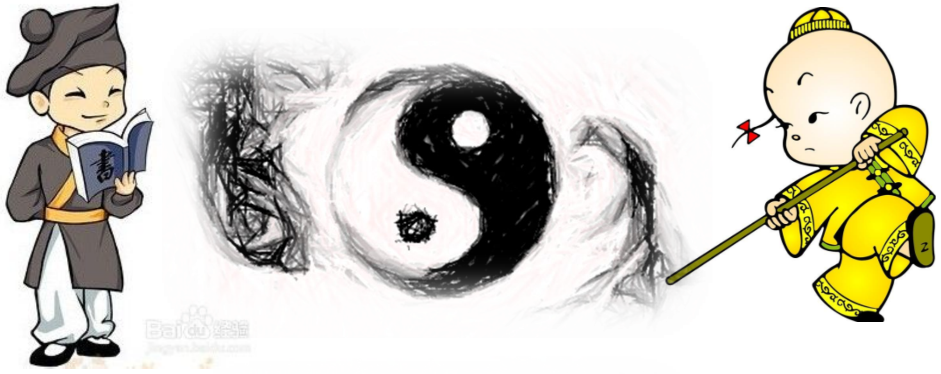
底层视觉任务中的

模型驱动



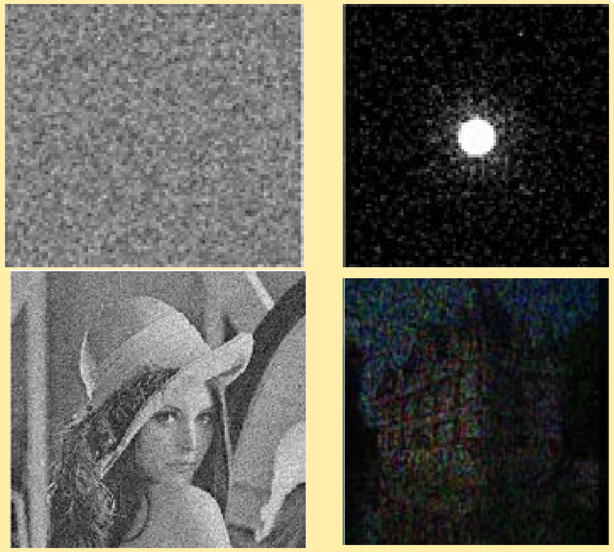
数据驱动

孟德宇
西安交通大学
dymeng@mail.xjtu.edu.cn
http://gr.xjtu.edu.cn/web/dymeng

Image Restoration problem

The inverse problem: $Y = A(X) + \varepsilon$

Observation Y



- Image super-resolution
- Image denoising
- Image deblurring
- ......

Recovery X

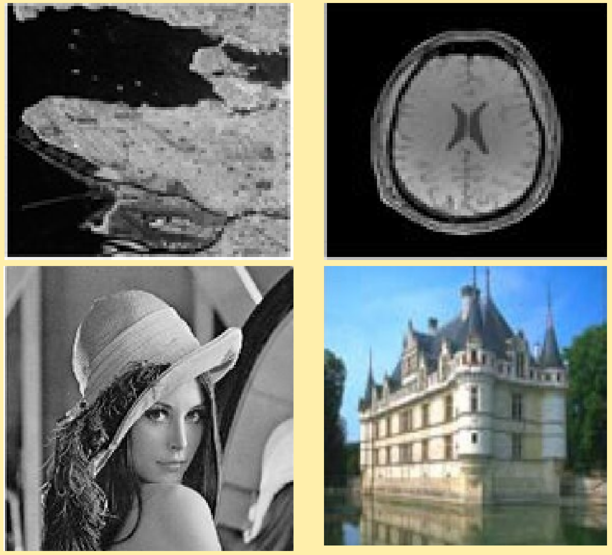
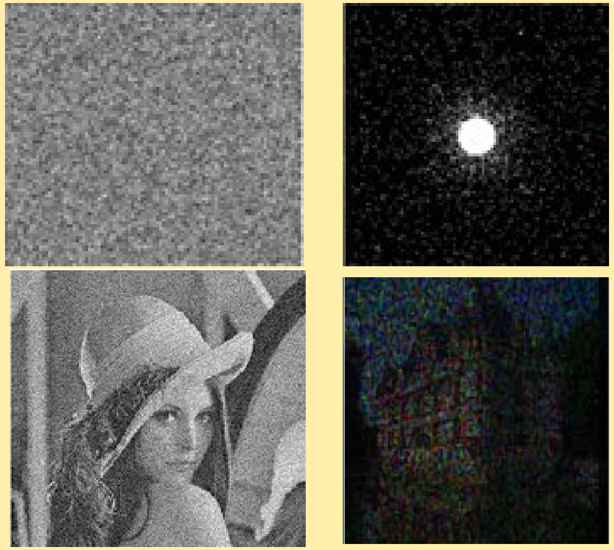


Image Restoration problem

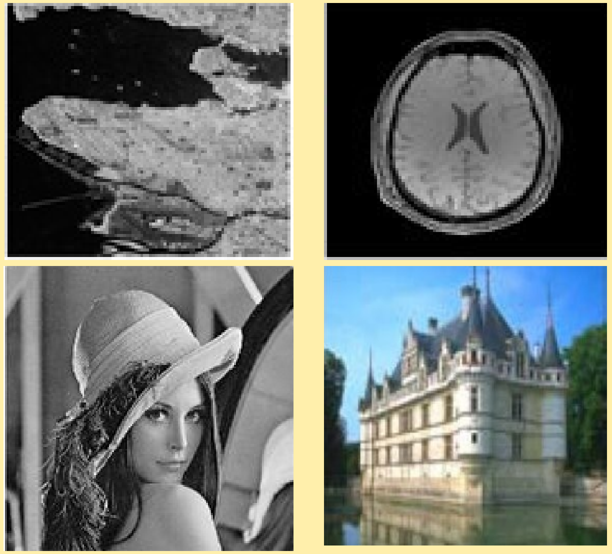
The inverse problem: $Y = A(X) + \varepsilon$

Observation Y



- Image super-resolution
- **Image denoising**
- Image deblurring
- ……

Recovery X



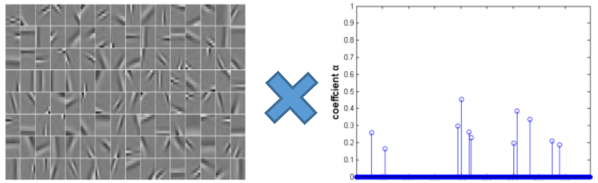
Model-driven Methodology

2010-2012

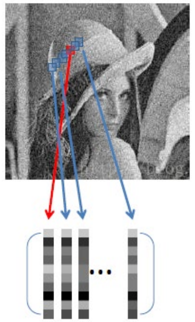
$$\arg\min_{Z} L(Y - Z) + \boxed{R(Z)}$$

Low rank

Sparsity



Non-local Similarity



Model-driven Methodology: Generative Understanding

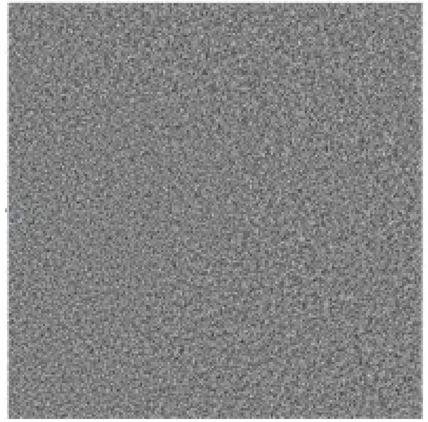
$$\arg\min_{Z} L(Y - Z) + R(Z)$$

Y

=

Z

+

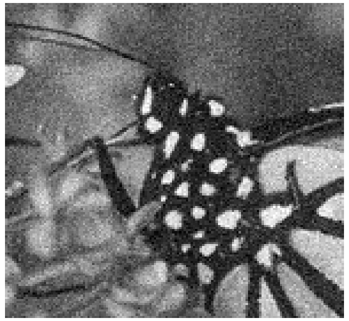


E

$$z \sim p(z);\ e \sim p(e) \quad \Longrightarrow \quad p(z, e|y) \sim \text{likelihood}(y|z, e)\,p(z)\,p(e)$$

Model-driven Methodology: Generative Understanding

$$\arg \min_{Z,E} L_E(Y - Z) + R(Z) + R(E)$$

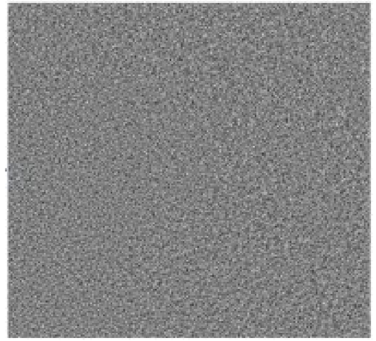


Y

=

Z

+



E

$$z \sim p(z); e \sim p(e)$$

$$\Rightarrow p(z, e|y) \sim \text{likelihood}(y|z, e)p(z)p(e)$$

$$e \sim \sum_k \pi_k N(e|0, {\sigma_k}^2)$$

DY Meng, D Ferznando, ICCV 2z013
Q, Zhao, DY Meng, et al., ICML, 2014

$$e \sim \sum_k \pi_k EP_{p_k}(e|0, \eta_k)$$

XY Cao, Q Zhao, , et al., ICCV 2015

$$\boldsymbol{e} \sim \sum_k \pi_k N(\boldsymbol{e}|0, \Sigma_k)$$

W Wei, LX Yi, , et al., ICCV 2017

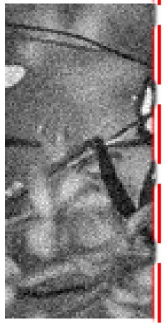
Model-driven Methodology: Generative Understanding

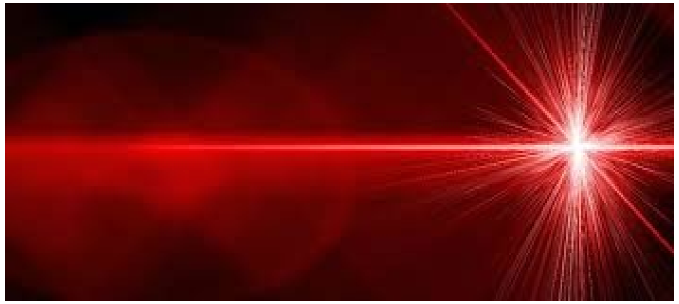
$\arg\min L(Y-Z)+P(Z)+P(E)$

$\sum \ldots \sigma_k{}^2)$

V 2z013

ML, 2014





$, \eta_k)$

/ 2015

$\text{z}\sim\text{p}$

$\sum_k \ldots, \Sigma_k)$

$\text{p(z, e|y)}\sim\text{likelihood(y|z, e)p(z)p(e)}$

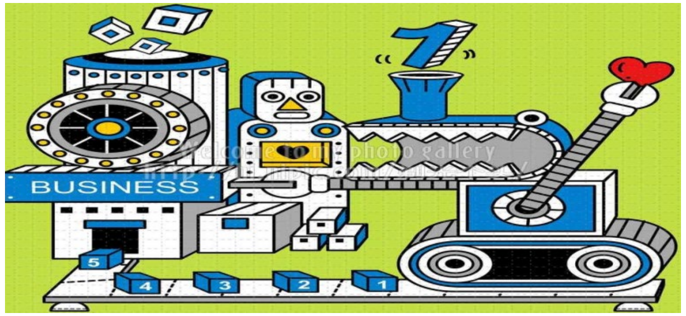
W Wei, LX Yi, , et al., ICCV 2017

Model-driven Methodology

$$\arg\min_{Z,E} L_E(Y - Z) + R(Z) + R(E)$$

$$\arg\max_{Z,E}\ p(Z, E|Y)$$

Y $\rightarrow$ Z = Algorithm(Y)



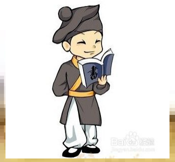
Model-driven Methodology

$$\arg\min_{Z} L(Y - Z) + R(Z)$$

$$p(z, e|y) \sim \mathrm{likelihood}(y|z, e)p(z)p(e)$$

$$\Rightarrow \arg\max_{Z,E} p(Z, E|Y)$$

$$Z = \mathrm{Algorithm}(Y)$$



文雅之风

无监督模式

可解释性

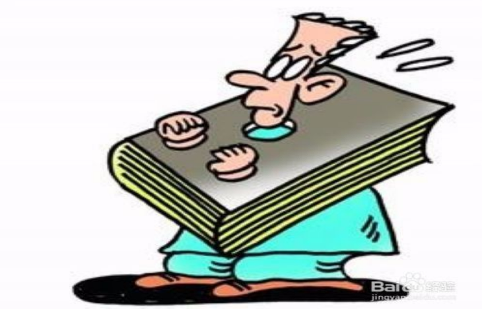
生成功能

预测速度慢

依赖先验假设

难以广泛适用

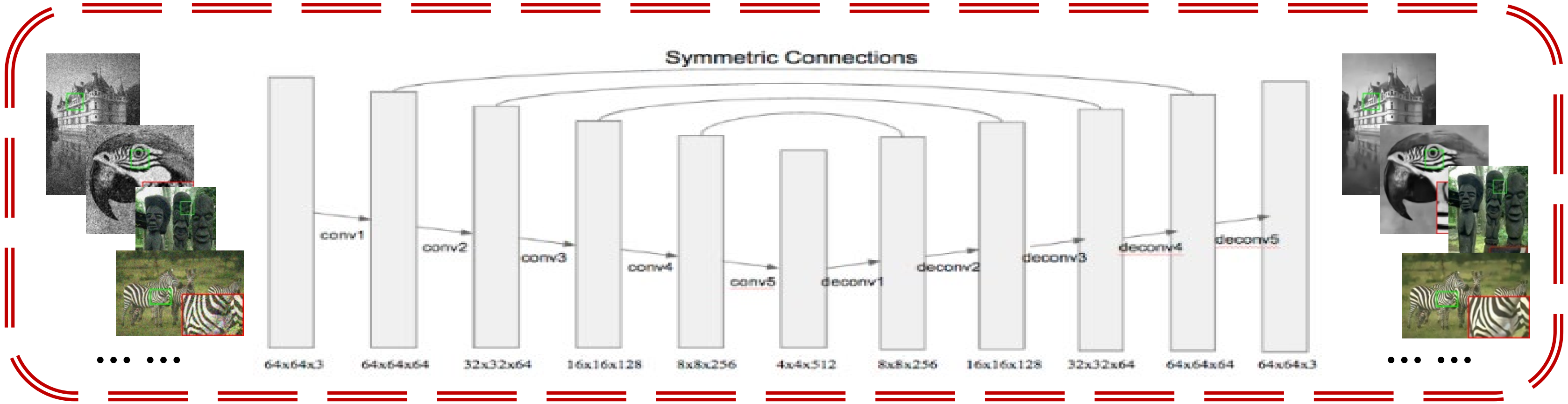
书呆子气



Data-driven Methodology: Learn Clean Image

2010-2012

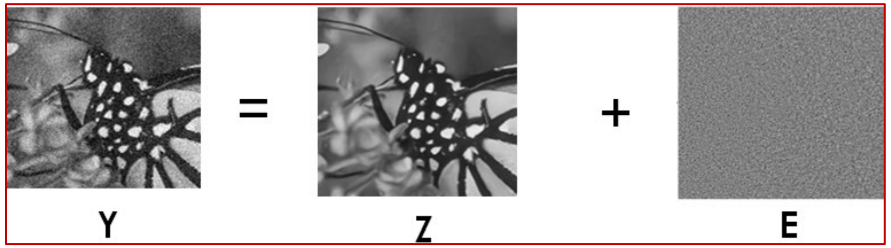
$$\arg\min_{W} ||Z - \mathrm{Network}_W(Y)||_2$$



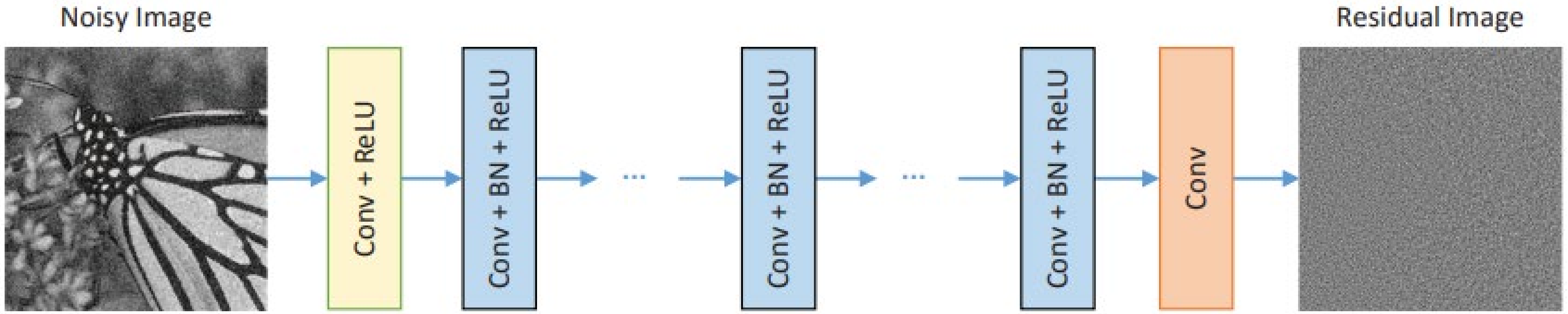
$$Y \longrightarrow Z = \mathrm{Network}_W(Y)$$

Data-driven Methodology: Learn Noise

2010-2012



$$\arg\min_{W} \|E - \mathrm{Network}_W(Y)\|_2$$



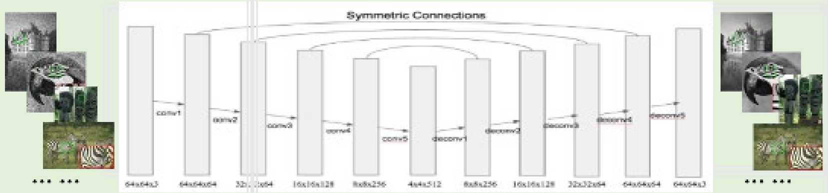
Residual Network

$Y \rightarrow E = \mathrm{Network}_W(Y)$

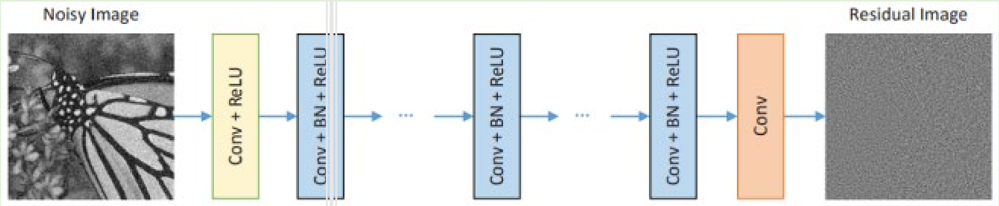
Zhang, Zuo, Chen, Meng, Zhang, TIP, 2017

Data-driven Methodology

$$\arg\min_{W} ||Z - \mathrm{Network}_W(Y)||_2$$



$$\arg\min_{W} ||E - \mathrm{Network}_W(Y)||_2$$



$$Z = \mathrm{Network}_W(Y)$$

勇武之气

预测速度快

无须先验假设

易拟合广泛规律

依赖标记

解释性差

无生成功能

鲁莽粗暴

$$\arg\min_{Z} L(Y-Z)+R(Z)$$

$$p(z,e|y)\sim \text{likelihood}(y|z,e)p(z)p(e)$$

$$\Rightarrow \arg\max_{Z,E} \; p(Z,E|Y)$$

无监督模式 | 可解释性 | 生成功能

预测速度慢 | 依赖先验假设 | 难以广泛适用

$Z = \text{Algorithm}(Y)$

文雅之风

OR

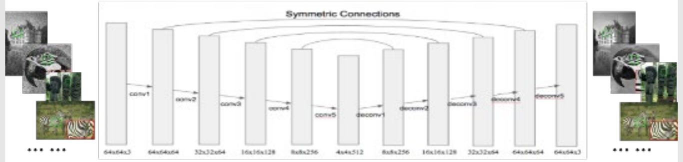
勇武之气

$Z = \text{Network}_W(Y)$

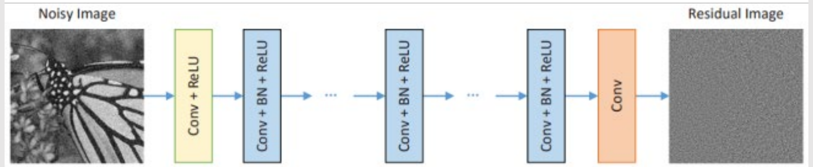
依赖标记 | 解释性差 | 无生成功能

预测速度快 | 无须先验假设 | 易拟合广泛规律

$$\arg\min_{W} \; ||Z-\text{Network}_W(Y)||_2$$



$$\arg\min_{W} \; ||E-\text{Network}_W(Y)||_2$$



数模结合第一式

外练筋骨皮

模型

网络

（跳出模仿）在师傅指导下，进行有方向性的训练

（跳出有监督）在模型启发下，指导网络数据合理的梯度下降方向对网络参数进行训练

$$\arg\min_{Z} L(Y - Z) + R(Z)$$

$$p(z, e|y) \sim likelihood(y|z, e)p(z)p(e)$$

$$\Rightarrow \arg\max_{Z,E} \; p(Z, E|Y)$$

无监督模式 可解释性 生成功能 预测速度慢 依赖先验假设 难以广泛适用

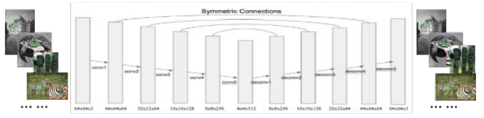
$Z = Algorithm(Y)$

外练筋骨皮

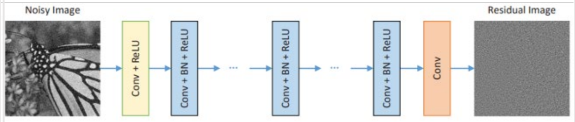
$Z = Network_W(Y)$

依赖标记 解释性差 无生成功能 预测速度快 无须先验假设 易拟合广泛规律

$$\arg\min_{W} ||Z - Network_W(Y)||_2$$



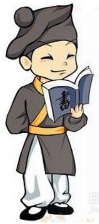
$$\arg\min_{W} ||E - Network_W(Y)||_2$$



$$\arg\min_{Z} L(Y - Z) + R(Z)$$

$$p(z, e|y) \sim \text{likelihood}(y|z, e)p(z)p(e)$$

$$\Rightarrow \arg\max_{Z,E} p(Z, E|Y)$$



无监督模式

可解

慢

依赖先验假设

难以广泛适用

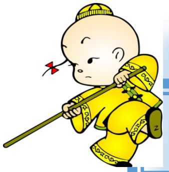
Unsupervised Data

$$\arg\min_{W} L(X - \text{Network}_W(X)) + R(W)$$

$$+$$

$$\arg\min_{W} ||Y - \text{Network}_W(X)||_2$$

Supervised Data



依赖标记

解释性差

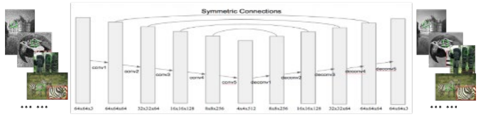
无生成功能

预测速度快

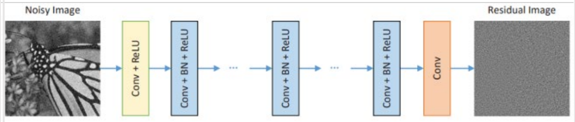
无须先验假设

易拟合广泛规律

$$\arg\min_{W} ||Z - \text{Network}_W(Y)||_2$$

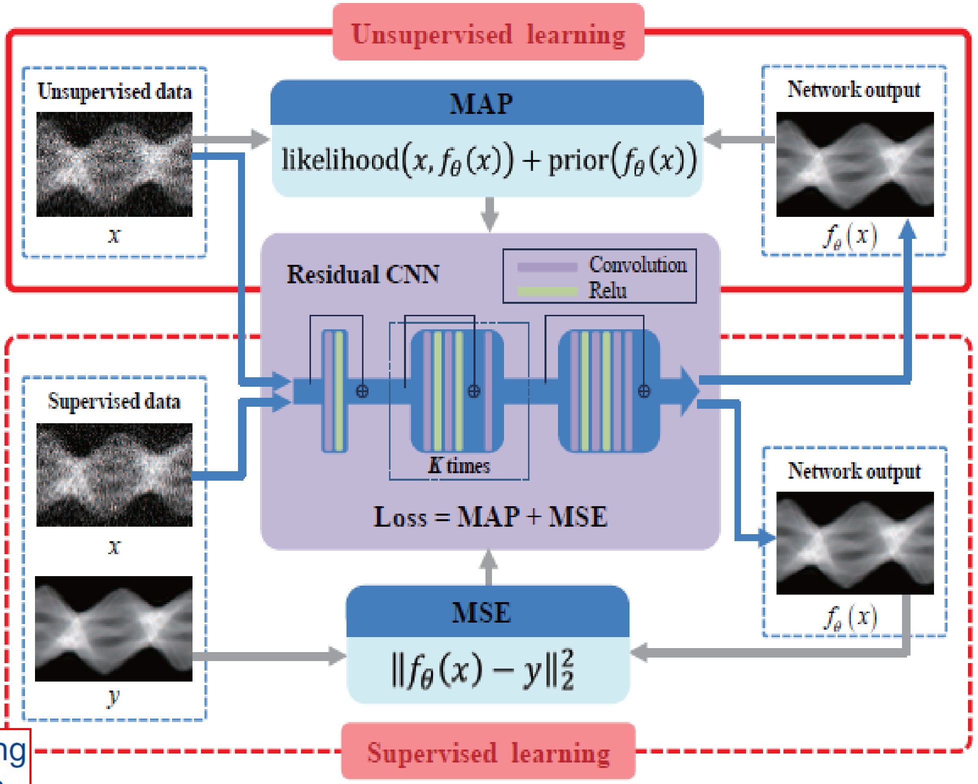


$$\arg\min_{W} ||E - \text{Network}_W(Y)||_2$$



Attempt 1

Unsupervised/Semi-supervised Deep Learning for Low-dose CT Enhancement



Probabilistic understanding has been presented in our TMI18 paper

Robust Low-Dose CT Sinogram Preprocessing via Exploiting Noise-Generating Mechanism

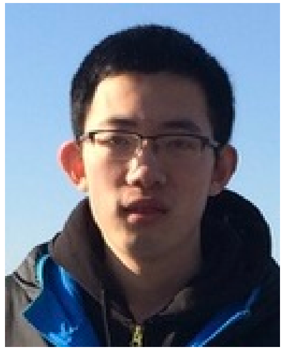
Qi Xie, Dong Zeng, Qian Zhao, Deyu Meng, Zongben Xu, Zhengrong Liang, and Jianhua Ma

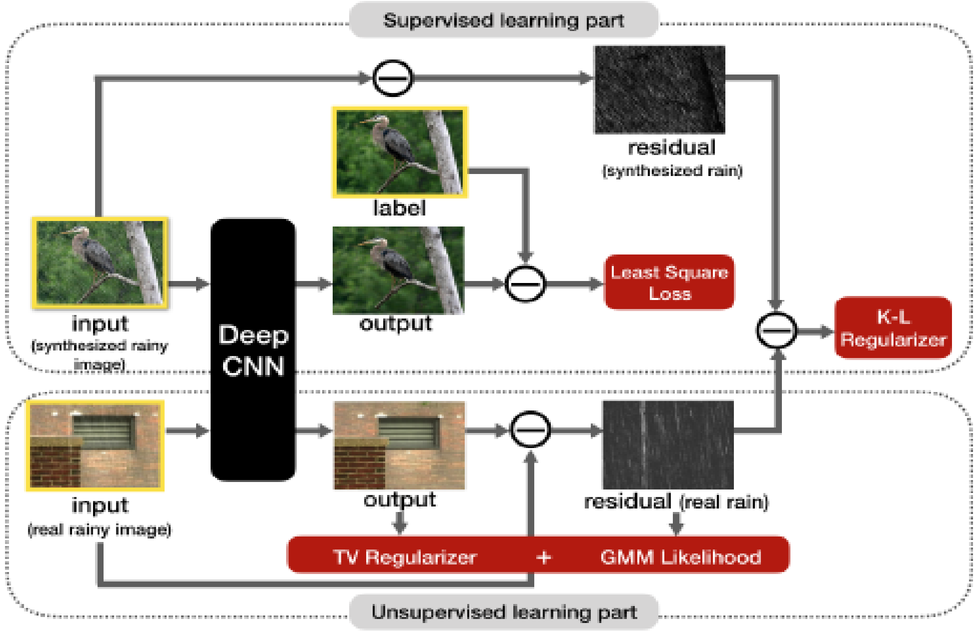
Geng, Deng, Zhao, Xie, Zeng, Ma, Zuo, Meng, arxiv, 2018

Attempt 2

Semi-supervised Transfer Learning for Image Rain Removal

Wei Wei[1,2], Deyu Meng[1]*, Qian Zhao[1], Zongben Xu[1], Ying Wu[2]
[1]School of Mathematics and Statistics, Xi'an Jiaotong University, Xi'an, China
[2]Department of Electrical and Computer Engineering, Northwestern University, IL, USA





Probabilistic understanding has been presented in our ICCV17 paper

Should We Encode Rain Streaks in Video as Deterministic or Stochastic?

Wei Wei[1], Lixuan Yi[1], Qi Xie[1], Qian Zhao[1,2], Deyu Meng[1,2,*], Zongben Xu[1,2]

Wei, Meng, Zhao, Xu, Wu, CVPR, 2019

数模结合第二式

内
练
一
口
气

模型

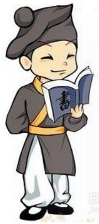
网络

修炼内在，与环境一致

构建网络结构，与模型求解算法一致

$$\arg\min_{Z} L(Y-Z)+R(Z)$$

$$p(z,e|y)\sim \mathrm{likelihood}(y|z,e)p(z)p(e) \Rightarrow \arg\max_{Z,E} p(Z,E|Y)$$



无监督模式 | 可解释性 | 生成功能 | 预测速度慢 | 依赖先验假设 | 难以广泛适用

Z = Algorithm(Y)

内练一口气

$Z = \mathrm{Network}_W(Y)$

依赖标记 | **解释性差** | 无生成功能 | 预测速度快 | 无须先验假设 | 易拟合广泛规律

Unsupervised Data

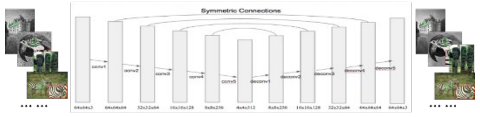
$$\arg\min_{W} L(X-\mathrm{Network}_W(X))+R(W)$$

+

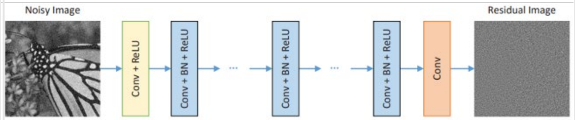
$$\arg\min_{W} ||Y-\mathrm{Network}_W(X)||_2$$

Supervised Data

$$\arg\min_{W} ||Z-\mathrm{Network}_W(Y)||_2$$



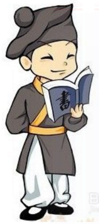
$$\arg\min_{W} ||E-\mathrm{Network}_W(Y)||_2$$



$$\arg\min_{Z} L(Y - Z) + \ldots$$

$$p(z,e|y) \sim likelihood(y|z,e)p(z)p(e)$$

$$\ldots|Y)$$



无监督模式

可解释性

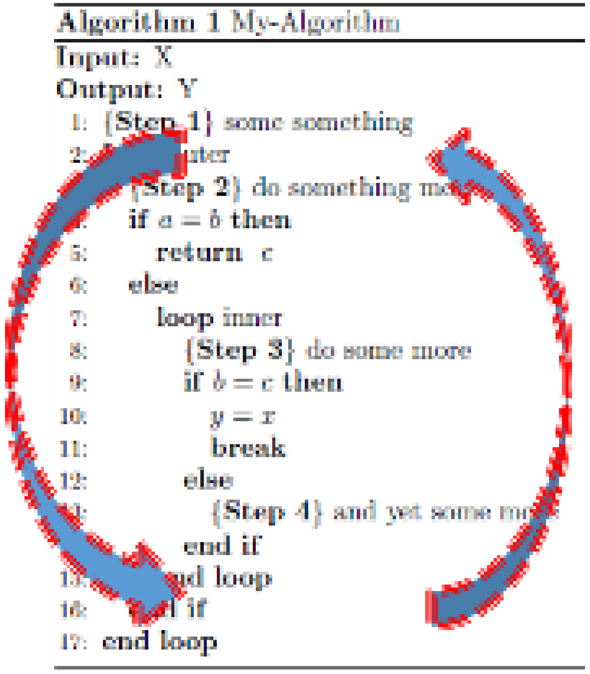
…泛适用

依赖标记

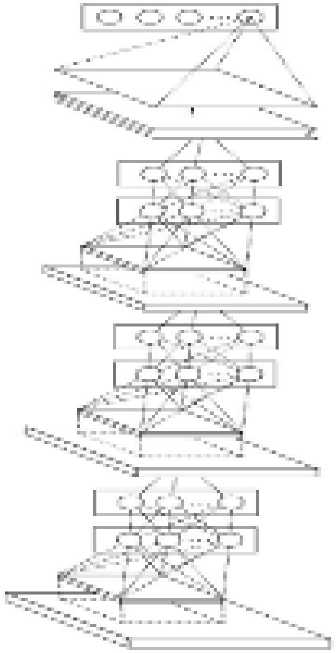
解释性差

无…

…广泛规律



Algorithm



Network

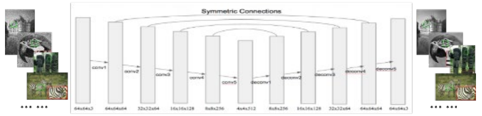
Unsupervised Data

$$\arg\min_{W} L(X - Network_W(X)) + R(W)$$

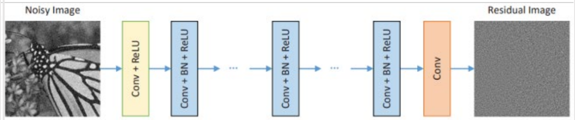
$$\arg\min_{W} ||Y - Network_W(X)||_2$$

Supervised Data

$$\arg\min_{W} ||Z - Network_W(Y)||_2$$



$$\arg\min_{W} ||E - Network_W(Y)||_2$$



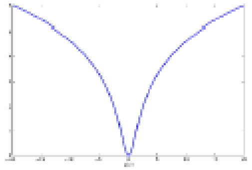
Deep Unfolding

- Field of Experts (FoE) energy: $\min_u \sum_{i=1}^{N_k} \sum_{p=1}^{N} \rho_i((K_i u)_p)$

  Roth and Black, IJCV 2009

$$\boxed{\psi(u) = \nabla_u \mathcal{D}(u)}$$

$$\boxed{\rho'(z) \;=\; \phi(z)}$$



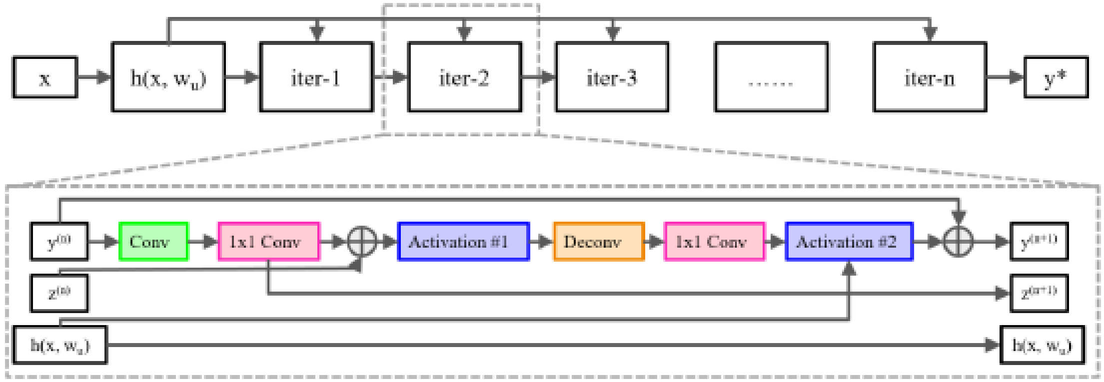
$\rho(z) = \log(1 + z^2)$

- Half-quadratic splitting $\min_{u,z} \sum_{i=1}^{N_k} \sum_{p=1}^{N} \left(\rho_i(z_p) + \frac{\beta}{2}(z - K_i u)_p \right)$

  Schmidt and Roth, CVPR 2014

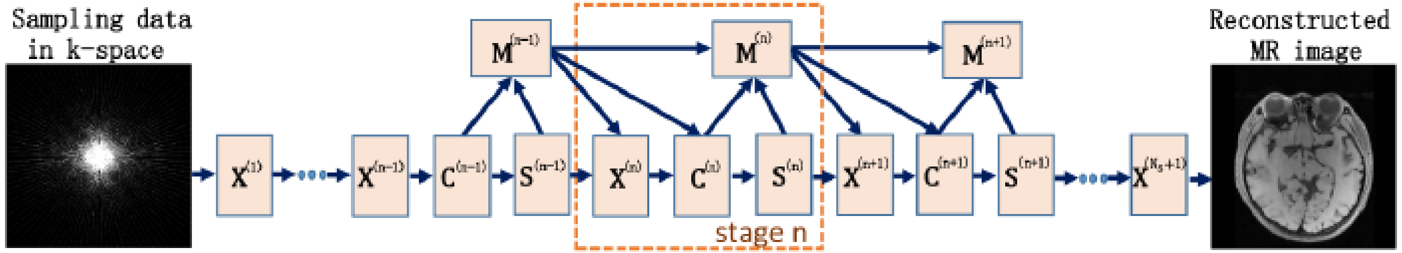
- Primal dual proximal scheme

  Wang et al., NIPS 2016



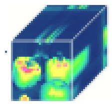
- Alternating direction method

  Yang et al., NIPS 2016



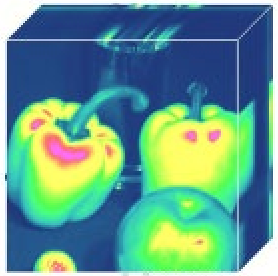
Our attempt: Hyper-spectral Image Fusion

$\mathcal{Y} \in \mathbb{R}^{H\times W\times s}$



$\mathcal{Z} \in \mathbb{R}^{h\times w\times S}$

$$Y = XR + N_y,$$
$$Z = CX + N_z,$$



$\mathcal{X} \in \mathbb{R}^{H\times W\times S}$

$$\min_{\hat{X}} \|Y - \hat{X}R\|_F^2 + \lambda\|Z - C\hat{X}\|_F^2 + \beta P(\hat{X})$$

$$\Downarrow$$

$$\min_{\hat{X},\hat{Y},A,B,C} \|YA + \hat{Y}B - \hat{X}\|_F^2 + \alpha\|C(\hat{X}) - Z\|_F^2 + \beta P(\hat{Y})$$

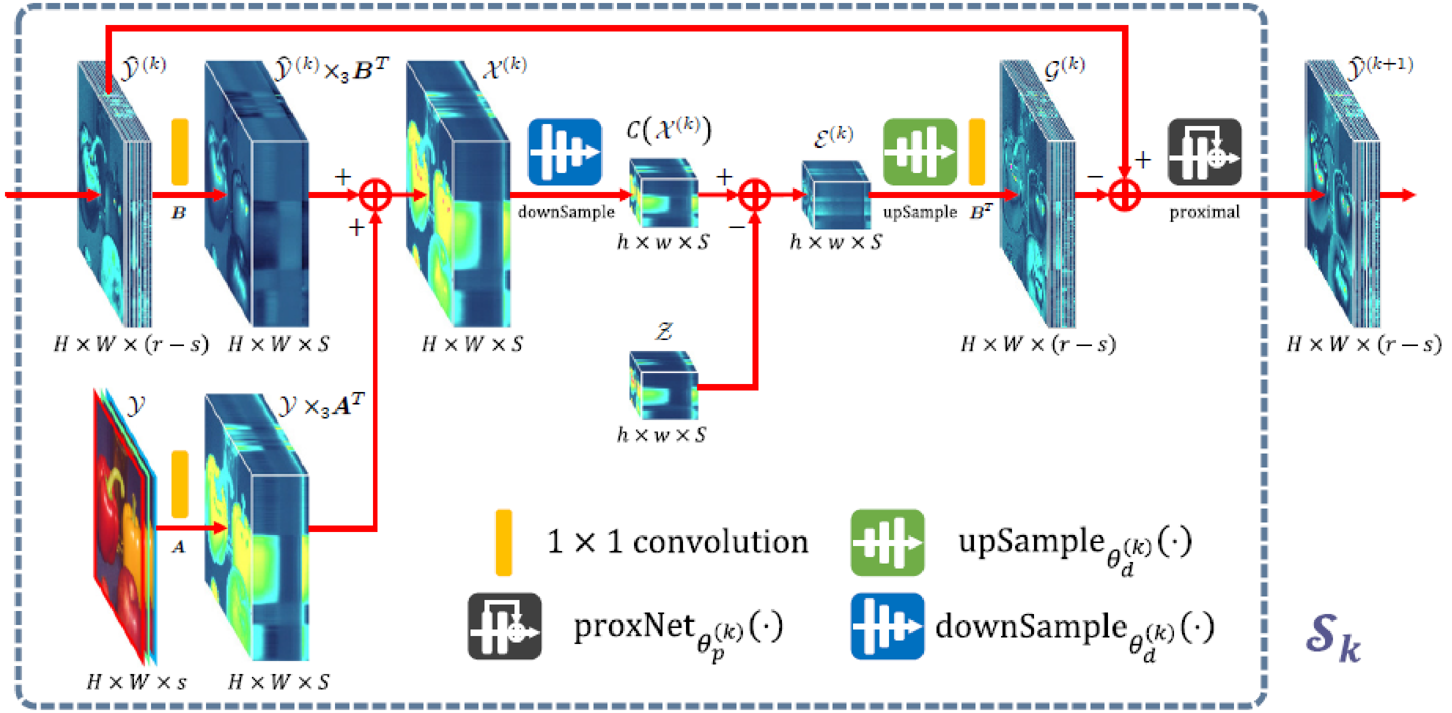
- $\hat{X}_{k+\frac{1}{2}} = YA_{k+1} + \hat{Y}_k B_k$
- $E_k = C_\theta\left(\hat{X}_{k+\frac{1}{2}}\right) - Z$
- $\hat{X}_{k+1} = \hat{X}_{k+\frac{1}{2}} - \frac{\lambda}{2+L} C'_\theta(E_k)$
- $\hat{Y}_{k+1} = f_{P,B_k}(\hat{X}_{k+1} - YA_k)$

Xie, Zhao, Meng, Xu, CVPR, 2019

Our attempt: Hyper-spectral Image Fusion

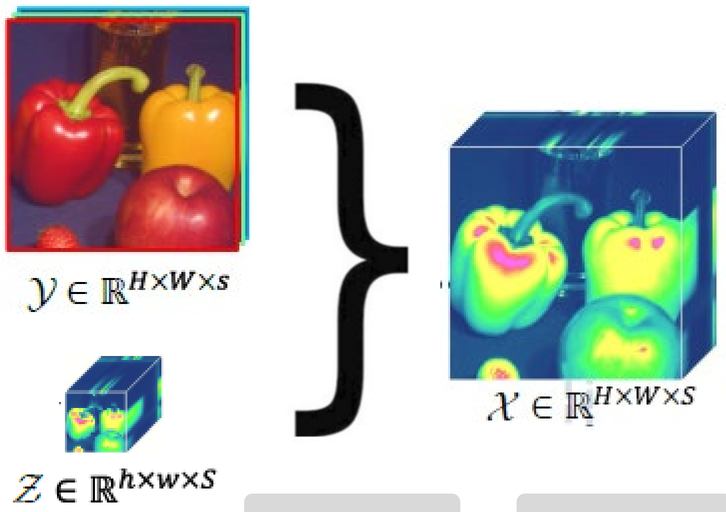
Iterative optimization algorithm	Network design
For $k = 1{:}K$ do:	In stage $k = 1{:}K$ of the network do:
$X^{(k)} = YA + \hat{Y}^{(k)}B$ →	$\mathcal{X}^{(k)} = \mathcal{Y} \times_3 A^T + \hat{\mathcal{Y}}^{(k)} \times_3 B^T$
$E^{(k)} = CX^{(k)} - Z$ →	$\mathcal{E}^{(k)} = \mathrm{downSample}_{\theta_d^{(k)}}\left(\mathcal{X}^{(k)}\right) - \mathcal{Z}$
$G^{(k)} = \eta C^T E^{(k)} B^T$ →	$\mathcal{G}^{(k)} = \eta \cdot \mathrm{upSample}_{\theta_u^{(k)}}\left(\mathcal{E}^{(k)}\right) \times_3 B$
$\hat{Y}^{(k+1)} = \mathrm{prox}_{\lambda\eta}\left(\hat{Y}^{(k)} - G^{(k)}\right)$ →	$\hat{\mathcal{Y}}^{(k+1)} = \mathrm{proxNet}_{\theta_p^{(k)}}\left(\hat{\mathcal{Y}}^{(k)} -\right.$

$$Y = XR + N_y,$$
$$Z = CX + N_z,$$

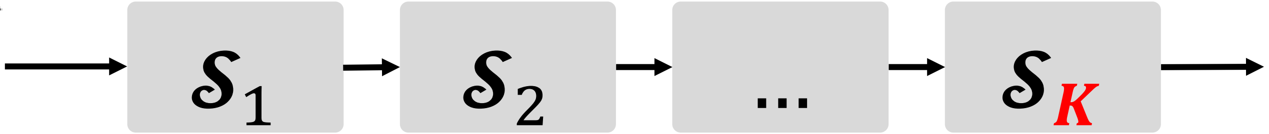


Xie, Zhao, Meng, Xu, CVPR, 2019

Our attempt: Hyper-spectral Image Fusion



$$Y = XR + N_y,$$
$$Z = CX + N_z,$$



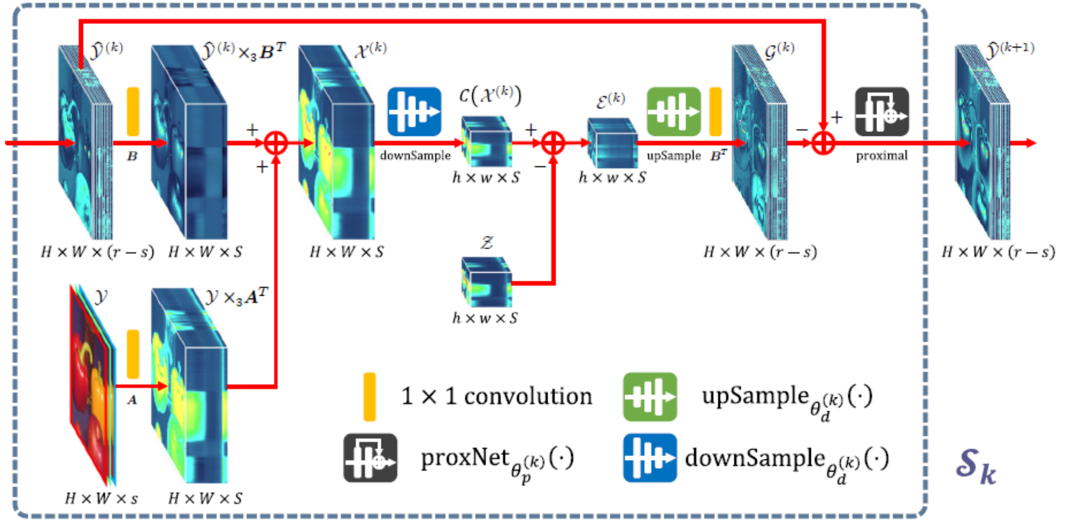


Table 1. Average performance of the competing methods over 12 testing samples of CAVE data set with respect to 5 PQIs.

	ResNet	MHF-net with (K, L)			
		$(4, 9)$	$(7, 5)$	$(10, 4)$	$(13, 2)$
PSNR	32.25	36.15	36.61	36.85	**37.23**
SAM	19.093	9.206	8.636	7.587	**7.298**
ERGA	141.28	92.94	88.56	86.53	**81.87**
SSIM	0.865	0.948	0.955	0.960	**0.962**
FSIM	0.966	0.974	0.975	0.975	**0.976**

Table 3. Average performance of the competing methods over 16 testing samples of Chikusei data set with respect to 5 PQIs.

	PSNR	SAM	ERGAS	SSIM	FSIM
FUSE	26.59	7.92	272.43	0.718	0.860
ICCV15	27.77	3.98	178.14	0.779	0.870
GLP-HS	28.85	4.17	163.60	0.796	0.903
SFIM-HS	28.50	4.22	167.85	0.793	0.900
GSA	27.08	5.39	238.63	0.673	0.835
CNMF	28.78	3.84	173.41	0.780	0.898
M-FUSE	24.85	6.62	282.02	0.642	0.849
SASFM	24.93	7.95	369.35	0.636	0.845
PNN	24.30	4.26	157.49	0.717	0.807
3D-CNN	30.51	**3.02**	129.11	0.869	0.933
ResNet	29.35	3.69	144.12	0.866	0.930
MHF-net	**32.26**	**3.02**	**109.55**	**0.890**	**0.946**

Xie, Zhao, Meng, Xu, CVPR, 2019

Our attempt: Blind Hyper-spectral Image Fusion

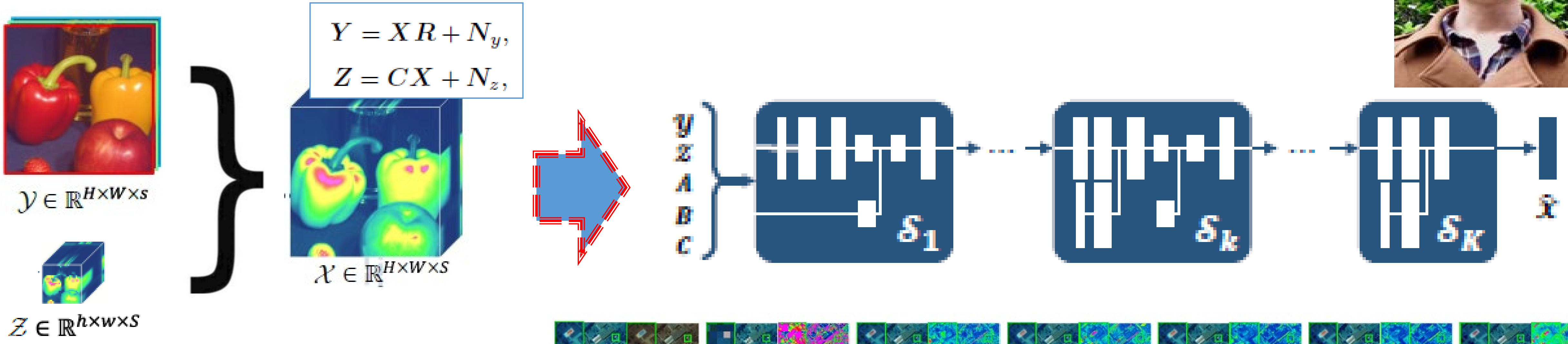
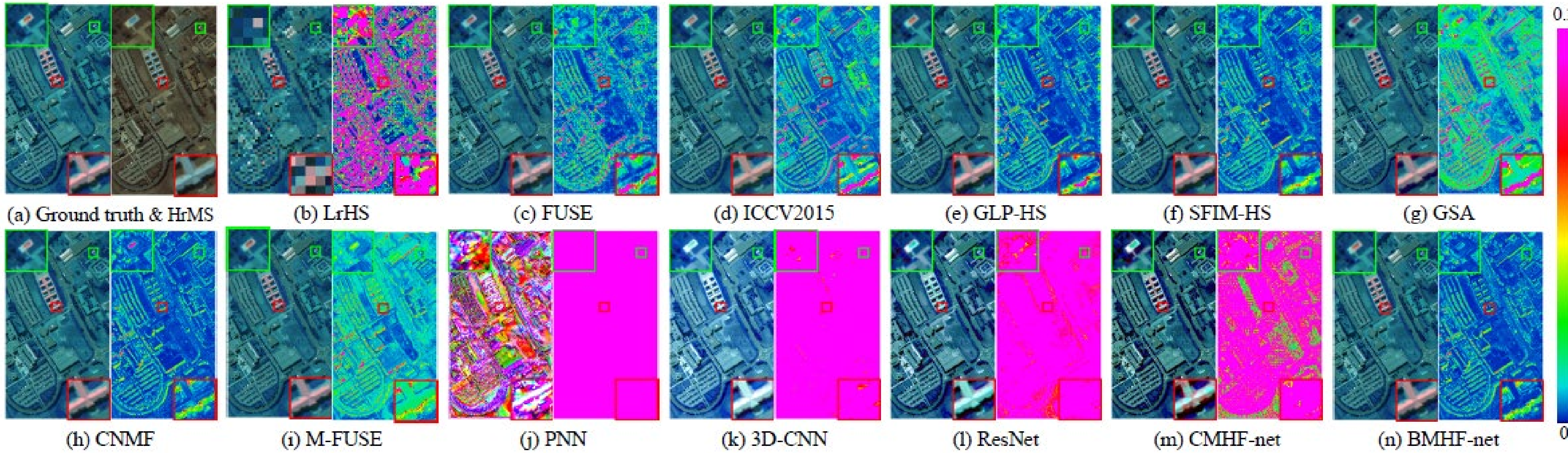


TABLE 6
Average performance of all competing methods over 12 testing im
of CAVE data set. For each image, we compute the average resul
10 random generated spectral and spatial responses.

	PSNR	SAM	ERGAS	SSIM	FSIM
FUSE	40.21	7.22	67.89	0.970	0.984
ICCV15	33.85	11.39	127.48	0.944	0.969
GLP-HS	39.32	7.50	66.86	0.968	0.978
SFIM-HS	36.96	7.71	155.89	0.963	0.976
GSA	36.04	8.52	93.39	0.948	0.974
CNMF	40.26	4.84	61.08	0.984	0.987
M-Fuse	33.65	9.56	125.63	0.904	0.975
PNN	16.70	38.07	777.28	0.139	0.904
3D-CNN	34.90	9.60	103.67	0.958	0.979
ResNet	34.10	14.06	117.21	0.917	0.979
CMHF-net	41.22	6.20	53.69	0.983	0.990
BMHF-net	**44.73**	**4.91**	**40.62**	**0.990**	**0.992**



Xie, Zhao, Meng, Xu, TPAMI, 2020

More Attempts

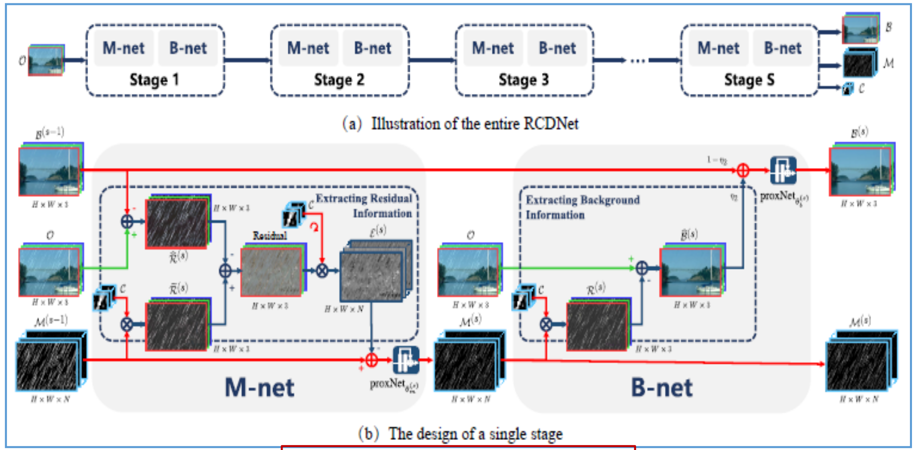
Single image deraining

$$\min_{\Theta} \mathcal{L}(\Theta) = \| \mathcal{X} - \mathcal{H}^{\perp} \circ \mathcal{B} - \mathcal{H} \circ \mathcal{F} - \mathcal{R} \|_F^2 + \lambda \| \mathcal{F} \|_{TV} + \alpha \| \mathcal{H} \|_{3DTV} + \beta \| \mathcal{H} \|_1 + b \sum_{k=1}^{K} \sum_{s=1}^{n_k} \| \mathcal{M}_{ks} \|_1$$

$$s.t. \quad \mathcal{B} = \mathrm{Fold}(U^T V)$$

$$\mathcal{R} = \sum_{k=1}^{K} \sum_{s=1}^{s_k} \mathcal{D}_{ks} \otimes \mathcal{M}_{ks}, \quad \| \mathcal{D}_{ks} \|_F^2 \leq 1,$$

Li, et al., CVPR, 2018



(a) Illustration of the entire RCDNet

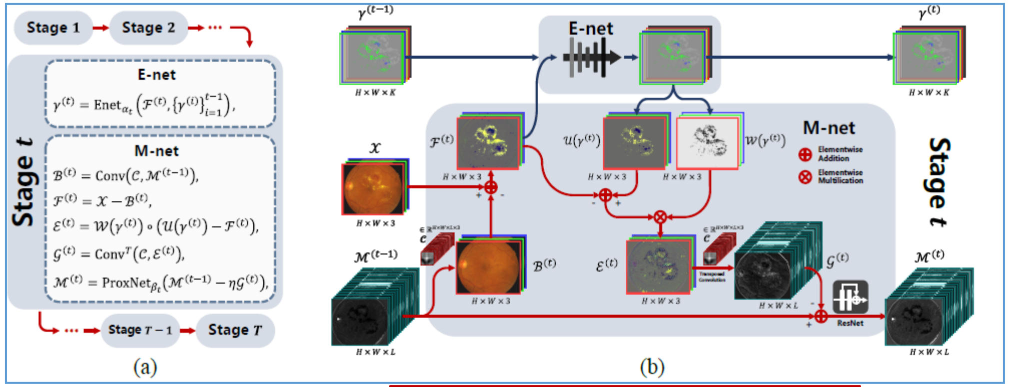
(b) The design of a single stage

Wang, et al., CVPR, 2019

Leision Detection

$$\min_{\Theta} - \sum_{i,j} \log \mathcal{N}((\mathbf{X}_1 - \mathbf{U}\mathbf{V}_1^T)_{ij} | 0, \sigma_1^2) - \sum_{i,\ell} \log \sum_{k=1}^{K} \pi_k \mathcal{N}((\mathbf{X}_2 - \mathbf{U}\mathbf{V}_2^T)_{i\ell} | 0, \sigma_k^2)$$

Wang, et al., TMI, 2019



Wang, et al., Submitted, 2020

数模结合第三式

万法归宗

网络

模型

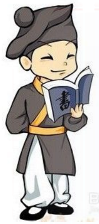
艰难探索，获得自然规律

通过对参数化网络进行数据学习，获得共性推断模型

$$\arg\min_{Z} L(Y - Z) + R(Z)$$

$$p(z, e|y) \sim \text{likelihood}(y|z, e)p(z)p(e)$$

$$\Rightarrow \arg\max_{Z,E} \; p(Z, E|Y)$$



无监督模式 | 可解释性 | 生成功能

预测速度慢 | 依赖先验假设 | 难以广泛适用

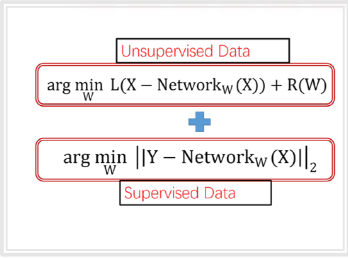
$$Z = \text{Algorithm}(Y)$$

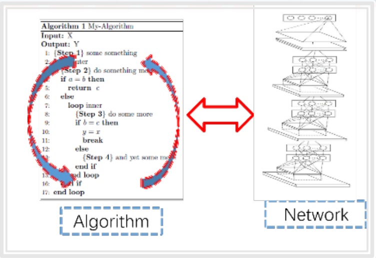
万法归宗

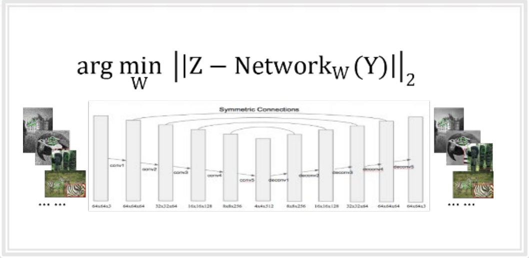
$$Z = \text{Network}_W(Y)$$

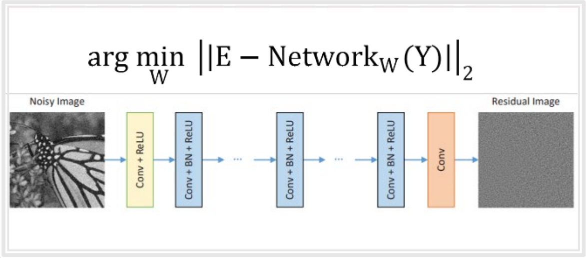
依赖标记 | 解释性差 | 无生成功能

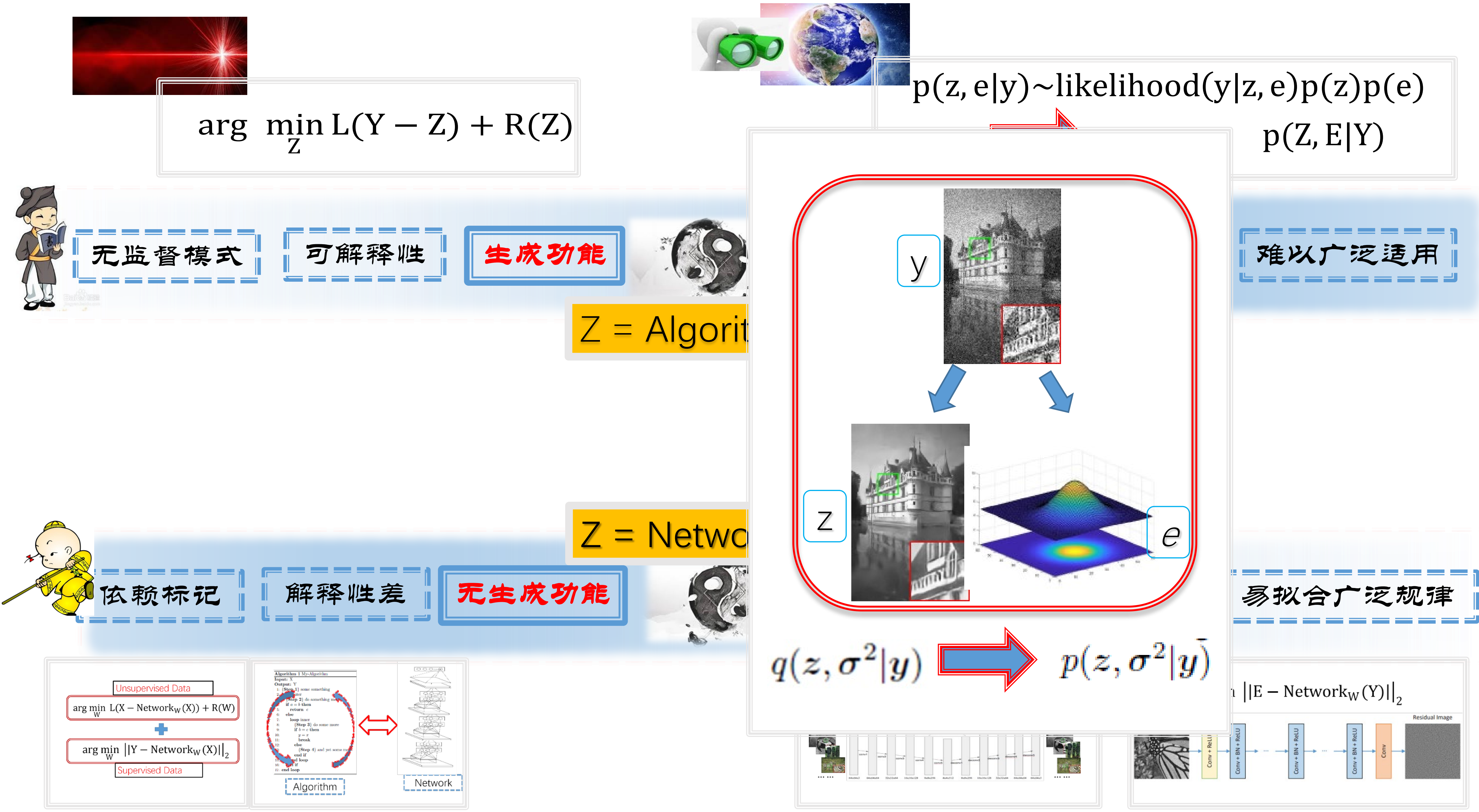
预测速度快 | 无须先验假设 | 易拟合广泛规律





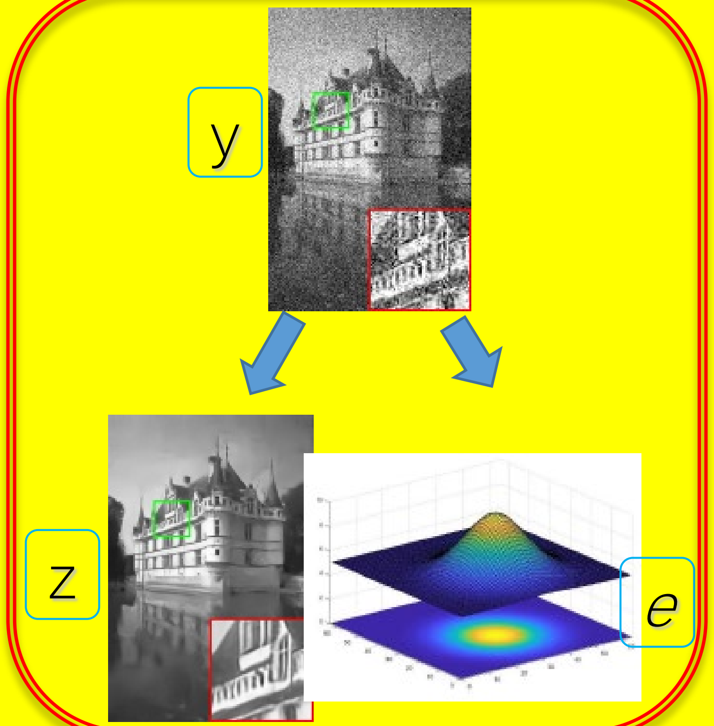


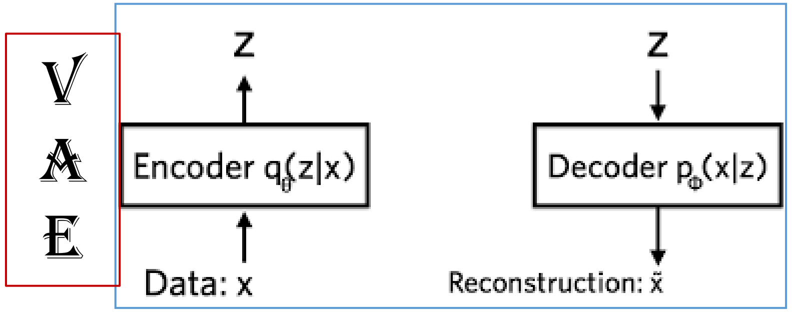


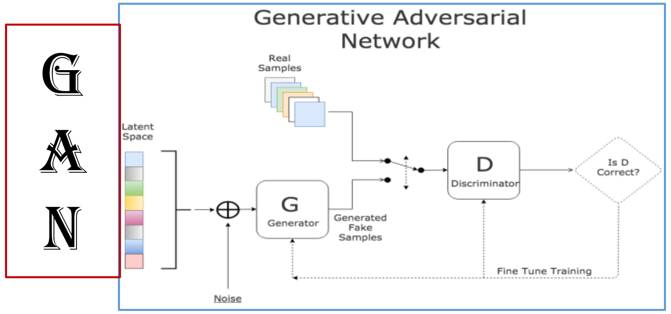

$\arg \min_{Z} L(Y - Z) + R(Z)$
$p(z, e|y) \sim likelihood(y|z, e)p(z)p(e)$
$p(Z, E|Y)$
无监督模式
可解释性
生成功能
难以广泛适用
Z = Algorit
y
z
e
Z = Netwo
依赖标记
解释性差
无生成功能
易拟合广泛规律
$q(z, \sigma^2|y)$
$p(z, \sigma^2|y)$
Unsupervised Data
$\arg \min_{W} L(X - Network_W(X)) + R(W)$
$\arg \min_{W} ||Y - Network_W(X)||_2$
Supervised Data
Algorithm
Network
$||E - Network_W(Y)||_2$
Residual Image

Model-driven Methodology: What we want?

$$q(z, \sigma^2 | y)$$







Varational Posterior

Real Posterior

$$p(z, \sigma^2 | y)$$

Variational Posterior

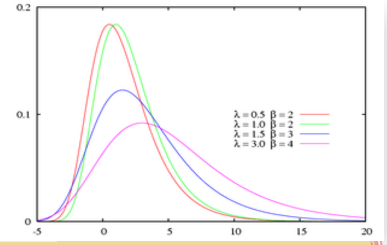
$$q(z, \sigma^2 | y) = q(z|y)q(\sigma^2|y)$$

$$q(z|y) = \prod_i^d \mathcal{N}(z_i | \mu_i(y; \boxed{W_D}), m_i^2(y; \boxed{W_D}))$$

D-Net

$$q(\sigma^2|y) = \prod_i^d \mathrm{IG}(\sigma_i^2 | \alpha_i(y; \boxed{W_S}), \beta_i(y; \boxed{W_S}))$$

S-Net



Network parameters W_D and W_S are shared by posteriors calculated on all training data

Yue, Yong, Zhao, Meng, NeurIPS, 2019

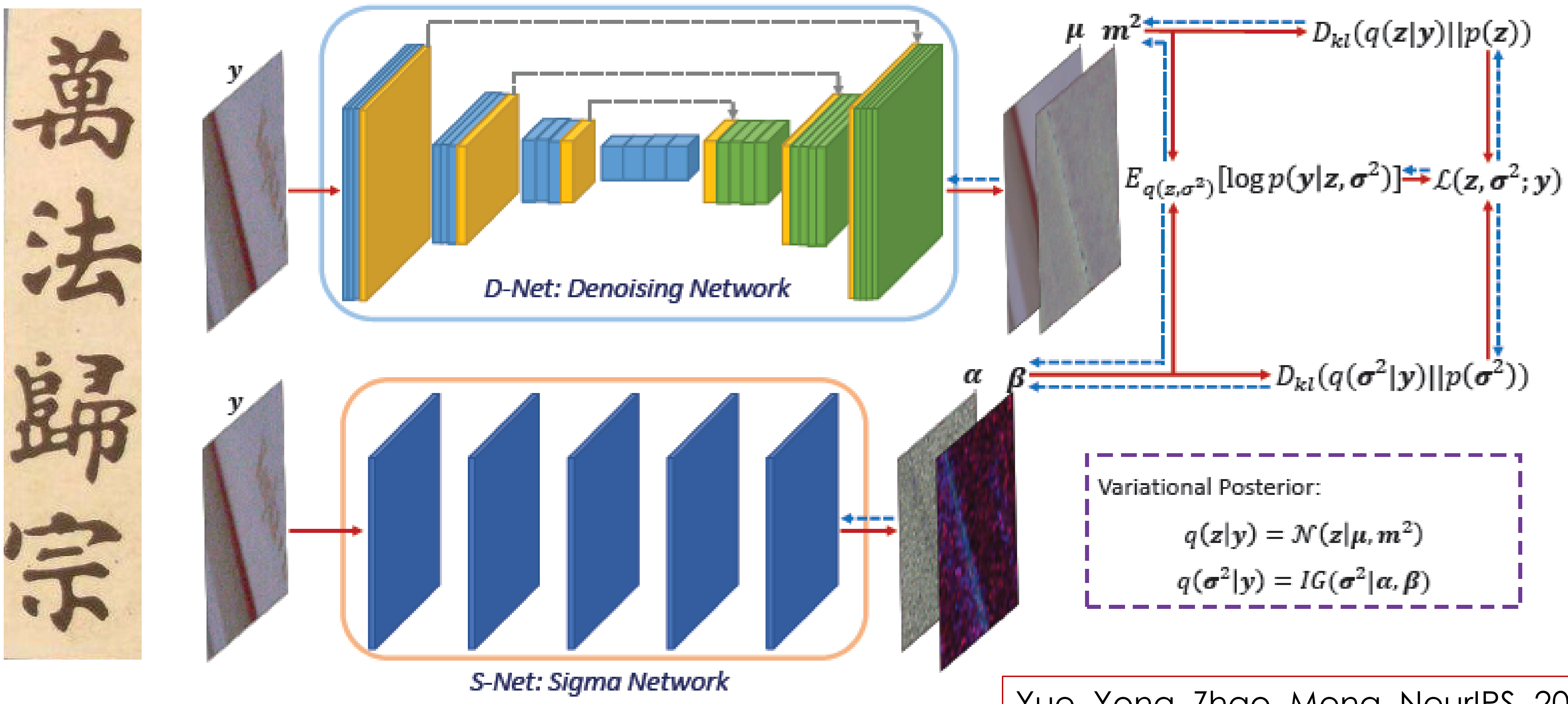
Objective: Minimizing KL Divergence

$$\min_{W_D, W_S} D_{KL}\left(q(z,\sigma^2|y)||p(z,\sigma^2|y)\right)$$

How?

Variational Inference!

Implementation Scheme



Variational Posterior:

$$q(\boldsymbol{z}|\boldsymbol{y}) = \mathcal{N}(\boldsymbol{z}|\boldsymbol{\mu}, \boldsymbol{m}^2)$$

$$q(\boldsymbol{\sigma}^2|\boldsymbol{y}) = IG(\boldsymbol{\sigma}^2|\boldsymbol{\alpha}, \boldsymbol{\beta})$$

Yue, Yong, Zhao, Meng, NeurIPS, 2019

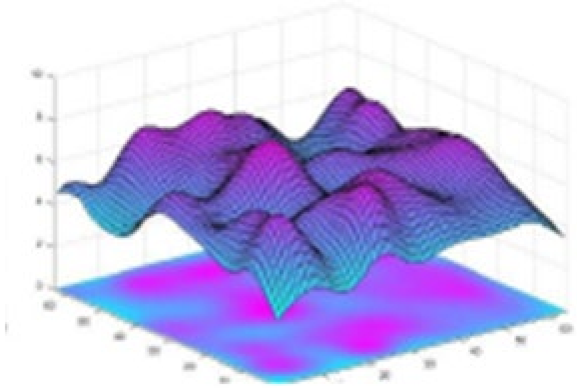
More Explanations on Rationality of This Objective

Variational Posterior:

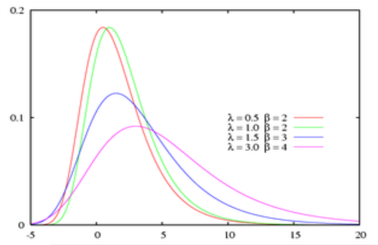
$$q(\mathbf{z}|\mathbf{y}) = \mathcal{N}(\mathbf{z}|\boldsymbol{\mu}, \boldsymbol{m}^2)$$

$$q(\boldsymbol{\sigma}^2|\mathbf{y}) = IG(\boldsymbol{\sigma}^2|\boldsymbol{\alpha}, \boldsymbol{\beta})$$

Restored Image



Extracted Noise Distribution

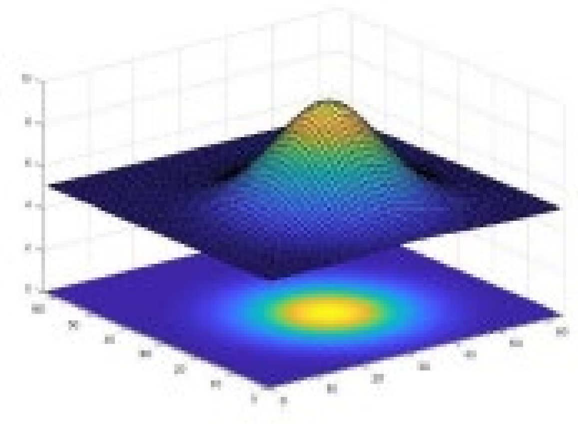


Yue, Yong, Zhao, Meng, NeurIPS, 2019

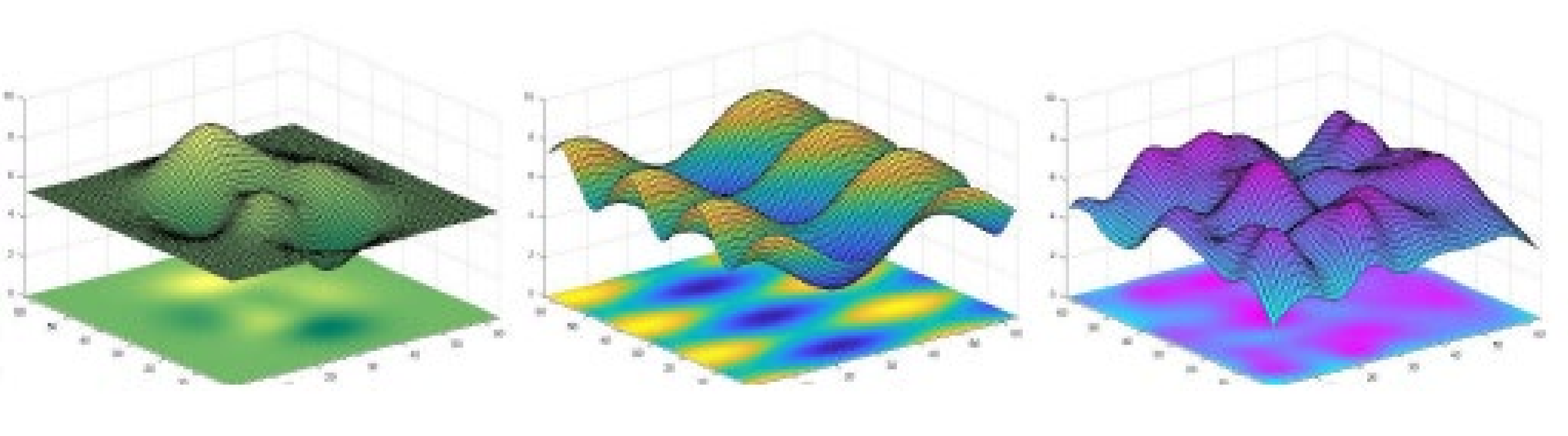
Synthetic Experiments

Training images:
- ✓ 432 images from BSD
- ✓ 400 images from ImageNet
- ✓ 4744 images from Waterloo

Test images:
- ✓ Set5
- ✓ LIVE1
- ✓ BSD68



Training Noise



Test Noise

Yue, et al., NeurIPS, 2019

Synthetic Experiments

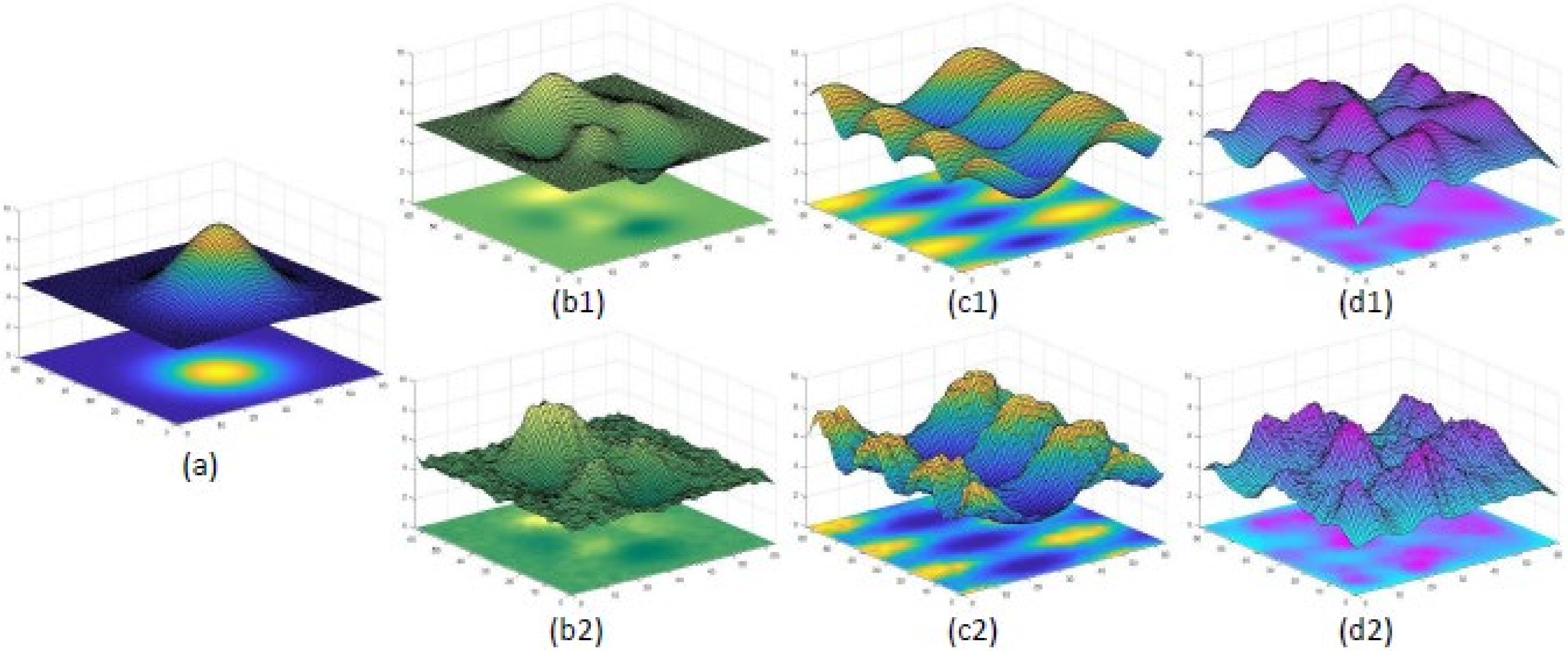
Table 1: The PSNR(dB) results of all competing methods on the three groups of test datasets. The best and second best results are highlighted in bold and Italic, respectively.

Cases	Datasets	Methods									
		CBM3D	WNNM	NCSR	MLP	DnCNN-B	FFDNet	FFDNet_v	FFDNet_e	UDNet	VDN
Case 1	Set5	27.76	26.53	26.62	27.26	29.87	*30.16*	30.15	27.90	28.13	**30.39**
	LIVE1	26.58	25.27	24.96	25.71	28.81	*28.99*	28.96	27.02	27.19	**29.22**
	BSD68	26.51	25.13	24.96	25.58	28.72	*28.78*	28.77	26.89	27.13	**29.02**
Case 2	Set5	26.34	24.61	25.76	25.73	29.05	*29.60*	29.56	25.87	26.01	**29.80**
	LIVE1	25.18	23.52	24.08	24.31	28.18	*28.58*	28.56	24.85	25.25	**28.82**
	BSD68	25.28	23.52	24.27	24.30	28.14	*28.43*	28.42	24.81	25.13	**28.67**
Case 3	Set5	27.88	26.07	26.84	26.88	29.17	*29.54*	29.49	27.60	27.54	**29.74**
	LIVE1	26.50	24.67	24.96	25.26	28.15	*28.39*	28.38	26.44	26.48	**28.65**
	BSD68	26.44	24.60	24.95	25.10	28.10	*28.22*	28.20	26.34	26.44	**28.46**

Table 2: The PSNR(dB) results of all competing methods on AWGN noise cases of three test datasets.

Sigma	Datasets	Methods								
		CBM3D	WNNM	NCSR	MLP	DnCNN-B	FFDNet	FFDNet_e	UDNet	VDN
$\sigma = 15$	Set5	33.42	32.92	32.57	-	34.04	34.30	*34.31*	34.19	**34.34**
	LIVE1	32.85	31.70	31.46	-	33.72	**33.96**	**33.96**	33.74	33.94
	BSD68	32.67	31.27	30.84	-	*33.87*	33.85	33.68	33.76	**33.90**
$\sigma = 25$	Set5	30.92	30.61	30.33	30.55	31.88	*32.10*	32.09	31.82	**32.24**
	LIVE1	30.05	29.15	29.05	29.16	31.23	*31.37*	*31.37*	31.09	**31.50**
	BSD68	29.83	28.62	28.35	28.93	*31.22*	31.21	31.20	31.02	**31.35**
$\sigma = 50$	Set5	28.16	27.58	27.20	27.59	28.95	*29.25*	*29.25*	28.87	**29.47**
	LIVE1	26.98	26.07	26.06	26.12	27.95	*28.10*	*28.10*	27.82	**28.36**
	BSD68	26.81	25.86	25.75	26.01	27.91	*27.95*	*27.95*	27.76	**28.19**

Synthetic Experiments



Yue, et al., NeurIPS, 2019

Real Experiments

Table 3: The PSNR (dB) results of all compared methods on SIDD Benchmark Dataset.

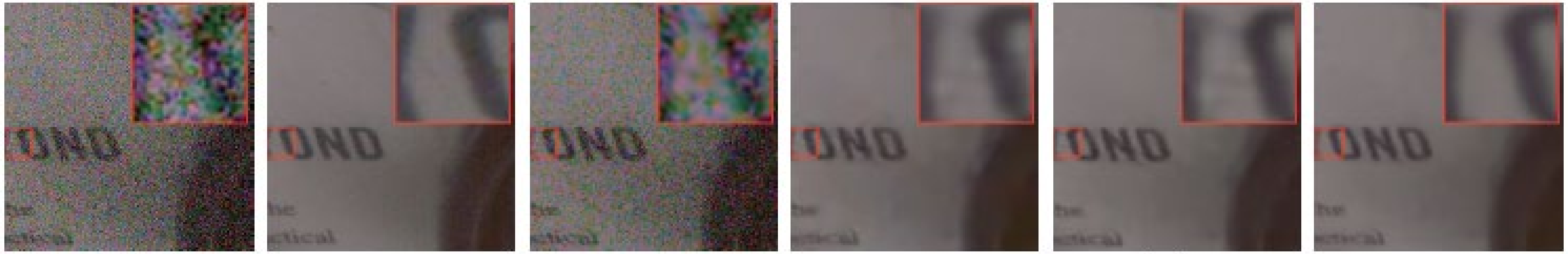
CBM3D	WNNM	MLP	DnCNN-B	CBDNet	VDN
25.65	25.78	24.71	23.66	33.28	39.02

Table 4: The PSNR (dB) results of all compared methods on SIDD validation set.

DnCNN-B	CBDNet	VDN
38.65	38.68	39.04

Table 5: The PSNR (dB) results of all competing methods on DND Benchmark Dataset.

CBM3D	WNNM	NCSR	MLP	DnCNN-B	FFDNet	CBDNet	VDN
34.51	34.67	34.05	34.23	37.90	37.61	38.06	38.35



(a) (b) (c) (d) (e) (f)

Figure 4: Denoising results on one typical image in the validation set of SIDD. (a) Noisy image, (b) Simulated "clean" image, (c) WNNM(21.80dB), (d) DnCNN (34.48dB), (e) CBDNet (34.84dB), (d) VDN (35.50dB).

Yue, et al., NeurIPS, 2019

Noise Generator!

Two perspectives of joint distribution

Noise removal perspective

$$p_R(x, y) = p_R(x|y)p(y)$$

$$y \sim p(y),\ \hat{x} = R(y) \Longrightarrow (\hat{x}, y)$$

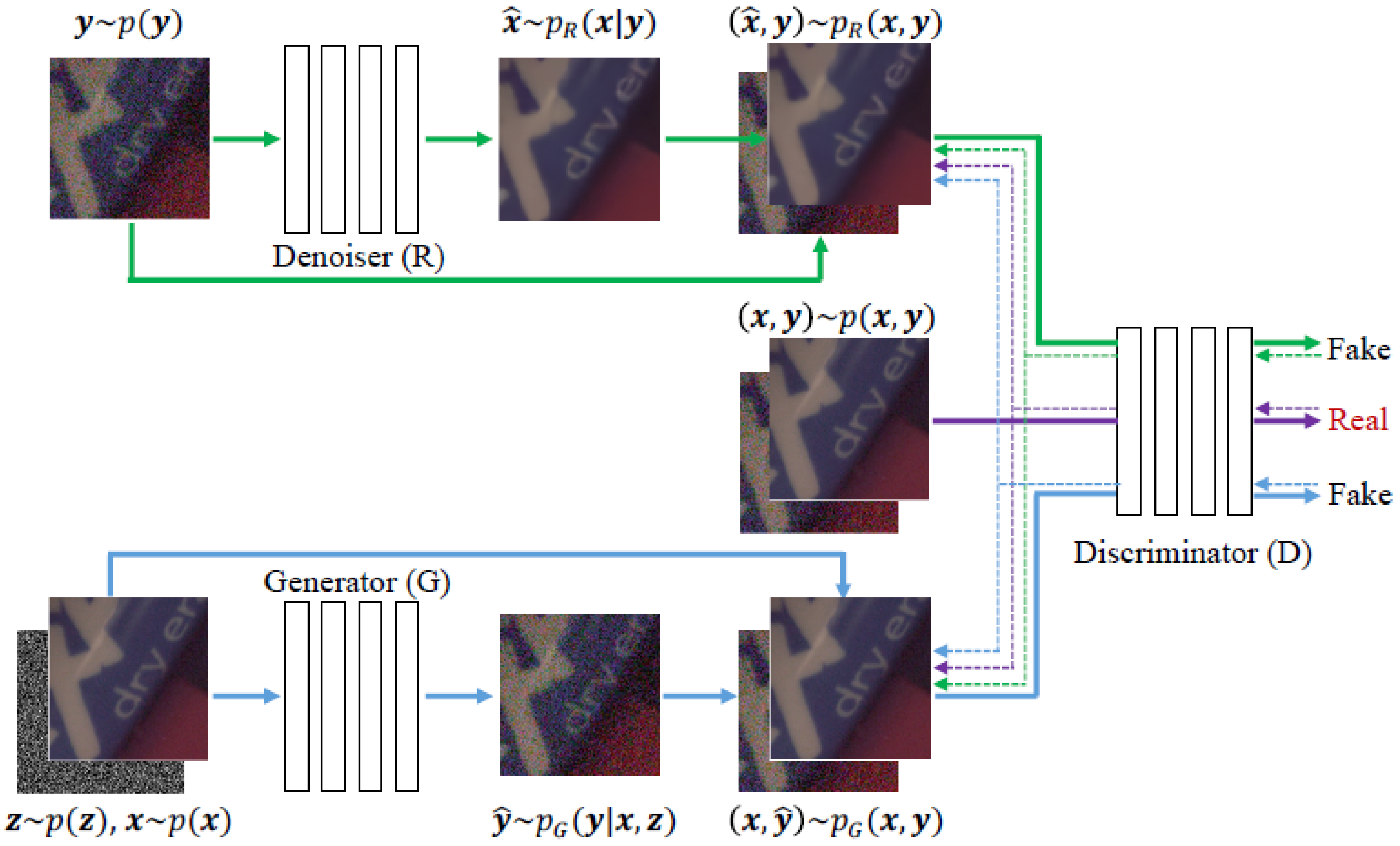
Noise generation perspective

$$p_G(x, y) = \int_z p_G(y|x, z)p(x)p(z)\mathrm{d}z$$

$$z \sim p(z),\ x \sim p(x),\ \hat{y} = G(x, z) \Longrightarrow (x, \hat{y})$$

Yue, Zhao, Zhang, Meng, ECCV, 2020

Noise Generator!



$$||\hat{x} - x||_1$$

$$\min_{R,G} \max_{D} \mathcal{L}_{\text{gan}}(R, G, D) = E_{(\boldsymbol{x},\boldsymbol{y})}[D(x, y)] - \alpha E_{(\hat{\boldsymbol{x}},\boldsymbol{y})}[D(\hat{x}, y)] - (1-\alpha) E_{(\boldsymbol{x},\hat{\boldsymbol{y}})}[D(x, \hat{y})]$$

$$||\mathcal{GF}(\hat{y} - x) - \mathcal{GF}(y - x)||_1$$

Yue, Zhao, Zhang, Meng, ECCV, 2020

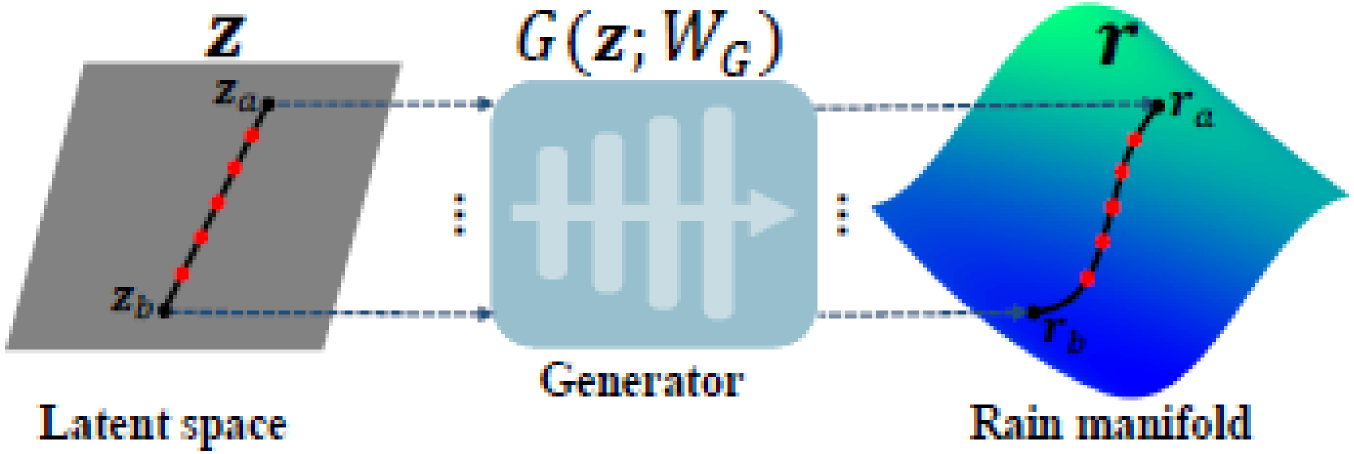
Noise Generator!

Metrics	Methods			
	CBDNet	ULRD	GRDN	DANet
PGap↓	8.30	4.90	2.28	**2.06**
AKLD↓	0.728	0.545	0.443	**0.212**

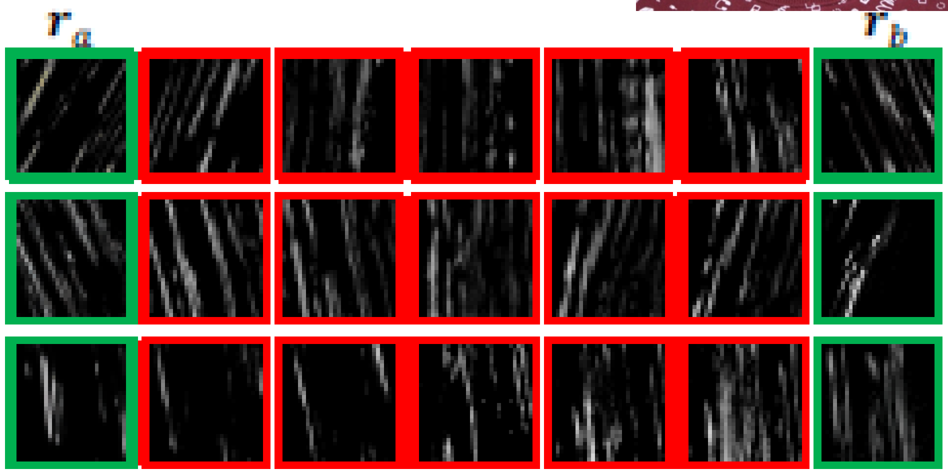
Datasets	Metrics	Methods							
		CBM3D	WNNM	DnCNN	CBDNet	RIDNet	VDN	DANet	$DANet_+$
Testing	PSNR↑	25.65	25.78	23.66	33.28	-	39.26	39.25	**39.43**
	SSIM↑	0.685	0.809	0.583	0.868	-	0.955	0.955	**0.956**
Validation	PSNR↑	25.29	26.31	38.56	38.68	38.71	39.29	39.30	**39.47**
	SSIM↑	0.412	0.524	0.910	0.909	0.913	0.911	0.916	**0.918**

Yue, Zhao, Zhang, Meng, ECCV, 2020

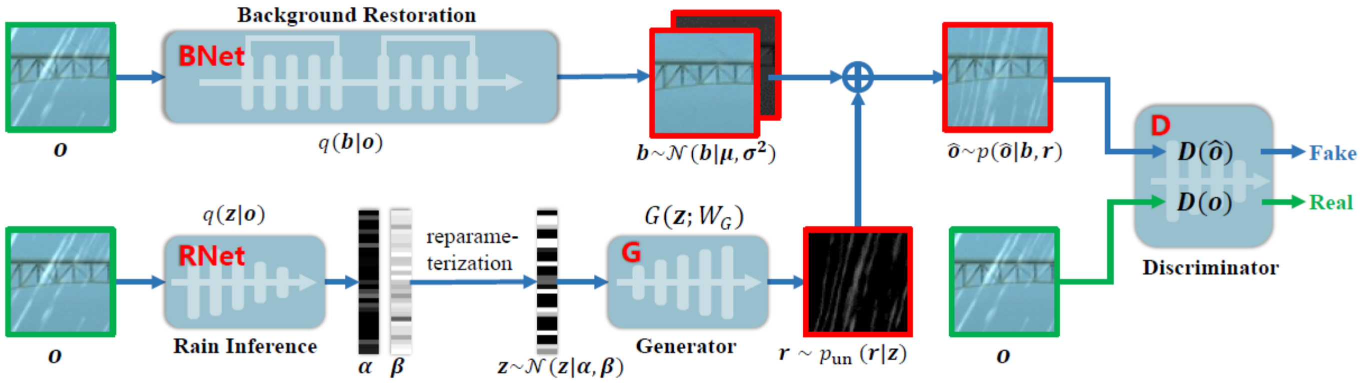
Rain Generator!



(a) The flowchart of rain generation



(b) Three groups of interpolation experiments



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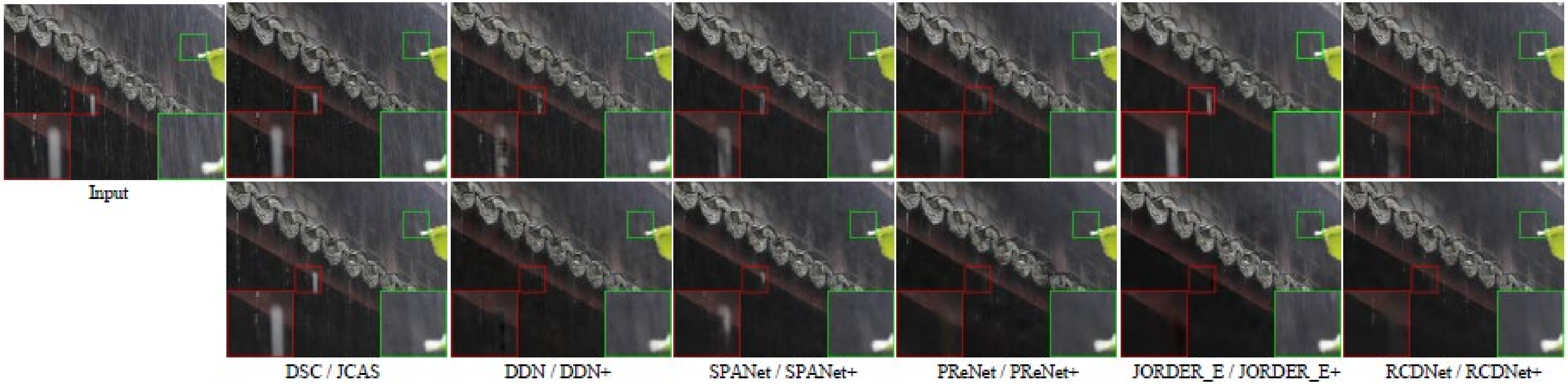
Rain Generator!



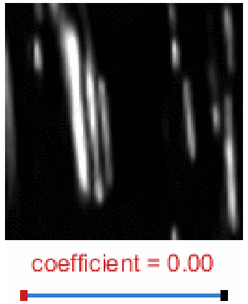
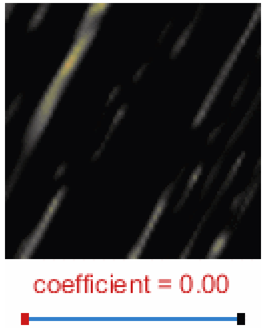


Table 1: PSNR and SSIM comparisons on synthetic datasets. '+' denotes the one trained on a larger training dataset augmented by the proposed VRGNet, i.e., augmented training.

Methods		Input	DSC	JCAS	DDN	DDN+	SPANet	SPANet+	PReNet	PReNet+	JORDER_E	JORDER_E+	RCDNet	RCDNet+
Rain100L	PSNR	26.90	27.34	28.54	32.38	35.56	35.33	35.83	37.42	37.84	37.68	38.01	39.13	39.21
	SSIM	0.838	0.849	0.852	0.926	0.966	0.969	0.972	0.979	0.980	0.979	0.980	0.984	0.984
Rain100H	PSNR	13.56	13.77	14.62	22.85	26.99	25.11	27.24	30.11	30.48	30.50	32.26	31.28	32.40
	SSIM	0.371	0.312	0.451	0.725	0.797	0.833	0.883	0.905	0.910	0.897	0.920	0.909	0.921
Rain1400	PSNR	25.24	27.88	26.20	28.45	30.27	29.85	30.24	32.21	32.51	32.00	32.85	33.04	33.44
	SSIM	0.810	0.839	0.847	0.889	0.917	0.915	0.927	0.943	0.945	0.935	0.946	0.947	0.951



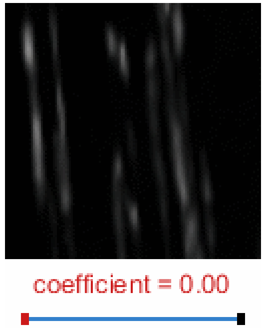


Table 2: PSNR and SSIM comparisons on SPA-Data testing set.

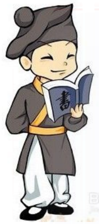
Methods		Input	DSC	JCAS	DDN	DDN+	SPANet	SPANet+	PReNet	PReNet+	JORDER_E	JORDER_E+	RCDNet	RCDNet+
SPA-Data	PSNR	34.15	34.95	34.95	36.16	39.47	38.14	38.59	40.16	40.27	40.78	41.49	41.47	41.55
	SSIM	0.927	0.942	0.945	0.946	0.974	0.973	0.974	0.981	0.984	0.980	0.985	0.983	0.985

Wang, Yue, Zhao, Meng, Submitted, 2020

$$\arg\min_{Z} L(Y-Z)+R(Z)$$

$$p(z,e|y)\sim likelihood(y|z,e)p(z)p(e)$$

$$\Rightarrow \arg\max_{Z,E}\ p(Z,E|Y)$$



无监督模式 | 可解释性 | 生成功能

预测速度慢 | 依赖先验假设 | 难以广泛适用

Z = Algorithm(Y)

$$Y = A(X)+\varepsilon$$

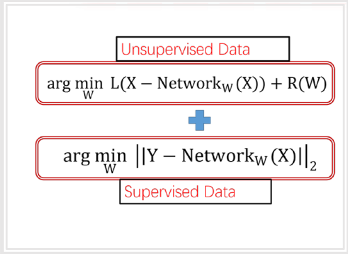
Observation Y

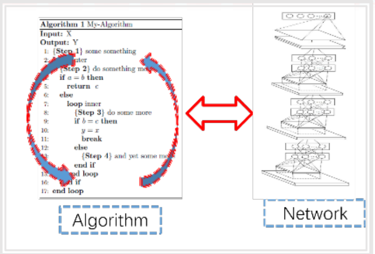
Recovery X

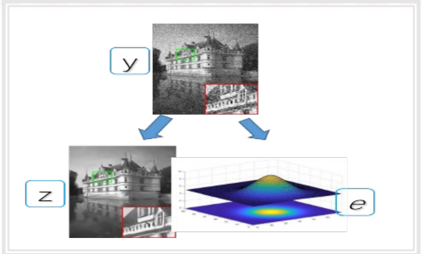
Z= $\mathrm{Network}_W$(Y)

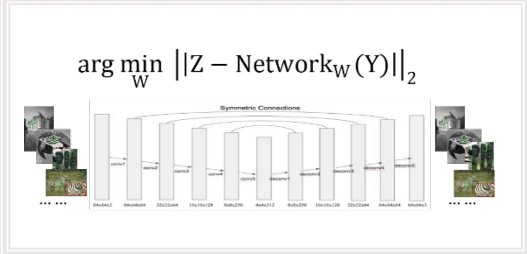
依赖标记 | 解释性差 | 无生成功能

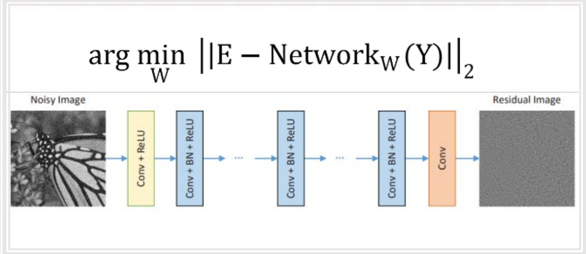
预测速度快 | 无须先验假设 | 易拟合广泛规律







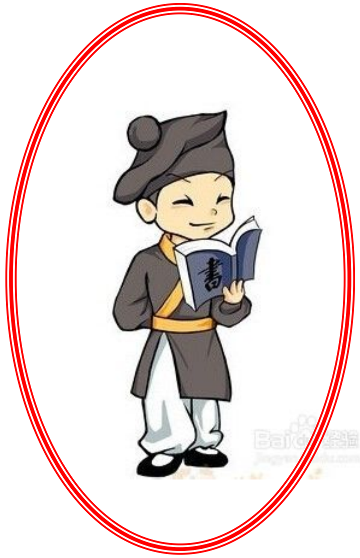


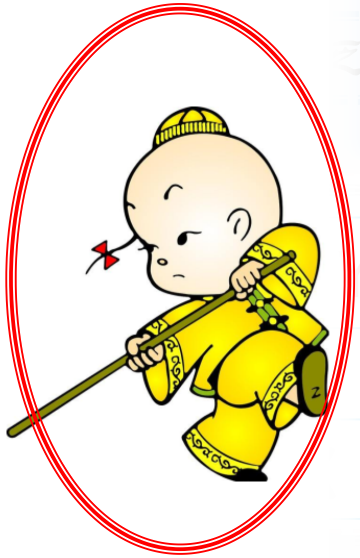


$p(z,e|y) \sim \text{likelihood}(y|z,e)\,p(z)\,p(e)$

外练筋骨皮

内练一口气





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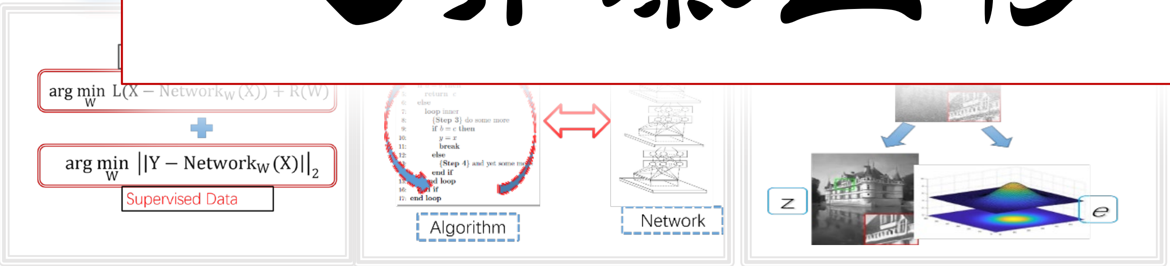

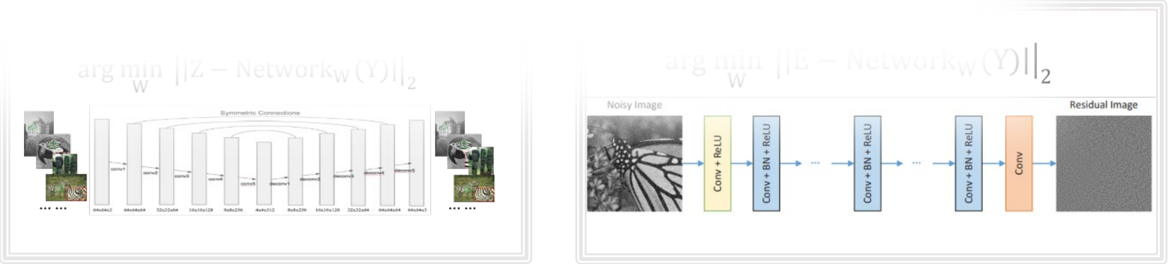

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