



# Learning step sizes for unfolded sparse coding

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Golden ratio

(Original size: 32.361×200 bp)



## Solving sparse linear inverse problems

- **Objective:** Solve the Lasso for a fixed  $D$  and  $x \sim \mathbb{P}$ .

$$z^*(x) = \underset{z}{\operatorname{argmin}} F_x(z) = \frac{1}{2} \|x - Dz\|_2^2 + \lambda \|z\|_1$$

- **Iterative algorithm:** Use ISTA for each  $x$
- **Deep Learning:** Use a NN to learn a mapping

$$\Phi_{\Theta}^T : x \mapsto z^*(x); \quad \text{for } x \sim \mathbb{P}$$

## Learned ISTA

[Gregor & Le Cun 2010]

**ISTA:**  $z^{(t+1)} = \text{ST}(z^{(t)} - \gamma D^\top (Dz^{(t)} - x), \gamma \lambda)$ ,  
where  $\gamma$  is the step size, usually chosen as  $1/L$ .

**LISTA:** Let  $W_z = I_m - \gamma D^\top D$ ;  $W_x = \gamma D^\top$  and  $\beta = \gamma$

$$z^{(t+1)} = \text{ST}(W_z z^{(t)} + W_x x, \lambda \beta)$$

**Re-parametrization:**

skjhfkjhdskjdfh

$$W_z = I_m - \alpha W^\top D; \quad W_x = \alpha W^\top$$

- Learn parameters  $\Theta = \{W^{(t)}, \alpha^{(t)}, \beta^{(t)}\}$

**Supervised learning**

**Semi-supervised learning**

**Unsupervised learning**

Ground truth  
available  $s_1, \dots, s_N$

Compute  
 $s_i = \underset{z}{\operatorname{argmin}} F_{x_i}(z)$

Learn to solve the  
Lasso

$$\sum_{i=1}^N (\Phi_{\Theta}^T(x_i) - s_i)^2$$

$$\sum_{i=1}^N (\Phi_{\Theta}^T(x_i) - s_i)^2$$

$$\sum_{i=1}^N F_{x_i}(\Phi_{\Theta}^T(x_i))$$

## Local smoothness constants

- $L = \max \|Dz\|_2^2$  subject to  $\|z\|_2 = 1$

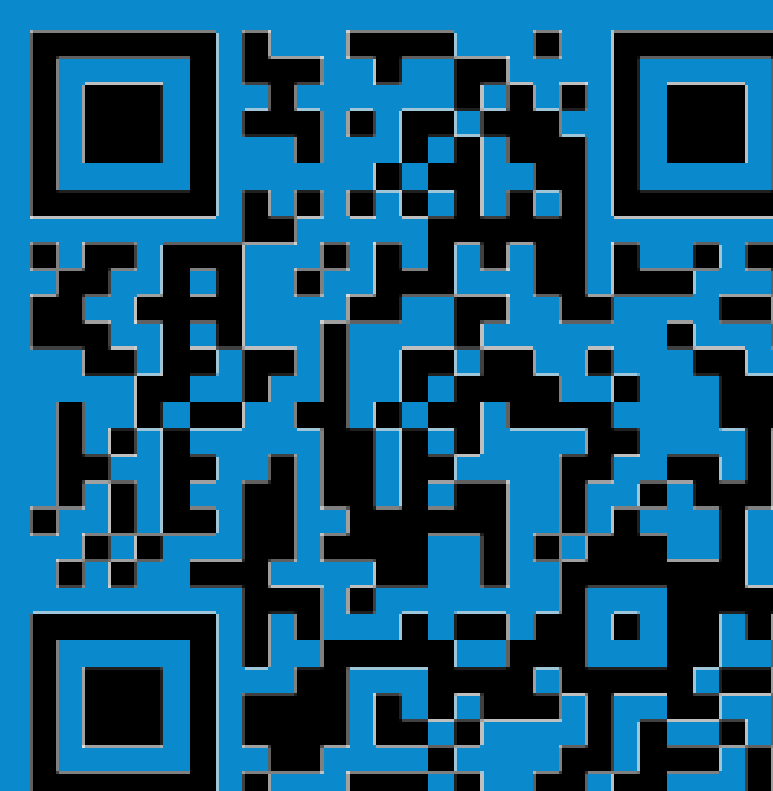
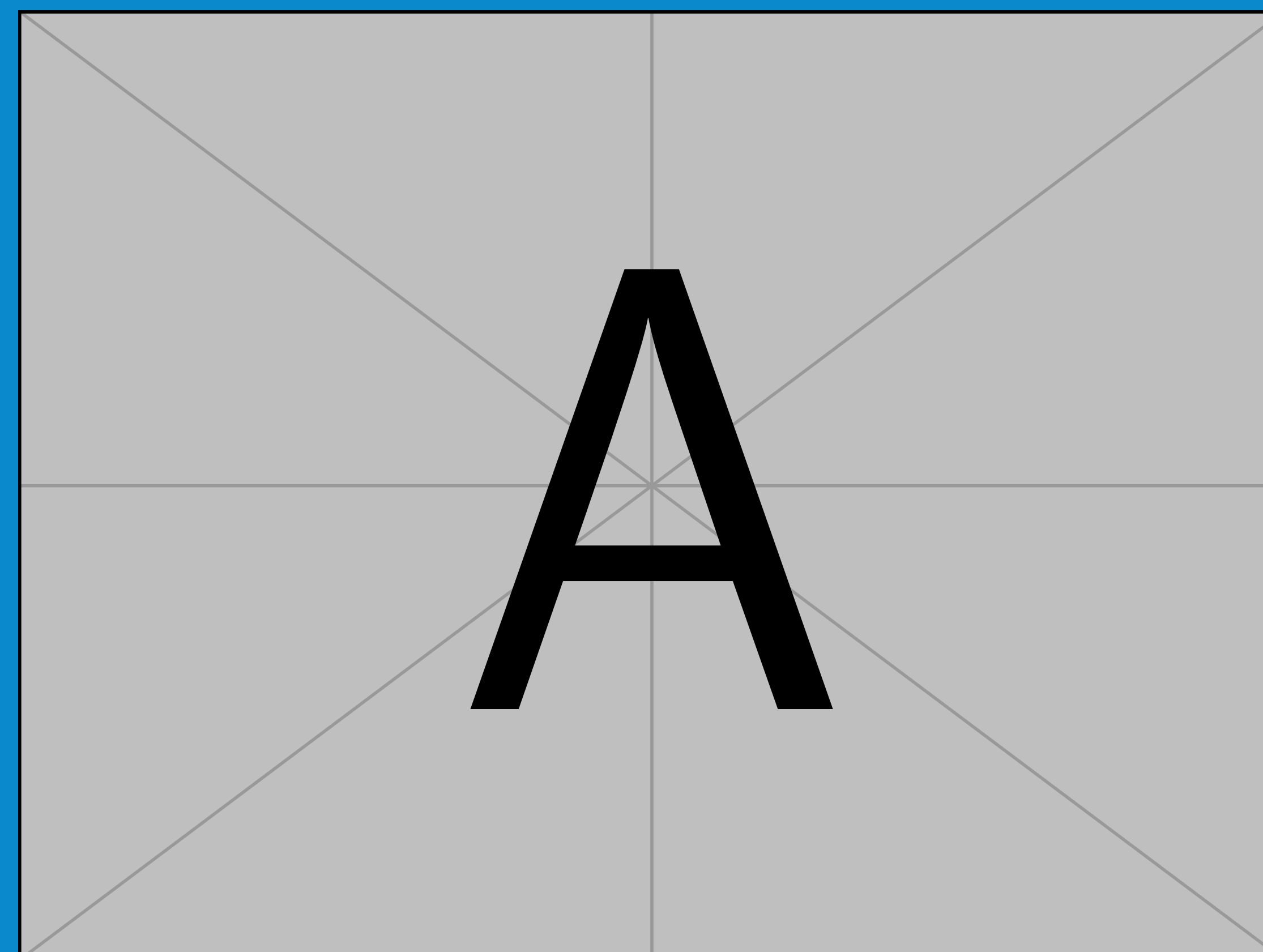
$$\begin{aligned} F_x(z) &= f_x(z^{(t)}) + \langle \nabla f_x(z^{(t)}), z - z^{(t)} \rangle + \frac{1}{2} \|D(z - z^{(t)})\|_2^2 + \lambda \|z\|_1 \\ &\leq f_x(z^{(t)}) + \langle \nabla f_x(z^{(t)}), z - z^{(t)} \rangle + \frac{L}{2} \|z - z^{(t)}\|_2^2 + \lambda \|z\|_1 \end{aligned}$$

- $L_S = \max \|Dz\|_2^2$  subject to  $\|z\|_2 = 1, \text{Supp}(z) \subset S$ .

ISTA with **greater step-size:**  $\gamma = 1/L_s$

**Theorem:** The weights of a neural network trained to solve the lasso asymptotically only learn a step size.

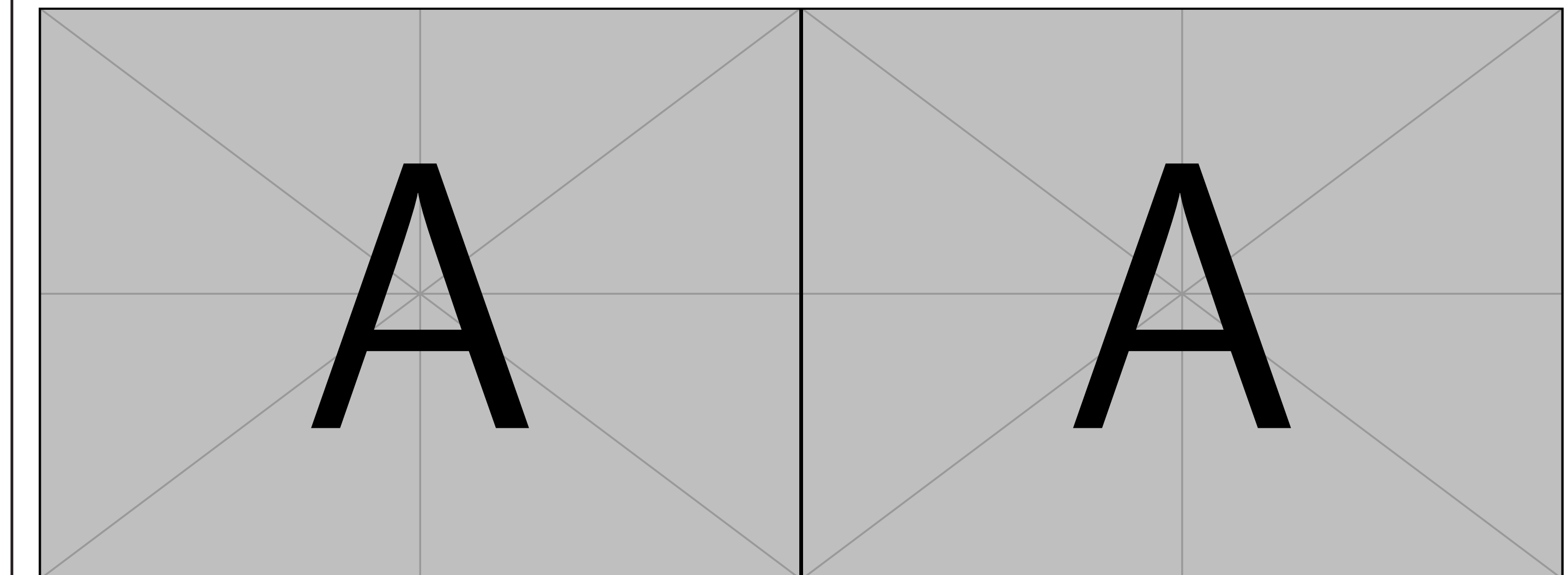
$$\frac{\alpha^{(t)}}{\beta^{(t)}} W^{(t)} \xrightarrow[t \rightarrow \infty]{} D$$



## Improving ISTA step-size

*Better step-sizes for ISTA*

- Back-tracking line-search
- **OISTA:** Adapt step-sizes to **Local smoothness constants**  $L_S$
- **SLISTA:** Learn only step-sizes with LISTA.



The step-sizes learned by SLISTA tend to be in  $[\frac{1}{L_s}, \frac{2}{L_s}]$ .

## Varying the sparsity

SLISTA works better when  $z^*$  is sparse as this reduces  $L_S$ .

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## References

- Gregor, K. & Le Cun, Y. (2010) [Learning Fast Approximations of Sparse Coding](#). ICML.
- Chen, Y., Liu, J., Wang, Z. & Yin, W. (2018) [Theoretical Linear Con](#)