CoE202 Fundamentals of Artificial intelligence <Big Data Analysis and Machine Learning>

Introduction

Prof. Young-Gyu Yoon School of EE, KAIST

KAIST EE

Neuro-Instrumentation &

Instructor & TAs

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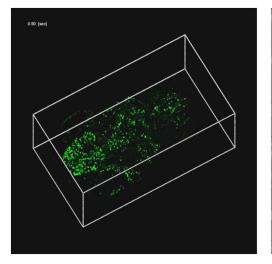
TA office hour: to be announced

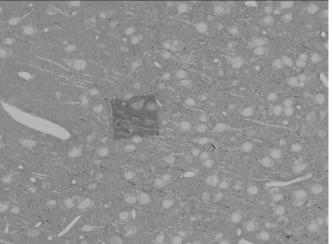
Instructor: Young-Gyu Yoon

- B.S. KAIST
- M.S. KAIST
 - Advised by Prof. SeongHwan Cho
 - Mixed-signal circuit (analog-to-digital converter design)
- Ph.D. MIT
 - · Advised by Prof. Ed Boyden
 - Neuro-engineering (brain imaging & brain image analysis)
- Research engineer @ KAIST Institute
- Postdoc @ MIT
- Assistant professor @ KAIST

Instructor: Young-Gyu Yoon

- Principal investigator of Neuro-Instrumentation and Computational Analysis (NICA) Lab
 - Develop technologies for reverse-engineering a brain as a circuit
- Research Area





Contents

- Course logistics
- Course overview
 - Introduction to circuit engineering
 - Intended learning outcomes
 - Course topics

Course logistics

- Class website
 - Basics of Artificial Intelligence<Big data analyse and machine learning> CoE202(A) @ http://klms.kaist.ac.kr
 - Lecture notes & materials will be posted
- Class hours
 - 16:00AM 17:30PM (Tue/Thu)

- Class room
 - Online lecture (zoom)

Course logistics

- Midterm Exam
 - Two hours (Midterm)
 - Open book
 - No electronic device allowed
- Assignments
 - 3 programming assignments
 - Submit your iPython Notebook
- Final project
 - 1 final project (no final exam!)
 - Submit your report & iPython Notebook
 - Implementing your own neural network

Course logistics

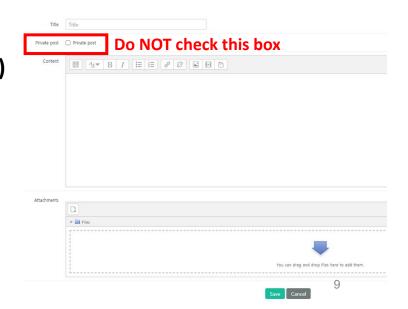
- Grading
 - Assignments (30%), Midterm exam (30%), Final exam (30%), Class participation (10%)
 - Grading 'may' be separately done for two groups
 - Group A: 3rd (or higher) year EE & CS students
 - Group B: other students
- Class participation
 - Attendance
 - In-class participation

Syllabus

CoE202 Q&A

- 1. Please Make your questions public, not private.
- 2. Please Use Q&A board @ KLMS, not e-mail.

We will not reply to private questions unless the question is 100% personal (e.g., claim)



CoE202 Q&A rules

- 1Please follow simple form for Title.
 - 1. [homework name, code name, Lecture name] short summary
 - 1. [HW1] typo at load mat function
 - 2. [note06.ipynb] Model does not converge
 - 3. [Week 5] Backpropagation implementation
- 2. Specify well. Upload your code snippet, environment and results so that we can help you efficiently.
- Check others' question. You can get answer or hint. Please do not make duplicate question.

전기 및 전자공학부 학업 윤리 규정 제정 시행



- 올바른 학업 윤리의식 함양 및 건전한 면학 분위기 확립
- 윤리위반행위에 대한 경각심 고취를 통한 윤리위반행위 사전 예방
- 윤리위반행위 발생 시 체계적인 대응 및 재발방지



- 각 수업에서 허용하는 수업자료의 공유 및 참고 정책 사전 공지
- 정책 위반 행위 발생 시 규정에 명시된 절차에 따라 EE 학생 윤리 위원회에서 관련 조사/심의/학생지도/ 징계 진행
- ※ EE 홈페이지 공지사항에 학업 윤리 규정 전문 게시 https://ee.kaist.ac.kr/node/15358 학업 윤리 위반 행위 관련 신고/문의처 eehonor@kaist.ac.kr



수업자료 공유정책 (현 학기 중 공유/이후 학기 공유를 모두 포함)	가능여부 (o/x)	비고* (수업 별 특수 정책이 있는 경우 명시)
출제된 과제 및 과제풀이의 공유 및 배포		
제공된 강의 자료의 공유 및 배포		
출제된 시험문제의 공유 및 배포		

이전 수업자료 참고정책	가능여부 (o/x)	비고* (수업 별 특수 정책이 있는 경우 명시)
과제 수행 시 이전 기출 과제 및 과제풀이 참조		
과제 수행 시 수강생 간의 토론/협업		
시험 준비 시, 이전 기출문제 자료 참조		



학업윤리 위반 사례 공유

위반행위	 처분내용	발생 횟수	비고
HEOH	MEHO	20 % 1	-1-
과제물 표절	학부 내 징계 사회봉사 30시간	14	
허용되지 않은 자료 제공 및 전달	학부 내 징계 사회봉사 15시간	9	
부정행위 방조 및 허용되지 않은 자료 단순 열람	경고 (경고메일 발송)	3	
튜터의 윤리위반	학부 내 징계 사회봉사 30시간,	2	튜터링 과정에서 튜티에게 부정행위를 권유 및 지원한 경우
시험부정행위	유기정학 2개월, 사회봉사활동 100시간	2	전기및전자공학부 과목에서 발생한 부정행위 EE학생 윤리규정에 따라 처분.
Матооп	학부 내 징계 사회봉사 60시간	1	타과 과목에서 발생한 부정행위, 과목 담당 교 수가 학생 징계를 요청하지 않은 케이스
시험부정행위 (익명제보)	-	1	진상조사/면담/심의를 진행하였으나, 제보내용 외 부정행위를 확정할 수 있는 근거 가 없어 처분하지 않음.

Policies

Sharing distributed material (present semester and after)

	Permission	Note*
Assignments & solutions	O*	*only private sharing allowed (i.e., do not upload on internet)
Lecture material	0*	*only private sharing allowed (i.e., do not upload on internet)
Exams questions	0*	*only private sharing allowed (i.e., do not upload on internet)

Reference material

	Permission	Note*
Previous assignments & solutions	0	
Discussion among students	0*	*Students are encouraged to discuss
Previous Exams	0	

Required background knowledge

- The courses assumes that the students are familiar with the "basics" of
 - Calculus

$$\nabla f(x, y, z) = \frac{\partial f}{\partial x} \mathbf{i} + \frac{\partial f}{\partial y} \mathbf{j} + \frac{\partial f}{\partial z} \mathbf{k} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \\ \frac{\partial f}{\partial z} \end{bmatrix}$$

Linear algebra

$$X^T Y = X^T X \theta \qquad \theta = (X^T X)^{-1} X^T Y$$

Probability

$$P(A|B)P(B) = P(B|A)P(A)$$

Python programming

```
def quicksort(arr):
    if len(arr) <= 1:
        return arr
    pivot = arr[len(arr) // 2]
    left = [x for x in arr if x < pivot]
    middle = [x for x in arr if x == pivot]
    right = [x for x in arr if x > pivot]
    return quicksort(left) + middle + quicksort(right)
```

What is an artificial intelligence?



Definition of machine learning

• A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.

- Mitchell (1997)

Algorithms that

- improve their performance
- at some task
- with experience

Types of machine learning

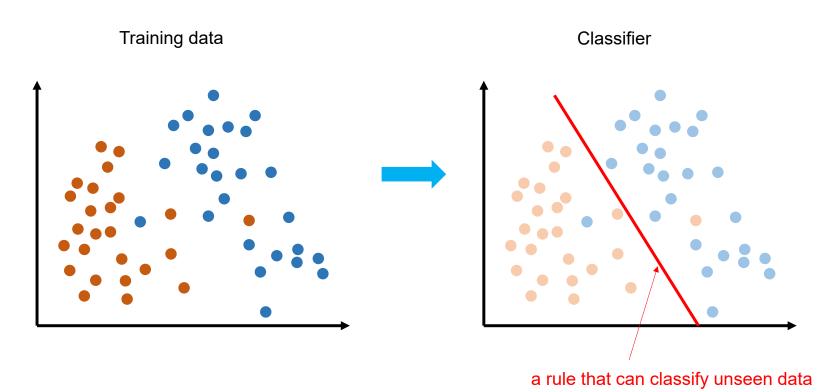
• **Supervised learning**: <u>learning a function</u> that maps an input to an output based on example input-output pairs

- **Unsupervised learning**: <u>looking for previously undetected</u> <u>patterns in a data set</u> with no pre-existing labels and without human supervision
- Reinforcement learning: enabling an agent to learn in an interactive environment by trial and error using feedback from its own actions and experiences

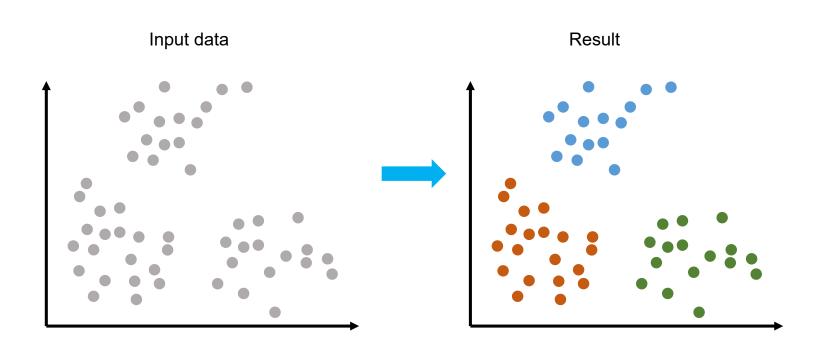
Types of machine learning

- **Supervised learning**: "I'll give you some pairs of questions and answers. Learn from these pairs to be able to answer to other questions."
 - Regression
 - Classification
- Unsupervised learning: "I'll give you some unlabeled data. Try to find if there's any interesting structure or pattern in the data."
 - Clustering
 - Dimension reduction
- Reinforcement learning: "I cannot teach you what to do, but I can give scores to what you did. Based on the scores you got from what you did, learn what to do."

Supervised learning



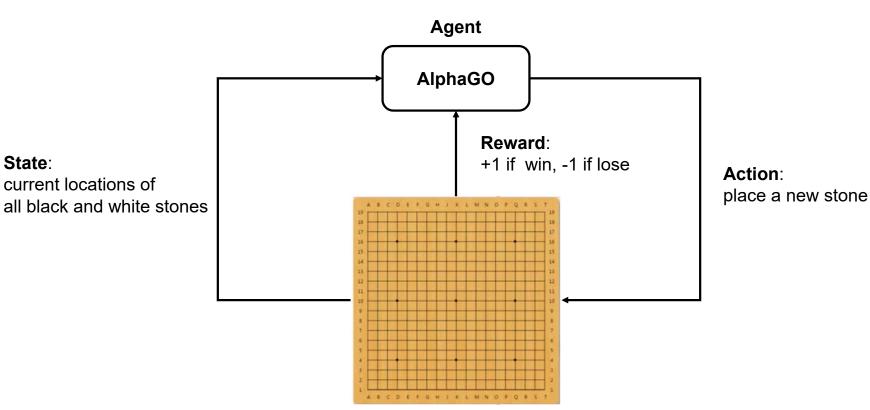
Unsupervised learning



Reinforcement learning

State:

current locations of



The goal of this course...

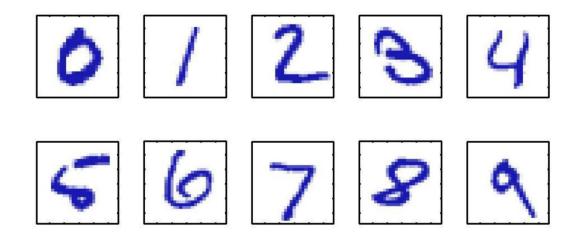
Instructor's goal

- is to convince you that Al is not difficult
- is to convince you that AI is not different than polynomial curve fitting
- is to provide the basics and fundamentals of Al

Student's goal

- is to understand the basics and fundamentals of Al
- is to be able to design a simple Al

Handwritten Digit Recognition



 Let's say we want to implement a <u>program that can recognize</u> <u>handwritten digits</u>. How can we design such program?

Handwritten Digit Recognition



Design an algorithm that can detect a circular shape (but how?)



Design an algorithm that can detect a vertical line



Design an algorithm that can ...

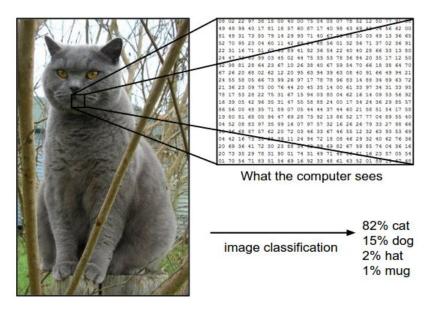
- And...remember that these are handwritten
 - Everyone has different handwriting

Image Classification



• Let's say we want to implement a <u>program that can classify</u> <u>images</u>. How can we design such program?

Image Classification



• For example, an image classification algorithm will take a numerical array (512 x 512 x 3) as the input, and generate another array (10x1) as the output

om ce231n

We need a measure of "similarity"





Theses images do look visually similar to human

We need a measure of "similarity"

```
\begin{pmatrix} 111 & 221 & 56 & 124 & 198 & 129 & 15 & 91 & 198 \\ 12 & 232 & 236 & 134 & 91 & 99 & 32 & 143 & 108 \\ 16 & 223 & 81 & 55 & 146 & 15 & 16 & 72 & 211 \\ 116 & 53 & 31 & 77 & 177 & 163 & 16 & 12 & 22 \\ 36 & 23 & 131 & 87 & 64 & 99 & 46 & 176 & 143 \\ 116 & 222 & 85 & 44 & 126 & 9 & 6 & 192 & 197 \\ 255 & 123 & 123 & 124 & 77 & 19 & 156 & 82 & 211 \\ 122 & 200 & 203 & 24 & 21 & 18 & 191 & 199 & 1 \end{pmatrix}
```

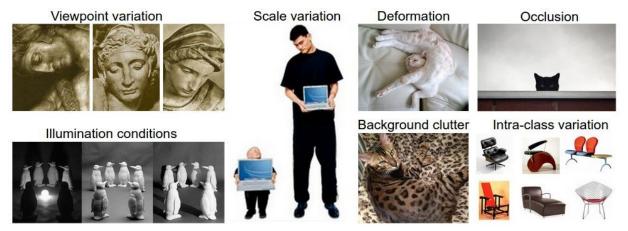
```
\begin{pmatrix} 44 & 221 & 26 & 34 & 178 & 19 & 61 & 91 & 98 \\ 12 & 232 & 136 & 134 & 91 & 99 & 32 & 53 & 18 \\ 16 & 43 & 93 & 105 & 66 & 15 & 16 & 72 & 3 \\ 116 & 53 & 4 & 77 & 14 & 93 & 71 & 33 & 2 \\ 36 & 23 & 41 & 157 & 64 & 18 & 200 & 176 & 3 \\ 26 & 222 & 85 & 44 & 126 & 9 & 6 & 192 & 7 \\ 65 & 123 & 123 & 124 & 177 & 19 & 156 & 42 & 121 \\ 32 & 100 & 103 & 124 & 121 & 218 & 11 & 99 & 1 \\ \end{pmatrix}
```

- But, will these matrices look *similar to the computer?
- How can we define the similarity of two different matrices for image classification?

Challenges in image classification

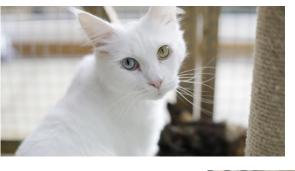
- Viewpoint variation. A single instance of an object can be oriented in many ways with respect to the camera
- **Scale variation**. Visual classes often exhibit variation in their size (size in the real world, not only in terms of their extent in the image)
- **Deformation**. Many objects of interest are not rigid bodies and can be deformed in extreme ways
- **Occlusion**. The objects of interest can be occluded. Sometimes only a small portion of an object (as little as few pixels) could be visible
- **Illumination conditions**. The effects of illumination are drastic on the pixel level
- Background clutter. The objects of interest may blend into their environment, making them hard to
 identify
- **Intra-class variation**. The classes of interest can often be relatively broad, such as *chair*. There are many different types of these objects, each with their own appearance

Challenges in image classification



- Viewpoint variation
- Scale variation
- Deformation
- Occlusion
- Illumination conditions
- Background clutter
- Intra-class variation

Question







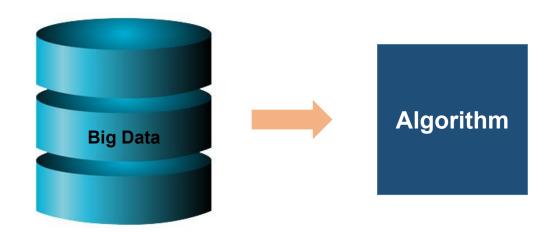






- Despite all these issues, we (human) have no problem in recognizing that these are cats
- How can our algorithms do the same?

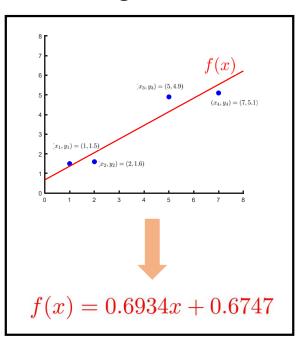
Data-driven approach



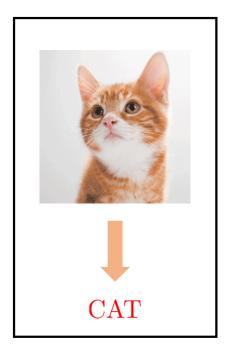
- What if we can design a program that can analyze the data and make its own algorithm?
 - Give all possible variations (viewpoint, scale, etc) and just let the program make the algorithm

Revisit: Goal

Regression



Classification



Course overlook

- Supervised Learning
 - Regression
 - Linear fitting
 - Polynomial fitting
 - Classification
 - Linear classification
 - Nonlinear classification (neural network)
- Unsupervised learning
 - Clustering
 - Autoencoder
- Reinforcement learning

Class organization

- Class types
 - Lecture
 - Focus on theoretical aspects
 - Activity
 - Hands-on practice (python programming using Google Colab)
 - The instructor will show you an example
 - A task, similar to the example, will be given to students
- The purpose is to
 - Learn fundamental theories
 - Experience basic machine learning
 - Bridge the gap between theory and practice

Summary

- Course logistics
- Definition of artificial intelligence
 - Supervised learning
 - Unsupervised learning
 - Reinforcement learning
- Image classification
 - Challenges in image classification
- Data driven approach

References

- Lecture notes
 - MIT 6.036 Intro to Machine Learning
 - https://www.mit.edu/~lindrew/6.036.pdf
 - Stanford CS229
 - http://cs229.stanford.edu/syllabus-summer2020.html
- Website
 - CS231n course website: https://cs231n.github.io/