NPTEL ONLINE CERTIFICATION COURSES

Course Name: Deep Learning

Faculty Name: Prof. P. K. Biswas

Department : E & ECE, IIT Kharagpur

Topic

Lecture 46: Normalization

CONCEPTS COVERED

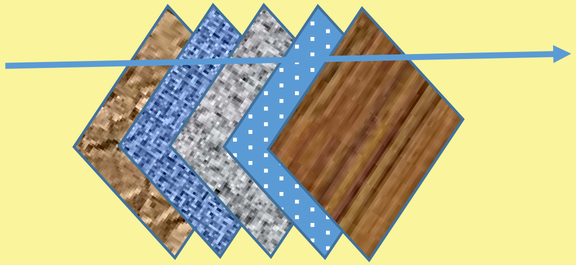
Concepts Covered:

- Deep Neural Network
  - Gradient Descent Challenges
  - Normalization
  - Batch Normalization
  - Layer Normalization
  - Instance Normalization
  - Group Normalization

Normalization

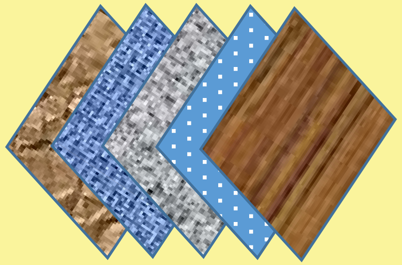
Local Response Normalization (Inter-Channel)

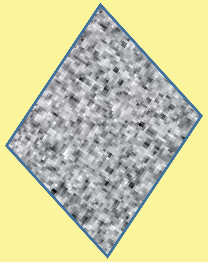
$$b_{x,y}^{i} = \frac{a_{x,y}^{i}}{\left(k + \alpha \sum_{j=\max(0,i-n/2)}^{\min(N-1,i+n/2)} \left(a_{x,y}^{j}\right)^2\right)^{\beta}}$$



Local Response Normalization (Intra-Channel)

$$b_{x,y}^{i} = \frac{a_{x,y}^{i}}{\left(k + \alpha \sum_{p=\max(0,x-n/2)}^{\max(W,x+n/2)} \sum_{q=\max(0,y-n/2)}^{\min(H,y+n/2)} \left(a_{p,q}^{i}\right)^{2}\right)^{\beta}}$$



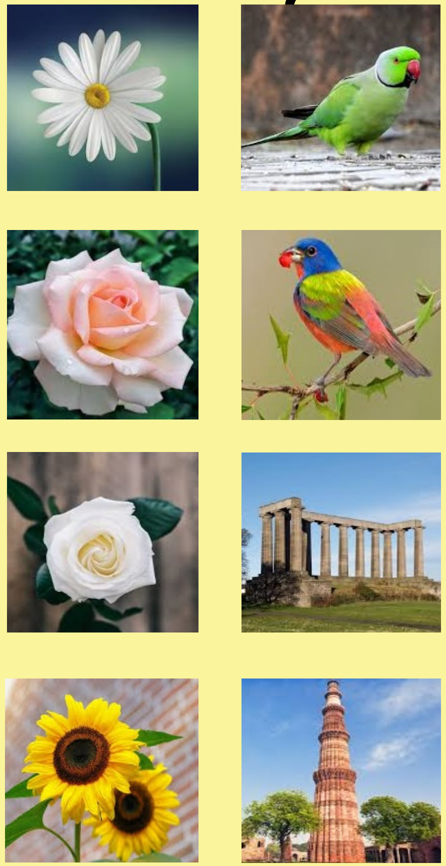


Normalization

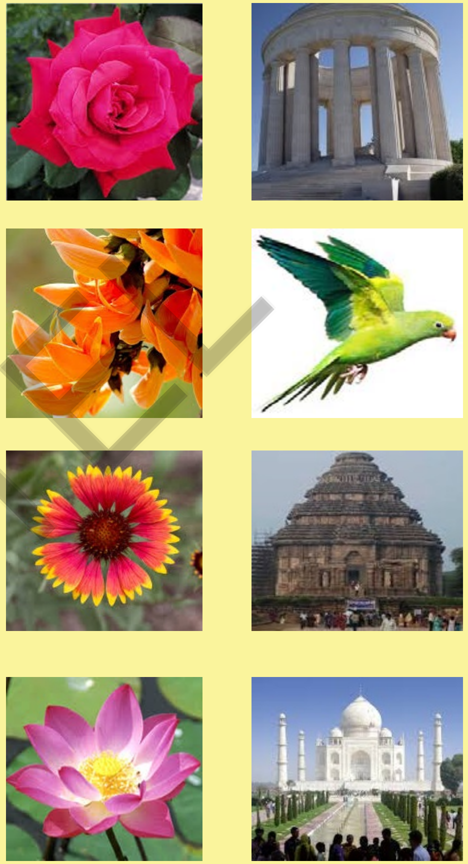
- Normalization that address the problem of covariate shift.
- Makes learning process faster.
- Different layers learn independently of others.

What does a classifier learn?

Why normalization ?



Batch 1



Batch 2

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Thank you

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Faculty Name: Prof. P. K. Biswas
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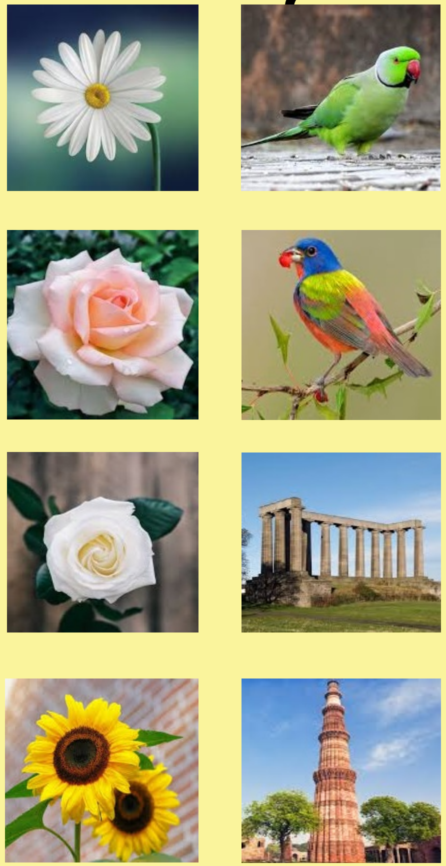
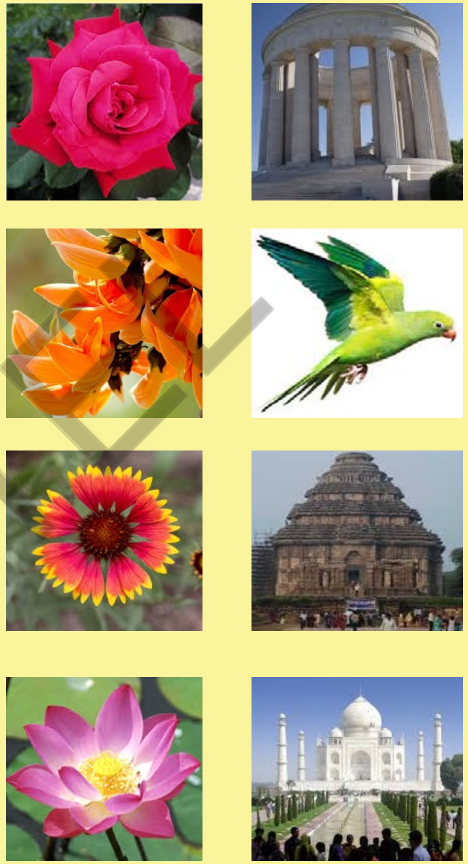
Topic

Lecture 47

Why normalization ?



Batch 1



Batch 2

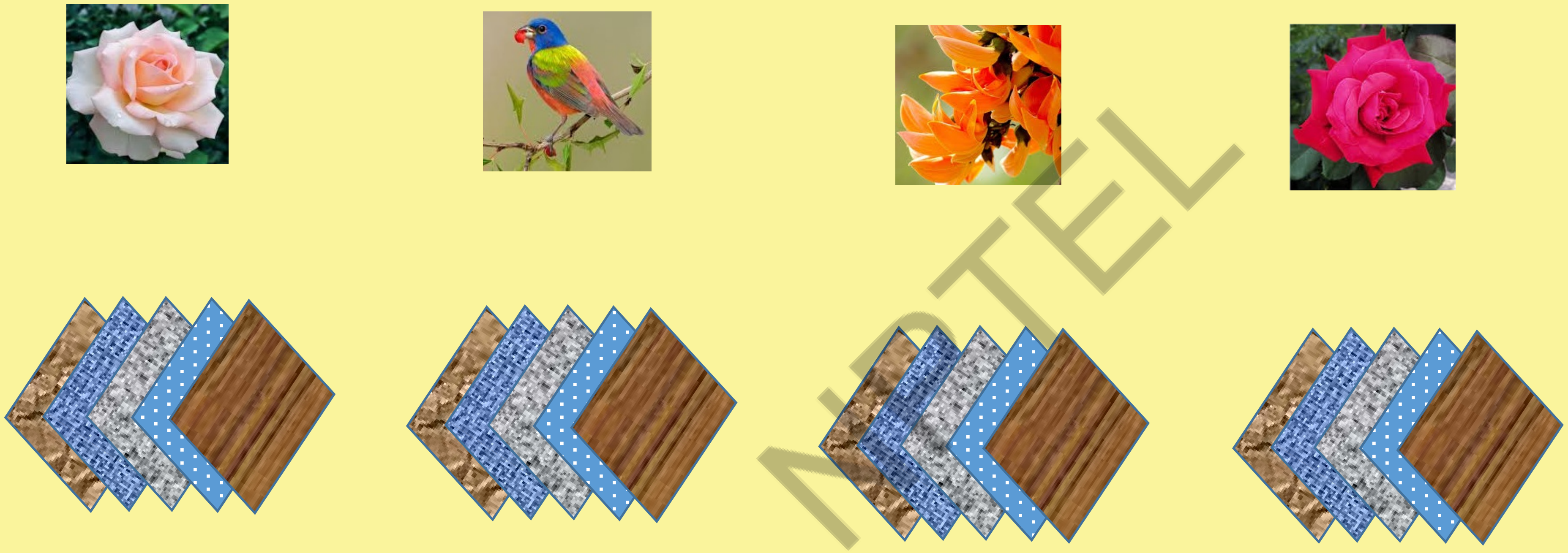
Normalization In Hidden Layers

Different normalization techniques

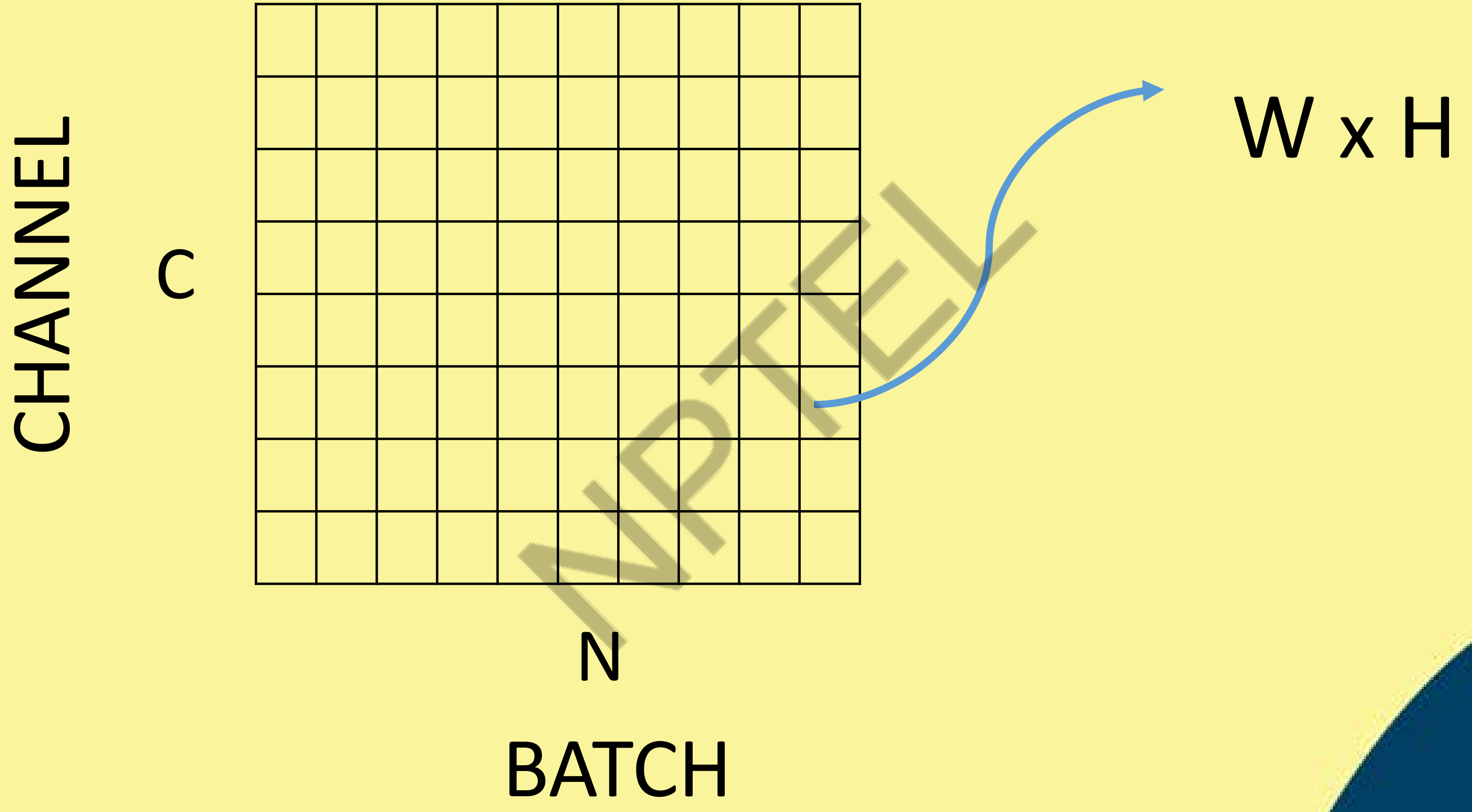
- Batch Normalization
- Layer Normalization
- Instance Normalization
- Group Normalization

Batch Normalization

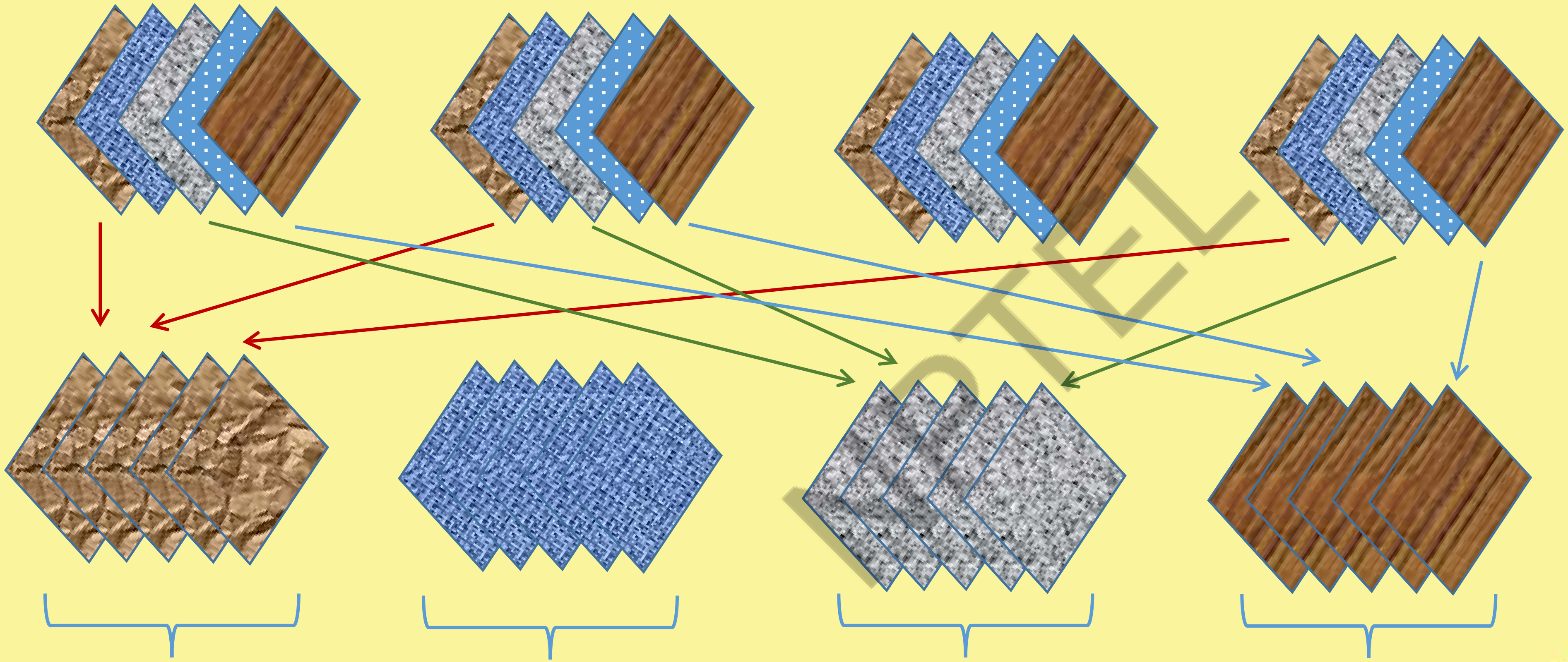
Batch Normalization



Normalization



Batch Normalization



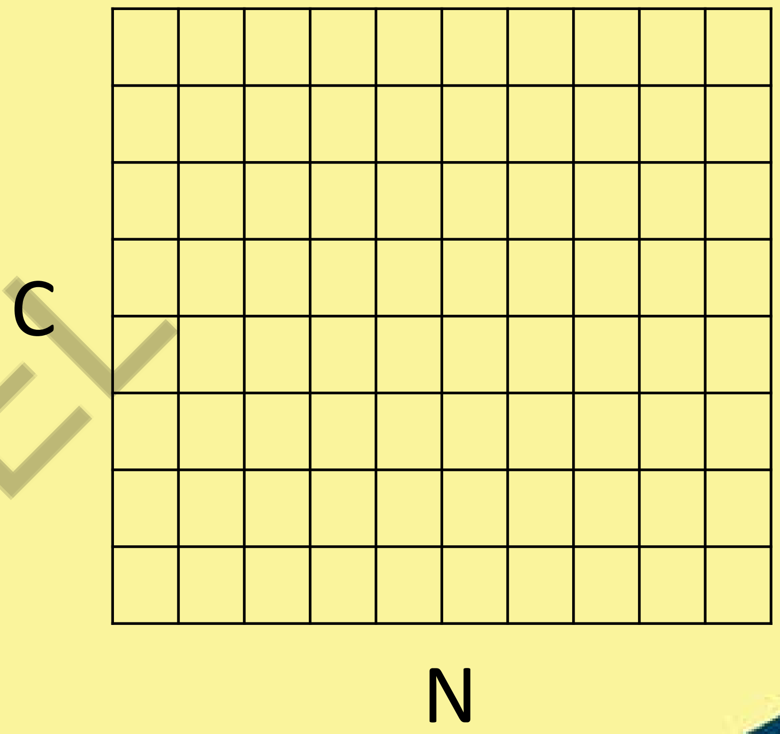
Batch Normalization

$$x \in \mathbb{R}^{N \times C \times W \times H}$$

$$\mu_C = \frac{1}{NWH} \sum_{i=1}^{N} \sum_{j=1}^{W} \sum_{k=1}^{H} x_{iCjk}$$

$$\sigma_C^2 = \frac{1}{NWH} \sum_{i=1}^{N} \sum_{j=1}^{W} \sum_{k=1}^{H} (x_{iCjk} - \mu_C)^2$$

$$\hat{x} = \frac{x - \mu_C}{\sqrt{\sigma_C^2 + \epsilon}}$$



Batch Normalization

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma\widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Batch Normalization

$$\frac{\partial \ell}{\partial \widehat{x}_i} = \frac{\partial \ell}{\partial y_i} \cdot \gamma$$

$$\frac{\partial \ell}{\partial \sigma_{\mathcal{B}}^2} = \sum_{i=1}^{m} \frac{\partial \ell}{\partial \widehat{x}_i} \cdot (x_i - \mu_{\mathcal{B}}) \cdot \frac{-1}{2}(\sigma_{\mathcal{B}}^2 + \epsilon)^{-3/2}$$

$$\frac{\partial \ell}{\partial \mu_{\mathcal{B}}} = \left(\sum_{i=1}^{m} \frac{\partial \ell}{\partial \widehat{x}_i} \cdot \frac{-1}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \right) + \frac{\partial \ell}{\partial \sigma_{\mathcal{B}}^2} \cdot \frac{\sum_{i=1}^{m} -2(x_i - \mu_{\mathcal{B}})}{m}$$

$$\frac{\partial \ell}{\partial x_i} = \frac{\partial \ell}{\partial \widehat{x}_i} \cdot \frac{1}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} + \frac{\partial \ell}{\partial \sigma_{\mathcal{B}}^2} \cdot \frac{2(x_i - \mu_{\mathcal{B}})}{m} + \frac{\partial \ell}{\partial \mu_{\mathcal{B}}} \cdot \frac{1}{m}$$

$$\frac{\partial \ell}{\partial \gamma} = \sum_{i=1}^{m} \frac{\partial \ell}{\partial y_i} \cdot \widehat{x}_i$$

$$\frac{\partial \ell}{\partial \beta} = \sum_{i=1}^{m} \frac{\partial \ell}{\partial y_i}$$

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Thank you

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Course Name: Deep Learning

Faculty Name: Prof. P. K. Biswas

Department : E & ECE, IIT Kharagpur

Topic

Lecture 48: Normalization - III

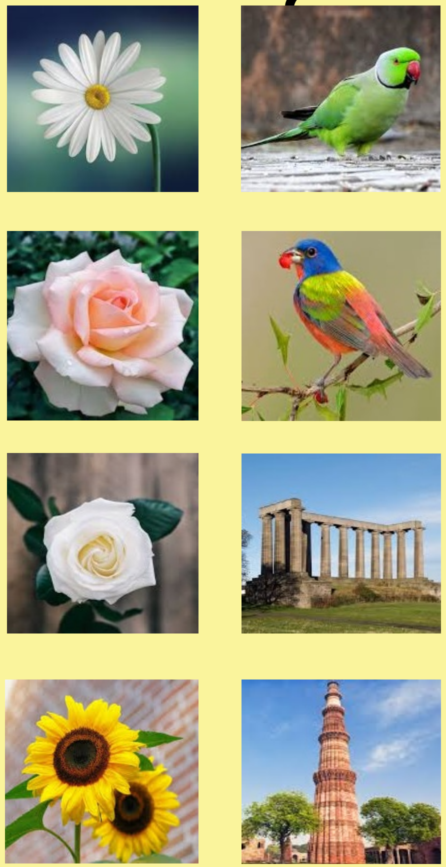
CONCEPTS COVERED

Concepts Covered:

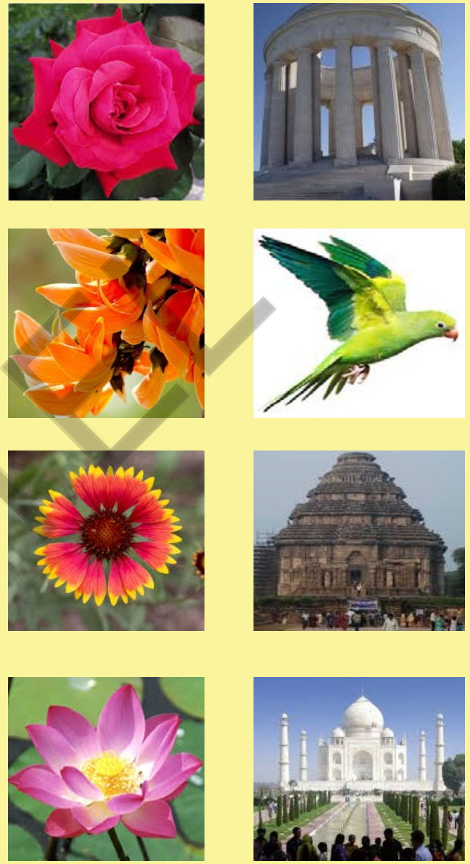
- Deep Neural Network
  - Normalization
  - Batch Normalization
  - Layer Normalization
  - Instance Normalization
  - Group Normalization

Normalization

Why normalization ?



Batch 1



Batch 2

Normalization In Hidden Layers

Different normalization techniques

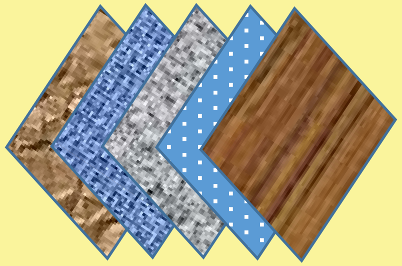
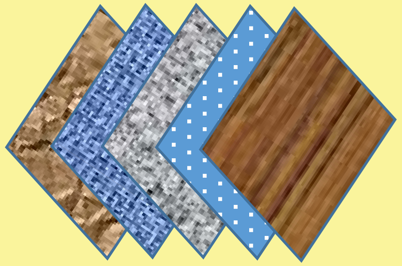
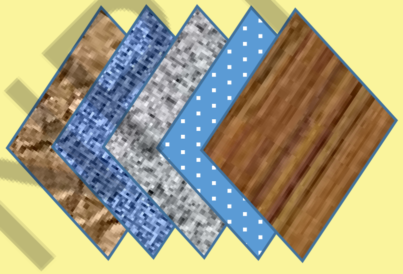
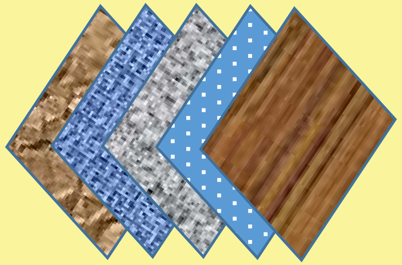
- Batch Normalization
- Layer Normalization
- Instance Normalization
- Group Normalization

Batch Normalization

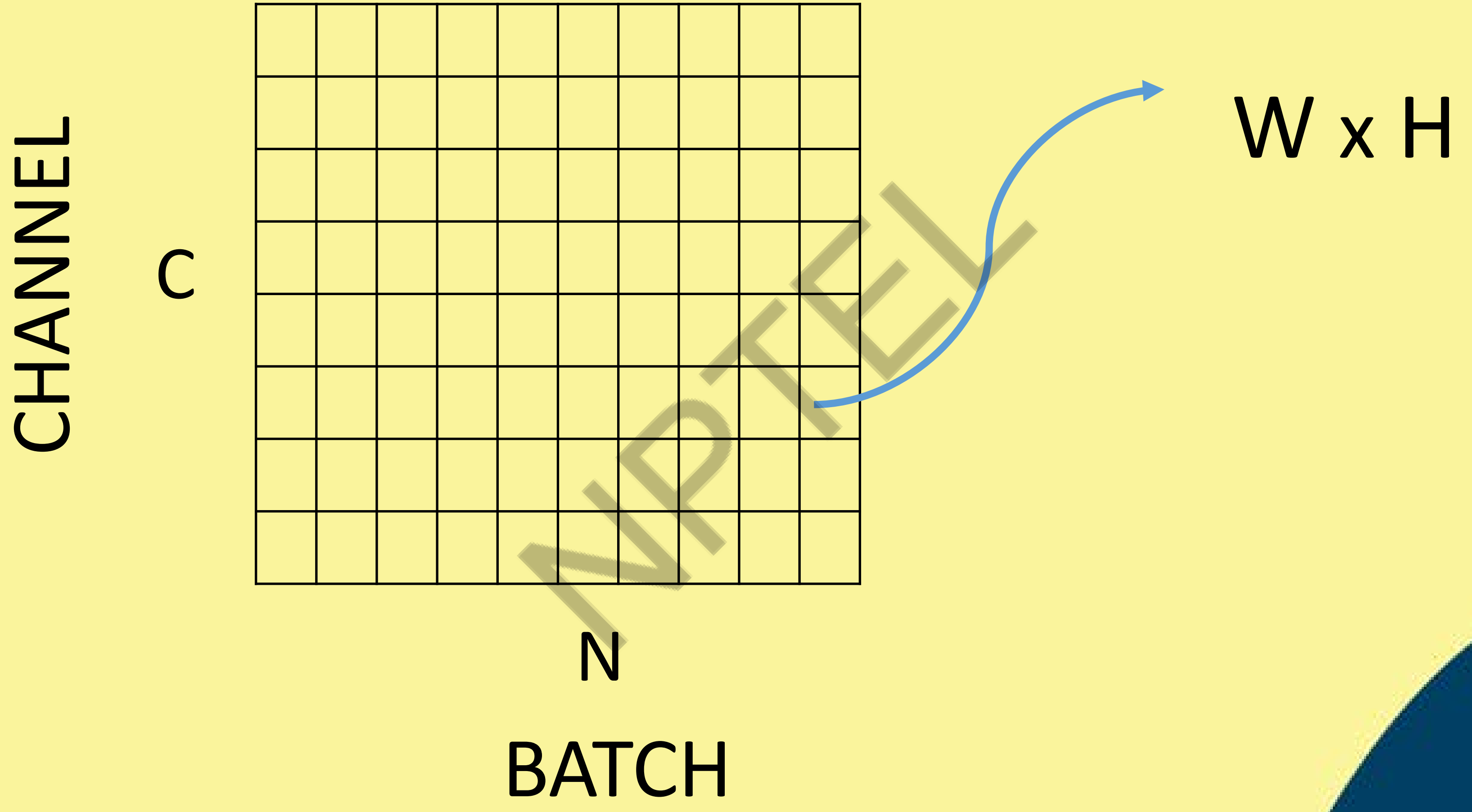
Batch Normalization



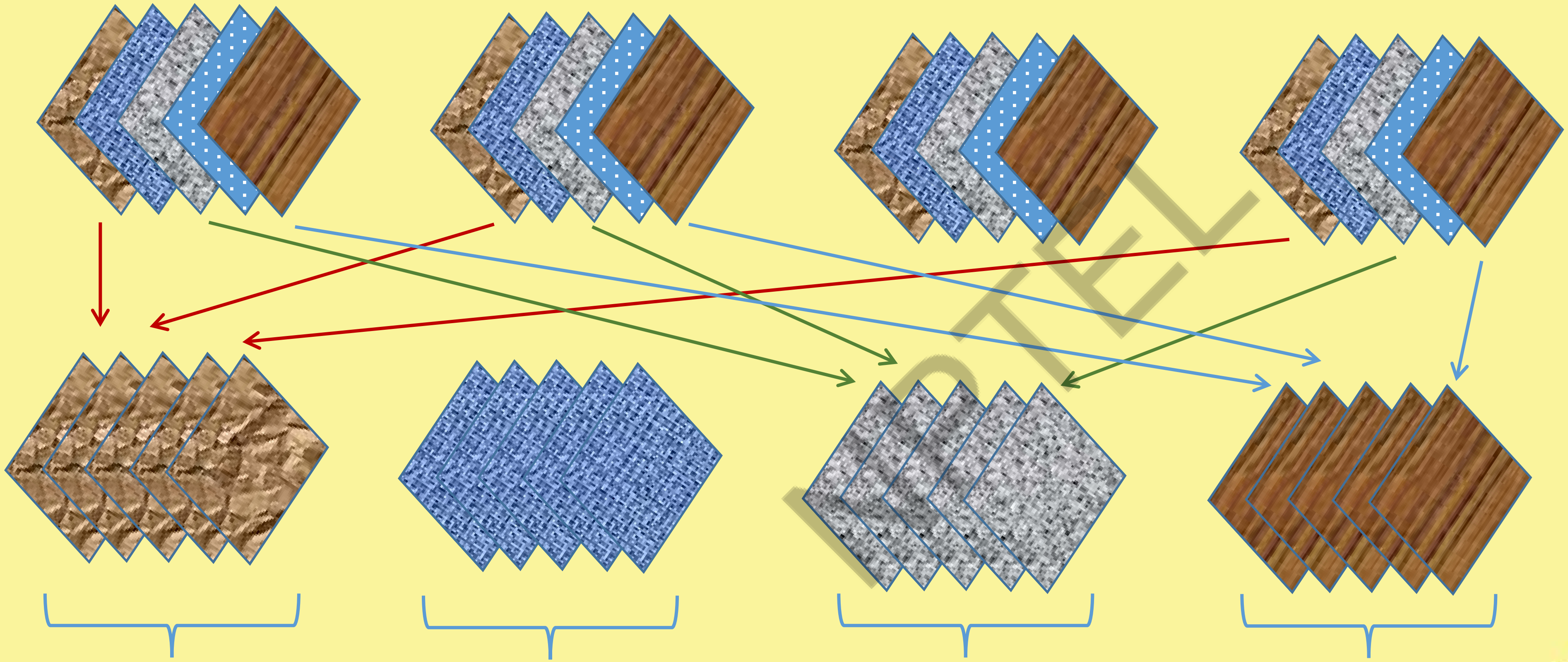


Normalization



Batch Normalization



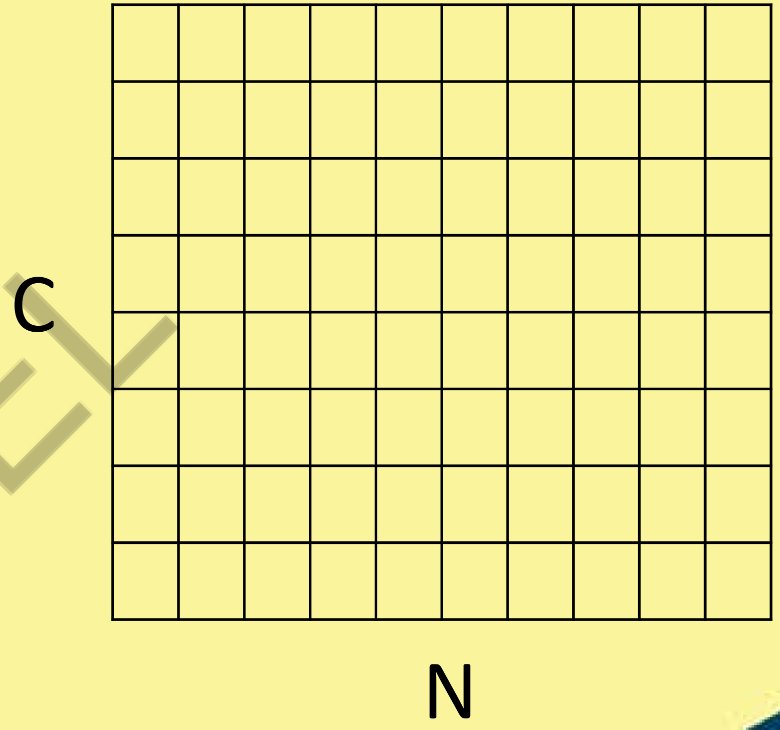
Batch Normalization

$$x \in \mathbb{R}^{N \times C \times W \times H}$$

$$\mu_C = \frac{1}{NWH} \sum_{i=1}^{N} \sum_{j=1}^{W} \sum_{k=1}^{H} x_{iCjk}$$

$$\sigma_C^2 = \frac{1}{NWH} \sum_{i=1}^{N} \sum_{j=1}^{W} \sum_{k=1}^{H} (x_{iCjk} - \mu_C)^2$$

$$\hat{x} = \frac{x - \mu_C}{\sqrt{\sigma_C^2 + \epsilon}}$$



Batch Normalization

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1\ldots m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Batch Normalization

$$\frac{\partial \ell}{\partial \widehat{x}_i} = \frac{\partial \ell}{\partial y_i} \cdot \gamma$$

$$\frac{\partial \ell}{\partial \sigma_{\mathcal{B}}^2} = \sum_{i=1}^{m} \frac{\partial \ell}{\partial \widehat{x}_i} \cdot (x_i - \mu_{\mathcal{B}}) \cdot \frac{-1}{2}(\sigma_{\mathcal{B}}^2 + \epsilon)^{-3/2}$$

$$\frac{\partial \ell}{\partial \mu_{\mathcal{B}}} = \left(\sum_{i=1}^{m} \frac{\partial \ell}{\partial \widehat{x}_i} \cdot \frac{-1}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \right) + \frac{\partial \ell}{\partial \sigma_{\mathcal{B}}^2} \cdot \frac{\sum_{i=1}^{m} -2(x_i - \mu_{\mathcal{B}})}{m}$$

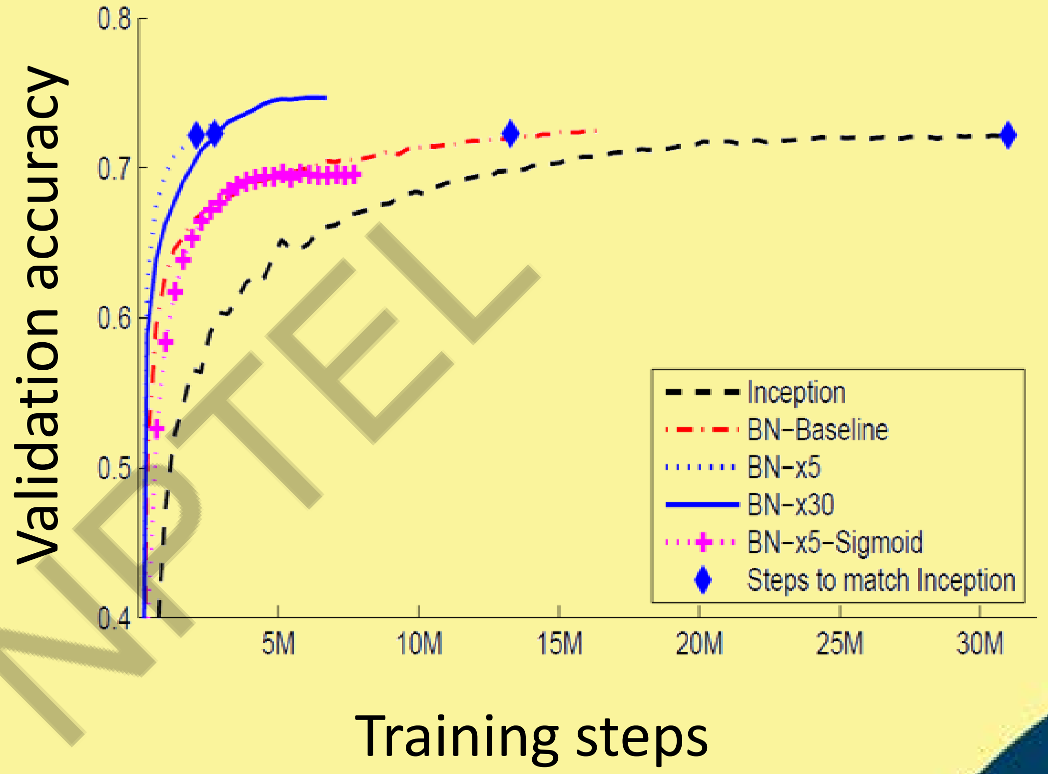
$$\frac{\partial \ell}{\partial x_i} = \frac{\partial \ell}{\partial \widehat{x}_i} \cdot \frac{1}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} + \frac{\partial \ell}{\partial \sigma_{\mathcal{B}}^2} \cdot \frac{2(x_i - \mu_{\mathcal{B}})}{m} + \frac{\partial \ell}{\partial \mu_{\mathcal{B}}} \cdot \frac{1}{m}$$

$$\frac{\partial \ell}{\partial \gamma} = \sum_{i=1}^{m} \frac{\partial \ell}{\partial y_i} \cdot \widehat{x}_i$$

$$\frac{\partial \ell}{\partial \beta} = \sum_{i=1}^{m} \frac{\partial \ell}{\partial y_i}$$

Effect of Batch Normalization

- **Inception:** A network, trained with the initial learning rate of 0.0015.
- **BN-Baseline:** Same as Inception with Batch Normalization before each nonlinearity.
- **BN-x5:** The initial learning rate was
- increased by a factor of 5, to 0.0075.
- **BN-x30:** Like BN-x5, but with the initial learning rate 0.045 (30 times that of Inception).
- **BN-x5-Sigmoid:** Like BN-x5, but with sigmoid nonlinearity instead of ReLU.



Ioffe, Sergey, and Christian Szegedy. "Batch normalization: Accelerating deep network training by reducing internal covariate shift." arXiv preprint arXiv:1502.03167 (2015)

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Thank you

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Course Name: Deep Learning

Faculty Name: Prof. P. K. Biswas

Department : E & ECE, IIT Kharagpur

Topic

Lecture 49: Normalization - IV

CONCEPTS COVERED

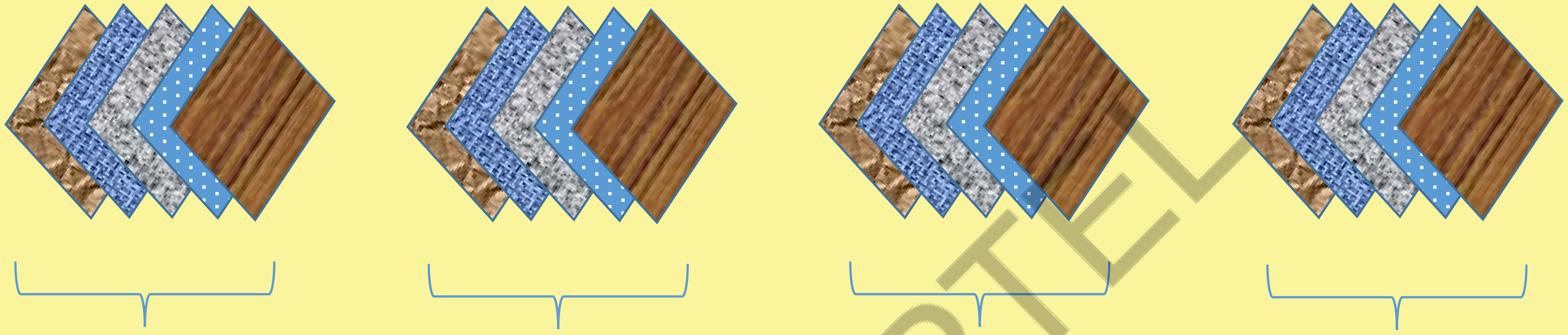
Concepts Covered:

- Deep Neural Network
    - Normalization
    - Batch Normalization
    - Layer Normalization
    - Instance Normalization
    - Group Normalization

Normalization

Layer Normalization

Layer Normalization



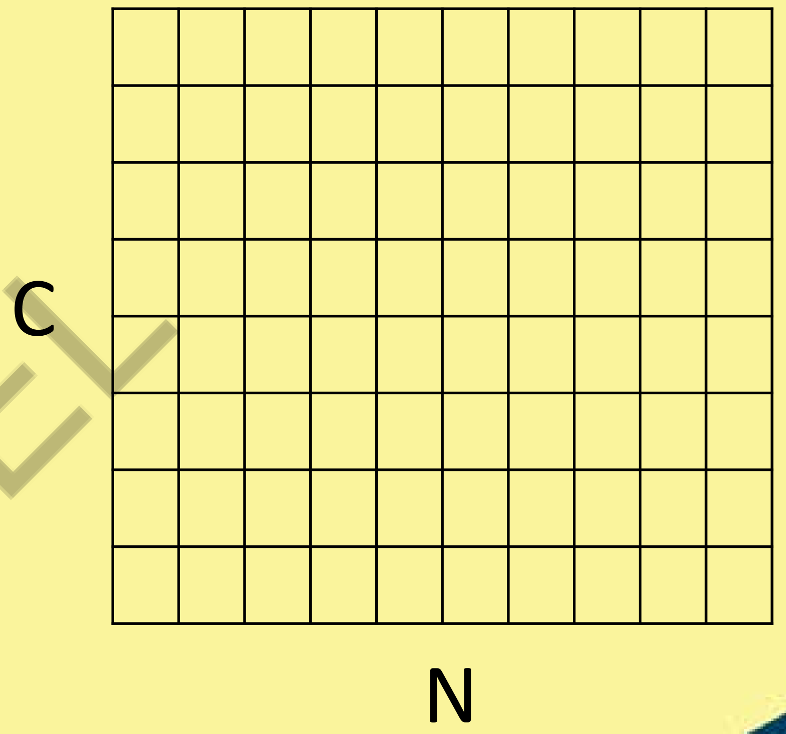
Layer Normalization

$$x \in \mathbb{R}^{N \times C \times W \times H}$$

$$\mu_N = \frac{1}{CWH} \sum_{i=1}^{C} \sum_{j=1}^{W} \sum_{k=1}^{H} x_{Nijk}$$

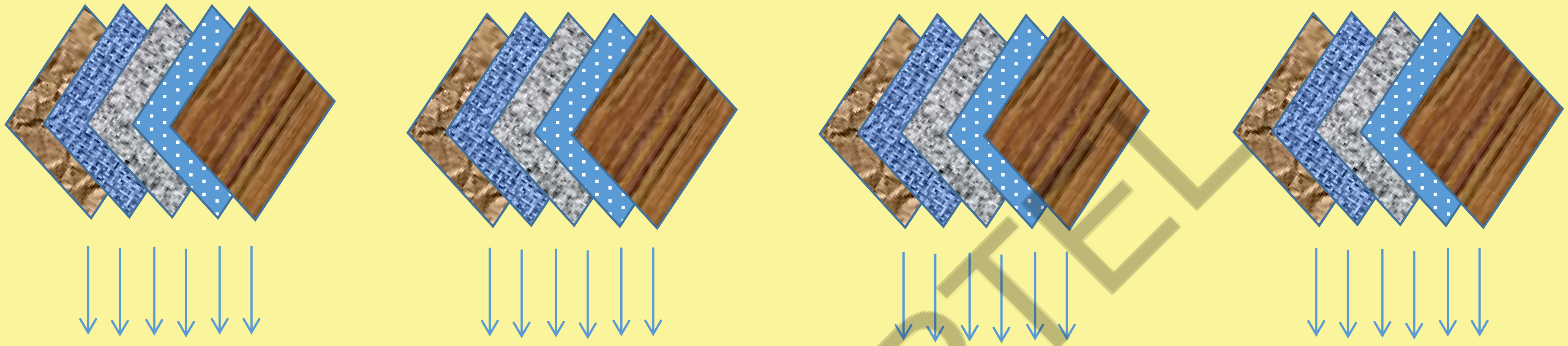
$$\sigma_N^2 = \frac{1}{CWH} \sum_{i=1}^{C} \sum_{j=1}^{W} \sum_{k=1}^{H} (x_{Nijk} - \mu_N)^2$$

$$\hat{x} = \frac{x - \mu_N}{\sqrt{\sigma_N^2 + \epsilon}}$$



Instance Normalization

Instance Normalization



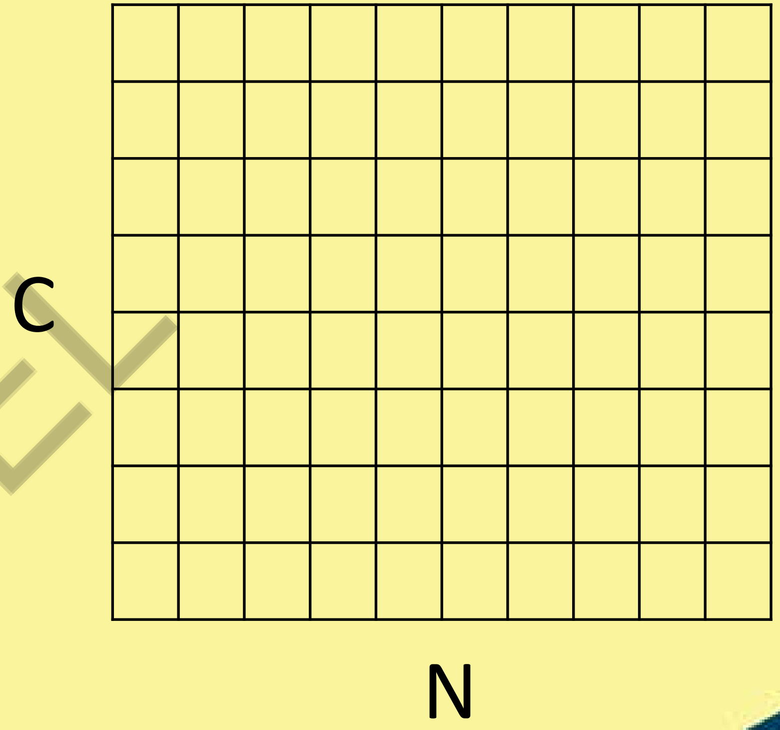
Instance Normalization

$x \in \mathbb{R}^{N\times C\times W\times H}$

$$\mu_{NC} = \frac{1}{WH}\sum_{j=1}^{W}\sum_{k=1}^{H} x_{Nijk}$$

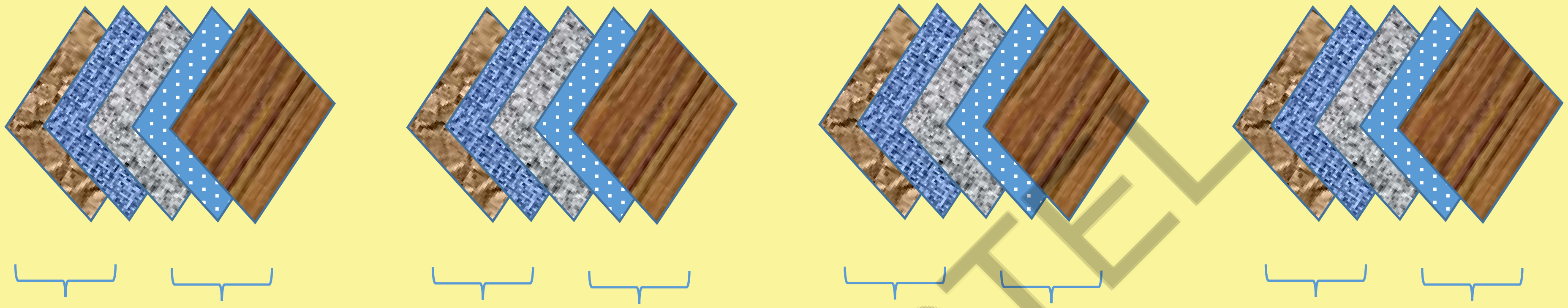
$$\sigma_{NC}^2 = \frac{1}{WH}\sum_{j=1}^{W}\sum_{k=1}^{H} (x_{Nijk} - \mu_N)^2$$

$$\hat{x} = \frac{x - \mu_{NC}}{\sqrt{\sigma_{NC}^2 + \epsilon}}$$



Group Normalization

Group Normalization



Group Normalization

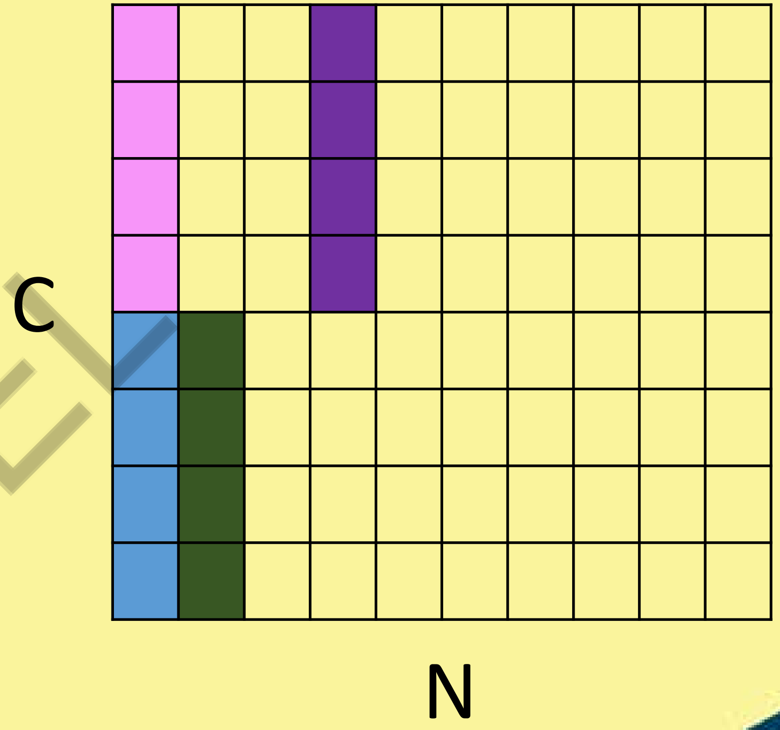
$x \in \mathbb{R}^{N\times C\times W\times H} \rightarrow \mathbb{R}^{N\times G\times C'\times W\times H} \quad C = G.C'$

G=number of groups

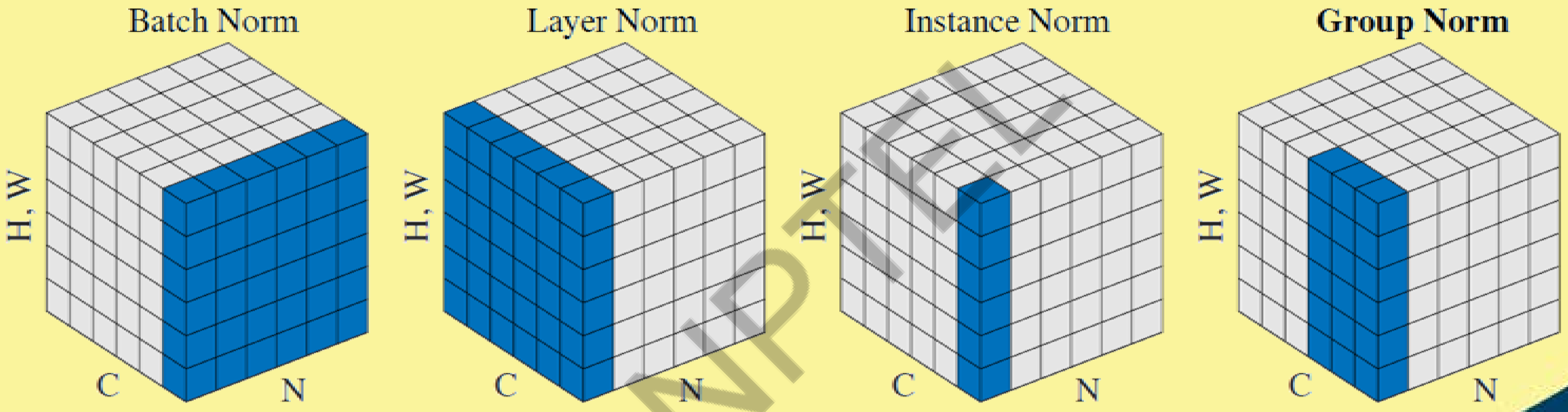
C'=number of channel per group

$$\mu_{NG} = \frac{1}{C'WH}\sum_{i=1}^{C'}\sum_{j=1}^{W}\sum_{k=1}^{H} x_{NGijk}$$

$$\sigma_{NG}^2 = \frac{1}{C'WH}\sum_{i=1}^{C'}\sum_{j=1}^{W}\sum_{k=1}^{H} (x_{NGijk} - \mu_{NG})^2$$

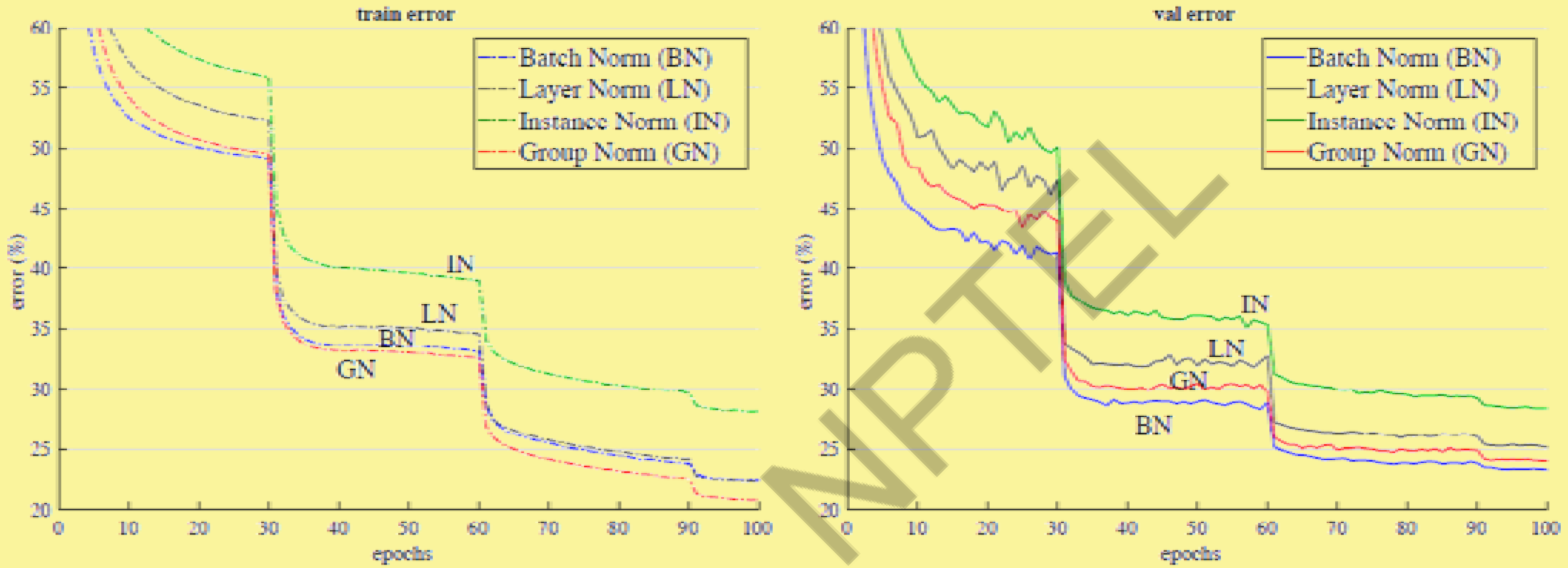


$$\hat{x} = \frac{x - \mu_{NG}}{\sqrt{\sigma_{NG}^2 + \epsilon}}$$



https://mlexplained.com/2018/11/30/an-overview-of-normalization-methods-in-deep-learning/

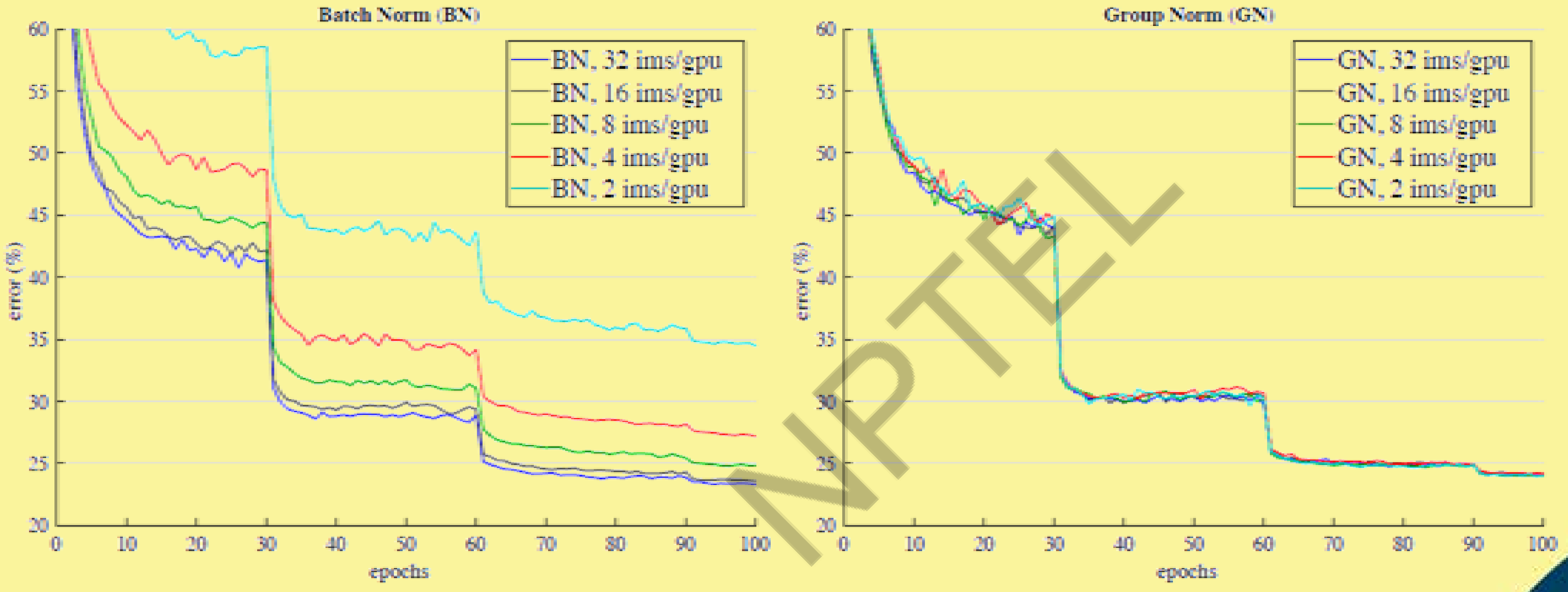
BN/LN/IN/GN Normalization



Model Name: Resnet-50, Dataset: Imagenet, Batch size: 32

Wu, Yuxin, and Kaiming He. "Group normalization." Proceedings of the European Conference on Computer Vision (ECCV). 2018.

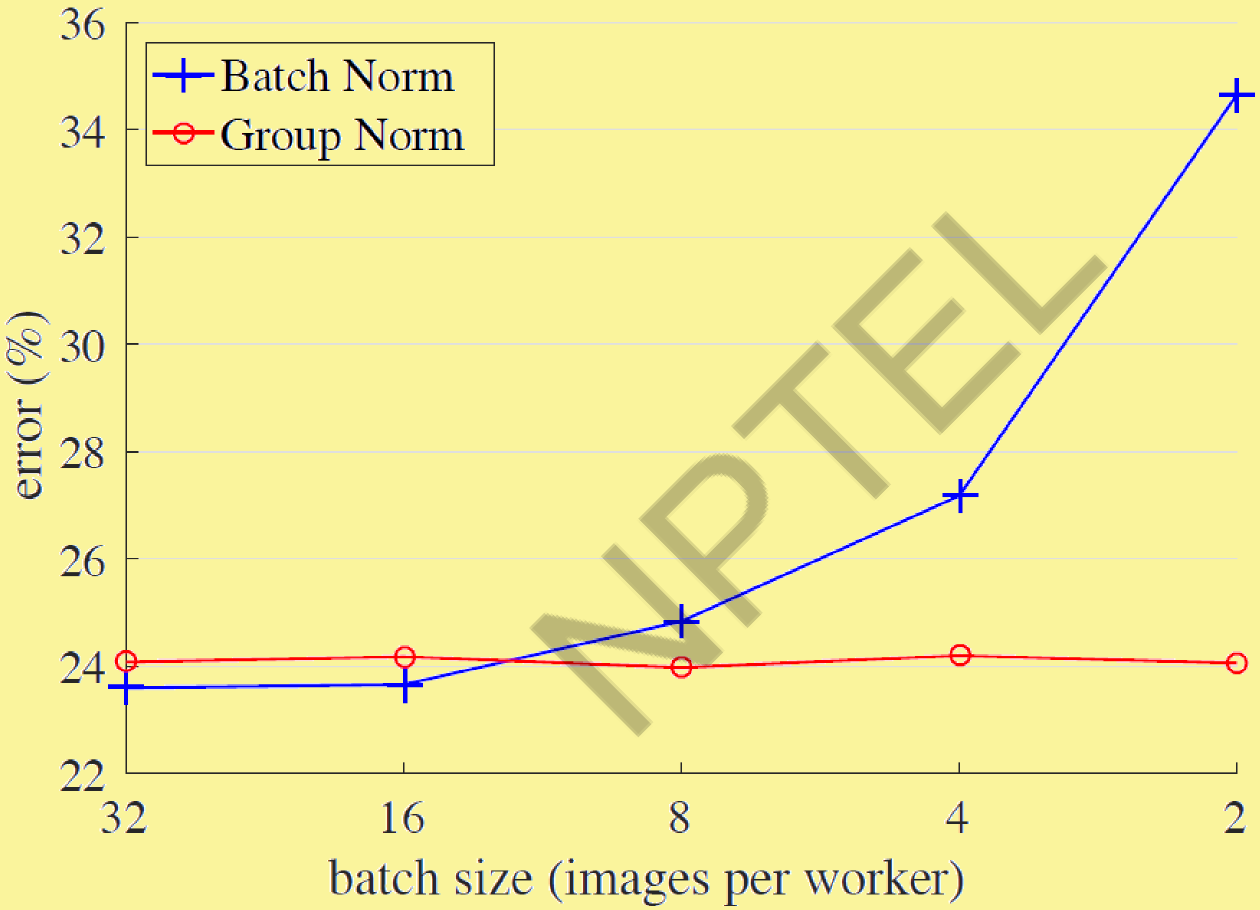
Batch/Group Normalization



Model Name: Resnet-50, Dataset: Imagenet

Wu, Yuxin, and Kaiming He. "Group normalization." Proceedings of the European Conference on Computer Vision (ECCV). 2018.

Batch/Group Normalization



Wu, Yuxin, and Kaiming He. "Group normalization." Proceedings of the European Conference on Computer Vision (ECCV). 2018.

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Course Name: Deep Learning

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

Topic

Lecture 50: Training Tricks

CONCEPTS COVERED

Concepts Covered:

- Deep Neural Network
  - Normalization
  - Underfitting/Ovefitting
  - Regularization
  - Dropout
  - Early Stopping

Regularization
Early stopping

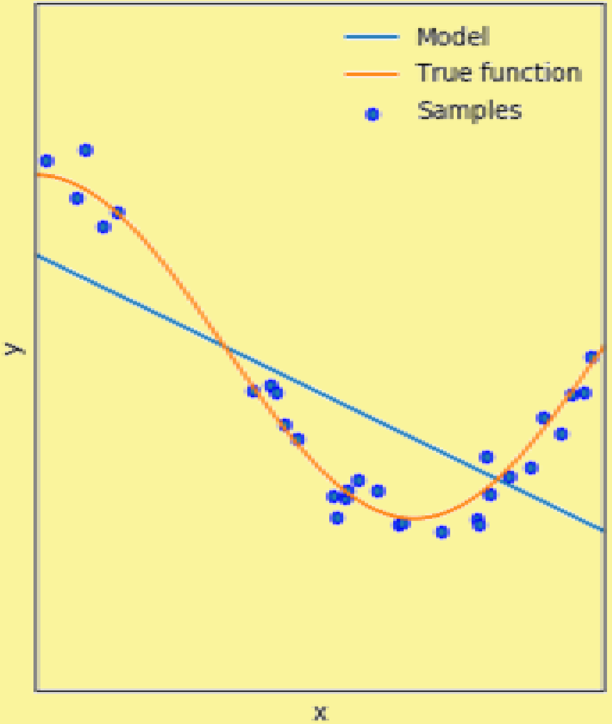
Overfitting/Underfitting

- Overfitting occurs when a statistical model or machine learning algorithm captures the noise of the data.
- Intuitively, overfitting occurs when the model or the algorithm fits the data too well.

- A statistical model or a machine learning algorithm is said to have underfitting when it cannot capture the underlying trend of the data.

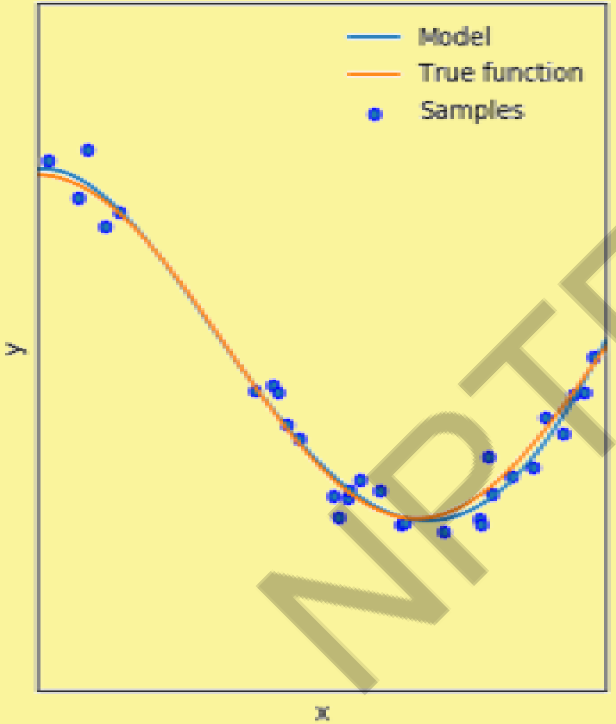
Overfitting/Underfitting: Regression

Degree: 1



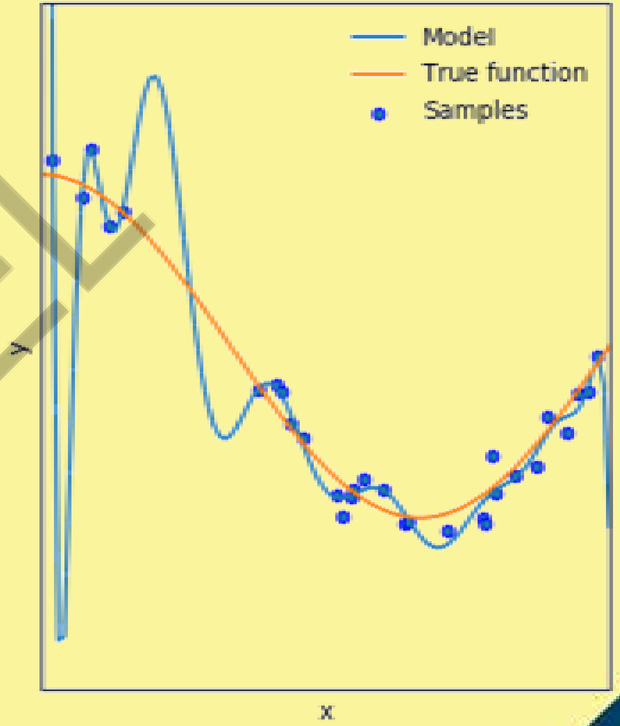
Underfit

Degree: 4



Perfectly fit

Degree: 15



Overfit

Image Source: Internet

Overfitting/Underfitting: Classification

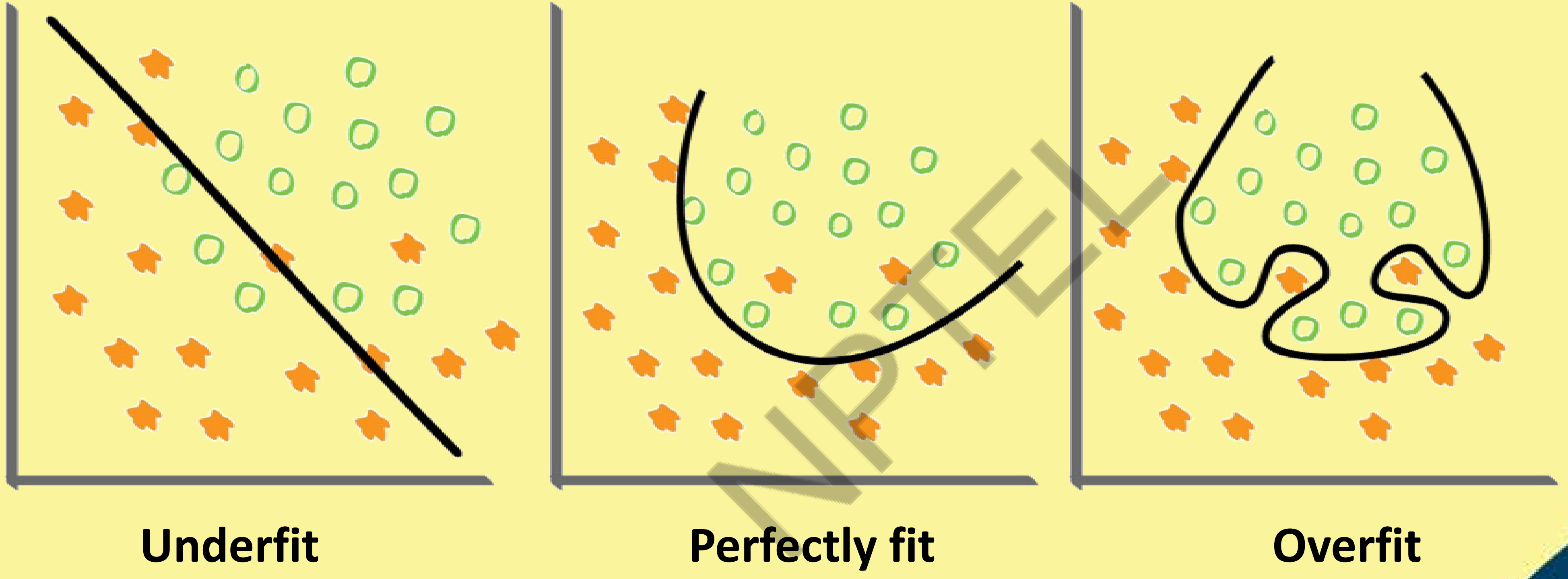


Image Source: Internet

Regularization

- Regularization is a way to prevent overfitting.
- L1 and L2 are the most common types of regularization used in training deep models.
- General cost function with regularization for training is defined as: Cost function = Loss + Regularization term
- Due to this regularization term, the numerical values of weights decrease because it assumes that a neural network with smaller weights leads to simpler models.
- So this helps to reduce overfitting.

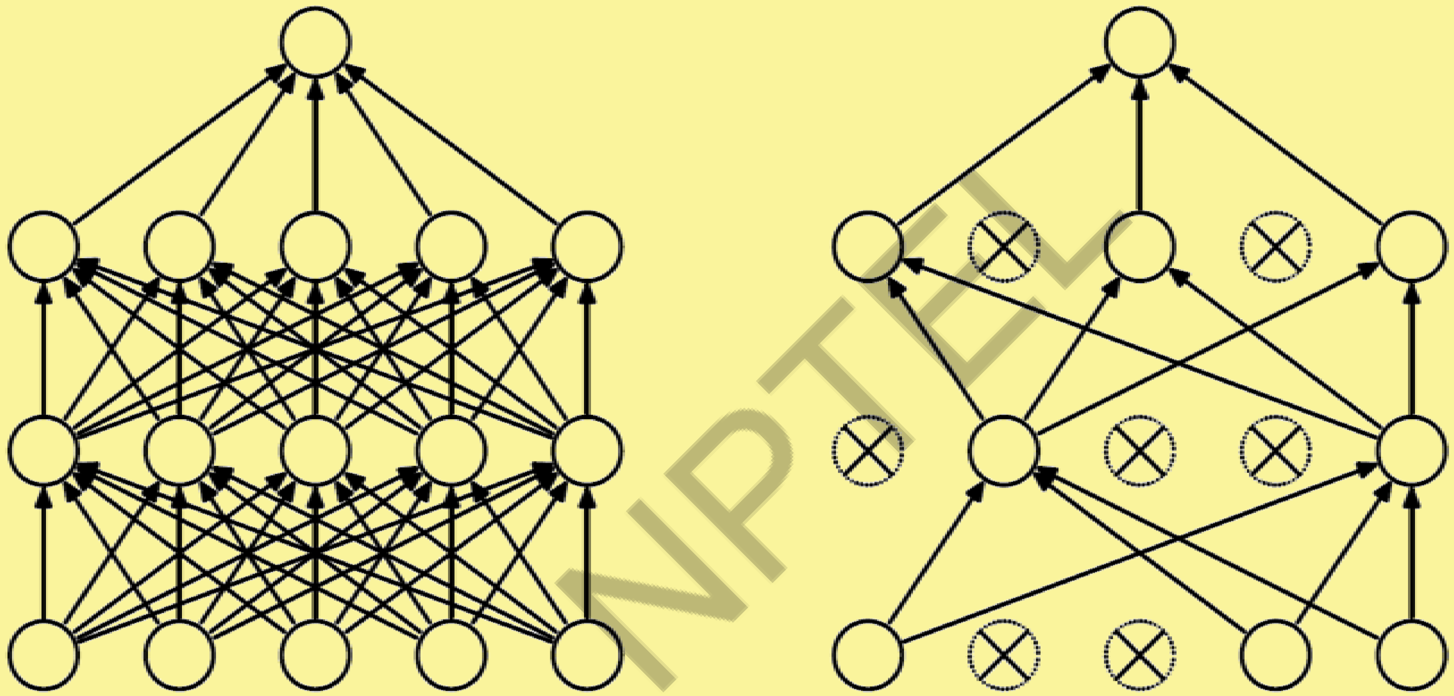
Regularization: L1 & L2

- L1 regularizer: Cost function = Loss + $\lambda \sum |w|$
  - It penalizes absolute value of weights
  - It can make some weights to zero. So useful for model compression.
  - λ is a regularization hyper parameter. Controls the relative weight.
- L2 regularizer: Cost function = Loss + $\lambda \sum ||w||^2$
  - It penalizes second norm of weights.
  - It is also termed as weight decay as it pushes the weights near to zero. But it does not make exactly zero always.

Data Augmentation

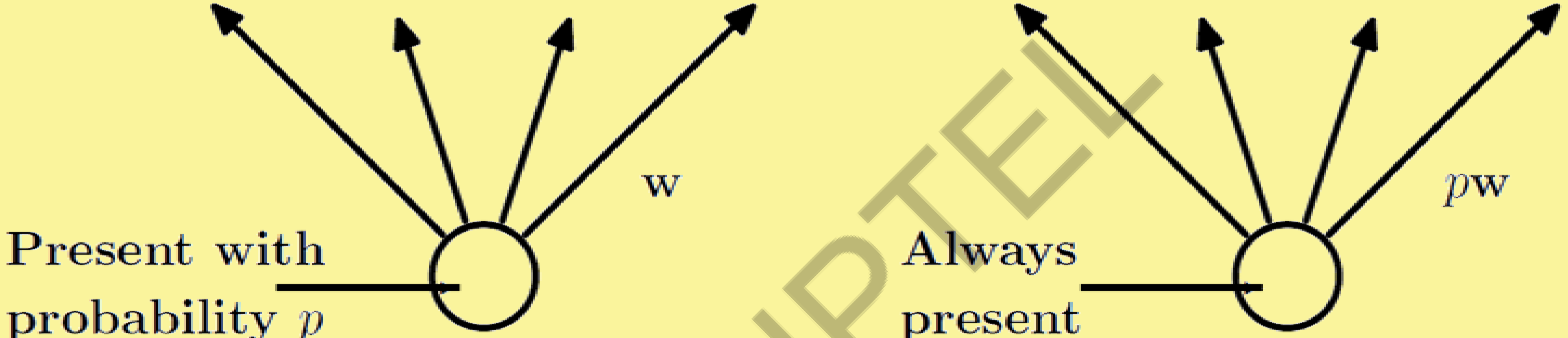
- Increasing the size of training data is a way to prevent overfitting.
- It is difficult and costly to increase the training data.
- Data augmentation is a way to create a different image from one image while keeping the context same.
- There are a few ways of augmenting training data– rotating, flipping, scaling, shifting, contrast enhancement, brightness control, etc.

Dropout



Srivastava, Nitish, et al. "Dropout: a simple way to prevent neural networks from overfitting." The Journal of Machine Learning Research 15.1 (2014)

Dropout

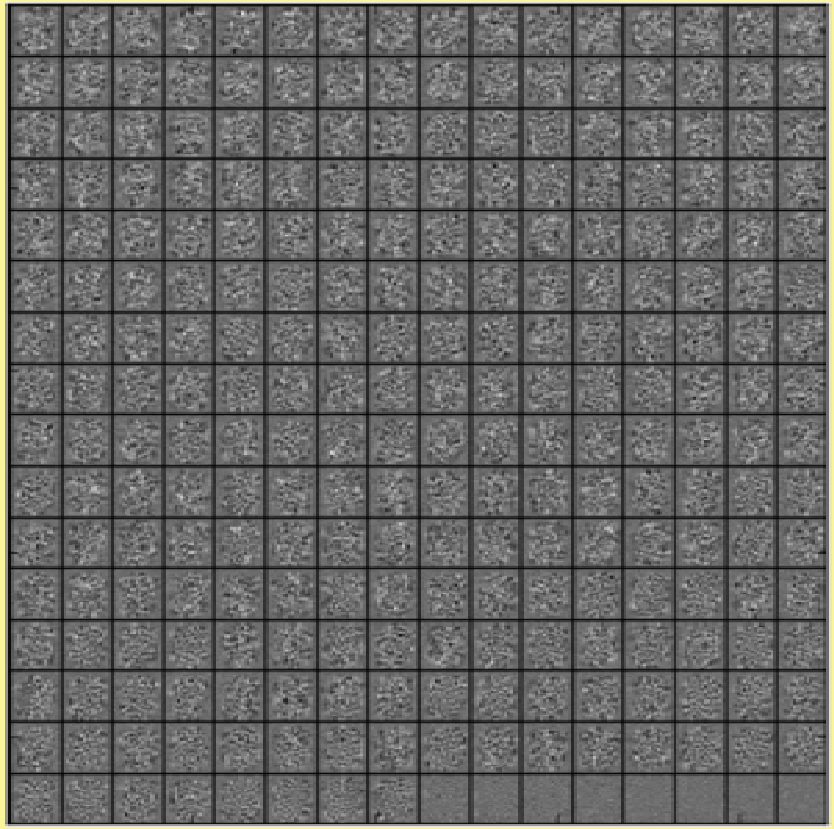


During Training

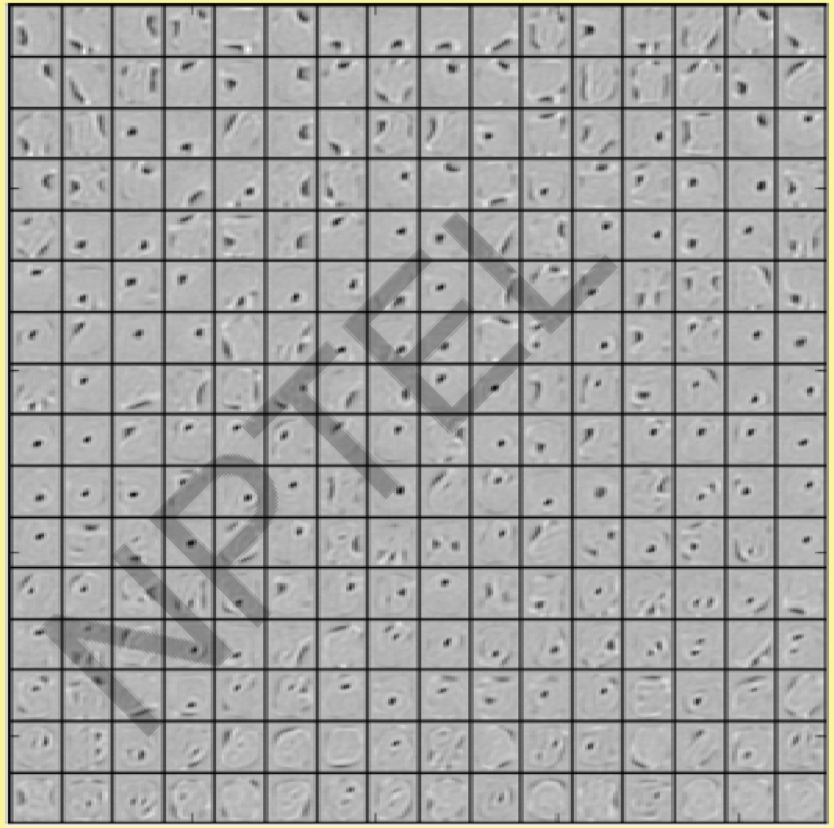
During Testing

Srivastava, Nitish, et al. "Dropout: a simple way to prevent neural networks from overfitting." The Journal of Machine Learning Research 15.1 (2014)

Dropout: Effect on learned features



Without dropout

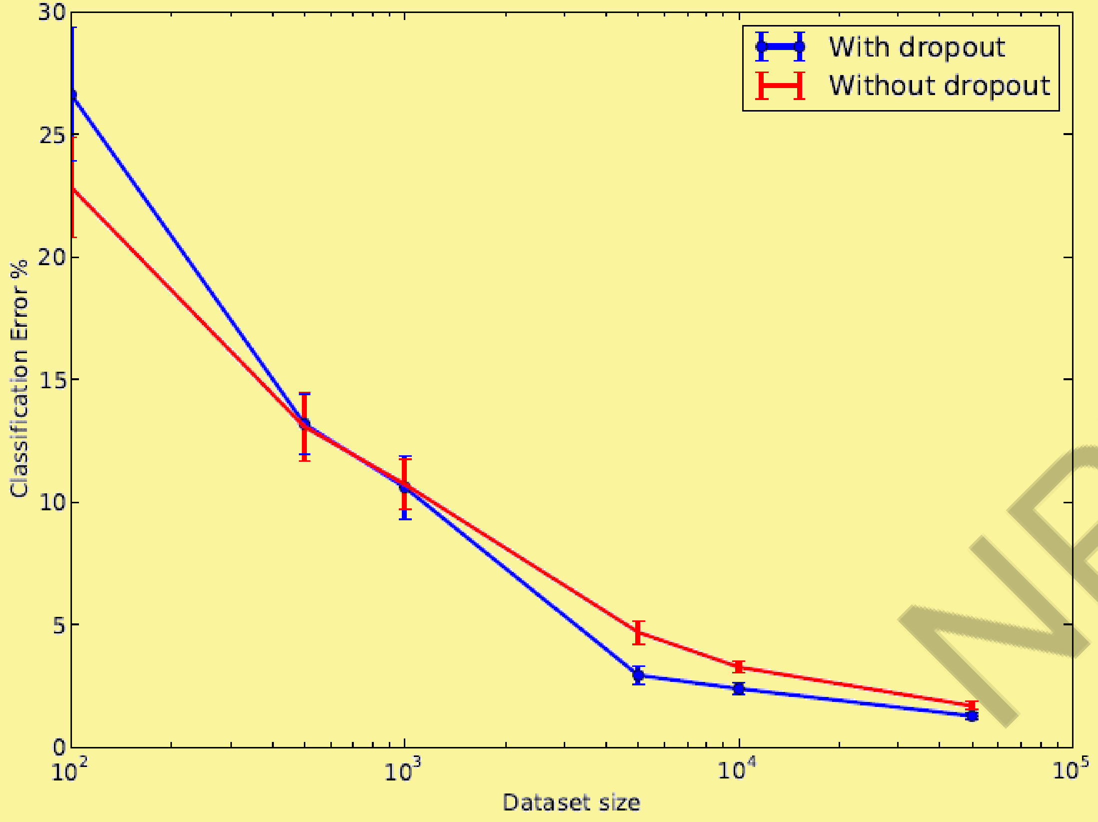


With dropout

Features learned by an autoencoder on MNIST with a single hidden layer of 256 rectified linear units with/ without dropout.

Srivastava, Nitish, et al. "Dropout: a simple way to prevent neural networks from overfitting." The Journal of Machine Learning Research 15.1 (2014)

Dropout: Effect on Data Size



- While model complexity is fixed, dropout does not generalize the model for very small amount of data
- As the size of the data set is increased, the gain from doing dropout increases up to a point and then declines.
- There is a sweet spot where amount of data is large enough.

Srivastava, Nitish, et al. "Dropout: a simple way to prevent neural networks from overfitting." The Journal of Machine Learning Research 15.1 (2014)

Early Stopping

- Hyperparameters need to be tuned for good performance while training neural networks.
- Number of iteration is a hyperparameter to be tuned. Lesser iteration may lead to underfit and more iteration may lead to overfit.
- Early stopping attempts to remove the need of manually setting this value.
- It can also be considered a type of regularization method.

Image Source: Internet

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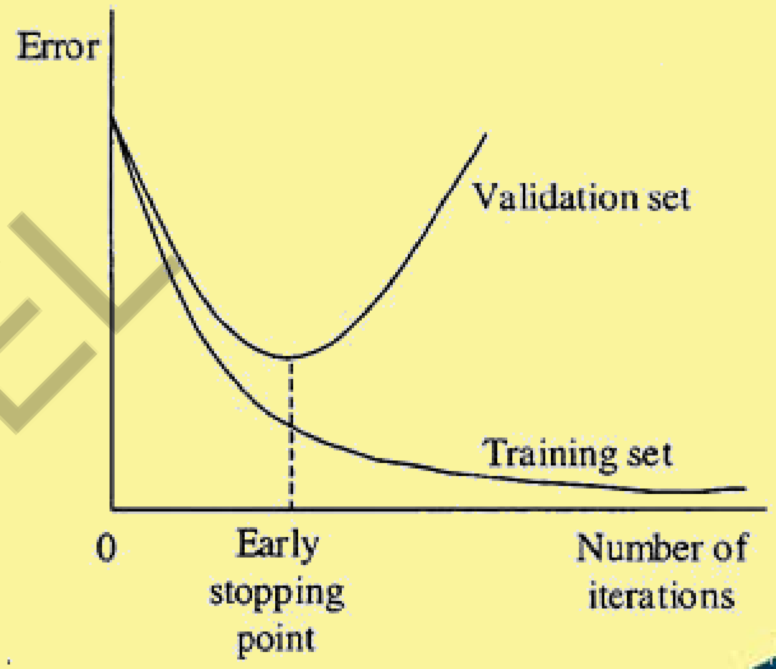

Image Source: Internet

Early Stopping

Early stopping algorithm is as follows:

- ❑ Split data into train, validation and test set
- ❑ After each training epoch:
  - ❑ Evaluate the model performance using validation data
  - ❑ Save the best model evaluated on validation data
- ❑ Use final model that has the best validation performance for testing.

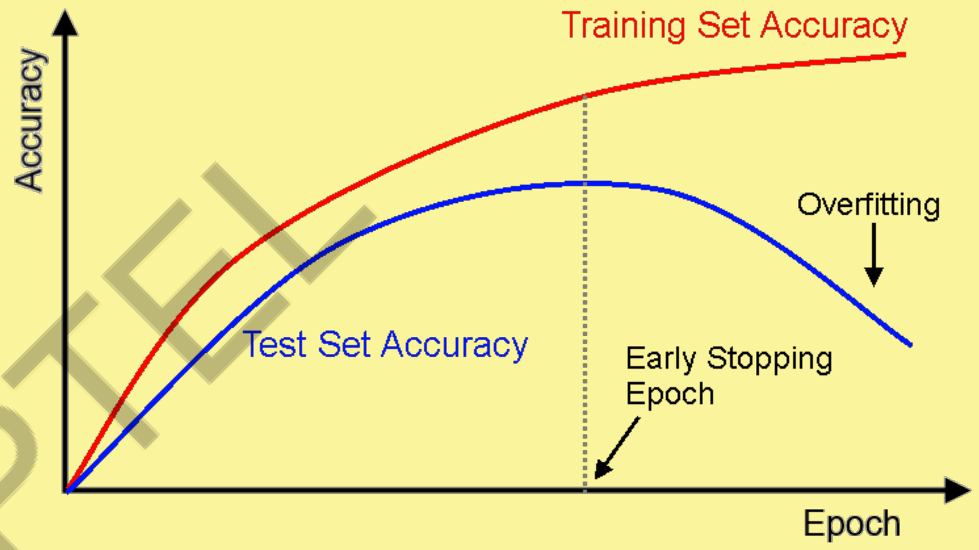

Image Source: Internet

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Thank you