

CPE 486/586: Deep Learning for Engineering Applications

04 Training Neural Networks and Computational Thinking

Spring 2026

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Outline

1. Recap

2. Training a Neural Network

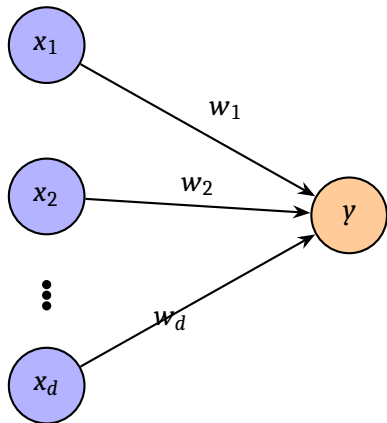
2.1 Data Preprocessing

2.2 Data Preprocessing

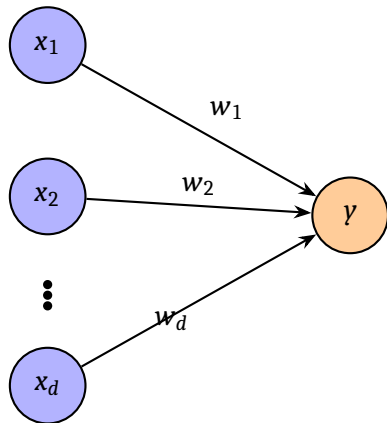
Recap

0	1	0	1	1	0	0	1	1	1	1	0	1	0	0	0	1	0	1	0
0	0	0	1	1	1	0	1	1	0	0	1	0	1	0	0	1	0	1	1
0	1	0	1	1	0	0	0	1	1	0	0	1	1	0	1	0	1	0	0

Linear Layer

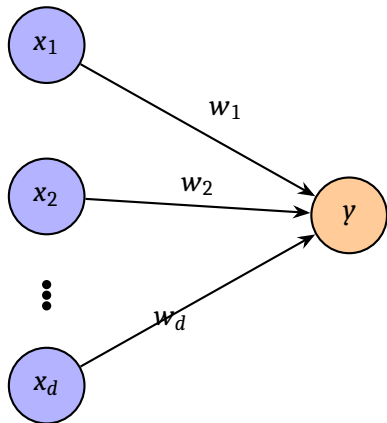


Linear Layer



$$y = \sum_{i=1}^n w_i x_i$$

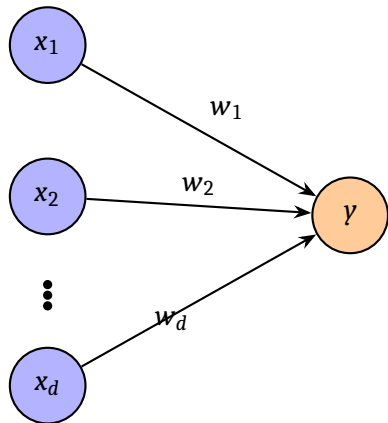
Linear Layer



$$y = \sum_{i=1}^n w_i x_i$$

$$\mathbf{w} = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_d \end{bmatrix} \quad \mathbf{x} = [x_1 \quad x_2 \quad \cdots \quad x_d]$$

Linear Layer

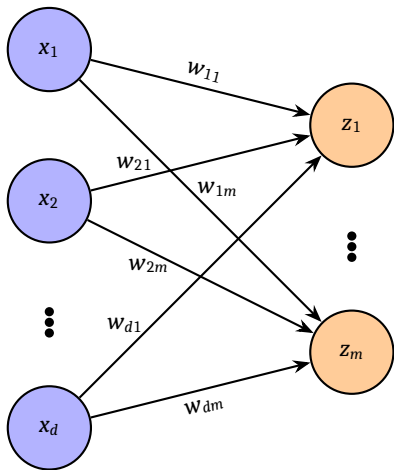


$$y = \sum_{i=1}^n w_i x_i$$

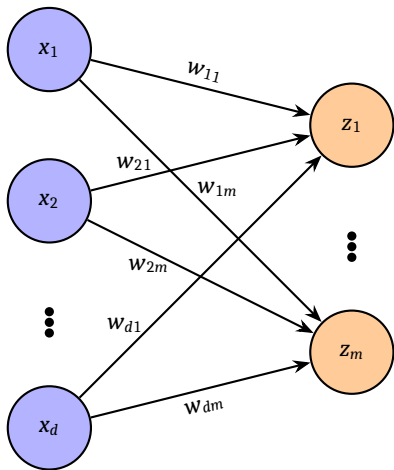
$$\mathbf{w} = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_d \end{bmatrix} \quad \mathbf{x} = [x_1 \quad x_2 \quad \cdots \quad x_d]$$

$$\Rightarrow y = \mathbf{xw}$$

Linear Layer: Case of Hidden Layer

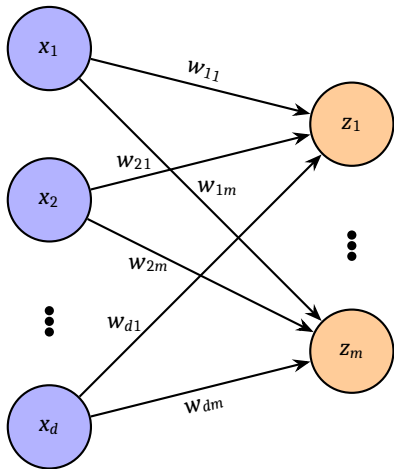


Linear Layer: Case of Hidden Layer



$$z_m = \sum_{i=1}^n x_i w_{im}$$

Linear Layer: Case of Hidden Layer



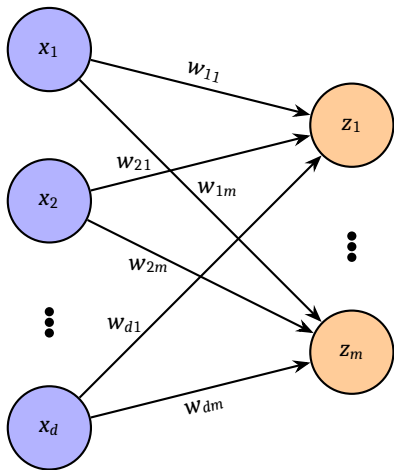
$$z_m = \sum_{i=1}^n x_i w_{im}$$

$$\mathbf{z} = \begin{bmatrix} z_1 & z_2 & \vdots & z_m \end{bmatrix}_{1 \times m}$$

$$W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1m} \\ w_{21} & w_{22} & \cdots & w_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ w_{d1} & w_{d2} & \cdots & w_{dm} \end{bmatrix}_{d \times m}$$

$$\mathbf{x} = \begin{bmatrix} x_1 & x_2 & \cdots & x_d \end{bmatrix}_{1 \times d}$$

Linear Layer: Case of Hidden Layer



$$z_m = \sum_{i=1}^n x_i w_{im}$$

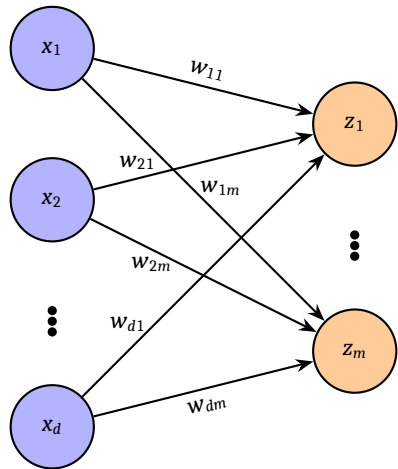
$$\mathbf{z} = \begin{bmatrix} z_1 & z_2 & \vdots & z_m \end{bmatrix}_{1 \times m}$$

$$W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1m} \\ w_{21} & w_{22} & \cdots & w_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ w_{d1} & w_{d2} & \cdots & w_{dm} \end{bmatrix}_{d \times m}$$

$$\mathbf{x} = \begin{bmatrix} x_1 & x_2 & \cdots & x_d \end{bmatrix}_{1 \times d}$$

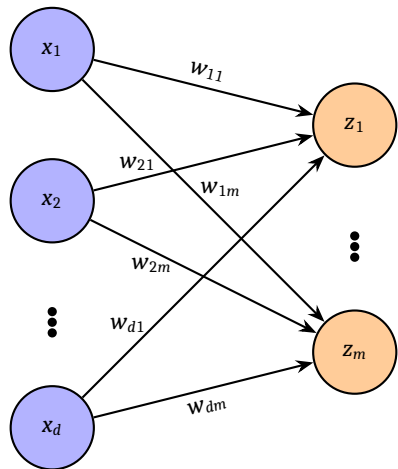
$$\Rightarrow \mathbf{z} = \mathbf{x}W$$

Linear Layer: Case of Hidden Layer



That was the case of one sample, if we consider n sample, then?

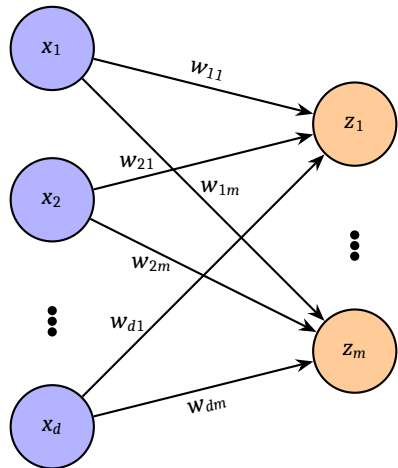
Linear Layer: Case of Hidden Layer



That was the case of one sample, if we consider n sample, then?

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1d} \\ x_{21} & x_{22} & \cdots & x_{2d} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nd} \end{bmatrix}$$

Linear Layer: Case of Hidden Layer



That was the case of one sample, if we consider n sample, then?

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1d} \\ x_{21} & x_{22} & \cdots & x_{2d} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nd} \end{bmatrix}$$

$$\Rightarrow Z = XW$$

Nonlinear Operation

$$A = \sigma(Z)$$

which will use elementwise operation.

Training a Neural Network

1	0	1	1	0	0	1	0	1	1	1	1	1	0	0	1	1	0	1	0
1	1	1	0	0	0	0	1	0	1	1	1	0	1	0	0	0	0	1	0
0	1	0	0	1	1	0	1	0	1	1	1	0	0	0	0	0	0	1	0

How to Train your Neural Network

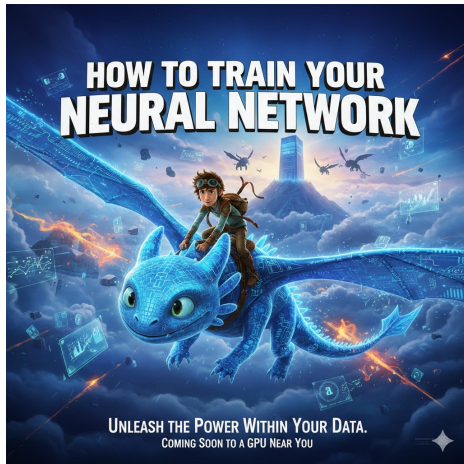


Image generation from Google Gemini.

Training a Neural Network

Some criteria to consider:

- 1 Data Preprocessing:
Normalization/Standardization
- 2 Batch Size
- 3 Batch Normalization
- 4 Dropout
- 5 Early-Stopping
- 6 Learning-Rate Scheduling
- 7 Optimizer Selection
- 8 Weight Initialization
- 9 Activation Functions
- 10 Network Depth & Width
- 11 Skip/Residual Connections
- 12 Regularization
- 13 Loss Functions
- 14 Gradient Clipping
- 15 Warm-Up Scheduling

Training a Neural Network

Data Preprocessing



1	0	0	1	0	1	1	1	1	1	1	1	0	0	0	0
0	0	0	0	1	0	0	1	0	1	1	1	1	0	1	0

Imputing Missing Values

Definition

The process of filling miss values or correct known errors is called **imputation**.

		Feature Index →				
		x_1	x_2	x_3	x_4	x_5
Sample Index ↓	Sample 0	2.3	4.1	NaN	3.7	1.9
	Sample 1	5.2	NaN	2.8	1.5	4.3
	Sample 2	1.1	3.4	2.6	NaN	5.1
	Sample 3	NaN	2.2	4.0	3.3	2.9
	Sample 4	3.5	1.8	2.1	4.5	NaN
	Sample 5	2.7	3.9	NULL	1.2	4.6

Legend:

- Feature header
- Valid data
- Missing (NaN)

Figure: Data Table Structure: Features as Columns, Samples as Rows. Red cells indicate missing values (NaN) that require imputation before model training.

Common Types of Missing Values

- 1 Missing Completely at Random (MCAR), i.e. the probability of being missing is not related to the data and is only dependent on some parameter ϕ .
- 2 Missing at Random (MAR), i.e., the missingness probability is only related to the observed variables in the data.
- 3 Missing not at random (MNAR), neither of the above, and the missingness probability is related to missing values of the incomplete variable, which are unknown to us, even after conditioning on observed information

Common Imputation Methods

- 1 Get rid of those samples where missing # features exceed certain number (or percentage)
- 2 Get rid of features where # missing values exceed certain numbers (or percentage)
- 3 Sample Mean (only for continuous data)
- 4 Sample Median (only for continuous data)
- 5 k-Nearest Neighbors (kNN) imputation
- 6 Expectation-Maximization (EM) imputation
- 7 Bayesian Approach

Mean and median approach or anything similar would fail to quantify uncertainty in the estimated missing value.

Bayesian Estimation for Missing Data

- 1 Model your data first (probabilistic modeling): e.g. normal distribution.
- 2 Compute prior distribution over unknown parameters.
- 3 Calculate posterior: update the prior using observed data as (Bayes' Theorem in the play). This gives a posterior distribution over model parameters and missing values.
- 4 Draw samples using Markov Chain Monte Carlo simulation that will be plausible missing values.

Under a Bayesian framework, missing observations can be thought of as any other parameter in the model whose distribution needs to be determined.

Bayesian Framework

Posterior Distribution

$$p(\boldsymbol{\theta} | X) = \frac{p(\mathbf{X} | \boldsymbol{\theta}) p(\boldsymbol{\theta})}{\int_{-\infty}^{\infty} p(\mathbf{X} | \boldsymbol{\theta}) p(\boldsymbol{\theta}) d\boldsymbol{\theta}} \propto p(\mathbf{X} | \boldsymbol{\theta}) p(\boldsymbol{\theta})$$

$p(\mathbf{X} | \boldsymbol{\theta})$ is likelihood, $p(\boldsymbol{\theta})$ is prior.

$$p(\mathbf{X}_{mis} | \mathbf{X}_{obs}) = \int p(\mathbf{X}_{mis} | \mathbf{X}_{obs}, \boldsymbol{\theta}) p(\boldsymbol{\theta} | \mathbf{X}_{obs}) d\boldsymbol{\theta}.$$

Calculating posterior is hard, so we use Monte Carlo methods (Markov Chain Monte Carlo (MCMC)).

An example code for MCMC imputation using PyMC is available at

https://www.pymc.io/projects/examples/en/latest/howto/Missing_Data_Imputation.html

Normalization/Standardization

Definition

In simpler terms: adjusting values measured on different scales to a common scale is **Normalization**.

Otherwise, aligning entire probability distribution of adjusted values is **Normalization**.

Standard Normalization

$$\hat{x} = \frac{x - \mu}{\sigma}$$

Minmax Normalization

$$\hat{x} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Training a Neural Network

Data Preprocessing



0	1	1	1	0	0	0	1	1	0	1	1	1	0	0
1	0	1	0	1	0	1	0	1	1	0	0	0	0	1

Batch Size

References and Additional Reading

- 1 He, Yulei, Guangyu Zhang, and Chiu-Hsieh Hsu. **Multiple imputation of missing data in practice: basic theory and analysis strategies**. Chapman and Hall/CRC, 2021.
- 2 Huang, Lei. Normalization Techniques in Deep Learning. Cham: Springer, 2022.