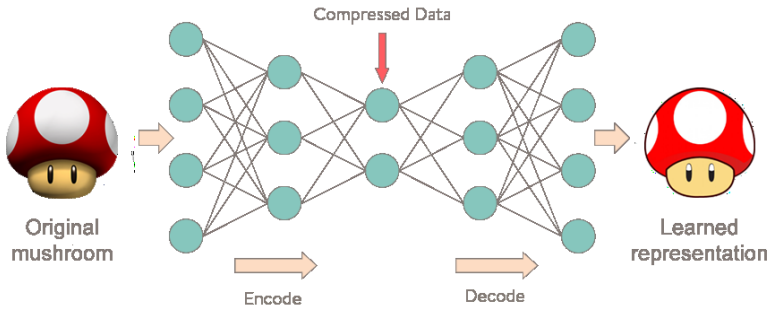
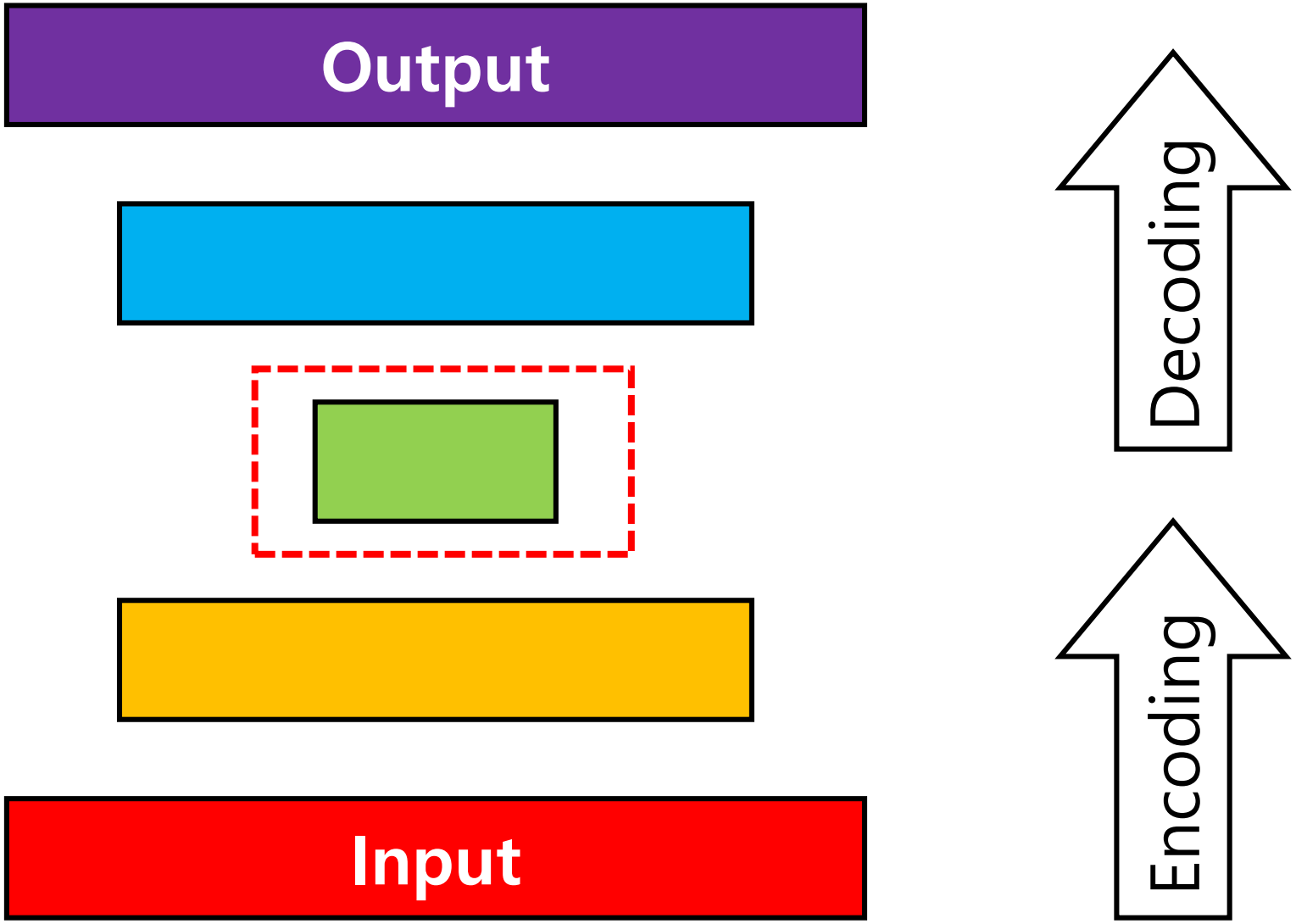
AutoEncoder



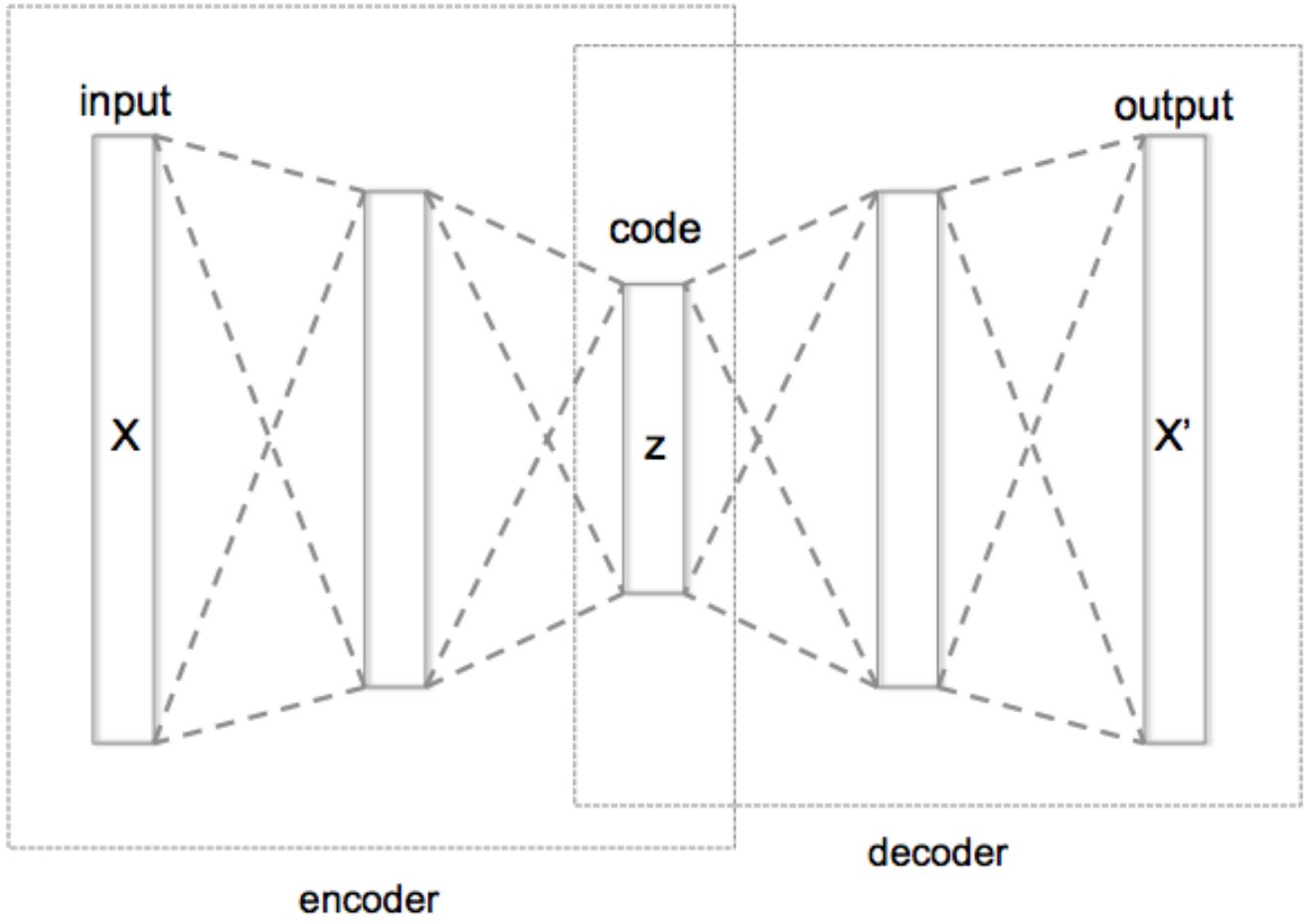
Fast Campus
Start Deep Learning with Tensorflow

Auto-Encoder



Auto-Encoder

- Encoder + Decoder Structure



Auto-Encoder

- Unsupervised approach for learning a lower-dimensional feature representation from unlabeled training data

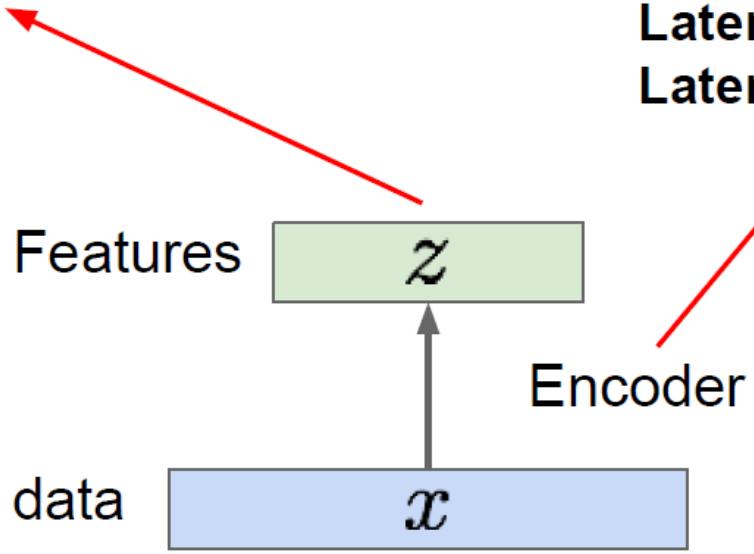
Unsupervised approach for learning a lower-dimensional feature representation from unlabeled training data

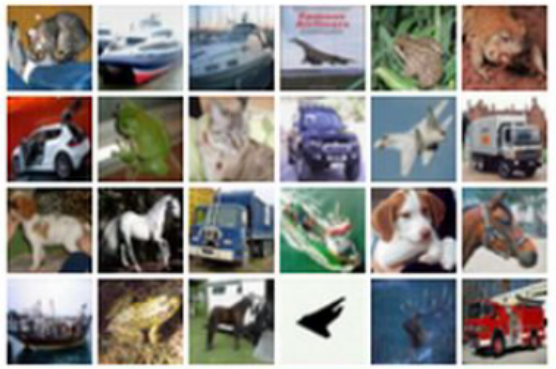
z usually smaller than **x**
(dimensionality reduction)

Q: Why dimensionality reduction?

A: Want features to capture meaningful factors of variation in data

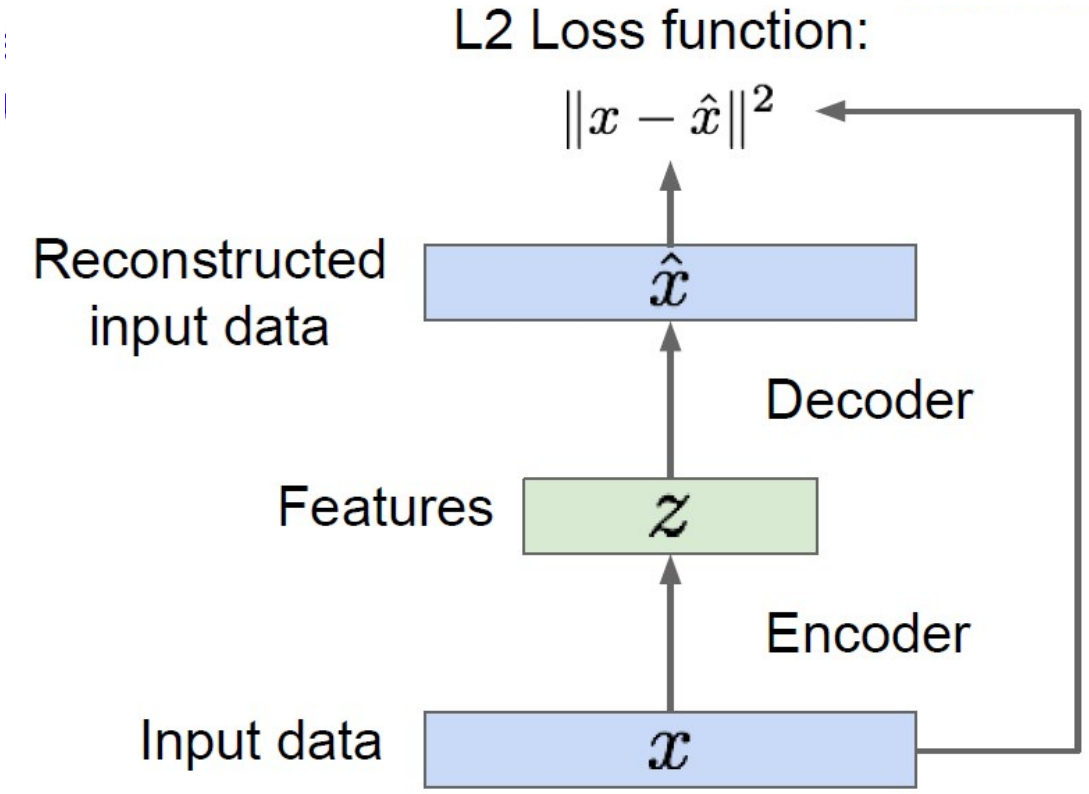
Originally: Linear + nonlinearity (sigmoid)
Later: Deep, fully-connected
Later: ReLU CNN

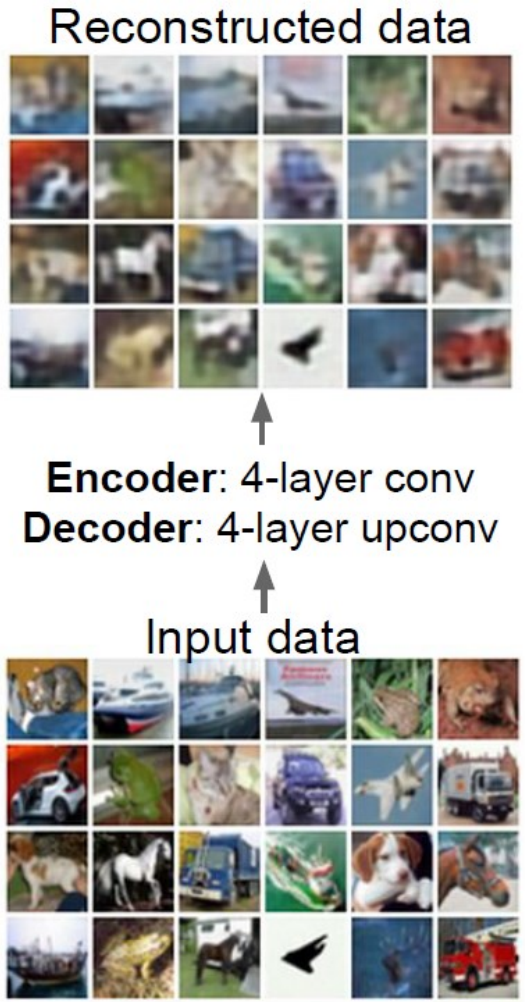




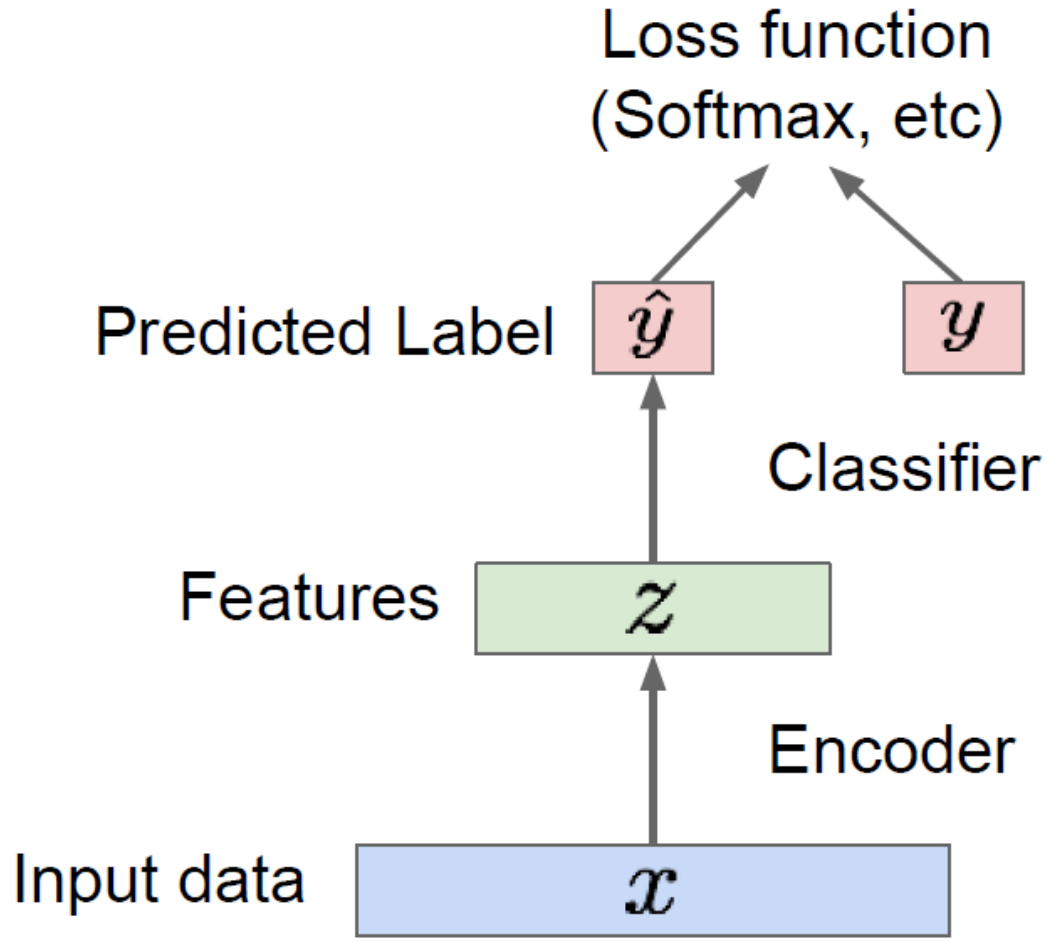
Auto-Encoder

- Train such that features can be used to reconstruct original data
  "Autoencoding" - encoding itself





Initialize a Supervised Model



Encoder can be used to initialize a **supervised** model

Fine-tune encoder jointly with classifier

bird plane
dog deer truck

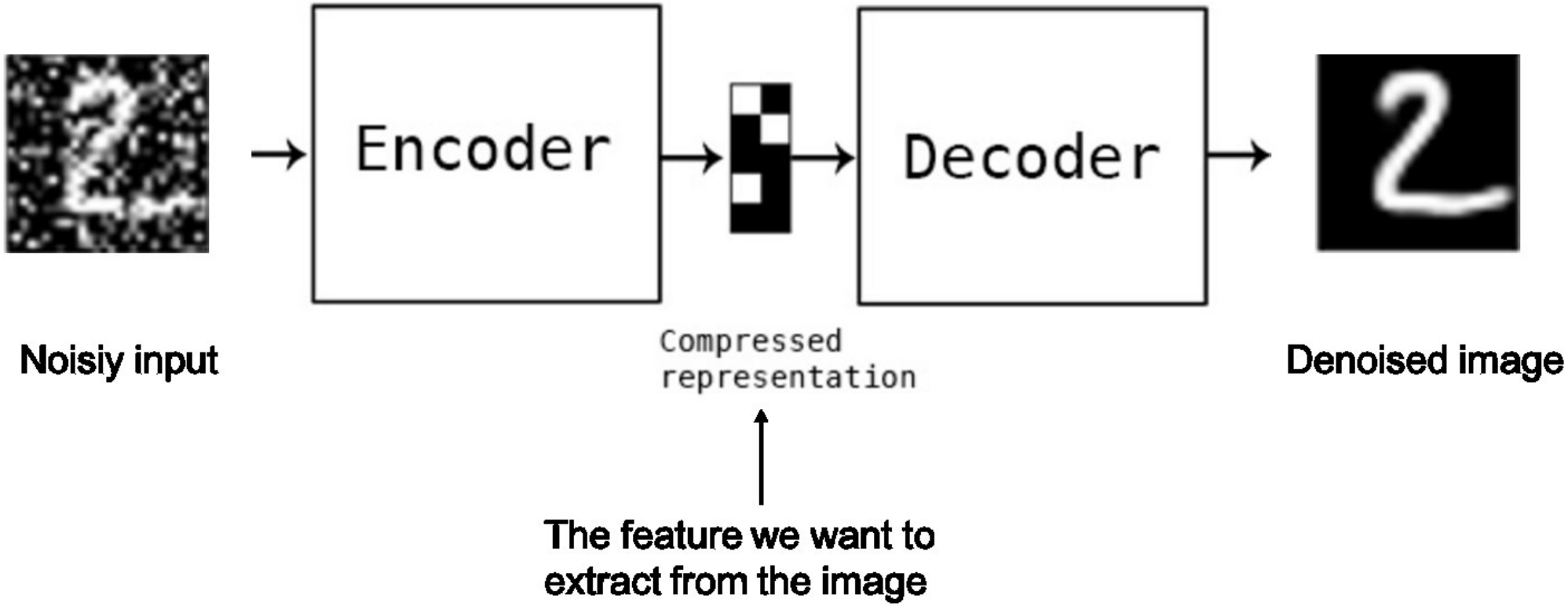
Train for final task (sometimes with small data)

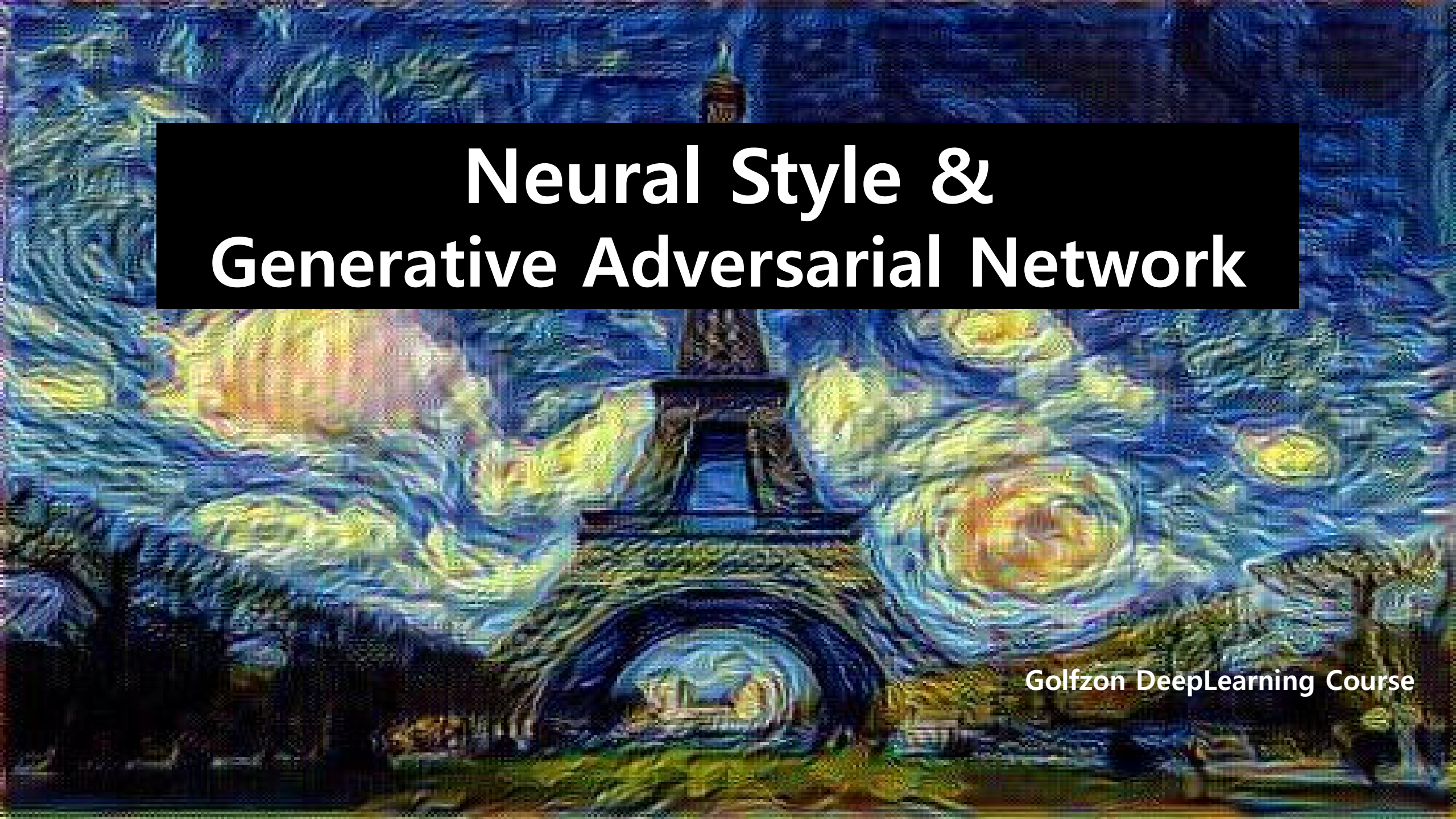
Denoising Auto-Encoder

- Input and output data of the auto-encoder is basically **identical**

- Then, how can we make this network to have **denoising power**?

Denoising Auto-Encoder



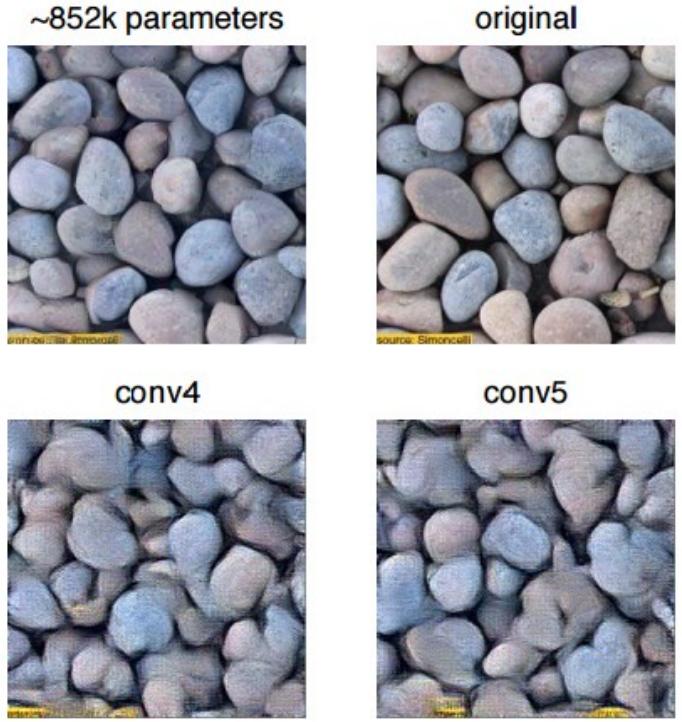


Neural Style & Generative Adversarial Network

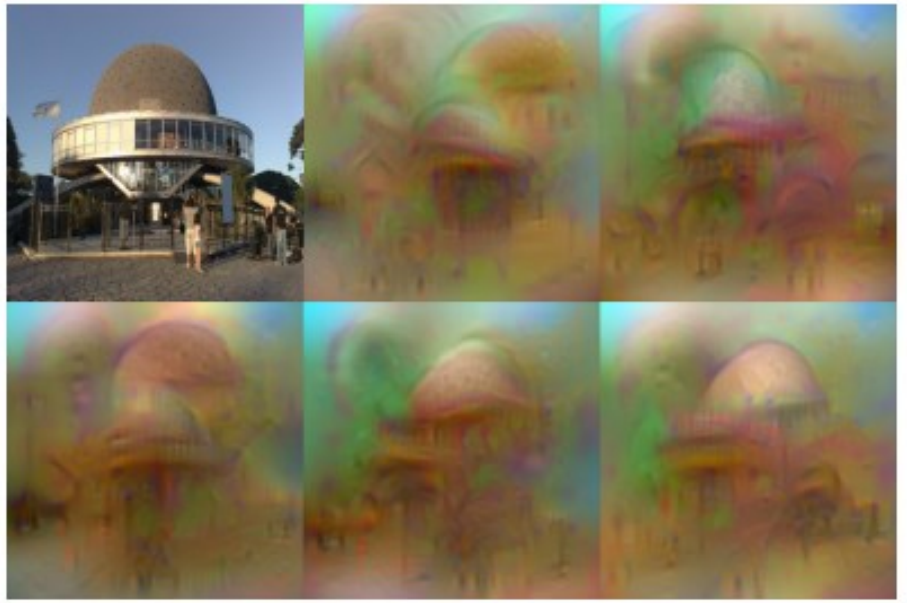
Golfzon DeepLearning Course

Preliminaries

Texture Synthesis Using Convolutional Neural Networks
NIPS2015



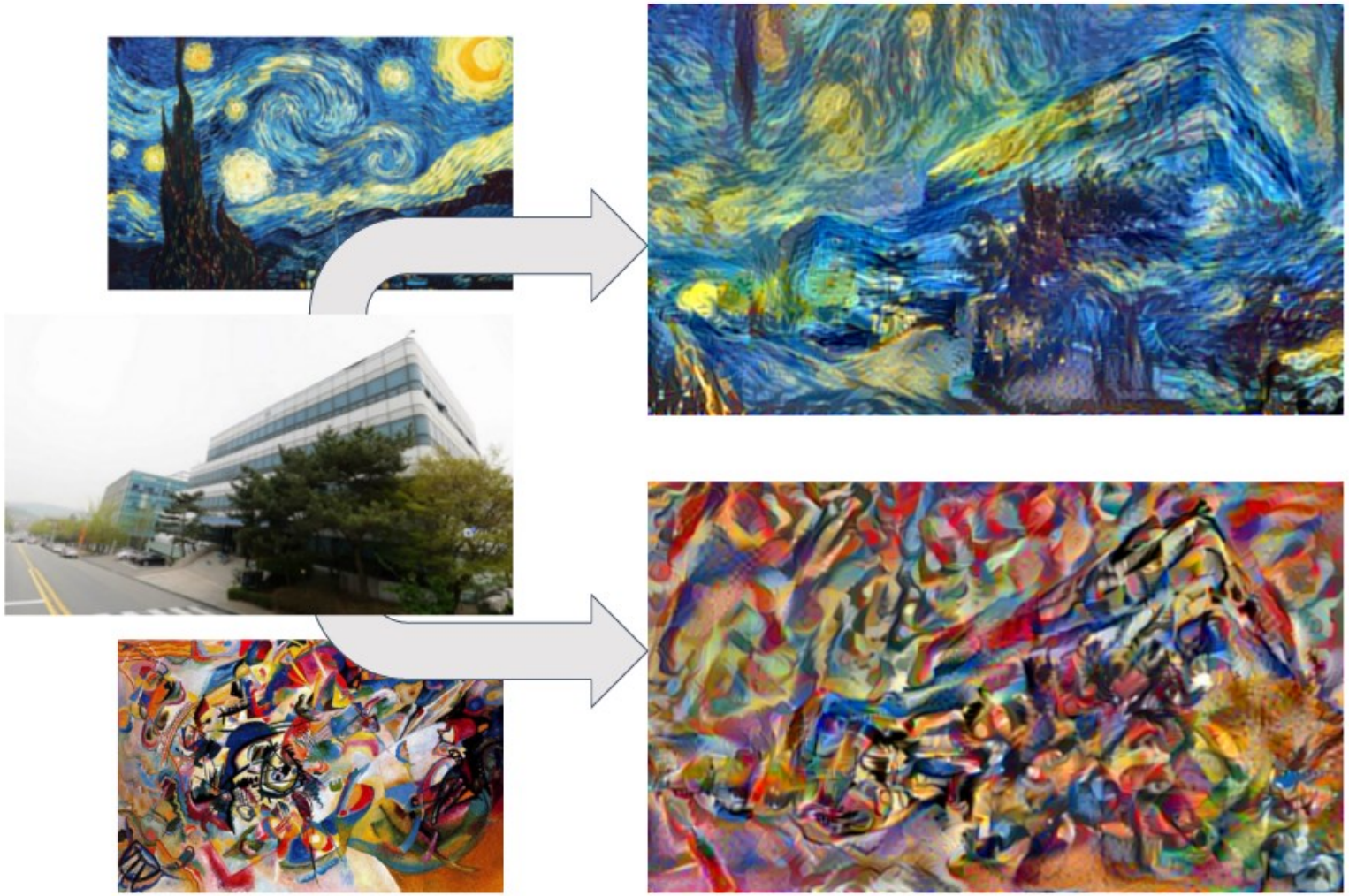
Understanding Deep Image Representations by Inverting Them
CVPR2015



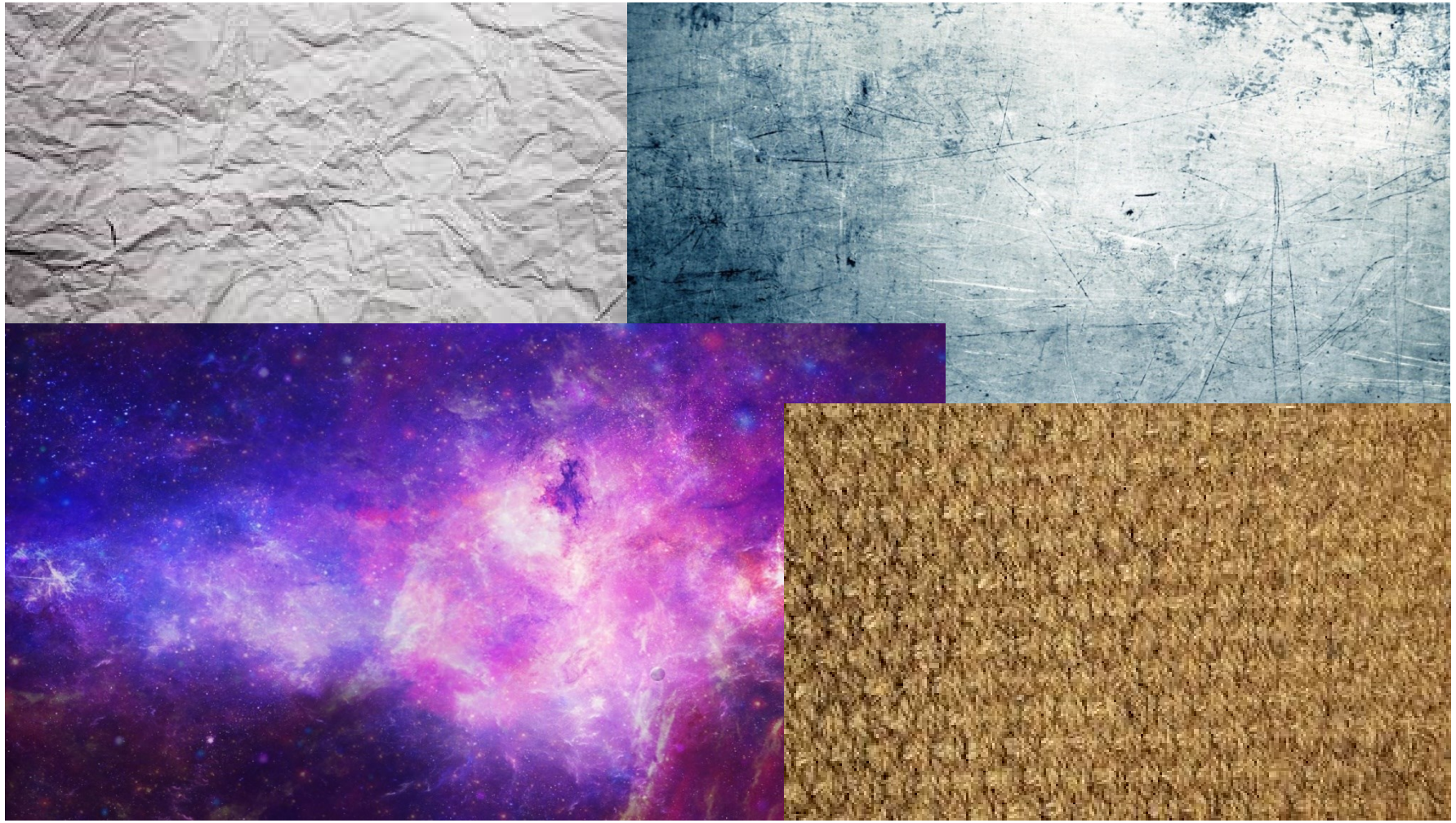
A Neural Algorithm of Artistic Style

Texture Synthesis Using Convolutional Neural Networks -NIPS2015

A Neural Algorithm of Artistic Style



Texture

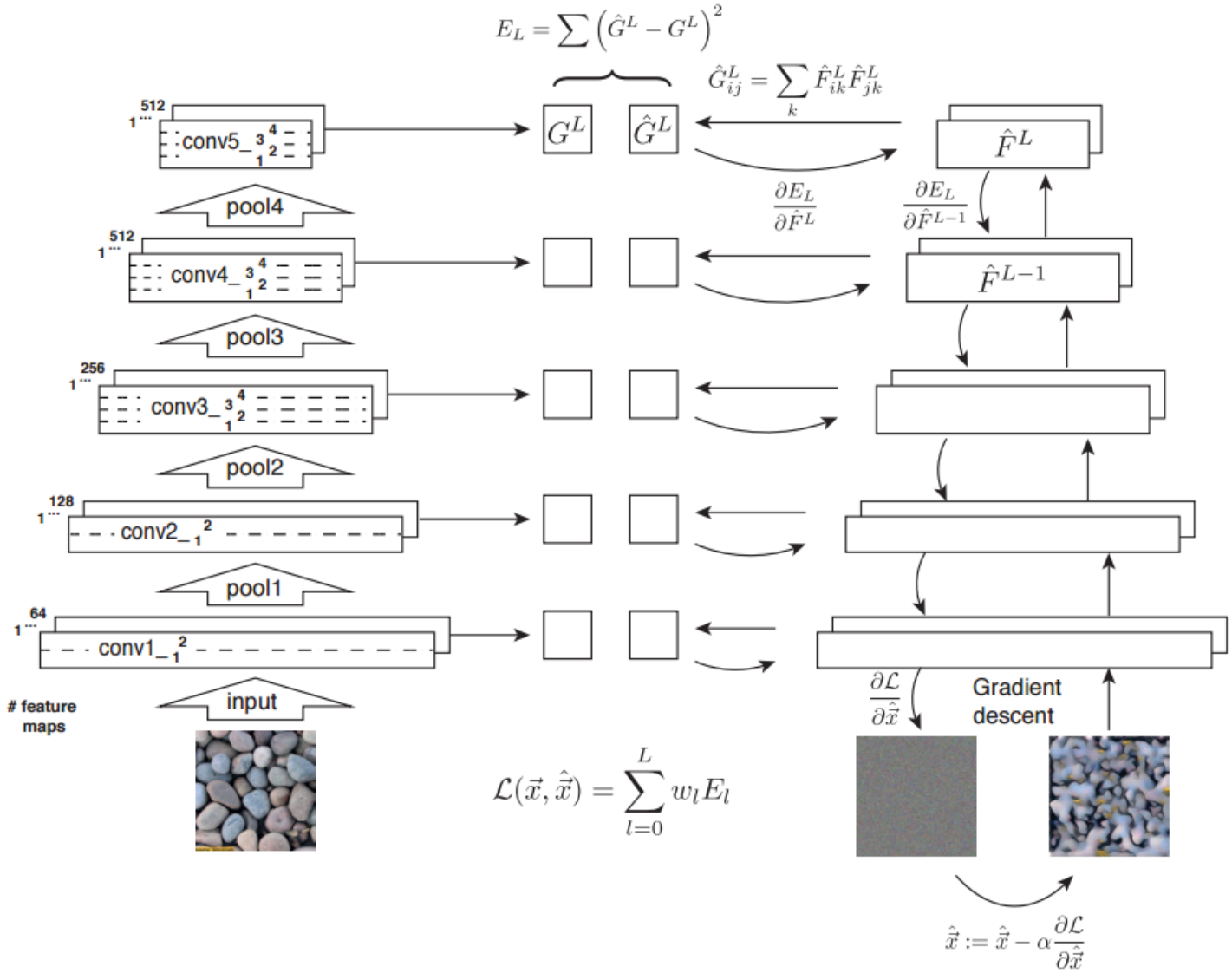


Visual texture synthesis

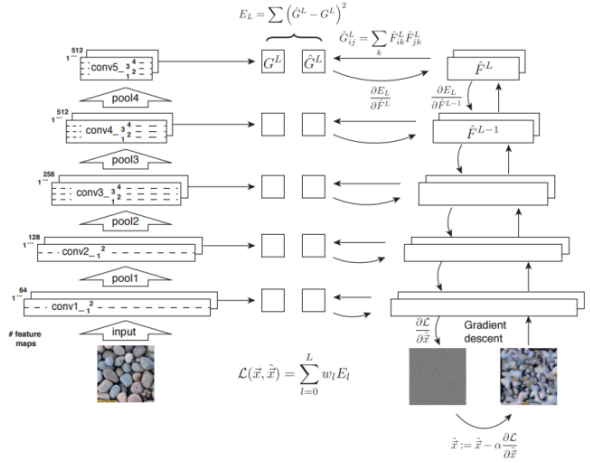
- Which one do you think is real?
- Right one is real.
- Goal of **texture synthesis** is to produce (arbitrarily many) new samples from an example texture.

Results of this work

How?


$E_L = \sum \left(\hat{G}^L - G^L\right)^2$
$\hat{G}^L_{ij} = \sum_k \hat{F}^L_{ik}\hat{F}^L_{jk}$
conv5_3
conv4_3
conv3_3
conv2_2
conv1_2
pool4
pool3
pool2
pool1
input
512
512
256
128
64
feature maps
G^L
$\hat{G}^L$
$\hat{F}^L$
$\hat{F}^{L-1}$
$\frac{\partial E_L}{\partial \hat{F}^L}$
$\frac{\partial E_L}{\partial \hat{F}^{L-1}}$
$\mathcal{L}(\vec{x}, \hat{\vec{x}}) = \sum_{l=0}^{L} w_l E_l$
$\frac{\partial \mathcal{L}}{\partial \hat{\vec{x}}}$
Gradient descent
$\hat{\vec{x}} := \hat{\vec{x}} - \alpha \frac{\partial \mathcal{L}}{\partial \hat{\vec{x}}}$

Texture Model



X_a F_a^1 F_a^2 F_a^3

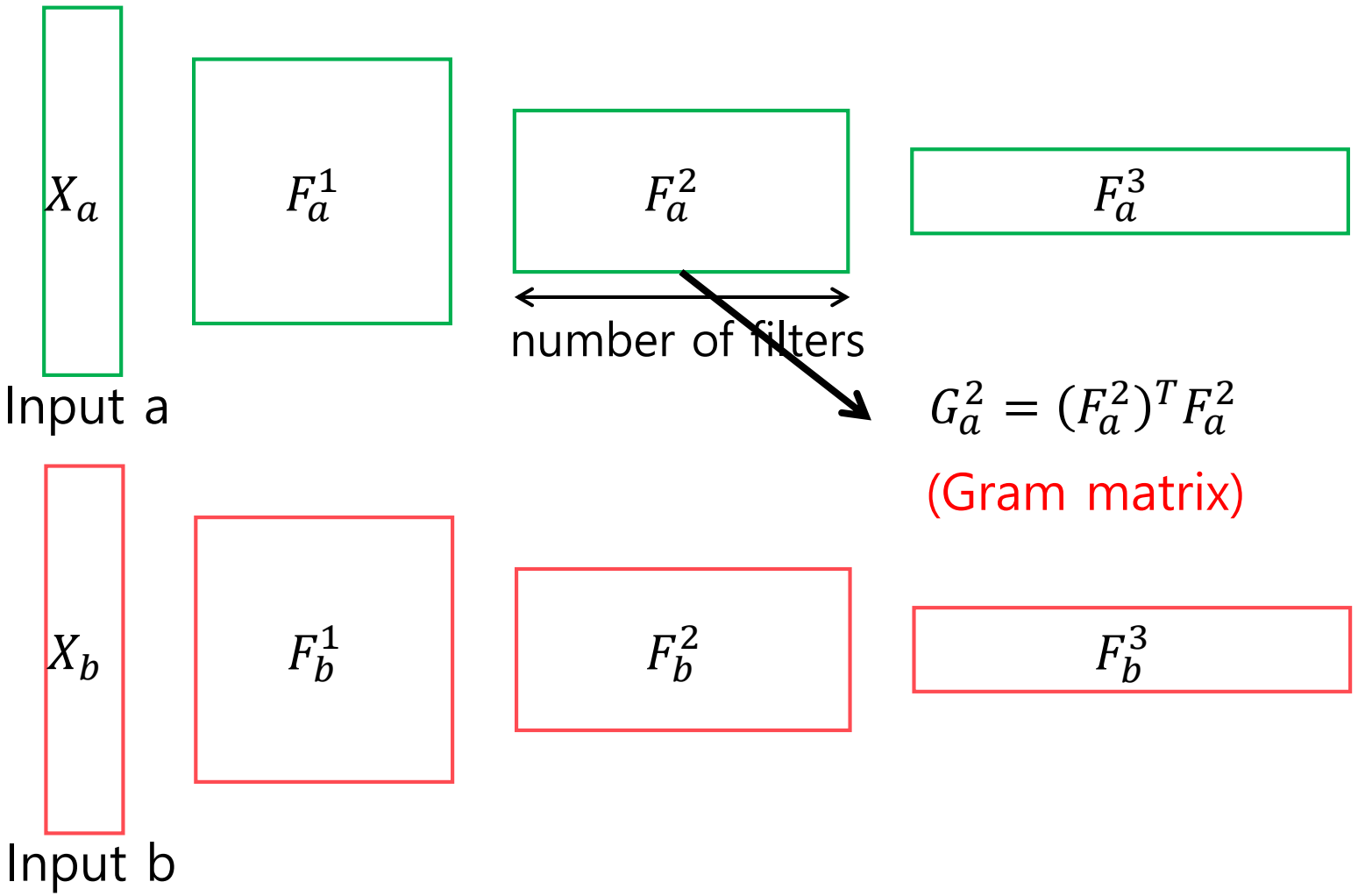
number of filters

Input a

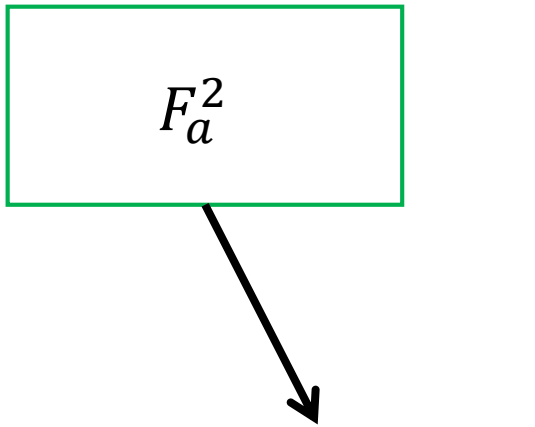
X_b F_b^1 F_b^2 F_b^3

Input b

Feature Correlations

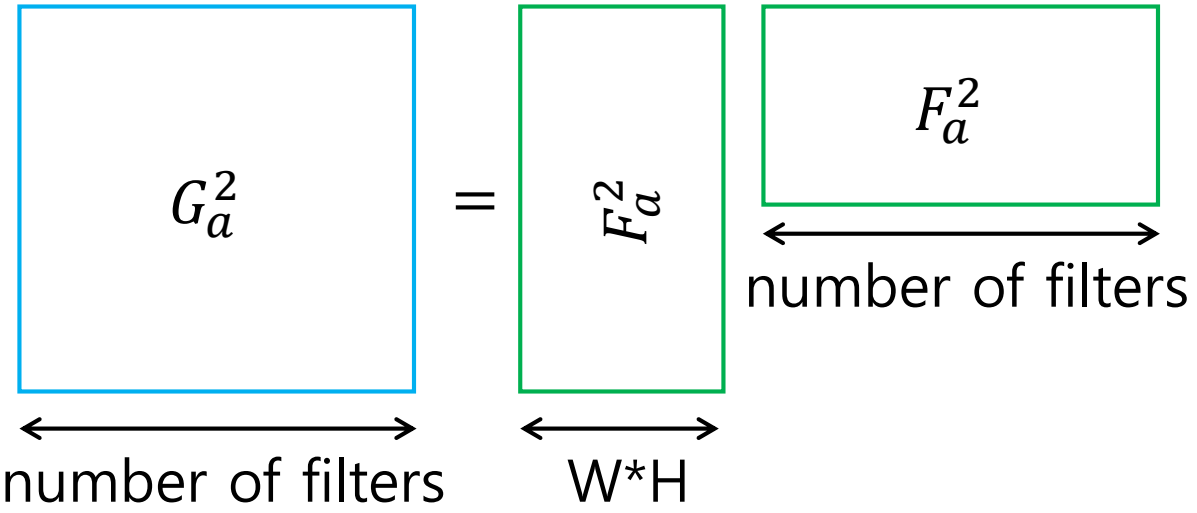


Feature Correlations

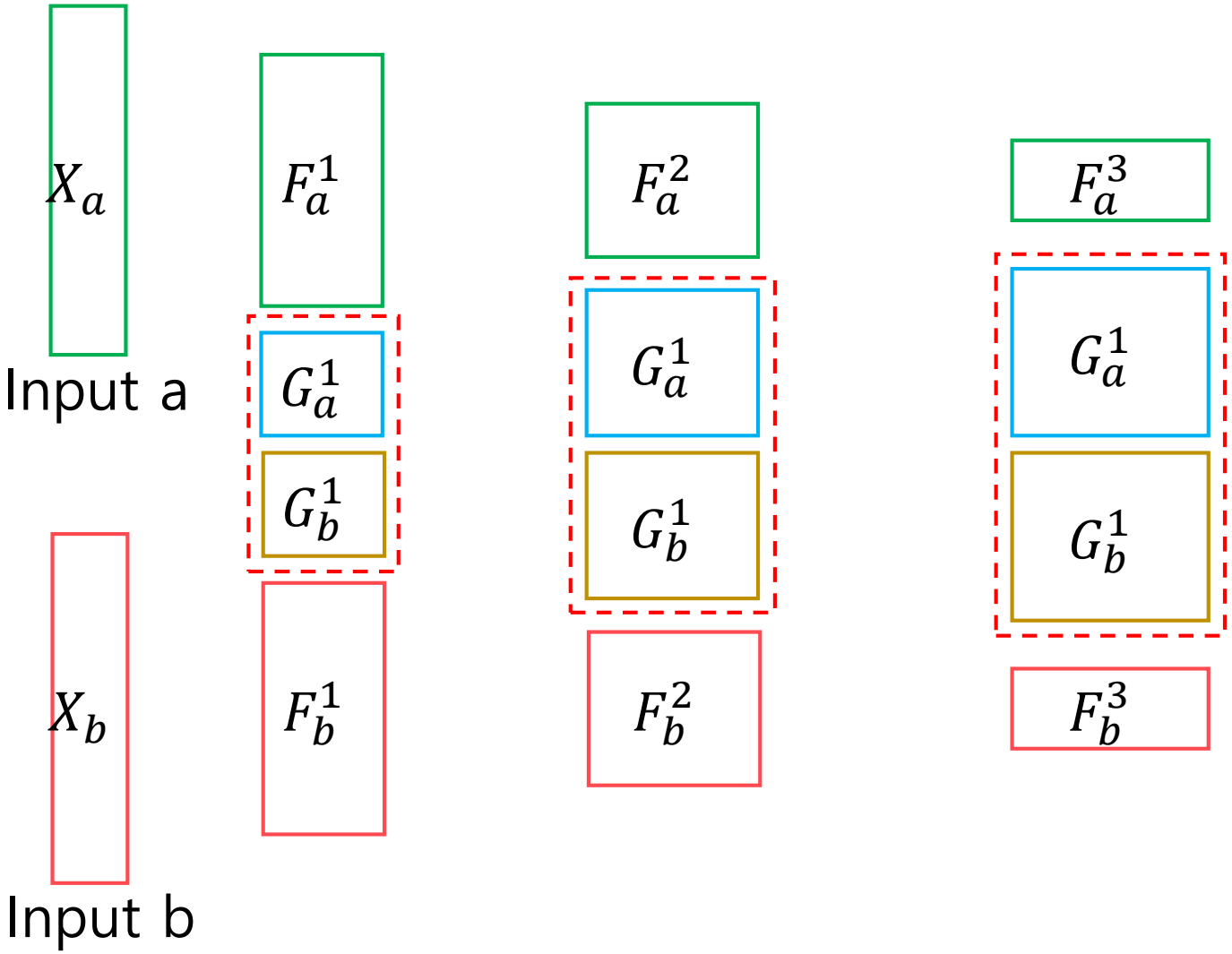


$$G_a^2 = (F_a^2)^T F_a^2$$

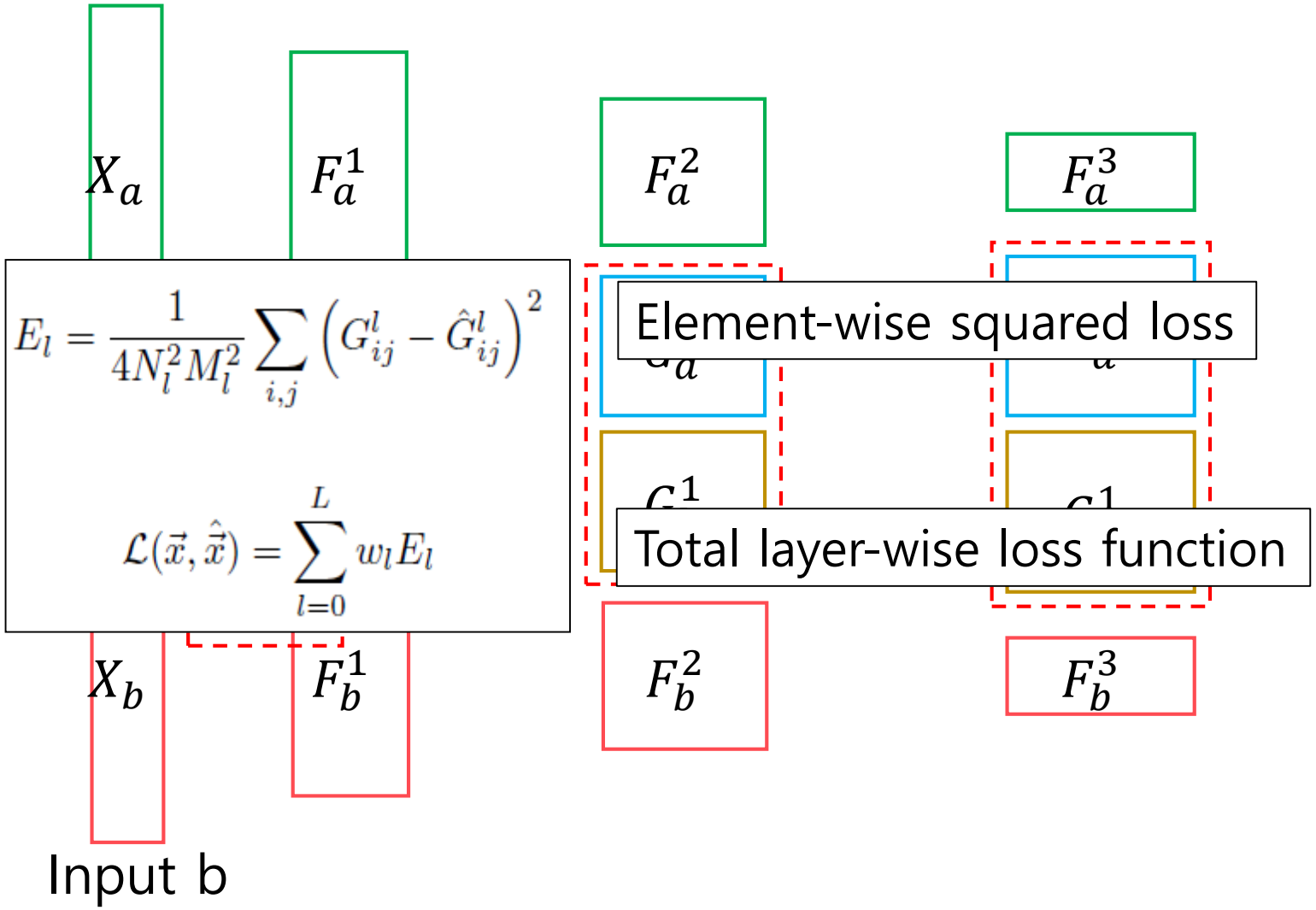
(Gram matrix)



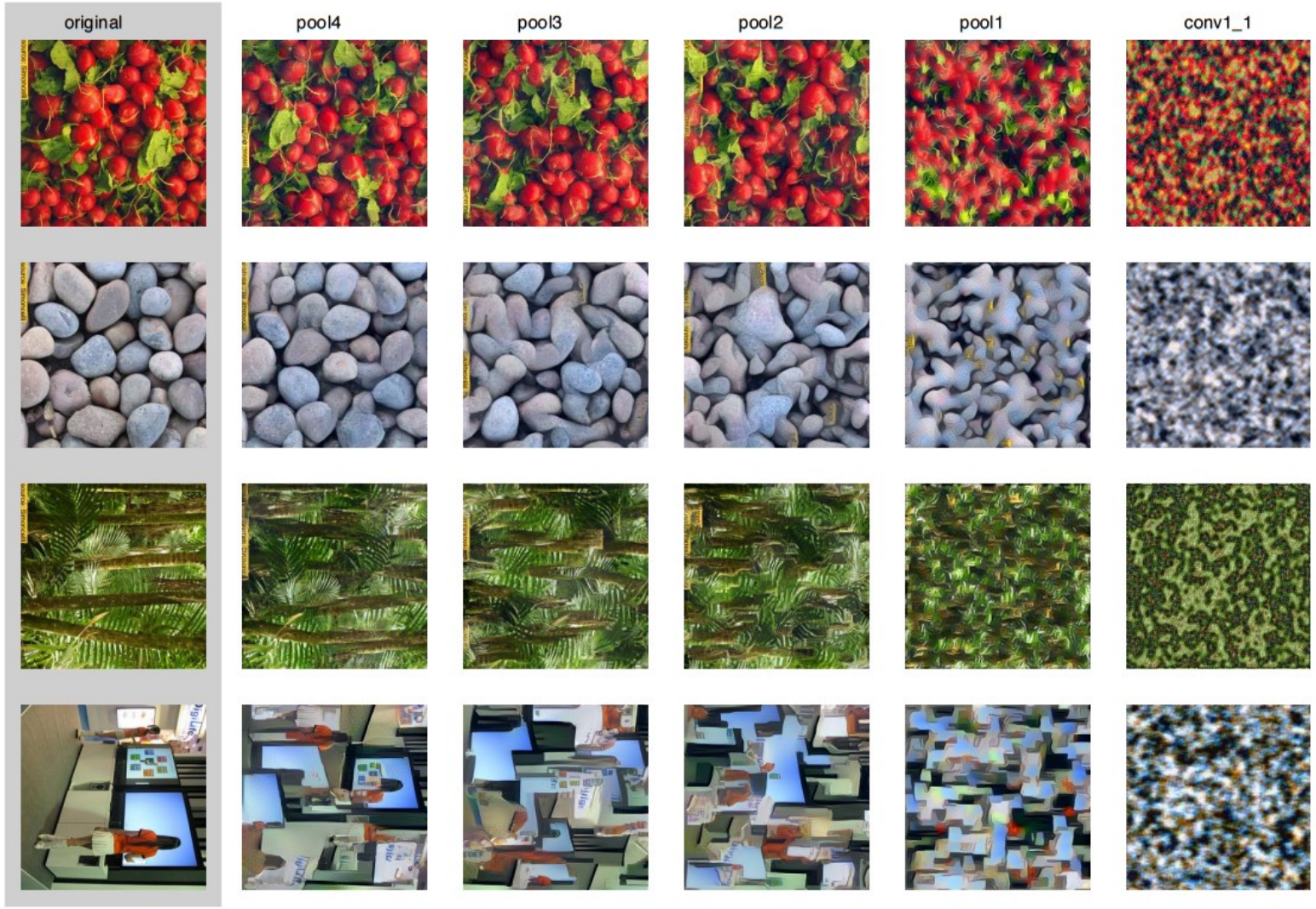
Texture Generation



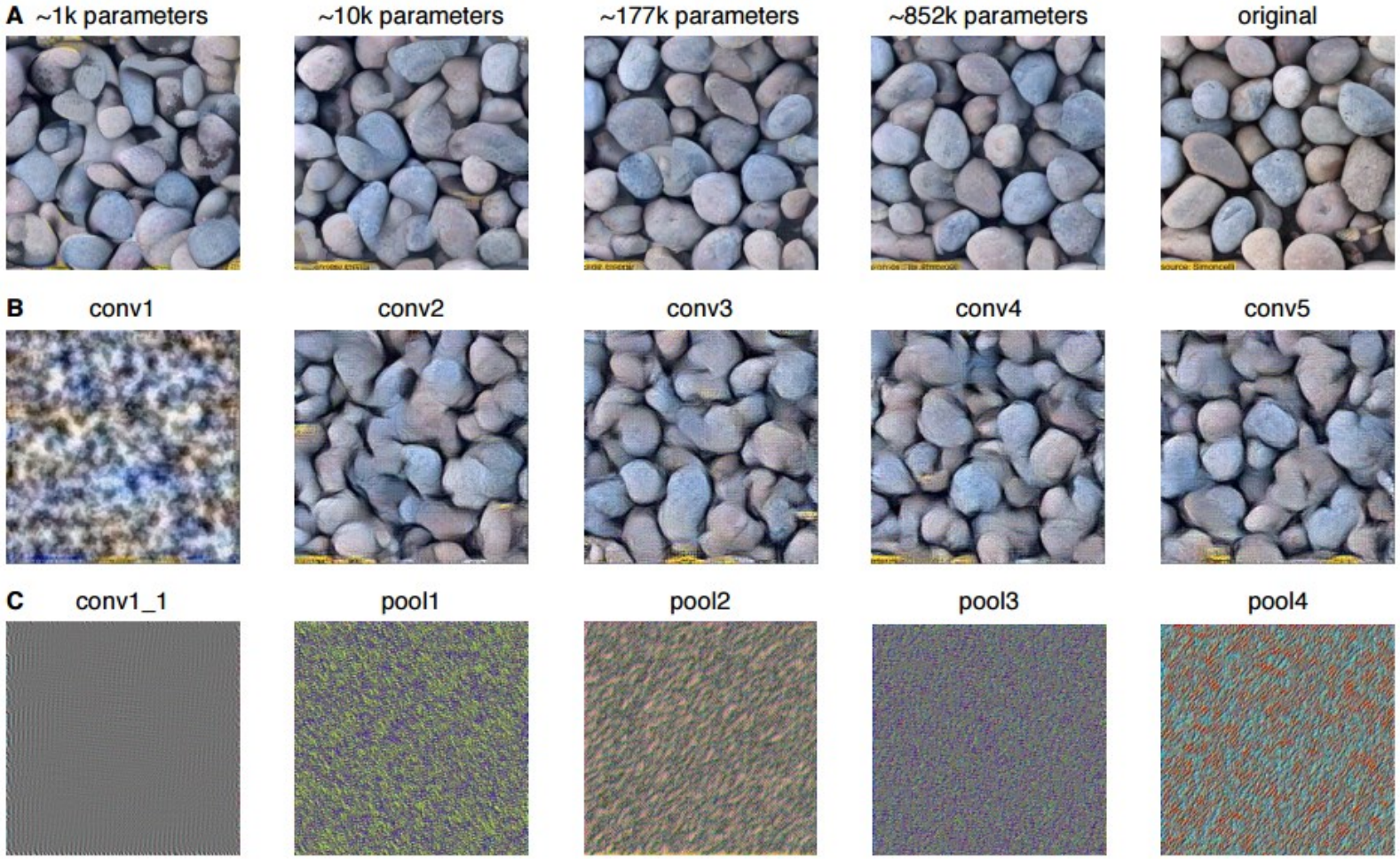
Texture Generation



Results



Results


A ~1k parameters
~10k parameters
~177k parameters
~852k parameters
original
B conv1
conv2
conv3
conv4
conv5
C conv1_1
pool1
pool2
pool3
pool4

Understanding Deep Image Representations by Inverting Them -CVPR2015

Reconstruction from feature map

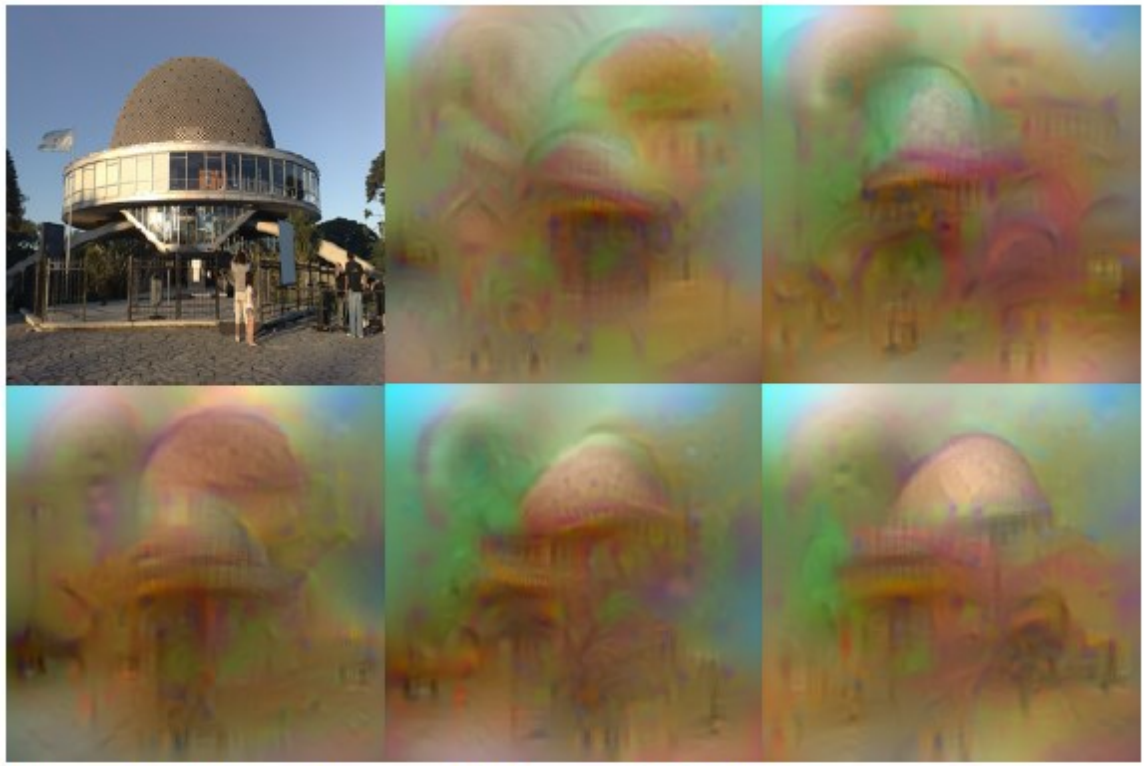
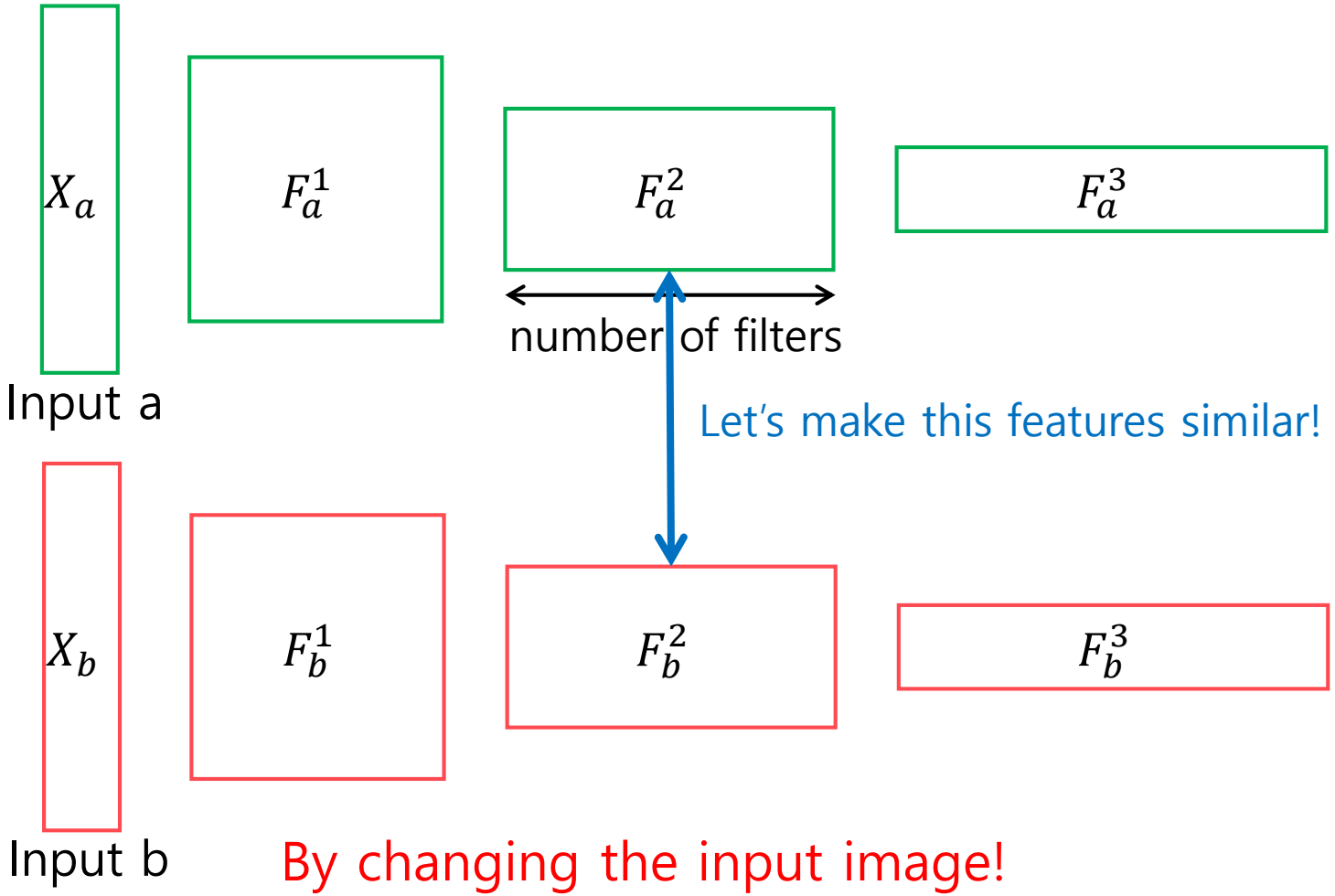


Figure 1. **What is encoded by a CNN?** The figure shows five possible reconstructions of the reference image obtained from the 1,000-dimensional code extracted at the penultimate layer of a reference CNN[15] (before the softmax is applied) trained on the ImageNet data. From the viewpoint of the model, all these images are practically equivalent. This image is best viewed in color/screen.

Reconstruction from feature map



Receptive Field

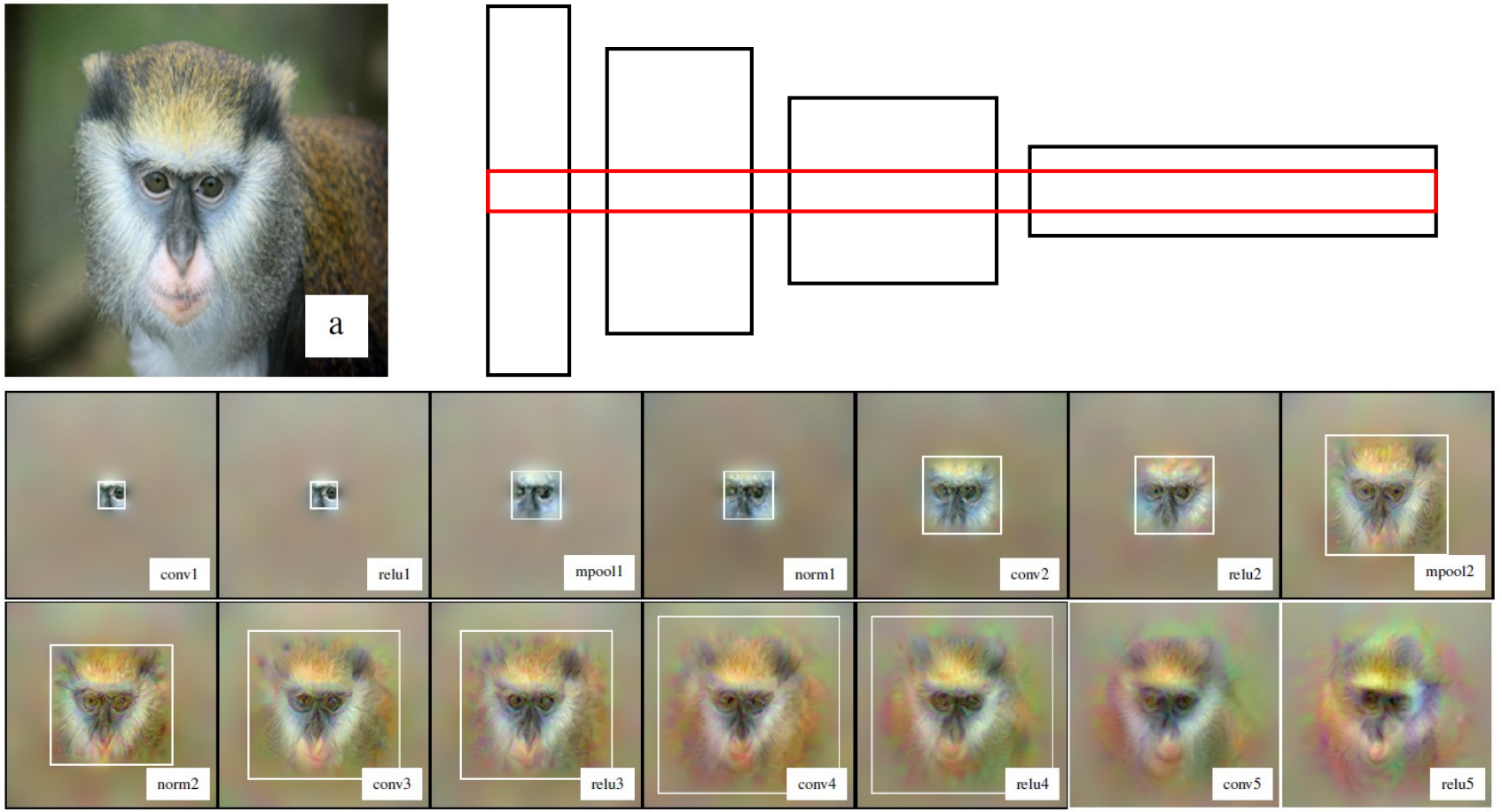
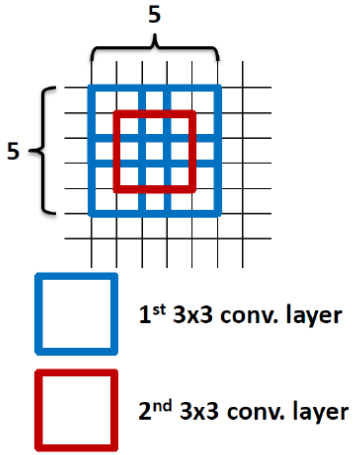


Figure 9. **CNN receptive field.** Reconstructions of the image of Fig. 5.a from the central 5×5 neuron fields at different depths of CNN-A. The white box marks the field of view of the 5×5 neuron field. The field of view is the entire image for conv5 and relu5.

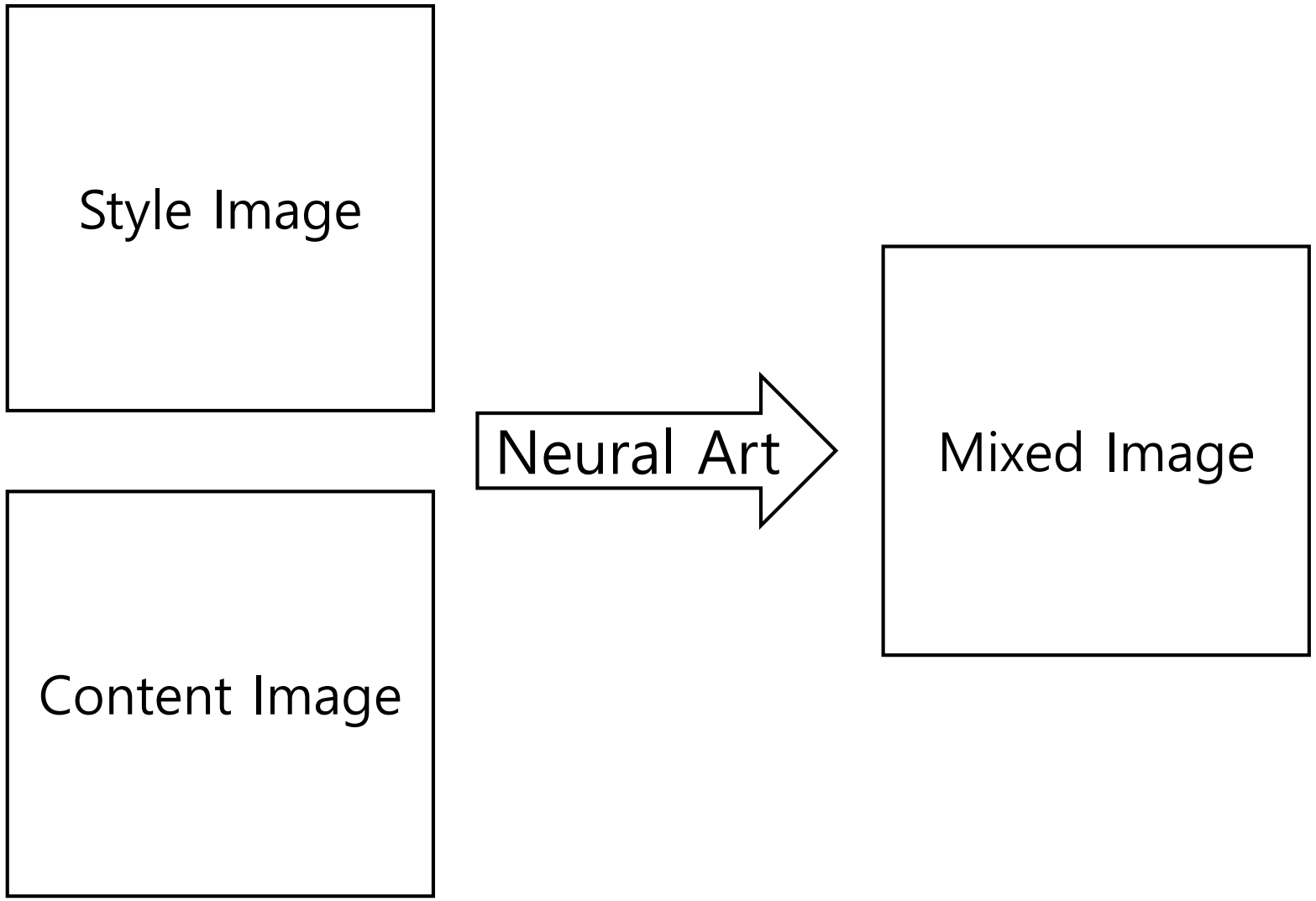
VGG

- 3x3 filter만 반복해서 사용
- Why??
  - Convolution filter를 stack하면 더 큰 receptive field를 가질 수 있음
    - 2개의 3x3 filter = 5x5 filter
    - 3개의 3x3 filter = 7x7 filter
  - Parameter수는 큰 filter 사용하는 경우에 비하여 감소 → regularization 효과

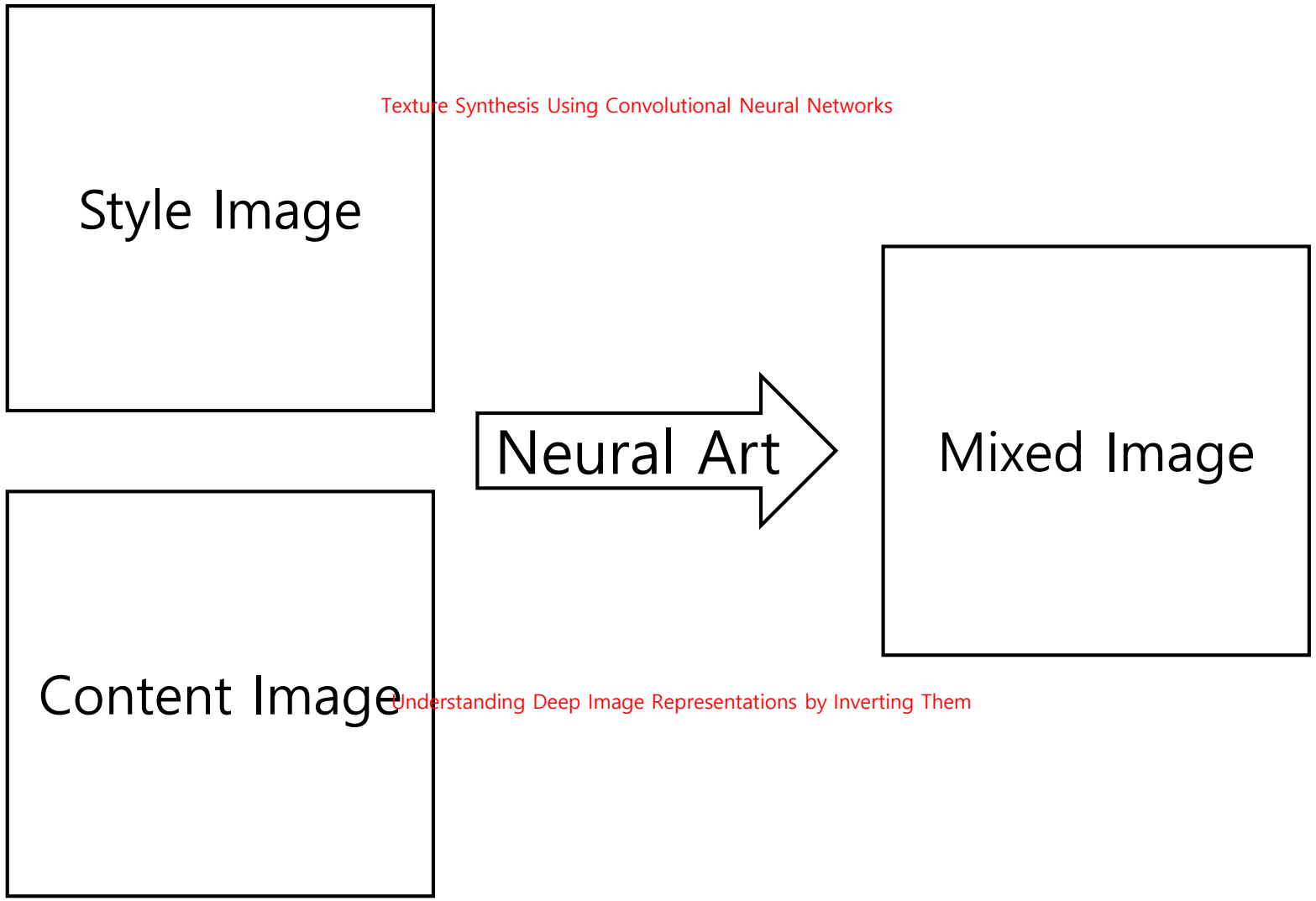


A Neural Algorithm of Artistic Style

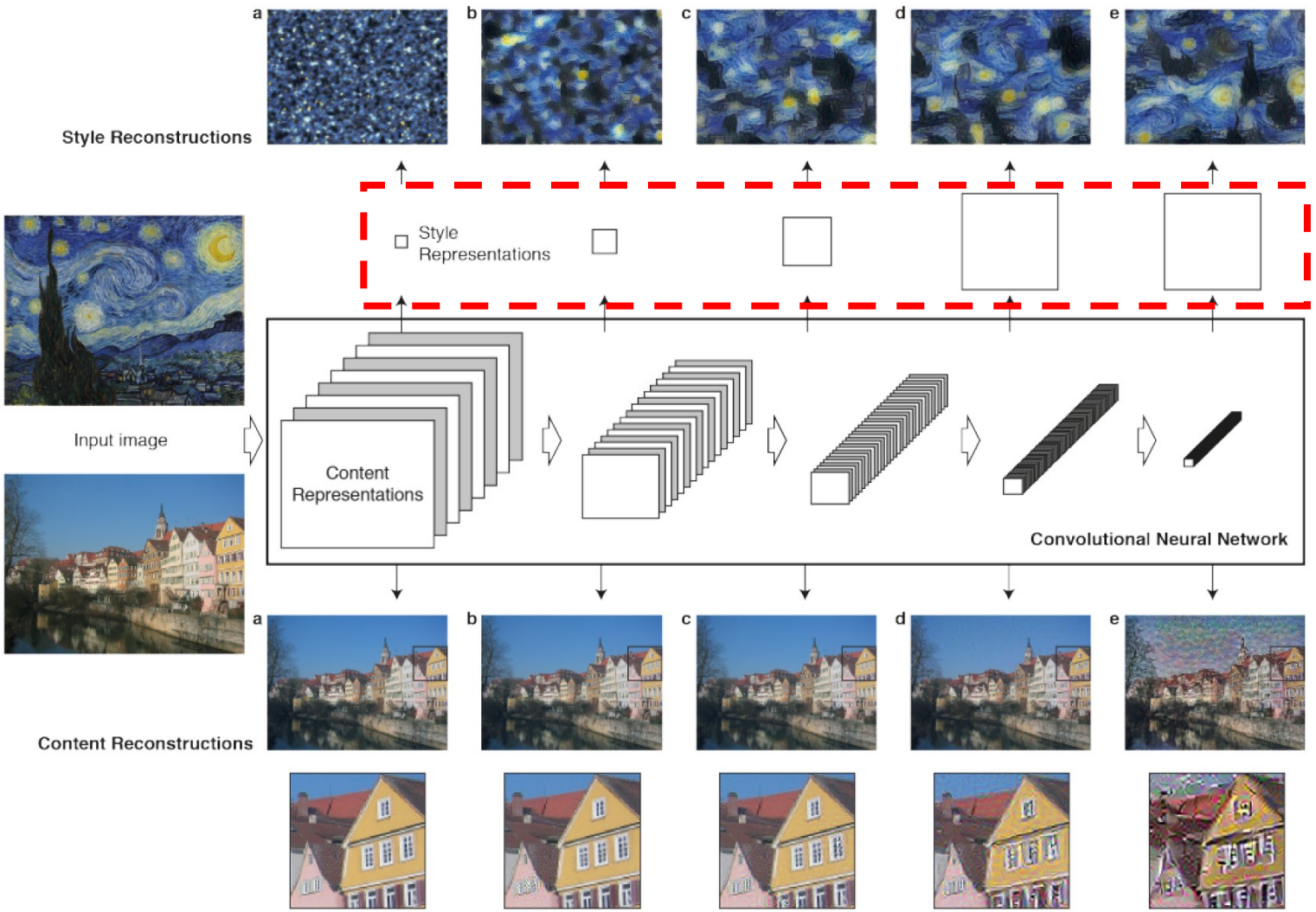
How?



How?


Texture Synthesis Using Convolutional Neural Networks
Style Image
Neural Art
Mixed Image
Content Image
Understanding Deep Image Representations by Inverting Them

How?


a
b
c
d
e
Style Reconstructions
Style Representations
Gram matrix
Input image
Content Representations
Convolutional Neural Network
Content Reconstructions

Neural Art

$\vec{p}$: original photo, $\vec{a}$: original artwork
$\vec{x}$: image to be generated

Content

$$\mathcal{L}_{content}(\vec{p}, \vec{x}, l) = \frac{1}{2} \sum_{i,j} \left(F_{ij}^l - P_{ij}^l\right)^2 .$$

$$\frac{\partial \mathcal{L}_{content}}{\partial F_{ij}^l} = \begin{cases} \left(F^l - P^l\right)_{ij} & \text{if } F_{ij}^l > 0 \\ 0 & \text{if } F_{ij}^l < 0 . \end{cases}$$

Style

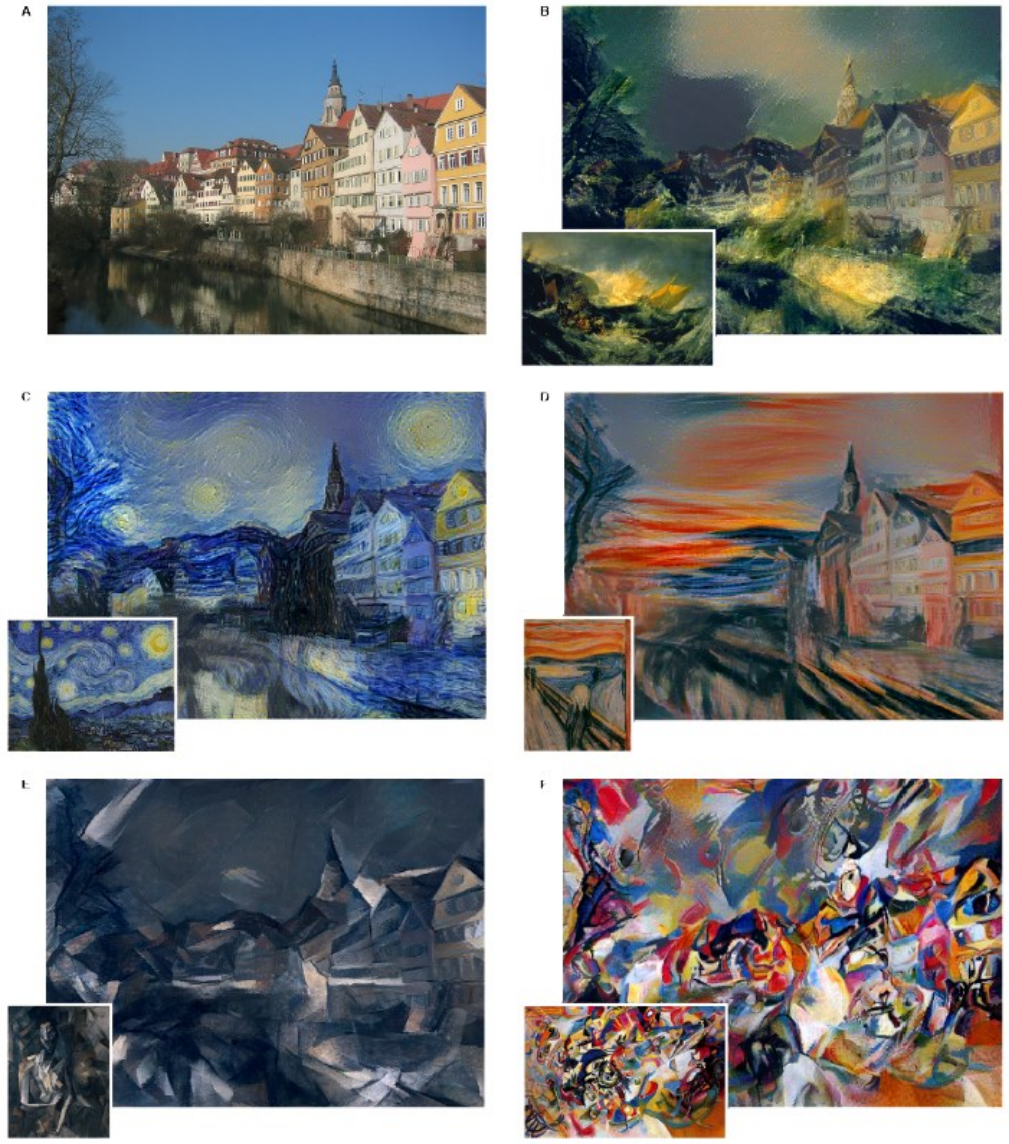
$$E_l = \frac{1}{4N_l^2 M_l^2} \sum_{i,j} \left(G_{ij}^l - A_{ij}^l\right)^2 \qquad G_{ij}^l = \sum_k F_{ik}^l F_{jk}^l .$$

$$\mathcal{L}_{style}(\vec{a}, \vec{x}) = \sum_{l=0}^{L} w_l E_l$$

Total loss = content loss + style loss

$$\mathcal{L}_{total}(\vec{p}, \vec{a}, \vec{x}) = \alpha \mathcal{L}_{content}(\vec{p}, \vec{x}) + \beta \mathcal{L}_{style}(\vec{a}, \vec{x})$$

Results



Results