CNN Visualizations

Seoul AI Meetup

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Content

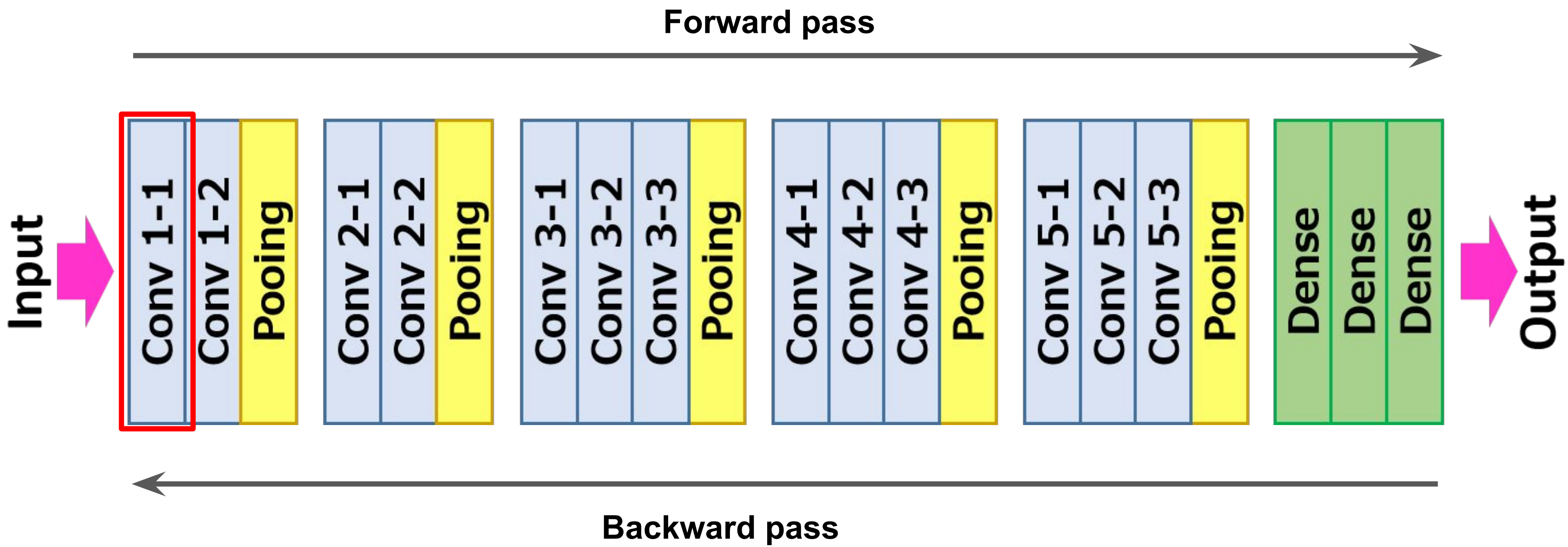
1. Visualization of convolutional weights from the **first layer**
2. Visualization of patterns learned by **higher layers**
3. Weakly Supervised Object Localization

Motivation

- Understand better dynamics of CNN
- Debugging of network
- Verification of network decisions

Visualization of convolutional weights from the first layer

VGG-16

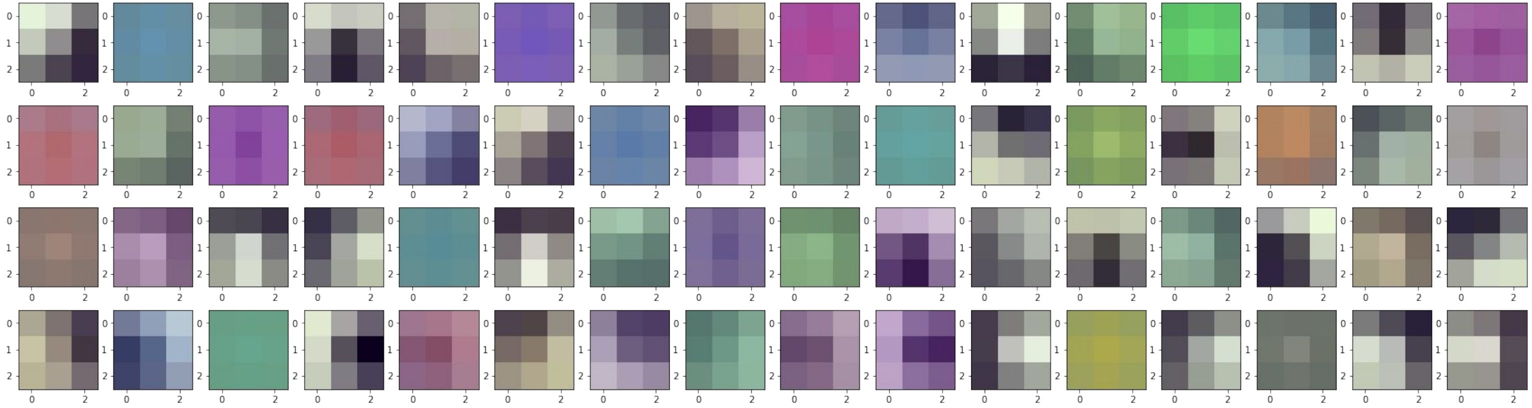


- compute gradients
- update weights

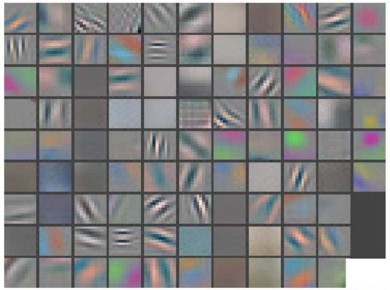
image from http://www.renom.jp/

conv1_1

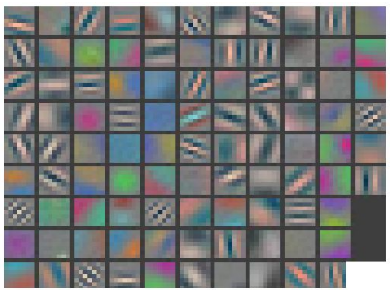
3x3



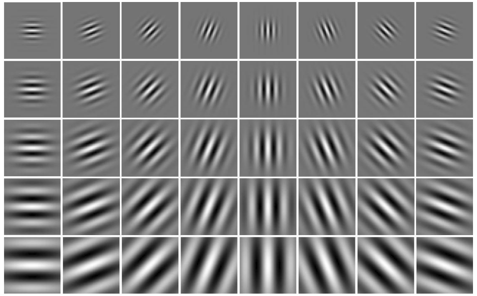
11x11



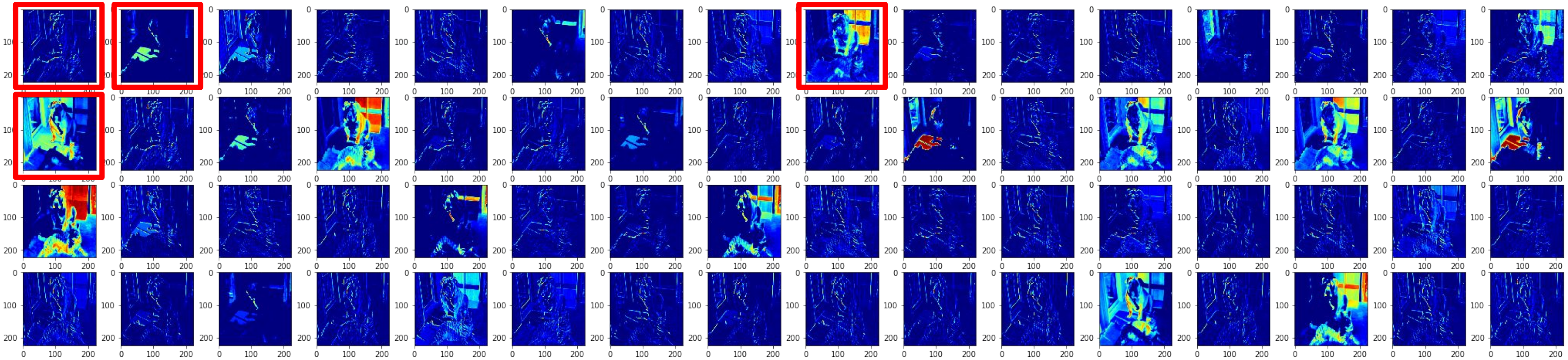
7x7

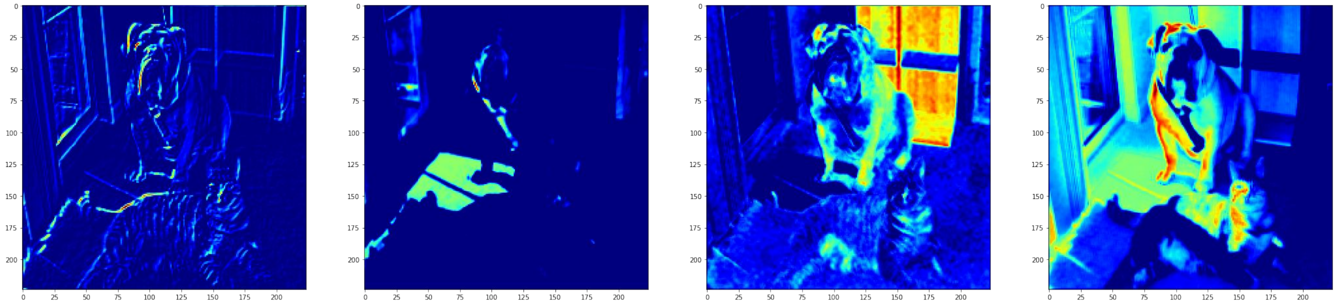


Gabor filters (~1980)



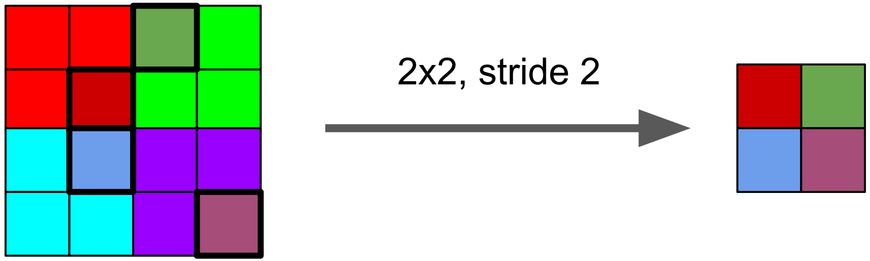
conv1_1 output





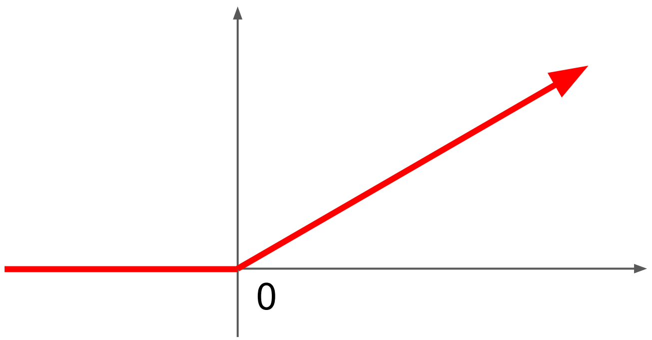
Visualization of patterns learned by higher layers

Max pooling



Rectified Linear Unit (ReLU)

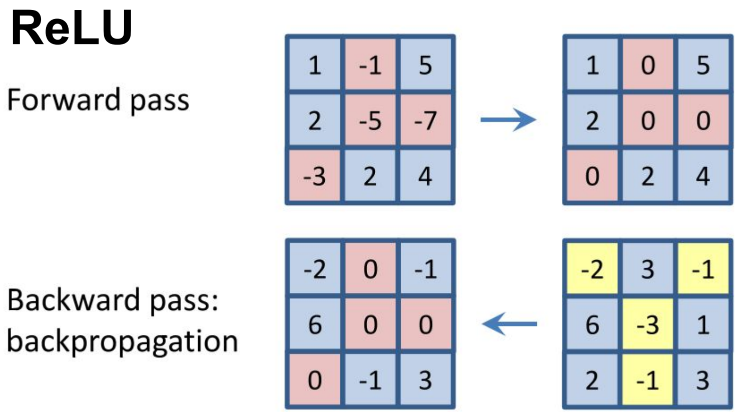
```
class ReLU(object):
  def _init_(self):
    self.input, self.output = None, None
    self.bottom, self.up = None, None
    self.grad = None

  def forward(self, input):
    self.input = input
    self.output = np.maximum(0.0, input)

  def backward(self):
    self.grad = self.up.grad.copy()
    self.grad[self.input <= 0.0] = 0.0
```

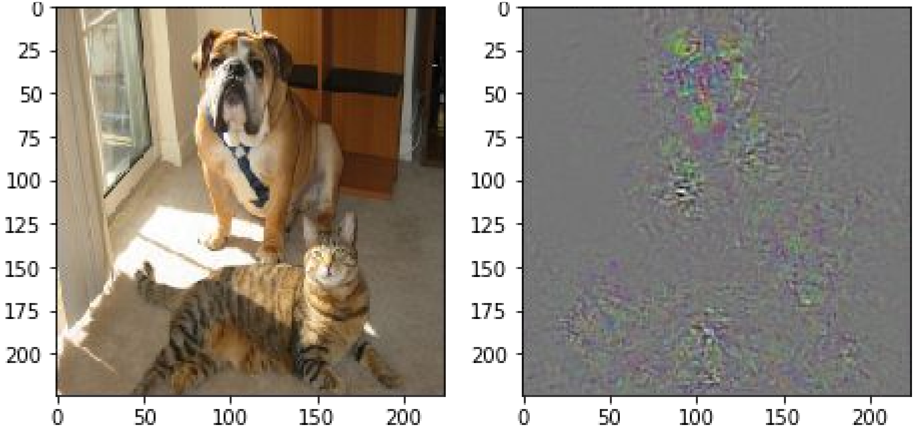


Backpropagation

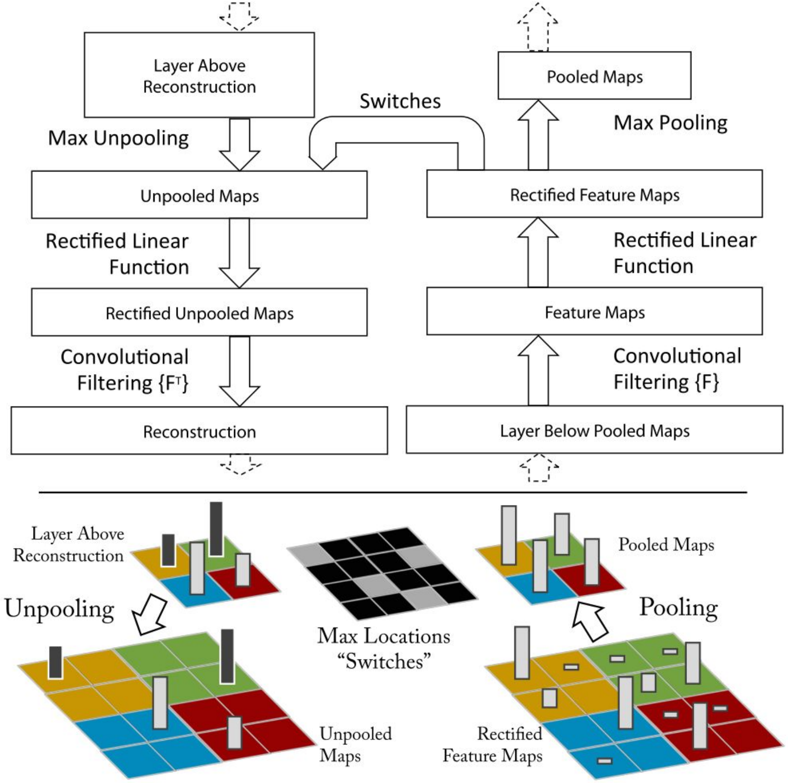
An alternative way of visualizing the part of an image that most activates a given neuron is to use a simple backward pass of the activation of a single neuron after a forward pass through the network; thus computing the gradient of the activation w.r.t. the image.

$$\frac{\partial cost}{\partial image}$$





Deconvnet



A deconvnet can be thought of as a convnet model that uses the same components (filtering, pooling) but in reverse, so **instead of mapping pixels to features does the opposite**.

Figure 1. Top: A deconvnet layer (left) attached to a convnet layer (right). The deconvnet will reconstruct an approximate version of the convnet features from the layer beneath. Bottom: An illustration of the unpooling operation in the deconvnet, using *switches* which record the location of the local max in each pooling region (colored zones) during pooling in the convnet.

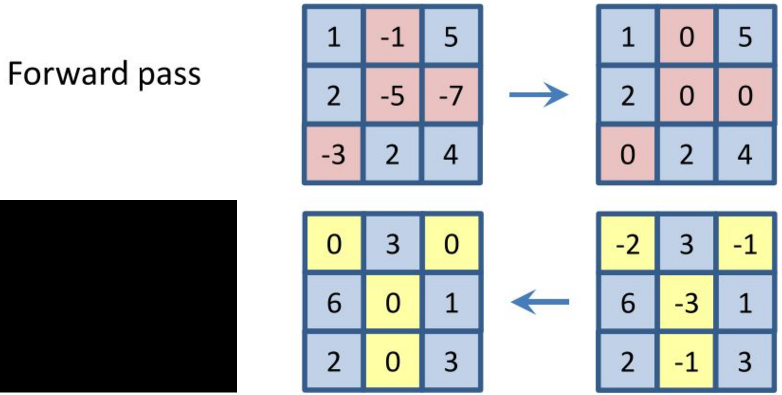
diagram from Visualizing and Understanding Convolutional Networks arXiv:1311.2901v3

Deconvnet

The “**deconvolution” is equivalent to a backward pass** through the network, except that when propagating through a nonlinearity, its **gradient is solely computed based on the top gradient signal, ignoring the bottom input**.

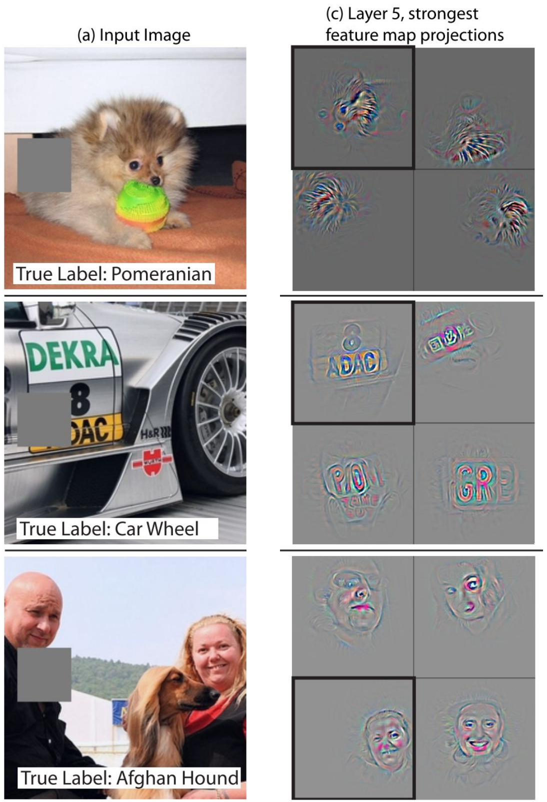
In case of the ReLU nonlinearity this amounts to setting to zero certain entries based on the top gradient.

ReLU




```
def backward(self):
  self.grad = self.up.grad.copy()
  self.grad[self.up.grad <= 0.0] = 0.0
```

Deconvnet



(c) a visualization of this feature map projected down into the input image (black square), along with visualizations of this map from other images.

figure from Visualizing and Understanding Convolutional Networks

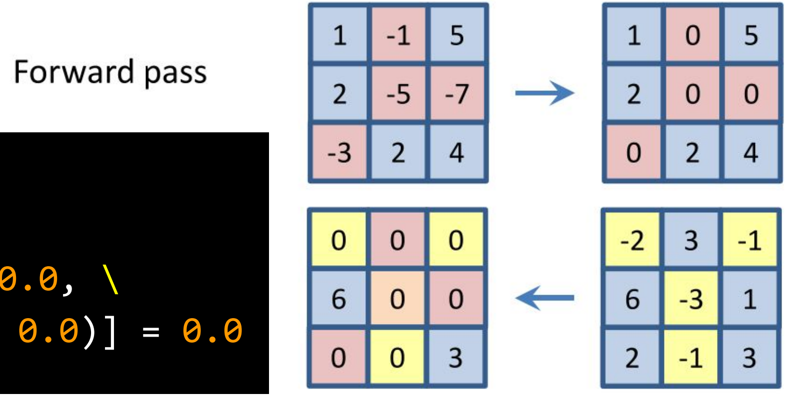
Guided Backpropagation

Combination of Deconvolution and Backpropagation approach.

Rather than masking out values corresponding to **negative entries** of the top gradient ('deconvnet') or bottom data (backpropagation), we mask out the values for which **at least one of these values is negative.**

ReLU

```
def backward(self):
  self.grad = self.up.grad.copy()
  self.grad[np.logical_or(self.grad <= 0.0, \
                          self.input <= 0.0)] = 0.0
```



Guided Backpropagation

Prevents backward flow of negative gradients, corresponding to the neurons which decrease the activation of the higher layer unit we aim to visualize.

Works well **without switches**.

The **bottom-up signal** in form of the pattern of bottom ReLU activations **substitutes the switches**.

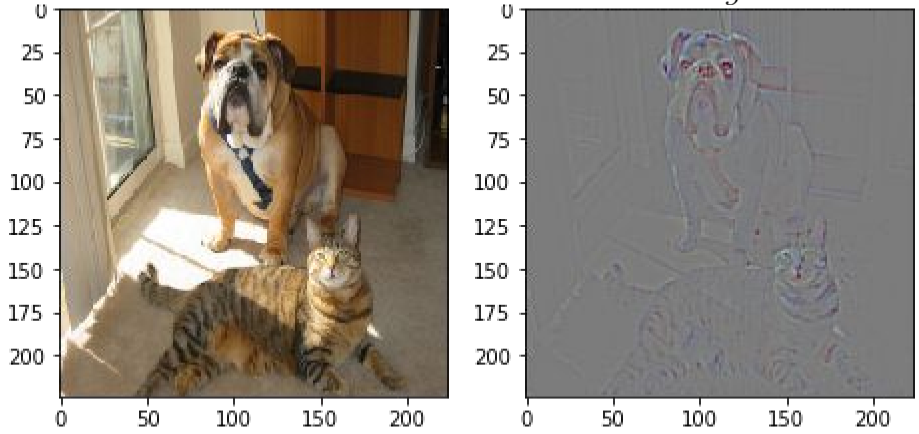
https://gist.github.com/falcondai/561d5eec7fed9ebf48751d124a77b087

Guided Backpropagation Tensorflow

```
import tensorflow as tf

from tensorflow.python.framework import ops
from tensorflow.python.ops import gen_nn_ops

@ops.RegisterGradient("GuidedRelu")
def _GuidedReluGrad(op, grad):
  return tf.where(grad > 0.0,
                  gen_nn_ops._relu_grad(grad, op.outputs[0]),
                  tf.zeros(grad.get_shape()))

g = tf.Graph()
with g.as_default():
  with g.gradient_override_map({"Relu": "GuidedRelu"}):
    M = model()  # example
```

Guided Backpropagation

$$\frac{\partial cost}{\partial image}$$



Weakly Supervised Object Localization

Occlusion sensitivity

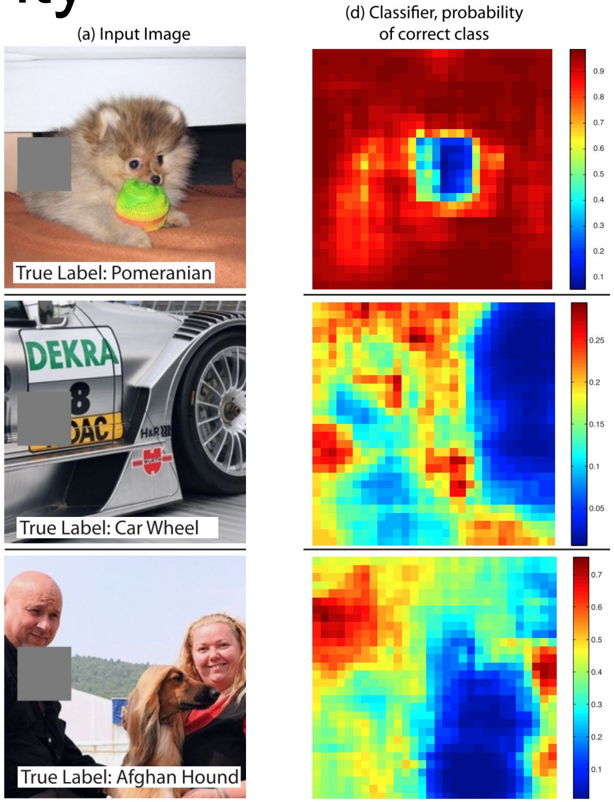
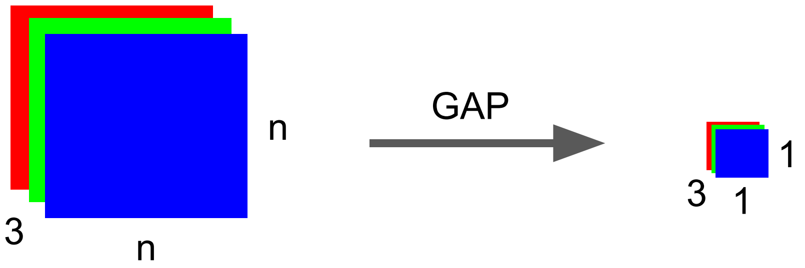


image from Visualizing and Understanding Convolutional Networks

Class Activation Mapping (CAM)

- "A class activation map for a particular category indicates the discriminative image regions used by the CNN to identify that category."
- Top-5 error for object localization on ILSVRC 2014
  - CAM 37.1%
  - VGG 25.3 %
  - Cldi-KAIST 46.8%

Global Average Pooling (GAP) layer



Class Activation Mapping (CAM)

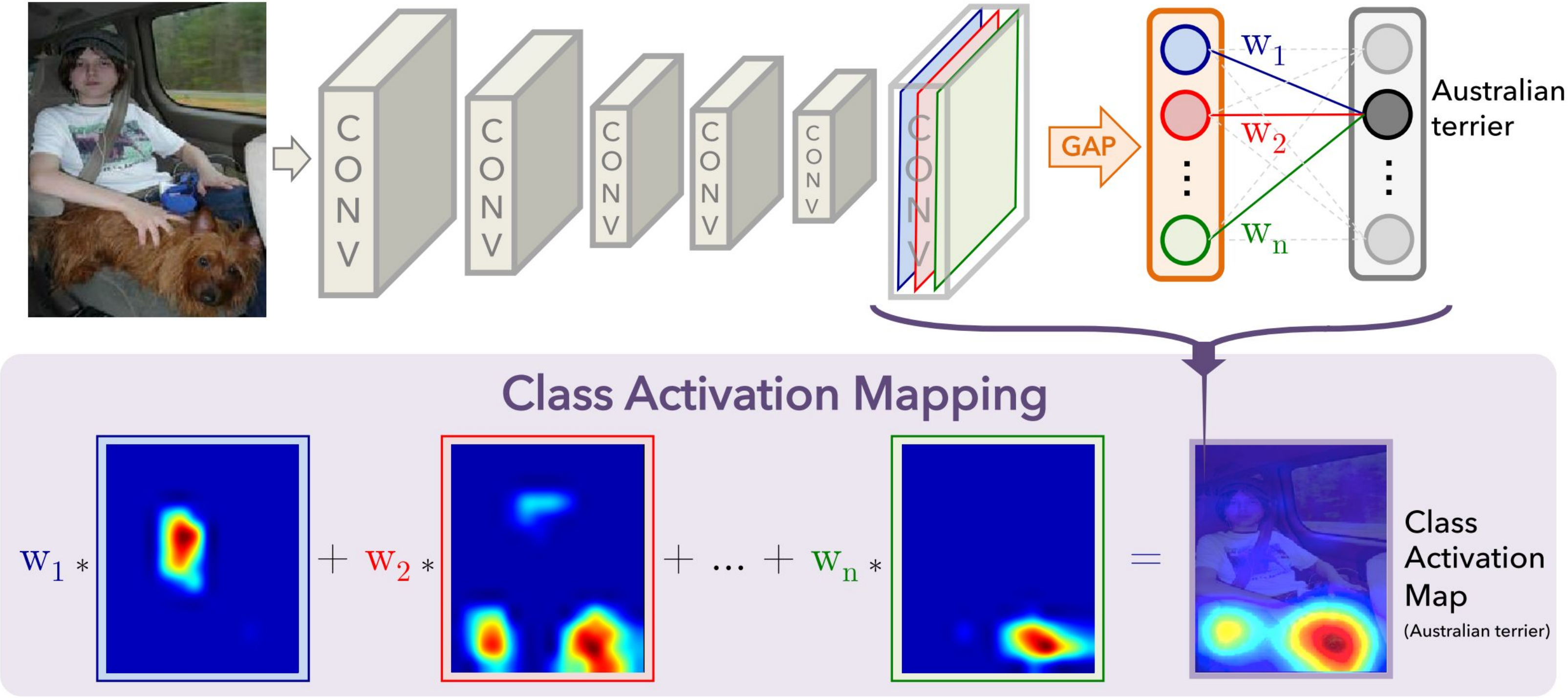


diagram from Learning Deep Features for Discriminative Localization

Class Activation Mapping (CAM)

- Advantages
  - Simple way of obtaining localization per class
- Disadvantages
  - Need to be retrained if network is lacking GAP layer.
  - (if we want to apply to VGG-16 we have to remove 2 fully-connected layers)
- Details
  - **Does not average, just sum, could be a problem if directly connected to softmax** (http://seoulai.com/Knowledge_Distillation_Temperature)

Grad-CAM

- Another “visual explanation” method
- Advantages
  - No need for architectural changes or re-training
  - Applicable to many types on networks
    - CNNs with fully-connected layers (e.g. VGG)
    - CNNs used for structured outputs (e.g. captioning)
    - CNNs used in tasks with multi-modal inputs (e.g. VQA) or reinforcement learning
- Disadvantages
  - Need to compute gradients up to feature map of interest

Grad-CAM

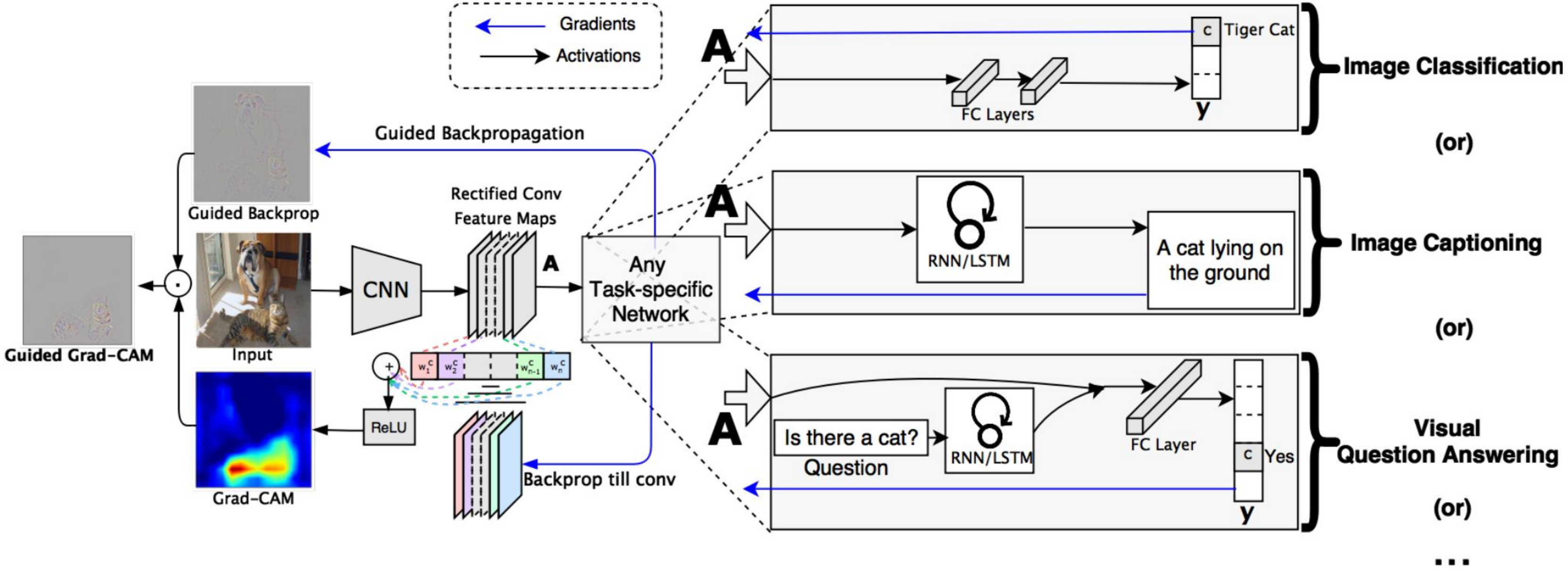


diagram from Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization

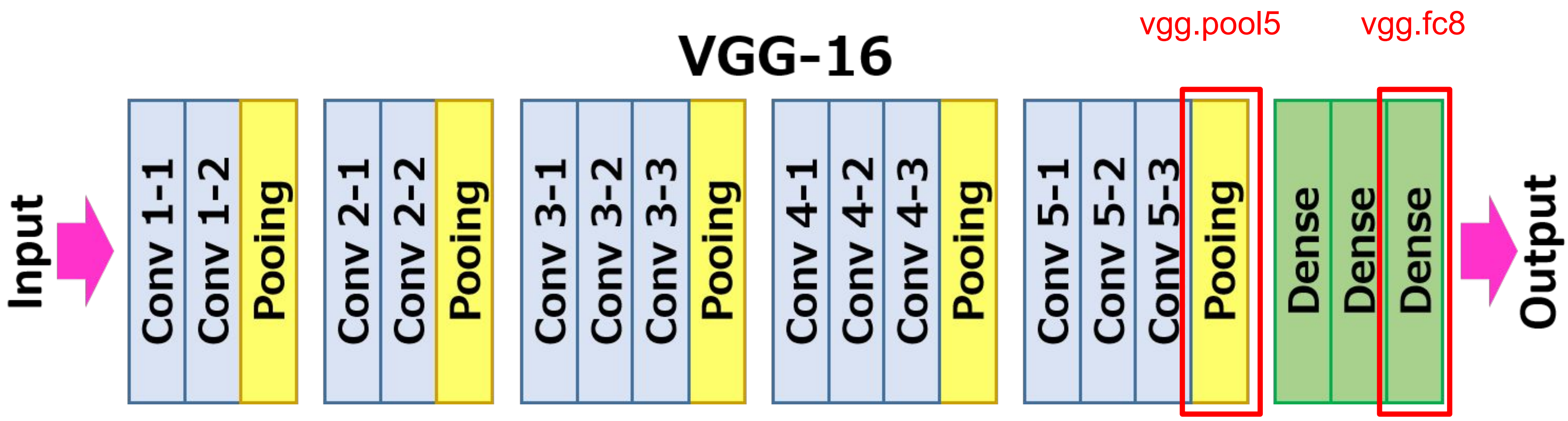
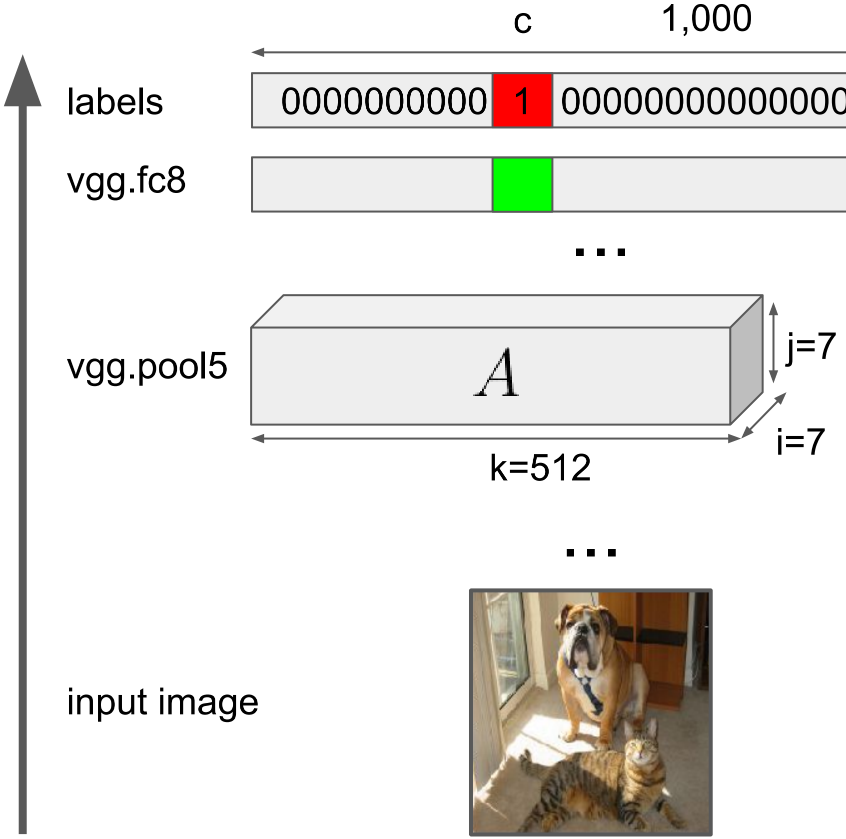


image from http://www.renom.jp/

Forward



Backward

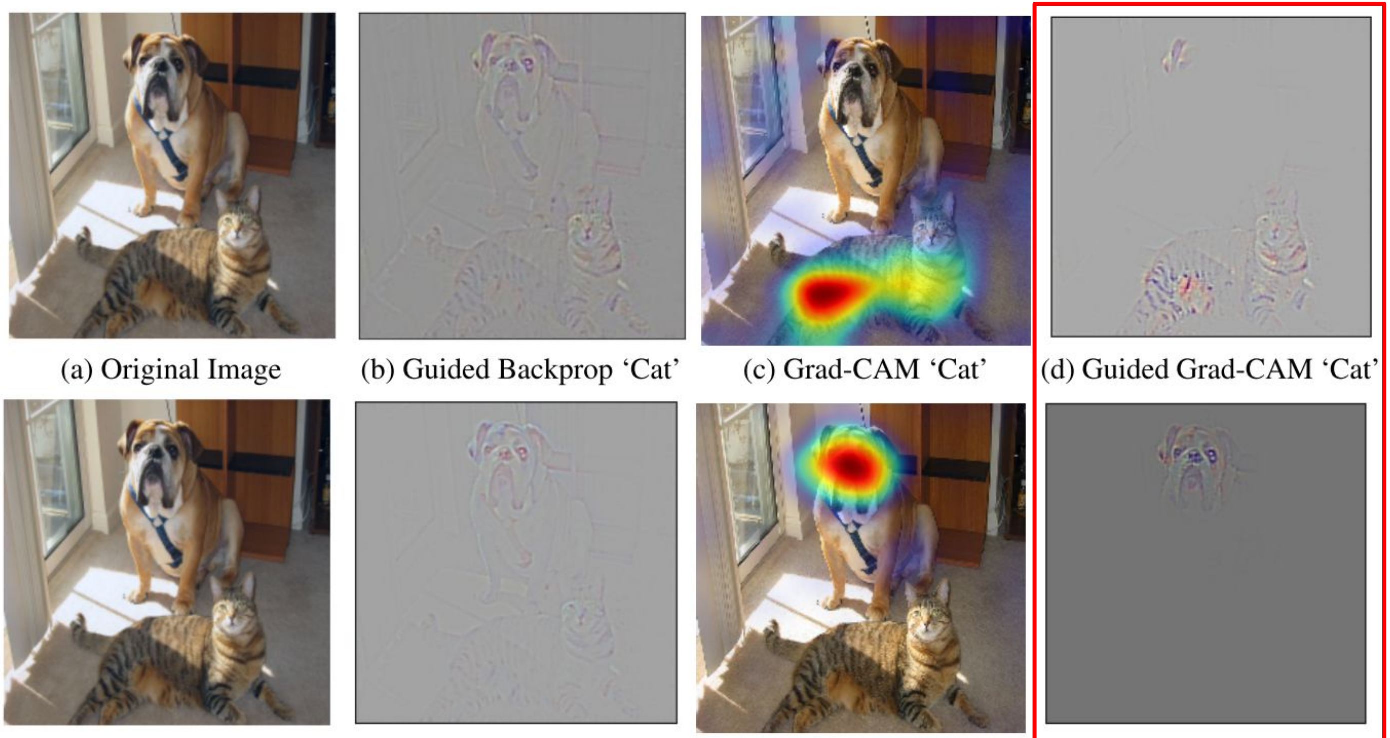
y^c = 1 *

$$\alpha_k^c = \overbrace{\frac{1}{Z}\sum_i \sum_j}^{\text{global average pooling}} \underbrace{\frac{\partial y^c}{\partial A_{ij}^k}}_{\text{gradients via backprop}}$$

$$L^c_{\text{Grad-CAM}} = ReLU \underbrace{\left(\sum_k \alpha_k^c A^k\right)}_{\text{linear combination}}$$

Keep only features that have positive influence.

Guided Grad-CAM



(a) Original Image (b) Guided Backprop 'Cat' (c) Grad-CAM 'Cat' (d) Guided Grad-CAM 'Cat'

(g) Original Image (h) Guided Backprop 'Dog' (i) Grad-CAM 'Dog' (j) Guided Grad-CAM 'Dog'

figure from Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization

References

Deconvnet
Visualizing and Understanding Convolutional Networks, Matthew D. Zeiler and Rob Fergus, 2013

Guided Backpropagation
Striving For Simplicity: The All Convolutional Net, Jost Tobias Springenberg et al., 2015

CAM
Learning Deep Features for Discriminative Localization, Bolei Zhou et al., 2015

Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization, Ramprasaath R. Selvaraju et al., 2017