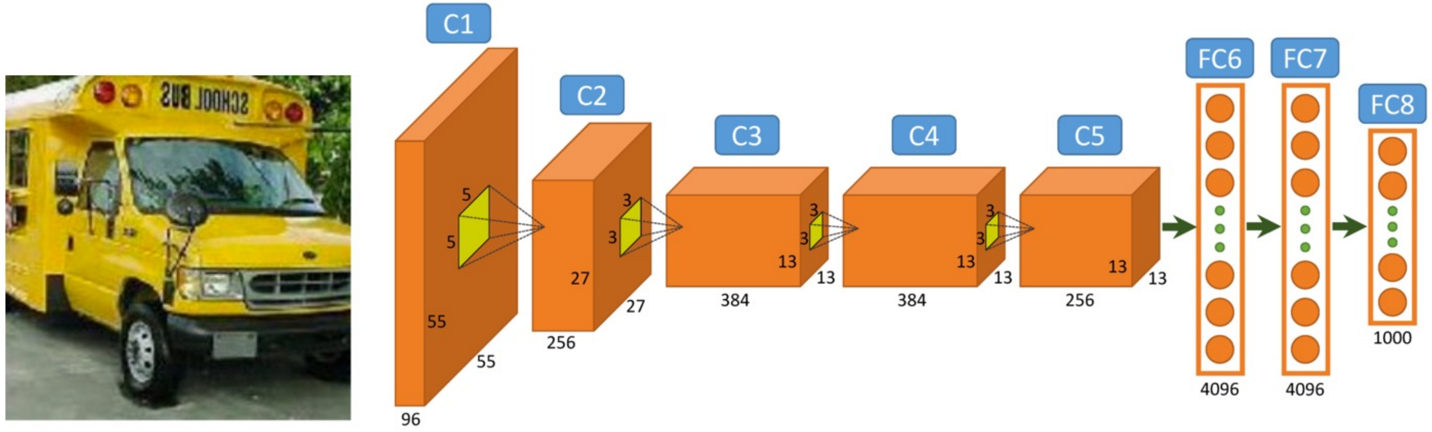
Deep Learning for Vision & Language

Feature-space Optimization: Adversarial Examples, GANs, Style Transfer

RICE UNIVERSITY

What we have been doing: Optimize weights in the network to predict bus (correct class).

I $\qquad\qquad y = f(I; w) \qquad\qquad L(y, bus)$

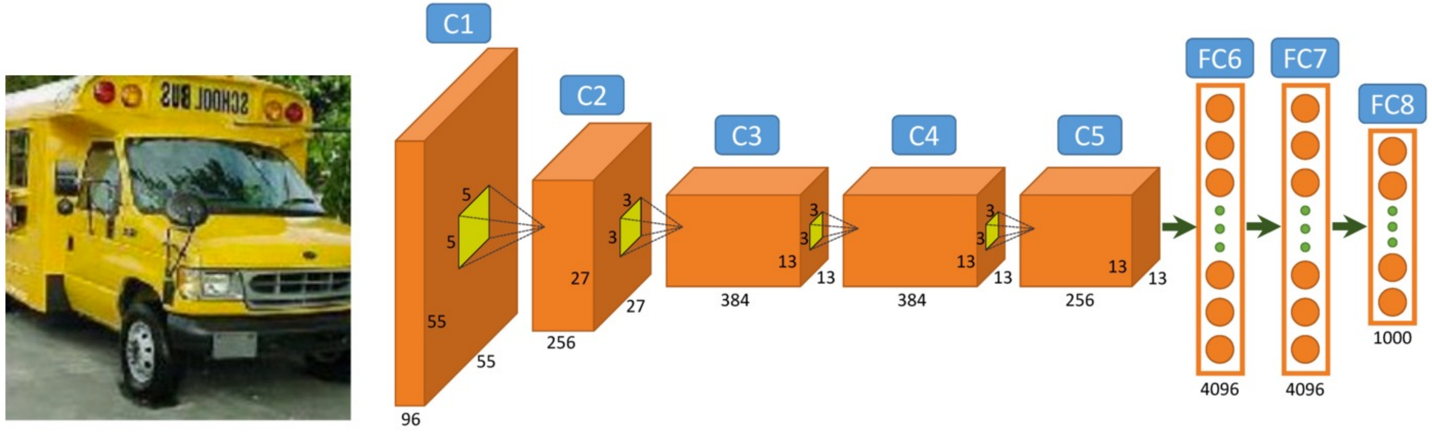


bus

$$w = w - \lambda \frac{\partial L}{\partial w}$$

New Idea: Create Adversarial Inputs by optimizing the input image to predict ostrich (wrong class).

I $\quad\quad$ $y = f(I; w)$ $\quad\quad$ $L(y, ostrich)$

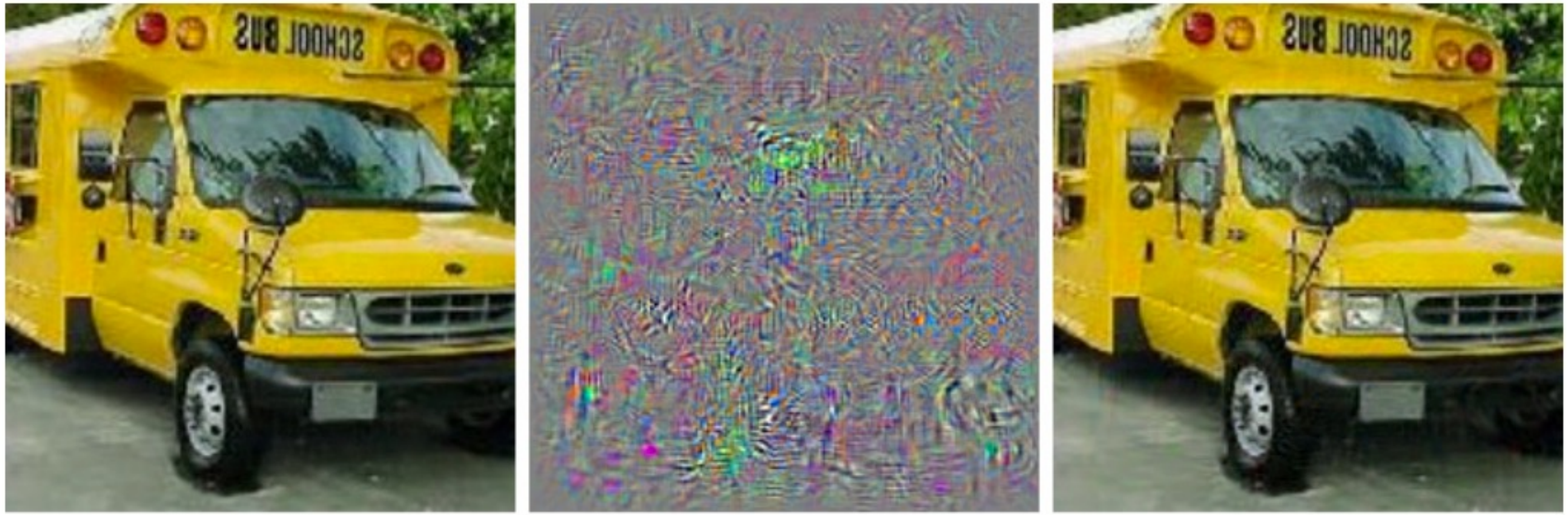


ostrich

$$I = I - \lambda \frac{\partial L}{\partial I}$$

Work on Adversarial examples by Goodfellow et al. , Szegedy et. al., etc.

Convnets (optimize input to predict ostrich)



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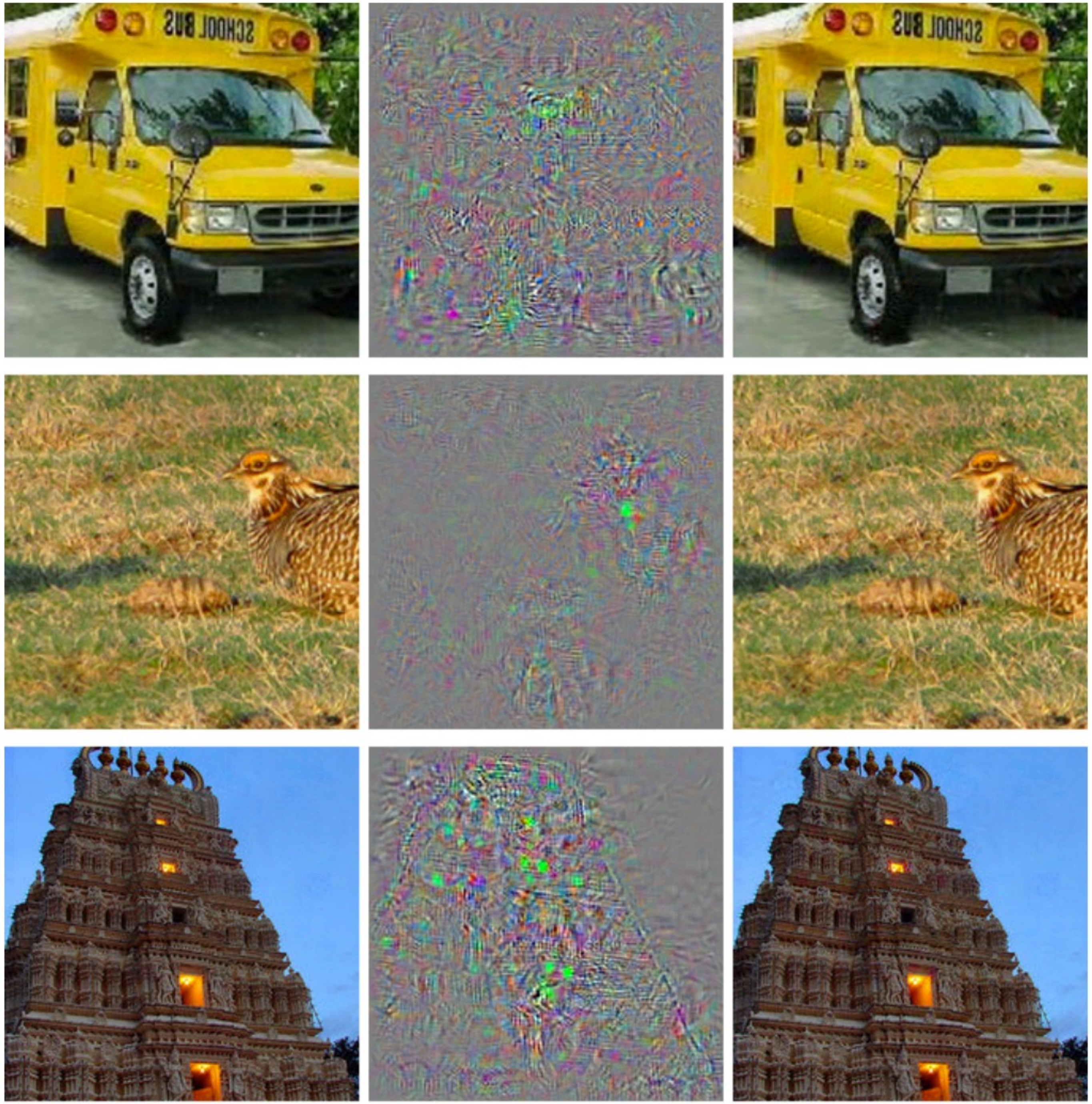
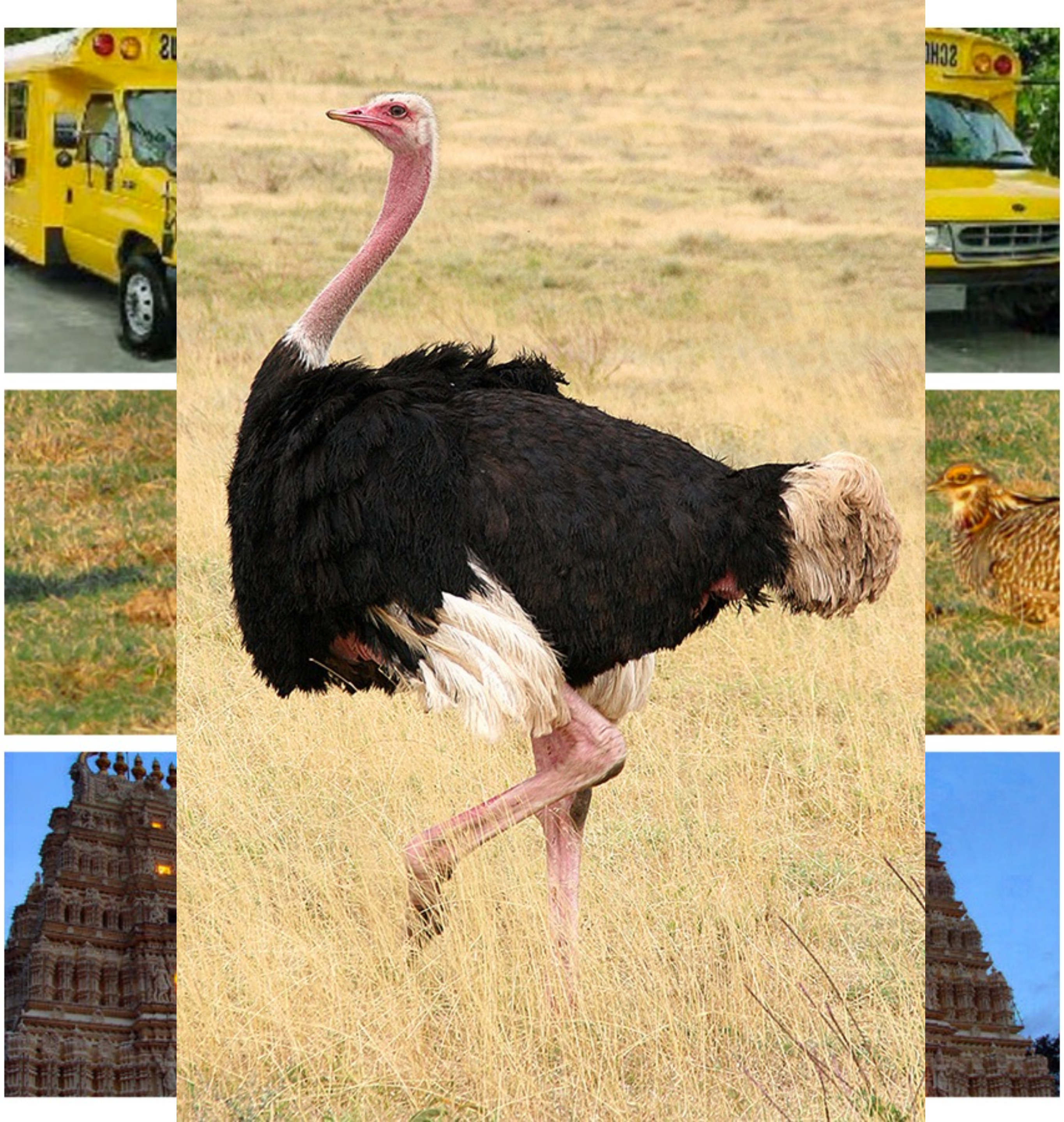


All get predicted as ostrich



Deep Neural Networks are Easily Fooled: High Confidence Predictions for Unrecognizable Images

Anh Nguyen, Jason Yosinski, Jeff Clune, 2014

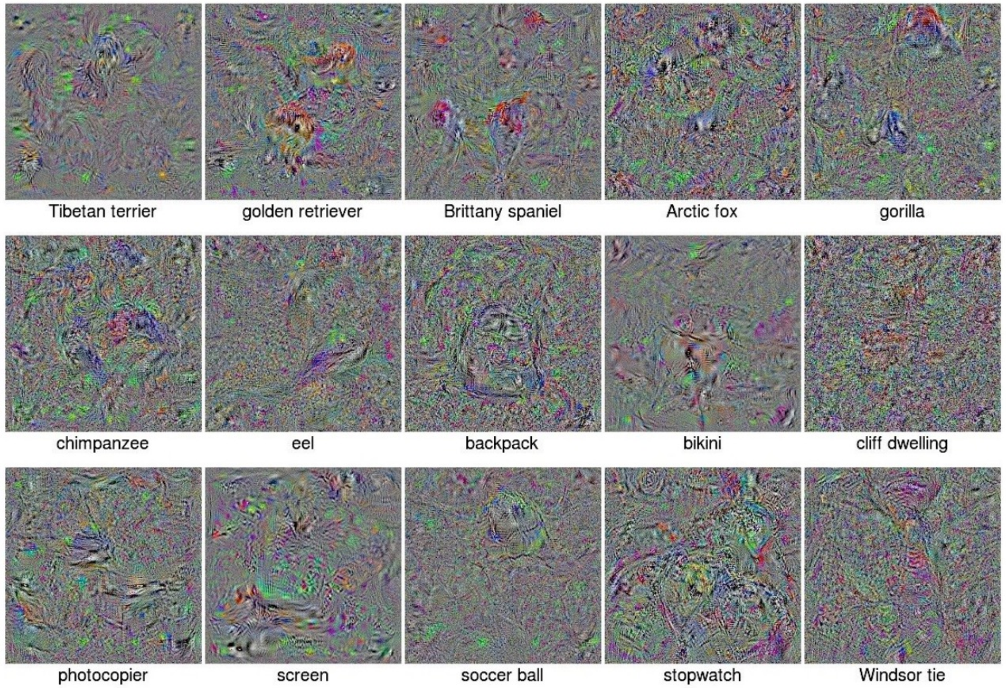
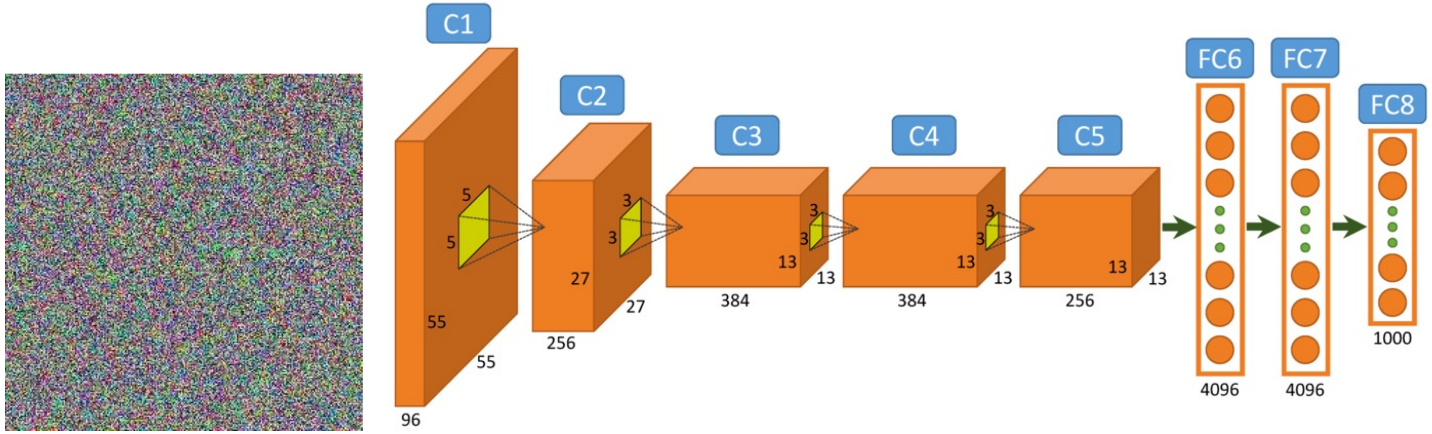


Figure 13. Images found by maximizing the softmax output for classes via gradient ascent [11, 26]. Optimization begins at the ImageNet mean (plus small Gaussian noise to break symmetry) and continues until the DNN confidence for the target class reaches 99.99%. Images are shown with the mean subtracted. Adding regularization makes images more recognizable but results in slightly lower confidence scores (see supplementary material).

New Idea: Create Adversarial Inputs by optimizing the input image to predict ostrich (wrong class).

I $\qquad y = f(I; w) \qquad L(y, parking\ meter)$



parking meter

$$I = I - \lambda \frac{\partial L}{\partial I}$$

Work on Adversarial examples by Goodfellow et al. , Szegedy et. al., etc.

parking meter: 0.999679

Total Variation Regularization

A second richer regulariser is *total variation* (TV) $\mathcal{R}_{V^\beta}(\mathbf{x})$, encouraging images to consist of piece-wise constant patches. For continuous functions (or distributions) $f : \mathbb{R}^{H \times W} \supset \Omega \to \mathbb{R}$, the TV norm is given by:

$$\mathcal{R}_{V^\beta}(f) = \int_\Omega \left(\left(\frac{\partial f}{\partial u}(u,v) \right)^2 + \left(\frac{\partial f}{\partial v}(u,v) \right)^2 \right)^{\frac{\beta}{2}} du\, dv$$

where $\beta = 1$. Here images are discrete ($\mathbf{x} \in \mathbb{R}^{H \times W}$) and the TV norm is replaced by the finite-difference approximation:

$$\mathcal{R}_{V^\beta}(\mathbf{x}) = \sum_{i,j} \left((x_{i,j+1} - x_{ij})^2 + (x_{i+1,j} - x_{ij})^2 \right)^{\frac{\beta}{2}}.$$

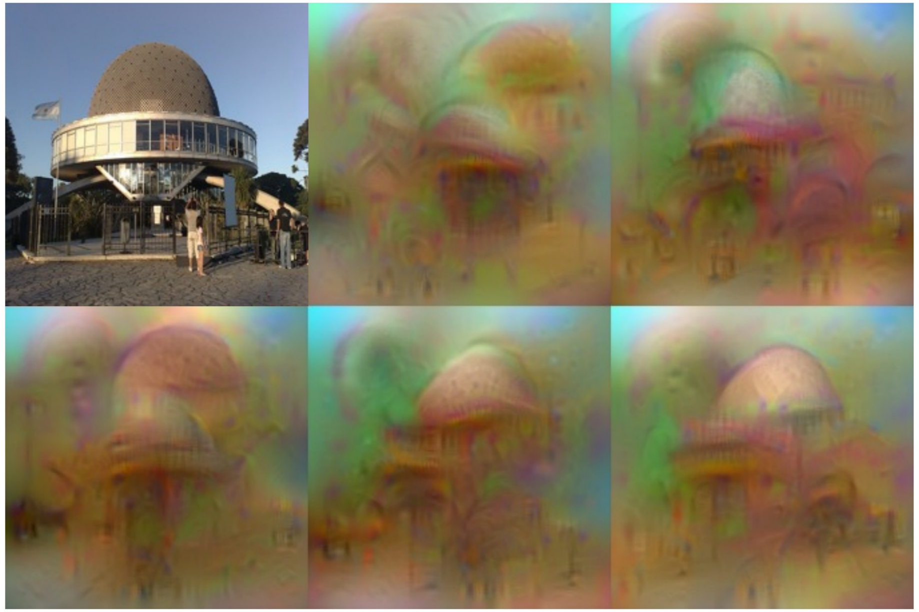
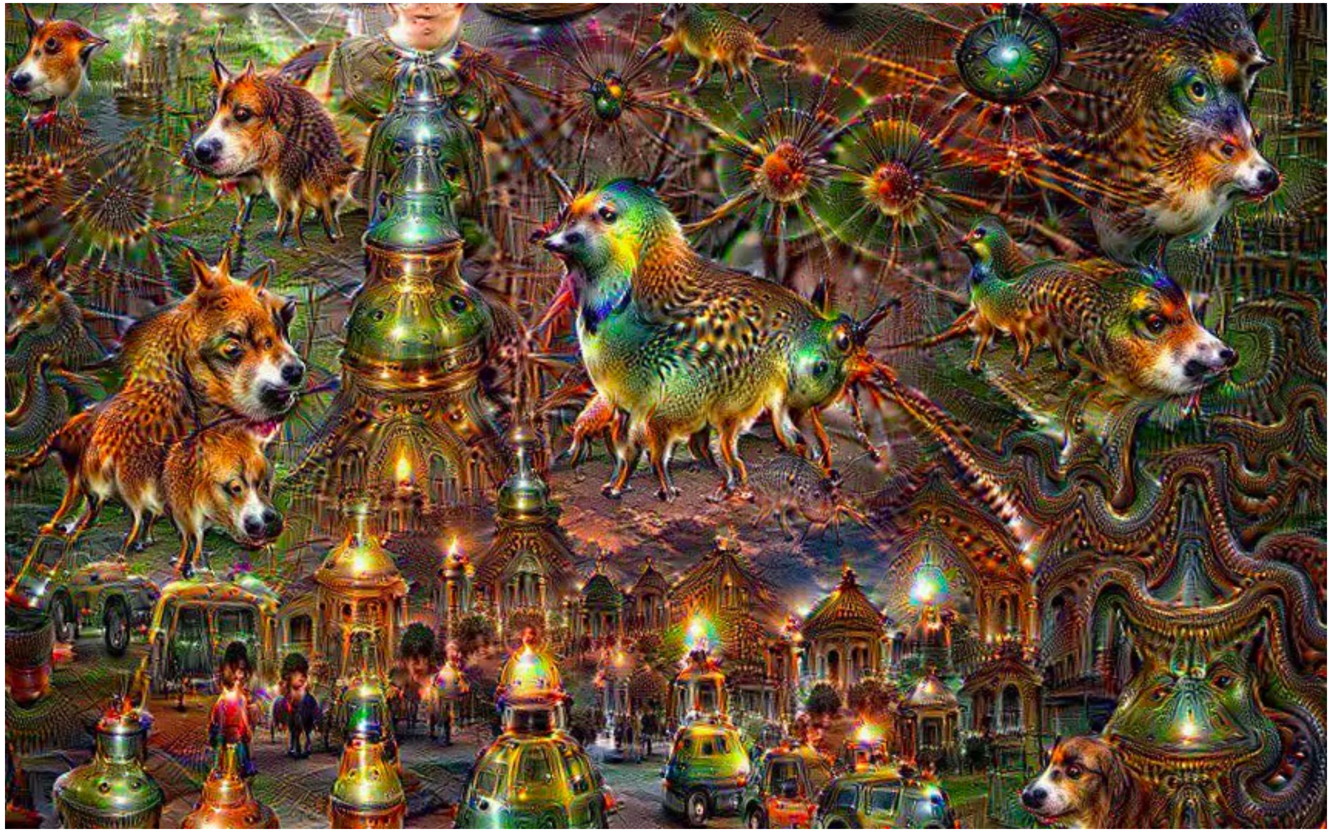


Figure 1. **What is encoded by a CNN?** The figure shows five possible reconstructions of the reference image obtained from the 1,000-dimensional code extracted at the penultimate layer of a reference CNN[13] (before the softmax is applied) trained on the ImageNet data. From the viewpoint of the model, all these images are practically equivalent. This image is best viewed in color/screen.

Mahendran and Vedaldi, Understanding Deep Image Representations by Inverting Them, 2014

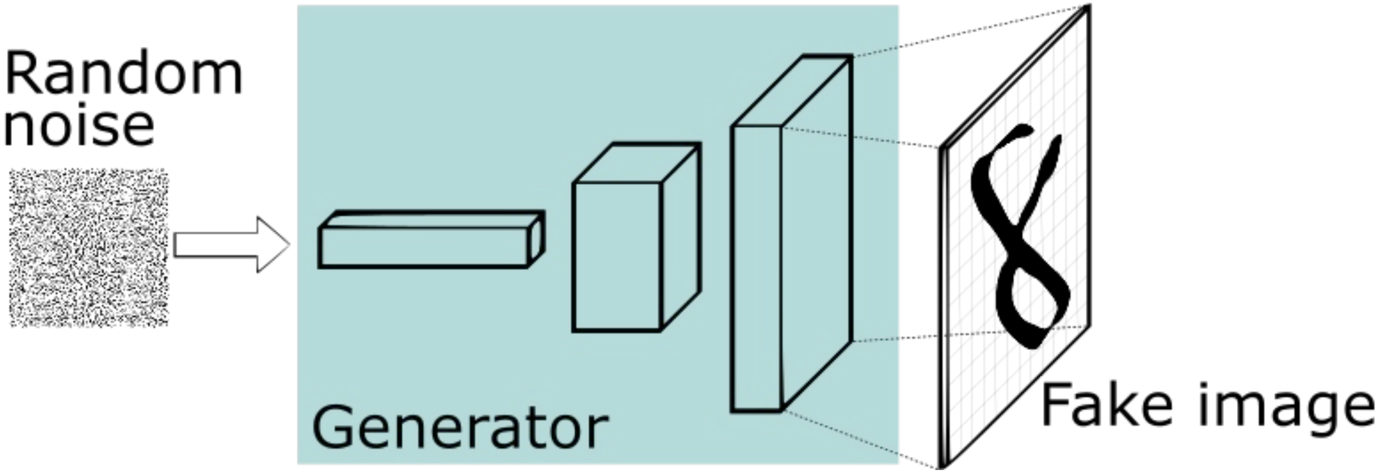
Taking the idea to the extreme: Google's DeepDream



https://research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html

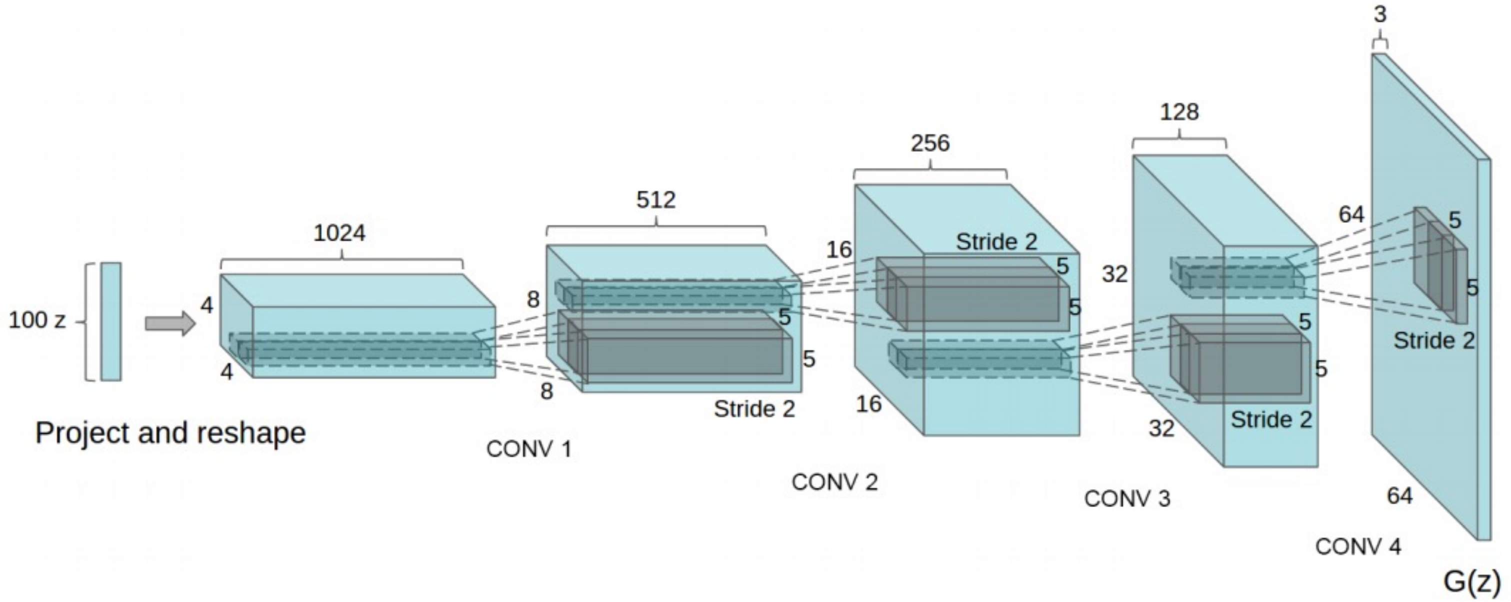
Generate your own in Pytorch: https://github.com/XavierLinNow/deepdream_pytorch

Generative Adversarial Networks (GAN) [Goodfellow et al 2014]



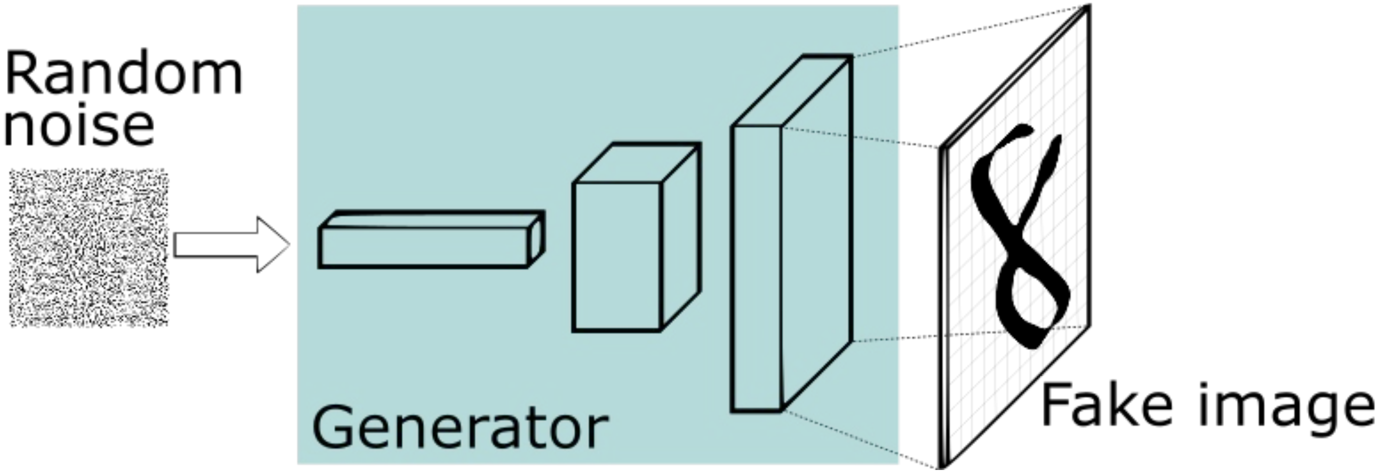
https://deeplearning4j.org/generative-adversarial-network

Generative Network (closer look)



Radford et. al. Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks. ICLR 2016

Generative Adversarial Networks (GAN) [Goodfellow et al.]



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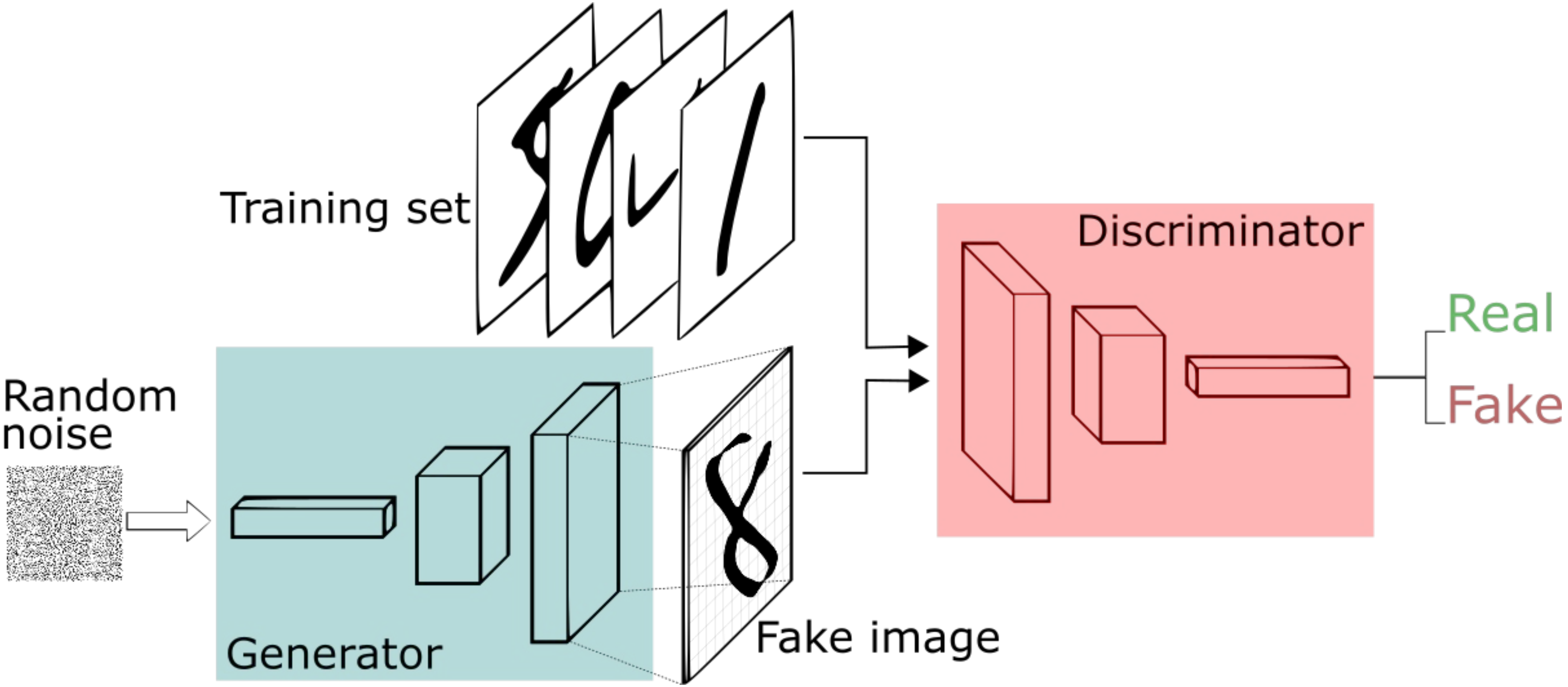

https://deeplearning4j.org/generative-adversarial-network

Algorithm 1 Minibatch stochastic gradient descent training of generative adversarial nets. The number of steps to apply to the discriminator, k, is a hyperparameter. We used $k = 1$, the least expensive option, in our experiments.

for number of training iterations **do**

  for k steps **do**

  - Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  - Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
  - Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right) \right].$$

  end for

  - Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  - Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).$$

end for

The gradient-based updates can use any standard gradient-based learning rule. We used momentum in our experiments.

Goodfellow et al. NeurIPS 2014

Update Discriminator D

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  end for

Update Generator G

  - Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \dots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  - Update the generator by descending its stochastic gradient:

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end for

The gradient-based updates can use any standard gradient-based learning rule. We used momentum in our experiments.

Goodfellow et al. NeurIPS 2014

Until Desirable Results are Achieved?

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for number of training iterations **do**
  for k steps **do**
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  end for
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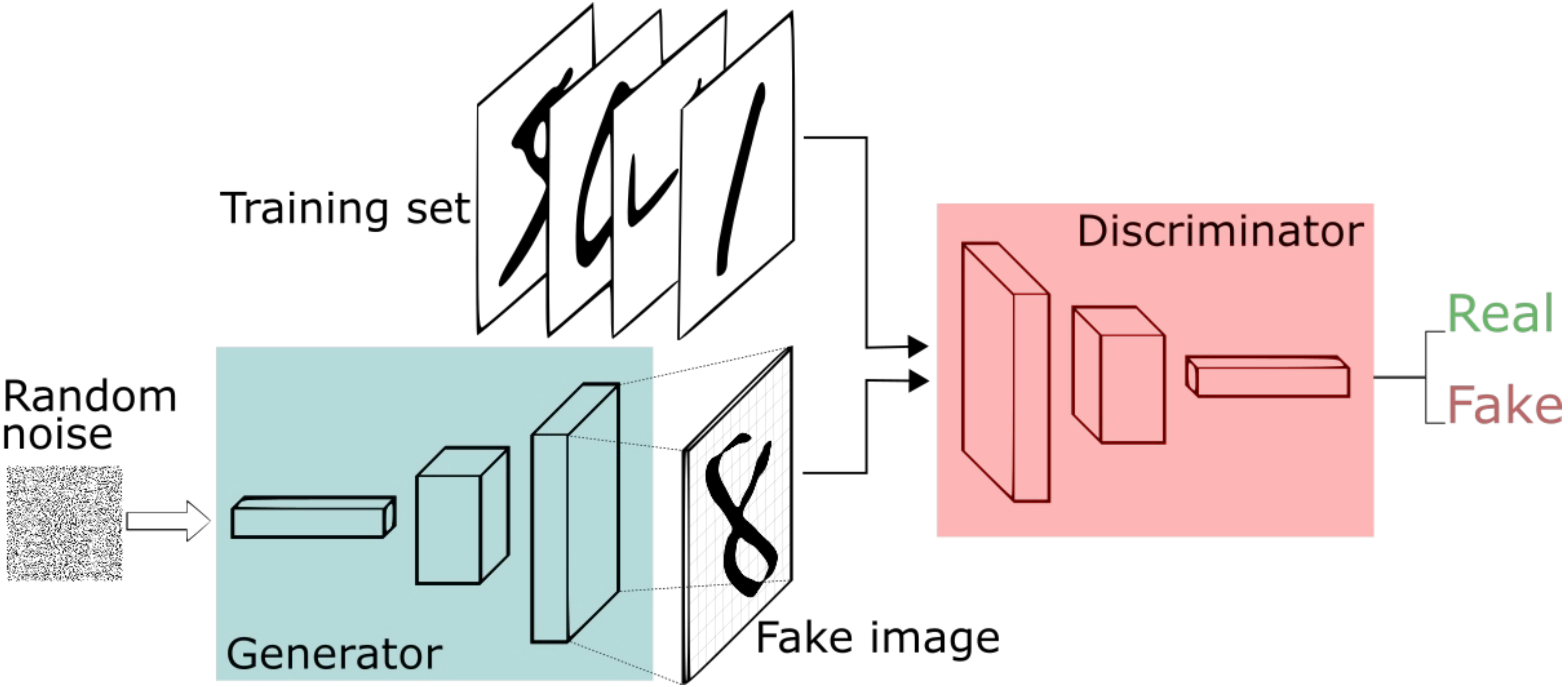
Goodfellow et al. NeurIPS 2014

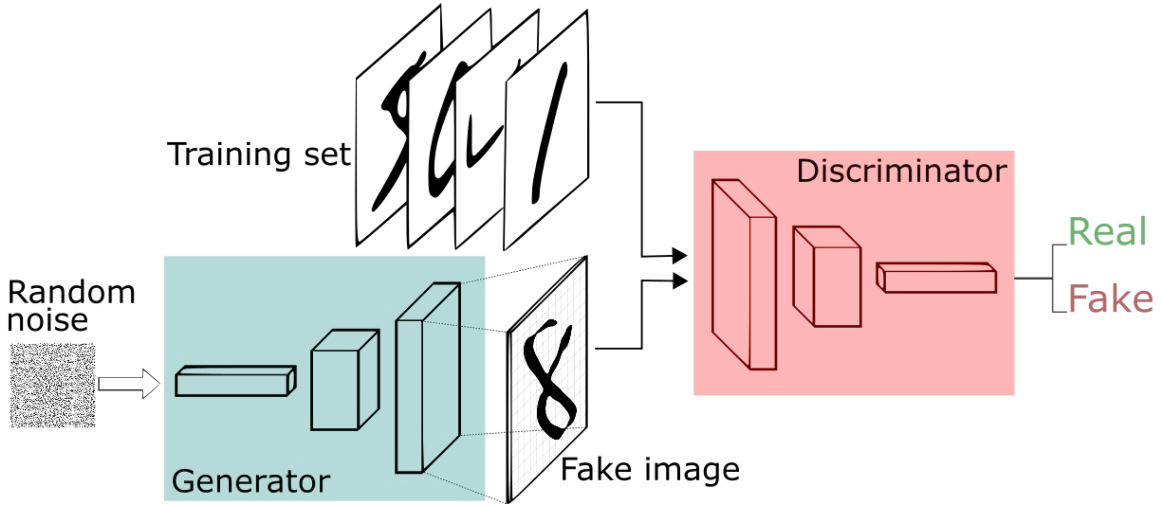
Generative Adversarial Networks (GAN) [Goodfellow et al.]



https://deeplearning4j.org/generative-adversarial-network

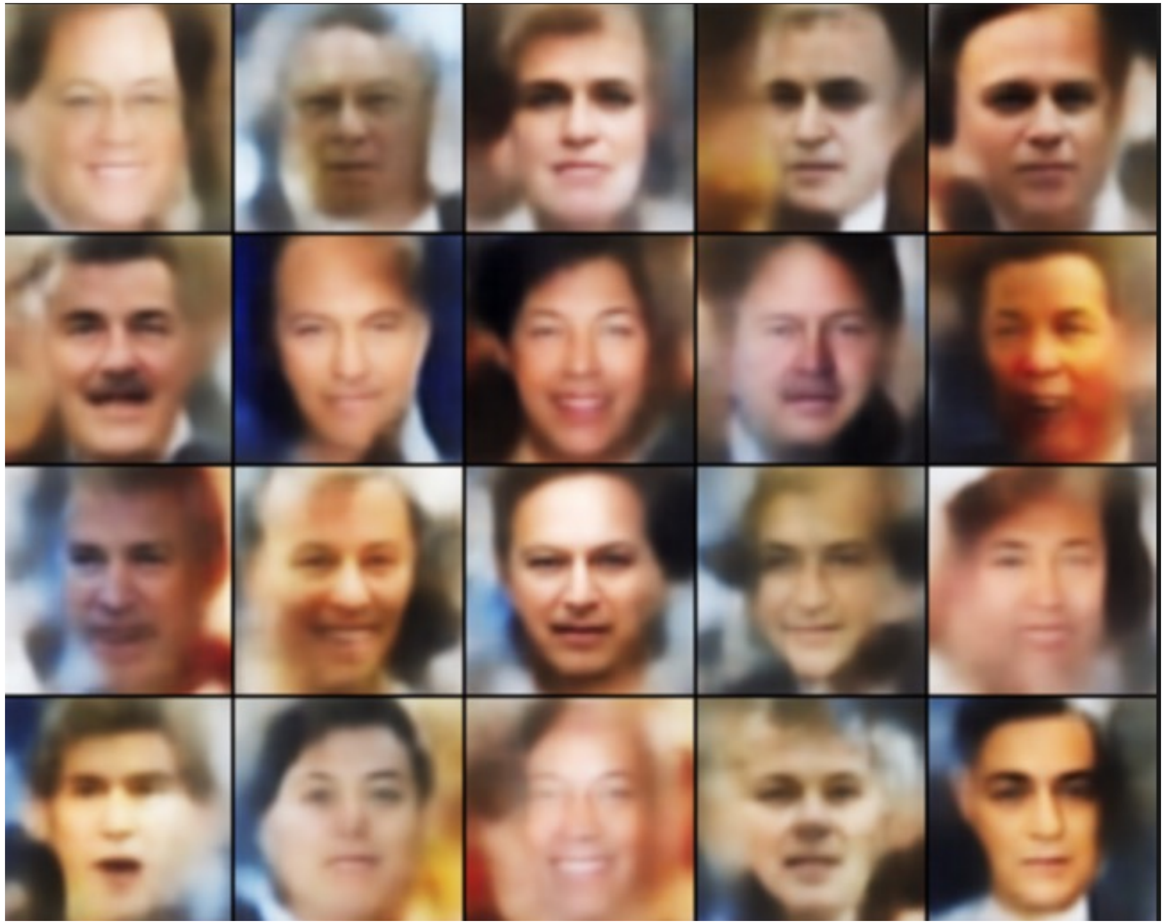
Generative Adversarial Networks (GAN) [Goodfellow et al.]

- GANs are hard to train, loss for the discriminator and generator might fluctuate.
- There are many choices for loss, and other auxiliary signals.
- Training of these models is even less well understood than for other deep models.



https://deeplearning4j.org/generative-adversarial-network

Basic GAN Results (Example implementation is provided in Pytorch's examples)



http://torch.ch/blog/2015/11/13/gan.html

NVidia's progressive GANs ICLR 2018

Google’s BigGAN

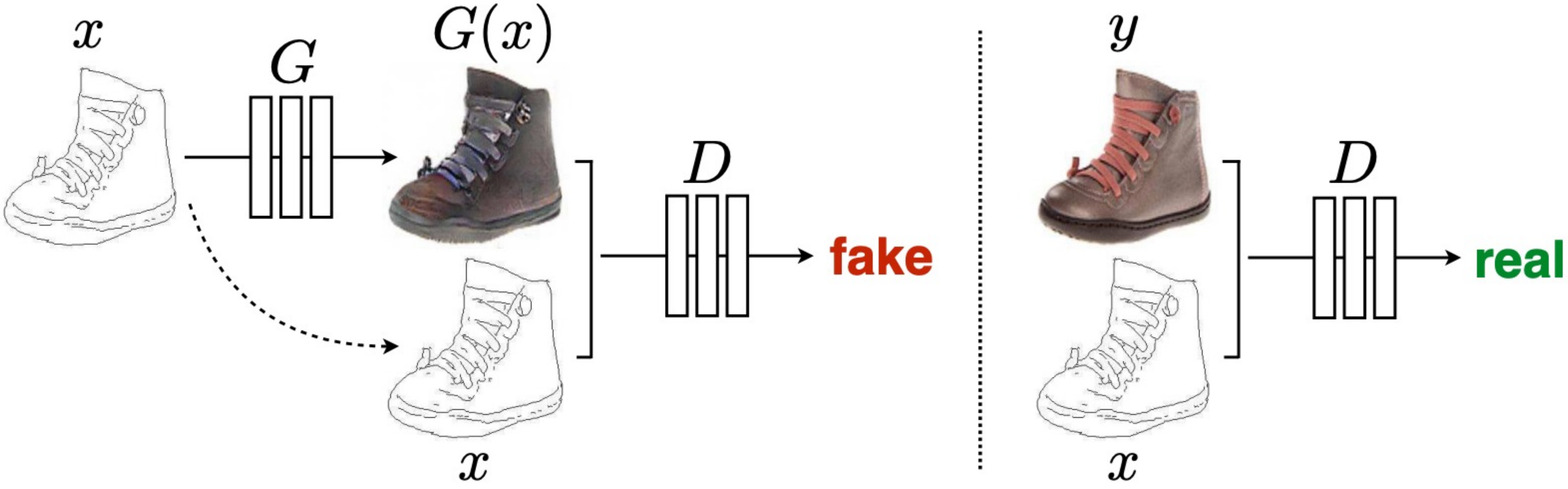
Google's BigGAN

Teddy Bear

Microphone

http://aiweirdness.com/post/179626595787/the-creepiest-images-generated-by-biggan

Conditional GANs: Input is not just Noise

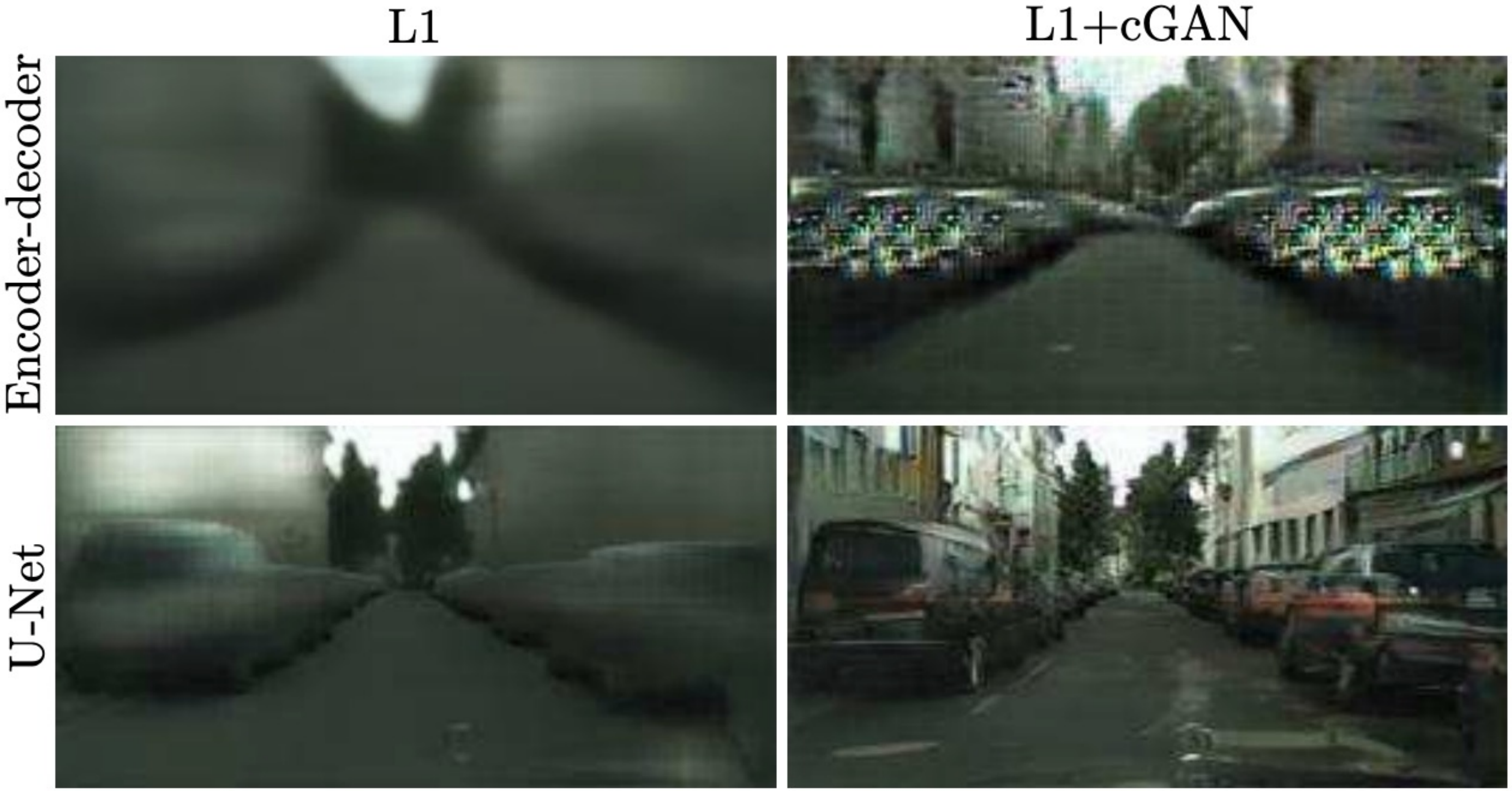


Isola et al. CVPR 2017: Image-to-Image Translation with Conditional Adversarial Networks

Conditional GANs: Also Hard to Train

Result they obtained with a regular Fully Convolutional Network

Result they obtained with a U-Net network (with skip-connections)



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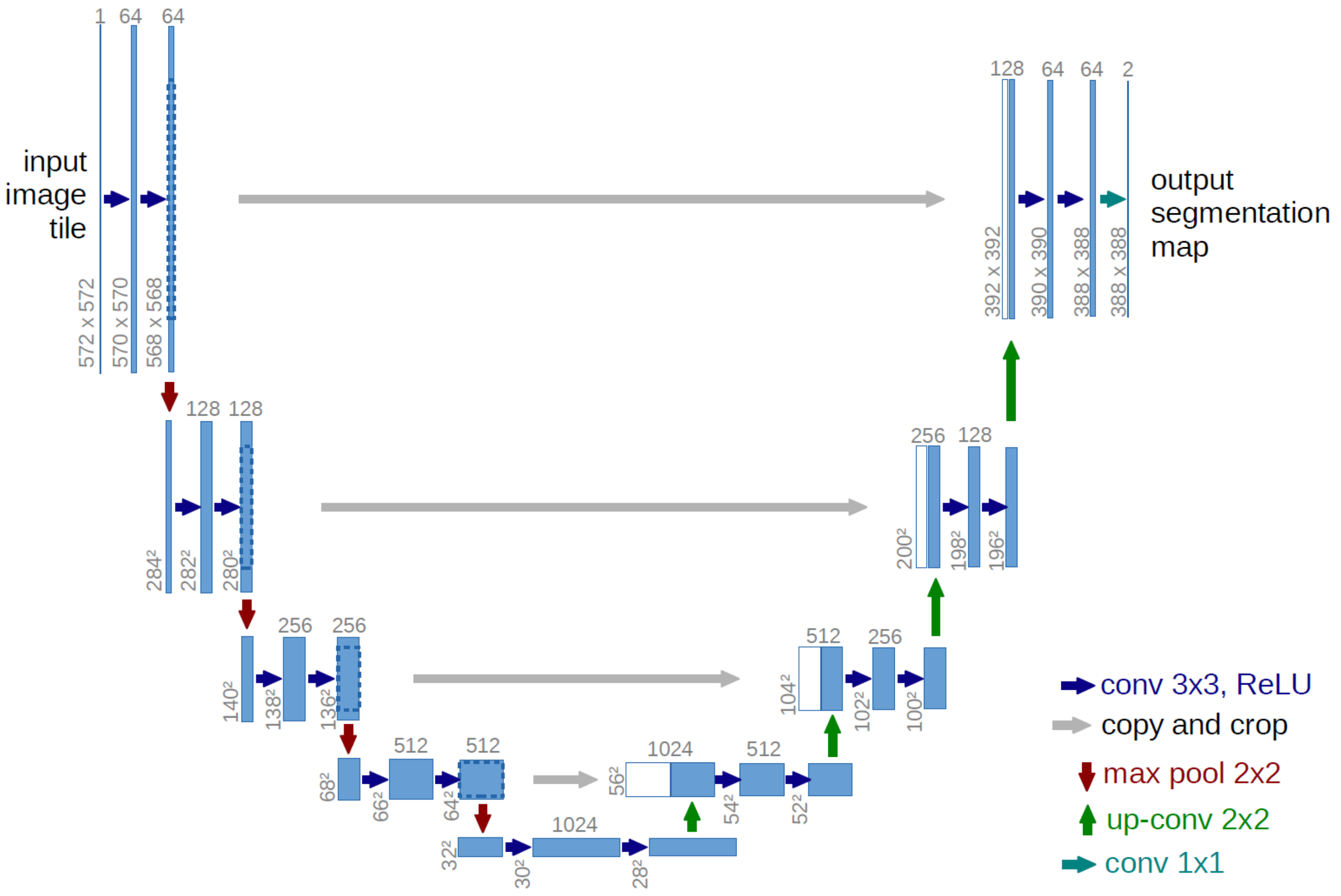


Ronneberger et al. MICCAI 2015. U-Net: Convolutional Networks for Biomedical Image Segmentation

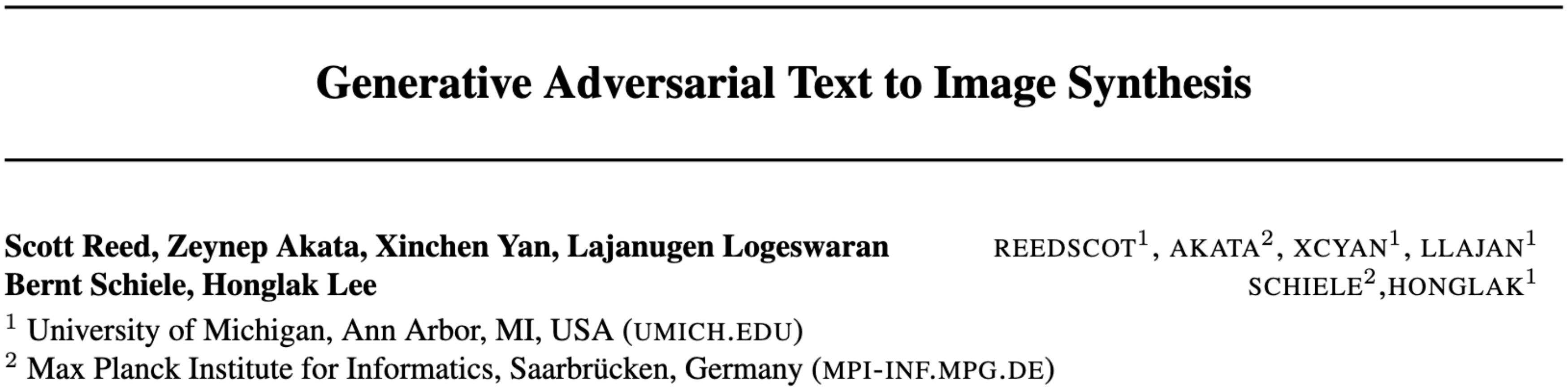
Conditional GANs / Text-conditioned

AttnGAN: Fine-Grained Text to Image Generation with Attentional Generative Adversarial Networks

Tao Xu*[1], Pengchuan Zhang[2], Qiuyuan Huang[2],
Han Zhang[3], Zhe Gan[4], Xiaolei Huang[1], Xiaodong He[2]

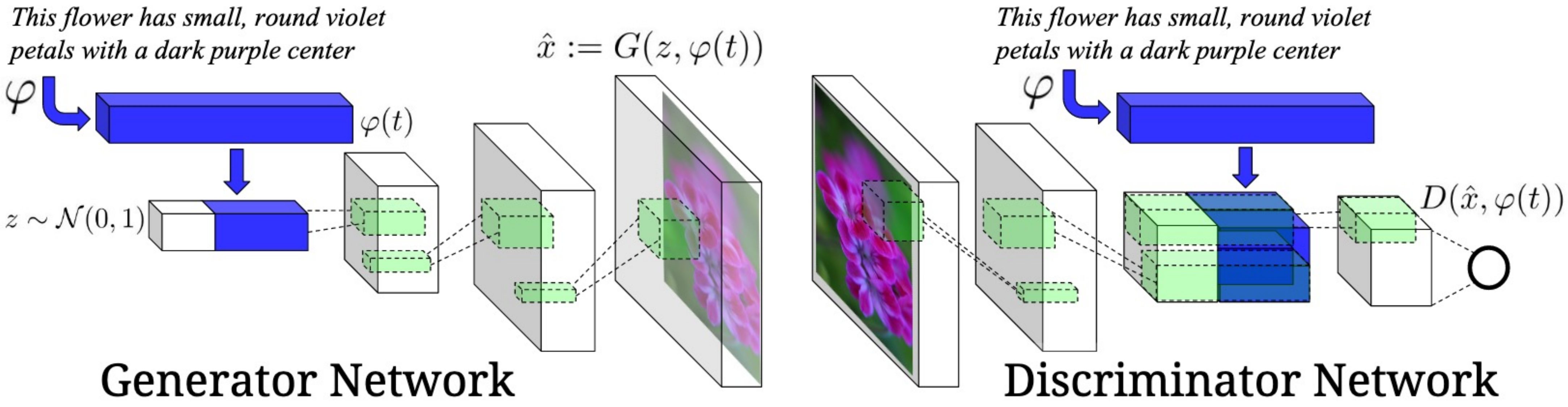
[1]Lehigh University [2]Microsoft Research [3]Rutgers University [4]Duke University
{tax313, xih206}@lehigh.edu, {penzhan, qihua, xiaohe}@microsoft.com
han.zhang@cs.rutgers.edu, zhe.gan@duke.edu

Conditional GANs / Text-conditioned


Generative Adversarial Text to Image Synthesis

Scott Reed, Zeynep Akata, Xinchen Yan, Lajanugen Logeswaran REEDSCOT[1], AKATA[2], XCYAN[1], LLAJAN[1]
Bernt Schiele, Honglak Lee SCHIELE[2],HONGLAK[1]
[1] University of Michigan, Ann Arbor, MI, USA (UMICH.EDU)
[2] Max Planck Institute for Informatics, Saarbrücken, Germany (MPI-INF.MPG.DE)

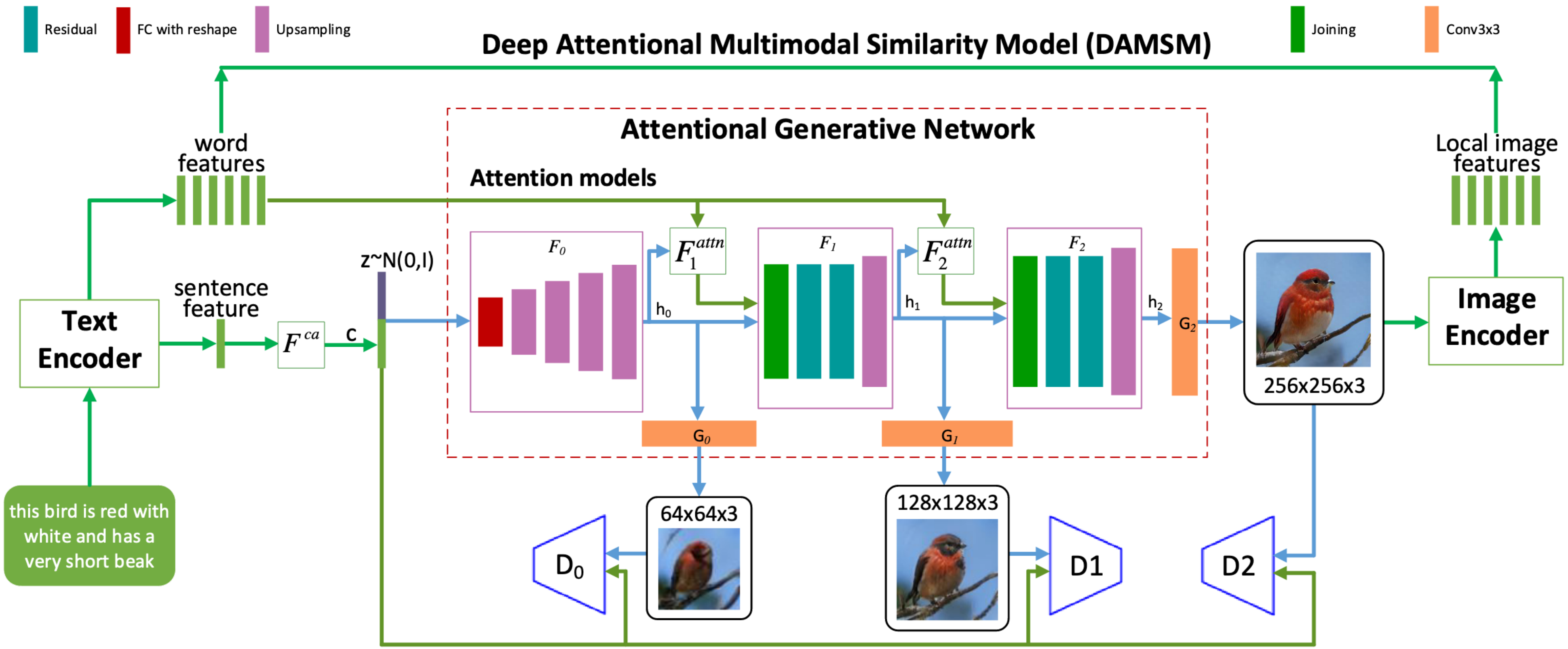
Conditional GANs / Text-conditioned



Conditional GANs / Text-conditioned

this small bird has a pink breast and crown, and black primaries and secondaries.

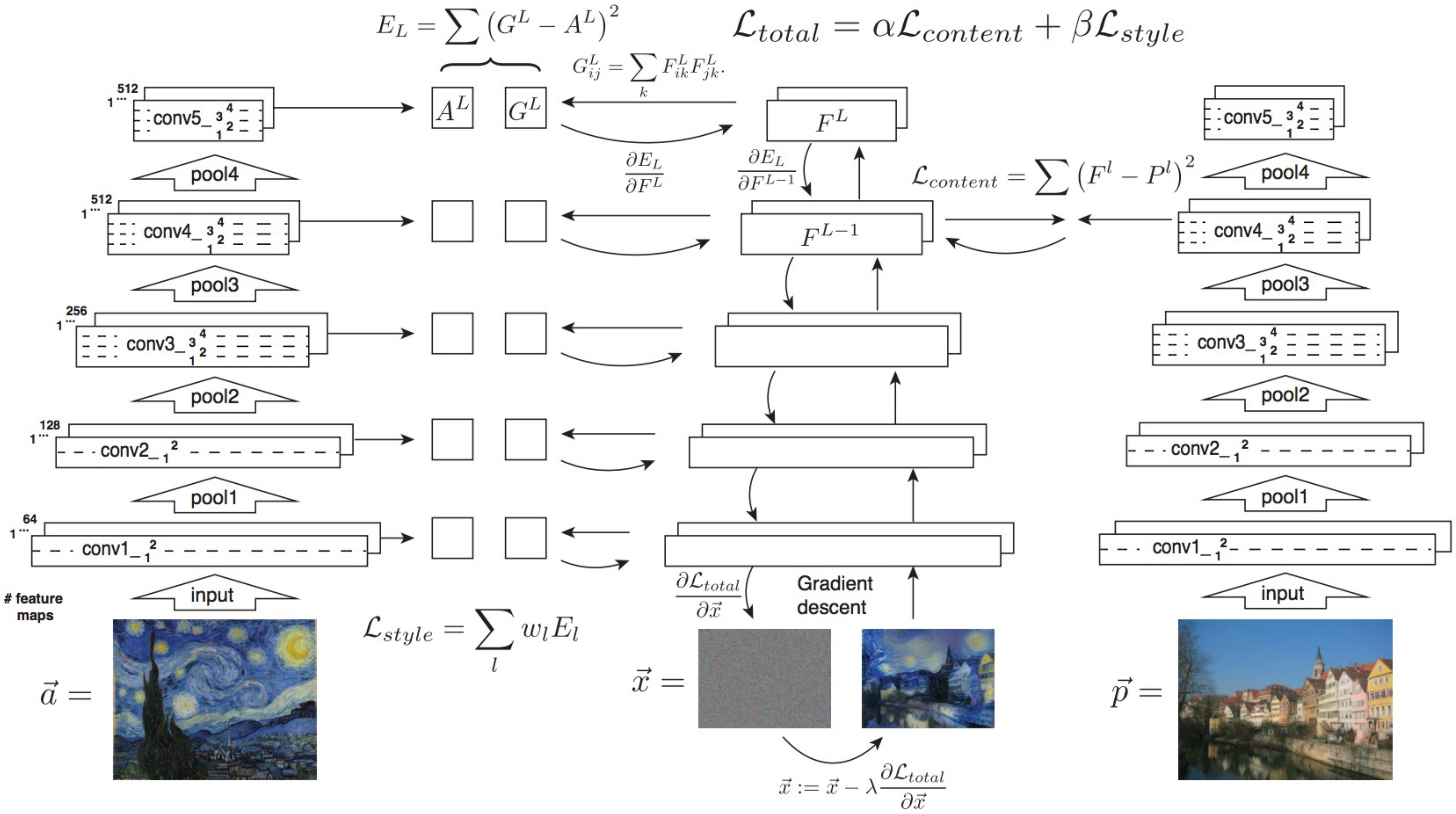
Conditional GANs / Text-conditioned



Conditional GANs / Text-conditioned

More on the Idea of Feature Space Optimization

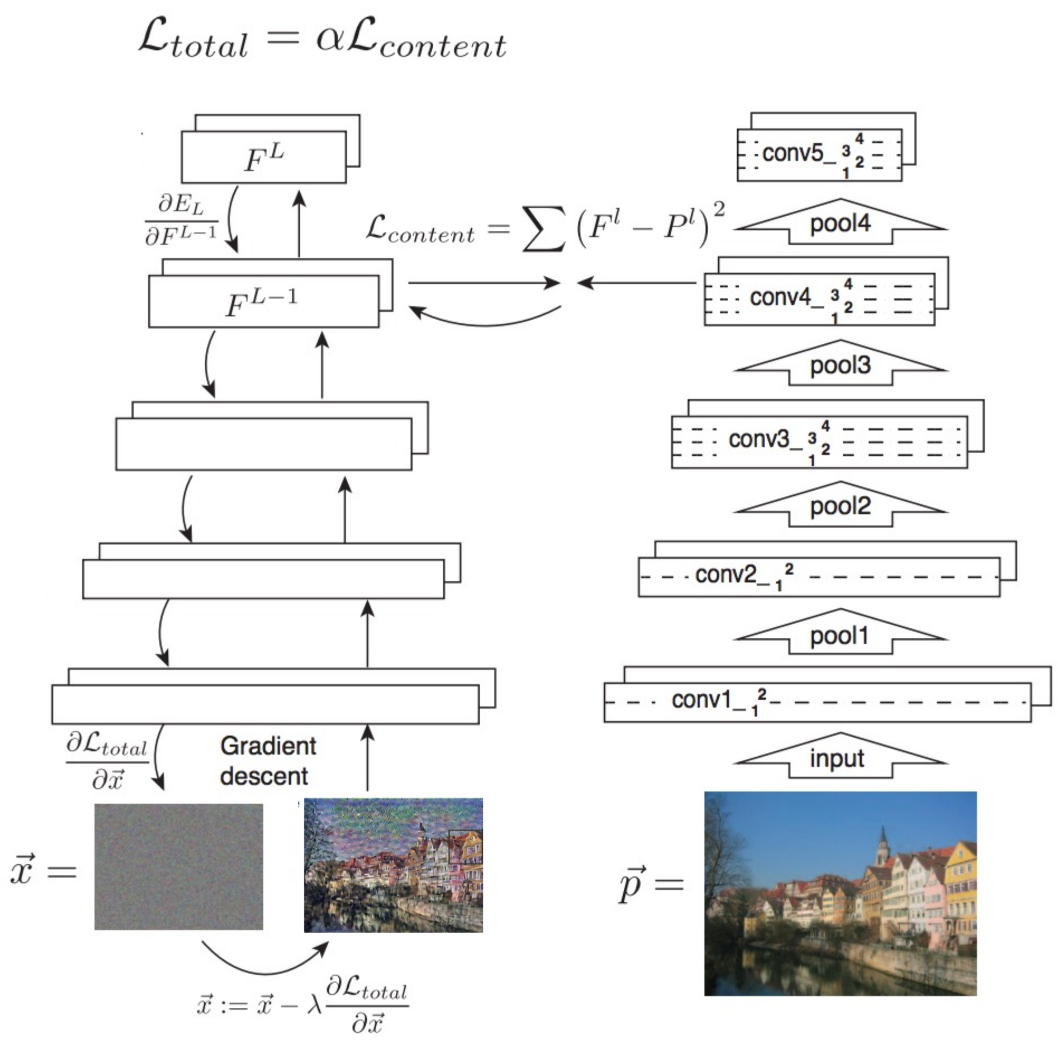
Gatys et. al. Image Style Transfer Using Convolutional Neural Networks. CVPR 2016



$E_L = \sum (G^L - A^L)^2$
$\mathcal{L}_{total} = \alpha \mathcal{L}_{content} + \beta \mathcal{L}_{style}$
$G^L_{ij} = \sum_k F^L_{ik} F^L_{jk}.$
A^L
G^L
F^L
F^{L-1}
$\frac{\partial E_L}{\partial F^L}$
$\frac{\partial E_L}{\partial F^{L-1}}$
$\mathcal{L}_{content} = \sum (F^l - P^l)^2$
conv5_1 2 3 4
pool4
conv4_1 2 3 4
pool3
conv3_1 2 3 4
pool2
conv2_1 2
pool1
conv1_1 2
input
512
512
256
128
64
feature maps
$\mathcal{L}_{style} = \sum_l w_l E_l$
$\frac{\partial \mathcal{L}_{total}}{\partial \vec{x}}$
Gradient descent
$\vec{a} =$
$\vec{x} =$
$\vec{p} =$
$\vec{x} := \vec{x} - \lambda \frac{\partial \mathcal{L}_{total}}{\partial \vec{x}}$

Gatys et. al. Image Style Transfer Using Convolutional Neural Networks. CVPR 2016

Idea 1: Image Reconstruction from Features



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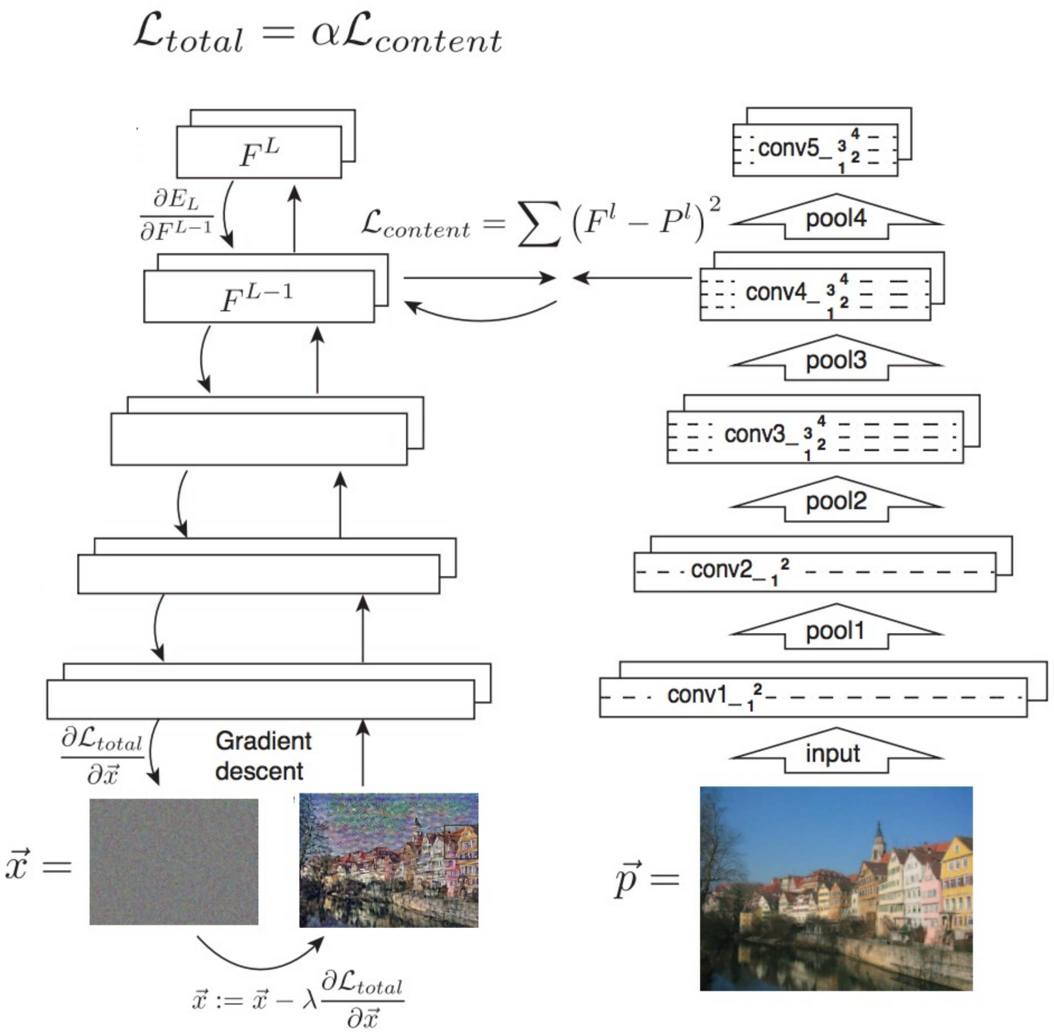
$$\mathcal{L}_{content} = \sum (F^l - P^l)^2$$



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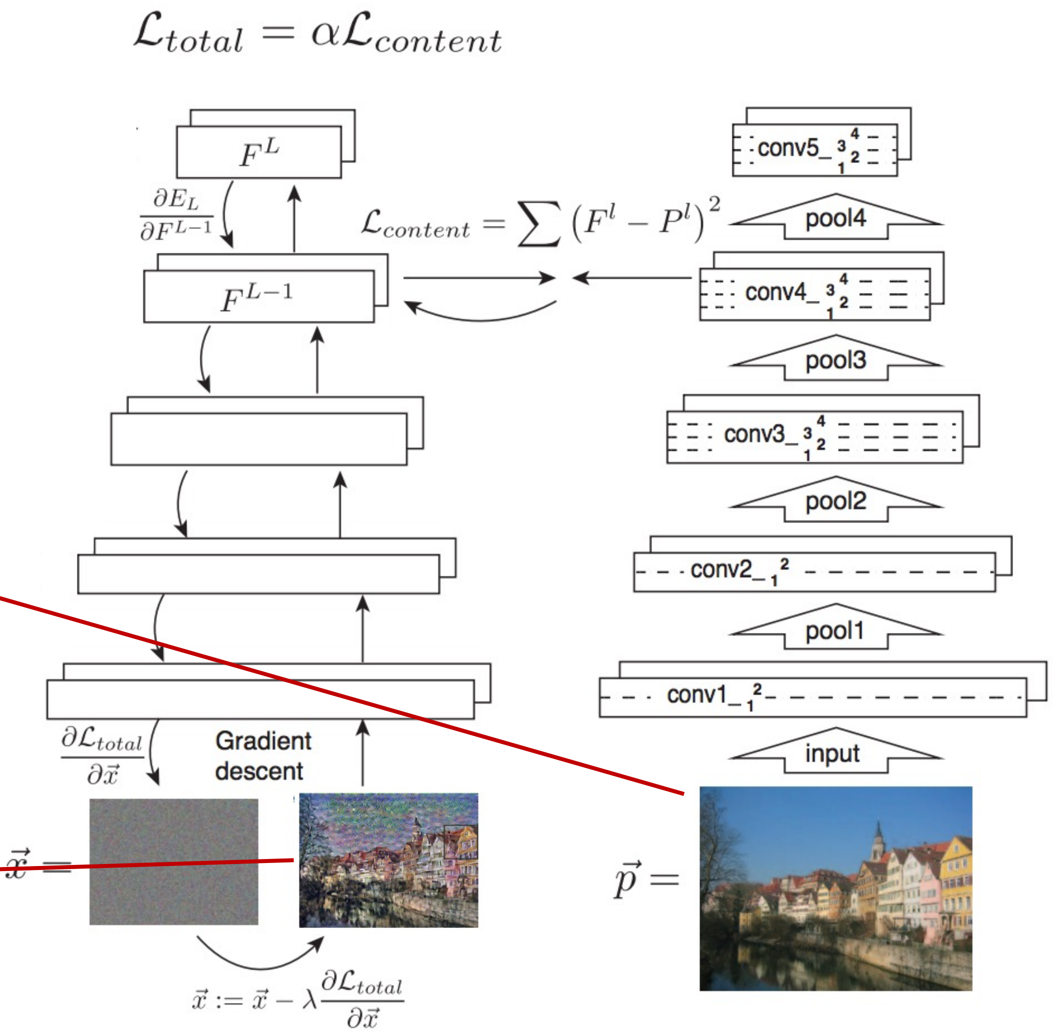

Gatys et. al. Image Style Transfer Using Convolutional Neural Networks. CVPR 2016

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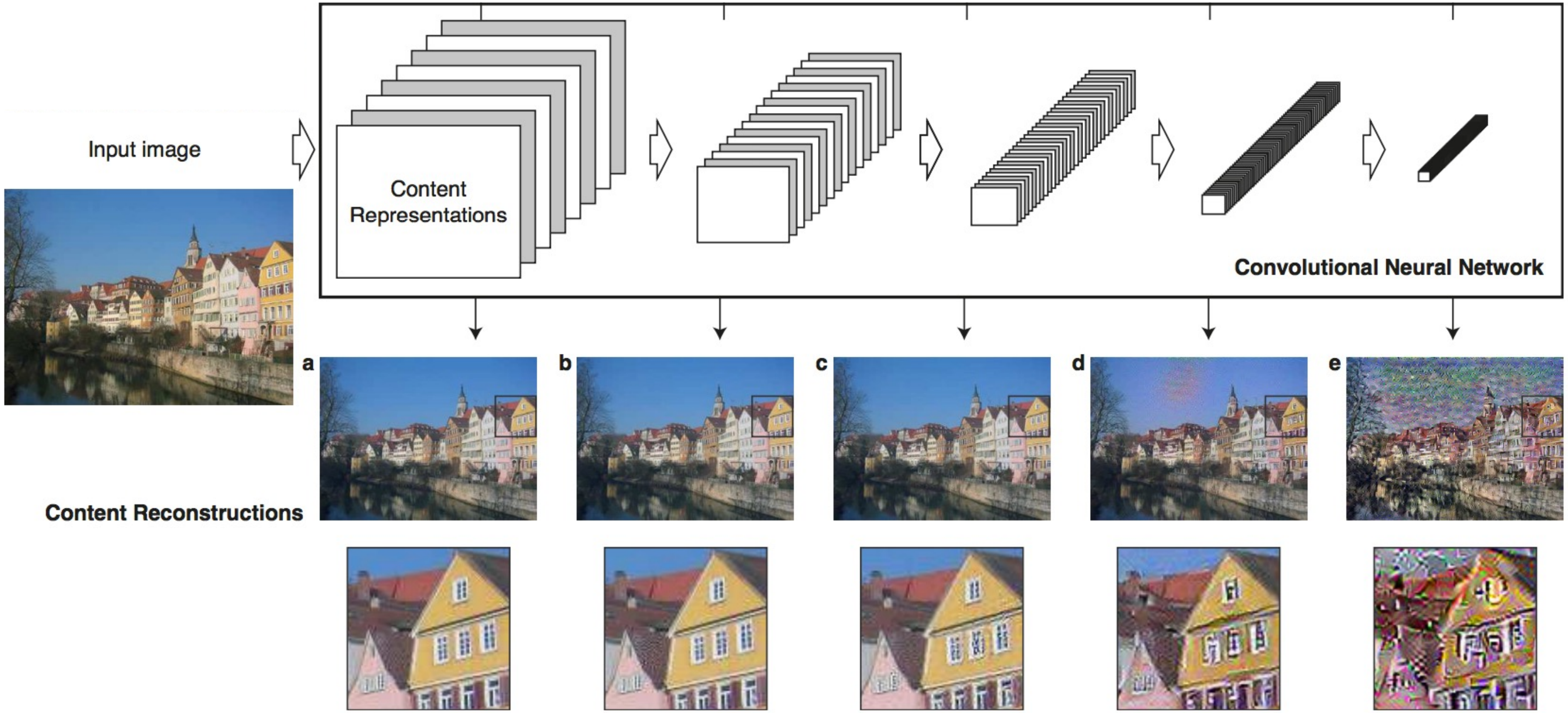

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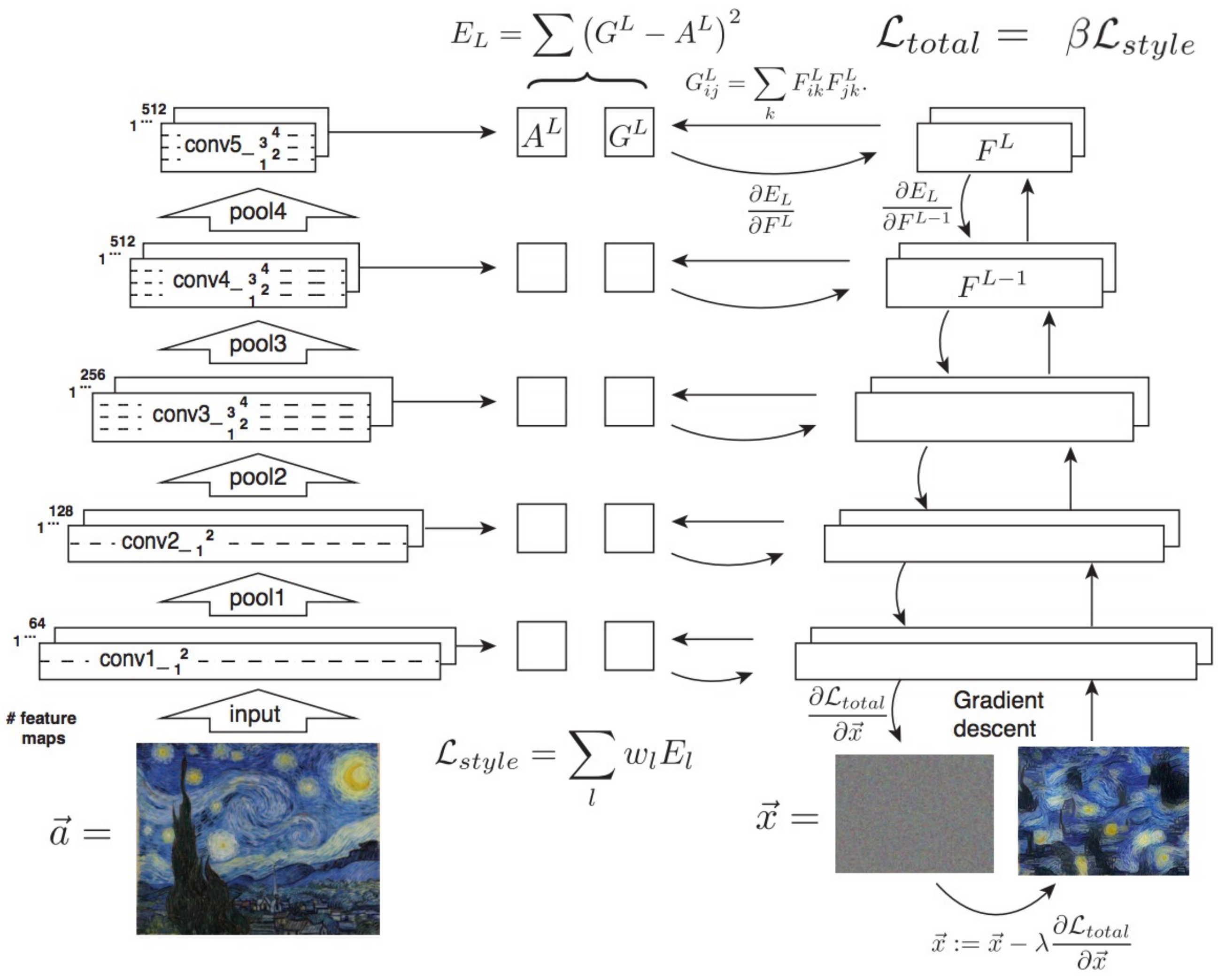
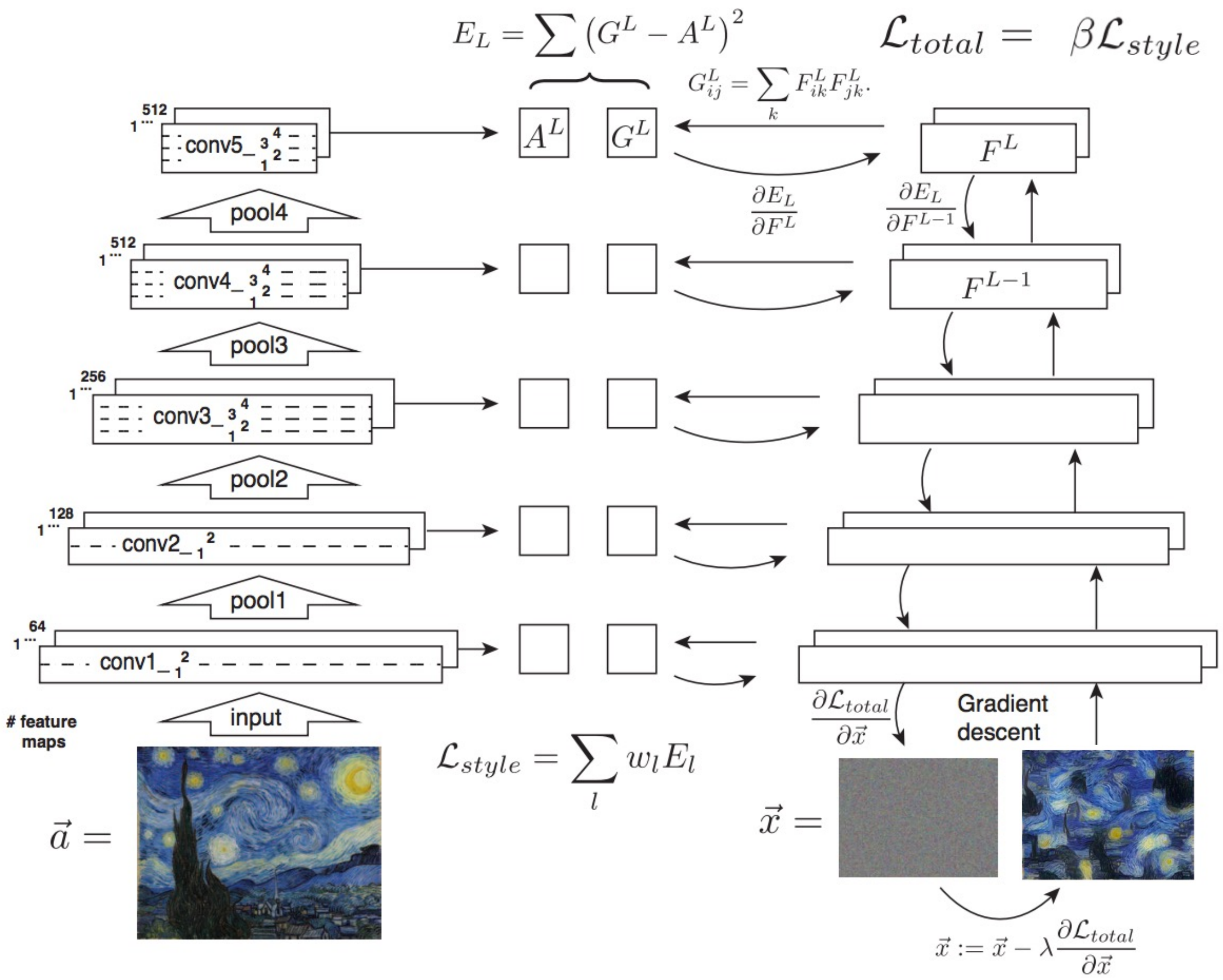


Idea 2: Backpropagation of Style

Gatys et. al. Image Style Transfer Using Convolutional Neural Networks. CVPR 2016



Idea 2: Backpropagation of Style

$$G^l_{ij} = \sum_k F^l_{ik} F^l_{jk}.$$

$$E_L = \sum (G^L - A^L)^2$$

Gatys et. al. Image Style Transfer Using Convolutional Neural Networks. CVPR 2016

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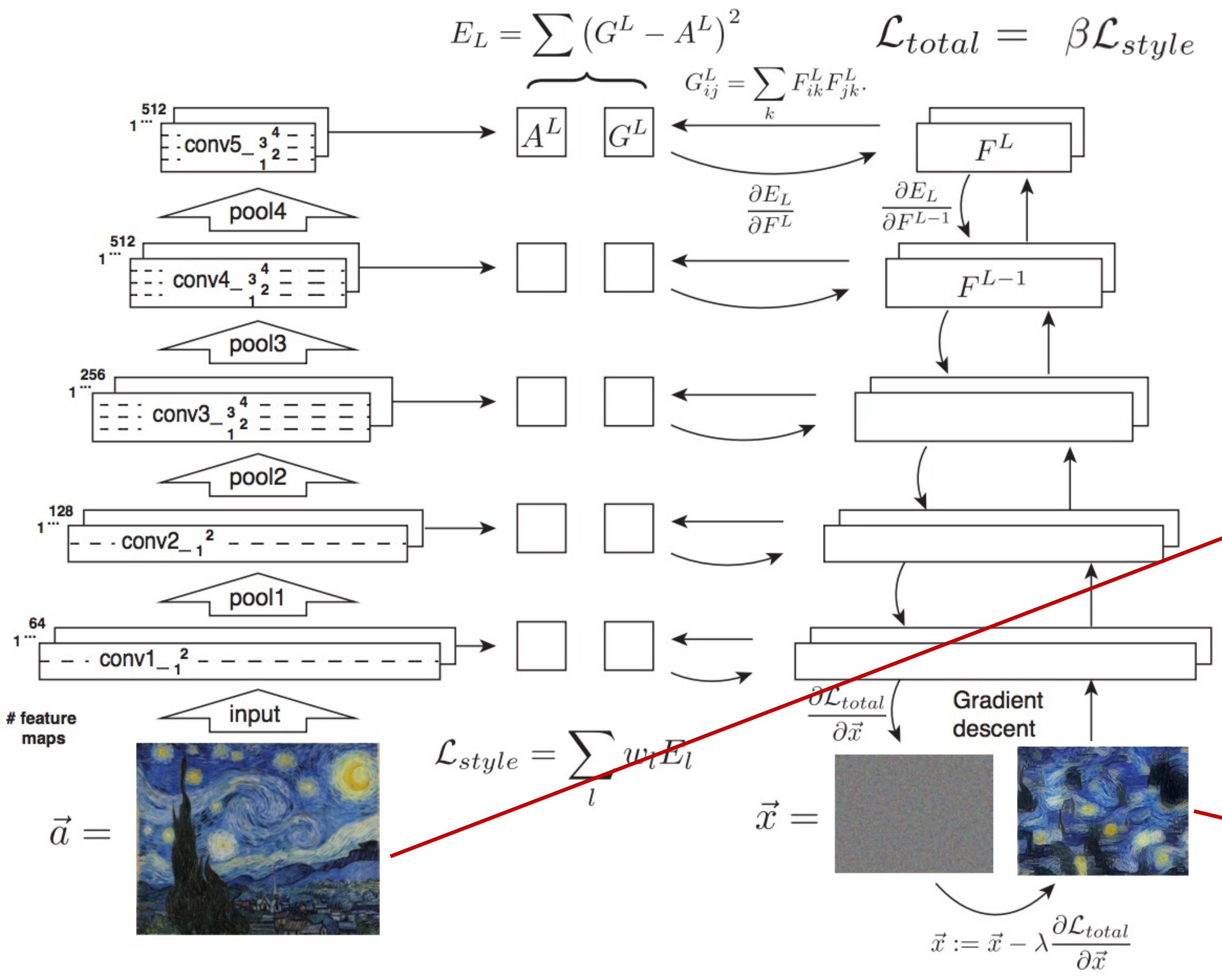

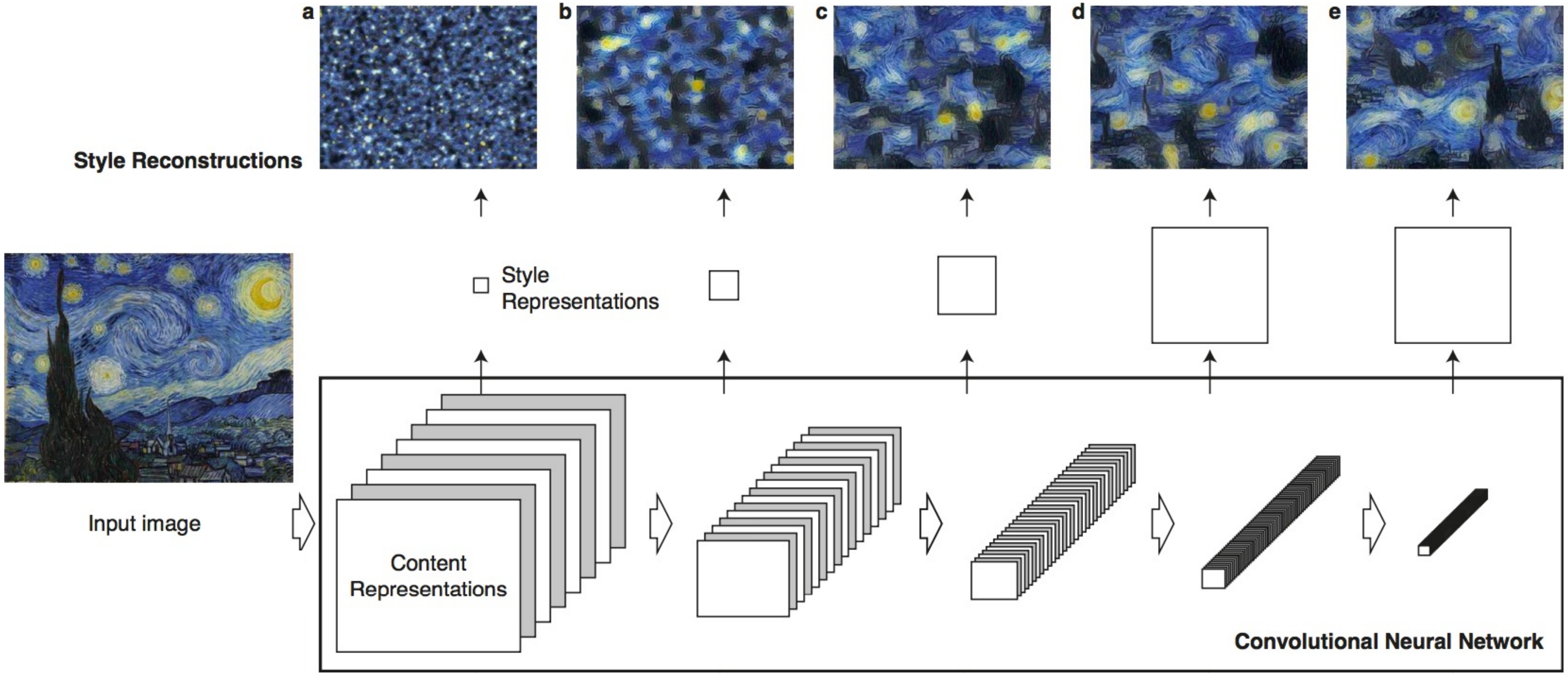

$$G_{ij}^{l} = \sum_{k} F_{ik}^{l} F_{jk}^{l}.$$

$$E_L = \sum \left(G^L - A^L\right)^2$$

Gatys et. al. Image Style Transfer Using Convolutional Neural Networks. CVPR 2016

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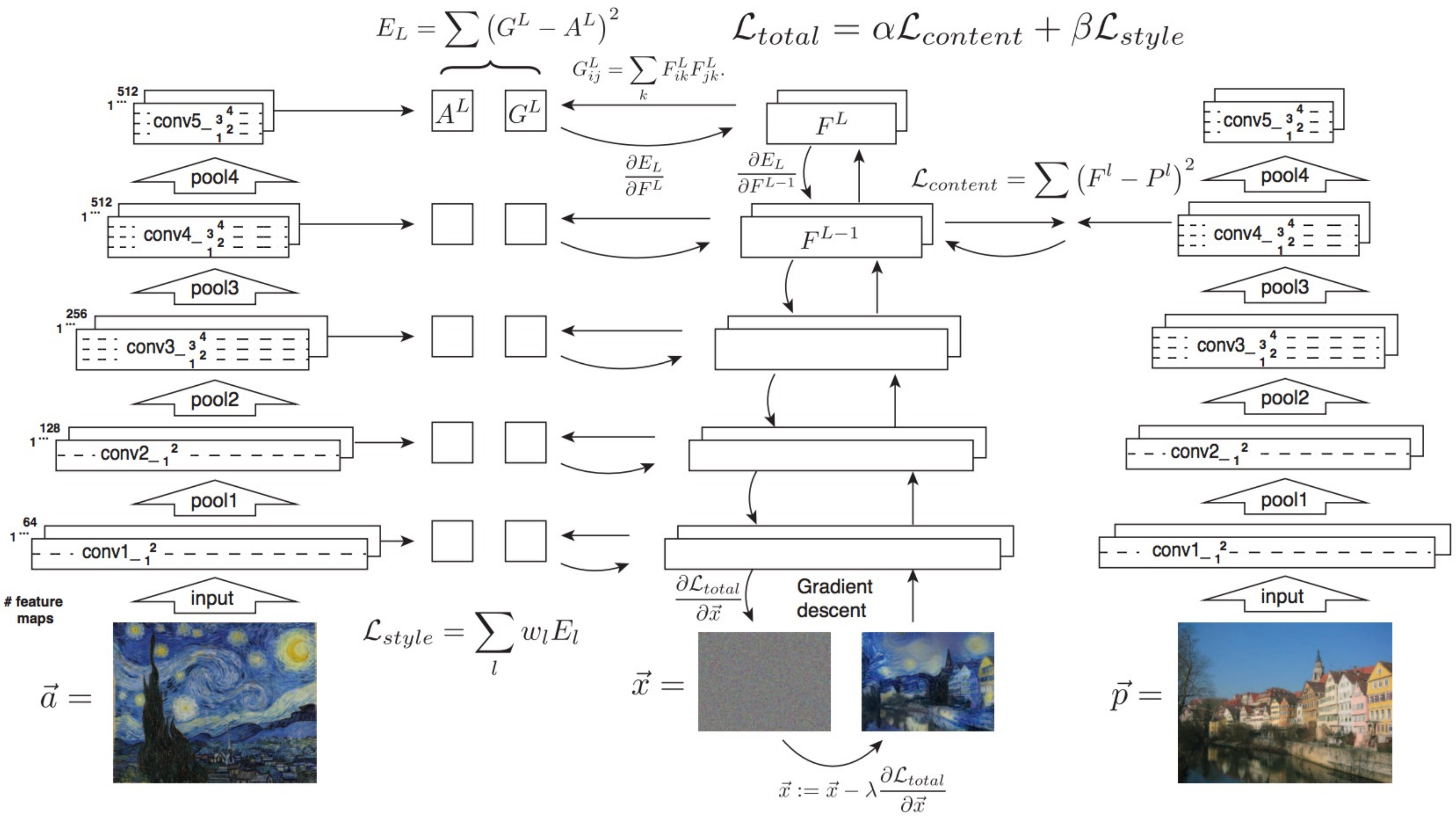

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Questions