Lecture 23 - Deep Learning II

Batch Normalization

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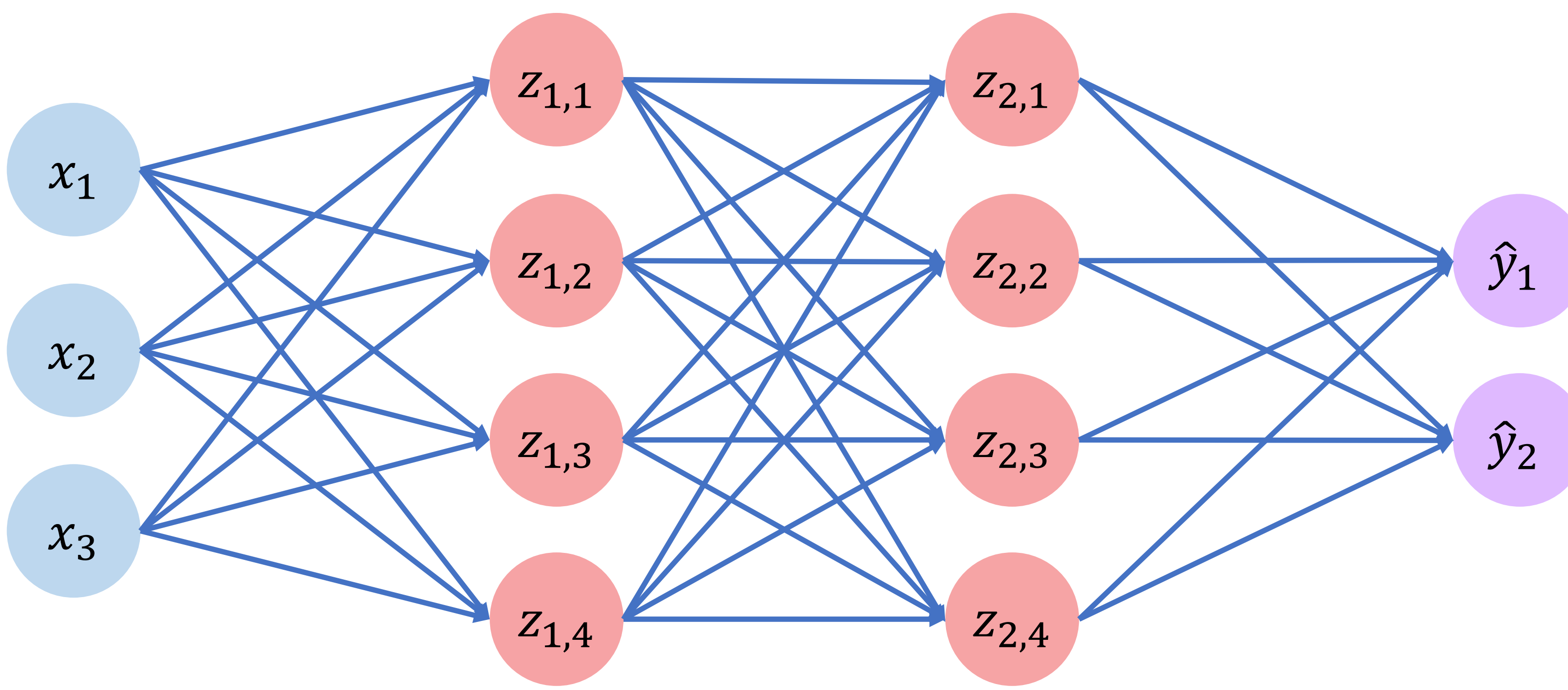
07.07.2021

Slides credits to P. M. Olmos, UC3M

Internal shift

- Training Deep Neural Networks is **complicated** by the fact that **the distribution of each layer's inputs changes during training**, as the parameters of the previous layers change
- We refer to this phenomenon as **internal covariate shift**
- **This slows down the training** by requiring lower learning rates, and **makes it notoriously hard to train models with saturating nonlinearities**



Batch Normalization

- By **fixing the distribution of the layer inputs** as the training progresses, we expect to improve the training speed
- Batch Normalization performs input normalization in a way that is **differentiable** and **does not require the analysis of the entire training set** after every parameter update
- **Normalize each scalar feature independently**
- Scale the normalized input **with trainable parameters**

Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift

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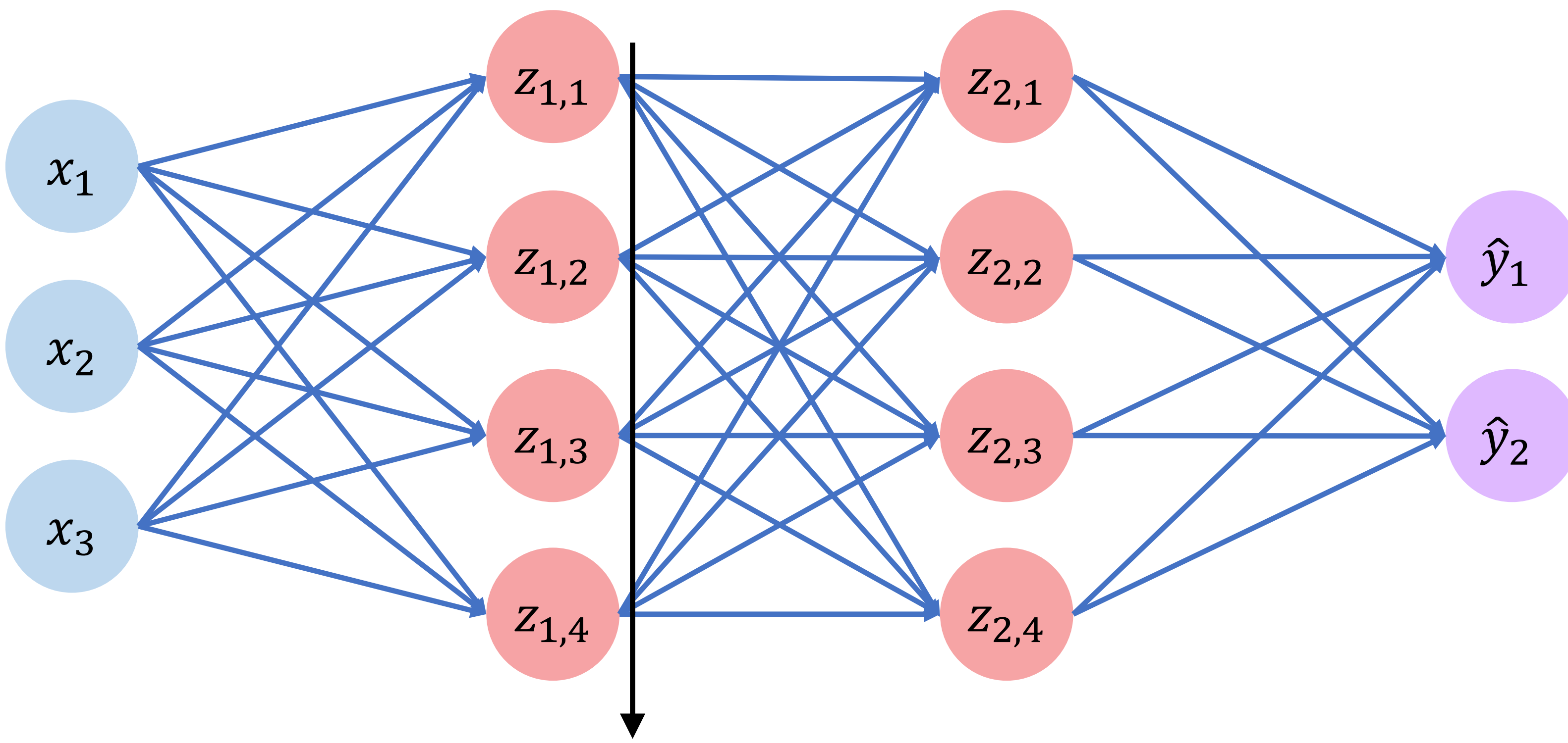
Batch Normalization

- Mini-batch of size M



Batch Normalization

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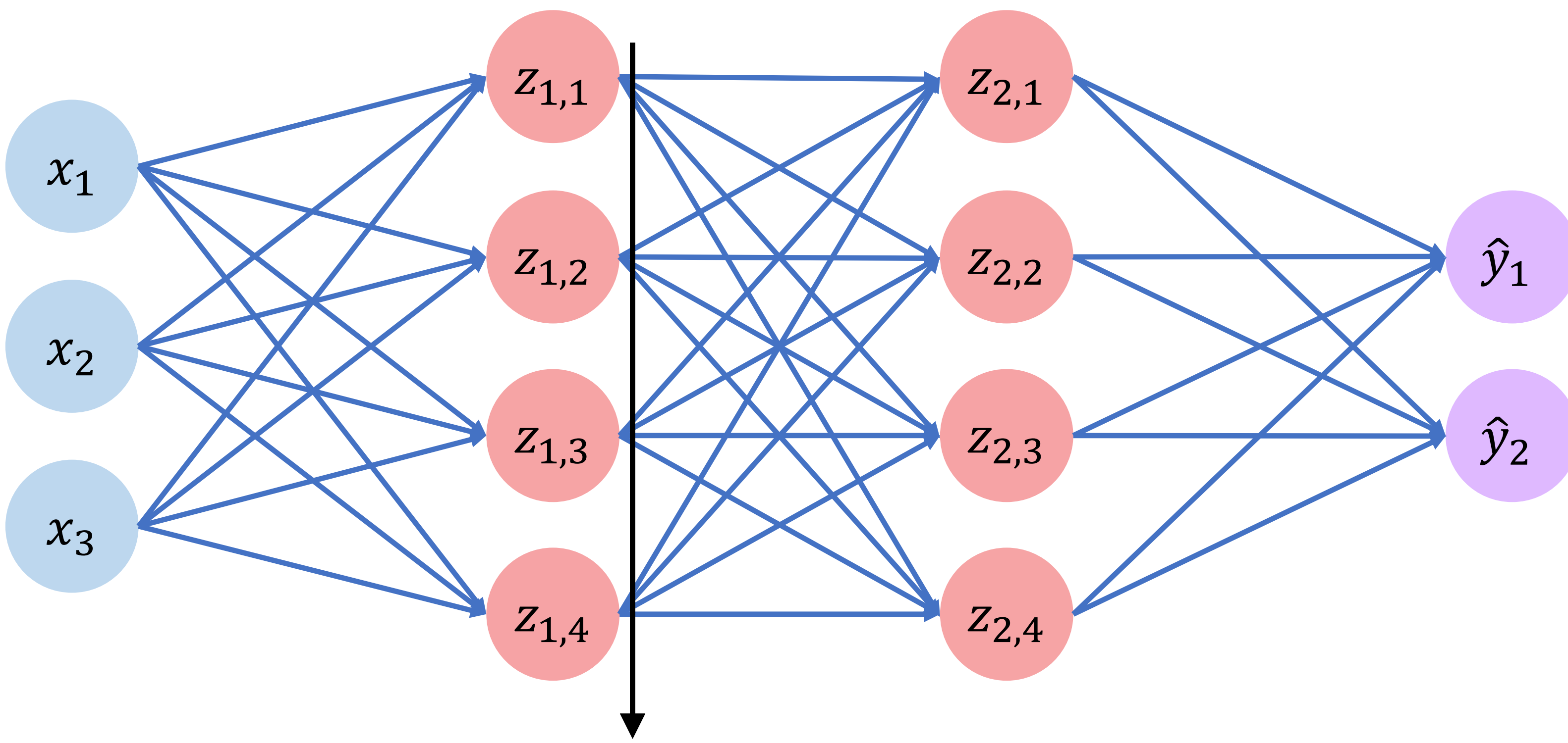

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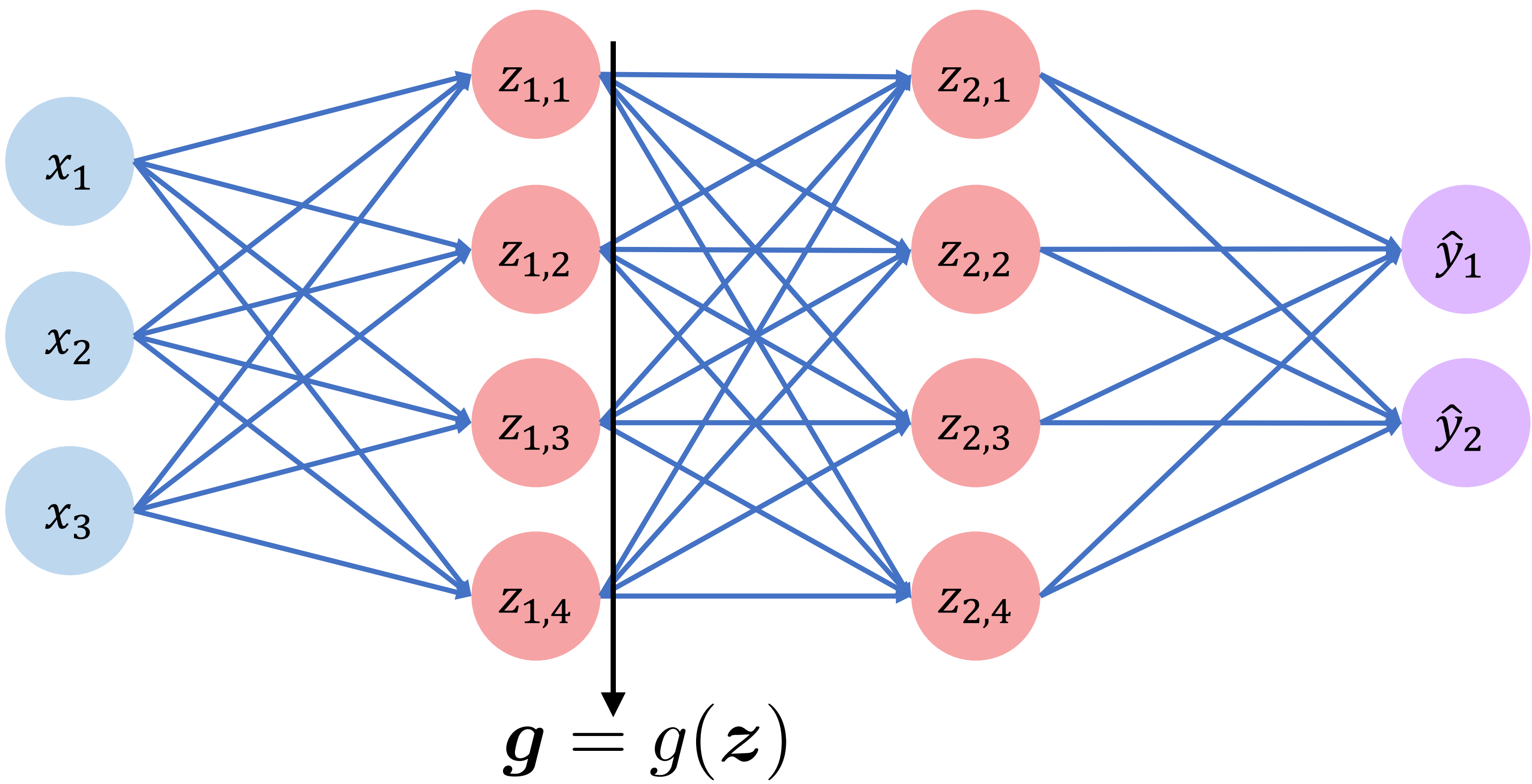
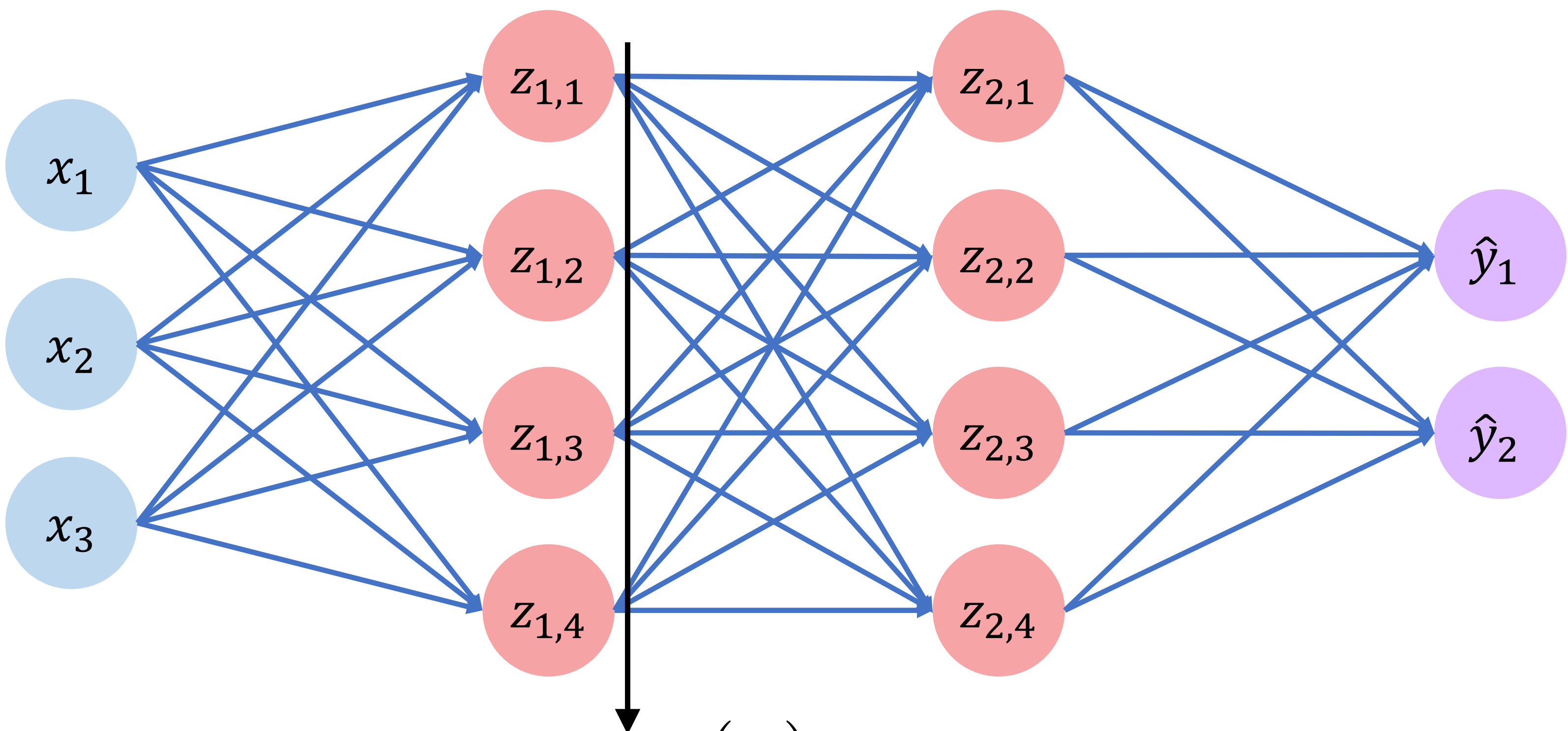


Batch Normalization

- Mini-batch of size M



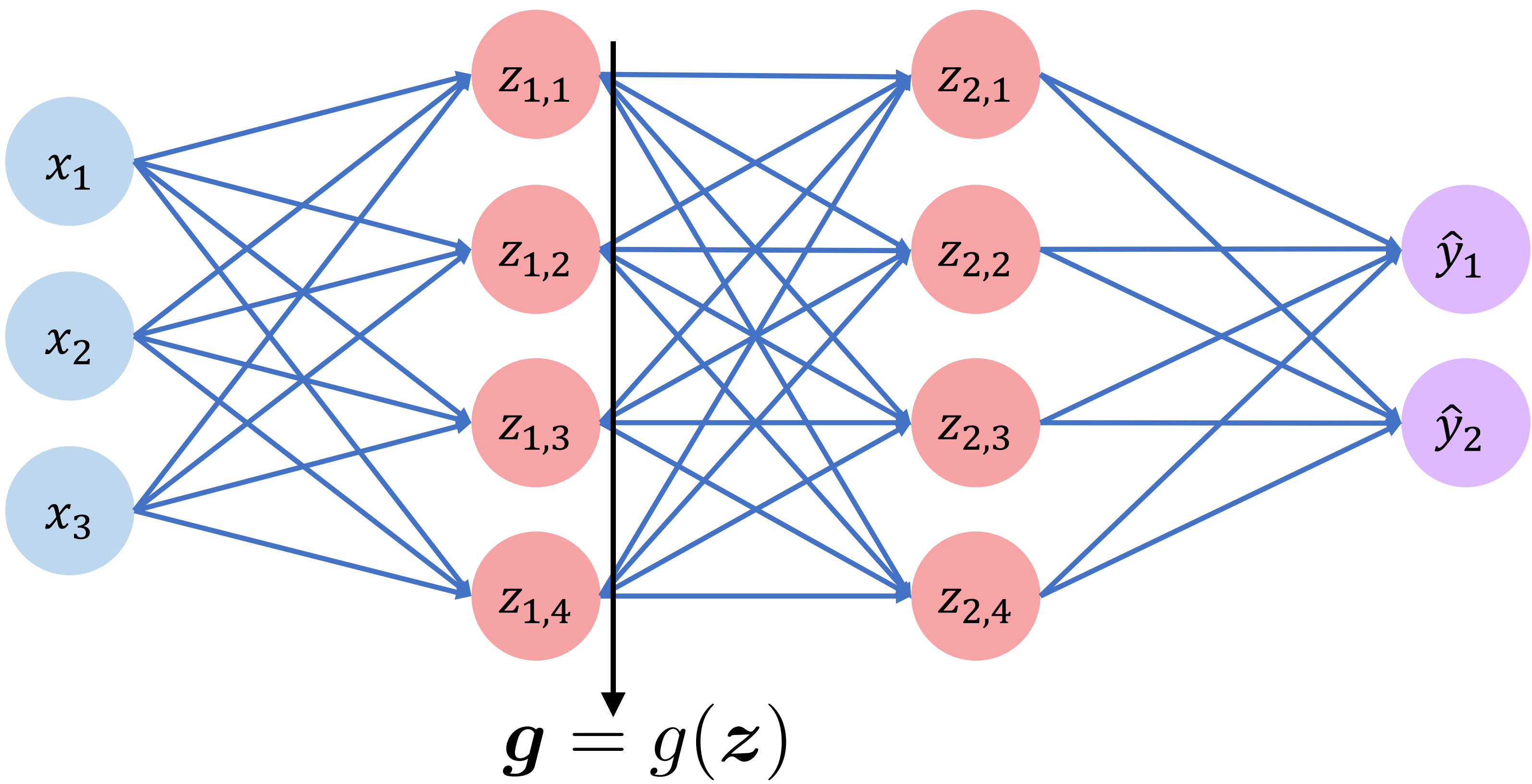
$$\boldsymbol{g} = g(\boldsymbol{z})$$

Mini-batch mean

$$\mu_j \leftarrow \frac{1}{M} \sum_{i=1}^{M} z_j^{(i)}$$

Batch Normalization

- Mini-batch of size M



Mini-batch mean

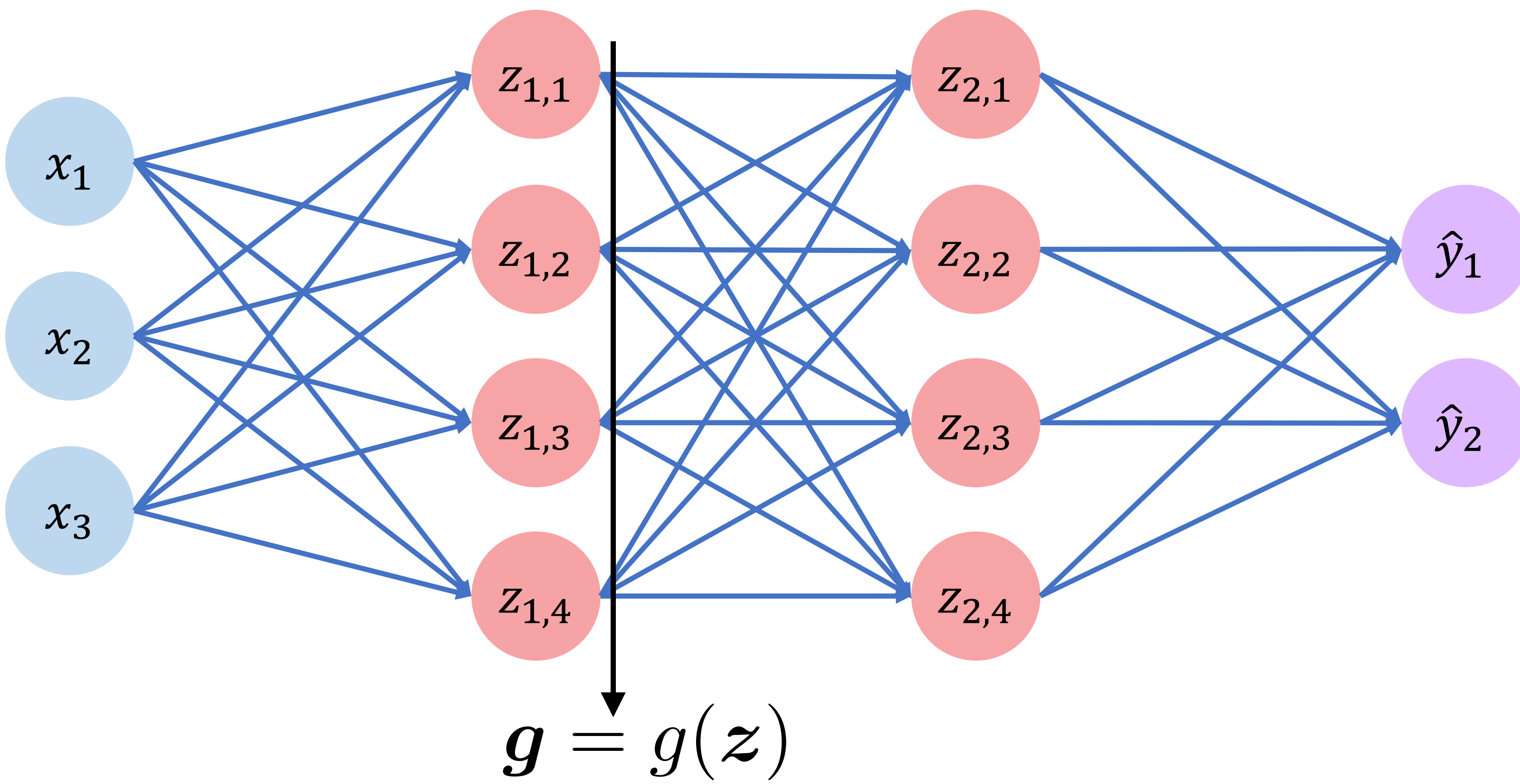
$$\mu_j \leftarrow \frac{1}{M}\sum_{i=1}^{M} z_j^{(i)}$$

Mini-batch variance

$$\sigma_j^2 \leftarrow \frac{1}{M}\sum_{i=1}^{M}(z_j^{(i)} - \mu_j)^2$$

Batch Normalization

- Mini-batch of size M



Mini-batch mean

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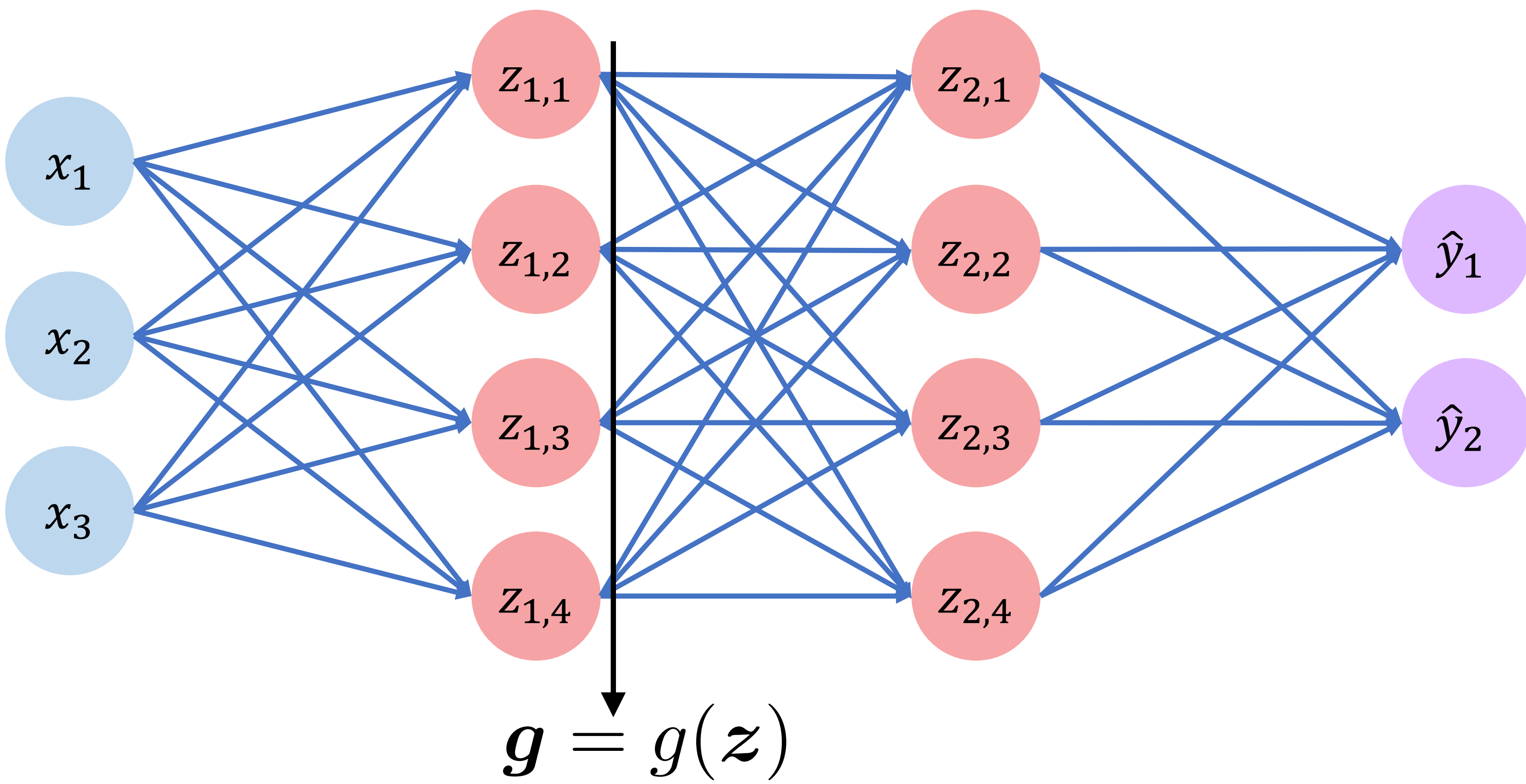
$$\sigma_j^2 \leftarrow \frac{1}{M}\sum_{i=1}^{M}(z_j^{(i)} - \mu_j)^2$$

Normalize

$$\hat{z}_j^{(i)} = \frac{z_j - \mu_j}{\sqrt{\sigma_j^2}}$$

Batch Normalization

- Mini-batch of size M



Mini-batch mean

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Mini-batch variance

$$\sigma_j^2 \leftarrow \frac{1}{M} \sum_{i=1}^{M} (z_j^{(i)} - \mu_j)^2$$

Normalize

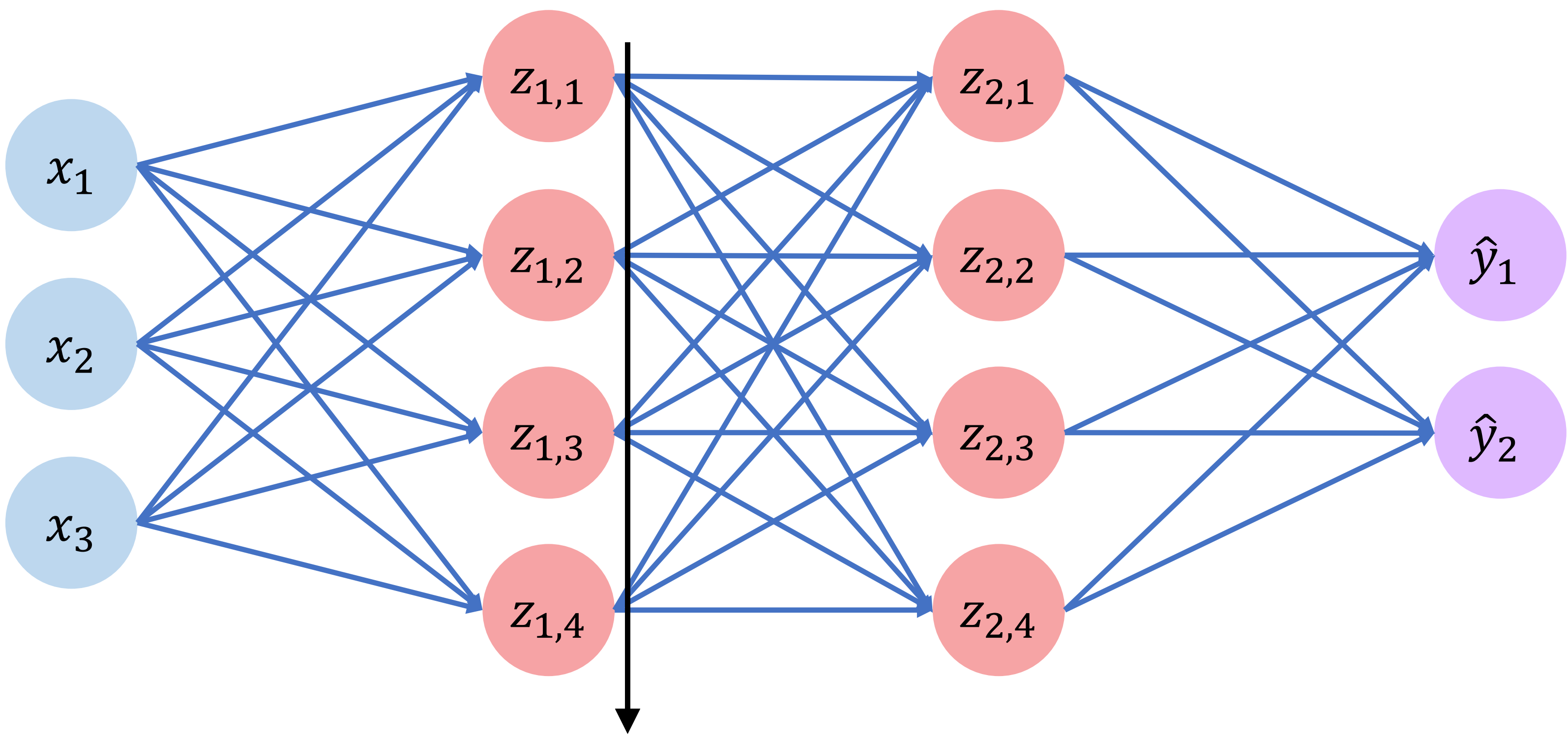
$$\hat{z}_j^{(i)} = \frac{z_j - \mu_j}{\sqrt{\sigma_j^2}}$$

Scale and shift

$$a_j^{(i)} = \gamma \hat{z}_j^{(i)} + \beta$$

Batch Normalization

- Mini-batch of size M



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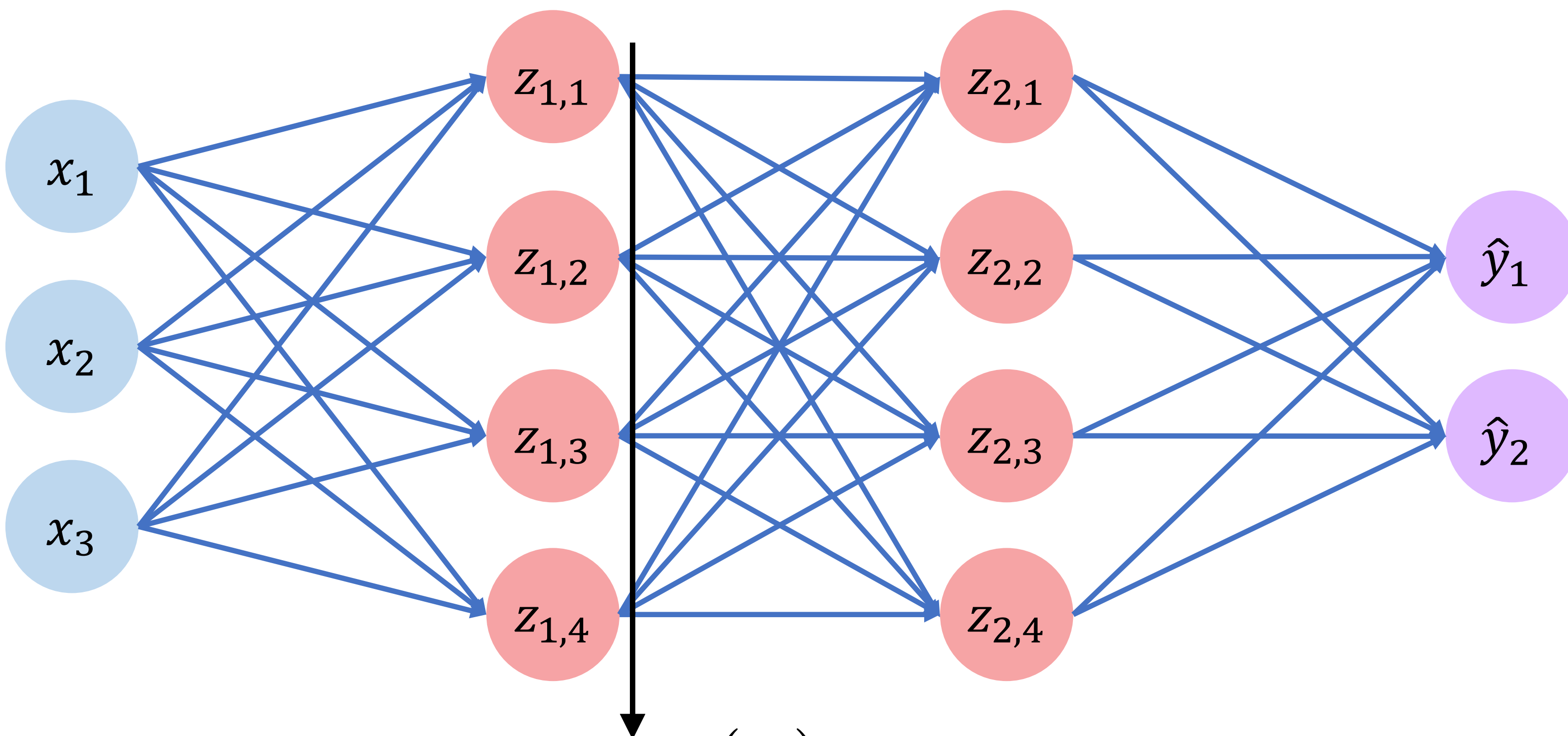
Batch Normalization

- Mini-batch of size M



$$\boldsymbol{g} = g(\boldsymbol{a})$$

Input to the non-linear activation

Mini-batch mean

$$\mu_j \leftarrow \frac{1}{M}\sum_{i=1}^{M} z_j^{(i)}$$

Mini-batch variance

$$\sigma_j^2 \leftarrow \frac{1}{M}\sum_{i=1}^{M} (z_j^{(i)} - \mu_j)^2$$

Normalize

$$\hat{z}_j^{(i)} = \frac{z_j - \mu_j}{\sqrt{\sigma_j^2}}$$

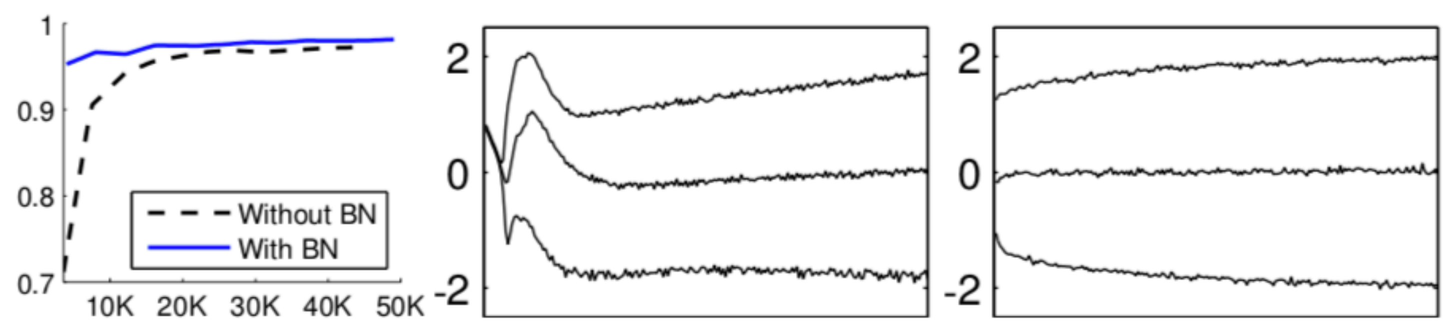
Scale and shift

$$a_j^{(i)} = \gamma \hat{z}_j^{(i)} + \beta$$

Batch Normalization

- During evaluation, we normalize according to the **whole validation/test datasets**. γ, β parameters are fixed!

- For CNNs, we jointly **normalise all pixels in the same feature map**



(a) (b) Without BN (c) With BN

Figure 1. (a) *The test accuracy of the MNIST network trained with and without Batch Normalization, vs. the number of training steps. Batch Normalization helps the network train faster and achieve higher accuracy.* (b, c) *The evolution of input distributions to a typical sigmoid, over the course of training, shown as* $\{15, 50, 85\}$*th percentiles. Batch Normalization makes the distribution more stable and reduces the internal covariate shift.*