Deep Learning

09 Training DNNs II

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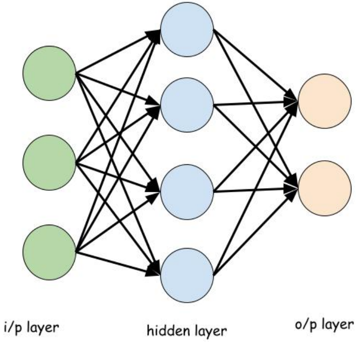
- Mean subtraction and division by standard deviation per channel (e.g. ResNet)
- PCA or whitening are not common

2. Weight Initialization



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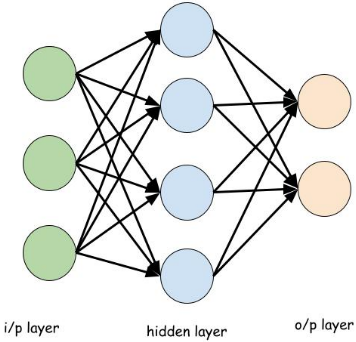

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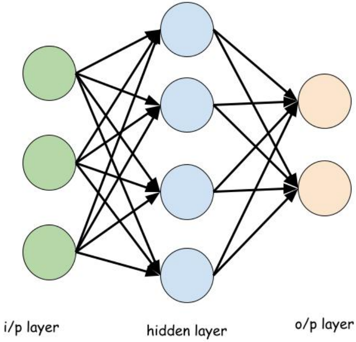

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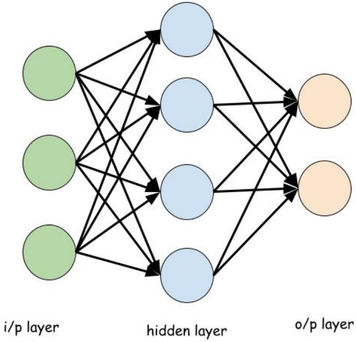

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- Hence, we need different values as weights!

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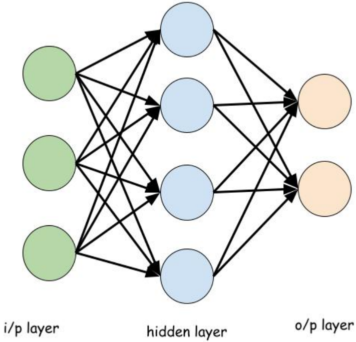

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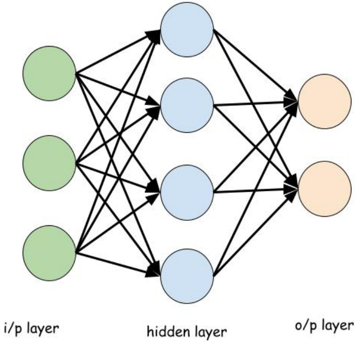

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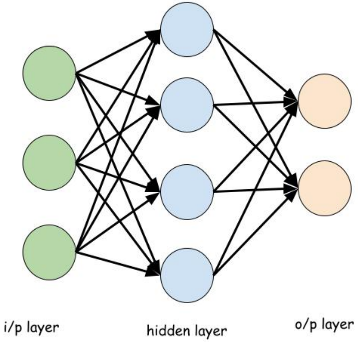

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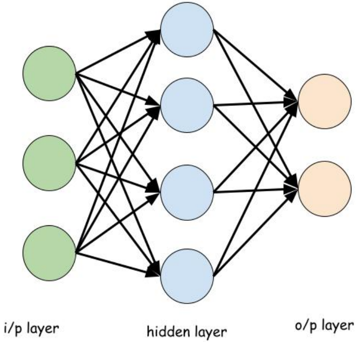

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- Different weights $\rightarrow$ different o/p range of the neurons

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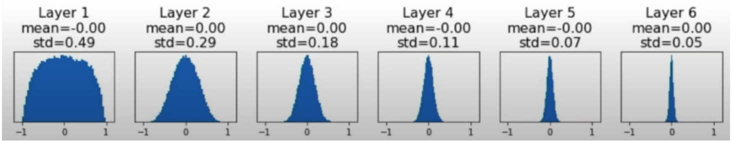

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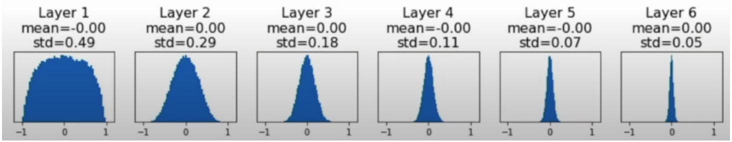

- All zero gradients, no learning!

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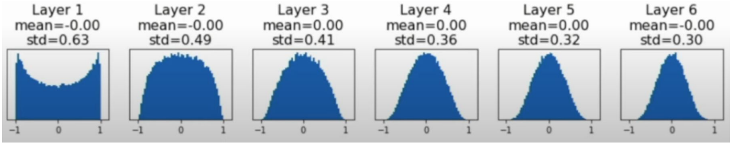
- 

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- $\rightarrow$ var$(w_i) = \frac{1}{d_{l-1}}$

2b. Weight Initialization with ReLU activations

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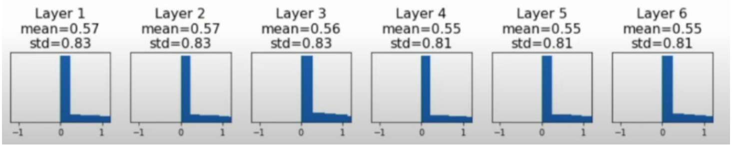
- std=sqrt$(2/d_{l-1})$



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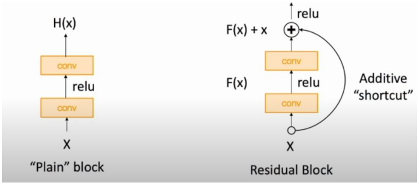
2c. Weight Initialization: Residual Networks



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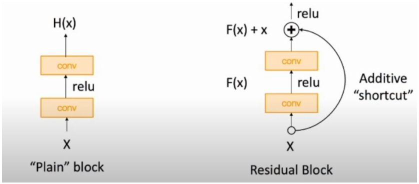

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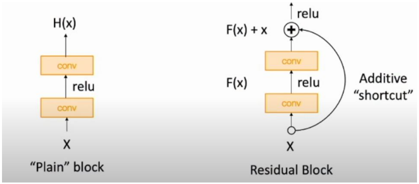

- MSRA initialization: $\text{Var}(F(x)+x) > \text{Var}(x)$
- Variance grows!
- Solution: Initialize the first Conv layer with MSRA, and the second one with zero $\rightarrow$ $\text{Var}(x+F(x)) = \text{Var}(x)$

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3. Deep Regularization

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2. It has to be profitable!

3. Deep Regularization

1. Most often the best-fitting model is a large model that has been appropriately regularized

3. Deep Regularization

- Parameter Norm penalties (l_2, l_1, etc.)
- Dataset Augmentation
- Noise Robustness
- Semi-Supervised Learning
- Multi-Task Learning (Parameter sharing)
- Sparse Representation
- Dropout
- etc.

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2. Bias controls only a single variable as opposed to weight which connects two
3. Regularizing biases may induce underfitting

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3. Norm penalties induce different desired behaviors based on the exact penalty imposed

3b. Dataset Augmentation

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3. Create fake data and add it to the training data, called Dataset augmentation

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2. Difficult for density estimation task (unless we have solved the estimation problem)

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4. Should restrict to label preserving transformations

3c. Multi-Task Learning

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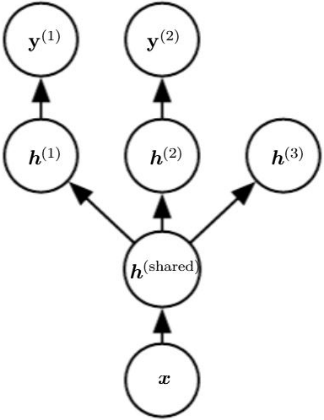

3d. Dropout

భారతీయ సాంకేతిక విజ్ఞాన సంస్థ హైదరాబాద్
भारतीय प्रौद्योगिकी संस्थान हैदराबाद
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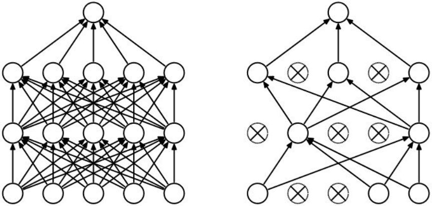

(a) Standard Neural Net (b) After applying dropout.

Figure 1: Dropout Neural Net Model. **Left**: A standard neural net with 2 hidden layers. **Right**: An example of a thinned net produced by applying dropout to the network on the left. Crossed units have been dropped.

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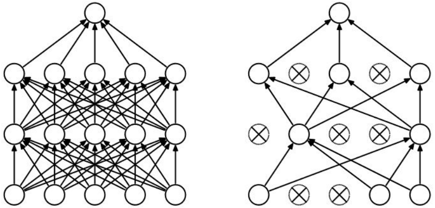
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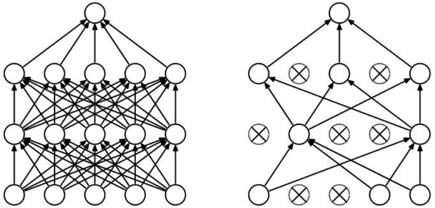

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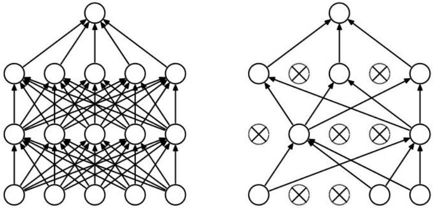
4. Backpropagation happens through the remaining activations



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2. Distributes the representation among all the units (forces the network to learn redundancy)

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2. For each sample, as many Bernoulli variables as units are sampled independently for dropping the units.

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2. Every possible binary mask results in a member of the ensemble
3. E.g. a dense layer with 10 units has 2^{10} masks!

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4. Leads to dropping no unit but multiply the activations with the probability of retaining

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2. More parameters are the dense layers $\rightarrow$ usually applied there
3. Not much used after ResNets!

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1. Gradient Descent converges faster with feature scaling $(x \leftarrow \frac{x-\mu}{\sigma})$
2. Batch Normalization (BN) is a normalization method for intermediate layers of NNs $\rightarrow$ performs whitening to the intermediate layer activations

3e. Batch Normalization (BN)

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

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

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

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

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

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

γ and β are learn-able parameters

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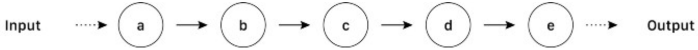
2. BN makes the activation of each neuron to be Gaussian distributed
3. ICS is undesirable because the layers need to adapt to the new distribution of activations
4. With BN, it is reduced to new pair of parameters, but the distribution remains Gaussian

3e. Batch Normalization (BN)

1. Mitigates interdependency between hidden layers during training



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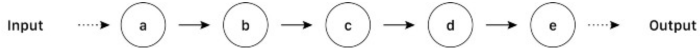

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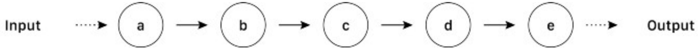

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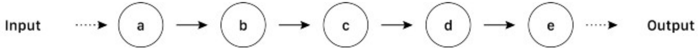

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3. if we want to adjust the input distribution of a specific hidden unit, we need to consider the whole sequence of layers (w/o BN)
4. BN acts like a valve which holds back the flow, and allows its regulation using β and γ

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3. Allows higher learning rates (less danger of vanishing/exploding gradients)

Regularization: General idea

1. Make all the assumptions explicit $\rightarrow$ appropriate inductive biases