

1강

AI, 머신러닝, 딥러닝, 어떻게 다를까요?

WHATEVER YOU WANT, MAKE IT REAL.

강사 최윤희

1. AI, 머신러닝, 딥러닝의 차이 이해

2. 머신러닝 Basics

3. 머신러닝 문제의 분류

4. 학습 방법의 분류

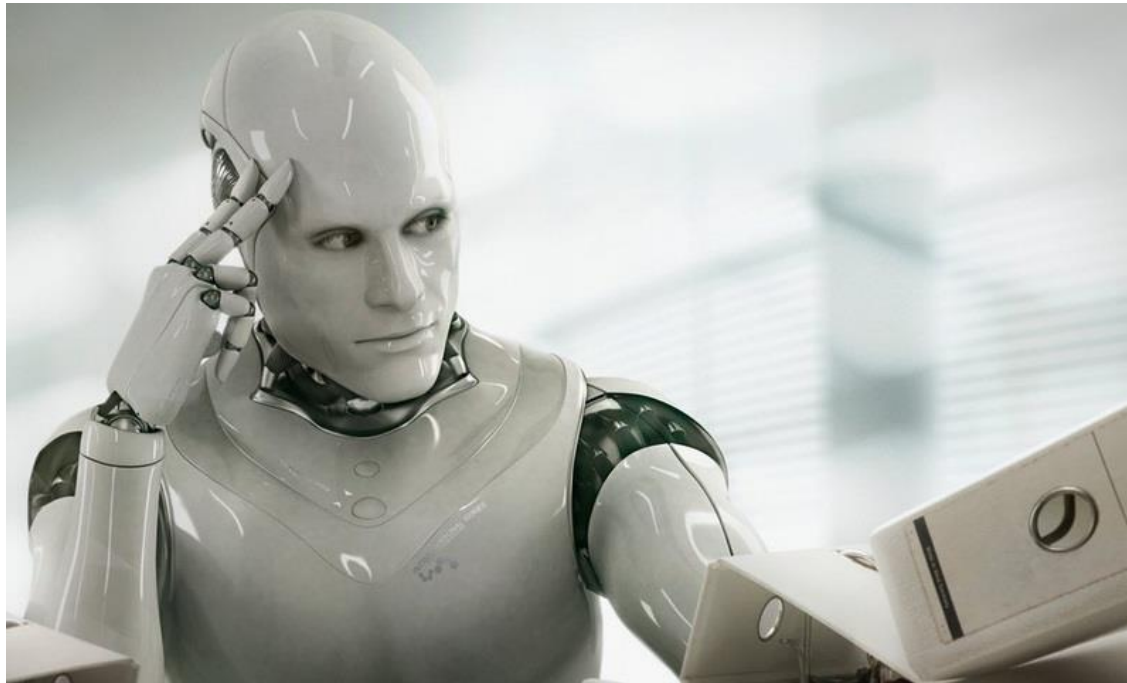
5. (실습) Colab, Python, NumPy 튜토리얼



1. AI, 머신러닝, 딥러닝의 차이 이해



Artificial Intelligence?



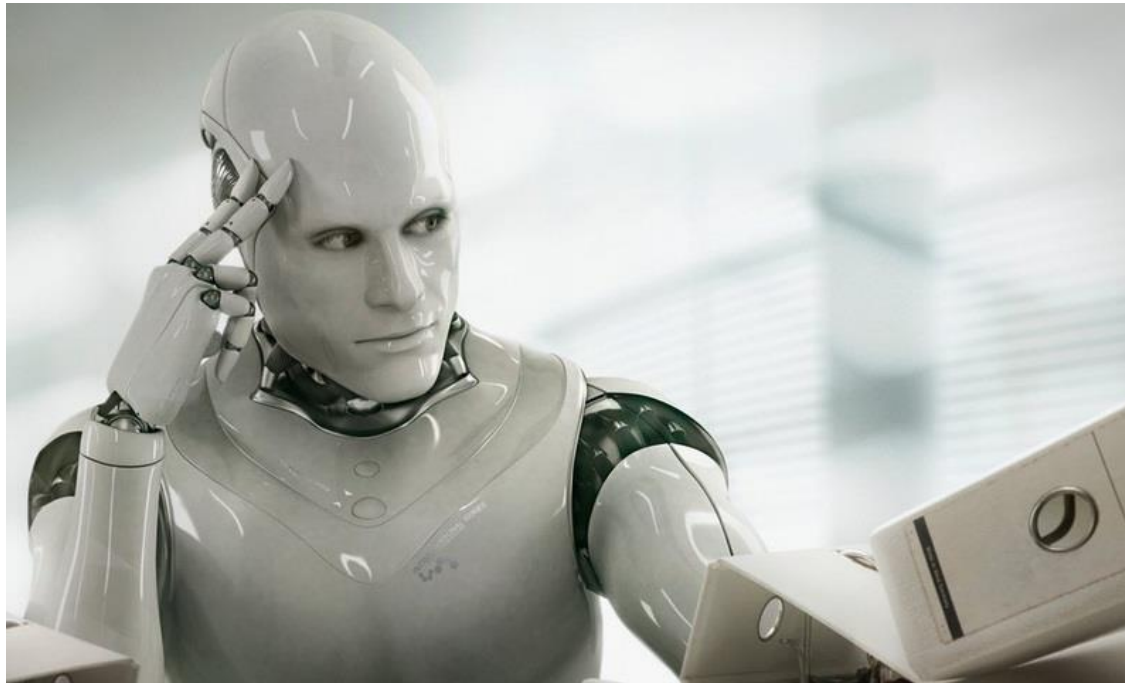
*Thinking Robot – Image by
Blutgruppe/Corbis*



AI \supset Machine Learning \supset Deep Learning

Artificial Intelligence (AI)

Definition: (Wikipedia) Intelligence demonstrated by machine

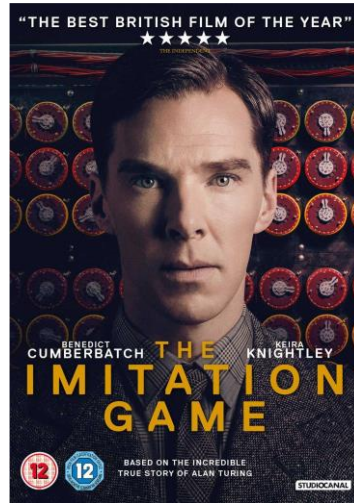
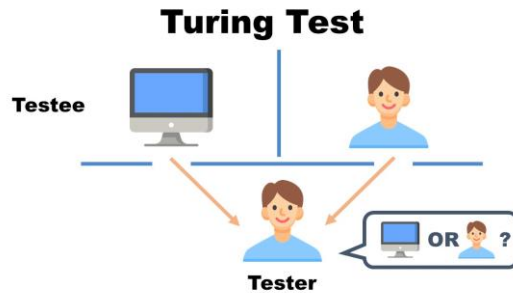


*Thinking Robot – Image by
Blutgruppe/Corbis*

A program that can $\left\{ \begin{array}{l} \text{think} \\ \text{act} \end{array} \right.$ $\left\{ \begin{array}{l} \text{like human.} \\ \text{rationally.} \end{array} \right.$

(Russell & Norvig)

- Acting Humanly



- Thinking Humanly

- Cognitive science
- Theories of internal activities of the brain

- Thinking Rationally

- Laws of Thought
- Logic

- Acting Rationally

- Doing the right thing; which maximizes expected utility.
- Engineering mind-set

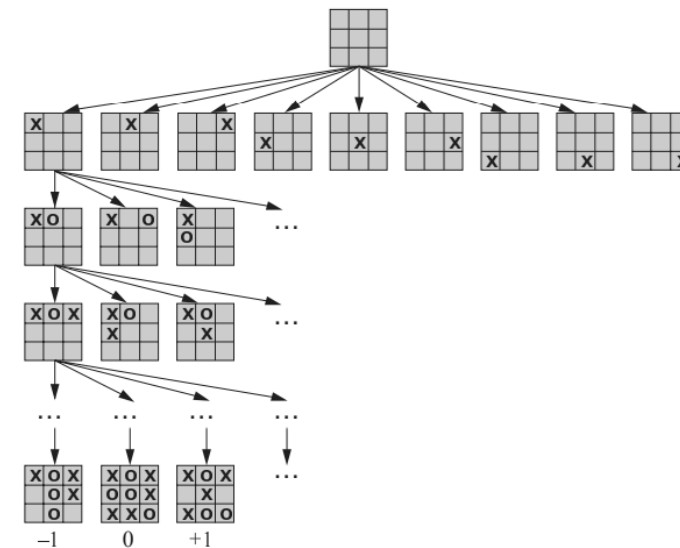
Traditional AI



Avengers: Infinity War, (2018), from IMDb

Traditional AI

- Search Algorithms. ex) IBM Deep Blue
- Propositional Logic
- First-Order Logic
- Planning

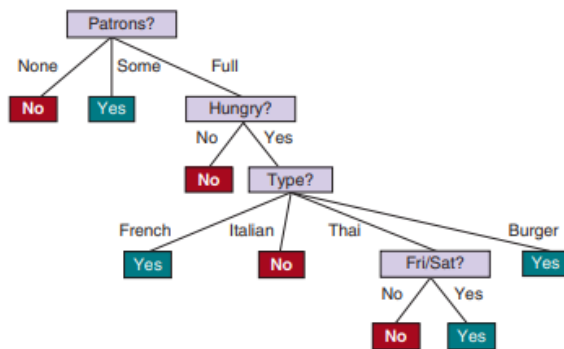
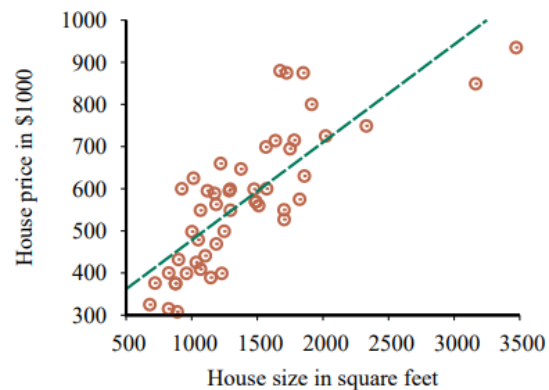


$Init(On(A, Table) \wedge On(B, Table) \wedge On(C, A) \wedge Block(A) \wedge Block(B) \wedge Block(C) \wedge Clear(B) \wedge Clear(C))$
 $Goal(On(A, B) \wedge On(B, C))$
 $Action(Move(b, x, y),$
 Precond: $On(b, x) \wedge Clear(b) \wedge Clear(y) \wedge Block(b) \wedge Block(y)$
 $\wedge (b \neq x) \wedge (b \neq y) \wedge (x \neq y),$
 Effect: $On(b, y) \wedge Clear(x) \wedge \neg On(b, x) \wedge \neg Clear(y))$
 $Action(MoveToTable(b, x),$
 Precond: $On(b, x) \wedge Clear(b) \wedge Block(b) \wedge (b \neq x),$
 Effect: $On(b, Table) \wedge Clear(x) \wedge \neg On(b, x))$



Machine Learning

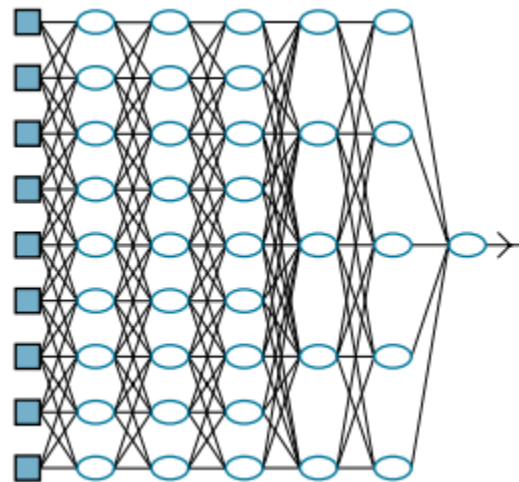
- Limitations of explicit programming
 - ex) 자율주행
- Machine Learning: **Learning from Data**
- Learning: To improve its **performance** on **future tasks** after making **observations** about the world.
- Ex) Linear regression, Decision tree, K-means Clustering
- Its performance improves as they are exposed to more data over time.



source: <http://aima.cs.berkeley.edu/figures.pdf>

Deep Learning

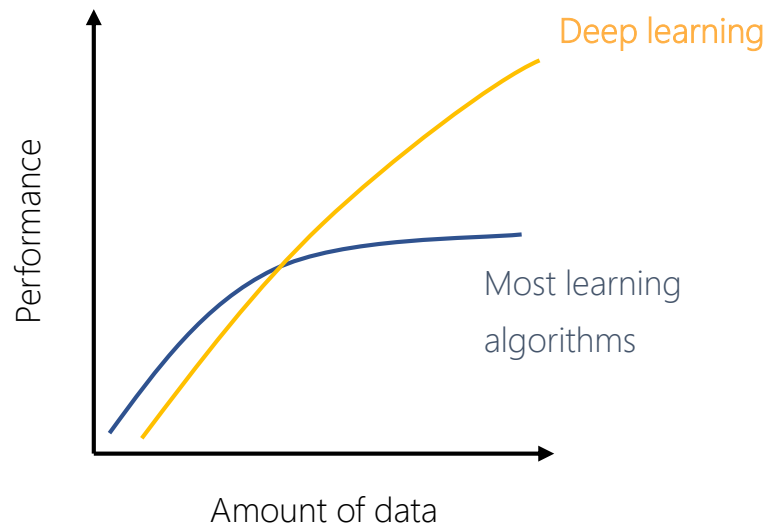
- Deep learning: Hierarchical representation learning
- representation: feature at each layer in neural networks
- Three key components
 - Deep Neural network
 - Big data
 - Hardware: GPU, Memory



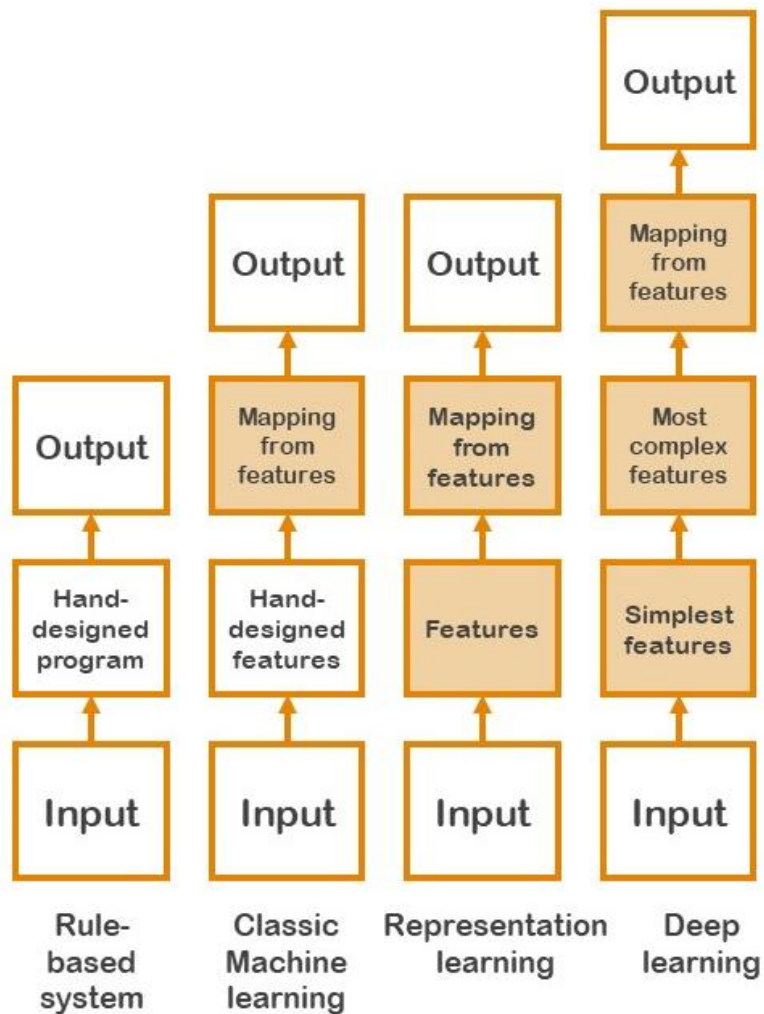
source: <http://aima.cs.berkeley.edu/figures.pdf>

Deep Learning의 현 주소

- 인간 이하의 성능
 - 범용 인공지능
 - 데이터가 귀하고, 전문가에 의존하는 분야. ex) medical
- 인간 수준의 성능
 - 일부 perception 문제: visual / speech recognition
- 인간 이상의 성능
 - Structured big data가 있는 분야. ex) 추천알고리즘
 - 일부 perception 문제, Game play



Wrap-up



Shaded boxes:

데이터로 부터 학습하는 요소



2. 머신러닝 Basics

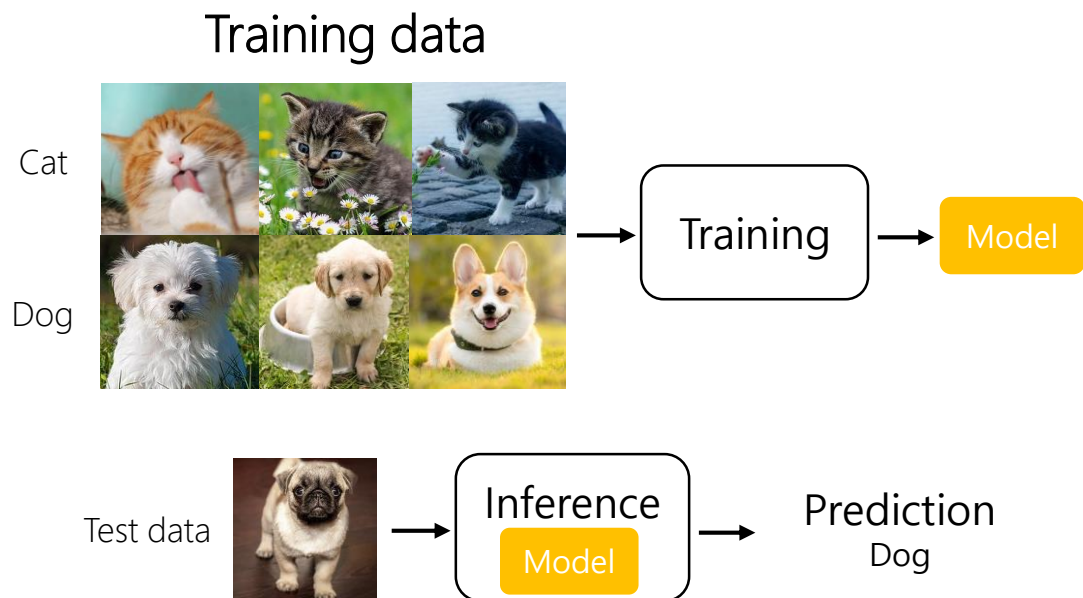


Machine Learning Basics - (1)

- Two steps of machine learning (ML)
 - Training (learning): Fit a model with **training data**.
 - Test (Inference): Apply the trained model with **test data**, measure the **performance**.

- Data set**

- training set: for fitting
- validation set (dev set): for model selection
- test set: for generalization



Machine Learning Basics - (2)

- k-fold cross validation: Useful when the number of training data are not sufficient.
 1. Spilt the data k into k equal subsets.
 2. Perform k rounds of learning:

On each round, 1/k of the data is held out as a test set and the remaining examples are used as training data.
 3. Compute the average test set error of the k rounds.
- Performance measure: Loss function, Task에 따라 다름
 - ex) classification: accuracy or error rate E
 - training/dev/test sets에서 성능 측정 $\rightarrow E_{train}, E_{dev}, E_{test}$

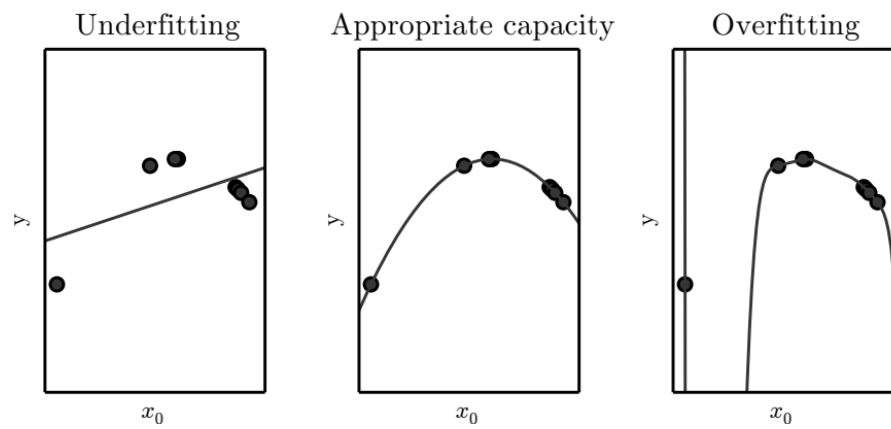
Absolute value loss:	$L_1(y, \hat{y}) = y - \hat{y} $
Squared error loss:	$L_2(y, \hat{y}) = (y - \hat{y})^2$
0/1 loss:	$L_{0/1}(y, \hat{y}) = 0 \text{ if } y = \hat{y}, \text{ else } 1$

Objective of ML

- ML의 목표: Perform well on **unseen** data
 - Generalization error $E_{gen} = 0$ in theory
 - $E_{test} \simeq 0$ in practice
 - Split into two objectives: $E_{train} \simeq 0, E_{test} \simeq E_{train}$
- Objective 1: $E_{train} \simeq 0$
 - optimization, more complex model
 - failure: **underfitting** → **high bias**
- Objective 2: $E_{test} \simeq E_{train}$
 - regularization, more data
 - failure: **overfitting** → **high variance**

How to choose a model?

- Capacity of a Model: The ability of the model to fit various functions
- Choosing a model: Occam's razor
 - Prefer the simplest hypothesis consistent with the data.



source: Goodfellow 2016

A tradeoff in ML

- approximation-generalization tradeoff or bias-variance tradeoff

$$E_{test} \simeq E_{train} \simeq 0$$

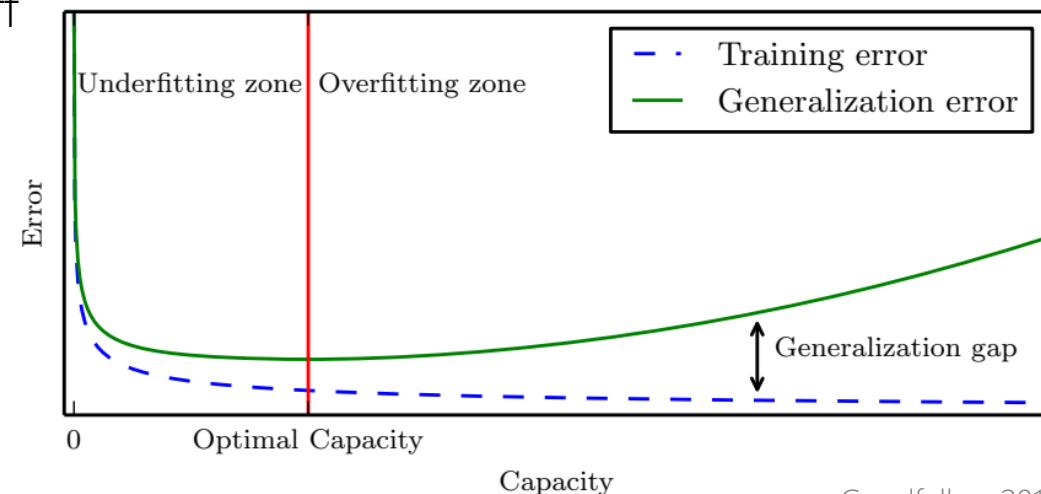
complex model is better

simple model is better

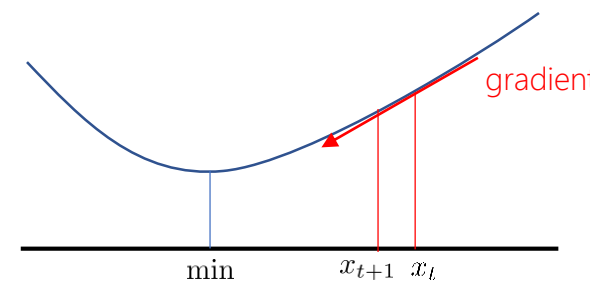
- 해결책:

- optimization: bias reduction (better approximation)
 - finds model parameters that minimize error
- regularization: variance reduction (better generalization)
 - constrains model capacity

- complex model + effective regularization + big data



source: Goodfellow 2016



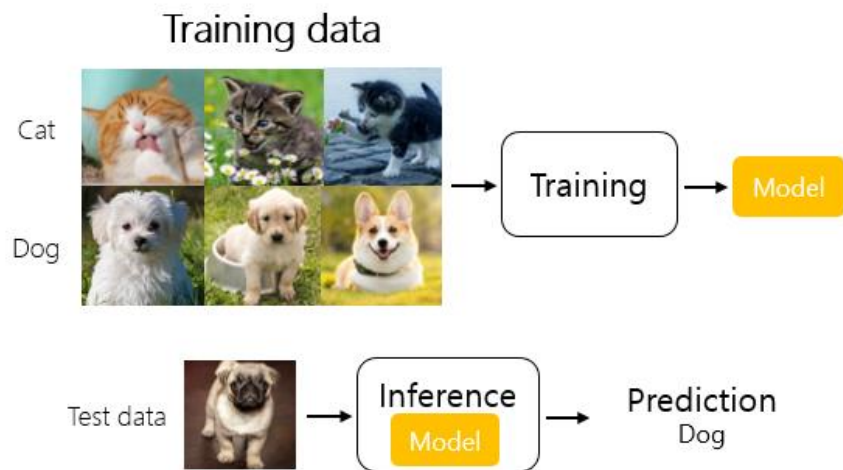
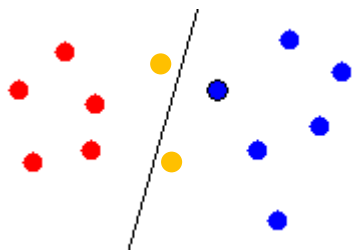
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3. 머신러닝 문제의 분류

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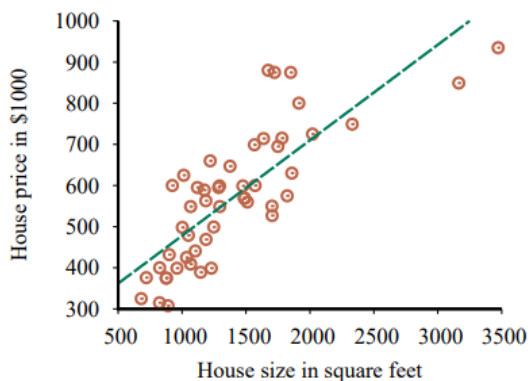
Classification

- Classification
 - Data set: $\{(x_i, y_i): i=1,...,N\}$
 - x_i : input data, y_i : class label
 - Given a new input data, classify its label.

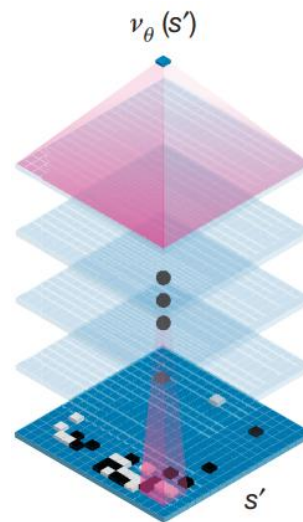


Regression

- Regression
 - Data set: $\{(x_i, y_i): i=1, \dots, N\}$
 - x_i : input data, y_i : output data
 - Given the data set, find a function f such that $f(x_i) \approx y_i$.
- Linear regression, Logistic regression



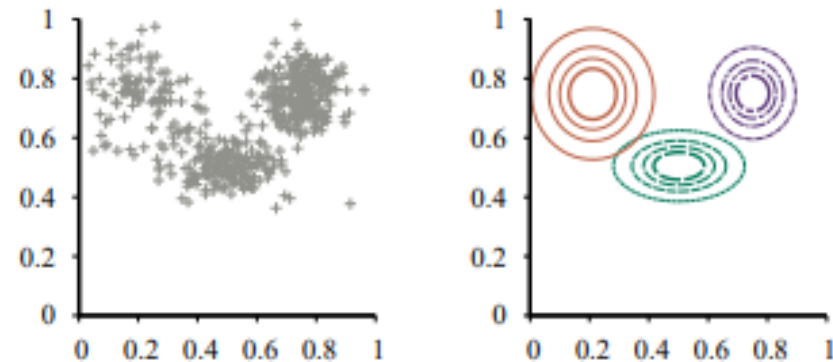
source: <http://aima.cs.berkeley.edu/figures.pdf>



D. Silver, et al., 2016

Density Estimation

- Density Estimation
 - Data set: $\{x_i: i=1, \dots, N\}$
 - x_i : input data
 - Given the data set, find the distribution (or a simpler description) of x_i .



source: <http://aima.cs.berkeley.edu/figures.pdf>

and so on..

- Computer Vision: semantic segmentation, object detection, image generation
- Natural Language Processing: Language Modelling, Machine Translation, Question Answering
- Speech Recognition, Speech Synthesis, Playing Games
- State-of-the-art papers with code
 - <https://paperswithcode.com/sota>

Browse State-of-the-Art

5,443 benchmarks 2,459 tasks 54,640 papers with code



4. 학습 방법의 분류

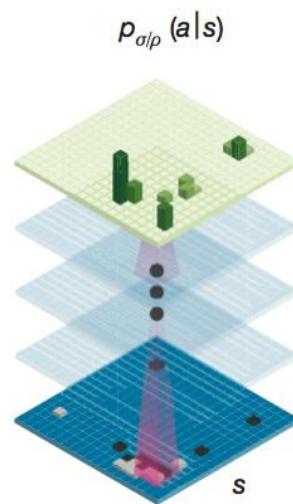


Types of ML

- Training data의 형태에 따라 분류
- Supervised Learning (지도학습)
 - Training with labeled datasets
- Unsupervised Learning (비지도학습)
 - Training with unlabeled datasets
- Reinforcement Learning (강화학습)
 - Learns from a series of reinforcements – rewards or punishments
- Semi-supervised learning, Self-supervised learning

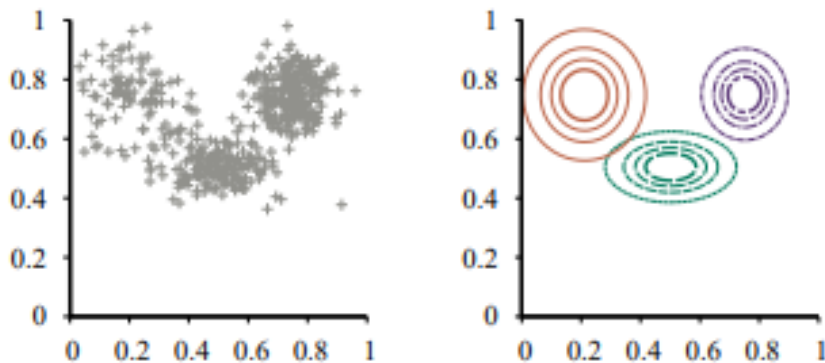
Supervised Learning

- Most common, successful so far
- A **labeled** training set $\{(x_i, y_i): i=1, \dots, N\}$
 - where each y was generated by an unknown function $y = f(x)$
 - discover a function $h \in \mathcal{H}$ (hypothesis) that best approximates the true function.
- Classification, Regression
- Supervision is pricey, but priceless.
- AlphaGo, Siri, Google Translator

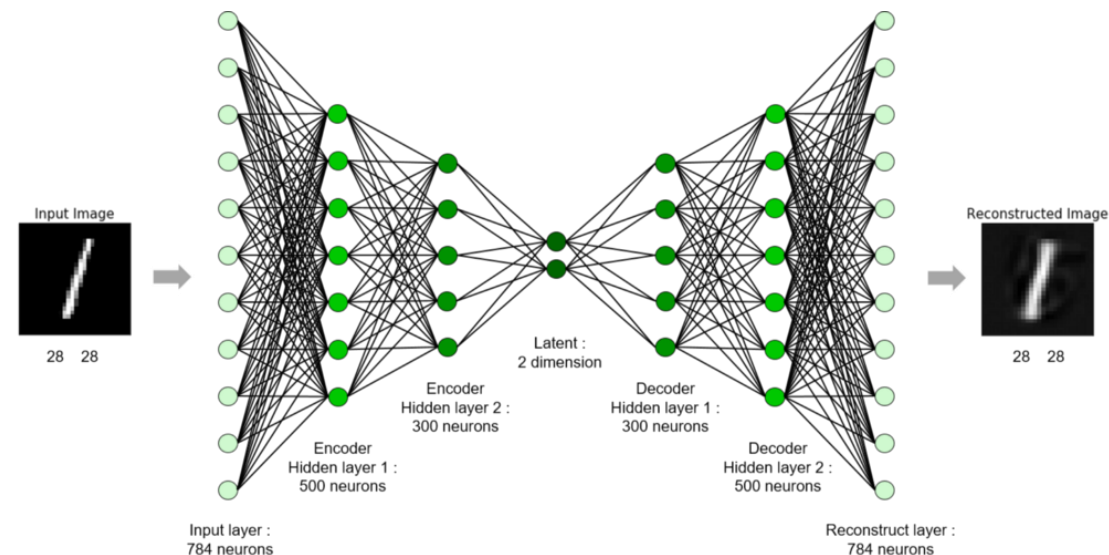


Unsupervised Learning

- An **unlabeled** training set $\{x_i: i=1,...,N\}$
 - Learn patterns in the input data.
- Clustering, Dimensionality reduction (PCA, Autoencoder)
- Lower accuracy
- For pre-training, feature extraction



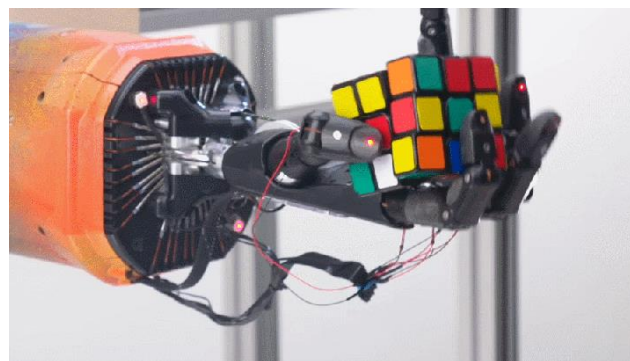
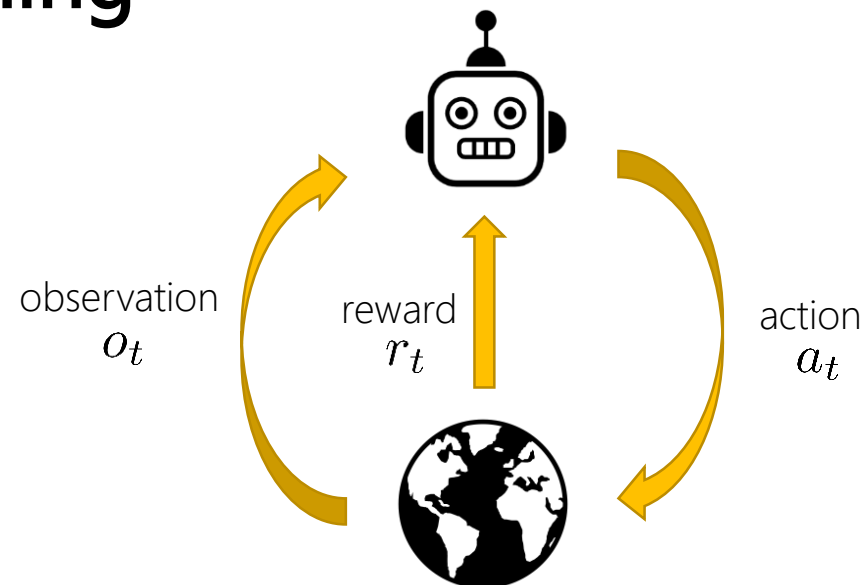
source: <http://aima.cs.berkeley.edu/figures.pdf>



<https://techblog-history-younghunjo1.tistory.com/130>

Reinforcement Learning

- Similar to how a dog learns.
- No supervisor, only a reward signal.
- Sequential decision making
- Playing Go games, Atari games
- Robotics



source: <https://openai.com/blog/solving-rubiks-cube/>



5. (실습) Colab, Python, NumPy 튜토리얼



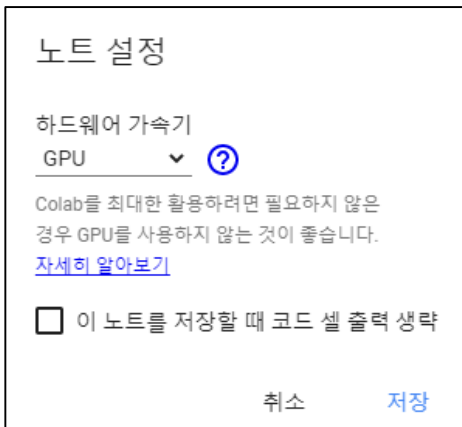
Google Colaboratory

- colab.research.google.com
- Colab \approx Google Drive + Jupyter Notebook
- 브라우저에서 Python을 작성하고 구글 클라우드 서버에서 실행
- 구글 서버의 GPU, TPU까지 무료로 사용!
- Free of 설치 문제: preinstalled packages
- 간편한 공유
- 단, 최대 12시간까지 세션 유지 (Free version)



Google Colaboratory - Tips

- Resources aren't guaranteed.
 - idle for some amount of time or connection time exceeds → Session disconnects.
 - 자주 저장하는 습관!
- GPU 사용
 - 상단 메뉴바의 런타임 → 런타임 유형 변경 → 하드웨어 가속기 GPU로 변경 후 저장
 - 최근에 GPU를 사용한 경우 GPU 할당 우선순위가 밀려나므로 사용하기 직전에 변경 추천



Let's get started!

- [과제 파일](#) 다운로드 후 로컬에서 압축해제
- 자신의 구글 드라이브에 아래의 디렉토리로 두 개의 노트북 파일 및 데이터 폴더 업로드
 - MyDrive/Colab Notebooks/Lab 1-1. Python, Numpy.ipynb
 - MyDrive/Colab Notebooks/Lab 1-2. Linear Regression.ipynb
 - MyDrive/Colab Notebooks/data