# Texture Networks: Feed-forward Synthesis of Textures and Stylized Images

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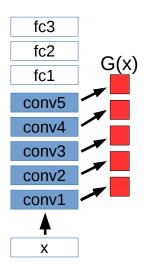
#### Structure

	Texture generation	Stylization
Optimization (Gatys et al.)	1	2
Feedforward (Ulyanov et al.)	3	4

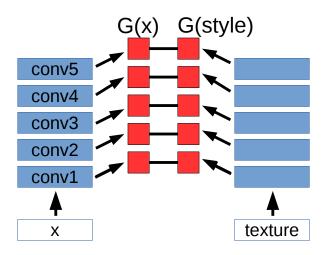
And more!



## **Texture Synthesis**



- Input image x is fed to VGG19
- Activation maps  $F_i^{(l)}$  contain full description of the image
- Gram matirices  $G_{ij}^{(l)} = (F_i^{(l)}, F_j^{(l)})$  describe texture, spatial information is lost



Distance from image x to a fixed texture sample is defined by

$$L_{\text{texture}}(\textbf{\textit{x}}) = \sum_{\textit{\textit{I}} \in \textit{\textit{L}}_\textit{\textit{I}}} \| \textbf{\textit{G}}_{\textit{\textit{ij}}}^{\textit{\textit{(I)}}}(\textbf{\textit{x}}) - \textbf{\textit{G}}_{\textit{\textit{ij}}}^{\textit{\textit{(I)}}}(\text{texture}) \|_{\textit{\textit{F}}}^2$$

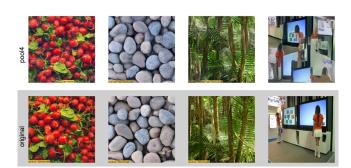
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#### **Texture Generation**

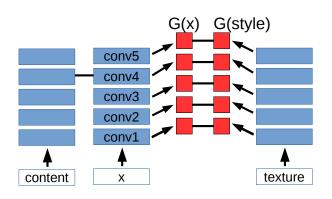
• Constuct texture  $x_0$  by minimization

$$x_0 = \operatorname{argmin} L(x)$$

- L-BFGS, several hundreds iterations
- pixels of  $x_0$  are initialized with noise  $N(0, \sigma)$

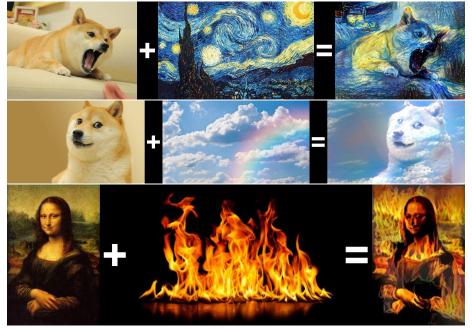


## Image Stylization

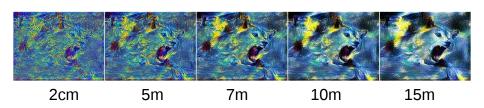


$$L_{\text{content}}(\mathbf{X}) = \sum_{l \in L_c} \|\mathbf{F}^{(l)}(\mathbf{X}) - \mathbf{F}^{(l)}(\text{content})\|_F^2$$

$$L(\mathbf{x}) = \alpha L_{\text{texture}}(\mathbf{x}) + \beta L_{\text{content}}(\mathbf{x})$$

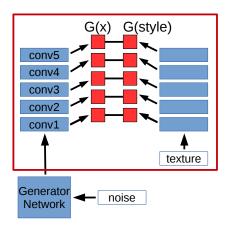


## **Timing**



- Single image takes several minutes on GPU and hours on CPU
- We can make it faster, both for texture generation and image stylization tasks

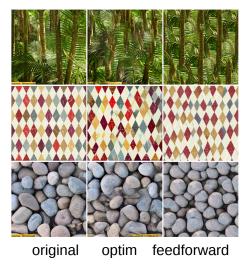
#### **Feedforward Texture Generation**



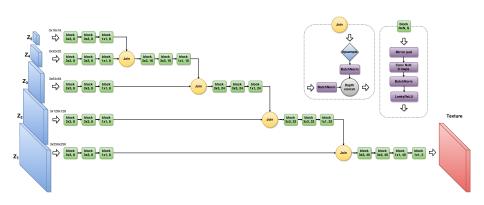
- Train generator network with loss L
- After that, produce images in single pass instead of hundreds iterations

#### **Generated Textures**

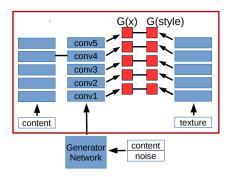
Quality is similar to images obtained by otimization



#### **Generator Network**

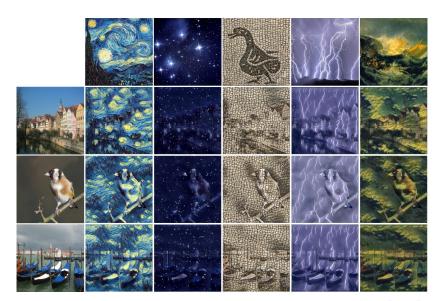


## Feedforward Image Stylization



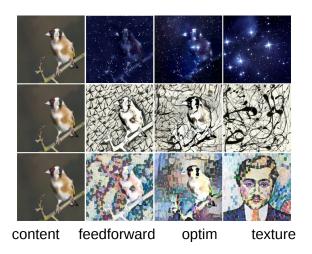
- Similar to texture generation
- + content loss
- Generator recieves noise and content image as inputs

## **Stylization Examples**



## **Stylization Examples**

Feedforward generation results are mostly inferior to optimization results



## Edge effects













- Generator will cheat the loss if it is possible
- Padding with zeros allows generator to infer position of a given pixel and produce fixed patterns
- We use circular padding to overcome this problem

### Do we need pretrained weights?

- Gatys et al. say yes
- Contradicting results were published
- If pretrained weights are not needed, we can apply same methods to other domains, such as sound and speech

#### Code

- Optimizational image stylization is avaliable for every deep learning library, but Torch implementation is the most popular:
  - https://github.com/jcjohnson/neural-style
- Our Torch implementation of feed-forward method: https://github.com/DmitryUlyanov/texture\_nets
  Tensorflow is also available, lasagne is coming soon
- Check out our demo for feedforward neural doodling: http://likemo.net/

#### Conclusion

- We have presented a new approach for for texture synthesis and image stylization in a feed-forward way
- Complex loss function is used. It involves deep nets assessing the performance of the feed-forward generator
- Two orders of magnitude faster compared to optimisation approach by Gatys et al.
- Comparable quality for texture generation, slightly worse for image stylization
- Future work: better generation architectures, video, sound?