DMQA Open Seminar

Image Denoising

2024. 05. 10

김성수

Data Mining and Quality Analytics Lab

고려대학교
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- Data Mining & Quality Analytics Lab. (김성범 교수님)
- 석박통합 과정 (2022.03 ~ Present)

❖ **Research Interest**

- Computer Vision (Image Restoration, Scene Text Recognition)
- Self/Semi-supervised Learning

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목차

❖ **Introduction**

❖ **Algorithms**

① Supervised Learning

- Paired Noisy-Clean Images
- Unpaired Noisy-Clean Images

② Self-supervised Learning

- Paired Noisy-Noisy Images
- Single Noisy Image
  - Blind Spot Network
  - Deep Image Prior

❖ **Conclusion**

Introduction

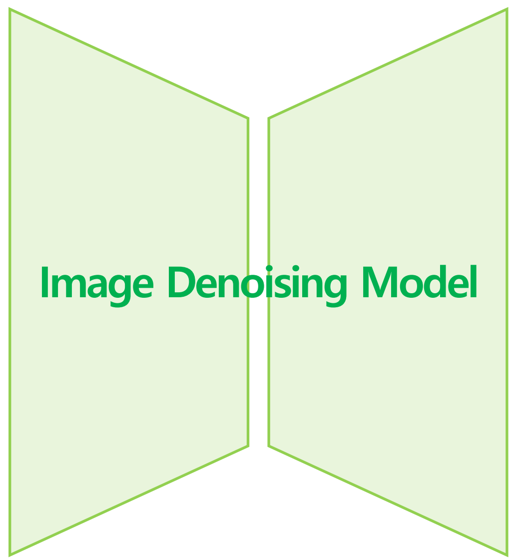
Introduction

Definition

❖ **Image Denoising이란?**

- 이미지 내 존재하는 Noise를 제거하는 Task

[Input Image]



[Output Image]

Noisy Image

Clean Image

Noise 제거

Introduction

Goal

❖ Image Denoising의 목표

- **"이미지 내 다양한 Noise에 강건한 모델 확립"**
  - ➢ 다양한 Noise 종류: Gaussian Noise, Poisson Noise, Salt-and-Pepper Noise …

https://blog.naver.com/neverabandon/100053992226

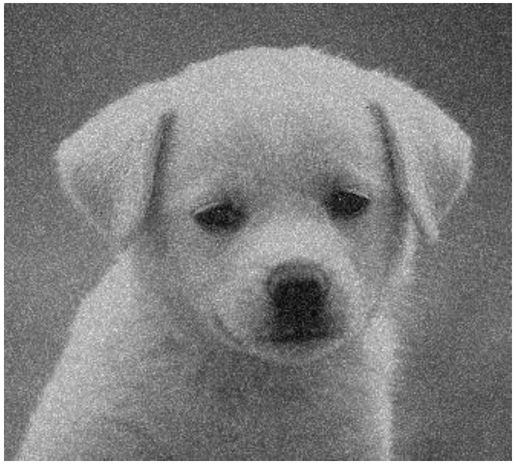
Introduction

Image Denoising in Real-World

❖ Real-World Image Denoising

- **Complex**: 단일 Noise가 아닌, 여러 Noise가 결합된 형태
    - ➢ Ex) Gaussian Noise + Salt-and-Pepper Noise + …
- **Unknown**: 이미지 내 Noise의 종류는 알려지지 않음

Noise Type: ?



Noise Type: ?

Noise Type: ?

https://media.cheggcdn.com/media/8c7/8c7f3063-bccd-49ef-a483-c160557d6ef4/phpAtYk4M.png
https://www.inf.ufrgs.br/~eslgastal/AdaptiveManifolds/Application_Examples/Non-Local_Means_Denoising/kodim23-noise-std51.png
https://www.inf.ufrgs.br/~eslgastal/AdaptiveManifolds/Application_Examples/Non-Local_Means_Denoising/kodim23-noise-std51.png

Introduction

Taxonomy

❖ Overall Taxonomy

① **Computer Vision Algorithm**: 학습 없이 수리적 알고리즘 활용

② **Supervised Learning**: Noisy Image (X) ↔ Clean Image (Y)에 대하여 학습

③ **Self-supervised Learning**: Clean Image (Y) 없이 Noisy Image (X) 로만 학습

Noisy Image

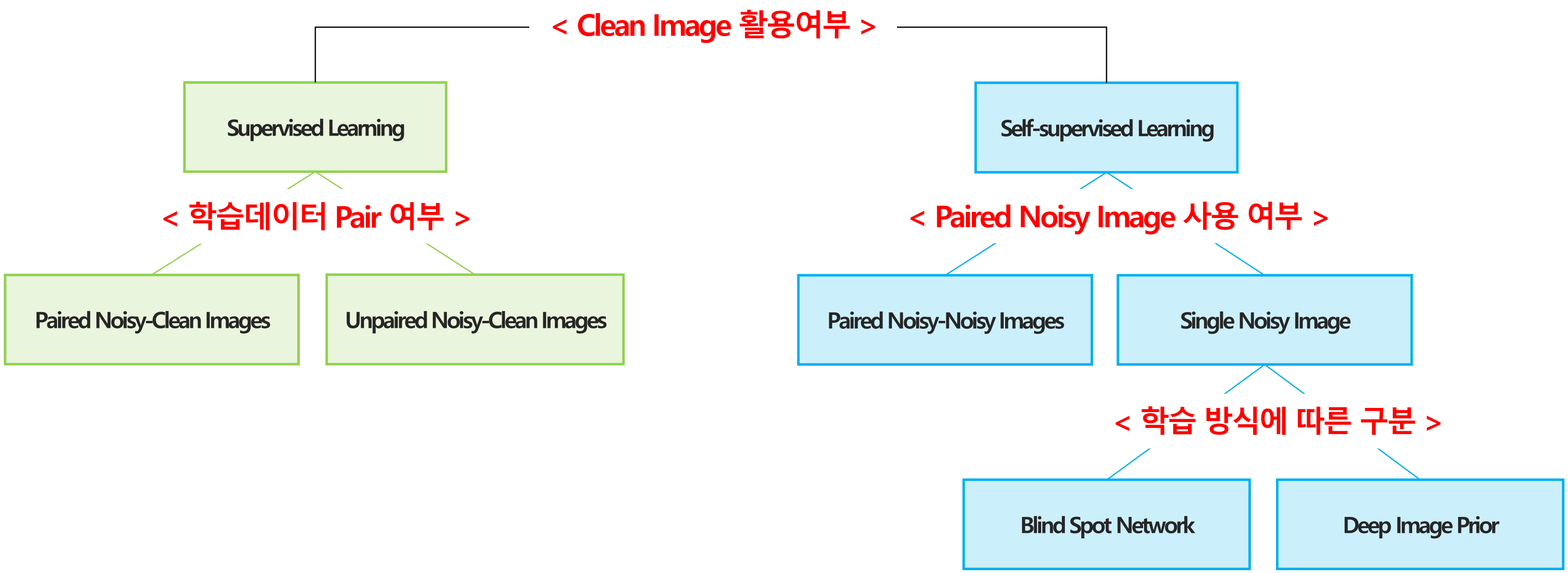
Clean Image

	Computer Vision Algorithm	Supervised Learning	Self-supervised Learning
학습여부	X	O	O
Clean Image 필요 여부	X	O	X

Introduction

Taxonomy

❖ Image Denoising Taxonomy



Algorithms (1)

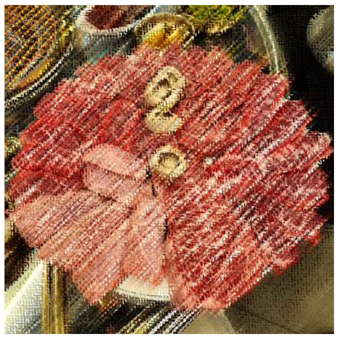
[Supervised Learning]

Algorithms: Supervised Learning

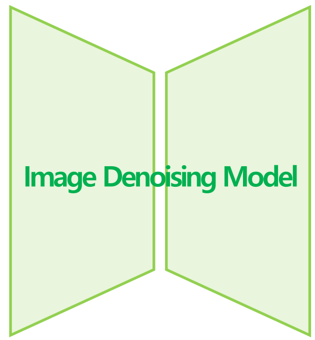
Supervised Learning-based Image Denoising

❖ **Supervised Learning : Noisy Image와 Clean Image를 모두 활용**

[Input Image]



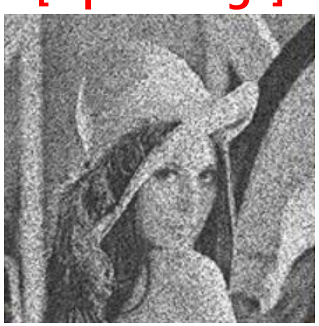
Noisy Image



[Output Image]

Clean Image

[Input Image]

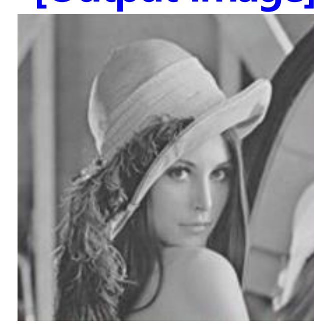


[Output Image]

Paired Noisy-Clean Images

[Input Image]

[Output Image]



Unpaired Noisy-Clean Images

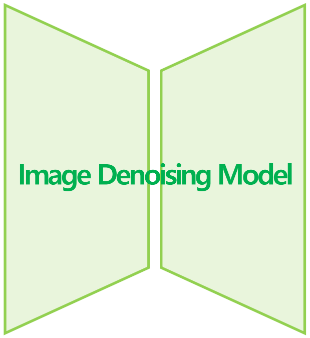
Algorithms: Supervised Learning

Supervised Learning (1): Paired Noisy-Clean Images

❖ Paired Noisy-Clean Images

[Input Image]

Noisy Image



[Output Image]

Clean Image

***** 한계 *****

" 동일한 장면에 대한 서로 다른 이미지는 현실에 거의 존재하지 않음 "

Algorithms: Supervised Learning

Supervised Learning (1): Paired Noisy-Clean Images

Supervised Learning

<학습데이터 Pair 여부>

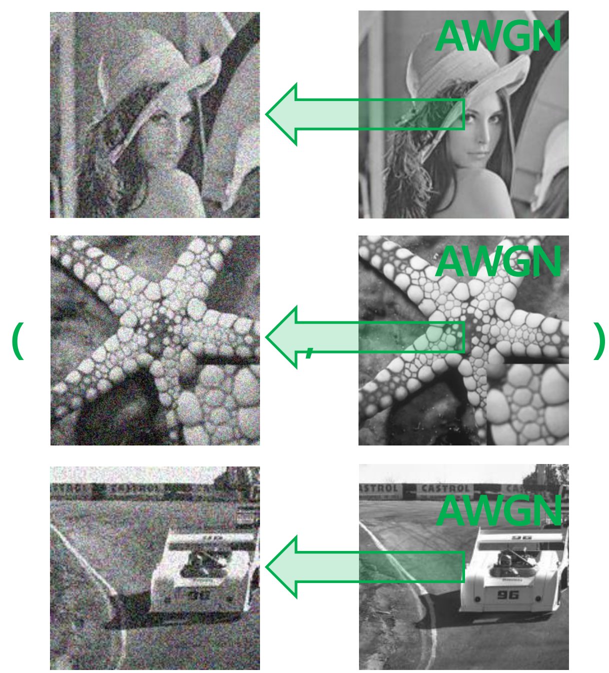
Paired Noisy-Clean Images | Unpaired Noisy-Clean Images

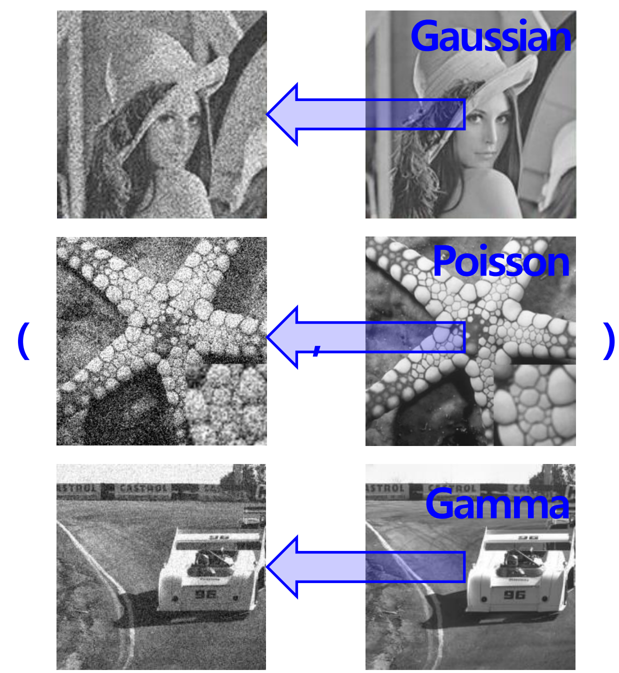
❖ Paired Noisy-Clean Images

[학습 데이터를 합성하여 해결]

★ Clean Image에 Noise를 인위적으로 부여 → Noisy 이미지 획득★

(X, Y) = (Noisy, Clean) =



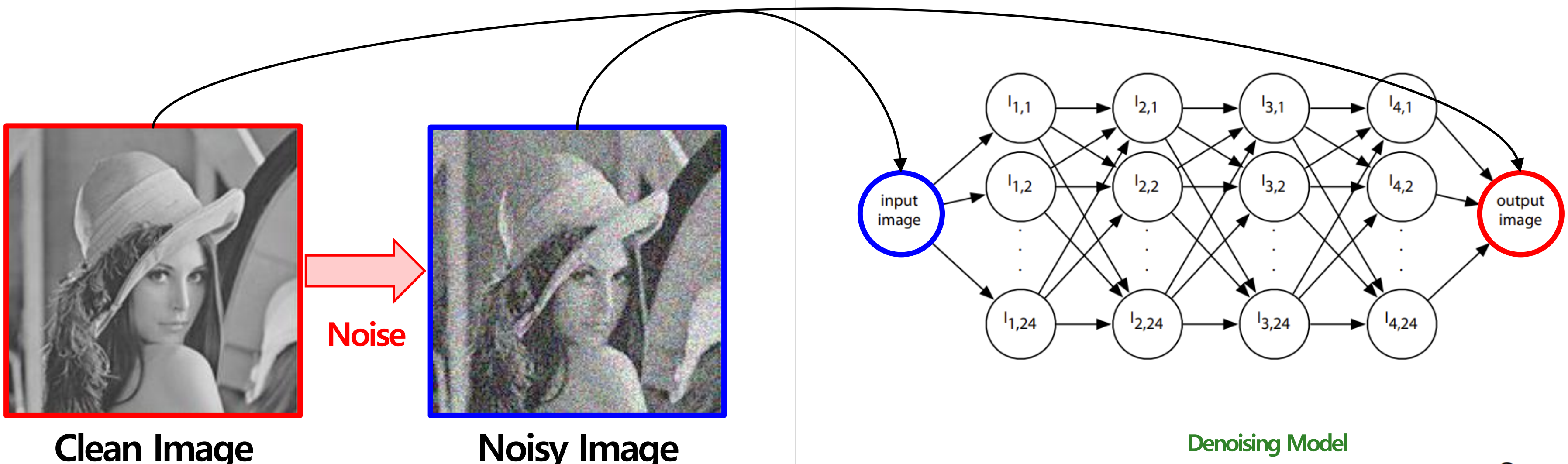


Algorithms: Supervised Learning

Supervised Learning (1): Paired Noisy-Clean Images

❖ Paired Noisy-Clean Images (1/2): Jain et al (2008, NIPS)

- Denoising에 딥러닝을 적용한 첫번째 방법론
  - 입력: Noisy Image / Output: Clean Image



$$\min_\phi \sum_i (\underbrace{x_i}_{\text{Clean Image}} - \overbrace{F_\phi}^{\text{Denoising Model}}(\underbrace{n(x_i)}_{\text{Noisy Image}}))^2)$$

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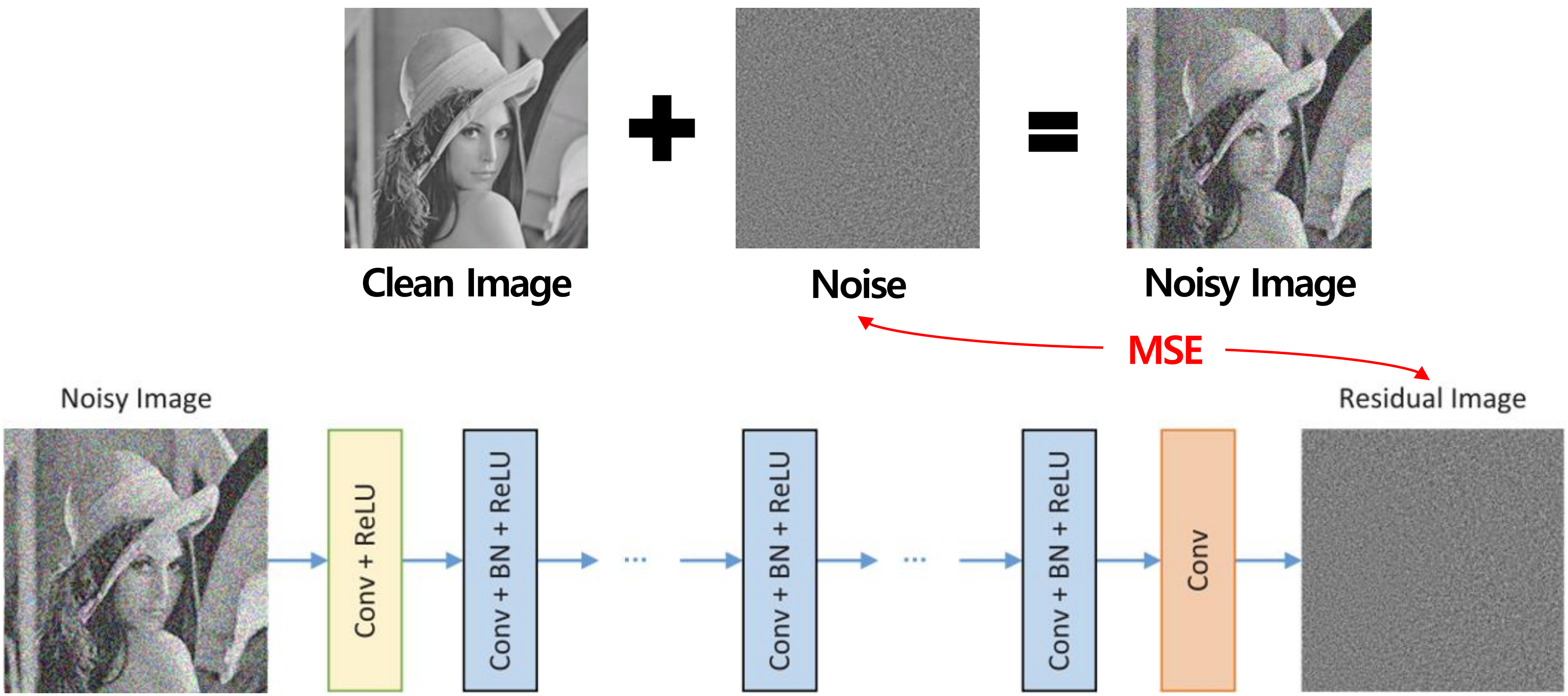
Algorithms: Supervised Learning

Supervised Learning (1): Paired Noisy-Clean Images

❖ Paired Noisy-Clean Images (2/2): DnCNN (2017, TIP)

- Train: 이미지를 직접 Denoising하는 것이 아닌, 이미지에서 Noise를 분리하는 것을 학습
  - ➢ 입력: Noise Image / Output: **<u>Residual Map</u>**
  - ➢ 학습 목표의 명확성: Noise 제거 및 이미지 생성 → 제거해야 할 Noise만 학습

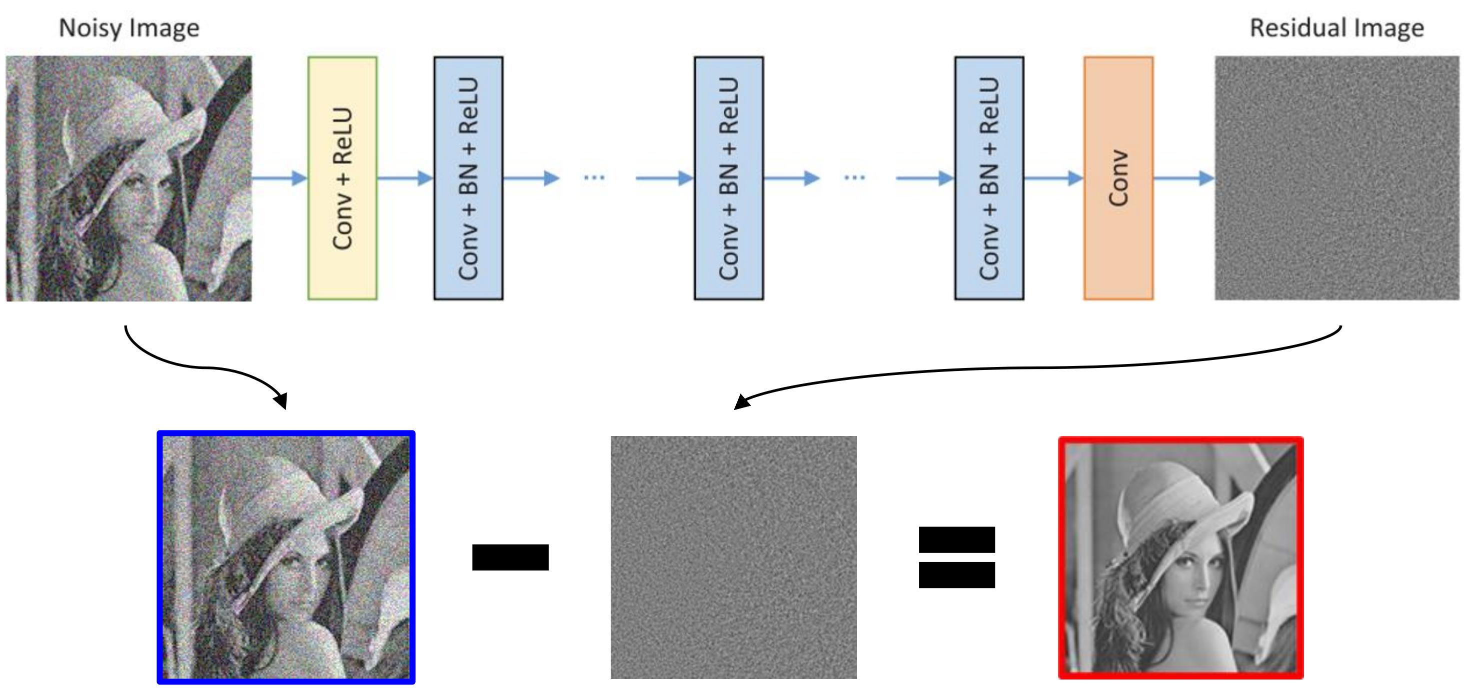


Algorithms: Supervised Learning

Supervised Learning (1): Paired Noisy-Clean Images

❖ Paired Noisy-Clean Images (2/2): DnCNN (2017, TIP)

- Inference: 기존 Noisy 이미지에서 Residual Map을 빼주어 최종 Clean Image 생성
  - ① Noisy 이미지를 DnCNN에 넣어 Residual Image 산출
  - ② 최종적인 Clean Image = Noisy 이미지 – Residual Image



Target Image
(최종 Output)

Algorithms: Supervised Learning

Supervised Learning (2): Unpaired Noisy-Clean Images

❖ Unpaired Noisy-Clean Images

실제 이미지들을 활용하여 Real-World Noise를 효과적으로 활용하자!

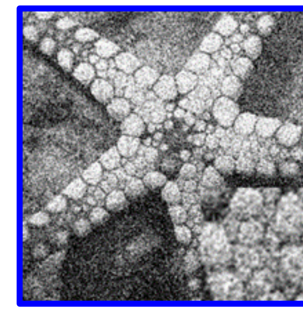
Clean Image

VS

Noisy Image

Clean Image

VS



Noisy Image

Paired → **Unpaired**

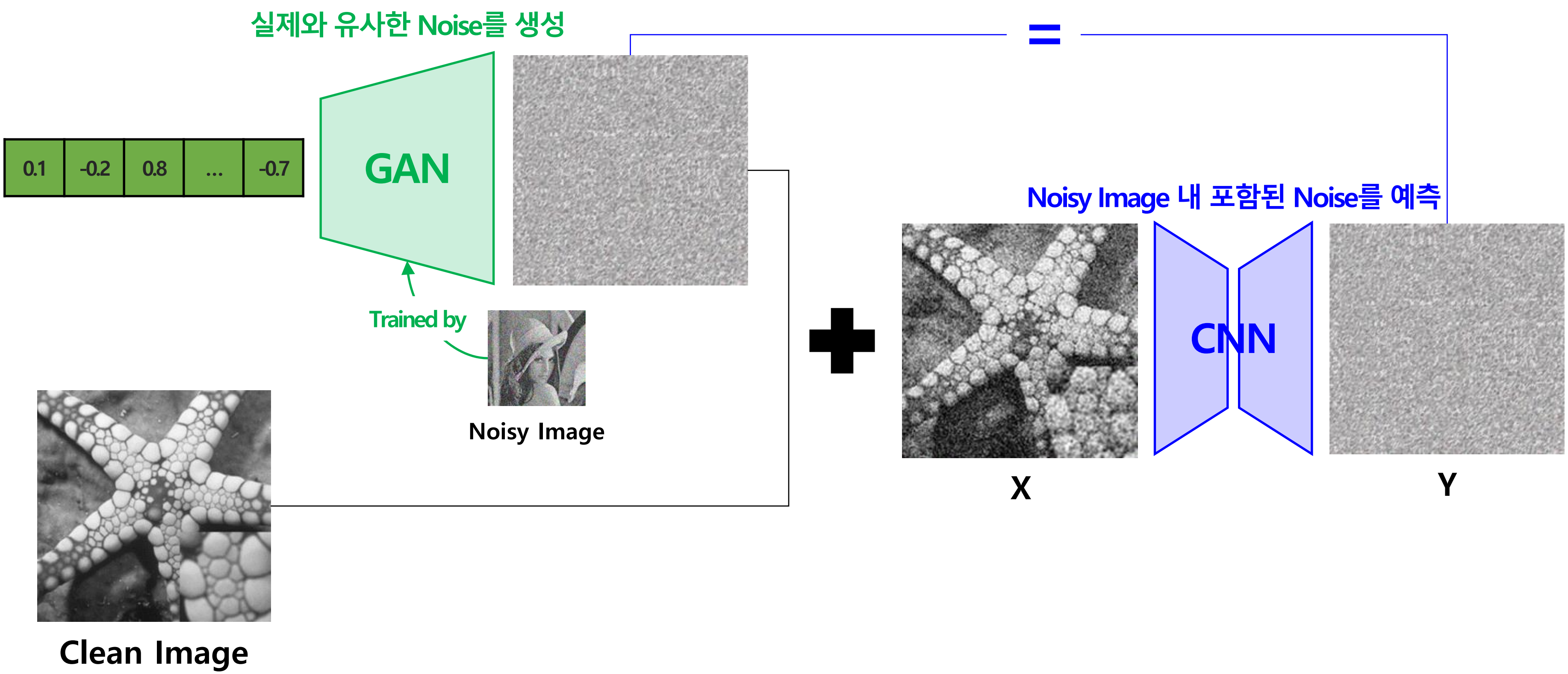
Paired	Unpaired
실제 Clean & 합성 Noisy 이미지를 활용	실제 Clean & 실제 Noisy 이미지를 활용
Clean & Noisy 이미지가 대응	Clean & Noisy 이미지가 대응되지 않음
Real-World Noise 학습에 어려움 존재	Real-World Noise 학습 가능

Algorithms: Supervised Learning

Supervised Learning (2): Unpaired Noisy-Clean Images

❖ Unpaired Noisy-Clean Images: GCBD (2018, CVPR)

- GCBD: GAN-CNN based Blind Denoiser (GAN 및 CNN의 2-stage 구조로 구성)

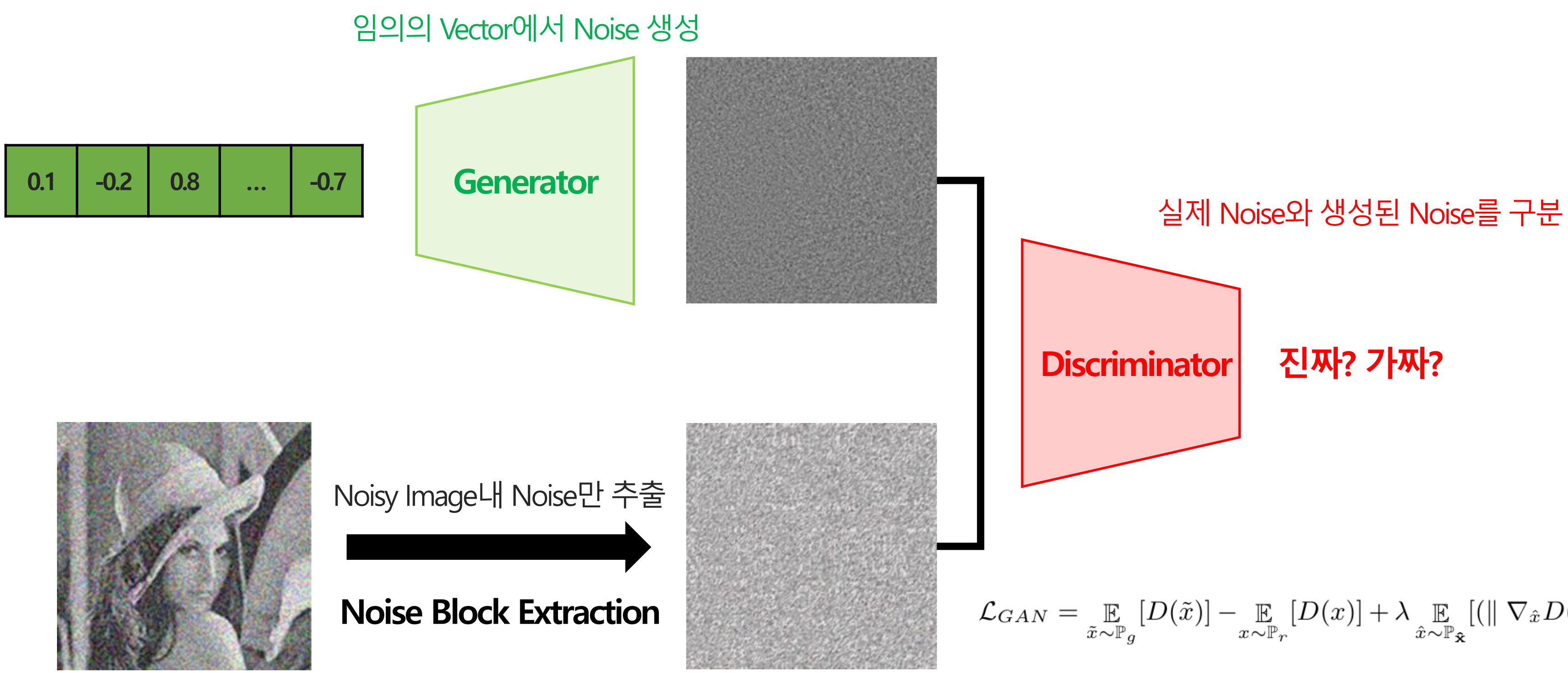


Algorithms: Supervised Learning

Supervised Learning (2): Unpaired Noisy-Clean Images

❖ Unpaired Noisy-Clean Images: GCBD (2018, CVPR)

- Phase1 - GAN: Generator와 Discriminator가 적대적으로 학습 (WGAN-GP 기반)



$$\mathcal{L}_{GAN} = \underset{\tilde{x}\sim\mathbb{P}_g}{\mathbb{E}}[D(\tilde{x})] - \underset{x\sim\mathbb{P}_r}{\mathbb{E}}[D(x)] + \lambda \underset{\hat{x}\sim\mathbb{P}_{\hat{x}}}{\mathbb{E}}[(\| \nabla_{\hat{x}} D(\hat{x}) \|_2 - 1)^2],$$

Algorithms: Supervised Learning

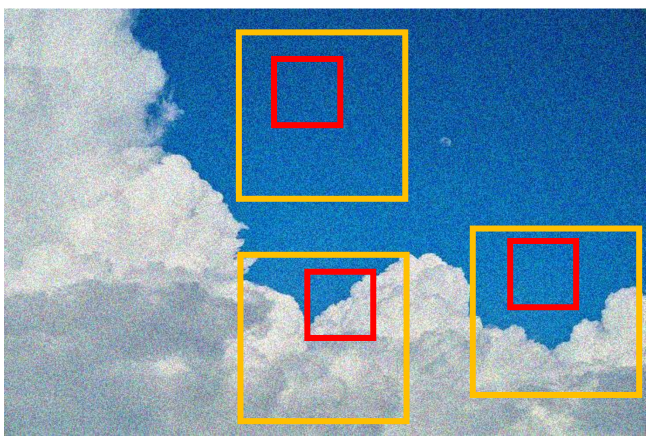
Supervised Learning (2): Unpaired Noisy-Clean Images

❖ Unpaired Noisy-Clean Images: GCBD (2018, CVPR)

- Phase1 - GAN: Generator와 Discriminator가 적대적으로 학습 (WGAN-GP 기반)

[Noise Block Estimation]

Noisy 이미지만으로 Noise 패치 추출 (Hand-crafted 방식)



큰 패치 p_i와 p_i 내 작은 패치인 q_j^i 를 활용

p_i: 전체 이미지를 Sliding

q_j^i: p_i 내부를 Sliding

① 두 패치 내 픽셀들의 평균 및 분산 차이가 아래 범위를 만족 → p_i 필터링

$$\left|Mean(q_j^i) - Mean(p_i)\right| \leq \mu \cdot Mean(p_i)$$

$$\left|Var(q_j^i) - Var(p_i)\right| \leq \gamma \cdot Var(p_i)$$

" 위 조건을 만족하는 p_i: 변화가 거의 없는 패치 (ex. 벽, 하늘 등) "

② 평균 픽셀만큼 빼주기

$$Noise_i = p_i - Mean(p_i)$$

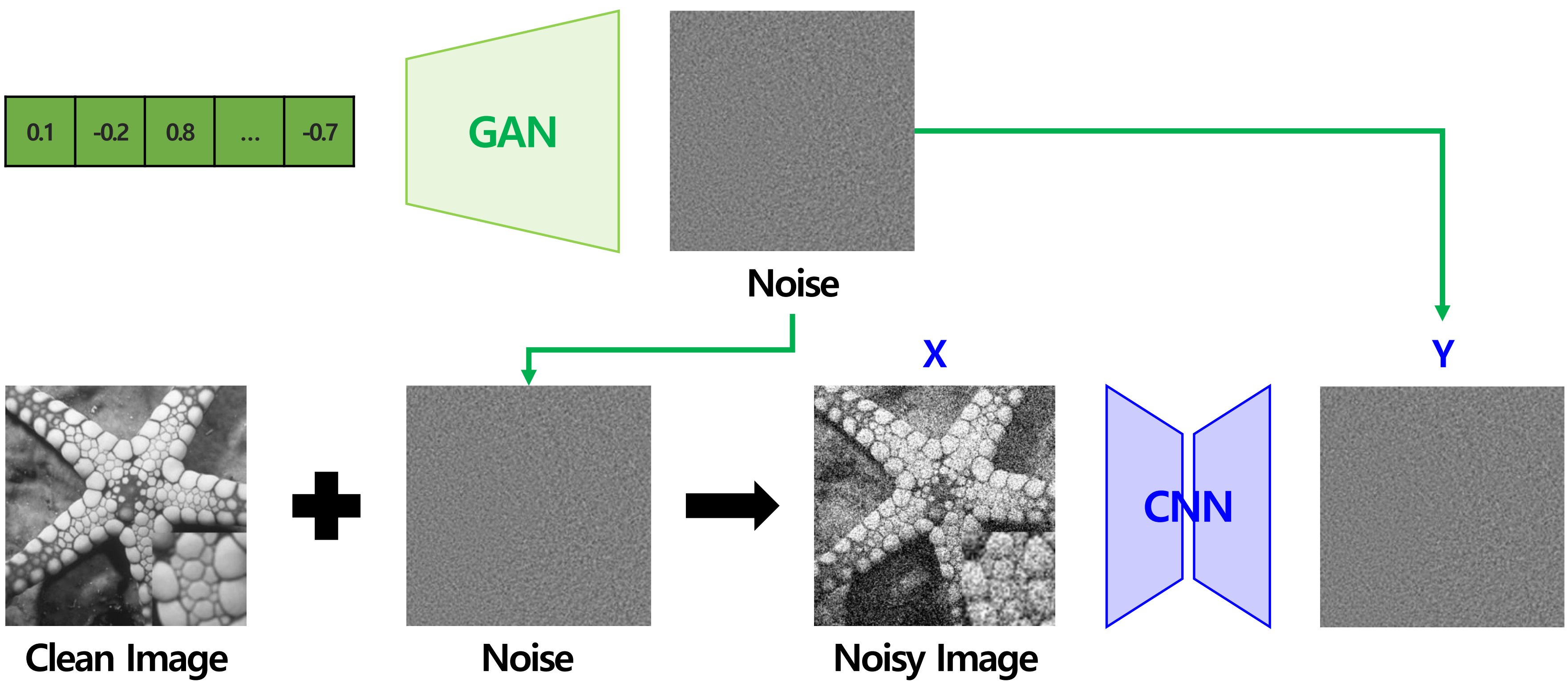
" 변화가 거의 없는 패치 = 모든 픽셀이 유사 = 평균: 각 Pixel의 Content 대변 "

Algorithms: Supervised Learning

Supervised Learning (2): Unpaired Noisy-Clean Images

❖ Unpaired Noisy-Clean Images: GCBD (2018, CVPR)

- Phase2 - CNN: Noisy Image(Clean Image + Noise)에 포함된 Noise를 예측
  - ➢ GAN에서 Noise를 생성한 후, Clean Image와 결합하여 Noisy Image 생성
  - ➢ 서로 대응되는 Noisy-Clean Image Pair를 만든 후, DnCNN 구조를 기반으로 학습

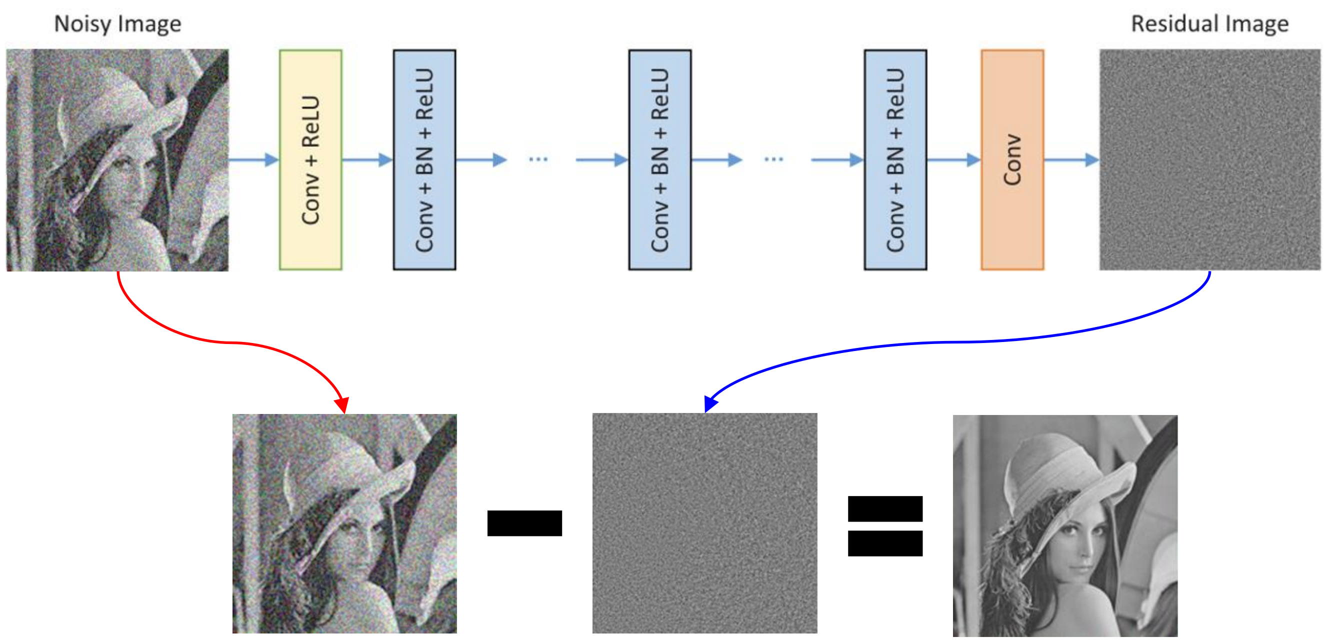


Algorithms: Supervised Learning

Supervised Learning (2): Unpaired Noisy-Clean Images

❖ Unpaired Noisy-Clean Images: GCBD (2018, CVPR)

- Inference: Noisy 이미지 내 Noise를 예측
  - ➢ 최종 Output = Noisy Image – 예측된 Noise



Algorithms: Supervised Learning

Summary

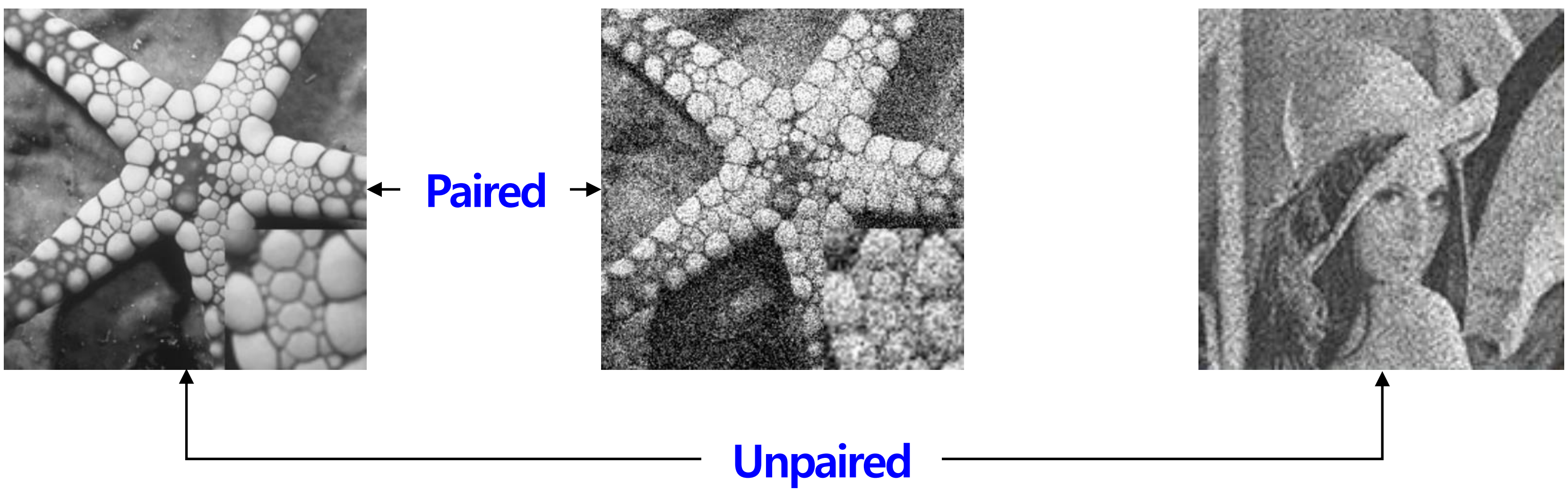
Supervised Learning

<학습데이터 Pair 여부>

Paired Noisy-Clean Images | Unpaired Noisy-Clean Images

❖ Supervised Learning

- Paired Noisy-Clean Images: 실제 Clean Image로부터 합성 Noisy Image를 생성하여 Pair 생성
- Unpaired Noisy-Clean Images: Pair가 아닌 실제 Clean 및 실제 Noisy 이미지를 활용
  - ➢ Noise 추정 모델에 대한 필요성 제거



" 여전한 제약: Clean Image가 필요하다 "

Algorithms (2)

[Self-supervised Learning]

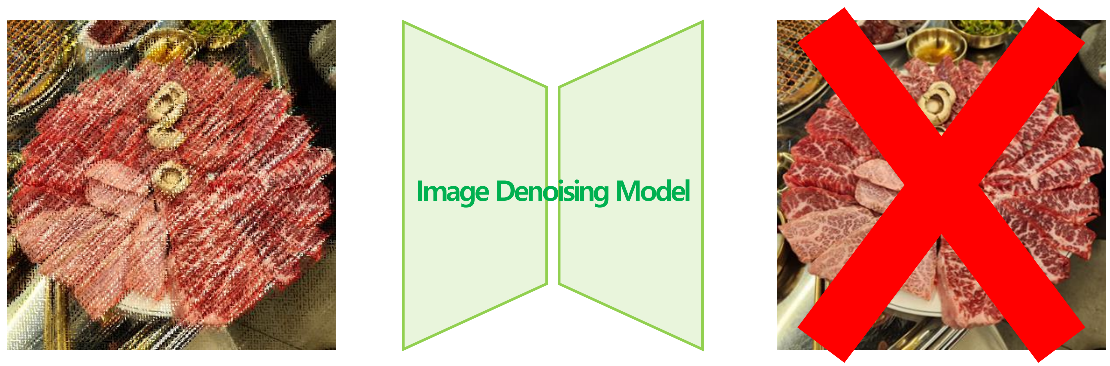
Algorithms: Self-supervised Learning

Self-supervised Learning-based Image Denoising

❖ Supervised Learning → Self-supervised Learning

- 핵심: 현실에서는 Noise가 없는 Clean Image를 구하는 것이 가장 어려움
- <u>Motivation: Noisy Image만 있는 상황에서 Denoising 모델을 학습할 수는 없을까?</u>

“ Clean 이미지 없이, 오직 Noisy 이미지들만으로 학습해보자. ”



Noisy Image　　　　Clean Image

Supervised → Self-supervised

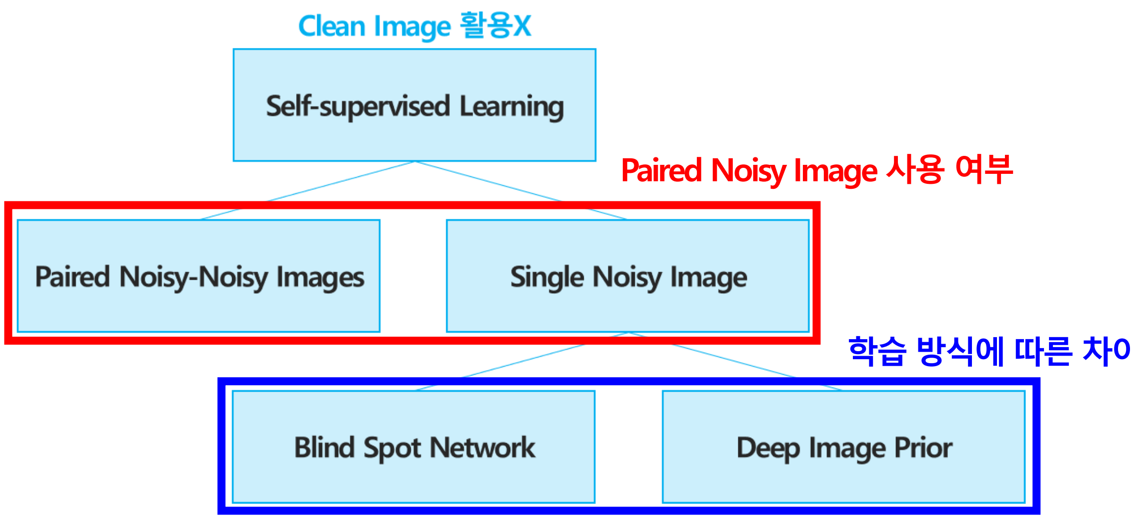
Clean(Y) 및 Noisy(X) Image를 모두 활용　　　　Noisy(X) Image만 활용

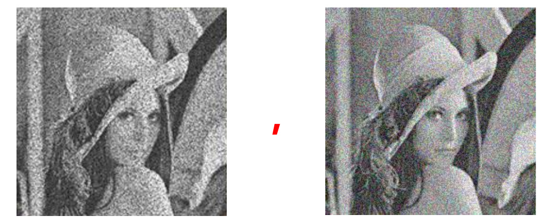
Algorithms: Self-supervised Learning

Self-supervised Learning-based Image Denoising

❖ Self-supervised Learning

- Paired Noisy-Noisy Images: 동일한 장면의 Noisy Image 쌍으로 모델을 학습
- Single Noisy Image: 오직 Noisy 이미지만으로 모델 학습



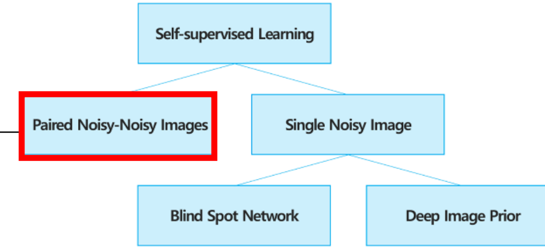


Paired Noisy-Noisy Images

Single Noisy Image

Algorithms: Self-supervised Learning

Self-supervised Learning (1): Paired Noisy-Noisy Images



❖ Paired Noisy-Noisy Images: Noise2Noise (2018, ICML)

- Clean Image 없이 오직 Noisy Image Pair만으로 모델을 학습
- Noise Image①의 복원결과가 Noisy Image②가 되도록 학습

Noisy Image① **(X)**

Restored Noisy Image①

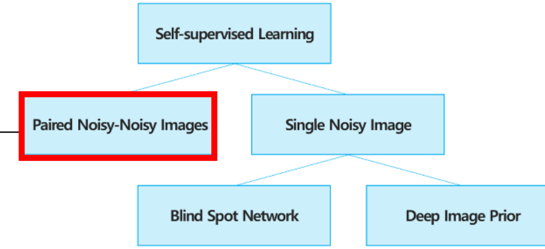
Noisy Image② **(Y)**

★ 동일한 장면에 해당하는 서로 다른 Noisy Image를 필요로 함 ★

$$\arg\min_{\theta} \mathbb{E}_{\mathbf{x},\mathbf{y},\mathbf{z}} \|f_\theta(\mathbf{y}) - \mathbf{z}\|_2^2$$

Algorithms: Self-supervised Learning

Self-supervised Learning (1): Paired Noisy-Noisy Images



❖ **Paired Noisy-Noisy Images: Noise2Noise (2018, ICML)**

< Ill-posed Problem >

Noisy Image에 정답이 가능한 Clean Image는 하나의 형태가 아님

Noisy Image①
(Input)

Clean Image①
(Output)

Clean Image②
(Output)

Clean Image③
(Output)

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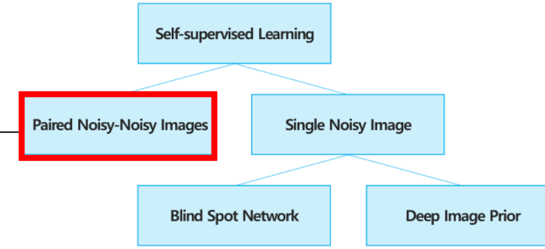
Algorithms: Self-supervised Learning



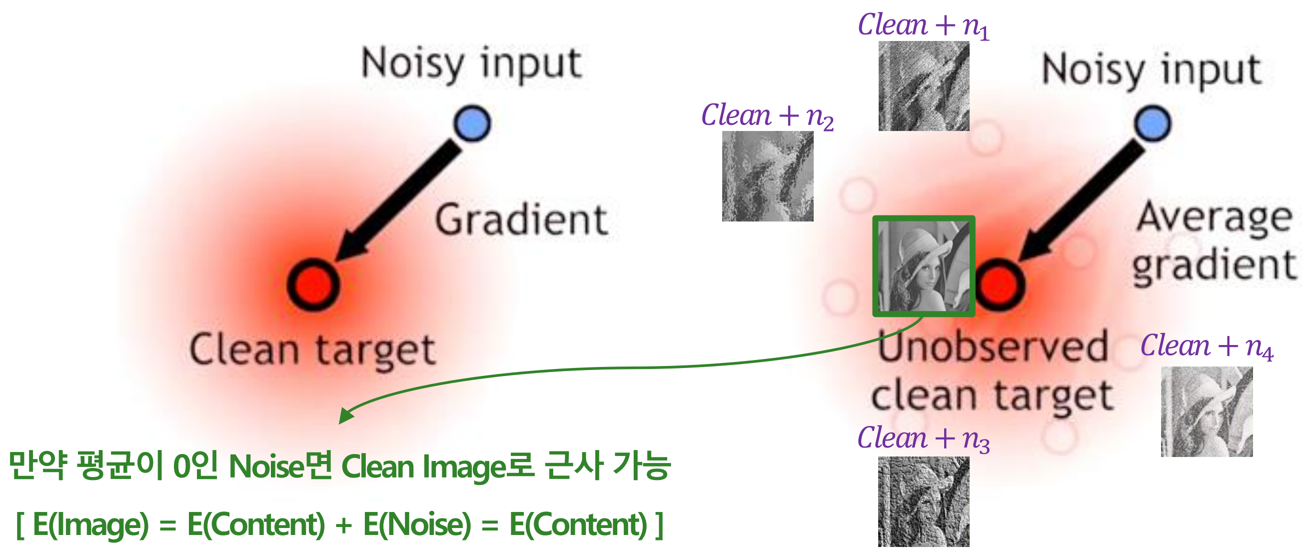
Self-supervised Learning (1): Paired Noisy-Noisy Images

❖ **Paired Noisy-Noisy Images: Noise2Noise (2018, ICML)**

< Ill-posed Problem >

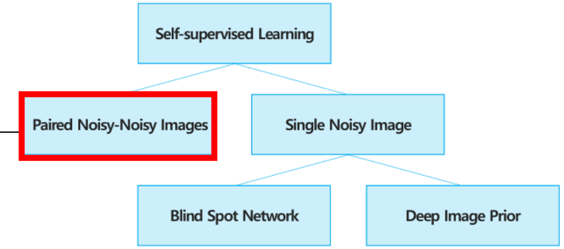
Noisy Image에 정답이 가능한 Clean Image는 하나의 형태가 아님

" L2 Loss로 학습 시, 정답이 가능한 여러 Clean Image 중 평균값으로 학습 "



Target이 되는 Noisy Image도 가능한 Clean Image 중 하나이다.

Algorithms: Self-supervised Learning



Self-supervised Learning (1): Paired Noisy-Noisy Images

❖ Paired Noisy-Noisy Images: Noise2Noise (2018, ICML)

- 왜 L2 Loss는 평균이 최적일까?

가능한 여러 Clean Image

$$L(\hat{y}) = \frac{1}{n}\sum_{i=1}^{n}(\underline{\hat{y}} - \underline{y_i})^2$$

L2 Loss

L2 Loss를 최소화하는 최적값

$$\Rightarrow \frac{d}{d\hat{y}}L(\hat{y}) = \frac{d}{d\hat{y}}\left(\frac{1}{n}\sum_{i=1}^{n}(\hat{y} - y_i)^2\right) = \frac{2}{n}\sum_{i=1}^{n}(\hat{y} - y_i) = 0$$

미분=0

$$\Rightarrow \sum_{i=1}^{n}\hat{y} = \sum_{i=1}^{n}y_i$$

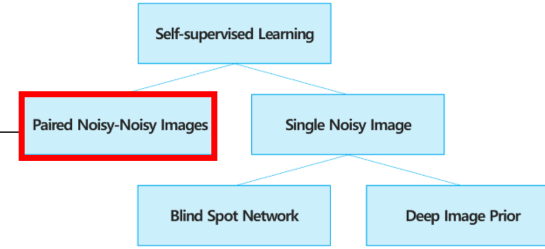
$$\Rightarrow n\hat{y} = \sum_{i=1}^{n}y_i$$

$$\Rightarrow \hat{y} = \frac{1}{n}\sum_{i=1}^{n}y_i$$

L2 Loss의 최적값: 여러 데이터 포인트들의 평균

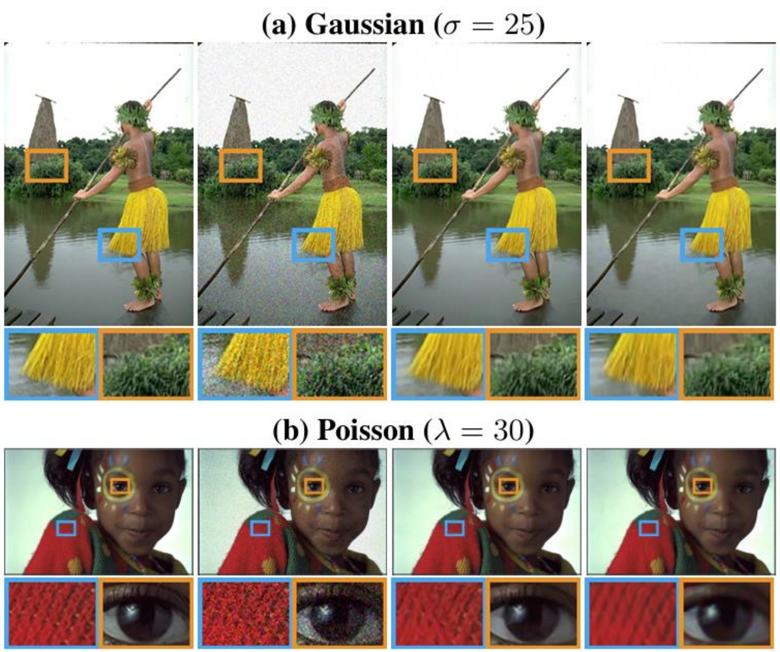
Algorithms: Self-supervised Learning

Self-supervised Learning (1): Paired Noisy-Noisy Images



❖ Paired Noisy-Noisy Images: Noise2Noise (2018, ICML)

- Noise2Noise: 평균이 0이 아닌 Noise에서 L2 Loss는 어려움을 겪음
  - ➢ 상황에 따라 L1 Loss가 효과를 보이는 경우도 존재 (Task에 따라 Loss 선택의 중요성)
  - * L1 Loss의 최적: 중간값



GT Input Ours Comparison

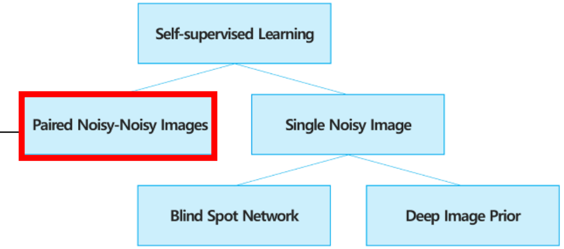
[Text Removal]

Text Removal: 주어진 픽셀과 전혀 색상의 Text를 제거

이상치에 민감한 평균보다, 이상치에 강건한 중간값이 우수

Algorithms: Self-supervised Learning

Self-supervised Learning (1): Paired Noisy-Noisy Images



❖ Paired Noisy-Noisy Images: Noise2Noise (2018, ICML)

- Noise2Noise: 평균이 0이 아닌 Noise에서 L2 Loss는 어려움을 겪음
  - ➢ 상황에 따라 L1 Loss가 효과를 보이는 경우도 존재 (Task에 따라 Loss 선택의 중요성)

    * L1 Loss의 최적: 중간값

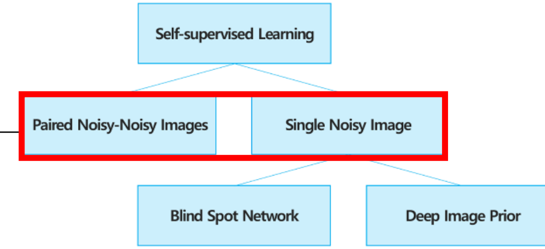
① Noise에 대한 가정 불필요

② Noise 추정 모델 불필요

③ 동일한 장면에 대한 Noisy-Noisy Pair 구축이 매우 어려움

④ Noise 특성에 따른 Loss 선택의 어려움

Algorithms: Supervised Learning



Definition for Single Noisy Image

❖ **Paired Noisy-Noisy Images → Single Noisy Image**

- Paired Noisy-Noisy Images: 학습 데이터 쌍 (Noisy Pair) 구축에 어려움이 존재

" 하나의 Noisy Image 만으로 학습 할 수는 없을까? "

( , )  ()

Paired Noisy-Noisy Images

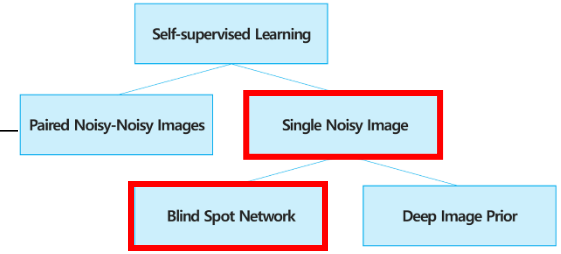
Noisy Pair 구축에 어려움 존재

Single Noisy Image

Noisy Pair 없이 학습 가능

Algorithms: Self-supervised Learning

Self-supervised Learning (2): Blind Spot Network

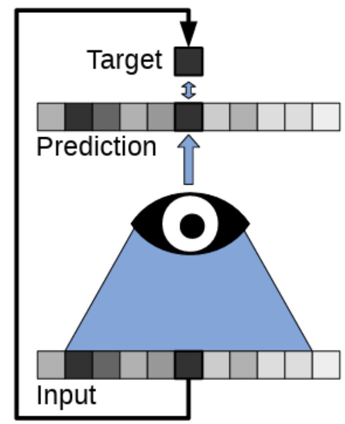


❖ Blind Spot Network: Noise2Void (2019, CVPR)

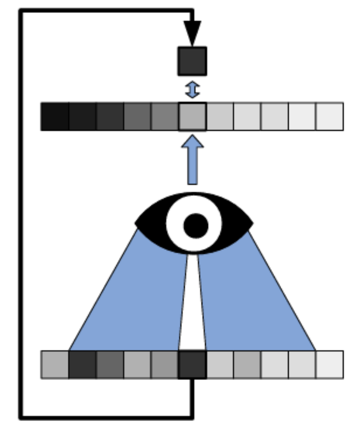
- Blind Spot Network (BSN): 입력 이미지에서 특정 영역을 주변 정보로 복원하면서 학습
  - ➢ 이때, 자기 자신에 대한 픽셀 값을 "보지 못하게" 모델링 한다는 특징을 가짐

[특정 픽셀을 가린 이미지]

[특정 픽셀을 채움]



[기존 Convolution Network]

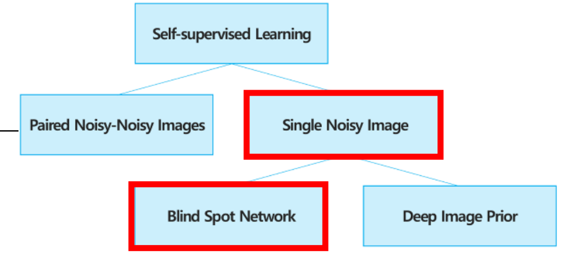


[Blind Spot Network]

" 가려진 Pixel을 주변 정보만을 활용하여 예측 "

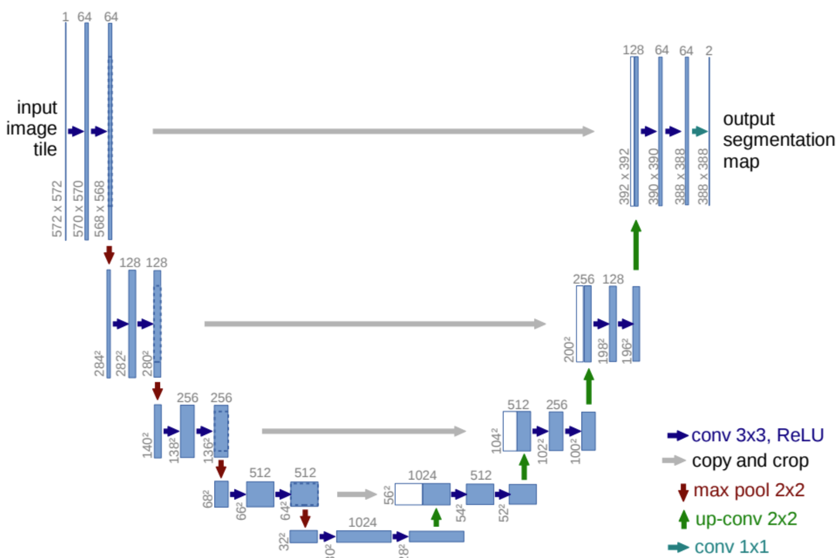
Algorithms: Self-supervised Learning

Self-supervised Learning (2): Blind Spot Network

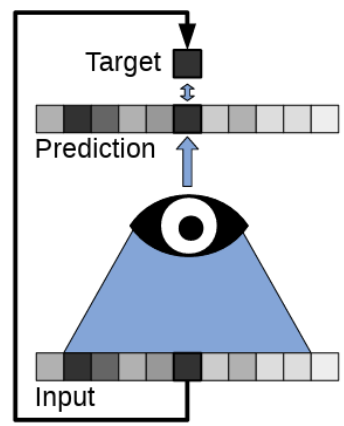


❖ Blind Spot Network: Noise2Void (2019, CVPR)

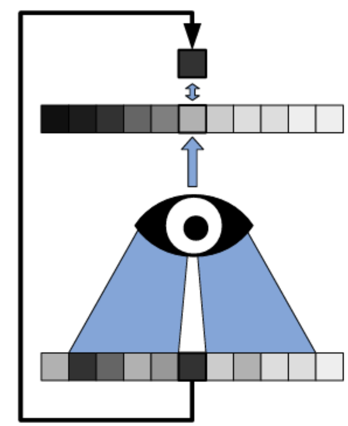
- Blind Spot Network (BSN): 입력 이미지에서 특정 영역을 주변 정보로 복원하면서 학습
  - ➢ 이때, 자기 자신에 대한 픽셀 값을 "보지 못하게" 모델링 한다는 특징을 가짐



" 모델 내 모든 Conv Layer는 모두 BSN으로 구성 "



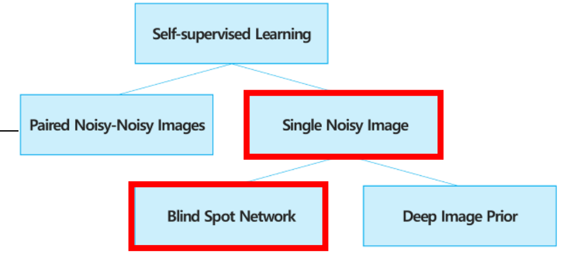
[기존 Convolution Network]



[Blind Spot Network]

Algorithms: Self-supervised Learning

Self-supervised Learning (2): Blind Spot Network



❖ Blind Spot Network: Noise2Void (2019, CVPR)

- Noise2Void: Image는 Signal과 Noise의 조합으로 구성

Noisy Image

Signal

가정①

Signal은 픽셀 간 독립적이지 않음

Noise

가정②

Noise는 픽셀 간 독립

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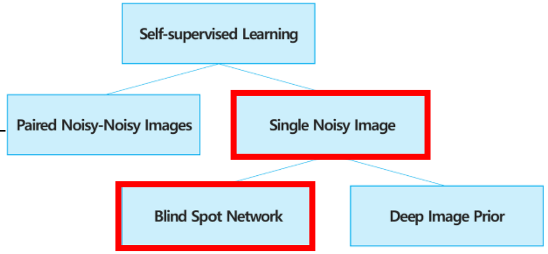
Algorithms: Self-supervised Learning

Self-supervised Learning (2): Blind Spot Network

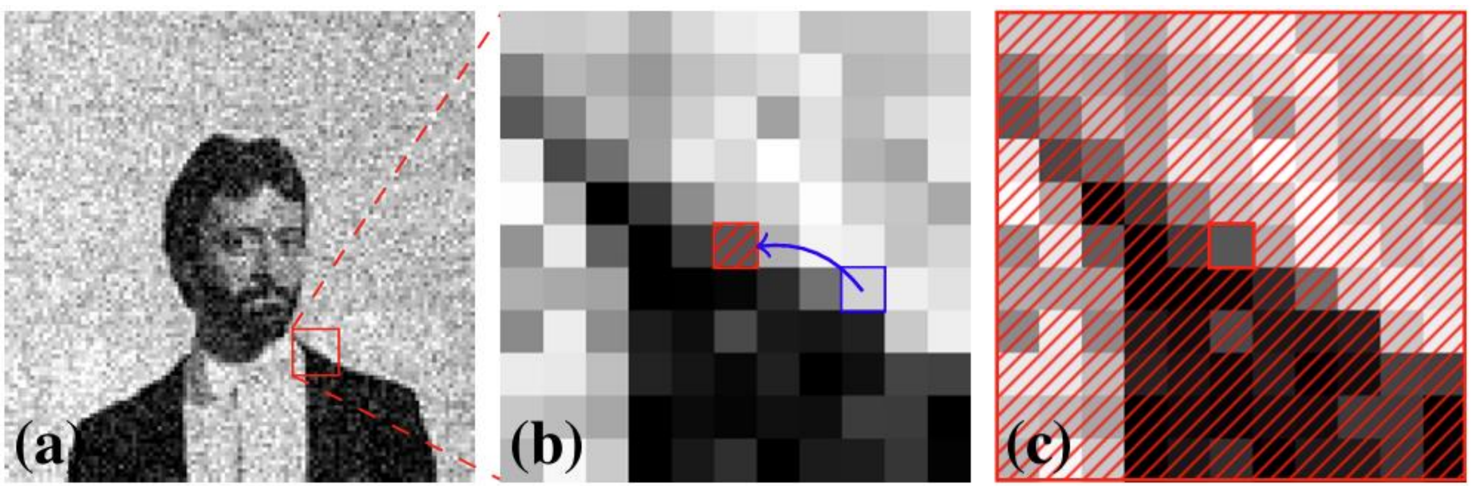


❖ Blind Spot Network: Noise2Void (2019, CVPR)

- Noise2Void: Blind Spot Network를 활용하여 Denoising을 수행
  ① Pixel Masking: Input Image 내 특정 N개 픽셀을 주변 픽셀 값으로 대체
  ② BSN: 해당 이미지를 BSN을 통과
  ③ Loss 산출: N개 픽셀에 대해서 Loss 산출

j번째 이미지 내 Masking 된 픽셀 i

$$\arg\min_{\boldsymbol{\theta}} \sum_j \sum_i L\left(f(\underline{\tilde{\boldsymbol{x}}^j_{\mathrm{RF}(i)}}; \boldsymbol{\theta}), \boldsymbol{x}^j_i \right).$$

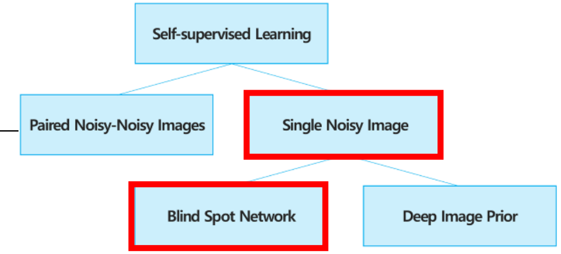


(a), (b): Pixel Masking
특정 Random 픽셀 값을 주변 값으로 대체

(c): BSN
주변 픽셀값만으로 자기 자신의 픽셀값 예측

Algorithms: Self-supervised Learning

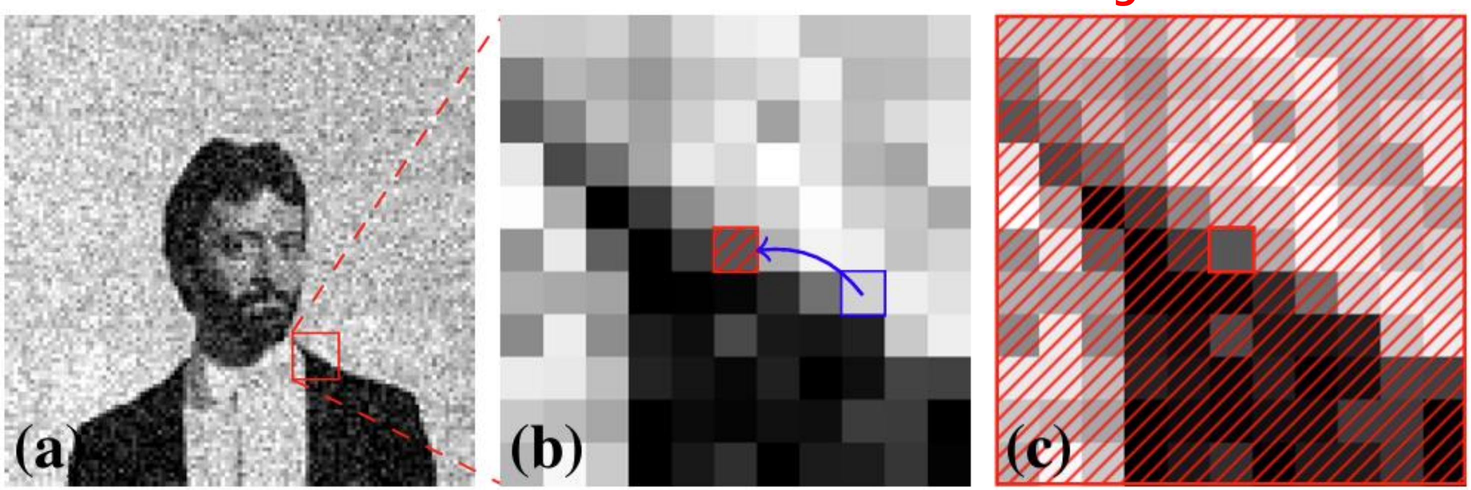
Self-supervised Learning (2): Blind Spot Network



❖ Blind Spot Network: Noise2Void (2019, CVPR)

- Why BSN is Effective?: Center Pixel을 Masking하여 Identity Mapping 방지 가능
  - ➢ Signal → 주변 픽셀과 종속적 → 주변 픽셀만으로 복원 가능
  - ➢ Noise → 주변 픽셀과 독립적 → 주변 픽셀 정보로는 복원되지 않음

순수한 Signal 정보만 복원 가능



" 단점: 가장 중요한 자기 자신 정보를 활용하지 않기에, 충분한 정보 활용이 어려움 "

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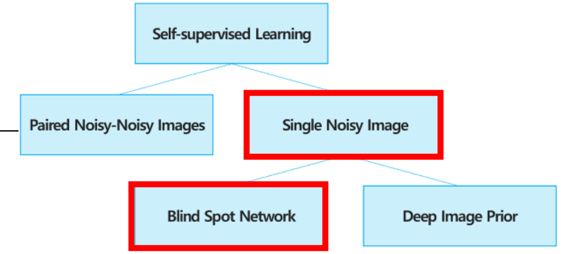
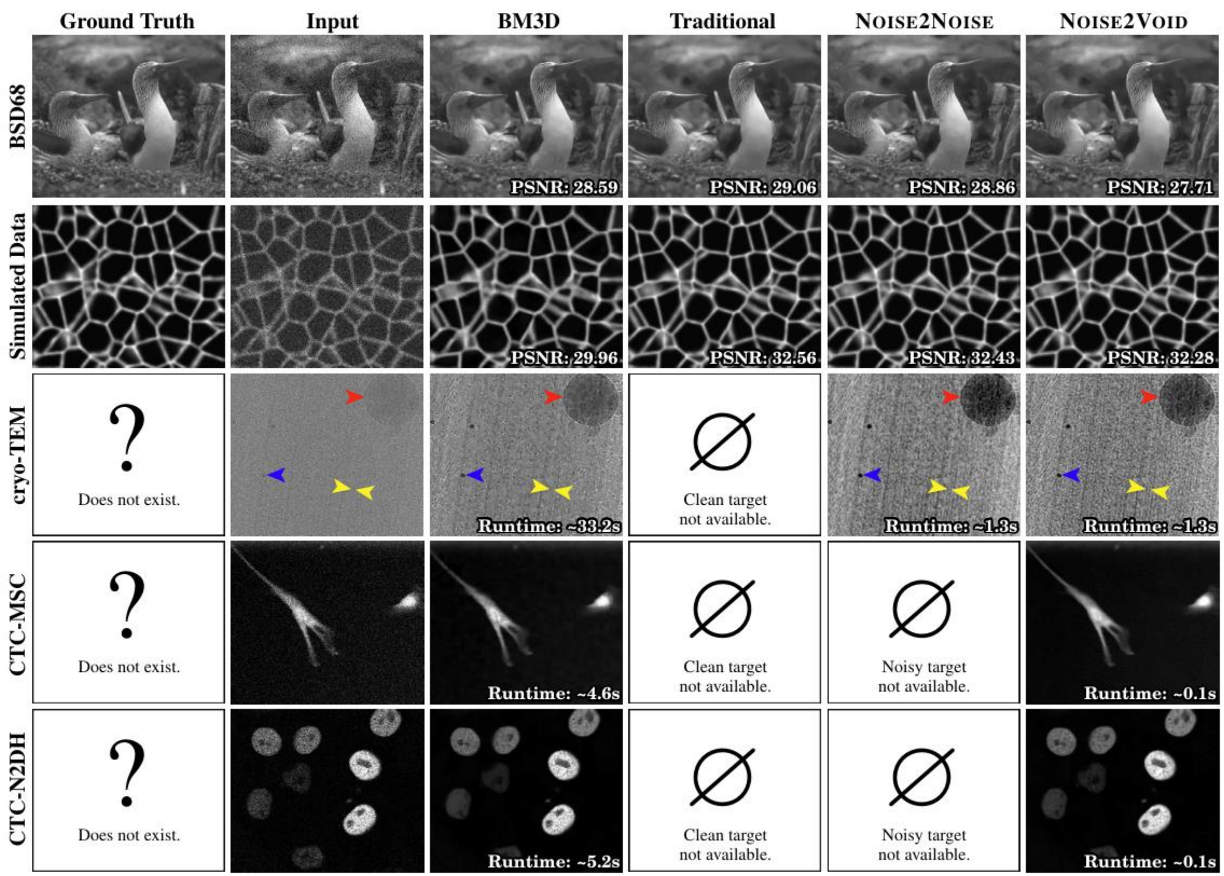
Algorithms: Self-supervised Learning

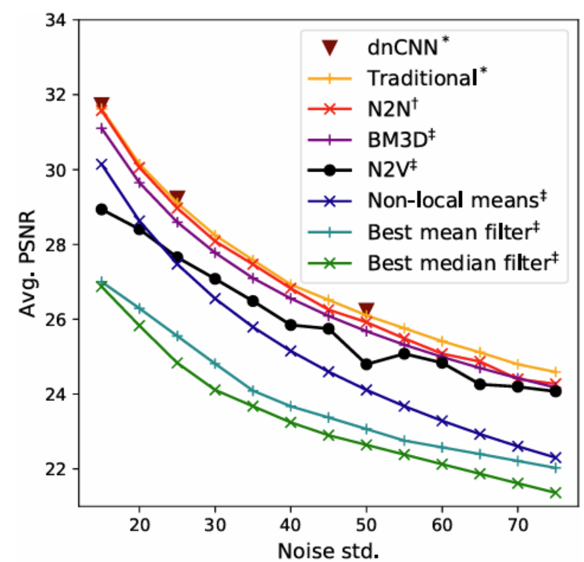
Self-supervised Learning (2): Blind Spot Network



❖ Blind Spot Network: Noise2Void (2019, CVPR)

- 실험결과: Computer Vision 알고리즘보다는 우월, N2N과는 거의 유사
  - ➢ 자기 자신 픽셀 정보를 활용하지 않기에, 다른 네트워크보다 정보를 덜 사용하기 때문





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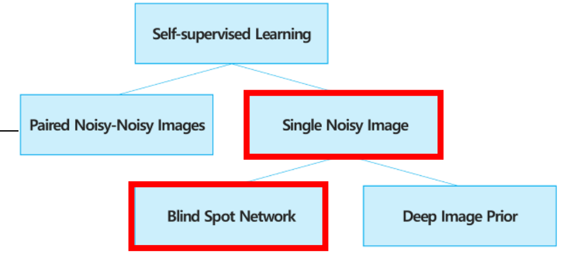
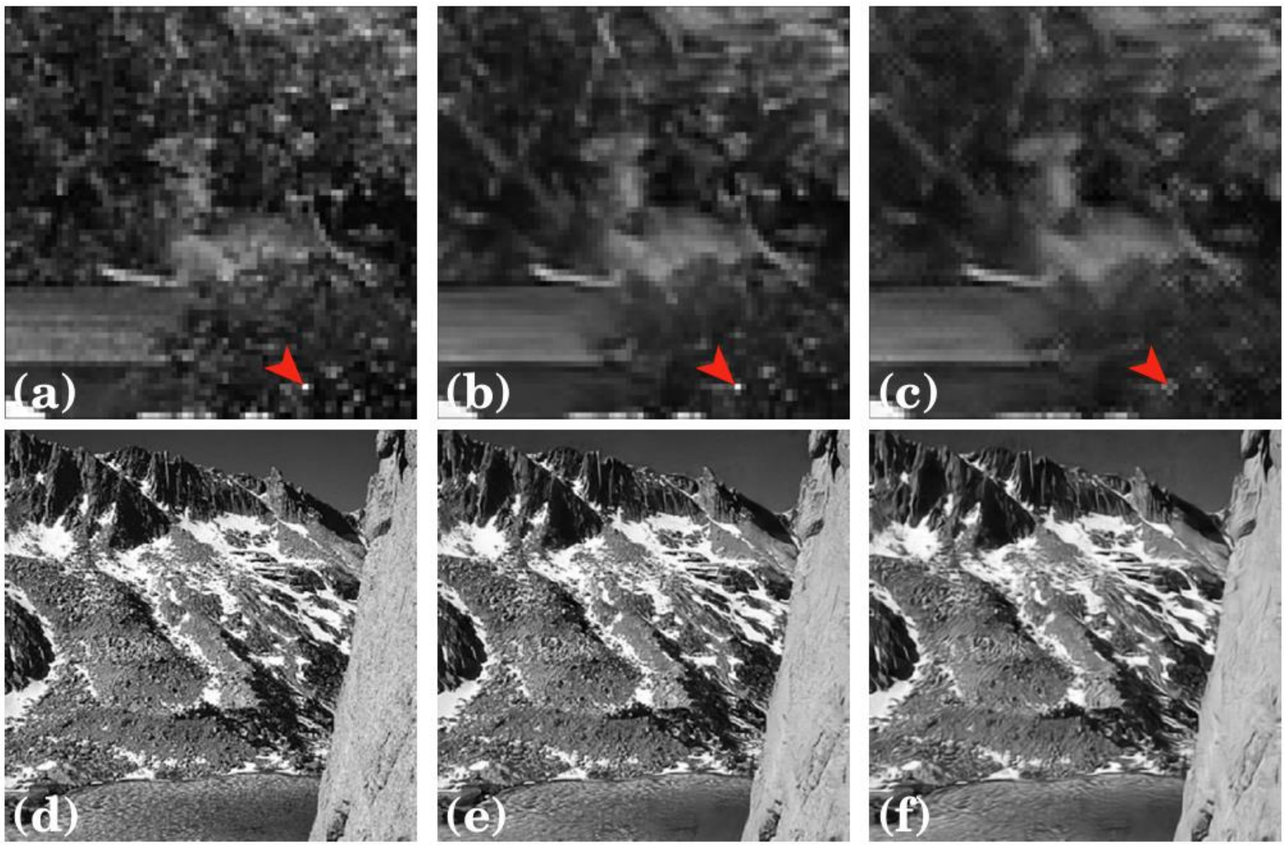
Algorithms: Self-supervised Learning

Self-supervised Learning (2): Blind Spot Network

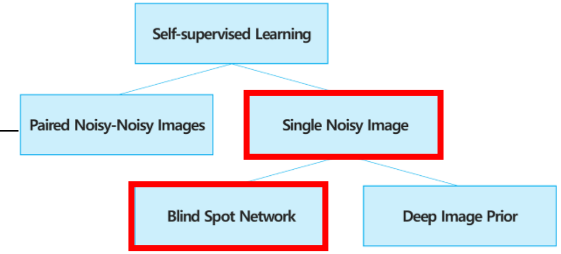


❖ Blind Spot Network: Noise2Void (2019, CVPR)

- Failure Case①: 주변 픽셀 정보만으로 Center Pixel을 예측하기 어려운 이미지
  - ➢ 이미지 픽셀이 매우 불규칙하여 주변 정보만으로 Center Pixel을 유추하기 어려움



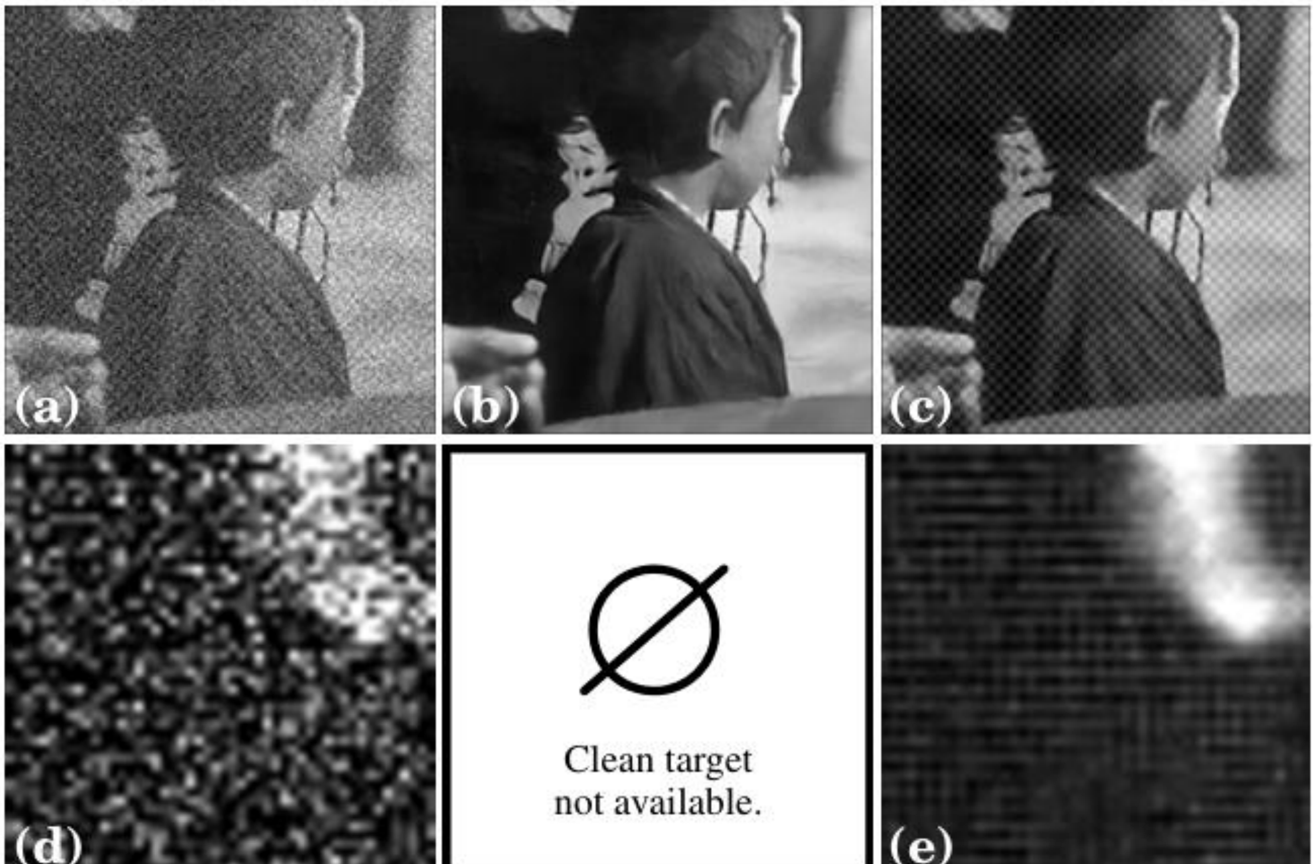
Algorithms: Self-supervised Learning



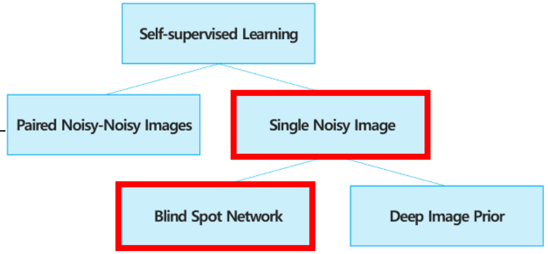
Self-supervised Learning (2): Blind Spot Network

❖ Blind Spot Network: Noise2Void (2019, CVPR)

- Failure Case② Signal과 종속적인 Noise가 포함된 이미지
  - ➢ Signal 및 Noise가 주변 픽셀과 모두 종속적이기에, BSN이 Noise도 함께 복원



Algorithms: Self-supervised Learning



Self-supervised Learning (2): Blind Spot Network

❖ Blind Spot Network: Noise2Void (2019, CVPR)

- Failure Case② Signal과 종속적인 Noise가 포함된 이미지
  - ➢ Signal 및 Noise가 주변 픽셀과 모두 종속적이기에, BSN이 Noise도 함께 복원

① Noise Pair가 불필요

② Noise에 대한 사전 지식이 불필요

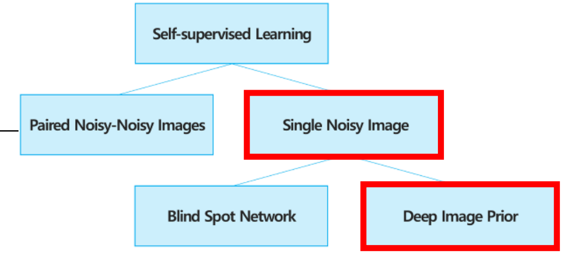
③ Noise가 Signal과 독립적인 경우 효과적 (이미지에 대한 가정 필요)

④ 복잡한 픽셀의 이미지에서는 활용이 어려움

⑤ 자기 자신의 정보를 활용하지 못하기에, 정보손실 발생

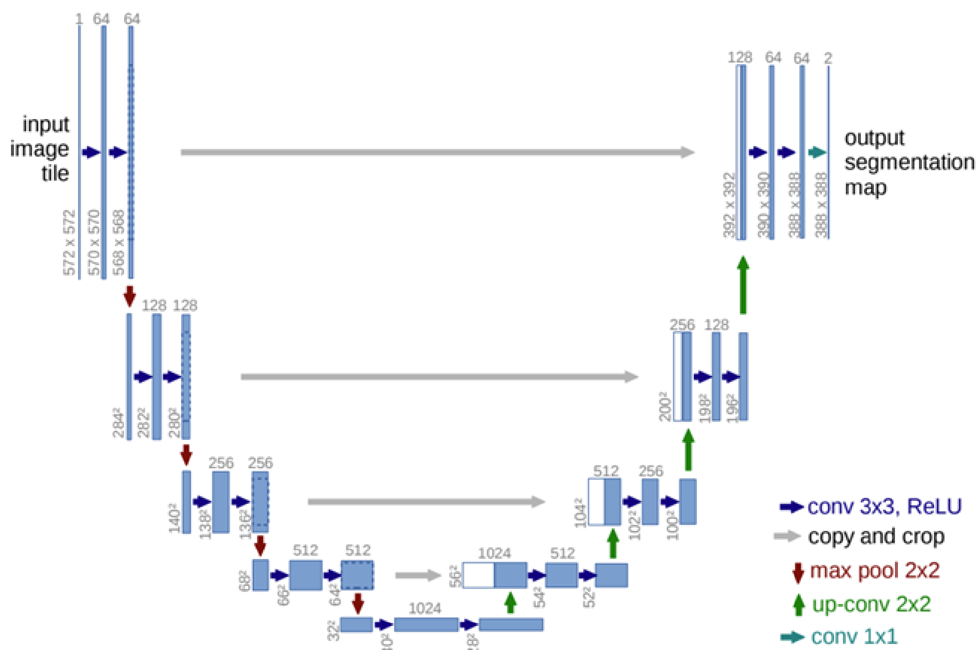
Algorithms: Supervised Learning

Self-supervised Learning (3): Deep Image Prior



❖ Deep Image Prior: Deep Image Prior (2017, CVPR)

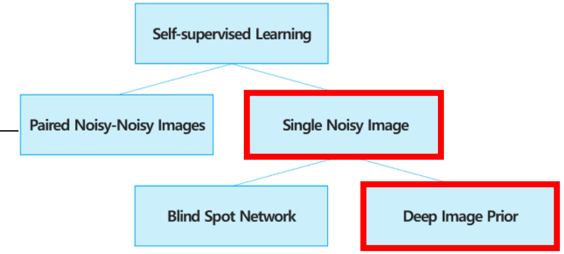
- " 무작위로 초기화된 모델은 그 자체 만으로 Clean Image에 대한 사전지식을 갖고 있다. "
  - ➢ 인공지능 모델은 풍부한 양질의 데이터만 중요한 것이 아니다.
  - ➢ 모델 구조 그 자체만으로 충분히 Noisy Image를 Clean Image로 복원 가능



" 모델의 사전지식으로 오직 한 장의 Noisy Image 만으로 Clean Image를 복원할 수 있다. "

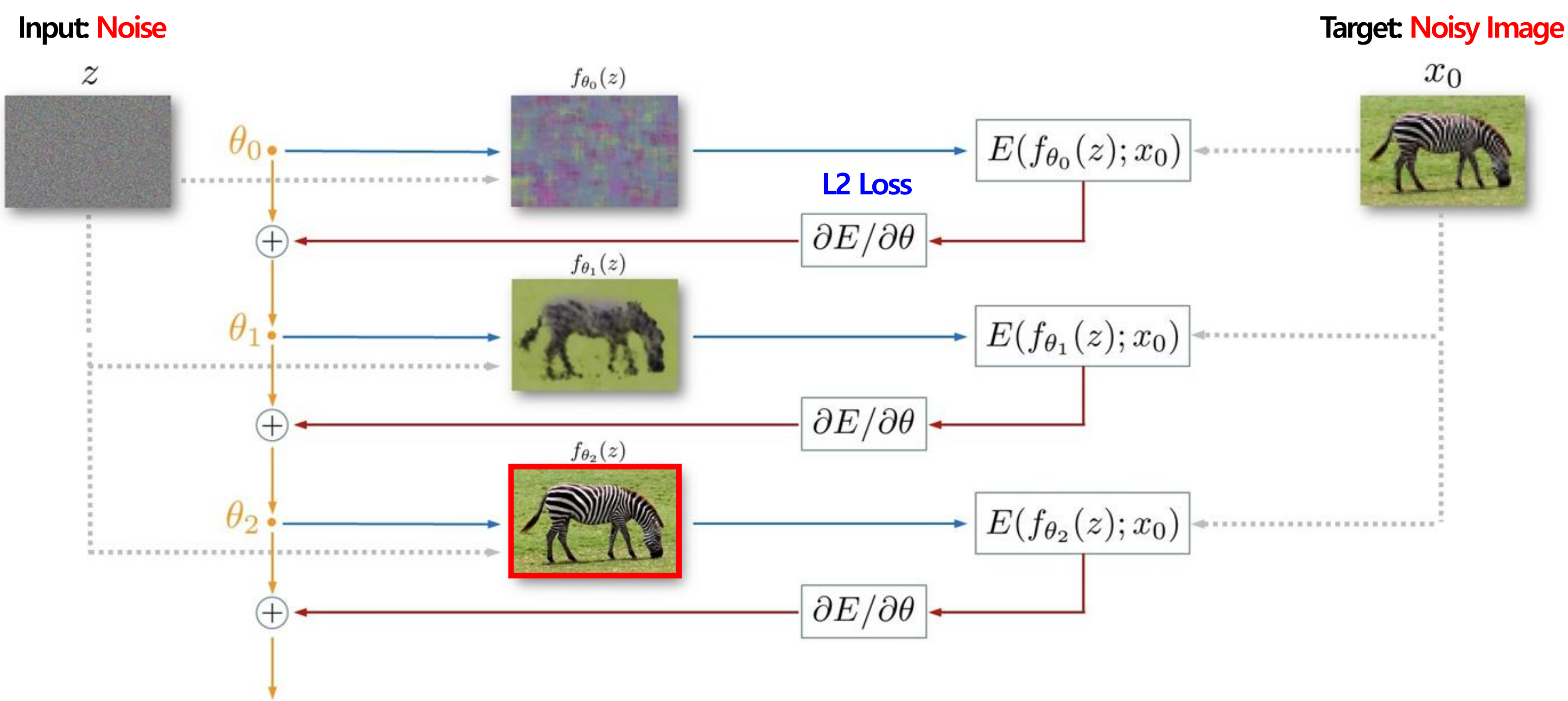
Algorithms: Supervised Learning

Self-supervised Learning (3): Deep Image Prior



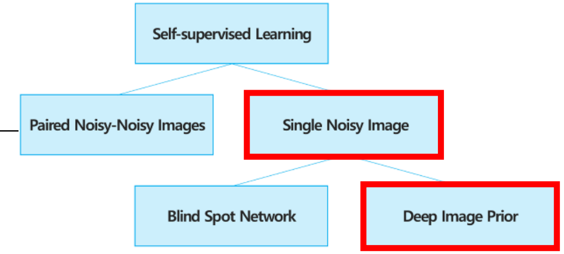
❖ Deep Image Prior: Deep Image Prior (2017, CVPR)

- Deep Image Prior: 한 장의 이미지에 여러 Iteration을 거치면 Clean Image 획득 가능



Algorithms: Supervised Learning

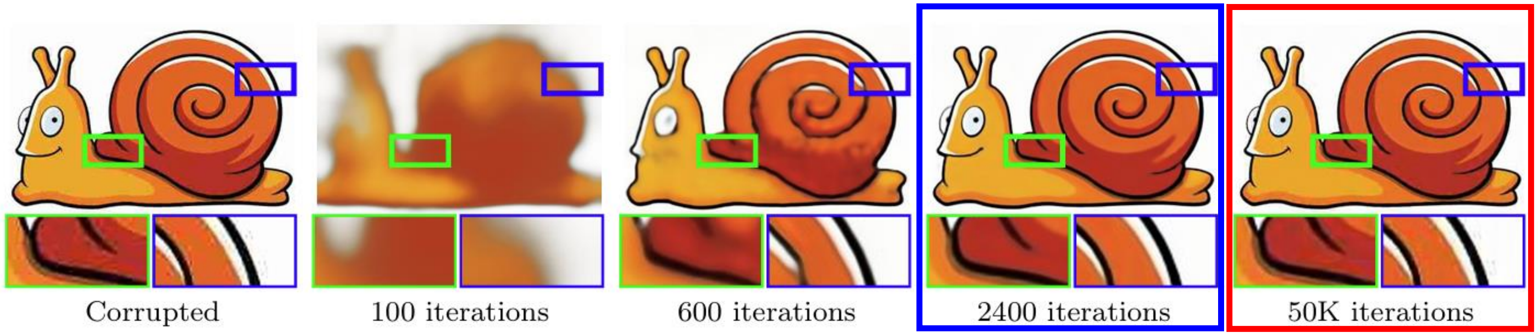
Self-supervised Learning (3): Deep Image Prior



❖ **Deep Image Prior: Deep Image Prior (2017, CVPR)**

Early Stopping으로 중간에 적절히 Stop 시, Clean Image 획득 가능

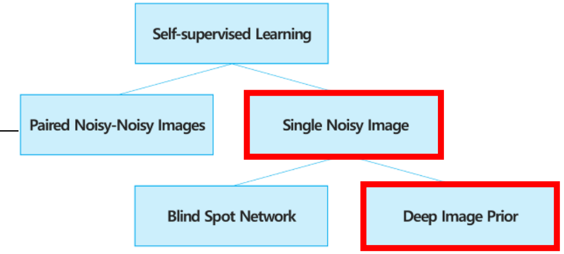
Best Iteration (Early Stopping)



지나친 학습: Noisy Image와 유사

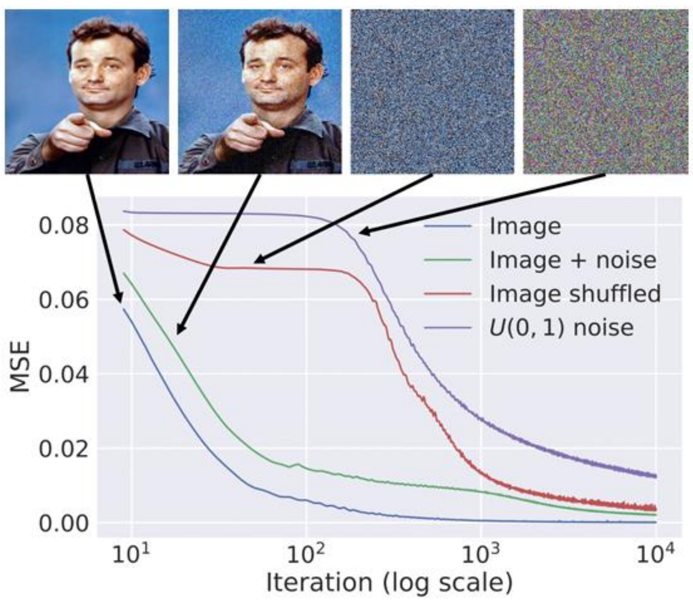
Algorithms: Supervised Learning

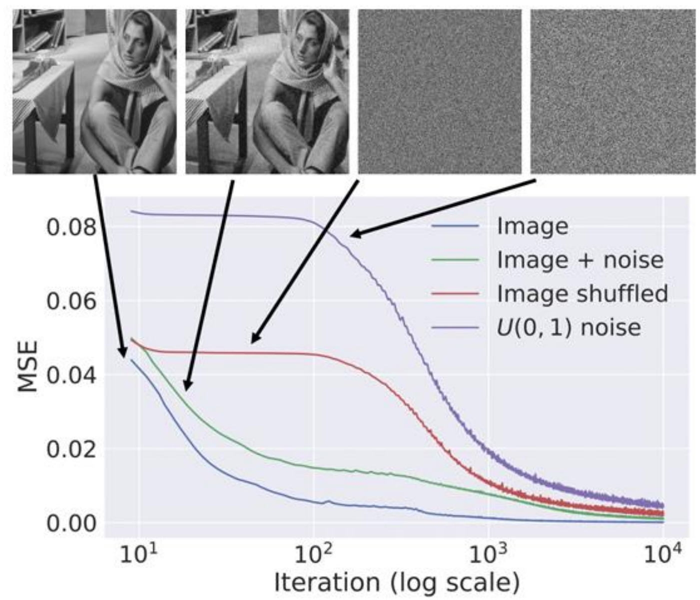
Self-supervised Learning (3): Deep Image Prior



❖ Deep Image Prior: Deep Image Prior (2017, CVPR)

- Early Stopping Point: Noise에 대해 Loss가 급감하는 지점
  - ➢ Loss 급감구간: 모델이 Noise에 피팅 되지 않다가 Noise에 적합되기 시작한 구간
  - ➢ Optimal Point를 찾기까지 이미지 당 평균 30분 소요

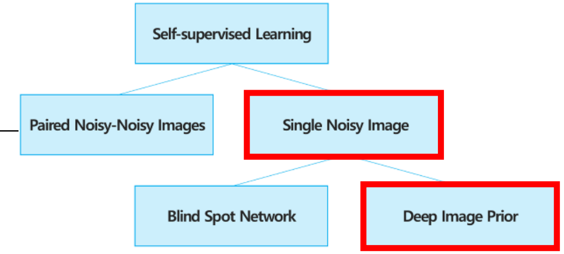




① Input이 자연스러울수록 수렴이 빠름

② Noise가 Input이더라도, 오랜 시간 후 충분히 수렴할 수 있음

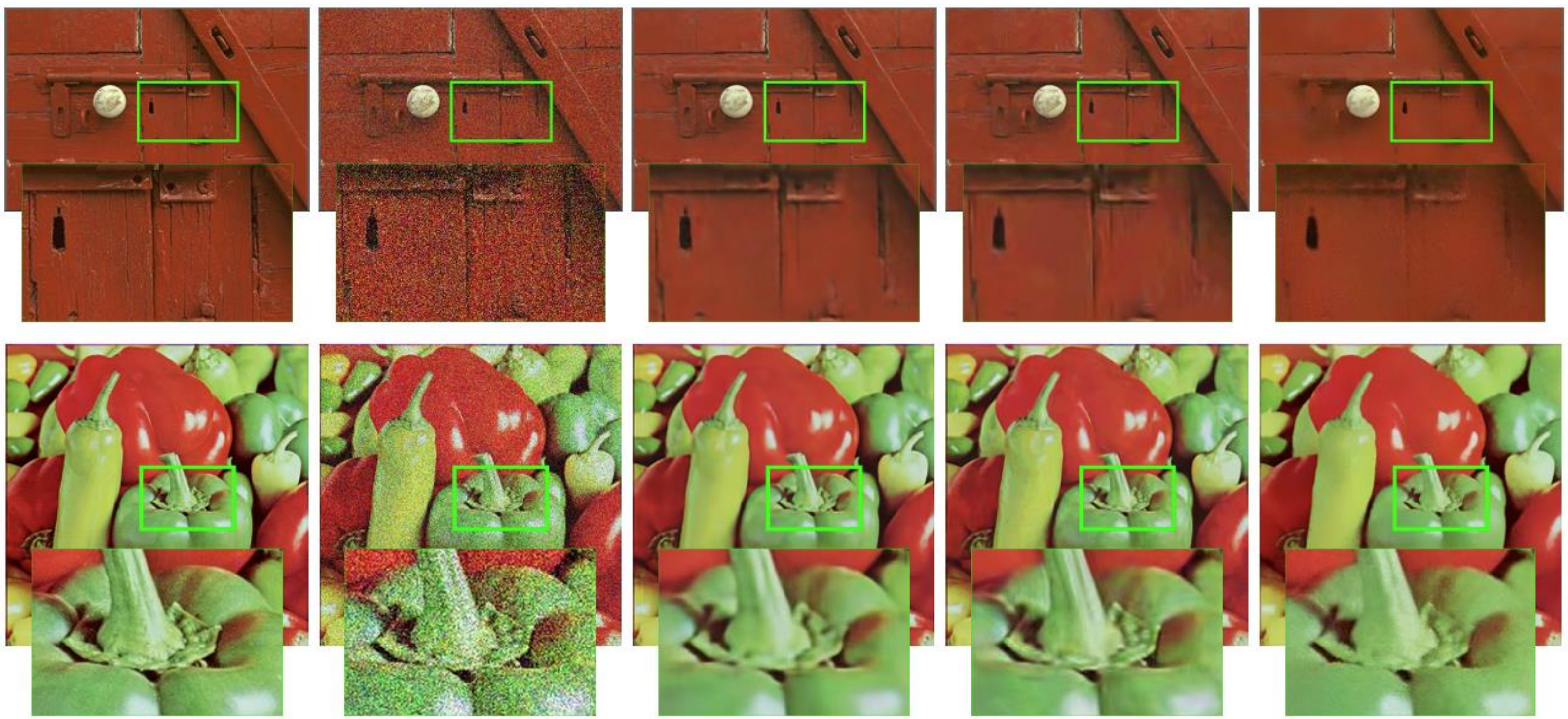
Algorithms: Supervised Learning



Self-supervised Learning (3): Deep Image Prior

❖ Deep Image Prior: Deep Image Prior (2017, CVPR)

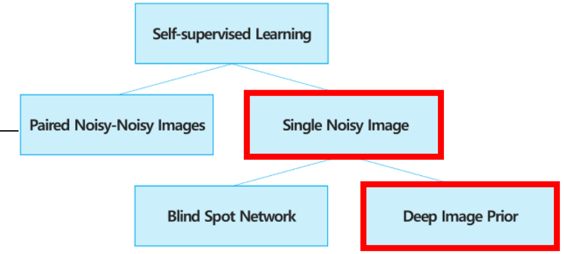
- 실험결과: Real-world 이미지에 우수한 Denoising 성능을 보임



(a) GT (b) Input (c) Ours (d) CBM3D (e) NLM

Algorithms: Supervised Learning

Self-supervised Learning (3): Deep Image Prior



❖ **Deep Image Prior: Deep Image Prior (2017, CVPR)**

- 실험결과: Real-world 이미지에 우수한 Denoising 성능을 보임

① 오직 단 한 장의 Noisy Image만으로 Denoising 모델 학습 가능

② 이미지마다 개별 모델이 필요

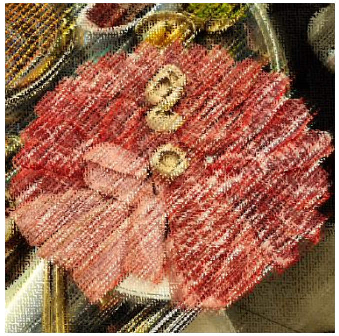
③ 학습과 추론이 평균적으로 30분이라는 긴 시간동안 이루어짐

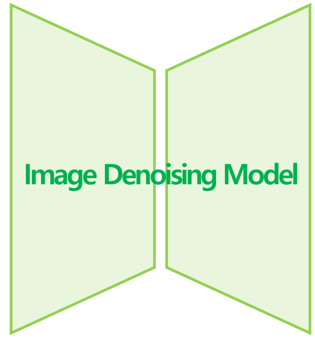
④Early Stopping 및 Model 구조 선정에 어려움 존재

Conclusion

Conclusion

Noisy Image





Clean Image

<Supervised Learning>

[Clean Image (0)]

Paired Noisy-Clean Images

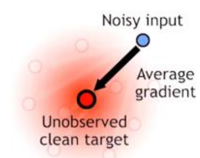
Unpaired Noisy-Clean Images

① 쉽게 Noisy Image 합성 가능
② Noise에 대한 사전지식 필요

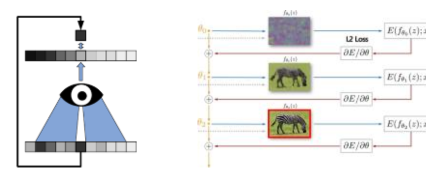
① Noise에 대한 사전지식 불필요
② 두 개의 모델에 의존

<Self-supervised Learning>

[Clean Image (X)]



Paired Noisy-Noisy Images



Single Noisy Image

① Noise 모델 및 가정 불필요
② 실제 Noisy Pair가 필요

① 실제 Noisy Pair 불필요
② Noise에 대한 학습 어려움

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Thank you!