





NPTEL ONLINE CERTIFICATION COURSES

Course Name: Deep Learning

Faculty Name: Prof. P. K. Biswas

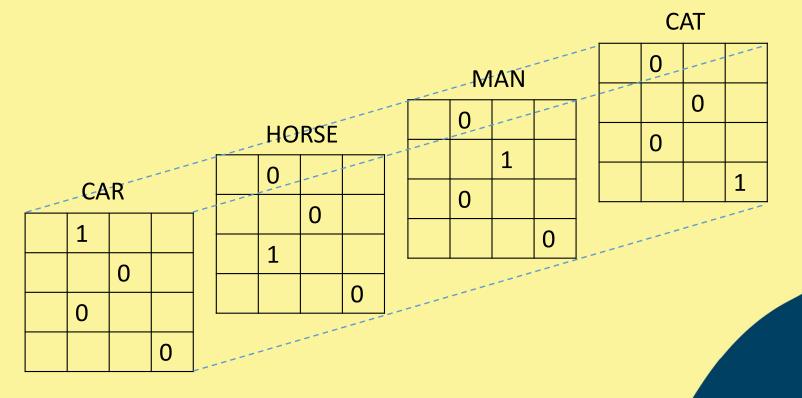
Department: E & ECE, IIT Kharagpur

Topic

Lecture 56: Image Denoising

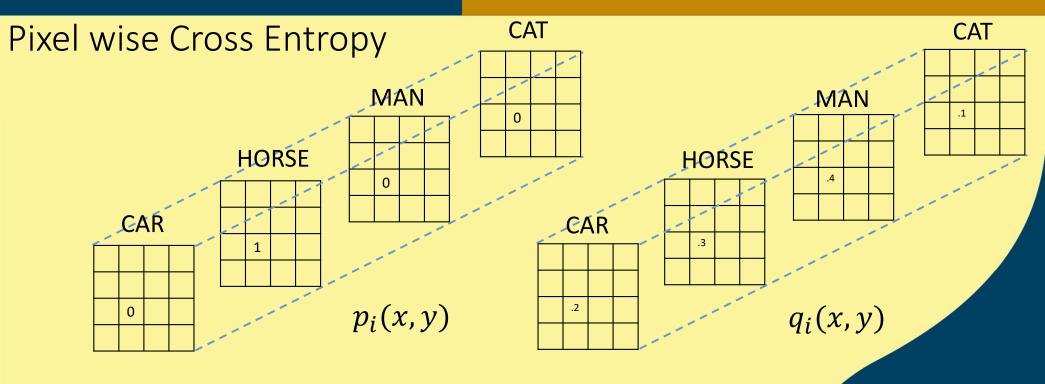
Concepts Covered: ☐ FCN/Deconv NN Training ☐ Pixelwise Entropy Loss ☐ Dice Loss **CONCEPTS COVERED** ☐ Image Restoration ☐ Image Restoration Network ☐ Low dose C.T. denoising

Training for Sem Segmentation









$$L = -\frac{1}{N} \sum_{N} \sum_{x,y} p_i(x,y) . \log q_i(x,y)$$





Dice Loss

- ☐ Another popular loss function for image segmentation tasks is based on the Dice coefficient.
- ☐ A measure of overlap between two samples.
- ☐ This measure ranges from 0 to 1 where a Dice coefficient of 1 denotes perfect and complete overlap.

$$Dice = \frac{2|A \cap B|}{|A| + |B|}$$

- ☐ |A∩B| represents the common elements between sets A and B
- ☐ |A| represents the number of elements in set A (and likewise for set B)
- □ |A∩B| is the element-wise multiplication between the prediction and target mask, and then sum the resulting matrix





Dice Loss

$$|A \cap B| = \begin{bmatrix} 0.01 & 0.03 & 0.02 & 0.02 \\ 0.05 & 0.12 & 0.09 & 0.07 \\ 0.89 & 0.85 & 0.88 & 0.91 \\ 0.99 & 0.97 & 0.95 & 0.97 \end{bmatrix} * \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{bmatrix} \xrightarrow{\text{element-wise multiply}} \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0.89 & 0.85 & 0.88 & 0.91 \\ 0.99 & 0.97 & 0.95 & 0.97 \end{bmatrix}$$
 prediction target

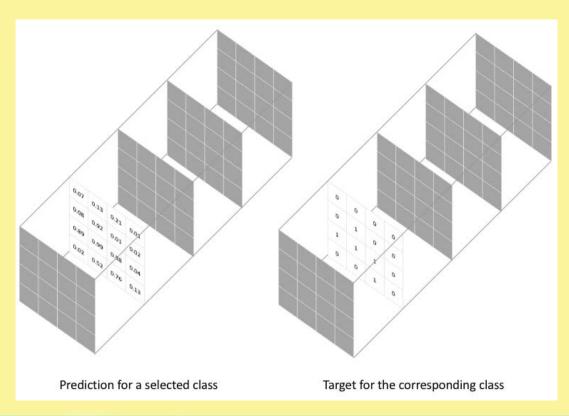




Image Source :

https://www.jeremyjordan.me/semantic-segmentation/

Dice Loss



$$L(class) = 1 - \frac{2\sum_{\forall x,y} t(x,y). p(x,y)}{\sum_{\forall x,y} t(x,y)^{2} + \sum_{\forall x,y} p(x,y)^{2}}$$

$$L = \sum_{\forall class} L(class)$$



mage Source: https://www.jeremyjordan.me/semantic-segmentation/

Image Restoration

- ☐ A general Image degradation operation consists of a degradation operator followed by additive noise.
- ☐ Image restoration is fundamental problem in image processing research.
- ☐ There are different type of restoration process like: deblurring, denoising, super resolution, inpainting etc depending on the degradation function H.
- ☐ Image restoration becomes a problem of image denoising if degradation operator is an identity matrix.

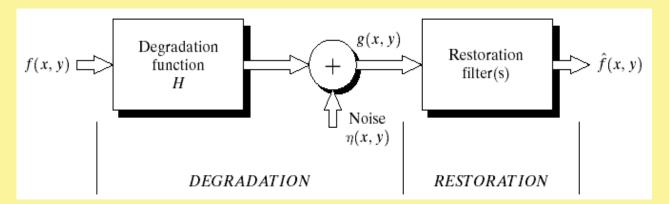






Image Denoising



Image effected with white Gaussian noise



Clean Image





Image Restoration Network

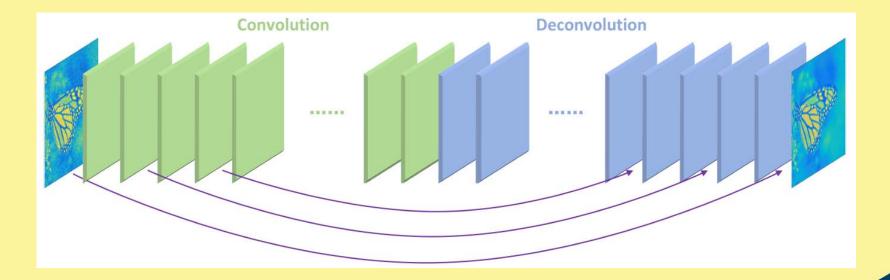






Image Restoration Network

- ☐ The network contains layers of symmetric convolution (encoder) and deconvolution (decoder).
- ☐ Convolutional layers successively down-sample the input image content into a small size abstraction.
- Deconvolutional layers then up-sample the abstraction back into its original resolution.
- ☐ The convolutional layers act as the feature extractor, which capture the abstraction of image contents while eliminating noises/corruptions
- ☐ The deconvolutional layers are then combined to recover the details of image contents.
- ☐ Deconvolutional layers associate a single input activation with multiple outputs.
- ☐ Deconvolution is usually used as learnable up-sampling layers.





Comparison with Fully Convolutional Network

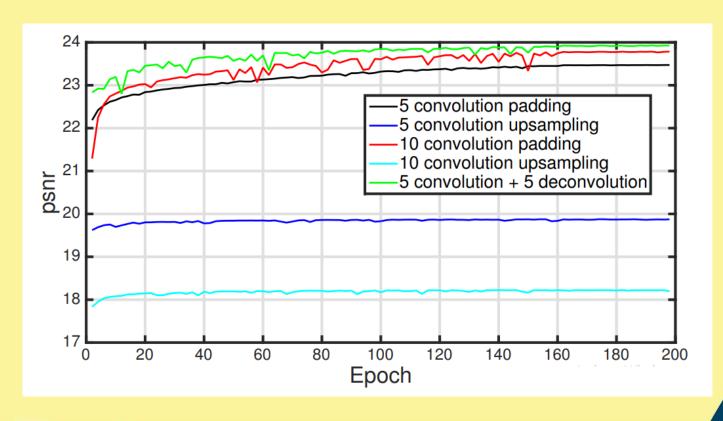
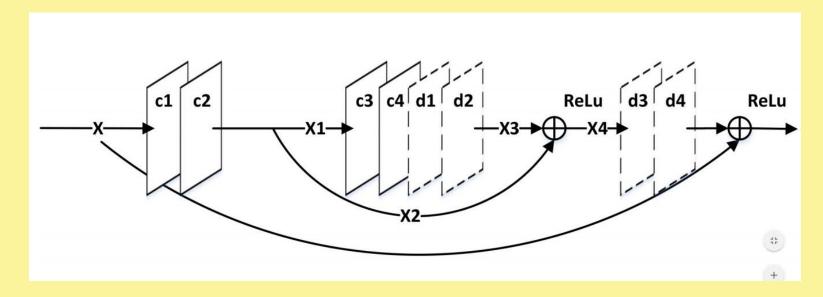






Image Restoration Network







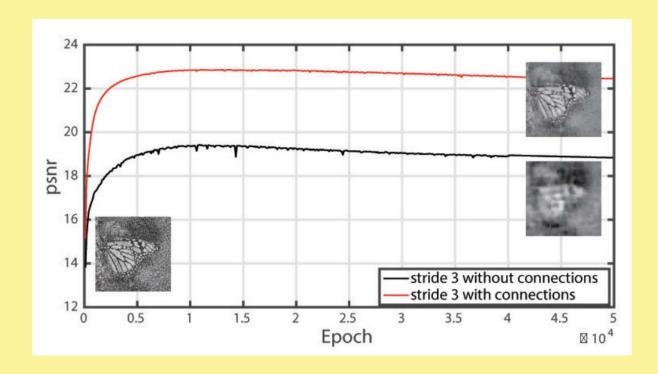
Why Skip Connections?

- ☐ As the network goes deeper image details are lost, making it difficult for deconvolution recovering them.
- ☐ The feature maps passed by skip connections carry much image detail, which helps deconvolution to recover an improved clean version of the image.
- ☐ The skip connections also achieve benefits on backpropagating the gradient to bottom layers, which makes training deeper network much easier.





Why Skip Connections?







Training the Restoration Network

- Learning the end-to-end mapping from corrupted images to clean images needs to estimate the weights Θ represented by the convolutional and deconvolutional kernels.
- \square Specifically, given a collection of N training sample pairs $\{Xi, Y_i\}$, where X_i is a noisy image and Y_i is the clean version as the ground truth. We can minimize the following Mean Squared Error (MSE):

$$L(\Theta) = \frac{1}{N} \sum_{i=1}^{N} ||F(X_i; \Theta) - Y_i||_F^2$$

- ☐ Traditionally, a network can learn the mapping from the corrupted image to the clean version directly.
- ☐ However, it has been reported the if the network learns for the additive corruption from the input image then the network converges fast to a minima.





Low Dose CT denoising

- ☐ X-RAY computed tomography (CT) has been widely utilized in clinical, industrial and other applications.
- ☐ Due to the increasing use of medical CT, concerns have been expressed on the overall radiation dose to a patient.
- ☐ We can lower the radiation dose of a CT image by lowering the operating current, or shortening the exposure time.
- ☐ This type of lower dose CT image is known as Low dose CT images.
- ☐ However doing so results in distorting the image.
- ☐ A example of low dose CT image distorted with photon noise is given.







Low Dose CT Denoising



Low dose CT image



Normal dose CT image

- ☐ Due to presence of noise low dose CT images some time loose their diagnosis value
- Many important nodules are no more visible in Low dose CT image.



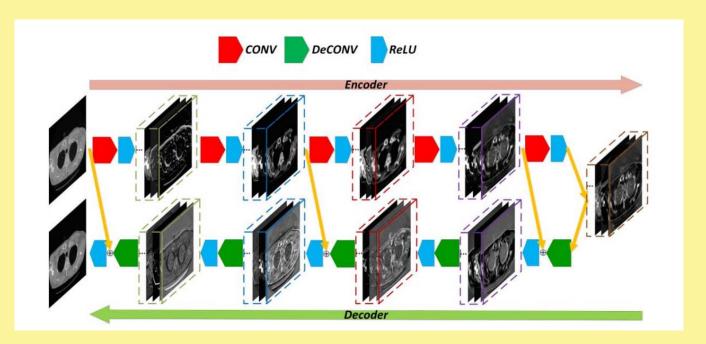


Image Source:

https://www.aapm.org/GrandChallenge/LowDoseCT/

Low Dose CT Denoising

Deep Learning network can be applied to solve this real life crucial problem. A network with architecture of previous network can effectively remove noise from this low dose CT images and can recover the visibility.

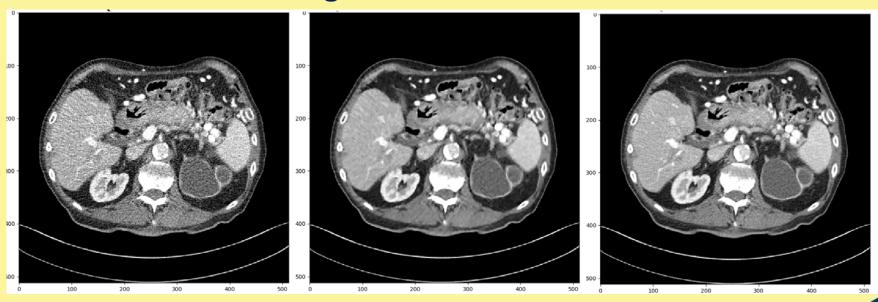






Source: Chen, Hu, Yi Zhang, Mannudeep K. Kalra, Feng Lin, Yang Chen, Peixi Liao, Jiliu Zhou, and Ge Wang. "Low-dose CT with a residual encoder-decoder convolutional neural network." *IEEE transactions on medical imaging* 36, no. 12 (2017): 2524-2535.

Low Dose CT Denoising



Low Dose Restored Normal Dose











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