





NPTEL ONLINE CERTIFICATION COURSES

Course Name: Deep Learning

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Department: E & ECE, IIT Kharagpur

Topic

Lecture 38: Popular CNN Models II

CONCEPTS COVERED

Concepts Covered:

- ☐ CNN
 - ☐ LeNet
 - □ ILSVRC
 - □ AlexNet
 - ☐ VGG Net
 - ☐ GoogLeNet
 - **u** etc.



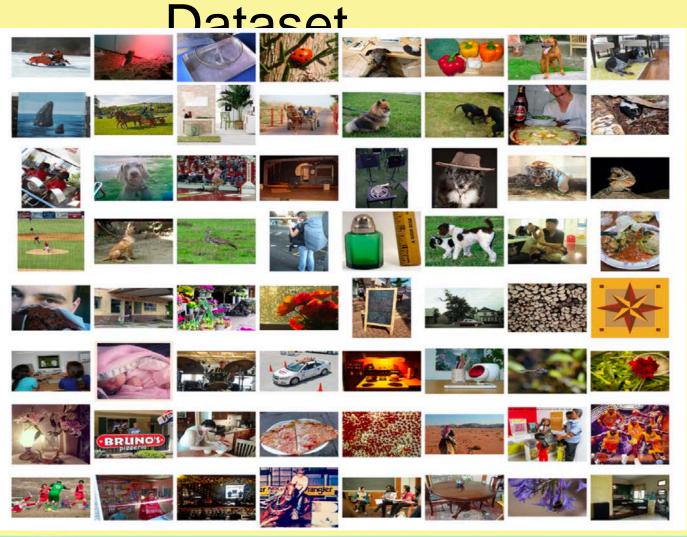


AlexNet ILSVRC 2012 Winer





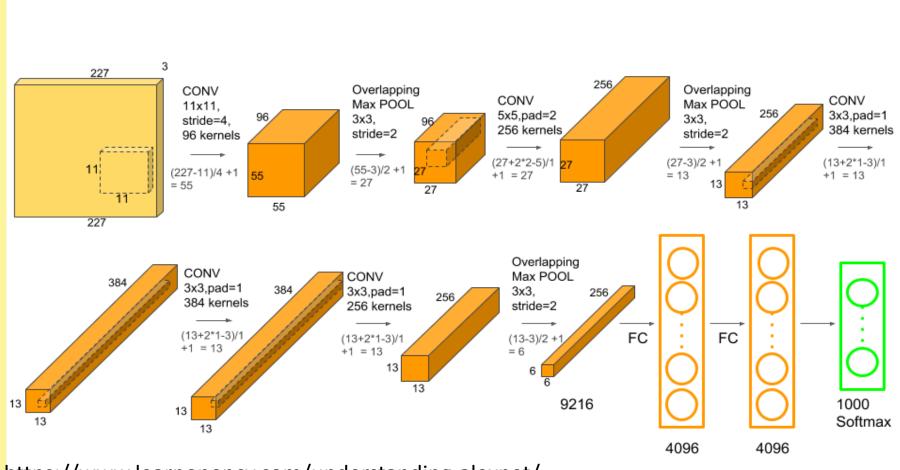
Sample Images from ImageNet





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ILSVRC 2012 Winner

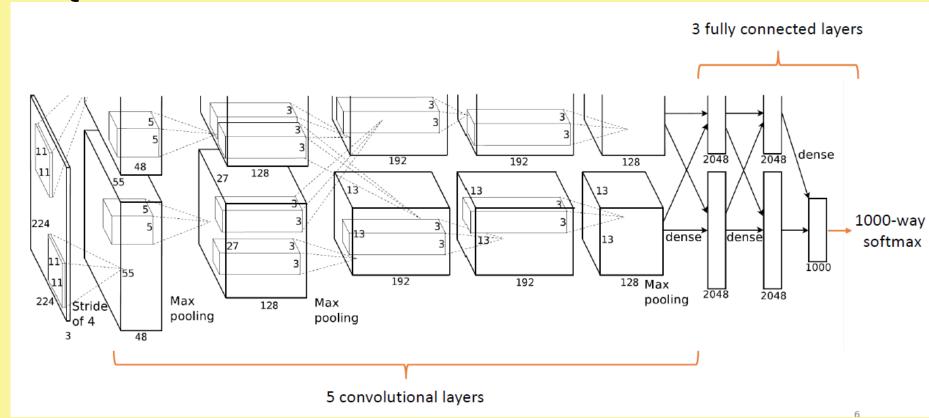






AlexNe

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Krizhevsky Alex, Ilya Sutskever and Geoffrey E. Hilton, "Imagenet Classification with deep convolutional neural networks", Advances in Neural Information Processing Systems, 2012

AlexN

- et
- ☐ 60 Million parameters and 650000 neurons.
- ☐ The network is split into two pipelines and was trained on two GPU.
- ☐ Input Image size 256 x 256 RGB.
- ☐ Grey scale images to be replicated to obtain 3-Channel RGB
- ☐ Random crops of size 227 x 227 are fed to the input layer of AlexNet.
- ☐ Stochastic Gradient Descent with Momentum Optimizer.
- ☐ Top-5 error rate 15.3%.





Vanishing Gradient Problem

- ☐ Uses ReLU activation instead of sigmoidal function.
- ☐ ReLU output is unbounded- uses Local Response Normalization (LRN).
- ☐ LRN carries out a normalization amplifying the excited neuron while dampening the surrounding neurons at the same time in a local neighbourhood.
- ☐ Encourage *Lateral Inhibition*: concept in neuro biology that indicates capacity of a neuron to reduce activity of its neighbours.



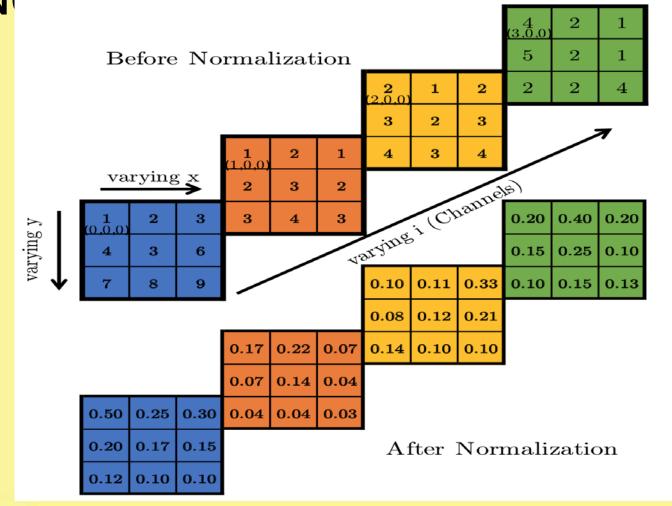


Local Response Normalization (Inter-Channel)

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



Local Response Normalization







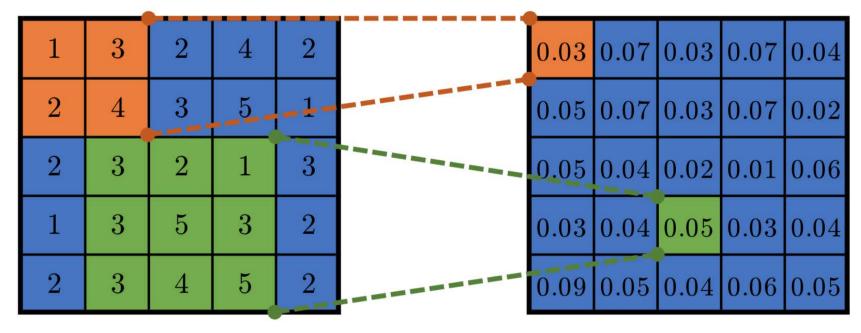
https://towardsdatascience.com/difference-between-local-response-normalization-and-batch-normalization-272308c034ac

Local Response Normalization (Intra-Channel)

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



Local Response Normalization



Before Normalization

After Normalization





Reducing Overfitting

- ☐ Train the network with different variants of the same image helps avoiding overfitting.
 - Generate additional data from existing data (Augmentation).
 - Data augmentation by mirroring.
 - Data Augmentation by random crops.
- ☐ Dropout Regularization.



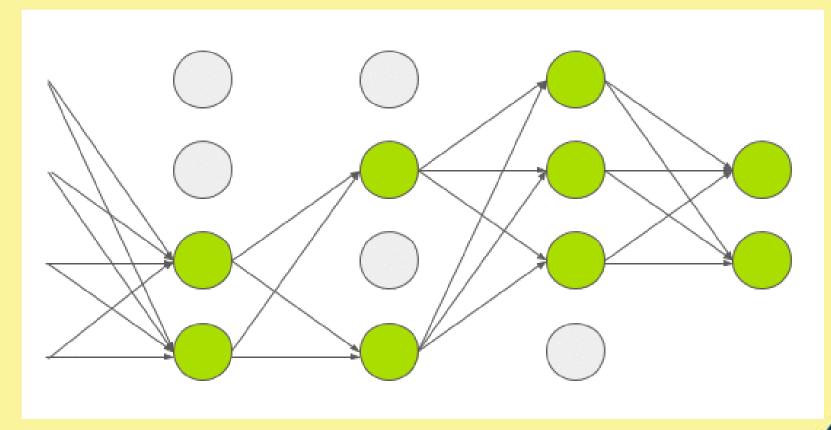


- ☐ Regularization Technique proposed by Srivastava et. al. in 2014.
- ☐ During training randomly selected neurons are dropped from the network (with probability 0.5) temporarily.
- ☐ Their activations are not passed to the downstream neurons in the forward pass.
- ☐ In the backward pass weight updates are not applied to theses neurons.





Dropou t







How does it help?

- ☐ While training weights of neurons are tuned for specific features that provides some sort of specialization.
- □ Neighbouring neurons starts relying on these specializations (co-adaptation).
- ☐ This leads to a neural network model too specialized to the training data.
- ☐ As neurons are randomly dropped other neurons have to step in to compensate.
- ☐ Thus the network learns multiple independent representations

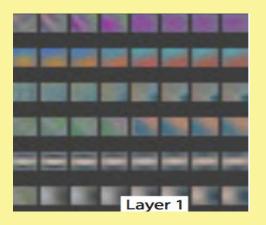


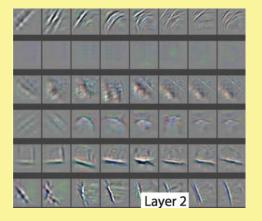


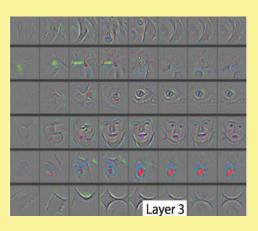
Srivastava Nitish et. al. "Dropout: A Simple Way to Prevent Neural Networks from Overfitting" Journal of Machine Learning Research 15 (2014), 1929-1958

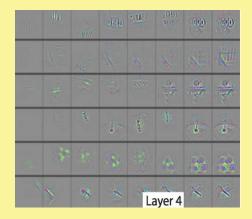
Learned Features

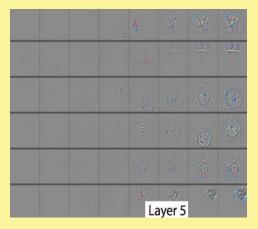
















How does it help?

- ☐ This makes the network less sensitive to specific weights.
- ☐ Enhances the generalization capability of the network
- Less vulnerable to overfitting.
- ☐ The whole network is used during testing there is no dropout.
- Dropout increases number of iterations for the network to converge.
- But helps avoid overfitting.











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Thank you