NYU TANDON SCHOOL OF ENGINEERING

Advanced Project Updating

Haoyu Fang

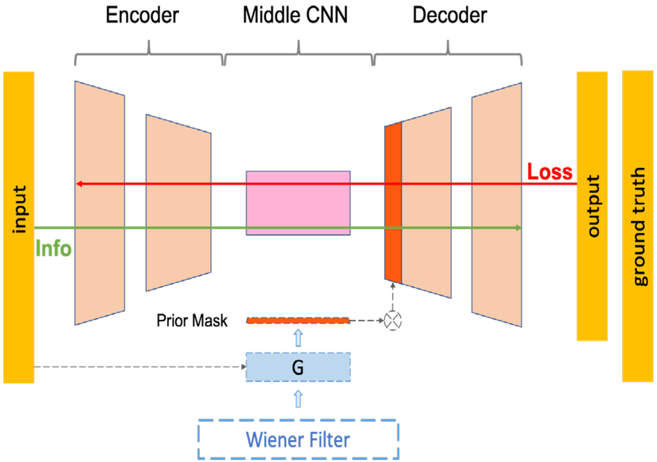
Outline

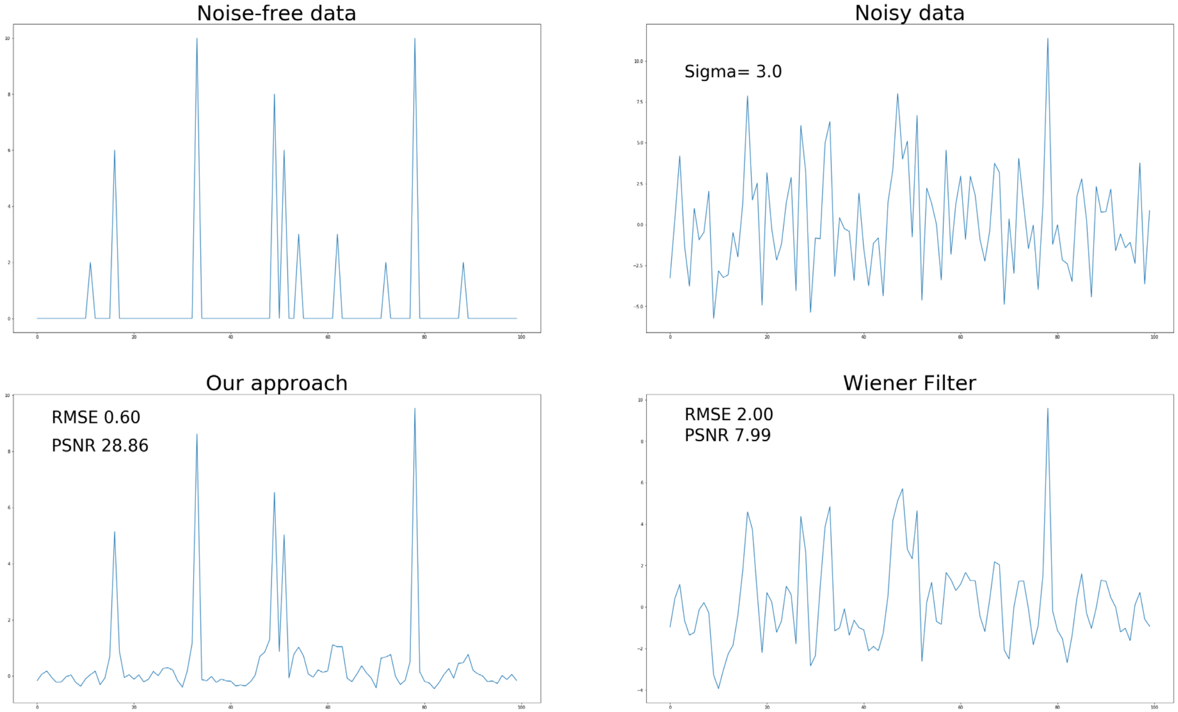
1. **Previous progress**
   1) **An interpretable neural networks with prior guidance**
   2) **Experimental results on signal denoising tasks**
2. Current implementation and experiments
   1) DNN-based denoising algorithm overview
   2) Third-party-library-free implementation (mainly based on Numpy)
   3) Experiments about batch normalization
3. Analysis and inspiration
   1) A signal-processing interpretation of DNN-based deep denoising algorithms
   2) Batch normalization layer with sparse regularization
4. Future work

Previous progress

Results of signal denoising on a synthesized data

The proposed interpretable neural networks with prior guidance





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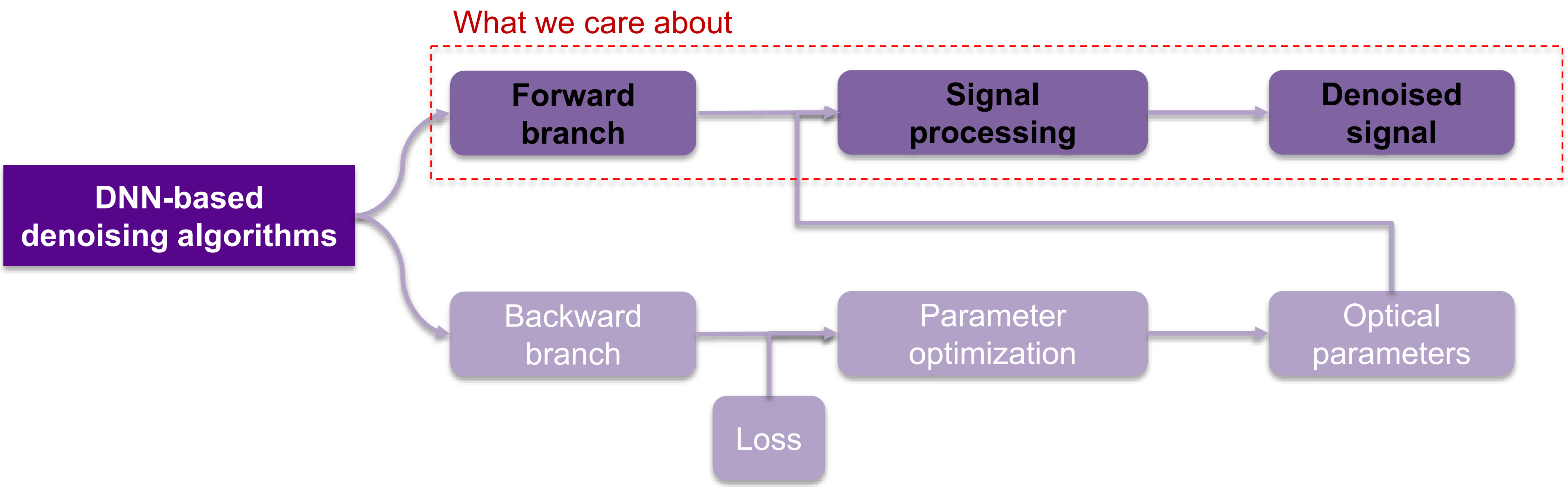
DNN-based denoising algorithms



Third-party-library-free implementation

Improved model (weights and bias):

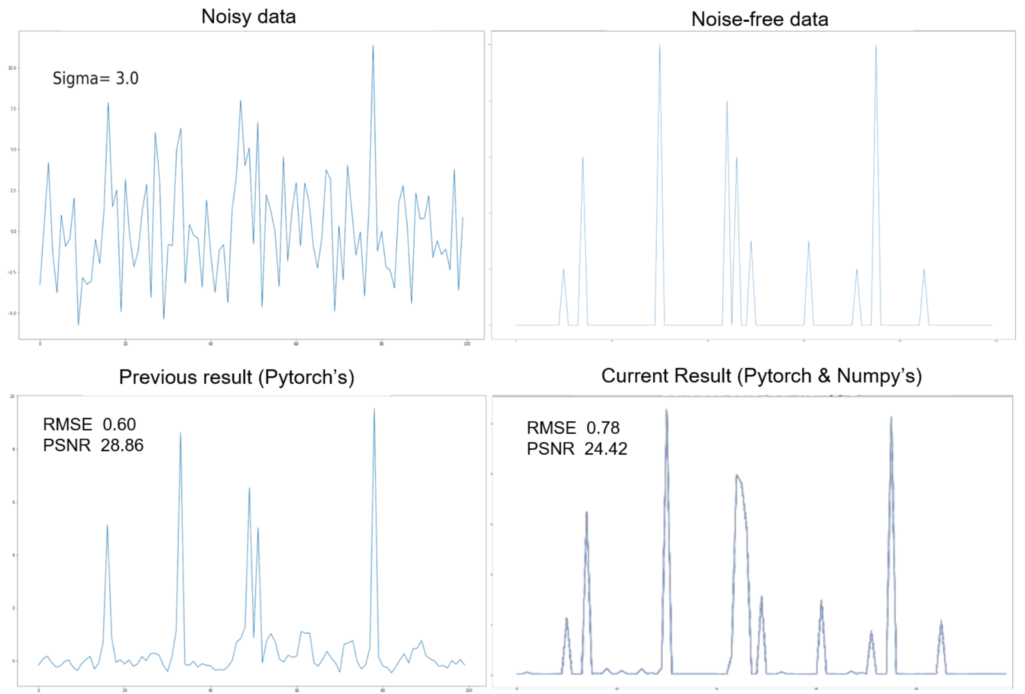
- ❑ Learning rate scheduler
- ❑ Gradient scaling
- ❑ Avoiding local optimums

Results:

- ❑ Stable training
- ❑ High average accuracy
- ❑ Removing most fluctuations
- ❑ Worsen in some cases

Causes:

- ❑ Specific cases follow local optimums' distribution
- ❑ Small training batch size
- ❑ Slight differences in input samples



Third-party-library-free implementation

Implemented components
(details are shown in the report):

- ❑ Convolutional layer

$$out(C_{out_i}, j) = bias(C_{out_i}) + \Sigma_{k=0}^{C_{in}-1} weights(C_{out_i}, k) \odot input,$$

- ❑ Batch normalization layer

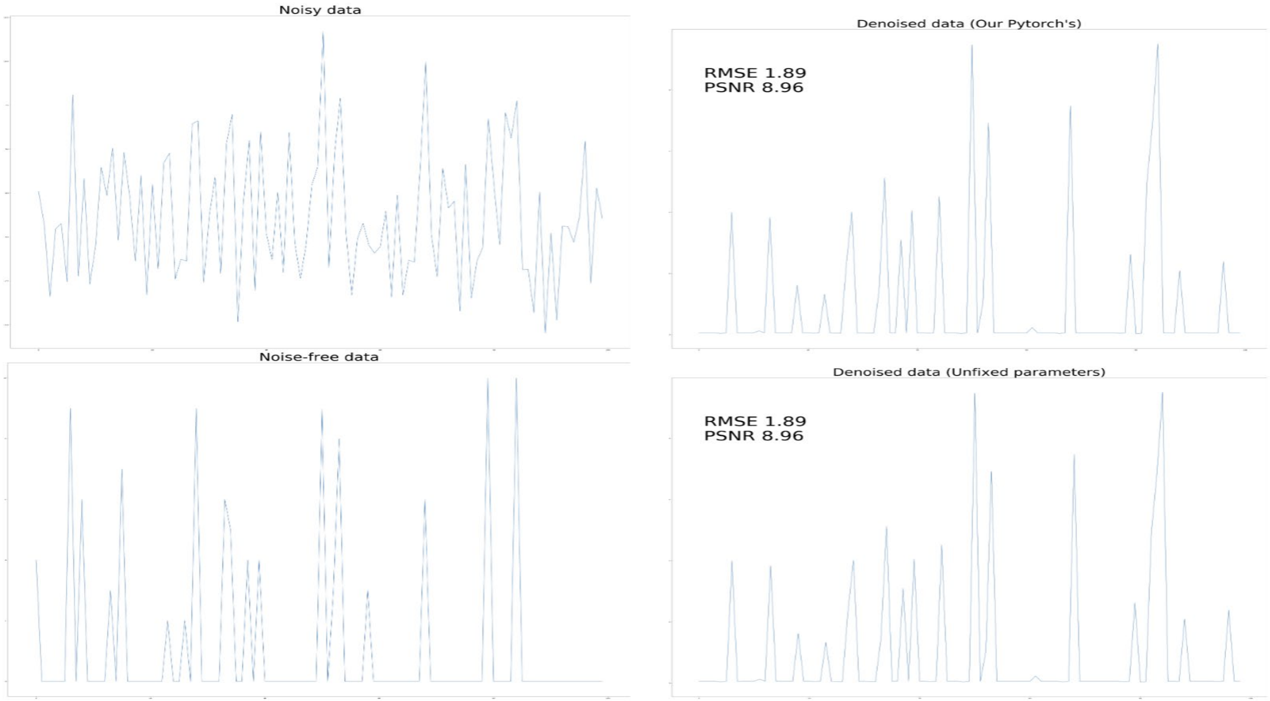
$$y = \frac{x - E[x]}{\sqrt{Var[x] + \epsilon}} * \gamma + \beta,$$

- ❑ Max pooling / Average pooling layer
- ❑ Wiener filter and prior learning network

$$y = \begin{cases} \frac{\sigma^2}{\sigma_x^2} m_x + (1 - \frac{\sigma^2}{\sigma_x^2})x = \frac{(\sigma_x^2 - \sigma^2)x}{\sigma_x^2} + \frac{\sigma^2 m_x}{\sigma_x^2} \\ m_x \end{cases},$$

Third-party-library-free implementation

Compared with third-party-library-based implementation (Pytorch)



Pytorch- and Numpy-based are identical

Observations on influence of Batch normalization

Comparison between networks without vs with BN layer

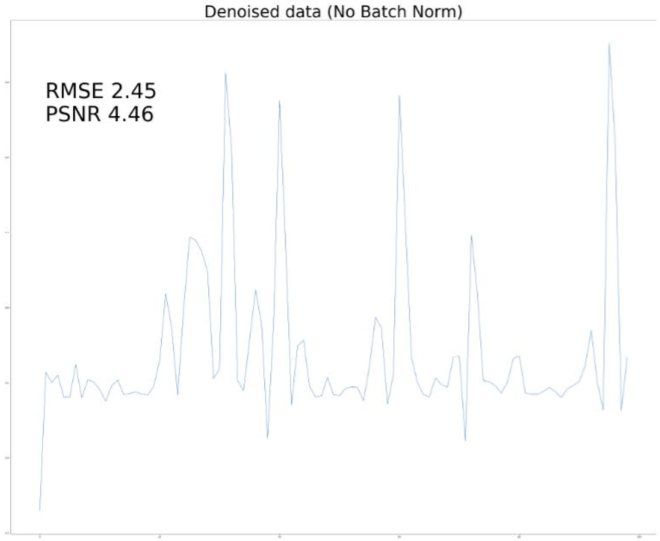


Figure 3: No batch normalization layer (network trained after 200 epochs).

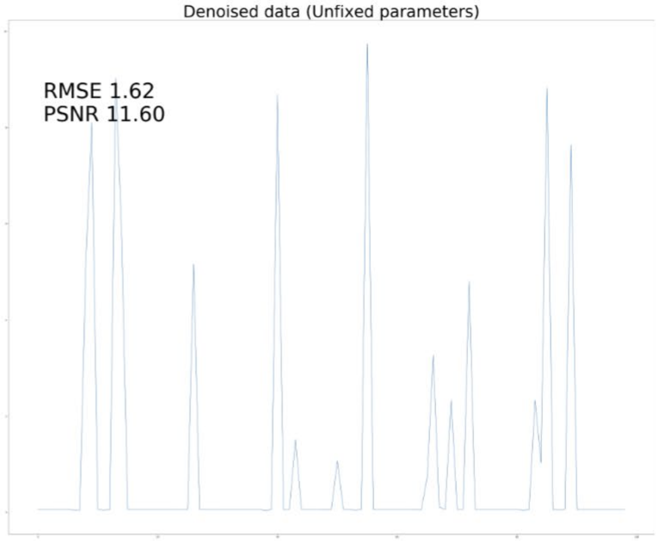


Figure 4: Batch normalization layer with unfixed means and SDs (network trained after 200 epochs).

Batch normalization shows great influence to the denoising results no matter which mode is chosen, even if there is only one sample in each mini-batch.

Observations on influence of Batch normalization

The purpose of batch normalization:

- ❑ Concentrate all latent features to a local mean by recentering and rescaling the feature representations (optimize probability distribution)
- ❑ Filtering the latent feature, control the outliers and reduce their aspects (signal processing view)
- ❑ Batch normalization layer has two modes: fixed-parameter mode and unfixed-parameter mode

- Fixed parameters mode

$$x = \gamma \frac{x - \mathrm{Mean}_{global}}{\sqrt{Var_{global} + \varepsilon}} + \beta$$

- Unfixed parameters mode

$$x = \gamma \frac{x - E(x)}{\sqrt{Var(x) + \varepsilon}} + \beta$$

E(x) and Var(x) belongs to current batch.

Observations on influence of Batch normalization

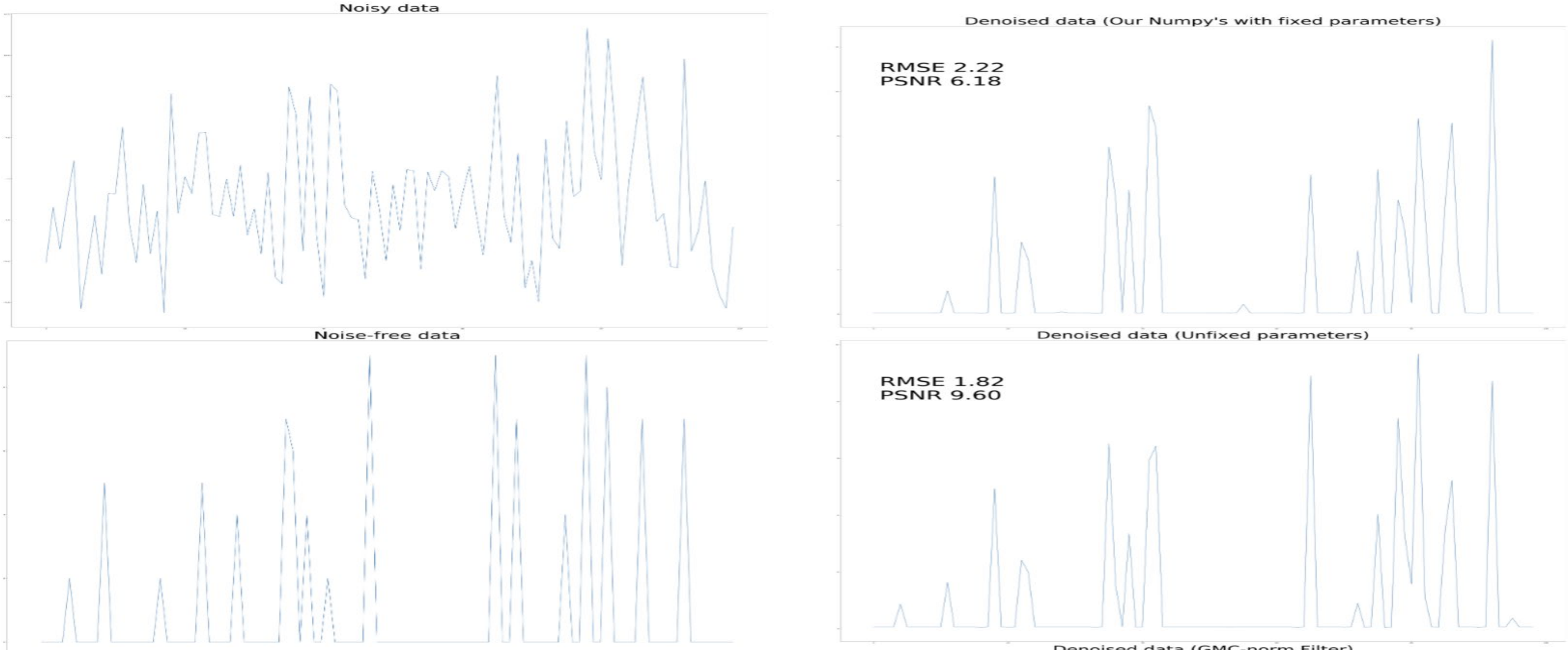
Comparison between BN layer with fixed vs unfixed mode

Experiment No.	fixed-parameter	unfixed-parameter	wiener filter	L1-norm filter	GMC-norm filter [15]
PSNR					
1	9.57	9.93	4.85	4.59	1.71
2	9.65	9.77	4.96	4.46	1.71
3	9.56	9.88	4.75	4.56	1.58
Average	9.59	9.86	4.85	4.54	1.66
RMSE					
1	1.84	1.80	2.40	2.44	2.88
2	1.83	1.82	2.39	2.45	2.88
3	1.84	1.80	2.41	2.44	2.90
Average	1.84	1.81	2.40	2.44	2.89

The unfixed mode has higher average accuracy than fixed mode and show superior performance in most cases.

Observations on influence of Batch normalization

Comparison between BN layer with fixed vs unfixed mode



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A signal-processing interpretation of DNN-based deep denoising algorithms

A standard convolutional layer

$$\begin{cases} x = x_i * k \\ x = \gamma \dfrac{x - Mean}{\sqrt{Var + \varepsilon}} + \beta \\ x_{i+1} = relu(x) = |x| \end{cases}$$

Signal-processing interpretation

$$x_{i+1} = \text{argmin}(x)\text{: Loss}(label_i - x * k) + \left|\gamma \frac{x - Mean}{\sqrt{Var + \varepsilon}} + \beta - x\right|$$

$$Training: K^*, \Gamma^*, B^* = argmin_{K,\Gamma,B}\{\mathscr{L}(Y - \Omega(X \odot K)) + [\Gamma|| \frac{X - E(X)}{\sqrt{Var(X)}} + B - X||\},$$

$$Testing: X^* = argmin_X\{\Omega(X \odot K) + [\Gamma|| \frac{X - E(X)}{\sqrt{Var(X)}} + B - X||]\},$$

Batch normalization layer with sparse regularization

Knowing that the batch normalization layer filter the input feature and sparse feature input helps the network converge fast and stable;

Features show big difference among layers;

Is it possible to sparsify latent features while concentrate their distribution?

$$Training : K^*, \Gamma^*, B^*, \Lambda^* = argmin_{K,\Gamma,B}\{\mathscr{L}(Y - \Omega(X \odot K)) + [\Gamma||\frac{X - E(X)}{\sqrt{Var(X)}} - X + B|| + \Lambda||X||^p]\},$$

$$Testing : X^* = argmin_X\{\Omega(X \odot K) + [\Gamma||\frac{X - E(X)}{\sqrt{Var(X)}} + B - X|| + \Lambda||X||^p]\},$$

Theoretically, adding a proper regularization as above term in the energy function can further constrain the sparsity of output features. In practice, to replace the batch normalization layer with an adaptive filter with sparse regularization can achieve this goal.

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Future work

- Explore a general form for unsupervised DNN-based denoising algorithms which approximate practical denoising applications and process signals without labels' information;

- Try different adaptive filters with various sparse regularizations to take the place of traditional batch normalization layers and check if the performance get improved.

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Thank you!!