Noise2Noise and Zero-Shot Noise2Noise

Image Restoration without clean data

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- Applicable to any noise with zero mean.
- Demonstrates surprising effectiveness across domains.

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- Eliminate the need for large datasets make N2N zero-shot and image-specific.
- Focus on practical use in low-data or real-world scenarios.

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- Hence:

$$\arg\min_\theta \mathcal{L}_{\text{noisy}} = \arg\min_\theta \mathcal{L}_{\text{clean}}$$

Finite Corrupted Data in L_2 Minimization (Part 1)

Problem Setup:

- We want to compute the expected error in L_2 norm minimization.
- We have corrupted targets $\{y_i\}_{i=1}^N$ instead of clean targets.
- N is a finite number.
- y_i are arbitrary random variables with $E\{y_i\} = \bar{y}_i$.

Key Idea: The point of least deviation is found at the mean.

Expected Squared Difference: The expected squared difference between the means across realizations of the noise is:

$$E_y\left[\left(\frac{1}{N}\sum_{i=1}^{N} y_i - \bar{y}\right)^2\right] = \frac{1}{N^2} E_y\left[\left(\sum_{i=1}^{N} y_i\right)^2 - 2\bar{y}\left(\sum_{i=1}^{N} y_i\right) + \bar{y}^2\right]$$

$$= \frac{1}{N^2}\left[E_y\left(\sum_{i=1}^{N} y_i\right)^2 - 2\bar{y}E_y\left(\sum_{i=1}^{N} y_i\right) + N^2\bar{y}^2\right]$$

Finite Corrupted Data in L_2 Minimization (Part 2)

Following on from the previous slide:

$$= \frac{1}{N^2}\left[E_y\left(\sum_{i=1}^{N} y_i^2 + \sum_{i\neq j} y_i y_j\right) - 2\bar{y}N\bar{y} + N^2\bar{y}^2\right]$$

$$= \frac{1}{N^2}\left[\sum_{i=1}^{N} Var(y_i) + \sum_{i\neq j} Cov(y_i, y_j)\right]$$

Where we have used $E(\sum y_i) = \sum E(y_i) = N\bar{y}$ and basic properties of variance and covariance.

Simplification (Mutually Uncorrelated Case): If the corruptions are mutually uncorrelated, then $Cov(y_i, y_j) = 0$ for $i \neq j$. The equation simplifies to:

$$\frac{1}{N^2}\sum_{i=1}^{N} Var(y_i) = \frac{1}{N}\left[\frac{1}{N}\sum_{i=1}^{N} Var(y_i)\right] \quad (1)$$

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- **What:** Efficient, dataset-free image denoising method.

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- **Key Advantage:** Uses a lightweight network (~20k params) $\rightarrow$ Fast computation (vs. DIP/Self2Self).
- **Foundation:** Leverages Noise2Noise (N2N) & Neighbour2Neighbour principles via novel downsampling.

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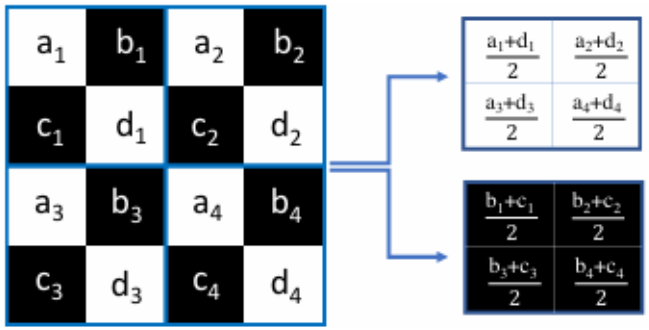
- **Training:** A small, lightweight network is trained *specifically* on this generated pair $(D_1(y), D_2(y))$ for each input image y.

ZS-N2N Method: Image Pair Downsampler

- **Input:** Noisy image y (Size: $H \times W \times C$)



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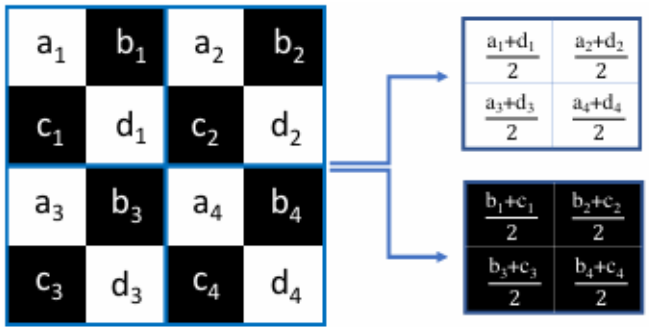

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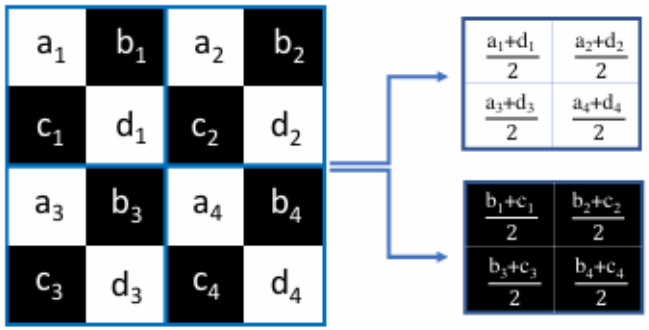

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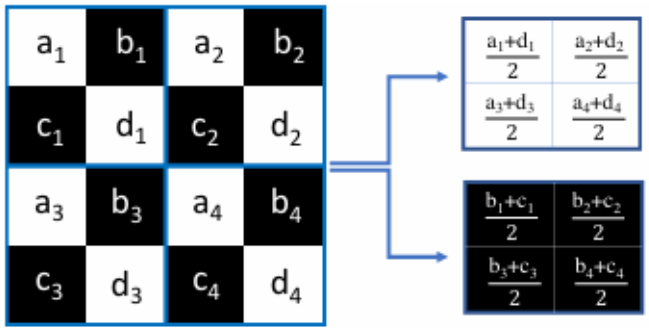

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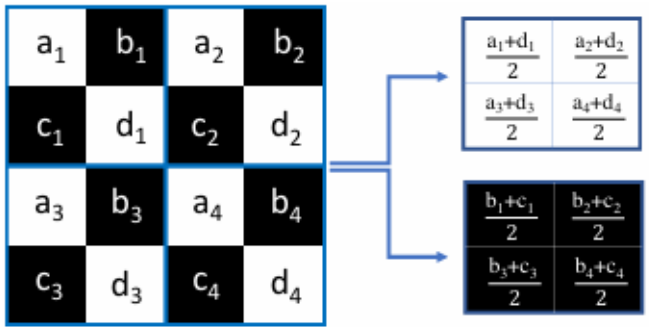

ZS-N2N Method: Why is Noise Independent in D_1, D_2?

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- **Result:** Averaging distinct, independent noise samples preserves independence between the noise components in $D_1(y)$ and $D_2(y)$.

ZS-N2N Method: Training Loss

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Trained via gradient descent (1k-2k iterations).

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- **Final Loss:** $\mathcal{L}(\theta) = \mathcal{L}_{\text{res}}(\theta) + \mathcal{L}_{\text{cons}}(\theta)$

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- **Benefits:** Fast training/inference, CPU feasible, avoids overfitting.

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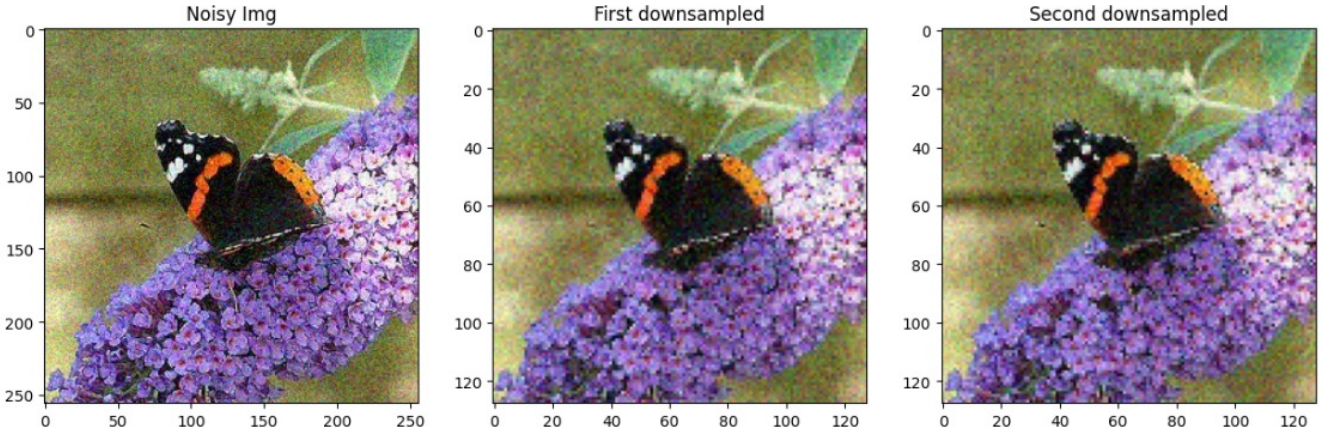
- **Equation:**

$$\hat{x} = y - f_{\hat{\theta}}(y)$$

where $\hat{x}$ is the clean image estimate.

Sample Image



(Downsampled Images)

(Denoised Image)

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- Dataset: 500 training images from ImageNet (256×256), 50 test images (Kodak + BSD300).
- Corruptions: Gaussian noise (25, 50, 75), Poisson noise ($\lambda = 15, 20, 25$).

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- Validation: 15%

Convergence Graph

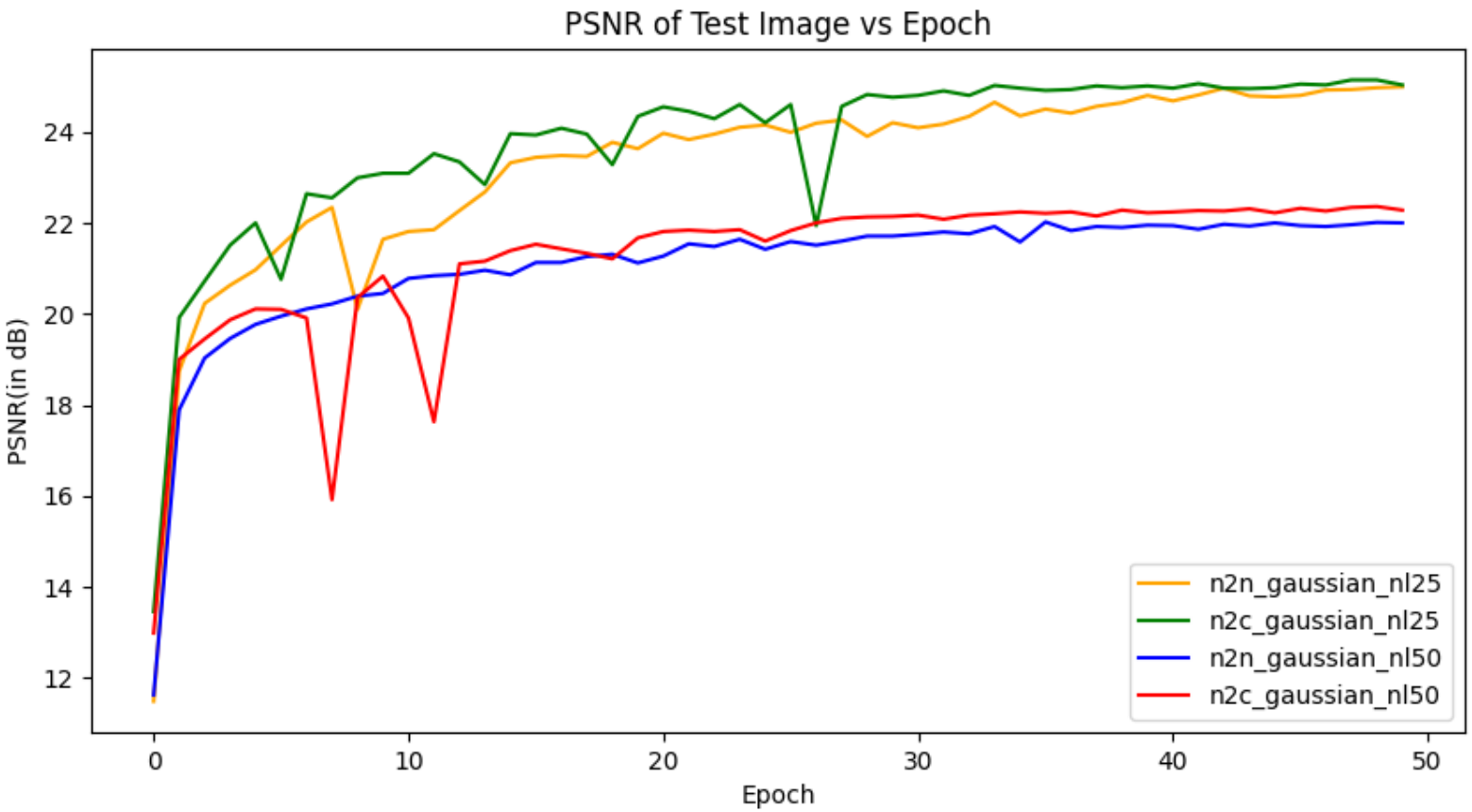

Figure 1: PSNR vs Epoch for different models

Classical Comparison Methods

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- ANSC used for Poisson denoising.

Table of Data for comparison

Table 1: Average PSNR (dB) of Models Under Different Noise Conditions

Model	Gaussian Noise			Poisson Noise		
	$\sigma = 25$	$\sigma = 50$	$\sigma = 75$	$\lambda = 15$	$\lambda = 20$	$\lambda = 25$
Noise Level (image)	20.45 ± 0.48	14.88 ± 0.64	12.01 ± 0.56	16.08 ± 1.58	17.25 ± 1.62	18.16 ± 1.66
Simple CNN (clean)	**28.16 ± 1.98**	24.45 ± 2.22	22.24 ± 2.12	**25.41 ± 2.50**	26.01 ± 2.62	**26.50 ± 2.38**
N2C (UNet)	27.37 ± 2.40	**25.05 ± 3.16**	**24.19 ± 3.38**	25.22 ± 2.86	**26.36 ± 2.98**	26.36 ± 3.00
Simple CNN (noisy)	27.30 ± 1.54	23.60 ± 2.22	21.34 ± 2.44	24.66 ± 2.62	25.52 ± 2.62	25.98 ± 2.42
N2N (UNet)	27.55 ± 2.34	24.20 ± 2.88	22.54 ± 2.94	24.73 ± 3.22	25.68 ± 2.94	26.41 ± 2.94
Zero-shot N2N	28.40 ± 2.78	24.21 ± 2.68	21.50 ± 2.48	25.20 ± 3.16	26.13 ± 3.02	26.78 ± 3.02
BM3D	28.09 ± 4.32	24.87 ± 4.45	22.88 ± 4.52	–	–	–
ANSC	–	–	–	22.13 ± 5.00	22.23 ± 5.06	22.29 ± 5.10

Sample Images

Zero-Shot N2N Setup and Evaluation

- ZS-N2N evaluated with L = 2, 3, 4 layer networks.

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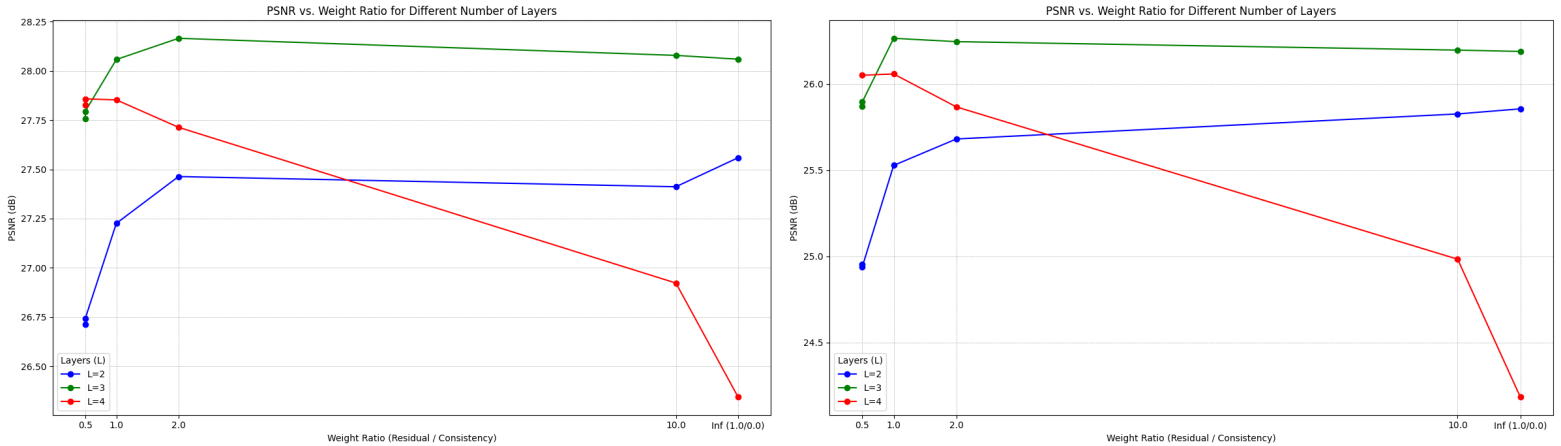
Key Results and Performance



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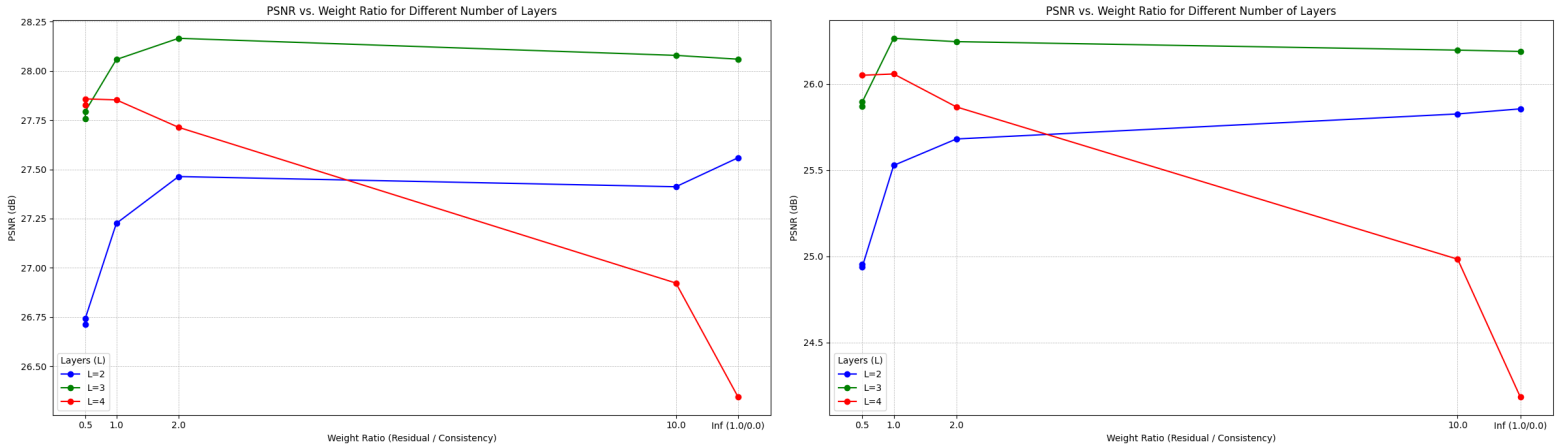

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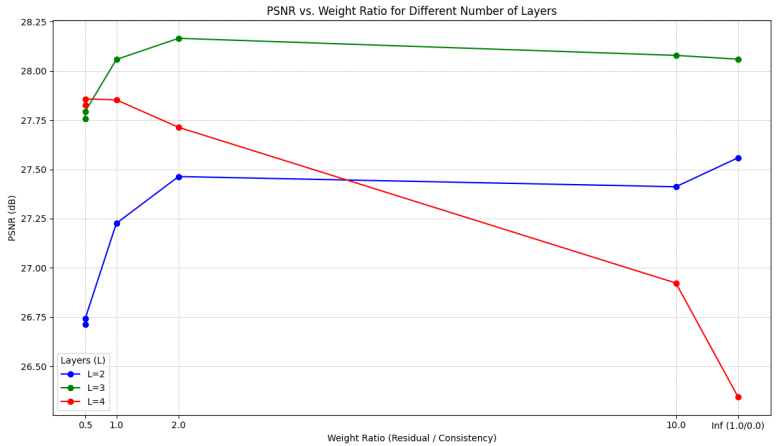

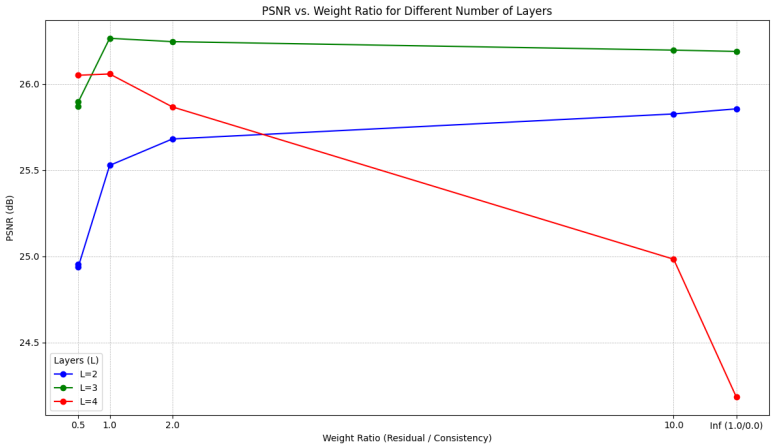

- L=3: Best performance for Res/Cons ≥ 1.0.
- L=2: Worst, better only when no consistency loss.
- L=4: Good only with low Res/Cons (e.g., 0.5), degrades at high ratios.

Insights

The results highlight a trade-off between model capacity and the need for regularization via the consistency loss:

- The $L = 3$ network strikes an effective balance, confirming the effectiveness of the model chosen in the original paper.

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- The higher-capacity $L = 4$ network is prone to overfitting the downsampled noise patterns when the consistency loss (regularization) is weak. It relies heavily on this regularization to generalize effectively to the full-resolution image.
- The $L = 2$ network appears under-capacitated for the task, and the consistency loss constraint seems to hinder its performance rather than help it.

Progress Summary

- Our experiments confirmed the N2N principle, showing that models trained on noisy pairs can achieve competitive performance compared to classical methods like BM3D and ANSC, particularly when appropriate network architectures like U-Nets are employed.

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- Established an interesting trend between model performance and loss weights for different network depths.

References I

Chen, Xinlei and Kaiming He (2020). *Exploring simple siamese representation learning*. URL: https://arxiv.org/pdf/2011.10566.

Dabov, Kostadin et al. (2007). "Image denoising by sparse 3-D transform-domain collaborative filtering". In: *IEEE Transactions on Image Processing* 16.8, pp. 2080–2095. DOI: 10.1109/TIP.2007.901238.

Huang, Tao et al. (2021). "Neighbor2neighbor: Self-supervised denoising from single noisy images". In: *Conference paper at CVPR 2021*. URL: https://arxiv.org/pdf/2101.02824.

References II

Lehtinen, Jaakko et al. (2018). "Noise2Noise: Learning Image Restoration without Clean Data". In: *Proceedings of the 35th International Conference on Machine Learning (ICML)*, pp. 2965–2974. URL: http://proceedings.mlr.press/v80/lehtinen18a.html.

Makitalo, Markku and Alessandro Foi (2013). "Optimal inversion of the generalized Anscombe transformation for Poisson-Gaussian noise". In: *IEEE Transactions on Image Processing* 22.1, pp. 91–103. DOI: 10.1109/TIP.2012.2210725.

Mansour, Youssef and Reinhard Heckel (2023). "Zero-Shot Noise2Noise: Efficient Image Denoising without any Data". In: *Conference paper at CVPR 2023*. URL: https://arxiv.org/pdf/2303.11253.

References III

Ronneberger, Olaf, Philipp Fischer, and Thomas Brox (2015). "U-Net: Convolutional Networks for Biomedical Image Segmentation". In: *International Conference on Medical Image Computing and Computer-Assisted Intervention*. Springer, pp. 234–241. DOI: 10.1007/978-3-319-24574-4_28.

Contributions

- **Swarnava:** Literature review of N2N, created reports and slides. Contributed to N2N implementation.
- **Debanjan:** N2N, N2C and CNN implementation with Vipul, dataset and experiment report creation. Gaussian noise model training and BM3D.
- **Omar Muhammad:** Literature review of ZS-N2N, Implemented the experiment on hyperparameter sensitivity, created the report and presentation. Presenting with Swarnava.
- **Vipul:** N2N, N2C and CNN implementation with Debanjan. Poisson noise model training and comparison with Anscombe Image Denoiser.

Thank You / Questions?

Thank You!

Questions?