

# *Applied Deep Learning*



## Practical Tips



March 17th, 2020 <http://adl.miulab.tw>



國立臺灣大學  
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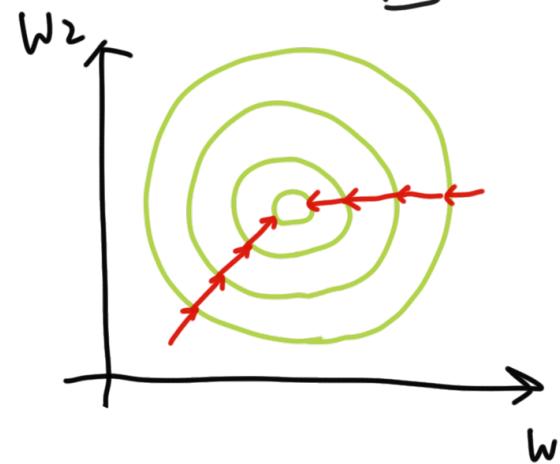
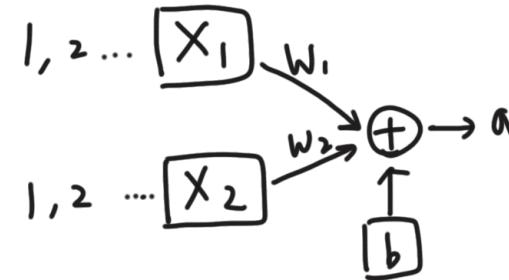
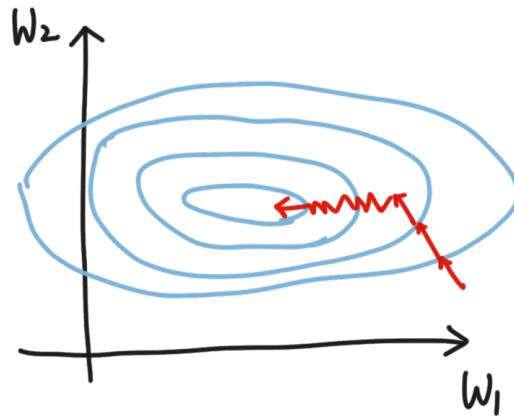
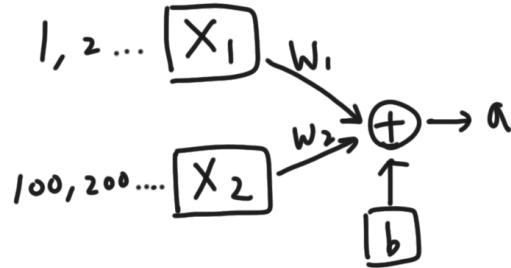
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# Mini-Batch Training



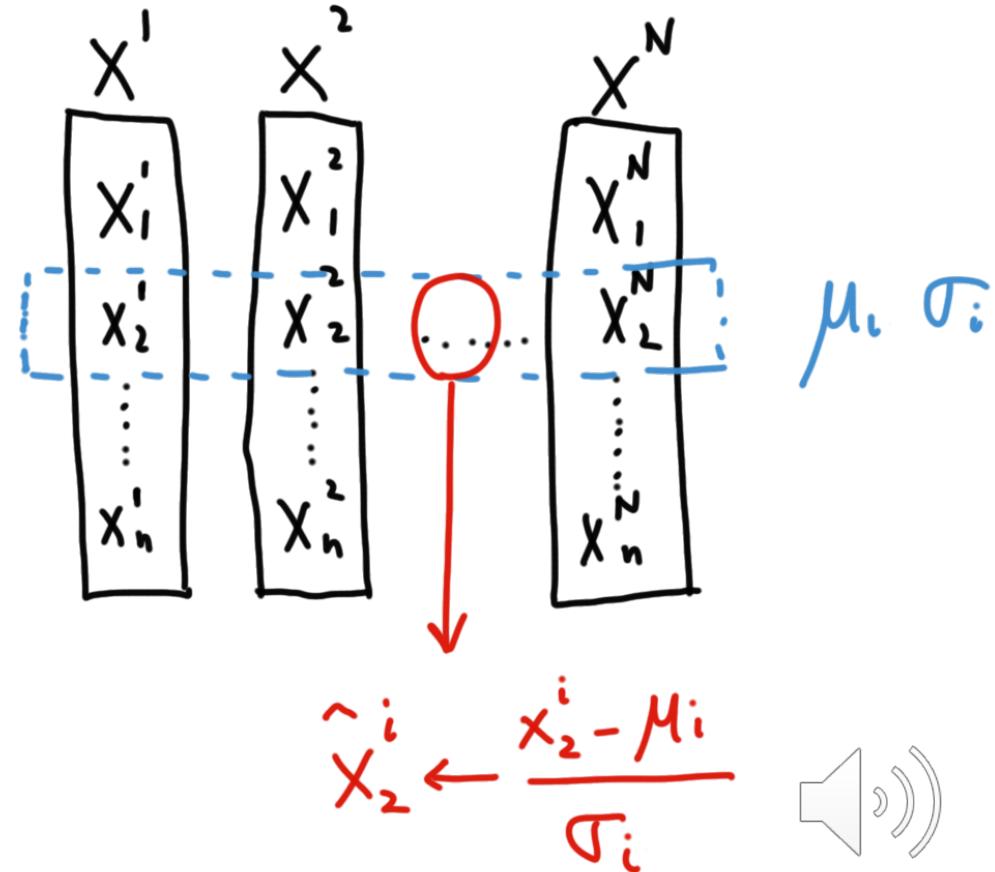
# Feature Scaling

- Idea: make sure features are on the same scale



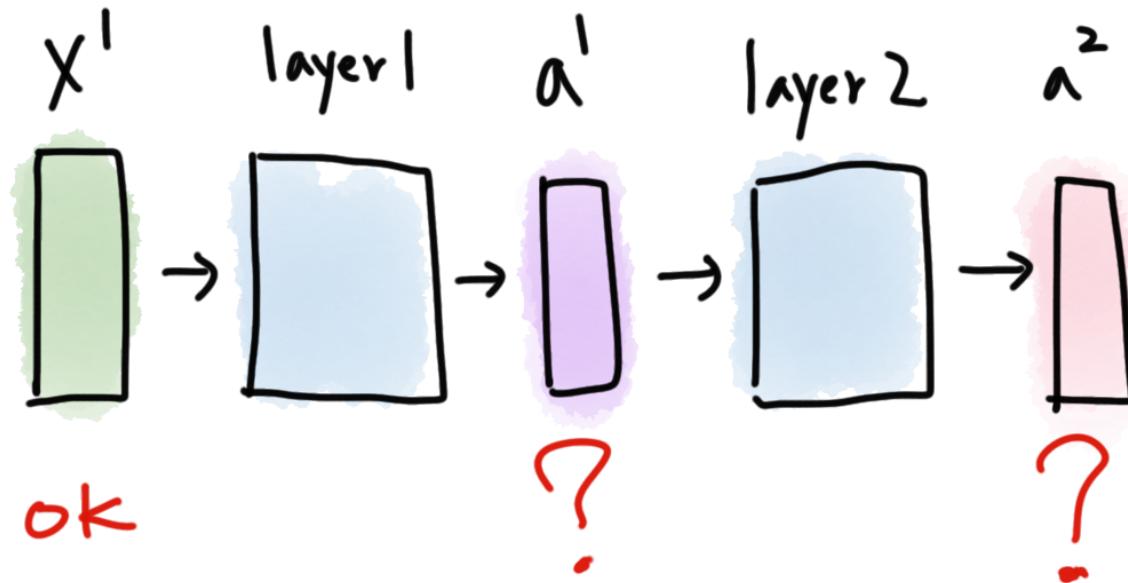
# Feature Scaling

- for each dimension, compute mean and standard deviation
- the means of normalized feature vectors are all 0 and the variances are all 1

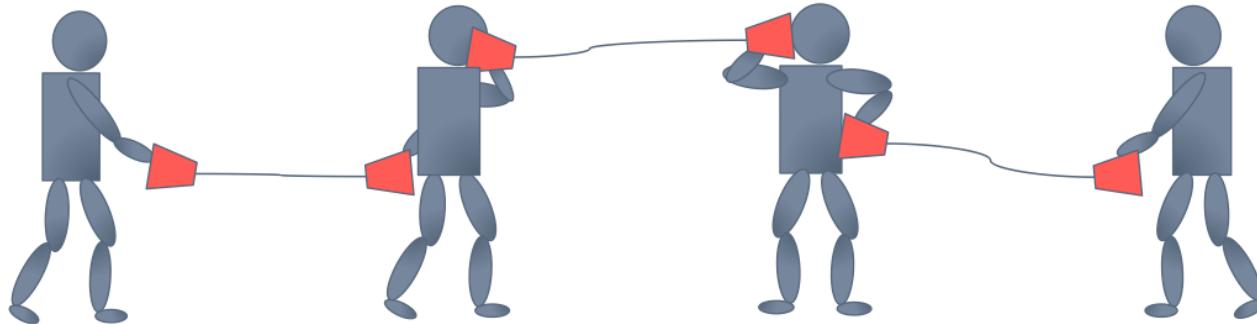
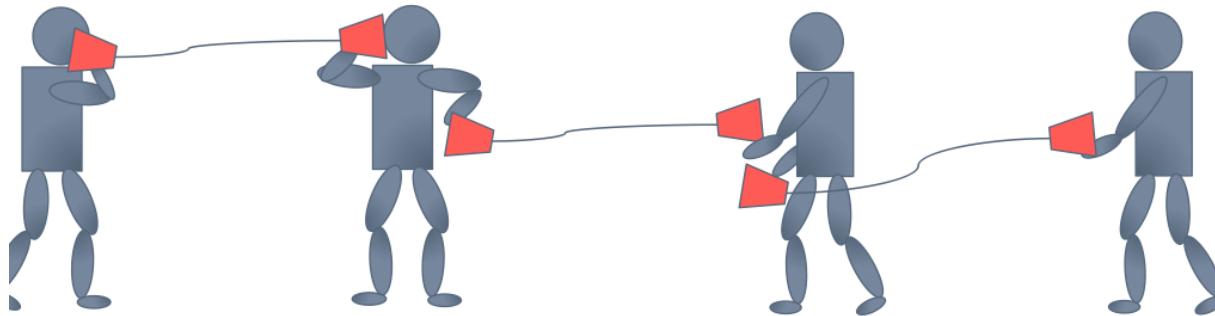


# Hidden States as Features

- statistics of hidden states keep changing during training

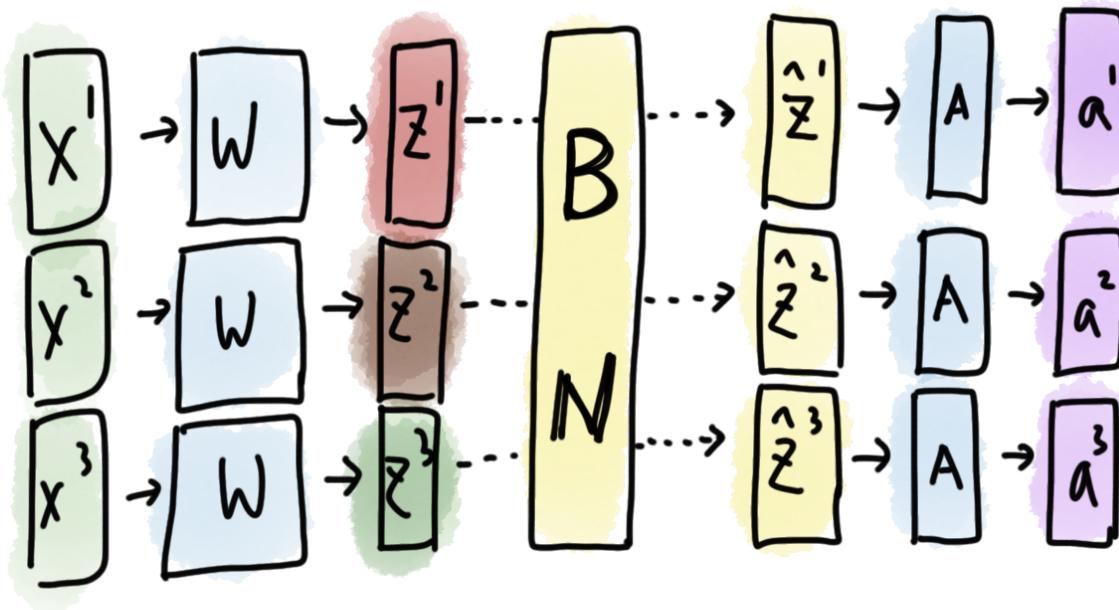


# Internal Covariate Shift



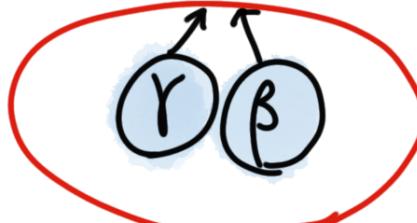
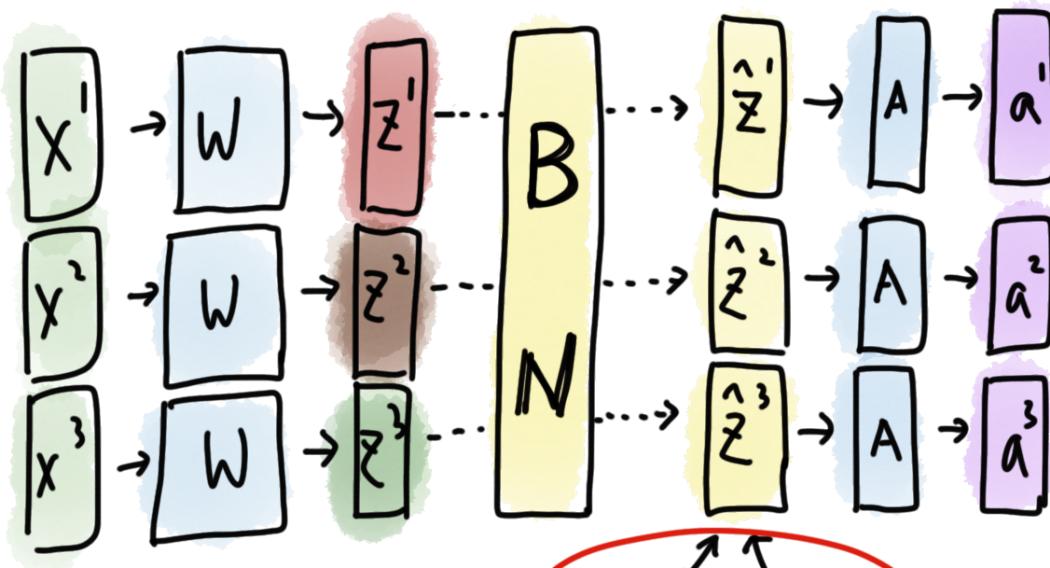
# Batch Normalization

$$\hat{z}^i = \frac{z^i - \mu}{\sigma}$$



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$$\hat{z}^i = \frac{z^i - \mu}{\sigma} \quad \hat{z}^i = \gamma \cdot \hat{z}^i + \beta$$



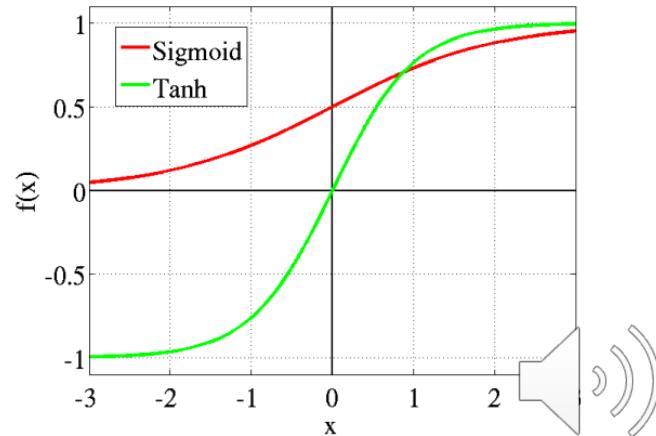
# Batch Normalization

- learnable parameters  $\gamma$  and  $\beta$  to rescale and reshift distribution to preserve model capacity
- do not have “batch” in testing phase
- Ideal solution: computing mean and variance based on the whole training set
- practical solution: computing moving average of mean and variance of batches after convergence



# Closer Look

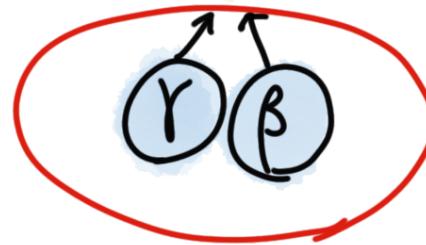
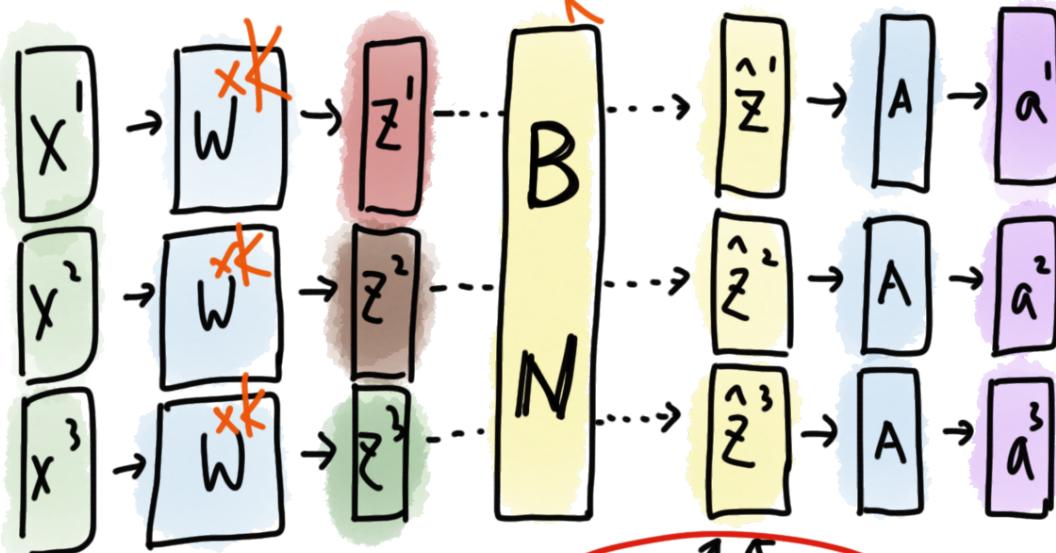
- Interval Covariate Shift?
- usually apply before activation function
- avoid exploding/vanishing gradients, especially for sigmoid and tanh activation functions
- batch size should be large
- not suitable for dynamic structure



# Closer Look

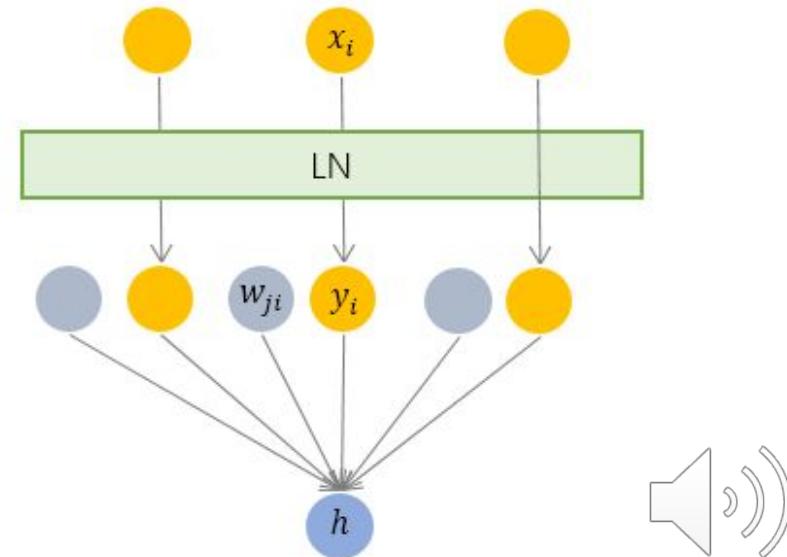
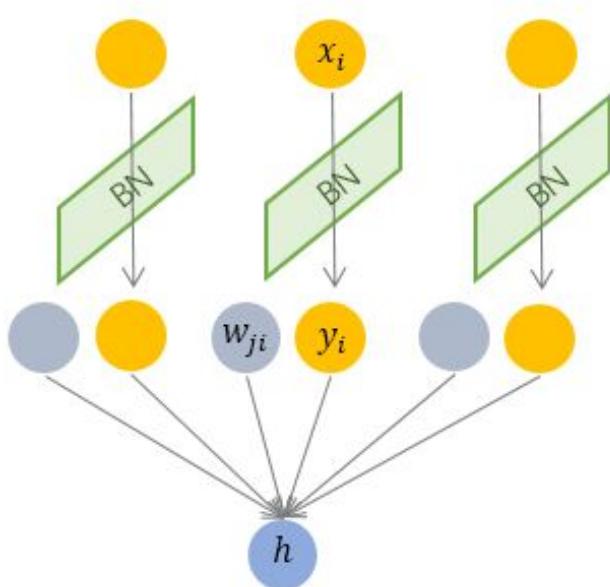
- Unsensitive to weights

$$\hat{z}^i = \frac{k_i}{K\sigma} z^i - \mu \quad \hat{z}^i = \gamma \cdot z^i + \beta$$



# Layer Normalization

- can be used in (1) small batch scenario, even a single data sample and (2) dynamic network structures like RNN



# More Kinds of Normalization

- Weight Normalization
- Instance Normalization
- Group Normalization
- Spectral Normalization



# How big is your batch size?

- Intuitive idea: my GPU memory is enough → increase the batch size
- ...Is it correct?

推文

Yann LeCun  
@ylecun

Training with large minibatches is bad for your health.  
More importantly, it's bad for your test error.  
Friends dont let friends use minibatches larger than 32.  
[arxiv.org/abs/1804.07612](https://arxiv.org/abs/1804.07612)

翻譯推文  
上午5:00 · 2018年4月27日 · Facebook

463 轉推 1,304 喜歡次數

# How big is your batch size?

- The paper titled “*Revisiting Small Batch Training for Deep Neural Networks*”
- Quote from the paper: “*In all cases the best results have been obtained with batch sizes  $m= 32$  or smaller, often as small as  $m= 2$  or  $m= 4$ . With BN and larger datasets, larger batch sizes can be useful, up to batch size  $m= 32$  or  $m= 64$ .*”



# Learning Rate

- Intuitive/simple idea: reduce the learning rate by some factor every few epochs.
  - At the beginning, we are far from the destination, so use a larger learning rate
  - After several epochs, as we get closer to the destination, reduce the learning rate
- Better idea: give different parameters different learning rates
  - Adaptive optimizers: Adagrad, RMSprop, Adam etc.



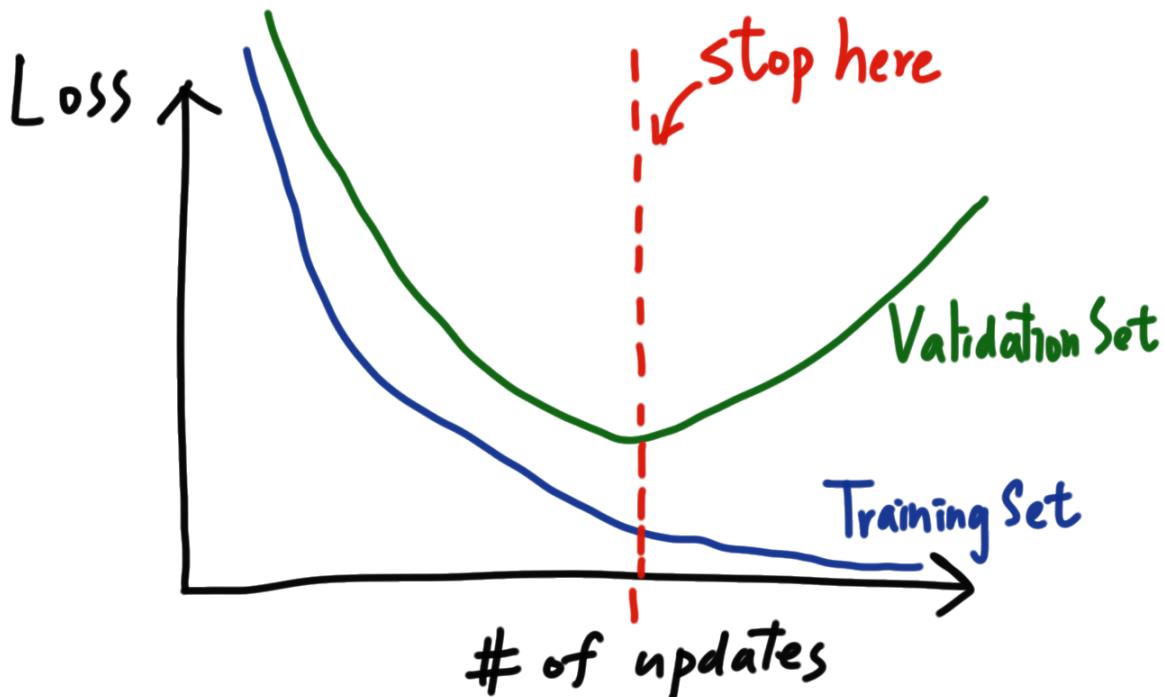
# Generalization

To Prevent Overfitting



# Early Stopping

- Q: how many epochs should we train the models?



# Weight Decay

- Smaller weights are preferred. Why?
- $(x, y)$  vs  $(x', y)$  where  $x' = x + \varepsilon$
- $z = w \cdot x$
- $z' = w \cdot x' = w \cdot (x + \varepsilon) = z + w \cdot \varepsilon$
- To minimize the effect of noise, we want weights close to zero.



# Regularization

- Add a weight constraint term into the objective

$$L' = L + L_r(w)$$

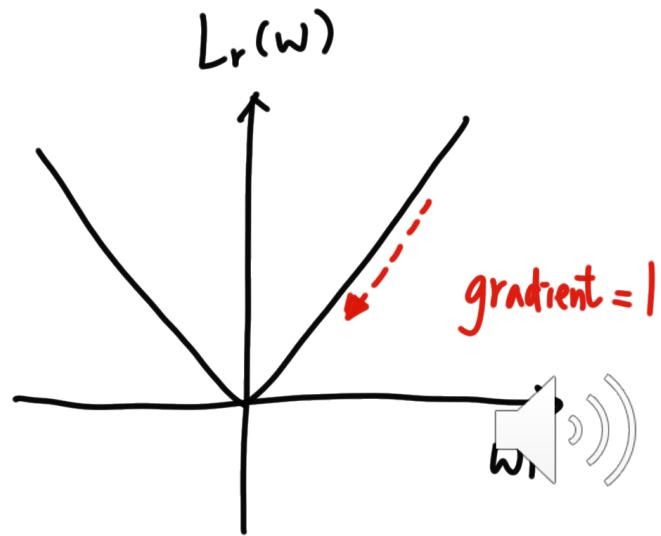
- By minimizing the loss, the weights will become smaller.



# L1 Regularization

$$L_r(w) = \lambda \sum_{i=1}^N |w_i|$$

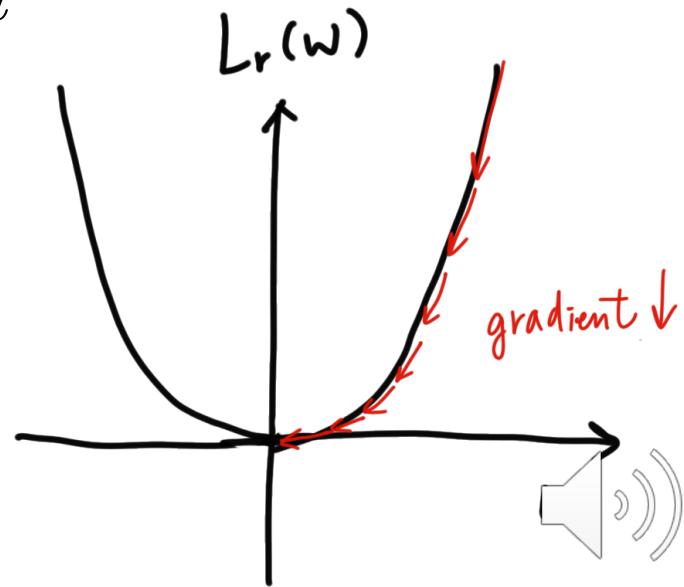
- feature selection/parameter sparsity



# L2 Regularization

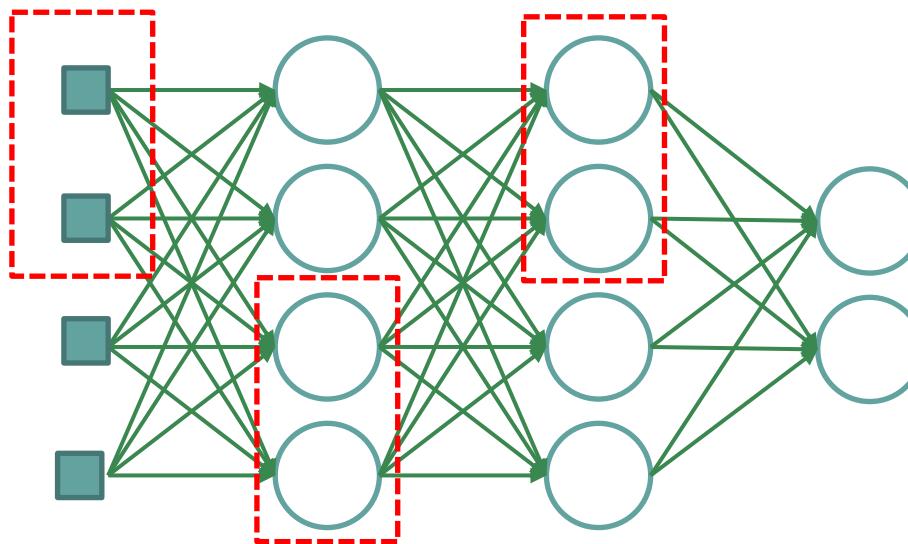
$$L_r(w) = \lambda \sum_{i=1}^N w_i^2$$

- "One should always try L2 first."
- encourage all weights to be small



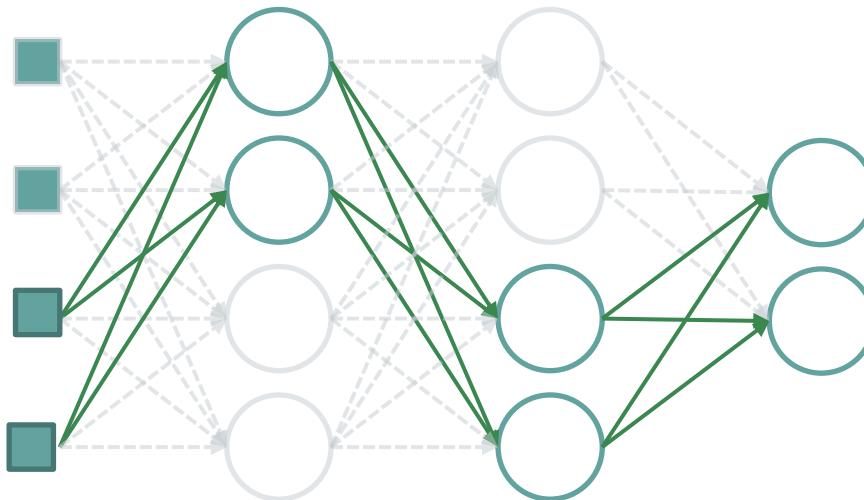
# Dropout

- In each iteration of training, each neuron has p% probability to dropout



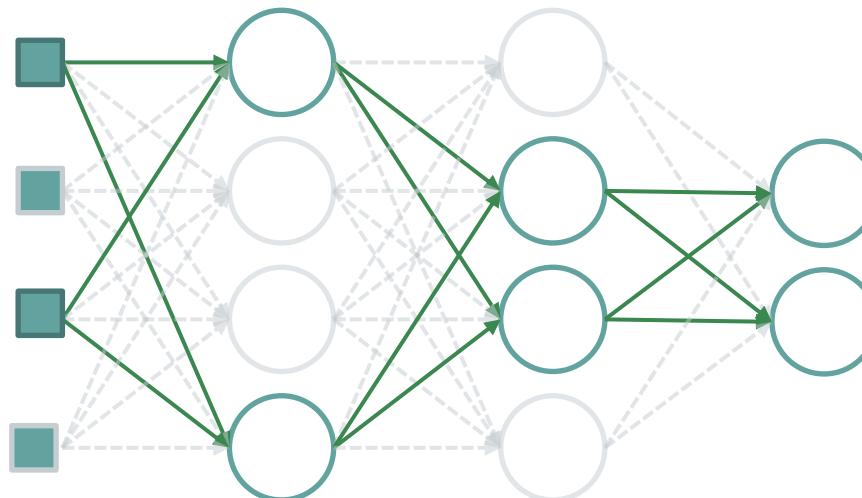
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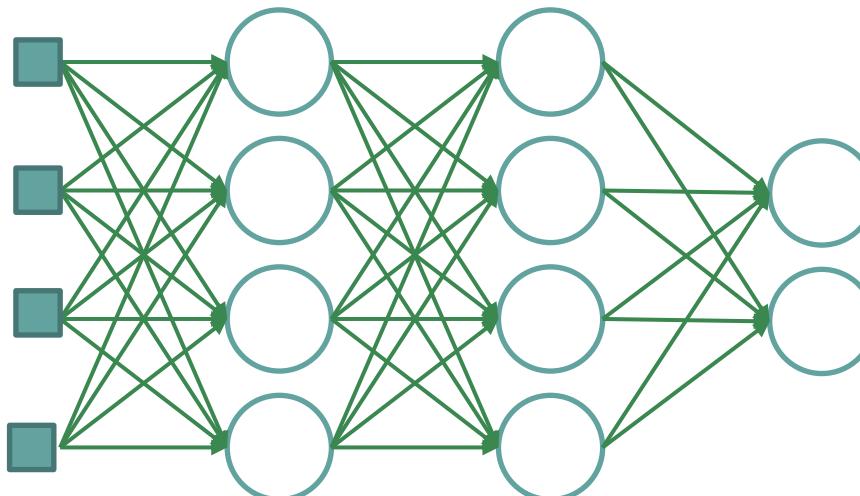
# Dropout

- For each iteration, we resample the dropout neurons
- Using a new network for training



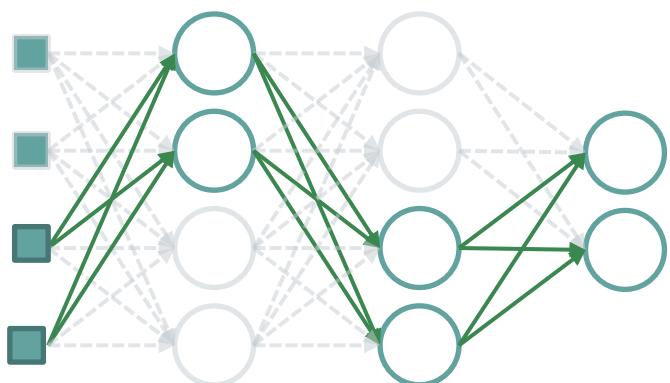
# Dropout

- When testing, no dropout and all the weights times  $(100-p)\%$
- Why?

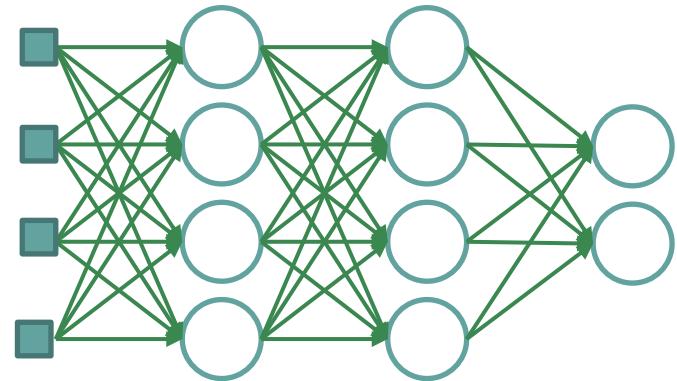


# Dropout

- Assume  $p = 0.5$



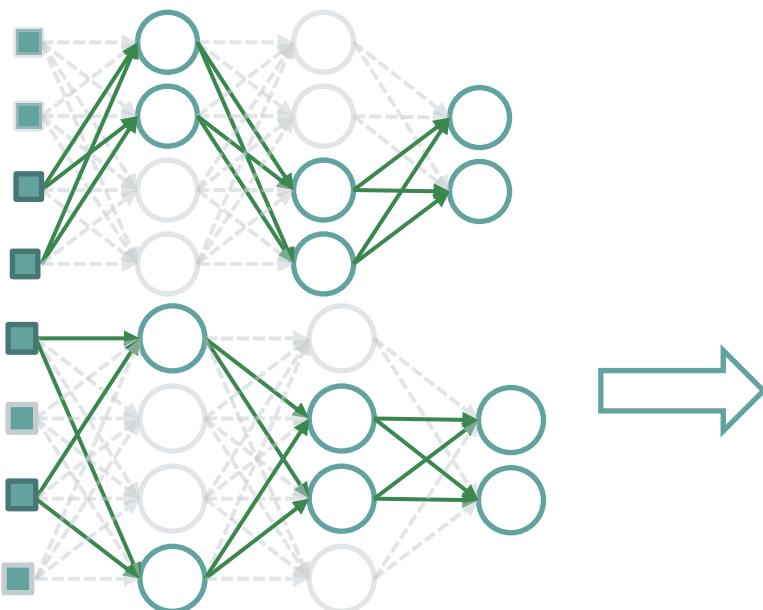
$$z = w \cdot x$$



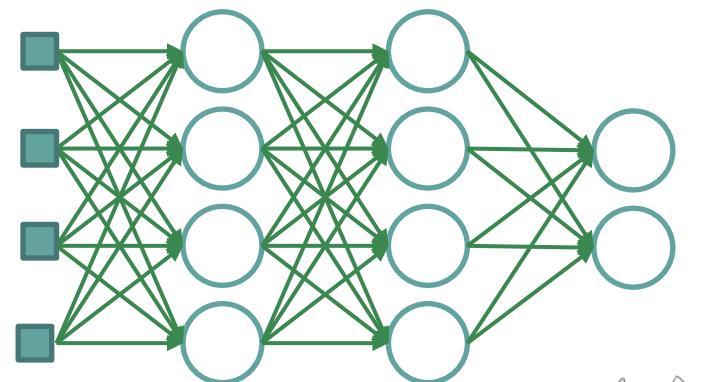
$$z' \approx 2z$$
$$z' \cdot (1 - p) \approx z$$

# Dropout

## Ensemble



Train a bunch of networks

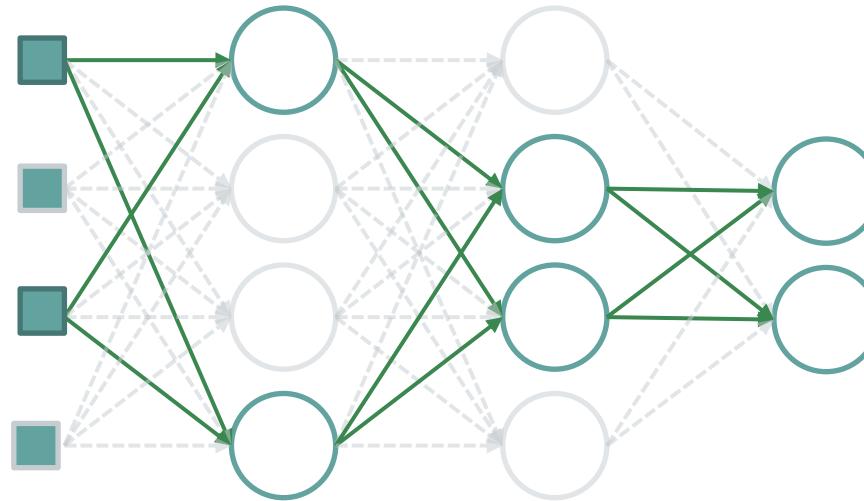


Average the results



# Dropout

- depress the capacity → unleash the potential
- your teammate is a free rider → you need to work harder



# References

- [https://www.csie.ntu.edu.tw/~yvchen/f106-adl/doc/171116+171120\\_Tip.pdf](https://www.csie.ntu.edu.tw/~yvchen/f106-adl/doc/171116+171120_Tip.pdf)
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- [http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS\\_2015\\_2/Lecture/Deep%20More%20\(v2\).pdf](http://speech.ee.ntu.edu.tw/~tlkagk/courses/MLDS_2015_2/Lecture/Deep%20More%20(v2).pdf)

