

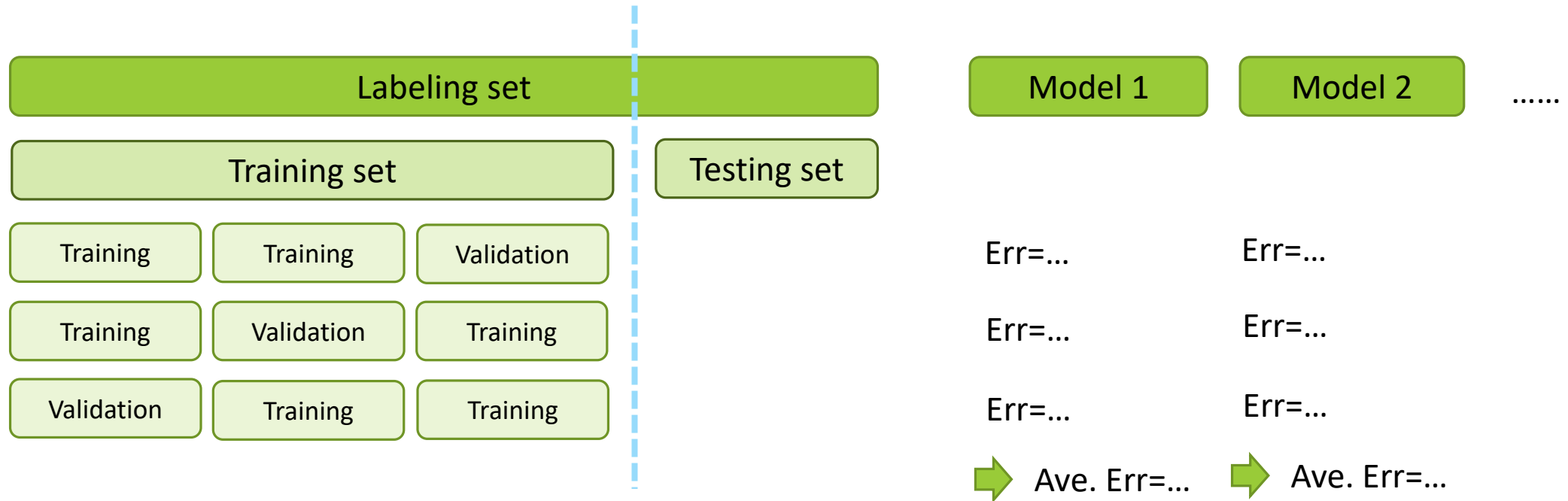
機器學習於材料資訊的應用

Machine Learning on Material Informatics

陳南佑(NAN-YOW CHEN)

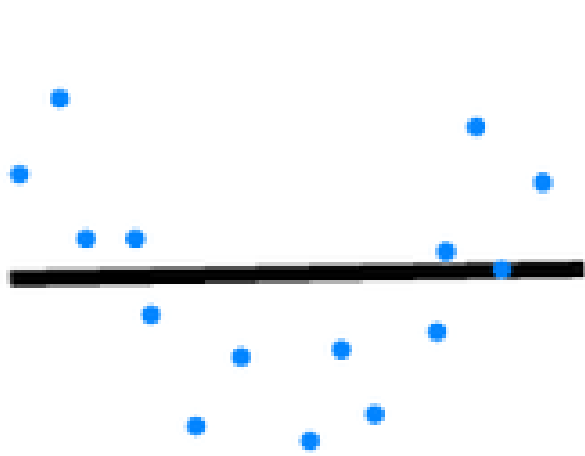
楊安正(AN-CHENG YANG)

Cross validation – N fold

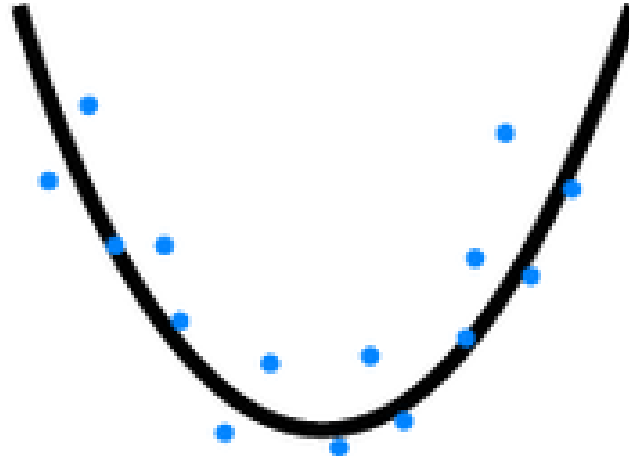


- Pick the model which has the smallest average error.
- Use all training set to train machine again.
- Apply machine (neuron network) to the testing set to see the accuracy.

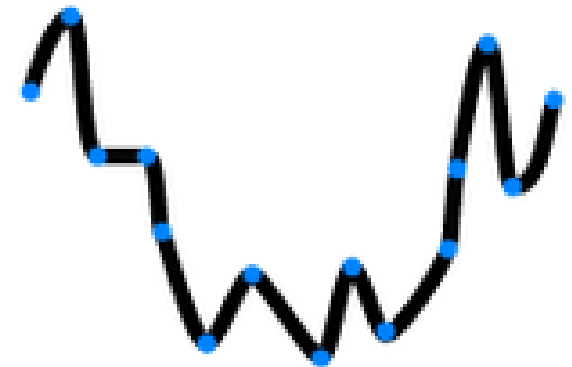
Overfitting



Underfitting



Desired

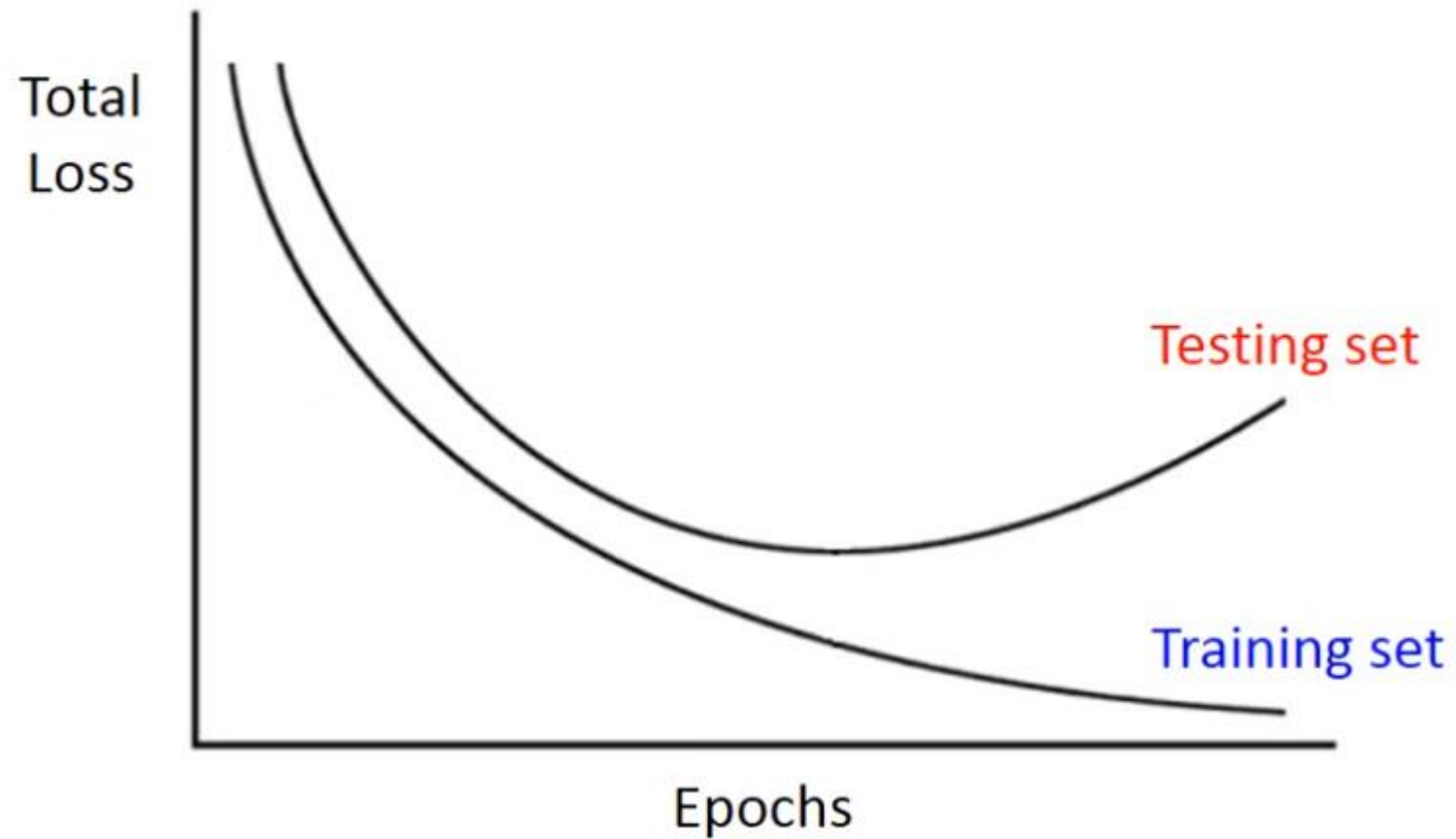


Overfitting

How to detect overfitting?

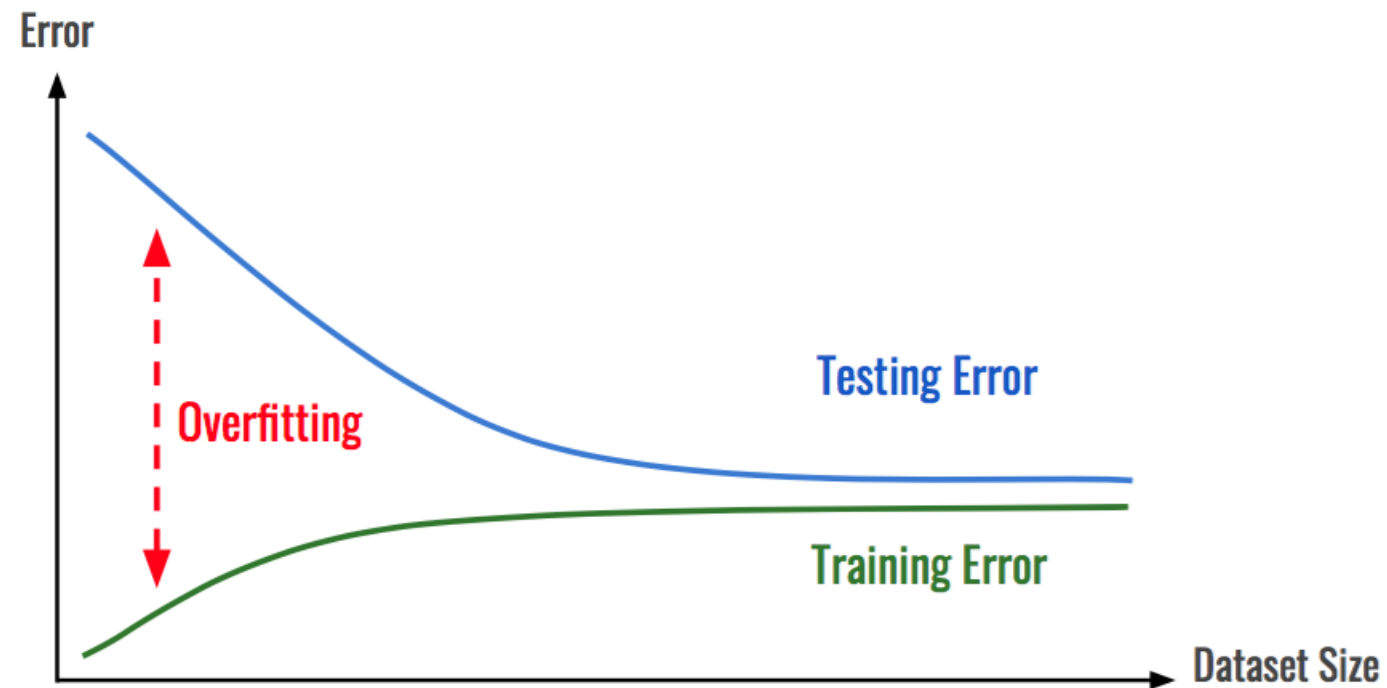
	Low Training Error	High Training Error
Low Testing Error	The model is learning!	Probably some error in your code. Or you've created a <i>psychic</i> AI.
High Testing Error	OVERFITTING	The model is not learning.

How to detect overfitting?



How to prevent overfitting?

- From data:
 - Gather more data



How to prevent overfitting?

- From data:
 - Gather more data
 - Data augmentation & Noise



Original



1st Variation



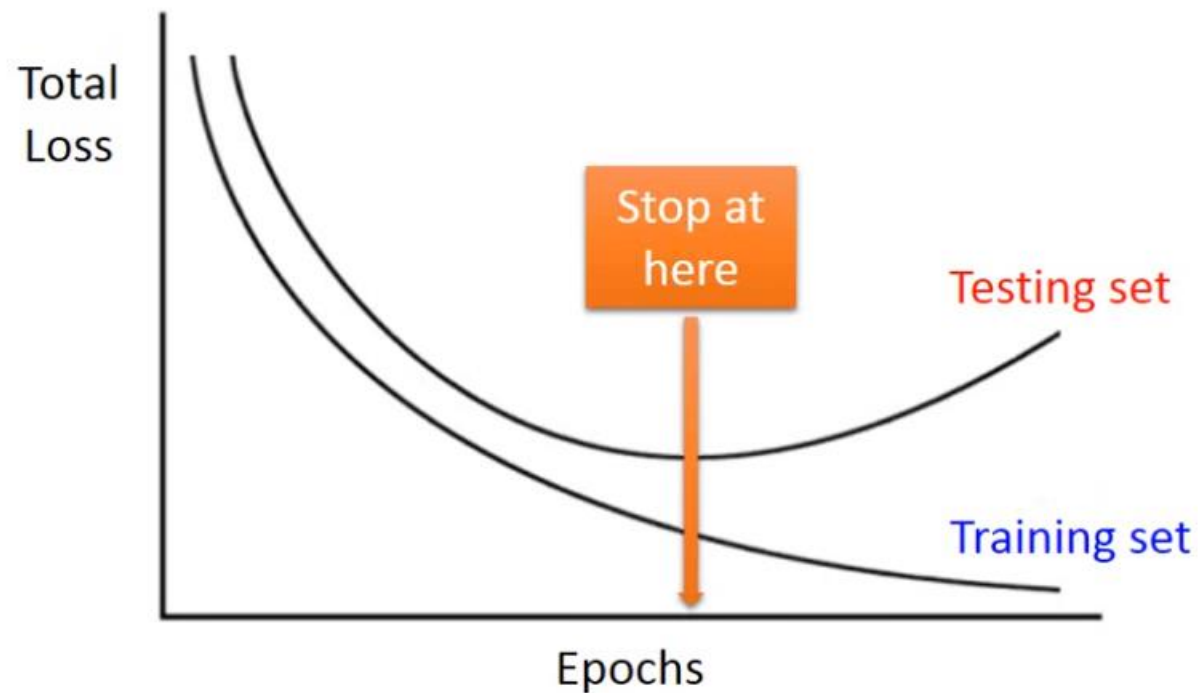
2nd Variation



3rd Variation

How to prevent overfitting?

- From model:
 - Early termination (early stop)



How to prevent overfitting?

□ From model:

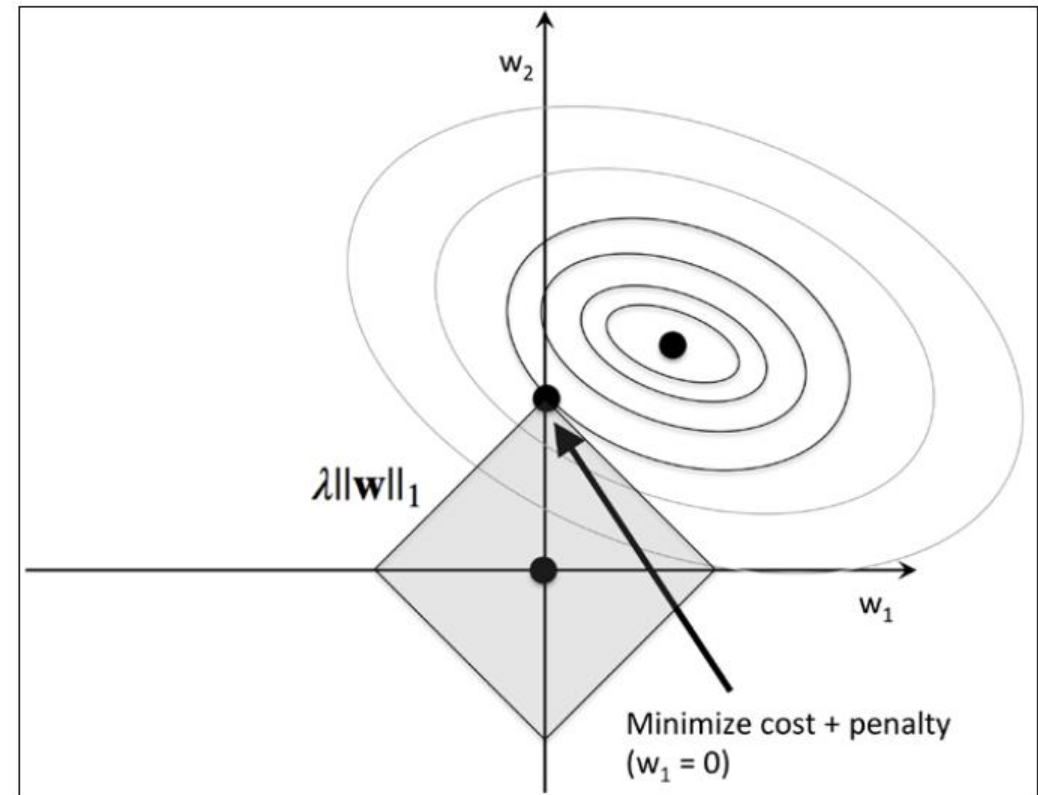
- Early Termination (early stop)
- Regularization (weight decay): L1 & L2

L1 Regularization

$$\text{Cost} = \sum_{i=0}^N (y_i - \sum_{j=0}^M x_{ij} W_j)^2 + \lambda \sum_{j=0}^M |W_j|$$

L2 Regularization

$$\text{Cost} = \underbrace{\sum_{i=0}^N (y_i - \sum_{j=0}^M x_{ij} W_j)^2}_{\text{Loss function}} + \underbrace{\lambda \sum_{j=0}^M W_j^2}_{\text{Regularization Term}}$$



How to prevent overfitting?

□ From model:

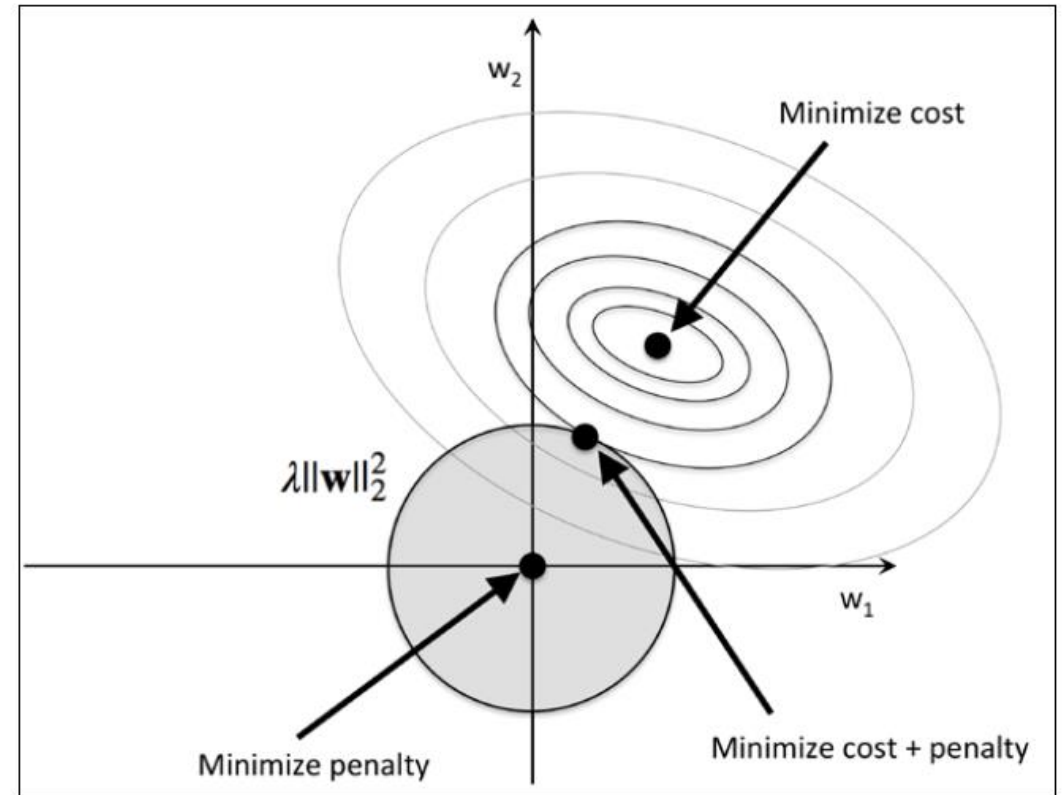
- Early Termination (early stop)
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L1 Regularization

$$\text{Cost} = \sum_{i=0}^N (y_i - \sum_{j=0}^M x_{ij} W_j)^2 + \lambda \sum_{j=0}^M |W_j|$$

L2 Regularization

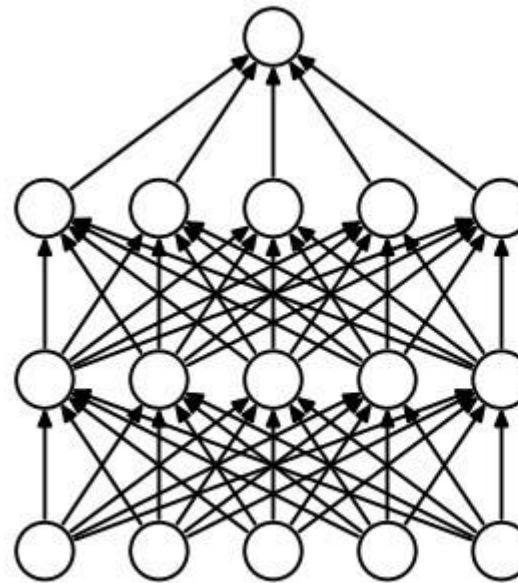
$$\text{Cost} = \underbrace{\sum_{i=0}^N (y_i - \sum_{j=0}^M x_{ij} W_j)^2}_{\text{Loss function}} + \underbrace{\lambda \sum_{j=0}^M W_j^2}_{\text{Regularization Term}}$$



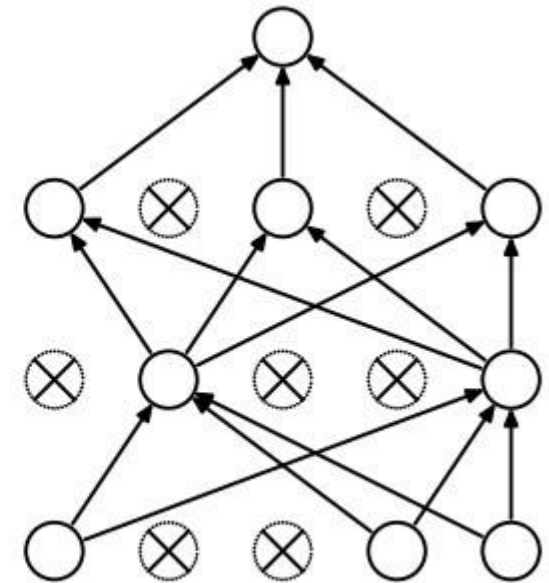
How to prevent overfitting?

□ From model:

- Early Termination (early stop)
- Regularization (weight decay): L1 & L2
- Dropout

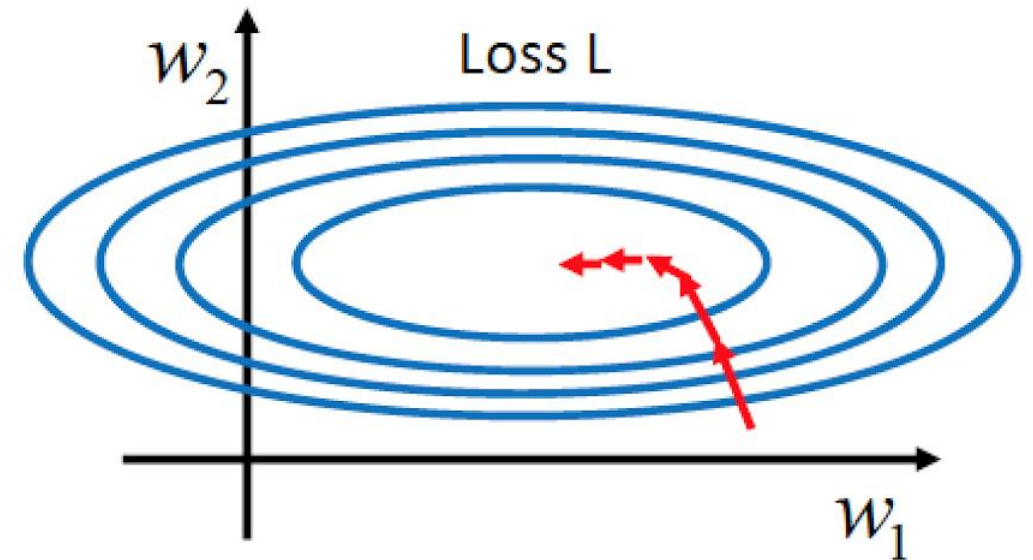
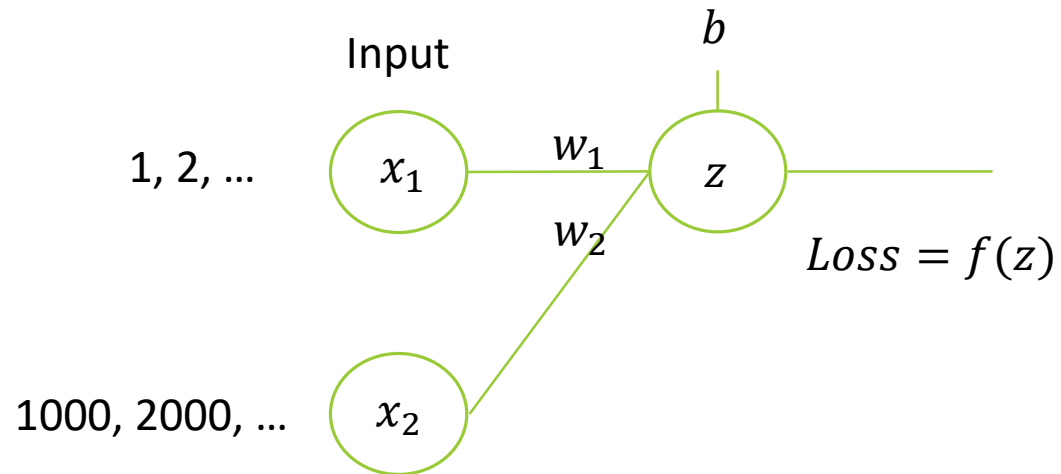


(a) Standard Neural Net

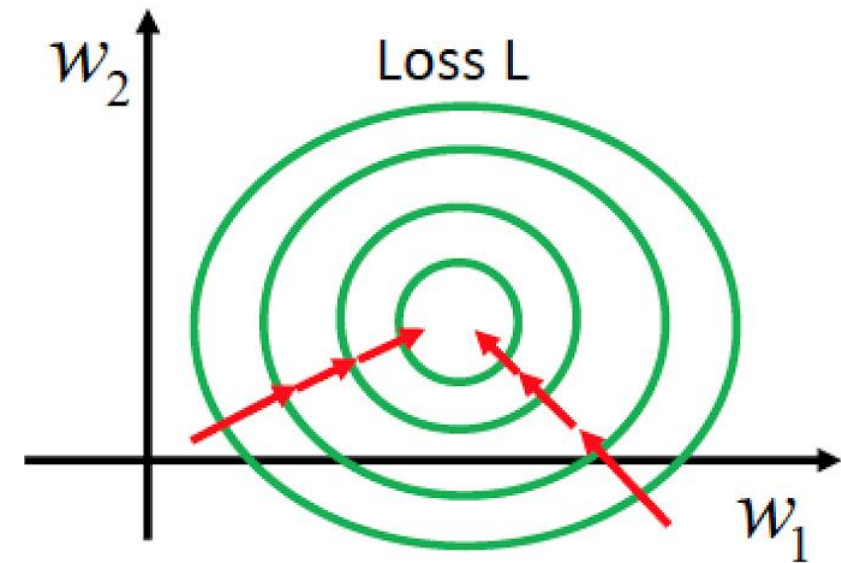
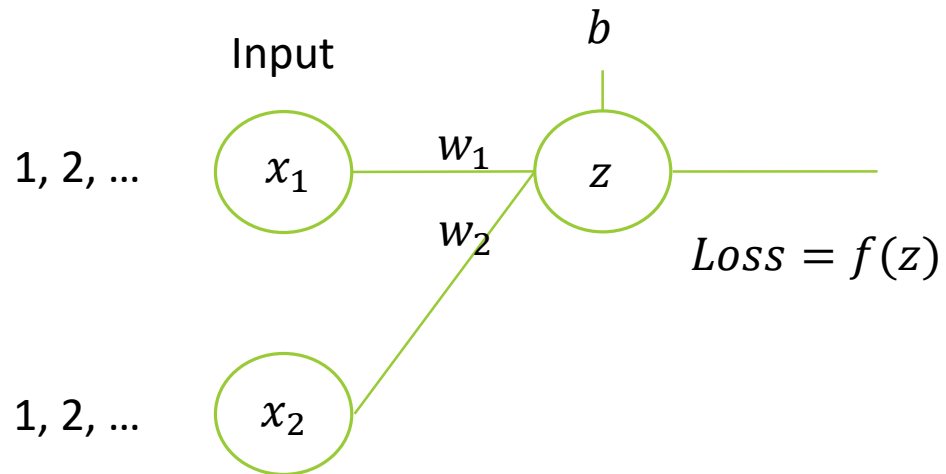


(b) After applying dropout.

Feature scaling



Feature scaling



Feature scaling

- Rescaling (min-max normalization)

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

- Mean normalization

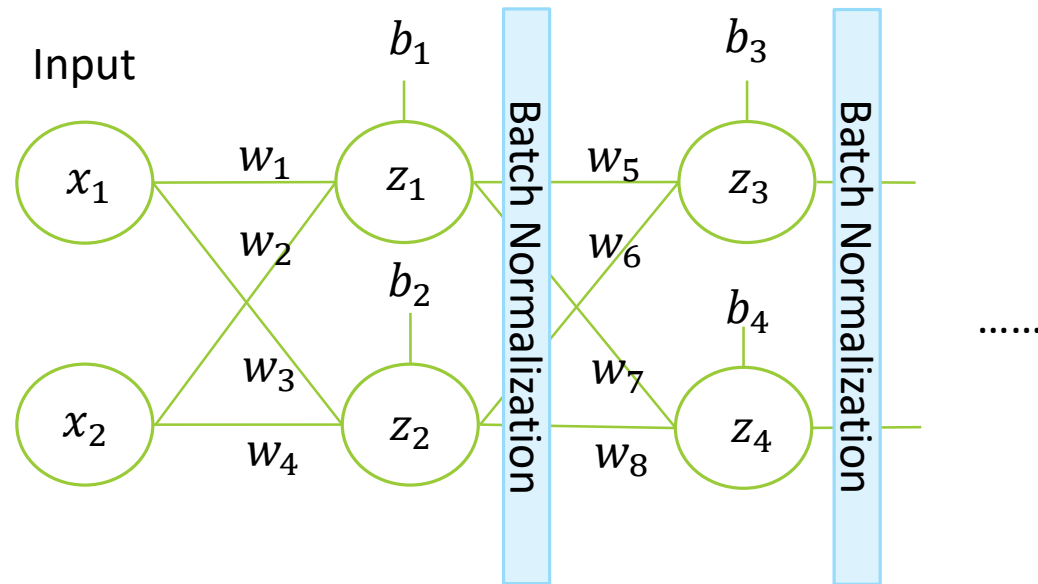
$$x' = \frac{x - \text{average}(x)}{\max(x) - \min(x)}$$

- Standardization (Z-score)

$$x' = \frac{x - \bar{x}}{\sigma}$$

where σ is its standard deviation.

How about hidden layers?



Input: Values of x over a mini-batch: $\mathcal{B} = \{x_1 \dots x_m\}$;

Parameters to be learned: γ, β

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

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

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

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

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

Algorithm 1: Batch Normalizing Transform, applied to activation x over a mini-batch.

➔ Use batch normalization!

`tf.layers.batch_normalization()`
`keras.layers.BatchNormalization()`

Batch normalization

- Usually added before activation function.
- Can reduce training time.
- Can use high learning rate.
- Let learning is less affected by initialization of weights.
- Can build more deep network.
- Can reduce the demand for regularization.

Next class

□ Case study

