2018.07.20

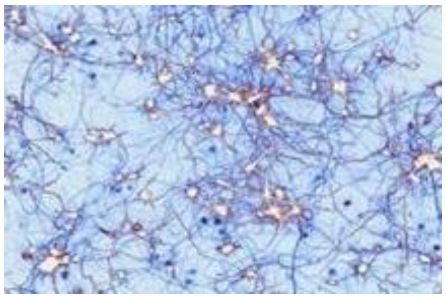
Advanced Style Transfer Using Convolutional Neural Networks

이지윤

Contents

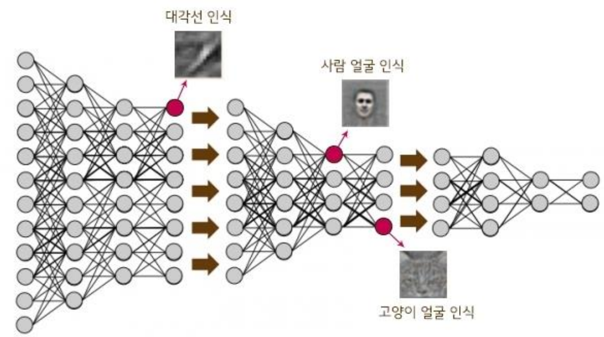
Deep Learning

❖ 딥러닝은 인간의 두뇌와 비슷한 모양의 인공 신경망을 형성하는 일종의 기계 학습



사람 Neuron Network

약 860억 개의 뉴런, 15개 층으로 구성된 여러 개의 모델



딥러닝 Neuron Network

46개의 퍼셉트론, 9개 층으로 구성된 한 개의 모델

❖ 초기 딥러닝 한계점 극복

- Vanishing Gradient
  : ReLU, Maxout ..
- Overfitting
  : Drop out
- DATA
  :Big data
- 긴 학습시간
  : 고성능 하드웨어 (GPU..)

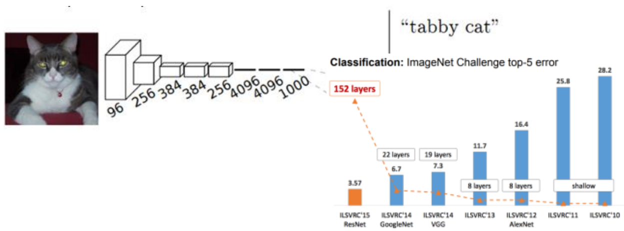
딥러닝의 시대!!

Application of Image Data to Deep Learning

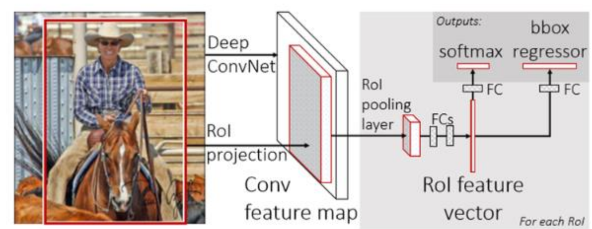
❖ 딥러닝은 이미지 데이터에 효과적

- ImageNet
  - 100만 장이 넘는 이미지 데이터 셋 (Class 구분)
  - 이미지데이터가 딥러닝 기술에 학습될 수 있는 환경 구축

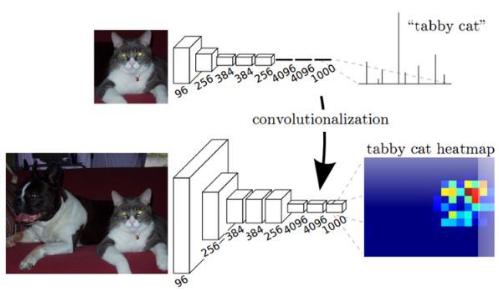
- Image Classification



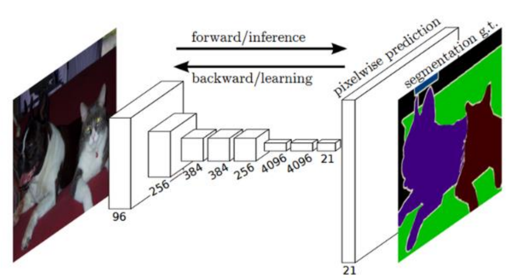
- Image Detection



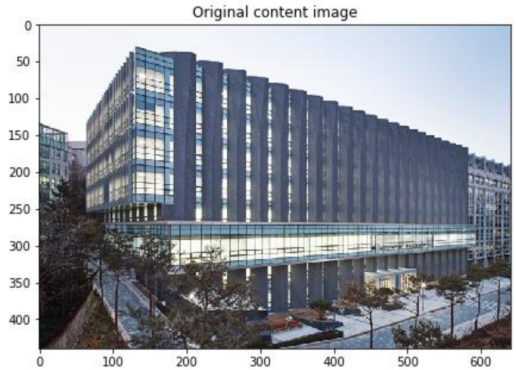
- Image Activation Map

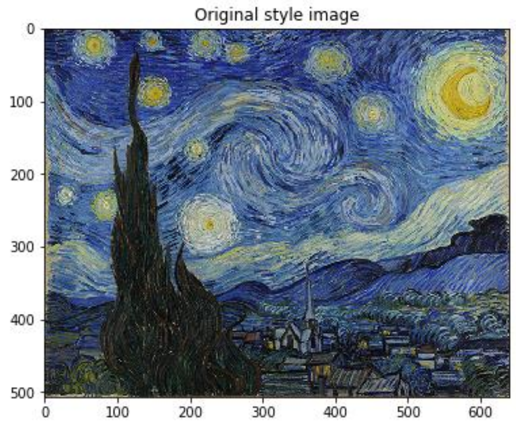


- Semantic Segmentation

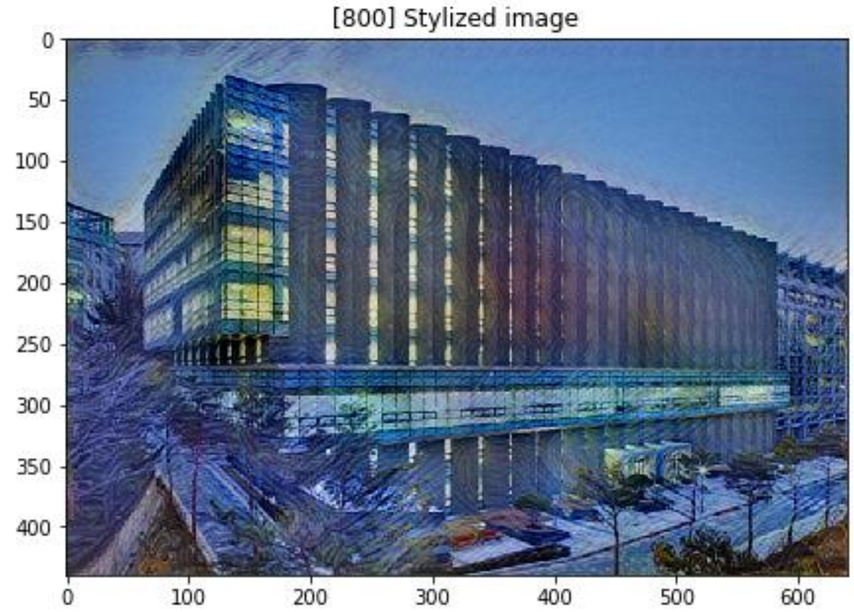


What is Style Transfer?!





Input



Output
(Synthesized Image)

Style Transfer

❖ Pre-trained networks 기반으로 '이미지' 학습

1. Image Style Transfer Using Convolutional Neural Networks
2. Generating an Eastern-Style Painting from a Photo based DNN
3. Deep Photo Transfer

❖ GAN을 기반으로 'Style Transfer 모델'을 직접 학습

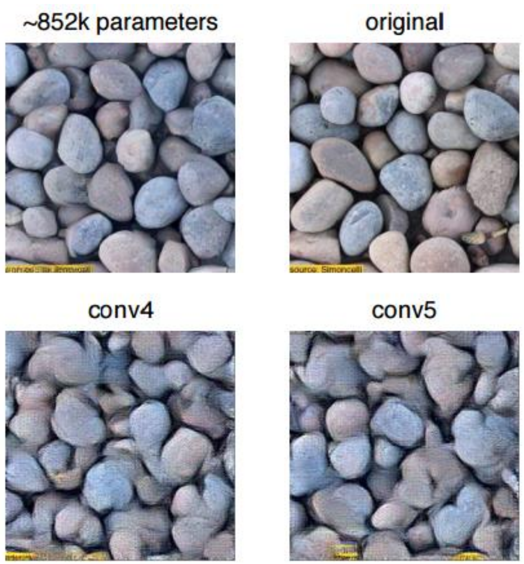
1. Image-to-Image Translation with Conditional Adversarial Networks (Pix2Pix)
2. Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks (Cycle GAN)

Image Style Transfer Using CNN

❖ Preliminaries

Texture Synthesis Using Convolutional Neural Networks NIPS2015

Texture reconstruction : 질감 정의 및 생성



Understanding Deep Image Representations by Inverting Them CVPR2015

Content reconstruction : 원래 이미지 최대한 복원

Gatys, Leon A., Alexander S. Ecker, and Matthias Bethge. "Image style transfer using convolutional neural networks." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2016.

Image Style Transfer Using CNN

❖ Synthesized image 생성에 *Pre–trained CNN* 사용

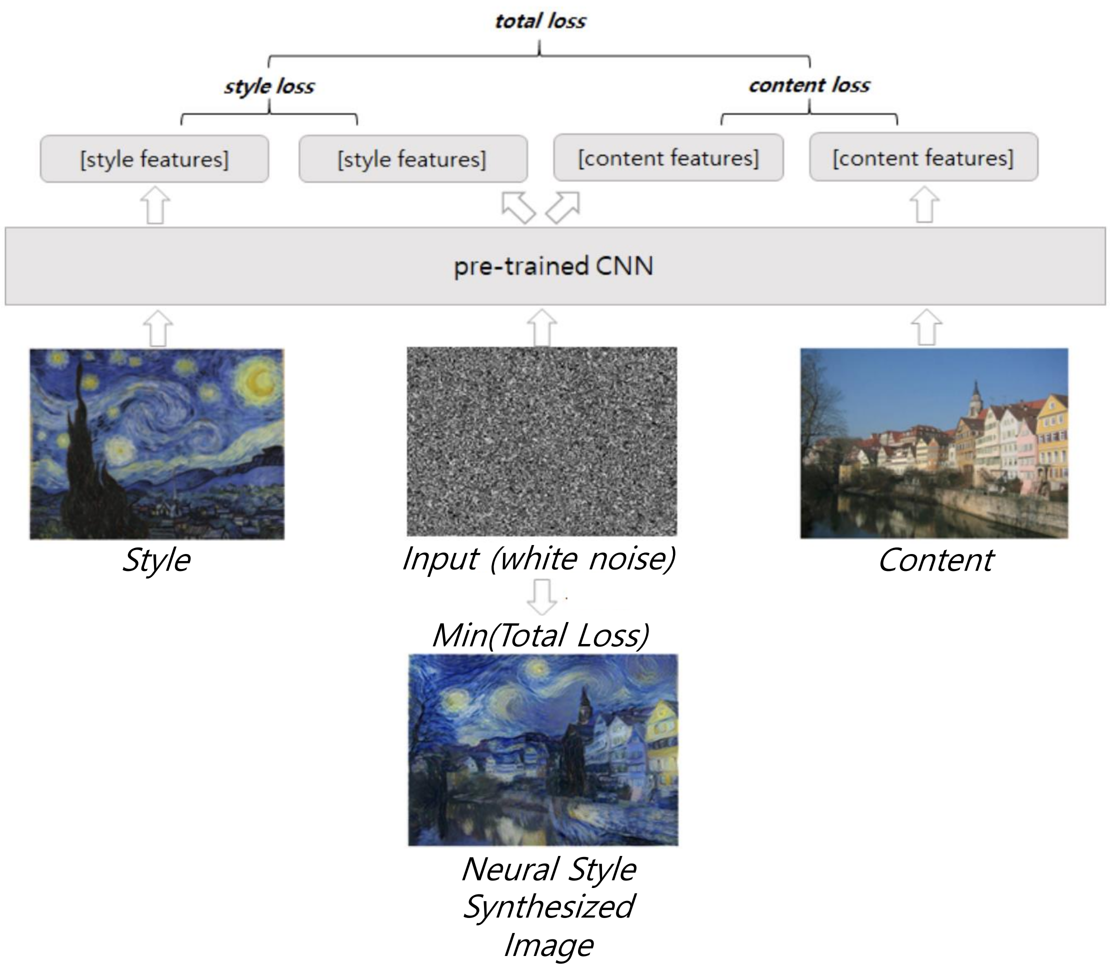


Image Style Transfer Using CNN

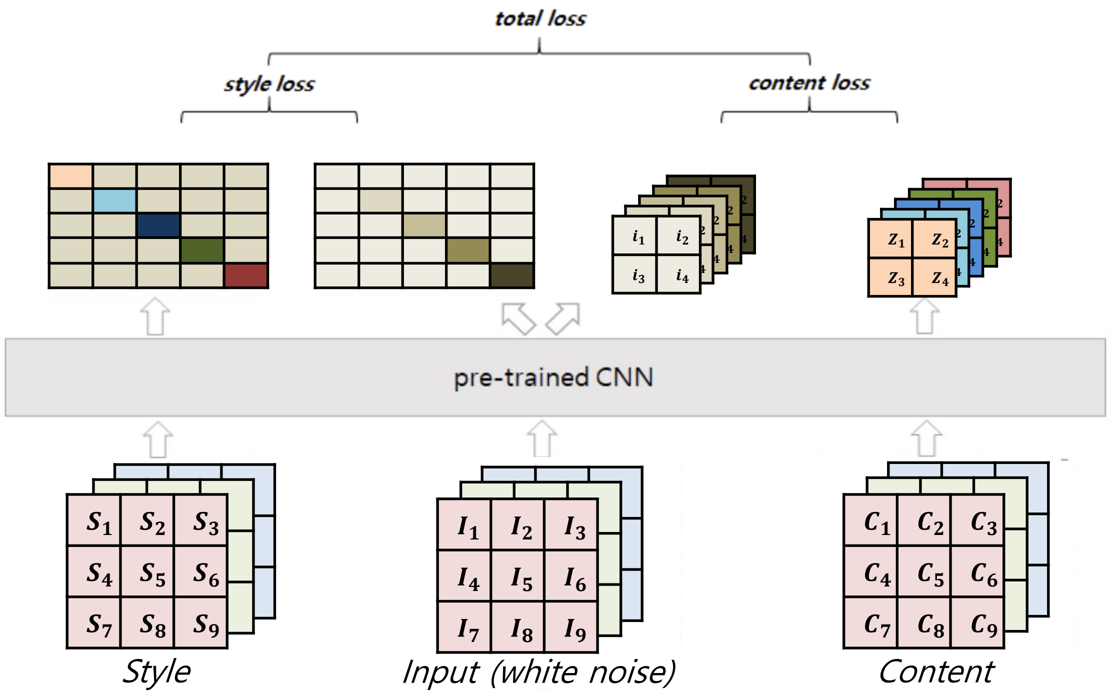


Image Style Transfer Using CNN

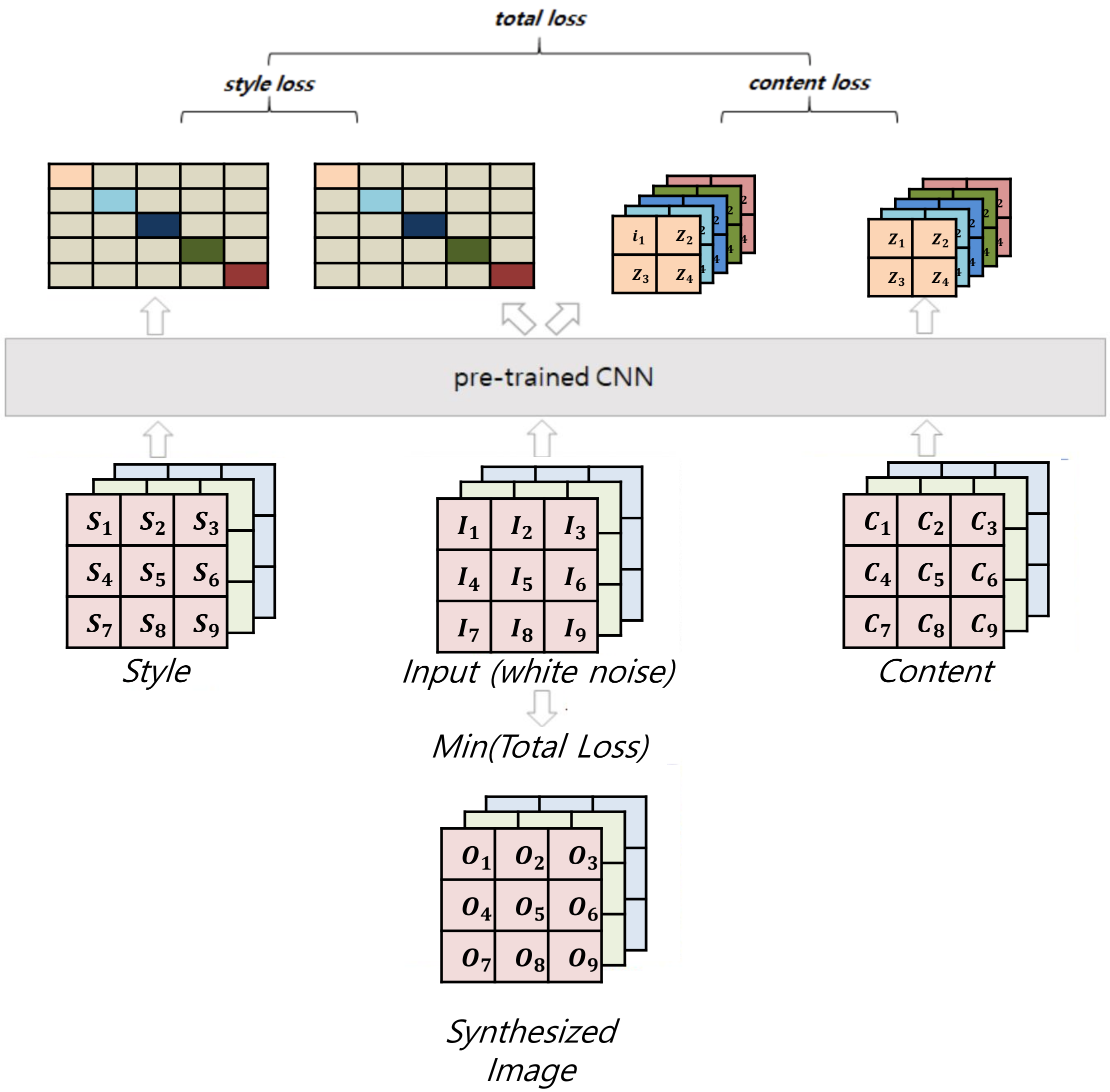
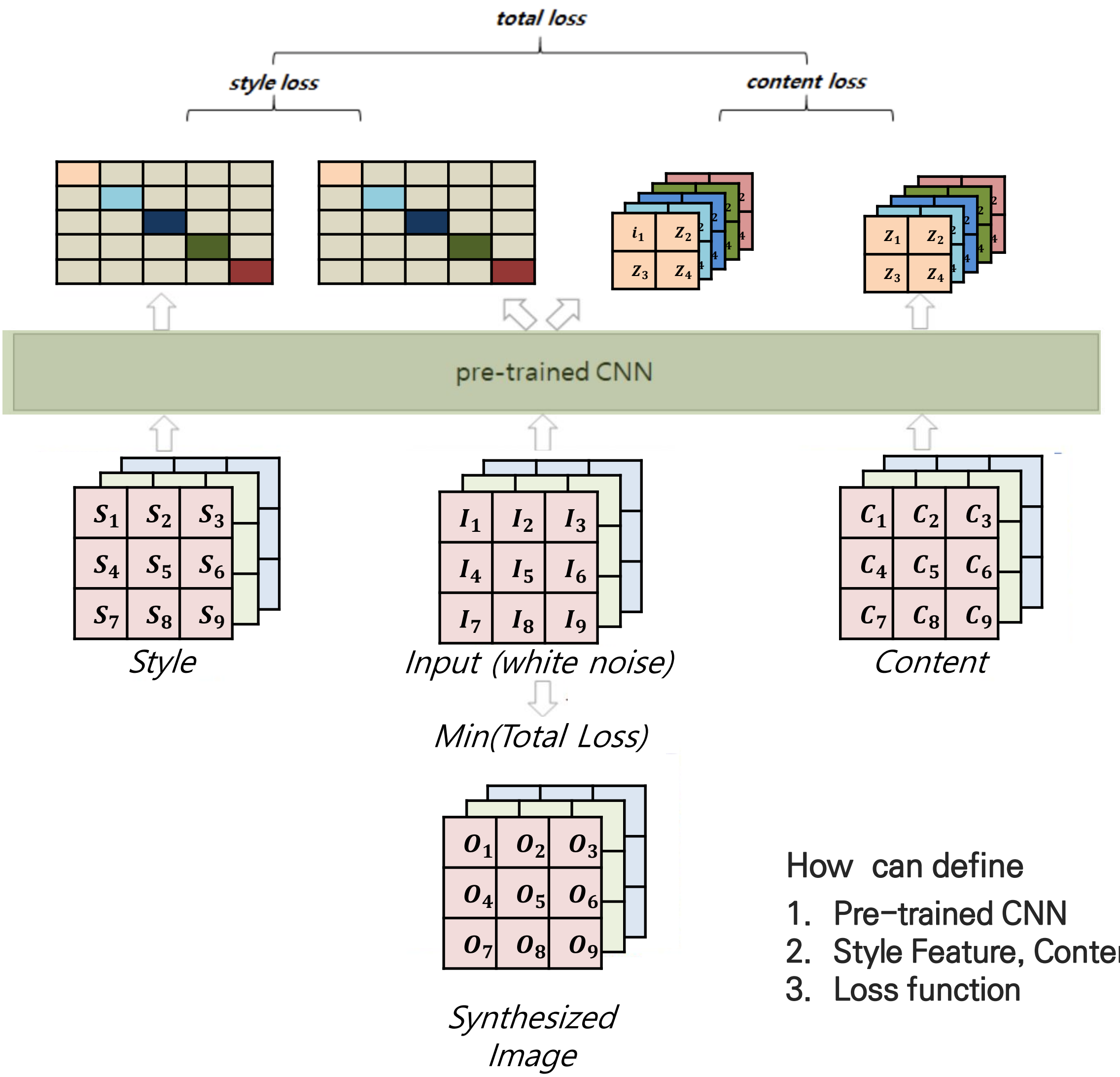


Image Style Transfer Using CNN



How can define

1. Pre-trained CNN
2. Style Feature, Content Feature
3. Loss function

Image Style Transfer Using CNN

❖ Pre-trained CNN

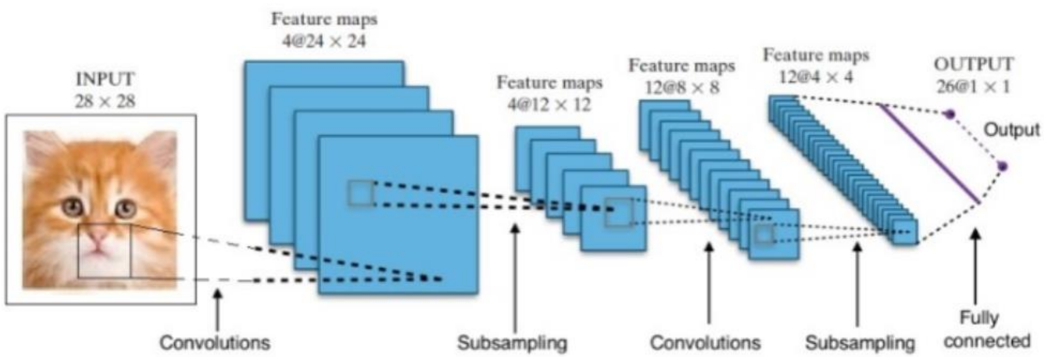
- **Large-datasets을 통해 사전 학습된 CNN**

  결과적으로 비교적 잘 학습된 공간계층구조(Spatial Hierarchy) 갖음

  ex) ImageNet으로 학습한 VGG-19

- **Small-datasets 을 사전 학습된 CNN을 사용하는 것은 매우 효과적인 접근법**

- **새로운 데이터는 CNN의 사전 학습에 사용된 데이터와 유사해야 함**

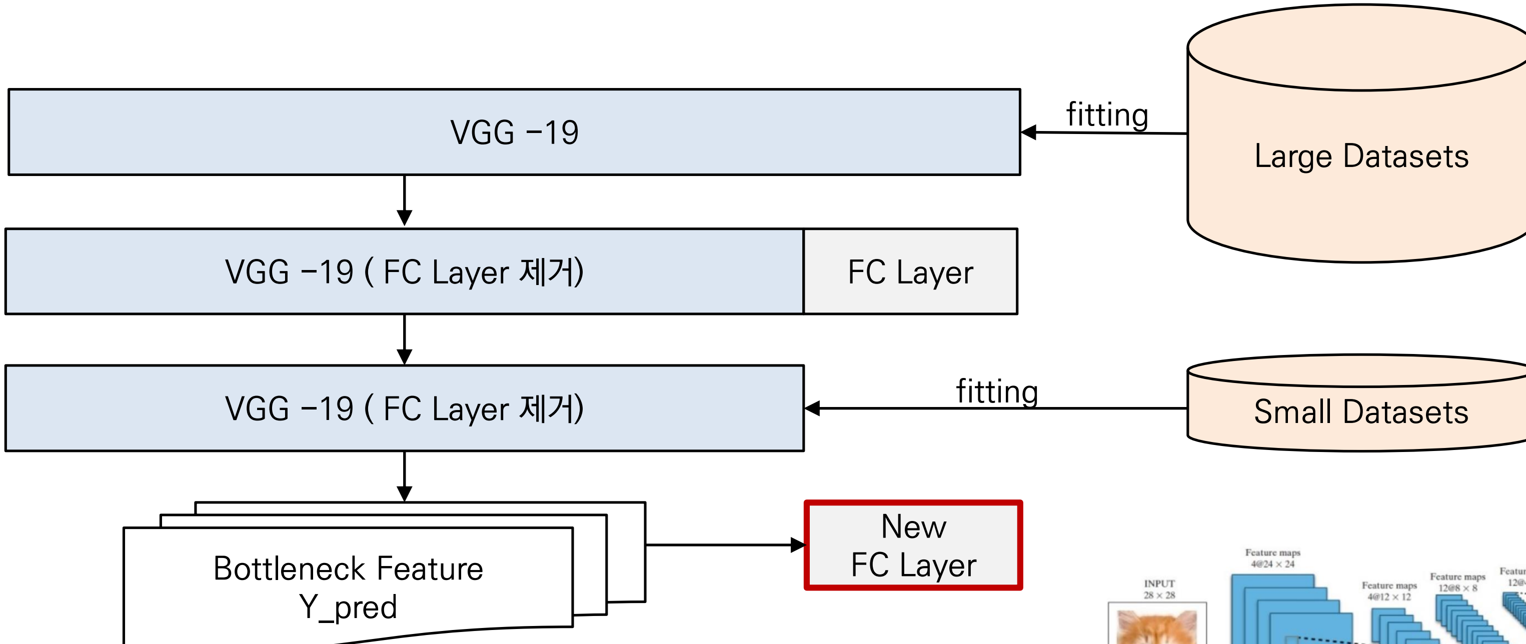


Karen Simonyan and Andrew Zisserman, “Very Deep Convolutional Networks for Large-Scale Image Recog- nition,” arXiv (2014), https://arxiv.org/abs/1409.1556.

Image Style Transfer Using CNN

❖ Using Pre-trained CNN

- **Feature Extraction**
  - Pre-trained CNN의 FC Layer 제거한 뒤 새로운 데이터에 대해 FC Layer 학습하여 Feature Extraction 도구로 사용 (New Classifier 생성)



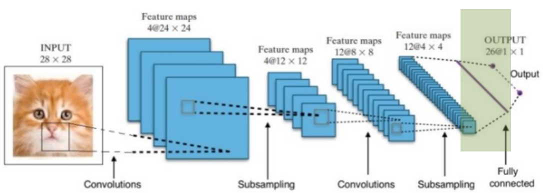
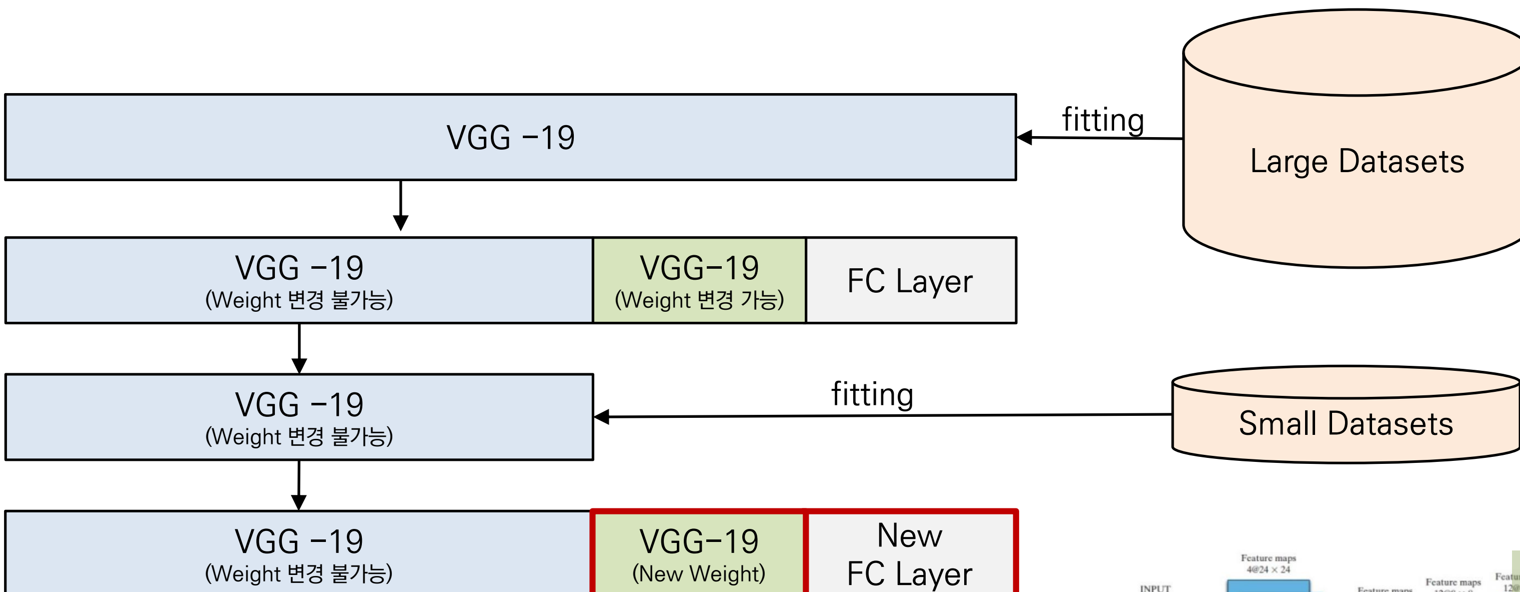


Image Style Transfer Using CNN

❖ Using Pre-trained CNN

- Fine-tuning
  - FC Layer 뿐만 CNN 뒤쪽 일부 은닉층에 대해서 가중치 미세조정
  - CNN 뒤쪽의 레이어들이 원본 자료에 포함된 클래스 세부사항을 지님



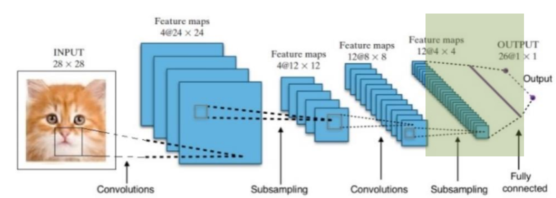


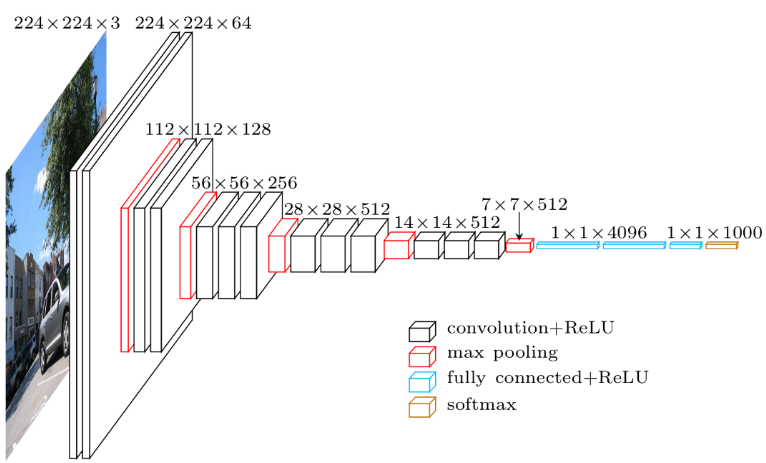
Image Style Transfer Using CNN

❖ Pre-trained CNN using 'VGG-19'

- 3X3 작은 Convolutional Filter(Stride=1)로 깊게(16-19 weight layers)구성
- 16개의 Convolutional Layer, 5개의 pooling layer, 3개의 fully connected layer 로 구성

❖ Pre-trained 위한 추가적인 처리

- Max pooling 대신 Average pooling 사용
- FC Layer 제거 (Feature Extraction의 목적으로 사용)



ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Image Style Transfer Using CNN

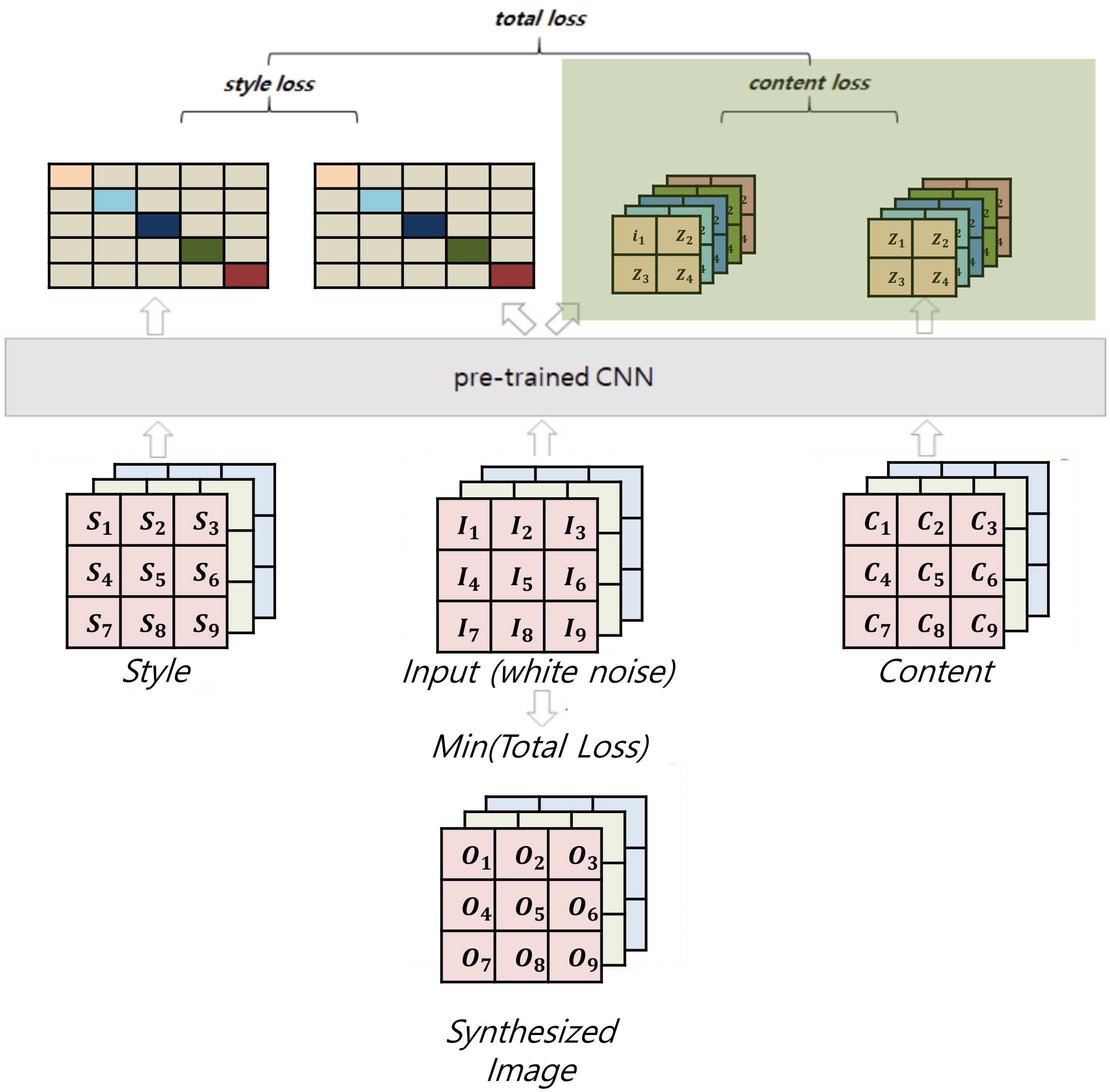
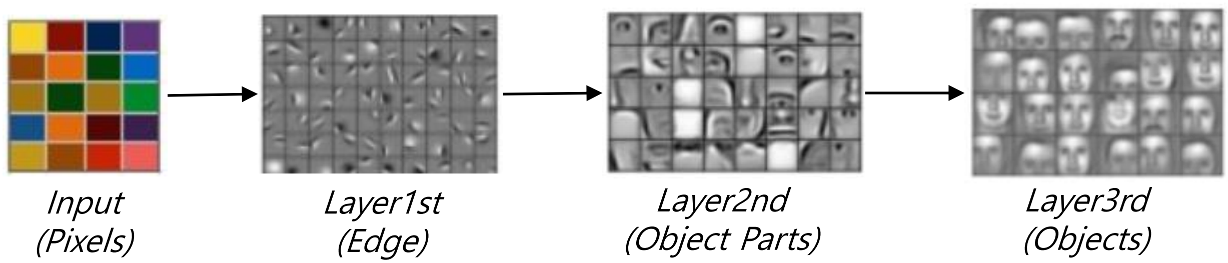


Image Style Transfer Using CNN

❖ Content : the higher-level macrostructure of the image

❖ Convolution Layer

- Layer가 깊어질수록 **global and abstract**(macrostructure) 특징 정보



❖ Content Feature : Representations of the upper Layers

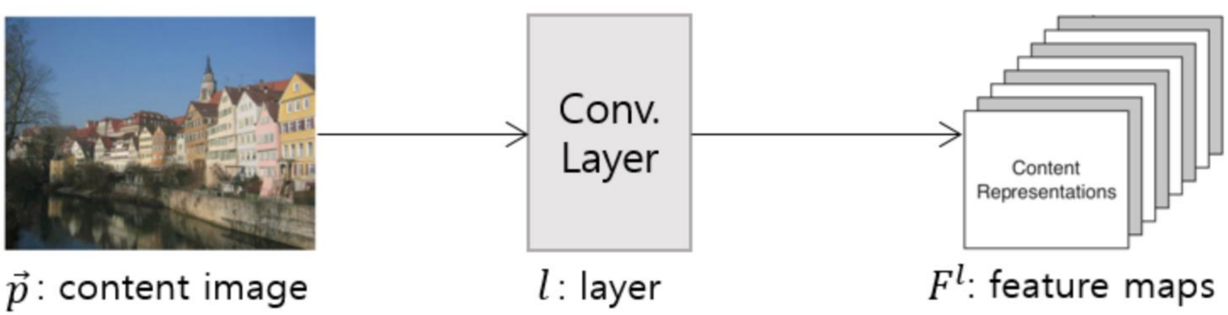
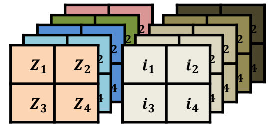


Image Style Transfer Using CNN

❖ Content Loss



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

$$\frac{\partial \mathcal{L}_{content}}{\partial F_{ij}^{l}} = \begin{cases} \left(F^l - P^l\right)_{ij} & \text{if } F_{ij}^{l} > 0 \\ 0 & \text{if } F_{ij}^{l} < 0\,. \end{cases}$$

F_{ij}^{l} = Content Image 의 Feature maps

i번째 필터의 j번째 위치 값 (l번째 Layer)

P_{ij}^{l} = Synthesized Image 의 Feature maps

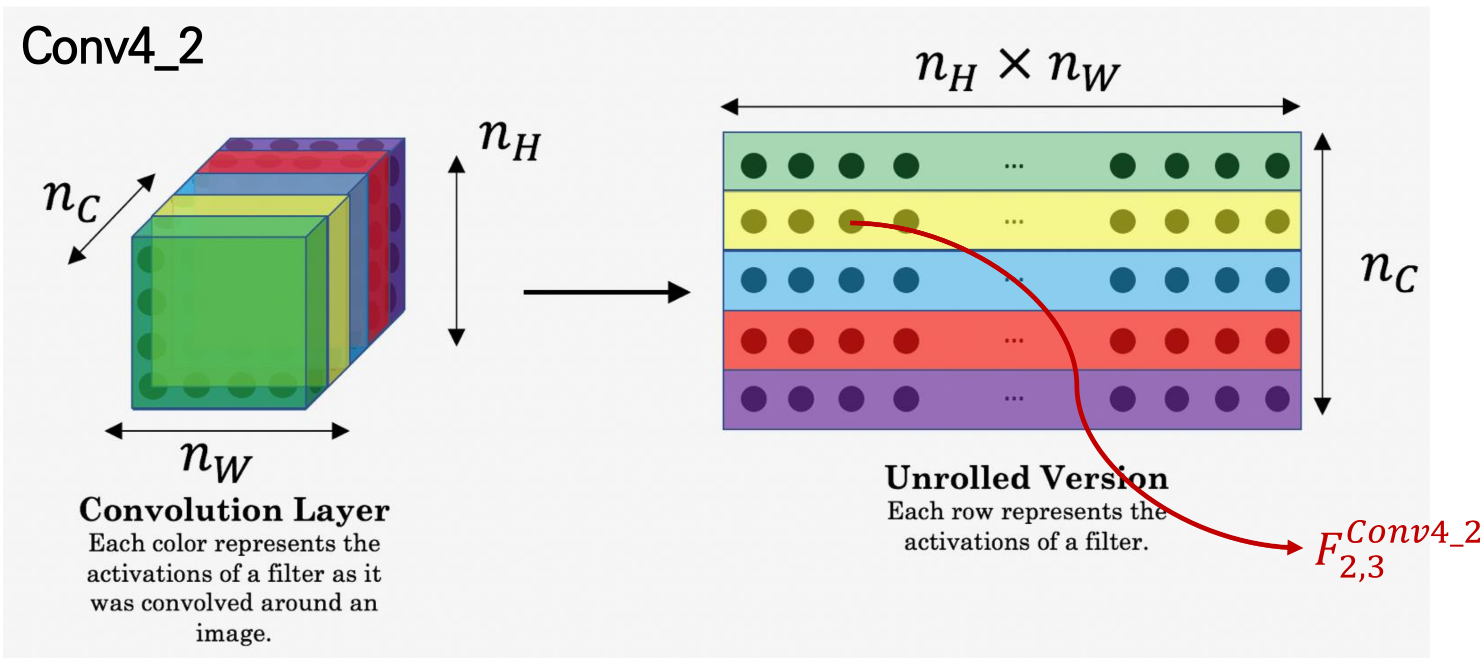


Image Style Transfer Using CNN

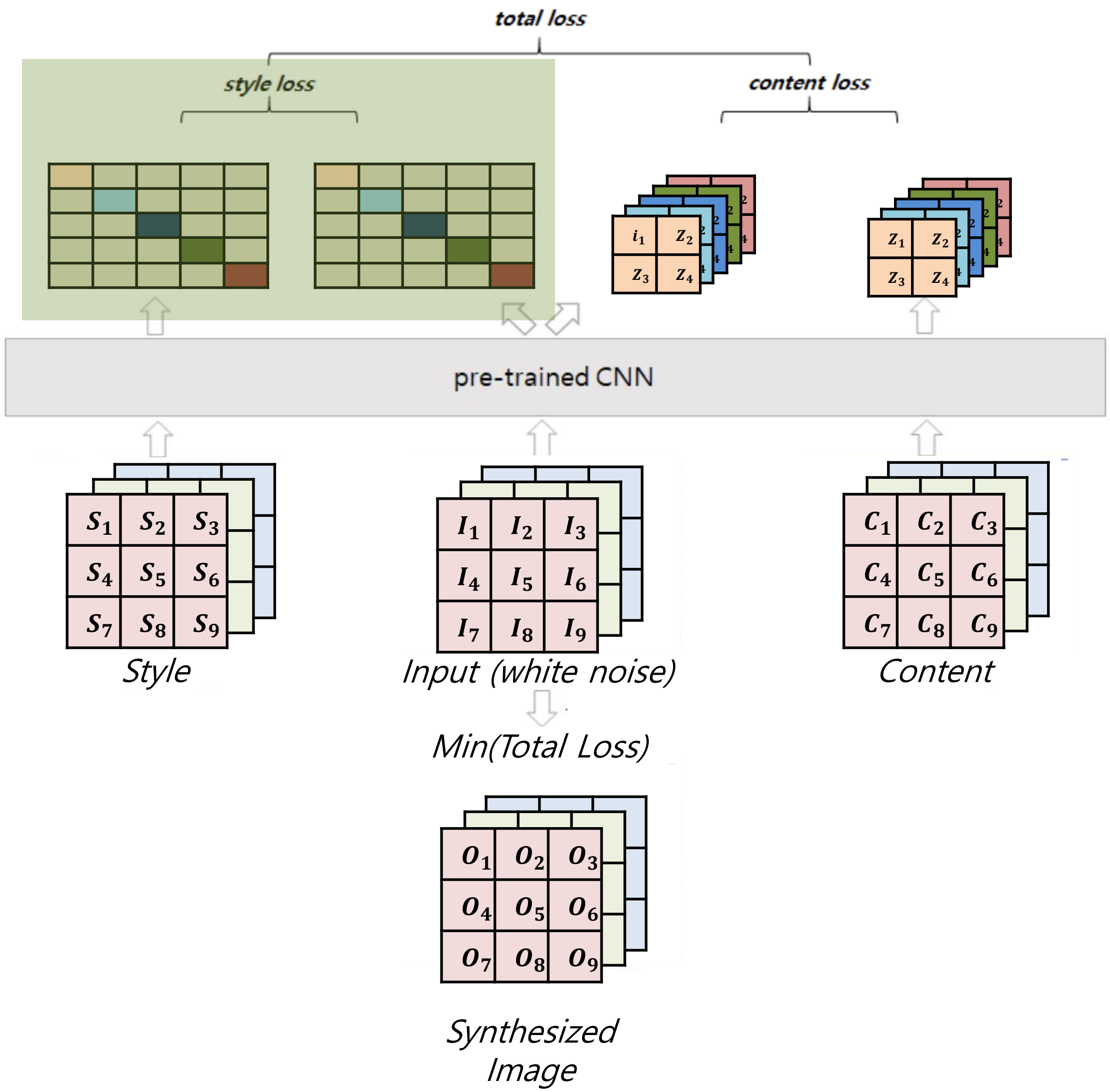
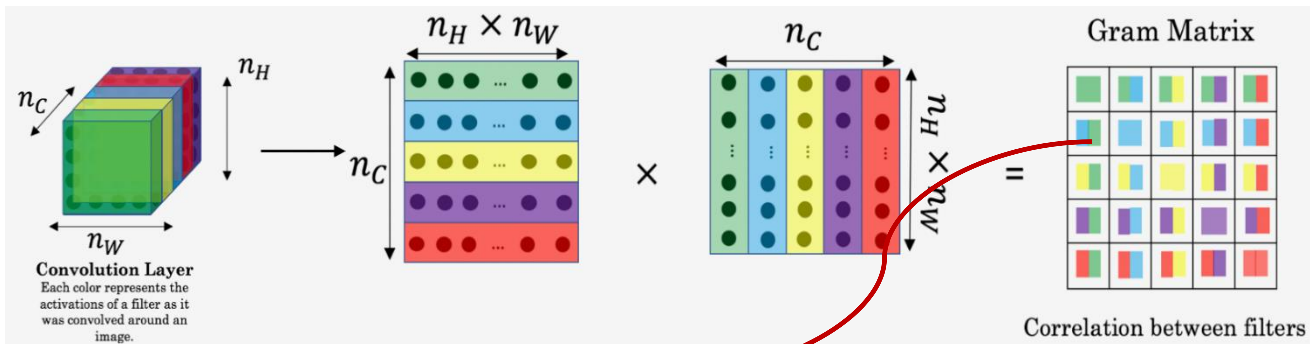


Image Style Transfer Using CNN

❖ Style : textures, colors in the image, Spatially repeated pattern

❖ Style Feature

- 같은 Layer에 있는 Feature map의 Correlation = **Gram matrix**



$G_{2,1}^{Conv4\_2}$

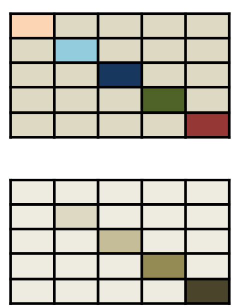
Covariance Matrix

❖ Style Loss

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

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

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



G_{ij}^l = l번째 Layer의 Gram matrix

i번째 필터와 j번째 필터의 Correlation

E_l = l번째 Layer 의 Style loss contribution

L = Loss에 영향을 주는 Layer 개수

w_l = 합이 1인 Layer weight

Image Style Transfer Using CNN

- **Total Loss**

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

p = Content Image

a = Style Image

x = Synthesis Image

- **Back-Propagation을 통해 Synthesized(x) Update** $\vec{x} = \vec{x} - \lambda\frac{\partial\mathcal{L}_{total}}{\partial\vec{x}}$

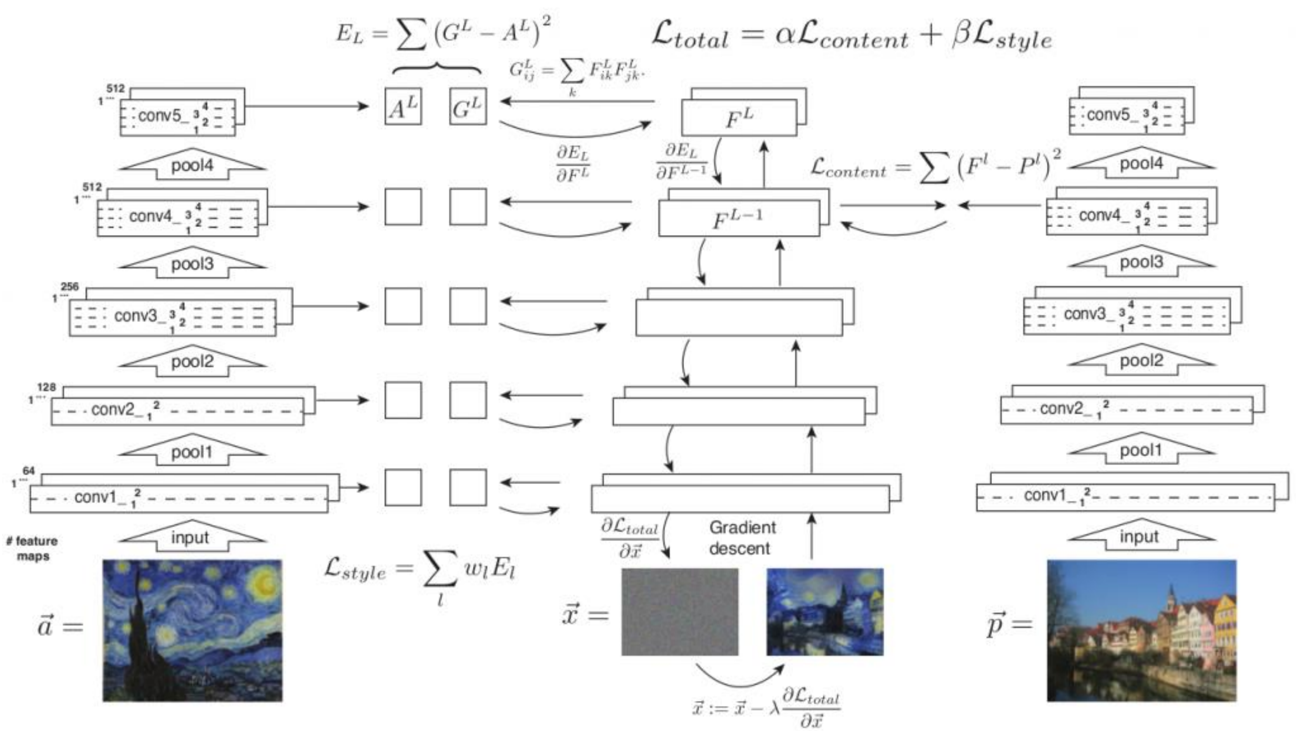


Image Style Transfer Using CNN

❖ Results

- ***α/β***

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

- **Content Layer**
  - Conv2_2 일 때가 Conv4_2일 때 보다 사실적
  - 하위 Layer에 pixel단위 정보가 더 많음

Generating an Eastern-Style Painting from a Photo

❖ 동양화 그림의 Style Transfer

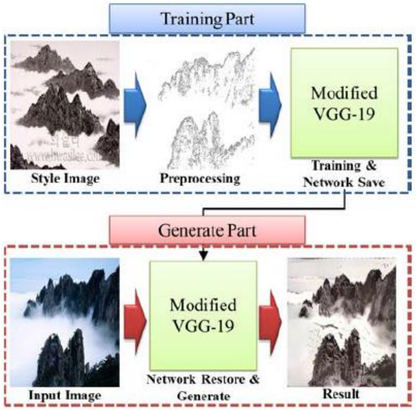
❖ Limitation Style Transfer using CNN

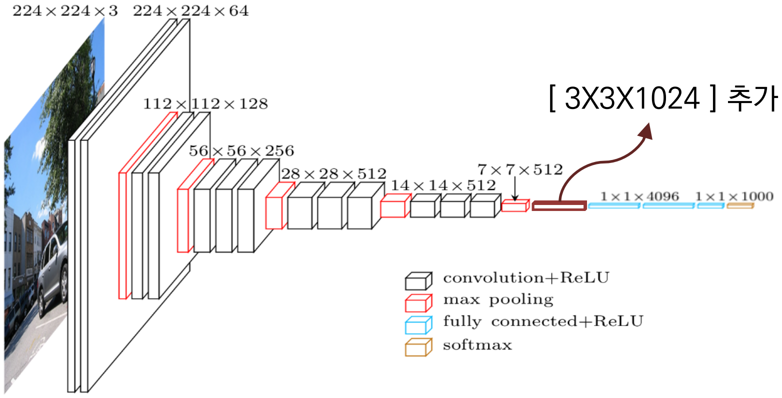
- 동양화의 경우, 색채가 다양하지 않고 여백이 많음
- Conv Layer 통해 Feature Extraction 어려움

Content *Style* *Neural Style*

❖ Suggestion

- 객체의 윤곽을 검출하는 Canny Edge를 통해 이미지 전처리 (Noise Edge Elimination)
- 기존 VGG-19에 Convl Layer를 한 개 추가하여 학습





Canny, John. "A computational approach to edge detection." IEEE Transactions on pattern analysis and machine intelligence 6 (1986): 679-698.

Deep Photo Transfer

❖ Photo Style Transfer using CNN

Luan, Fujun, et al. "Deep photo style transfer." *CoRR, abs/1703.07511* 2 (2017).

Deep Photo Transfer

❖ Photographs의 Style Transfer

Content *Style* *Neural Style* *Deep Photo Style*

❖ Limitation Style Transfer using CNN

- Edge와 규칙적인 패턴에 대해서 왜곡하는 경향
- Style(Texture)을 Global하게 정의하기 때문에 Spatial한 변화만 요구하는 경우 부적합

❖ Suggestion

- **Photorealism Regularization (For Content)**

  Content의 구조를 더 보존해서, 사실적인(Photorealistic)Image 생성하도록 유도

- **Augmented style loss with semantic segmentation (For Style)**

  기존의 Style loss의 한계 지적, Semantic Segmentation method 적용하여 Style loss정의

Deep Photo Transfer

❖ Photorealism Regularization

Content의 구조를 더 보존해서, 사실적인(Photorealistic)Image 생성하도록 유도

- **Content의 Edge에 왜곡이 발생한다면 Penalty 주는 Loss function L_m 정의**

$$\mathcal{L}_m = \sum_{c=1}^{3} V_c[O]^T \mathcal{M}_I V_c[O]$$

c	=	Channel	$V_c[O]$	=	Channel c의 Output Image O를 [NX1]로 벡터화
O	=	Output Image	$\mathcal{M}_I$	=	Matting Laplacian Matrix
I	=	Input Image(Content)			Input Image I가 N픽셀이라면, [NXN] 인 행렬

$$\frac{\mathrm{d}\mathcal{L}_m}{\mathrm{d}V_c[O]} = 2\mathcal{M}_I V_c[O]$$

- **$\mathcal{M}_I$(Matting Laplacian Matrix)**
  - Matting : Image의 전경(Foreground Object)을 분리시키는 기술

    Content Image의 Object와 생성된 Output Image의 Object 경계 일치

  - 전경(Foreground Object)을 잘 분리하지 못하면 L_m을 통해 Penalty

Levin, Anat, Dani Lischinski, and Yair Weiss. "A closed form solution to natural image matting." *Computer Vision and Pattern Recognition, 2006 IEEE Computer Society Conference on*. Vol. 1. IEEE, 2006.

Advanced Style Transfer using CNN – Replace Loss Term

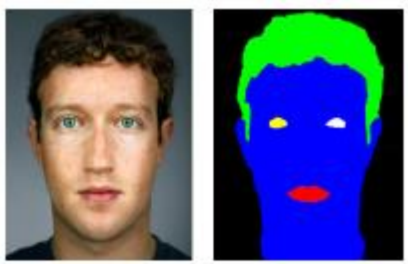
Deep Photo Transfer

❖ Augmented style loss with semantic segmentation

기존의 Style loss의 한계 지적, Semantic Segmentation method 적용하여 Style loss정의

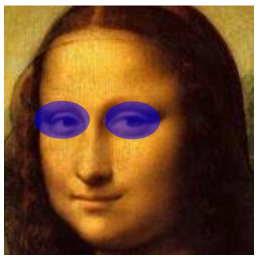
- **Style과 Content의 Mismatch문제(Spill over) 발생 방지**

  – Style의 Segment를 반영한 Gram matrix로 Image생성 (Localized Style)



Example of segmented image

Contents



Style

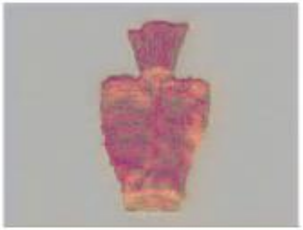
Output

- **Style Image와 Content Image의 그림 구조가 유사해야 하는 전제조건이 필요**

  Content Image를 통해 생성된 Output Image에 Localized Style Transfer 적용이 유의미

Contents

Style



Output

Deep Photo Transfer

- **Redefined Style loss**

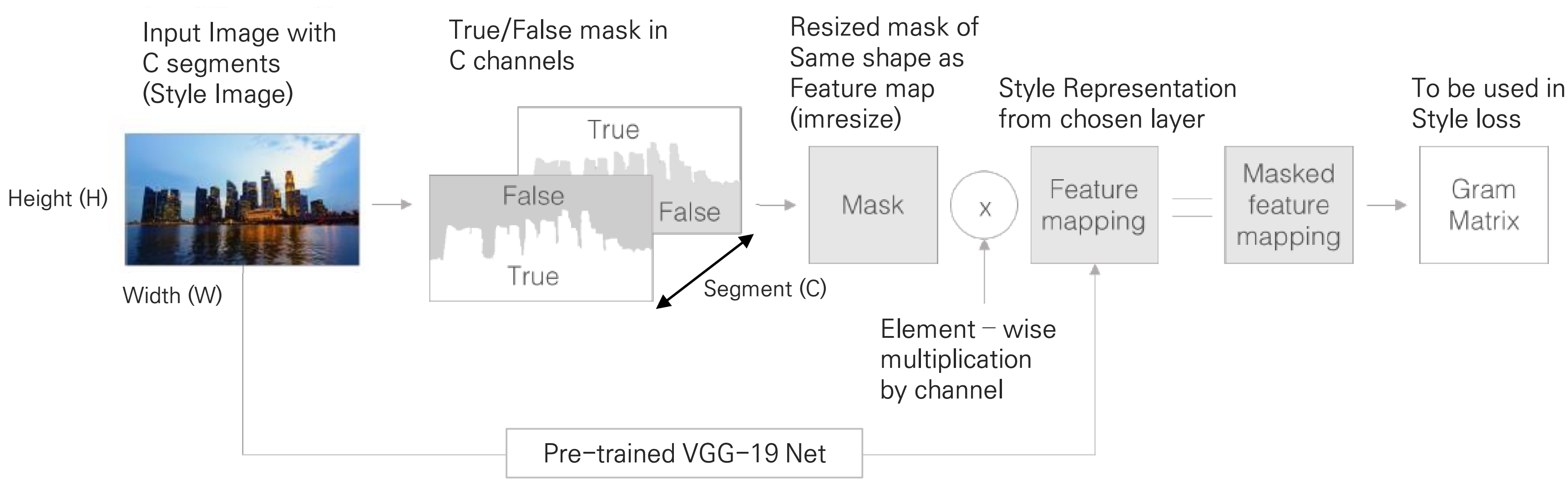
$$\mathcal{L}_{s+}^{\ell} = \sum_{c=1}^{C} \frac{1}{2N_{\ell,c}^{2}} \sum_{ij} (G_{\ell,c}[O] - G_{\ell,c}[S])_{ij}^{2}$$

$$F_{\ell,c}[O] = F_{\ell}[O] M_{\ell,c}[I] \quad F_{\ell,c}[S] = F_{\ell}[S] M_{\ell,c}[S]$$

C = # of segment in Image
Semantic Segmentation mask의 채널 수

$M_{l,c}[\cdot]$ = Layer l 의 c번째 segment Image의 Mask

$G_{l,c}[\cdot]$ = $F_{l,c}[\cdot]$ 와 일치하는 Gram matrix



Deep Photo Transfer

❖ Photorealism Regularization (For Content)

$$\mathcal{L}_m = \sum_{c=1}^{3} V_c[O]^T \mathcal{M}_I V_c[O]$$

❖ Redefined Style loss (For Style)

$$\mathcal{L}_{s+}^{\ell} = \sum_{c=1}^{C} \frac{1}{2N_{\ell,c}^2} \sum_{ij} (G_{\ell,c}[O] - G_{\ell,c}[S])_{ij}^2$$

❖ Total Loss

$$\mathcal{L}_{\text{total}} = \sum_{l=1}^{L} \alpha_\ell \mathcal{L}_c^\ell + \Gamma \sum_{\ell=1}^{L} \beta_\ell \mathcal{L}_{s+}^\ell + \lambda \mathcal{L}_m$$

α_l, β_l	=	Weight to configure layer preferences
Γ	=	Weight that controls the style loss
λ	=	Weight that photorealism regularization

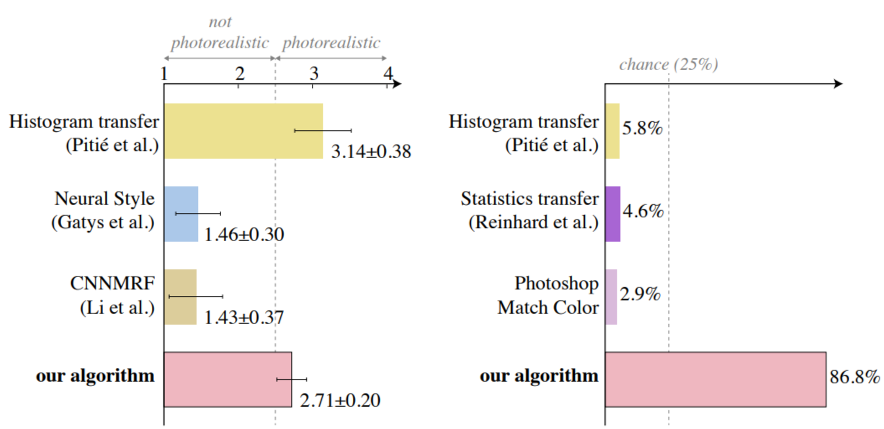
Deep Photo Transfer

❖ Results

- $1/\lambda \propto$ 왜곡

(a) Input and Style (b) $\lambda = 1$ (c) $\lambda = 10^2$ (d) $\lambda = 10^4$, our result (e) $\lambda = 10^6$ (f) $\lambda = 10^8$

- Compare with other models



(a) Photorealism scores (b) Style faithfulness preference

Results

- ❖ Input Image의 특성과 Output Image의 목적에 따라 적합한 CNN 구조 및 Loss function 다양하게 변환
- ❖ 각기 다른 특징을 지닌 Image들에 대해 적용하고자 한다면 Style Transfer를 하기 앞서 전처리 필요
- ❖ 합성의 결과에 대한 정합성은 주관적이라는 한계
- ❖ Image Style Transfer 이외에도 Audio Style Transfer, Video Style Transfer 등 다양한 Application연구 활발

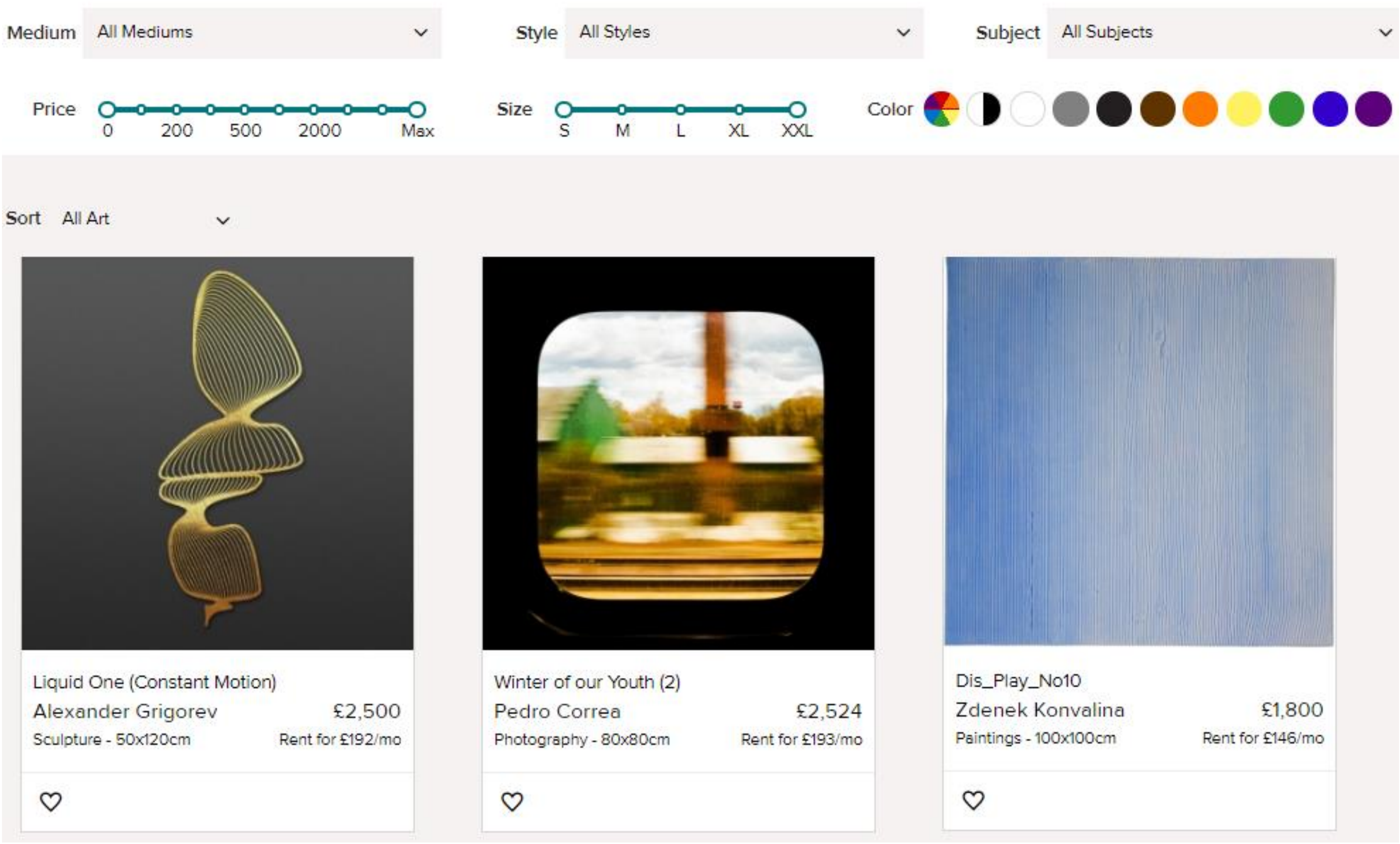
Graph Based Art Recommendation System

안건이 이지윤 윤석채 김다연

introduction

Art Rental Service : Rise Art

❖ 16720개 작품, 858명 작가



Art Recommendation System

❖ 연관성 높은 작품 추천

Recommendation List

Artist ‘A’

?

Art Recommendation System

❖ 연관성 높은 작품 추천

Recommendation List

Artist 'A'

Artist 'A'

Artist 'B'

Artist 'C'

Data Summary

Text

This is one of a series of historical or celebrity personality portraits. They belong to … W… of …

"Danilov" is inpired by the artist's childhood memories of colours and symbols used in the … is … of … se… ha… the …

"The Sky Blue One" is No. 11 of the "Andy Series". The "Andy Series" is an ongoing and numbered Popart series, that covers day-to-day topics in a humerous way such as fashion, future, growing up, various views of life and much more. Every painting has a primary colour naming it (The Red One, The Pink One etc.). On all paintings indirectly a person called "Andy" is playing a role, but you never see him.

Image

Meta

Price Style Subject

Type Year

TF-IDF
Dov2Vec

Convolutional
AutoEncoder

Weight

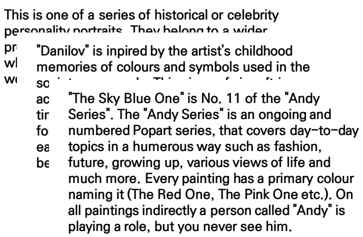
Graph Based Similarity

Text + Image Distance Matrix

❖ 단순 concatenate (Text , Image)으로 Distance를 구하면 생기는 문제점

- Text와 Image는 속성이 다름
- concatenate을 하면서 차원의 저주(2^n)가 생겨 Distance 반영이 어려움

Text



Shape: [7922,64]

+

Image

Shape: [7922,64]

=

Text + Image

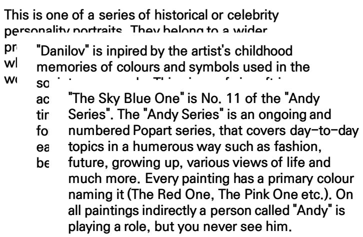
Shape: [7922,128]

Text + Image Distance Matrix

❖ 단순 concatenate (Text , Image)으로 Distance를 구하면 생기는 문제점

- Text와 Image는 속성이 다름
- concatenate을 하면서 차원의 저주(2^n)가 생겨 Distance 반영이 어려움

Text



Shape: [7922,64]

+

Image

Shape: [7922,64]

=

Text + Image

$$\begin{matrix} 0 & & & & \\ & 0 & & & \\ & & \cdots & & \\ & & & 0 & \\ & & & & 0 \end{matrix}$$

Distance Matrix

Shape: [7922,7922]

Text + Image Distance Matrix

❖ Text, Image 각각 Distance Matrix를 구하여 선형 결합

- Text와 Image의 속성이 다른 것에 대한 해결책
- Distance Matrix를 구할 때 차원의 저주가 발생하지 않음
- Hyperparameter인 α로 Text와 Image 조절 가능

Text

This is one of a series of historical or celebrity personality portraits. They belong to a wider

"Danilov" is inpired by the artist's childhood memories of colours and symbols used in the

"The Sky Blue One" is No. 11 of the "Andy Series". The "Andy Series" is an ongoing and numbered Popart series, that covers day-to-day topics in a humerous way such as fashion, future, growing up, various views of life and much more. Every painting has a primary colour naming it (The Red One, The Pink One etc.). On all paintings indirectly a person called "Andy" is playing a role, but you never see him.

Shape: [7922,64]

Image

Shape: [7922,64]

Text + Image Distance Matrix

❖ Text, Image 각각 Distance Matrix를 구하여 선형 결합

- Text와 Image의 속성이 다른 것에 대한 해결책
- Distance Matrix를 구할 때 차원의 저주가 발생하지 않음
- Hyperparameter인 α로 Text와 Image 조절 가능

α

Text

0
0
…
0
0

Distance Matrix

Shape: [7922,7922]

$+ (1-\alpha)$

Image

0
0
…
0
0

Distance Matrix

Shape: [7922,7922]

$0 \leq \alpha \leq 1$

Improving Weight Using Meta Data

❖ Meta Data 활용

Art_title_name	Style	Subject	Year	Art_Abstract
The Pheasant	Surrealistic	Portraits & People	2015	The PheasantPart of the 'Ghostjumps and Wormholes' series
visits Danny Kaye through th	Surrealistic	Portraits & People	2014	is one of a series in which we juxtapose images in such a way that new stories
Marlene of the Lobsters	Surrealistic	Portraits & People	2015	Marlene of the LobstersPart of the 'Ghostjumps and Wormholes' series.
John of the Stagbeetles	Surrealistic	Portraits & People	2015	John of the StagbeetlesPart of the 'Ghostjumps and Wormholes' series
The Chums	Surrealistic	Animals	2016	The ChumsOne of our first oil paintings done from a still life set up.
Dickens	Surrealistic	Portraits & People	2013	portraits. They belong to a wider project called 'Ghostjumps and Wormholes' v
Strindberg	Surrealistic	Portraits & People	2014	y portraits. They belong to a wider project called 'Ghostjumps and Wormholes'
Rossini	Surrealistic	Portraits & People	2013	portraits. They belong to a wider project called 'Ghostjumps and Wormholes' w
Nehru	Surrealistic	Portraits & People	2013	portraits. They belong to a wider project called 'Ghostjumps and Wormholes' w
Paul Newman	Surrealistic	Portraits & People	2014	lity portraits. They belong to a wider project called 'Ghostjumps and Wormhole
Kirk Douglas	Surrealistic	Portraits & People	2014	ity portraits. They belong to a wider project called 'Ghostjumps and Wormholes
Charles Darwin	Surrealistic	Portraits & People	2013	ality portraits. They belong to a wider project called 'Ghostjumps and Wormhol
Interior with Bird	Surrealistic	Animals	2015	Interior with BirdOne of a series of wildlife in human interiors
Danilov	Pop Art	Transport & Auto	2015	e of aircraft is actually built out of wood, and the erosion of time is painted on
Ashley	Pop Art	Portraits & People	2017	ilt on wood, the effects of wear and aging are a "trompe l'oeil" that were paint
France 120	Pop Art	Transport & Auto	2016	artwork is singular in its details and each wooden structure carry unique reliefs.
Japan 110	Pop Art	Transport & Auto	2016	artwork is singular in its details and each wooden structure carry unique reliefs.
America 120 Green line	Pop Art	Transport & Auto	2018	ge, each artwork is singular in its details and each wooden structure carry uniq

Style: Surrealistic, Pop Art, Abstract, Figurative, Street Art … Cartoon → 총 15 가지

Subject: Animals, Landscapes, Fashion, Still Life, Urban, Food … Sports → 총 21 가지

Year: 1965 ~ 2018 → 총 40년

Improving Weight Using Meta Data

❖ Meta Data 활용 : Distance(Weight)를 향상 시킴

- 같은 Type Art에 대해 Weight를 적용시켜 기존 Distance를 끌어 당겨 줌
- 다른 Type Art에 대해 Penalty를 적용시켜 기존 Distance를 유지

- Type의 종류는 Style, Subject, Year 총 3가지 채택

Actual Computation

$$W_{ij} = \exp\left(-\frac{N^2\left(\sum_{k=1}^{N}\left(\lambda^{(k)} \cdot x_{ij}{}^{(k)}\right)\right)}{\sum_{k=1}^{N} A^{(k)}}\right)$$

W_{ij} : $Weght\ of\ between\ picture\ i\ and\ picture\ j$

- 각 Meta data들 간 비중 고려 (λ값 추가)
- 반영하는 Meta data의 수가 많을수록 (W 감소 : 유사도 증가)
- 평균 Meta data내 항목 수가 많다면 (W 증가 : 유사도 감소)

N : $Number\ of\ meta\ data$

$\lambda^{(k)}$: $Weight\ of\ meta\ data$
$\sum(\lambda^{(k)}) = 1,\ k = 1, 2, \cdots N$

$A^{(k)}$: $Number\ of\ types\ in\ each\ meta\ data$
$k = 1, 2, \cdots N$

$$x_{ij}{}^{(k)} \begin{cases} 1 & , if\ \ same\ type\ in\ each\ meta\ data \\ 0 & , otherwise \qquad\qquad (for\ \forall\ i, j) \end{cases}$$

Feature weighting (FW) assigns different levels of importance to different features. (Debnath et al., 2008)

Improving Weight Using Meta Data

❖ Meta Data 활용 : Distance(Weight)를 향상 시킴

- 같은 Type Art에 대해 Weight를 적용시켜 기존 Distance를 끌어 당겨 줌
- 다른 Type Art에 대해 Penalty를 적용시켜 기존 Distance를 유지

- Type의 종류는 Style, Subject, Year 총 3가지 채택

Actual Computation

$$W_{ij} = \exp\left(-\frac{N^2\left(\lambda^{(Style)} \cdot x_{ij}{}^{(Style)} + \lambda^{(Subject)} \cdot x_{ij}{}^{(Subject)} + \lambda^{(Year)} \cdot x_{ij}{}^{(Year)}\right)}{A^{(Style)} + A^{(Subject)} + A^{(Year)}}\right)$$

$$= \exp\left(-\frac{3^2\left(0.4 \cdot x_{ij}{}^{(Style)} + 0.4 \cdot x_{ij}{}^{(Subject)} + 0.2 \cdot x_{ij}{}^{(Year)}\right)}{15 + 21 + 40}\right)$$

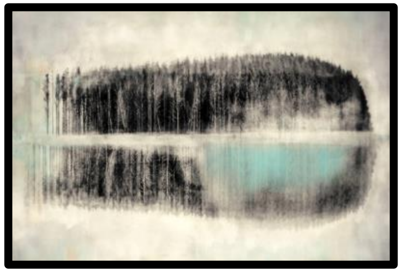
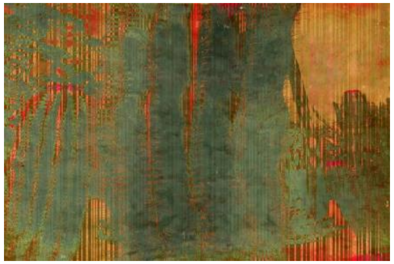
$$= [0.8883, 1]$$

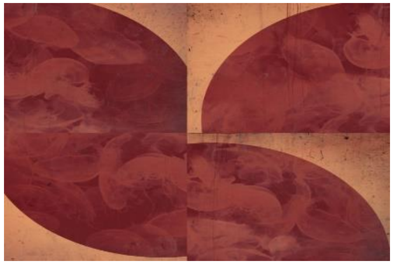
Feature weighting (FW) assigns different levels of importance to different features. (Debnath et al., 2008)

Art Recommendation

Text	Image	Meta
100%	0%	0
		1
50%	50%	0
		1
0%	100%	0
		1

❖ Text 100%, Image 0%, Meta(X) – Top 7

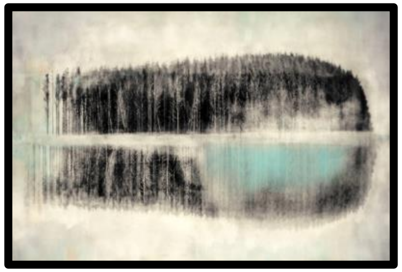




Art Recommendation

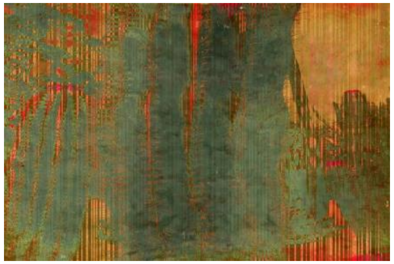
Text	Image	Meta
100%	0%	0
		1
50%	50%	0
		1
0%	100%	0
		1

❖ Text 100%, Image 0%, Meta(X) – Top 7



Stavanger blue - Limited Edition Fine Art print
Stavanger blue Fine Art photographic print, professionally hand printed on fine art Giclee cotton gallery paper using archival pigment ink. Signed, numbered with certificate of authenticity.

Artists original photograph is worked in layers using oils overlaid in post production to produce the final work. This is a limited edition print, signed and number by the artist. Limited edition print signed and numbered by the artist. Giclee Hahnemhle Fine Art gallery paper 308 gsm printed using archival pigmented inks.



Cactus blooms bright - Limited Edition Fine Art print
Desert blooms at the cactus oasis, composite pop art inspired by mid century advertising, using layers and paint on canvas combined digitally on paper.

Fine Art photographic print,

Monterey green - Limited edition fine art print.

Monterey green, California's swimming jellyfish part of the underwater portfolio inspired by mid century graphics. Original worked in layers using textures and washes to create the final print.

Fine Art photographic print, professionally hand printed on Giclee 310gsm Museum gallery paper using archival pigment ink. Limited edition print signed and numbered by the artist.

Happy to create bespoke size prints for clients, please get in touch with any print requirements.

Monterey Pink - Limited edition fine art print

Monterey Pink, California's swimming jellyfish part of the underwater portfolio inspired by mid century graphics. Original worked in layers using textures, paint washes and drawings to create the final print.

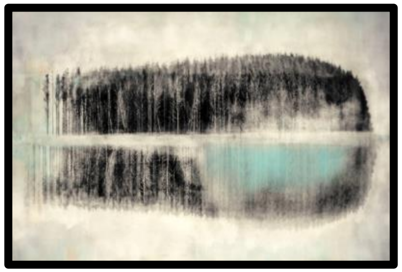
Fine Art photographic print, professionally hand printed on Giclee 308gsm Museum gallery paper using archival pigment ink. Limited edition print signed and numbered by the artist.

Happy to create bespoke size prints for clients, please get in touch with print requirements.

Art Recommendation

Text	Image	Meta
100%	0%	0
100%	0%	1
50%	50%	0
50%	50%	1
0%	100%	0
0%	100%	1

❖ Text 0%, Image 100%, Meta(X) – Top 7





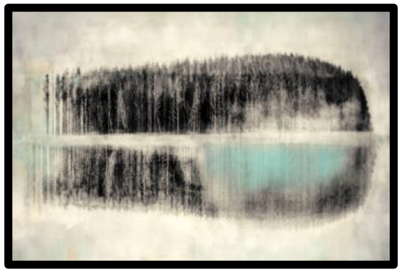


Survey & Results

Art Recommendation

Text	Image	Meta
100%	0%	0
		1
50%	50%	0
		1
0%	100%	0
		1

❖ Text 50%, Image 50%, Meta(X) – Top 7



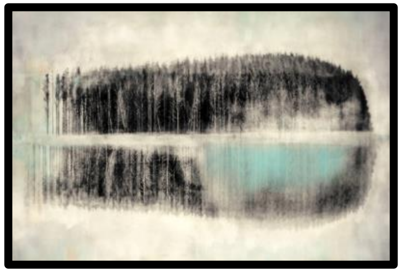




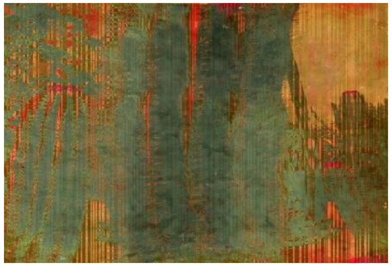

Text	Image	Meta
100%	0%	0
		1
50%	50%	0
		1
0%	100%	0
		1

Art Recommendation

❖ Text 100%, Image 0%, Meta(O) – Top 7



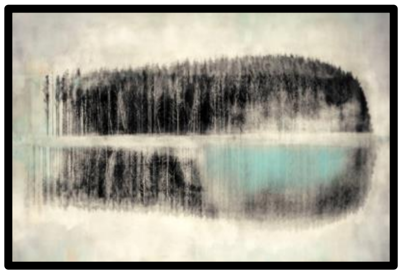





Art Recommendation

Text	Image	Meta
100%	0%	0
		1
50%	50%	0
		1
0%	100%	0
		1

- Text 0%, Image 100%, Meta(O) – Top 7





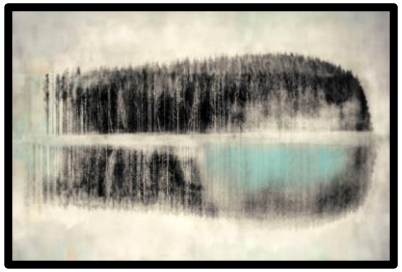


Text	Image	Meta
100%	0%	0
		1
50%	50%	0
		1
0%	100%	0
		1

Survey & Results

Art Recommendation

❖ Text 50%, Image 50%, Meta(O) – Top 7








Performance Evaluation Method

❖ 조사 결과

- 목적: 어떤 방법론을 바탕으로 한 추천 시스템이 소비자 선호도에 가장 긍정적 영향을 미칠 것인가?

1. Only image vs Only text vs Image + Text

   Only image (69%), **Only text (75%)**, Image + Text(72%)

2. Hyperparameter(α) 조정

   TF-IDF기준 Image : Text → **0 : 1 (75%)**

   2 : 8 (74%)

   5 : 5 (71%)

   8 : 2 (70%)

3. Non-meta vs Meta

   Non-meta (69%), **Meta(73%)**

4. TF-IDF vs Doc2vec

   TF-IDF (73%), Doc2vec(69%)

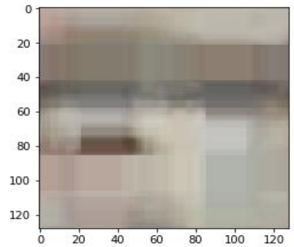
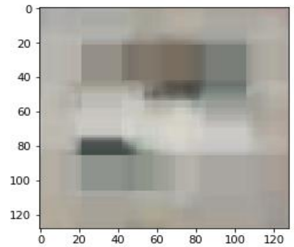
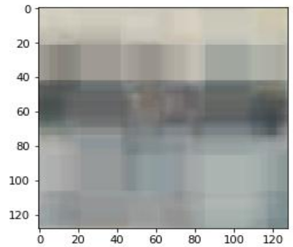
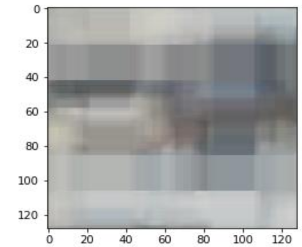
기존 연구 한계 및 개선

Text	Image	Meta
100%	0%	0
		1
50%	50%	0
		1
0%	100%	0
		1

1. Image Embedding




- CAE

- Generate Texture Image




기존 연구 한계 및 개선

❖ Text, Image, Texture 각각 Distance Matrix를 구하여 선형 결합

- Text, Image, Texture 의 속성이 다른 것에 대한 해결책

α

Text

0
0
…
0
0

Distance Matrix

Shape: [7922,7922]

$+ \; \dfrac{(1-\alpha)}{n}$

Image

0
0
…
0
0

Distance Matrix

Shape: [7922,7922]

$+ \; 1 - \dfrac{(1-\alpha)}{n}$

Texture

0
0
…
0
0

Distance Matrix

Shape: [7922,7922]

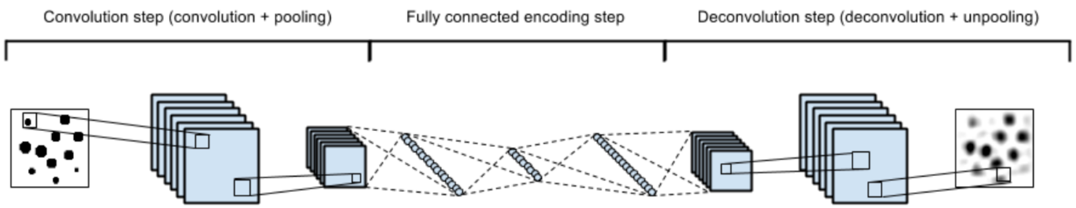
$0 \leq \alpha \leq 1$

기존 연구 한계 및 개선

❖ Image Embedding

기존 연구에서는 CAE를 활용하여 Image Embedding을 진행

다양한 Embedding시도(Pre-trained CNN, U net)외에도 Embedding에 대한 Performance measure확인



Shape: [7922,128,128,3]   Shape: [7922,64]   Shape: [7922,128,128,3]

Layer	Size out	Pooling / Sampling	Output Size
Input	7922, 128, 128, 3		
Convolution	7922, 128, 128, 64	4X4	7922, 32, 32, 64
Convolution	7922, 32, 32, 128	4X4	7922, 8, 8, 128
Convolution	7922, 8, 8, 256	4X4	7922, 2, 2, 256
Bottle Neck			7922, 64
		4X4	7922, 8, 8, 256
Deconvolution	7922, 8, 8, 256	4X4	7922, 32, 32, 256
Deconvolution	7922, 32, 32, 128	4X4	7922, 128, 128, 128
Deconvolution	7922, 128, 128, 3		

Loss : 0.023 , Acc : 0.675

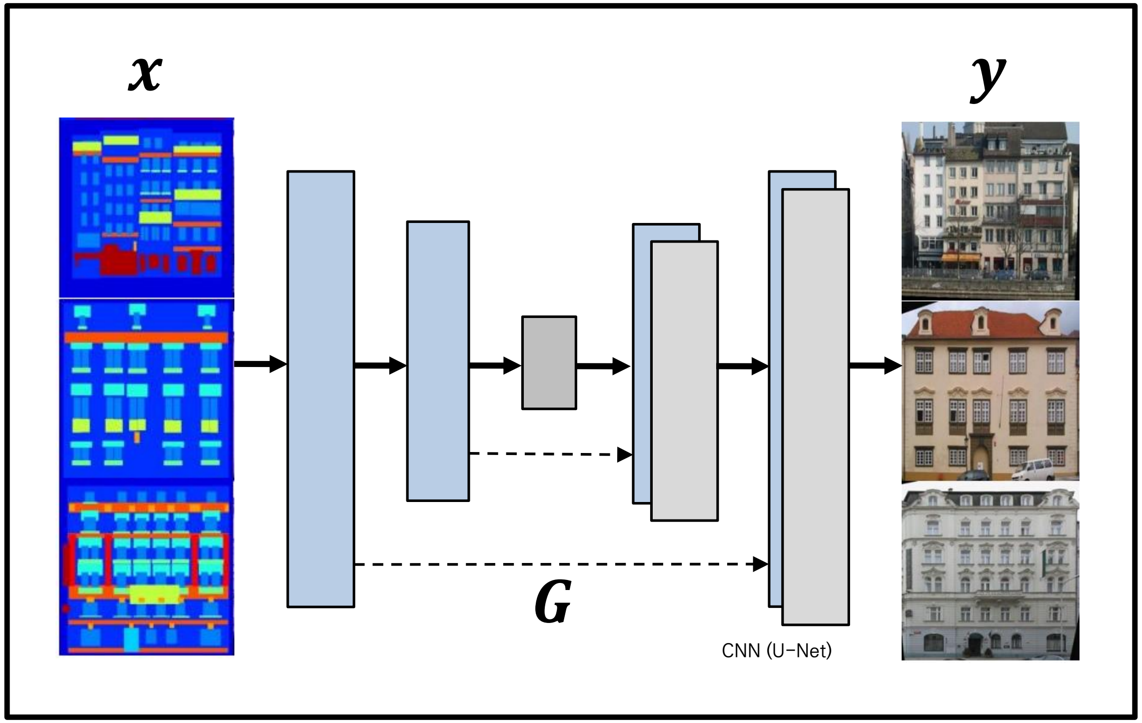
Thank you

Appendix

Pix2Pix

❖ Paired Image를 학습 (Supervised)

- Train



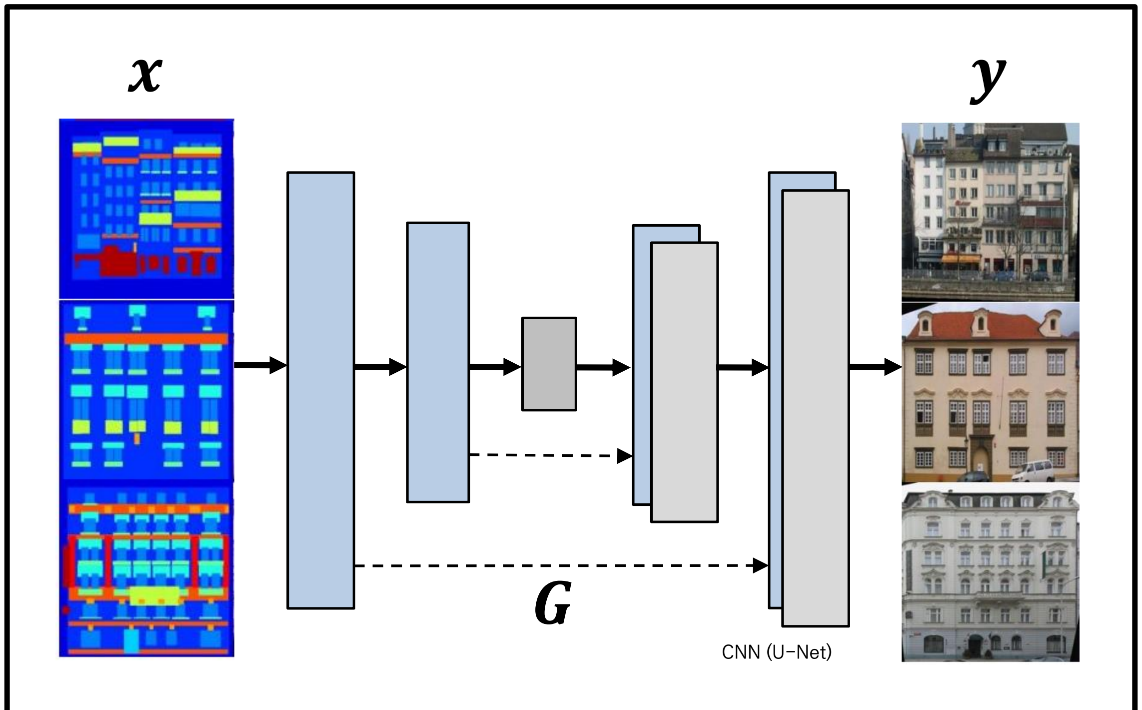
- L1 Loss

$$\min\left(\sum_{(x,y)} \|y - \hat{y}\|_1\right) = \min\left(\sum_{(x,y)} \|y - G(x)\|_1\right)$$

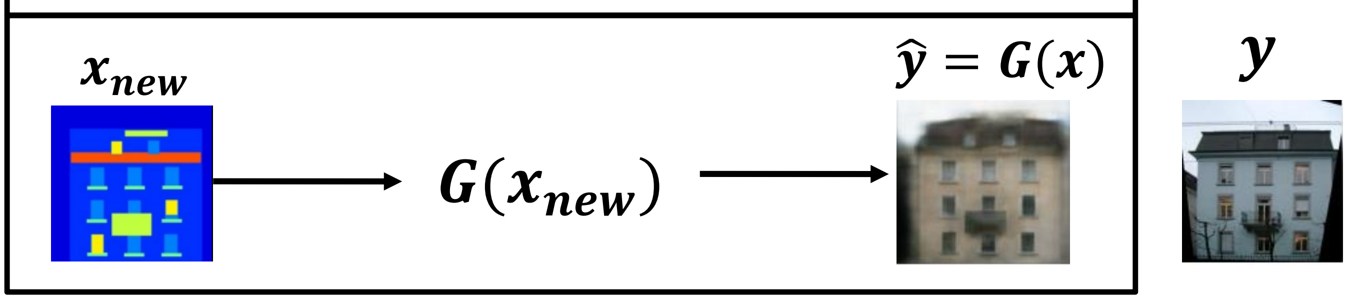
Pix2Pix

❖ L1 Loss 로 학습

- Train



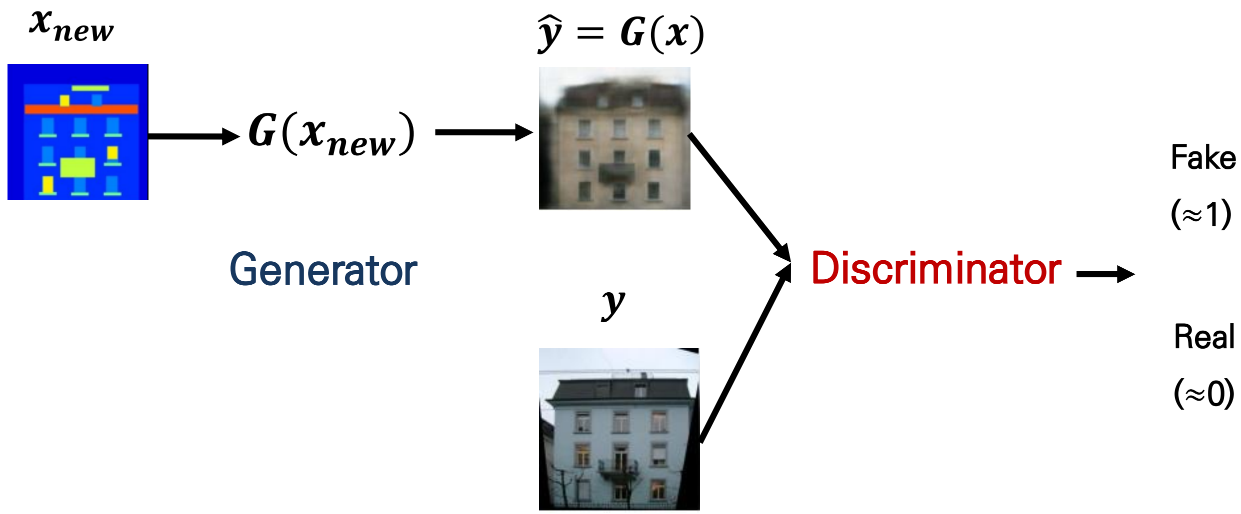
- Test



Pix2Pix

❖ GAN Term

- GAN



- Loss

$$arg \max_{D} E_{x,y} \left(\underbrace{logD(G(x))}_{\approx 1} + \underbrace{\log(1 - D(y))}_{\approx 0} \right)$$

$$arg \min_{G} E_{x,y} \left(\underbrace{logD(G(x))}_{\approx 0} + \underbrace{\log(1 - D(y))}_{\approx 1} \right)$$

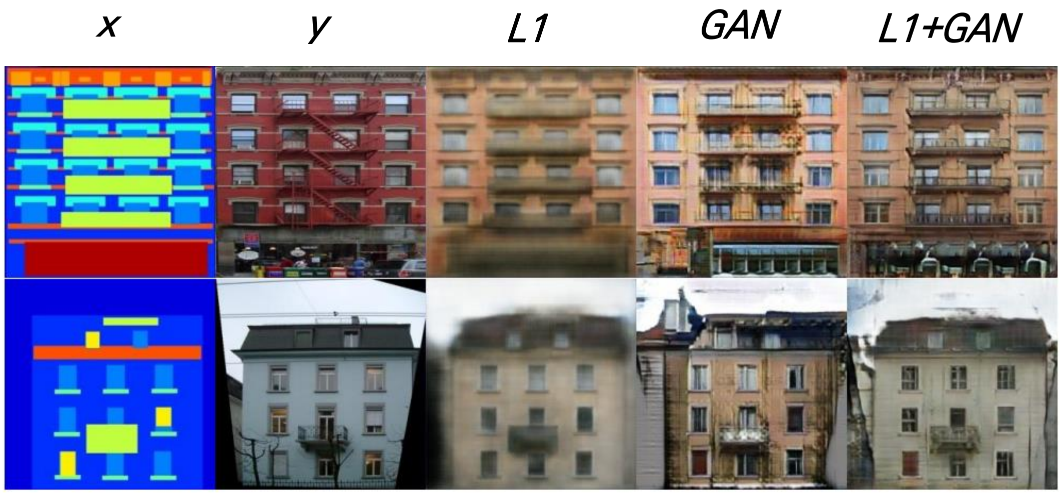
$$\boldsymbol{arg \min_{G} \max_{D} E_{x,y} \left(logD(G(x)) + \log(1 - D(y)) \right)}$$

Pix2Pix

❖ L1 + GAN Loss

$$arg\min_{G}\max_{D} E_{x,y}\left(logD\big(G(x)\big)+log(1-D(y))\right)+\lambda E_{x,y}\|y-G(x)\|_1$$

❖ Results



- L1+GAN loss를 사용한 학습이 더 Photorealism반영

Performance Evaluation Method

❖ 조사 개요

- 목적: 어떤 방법론을 바탕으로 한 추천 시스템이 소비자 선호도에 가장 긍정적 영향을 미칠 것인가?
  1. Only image vs Only text vs Image + Text
  2. Hyperparameter(α) 조정 Image : Text → 8 : 2 vs. 5 : 5 vs. 2 : 8
  3. Non-meta vs Meta
  4. TF-IDF vs Doc2vec

Image	Text	Text + Image	Meta
1. Random	2.1. TF-IDF (α=1)	2.1.1. α=0.8 (img 0.2)	(0,1)
		2.1.2. α=0.5 (img 0.5)	(0,1)
		2.1.3. α=0.2 (img 0.8)	(0,1)
	2.2. Doc2Vec (α=1)	2.2.1. α=0.8 (img 0.2)	(0,1)
		2.2.2. α=0.5 (img 0.5)	(0,1)
		2.2.3. α=0.2 (img 0.8)	(0,1)
	2.3	2.3. α=0 (Img 1)	(0,1)

18개 (9X2) model 비교

qualtrics. amazonmechanical turk beta Artificial Artificial Intelligence

Performance Evaluation Method

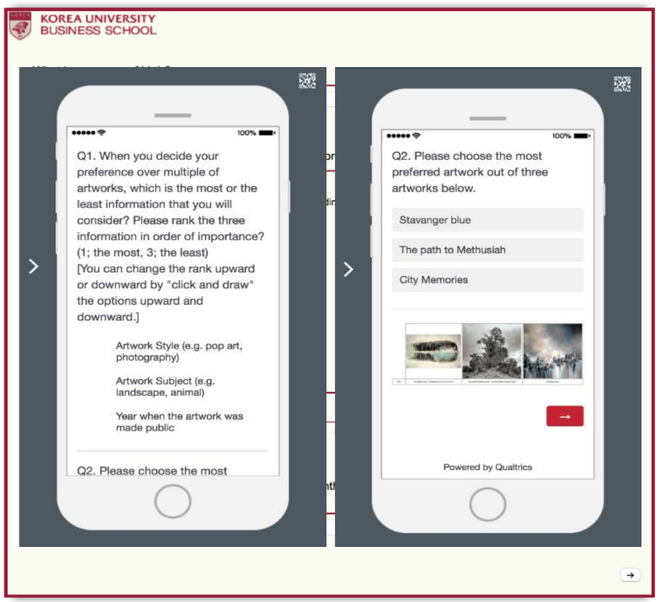
❖ 조사 과정

- 최빈 words 중 독립적인 단어 3개 추출

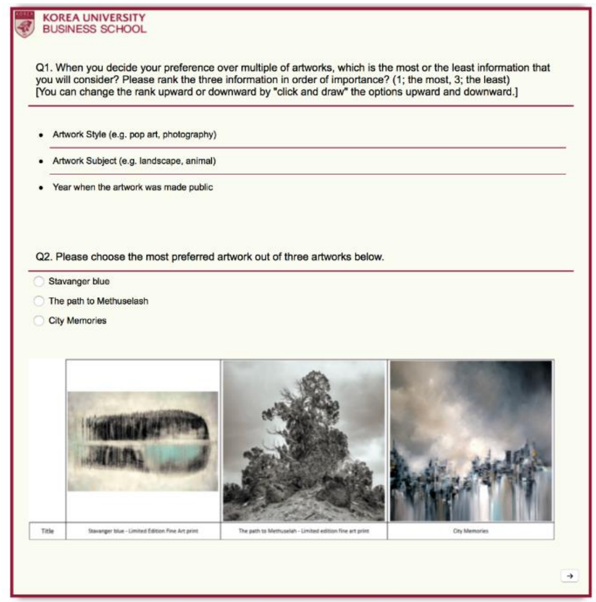
  – City, Landscape, Blue

- 각 그림에 대해 유사도가 높은 그림 15개 추출

  – 각 그림에 대한 설문에는 Top 5 ~ Top 10 의 그림 사용



Survey Powered By Qualtrics



Survey Powered By Qualtrics

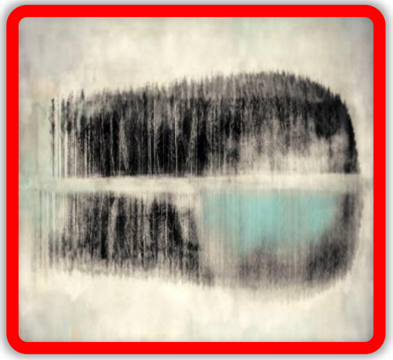
Performance Evaluation Method

❖ 조사 과정

Q1. 그림을 구매할 때 아래 내용 중 무엇을 가장 고려하는 편인가요? 순서대로 배치해주세요.

1. Style (e.g., Surrealistic, Pop Art, Abstract, Figurative, Street Art … Cartoon)
2. Subject (e.g., Animals, Landscapes, Fashion, Still Life, Urban, Food … Sports)
3. Year (작품의 제작 연도)

Q2. 귀하에게 미술 작품을 추천하려고 합니다.
아래 3가지 그림 중 가장 마음에 드는 그림 하나를 선택해주세요.



Stavanger blue

The path to Methuselash

City memories

Performance Evaluation Method

❖ 조사 과정

Image 100%

KOREA UNIVERSITY BUSINESS SCHOOL

Q.3_1 Look at artworks below and measure your preference for each artwork base on the preference you have shown in the Q2.

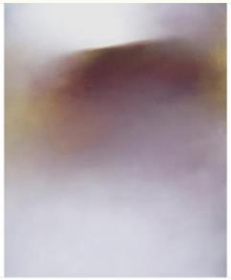
	I like this artwork.	I do not like this.
El Pas da la Casa	✓	○
Winter Parkland II	○	✓
Golden II	○	✓
VIETNAM STORIES 2.	○	✓
Qweesh not Quiche	✓	○

Title: El Pas da la Casa

Art abstract
An amalgamation of experiences

Title: Winter Parkland II

Art abstract
A wintry Christmassy scene showing the deer grazing in Richmond park just after snowfall. The deer are silhouetted against the white background, with warm highlights brought out on their backs and in the majestic trees beside them.



Title: Golden II

Art abstract
Bright sunlight reflects violet and lavender off the calm water. Abstraction of Chesil Beach along the Dorset coast, the sea on both sides of the rocks, with gold paint shimmering along the sides. Original acrylic abstract seascape painting on canvas. Inspired by Chesil Beach, Weymouth, Dorset coast, England.

Title: VIETNAM STORIES 2.

Art abstract
A large Giclee print of a beautiful dark coloured dog sitting under a table in the historical town of Hoi An, Vietnam.
Would look fantastic on the wall at home or work place !
This stunning image is part of a new collection of mine titled ' VIETNAM STORIES '.
A high quality Giclee print on Luxurious looking Harman Gloss Warmtone paper.
This 320 g.s.m. fibre-based paper gives you creamy whites and velvety blacks. The special coating gives you a high gloss, optical image density and vibrancy.

Title: Qweesh not Quiche

Art abstract
SQweesh Not Quiche (Queen not Keen) is one of five prints inspired by episodes from McLean's autobiography 'Mixed Grillings'. which is a series of 150 true stories of which food is the central motif. Excerpts from the text have been incorporated into the composition; displaying the artist's quirky and unique sense of humour. Each work represents a memory, a story, a slice of the artist's life and his artistic response to that memory; and as such they constitute his most personal work in recent years. Each print is hand-worked by the artist.

Performance Evaluation Method

❖ 조사 과정

TF-IDF 80%
Image 20%

KOREA UNIVERSITY
BUSINESS SCHOOL

Q.3_3 Look at artworks below and measure your preference for each artwork base on the preference you have shown in the Q2.

	I like this artwork.	I do not like this.
Monterey Bronze	✓	○
Cape Hills	○	✓
Palm South Africa - Limited Edition Fine Art print	○	✓
Monterey gold	✓	○
Sound of sea	✓	○

Title: Monterey Bronze

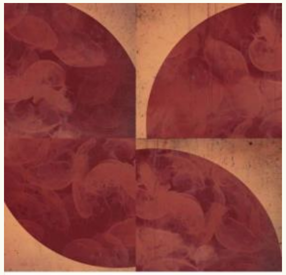
Art abstract
Monterey's bronze and all that glitters, California's swimming jellyfish part of the underwater portfolio. Original photography worked in layers, adding gold paint, textures and washes to create the final print.
Fine Art photographic print, professionally hand printed on Giclee 310gsm Museum gallery paper using archival pigment ink. Limited edition print signed and numbered by the artist.

Title: Cape Hills

Art abstract
The Cape hills surrounding the mother city, South Africa's Cape Town. Mediterranean pine trees draw lines across the rising hills.
Shades of blue and green across the horizon. Mixing photography, drawing and painting to produce the final art work
Print combines photography and watercolour pastels to create the final limited edition on paper.
Fine Art photographic print, professionally hand printed on fine art Giclee cotton gallery paper using archival pigment ink.

Title: Palm South Africa - Limited Edition Fine Art print

Art abstract
Palm print made in South Africa, black and white warm toned print, echoing the warmth of the South African sun. Fine Art photographic print, professionally hand printed professionally on fine art Giclee gallery museum paper by the artist. Limited edition print signed and numbered by the artist.



Title: Monterey gold

Art abstract
Monterey's gold, and all that glitters, California's swimming jellyfish part of the underwater portfolio. Original photography worked in layers using collage, textures and washes to create the final print.
Fine Art photographic print, professionally hand printed on Giclee 310gsm Museum gallery paper using archival pigment ink. Limited edition print signed and numbered by the artist.
Happy to create bespoke size prints for clients, please get in touch with any print requirements.

Title: Sound of sea

Art abstract
Sound of the sea, shades of sea blue, waters moving, warm sands looking across the Pacific ocean from the shores of California. The print was created mixing black and white photographic long exposures with paint, layered digitally to create the print on museum grade paper. Limited edition print signed and numbered by the artist. Baryta art paper at 310gsm Giclee museum print using archival inks. If you prefer the artwork mounted under Plexiglass or on Aluminium Dibond ready to hangplease contact us.

Performance Evaluation Method

❖ 조사 결과

		The number of Respondents: 175				The number of Respondents: 174				
		Non-Meta				Meta				Non-Meta+Meta
		City	Landscape	Blue	Total	City	Landscape	Blue	Total	
image100%	like	190	232	175	597	127	304	175	606	1203
	total	285	360	235	880	210	422	235	867	1747
	ratio	67%	64%	74%	68%	60%	72%	74%	70%	69%
TF-IDF 100%, Image 0%	like	219	262	175	656	156	320	175	651	1307
	total	285	360	235	880	210	422	235	867	1747
	ratio	77%	73%	74%	75%	74%	76%	74%	75%	75%
TF-IDF 80%, Image 20%	like	222	268	166	656	163	313	166	642	1298
	total	285	360	235	880	210	422	235	867	1747
	ratio	78%	74%	71%	75%	78%	74%	71%	74%	74%
TF-IDF 50%, Image 50%	like	190	233	179	602	159	303	179	641	1243
	total	285	360	235	880	210	422	235	867	1747
	ratio	67%	65%	76%	68%	76%	72%	76%	74%	71%
TF-IDF 20%, Image 80%	like	199	220	178	597	139	317	178	634	1231
	total	285	360	235	880	210	422	235	867	1747
	ratio	70%	61%	76%	68%	66%	75%	76%	73%	70%
Doc2Vec 100%, Image 0 %	like	175	262	167	604	140	328	167	635	1239
	total	285	360	235	880	210	422	235	867	1747
	ratio	61%	73%	71%	69%	67%	78%	71%	73%	71%
Doc2Vec 80%, Image 20 %	like	157	207	172	536	155	291	172	618	1154
	total	285	360	235	880	210	422	235	867	1747
	ratio	55%	58%	73%	61%	74%	69%	73%	71%	66%
Doc2Vec 50%, Image 50 %	like	171	250	181	602	140	296	181	617	1219
	total	285	360	235	880	210	422	235	867	1747
	ratio	60%	69%	77%	68%	67%	70%	77%	71%	70%
Doc2Vec 20%, Image 80 %	like	178	223	169	570	133	292	169	594	1164
	total	285	360	235	880	210	422	235	867	1747
	ratio	62%	62%	72%	65%	63%	69%	72%	69%	67%

like	4823
total	7040
ratio	**69%**

like	5032
total	6936
ratio	**73%**

END