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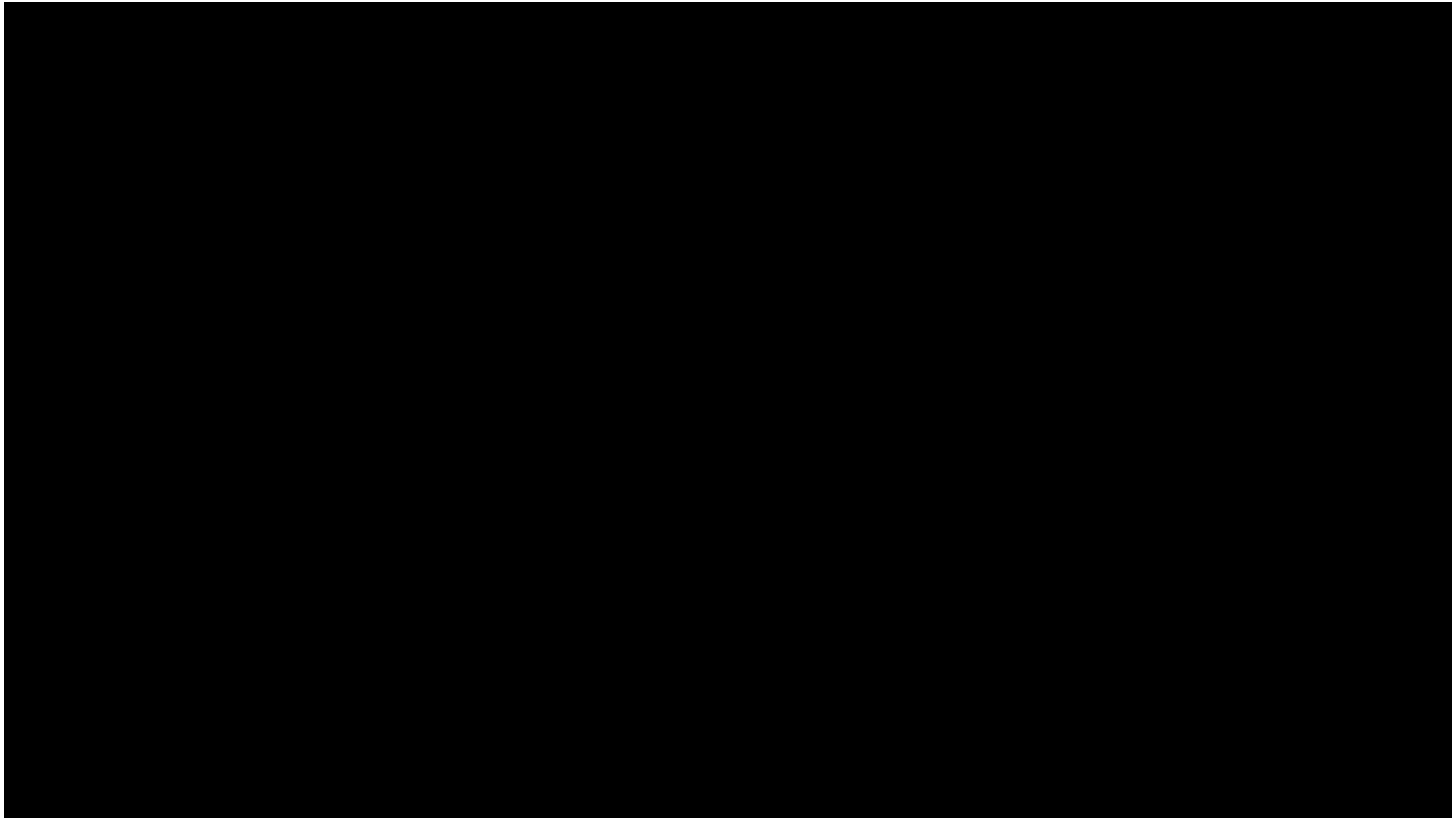
Face recognition

What is face recognition?

Face recognition



[Courtesy of Baidu]

Face verification vs. face recognition

→ Verification

1:1 99% 99.9

- Input image, name/ID
- Output whether the input image is that of the claimed person

→ Recognition

1:K

K=100 ←

- Has a database of K persons
- Get an input image
- Output ID if the image is any of the K persons (or "not recognized")

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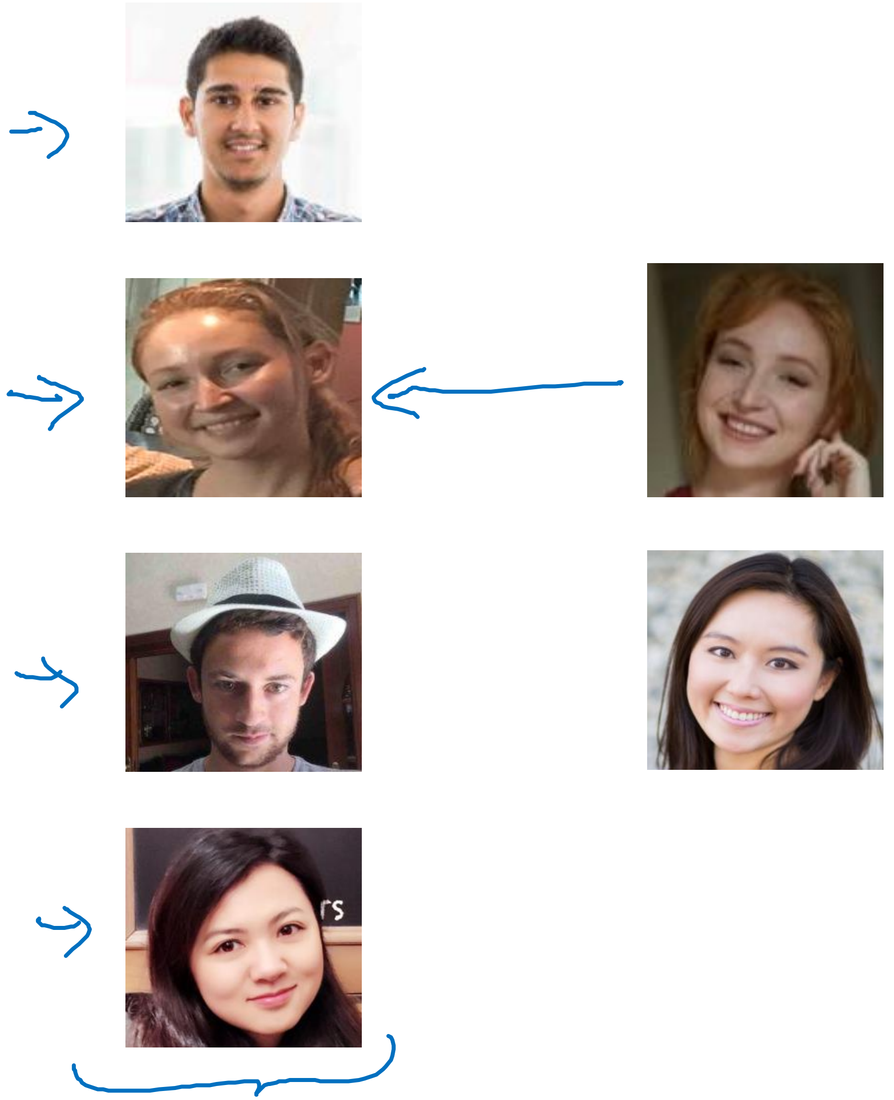
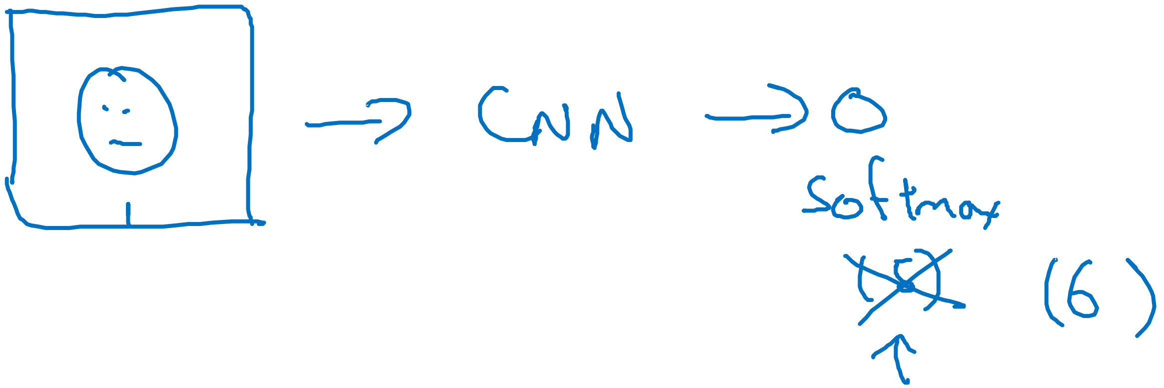
Face recognition

One-shot learning

One-shot learning



Learning from one example to recognize the person again



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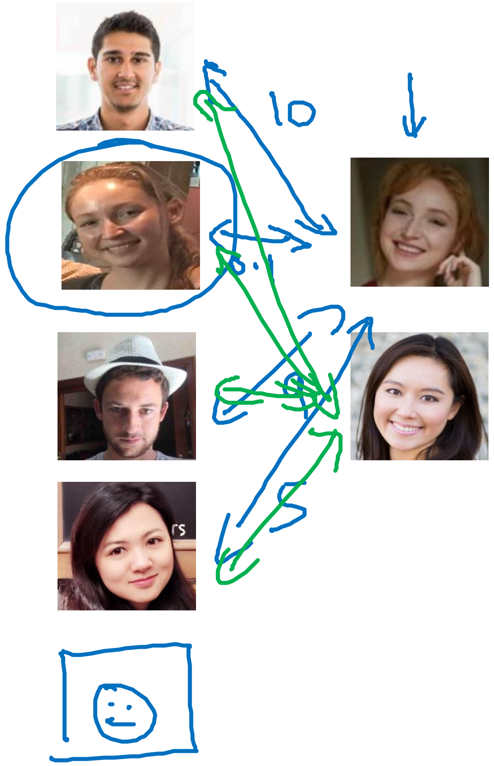
Learning a "similarity" function

- $d(\text{img1},\text{img2})$ = degree of difference between images

If $d(\text{img1},\text{img2}) \leq \tau$ "same"

$> \tau$ "different"

Verification.



d(img1, img2)

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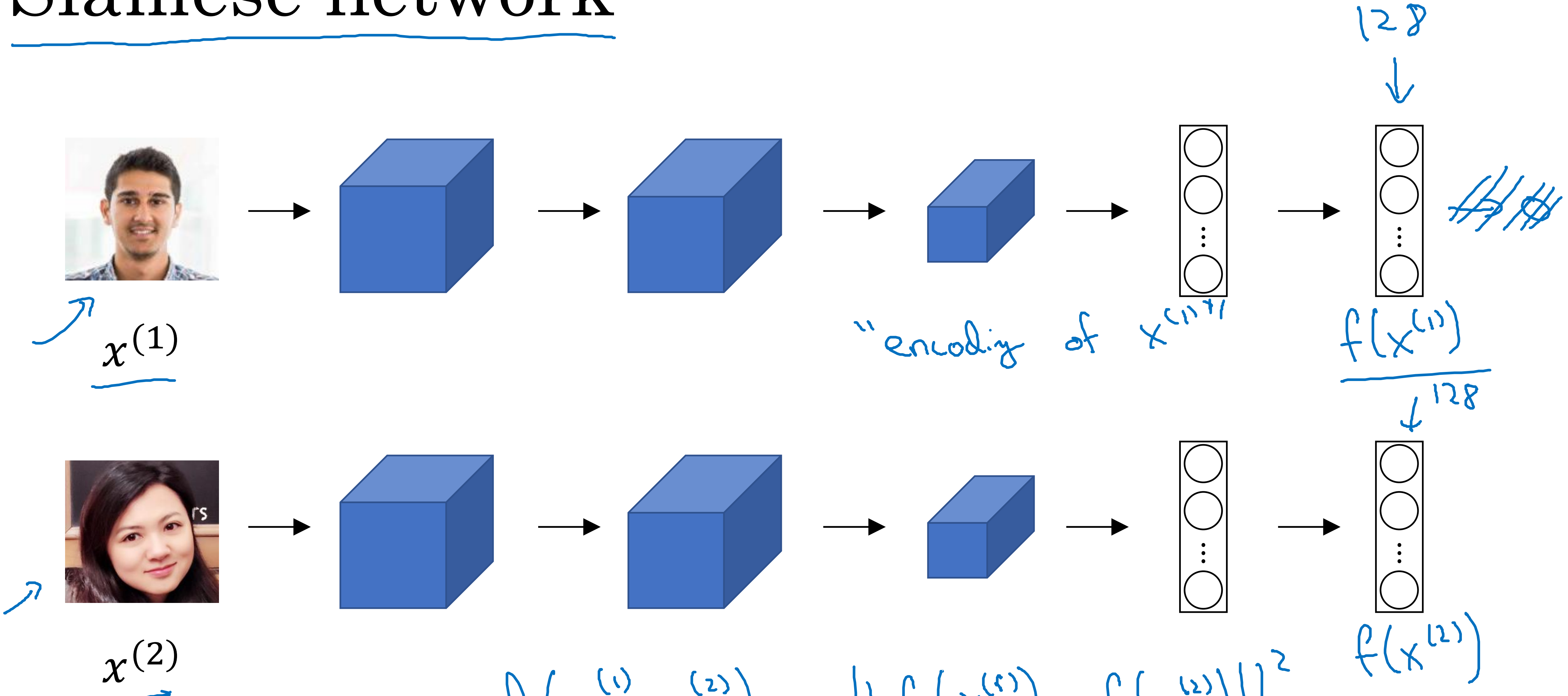
Face recognition

Siamese network

Siamese network



$$\rightarrow d(x^{(1)}, x^{(2)}) = \| f(x^{(1)}) - f(x^{(2)}) \|_2^2$$

[Taigman et. al., 2014. $\boxed{\text{DeepFace}}$ closing the gap to human level performance]

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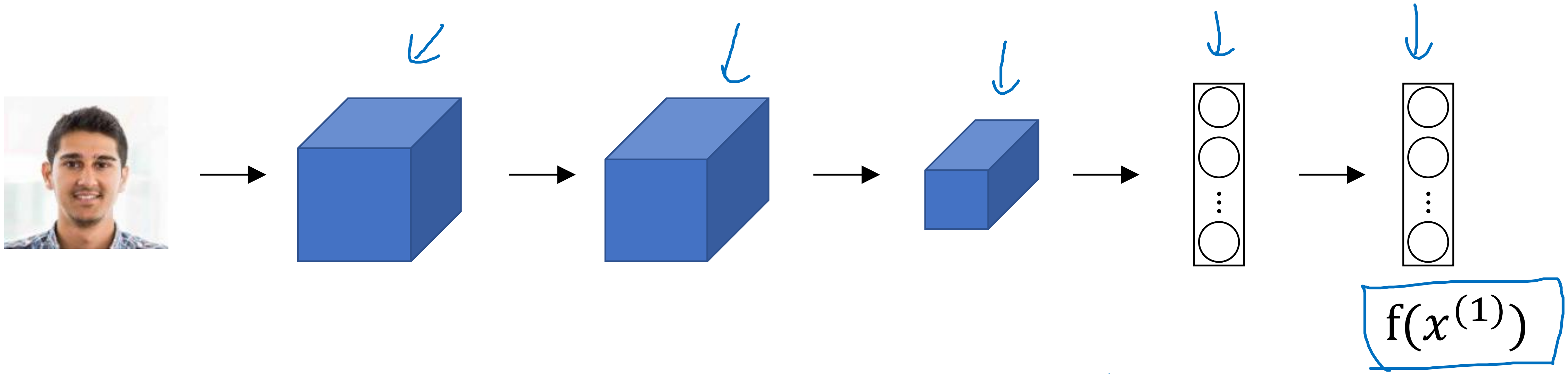
Goal of learning



Parameters of NN define an encoding $f(x^{(i)})$ 128

Learn parameters so that:

If $x^{(i)}, x^{(j)}$ are the same person, $\|f(x^{(i)}) - f(x^{(j)})\|^2$ is small.

If $x^{(i)}, x^{(j)}$ are different persons, $\|f(x^{(i)}) - f(x^{(j)})\|^2$ is large.

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Face recognition

Triplet loss

Learning Objective

Anchor   Positive   Anchor   Negative

A P A N

$d(A,P) = 0.5$ $\rightarrow 0.2$ $d(A,N) = \cancel{0.51}$ 0.7

Want: $\underbrace{\|f(A)-f(P)\|^2}_{d(A,P)} + \alpha \le \underbrace{\|f(A)-f(N)\|^2}_{d(A,N)}$

$$\boxed{\underbrace{\|f(A)-f(P)\|^2}_{0} - \underbrace{\|f(A)-f(N)\|^2}_{0} + \underbrace{\alpha}_{\text{margin}} \le 0}$$

$f(\text{img}) = \vec{0}$

[Schroff et al.,2015, FaceNet: A unified embedding for face recognition and clustering]

Loss function

Given 3 images A, P, N:

$$\mathcal{L}(A,P,N) = \max\left(\boxed{\|f(A)-f(P)\|^2 - \|f(A)-f(N)\|^2 + \alpha}, 0\right)$$

$\leq 0 \quad > 0$

$$J = \sum_{i=1}^{m} \mathcal{L}(A^{(i)}, P^{(i)}, N^{(i)})$$

A, P

Training set: 10k pictures of 1k persons

[Schroff et al.,2015, FaceNet: A unified embedding for face recognition and clustering]

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Choosing the triplets A,P,N

During training, if A,P,N are chosen randomly, $d(A,P) + \alpha \leq d(A,N)$ is easily satisfied.

$\|f(A)-f(P)\|^2 + \alpha \leq \|f(A)-f(N)\|^2$

Choose triplets that're "hard" to train on.

$d(A,P) + \alpha \leq d(A,N)$

$d(A,P) \approx d(A,N)$

$\downarrow \qquad \uparrow$

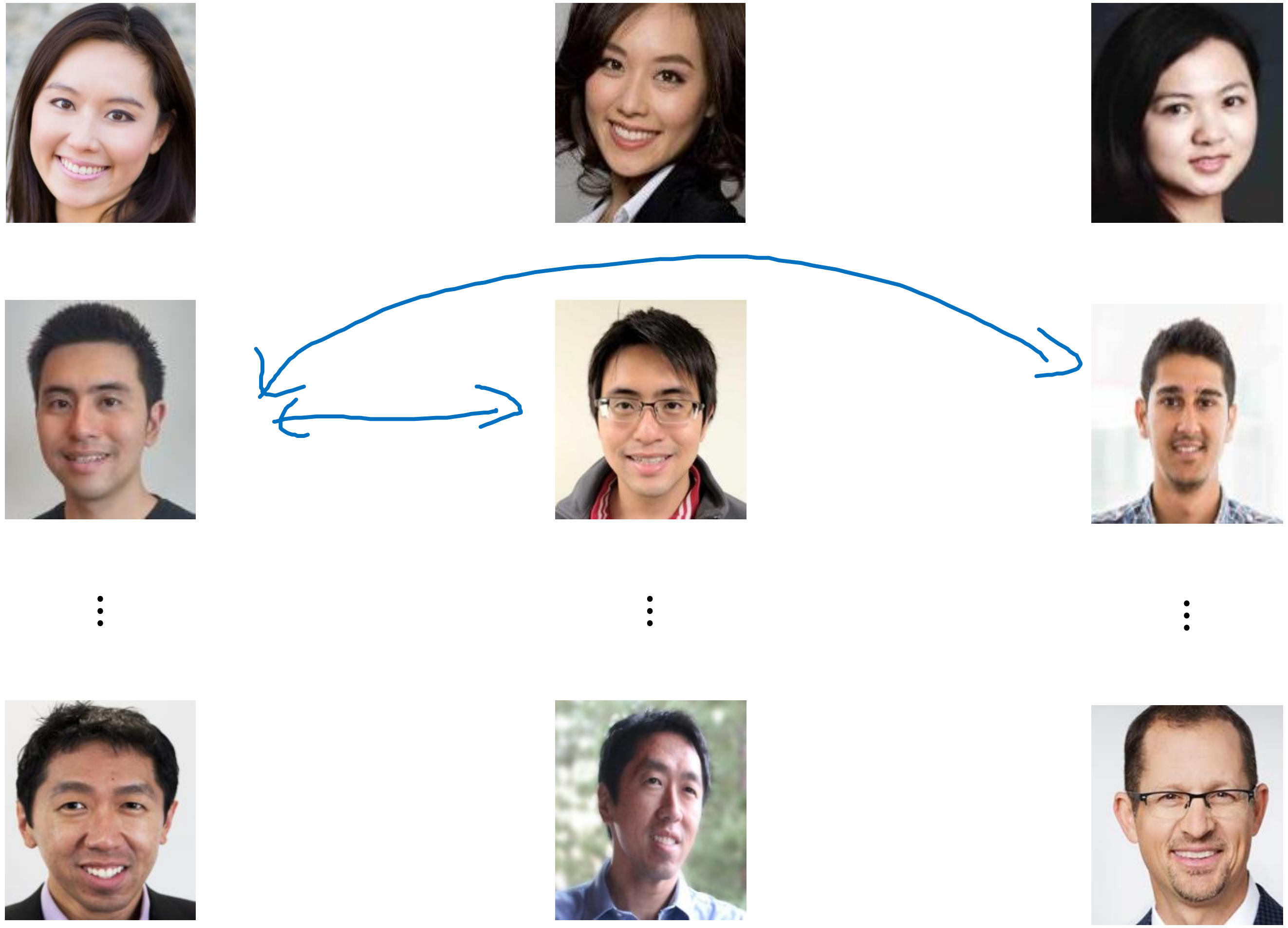
Face Net

Deep Face

[Schroff et al.,2015, FaceNet: A unified embedding for face recognition and clustering]

Training set using triplet loss

Anchor | Positive | Negative



J

$d(x^{(i)}, x^{(j)})$

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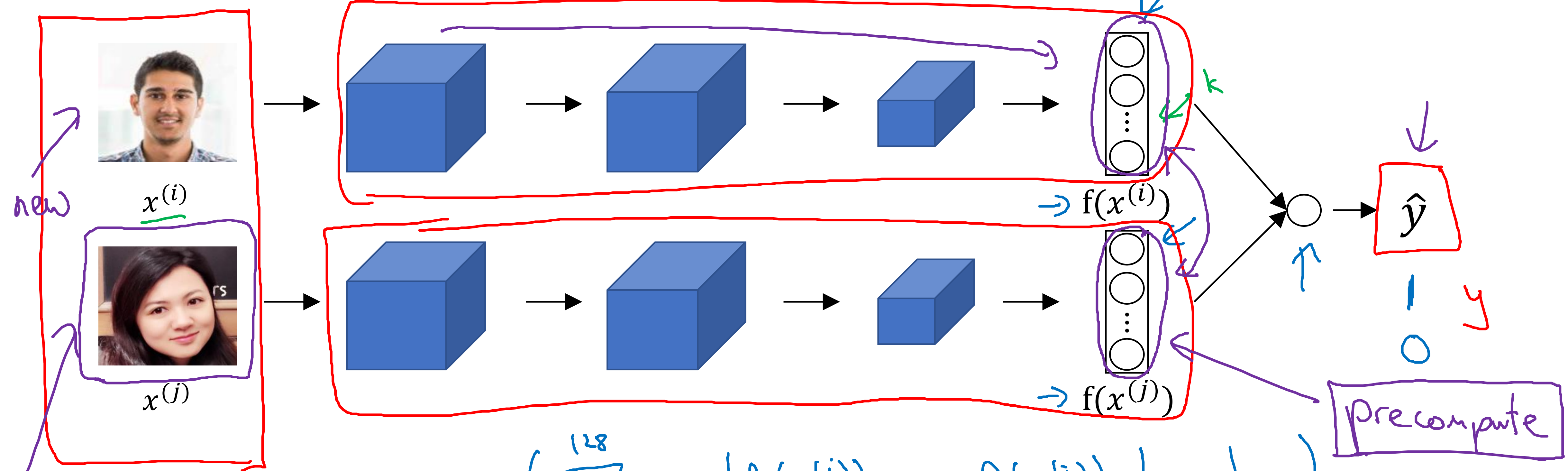
Face recognition

Face verification and binary classification

Learning the similarity function



Database ✗

$$\hat{y} = \sigma\left(\sum_{k=1}^{128} w_i \underbrace{\left|f(x^{(i)})_k - f(x^{(j)})_k\right|}_{\frac{\left(f(x^{(i)})_k - f(x^{(j)})_k\right)^2}{f(x^{(i)})_k + f(x^{(j)})_k}} + b\right)$$

χ^2

[Taigman et. al., 2014. DeepFace closing the gap to human level performance]

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Face verification supervised learning

x	y	
	1	"same"
	0	"different"
	0	
	1	

[Taigman et. al., 2014. DeepFace closing the gap to human level performance]

Neural Style Transfer

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What is neural style transfer?

Neural style transfer

Content (C) Style (S)

Generated image (G)

Content (C) Style (S)

Generated image (G)

[Images generated by Justin Johnson]

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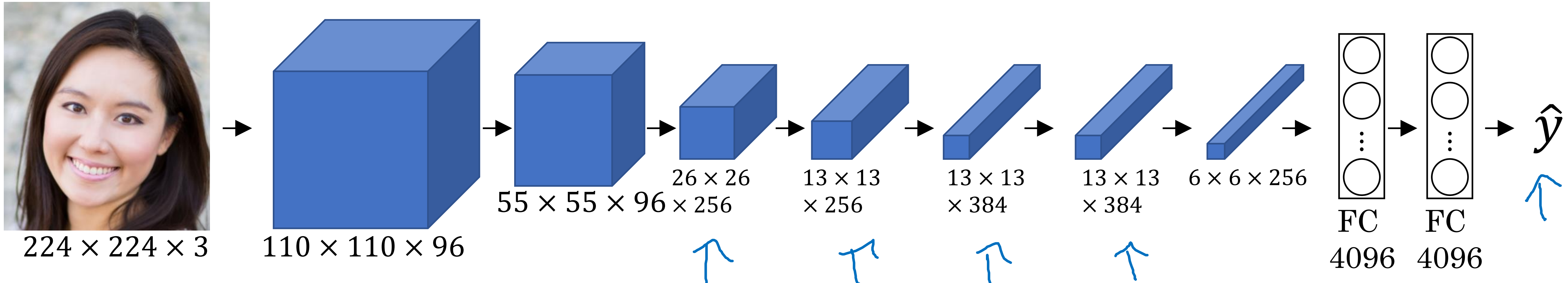
Neural Style Transfer

What are deep ConvNets learning?

Visualizing what a deep network is learning



Pick a unit in layer 1. Find the nine image patches that maximize the unit's activation.

Repeat for other units.

[Zeiler and Fergus., 2013, Visualizing and understanding convolutional networks]

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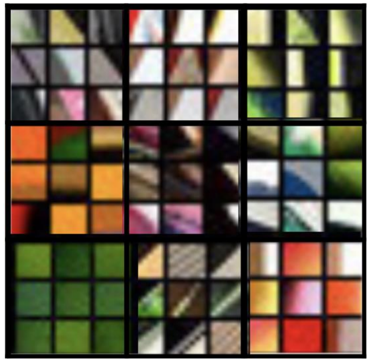
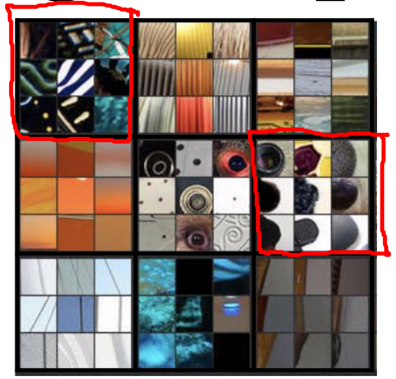
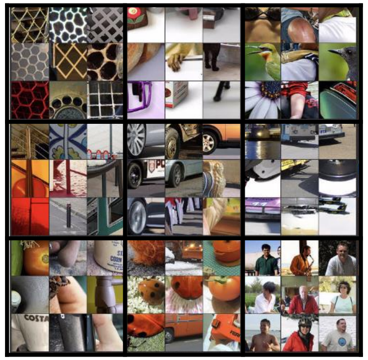
Visualizing deep layers



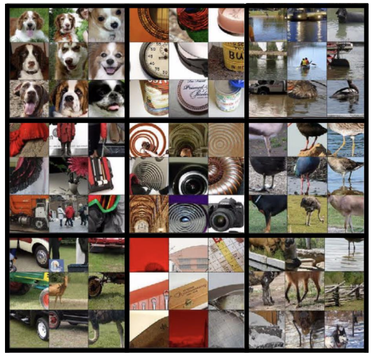
Layer 1



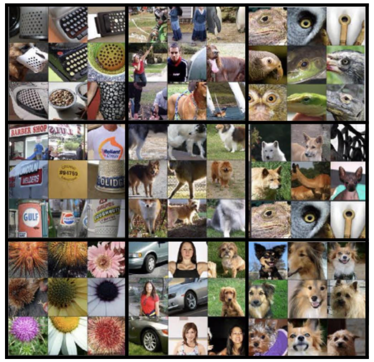
Layer 2



Layer 3



Layer 4



Layer 5

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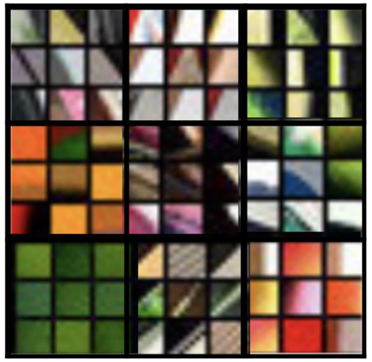
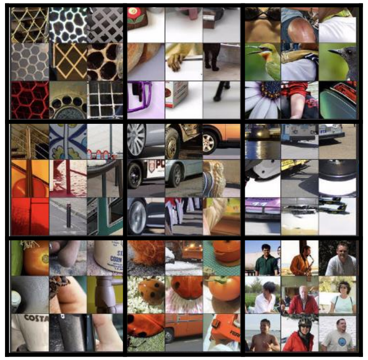
Visualizing deep layers: Layer 1

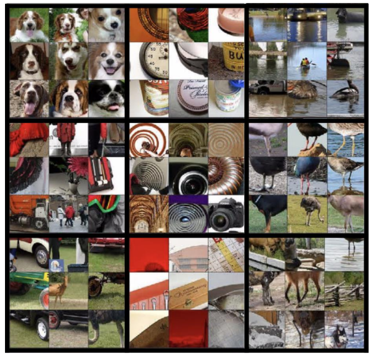


Layer 1

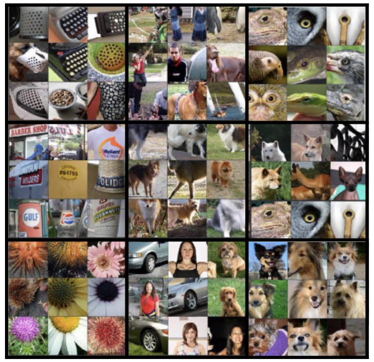
Layer 2



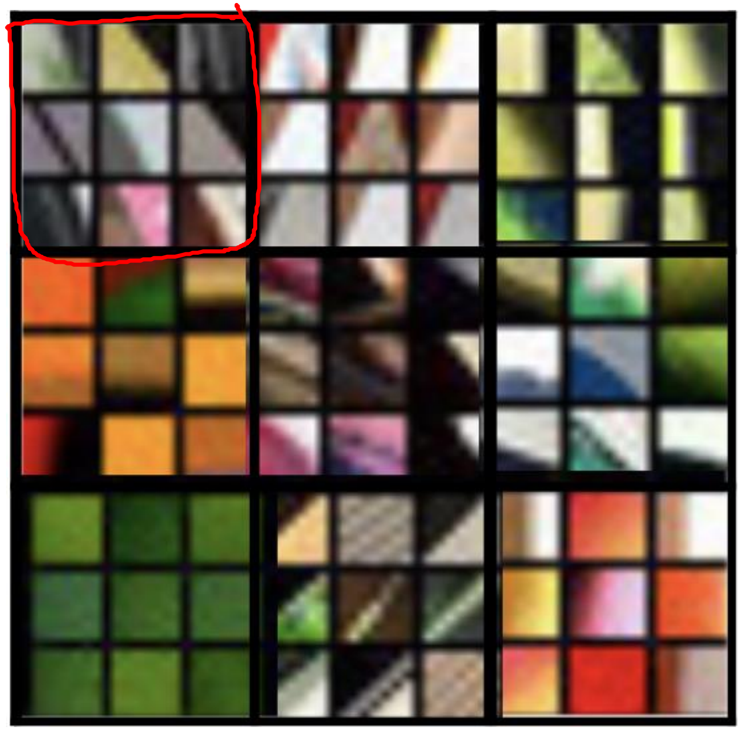
Layer 3

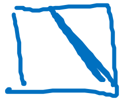


Layer 4



Layer 5





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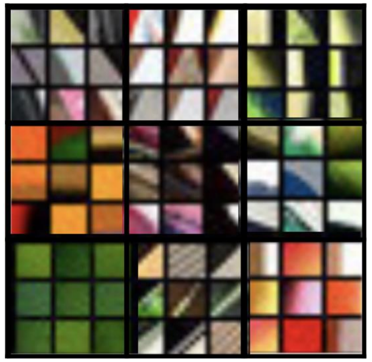
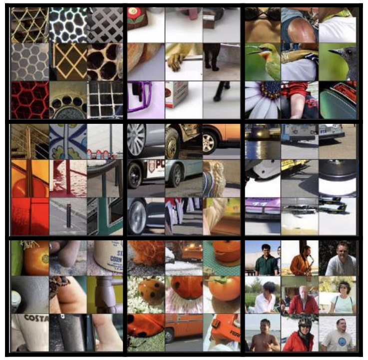
Visualizing deep layers: Layer 2

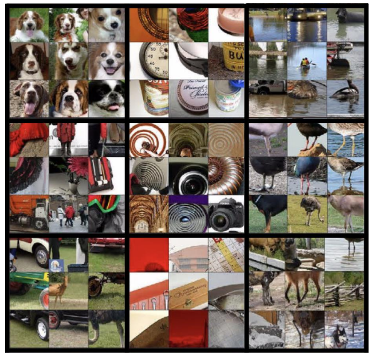


Layer 1

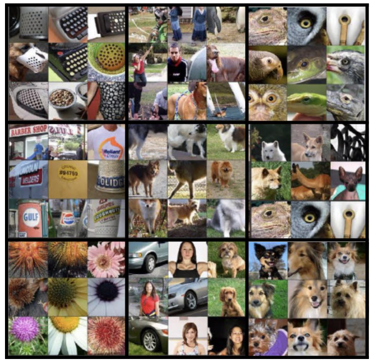
Layer 2



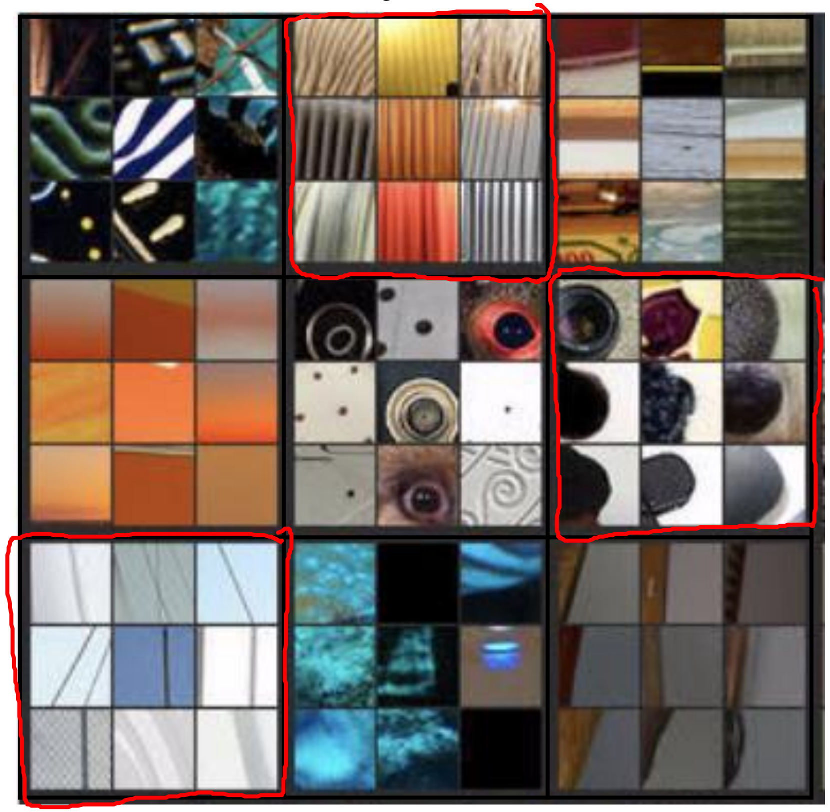
Layer 3



Layer 4



Layer 5



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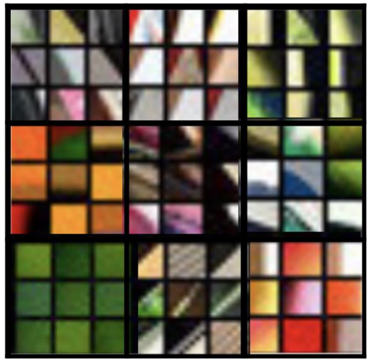
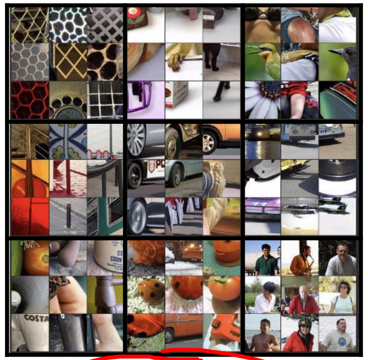
Visualizing deep layers: Layer 3

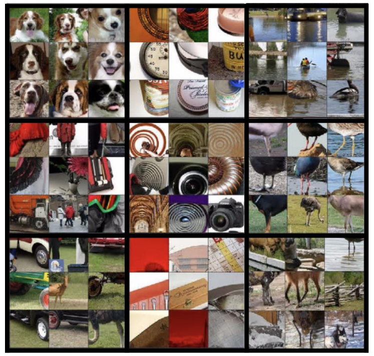


Layer 1

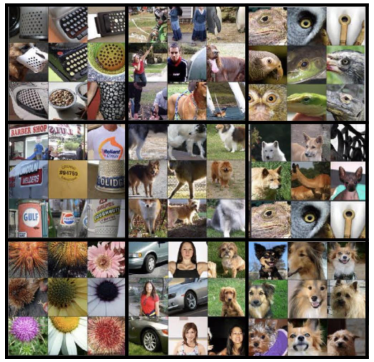
Layer 2



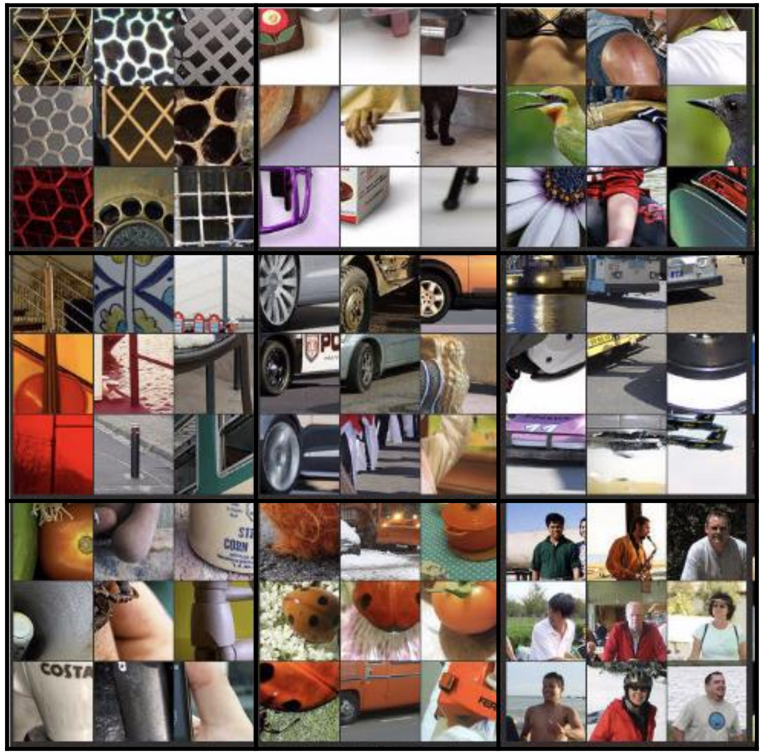
Layer 3



Layer 4



Layer 5



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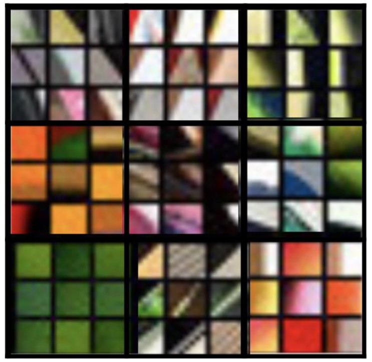
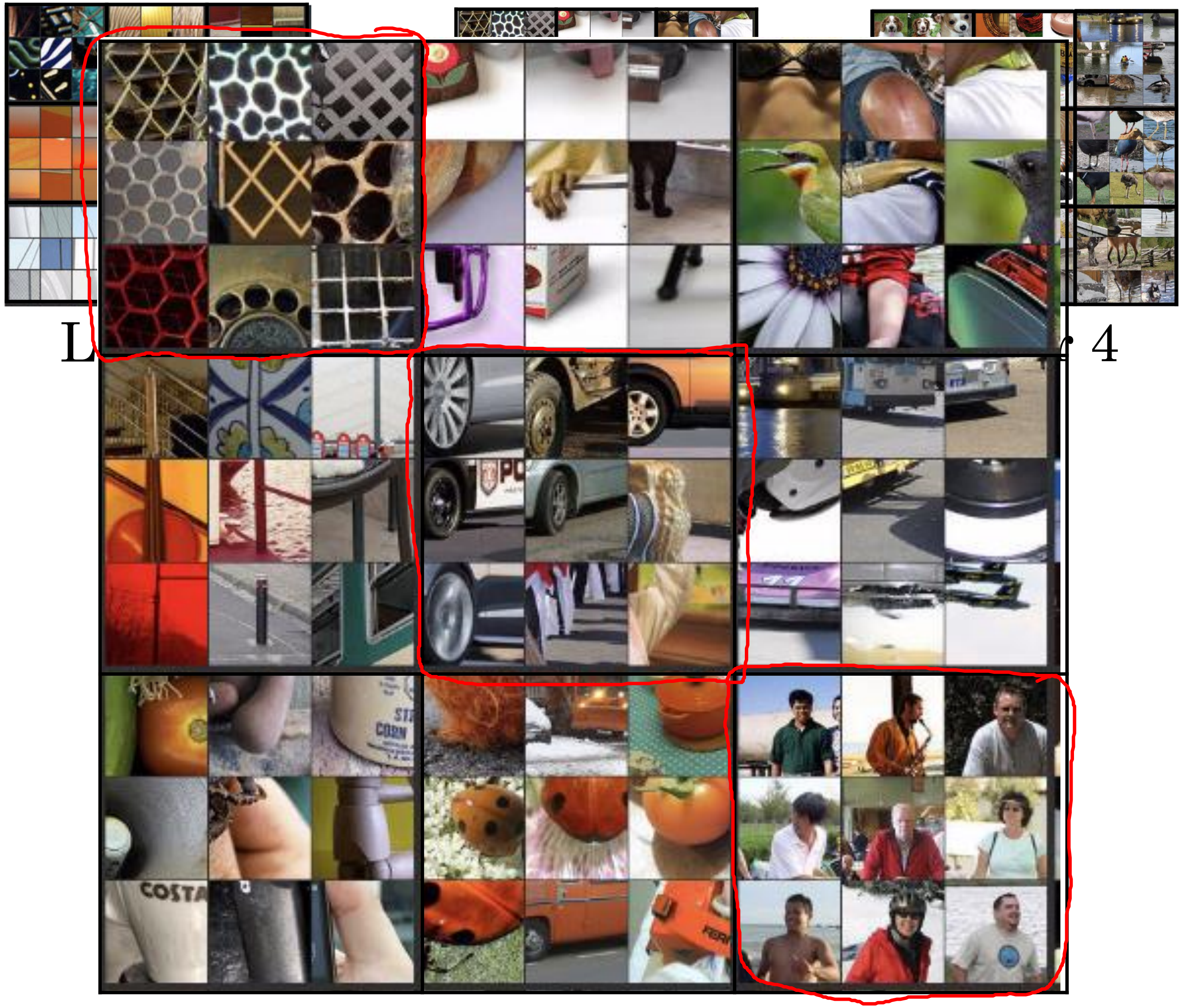
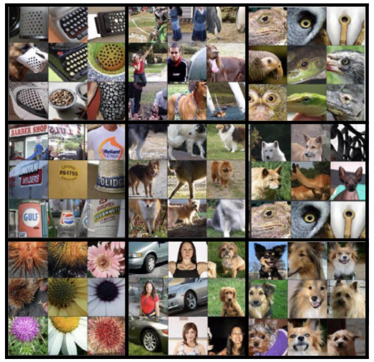
Visualizing deep layers: Layer 3



Layer 1





Layer 5

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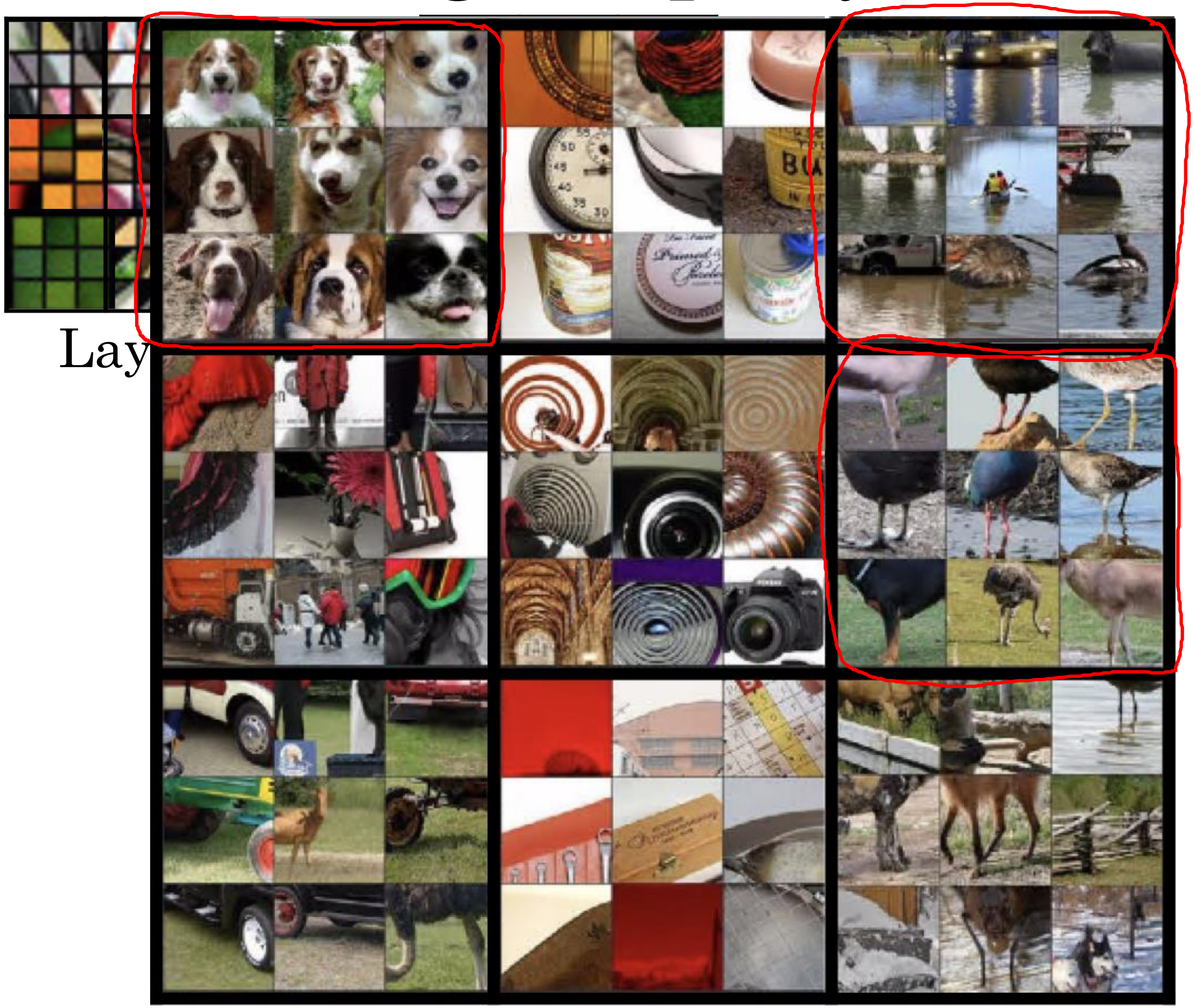
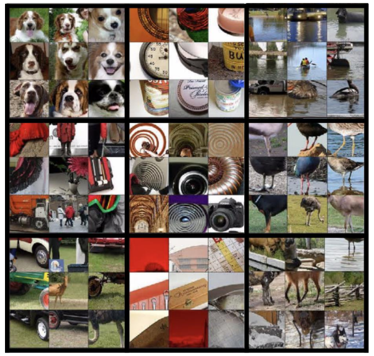
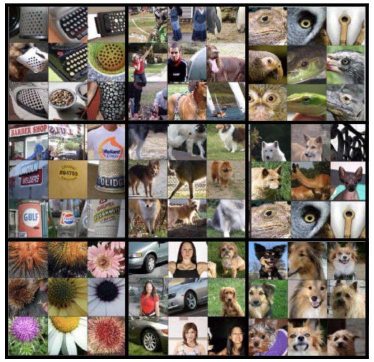
Visualizing deep layers: Layer 4



Lay

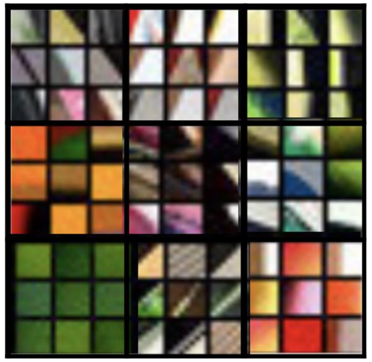


Layer 4



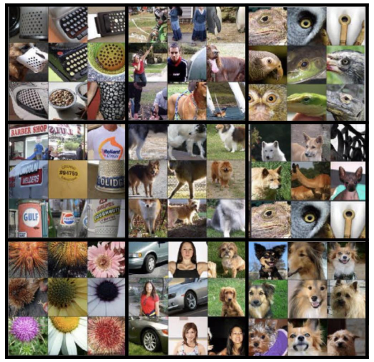
Layer 5

Visualizing deep layers: Layer 5



Layer 1

L



Layer 5

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Neural Style Transfer

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Cost function

Neural style transfer cost function

Content C

Style S

Generated image G

$$J(G) = \alpha J_{content}(C, G) + \beta J_{style}(S, G)$$

[Gatys et al., 2015. A neural algorithm of artistic style. Images on slide generated by Justin Johnson]

Find the generated image G

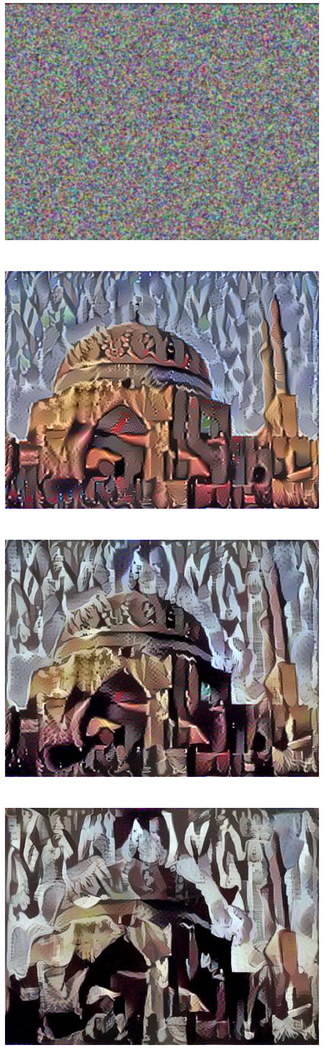
1. Initiate G randomly

   $\underline{G}: \underline{100} \times \underline{100} \times 3$

   RGB

2. Use gradient descent to minimize $\underline{J(G)}$

$$G := G - \frac{\partial}{\partial G} J(G)$$



[Gatys et al., 2015. A neural algorithm of artistic style]

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Neural Style Transfer

Content cost function

Content cost function

$$J(G) = \alpha \underline{J_{content}(C, G)} + \beta J_{style}(S, G)$$

- Say you use hidden layer l to compute content cost.
- Use pre-trained ConvNet. (E.g., VGG network)
- Let $a^{[l](C)}$ and $a^{[l](G)}$ be the activation of layer l on the images
- If $a^{[l](C)}$ and $a^{[l](G)}$ are similar, both images have similar content

$$J_{content}(C, G) = \frac{1}{2} \underbrace{\| a^{[l](C)} - a^{[l](G)} \|^2}$$

[Gatys et al., 2015. A neural algorithm of artistic style]

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Neural Style Transfer

Style cost function

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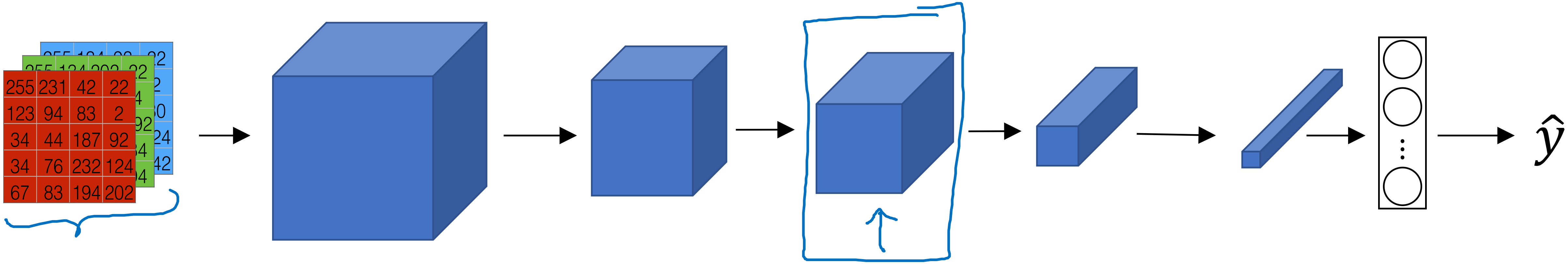
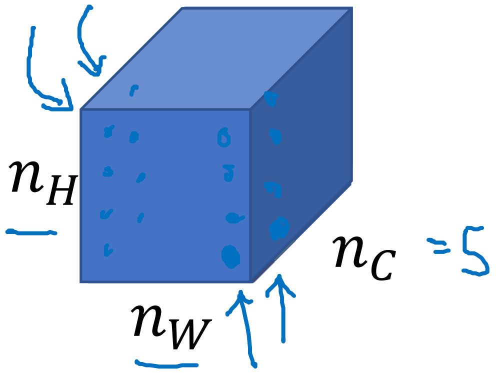
Meaning of the "style" of an image



Say you are using layer l's activation to measure "style."
Define style as correlation between activations across channels.



How correlated are the activations across different channels?

[Gatys et al., 2015. A neural algorithm of artistic style]

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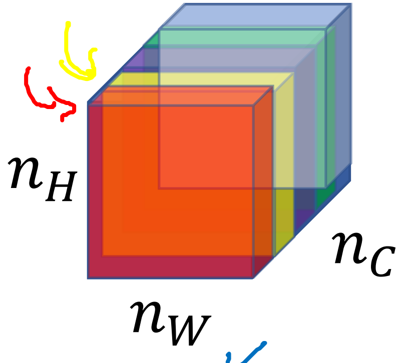
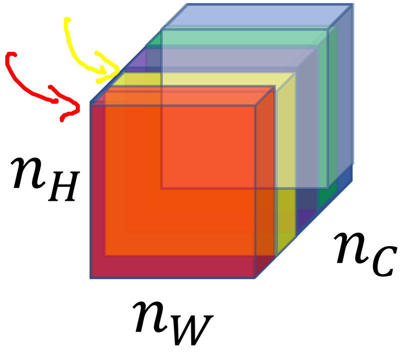
Intuition about style of an image

Style image

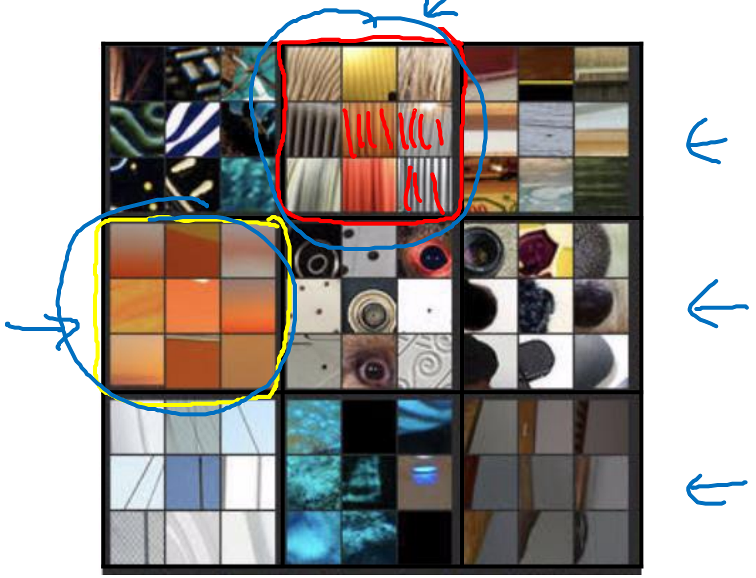


Generated Image



Correlated?

Uncorrelated



[Gatys et al., 2015. A neural algorithm of artistic style]

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Style matrix

Let $\underline{a^{[l]}_{i,j,k}}$ = activation at (i, j, k). $\underline{G^{[l]}}$ is $n_c^{[l]} \times n_c^{[l]}$

H W C

n_c

$G^{[l]}_{kk'}$

$k = 1, \ldots, n_c^{[l]}$

$$\rightarrow G^{[l](S)}_{kk'} = \sum_{i=1}^{n_H^{[l]}} \sum_{j=1}^{n_W^{[l]}} a^{[l](S)}_{ijk} \, a^{[l](S)}_{ijk'}$$

$$\rightarrow G^{[l](G)}_{kk'} = \sum_{i=1}^{n_H^{[l]}} \sum_{j=1}^{n_W^{[l]}} a^{[l](G)}_{ijk} \, a^{[l](G)}_{ijk}$$

"Gram matrix"

$$J^{[l]}_{style}(S, G) = \frac{1}{(\ldots)} \left\| G^{[l](S)} - G^{[l](G)} \right\|_F^2$$

$$= \frac{1}{(2 n_H^{[l]} n_W^{[l]} n_c^{[l]})^2} \sum_k \sum_{k'} \left(G^{[l](S)}_{kk'} - G^{[l](G)}_{kk'} \right)^2$$

β

[Gatys et al., 2015. A neural algorithm of artistic style]

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Style cost function

$$\| G^{[l](S)} - G^{[l](G)} \|_F^2$$

$$J_{style}^{[l]}(S,G) = \frac{1}{\left(2n_H^{[l]}n_W^{[l]}n_C^{[l]}\right)^2}\sum_k \sum_{k'} (G_{kk'}^{[l](S)} - G_{kk'}^{[l](G)})$$

$$J_{style}(S,G) = \sum_l \lambda^{[l]} J_{style}^{[l]}(S,G)$$

$$\underbrace{J(G)}_{G} = \alpha J_{content}(C,G) + \beta J_{style}(S,G)$$

[Gatys et al., 2015. A neural algorithm of artistic style]

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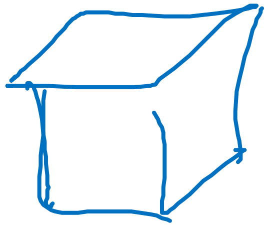
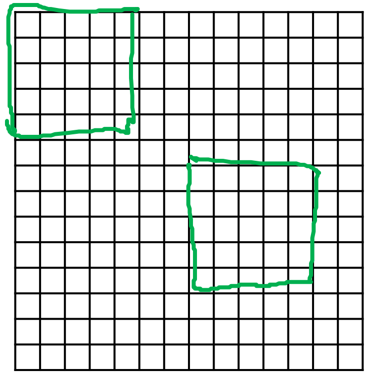
Convolutional Networks in 1D or 3D

1D and 3D generalizations of models

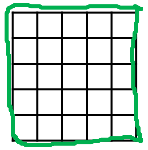
Convolutions in 2D and 1D





2D input image
14×14

*



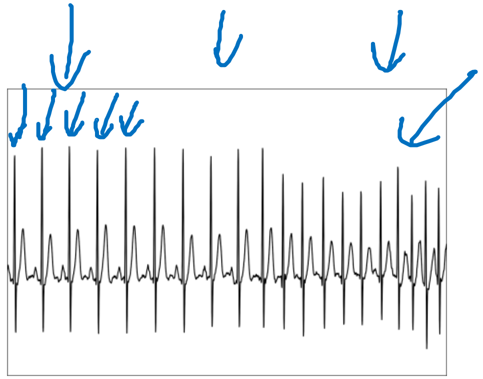
2D filter
5×5

$14 \times 14 \times 3 \; * \; 5 \times 5 \times 3$

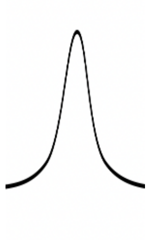
$\rightarrow 10 \times 10 \times 16$

$10 \times 10 \times 16 \; * \; 5 \times 5 \times 16$

$\rightarrow 6 \times 6 \times 32$



*



1	20	15	3	18	12	4	17

14

1	3	10	3	1

5

$14 \times 1 \; * \; 5 \times 1$

$\rightarrow 10 \times 16$

$10 \times 16 \; * \; 5 \times 16$

$\rightarrow 6 \times 32$

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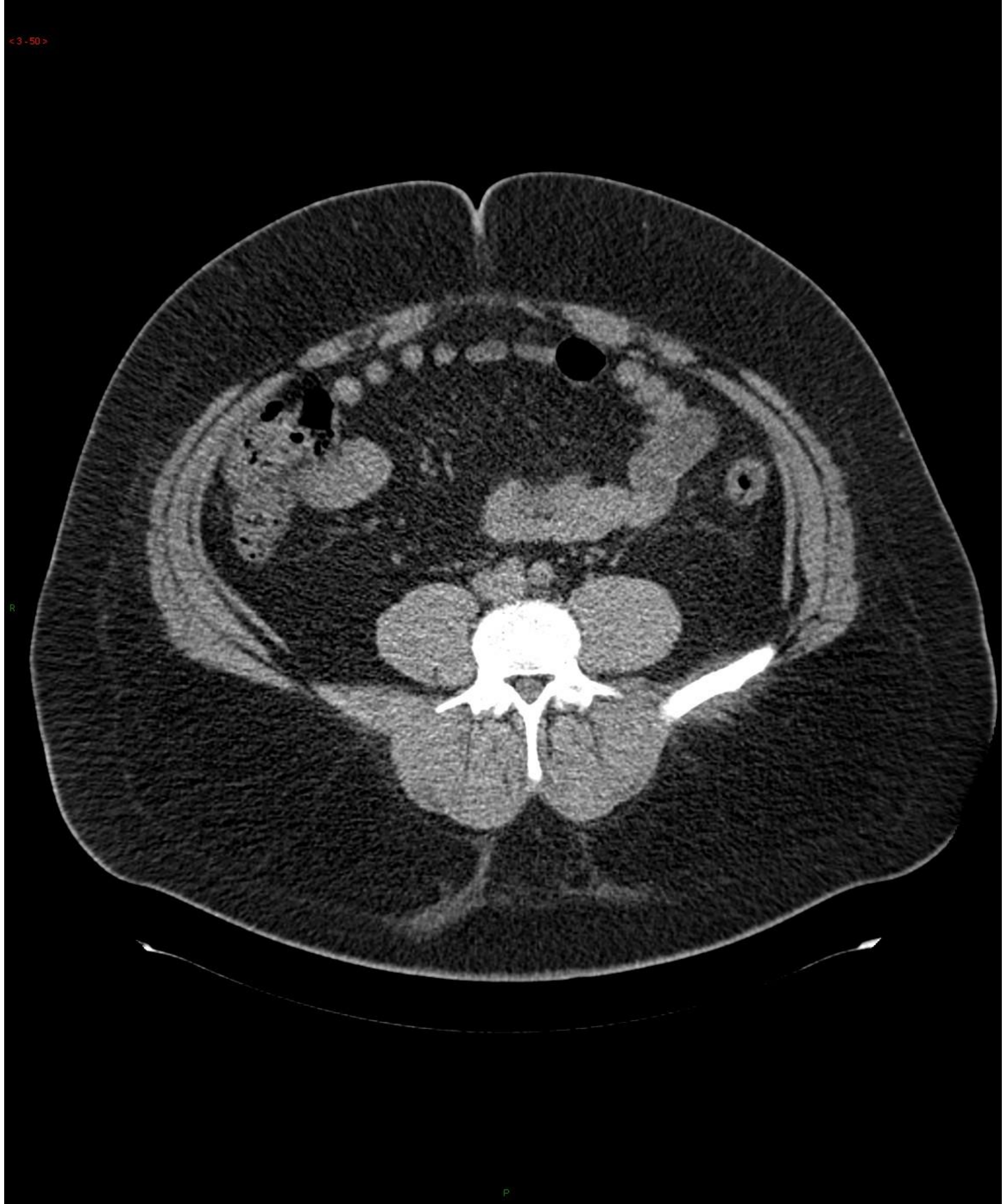
3D data



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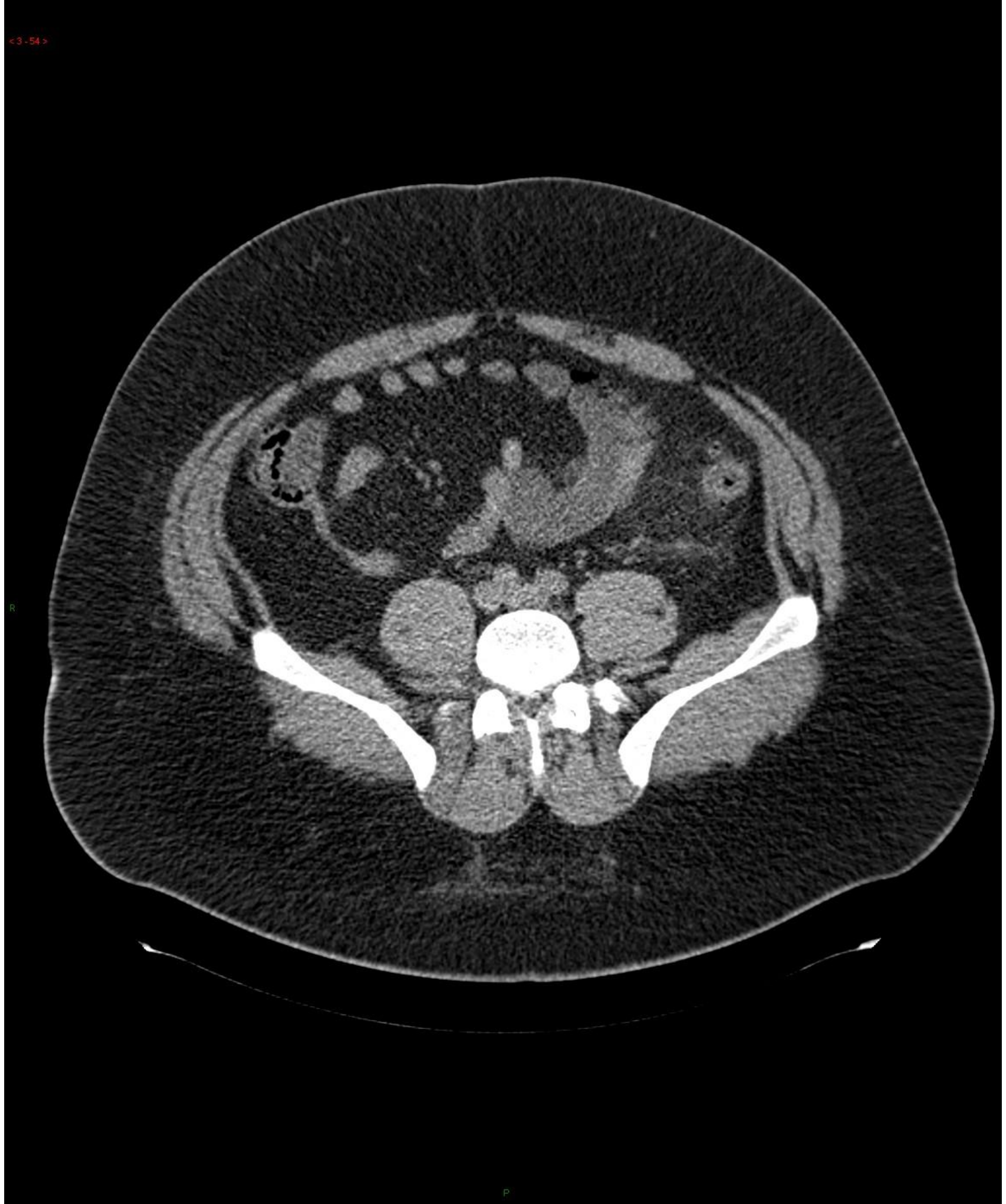
3D data

Andrew Ng

3D data



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3D data

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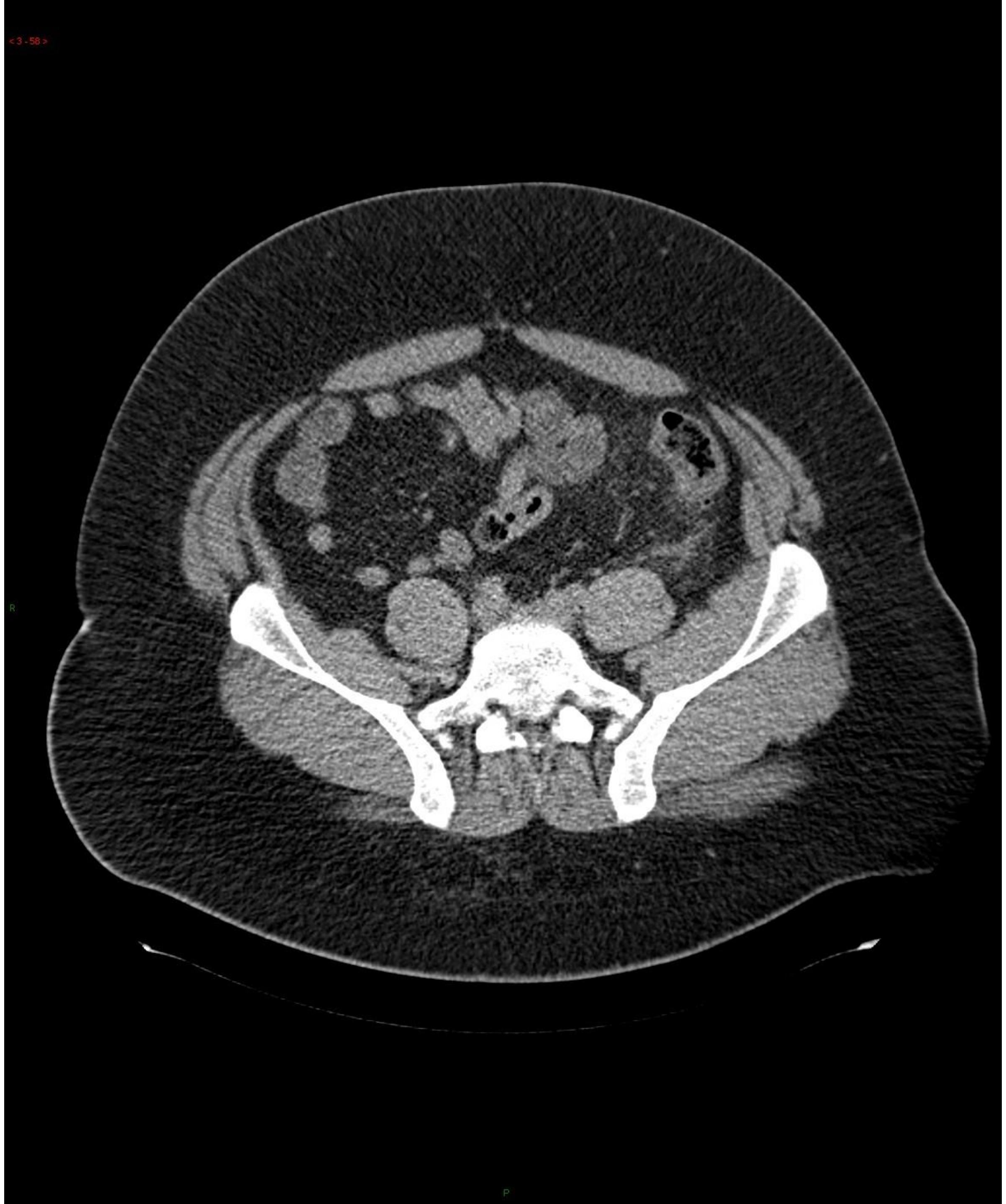

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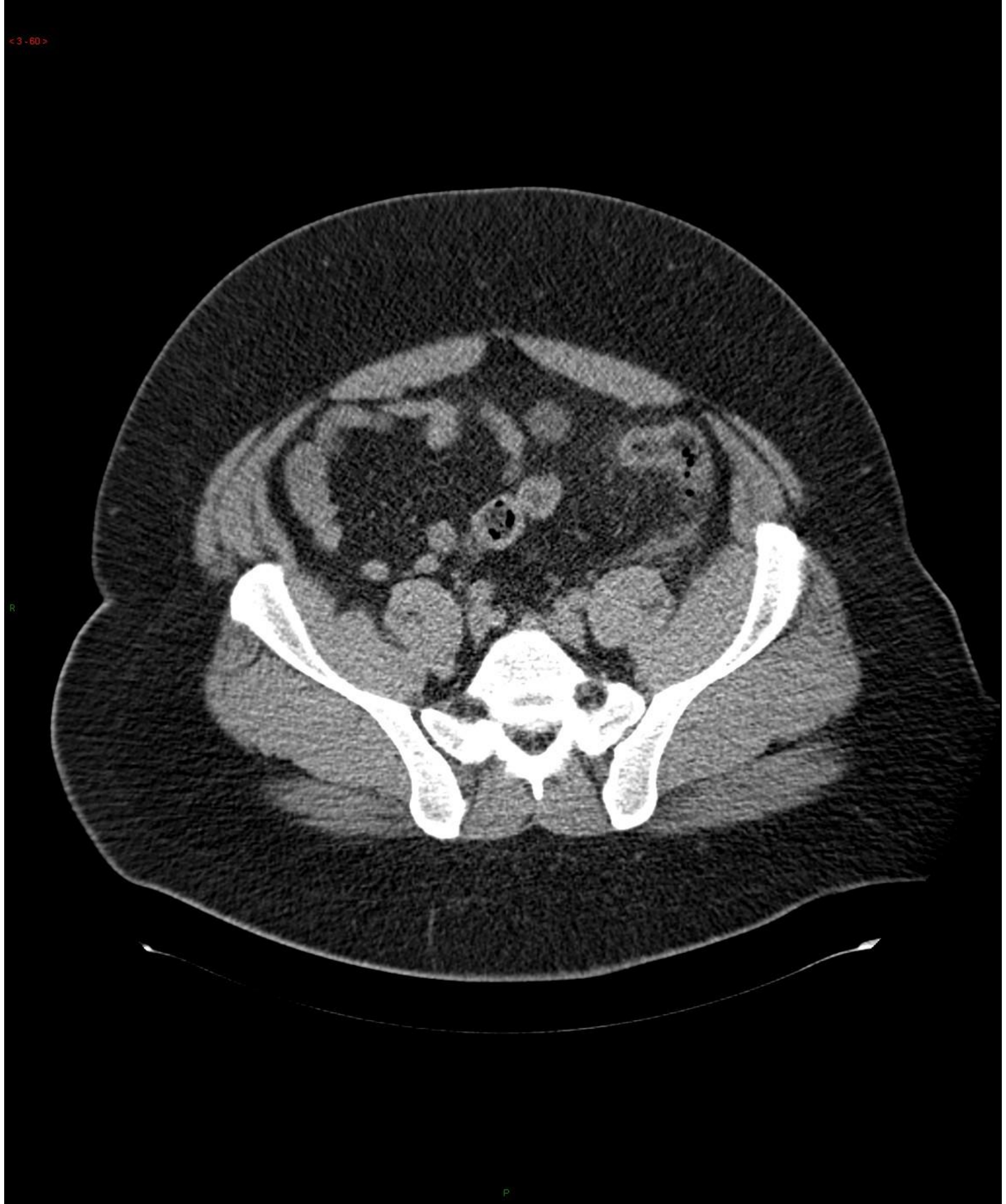
3D data



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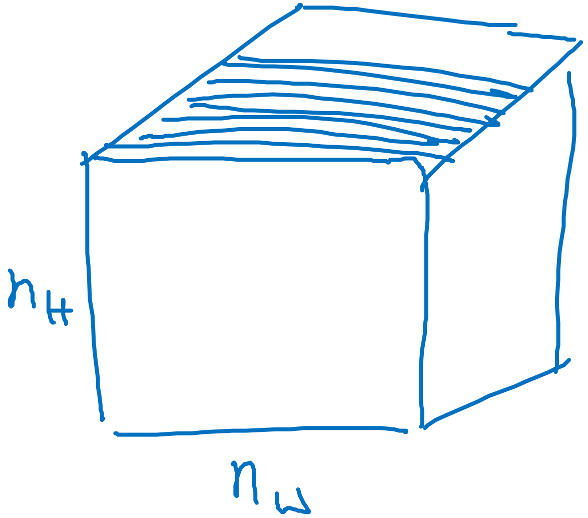
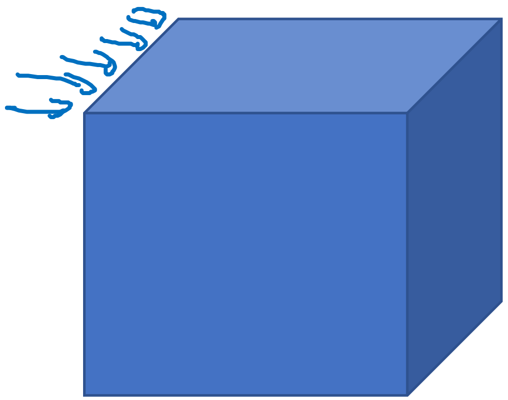
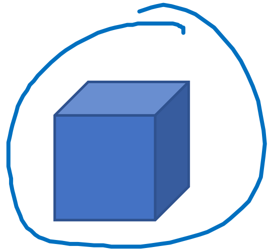


3D convolution



3D volume

*



3D filter

$$\underbrace{14 \times 14 \times 14}\ \times \overset{n_c}{1}$$

$$* \ 5 \times 5 \times 5 \times 1$$

16 filters

$$\rightarrow 10 \times 10 \times 10 \times 16$$

$$* \ 5 \times 5 \times 5 \times 16$$

32 filters

$$\rightarrow 6 \times 6 \times 6 \times 32$$

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