

DeConvolution vs Deep Visualization

Evaluation of Deep Visualization Techniques

Anil Kumar Motupalli, Buddha Puneeth Nandanoor, *Masters(MCS) Computer Science*

Abstract—Deconvolution and Deep Visualization toolbox are most popular tools used in visualizing the Deep Convolution Neural networks. They produce images at selected layer that best represents the outcome of that layer for a given input. As part of this project, we want to evaluate the efficiency of these two techniques. This experiment includes two main steps, the first one is visualizing the output layer for class and the second step is feeding the images obtained from the previous step to the same network and other network to get the confidence values of that image for that class. This will tell us which technique is visualizing efficiently.



1 INTRODUCTION

Data Visualization is used in Machine Learning to find the relation between the features and evaluating results. This visualization is only useful in analyzing only the input and output layers of the deep layer. However, it is very difficult to infer what happens in the hidden layers. There are different methods to visualize the input and activations of hidden layers. As a part of this course project, we want to evaluate the two techniques predominantly used to visualize the Deep Convolution Networks.

Along with deconvolution there is one more technique developed by Jason Yosinski and team that can be used to visualize what happens in hidden layers. One such technique is visualizing activations in the hidden layers. To get clearer images Yosinski's team visualized the DNN nodes by using regularized optimization in image space (Jason Yosinski). This can be converted into optimization problem of the form (Jason Yosinski):

$$\mathbf{x}^* = \arg \max_{\mathbf{x}} (a_i(\mathbf{x}) - R_\theta(\mathbf{x}))$$

$$\mathbf{x} \leftarrow r_\theta \left(\mathbf{x} + \eta \frac{\partial a_i}{\partial \mathbf{x}} \right)$$

2 BACKGROUND

2.1 Deconvolution

This model is same as convolution model and also with same components but key point here is we do it in reverse. To check a particular activation, we need to set all other activations in the layer to zero and pass the feature maps as input. Up on which we do unpooling, rectification and filtering. As a result, we will get activity in previous layer which causes this activation. We need to continue this rebuilding process until we reach input layer. (Matthew D. Zeiler)

Where \mathbf{x} is an image, $a_i(\mathbf{x})$ is the activation at that node and $R_\theta(\mathbf{x})$ is the regularization function. This can be solved by gradient descent where each iteration updates \mathbf{x} using the following formula. (Jason Yosinski)

Where $r_\theta(\mathbf{x})$ maps the \mathbf{x} into more regularized version. η is the gradient descent step size or simple learning rate. The main difference between a regularizer used in training and this regularizer is while learning regularizer penalizes the higher weights but here it gives a direction for \mathbf{x} . (Jason Yosinski).

2.2 Yosinski's visualization

- Anil Kumar Motupalli ASURITE: amotupal E-mail: amotupal@asu.edu.
- Buddha Puneeth Nandanoor ASURITE: bnandano E-mail: bnandano@asu.edu.

3 RESEARCH QUESTIONS

3.1 Can we evaluate and compare Deep Visualization Techniques?

When we are multiple solutions for a single problem, to choose the right one we need to have some benchmarking or scale to compare. We build and train a model and upon which we will run both these techniques. We decided to compare above two techniques based on the result it generates

3.2 What if we do a forward pass with the visualization generated by deep visualization techniques?

We take the visualization result generated with those techniques and pass it as input to the same network in similar way how we pass our test set. The model will give the prediction for that.

3.3 Can we evaluate the accuracy of a deep visualization technique?

If the prediction in above case is correct for both techniques, we can either judge both are equally efficient or we can try it using some other model like alex net. Else, we can evaluate based on the actual prediction or we can take confidence level and make comparisons.

4 PROJECT TIMELINE

Task	Deadline
Reading and design	Feb 24
Implementation	Mar 20
Analysis	April 10
Report	April 20

5 TASK DISTRIBUTION

We are exploring the idea together now, we will take each one technique and implement. Later, we do combined analysis and prepare report.

6 EXPERIMENTS AND DIRECTION OF ANALYSIS

As part of this project we want to analyze two ImageNet pretrained networks, Implement the two devoncolution techniques and evaluate them by comparing the confidence values of the images generated.

We will load pretrained models of AlexNet and GoogleNet as ResNet is too huge to handle. We will then build deconvolution technique of top of one of the network using CNTK. We choose CNTK because of the availablility of that on all the platforms and there is a lot of scope to contribute to the library because of it's infancy.

After developing the deconvolution techniques, we will run the following experiments to evaluate which technique accurately represent the nodes.

- 1) We will run these deconvolution techniques to visualize the nodes in the output layer of the Neural net. Since the output layer represent the confidence values for each class, Image generated for a particular output node should represent the class that the output node represents. Using that image in a forward pass should yield that class with very high confidence. We will perform this process for Deconvolution, Deconvolution with image priors and Deconvolution with priors and regularization to see which process best visualizes what the nodes represent.
- 2) In Deconvolution, we visualize a node by adding the input gradient to a base image to obtain the representation of that class. Instead of using a black image what if we take a regular image and substract the gradients of input that contributes to the other classes? It should generate images that are only classified into class. What if we train a net with those classes? We want to execute this project to answer these questions.

7 RELEVANCY WITH COURSEWORK

As part of this project we will implement and analyze Backpropagation, Regularization, Convolution Neural Networks, Deconvolution, popular nets from Imagenet topics from the scope of the course.

BIBLIOGRAPHY

Matthew D. Zeiler, R. F. (n.d.). Visualizing and Understanding Convolutional Networks.

Jason Yosinski, J. C. (n.d.). Understanding Neural Networks Through Deep Visualization. 2015.