

# Learned Convolutional Sparse Coding



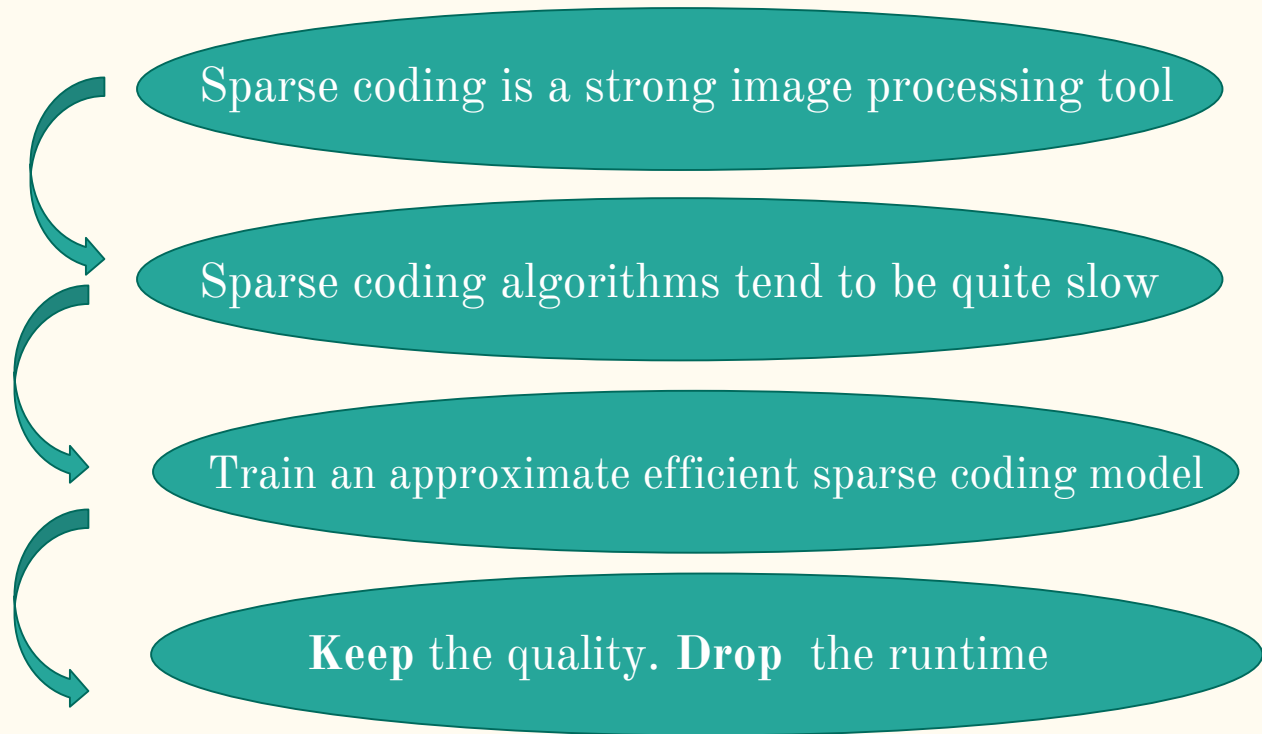
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# Outline

- Motivation and applications
- Brief sparse coding background
- (ASC) Approximate sparse coding
- (CSC) Convolution sparse coding
- (ACSC) Approximate Convolution sparse coding

# ACSC - real-time image processing



# ACSC - advantages

**Sparse coding** has been shown to work well for Image processing task.  
Yet, it tends to be slow ➡ Requires multiple minutes on CPU.

**Approximate convolutional sparse coding** cuts the runtime to a fraction while maintaining the sparse coding performance.  
➡ Requires **less than a second** on a CPU.

# ACSC - Image denoising example

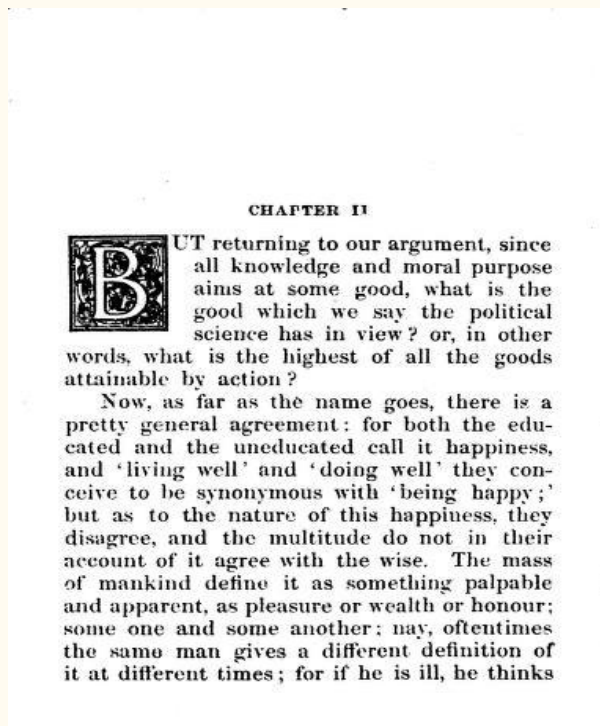
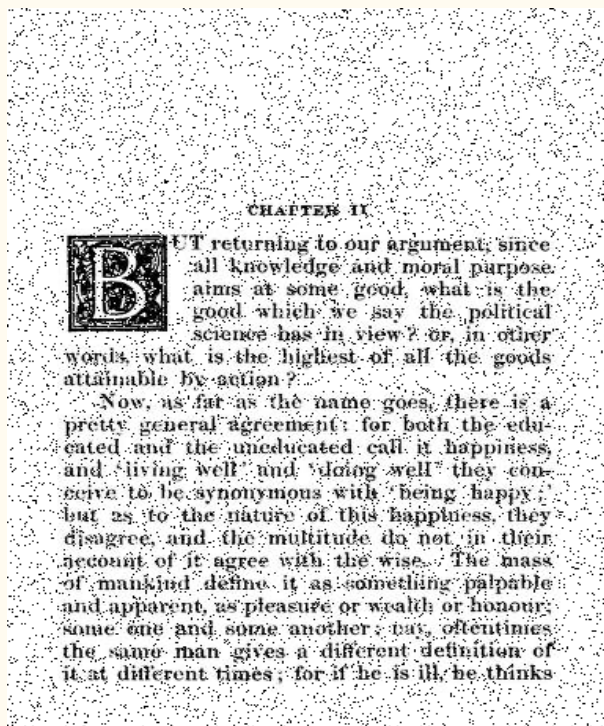


ACSC (0.7 sec) PSNR 29.88 dB

KSVD (70 sec) PSNR 28.67 dB

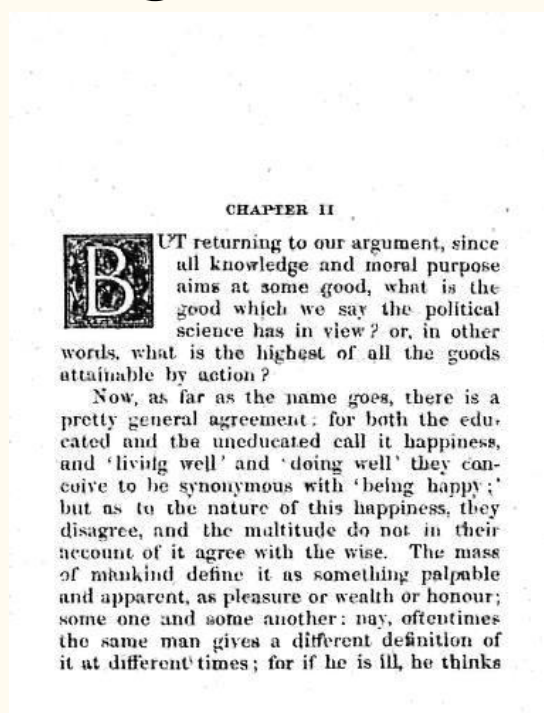
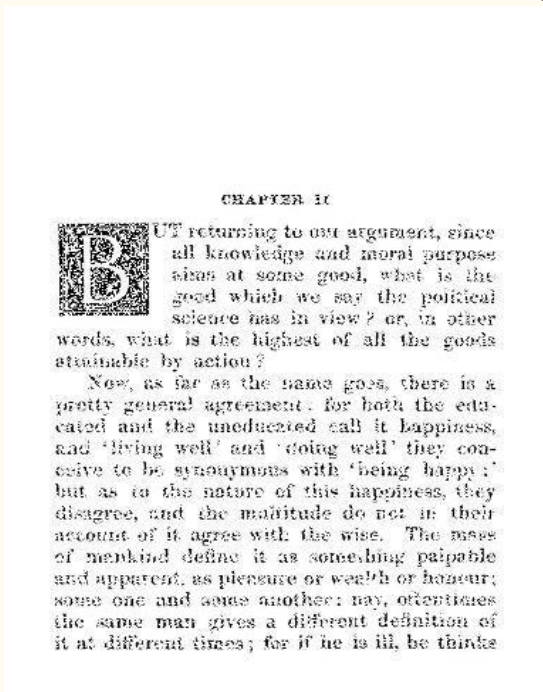
**x100 speedup** compared to OMP sparse coding in KSVD

# ACSC - Document S&P denoising



ACSC (0.43 sec) PSNR 30.2 dB

# ACSC - Document inpainting



ACSC (0.43 sec) PSNR 30.13 dB

# Sparse Code problem setup

Given An input  $X$  and an over complete matrix  $D$

Find  $Z^*$  such that:

$$X = DZ^* \quad \|Z^*\|_0 < \|Z\|_0 \quad \forall Z \in \{Z | X = DZ\}$$



# Sparse Code problem setup

Given An input  $X$  and an over complete matrix  $D$

Find  $Z^*$  such that:

$$X = DZ^* \quad \|Z^*\|_0 < \|Z\|_0 \quad \forall Z \in \{Z | X = DZ\}$$

Solving the above is intractable due to the  $\ell_0$  norm.

Can be approximated by  $\ell_1$  relaxation

Leads to the LASSO minimization problem

$$Z_{lasso}^* = \mathbf{argmin}_Z \|X - DZ\|_2^2 + \lambda \|Z\|_1$$

# Sparse Code setup - solving LASSO

Use the proximal gradient technique -

$$f(x) = g(x) + h(x)$$

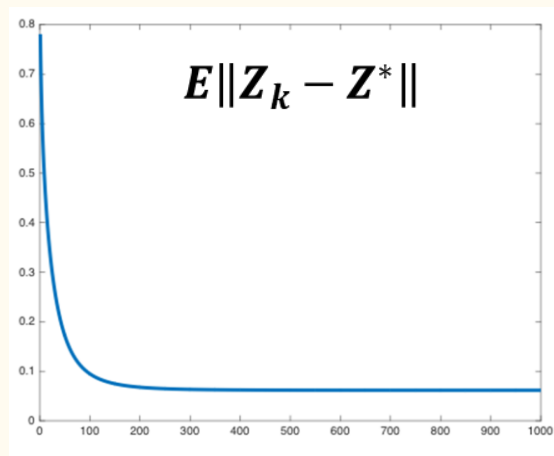
$$x^{(k)} = \text{prox}_{t_k, h}(x^{(k-1)} - t_k \nabla g(x^{(k-1)}))$$

↓ ISTA

$$Z_{k+1} = S_{\lambda/L}(Z_k + D^T(X - DZ_k))$$

This is an iterative method

Many iterations may be required for convergence!



# Sparse Code setup - solving LASSO

Long convergence time of ISTA can be an issue for time sensitive applications

→ An acceleration strategy that approximates the solution is required

Learned ISTA (LISTA): Replaces linear operations and threshold in ISTA with learned ones

$$Z_{k+1} = S_{\lambda/L} \left( (I - D^T D) Z_k + D^T X \right)$$

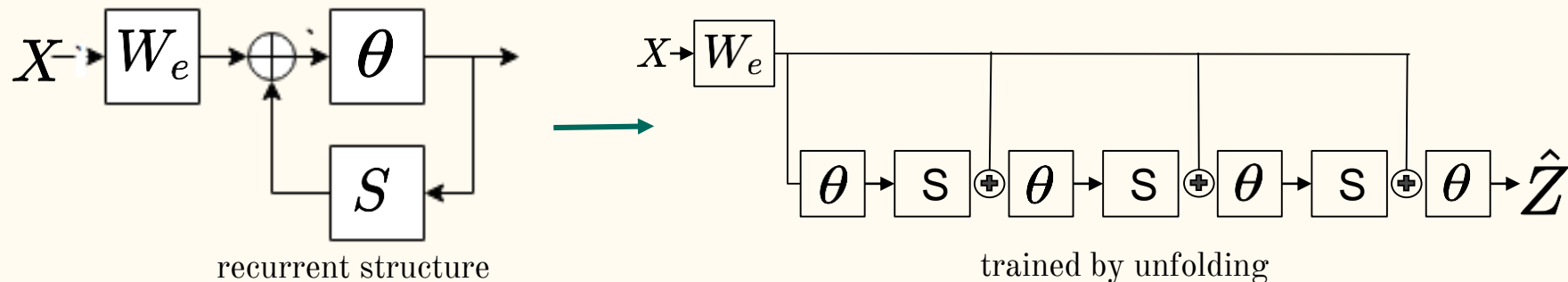
↓  
LISTA

$$Z_{k+1} = S_{\theta} (S Z_k + W_e X)$$

# Using Learned-ISTA as a SC approximation

Given a fixed number of iterations learn the matrices  $S$  and  $W$  and the thresholds  $\theta$

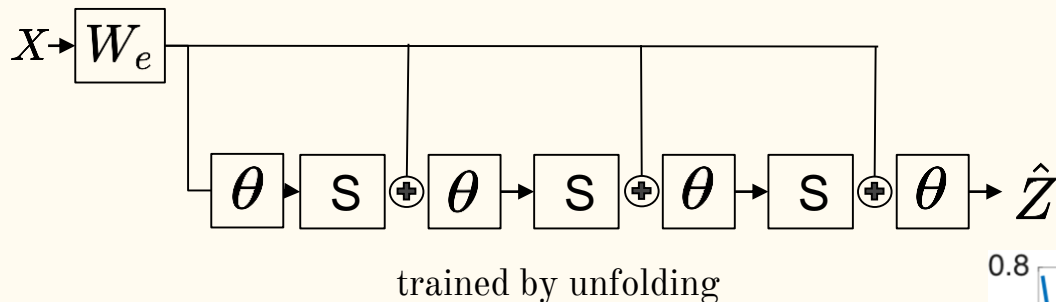
$$Z_{k+1} = S_{\theta}(SZ_k + W_e X)$$



$$L(W, X^p) = \frac{1}{2} \|Z^{*p} - f_e(W, X^p)\|_2^2$$

# LISTA training

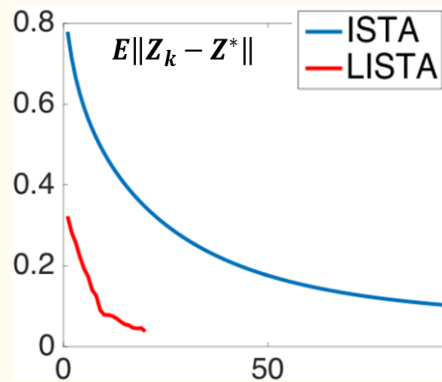
LISTA iteration:  $Z_{k+1} = S_{\theta}(SZ_k + W_e X)$



Train using loss function:

$$L(W, X^p) = \frac{1}{2} \|Z^{*p} - f_e(W, X^p)\|_2^2$$

Where  $Z^{*p}$  is the sparse code of  $X^p$



# LISTA disadvantages

LISTA is a patch based method.

Therefore, we have

- Loss of spatial information.
- Inefficient for large patches
- Image properties not incorporated (i.e. translation invariance).

Solution: Use convolutional structure.

# Approximate Convolutional Sparse Coding (ACSC)

Learn a **convolutional** sparse coding of the whole image instead of patches

➡ A global algorithm:

- Image is processed as whole.
- Efficient.
- Convolution based → inherently incorporates image properties.

This overcomes the disadvantages of LISTA being a patch based method:

- Loss of spatial information.
- Not Inefficient for large patches
- Image properties not incorporated (i.e. translation invariance)

# Standard Convolutional Sparse Coding (CSC)

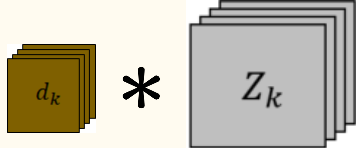
In convolutional sparse coding we replace the regular dictionary with a convolutional one:

Given input  $X$ , solve:

$$\mathbf{argmin}_{d,z} = \|X - \sum_{k=1}^K d_k * Z_k\|_2^2 + \beta \sum_{k=1}^K \|Z_k\|_1 \quad \text{s.t.} \quad \|d_k\|_2 \leq 1$$

In other word --

Find a set of kernels  $d$  that reconstruct  $X$  with sparse feature maps  $Z$

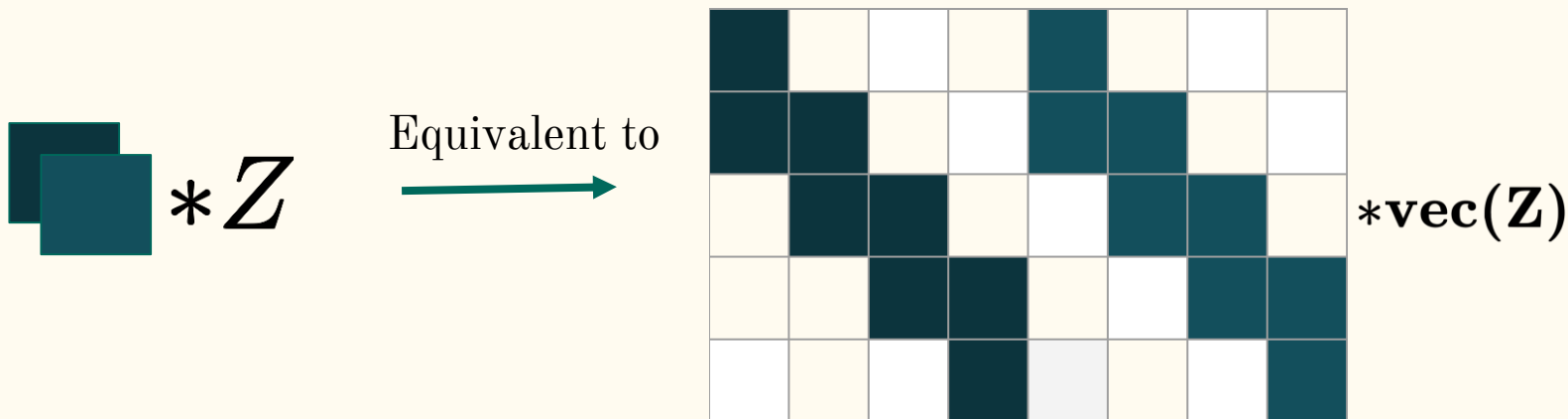
$$X = \sum_k d_k * Z_k$$




# Convolutional Sparse Coding as Regular Sparse Coding

Convolutional Sparse Coding (CSC)  $\longleftrightarrow$  Regular Sparse Coding (SC)

A convolutional dictionary is a concatenation of toeplitz matrices



# From SC to CSC

Rewrite ISTA as a solution to CSC problem

Assuming  $\mathbf{D}$  is a concatenation of toeplitz matrices we can replace matrix multiplication with convolution

$\mathbf{D}$  is a toeplitz matrix

$$Z_{k+1} = S_{\lambda/L}((I - D^T D)Z_k + D^T X)$$

Convolutional ISTA

$$Z_{k+1} = S_{\lambda/L}(Z_k - \hat{d} * (d * Z_k) + \hat{d} * X)$$

$$d \in \mathbb{R}^{s \times s \times M \times C}$$

$$\hat{d} \in \mathbb{R}^{s \times s \times C \times M}$$

# From CSC to Approximate CSC

Approximate Convolutional sparse coding (ACSC): Replaces convolutional operations and threshold in Convolutional ISTA solution with learned ones

$$Z_{k+1} = S_{\lambda/L}(Z_k - \hat{d} * (d * Z_k) + \hat{d} * X)$$

↓ ACSC

$$Z_{k+1} = S_{\theta}(Z_k - w_e * (w_d * Z_k) + w_e * X)$$

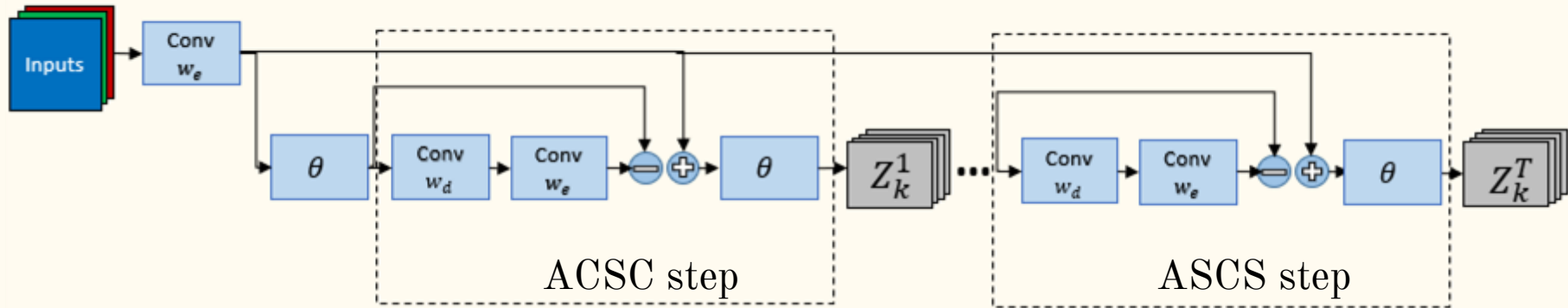
$$w_d \in \mathbb{R}^{s \times s \times M \times C}$$

$$w_e \in \mathbb{R}^{s \times s \times C \times M}$$

# Approximate CSC architecture

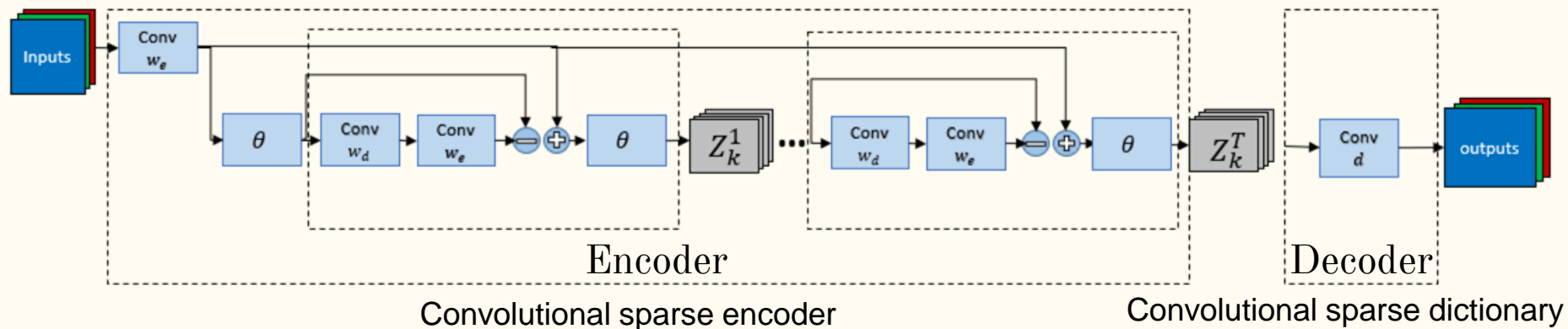
$$Z_{k+1} = S_{\theta}(Z_k - w_e * (w_d * Z_k) + w_e * X)$$

Proposed recurrent architecture for CSC with unfold of T steps



# Approximate CSC with dictionary learning

Train end to end as a sparse autoencoder



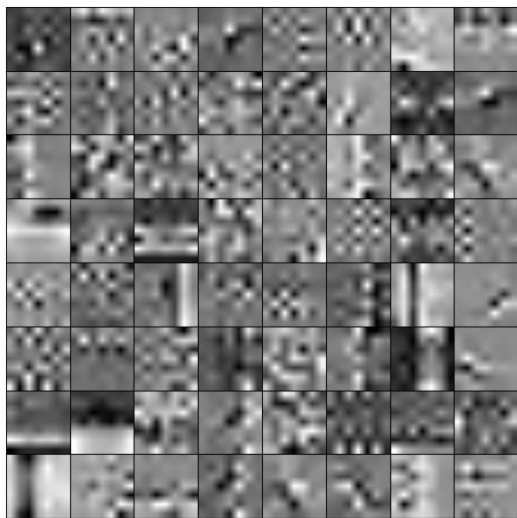
We learn in our framework both the sparse coding and the dictionary  
In LISTA, only the sparse coding is being learned

# Training ACSC autoencoder

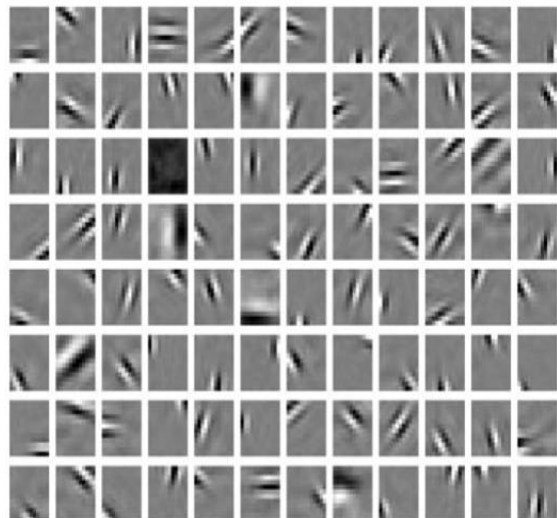
- Initialization is important  $\longrightarrow w_d = d = \mathbf{flipud}(\mathbf{fliplr}(w_e))$
- We found kernel of size 7x7 to give best results.
- We found Unfolding 3 time step to be sufficient
- Use loss function  $L(x, \hat{x}) = \alpha(1 - \mathbf{ms\_ssim}(x, \hat{x})) + (1 - \alpha)\|x - \hat{x}\|_1$   
H. Zhao, O. Gallo, I. Frosio, and J. Kautz, “Loss functions for image restoration with neural networks,”

# Approximate CSC and dictionary learning

Learned convolution dictionary



Classical sparse dictionary



Classical approach tends to learn the same atom with a translation.  
Convolution dictionary a single atom covers all translation.

# Approximate CSC Tasks

Example result on denoising task



ACSC (0.56 sec) PSNR 32.11 dB

KSVD (57 sec) PSNR 32.09 dB

**x100 speedup** compared to OMP sparse coding in KSVD



# Approximate CSC Tasks

Example result on denoising task



ACSC (0.6 sec) PSNR 30.14 dB

KSVD (64 sec) PSNR 30.05 dB

**x100 speedup** compared to OMP sparse coding in KSVD

# Approximate CSC Tasks

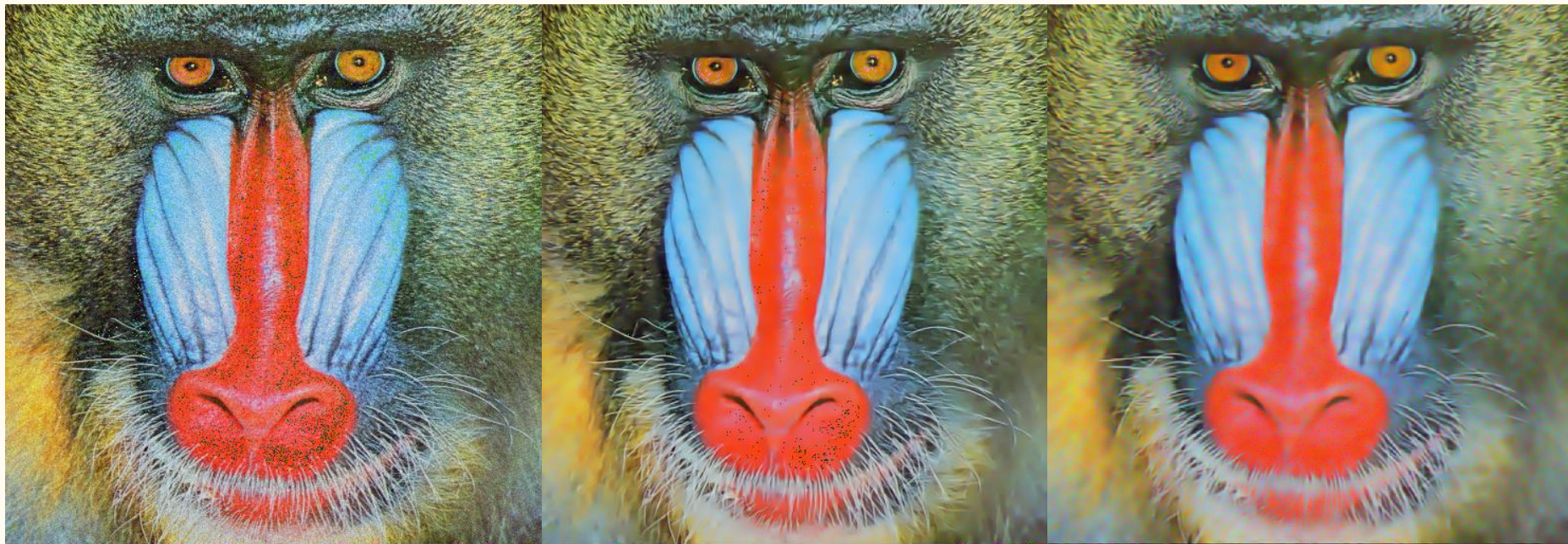
Example result on inpainting task



ACSC (0.57 sec) PSNR 32.3 dB

# Approximate CSC Tasks

Example result on denoising task



ACSC (0.83 sec) PSNR 30.32 dB

KSVD (78 sec) PSNR 30.21 dB

**x100 speedup** compared to OMP sparse coding in KSVD

# Approximate CSC Tasks

Example result on inpainting task



ACSC (0.48 sec) PSNR 30.32 dB

Heide et al.(320 sec) PSNR 30.21 dB

**x650 speedup** compared to Heide et al. (Fast and Flexible Convolutional sparse coding)

# Approximate CSC Tasks

Example result on document denoising task

<b>CLOSED</b>		19. Febr. 1952	Munich
INDEX CARD A.I.D.C.		EMIGRATION SERVICE	
Last Name	LEWKOWICZ	File No.	Engl.6.
First Name	Ludwig	Sex	m
Address	Feldafing.DPC.	Opening Date	
Birthdate	8.9.23	Birthplace	Warschau
Nationality:		in transit from:	
Present	Former	Accompanied by	
Occupation:			
Present	Former	Closing Date	
Country of destination	England.		
Cross reference; File No. Aust 630 see Canada-Part closed			

<b>CLOSED</b>		19. Febr. 1952	Munich
INDEX CARD A.I.D.C.		EMIGRATION SERVICE	
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# Conclusion

- LISTA is good for accelerating sparse coding for patches
- Yet, it is slow when working on images as a whole
- Our proposed learned CSC is good for processing the whole image
- Provide comparable performance to other sparse coding based techniques on images with up to x100 speedup

# Thank You!

