Speech Denoising via Nonnegative Matrix Factorization

Сколково

Your Answer

Oleg Alenkin
Artyom Chashchin
Vladimir Chernykh
German Novikov

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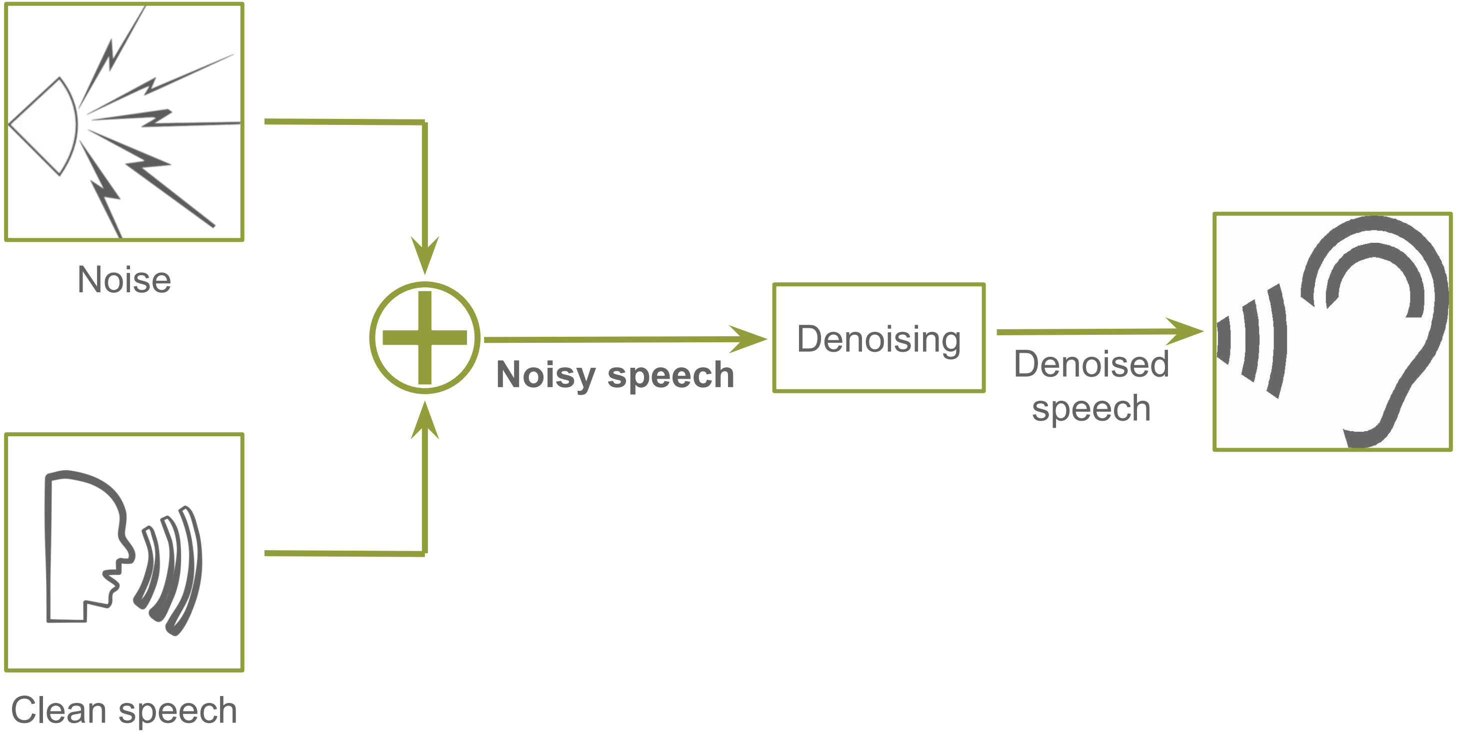
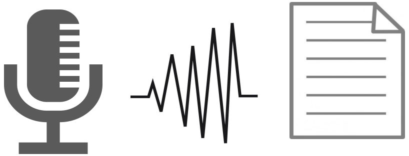
Problem


Noise
Clean speech
Noisy speech
Denoising
Denoised speech

Applications

Automatic Speech Recognition



Telephone conversations

Hearing aids

Data

- CHiME Speech Separation and Recognition Challenge
  http://spandh.dcs.shef.ac.uk/chime_challenge/chime_download.html
  Recordings of WSJ utterances + 8 hours of noise

- Berlin Database of Emotional Speech
  http://www.emodb.bilderbar.info/download/
  Clean utterances

- Aurora noising
  http://aurora.hsnr.de/download.html

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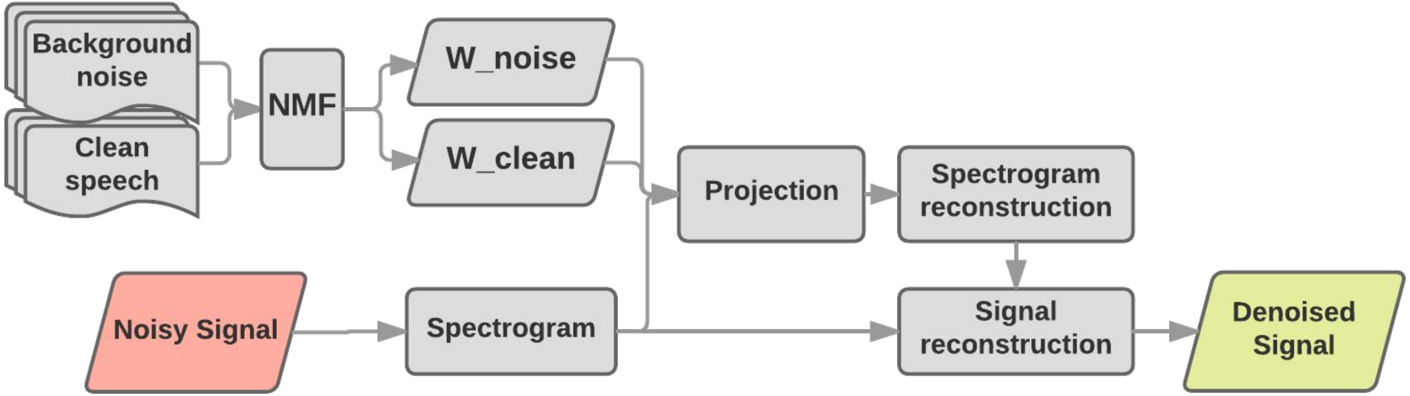
Solution

- Learn frequency patterns from speech and noise via NMF
- Decompose new signal on joint “dictionary” of patterns
- Take only projection corresponding to “clean speech”



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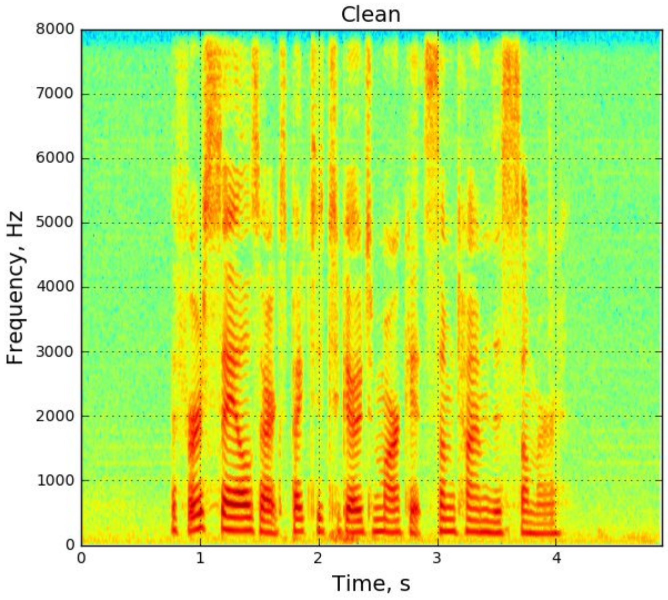
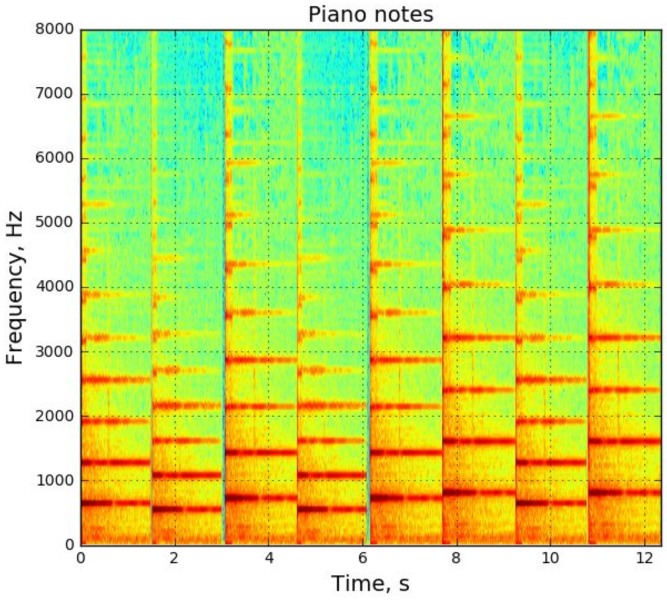
Spectrogram

- Represent signal in Time-Frequency domain
- Built via Short-Term Fourier Transform - FFT with sliding overlapped window
- STFT - Complex spectrogram S ⇒ Amplitudes V





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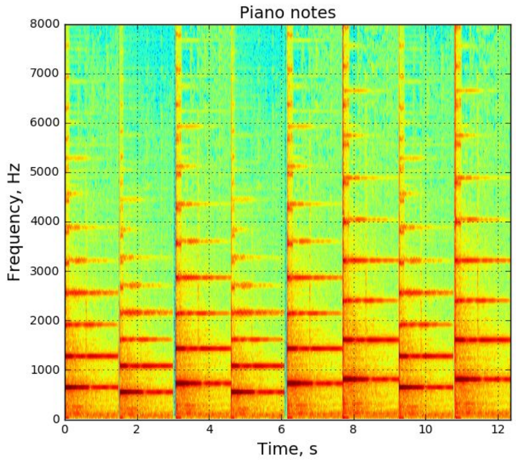
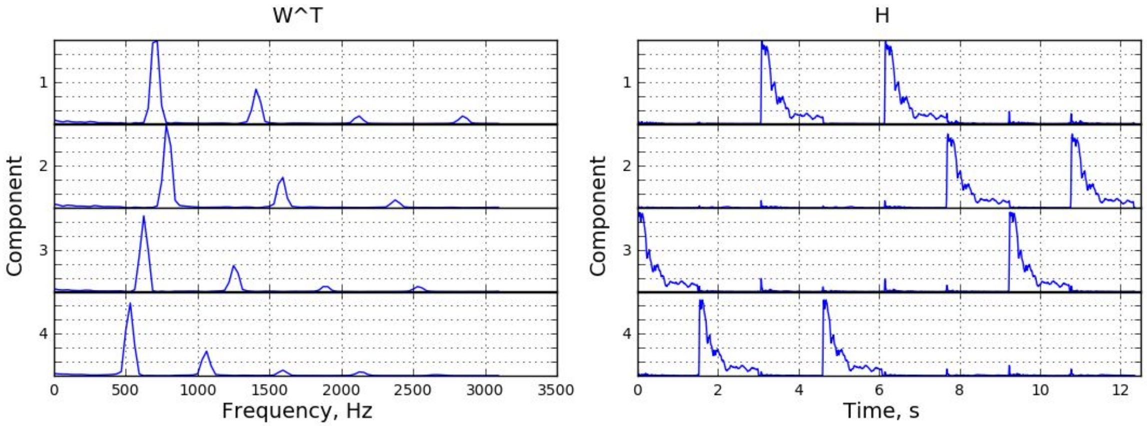
NMF

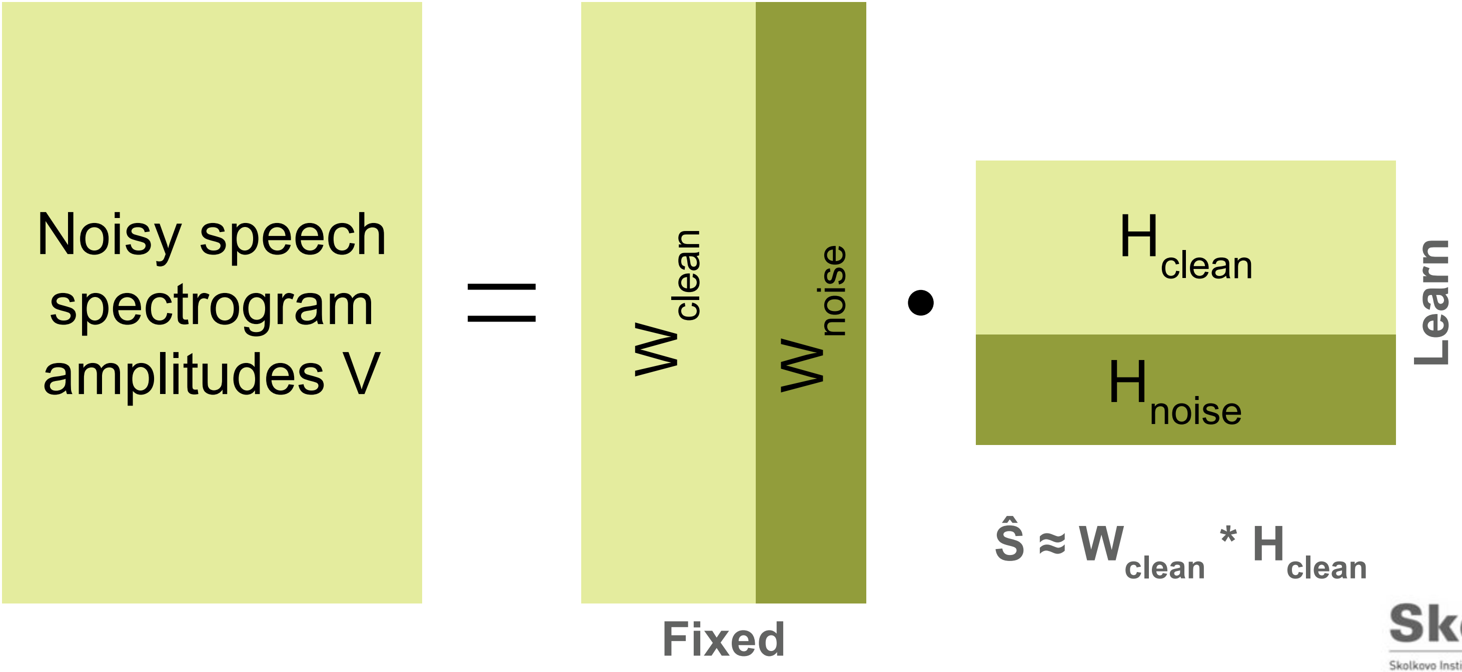
- Factorization **V ≈ W * H**, where V, W, H - real nonnegative
- Interpretation: W - frequency patterns, H - time-activation matrix
- Hidden dimension ≈ number of phonemes ≈ 40
- Learn speech and noise “building blocks”





Projection

- Join “dictionaries” - concatenate matrices W_{noise} and W_{clean}
- Project signal onto them



$$\hat{S} \approx W_{clean} * H_{clean}$$

NMF: how to compute

Optimization problem:

$$(W^*, H^*) = \text{argmin}_{W \geq 0, H \geq 0} D(V, WH)$$

$$D(P, Q) = \sum_{i=1}^{m} \sum_{j=1}^{n} d(p_{ij}, q_{ij})$$

The most popular metrics:

$$d(p, q) = (p - q)^2$$ Frobenius norm

$$d(p, q) = p \ln(\frac{p}{q}) - p + q$$ KL divergence

Multiplicative Update Method:

$$[\nabla_H]_{kj} = \frac{\partial D(V, WH)}{\partial h_{kj}} = [\nabla_H^+]_{kj} - [\nabla_H^-]_{kj}$$

$$h_{kj} \leftarrow h_{kj} - \frac{h_{kj}}{[\nabla_H^+]_{kj}} \left([\nabla_H^+]_{kj} - [\nabla_H^-]_{kj}\right)$$

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NMF: how to compute

Alternating Nonnegative Least Squares:

1) Initialize $W^1_{ia} \geq 0, H^1_{bj} \geq 0, \forall a, i, b, j.$

2) For k=1,2,...

$$W^{k+1} = \mathrm{argmin}_{W \geq 0} D\left(V, W H^k\right),$$
$$H^{k+1} = \mathrm{argmin}_{H \geq 0} D\left(V, W^{k+1} H\right).$$

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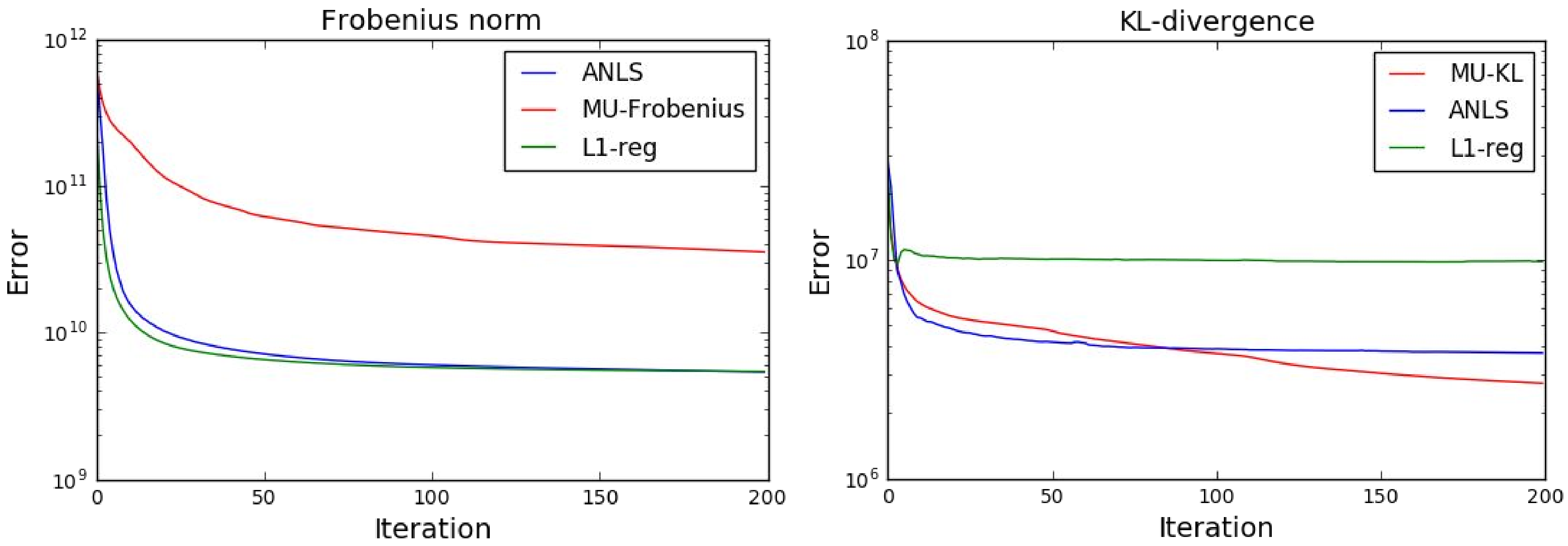
Methods’ Convergence



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Quasi-Newton method

$$(W^*, H^*) = \mathrm{argmin}_{W>0,H>0} D_{KL}(V, WH)$$

$$W \leftarrow \max(\varepsilon, W - H_W^{-1} \nabla_W D_{KL})$$

$$\nabla_W D_{KL} = H^T J_{M\times K} - H^T (V \oslash (WH))$$

$$H_W = \mathrm{diag}\{h_{W,m},\ m = 1, \dots, M\}$$

$$h_{W,m} = H \mathrm{diag}\{[V \oslash (Q \otimes Q)]_{m,:}\} H^T$$

$$H \leftarrow \max(\varepsilon, H - H_H^{-1} \nabla_H D_{KL})$$

$$\nabla_H D_{KL} = J_{M\times K} W^T - (V \oslash (WH)) W^T$$

$$H_H = \mathrm{diag}\{h_{H,k},\ k = 1, \dots, K\}$$

$$h_{H,k} = W^T \mathrm{diag}\{[V \oslash (Q \otimes Q)]_{:,k}\} W$$

Problem: hard to compute inverse Hessian

Signal reconstruction

- Naive method with zero phase:

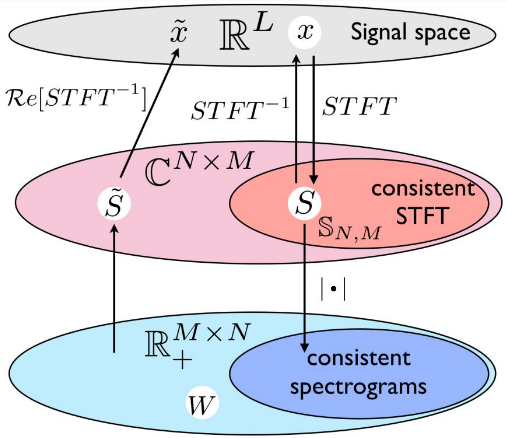
$$\hat{X} = STFT^{-1}(\hat{S})$$

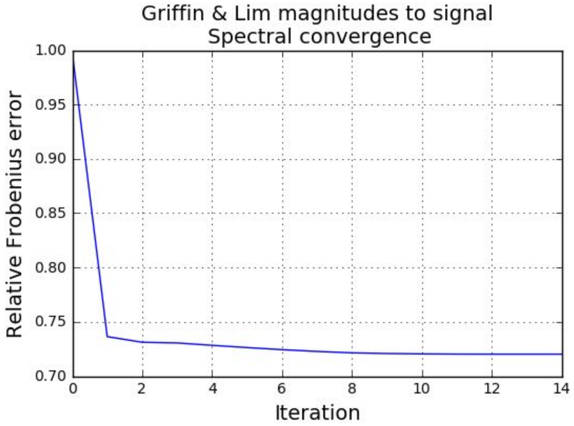
- Noisy signal phases:

$$\hat{X} = STFT^{-1}(\hat{S} \times \exp\left(i\angle STFT(X_{noisy})\right))$$

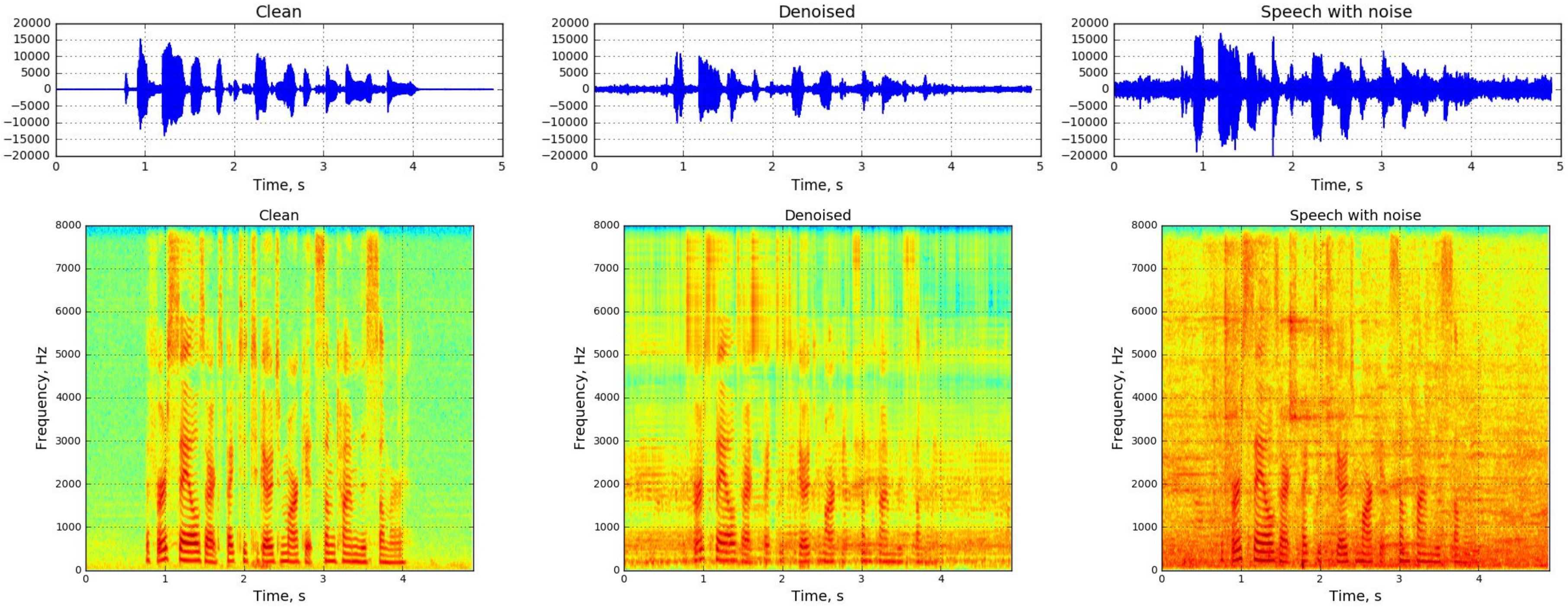
- Griffin & Lim iterative method:

$$\hat{X}_n = STFT^{-1}(\hat{S} \times \exp(i\angle STFT(\hat{X}_{n-1})))$$





Demo



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