Debugging the Internals of Convolutional Networks

eXplainable AI paper presentation

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Outline

1. Introduction and main goal
2. Feature-Map artifacts
3. Asymmetries in the learned weights
4. Limitations and conclusions

Introduction and main goal

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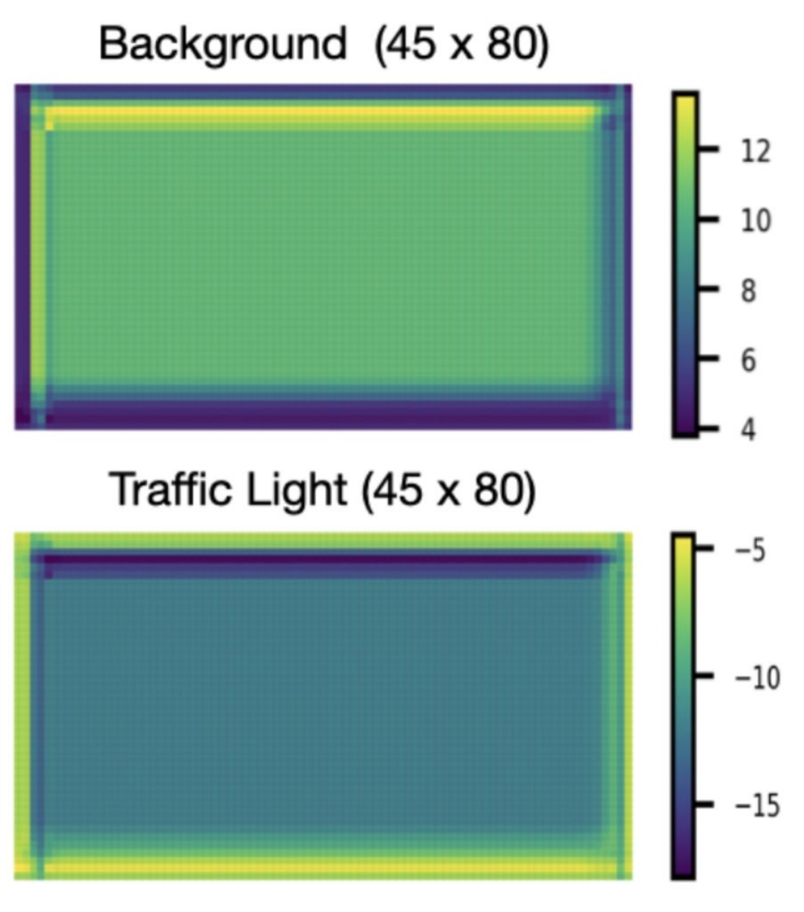
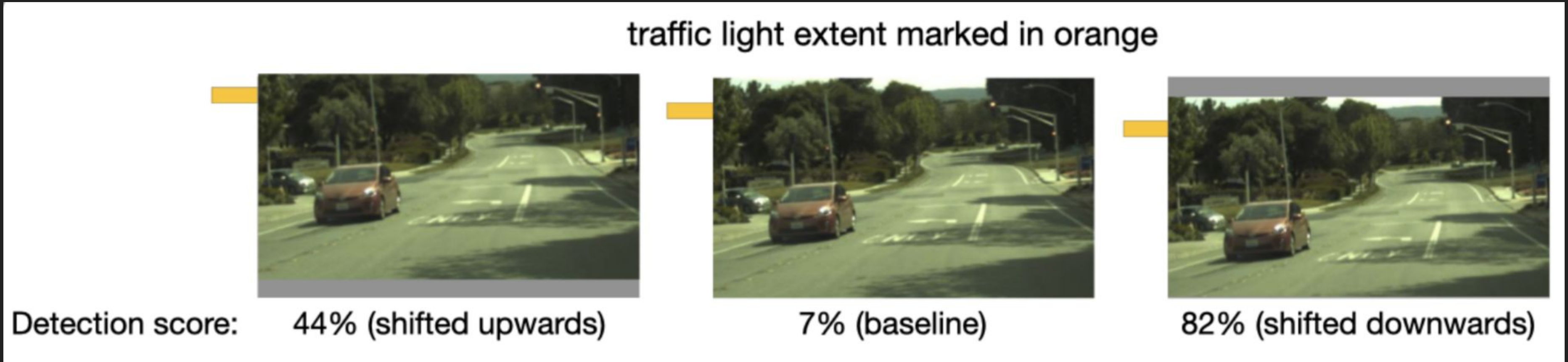
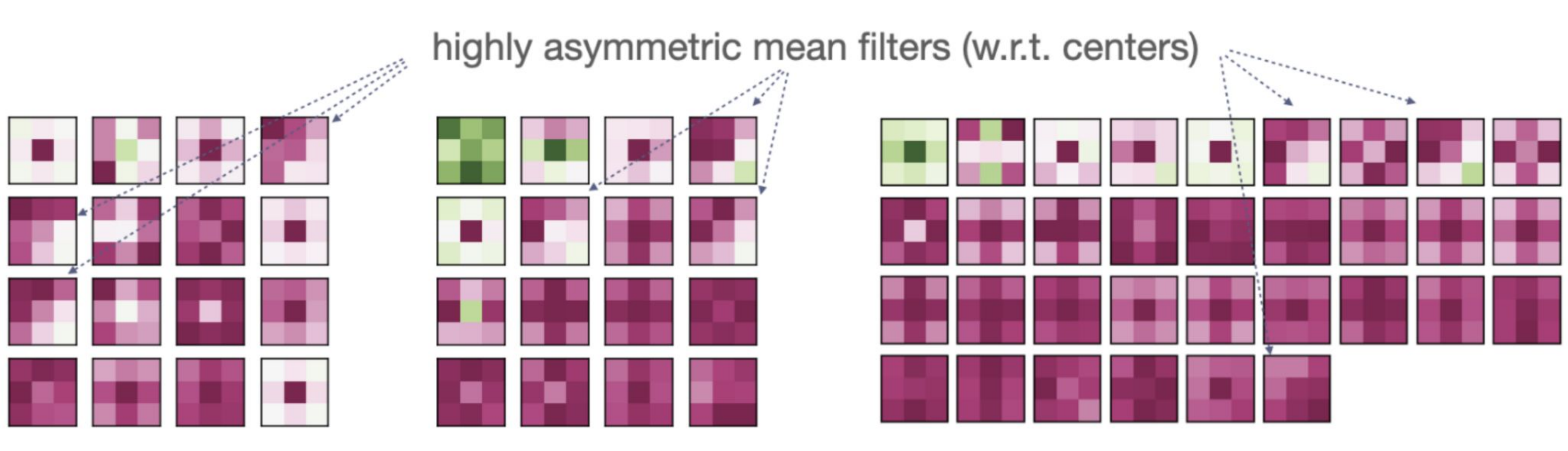
- In feature maps, these can be seen as artifacts
- The effects can further manifest in the form of asymmetries in the learned weights
- Later, we will discuss the details of why such problems emerge in ConvNets



Background (45 x 80)
12
10
8
6
4
Traffic Light (45 x 80)
−5
−10
−15


traffic light extent marked in orange
Detection score:
44% (shifted upwards)
7% (baseline)
82% (shifted downwards)


highly asymmetric mean filters (w.r.t. centers)

Main goal

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Detecting, visualizing and explaining biases in CNN models (artifacts, asymmetries) caused by specifics of the convolutional arithmetic

Feature-Map artifacts

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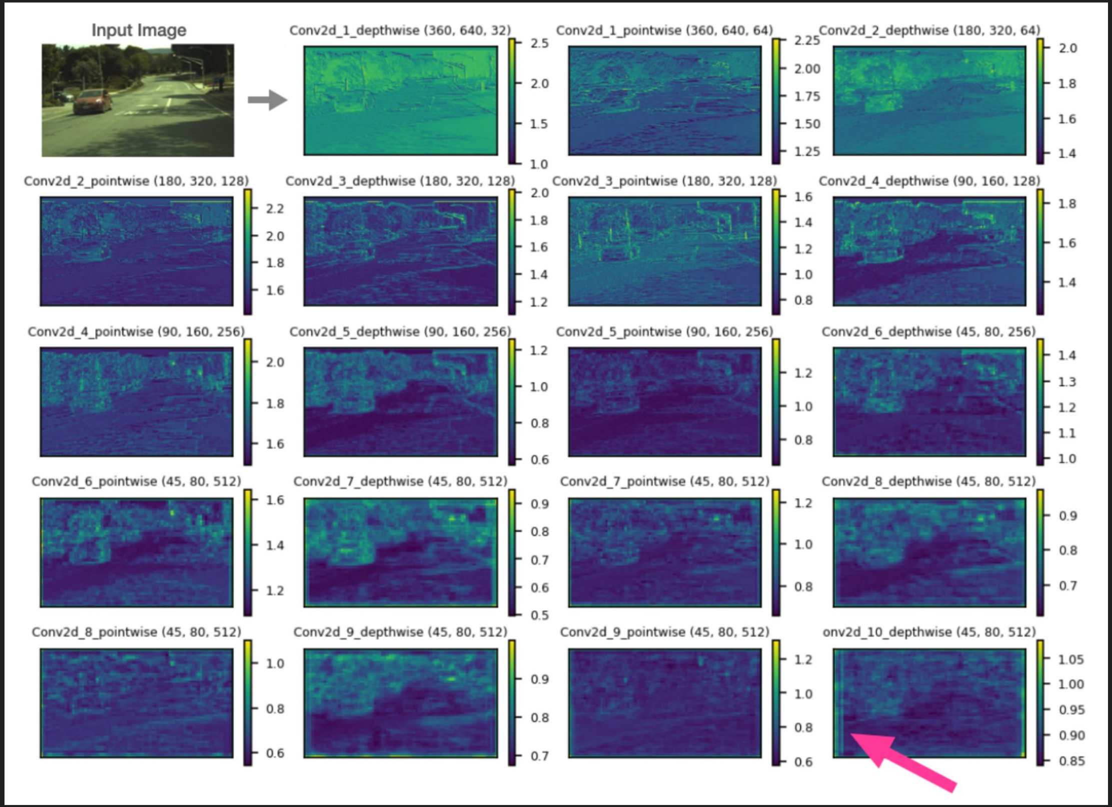
- This poses challenges regarding scalability and ability to spot the artifacts
- To enable scalable inspection, we can aggregate the feature maps per layer and provide an overview

How to inspect feature maps?



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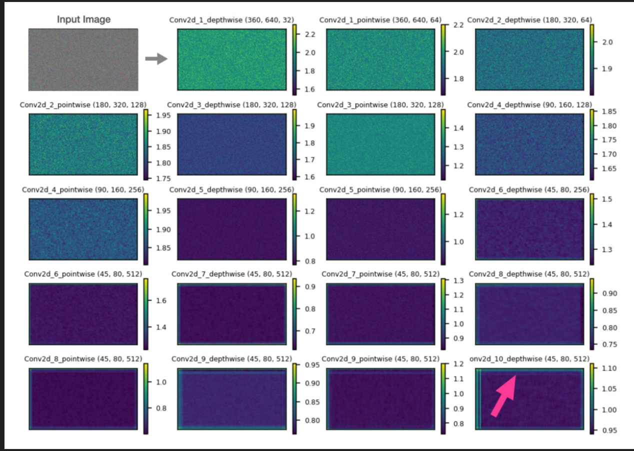

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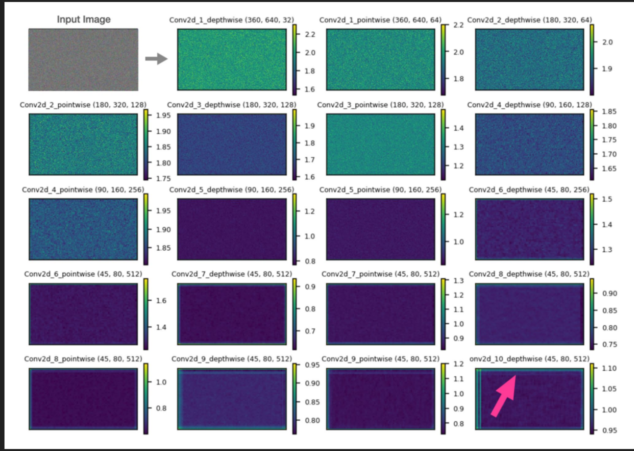

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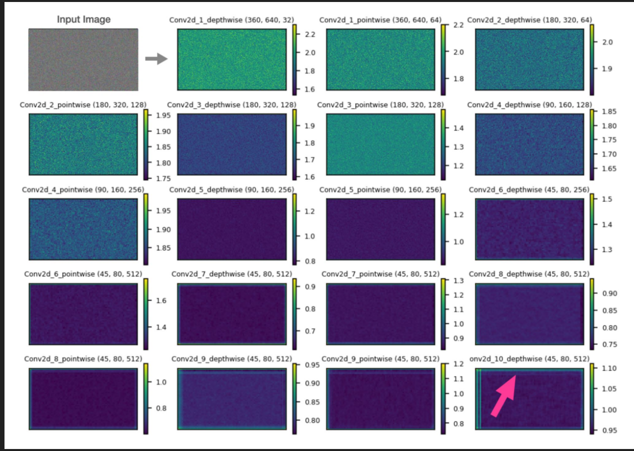

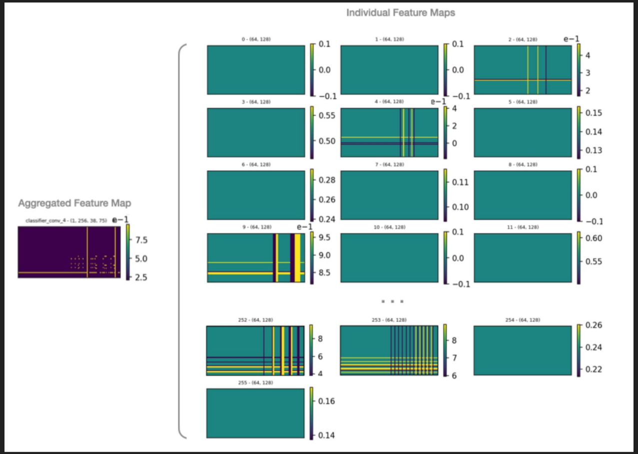

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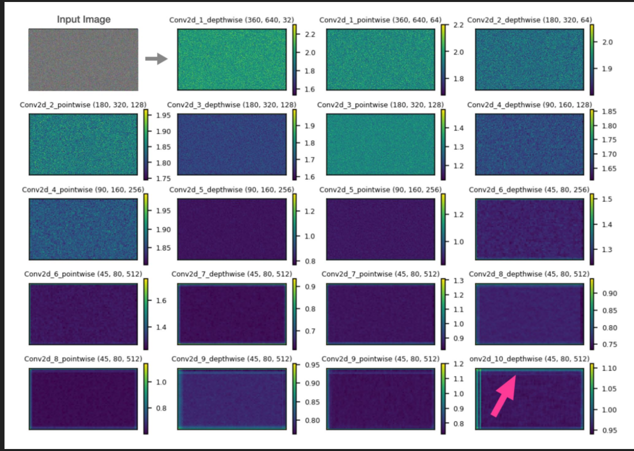
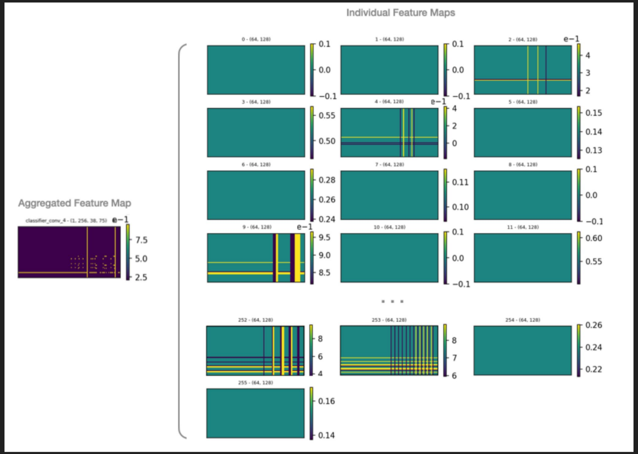
- Simplified input





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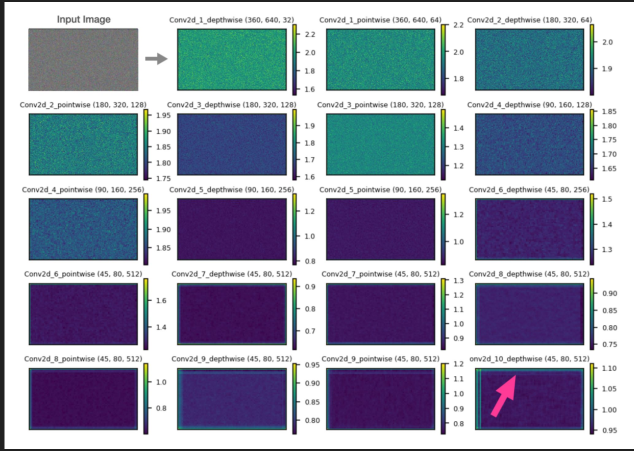

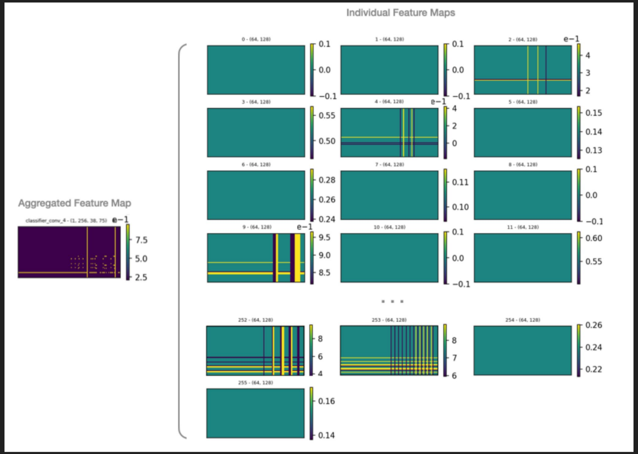

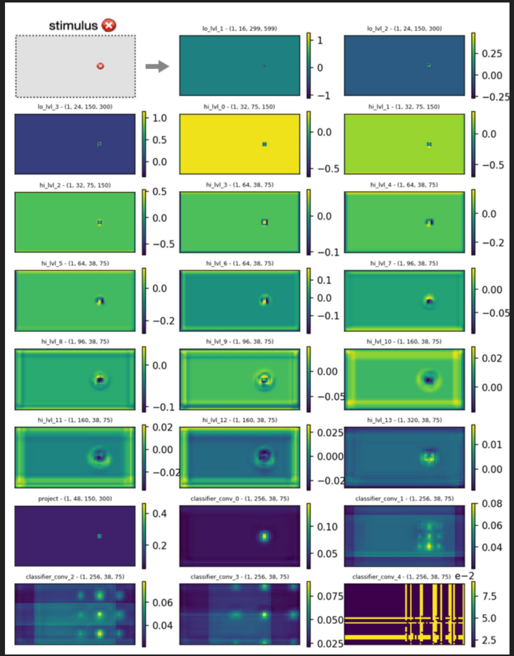

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- Over multiple layers, this boundary interacts with neighboring values
- The artificial motive gradually interferes with the activation patterns inside the feature maps
- This can have a significant impact on small object detection

Asymmetries in the learned weights

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- Layers ignore parts of the padding applied when their input size is an even number
- This leads to patterns in kernels caused by the model architecture rather than data

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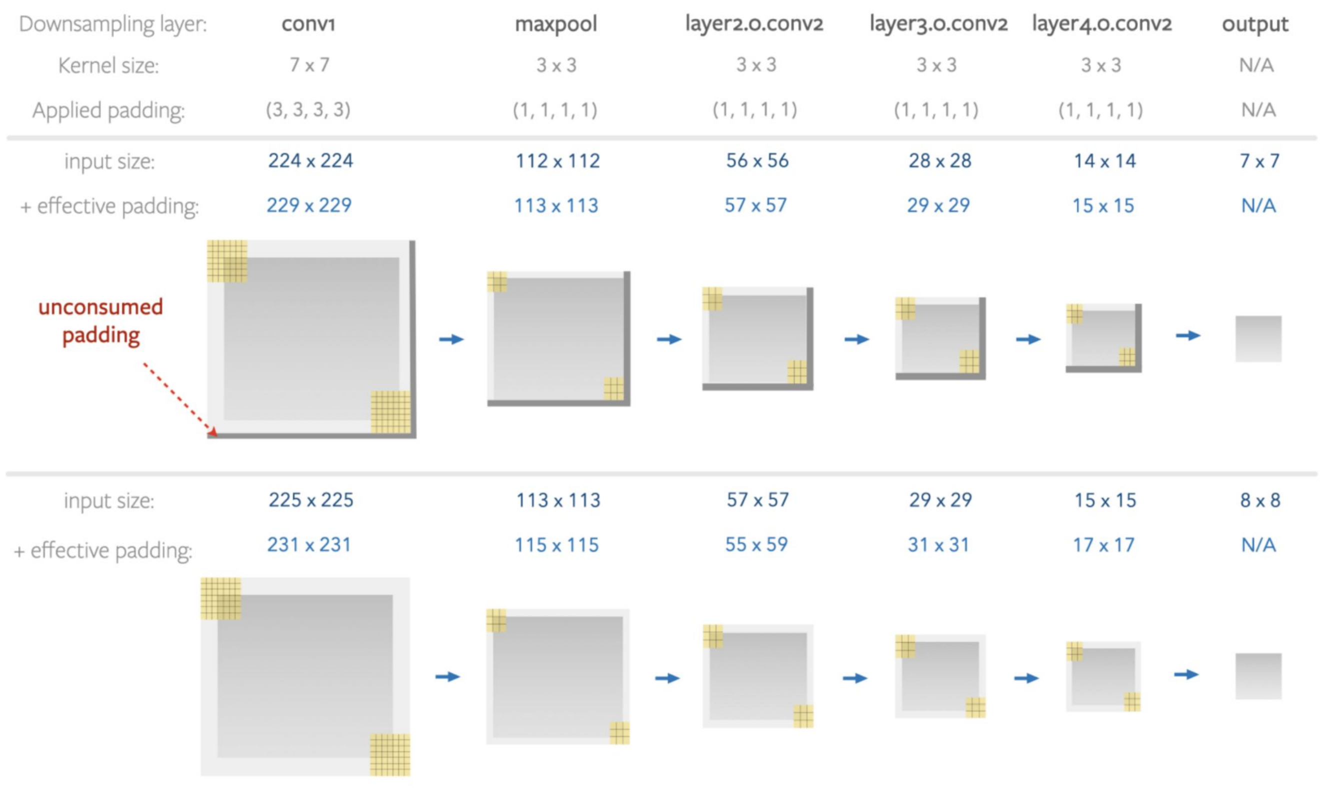

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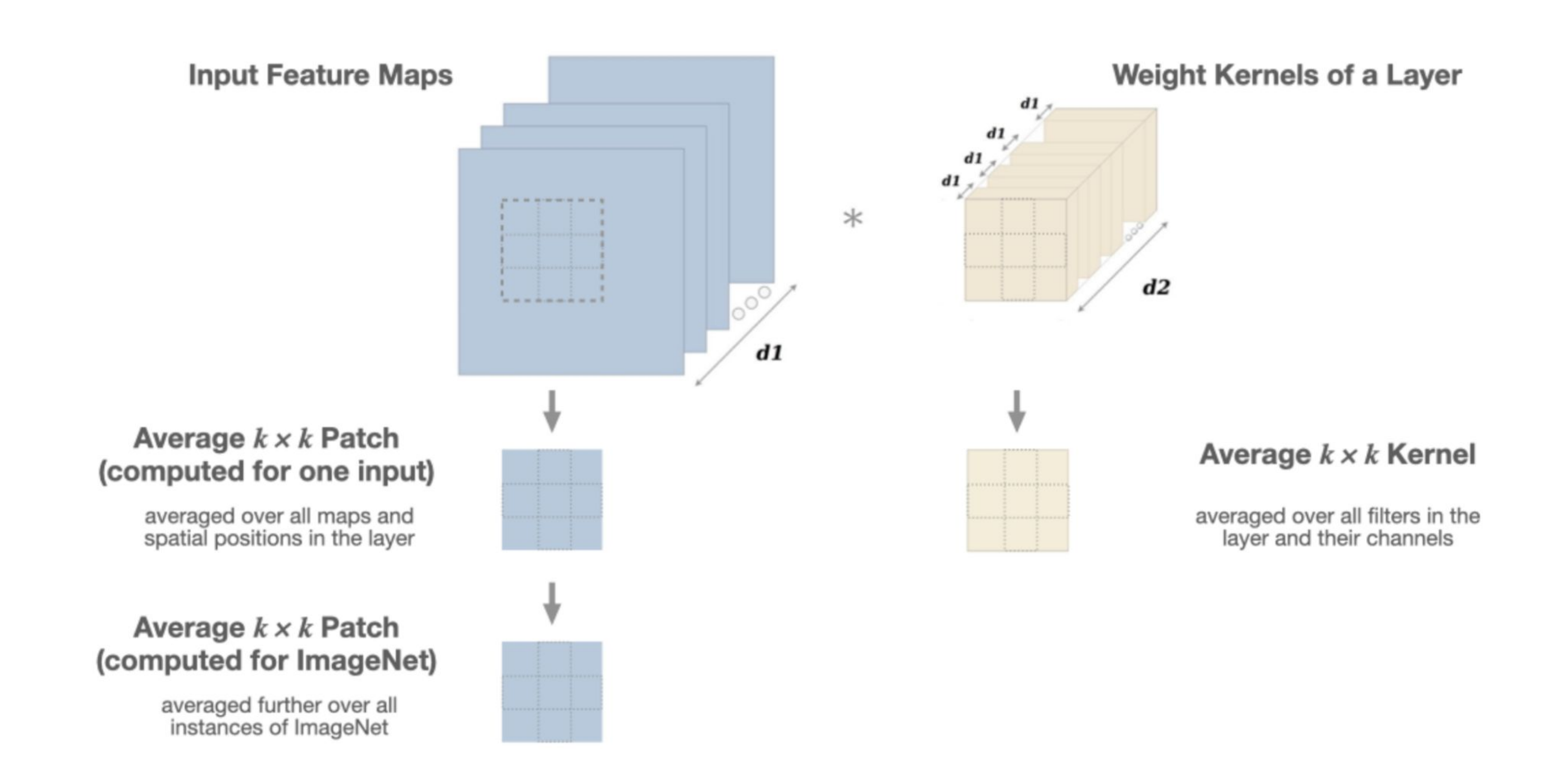
- We can then average the input over the spatial positions, channels, and instances of the training set
- In addition, we can also compute the mean k × k kernel in the weights of the corresponding layer

Examining asymmetries



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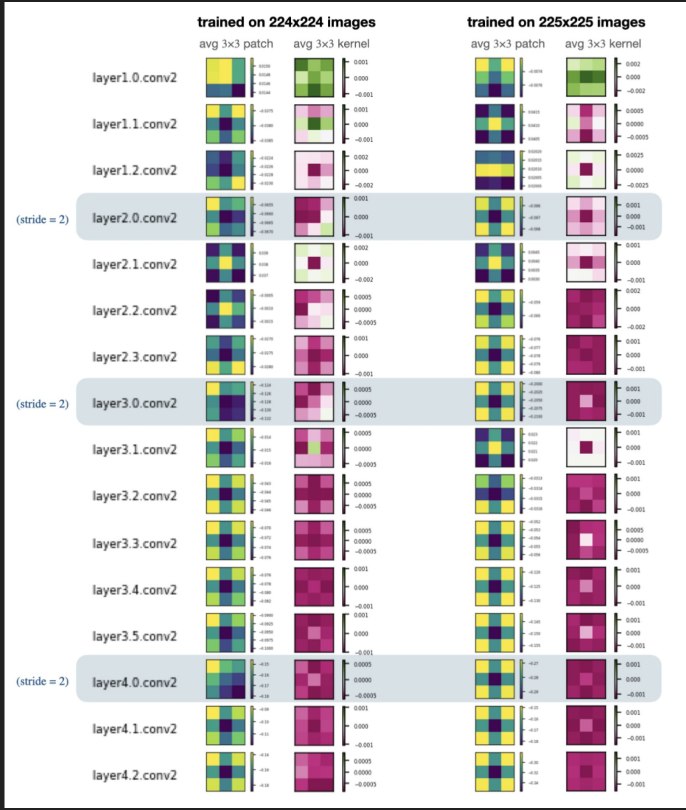

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- The asymmetries appear when the model is trained on 224 × 224 images
- Mean kernels of stride-convolution downsampling layers exhibit similar asymmetrie

Limitations and conclusions

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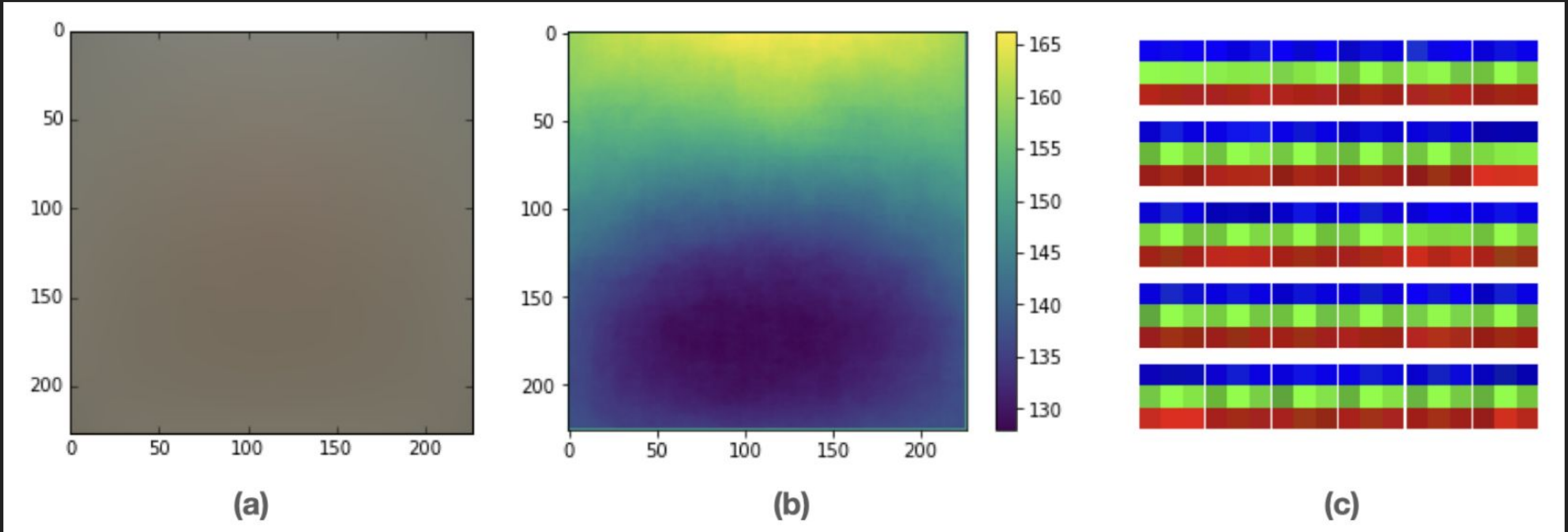
- Moreover, the asymmetries might not be an artifact of CNN arithmetic, but rather reflect properties of the dataset
- Analyzing the dataset features and examining the weight kernels under different hyperparameters can help determine possible reasons



0
50
100
150
200
0
50
100
150
200
(a)
0
50
100
150
200
0
50
100
150
200
165
160
155
150
145
140
135
130
(b)
(c)

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- Computing the mean feature map and kernel in a layer is crucial to expose spatial bias and asymmetries
- Considering multiple visual representations of the model internals is helpful to iteratively reveal patterns
- Aspects of convolutional arithmetic cause variations in model representation. Mitigating them is important to improve robustness and accuracy

Thank you for your attention!