AI-Aided Signal Reconstruction for Inverse Problems

Workshop “Sensornahe KI/ Sensor AI”

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joint work Martin Reiche, Osman Musa and Tom Szollmann

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Goal: for given observation $\boldsymbol{y}$ and forward operator $\boldsymbol{A}$:

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Examples for explicit (but very simple) structures

- Sparsity/compressibility in some domain
- Low-rankness

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BUT real data can have complicated structure - **AI ?**

Outline

I will discuss some exemplary directions...

- Inverse problems and deep neural networks
- Phase retrieval with deep generative models
- Unrolling of iterative algorithms

Inverse Problems with Neural Networks

Inverse Problems / Regularization

Promote desired solutions by selecting an appropriate regularizer $R : \mathbb{R}^n \to \mathbb{R}_+$

$$\min_{\boldsymbol{x}} \quad \|\boldsymbol{A}(\boldsymbol{x}) - \boldsymbol{y}\|_2^2 + \lambda R(\boldsymbol{x}),$$

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Examples for $R(\boldsymbol{x})$:

- Tikhonov regularization $\|\boldsymbol{W}\boldsymbol{x}\|_2^2$
- Sparsity w.r.t. some basis/dictionary: $\|\boldsymbol{W}\boldsymbol{x}\|_1$
- Piece-wise constant signal: $\|\boldsymbol{x}\|_{\mathrm{TV}}$
- ...

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But what if desired properties can not be described mathematically?

Inverse Problems / Regularization

Assume, we have only an (algorithmic) denoiser $f : \mathbb{R}^n \to \mathbb{R}^n$ satisfying for example

$$f(\boldsymbol{x} + \boldsymbol{\eta}) \approx \boldsymbol{x} \qquad \text{for } \boldsymbol{\eta} \sim \mathcal{N}(\mathbf{0}, \sigma^2 \boldsymbol{I}_n)$$

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Simple approach, build regularizer: $R(\boldsymbol{x}) = \|\boldsymbol{x} - f(\boldsymbol{x})\|_p^p$

- theoretical works: *Network Tikhonov - NETT* ([Li etal, 2018])
- but, computing $\nabla R(\boldsymbol{x})$ for descent algorithms ?

  ...difficult for "algorithmic" f (maybe numerically or auto-differentiation...)

can we do something **without computing gradients** ?

If denoiser f is locally homogeneous, non-expansive and has symmetric Jacobian. Then

$$R_{\mathrm{RED}}(\boldsymbol{x}) = \boldsymbol{x}^{\mathsf{T}}(\boldsymbol{x} - f(\boldsymbol{x})) \geq 0$$

and $\quad \nabla R_{\mathrm{RED}}(\boldsymbol{x}) = \boldsymbol{x} - f(\boldsymbol{x})$ [Romano, 2016 and Reehorst, 2018]

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- super fast&simply, $\nabla f(\boldsymbol{x})$ not needed
- can be used with plug&play algorithms like *ADMM*
- use existing denoiser networks like DnCNN [Zhang etal, 2017]
- above conditions rarely satisfied, **but** usually works nonetheless.

Constrain also signal domain, e.g., by learning from data!!

Inverse Problems / Generative Models

Generative models based on *neural networks* work well for learning complicated signal domains

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`https://www.thispersondoesnotexist.com`

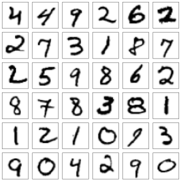
Optimize with relevant signals $\boldsymbol{x}$ in the first place.

$\rightarrow$ Learn signal distribution from training data

$\rightarrow$ yields **generator** $G : \mathbb{R}^k \rightarrow \mathbb{R}^n$

Inverse Problems / Generative Models

A *Variational Auto-Encoder* [Kingma, 2013] does just that:



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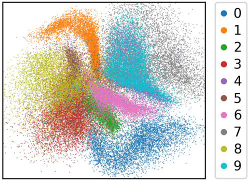

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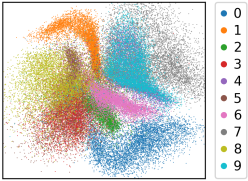

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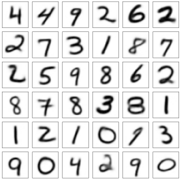

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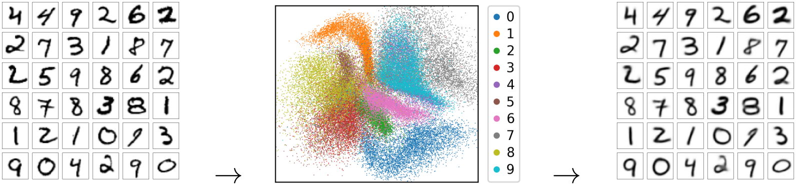

Take decoder of VAE as signal generator $G : \mathbb{R}^k \to \mathbb{R}^n$ and solve

$$\min_{\boldsymbol{z}} \tfrac{1}{2} \|\boldsymbol{A} G(\boldsymbol{z}) - \boldsymbol{y}\|_2^2 + \lambda \cdot R(G(z))$$

latent variable $\boldsymbol{z}$, $\boldsymbol{x} = G(\boldsymbol{z})$ generated image

Inverse Problems / Generative Models

Theoretical Guarantees ?

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Theorem ([Bora etal,2017])

Let $G : \mathbb{R}^k \to \mathbb{R}^n$ *be a d-layer feed-forward neural network with ReLU activations and* $\boldsymbol{A} \in \mathbb{R}^{m,n}$ *with* $A_{i,j} \sim \mathcal{N}(0, 1/m)$ *where* $m \simeq kd \log n$. *Let*

$$\boldsymbol{y} = \boldsymbol{A}\boldsymbol{x} + \boldsymbol{\eta} \qquad \text{for } \boldsymbol{x} \in \mathbb{R}^n \text{ and noise } \boldsymbol{\eta} \in \mathbb{R}^m.$$

Assume that $\boldsymbol{z}^*$ *minimizes* $\|\boldsymbol{A}G(\boldsymbol{z}) - \boldsymbol{y}\|_2$ *within* ϵ *from the optimum. Then with high probability,*

$$\|G(\boldsymbol{z}^*) - \boldsymbol{x}\|_2 \leq 6 \min_z \|G(\boldsymbol{z}) - \boldsymbol{x}\|_2 + 3\|\boldsymbol{\eta}\|_2 + 2\epsilon.$$

- compressed sensing inspired proofs

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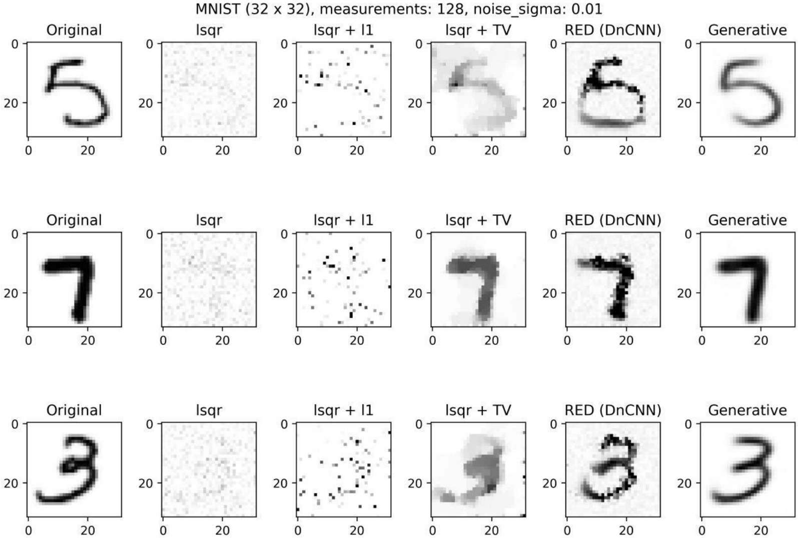
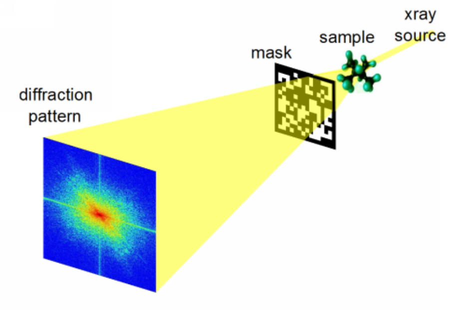
- ☹ how to compute $\boldsymbol{z}^*$ sufficently accurate (non-convex!) ?
- ☹ undesired dimension scaling is for untrained networks

Inverse Problems / Generative Models

MNIST with Gaussian $A \in \mathbb{R}^{128 \times 1024}$, subsampling=1/8



Phase Retrieval with Generative Prior



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Classical problem in physics, engineering and applied math

$$\min_{\mathbf{x}} \|\mathbf{y} - |\mathbf{A}\mathbf{x}|^2\|_2^2 + \lambda R(\mathbf{x})$$

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$$\min_{\mathbf{x}} \|\mathbf{y} - |\mathbf{Ax}|^2\|_2^2 + \lambda R(\mathbf{x})$$

- *nonconvex* but descent methods (like Wirtinger flow) empirically succeed if **initialization is close to optimal value**
- unique solution ?

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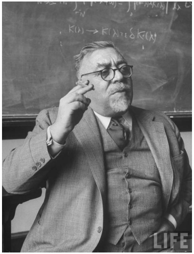

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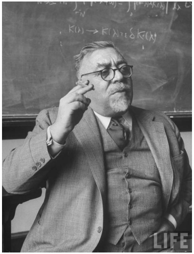
- **solve this problem with as few observations as possible!!**



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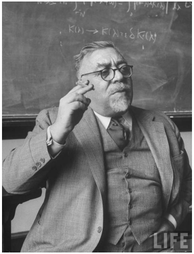

Use trained network $G : \mathbb{R}^k \to \mathbb{R}^n$ [Asim et al., 2019] and [Shamshad et al., 2018]:

$$\min_{\mathbf{z}} \|\mathbf{y} - |\mathbf{A}G(\mathbf{z})|^2\|_2^2 + \lambda \|G(\mathbf{z})\|_{\mathrm{TV}}$$

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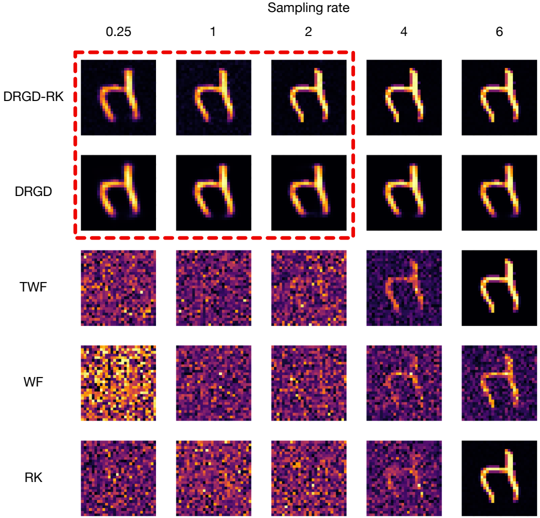
2. refine, for $x \in \mathbb{R}^n$ solve with (superfast) *Randomized Kaczmarz*:

$$\hat{\mathbf{x}} := \operatorname*{argmin}_{\mathbf{x} \in \mathbb{R}^n} \|\mathbf{y} - |\mathbf{A}\mathbf{x}|^2\|_2^2$$

initialized with $\tilde{\mathbf{x}} = G(\tilde{\mathbf{z}})$, overcomes model error of G

Results for MNIST



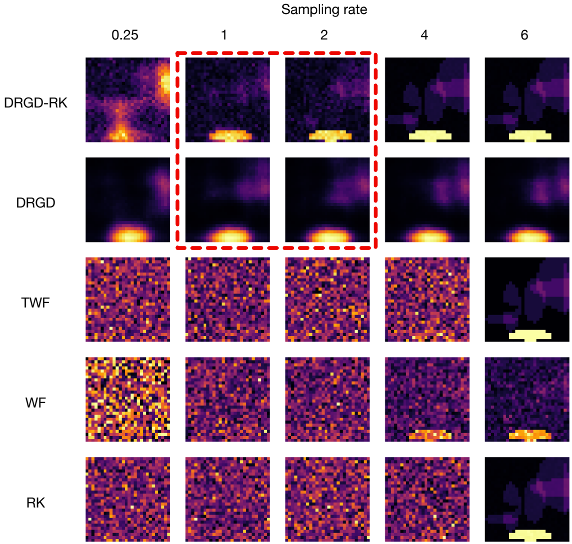
- $y = |Ax|^2$
- $A \in \mathbb{C}^{m\times n}$

  iid. complex normal
- $x = 28 \times 28$ MNIST
- sampling rate= $\frac{m}{n}$

- WF=Wirtinger flow
- TWF=truncted WF
- RK=random Kaczmark
- DRGD-RK=deep gradient+RK

same SSIM achieved at 1/6 sampling rate and 1/100 runtime ...

Results for Shepp-Logan



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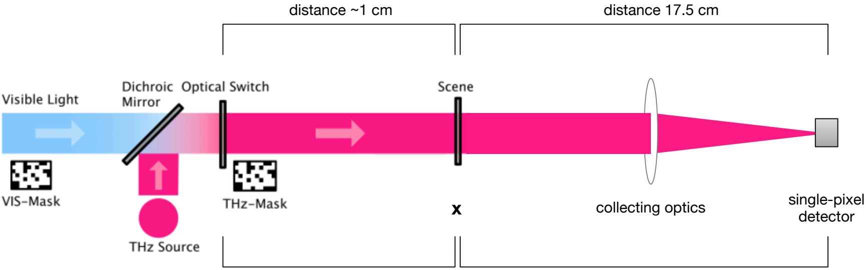
Phase Retrieval for THz Imaging

Cooperation on computational imaging with S. Augustin (DLR/HU)



forward model $\boldsymbol{A}$:

- random iid. binary masks
- discretized diffraction model ($D_{\mathrm{M}\to\mathrm{S}}$ & $D_{\mathrm{S}\to\mathrm{D}}$) [Katkovnik et al., 2009]

Phase Retrieval for THz Imaging

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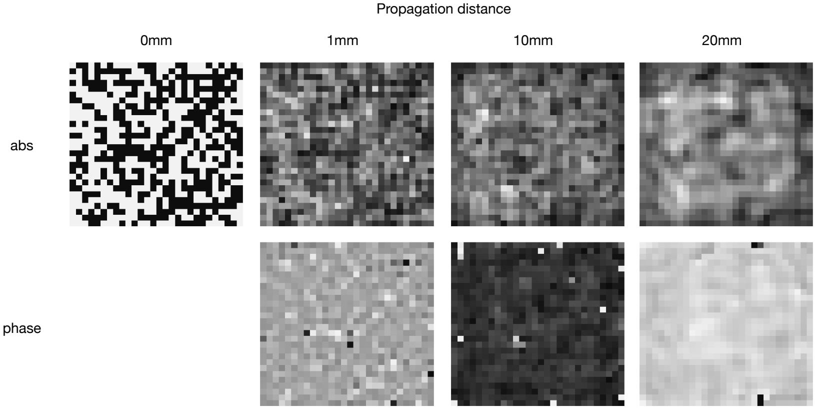
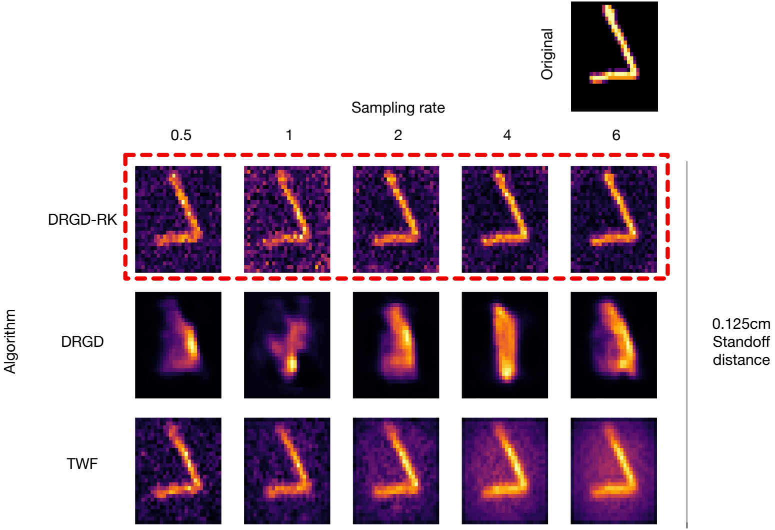
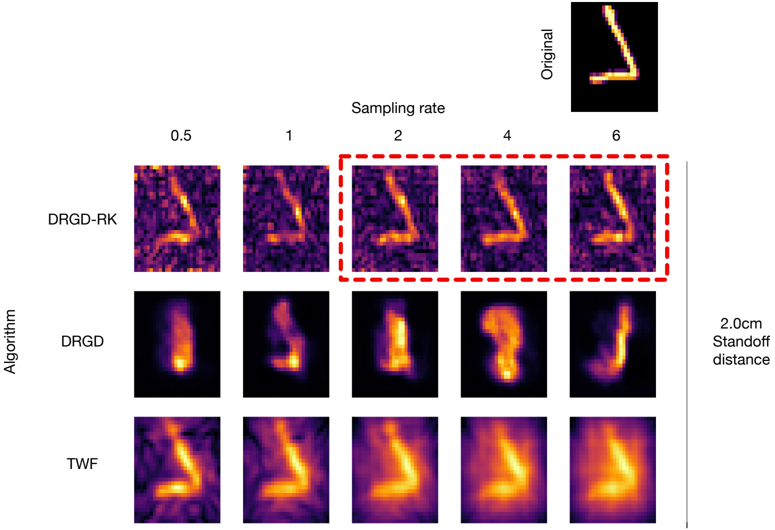


diffraction matrices $D_{\mathrm{M}\to\mathrm{S}}$ loosing rank with increased propagation distance [Katkovnik et al., 2009]

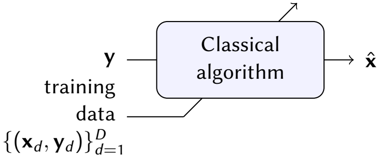
Results for MNIST at 0.125cm stand-off



Results for MNIST at 2.0cm stand-off



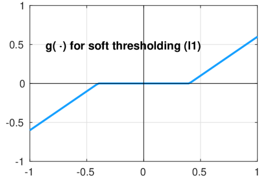
Unfolding Iterative Algorithms



Unfolding Algorithms into Networks

- recover a sparse $\boldsymbol{x}$ from $\boldsymbol{y} = \boldsymbol{A}\boldsymbol{x} + \boldsymbol{e}$ where $\boldsymbol{e} \sim N(0, \sigma^2)$
- popular algorithm like ISTA [Daubechies etal, 2004]

$$\hat{\mathbf{x}}^{t+1} = g(\mathbf{S}\hat{\mathbf{x}}^{t} + \mathbf{B}\mathbf{y}) \quad \text{with} \quad \begin{array}{l} \mathbf{S} \triangleq \mathbf{I} - \mathbf{A}^T\mathbf{A} \\ \mathbf{B} \triangleq \mathbf{A}^T \end{array}$$



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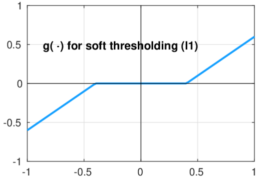

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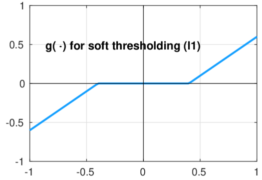

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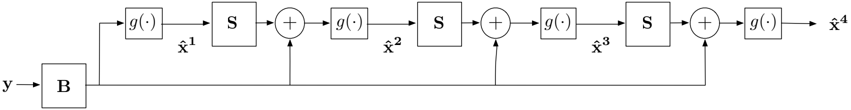
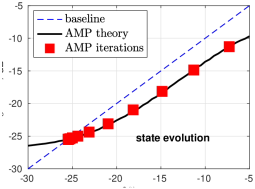
learned ISTA (LISTA): unfold iterations as net and "learn" improved parameters using training data [Gregor &LeCun, 2010]



Unfolding Algorithms into Networks

- *Approximate message passing* (AMP) with Onsager-decoupled iterations [Donoho, Maleki & Montanari 2009], unfold…
- ”learned AMP” (LAMP) [Borgerding & Schniter, 2016]



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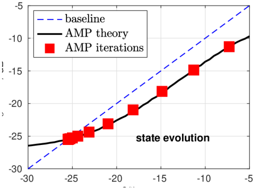
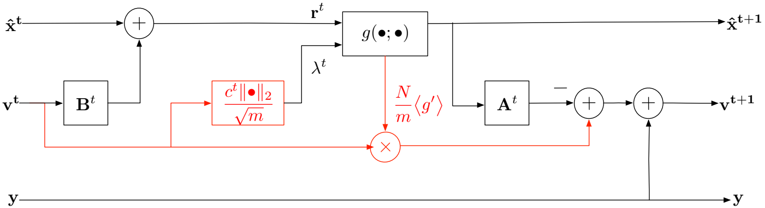


t^{th} layer: LISTA $\rightarrow$ LAMP (Onsager-decoupled layers)



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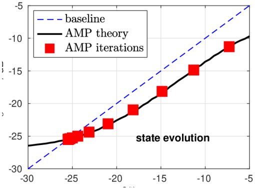
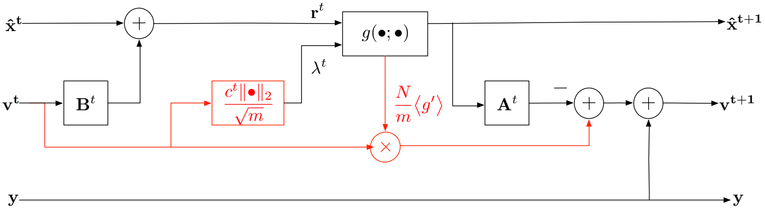
- *Approximate message passing* (AMP) with Onsager-decoupled iterations [Donoho, Maleki & Montanari 2009], unfold...
- "learned AMP" (LAMP) [Borgerding & Schniter, 2016]

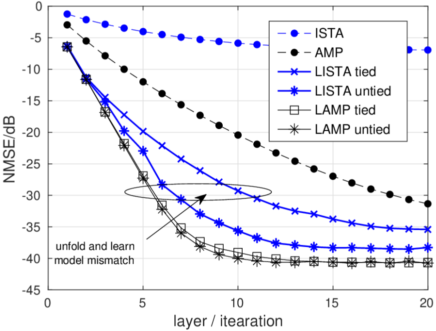


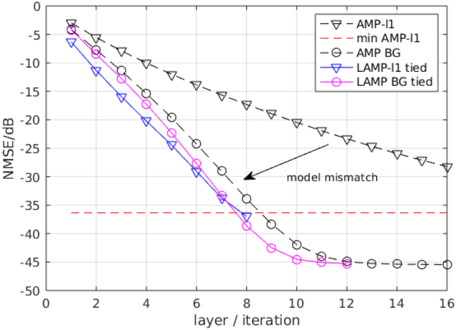
t^{th} layer: LISTA $\to$ LAMP (Onsager-decoupled layers)



can we learn the denoiser matched to unknown prior?

Unfolding Algorithms into Networks





- learned algorithms adapt to unknown “prior”
- substantially reduced iteration count

Conclusion

- neural networks as realistic data priors in recovery algorithms

... learned regularizer/ denoiser / proximal mapping

... generative model (VAE/GAN etc.)

- helpful in solving challenging problems like *phase retrieval* for realistic data

... overcome generator model error by using only as initialization to fast traditional algorithms

- unfolding iterative algorithms and tuning

Conclusion

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Thank you!

References

S. Augustin, P. Jung, S. Frohmann, H.-W. Hübers (2019)
Terahertz dynamic aperture imaging at stand-off distances using a Compressed Sensing protocol
arXiv 1902.07935v1

F. Krahmer, Y.-K. Liu (2018)
Phase Retrieval Without Small-Ball Probability Assumptions
IEEE Transactions on Information Theory 10.1109/TIT.2017.2757520

E. J. Candes, X. Li, M. Soltanolkotabi (2015)
Phase Retrieval via Wirtinger Flow: Theory and Algorithms
IEEE Transactions on Information Theory 10.1109/TIT.2015.2399924

P. Hand, O. Leong, V. Voroninski (2018)
Phase Retrieval under a Generative Prior
Advances in Neural Information Processing Systems NIPS 31

References

T. Karras, S. Laine, T. Aila (2018)
A Style-Based Generator Architecture for Generative Adversarial Networks
arXiv 1812.04948

M. Asim, A. Ahmed, P. Hand (2019)
Invertible generative models for inverse problems: mitigating representation error and dataset bias
arXiv 1905.11672

F. Shamshad, A. Ahmed (2018)
Robust Compressive Phase Retrieval via Deep Generative Priors
arXiv 1808.05854

Y. LeCun (1998)
The MNIST database of handwritten digits
`http://yann.lecun.com/exdb/mnist/`

References

A. Chambolle, V. Caselles, M. Novaga, D. Cremers, T. Pock (2009)
An introduction to Total Variation for Image Analysis
HAL 00437581

Y. S. Tan, R. Vershynin (2017)
Phase Retrieval via Randomized Kaczmarz: Theoretical Guarantees
arXiv 1706.09993

K. Wei (2015)
Solving systems of phaseless equations via Kaczmarz methods: A proof of concept study
arXiv 1502.01822

L. A. Shepp, B. F. Logan (1974)
The Fourier reconstruction of a head section
DOI 10.1109/TNS.1974.6499235

References

V. Katkovnik, A. Migukin, J. Astola (2009)
Backward discrete wave field propagation modeling as an inverse problem: toward perfect reconstruction of wave field distributions
http://www.cs.tut.fi/~lasip/DDT/MATRIX_DDT.pdf

References

A. Bora, A. Jalal, E. Price, and A. G. Dimakis, *Compressed Sensing using Generative Models*, arXiv e-prints, 2017, arXiv:1703.03208, p. arXiv:1703.03208, https://arxiv.org/abs/1703.03208.

D. P. Kingma and M. Welling, *Auto-Encoding Variational Bayes*, arXiv e-prints, 2013, arXiv:1312.6114, p. arXiv:1312.6114, https://arxiv.org/abs/1312.6114.

H. Li, J. Schwab, S. Antholzer, and M. Haltmeier, *NETT: Solving Inverse Problems with Deep Neural Networks*, arXiv e-prints, 2018, arXiv:1803.00092, p. arXiv:1803.00092, https://arxiv.org/abs/1803.00092.

S. Antholzer, J. Schwab, J. Bauer-Marschallinger, P. Burgholzer, and M. Haltmeier, *NETT Regularization for Compressed Sensing Photoacoustic Tomography*, arXiv e-prints, 2019, arXiv:1901.11158, p. arXiv:1901.11158, https://arxiv.org/abs/1901.11158.

Y. Romano, M. Elad, and P. Milanfar, *The little engine that could: Regularization by denoising (RED)*, CoRR, abs/1611.02862 2016, http://arxiv.org/abs/1611.02862, https://arxiv.org/abs/1611.02862.

E. T. Reehorst and P. Schniter, *Regularization by denoising: Clarifications and*