**Noise2Noise: Learning Image Restoration without Clean Data**

**Main idea**

learning to map corrupted observations to clean signals – with a simple and powerful conclusion:

**it is possible to learn to restore images by only looking at corrupted examples**, at a performance at and sometimes exceeding training using clean data, without explicit image priors or likelihood models of the corruption.

**Summary**

Can we learn to denoise images with noisy images only?

The authors motivate their work with a temperature predictor example. If we are given the temperature of the last few days then using an **L2 loss** predictor will lead to a model that predicts the mean of given samples as the temperature on the next day(the average of all plausible explanations). Similarly, if a model is given noisy images as targets ( where the input is also a noisy image that has to be denoised ), then the model will learn to predict the mean as it's impossible to predict random noise. They then go on experimenting with different noises.

L2 Loss Function is used to minimize the error which is the sum of all the squared differences between the true value and the predicted value.

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For the experiments, they use a recent State-of-art **model** **RED30:** a 30-layer hierarchical residual network with 128 feature maps, which has been demonstrated to be very effective in a wide range of image restoration tasks, including Gaussian noise.

they then explain how this model is trained with noisy images in a slightly odd manner. Though what they broadly mean is that there are three training cases:

**1. The traditional case-** (Additive Gaussian Noise, Poisson noise, Multiplicative Bernoulli noise, Text removal, Random-valued impulse noise)

We train the network using 256×256-pixel crops drawn from the 50k images in the IMAGENET validation set. We furthermore randomize the noise standard deviation σ ∈ [0, 50] separately for each training example, i.e., the network has to estimate the magnitude of noise while removing it.

We use three well-known datasets: BSD300, SET14, and KODAK2.

**2. the model is trained with target also being possibly noisy-** (Monte Carlo Rendering) Denoising Monte Carlo rendered images We trained a denoiser for Monte Carlo path traced images rendered using 64 samples per pixel (spp). the training set consisted of 860 architectural images, and the validation was done using 34 images from a different set of scenes.

**3. Noise2Noise case:** (Magnetic Resonance Imaging (MRI)) The training set contained 5000 images in 256×256 resolution from 50 subjects, and for validation, we chose 1000 random images from 10 different subjects. The baseline PSNR of the sparsely sampled input images was 20.03 dB when reconstructed directly using IFFT.

They report that Case III performs the best, then case II and then case I.

The reason is that in case 3 there are more real images on the same budget of 2000 images. While case 2 has much more training samples than any of them.

They are showing that it is possible to denoise images with only noisy samples.