

## A Neural Algorithm of Artistic Style

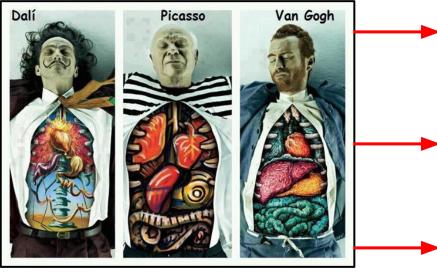
Leon A. Gatys et. al



Presented by Jackie Chu

## **The Question**

Can we apply <u>any</u> style to <u>any</u> content?



MASP Art School campaign done by DDB Brazil

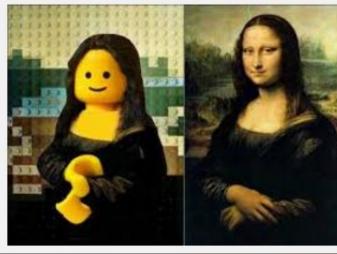


Google search on "images"

#### **"Previous Work"**



Print by James Hance





http://www.artfido.com/blog/artist-photoshops-her-fatcat-into-famous-artworks/

http://thirddime.com/blog/10\_awesome\_lego\_versions\_of\_famous\_paintings/

## **Previous Work: Learning Styles**



"We also show that style is highly content-dependent."

## Contributions

• Learn best pairing between **content** and **style** 



#### **Contributions: Visual Results**



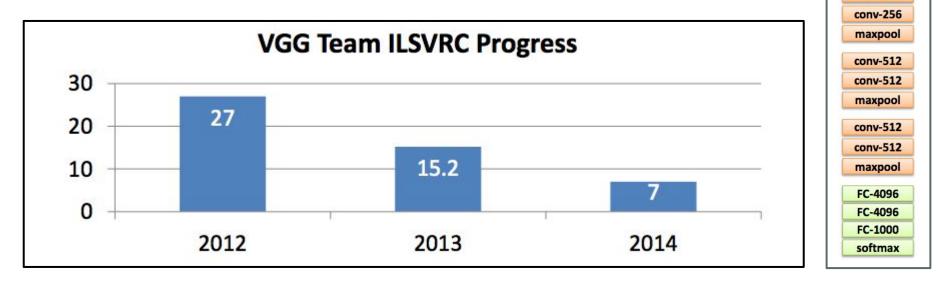
https://www.youtube.com/watch?v=g9BxlwIQWIc

https://youtu.be/cB84sgqlkR4?t=27

- Leverage CNNs
  - Trained for object recognition
- Jointly learn content and style
  - Texture synthesis captures style
  - Separate representations of content and style
  - Recombinations of content and style based on loss functions

Very Deep ConvNets (VGG)

• Key factors: small kernels, stride of 1, ReLU, deeper depths

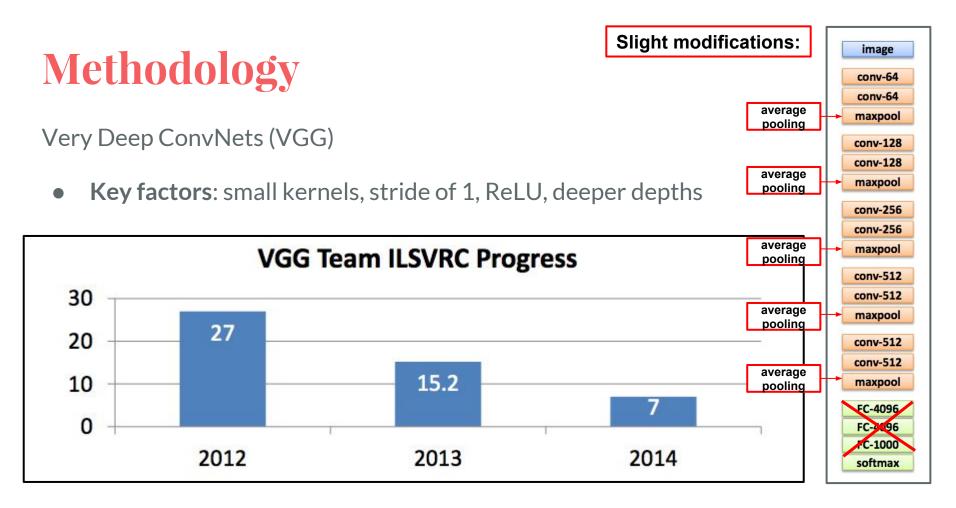


image

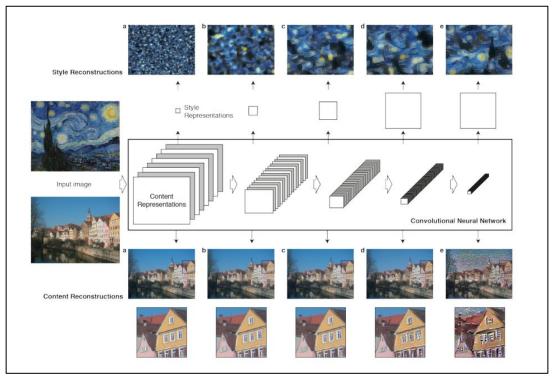
conv-64 conv-64 maxpool

conv-128 conv-128 maxpool

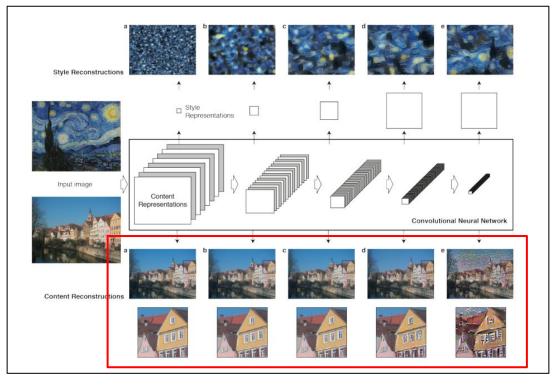
conv-256

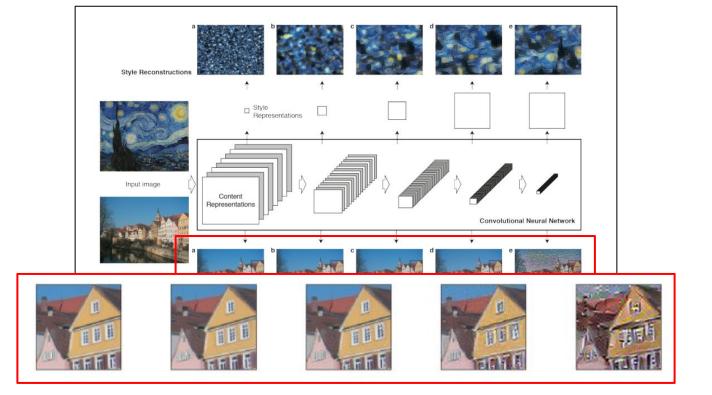


- More flexibility!
- Content and style trained separately (for the most part)
  - $\circ$  Cannot have perfect synthesis  $\rightarrow$  loss functions with its parameters



Gatys, Leon, et al. "A Neural Algorithm of Artistic Style." arXiv (2015).





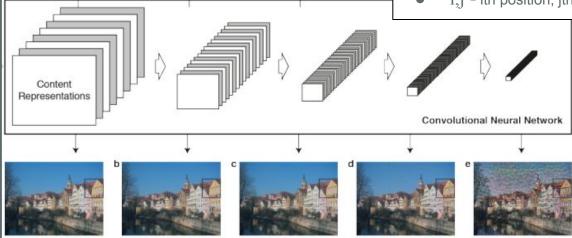
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## **Loss Function: Content**

*p* - original image

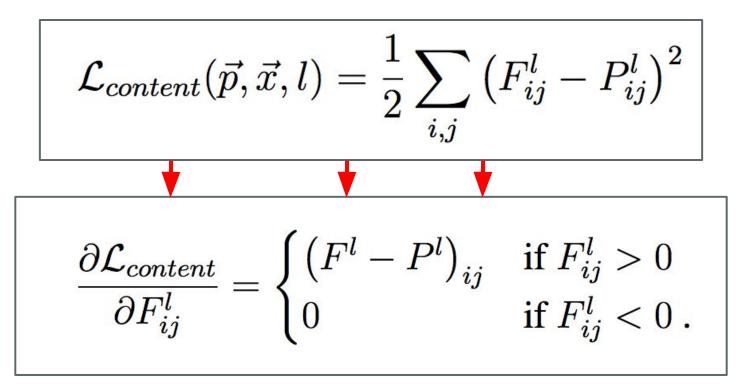
- x generated image
  - F responses stored in matrix
- P feature representation of original image
- i,j ith position, jth filter

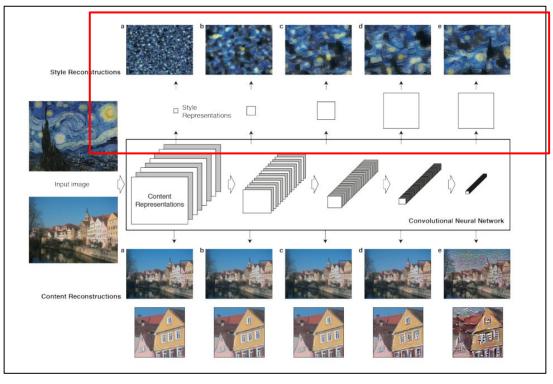




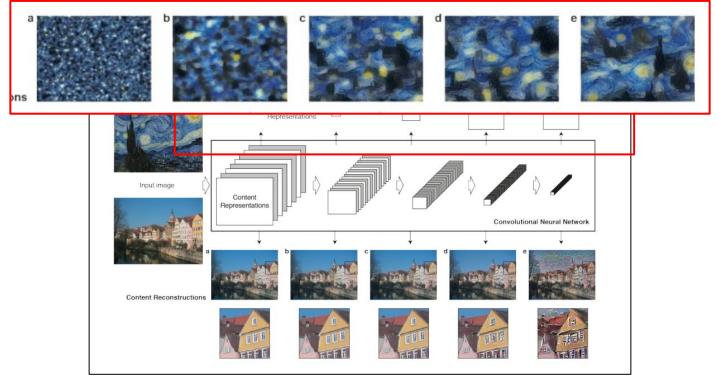
$$\mathcal{L}_{content}(\vec{p}, \vec{x}, l) = \frac{1}{2} \sum_{i,j} \left( F_{ij}^l - P_{ij}^l \right)^2$$

#### **Loss Function: Content**





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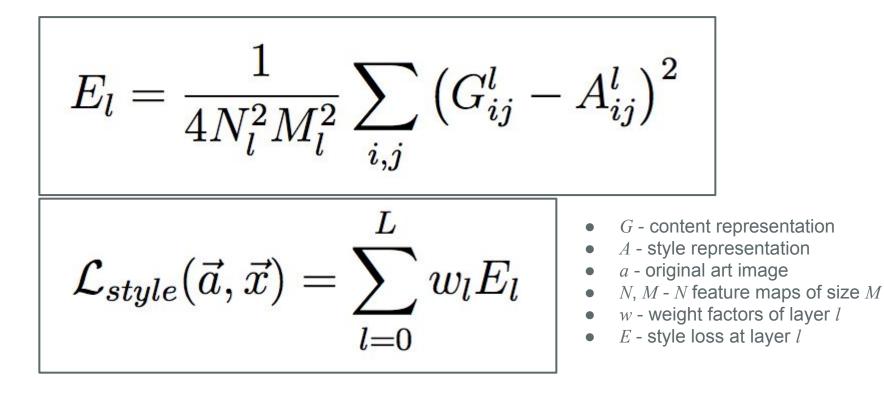


# **Methodology: Texture Synthesis**

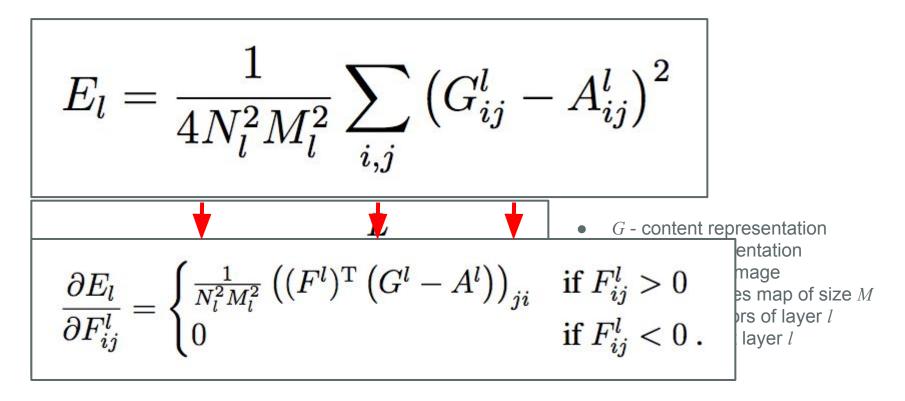
- As previously seen:
  - Create textures from feature representations
  - Discriminative
  - Captures salient features
  - Also uses VGG architecture



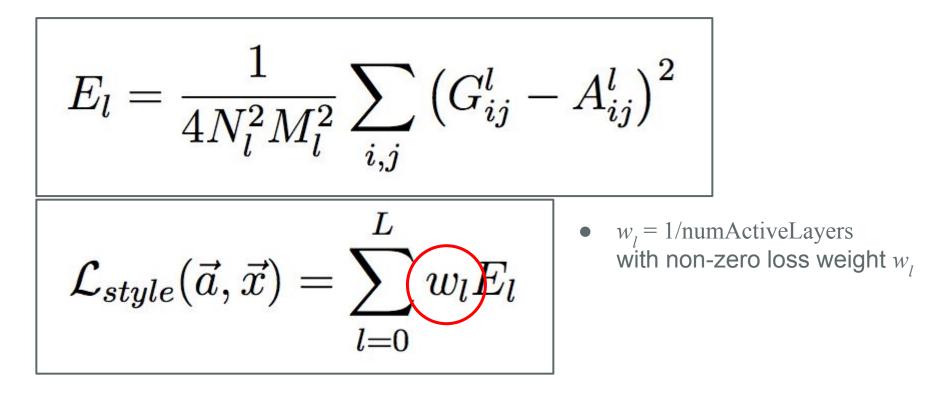
## **Loss Function: Style**



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## **Loss Function: Style**



#### **Loss Function: All together**

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

•  $\alpha$  and  $\beta$  are parameters to control regularization

#### **Loss Function: All together**

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

- $\alpha$  and  $\beta$  are parameters to control regularization
- alpha / beta



#### **Content/Style Representations**

10<sup>-5</sup>

10<sup>-2</sup>



Conv1\_1

Conv5\_1

Gatys, Leon, et al. "A Neural Algorithm of Artistic Style." arXiv (2015).

#### **Content/Style Representations**



#### • Content represented in lower layers

#### **Content/Style Representations**



10<sup>-5</sup>

10-2

Style represented in feature space
 o local arrangements, textural information

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## Conclusions

 Learn best pairing between content and style

 (Mostly) separable

