Advanced Machine Learning Methods
Project CNN

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Abstract

I trained a Convolutional Neural Network on GPU for classifying images using the tiny ImageNet data set. The model is built after googlenet's [3] architecture using the python library lasagne [2], which is built on top of theano [1]. The CNN network consist of 22 layers and achived a total accuracy of 30 % when having 100 different classes. A reduced version with 20 different classes got a total of 37 % accuracy on the test-set. More in depth analysis would have been considered if I had more time available to test several CNN networks. I also cut the original data set of 200 to 100 classes to reduce training time as I calculated it would take me up to three days to train with the 200 classes.

1. Introduction

A common problem in machine learning is to effective representation of complex inputs such as image and video. Over the past years deep learning has proven to perform on such complex problems. I use Convolutional Neural Networks for image classifications on the tiny ImageNet dataset, a smaller version of the ImageNet [5] challenge dataset.

2. Method

2.1 Model

The model used to build the classifier is a model based on the googlenet architecture. I used the library lasagne [2] which is built on theano for deep learning. I also found the recipie for the model online [4]. The network has 22 layers where 9 of the layers is inception layers with dimensionality reductions.

2.2 Data Set

Tiny ImageNet is a dataset with 120,000 labeled images into 200 different categories. The dataset is similar to the ImageNet used in the ILSVRC benchmark, known as the ImageNet challenge. The images in the tiny dataset have lower resolution and it's an smaller dataset in total. Each of the 200 categories consists of 500 training samples with a 64x64 resolution. The raw RGB pixel-values of these images areextracted and fed to the CNN network.

3. Experiment

4. Results

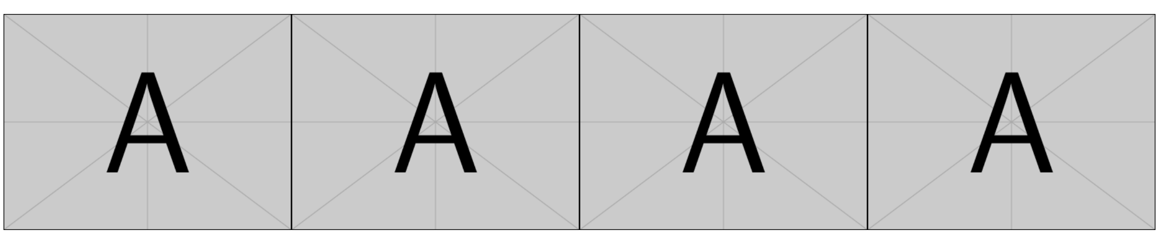
In order to test my program to see if it would run, I first classified a smaller version of the dataset with only 20 classes. This took around 3 hours running 500 epochs. After having confirmed everything worked with a low number of classes, I wanted to test if I could run for the whole dataset with 200 classes. Starting to train the classes with 200 classes took me around 380seconds per epoch, and I realized I would have to run for many days to complete it. I therefore decided to reduce down to 100 classes with epoch of 250. With 100 classes it now took me 190 seconds per epoch, and running 250 epochs it took me around 14 hours to complete it. I could have let the network run at 200 classes and rather reduce the layers to make the network less deep, or significantly reduce number of epochs. I chose not to do this to keep the depth of the network.

Figure 1: TSNE Embedding of Tiny Imagenet CNN Codes

Table 1: Shows results for running classification on Googlenet

# classes	# training	# validation	# testing	# epoch	test-loss	Accuracy
20	6903	1480	1480	500	10.9	39.30
100	39340	4928	9835	250	9.95	29.31

As we can see on the validation accuracy after numbers of epochs, it stopped improved very little after 20 epochs, making it stuck at around 28 % accuracy.



(a) A gull (b) A gull2 (c) A tiger (d) A mouse

Figure 2: Classifications

Table 2: Shows results for validation accuracy for Googlenet on tiny ImageNet with 100 classes on some epochs

Epoch	Val accuracy
1	2.24 %
5	7.29 %
10	18.4 %
20	26.87 %
30	27.38 %
50	28.48 %
100	30.00 %
150	29.20 %
200	28.93 %
250	29.69 %

5. Conclusion

References

[1] J. Bergstra, O. Breuleux, F. Bastien, P. Lamblin, R. Pascanu, G. Desjardins, J. Turian, D. Warde-Farley and Y. Bengio. Theano: A CPU and GPU Math Expression Compiler. Proceedings of the Python for Scientific Computing Conference (SciPy) 2010. June 30 - July 3, Austin, TX

[2] Sander Dieleman, Lasagne is a lightweight library to build and train neural networks in Theano. `https://github.com/Lasagne/Lasagne`

[3] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. E. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, A. Rabinovich. Going Deeper with Convolutions, 2014. `http://arxiv.org/abs/1409.4842`

[4] `https://github.com/Lasagne/Recipes/blob/master/modelzoo/googlenet.py`

[5] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. FeiFei. ImageNet: A large-scale hierarchical image database. In CVPR, 2009

Code

main.py

```
import numpy as np
import lasagne
import theano
import theano.tensor as T
import vgg16
import googlenet
import pickle
import time

from preprocess import load_dataset, generate_url_zip

def iterate_minibatches(inputs, targets, batchsize, shuffle=False):
    assert len(inputs) == len(targets)
    if shuffle:
        indices = np.arange(len(inputs))
        np.random.shuffle(indices)
    for start_idx in range(0, len(inputs) - batchsize + 1, batchsize):
        if shuffle:
            excerpt = indices[start_idx:start_idx + batchsize]
        else:
            excerpt = slice(start_idx, start_idx + batchsize)
        yield inputs[excerpt], targets[excerpt]

def train_network(num_epochs, X_train, y_train, X_val, y_val, train_fn, val_fn, network):
    save_iterals = {0, 49, 99, 199, 249}
    results = []
    # We iterate over epochs:
    for epoch in range(num_epochs):
        # In each epoch, we do a full pass over the training data:
        train_err = 0
        train_batches = 0
        start_time = time.time()

        print("   pass over training data...")
        for batch in iterate_minibatches(X_train, y_train, 500, shuffle=True):
            inputs, targets = batch
            train_err += train_fn(inputs, targets)
            train_batches += 1

        print("   pass over validation data...")
        # And a full pass over the validation data:
        val_err = 0
        val_acc = 0
        val_batches = 0
        for batch in iterate_minibatches(X_val, y_val, 500, shuffle=False):
            inputs, targets = batch
            err, acc = val_fn(inputs, targets)
            val_err += err
            val_acc += acc
            val_batches += 1

        # Then we print the results for this epoch:
        print("Epoch {} of {} took {:.3f}s".format(epoch + 1, num_epochs, time.time() - start_time))
        print("  training loss:\t\t{:.6f}".format(train_err / train_batches))
        print("  validation loss:\t\t{:.6f}".format(val_err / val_batches))
        print("  validation accuracy:\t\t{:.2f} %".format(val_acc / val_batches * 100))

        results.append(val_acc / val_batches * 100)

        if epoch in save_iterals: # Store the network while training
            np.savez("epoch_googlenet_100_" + str(epoch + 1) +".npz", *lasagne.layers.get_all_param_values(network))


    np.savez('googlenet_epochs.npz', results)



def test_network(X_test, y_test, val_fn):
    test_err = 0
    test_acc = 0
    test_batches = 0
    for batch in iterate_minibatches(X_test, y_test, 500, shuffle=False):
        inputs, targets = batch
        err, acc = val_fn(inputs, targets)
        test_err += err
        test_acc += acc
        test_batches += 1
    print("Final results:")
    print("  test loss:\t\t\t{:.6f}".format(test_err / test_batches))
    print("  test accuracy:\t\t{:.2f} %".format(
        test_acc / test_batches * 100))

def build_parameter_update(network, loss):
```

```
    # create parameter update expressions
    params = lasagne.layers.get_all_params(network, trainable=True)
    updates = lasagne.updates.nesterov_momentum(loss, params, learning_rate=0.01,
                                                momentum=0.9)
    return updates


def build_loss(network, target_var):
    # Create a loss expression for training, i.e., a scalar objective we want
    # to minimize (for our multi-class problem, it is the cross-entropy loss):
    prediction = lasagne.layers.get_output(network)
    loss = lasagne.objectives.categorical_crossentropy(prediction, target_var)
    loss = loss.mean()
    return loss

def build_test_loss(network, target_var):
    # Create a loss expression for validation/testing. The crucial difference
    # here is that we do a deterministic forward pass through the network,
    # disabling dropout layers.
    test_prediction = lasagne.layers.get_output(network, deterministic=True)
    test_loss = lasagne.objectives.categorical_crossentropy(test_prediction,
                                                            target_var)
    test_loss = test_loss.mean()
    # As a bonus, also create an expression for the classification accuracy:
    test_acc = T.mean(T.eq(T.argmax(test_prediction, axis=1), target_var),
                      dtype=theano.config.floatX)

    return test_loss, test_acc

def main(num_epochs=250):
    print("Loading data...")
    X_train, y_train, X_val, y_val, X_test, y_test = generate_url_zip()

    print "X_train: ", X_train.shape, " y_train: ", y_train.shape
    print "X_val: ", X_val.shape, " y_val: ", y_val.shape

    input_var = T.tensor4('inputs')
    target_var = T.ivector('targets')

    print("Building network...")
    #network = vgg16.build_model(input_var)
    network = googlenet.build_model(input_var)
    # Create a loss expression for training
    loss = build_loss(network, target_var)

    # create parameter update expressions
    updates = build_parameter_update(network, loss)

    # Create a loss expression for validation/testing.
    test_loss, test_acc = build_test_loss(network, target_var)

    # Compile a function performing a training step on a mini-batch (by giving
    # the updates dictionary) and returning the corresponding training loss:
    print("Setting training function...")
    train_fn = theano.function([input_var, target_var], loss, updates=updates)

    # Compile a second function computing the validation loss and accuracy:
    print("Setting validation function for loss and accuracy...")
    val_fn = theano.function([input_var, target_var], [test_loss, test_acc])

    # Finally, launch the training loop.
    print("Starting training...")
    train_network(num_epochs, X_train, y_train, X_val, y_val, train_fn, val_fn, network)

    # After training, we compute and print the test error:
    print("Starting testing...")
    test_network(X_test, y_test, val_fn)

    # Save network
    np.savez('trained_googlenet_100.npz', *lasagne.layers.get_all_param_values(network))

    # And load them again later on like this:
    # with np.load('model.npz') as f:
    #     param_values = [f['arr_%d' % i] for i in range(len(f.files))]
    # lasagne.layers.set_all_param_values(network, param_values)


if __name__ == "__main__":
    main()
```

googlenet.py

```
# BLVC Googlenet, model from the paper:
# "Going Deeper with Convolutions"
# Original source:
# https://github.com/BVLC/caffe/tree/master/models/bvlc_googlenet
# License: unrestricted use
```

```python
# Download pretrained weights from:
# https://s3.amazonaws.com/lasagne/recipes/pretrained/imagenet/blvc_googlenet.pkl

from lasagne.layers import InputLayer
from lasagne.layers import DenseLayer
from lasagne.layers import ConcatLayer
from lasagne.layers import NonlinearityLayer
from lasagne.layers import GlobalPoolLayer
from lasagne.layers.dnn import Conv2DDNNLayer as ConvLayer
from lasagne.layers.dnn import MaxPool2DDNNLayer as PoolLayerDNN
from lasagne.layers import MaxPool2DLayer as PoolLayer
from lasagne.layers import LocalResponseNormalization2DLayer as LRNLayer
from lasagne.nonlinearities import softmax, linear


def build_inception_module(name, input_layer, nfilters):
    # nfilters: (pool_proj, 1x1, 3x3_reduce, 3x3, 5x5_reduce, 5x5)
    net = {}
    net['pool'] = PoolLayerDNN(input_layer, pool_size=3, stride=1, pad=1)
    net['pool_proj'] = ConvLayer(net['pool'], nfilters[0], 1, flip_filters=False)

    net['1x1'] = ConvLayer(input_layer, nfilters[1], 1, flip_filters=False)

    net['3x3_reduce'] = ConvLayer(input_layer, nfilters[2], 1, flip_filters=False)
    net['3x3'] = ConvLayer(net['3x3_reduce'], nfilters[3], 3, pad=1, flip_filters=False)

    net['5x5_reduce'] = ConvLayer(input_layer, nfilters[4], 1, flip_filters=False)
    net['5x5'] = ConvLayer(net['5x5_reduce'], nfilters[5], 5, pad=2, flip_filters=False)

    net['output'] = ConcatLayer([
        net['1x1'],
        net['3x3'],
        net['5x5'],
        net['pool_proj'],
        ])

    return {'{}/{}'.format(name, k): v for k, v in net.items()}


def build_model(input_var = None):
    net = {}
    net['input'] = InputLayer((None, 3, None, None), input_var = input_var)
    net['conv1/7x7_s2'] = ConvLayer(net['input'], 64, 7, stride=2, pad=3, flip_filters=False)
    net['pool1/3x3_s2'] = PoolLayer(net['conv1/7x7_s2'], pool_size=3, stride=2, ignore_border=False)
    net['pool1/norm1'] = LRNLayer(net['pool1/3x3_s2'], alpha=0.00002, k=1)
    net['conv2/3x3_reduce'] = ConvLayer(net['pool1/norm1'], 64, 1, flip_filters=False)
    net['conv2/3x3'] = ConvLayer(net['conv2/3x3_reduce'], 192, 3, pad=1, flip_filters=False)
    net['conv2/norm2'] = LRNLayer(net['conv2/3x3'], alpha=0.00002, k=1)
    net['pool2/3x3_s2'] = PoolLayer(net['conv2/norm2'], pool_size=3, stride=2, ignore_border=False)

    net.update(build_inception_module('inception_3a',
                                      net['pool2/3x3_s2'],
                                      [32, 64, 96, 128, 16, 32]))
    net.update(build_inception_module('inception_3b',
                                      net['inception_3a/output'],
                                      [64, 128, 128, 192, 32, 96]))
    net['pool3/3x3_s2'] = PoolLayer(net['inception_3b/output'], pool_size=3, stride=2, ignore_border=False)

    net.update(build_inception_module('inception_4a',
                                      net['pool3/3x3_s2'],
                                      [64, 192, 96, 208, 16, 48]))
    net.update(build_inception_module('inception_4b',
                                      net['inception_4a/output'],
                                      [64, 160, 112, 224, 24, 64]))
    net.update(build_inception_module('inception_4c',
                                      net['inception_4b/output'],
                                      [64, 128, 128, 256, 24, 64]))
    net.update(build_inception_module('inception_4d',
                                      net['inception_4c/output'],
                                      [64, 112, 144, 288, 32, 64]))
    net.update(build_inception_module('inception_4e',
                                      net['inception_4d/output'],
                                      [128, 256, 160, 320, 32, 128]))
    net['pool4/3x3_s2'] = PoolLayer(net['inception_4e/output'], pool_size=3, stride=2, ignore_border=False)

    net.update(build_inception_module('inception_5a',
                                      net['pool4/3x3_s2'],
                                      [128, 256, 160, 320, 32, 128]))
    net.update(build_inception_module('inception_5b',
                                      net['inception_5a/output'],
                                      [128, 384, 192, 384, 48, 128]))

    net['pool5/7x7_s1'] = GlobalPoolLayer(net['inception_5b/output'])
    net['loss3/classifier'] = DenseLayer(net['pool5/7x7_s1'],
                                         num_units=1000,
                                         nonlinearity=linear)
```

```
    net['prob'] = NonlinearityLayer(net['loss3/classifier'],
                                    nonlinearity=softmax)
    return net['prob']
```

preprocess_zip.py

```
import numpy as np
import h5py
import zipfile
from random import shuffle
from math import floor
from PIL import Image
from StringIO import StringIO

def split_dataset(X, y, test_size = 0.2, val = False):
    print len(X), len(y)
    data = zip(X, y)
    shuffle(data)
    X, y = zip(*data)

    if val:
        split_point = int(floor(len(X)*(1 - test_size * 2)))
        X_train, y_train = X[:split_point], y[:split_point]
        X_test_val, y_test_val = X[split_point:], y[split_point:]
        split_point = int(floor(len(X_test_val)*0.5))
        X_test, y_test, X_val, y_val = X_test_val[:split_point], y_test_val[:split_point], \
                                       X_test_val[split_point:], y_test_val[split_point:]

        return np.array(X_train), np.array(y_train), np.array(X_test)\
            , np.array(y_test), np.array(X_val), np.array(y_val)
    else:
        split_point = int(floor(len(X)*(1 - test_size)))
        return np.array(X[:split_point]), np.array(y[:split_point]), \
                                               np.array(X[split_point:]), np.array(y[split_point:])


def load_zip_training_set(path, wnids, archive):
    X = []
    y = []
    i = 0
    for class_id in wnids:
        bbox_file = path + class_id + "/" + class_id + "_boxes.txt"
        for line  in archive.open(bbox_file):
            words = line.split()
            img = archive.read(path + class_id + "/images/" + words[0])
            img = Image.open(StringIO(img))
            image = np.array(img)
            if image.ndim == 3:
                image = np.rollaxis(image, 2)
                X.append(image) # Append image to dataset
                y.append(i)
        i = i + 1

    return np.array(X, dtype=np.uint8), np.array(y, dtype=np.uint8)

def find_label(wnids, wnid):
    i = 0
    for line in wnids:
        if line == wnid:
            return i
        i = i + 1
    return None

def load_zip_val_set(path, wnids, archive):
    X = []
    y = []
    val_annotations = path + "val_annotations.txt"
    for line in archive.open(val_annotations):
        words = line.split()
        img = archive.read(path + "images/" + words[0])
        img = Image.open(StringIO(img))
        image = np.array(img)
        label = find_label(wnids, words[1])
        if image.ndim == 3 and label != None:
            image = np.rollaxis(image, 2)
            X.append(image) # Append image to dataset
            y.append(find_label(wnids, words[1]))

    return np.array(X, dtype=np.uint8), np.array(y, dtype=np.uint8)

def generate_url_zip():
    zip_url = "tiny-imagenet-200.zip"
    train_path = "tiny-imagenet-200/train/"
    val_path = "tiny-imagenet-200/val/"
    test_path = "tiny-imagenet-200/test/"
    wnid_file = "tiny-imagenet-200/wnids.txt"
```

```
    print "Reading from zip..."
    archive = zipfile.ZipFile(zip_url, 'r') # Open the archive
    wnids = [line.strip() for line in archive.open(wnid_file)] # Load list over classes
    wnids = wnids[:100] # Load only the 100 first classes

    print "Loading training set..."
    X, y = load_zip_training_set(train_path, wnids, archive)

    print "Loading validation set.."
    X_val, y_val = load_zip_val_set(val_path, wnids, archive)

    X_train, y_train, X_test, y_test =  split_dataset(X, y, test_size = 0.2)
    print(X_train.shape, y_train.shape, X_val.shape, y_val.shape, X_test.shape, y_test.shape)

    return X_train.astype(np.uint8), y_train.astype(np.uint8), X_val.astype(np.uint8), y_val.astype(np.uint8), X_test.a

if __name__ == "__main__":
    generate_url_zip()
```

classify a image

```
import numpy as np
import matplotlib.pyplot as plt
import lasagne
import googlenet

def load_pickle_googlenet():
    import pickle
    model = pickle.load(open('vgg_cnn_s.pkl'))
    CLASSES = model['synset words']
    MEAN_IMAGE = model['mean image']
    lasagne.layers.set_all_param_values(output_layer, model['values'])

    return output_layer

def load_network():
    network = googlenet.build_model()
    with np.load('trained_alexnet_200.npz') as f:
        param_values = [f['arr_%d' % i] for i in range(len(f.files))]
    lasagne.layers.set_all_param_values(network, param_values)

    return network

def load_test_images(image_urls):
    images = []
    images_raw = []

    for url in image_urls:
        img = Image.open(url)
        image = np.array(img)
        images_raw.append(image)
        image = np.rollaxis(image)
        images.append(image)

    return images, images_raw

def random_test_images(image_urls, num_samples = 5):
    np.random.seed(23)
    image_urls = image_urls[:num_samples]
    images, images_raw = load_test_images(image_urls)

    return images, images_raw

def load_classes(wnid_file):
    return [line.strip() for line in open(wnid_file)]

def print_predictions(images, images_raw, network, classes):
    for i in range(len(images)):
            prob = np.array(lasagne.layers.get_output(network, images[i], deterministic=True).eval())
            top5 = np.argsort(prob[0])[-1:-6:-1]

            plt.figure()
            plt.imread(images_raw[i].astype('uint8'))
            plt.axis('off')
            for n, label in enumerate(top5):
                plt.text(250, 70 + n * 20, '{}. {}'.format(n+1, classes[label]), fontsize=14)

            plt.save("predicted_" + str(i) + ".JPEG")
            print "Saved plot: predicted_" + str(i) + ".JPEG"
            i = i + 1

def main():
    wnid_file = "/home/thomas/data/dataset/tiny-imagenet-200/wnids.txt"
    test_path = "tiny-imagenet-200/test/"

    network = load_network()
```

```
    #network = load_pickle_googlenet()
    images, images_raw = random_test_images()
    classes = load_classes(wnid_file)
    print_predictions(images, images_raw, network, classes)

if __name__=="__main__":
    main()
```