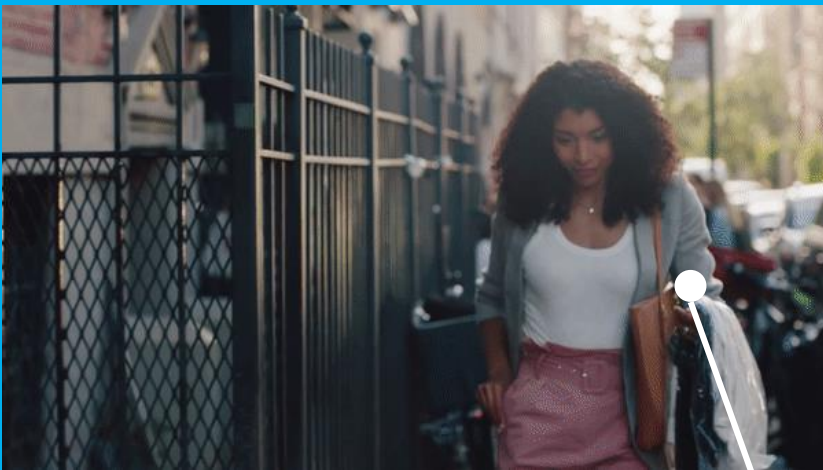


**KAIST**  
**교육**

**9년 동안의  
이야기**

2021년 5월 26일 교육혁신의 날 행사

**서창호**  
전기 및 전자공학부

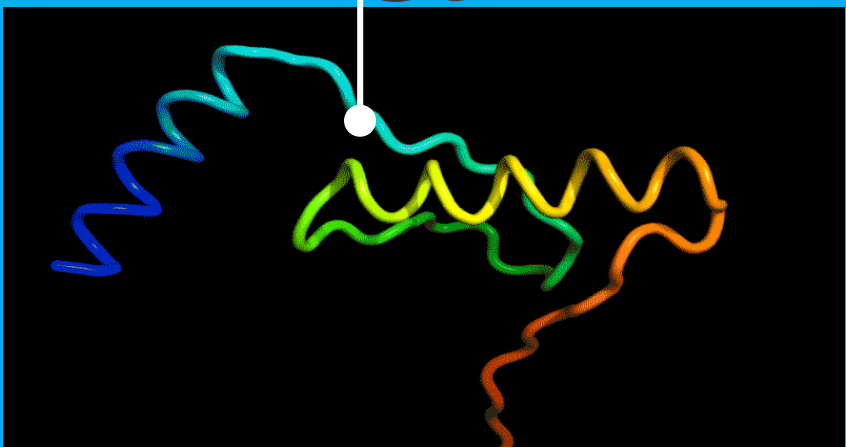
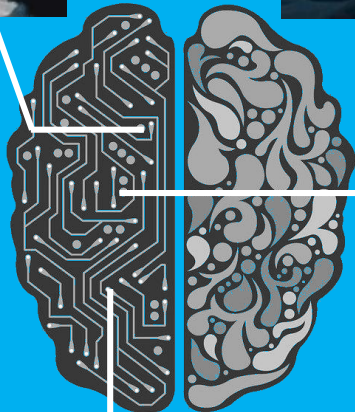


Google assistant



자율주행

AI



단백질 구조 예측

# AI fundamentals

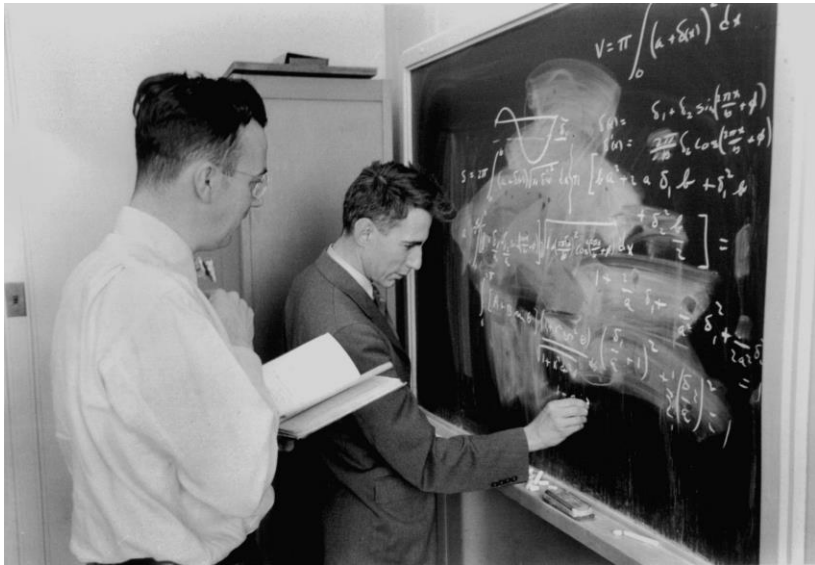
**최적화**

**확률**

**정보이론**

**통신**

# 융합 수업



이론



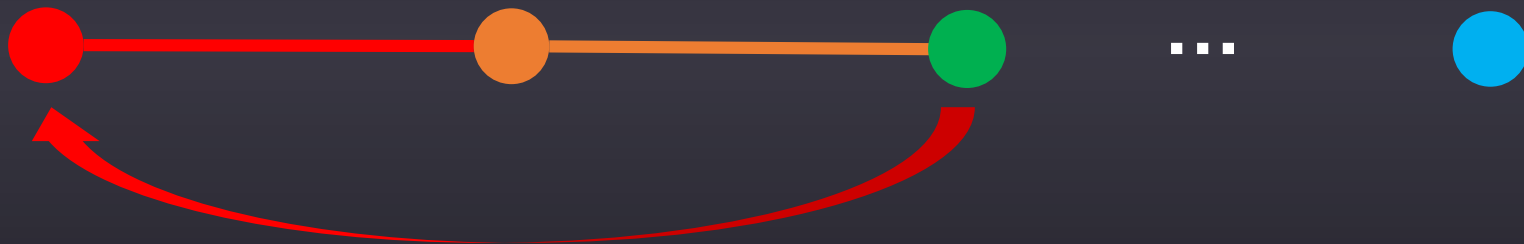
구현

수업 전  
(예습)

수업 당일  
(학습)

수업 후  
(복습)

시험 전  
(핵심 공부)



매 주

# Course notes

## Lecture 2: Definition of Convex Optimization

### Recap

Last time, I told you a story of how the optimization theory was developed. There were two breakthroughs in the history of optimization. The first was made by the famous Gauss. In the process of solving an astronomy problem of figuring out the orbit of Ceres (which many astronomers were trying to address in the 1800s), he could develop an optimization problem, which is now known as the least-squares problem. The beauty of the least-squares problem is two-folded: (i) it has a closed form solution; (ii) there is an algorithm which enables computing the matrix inverse efficiently which is required to compute the solution. It turned out the beauty of the problem opened up the optimization field and has played a significant role in the field.

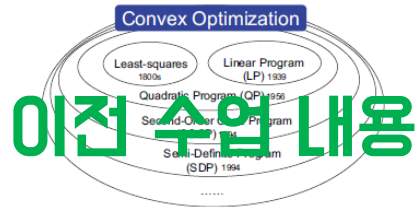


Figure 1: A class of tractable optimization problems: Convex optimization.

The second breakthrough was made by Leonid Kantorovich. In the process of solving a military-related resource-allocation problem, he could formulate a problem which is now known as linear program (LP). The good thing of LP is that there developed an efficient algorithm which allows us to compute the optimal solution reliably and efficiently although the closed form solution is unknown. In other words, Kantorovich came up with the concept of *tractable* optimization problems which can be solved via an algorithm without the knowledge of the optimal solution form. This motivated many followers to mimic his approach, thereby coming up with a class of tractable optimization problems: convex optimization; see Fig. 1.

### Today's lecture

The goal of today's lecture is to understand what convex optimization is. To this end, we will cover four steps sequentially. First, we will give the standard mathematical formulation of optimization problem. Second, we will present the definition of *convex optimization*. One of our main interest requires the knowledge of *convex function*. Even the definition of *convex functions* relies on the concept of *convex sets*. So in the second part, we will study what the convex set is and also investigate some important examples in an effort to be familiar with the concept. Next we will study the definition of convex functions together with a couple of examples and crucial

이전 수업 내용

Previously we investigated examples of convex sets where only affine functions are introduced. Actually there are many convex sets which concern convex functions. Here we list a couple of such examples.

One such example is:

$$S = \{x : f(x) \leq 0\} \quad (13)$$

where  $f(x)$  is a convex function. Here is the proof that  $S$  is a convex set. Suppose  $x, y \in S$ . Then,  $f(x) \leq 0$  and  $f(y) \leq 0$ . This together with the convexity of  $f$ , reflected in the condition (9), gives:

$$f(\lambda x + (1 - \lambda)y) \leq 0,$$

which in turn implies that  $\lambda x + (1 - \lambda)y \in S$ . This completes the proof.

Another example is the intersection of such convex sets:

$$S = S_1 \cap S_2 \\ S_1 = \{x : f_1(x) \leq 0\}, \quad S_2 = \{x : f_2(x) \leq 0\}. \quad (14)$$

Try the proof in Problem Set (PS) 1. Actually the intersection of arbitrary convex sets is also convex - check in PS1 as well.

### Convex optimization problem in standard form

We are now ready to define the convex optimization problem. It is an optimization problem which satisfies the following three: (i) The objective function is convex; (ii) The set induced by inequality constraints is convex; and (iii) The set induced by equality constraints is convex. So the standard form of the convex optimization problem is (2) in which (i)  $f(x)$  is convex; (ii)  $f_i(x)$  is convex; and (iii)  $h_i(x)$  is affine. Notice that the set induced by affine equality constraints

### Look ahead

Of course there is a reason why a convex optimization problem is considered in such a manner. This is because the way of determining whether the problem is tractable or not, we will provide an intuition as to why convex optimization is tractable. We will then be investigating one instance of convex optimization: Linear Program (LP).

다음 수업 내용

예습을 위한 6~7 pages 노트 제공

# Preview slides

## Convex function

**Definition:** A real-valued function  $f(x)$  is said to be convex if

(i)

(ii)

14

수업 전 **빈칸**으로 구성된 슬라이드 제공

**→ 능동적 수업참여 유도**

# Lecture slides

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## Convex function

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**Definition:** A real-valued function  $f(x)$  is said to be convex if

- (i)  $x, y \in \text{dom } f :$   $\forall \lambda \in [0, 1]$   
 $f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y)$
- (ii)  $\text{dom } f$  convex set

수업 후 정답이 채워진 슬라이드 제공



# Lecture videos

Recap: A simplified form

$$\min_{G(\cdot)} \min_{Q_{Y,Y}} \sum_{z \in \mathcal{Y}} \sum_{\hat{z} \in \hat{\mathcal{Y}}} Q_{Y,\hat{Y}}(z, \hat{z}) \|z - \hat{z}\| :$$
$$\sum_{\hat{z} \in \hat{\mathcal{Y}}} Q_{Y,\hat{Y}}(z, \hat{z}) = Q_Y(z) \quad \forall z \in \mathcal{Y}$$
$$\sum_{z \in \mathcal{Y}} Q_{Y,\hat{Y}}(z, \hat{z}) = Q_{\hat{Y}}(\hat{z}) \quad \forall \hat{z} \in \hat{\mathcal{Y}}$$
$$-Q_{Y,\hat{Y}}(z, \hat{z}) \leq 0$$

▶ 모두 재생

## EE424: Introduction to Optimization Techniques

동영상 107개 · 조회수 4,785회 · 최종 업데이트: 2020. 12. 3.

일부 공개



EE424 Introduction to Optimization techniques

구독중



00 Lecture 2: Annouement&Recap&Introduction  
EE210 Probability and Introductory Random Processes  
15:06  
**이전 수업 내용**

01 Lecture 2: Part I. Mathematical formulation of optimization problems  
EE210 Probability and Introductory Random Processes  
12:00

02 Lecture 2: Part II. Convex set  
EE210 Probability and Introductory Random Processes  
25:29  
**이번 수업 내용**

03 Lecture 2: Part III. Convex function  
EE210 Probability and Introductory Random Processes  
17:24

04 Lecture 2: Part IV. Definition of convex optimization  
EE210 Probability and Introductory Random Processes  
7:17  
**다음 수업 내용**

효율적인 복습을 위한 파트별 편집 동영상 제공

W-based opt.

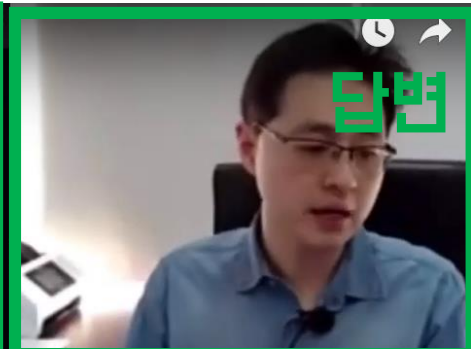
$$\arg \min_{G(\cdot)} \max_{\psi(\cdot)} \frac{1}{m} \sum_{i=1}^m \psi(\hat{y}_i^{(i)}) - \frac{1}{m} \sum_{i=1}^m \psi(y_i^{(i)})$$

$\hat{y}^{(i)}$   
 $\hat{y}^{(i)}$   
 $\hat{y}^{(i)}$

$G^*(\cdot)$ ,  $\psi^*(\cdot)$

Generative model → Can generate fake data

$\hat{y}^{**} = \text{답변}$



질문

발신자20205577 장민석수신자모두:  
아, 여기서는 generator 를 만드는데 하는  
거지, generator 를 활용하는 건 아니죠?

발신자20180505 이준원수신자모두:  
hanks  
then can we view the subproblem as  
discriminator, and G() as generator in  
GAN?

발신자Oleksii Nasypanyi수신자모두:  
it is almost the same question as prev  
so i got that  
yes

# 양방향 인터랙션을 통한 효율적 비대면 강의

# Problem sets

EE424 Introduction to Optimization  
KAIST, Fall 2020

September 3, 2020  
Changho Suh (chsuh@kaist.ac.kr)

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## Problem Set 1

---

*Due: September 11 (Friday)*

*Note 1: Submit your solution (a soft copy) to klms system (PS1 tap is created in our website).*

*Note 2: Each problem will be graded by a different TA (indexed by TA1, TA2, TA3):*

*TA1: Sihyung; TA2: Jongseong; TA3: Jinyeop*

1. (TA1) (*Least Squares*) Let  $A := [a_1 \cdots a_m]^T$  and  $b := [b_1 \cdots b_m]^T$  where  $a_i \in \mathbf{R}^d$  and  $b_i \in \mathbf{R}$ ,  $i \in \{1, \dots, m\}$ .

(a) Consider a function  $f : \mathbf{R}^d \rightarrow \mathbf{R} : f(x) = \|a_1^T x - b_1\| + \cdots + \|a_m^T x - b_m\|$ . A student claims that the function  $f$  can be represented as:

$$f(x) = \|Ax - b\|. \quad (1)$$

Prove or disprove the claim.

(b) Consider another function  $f : \mathbf{R}^d \rightarrow \mathbf{R}$ :

$$f(x) = \|Ax - b\|^2. \quad (2)$$

(Only) using the definition of a convex function, show that  $f(x)$  is convex in  $x$ .

# 1. 수업내용 이해도 향상을 위한 관련 문제 제출

# Problem sets

6. (TA1) (*Monty Hall Problem – Python lab*) In this problem, you are asked to perform some simulations to empirically verify what we proved in the Monty Hall Problem:

$$\mathbb{P}(\text{win w/ sticking}) = \frac{1}{3}; \quad (2)$$

$$\mathbb{P}(\text{win w/ switching}) = \frac{2}{3}. \quad (3)$$

For your sake, let us repeat the game procedure. Suppose there are three doors. The prize “car” is behind one door, but it is unknown to the trader, while being revealed to the host (Monty Hall). Behind the other two doors there are two goats (sort of “qquang”). The trader is first asked to choose one out of three doors. The host then opens one door behind which there is a goat. Next, the trader is given an option between *sticking* with the initial choice vs *switching* to another unopened door. Let  $N$  be the number of games tried out in simulation.

(a) Suppose the trader takes the *sticking* strategy. Implement a Python function that returns 1 (for winning) or 0 (for losing) for one game.

*Hint: You may want to use functions like `random.randint`.*

(b) Using the python function in part (a), plot the empirical winning rate ( $= \frac{\text{number of winnings}}{N}$ ) as a function of  $N$ . How does the winning rate converge in light of (2) as  $N$  grows?

(c) Now suppose the trader takes the *switching* strategy. Repeat parts (a) and (b). Of course, in this case, you should compare to (3).

Solution:

(a) In sticking strategy, set `switch` as false and `num_doors` as 3. With `random.randint(0, num_doors-1)`, we randomly choose the location of car and player between 0, 1 and 2. In this problem, we don't care about switching. If the index of player is equal to the index of car, the program code returns 1, otherwise 0.

```
In [1]: import random
import math
import matplotlib.pyplot as plt
```

```
In [2]: def open_doors(num_doors: int, door_car: int, door_player: int) -> int:
...
    num_doors: number of doors
    door_car: the index of the door with car behind
    door_player: the index of the door which player chose
...
    if door_player != door_car:
        return door_car
    else:
        return (door_player + 1) % num_doors
```

```
In [3]: def game(switch: bool, num_doors: int) -> int:
...
    switch: whether the player switch or not
    num_doors: number of doors
...
    doors = [x for x in range(num_doors)] # index of doors
    door_car = random.randint(0, num_doors-1) # index of the door with car behind
    door_player = random.randint(0, num_doors-1) # index of the door player chose
...
    door_left_closed = open_doors(num_doors, door_car, door_player)
...
    if switch:
        door_player = door_left_closed
...
    return 1 if door_player == door_car else 0
```

## 2. Python/TensorFlow 활용 코딩 문제 제출

# Exam guidelines

EE321 Communication Engineering  
KAIST, Spring 2020

June 8, 2020  
Changho Suh (chsuh@kaist.ac.kr)

## Final instructions

**Logistics:** The exam runs live online via zoom, as promised. It starts from 12:50 pm and ends at 2:10 pm on June 17 (Wednesday), 2020. You are allowed to use one cheating sheet, A4-sized and double-sided. The total score is 100 + 10 points. The maximum score that you can get is 100 points though. The overflowing points (if any) would contribute to compensating for a loss (if any) that occurred in your midterm exam. Please show all of your work in details to maximize chances for partial credits. For details, see “final notice” that would be uploaded by the head TA (Minguen Kang) on KLMS.

**Contents:** The best preparation for the final is to carefully review all of the lecture slides, course notes, problem sets, exercise problems and related reference. I strongly recommend this as a first-order preparation tool. Here is a summary of the key topics covered in this course as well as the corresponding references.

- (a) A digital communication architecture  
CN1, LS1.  
Prob 4,5 in PS1.
- (b) Review of probability laws and random variable  
Chapters 1 ~ 3 in BT.  
Prob 1 ~ 3 in PS1; Prob 1,2 in PS2; Prob 1 ~ 3 in PS3; Prob 1 in PS4; Prob 1 ~ 5 in EP1.
- (c) Gaussian noise model, PAM, optimum receiver principles, error probability analysis  
CN2 ~ 6, LS2 ~ 6.  
Prob 6 of PS1; Prob 3 ~ 6 in PS2; Prob 4 ~ 7 in PS3; Prob 2 in PS4; Prob 6 in EP1.
- (d) Sequential communication and repetition coding  
CN7 ~ 8, LS7 ~ 8.  
Prob 5 ~ 7 in PS3, Prob 2 ~ 6 in PS4; Prob 7 in EP1; Prob 1 in PS5.
- (e) Capacity of the AWGN channel  
CN9, LS9.  
Prob 7 in PS4; Prob 8 in EP1.
- (f) Waveform shaping  
CN10 ~ 11, LS10 ~ 11.  
Prob 2 ~ 3 in PS5.
- (g) ISI channel modeling  
CN12 ~ 13, LS12 ~ 13.  
Prob 4 ~ 5 in PS5.
- (h) Viterbi algorithm  
CN13 ~ 14, LS13 ~ 14.  
Prob 6 in PS5; Prob 1 in PS6.

시험 전 어느 부분을 공부 해야하는지 알려줌

→ 중요한 부분을 효율적으로 공부함

# Textbooks

최적화

**출판 승인**

정보이론

확률

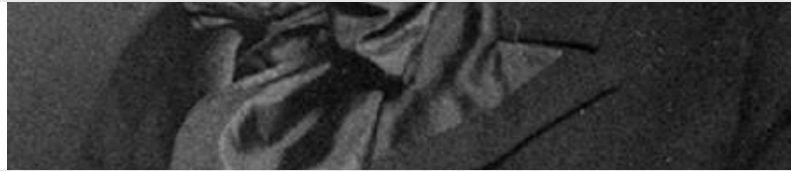
**출판 리뷰 중**

통신

교육에 대한

세 가지 생각

“교육은 양동이를 채우는 것이 아니라  
불을 지피는 것이다.”

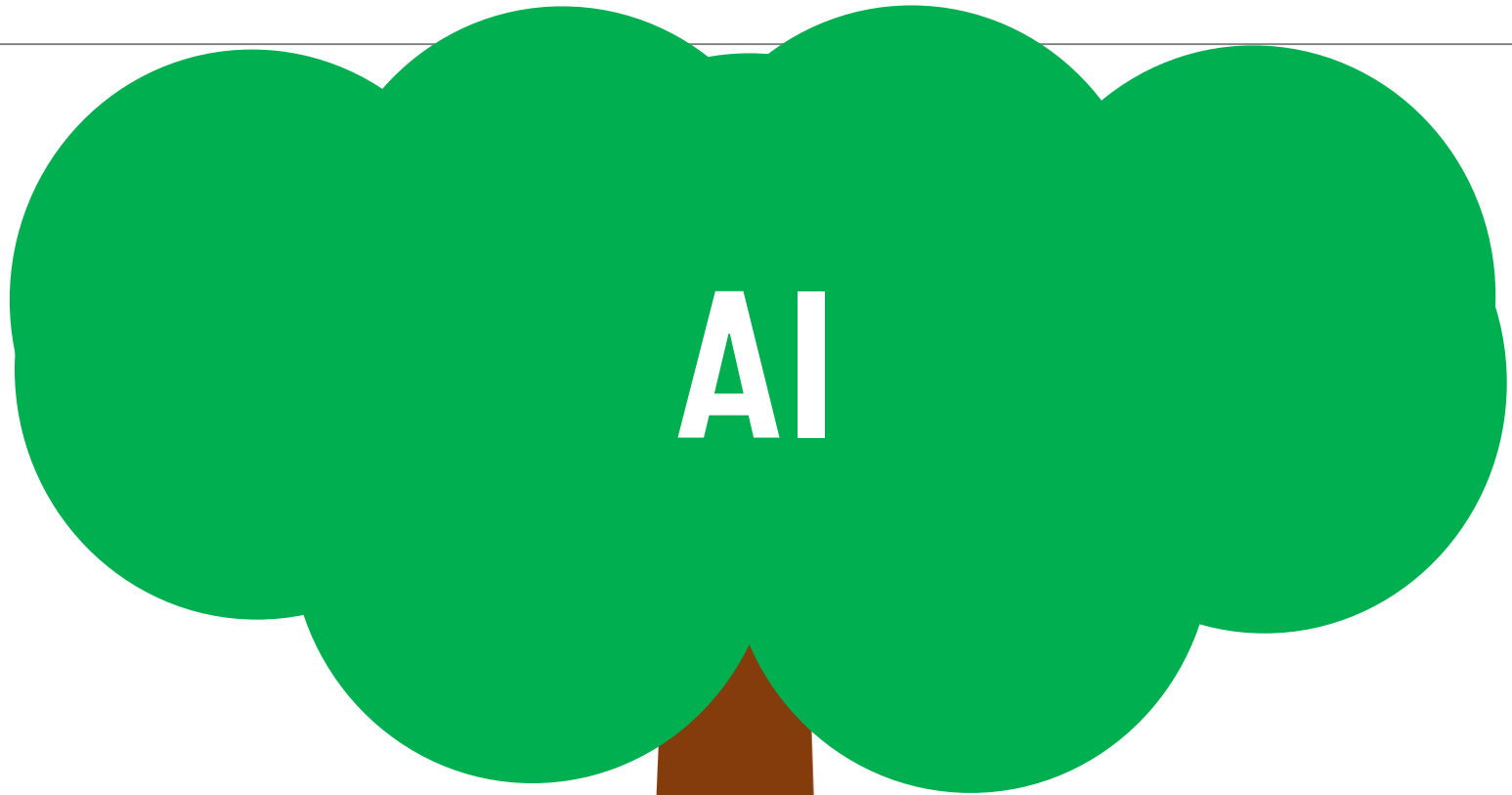


## 1. 동기 부여 최우선



# 2. 사례 중심교육

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Fundamentals

유 퀴즈!

제106화 N주년  
개교 50주년 카이스트 총장



# 3. **다양성**