Noise2Self: Blind Denoising by Self-Supervision

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Supervision

\[ \| f(x) - y \|^2 \]
Self-Supervision?
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\[ \| f(x) - x \|^2 \]
Self-Supervision?

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\[ f^* = \text{Identity} \]
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\[ f^* \text{ Identity} \]
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\[ f^* = \mathbb{E}[x_{-J} | x_J] \]
Single-Image Self-Supervised CNN Training
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J-invariant Deep CNN
J-invariant Deep CNN
Gaussian Processes

Matrix Factorization

Single-Cell Sequencing

Definitions

Definition. Let $\mathcal{J}$ be a partition of the dimensions $\{1, \ldots, m\}$ and let $J \in \mathcal{J}$. A function $f : \mathbb{R}^m \to \mathbb{R}^m$ is $J$-invariant if $f(x)_j$ does not depend on the value of $x_j$. It is $\mathcal{J}$-invariant if it is $J$-invariant for each $J \in \mathcal{J}$.

Theorems

Proposition 3. Let $x, y$ be random variables and let $x^G$ and $y^G$ be Gaussian random variables with the same covariance matrix. Let $f^*_J$ and $f^*_J$ be the corresponding optimal $\mathcal{J}$-invariant predictors. Then

$$\mathbb{E}\|y - f^*_J(x)\|^2 \leq \mathbb{E}\|y - f^*_J(x)\|^2.$$
donut

noisy
noisy

donut
Radius of median filter

MSE

self-supervised

ground truth

noisy

noisy