Deep Learning for Computer Vision

Dr. Konda Reddy Mopuri
Mehta Family School of Data Science and Artificial Intelligence
IIT Guwahati
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- MLP, CNNs and different families of architecture
- (today) Some of the important training aspects of CNNs

Data preprocessing for Computer vision

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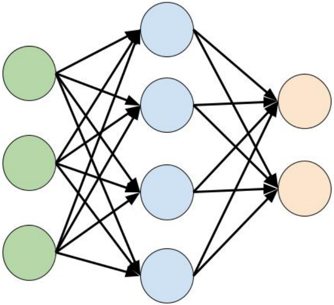
- Mean subtraction and division by standard deviation per channel (e.g. ResNet)
- PCA or whitening are not common

Weight Initialization



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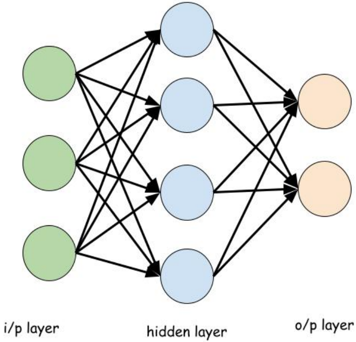

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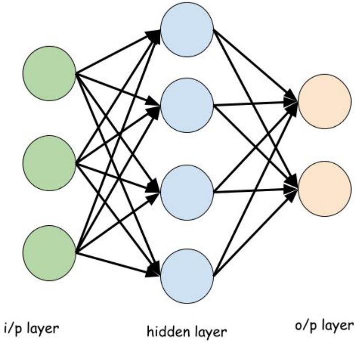

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- Or, a different constant?
- Leads to a failure mode (often known as the 'symmetry' problem)

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  `W = 0.001 * np.random.randn(`d_l, d_{l-1}`)`

Figure credits: Dr Justin Johnson, U Michigan

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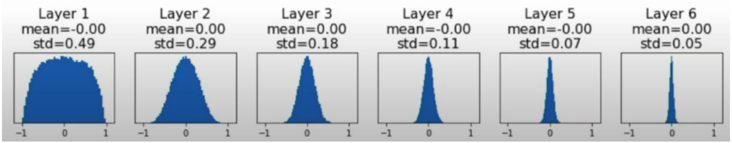

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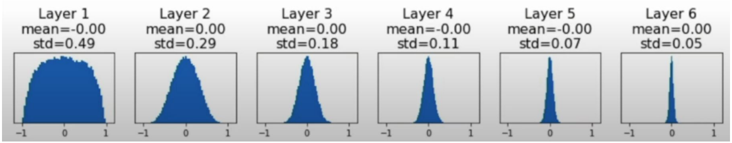

- All zero gradients, no learning!

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Xavier Initialization

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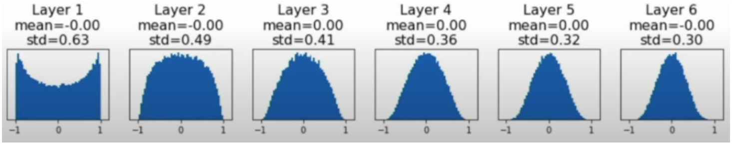
- 

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

Weight Initialization with ReLU activations

- Kaiming He or MSRA initialization

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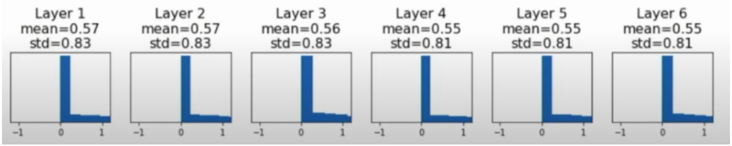
- `std=sqrt`$(2/d_{l-1})$



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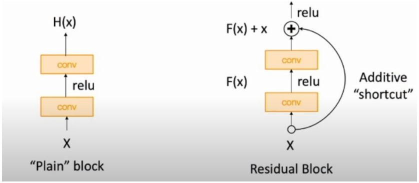
Weight Initialization: Residual Networks



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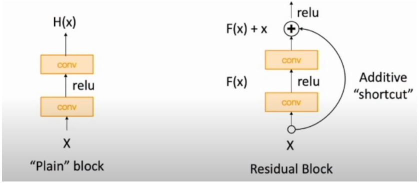

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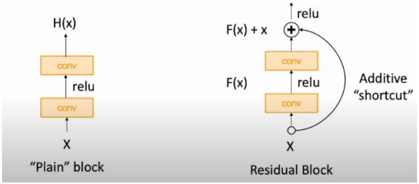

- MSRA initialization: $\text{Var}(F(x)+x) > \text{Var}(x)$
- Variance grows!
- Solution: Initialize the first Conv layer with MSRA, and the second one with zero $\rightarrow \text{Var}(x+F(x)) = \text{Var}(x)$

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Deep Regularization

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2. Trade increased bias for decreased variance

Deep Regularization

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2. In practice we almost never have access to the true data generating process, and which is almost certainly outside the model family

Deep Regularization

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

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

Dataset Augmentation

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2. In practice training data is limited
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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3. Hand-designed augmentations in some domains can result in dramatic improvements
4. Should restrict to label preserving transformations

Multi-Task Learning

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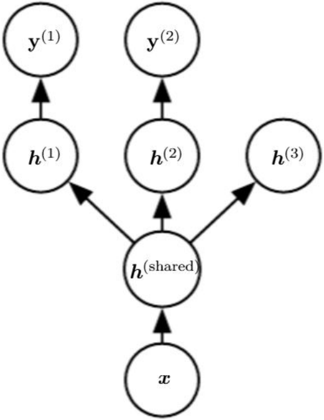

Dropout

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

Dropout

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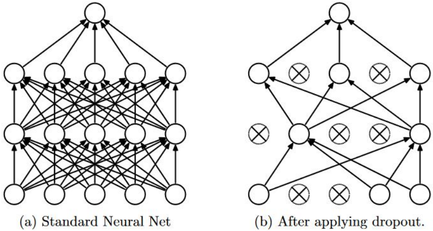

Figure 1: Dropout Neural Net Model. **Left**: A standard neural net with 2 hidden layers. **Right**: An example of a thinned net produced by applying dropout to the network on the left. Crossed units have been dropped.

Figure from Srivastava et al. 2014

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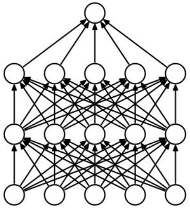

(a) Standard Neural Net

(b) After applying dropout.

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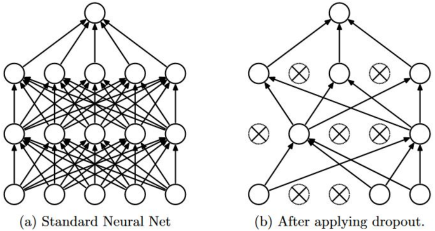

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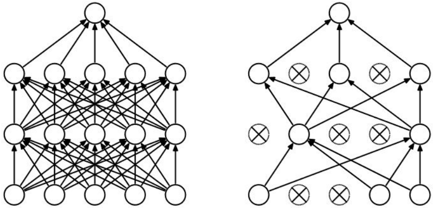
4. Backpropagation happens through the remaining activations



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Dropout: Interpretation

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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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2. Batch Normalization (BN) is a normalization method for intermediate layers of NNs $\rightarrow$ performs whitening to the intermediate layer activations

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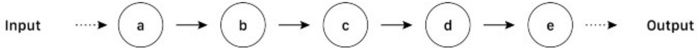
2. BN makes the activation of each neuron to be Gaussian distributed
3. ICS is undesirable because the layers need to adapt to the new distribution of activations
4. With BN, it is reduced to new pair of parameters, but the distribution remains Gaussian

Batch Normalization (BN)

1. Mitigates interdependency between hidden layers during training



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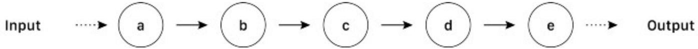

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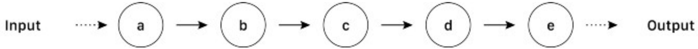

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$$\text{Input} \dashrightarrow (a) \rightarrow (b) \rightarrow (c) \rightarrow (d) \rightarrow (e) \dashrightarrow \text{Output}$$

2. $\partial(a) = \partial(b) \cdot \partial(c) \cdot \partial(d) \cdot \partial(e)$
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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2. Reduces the demand for additional regularizers (Batch statistics)

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2. Reduces the demand for additional regularizers (Batch statistics)
3. Allows higher learning rates (less danger of vanishing/exploding gradients)

Regularization: General idea

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2. Have a mechanism for marginalizing while testing
3. Some of the instances
   Dropout
   Batch Normalization
   Data Augmentation
   Drop Connect (drop weights instead)
   Fractioinal MaxPooling
   Stochastic Depth
   Mixup
   Cutout
   CutMix, etc.