Style Transfer by Deep Learning

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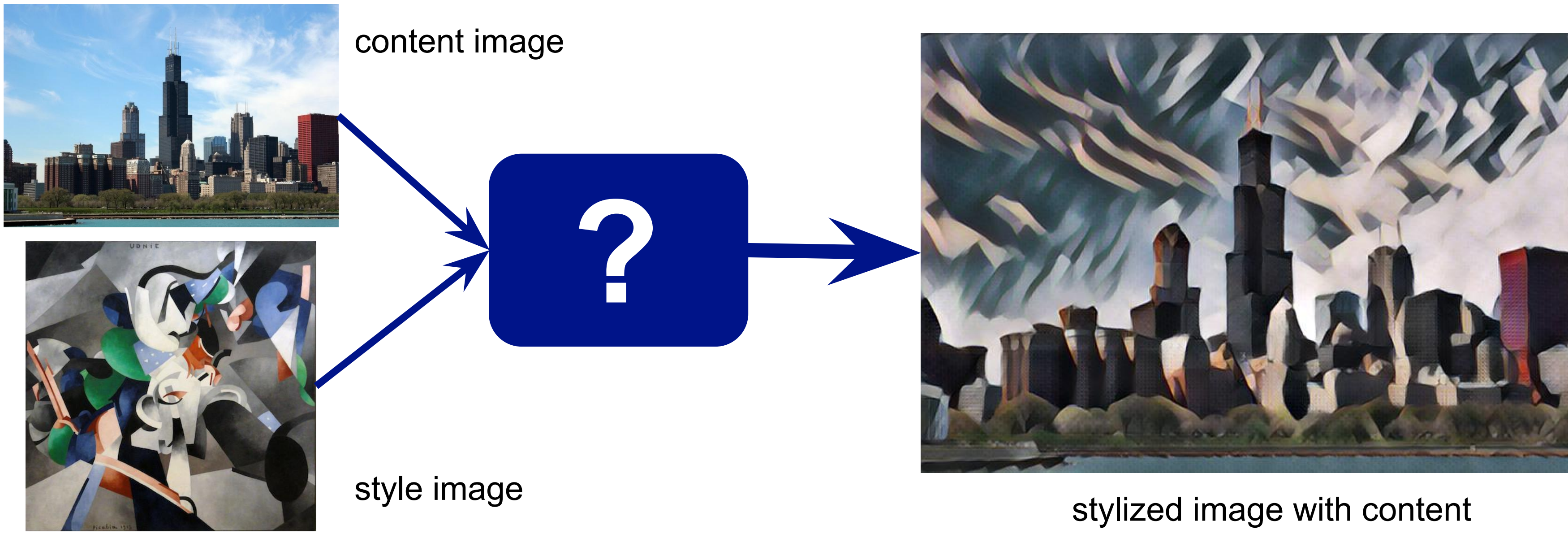
Style Transfer by Deep Learning : Motivations

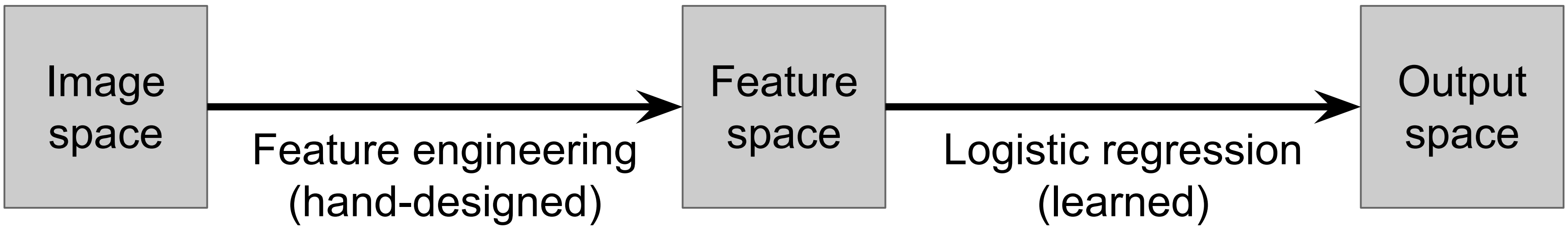


- **Generative task**
  - From an image, generate a new one
- **Introduction to more complex tasks**
  - Super-resolution and colorisation
- **CNNs understanding is required**
  - Hierarchy of representations
  - Feature spaces

- Machine Learning vs Deep Learning
- CNNs visualizing and understanding
- Content and style representations
- Optimization-based style transfer
- Feed-forward method with learning
- Arbitrary style transfer

Machine Learning vs Deep Learning

Machine Learning pipeline

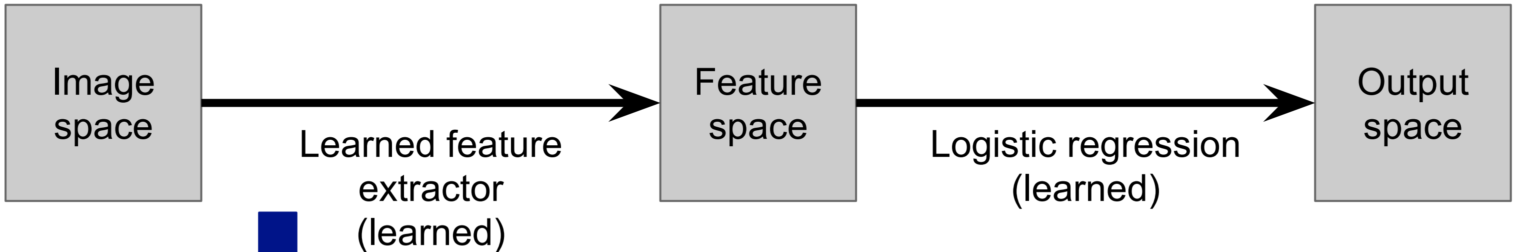


- Domain dependence
- Need expert domain to tune
- Hard to extract complex patterns

For images : HOG features, SIFT methods, Histograms, LBP features, ….

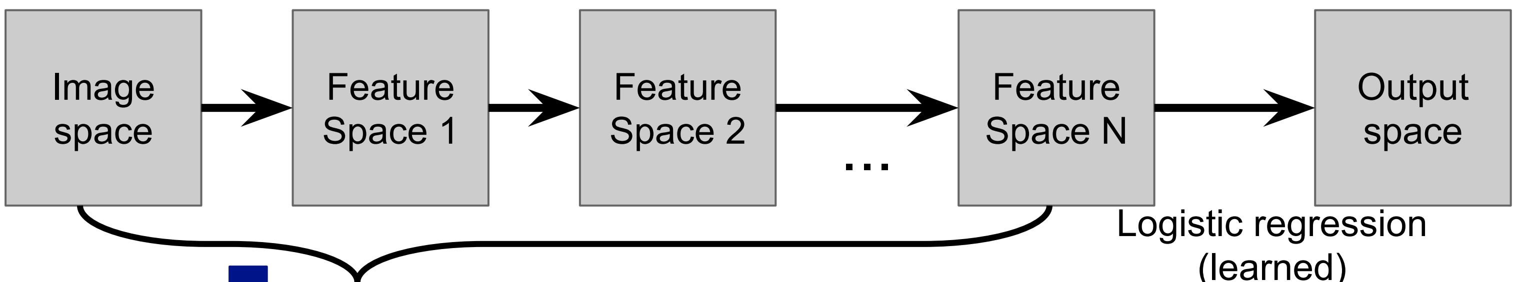
Representation Learning

Representation Learning approach



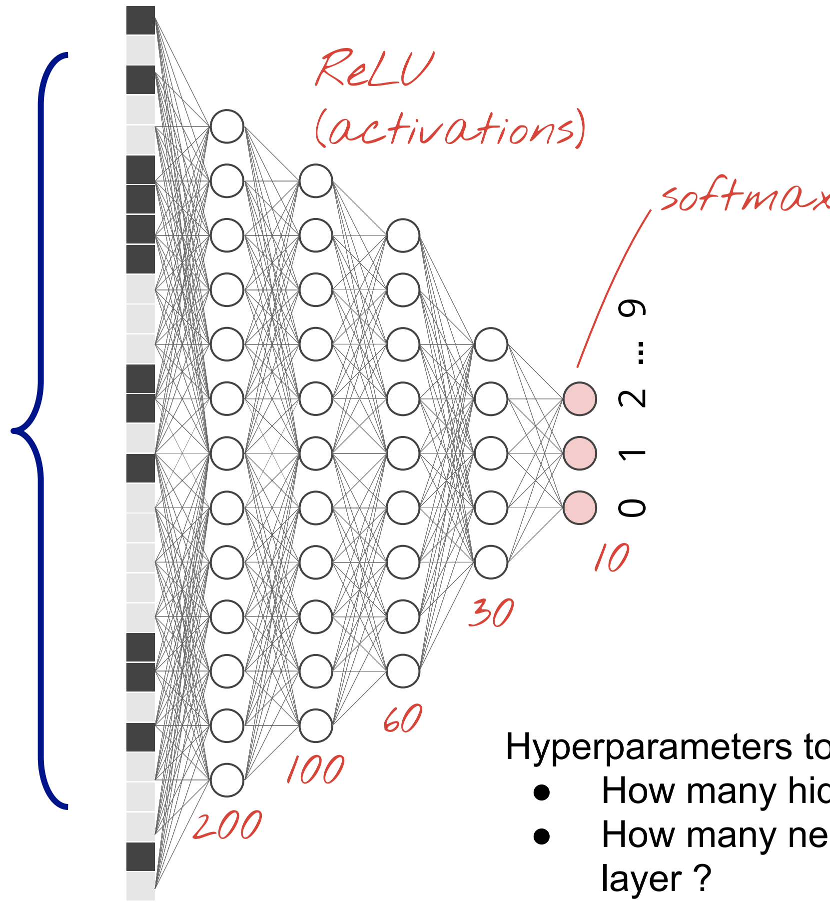
- Learns a new representation of the data
- Ex : PCA (Principal Component Analysis)

Deep Representation Learning approach

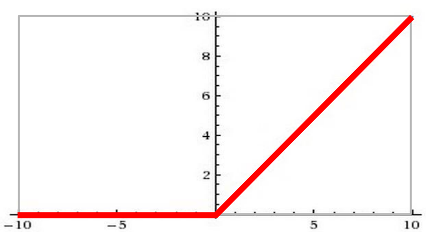


- **Learns a hierarchy of representations**
- **Can be done with Neural Networks**

Deep Neural Networks



ReLU function



Hyperparameters to tune:

- How many hidden layers ?
- How many neurons per layer ?
- Which activation ?
- Regularization ?

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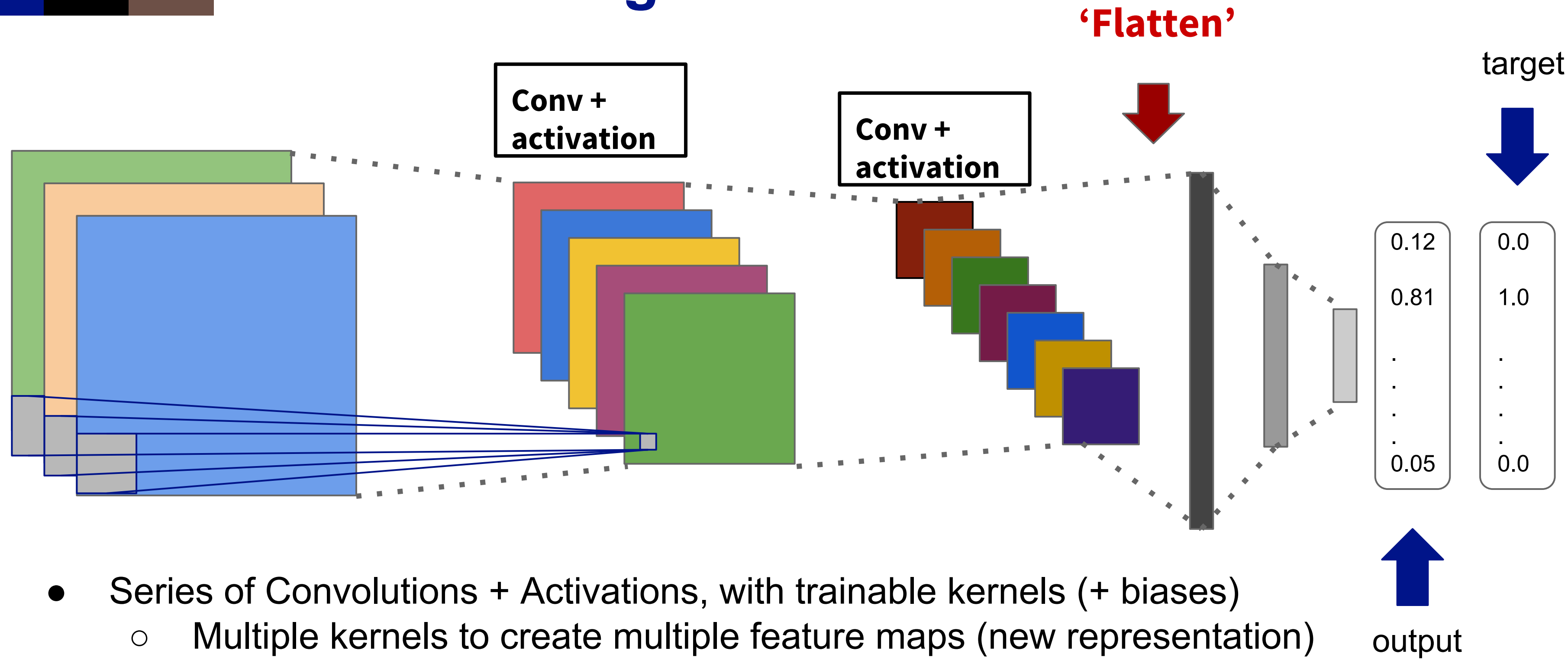
Traditional Machine Learning Flow

Deep Learning Flow

CNNs visualizing and understanding

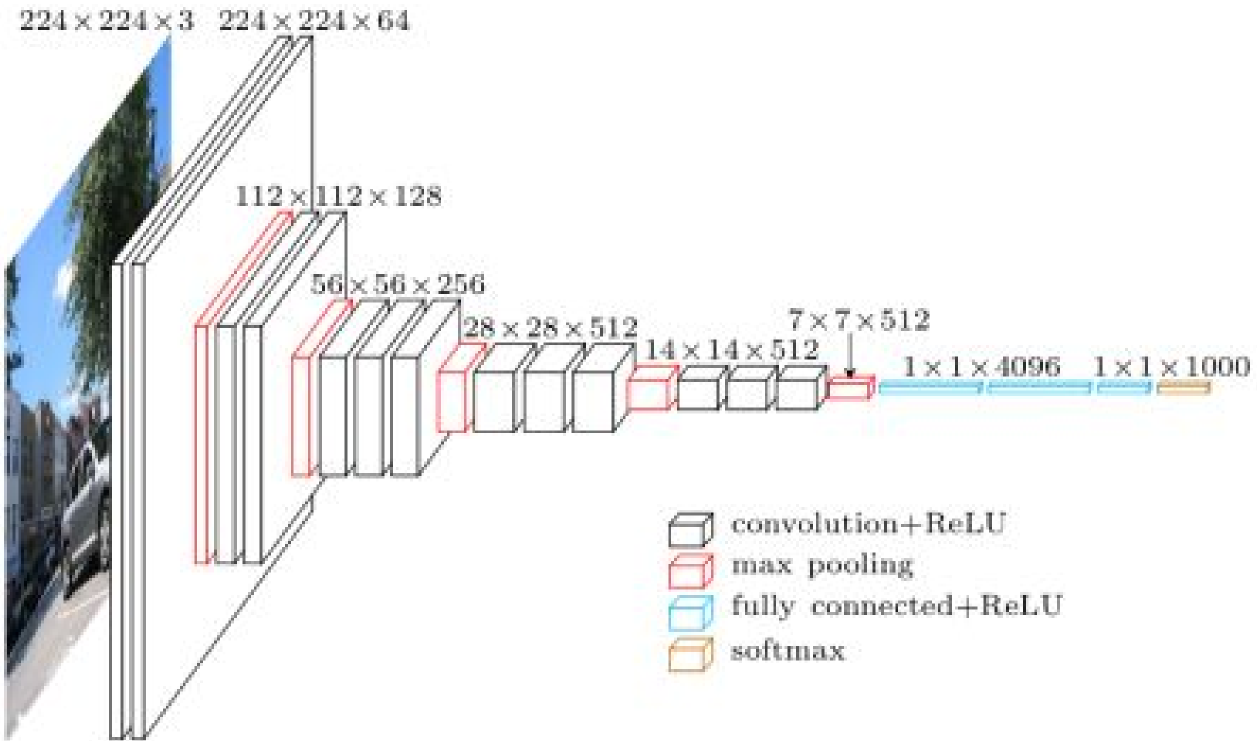
CNNs for Image Classification



- Series of Convolutions + Activations, with trainable kernels (+ biases)
  - Multiple kernels to create multiple feature maps (new representation)
- Pooling operations to reduce the dimensions of the feature maps
- 'Flatten' operation, representation as a vector
- Fully-Connected layers (Multilayer Perceptron)
  - Learned : weight matrix and bias vector
- Training (weight-update) on error
  - Classification : cross entropy

Deep Network : VGG-16

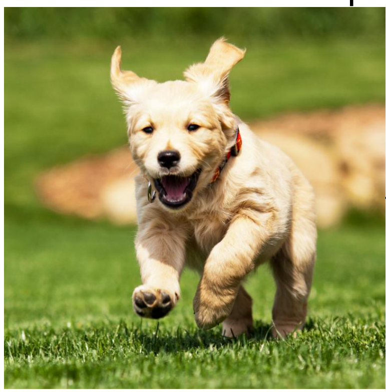
- Simple : no **inception modules** or **residual connections**
- Trained for **image classification** on ImageNet (1000 classes)
- State of the art in 2014 (92.7% top-5 test accuracy)
- 138,357,544 parameters (10% conv weights, 90% FC layers)
- No residual connections, or inception modules : Deep simple model



CNNs visualizing

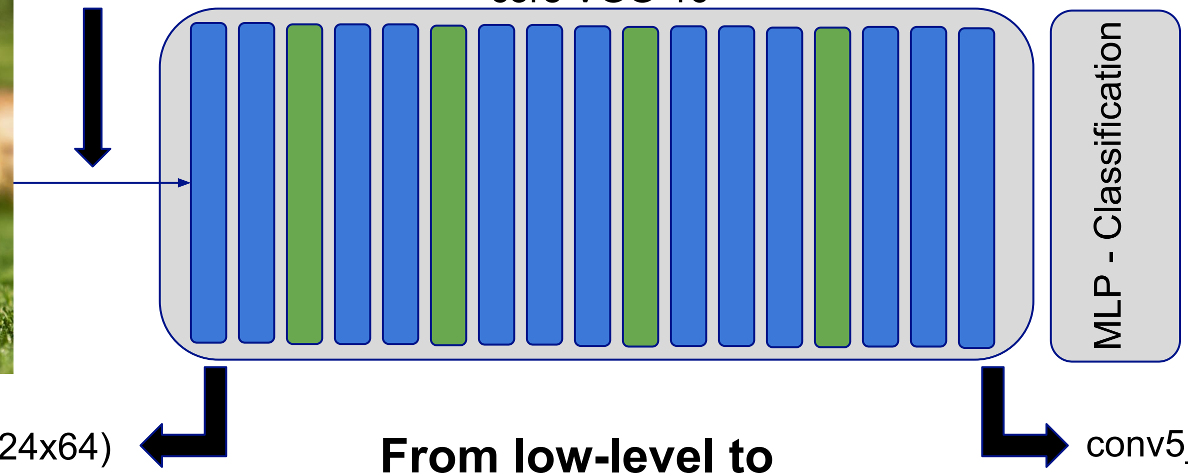
Convolution + ReLU

Pooling



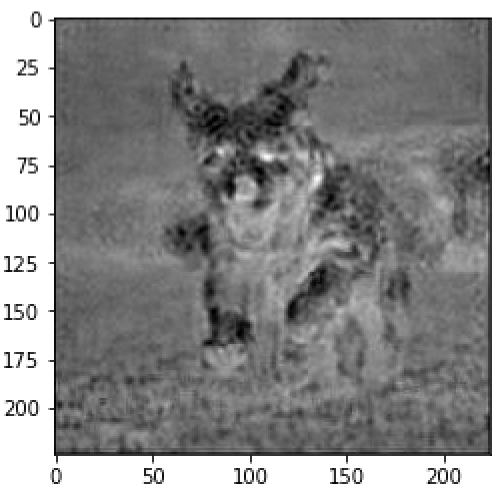
preprocessing

core VGG-16

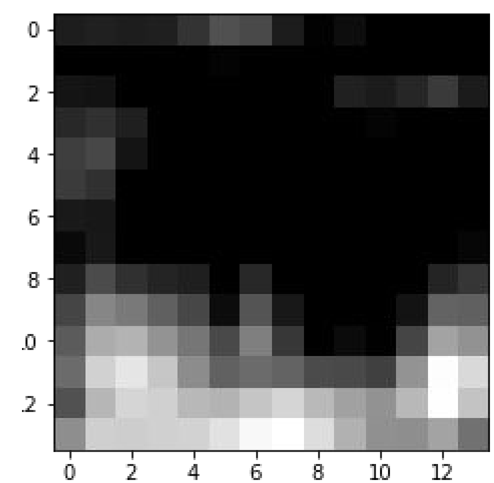


conv1_1 (224x224x64)

conv5_3 (14x14x512)



From low-level to high-level feature spaces

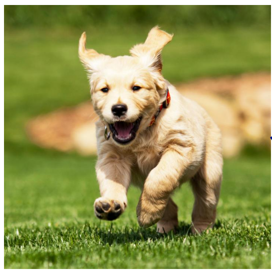


Additional visualization methods :
- Deep Dream approach [2]
  - Optimization-based
- Zeiler & Fergus [3]
  - Transposed convolutions and unpooling operations

Content & style representations

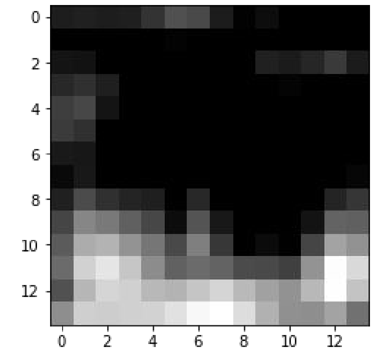
Content Representation/Reconstruction

x_c

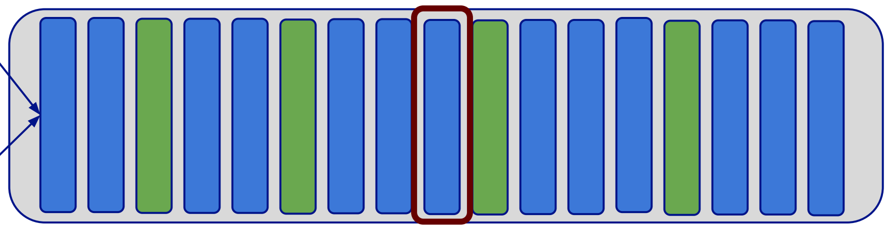


$\Phi_j(x)$ Activations of the *j*th layer

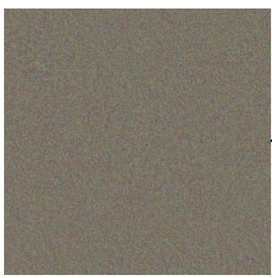
Eg : $\Phi_j(x)[40]$



conv3_3 : 56x56x256



Fixed VGG-16



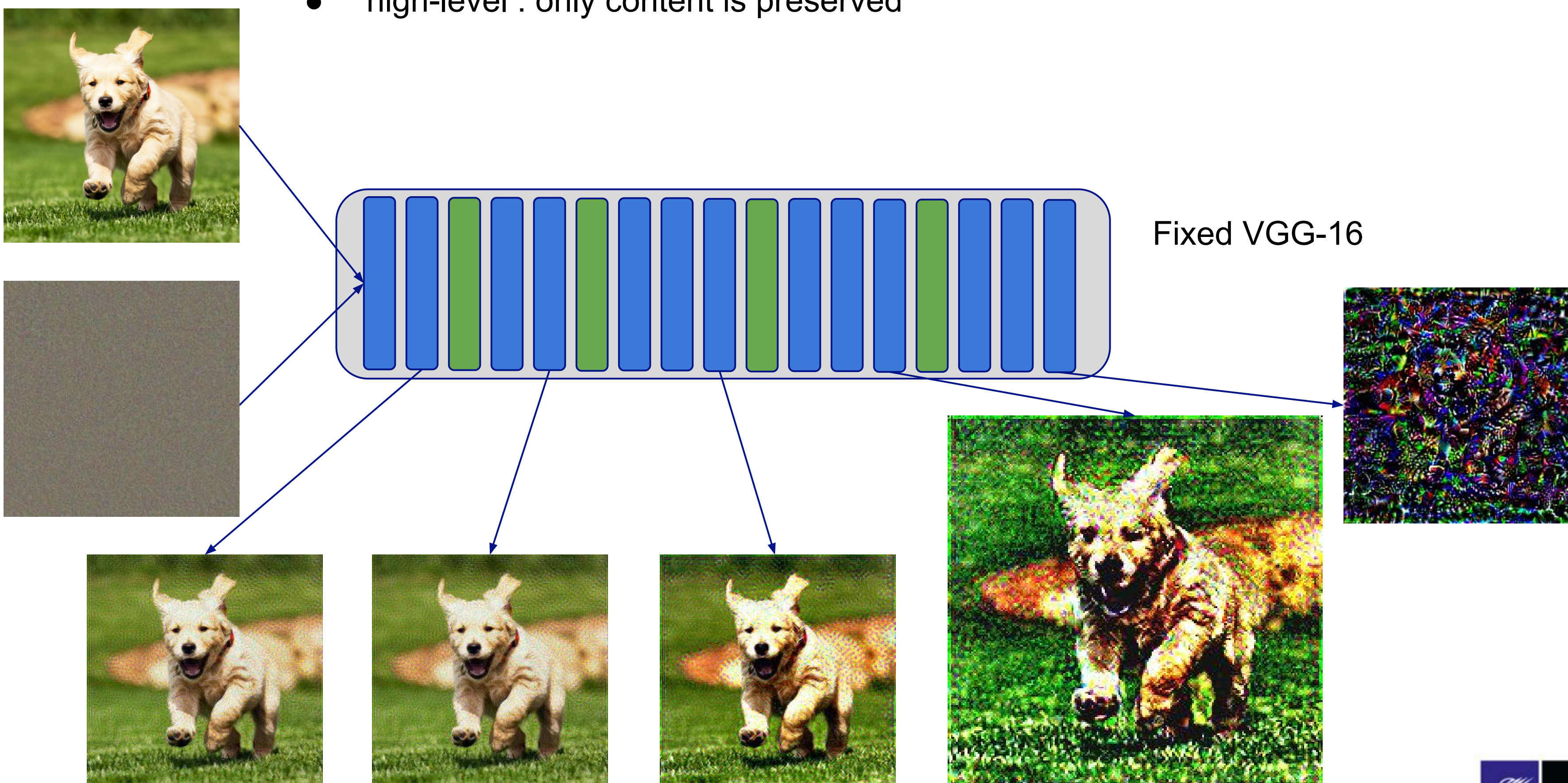
x

$$\hat{x} = \underset{x}{\operatorname{argmin}} \; ||\Phi_j(x) - \Phi_j(x_c)||_2^2$$

- Goal : find an image with the same activations at a given layer (all feature maps)
- Optimization problem, start from a random image

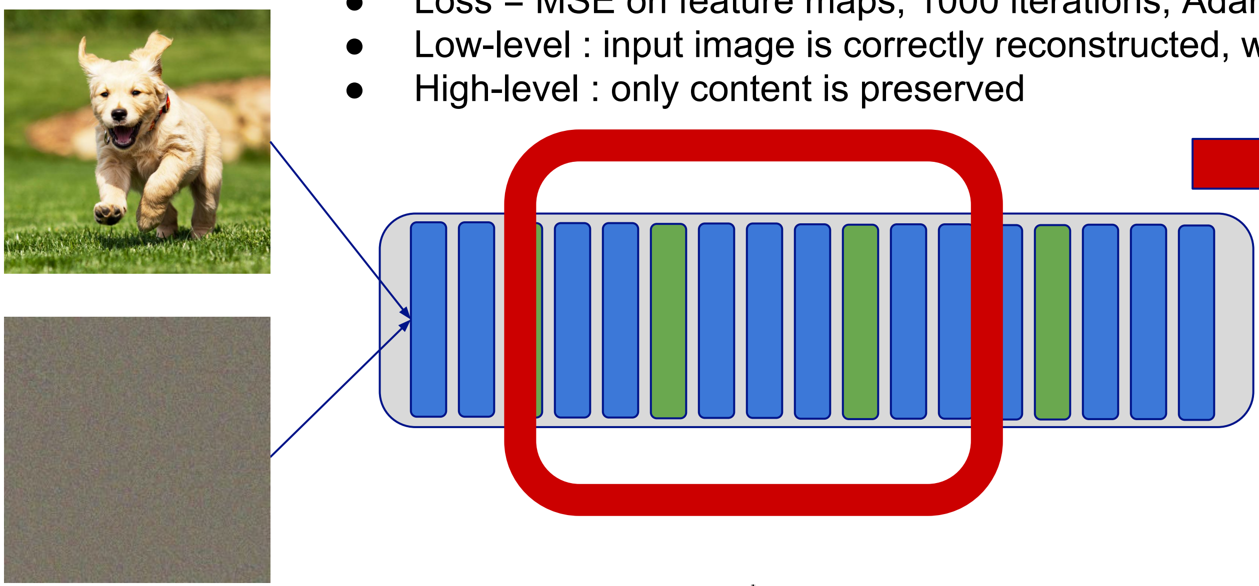
Content Representation/Reconstruction

- gradient descent optimization on input image, network does not change
- loss = MSE on feature maps, 1000 iterations, Adam (lr=2.0)
- low-level : input image is correctly reconstructed, with pixel-level details
- high-level : only content is preserved



Content Representation/Reconstruction

- From a random image, reconstruct the feature maps obtained with a normal image, on a specific layer
- Gradient descent optimization on image input, network does not change
- Loss = MSE on feature maps, 1000 iterations, Adam (lr=2.0)
- Low-level : input image is correctly reconstructed, with pixel-level details
- High-level : only content is preserved



Fixed VGG-16

Content only

$$L_c(x, x_c) = \frac{1}{C_j H_j W_j} ||\phi_j(x_c) - \phi_j(x)||_2^2$$

Style Representation/Reconstruction

- Needs more complex statistics on feature maps : **Gram matrix**
  - Second-order statistics
  - Can capture texture information, no spatial information
- For a given layer j with C_j feature maps of size (W_j, H_j)
- The Gram matrix is a (C_j, C_j) matrix :

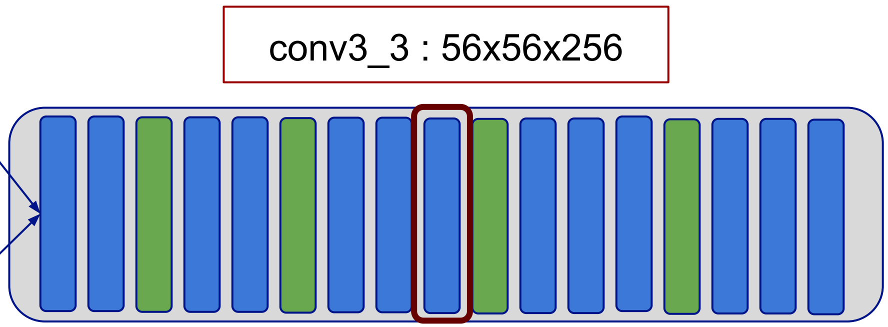
$$G_j(x)_{c_1,c_2} = \mathbb{E}[\ \Phi_j(x)[c_1] * \Phi_j(x)[c_2]\ ]$$

- Where $*$ is an element-wise operation between 2 feature maps (Hadamard product)
- Contains the correlation between every pair of feature maps

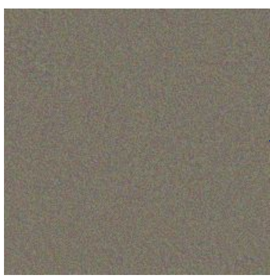
Style Representation/Reconstruction

x_s

$G_j(x)$ Gram matrix of the *j*th layer (256 x 256)



Fixed VGG-16



x

$$\hat{x} = \underset{x}{\mathrm{argmin}} \; ||G_j(x) - G_j(x_s)||_2^2$$

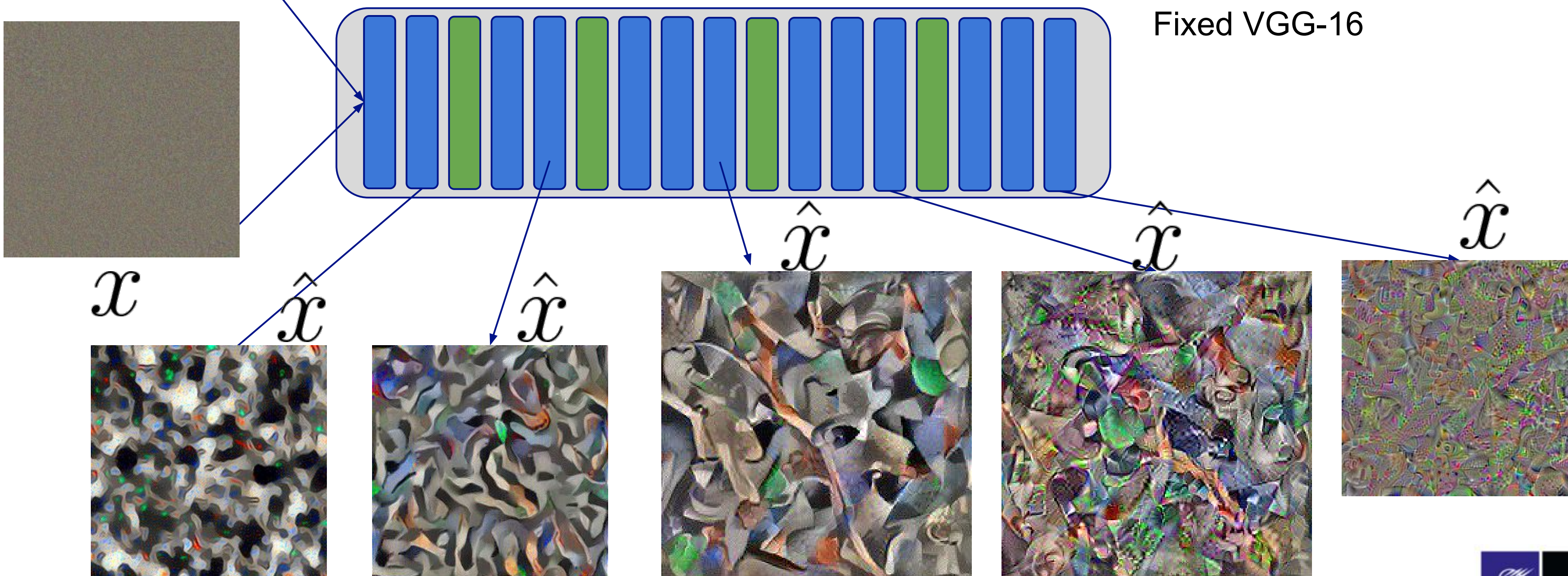
- Goal : To find an image with the same Gram matrix for a given layer
- Optimization problem: Start from a random image

Style Representation/Reconstruction

- Gradient descent optimization on image input, network is freezed
- Loss = MSE on feature maps, 1000 iterations, Adam (lr=2.0)
- Low-level : Small and simple patterns
- High-level : More complex patterns

x_S

$$L_S(x, x_S) = \sum_j \frac{\lambda_j}{C_j^2} ||G_j(x_S) - G_j(x)||_2^2$$



Content & Style Representations

- Content is preserved in high level features
- Style is present in second-order statistics in low and medium levels
- Content and Style are separable
- *content_loss* and a *style_loss* are defined
- Combine style and loss from different images is possible, via feature extraction learned within a VGG network, trained for image classification

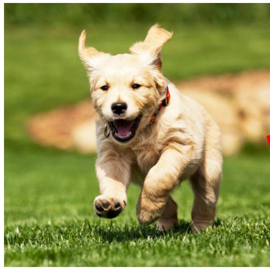
Optimization-based approach for style transfer

Approach proposed by

- Gatys et al [4, 10]
- Ruder et al [5]

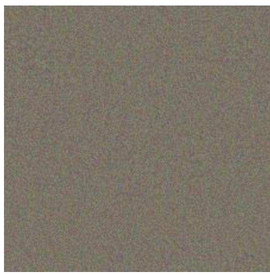
Mix content & style via specific losses

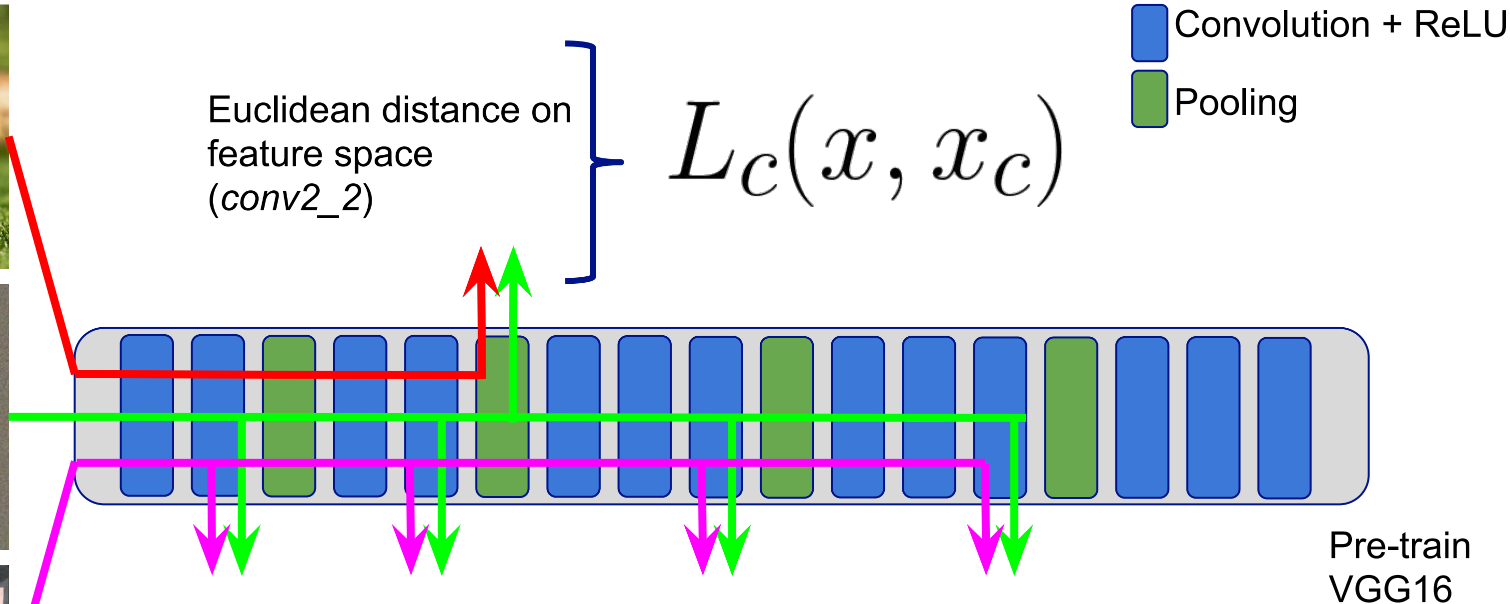
x_c



Euclidean distance on feature space (*conv2_2*) $L_c(x, x_c)$

x





x_s

$L_s(x, x_s)$ Weighted sum over euclidean distances between Gram matrices (*con1_2, con2_2, conv3_3, conv4_3*)

$$L(x, x_s, x_c) = \alpha L_s(x, x_s) + \beta L_c(x, x_c)$$

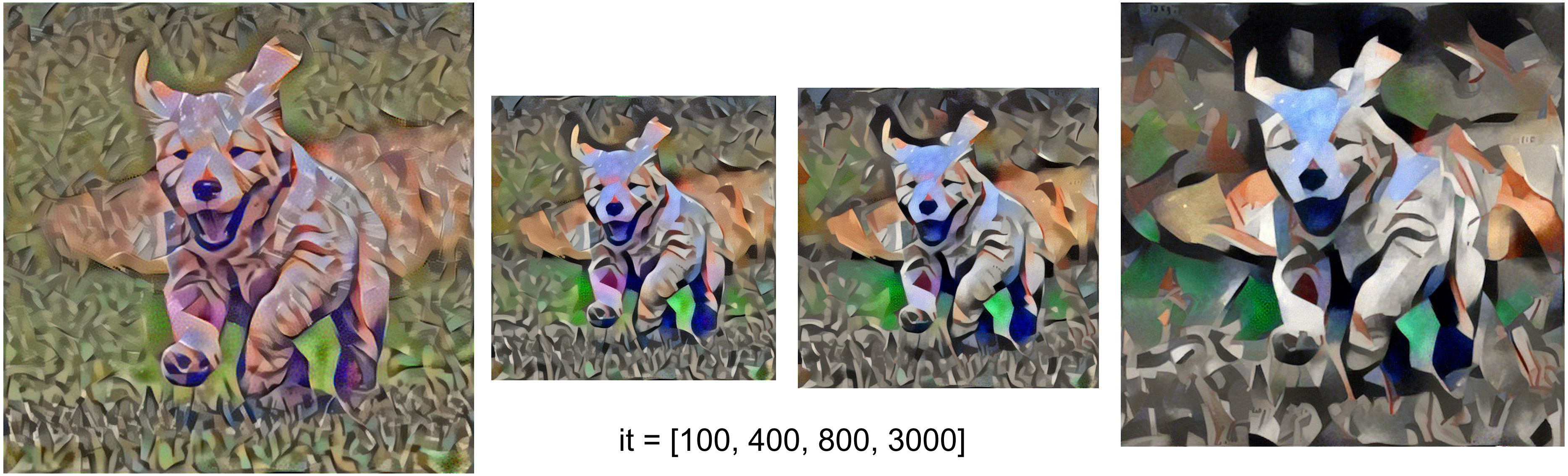
Optimization process

- Compute *content_target* (feature maps) with *content_image*
- Compute *style_target* (Gram matrices) with *style_image*
- Start from a random image (*input_image*)
- Optimization process :
  - Compute *content_loss* and *style_loss* with targets + *input_image*
  - Minimize this loss by modifying *input_image*
  - Possible thanks to gradient-descent method (like Adam)

TensorFlow Implementation

- TensorFlow implementation (version 1.1.0, Python 3.5)
- With TensorBoard annotations (Graph and metrics visualization)
- Jupyter notebooks and Conda/Docker envs
- GitHub: JGuillaumin/style-transfer-workshop

TensorFlow implementation



it = [100, 400, 800, 3000]

Results

- Produce high-quality images
- Easy to tune effects (more content ? more style ?)
- Any input/output size

- Running time (1000 #iter)
  - GPU (GTX 1070) : ~ 5 min (1920 CUDA cores)
  - CPU (i7-7700K) : ~ 150 min (4 cores x 2 threads)

- Avoid any real-time applications
- But perceptual loss (content+style) is defined

Improvements

- Time dependency for video transformation (see [5])
- Change optimizer : L-BFGS !
- Tune weights between style and content loss
- Start from : content image, style image, noisy image, or a mix.
- Color constraint : preserve color from content image ! (see [10])

from : github.com/tensorflow/magenta

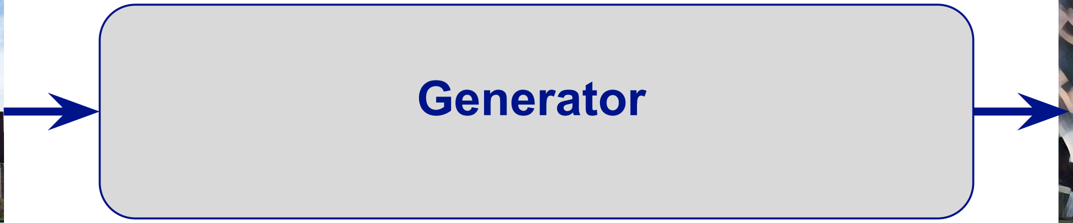
Feed-forward method with learning

Approach proposed by

- Ulyanov et al [6, 7]
- Johnson et al [8]

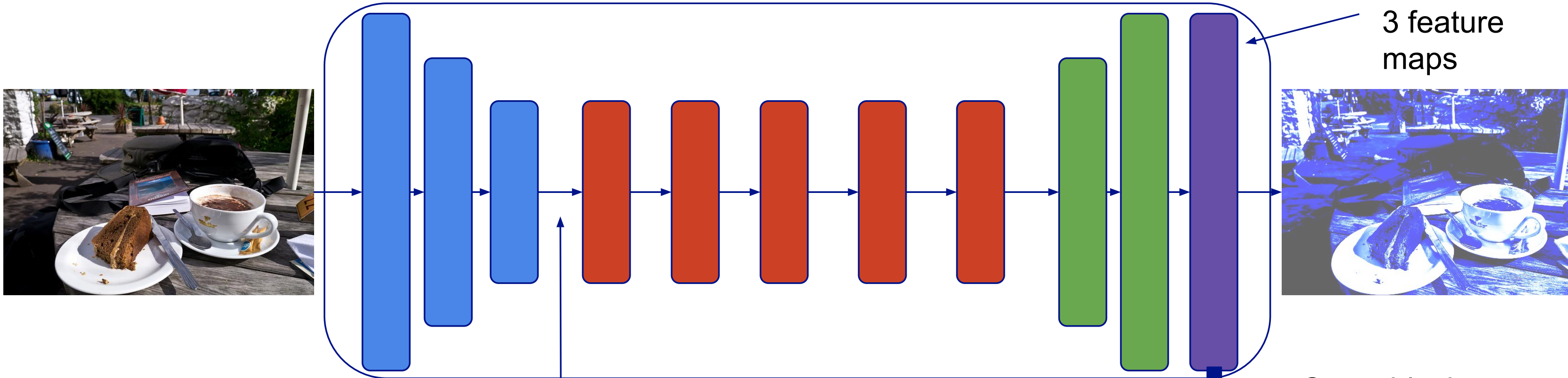
Feed-forward method

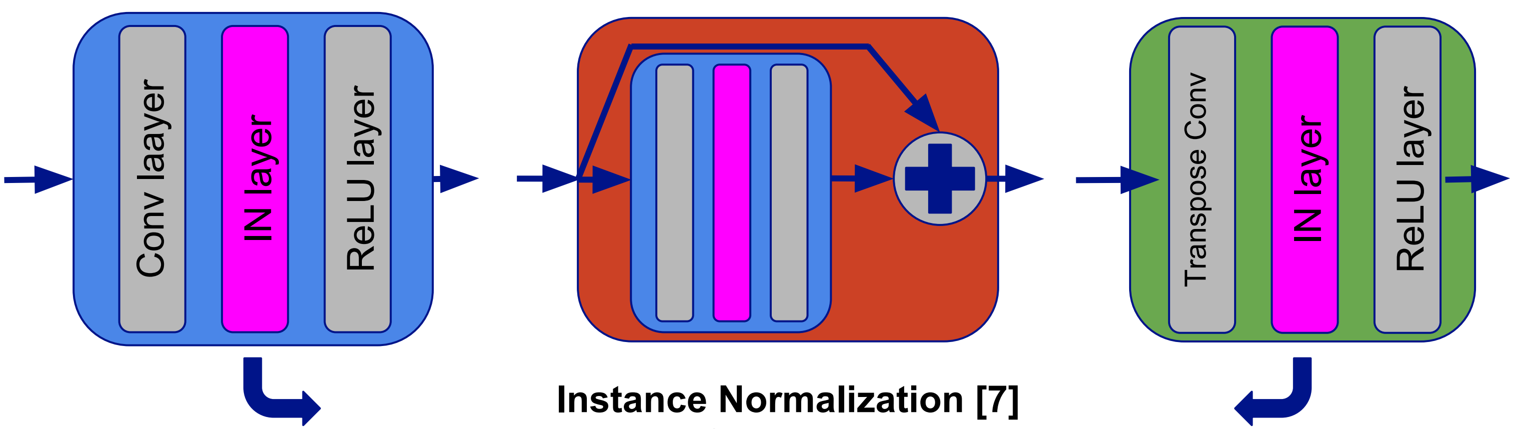
- Train a network to obtain a stylized image in one pass as an output
- Used for one specific style (fixed)



- Trained to add this style
- With a dataset of content images
- Same input/output size

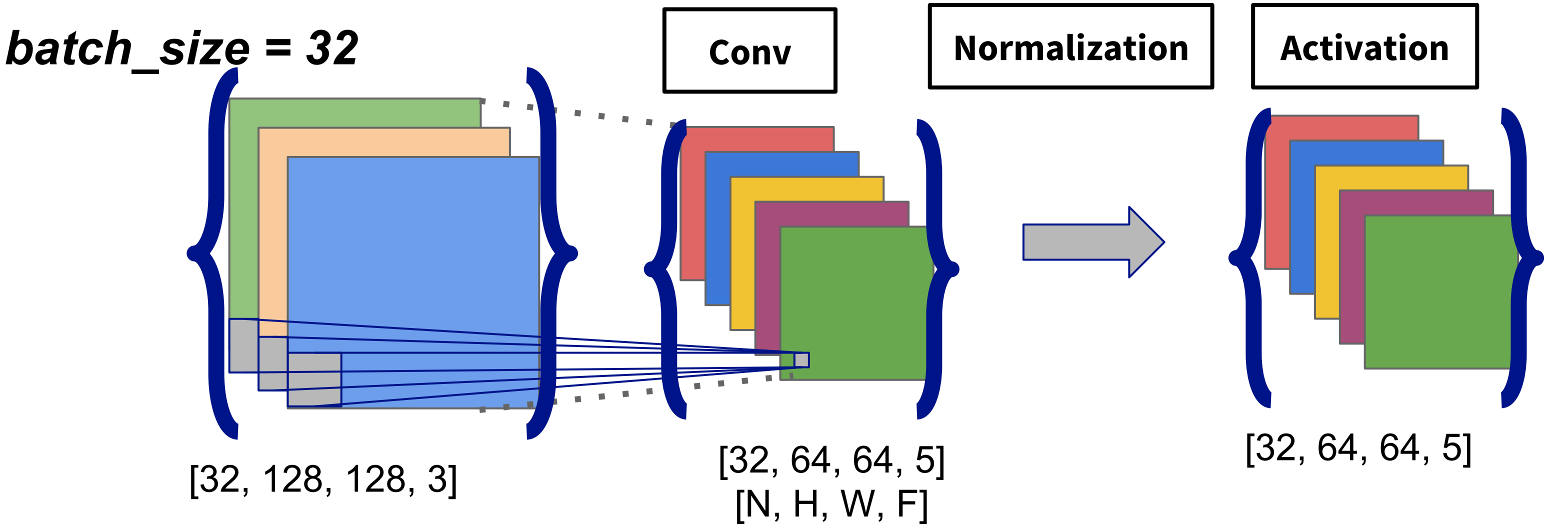
What type of structures for the generator ?





Instance Normalization [7]
Variant of Batch Normalization

Batch Normalization vs. Instance Normalization



$$BN_f(x) = \gamma \frac{x - \mu_f(x)}{\sigma_f(x)} + \beta$$

channel-wise

$$IN_{n,f}(x) = \gamma \frac{x - \mu_{n,f}(x)}{\sigma_{n,f}(x)} + \beta$$

(sample,channel)-wise

How to train a generator ?

$$L_c(x_c, \theta)$$

content image x_c

Generator
θ

$G_\theta(x_c)$

pre-trained VGG-16

style image x_s

$$L_s(x_s, \theta)$$

- Train with batch of content images
- Minimize total loss w.r.t. theta

Need a dataset of content images

- COCO dataset, about 80k images
- Only 1 style image

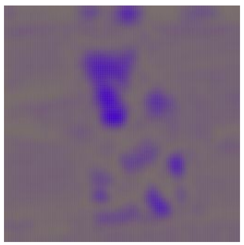
Training process (loop) :
- Take a batch of samples from COCO
- Pass this batch through the generator to get generated images
- Compute *style_loss* between the generated images and the style image
- Compute *content_loss* between the generated images and the original ones
- Minimize the *total_loss* by updating the weights from the generator

Training information :
- Adam optimizer (*lr=0.05*)
- Only 20k iterations (with *batch_size=4*)
- For 512x512x3:
  - Training time (on GTX 1070) : 10 hours
  - Inference time : 330 ms (GTX 1070)

Results and improvements

- With a new content image :

it = 1

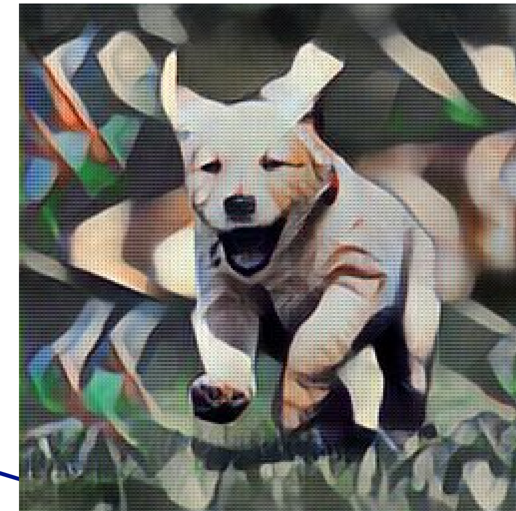


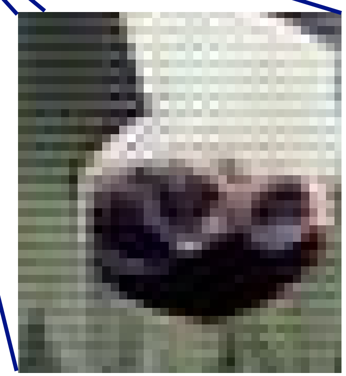
it = 500

it = 2000

it = 12000

it = 20000





- Learn to apply only one style !
- In [9] (ICLR 2017) :
  - Add ‘**Conditional Instance Normalization**’
  - Learn to apply a fixed set of styles (until 64)
  - Can learn quickly a new style (incremental learning)

- Use **resized convolutions** instead of transposed convolutions : Improves quality
- Add **variational loss** to encourage spatial smoothness

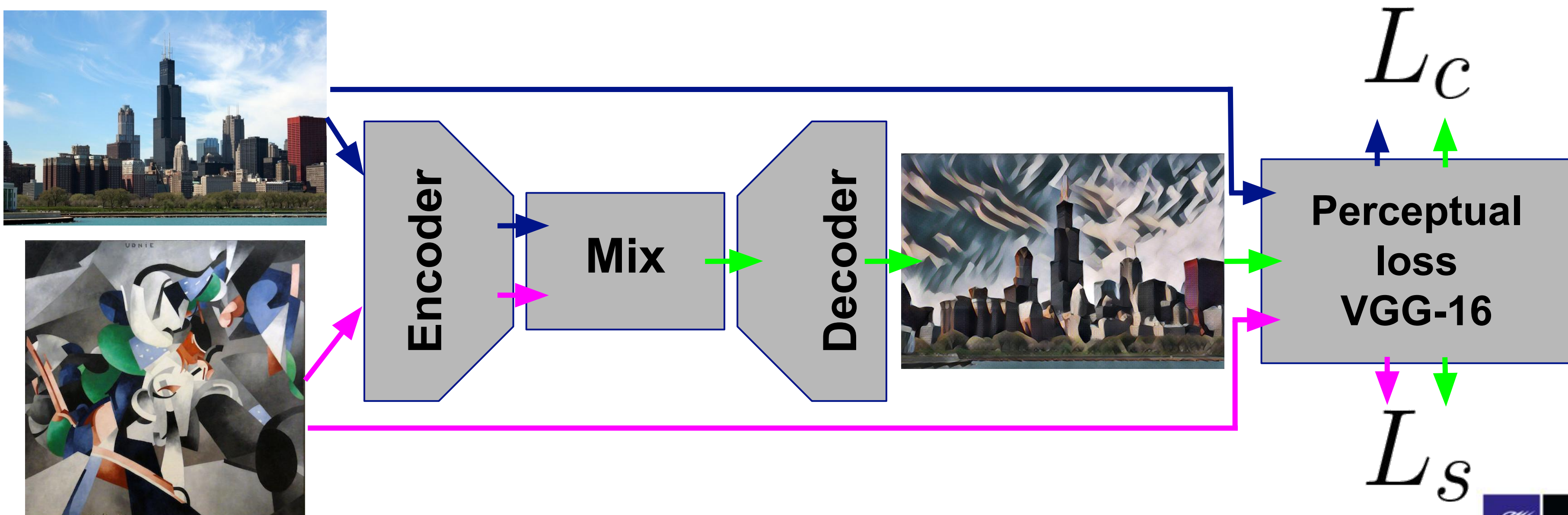
Arbitrary style transfer

Approach proposed by :

- X. Huang, S. Belongie [11] (ICLR 2017)

Mix content & style images within the generator

- **Goal** : train a generator to produce stylized images **from any style** with any content
- **Previous approach** : style is learned in the generator via the *style_loss*
- **New approach : mix content and style images in feature space !**
  - Use **encoder-decoder** structure
  - Mix encoded content and style images
  - Use the **same perceptual loss** (*content_loss* + *style_loss*)
  - Trained on a **content dataset** (COCO) and a **painting dataset** (WikiArt)



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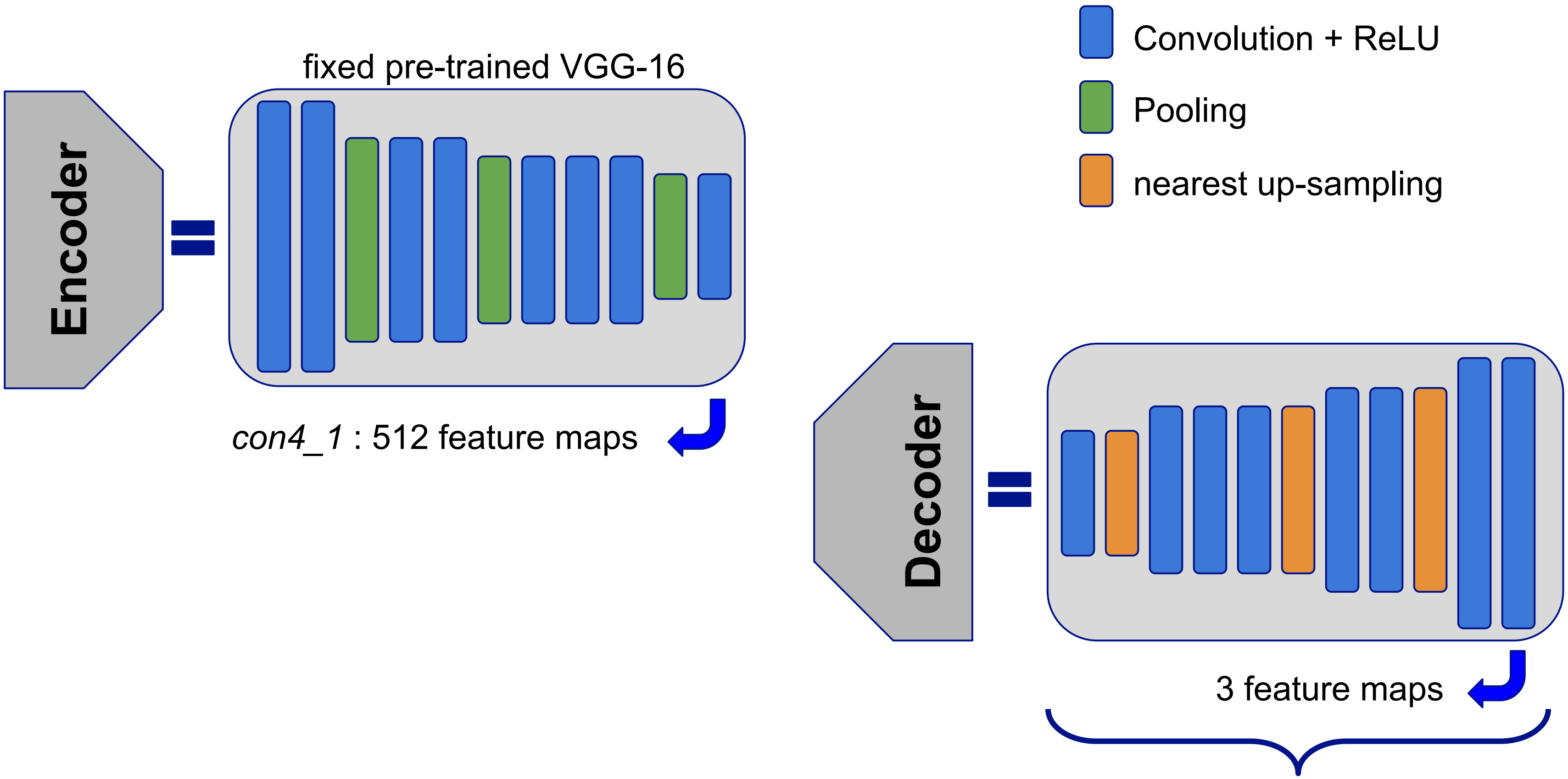
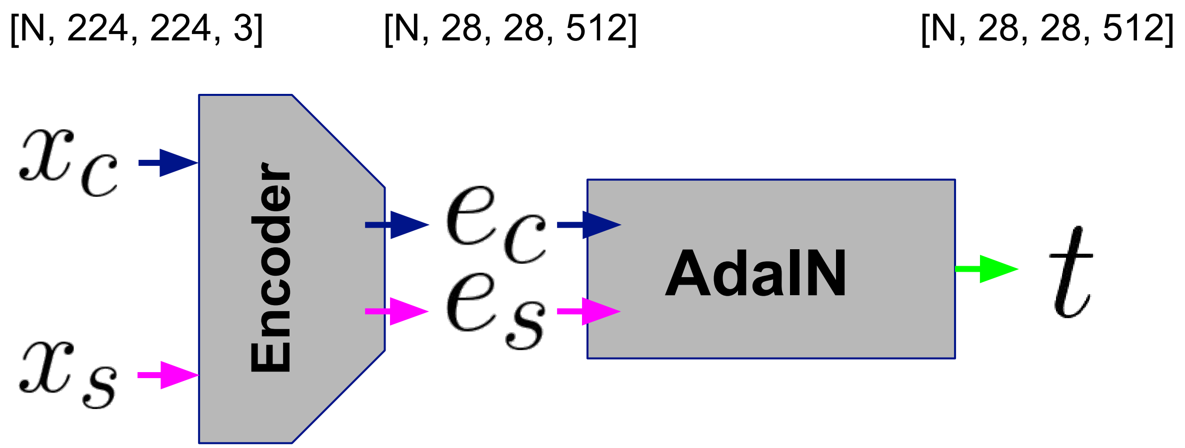
Encoder/Decoder + Adaptive IN



- the decoder mirrors the encoder
- to train !

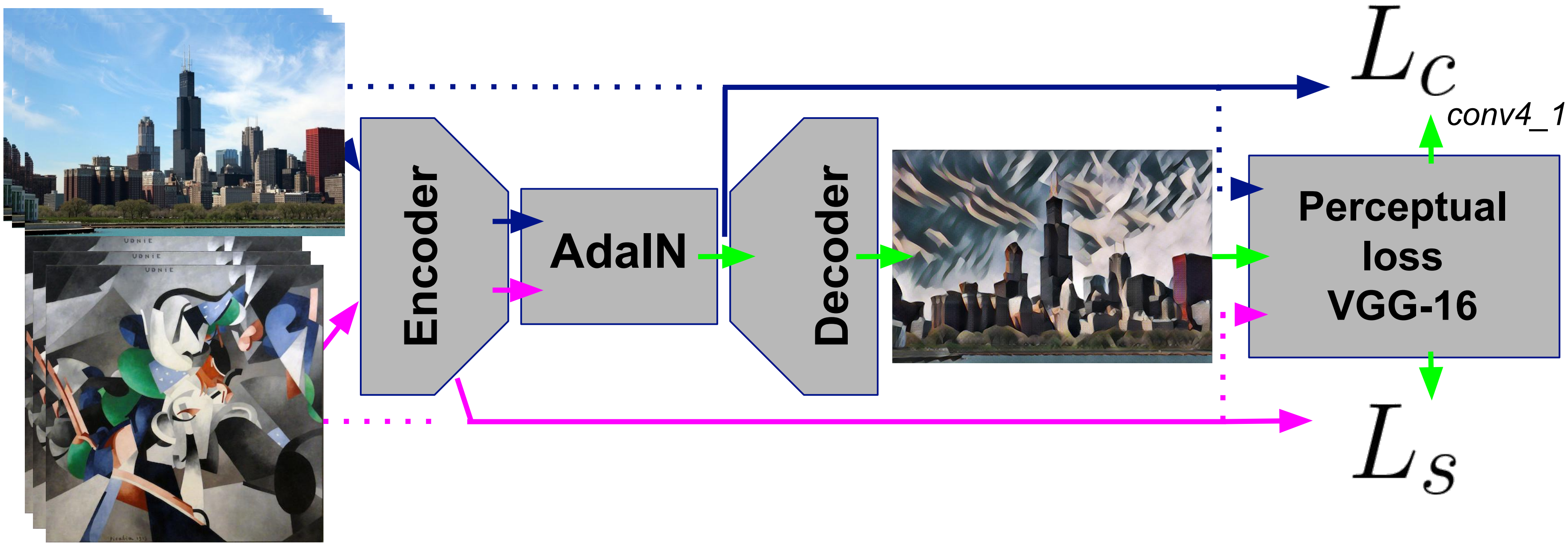
Adaptive Instance Normalization



$$AdaIN_{n,f}(e_c, e_s) = \sigma_{n,f}(e_s)\frac{e_c - \mu_{n,f}(e_c)}{\sigma_{n,f}(e_c)} + \mu_{n,f}(e_s)$$

- per sample (n) and per channel (f) statistics alignment
- producing the target feature maps

How to train the decoder ?



- trained with batches of content-styles image pairs
- different contents and styles within the same batch !
- 80k content images (MS COCO) + 80k paintings (WikiArt.org)

Results

- Training time : about 24 hours (GTX 1070, 200k iterations)

- Decoder-AdaIN-decoder can apply any new style !
- High-quality images (similar to optimization-based approach)
- Inference time : ~ 450ms (256x256)

$\alpha = 0$ $\alpha = 0.25$ $\alpha = 0.5$ $\alpha = 0.75$ $\alpha = 1$ Style

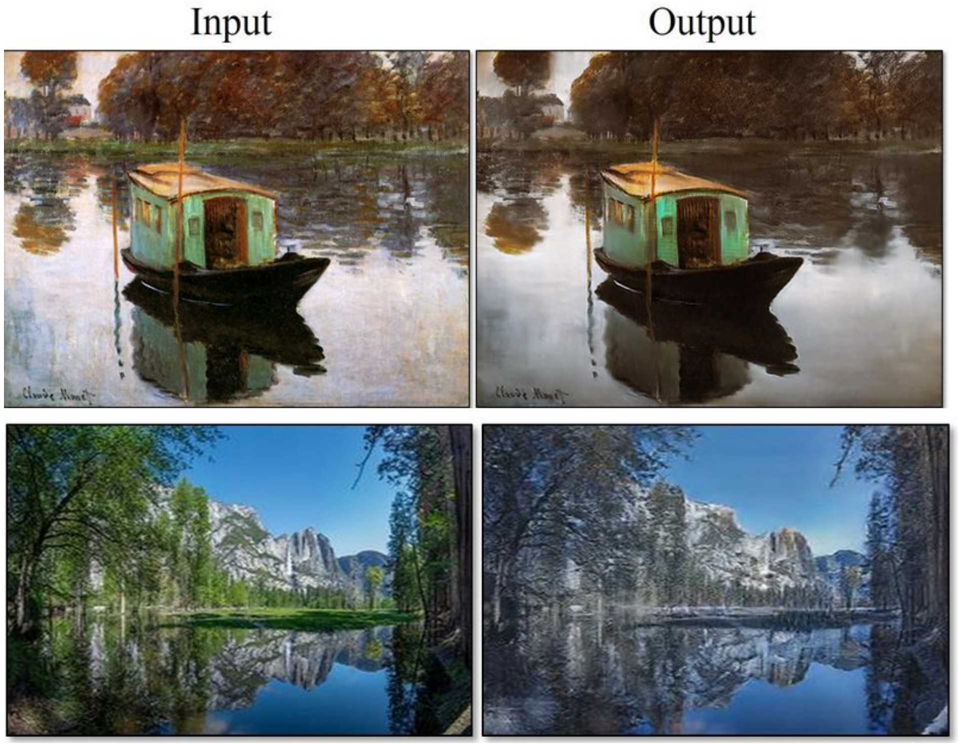
from github.com/xunhuang1995/AdaIN-style

Conclusion - Style Transfer

	Content	Style	Production	Training
Gatys et al (2015)	1	1	~ 5 min	X
Johnson Ulyanov (2016)	infinite	fixed number, until 64	~ 300ms	~ 4 hours
X Huang (2017)	infinite	infinite	~ 450 ms	~ days

Conclusion

- Resolve complex task by working on feature spaces
- Introduction to more complex tasks
  - Colorisation
  - Super-resolution
  - Inverse style transfer
  - Season transfer
  - Color transfer



from github.com/junyanz/CycleGAN

Online resources

github.com/JGuillaumin/style-transfer-workshop

- Several Jupyter notebooks
- All methods presented here and more
- Implementation with TensorFlow 1.1, Python 3.5
- With TensorBoard annotations
- Conda env and Dockerfiles (CPU and GPU)

Online in few days

Thank you

?

Resources

[1] : K. Simonyan, A. Zisserman : “Very Deep Convolutional Networks for Large-Scale Image Recognition”, 2014, arXiv:1409.1556

[2] : About Deep Dream visualization technique : “Inceptionism: Going Deeper into Neural Networks”

[3] : M. Zeiler, R. Fergus: Visualizing and Understanding Convolutional Networks, 2013 arXiv:1311.2901

[4] : L. Gatys, A. Ecker, M. Bethge : A neural algorithm of artistic style, 2015, arXiv:1508.06576

[5] : M. Ruder, A. Dosovitskiy, T. Brox : Artistic style transfer for video, 2016, arXiv:1604.08610

[6] : D. Ulyanov et al : Texture Networks: Feed-forward Synthesis of Textures and Stylized Images, 2016, arXiv:1603.03417

[7] : D. Ulyanov et al : Instance Normalization: The Missing Ingredient for Fast Stylization, 2016, arXiv:1607.08022

[8] : J. Johnson et al : Perceptual losses for real-time style transfer and super-resolution, 2016, arXiv:1603.08155

[9] : V. Dumoulin et al : A learned representation for artistic style, 2017, arXiv:1610.07629

[10] : Gatys et al : Preserving color in Neural Artistic Style Transfer, 2016, arXiv:1606.05897

[11] X. Huang and S. Belongie : Arbitrary Style Transfer in real-time with AdaIN, 2017, arXiv:1703.06868