2018.12.15

Image Style Transfer with CNN

Image Style Transfer Using Convolutional Neural Networks

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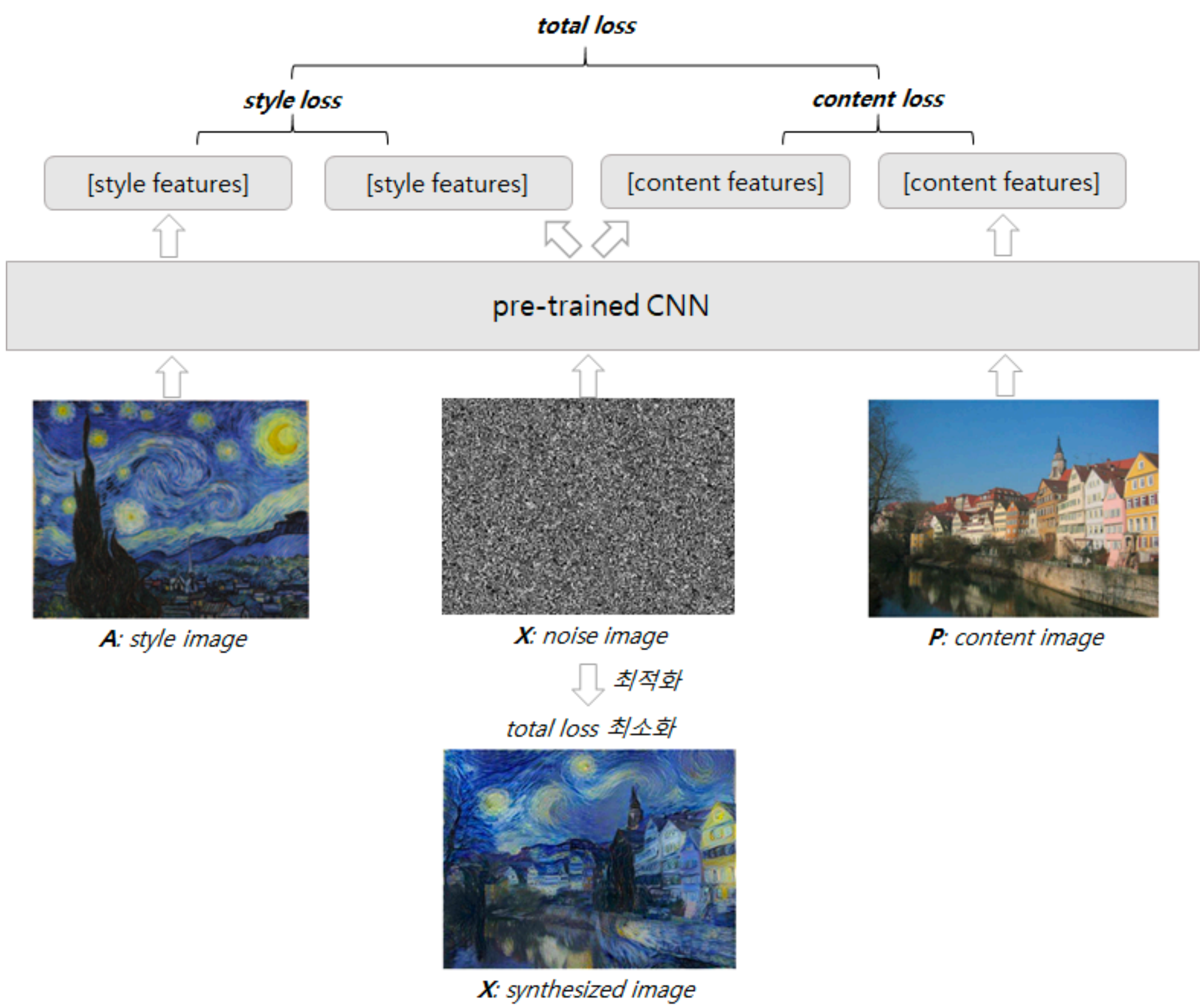
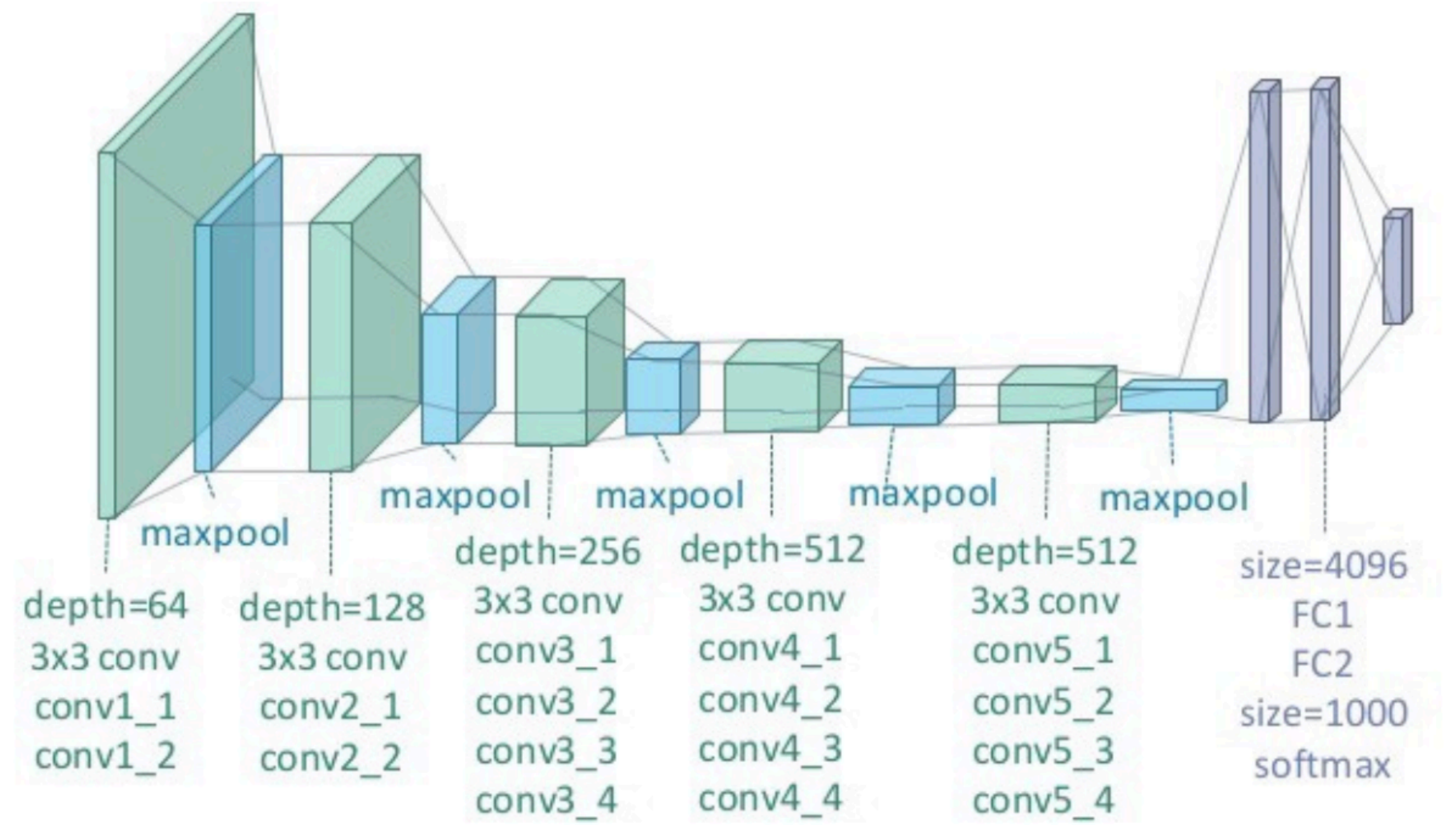
***P**: content image*   ***A**: style image*   ***X**: synthesized image*

$$
\begin{aligned}
loss \;=\;& distance(style(reference) - style(new)) + \\
& distance(content(original) - content(new))
\end{aligned}
$$



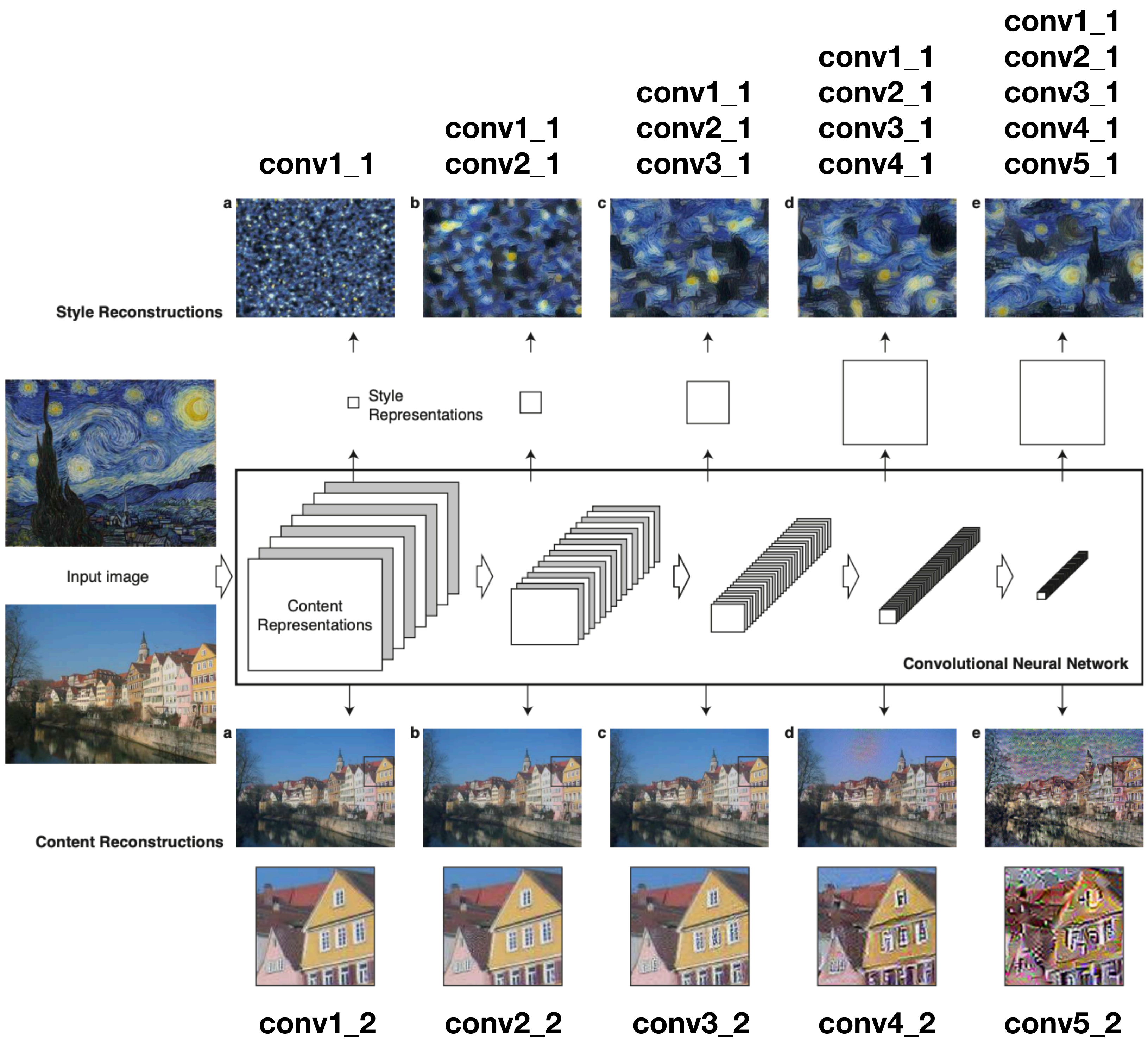
https://www.popit.kr/neural-style-transfer-%EB%94%B0%EB%9D%BC%ED%95%98%EA%B8%B0/

모델: VGG19

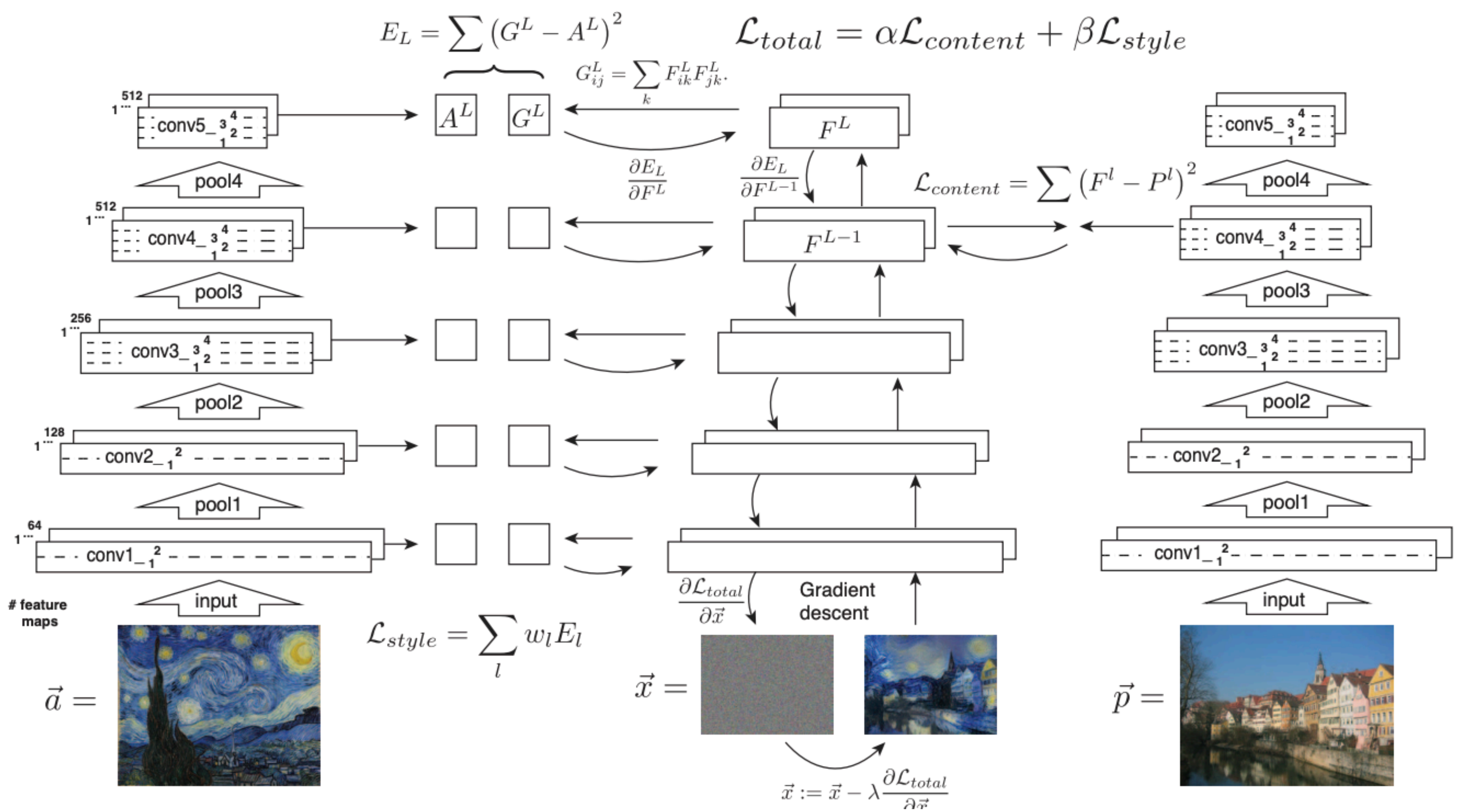


https://www.slideshare.net/ckmarkohchang/applied-deep-learning-1103-convolutional-neural-networks

두 가지 방법의 Reconstruction



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



Deep image representation

Content

High-level layer의 feature map 사용
→ 이미지의 **전역적인 특성**을 보유
→ **Content 복원**에 필수적인 요소들만 가져옴

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

Style

Style(Texture)은 공간적인 정보와 **무관**해야 함
→ 각 layer의 **feature map 사이의 상관관계**

Gram matrix → correlation을 얻어냄

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

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

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

Style Transfer

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

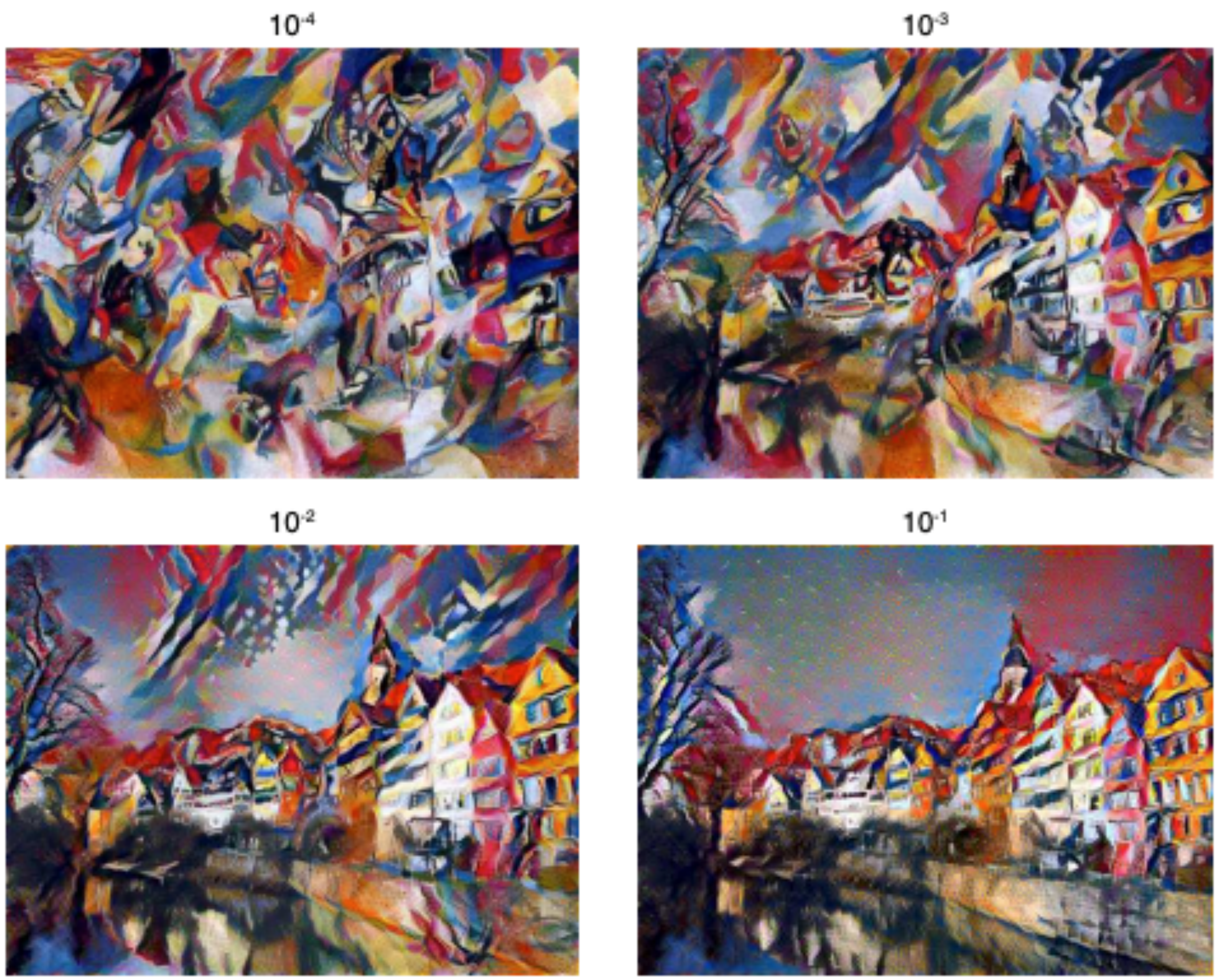
gradient descent
with **L-BFGS**

Limited-memory-**B**royden–**F**letcher–**G**oldfarb–**S**hanno algorithm

최적화하려는 영역을 **2차 함수**로 가정
2차 도함수 대신에 Hessian 행렬 정보를 이용

variable의 갯수가 많을 때 **가볍다**

Content와 Style matching의 Trade-off



▲ α/β의 비율에 따른 이미지 변화

Content 복원을 위한 layer 선택

깊은 레이어에서
content reconstruction을 할 수록
이미지의 *detailed pixel information*와
*texture*는 사라진다

경사하강법을 위한 초기화 방법

A: content 이미지
B: style 이미지
C: 화이트 노이즈 이미지

→ 큰 영향은 없다