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Date: 03/19/2021

HOMEWORK #3: Image Classification

CSCI 543: Assignment 3

Problem #1: Convolutional Neural Network

Report:

Building a Convnet from Scratch

(Dog vs. Cat Image Classification)

Abstract

I implement and run a tutorial (with some modification) on image classification via machine learning(ML) deep neural network. More specifically, I perform binary classification on an image dataset by convolutional neural network. This image dataset contains cats and dogs image files (jpg format) stored on disk which is unstructured data. I build a convolutional network with the following layers (i) input layer, (ii) 2D convolutional layer, (iii) 2D max pooling layer, (iv) flatten layer, and (v) dense layer. I perform this implementation of image classification using python programming language. Besides, I am using Keras, TensorFlow etc. for image preprocessing, image reshaping and building this Convolution Neural Network model for image classification. This ML ConvNet model can analyze images from the dataset and able to detect cat/dog from those images. Thus it performs binary classification to separate cat/dog from images. With 12 epochs this model shows 98% accuracy during training the model and 73% accuracy during the validation phase. This shows 'overfitting' this model.

TensorFlow tutorial link: https://colab.research.google.com/github/google/eng-edu/blob/master/ml/pc/exercises/image_classification_part1.ipynb

My code in google drive (Colab):
https://colab.research.google.com/drive/12YhohJGv39n9meCMgGB6U_Qmm4sz3EYG?usp=sharing

Tools: Python programming language, Keras, TensorFlow, Google Colab, Google Drive, Google Cloud Storage.

Dataset Details

The original dataset is available on the Kaggle which contains 25,000 images for cats and dogs. I am using 2000 images of cats and dogs for training purpose and 1000 images of cats and dogs for validation purpose. So, a total of 3000 images of cats and dogs are used in this work. I am using a subset from the full dataset to reduce the time during the training of this ML model. The zip file of the dataset used in this work is stored on google cloud storage system. URL of this unstructured image dataset is - `https://storage.googleapis.com/mledu-`

`datasets/cats_and_dogs_filtered.zip`. Machine learning model usually required three types of dataset to perform any experimental analysis, (i) 'train dataset' to train the model, (ii) 'validation dataset' for evaluation the quality of the model, (iii) 'test dataset' to test the model after the model has gone through the validation process. I don't go through testing process, that's why; 'test dataset' is not required in this work. This image dataset has two type of data; train data, validation data. The distribution of the dataset is shown in the following.

```
total training cat images: 1000
total training dog images: 1000
total validation cat images: 500
total validation dog images: 500
```

Data Preprocessing

Data preprocessing and normalization makes data suitable to fit into the ML model. I set up data generators that will read images from the source dataset and convert them to float32 tensors, and feed them (with their labels) to this convolutional network. To normalize image data, I use min-max normalization method. This method rescaled all images by 1./255 which limit the range within 0 to 1. Besides, to be consistent all image is resized to 150x150 (height x width). I am inserting 20 images at a time by setting batch size at 20.

The ML Approach

I am performing image classification using Convolutional Neural Network that is a well-known Machine Learning (ML) approach for image data analysis. I build a Convolutional Deep Neural Network with multiple layers to train and evaluate this ML model with the image dataset. This is a ten-layer Deep Neural Network ML model. These are - One input layer, three convolution layers, three max pooling layers, one flatten layer, two dense layers. These ten layer sequentially build the classifier to classify cat and dog images. Model layers are given below.

i. **Input Layer:** This layer takes image data as input for further analysis. All image data must be in same size before fed into the model. In this layer each image is reshaped by 150x150x3. Here, 150x150 for the image pixels, and 3 for three color channels: R, G, B.
ii. **Convolution Layer(2D):** This is a convolutional layer which support 2D images. I am using 3 stack of Convolution and Max pooling layer in this ML model. The first convolution layer extracts 16 filters, 2nd one extract 32 filters and last one extract 64 filters. Each of these layers consider 3x3 matrix window.
iii. **Max Pooling Layer (2D):** Max Polling layer supports 2D images. This extract maximum vector from previous layer matrix and reduce the size using 2x2 matrix window. I am using 3 max pooling layers with 3 convolution layers.
iv. **Flatten Layer:** This layer map features from the previous layer to a 1-dimensinal tensor so that this can be connected with a fully connected layer.
v. **Dense Layer:** Output from the previous layer piped through 512 hidden neurons.
vi. **Dense_1(Output) Layer:** Final single output neuron.

The sequence of these layers are illustrated in the following figure 1. The figure 1 also shows output shape of each layer and total number of trainable parameters generated from this machine learning model.

```
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 150, 150, 3)]     0
_________________________________________________________________
conv2d (Conv2D)              (None, 148, 148, 16)      448
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 74, 74, 16)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 72, 72, 32)        4640
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 36, 36, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 34, 34, 64)        18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 17, 17, 64)        0
_________________________________________________________________
flatten (Flatten)            (None, 18496)             0
_________________________________________________________________
dense (Dense)                (None, 512)               9470464
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 513
=================================================================
Total params: 9,494,561
Trainable params: 9,494,561
Non-trainable params: 0
```

Figure 1: Model Summary.

Two activation function is used within these layers.

i. **Relu** – All layers use relu activation function. Relu overcome vanishing gradient prolem, learning faster and better. Relu is default for Convolutional Neural Network.
ii. **Sigmoid** – This is a binary classification which will require ‘0’ or ‘1’ label to classify cats and dogs in the images. That’s why I am using ‘sigmoid’ activation function in this work. Only output(Dense_1) layer use sigmoid activation function.

RMSProp (Root Mean Squire Propagation) is used as optimization algorithm in this model. This preferable because this automates learning rate tuning. Initial learning rate is 0.001 in this model. Other optimizer like ‘Adam’ also work equally for this model.

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The complete procedure of this ML approach for Image Classification is shown below.

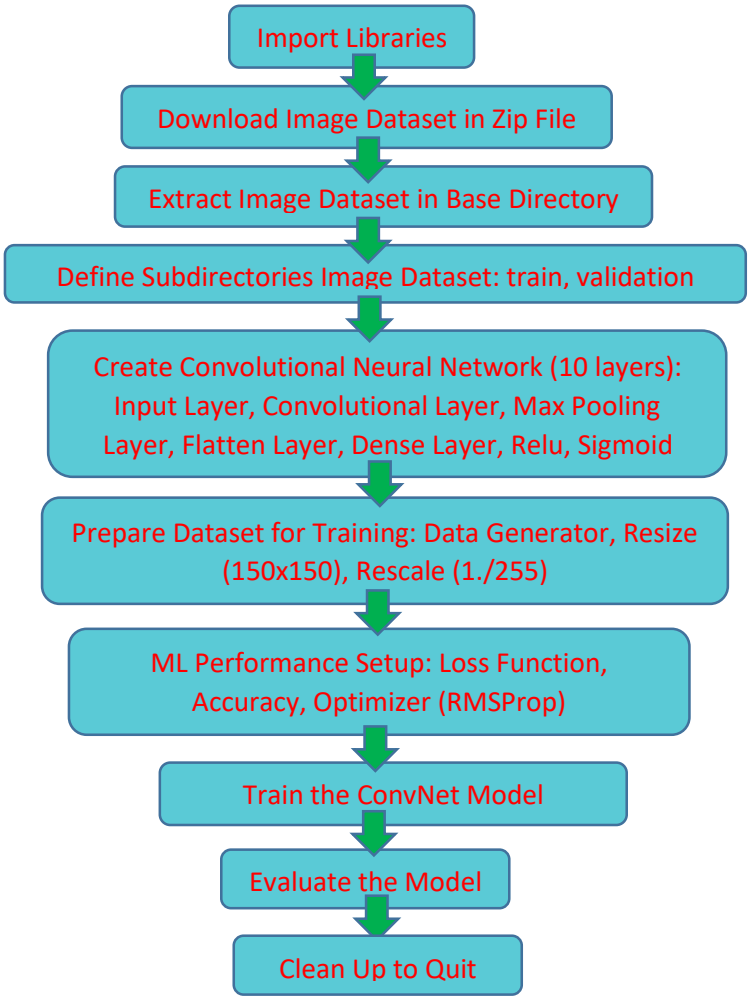

Figure 2: Complete procedure of this ConvNet ML approach for Image Classification

ML Model Performance

To evaluate the performance of this ConvNet model, I perform loss analysis for the training and validation dataset using 'Binary Crossentropy' loss function and also determine the accuracy for these two datasets. Figure 3 and figure 4 present the accuracy and loss during training and validation phase. Maximum accuracy from this model is given below.

```
Training Data Accuracy: 0.9869999885559082 (99%)
Validation Data Accuracy 0.7200000286102295 (72%)
```

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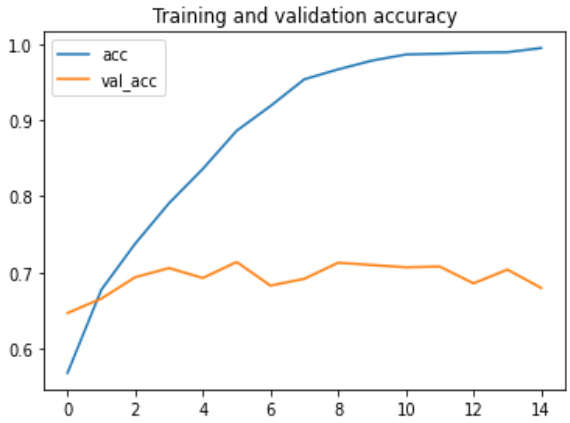

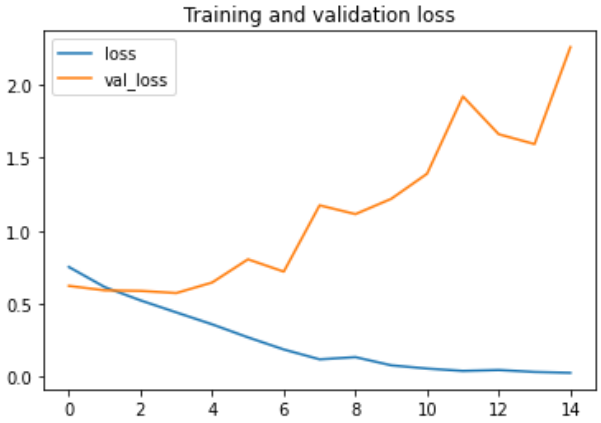

Figure 3.: Training and Validation Accuracy

Figure 4.: Training and Validation Loss

From these figures it is clear that this ML model is "overfitting". Figure 3 shows training accuracy of this model is very close to 99% while during validation accuracy is near to 72%. This is because this model considers some features which are irrelevant for image prediction. When there are a small number of training examples, the model sometimes learns from noises or unwanted details from training examples. To overcome this "overfitting" one easy solution is train this model with more data. Some ways to overcome "overfitting" a model is given below.

i. Reduce overfitting by training the network on more examples. I should consider the full 25,000 images for this model, instead of the subset (3000 images).
ii. Reduce overfitting by changing the complexity of the network. The complexity can be by changing number of weights (network structure) in the network. Another approach to controlling the complexity of a model is changing the value of weights in the network (network parameter).
iii. Reduce overfitting by data augmentation. This approach generates additional training data from the existing examples by augmenting them using random transformations that yield believable-looking images. For example, rotate image, zoom in or zoom out etc.
iv. Reduce overfitting by "dropout" is a form of regularization. Applying dropout to a layer means randomly drops out (by setting the activation to zero) a number of output units from the layer during the training process.

Codes with Comments:

I am giving explanation of each line segment from my implementation of this ConvNet neural network to perform image classification.

Colab link for the code:
https://colab.research.google.com/drive/12YhohJGv39n9meCMgGB6U_Qmm4sz3EYG?usp=sharing

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"""image_classification_CNN1.ipynb

Automatically generated by Colaboratory.

Original file is located at

https://colab.research.google.com/drive/12YhohJGv39n9meCMgGB6U_Qmm4sz3EYG

"""

```
# include libraries/packages
import os
#import zipfile
import tensorflow as tf
from tensorflow.keras import layers
from tensorflow.keras import Model
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
#from tensorflow.keras import losses
from tensorflow.keras.optimizers import RMSprop
#from tensorflow.keras import preprocessing
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import numpy as np
import random
from tensorflow.keras.preprocessing.image import img_to_array, load_img

# Check tensorflow version
print(tf.version.VERSION)
print(tf.__version__)

# Download Image dataset on disk and explore the dataset
url = "https://storage.googleapis.com/mledu-datasets/cats_and_dogs_filtered.zip"
```

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```
dataset = tf.keras.utils.get_file( "cats_and_dogs_filtered.zip", url, extract = True, cache_dir='.', cache_subdir='')

base_dir = os.path.join(os.path.dirname(dataset),'cats_and_dogs_filtered')


# Print path for base directory

base_dir


# base directory contains train and validation subdirectories for the training and validation datasets


# train and validation subdirectories

train_dir = os.path.join(base_dir, 'train')

validation_dir = os.path.join(base_dir, 'validation')


# Directory with training cat pictures

train_cats_dir = os.path.join(train_dir, 'cats')


# Directory with training dog pictures

train_dogs_dir = os.path.join(train_dir, 'dogs')


# Directory with validation cat pictures

validation_cats_dir = os.path.join(validation_dir, 'cats')


# Directory with validation dog pictures

validation_dogs_dir = os.path.join(validation_dir, 'dogs')


# let's see first 10 filenames in the cats and dogs train directories (file naming conventions are the same in the validation directory)
```

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os.listdir() - Return a list containing the names of the entries in the directory given by path. The list is in arbitrary order, and does not include the special entries.

```
train_cat_fnames = os.listdir(train_cats_dir)

print(train_cat_fnames[:10])


train_dog_fnames = os.listdir(train_dogs_dir)

train_dog_fnames.sort()

print(train_dog_fnames[:10])


# Let's find out the total number of cat and dog images in the train and validation directories


print('total training cat images:', len(os.listdir(train_cats_dir)))

print('total training dog images:', len(os.listdir(train_dogs_dir)))

print('total validation cat images:', len(os.listdir(validation_cats_dir)))

print('total validation dog images:', len(os.listdir(validation_dogs_dir)))


# Commented out IPython magic to ensure Python compatibility.

#let's take a look at a few pictures to get a better sense of what the cat and dog datasets look like. First, configure the matplot parameters

# With this inline backend, the output of plotting commands is displayed inline within frontends like the google colab, directly below the code cell that produced it.

# %matplotlib inline


# Parameters for the graph; this will output images in a 4x4 configuration

nrows = 4

ncols = 4


# Index for iterating over images
```

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```
pic_index = 0

# Display a batch of 8 cat and 8 dog pictures.

# Get the current figure.If no current figure exists, a new one is created using figure().
fig = plt.gcf()
# Set size of figure to fit 4x4 configuration pics
fig.set_size_inches(ncols * 4, nrows * 4)

pic_index += 8
next_cat_pix = [os.path.join(train_cats_dir, fname)
                for fname in train_cat_fnames[pic_index-8:pic_index]]
next_dog_pix = [os.path.join(train_dogs_dir, fname)
                for fname in train_dog_fnames[pic_index-8:pic_index]]

for i, img_path in enumerate(next_cat_pix+next_dog_pix):
  # Set up subplot; subplot indices start at 1
  sp = plt.subplot(nrows, ncols, i + 1)
  sp.axis('Off') # Don't show axes (or gridlines)

  img = mpimg.imread(img_path)
  plt.imshow(img)

plt.show()

# Building a Small Convnet from Scratch

# Our input feature map is 150x150x3: 150x150 for the image pixels, and 3 for the three color channels: R, G, and B
```

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```
img_input = layers.Input(shape=(150, 150, 3))

# First convolution extracts 16 filters that are 3x3
# Convolution is followed by max-pooling layer with a 2x2 window
# Relu overcome vanishing gradient prolem, learning faster and better. Relu is default for Convolutional Neural Network.
x = layers.Conv2D(16, 3, activation='relu')(img_input)
x = layers.MaxPooling2D(2)(x)

# Second convolution extracts 32 filters that are 3x3
# Convolution is followed by max-pooling layer with a 2x2 window
x = layers.Conv2D(32, 3, activation='relu')(x)
x = layers.MaxPooling2D(2)(x)

# Third convolution extracts 64 filters that are 3x3
# Convolution is followed by max-pooling layer with a 2x2 window
x = layers.Conv2D(64, 3, activation='relu')(x)
x = layers.MaxPooling2D(2)(x)

# Flatten feature map to a 1-dim tensor so we can add fully connected layers
x = layers.Flatten()(x)

# Create a fully connected layer with ReLU activation and 512 hidden units
x = layers.Dense(512, activation='relu')(x)

# Create output layer with a single node and sigmoid activation
output = layers.Dense(1, activation='sigmoid')(x)

# Create model:
```

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```
# input = input feature map

# output = input feature map + stacked convolution/maxpooling layers + fully

# connected layer + sigmoid output layer

model = Model(img_input, output)


# summarize the model architecture

# The convolution layers reduce the size of the feature maps by a bit due to padding, and each pooling layer halves the feature map.

model.summary()


#  We will train our model with the binary_crossentropy loss, because it's a binary classification problem and our final activation is a sigmoid.

# We will use the rmsprop optimizer with a learning rate of 0.001 (Other optimizers, such as Adam and Adagrad, also automatically adapt the learning rate during training, and would work equally well here.)


model.compile(loss='binary_crossentropy',

              optimizer=RMSprop(lr=0.001),

              metrics=['acc'])


# Data Preprocessing

# Let's set up data generators that will read pictures in our source folders, convert them to float32 tensors, and feed them (with their labels) to our network.

# We'll have one generator for the training images and one for the validation images.

# Our generators will yield batches of 20 images of size 150x150 and their labels (binary).

# we will preprocess our images by normalizing the pixel values to be in the [0, 1] range (originally all values are in the [0, 255] range).


# All images will be rescaled by 1./255 (min-max normalization)
```

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```
# In Keras this can be done via the keras.preprocessing.image.ImageDataGenerator class using the rescale parameter.

train_datagen = ImageDataGenerator(rescale=1./255)

val_datagen = ImageDataGenerator(rescale=1./255)


# Flow training images in batches of 20 using train_datagen generator

train_generator = train_datagen.flow_from_directory(

        train_dir,  # This is the source directory for training images

        target_size=(150, 150),  # All images will be resized to 150x150

        batch_size=20,

        # Since we use binary_crossentropy loss, we need binary labels

        class_mode='binary')


# Flow validation images in batches of 20 using val_datagen generator

validation_generator = val_datagen.flow_from_directory(

        validation_dir,

        target_size=(150, 150),

        batch_size=20,

        class_mode='binary')


# Training


history = model.fit(

      train_generator,

      steps_per_epoch=100,  # 2000 images = batch_size * steps

      epochs=15,

      validation_data=validation_generator,

      validation_steps=50,  # 1000 images = batch_size * steps

      verbose=2)
```

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Visualizing Intermediate Representations

we go from the raw pixels of the images to increasingly abstract and compact representations.

Let's define a new Model that will take an image as input, and will output intermediate representations for all layers in the previous model after the first.

These representations carry increasingly less information about the original pixels of the image, but increasingly refined information about the class of the image.

```
successive_outputs = [layer.output for layer in model.layers[1:]]

visualization_model = Model(img_input, successive_outputs)
```

Let's prepare a random input image of a cat or dog from the training set.

```
cat_img_files = [os.path.join(train_cats_dir, f) for f in train_cat_fnames]

dog_img_files = [os.path.join(train_dogs_dir, f) for f in train_dog_fnames]

img_path = random.choice(cat_img_files + dog_img_files)
```

```
img = load_img(img_path, target_size=(150, 150))  # this is a PIL image

x = img_to_array(img)  # Numpy array with shape (150, 150, 3)

x = x.reshape((1,) + x.shape)  # Numpy array with shape (1, 150, 150, 3)
```

Rescale by 1/255

```
x /= 255
```

Let's run our image through our network, thus obtaining all

intermediate representations for this image.

```
successive_feature_maps = visualization_model.predict(x)
```

These are the names of the layers, so can have them as part of our plot

```
layer_names = [layer.name for layer in model.layers]
```

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```
# Now let's display our representations
for layer_name, feature_map in zip(layer_names, successive_feature_maps):
  if len(feature_map.shape) == 4:
    # Just do this for the conv / maxpool layers, not the fully-connected layers
    n_features = feature_map.shape[-1]  # number of features in feature map
    # The feature map has shape (1, size, size, n_features)
    size = feature_map.shape[1]
    # We will tile our images in this matrix
    display_grid = np.zeros((size, size * n_features))
    for i in range(n_features):
      # Postprocess the feature to make it visually palatable
      x = feature_map[0, :, :, i]
      x -= x.mean()
      x /= x.std()
      x *= 64
      x += 128
      x = np.clip(x, 0, 255).astype('uint8')
      # We'll tile each filter into this big horizontal grid
      display_grid[:, i * size : (i + 1) * size] = x
    # Display the grid
    scale = 20. / n_features
    plt.figure(figsize=(scale * n_features, scale))
    plt.title(layer_name)
    plt.grid(False)
    plt.imshow(display_grid, aspect='auto', cmap='viridis')

# Evaluating Accuracy and Loss for the Model
```

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```
# Retrieve a list of accuracy results on training and validation data
# sets for each training epoch
acc = history.history['acc']
val_acc = history.history['val_acc']

# Retrieve a list of list results on training and validation data
# sets for each training epoch
loss = history.history['loss']
val_loss = history.history['val_loss']

# Get number of epochs
epochs = range(len(acc))

# Plot training and validation accuracy per epoch
a, = plt.plot(epochs, acc)
b, = plt.plot(epochs, val_acc)
plt.title('Training and validation accuracy')
plt.legend([a, b],["acc", "val_acc"])
plt.show()

# Plot training and validation loss per epoch
c,= plt.plot(epochs, loss)
d,= plt.plot(epochs, val_loss)
plt.title('Training and validation loss')
plt.legend([c, d],["loss", "val_loss"])

print("Training Data Accuracy:",max(acc))
```

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```
print("Training Data Loss:",max(loss))

print("Validation Data Accuracy",max(val_acc))

print("Validation Data Loss",max(val_loss))


# terminate the kernel and free memory resources


#import os, signal

#os.kill(os.getpid(), signal.SIGKILL)
```