Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps

Paper | Notes | Implementation

Class Model Visualization

We start from an initial image and try to find the image that would lead to the highest possible score for the chosen class.

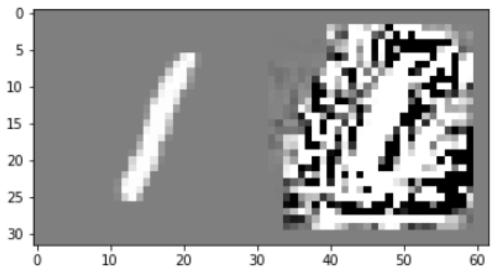
To do so, we try to **maximize:** $L(w_c, x) = logp(w_c|x) - \lambda|x|_2^2$ w.r.t. to the image x. $w_c$corresponds to the chosen class for which we want to find the prototype. The weights of the model are, in this case, fixed and we use backprop to calculate the gradient of the function w.r.t. to the input image x and iteratively update x.

The update rule equals $x = x + \alpha\, \partial f(x)\, /\partial x$

Possible starting points:

- Random noise
- Zero image and then add the training set mean image
- Random image from the training set

Results: Left picture is generated by starting with a random image from the dataset. The second image we start with random noise and try to generate a sample for class 8.



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Recognized class is [8]
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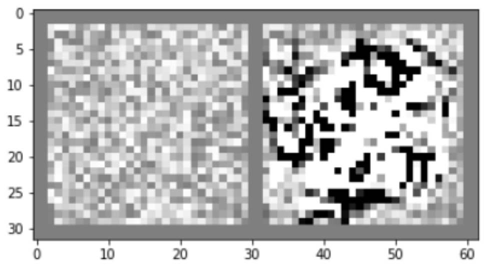
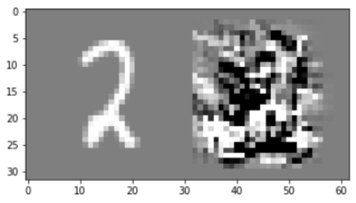
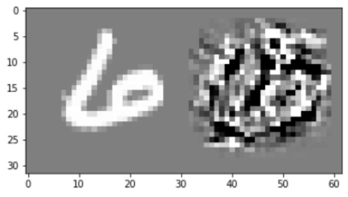
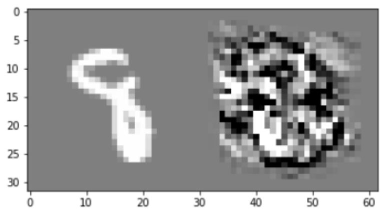


Image-Specific Class Saliency Visualization

Here, we try to explain a classification decision for a given image by highlighting the pixels of the image which had the biggest impact on the output of the DNN.

To do so, we run the forward pass of the DNN and use backprop to calculate the gradient w.r.t the input image starting from the classified class $\partial f(w_c|x)\, /\partial x$. The calculated gradient is then visualized. Furthermore, the saliency maps can be used for object localization directly without the need for any further training. Here, we regard data points with a value beyond a certain threshold as the recognized object and the remaining pixels as the background.

Results: Saliency maps for three randomly selected images from the dataset.

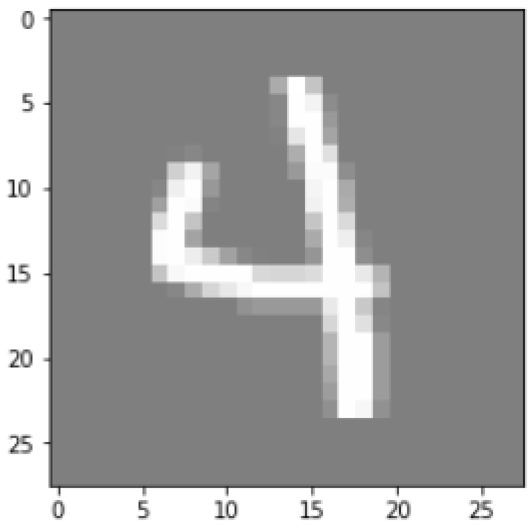




Relation to Deconvolutional Networks

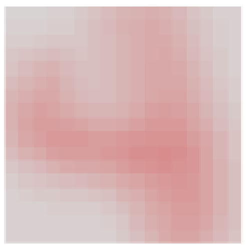
There is an intrinsic correlation between **DeConvNet** and the gradient-based visualization. The calculation of the gradient of popular layers like **CONV, MAXPOOL** and activations like **ReLU** and their **DeConvNet** counterparts follow the same approach and ultimately lead to very similar results. Based on this, the gradient-based approach can be seen as a generalization of the **DeConvNet**, since it can be used with many more layers than its counterpart.

LRP Implementation for convolutional rule:

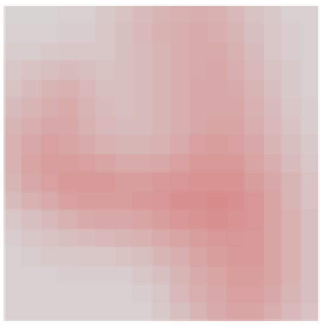
We use the same architecture (Conv->Conv->Fc->Fc) as the one we use in Activation Maximization and Saliency Map but convert the fully connected layers to convolutional layers.



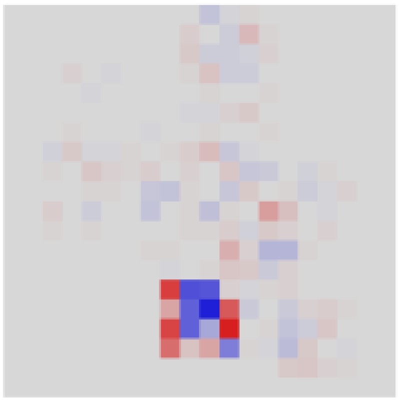
Input image

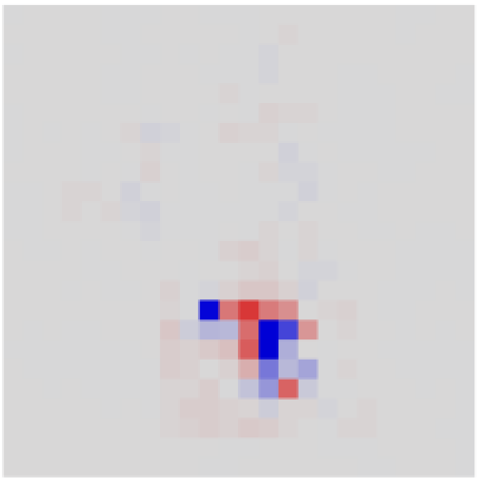


Heatmap from the last layer (FC)



Heatmap from the second last layer (FC)


Heatmap from the second layer (Conv)


Heatmap from the first layer (Conv)

The last two heatmaps seem a bit incorrect due to the conversion from FC to Conv. We are still in progress for this part.

Q's

- Should we research more about **DeConvNet**?