Convolutional Neural Networks 4
Saliency Maps

CS109B Data Science 2

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Outline

Saliency maps

1. Gradient Base
2. Deconvolution, Guided Backpropagation Algorithm
3. Class Activation Map (CAM), Grad-CAM and Guided Grad-CAM

Saliency maps

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But your Deep Learning Network might not be as smart as you. It might classify it as a cat, a lion or Pavlos!

What are the reasons for that?

Saliency maps

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But your Deep Learning Network might not be as smart as you. It might classify it as a cat, a lion or Pavlos!

<u>What are the reasons for that?</u>

- bias in training data
- no regularization
- or your network has seen too many celebrities [therefor Pavlos]

Saliency maps

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Note: In the previous lecture, we looked at the occlusion method. Occlusion method is a forward pass attribution method. In this lecture, we will be looking at backward methods for decision attribution.

Saliency maps: Methods

Saliency map is the oldest and most frequently used explanation method for interpreting the predictions of convolutional neural networks (CNNs).

There are five main approaches to getting the saliency map:

1. **Gradient Based Backpropagation,** Symonian et al. 2013
2. **Deconvolutional Networks,** Zeiler and Fergus 2013
3. **Guided Backpropagation Algorithm,** Springenberg et al. 2014
4. **Class Activation Maps,** Zhou et al. 2016
5. **Grad-CAM and Guided Grad-CAM,** Selvaraju et al. 2016

Saliency maps: Notes

Note1: The method which is referred to as “Gradients” is sometimes also referred to as “backpropagation” or even just “saliency mapping” – although the other techniques are also ways to accomplish “saliency mapping.

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Note 2: The sole difference between Gradient Based and Deconvolution is how they backpropagate through the ReLU. Only the Gradient approach computes the gradient; Deconvolution modifies the backpropagation step to do something slightly different. As we will see, this makes a crucial difference for the saliency maps!

Saliency Maps with Gradient Based Backprop

For a learned classification ConvNet and a class of interest, the visualization method consists of numerically generating an image representing the class in terms of the ConvNet class scoring model.

How? For an image I, a class c, and a classification ConvNet with the class score function $S_c(I)$, we would like to rank the pixels of I based on their influence on the score $S_c(I)$.

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$$\boxed{\arg\max_I \; S_c(I)}$$

We need to L2-regularise, such that I is bounded:

$$\boxed{\arg\max_I \; S_c(I) - \lambda ||I||^2{}_2}$$

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Finding the image that maximizes the logits or any element of the feature map is called activation maximization.

We need to L2-regularise, such that I is bounded:

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Saliency Maps with Gradient Based Backprop

$S_c(I)$ are the logits, not the output of the softmax

Symonian et al. were the first to propose a method that uses the backpropagation algorithm to compute the gradients of logits w.r.t. to the input of the network while the weights are fixed (for training the network, the gradients are computed w.r.t. the parameters of the network). Using Taylor expansions, we can show that:

$$\boxed{S_c(I) \approx w^T I + b}$$

where

$$\boxed{w = \left.\frac{\partial S_c}{\partial I}\right|_{I_o}}$$

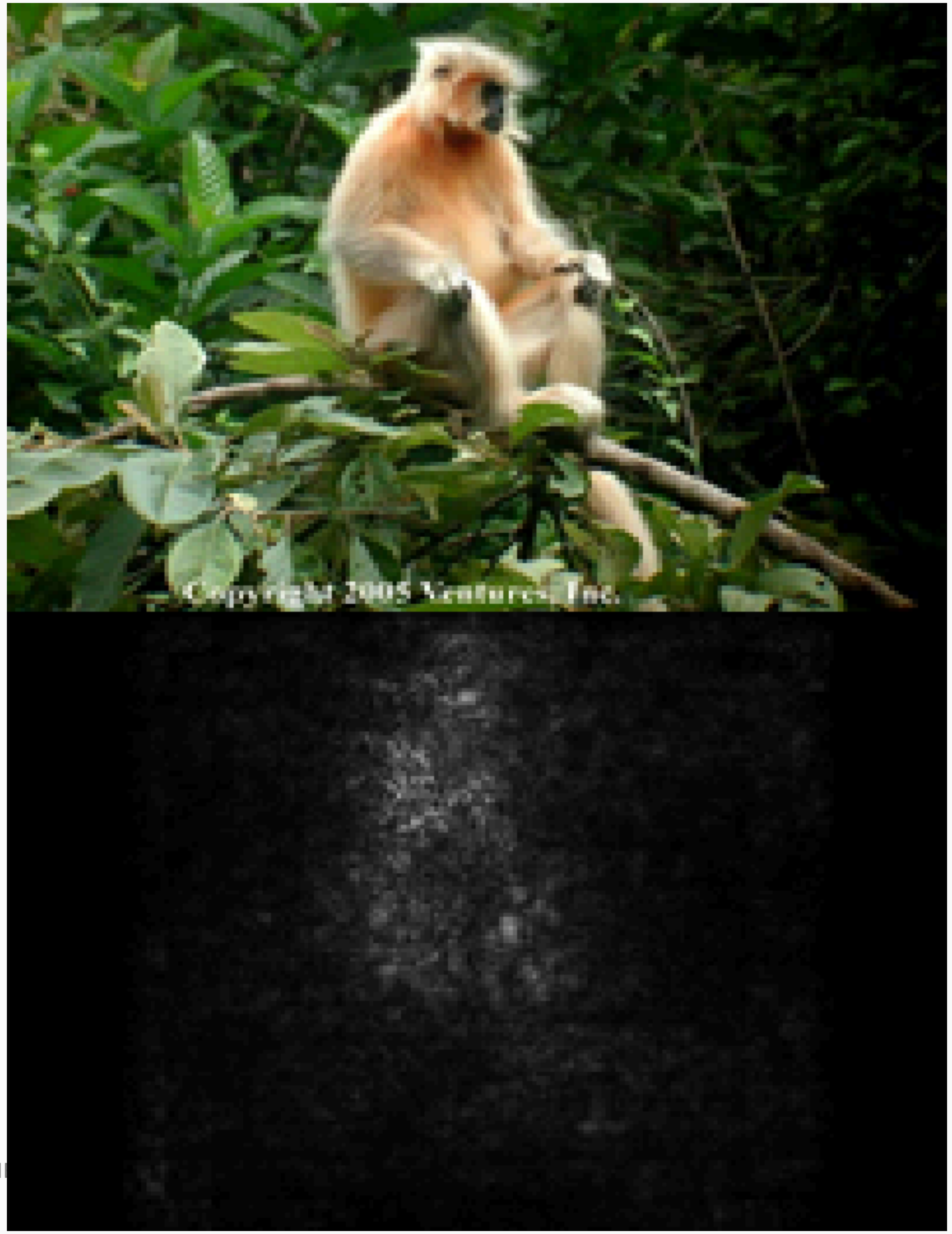
Using backpropagation, we can highlight pixels of the input image based on the amount of the gradient they receive, which shows their contribution to the final score.

Saliency Maps with Gradient Based Backprop

The maps were extracted using a single back-propagation pass through a classification ConvNet.

No additional annotation (except for the image labels) was used in training.

Note: For color images like the one shown here, we take the maximum derivative of the three derivatives.



Symonian et al, [Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps](), 2013

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Saliency Maps with DeconvNet

Zeiler and Fergus proposed a method able to recognize what features in the input image an intermediate layer of the network is looking for.

The method is known as **Deconvolutional Network** (DeconvNet) because it inverts the operations from a particular layer to the input using that specific layer's activation.

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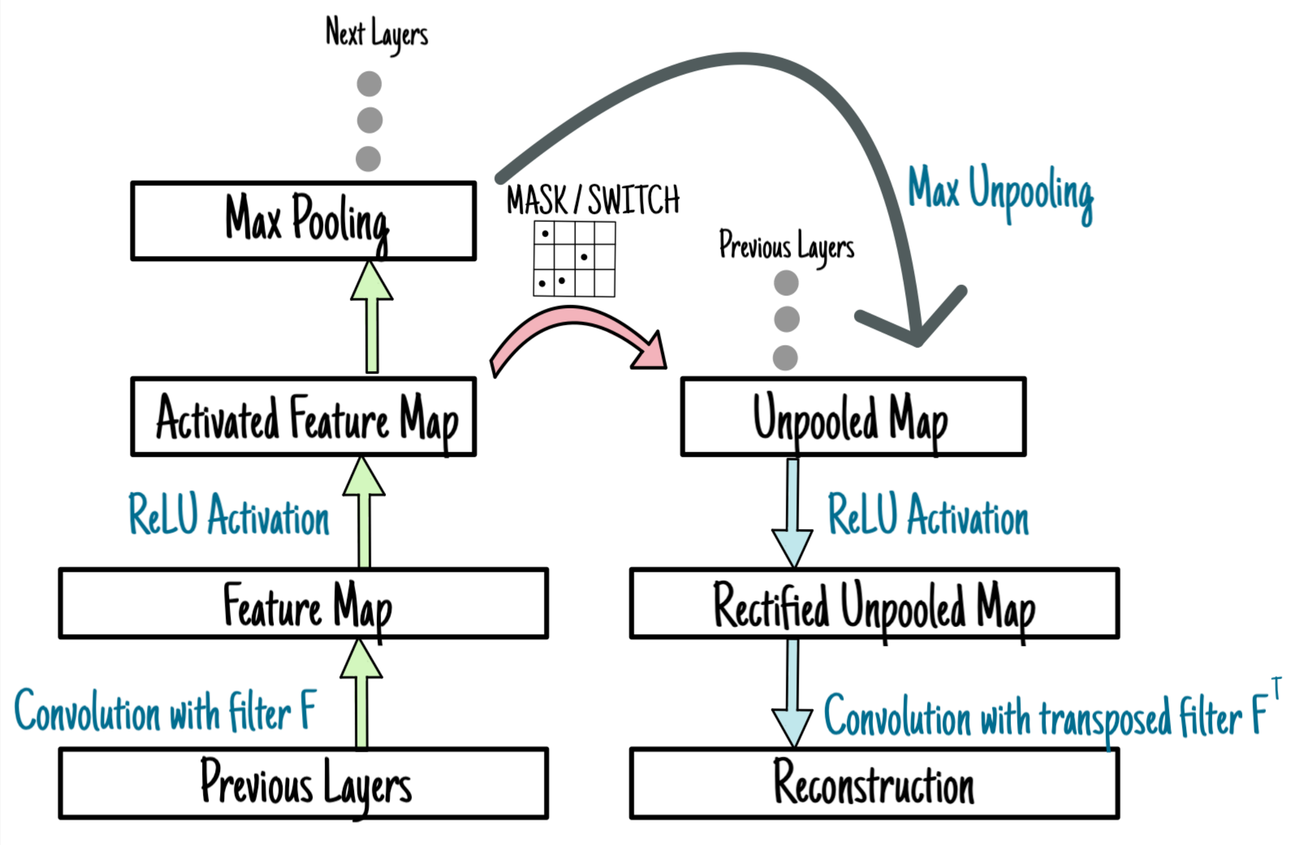
- **Unpooling** as the inverse of pooling
- **Deconvolution** to backpropagate the derivatives
- **Inverse ReLU** to remove the negative values as the inverse of itself

Saliency Maps with DeconvNet

The whole process is illustrated in the figure on the right.

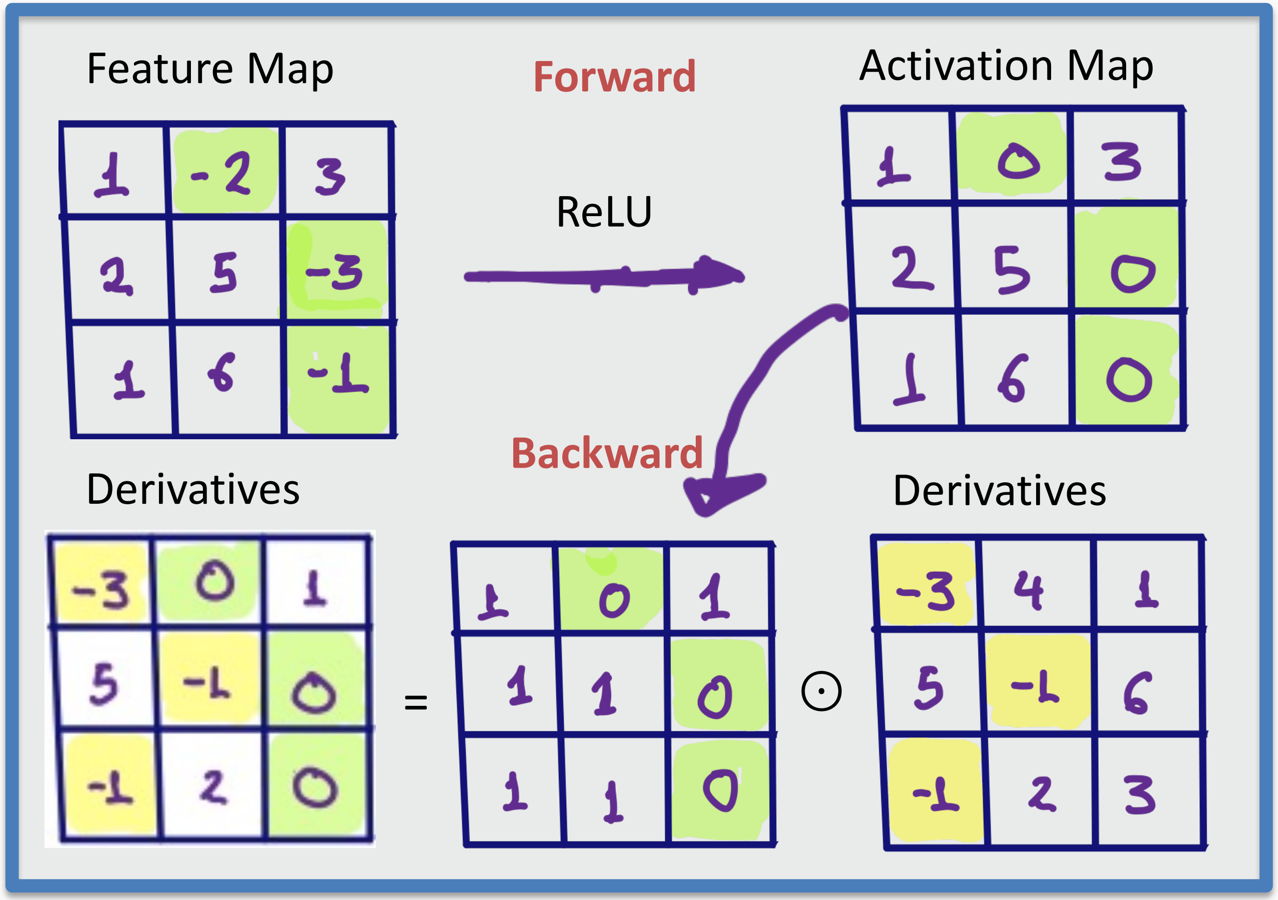
The authors used a module called **switch (mask)** to recover maxima positions in the forward pass because the pooling operation is non-invertible.



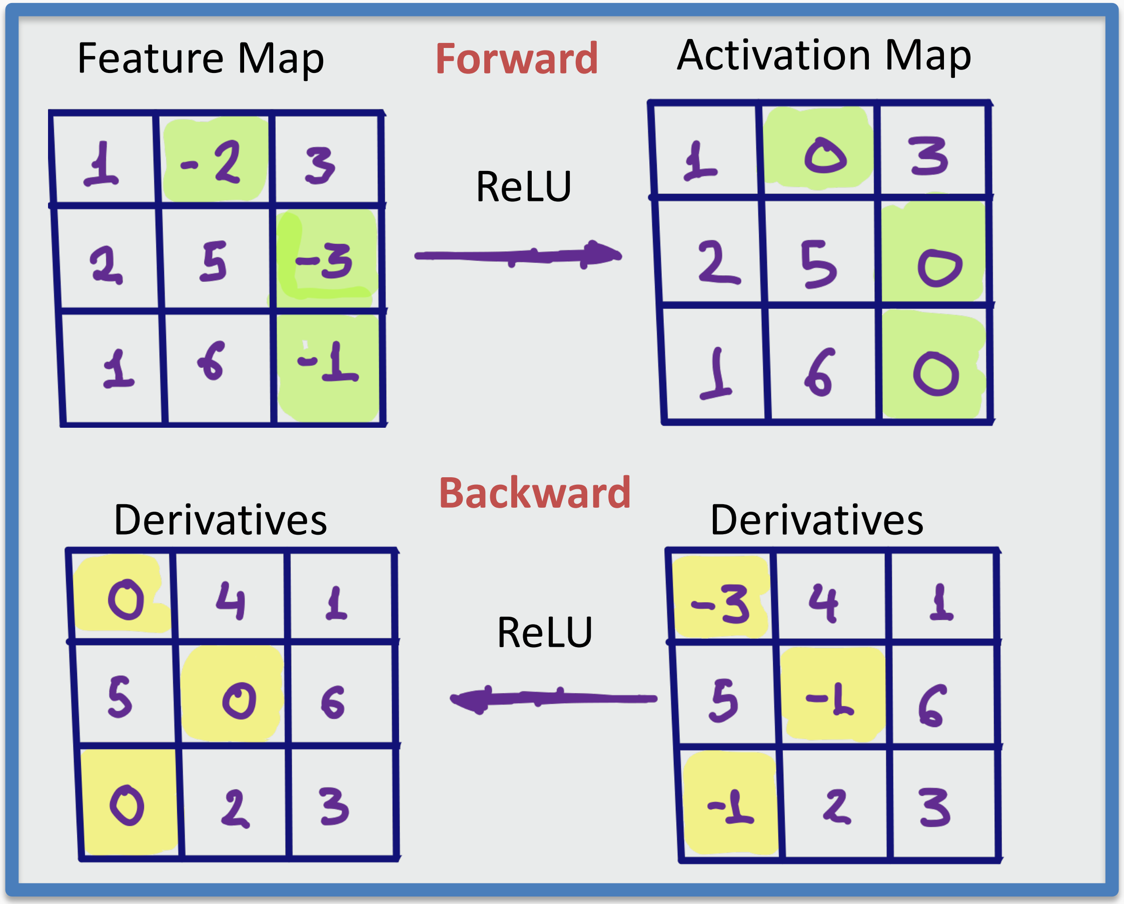
Zeiler and Fergus, [Visualizing and Understanding Convolutional Networks](), 2013

Saliency Maps with DeconvNet: Inverse ReLU

Vanilla BackPropagation



Deconvolution



Given an input image, perform the forward pass to the layer we are interested in, set to zero all activations except one and propagate back to the input image.

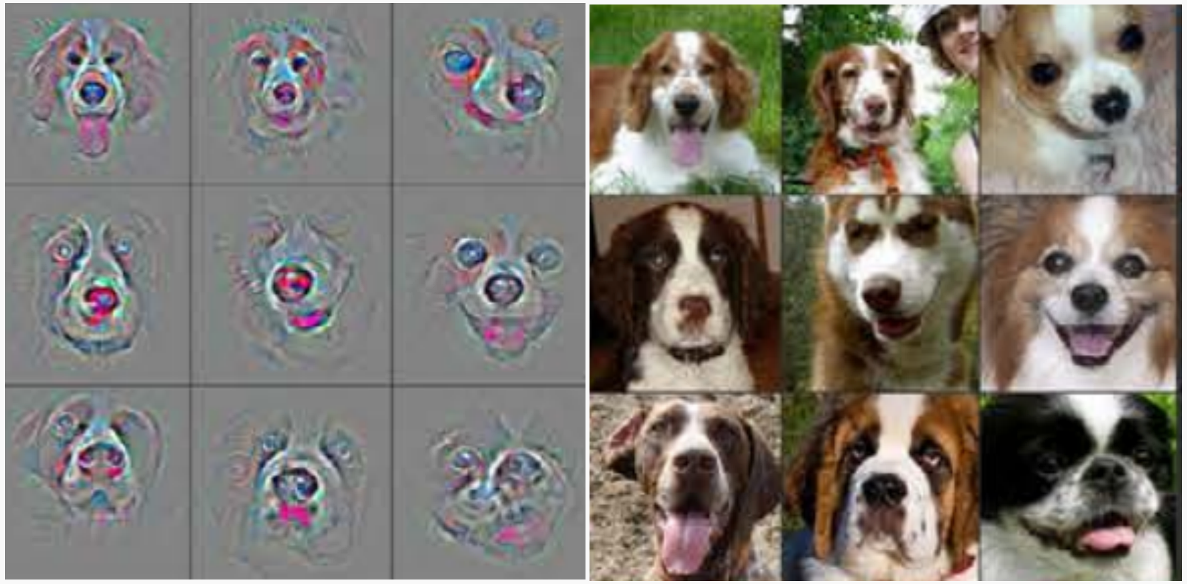
Different methods of propagating back through a ReLU nonlinearity.

Saliency Maps with DeconvNet

Two examples of patterns that cause high activations in feature maps of layer 4 and layer 5.

Layer 4

Layer 5



Right panels, image patches showing which patterns from the training set activate the feature map.

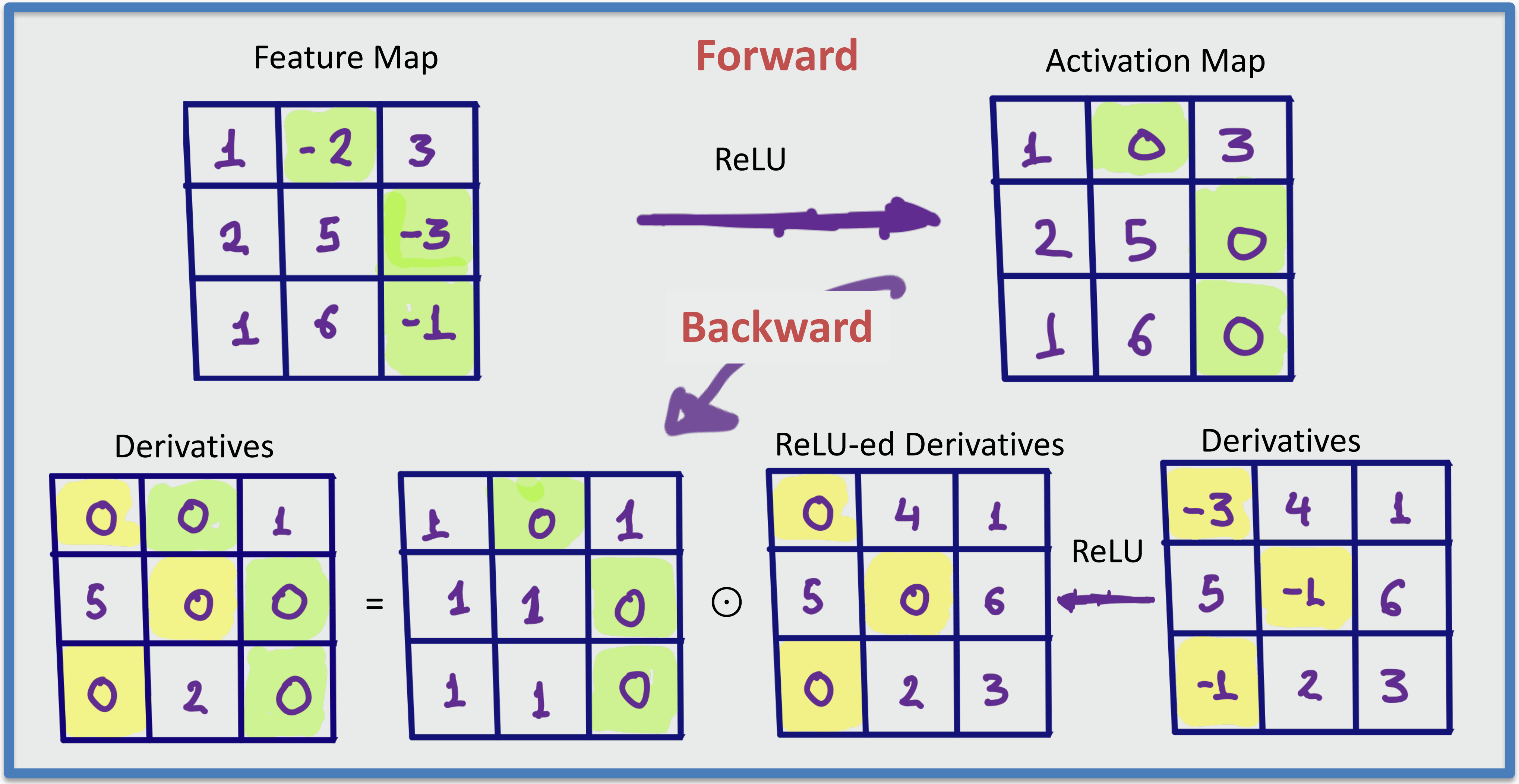
Zeiler and Fergus, [Visualizing and Understanding Convolutional Networks](), 2013

Saliency Maps Guided Backpropagation Algorithm

Springenberg et al. **combined** DeconvNet and Gradient-Based Backpropagation and proposed the **Guided Backpropagation Algorithm** as another way of getting saliency maps.

Instead of masking the importance signal based on the positions of negative values of the input in forward-pass (backpropagation) or the negative values from the reconstruction signal flowing from top to bottom (deconvolution), they **mask the signal if each one of these cases occurs**.

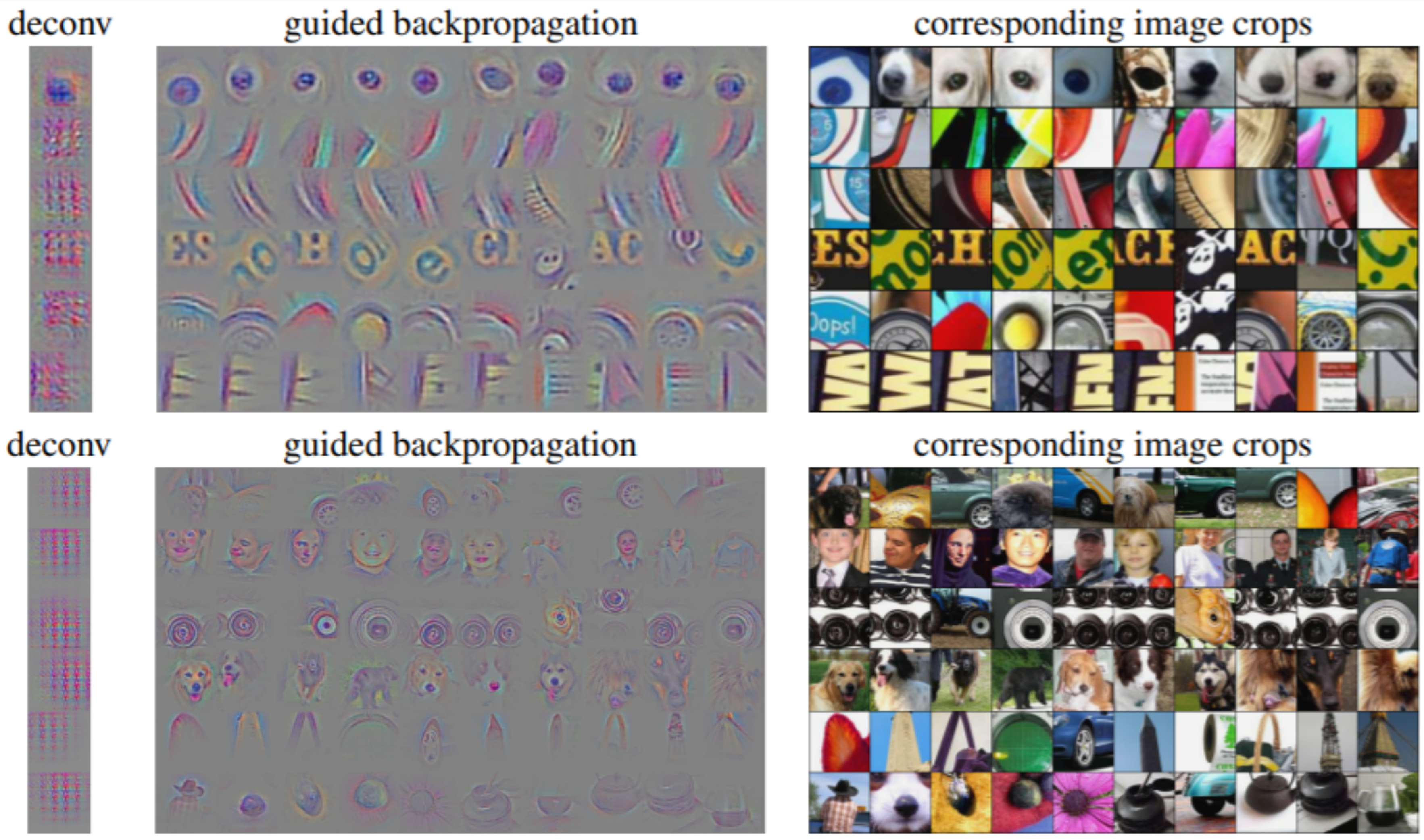
Saliency Maps Guided Backpropagation Algorithm



Saliency Maps Guided Backpropagation Algorithm

Visualization of patterns learned by the layer conv6 (top) and layer conv9 (bottom) of the network trained on ImageNet. Each row corresponds to one filter.

The visualization using “guided backpropagation” is based on the top 10 image patches activating this filter taken from the ImageNet dataset.



Springenberg et al., [Striving for Simplicity](), 2014

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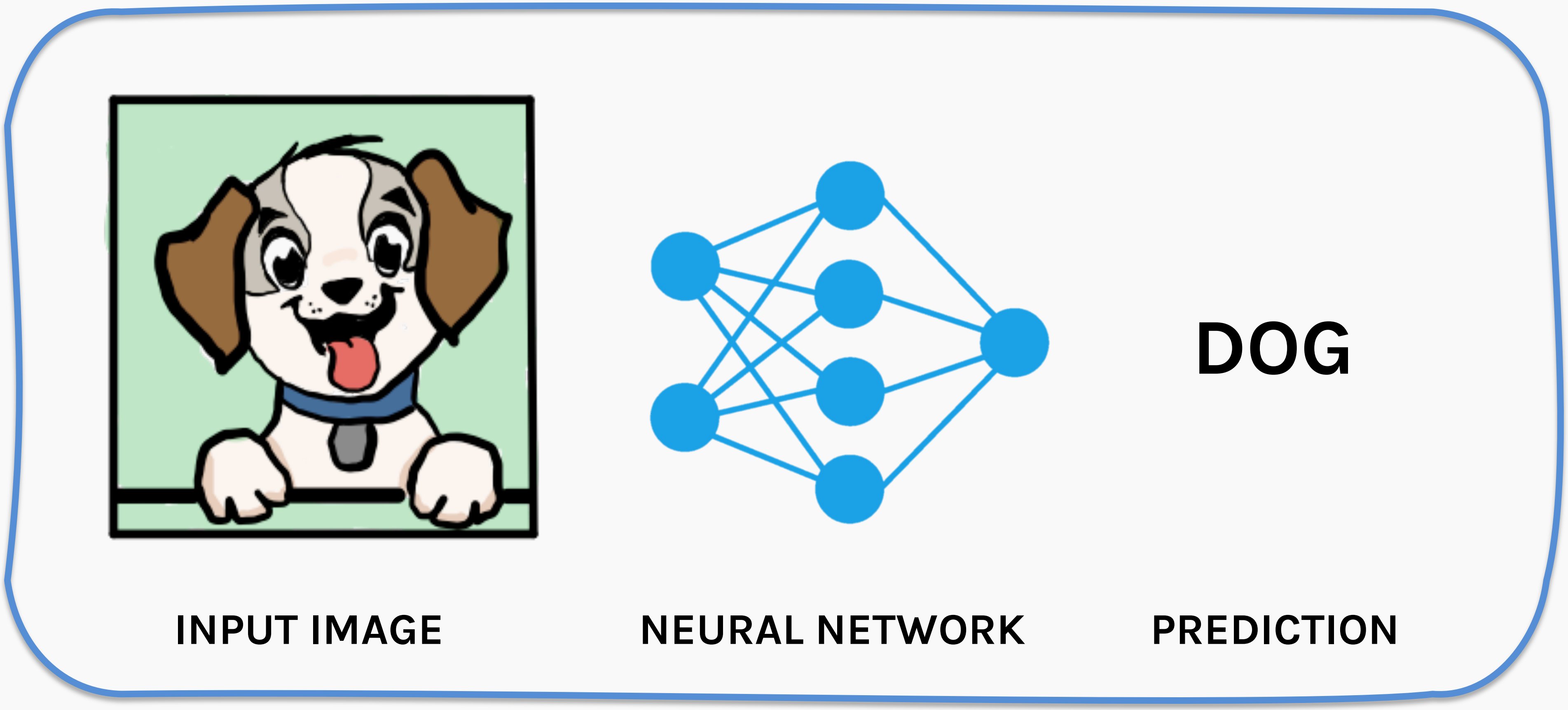
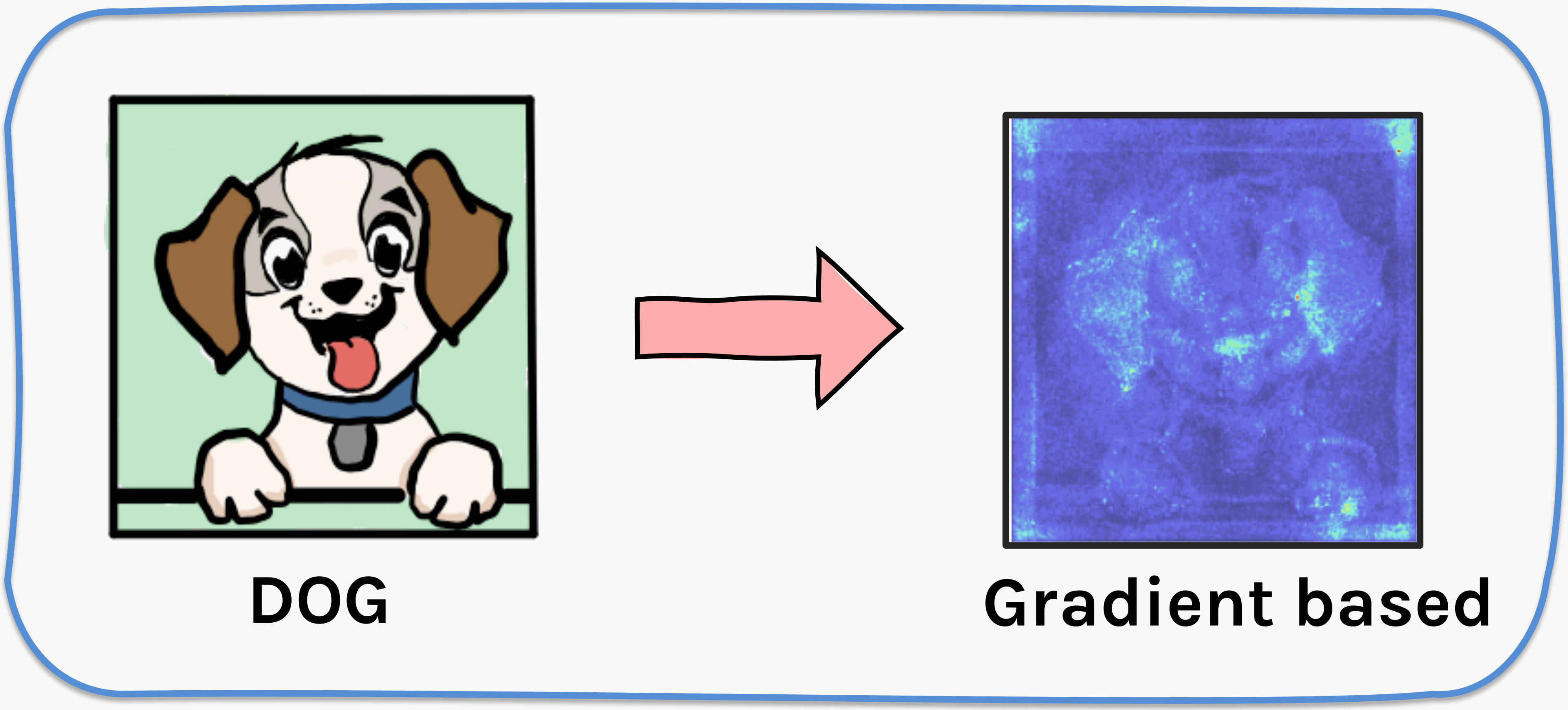
Class Activation Mapping (CAM)



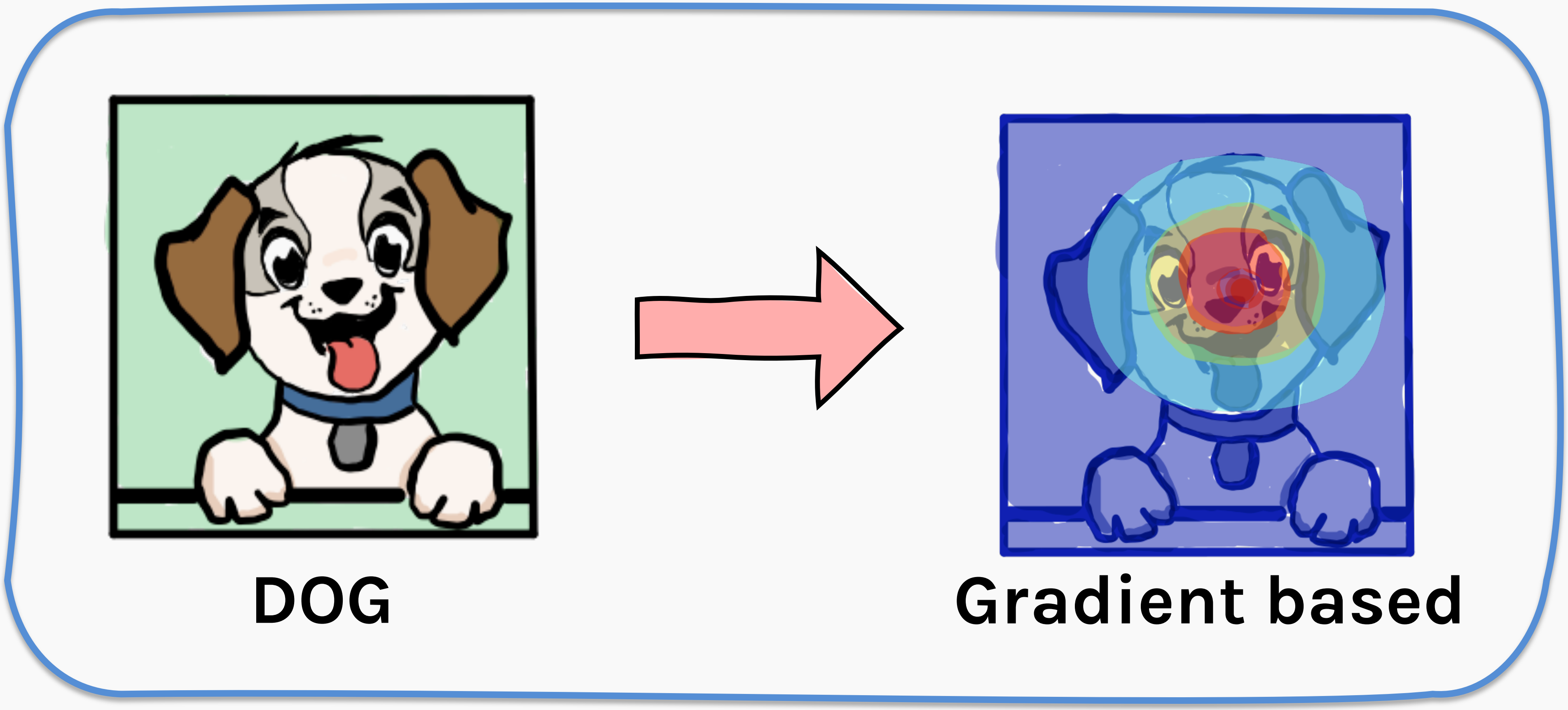
An image classification CNN takes an input image and outputs the image label. We want the know what part of the image the model is "looking" at, while making the prediction?

Class Activation Mapping (CAM)



Gradient based methods give us pixel by pixel "activation". However, these are not very useful for localized feature display, for e.g., the dog in the image.

Class Activation Mapping (CAM)



WHAT WE WANT?

A method to estimate which sub-part of the image the model focuses at when making a particular prediction. For example, Dog in the above image.

Class Activation Mapping (CAM)

SOLUTION: CLASS ACTIVATION MAPPING

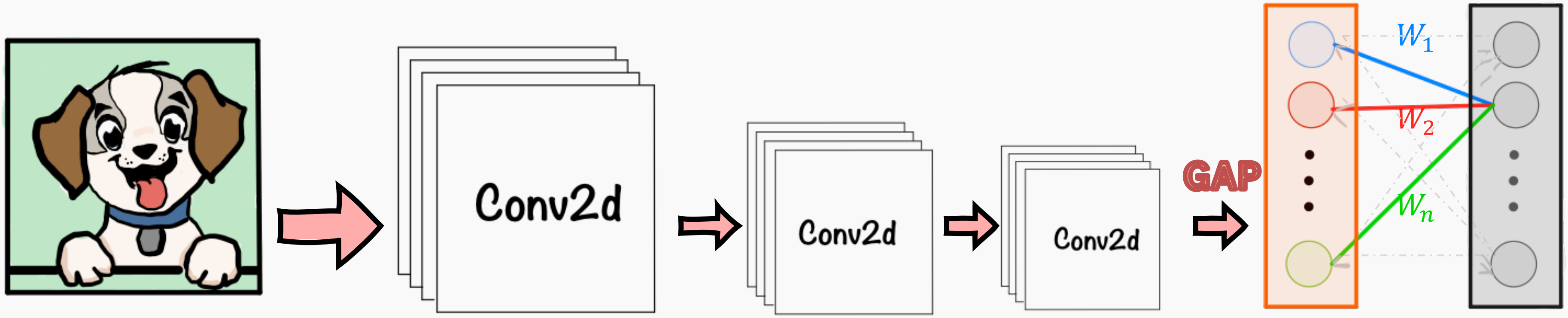
Class Activation Mapping is another explanation method for interpreting convolutional neural networks (CNNs) introduced by [Zhou et al. 2016](#).

They proposed a network where the fully connected layers at the very end of the model have been replaced by a layer named **Global Average Pooling (GAP)** and combined with a class activation mapping (CAM) technique.

Class Activation Mapping (CAM)

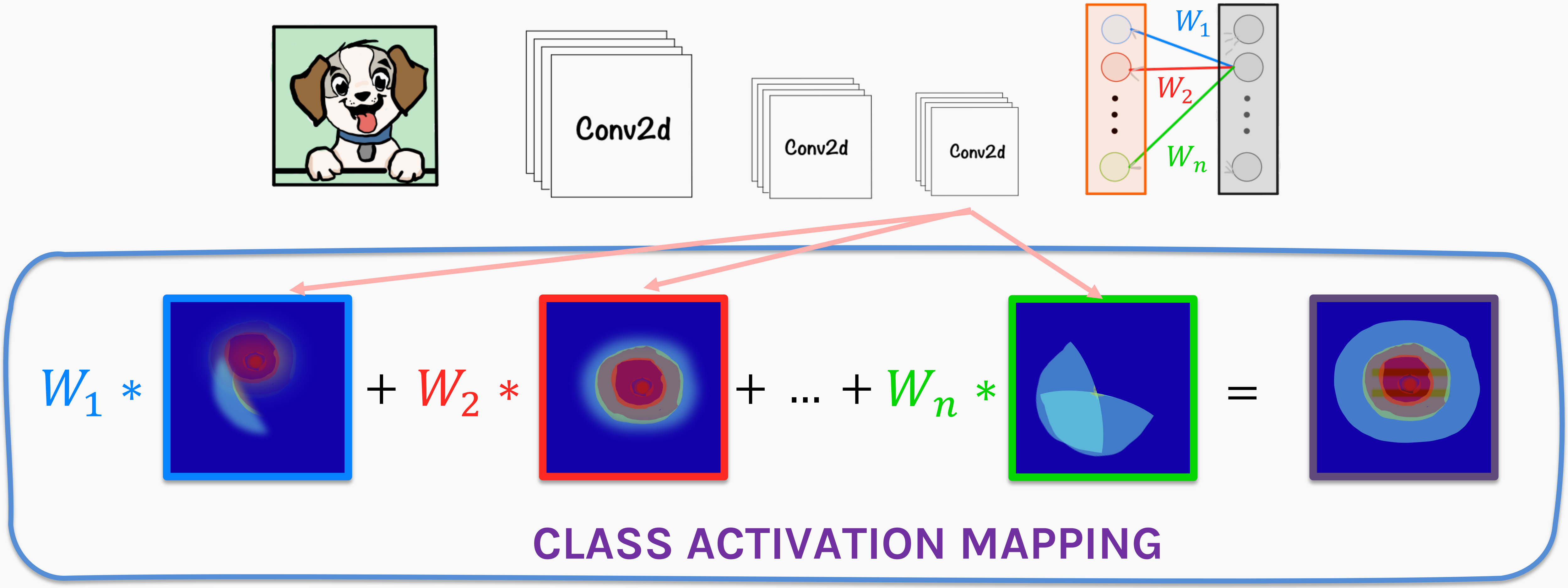
HOW DO WE DO IT?

- Instead of Dense layer, we use a Global Average Pooling **(GAP)** to average the activations of each feature map
- Each of the averages is concatenated into a single vector (shown in color red below)
- Then, a weighted sum of the resulted vector is fed to the final softmax loss layer.



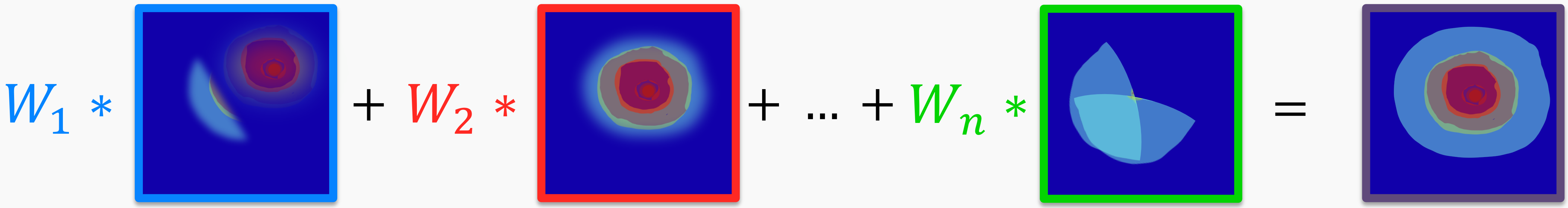
Class Activation Mapping (CAM)

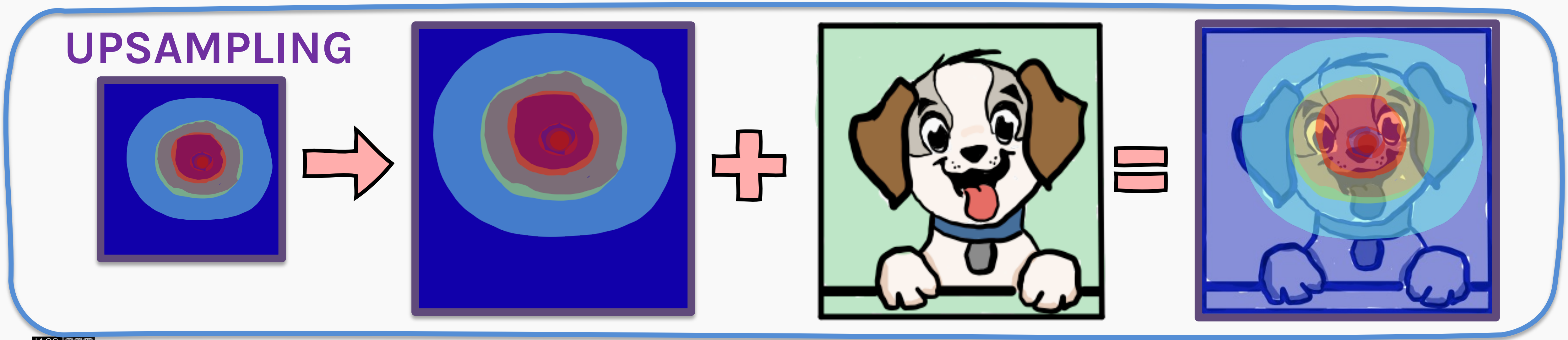
Finally, for a particular prediction, we take the weighted sum of the feature maps (where W_i comes from the GAP of the i^{th} feature map



Class Activation Mapping (CAM)

We then upsample the *weighted* feature map to the image dimensions to get the output






how many layers of convolution are you on
like,, maybe 5, or 6 right now. my dude
this was supposed to be legs
you are like a little baby
watch this

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More on Class Activation Mapping (CAM)

Other approaches to Class Activation Mapping have been developed by [Selvaraju et al. 2016](#):

- **Grad-CAM**: is a more versatile version of CAM that can produce visual explanations for any **arbitrary** CNN, even if the network contains a stack of fully connected layers as well (e.g. the VGG networks);

- **Guided Grad-CAM:** by adding an element-wise multiplication of guided-backpropagation visualization.

Class Activation Mapping (CAM): **GRAD-CAM**

The basic idea behind Grad-CAM is the same as the basic idea behind CAM: we want to exploit the spatial information that is preserved through convolutional layers, in order to understand which parts of an input image were important for a classification decision.

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Grad-CAM is applied to a neural network that is done training; in other words, the weights of the neural network are fixed. We feed an image into the network to calculate the Grad-CAM heatmap for that image for a chosen class of interest.

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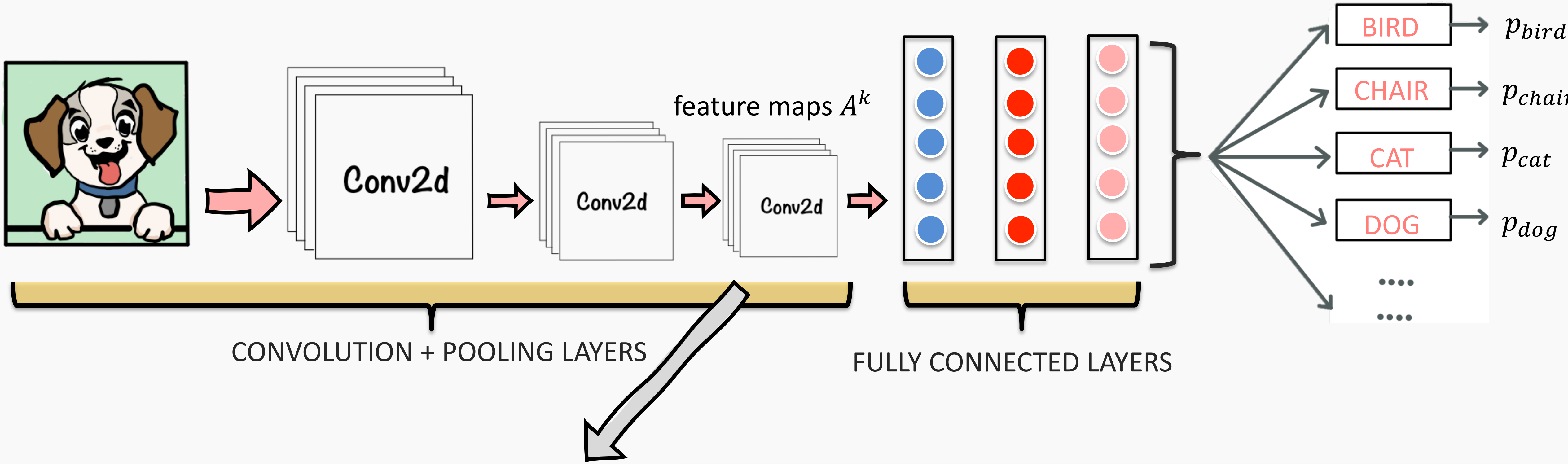
Both CAM and Grad-CAM are local backpropagation-based interpretation methods. They are model-specific as they can be used exclusively for interpretation of convolutional neural networks.

Class Activation Mapping (CAM): **GRAD-CAM**



$$\alpha_k^c = \frac{1}{Z} \sum_{i,j} \frac{\partial y^c}{\partial A_{ij}^k}$$

Instead of the Global Average Pooling layer, we compute the derivative of the logit with respect to the feature maps using the equation on the left

Class Activation Mapping (CAM): GRAD-CAM

First, the gradient of the logits, y^c, of the class c w.r.t the activations maps of the final convolutional layer is computed and then the gradients are averaged across each feature map to give us an importance score.

$$\alpha_k^c = \frac{1}{Z}\sum_{i,j}\frac{\partial y^c}{\partial A_{ij}^k}$$

y^c is the logit for class c

α_k^c is the importance of feature map k for the class c

Z is some normalization

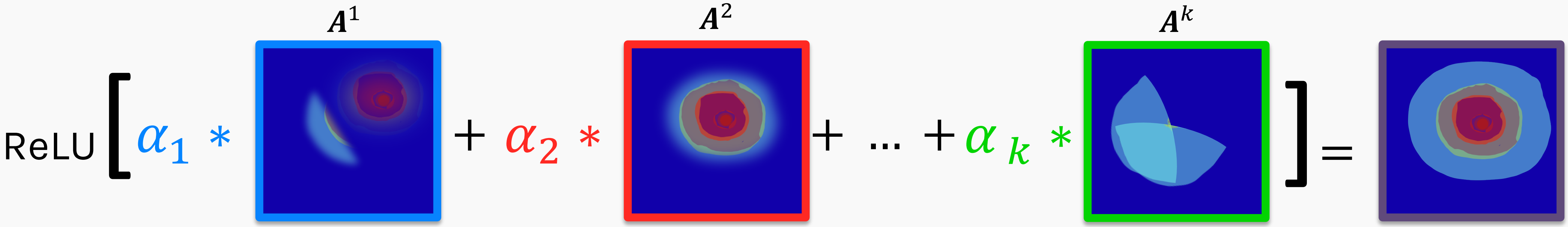
Summing over all elements of the elements of the k activation map (aka **global average pooling**)

A_{ij}^k is the I,j element of the k activation map of the last activation layer

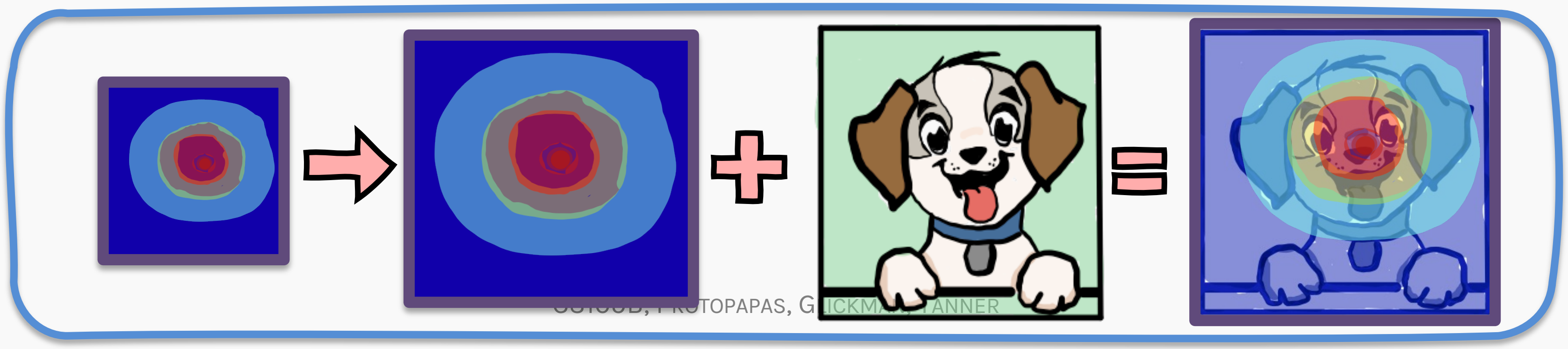
Class Activation Mapping (CAM): GRAD-CAM

Combine the feature maps as we did in the CAM before except that here, we use the α's instead of the W and we also activate the

$$S^{c}_{Grad-CAM} = \mathrm{ReLU}\left(\sum_{k} \alpha^{c}_{k} \boldsymbol{A}^{k}\right)$$



UPSAMPLING



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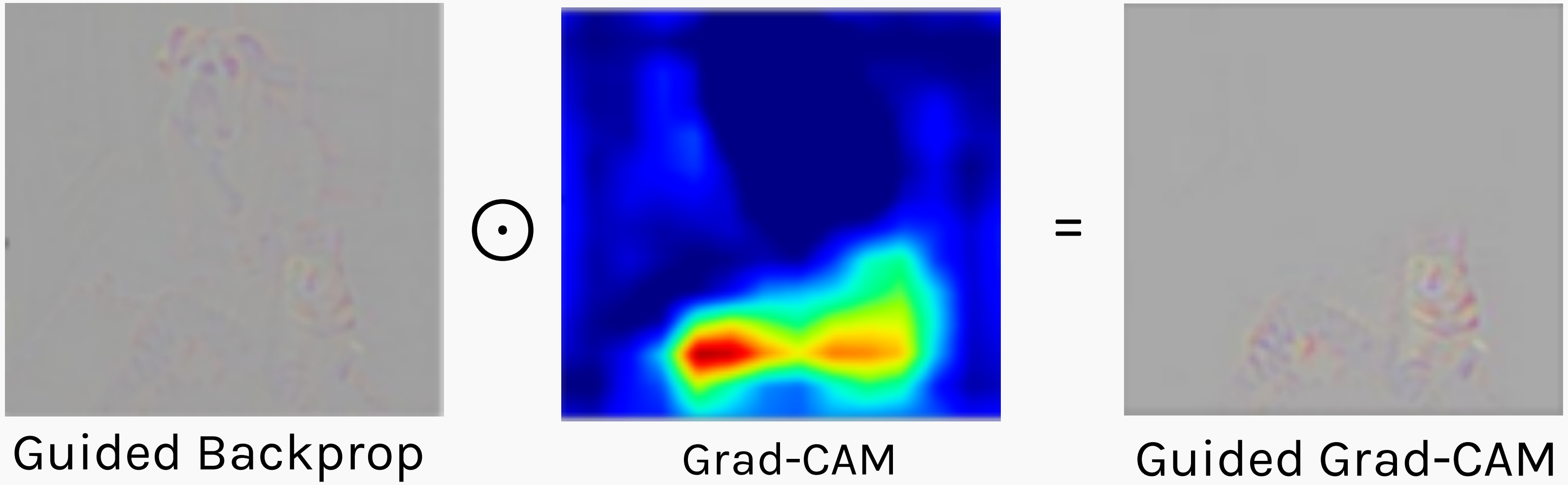
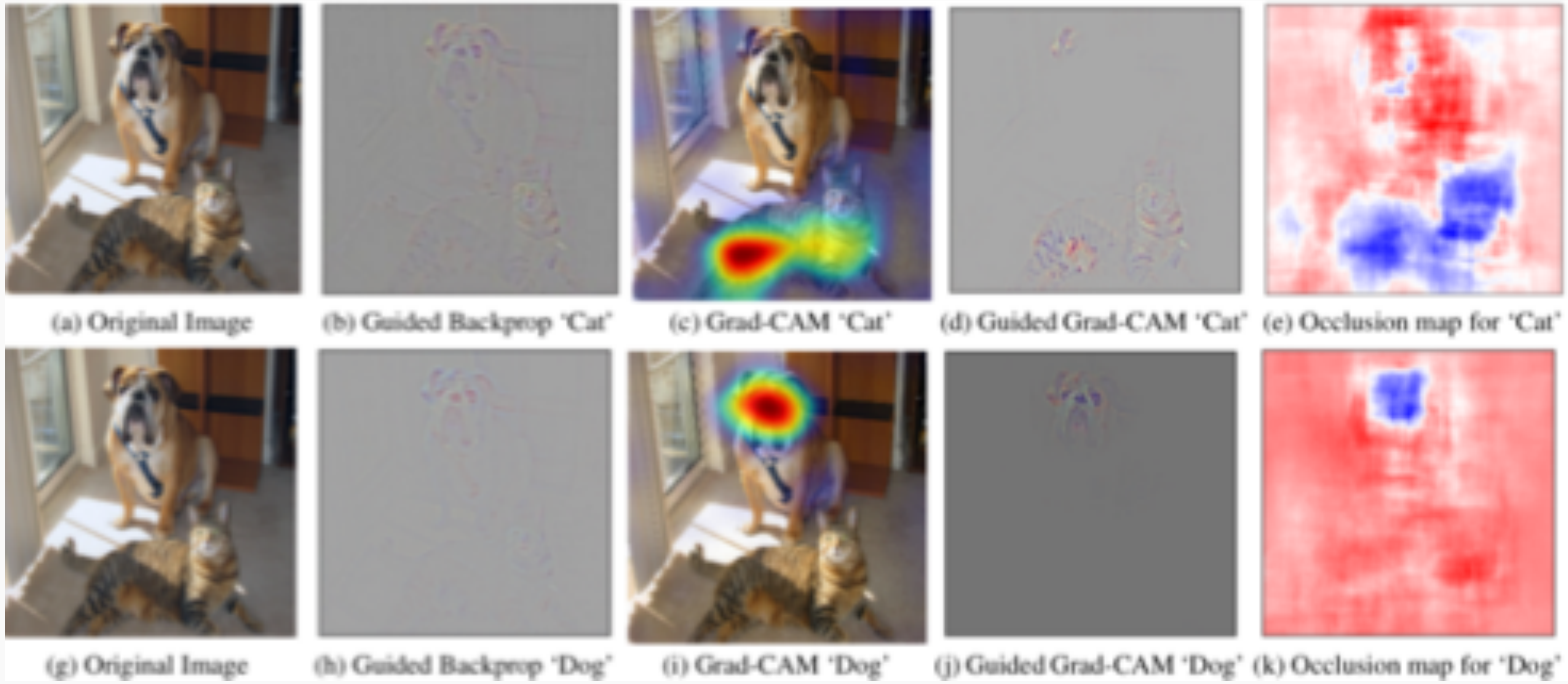
Class Activation Mapping (CAM): Guided GRAD-CAM

Grad-CAM can only produce coarse-grained visualizations.

Guided Grad-CAM combines Guided-Backpropagation with Grad-CAM by simply perform an element-wise multiplication of Guided-Backpropagation with Grad-CAM.





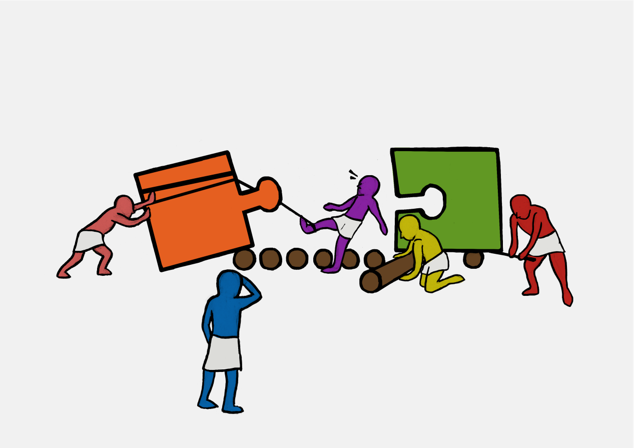
Saliency Maps: Limitations

Saliency map is an interpretable technique to investigate hidden layers in CNNs. It is **a local gradient-based backpropagation interpretation method**, and it could be used for any arbitrary artificial neural network (**model-agnostic**).

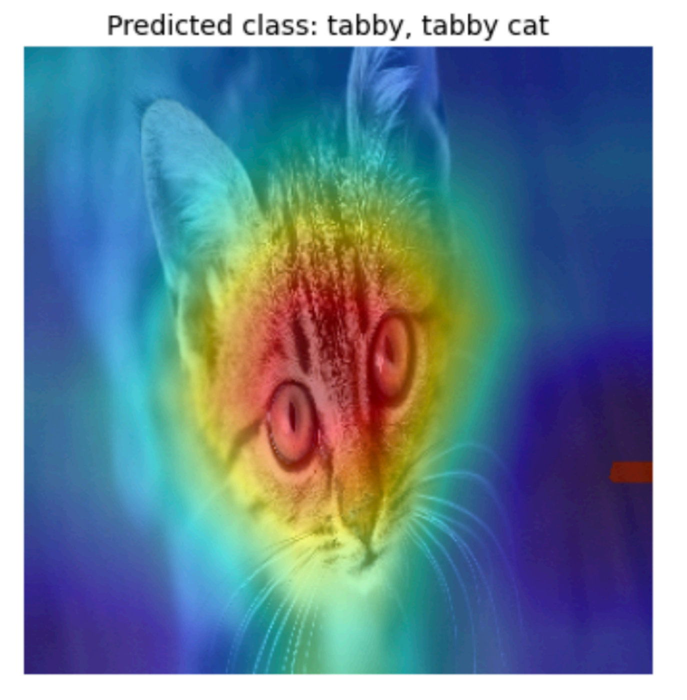
However, some **limitations** of the method has been raised because:

- Saliency maps are not always reliable. Indeed, subtracting the mean and normalizations, can make undesirable changes in saliency maps as shown by Kindermans et al. 2018;
- Saliency maps are vulnerable to adversarial attacks Ghorbani et al. 2019.
- Adebayo et al. 2018 tested many saliency maps techniques and found that Grad-CAM and gradient base are the most reliable.

Exercise:



The goal of this exercise is to build a saliency map using Grad-CAM.
Your final image may resemble the one on the right.



An important skill to learn from this exercise is how to use [tf.GradientTape()](https://www.tensorflow.org/api_docs/python/tf/GradientTape) to find the gradients of the output with respect to the activations.

Knowing how to use GradientTape() is like having the key to the kingdom of DeepLearning.