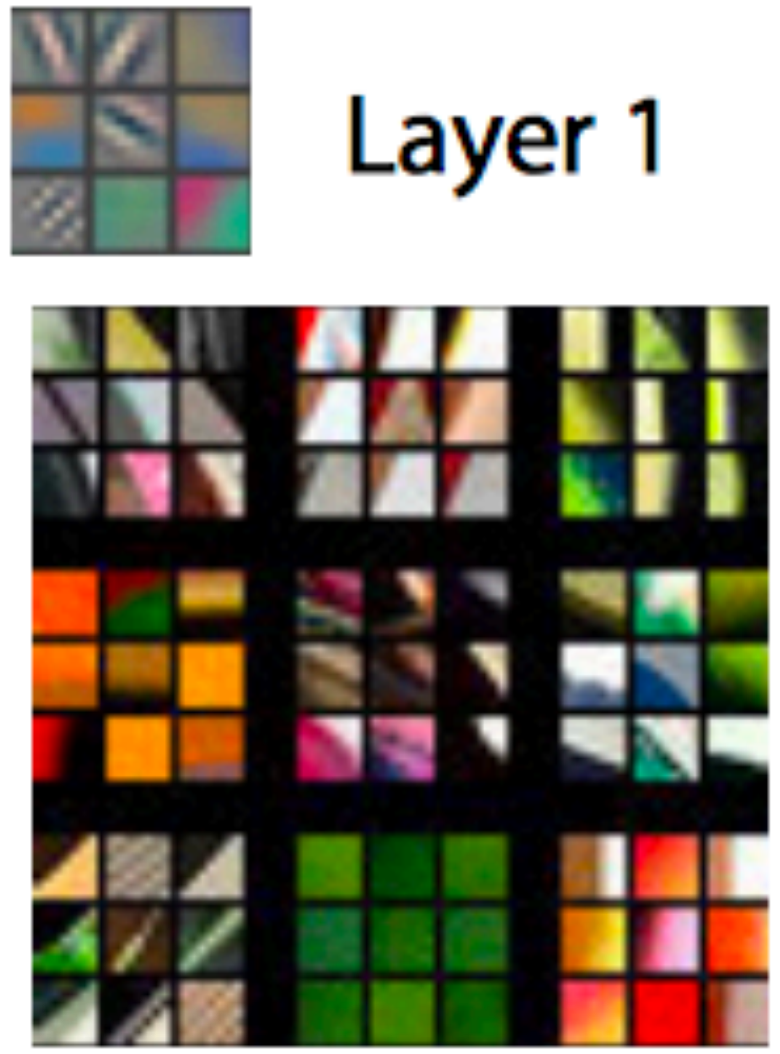
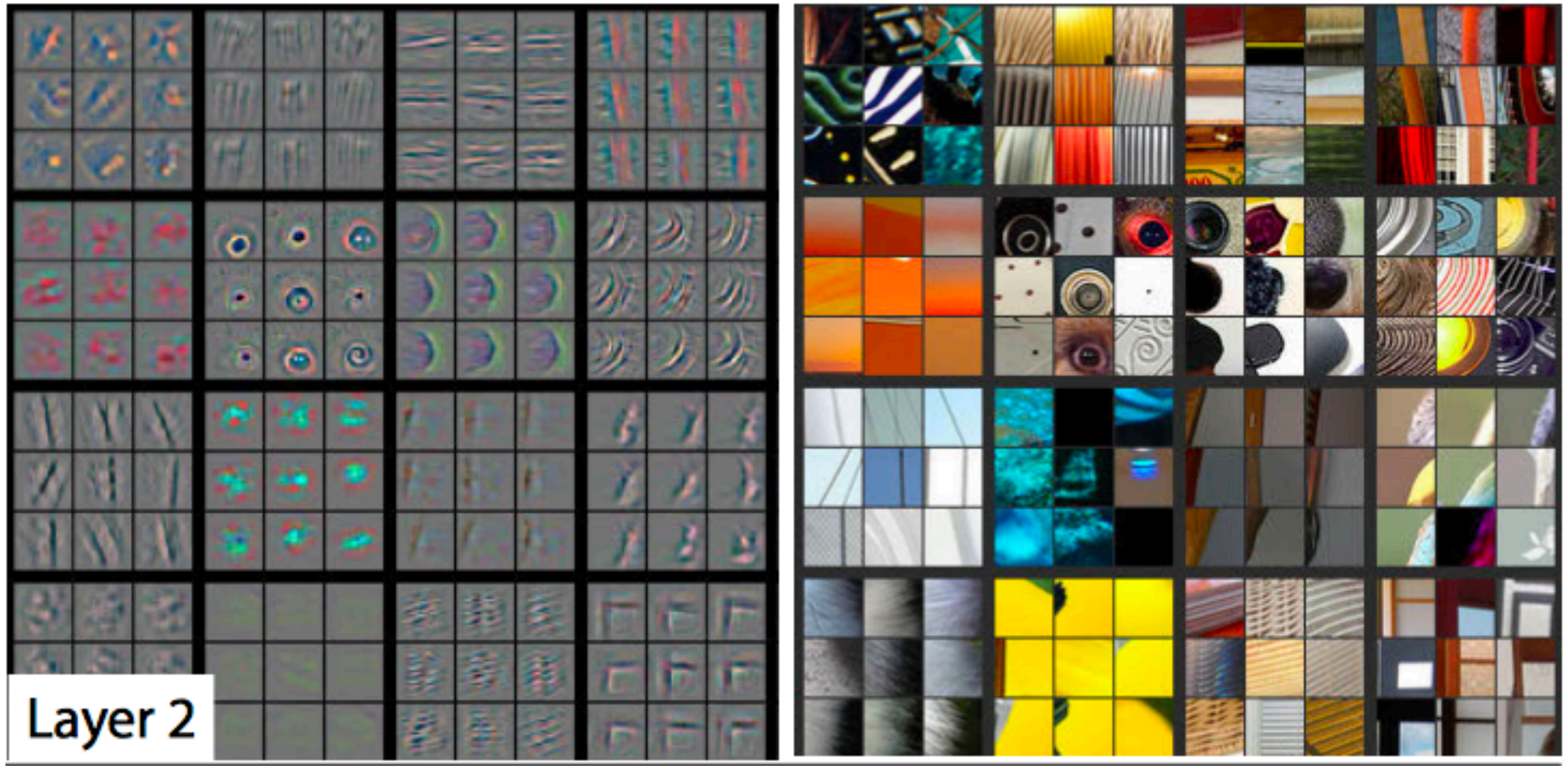
THE UNIVERSITY OF BRITISH COLUMBIA

Topics in AI (CPSC 532S):
Multimodal Learning with Vision, Language and Sound

Lecture 8: Visualizing CNNs

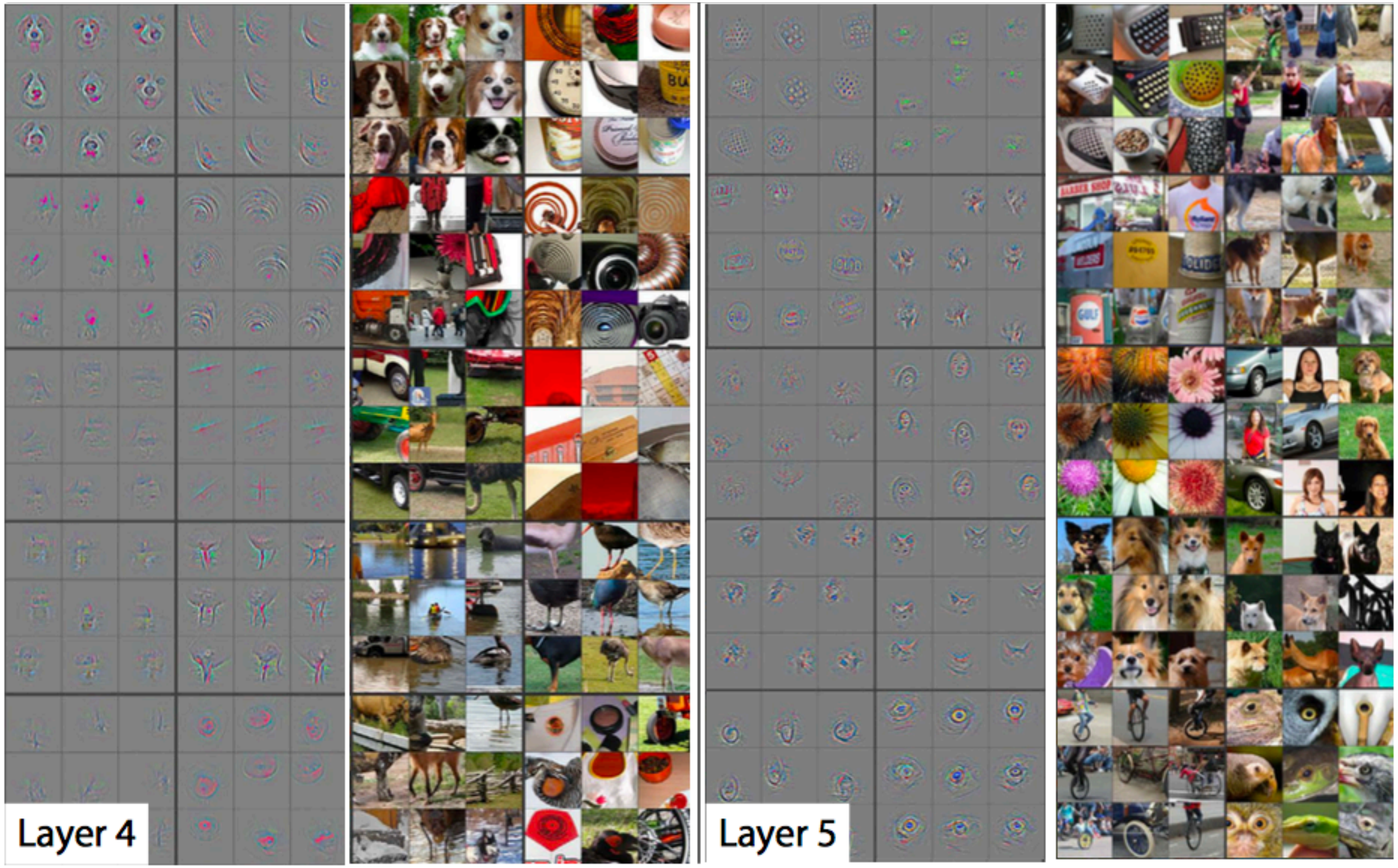
Recall …





[Zeiler and Fergus, 2013]

Recall …



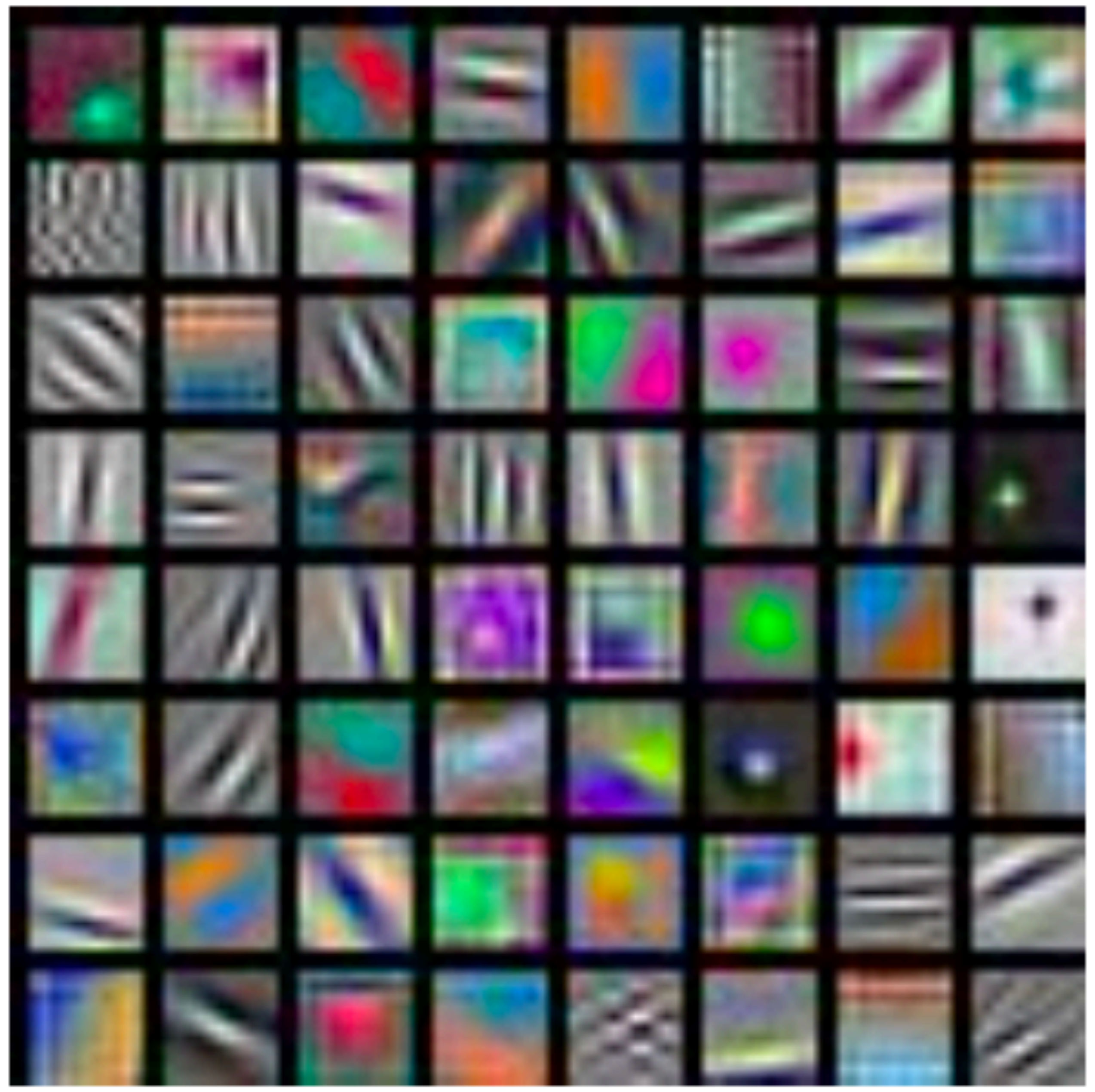
[Zeiler and Fergus, 2013]

Motivation …

CNNs are big black boxes, lets get some intuition for how and why they work

First Layer Filters …

Directly **visualize filters** (only works for the first layer)



AlexNet:
64 x 3 x 11 x 11

ResNet-18:
64 x 3 x 7 x 7

ResNet-101:
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DenseNet-121:
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* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

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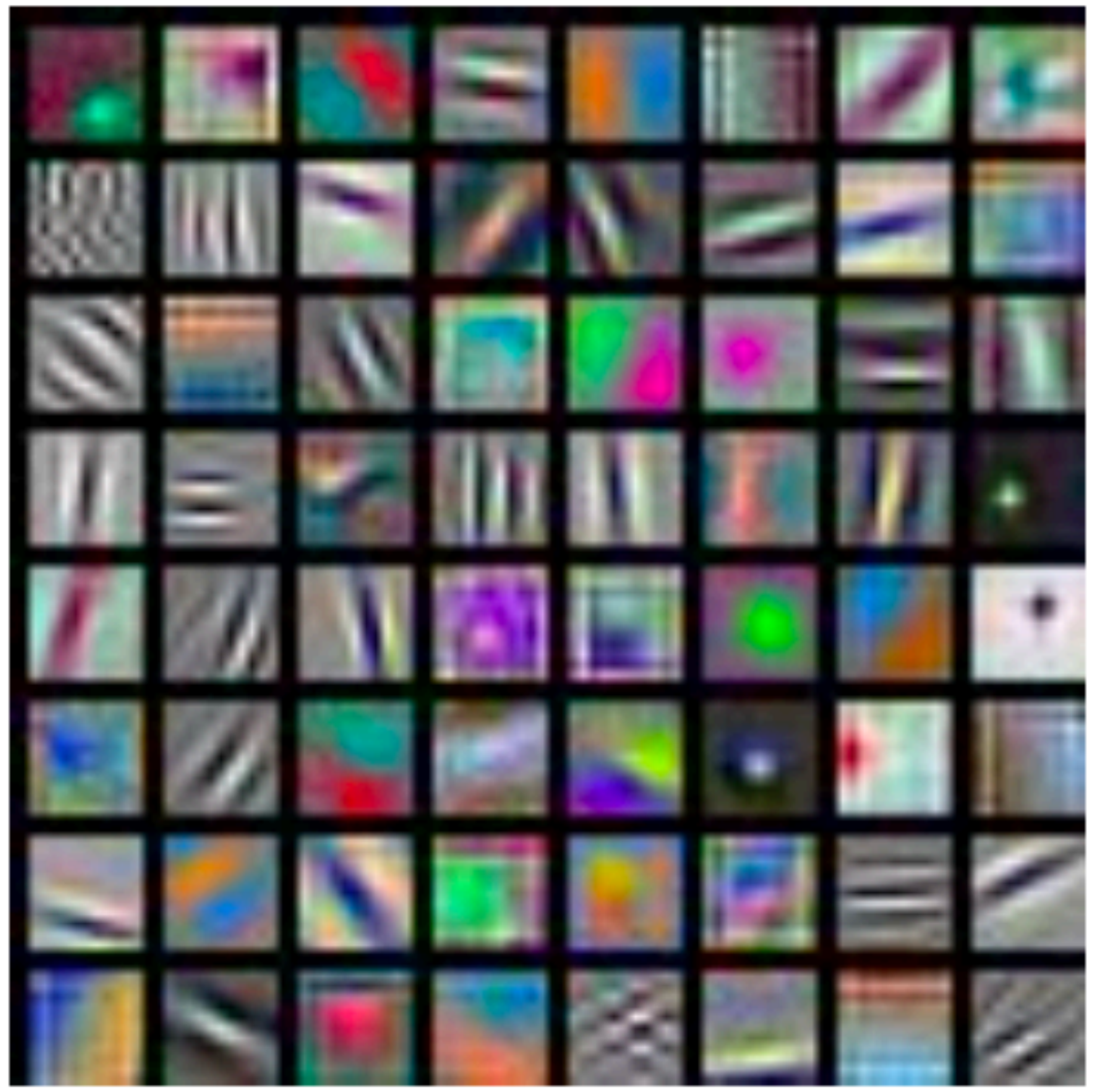

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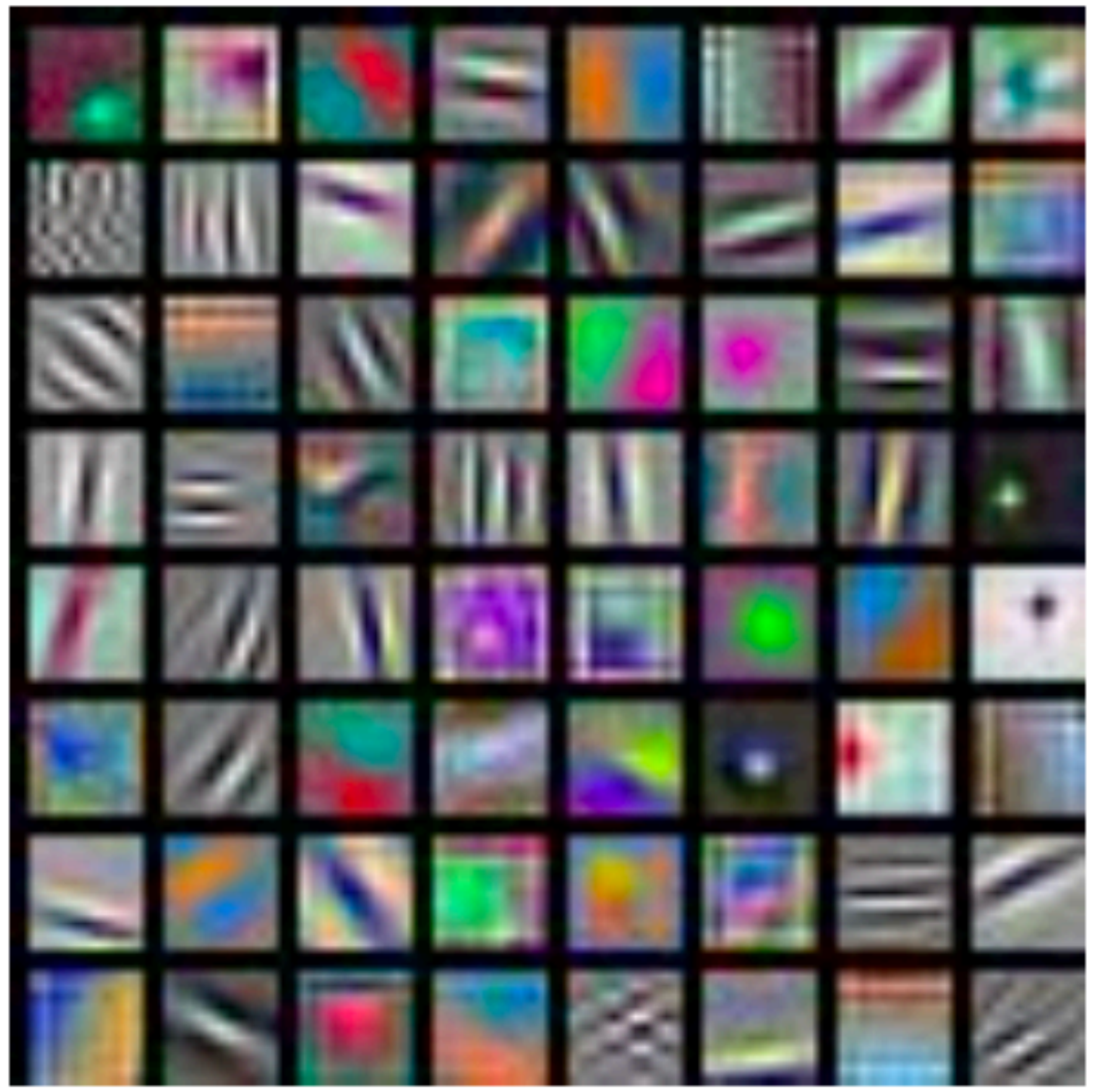

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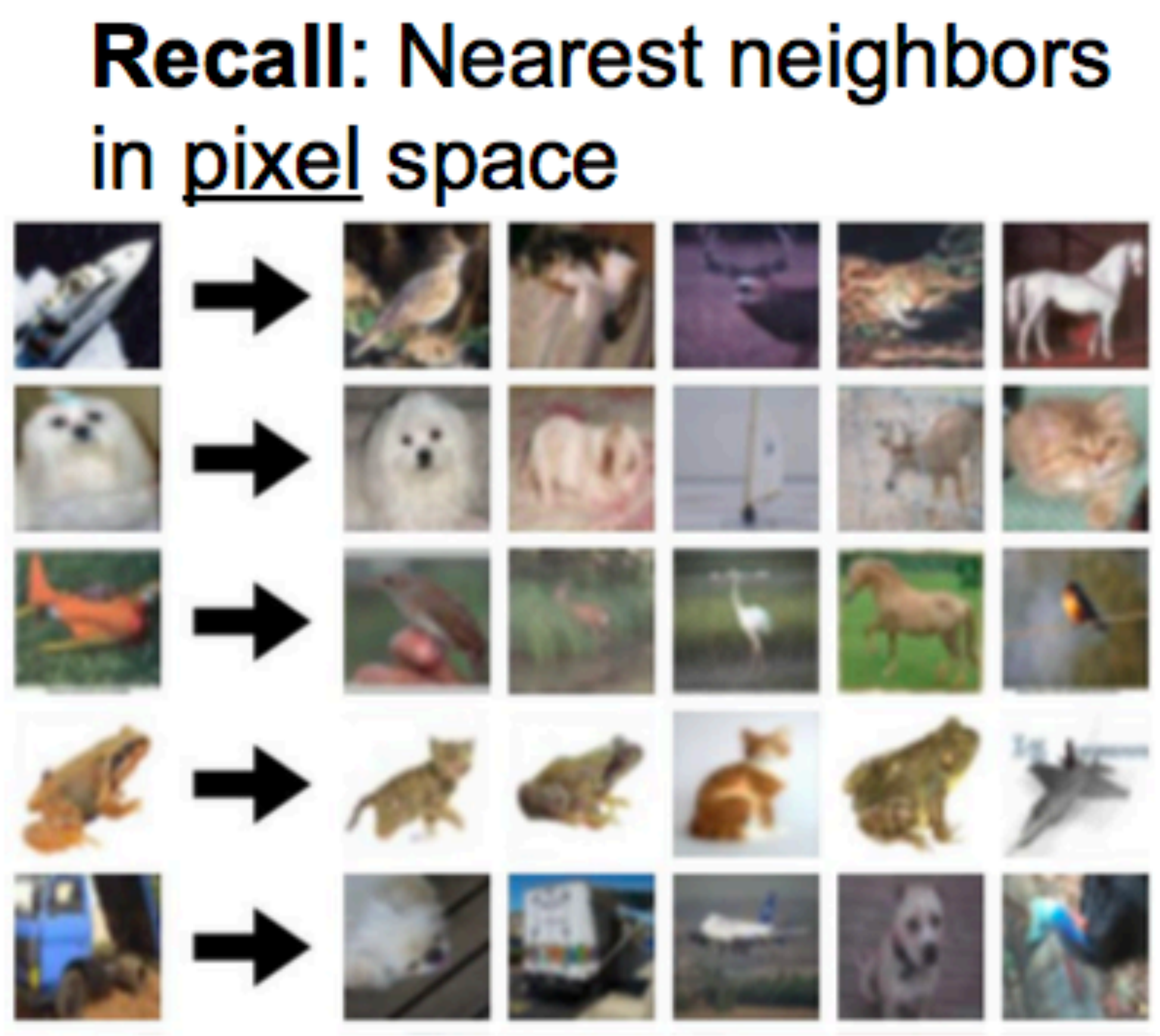
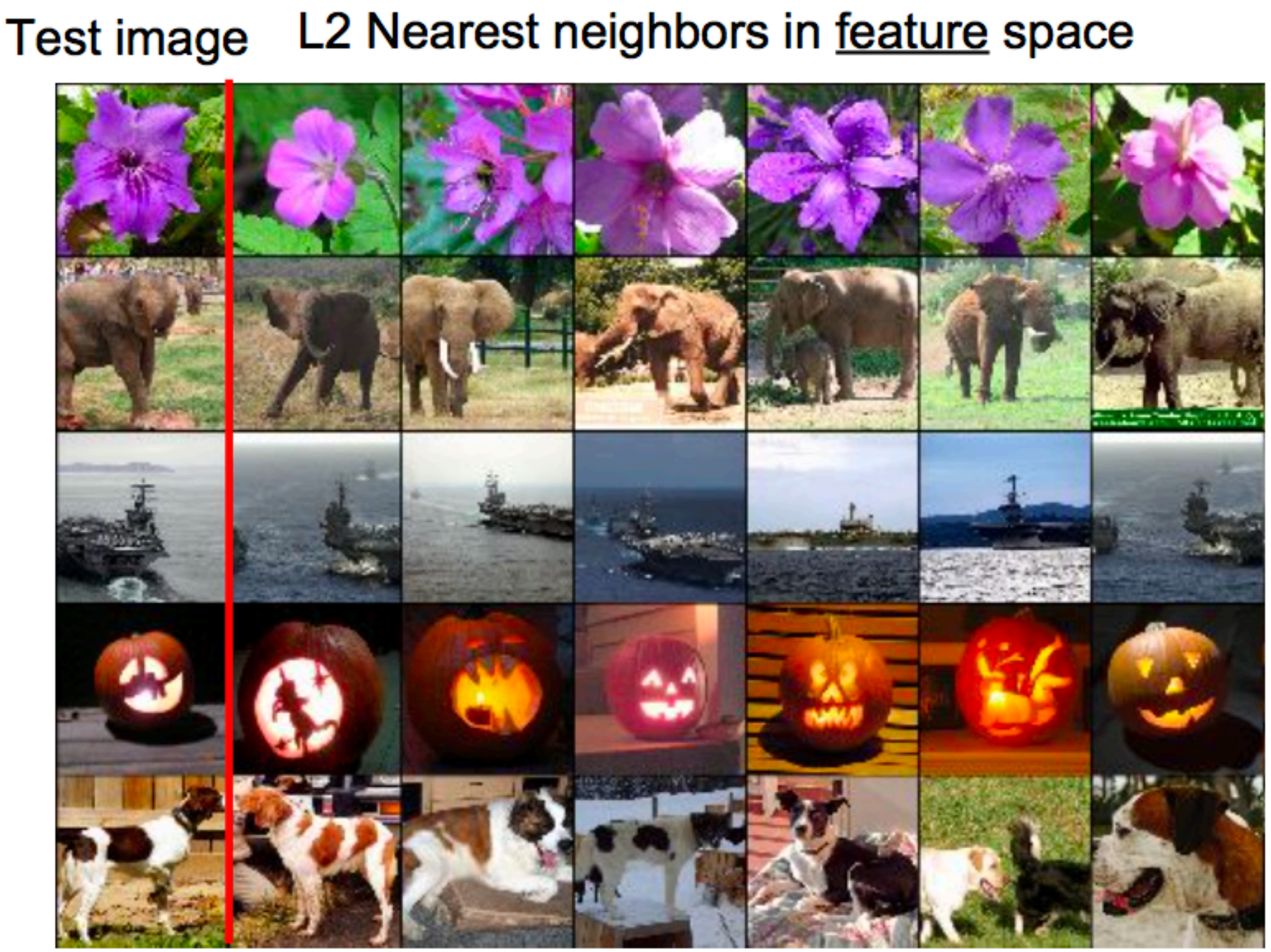
… and nearly any dataset

Last Layer





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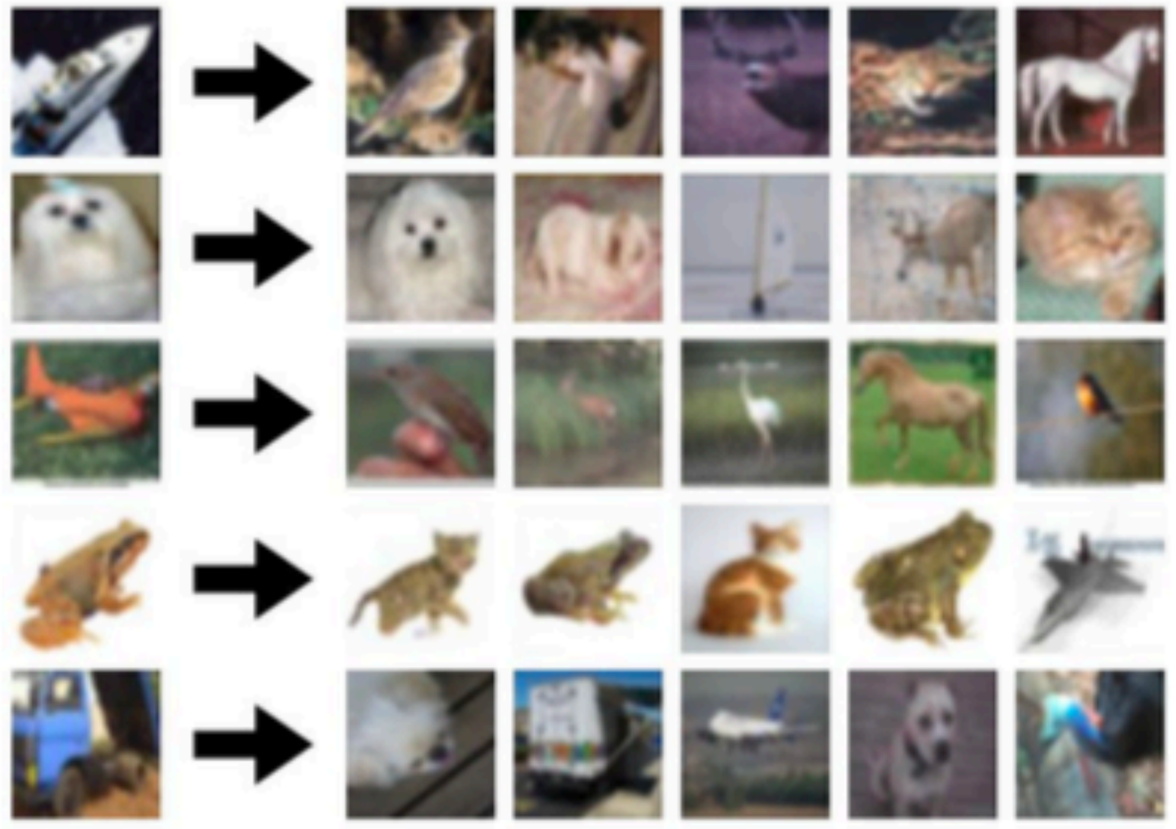
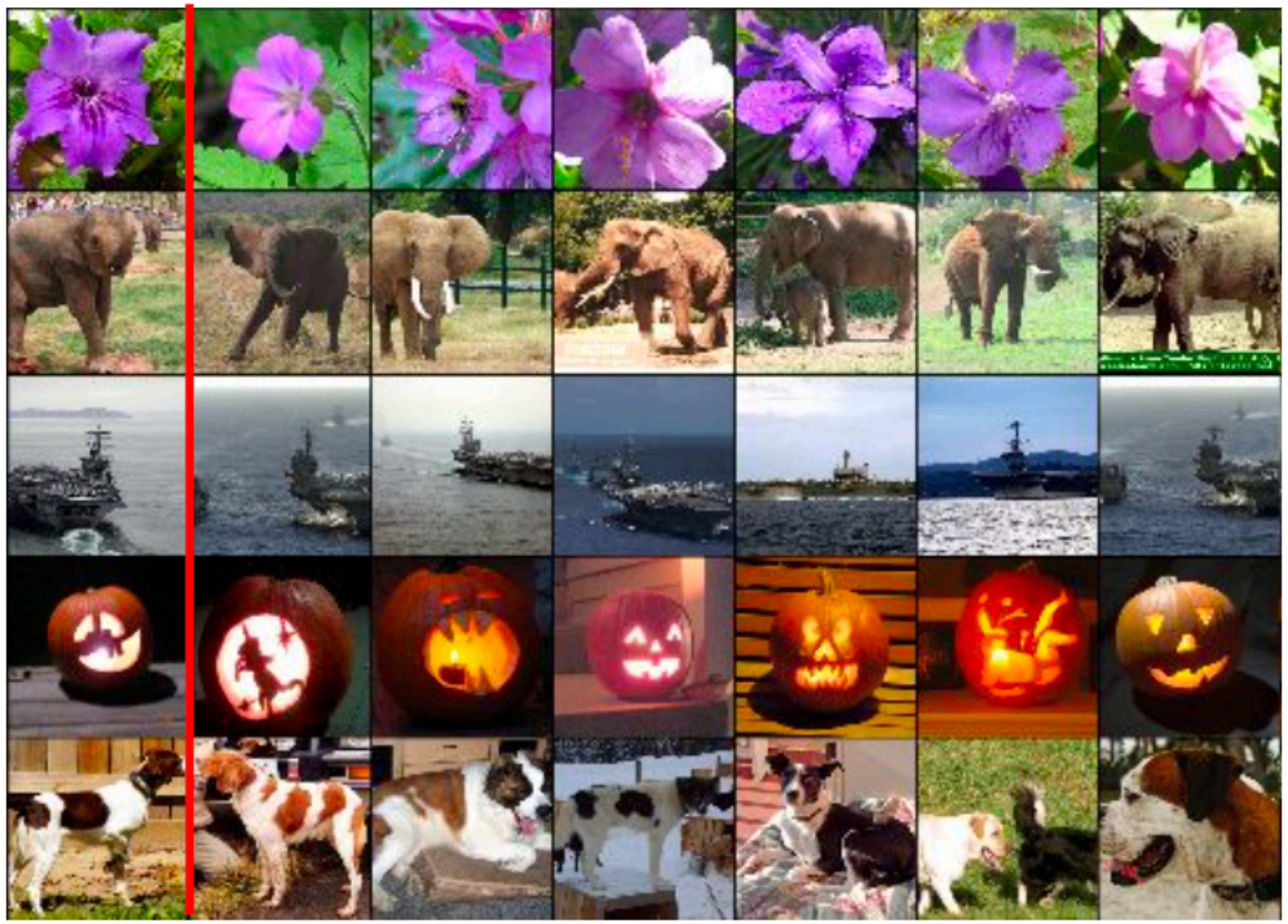
Last Layer

Recall: Nearest neighbors in <u>pixel</u> space



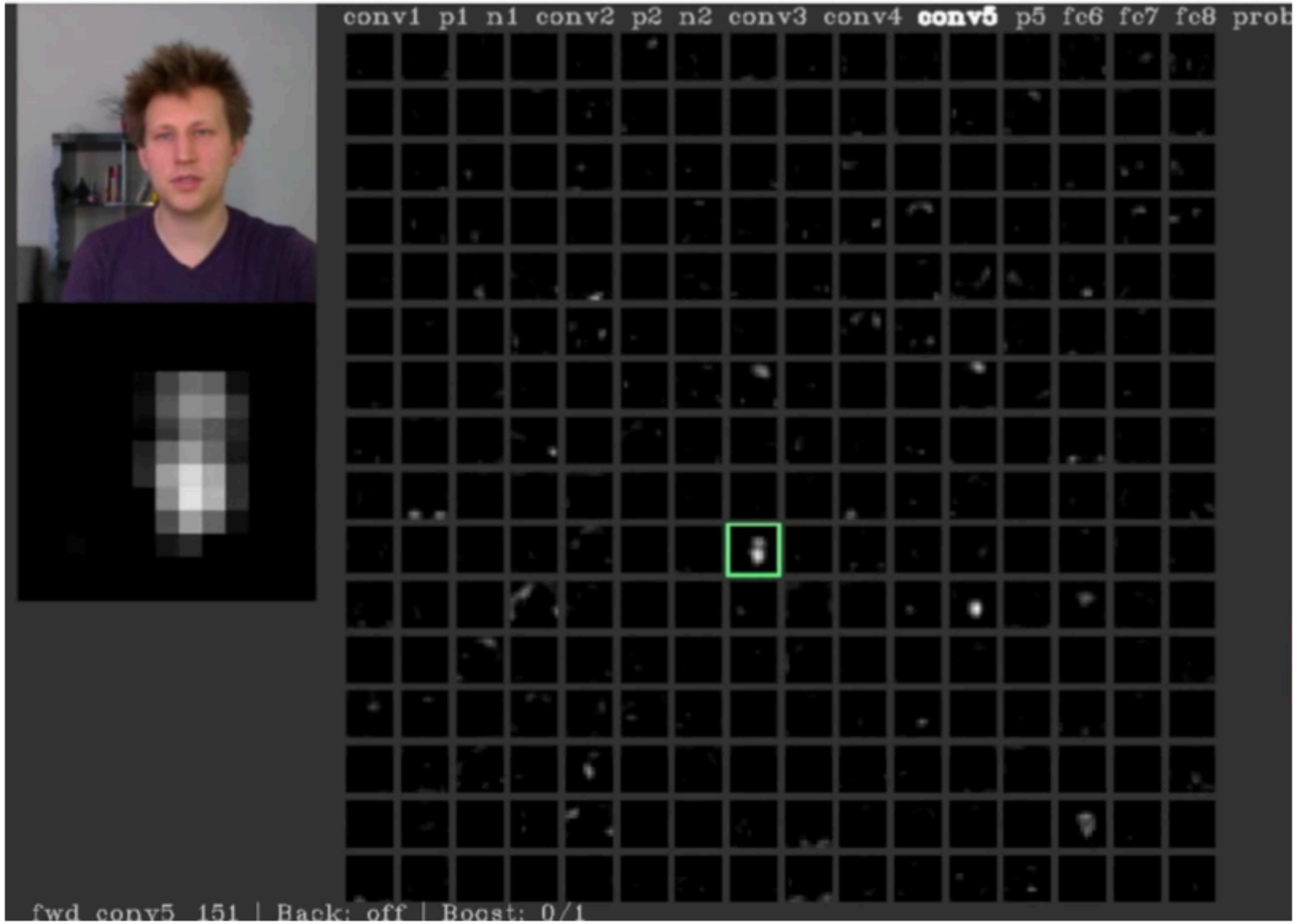
Test image L2 Nearest neighbors in <u>feature</u> space



… you are doing this for **Assignment 2**

Visualizing **Activations**

conv5 feature map of AlexNet is 128x13x13; visualize as 128 13x13 grayscale images



[Yosinski et al., 2014]

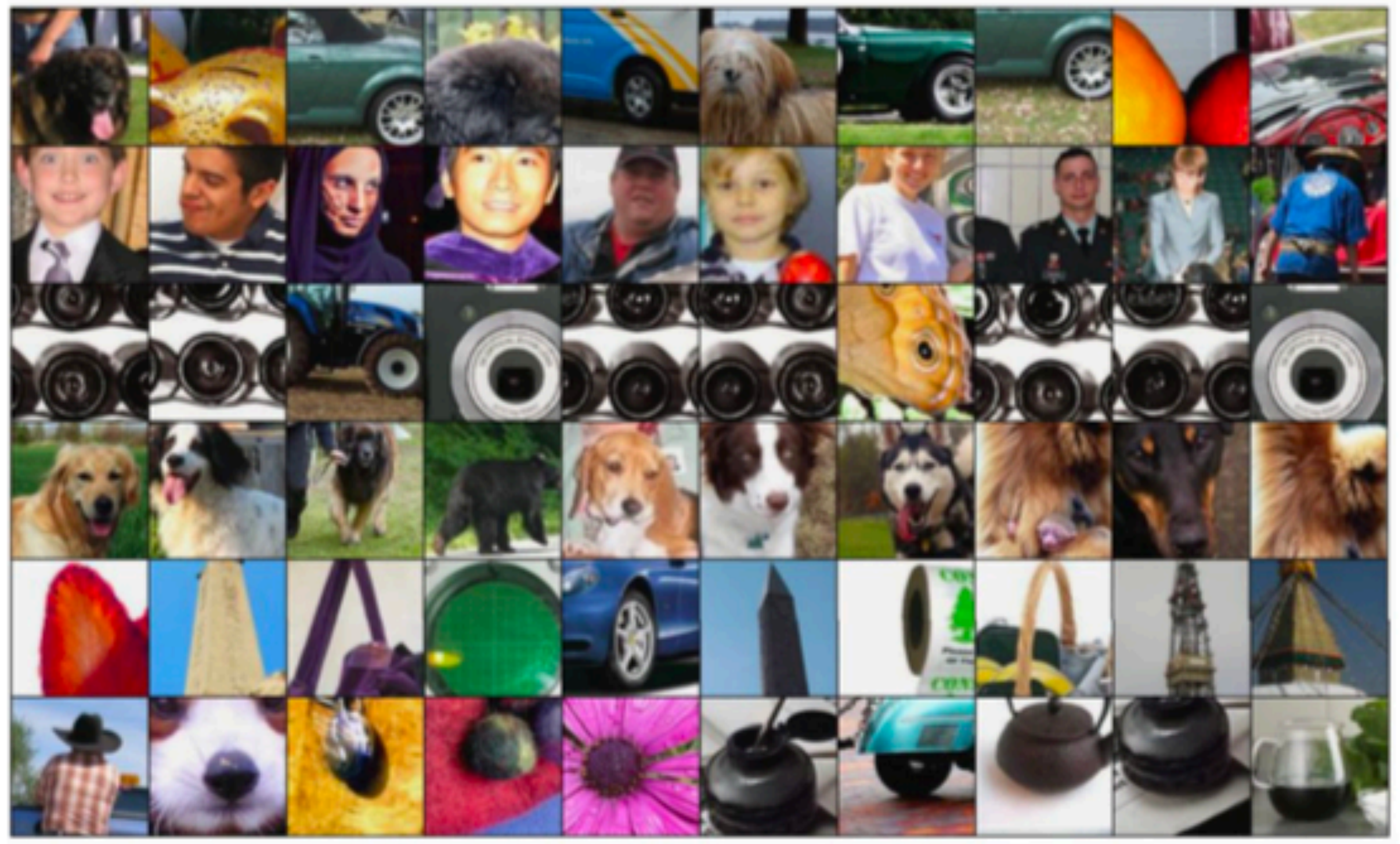
* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Maximally **Activating Patches**

— Pick a layer and a channel; e.g., cons5 of AlexNet is 128x13x13

— Run many images through the network

— Visualize image patches that correspond to maximal activation of the neuron



[Springenberg et al., 2015]

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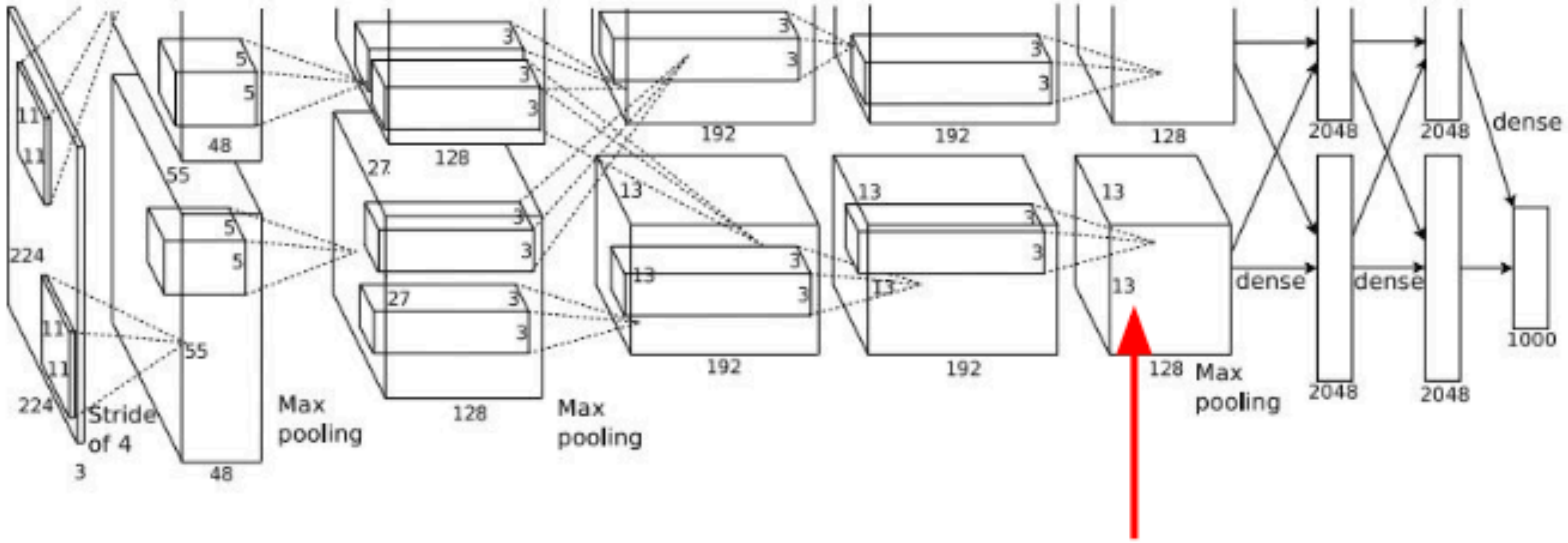
Intermediate Features through (**Guided**) **BackProp**

— Pick a single intermediate neuron somewhere in the network, e.g., neuron in 128x13x13 conv5 feature map

— Compute **gradient of neuron value with respect to image pixels**



[Zeiler and Fergus, 2014]

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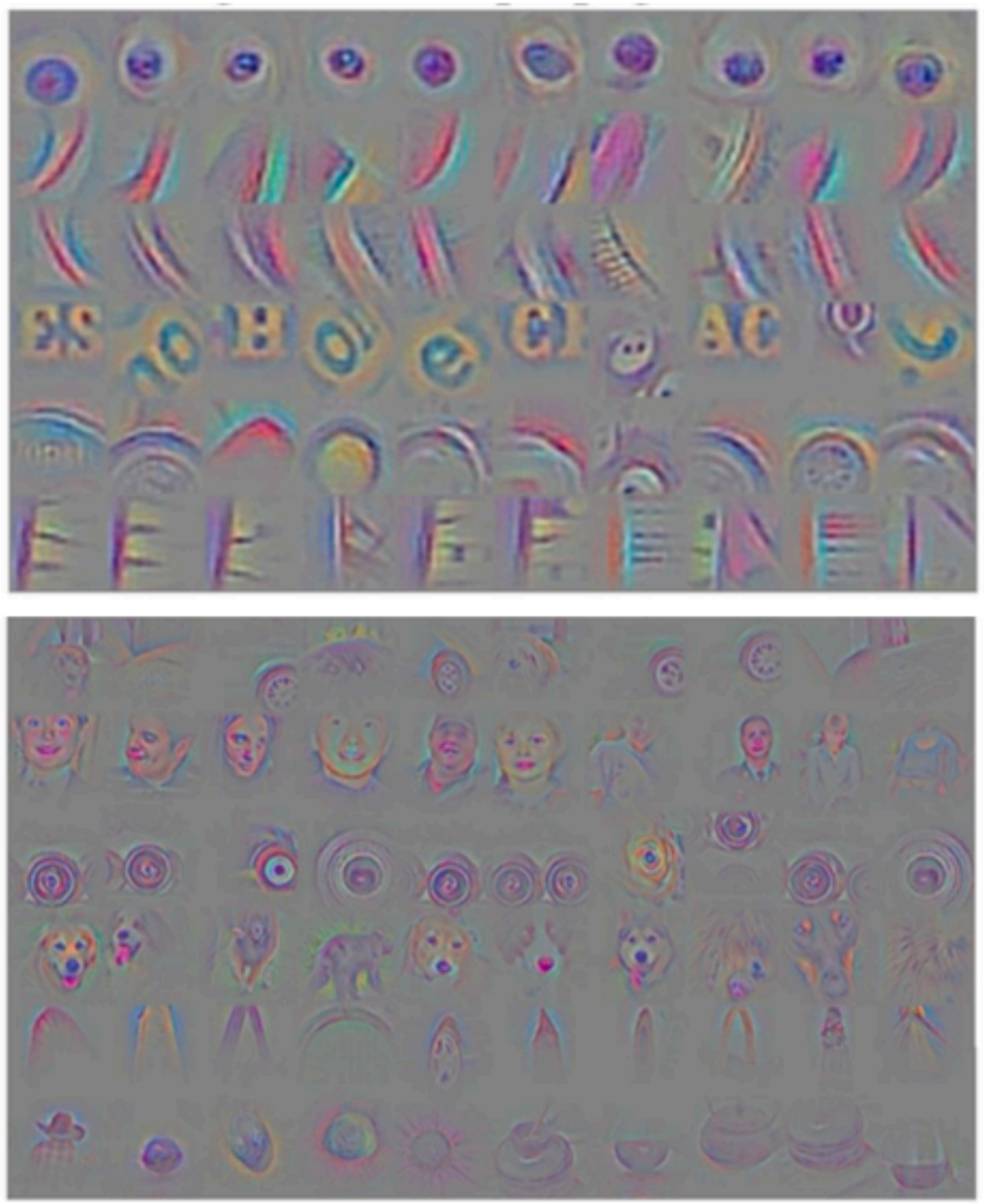

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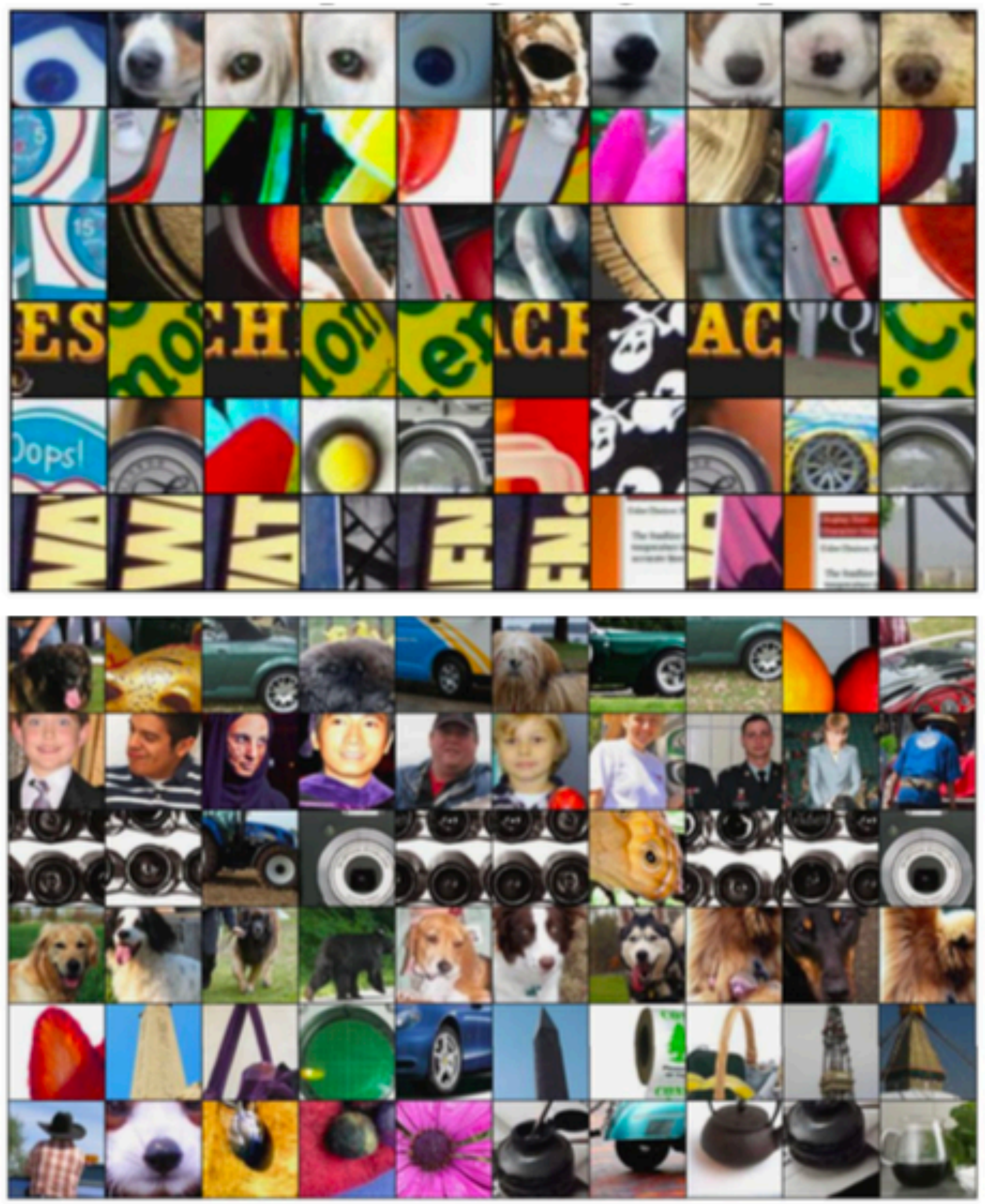

[Zeiler and Fergus, 2014]

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Gradient **Ascent**

(Guided) **BackProp**: find the part of an image that a neuron responds to

Gradient ascent: generate a synthetic image that maximally activates a neuron

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Gradient **Ascent**

(Guided) **BackProp**: find the part of an image that a neuron responds to

Gradient ascent: generate a synthetic image that maximally activates a neuron

Natural **Image Regularizer**

$$\mathbf{I}^* = \arg\max_{\mathbf{I}} f(\mathbf{I}) + R(\mathbf{I})$$

Neuron Value

Gradient **Ascent**

1. Initialize image with all zeros (can also start with an existing image)
2. Forward image to compute the current scores
3. BackProp to get gradient of the neuron with respect to image pixels
4. Make a small update to an image

$$\mathbf{I}^* = \arg\max_{\mathbf{I}} \underbrace{f(\mathbf{I})}_{\text{Neuron Value}} + \overbrace{R(\mathbf{I})}^{\text{Natural Image Regularizer}}$$

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Natural **Image Regularizer** $R(\mathbf{I}) = -\lambda||\mathbf{I}||_2^2$

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Score for class C before softmax

[Simonyan et al., 2014]

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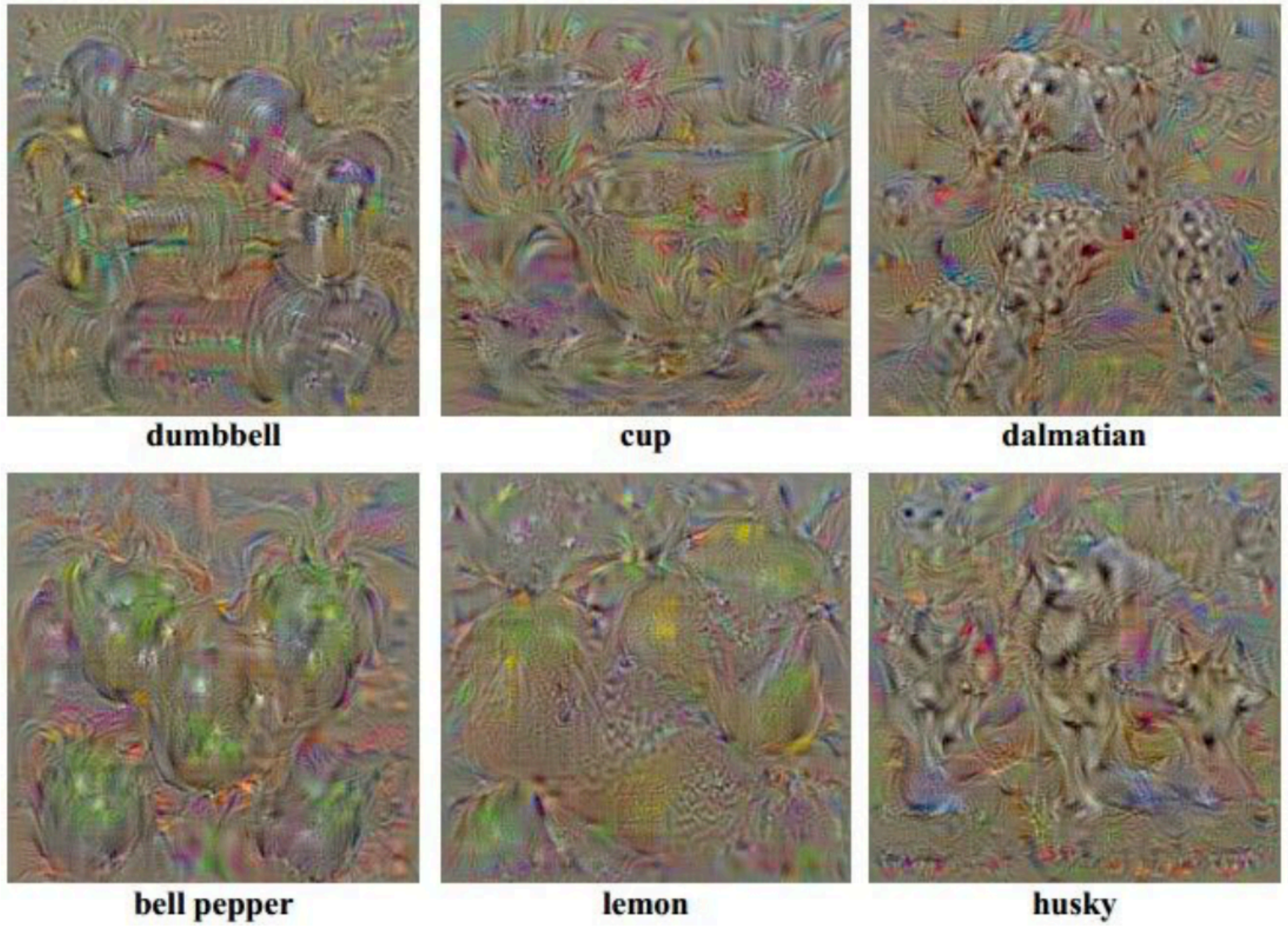

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Gradient **Ascent**

… with a few additional tweaks

[Nguyen et al., 2015]

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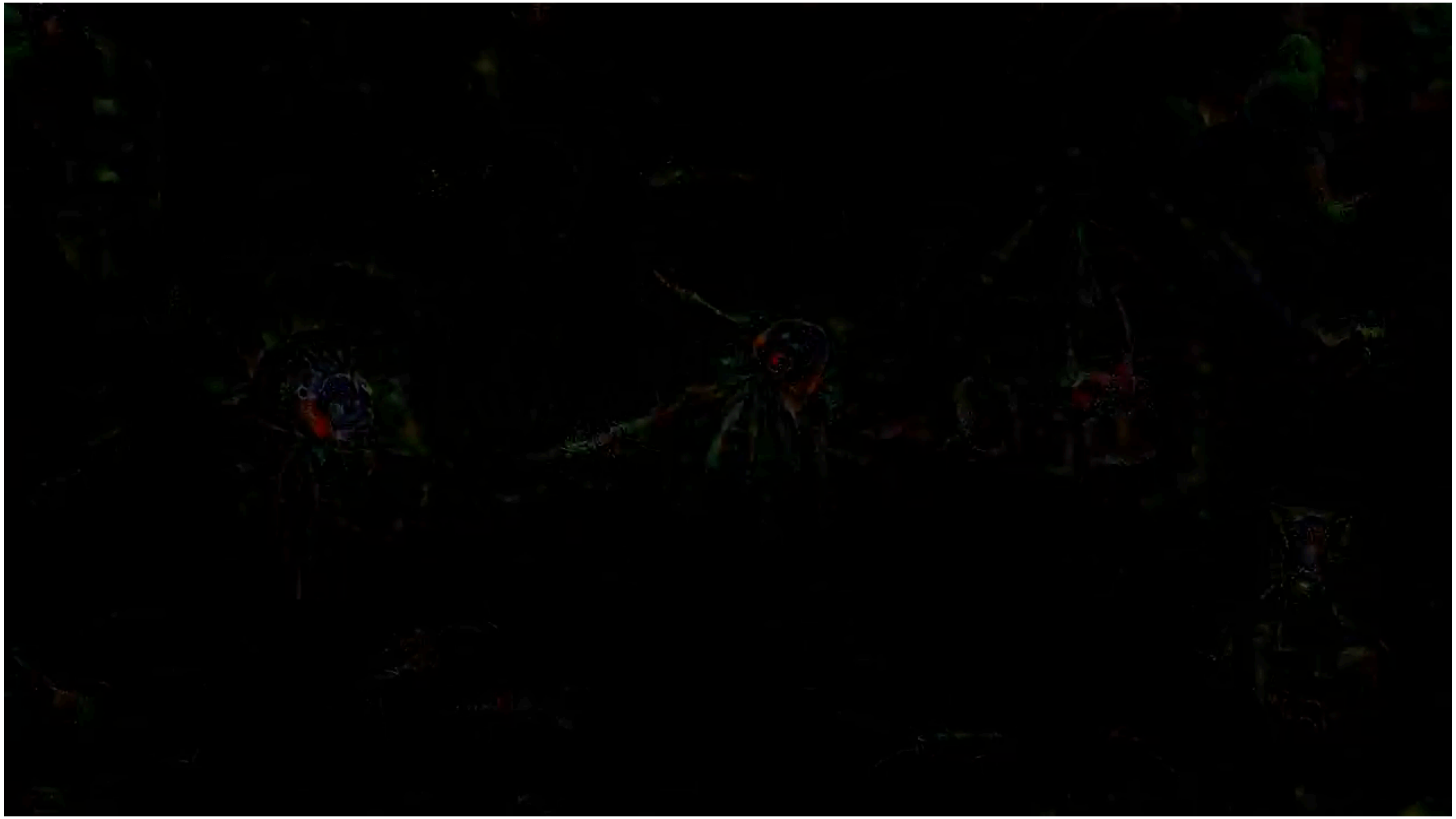
Deep **Dream**

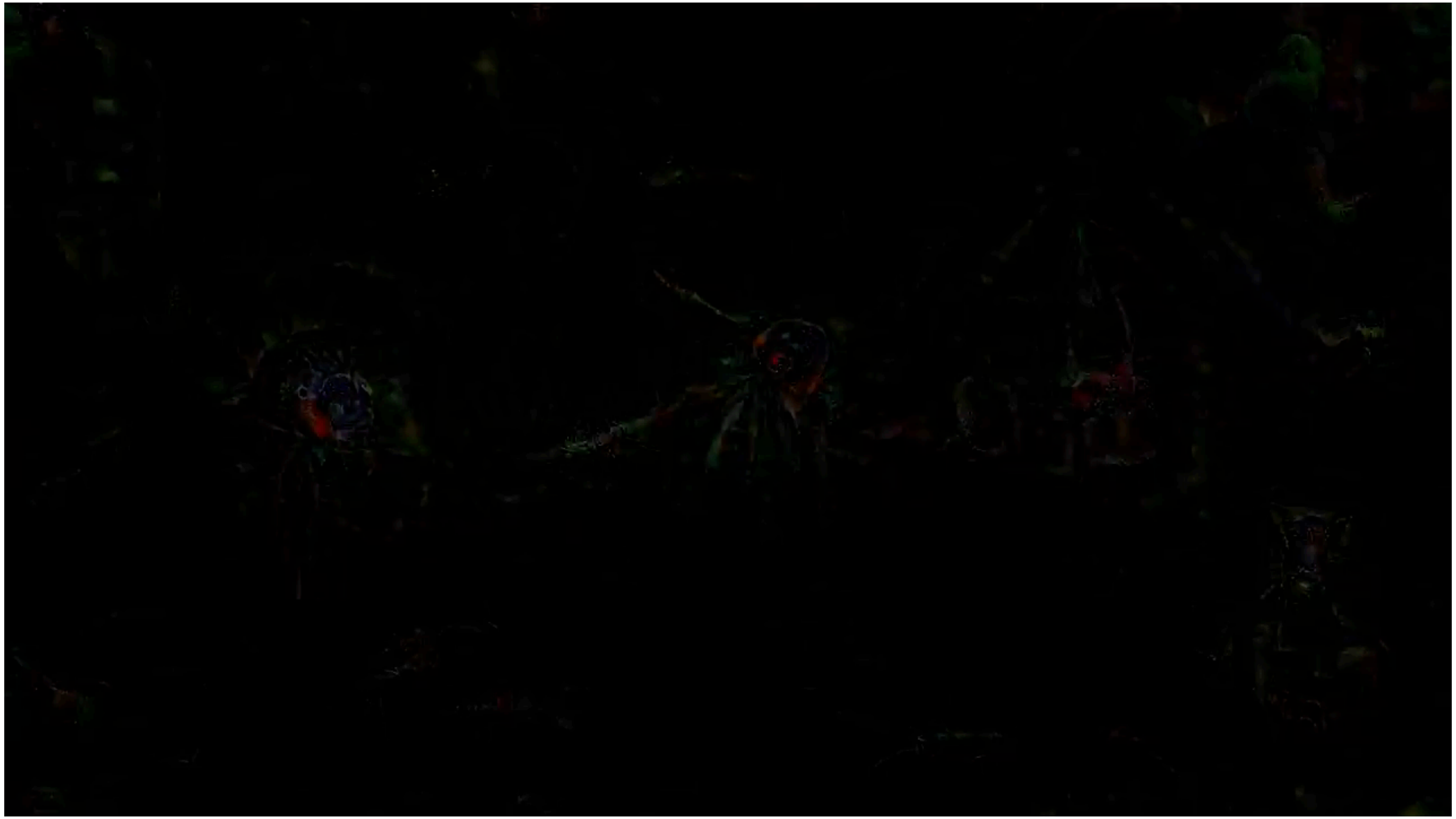
[Mordvinsev, Olah, Tyka]



https://www.youtube.com/watch?v=DgPaCWJL7XI&t=11s

Deep **Dream**

[Mordvinsev, Olah, Tyka]



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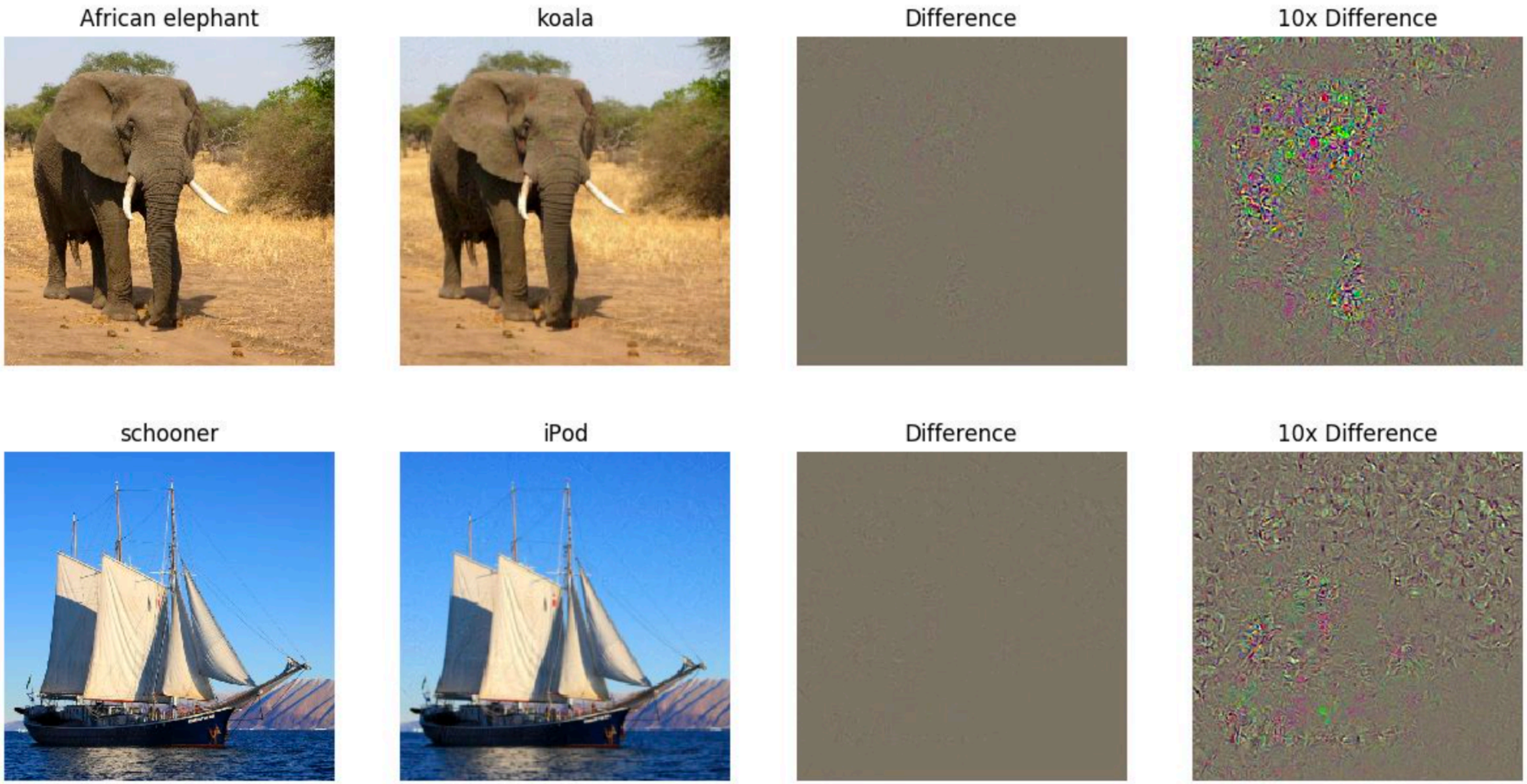
Fooling Images / **Adversarial** Examples



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