

AI4M_C3_M3_lecture_notebook_gradcam

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1 Introduction To GradCAM (Part 1) - Lecture Notebook

In this lecture notebook we'll be looking at an introduction to Grad-CAM, a powerful technique for interpreting Convolutional Neural Networks. Grad-CAM stands for Gradient-weighted Class Activation Mapping.

CNN's are very flexible models and their great predictive power comes at the cost of losing interpretability (something that is true for all Artificial Neural Networks). Grad-CAM attempts to solve this by giving us a graphical visualisation of parts of an image that are the most relevant for the CNN when predicting a particular class.

Aside from working on some Grad-CAM concepts we'll also look at how we can use Keras to access some concrete information of our model. Let's dive into it!

```
In [2]: import keras
        from keras import backend as K
        from util import *
```

Using TensorFlow backend.

The `load_C3M3_model()` function has been taken care of and its internals are out of the scope of this notebook. But if it intrigues you, you can take a look at it in `util.py`

```
In [3]: # Load the model we are going to be using
        model = load_C3M3_model()
```

```
Got loss weights
Loaded DenseNet
Added layers
Compiled Model
Loaded Weights
```

As you may already know, we can check the architecture of our model using the `summary()` method.

After running the code block below we'll see that this model has a lot of layers. One advantage of Grad-CAM over previous attempts of interpreting CNN's (such as CAM) is that it is architecture agnostic. This means it can be used for CNN's with complex architectures such as this one:

```
In [4]: # Print all of the model's layers
        model.summary()
```

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	(None, None, None, 3 0		
zero_padding2d_1 (ZeroPadding2D)	(None, None, None, 3 0		input_1[0] [0]
conv1/conv (Conv2D)	(None, None, None, 6 9408		zero_padding2d_1[0] [0]
conv1/bn (BatchNormalization)	(None, None, None, 6 256		conv1/conv[0] [0]
conv1/relu (Activation)	(None, None, None, 6 0		conv1/bn[0] [0]
zero_padding2d_2 (ZeroPadding2D)	(None, None, None, 6 0		conv1/relu[0] [0]
pool1 (MaxPooling2D)	(None, None, None, 6 0		zero_padding2d_2[0] [0]
conv2_block1_0_bn (BatchNormali	(None, None, None, 6 256		pool1[0] [0]
conv2_block1_0_relu (Activation	(None, None, None, 6 0		conv2_block1_0_bn[0] [0]
conv2_block1_1_conv (Conv2D)	(None, None, None, 1 8192		conv2_block1_0_relu[0] [0]
conv2_block1_1_bn (BatchNormali	(None, None, None, 1 512		conv2_block1_1_conv[0] [0]
conv2_block1_1_relu (Activation	(None, None, None, 1 0		conv2_block1_1_bn[0] [0]
conv2_block1_2_conv (Conv2D)	(None, None, None, 3 36864		conv2_block1_1_relu[0] [0]
conv2_block1_concat (Concatenat	(None, None, None, 9 0		pool1[0] [0] conv2_block1_2_conv[0] [0]
conv2_block2_0_bn (BatchNormali	(None, None, None, 9 384		conv2_block1_concat[0] [0]
conv2_block2_0_relu (Activation	(None, None, None, 9 0		conv2_block2_0_bn[0] [0]
conv2_block2_1_conv (Conv2D)	(None, None, None, 1 12288		conv2_block2_0_relu[0] [0]
conv2_block2_1_bn (BatchNormali	(None, None, None, 1 512		conv2_block2_1_conv[0] [0]
conv2_block2_1_relu (Activation	(None, None, None, 1 0		conv2_block2_1_bn[0] [0]
conv2_block2_2_conv (Conv2D)	(None, None, None, 3 36864		conv2_block2_1_relu[0] [0]
conv2_block2_concat (Concatenat	(None, None, None, 1 0		conv2_block1_concat[0] [0]

		conv2_block2_2_conv[0][0]
conv2_block3_0_bn (BatchNormali	(None, None, None, 1 512	conv2_block2_concat[0][0]
conv2_block3_0_relu (Activation	(None, None, None, 1 0	conv2_block3_0_bn[0][0]
conv2_block3_1_conv (Conv2D)	(None, None, None, 1 16384	conv2_block3_0_relu[0][0]
conv2_block3_1_bn (BatchNormali	(None, None, None, 1 512	conv2_block3_1_conv[0][0]
conv2_block3_1_relu (Activation	(None, None, None, 1 0	conv2_block3_1_bn[0][0]
conv2_block3_2_conv (Conv2D)	(None, None, None, 3 36864	conv2_block3_1_relu[0][0]
conv2_block3_concat (Concatenat	(None, None, None, 1 0	conv2_block2_concat[0][0] conv2_block3_2_conv[0][0]
conv2_block4_0_bn (BatchNormali	(None, None, None, 1 640	conv2_block3_concat[0][0]
conv2_block4_0_relu (Activation	(None, None, None, 1 0	conv2_block4_0_bn[0][0]
conv2_block4_1_conv (Conv2D)	(None, None, None, 1 20480	conv2_block4_0_relu[0][0]
conv2_block4_1_bn (BatchNormali	(None, None, None, 1 512	conv2_block4_1_conv[0][0]
conv2_block4_1_relu (Activation	(None, None, None, 1 0	conv2_block4_1_bn[0][0]
conv2_block4_2_conv (Conv2D)	(None, None, None, 3 36864	conv2_block4_1_relu[0][0]
conv2_block4_concat (Concatenat	(None, None, None, 1 0	conv2_block3_concat[0][0] conv2_block4_2_conv[0][0]
conv2_block5_0_bn (BatchNormali	(None, None, None, 1 768	conv2_block4_concat[0][0]
conv2_block5_0_relu (Activation	(None, None, None, 1 0	conv2_block5_0_bn[0][0]
conv2_block5_1_conv (Conv2D)	(None, None, None, 1 24576	conv2_block5_0_relu[0][0]
conv2_block5_1_bn (BatchNormali	(None, None, None, 1 512	conv2_block5_1_conv[0][0]
conv2_block5_1_relu (Activation	(None, None, None, 1 0	conv2_block5_1_bn[0][0]
conv2_block5_2_conv (Conv2D)	(None, None, None, 3 36864	conv2_block5_1_relu[0][0]
conv2_block5_concat (Concatenat	(None, None, None, 2 0	conv2_block4_concat[0][0] conv2_block5_2_conv[0][0]
conv2_block6_0_bn (BatchNormali	(None, None, None, 2 896	conv2_block5_concat[0][0]

conv2_block6_0_relu	(Activation (None, None, None, 2 0	conv2_block6_0_bn[0][0]
conv2_block6_1_conv	(Conv2D) (None, None, None, 1 28672	conv2_block6_0_relu[0][0]
conv2_block6_1_bn	(BatchNormali (None, None, None, 1 512	conv2_block6_1_conv[0][0]
conv2_block6_1_relu	(Activation (None, None, None, 1 0	conv2_block6_1_bn[0][0]
conv2_block6_2_conv	(Conv2D) (None, None, None, 3 36864	conv2_block6_1_relu[0][0]
conv2_block6_concat	(Concatenat (None, None, None, 2 0	conv2_block5_concat[0][0] conv2_block6_2_conv[0][0]
pool2_bn	(BatchNormalization) (None, None, None, 2 1024	conv2_block6_concat[0][0]
pool2_relu	(Activation) (None, None, None, 2 0	pool2_bn[0][0]
pool2_conv	(Conv2D) (None, None, None, 1 32768	pool2_relu[0][0]
pool2_pool	(AveragePooling2D) (None, None, None, 1 0	pool2_conv[0][0]
conv3_block1_0_bn	(BatchNormali (None, None, None, 1 512	pool2_pool[0][0]
conv3_block1_0_relu	(Activation (None, None, None, 1 0	conv3_block1_0_bn[0][0]
conv3_block1_1_conv	(Conv2D) (None, None, None, 1 16384	conv3_block1_0_relu[0][0]
conv3_block1_1_bn	(BatchNormali (None, None, None, 1 512	conv3_block1_1_conv[0][0]
conv3_block1_1_relu	(Activation (None, None, None, 1 0	conv3_block1_1_bn[0][0]
conv3_block1_2_conv	(Conv2D) (None, None, None, 3 36864	conv3_block1_1_relu[0][0]
conv3_block1_concat	(Concatenat (None, None, None, 1 0	pool2_pool[0][0] conv3_block1_2_conv[0][0]
conv3_block2_0_bn	(BatchNormali (None, None, None, 1 640	conv3_block1_concat[0][0]
conv3_block2_0_relu	(Activation (None, None, None, 1 0	conv3_block2_0_bn[0][0]
conv3_block2_1_conv	(Conv2D) (None, None, None, 1 20480	conv3_block2_0_relu[0][0]
conv3_block2_1_bn	(BatchNormali (None, None, None, 1 512	conv3_block2_1_conv[0][0]
conv3_block2_1_relu	(Activation (None, None, None, 1 0	conv3_block2_1_bn[0][0]
conv3_block2_2_conv	(Conv2D) (None, None, None, 3 36864	conv3_block2_1_relu[0][0]

conv3_block2_concat (Concatenat	(None, None, None, 1 0	conv3_block1_concat[0][0] conv3_block2_2_conv[0][0]
conv3_block3_0_bn (BatchNormali	(None, None, None, 1 768	conv3_block2_concat[0][0]
conv3_block3_0_relu (Activation	(None, None, None, 1 0	conv3_block3_0_bn[0][0]
conv3_block3_1_conv (Conv2D)	(None, None, None, 1 24576	conv3_block3_0_relu[0][0]
conv3_block3_1_bn (BatchNormali	(None, None, None, 1 512	conv3_block3_1_conv[0][0]
conv3_block3_1_relu (Activation	(None, None, None, 1 0	conv3_block3_1_bn[0][0]
conv3_block3_2_conv (Conv2D)	(None, None, None, 3 36864	conv3_block3_1_relu[0][0]
conv3_block3_concat (Concatenat	(None, None, None, 2 0	conv3_block2_concat[0][0] conv3_block3_2_conv[0][0]
conv3_block4_0_bn (BatchNormali	(None, None, None, 2 896	conv3_block3_concat[0][0]
conv3_block4_0_relu (Activation	(None, None, None, 2 0	conv3_block4_0_bn[0][0]
conv3_block4_1_conv (Conv2D)	(None, None, None, 1 28672	conv3_block4_0_relu[0][0]
conv3_block4_1_bn (BatchNormali	(None, None, None, 1 512	conv3_block4_1_conv[0][0]
conv3_block4_1_relu (Activation	(None, None, None, 1 0	conv3_block4_1_bn[0][0]
conv3_block4_2_conv (Conv2D)	(None, None, None, 3 36864	conv3_block4_1_relu[0][0]
conv3_block4_concat (Concatenat	(None, None, None, 2 0	conv3_block3_concat[0][0] conv3_block4_2_conv[0][0]
conv3_block5_0_bn (BatchNormali	(None, None, None, 2 1024	conv3_block4_concat[0][0]
conv3_block5_0_relu (Activation	(None, None, None, 2 0	conv3_block5_0_bn[0][0]
conv3_block5_1_conv (Conv2D)	(None, None, None, 1 32768	conv3_block5_0_relu[0][0]
conv3_block5_1_bn (BatchNormali	(None, None, None, 1 512	conv3_block5_1_conv[0][0]
conv3_block5_1_relu (Activation	(None, None, None, 1 0	conv3_block5_1_bn[0][0]
conv3_block5_2_conv (Conv2D)	(None, None, None, 3 36864	conv3_block5_1_relu[0][0]
conv3_block5_concat (Concatenat	(None, None, None, 2 0	conv3_block4_concat[0][0] conv3_block5_2_conv[0][0]

conv3_block6_0_bn (BatchNormali	(None, None, None, 2 1152	conv3_block5_concat[0][0]
conv3_block6_0_relu (Activation	(None, None, None, 2 0	conv3_block6_0_bn[0][0]
conv3_block6_1_conv (Conv2D)	(None, None, None, 1 36864	conv3_block6_0_relu[0][0]
conv3_block6_1_bn (BatchNormali	(None, None, None, 1 512	conv3_block6_1_conv[0][0]
conv3_block6_1_relu (Activation	(None, None, None, 1 0	conv3_block6_1_bn[0][0]
conv3_block6_2_conv (Conv2D)	(None, None, None, 3 36864	conv3_block6_1_relu[0][0]
conv3_block6_concat (Concatenat	(None, None, None, 3 0	conv3_block5_concat[0][0] conv3_block6_2_conv[0][0]
conv3_block7_0_bn (BatchNormali	(None, None, None, 3 1280	conv3_block6_concat[0][0]
conv3_block7_0_relu (Activation	(None, None, None, 3 0	conv3_block7_0_bn[0][0]
conv3_block7_1_conv (Conv2D)	(None, None, None, 1 40960	conv3_block7_0_relu[0][0]
conv3_block7_1_bn (BatchNormali	(None, None, None, 1 512	conv3_block7_1_conv[0][0]
conv3_block7_1_relu (Activation	(None, None, None, 1 0	conv3_block7_1_bn[0][0]
conv3_block7_2_conv (Conv2D)	(None, None, None, 3 36864	conv3_block7_1_relu[0][0]
conv3_block7_concat (Concatenat	(None, None, None, 3 0	conv3_block6_concat[0][0] conv3_block7_2_conv[0][0]
conv3_block8_0_bn (BatchNormali	(None, None, None, 3 1408	conv3_block7_concat[0][0]
conv3_block8_0_relu (Activation	(None, None, None, 3 0	conv3_block8_0_bn[0][0]
conv3_block8_1_conv (Conv2D)	(None, None, None, 1 45056	conv3_block8_0_relu[0][0]
conv3_block8_1_bn (BatchNormali	(None, None, None, 1 512	conv3_block8_1_conv[0][0]
conv3_block8_1_relu (Activation	(None, None, None, 1 0	conv3_block8_1_bn[0][0]
conv3_block8_2_conv (Conv2D)	(None, None, None, 3 36864	conv3_block8_1_relu[0][0]
conv3_block8_concat (Concatenat	(None, None, None, 3 0	conv3_block7_concat[0][0] conv3_block8_2_conv[0][0]
conv3_block9_0_bn (BatchNormali	(None, None, None, 3 1536	conv3_block8_concat[0][0]

conv3_block9_0_relu (Activation	(None, None, None, 3 0	conv3_block9_0_bn[0][0]
conv3_block9_1_conv (Conv2D)	(None, None, None, 1 49152	conv3_block9_0_relu[0][0]
conv3_block9_1_bn (BatchNormali	(None, None, None, 1 512	conv3_block9_1_conv[0][0]
conv3_block9_1_relu (Activation	(None, None, None, 1 0	conv3_block9_1_bn[0][0]
conv3_block9_2_conv (Conv2D)	(None, None, None, 3 36864	conv3_block9_1_relu[0][0]
conv3_block9_concat (Concatenat	(None, None, None, 4 0	conv3_block8_concat[0][0] conv3_block9_2_conv[0][0]
conv3_block10_0_bn (BatchNormal	(None, None, None, 4 1664	conv3_block9_concat[0][0]
conv3_block10_0_relu (Activatio	(None, None, None, 4 0	conv3_block10_0_bn[0][0]
conv3_block10_1_conv (Conv2D)	(None, None, None, 1 53248	conv3_block10_0_relu[0][0]
conv3_block10_1_bn (BatchNormal	(None, None, None, 1 512	conv3_block10_1_conv[0][0]
conv3_block10_1_relu (Activatio	(None, None, None, 1 0	conv3_block10_1_bn[0][0]
conv3_block10_2_conv (Conv2D)	(None, None, None, 3 36864	conv3_block10_1_relu[0][0]
conv3_block10_concat (Concatena	(None, None, None, 4 0	conv3_block9_concat[0][0] conv3_block10_2_conv[0][0]
conv3_block11_0_bn (BatchNormal	(None, None, None, 4 1792	conv3_block10_concat[0][0]
conv3_block11_0_relu (Activatio	(None, None, None, 4 0	conv3_block11_0_bn[0][0]
conv3_block11_1_conv (Conv2D)	(None, None, None, 1 57344	conv3_block11_0_relu[0][0]
conv3_block11_1_bn (BatchNormal	(None, None, None, 1 512	conv3_block11_1_conv[0][0]
conv3_block11_1_relu (Activatio	(None, None, None, 1 0	conv3_block11_1_bn[0][0]
conv3_block11_2_conv (Conv2D)	(None, None, None, 3 36864	conv3_block11_1_relu[0][0]
conv3_block11_concat (Concatena	(None, None, None, 4 0	conv3_block10_concat[0][0] conv3_block11_2_conv[0][0]
conv3_block12_0_bn (BatchNormal	(None, None, None, 4 1920	conv3_block11_concat[0][0]
conv3_block12_0_relu (Activatio	(None, None, None, 4 0	conv3_block12_0_bn[0][0]
conv3_block12_1_conv (Conv2D)	(None, None, None, 1 61440	conv3_block12_0_relu[0][0]

conv3_block12_1_bn (BatchNormal	(None, None, None, 1 512	conv3_block12_1_conv[0][0]
conv3_block12_1_relu (Activatio	(None, None, None, 1 0	conv3_block12_1_bn[0][0]
conv3_block12_2_conv (Conv2D)	(None, None, None, 3 36864	conv3_block12_1_relu[0][0]
conv3_block12_concat (Concatena	(None, None, None, 5 0	conv3_block11_concat[0][0] conv3_block12_2_conv[0][0]
pool3_bn (BatchNormalization)	(None, None, None, 5 2048	conv3_block12_concat[0][0]
pool3_relu (Activation)	(None, None, None, 5 0	pool3_bn[0][0]
pool3_conv (Conv2D)	(None, None, None, 2 131072	pool3_relu[0][0]
pool3_pool (AveragePooling2D)	(None, None, None, 2 0	pool3_conv[0][0]
conv4_block1_0_bn (BatchNormali	(None, None, None, 2 1024	pool3_pool[0][0]
conv4_block1_0_relu (Activation	(None, None, None, 2 0	conv4_block1_0_bn[0][0]
conv4_block1_1_conv (Conv2D)	(None, None, None, 1 32768	conv4_block1_0_relu[0][0]
conv4_block1_1_bn (BatchNormali	(None, None, None, 1 512	conv4_block1_1_conv[0][0]
conv4_block1_1_relu (Activation	(None, None, None, 1 0	conv4_block1_1_bn[0][0]
conv4_block1_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block1_1_relu[0][0]
conv4_block1_concat (Concatenat	(None, None, None, 2 0	pool3_pool[0][0] conv4_block1_2_conv[0][0]
conv4_block2_0_bn (BatchNormali	(None, None, None, 2 1152	conv4_block1_concat[0][0]
conv4_block2_0_relu (Activation	(None, None, None, 2 0	conv4_block2_0_bn[0][0]
conv4_block2_1_conv (Conv2D)	(None, None, None, 1 36864	conv4_block2_0_relu[0][0]
conv4_block2_1_bn (BatchNormali	(None, None, None, 1 512	conv4_block2_1_conv[0][0]
conv4_block2_1_relu (Activation	(None, None, None, 1 0	conv4_block2_1_bn[0][0]
conv4_block2_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block2_1_relu[0][0]
conv4_block2_concat (Concatenat	(None, None, None, 3 0	conv4_block1_concat[0][0] conv4_block2_2_conv[0][0]

conv4_block3_0_bn (BatchNormali	(None, None, None, 3 1280	conv4_block2_concat[0][0]
conv4_block3_0_relu (Activation	(None, None, None, 3 0	conv4_block3_0_bn[0][0]
conv4_block3_1_conv (Conv2D)	(None, None, None, 1 40960	conv4_block3_0_relu[0][0]
conv4_block3_1_bn (BatchNormali	(None, None, None, 1 512	conv4_block3_1_conv[0][0]
conv4_block3_1_relu (Activation	(None, None, None, 1 0	conv4_block3_1_bn[0][0]
conv4_block3_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block3_1_relu[0][0]
conv4_block3_concat (Concatenat	(None, None, None, 3 0	conv4_block2_concat[0][0] conv4_block3_2_conv[0][0]
conv4_block4_0_bn (BatchNormali	(None, None, None, 3 1408	conv4_block3_concat[0][0]
conv4_block4_0_relu (Activation	(None, None, None, 3 0	conv4_block4_0_bn[0][0]
conv4_block4_1_conv (Conv2D)	(None, None, None, 1 45056	conv4_block4_0_relu[0][0]
conv4_block4_1_bn (BatchNormali	(None, None, None, 1 512	conv4_block4_1_conv[0][0]
conv4_block4_1_relu (Activation	(None, None, None, 1 0	conv4_block4_1_bn[0][0]
conv4_block4_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block4_1_relu[0][0]
conv4_block4_concat (Concatenat	(None, None, None, 3 0	conv4_block3_concat[0][0] conv4_block4_2_conv[0][0]
conv4_block5_0_bn (BatchNormali	(None, None, None, 3 1536	conv4_block4_concat[0][0]
conv4_block5_0_relu (Activation	(None, None, None, 3 0	conv4_block5_0_bn[0][0]
conv4_block5_1_conv (Conv2D)	(None, None, None, 1 49152	conv4_block5_0_relu[0][0]
conv4_block5_1_bn (BatchNormali	(None, None, None, 1 512	conv4_block5_1_conv[0][0]
conv4_block5_1_relu (Activation	(None, None, None, 1 0	conv4_block5_1_bn[0][0]
conv4_block5_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block5_1_relu[0][0]
conv4_block5_concat (Concatenat	(None, None, None, 4 0	conv4_block4_concat[0][0] conv4_block5_2_conv[0][0]
conv4_block6_0_bn (BatchNormali	(None, None, None, 4 1664	conv4_block5_concat[0][0]
conv4_block6_0_relu (Activation	(None, None, None, 4 0	conv4_block6_0_bn[0][0]

conv4_block6_1_conv (Conv2D)	(None, None, None, 1 53248	conv4_block6_0_relu[0][0]
conv4_block6_1_bn (BatchNormali	(None, None, None, 1 512	conv4_block6_1_conv[0][0]
conv4_block6_1_relu (Activation	(None, None, None, 1 0	conv4_block6_1_bn[0][0]
conv4_block6_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block6_1_relu[0][0]
conv4_block6_concat (Concatenat	(None, None, None, 4 0	conv4_block5_concat[0][0] conv4_block6_2_conv[0][0]
conv4_block7_0_bn (BatchNormali	(None, None, None, 4 1792	conv4_block6_concat[0][0]
conv4_block7_0_relu (Activation	(None, None, None, 4 0	conv4_block7_0_bn[0][0]
conv4_block7_1_conv (Conv2D)	(None, None, None, 1 57344	conv4_block7_0_relu[0][0]
conv4_block7_1_bn (BatchNormali	(None, None, None, 1 512	conv4_block7_1_conv[0][0]
conv4_block7_1_relu (Activation	(None, None, None, 1 0	conv4_block7_1_bn[0][0]
conv4_block7_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block7_1_relu[0][0]
conv4_block7_concat (Concatenat	(None, None, None, 4 0	conv4_block6_concat[0][0] conv4_block7_2_conv[0][0]
conv4_block8_0_bn (BatchNormali	(None, None, None, 4 1920	conv4_block7_concat[0][0]
conv4_block8_0_relu (Activation	(None, None, None, 4 0	conv4_block8_0_bn[0][0]
conv4_block8_1_conv (Conv2D)	(None, None, None, 1 61440	conv4_block8_0_relu[0][0]
conv4_block8_1_bn (BatchNormali	(None, None, None, 1 512	conv4_block8_1_conv[0][0]
conv4_block8_1_relu (Activation	(None, None, None, 1 0	conv4_block8_1_bn[0][0]
conv4_block8_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block8_1_relu[0][0]
conv4_block8_concat (Concatenat	(None, None, None, 5 0	conv4_block7_concat[0][0] conv4_block8_2_conv[0][0]
conv4_block9_0_bn (BatchNormali	(None, None, None, 5 2048	conv4_block8_concat[0][0]
conv4_block9_0_relu (Activation	(None, None, None, 5 0	conv4_block9_0_bn[0][0]
conv4_block9_1_conv (Conv2D)	(None, None, None, 1 65536	conv4_block9_0_relu[0][0]

conv4_block9_1_bn (BatchNormali	(None, None, None, 1 512	conv4_block9_1_conv[0][0]
conv4_block9_1_relu (Activation	(None, None, None, 1 0	conv4_block9_1_bn[0][0]
conv4_block9_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block9_1_relu[0][0]
conv4_block9_concat (Concatenat	(None, None, None, 5 0	conv4_block8_concat[0][0] conv4_block9_2_conv[0][0]
conv4_block10_0_bn (BatchNormal	(None, None, None, 5 2176	conv4_block9_concat[0][0]
conv4_block10_0_relu (Activatio	(None, None, None, 5 0	conv4_block10_0_bn[0][0]
conv4_block10_1_conv (Conv2D)	(None, None, None, 1 69632	conv4_block10_0_relu[0][0]
conv4_block10_1_bn (BatchNormal	(None, None, None, 1 512	conv4_block10_1_conv[0][0]
conv4_block10_1_relu (Activatio	(None, None, None, 1 0	conv4_block10_1_bn[0][0]
conv4_block10_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block10_1_relu[0][0]
conv4_block10_concat (Concatena	(None, None, None, 5 0	conv4_block9_concat[0][0] conv4_block10_2_conv[0][0]
conv4_block11_0_bn (BatchNormal	(None, None, None, 5 2304	conv4_block10_concat[0][0]
conv4_block11_0_relu (Activatio	(None, None, None, 5 0	conv4_block11_0_bn[0][0]
conv4_block11_1_conv (Conv2D)	(None, None, None, 1 73728	conv4_block11_0_relu[0][0]
conv4_block11_1_bn (BatchNormal	(None, None, None, 1 512	conv4_block11_1_conv[0][0]
conv4_block11_1_relu (Activatio	(None, None, None, 1 0	conv4_block11_1_bn[0][0]
conv4_block11_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block11_1_relu[0][0]
conv4_block11_concat (Concatena	(None, None, None, 6 0	conv4_block10_concat[0][0] conv4_block11_2_conv[0][0]
conv4_block12_0_bn (BatchNormal	(None, None, None, 6 2432	conv4_block11_concat[0][0]
conv4_block12_0_relu (Activatio	(None, None, None, 6 0	conv4_block12_0_bn[0][0]
conv4_block12_1_conv (Conv2D)	(None, None, None, 1 77824	conv4_block12_0_relu[0][0]
conv4_block12_1_bn (BatchNormal	(None, None, None, 1 512	conv4_block12_1_conv[0][0]
conv4_block12_1_relu (Activatio	(None, None, None, 1 0	conv4_block12_1_bn[0][0]

conv4_block12_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block12_1_relu[0][0]
conv4_block12_concat (Concatena	(None, None, None, 6 0	conv4_block11_concat[0][0] conv4_block12_2_conv[0][0]
conv4_block13_0_bn (BatchNormal	(None, None, None, 6 2560	conv4_block12_concat[0][0]
conv4_block13_0_relu (Activatio	(None, None, None, 6 0	conv4_block13_0_bn[0][0]
conv4_block13_1_conv (Conv2D)	(None, None, None, 1 81920	conv4_block13_0_relu[0][0]
conv4_block13_1_bn (BatchNormal	(None, None, None, 1 512	conv4_block13_1_conv[0][0]
conv4_block13_1_relu (Activatio	(None, None, None, 1 0	conv4_block13_1_bn[0][0]
conv4_block13_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block13_1_relu[0][0]
conv4_block13_concat (Concatena	(None, None, None, 6 0	conv4_block12_concat[0][0] conv4_block13_2_conv[0][0]
conv4_block14_0_bn (BatchNormal	(None, None, None, 6 2688	conv4_block13_concat[0][0]
conv4_block14_0_relu (Activatio	(None, None, None, 6 0	conv4_block14_0_bn[0][0]
conv4_block14_1_conv (Conv2D)	(None, None, None, 1 86016	conv4_block14_0_relu[0][0]
conv4_block14_1_bn (BatchNormal	(None, None, None, 1 512	conv4_block14_1_conv[0][0]
conv4_block14_1_relu (Activatio	(None, None, None, 1 0	conv4_block14_1_bn[0][0]
conv4_block14_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block14_1_relu[0][0]
conv4_block14_concat (Concatena	(None, None, None, 7 0	conv4_block13_concat[0][0] conv4_block14_2_conv[0][0]
conv4_block15_0_bn (BatchNormal	(None, None, None, 7 2816	conv4_block14_concat[0][0]
conv4_block15_0_relu (Activatio	(None, None, None, 7 0	conv4_block15_0_bn[0][0]
conv4_block15_1_conv (Conv2D)	(None, None, None, 1 90112	conv4_block15_0_relu[0][0]
conv4_block15_1_bn (BatchNormal	(None, None, None, 1 512	conv4_block15_1_conv[0][0]
conv4_block15_1_relu (Activatio	(None, None, None, 1 0	conv4_block15_1_bn[0][0]
conv4_block15_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block15_1_relu[0][0]

conv4_block15_concat (Concatena	(None, None, None, 7 0	conv4_block14_concat[0][0]	conv4_block15_2_conv[0][0]

conv4_block16_0_bn (BatchNormal	(None, None, None, 7 2944	conv4_block15_concat[0][0]	

conv4_block16_0_relu (Activatio	(None, None, None, 7 0	conv4_block16_0_bn[0][0]	

conv4_block16_1_conv (Conv2D)	(None, None, None, 1 94208	conv4_block16_0_relu[0][0]	

conv4_block16_1_bn (BatchNormal	(None, None, None, 1 512	conv4_block16_1_conv[0][0]	

conv4_block16_1_relu (Activatio	(None, None, None, 1 0	conv4_block16_1_bn[0][0]	

conv4_block16_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block16_1_relu[0][0]	

conv4_block16_concat (Concatena	(None, None, None, 7 0	conv4_block15_concat[0][0]	conv4_block16_2_conv[0][0]

conv4_block17_0_bn (BatchNormal	(None, None, None, 7 3072	conv4_block16_concat[0][0]	

conv4_block17_0_relu (Activatio	(None, None, None, 7 0	conv4_block17_0_bn[0][0]	

conv4_block17_1_conv (Conv2D)	(None, None, None, 1 98304	conv4_block17_0_relu[0][0]	

conv4_block17_1_bn (BatchNormal	(None, None, None, 1 512	conv4_block17_1_conv[0][0]	

conv4_block17_1_relu (Activatio	(None, None, None, 1 0	conv4_block17_1_bn[0][0]	

conv4_block17_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block17_1_relu[0][0]	

conv4_block17_concat (Concatena	(None, None, None, 8 0	conv4_block16_concat[0][0]	conv4_block17_2_conv[0][0]

conv4_block18_0_bn (BatchNormal	(None, None, None, 8 3200	conv4_block17_concat[0][0]	

conv4_block18_0_relu (Activatio	(None, None, None, 8 0	conv4_block18_0_bn[0][0]	

conv4_block18_1_conv (Conv2D)	(None, None, None, 1 102400	conv4_block18_0_relu[0][0]	

conv4_block18_1_bn (BatchNormal	(None, None, None, 1 512	conv4_block18_1_conv[0][0]	

conv4_block18_1_relu (Activatio	(None, None, None, 1 0	conv4_block18_1_bn[0][0]	

conv4_block18_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block18_1_relu[0][0]	

conv4_block18_concat (Concatena	(None, None, None, 8 0	conv4_block17_concat[0][0]	conv4_block18_2_conv[0][0]

conv4_block19_0_bn (BatchNormal	(None, None, None, 8 3328	conv4_block18_concat[0][0]
conv4_block19_0_relu (Activatio	(None, None, None, 8 0	conv4_block19_0_bn[0][0]
conv4_block19_1_conv (Conv2D)	(None, None, None, 1 106496	conv4_block19_0_relu[0][0]
conv4_block19_1_bn (BatchNormal	(None, None, None, 1 512	conv4_block19_1_conv[0][0]
conv4_block19_1_relu (Activatio	(None, None, None, 1 0	conv4_block19_1_bn[0][0]
conv4_block19_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block19_1_relu[0][0]
conv4_block19_concat (Concatena	(None, None, None, 8 0	conv4_block18_concat[0][0] conv4_block19_2_conv[0][0]
conv4_block20_0_bn (BatchNormal	(None, None, None, 8 3456	conv4_block19_concat[0][0]
conv4_block20_0_relu (Activatio	(None, None, None, 8 0	conv4_block20_0_bn[0][0]
conv4_block20_1_conv (Conv2D)	(None, None, None, 1 110592	conv4_block20_0_relu[0][0]
conv4_block20_1_bn (BatchNormal	(None, None, None, 1 512	conv4_block20_1_conv[0][0]
conv4_block20_1_relu (Activatio	(None, None, None, 1 0	conv4_block20_1_bn[0][0]
conv4_block20_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block20_1_relu[0][0]
conv4_block20_concat (Concatena	(None, None, None, 8 0	conv4_block19_concat[0][0] conv4_block20_2_conv[0][0]
conv4_block21_0_bn (BatchNormal	(None, None, None, 8 3584	conv4_block20_concat[0][0]
conv4_block21_0_relu (Activatio	(None, None, None, 8 0	conv4_block21_0_bn[0][0]
conv4_block21_1_conv (Conv2D)	(None, None, None, 1 114688	conv4_block21_0_relu[0][0]
conv4_block21_1_bn (BatchNormal	(None, None, None, 1 512	conv4_block21_1_conv[0][0]
conv4_block21_1_relu (Activatio	(None, None, None, 1 0	conv4_block21_1_bn[0][0]
conv4_block21_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block21_1_relu[0][0]
conv4_block21_concat (Concatena	(None, None, None, 9 0	conv4_block20_concat[0][0] conv4_block21_2_conv[0][0]
conv4_block22_0_bn (BatchNormal	(None, None, None, 9 3712	conv4_block21_concat[0][0]
conv4_block22_0_relu (Activatio	(None, None, None, 9 0	conv4_block22_0_bn[0][0]

conv4_block22_1_conv (Conv2D)	(None, None, None, 1 118784	conv4_block22_0_relu[0][0]
conv4_block22_1_bn (BatchNormal	(None, None, None, 1 512	conv4_block22_1_conv[0][0]
conv4_block22_1_relu (Activatio	(None, None, None, 1 0	conv4_block22_1_bn[0][0]
conv4_block22_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block22_1_relu[0][0]
conv4_block22_concat (Concatena	(None, None, None, 9 0	conv4_block21_concat[0][0] conv4_block22_2_conv[0][0]
conv4_block23_0_bn (BatchNormal	(None, None, None, 9 3840	conv4_block22_concat[0][0]
conv4_block23_0_relu (Activatio	(None, None, None, 9 0	conv4_block23_0_bn[0][0]
conv4_block23_1_conv (Conv2D)	(None, None, None, 1 122880	conv4_block23_0_relu[0][0]
conv4_block23_1_bn (BatchNormal	(None, None, None, 1 512	conv4_block23_1_conv[0][0]
conv4_block23_1_relu (Activatio	(None, None, None, 1 0	conv4_block23_1_bn[0][0]
conv4_block23_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block23_1_relu[0][0]
conv4_block23_concat (Concatena	(None, None, None, 9 0	conv4_block22_concat[0][0] conv4_block23_2_conv[0][0]
conv4_block24_0_bn (BatchNormal	(None, None, None, 9 3968	conv4_block23_concat[0][0]
conv4_block24_0_relu (Activatio	(None, None, None, 9 0	conv4_block24_0_bn[0][0]
conv4_block24_1_conv (Conv2D)	(None, None, None, 1 126976	conv4_block24_0_relu[0][0]
conv4_block24_1_bn (BatchNormal	(None, None, None, 1 512	conv4_block24_1_conv[0][0]
conv4_block24_1_relu (Activatio	(None, None, None, 1 0	conv4_block24_1_bn[0][0]
conv4_block24_2_conv (Conv2D)	(None, None, None, 3 36864	conv4_block24_1_relu[0][0]
conv4_block24_concat (Concatena	(None, None, None, 1 0	conv4_block23_concat[0][0] conv4_block24_2_conv[0][0]
pool4_bn (BatchNormalization)	(None, None, None, 1 4096	conv4_block24_concat[0][0]
pool4_relu (Activation)	(None, None, None, 1 0	pool4_bn[0][0]
pool4_conv (Conv2D)	(None, None, None, 5 524288	pool4_relu[0][0]

pool4_pool (AveragePooling2D)	(None, None, None, 5 0	pool4_conv[0][0]
conv5_block1_0_bn (BatchNormali	(None, None, None, 5 2048	pool4_pool[0][0]
conv5_block1_0_relu (Activation	(None, None, None, 5 0	conv5_block1_0_bn[0][0]
conv5_block1_1_conv (Conv2D)	(None, None, None, 1 65536	conv5_block1_0_relu[0][0]
conv5_block1_1_bn (BatchNormali	(None, None, None, 1 512	conv5_block1_1_conv[0][0]
conv5_block1_1_relu (Activation	(None, None, None, 1 0	conv5_block1_1_bn[0][0]
conv5_block1_2_conv (Conv2D)	(None, None, None, 3 36864	conv5_block1_1_relu[0][0]
conv5_block1_concat (Concatenat	(None, None, None, 5 0	pool4_pool[0][0] conv5_block1_2_conv[0][0]
conv5_block2_0_bn (BatchNormali	(None, None, None, 5 2176	conv5_block1_concat[0][0]
conv5_block2_0_relu (Activation	(None, None, None, 5 0	conv5_block2_0_bn[0][0]
conv5_block2_1_conv (Conv2D)	(None, None, None, 1 69632	conv5_block2_0_relu[0][0]
conv5_block2_1_bn (BatchNormali	(None, None, None, 1 512	conv5_block2_1_conv[0][0]
conv5_block2_1_relu (Activation	(None, None, None, 1 0	conv5_block2_1_bn[0][0]
conv5_block2_2_conv (Conv2D)	(None, None, None, 3 36864	conv5_block2_1_relu[0][0]
conv5_block2_concat (Concatenat	(None, None, None, 5 0	conv5_block1_concat[0][0] conv5_block2_2_conv[0][0]
conv5_block3_0_bn (BatchNormali	(None, None, None, 5 2304	conv5_block2_concat[0][0]
conv5_block3_0_relu (Activation	(None, None, None, 5 0	conv5_block3_0_bn[0][0]
conv5_block3_1_conv (Conv2D)	(None, None, None, 1 73728	conv5_block3_0_relu[0][0]
conv5_block3_1_bn (BatchNormali	(None, None, None, 1 512	conv5_block3_1_conv[0][0]
conv5_block3_1_relu (Activation	(None, None, None, 1 0	conv5_block3_1_bn[0][0]
conv5_block3_2_conv (Conv2D)	(None, None, None, 3 36864	conv5_block3_1_relu[0][0]
conv5_block3_concat (Concatenat	(None, None, None, 6 0	conv5_block2_concat[0][0] conv5_block3_2_conv[0][0]
conv5_block4_0_bn (BatchNormali	(None, None, None, 6 2432	conv5_block3_concat[0][0]

conv5_block4_0_relu (Activation	(None, None, None, 6 0	conv5_block4_0_bn[0][0]
conv5_block4_1_conv (Conv2D)	(None, None, None, 1 77824	conv5_block4_0_relu[0][0]
conv5_block4_1_bn (BatchNormali	(None, None, None, 1 512	conv5_block4_1_conv[0][0]
conv5_block4_1_relu (Activation	(None, None, None, 1 0	conv5_block4_1_bn[0][0]
conv5_block4_2_conv (Conv2D)	(None, None, None, 3 36864	conv5_block4_1_relu[0][0]
conv5_block4_concat (Concatenat	(None, None, None, 6 0	conv5_block3_concat[0][0] conv5_block4_2_conv[0][0]
conv5_block5_0_bn (BatchNormali	(None, None, None, 6 2560	conv5_block4_concat[0][0]
conv5_block5_0_relu (Activation	(None, None, None, 6 0	conv5_block5_0_bn[0][0]
conv5_block5_1_conv (Conv2D)	(None, None, None, 1 81920	conv5_block5_0_relu[0][0]
conv5_block5_1_bn (BatchNormali	(None, None, None, 1 512	conv5_block5_1_conv[0][0]
conv5_block5_1_relu (Activation	(None, None, None, 1 0	conv5_block5_1_bn[0][0]
conv5_block5_2_conv (Conv2D)	(None, None, None, 3 36864	conv5_block5_1_relu[0][0]
conv5_block5_concat (Concatenat	(None, None, None, 6 0	conv5_block4_concat[0][0] conv5_block5_2_conv[0][0]
conv5_block6_0_bn (BatchNormali	(None, None, None, 6 2688	conv5_block5_concat[0][0]
conv5_block6_0_relu (Activation	(None, None, None, 6 0	conv5_block6_0_bn[0][0]
conv5_block6_1_conv (Conv2D)	(None, None, None, 1 86016	conv5_block6_0_relu[0][0]
conv5_block6_1_bn (BatchNormali	(None, None, None, 1 512	conv5_block6_1_conv[0][0]
conv5_block6_1_relu (Activation	(None, None, None, 1 0	conv5_block6_1_bn[0][0]
conv5_block6_2_conv (Conv2D)	(None, None, None, 3 36864	conv5_block6_1_relu[0][0]
conv5_block6_concat (Concatenat	(None, None, None, 7 0	conv5_block5_concat[0][0] conv5_block6_2_conv[0][0]
conv5_block7_0_bn (BatchNormali	(None, None, None, 7 2816	conv5_block6_concat[0][0]
conv5_block7_0_relu (Activation	(None, None, None, 7 0	conv5_block7_0_bn[0][0]

conv5_block7_1_conv (Conv2D)	(None, None, None, 1 90112	conv5_block7_0_relu[0][0]
conv5_block7_1_bn (BatchNormali	(None, None, None, 1 512	conv5_block7_1_conv[0][0]
conv5_block7_1_relu (Activation	(None, None, None, 1 0	conv5_block7_1_bn[0][0]
conv5_block7_2_conv (Conv2D)	(None, None, None, 3 36864	conv5_block7_1_relu[0][0]
conv5_block7_concat (Concatenat	(None, None, None, 7 0	conv5_block6_concat[0][0] conv5_block7_2_conv[0][0]
conv5_block8_0_bn (BatchNormali	(None, None, None, 7 2944	conv5_block7_concat[0][0]
conv5_block8_0_relu (Activation	(None, None, None, 7 0	conv5_block8_0_bn[0][0]
conv5_block8_1_conv (Conv2D)	(None, None, None, 1 94208	conv5_block8_0_relu[0][0]
conv5_block8_1_bn (BatchNormali	(None, None, None, 1 512	conv5_block8_1_conv[0][0]
conv5_block8_1_relu (Activation	(None, None, None, 1 0	conv5_block8_1_bn[0][0]
conv5_block8_2_conv (Conv2D)	(None, None, None, 3 36864	conv5_block8_1_relu[0][0]
conv5_block8_concat (Concatenat	(None, None, None, 7 0	conv5_block7_concat[0][0] conv5_block8_2_conv[0][0]
conv5_block9_0_bn (BatchNormali	(None, None, None, 7 3072	conv5_block8_concat[0][0]
conv5_block9_0_relu (Activation	(None, None, None, 7 0	conv5_block9_0_bn[0][0]
conv5_block9_1_conv (Conv2D)	(None, None, None, 1 98304	conv5_block9_0_relu[0][0]
conv5_block9_1_bn (BatchNormali	(None, None, None, 1 512	conv5_block9_1_conv[0][0]
conv5_block9_1_relu (Activation	(None, None, None, 1 0	conv5_block9_1_bn[0][0]
conv5_block9_2_conv (Conv2D)	(None, None, None, 3 36864	conv5_block9_1_relu[0][0]
conv5_block9_concat (Concatenat	(None, None, None, 8 0	conv5_block8_concat[0][0] conv5_block9_2_conv[0][0]
conv5_block10_0_bn (BatchNormal	(None, None, None, 8 3200	conv5_block9_concat[0][0]
conv5_block10_0_relu (Activatio	(None, None, None, 8 0	conv5_block10_0_bn[0][0]
conv5_block10_1_conv (Conv2D)	(None, None, None, 1 102400	conv5_block10_0_relu[0][0]
conv5_block10_1_bn (BatchNormal	(None, None, None, 1 512	conv5_block10_1_conv[0][0]

conv5_block10_1_relu (Activatio	(None, None, None, 1 0	conv5_block10_1_bn[0][0]
conv5_block10_2_conv (Conv2D)	(None, None, None, 3 36864	conv5_block10_1_relu[0][0]
conv5_block10_concat (Concatena	(None, None, None, 8 0	conv5_block9_concat[0][0] conv5_block10_2_conv[0][0]
conv5_block11_0_bn (BatchNormal	(None, None, None, 8 3328	conv5_block10_concat[0][0]
conv5_block11_0_relu (Activatio	(None, None, None, 8 0	conv5_block11_0_bn[0][0]
conv5_block11_1_conv (Conv2D)	(None, None, None, 1 106496	conv5_block11_0_relu[0][0]
conv5_block11_1_bn (BatchNormal	(None, None, None, 1 512	conv5_block11_1_conv[0][0]
conv5_block11_1_relu (Activatio	(None, None, None, 1 0	conv5_block11_1_bn[0][0]
conv5_block11_2_conv (Conv2D)	(None, None, None, 3 36864	conv5_block11_1_relu[0][0]
conv5_block11_concat (Concatena	(None, None, None, 8 0	conv5_block10_concat[0][0] conv5_block11_2_conv[0][0]
conv5_block12_0_bn (BatchNormal	(None, None, None, 8 3456	conv5_block11_concat[0][0]
conv5_block12_0_relu (Activatio	(None, None, None, 8 0	conv5_block12_0_bn[0][0]
conv5_block12_1_conv (Conv2D)	(None, None, None, 1 110592	conv5_block12_0_relu[0][0]
conv5_block12_1_bn (BatchNormal	(None, None, None, 1 512	conv5_block12_1_conv[0][0]
conv5_block12_1_relu (Activatio	(None, None, None, 1 0	conv5_block12_1_bn[0][0]
conv5_block12_2_conv (Conv2D)	(None, None, None, 3 36864	conv5_block12_1_relu[0][0]
conv5_block12_concat (Concatena	(None, None, None, 8 0	conv5_block11_concat[0][0] conv5_block12_2_conv[0][0]
conv5_block13_0_bn (BatchNormal	(None, None, None, 8 3584	conv5_block12_concat[0][0]
conv5_block13_0_relu (Activatio	(None, None, None, 8 0	conv5_block13_0_bn[0][0]
conv5_block13_1_conv (Conv2D)	(None, None, None, 1 114688	conv5_block13_0_relu[0][0]
conv5_block13_1_bn (BatchNormal	(None, None, None, 1 512	conv5_block13_1_conv[0][0]
conv5_block13_1_relu (Activatio	(None, None, None, 1 0	conv5_block13_1_bn[0][0]

conv5_block13_2_conv (Conv2D)	(None, None, None, 3 36864	conv5_block13_1_relu[0][0]
conv5_block13_concat (Concatena	(None, None, None, 9 0	conv5_block12_concat[0][0] conv5_block13_2_conv[0][0]
conv5_block14_0_bn (BatchNormal	(None, None, None, 9 3712	conv5_block13_concat[0][0]
conv5_block14_0_relu (Activatio	(None, None, None, 9 0	conv5_block14_0_bn[0][0]
conv5_block14_1_conv (Conv2D)	(None, None, None, 1 118784	conv5_block14_0_relu[0][0]
conv5_block14_1_bn (BatchNormal	(None, None, None, 1 512	conv5_block14_1_conv[0][0]
conv5_block14_1_relu (Activatio	(None, None, None, 1 0	conv5_block14_1_bn[0][0]
conv5_block14_2_conv (Conv2D)	(None, None, None, 3 36864	conv5_block14_1_relu[0][0]
conv5_block14_concat (Concatena	(None, None, None, 9 0	conv5_block13_concat[0][0] conv5_block14_2_conv[0][0]
conv5_block15_0_bn (BatchNormal	(None, None, None, 9 3840	conv5_block14_concat[0][0]
conv5_block15_0_relu (Activatio	(None, None, None, 9 0	conv5_block15_0_bn[0][0]
conv5_block15_1_conv (Conv2D)	(None, None, None, 1 122880	conv5_block15_0_relu[0][0]
conv5_block15_1_bn (BatchNormal	(None, None, None, 1 512	conv5_block15_1_conv[0][0]
conv5_block15_1_relu (Activatio	(None, None, None, 1 0	conv5_block15_1_bn[0][0]
conv5_block15_2_conv (Conv2D)	(None, None, None, 3 36864	conv5_block15_1_relu[0][0]
conv5_block15_concat (Concatena	(None, None, None, 9 0	conv5_block14_concat[0][0] conv5_block15_2_conv[0][0]
conv5_block16_0_bn (BatchNormal	(None, None, None, 9 3968	conv5_block15_concat[0][0]
conv5_block16_0_relu (Activatio	(None, None, None, 9 0	conv5_block16_0_bn[0][0]
conv5_block16_1_conv (Conv2D)	(None, None, None, 1 126976	conv5_block16_0_relu[0][0]
conv5_block16_1_bn (BatchNormal	(None, None, None, 1 512	conv5_block16_1_conv[0][0]
conv5_block16_1_relu (Activatio	(None, None, None, 1 0	conv5_block16_1_bn[0][0]
conv5_block16_2_conv (Conv2D)	(None, None, None, 3 36864	conv5_block16_1_relu[0][0]
conv5_block16_concat (Concatena	(None, None, None, 1 0	conv5_block15_concat[0][0]

			conv5_block16_2_conv[0][0]
bn (BatchNormalization)	(None, None, None, 1	4096	conv5_block16_concat[0][0]
global_average_pooling2d_1 (Glo	(None, 1024)	0	bn[0][0]
dense_1 (Dense)	(None, 14)	14350	global_average_pooling2d_1[0]

Total params: 7,051,854
Trainable params: 6,968,206
Non-trainable params: 83,648

Keras models include abundant information about the elements that make them up. You can check all of the available methods and attributes of this class by using the `dir()` method:

```
In [5]: # Printing out methods and attributes for Keras model
        print(f"Keras' models have the following methods and attributes: \n\n{dir(model)}")
```

Keras' models have the following methods and attributes:

```
['__call__', '__class__', '__delattr__', '__dict__', '__dir__', '__doc__', '__eq__', '__format__
```

Wow, this certainly is a lot! These models are indeed very complex.

What we are interested in are the layers of the model which can be easily accessed as an attribute using the dot notation. They are a list of layers, which can be confirmed by checking its type:

```
In [6]: # Check the type of the model's layers
        type(model.layers)
```

```
Out[6]: list
```

```
In [7]: # Print 5 first layers along with their names
        for i in range(5):
            l = model.layers[i]
            print(f"Layer number {i}: \n{l} \nWith name: {l.name} \n")
```

```
Layer number 0:
<keras.engine.topology.InputLayer object at 0x7ff350cece80>
With name: input_1
```

```
Layer number 1:
<keras.layers.convolutional.ZeroPadding2D object at 0x7ff350cb00f0>
With name: zero_padding2d_1
```

```
Layer number 2:
```

```
<keras.layers.convolutional.Conv2D object at 0x7ff350cb0128>  
With name: conv1/conv
```

Layer number 3:

```
<keras.layers.normalization.BatchNormalization object at 0x7ff350cb03c8>  
With name: conv1/bn
```

Layer number 4:

```
<keras.layers.core.Activation object at 0x7ff350a399e8>  
With name: conv1/relu
```

Let's check how many layers our model has:

```
In [8]: # Print number of layers in our model  
        print(f"The model has {len(model.layers)} layers")
```

The model has 428 layers

Our main goal is interpreting the representations which the neural net is creating for classifying our images. But as you can see this architecture has many layers.

Actually we are really interested in the representations that the convolutional layers produce because these are the layers that (hopefully) recognize concrete elements within the images. We are also interested in the “concatenate” layers because in our model's architecture they concatenate convolutional layers.

Let's check how many of those we have:

```
In [9]: # Number of layers that are of type "Convolutional" or "Concatenate"  
        len([l for l in model.layers if ("conv" in str(type(l))) or ("Concatenate" in str(type
```

Out[9]: 180

This number is still very big to try to interpret each one of these layers individually.

One characteristic of CNN's is that the earlier layers capture low-level features such as edges in an image while the deeper layers capture high-level concepts such as physical features of a “Cat”.

Because of this **Grad-CAM usually focuses on the last layers, as they provide a better picture of what the network is paying attention to when classifying a particular class.** Let's grab the last concatenate layer of our model. Luckily Keras API makes this quite easy:

```
In [10]: # Save the desired layer in a variable  
         layer = model.layers[424]  
  
         # Print layer  
         layer
```

Out[10]: <keras.layers.merge.Concatenate at 0x7ff2248889e8>

This approach is not the best since we will need to know the exact index of the desired layer. Luckily we can use the `get_layer()` method in conjunction with the layer's name to get the same result.

Remember you can get the name from the information displayed earlier with the `summary()` method.

```
In [11]: # Save the desired layer in a variable
        layer = model.get_layer("conv5_block16_concat")

        # Print layer
        layer
```

```
Out[11]: <keras.layers.merge.Concatenate at 0x7ff2248889e8>
```

Let's check what methods and attributes we have available when working with this layer:

```
In [12]: # Printing out methods and attributes for Keras' layer
        print(f"Keras' layers have the following methods and attributes: \n\n{dir(layer)}")
```

Keras' layers have the following methods and attributes:

```
['__call__', '__class__', '__delattr__', '__dict__', '__dir__', '__doc__', '__eq__', '__format__',
```

Since we want to know the representations which this layer is abstracting from the images we should be interested in the output from this layer. Luckily we have this attribute available:

```
In [13]: # Print layer's output
        layer.output
```

```
Out[13]: <tf.Tensor 'conv5_block16_concat/concat:0' shape=(?, ?, ?, 1024) dtype=float32>
```

Do you notice something odd? The shape of this tensor is undefined for some dimensions. This is because this tensor is just a placeholder and it doesn't really contain information about the activations that occurred in this layer.

To compute the actual activation values given an input we will need to use a **Keras function**.

This function accepts lists of input and output placeholders and can be used with an actual input to compute the respective output of the layer associated to the placeholder for that given input.

Before jumping onto the Keras function we should rewind a little bit to get the placeholder tensor associated with the input. You can get this from the model's input:

```
In [14]: # Print model's input tensor placeholder
        model.input
```

```
Out[14]: <tf.Tensor 'input_1:0' shape=(?, ?, ?, 3) dtype=float32>
```

We can see that this is a placeholder as well. Now let's instantiate our Keras function using Keras backend. Please be aware that this **function expects its arguments as lists or tuples**:

```
In [15]: # Instantiate the function to compute the activations of the last convolutional layer
last_layer_activations_function = K.function([model.input], [layer.output])

# Print the Keras function
last_layer_activations_function
```

```
Out[15]: <keras.backend.tensorflow_backend.Function at 0x7ff221316ba8>
```

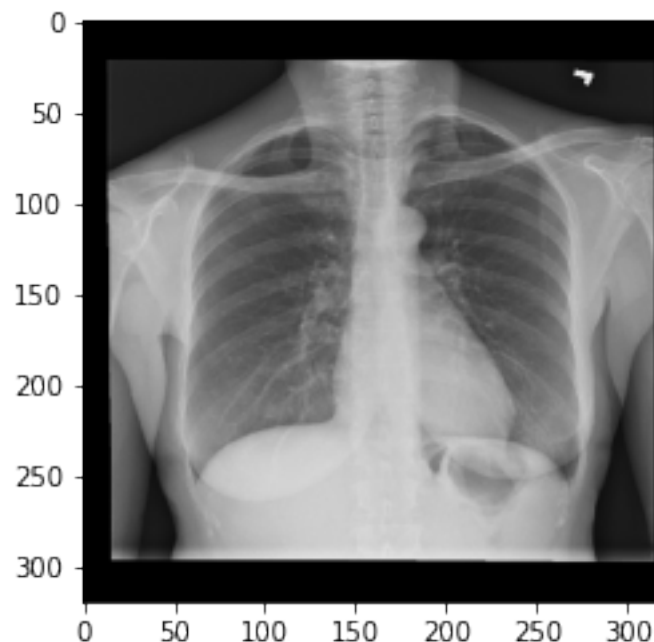
Let's test the functions for computing the last layer activation which we just defined on a particular image. Don't worry about the code to load the image, this has been taken care of for you. You should only care that an image ready to be processed will be saved in the x variable:

```
In [16]: # Load dataframe that contains information about the dataset of images
df = pd.read_csv("nih_new/train-small.csv")

# Path to the actual image
im_path = 'nih_new/images-small/00000599_000.png'

# Load the image and save it to a variable
x = load_image(im_path, df, preprocess=False)

# Display the image
plt.imshow(x, cmap = 'gray')
plt.show()
```

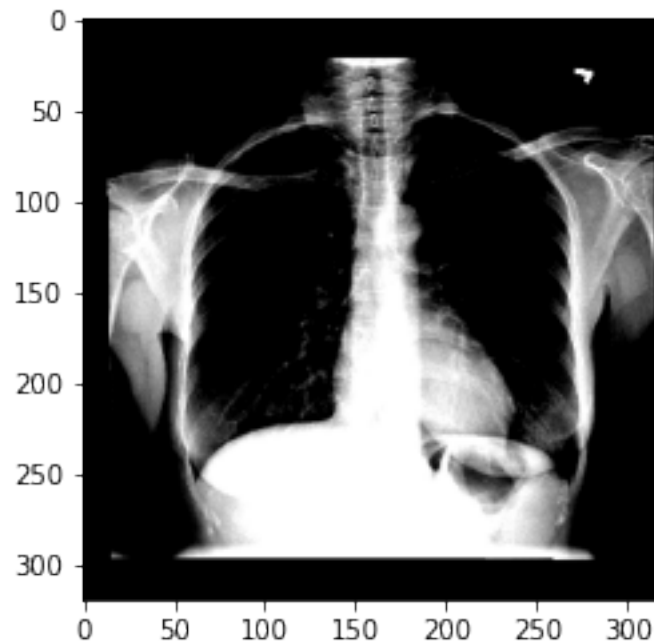


We should normalize this image before going forward, this has also been taken care of:


```
In [17]: # Calculate mean and standard deviation of a batch of images
mean, std = get_mean_std_per_batch(df)

# Normalize image
x = load_image_normalize(im_path, mean, std)
# Display the image
plt.imshow(x.squeeze(), cmap = 'gray')
plt.show()
```

Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255]



Now we have everything we need to compute the actual values of the last layer activations. In this case we should also **provide the input as a list or tuple**:

```
In [18]: # Run the function on the image and save it in a variable
actual_activations = last_layer_activations_function([x])
actual_activations
```

```
Out[18]: [array([[[[-0.23702383,  0.1054067 , -0.09539237, ...,  0.19466937,
                    -0.07553095,  0.21800742],
                  [-0.3608293 , -0.49694395, -0.8985988 , ...,  0.28263342,
                    -0.08797086,  0.32878476],
                  [-0.2681642 , -0.26400208, -0.89956033, ...,  0.23807381,
                    -0.07753395,  0.271367  ],
                  ...,
                  [-0.3738516 , -0.29830033, -0.8859294 , ...,  0.13269609,
```

```

-0.09081772, 0.16981669],
[-0.25935197, -0.05493974, -0.51206 , ..., 0.28128588,
-0.11679479, 0.32220238],
[-0.241157 , 0.23221722, -0.08264475, ..., 0.14615746,
-0.07138451, 0.21461329]],

[[-0.3868346 , 0.04625287, -0.48729265, ..., 0.24962625,
-0.11925422, 0.31549245],
[-0.17229678, -0.41012964, -0.26488608, ..., 0.4301238 ,
-0.15064242, 0.493559 ],
[-0.48088574, -0.47438028, -0.42633063, ..., 0.2581186 ,
-0.11581598, 0.33084315],
...,
[-0.34574437, -0.6549144 , -0.57052696, ..., 0.15628804,
-0.10776094, 0.18880478],
[-0.54574436, -0.9951541 , -0.54874784, ..., 0.32031807,
-0.13615817, 0.3260019 ],
[-0.56063986, -0.21032241, 0.00390708, ..., 0.18183768,
-0.0682081 , 0.21392506]],

[[-0.4730839 , -0.02347994, -0.43232355, ..., 0.27270523,
-0.11322275, 0.2432285 ],
[-1.2484052 , -1.0704248 , -0.3053118 , ..., 0.454308 ,
-0.1501662 , 0.35555303],
[-0.8810173 , -0.6242399 , -0.5386256 , ..., 0.29572266,
-0.09585512, 0.20475927],
...,
[-1.3751011 , 0.13930295, 0.23743618, ..., 0.06184677,
-0.05869364, 0.08984356],
[-0.8771509 , -0.04209949, 1.1667961 , ..., 0.18854713,
-0.06257953, 0.15155955],
[-0.7432046 , -0.19918242, 0.9913299 , ..., 0.0793993 ,
-0.02839849, 0.08045889]],

...,

[[-0.5960772 , -0.00482173, 0.14680746, ..., 0.3655157 ,
-0.15409034, 0.48892158],
[-0.37668312, 0.71335745, -0.031999 , ..., 0.4122941 ,
-0.1257244 , 0.73066866],
[-2.0470808 , -1.2017248 , -0.78999186, ..., 0.19864726,
0.17223702, 0.8854867 ],
...,
[-2.0258265 , -0.8218878 , -0.6006702 , ..., 0.00795583,
0.11177041, 1.42233 ],
[-1.6262685 , 0.09990728, -0.5643097 , ..., 0.16129252,
-0.07851787, 1.5067396 ],
[-0.8862725 , 0.07348883, 0.32334697, ..., -0.12776697,

```

```

0.10194322, 1.0539756 ]],

[[-0.6044072 , -0.0240733 , -0.49380025, ..., 0.28898105,
  -0.15708804, 0.4663337 ],
 [-0.524331 , 0.13514982, -0.45060417, ..., 0.44769403,
  -0.2381051 , 0.65325516],
 [-0.44161716, 0.6040169 , -1.5322777 , ..., 0.3392639 ,
  -0.15121244, 0.52864605],
 ...,
 [-0.78013825, -0.0961304 , -1.0196183 , ..., 0.07627262,
  -0.08315185, 0.7585078 ],
 [-0.26460856, 0.41444945, -0.9215252 , ..., 0.29149723,
  -0.22252335, 0.89126205],
 [-0.5027085 , -0.11727619, -0.5962626 , ..., 0.04195292,
  -0.08922879, 0.7027127 ]],

[[-0.89180255, 0.21321994, 0.496118 , ..., 0.26252916,
  -0.11067075, 0.24559288],
 [-0.9888345 , -0.17132482, 0.3721898 , ..., 0.34661293,
  -0.12382239, 0.3389768 ],
 [-0.65068513, -0.00451049, -0.27235806, ..., 0.2712055 ,
  -0.09665748, 0.28318712],
 ...,
 [-0.5136519 , 0.70400333, -0.06819835, ..., 0.16268368,
  -0.08299141, 0.24743526],
 [-0.5870072 , 0.3031031 , 0.22909215, ..., 0.25060678,
  -0.11670539, 0.30383188],
 [-0.61077654, 0.22875792, 0.54413295, ..., 0.1768849 ,
  -0.05819542, 0.25265226]]], dtype=float32)]

```

An important intermediary step is to trim the batch dimension which can be done like this. This is necessary because we are applying Grad-CAM to a single image rather than to a batch of images:

```

In [19]: # Remove batch dimension
         actual_activations = actual_activations[0][0, :]

In [20]: # Print shape of the activation array
         print(f"Activations of last convolutional layer have shape: {actual_activations.shape}")

         # Print activation array
         actual_activations

```

Activations of last convolutional layer have shape: (10, 10, 1024)

```

Out[20]: array([[[-0.23702383, 0.1054067 , -0.09539237, ..., 0.19466937,
  -0.07553095, 0.21800742],
 [-0.3608293 , -0.49694395, -0.8985988 , ..., 0.28263342,

```

```

-0.08797086, 0.32878476],
[-0.2681642 , -0.26400208, -0.89956033, ..., 0.23807381,
-0.07753395, 0.271367 ],
...,
[-0.3738516 , -0.29830033, -0.8859294 , ..., 0.13269609,
-0.09081772, 0.16981669],
[-0.25935197, -0.05493974, -0.51206 , ..., 0.28128588,
-0.11679479, 0.32220238],
[-0.241157 , 0.23221722, -0.08264475, ..., 0.14615746,
-0.07138451, 0.21461329]],

[[-0.3868346 , 0.04625287, -0.48729265, ..., 0.24962625,
-0.11925422, 0.31549245],
[-0.17229678, -0.41012964, -0.26488608, ..., 0.4301238 ,
-0.15064242, 0.493559 ],
[-0.48088574, -0.47438028, -0.42633063, ..., 0.2581186 ,
-0.11581598, 0.33084315],
...,
[-0.34574437, -0.6549144 , -0.57052696, ..., 0.15628804,
-0.10776094, 0.18880478],
[-0.54574436, -0.9951541 , -0.54874784, ..., 0.32031807,
-0.13615817, 0.3260019 ],
[-0.56063986, -0.21032241, 0.00390708, ..., 0.18183768,
-0.0682081 , 0.21392506]],

[[-0.4730839 , -0.02347994, -0.43232355, ..., 0.27270523,
-0.11322275, 0.2432285 ],
[-1.2484052 , -1.0704248 , -0.3053118 , ..., 0.454308 ,
-0.1501662 , 0.35555303],
[-0.8810173 , -0.6242399 , -0.5386256 , ..., 0.29572266,
-0.09585512, 0.20475927],
...,
[-1.3751011 , 0.13930295, 0.23743618, ..., 0.06184677,
-0.05869364, 0.08984356],
[-0.8771509 , -0.04209949, 1.1667961 , ..., 0.18854713,
-0.06257953, 0.15155955],
[-0.7432046 , -0.19918242, 0.9913299 , ..., 0.0793993 ,
-0.02839849, 0.08045889]],

...,

[[-0.5960772 , -0.00482173, 0.14680746, ..., 0.3655157 ,
-0.15409034, 0.48892158],
[-0.37668312, 0.71335745, -0.031999 , ..., 0.4122941 ,
-0.1257244 , 0.73066866],
[-2.0470808 , -1.2017248 , -0.78999186, ..., 0.19864726,
0.17223702, 0.8854867 ],
...,

```

```

[-2.0258265 , -0.8218878 , -0.6006702 , ...,  0.00795583,
  0.11177041,  1.42233   ],
[-1.6262685 ,  0.09990728, -0.5643097 , ...,  0.16129252,
 -0.07851787,  1.5067396 ],
[-0.8862725 ,  0.07348883,  0.32334697, ..., -0.12776697,
  0.10194322,  1.0539756 ]],

[[-0.6044072 , -0.0240733 , -0.49380025, ...,  0.28898105,
 -0.15708804,  0.4663337 ],
 [-0.524331   ,  0.13514982, -0.45060417, ...,  0.44769403,
 -0.2381051   ,  0.65325516],
 [-0.44161716,  0.6040169 , -1.5322777 , ...,  0.3392639 ,
 -0.15121244,  0.52864605],
 ...,
 [-0.78013825, -0.0961304 , -1.0196183 , ...,  0.07627262,
 -0.08315185,  0.7585078 ],
 [-0.26460856,  0.41444945, -0.9215252 , ...,  0.29149723,
 -0.22252335,  0.89126205],
 [-0.5027085 , -0.11727619, -0.5962626 , ...,  0.04195292,
 -0.08922879,  0.7027127 ]],

[[-0.89180255,  0.21321994,  0.496118   , ...,  0.26252916,
 -0.11067075,  0.24559288],
 [-0.9888345 , -0.17132482,  0.3721898 , ...,  0.34661293,
 -0.12382239,  0.3389768 ],
 [-0.65068513, -0.00451049, -0.27235806, ...,  0.2712055 ,
 -0.09665748,  0.28318712],
 ...,
 [-0.5136519 ,  0.70400333, -0.06819835, ...,  0.16268368,
 -0.08299141,  0.24743526],
 [-0.5870072 ,  0.3031031 ,  0.22909215, ...,  0.25060678,
 -0.11670539,  0.30383188],
 [-0.61077654,  0.22875792,  0.54413295, ...,  0.1768849 ,
 -0.05819542,  0.25265226]]], dtype=float32)

```

```

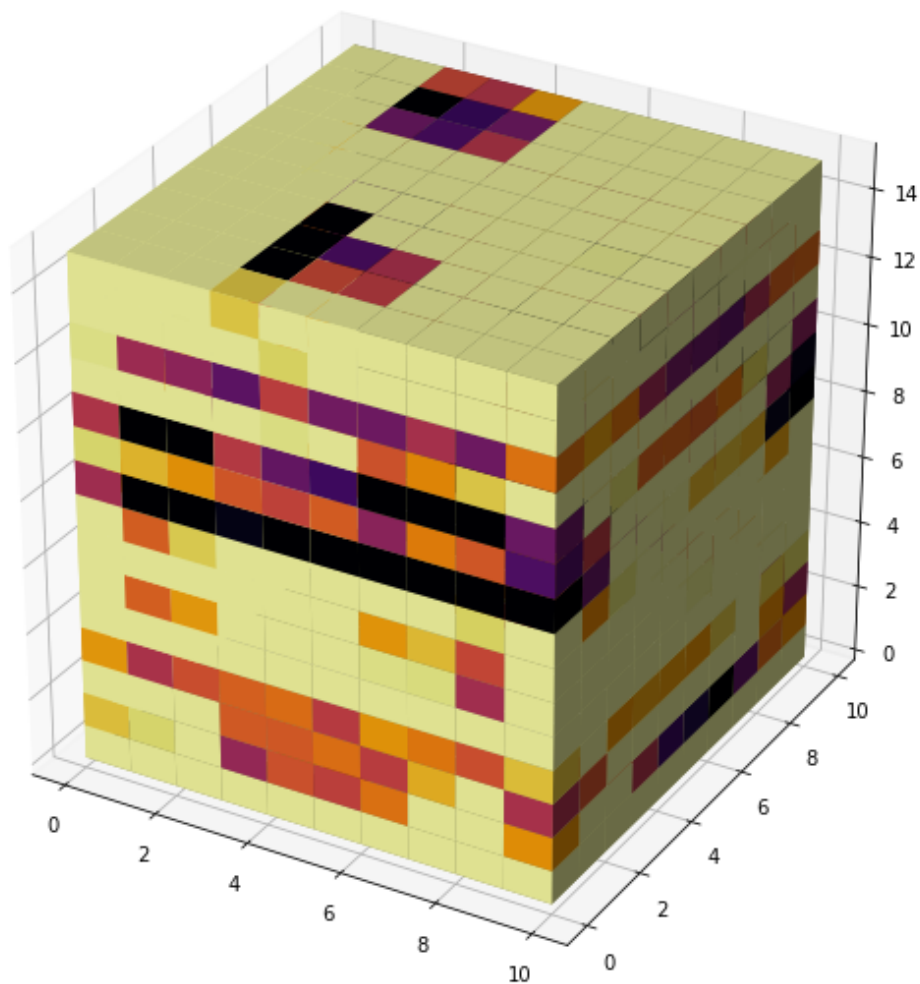
In [31]: print(actual_activations.shape)
from mpl_toolkits.mplot3d import Axes3D
fig = plt.figure(figsize=(10,10))
ax = fig.gca(projection='3d')
cmap = plt.get_cmap("inferno_r")
ax.voxels(actual_activations[:, :, 0:15], facecolors= cmap(actual_activations[:, :, :
plt.show()

```

```

(10, 10, 1024)

```



Looks like everything worked out nicely! This is all for this lecture notebook (Grad-CAM Part 1). In Part 2 we will see how to calculate the gradients of the model's output with respect to the activations in this layer. This is the "Grad" part of Grad-CAM.

Congratulations on finishing this lecture notebook! Hopefully you will now have a better understanding of how to leverage Keras's API power for computing activations in specific layers. Keep it up!

```
In [41]: import numpy as np
         from matplotlib import cm

         def normalize(arr):
             arr_min = np.min(arr)
             return (arr-arr_min)/(np.max(arr)-arr_min)
         def explode(data):
             shape_arr = np.array(data.shape)
```

```

size = shape_arr[:3]*2 - 1
exploded = np.zeros(np.concatenate([size, shape_arr[3:]]), dtype=data.dtype)
exploded[:, :2, :2] = data
return exploded

def expand_coordinates(indices):
    x, y, z = indices
    x[1::2, :, :] += 1
    y[:, 1::2, :] += 1
    z[:, :, 1::2] += 1
    return x, y, z

def plot_cube(cube, angle=320):
    cube = normalize(cube)

    facecolors = cm.viridis(cube)
    facecolors[:, :, :, -1] = cube
    facecolors = explode(facecolors)

    filled = facecolors[:, :, :, -1] != 0
    x, y, z = expand_coordinates(np.indices(np.array(filled.shape) + 1))

    fig = plt.figure(figsize=(20, 20))
    ax = fig.gca(projection='3d')
    ax.view_init(30, angle)
    #ax.set_xlim(right=10*2)
    #ax.set_ylim(top=10*2)
    #ax.set_zlim(top=10*2)

    ax.voxels(x, y, z, filled, facecolors=facecolors, shade=False)
    plt.show()

```

```
In [44]: plot_cube(actual_activations[:, :, 1000:1005])
```

