Week 7 Report

CAM Changes

As discussed last week, we tried our CAM and Grad-CAM implementations with another model we trained. Our theory proved right and the main issue of the older results was indeed the huge upsampling that was taking place. The results with the new model look significantly better for both the CAM and Grad-CAM versions. A full overview of the results and the model architectures can be seen in the repository. Below a short snippet of the results that we managed to generate.

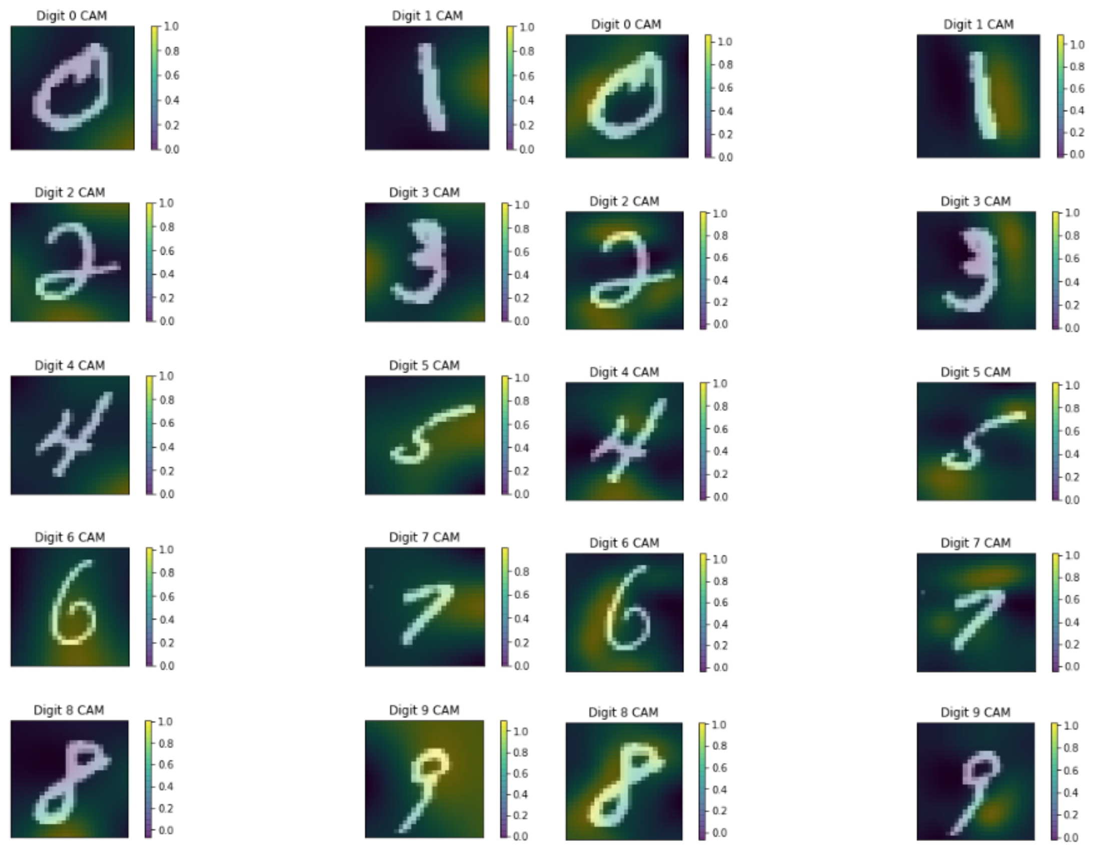


Fig 1. CAM results: Left picture is using the last week’s model. Right picture is using the new one.

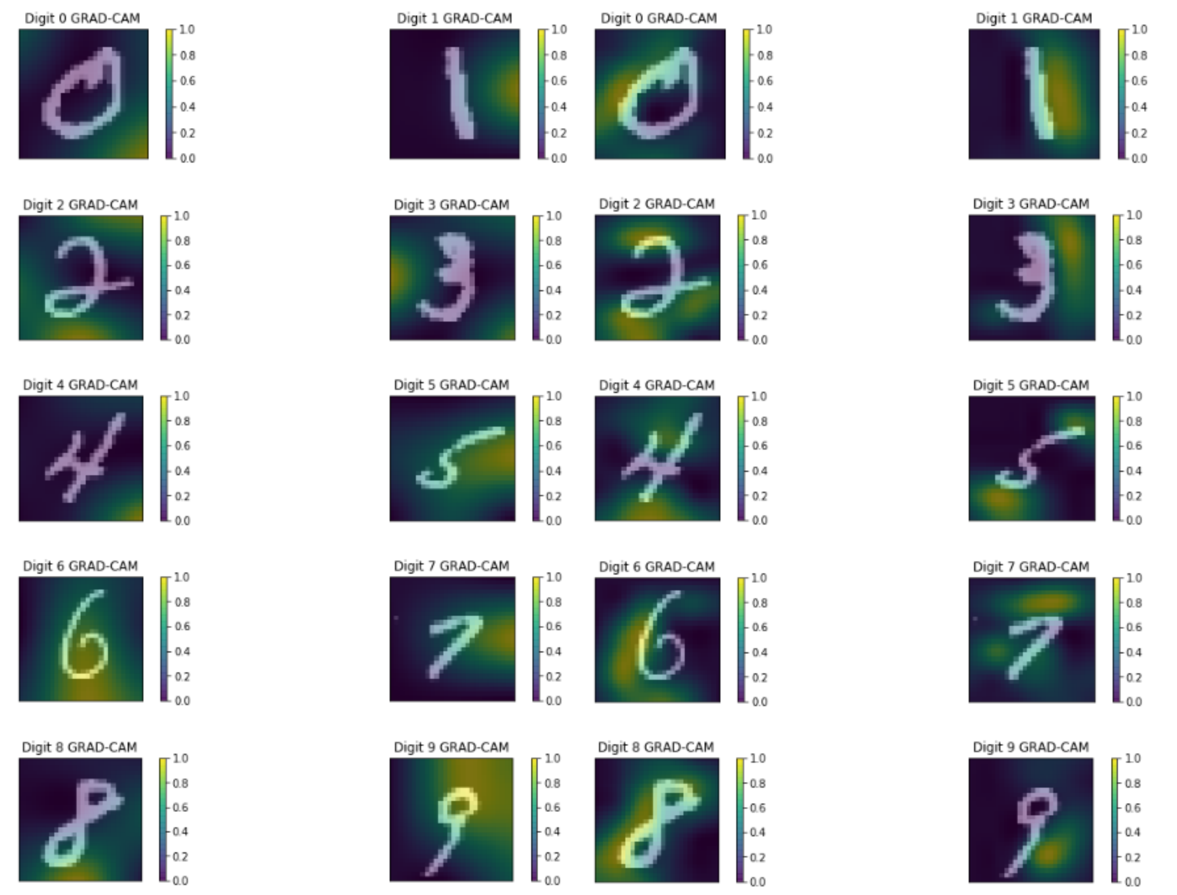


Fig 2. Grad-CAM results: Left picture is with the old model. Right picture is using the new one.

AM & Saliency migration to the nn_interpretability package

As last week we started to clearly structure our code in a package-like style, we took some time this week to migrate all our Activation Maximization implementations and the Saliency Map implementation to the new format. While doing so, we found out that the current generative models that we have are not always performing very well, so we will take some time in the upcoming week to improve their performance. Also, we took a look at the RBM implementation we received and are going to integrate it into our code in the next week.

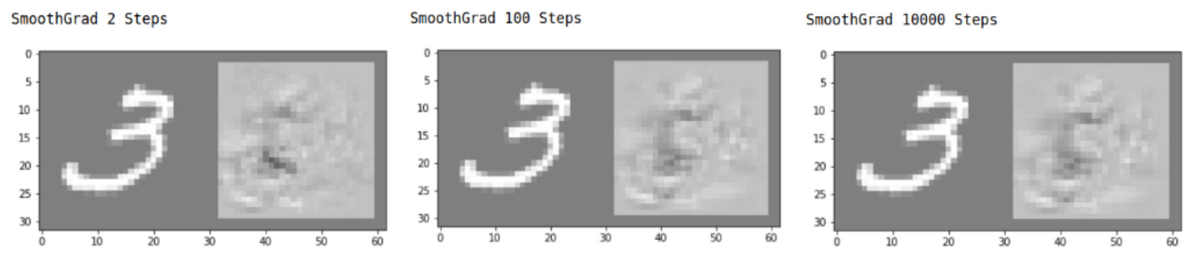
SmoothGrad: removing noise by adding noise | Paper | Notes | Implementation

SmoothGrad

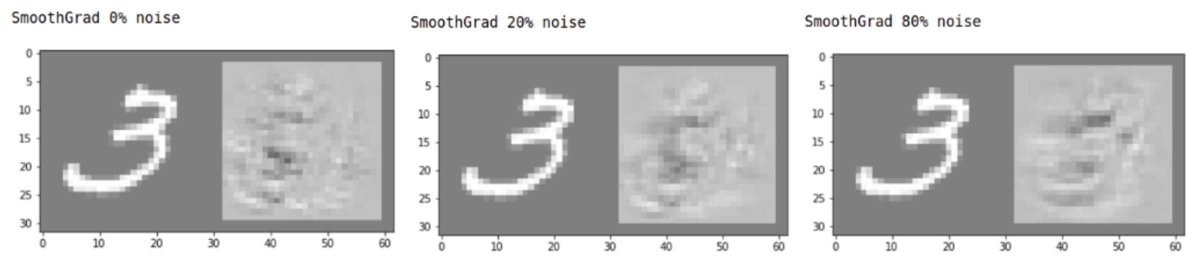
SmoothGrad can sharpen gradient-based sensitivity maps. The sensitivity maps based on raw gradients (vanilla backpropagation) are visually noisy. An explanation for the noise is that the derivative of the function may fluctuate sharply at small scales. In other words, due to the non-smooth derivative of the function (e.g. discontinuities caused by ReLU) there are many meaningless local variations which appear as noise in sensitivity maps. Because the local fluctuations are meaningless, we compute a **local average** of gradient values with a **Gaussian kernel** to smooth the derivative of the function.

$$\hat{M_c}(x) = \frac{1}{n}\sum_{1}^{n} M_c(x + \mathcal{N}(0, \sigma^2))$$

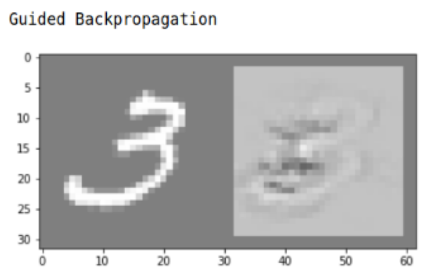
Formula for SmoothGrad in a stochastic approximation in practice, Mc is the derivative of the function with respect to the image added Gaussian noise

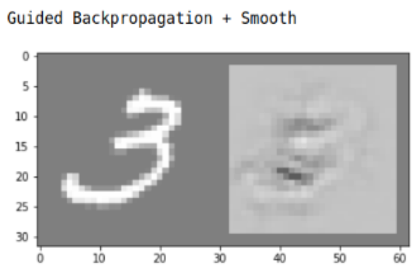


Sample size n: Estimated gradient becomes smoother as n increases. However, there was little apparent change in the visualizations for n > 50.



Standard deviation of Gaussian noise: In the paper it is suggested that 10%-20% noise can sharpen the sensitivity map while still maintain the structure of the original image. 0% noise is equal to vanilla backpropagation





Combining SmoothGrad with guided backpropagation

SmoothGrad has the highest impact when the object is surrounded with **uniform background color**. This implies noise may have a differential effect on the sensitivity to different textures. SmoothGrad qualitatively shows better **discriminativity** over the other gradient-based methods, on the contrary guided backpropagation shows the weakest discriminativity.

Techniques for Visualization

- Absolute value of gradients: When the object of interest has the **same color across the classes** (MNIST), it is recommended not to convert to absolute values. The positive gradients indecate positive signal to the class. On the other hand, for ImageNet dataset (Maybe also CIFAR) taking the absolute value of the gradient produced clearer pictures, because the direction is **context dependent**.
- Capping outlying values: The presence of few pixels that have much higher gradients than the average, which is utilized in generating adversarial examples.
- Multiplying maps with the input images: Make sense when we view the importance of the feature as their contribution(weights) to the total score. However for **black pixels** it will never show up on the sensitivity map.