# Efficient Un-supervised Neural Network Learning for Image Restoration and Generation

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*Digital images are often degraded by undesired artifacts such as noise or blur, which require image restoration tools to remove or reduce them. Many of these tools are nowadays destined for mobile platforms in practical digital imaging applications and there is an ever-growing need for efficient image restoration and generation techniques. We propose new unsupervised algorithms with improved speed and robustness to various types of degradations including a priori unknown ones.*

With recent advances in deep learning, image restoration has significantly improved in terms of restoration quality. These results, however, rely on an enormous number of ground truth images, both noisy and clean, for training. Adding realistic noise via simulation is complex, so CSEM has been investigating un-supervised techniques to remove the need of a label data set.

### Image Restoration using Plug-and-Play CNN MAP Denoisers

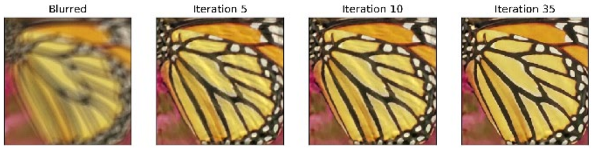
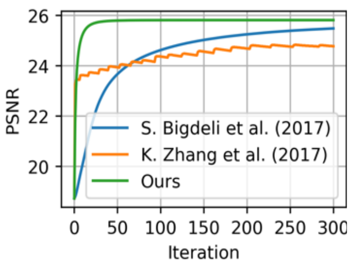



*Figure 1: Deblurring iterations of our optimization. Our MAP denoiser network encourages sharp edges and removes undesired artifacts.*

Plug-and-play denoisers can be used to perform generic image restoration tasks independent of the degradation type. These methods build on the fact that the Maximum a Posteriori (MAP) optimization can be solved using smaller sub-problems, including a MAP denoising optimization. We present the first end-to-end approach to MAP estimation for image denoising using deep neural networks [1]. We show that our method is guaranteed to minimize the MAP denoising objective, which is then used in an optimization algorithm for generic image restoration. A deblurring example of this optimization process is depicted in Figure 1. As shown on the right, experimental results show that the proposed method can achieve 70x faster performance compared to the state of the art (SOTA) while maintaining the theoretical guarantees of MAP. This brings the method closer to the application in mobile devices.




### Efficient Blind-Spot Architecture for Image Denoising

Blind-spot neural network architectures allow estimating a pixel value by only using the values of its neighboring pixels. They are often used in denoising as they can be trained directly on noisy images while avoiding trivial solutions by-design. In contrast to existing complex approaches, we propose a novel fully convolutional architecture that uses simple dilations [2]. As shown in Figure 2, our approach achieves SOTA denoising results in public benchmarks and overperforms the existing methods when the noise level is different from the training one.

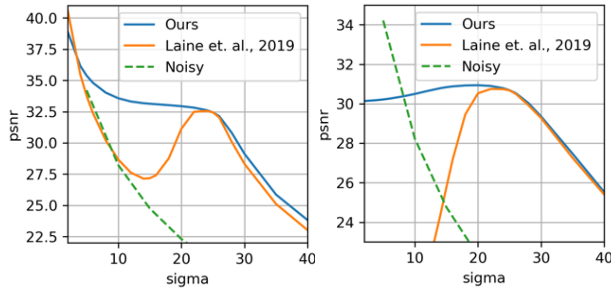



*Figure 2: Denoising performance of methods trained with white noise with $\sigma = 25$ on different test noise variances. Prediction with (left) or and without (right) the knowledge of the noise distribution at inference time.*

### Learning Generative Models using Denoising Density Estimators

Learning probabilistic models that can estimate the density of a given set of samples, and generate samples from that density, is one of the fundamental challenges in unsupervised machine learning. We introduce a new generative model based on denoising density estimators (DDEs), which are scalar functions parameterized by neural networks, that are efficiently trained to represent kernel density estimators of the data [3]. Leveraging DDEs, our main contribution is a novel technique to obtain generative models by minimizing the KL-divergence directly. We prove that our algorithm for obtaining generative models is guaranteed to converge to the correct solution. Experimental results demonstrate substantial improvement in density estimation and competitive performance in generative model training. Figure 3 shows that the method is capable of generating realistically looking images.

*Figure 3: Results on 32 × 32 images from the CelebA dataset (Liu et al., 2015). (left) generated, (right) real data.*

### Summary

In addition to the high accuracy and precision, our techniques have also high computational efficiency. Our method for unsupervised denoising surpasses the SOTA in precision while reducing the computation operations up to a factor of 4. Similarly, our generic image restoration approach improves both speed and precision with respect to other approaches. Finally, we have introduced a new technique in unsupervised density estimation that is significantly more efficient than prior work and can be used as a framework to train generative models.

[1] S. A. Bigdeli, *et al.*, "Image Restoration using Plug-and-Play CNN MAP Denoisers", VISAPP (2020).

[2] D. Honzátko, *et al.*, "Efficient Blind-Spot Neural Network Architecture for Image Denoising", 7th Swiss Conf. on Data Science (2020).

[3] S. A. Bigdeli, G. Lin, T. Portenier, L. A. Dunbar, M. Zwicker, "Learning Generative Models using Denoising Density Estimators", arXiv preprint arXiv:2001.02728 (2020).