NEURO 511a Border Ownership Project Report

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1 Introduction

It has been shown that some V2 neurons are uniquely selective for object border ownership (Zhou, Friedman, and Von Der Heydt 2000). Border ownership relates to when, in a visual scene, objects overlap in the field of view allowing a foreground form to block or occlude the view of background objects. This produces visual borders that are owned by the foreground objects and not the background. Neurons that respond uniquely to edges in their receptive field (RF) that belong to a specific foreground object are found in areas V1, V2, and V4 of awake behaving monkeys (Zhou, Friedman, and Von Der Heydt 2000). This suggests that neurons receive a global context signal and are either suppressed or activated to respond based on the context of the edge detected in their RF. Based on the quick time span of this phenomena it is hypothesized that the border-ownership effect is generated within the visual cortex rather than projected down from higher levels (Zhou, Friedman, and Von Der Heydt 2000). This phenomena remains to be confirmed in artificial neural network (ANN) models of the visual cortex. If neurons of ANN visual cortex models are found to behave similarly, it would lend additional evidence to suggest that object detection is achieved by similar means in ANNs and the visual cortex. It would also provide a foundation for investigating the mechanism by which this global context is transmitted within the ANN, thus providing a hypothesis generating platform from which experiments can be proposed to better describe this phenomena in vivo.

2 Methods

2.1 Stimulus

In pursuing this investigation in ANNs, the early convolutional layers of the pytorch implementation of AlexNet (conv2, conv3, conv4, conv5) were targeted. Stimuli were generated to mimic those used for border ownership studies in monkey visual cortex (Zhou, Friedman, and Von Der Heydt 2000) and mapped to the maximal receptive field (MRF) of each convolutional layer kernel. The displays of Zhou et al. are shown in Figure 1 and were designed to present edges to a RF that have the same local features, but could be presented as part of different shapes. The replicated displays used in this study for stimulating the ANN are shown in Figure 2 and Figure 3. The mean response of these kernels to the stimuli are compared to determine if there are instances where kernels respond to certain broader contexts of the same RF edge. True border ownership kernels will be identified as those that either respond only in a single instance of border context, or respond differentially in either border context case. The main steps of this process are as follows:

1. Input RF statistics describing the size, orientation, position, and responsivity (as defined by f_nat value). Filter kernels of interest in each convolutional layer by thresholding the f_nat statistic at 0.4. This means that only kernels that respond to RF mapping stimuli within at least 40% of the average of the top 10 responses of that kernel to natural images are considered for further analysis.

2. Generate stimuli for each kernel of interest in convolutional layers 2, 3, 4, and 5 according to the size, orientation, and position parameters describing the kernel MRF.

3. Compute sensitivity metric for each kernel for each border ownership case. That is, determine if a kernel responds differentially to border context in both the simple and overlapped stimuli sets in either

contrast case (see Figure 1). The sensitivity metric of a kernel to a particular edge for a given contrast is defined as:

$$\text{sensitivity} = \frac{|\mu_1 - \mu_2|}{max\left(|\mu_1|, |\mu_2|\right)} \cdot \frac{1}{f_{nat}} \tag{1}$$

This metric is the percent difference between the responses to either border context, normalized by the f_nat kernel statistic. High sensitivity values will thus indicate kernels that have differences in border context responses, per stimuli case, that are much larger than the maximal individual response to either border context alone. Normalizing by the f_nat score allows for comparison between kernels that may be differentially stimulated by the RF mapping stimuli.

4. Visualize the sensitivity metrics in each border ownership case normalized by f_nat value for each convolutional layer.

5. Condition sensitivity metric on whether the kernel responds in the inverse contrast case to determine if the kernel is simply sensitive to local contrast changes. This is accomplished by first filtering by kernels that respond differentially to an A or B image or a C or D image (see Figure 1). This indicates that the kernel could be a candidate for border ownership, but also could be simply contrast sensitive. To account for this, these kernels are then filtered for those that do not respond differentially when the contrast of the image set is inverted (i.e. Case 1 to Case 2, and Case 3 to Case 4). These kernels are said to have border ownership responses that are "contrast invariant".

6. Visualize the top contrast invariant sensitivity metric kernels in each border ownership case (simple stimuli, overlapped figure stimuli) for each convolutional layer.

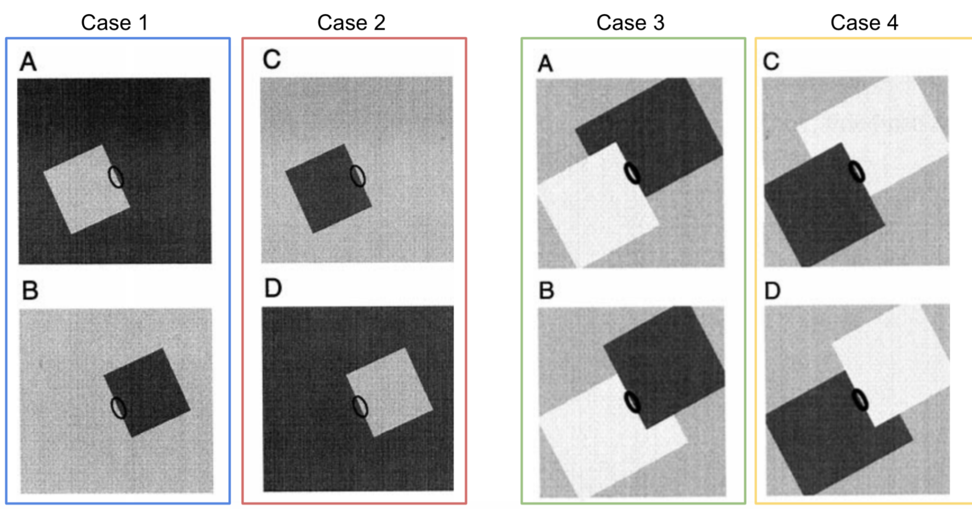


Figure 1: Case 1 and Case 2 represent the standard test for determining the effect of border ownership on edge responses. In A and B for Case 1, identical contrast edges are presented in the RF (ellipses), but in A, the edge is the right side of a dark square, in B, it is the left side of a light square. The relation is analogous between C and D of Case 2, with reversed contrasts. The elliptical region indicates the neighborhood of the RF in which displays A and B (or C and D) are identical. (Zhou, Friedman, and Von Der Heydt 2000). Case 3 and Case 4 represent the overlapped figure test cases. Similar to the first two cases, identical contrast edges are presented in the RF (ellipses) in A and B displays, and C and D displays respectively. Case 3 and Case 4 are likewise simply differentiated by contrast reversal.

3 Results

As delineated in the methods section, the first step was to identify how many kernels by convolutional layer responded differentially in each stimulus case (see Figure 1). Figure 4 demonstrates the sensitivity

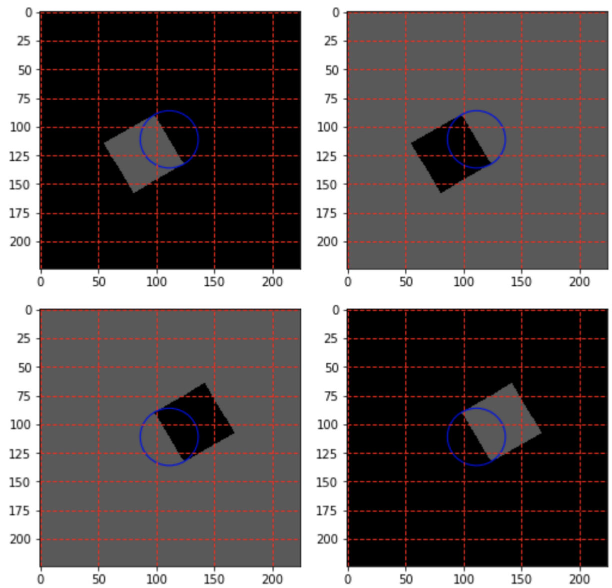


Figure 2: Displays designed to mimic those shown in Figure 1. The blue circle represents the MRF target. The length of the border within this circle was adjusted to match the MRF size if each kernel of interest.

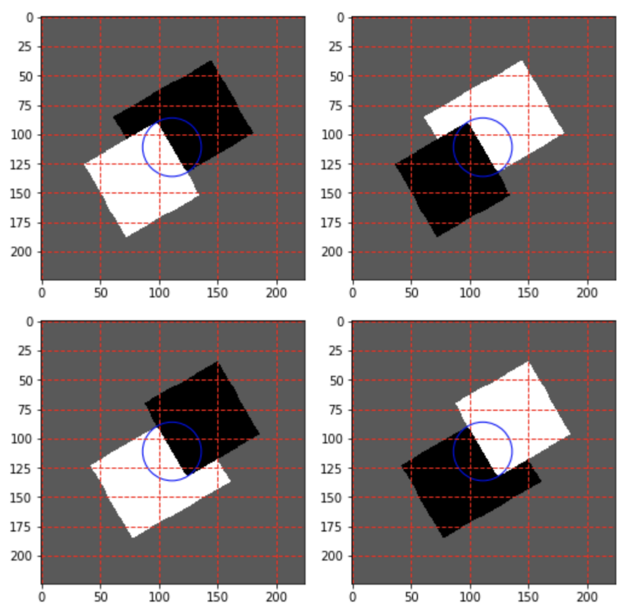


Figure 3: Displays designed to mimic those shown in Figure 1 for the overlapping figure test. The blue circle represents the MRF target. The length of the border within this circle was adjusted to match the MRF size if each kernel of interest.

metric values (Equation 3) for the kernels of each convolutional layer in each stimuli case. These histograms illustrate that there are some kernels that may indeed have border ownership characteristics because there are sensitivity values greater than 0 indicating differential response to border context. The next step was to determine if this response was contrast invariant. To do this, the kernels that responded differentially to the border context in each of the 4 stimuli cases, above a sensitivity threshold of 0.5, were then extracted as subsets to calculate the "inter-case" sensitivity. This is termed the "differential sensitivity" and is calculated using the same formula for sensitivity (Equation 3), but instead of using the kernel response averages, the compared values are instead the kernel sensitivities in either contrast case. That is, the percent difference in sensitivity between a kernel response in Case 1 versus Case 2 and/or Case 3 and Case 4. The histograms of these differential sensitivity values are plotted in Figure 5 for each comparison case (i.e. Case 1 vs Case 2, and Case 3 vs Case 4) across each convolutional layer tested. From these distributions, the kernels that are the most promising candidates for encoding border ownership are those that have differential sensitivities close to 0. This is because we are interested in kernels that are sensitive to border ownership regardless of the contrast of the stimulus presented, so we would anticipate a differential sensitivity of 0 for a kernel to demonstrate contrast invariant border ownership. To visualize which kernels in each convolutional layer satisfy this requirement, differential sensitivities are plotted for kernels falling below a certain threshold (Figures 6-13).

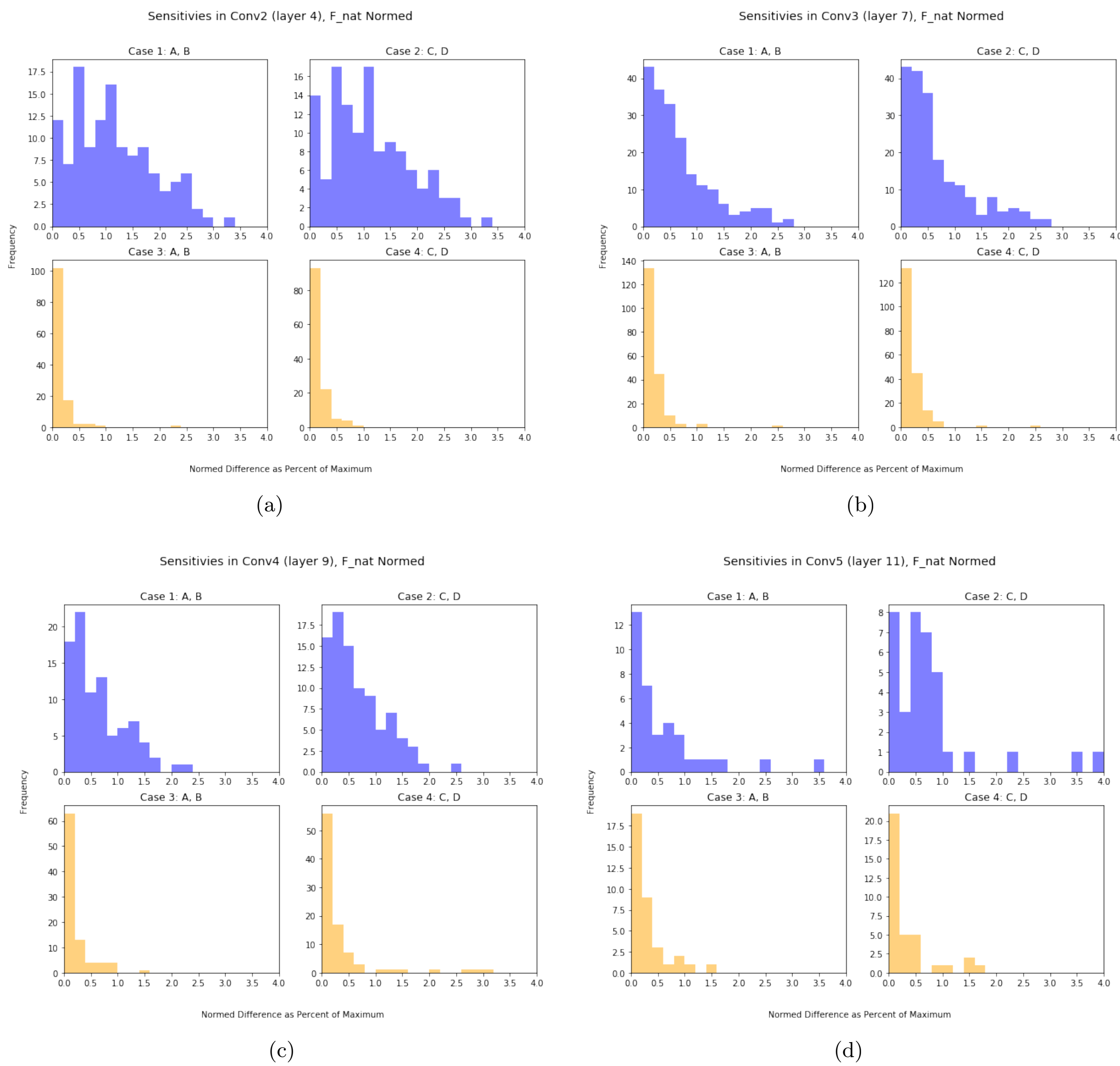
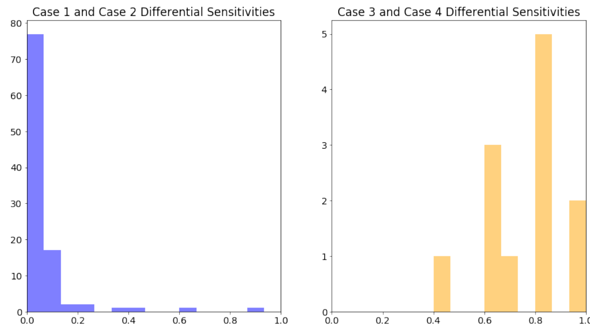
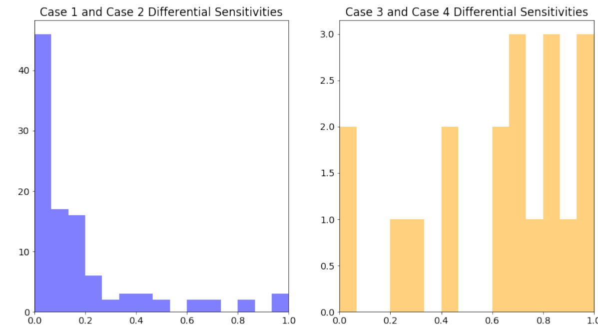


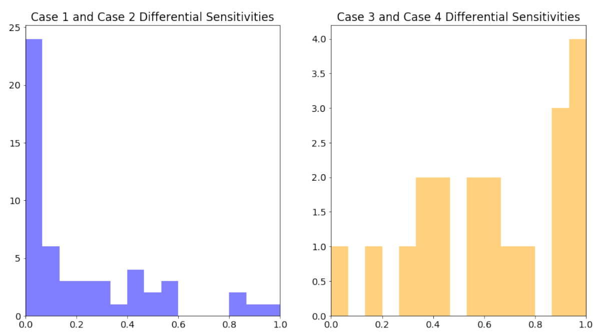
Figure 4: Sensitivity value histograms for each border ownership case (see Figure 1) for (a) Conv2 (b) Conv3 (c) Conv4 and (d) Conv5



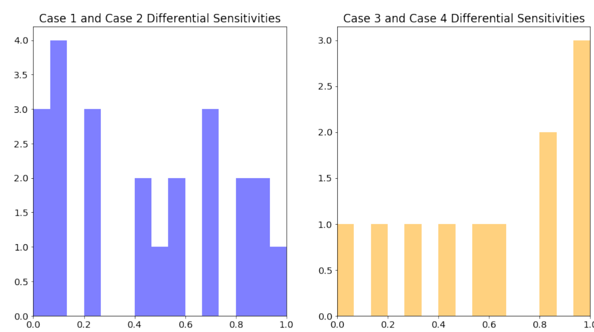
(a)



(b)



(c)



(d)

Figure 5: Differential Sensitivity value histograms for each border ownership case to visualize how many kernels respond specifically to border ownership and are contrast invariant. Differential Sensitivity is the percent difference between kernel sensitivity in case 1 and case 2 and/or case 3 and case 4. Histograms are plotted for (a) conv2 (b) conv3 (c) conv4 and (d) conv5.

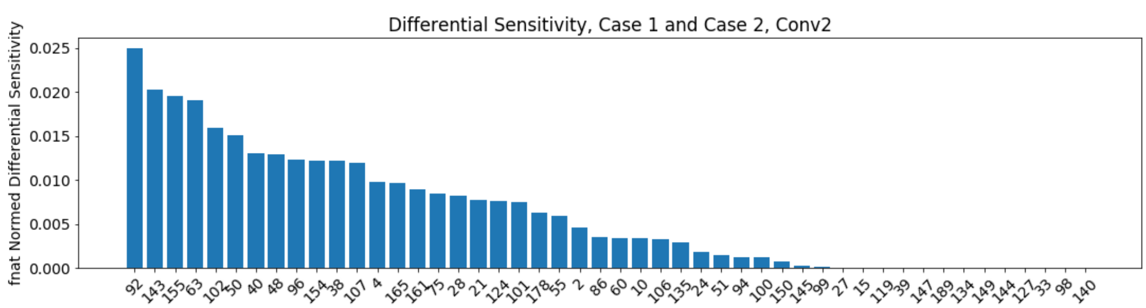


Figure 6: AlexNet Conv2 lowest differential sensitivity kernels for stimuli in Case 1 and Case 2 (See Figure 1). The top candidates for simple stimulus case border ownership are the kernels with the smallest values. These are the kernels that least respond to image contrast, but respond differentially to either border context instance.

4 Conclusions

In general, the analysis as presented seems to suggest that kernels are more sensitive to border ownership in the simple stimulus case (Case 1 and Case 2) versus the overlapping figure stimulus case (Case 3 and Case 4). It is not immediately clear why this should be the case, as within the MRF region the border stimulus is nearly identical to that of the simple stimulus case. Another overall result appears to be that earlier convolutional layers tend to have more contrast invariant border ownership kernel candidates than later layers (see Figure 5). There are some quality candidates across the 4 convolutional layers explored here,

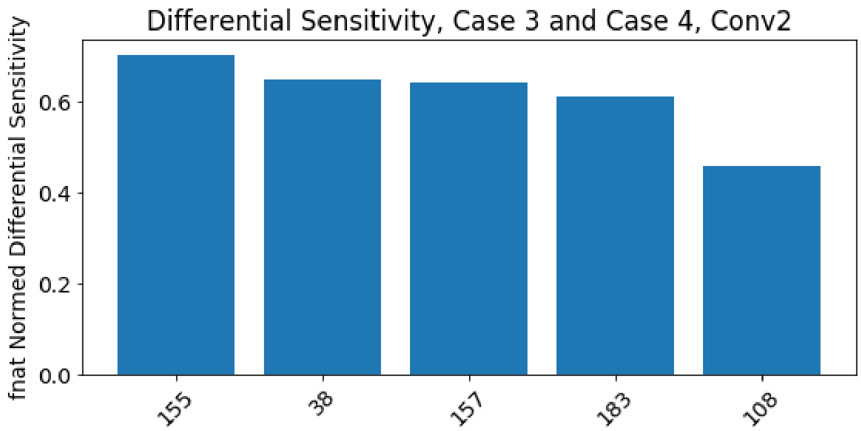


Figure 7: AlexNet Conv2 lowest differential sensitivity kernels for stimuli in Case 3 and Case 4 (See Figure 1). The top candidates for overlapping figure border ownership are the kernels with the smallest values. These are the kernels that least respond to image contrast, but respond differentially to either border context instance.

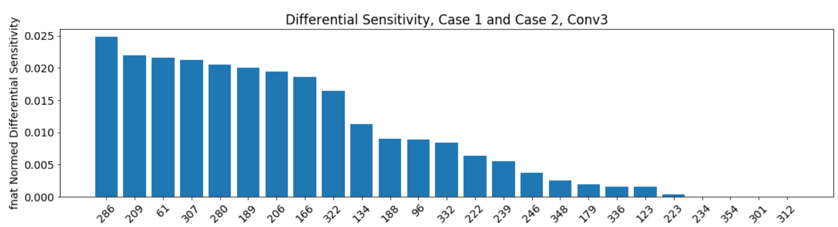


Figure 8: AlexNet Conv3 lowest differential sensitivity kernels for stimuli in Case 1 and Case 2 (See Figure 1). The top candidates for simple stimulus case border ownership are the kernels with the smallest values. These are the kernels that least respond to image contrast, but respond differentially to either border context instance.

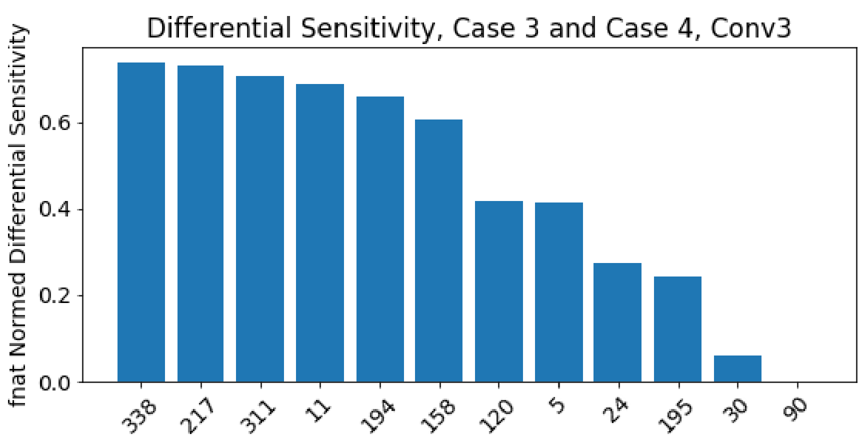


Figure 9: AlexNet Conv3 lowest differential sensitivity kernels for stimuli in Case 3 and Case 4 (See Figure 1). The top candidates for overlapping figure border ownership are the kernels with the smallest values. These are the kernels that least respond to image contrast, but respond differentially to either border context instance.

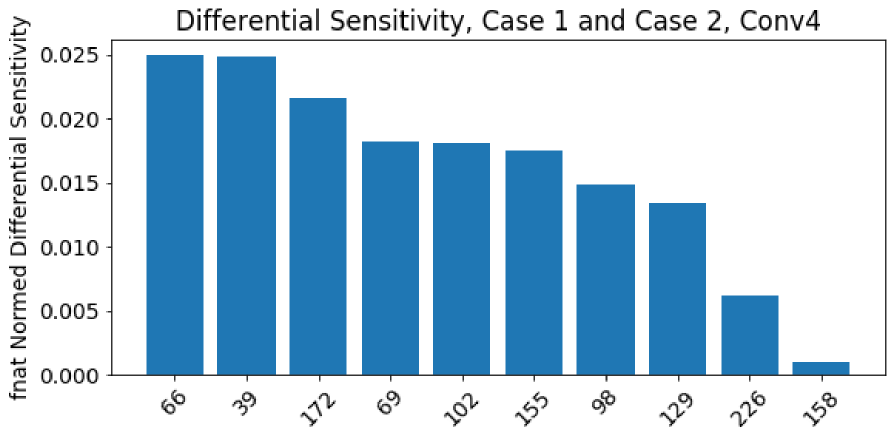


Figure 10: AlexNet Conv4 lowest differential sensitivity kernels for stimuli in Case 1 and Case 2 (See Figure 1). The top candidates for simple stimulus case border ownership are the kernels with the smallest values. These are the kernels that least respond to image contrast, but respond differentially to either border context instance.

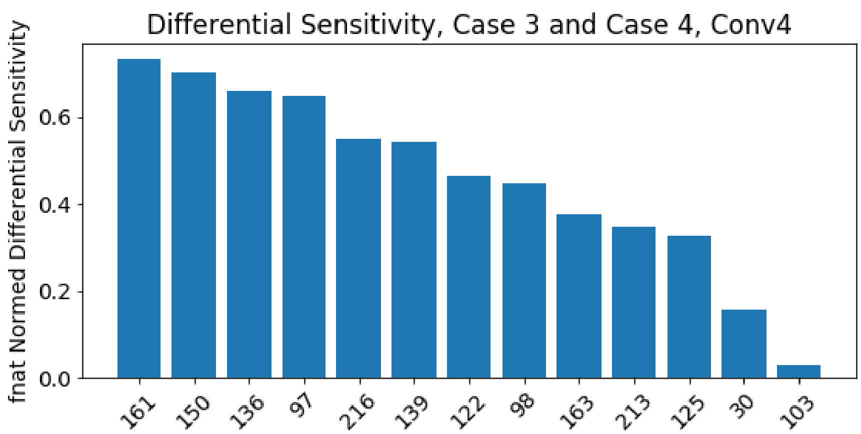


Figure 11: AlexNet Conv4 lowest differential sensitivity kernels for stimuli in Case 3 and Case 4 (See Figure 1). The top candidates for overlapping figure border ownership are the kernels with the smallest values. These are the kernels that least respond to image contrast, but respond differentially to either border context instance.

but to most thoroughly argue for these kernels as border ownership kernels, some additional work still needs to be completed. One current shortcoming is that the stimuli were scaled to fit the exact size of the reported MRF for each kernel. A such, size invariance of border ownership response remains to be demonstrated. Additionally, orientation invariance will also need to be shown. Overall, the work presented here represents a significant first step towards characterizing border ownership kernels in the early convolutional layers of the pytorch implementation of AlexNet.

References

Zhou, H, H S Friedman, and R Von Der Heydt (2000). "Coding of border ownership in monkey visual cortex". eng. In: *The Journal of neuroscience : the official journal of the Society for Neuroscience* 20.17, p. 6594. ISSN: 0270-6474.

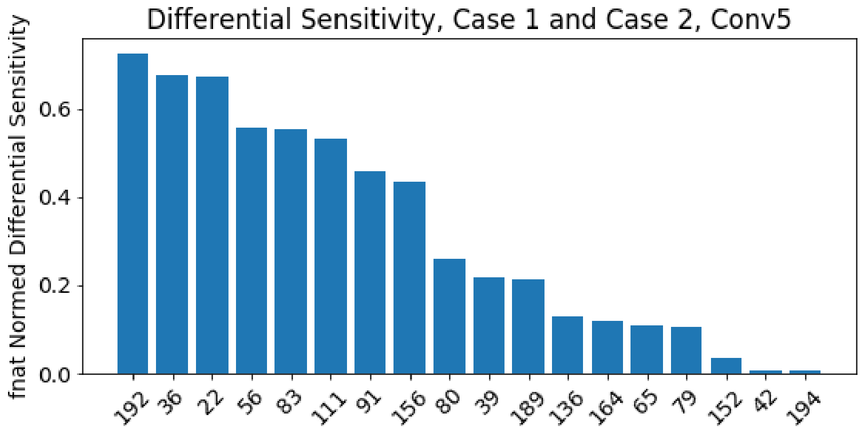


Figure 12: AlexNet Conv5 lowest differential sensitivity kernels for stimuli in Case 1 and Case 2 (See Figure 1). The top candidates for simple stimulus case border ownership are the kernels with the smallest values. These are the kernels that least respond to image contrast, but respond differentially to either border context instance.

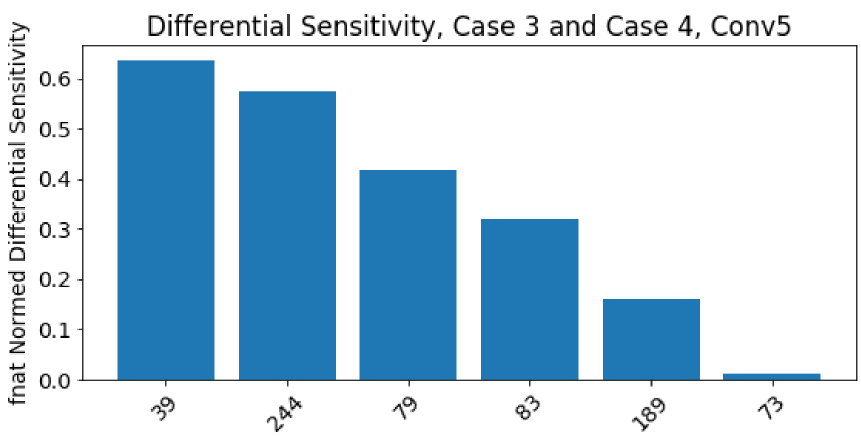


Figure 13: AlexNet Conv5 lowest differential sensitivity kernels for stimuli in Case 3 and Case 4 (See Figure 1). The top candidates for overlapping figure border ownership are the kernels with the smallest values. These are the kernels that least respond to image contrast, but respond differentially to either border context instance.