NEURALDIVERGENCE: Exploring and Understanding Neural Networks by Comparing Activation Distributions

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The interface of NeuralDivergence

1. LAYERS
2. CLASSES
3. INSTANCES

Figure 1: NEURALDIVERGENCE enables users to explore and understand deep neural networks by comparing aggregated activation distributions across layers, classes, and instances. Here, our user Rachael explores how one-pixel attack harms a model’s prediction. She selects: 1⃝ the network’s last two layers (dense_1, dense_2) from the Layers view; 2⃝ the cat (orange) and dog (purple) classes from the Classes view; and 3⃝ a pair of attacked (red) and benign (black) cat images from the Instances view; one pixel in attacked version has been manipulated to fool the network. 4⃝ In Activation view, each neuron’s activation distribution is displayed as a horizontal density bar graph. Noting the distribution similarities between cat and dog, 5a⃝ Rachael wants to discover how activations of the manipulated cat image resemble those of dogs', so she sorts the neurons by activations of the attacked input, revealing that attacked image, though classified as a dog, is activating the network quite differently from majority of dog images, with large “neural divergence”.

ABSTRACT

As deep neural networks are increasingly used in solving high-stake problems, there is a pressing need to understand their internal decision mechanisms. Visualization has helped address this problem by assisting with interpreting complex deep neural networks. However, current tools often support only single data instances, or visualize layers in isolation. We present NEURALDIVERGENCE, an interactive visualization system that uses activation distributions as a high-level summary of what a model has learned. NEURALDIVERGENCE enables users to interactively summarize and compare activation distributions across layers, classes, and instances (e.g., pairs of adversarial attacked and benign images), helping them gain better understanding of neural network models.

Index Terms: Human-centered computing—Visualization;

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1 INTRODUCTION

Do deep neural networks see the world like humans do? Given the complex internal structure of neural networks, this remains a question with no definitive answers. In practice, complex models are often used as “black boxes”, which can be detrimental. For model developers, they may not know how to fix the model when it fails. For example, the rich body of research on adversarial machine learning has shown that it is easy to manipulate the pixels of an image in ways that are visually imperceptible to humans, yet would fool a model [1, 2]. To identify the causes of such problems and to improve neural network robustness, it is important to understand how the models operate.

Visualizing neuron activations, internal representations of input data that is transformed into the final prediction, is a useful technique to understand how a model makes predictions [3, 4]. However, activations are commonly represented as high-dimensional tensors, which are challenging to visualize. Current tools often support only single data instances, or visualize layers in isolation.

We present NEURALDIVERGENCE, a system that helps users better understand neural network predictions through interactive summarization and comparison of neuron activation distributions. NEURALDIVERGENCE’s major contributions include:
Summary representation for high-dimensional activations. **NEURALDIVERGENCE** compresses high-dimensional activation values of a neuron into an activation distribution representation, that can be compactly visualized, as a horizontal density bar graph (Fig. 1, at 4). These activation distributions provide a high-level summary of the learned representations inside a neural network.

**Interactive, flexible comparison across layers, classes, and instances.** Popular neural network architectures often consist of many layers. To gain a more comprehensive understanding of such models’ learned representations, it is helpful for a user to explore multiple layers at a time, to help discover potential correlations and cross-layer patterns. Furthermore, an effective way to understand how neural models work is to inspect how they respond to different inputs [4]; practitioners often curate “test cases” that they are familiar with, so they can spot-check their models; also, they often want to perform subset-level analysis (e.g., by considering all images of a class), which works well for large datasets, where instance-by-instance exploration would be too time consuming. **NEURALDIVERGENCE** flexibly supports both instance-level and class-level activation summarization, across user-selected layers.

**2 Illustrative Scenario**

We provide a scenario to demonstrate how **NEURALDIVERGENCE** can help users better understand complex neural network models. Our user Rachael is a security analyst studying the one-pixel attack [5] applied on the VGG16 model [6]. When trained on the CIFAR-10 benchmark dataset [7], the model attains a 93% test accuracy. However, by manipulating just one pixel (see Fig. 1, at 3), the attack can fool the network with great success. Rachael wants to understand why it works and come up with a countering defense.

Rachael wants to start with concrete examples of successful attacks, then generalize her understanding to the whole dataset. Therefore, she selects a cat image and generates its adversarial version (differs by only one pixel) that would fool the network into misclassifying it as a dog (Fig. 1, at 3). Based on Rachael’s experience working with deep learning models, she knows that a model’s performance is strongly correlated with its last layers, thus it would be informative to analyze them first. From the Layers view (Fig. 1, at 1), she selects the last two layers (dense_1, dense_2).

While it is helpful to compare the neuron activations of the benign and adversarial cat images, Rachael expects it would be even more beneficial to compare them with those of all cat images and all dog images, which may help her discover the similarities of the two classes, and ultimately understand why changing one pixel is sufficient to fool the network. So, in the Activation view (Fig. 1, at 4), she visualizes them all. Each neuron’s activation distribution is visualized as a binned horizontal bar graph, whose opacity encodes activation densities (a more opaque bin means more images produce that bin’s activation values). As the adversarial cat image is a single attack, and the vertical axis represents the individual neurons in the layer. A activation distribution bars (Fig. 1, at 5a), the magnified area on the vertical axis). This allows users to keep track of interesting neurons in different conditions. Second, users can sort the neurons by multiple methods. These include sorting by the median activation of a class (Fig. 1, at 4a and 4b), an attacked image (Fig. 1, at 5a), and a benign image (Fig. 1, at 5b). **NEURALDIVERGENCE** also supports sorting by the subtraction of activations of two different items. Users can select the items from the median activation of classes, an attacked image, or a benign image.

Implemented in JavaScript and HTML, **NEURALDIVERGENCE** runs in modern web browsers. D3.js is used to visualize the activation distributions. A demo is available at http://haekyu.com/neural-divergence/.

**3 System Design**

**NEURALDIVERGENCE** consists of two main components: Selection views (Fig. 1, at 1, 2, 3) and Activation view (Fig. 1, at 4). Below, we describe each component.

**Selection views** allow users to control which subsets of data are included in the neural activation visualization. These include the Layers view for selecting which layers to visualize (Fig. 1, at 1), the Classes view for selecting which classes to compare (Fig. 1, at 2), and the Instances view for selecting a pair of attacked and benign images (Fig. 1, at 3). Users can select their desired layers, classes, and data instances by the corresponding toggles: displayed items are colored, and hidden items are grayed out. Classes and instances are each represented by a unique color.

**Activation view** displays the neural activation distributions. For each selected layer, the activations are presented in a horizontal bar graph, where the horizontal axis represents the activation magnitude and the vertical axis represents the individual neurons in the layer. A horizontal bar for each neuron uses opacity to encode the density of the distribution. Users can interact with Activation view in two ways. First, they can display or hide neurons by clicking the corresponding activation distribution bars (Fig. 1, at 5a, the magnified area on the vertical axis). This allows users to keep track of interesting neurons in different conditions. Second, users can sort the neurons by multiple methods. These include sorting by the median activation of a class (Fig. 1, at 4a and 4b), an attacked image (Fig. 1, at 5a), and a benign image (Fig. 1, at 5b). **NEURALDIVERGENCE** also supports sorting by the subtraction of activations of two different items. Users can select the items from the median activation of classes, an attacked image, or a benign image.

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**4 Conclusion**

We presented **NEURALDIVERGENCE**, an interactive system we are developing that visualizes activation distributions to help understand neural networks. It enables flexible comparisons across various layers, classes, and instances. Users can explore neural networks by interacting with the system, such as filtering to their desired classes, marking specific neurons, or applying different sorting options.

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