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# A lifted l1/l2 constraint for sparse blind deconvolution

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## Blind deconvolution

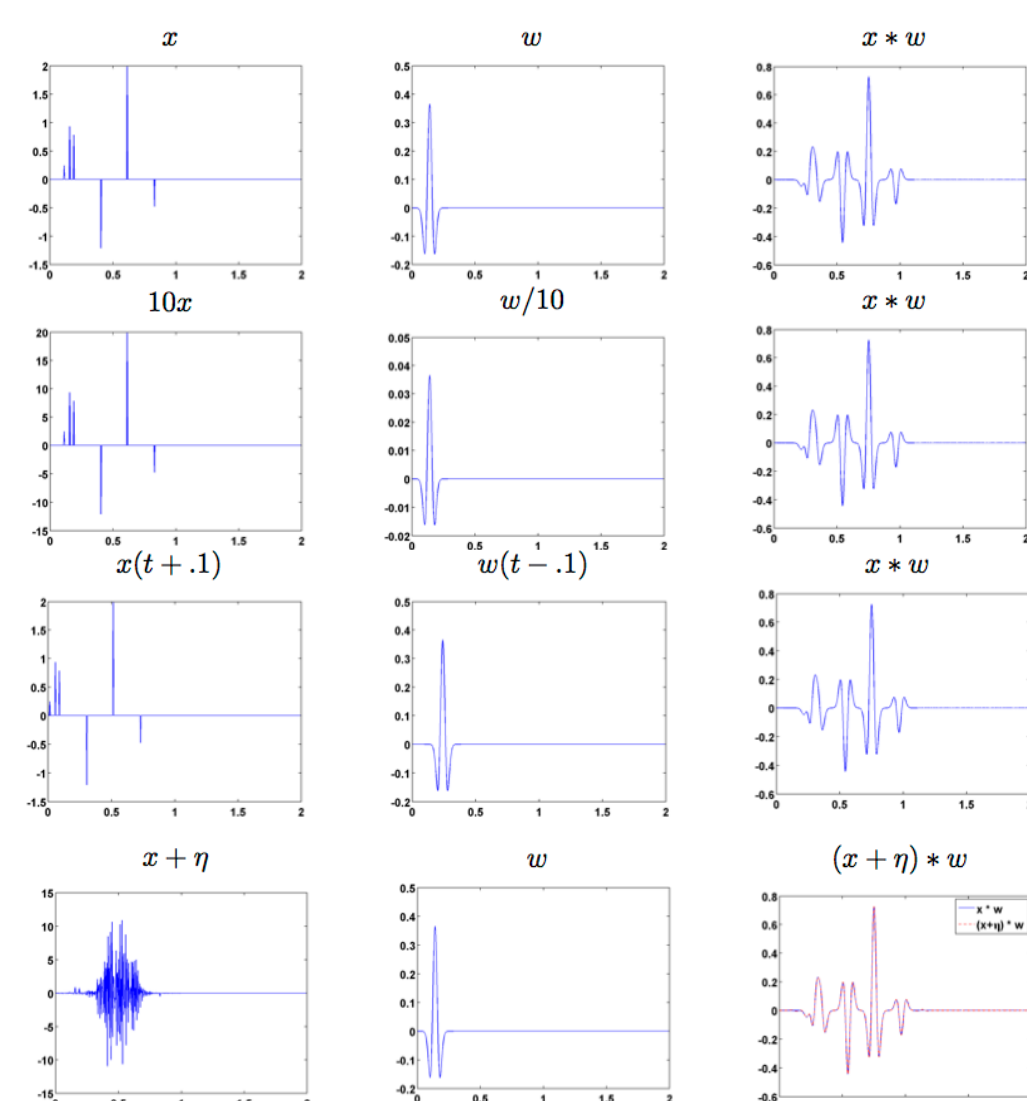
$$y = w * x = (\alpha w) * \left(\frac{1}{\alpha} x\right) = w(t - t_0) * x(t + t_0)$$

The problem is ill-posed—has scaling and shift ambiguities. Regularization CANNOT avoid these ambiguities.

### Usual assumptions and regularizations

- $w$  is short in time
- $x$  is nearly sparse
- $\ell_2$  penalty on  $w$
- $\ell_1$  penalty on  $x$

Figure 1. row 1: original signal, kernel and convolution  
row 2: scaling ambiguity  
row 3: shift ambiguity  
row 4: other ambiguity



## Solving the optimization problem (method of multipliers)

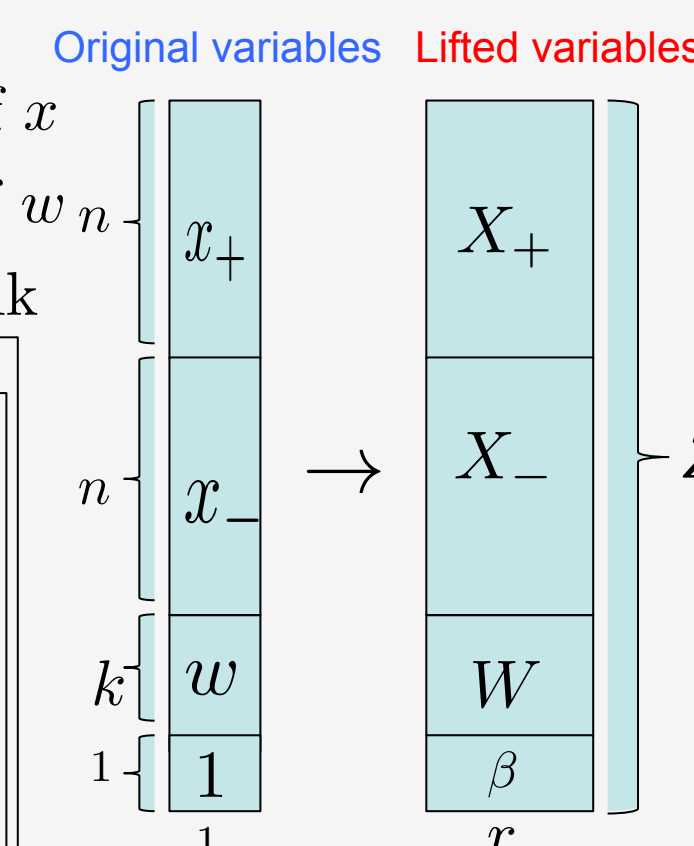
Original problem (non-convex, non differentiable)

$$\min_{x,w} \log(\|x\|_1 / \|x\|_2)$$

subject to  $\|\hat{y} - \text{diag}(\hat{w}\hat{x}^T) - \text{diag}(\hat{y}\hat{x}^T)\|_2 \leq \epsilon$  data constraint  
 $\|x\|_\infty \leq 1$  box constraint

Lifting: Mitigate local minima

$n$ : length of  $x$   
 $k$ : length of  $w$   
 $r$ : lifted rank



Split  $x$  into positive and negative parts (non-convex, differentiable at  $x \neq 0$ )  $x = x_+ - x_-$

$$\min_{x,w} \log\left(\sum x_+ + \sum x_-\right) / (\|x_+ + x_-\|_2)$$

subject to  $\|\hat{y} - \text{diag}(\hat{w}\hat{x}^T) - \text{diag}(\hat{y}\hat{x}^T)\|_2 \leq \epsilon$  data constraint  
 $0 \leq x_+, x_- \leq 1$  box constraint  
 $\langle x_+, x_- \rangle = 0$  non-overlapping constraint

## Blind deconvolution with multiples

$$y = w * x - w * x * x + w * x * x * x \dots$$

$$= w * x - y * x$$

### Traditional solver (EPSI)

- Assume  $w$  is short in time:  $w = Ch$ ,  $C = [I, 0]$ .
- Put  $\ell_1$  penalty on  $x$ ,  $(\hat{w}, \hat{x}) = \arg \min_{w,x} \|y - w * x + y * x\|_2 + \lambda \|x\|_1$
- Alternatively update  $x$  and  $w$ .

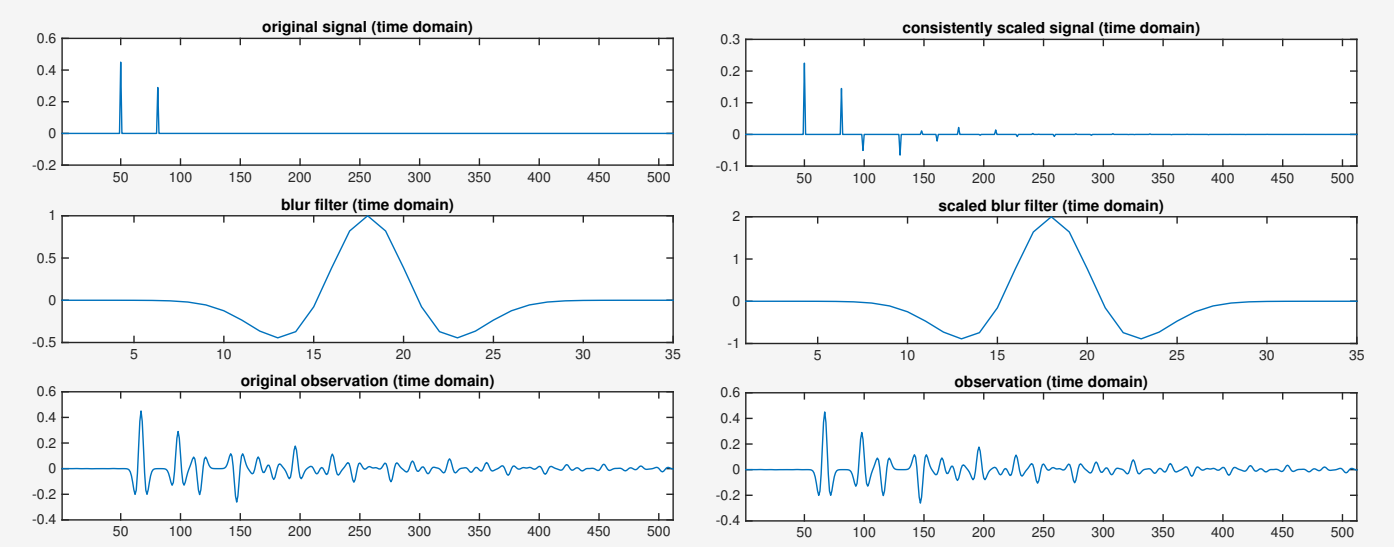


Figure 2. Left: original kernel and signal  $\|x\|_1 \approx 0.74$   
Right: scaled kernel and signal,  $\|\hat{x}_\alpha\|_1 \approx 0.59$  with  $\alpha = 2$ .

Observation: the scaling(shift) ambiguity is still there

$$\hat{y} = \hat{x}(\hat{w} - \hat{y}) = \hat{x}_\alpha(\hat{w}_\alpha - \hat{y}) \text{ where } w_\alpha = \alpha w, \hat{x}_\alpha = \frac{\hat{x}}{(\alpha - 1)\hat{x} + \alpha}$$

## Resolving the scaling issue with an $\ell_1/\ell_2$ penalty

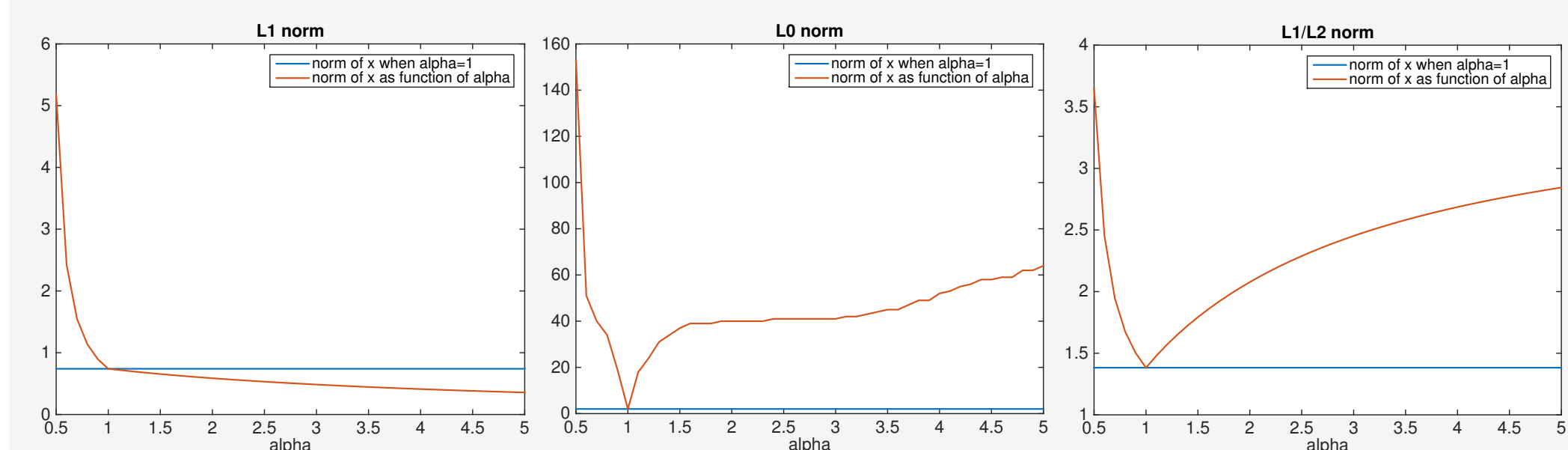


Figure 3. Which norm to choose? How do  $\|x_\alpha\|_0$ ,  $\|x_\alpha\|_1$  and  $\|x_\alpha\|_1 / \|x_\alpha\|_2$  change with  $\alpha$ ?

So we will use the  $\ell_1/\ell_2$  constraint and solve  $\min \log \frac{\|x\|_1}{\|x\|_2}$  subject to  $\|y - w * x + y * x\|_2 \leq \epsilon$

## Final optimization problem

$$\min_{x_+, x_-, w, \beta} \text{Trace}(Z^T Z) - \|Z^T Z\|_F + \log \frac{\mathbf{1}^T (X_+ + X_-)(X_+ + X_-)^T \mathbf{1}}{\text{Trace}(X_+ - X_-)(X_+ - X_-)^T}$$

Low rank penalty (green box), L1 norm (red box), L2 norm (blue box)

subject to  $\|\hat{y} - \text{diag}(\hat{W}\hat{X}^T) - \text{diag}(\hat{y}\hat{X}\beta^T)\|_2 \leq \epsilon$  data constraint  
 $0 \leq X_+, X_- \leq 1$  box constraint  
 $\langle X_+, X_- \rangle = 0$  non-overlapping constraint  
 $\|\beta\|_2 = 1$  weights sum up to 1

Reconstruct  $(x, w)$  from  $Z$

extract the first left singular vector  $v$ , and singular value  $\sigma$  of  $Z$

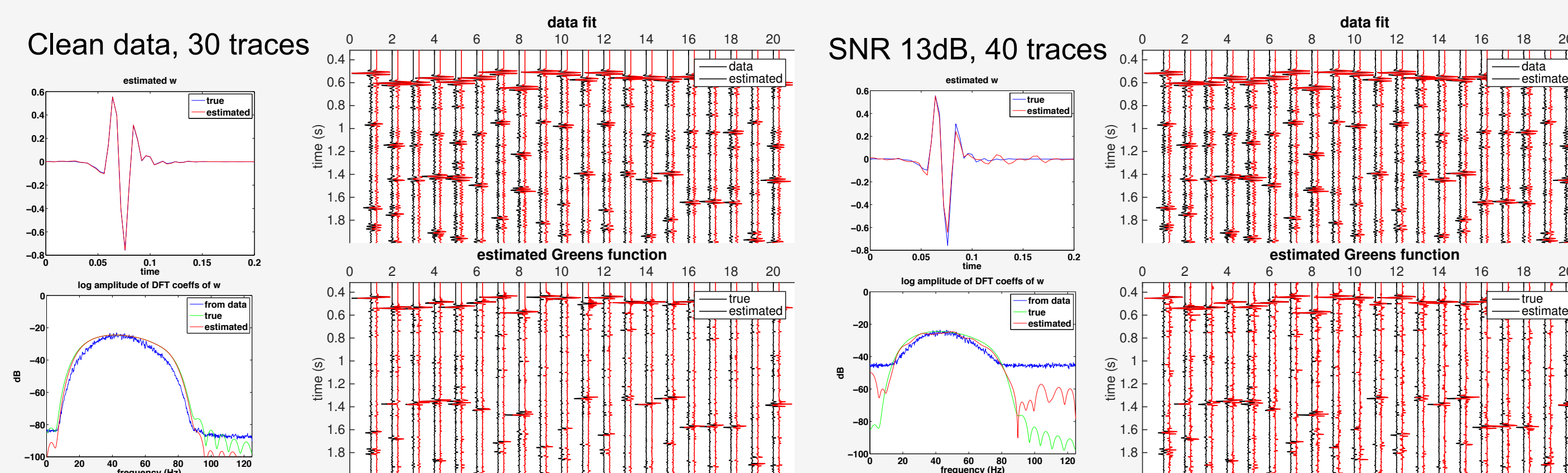
$$x_+ = \sigma v(1, \dots, n)$$

$$x_- = \sigma v(n + 1, \dots, 2n)$$

$$w = \sigma v(2n + 1, \dots, 2n + k)$$

## Pluto1.5 data

Initial guess:  $w = 0$ ,  $x =$  normalized random Gaussian vector



†John "Ernie" Esser (May 19, 1980 – March 8, 2015)

This work is a reflection of Ernie's extraordinary contributions to this challenging problem. Unfortunately, Ernie was not able to see the final results of his original work. We miss him dearly, and will continue to work on this exciting approach.

## Acknowledgements

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