Deep Learning application to large-scale image retrieval

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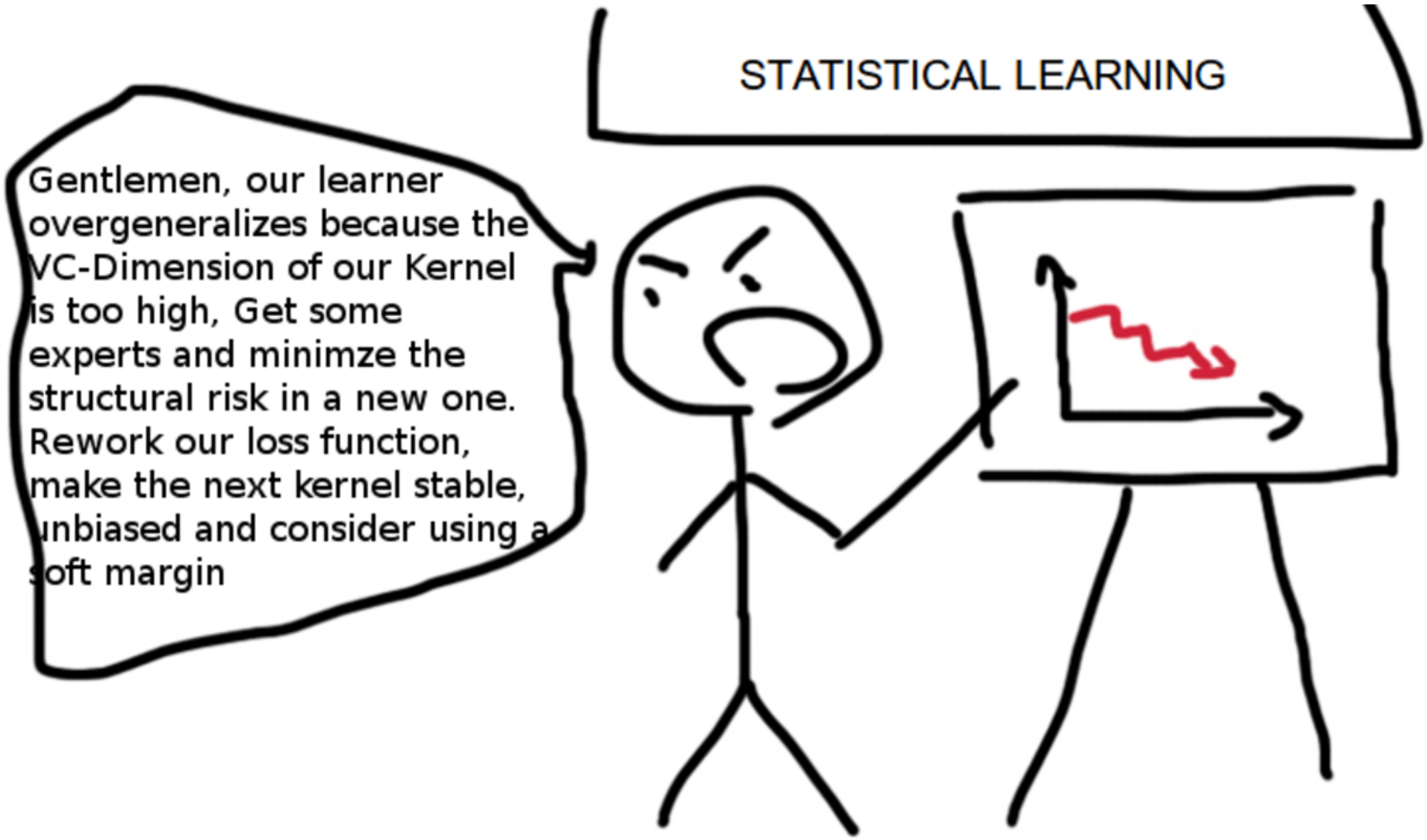
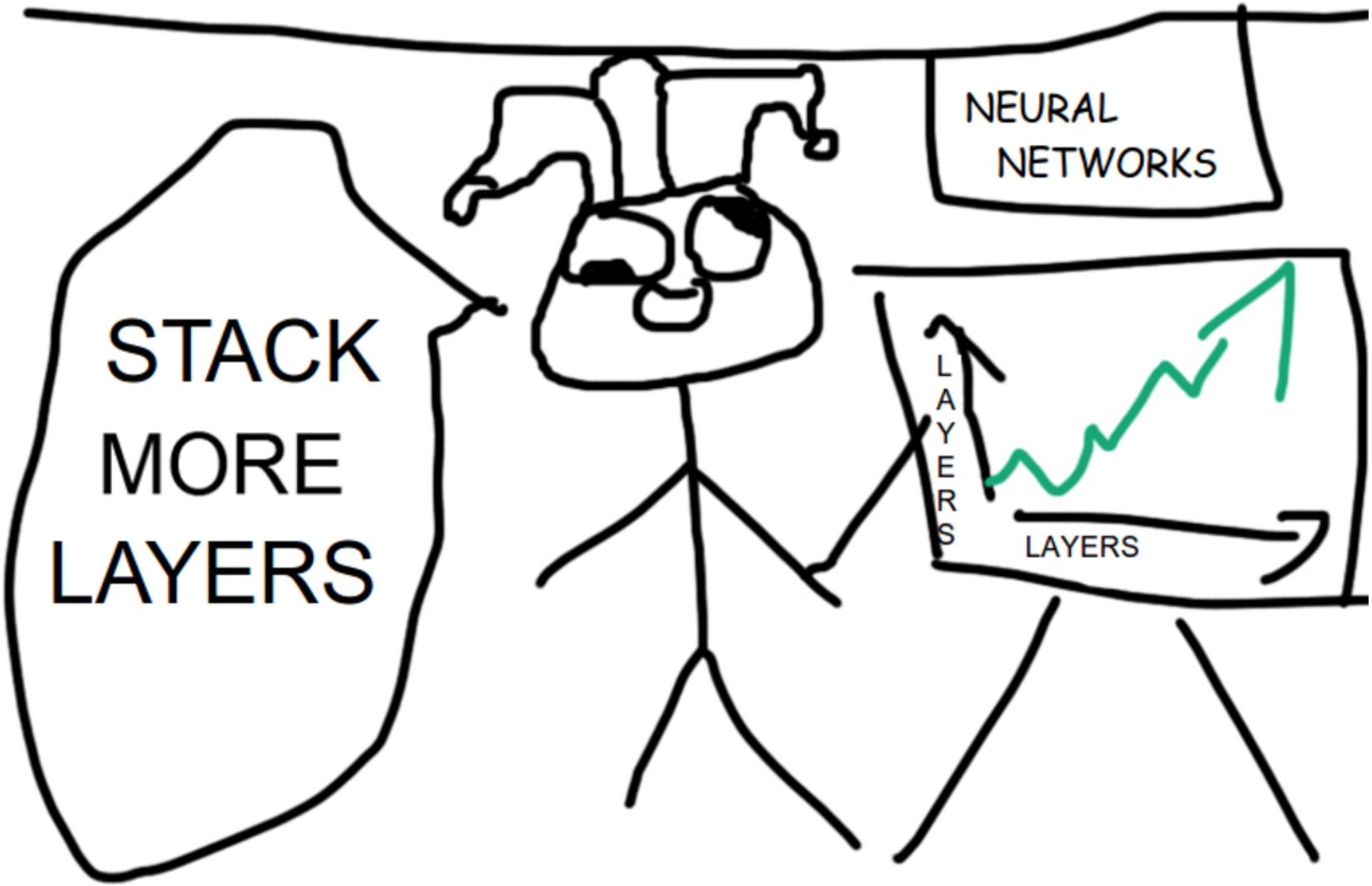
Classical approach



Modern approach



Linear models

Linear regression

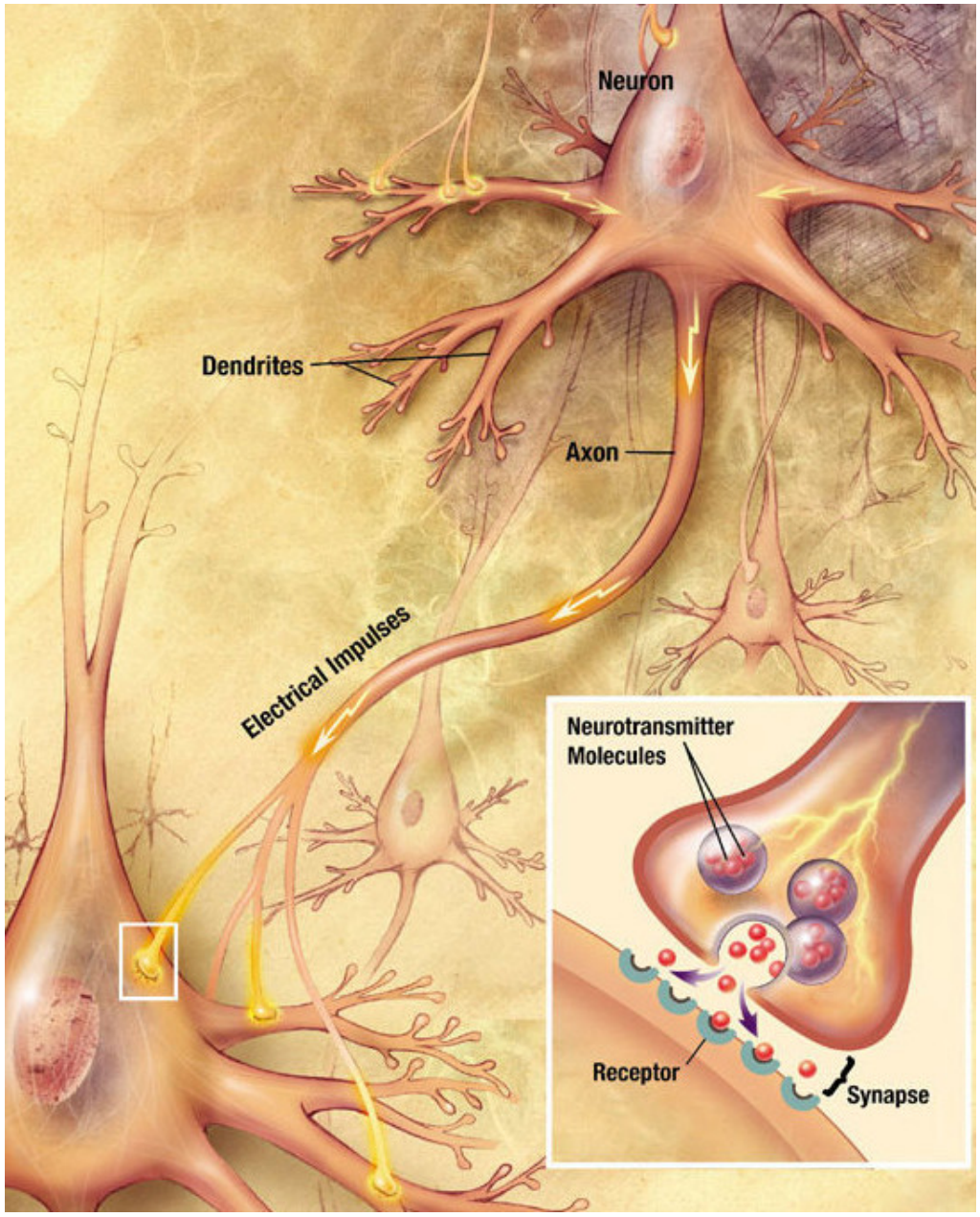
$$\hat{y} = w_0 + \sum_{i=1}^{N} w_i x_i$$

Logistic regression

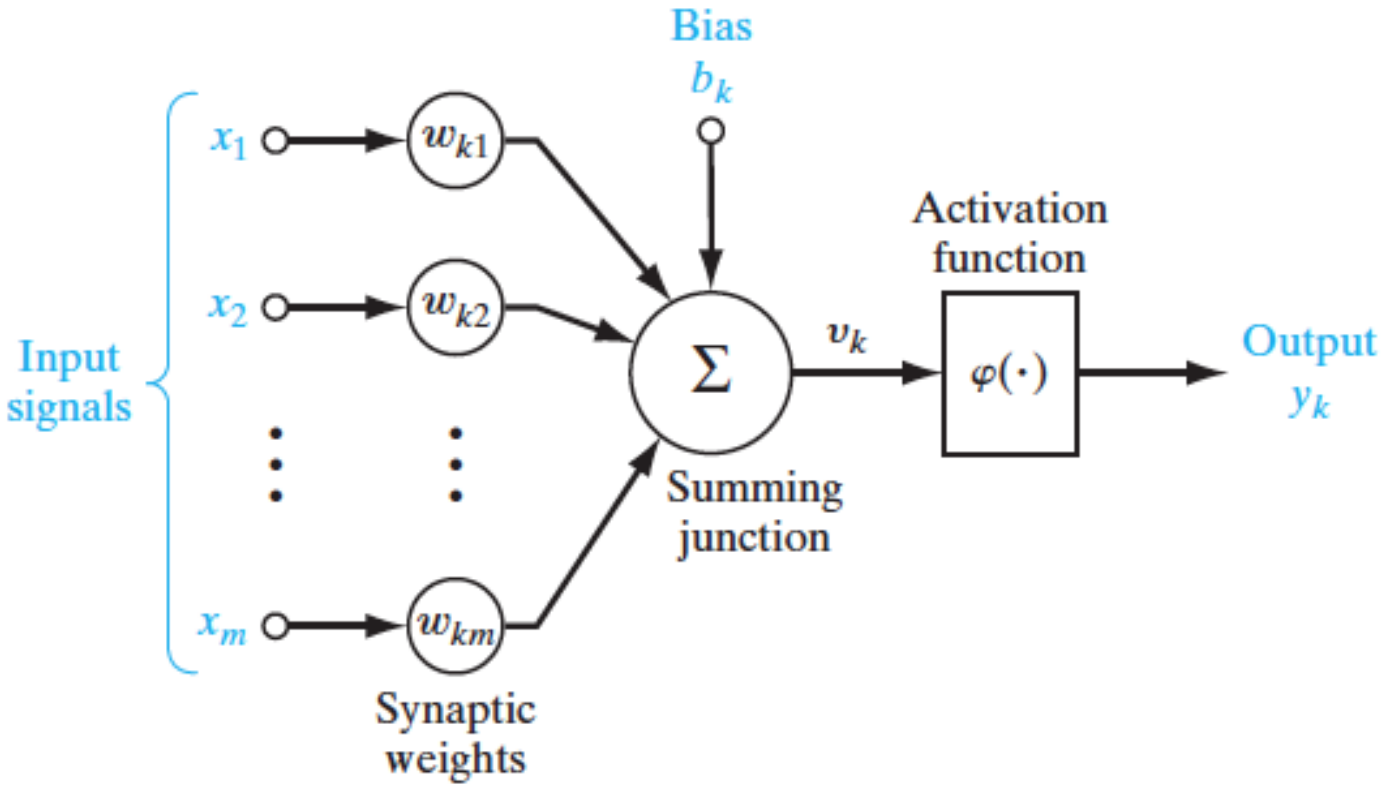
$$\hat{p}(y = 1) = \sigma\left(w_0 + \sum_{i=1}^{N} w_i x_i\right)$$

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

Biological neuron



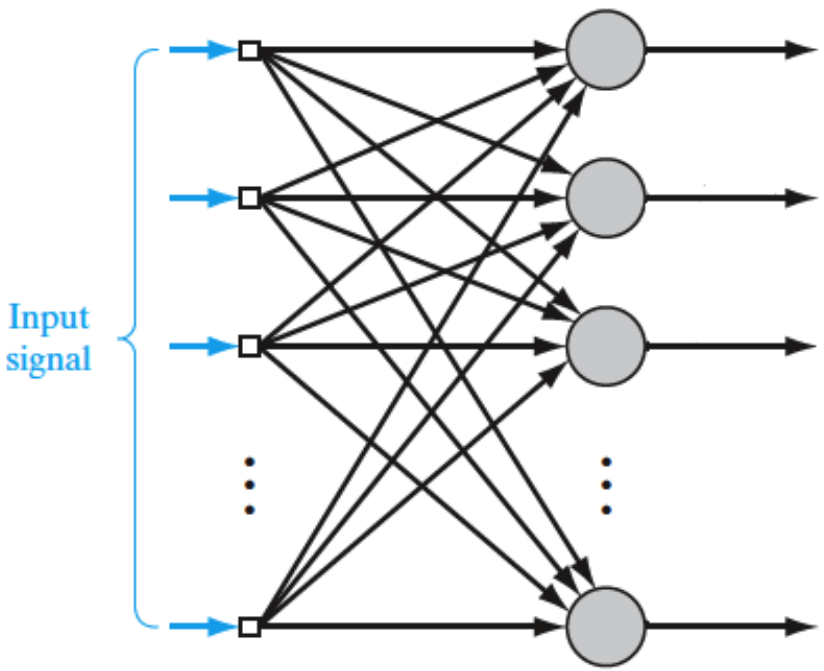
Artificial neuron



Generalized linear model

$$\hat{y} \quad = \quad g^{-1}\left(w_0 + \sum_{i=1}^{N} w_i x_i\right)$$

Single layer network



MaxEnt model

$$\hat{h}_k = w_{k,0} + \sum_{i=1}^{N} w_{k,i} x_i$$

$$\hat{p}(y = C_k) = \frac{e^{h_k}}{\sum_{j=1}^{K} e^{h_j}}$$

Universal approximation theorem

Let we have:

- $\phi(x)$ is nonconstant, bounded, and monotonically-increasing continuous function;
- I_m is m-dimensional unit hypercube $[0,1]^m$
- $C(I_m)$ is space of all continuous functions on I_m

then:

- $\forall f \in C(I_m) \wedge \forall \epsilon > 0$
- $\exists N \in \mathbb{N} \wedge v_i, b_i \in \mathbb{R} \wedge w_i \in \mathbb{R}^m, \text{where} i = 1, \ldots, N$

we can define

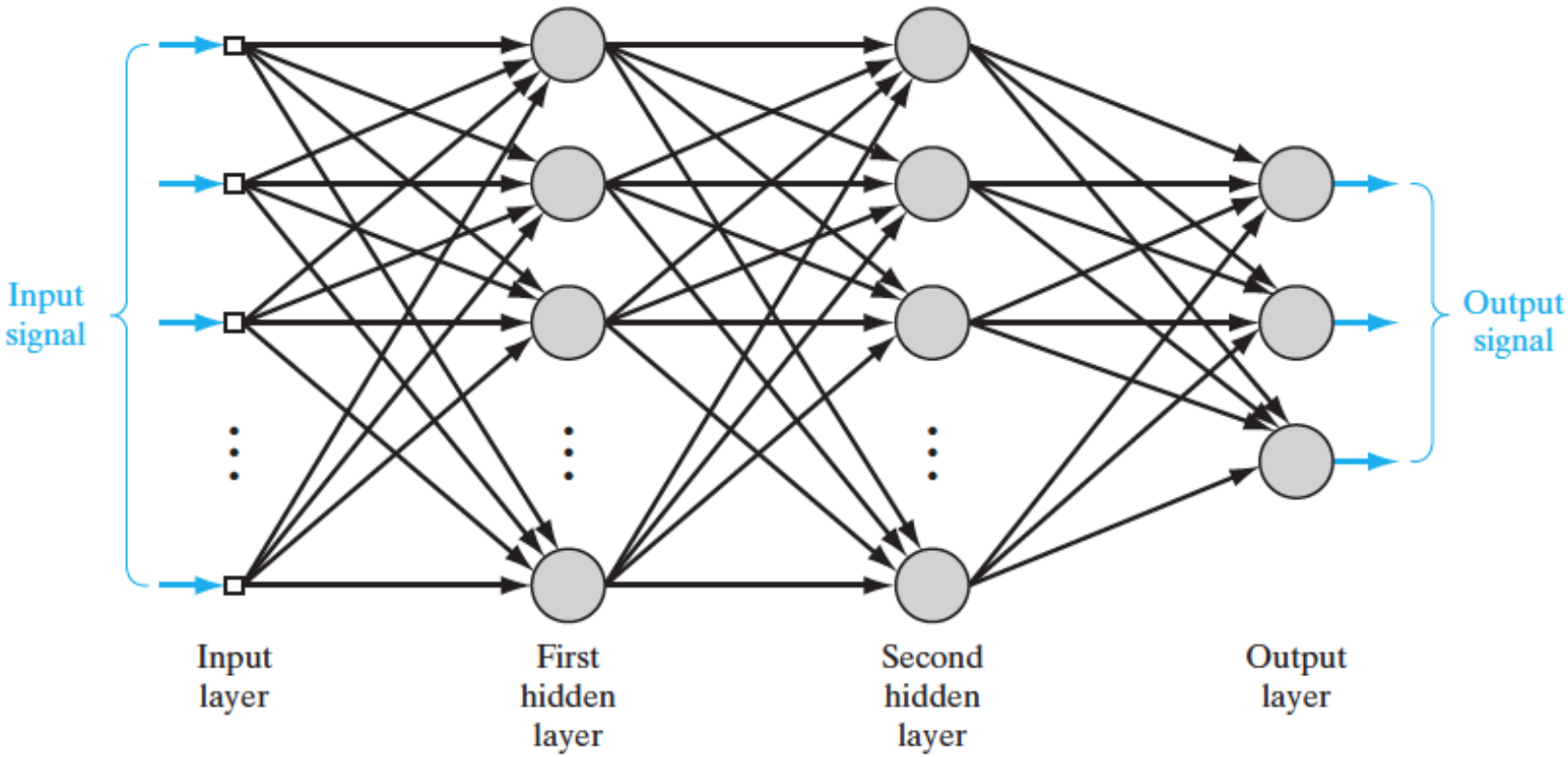
$$F(x) = \sum_{i=1}^{N} v_i \phi \left(b_i + \sum_{j=1}^{m} w_{ij} x_j \right)$$

such that

$$\forall x \in I_m : |F(x) - f(x)| < \epsilon$$

- *which network topology is produced by this theorem?*

Shallow network

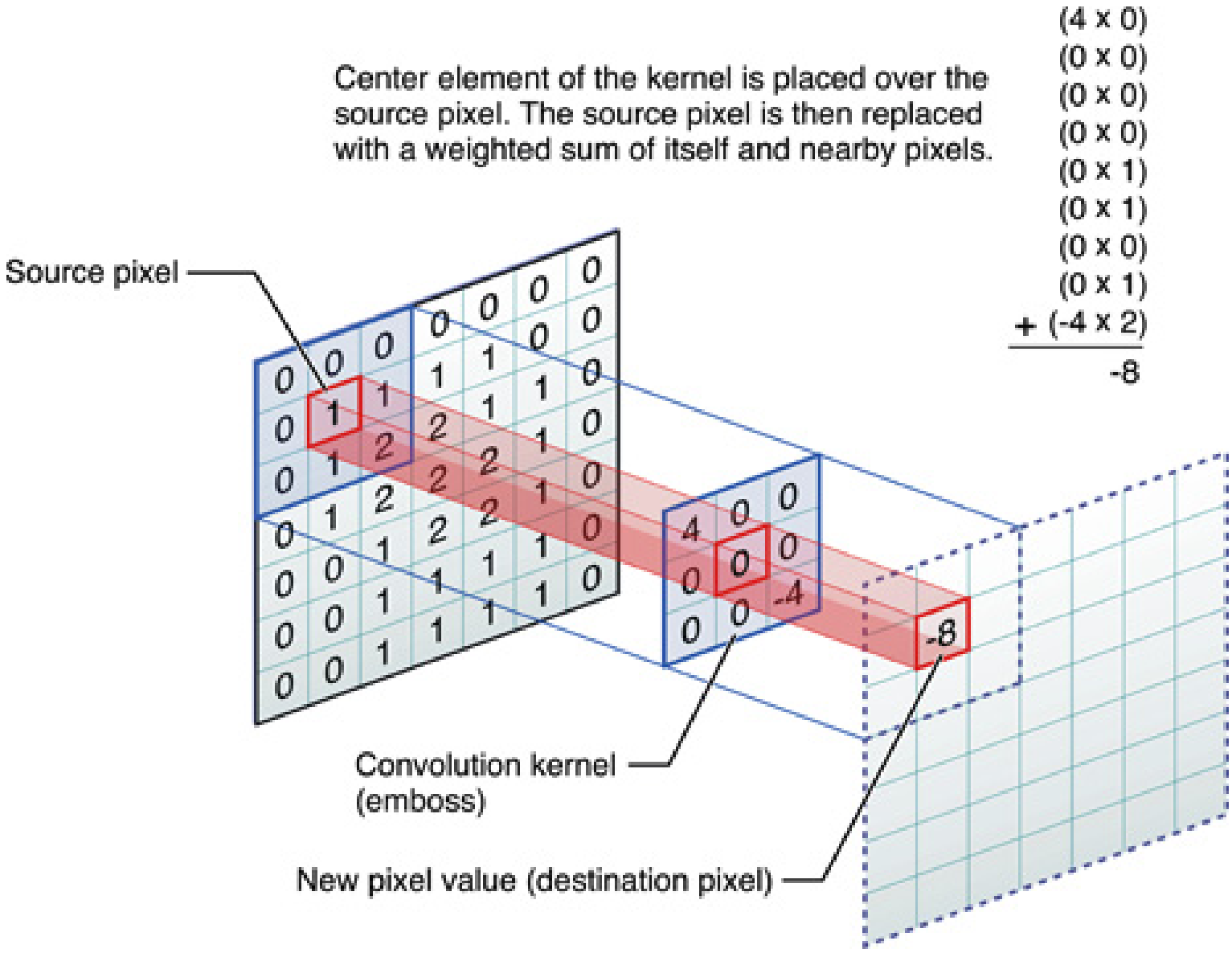


- *how many parameters second hidden layer requires?*

What next?

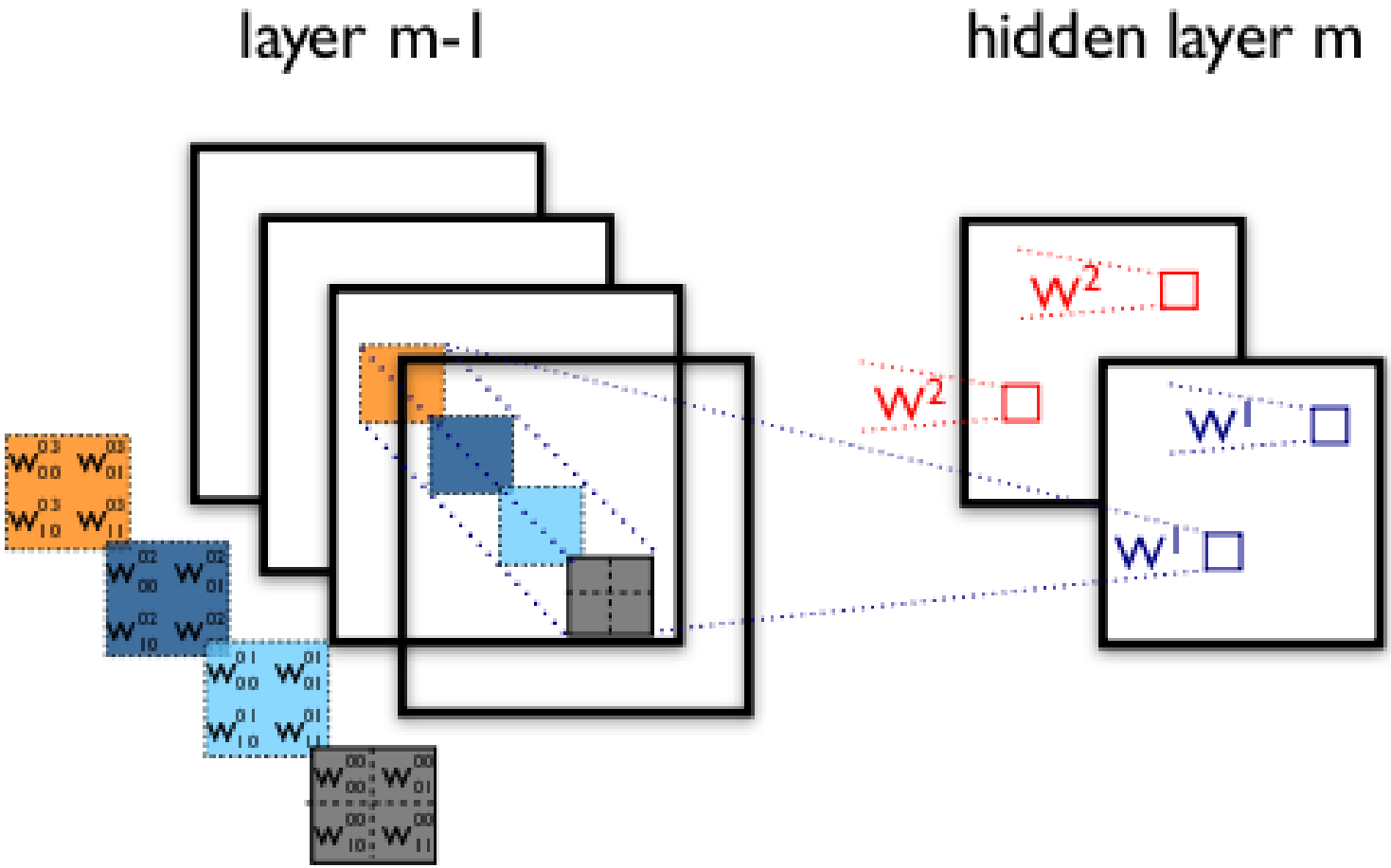
- solution is to simplify network

Convolutions



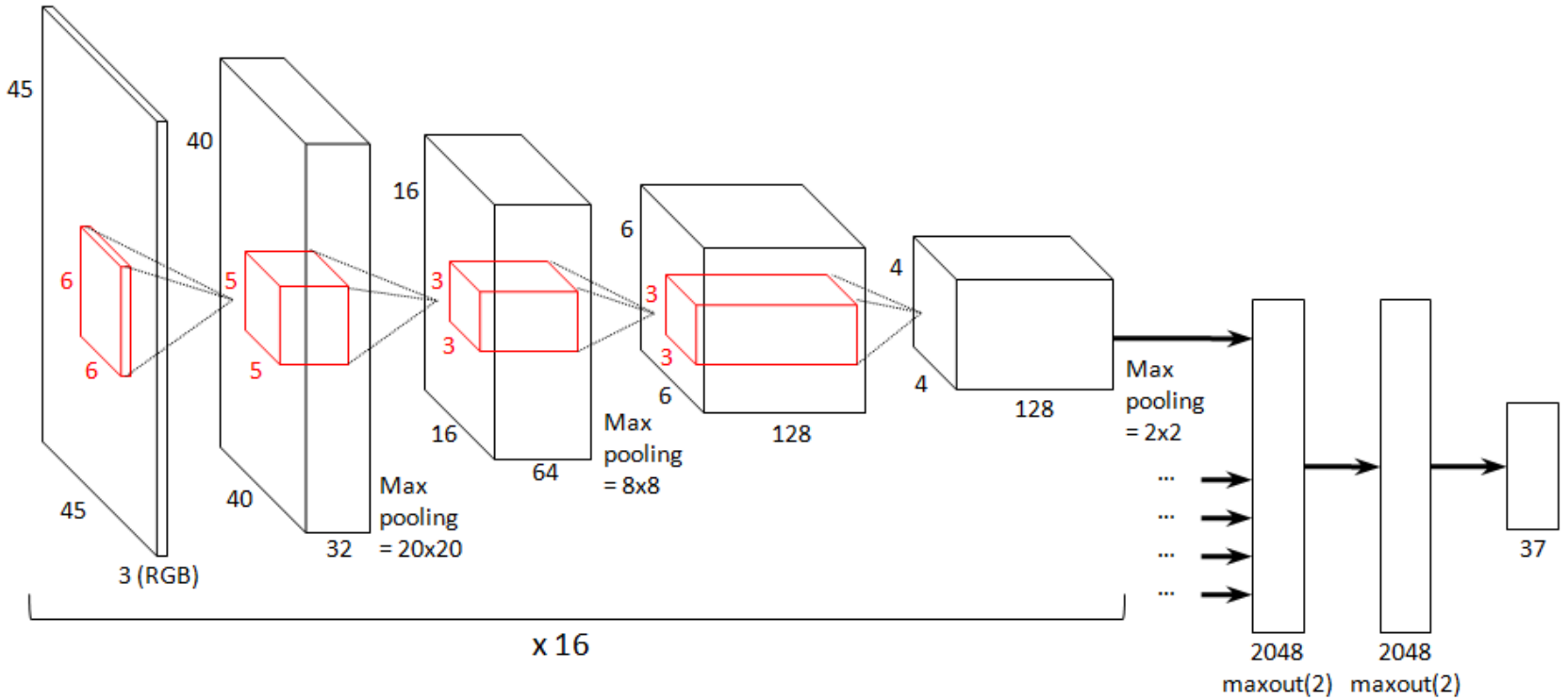
- https://github.com/vdumoulin/conv_arithmetic

Filter bank



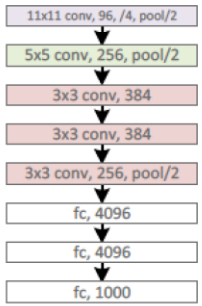
- *how many parameters second convolutional hidden layer requires now?*

Deep convolutional network

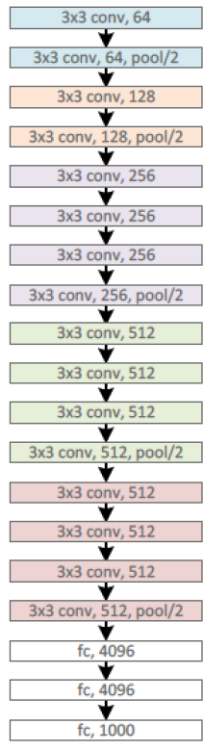


Very deep convolutional network

AlexNet, 8 layers
(ILSVRC 2012)



VGG, 19 layers
(ILSVRC 2014)



GoogleNet, 22 layers
(ILSVRC 2014)

Very very deep convolutional network

AlexNet, 8 layers
(ILSVRC 2012)

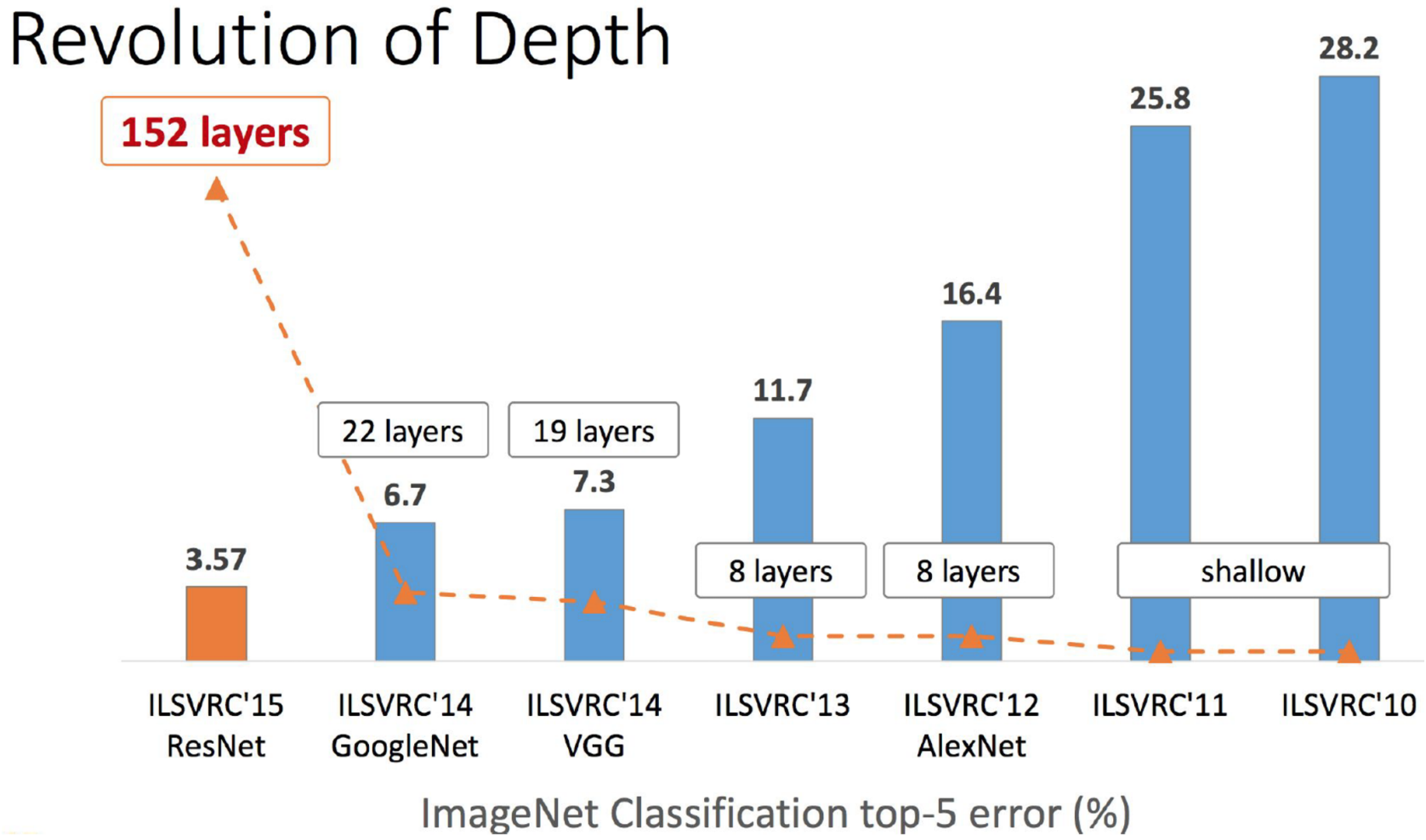
VGG, 19 layers
(ILSVRC 2014)

ResNet, 152 layers
(ILSVRC 2015)

...


MOAR LAYERS
MOAR MOAR MOAR

State-of-the-art



Opening the black box

Given a network F with parameters Θ and input image x, lets also define output of each layer as F_i:

Training

$$\Delta\Theta = -\lambda \frac{\partial F(x, \Theta)}{\partial \Theta}$$

Understanding

$$\Delta x = \frac{\partial F_i(x, \Theta)}{\partial x}$$

How network see the world, #1

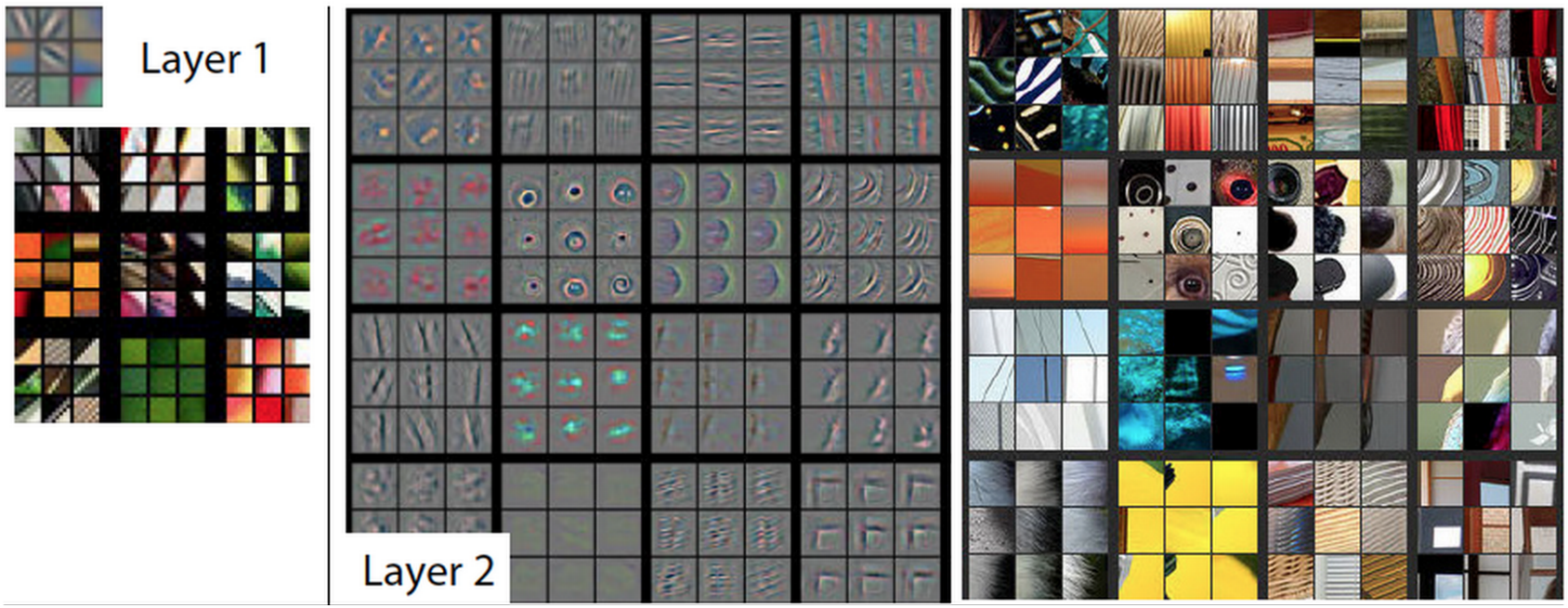
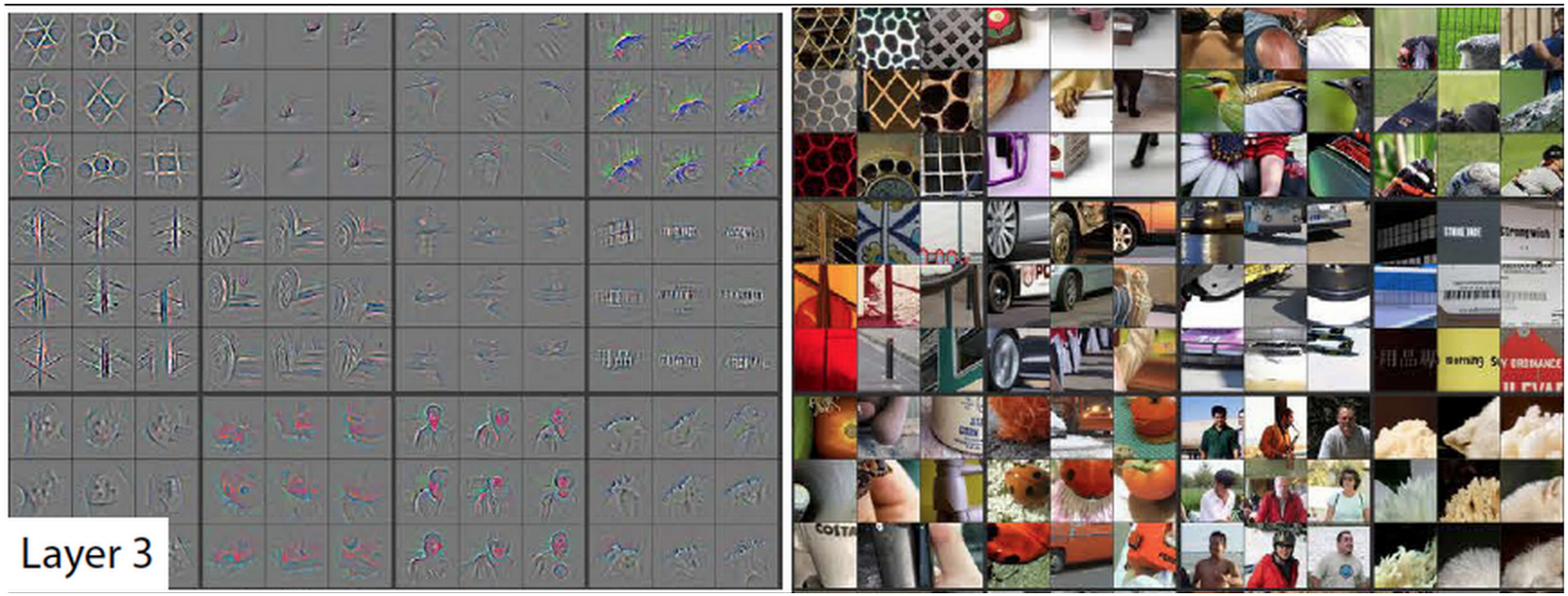


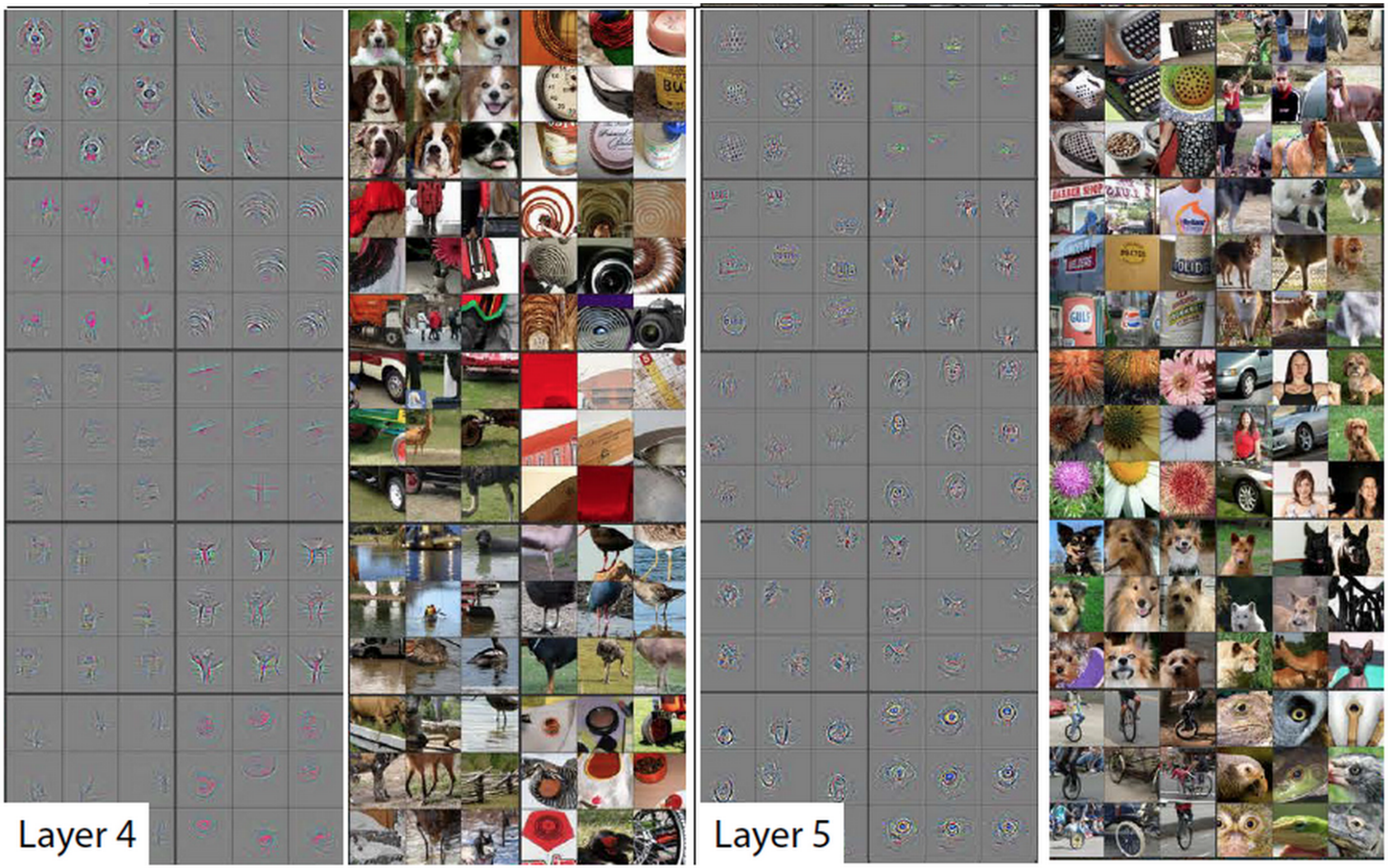
Figure 1: Visualizing and Understanding Convolutional Network [1]

[1] Matthew D. Zeiler and Rob Fergus

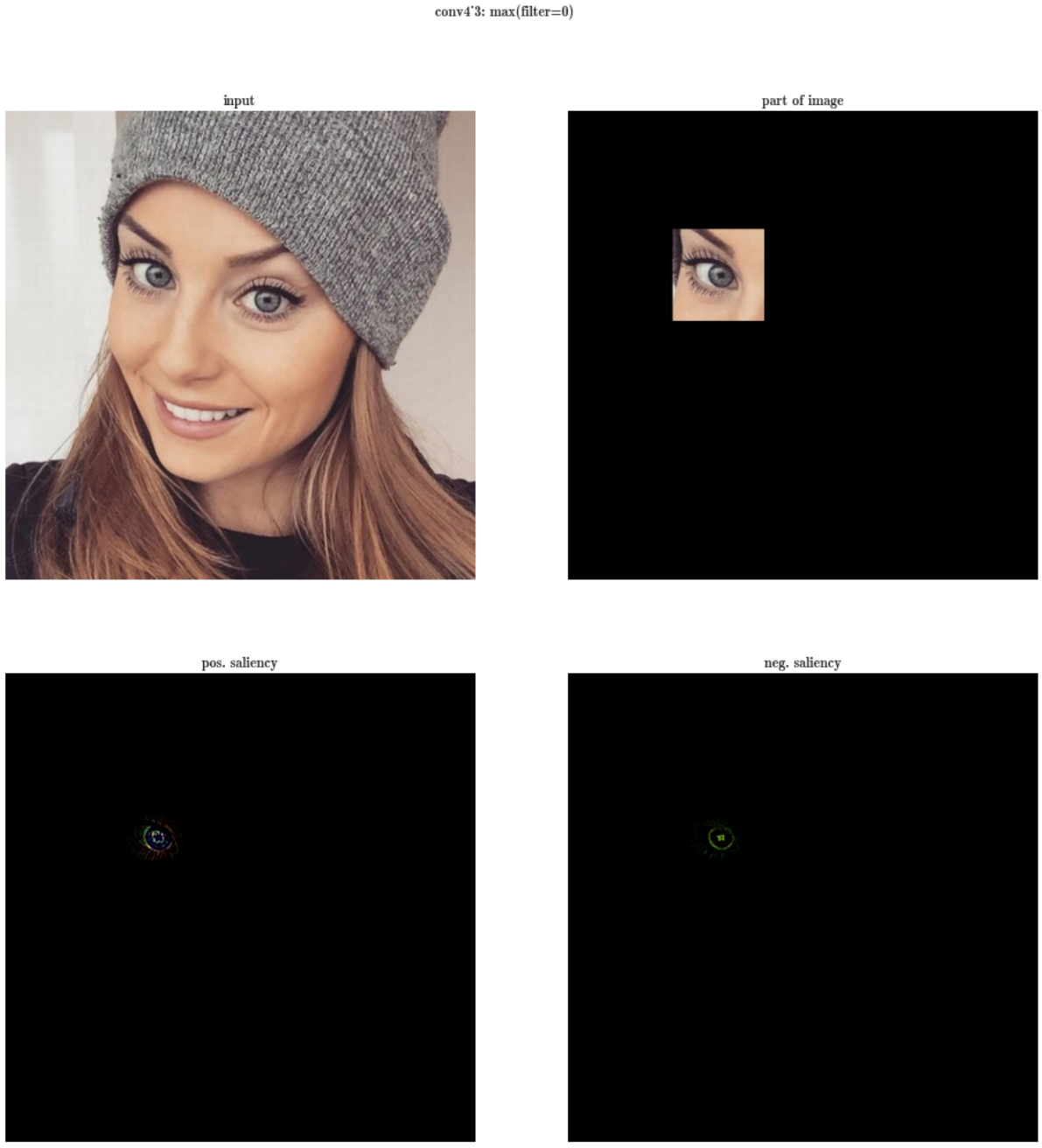
How network see the world, #2



How network see the world, #3



Eye filter, #1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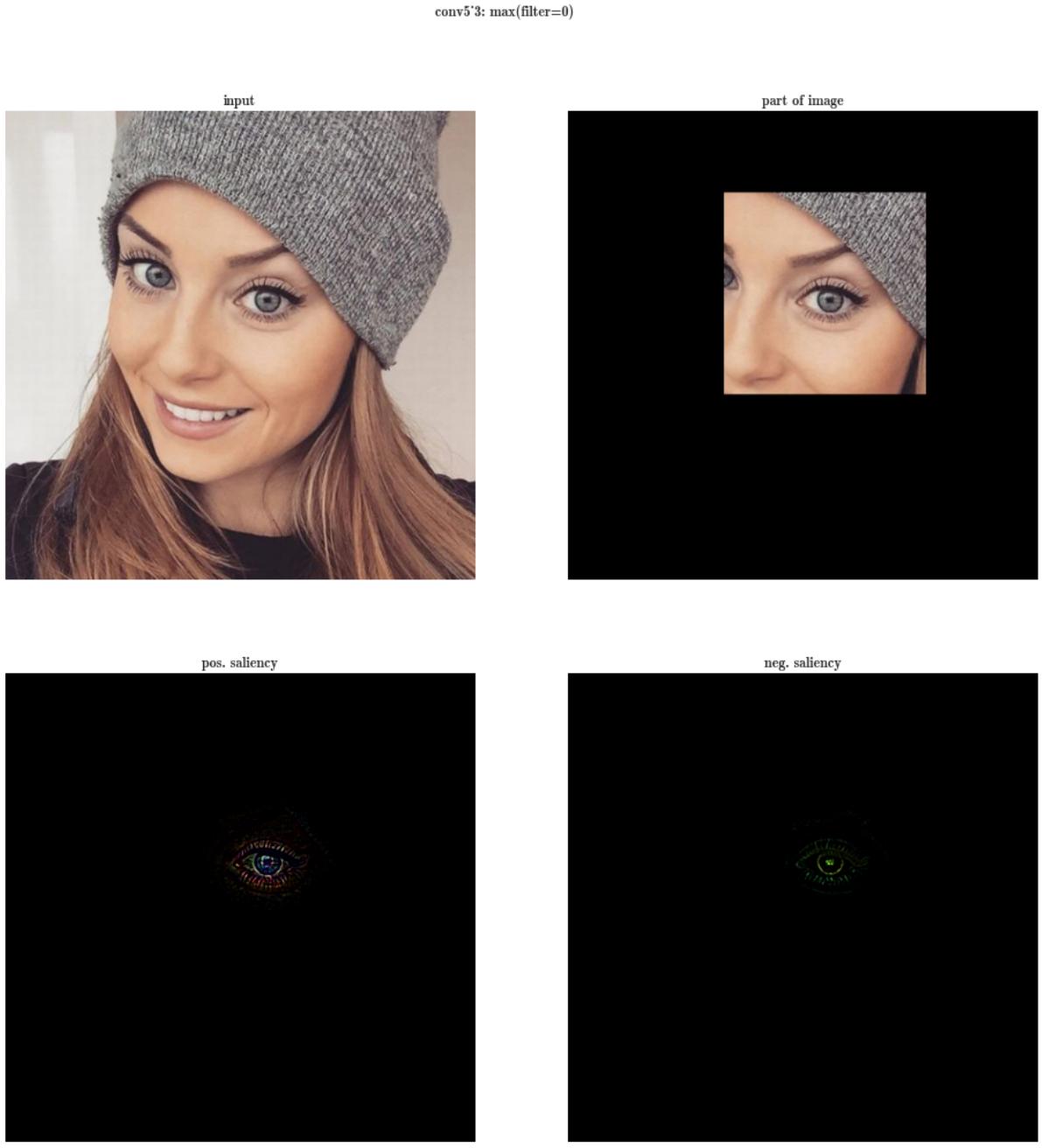
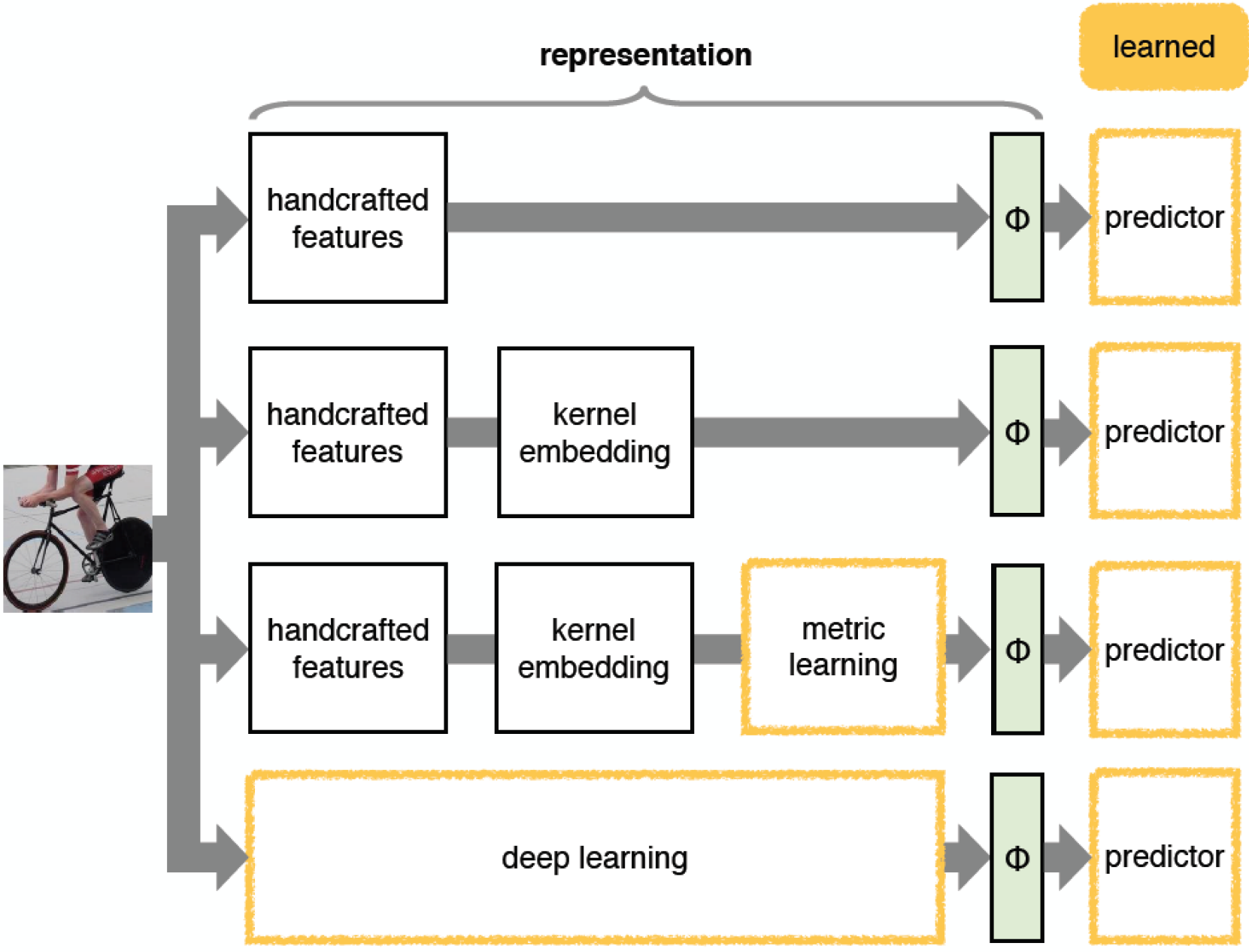
input
part of image
pos. saliency
neg. saliency

Eye filter, #2


conv5'3: max(filter=0)
input
part of image
pos. saliency
neg. saliency

Deep learning = Representation learning



Semantic hashing

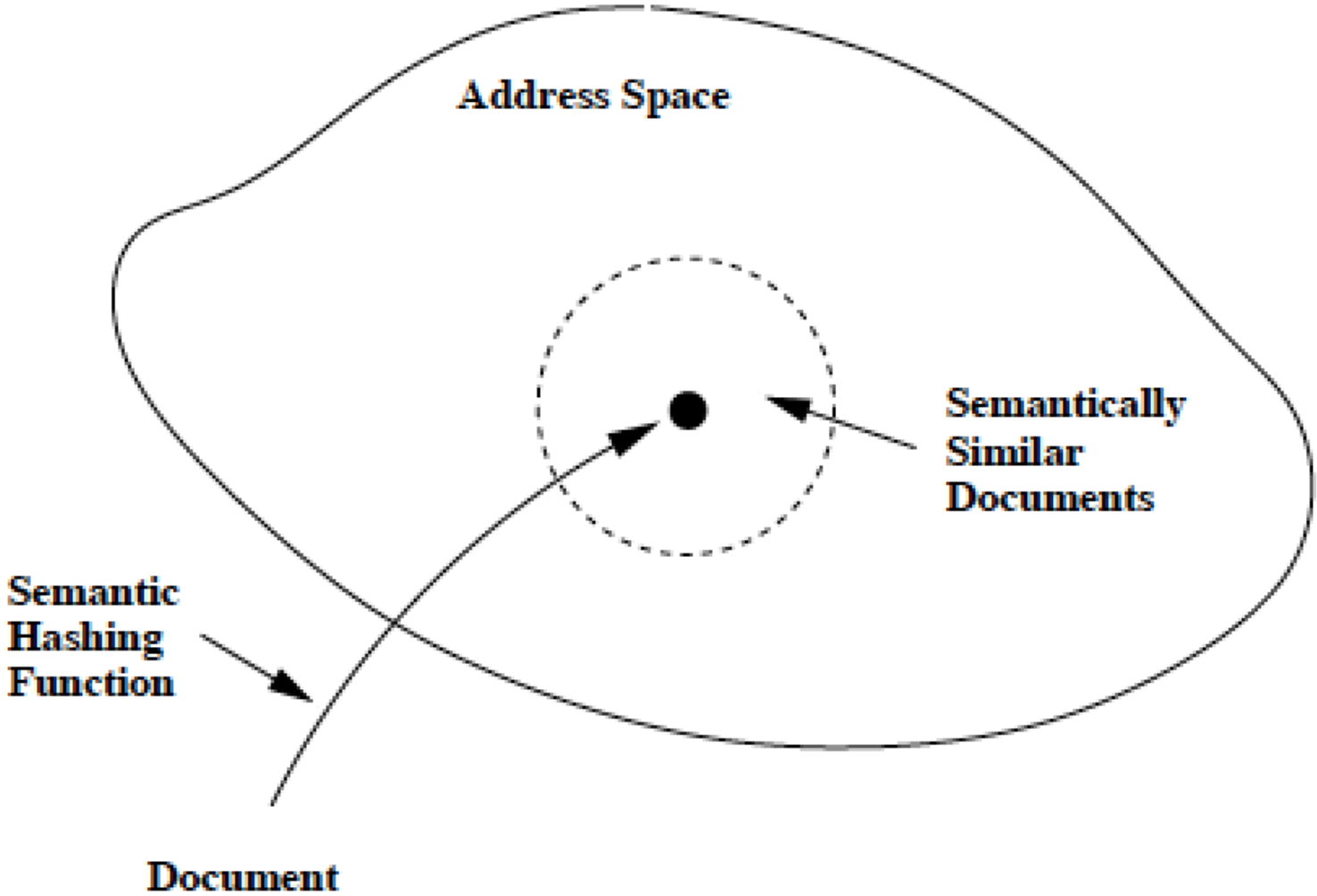


Figure 2: Semantic representation[2]

[2]Semantic Hashing (Salakhutdinov, Hinton)

Deep sparse autoencoder

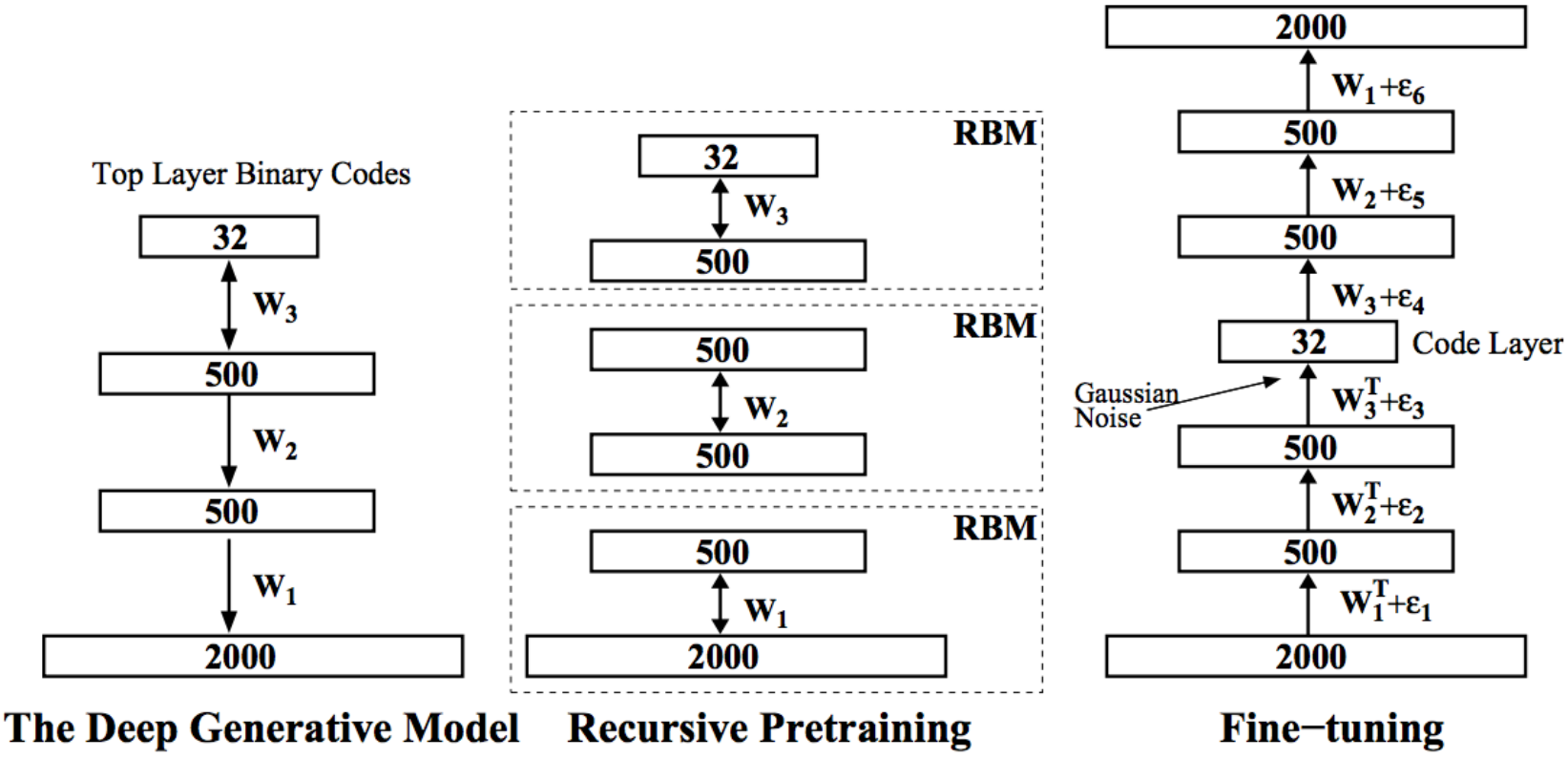
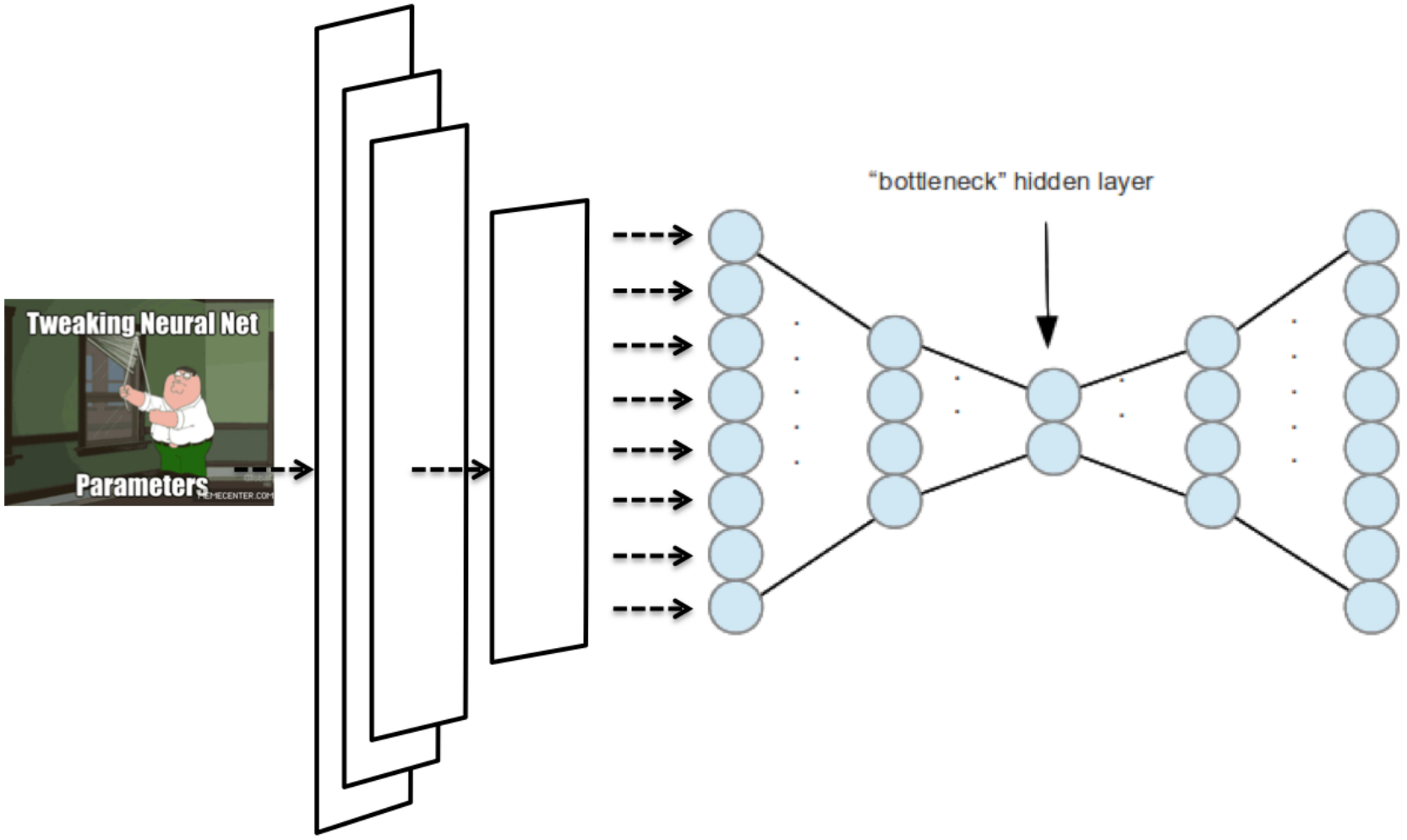


Figure 3: Training of deep autoencoder[3]

[3]Semantic Hashing (Salakhutdinov, Hinton)

Compression



Visualization, #1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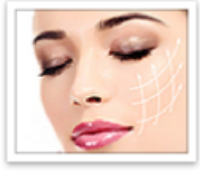
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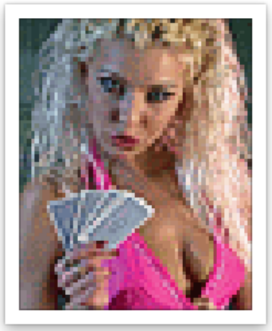
Visualization, #2



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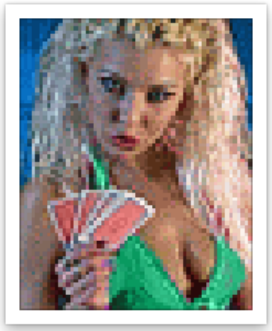

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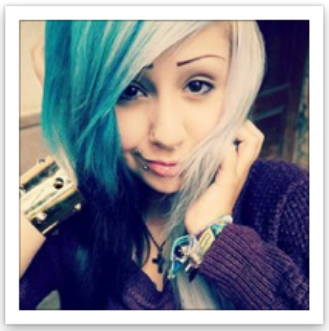

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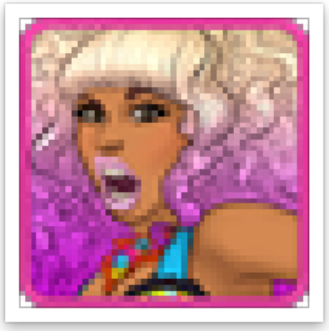

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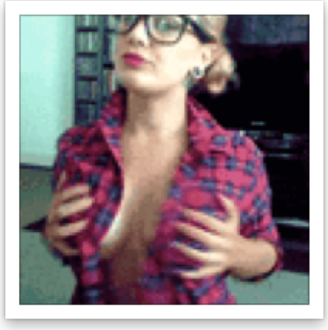

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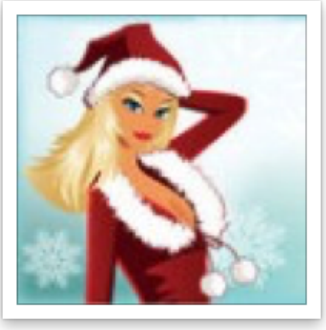

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Visualization, #3

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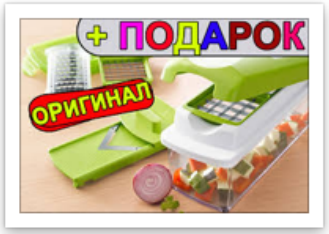

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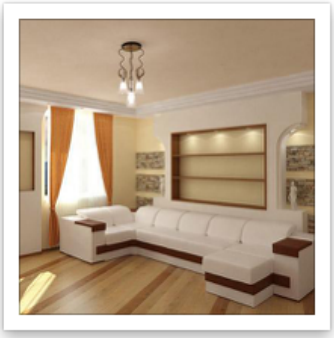
Visualization, #4



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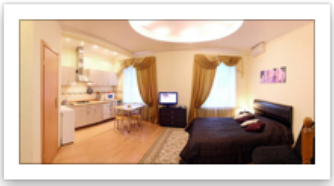

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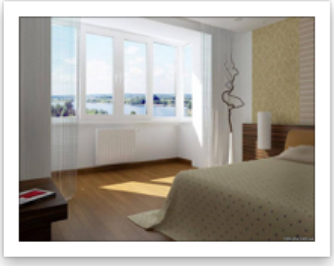

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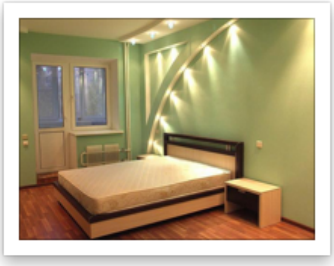

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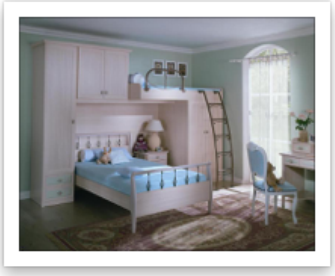

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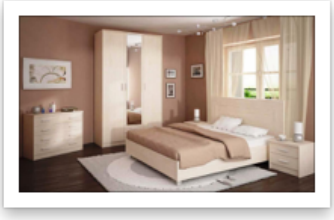

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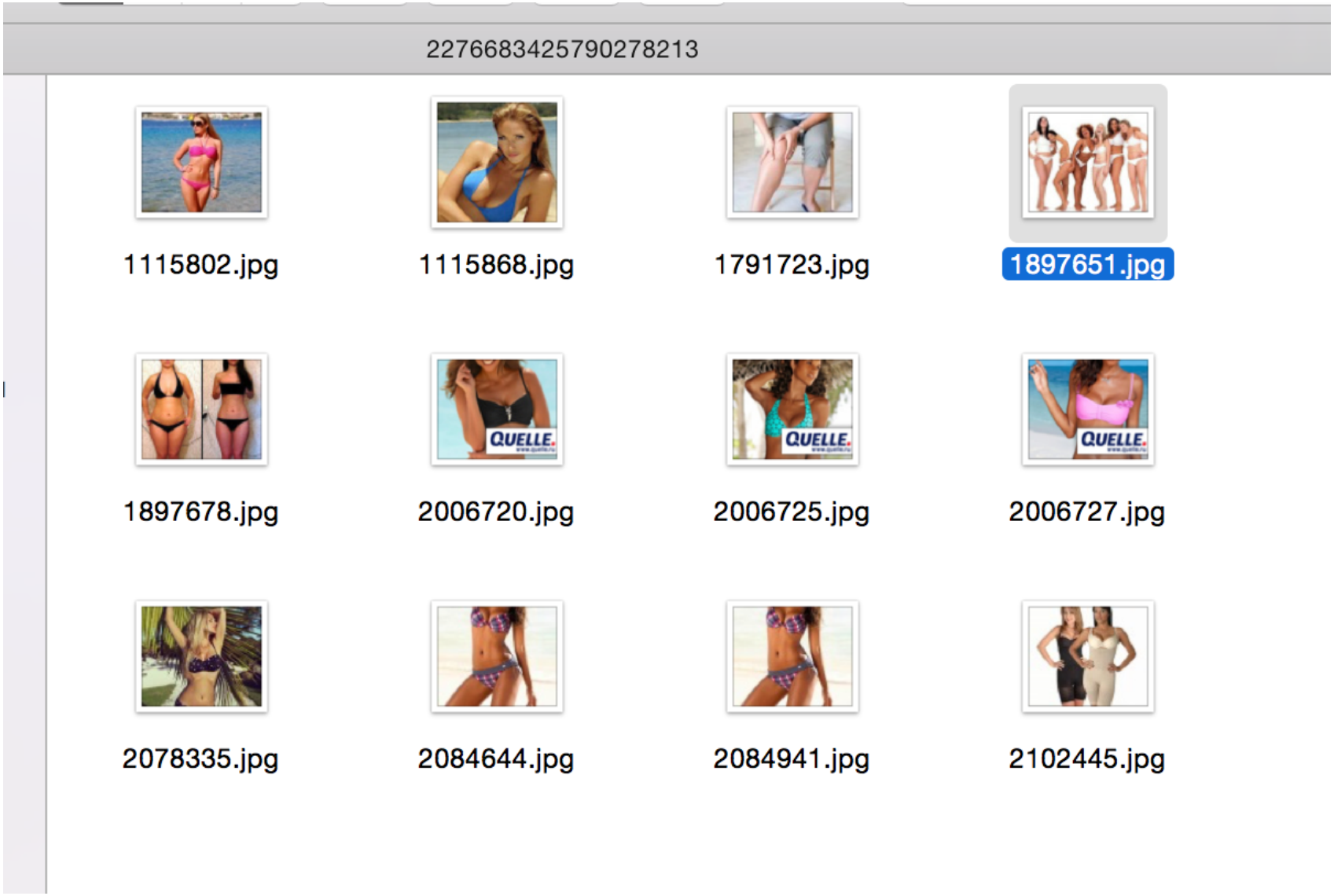

Visualization, #6


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Visualization, #7

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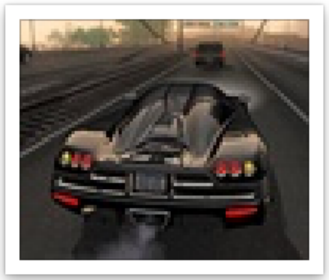

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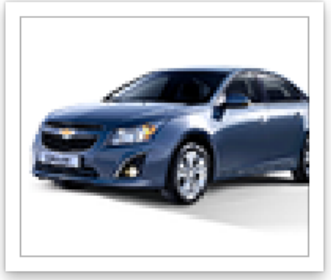

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