assignment_6.2b_cifar10

January 9, 2022

0.0.1 Assignment 6.2b

Using section 5.2 in Deep Learning with Python as a guide, create a ConvNet model that classifies images CIFAR10 small images classification dataset

– This time includes dropout and data-augmentation.

– Save the model, predictions, metrics, and validation plots in the dsc650/assignments/assignment06/results directory.

[1]:
```
import json
from pathlib import Path
import os

current_dir = Path(os.getcwd()).absolute()
results_dir = current_dir.joinpath('results')

print(current_dir)
print(results_dir)
```

```
c:\Users\saman\git_repos\dsc650\dsc650\assignments\assignment06
c:\Users\saman\git_repos\dsc650\dsc650\assignments\assignment06\results
```

[2]:
```
# loading the required libraries and packages
import keras
from keras.models import Sequential
from keras.layers import Dense
from keras.utils import to_categorical
import matplotlib.pyplot as plt

from keras.datasets import cifar10

from keras.layers import Dropout
from keras.layers import Flatten

from keras.layers.convolutional import Conv2D
from keras.layers.convolutional import MaxPooling2D

from keras.utils import np_utils
from keras.preprocessing.image import ImageDataGenerator
```

```
Using TensorFlow backend.
```

0.1 Data

Here we are using the CIFAR10 small images dataset to classify the images.

This is a dataset of 50,000 32X32 color training images and 10,000 test images labeled over 10 categories.

[3]:
```
# Data preparation is required before training the model
def load_dataset():

        # loading the CIFAR10 dataset and create the training and test arrays
        (X_train, y_train), (X_test, y_test) = cifar10.load_data()

        # Lines 1 and 2 reshapes the inputs
        X_train = X_train.reshape((X_train.shape[0], 32, 32, 3)).
 ↪astype('float32')
        X_test = X_test.reshape((X_test.shape[0], 32, 32, 3)).astype('float32')

        # Lines 3 and 4
        # Normalization of the input values (image pixels) from 0 and 255 to 0.1
        X_train = X_train / 255
        X_test = X_test / 255

        # Lines 5 and 6
        # one-hot encoding of the target variables
        y_train = np_utils.to_categorical(y_train)
        y_test = np_utils.to_categorical(y_test)

        num_classes = y_test.shape[1]

        return X_train, X_test, y_train, y_test
```

[8]:
```
# loading the CIFAR10 dataset and create the training and test arrays
(X_train, y_train), (X_test, y_test) = cifar10.load_data()

# Lines 1 and 2 reshapes the inputs
X_train = X_train.reshape((X_train.shape[0], 32, 32, 3)).astype('float32')
X_test = X_test.reshape((X_test.shape[0], 32, 32, 3)).astype('float32')

# Lines 3 and 4
# Normalization of the input values (image pixels) from 0 and 255 to 0.1
X_train = X_train / 255
X_test = X_test / 255

# Lines 5 and 6
# one-hot encoding of the target variables
```

```
y_train = np_utils.to_categorical(y_train)
y_test = np_utils.to_categorical(y_test)

num_classes = y_test.shape[1]
```

[9]:
```
# load_dataset()
print(f'Training set: {X_train.shape}')
```

```
Training set: (50000, 32, 32, 3)
```

[11]:
```
def cnn_model_dropout():
        # function to create the CNN model
        # Create model
        model = Sequential()  # model type is sequetial
        # Stacking convolutional layers with small 3 X 3 filters
        # It is followed by a max pooling layer.
        # Each of the above blocks are repeated where the number of filters in␣
 ↪each block is increased.
        # Also the depth of the network such as 32,64 are also increased
        # Rectified Linear Activation ReLu is most widely used. It makes the␣
 ↪network sparse and efficient
        model.add(Conv2D(32, (3, 3), input_shape=(32, 32, 3),␣
 ↪activation='relu'))
#         model.add(Conv2D(32, (3, 3), activation='relu'))
        # Adding the pooling layer
        model.add(MaxPooling2D())
        model.add(Dropout(0.2))

        model.add(Conv2D(64, (3, 3), activation='relu'))
#         model.add(Conv2D(64, (3, 3), activation='relu'))
        # Adding the pooling layer
        model.add(MaxPooling2D())
        model.add(Dropout(0.2))

        model.add(Conv2D(128, (3, 3), activation='relu'))
#         model.add(Conv2D(128, (3, 3), activation='relu'))
        # Adding the pooling layer
        model.add(MaxPooling2D())
        model.add(Dropout(0.2))

        # Flatten layer converts the 2D matrix data to a vector
        model.add(Flatten())
        # Fully connected dense layer with 128 neurons
        model.add(Dense(128, activation='relu'))
        model.add(Dropout(0.2))
        # output layer which has 10 neurons for the 10 classes
        model.add(Dense(10, activation='softmax'))
```

```
        return model
```

[21]:

```
# Plotting the results
def summary_plot(history):

        acc = history.history['accuracy']
        val_acc = history.history['val_accuracy']
        loss = history.history['loss']
        val_loss = history.history['val_loss']

        epochs = range(1, len(acc) + 1)

        plt.plot(epochs, acc, 'bo', label='Training acc')
        plt.plot(epochs, val_acc, 'b', label='Validation acc')
        plt.title('Training and validation accuracy')
        plt.legend()

        plt.figure()

        plt.plot(epochs, loss, 'bo', label='Training loss')
        plt.plot(epochs, val_loss, 'b', label='Validation loss')
        plt.title('Training and validation loss')
        plt.legend()

        plt.show()
```

[5]:

```
def summarize_diagnostics(history):
        plt.subplot(211)
        plt.title('Cross Entropy Loss')
        plt.plot(history.history['loss'], color='blue', label='train')
        plt.plot(history.history['val_loss'], color='orange', label='test')
        # plot accuracy
        plt.subplot(212)
        plt.title('Classification Accuracy')
        plt.plot(history.history['accuracy'], color='blue', label='train')
        plt.plot(history.history['val_accuracy'], color='orange', label='test')
        # save plot to file
        plt.savefig(f'{results_dir}\\2_plot.png')
        plt.show()
        plt.close()
```

[17]:

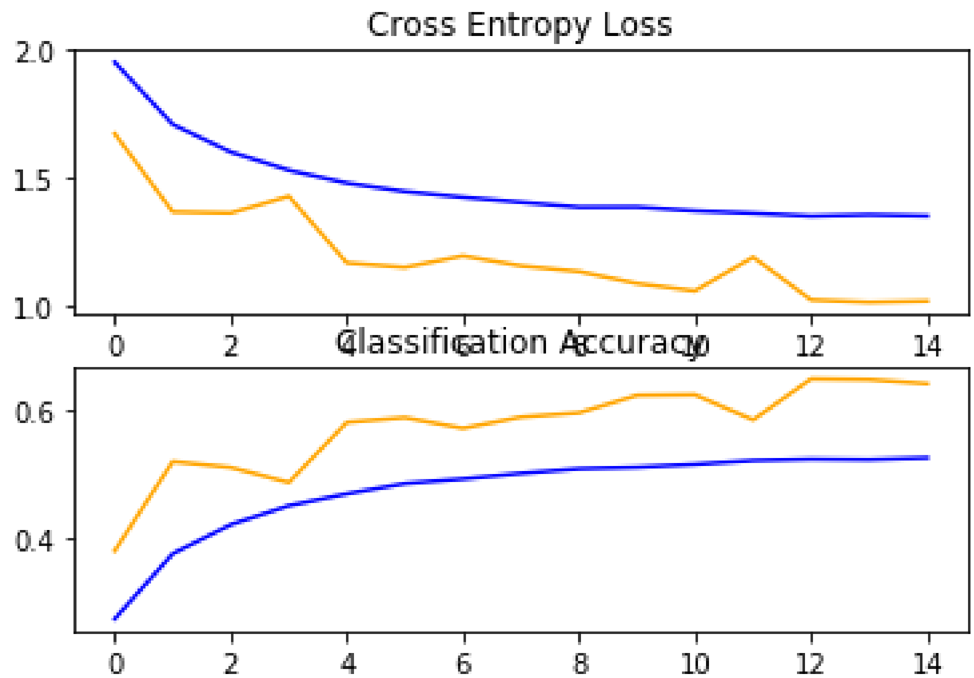
```
def run_model():

        print('Load dataset')
        load_dataset()
```

```
    print('dataset loaded')
    print(f'Training set: {X_train.shape}')
    print(f'Test Set: {X_test.shape}')
    print(f'Number of categories : {num_classes}')

    print('Build model')
    # model = cnn_model()
    model = cnn_model_dropout()
    print('Model is defined')
    print('Summary of the model.')
    model.summary()

    print('Compile Model')
    model.compile(loss='categorical_crossentropy', optimizer='rmsprop',␣
↪metrics=['accuracy'])
    print('Model compiled')

    # Create data generator
    datagen = ImageDataGenerator(
        rotation_range=40,
        width_shift_range=0.2,
        height_shift_range=0.2,
        shear_range=0.2,
        zoom_range=0.2,
        horizontal_flip=True,
        fill_mode='nearest')
    # prepare iterator
    it_train = datagen.flow(X_train, y_train, batch_size=64)
    steps = int(X_train.shape[0]/64)
    print('Model fitting')
    history = model.fit_generator(it_train, steps_per_epoch = steps,␣
↪validation_data=(X_test, y_test), epochs=15)

    print('Saving the model')
    model.save(f'{results_dir}\\assignment_6.2b_cifar10.h5')

    print('Evaluating the model on the test data')
    scores = model.evaluate(X_test, y_test, verbose=0)

    print("CNN Accuracy: %.3f%%" % (scores[1]*100.0))

    print('Output summary')
    # summary_plot(history)
    summarize_diagnostics(history)
```

[18]:
```
run_model()
```

```
Load dataset
dataset loaded
Training set: (50000, 32, 32, 3)
Test Set: (10000, 32, 32, 3)
Number of categories : 10
Build model
Model is defined
Summary of the model.
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_13 (Conv2D)           (None, 30, 30, 32)        896
_________________________________________________________________
max_pooling2d_10 (MaxPooling (None, 15, 15, 32)        0
_________________________________________________________________
dropout_11 (Dropout)         (None, 15, 15, 32)        0
_________________________________________________________________
conv2d_14 (Conv2D)           (None, 13, 13, 64)        18496
_________________________________________________________________
max_pooling2d_11 (MaxPooling (None, 6, 6, 64)          0
_________________________________________________________________
dropout_12 (Dropout)         (None, 6, 6, 64)          0
_________________________________________________________________
conv2d_15 (Conv2D)           (None, 4, 4, 128)         73856
_________________________________________________________________
max_pooling2d_12 (MaxPooling (None, 2, 2, 128)         0
_________________________________________________________________
dropout_13 (Dropout)         (None, 2, 2, 128)         0
_________________________________________________________________
flatten_3 (Flatten)          (None, 512)               0
_________________________________________________________________
dense_5 (Dense)              (None, 128)               65664
_________________________________________________________________
dropout_14 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_6 (Dense)              (None, 10)                1290
=================================================================
Total params: 160,202
Trainable params: 160,202
Non-trainable params: 0
_________________________________________________________________
Compile Model
Model compiled
Model fitting
Epoch 1/15
781/781 [==============================] - 60s 76ms/step - loss: 1.9537 -
accuracy: 0.2730 - val_loss: 1.6748 - val_accuracy: 0.3796
```

```
Epoch 2/15
781/781 [==============================] - 59s 76ms/step - loss: 1.7110 -
accuracy: 0.3750 - val_loss: 1.3704 - val_accuracy: 0.5188
Epoch 3/15
781/781 [==============================] - 68s 88ms/step - loss: 1.6033 -
accuracy: 0.4203 - val_loss: 1.3661 - val_accuracy: 0.5096
Epoch 4/15
781/781 [==============================] - 65s 83ms/step - loss: 1.5326 -
accuracy: 0.4498 - val_loss: 1.4312 - val_accuracy: 0.4861
Epoch 5/15
781/781 [==============================] - 63s 80ms/step - loss: 1.4827 -
accuracy: 0.4683 - val_loss: 1.1713 - val_accuracy: 0.5802
Epoch 6/15
781/781 [==============================] - 67s 86ms/step - loss: 1.4497 -
accuracy: 0.4844 - val_loss: 1.1538 - val_accuracy: 0.5875
Epoch 7/15
781/781 [==============================] - 65s 83ms/step - loss: 1.4273 -
accuracy: 0.4917 - val_loss: 1.1986 - val_accuracy: 0.5708
Epoch 8/15
781/781 [==============================] - 64s 81ms/step - loss: 1.4080 -
accuracy: 0.5003 - val_loss: 1.1596 - val_accuracy: 0.5884
Epoch 9/15
781/781 [==============================] - 67s 86ms/step - loss: 1.3886 -
accuracy: 0.5076 - val_loss: 1.1374 - val_accuracy: 0.5951
Epoch 10/15
781/781 [==============================] - 64s 82ms/step - loss: 1.3890 -
accuracy: 0.5099 - val_loss: 1.0909 - val_accuracy: 0.6222
Epoch 11/15
781/781 [==============================] - 66s 85ms/step - loss: 1.3741 -
accuracy: 0.5144 - val_loss: 1.0623 - val_accuracy: 0.6231
Epoch 12/15
781/781 [==============================] - 65s 83ms/step - loss: 1.3646 -
accuracy: 0.5205 - val_loss: 1.1935 - val_accuracy: 0.5840
Epoch 13/15
781/781 [==============================] - 63s 81ms/step - loss: 1.3537 -
accuracy: 0.5226 - val_loss: 1.0272 - val_accuracy: 0.6479
Epoch 14/15
781/781 [==============================] - 76s 97ms/step - loss: 1.3585 -
accuracy: 0.5218 - val_loss: 1.0183 - val_accuracy: 0.6468
Epoch 15/15
781/781 [==============================] - 63s 80ms/step - loss: 1.3541 -
accuracy: 0.5245 - val_loss: 1.0227 - val_accuracy: 0.6403
Saving the model
Evaluating the model on the test data
CNN Accuracy: 64.030%
Output summary
```


Cross Entropy Loss
2.0
1.5
1.0
0
2
4
6
8
10
12
14
Classification Accuracy
0.6
0.4
0
2
4
6
8
10
12
14