BST 261: Data Science II
Lecture 7

Convolutional Neural Networks (CNNs): Fine-tuning and Visualizing what CNNs Learn

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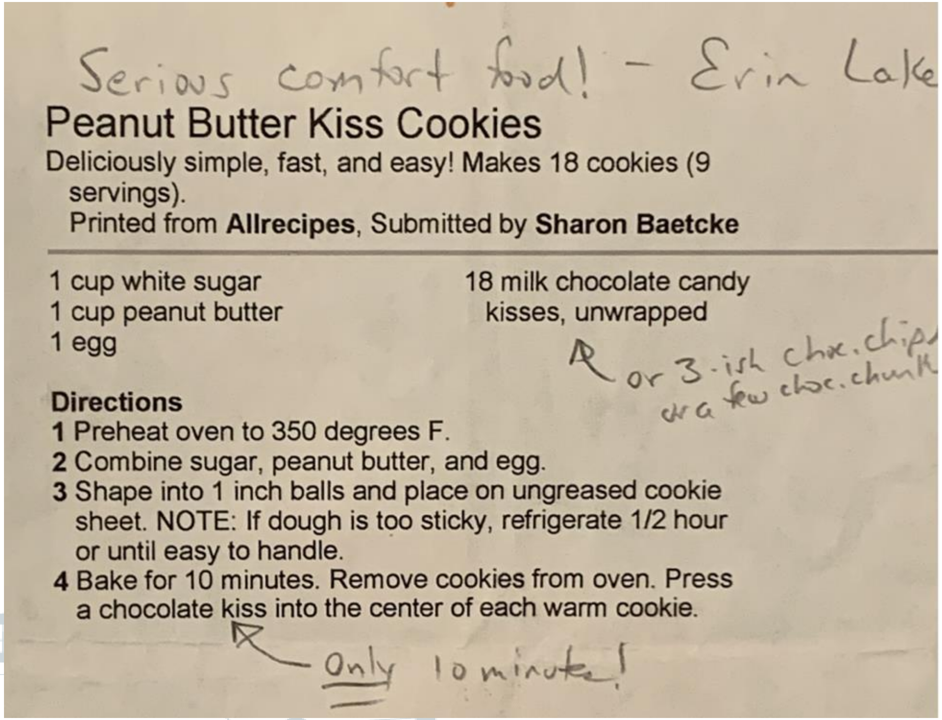
Spring 2

Recipe of the Day!

Brought to you by Dr. Erin Lake!



Serious comfort food! - Erin Lake

Peanut Butter Kiss Cookies

Deliciously simple, fast, and easy! Makes 18 cookies (9 servings).
Printed from **Allrecipes**, Submitted by **Sharon Baetcke**

1 cup white sugar
1 cup peanut butter
1 egg

18 milk chocolate candy kisses, unwrapped

or 3-ish choc.chips or a few choc.chunks

Directions

1 Preheat oven to 350 degrees F.
2 Combine sugar, peanut butter, and egg.
3 Shape into 1 inch balls and place on ungreased cookie sheet. NOTE: If dough is too sticky, refrigerate 1/2 hour or until easy to handle.
4 Bake for 10 minutes. Remove cookies from oven. Press a chocolate kiss into the center of each warm cookie.

Only 10 minutes!

Administrivia

Sign up for a group! (on Canvas)

April 19th, guest lecture by Jana Lipkova on Deep Learning for Pathology (over Zoom, but we’ll probably be here in person as well)

Internship opportunity at Mayo Clinic!

Opportunity to work in the AI division of the ENT Department at Mayo Clinic. (Best hospital in the world!)

Paid summer internship, available from mid-May to mid-August (flexible). Hybrid (in-person for a few weeks at Mayo Clinic, then remote the rest of the summer).

Mentorship team including Data Scientists/Informaticians/Industrial Engineers.

Operations research / industrial engineering / optimization / consulting experience valued.

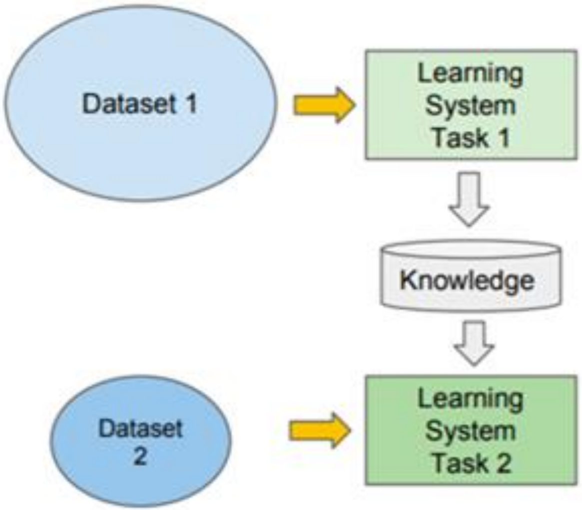
Work will focus on optimizing operating room planning, with opportunities for several side projects including CNN development, scientific publications, etc.

If interested email CV with a cover email to santiagoromerobrufau@hsph.harvard.edu

Fine-tuning

Transfer Learning

- Learning of a new tasks relies on the previous learned tasks:
  - Learning process can be faster, more accurate and/or need less training data



Fine-tuning

- **Fine-tuning** consists of unfreezing a few of the top layers of a frozen model base used for feature extraction, and jointly training both the newly added part of the model (the dense layers used to classify), and these top unfrozen layers
  - This slightly adjusts the more abstract representations of the pretrained model in an effort to make them more relevant for the problem at hand
  - **It is only possible to fine-tune the top layers of the convolutional base**, and only after the added classifier layers have been trained

Steps

- Add your custom network on top of an obtained pretrained base network
- Freeze the base network
- Train the part you added
- Unfreeze some layers in the base network
- Jointly train both the unfrozen layers and top layers

We did the first 3 steps when we did feature extraction

Fine-tuning

- In practice it is good to unfreeze 2-3 top layers of the base

- The more layers you unfreeze, the more parameters that need to be trained, and the higher the risk of overfitting (longer to train as well)

- Note that **earlier layers in the base encode more generic, reusable features, and layers higher up encode more specialized features**. Thus, it's more useful to fine-tune layers higher up in the base

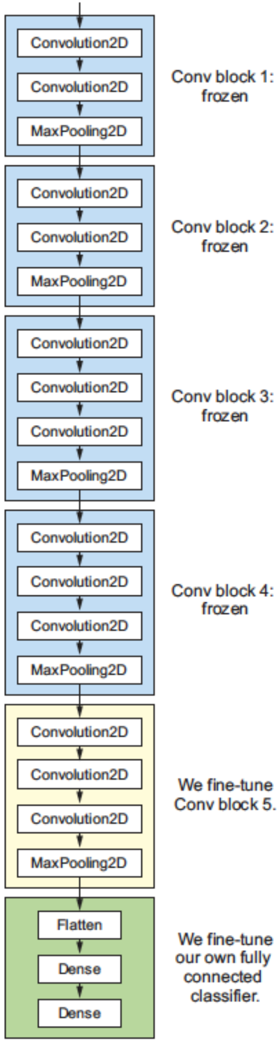


Figure 5.19 Fine-tuning the last convolutional block of the VGG16 network

We only unfreeze and fine-tune the last block of layers.

```
conv_base.trainable = True

set_trainable = False
for layer in conv_base.layers:
    if layer.name == 'block5_conv1':
        set_trainable = True
    if set_trainable:
        layer.trainable = True
    else:
        layer.trainable = False
```

We need to say which pretrained blocks (and layers) should be kept frozen (make untrainable) and which one we want to unfreeze (make trainable).

```
model.compile(loss='binary_crossentropy',
              optimizer=tf.keras.optimizers.RMSprop(lr=1e-5),
              metrics=['accuracy'])

history = model.fit(
      train_generator,
      steps_per_epoch=100,
      epochs=100,
      validation_data=validation_generator,
      validation_steps=50)
```

Visualizing what CNNs Learn

Visualizing What CNNs Learn

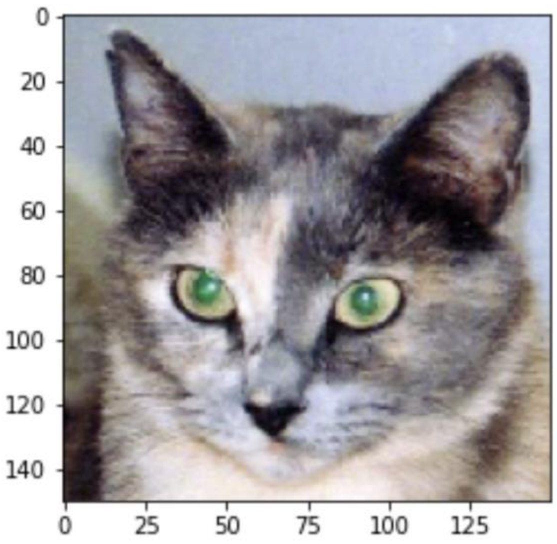
- It is possible to visualize and interpret the learned representations of your CNN
- 3 of the most useful visualizations are:
    - **Visualizing intermediate activations**
        - Useful for understanding how successive layers transform their input and getting an idea of the meaning of individual filters
    - **Visualizing filters**
        - Useful for understanding what visual pattern or concept each filter in a CNN is receptive to
    - **Visualizing heatmaps** of class activations in an image
        - Useful for understanding which parts of an image were identified as belonging to a given class

Visualizing Intermediate Outputs

Visualizing Intermediate Outputs

- [Colab notebook]
- Display the feature maps that are output by various convolution and pooling layers
- You should look at each channel separately

```
img_path = os.path.join(test_dir, 'cats/cat.1700.jpg')

# We preprocess the image into a 4D tensor
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)
# Remember that the model was trained on inputs
# that were preprocessed in the following way:
img_tensor /= 255.

# Its shape is (1, 150, 150, 3)
print(img_tensor.shape)
```



Visualizing Intermediate Outputs

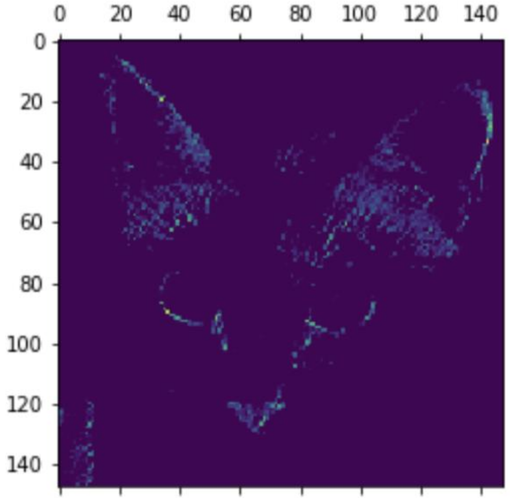
```python
from keras import models

# Extracts the outputs of the top 8 layers:
layer_outputs = [layer.output for layer in model.layers[:8]]
# Creates a model that will return these outputs, given the model input:
activation_model = tf.keras.models.Model(inputs=model.input, outputs=layer_outputs)

# This will return a list of 5 Numpy arrays:
# one array per layer activation
activations = activation_model.predict(img_tensor)

first_layer_activation = activations[0]

import matplotlib.pyplot as plt

plt.matshow(first_layer_activation[0, :, :, 11], cmap = 'viridis')
plt.show()
```

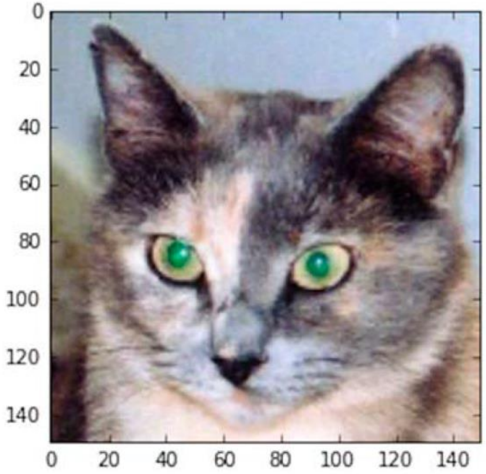
This will save the outputs or “activations” for each filter in every layer

Let’s look at the filters in the first layer

We’ll visualize what patterns this filter is picking up

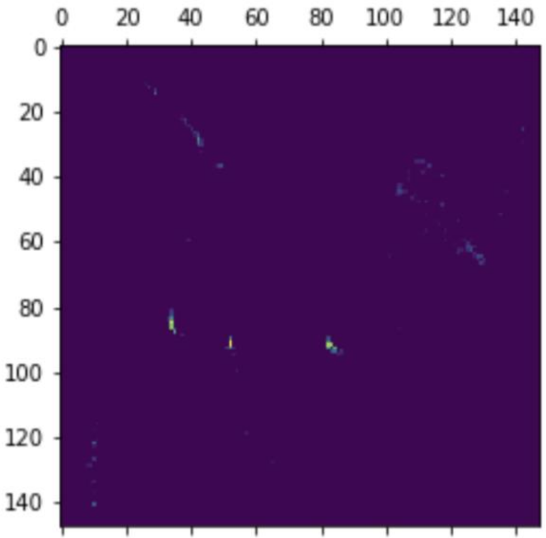
Visualizing Intermediate Outputs

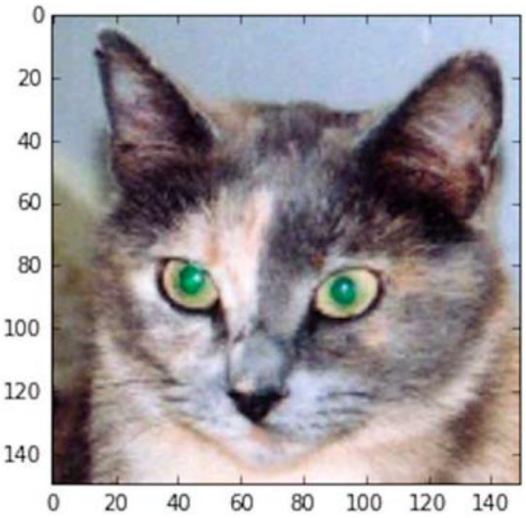




Diagonal/rounded edges filter?

Visualizing Intermediate Outputs

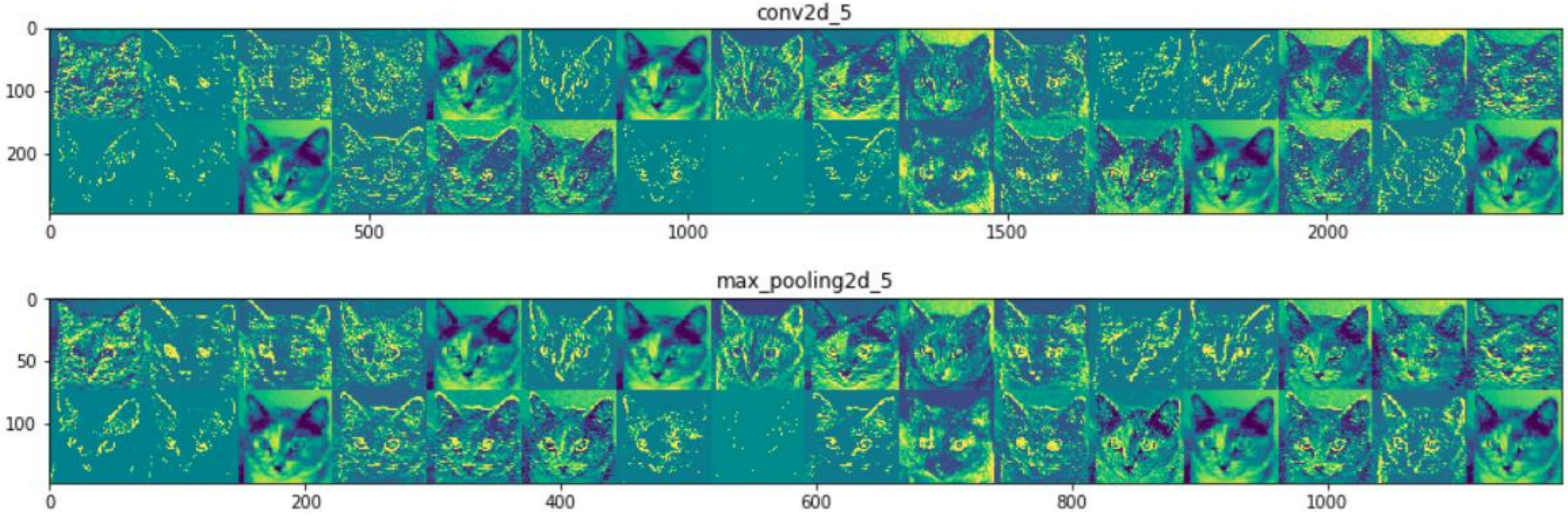




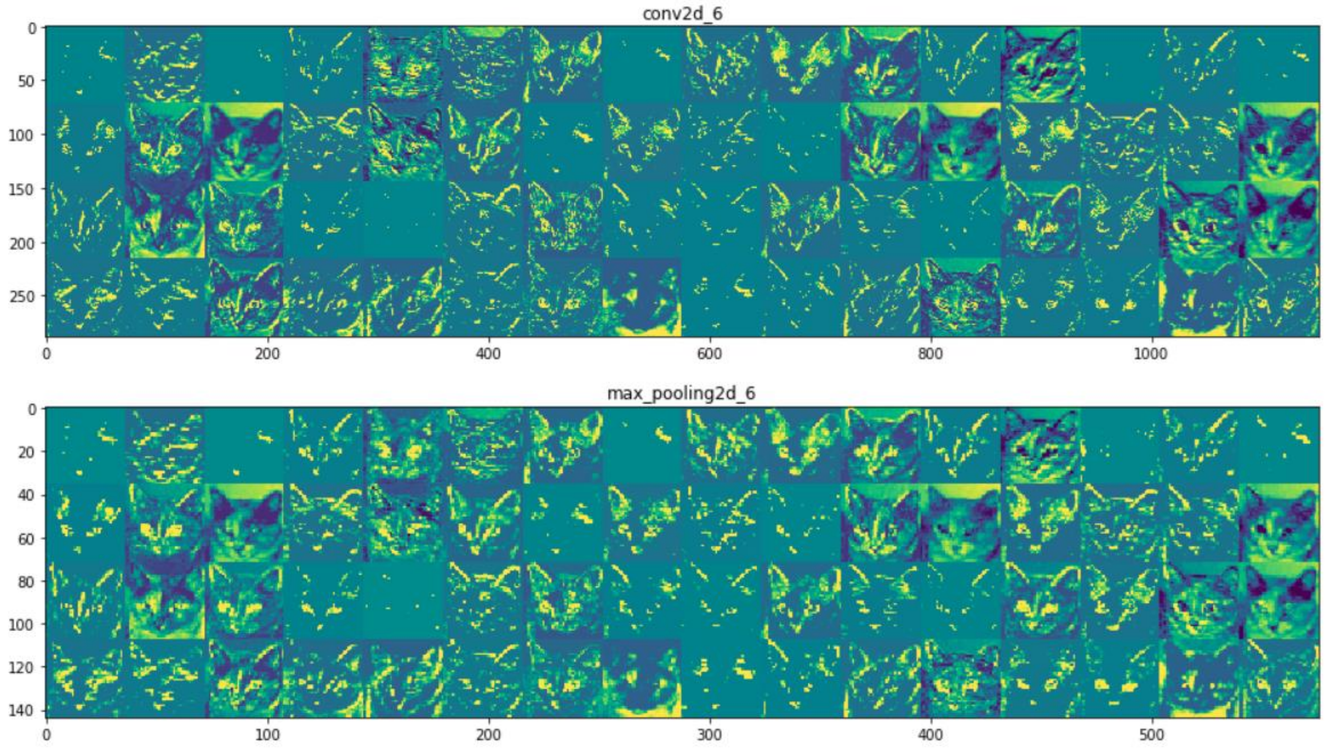
"Yellow edges" filter?

Visualizing Intermediate Outputs

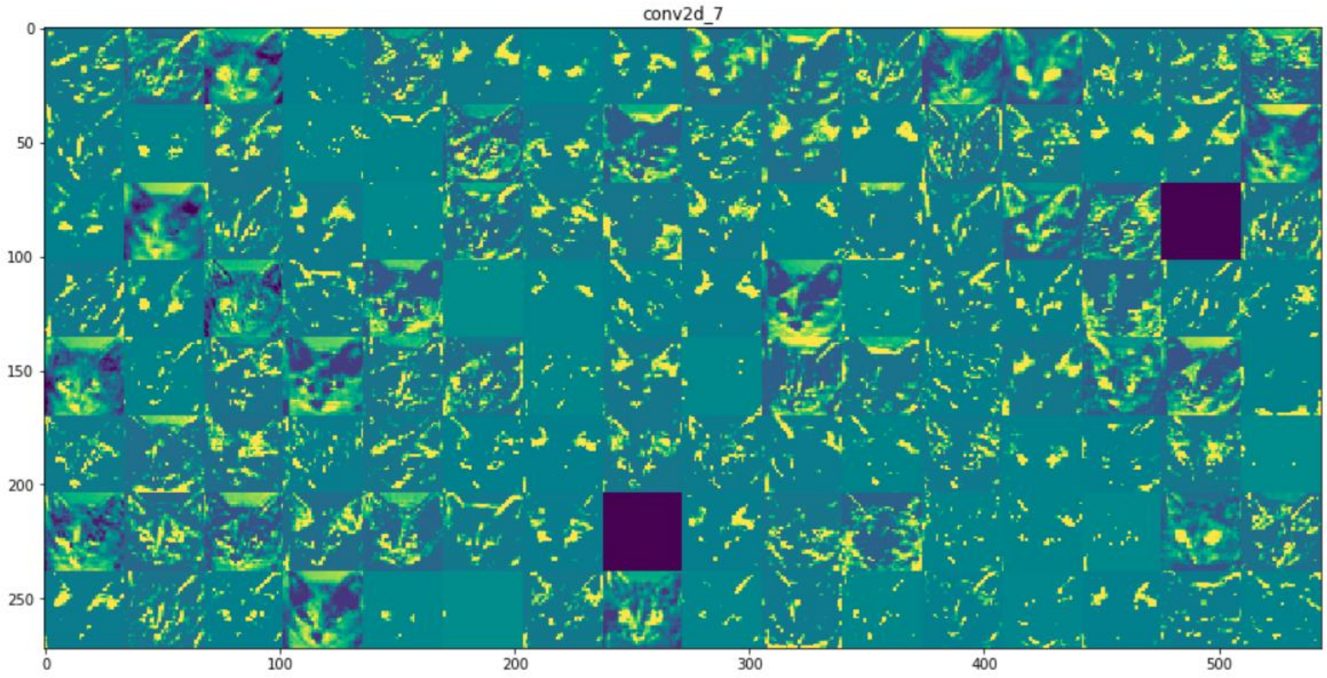
- We can also look at what pattern each filter in every layer is picking up on



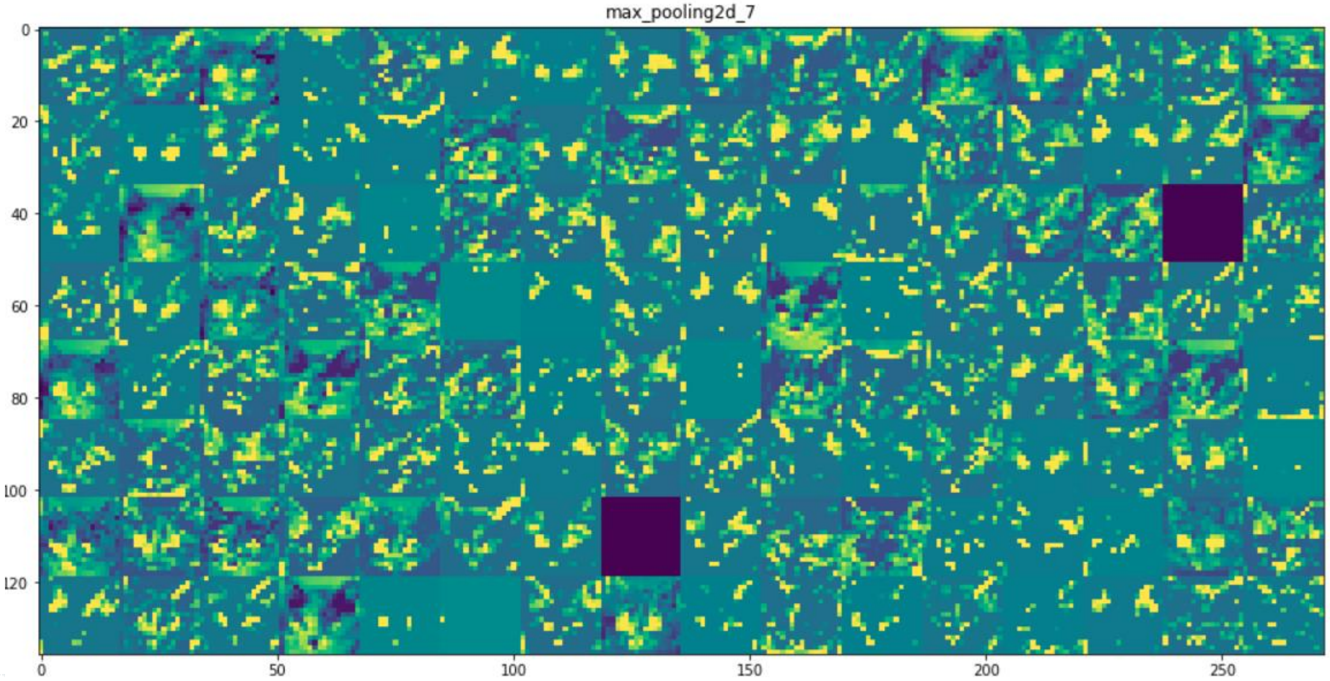
Visualizing Intermediate Outputs



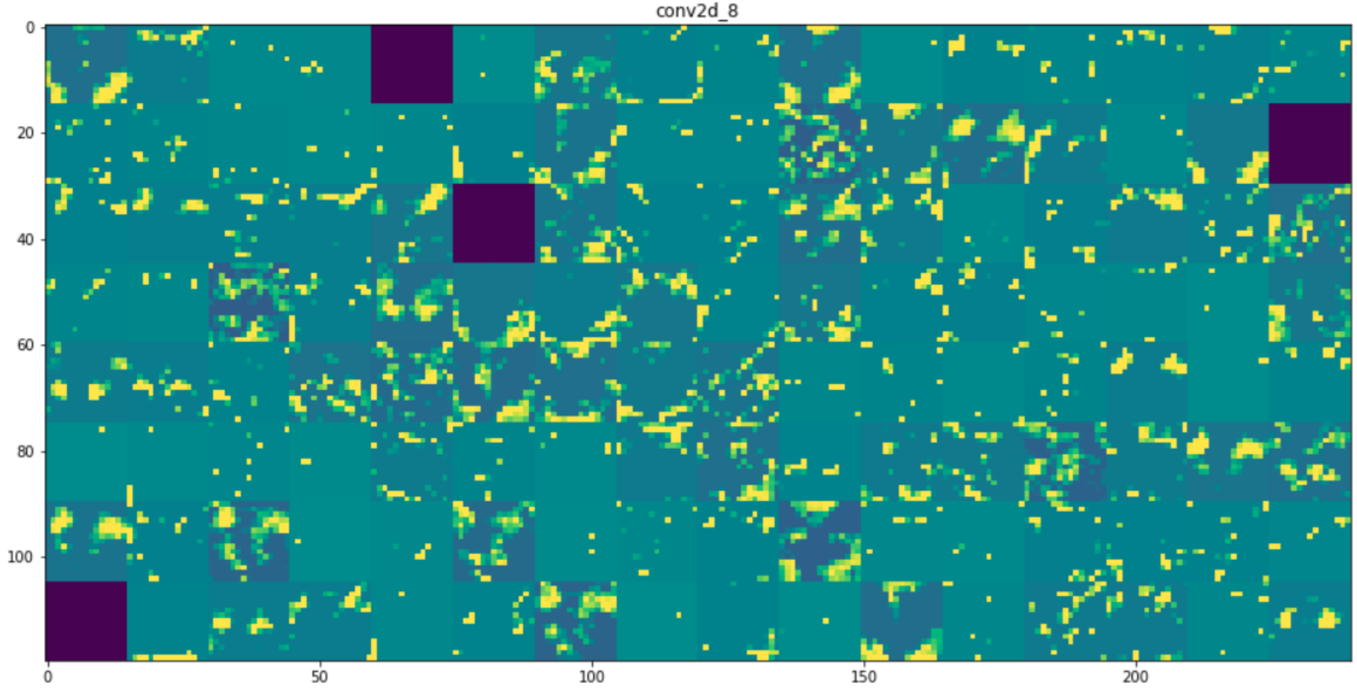
Visualizing Intermediate Outputs



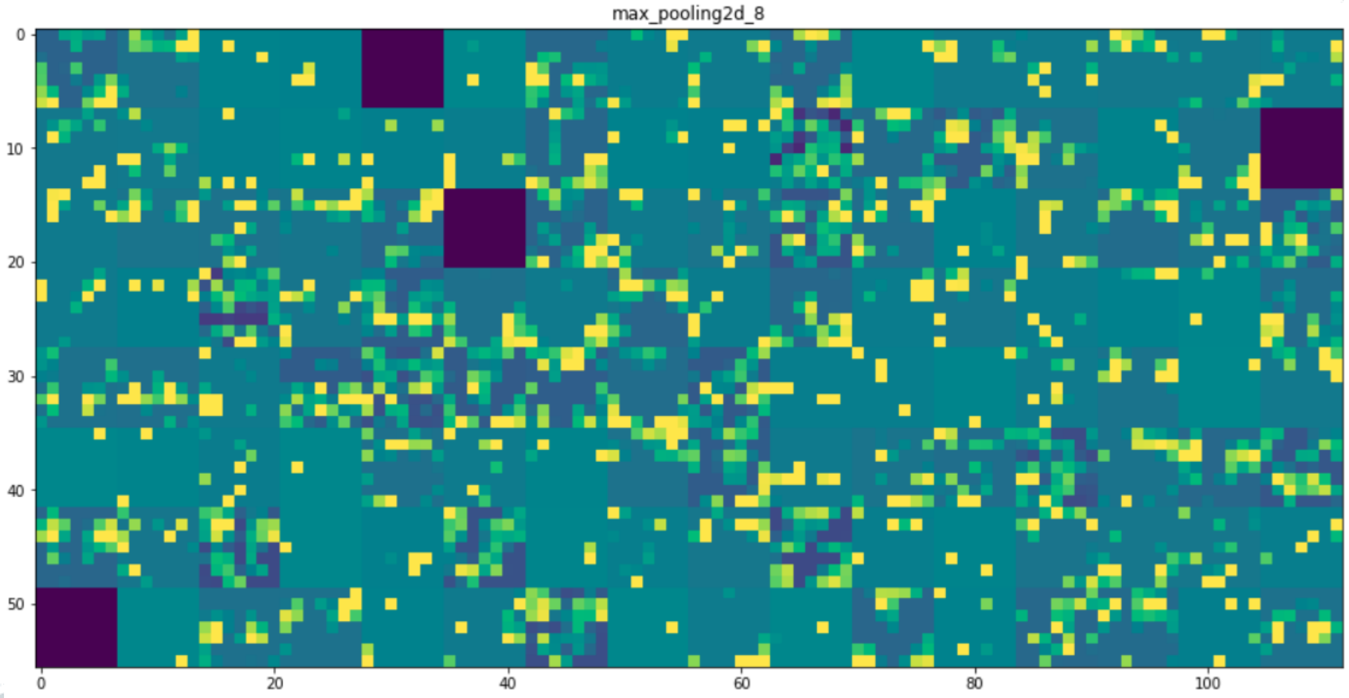
Visualizing Intermediate Outputs



Visualizing Intermediate Outputs



Visualizing Intermediate Outputs



Visualizing Intermediate Outputs

- The first layer acts as a collection of edge detectors
- The later layers contain more abstract activations that are less visually interpretable
- Deeper layers carry less information about visual contents of the image, and more information related to the class of the image

Visualizing Intermediate Outputs

- The sparsity of the activations increases with the depth of the layer

- Blank activations mean the pattern encoded by that filter isn’t found in the input image

Visualizing Filters

Visualizing Filters

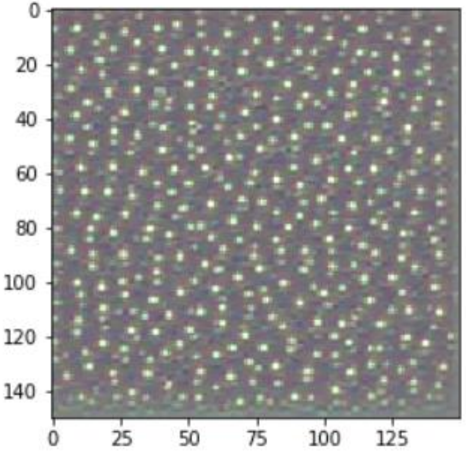
- Shows the visual pattern that each filter is meant to respond to
- This is done with gradient ascent in input space: applying gradient descent to the value of the input image to maximize the response of a specific filter, starting with a blank input image
- The resulting image will be one that the chosen filter is maximally responsive to

Visualizing Filters

- Steps:
  - Build a loss function that maximizes the value of a given filter in a given convolution layer
  - Use stochastic gradient descent to adjust the values of the input image in order to maximize the activation value

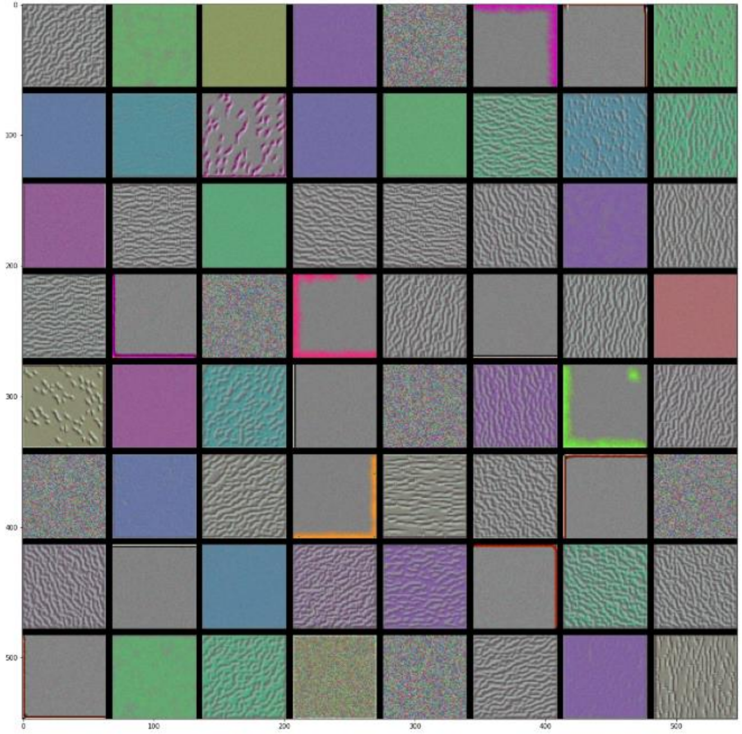
Visualizing Filters

The “polka dots” filter



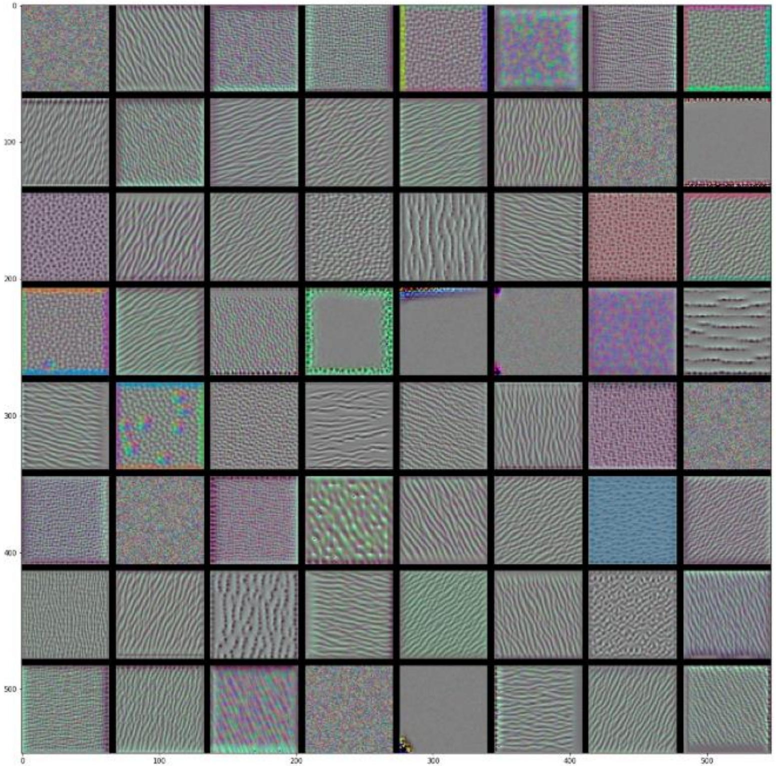
Visualizing Filters

- Filters from the 1st convolution block



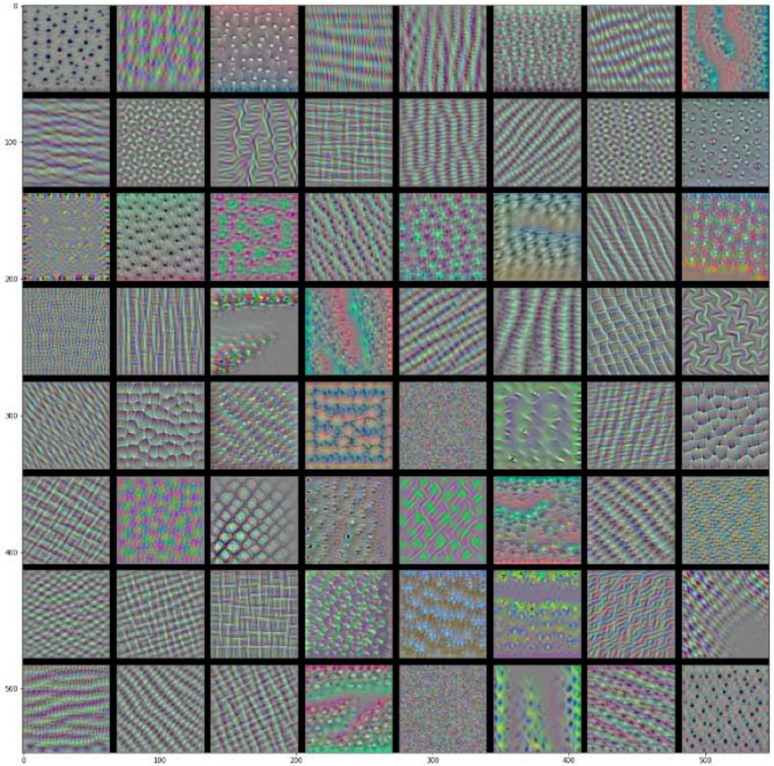
Visualizing Filters

- Filters from the second convolution block



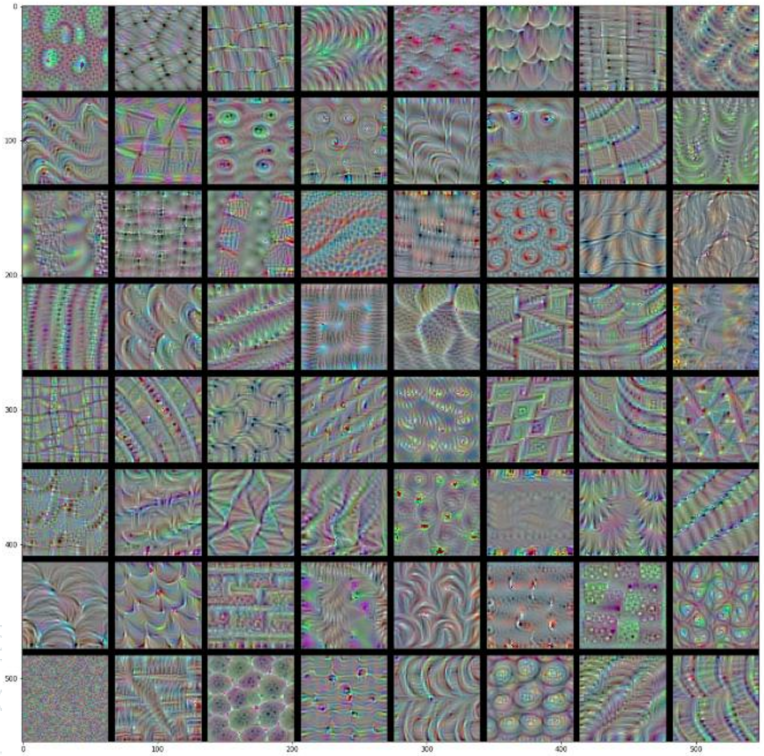
Visualizing Filters

- Filters from the third convolution block



Visualizing Filters

- Filters from the fourth convolution block



Inceptionism

https://ai.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html

The idea is to select a layer, and tell it to amplify what it detects

Visualizing Filters

- The filters get increasingly complex and refined as you go deeper in the model

- The filters from the first layer encode single directional edges and colors

- The next set of filters encode simple textures made from combinations of edges and colors

- The filters in later layers resemble textures found in natural images - eyes, feathers, leaves, etc.

Visualizing Heatmaps of Class Activation

Visualizing Heatmaps of Class Activation

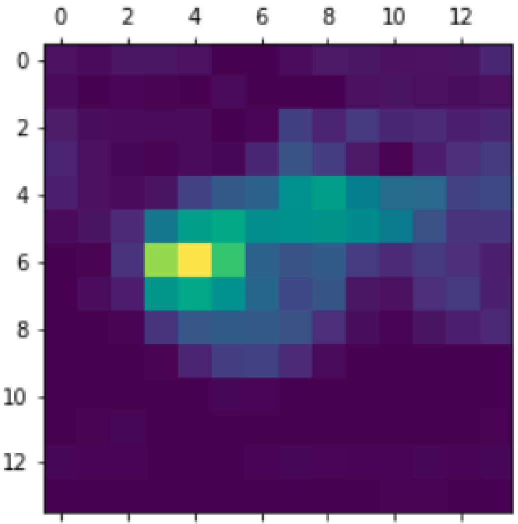
- Great for understanding which parts of an image led the network to its final classification
- Helpful for debugging the decision process
- This also allows you to locate specific objects in an image
- Called class activation map (CAM) visualization
- A class activation heatmap is a 2D grid of scores associated with a specific output class, computed for every location in an input image, indicating how important each location is with respect to the class under consideration

Visualizing Heatmaps of Class Activation

- When we run this image of African elephants through the VGG16 network, the following are the top 3 predictions:
  - African elephant (with 92.5% probability)
  - Tusker (with 7% probability)
  - Indian elephant (with 0.4% probability)

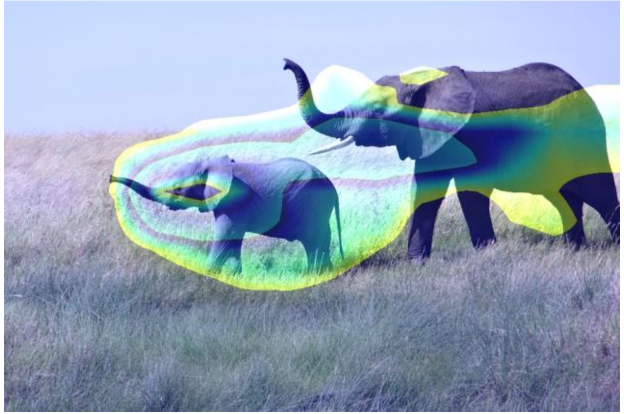
Visualizing Heatmaps of Class Activation

- Lighter colors (yellow, green) correspond to greater activation and darker colors (blue, purple) to less or no activation, allowing us to see which parts of the image were used for the classification



Visualizing Heatmaps of Class Activation

- We can then overlap these activations with the original image to see exactly what and where in the image was used in classification



Visualizing Heatmaps of Class Activation

- When we run this image of a Turkish Shepherd through the VGG16 network, the following are the top 3 predictions:

Visualizing Heatmaps of Class Activation

- When we run this image of a Turkish Shepherd through the VGG16 network, the following are the top 3 predictions:
  - Saluki (with 65.9% probability)

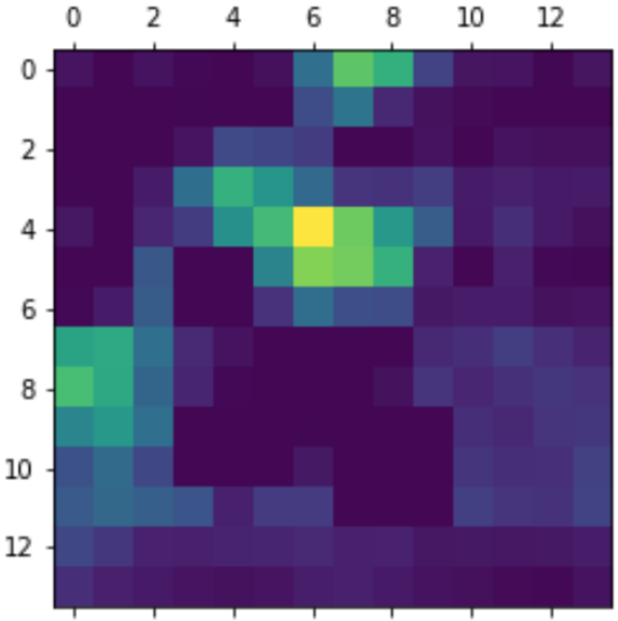
Visualizing Heatmaps of Class Activation

- When we run this image of a Turkish Shepherd through the VGG16 network, the following are the top 3 predictions:
  - Saluki (with 65.9% probability)
  - Whippet (with 6.3% probability)

Visualizing Heatmaps of Class Activation

- When we run this image of a Turkish Shepherd through the VGG16 network, the following are the top 3 predictions:
  - Saluki (with 65.9% probability)
  - Whippet (with 6.3% probability)
  - Labrador retriever (with 3.9% probability)

Visualizing Heatmaps of Class Activation



Visualizing Heatmaps of Class Activation

Visualizing Heatmaps of Class Activation

- When we run this image of a Harvard gate through the VGG16 network, the following are the top 3 predictions:

Visualizing Heatmaps of Class Activation

- When we run this image of a Harvard gate through the VGG16 network, the following are the top 3 predictions:
  - Prison (with 41.3% probability)

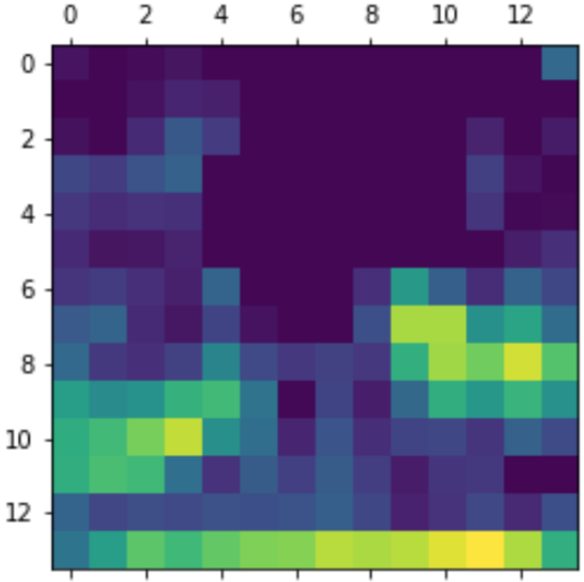
Visualizing Heatmaps of Class Activation

- When we run this image of a Harvard gate through the VGG16 network, the following are the top 3 predictions:
  - Prison (with 41.3% probability)
  - Fire screen (with 10.6% probability)

Visualizing Heatmaps of Class Activation

- When we run this image of a Harvard gate through the VGG16 network, the following are the top 3 predictions:
    - Prison (with 41.3% probability)
    - Fire screen (with 10.6% probability)
    - Monastery (with 7.7% probability)

Visualizing Heatmaps of Class Activation



Visualizing Heatmaps of Class Activation

Transfer Learning

- Learning of a new tasks relies on the previous learned tasks:
  - Learning process can be faster, more accurate and/or need less training data