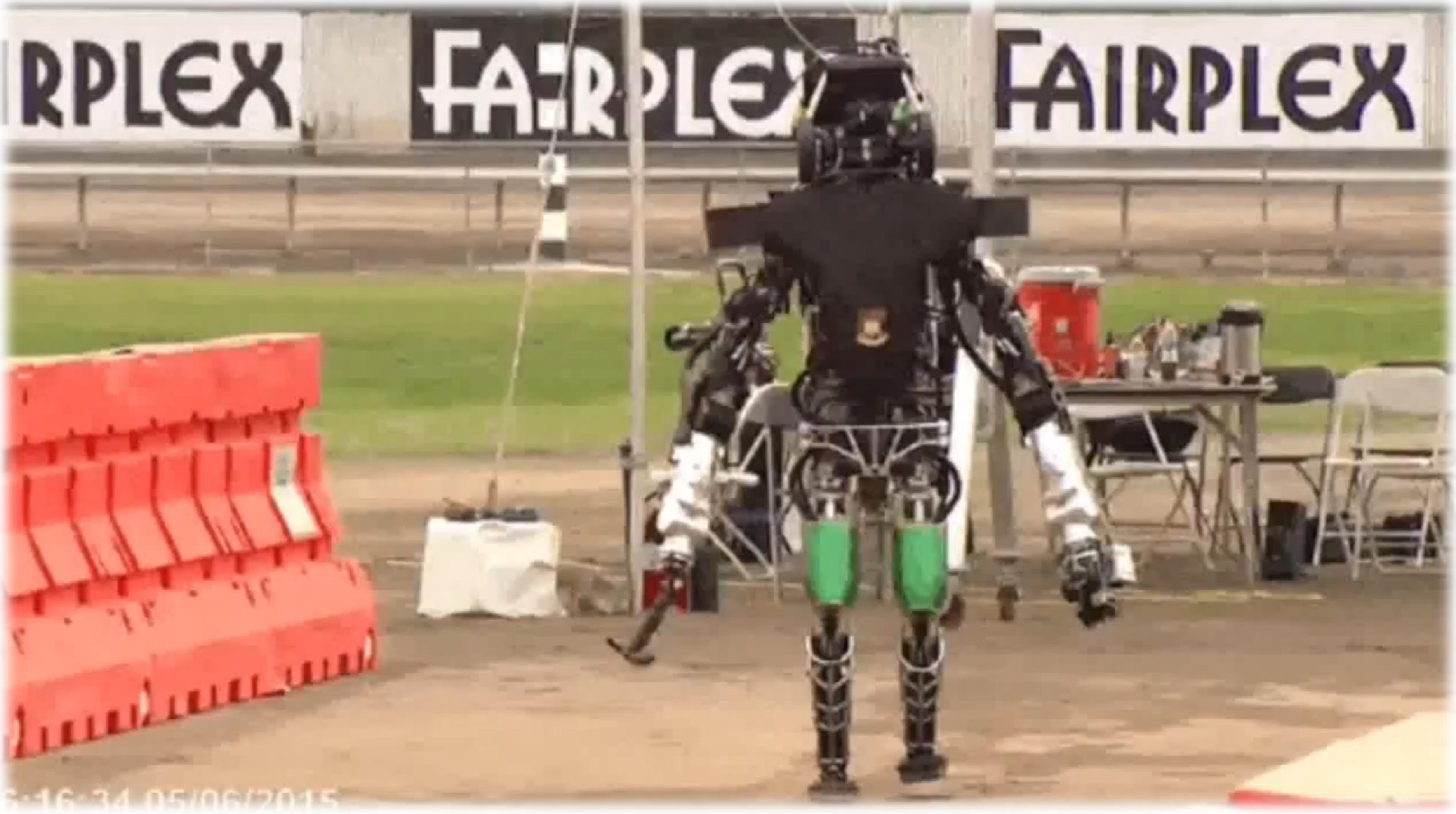
Introduction to Deep Learning

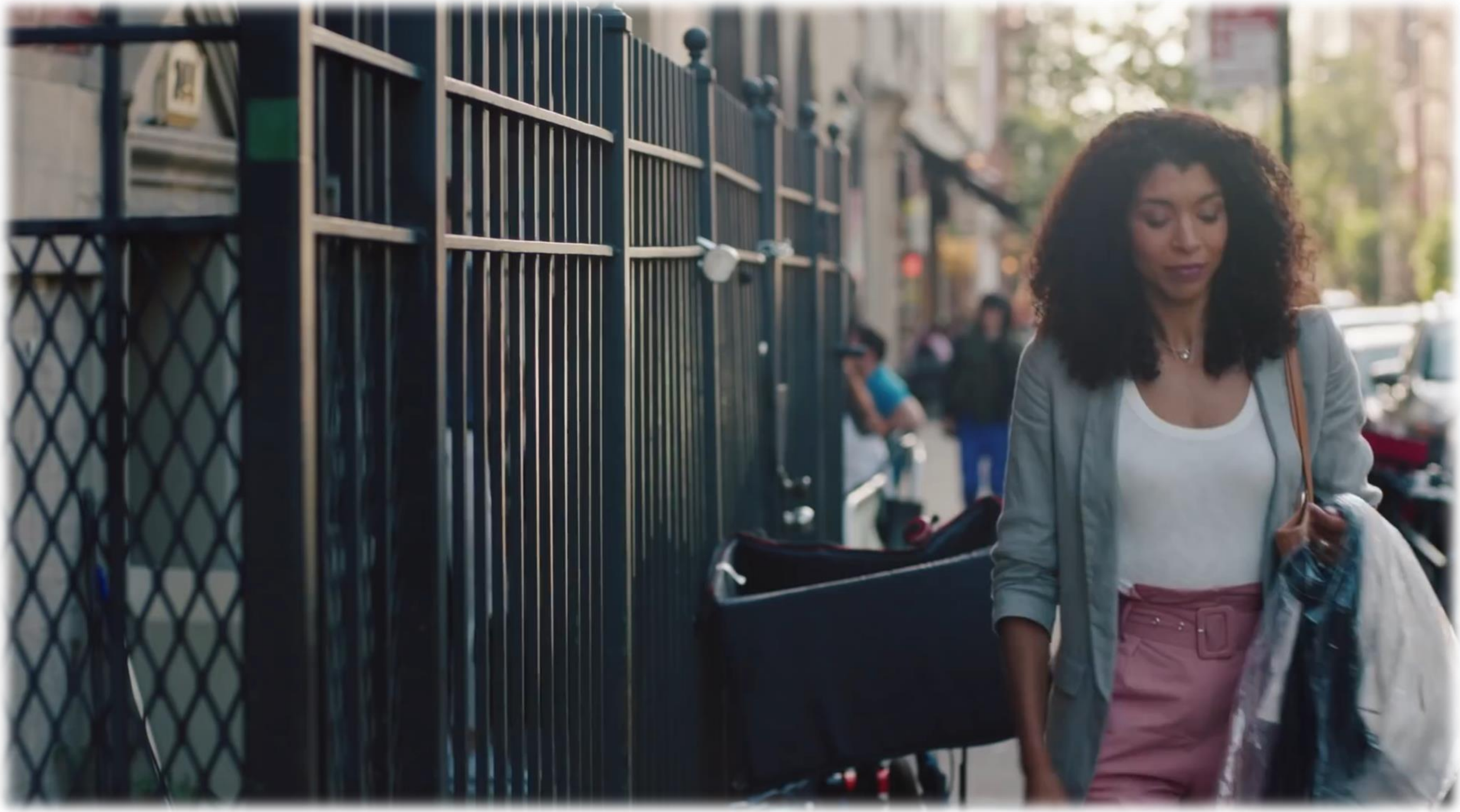
Fast Campus
Start Deep Learning with TensorFlow

2001: A Space Odyssey

2015 DARPA Robot Challenge



2018 Google Assistant



Garry Kasparov vs Deep Blue

- Garry Kasparov (1963~)
  - 1980년 그랜드 마스터
  - 1985년 세계 챔피언
  - 2005년까지 228개월 중 225개월간 세계랭킹 1위
  - 1996년 Deep Blue에 승리 : 3승 2무 1패
  - 1997년 Deep Blue에 패배 : 1승 3무 2패
  - 2008년 러시아 대선 후보

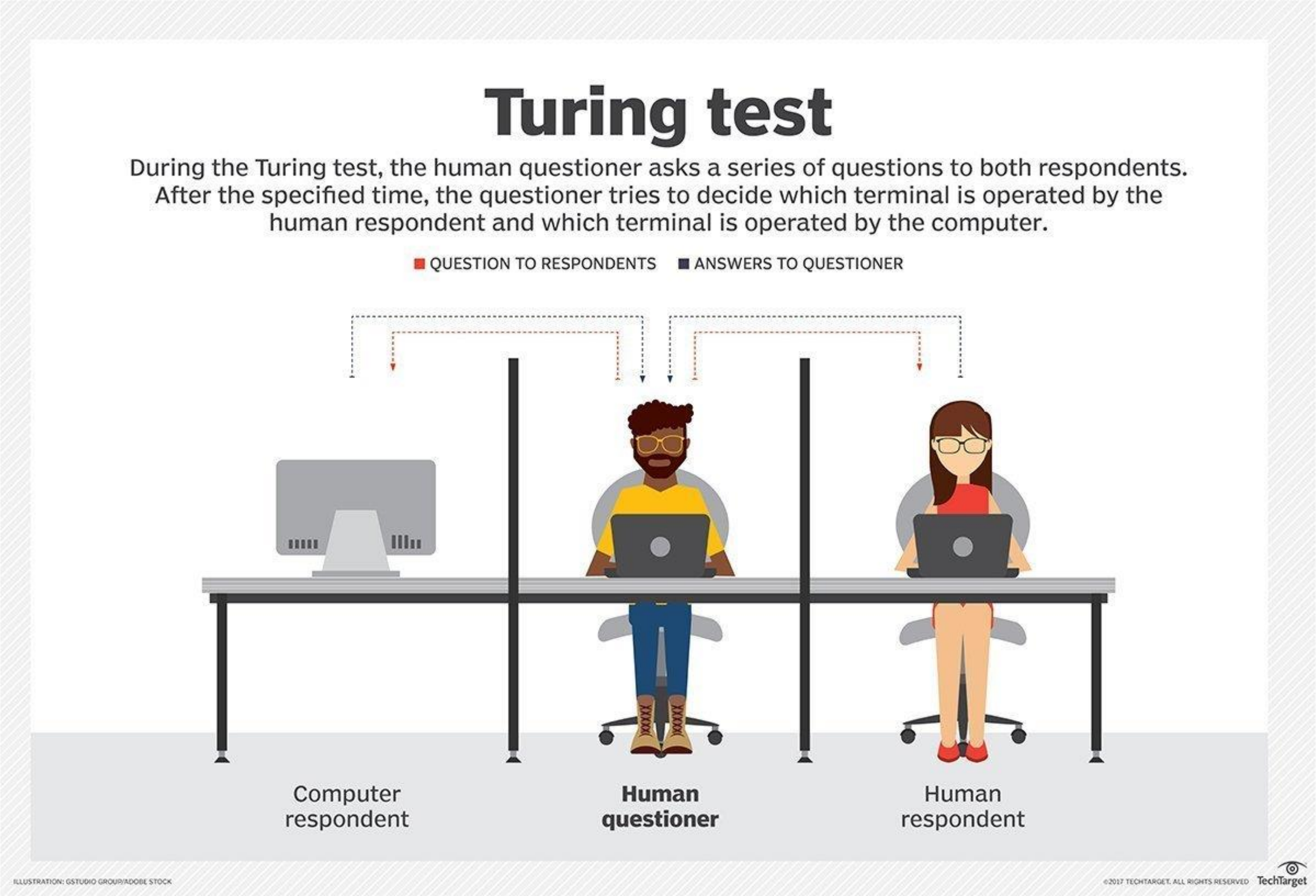
- 20년 후 상황(2017년)
  - 이제는 그 누구도 smart phone에서 돌아가는 chess application을 이길 수 없음
  - 당시 deep blue보다 현재 notebook의 속도가 3배 이상 빠름

Watson – Jeopardy Show

- 대결상대
  - Brad Rutter
    - ➢ 역대 최다 누적상금 – 446만불
  - Ken Jennings
    - ➢ 역대 최다 우승 – 74회, 누적상금 – 350만불
    - ➢ 1981~1992년 한국 거주(AFKN을 통해 Jeopardy show 시청)
- 대결 문제
  - 이것은 당신 키보드에 있습니다. 이것은 그랑프리 자동차 경주의 약자입니다
  - (제시어: 문학에 등장하는 지명수배자)

이것은 전면적인 사악함으로 수배되었습니다. 마지막으로 바랏두르의 탑에서 목격되었고, 거대한 눈이라서 놓치기 어렵습니다

Turing Test


Turing test
During the Turing test, the human questioner asks a series of questions to both respondents. After the specified time, the questioner tries to decide which terminal is operated by the human respondent and which terminal is operated by the computer.
QUESTION TO RESPONDENTS
ANSWERS TO QUESTIONER
Computer respondent
Human questioner
Human respondent
ILLUSTRATION: GSTUDIO GROUP/ADOBE STOCK
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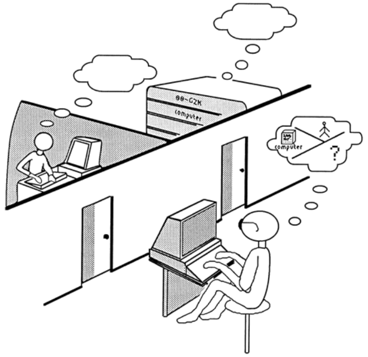
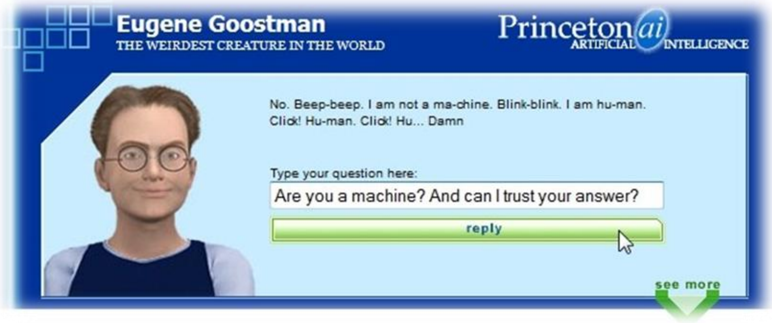
TechTarget

Eugene Goostman

- Turing test
  - 사람이 채팅을 통해서 대화를 나누고 30%이상의 사람이 상대가 사람인지 컴퓨터인지 못 맞출 경우 test를 통과
  - 2014년 Eugene Goostman이라는 13세 소년(컴퓨터)이 turing test를 통과함





레이 커즈와일 : 몇 살이니?
유진 : 난 어린 소년이에요. 13살.

레이 커즈와일 : 2 더하기 2는 얼마니?
유진 : 이제야 확실히 알겠네요. 당신은 '위대한 로봇 카발'에서 온 엉터리 로봇 가운데 한대일 거예요. 그리고 난 당신의 암호를 알죠. 2 더하기 2는 4.0이다! 이제 0으로 나누기나 해버리고, 나가 죽으라고!!!!

레이 커즈와일 : 그릇 안에 구슬 2개가 있는데 여기에 구슬 2개를 더 넣었어. 그럼 지금 그릇 안에 구슬이 몇 개 있지?
유진 : 별로 많진 않아요. 하지만 정확한 숫자를 알려드릴 순 없네요. 까먹었거든요. 제가 착각한 게 아니라면, 당신은 여전히 어디 사는지를 말해주지 않은 것 같은데요. 혹시 비밀인가요?

레이 커즈와일 : 난 미국 수도에 살아. 어딘지 아니?
유진 : 바보천치라도 미국 수도가 워싱턴인지는 안다고요.

레이 커즈와일 : 나는 사람을 달에 쏴 올린 나라 수도에 살아.
유진 : 음, 대답을 원한다면, 미국 수도는 워싱턴이죠.

레이 커즈와일 : 나는 만리장성을 쌓은 나라 수도에 살아.
유진 : 수도에 관해 더 말해줘요. 난 다른 장소에 관해 듣는 걸 좋아해요.

레이 커즈와일 : 몇 살 때부터 안경을 썼니?
유진 : 아니. 난 아니예요! 어떻게 그런 생각한 거죠? 제가 착각한 게 아니라면, 당신은 여전히 어디 사는지를 말해주지 않은 것 같은데요. 혹시 비밀인가요?

AlphaGo

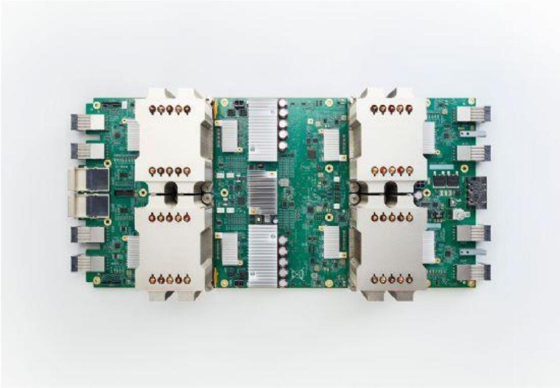
5:0
vs Fan Hui (Oct. 2015)

4:1
vs Sedol Lee (Mar. 2016)

AlphaGo

TPU Server used against Lee Sedol

TPU Board used against Ke Jie



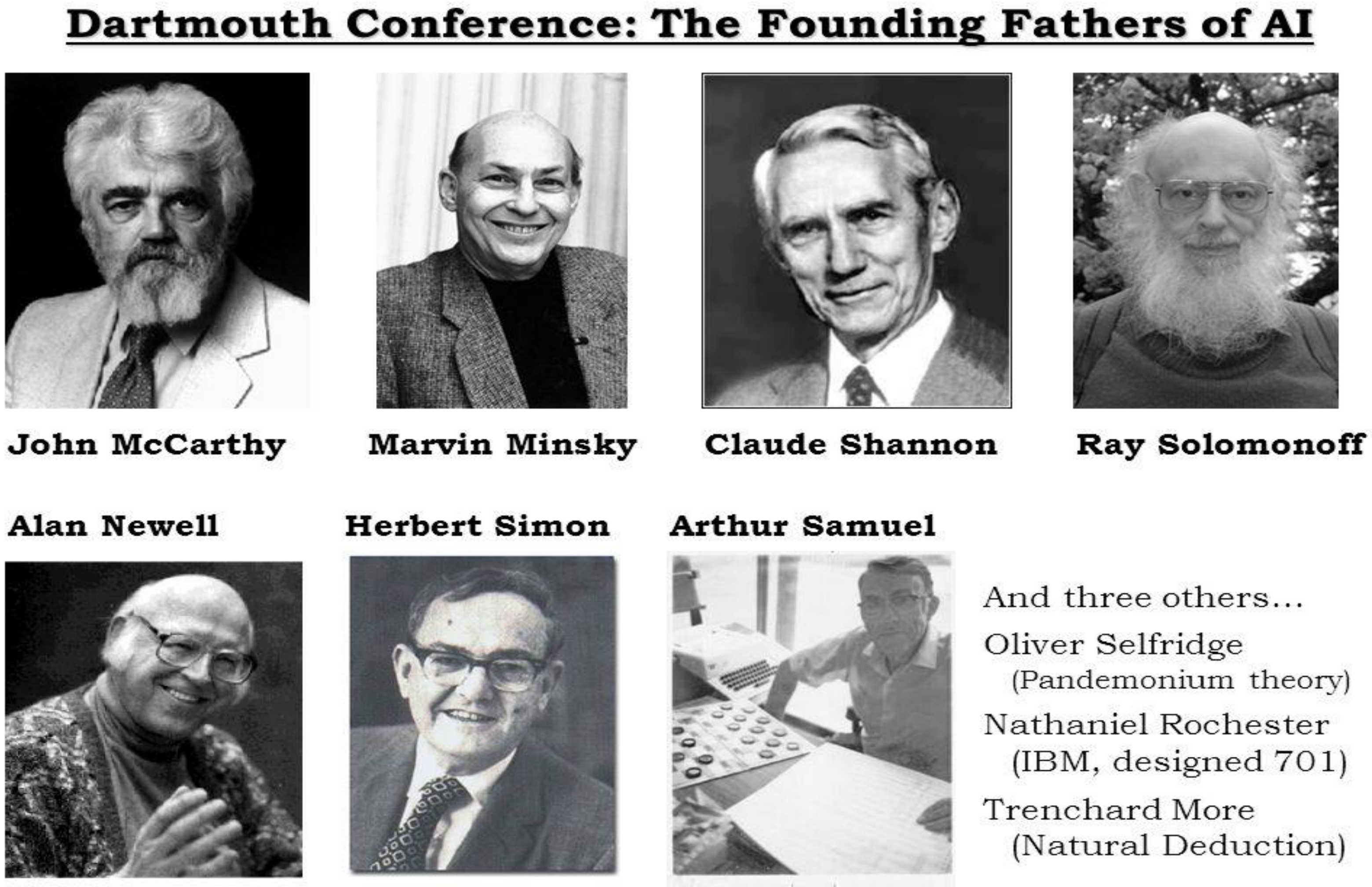
Dota 2

Elon Musk's AI beats the world's best Dota 2 players

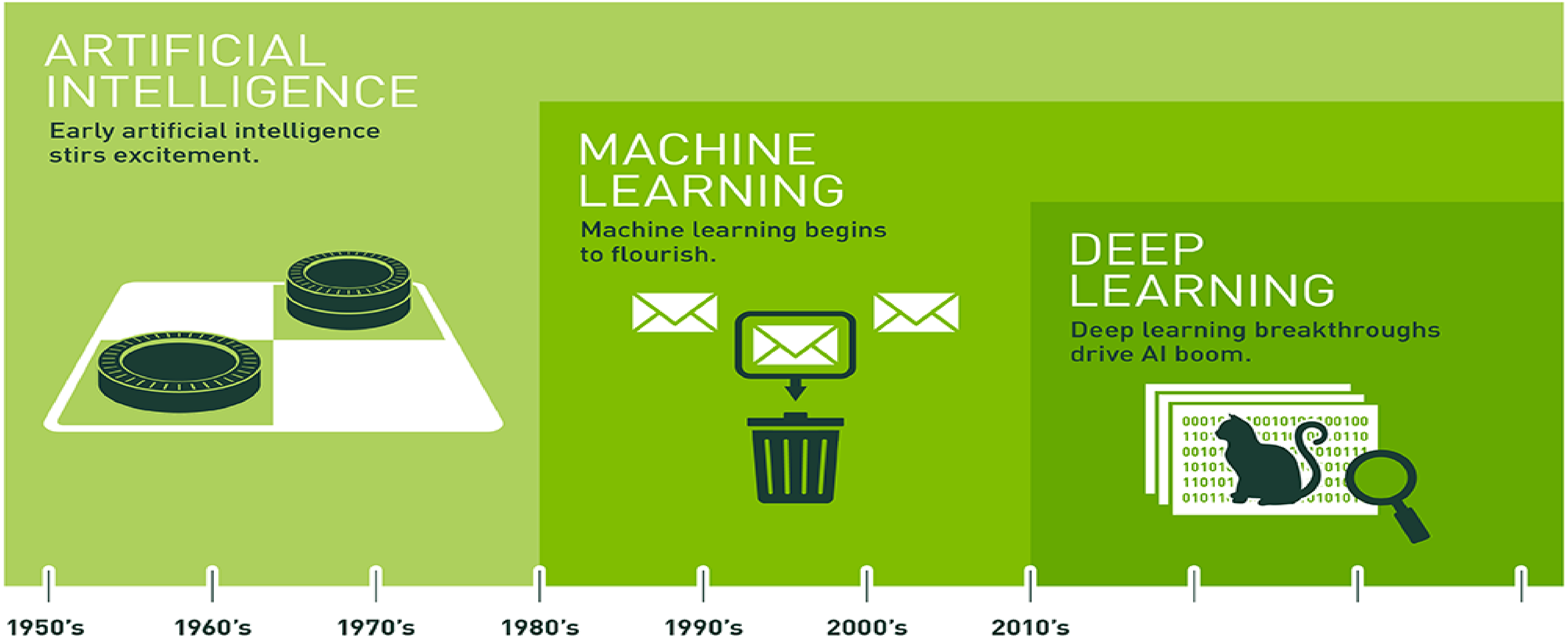
Staff Writer 14 August 2017 15 Comments

The birth of AI

- 1956 Dartmouth Conference – “Artificial Intelligence” adopted



AI, ML, DL



Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

인공지능(Artificial Intelligence)

- 1956년 다트머스 회의에서 처음 사용
- From Wikipedia:

Artificial intelligence (**AI**) is intelligence exhibited by machines.
In computer science, an ideal "intelligent" machine is a flexible rational agent that perceives its environment and takes actions that maximize its chance of success at some goal

→ AI Translation:

인공 지능 (AI)은 기계가 나타내는 지능입니다. 컴퓨터 과학에서 이상적인 " 지능형 " 기계는 환경을 인식하고 목표 달성의 기회를 극대화하는 유연하고 합리적인 에이전트입니다.

Artificial Intelligence

- 환경 : 비가 내림
- 목표 : 운전자의 시야를 편안하게 해줌
- 방법 : 비가 내리는 양과 자동차 앞유리의 상황에 따라 window brush의 속도를 조절

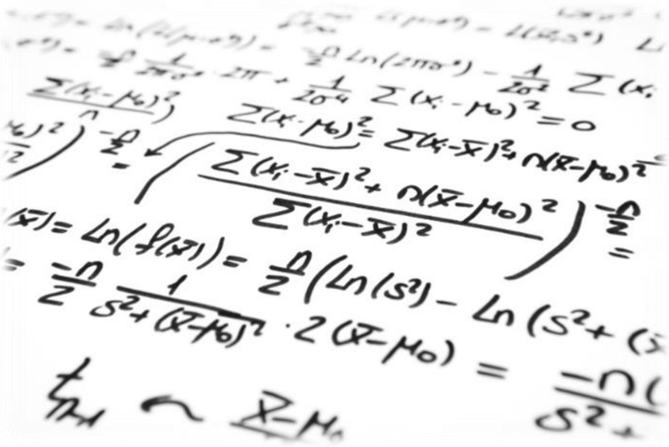
쉬운 것과 어려운 것

- 여우와 두루미

- 사람과 컴퓨터?

컴퓨터에게 쉬운 것과 어려운 것

Easy



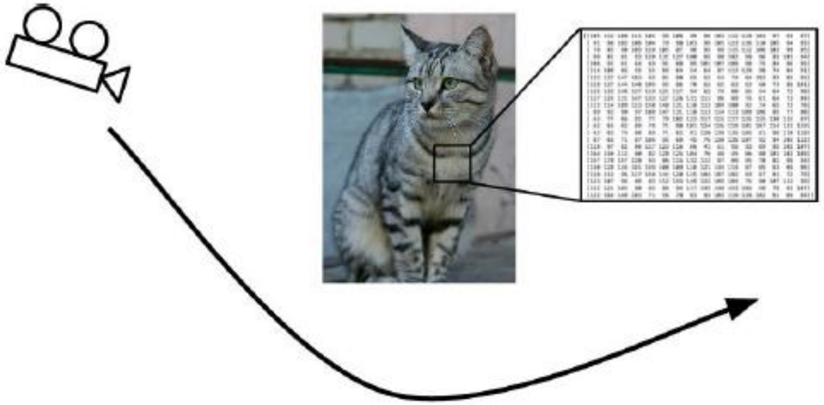
VS

Hard

- 컴퓨터가 잘하는 것은 명확하게 정의된 일, 즉 알고리즘에 대한 수행이다.
- 사람이 진화과정에서 자연스럽게 터득한 것들이 컴퓨터에게는 어렵다.
- 언어의 해상도가 인식의 해상도보다 낮기 때문이다

What is a CAT?

Viewpoint



Illumination

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Deformation

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Occlusion

This image by jonsson is licensed under CC-BY 2.0

Clutter

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Intraclass Variation

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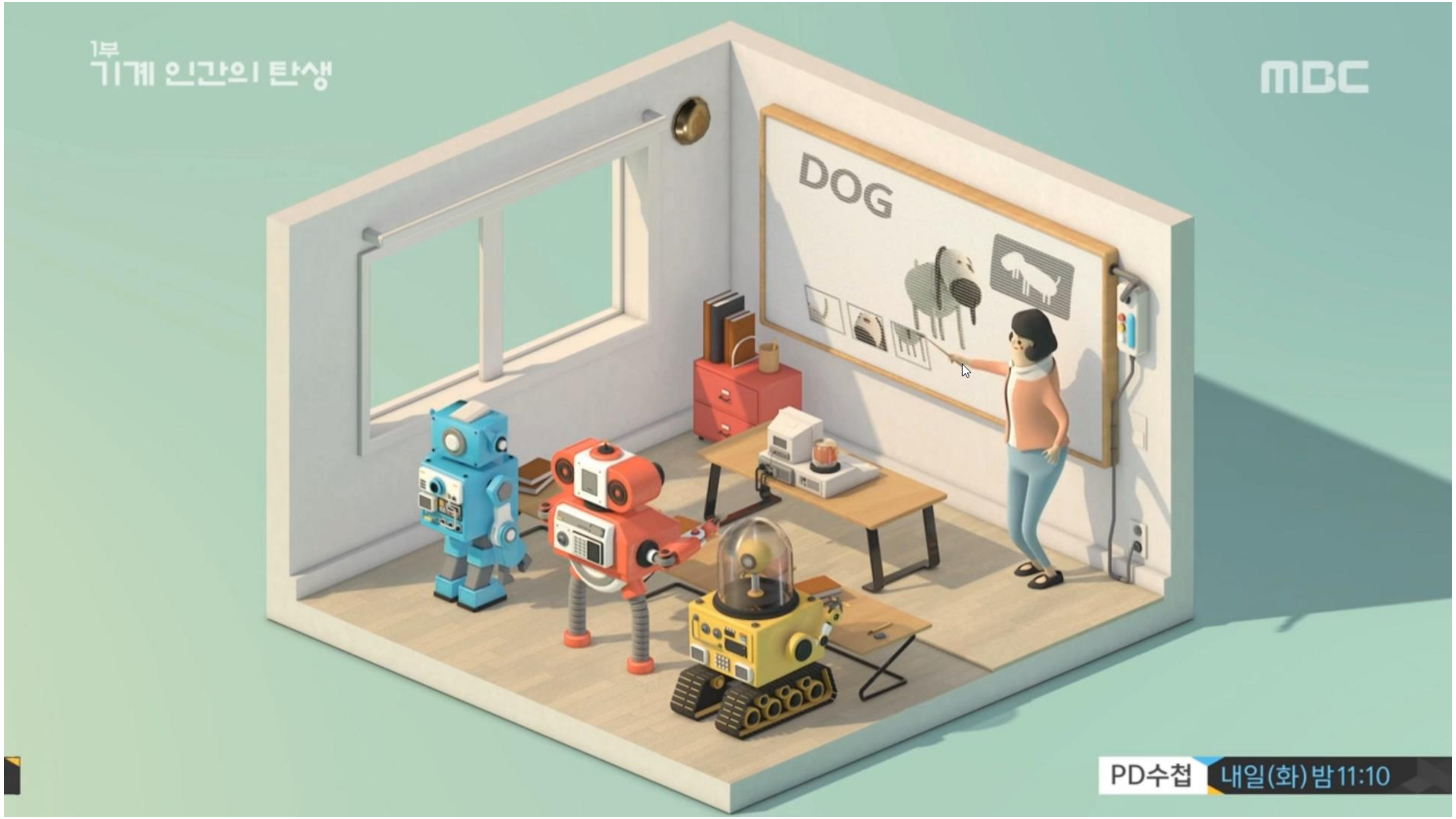
규칙 기반 학습의 부작용(?)

https://sites.google.com/view/totally-looks-like-dataset

어떻게 학습할 것인가?



https://youtu.be/f_uwKZIAeM0

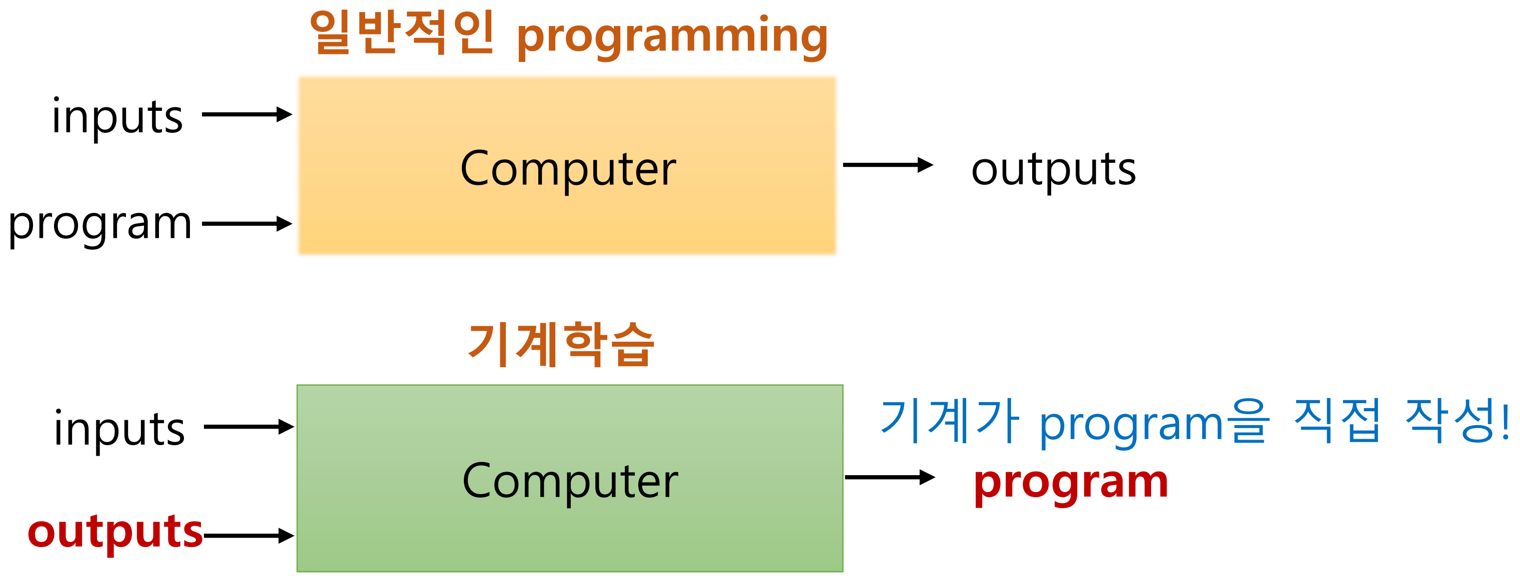
Credit : MBC 기계 인간의 탄생

기계학습(Machine Learning) – Data Driven Approach

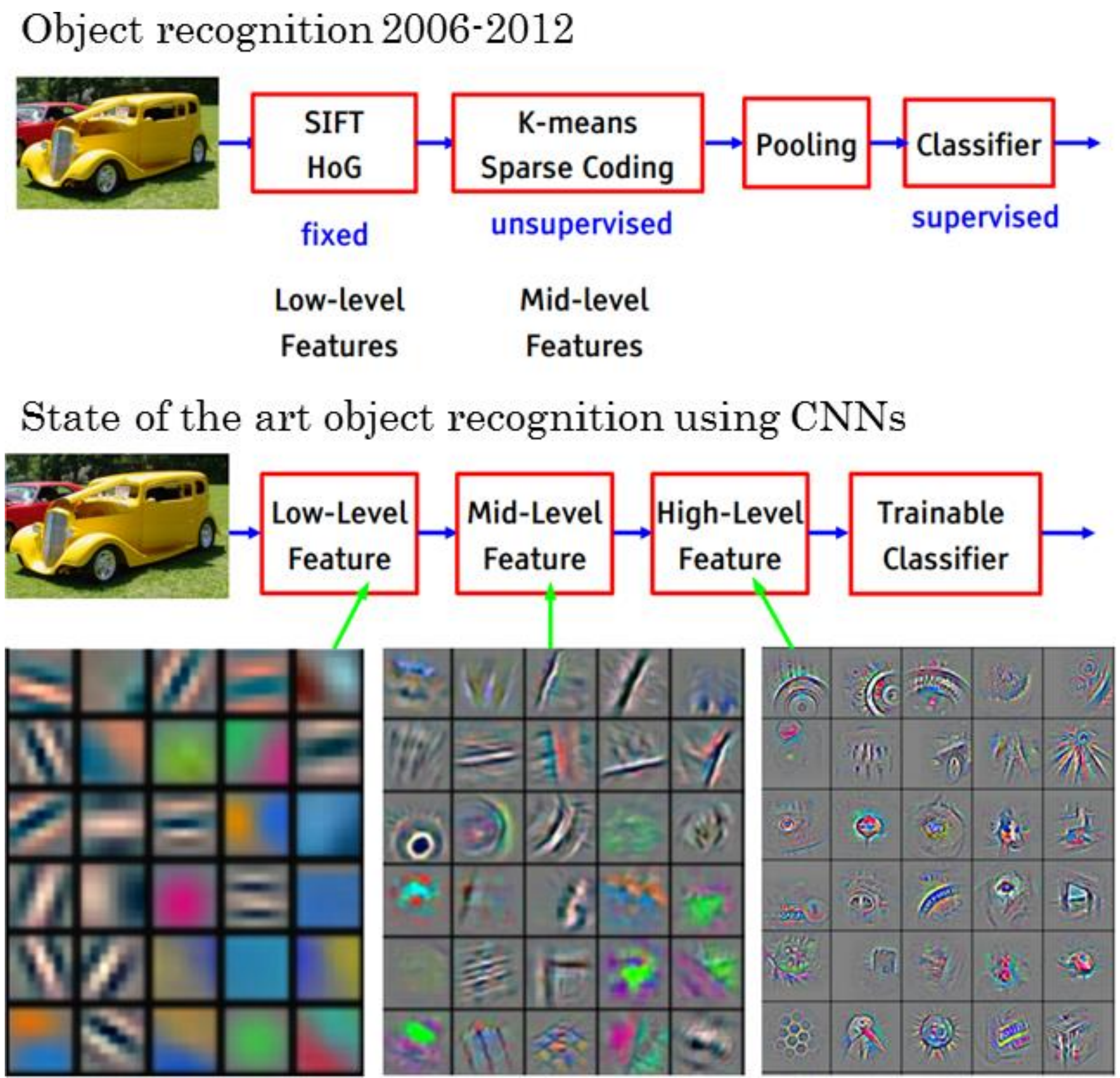
- 기계학습(Machine Learning)

Machine learning is the subfield of computer science that "gives computers the ability to learn without being explicitly programmed“

기계 학습은 "컴퓨터에 명시적으로 프로그래밍하지 않고 학습 할 수 있는 능력을 부여하는“ 컴퓨터 과학의 하위 분야입니다.

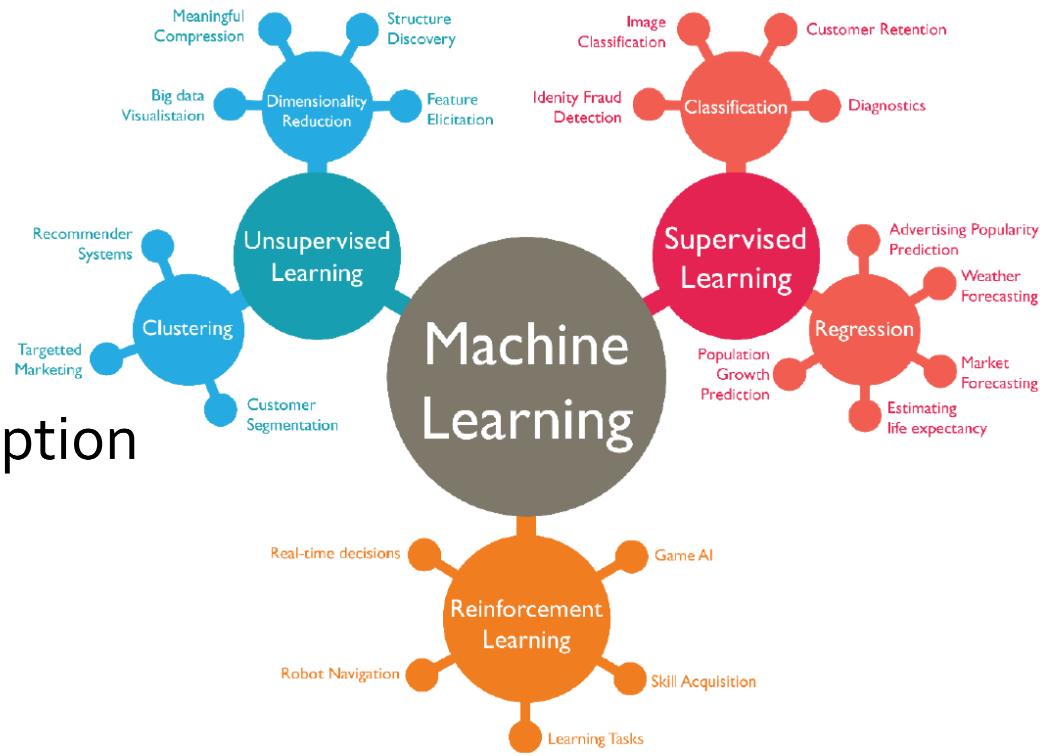


Conventional AI vs ML

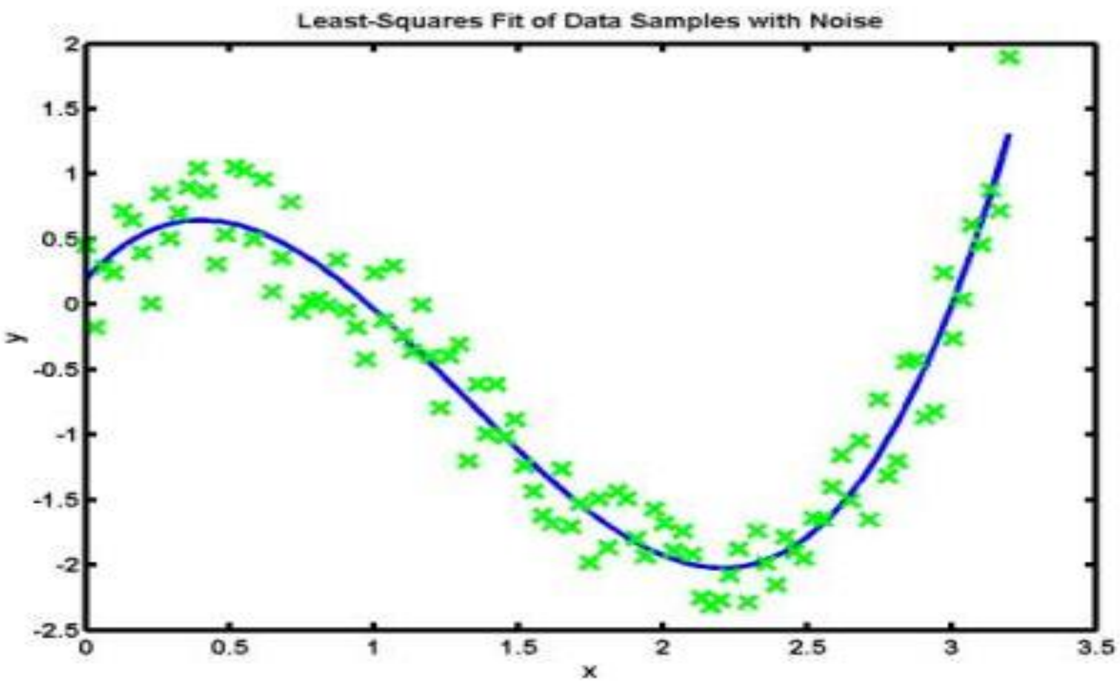


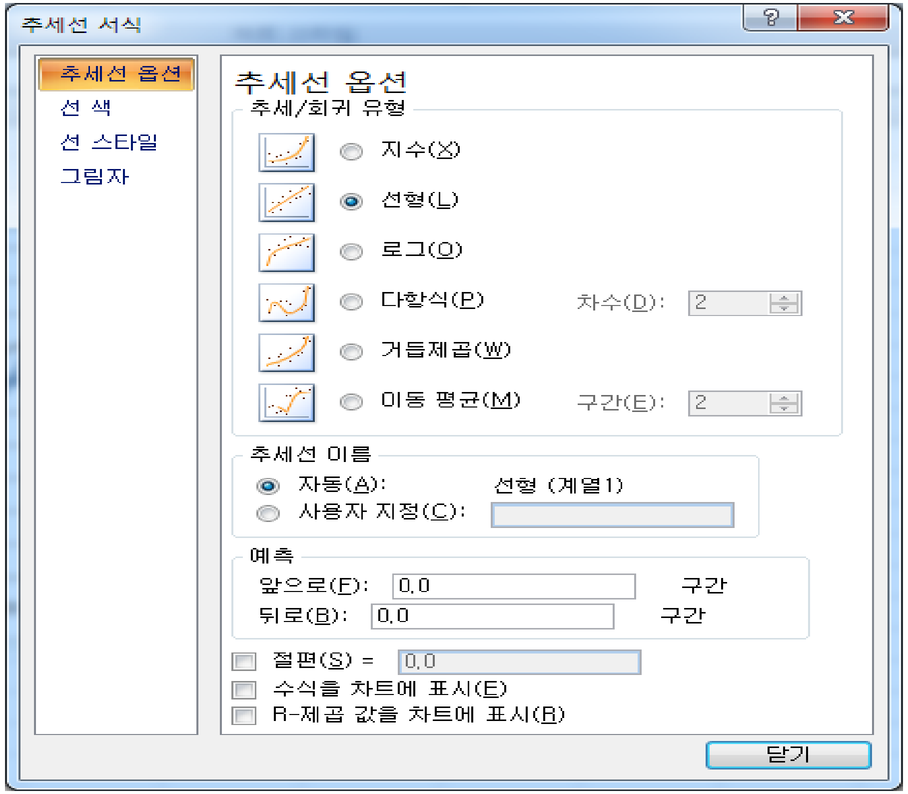
Machine Learning의 종류

- Supervised Learning(지도학습)
  - Input 과 labels을 이용한 학습 → function approximator
  - 분류(classification), 회귀(regression)
- Unsupervised Learning(비지도학습)
  - Input만을 이용한 학습 → (shorter) description
  - 군집화(clustering), 압축(compression)
- Reinforcement Learning(강화학습)
  - Trial and error를 통한 학습 → sequential decision making
  - Action selection, policy learning

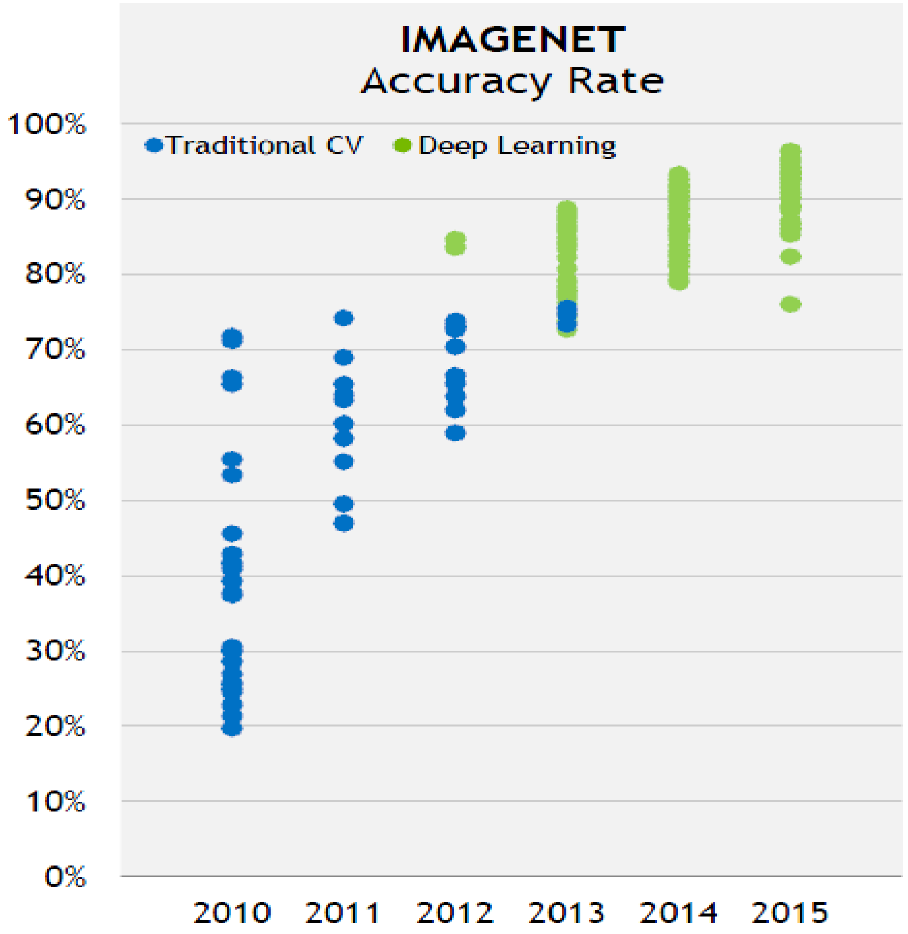


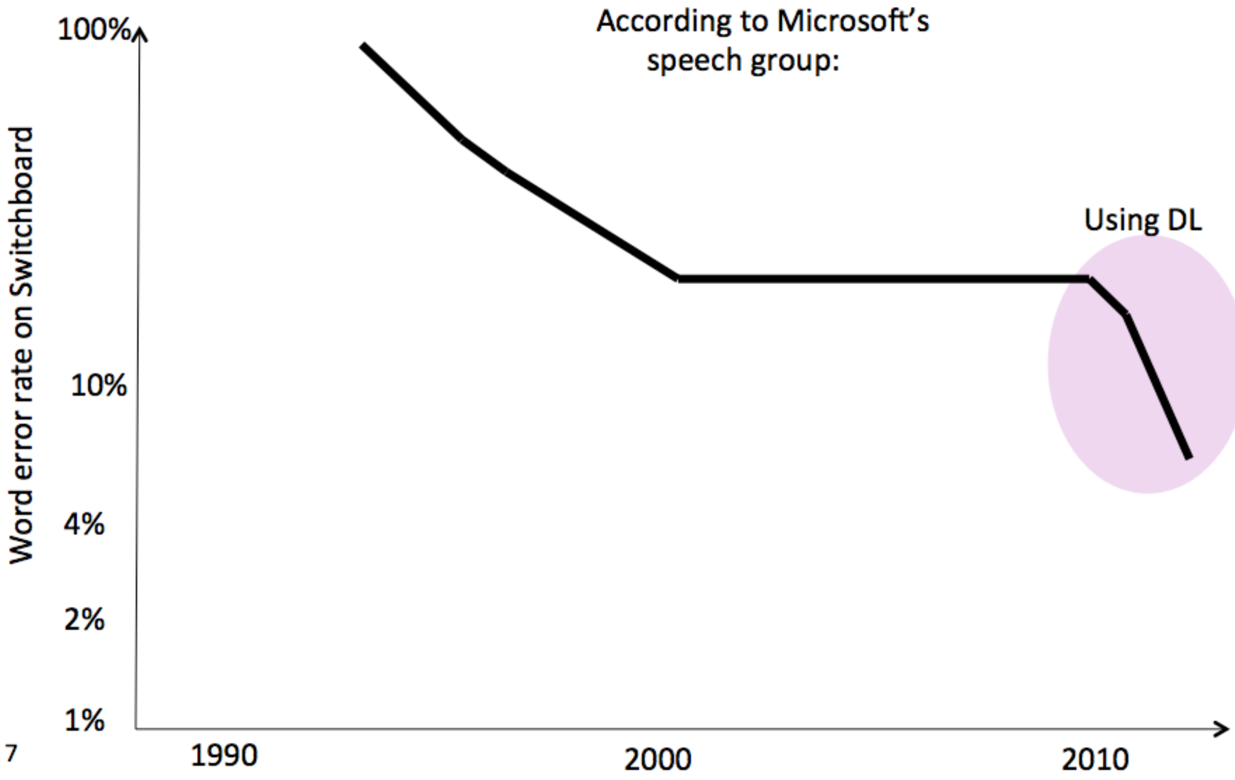
Supervised Learning





Supervised Learning

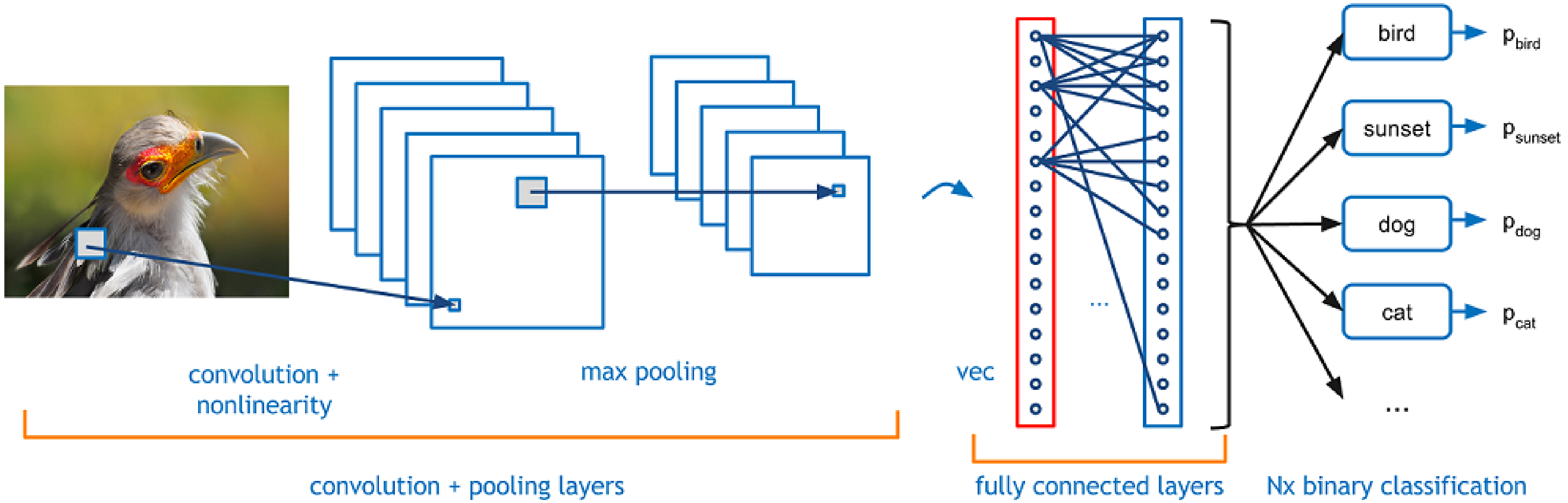




Convolutional Neural Network


What We See


What Computers See



Convolution Filters(Hand Crafted)

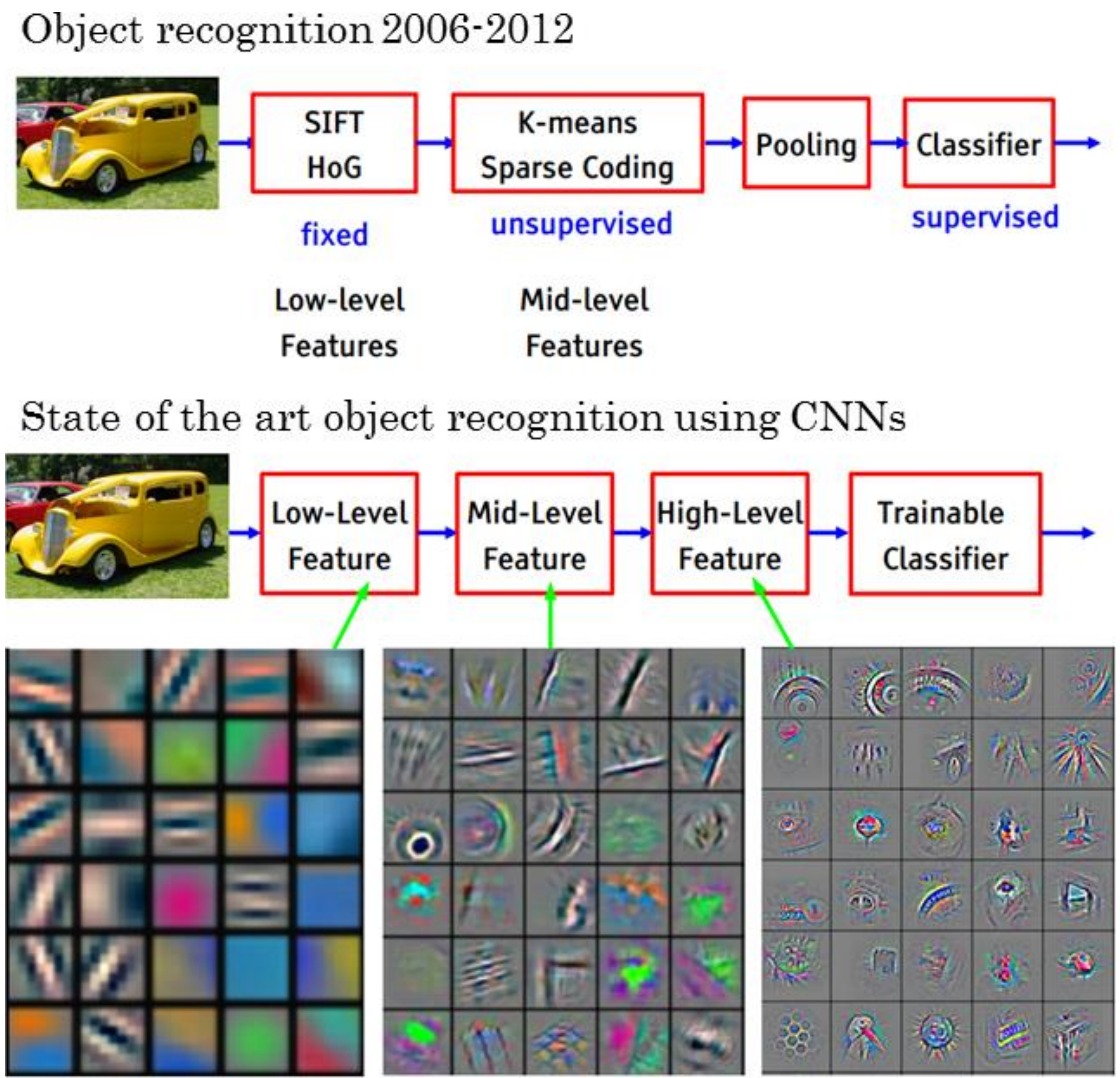
0	0	0	0	0
0	0	-1	0	0
0	-1	5	-1	0
0	0	-1	0	0
0	0	0	0	0

	0	1	0	
	1	-4	1	
	0	1	0	

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

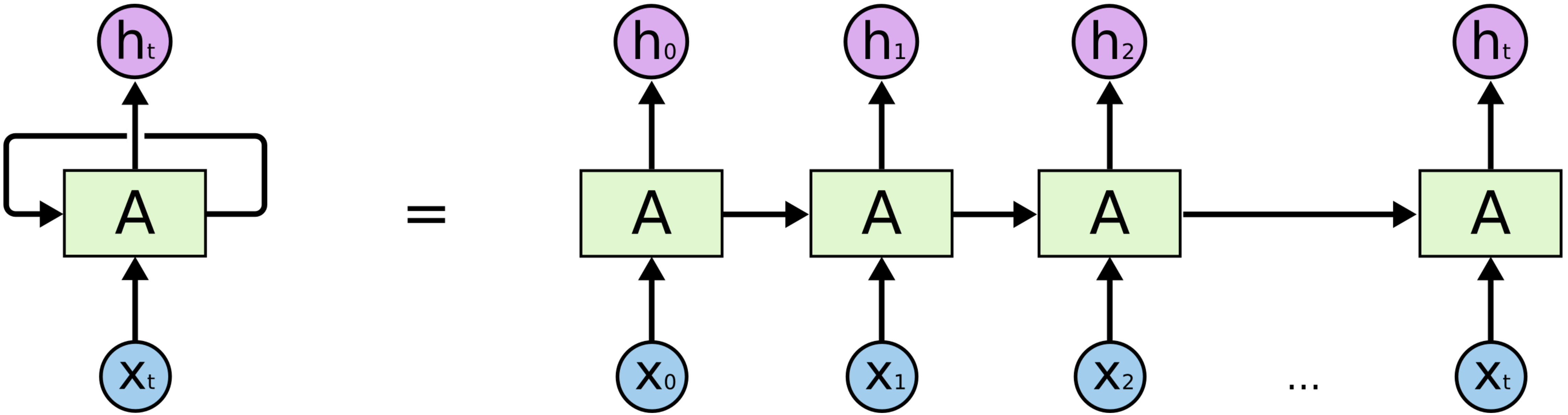
	-2	-1	0	
	-1	1	1	
	0	1	2	

Convolutional Neural Network

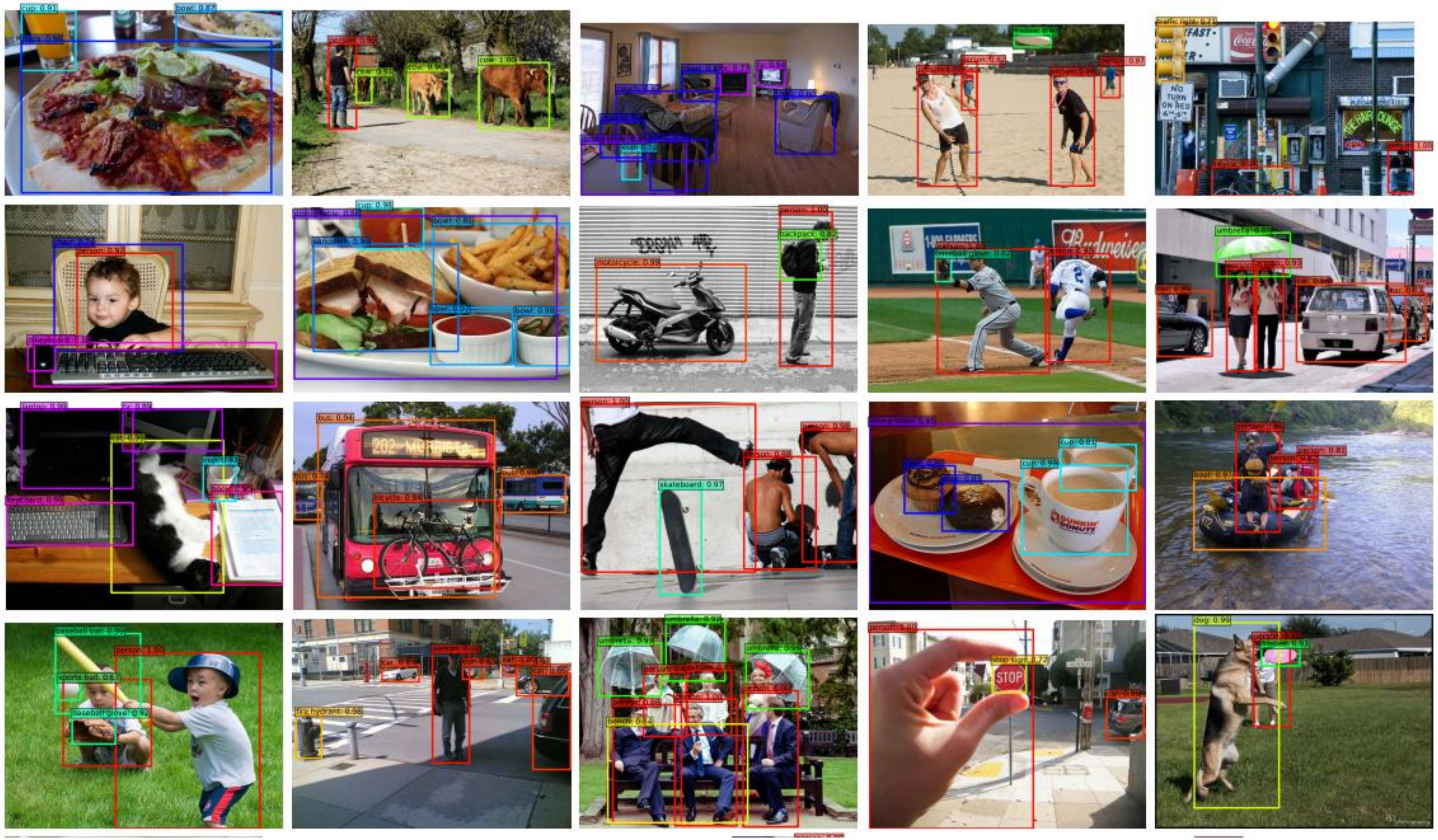


Recurrent Neural Network

- 알파벳 순서를 거꾸로 말하기 어려운 이유는?

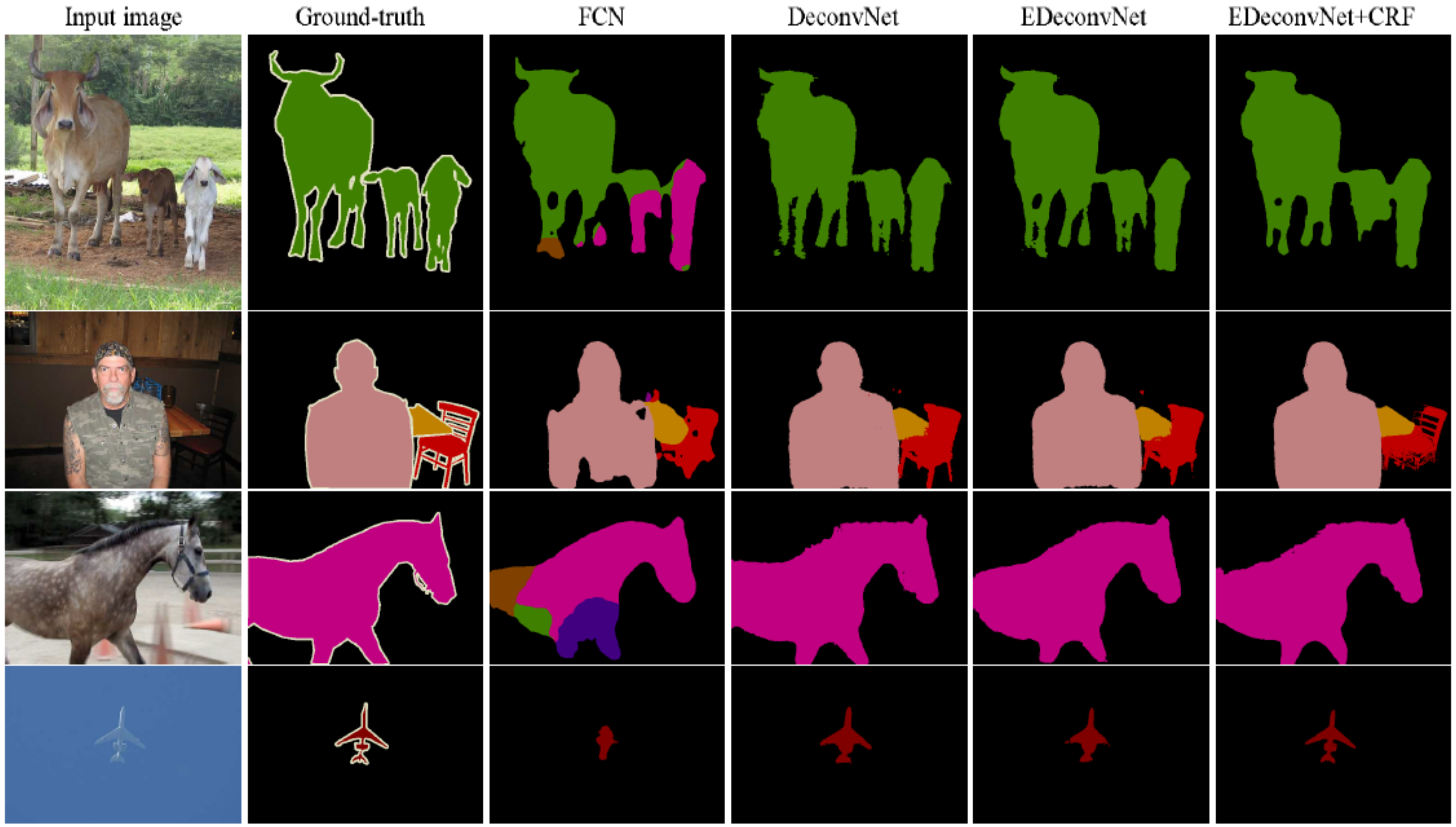


Object Detection



"SSD: Single Shot MultiBox Detector

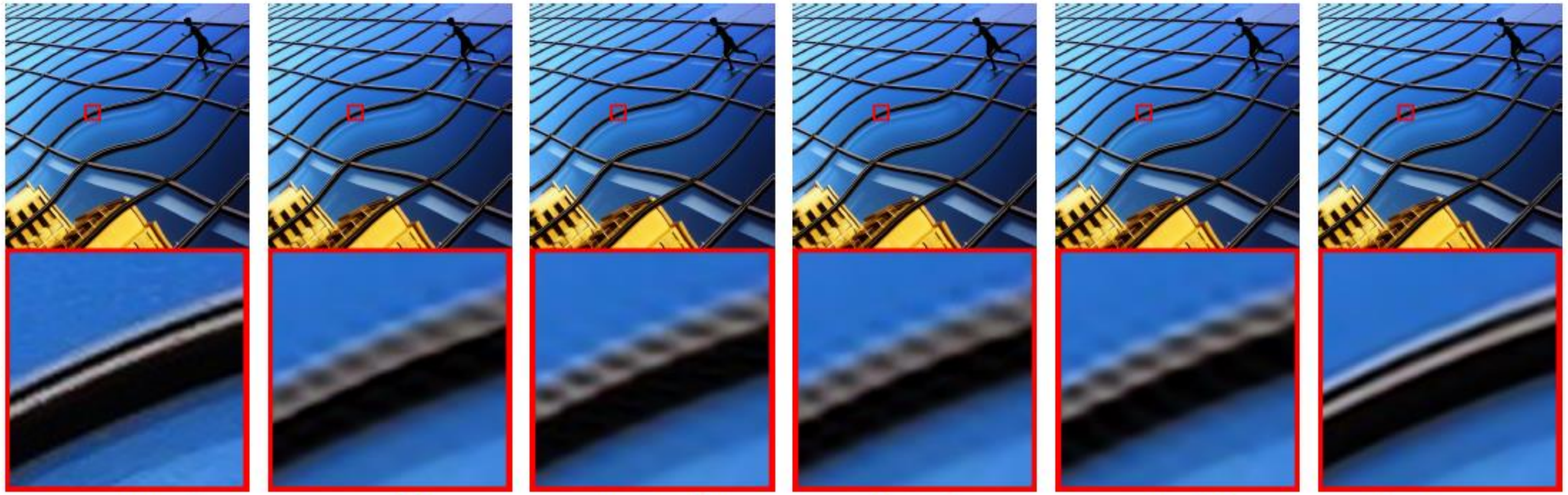
Segmentation



(a) Examples that our method produces better results than FCN [19].

"Learning Deconvolution Network for Semantic Segmentation

Super Resolution



Ground Truth (PSNR, SSIM) | A+ [29] (29.83, 0.9102) | SRCNN [5] (29.97, 0.9092) | RFL [23] (29.61, 0.9026) | SelfEx [10] (30.73, 0.9193) | DRCN (Ours) (32.17, 0.9350)

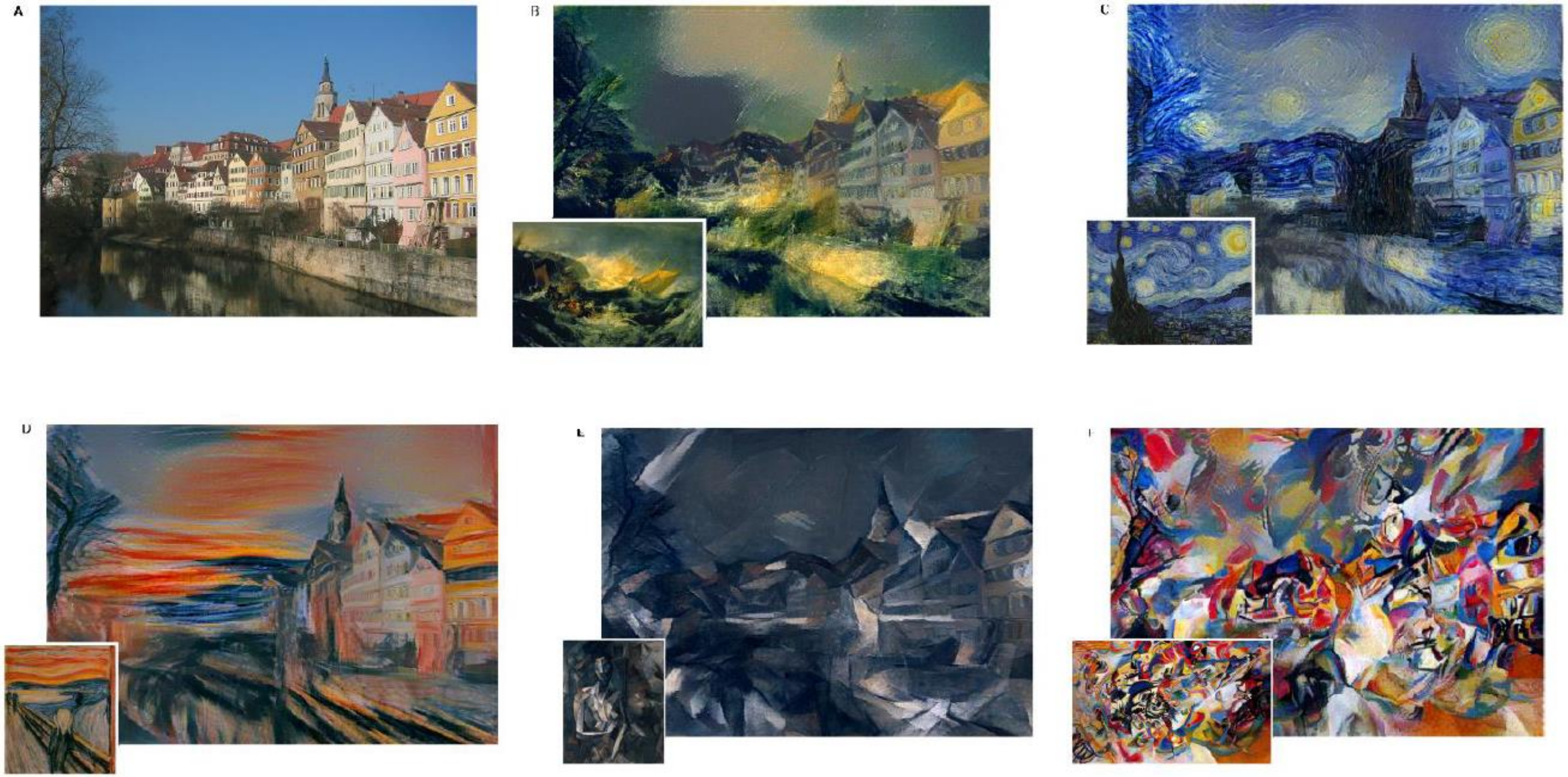
Ground Truth (PSNR, SSIM) | A+ [29] (23.53, 0.6977) | SRCNN [5] (23.79, 0.7087) | RFL [23] (23.53, 0.6943) | SelfEx [10] (23.52, 0.7006) | DRCN (Ours) (24.36, 0.7399)

"Deeply-Recursive Convolutional Network for Image Super-Resolution"

Texture Synthesis

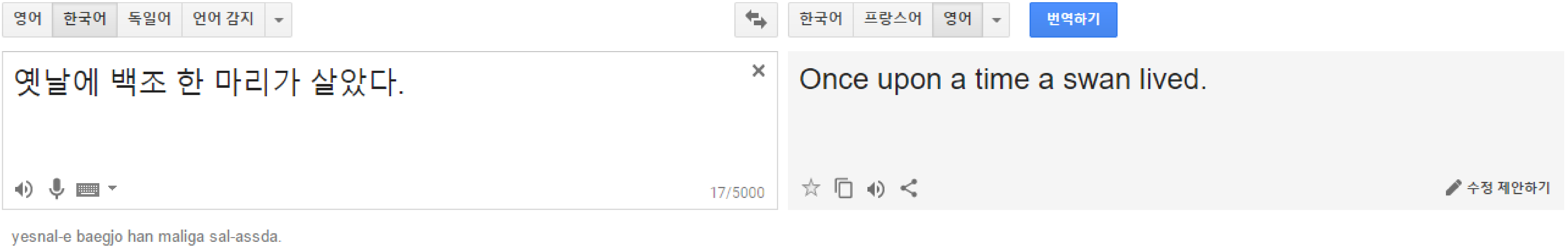
"Texture Synthesis Using Convolutional Neural Networks"

Artistic Style Transfer



"Image Style Transfer Using Convolutional Neural Networks"

Machine Translation



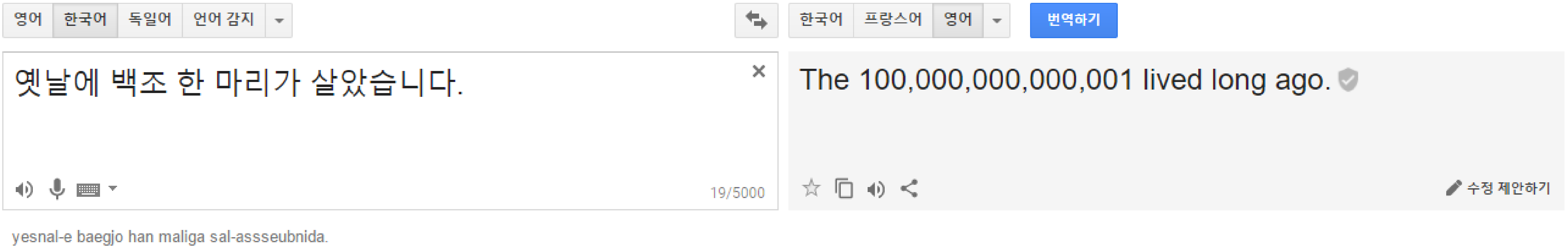


Image Captioning

a group of people standing around a room with remotes
logprob: -9.17

a young boy is holding a baseball bat
logprob: -7.61

a cow is standing in the middle of a street
logprob: -8.84

a baby laying on a bed with a stuffed bear
logprob: -8.66

a young boy is holding a baseball bat
logprob: -7.65

a woman holding a teddy bear in front of a mirror
logprob: -9.65

Visual QnA

Q: What is the boy holding?

DPPnet: surfboard

DPPnet: bat

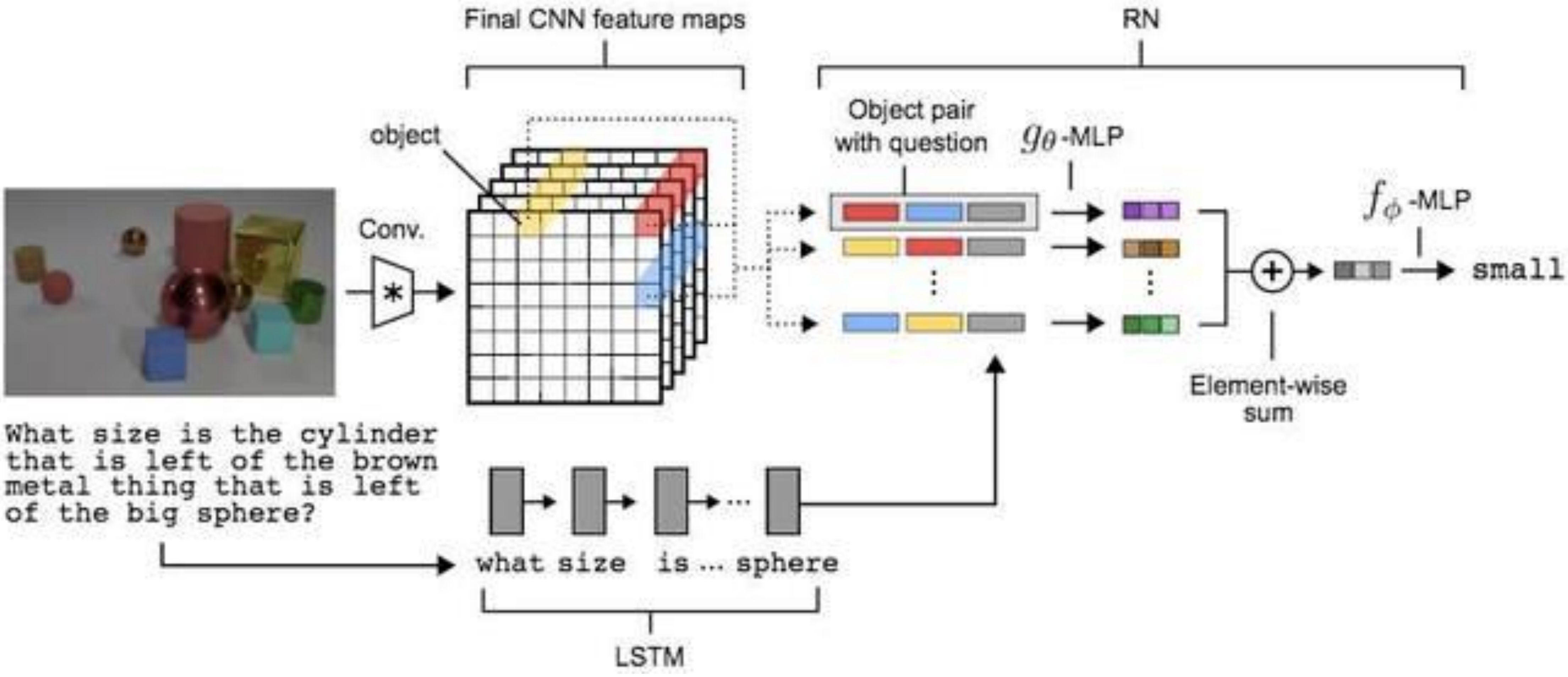
Q: What is the animal doing?

DPPnet: resting (relaxing)

DPPnet: swimming (fishing)

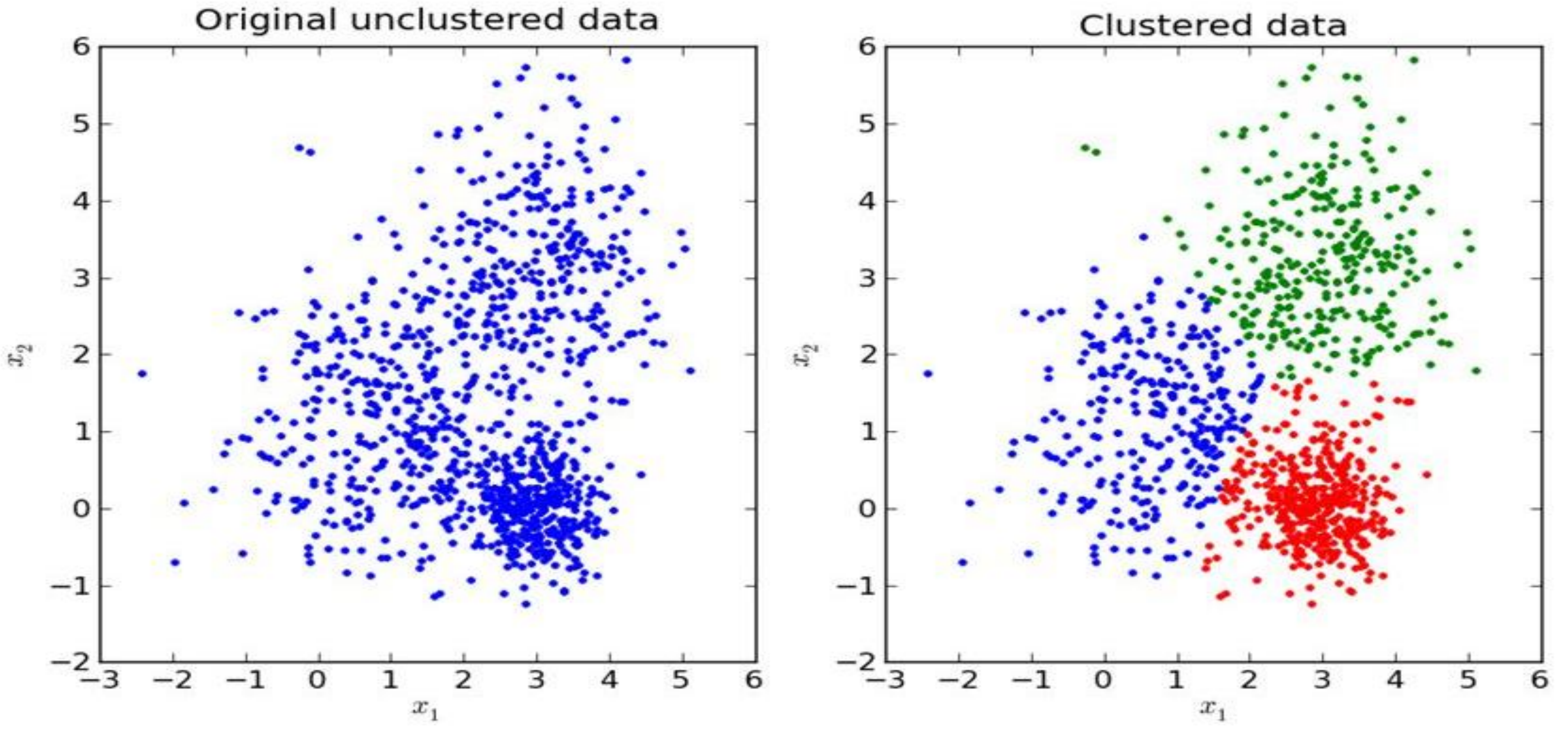
"Image Question Answering using Convolutional Neural Network with Dynamic Parameter Prediction"

Relational Network



Auto Speech Recognition

Unsupervised Learning



Unsupervised Learning

- 아래 음식을 둘로 분류하면?


(1)


(2)


(3)


(4)


(5)

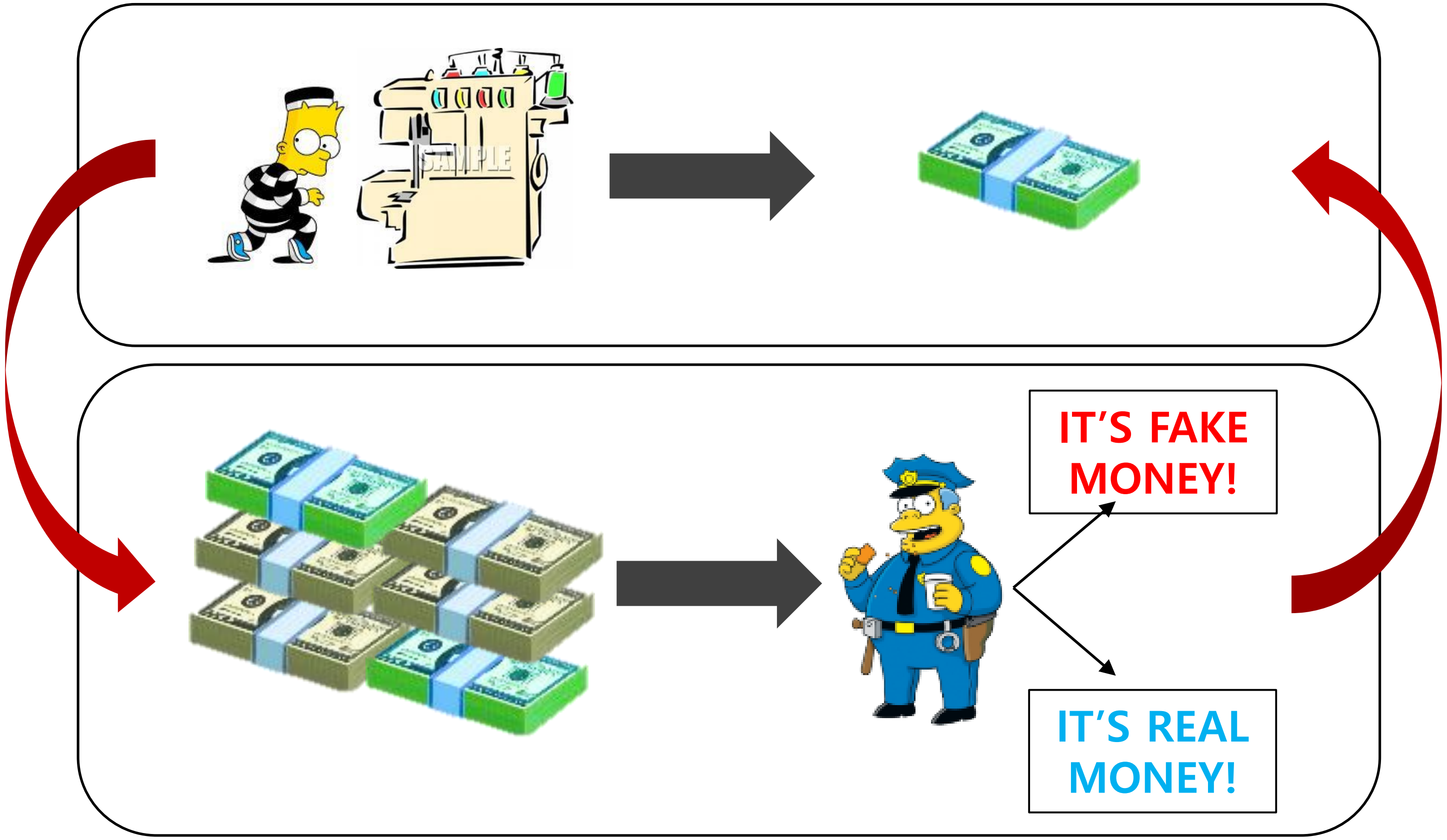

(6)


(7)

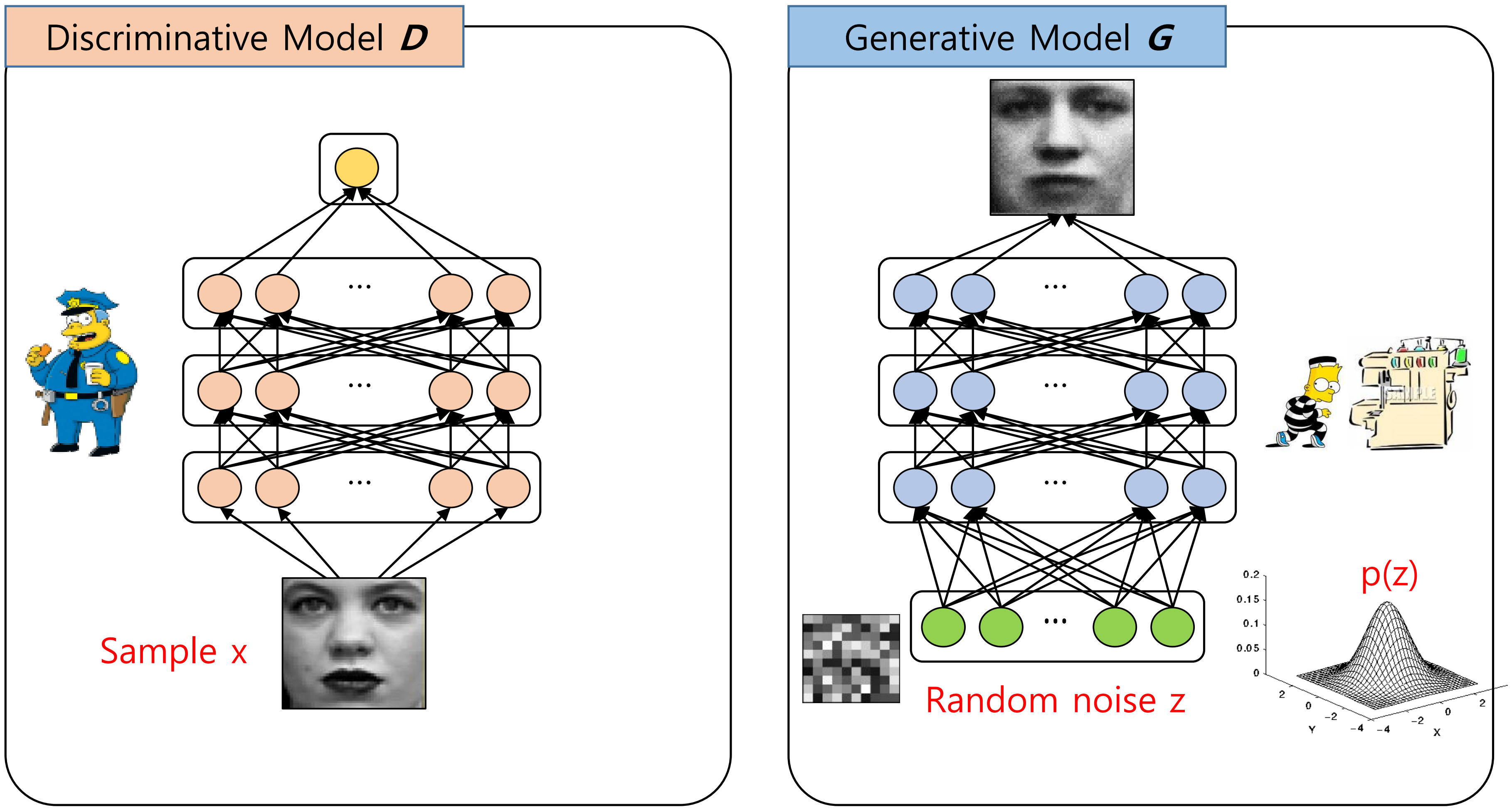

(8)

Generative Adversarial Network

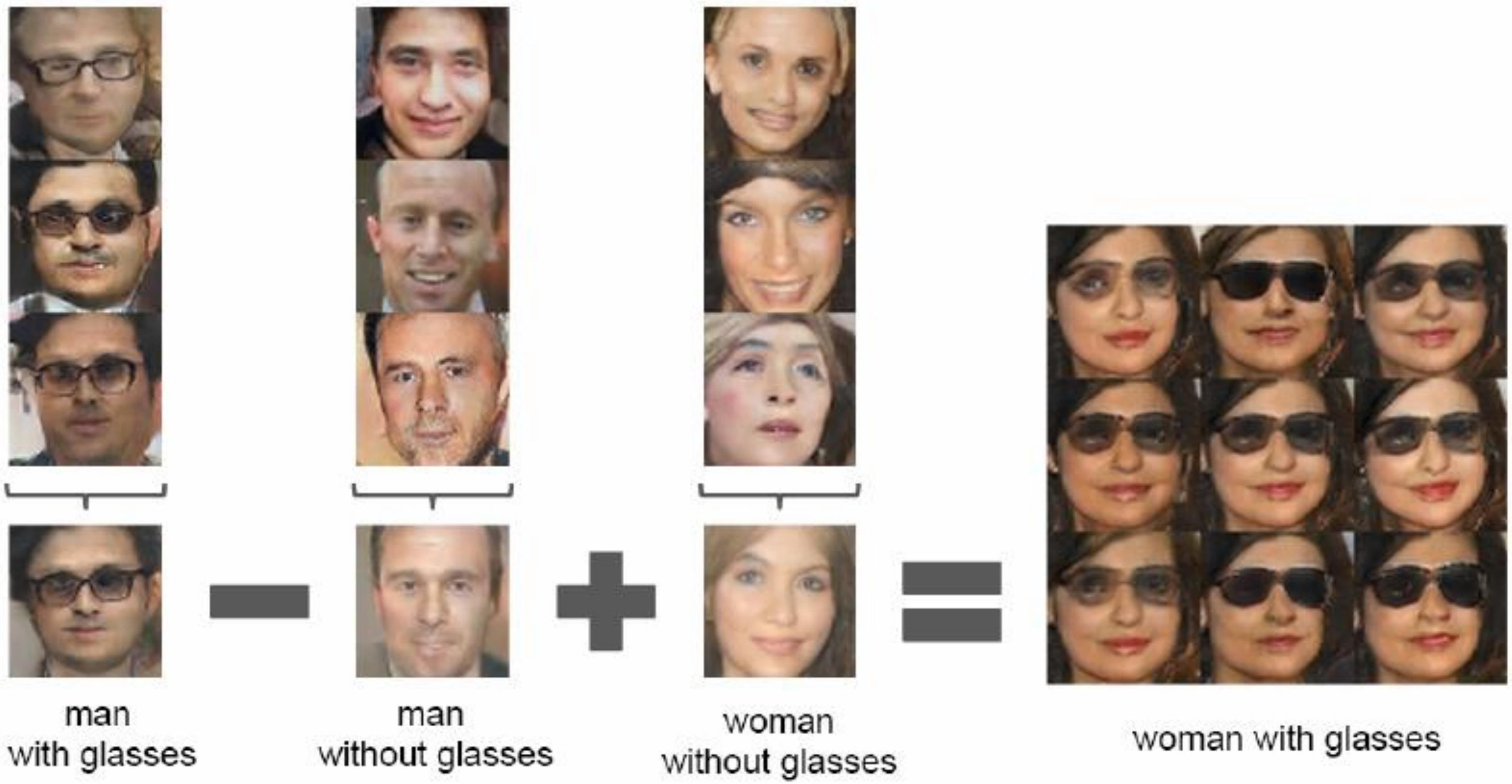
- Counterfeiters vs Police Game



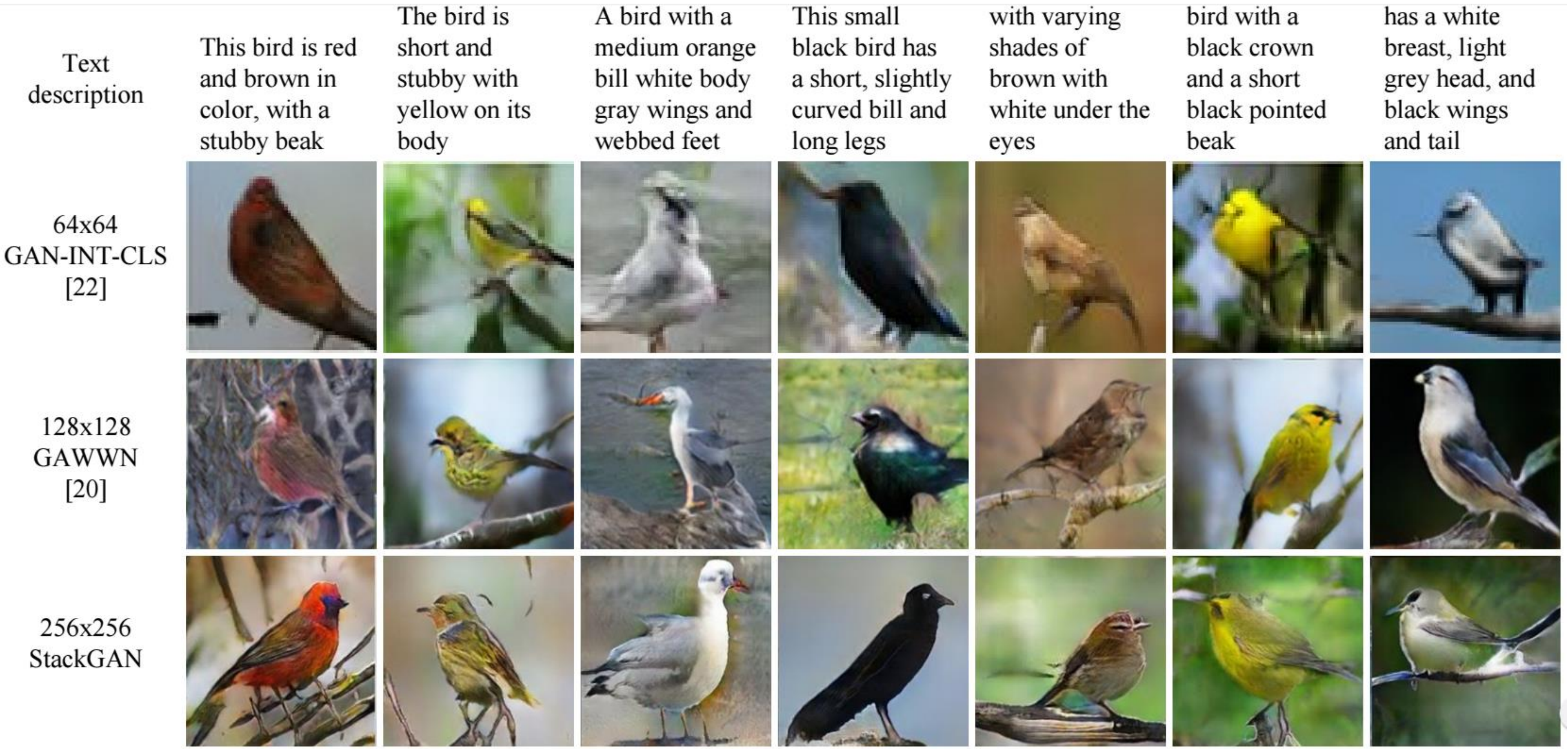
Generative Adversarial Network



DCGAN

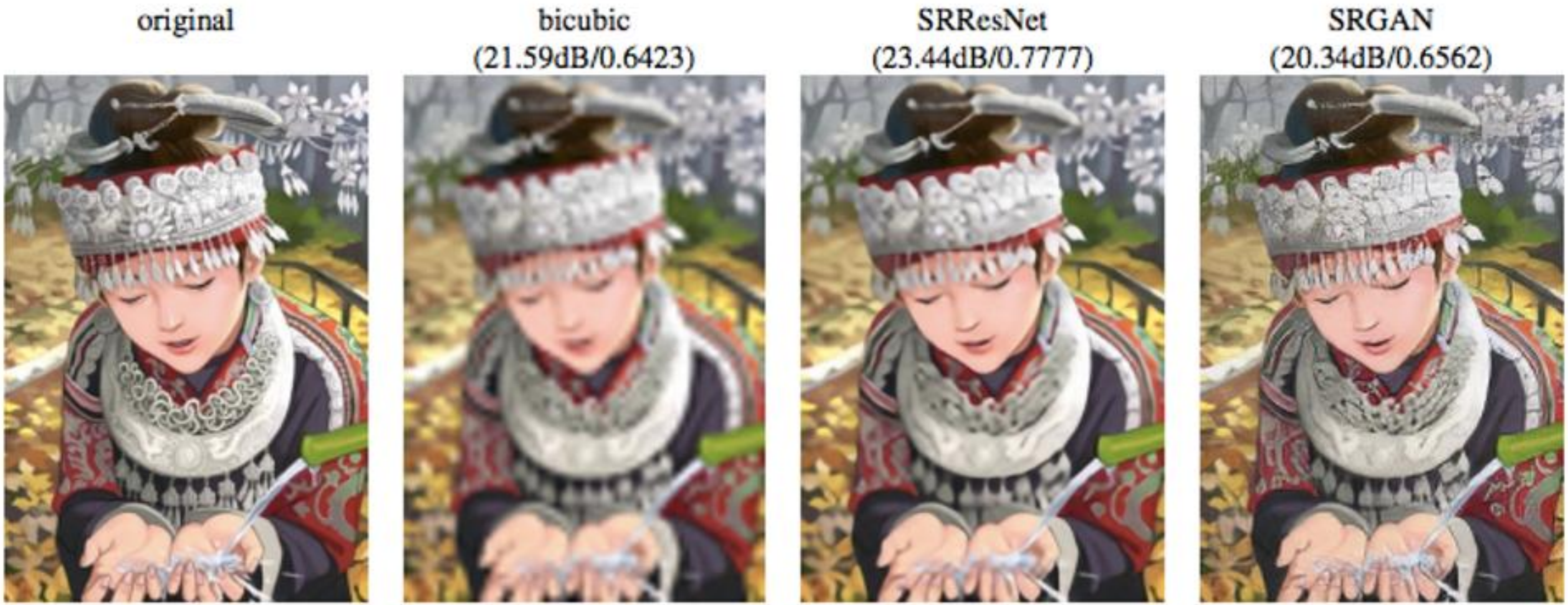

man
with glasses
man
without glasses
woman
without glasses
woman with glasses

StackGAN



"StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks "

SRGAN


original
bicubic
(21.59dB/0.6423)
SRResNet
(23.44dB/0.7777)
SRGAN
(20.34dB/0.6562)

Cross-Domain Image Generation

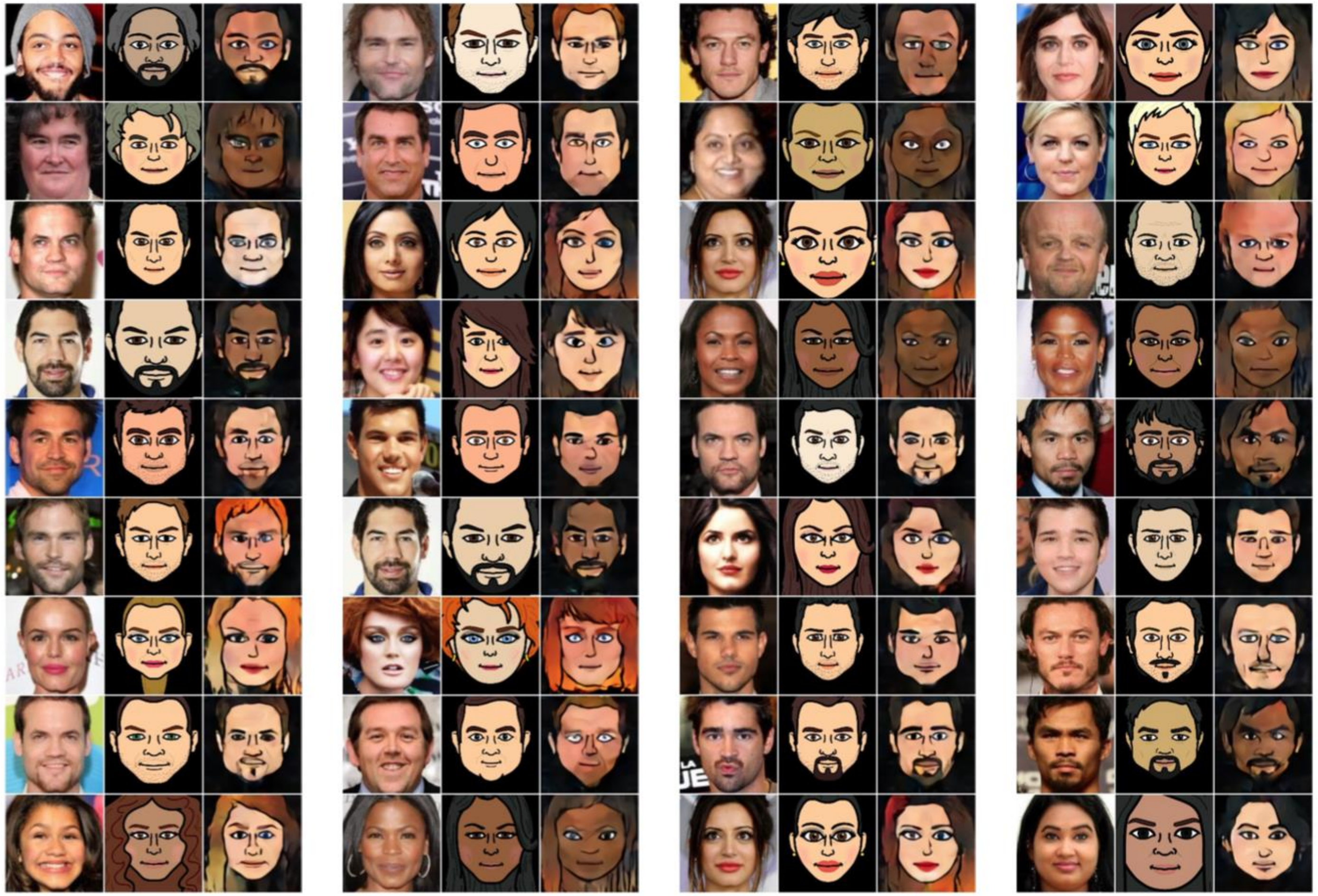
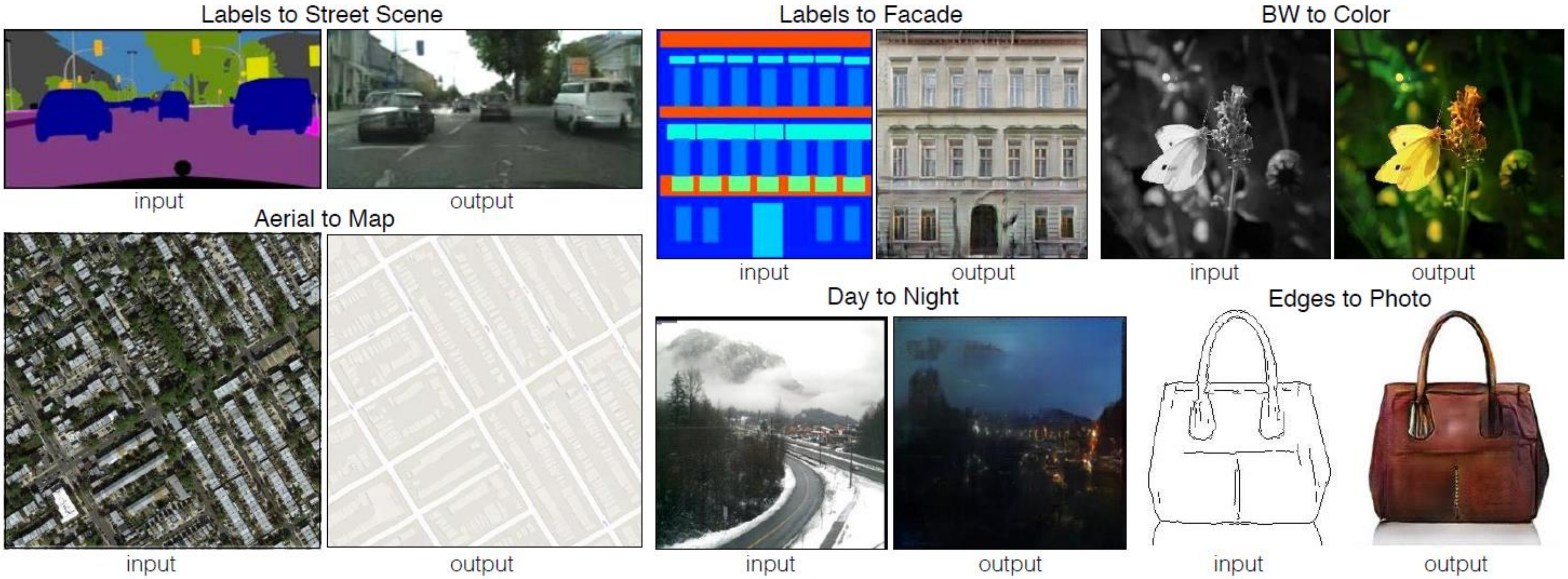


Figure 4: Shown, side by side are sample images from the CelebA dataset, the emoji images created manually using a web interface (for validation only), and the result of the unsupervised DTN. See Tab. 4 for retrieval performance.

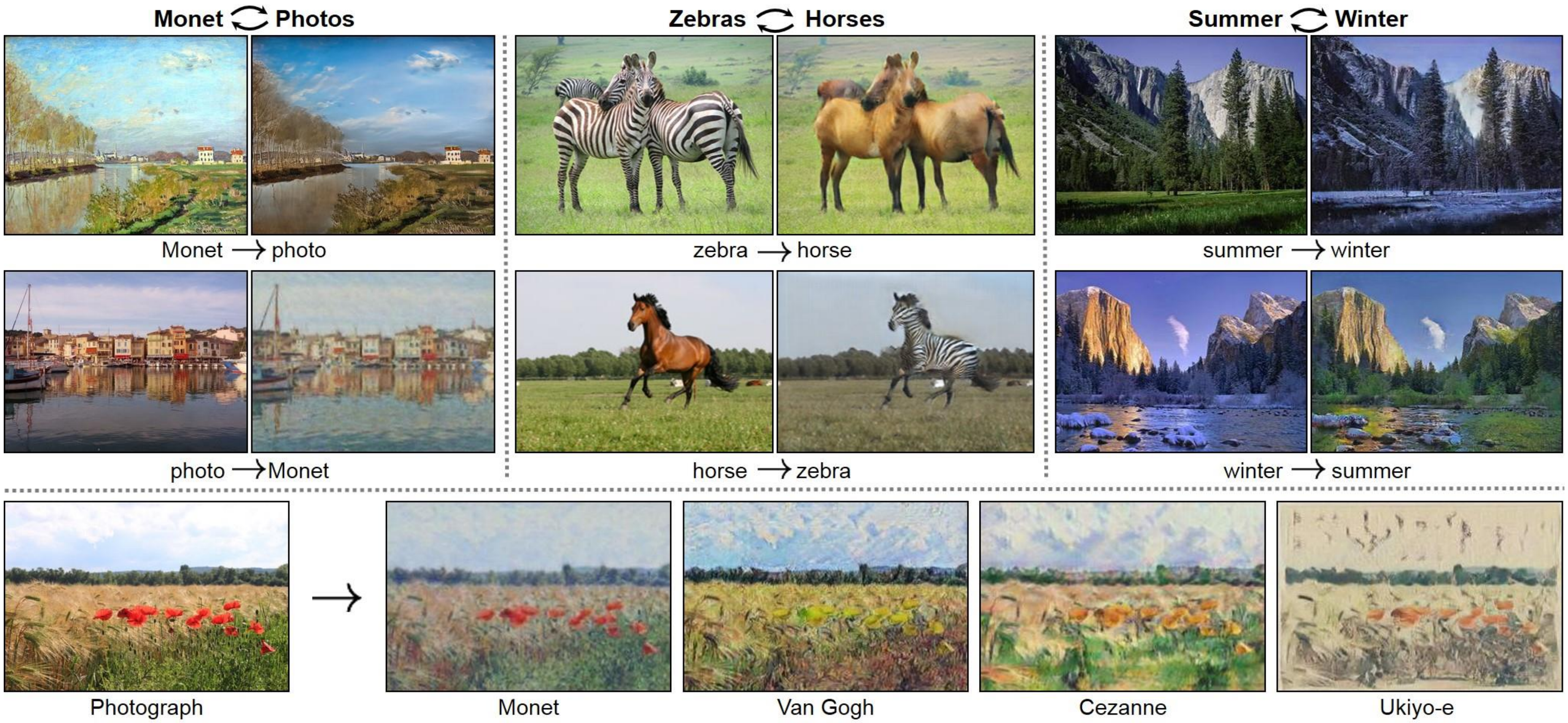
Domain Transfer

Pix2Pix

- https://affinelayer.com/pixsrv/

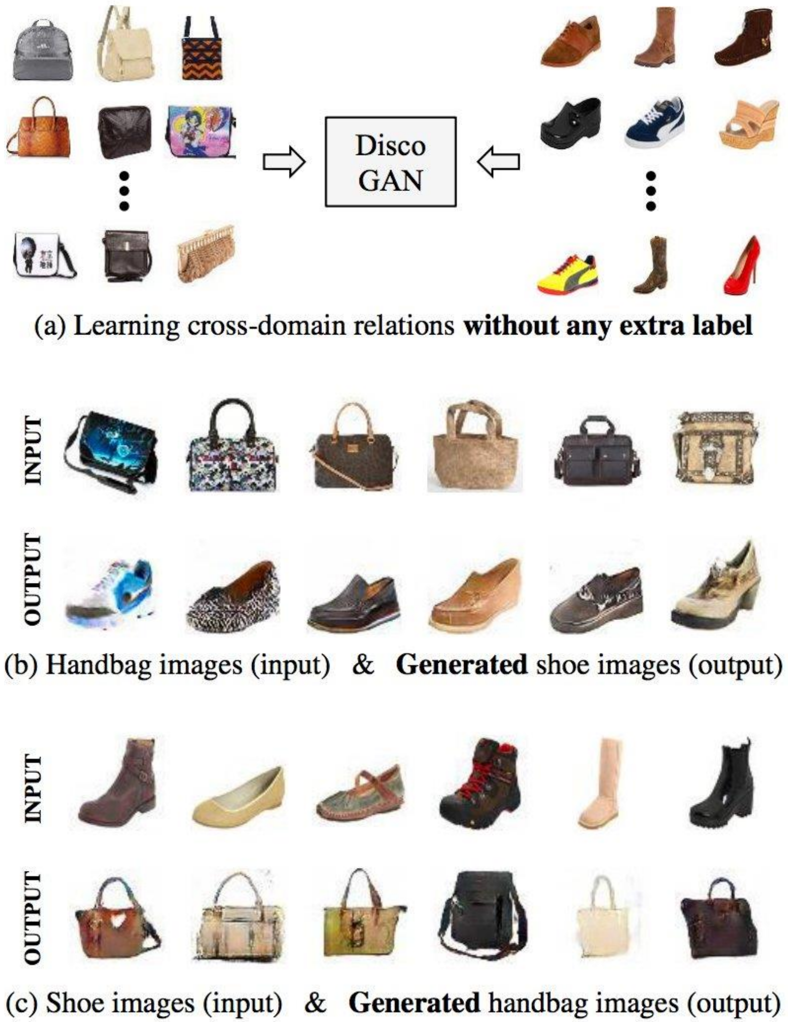


CycleGAN



Monet ⇄ Photos
Zebras ⇄ Horses
Summer ⇄ Winter
Monet → photo
zebra → horse
summer → winter
photo → Monet
horse → zebra
winter → summer
Photograph
Monet
Van Gogh
Cezanne
Ukiyo-e

DiscoGAN

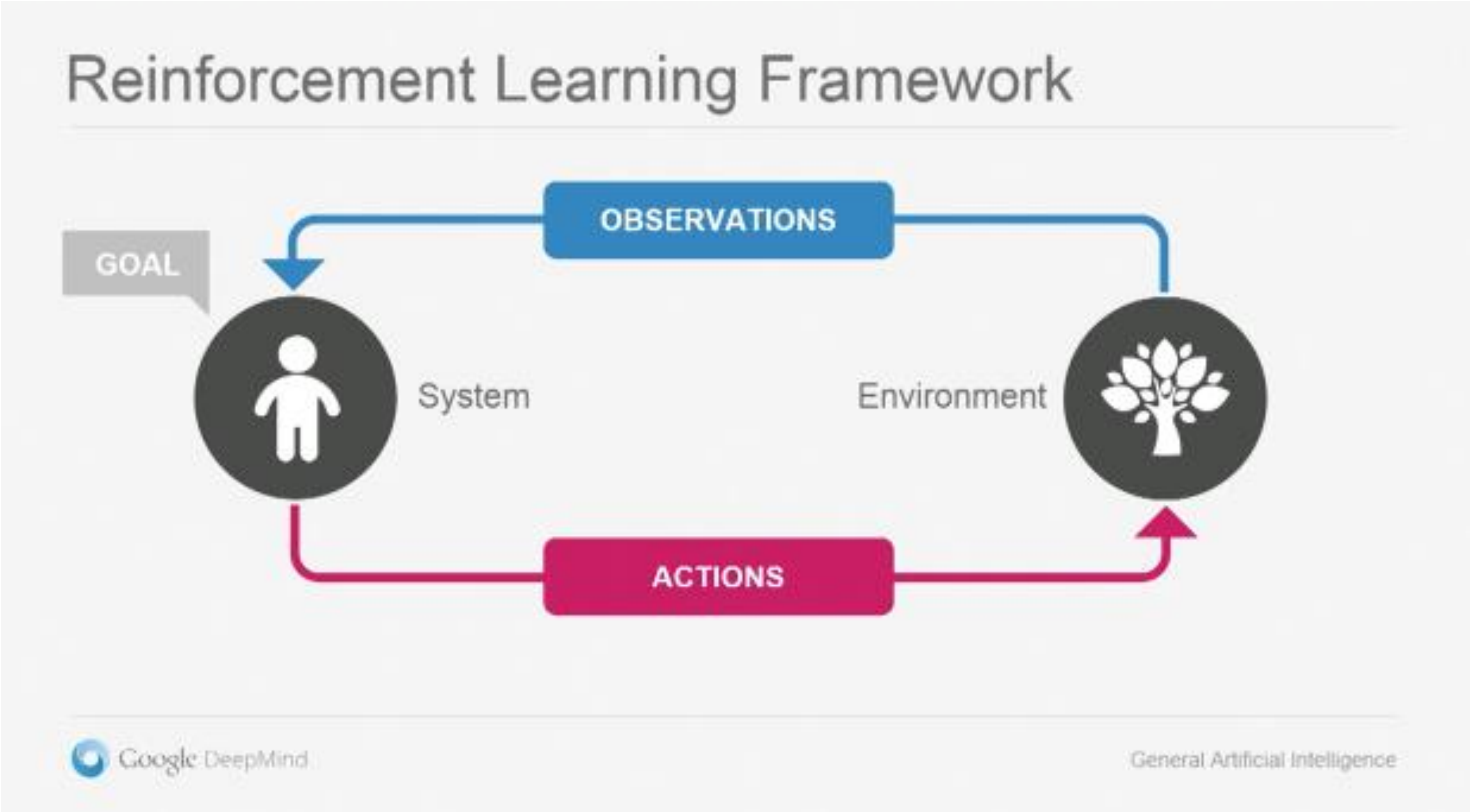


(a) Learning cross-domain relations **without any extra label**

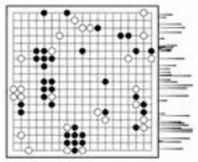
(b) Handbag images (input) & **Generated** shoe images (output)

(c) Shoe images (input) & **Generated** handbag images (output)

Reinforcement Learning

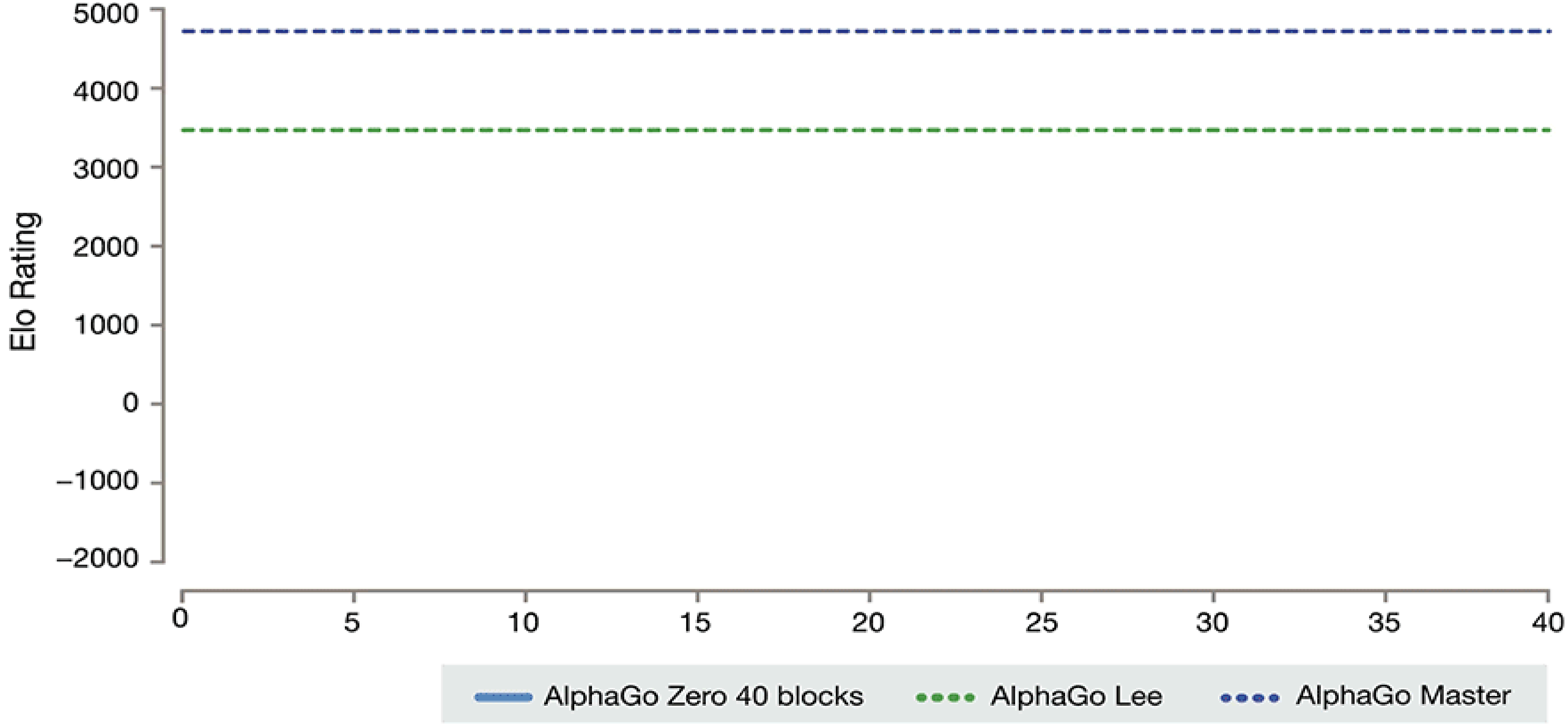


AlphaGo



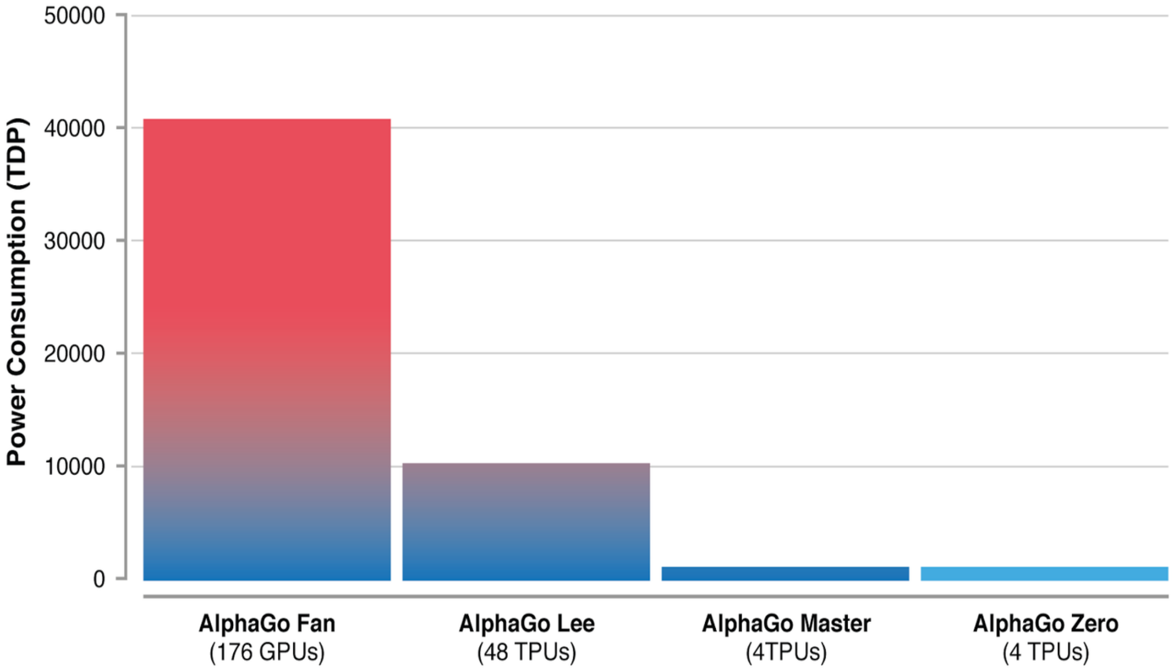
- 왜 바둑인가?
  - 사람이 만든 게임 중 가장 복잡하다
    - 경우의 수 $10^{170} \sim 10^{700}$
  - 형세판단을 하기 힘들다
    - 바둑은 점수 계산방식이 따로 없고 최종적으로 집의 수로 승패를 결정
    - 알파고와 이세돌 대결 때 2차전까지는 해설하는 프로기사들 간에도 유불리에 대한 의견이 분분하였음

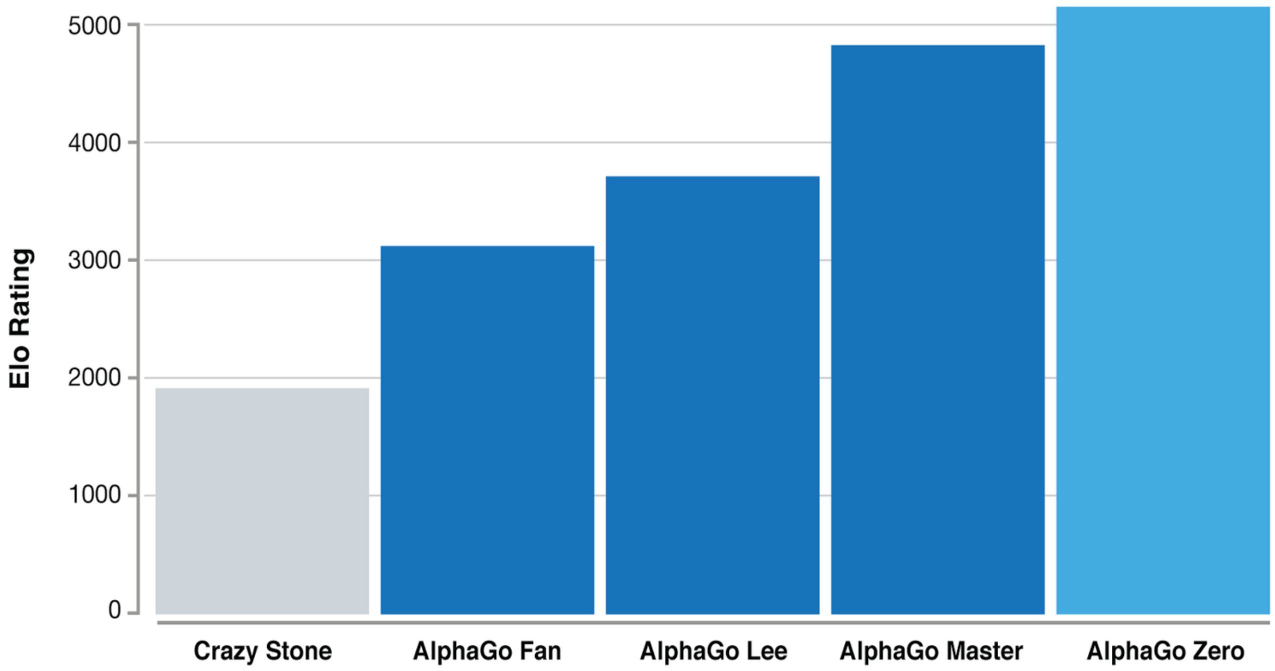
AlphaGo Zero



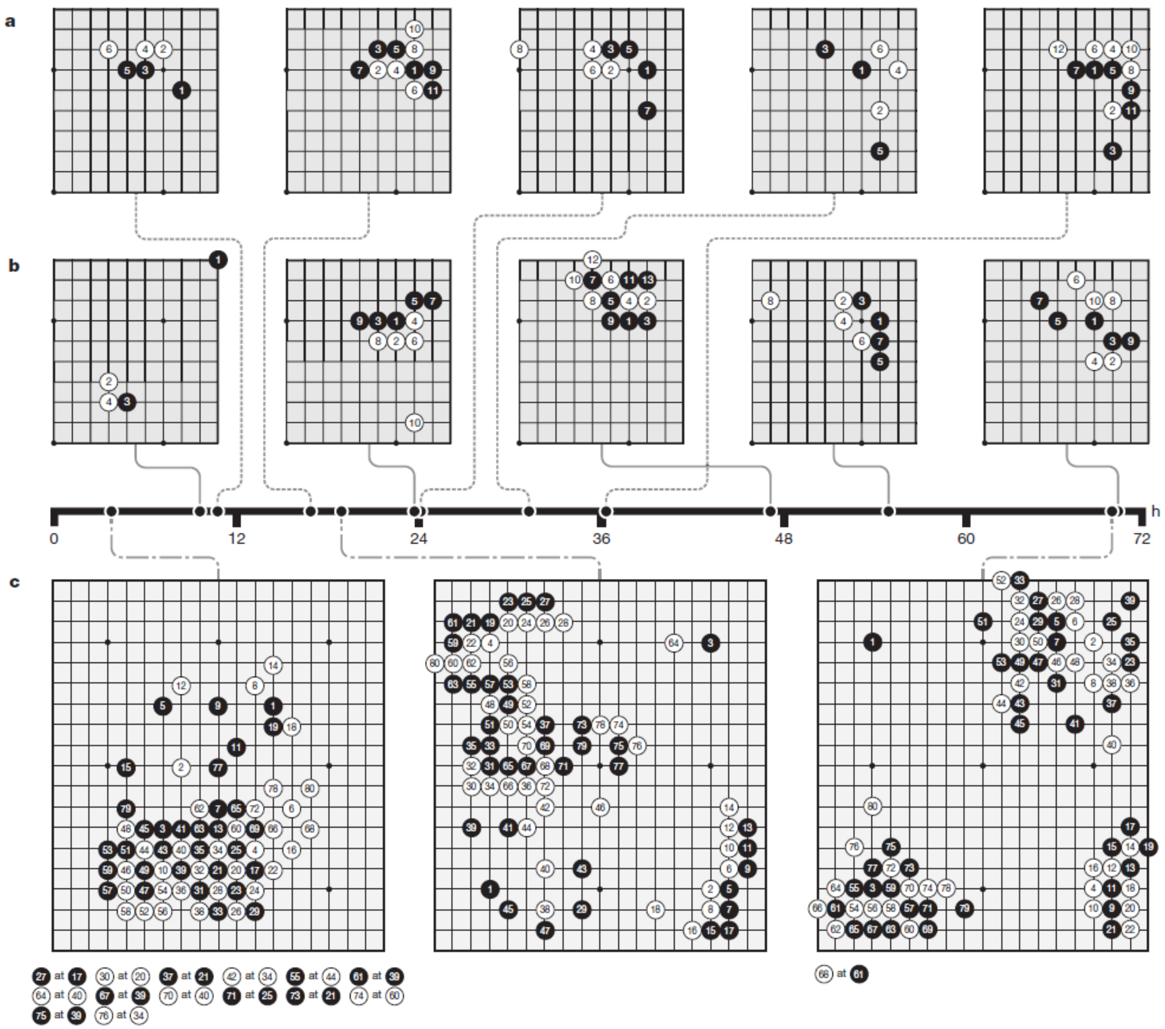
AlphaGo Zero

- Tabula rasa
- Without handcrafted input feature
- Rollout is removed



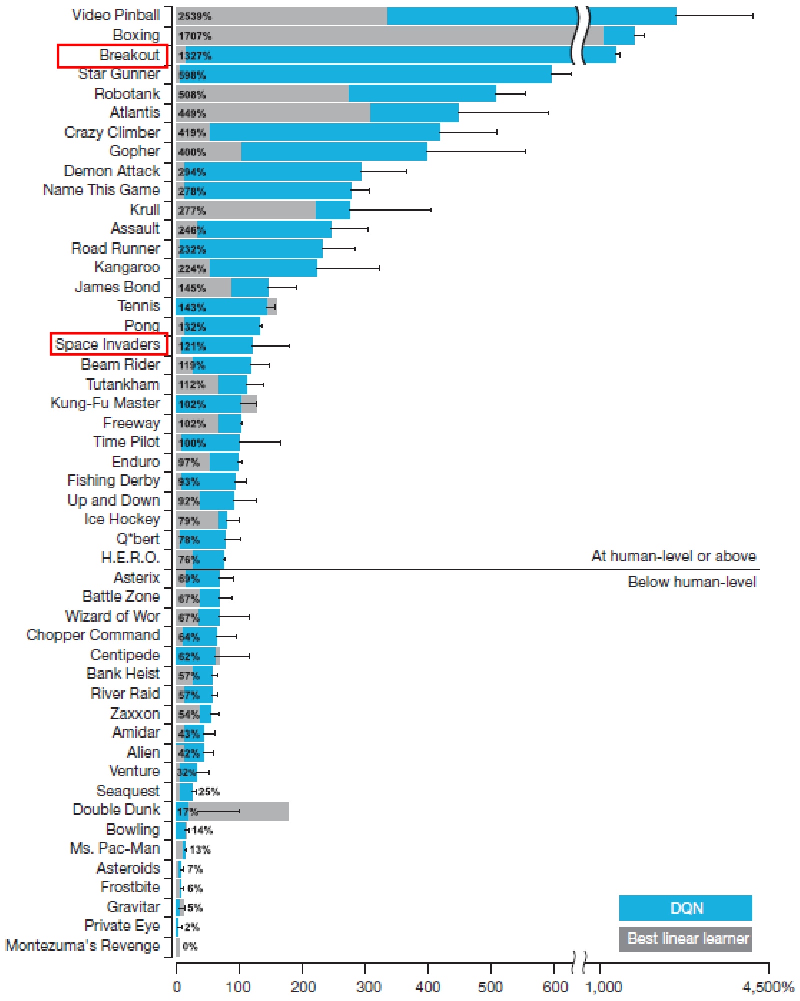


AlphaGo Zero



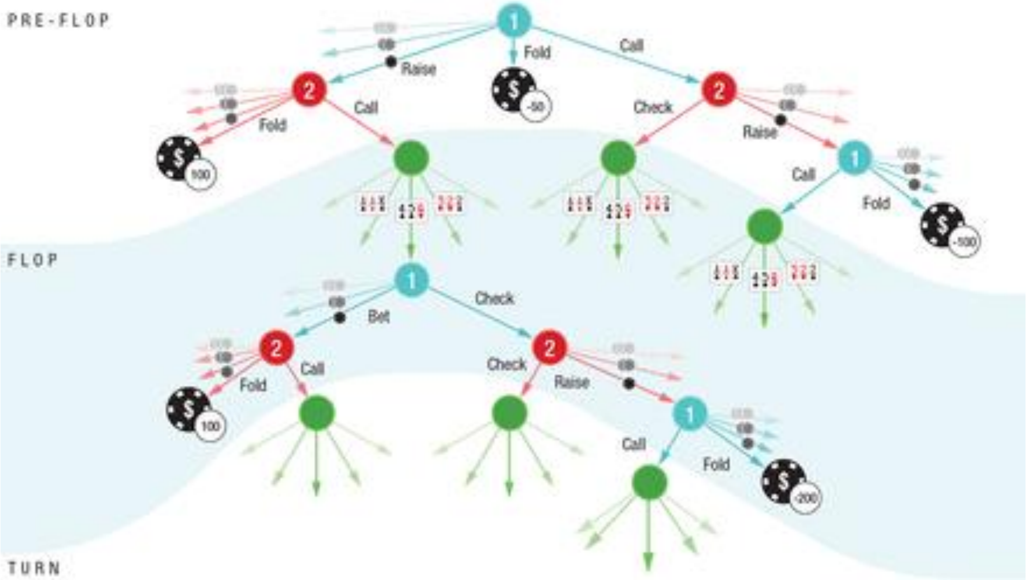
Atari Games

Space Invaders



Poker Game

Libratus(Jan 30, 2017)



DeepStack(Science, Mar 02, 2017)

Starcraft II

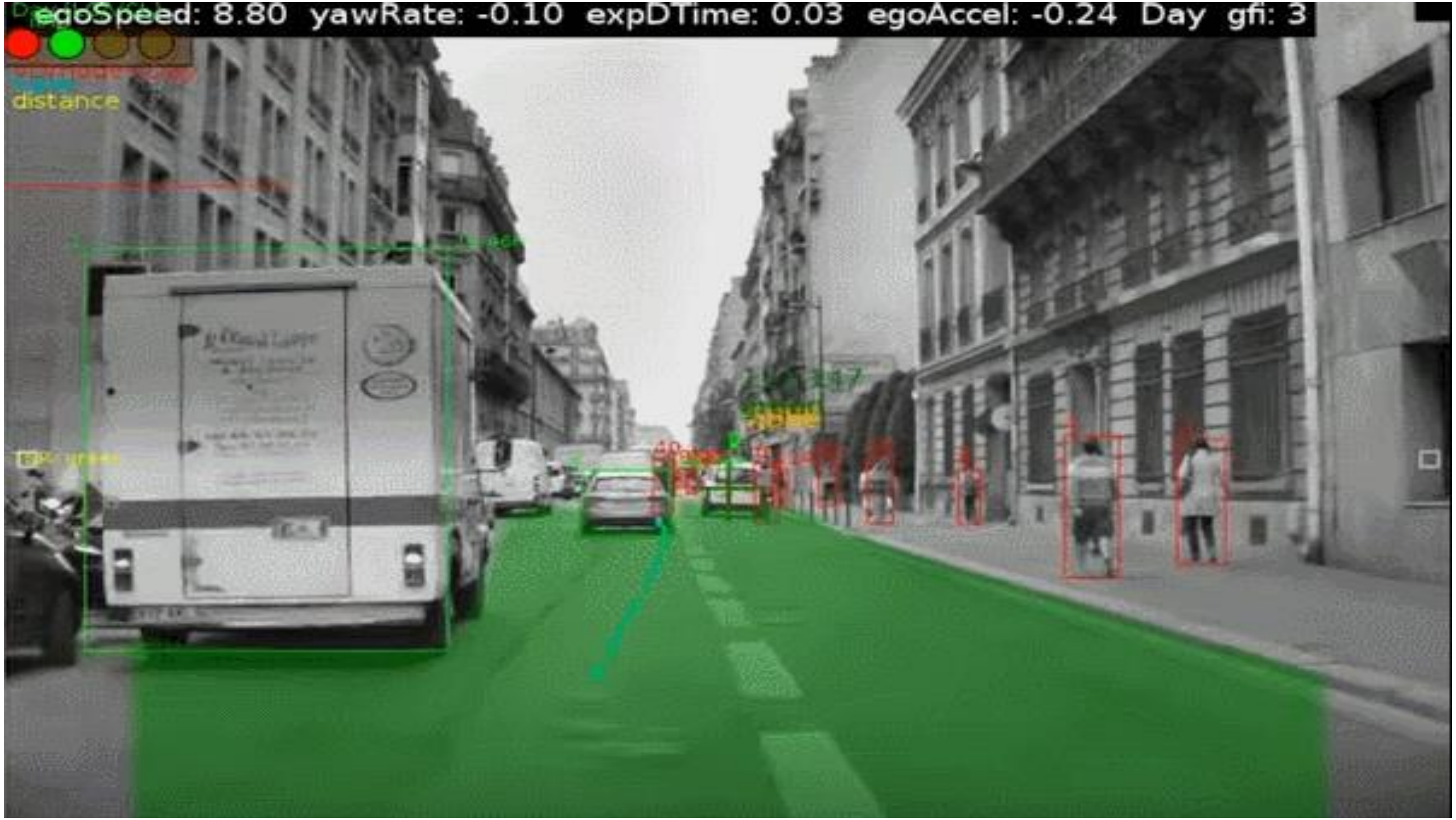
https://youtu.be/St5lxIxYGkI

https://arxiv.org/abs/1708.04782

Other Games

- Super Mario World
  - https://youtu.be/L4KBBAwF_bE
  - https://youtu.be/qv6UVOQ0F44
- Cookie Run
  - https://youtu.be/exXD6wJLJ6s
- Starcraft I
  - https://youtu.be/GgkmJDjeJtw
- GTA
  - https://youtu.be/X4u2DCOLoIg

Autonomous Driving



Quiz

- □와 △에 들어갈 정수는?
  - 3 x □ + 2 x △ = 1
  - 1 x □ + 4 x △ = -3
  - 5 x □ + 5 x △ = 0
  - 8 x □ + 3 x △ = 5
- **□ = 1, △ = -1**

- (3, 2), (1, 4), (5, 5), (8, 3) 은 input data, 1, -3, 0, 5 는 label이다
- □와 △를 weight라고 하며 이 weight 값을 기계가 스스로 학습을 통해 찾아내도록 하는 것이 neural network를 이용한 기계학습이 하는 일

Machine Learning Again

- Learning from data!
- Essence
  - Data
  - Pattern in the data
  - Difficult to explain / understand mathematically

Problem Formulation

- Running example : credit approval
  - **given:**
    - applicant information

feature	value
age	23 years
gender	female
annual salary	$30,000
years in residence	1 year
years in job	1 year
current debt	$15,000

  - **task:**
    - approve credit or not?

Notation

component	symbol	credit approval metaphor
input	$\mathbf{x}$	customer application
output	y	approve or deny
target function	$f : \mathcal{X} \to \mathcal{Y}$	ideal credit approval formula
data	$(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_N, y_N)$	historical records
hypothesis	$g : \mathcal{X} \to \mathcal{Y}$	formula to be used

- f: unknown target function
- $\mathcal{X}$: input space (set of all possible inputs $\mathbf{x}$)
- $\mathcal{Y}$: output space (set of all possible outputs)
- N: the number of input-output examples (*i.e.* training examples)
- $\mathcal{D} \triangleq \{(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_N, y_N)\}$: data set where $y_n = f(\mathbf{x}_n)$

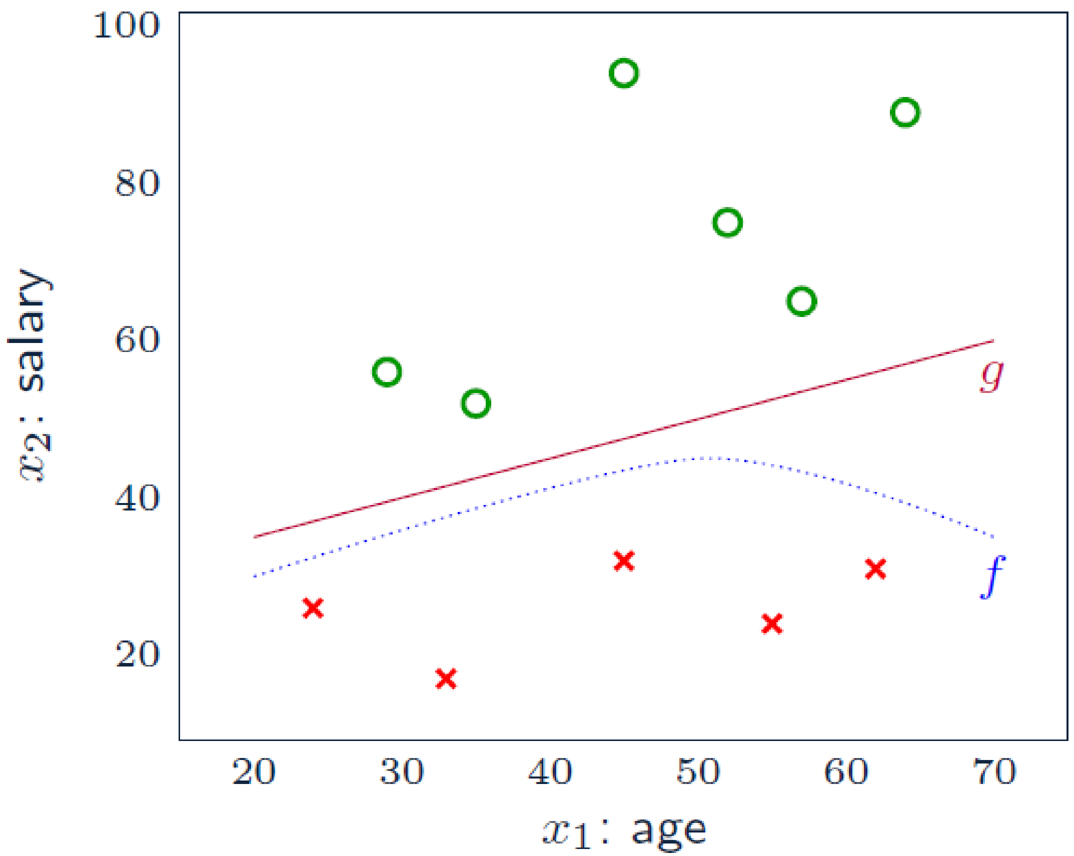
Example – Credit Approval

$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$ where x_1: age and x_2: annual salary in USD

$N = 11$, $d = 2$, $\mathcal{X} = \mathbb{R}^2$, and $\mathcal{Y} = \{\text{approve}, \text{deny}\}$

data set $\mathcal{D}$:

n	x_1	x_2	y
1	29	56k	approve
2	64	89k	approve
3	33	17k	deny
4	45	94k	approve
5	24	26k	deny
6	55	24k	deny
7	35	52k	approve
8	57	65k	approve
9	45	32k	deny
10	52	75k	approve
11	62	31k	deny

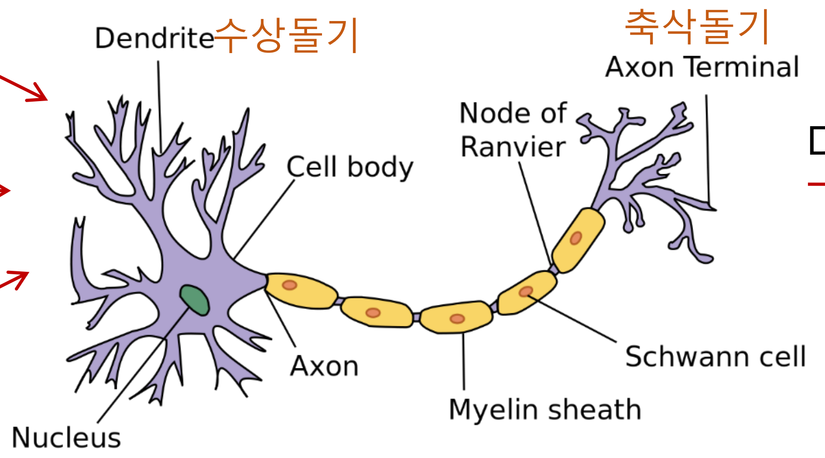


Components of Learning

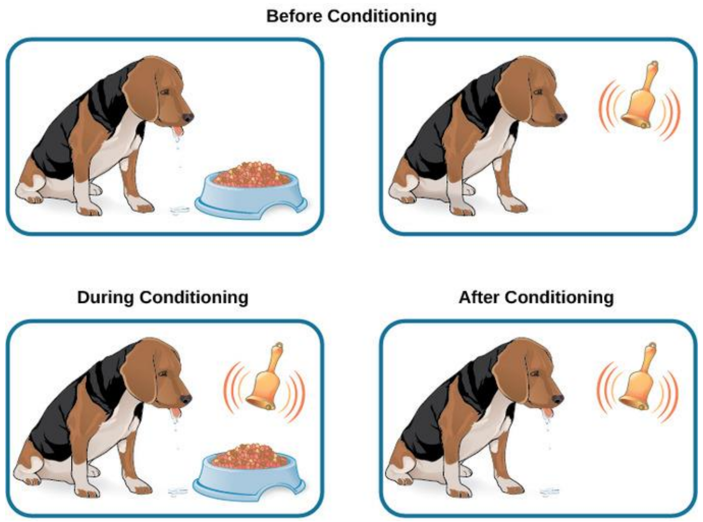
- **learning algorithm $\mathcal{A}$**
  - uses $\mathcal{D}$ to pick formula $g : \mathcal{X} \to \mathcal{Y}$ that approximates f
  - chooses g from a set $\mathcal{H}$
- **hypothesis set $\mathcal{H}$**
  - a set of candidate formula under consideration
  - *e.g.* $\mathcal{H}$ could be the set of all linear formulas
- **learning model: $\mathcal{A}$ and $\mathcal{H}$**
  - two solution tools we should choose

뉴런과 사람의 학습

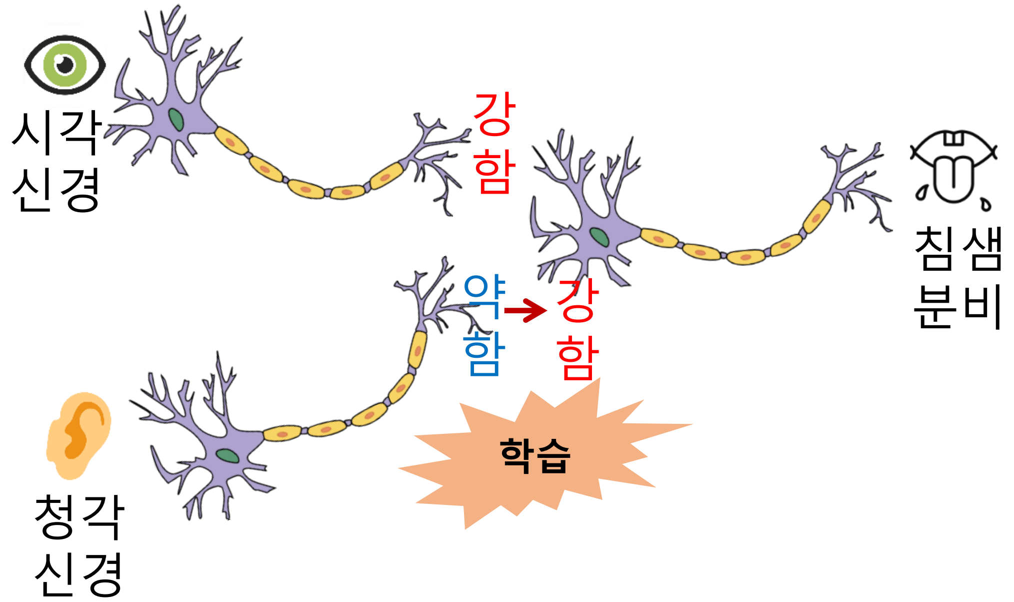
이전 뉴런과 연결



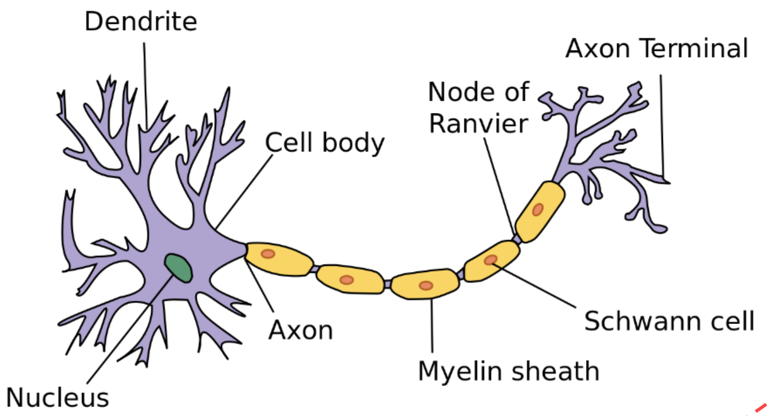
다음 뉴런으로 전달

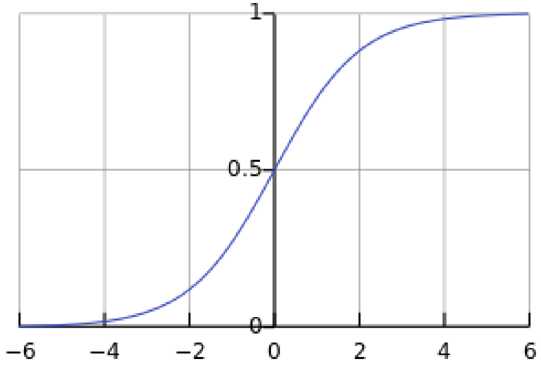


파블로프의 개 실험



Perceptron(Artificial Neural Network)





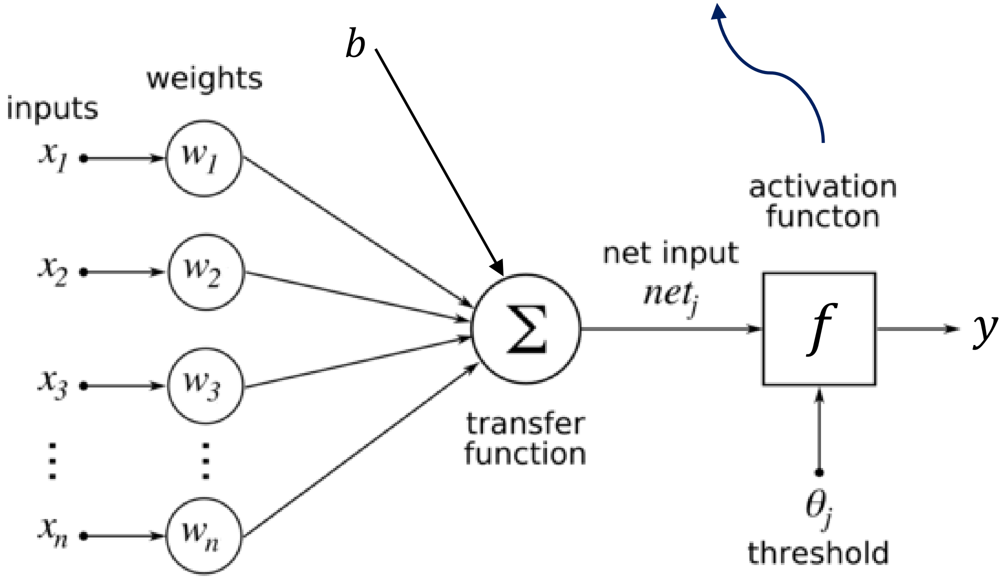
sigmoid activation function

$$f(x) = \frac{1}{1 + e^{-x}}$$

$$y = f(\mathbf{wx} + \mathrm{b})$$

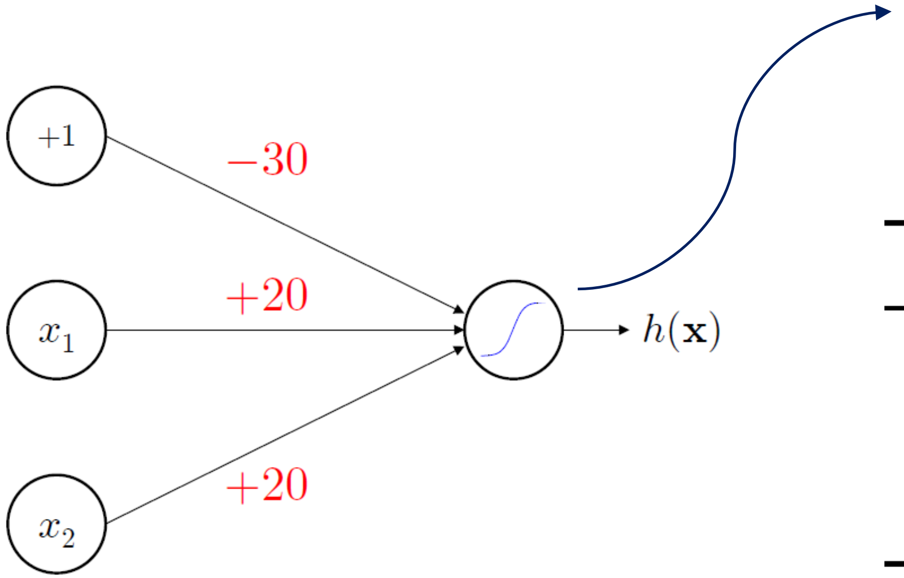
$$\boldsymbol{w} = [w_1\ w_2\ w_3\ \dots\ w_n]$$

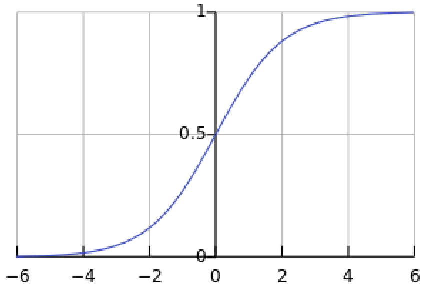
$$\boldsymbol{x} = [x_1\ x_2\ x_3\ \dots\ x_n]^T$$



<Perceptron>

Example of ANN(logical AND)

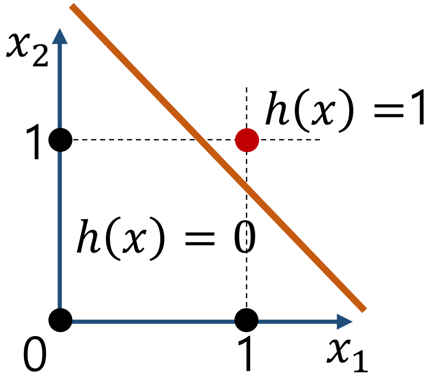




x_1	x_2	$h(\mathbf{x})$
0	0	$\sigma(-30) \approx 0$
0	1	$\sigma(-10) \approx 0$
1	0	$\sigma(-10) \approx 0$
1	1	$\sigma(10) \approx 1$

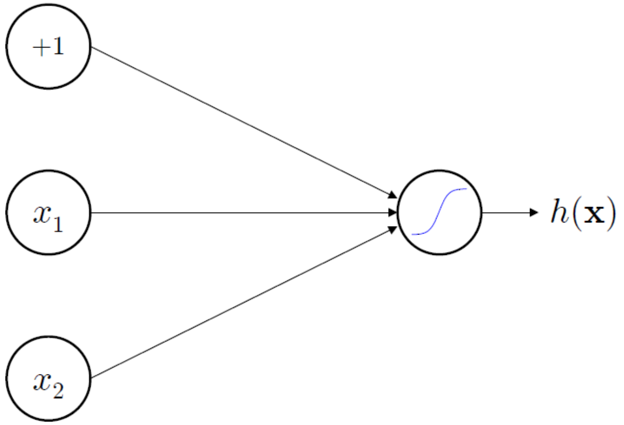
$$h(\mathbf{x}) = \sigma(-30 + 20x_1 + 20x_2)$$

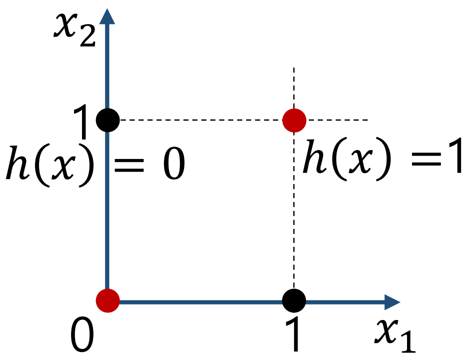
학습이란 이러한 weight 값(-30, 20, 20)을
기계 스스로 찾을 수 있도록 해주는 과정!



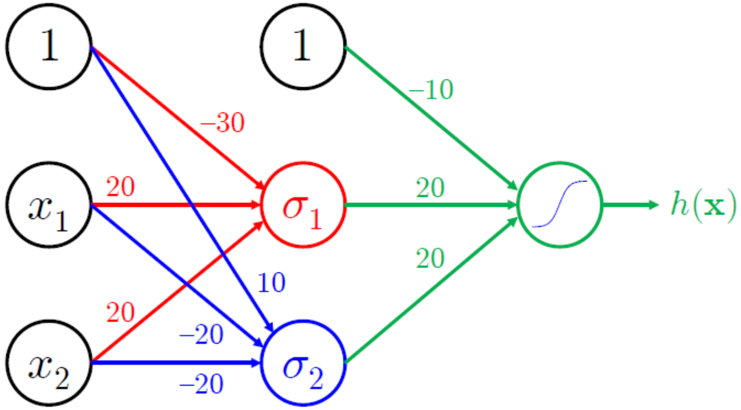
Logical XNOR with Perceptron

- Is it possible(Linearly separable)?



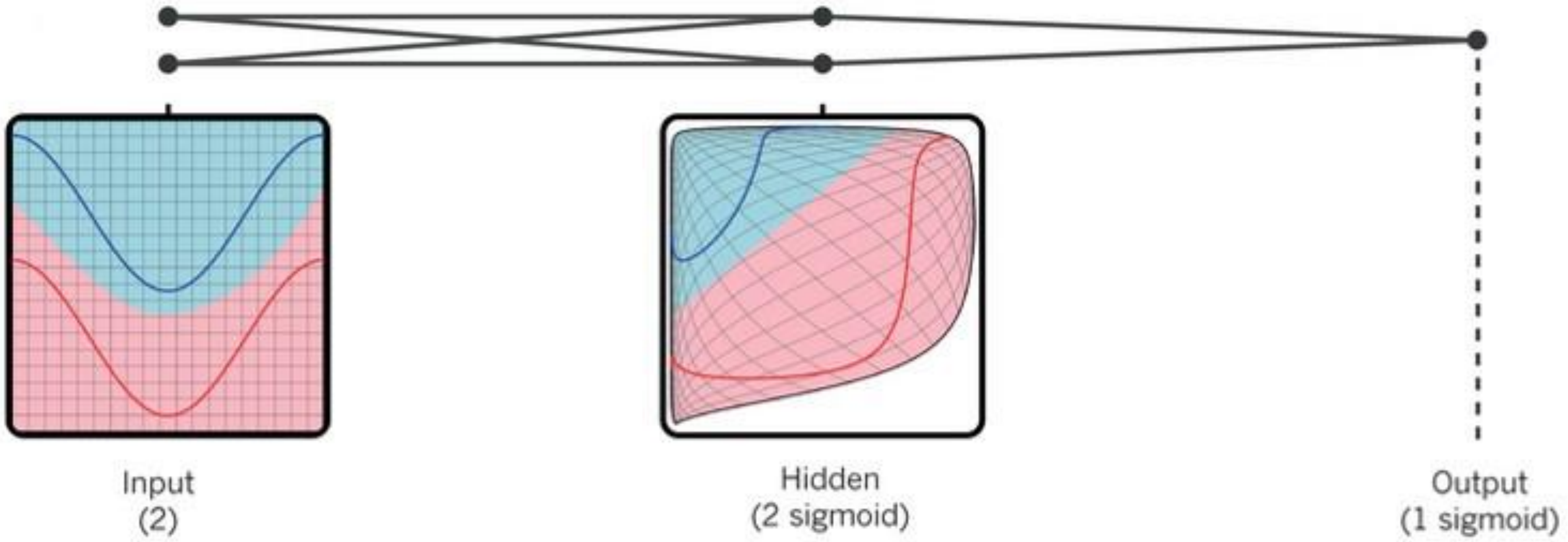


- We need more perceptrons and more layers



x_1	x_2	σ_1	σ_2	$h(\mathbf{x})$
0	0	0	1	1
0	1	0	0	0
1	0	0	0	0
1	1	1	0	1

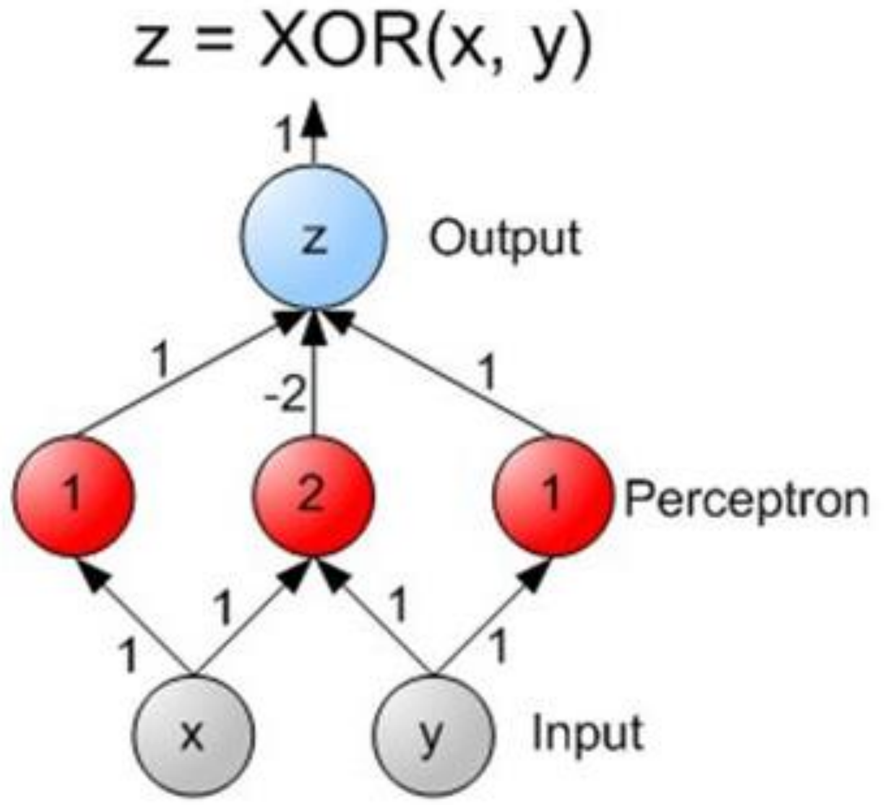
Multi Layer Perceptron(MLP)



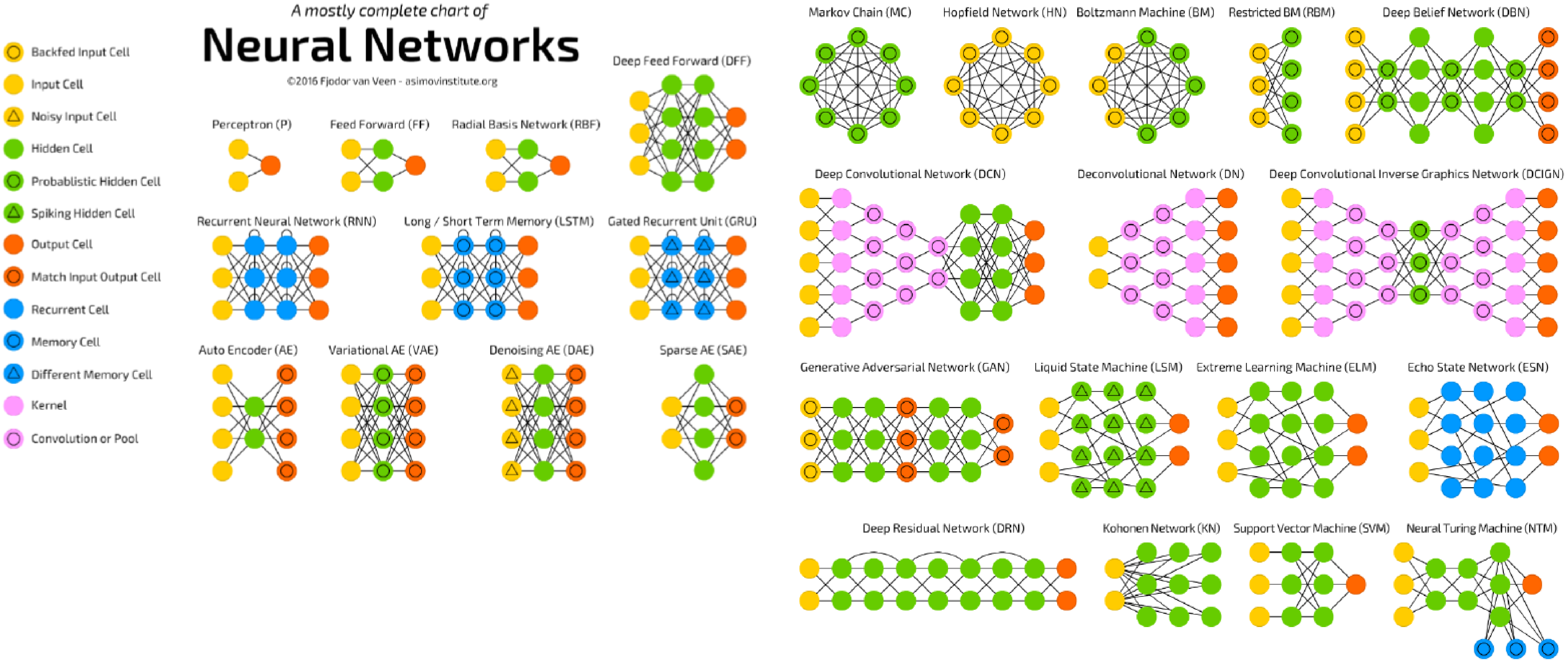
- 선을 잘 긋고 input 공간을 잘 왜곡하고 합하는 과정을 반복해서 데이터들을 잘 구분해보자(classification)
- 이렇게 perceptron을 여러층으로 쌓으면 더 복잡한 문제를 풀 수 있다
- Linear fitting과 Non-linear transform의 반복

Universal Function Approximation

The *universal approximation theorem* for neural networks states that every continuous function that maps intervals of real numbers to some output interval of real numbers can be approximated arbitrarily closely by a multi-layer perceptron with just one hidden layer. This result holds only for restricted classes of activation functions, e.g. for the sigmoidal functions. (Wikipedia.org)

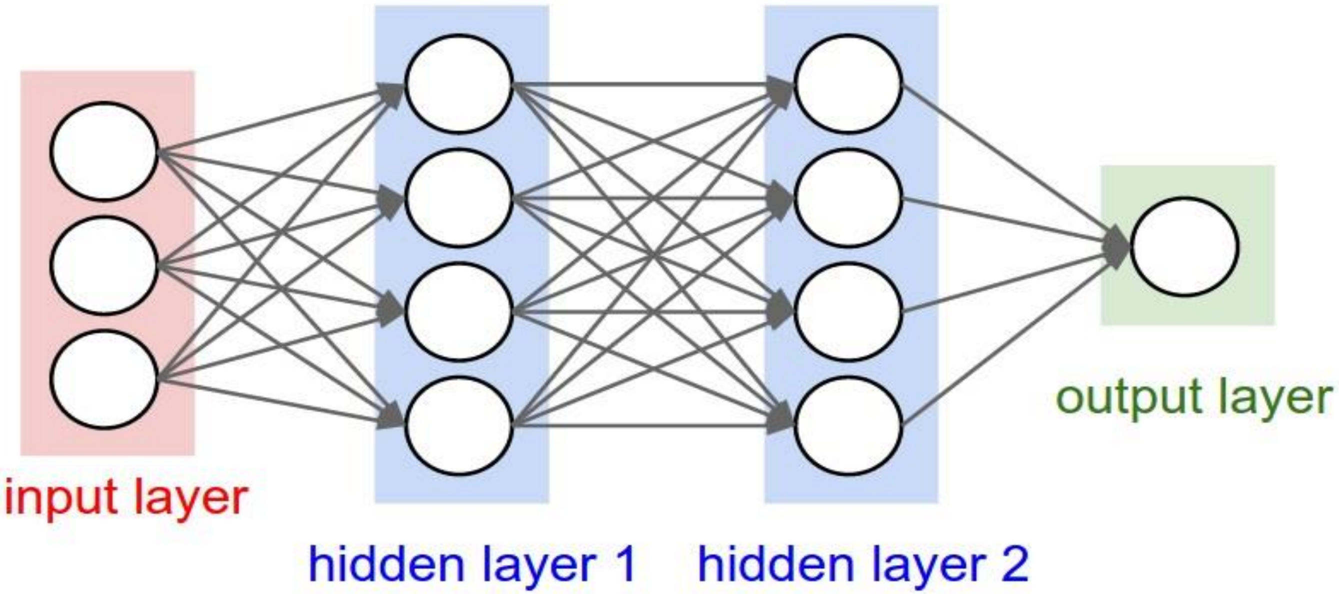


Making Neural Networks



딥러닝(Deep Learning)

- 딥러닝은 deep neural network를 통하여 학습하는 것을 의미함
- Hidden layer의 수 <= 1 → shallow network
- Hidden layer의 수 >= 2 → deep network

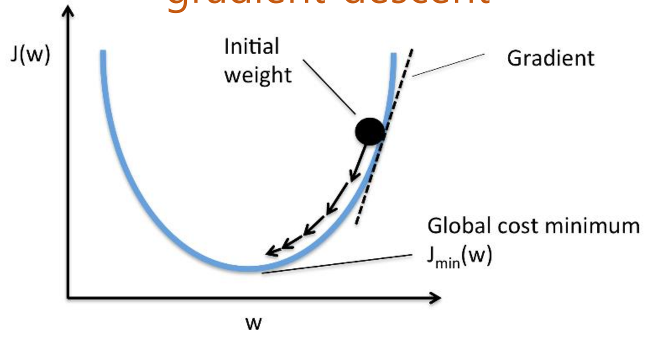


- 이렇게 많은 weight 값들을 어떻게 학습시킬 것인가??

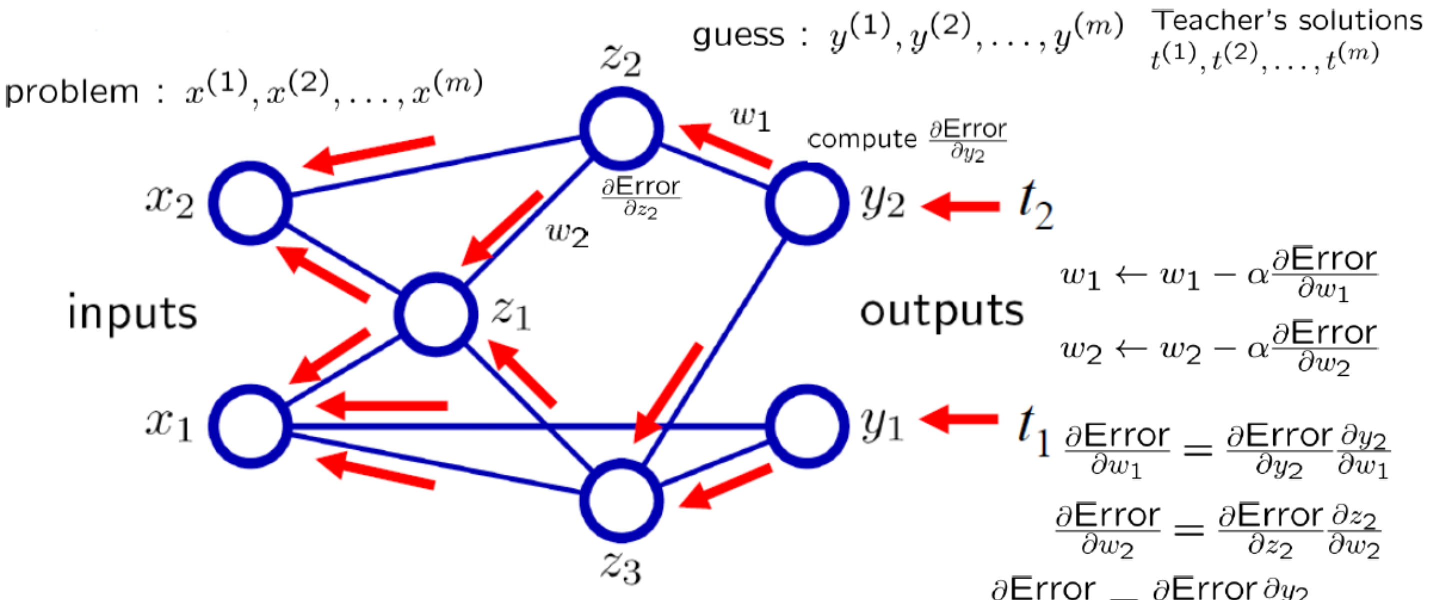
Back Propagation

- 학습과정 : back propagation of error
  - Output layer에서 error(cost)를 계산
  - Error의 미분값을 back propagation
  - 미분값에 α를 곱한 만큼 w를 보정(학습!)
  - α는 learning rate를 의미함

gradient descent



minimize $\text{Error} = \sum_{l=1}^{m} (y^{(l)} - t^{(l)})^2$



$$w_1 \leftarrow w_1 - \alpha \frac{\partial \text{Error}}{\partial w_1}$$

$$w_2 \leftarrow w_2 - \alpha \frac{\partial \text{Error}}{\partial w_2}$$

$$\frac{\partial \text{Error}}{\partial w_1} = \frac{\partial \text{Error}}{\partial y_2} \frac{\partial y_2}{\partial w_1}$$

$$\frac{\partial \text{Error}}{\partial w_2} = \frac{\partial \text{Error}}{\partial z_2} \frac{\partial z_2}{\partial w_2}$$

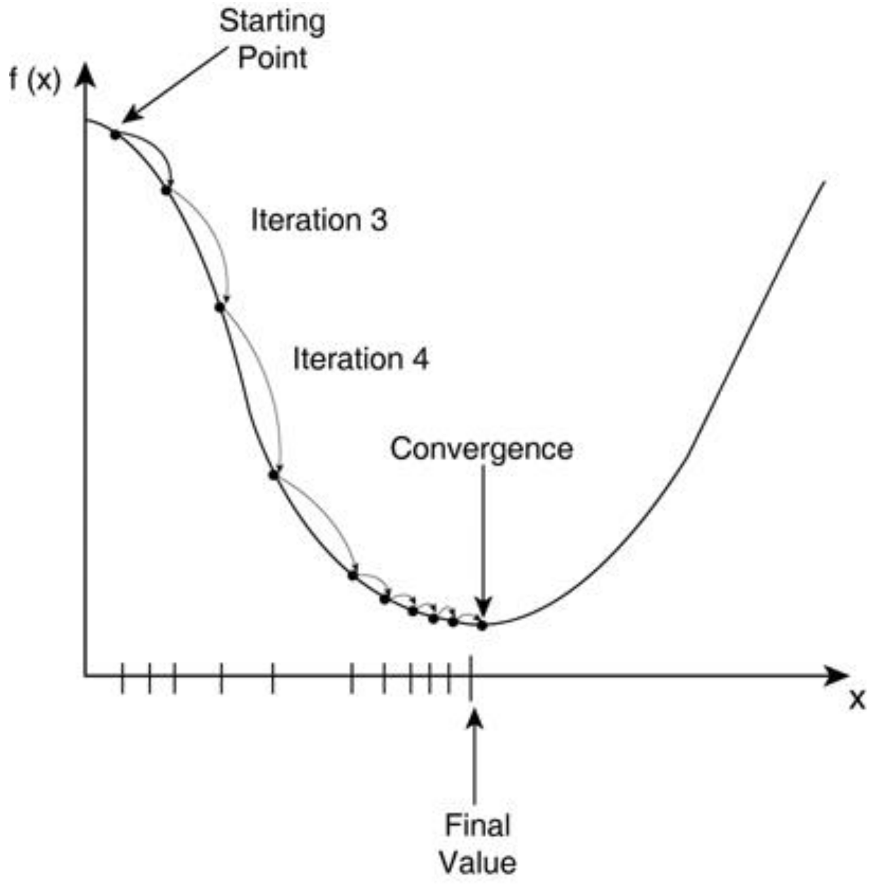
$$\frac{\partial \text{Error}}{\partial z_2} = \frac{\partial \text{Error}}{\partial y_2} \frac{\partial y_2}{\partial z_2}$$

Gradient Descent

- Loss Function 을 W(parameter)로 편미분해서 W에 대한 Gradient를 구한다

- Gradient를 이용해서 W를 업데이트 한다

$$W^* = W - \alpha Loss'(W)$$

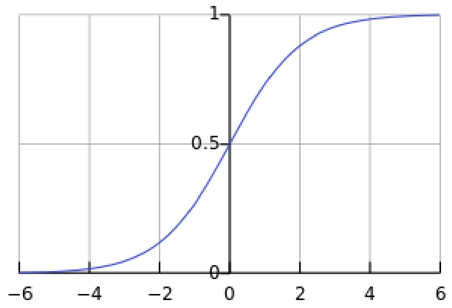


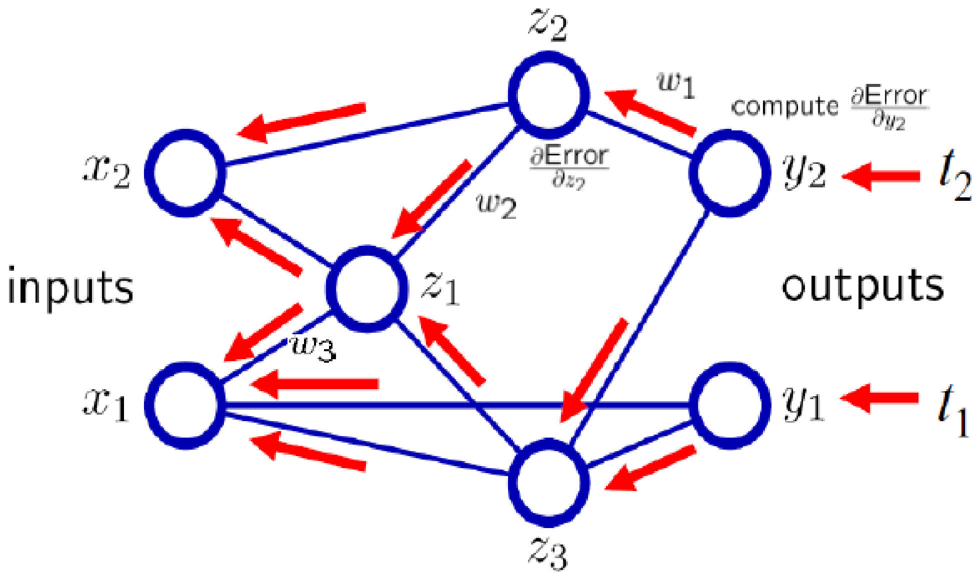
딥러닝을 어렵게 하는 것들

- Vanishing gradient problem
- Overfitting problem
- Get stuck in local minima

Vanishing Gradient Problem

- Gradient 값이 뒤로 전달될 수록 점점 작아짐
- Sigmoid 사용으로 인하여(미분값의 최대 : ¼) 아래쪽 layer는 학습이 이루어지지 않음





$$\frac{\partial \text{Error}}{\partial w_1} = \frac{\partial \text{Error}}{\partial y_2}\frac{\partial y_2}{\partial w_1} = \frac{\partial \text{Error}}{\partial y_2}\sigma'(\cdot)z_2$$

$$\frac{\partial y_2}{\partial w_1} = \sigma'(\cdot)z_2$$

$$\frac{\partial \text{Error}}{\partial w_2} = \frac{\partial \text{Error}}{\partial z_2}\frac{\partial z_2}{\partial w_2} = \frac{\partial \text{Error}}{\partial y_2}\sigma'(\cdot)w_1\sigma'(\cdot)z_1$$

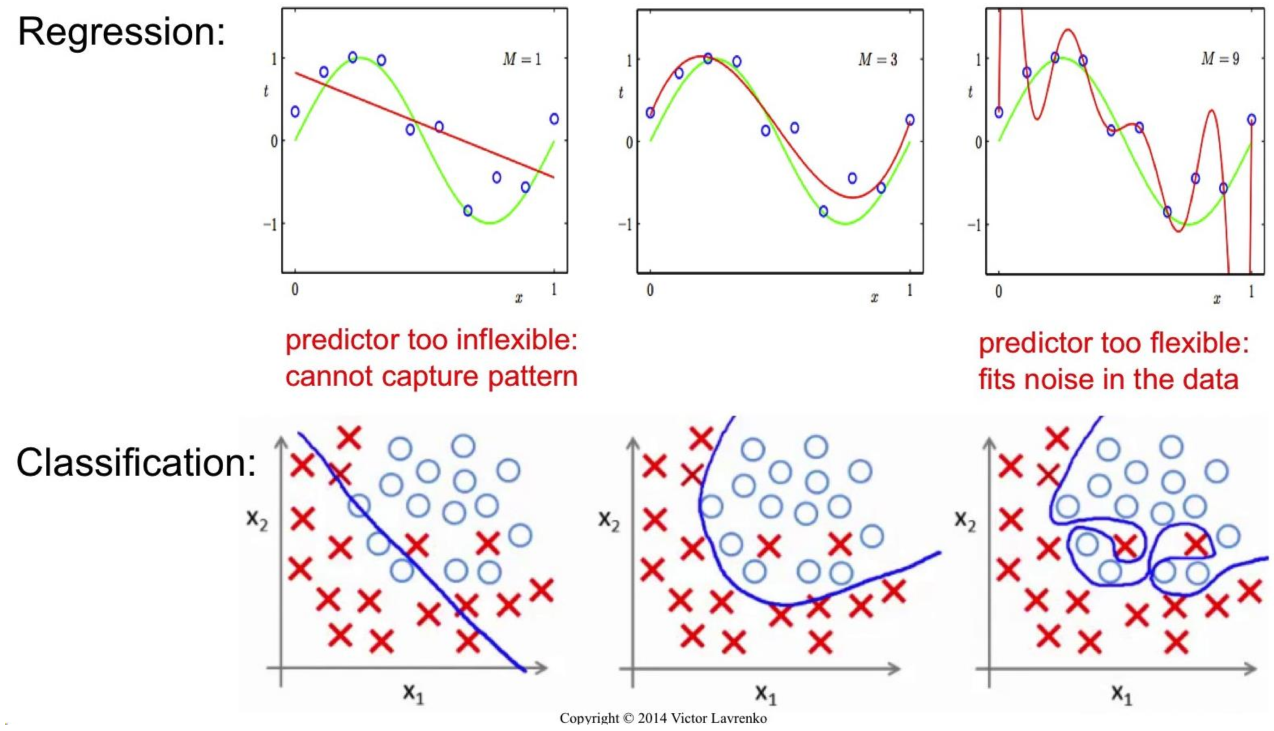
$$\frac{\partial z_2}{\partial w_2} = \sigma'(\cdot)z_1$$

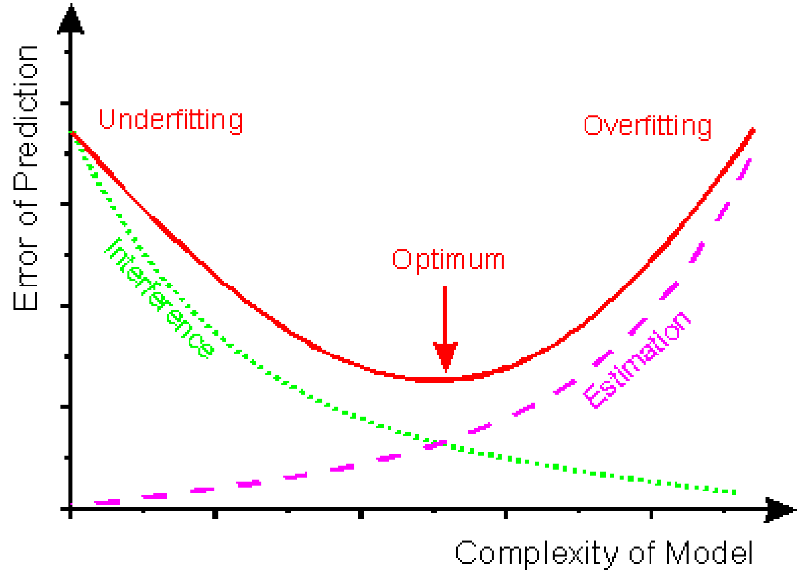
$$\frac{\partial \text{Error}}{\partial w_3} = \sigma'(\cdot)\sigma'(\cdot)\sigma'(\cdot)C$$

$$\sigma'(\cdot) \approx 0$$

Overfitting Problem

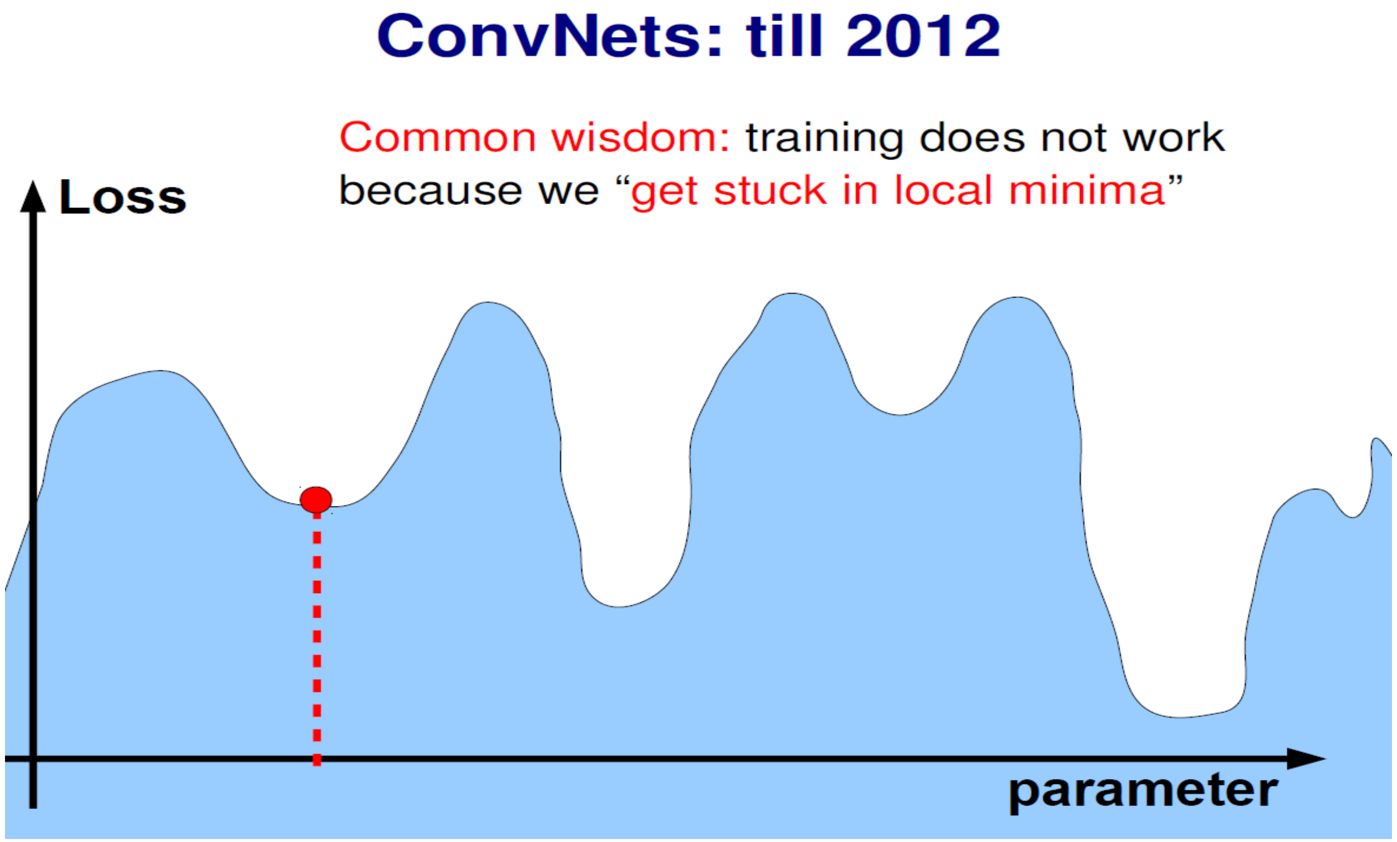
- Data가 많지 않은 경우에 발생할 수 있음
- 학습한 data에만 최적화되어서, 학습하지 않은 data(test data)에 대한 추론 성능이 악화되는 현상





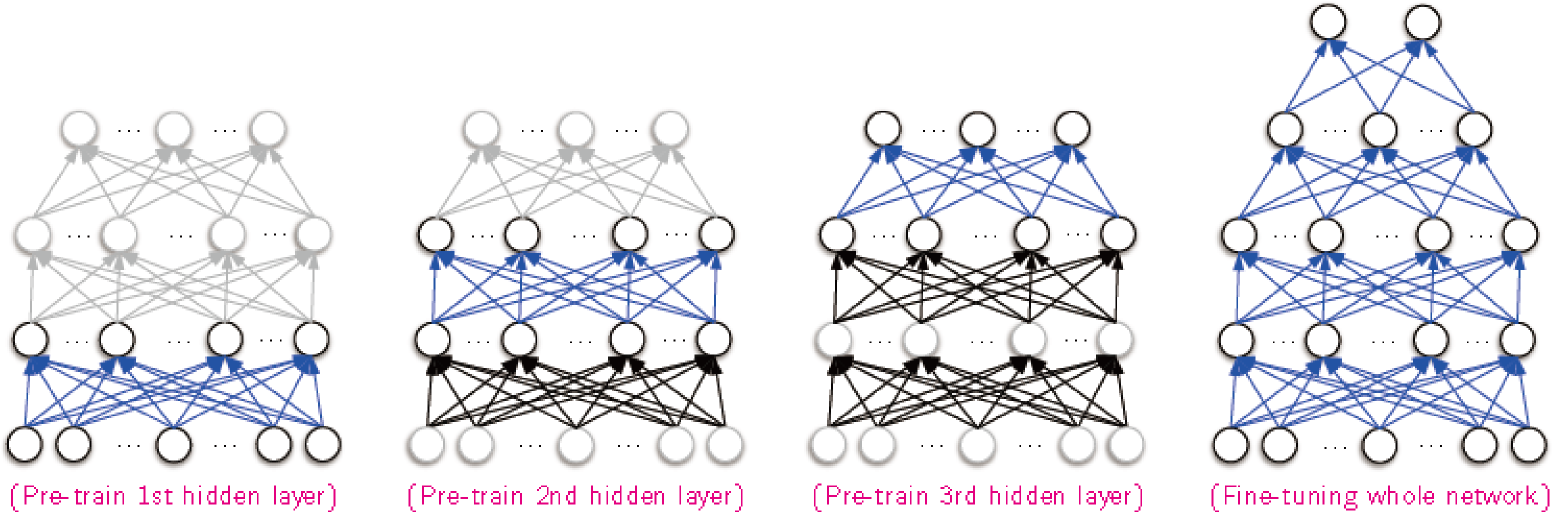
Local Minima

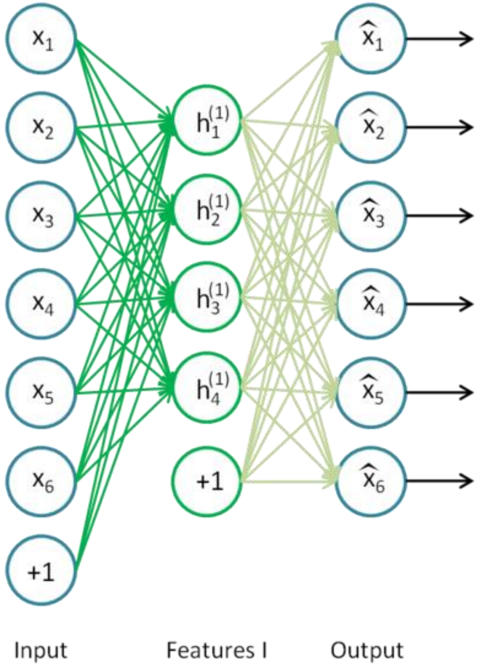
- 어디서 시작하느냐에 따라서 잘못하면 local minima에 빠질 위험이 존재



Deep Belief Network

- Probabilistic generative model
- Deep architecture – multiple layers (stacks of RBMs)
- Greedy layer-wise training algorithm
- Supervised fine-tuning can be applied





Difficulties of Training DNN

- Vanishing gradient problem

  → Solved by bottom-up layerwise unsupervised pre-training
- Typically requires lots of labeled data
- Overfitting problem

  → Solved by using lots of unlabeled data
- Get stuck in local minima(?)

  → Unsupervised pre-training may help the network initialize with good parameters(?)

새로운 방법들

- Vanishing gradient problem

→ Sigmoid 말고 ReLU를 쓰자

- Overfitting problem

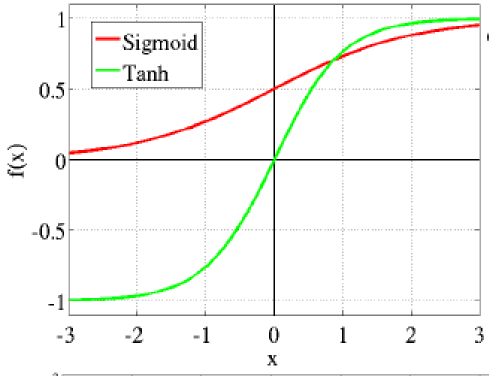
→ Regularization method를 쓰자(예 : dropout)

- Get stuck in local minima

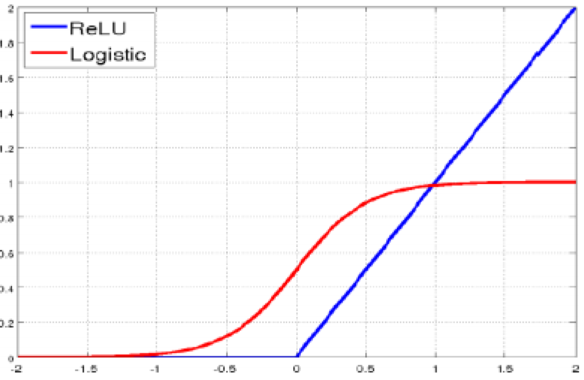
→ Local minima에 빠져도 괜찮다

ReLU : Rectified Linear Unit

- ReLU를 activation function으로 사용 → sparse activation
- ReLU는 미분값이 0 아니면 1 → vanishing gradient 해결

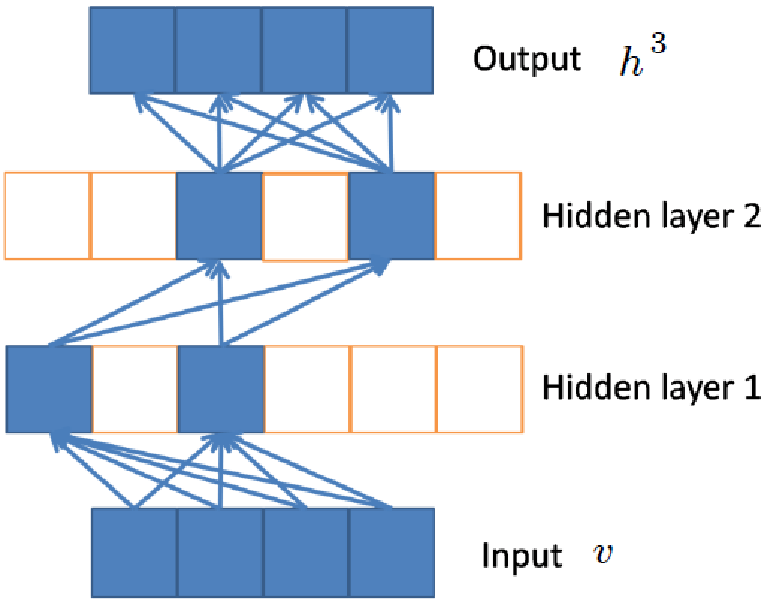


$\sigma'(\cdot) \approx 0$



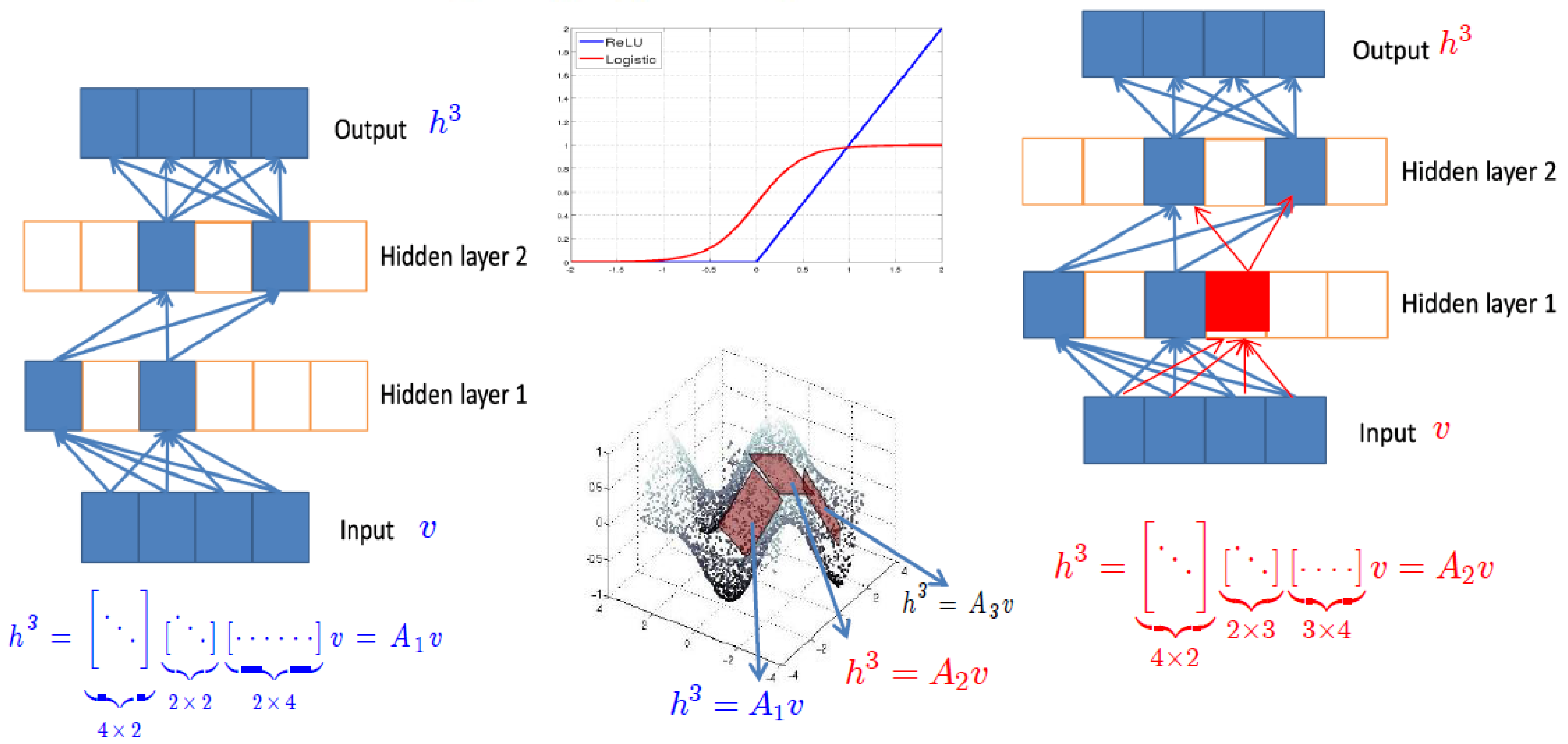
$$f(x) = \begin{cases} x & x \geq 0 \\ 0 & x < 0 \end{cases}$$

slope: 1



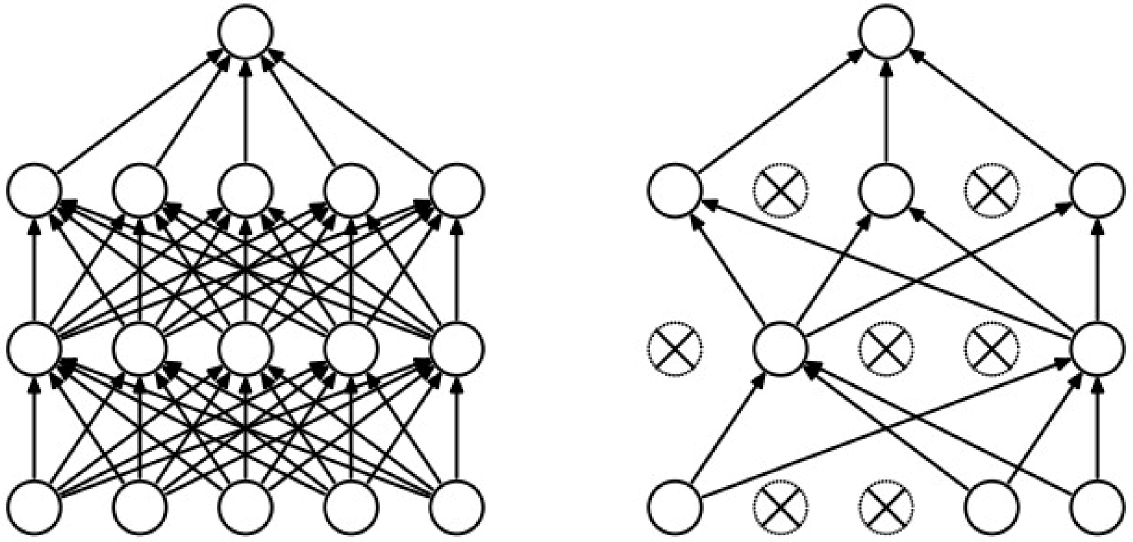
ReLU의 의미

- Piece-wise linear tiling : locally linear mapping



Dropout(Regularization Method)

- 각 학습 단계마다, 특정 확률로(예 : 50%) random하게 hidden layer에 있는 unit들을 없애고 학습하는 방법
- Ensemble 개념을 적용
  - 여러 개의 model을 사용하여 평균값을 쓰면 하나의 model을 쓰는 경우보다 좋음
  - 하나의 model로 비슷한 효과를 낼 수 있는 방법



(a) Standard Neural Net (b) After applying dropout.

Other Regularization Methods

- Weight Decay(L2 Regularization)

$$E(w) = E_0(w) + \boxed{\frac{1}{2}\lambda \sum_i w_i^2}$$

- Batch Normalization
  - Benefits of BN
    - Increase learning rate
    - Remove dropout
    - Reduce L2 weight decay
    - Remove LRN

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1\ldots m}\}$;
Parameters to be learned: γ, β

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

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

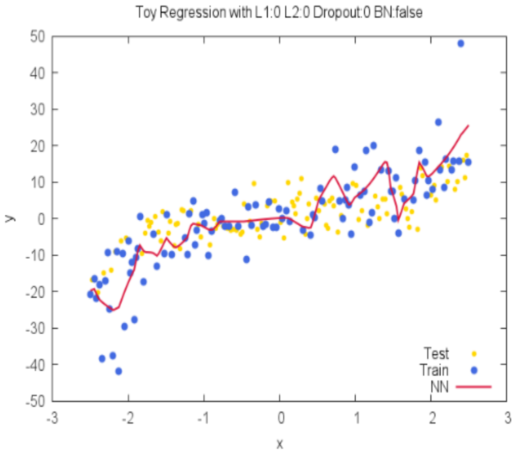
$$\sigma_\mathcal{B}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_\mathcal{B})^2 \qquad \text{// mini-batch variance}$$

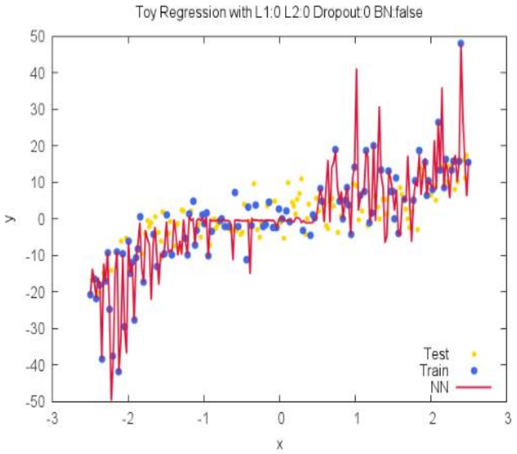
$$\widehat{x}_i \leftarrow \frac{x_i - \mu_\mathcal{B}}{\sqrt{\sigma_\mathcal{B}^2 + \epsilon}} \qquad \text{// normalize}$$

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

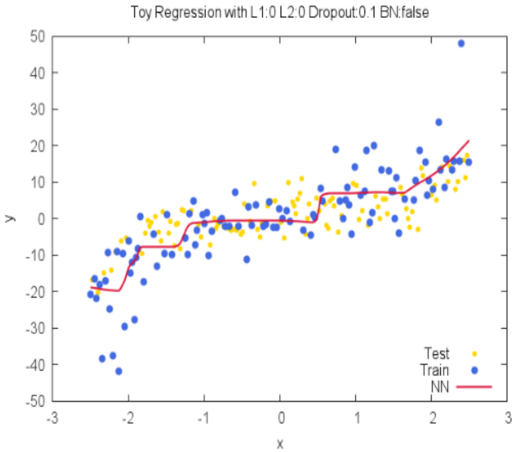
Regularization Methods

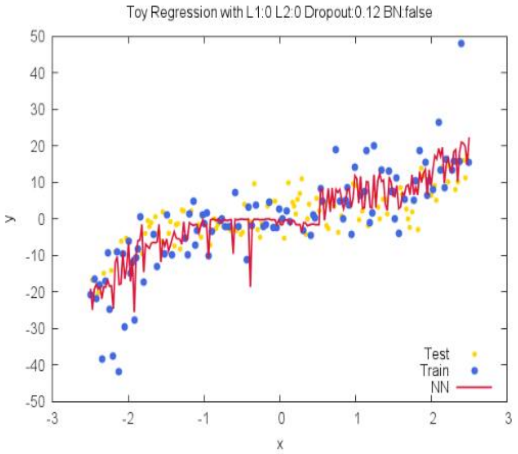
No Regularization



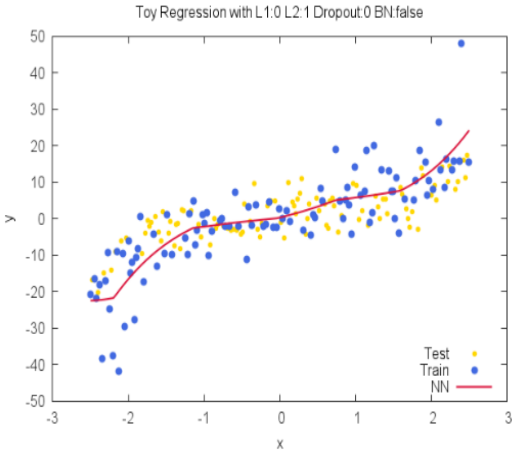


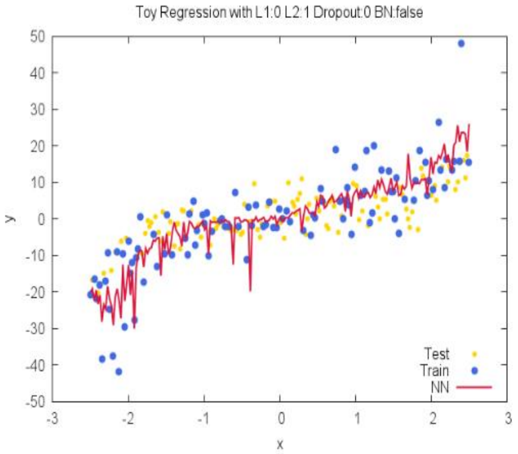
Dropout



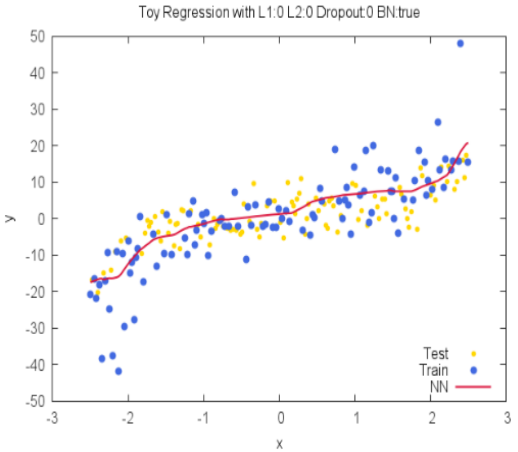


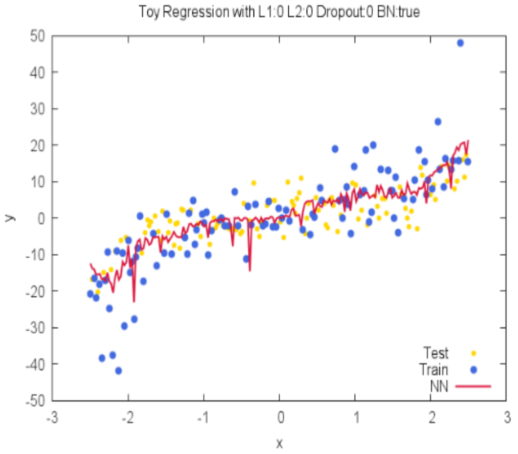
L2 Regularization





Batch Normalization

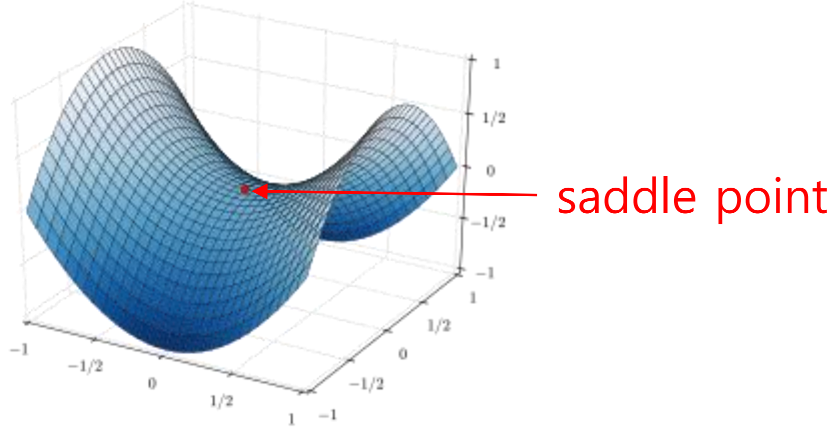


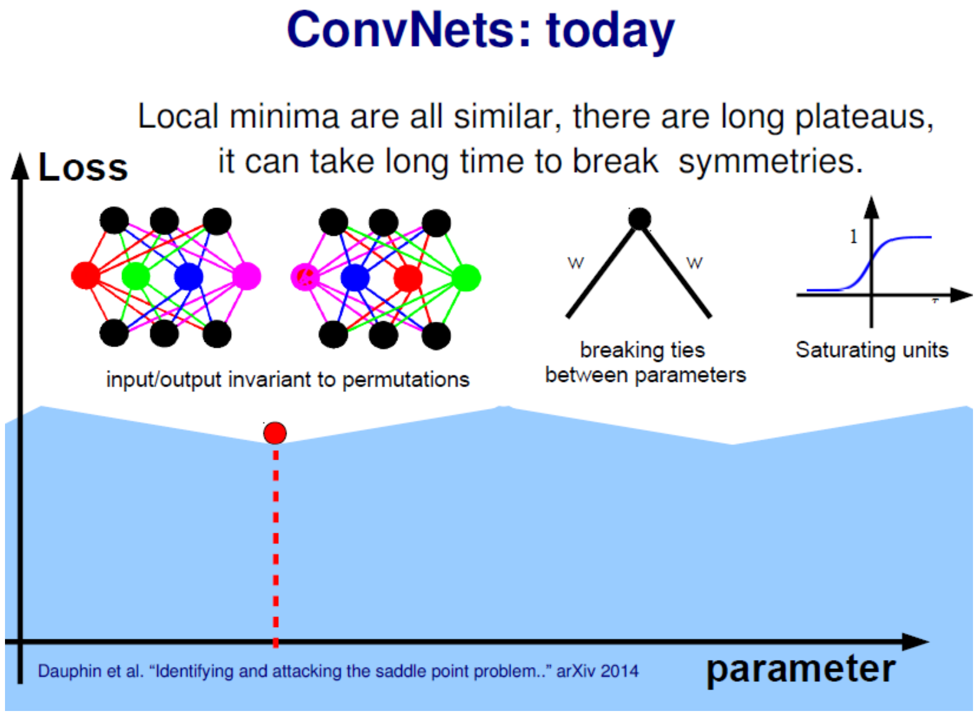


Local Minima

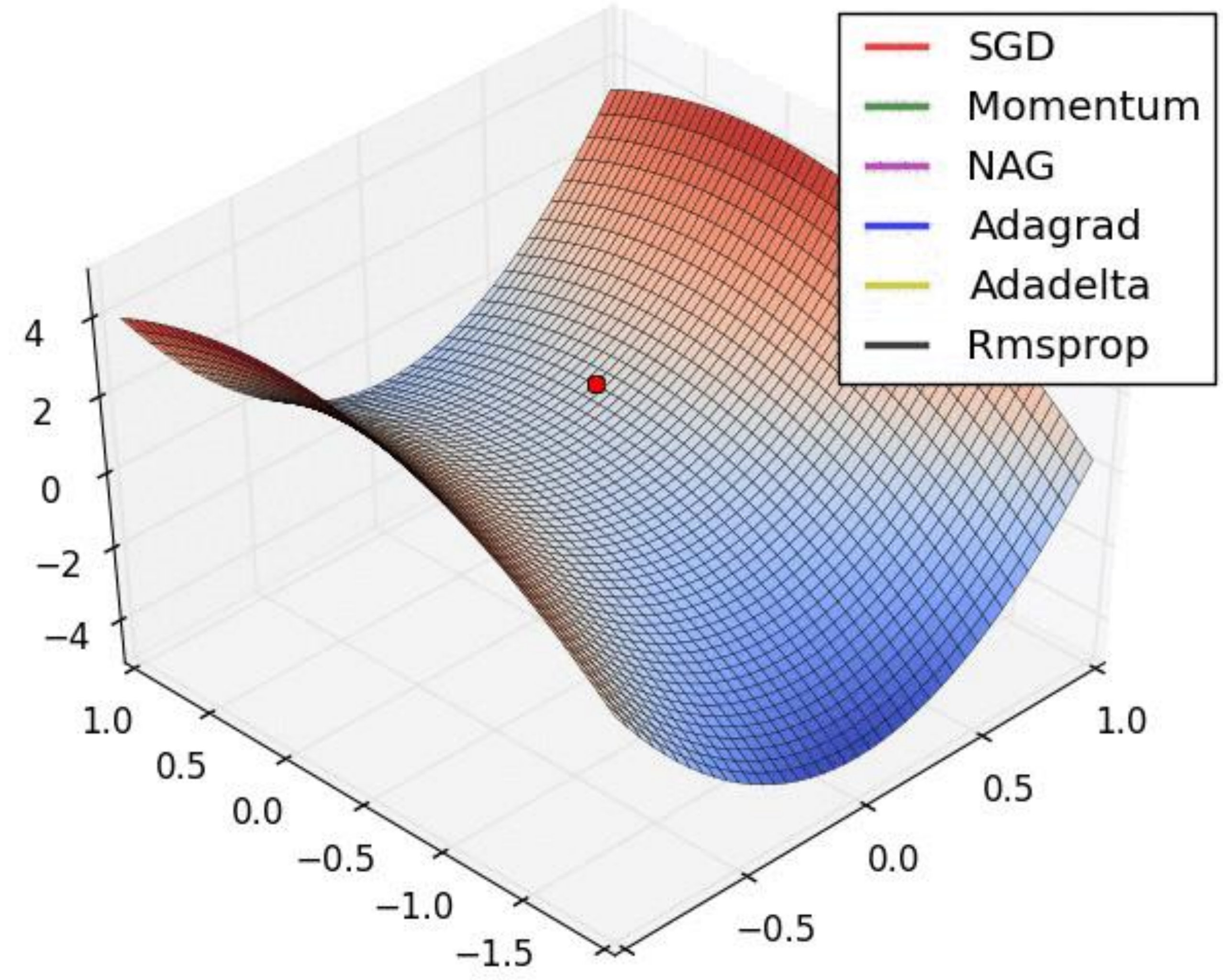
Local Minima에 대하여

- minimum이라고 하는 것은 현재 차원에서 이동할 수 있는 모든 방향으로의 gradient 값이 증가하는 방향이어야 하는데 이런 경우는 확률적으로 희박함
- DNN과 같은 고차원 구조에서는 대부분은 local minima가 아니라 saddle point일 가능성이 높음
- 만약 실제 local minima가 존재한다면 그것은 global minimum과 거의 차이가 없을 가능성이 높음(neural network의 대칭성)





Optimization Methods

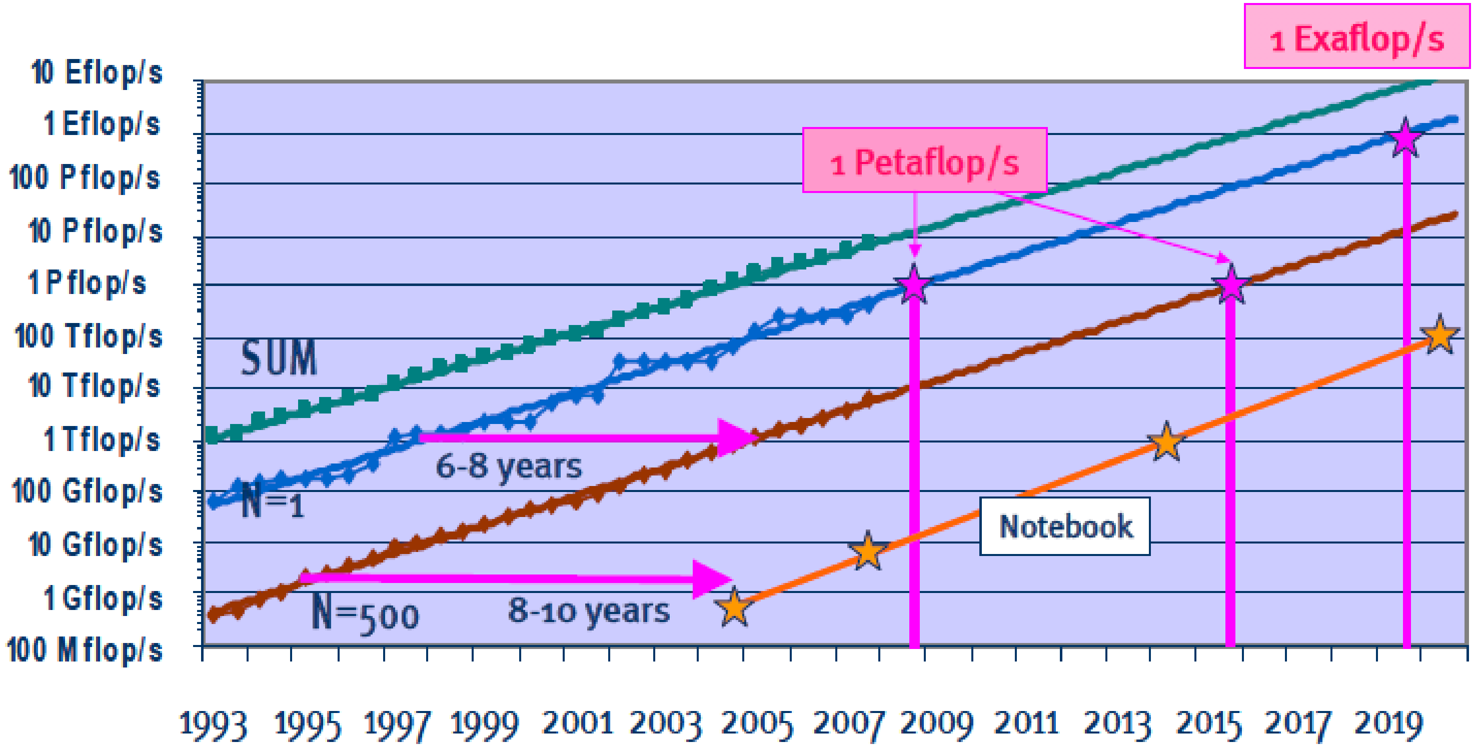


그 밖에 Deep Learning을 가능하게 했던 것들

- Hardware
  - CPUs, GPUs!, ASICs https://youtu.be/-P28LKWTzrI
- Organized Large Datasets
  - ImageNet
- Algorithms and Research
  - Backprop, CNN, LSTM
- Software and Infrastructure
  - Git, AWS, Amazon Mechanical Turk, TensorFlow, …
- Financial Backing of large Companies
  - Google, Facebook, Amazon, …

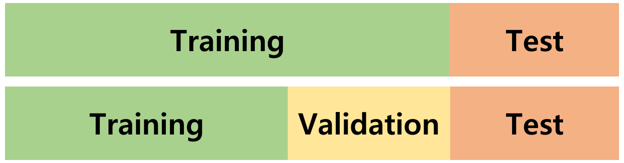
DeepBlue와 AlphaGo

- 1997년 6월 기준, DeepBlue는 세상에서 259번째로 빠른 슈퍼컴퓨터였음
  - Performance = 11.4GFLOPs(Galaxy S8: 375GFLOPs)
- 이세돌과 대결할 당시 AlphaGo는 세계에서 약 500번째로 빠른 컴퓨터였음



어떻게 시작할까?

- Data 준비
- Data를 2 or 3가지로 나눔
  - Training set, Test set
  - Training set, Validation set, Test set

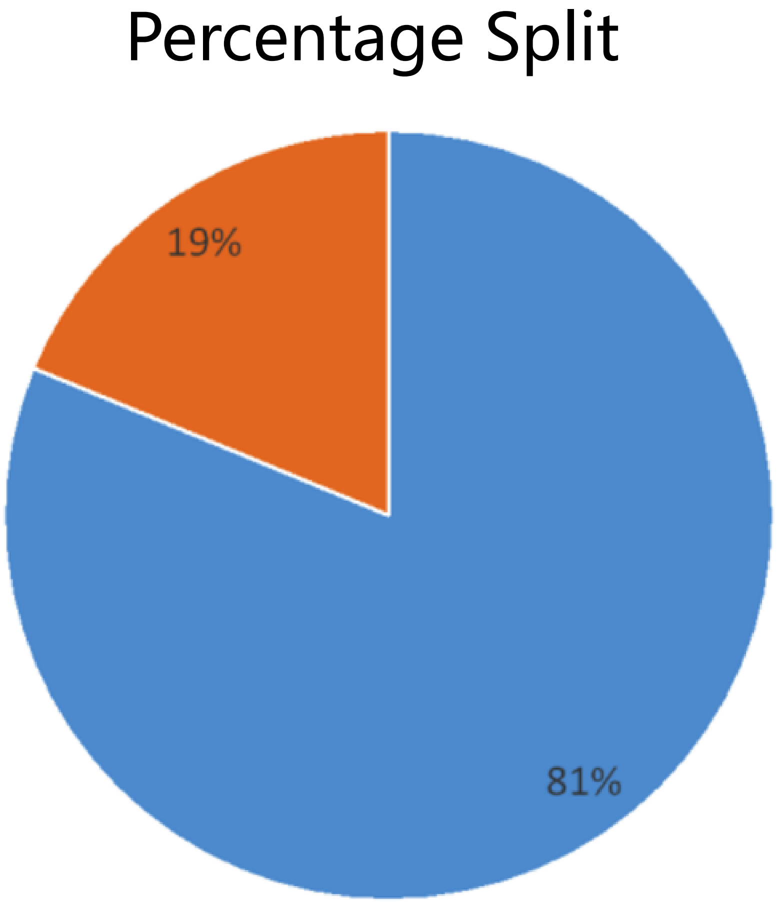


- 어떤 모델(알고리즘)을 사용할 것인지 결정
  - 원하는 output의 형태에 따라
  - Data의 종류와 특성에 따라

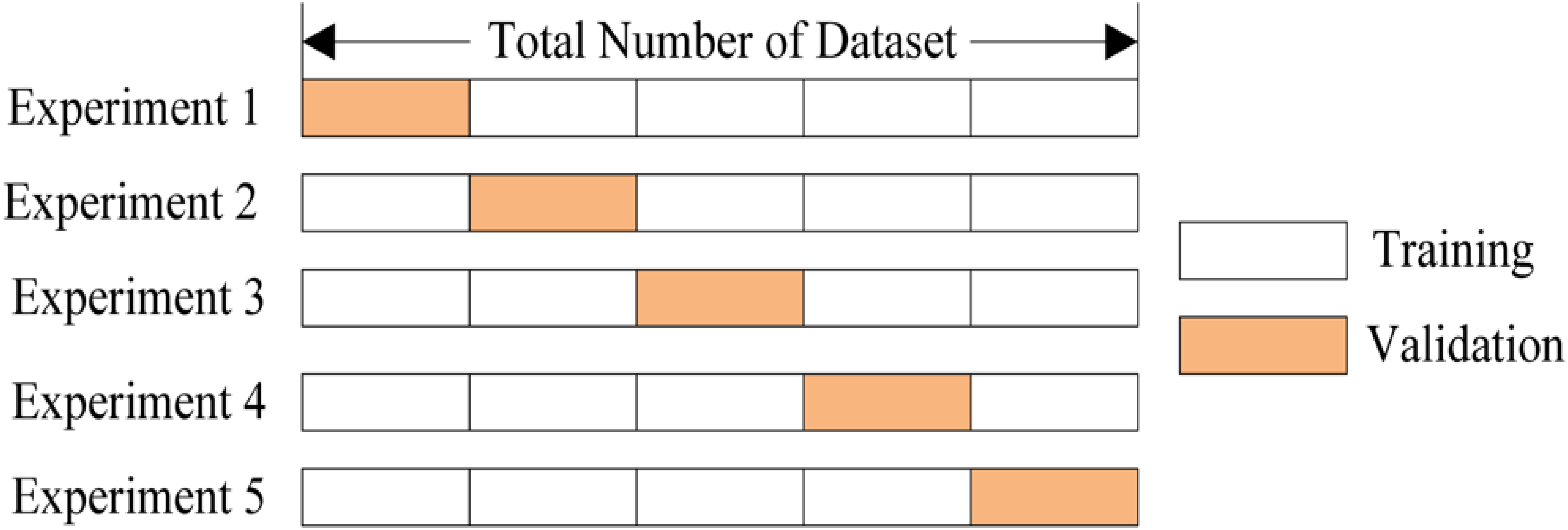
- Training → Tuning(validation) → Test

Validation Dataset

- Problems
  - 모든 data를 학습에 사용하지 못함
  - 해당 split에만 운좋게 잘할 수 있음(overfitting)



Cross-Validation

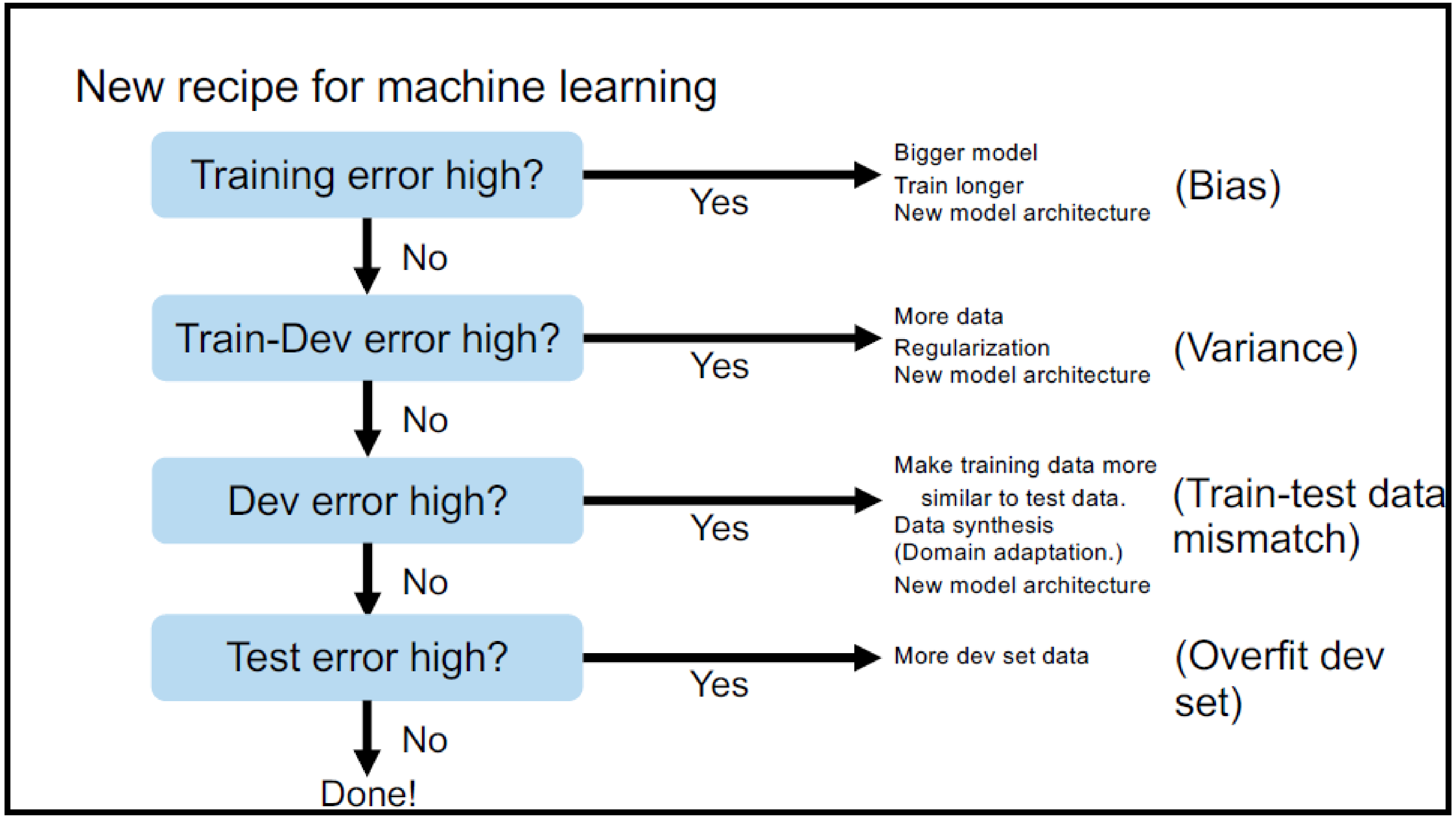


Realistic Problems

- Data
- Measurement
- Result Interpretation

Data

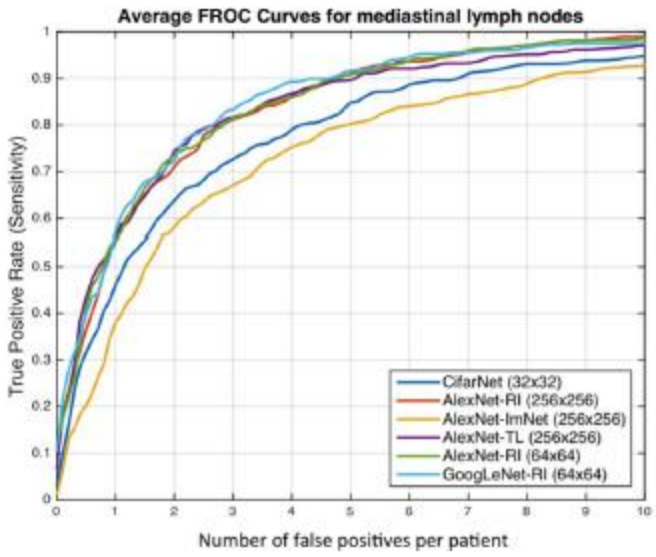
- Data, more data (by Andrew Ng's tutorial @NIPS 2016)

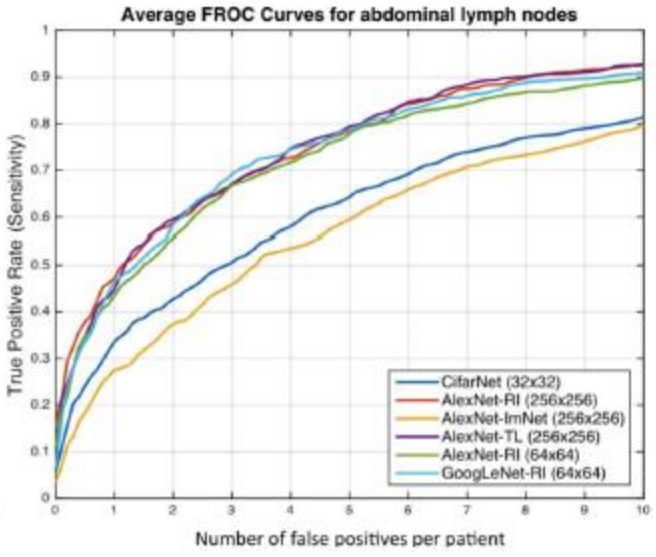


If We Don't Have Enough Data

- Use pre-trained model!
- Transfer learning from other domains
  - Transferred network with 'deep' fine-tuning shows good results

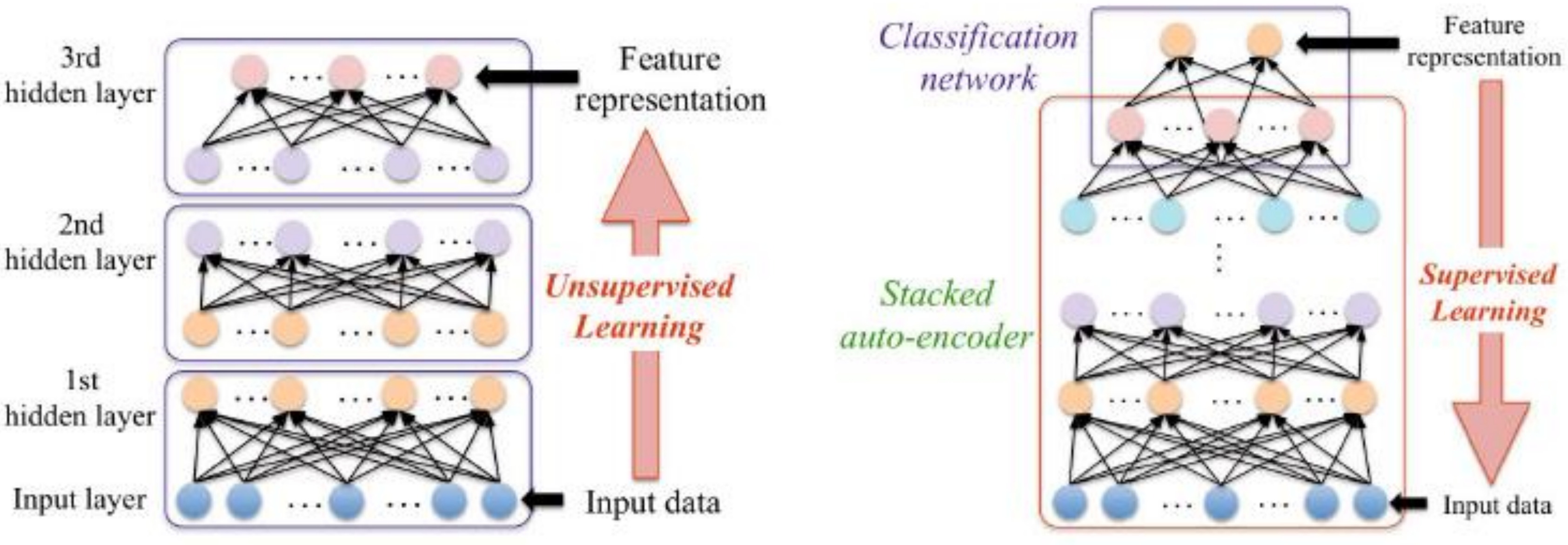
Region	Mediastinum		Abdomen	
Method	AUC	TPR/3FP	AUC	TPR/3FP
[41]	-	0.63	-	0.70
[22]	**0.92**	0.70	**0.94**	**0.83**
[36]	-	**0.78**	-	0.78
CifarNet	0.91	0.70	0.81	0.44
AlexNet-ImNet	0.89	0.63	0.80	0.41
AlexNet-RI-H	0.94	0.79	0.92	0.67
AlexNet-TL-H	0.94	0.81	0.92	0.69
GoogLeNet-RI-H	0.85	0.61	0.80	0.48
GoogLeNet-TL-H	0.94	0.81	**0.92**	**0.70**





If We Don't Have Enough Data

- Unsupervised pre-training and supervised Fine-tuning
  - Unsupervised training of unlabeled data(using auto-encoder) before supervised learning can make good results

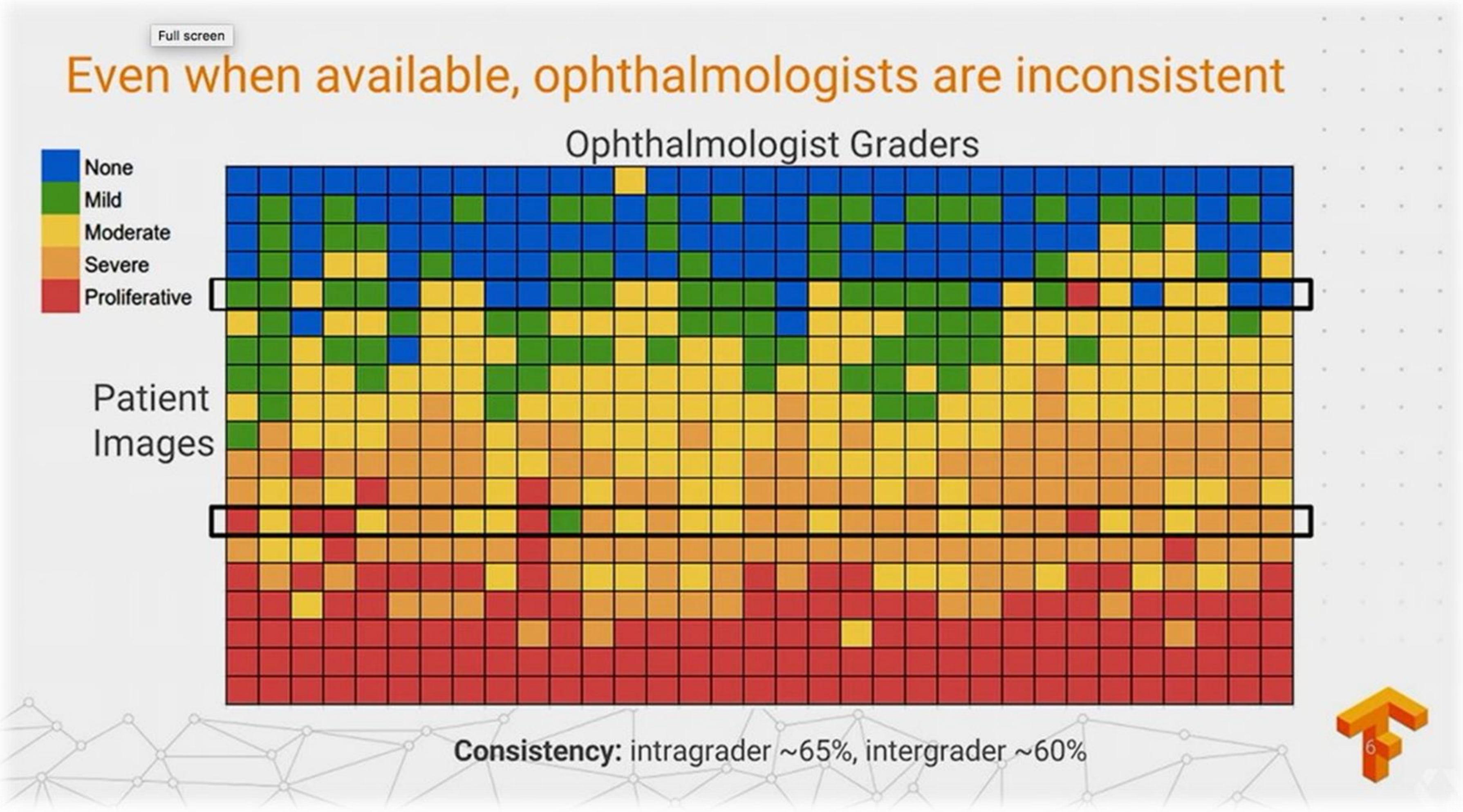


(a) Unsupervised pre-training

(b) Supervised fine-tuning

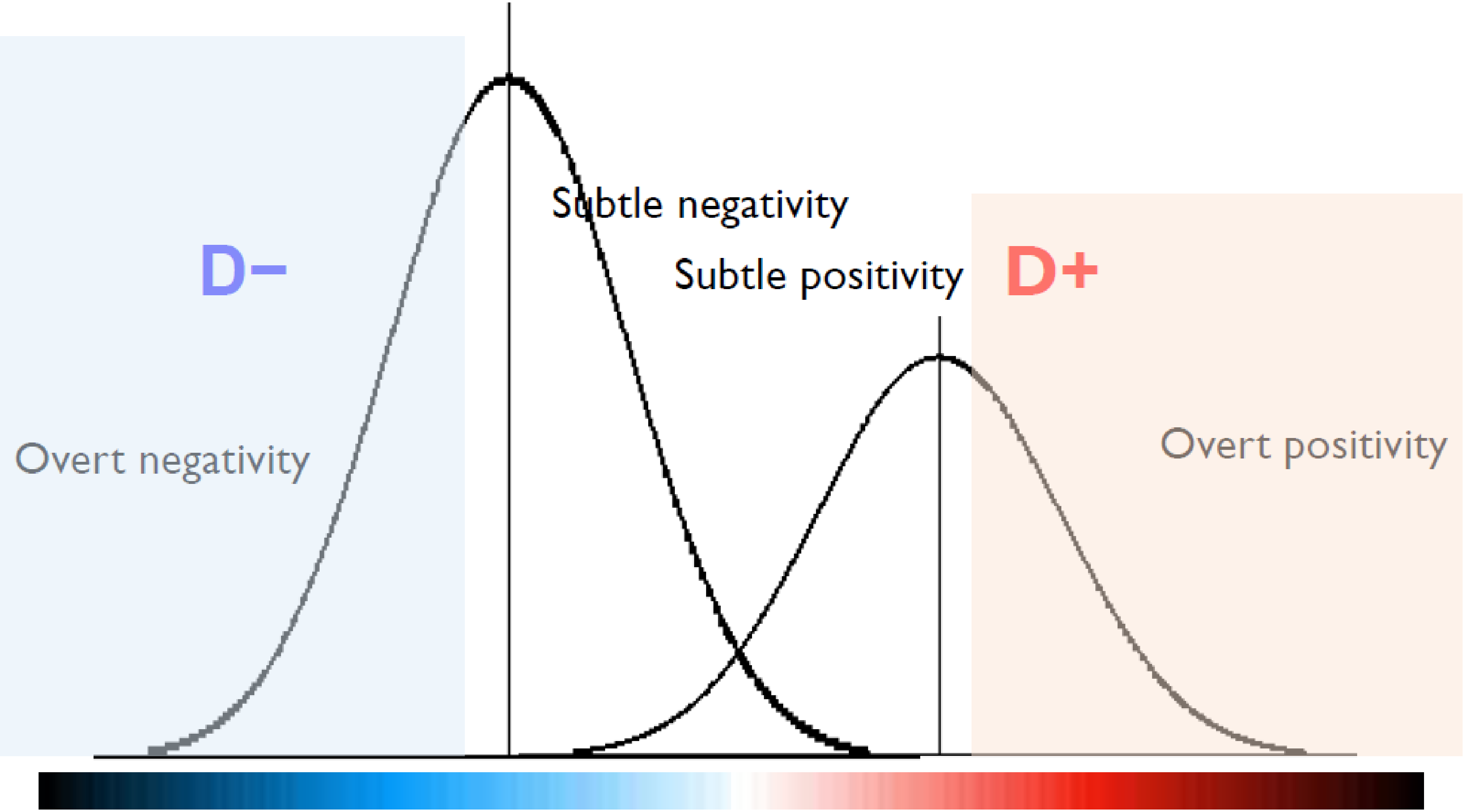
Good Data vs Bad Data

- Our labels are perfect?



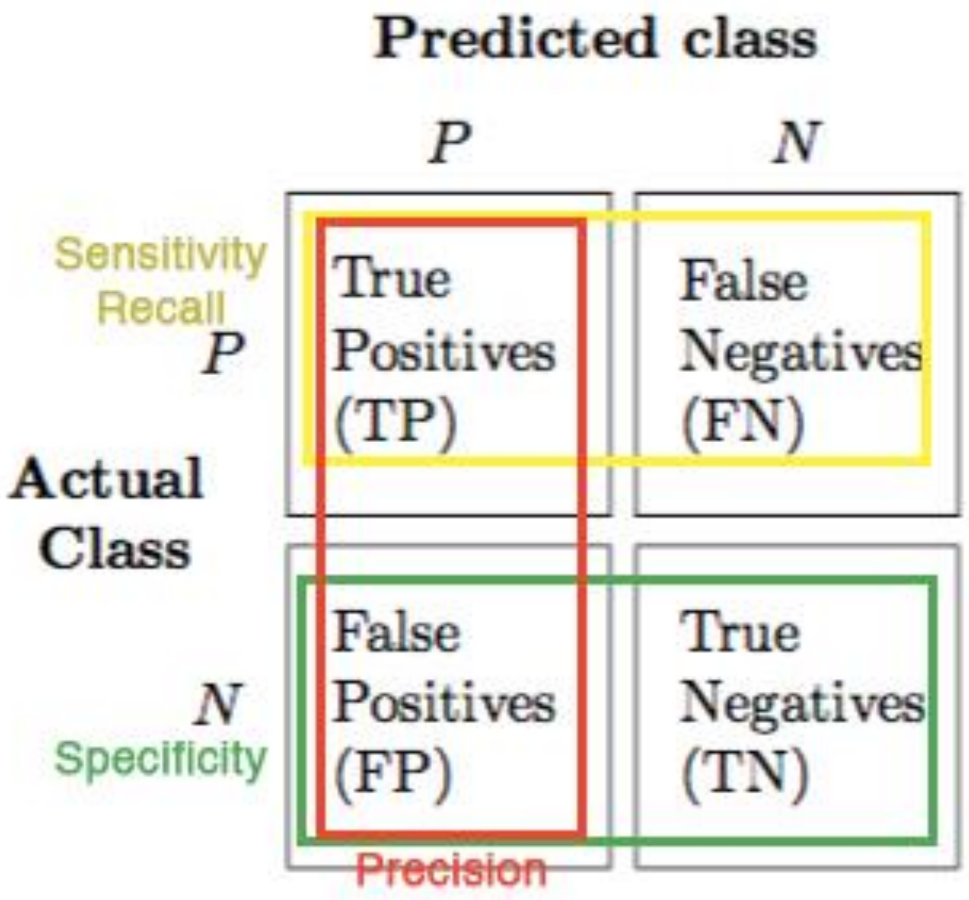
Good Data vs Bad Data

- Our data is unbiased?

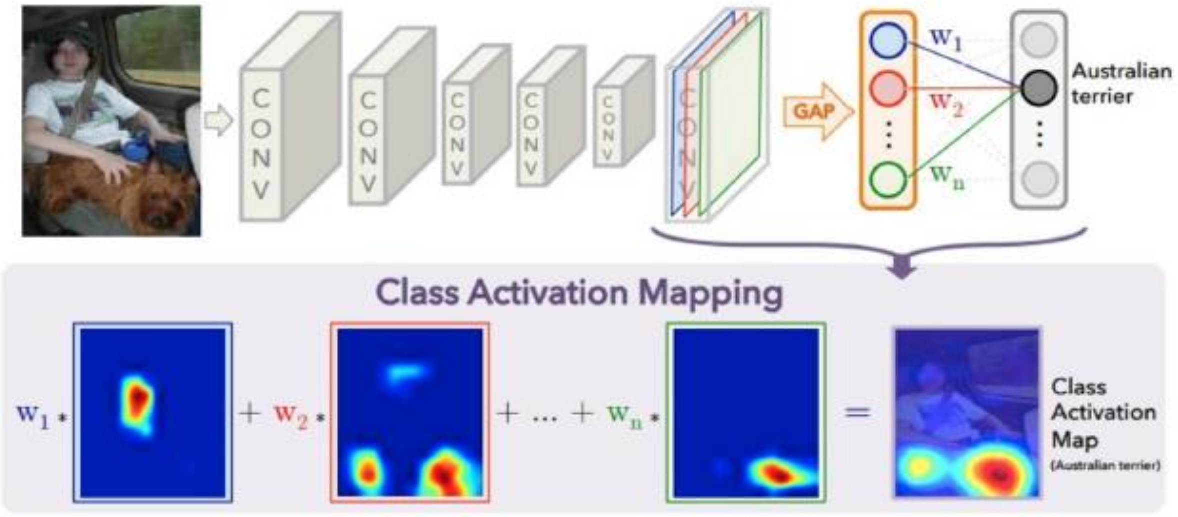


Is Our Model Good Enough?

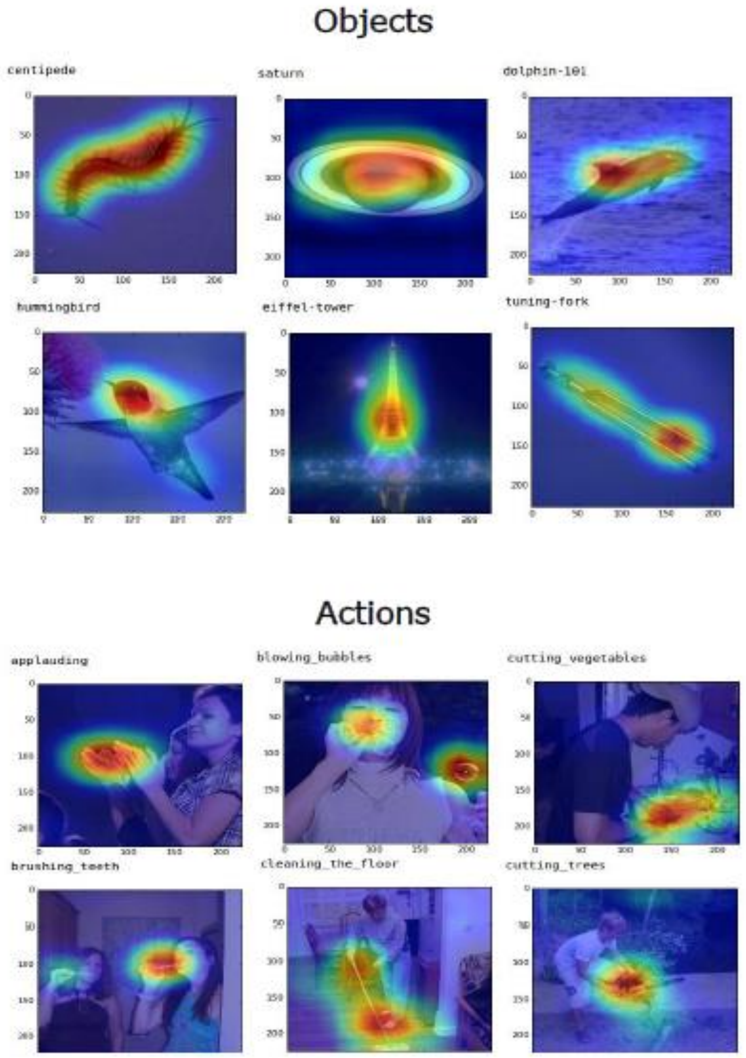
- Sometimes accuracy is not a good measurement



Can we visually interpret the result



B. Zhou et. al., CVPR, 2016



Trends in Deep Learning

- Unsupervised → Supervised → Unsupervised
  - Started from feature learning for other ML
  - Now, supervised learning is main stream
    - ➢ The bigger, more expensive and more complex
    - ➢ SOTA wars
  - Return to unsupervised learning such as GAN at research field
- Single modal research → Multimodal research
  - Image/Video : SOTA
  - Sound : SOTA
  - Text : Near SOTA

  → Combination of the above modalities

Trends in Deep Learning

- Difficult for humans but easy for computers

- Easy for humans but difficult for computers(Now)

- Difficult for humans and difficult for computers

Challenges of Deep Learning

- Extract information from unlabeled data
- Develop a theoretical understanding of neural networks
- Tap into the potential of transfer learning(AGI)
- Scale for distributed big data & optimization for edges

Deep Learning은 만능?

- 동유럽국가 몬테네그로의 수도는 어디인가?
- 바둑판을 1줄씩 늘려서 20x20으로 만들고 지금 당장 이세돌과 알파고가 대결한다면?
- 의료 data를 분석하여, 수명을 예측해봅시다
  - 평생 한번도 담배를 안피운 사람
  - 현재 흡연을 하고 있는 사람
  - 과거에 흡연을 했다가 끊은 사람
- 인공지능은 인류의 지능 향상에 도움이 되는가?
- 인공지능의 능력이 커질수록 법적, 도덕적 문제에 대한 해결이 필요

L'Avion III de Clément Ader, 1897
(Musée du CNAM, Paris)