

# 인공지능과 계산수학



끈기 ( 영화 “파운더”에서)

이 세상 무엇도 끈기를 대신할 수 없습니다.

재능? 재능 있는데 성공하지 못했던 사람들로 세상은 차고 넘칩니다.

천재성? 불운의 천재란 표현도 핑계에 불과해요.

교육? 세상은 공부만 많이 한 멍청이로 가득하죠.

오직 끈기와 투지만이 강력한 힘을 가집니다



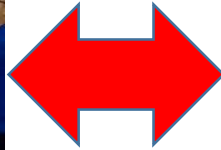
**강원-충청 수학회 2017년 6월 8일**

연세대 계산과학공학과 서진근 (전공: 수학)

# Learning Science by Doing Science



책을 통해 기초 이론 이해.  
그러나, 실전 경험 없이 책만 공부하면 왜곡된  
사고 고착됨. (예: 교수, 학자)



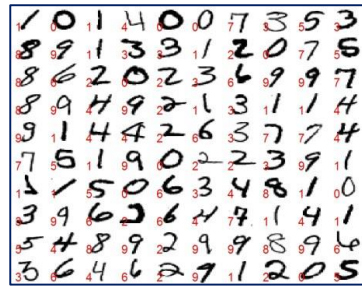
사회에 필요한 인재가 되려면 실전과 토론을  
통해 현실성 있는 정확한 지식 획득 필요.

# 기계학습(ML) 이란?

기계학습은 컴퓨터가 학습할 수 있도록 하는 알고리즘과 기술을 개발하는 분야.

**지도학습(Supervised learning)** is the machine learning technique of finding a feed-forward function  $f(\mathbf{x}) = \mathbf{y}$  from labeled training data,  $\{(\mathbf{x}^{(i)}, \mathbf{y}^{(i)}): i = 1, \dots, m\}$ , such that  $f(\mathbf{x}^{(i)}) = \mathbf{y}^{(i)}, i = 1, \dots, m$ .

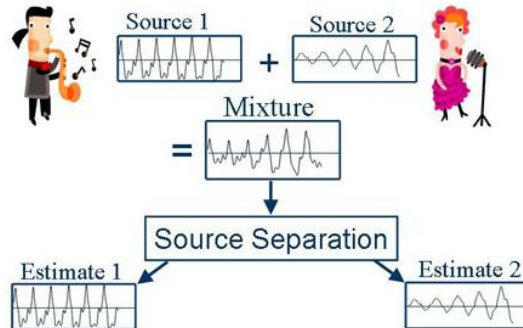
Training data  $\{(\mathbf{x}^{(i)}, \mathbf{y}^{(i)}): i = 1, \dots, m\}$



$$f \left( \begin{array}{c} \text{[Handwritten digit 5]} \end{array} \right) = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

## 자율학습(Unsupervised learning)

infer a function to describe hidden structure from unlabeled data leaving it on its own to find structure in its input.



## 강화학습(Reinforcement learning)

concerned with how software agents ought to take a actions in an environment so as to maximize some notion of cumulative reward.





# 4차 산업혁명의 이해

## 1970/80년대 연세대 주위의 거리

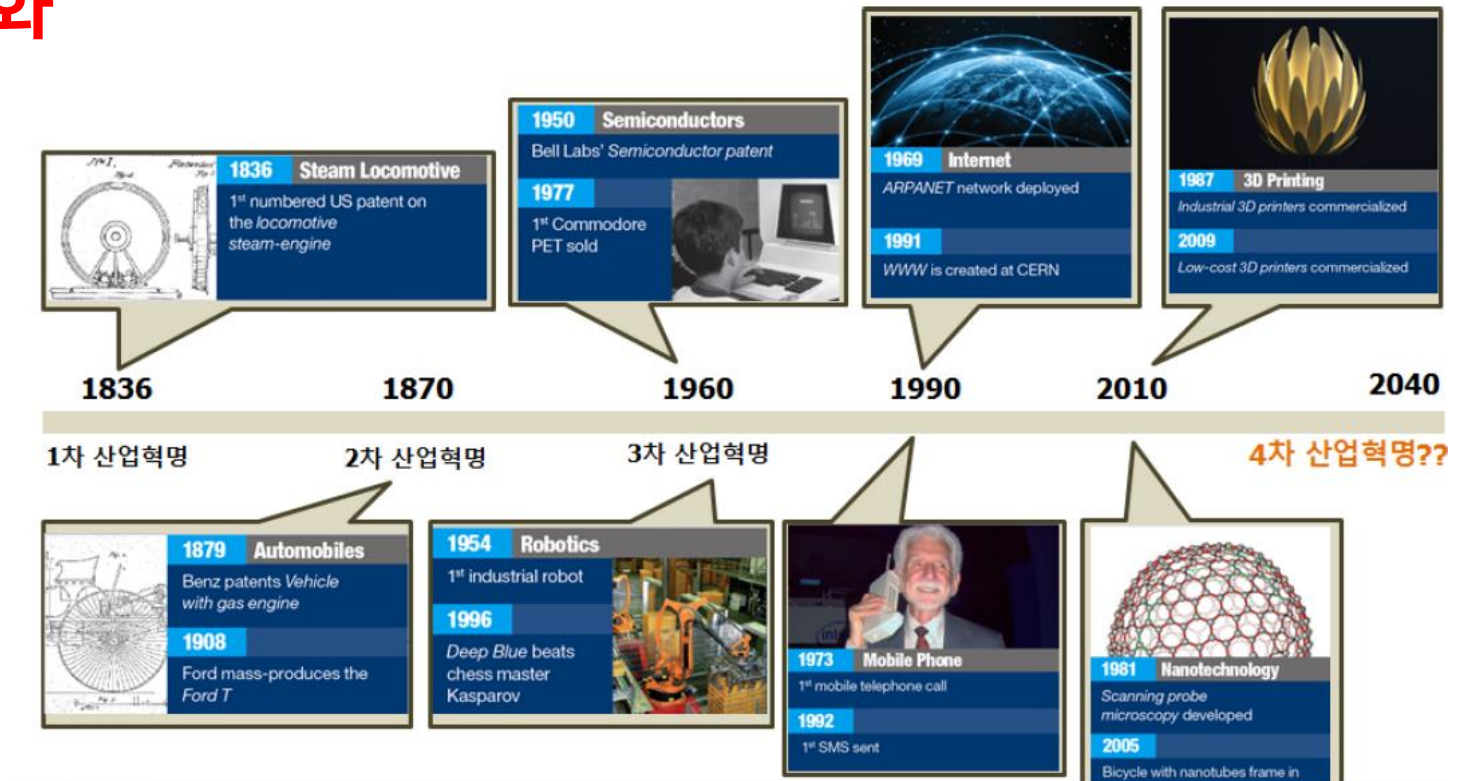


# 4차 산업혁명

인류 역사 변화의 중심에는 새로운 기술의 등장과 기술적 혁신이 자리하고 있었고, 새로운 기술의 등장은 단순히 기술적 변화에 그치지 않고 전 세계의 사회 및 경제구조에 큰 변화를 일으켰다. 기술적 혁신과 이로 인해 일어난 사회·경제적 큰 변화가 나타난 시기를 우리는 '산업혁명' 이라고 부르고 있다.

## • 미래 일자리 지형 변화

## • '기술적 혁신'이 인건비 절감 ....





# 일자리 지형의 변화



화이트칼라의 고용불안, 비대해진 도소매 자영업, 희망 직종과 노동시장의 괴리

## 지식기반의 전문/기술직의 꾸준한 증가세

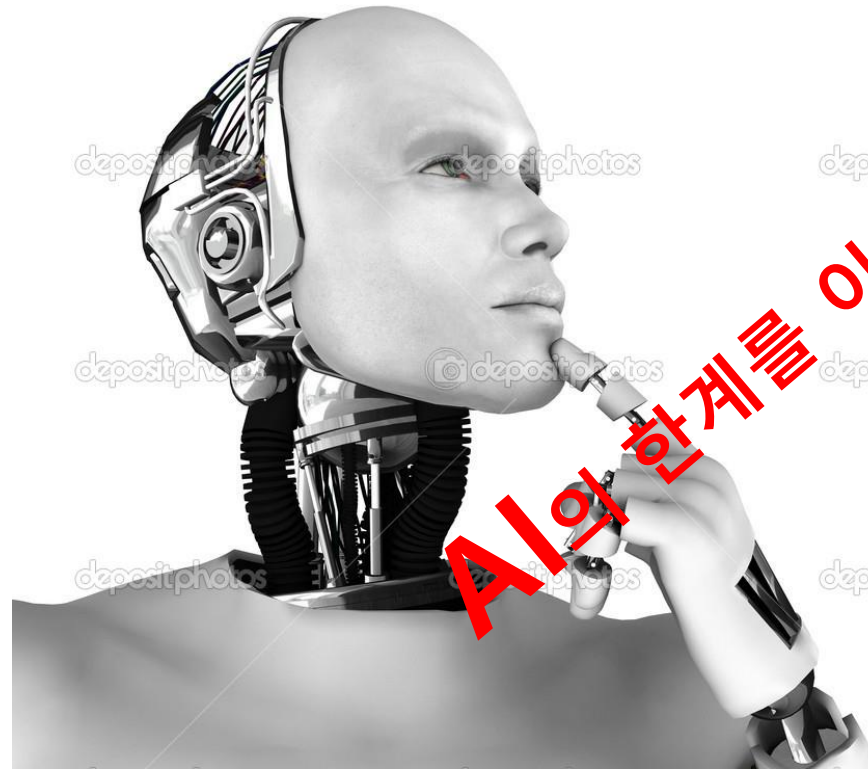


1970년대 부터 화이트칼라(white collar)로 불리는 사무직 과 서비스/판매직의 높은 증가세를 보여주었다. 그러나 이러한 경향은 2000년대 들어서면서 다른 양상을 보이고 있는데 1997년 말 대규모 구조 조정 등으로 인해 사무직이 감소하는 양상을 보이기도 했으며, 3차 산업의 증가에 따라 높은 증가세를 보이던 서비스/판매직 역시 정체되거나 감소하는 양상을 보이고 있다.

반면 지난 40년간 꾸준한 증가세를 보인 전문/기술직은 2000년대 이후에도 글로벌화와 지식기반 산업화에 따라 골드칼라(gold collar)로 불리며 꾸준한 증가세



인공지능은 인간의  
시간과 노력을  
절감하는 수단은 될  
수 있지만,  
숙련된 전문가를  
대체하는데 한계가  
있다.



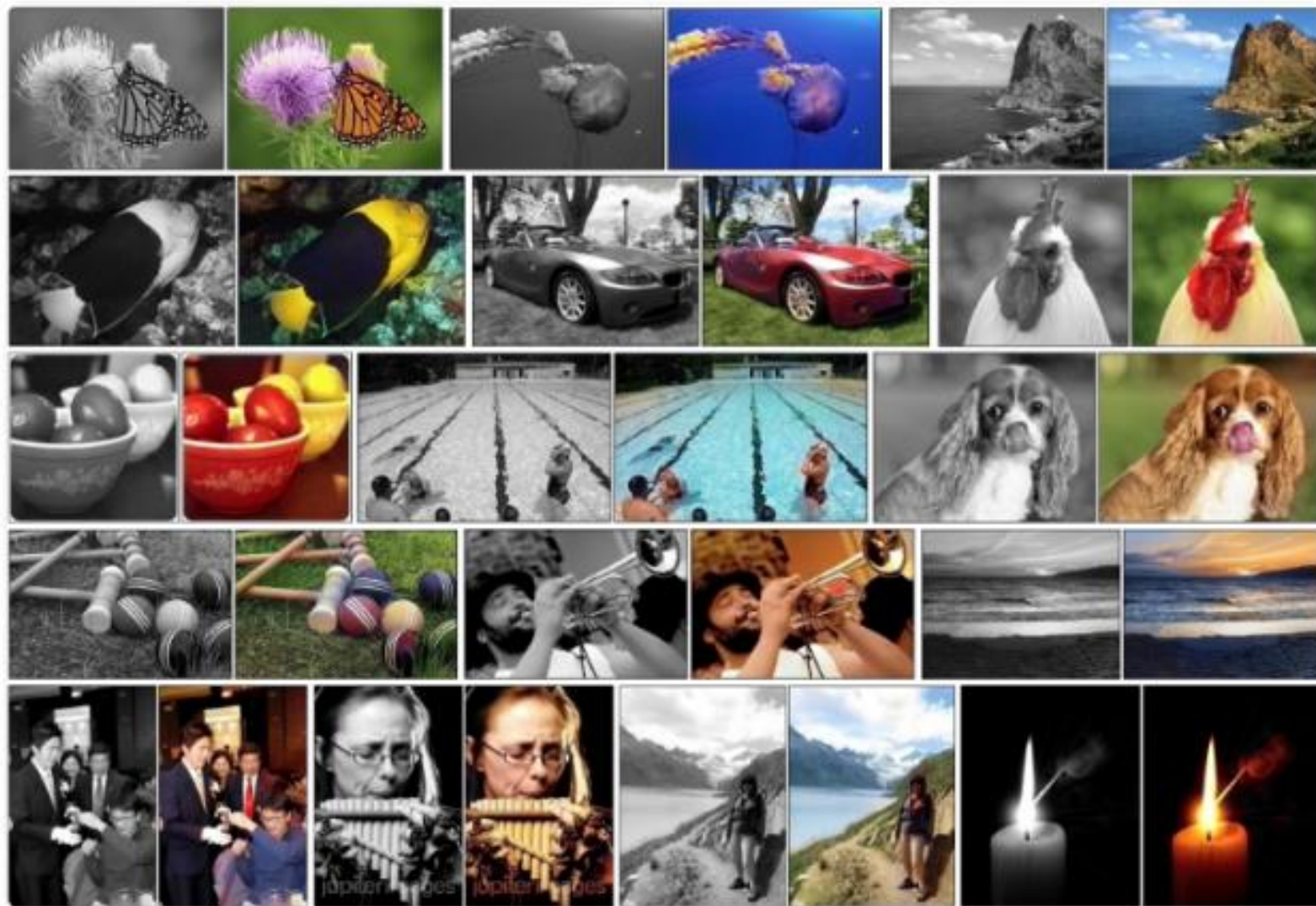
시야한계를 이해해야 ...

**딥러닝의 8 가지 혁신적 응용**



# 1. Automatic Colorization of Black and White Images

인간의 단순  
반복적인  
업무 대체



Colorization of Black and White Photographs

Image taken from [Richard Zhang](#), [Phillip Isola](#) and [Alexei A. Efros](#).

# 인간의 단순 반복적인 업무 대체

## 2. Automatically Adding Sounds To Silent Movies

In this task the system must synthesize sounds to match a silent video.

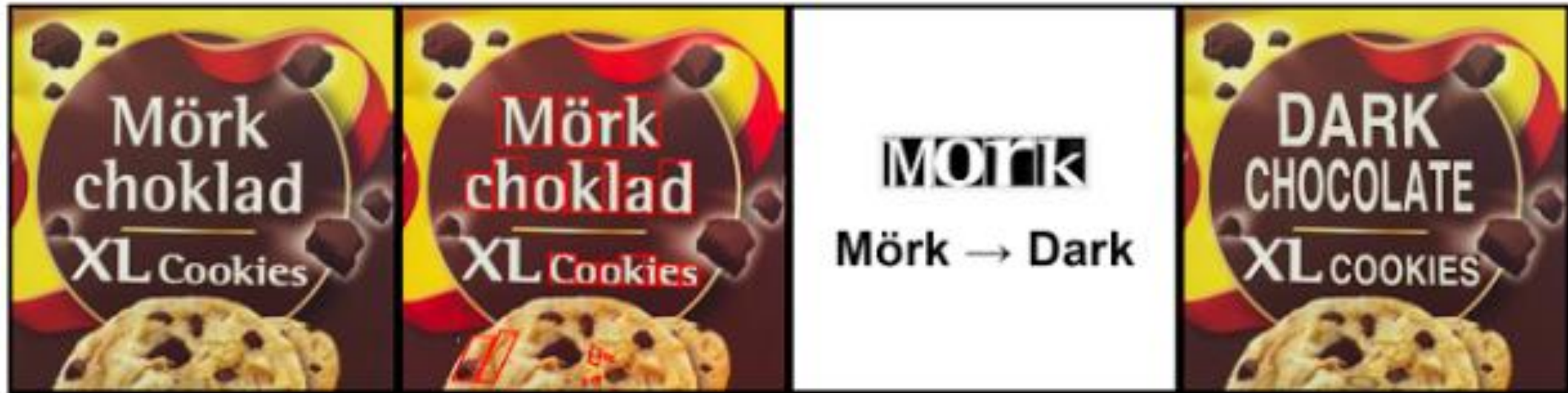




## 3. Automatic Machine Translation

This is a task where given words, phrase or sentence in one language, automatically translate it into another language.

Automatic machine translation has been around for a long time, but deep learning is achieving top results in two specific areas: Automatic Translation of Text. Automatic Translation of Images.



Instant Visual Translation

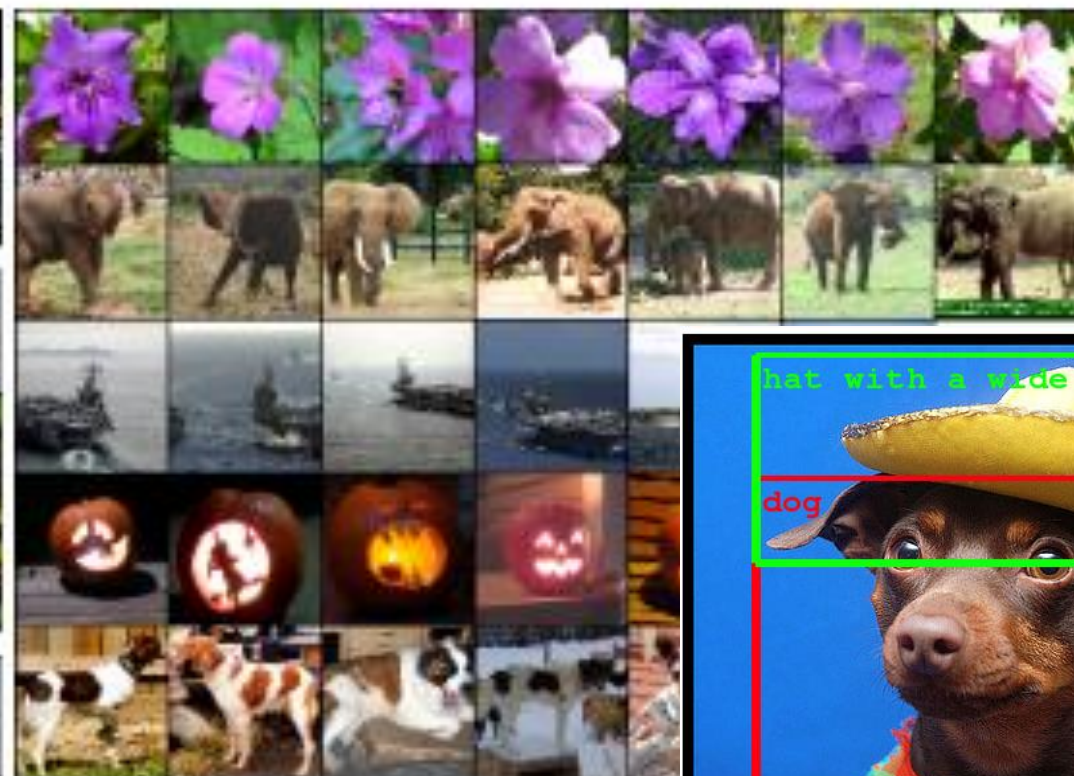
Example of instant visual translation, taken from the [Google Blog](#).



# 인간의 단순 반복적인 업무 대체

## 4. Object Classification and Detection in Photographs

This task requires the classification of objects within a photograph as one of a set of previously known objects.

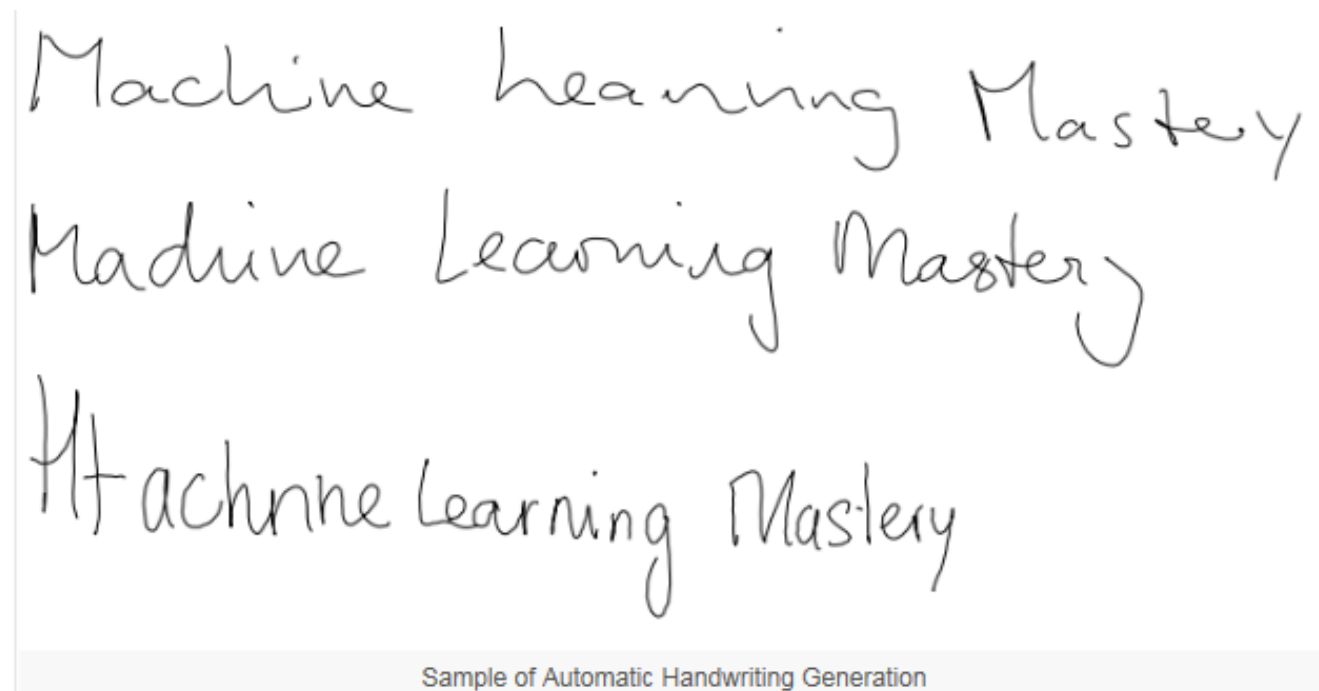


Example of Object Classification

Taken from [ImageNet Classification with Deep Convolutional Neural Networks](#)

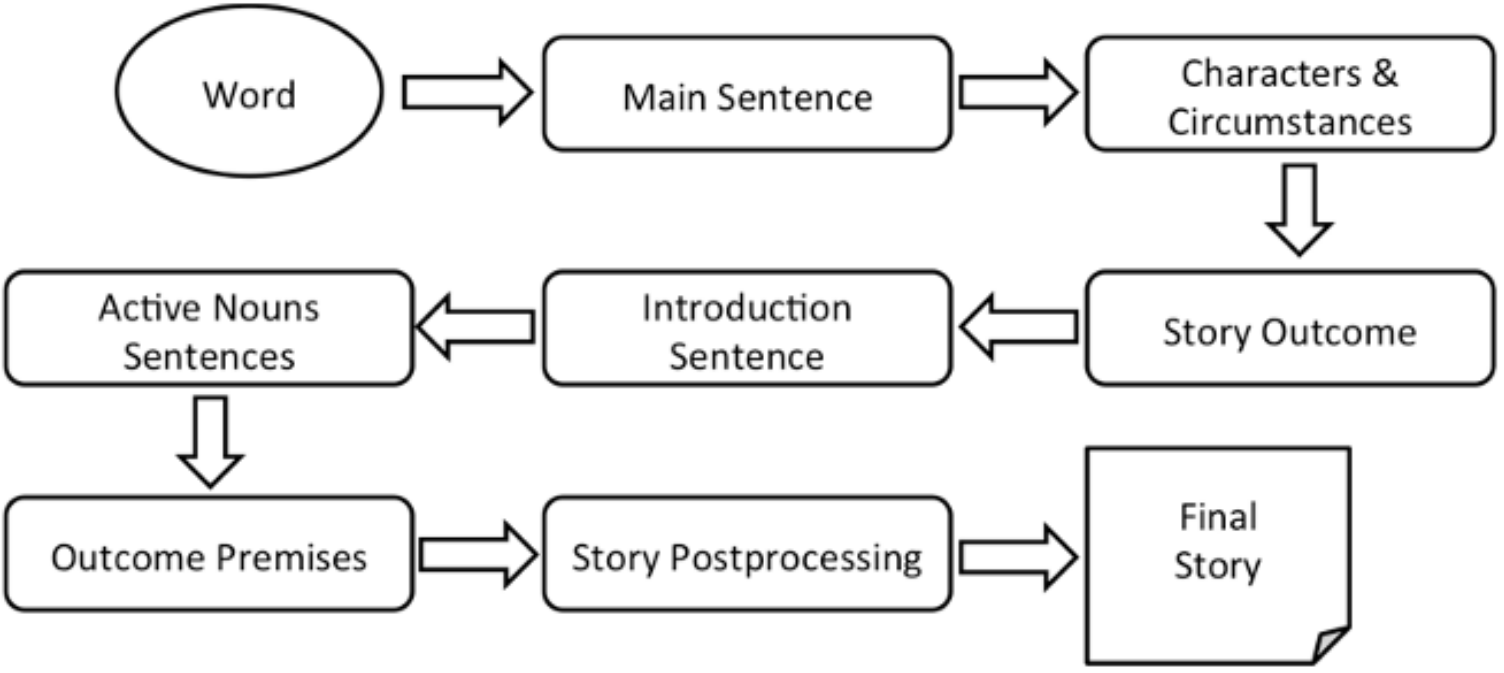
Example of Object Detection within Photographs  
Taken from the [Google Blog](#).

## 5. Automatic Handwriting Generation



## 6. Automatic Text Generation

This is an interesting task, where a corpus of text is learned and from this model new text is generated, word-by-word or character-by-character.





# 인간의 단순 반복적인 업무 대체

## 7. Automatic Image Caption Generation

Automatic image captioning is the task where given an image the system must generate a caption that describes the contents of the image.



"man in black shirt is playing guitar."



"construction worker in orange safety vest is working on road."



"two young girls are playing with lego toy."



"girl in pink dress is jumping in air."



"black and white dog jumps over bar."



"young girl in pink shirt is swinging on swing."

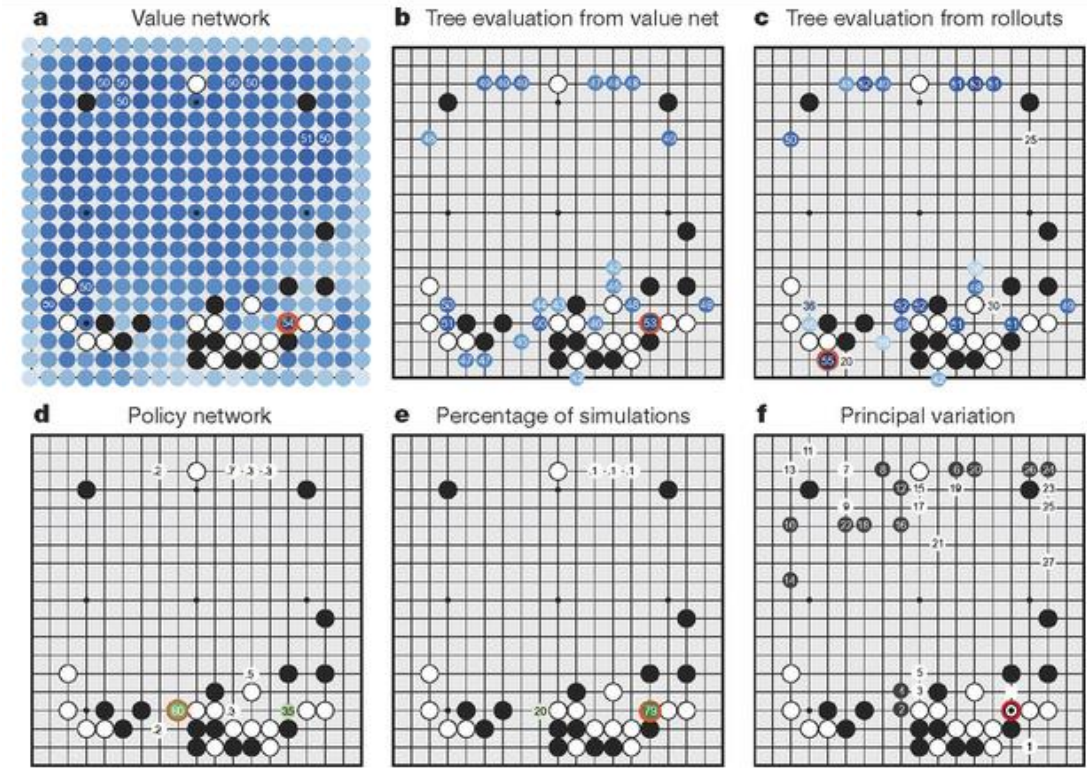
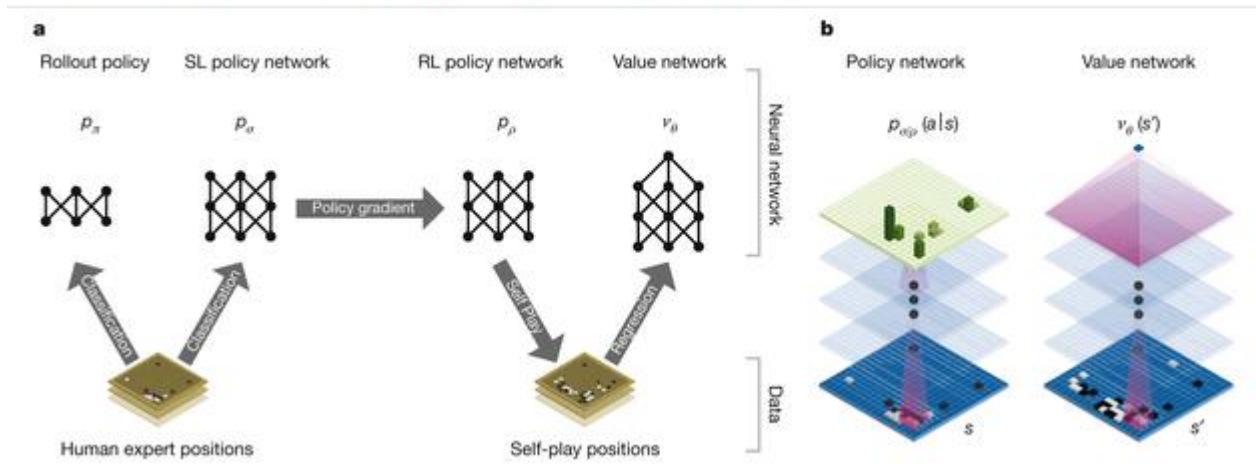
## 8. Automatic Game Playing



High-fidelity CRISPR–Cas9 nucleases with no detectable genome-wide off-target effects

Benjamin P. Kleinstiver, Vikram Pattanayak, Michelle S. Prew, Shengdar Q. Tsai, Nhu T. Nguyen, Zongli Zheng & J. Keith Joung

Figure 1: Neural network training pipeline and architecture.





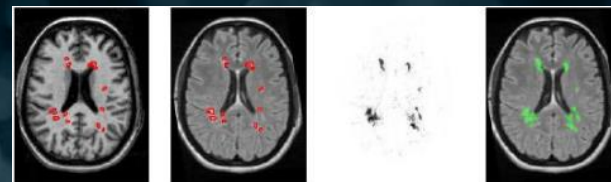
의사의 단순 반복적인 업무 대체

# 딥 러닝으로 의료영상 판독



## Machine Learning for Medical Image Analysis

A. Criminisi & the InnerEye team @ MSRC



Microsoft Research



의료에서 딥러닝:

## 숙련된 전문의를 대체하는데 한계가 있다.

최근 수년간 딥러닝기술의 획기적인 개선은 고성능 GPU 컴퓨팅과 빅데이터의 분석/활용 기술의 급속한 발전, 그리고 구글, 페이스북, IBM 등의 적극적인 투자 때문인 듯하다. 의료영상 판독에서 딥러닝 기술은 Training data가 쌓여감에 따라 정확도가 급속히 향상되어가고 있어, 전 세계적으로 많은 인공지능기업들이 의료분야에 사업화를 시도하고 있다. 구글은 딥러닝 기술을 당뇨성 망박변증 진단에 적용하였고, IBM은 인공지능 왓슨을 암 치료에 활용했고, 애플은 헬스케어 휴대용기기와 기존의 의료시스템의 통합을 통해 지능형 의료서비스를 제공하려 하며, 삼성메디슨도 딥러닝 기술을 초음파영상의 판독에 접목하려 시도하고 있다.

인간이 플마를 100m 경주에서 이길 수 없듯이, 의료현장에서 딥러닝은 극복하기 어려운 한계를 가지고 있다. 기계학습에 필요한 Training Data는 여러 의사들의 판독에 의해 수집되며, 기계학습능력은 다수의 판독을 반영하는 training data를 기반으로 형성되기에 근본적으로 소수의 전문의에 의해서만 발견되는 병은 무시되어진다. 따라서, 인공지능은 의료진의 시간과 노력을 절감하는 수단은 될 수 있지만, 숙련된 전문의를 대체하는데 한계가 있다.

# 딥 러닝으로 의료영상 판독

The accumulation of X-rays, CT scans and MRIs means that doctors face an enormous task of sifting through this medical data in order to reach diagnoses. But now, **thanks to advances in machine learning, this task is becoming much easier.**

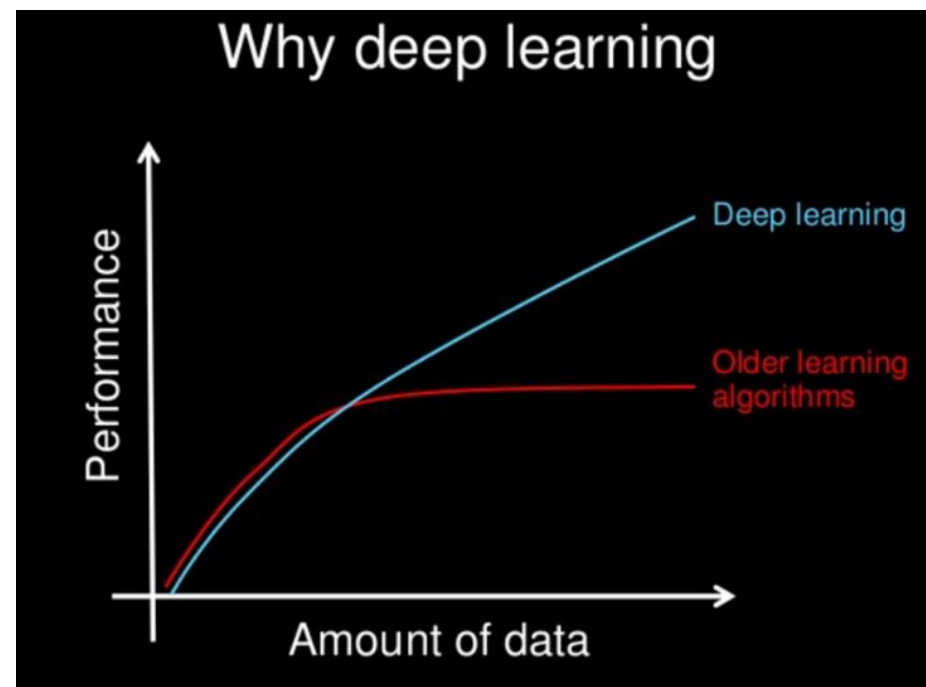
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Computing

## Why IBM Just Bought Billions of Medical Images for Watson to Look At

IBM seeks to transform image-based diagnostics by combining its cognitive computing technology with a massive collection of medical images.

by Mike Orcutt   August 11, 2015



# 삼성 메디슨, 딥러닝을 이용한 초음파 진단기

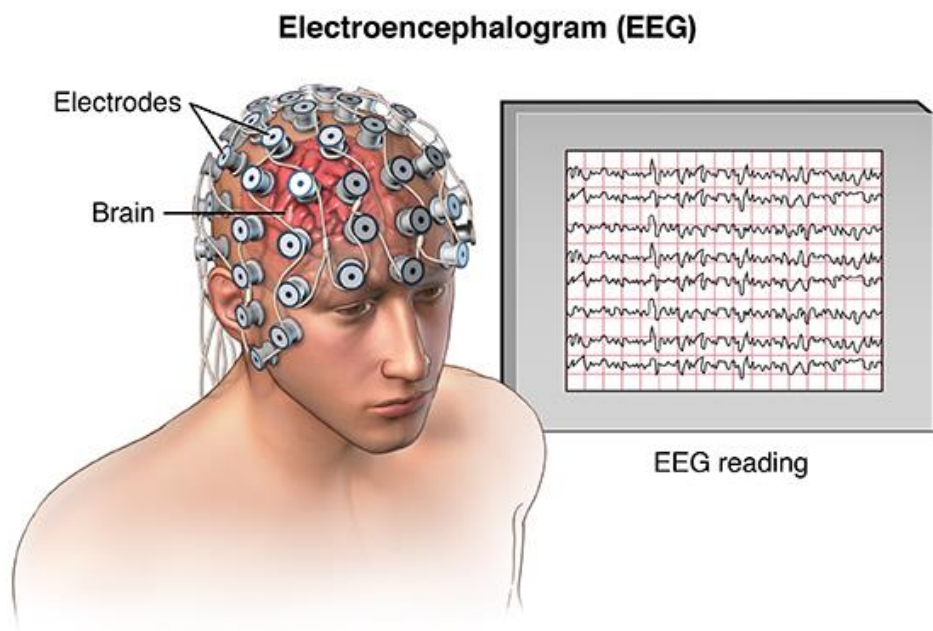
Samsung built deep learning system – a very powerful computer that could process the images, and fed the large set of data it acquired so the machine could learn how to better analyze breast lesions.



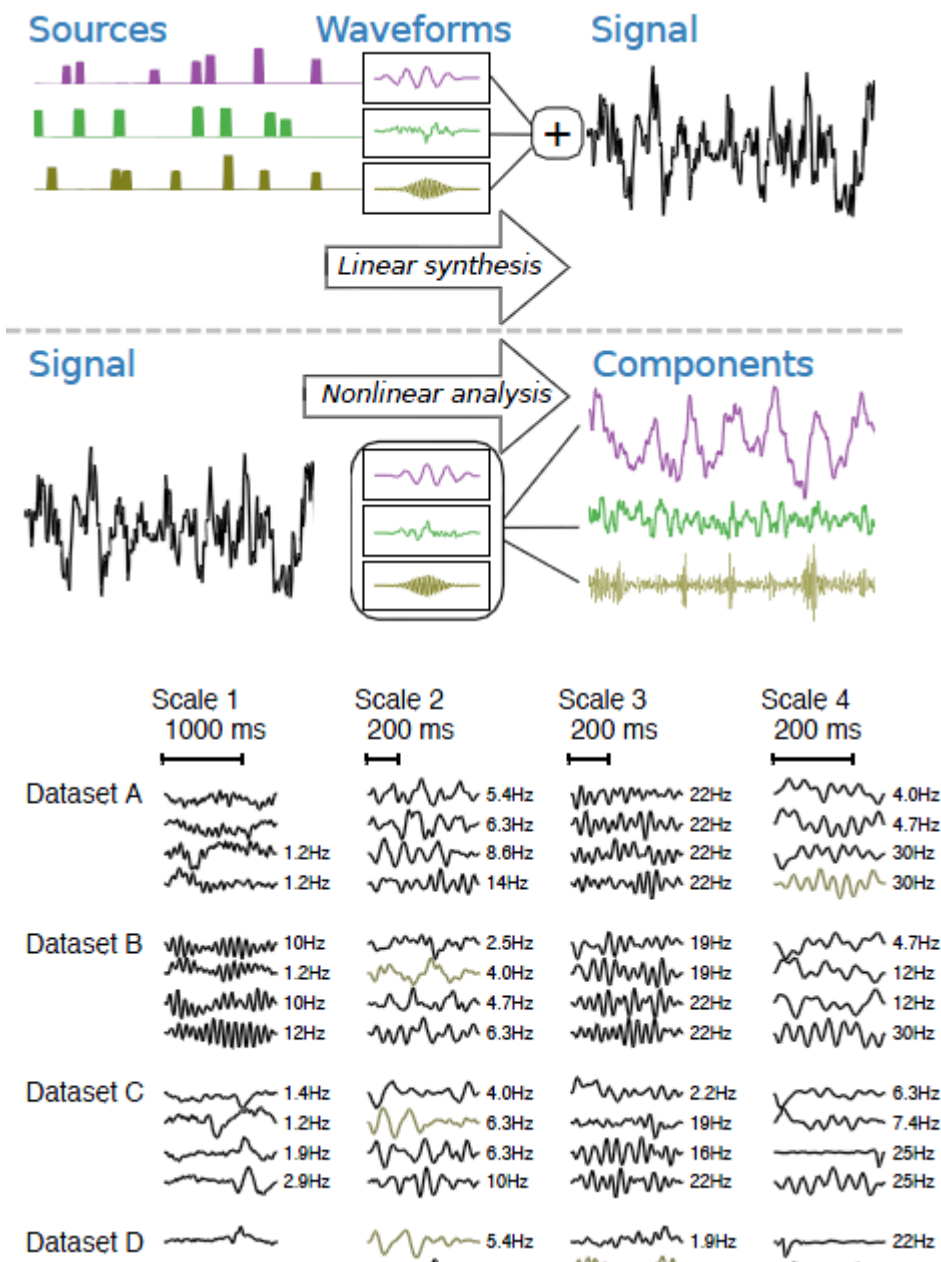


# 딥러닝으로 뇌기능 분석

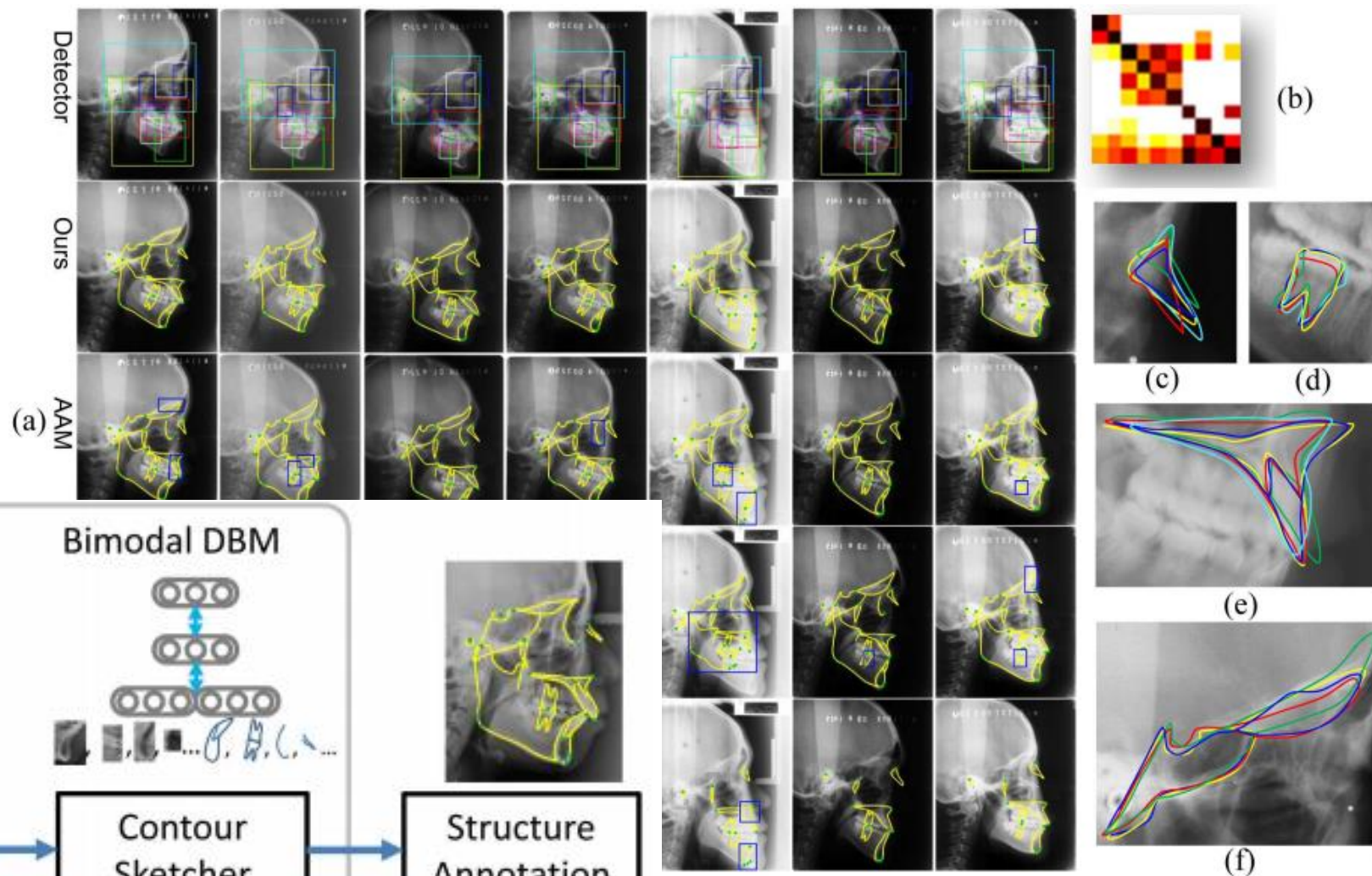
**Objective:** demonstrate an algorithm to automatically learn the time-limited waveforms associated with phasic events that repeatedly appear throughout an electroencephalogram



**Method:**

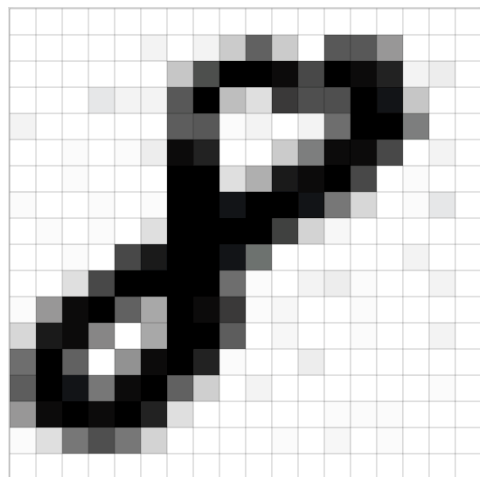


# 딥러닝으로 인체 해부학적 구조 추출



# 딥러닝 이해

## What human sees



## What machine sees

[illegible]

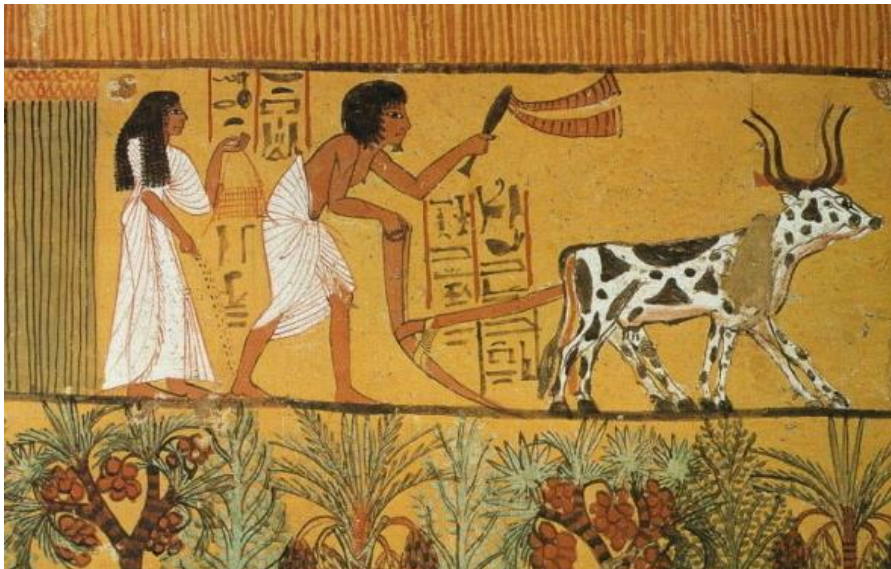
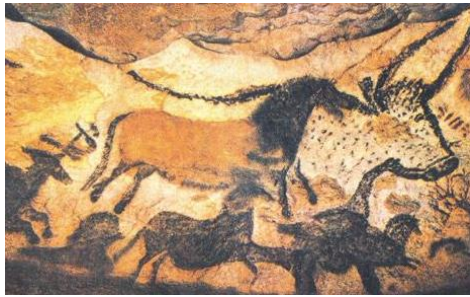
IN CS, IT CAN BE HARD TO EXPLAIN  
THE DIFFERENCE BETWEEN THE EASY  
AND THE VIRTUALLY IMPOSSIBLE.

## 숫자 이미지 인식



# Dimensionality Reduction

In order to perform feature extraction/selection from high dimensional data, we need dimensionality reduction, which can be achieved by identifying the patterns in the data with **highlighting their similarities and dissimilarities.**





# Semantic expression

Machine learning can create semantic expressions.



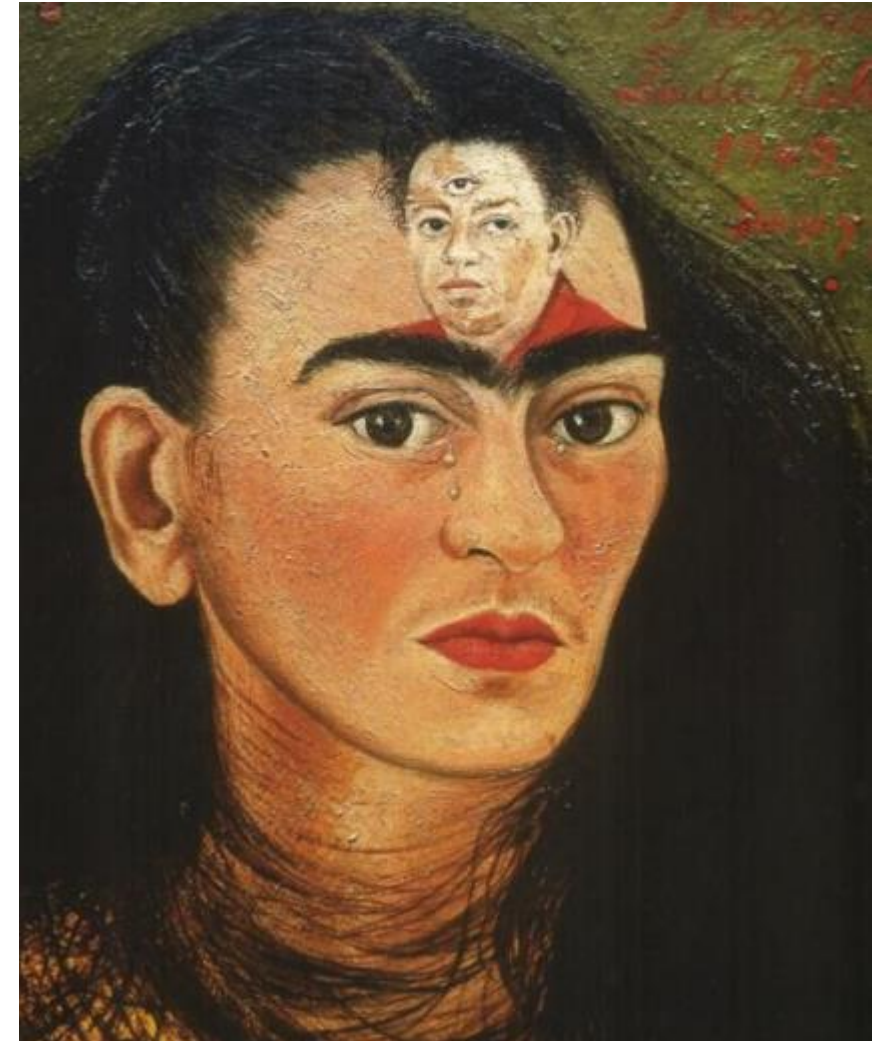
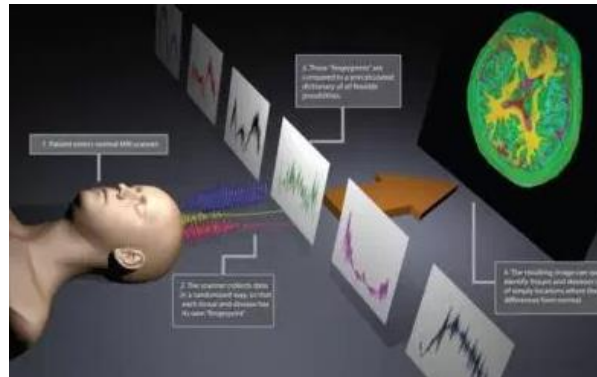


# Multi-view expression

Use multi-view to describe her feeling or thinking.



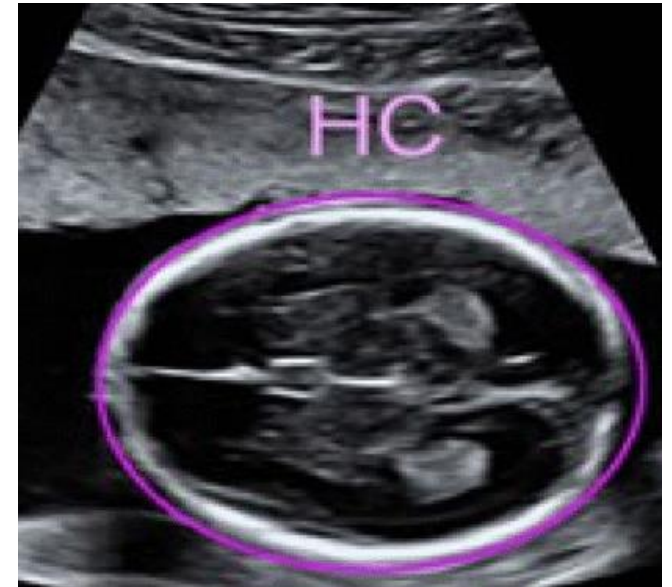
MR finger printing



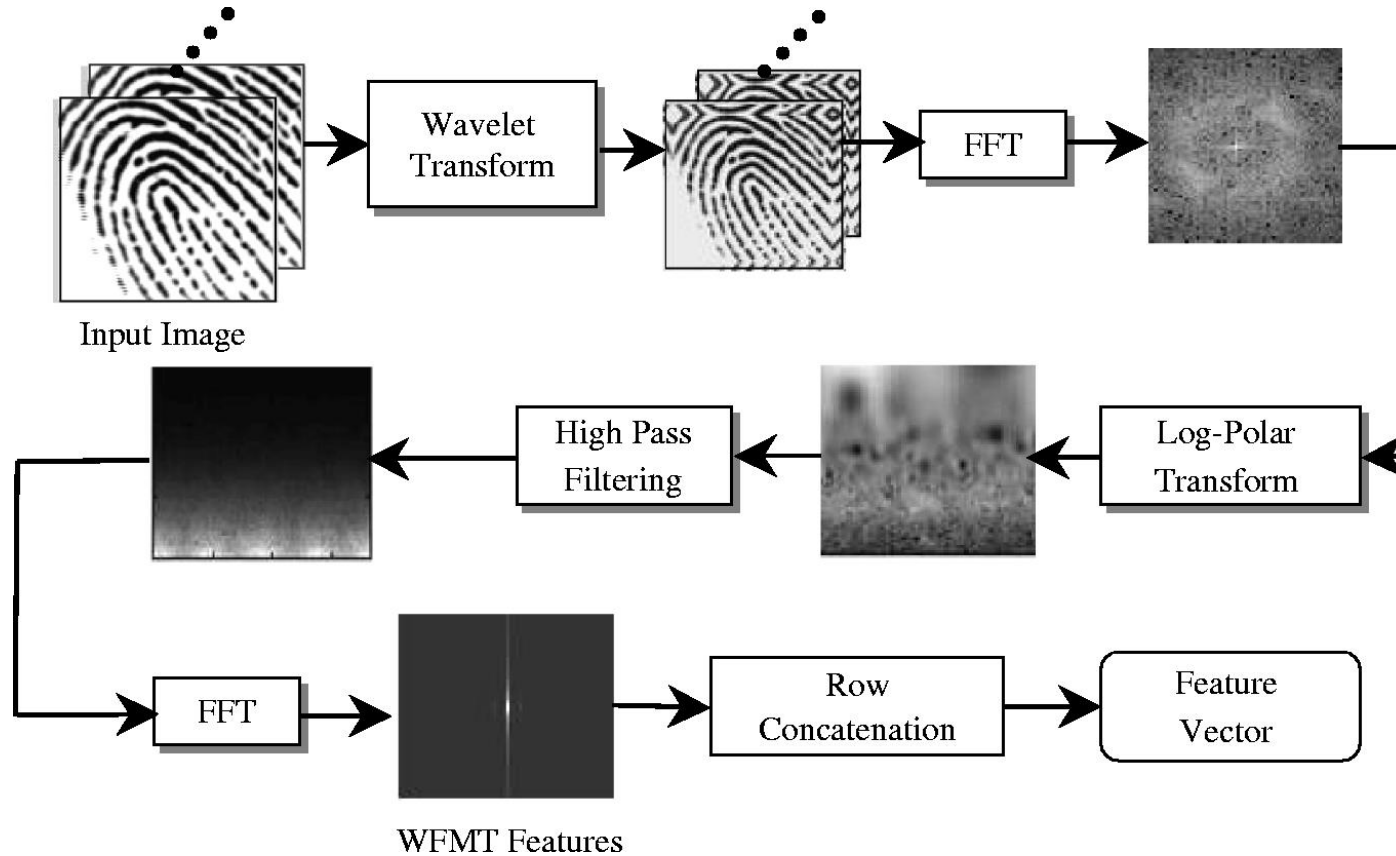


To quantify expression and to provide similarity and dissimilarity, we use

# Biometry



# 지문인식 Fingerprint recognition: Easy due to its three basic patterns: arch, loop and whorl.



Scientists have found that family members often share the same general fingerprint patterns, leading to the belief that these patterns are inherited

# 얼굴 인식이 어려운 이유

같은 사람을 다르게 보이게 하는 요인들은?



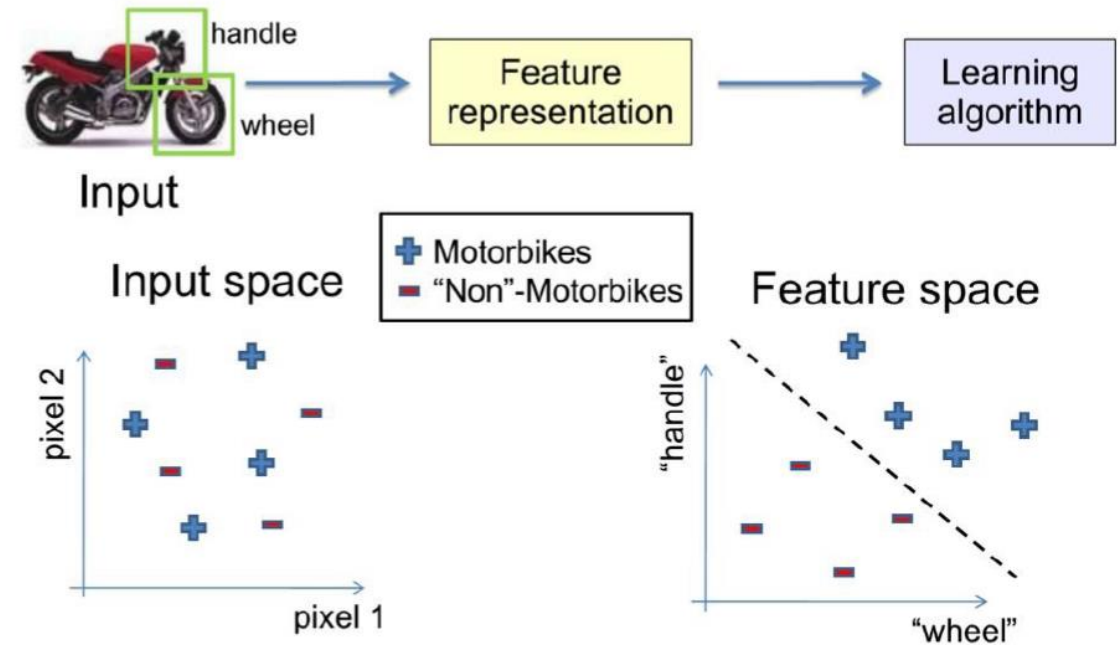
**?? Any pattern??**



# 기계학습-특징 추출하는 방식 학습

Low level sensing-Preprocessing-Feature extraction-  
-Feature selection-Inference, Prediction, Recognition

- Most critical for accuracy
- Account for most of the computation for testing
- Most time-consuming in development cycle
- Often had-craft in practice



**특징 추출 학습: instead of designing features, let's design feature learners...**

# 지도 학습(Supervised Learning)

Given training data  $\{(x^{(i)}, y^{(i)}): i = 1, \dots, m\}$  (학습지)

SL is machine learning technique of **finding a feed-forward function**  $f(x) = y$  such that  $f(x^{(i)}) = y^{(i)}, i = 1, \dots, m$

예: 숫자  
이미지 인식

$f \left( \begin{matrix} x = \text{image with} \\ n \text{ pixels} \end{matrix} \right) = y = \begin{pmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \\ y_6 \\ y_7 \\ y_8 \\ y_9 \\ y_{10} \end{pmatrix}$

$y_1 = 1$  corresponds to  $x = 0$ .

$y_5 = 0$  corresponds to  $x \neq 4$ .

$f \left( \begin{matrix} \text{Image of } 5 \end{matrix} \right) = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}$

$f \left( \begin{matrix} \text{Image of } 9 \end{matrix} \right) = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{pmatrix}$

학습지      Training data  $\{(x^{(i)}, y^{(i)}): i = 1, \dots, m\}$

1	0	1	4	0	0	7	3	5	3
8	9	1	3	3	1	2	0	7	5
8	6	2	0	2	3	6	9	9	7
8	9	4	9	2	1	3	1	1	4
9	1	4	4	2	6	3	7	7	4
7	5	1	9	0	2	2	3	9	1
1	1	5	0	6	3	4	8	1	0
3	9	6	2	6	4	7	1	4	1
5	4	8	9	2	9	9	8	9	6
3	6	4	6	2	9	1	2	0	5

# Deep learning: Convolution Neural Network

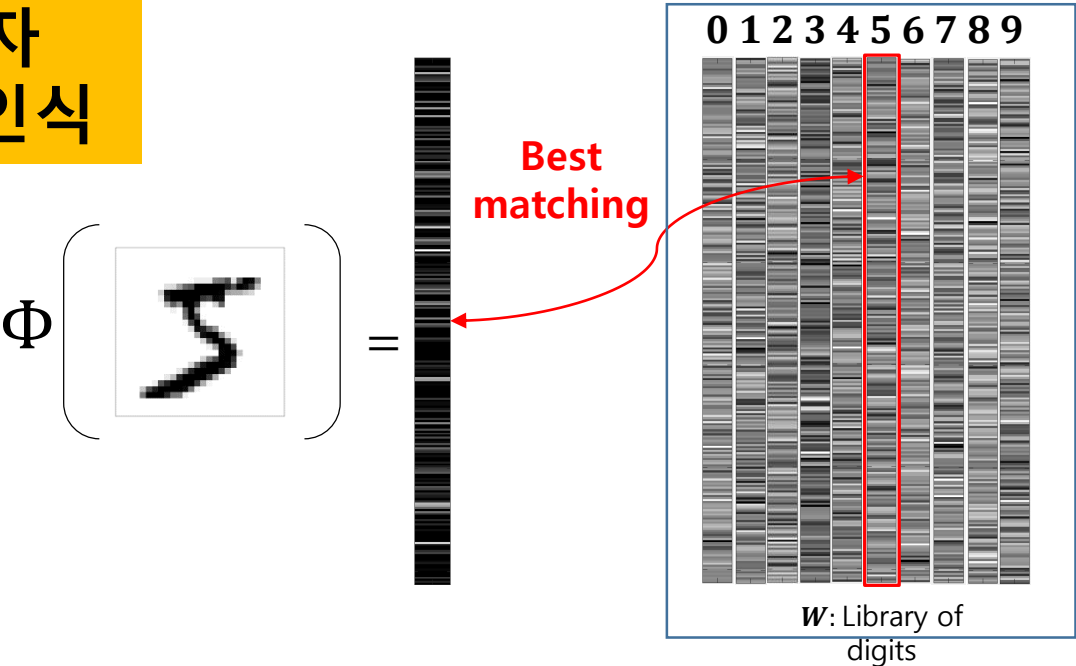
In deep convolution neural network the feed-forward function  $f$  is often given by

$$f(x) = f_0(\Phi(x)) \qquad \Phi(x) = g\left(W^k g\left(W^{k-1} \dots \left(g\left(W^2\left(g(W^1 x)\right)\right) \dots \right)\right)\right)$$

$g$  is a vector valued function. Ex)  $g$  is ReLU or pooling.  
 $x = (x, 1)$ ,  $W =$  (weight & bias).

The mission of CNN is to determine  $W^j, j = 1, \dots, k$ , from the training data  $\{(x^{(i)}, y^{(i)}): i = 1, \dots, m\}$ .

예: 숫자  
이미지 인식



$$f_0\left(\Phi\left(\begin{array}{c} \text{Image of 5} \end{array}\right)\right) = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$



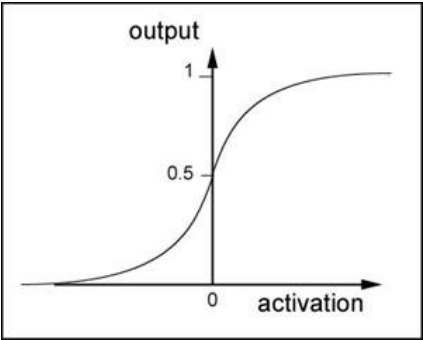
# Deep learning: Convolution Neural Network

예: 숫자  
이미지 인식

$$f\left(\begin{array}{c} \text{Σ} \end{array}\right) = f_0\left(\Phi\left(\begin{array}{c} \text{Σ} \end{array}\right)\right) = f_0\left(\begin{array}{c} \text{Σ} \end{array}\right) =$$

$$= \sigma \left( \begin{array}{c} \text{Matrix of 10x1000 grayscale images} \\ \text{Vector of 1000 grayscale images} \end{array} \right) = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

$$\sigma(s) = \frac{1}{1 + e^{-s}}$$



Finding the following  $\Phi(x)$  is the dream of kernel Learning Algorithms

$\Phi$  is a **contractive** operator which reduces the range of variations of  $x$ , while still **separating** different values of  $f$ :

$$\Phi(x) \neq \Phi(x') \text{ if } f(x) \neq f(x')$$

예: 숫자  
이미지 인식

같은 것을 다르게 보이게하는 요인들은?

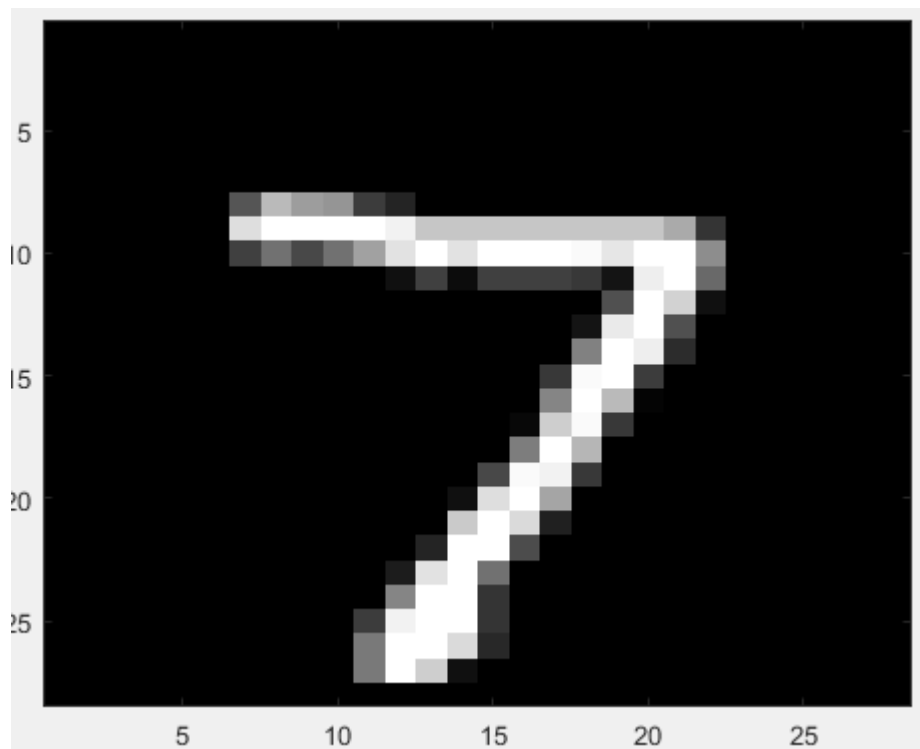
$$\Phi \left( \begin{array}{|c|} \hline 2 \\ \hline \end{array} \right) \approx \Phi \left( \begin{array}{|c|} \hline 2 \\ \hline \end{array} \right) \approx \Phi \left( \begin{array}{|c|} \hline 2 \\ \hline \end{array} \right) \approx \Phi \left( \begin{array}{|c|} \hline 2 \\ \hline \end{array} \right) \approx \Phi \left( \begin{array}{|c|} \hline 2 \\ \hline \end{array} \right)$$

Invariants: translations, diffeomorphisms (scaling, rotations,...)

$$\Phi \left( \begin{array}{|c|} \hline 2 \\ \hline \end{array} \right) \neq \Phi \left( \begin{array}{|c|} \hline 8 \\ \hline \end{array} \right) \neq \Phi \left( \begin{array}{|c|} \hline 7 \\ \hline \end{array} \right)$$

# Input layer

Input [1@28x28] - C1[32@24x24] - P2[32@12x12] - C3[64@8x8] - P4[64@4x4] - F5[256@1x1] - output[10]



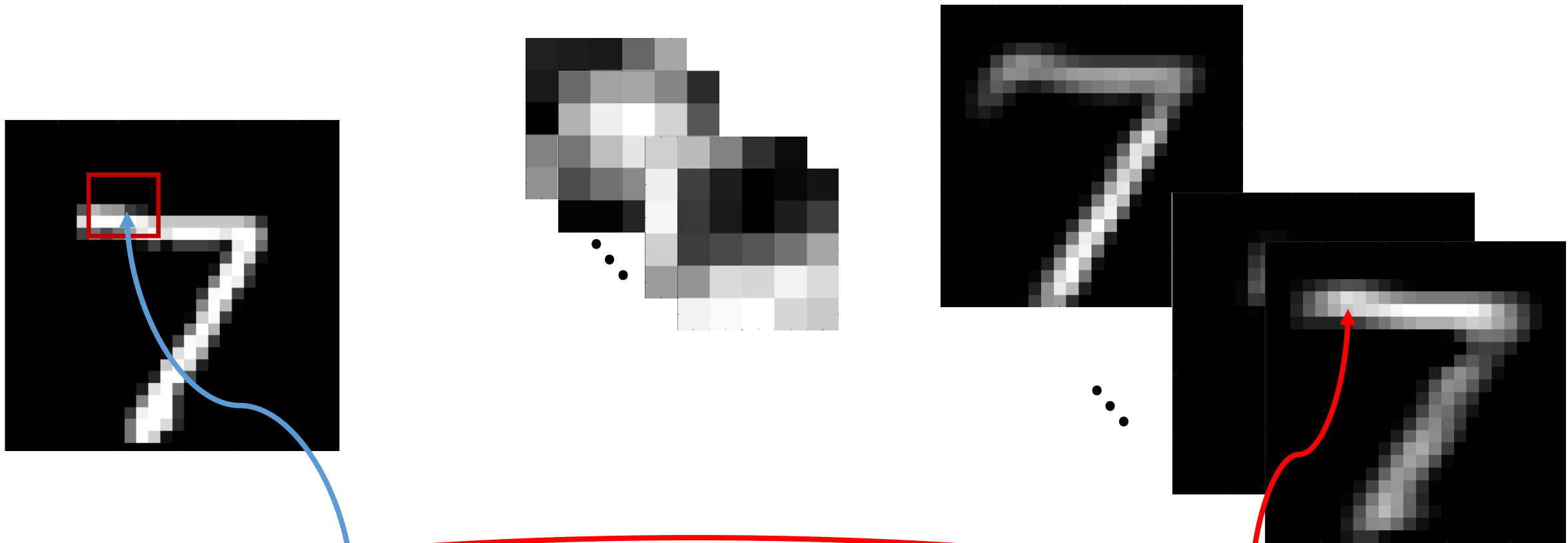
Input [1@28x28]

$$\mathbf{h}^0 = \begin{bmatrix} x_{1,1} & \cdots & x_{1,28} \\ \vdots & \ddots & \vdots \\ x_{28,1} & \cdots & x_{28,28} \end{bmatrix}$$



# Layer 1 (convolutional)

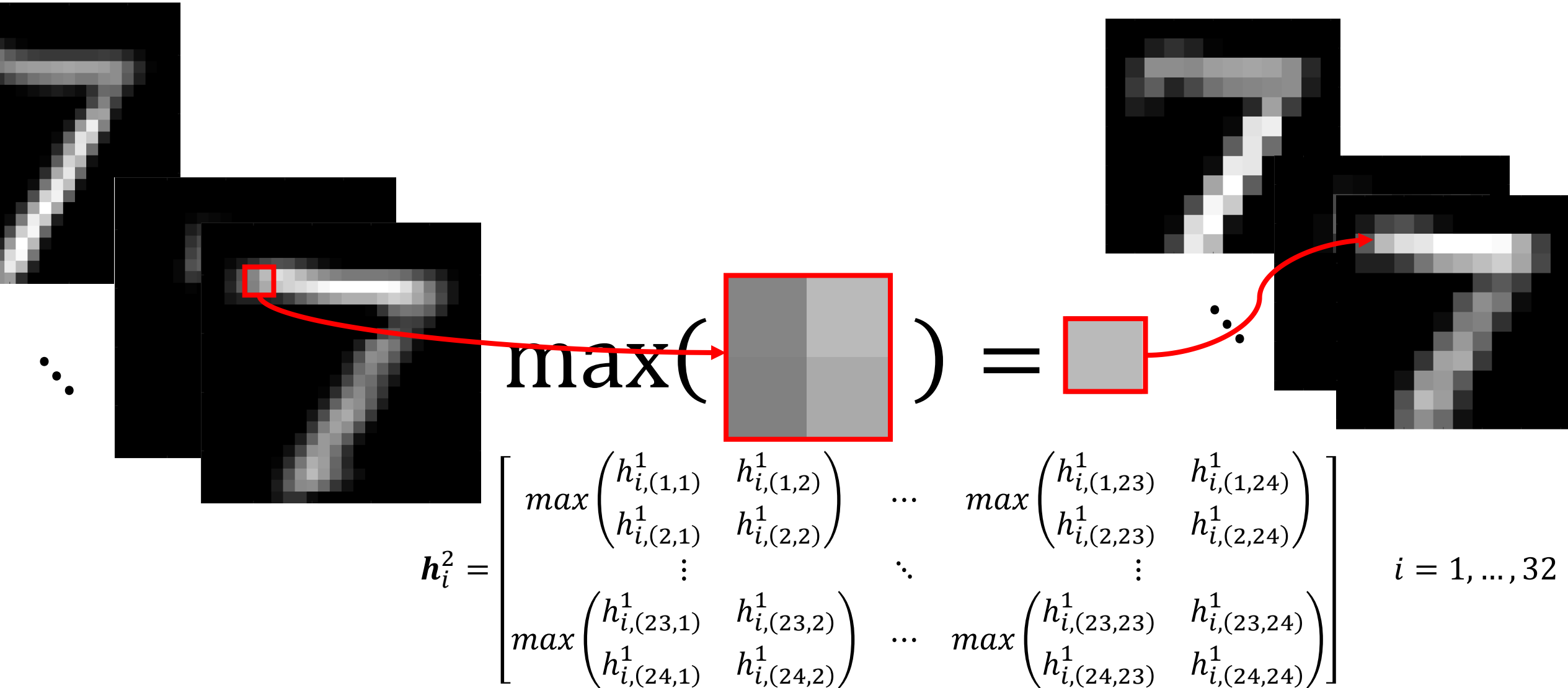
Input [1@28x28] - **C1[32@24x24]** - P2[32@12x12] - C3[64@8x8] - P4[64@4x4] - F5[256@1x1] - output[10]



$$g(\mathbf{w}_1^1 * \mathbf{h}^0(10,10) + b_1^1) = g(\langle \begin{bmatrix} \text{feature map} \end{bmatrix}, \begin{bmatrix} \text{feature map} \end{bmatrix} \rangle + b_1^1)$$

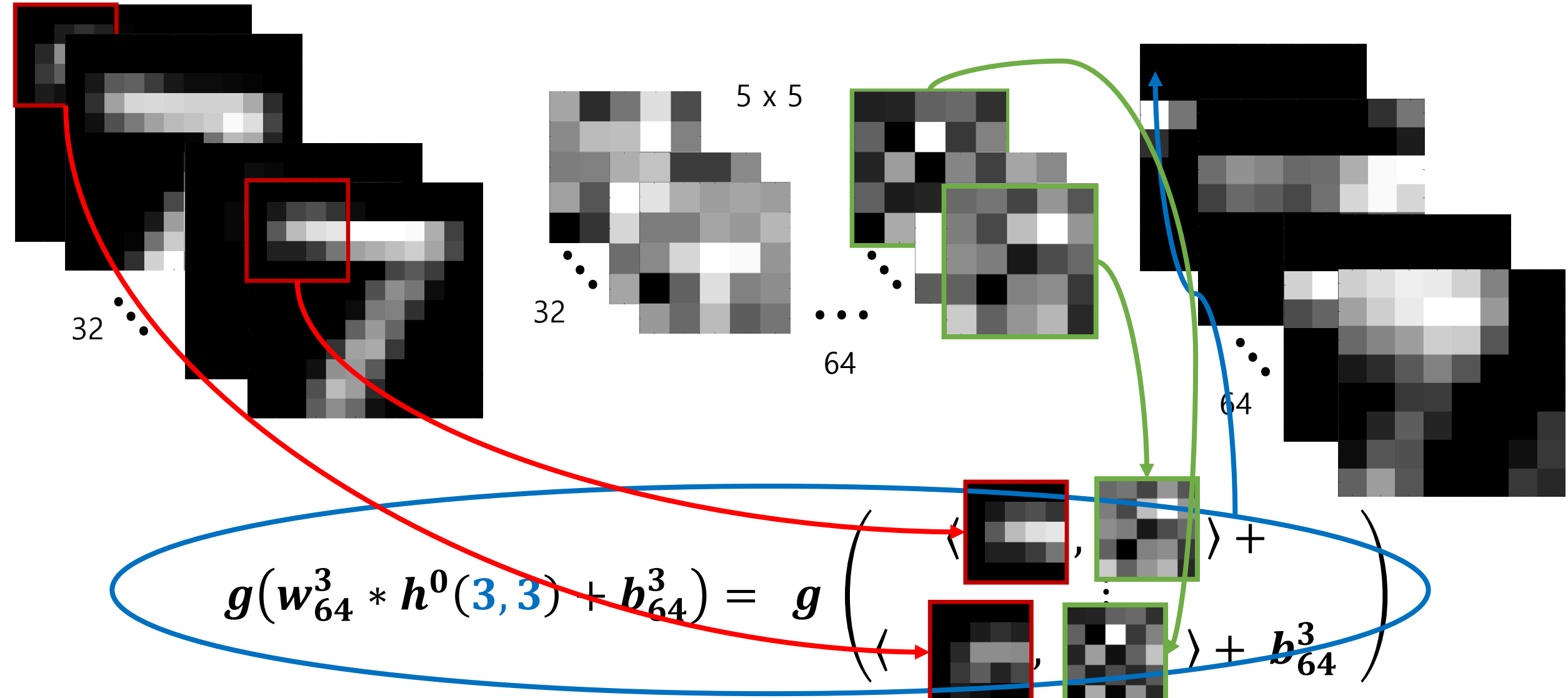
# Layer 2 (pooling)

Input [1@28x28] - C1[32@24x24] - **P2[32@12x12]** - C3[64@8x8] - P4[64@4x4] - F5[256@1x1] - output[10]



# Layer 3 (convolution)

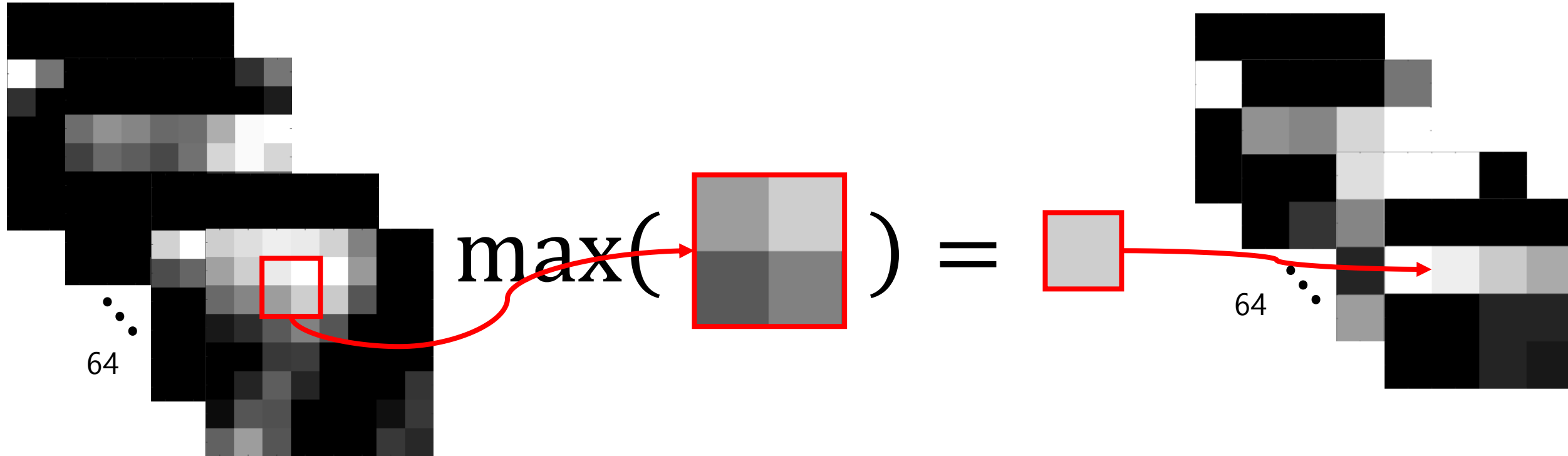
Input [1@28x28] - C1[32@24x24] - P2[32@12x12] - **C3[64@8x8]** - P4[64@4x4] - F5[256@1x1] - output[10]





# Layer 4 (pooling)

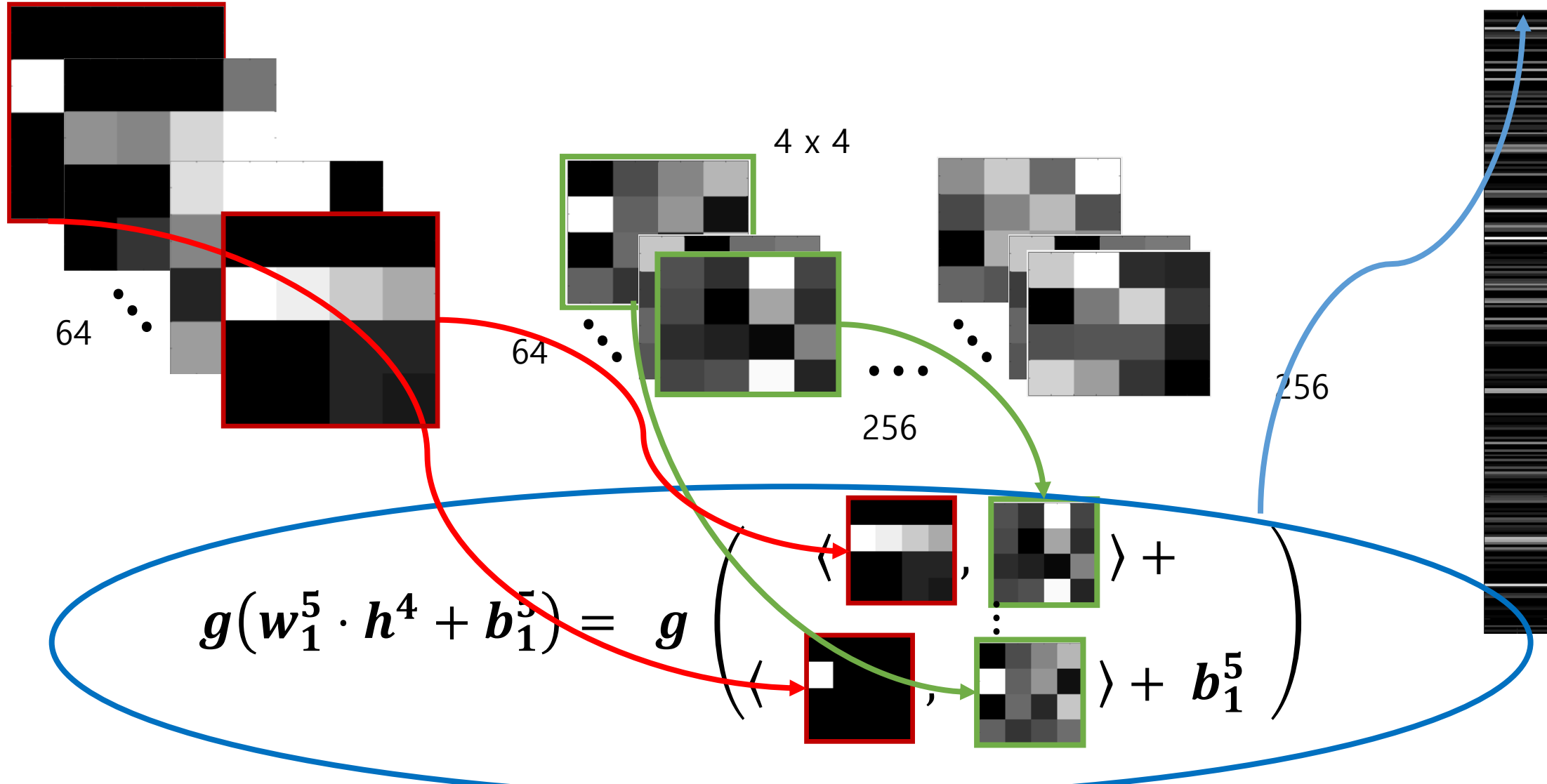
Input [1@28x28] - C1[32@24x24] - P2[32@12x12] - C3[64@8x8] - **P4[64@4x4]** - F5[256@1x1] - output[10]



$$h_i^4 = \begin{bmatrix} \max \begin{pmatrix} h_{i,(1,1)}^3 & h_{i,(1,2)}^3 \\ h_{i,(2,1)}^3 & h_{i,(2,2)}^3 \\ \vdots & \vdots \end{pmatrix} & \dots & \max \begin{pmatrix} h_{i,(1,7)}^3 & h_{i,(1,8)}^3 \\ h_{i,(2,7)}^3 & h_{i,(2,8)}^3 \\ \vdots & \vdots \end{pmatrix} \\ \max \begin{pmatrix} h_{i,(7,1)}^3 & h_{i,(7,2)}^3 \\ h_{i,(8,1)}^3 & h_{i,(8,2)}^3 \end{pmatrix} & \dots & \max \begin{pmatrix} h_{i,(7,7)}^3 & h_{i,(7,8)}^3 \\ h_{i,(8,7)}^3 & h_{i,(8,8)}^3 \end{pmatrix} \end{bmatrix} \quad i = 1, \dots, 64.$$

# Layer 5 (fully-connected)

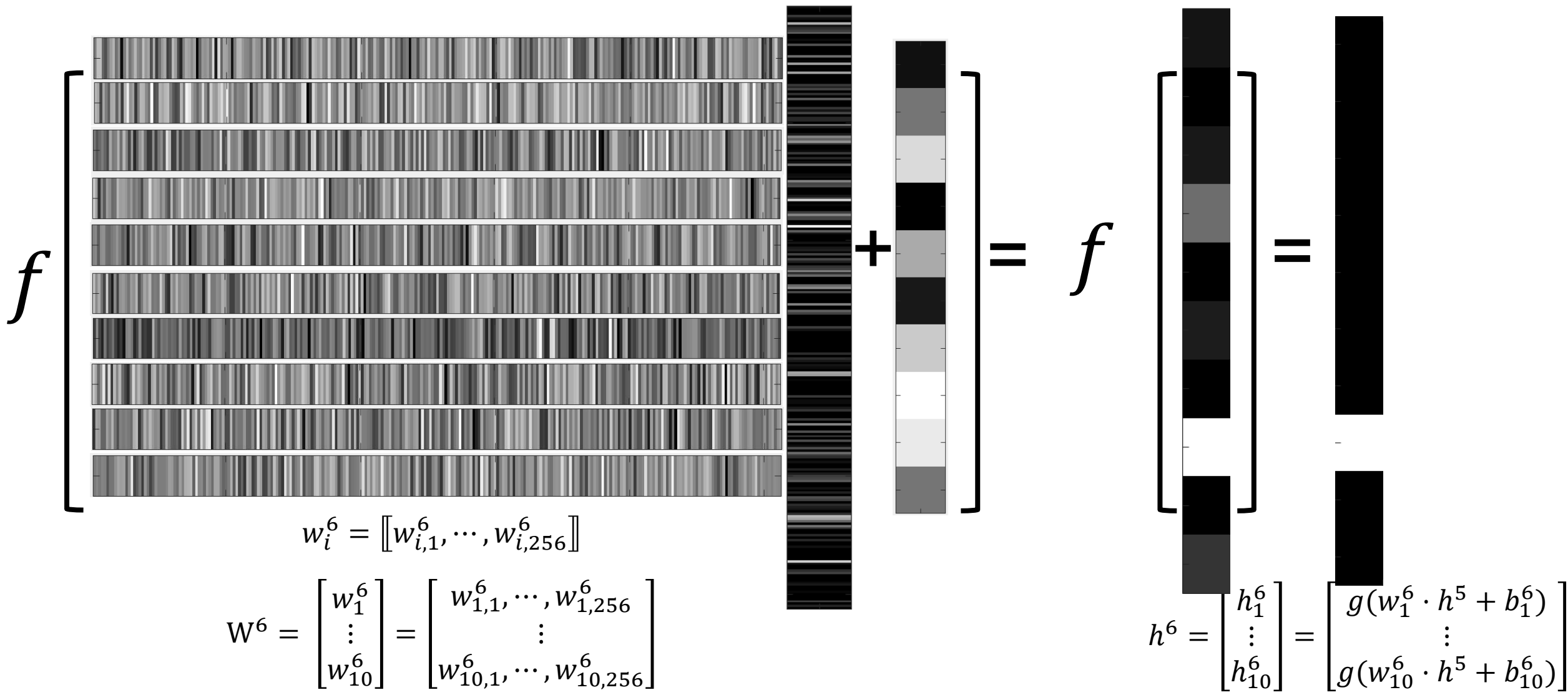
Input [1@28x28] - C1[32@24x24] - P2[32@12x12] - C3[64@8x8] - P4[64@4x4] - **F5[256@1x1]** - output[10]



# Output

중고생에게는 어려우니 수학이 딥러닝에 쓰이고 있다는 것만 느껴세요.

Input [1@28x28] - C1[32@24x24] - P2[32@12x12] - C3[64@8x8] - P4[64@4x4] - F5[256@1x1] - output[10]

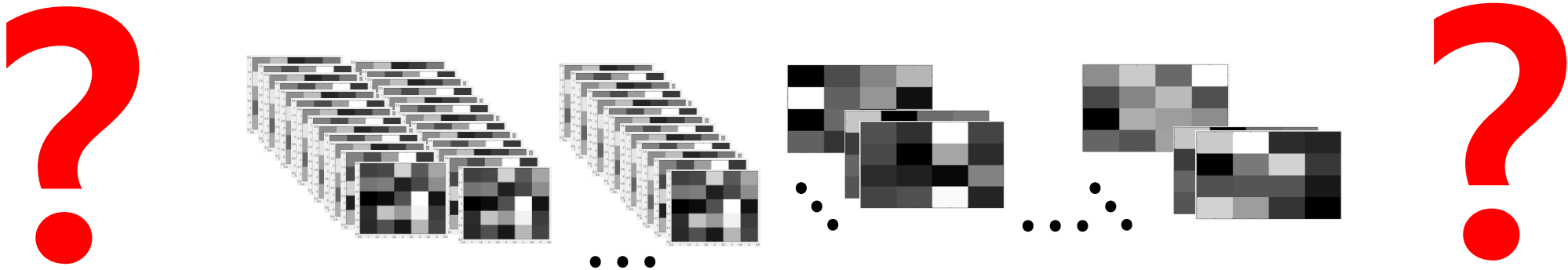




중고생에게는 어려우니 수학이 딥러닝에 쓰이고 있다는 것만 느껴세요.

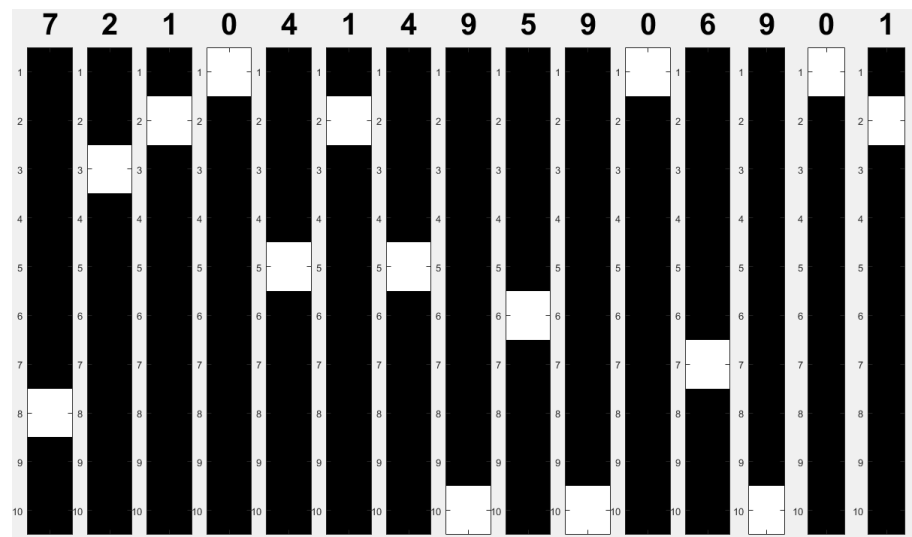
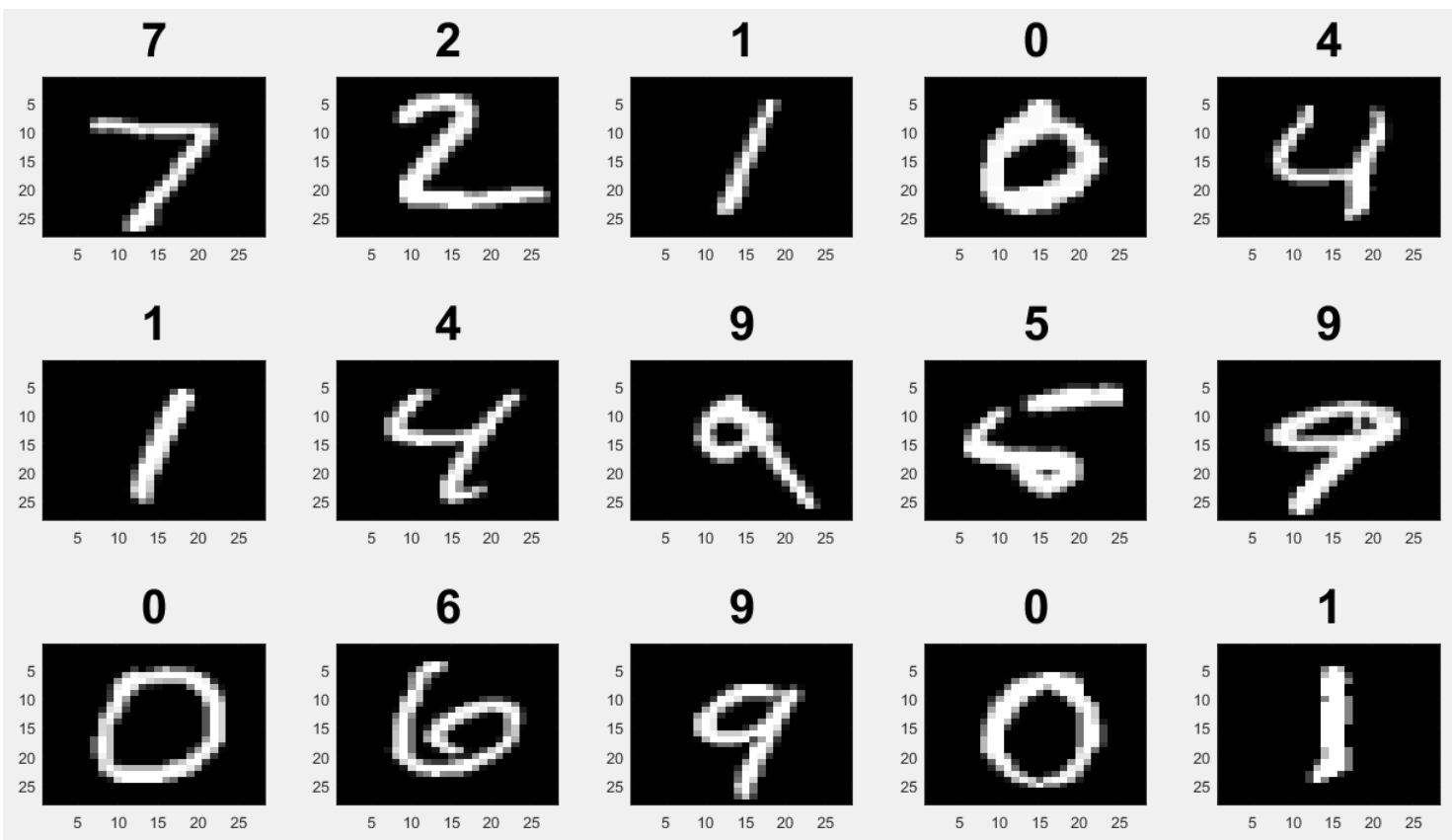
# 역전파알고리즘

역전파알고리즘은 학습지(training set)를 이용해 답안지와 답을 맞춰보면서 신경망을 학습(find weights and biases)시키는 방식이다.



# 역전파 알고리즘

# Training Data



# 학습목표는 신경망의 가중치(weight)와 bias를 알아내는것

$$w_i^1, b_i^1 \text{ for } i = 1, \dots, 32 \Rightarrow (5 \times 5 + 1) \times 32 \text{ unknowns}$$

$$w_i^3, b_i^3 \text{ for } i = 1, \dots, 64 \Rightarrow (5 \times 5 \times 32 + 1) \times 64 \text{ unknowns}$$

$$w_i^5, b_i^5 \text{ for } i = 1, \dots, 256 \Rightarrow (4 \times 4 \times 64 + 1) \times 256 \text{ unknowns}$$

$$w_i^6, b_i^6 \text{ for } i = 1, \dots, 10 \Rightarrow (256 + 1) \times 10 \text{ unknowns}$$

$W = [w^1, b^1, w^3, b^3, w^5, b^5, w^6, b^6]$  는 다음의 오차를 최소화하는 것

$$E(W) = \frac{1}{2} \sum_{k=1}^{2000} \|O(x[k]) - T[k]\|^2 .$$

$W$ 는 기울기 하강법으로 update 해나감

$$W \leftarrow W - \eta \nabla_W E$$

여기서  $\eta$  는 학습속도.

중고생에게는 어려우니 수학이 딥러닝에 쓰이고 있다는 것만 느끼세요.



# Express $E(W)$ in term of $x[k]$

중고생에게는 어려우니 수학이 딥러닝에 쓰이고 있다는 것만 느껴세요.

$$\mathbf{o}(\mathbf{x}[k]) = f(\mathbf{h}_k^6) = f(\mathbf{W}^6 \mathbf{h}_k^5 + \mathbf{b}^6)$$

$E(W)$

$$= \frac{1}{2} \sum_{k=1}^{2000} \|f(\mathbf{W}^6 \mathbf{h}_k^5 + \mathbf{b}^6) - \mathbf{T}[k]\|^2$$

$$= \frac{1}{2} \sum_{k=1}^{2000} \|f(\mathbf{W}^6 g(\mathbf{W}^5 \mathbf{h}_k^4 + \mathbf{b}^5) + \mathbf{b}^6) - \mathbf{T}[k]\|^2$$

$$= \frac{1}{2} \sum_{k=1}^{2000} \|f(\mathbf{W}^6 g(\mathbf{W}^5 P_4(\mathbf{h}_k^3) + \mathbf{b}^5) + \mathbf{b}^6) - \mathbf{T}[k]\|^2$$

$$= \frac{1}{2} \sum_{k=1}^{2000} \|f(\mathbf{W}^6 g(\mathbf{W}^5 P_4(g(\mathbf{W}^3 \mathbf{h}_k^2 + \mathbf{b}^3)) + \mathbf{b}^5) + \mathbf{b}^6) - \mathbf{T}[k]\|^2$$

$$= \frac{1}{2} \sum_{k=1}^{2000} \|f(\mathbf{W}^6 g(\mathbf{W}^5 P_4(g(\mathbf{W}^3 P_2(\mathbf{h}_k^1) + \mathbf{b}^3)) + \mathbf{b}^5) + \mathbf{b}^6) - \mathbf{T}[k]\|^2$$

$$= \frac{1}{2} \sum_{k=1}^{2000} \|f(\mathbf{W}^6 g(\mathbf{W}^5 P_4(g(\mathbf{W}^3 P_2(g(\mathbf{W}^1 \mathbf{x}[k] + \mathbf{b}^1)) + \mathbf{b}^3)) + \mathbf{b}^5) + \mathbf{b}^6) - \mathbf{T}[k]\|^2$$

중고생에게는 어려우니 수학이 딥러닝에 쓰이고 있다는 것만 느끼세요.

# Gradient of E(W) (F-layer)

$W^6, b^6$

Input [1@28x28] - C1[32@24x24] - P2[32@12x12] - C3[64@8x8] - P4[64@4x4] - F5[256@1x1] - output[10]

$$\begin{aligned}\frac{\partial E}{\partial \mathbf{w}_i^6} &= \sum_{k=1}^{2000} \frac{\partial E}{\partial h_{k,l}^6} \frac{\partial h_{k,l}^6}{\partial \mathbf{w}_i^6} \\ &= \frac{\partial}{\partial \mathbf{w}_i^6} \frac{1}{2} \sum_{k=1}^{2000} \|f(\mathbf{W}^6 \mathbf{h}_k^5 + \mathbf{b}^6) - \mathbf{T}[k]\|^2 \\ &= \sum_{k=1}^{2000} (f(\mathbf{w}_i^6 \mathbf{h}_k^5 + b_i^6) - T_i[k]) f'(\mathbf{w}_i^6 \mathbf{h}_k^5 + b_i^6) \mathbf{h}_k^5\end{aligned}$$

$$\begin{aligned}\frac{\partial E}{\partial b_i^6} &= \frac{\partial}{\partial b_i^6} \frac{1}{2} \sum_{k=1}^{2000} \|f(\mathbf{W}^6 \mathbf{h}_k^5 + \mathbf{b}^6) - \mathbf{T}[k]\|^2 \\ &= \sum_{k=1}^{2000} (f(\mathbf{w}_i^6 \mathbf{h}_k^5 + b_i^6) - T_i[k]) f'(\mathbf{w}_i^6 \mathbf{h}_k^5 + b_i^6)\end{aligned}$$

# Gradient of E(W) (F-layer)

Input [1@28x28] - C1[32@24x24] - P2[32@12x12] - C3[64@8x8] - P4[64@4x4] - F5[256@1x1] - output[10]

$W^5, b^5$

$$\begin{aligned} \frac{\partial E}{\partial \mathbf{w}_i^5} &= \frac{\partial}{\partial \mathbf{w}_i^5} \frac{1}{2} \sum_{k=1}^{2000} \|f(\mathbf{W}^6 g(\mathbf{W}^5 \mathbf{h}_k^4 + \mathbf{b}^5) + \mathbf{b}^6) - \mathbf{T}[k]\|^2 \\ &= \sum_{k=1}^{2000} \sum_l \frac{\partial E}{\partial h_{k,l}^6} \frac{\partial h_{k,l}^6}{\partial h_{k,i}^5} \frac{\partial h_{k,i}^5}{\partial \mathbf{w}_i^5} \\ &= \sum_{k=1}^{2000} \sum_l [(f(\mathbf{w}_l^6 \mathbf{h}_k^5 + b_l^6) - T_l[k]) f'(\mathbf{w}_l^6 \mathbf{h}_k^5 + b_l^6) \mathbf{w}_{l,i}^6] g'(\mathbf{w}_i^5 \mathbf{h}_k^4 + b_i^5) \mathbf{h}_k^4 \end{aligned}$$

$g'(\mathbf{w}_i^5 \mathbf{h}_k^4 + b_i^5)$  의 의미는?

활성화된 노드를 통해서만 반응이 역전파.

$$g'(x) = \begin{cases} 1 & 0 \leq x \\ 0 & 0 > x \end{cases}$$

중고생에게는 어려우니 수학이 딥러닝에 쓰이고 있다는 것만 느껴세요.

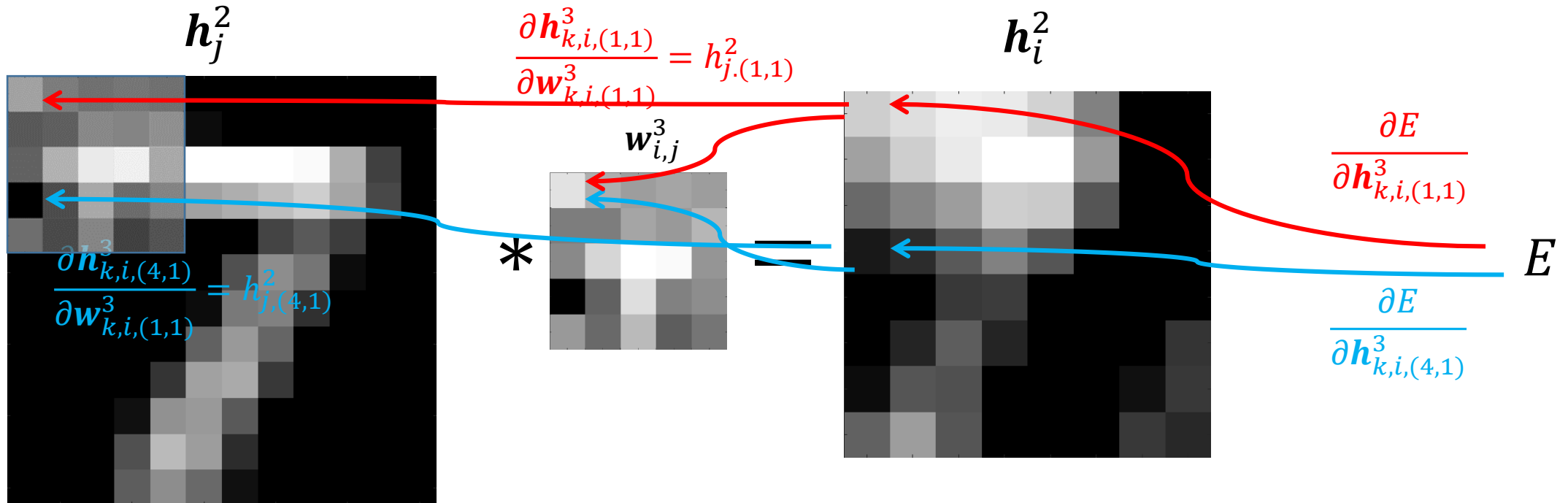


# Gradient of E(W) (C-layer)

중고생에게는 어려우니 수학이 딥러닝에 쓰이고 있다는 것만 느껴세요.

Input [1@28x28] - C1[32@24x24] - P2[32@12x12] - C3[64@8x8] - P4[64@4x4] - F5[256@1x1] - output[10]

$$\frac{\partial E}{\partial w_{i,j,(1,1)}^3} = \sum_k \sum_{1 \leq m,n \leq 8} \frac{\partial E}{\partial h_{k,i,(m,n)}^3} \frac{\partial h_{k,i,(m,n)}^3}{\partial w_{i,j,(1,1)}^3} = \sum_k \sum_{1 \leq m,n \leq 8} \frac{\partial E}{\partial h_{k,i,(m,n)}^3} h_{j,(m,n)}^2$$

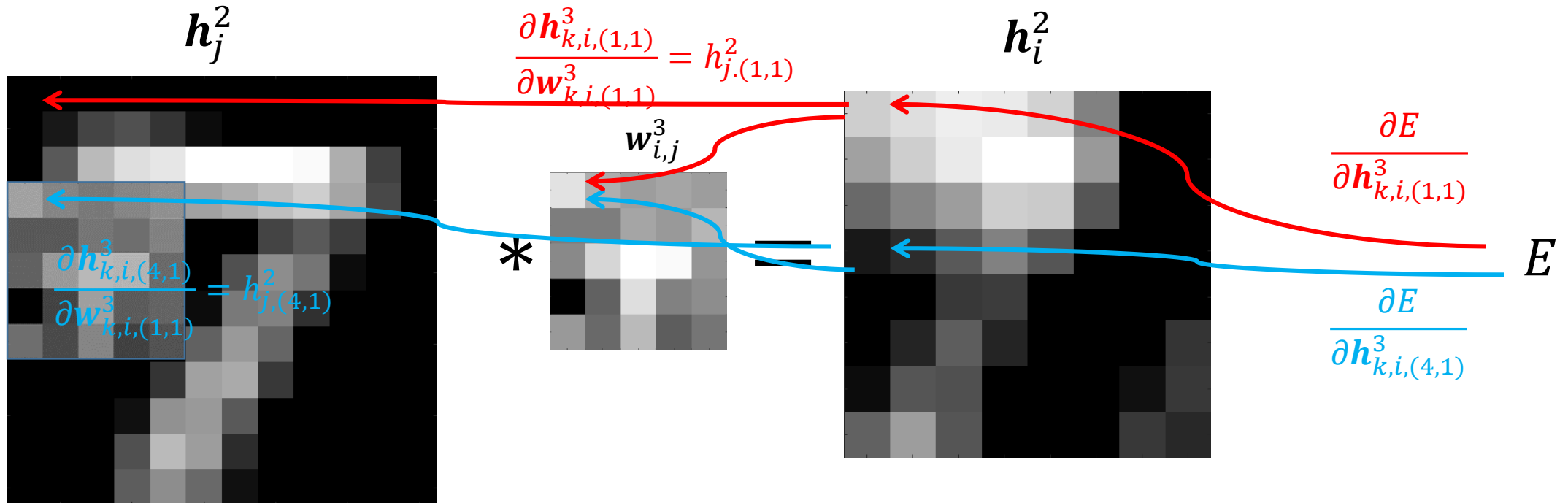


# Gradient of E(W) (C-layer)

중고생에게는 어려우니 수학이 딥러닝에 쓰이고 있다는 것만 느껴세요.

Input [1@28x28] - C1[32@24x24] - P2[32@12x12] - C3[64@8x8] - P4[64@4x4] - F5[256@1x1] - output[10]

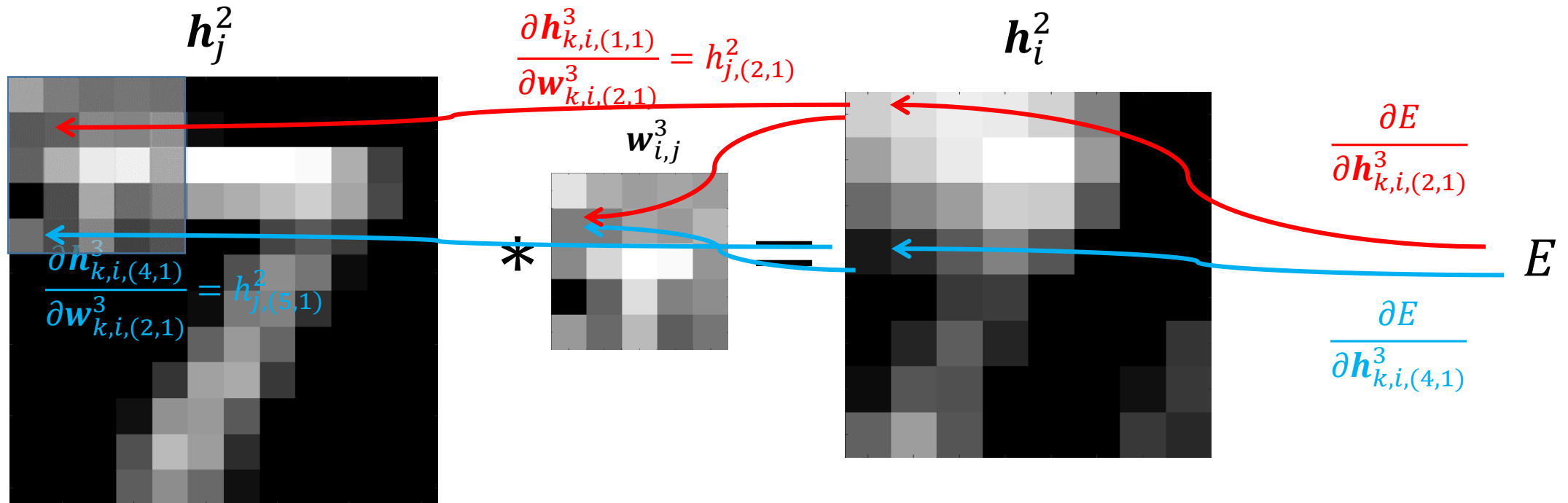
$$\frac{\partial E}{\partial w_{i,j,(1,1)}^3} = \sum_k \sum_{1 \leq m,n \leq 8} \frac{\partial E}{\partial h_{k,i,(m,n)}^3} \frac{\partial h_{k,i,(m,n)}^3}{\partial w_{i,j,(1,1)}^3} = \sum_k \sum_{1 \leq m,n \leq 8} \frac{\partial E}{\partial h_{k,i,(m,n)}^3} h_{j,(m,n)}^2$$



# Gradient of E(W) (C-layer)

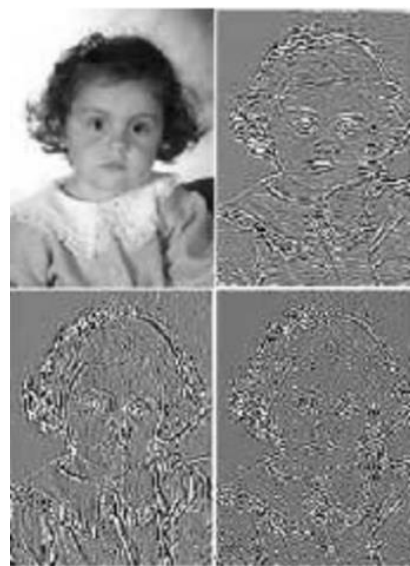
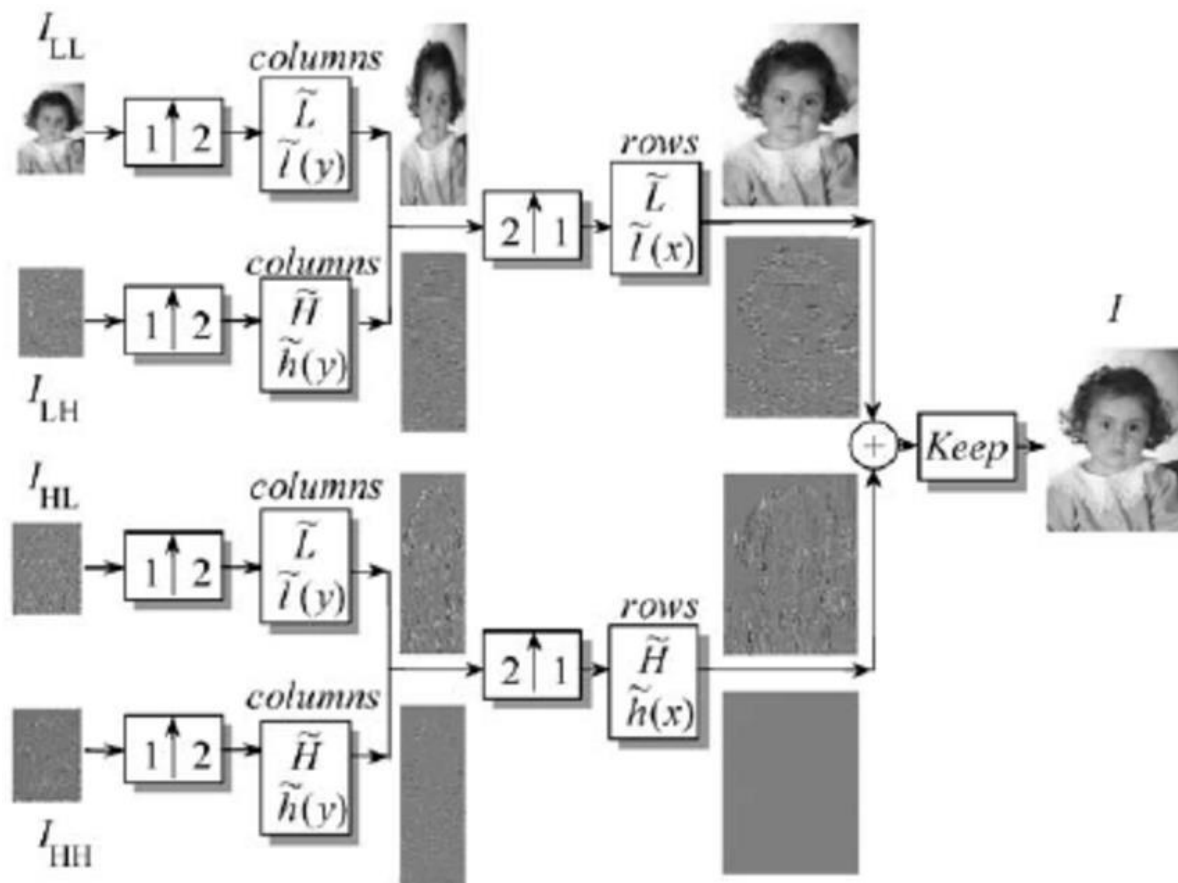
Input [1@28x28] - C1[32@24x24] - P2[32@12x12] - C3[64@8x8] - P4[64@4x4] - F5[256@1x1] - output[10]

$$\frac{\partial E}{\partial \mathbf{w}_{i,j,(2,1)}^3} = \sum_k \sum_{1 \leq m,n \leq 8} \frac{\partial E}{\partial \mathbf{h}_{k,i,(m,n)}^3} \frac{\partial \mathbf{h}_{k,i,(m,n)}^3}{\partial \mathbf{w}_{i,j,(2,1)}^3} = \sum_k \sum_{1 \leq m,n \leq 8} \frac{\partial E}{\partial \mathbf{h}_{k,i,(m,n)}^3} h_{j,(m+1,n)}^2$$

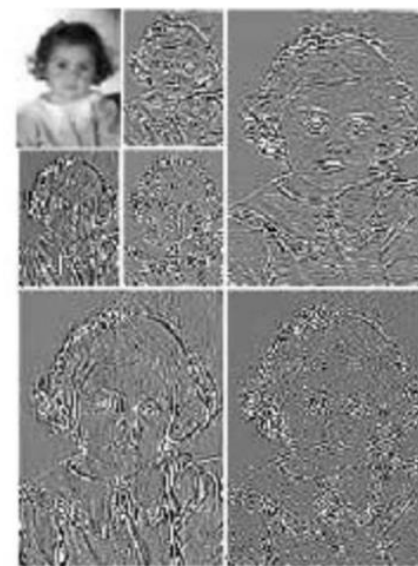




# 딥러닝 CNN은 Wavelet과 유사



(a)

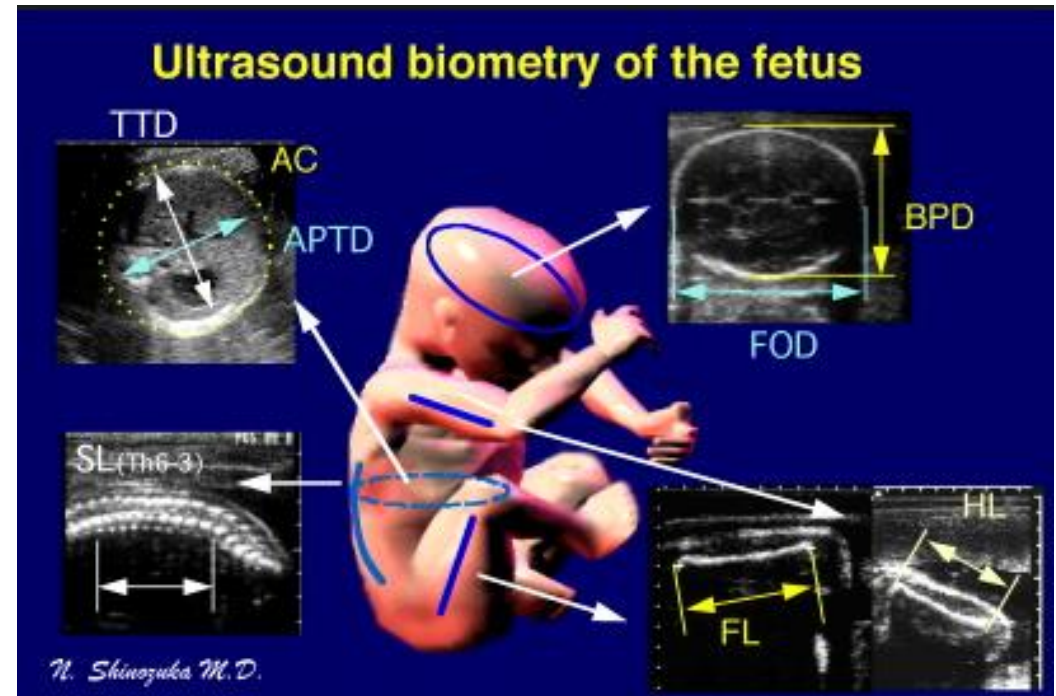


(b)

# 산부인과 초음파에서 기계학습

- 딥러닝을 이용한 태아의  
복부둘레 측정

장재성(NIMS), 이성민, 김부권(연세대)



# Automated Fetal Biometry

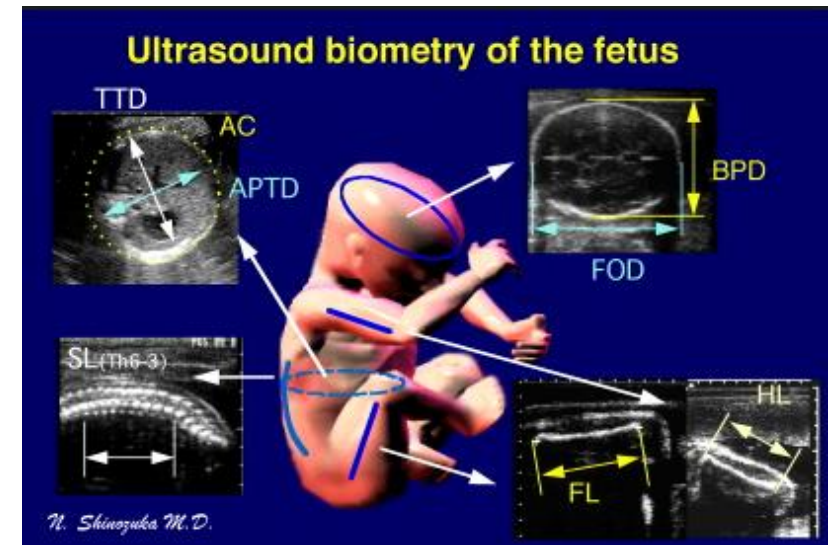
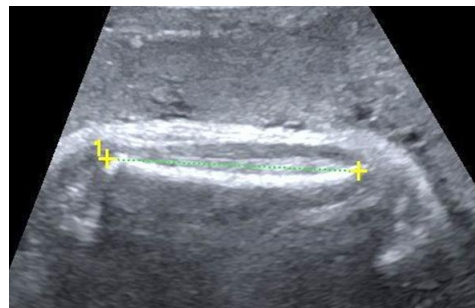
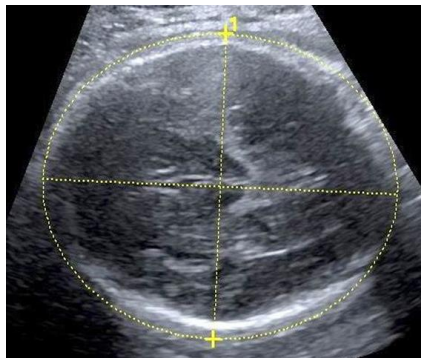
to estimate fetal weight & fetal growth abnormalities

## 목표: Improve clinical workflow

ergonomic stress 감소/업무process 간소화/ 문서작업 최소화

- Head (BPD, OFD, HC, Cephalic index)
- Thorax (Axis, Heart circumference Area, Thoracic circumference area, Head/Thorax ratio)
- Abdomen Circumference (AC),
- Bones: Femur (Femur length), Other Bones(optional)

## Sub-challenges (HC, BPD, Femur length)



## Challenge (AC)



현존하는 방식 : 정확도 매우 낮음

# Automated or Semi-automated Fetal Biometry

# 기존 기술 평가

## Siemens X3000 PE



Manual fetal biometric measurements by 2-dimensional (2D) sonography are an integral part of routine obstetric practice. Recently, an automated method for fetal biometry has been introduced in some sonographic equipment (*syngo Auto OB measurements*, S2000 ultrasound system; Siemens Healthcare,

2013년 논문: syngo Auto OB measurements 소프트웨어 사용으로 **HC, BPD, Femur length, AC** 측정시간 절약.  
....이러한 논문들은 실질적인 가치보다는 ...

### Personal Opinion

- 자동화 기능에 대한 만족도가 아직은 낮은 수준.
- AC: 기존의 |Image Gradient|와 active contour을 이용한 방식으로서는 실용화 어려울 듯.

IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 33, NO. 4, APRIL 2014

## Automatic Fetal Head Measurements from Sonographic Images

Vikram  
David F

1996년 논문 (김용민 전 포항공대 총장이 저자)

Active contour 방식, |Image Gradient|가 큰 지점에서 contour stop

## Evaluation and Comparison of Current Fetal Ultrasound Image Segmentation Methods for Biometric Measurements: A Grand Challenge

2014년 논문: Challenge US: Biometric measurements from Fetal US images. 이분야 전문가 5팀이 경합. 모두 상대적으로 쉬운 head 와 femur 다름. AC는 어려워 모두 포기.

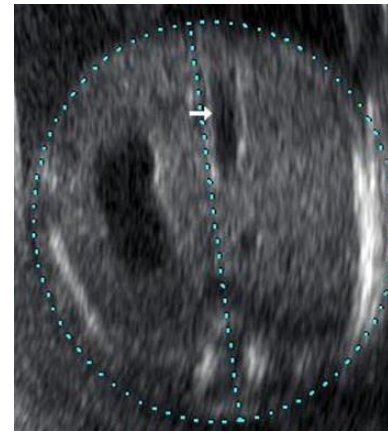
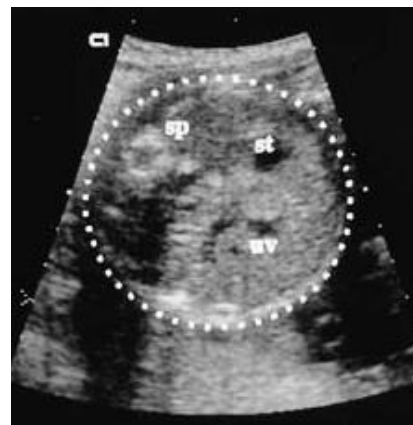


## Automated or Semi-automated Fetal Biometry

# 자동화가 어려운 이유

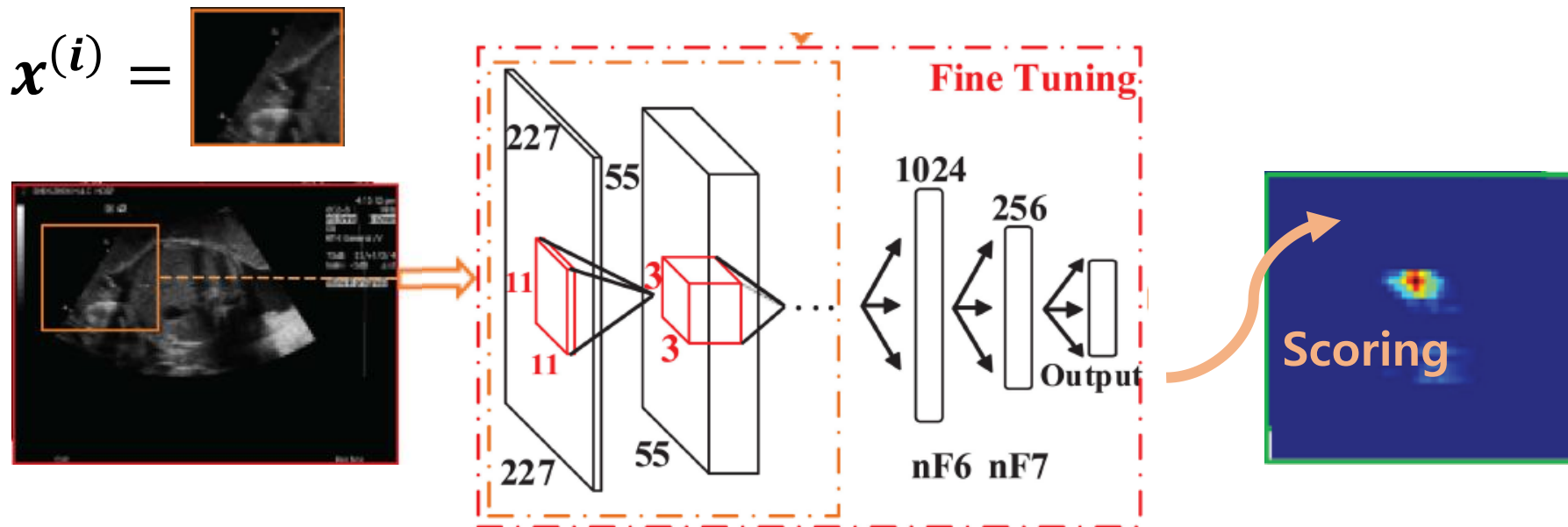
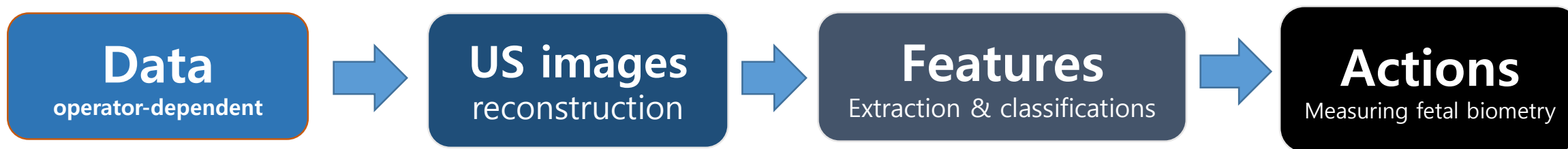
- US images are operator-dependent, patient-specific, and machine-specific.
- 특히 AC가 어려운 이유는 "low contrast against surroundings and non-uniform contrast"

CT, MRI와는 차원이 다른 어려움이 있음



# Deep Learning 방식 for Automated Fetal Biometry

딥러닝 방식이 성공하기 까지는 상당한 어려움은 있으나 결국은 성공할 듯.  
기존 방식(|Image Gradient|와 active contour)으로는 어려울 듯.



# 꿈 에서 껌 으로

Deep Learning will not produce universal algorithm.

DL in  
medicine

?

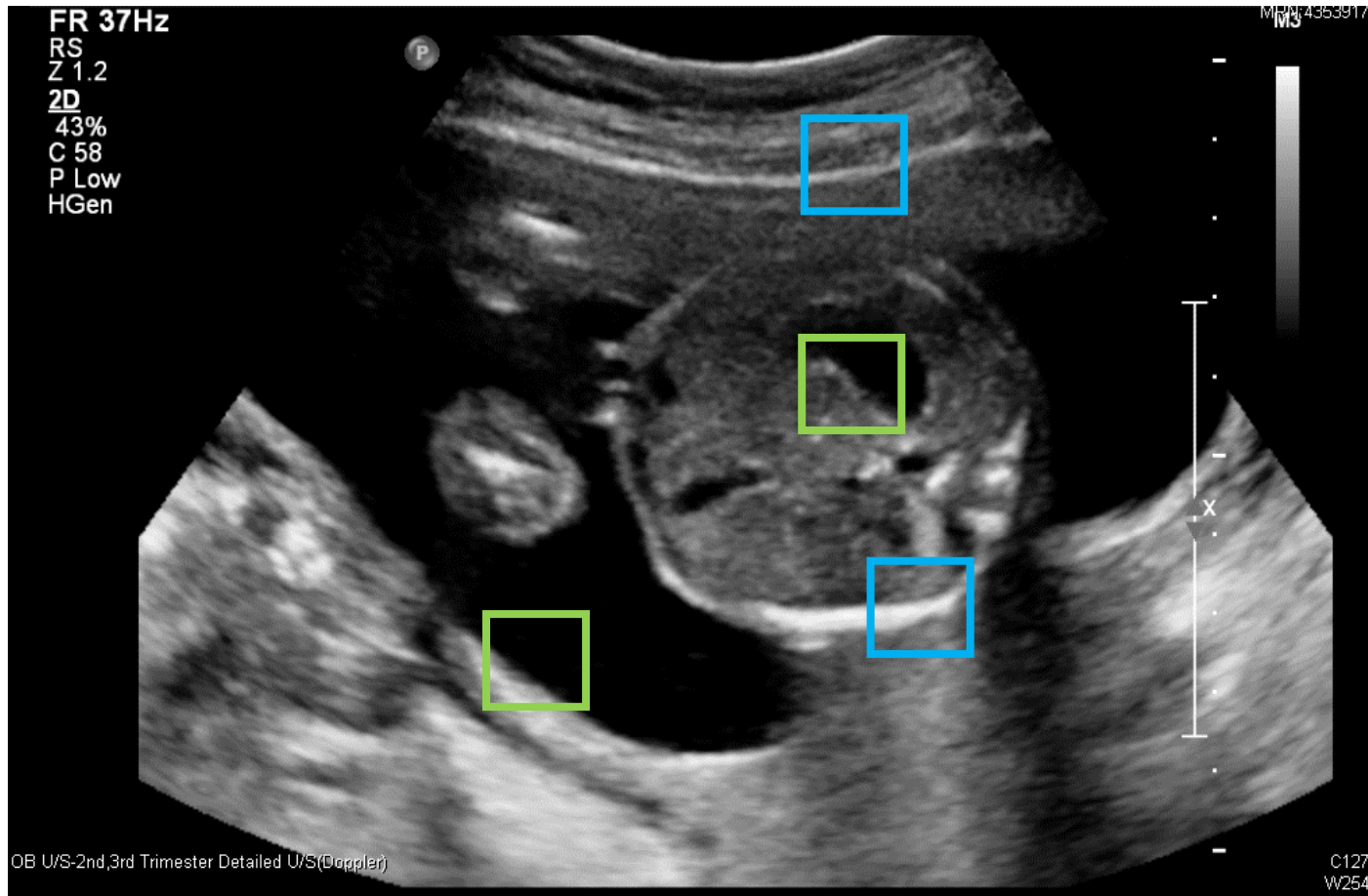
DL in vision, audio, etc.

- 초음파 영상에서의 Deep Learning은 차원이 다르다
- 10년 이내에 성공하겠지만 1-2년 이내는 아닌 듯...
- 진단에 별로 의미/가치 없는 성과위주의 DL은 자주 등장할 듯... (저널 논문들 신뢰 안함)

**Deep Learning** 성공이유

- Big Data
- Faster computer power
- Smarter weight initialization
- Better nonlinear transformation
- Fine-tuning pre-trained parameters via backpropagation

# CNN 방식의 단순 적용은 실패가능성 높음



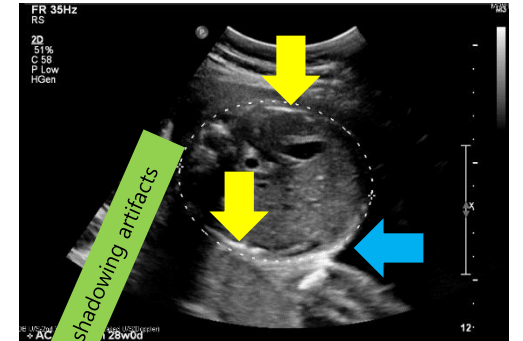
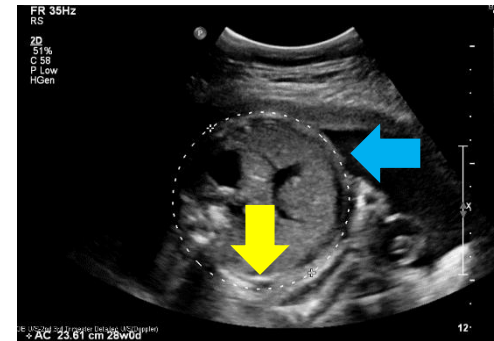
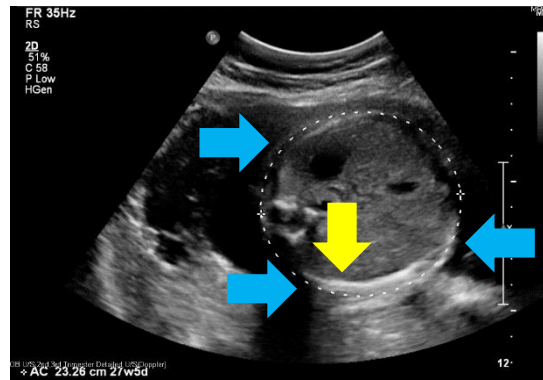
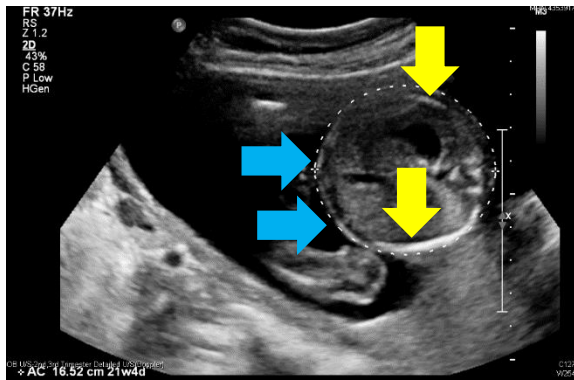
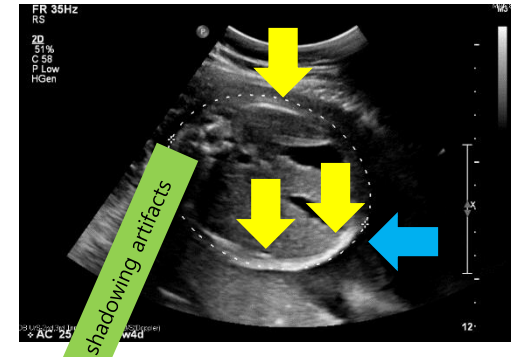
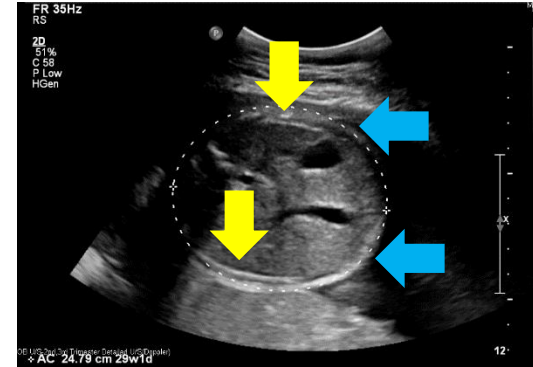
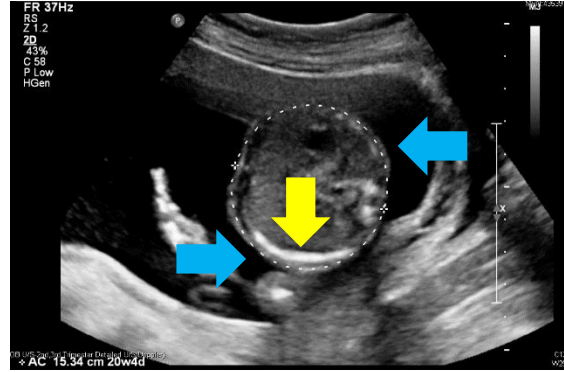
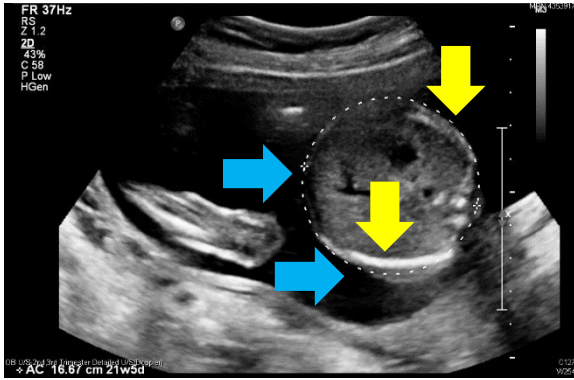
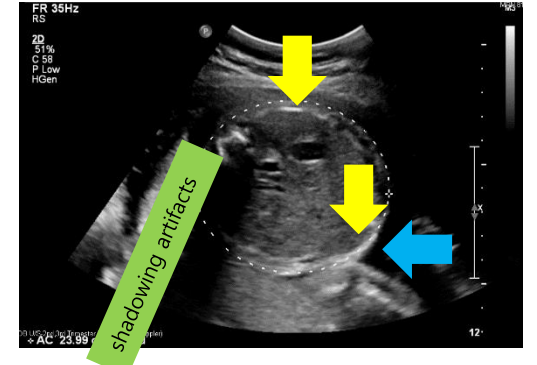
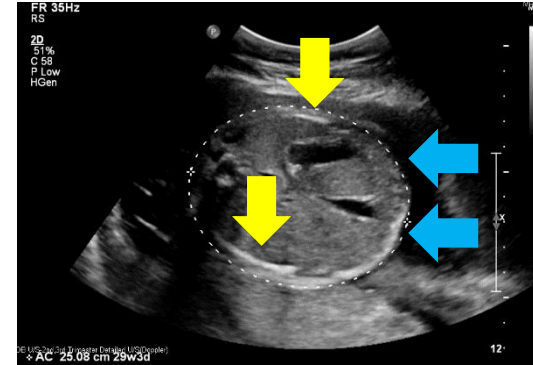
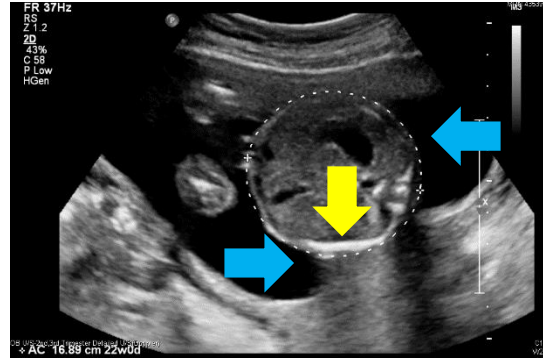
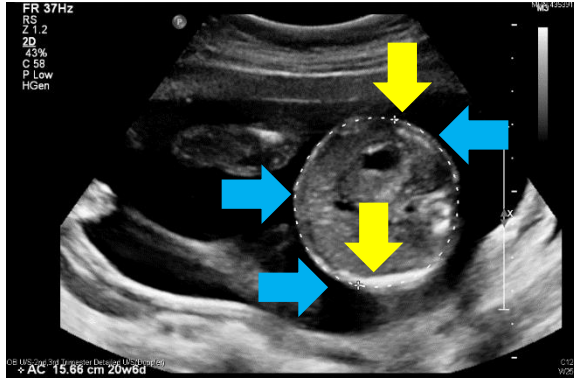
- CNN 접근 방식: 이미지 패치만을 분석하여 분류함
- ✓ 초음파 영상에 있어선 이미지 패치만을 바라보는 방법은 전문가의 판단 과정을 적절히 반영하지 않음



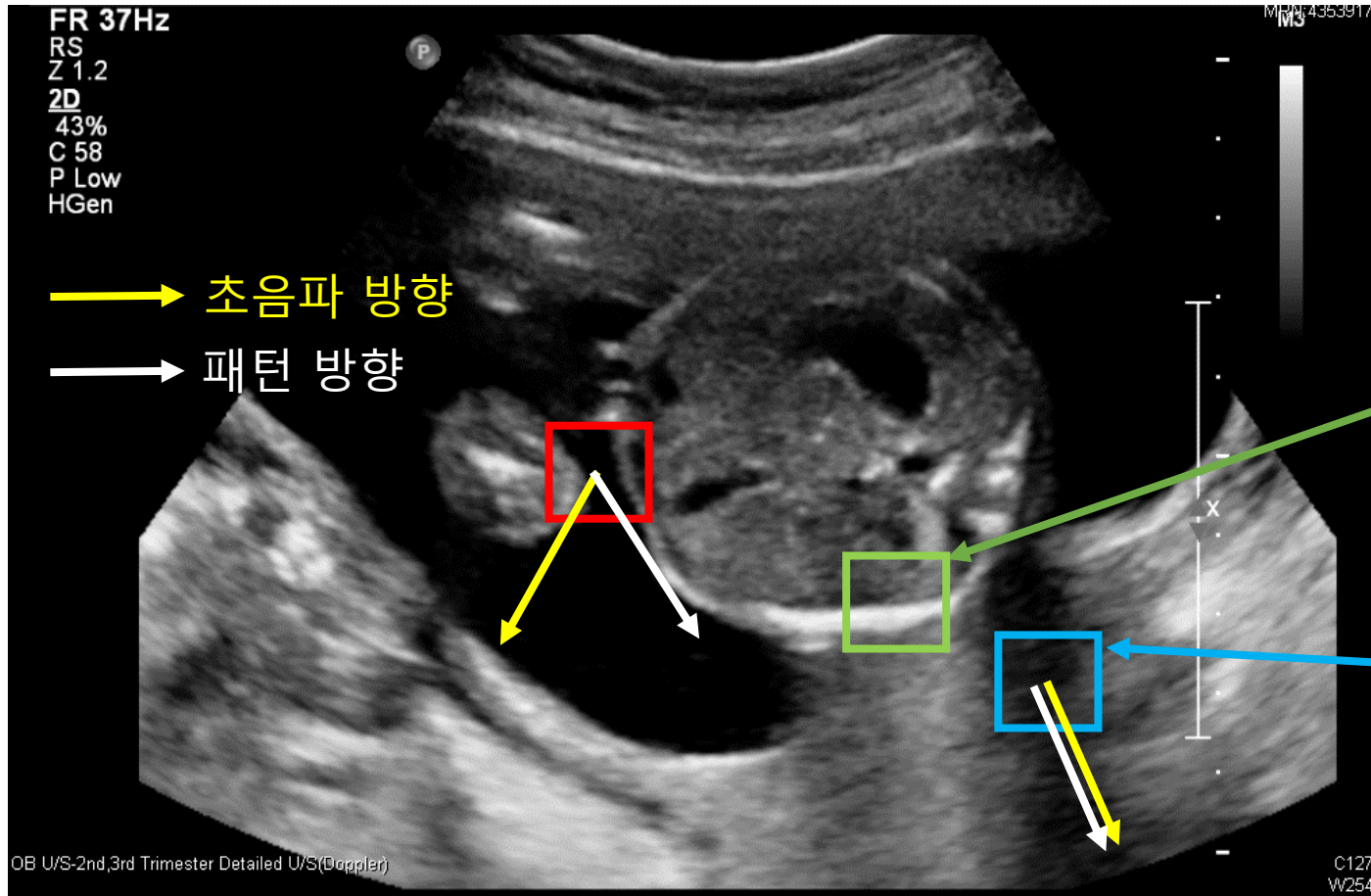
# 특징 분석

↓ 갈비뼈 ↓ 양수

shadowing artifacts



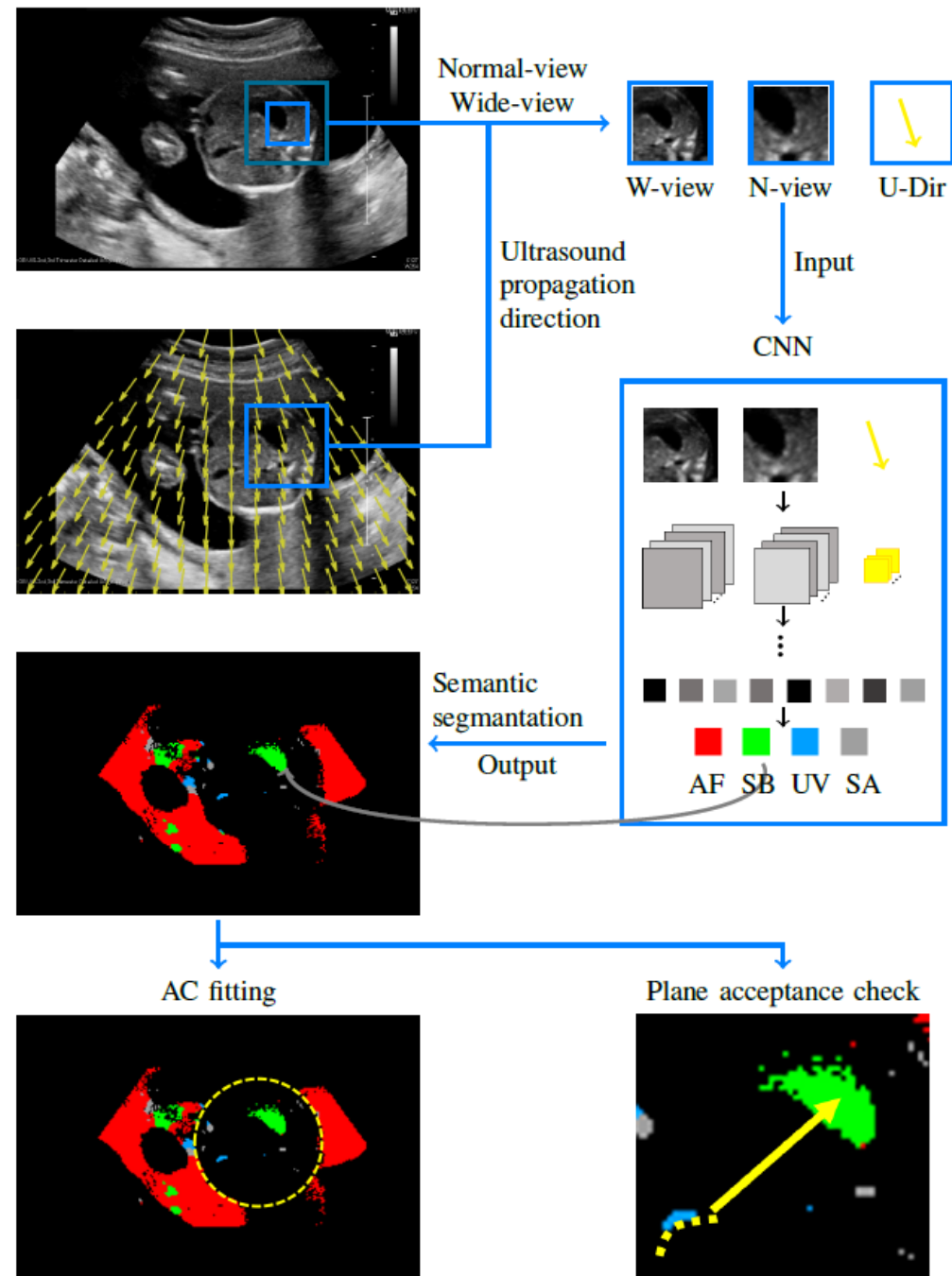
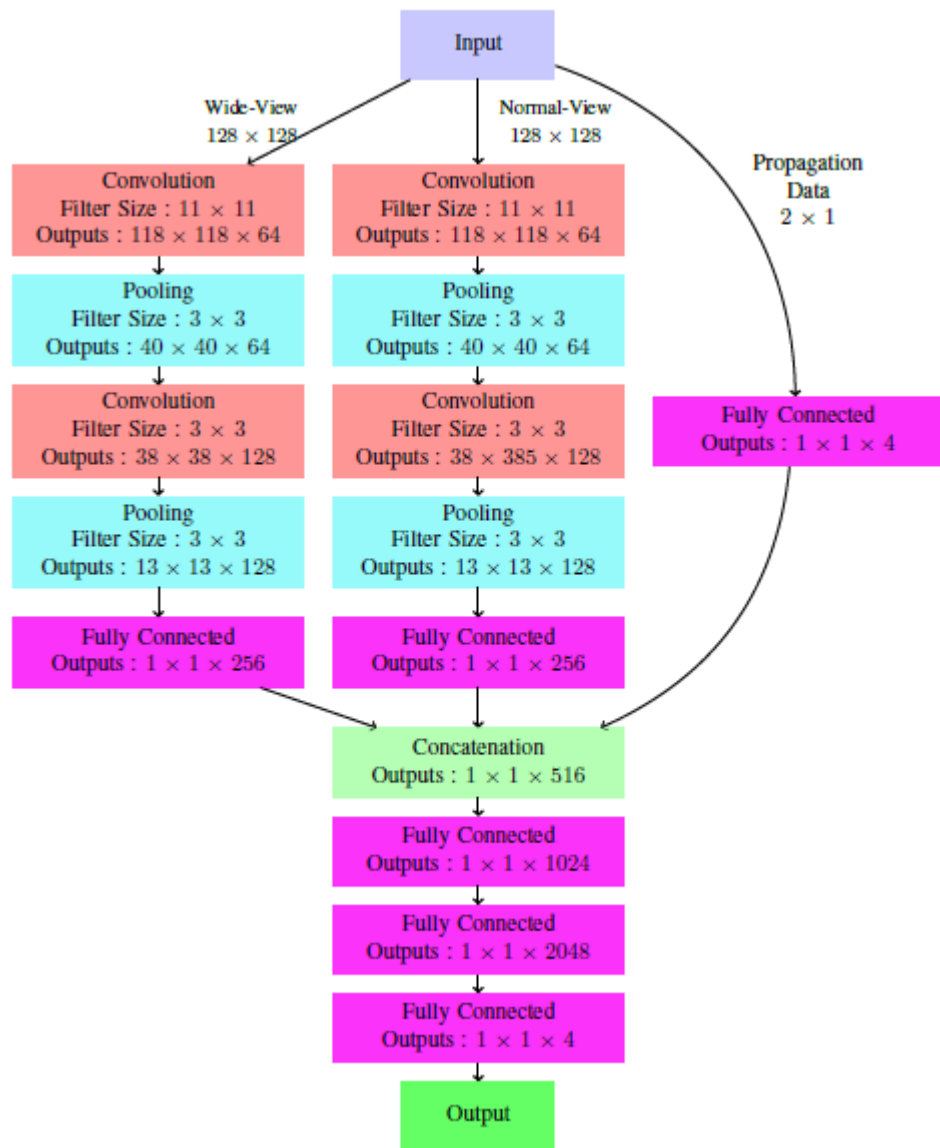
# 초음파의 진행 방향, 모델의 특성, 영상왜곡을 모두 반영하는 딥러닝 방식 개발 필요



- 이패치를 갈비뼈라고 판단하는 근거 중에는 위치정보가 반영되어 있음

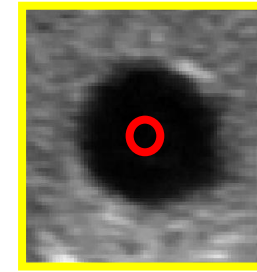
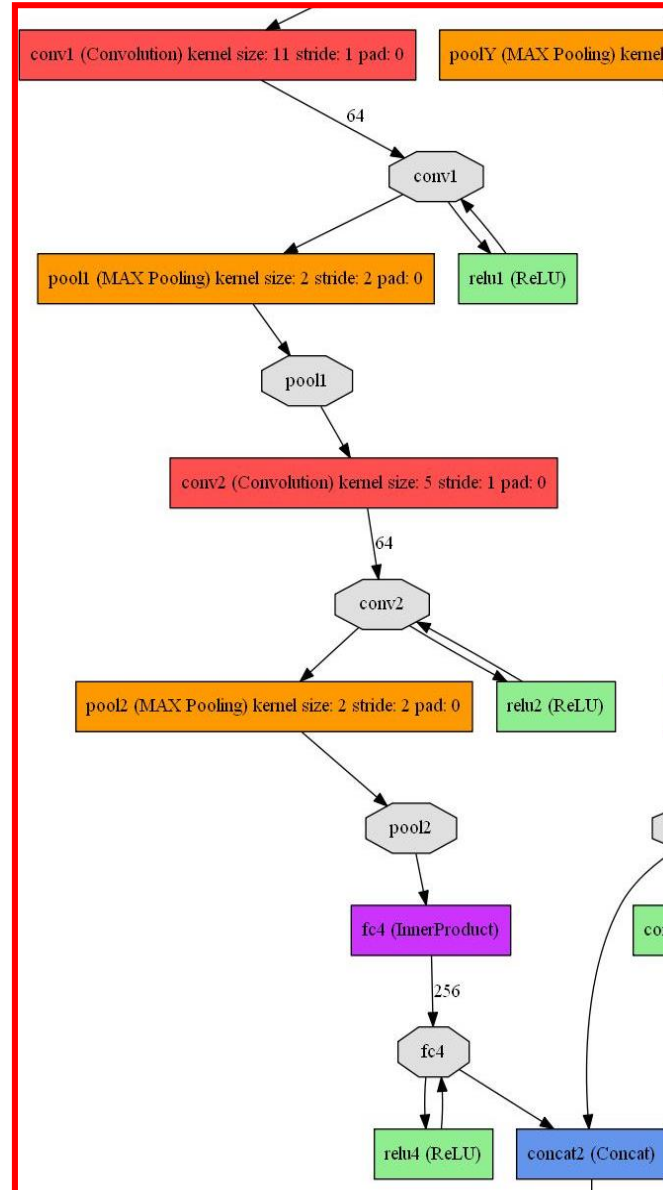
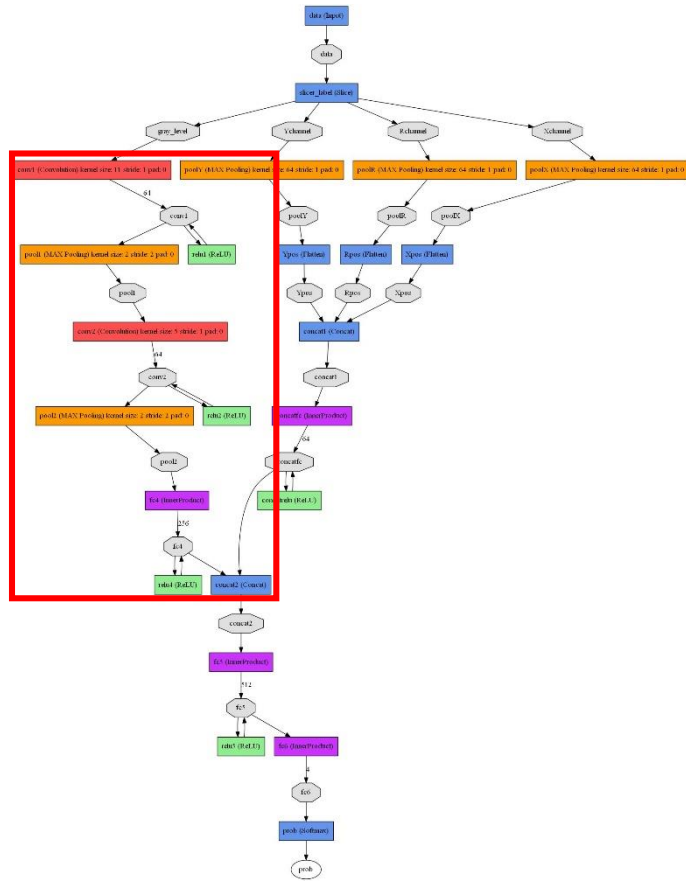
- shadowing artifact라 판단하는 근거는 초음파가 등뼈에서 반사됨을 알기 때문

# 제안 1: 딥러닝에 이미지 특징과 초음파 진행 방향 반영

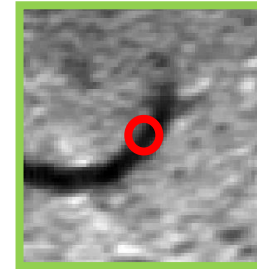




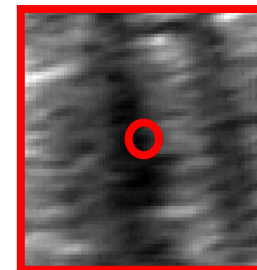
# 제안2: 복부영상에서 발견되는 특징 반영



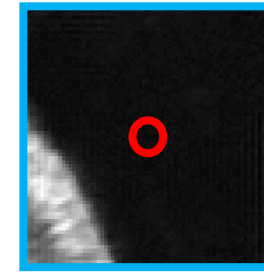
Stomach  
bubble



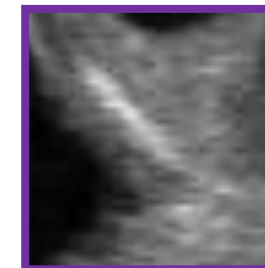
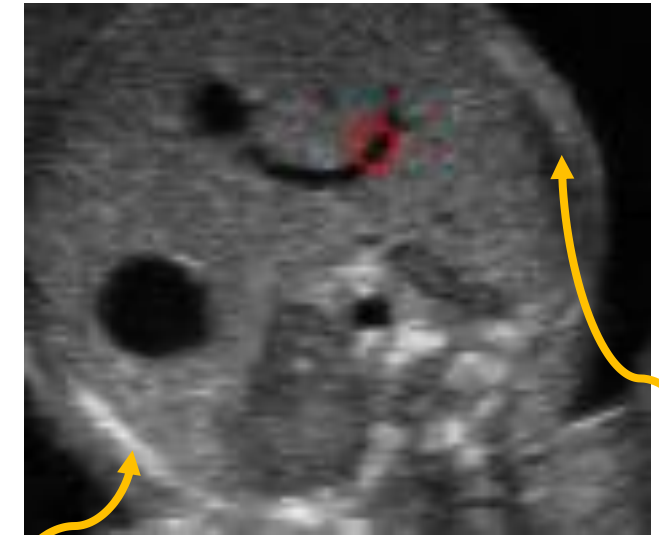
Umbilical  
vein



Shadowing  
artifact



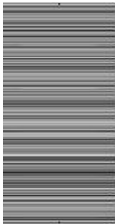
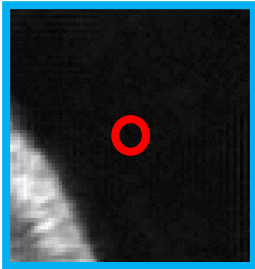
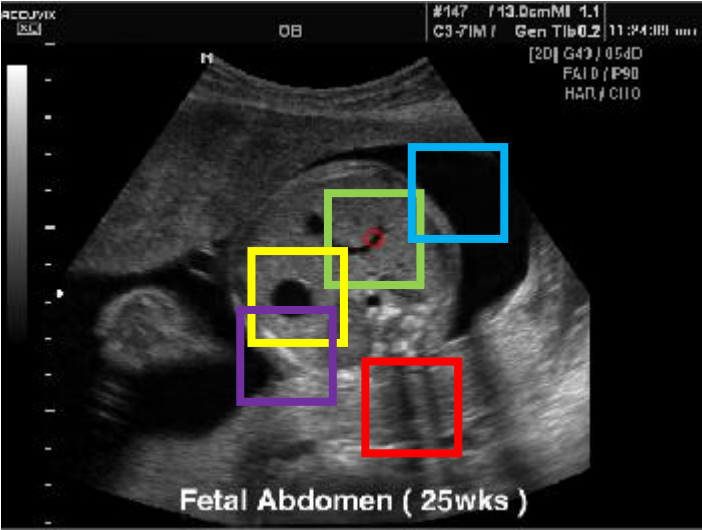
양수



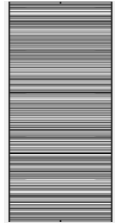
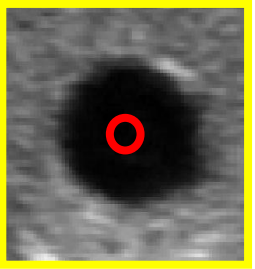
갈비뼈



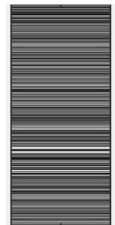
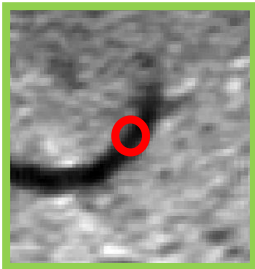
# 딥러닝을 이용한 해부학적 특징 추적



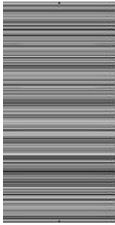
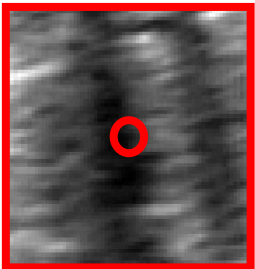
Amniotic fluid

$$\begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$


Stomach bubble

$$\begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$


Umbilical vein

$$\begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}$$


Shadowing artifact

$$\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$$

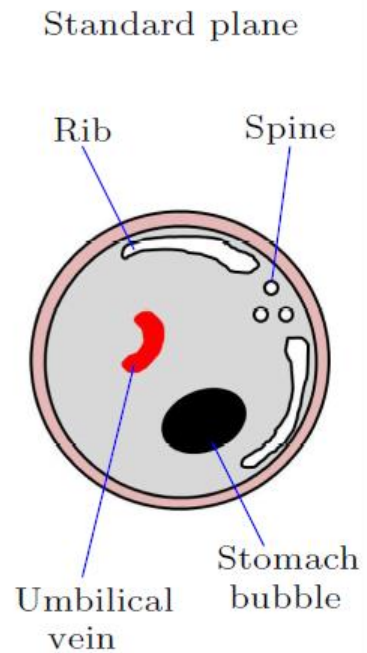

갈비뼈

$$\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

Classification

$$y(\text{feature image}, \Theta) = g(\text{feature vector}) = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$$

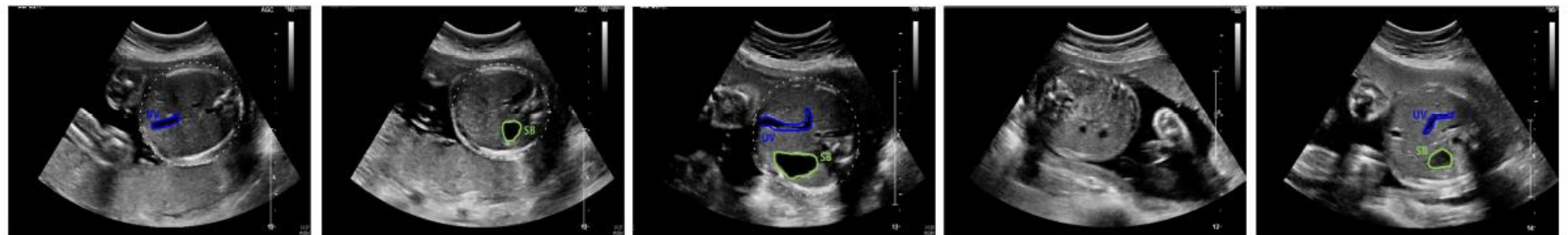
# 딤러닝 방식 TEST



Correct AC planes



Incorrect AC planes



SB is not seen

UV is not seen

UV seen closely  
to anterior wall

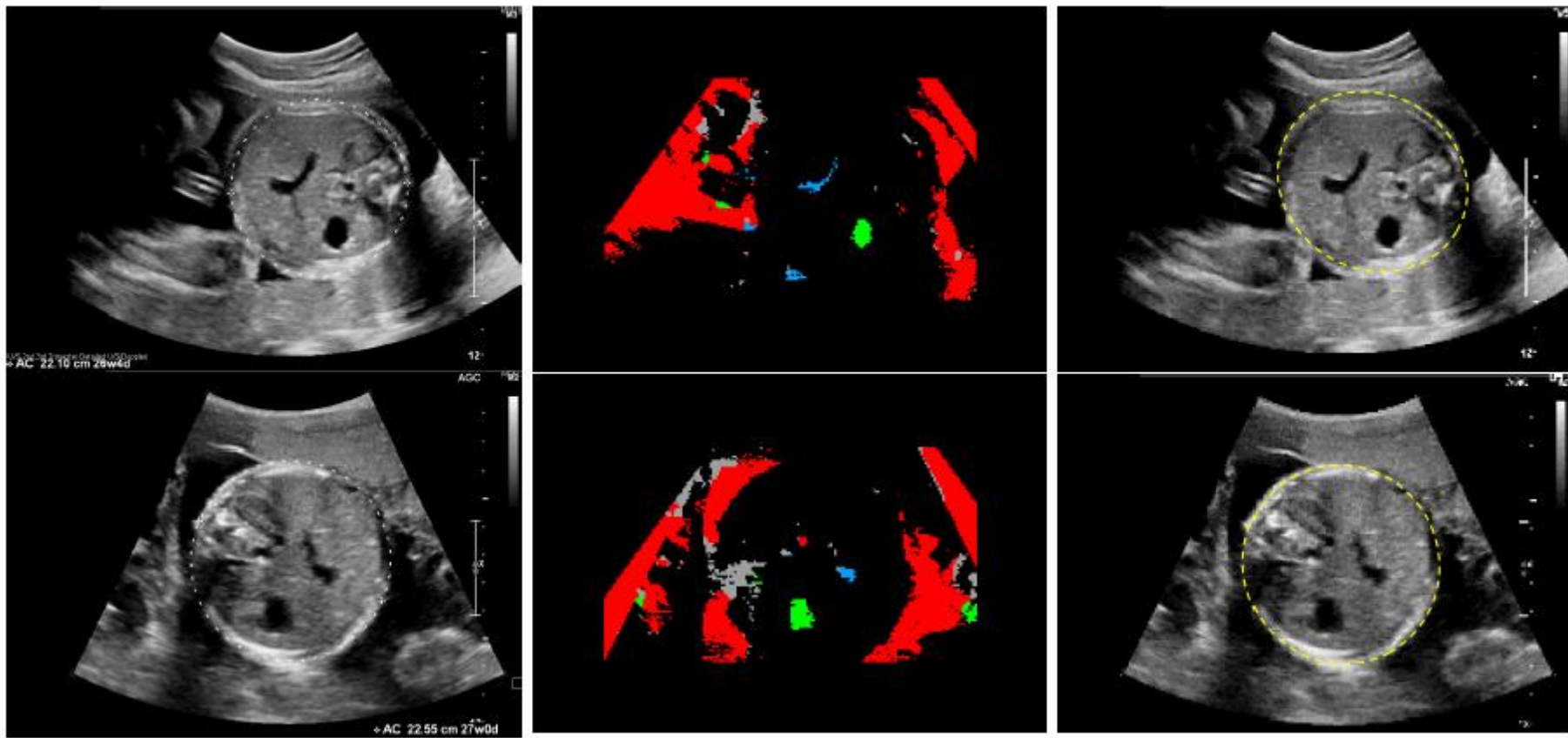
Both SB and  
UV are not  
well visualized

UV bent to  
wrong direction

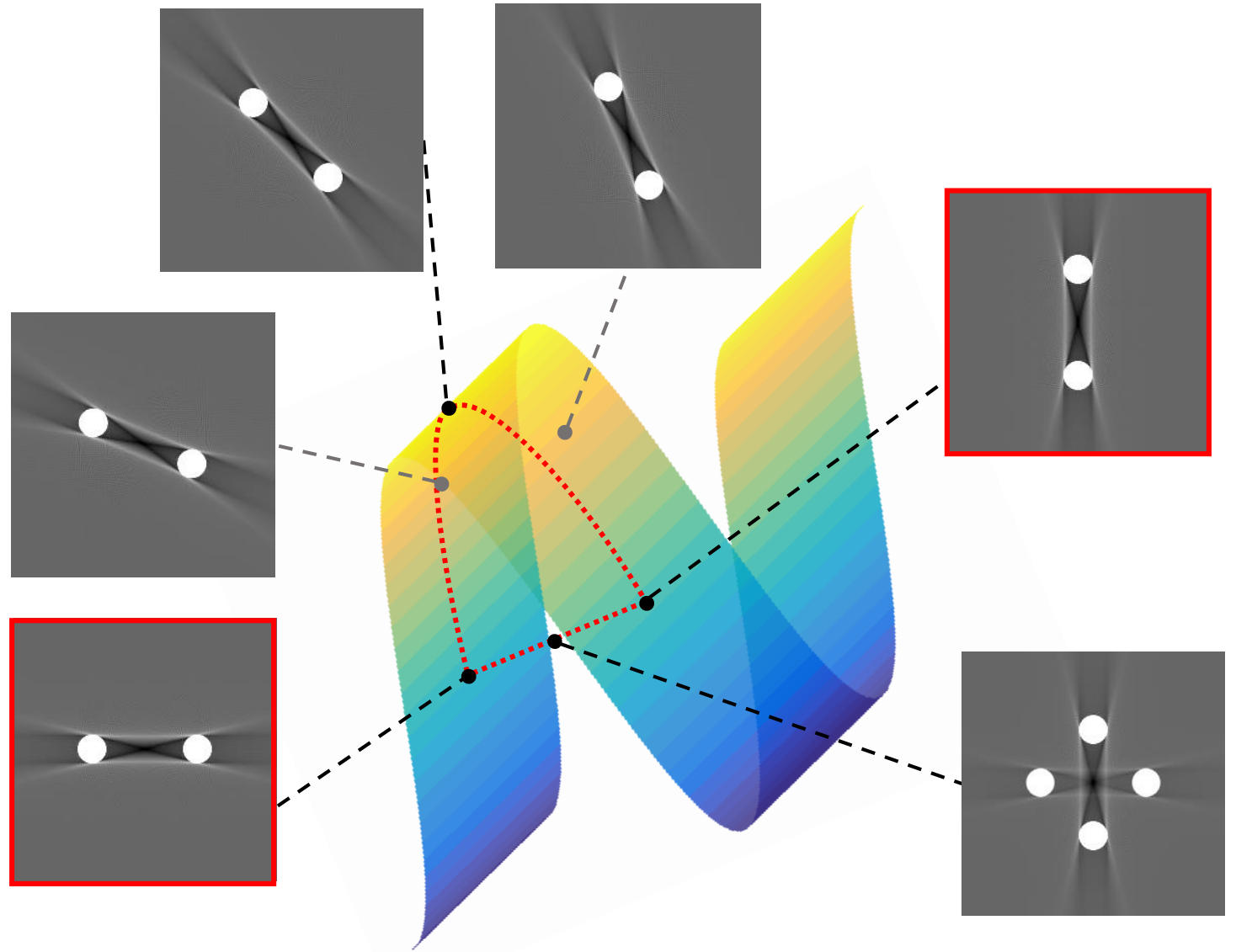
# 딥러닝 방식 TEST

일반적인 Deep learning 방식이 성공하려면 (양질의) 엄청난 training data 필요. 결국 10년 이내에는 성공하기 어려울 듯.

이미지 특징과 초음파 진행 방향 반영한 딥러닝 방식은 (상대적으로) 적은 training data로 성공할 듯.



# Manifold Learning & GANs

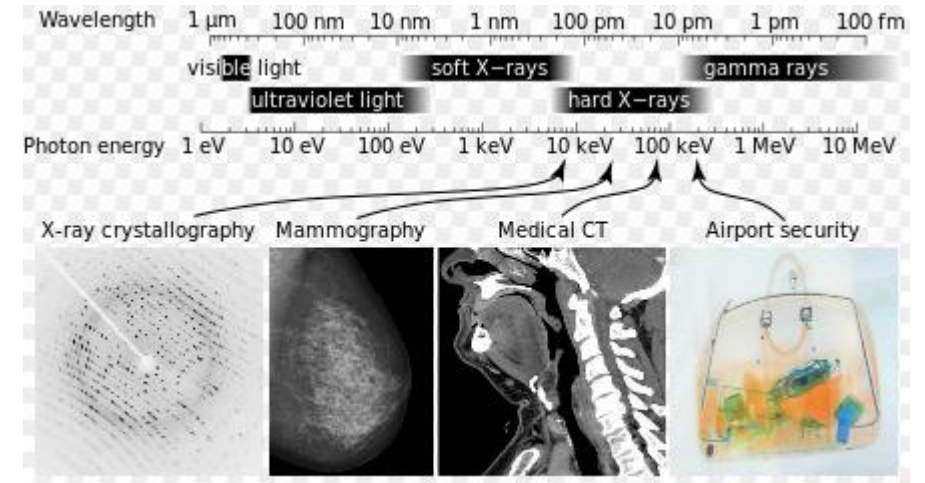
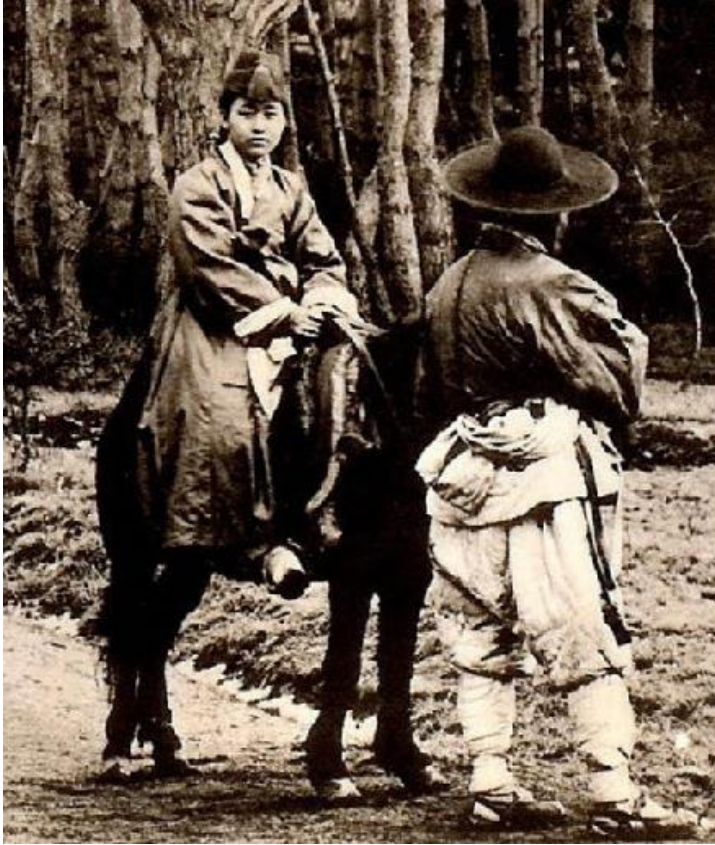


박형석(NIMS), 김성민, 김화평(연세대)



# Simple & Direct Expression

without computational process

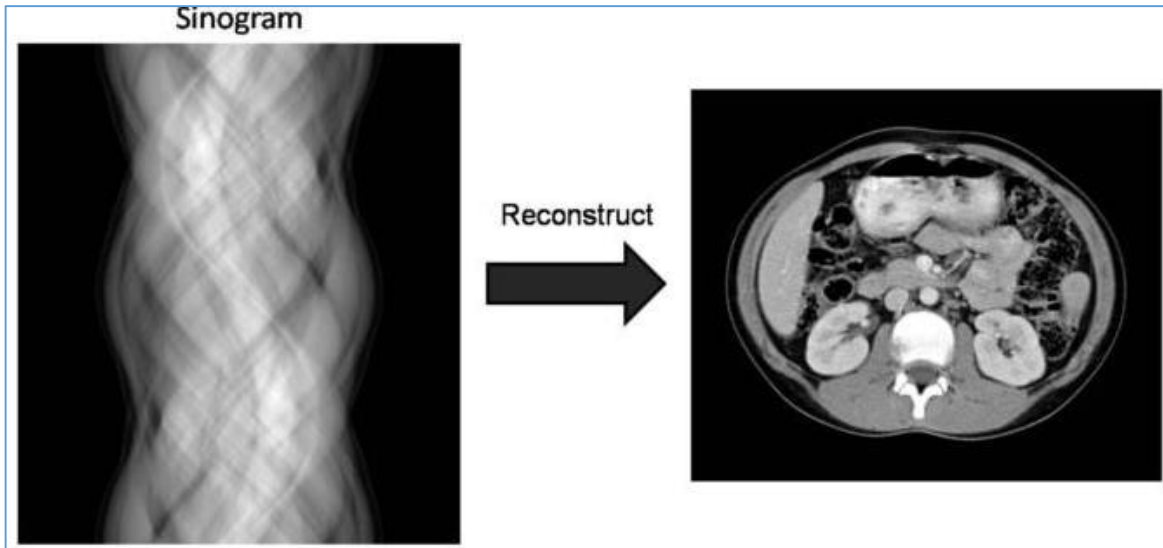


- Electromagnetic energy in each photon of light causes a chemical change to the photographic detectors that are coated on the film.

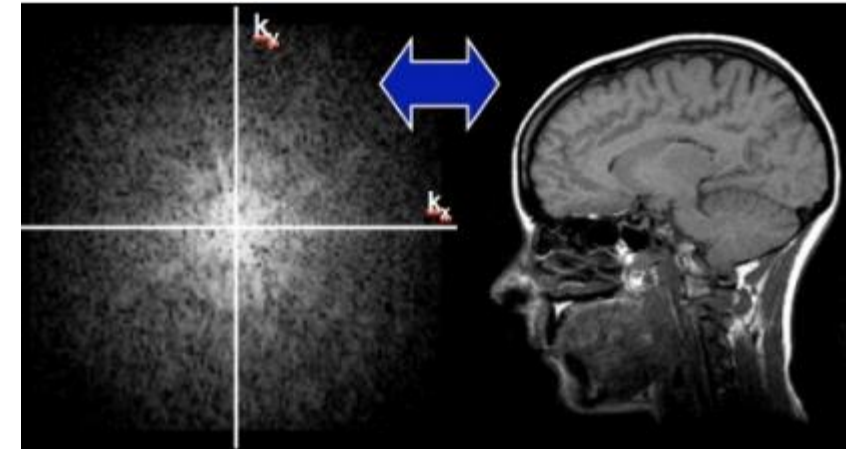
- X-rays(a form of electromagnetic radiation below 0.2 nm wavelength) are used to visualize the inside of objects.

# Direct Tomographic Expression with computational process

CT



MRI



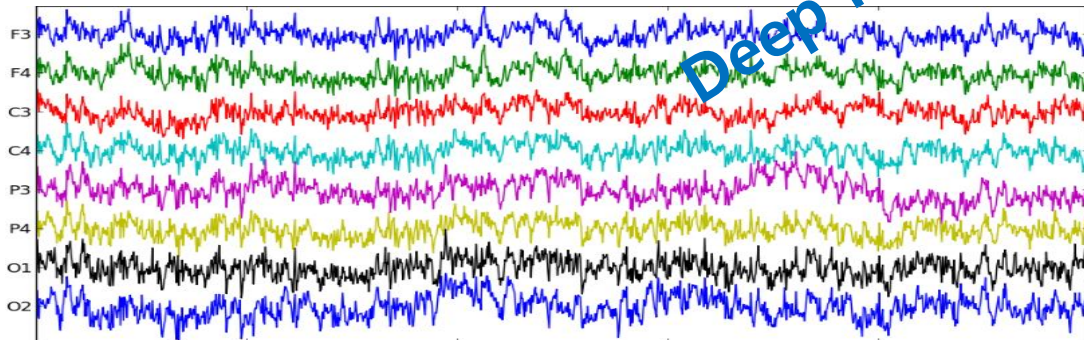
- Image reconstruction is based on **linear relationship** between measured data and image to be reconstructed.



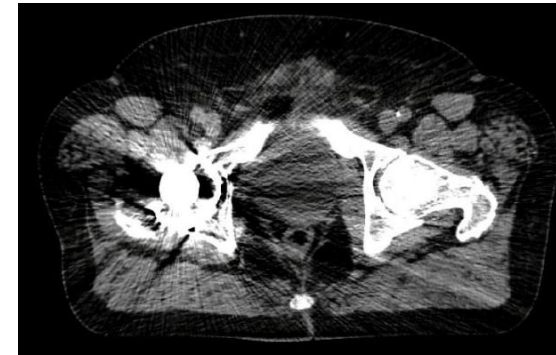
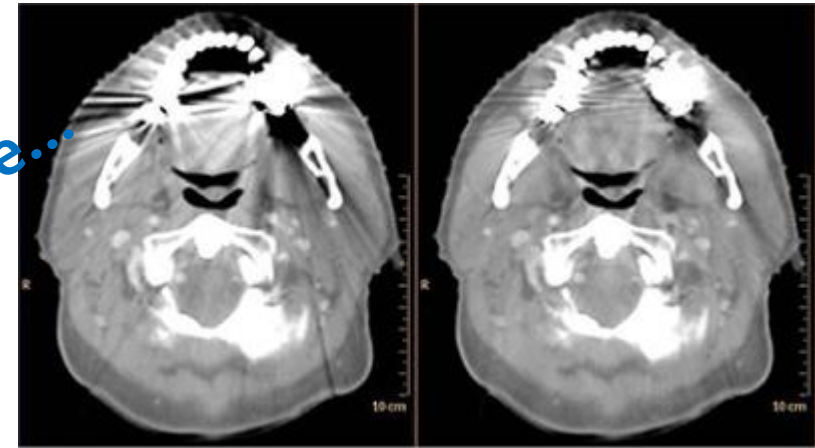
# Nonlinear ill-posed inverse problem

It is difficult to find robust solution. Existing methods rely on

- iterative methods to deal with nonlinearity
- Regularization methods to deal with ill-posedness.



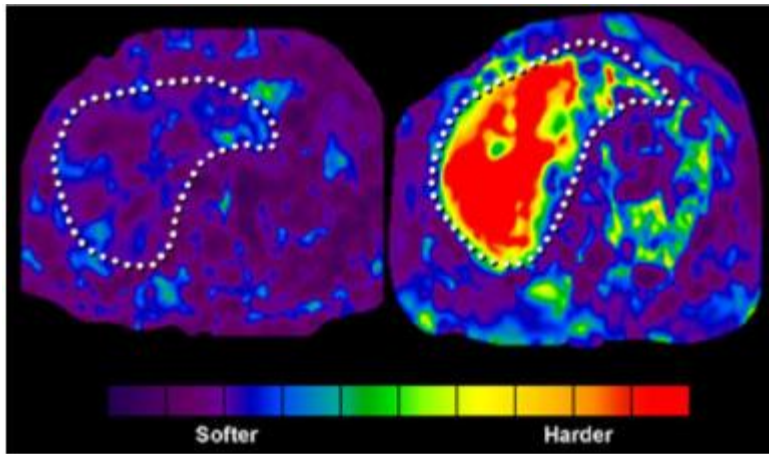
**EEG**



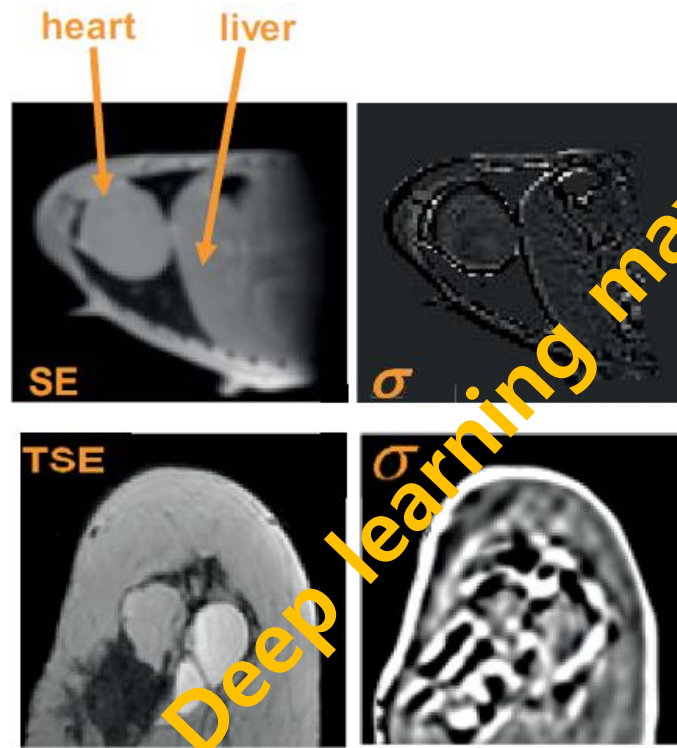
**CT Metal artifact reduction**

Deep learning may handle...

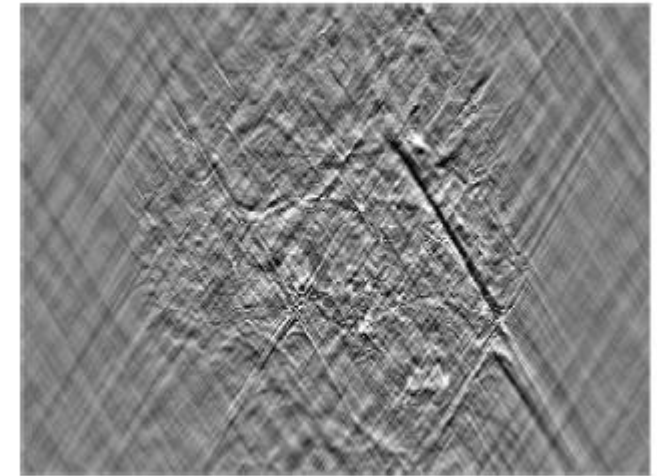
Various medical imaging modalities are suffered from their **nonlinear & ill-posed structure with mathematical modelling uncertainties.**



Elastography



Electrical Property Imaging



Quantitative Susceptibility Mapping (QSM)

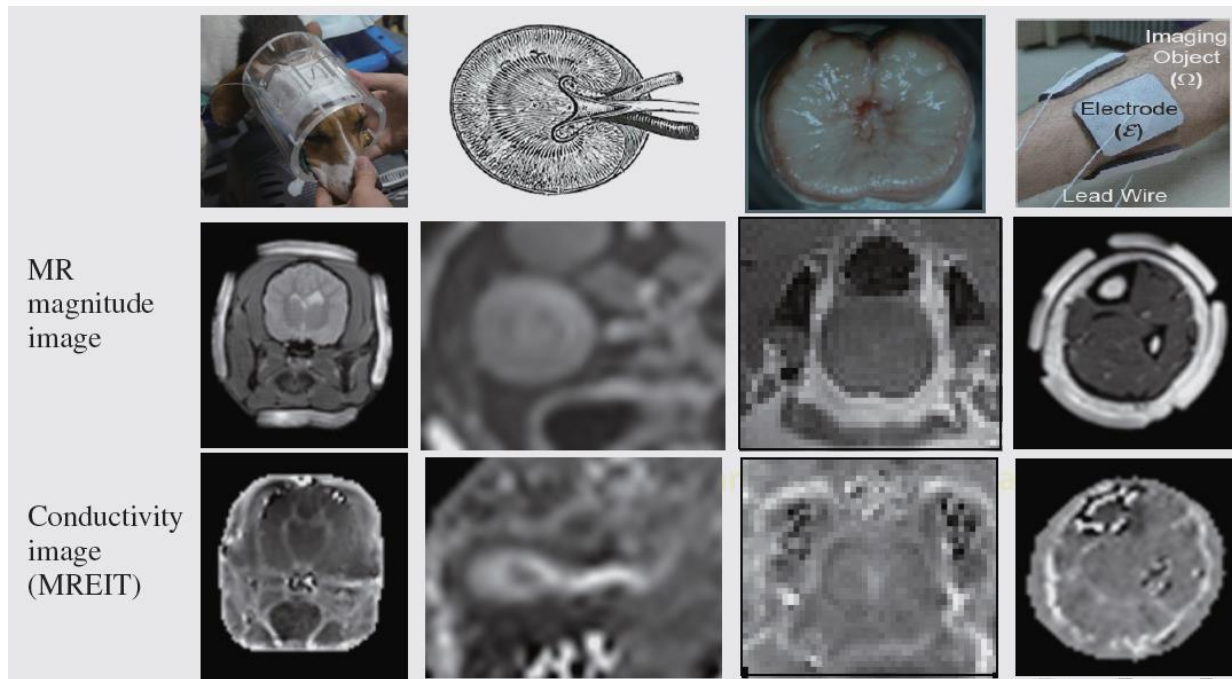
These models ignore nonlinear terms (e.g. the change in direction of wave propagation due to a change in its transmission medium)

Reconstruction model is wave-like, but image to be reconstructed is NOT.

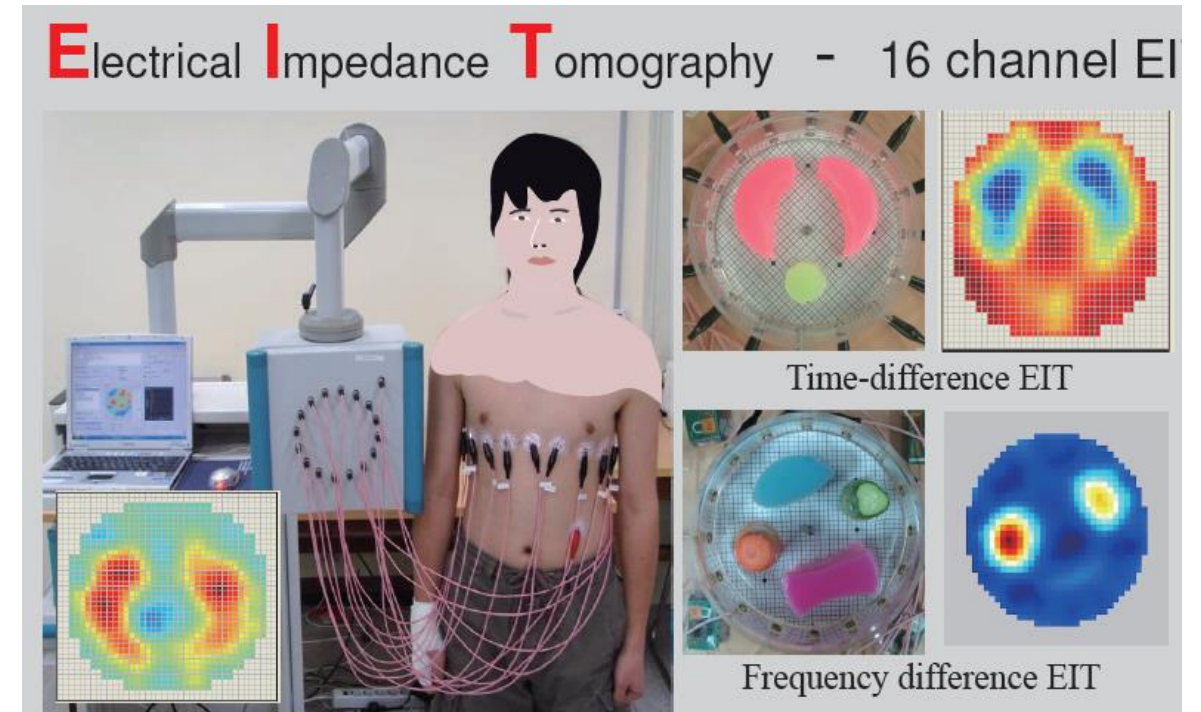


To solve nonlinear inverse problem, we use linearized approach, which provide only **image contrast imaging** instead of absolute imaging.

Deep learning may provide ...



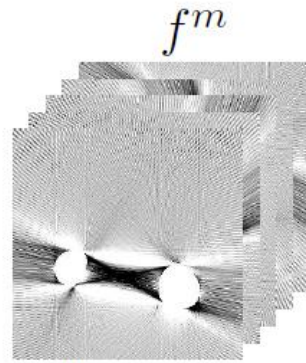
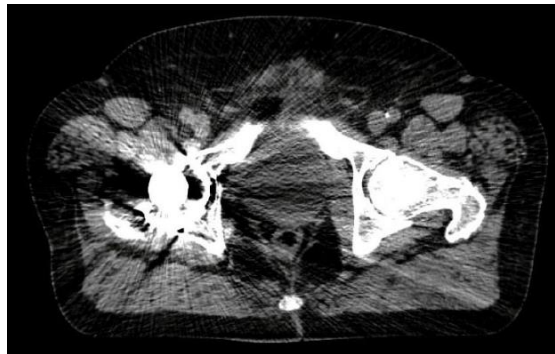
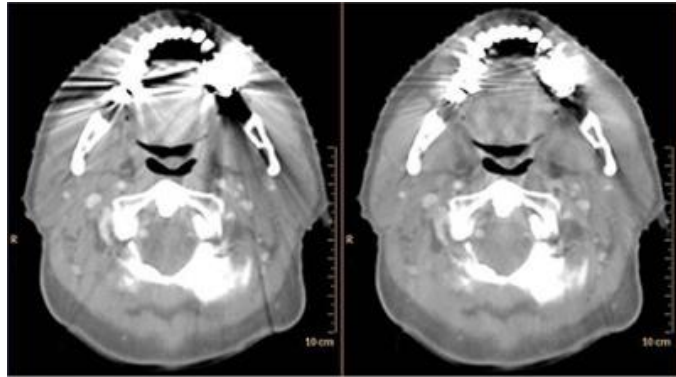
MREIT images



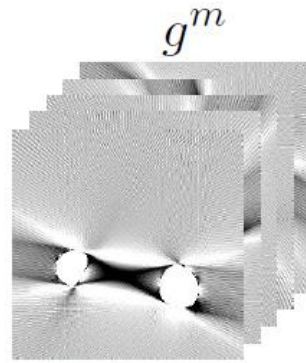
EIT imaging

# 인공지능을 이용한 CT Metal artifact reduction

박형석(NIMS),  
김성민, 김화평(연세대)

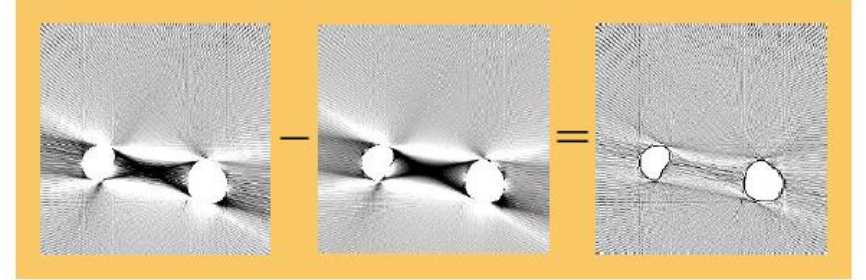


CT images



formula based artifact

The difference between  $f^m$  and  $g^m$



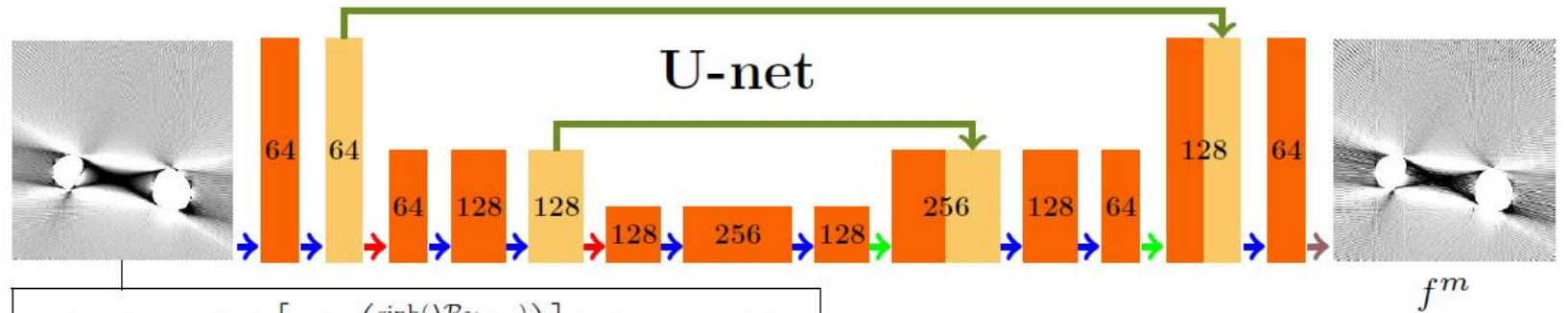
→ Conv  $3 \times 3$ , ReLU

→ Max pooling  $2 \times 2$

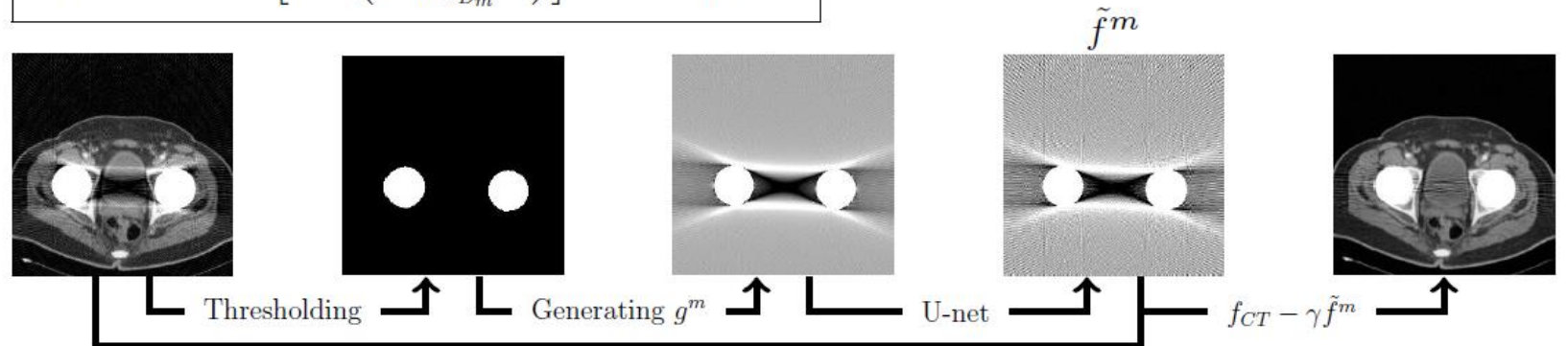
→ Avg unpooling  $2 \times 2$

→ Copy and Concat

→ Conv  $1 \times 1$



$$g^m(x) = -\mathcal{R}^{-1} \left[ -\ln \left( \frac{\sinh(\lambda \mathcal{R} \chi_{D_m})}{\lambda \mathcal{R} \chi_{D_m}} \right) \right] (x) + c \chi_{D_m}(x)$$





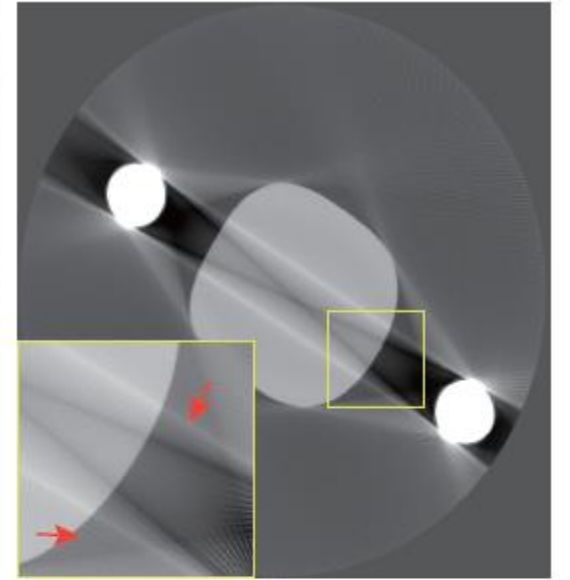
# 실험 검증

실험검증에 소홀한  
이론은

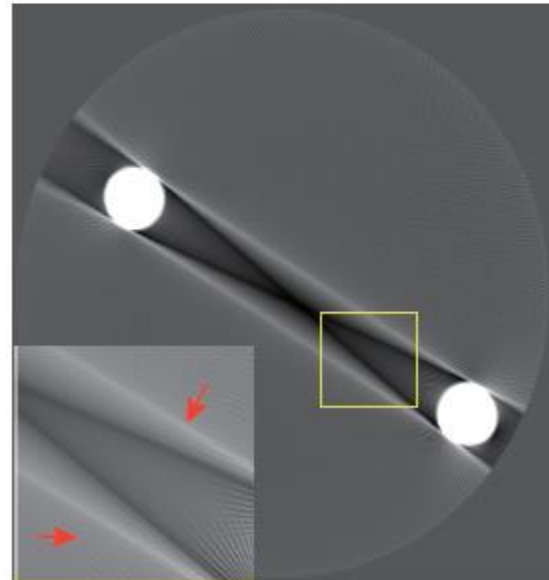
“공익에 소홀한  
자기사랑”에  
빠지기 쉽다.



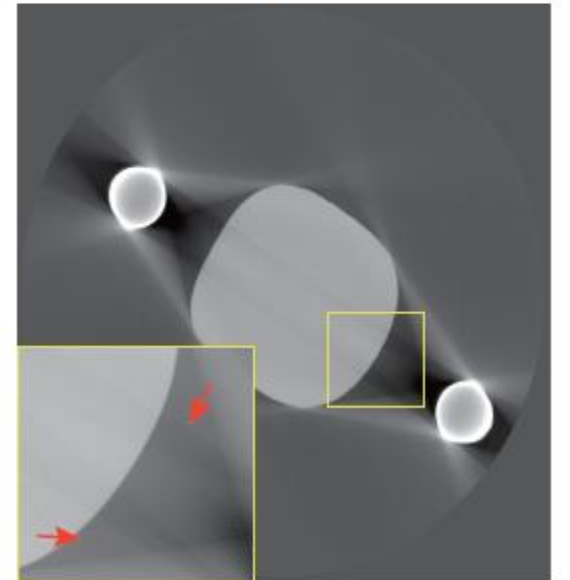
(a)



(b)

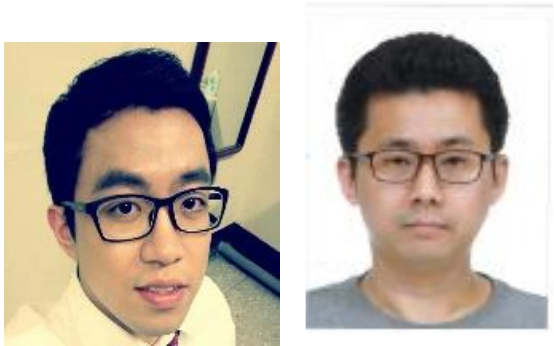


(c)



(d)

# 감사합니다.



끈기 ( 영화 “파운더”에서)

이 세상 무엇도 끈기를 대신할 수 없습니다.  
재능? 재능 있는데 성공하지 못했던 사람들로  
세상은 차고 넘칩니다.



천재성? 불운의 천재란 표현도 핑계에 불과해요.  
교육? 세상은 공부만 많이 한 멍청이로  
가득하죠.

오직 끈기와 투지만이 강력한 힘을 가집니다.

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