Machine Learning (ML) and Deep Learning

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- Artificial Neural Network (ANN)
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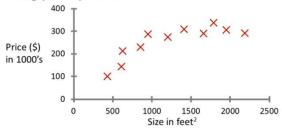
Introduction

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Problems – Regression

• Finding the relationship between one dependent variable and a series of other variables (independent variables)

Housing price prediction.

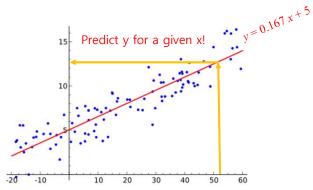


https://www.holehouse.org/mlclass/01_02_Introduction_regression_analysis_and_gr.html

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Problems – Regression

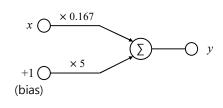
• Linear regression



https://en.wikipedia.org/wiki/Linear_regression

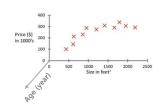
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Graphical representation

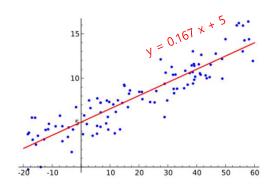


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Problems – Regression



• Linear regression



https://en.wikipedia.org/wiki/Linear_regression

How to obtain the linear regression model?

$$\hat{y} = \theta_0 + \theta_1 \cdot x_1$$

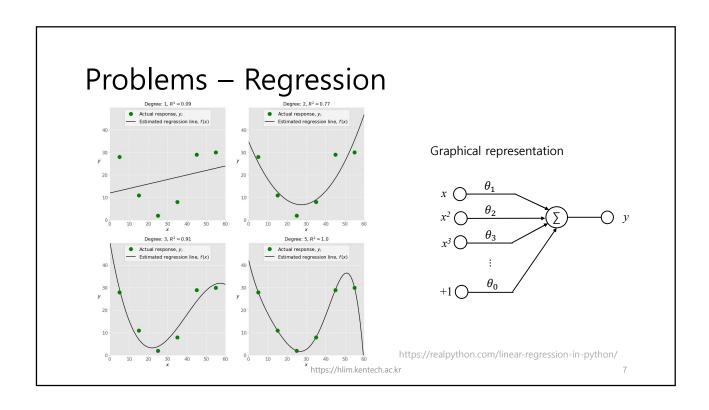
$$\hat{y} = \theta_0 + \theta_1 \cdot x_1 + \theta_2 \cdot x_2$$

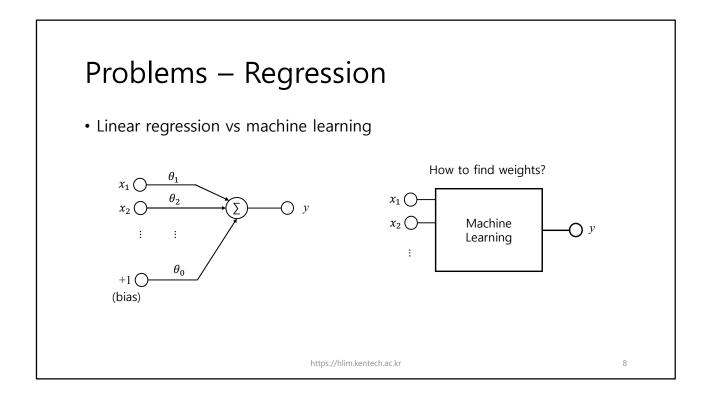
$$\hat{y} = \theta_0 + \theta_1 \cdot x_1 + \dots + \theta_n \cdot x_n$$

Solution:

$$\widehat{\boldsymbol{\theta}} = (\boldsymbol{X}^T \boldsymbol{X})^{-1} \boldsymbol{X}^T \mathbf{y}$$

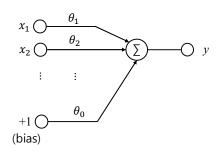
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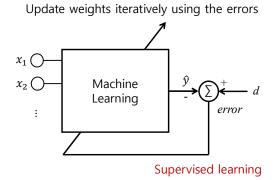




Problems – Regression

• Linear regression vs machine learning





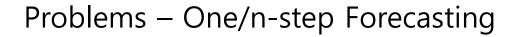
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Problems – One/n-step Forecasting



What will be the stock price in tomorrow?





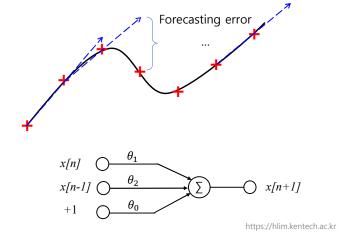
What will be the stock price in tomorrow?

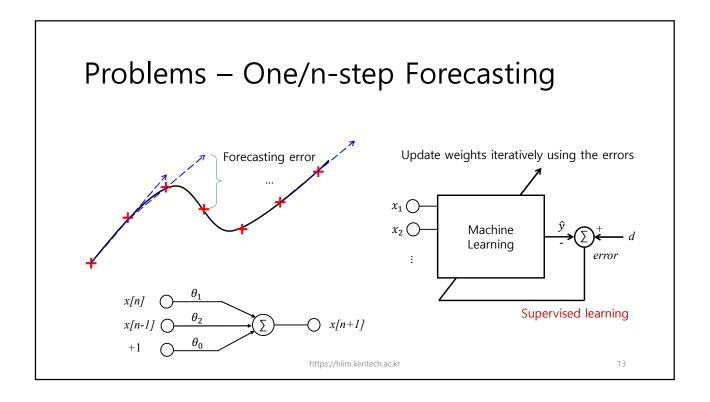
Naïve solution: Today price will be the tomorrow price.

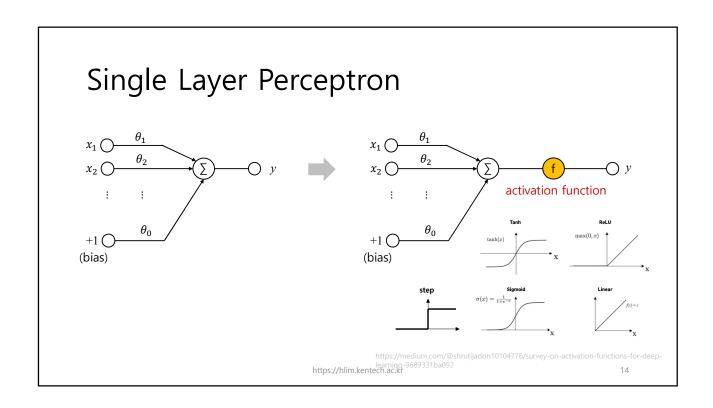
However, it could be higher or lower.

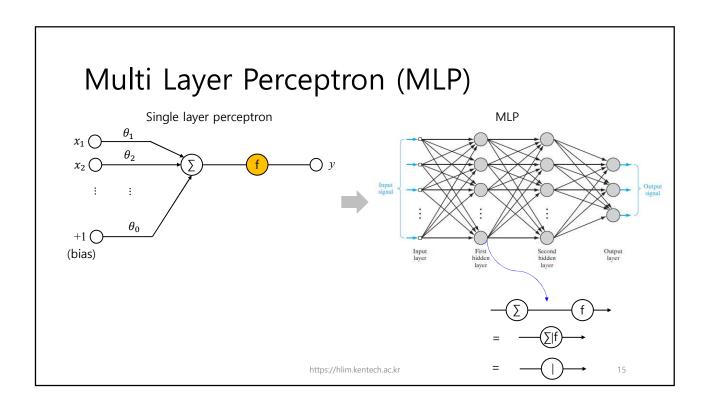
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Problems – One/n-step Forecasting









Artificial Neural Network (ANN)

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Single Layer Perceptron

• Frank Rosenblatt (Ph.D. in Psychology, Cornell)

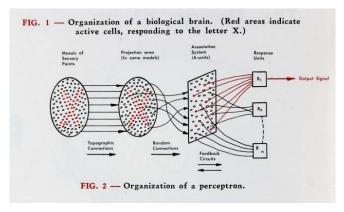


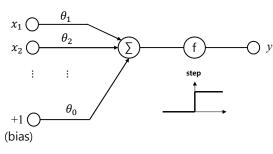


https://news.cornell.edu/stories/2019/09/professors-perceptron-paved-way-ai-60-years-too-soon https://hlim.kentech.ac.kr

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Single Layer Perceptron



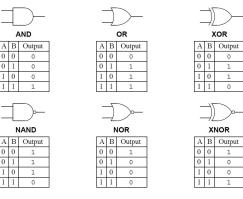


Rosenblatt's single-layer perceptron cannot classify input patterns that are not linearly separable.

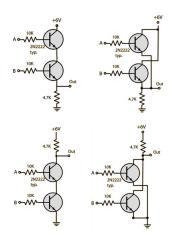
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Logic Gates

• Logic gates: AND, OR, XOR, ...



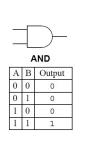
https://instrumentationtools.com/logic-gates/ https://hlim.kentech.ac.kr

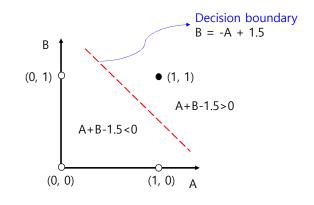


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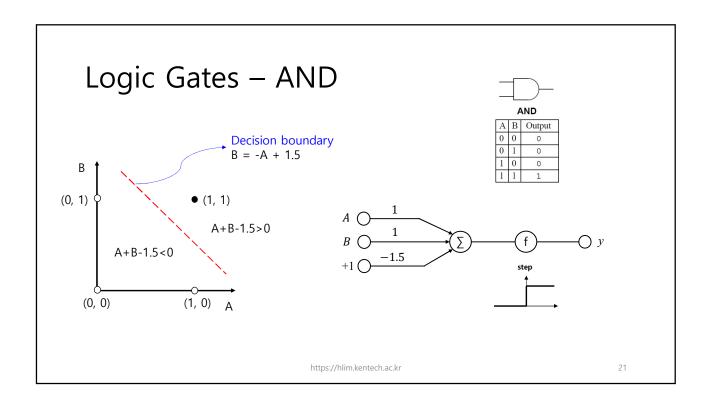
Logic Gates – AND

• Decision boundary of AND



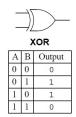


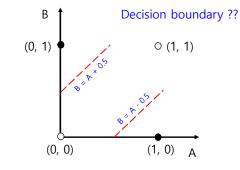
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Logic Gates – XOR

• Decision boundary of XOR





Rosenblatt's single-layer perceptron cannot classify input patterns that are not linearly separable.

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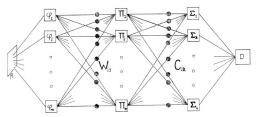
MLP Can Do IT, But ...

• Minsky and Papert, 1969

[206] 12.4 Learning Theory

[256] Epilogue





It ought to be possible to devise a <u>training algorithm</u> to optimize the weights in this using, say, the magnitude of a reinforcement signal to communicate to the net the cost of an error. We have not investigated this.

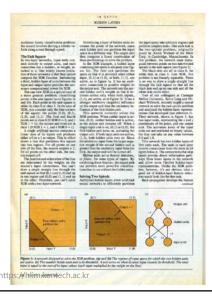
the above quotation as saying that, until recently, connectionism had been paralyzed by the following dilemma:

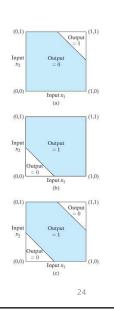
Perceptrons could learn anything that they could represent, but they were too limited in what they could represent.

Multilayered networks were less limited in what they could represent, but they had no reliable learning procedure.

Logic Gates – XOR Touretzky and Pomerleau, 1989

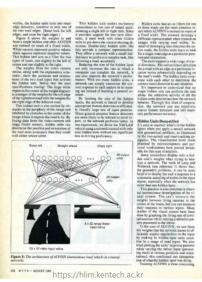


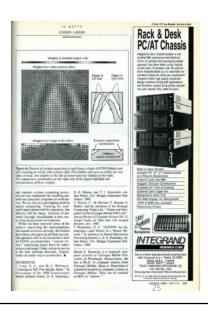




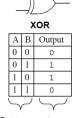
Logic Gates – XOR









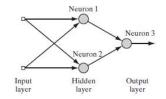


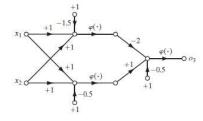
Pattern Class (2-bit) (0/1)



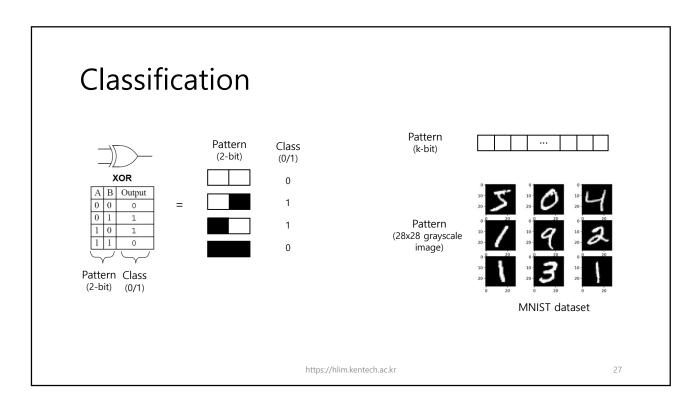
(0/1) 0 1

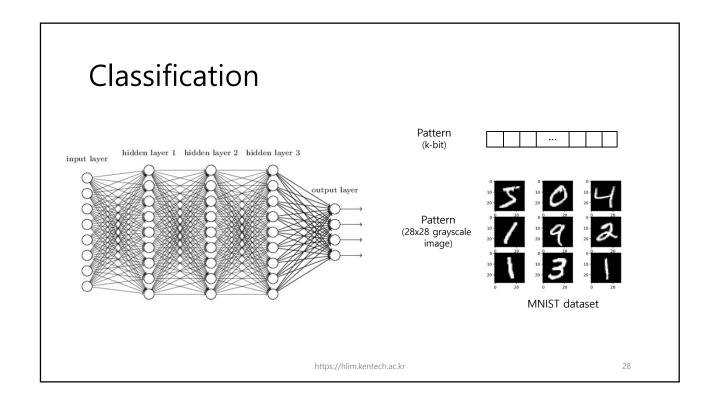
Class



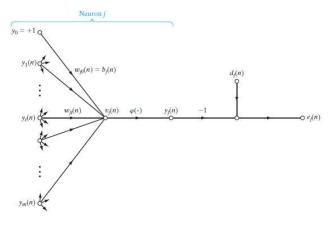


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The Back-Propagation Algorithm



Total Error

$$\begin{aligned} \mathscr{E}(n) &= \sum_{j \in C} \mathscr{E}_j(n) \\ &= \frac{1}{2} \sum_{j \in C} e_j^2(n) \end{aligned}$$

By Chain Rule

$$\frac{\partial \mathcal{E}(n)}{\partial w_{ji}(n)} = \frac{\partial \mathcal{E}(n)}{\partial e_j(n)} \frac{\partial e_j(n)}{\partial y_j(n)} \frac{\partial y_j(n)}{\partial v_j(n)} \frac{\partial v_j(n)}{\partial w_{ji}(n)}$$

$$\frac{\partial \mathcal{E}(n)}{\partial w_{ji}(n)} = -e_{j}(n)\varphi_{j}'(v_{j}(n))y_{i}(n)$$

$$\Delta w_{ji}(n) = -\eta rac{\partial \mathscr{C}(n)}{\partial w_{ji}(n)}$$

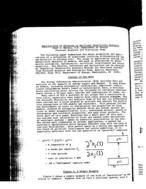
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The Back-Propagation Algorithm







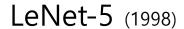
David Rumelhart, Geoffrey Hinton, Ronald Williams



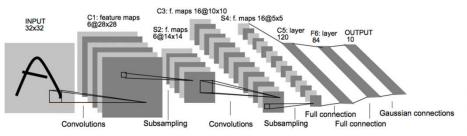
Harvard Univ. 1974 / LNCIS 1982

Nature 1986

 $\label{limit} \begin{array}{ll} & \text{https://hlim.kentech.ac.kr} \\ & \text{https://machinelearningknowledge.ai/timeline/finally-backpropagation-meets-neural-network/} \end{array}$



 Yann LeCun, Leon Bottou, Yoshua Bengio, Patrick Haffner, "Gradient-Based Learning Applied to Document Recognition," Proc of The IEEE, 1998



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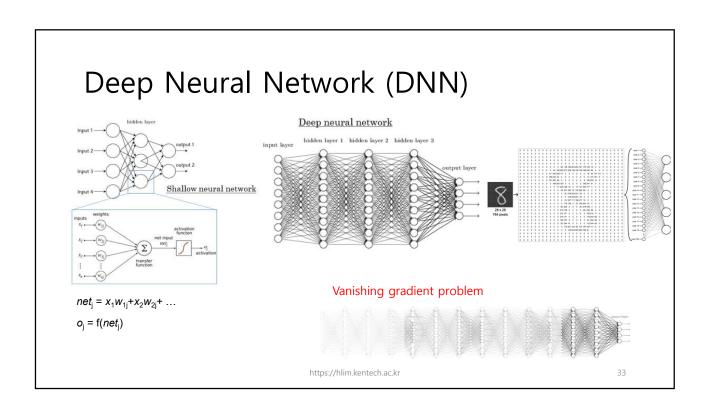
Vanishing gradient

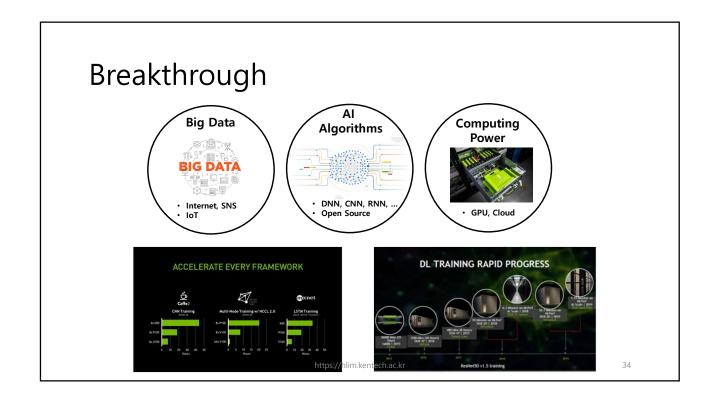


Research on other ML algorithms?

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Deep Learning





Why NOT Working Well in the Past?

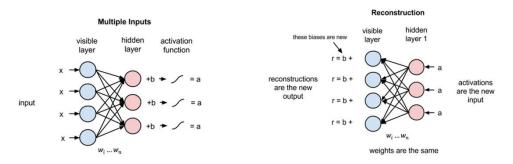
- · Geoffrey Hinton's Summary
 - Our labeled datasets were thousands of times too small.
 - Our computers were millions of times too slow.
 - We initialized the weights in a stupid way.
 - We used the wrong type of non-linearity.

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Rebranded to "Deep Learning"

- "Rebrand" the frowned-upon field of neural nets with the moniker "deep learning"
- Hinton, Simon Osindero, and Yee-Whye The, "A fast learning algorithm for deep belief nets," Neural computation, 2006.



https://steemit.com/kr/@yoonheeseung/2-restricted-battps:

