

Visualizing_Activations

October 21, 2018

1 Visualizing Activations

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In [23]: # First lets import our cats and dogs model
         from keras.models import load_model

         import warnings
         warnings.filterwarnings('ignore')

         model = load_model('cats_and_dogs_small_2.h5')
         model.summary()
```

Layer (type)	Output Shape	Param #
conv2d_9 (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d_9 (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_10 (Conv2D)	(None, 72, 72, 64)	18496
max_pooling2d_10 (MaxPooling2D)	(None, 36, 36, 64)	0
conv2d_11 (Conv2D)	(None, 34, 34, 128)	73856
max_pooling2d_11 (MaxPooling2D)	(None, 17, 17, 128)	0
conv2d_12 (Conv2D)	(None, 15, 15, 128)	147584
max_pooling2d_12 (MaxPooling2D)	(None, 7, 7, 128)	0
flatten_3 (Flatten)	(None, 6272)	0
dropout_2 (Dropout)	(None, 6272)	0
dense_4 (Dense)	(None, 512)	3211776
dense_5 (Dense)	(None, 1)	513

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Total params: 3,453,121
Trainable params: 3,453,121
Non-trainable params: 0
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In [2]: # now we need an image not used to train the network
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img_path = 'PetImages/Cat/10095.jpg'

from keras.preprocessing import image
import numpy as np

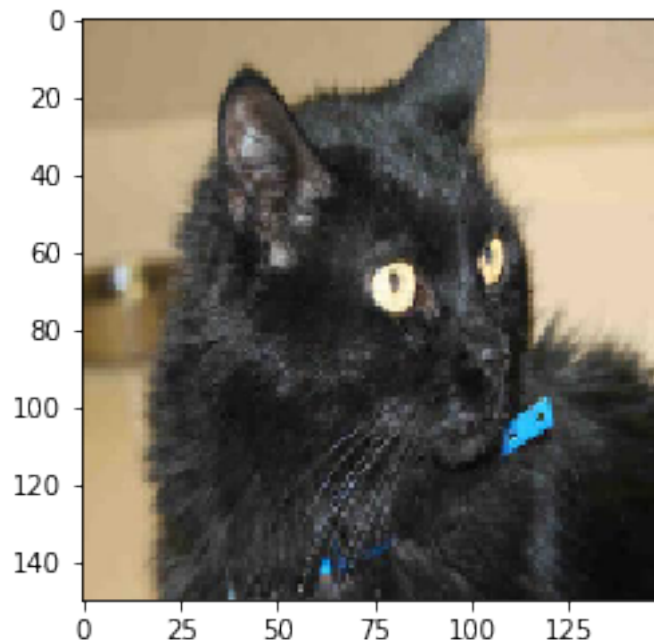
img = image.load_img(img_path, target_size=(150, 150))
img_tensor = image.img_to_array(img)
img_tensor = np.expand_dims(img_tensor, axis=0)
img_tensor /= 255
```

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In [3]: print(img_tensor.shape)
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(1, 150, 150, 3)
```

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In [5]: # lets see our image
# side note I had to run this block twice, idk why
import matplotlib.pyplot as plt
```

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plt.imshow(img_tensor[0])
plt.show()
```



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In [6]: from keras import models

        layer_outputs = [layer.output for layer in model.layers[:8]]
        activation_model = models.Model(inputs=model.input, output=layer_outputs)

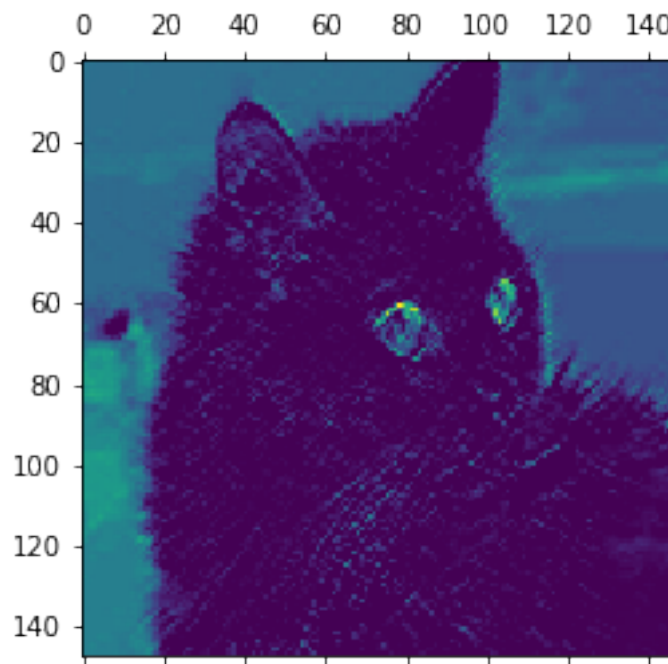
In [7]: activations = activation_model.predict(img_tensor)

In [8]: first_layer_activation = activations[0]
        print(first_layer_activation.shape)

(1, 148, 148, 32)

In [9]: plt.matshow(first_layer_activation[0, :, :, 24], cmap='viridis')
        plt.show()

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In [22]: layer_names = []
        for layer in model.layers[:8]:
            layer_names.append(layer.name)

        images_per_row = 16

        for layer_name, layer_activation in zip(layer_names, activations):

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n_features = layer_activation.shape[-1]

size = layer_activation.shape[1]

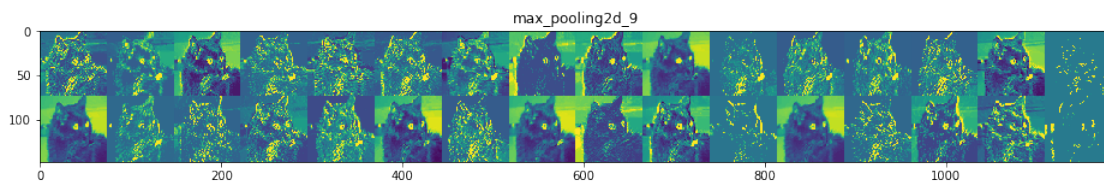
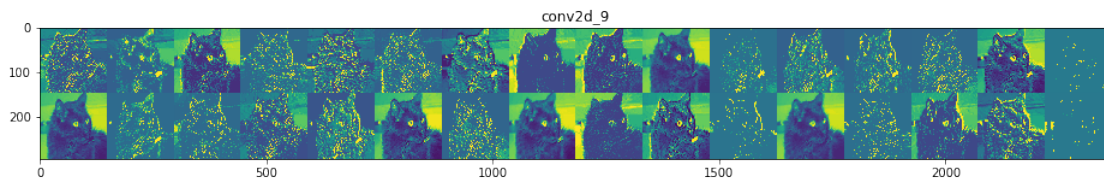
n_cols = n_features // images_per_row
display_grid = np.zeros((size * n_cols, images_per_row * size))

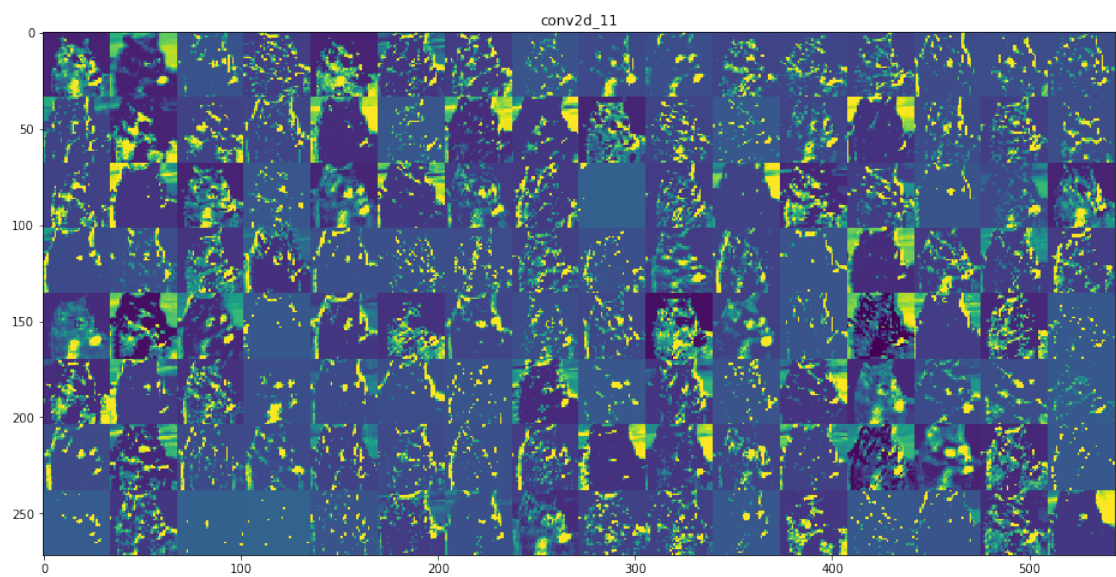
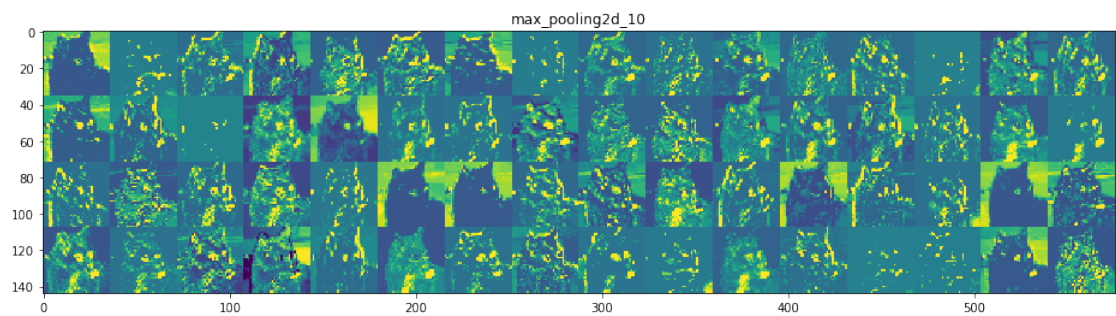
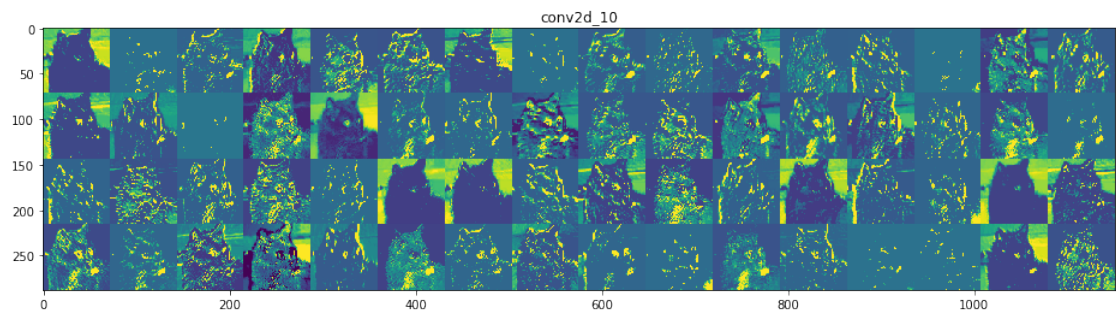
for col in range(n_cols):
    for row in range(images_per_row):
        channel_image = layer_activation[0, :, :, col * images_per_row + row]

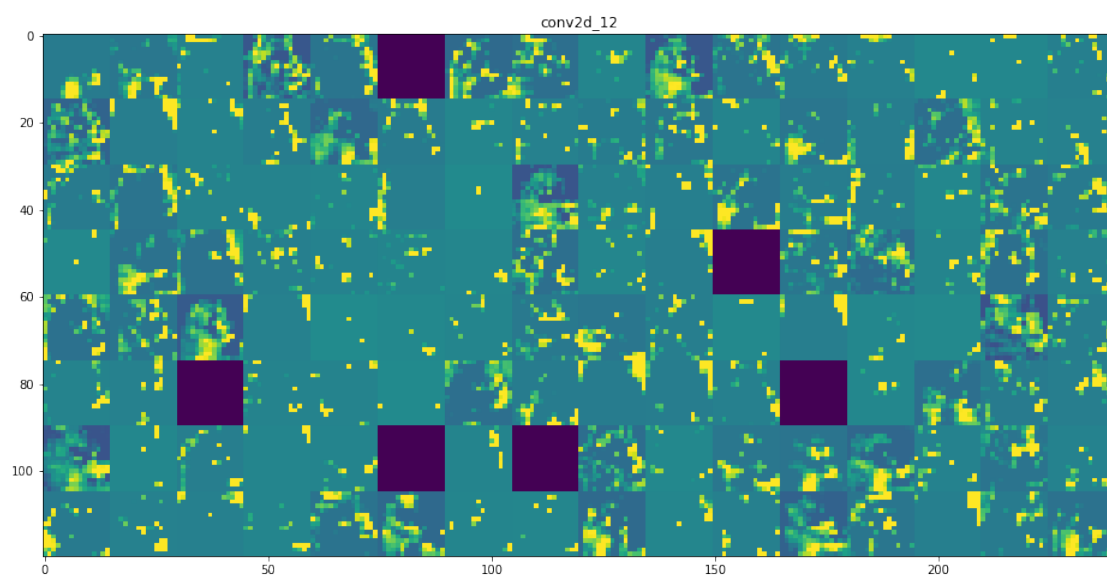
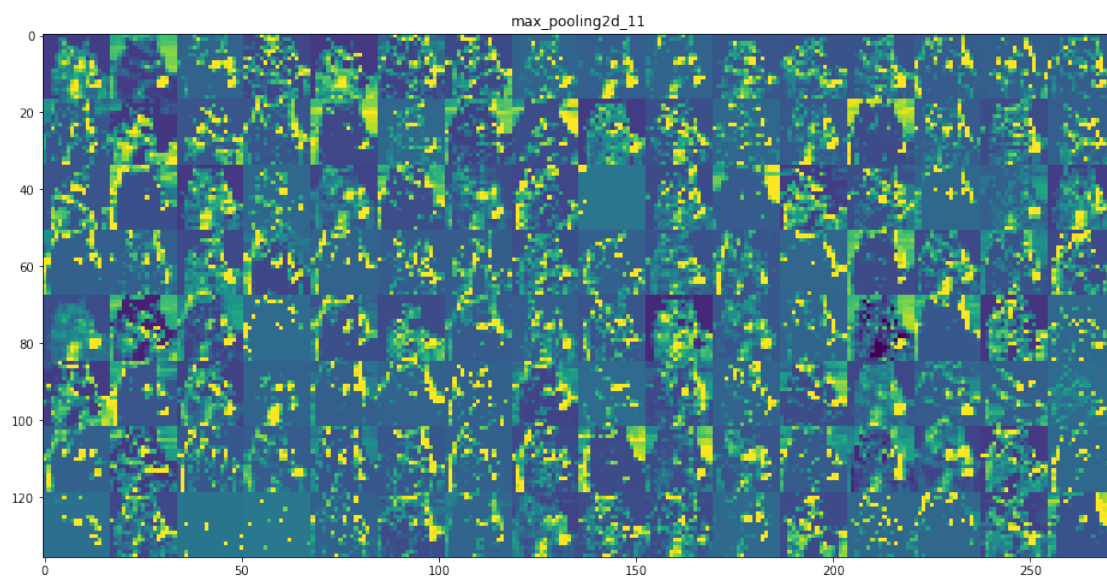
        channel_image -= channel_image.mean()
        channel_image /= channel_image.std()
        channel_image *= 64
        channel_image += 128
        channel_image = np.clip(channel_image, 0, 255).astype('uint8')
        display_grid[col * size : (col + 1) * size,
                        row * size : (row + 1) * size] = channel_image

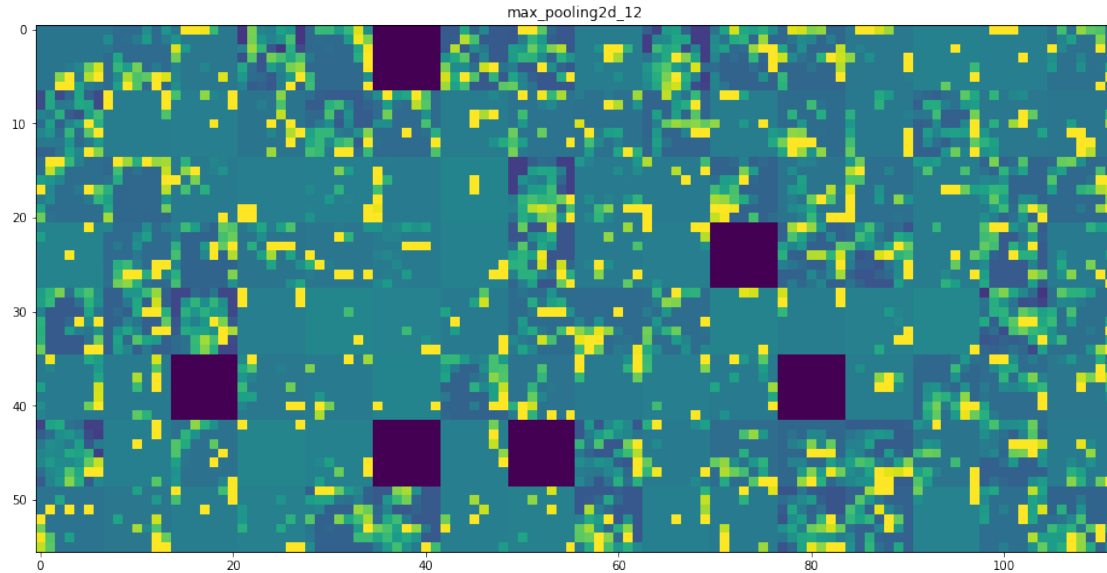
scale = 1./size
plt.figure(figsize=(scale * display_grid.shape[1],
                    scale * display_grid.shape[0]))
plt.title(layer_name)
plt.grid(False)
plt.imshow(display_grid, aspect='auto', cmap='viridis')
plt.show()

```









1.1 Some things to note

- This first layer is a collection of various edge detectors. At this stage the activations retain almost all of the information present in the picture.
- Going higher the activations become increasingly abstract. They are encoding things like 'cat ear' or 'cat eye'. Higher representation contain less information about the visual contents of the image, and increasingly more information about the class of the image
- The sparsity of the activations increases with the depth of the layer. In the first image all of the filters are activated by the input image. In later layers more and more filters are blank. This shows that the pattern encoded by the filter isn't found in the input image.