Deep Learning

09 Training DNNs II

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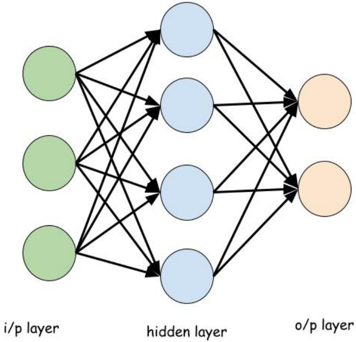
- Mean subtraction and division by standard deviation per channel (e.g. ResNet)
- PCA or whitening are not common

2. Weight Initialization



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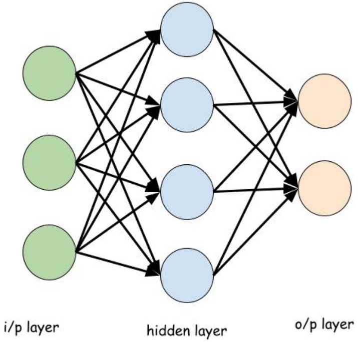

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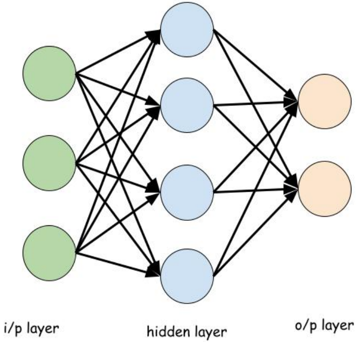

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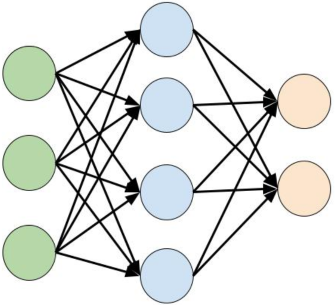

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- Leads to a failure mode (often known as the 'symmetry' problem)
- Hence, we need different values as weights!

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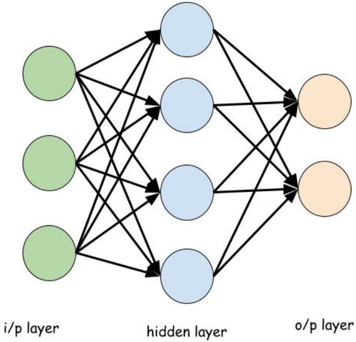

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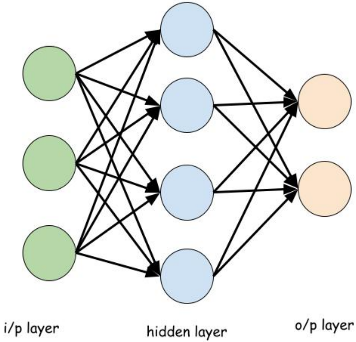

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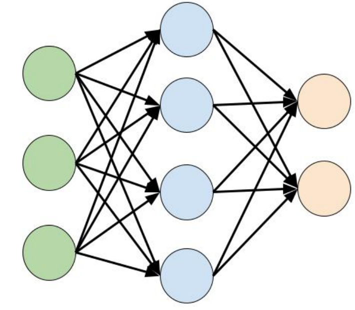

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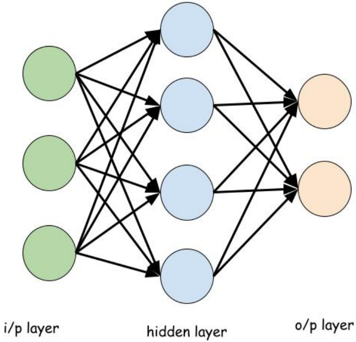

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- Different weights $\rightarrow$ different o/p range of the neurons

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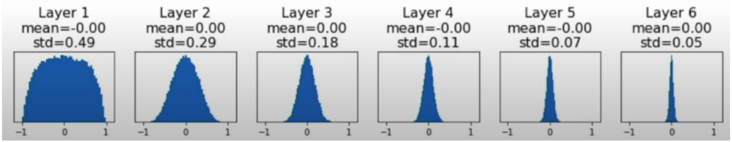

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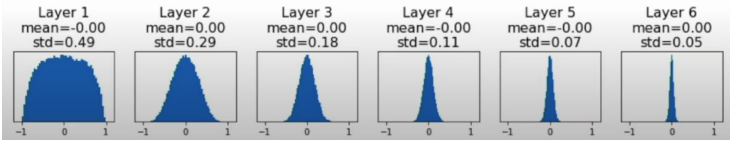

- All zero gradients, no learning!

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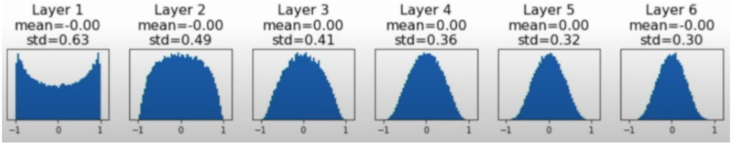
- 

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

2b. Weight Initialization with ReLU activations

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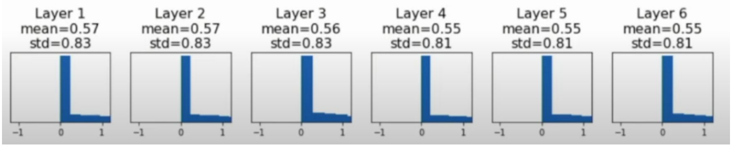
- std=sqrt$(2/d_{l-1})$



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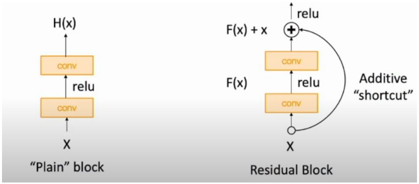
2c. Weight Initialization: Residual Networks



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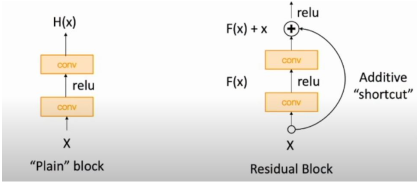

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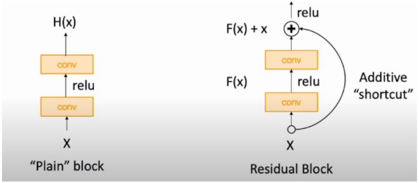

- MSRA initialization: Var(F(x)+x) $>$ Var(x)
- Variance grows!
- Solution: Initialize the first Conv layer with MSRA, and the second one with zero $\rightarrow$ Var(x+F(x)) $=$ Var(x)

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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.

3a. Parameter Norm Penalties

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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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2. L_1 regularization: $\tilde{\mathcal{J}} = \alpha |w|_1 + \mathcal{J}(w; X, y)$
3. Norm penalties induce different desired behaviors based on the exact penalty imposed

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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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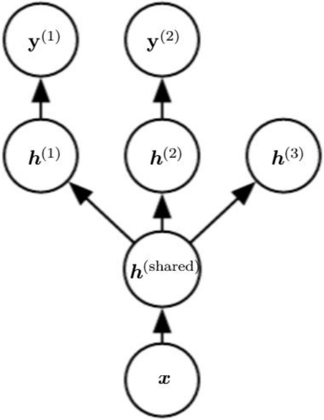

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2. Dropout is one such ('deep') regularization technique (Srivastava et al. 2014)

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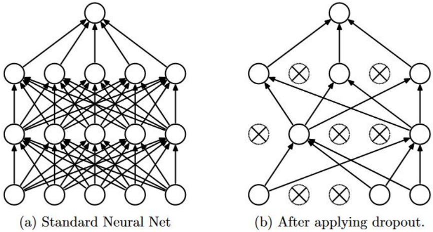

Figure 1: Dropout Neural Net Model. **Left**: A standard neural net with 2 hidden layers. **Right**: An example of a thinned net produced by applying dropout to the network on the left. Crossed units have been dropped.

Figure from Srivastava et al. 2014

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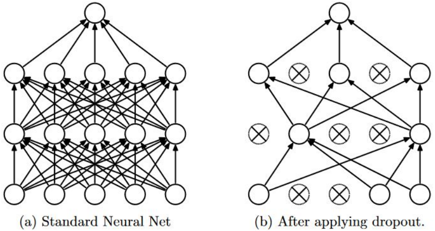

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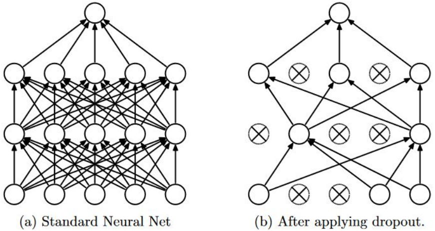

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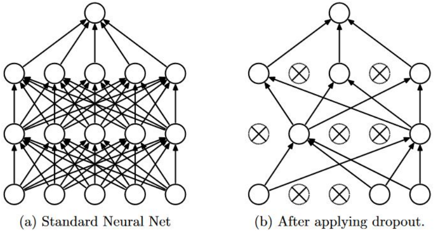
4. Backpropagation happens through the remaining activations



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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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5. The standard variant uses the 'inverted dropout'. Multiplies activations by $\frac{1}{(1-p)}$ during train and keeps the network untouched during test.

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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)

భారతీయ సాంకేతిక విజ్ఞాన సంస్థ హైదరాబాద్
भारतीय प्रौद्योगिकी संस्थान हैदराबाद
Indian Institute of Technology Hyderabad

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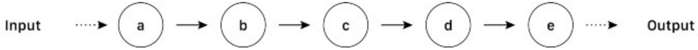
2. BN makes the activation of each neuron to be Gaussian distributed
3. ICS is undesirable because the layers need to adapt to the new distribution of activations
4. With BN, it is reduced to new pair of parameters, but the distribution remains Gaussian

3e. Batch Normalization (BN)

1. Mitigates interdependency between hidden layers during training



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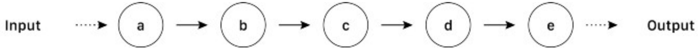

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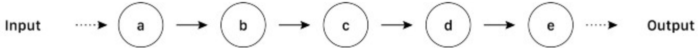

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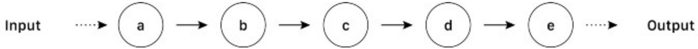

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3. if we want to adjust the input distribution of a specific hidden unit, we need to consider the whole sequence of layers (w/o BN)
4. BN acts like a valve which holds back the flow, and allows its regulation using β and γ

3e. Batch Normalization (BN)

1. Reduces training time (less ICS)

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

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3. Some of the instances
   Dropout
   Batch Normalization
   Data Augmentation
   Drop Connect (drop weights instead)
   Fractional MaxPooling
   Stochastic Depth
   Mixup
   Cutout
   CutMix, etc.