NPTEL ONLINE CERTIFICATION COURSES

Course Name: Deep Learning

Faculty Name: Prof. P. K. Biswas

Department : E & ECE, IIT Kharagpur

Topic

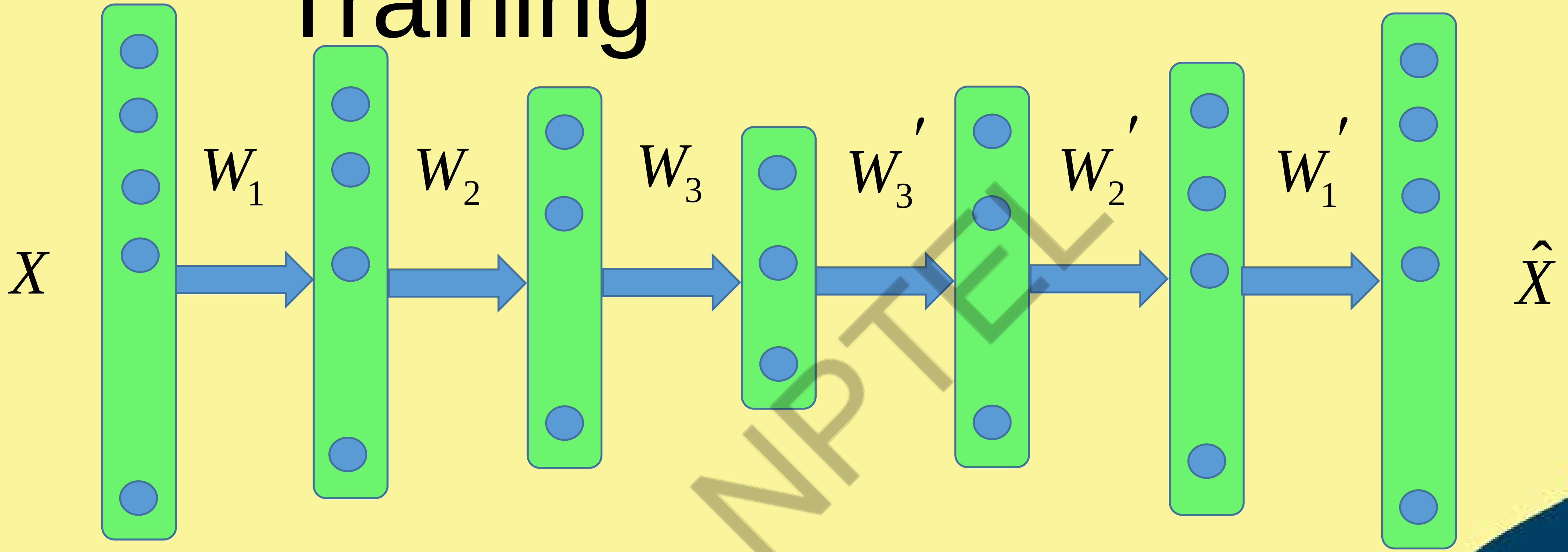
Lecture 31: Autoencoder Training

CONCEPTS COVERED

Concepts Covered:

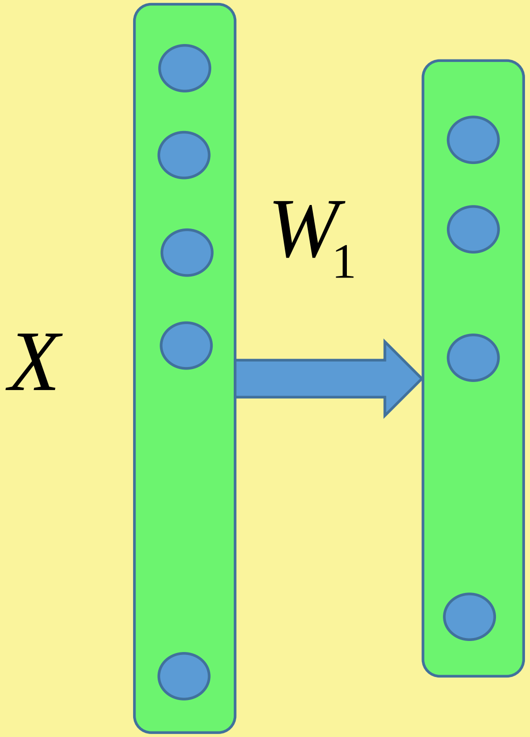
- Autoencoder
  - Undercomplete Autoencoder
  - Autoencoder vs. PCA
  - Deep Autoencoder Training
  - Sparse Autoencoder
  - Denoising Autoencoder
  - Contractive Autoencoder
  - Convolution Autoencoder

Autoencoder Training

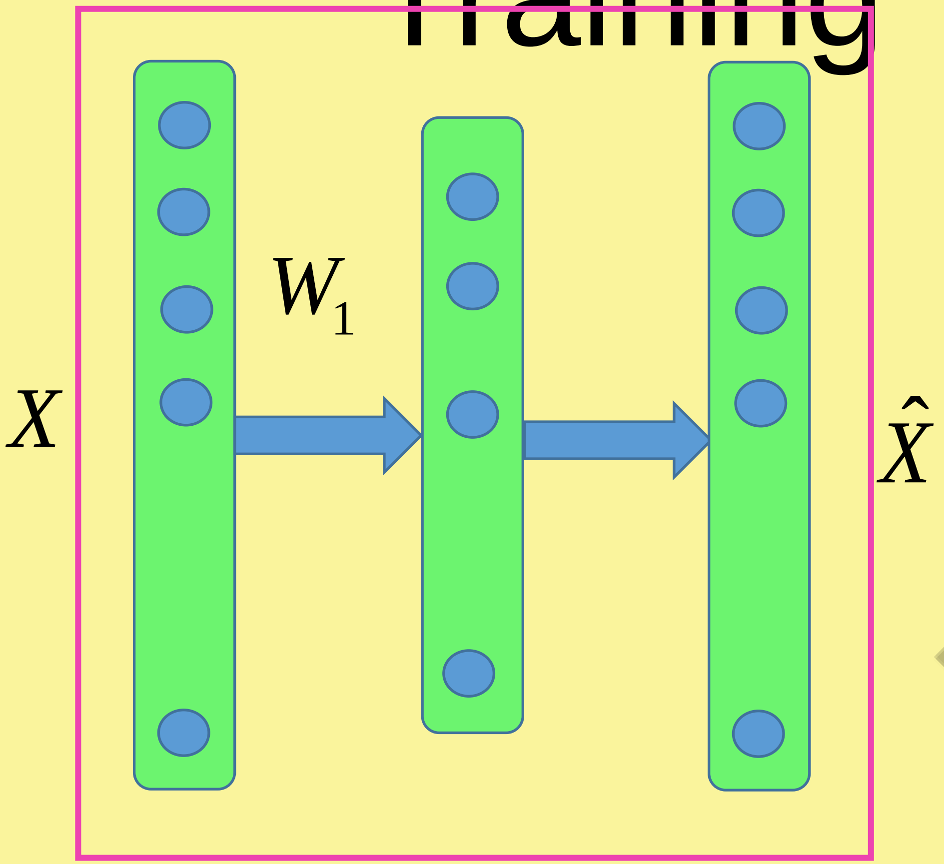


Layer by Layer Pretraining

Autoencoder Training

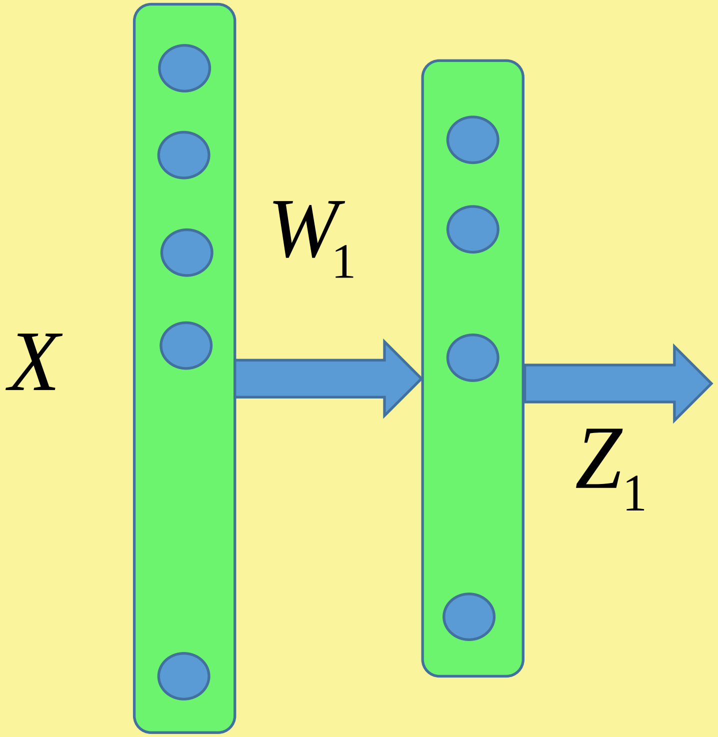


Autoencoder Training

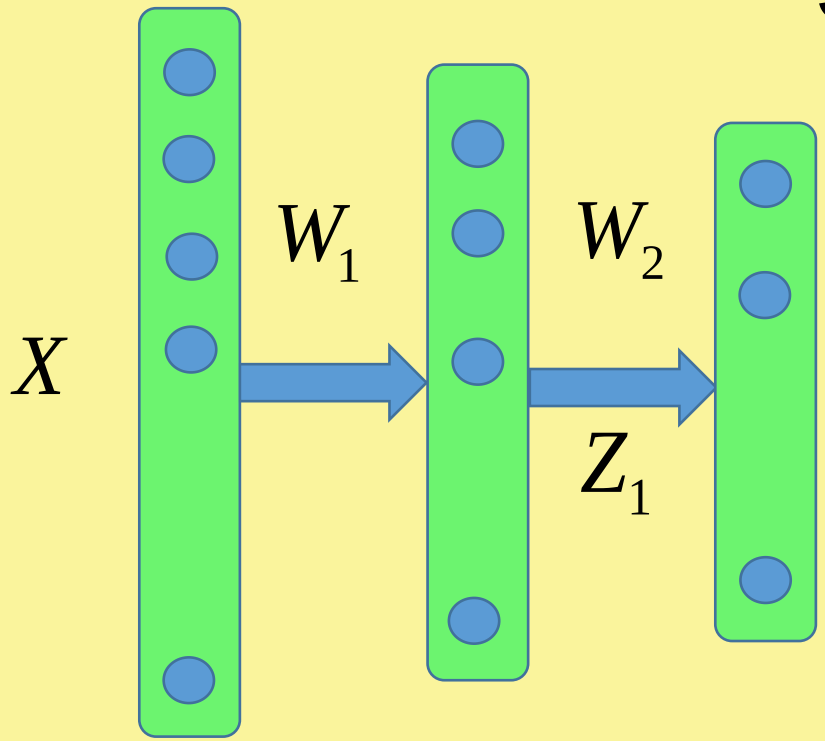


$L(X, \hat{X})$

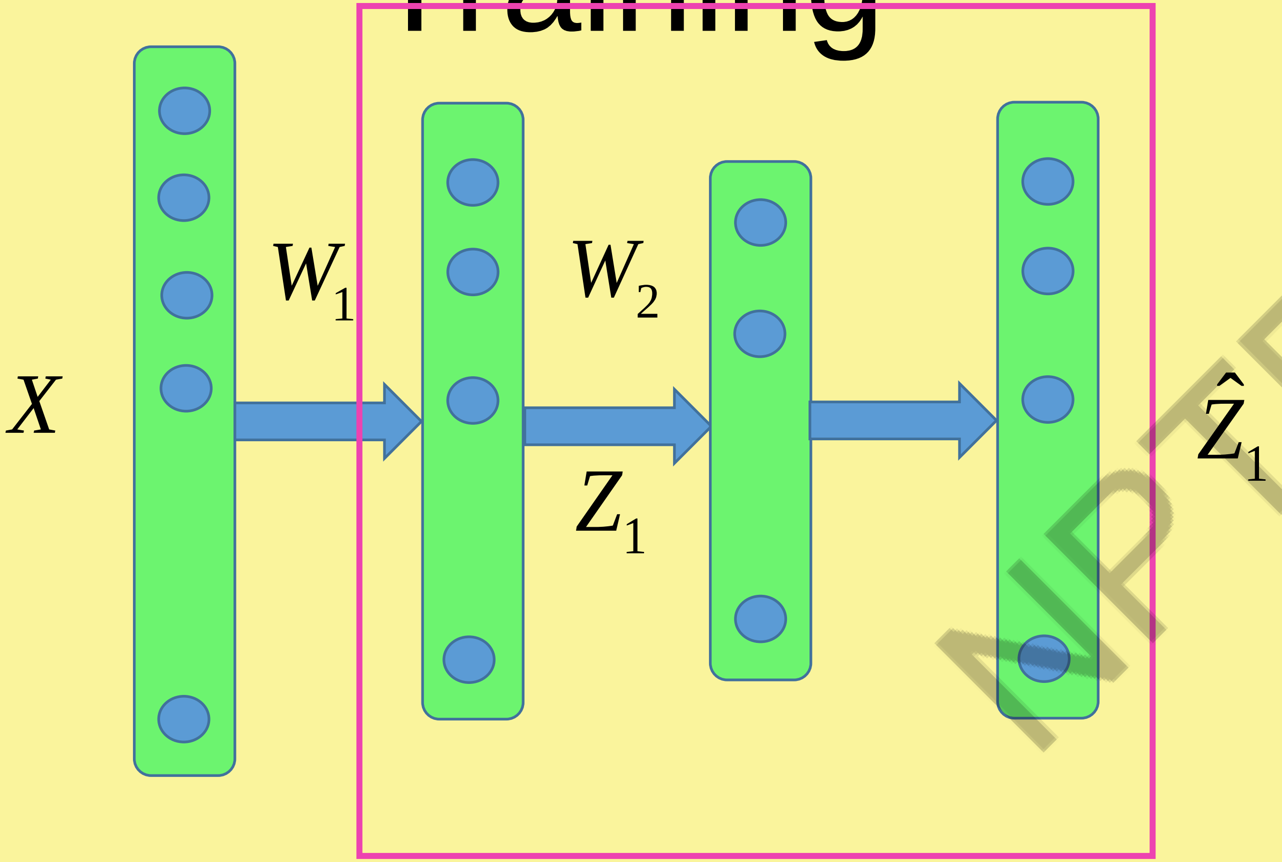
Autoencoder Training



Autoencoder Training

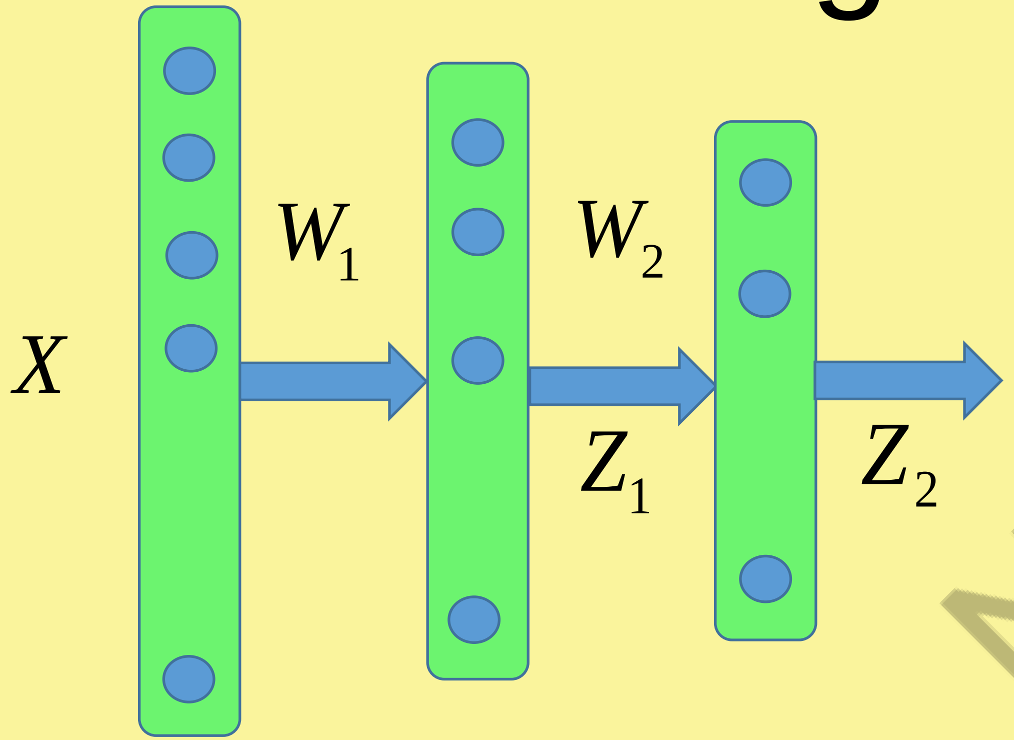


Autoencoder Training

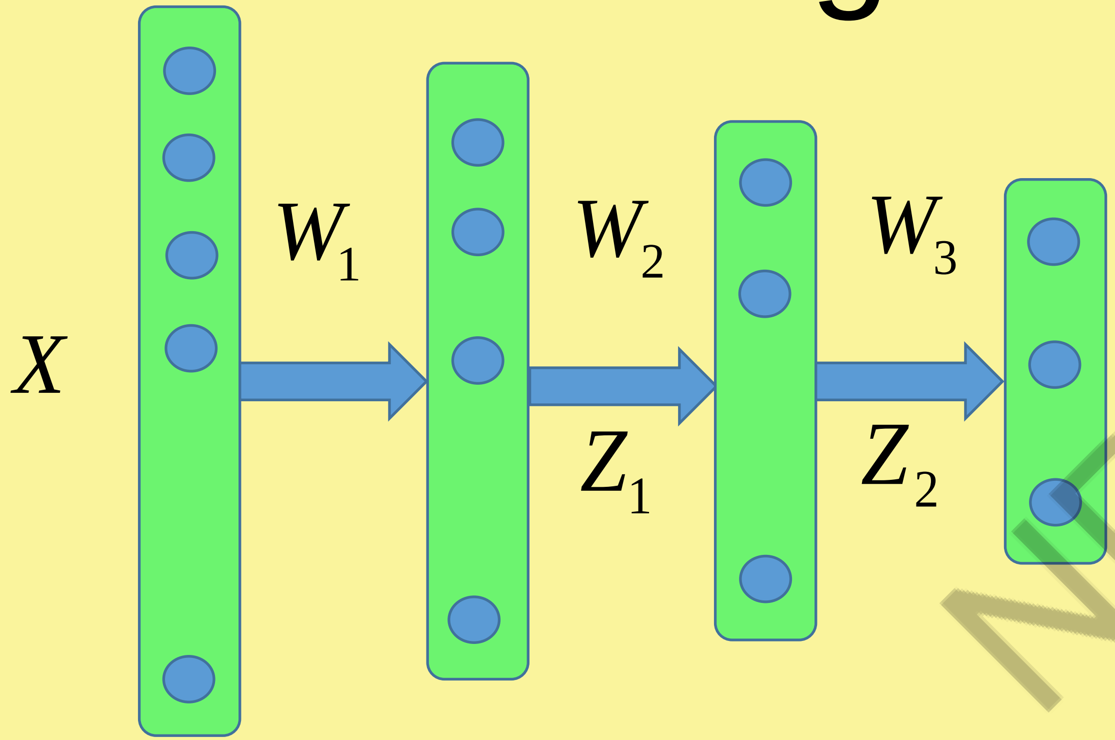


$L(Z_1, \hat{Z}_1)$

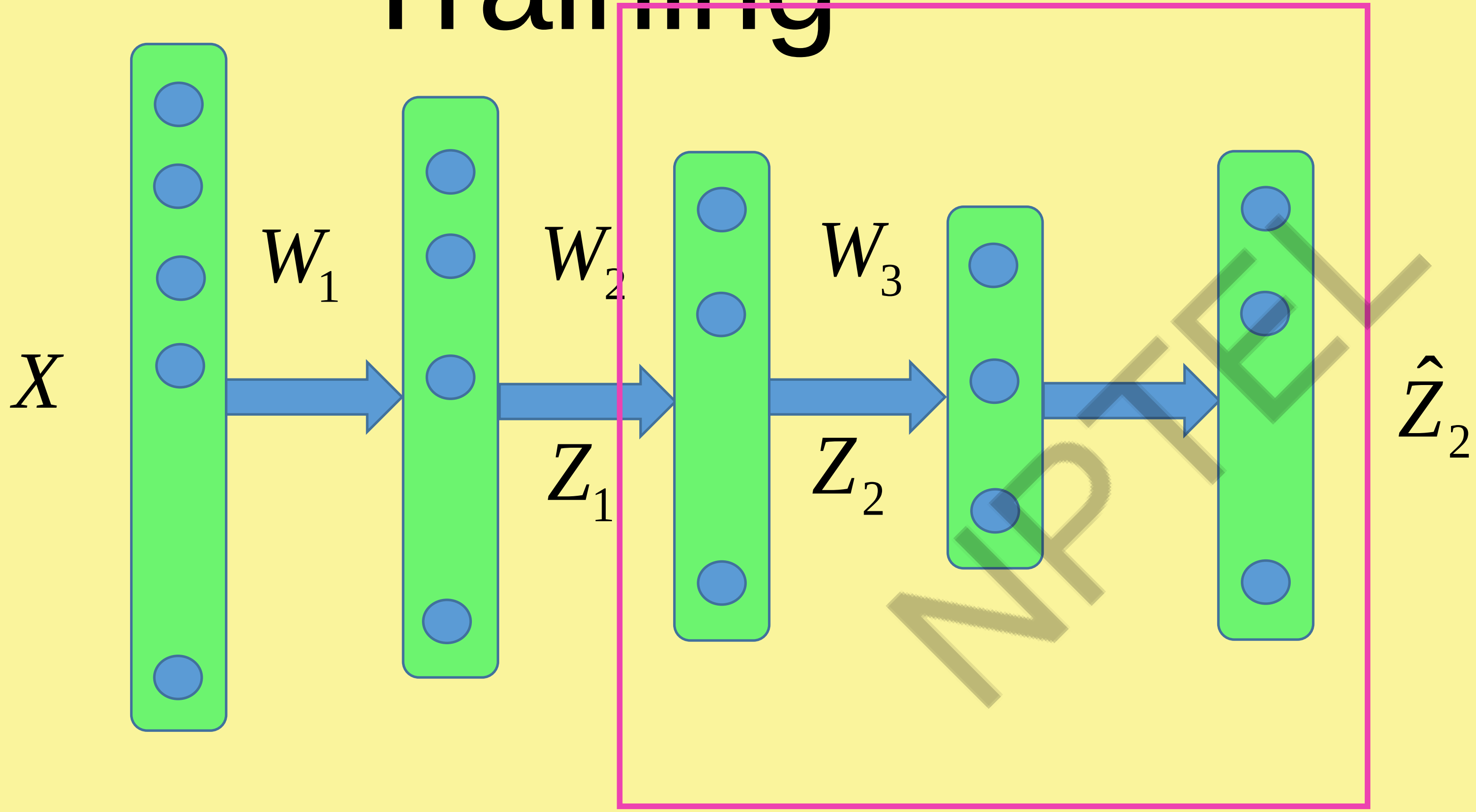
Autoencoder Training



Autoencoder Training

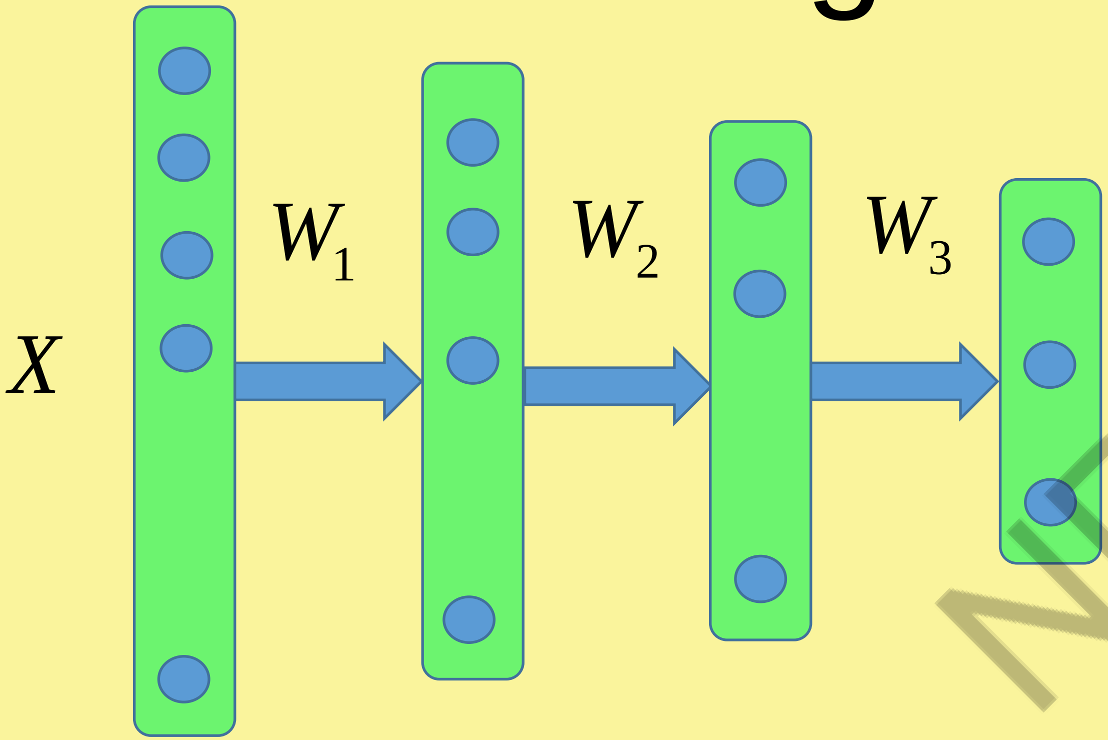


Autoencoder Training

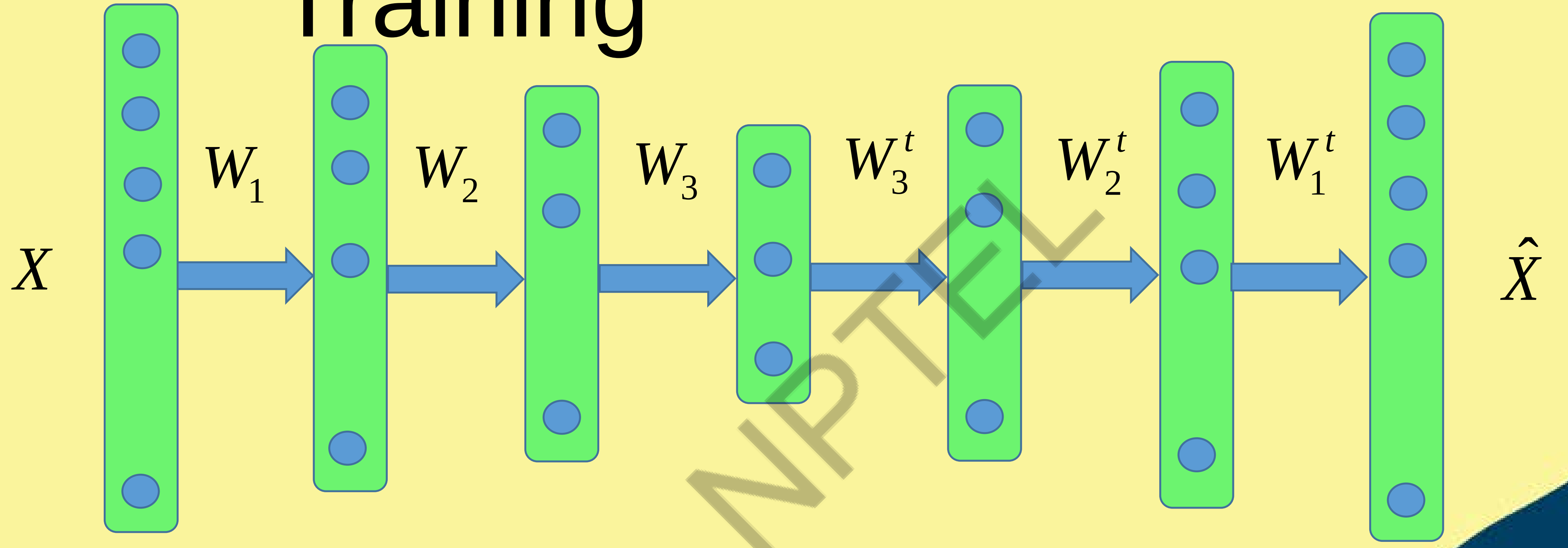


$L(Z_2, \hat{Z}_2)$

Autoencoder Training

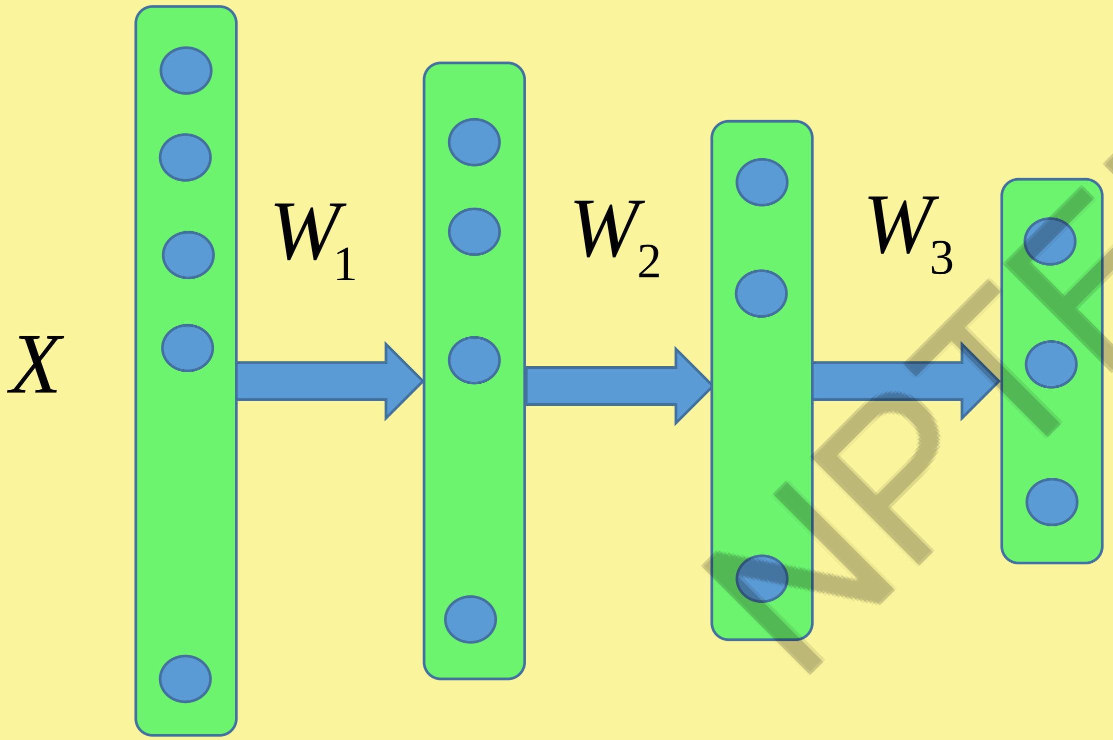


Autoencoder Training



$$L(X, \hat{X})$$

Applications



NPTEL ONLINE CERTIFICATION COURSES

Thank you

NPTEL ONLINE CERTIFICATION COURSES

Course Name: Deep Learning

Faculty Name: Prof. P. K. Biswas
Department : E & ECE, IIT Kharagpur

Topic

Lecture 32: Autoencoder Variants

CONCEPTS COVERED

Concepts Covered:

- Autoencoder
  - Undercomplete Autoencoder
  - Autoencoder vs. PCA
  - Deep Autoencoder Training
  - Sparse Autoencoder
  - Denoising Autoencoder
  - Contractive Autoencoder
  - Convolution Autoencoder

Sparse Autoencoder

Sparse Autoencoder

- Interesting features can be learnt even when number of nodes in the hidden layer is large.
- Introduce sparsity constraint on the hidden layer nodes that penalize activations within a layer.
- Network learns encoding-decoding that relies on activating a small number of neurons.

Regularizing Activations not the Weights

Sparsity Constraint

$a_j^h \rightarrow$ Activation of j^{th} Neuron in hidden layer h

$a_j^h \rightarrow 1 \Rightarrow$ Neuron is active

Average activation $\rightarrow \hat{\rho}_j = \frac{1}{m}\sum_{i=1}^{m} a_j^h(x_i)$

Constraint $\rightarrow \hat{\rho}_j = \rho$

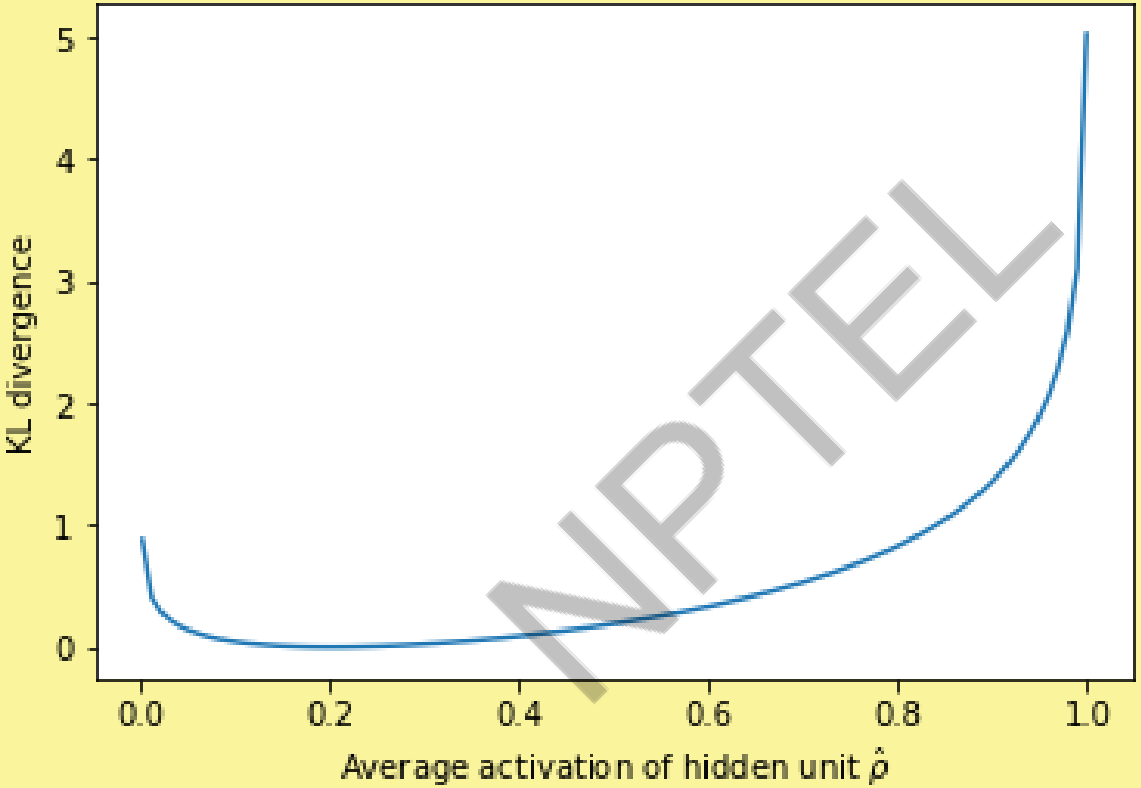
$\rho \rightarrow$ sparsity parameter (typically a small value)

Sparsity Constraint

$$\text{Regularizer}: \quad \sum_{j=1}^{N_h}\left[\rho\log\frac{\rho}{\hat{\rho}_j}+(1-\rho)\log\frac{1-\rho}{1-\hat{\rho}_j}\right] \Rightarrow \sum_{j=1}^{N_h} KL(\rho \,\|\, \hat{\rho}_j)$$

$$J_{sparse}(W) = L(X,\hat{X}) + \lambda\sum_{j} KL(\rho \,\|\, \hat{\rho}_j)$$

KL Divergence



https://www.jeremyjordan.me/autoencoders/

Sparsity Constraint

$$\delta_i^k = O_i^k(1-O_i^k)\sum_{j=1}^{M_{k+1}} \partial_j^{k+1} W_{ij}^{k+1}$$

$$\delta_i^k = O_i^k(1-O_i^k)\left[\left(\sum_{j=1}^{M_{k+1}} \partial_j^{k+1} W_{ij}^{k+1}\right) + \lambda\left(-\frac{\rho}{\hat{\rho}_i} + \frac{1-\rho}{1-\hat{\rho}_i}\right)\right]$$

Denoising Autoencoder

Denoising Autoencoder

- The Autoencoder learns a generalizable encoding-decoding scheme.
- An approach:- while training use corrupt data as input but output as uncorrupted original data.
- The model can not memorize the training data as input and target output is not same any more
- The Model learns a vector field to map the input data towards a low dimensional manifold.

NPTEL ONLINE CERTIFICATION COURSES

Thank you

NPTEL ONLINE CERTIFICATION COURSES

Course Name: Deep Learning

Faculty Name: Prof. P. K. Biswas
Department : E & ECE, IIT Kharagpur

Topic

Lecture 33: Autoencoder Variants

CONCEPTS COVERED

Concepts Covered:

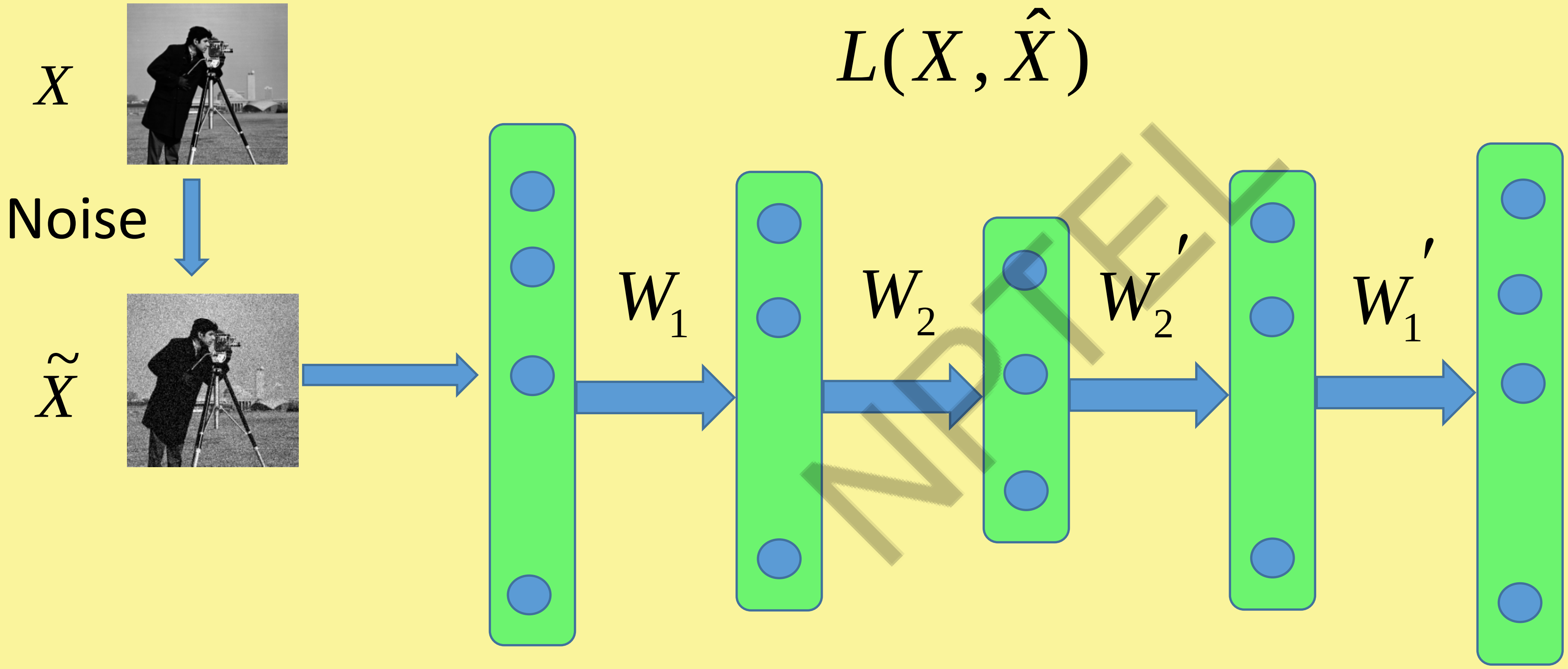
- Autoencoder
  - Undercomplete Autoencoder
  - Autoencoder vs. PCA
  - Deep Autoencoder Training
  - Sparse Autoencoder
  - Denoising Autoencoder
  - Contractive Autoencoder
  - Convolution Autoencoder

Denoising Autoencoder

Denoising Autoencoder

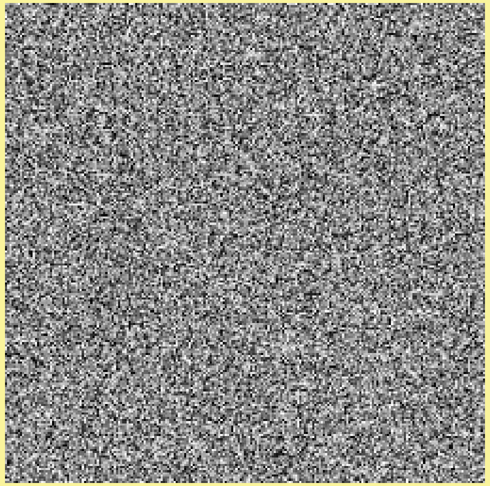
- ❖ The Autoencoder learns a generalizable encoding-decoding scheme.
- ❖ An approach:- while training use corrupt data as input but output as uncorrupted original data.
- ❖ The model can not memorize the training data as input and target output is not same any more
- ❖ The Model learns a vector field to map the input data towards a low dimensional manifold.

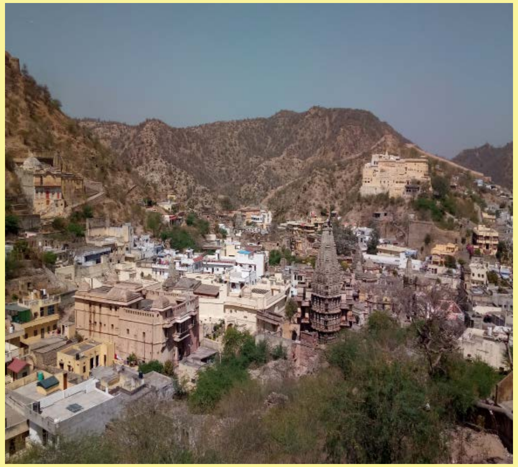
Denoising Autoencoder



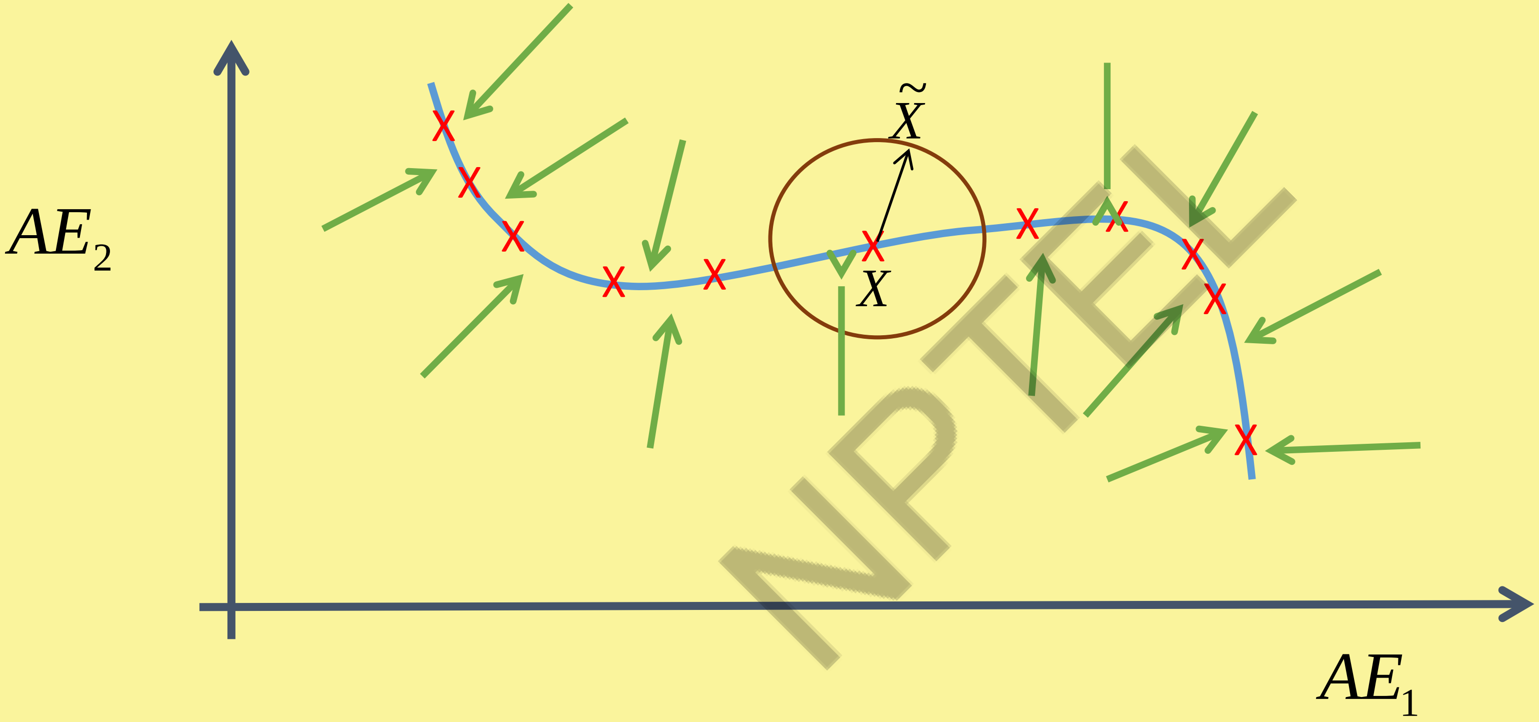
$$\hat{X} = r(X)$$
$$= g(f(\tilde{X}))$$

What is Manifold?





Manifold Learning



$r(x) - x$ Vector field

Contractive Autoencoder

Contractive Autoencoder

- For similar inputs- learned encoding (compressed domain representation should also be very similar.
- Hidden layer activation variation with input data should be small.

Effectively the Model learns to contract a neighborhood of Inputs to a small neighborhood of Outputs

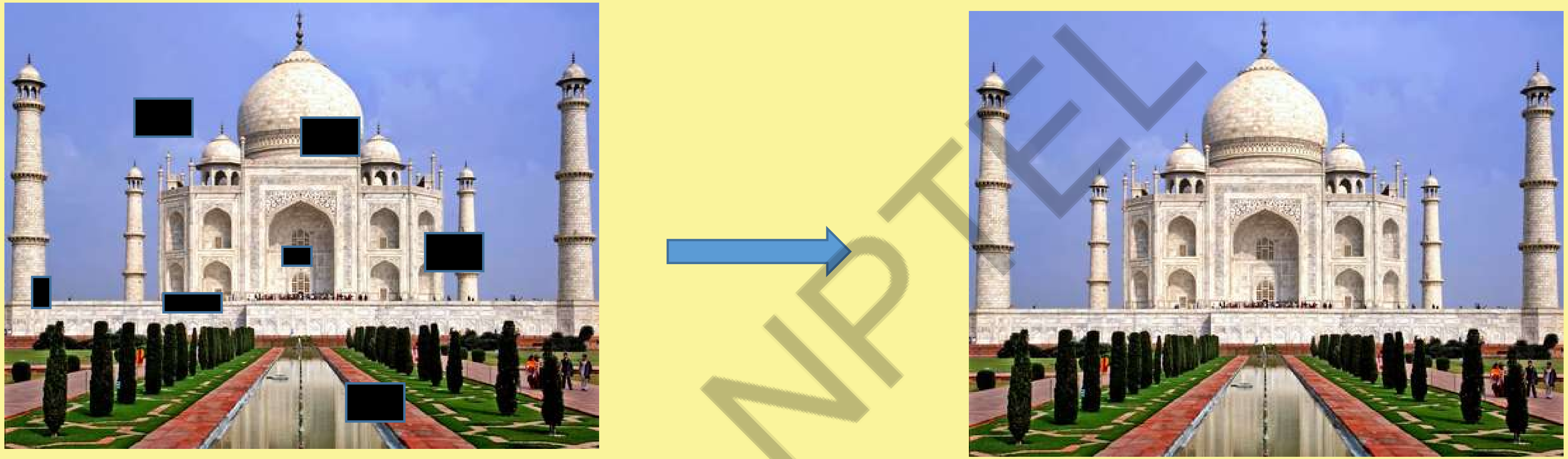
Regularization

$$\|A\|_F = \sqrt{\sum_{j=1}^{m}\sum_{i=1}^{N_h}|a_{ij}|^2}$$

$$J = \begin{bmatrix} \frac{\partial a_1^h(X)}{\partial x_1} & \frac{\partial a_1^h(X)}{\partial x_2} & .. & \frac{\partial a_1^h(X)}{\partial x_m} \\ \frac{\partial a_2^h(X)}{\partial x_1} & \frac{\partial a_2^h(X)}{\partial x_2} & .. & \frac{\partial a_2^h(X)}{\partial x_m} \\ .. & .. & .. & .. \\ \frac{\partial a_{N_h}^h(X)}{\partial x_1} & \frac{\partial a_{N_h}^h(X)}{\partial x_2} & .. & \frac{\partial a_{N_h}^h(X)}{\partial x_m} \end{bmatrix}$$

$$L(X,\hat{X}) + \lambda \sum_{i=1}^{N_h} \| \nabla_X a_i^h(X) \|^2$$

Applications



NPTEL ONLINE CERTIFICATION COURSES

NPTEL ONLINE CERTIFICATION COURSES

Course Name: Deep Learning

Faculty Name: Prof. P. K. Biswas
Department : E & ECE, IIT Kharagpur

Topic

Lecture 34: Convolutional Neural Network

CONCEPTS COVERED

Concepts Covered:

- CNN
  - Convolution
  - Linear Time Invariant (LTI) System
  - Linear Shift Invariant (LSI) System
  - Cross Correlation

LTI/ LSI

Convolution

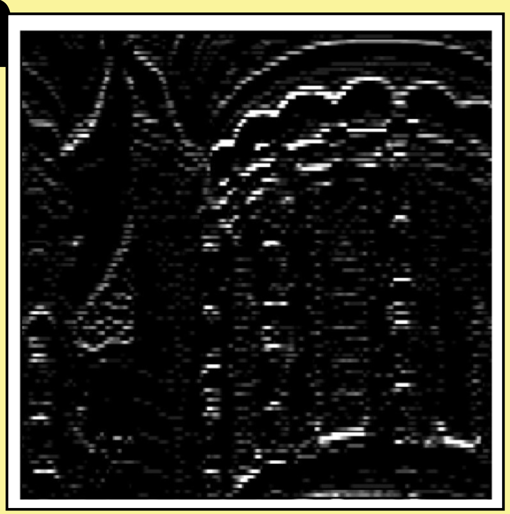
Convolution

-1	-2	-1
0	0	0
1	2	1

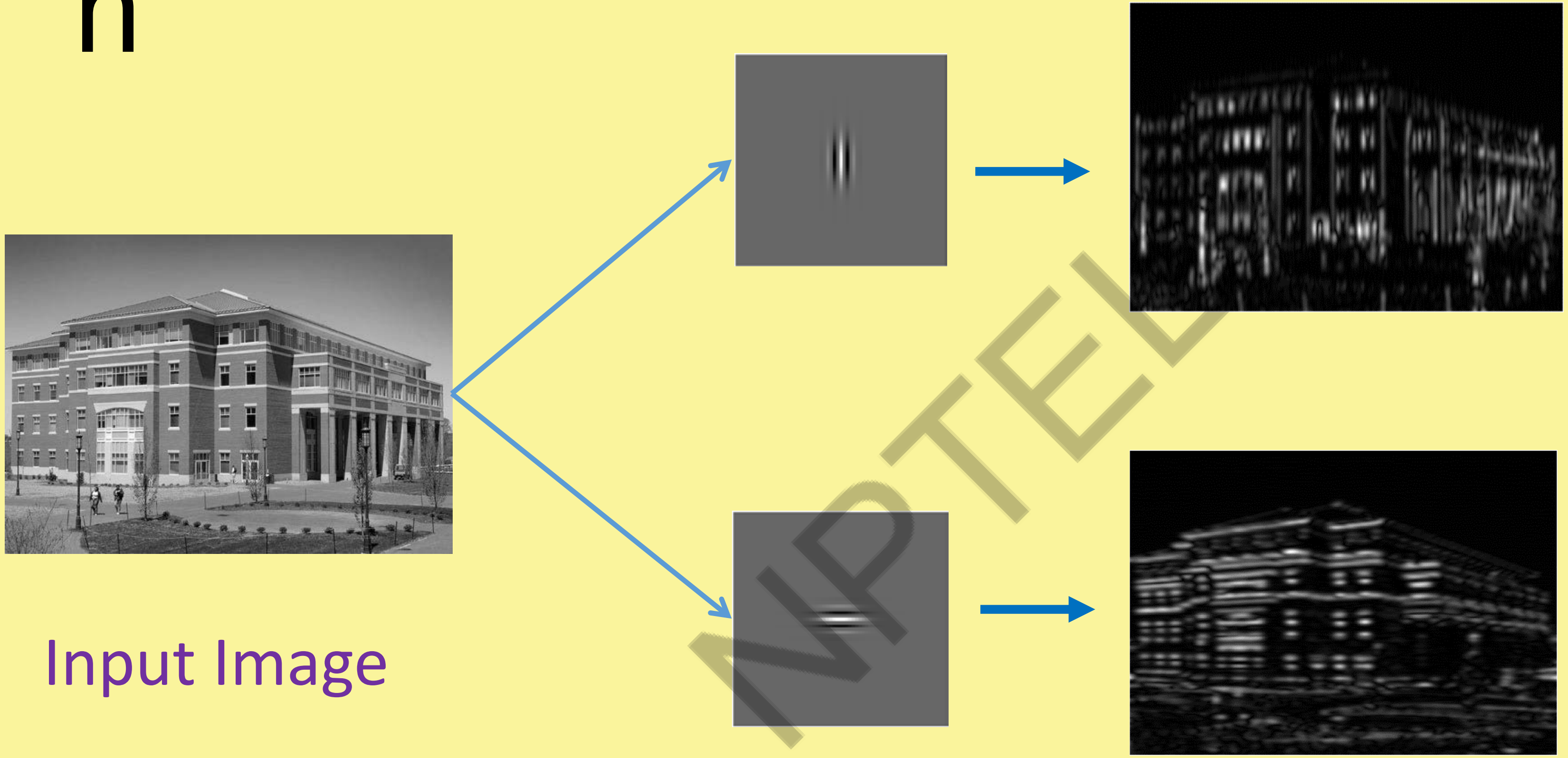
-1	0	1
-2	0	2
-1	0	1

Convolution

Convolution



Convolution



Input Image

Kernel

Feature Map

NPTEL ONLINE CERTIFICATION COURSES

Thank you

NPTEL ONLINE CERTIFICATION COURSES

Course Name: Deep Learning

Faculty Name: Prof. P. K. Biswas

Department : E & ECE, IIT Kharagpur

Topic

Lecture 35: Cross Correlation

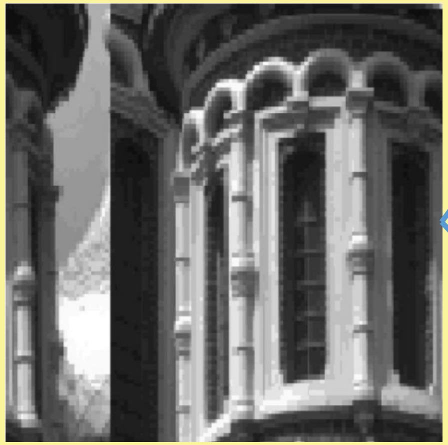
CONCEPTS COVERED

Concepts Covered:

- CNN
  - Convolution
  - Linear Time Invariant (LTI) System
  - Linear Shift Invariant (LSI) System
  - Cross Correlation

Convolution

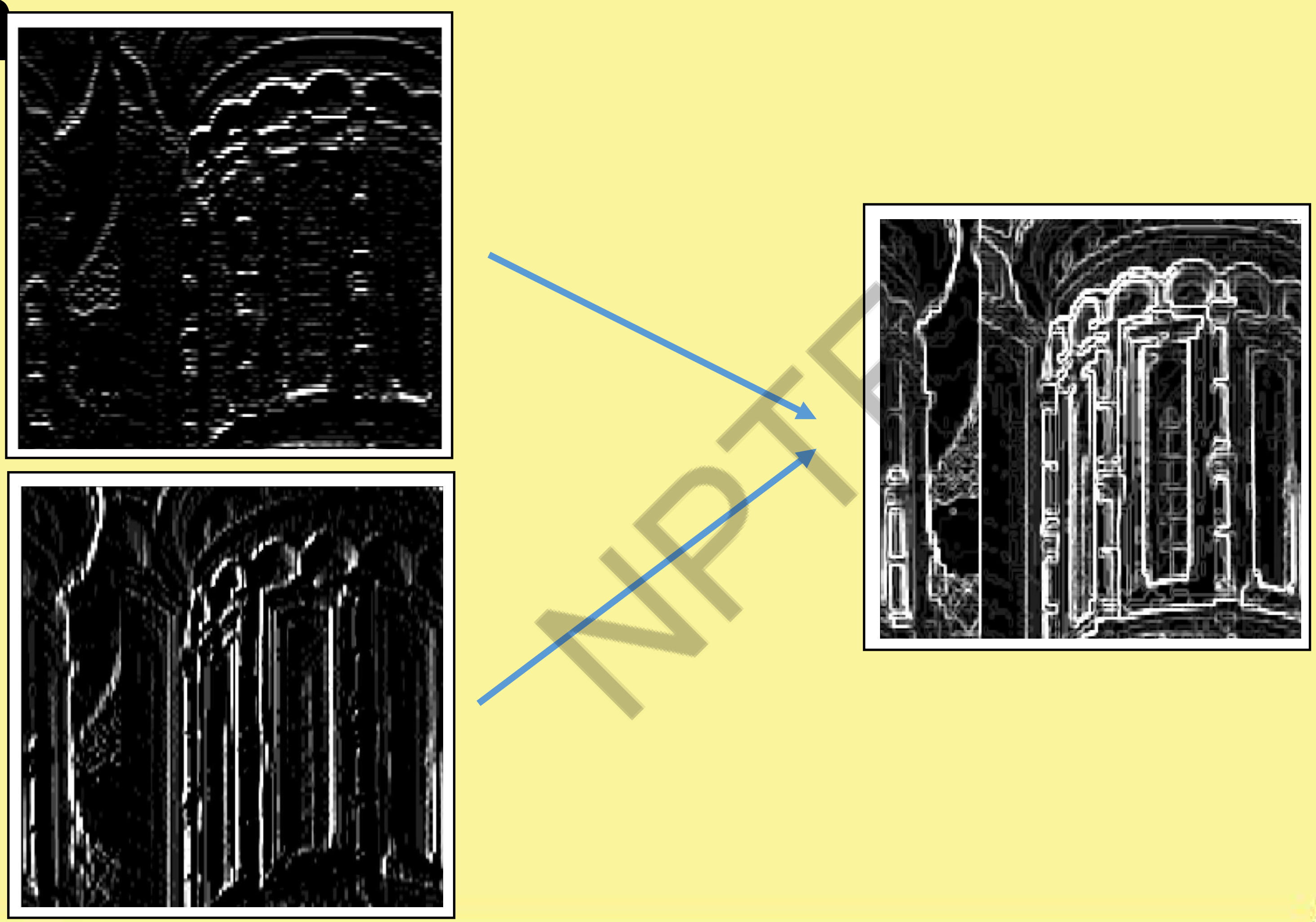
Convolution



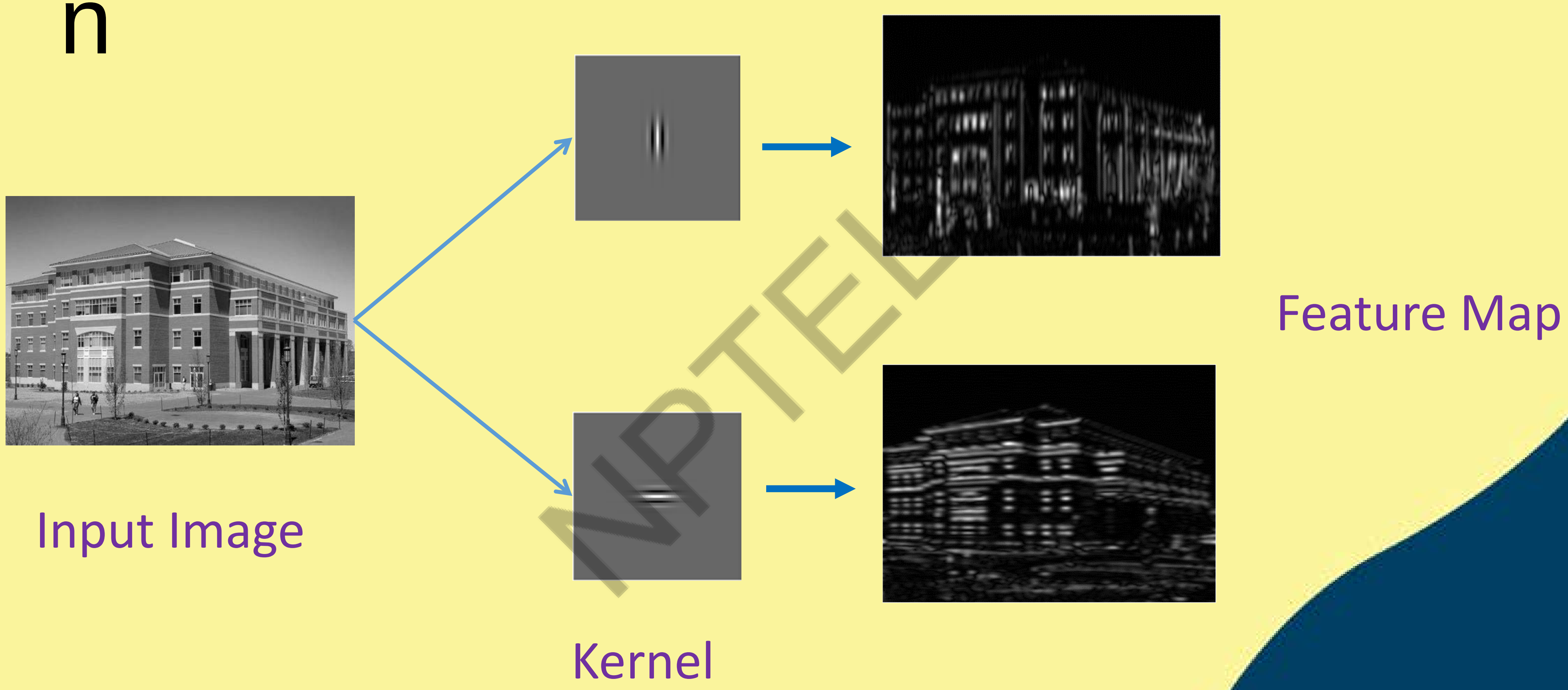
-1	-2	-1
0	0	0
1	2	1

-1	0	1
-2	0	2
-1	0	1

Convolution



Convolution



Cross Correlation

Cross Correlation

1	1	1	1	1	1
1	20	2	2	2	1
1	2	3	3	2	1
1	2	3	3	2	1
1	2	2	2	2	1
1	1	1	1	1	1

g

3	3	2
3	3	2
2	2	2

f

47	54	56	20	18	12
54	87	94	40	34	21
56	90	107	54	44	24
20	40	54	56	44	24
18	34	43	44	37	22
12	21	24	24	22	15

C_{fg}

Normalized Cross Correlation

$$C_{fg} \Big/ \left[\sum_u \sum_v g^2(x+u, y=v) \right]^{1/2}$$

Cross Correlation

$$\left[\sum_{u}\sum_{v} g^2(x+u, y+v)\right]^{\frac{1}{2}}$$

20.07	20.19	20.30	3.87	3.46	2.64
20.19	20.54	20.80	6.08	5.09	3.46
20.27	20.76	21.26	7.48	6.08	3.87
3.87	5.91	7.48	7.48	6.08	3.87
3.46	5.09	6.08	6.08	5.09	3.46
2.64	3.46	3.87	3.87	3.46	2.64

Cross Correlation

$$C_{fg}$$

$$\Big/ \left[\sum_{u}\sum_{v} g^2(x+u, y=v)\right]^{1/2}$$

2.34	2.67	2.75	5.16	5.2	4.54
2.67	4.2	4.51	6.5	6.67	6.06
2.76	4.33	5.03	7.2	7.23	6.2
5.16	6.76	7.21	7.48	7.23	6.2
5.2	6.67	7.07	7.23	7.26	6.35
4.54	6.06	6.20	6.20	6.35	5.68

1	1	1	1	1	1
1	20	2	2	2	1
1	2	3	3	2	1
1	2	3	3	2	1
1	2	2	2	2	1
1	1	1	1	1	1

NPTEL ONLINE CERTIFICATION COURSES

Thank you