Convolutional Networks (ConvNets) have recently improved image recognition performance thanks to end-to-end learning of deep feed-forward models from raw pixels. Deep learning is a marked departure from the previous state of the art, the Fisher Vector (FV), which relied on gradient-based encoding of local hand-crafted features. In this paper, we discuss the use of gradient-related information (the blue matrices) as transferable representations. Inspired by the Fisher Kernel, we study the gradient representation of ConvNets in a similar fashion to the FV. Second, we show that this gradient representation actually permits the use of gradient-related information (the blue matrices) as transferable representations.

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