Implantação do README Github LCAD Deep Learning 2017/2

Autores: Renan Mantuanelli de Aquino e Deivison Augusto da Vitória

Passo a passo de como criar uma CNN (Convolutional Neural Network) para identificação de carro, gato e cachorro usando Keras e Tensor Flow baseado na AlexNet e ZFNet usando Windows 10.

- 1. Instalar anaconda phyton
 - https://www.continuum.io/downloads)
- 2. Instalar spyder
 - Abrir anaconda navegator e instalar spyder
- 3. Instalar theano
 - Abrir anaconda prompt e instalar theano: pip install theano
- 4. Instalar tensorflow
 - Abrir anaconda prompt e instalar theano: pip install tensorflow
- 5. Instalar keras
 - Abrir anaconda prompt e instalar keras: pip install keras
- 6. Atualizar todos os programas recém instalados e outros pacotes do Anaconda
 - Abrir anaconda prompt e atualizar: conda update –all
- 7. Instalar o Vstudio 2015
- 8. Instalar cuda_8.0.61_win10
- 9. Instalar cuda 8.0.61.2 windows
- 10. Incluir caminho no Path:
 - edit system variables
 - Environment variables
 - System variables
 - Path Edit
 - New (inserir na última linha caminho que está instalado o cuda ex.: C:\Program Files\NVIDIA GPU Computing Toolkit\CUDA\bin)
- 11. Instalar GPU para utilização no Tensorflow
 - https://www.tensorflow.org/install_windows
 - Criar ambiente conda com nome tensorflow (abrir anaconda prompt)
 - ✓ conda create -n tensorflow python=3.5
 - Ativar ambiente conda (abrir anaconda prompt)
 - ✓ activate tensorflow
 - Atualizar tensorflow (abrir anaconda prompt)
 - ✓ pip install --ignore-installed --upgrade tensorflow
 - Instalar GPU versão do tensorflow
 - ✓ pip install --ignore-installed --upgrade tensorflow-gpu
 - Testar sucesso instalação digitando os comandos abaixo no spyder
 - ✓ Abrir spyder (phynton)
 - ✓ import tensorflow as tf

hello = tf.constant('Hello, TensorFlow!')

sess = tf.Session()

print(sess.run(hello))

- Se a instalação foi concluída com sucesso a saída (Console Phyton Spyder) irá retornar Hello, TensorFlow!
- 12. Criar a rede CNN baseado na ZFnet

""" Spyder Editor

Importando o tensorflow, keras, pacotes e bibliotecas

import tensorflow as tf

import keras

import numpy as np

from keras.models import Sequential

from keras.layers import Dense

from keras.layers import Dropout

from keras.layers import Activation

from keras.layers import Flatten

from keras.layers import Convolution2D

from keras.layers import Conv2D

from keras.layers import MaxPooling2D

from keras.layers import MaxPool2D

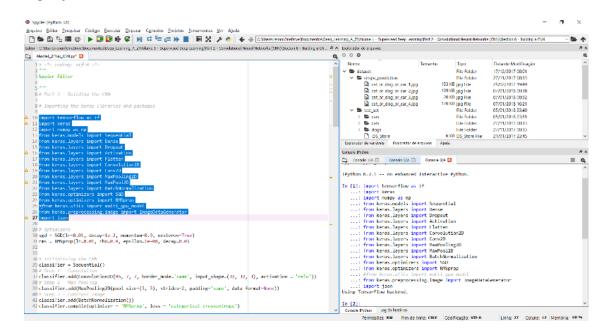
from keras.layers import BatchNormalization

from keras.optimizers import SGD

from keras.optimizers import RMSprop

from keras.utils import multi_gpu_model

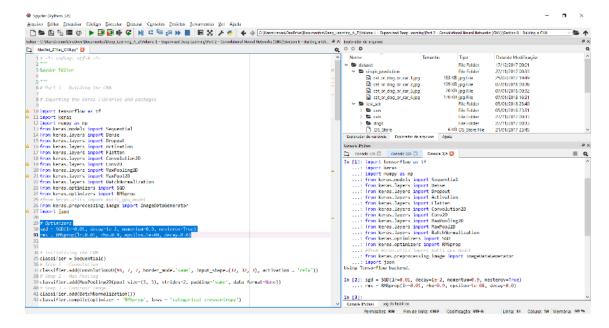
from keras.preprocessing.image import ImageDataGenerator import json



Definindo as variáveis e funções de otimizações para melhorar aprendizado no treinamento

sgd = SGD(lr=0.01, decay=1e-2, momentum=0.9, nesterov=True)

rms = RMSprop(lr=0.01, rho=0.9, epsilon=1e-08, decay=0.0)



Inicializando a rede Aquino&VitóriaFNET CNN

O tipo da rede será sequencial que é uma característica da CNN

classifier = Sequential()

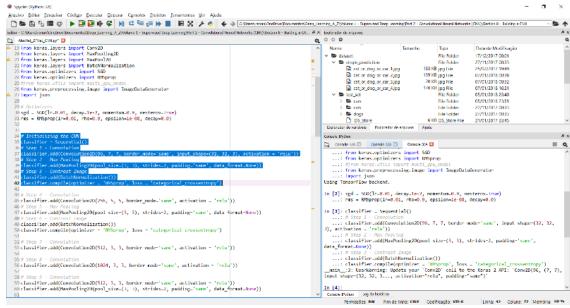
Step 1 – Convolution – 96 camadas, kernel 7x7, imagem entrada 32x32x3(RGB), função de ativação ReLU

classifier.add(Convolution2D(96, 7, 7, border_mode='same', input_shape=(32, 32, 3), activation = 'relu'))

Step 2 - Max Pooling - tamanho 3x3, passo2 classifier.add(MaxPooling2D(pool_size=(3, 3), strides=2, padding='same', data_format=None))

Step 3 - Contrast Image — aplicando operação de contraste local de normalização na saída do mapa de caracteríscica (feature map)

 $classifier.add(BatchNormalization())\\ classifier.compile(optimizer = 'RMSprop', loss = 'categorical_crossentropy')\\$



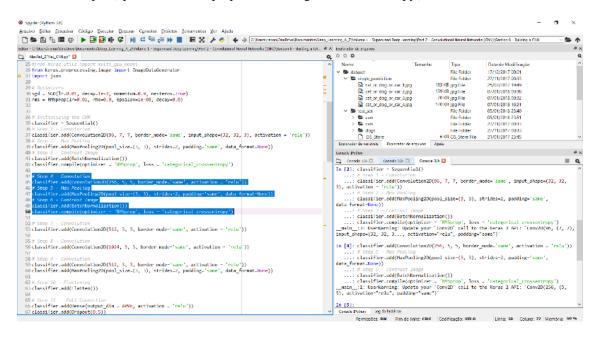
Step 4 – Convolution - 256 camadas, kernel 5x5, imagem entrada 16x16x256 função de ativação ReLU

classifier.add(Convolution2D(256, 5, 5, border_mode='same', activation = 'relu'))

Step 5 - Max Pooling - tamanho 3x3, passo2 classifier.add(MaxPooling2D(pool_size=(3, 3), strides=2, padding='same', data_format=None))

Step 6 - Contrast Image - aplicando operação de contraste local de normalização na saída do mapa de caracteríscica (feature map)

classifier.add(BatchNormalization())
classifier.compile(optimizer = 'RMSprop', loss = 'categorical_crossentropy')



Step 7 – Convolution - 512 camadas, kernel 3x3, imagem entrada 8x8x512, função de ativação ReLU

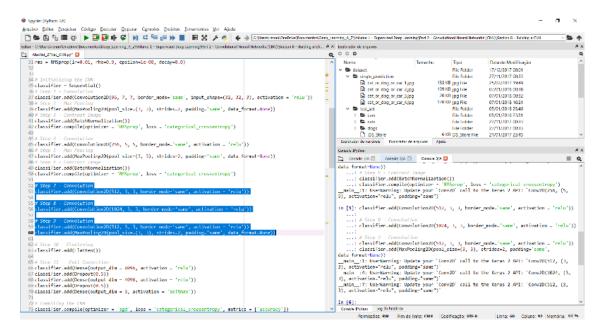
classifier.add(Convolution2D(512, 3, 3, border_mode='same', activation = 'relu'))

Step 8 - Convolution - 1024 camadas, kernel 3x3, imagem entrada 8x8x1024, função de ativação ReLU

classifier.add(Convolution2D(1024, 3, 3, border_mode='same', activation = 'relu'))

Step 9 - Convolution - 512 camadas, kernel 3x3, imagem entrada 8x8x512, função de ativação ReLU

classifier.add(Convolution2D(512, 3, 3, border_mode='same', activation = 'relu'))



Step 10 - Max Pooling - tamanho 3x3, passo2 classifier.add(MaxPooling2D(pool_size=(3, 3), strides=2, padding='same', data_format=None))

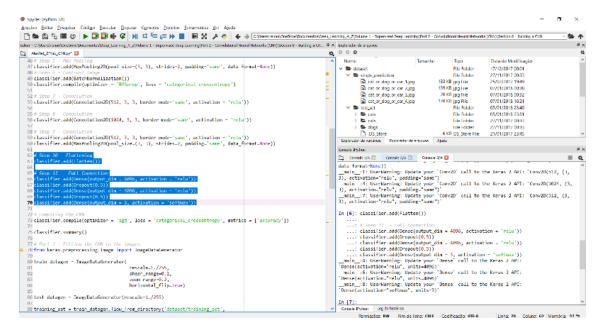
Step 11 – Flattening – preparação da saída da última etapa de convolução conforme necessário para entrada na camada primeira totalmente conectada com 8192 saídas (dimensões).

classifier.add(Flatten())

Step 12 - Full Connection – primeira camada totalmente conectada com 4096 dimensões, 33.558.528 parâmetros e função de ativação ReLU, desligamento de 50% dos neurônios (dropout). A segunda camada totalmente conectada com 4096 dimensões, 16.781.312 parâmetros e função de ativação ReLU, desligamento de 50% dos neurônios (dropout). A última camada classificadora do tipo softmax com três saídas (carro, gato ou cachorro) com 12.291 parâmetros.

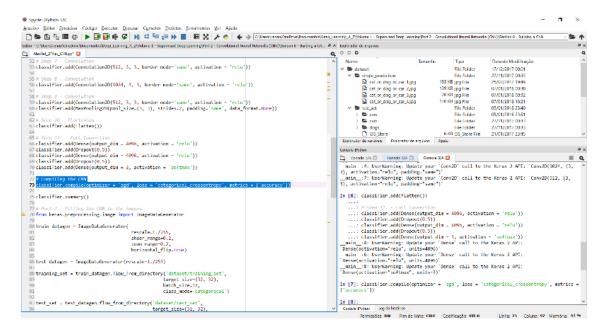
No caso da ZFNet a saída da última camada seria 1000, em funções da possibilidade de classificação de 1000 classes diferentes.

```
classifier.add(Dense(output_dim = 4096, activation = 'relu')) classifier.add(Dropout(0.5)) classifier.add(Dense(output_dim = 4096, activation = 'relu')) classifier.add(Dropout(0.5)) classifier.add(Dense(output_dim = 3, activation = 'softmax'))
```

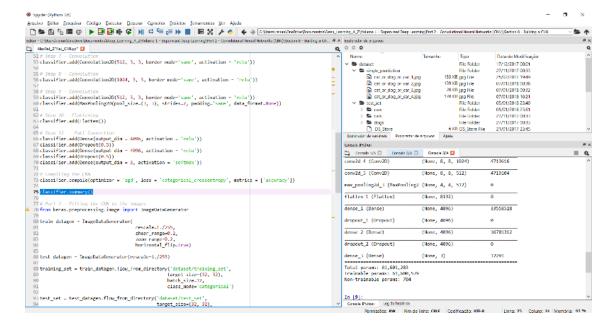


Compiling the CNN – Compilando a rede neural para classificação final (acuracidade) e verificação da arquitetura da rede

classifier.compile(optimizer = 'sgd', loss = 'categorical_crossentropy', metrics = ['accuracy'])



classifier.summary()

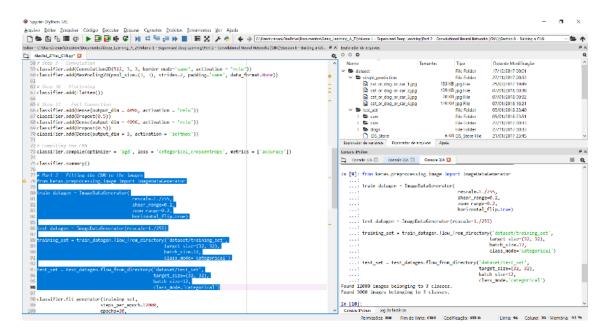


Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 32, 32, 9	6) 14208
max_pooling2d_1 (MaxPooling2 (None, 16, 16, 96) 0		
batch_normalization_1	(Batch (None, 16, 16,	96) 384
conv2d_2 (Conv2D)	(None, 16, 16, 2	56) 614656
max_pooling2d_2 (MaxPooling2 (None, 8, 8, 256) 0		
batch_normalization_2	(Batch (None, 8, 8, 2	56) 1024
conv2d_3 (Conv2D)	(None, 8, 8, 512) 1180160
conv2d_4 (Conv2D)	(None, 8, 8, 102	4) 4719616
conv2d_5 (Conv2D)	(None, 8, 8, 512) 4719104
max_pooling2d_3 (MaxPooling2 (None, 4, 4, 512) 0		
flatten_1 (Flatten)	(None, 8192)	0
dense_1 (Dense)	(None, 4096)	33558528
dropout_1 (Dropout)	(None, 4096)	0
dense_2 (Dense)	(None, 4096)	16781312
dropout_2 (Dropout)	(None, 4096)	0
dense_3 (Dense)	(None, 3)	12291
T-1-1 C4 C04 202		

Total params: 61,601,283 Trainable params: 61,600,579 Non-trainable params: 704

Part 2 – Fazendo a ligação da rede neural com as imagens para treino, teste/validação

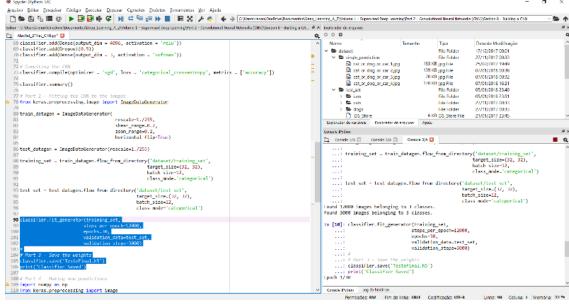
```
from keras.preprocessing.image import ImageDataGenerator
```



```
classifier.fit_generator(training_set,
steps_per_epoch=12000,
epochs=30,
validation_data=test_set,
validation_steps=3000)
```

Part 3 – Salvando os pesos após treino (aprendizado "memória" da rede)

```
classifier.save('TesteFinal.h5')
print('Classifier Saved')
```

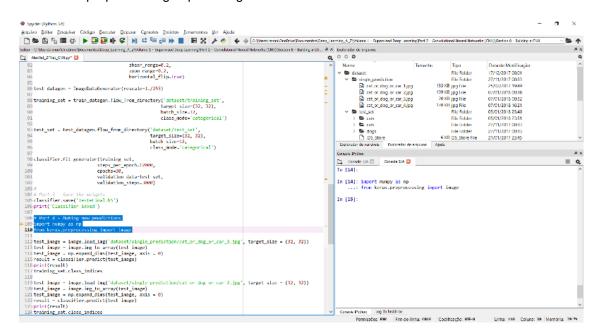


```
Epoch 1/30
0.4411 - acc: 0.7928 - val_loss: 0.3240 - val_acc: 0.8569
Epoch 2/30
0.2532 - acc: 0.8913 - val loss: 0.2935 - val acc: 0.8838
Epoch 3/30
0.1570 - acc: 0.9369 - val_loss: 0.3353 - val_acc: 0.8817
Epoch 4/30
0.0954 - acc: 0.9629 - val_loss: 0.3726 - val_acc: 0.8699
Epoch 5/30
0.0615 - acc: 0.9771 - val loss: 0.4296 - val acc: 0.8810
Epoch 6/30
0.0419 - acc: 0.9849 - val_loss: 0.5313 - val_acc: 0.8763
Epoch 7/30
0.0315 - acc: 0.9888 - val loss: 0.5310 - val acc: 0.8803
0.0249 - acc: 0.9913 - val_loss: 0.4968 - val_acc: 0.8817
Epoch 9/30
12000/12000 [=================] - 1548s 129ms/step - loss:
0.0188 - acc: 0.9936 - val_loss: 0.4857 - val_acc: 0.8947
Epoch 10/30
0.0155 - acc: 0.9945 - val loss: 0.4752 - val acc: 0.8896
Epoch 11/30
0.0148 - acc: 0.9948 - val_loss: 0.5251 - val_acc: 0.8889
Epoch 12/30
0.0121 - acc: 0.9956 - val_loss: 0.5172 - val_acc: 0.8886
Epoch 13/30
```

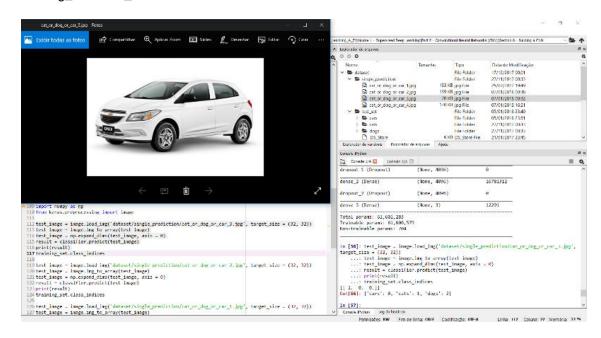
```
0.0116 - acc: 0.9960 - val_loss: 0.5079 - val_acc: 0.8935
Epoch 14/30
0.0081 - acc: 0.9971 - val loss: 0.5743 - val acc: 0.8947
Epoch 15/30
0.0097 - acc: 0.9965 - val loss: 0.5999 - val acc: 0.8870
Epoch 16/30
0.0085 - acc: 0.9972 - val_loss: 0.7481 - val_acc: 0.8732
Epoch 17/30
0.0069 - acc: 0.9976 - val loss: 0.5989 - val acc: 0.8936
Epoch 18/30
12000/12000 [===============] - 1548s 129ms/step - loss:
0.0070 - acc: 0.9977 - val_loss: 0.5413 - val_acc: 0.8943
Epoch 19/30
0.0047 - acc: 0.9983 - val loss: 0.6151 - val acc: 0.8958
Epoch 20/30
0.0067 - acc: 0.9977 - val_loss: 0.5877 - val_acc: 0.8902
Epoch 21/30
0.0048 - acc: 0.9983 - val loss: 0.5425 - val acc: 0.8988
Epoch 22/30
0.0053 - acc: 0.9983 - val loss: 0.6114 - val acc: 0.8904
Epoch 23/30
0.0047 - acc: 0.9985 - val_loss: 0.5633 - val_acc: 0.8944
Epoch 24/30
0.0042 - acc: 0.9986 - val loss: 0.5868 - val acc: 0.9000
Epoch 25/30
0.0036 - acc: 0.9988 - val loss: 0.6403 - val acc: 0.8978
Epoch 26/30
0.0037 - acc: 0.9988 - val_loss: 0.6719 - val_acc: 0.8914
Epoch 27/30
0.0041 - acc: 0.9986 - val_loss: 0.5864 - val_acc: 0.8962
Epoch 28/30
0.0038 - acc: 0.9988 - val_loss: 0.5740 - val_acc: 0.8957
Epoch 29/30
0.0032 - acc: 0.9990 - val loss: 0.6050 - val acc: 0.8961
Epoch 30/30
0.0037 - acc: 0.9987 - val_loss: 0.6404 - val_acc: 0.8955
Classifier Saved
```

Part 4 – Fazendo novas predições com a rede já treinada

import numpy as np from keras.preprocessing import image

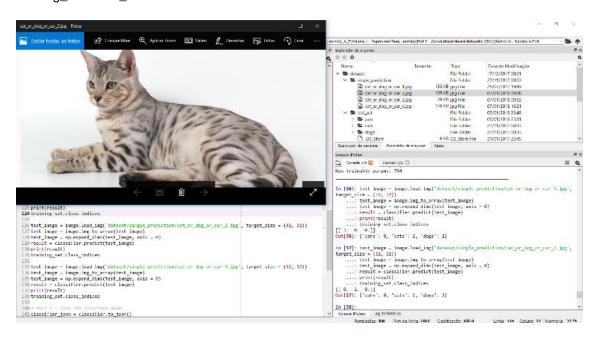


test_image = image.load_img('dataset/single_prediction/cat_or_dog_or_car_3.jpg', target_size = (32, 32)) test_image = image.img_to_array(test_image) test_image = np.expand_dims(test_image, axis = 0) result = classifier.predict(test_image) print(result) training_set.class_indices

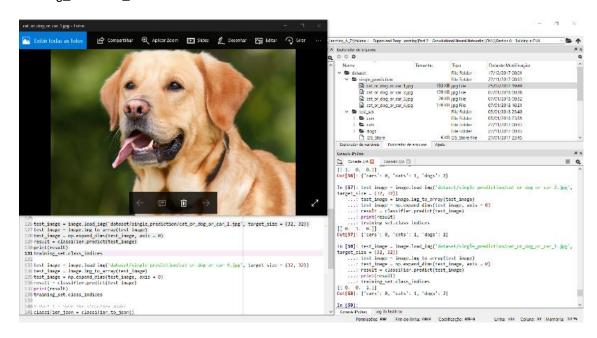


test_image = image.load_img('dataset/single_prediction/cat_or_dog_or_car_2.jpg', target_size = (32, 32)) test_image = image.img_to_array(test_image) test_image = np.expand_dims(test_image, axis = 0) result = classifier.predict(test_image)

print(result) training_set.class_indices

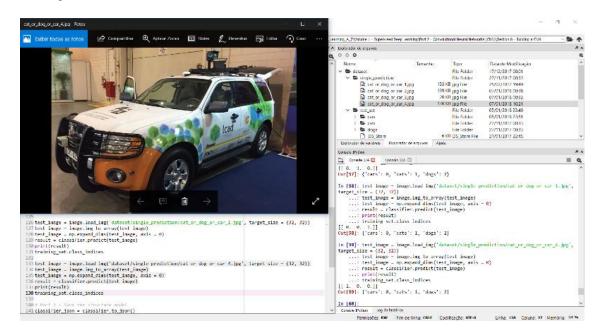


test_image = image.load_img('dataset/single_prediction/cat_or_dog_or_car_1.jpg', target_size = (32, 32)) test_image = image.img_to_array(test_image) test_image = np.expand_dims(test_image, axis = 0) result = classifier.predict(test_image) print(result) training_set.class_indices



test_image = image.load_img('dataset/single_prediction/cat_or_dog_or_car_4.jpg', target_size = (32, 32)) test_image = image.img_to_array(test_image) test_image = np.expand_dims(test_image, axis = 0) result = classifier.predict(test_image)

print(result) training_set.class_indices



Part 5 – Salvando a estrutura do modelo

classifier_json = classifier.to_json()
with open("Aquino&VitótiaNetStructure.json", "w") as json_file:
 json_file.write(classifier_json)

