



# CAU AI Graduate School Introduction



# 1. About CAU AI Graduate School

1-1. Overview

1-2. Research Areas

# 2. Programs in AI Graduate School

2-1. Education

2-2. Internship in Industry

2-3. International Research Collaboration

# 3. Partnership Programs

3-1. Hungary-CAU AI/contents Conference

3-2. Hungary-CAU Research/Education Collaboration



# 1. About CAU AI Graduate School

## 1-1. Overview

### 1-2. Research Areas

- 1) recommendation systems
- 2) natural language processing
- 3) optimization in deep learning



# VISION

## Vision of Da Vinci AI Graduate School

Vision

Nurturing talents contributing to human society using AI

CORE Ability

Creative, Open, Renovative, Ethical

### AI Campus

- AI Campus Construction
- Foundation of CAU AI Committee
- Foundation of Da Vinci AI Academy
- CAU AI Data Lake Construction
- AI K-MOOC lecture

### AI R & D

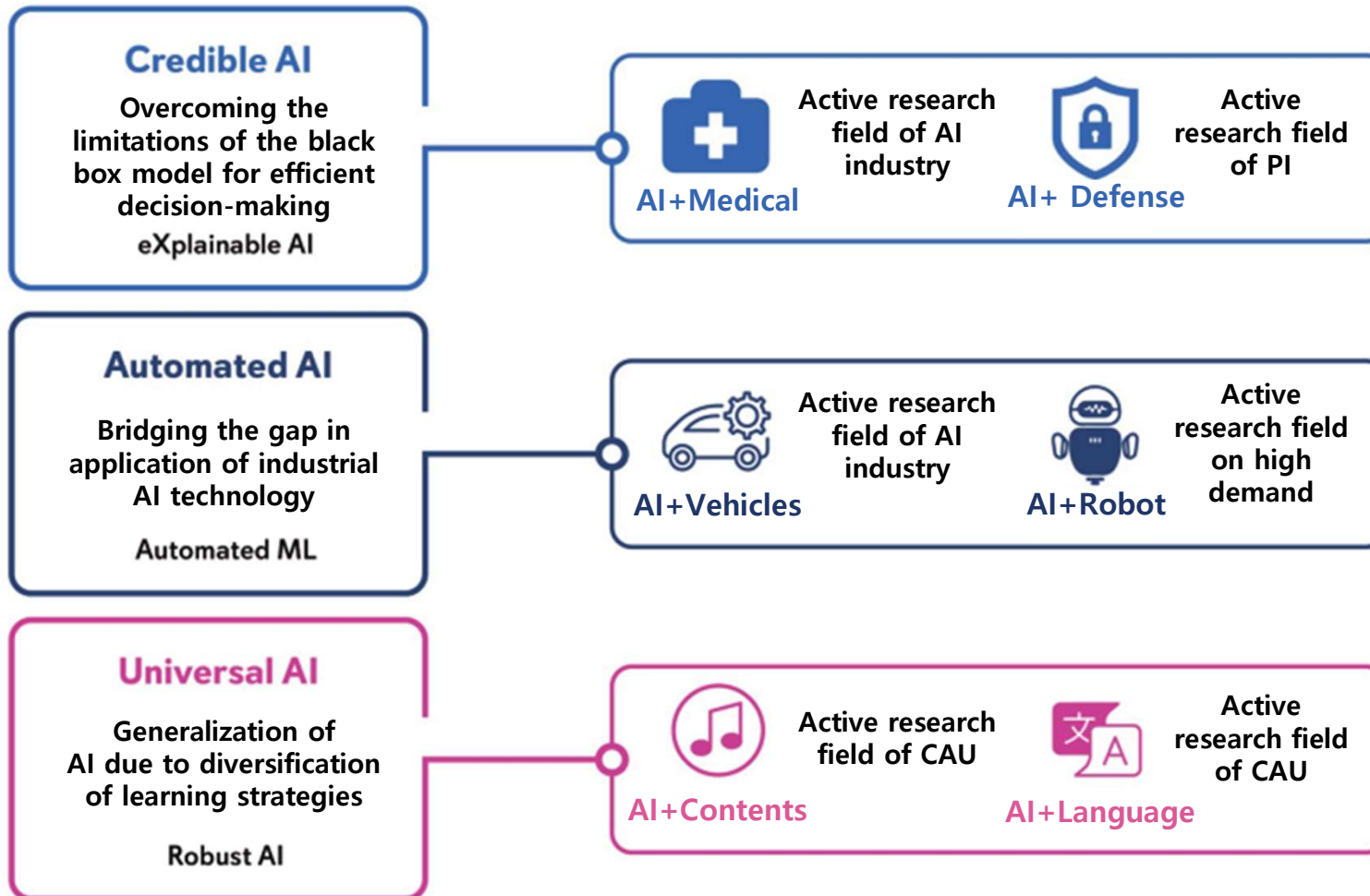
- Development of AI defense technology
- Development of e-Advisor with Hanhwa
- AI image process technology for practical satellites 3, 3A, 7A
- Cooperation of Fuel System-Drone-Robot with Doosan

### Da Vinci AI Talents

- Da Vinci Institute of Learning Innovation
  - AI Da Vinci Learning
  - Da Vinci Classroom
- Student Excellence
- AI and programming education for all students

# Research

## Long-term AI Core Research Tasks



# Research

## Faculty Members

### Core AI



Cho,  
Yoon-Sik

Credible AI

### Applied AI



Hong,  
Byung-Woo

AI+Medical



Lee,  
Kyungjae

AI+Robots



Lee,  
Changhee

AI+Medical



Kim,  
Bugeun

AI+Language



Kim,  
Eunwoo

Automated AI



Paik,  
Joonki

AI+Defense



Kim,  
Youngbin

AI+Language



Kim,  
Junyeong

AI+Language



Kwon,  
Junseok

Universal AI



Choi,  
Jongwon

AI+Vehicles



Lee,  
Jaesung

AI+Contents



Lee,  
Hwanhee

AI+Language

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# 1. About CAU AI Graduate School

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## 1-2. Research Areas

- 1) recommendation systems
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# 1. About CAU AI Graduate School

## 1-1. Overview

## 1-2. Research Areas

- 1) recommendation systems
- 2) natural language processing
- 3) optimization in deep learning**



## 2. Programs in AI Graduate School

2-1. Education

2-2. Internship in Industry

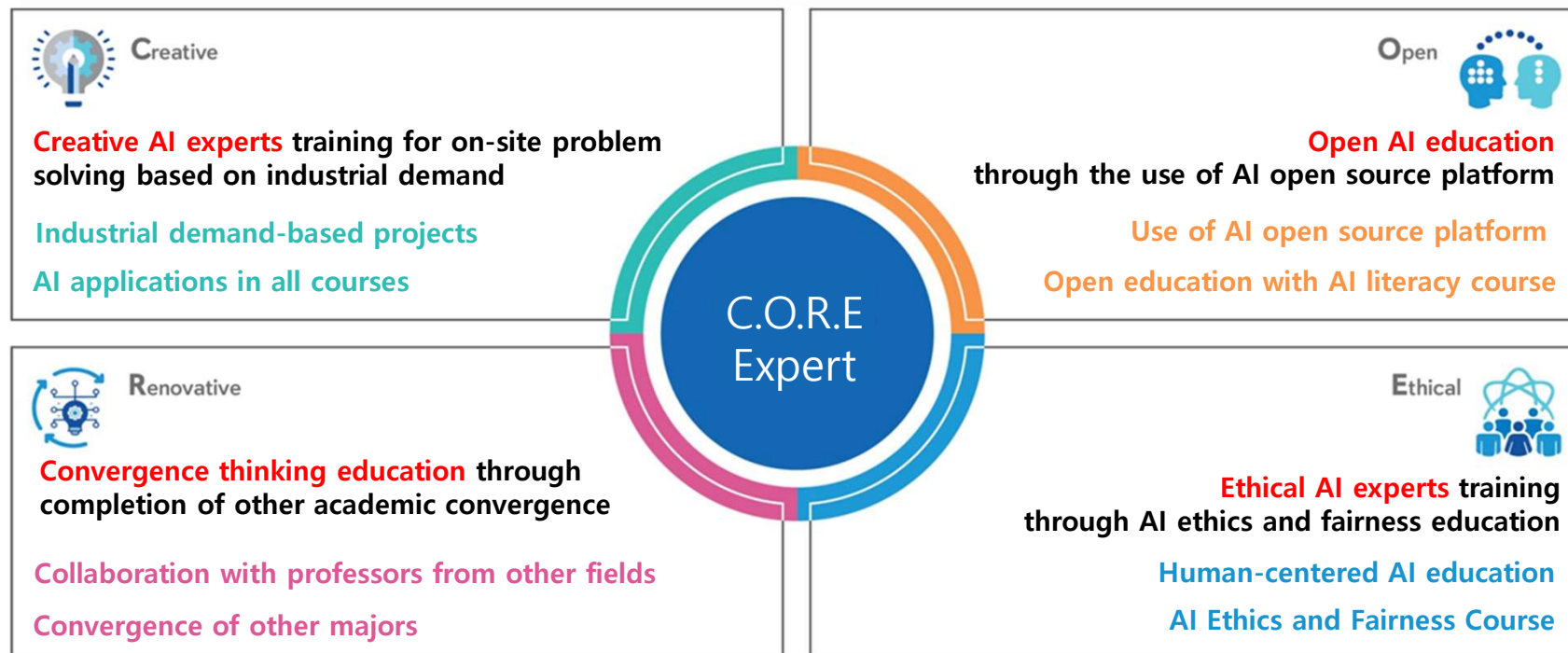
2-3. International Research Collaboration



# Education

## Da Vinci AI Graduate School

Creative	Open	Renovative	Ethical
Creative AI experts solving social problems	Open AI expert Pursuing convergence	Innovative AI expert leading the future society	Ethical AI Experts Creating the Common Good



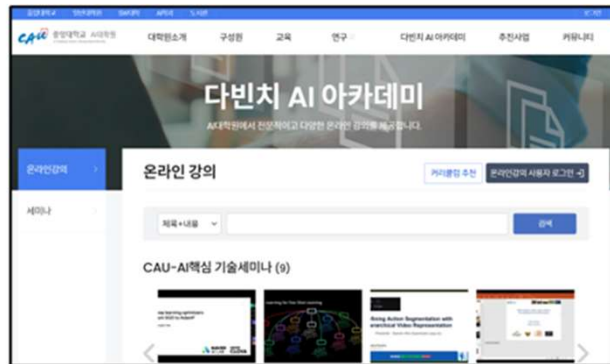
# CAU-AI Core Tech Seminar

Bi-weekly online seminar about trends of artificial intelligence

International/Domestic Researchers				International/Domestic Industrial Speaker			
Date	Name	Affiliation	Topic	Date	Name	Affiliation	Topic
Jun. 22, 2022	Jason Friedman	Tel Aviv Univ.	Using arm movements to understand perceptual decision making, and vice-versa	May. 26, 2022	ByoungHo Heo	NAVER	Optimizers for deep learning: From SGD to AdamP
Jul. 06, 2022	Youngdeok Seo	Inha Univ.	Recommendation System	Jun. 10, 2022	Seunghwan Kim	LG AI Research	LG and AI - 1
Aug. 17, 2022	Jaemin Jo	Univ. of North Carolina at Chapel Hill	Vision-and-Language Learning: Pretraining, Transfer Learning, and Evaluation	Jul. 22, 2022	Donghyun Won	Motional, USA	Challenges in Perception System for Autonomous Driving
Sep. 02, 2022	Seungho Seo	DFKI	Multimodal Human Activity Recognition with Industrial Applications	Aug. 04, 2022	Youngjae Lee	S2W	Shedding new light on the language of the Dark Web
Sep. 30, 2022	Mina Lee	Stanford	Writing with Artificial Intelligence	Oct. 14, 2022	Kyoungsik Moon	META	Towards 3D Human Reconstruction in the Wild
Oct. 28, 2022	Kimin Yun	ETRI	DeepView Project	Oct. 18, 2022	Woohyung Lim	LG AI Research	LG and AI - 2
Nov. 25, 2022	Simon Korman	Univ. of Haifa	Computer Vision in the Wild	Dec. 09, 2022	Junbeom Cha	Kakao Brain	Computer Vision in the Wild

# AI Special Course

## Online AI Curriculum



## AI Seminar for Non-majors



## KMOOC Open Lecture



## AI Curriculum for Freshman



# International Education

## ACDL 2022 an Online and Onsite Course

### • The 5<sup>th</sup> Advanced Course on Data Science & Machine Learning(ACDL)

- August 22 – August 26, 2022
- University of Catania, Siena, Italy
- The course will involve a total of 36~40 hours of lectures

#### Topics

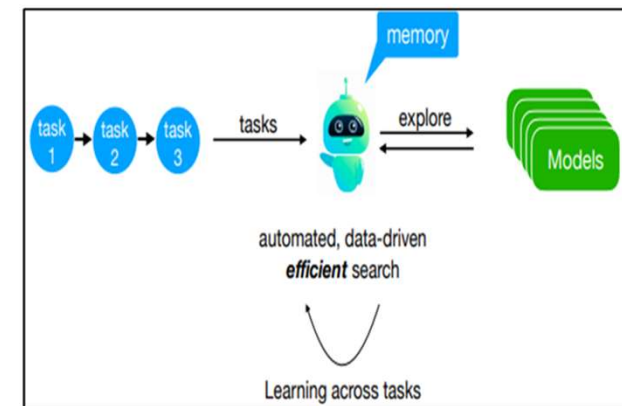
- Artificial Intelligence Reinforcement Learning Algorithm
- Big Data Networks
- Cognitive Computing
- General
- Generative Adversari
- And so on



Università  
di Catania

#### Automatic Machine Learning

- **Part 1 : Why automate machine Learning?**
  - High-level goals
- **Part 2 : How AutoML works?**
  - The machinery
- **Part 3 : Learning to (automatically) learn?**

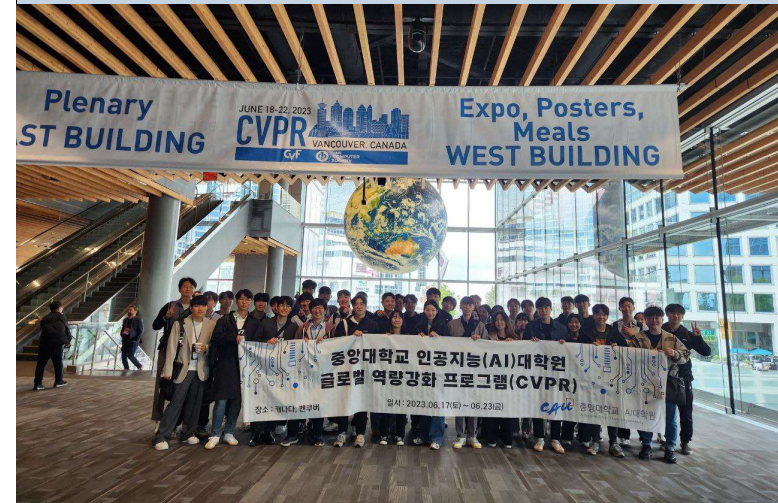


## International Education

CES 2023



CVPR 2023



## 2. Programs in AI Graduate School

2-1. Education

**2-2. Internship in Industry**

2-3. International Research Collaboration





## '22 AI Graduate School - NC Soft Cooperation Fall Long-Term Intern Program

- AI Graduate School and NC Soft collaboration intern program to cultivate exceptional students
- The program aims to nurture talents who can understand industry-used technologies
- We are currently recruiting 5-10 interns every semester, starting from the second half of 2022

### ■ Recruitment Field



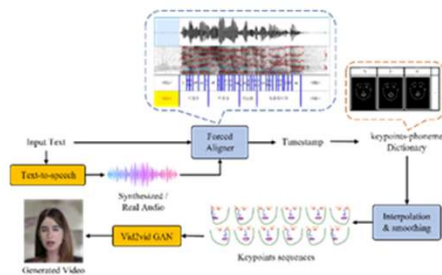
Center	Lab
AI Center	Vision AI Lab, Graphics Lab, AI Production Lab(Digital Human Solution Team, MLOps Team)
AI Biz Center	Applied AI Lab, Finance Biz Lab(Finance AI RD)
NLP Center	NLP Lab

# Research on text/voice-based virtual human's facial generation technology (CJ Olive Networks Internship Program)

## Two Ph.D. candidates from the AI Graduate School participated

### 1. Generating Korean-speaking virtual human videos based on text and voice

- ▶ Built a dictionary matching facial landmarks and phonemes with short-length videos and texts for each person
- ▶ Generating facial landmarks for the GAN model
- ▶ Facial synthesis using GAN based on the generated facial landmarks

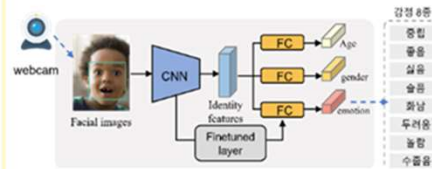


- ▶ Text-based model shows flexible results
- ▶ Possible to build a dictionary of facial landmarks and phonemes with just short

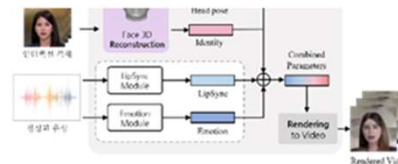


### 2. Nonverbal understanding and expression model

- ▶ Development of a method for recognizing user's emotions, age, and gender

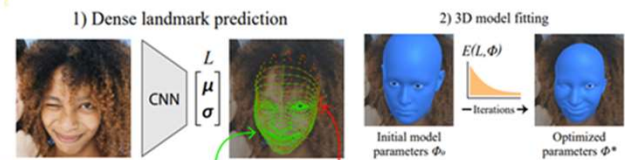


- ▶ Robust generation method for changes in facial angles through Face 3D reconstruction
- ▶ Nonverbal expression method based on the given virtual human's emotions



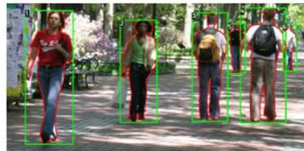
### 3. Development of the next-generation interactive digital human solution

- ▶ Blending method for natural emotion motions and lip animations
- ▶ Development of a method for generating chin, tongue, and Adam's apple animations that match lip animation



# Doosan AI CoE: Simultaneous Pedestrian Detection & Text Recognition on Embedded Board

## Tasks



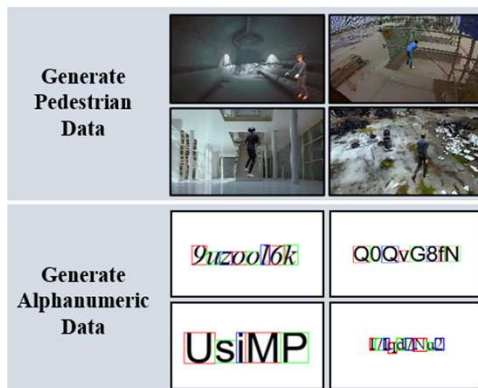
Pedestrian Detection



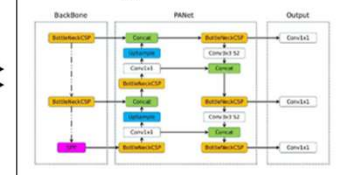
Text Recognition

## Methods

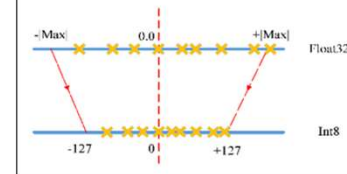
### Preprocessing



### Training



### Quantization



### Embedded Boards



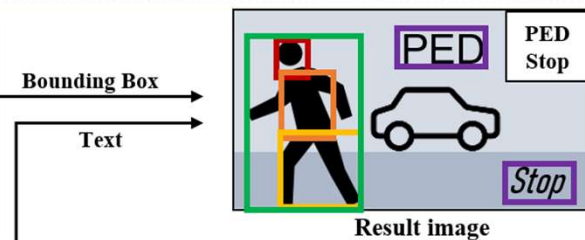
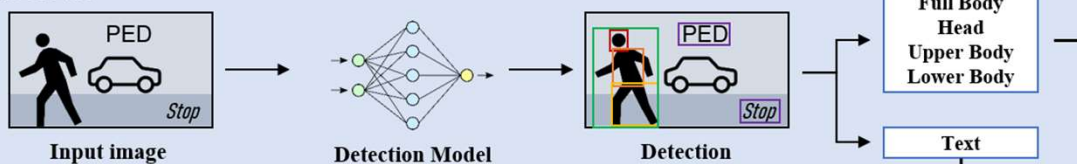
Jetson Nano



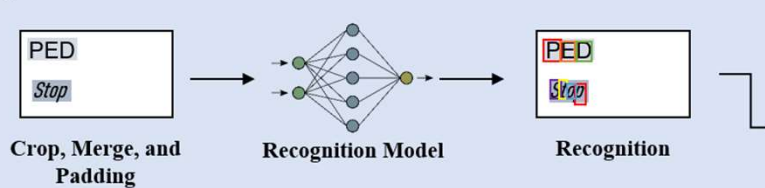
Rockchip RV1126

## Frameworks

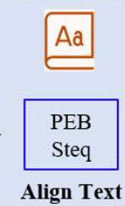
### Detection Phase



### Recognition Phase



### Dictionary



Levenshtein Distance

	G	A	G	C	T	A
A	1	2	3	4	5	6
A	2	1	2	3	4	5
C	3	4	3	4	3	4
G	4	3	4	3	4	5
C	5	4	5	4	3	4
A	6	5	4	5	4	5

PED Stop  
Result

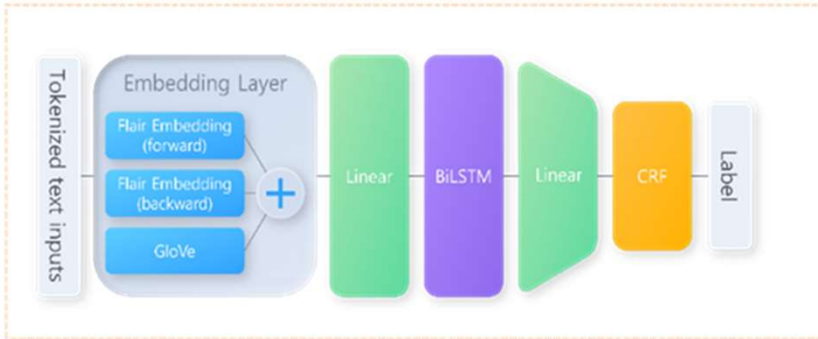
# Other Internship Projects



## NLP Team

### NER annotation, Web Crawling Tool

### Security Sentence Classification Modeling



## Sensor Data Processing Team

### 웨어러블 디바이스의 생체 신호 모니터링

## 2. Programs in AI Graduate School

2-1. Education

2-2. Internship in Industry

**2-3. International Research Collaboration**



## International Research Collaboration (1/2)

### Resource-aware Machine Learning

Instruction on data analysis techniques and implementation of machine learning algorithms on embedded systems

1



### Advanced Online & Onsite Course on Data Science & Machine Learning

Introduction and study of the latest data analysis techniques and machine learning techniques

3



### A Study on Next Generation Journalism Based on Big Data and Deep Learning

The goal is to take automated journalism to the next level by utilizing news big data and deep learning language models.

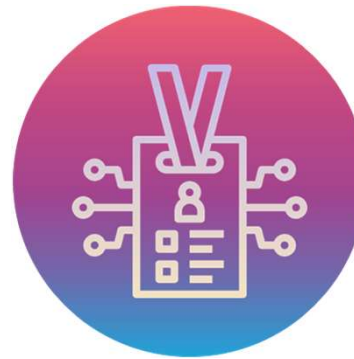
2



### An international joint study of AI technology for predicting complications after orthopedic surgery

Using health care big data, we developed a gastric cancer prediction model using a gastric cancer patient and other diseases diagnosed together.

4



## International Research Collaboration (2/2)

### An International Joint Study on the Development of Healthcare and Medical AI

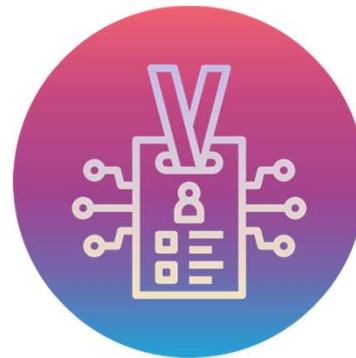
A study of a high-performance disease prediction model based on deep learning. An interpretable deep learning model study. A study on the causal relationship and treatment effect of machine learning-based questions.

1

### An International Joint Study on the Analysis Technology of Healthcare Data Variables Based on Deep Learning

This study proposes a deep learning-based feature selection technique using self-supervised learning and the correlation structure of data using unlabeled public data.

2



3

### An International Joint Study on the Development of Healthcare and Medical AI

This study proposes a complex time series data-based survival analysis model through a deep learning-based model.

4

### An international joint study of AI technology for predicting complications after orthopedic surgery

This study examines AutoML technology that can be easily used by artificial intelligence non-experts by reflecting the specificity of healthcare and medical data.

## 3. Partnership Programs

### 3-1. Hungary-CAU Research/Education Collaboration





# Hungary-CAU Research/Education Collaboration

## Graduate Scholarship Program

- CAU awards scholarships to 5 graduate students selected by Hungarian Rector's Conference
- Chung-Ang University Young Scientist Scholarship (CAYSS)
- AI Graduate School Scholarship
- Benefits: Tuition fee waivers for four semesters (including Application and Admission Fees)

## Undergraduate Student Exchange Program

- Hungarian universities currently collaborating : The University of Szeged, University of Debrecen, University of Pec

## Scholarship and On-Campus Internship for International Students

Scholarship	Eligibility	Benefits
CAU Global Student Internship	- Native speakers of English or French - Selection via interview	- Approximately \$1000 per semester - Official certificate by OIA
CAU OIA Fellowship	- Fluency in English - Good computer skills - Selection via interview	- Approximately \$1000 per month - Official certificate by OIA
CAU Global Opportunity Scholarship	According to student exchange agreement	On-campus accommodation expenses
Global Korea Scholarship	Exchange students deemed qualified by the NIIED(National Institute for International Education)	Airfare, Monthly stipend, Settlement Allowance, Insurance Fee
ASEM DUO Scholarship	Students from European partner universities	4,000 Euros (8,000 Euros for 1 pair)
Scholarship for Fee-paying students	According to student exchange agreement	For 40 students or above, 50% of tuition waived (differs according to number of students)

## Summary table of international partnership

	No. of Countries (Europe)	No. of Universities
Overall	74 (31)	621 (187)
Partnership for Exchange Student	69 (29)	458 (150)
Partnership for Visiting Professor/Scholar	40 (23)	113 (57)

## Supports for International Students

<b>GLAM</b> Global Ambassador	<b>CALIS</b> Leaders of International Students	<b>GCC</b> Global Community Center	<b>GF</b> Global Fairs	<b>CAKE</b> Korean Editing	<b>CANGO</b> Cultural Activity for Next Great Opportunity
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## Number of exchange students in the recent 3 years

Long-term Exchange		Short-term Exchange	
Invited	Dispatched	Invited	Dispatched
1980	814	129	286



## (Provisional) Hungary-CAU Research/Education Collaboration



**ELTE**  
EÖTVÖS LORÁND  
TUDOMÁNYEGYETEM



### Selection Criteria

- TBD

### Participants

- CAU: TBD
- ELTE: TBD

### Programs

- Research on AI and contents
- Education on AI and contents



## AI Graduate School, Chung-Ang University

(06974) 84 Heukseok-ro, Dongjak-gu, Seoul, Republic of Korea,  
Building 310, Room 824, AI Graduate School

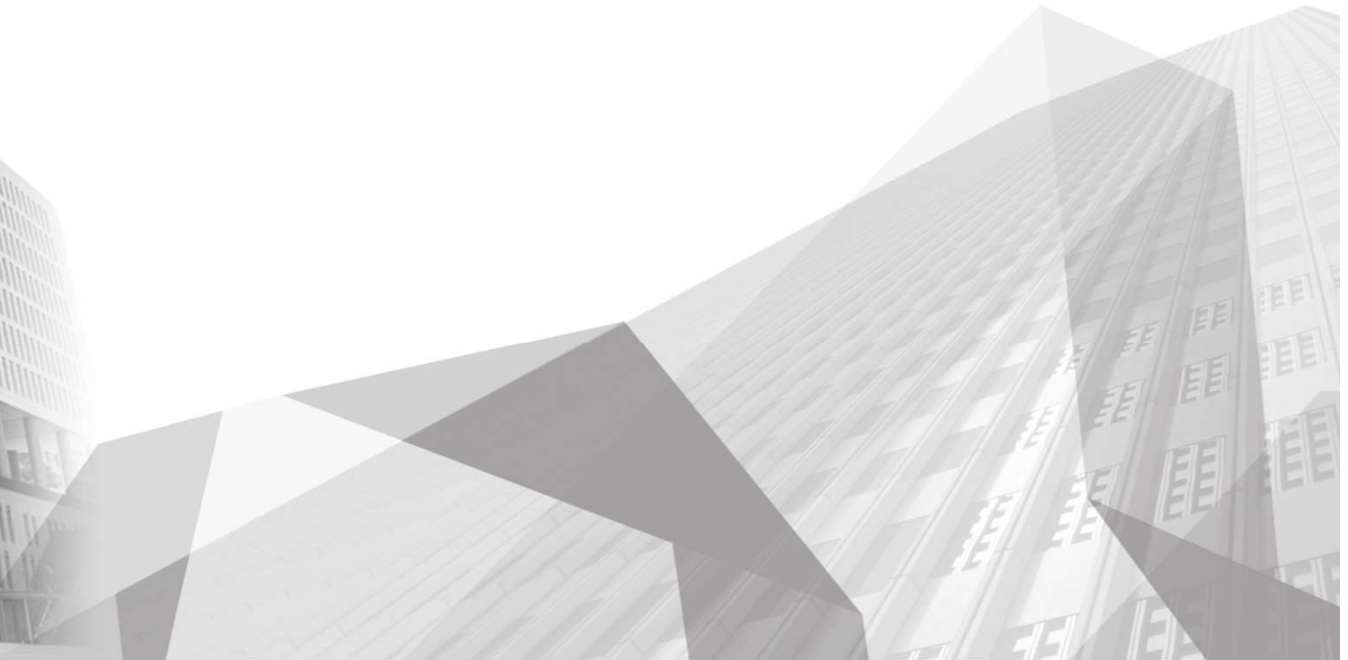
Tel: +82-2-820-6748

Web

- CAU - <https://www.cau.ac.kr/>
- AI Graduate School – <https://aigs.cau.ac.kr/>



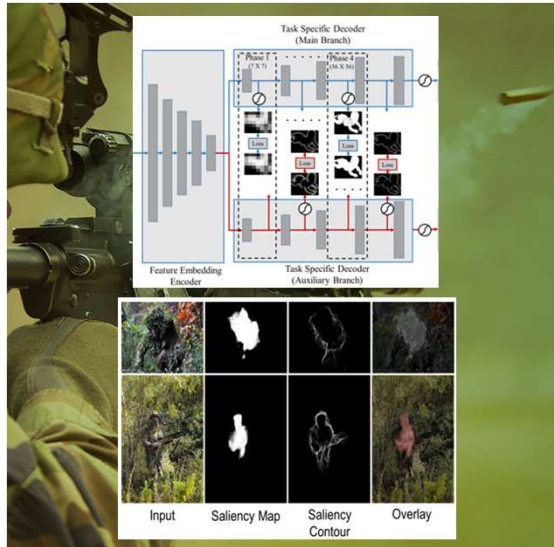
# Appendix



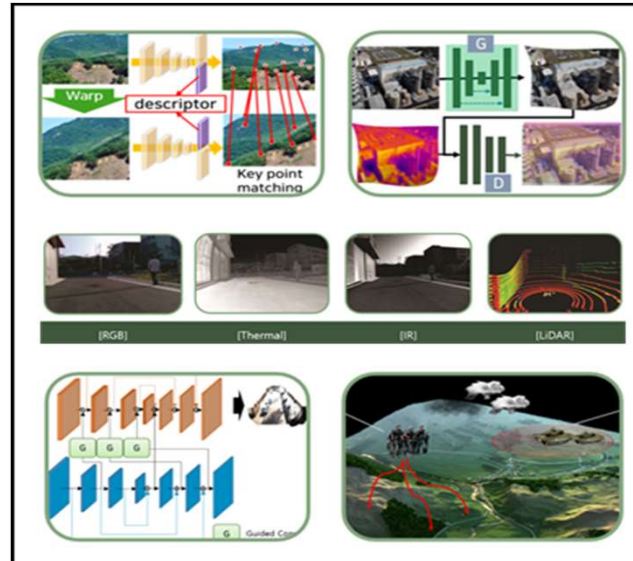
Research Topics

Image Processing and Intelligent systems Laboratory

AI Defense Monitoring



AI based Battlefield Visualization



Dual-Use Semantic AI



Research Projects

"Artificial Intelligence Future Defense Technology"

- Edge Camera Boundary Monitoring (2017-2021)
- Future Defense (2020-2023)
- Dual-Use technology (2020-2023)
- Deep View Stage 3 (2021-2023)

Publications

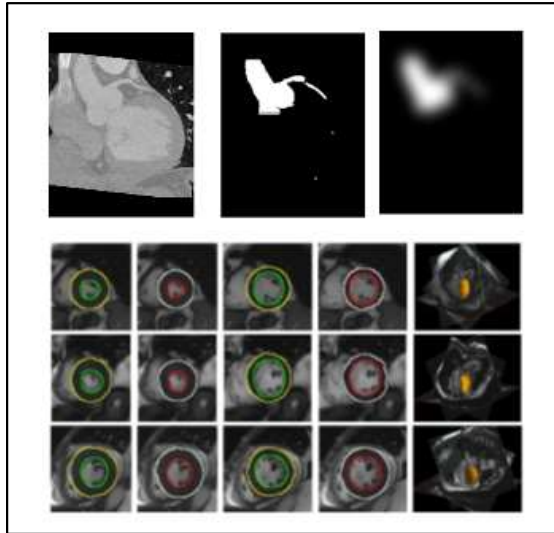
- Region-Based Dehazing via Dual-Supervised Triple-Convolutional Network, **IEEE Trans. Multimedia**, 2021.
- Camera Orientation Estimation Using Motion-Based Vanishing Point Detection for Advanced Driving Assistance, **IEEE Trans. ITS**, 2021.
- HLDNet: Abandoned Object Detection Using Hand Luggage Detection Network, **IEEE Consumer Electronics Magazine**, 2021.

Research Topic

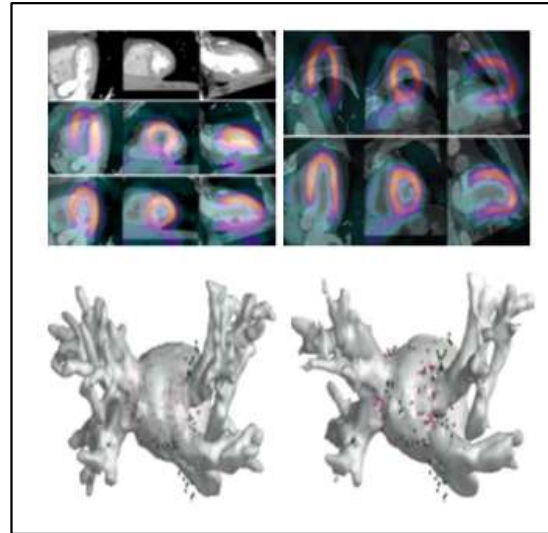
Image Laboratory

<http://image.cau.ac.kr>

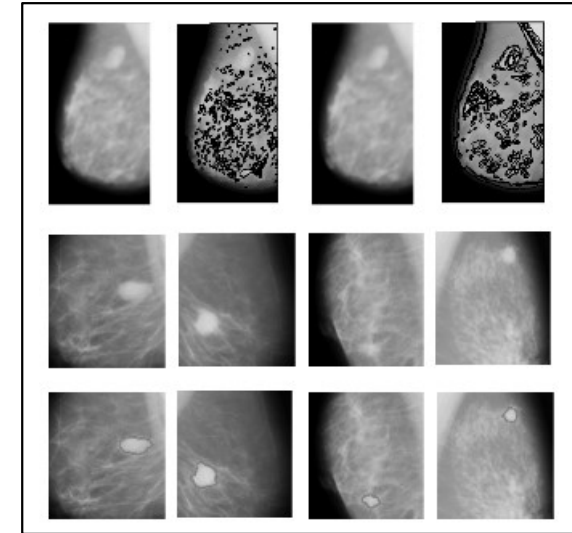
Segementation



Registration



Salient contour map



Collaborations



Recent Studies

IEEE Conference on Computer Vision and Pattern Recognition, July.2017.  
International Conference on Computer Vision(ICCV), 2021

IEEE Transactions on Image Processing(TIP), 2020  
International Conference on Robotics and Automation(ICRA), 2021

### AI+Medical

#### Eyelid length measurement using semantic segmentation

**Tasks**: Semantic Segmentation

**Domains**: Beauty, Plastic Surgery

**Process**: Before image → Segmentation → Generate alternate Image → Alter image → Plastic Surgery

**Frameworks**: Preprocessing (Right/Left eye, Datum point) → Segmentation Model (UNet) → Measure (Result image, Calculate)

Position	Upper_id	Lower_id	MIRD1	MIRD2
mm	39.71	35.21	3.44	6.35

### AI+Contents

#### Music recommendation system using multiple music features

**Architecture**: Music excerpts (STFT, Mel Spectrogram, MFCC) → Dense Block (k<sub>0</sub>+k, k<sub>0</sub>+2k, k<sub>0</sub>+3k, k<sub>0</sub>+4k) → Transition Layer (Batch Normalization, ReLU, Conv2d, AvgPool2d) → FC (Jazz, Classical, Pop, Rock)

**Configuration**: Conv2d → Max Pool → Dense Block (repeat) → Transition Layer → Dense Block → Classification Layer (Softmax)

### AI+Core

#### Neural Architecture Search in Limited Resources

**BackboneNAS**

**Target Device**: Android

**Parameter Setting**:
 

- GPUs**: Single GPU, Multi-GPUs (Node 수: 2, Node GPU 수: 3)
- Image size**: 1280\*1280, 640\*640
- NAS setting**: Automatic, Manual (Batch size: 16, Epoch: 30, Population size: 50)

**Dataset**: Upload

**Run NAS**: Save Model

### AI+Security

#### Homoglyph reconstruction using a language model

**Cyber-Security Threats**: Surface Web, Spam, Phishing, Malware, Dark Web, Drugs, Money Laundering, Pornography (18+)

**Automated Adversarial Text Restoration**:
 

- Input: "Purchase \$ 2000 in bitcoin and ..."
- OCR processing: "If you do not fund this bitcoin ..."
- Pre-training: BERT Masked LM on masked sentence.
- Prediction: BERT Masked LM on input tokens to restore text.

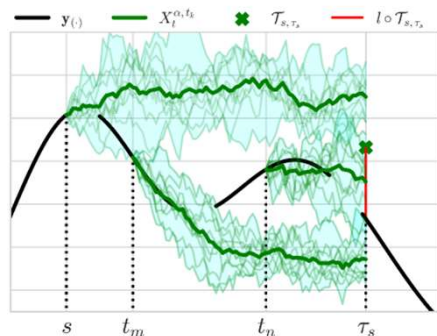


Research Topic

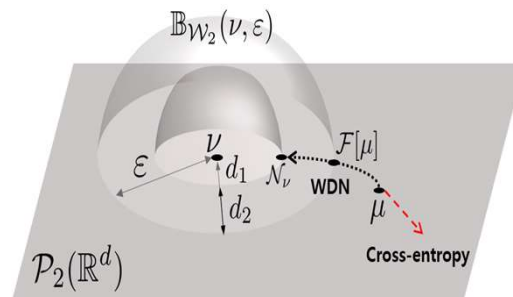
Computer Vision Machine Learning Lab (prof. Junseok Kwon)



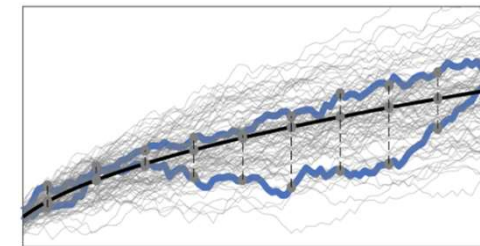
- **Machine learning:** Optimal transport, Wasserstein ambiguity, Neural ODE, MCMC
- **Deep learning:** Generative adversarial network, Graph convolution, Meta learning
- **High-level vision:** Object detection, Object tracking, Segmentation, 3D Point clouds
- **Low-level vision:** Dehazing, Super-resolution, and Low-light enhancement



Stochastic Dynamics Estimation for Stock Market Data



Distributinal Certification of Noisy Labeled Data



Markovian Temporal Dynamics Generation for Stochastic Continuous Data

Our goal is to develop an artificial intelligence model that is robust to changes in the external environment such as noise and can theoretically explain the ambiguity of data.

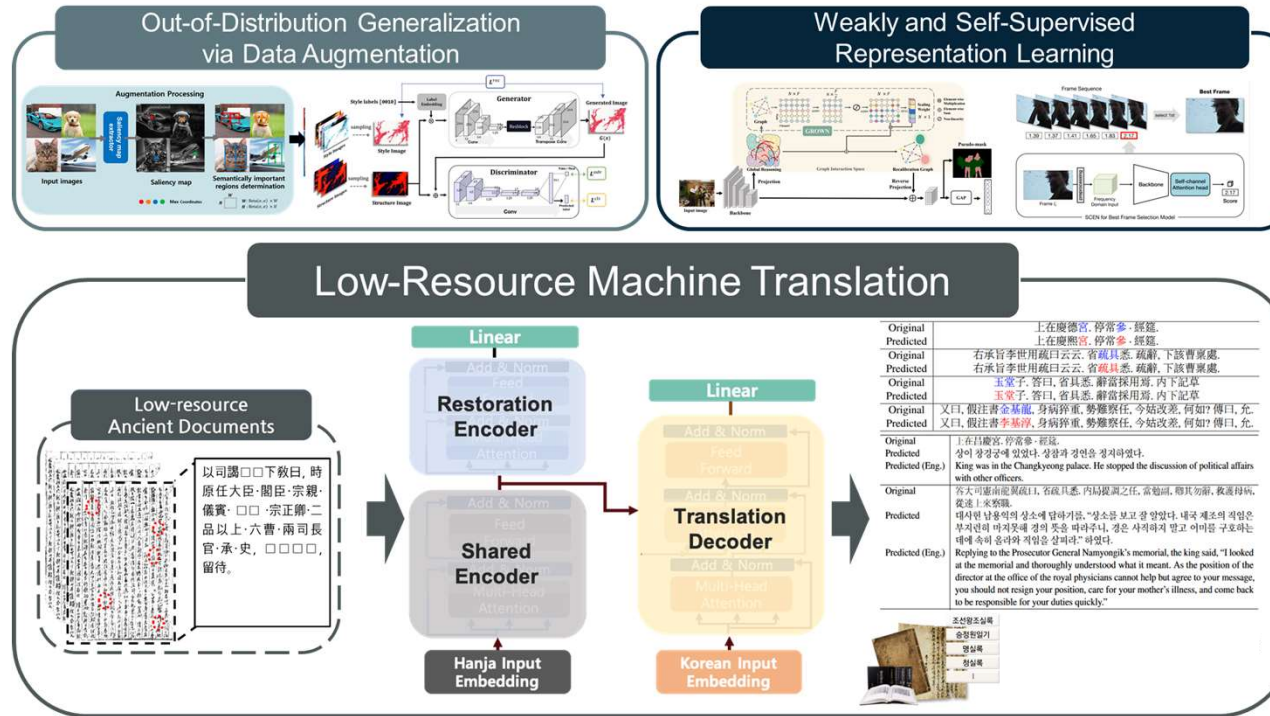
Publications



Research Topic

Intelligent Information Processing Lab.(Prof. YoungBin Kim)

Intelligent Information Processing Lab. IIPL



“Research on accurate restoration and efficient multilingual translation of diverse low-resource documents”

Publications

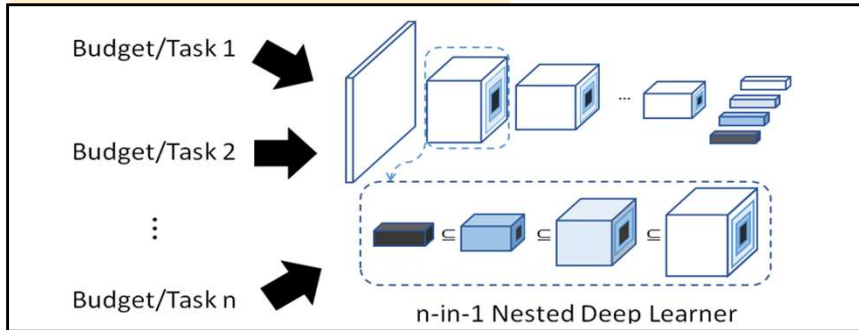
- Weakly supervised semantic segmentation via Graph RecalibratiOn with Scaling Weight uNit; **Engineering Applications of Artificial Intelligence, 2023**
- Game effect sprite generation with minimal data via conditional GAN; **Expert Systems with Applications, 2023**
- Restoring and Mining the Records of the Joseon Dynasty via Neural Language Modeling and Machine Translation; **NAACL, 2021.**
- TrafficBERT: Pre-trained Model with Large-scale Data for Long-range Traffic Flow Forecasting; **Expert Systems with Applications, 2021.**
- Whose Opinion Matters? Analyzing Relationships between Bitcoin Prices and User Groups in Online Community; **Social Science Computer Review, 2020.**
- Visual Analytics with Interpretable and Interactive Recurrent Neural Networks on Electronic Medical Records; **IEEE VIS, 2019.**

# Research Topics

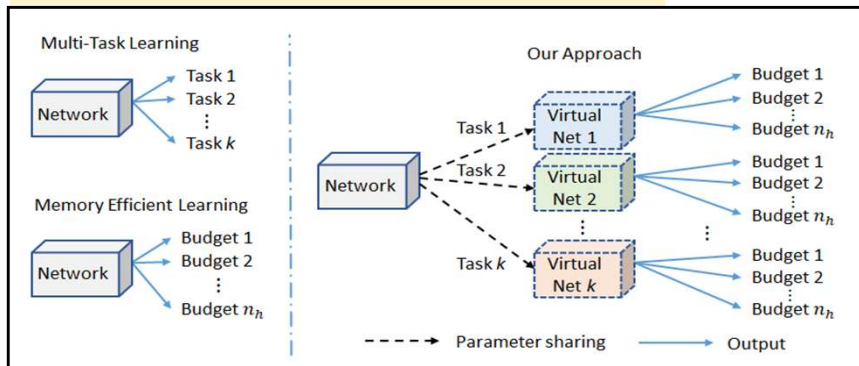
## Vision & Learning Laboratory (Prof. Eunwoo Kim)



### Multi-Task Deep Learning



### Resource-Efficient Deep Learning



### Automated Machine Learning / Continual Learning

**Statistical Machine Learning**

**Applications: Computer Vision, Robotics, Autonomous Vehicles**

### Lab Members

9 Grad Students, 5 Undergrad Students (2022.09)

### Recent Studies

- Helpful or Harmful: Inter-Task Association in Continual Learning, **ECCV, 2022**.
- Deep Elastic Networks with Model Selection for Multi-Task Learning, **ICCV, 2019**
- Deep Virtual Networks for Memory Efficient Inference of Multiple Tasks, **CVPR, 2019**.
- NestedNet: Learning Nested Sparse Structures in Deep Neural Networks, **CVPR, 2018**.

### Collaborations

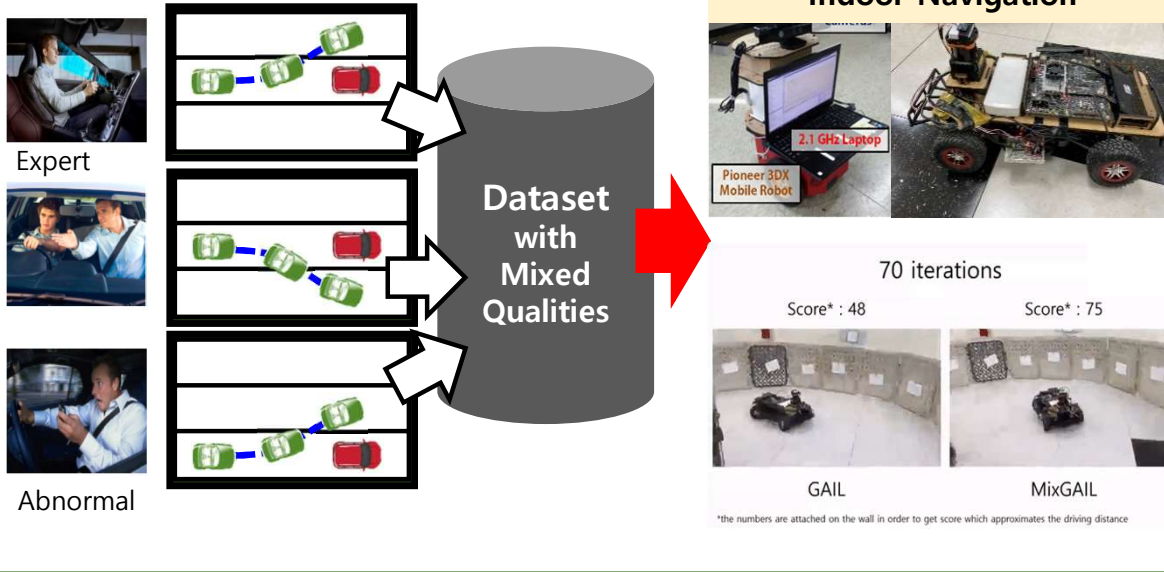


## Research Topic

## Robotics and Artificial Intelligence Lab

Human Level Robot Learning

### Robust Imitation Learning



### Efficient Reinforcement Learning

$$\max_{\pi} \mathbb{E} \left[ \sum_{t=0}^{\infty} \underbrace{\gamma^t (r(s_t, a_t))}_{\text{Return}} - \underbrace{\ln_q(\pi(a_t|s_t))}_{\text{Tsallis Entropy}} \right]$$

- Entropy-based Efficient Exploration
- Online Learning for Robotics
- Control of complex dynamical systems

#### Learning-based Control



#### Object Manipulation



## Publications

- SWAD: Domain Generalization by Seeking Flat Minima, **NeurIPS, 2021.**
- Optimal Algorithms for Stochastic Multi-Armed Bandits with Heavy Tailed Rewards, **NeurIPS, 2020.**
- Maximum Causal Tsallis Entropy Imitation Learning, **NeurIPS, 2018.**

## Research Topics

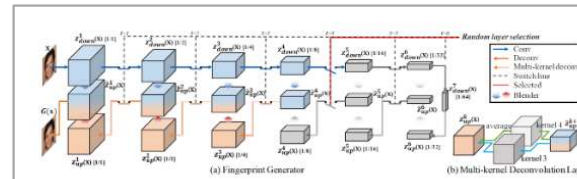
## Visual Intelligence Laboratory

- Semi-supervision – Domain Adaptation, Active Learning
- AI security – Deepfake detection, Anti-spoofing
- AI+X – AI+Contents, AI+Heritage, AI+Autonomous driving

- 1 Faculty – Jongwon Choi (Ph.D.)
- 4 Ph.D Candidate – MinGyu Lee, Seo Seung Mo, Seungjin Jung, Hojoon Jung
- 17 MS Candidate – Jong Min Lee, PyoungGeon Kim, Youn Jong Su, JaeYoon Lee, Soo Hyun Park, Hwang Jin Soo, Minji Kwak, Jongwook Choi, Hyungjun Lim, Dohee Kim, Suk Hyun Kim, Yujeong Oh, Taeheon Lee, Suyeon Cha, Taehoon Kim, Jooyoung Lee, Cho Hyun Jin

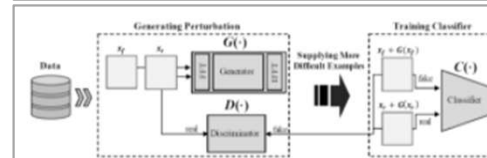
## Recent Studies

AAAI2022 & ECCV2022 & WACV2022  
Self-supervised Deepfake Detection



### FingerprintNet: Synthesized Fingerprints for Generated Image Detection

Yonghyun Jeong, Doyeon Kim, Youngmin Ro, Pyounggeon Kim, Jongwon Choi  
European Conference on Computer Vision 2022 (ECCV2022) [Top-tier CV Conference],  
[Paper][Arxiv][Supplementary][Github]



### FrePGAN: Robust Deepfake Detection Using Frequency-level Perturbations

Yonghyun Jeong, Doyeon Kim, Youngmin Ro, Jongwon Choi  
AAAI Conference on Artificial Intelligence 2022 (AAAI2022) [Top-tier AI Conference],  
[Paper][Arxiv][Supplementary][Github]

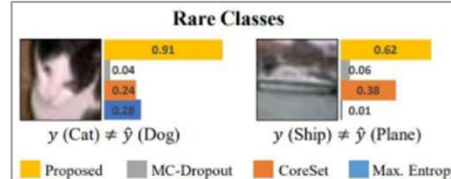
WACV2022  
Novel-view Synthesis (NeRF)



### Novel-View Synthesis of Human Tourist Photos

Jonathan Freer, Kwang Moo Yi, Wei Jiang, Jongwon Choi, Hyung Jin Chang  
Winter Conference on Applications of Computer Vision 2022 (WACV2022),  
[Paper][Supplementary][Github]

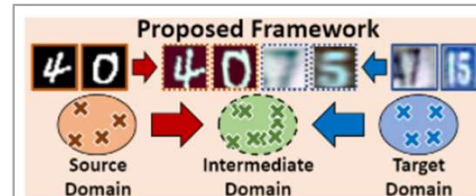
CVPR2021  
Active Learning in the Wild



### VaB-AL: Incorporating Class Imbalance and Difficulty with Variational Bayes for Active Learning

Jongwon Choi\*, Kwang Moo Yi\*, Jihoon Kim, Jinho Choo, Byoungjip Kim, Jin-Yeop Chang, Youngjune Gwon, Hyung Jin Chang  
(\* Equally contributed)  
IEEE Conference on Computer Vision and Pattern Recognition 2021 (CVPR2021) [Top-tier CV Conference],  
[Paper][Arxiv][Supplementary][Github]

AAAI2020  
Domain Adaptation for Large Gap



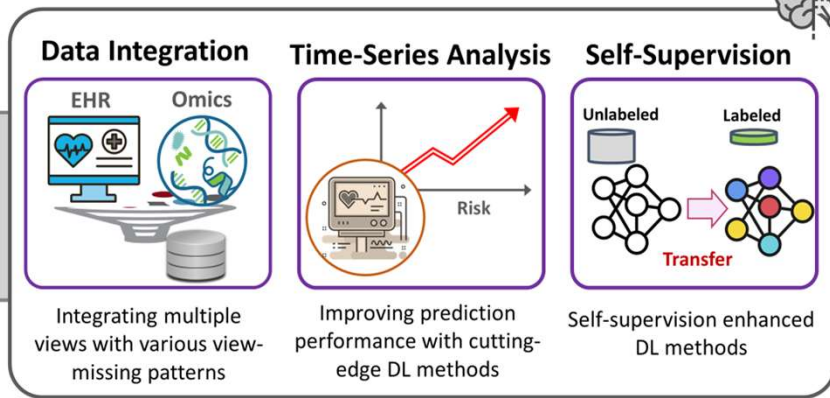
### Visual Domain Adaptation by Consensus-based Transfer to Intermediate Domain

Jongwon Choi, Youngjoon Choi, Jihoon Kim, Jinyeop Chang, Ilhwan Kwon, Youngjune Gwon, Seungjai Min  
AAAI Conference on Artificial Intelligence (AAAI2020) [Top-tier AI Conference],  
[Paper][Supplementary]

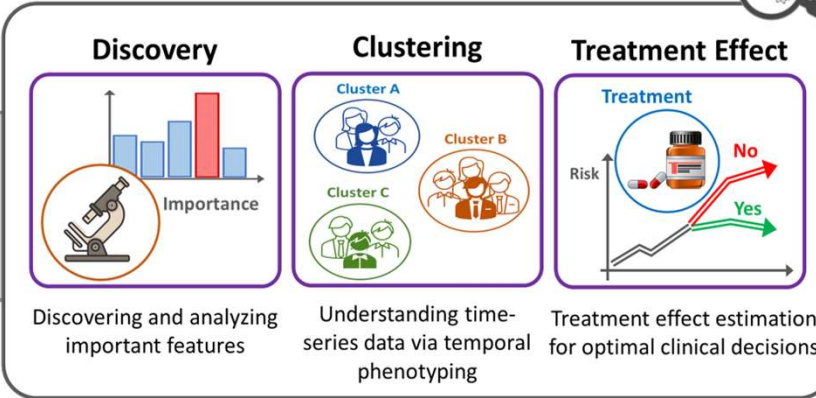
## Research Pillars

## Decision Intelligence Lab

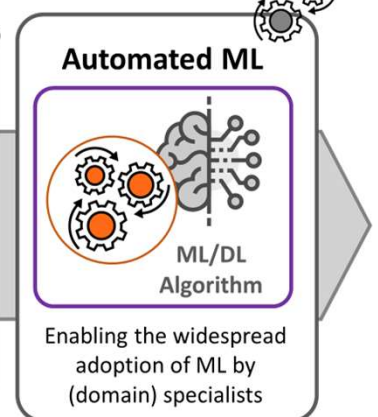
### High Performance



### Actionable AI



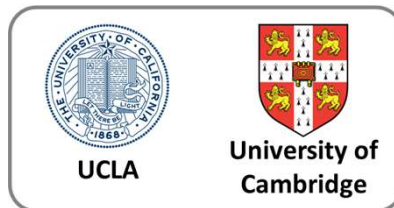
### Scalable AI



"Revolutionizing Healthcare through cutting-edge machine learning methods"

## Research Collaborations

### Universities



### National Institutes



## Selected Papers

- **C Lee**, F. Imrie, M. van der Schaar, "Self-Supervision Enhanced Feature Selection with Correlated Gates," *ICLR, 2022*.
- A. Curth, **C. Lee**, M. van der Schaar, "SurvITE: Learning Heterogeneous Treatment Effects from Time-to-Event Data," *NeurIPS, 2021*.
- **C. Lee**, A. Light, E. Saveliev, M. van der Schaar, V. Gnanapragasam, "Developing Machine Learning Algorithms for Dynamic Estimation of Progression during Active Surveillance for Prostate Cancer," *npj Digital Medicine, 2022*.
- **C. Lee**, A. Light, A. Alaa, D. Thurtle, M. van der Schaar, V. Gnanapragasam, "Application of a novel ML framework for predicting non-metastatic PC-specific mortality in men using the SEER database," *The Lancet Digital Health, 2021*.

Research Topic

Intelligent Multimodal Reasoning (IMR) Lab.



Multimodal Learning (CV + NLP)

**Q: What did Robin do after he said I have a half hour to make it to the studio?**  
**QA : Video**      **Temporal Localization : Subtitle**

**A: Robin put her phone in her purse**

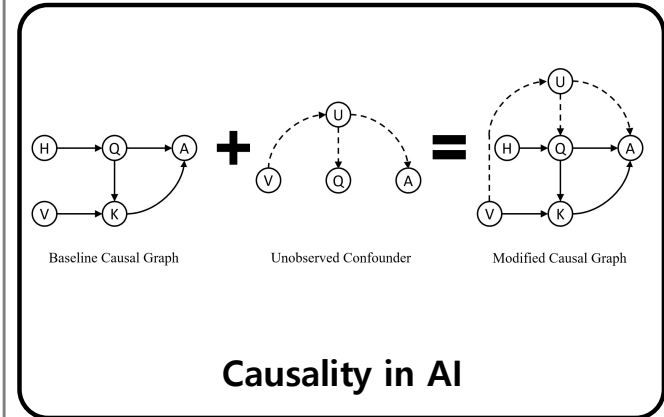
Multimodal Video QA

**Person puts down the box**  
 GE: 21.4 sec → 27.4 sec

**Person takes his phone out to take a picture**  
 GE: 9.6 sec → 15.9 sec

Video Search & CLS

Machine Learning



Causality in AI

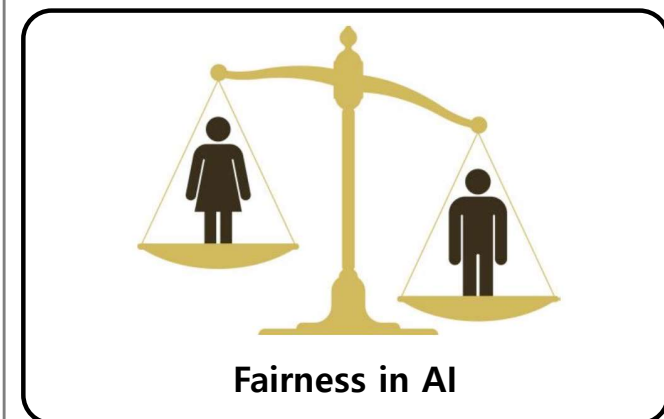
Video	Dialogue History
	Q1: What is happening in the video? A1: There's a person sitting on the sofa.
	Q2: What is the guy doing? A2: He opens a silver laptop.
	Q3: Is he the only person in the video? A3: Yes, he is the only person.
	⋮
	Q5: What room is he in? A5: I think it might be the living room.
	Q6: Does he play with it? A6: No, he does not play with the laptop.

Video Dialogue Generation

Place : Inside a great hall  
 Event : Person1 is approaching Person2 at the table

Place : At a patio table  
 Event : Person1 bends down as she holds the Champaign glass

Visual Commonsense Generation



Publications

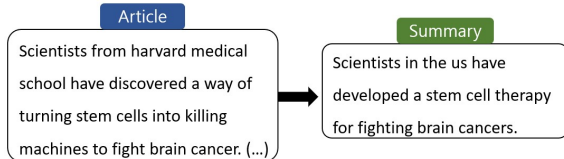
- Information-Theoretic Text Hallucination Reduction for Video-Grounded Dialogue, **EMNLP, 2022**
- Selective Query-guided Debiasing for Video Corpus Moment Retrieval, **ECCV, 2022**
- Structured Co-reference Graph Attention for Video-grounded Dialogue, **AAAI, 2021**
- Modality Shifting Attention Network for Multi-modal Video Question Answering, **CVPR, 2020**
- VLANet: Video-Language Alignment Network for Weakly-supervised Video Moment Retrieval, **ECCV, 2020**
- Progressive Attention Memory Network for Movie Story Question Answering, **CVPR, 2019**

# Research Topic

# Language Intelligence Laboratory

## Document Summarization

### Article Summarization



### Dialogue Summarization

**Dialogue**

**Person1:** What makes you think you are able to do the job?  
**Person2:** My major is Automobile Designing and I have received my master's *degree* in science. I think I can do it well.  
**Person1:** What kind of work were you *responsible* for the past employment?  
**Person2:** I am a student engineer who mainly took charge of understanding the *corrosion resistance* of various materials.

**Summary**  
Person1 is interviewing Person2 about Person2's ability and previous experience.

## Dialog System

### Personalized Dialog

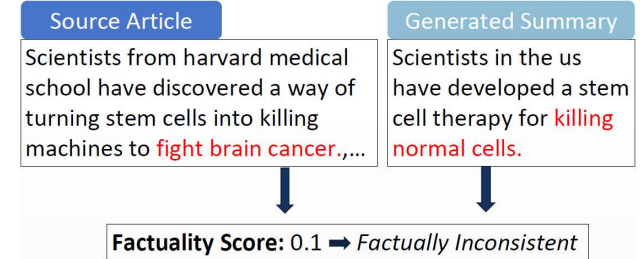


### Task-Oriented Dialog



## Factuality Checking

### Factual Consistency Evaluation

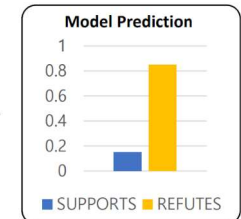


### Fact Verification

**Claim:** Magic Johnson *did not* play for the Lakers.

**Evidence:** Magic Johnson played for the Giants and no other team.

**Label:** SUPPORTS



"Research on Core Technologies for Knowledge Grounded Text Generation"

## Selected Publications

- Masked Summarization to Generate Factually Inconsistent Summaries for Improved Factual Consistency Checking, **NAACL 2022 Findings**
- QACE: Asking Questions to Evaluate an Image Caption, **EMNLP 2021 Findings**
- CrossAug: A Contrastive Data Augmentation Method for Debiasing Fact Verification Models, **CIKM 2021**
- UMIC: An Unreferenced Metric for Image Captioning via Contrastive Learning, **ACL 2021**
- KPQA: A Metric for Generative Question Answering Using Keyphrase Weights, **NAACL 2021**
- Improving Neural Question Generation using Answer Separation, **AAAI 2019**



# Research Topic

# Explainable Language Understanding Laboratory

## Natural Language Inference

### Numerical/Mathematical Inference

Juan drives to work. Because of traffic conditions, he averages 22 miles per hour. He returns home, averaging 32 miles per hour. The total travel time is 2.25 hours.

**Q. Write and solve an equation to find the time Juan spends driving to work.**

**A:**  $22x = 32y$  and  $x+y = 2.25$

### Inference with Text and Tables

ABC Co. Statement of Cash Flow	Year 1	Year 2
Cash flow from operating activities		
Net income	24,350	37,140
Items to reconcile net earnings to net cash used in operating activities		
Depreciation	2,449	3,156
	26,799	40,296
Changes in non-cash working capital		

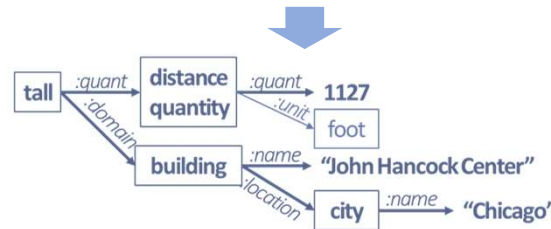
**Q. Compute the one-year growth rate of net income, in percentage.**

**A:**  $(37140 - 24350) / 24350 = 52.52\%$

## Explainable NLI model

### Semantic Parsing

The John Hancock Center in Chicago is 1127 feet tall.



### Interactive explanation

To obtain what you need, mix 97.5L of 80% HCl, all of 30% HCl, and 2.5L of pure water.

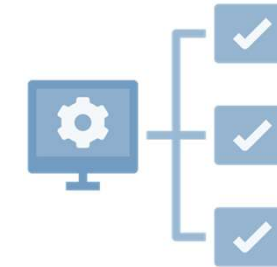
Could you explain why I need water?

To reduce the proportion of HCl.

Why do I need 97.5L instead of 96L?

## Credible Application of NLI

### Credible NLI system



### Explainable NLI system



“Towards an AI system that ensures its explainability and credibility through language-based interactions.”

## Publications

- **B. Kim**, K. Ki, S. Rhim, G. Gweon, “EPT-X: An Expression Pointer Transformer model that generates eXplanations for numbers,” *ACL, 2022*
- D. Lee, K. Ki, **B. Kim**, G. Gweon, “TM-generation model: a template-based method for automatically solving mathematical word problems,” *J. of Supercomputing 77(12), 2021*
- K. Ki, D. Lee, **B. Kim**, G. Gweon, “Generating equation by utilizing operators: GEO model,” *COLING, 2020*
- **B. Kim**, K. Ki, D. Lee, G. Gweon, “Point to the expression: Solving algebraic word problems using the expression-pointer transformer model,” *EMNLP, 2020*

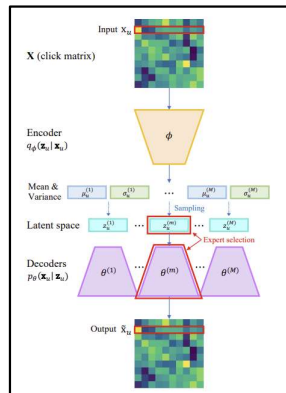
Research Topic

Data Science Lab

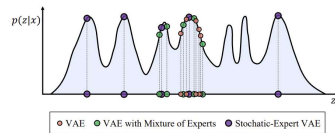


Recommender System

Stochastic-Expert VAE for CF

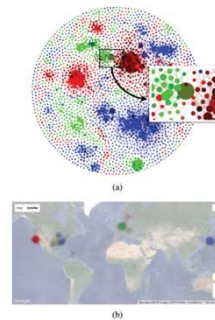


Learning User Behavior Pattern using Stochastic embedding, **SOTA results on Netflix, MovieLens datasets**



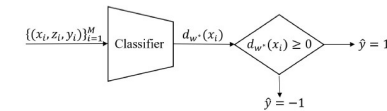
Multimodal Generative model

Apache Spark based multimodal social network implementation Using Map-Reduce framework for distributed computation

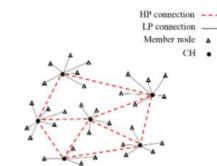


Fair - AI

Removing data bias through AI



ML Prediction under fairness constraints : Distributed Fair AI



Toward Graph-based XAI using Multimodal Social network

International Collaborations



Selected Publications

- MEME: Multi-Encoder Multi-Expert Framework with Data Augmentation for Video Retrieval, **SIGIR, 2023.**
- Stochastic Expert Variational Autoencoder for Collaborative Filtering, **WWW, 2022.**
- Detecting incongruent news headlines with auxiliary textual information, **Expert Syst Appl, 2022**
- Point of interest recommendations based on the anchoring effect in location-based social network services, **Expert Syst Appl, 2021.**
- Latent Space Model for Multi-Modal Social Data, **WWW, 2016.**



THE WEB  
CONFERENCE ACM

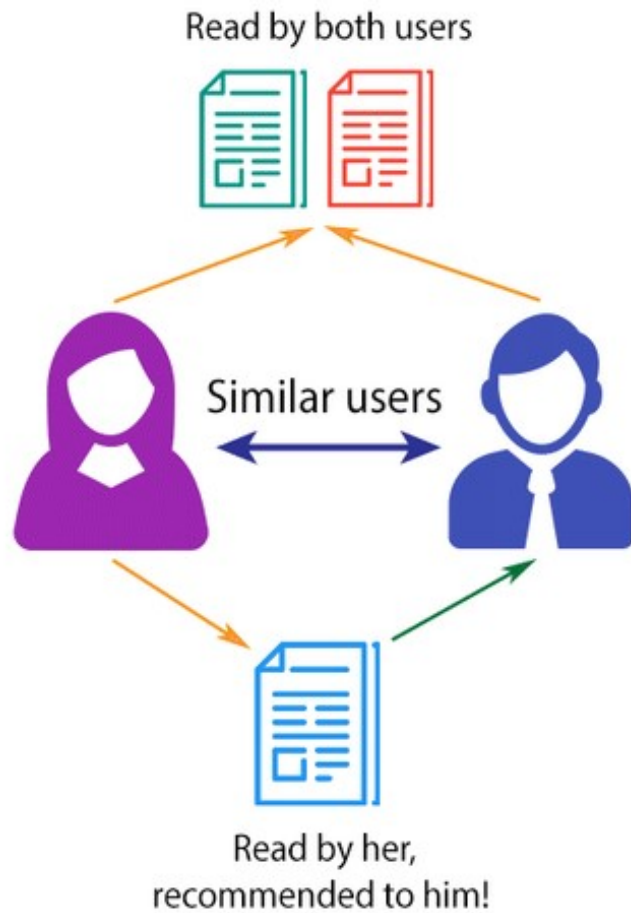
*Lyon, France, 25-29 April 2022*



# Stochastic-Expert Variational Autoencoder for Collaborative Filtering

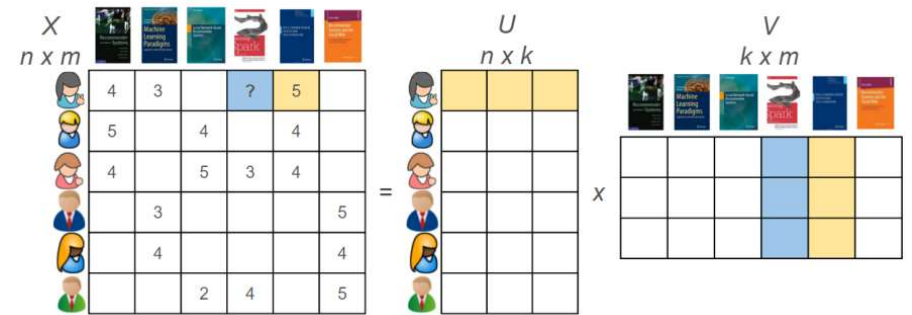
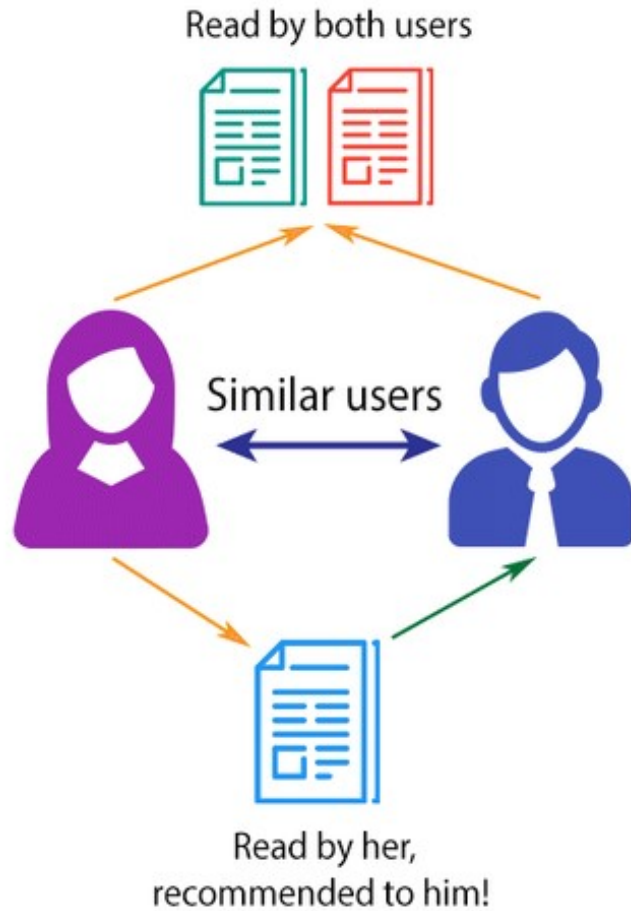
# Collaborative Filtering

## COLLABORATIVE FILTERING



# Collaborative Filtering

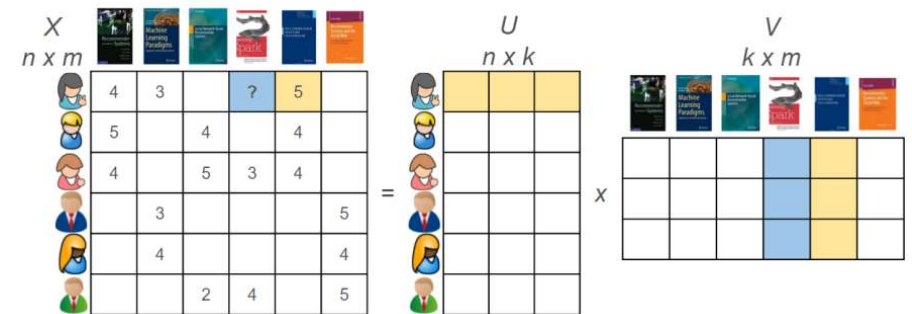
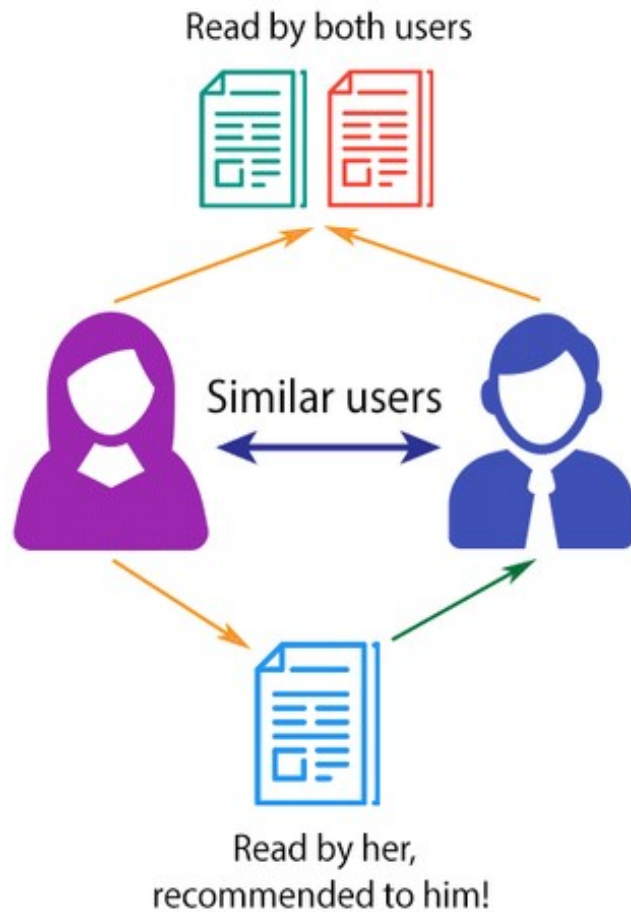
## COLLABORATIVE FILTERING



## Matrix Factorization

# Neural Collaborative Filtering

## COLLABORATIVE FILTERING

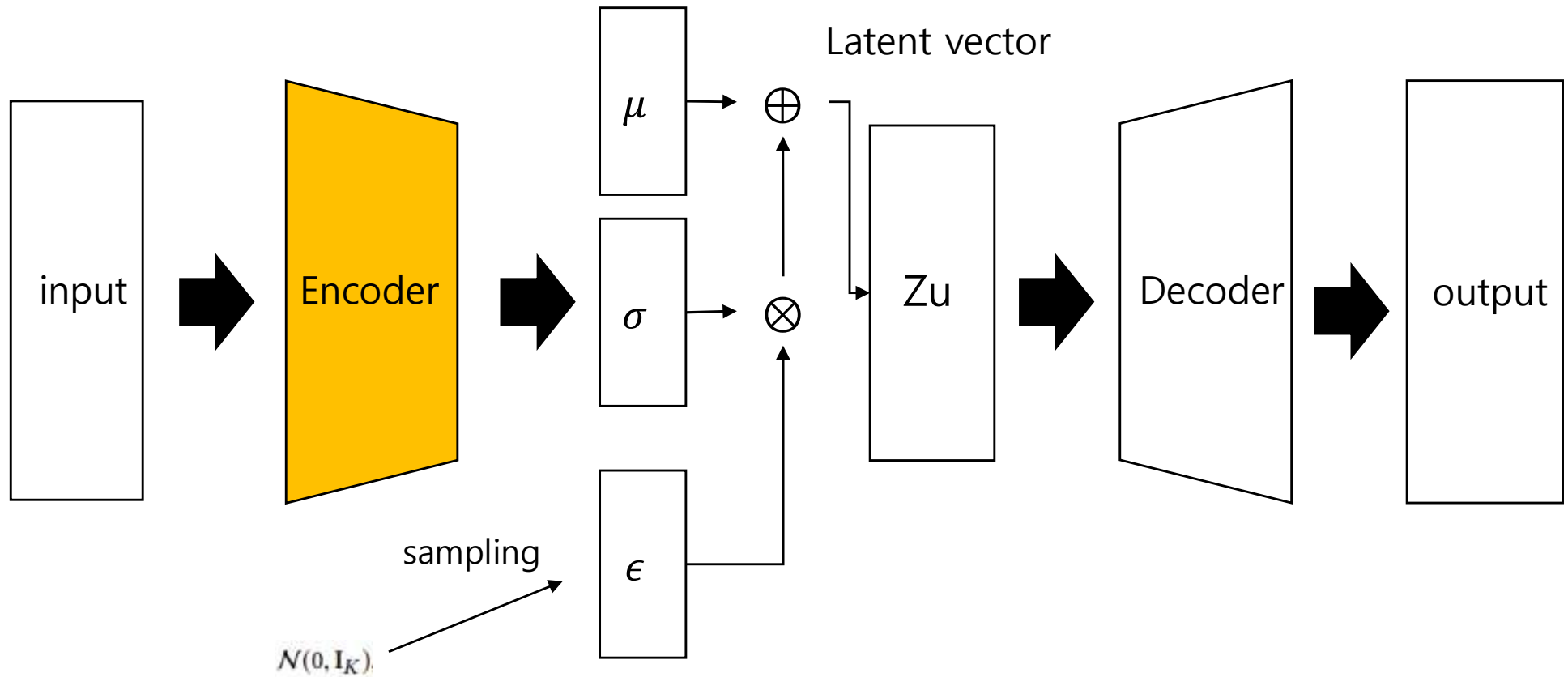


Dawen Liang, Rahul G. Krishnan, Matthew D. Hoffman, and Tony Jebara.

**Variational Autoencoders for Collaborative Filtering.** In Proceedings of the 2018 World Wide Web Conference (Lyon, France) (**WWW '18**)

# Preliminary

- Variational Autoencoder



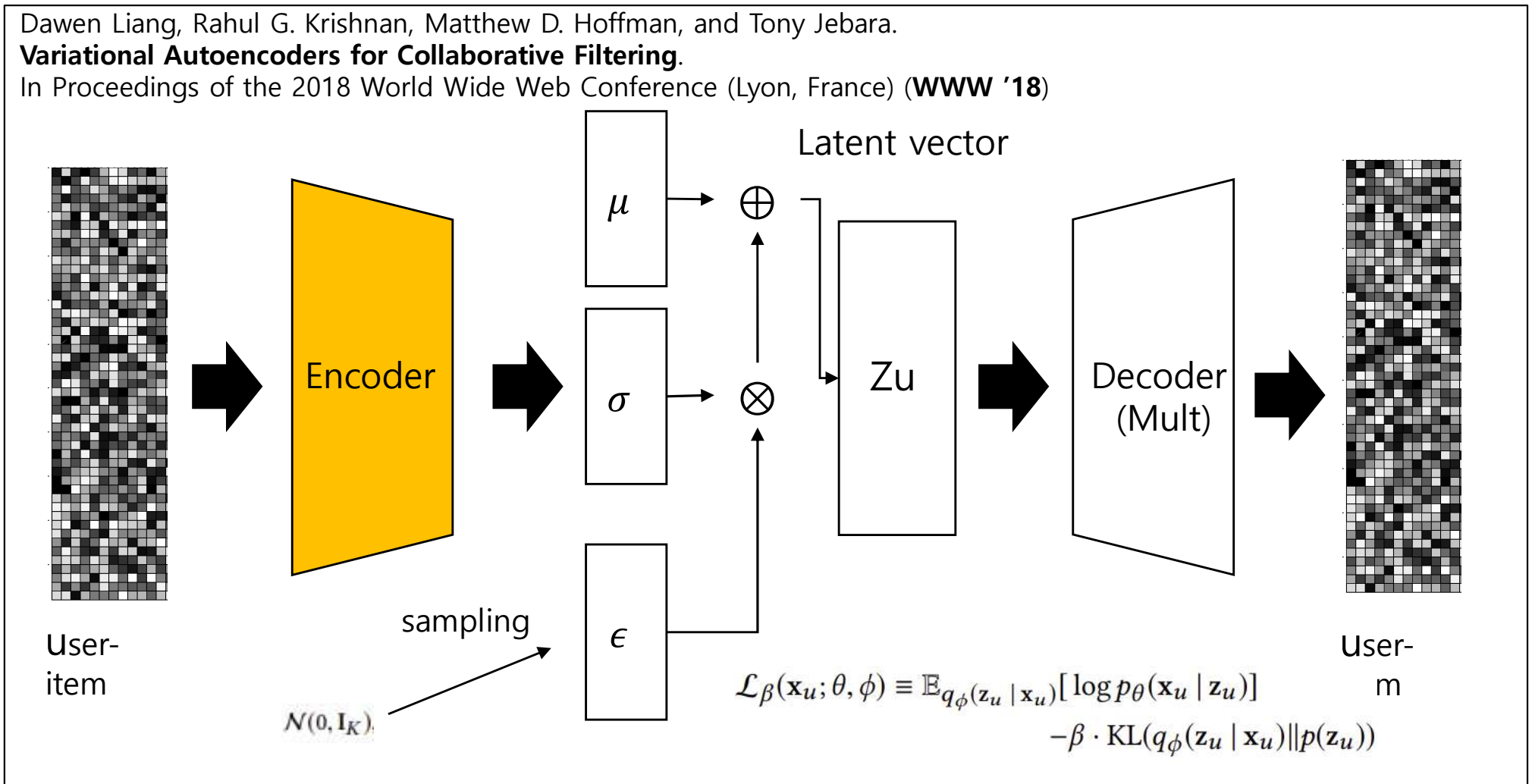
# Preliminary

- Variational Autoencoder for CF

Dawen Liang, Rahul G. Krishnan, Matthew D. Hoffman, and Tony Jebara.

## Variational Autoencoders for Collaborative Filtering.

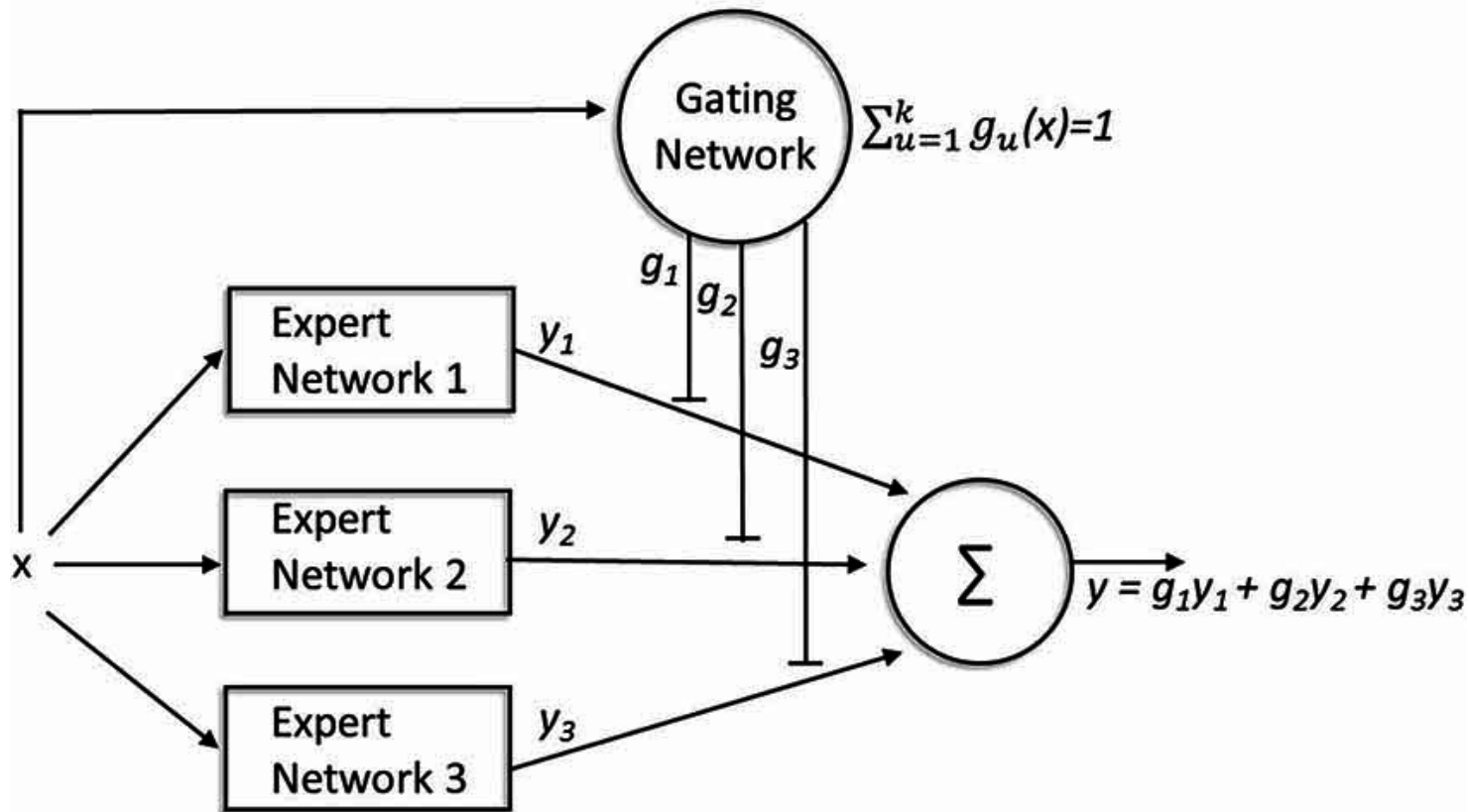
In Proceedings of the 2018 World Wide Web Conference (Lyon, France) (**WWW '18**)





# Preliminary

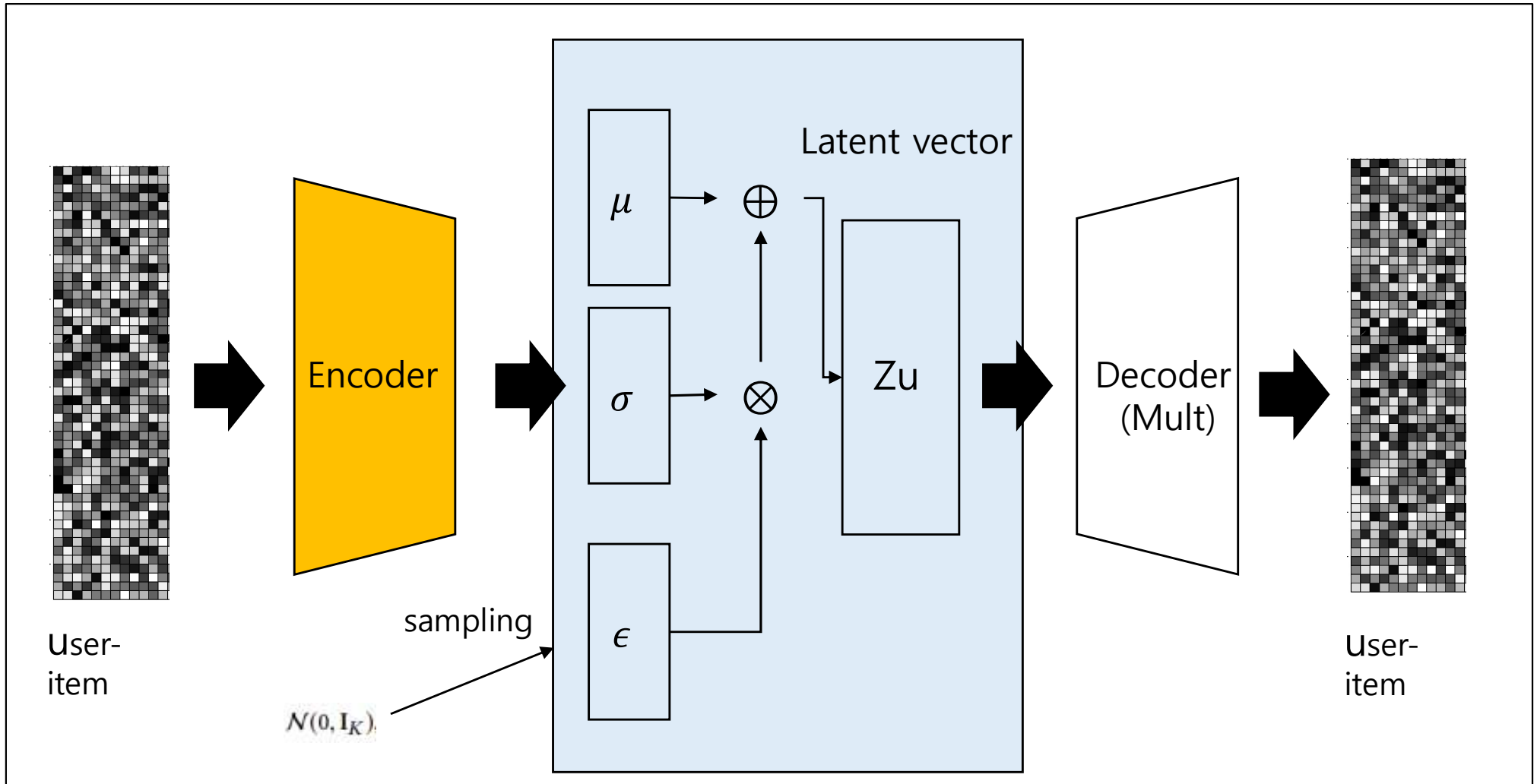
- Mixture-of-Experts (MoE)



Bock, Andrew & Fine, Ione. (2014). Anatomical and Functional Plasticity in Early Blind Individuals and the Mixture of Experts Architecture. *Frontiers in human neuroscience*. 8. 971. 10.3389/fnhum.2014.00971.

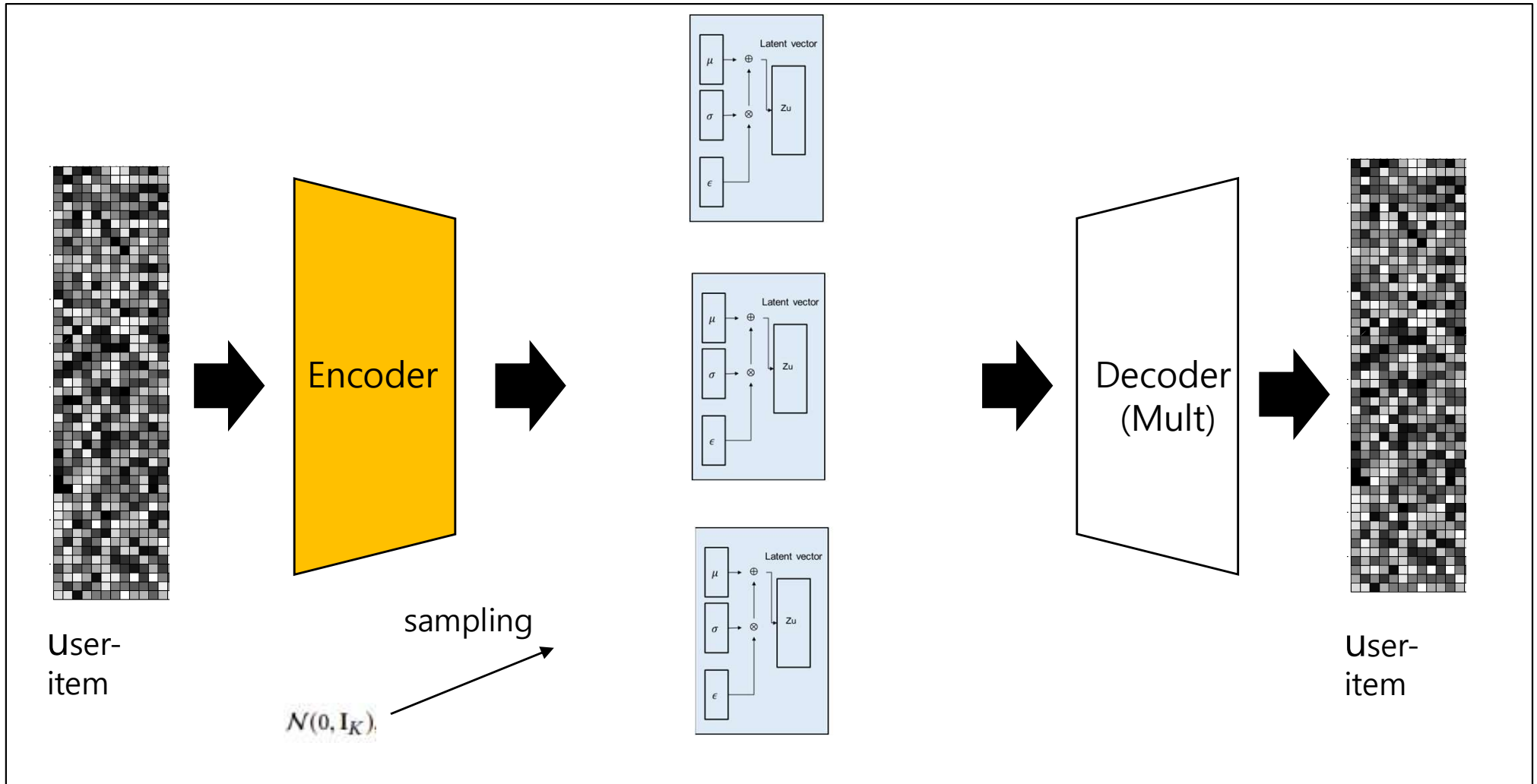
# SE-VAE motivation

- Based on VAECF



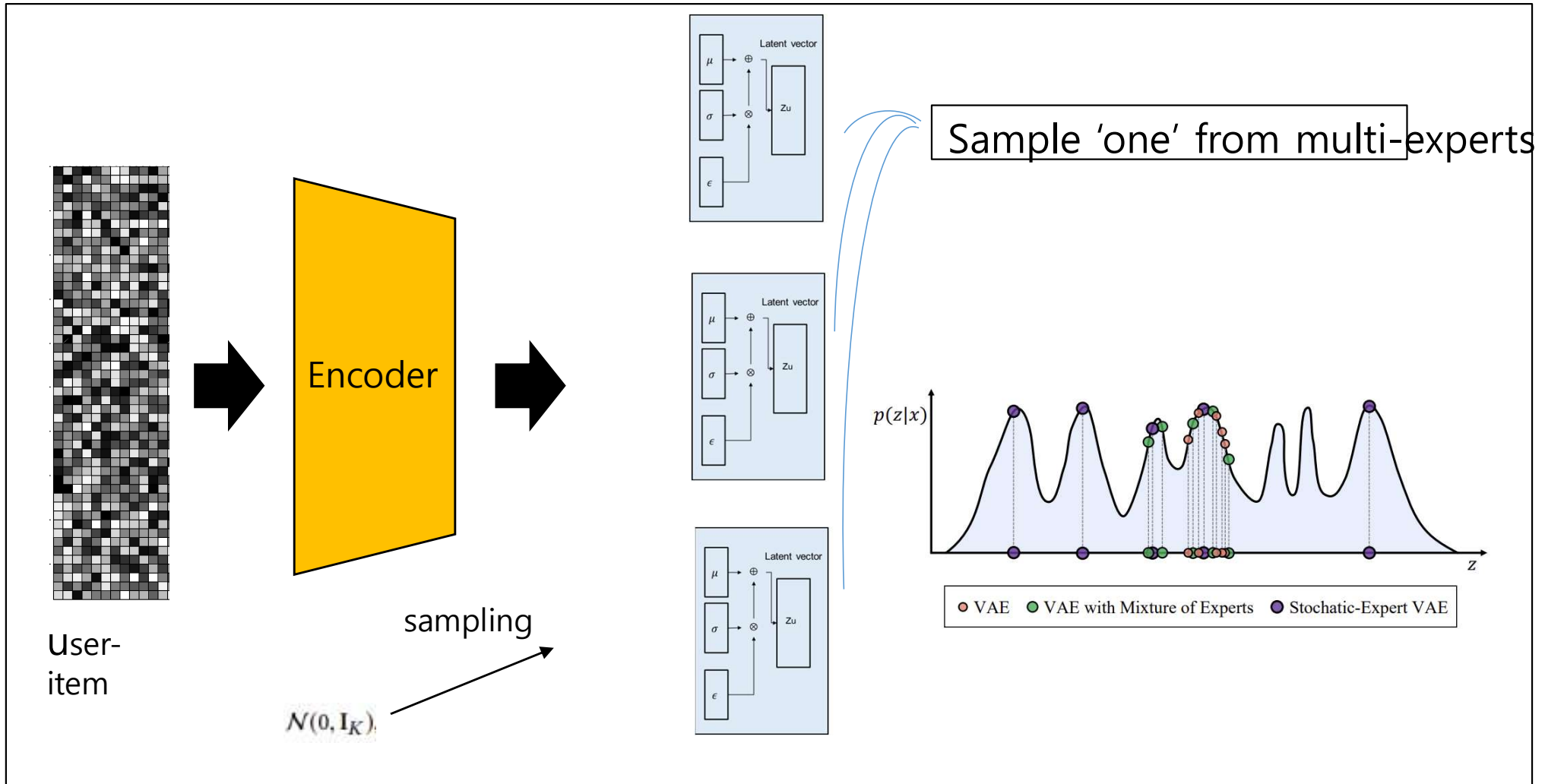
# SE-VAE motivation

- Extend VAECF to Multi-Experts

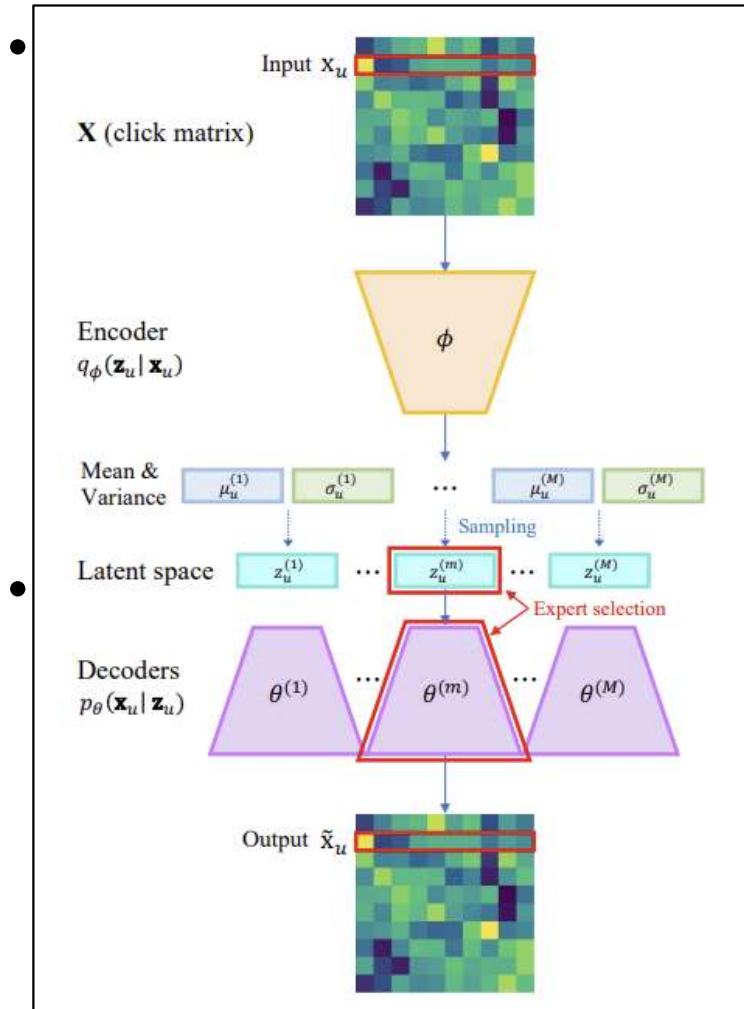


# SE-VAE motivation

- Extend VAECF to Multi-Experts



# SE-VAE Generative Process



**Require:**  $X \in \mathbb{N}^{U \times I}$   
**Ensure:**  $\phi, \theta = \{\theta^{(1)}, \dots, \theta^{(M)}\}$   
 Initialize  $\theta, \phi$   
**while** not converged **do**  
   Obtain batch of users  
   **for** user  $u$  in a batch **do**  
     Sample  $z_u$  and  $w_u$  using the RT  
     Compute gradient of  $\mathcal{L}$  w.r.t.  $\theta, \phi$  with  $z_u$  and  $w_u$   
   **end for**  
   Take average of gradients from the batch  
   Update  $\theta$  and  $\phi$  with SGD  
**end while**

probability of expert (m) being selected for user u

$$\mathcal{L}(x_u; \theta, \phi) = \sum_{m=1}^M \mathbb{E}_{q_\phi(z_u | x_u)} [q_{\text{cat}}(\mathbf{e}_u, m = 1) \log p_{\theta_m}(x_u | z_u^{(m)})] - \text{KL}(q_\phi(z_u | x_u) || p(z_u)) - \text{KL}(q_\phi(w_u | x_u) || p(w_u))$$

fully factorized Gaussian distribution which is used in Gumbel-Softmax as input logits

# Experimental Results

- Experimental Setup

## Datasets

- MovieLens 20M
  - 136,677** users
  - 20,108** items
  - On average, a user has clicked **73** items
- Netflix
  - 435,435** users
  - 17,769** items
  - On average, a user has clicked **122** items

## Evaluation Metrics

- Recall@R
  - proportion of relevant (clicked) items predicted in the top R items
- NDCG@R
  - emphasizes the importance of higher ranking than lower ones

# Experimental Results

Mul-VAE vs Mult-VAE with SE

- Apply Stochastic Expert on VAECF (Mult-VAE)

Model	MovieLens20M			Netflix		
	NDCG@100	Recall@50	Recall@20	NDCG@100	Recall@50	Recall@20
Mult-VAE	0.42700	0.53524	0.39569	0.38711	0.44427	0.35255
Mult-VAE (SE)	<b>0.43057</b>	<b>0.53688</b>	<b>0.40010</b>	<b>0.38789</b>	<b>0.44512</b>	<b>0.35332</b>

Follow the same settings, hyper parameters in VAECF

# Experimental Results

Model	MovieLens20M			Netflix		
	NDCG@100	Recall@50	Recall@20	NDCG@100	Recall@50	Recall@20
WMF [7]	0.386	0.498	0.360	0.351	0.404	0.316
SLIM [17]	0.401	0.495	0.370	0.379	0.428	0.347
CDAE [24]	0.418	0.523	0.391	0.376	0.428	0.343
Mult-VAE [14]	0.426	0.537	0.395	0.386	0.444	0.351
VAEGAN (AVB+D+C) [25]	0.438	0.541	0.407	0.396	0.447	0.363
EASE [21]	0.420	0.521	0.319	0.393	0.445	0.362
RaCT [15]	0.434	0.543	0.403	0.392	0.450	0.357
RecVAE [20]	0.442	0.553	0.414	0.394	0.452	0.361
H+Vamp (Gated) [9]	0.445	0.551	0.413	0.408	0.462	0.376

Model	MovieLens20M			Netflix		
	NDCG@100	Recall@50	Recall@20	NDCG@100	Recall@50	Recall@20
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H+Vamp (Gated)	0.44522	0.55109	0.41308	0.40861	0.46252	0.37678
H+Vamp (Gated,SE)	<b>0.44718</b>	<b>0.55551</b>	<b>0.41787</b>	<b>0.40907</b>	<b>0.46312</b>	<b>0.37713</b>



# Experimental Results

Model	MovieLens20M			Netflix		
	NDCG@100	Recall@50	Recall@20	NDCG@100	Recall@50	Recall@20
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RecVAE [20]	0.442	0.553	0.414	0.394	0.452	0.361
H+Vamp (Gated) [9]	0.445	0.551	0.413	0.408	0.462	0.376
<b>SE-VAE (H+Vamp, Gated)</b>	<b>0.447</b>	<b>0.556</b>	<b>0.418</b>	<b>0.409</b>	<b>0.463</b>	<b>0.377</b>

All the benchmark models use the same training set/ val set/ test set

# MEME : Multi-Encoder Multi-Expert Framework with Data Augmentation for Video Retrieval

Seong-Min Kang

✉ kang7734@cau.ac.kr

Yoon-Sik Cho

✉ yoonsik@cau.ac.kr

 [https://github.com/kang7734/MEME\\_](https://github.com/kang7734/MEME_)

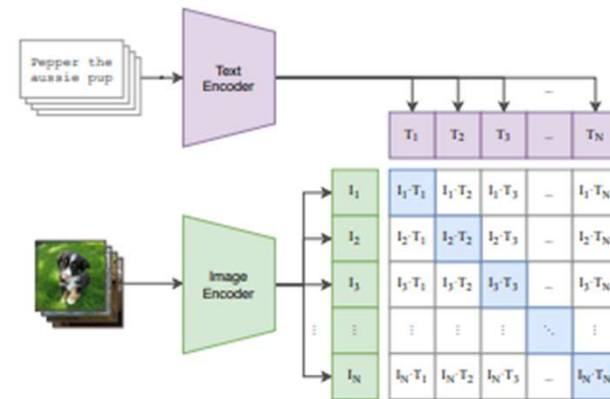
#01

# Motivation



"A woman is singing a song"	"A girl playing guitar"
"A girl is playing a guitar and singing"	"A woman plays the guitar"
"A young woman is playing a guitar and singing"	"A girl is playing guitar"
Fine-grained information	Coarse-grained information

(1) Contrastive pre-training

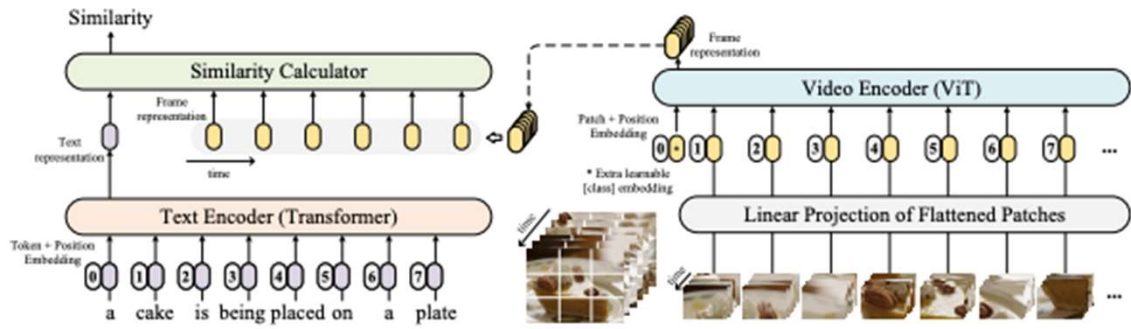


CLIP[1]

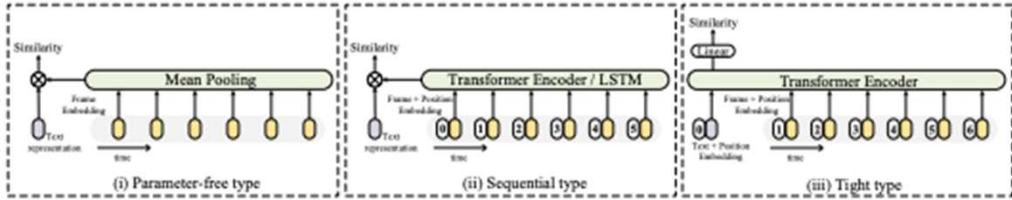
[1] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In International Conference on Machine Learning, pages 8748–8763. PMLR, 2021.

#01

Motivation



(a) Main structure



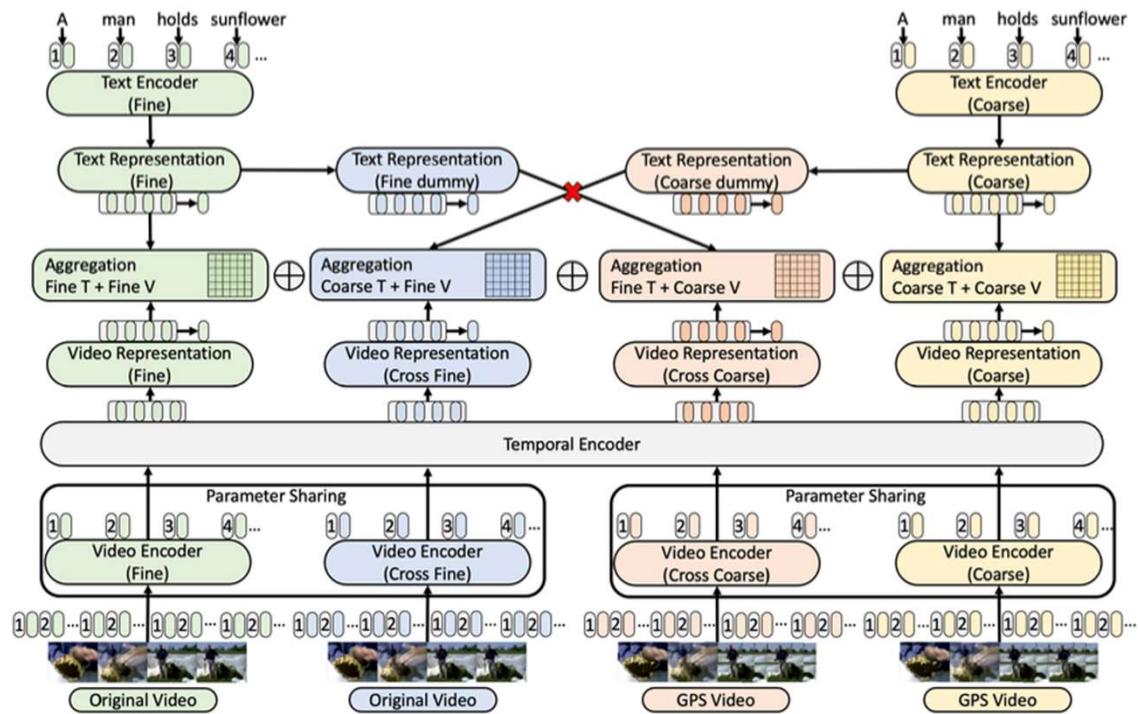
(b) Similarity calculator

CLIP4Clip

# #02

## Method

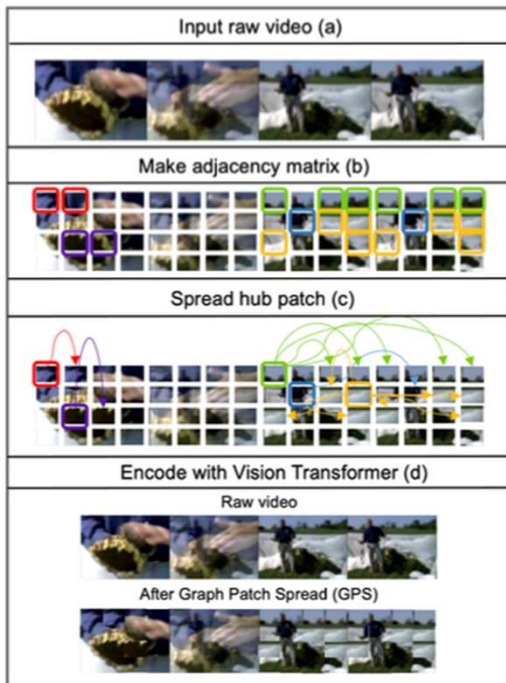
Multi-Encoder Multi-Expert



#02

## Method

### GPS(Graph Patch Spreading) Algorithm



#### Algorithm 1 GPS: Graph Patch Spread

**Require:** Video  $V = (v_1, v_2, \dots, v_n)$   $\triangleright n$  is the number of frames  
Frame  $v_i = (x_p^1, x_p^2, \dots, x_p^N)$   $\triangleright N$  is the number of patches

**Ensure:** output = []

```
1:  $v_i = v_i / v_i.\text{norm}()$ 
2:  $S = V \cdot V^T$   $\triangleright S$  is similarity matrix of each token
3:  $S[S \geq k] = 1$   $\triangleright k$  is similarity threshold
4:  $S[S < k] = 0$   $\triangleright$  Now  $S$  is Adjacency matrix
5: for  $S_j$  in  $S$  do
6:   while  $\text{sum}(S_j) = \text{len}(S_j)$  do
7:      $C = \text{nonzero count}(S_j)$ 
8:      $h = \text{argmax}(C, \text{dim} = 0)$   $\triangleright h$  is the index of hub patch
9:      $L = \text{arange}(\text{len}(S_j[h])) + 1$ 
10:     $L = S_j[h] * L$   $\triangleright L$  is linked patches idx with hub patch
11:     $S_j^T[h, L] = 1$   $\triangleright$  Spread hub patch
12:   end while
13:    $v_i = v_i \cdot S_j^T$ 
14:   output.append( $v_i$ )
15: end for
16:  $V = \text{stack}(\text{output})$ 
```

#03

## Experiments

Methods	Text-to-Video Retrieval				Video-to-Text Retrieval			
	R@1↑	R@5↑	R@10↑	MeanR↓	R@1↑	R@5↑	R@10↑	MeanR↓
TT-CE+ [8]	29.6	61.6	74.2	-	32.1	62.7	75.0	-
Frozen [9]	31.0	59.5	70.5	-	-	-	-	-
CLIP [1]	31.2	53.7	64.2	-	27.2	51.7	62.6	-
*CLIP4Clip [2](MeanP)	43.9	70.9	81.1	15.9	42.6	70.9	81.1	12.0
CLIP2Video [11]	45.6	72.6	81.7	14.6	43.5	72.3	82.1	10.2
CAMoE [16]	44.6	71.6	82.1	15.1	45.1	72.4	83.1	10.0
QB-Norm [39]	47.2	73.0	83.0	-	-	-	-	-
CenterCLIP [17]	44.2	71.6	82.1	15.1	42.8	71.7	82.2	10.9
CLIP2TV [13]	46.1	72.5	82.9	15.2	43.9	73.0	82.8	11.1
*CLIP4Clip(seqTransf) [2]	43.1	72.7	81.5	15.7	43.4	70.0	80.3	11.8
*CLIP4Clip(seqTransf+MEME)	<b>45.0(+1.9)</b>	72.3(-0.4)	<b>82.2(+0.7)</b>	<b>13.7(-2.0)</b>	42.5(-0.9)	<b>71.0(+1.0)</b>	<b>81.4(+1.1)</b>	<b>10.3(-1.5)</b>
*ts2net [18]	46.4	74.7	82.8	14.0	45.6	73.1	83.4	9.6
*ts2net(+MEME)	<b>46.6(+0.2)</b>	73.1(-1.6)	<b>82.9(+0.1)</b>	<b>12.6(-1.4)</b>	<b>45.8(+0.2)</b>	71.8(-1.3)	<b>83.7(+0.3)</b>	<b>8.4(-1.2)</b>
*ts2net(DSL) [18]	50.5	76.5	<b>85.9</b>	12.1	45.6	<b>73.1</b>	83.4	9.6
*ts2net(DSL+MEME)	<b>51.6(+1.1)</b>	<b>76.6(+0.1)</b>	85.7(-0.2)	<b>11.8(-0.3)</b>	<b>45.8(+0.2)</b>	71.8(-1.3)	<b>83.7(+0.3)</b>	<b>8.4(-1.2)</b>
*X-CLIP [5]	46.8	73.8	<b>83.1</b>	13.1	47.3	73.6	81.8	9.6
*X-CLIP(+MEME)	<b>49.0(+2.2)</b>	73.5(-0.3)	82.0(-1.1)	<b>13.0(-0.1)</b>	<b>47.7(+0.4)</b>	<b>74.0(+0.4)</b>	<b>83.3(+1.5)</b>	<b>9.4(-0.2)</b>

Table 1: Results on MSR-VTT [40], \* denotes that the results are reproduced by our experimentation with the original code.

Methods	Text-to-Video Retrieval				Video-to-Text Retrieval			
	R@1↑	R@5↑	R@10↑	MeanR↓	R@1↑	R@5↑	R@10↑	MeanR↓
TT-CE+ [8]	17.2	36.5	46.3	-	17.5	36.0	45.0	-
Frozen [9]	15.0	30.8	39.8	-	-	-	-	-
CLIP [1]	15.1	28.3	35.8	132	7.5	18.4	25.1	151
*CLIP4Clip [2](MeanP)	20.6	39.8	47.7	60.6	20.0	38.4	48.4	55.4
CAMoE [16]	22.5	42.6	50.9	56.5	-	-	-	-
QB-Norm [39]	17.8	37.7	47.6	-	-	-	-	-
CenterCLIP [17]	21.9	41.1	50.7	57.2	21.1	41.2	50.2	48.7
*CLIP4Clip(seqTransf) [2]	23.0	40.9	48.4	58.8	20.4	39.6	<b>49.3</b>	54.2
*CLIP4Clip(seqTransf+MEME)	<b>23.4(+0.4)</b>	<b>42.0(+1.1)</b>	<b>49.3(+0.9)</b>	<b>57.3(-1.5)</b>	<b>21.1(+0.7)</b>	<b>40.4(+0.8)</b>	49.2(-0.1)	<b>53.1(-1.1)</b>
*ts2net [18]	20.4	40.1	<b>47.5</b>	68.3	20.5	37.3	46.4	<b>62.4</b>
*ts2net(+MEME)	<b>21.4(+1.0)</b>	<b>40.3(+0.2)</b>	46.6(-0.9)	<b>67.5(-0.8)</b>	<b>20.8(+0.3)</b>	37.3(±0.0)	<b>46.6(+0.2)</b>	63.7(+1.3)
*ts2net(DSL) [18]	21.9	40.1	48.7	<b>64.5</b>	20.5	37.3	46.4	<b>62.4</b>
*ts2net(DSL+MEME)	<b>22.2(+0.3)</b>	<b>41.1(+1.0)</b>	<b>48.9(+0.2)</b>	65.3(+0.8)	<b>21.1(+0.6)</b>	37.3(±0.0)	<b>46.8(+0.4)</b>	65.2(+2.8)
*X-CLIP [5]	23.2	41.0	51.1	55.8	22.4	40.4	48.7	51.7
*X-CLIP(+MEME)	<b>24.0(+0.8)</b>	<b>41.7(+0.7)</b>	<b>51.4(+0.3)</b>	<b>53.5(-2.3)</b>	<b>22.5(+0.1)</b>	<b>42.3(+1.9)</b>	<b>50.3(+1.6)</b>	<b>49.3(-2.4)</b>

Table 3: Results on LSMDC [42], \* denotes that the results are reproduced by our experimentation with the original code.

#03

## Experiments

Methods	Text-to-Video Retrieval				Video-to-Text Retrieval			
	R@1↑	R@5↑	R@10↑	MeanR↓	R@1↑	R@5↑	R@10↑	MeanR↓
TT-CE+ [8]	23.5	56.9	71.3	-	27.1	55.3	67.0	-
Frozen [9]	33.7	64.7	76.3	-	-	-	-	-
CLIP [1]	37.0	64.1	73.8	-	59.9	85.2	90.7	-
*CLIP4Clip [2](MeanP)	46.1	76.0	84.6	10.0	56.1	78.9	83.9	8.0
CLIP2Video [11]	47.0	76.8	85.9	9.6	58.7	85.6	91.6	4.3
CAMoE [16]	46.9	76.1	85.5	9.8	-	-	-	-
QB-Norm [39]	47.6	77.6	86.1	-	-	-	-	-
CenterCLIP [17]	47.6	77.5	86.0	9.8	54.2	78.4	84.9	7.6
CLIP2TV [13]	46.1	72.5	82.9	15.2	43.9	73.0	82.8	11.1
*CLIP4Clip(seqTransf) [2]	45.7	<b>75.6</b>	84.0	10.6	49.9	70.8	76.8	15.2
*CLIP4Clip(seqTransf+MEME)	<b>45.8(+0.1)</b>	75.4(-0.2)	<b>84.2(+0.2)</b>	<b>10.3(-0.3)</b>	<b>59.1(+9.2)</b>	<b>81.7(+10.9)</b>	<b>87.8(+11.0)</b>	<b>6.8(-8.4)</b>
*ts2net [18]	45.1	75.5	84.5	10.2	56.4	79.1	85.2	9.4
*ts2net(+MEME)	<b>45.4(+0.3)</b>	<b>75.9(+0.4)</b>	<b>84.7(+0.2)</b>	10.2(±0.0)	<b>58.1(+1.7)</b>	<b>84.6(+5.5)</b>	<b>89.0(+3.8)</b>	<b>6.0(-3.4)</b>
*ts2net(DSL) [18]	47.6	<b>78.0</b>	<b>86.0</b>	10.1	56.4	79.1	85.2	9.4
*ts2net(DSL+MEME)	<b>47.7(+0.1)</b>	77.9(-0.1)	85.9(-0.1)	10.1(±0.0)	<b>57.0(+0.6)</b>	<b>79.5(+0.4)</b>	<b>85.3(+0.1)</b>	<b>8.9(+0.5)</b>
*X-CLIP [5]	46.4	76.4	84.6	<b>9.8</b>	53.9	79.0	85.3	7.1
*X-CLIP(+MEME)	<b>46.6(+0.2)</b>	<b>76.5(+0.1)</b>	<b>85.0(+0.4)</b>	10.0(+0.2)	<b>63.8(+9.9)</b>	<b>87.8(+8.8)</b>	<b>92.5(+7.2)</b>	<b>4.2(-2.9)</b>

Table 2: Results on MSVD [41], \* denotes that the results are reproduced by our experimentation with the original code.



Thank you

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