L15 EC500K

→ Sparse coding:

- Similar to volcabulary ⟷ doc, reperents doc by sparse vectors.

$$\vec{X}_i = \vec{W}^T \vec{z}_i$$

$\vec{X}_i$: $d \times 1$, $\vec{W}$: $d \times d$ ← dictionary, $\vec{z}_i$: $d \times 1$ ← sparse vector

- Unsupervised learning can't produce error to be minimized.

  One way is to assume a probablistic model to fit data into, ie: RBM, then use ML to train

  Aother way is Autoencoder.

- Think about PCA:

  Input: X

  Prediction: $z = W^T X$

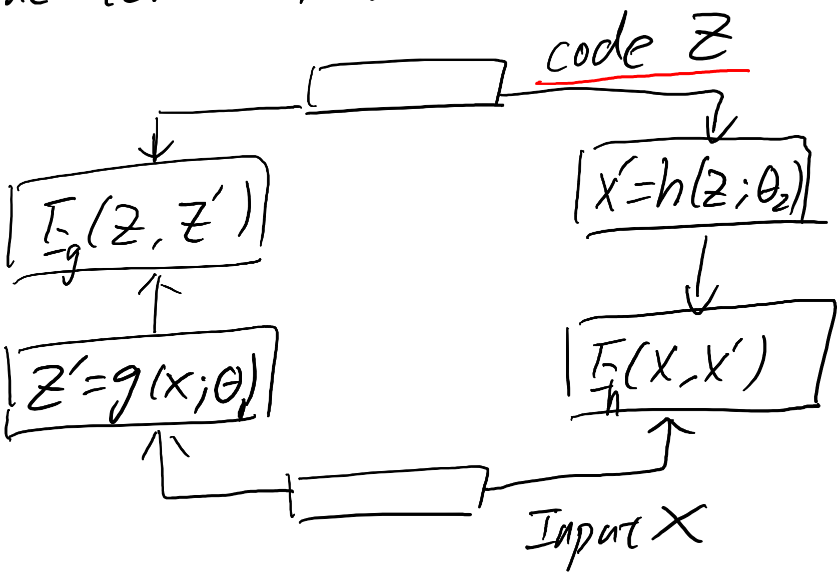
  Restore input from z: $X' = Wz$

  Error: $\sum_{i=1}^{n} \|x_i - WW^T x_i\|^2$ ← Reconstruction error

- Reconstraction of prediction should be either low dimention or in sparse high-dimension
- Other unsupervised: EM

→ Autoencoder

- Bottleneck vs overcomplete code.
- One common arch



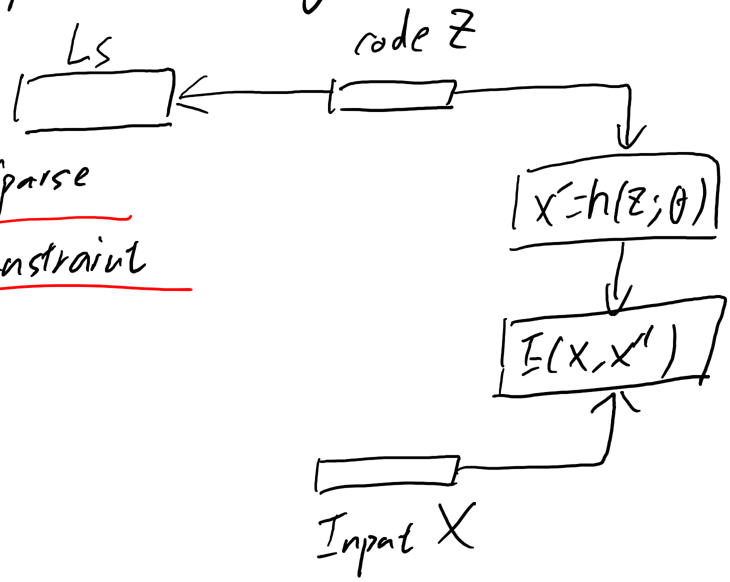
$\theta_1 = \vec{C}, b_C$

$\theta_2 = \vec{D}, b_D$

- Loss function = α · encoding energy + decode energy

  PCA doesn't have encoding energy
- The learning process is similar to EM algo
- Backprop needs gradients of $h(\,)$, E_g and E_h
- Two backprops needed due two there r two networks

→ Sparse coding

- 

$h = W^T z + b$

- Loss function $= \|x - x'\|_2^2 + \lambda L_s(z)$
- Not really an autoencoder, but popular before 2009
- Limitation: exploding W

- Sparse autoencoder
- Stacked sparse autoencoder