

Meta-learning For Solving Inverse Problem

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Motivation

- The problem of reconstructing x from observation y is called inverse problem.

$$y = A(x) + \epsilon$$

$A(\cdot)$: image formation process; ϵ : noise

- Many image processing problems can be formulated as inverse problems.
- Most inverse problems are ill-posed, therefore without any prior information, it is almost impossible for solvers to obtain a good solution.

- Current Methods:

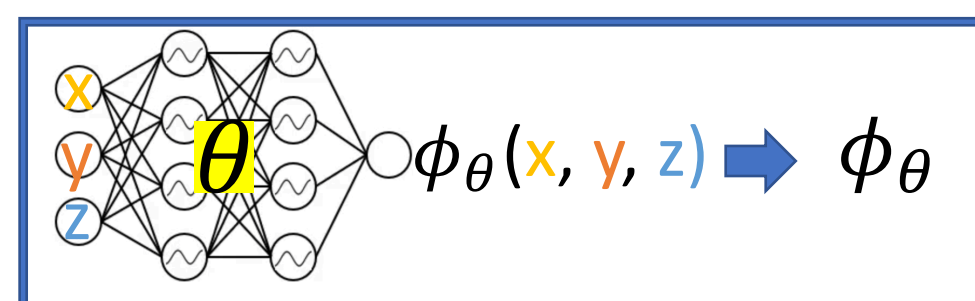
- Classical: **RED**[3] => no dataset information
- Neural Network: **UNet** => no model

Idea: We want to meta-learn an good initialization for the classical solver using dataset information.

Related Works

Implicit Representation:

- MLPs with sinusoidal activation functions (**SIREN**) can represent complex natural signals[1].



Meta-learning – MAML:

- Learn to Learn: an outer loop optimization is used to improve inner loop optimization[2].

[1] Sitzmann, V., Martel, J., Bergman, A., Lindell, D., & Wetzstein, G. (2020). Implicit Neural Representations with Periodic Activation

[2] Chelsea, F. and Pieter A. and Sergey L. (2017) Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks

[3] Yaniv R. and Michael E. and Peyman M. (2016) The Little Engine that Could: Regularization by Denoising (RED)

Algorithm 1: Training Scheme

Require: Distribution $\mathcal{T}$ over the ground truth signals, forward model $\mathcal{A}(\cdot)$, inner-loop learning rate α , number of inner-updates m , outer learning rate β

1: Initialize meta-parameter θ

2: **while** not done **do**

3: sample a batch of signals $x_i \sim \mathcal{T}$

4: **for all** x_i **do**

5: $y_i = \mathcal{A}(x_i) + \epsilon$

6: $\theta_i^0 = \theta$

7: **for** $k \leftarrow 0$ **to** $m - 1$ **do**

8: $x = f(\phi_{\theta_i^k})$

9: $L_{in}(\theta_i^k, y_i) = \|\mathcal{A}(x) - y_i\|_2^2$

10: $\theta_i^{k+1} \leftarrow \theta_i^k - \alpha \nabla_{\theta_i^k} L_{in}(\theta_i^k, y_i)$

11: **end**

12: $x = f(\phi_{\theta_i^m})$

13: $L_{outer} \leftarrow L_{outer} + \|x - x_i\|_2^2$

14: **end**

15: $\theta \leftarrow \theta - \beta \nabla_{\theta} L_{outer}$

16: **end**

Inner loop optimization

Outer-loop optimization

update θ in the direction that minimize $L_{out} = \|x - x_i\|_2^2 \rightarrow$ the difference between ground truth signal x_i , and the predicted signal from inner loop optimization x

Method

Idea: We hope to meta-learn a θ , the parameter of the SIREN, so that the final solution from the proposed inner loop optimization is close to the ground truth signal.

* Note: optimize L_{in} without any prior is not sufficient, as the problem is ill-posed. Therefore, we wrap the the optimization procedure in pink box by a meta-learning framework.

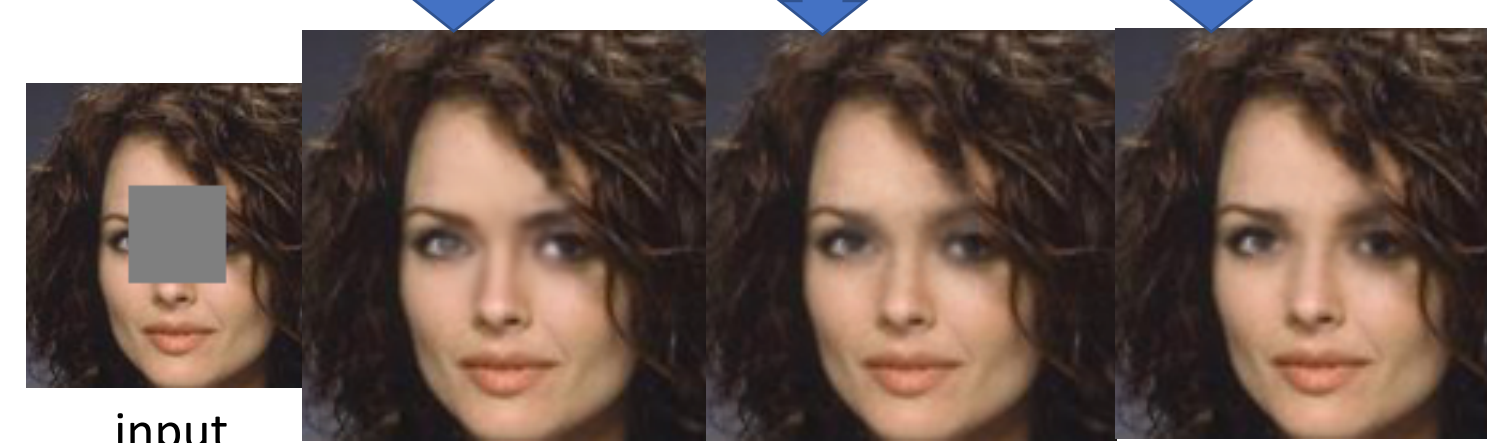
Experimental Results

We perform experiments on two low level image processing tasks with CelebA dataset:

- Inpainting: Classical Solver: gradient decent
(we test on different number of inner-loop updates for θ : 3/5 times (3/5-Meta))
- Deblurring: Classical Solver: RED + pre-trained CNN denoiser
(MetaRED+CNN: RED updates 3 times, θ updates 3 times)

Inpainting			
	U-Net	3-Meta	5-Meta
PSNR	32.9	32.3	32.6
SSIM	0.966	0.962	0.965
LPIPS	0.0226	0.0251	0.0244
MSE	6.8e-4	7.8e-4	7.5e-4

Deblurring			
	MetaRED+CNN	RED + CNN(12)	RED+CNN
PSNR	29.4	27.7	29.3
SSIM	0.918	0.898	0.913
LPIPS	0.0504	0.119	0.0801
MSE	1.2e-3	1.8e-3	1.3e-3



Discussion

- We wrap classical solvers with meta-learning to learn a prior across the dataset.
- From deblurring task, our approach gives us: better performance compare to run classical solver with fixed number of iterations; similar performance with RED run till convergence.
- For inpainting task, our method gives meaningful output but does not beat the baseline like U-Net.
- Future Direction:
 - Find a better way to incorporate prior into the inner loop optimization.