

Deep Learning

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Outline

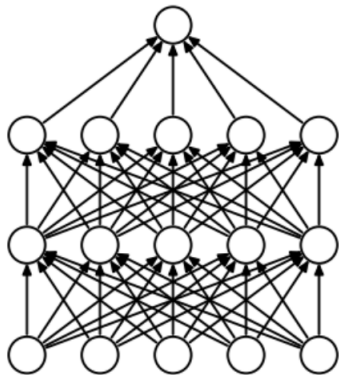
1 Dropout

2 Moving Average

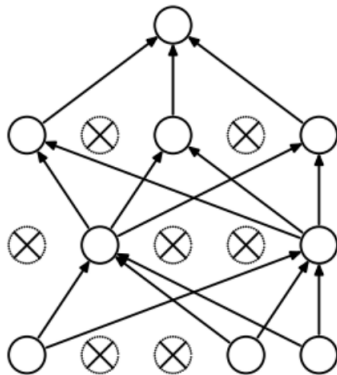
3 Batch Normalization

Dropout

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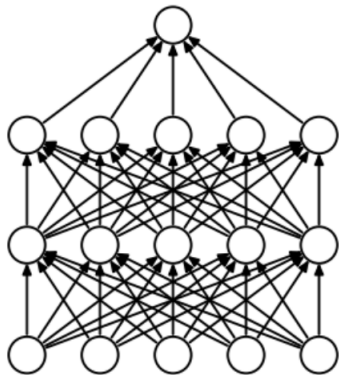


(a) Standard Neural Net

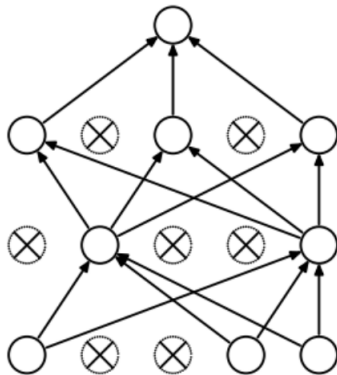


(b) After applying dropout.

Dropout



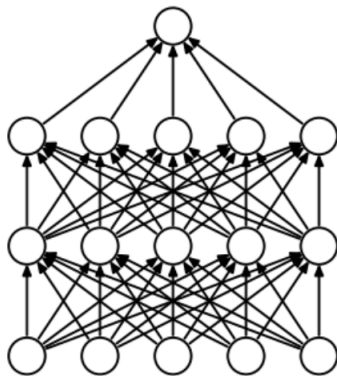
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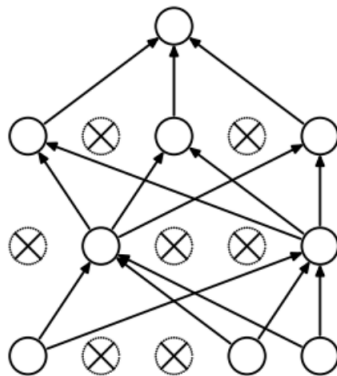
(b) After applying dropout.

What to do during the inference?

Dropout



(a) Standard Neural Net



(b) After applying dropout.

What to do during the inference?

Answer: Scale units by $\frac{1}{1 - \text{rate}}$ during the training and set $\text{rate}=1$ during the inference.

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Simple Moving Average

Definition 1

Simple moving average of the given data is the arithmetic mean of the previous k data.

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If you have the data x_1, x_2, \dots , then its simple moving average will be the following

$$\mu_n = \frac{x_{n-k+1} + \dots + x_n}{k}, n = k, k + 1, \dots$$

Cumulative Moving Average

Definition 2

Cumulative moving average of the given data is the arithmetic mean of the all previous data up to the current time.

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Note that

$$\begin{aligned}\mu_n &= \frac{(x_1 + x_2 + \dots + x_{n-1}) + x_n}{n} = \frac{(n-1)\mu_{n-1} + x_n}{n} \\ &= \left(1 - \frac{1}{n}\right) \mu_{n-1} + \frac{1}{n} x_n.\end{aligned}$$

Exponential Moving Average

If you have the data x_1, x_2, \dots , then its exponential moving average will be the following

$$\mu_1 = x_1,$$

$$\mu_n = \alpha \mu_{n-1} + (1 - \alpha) x_n, \quad n \geq 2$$

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It easy to see that sum of the coefficients is equal to 1.

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- Solution:
 - Fix the distribution of inputs into subnetwork.
- Effects:
 - Improve accuracy.
 - Faster learning.
 - Availability of high learning rates.

Batch Normalization

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_1 \dots x_m\}$;
Parameters to be learned: γ, β

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

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

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

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

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