Self Supervised Learning Methods for Imaging

Part 6: Future perspectives

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Finetuning

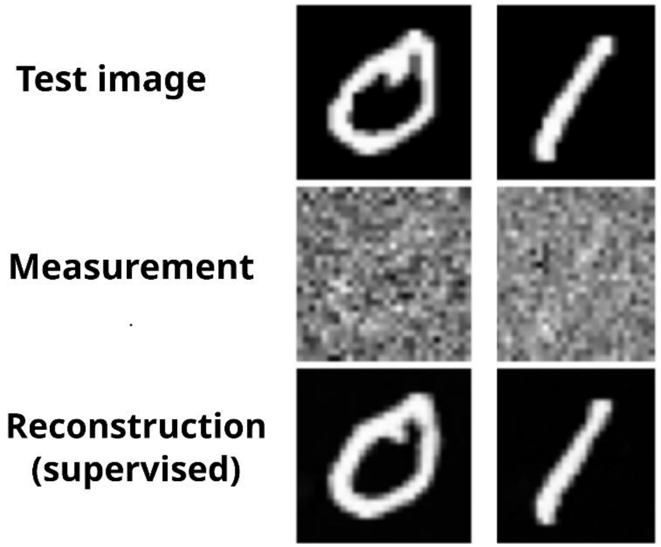
Can we leverage large scale pretrained models?

All methods can be used to finetune a model with real measurement data

- Finetuning techniques that leverage self-supervised losses
- How to leverage pretrained denoising diffusion models?
- Test time training

Single-Pixel Camera

- Operator is a random Bernoulli matrix with 20% undersampling ratio

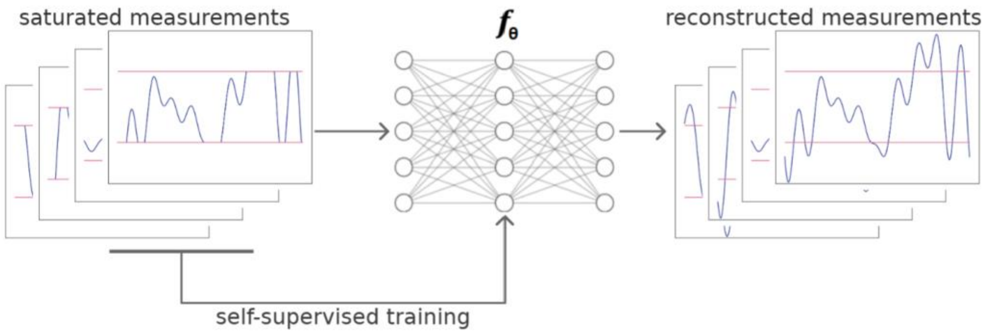


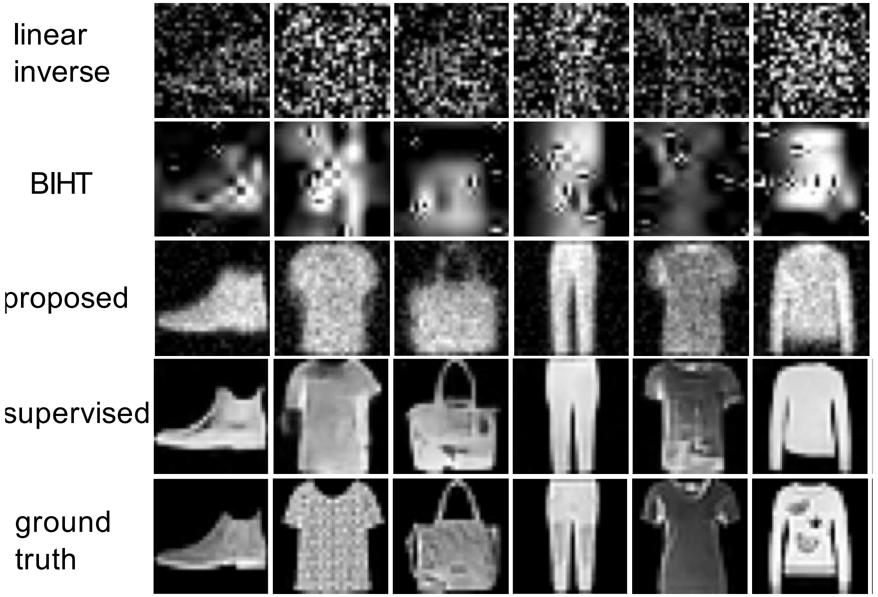
Non-Linear Inverse Problems

Can we handle non-linear inverse problems?

- $\boldsymbol{y} = \mathrm{sign}(A\boldsymbol{x})$ [T. and Jacques, 2023]

- $\boldsymbol{y} = \mathrm{clip}(\boldsymbol{x})$ [Sechaud et al., **EUSIPCO 2024**]





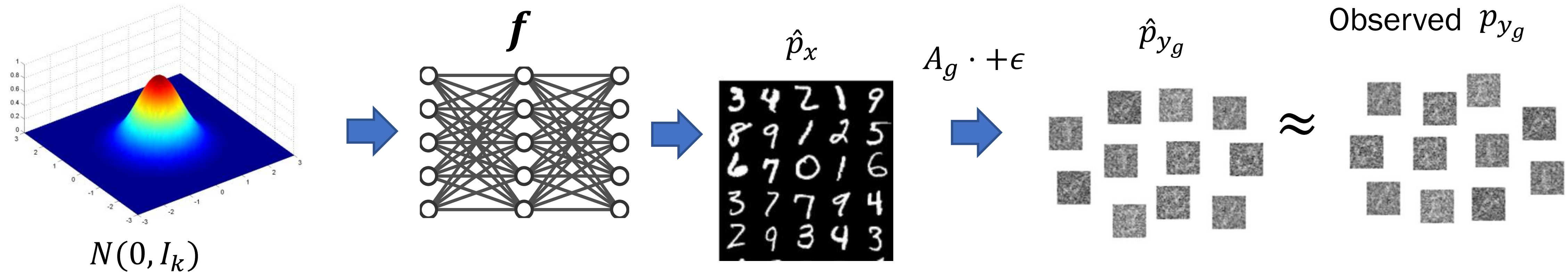
Sampling

Can we train posterior samplers, instead of MMSE estimators?

Learn a generative model for $p_{\boldsymbol{x}}$ [Bora, 2018]

$$\sum_g d(\hat{p}_{\boldsymbol{y}_g} || p_{\boldsymbol{y}_g}) \qquad \text{where } \hat{p}_{\boldsymbol{y}_g} = A_g \circ f \# N(0, I_k)$$

where the divergence d can be approximated using a discriminator.



Sampling

Can we train posterior samplers, instead of MMSE estimators?

- Diffusion methods rely on MMSE denoisers to obtain posterior samples

$$\underbrace{\mathbb{E}\{\boldsymbol{x}|\boldsymbol{y} = \boldsymbol{x} + \boldsymbol{\epsilon}\}}_{\text{Approximated via self-supervised denoising network}} = \boldsymbol{y} + \sigma^2 \nabla \log p(\boldsymbol{y})$$

- If we have incomplete measurements, use $\mathbb{E}\{\boldsymbol{x}|\boldsymbol{A}_g\boldsymbol{x}\} \circ A_g$ instead [Daras et al., 2024]

- Self-supervised variational autoencoders for posterior sampling [Prakash et al., 2020]

Uncertainty Quantification

Can we measure the uncertainty of the reconstructions?

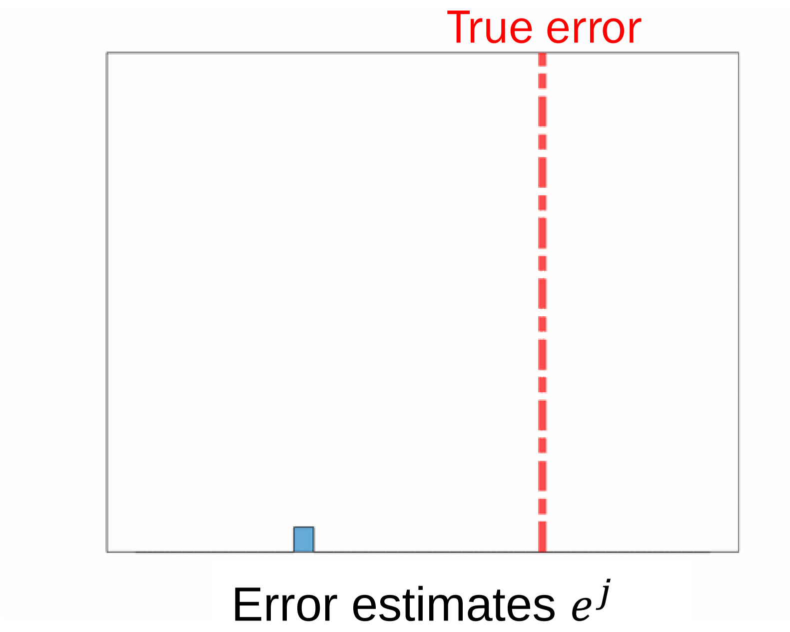
Self-supervised losses can also be used for uncertainty quantification!

- SURE can be used to assess reconstruction error in denoising

- SURE4SURE [Bellec et al., 2021] gives error variance estimates.

- EI loss can be seen as a bootstrapping technique

[T. & Pereyra, 2024] with well calibrated uncertainty estimates

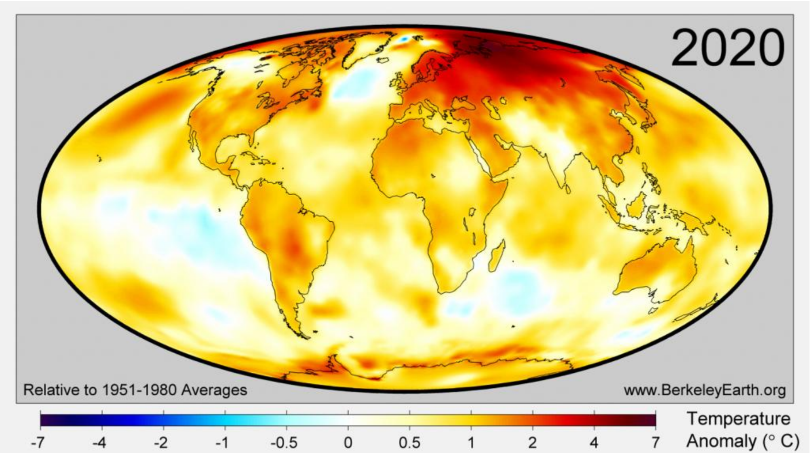


Beyond Images

Can we use these methods in other modalities?

Methods presented here can be extended to other data modalities

- Audio [Sechaud, 2024]
- Point clouds [Hermosilla, 2019]
- Graphs [Bronstein, 2021]



Task-Orientated Learning

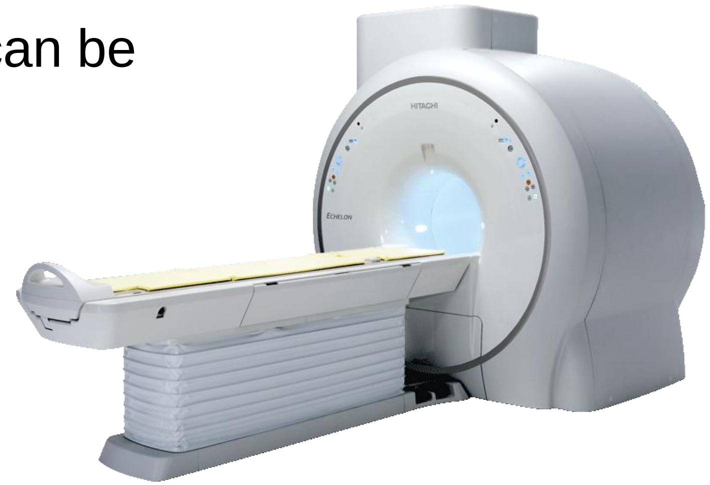
Often we are not interested in reconstructing, but rather some downstream task [Bourrier, 2014].

- Necessary and sufficient conditions for solving the downstream task
- Self-supervised learning losses in this case?

Large-Scale Problems

Can we apply these methods in large-scale imaging problems?

- Examples: 3D MRI and tomography
- GPU memory challenges: computing A during training can be expensive

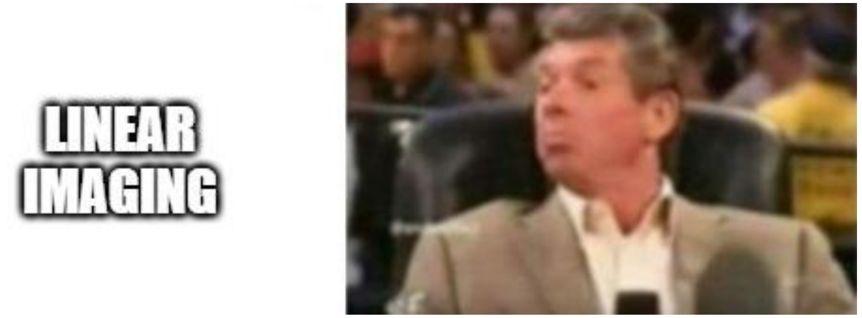


Conclusions

Self-supervised learning for imaging problems

- **Theory:** Necessary & sufficient conditions for learning
  - Unbiased risk estimators
  - Number of measurements
  - Interplay between forward operator & data invariance

- **Practice:** self-supervised losses
  - Can be applied to any model
  - Losses can be combined together



- Poor reconstructions
- Cannot handle noise/missing data

Quickstart Examples User Guide API Finding Help More

Examples

Section Navigation

- Basics
- Optimization
- Plug-and-Play
- Sampling
- Unfolded
- Patch Priors
- Self-Supervised Learning
- Adversarial Learning
- Advanced

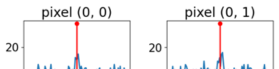
Examples

All the examples have a download link at the end. You can load the example's notebook on Google Colab and run them by adding the line

```
pip install git+https://github.com/deepinv/deepinv.git#egg=deepinv
```

to the top of the notebook (e.g., as in here).

Basics



Deep Inverse

References

The full reference list for this tutorial can be found here:

https://tachella.github.io/projects/selfsuptutorial/

Thanks for your attention!

Tachella.github.io

- ✓ Codes
- ✓ Presentations
- ✓ ... and more