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Face recognition

What is face recognition?

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Face recognition

[Courtesy of Baidu]

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Face verification vs. face recognition

Verification

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

Recognition

- 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

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One-shot learning



Learning from one example to recognize the person again

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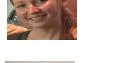
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Learning a “similarity” function

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

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

$> \tau$



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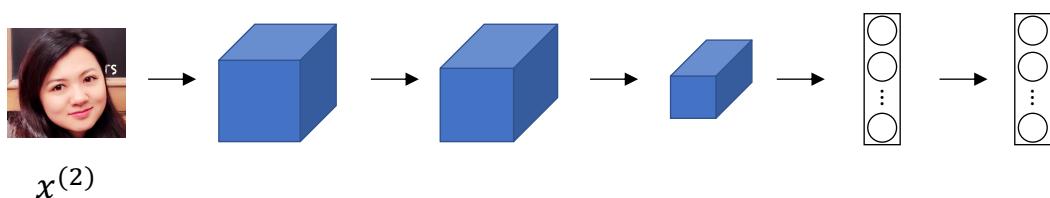
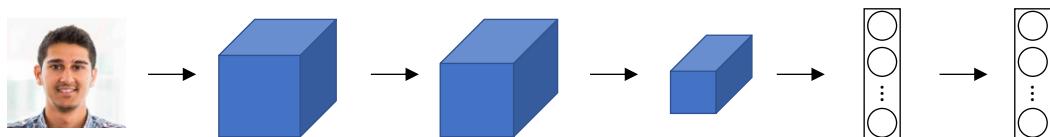
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Face recognition

Siamese network

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Siamese network

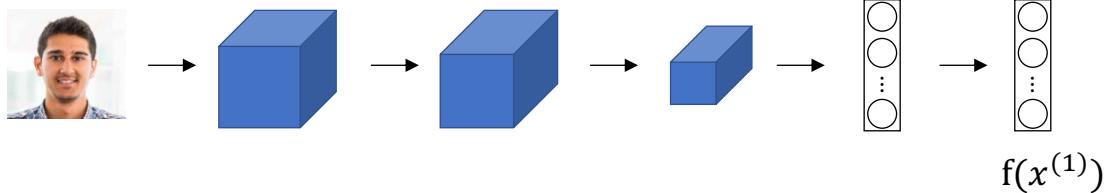


[Taigman et. al., 2014. DeepFace closing the gap to human level performance]

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Goal of learning



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

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

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Learning Objective



Anchor



Positive



Anchor



Negative

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

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Loss function

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.

Choose triplets that're “hard” to train on.

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

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Training set using triplet loss

Anchor



:



Positive



:



Negative



:



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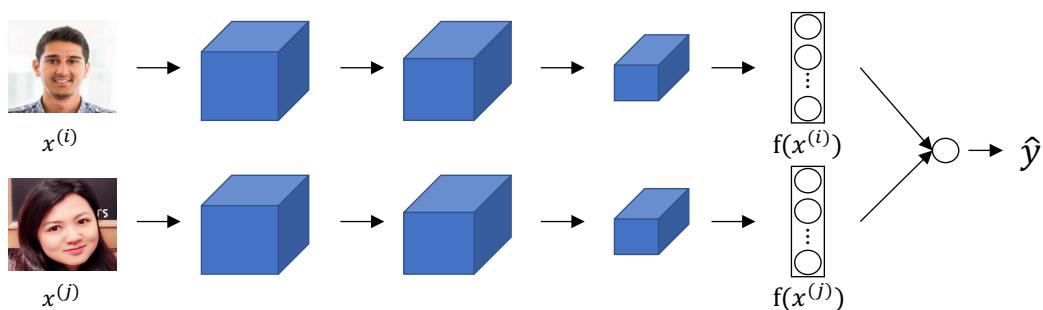
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Face recognition

Face verification and binary classification

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Learning the similarity function



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

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Face verification supervised learning

x	y
	1
	0
	0
	1
	1
	0

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

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Neural Style
Transfer

What is neural style
transfer?

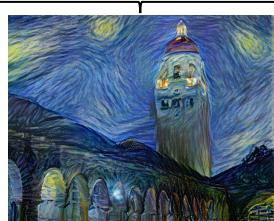
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Neural style transfer



Content

Style



Generated image



Content

Style



Generated image

[Images generated by Justin Johnson]

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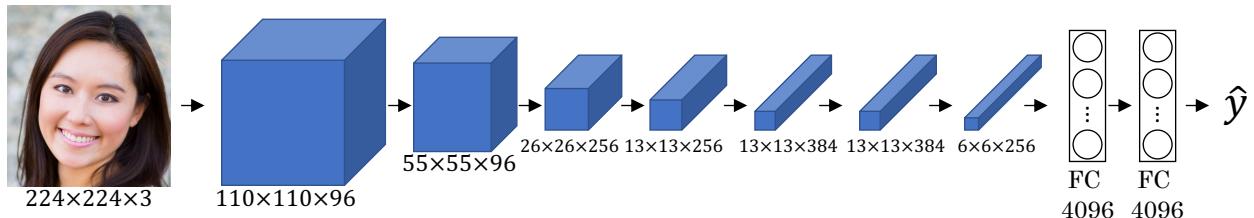
Neural Style Transfer

What are deep ConvNets learning?

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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



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Neural Style Transfer

Cost function

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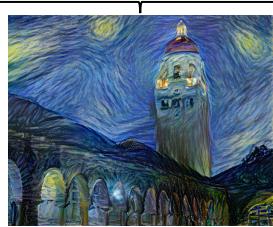
Neural style transfer cost function



Content C



Style S



Generated image G

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

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Find the generated image G

1. Initiate G randomly

$G: 100 \times 100 \times 3$



2. Use gradient descent to minimize $J(G)$



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

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Neural Style Transfer

Content cost function

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Content cost function

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

- 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

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

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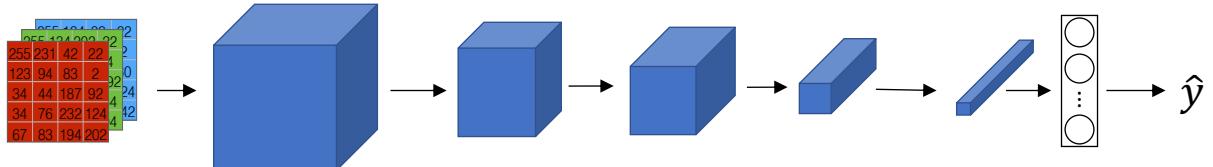
Neural Style Transfer

Style cost function

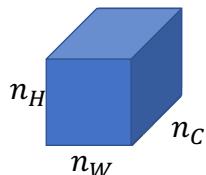
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Meaning of the “style” of an image



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?

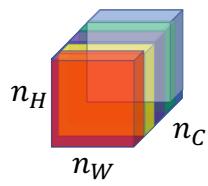
[Gatys et al., 2015. A neural algorithm of artistic style]

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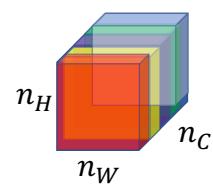
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Intuition about style of an image

Style image



Generated Image



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

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Style matrix

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

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

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Style cost function

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

[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

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Convolutions in 2D and 1D

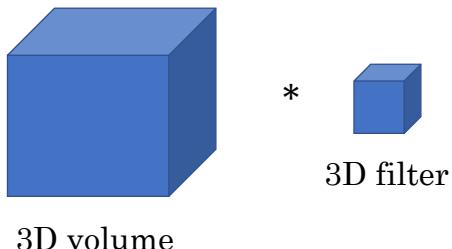
$$\begin{matrix} \text{2D input image} \\ 14 \times 14 \end{matrix} \quad * \quad \begin{matrix} \text{2D filter} \\ 5 \times 5 \end{matrix}$$

$$\begin{matrix} \text{1} & 20 & 15 & 3 & 18 & 12 & 4 & 17 \end{matrix} \quad * \quad \begin{matrix} \text{1} & 3 & 10 & 3 & 1 \end{matrix}$$

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3D convolution



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