MAP Optimization with NFs

SLIM

$$\underset{\mathbf{x}}{\operatorname{argmin}} \ \frac{1}{2}\|A\mathbf{x}-\mathbf{d}\|_2^2 + \log R(\mathbf{x})$$

Reparametrize optimization with trained generative network $\mathbf{x} = G_\theta(\mathbf{z})$

Data misfit becomes $\|A\mathbf{x}-\mathbf{d}\|_2 = \|AG_\theta(\mathbf{z})-\mathbf{d}\|_2$

Since latent $\mathbf{z}$ is gaussian the regularization is directly given $\log R(\mathbf{z}) = \|\mathbf{z}\|_2$

MAP Optimization becomes: $\underset{\mathbf{z}}{\operatorname{argmin}} \ \frac{1}{2}\|AG_\theta(\mathbf{z})-\mathbf{d}\|_2^2 + \frac{1}{2}\|\mathbf{z}\|_2^2$

Asim, Muhammad, et al. "Invertible generative models for inverse problems: mitigating representation error and dataset bias." International Conference on Machine Learning. PMLR, 2020.

MAP Optimization with NFs

$$\mathbf{x} = G_\theta(\mathbf{z})$$

What would the generative model be? $\|A\mathbf{x} - \mathbf{d}\|_2 = \|AG_\theta(\mathbf{z}) - \mathbf{d}\|_2$

GAN will be more susceptible to poor performance for out-of-training-distribution samples.

A normalizing flow which can theoretically fit anything so nothing out of its range.

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