffle = X.shape[0]
  idxes = npr.permutation(num_shuffle)
  return X[idxes], y[idxes]

def format_imgs(X,y, num_classes = num_classes):
  X_, y_ = shuffle(X, y)
  X_out = np.transpose(X_.reshape(-1,3,32,32), (0, 2, 3, 1))/255.
  Y_out = tf.keras.utils.to_categorical(y_, num_classes)
  return X_out, Y_out

train_images, train_labels = shuffle(train_images, train_labels)
test_images, test_labels = shuffle(test_images, test_labels)
X_train, y_train = format_imgs(train_images, train_labels)
X_test, y_test = format_imgs(test_images, test_labels)



#normalize
mu_X = np.mean(X_train)
sig_X = np.std(X_train)

X_train = (X_train-mu_X)/sig_X
X_test = (X_test-mu_X)/sig_X

X_train, X_val, y_train, y_val = train_test_split(X_train,
                                                  y_train,
                                                  test_size = 0.05,
                                                  random_state = SEED)

# Training generator
```

```
train_datagen = ImageDataGenerator(
    width_shift_range = 0.1,
    height_shift_range = 0.1,
    horizontal_flip = True,
)

train_generator = train_datagen.flow(
    X_train,
    y_train,
    batch_size=128,
)

#Validation generator
val_datagen = ImageDataGenerator()
val_generator = val_datagen.flow(
    X_val,
    y_val,
)

#Test generator
test_datagen = ImageDataGenerator()
test_generator = test_datagen.flow(
    X_test,
    y_test,
)

WEIGHT_DECAY = 7e-3

def res_layer(inputs,
              num_filters,
              kernel_size=3,
              activation='elu'):
  x = inputs
  x = BatchNormalization()(x)
  x = Activation(activation)(x)
  y = Conv2D(num_filters,
             kernel_size=kernel_size,
             padding='same',
             kernel_initializer='he_normal',
             kernel_regularizer=l2(WEIGHT_DECAY))(x)
  x = BatchNormalization()(y)
  x = Activation(activation)(x)
  x = Conv2D(num_filters,
             kernel_size=kernel_size,
```

```
              padding='same',
              kernel_initializer='he_normal',
              kernel_regularizer=l2(WEIGHT_DECAY))(x)
  x = BatchNormalization()(x)
  x = Activation(activation)(x)
  x = Conv2D(num_filters,
              kernel_size=kernel_size,
              padding='same',
              kernel_initializer='he_normal',
              kernel_regularizer=l2(WEIGHT_DECAY))(x)
  return Add()([y, x])

num_classes=10
num_filters = 16

#Create Model
inputs = Input(shape=X_train.shape[1:])
y = res_layer(inputs=inputs, num_filters=num_filters)
for i in range(2):
  y = MaxPooling2D(pool_size=2,strides=2)(y)
  num_filters*=2
  y = res_layer(inputs=y, num_filters=num_filters)
y = Activation("elu")(y)
y = MaxPooling2D(pool_size=8)(y)
y = Flatten()(y)
outputs = Dense(num_classes,
                activation='softmax',
                kernel_initializer='he_normal',
                activity_regularizer=l2(WEIGHT_DECAY))(y)
model = tf.keras.models.Model(inputs=inputs, outputs=outputs)

#summary
model.summary()

# Compile Model.
model.compile(loss = "categorical_crossentropy",
              optimizer = 'adam',
              metrics = ['acc'])

#Callbacks
def lr_schedule(epoch):
        lr = 1e-3
        if epoch > 90:
                lr *= 1e-3
```

```
        elif epoch > 70:
                lr *= 1e-2
        elif epoch > 40:
                lr *= 1e-1
        elif epoch > 20:
                lr *= 5e-1
        print('Learning rate: ', lr)
        return lr

lr_scheduler = LearningRateScheduler(lr_schedule)
callbacks = [lr_scheduler]

# Train the Model
history = model.fit(
    train_generator,
    batch_size = 128,
    epochs = 110,
    verbose = 1,
    validation_data = val_generator,
    callbacks = callbacks
)

# Learning Curve
plt.figure(figsize = (10,10))
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])

plt.xlabel('Epochs', fontsize = 14)
h = plt.ylabel('Loss',fontsize = 14)
h.set_rotation(0)
plt.title('Learning Curve', fontsize = 18)
plt.legend(['Training Loss', 'Validation Loss'])
plt.savefig('LearningCurveCifar10.eps', format='eps')
plt.show()

#Evaluate on test set
results = model.evaluate(test_generator, verbose=0)
print('Test Accuracy:', results[1])

"""Cifar100"""

def download_dataset(path, source='https://www.cs.toronto.edu/~kriz/'
                                  'cifar-100-python.tar.gz'):
    """
```

```python
    Downloads and extracts the dataset, if needed.
    https://github.com/vahidk/TensorflowFramework/blob/master/dataset/cifar100.py
    """
    files = ['train', 'test']
    for fn in files:
        if not os.path.exists(os.path.join(path, "cifar-100-python", fn)):
            break  # at least one file is missing
    else:
        return  # dataset is already complete

    print("Downloading and extracting %s into %s..." % (source, path))

    if sys.version_info[0] == 2:
        from urllib import urlopen
    else:
        from urllib.request import urlopen
    import tarfile
    if not os.path.exists(path):
        os.makedirs(path)
    u = urlopen(source)
    with tarfile.open(fileobj=u, mode='r|gz') as f:
        f.extractall(path=path)
    u.close()

def load_dataset(path = None):
    if path is None:
        path = os.path.join(os.path.expanduser('~'), 'data', 'cifar100')

    download_dataset(path)

    # training data
    data = pickle.load(open(os.path.join(path, "cifar-100-python", "train"),
                            'rb'), encoding='latin1')
    X_train = data['data']
    y_train = np.asarray(data['fine_labels'], np.int8)

    # test data
    data = pickle.load(open(os.path.join(path, 'cifar-100-python', 'test'),
                            'rb'), encoding='latin1')
    X_test = data['data']
    y_test = np.asarray(data['fine_labels'], np.int8)

    return X_train, y_train, X_test, y_test
```

```
train_images100, train_labels100, test_images100, test_labels100 = load_dataset()

plt.imshow(np.transpose(train_images100.reshape(-1, 3,32,32), (0, 2, 3, 1))[2])
train_labels100[2]

num_classes=100

train_images100, train_labels100 = shuffle(train_images100, train_labels100)
test_images100, test_labels100 = shuffle(test_images100, test_labels100)
X_train100, y_train100 = format_imgs(train_images100, train_labels100, num_classes)
X_test100, y_test100 = format_imgs(test_images100, test_labels100, num_classes)


#normalize
mu_X100 = np.mean(X_train100)
sig_X100 = np.std(X_train100)

X_train100 = (X_train100-mu_X100)/sig_X100
X_test100 = (X_test100-mu_X100)/sig_X100

X_train100, X_val100, y_train100, y_val100 = train_test_split(X_train100,
                                                              y_train100,
                                                              test_size = 0.05,
                                                              random_state = SEED)
# Training generator
train_datagen = ImageDataGenerator(
    width_shift_range = 0.1,
    height_shift_range = 0.1,
    horizontal_flip = True,
)

train_generator100 = train_datagen.flow(
    X_train100,
    y_train100,
    batch_size=128,
)

#Validation generator
val_datagen = ImageDataGenerator()
val_generator100 = val_datagen.flow(
    X_val100,
    y_val100,
)
```

```
#Test generator
test_datagen = ImageDataGenerator()
test_generator100 = test_datagen.flow(
    X_test100,
    y_test100,
)

num_filters = 16

#Create Model
inputs = Input(shape=X_train100.shape[1:])
y = res_layer(inputs=inputs, num_filters=num_filters)
for i in range(2):
  y = MaxPooling2D(pool_size=2,strides=2)(y)
  num_filters*=2
  y = res_layer(inputs=y, num_filters=num_filters)
y = Activation("elu")(y)
y = MaxPooling2D(pool_size=8)(y)
y = Flatten()(y)
outputs = Dense(num_classes,
                activation='softmax',
                kernel_initializer='he_normal',
                activity_regularizer=l2(WEIGHT_DECAY))(y)
model2 = tf.keras.models.Model(inputs=inputs, outputs=outputs)

#summary
model2.summary()

# Compile Model.
model2.compile(loss = "categorical_crossentropy",
              optimizer = 'adam',
              metrics = [TopKCategoricalAccuracy(k=5)])

#Callbacks
def lr_schedule(epoch):
        lr = 1e-3
        if epoch > 90:
                lr *= 1e-3
        elif epoch > 70:
                lr *= 1e-2
        elif epoch > 40:
                lr *= 1e-1
        elif epoch > 20:
                lr *= 5e-1
```

```
        print('Learning rate: ', lr)
        return lr

lr_scheduler = LearningRateScheduler(lr_schedule)
callbacks = [lr_scheduler]

# Train the Model
history2 = model2.fit(
    train_generator100,
    batch_size = 128,
    epochs = 100,
    verbose = 1,
    validation_data = val_generator100,
    callbacks = callbacks
)

# Learning Curve
plt.figure(figsize = (10,10))
plt.plot(history2.history['loss'])
plt.plot(history2.history['val_loss'])

plt.xlabel('Epochs', fontsize = 14)
h = plt.ylabel('Loss',fontsize = 14)
h.set_rotation(0)
plt.title('Learning Curve', fontsize = 18)
plt.legend(['Training Loss', 'Validation Loss'])
plt.savefig('LearningCurveCifar100.eps', format='eps')
plt.show()

#Evaluate on test set
results = model2.evaluate(test_generator100, verbose=0)
print('Test Top 5 Accuracy:', results[1])
```