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This branch is [8 commits ahead](#), [10 commits behind](#) master.

hoffm386 update preprocessing import to tf.keras ...

on Aug 25, 2022

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Visualizing Activation Functions - Lab

Introduction

Now that you've built your own CNN and seen how to visualize feature maps, its time to practice loading a pretrained model from file and visualize the learned features systematically. In this lab, you'll expand upon the code from the previous lesson in order to succinctly visualize all the channels from each layer in a CNN.

Objectives

In this lab you will:

- Load a saved Keras model
- Use Keras methods to visualize the activation functions in CNNs

Load a Model

For this lab, load the saved model 'cats_dogs_downsampled_with_augmentation_data.h5'. This saved file includes both the model architecture and the trained weights. See the `model.save()` method for further details. The model was built in order to help identify cat and dog pictures. Start simply by loading the model and pulling up a summary of the layers. (To load the model use the `keras.models.load_model()` function.)

```
from keras.models import load_model
model = load_model('cats_dogs_downsampled_with_augmentation_data.h5')
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
=====		
conv2d (Conv2D)	(None, 148, 148, 32)	896

max_pooling2d (MaxPooling2D)	(None, 74, 74, 32)	0

conv2d_1 (Conv2D)	(None, 72, 72, 64)	18496

max_pooling2d_1 (MaxPooling2D)	(None, 36, 36, 64)	0

conv2d_2 (Conv2D)	(None, 34, 34, 128)	73856

max_pooling2d_2 (MaxPooling2D)	(None, 17, 17, 128)	0

conv2d_3 (Conv2D)	(None, 15, 15, 128)	147584

max_pooling2d_3 (MaxPooling2D)	(None, 7, 7, 128)	0

flatten (Flatten)	(None, 6272)	0

dense (Dense)	(None, 512)	3211776

dense_1 (Dense)	(None, 1)	513
=====		
Total params: 3,453,121		
Trainable params: 3,453,121		
Non-trainable params: 0		

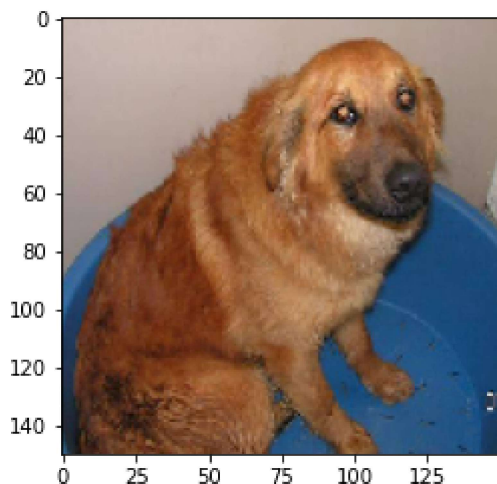
Load an Image

Before you plot the learned representations of the convolutional base, let's import an image and display it prior to processing. This will provide a comparison to the transformations formed by the model's feature maps.

Load and display the image 'dog.1100.jpg' .

```
from tensorflow.keras.preprocessing import image
import matplotlib.image as mpimg
import matplotlib.pyplot as plt
%matplotlib inline

filename = 'dog.1100.jpg'
img = image.load_img(filename, target_size=(150, 150))
plt.imshow(img)
plt.show()
```



Transform the Image to a Tensor and Visualize Again

Recall that you should always preprocess images into tensors when using deep learning. As such, preprocess this image and then redisplay the tensor.

```
import numpy as np

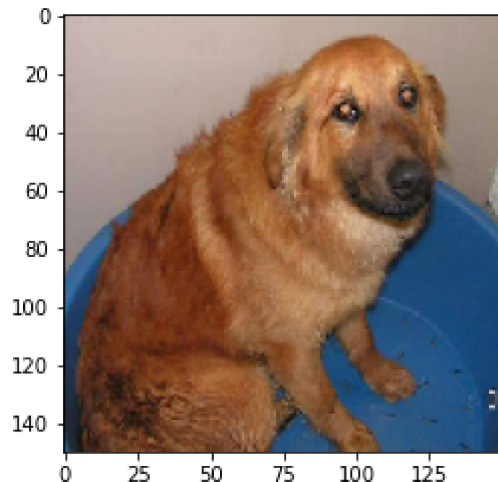
img_tensor = image.img_to_array(img)
img_tensor = np.expand_dims(img_tensor, axis=0)

# Follow the Original Model Preprocessing
img_tensor /= 255.
```

```
# Check tensor shape
print(img_tensor.shape)

# Preview an image
plt.imshow(img_tensor[0])
plt.show()
```

```
(1, 150, 150, 3)
```



Plot Feature Maps

Now that you've loaded a model, practice visualizing each of the channels for each of feature maps of the convolutional layers. Recall that this process will take a few steps. First, extract the feature maps, or layer outputs from each of the activation functions in the model. From there, generate models that transform the image from its raw state to these feature maps. You can then take these transformations and visualize each channel for each feature map.

To preview the results of the solution code, take a sneak peek at the *Intermediate_Activations_Visualized.pdf* file.

```
from keras import models
import math

# Extract model layer outputs
layer_outputs = [layer.output for layer in model.layers[:8]]

# Create a model for displaying the feature maps
activation_model = models.Model(inputs=model.input, outputs=layer_outputs)
```

```
activations = activation_model.predict(img_tensor)

# Extract Layer Names for Labelling
layer_names = []
for layer in model.layers[:8]:
    layer_names.append(layer.name)

total_features = sum([a.shape[-1] for a in activations])
total_features

n_cols = 16
n_rows = math.ceil(total_features / n_cols)

iteration = 0
fig, axes = plt.subplots(nrows=n_rows, ncols=n_cols, figsize=(n_cols, n_rows*1.5))

for layer_n, layer_activation in enumerate(activations):
    n_channels = layer_activation.shape[-1]
    for ch_idx in range(n_channels):
        row = iteration // n_cols
        column = iteration % n_cols

        ax = axes[row, column]

        channel_image = layer_activation[0,
                                         :, :,
                                         ch_idx]

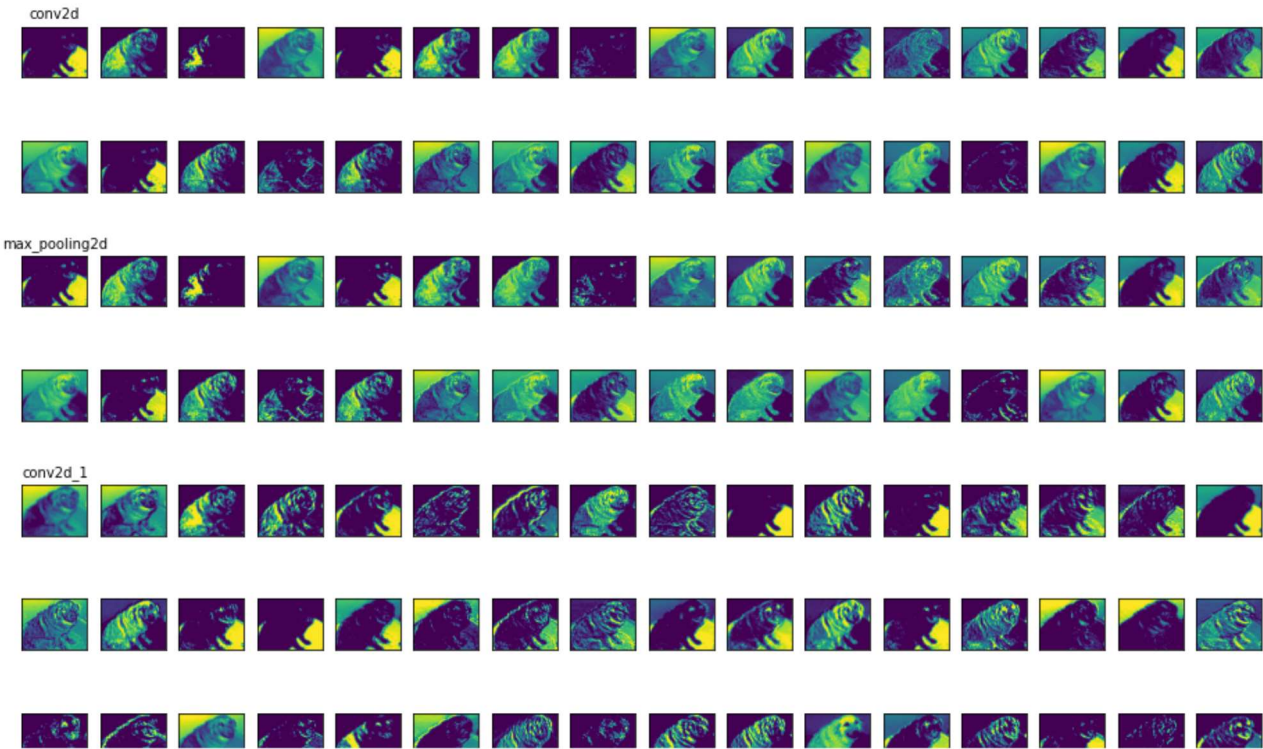
        # Post-process the feature to make it visually palatable
        channel_image -= channel_image.mean()
        channel_image /= channel_image.std()
        channel_image *= 64
        channel_image += 128
        channel_image = np.clip(channel_image, 0, 255).astype('uint8')

        ax.imshow(channel_image, aspect='auto', cmap='viridis')
        ax.get_xaxis().set_ticks([])
        ax.get_yaxis().set_ticks([])

        if ch_idx == 0:
            ax.set_title(layer_names[layer_n], fontsize=10)
        iteration += 1

fig.subplots_adjust(hspace=1.25)
plt.savefig('Intermediate_Activations_Visualized.pdf')
plt.show()
```

```
<ipython-input-4-37c6b5e4b2c0>:41: RuntimeWarning: invalid value encountered in  
true_divide  
  channel_image /= channel_image.std()
```



Summary

Nice work! In this lab, you practiced loading a model and then visualizing the activation feature maps learned by that model on your data! In the upcoming labs and sections you will build upon the first part of this and see how you can adapt the representations learned by more experienced models to your own applications which may have limited training data.

Releases

No releases published

Packages

No packages published

Contributors 6



Languages

● Jupyter Notebook 100.0%