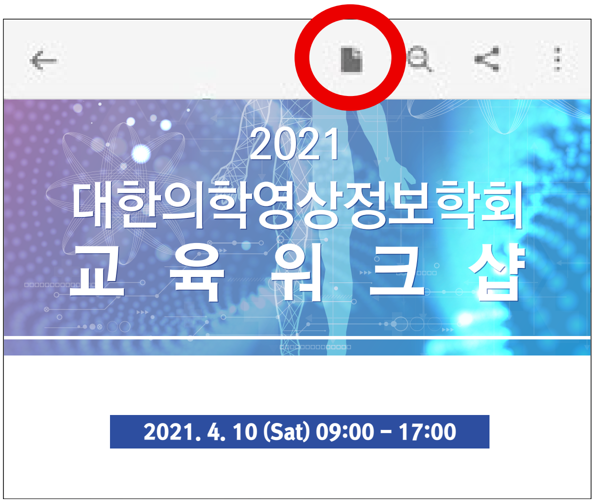
본 초록은 E-book으로 제작했습니다.
QR코드를 이용해 다운로드 후
아래와 같이 설정해주세요.

1. Adobe Acrobat Reader을 다운로드한다.
2. 다운로드 받은 초록 파일을 실행한다.
3. 화면 상단의 붉은 원 안의 표시된 부분을 누른다.



4. 화면 하단의 '페이지 단위'를 선택한다.

2021
대한의학영상정보학회
교 육 워 크 샵

2021. 4. 10 (Sat) 09:00 – 17:00

KOREAN SOCIETY OF
IMAGING INFORMATICS
IN MEDICINE

Program

09:00 – 09:10	Intro	정명진 성균관의대 서울삼성병원	
	Back to Basic		
09:10 – 09:35	Radiography	이준구 울산의대 서울아산병원	05
09:35 – 10:00	CT	장원 서울의대 분당서울대병원	07
10:00 – 10:25	MR	이영한 연세의대 세브란스병원	27
10:25 – 10:50	DICOM	김광기 가천의대 길병원	33
10:50 – 11:00	*Break*		
	GAN in Medical Imaging		
11:00 – 12:00	GAN 기초 이론, 종류, 응용	유재준 EPFL	40
12:00 – 12:30	데이터증강을 위한 GAN 및 평가방법	배현진 프로메디우스	42
12:30 – 13:30	*Lunch Break*		
	AI in Practice		
13:30 – 14:00	흉부방사선 영상진단	황의진 서울의대 서울대병원	52
14:00 – 14:30	AI in Practice at Radiation Oncology	김진성 연세의대 세브란스병원	59
14:30 – 15:00	Artificial intelligence in digital pathology intelligence	송상용 성균관의대 삼성서울병원	82
15:00 – 15:10	*Break*		
	Recent Issues of Medical AI		
15:10 – 15:40	Algorithm robustness and confidence	이지형 성균관대학교 인공지능대학원	85
15:40 – 16:20	임상 AI validation의 실제	한경화 연세의대 세브란스병원	105
16:20 – 16:50	Federated learning : recent improvements and challenges	양은호 한국과학기술원 AI 대학원	108

1

Back to Basic

CURRICULUM VITAE

이준구

울산의대 서울아산병원

EDUCATION	1997 – 2003	서울대학교 공과대학 원자핵공학과 학사
	2004 – 2011	서울대학교 방사선응용생명과학 협동과정 박사
CAREER	2009 – 2012	매사추세츠 종합 병원 (보스톤, 매사추세츠 주, 미국) 영상의학과 3D Imaging Lab. 연구보조원, 박사후 연구원
	2012 – 2014	피츠버그대학 (피츠버그, 펜실베니아 주, 미국) 영상의학과 Imaging Biomarker Lab. 연구조교수
	2014 – 2019	서울아산병원 의공학연구소 연구조교수
	2019 –	서울아산병원 의공학연구소 연구부교수

Radiography

최근 급속도로 발전하고 있는 인공지능 기술들이 의료분야에 적용되기 시작하였다. 특히, 컴퓨터 비젼과 관련된 기술들인 영상분류, 객체인식, 영역분할 등은 딥러닝을 통해 비약적인 성능향상이 이루어지고 있고, 연구 영역을 넘어서 많은 의료영상 관련 소프트웨어들로 개발되어 임상현장에서 사용되고 있다. 여러 의료영상 모달리티 중에서도 X-ray 영상은 환자들이 가장 많이 접하게 되며, 골절과 같은 응급의료상황, 검진에서 사용되는 흉부X-ray 영상, 그리고 mammography 에 이르기까지 다양한 의료현장에서 사용되고 있다.

본 강의에서는 이러한 X-ray 영상장치의 기본원리를 살펴보고, 각 사용례에 따른 영상에서의 특징을 살펴보고자 한다. 또한, 인공지능 연구를 위한 전처리 방법들을 살펴보고, 공개되어 있는 데이터베이스들을 소개하고자 한다.

마지막으로 연구실에서 수행하고 있는 흉부X선 영상 연구에 대해 말씀드리고자 한다. 흉부 X선 영상에서 주요 abnormality 를 분류하는 인공지능 모델, 흉부 X선 영상에서 cardiomegaly subtype을 분류하는 인공지능 연구 등을 소개하고자 한다.

CURRICULUM VITAE

장 원

서울의대 분당서울대병원

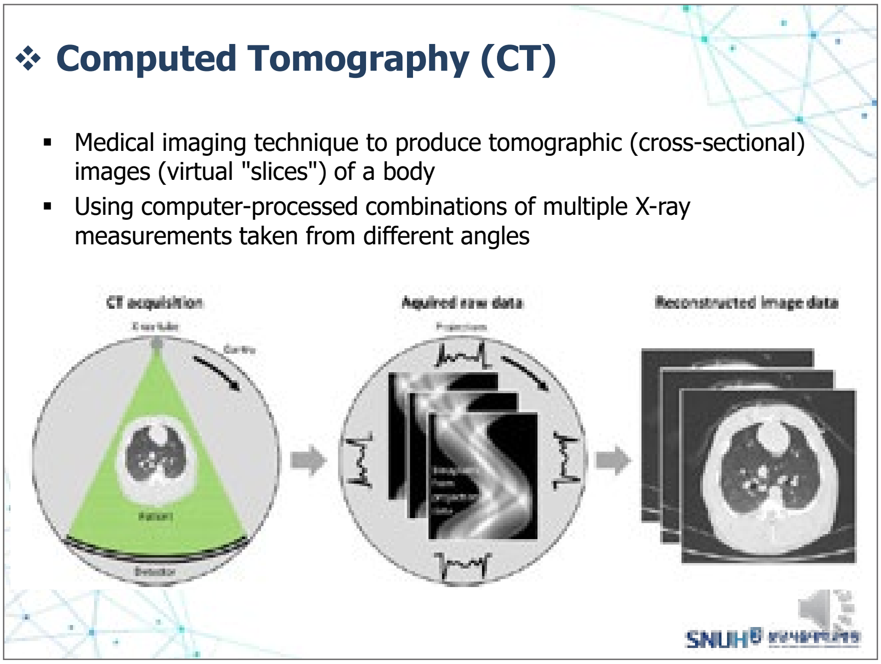
EDUCATION

2015 - 2017	Dep. of Radiology, Seoul National University College of Medicine, Seoul, Korea, , Ph.D.
2013 - 2015	Dep. of Radiology, Seoul National University College of Medicine, Seoul, Korea, M.S.
2003 - 2007	Seoul National University, College of Medicine, Seoul, Korea, M.D.

CAREER

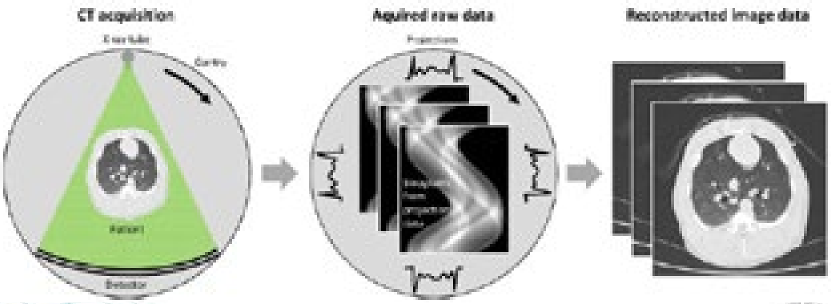
2017 - Present	Section of Gastrointestinal Imaging, Department of Radiology, Seoul National University Bundang Hospital, Seoul National University College of Medicine, Bundang, Korea, Clinical Assistant Professor
2016 - 2017	Section of Gastrointestinal Imaging, Department of Radiology, Seoul National University Hospital, Seoul National University College of Medicine, Seoul, Korea, Clinical Assistant Professor
2015 - 2016	Section of Gastrointestinal Imaging, Department of Radiology, Seoul National University Hospital, Seoul National University College of Medicine, Seoul, Korea, Instructor
2011 - 2015	Department of Radiology, Seoul National University Hospital, Seoul, Korea, Residency
2010 - 2011	Seoul National University Hospital, Seoul, Korea, Internship

CT


Computed Tomography (CT)
Medical imaging technique to produce tomographic (cross-sectional) images (virtual "slices") of a body
Using computer-processed combinations of multiple X-ray measurements taken from different angles
CT acquisition
Aquired raw data
Reconstructed image data
SNUH

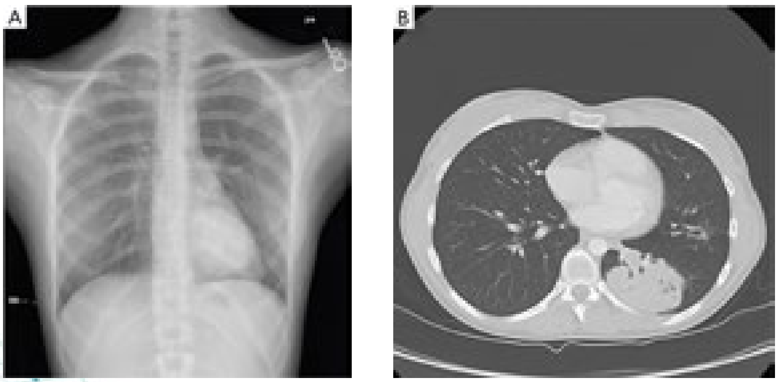
❖ Computed Tomography (CT)

- Medical imaging technique to produce tomographic (cross-sectional) images (virtual "slices") of a body
- Using computer-processed combinations of multiple X-ray measurements taken from different angles



SNUH

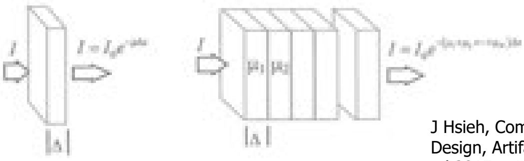
❖ Plain radiograph vs. CT



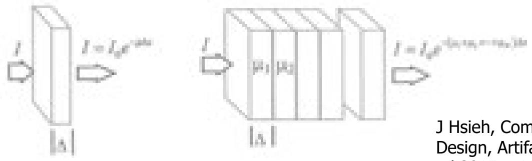
J Thorac Dis 2017;9(4):E364-E366

SNUH

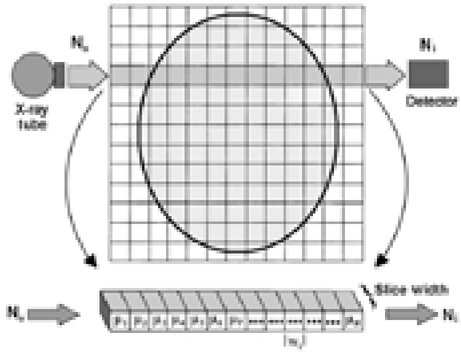
❖ Computed Tomography (CT)



J Hsieh, Computed Tomography: Principles, Design, Artifacts, and Recent Advances,3rd ed,2015, p44



J Hsieh, Computed Tomography: Principles, Design, Artifacts, and Recent Advances, 3rd ed, 2015, p44

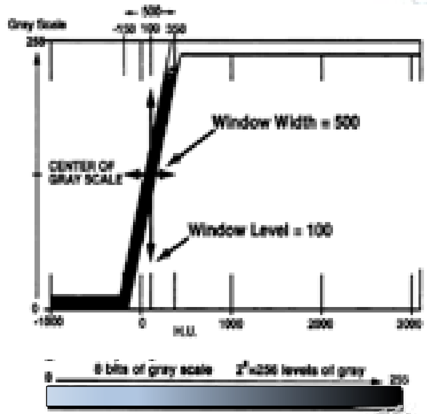


J Nucl Med Technol. 2007 Sep;35(3):115-28

- $\text{CT number} = \frac{\mu - \mu_{water}}{\mu_{water}} \times 1000\ (\text{HU})$

Material / Tissue	HU
Air	−1000
Lung	−600 to −400
Fat	−100 to −60
Water	0
Muscle	10 to 40
Blood	30 to 45
Soft tissue	40 to 80
Bone	400 to 3000

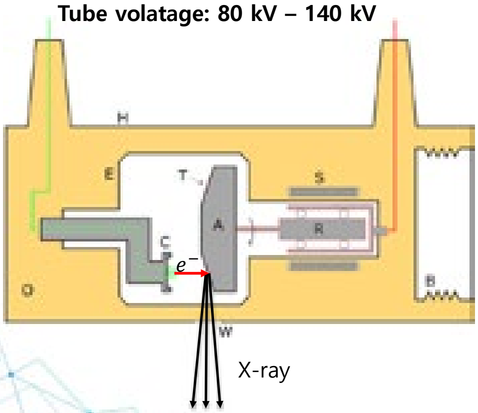
Taubmann O, Berger M, Bögel M, et al. Computed Tomography. 2018 Aug 3. In: Maier A, Steidl S, Christlein V, et al., editors. Medical Imaging Systems: An Introductory Guide [Internet]. Cham (CH): Springer; 2018.



RadloGraphics 1992; 12:825-837

❖ X-ray tube

Tube volatage: 80 kV – 140 kV

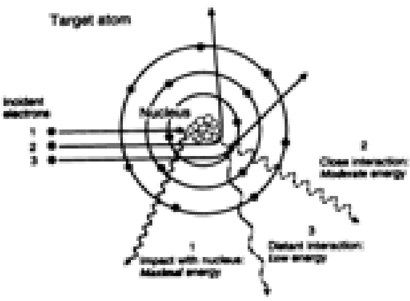


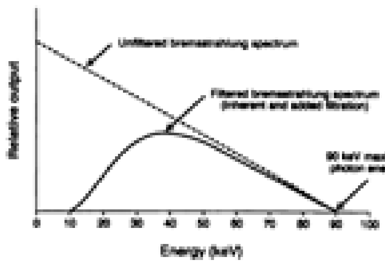
Symbol	English
A	Anode
B	Expansion bellows (provide sp ace for oil to expand)
C	Cathode (and heating-coil)
E	Tube envelope (evacuated)
H	Tube housing
O	Cooling dielectric oil
R	Rotor
S	Induction stator
T	Anode target
W	Tube window (Aluminium or Beryllium)

https://commons.wikimedia.org/wiki/File:Xraytubeinhousing_commons.png

❖ X-ray production

Bremsstrahlung X-ray production

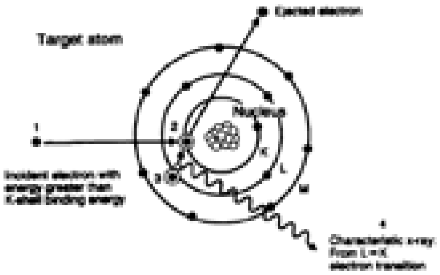


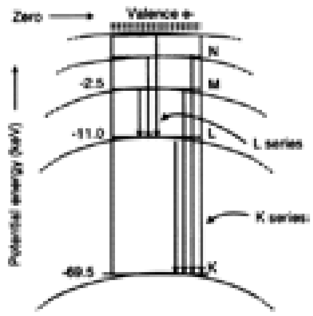


RadloGraphics 1997; 17:967-984

❖ X-ray production

Characteristic X-ray production

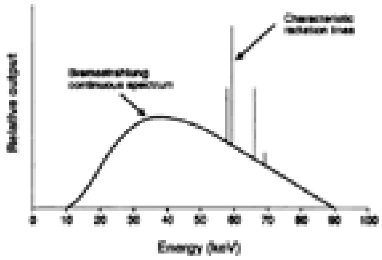


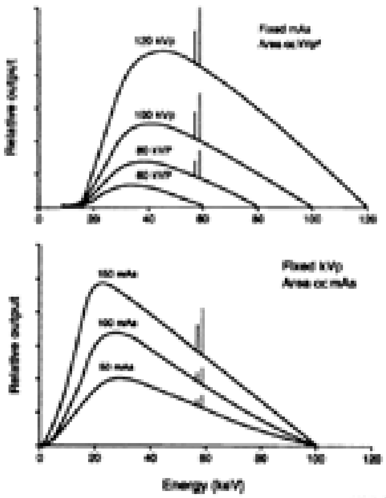


RadloGraphics 1997; 17:967-984

SNUH

❖ X-ray production





RadloGraphics 1997; 17:967-984

SNUH

❖ Interaction of X-rays with matter

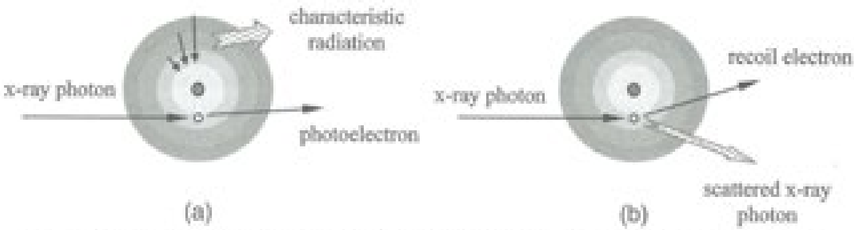
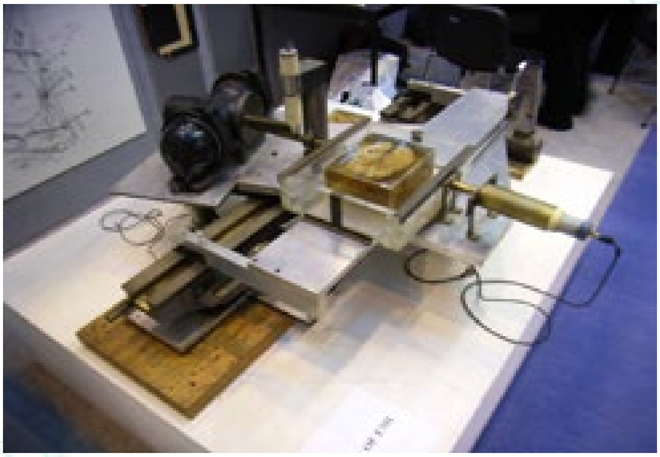


Figure 2.9 Illustrations of (a) photoelectric interaction and (b) Compton interaction.

- Photoelectric Effect $\propto Z^3$
- Compton Scattering $\propto$ Electron density

J Hsieh Computed Tomography: Principles, Design, Artifacts, and Recent Advances,3rd ed,2015, p39

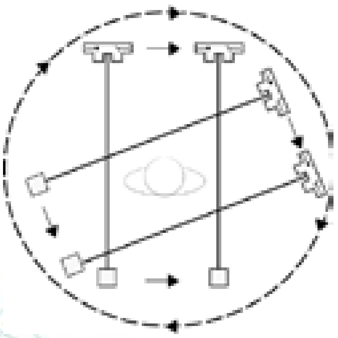
❖ Computed Tomography (CT)

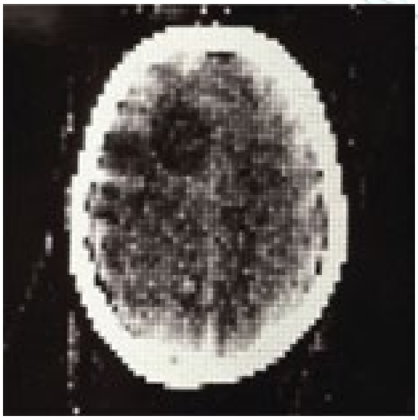


https://commons.wikimedia.org/wiki/File:RIMG0277.JPG

❖ Computed Tomography (CT)

1st Generation



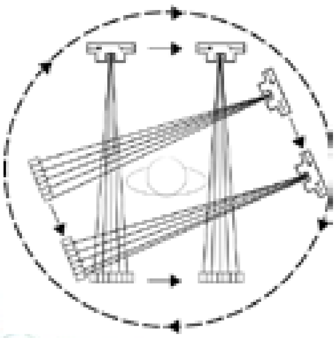


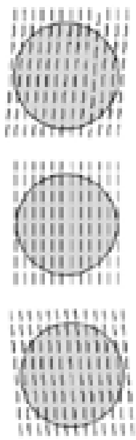
https://commons.wikimedia.org/wiki/File:TC1Gen.png

Taubmann O, Berger M, Bögel M, et al. Computed Tomography. 2018 Aug 3. In: Maier A, Steidl S, Christlein V, et al., editors. Medical Imaging Systems: An Introductory Guide [Internet]. Cham (CH): Springer; 2018.

❖ Computed Tomography (CT)

2nd Generation



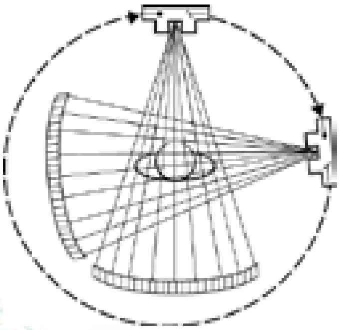


https://commons.wikimedia.org/wiki/File:TC2Gen.png

J Nucl Med Technol. 2007 Sep;35(3):115-28

❖ Computed Tomography (CT)

3rd Generation

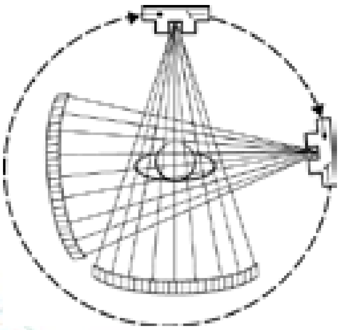


https://upload.wikimedia.org/wikipedia/commons/3/3f/TC3Gen.png

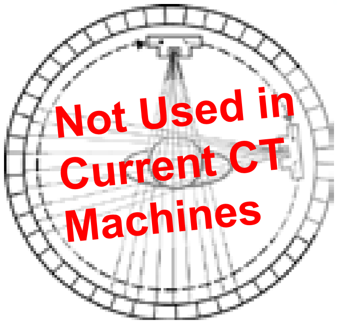
https://commons.wikimedia.org/wiki/File:TC4Gen.png

❖ Computed Tomography (CT)

3rd Generation



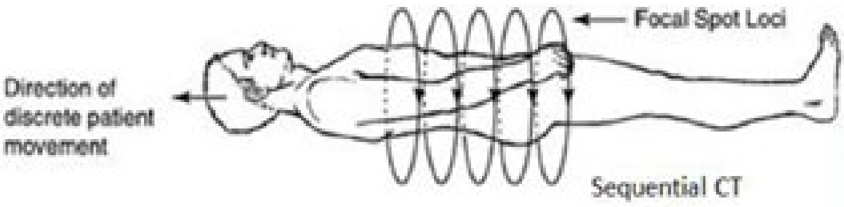
4th Generation



https://upload.wikimedia.org/wikipedia/commons/3/3f/TC3Gen.png

https://commons.wikimedia.org/wiki/File:TC4Gen.png

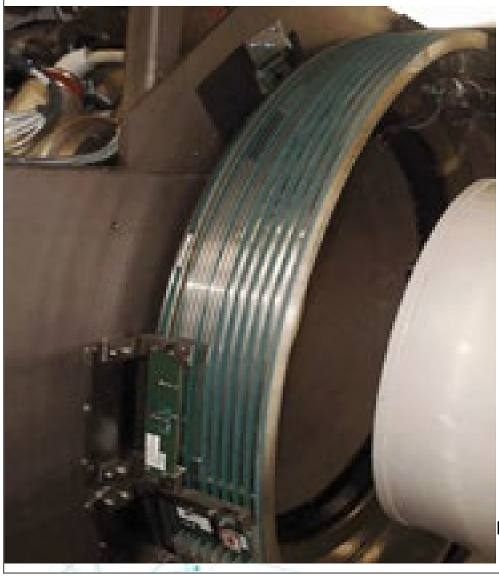
❖ Sequential Scan



Poster: "ECR 2013 / B-0279 / Comparison of radiation dose and image quality between sequential and spiral brain CT" by: "I. Pace, F. Zarb; Msida/MT"

SNUH

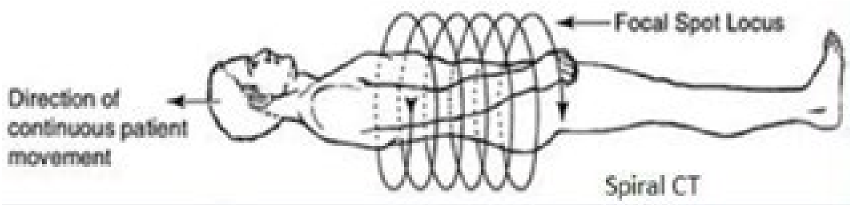
❖ Slip Ring Technology



http://www.wikiradiography.net/page/Slip_Rings

SNUH

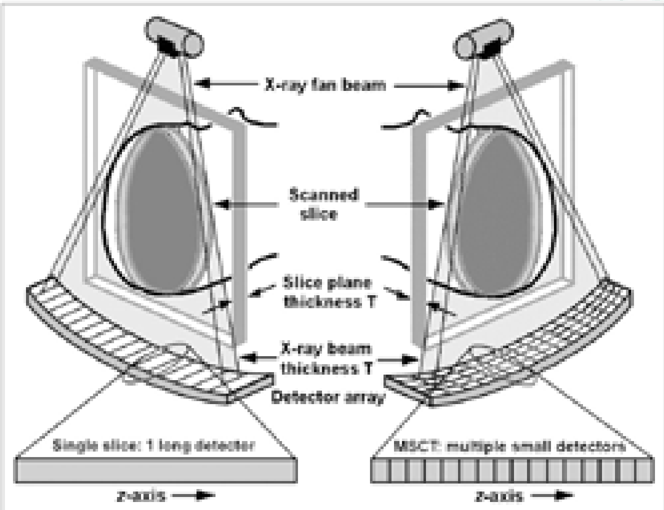
❖ Spiral Scan



Poster: "ECR 2013 / B-0279 / Comparison of radiation dose and image quality between sequential and spiral brain CT" by: "I. Pace, F. Zarb; Msida/MT"

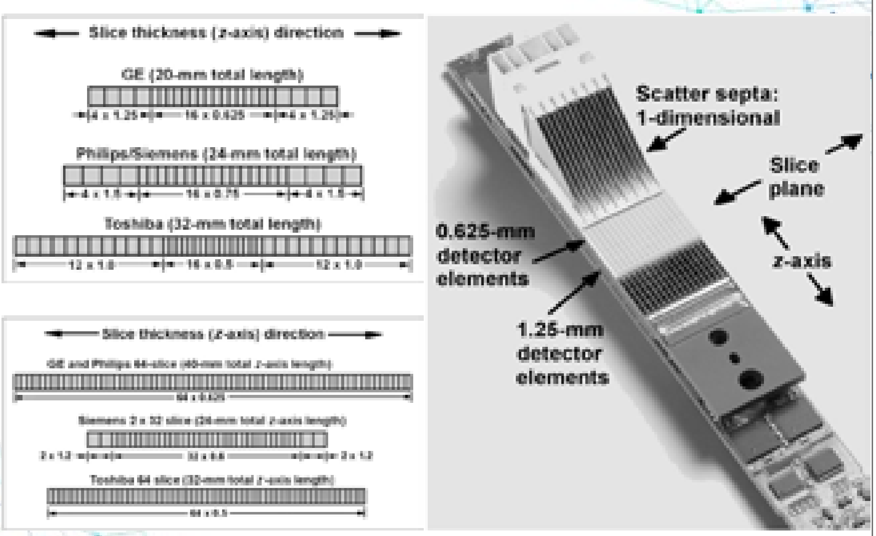
SNUH

❖ Multidetector CT (MDCT)



J Nucl Med Technol 2008; 36:57–68

SNUH

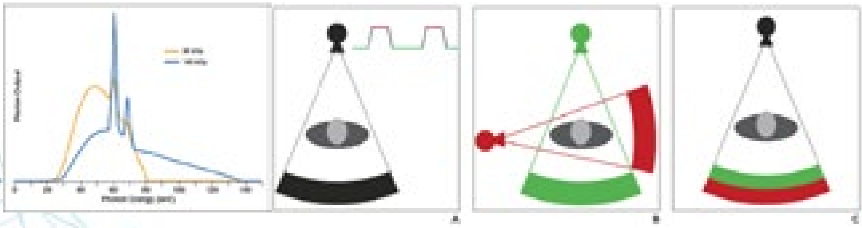


J Nucl Med Technol 2008; 36:57–68

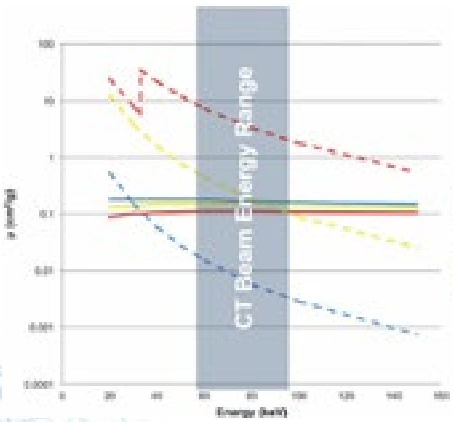
https://commons.wikimedia.org/wiki/File:CT_of_a_normal_abdomen_and_pelvis,_thumbnail.png

❖ Dual energy CT

- **Definition: CT that uses two photon spectra**
- **Technical approaches**
  - Rapid voltage switching
  - Dual-source CT
  - Multi-layer detector

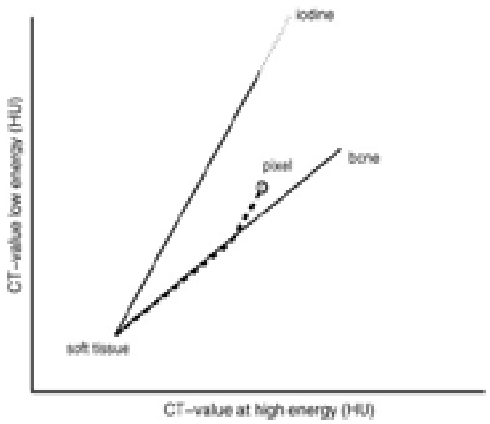


❖ Interaction of X-rays with matter

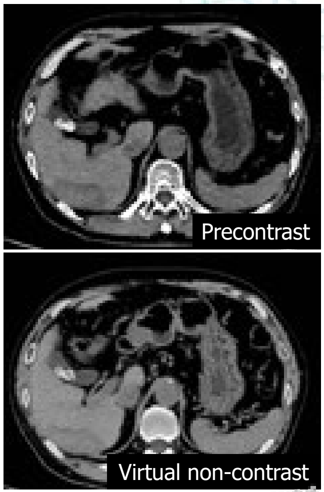


$$P_{\text{photoelectric}} \propto Z^3$$

❖ Dual energy CT



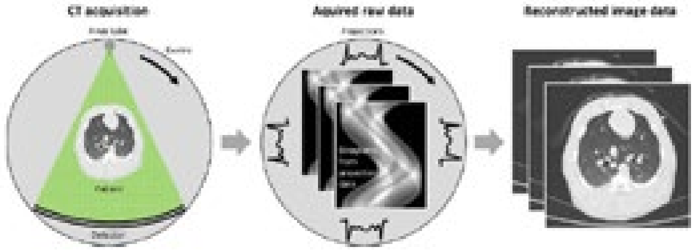
Material decomposition

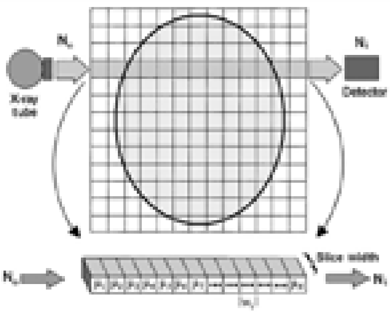


Martin P et al. EJR. 2008

SNUH

❖ Reconstruction





$$N_i = N_0 e^{-(w_1\mu_1)} e^{-(w_2\mu_2)} e^{-(w_3\mu_3)} \cdots\cdots e^{-(w_n\mu_n)}$$

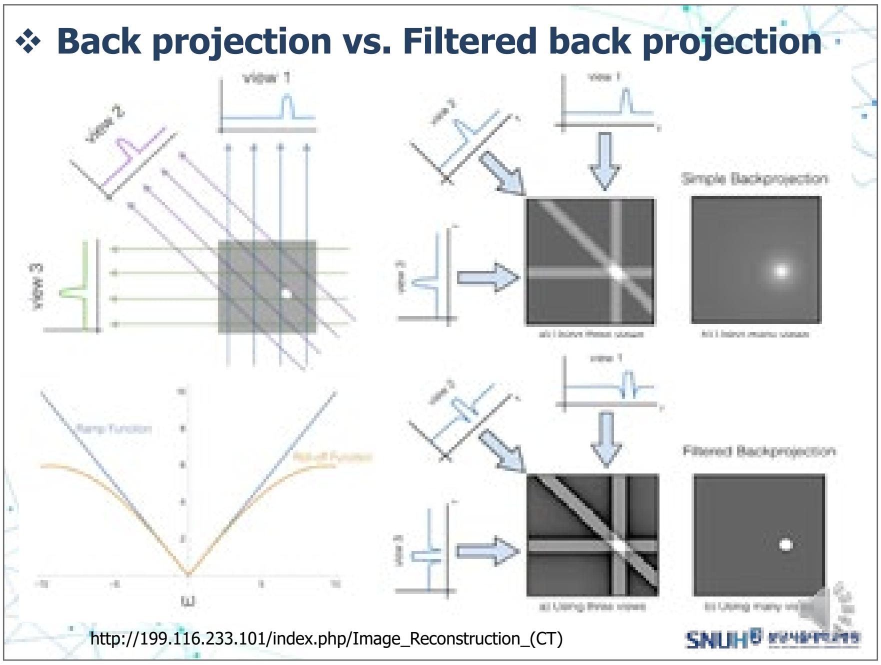
$$-\ln(N_i/N_0) = w_1\mu_1 + w_2\mu_2 + w_3\mu_3 \cdots\cdots + w_n\mu_n$$

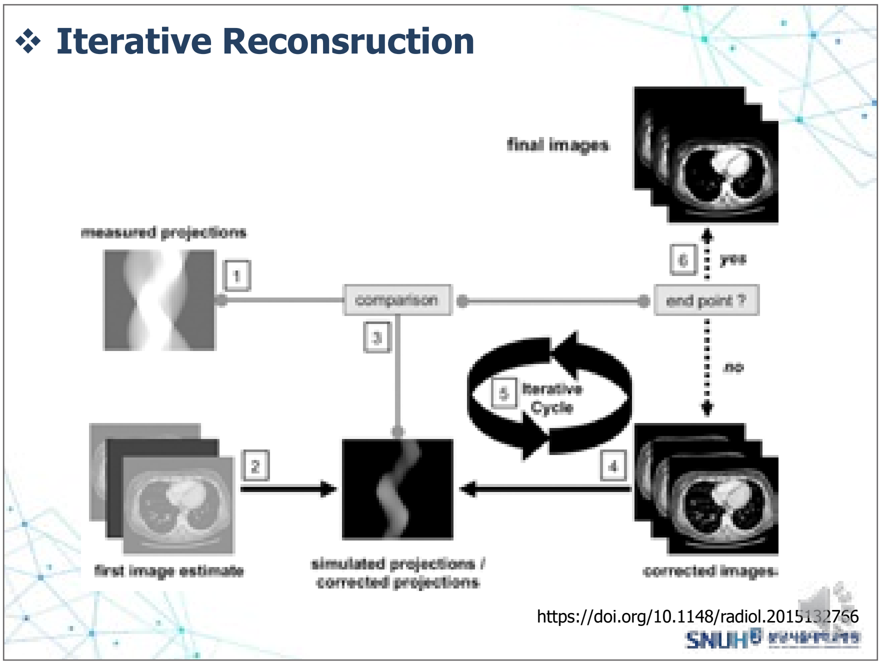
$$N_i' = u_1 + u_2 + u_3 + u_4 + \cdots\cdots + u_n$$

26만개(512x512) 의 연립 방정식?

J Nucl Med Technol 2007; 35:115-128

SNUH


❖ Back projection vs. Filtered back projection
view 1
view 2
view 3
Simple Backprojection
Filtered Backprojection
http://199.116.233.101/index.php/Image_Reconstruction_(CT)
SNUH

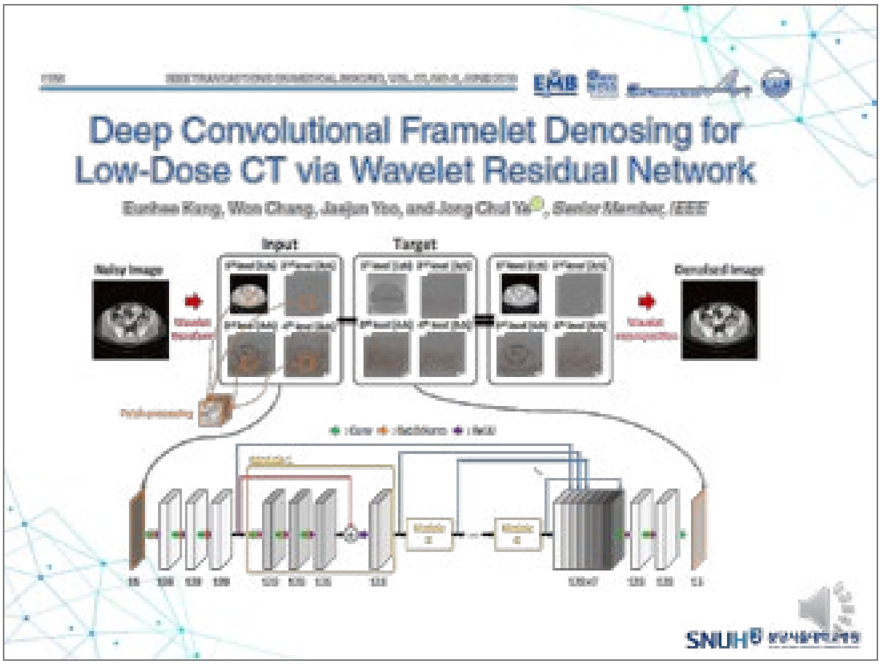

❖ Iterative Reconsruction
final images
measured projections
1
comparison
6
yes
end point ?
3
no
5 Iterative Cycle
2
4
first image estimate
simulated projections / corrected projections
corrected images
https://doi.org/10.1148/radiol.2015132766
SNUH

❖ Reconstruction methods

- **Filtered Back Projection (FBP)**
  - Pros: A speedy simple closed-form solution
  - Cons: feasible to noise, sometimes amplifying noise
- **Iterative Reconstruction (IR)**
  - A statistical model of the noise to improve image quality
  - Pros: Reduced image noise
  - Cons: Different image texture, Much slower than FBP

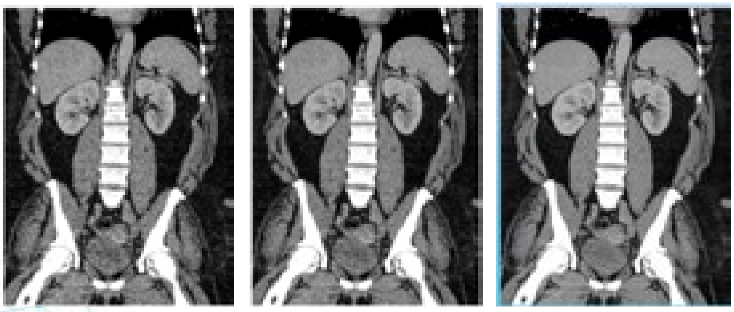
❖ Iterative reconstruction

- **Vendor specific**
  - **Unable to access sinogram data**
- **No significant progress over the recent years**



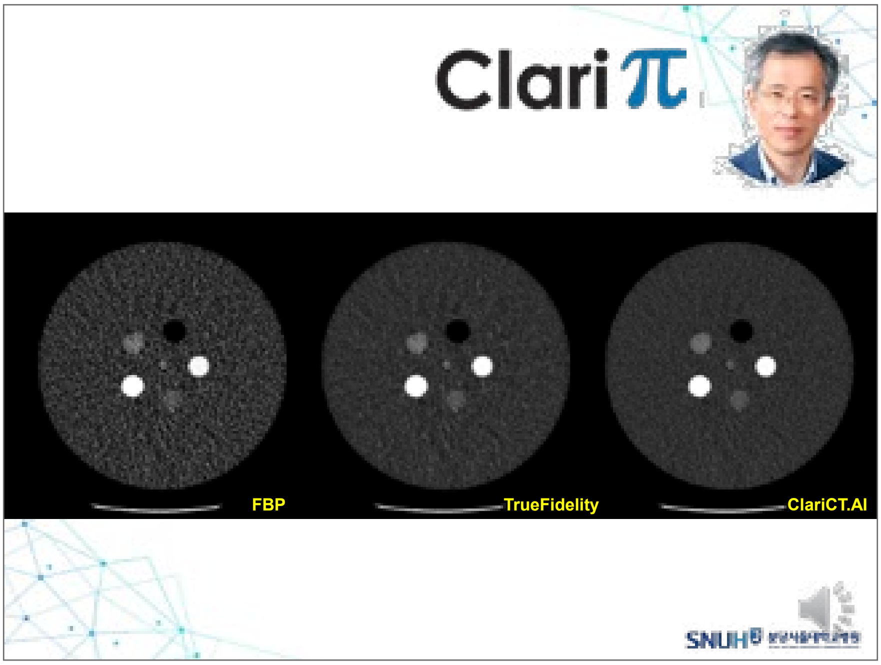
❖ Deep Learning Reconstruction Algorithm

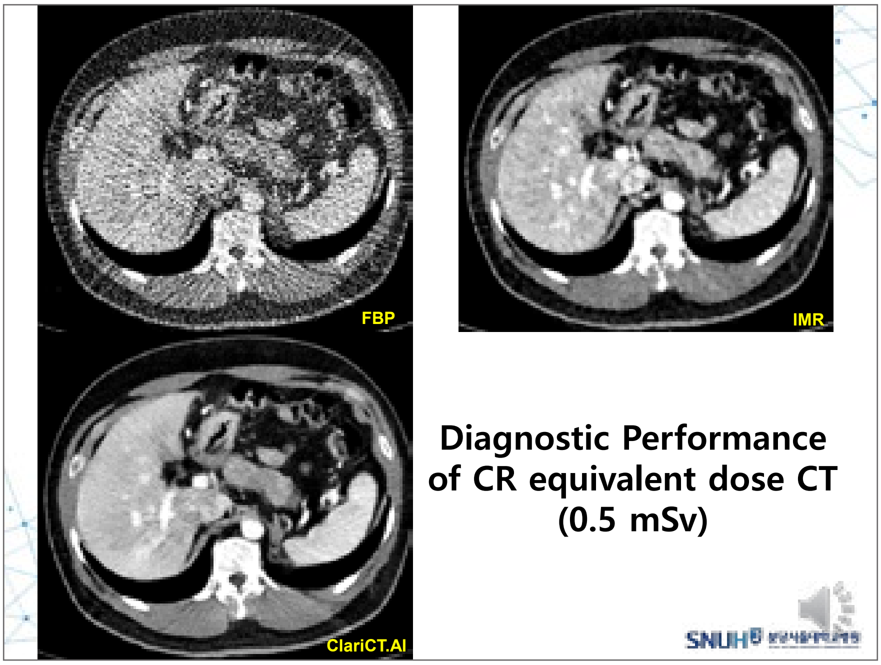
Filtered Back Projection (1972-2008) → Iterative Reconstruction (2008-2018) → Deep Learning Reconstruction (2018-Current)

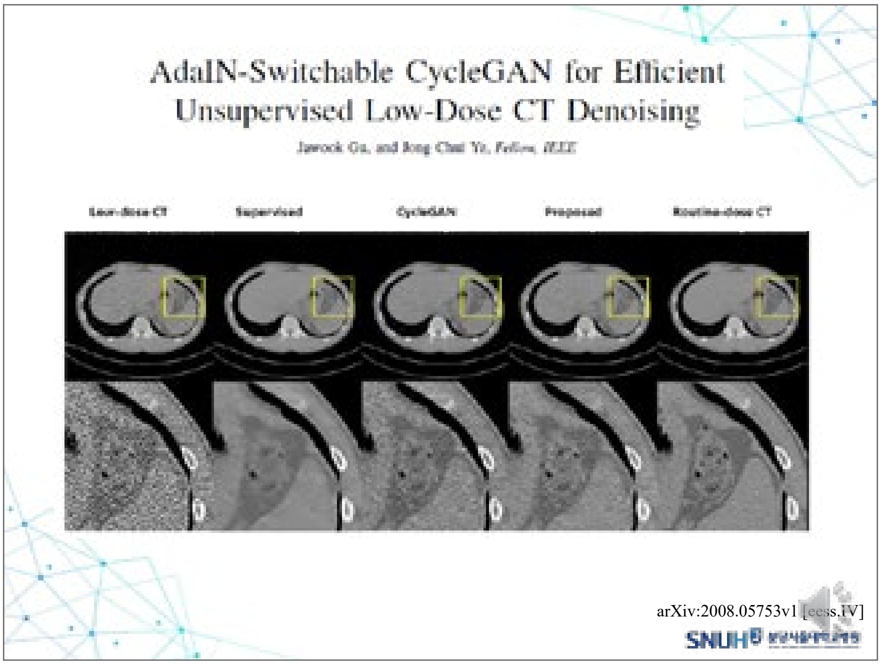


https://www.gehealthcare.com/products/truefidelity

SNUH


ClariPi
FBP
TrueFidelity
ClariCT.AI
SNUH


FBP
IMR
ClariCT.AI
Diagnostic Performance
of CR equivalent dose CT
(0.5 mSv)
SNUH


AdaIN-Switchable CycleGAN for Efficient
Unsupervised Low-Dose CT Denoising
Jawook Gu, and Jong Chul Ye, Fellow, IEEE
Low-dose CT
Supervised
CycleGAN
Proposed
Routine-dose CT
arXiv:2008.05753v1 [eess.IV]
SNUH

CURRICULUM VITAE

이 영 한

연세의대 세브란스병원

EDUCATION

1995 — 2001 연세대학교 원주의과대학 의학사
2003 — 2004 연세대학교 대학원 의학과 의학석사
2005 — 2007 연세대학교 대학원 의학과 의학박사

CAREER

2006 - 2009 국군의무사령부 국군원주병원 영상의학과
국군의무사령부 국군수도병원 영상의학과
2009 - 2012 연세대학교 의과대학 세브란스병원 영상의학과 강사
2012 - 2014 연세대학교 의과대학 세브란스병원 영상의학과 임상조교수
2016 - 2020 연세대학교 의과대학 세브란스병원 영상의학과 임상부교수
2021- 연세대학교 의과대학 세브란스병원 영상의학과 부교수

MR

KSIIM 10-Apr-2021

CONTENTS

- MRI : Hardware development → Image acquisition → Image processing
- AI / DL can improve MR reconstruction
- Faster scan and Eliminating motion

- MRI : Image Reconstruction
- Image Quality Improvement
- Quantitative imaging : Parametric Mapping

YONSEI UNIVERSITY SEVERANCE

KSIIM 10-Apr-2021

History of MR Imaging as seen through the pages of *Radiology*

Historical advances in the research and clinical applications of MRI

1. Hardware (magnets, gradients, RF coils, RF transmitter and receiver, MRI–compatible biopsy)
2. Imaging tech (pulse sequences, parallel imaging …)

Image quality has been dramatically improved with high-field-strength superconducting magnets, digital RF systems, phased-array coils : HW

YONSEI UNIVERSITY SEVERANCE

Radiology 2014;273(2 Suppl):S181-200

KSIIM 10-Apr-2021

Advances in MRI Hardware Design

- Basic: main magnet, gradients, shims, and RF coils
- *Current state-of-the-art* + future improvements and new development
- Patient monitoring : wireless , camera
- Patient throughput : Automatic planning, Interactive feedback during scan
- Planning efficiency : Monitoring of system performance
- New hybrid systems : MR linac, MR-HIFU

YONSEI UNIVERSITY SEVERANCE *Andrew Webb, PhD from Leiden Univ. | RSNA2020*

KSIIM 10-Apr-2021

MRI : Image Reconstruction

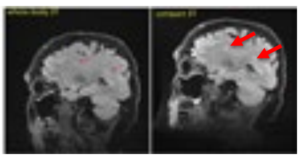
- NMR (nuclear magnetic resonance) → MRI : Spatial encoding capability of field gradient coils *Clin Orthop Relat Res 1989:3-6 , Br J Radiol 1977;50:188-194*
- Encoding scheme : Gradient field, in order to allocate a certain nuclear resonance frequency for a location → each signal location is inversely speculated from the encoded frequency spectrum : spatial frequency domain *k-space*
  - transform *k-space* into image domain : Fourier transformation (early history of MRI)

YONSEI UNIVERSITY SEVERANCE

KSIIM 10-Apr-2021

Gradient

1. Stronger gradients, Higher slew rate
2. Stronger gradients, Higher slew rate
3. Stronger gradients, Higher slew rate



Improved SNR and lesion conspicuity with C3T is evident from the shorter echo spacing, resulting in reduced T2 blurring of ETL and improved sharpness

- 8-channel brain coil: TR = 7600 ms; 256 × 256 acquisition matrix ; 24-cm FOV; 0.94 × 0.94 × 1.2 mm voxels; TE/TI = 93.0/2025 ms (whole-body), 91.3/2060 ms (C3T)
- Echo spacing = 4824 µs (whole-body) vs. 3544 µs (C3T)

YONSEI UNIVERSITY SEVERANCE *Magn Reson Med . 2018 Nov;80(5):2232-2245*

KSIIM 10-Apr-2021

Parallel Imaging

- *Parallel Imaging* : spatial encoding by using multi-channel phased array data
  - Faster data acquisition time
  - each channel data, independent spatial sensitivity
  - sensitivity maps to differentiate aliased images in *k-space* Magn Reson Med 1999;42:952-962 , Magn Reson Med 2002;47:1202-1210
  - (1) potential to go beyond Nyquist sampling theorem using additional information
  - (2) reducing the scan time
- Beyond the gradient field and PI: morphological priors for reconstructed images
  - Wavelet transform from sparse image data *Magn Reson Med 2007;58:1182-1195*

YONSEI UNIVERSITY SEVERANCE

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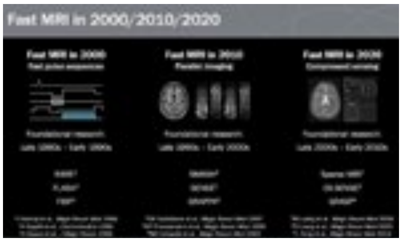
Fast Imaging



YONSEI UNIVERSITY SEVERANCE *Anthony Christodoulou, PhD from Cedars Sinai | RSNA2020*

KSIIM 10-Apr-2021

Deep Learning for MR Image Reconstruction

- 1) Data- driven prior
  - Identifying weights and biases in a neural network involves fitting parameters IEEE Trans Med Imaging 2018;37:1289-1296
  - Excellent quality and be robust to artifacts

    ←→ network is applied to data that was not involved in the training
- 2) High reconstruction speed
  - Deep learning approach: gradient calculation only for the back propagation step
  - manifold property of human brain images and proposed a neural network that transforms arbitrarily encoded *k-space* into images *Nature 2018;555:487-492, Magn Reson Med 2018;80:1189-1205*

YONSEI UNIVERSITY SEVERANCE *iMRI 2019;23:81-99*

KSIIM 10-Apr-2021

Deep Learning for MR Image Reconstruction

- 3) Optimization of nonlinear reconstruction
  - Variational network : CS reconstruction to find the best domain for sparsity enhancement and norm criteria for the reconstruction Magn Reson Med 2018;79:3055-3071, Magn Reson Med 2019;81:116-128.
  - Neural network for parallel imaging reconstruction Magn Reson Med 2019;81:439-453
  - NN that solves the parallel imaging in both *k-space* and image domains *prof. Hwang D et al, Magn Reson Med 2018;80:2188-2201*
  - Further investigation to integrate the benefits of the deep learning and model-based approaches Magn Reson Med 2018;79:3055-3071 , IEEE Trans Med Imaging 2019;38:394-405

YONSEI UNIVERSITY SEVERANCE *iMRI 2019;23:81-99*

KSIIM 10-Apr-2021

Image Quality

- 1. Denoising
  - conventional denoising methods: model-based methods, sparse coding, effective prior, and low-rank approaches, … *IEEE Trans Image Process 2006;15:3736-3745*
  - CNN algorithm by a convolution operator are iteratively solved by repeated convolutions and point-wise nonlinearities *IEEE Trans Image Process 2017;26:4509-4522*
  - residual learning method for solving CS reconstruction by showing that the noisy artifact originating from the randomly under-sampled *k-space* has a topologically simpler manifold than that of the original images *IEEE Trans Biomed Eng 2018;65:1985-1995*

YONSEI UNIVERSITY SEVERANCE *iMRI 2019;23:81-99*

KSIIM 10-Apr-2021

- 2. MR artifacts due to spatial encoding schemes and reconstruction algorithms
  - Various motion artifact
  - Conventional : prospective or retrospective *Magn Reson Med 2013;70:1608-1618, Magn Reson Med 2009;62:943-954, Magn Reson Med 2011;66:135-143*
    - motion detectors or external devices such as navigators or motion tracking
  - Deep learning methods *Proceeding ISMRM 2018 #1174, Proceeding ISMRM 2018 #2660*

YONSEI UNIVERSITY SEVERANCE *iMRI 2019;23:81-99*

KSIIM 10-Apr-2021

- 3. Super-resolution : restoring high-resolution images from low-resolution images
  - Deep learning application >> conventional SR methods *Med Phys 2018;45:3120-3131, Magn Reson Med 2018;80:2139-2154*
  - Super-resolution CNN (SRCNN) *IEEE 14th International Symposium on Biomedical Imaging (ISBI). 2017:197-200*
  - CNN with a residual framework between low and high frequency of *k-space* *Phys Med Biol 2018;63:085011 , Med Phys 2018;45:3120-3131*
  - Super-Resolution using Generative Adversarial Network (GAN) *arXiv:1803.01417*
  - Thin-slice musculoskeletal images from thick slice image *Magn Reson Med 2018;80:2139-2154*

KSIIM 10-Apr-2021

Fast Imaging

RSNA 2020

Anthony Christodoulou, PhD from Cedars Sinai | RSNA2020

KSIIM 10-Apr-2021

Quantitative imaging : Parametric Mapping

- *q-space* DL method : estimation of diffusion kurtosis from twelve-fold less data. *IEEE Trans Med Imaging 2016;35:1344-1351*
- Multilayer perceptron method for T2 map, SafeNet. *ISMRM 2018 #2277*
- Magnetic resonance fingerprinting (MRF) : multi-parametric map in a single scan *Nature 2013;495:187-192*
  - DL-based on the multilayer perceptron structure: dramatic reductions in reconstruction time + robustness *Magn Reson Med 2018;80:885-894*
- Quantitative susceptibility mapping (QSM)
  - at least three independent scans with different head orientations
    - Calculation of susceptibility through multiple orientation sampling (COSMOS) *Magn Reson Med 2009;61:196-204*
  - DL approach from a single orientation data *Neuroimage 2018;179:199-206*

iMRI 2019;23:81-99

CURRICULUM VITAE

김광기

가천의대 길병원

EDUCATION	1999 – 2005	서울대학교 의용생체공학과 졸업
CAREER	1998 – 2007	서울대학교 의학연구원 전임대우연구조교수
	2013 – 2015	Washington univ. in St. Louis 영상의학과 연구원
	2007 – 2017	국립암센터 의공학연구소 선임/책임/과장
	2017 -	가천대학교 부교수/교수
	2017 –	길병원 의료기기 R&D센터 센터장

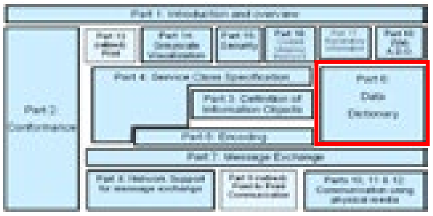
DICOM

DICOM Standard

- DICOM : Digital Imaging and Communications in Medicine
- The international standard for medical images and related information

- Part 1 ~ 22
  - Part6 : Data Dictionary

Part 19: Application Hosting
Part 20: Imaging Reports using HL7
Part 21: Transformations
Part 22: Real-Time Communication



The DICOM standard : a brief overview Article in
NATO Security through Science Series B: Physics and Biophysics · January 2008

2

DICOM Standard

- DICOM : Digital Imaging and Communications in Medicine
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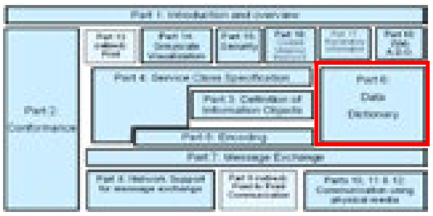


The DICOM standard : a brief overview Article in
NATO Security through Science Series B: Physics and Biophysics · January 2008

2

PACS

- Picture Archiving and Communication System
  - 환자의 의료영상을 디지털로 획득/저장/전송/관리하는 정보시스템
  - Picture(영상)
    - 의료기관에서 발생하는 모든 의료영상
  - Archiving(저장)
    - 의료영상들을 디지털 상태로 받아 컴퓨터에 저장하는 것
  - Communications(전송)
    - 네트워크, DICOM통신 프로토콜을 준수하는 의료영상들의 교환
  - System
    - 컴퓨터 H/W, S/W
    - 운영체제, Database, PACS 응용프로그램

3

PACS

- 영상의 밝기 조절 가능하고 길이, 각도등의 측정이 용이
- 필름의 분실 또는 훼손의 가능성이 없음
- 영구적인 보관이 가능
- 타 병원과의 정보 교환이 용이

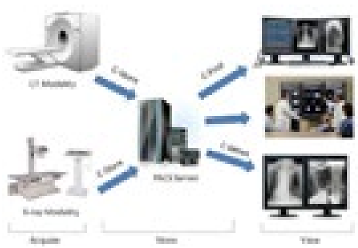
Weasis 화면캡처

4

DICOM Communication

- Command

Command	Description
C-Find	서버에 등록된 환자/영상 검색
C-Store	Modality에서 서버로 DICOM 전송
C-Move	서버에서 로컬로 DICOM 다운로드
WADO	Web Access to DICOM Object (Find, Store, Move등을 웹으로 구현)



An Agent-Based Infrastructure for Secure Medical Imaging System Integration, May 2014
Conference: 2014 IEEE 27th International Symposium on Computer-Based Medical Systems (CBMS)

5

DICOM Hierarchy

- Tree structure

Patient1 | Patient2 | Patient3 | ...

Study(CT) | Study(MR) | Study(US) | Study(CT) | ...

Series1 | Series2 | Series3 | Axial, Sagittal, Coronal, ...

Image1 | Image2 | Image3 | ...

DICOM file

6

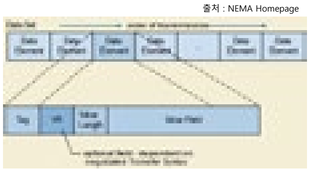
DICOM File

- Format

Preamble : 128bytes
Prefix : DICM

출처 : https://saravanansubramanian.com/makingsenseofdicomfile/

출처 : NEMA Homepage



- Value Representation
  - The data type and format of that Data Element's Value
  - AS : Age String
  - DA : Date
  - DT : Date Time
  - ST : Short Text
  - ...

7

DICOM Dataset

- Attribute Type

Type	Description
1	Required to be in the SOP Instance and shall have a valid value.
2	Required to be in the SOP Instance but may contain the value of "unknown", or a zero length value.
3	Optional. May or may not be included and could be zero length.
1C	Conditional. If a condition is met, then it is a Type 1 (required, cannot be zero). If condition is not met, then the tag is not sent.
2C	Conditional. If condition is met, then it is a Type 2 (required, zero length OK). If condition is not met, then the tag is not sent.

8

DICOM Dataset

- Patient Module Attributes

Attribute Name	Tag	Type	Description
Patient's Name	(0010, 0010)	2	Patient's full name.
Patient ID	(0010, 0020)	2	Primary hospital identification number or code for the patient.
Birth Date	(0010, 0030)	2	Birth date of the patient.
Gender	(0010, 0040)	2	Gender of the patient.

DICOM Dataset

- Study Module Attributes

Attribute Name	Tag	Type	Description
Study Date	(0008, 0020)	2	Date the Study started.
Study Time	(0008, 0030)	2	Time the Study started.
Accession Number	(0008, 0050)	2	A RIS generated number that identifies the order for the Study.
Referring Physician's Name	(0008, 0090)	2	Name of the patient's referring physician
Study Instance UID	(0020, 0008)	1	Unique identifier for the Study.
Study ID	(0020, 0010)	2	User or equipment generated Study identifier.

DICOM Dataset

- Series Module Attributes

Attribute Name	Tag	Type	Description
Modality	(0008, 0060)	1	Type of equipment that originally acquired the data used to create the images in this Series.
Series Instance UID	(0020, 000E)	1	Unique identifier of the Series.
Series Number	(0020, 0011)	2	A number that identifier this Series.
Laterality	(0020, 0060)	2C	Laterality of (paired) body part examined.

DICOM Dataset

- General Image Module Attributes

Attribute Name	Tag	Type	Description
Instance Number	(0020, 0013)	2	A number that identifies this images.
Patient Orientation	(0020, 0020)	2C	Patient direction of the rows and columns of the image.
Content Date	(0008, 0023)	2C	The date the image pixel data creation started.
Content Time	(0008, 0033)	2C	The time the image pixel data creation started.

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DICOM Dataset

- Image Pixel Macro Attributes

Attribute Name	Tag	Type	Description
Samples per Pixel	(0028,0002)	1	Number of samples (planes) in this image.
Photometric Interpretation	(0028,0004)	1	Specifies the intended interpretation of the pixel data.
Rows	(0028,0010)	1	Number of rows in the image.
Columns	(0028,0011)	1	Number of columns in the image.
Bits Allocated	(0028,0100)	1	Number of bits allocated for each pixel sample. Each sample shall have the same number of bits allocated.
Bits Stored	(0028,0101)	1	Number of bits stored for each pixel sample.
High Bit	(0028,0102)	1	Most significant bit for pixel sample data.
Pixel Representation	(0028,0103)	1	Data representation of the pixel samples.
Pixel Data	(7FE0,0010)	1C	A data stream of the pixel samples that comprise the Image.
Planar Configuration	(0028,0006)	1C	Indicates whether the pixel data are sent color-by-plane or color-by-pixel.

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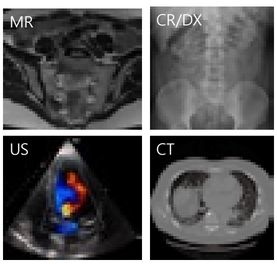
DICOM Pixel Data

- MR, X-ray : 0 ~ 4095 (12bits Grayscale)
- US : 0 ~ 255 (24bits Color)
- CT : -1024 ~ 3071 (12bits Grayscale)

CT HU	부위
-1024	검은색이며 공기(폐 내부)
0	물
3071	밀도 높은 치아 에나멜
-100	지방
100	근육
200	소주골/하악골
2000	피질골



출처 : boxdicom.com

14

2

GAN in Medical Imaging

CURRICULUM VITAE

유재준

EPFL

EDUCATION

2011	KAIST 학사 바이오및뇌공학과
2018	KAIST 박사 바이오및뇌공학과 바이오영상신호처리 연구실 / 지도교수 예종철 Thesis: “Machine Learning Approach for Inverse Scattering Problem”
2013	Thesis: “Neuroelectromagnetic Imaging of Correlated Sources Using a Novel Subspace Penalized Sparse Learning”
2013	KAIST 석사 바이오및뇌공학과 바이오영상신호처리 연구실 / 지도교수 예종철

CAREER

2021 -	UNIST AI 대학원 전임 & 전기전자공학 겸임 조교수 (예정)
2019 –	EPFL Postdoctoral researcher
2018 – 2019	NAVER Search&Clova AI research scientist

GAN 기초 이론, 종류, 응용

좋은 생성 모델의 기본 요소는 1) 모델이 의미 있는 정보를 배울 수 있도록 돕는 loss function과 regularization terms, 2) 이를 바탕으로 효율적이고 효과적으로 학습시킬 algorithm, 마지막으로 3) 제대로 된 평가를 해줄 수 있는 evaluation metric, 이렇게 세가지로 정리할 수 있습니다. 본 강의는 위와 같은 관점에서 최근 급격히 발전하고 있는 생성 모델에 대해 입문할 수 있는 기초를 제공하고 생성 모델을 영상 복원 문제에 적용한 사례들을 소개하겠습니다. 컴퓨터 비전 분야가 급격하게 발전하면서 다양한 생성 모델이 소개되고 있으나 이를 모두 다룰 수는 없기에, 본 강의에서는 여러 생성 모델 중 Generative Adversarial Networks (GANs)에 집중하여 기초적인 동작 원리와 한계점에 대해 개괄합니다. 이번 강의는 생성 모델 분야를 처음 접하는 초심자에게는 시작점을 제공하고, 이미 이 분야를 어느 정도 알고 있는 연구자들에게는 종합적인 정리를 제공하는 것을 목표로 합니다. 마지막으로 시간 여건이 허락하면 GANs 외에도 Deep Image Prior와 같은 독특한 형태의 생성 모델을 실제 영상 복원 문제에 적용한 사례를 함께 소개하겠습니다.

CURRICULUM VITAE

배 현 진

프로메디우스

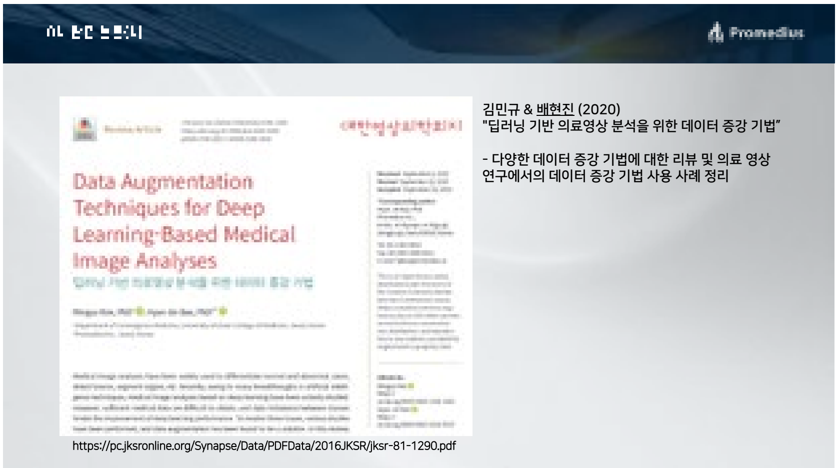
EDUCATION

2010 – 2017	연세대학교 천문우주학 (이학박사)
2008 – 2010	연세대학교 천문우주학 (이학석사)
2000 – 2008	연세대학교 천문우주학, 물리학 (이학학사, 이학학사)

CAREER

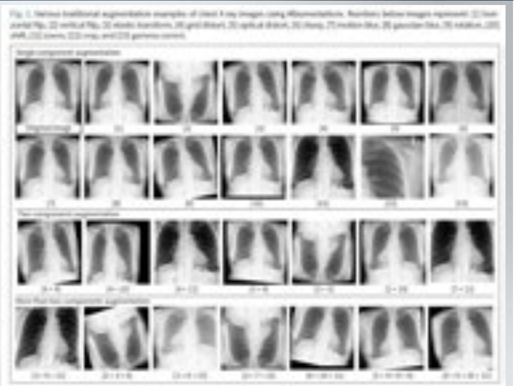
2013 – 2014	Visiting Scholar at Carnegie Institute for Science (US)
2017 – 2018	서울아산병원 박사후연구원
2018 – 2019	울산대학교 의과대학 리서치펠로우
2019 –	프로메디우스(주) 대표이사

데이터증강을 위한 GAN 및 평가방법

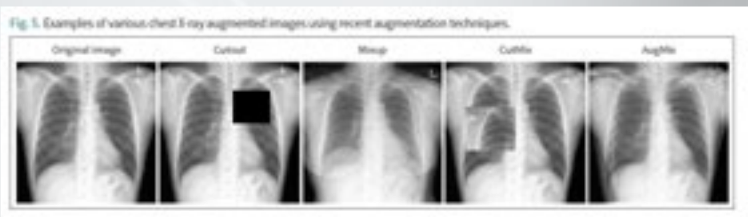


Data augmentation in data analysis are techniques used to increase the amount of data by adding slightly modified copies of already existing data or newly created synthetic data from existing data. It acts as a regularizer and helps reduce overfitting when training a machine learning model. It is closely related to oversampling in data analysis.

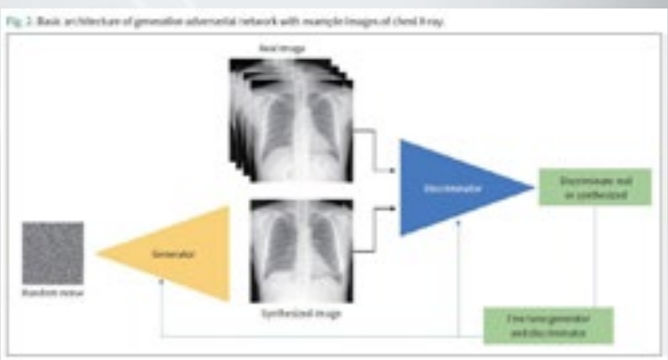
출처: https://en.wikipedia.org/wiki/Data_augmentation



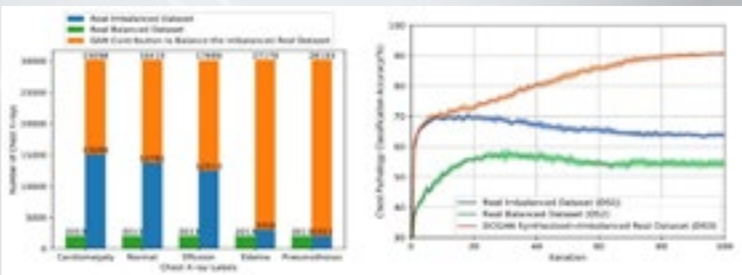
Albumentations 를 이용한 데이터 증강 예시 | https://github.com/albumentations-team/albumentations



1. Cutout (38): 영상 일부를 임의로 잘라내는 기법. 데이터 크기와 종류에 따라 최적의 마스크 크기를 찾아줘야 함.
2. Mixup (39): 두 개의 서로 다른 클래스의 영상을 하나로 섞는 기법. 영상 분할에서는 낮은 성능을 보임.
3. CutMix (40): 영상 일부를 임의로 자른 뒤 해당 영역에 다른 클래스의 영상을 붙이는 기법. 의미론적 속성을 잃을 가능성.
4. AugMix (41): 영상처리 기반 증강기법을 적용하여 여러 장을 합친 뒤 픽셀단위 블록 조합을 통해 하나의 영상 생성.

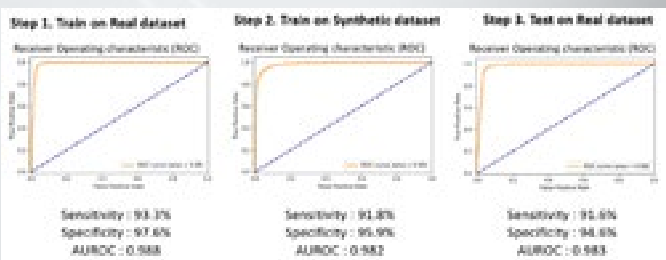


https://twitter.com/goodfellow_ian/status/1084973596236144640



Salehinejad et al. (2018) | https://pubmed.ncbi.nlm.nih.gov/30442603/

흉부 X-ray 영상에 대한 인공지능 분류 모델 개발에서 <u>합성영상을 추가 학습하는 경우</u> 실제 영상만 이용해 학습한 경우보다 <u>약 20% 이상 성능이 증가함</u>



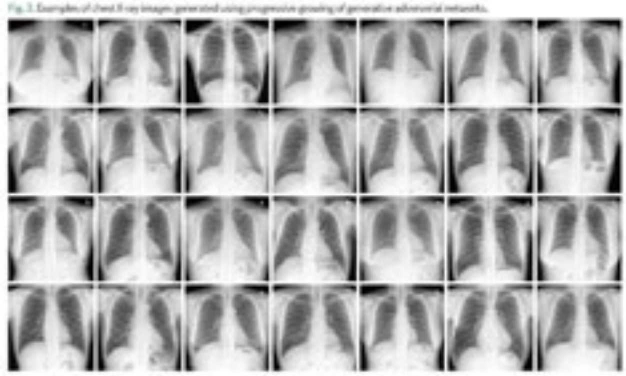
Jang et al. (in prep.)

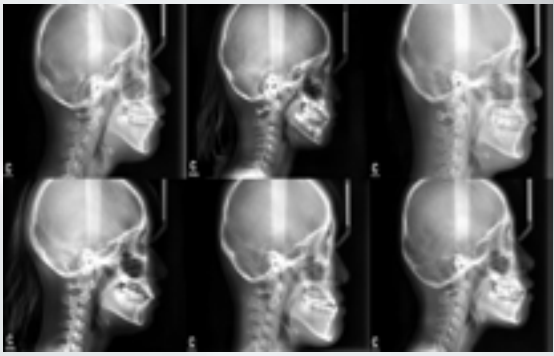
흉부 X-ray 영상에 대한 인공지능 분류 모델 개발에서 합성영상만으로 학습한 모델을 실제 영상 분류에 적용하는 경우, <u>실제 영상으로 학습한 모델에 비해 정확도 기준 약 1.7% 성능 저하</u>

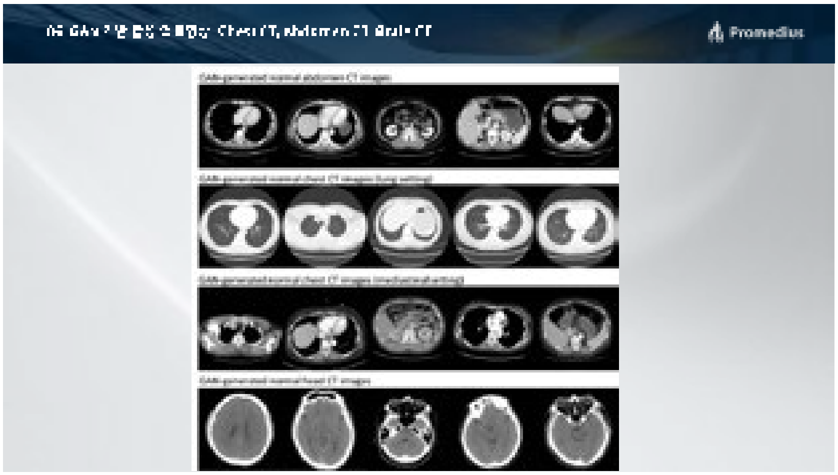
Classification task	ML model	Accuracy, trained on real images	Accuracy, trained on artificial images	Relative accuracy drop
Histology: norm and tumor	VGG16	**0.96**	**0.93**	**3.12%**
	K-NN	0.94	0.87	7.45%
	SVM	0.90	0.85	5.56%
	Random forest	0.93	0.86	7.53%
X-ray: by subject's gender	VGG16	**0.90**	**0.88**	**2.22%**
	K-NN	0.84	0.78	7.14%
	SVM	0.82	0.74	9.76%
	Random forest	0.83	0.72	13.25%
X-ray: by subject's age group	VGG16	**0.86**	**0.83**	**3.49%**
	K-NN	0.80	0.73	8.75%
	SVM	0.79	0.71	10.13%
	Random forest	0.80	0.70	12.50%

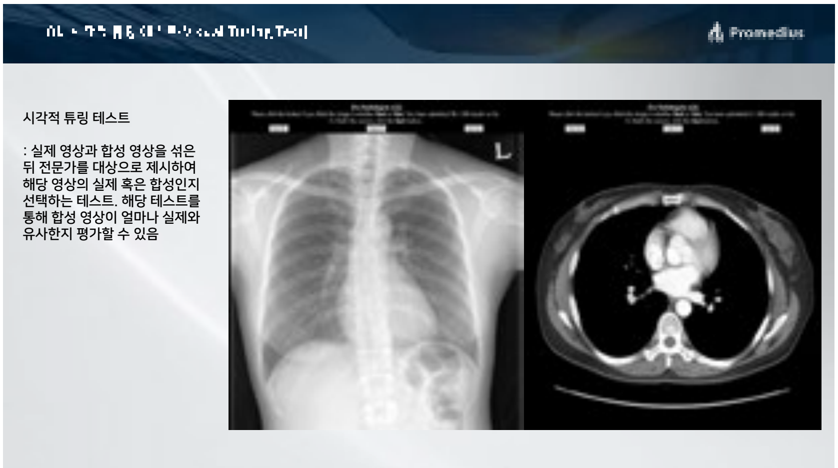
Kovalev & Kazlouski (2019) | https://arxiv.org/abs/1904.08688

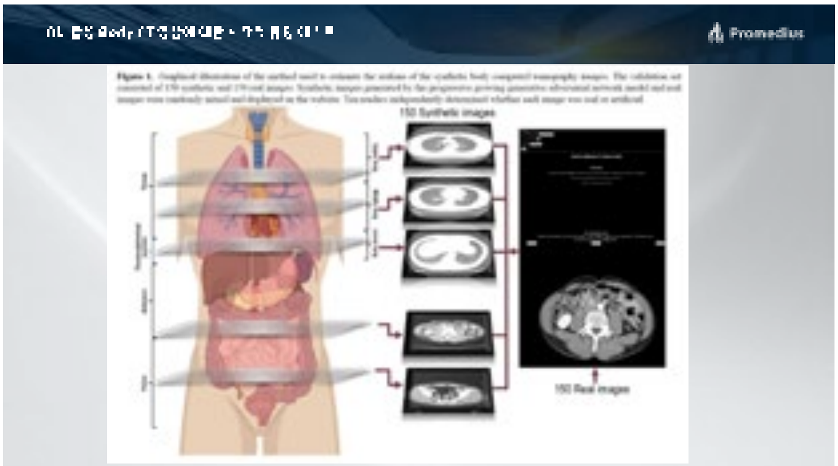
합성영상만을 이용해 인공지능 분류 모델 개발시 실제 영상 데이터를 이용한 모델 대비 약 2-3% 정도만 성능 하락함

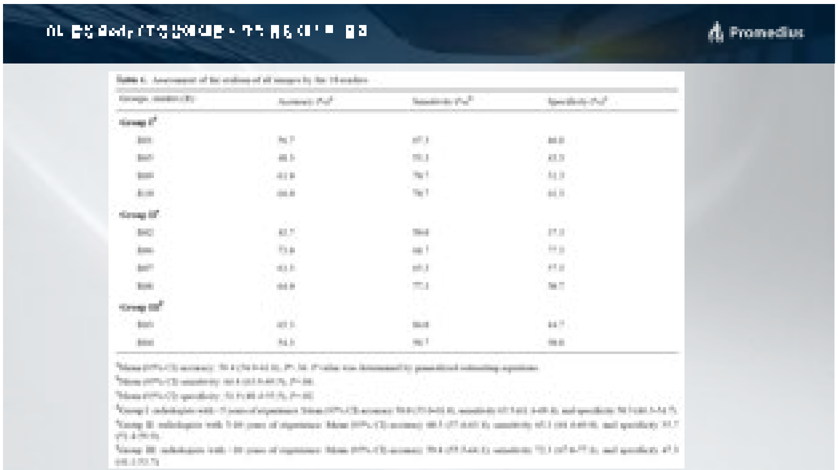


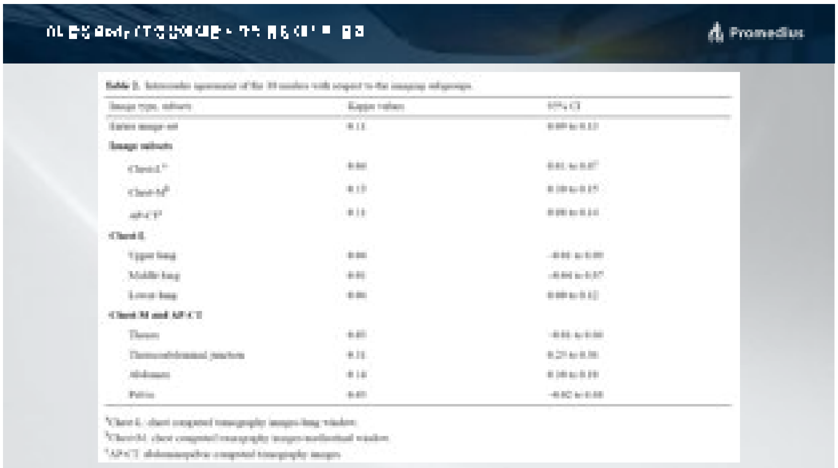


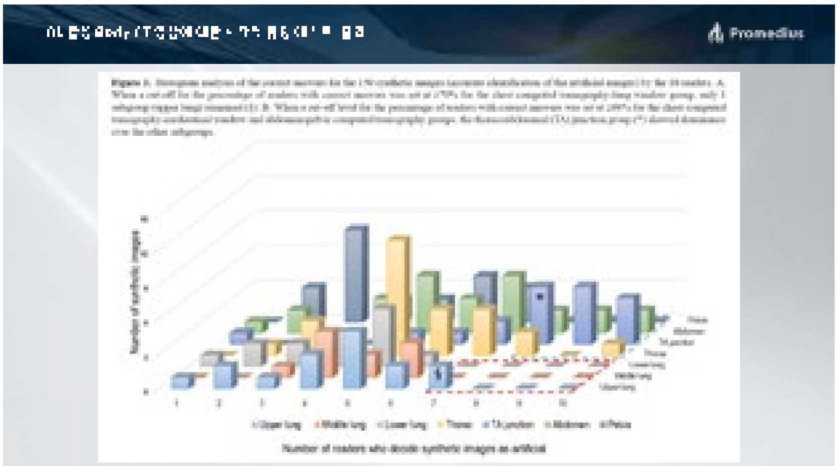

Promedius

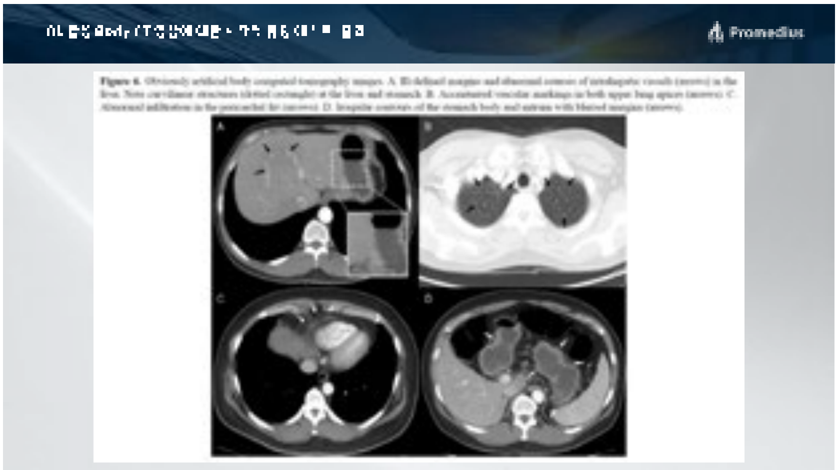

Promedius
시각적 튜링 테스트
: 실제 영상과 합성 영상을 섞은 뒤 전문가를 대상으로 제시하여 해당 영상의 실제 혹은 합성인지 선택하는 테스트. 해당 테스트를 통해 합성 영상이 얼마나 실제와 유사한지 평가할 수 있음
L

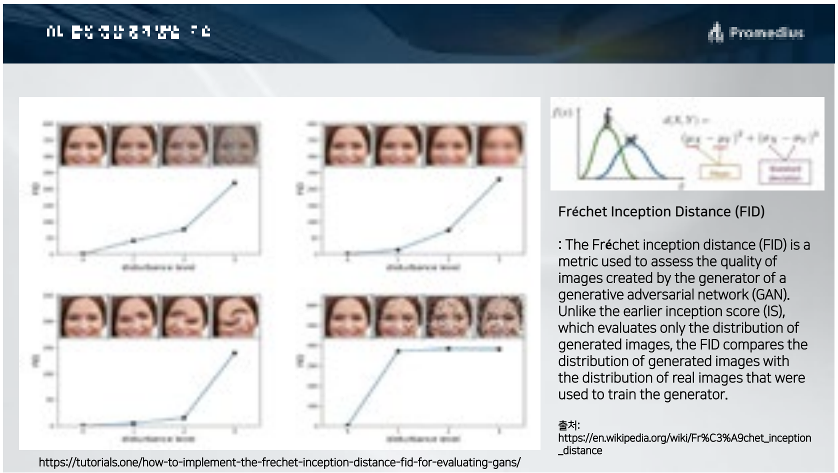

Promedius
150 Synthetic images
150 Real images

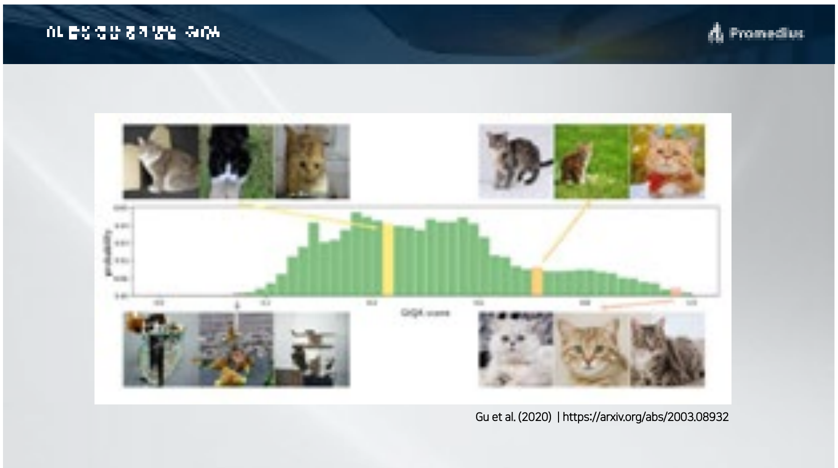

Promedius


Promedius


Promedius


Promedius


Promedius
Fréchet Inception Distance (FID)
: The Fréchet inception distance (FID) is a metric used to assess the quality of images created by the generator of a generative adversarial network (GAN). Unlike the earlier inception score (IS), which evaluates only the distribution of generated images, the FID compares the distribution of generated images with the distribution of real images that were used to train the generator.
출처:
https://en.wikipedia.org/wiki/Fr%C3%A9chet_inception_distance
https://tutorials.one/how-to-implement-the-frechet-inception-distance-fid-for-evaluating-gans/


Promedius
Gu et al. (2020) | https://arxiv.org/abs/2003.08932


Truncation 증가
Brock et al. (2018) | https://arxiv.org/abs/1809.11096
• 합성 영상을 만들기 위해 입력하는 임의의 Latent vector (z) 값이 갖는 분포 상에서 양 끝단을 경험적인 수치를 적용하여 잘라내는 기법
• 이를 통해 영상의 다양성은 일부 감소할 수 있지만 더 나은 품질을 얻을 수 있음

MEMO

3

AI in Practice

CURRICULUM VITAE

황 의 진

서울의대 서울대병원

EDUCATION

2006 – 2010	서울대학교 의과대학 의학과 학사
2012 – 2014	서울대학교 대학원 의과대학 의학과 석사 (영상의학전공)
2018 – 2020	서울대학교 대학원 의과대학 의학과 박사 (영상의학전공)

CAREER

2011 – 2014	서울대학교병원 영상의학과 전공의
2018 – 2019	서울대학교병원 영상의학과 임상강사 (흉부영상의학)
2019 – 2020	서울대학교병원 영상의학과 진료조교수
2020 –	서울대학교병원 영상의학과 임상조교수

흉부방사선 영상진단

흉부 X선 판독을 위한 인공지능

- 임상적 수요
  - 압도적인 검사건수
  - 판독의의 상대적 부족
  - 빈번한 판독 오류

  → 컴퓨터 보조 검출 or 진단 시스템에 대한 요구

- 기술적 용이성
  - 대규모 데이터 확보가 상대적으로 용이
  - 단일 2D 영상: 인공지능 기술 적용이 수월함

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흉부 X선 판독: AI가 무엇을 할 수 있을까?

- 병변 검출, 영상 분류
  - 결절, 폐렴, 기흉, ...
  - 정상 vs. 비정상
- 병변 특성화, 감별진단
  - 폐렴 vs. 폐부종, 폐암 vs. 결핵, ...
- 영상 간 비교
- 판독문 생성

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흉부 X선 판독을 위한 인공지능

- 국내 식약처 허가 흉부 X선 AI 의료기기 현황
  - 현재까지 개발, 허가된 AI들은 모두 "병변 검출"에 목적이 있음

제조사	제품명	허가일	대상 질환
루닛	Lunit InsightCXR Nodule	2018. 8	폐결절
삼성전자	Auto Lung Nodule Detection	2019. 6	폐결절
뷰노	Vuno Med Chest X-ray	2019. 8	폐결절, 폐경화, 간질성 음영, 흉막삼출, 기흉
루닛	Lunit Insight CXR MCA	2019. 10	폐결절, 폐경화, 기흉
루닛	Lunit Insight CXR	2020. 10	9개 주요 이상 소견

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어떻게 쓸 것인가? - 임상진료 적용 시나리오

- Pre-reading
  - AI가 먼저 영상 분석 → 판독의가 확인, 최종 판독
- Parallel reading
  - AI와 판독의가 각자 영상 분석 → 최종 판독의가 확인, 최종 판독
- Second reading
  - 판독의가 먼저 판독 → AI가 추가 이상 소견 분석 → 최종 판독

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어떻게 쓸 것인가? - 임상진료 적용 시나리오

- Triage/prioritization
  - 중증도, 긴급도에 따라 판독 우선순위 조정
- Over shoulder
  - 판독의의 판독에 오류가 있을 경우 AI가 개입 → 최종 판독
- Auto-assignment
  - 판독 난이도, 영상 특성에 따라 판독의 배정

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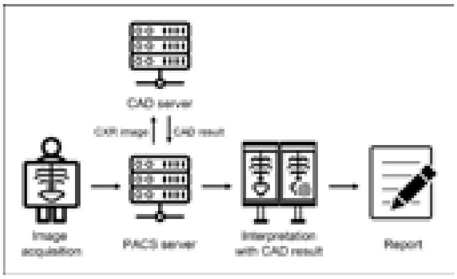
어떻게 쓸 것인가? – Experience in SNUH

- 폐결절 검출 AI (version 1)
  - 2019년 1월부터 실제 판독에 이용
  - 종양내과 외래 (암환자) 대상
  - 임상의가 의뢰하는 검사에만 적용
- 폐결절, 폐경화, 기흉 검출 AI (version 2)
  - 2020년 1월부터 실제 판독에 이용
  - 주로 종양내과, 호흡기내과, 흉부외과 환자 대상
  - 임상의가 의뢰하는 검사에만 적용
  - COVID 의심환자 선별검사, 확진자 추적검사
- 주요 9개 소견 검출 AI (version 3)
  - 2021년 3월부터 version 2와 병행 이용 중
  - 병원 내 전체 검사로 확대 적용 예정

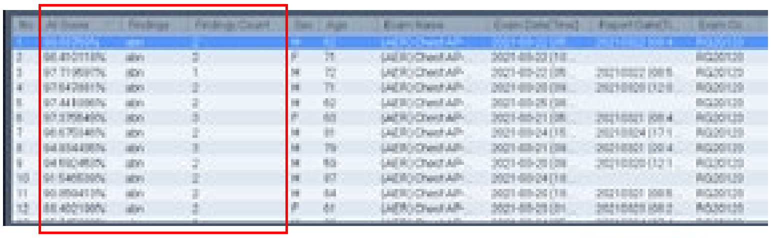
어떻게 쓸 것인가? – Experience in SNUH

- 판독 시에 원본 영상 + AI 분석 결과를 함께 참고
- 기존 검사와 동일하게 판독 시행



어떻게 쓸 것인가? – Experience in SNUH

- PACS worklist와 통합
  - 판독 우선순위 부여에 활용 가능



인공지능이 정말 도움이 될까?

- 판독 질 측면
  - 판독 정확도 향상
  - 질병 진단 정확도 향상
  - 환자 예후 개선
- 판독 효율성 측면
  - 판독 시간 단축, 판독할 검사 선별
  - 판독 대기 시간 단축
  - 비용효율성 개선, 환자 예후 개선, 환자 만족도 향상

→ 실제 임상 진료 상황에서 검증이 필요!

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AI 성능, 유효성 검증

- 임상 진료 밖에서 검증
  - Diagnostic case-control design
    - 특정 비율로 정상군, 비정상군을 따로 수집
    - 초기 성능, 기술적 타당도 검증
    - 과장된 유병률, 분명한 정상 vs. 비정상 분류, 명확한 정답
    - 실제 임상 상황에서 성능 보장 어려움
  - Diagnostic cohort design
    - 정상, 비정상에 관계 없이 특정 임상 상황 (코호트)를 먼저 정의
    - 실제 임상 진료 상황의 유병률, 환자/영상 스펙트럼 반영, 불분명한 정답
    - 유병률이 너무 낮은 경우 검증이 어려움
    - 실제 임상진료에의 영향 평가 불가능
      - AI 이용 후 판독 정확도 향상? 판독 대기 시간 단축? 환자 outcome 개선?

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AI 성능, 유효성 검증

- 임상 진료 안에서 검증
  - 실제 진료 상황에서의 판독 성능, AI - 판독의 간 interaction 반영
  - 환자 outcome 영향 평가 가능
  - 방법 1: AI 적용 전 vs. 후 비교
  - 방법 2: 전향적 무작위 비교 임상시험

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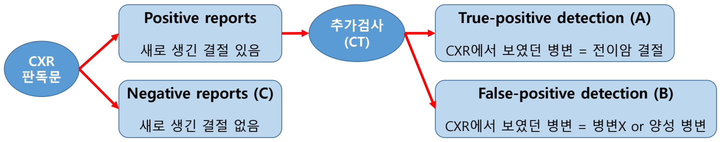
AI 성능, 유효성 검증

- AI 적용 전 vs. 후 비교: 사례 – 암환자에서 폐전이암 검출
  - AI 적용 전 (2018년 9월 ~ 12월) vs. AI 적용 후 (2019년 1월 ~ 4월)
    - 종양내과 외래 환자의 추적관찰 X선 검사
    - Age, Sex, Primary cancer에 대하여 양 group matching
    - 새롭게 생긴 전이암 결절에 대한 진단 성능 비교



- 양성률 (Positive rate) = (A+B) / (A+B+C)
- 진단 수득률 (Diagnostic yield) = A / (A+B+C)
- 가의뢰율 (False referral rate) = B / (A+B+C)

AI 성능, 유효성 검증

- AI 적용 전 vs. 후 비교: 사례 – 암환자에서 폐전이암 검출
  - AI 적용 전 (2018년 9월 ~ 12월) vs. AI 적용 후 (2019년 1월 ~ 4월)

	AI 보조판독	기존 판독	*P*-value
양성률	1.4%	0.60%	<.001
진단 수득률	0.86%	0.32%	.004
가의뢰율	0.34%	0.25%	.45
진단 수득률 (이전 CT에서 없었던 전이암 결절)	0.10%	0.089%	.83

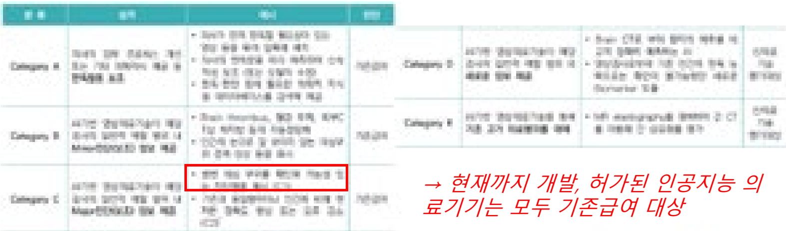
- AI 보조 판독이 실제 CXR 판독에서 새롭게 보이는 전이암 발견을 늘렸음
- 현실적으로는 CT가 이미 X-ray의 역할을 거의 대체하고 있음

AI 성능, 유효성 검증

- 임상 진료 안에서 검증 - 한계
  - AI 적용 전 vs. 후 비교
    - AI 적용 전 – 후 시간 경과에 따른 bias 불가피
  - 전향적 무작위 비교 임상시험
    - 시간, 비용, 노력이 많이 필요
    - 상대적으로 훨씬 빠른 AI 기술 발전 속도
  - 진단 정확도 이상의 지표 (환자 outcome, 판독 효율성, ...) 평가는 어려움
    - 흉부 X선 검사 결과가 진료에 미치는 영향이 작음
    - 흉부 X선 검사 결과와 관계 없이 진료 흐름이 이미 확립
    - 인공지능 보조 판독을 유용하게 활용할 수 있는 인프라 (PACS, EMR과 융합) 미비

인공지능 의료기기: 수가, 보험적용 가능성은?

1. 의료기기 제조허가: 식품의약품안전처
2. 신의료기술평가 대상 여부 확인: 심사평가원



→ *현재까지 개발, 허가된 인공지능 의료기기는 모두 기존급여 대상*

건강보험심사평가원. 혁신적 의료기술 요양급여 여부 평가 가이드라인. 2019.12

인공지능 의료기기: 수가, 보험적용 가능성은?

- 신의료기술평가: 보건의료연구원
  - 신의료기술: 안전성, 유효성 승인, 현장 도입 가능
  - 혁신의료기술 (조건부 신의료기술): 현장도입 가능, 3~5년 내 재평가
  - 연구단계 기술: 현장도입 불가능
- 요양급여대상 여부 결정: 심사평가원
  - 기존행위 대비 환자에게 이익이되는 요소가 크다면 별도 보상 고려

Level 3	• 기존 행위 대비 현저한 진단능력의 향상 • 새로운 진단적 가치 창출 또는 치료효과성	Category C2 Category D	별도보상 고려*
Level 4	• Level 3에 대해 비용효과성을 입증한 경우	Category C2 Category D Category E	별도보상 고려

→ *현재로서는 인공지능 이용 판독에 별도보상 기대 어려움*

SNUH

앞으로의 연구 개발 방향

1. AI 성능 개선
   - 임상 적용 후에도 계속적인 feed-back, 추가 training/update 필요
2. 병변 검출을 넘어서...
   - 병변 특성화, 감별진단
   - 영상 간 비교
   - 판독문 생성
   - 환자 outcome 예측
3. 기존 시스템 (PACS)와의 통합
   - 다양한 활용 시나리오 (Triage, Overshoulder, Critical finding report 등) 구현
   - Multiple vendor AI 통합 활용
4. 임상적 유효성 검증
   - 환자 outcome 영향 평가, Cost-effectiveness 평가
   - 전향적 임상시험 or 코호트 연구 필요

SNUH

CURRICULUM VITAE

김 진 성

연세의대 세브란스병원

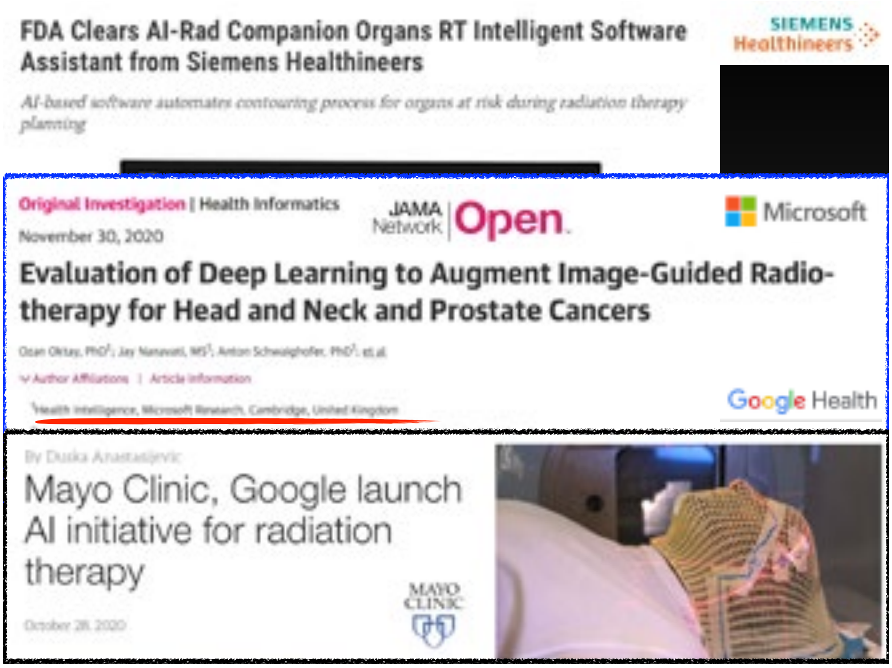
EDUCATION

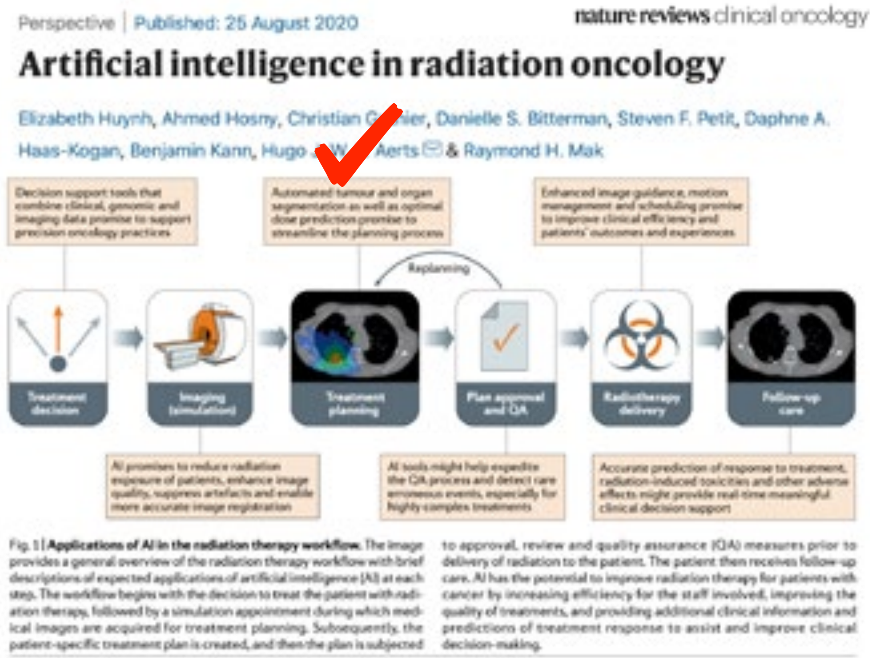
1996 – 2000	KAIST 원자력 및 양자공학과 학사
2000 – 2003	KAIST 원자력 및 양자공학과 석사
2003 – 2007	KAIST 원자력 및 양자공학과 박사

CAREER

2007 – 2009	국립암센터 양성자치료센터 박사 후 연구원 및 의학물리아카데미
2009 – 2016	삼성서울병원 방사선종양학과 Ph.D 조교수
2016 –	연세대학교 의과대학 방사선종양학교실 부교수

AI in practice at radiation oncology





Perspective | Published: 25 August 2020

nature reviews clinical oncology

Artificial intelligence in radiation oncology

Elizabeth Huynh, Ahmed Hosny, Christian G ier, Danielle S. Bitterman, Steven F. Petit, Daphne A. Haas-Kogan, Benjamin Kann, Hugo J. W. L. Aerts & Raymond H. Mak

Decision support tools that combine clinical, genomic and imaging data promise to support precision oncology practices

Automated tumour and organ segmentation as well as optimal dose prediction promise to streamline the planning process

Enhanced image guidance, motion management and scheduling promise to improve clinical efficiency and patients' outcomes and experiences

Replanning

Treatment decision

Imaging (simulation)

Treatment planning

Plan approval and QA

Radiotherapy delivery

Follow-up care

AI promises to reduce radiation exposure of patients, enhance image quality, suppress artefacts and enable more accurate image registration

AI tools might help expedite the QA process and detect rare erroneous events, especially for highly complex treatments

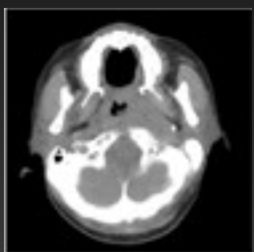
Accurate prediction of response to treatment, radiation-induced toxicities and other adverse effects might provide real-time meaningful clinical decision support

Fig. 1 | **Applications of AI in the radiation therapy workflow.** The image provides a general overview of the radiation therapy workflow with brief descriptions of expected applications of artificial intelligence (AI) at each step. The workflow begins with the decision to treat the patient with radiation therapy, followed by a simulation appointment during which medical images are acquired for treatment planning. Subsequently, the patient-specific treatment plan is created, and then the plan is subjected to approval, review and quality assurance (QA) measures prior to delivery of radiation to the patient. The patient then receives follow-up care. AI has the potential to improve radiation therapy for patients with cancer by increasing efficiency for the staff involved, improving the quality of treatments, and providing additional clinical information and predictions of treatment response to assist and improve clinical decision-making.

Image?

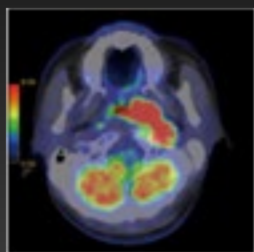
Image

- an artifact that depicts visual perception, such as a photograph or other two-dimensional picture, that resembles a subject—usually a physical object—and thus provides a depiction of it.
- In the context of signal processing, an image is a distributed amplitude of color but grayscale for medical imaging

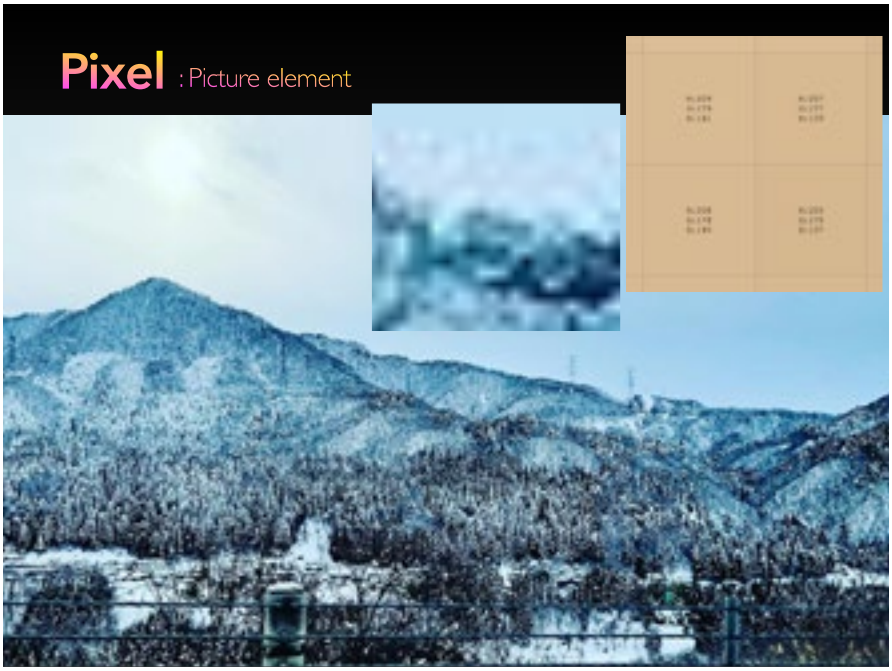


CT : Computed Tomography

MR : Magnetic Resonance



PET : Positron Emission Tomography


Pixel : Picture element

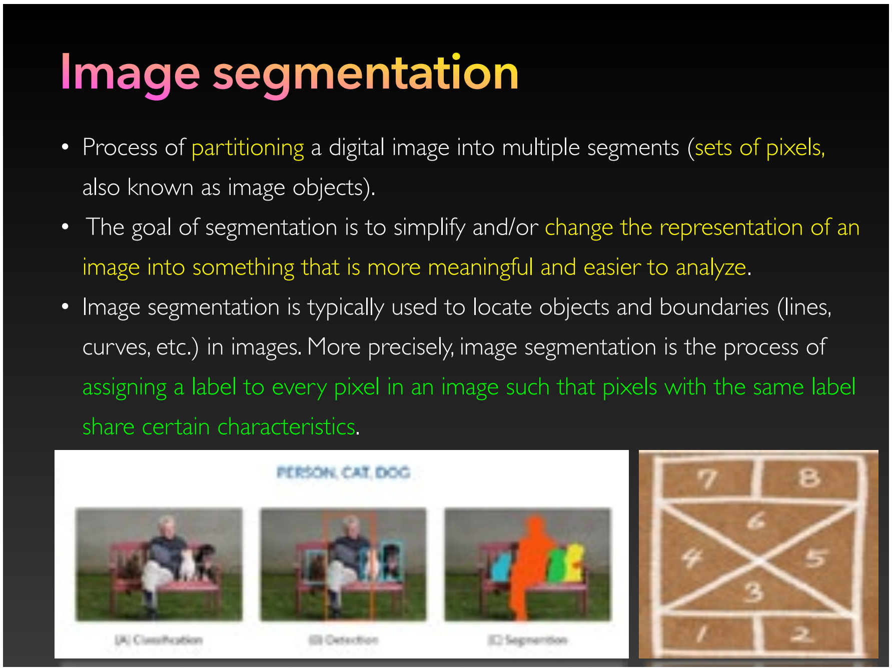


Image segmentation
• Process of partitioning a digital image into multiple segments (sets of pixels, also known as image objects).
• The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze.
• Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics.
PERSON, CAT, DOG

Radiation Therapy?

N Engl J Med. 2012 Jun 7;366(23):2207-14.


The NEW ENGLAND JOURNAL of MEDICINE

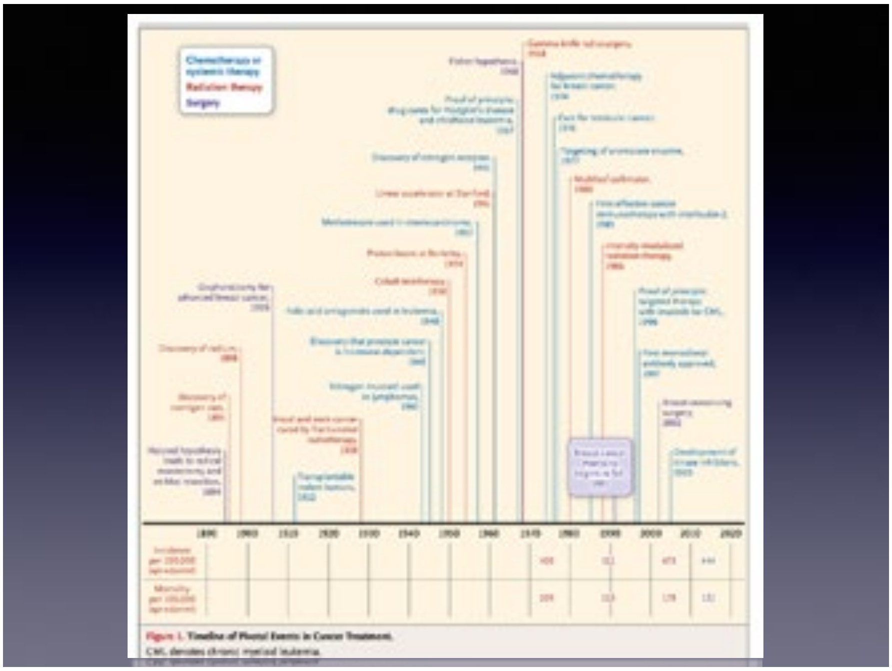
200 NEJM ANNIVERSARY ARTICLE

Two Hundred Years of Cancer Research

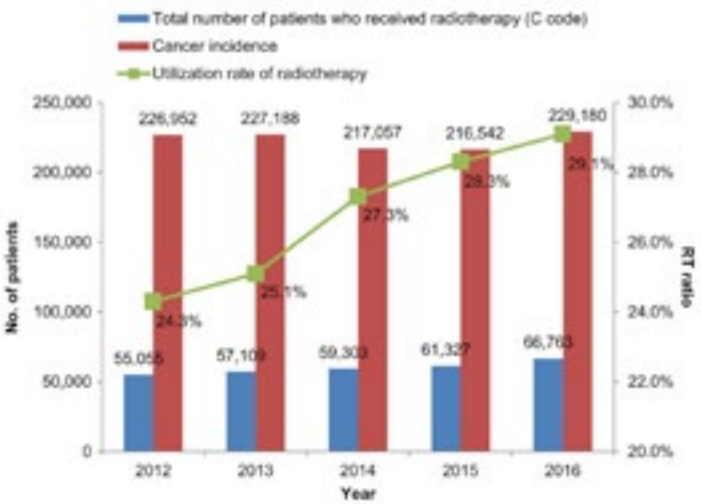
Vincent T. DeVita, Jr., M.D., and Steven A. Rosenberg, M.D., Ph.D.

IN THE 200 YEARS SINCE THE NEW ENGLAND JOURNAL OF MEDICINE WAS FOUNDED, cancer has gone from a black box to a blueprint. During the first century of the Journal's publication, medical practitioners could observe tumors, weigh them, and measure them but had few tools to examine the workings within the cancer cell. A few astute observers were ahead of their time, including Rudolf Virchow, who with the benefit of a microscope deduced the cellular origin of cancer in 1863,[1] and Stephen Paget, who in 1889 wisely mused about the seed-and-soil hypothesis of metastatic disease,[2] a theory that is coming into its own today (Table 1). Other key advances were the discovery of a viral cause of avian cancer by Peyton Rous in 1911[3] and the proposal by Theodor Boveri in 1914 that cancer can be triggered by chromosomal mutations.[4]

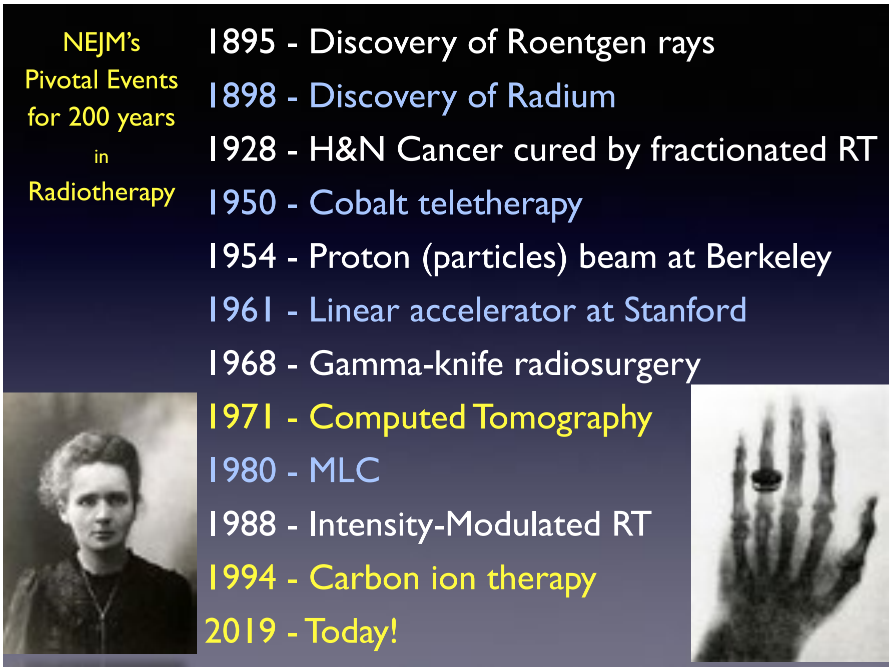
But the lid of the black box was not seriously pried open until 1944, when a retired scientist at Rockefeller University, Oswald Avery, reported the results of his beautifully clear experiments with the pneumococcal bacillus, which showed that cellular information was transmitted not by proteins but by DNA.[5] His work led directly to the important discovery of the structure of DNA by Watson and Crick in 1953.[6] Eight years later, the genetic code was broken by Nirenberg and colleagues,[7] and the central dogma of biology was established; that information was transmitted from DNA to RNA and resulted in the synthesis of proteins. Then, the first of a series

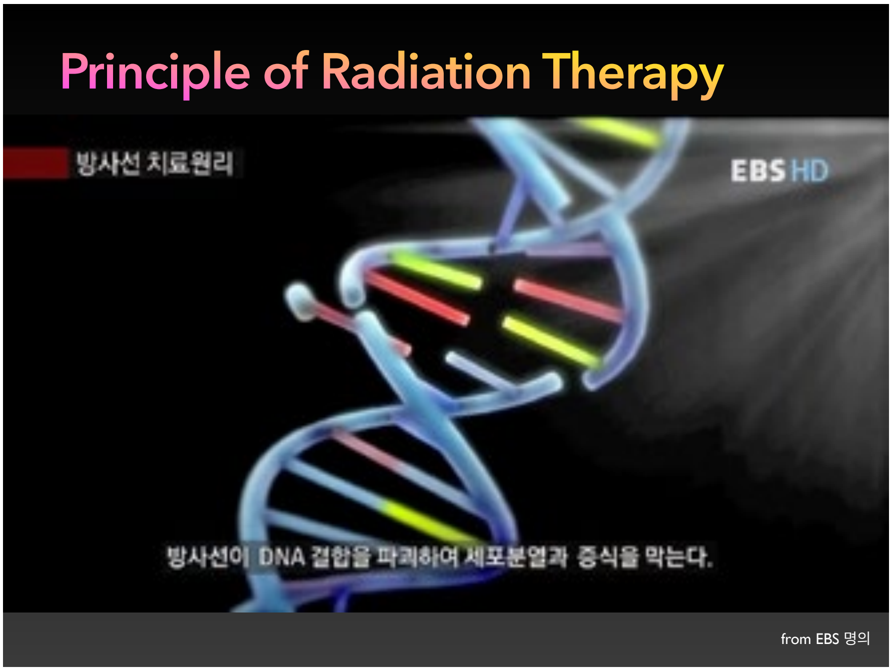


Utilization of Radiation Therapy



Journal of Radiation Research, Vol. 61, No. 2, 2020, pp. 249–256


NEJM's
Pivotal Events
for 200 years
in
Radiotherapy
1895 - Discovery of Roentgen rays
1898 - Discovery of Radium
1928 - H&N Cancer cured by fractionated RT
1950 - Cobalt teletherapy
1954 - Proton (particles) beam at Berkeley
1961 - Linear accelerator at Stanford
1968 - Gamma-knife radiosurgery
1971 - Computed Tomography
1980 - MLC
1988 - Intensity-Modulated RT
1994 - Carbon ion therapy
2019 - Today!

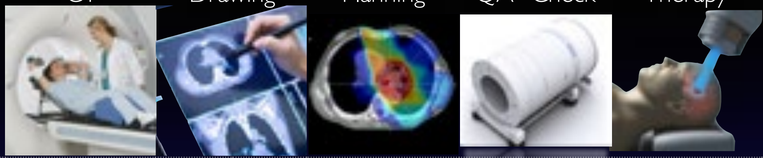

Principle of Radiation Therapy
방사선 치료원리
EBS HD
방사선이 DNA 결합을 파괴하여 세포분열과 증식을 막는다.
from EBS 명의

How much dose we need for RT?

- Lethal Dose (LD)
  - Dose of radiation expected to cause death to 50% of an exposed population within 30 days (Lethal Dose - LD 50/30) is in the range 4~5 Gy (4,000~5,000 mSv) received over a very short period.
- General CT : 1~5 cGy (10~50 mSv)
- RT Dose
  - Typical Dose for RT > 50~60 Gy (2Gy x 25~30 fraction)
  - SABR Dose > 10 Gy/fraction

5 Process
in
Radiation Therapy

5 Process in Radiation Therapy

	CT	Drawing		Planning	QA+Check	Therapy
						
Who	Radiation Therapist	Doctor Dosimetrist	Doctor	Dosimetrist Medical Physicist	Medical Physicist	Radiation Therapist
Time(min)	30	180	120	960	60	20
Machine Type	CT	SW (MIM, Mirada)		SW (RayStation, Eclipse)	SW (ARIA, MOSAIQ)	LINAC MR-LINAC
Imaging used in process	CT	CT (MR, PET, US)		CT	CT	2D X-ray CBCT MVCT MR
Purpose of Imaging	Localization	Segmentation		Dose Calculation	Dose Calculation	Localization Registration

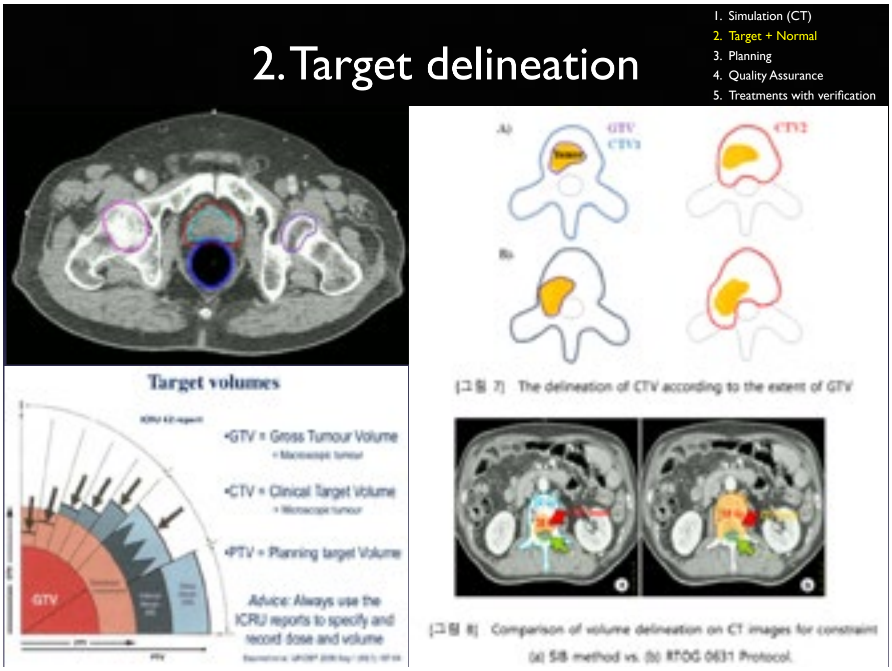
Medical Imaging is playing very important role in RT!

1. Simulation (CT)

1. Simulation (CT)
2. Target + Normal
3. Planning
4. Quality Assurance
5. Treatments with verification

- Patient's CT scan for planning

- MR, PET/CT and etc…

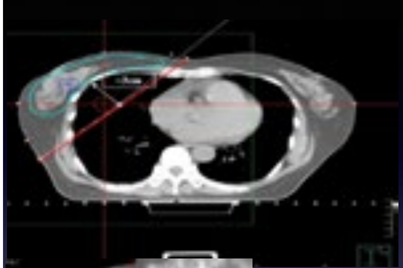


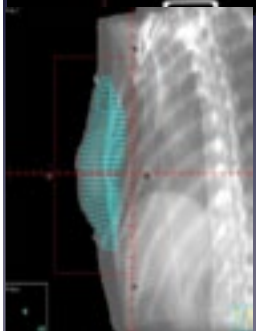
2. Target delineation
1. Simulation (CT)
2. Target + Normal
3. Planning
4. Quality Assurance
5. Treatments with verification
Target volumes
•GTV = Gross Tumour Volume
•CTV = Clinical Target Volume
•PTV = Planning target Volume
Advice: Always use the ICRU reports to specify and record dose and volume
GTV
A)
B)
GTV
CTV1
CTV2
[그림 7] The delineation of CTV according to the extent of GTV
[그림 8] Comparison of volume delineation on CT images for constraint
(a) SIB method vs. (b) RTOG 0631 Protocol.

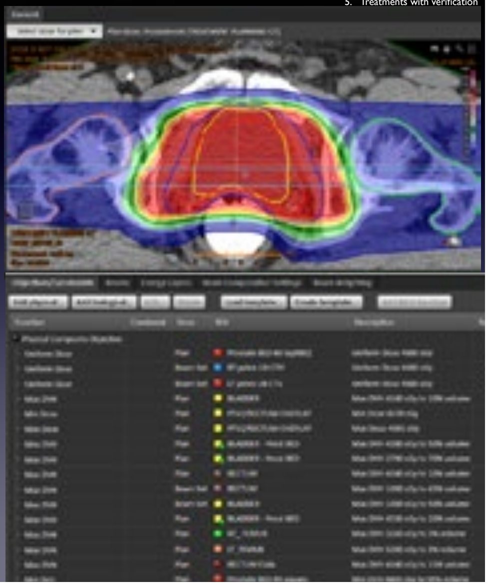
Contouring in MIM with expert!
1. Simulation (CT)
2. Target + Normal
3. Planning
4. Quality Assurance
5. Treatments with verification

3. Radiation Therapy Planning

1. Simulation (CT)
2. Target + Normal
3. Planning
4. Quality Assurance
5. Treatments with verification



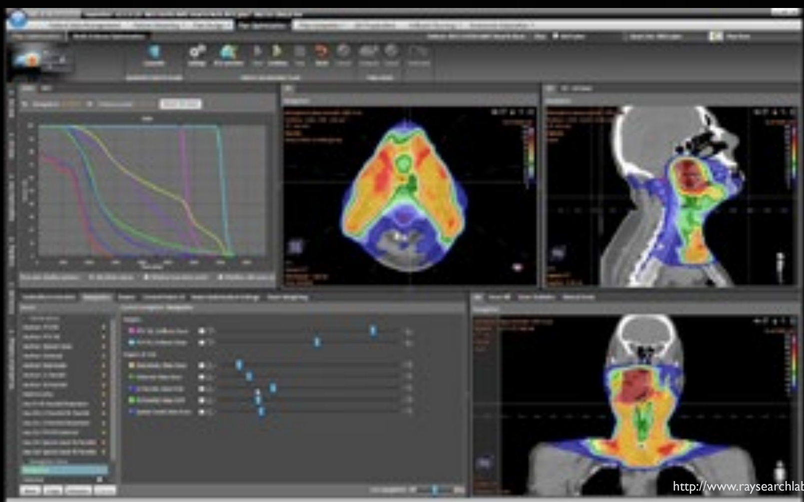




- Radiation type
- Beam Energy
- Beam angle
- Collimator
- Prescription
- DVH

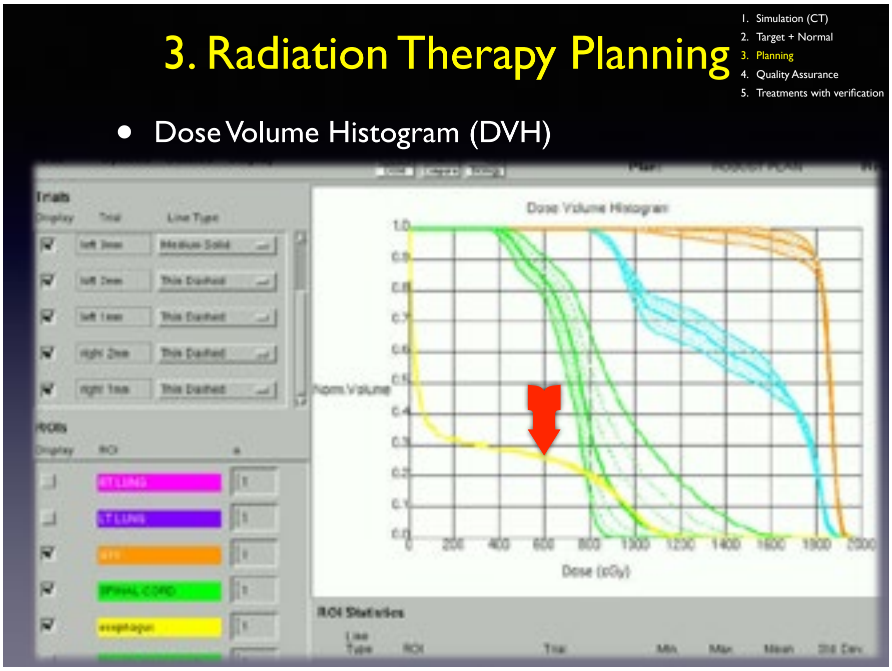
3. Radiation Therapy Planning

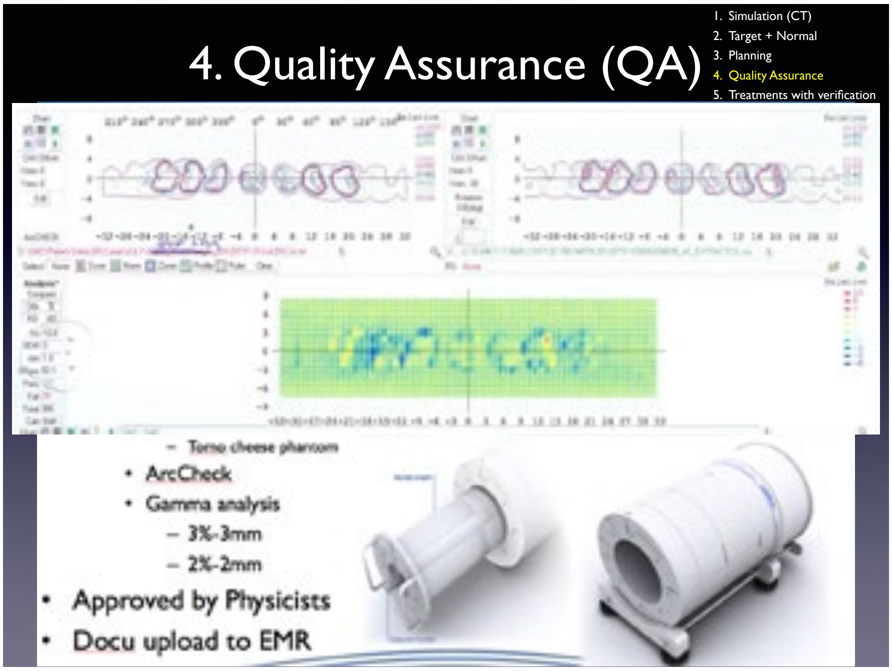
1. Simulation (CT)
2. Target + Normal
3. Planning
4. Quality Assurance
5. Treatments with verification



http://www.raysearchlabs.com

- Tumor: High dose
- Normal: Lower dose

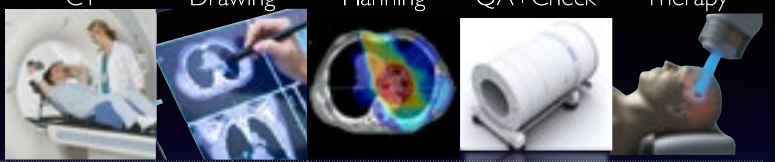

3. Radiation Therapy Planning
1. Simulation (CT)
2. Target + Normal
3. Planning
4. Quality Assurance
5. Treatments with verification
Dose Volume Histogram (DVH)
Trials
Dose Volume Histogram
Norm Volume
Dose (cGy)
ROI Statistics


4. Quality Assurance (QA)
1. Simulation (CT)
2. Target + Normal
3. Planning
4. Quality Assurance
5. Treatments with verification
– Tomo cheese phantom
• ArcCheck
• Gamma analysis
– 3%-3mm
– 2%-2mm
• Approved by Physicists
• Docu upload to EMR

5. Treatments with verification

1. Simulation (CT)
2. Target + Normal
3. Planning
4. Quality Assurance
5. Treatments with verification

5 Process in Radiation Therapy



	CT	Drawing		Planning	QA+Check	Therapy
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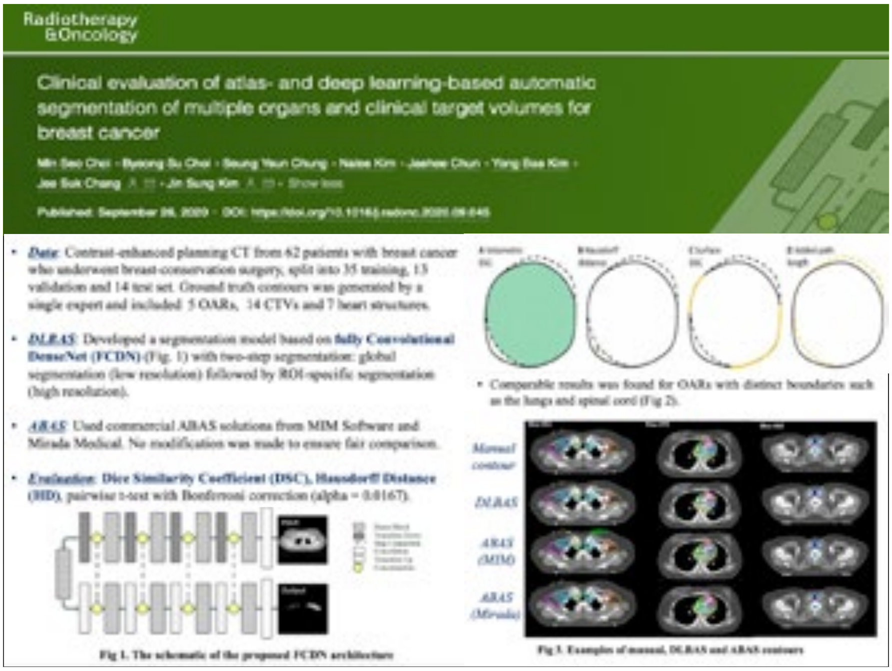
Medical Imaging is playing very important role in RT!

AI Segmentation Research in RT

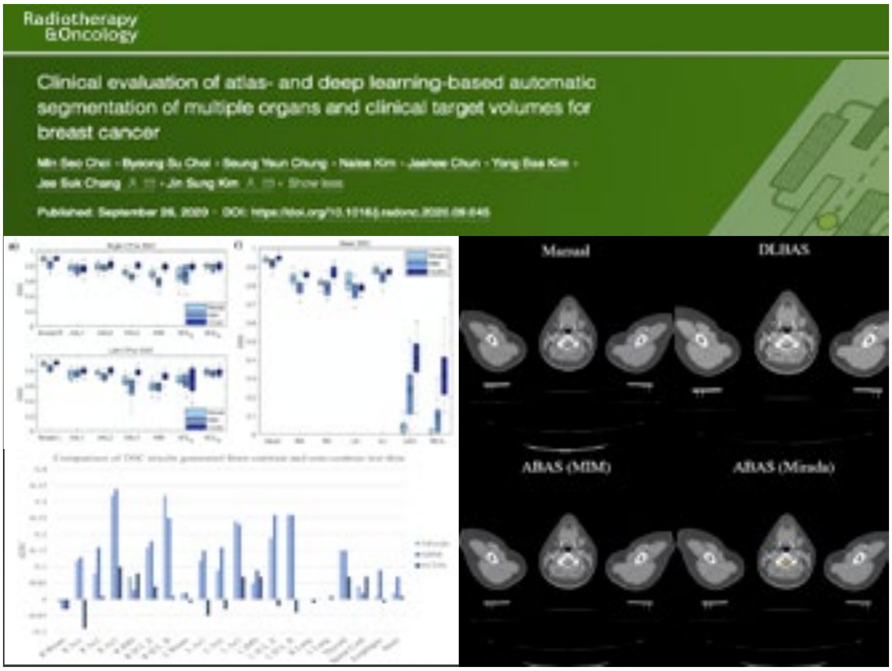
AI powered Segmentation

- Normal organ segmentation
- Tumor detection
- Tumor segmentation
- Platform for toxicity prediction
- Segmentation for adaptive radiation therapy

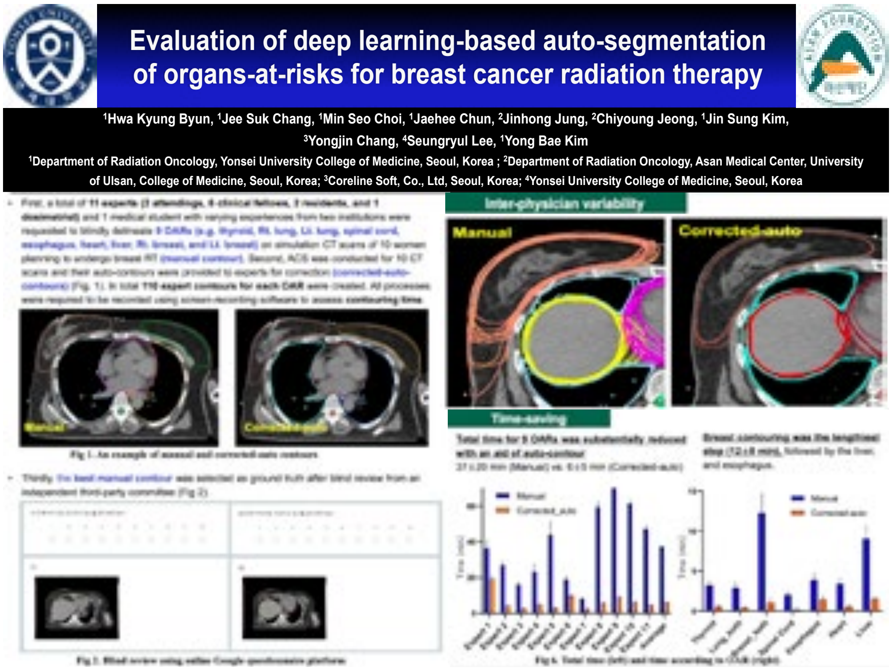
- Barriers for AI research
  - Dataset size
  - Data heterogeneity
  - Data curation
  - Lack of ground truth
  - Clinical data quality
  - Model explainability
  - Model robustness

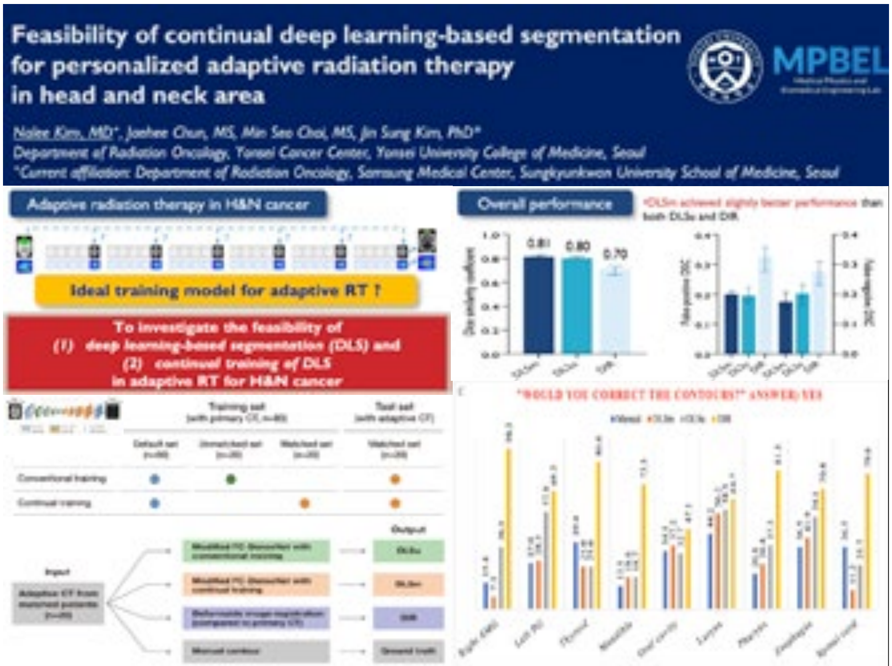


Radiotherapy &Oncology
Clinical evaluation of atlas- and deep learning-based automatic segmentation of multiple organs and clinical target volumes for breast cancer
Published: September 26, 2020
Data: Contrast-enhanced planning CT from 62 patients with breast cancer who underwent breast-conservation surgery, split into 35 training, 13 validation and 14 test set. Ground truth contours was generated by a single expert and included 5 OARs, 14 CTVs and 7 heart structures.
DLBAS: Developed a segmentation model based on fully Convolutional DenseNet (FCDN) (Fig. 1) with two-step segmentation: global segmentation (low resolution) followed by ROI-specific segmentation (high resolution).
ABAS: Used commercial ABAS solutions from MIM Software and Mirada Medical. No modification was made to ensure fair comparison.
Evaluation: Dice Similarity Coefficient (DSC), Hausdorff Distance (HD), pairwise t-test with Bonferroni correction (alpha = 0.0167).
Comparable results was found for OARs with distinct boundaries such as the lungs and spinal cord (Fig 2).
Manual contour
DLBAS
ABAS (MIM)
ABAS (Mirada)
Fig 1. The schematic of the proposed FCDN architecture
Fig 3. Examples of manual, DLBAS and ABAS contours



Radiotherapy &Oncology
Clinical evaluation of atlas- and deep learning-based automatic segmentation of multiple organs and clinical target volumes for breast cancer
Published: September 26, 2020
Manual
DLBAS
ABAS (MIM)
ABAS (Mirada)


Evaluation of deep learning-based auto-segmentation of organs-at-risks for breast cancer radiation therapy
[1]Hwa Kyung Byun, [1]Jee Suk Chang, [1]Min Seo Choi, [1]Jaehee Chun, [2]Jinhong Jung, [2]Chiyoung Jeong, [1]Jin Sung Kim, [3]Yongjin Chang, [4]Seungryul Lee, [1]Yong Bae Kim
[1]Department of Radiation Oncology, Yonsei University College of Medicine, Seoul, Korea ; [2]Department of Radiation Oncology, Asan Medical Center, University of Ulsan, College of Medicine, Seoul, Korea; [3]Coreline Soft, Co., Ltd, Seoul, Korea; [4]Yonsei University College of Medicine, Seoul, Korea
Inter-physician variability
Manual
Corrected-auto
Time-saving


Feasibility of continual deep learning-based segmentation for personalized adaptive radiation therapy in head and neck area
MPBEL
Adaptive radiation therapy in H&N cancer
Ideal training model for adaptive RT ?
To investigate the feasibility of
(1) deep learning-based segmentation (DLS) and
(2) continual training of DLS
in adaptive RT for H&N cancer
Overall performance
0.81
0.80
0.70

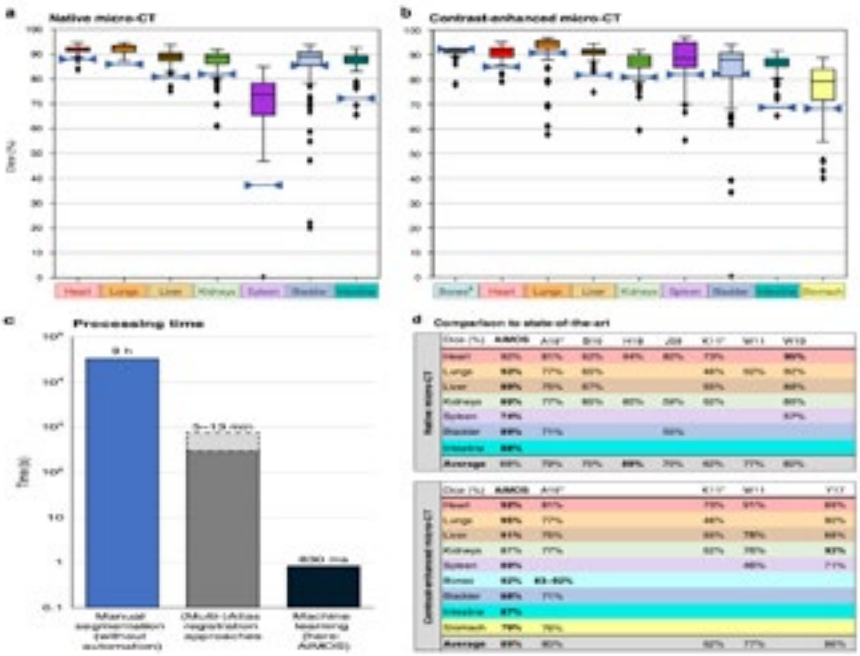

nature COMMUNICATIONS

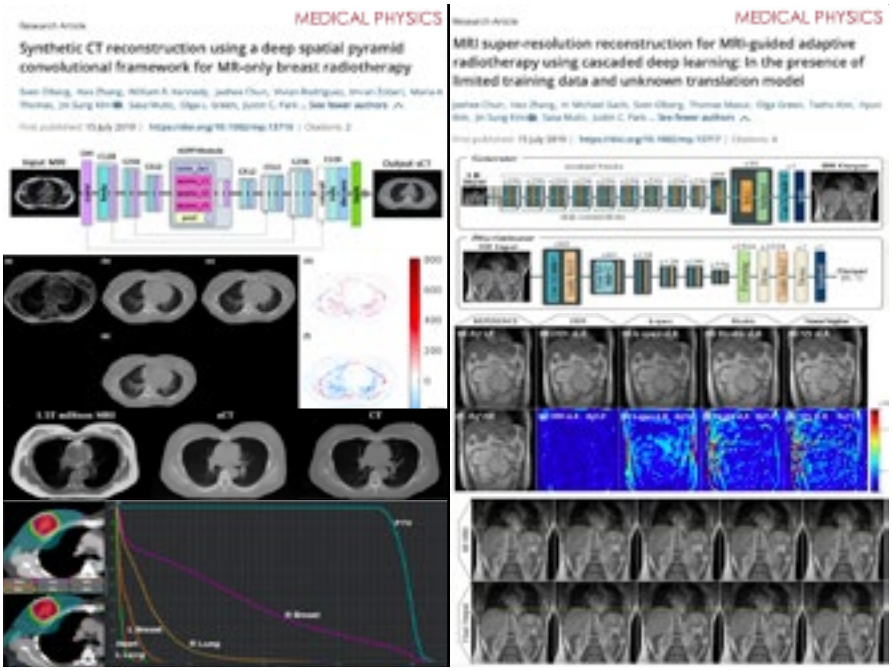
ARTICLE

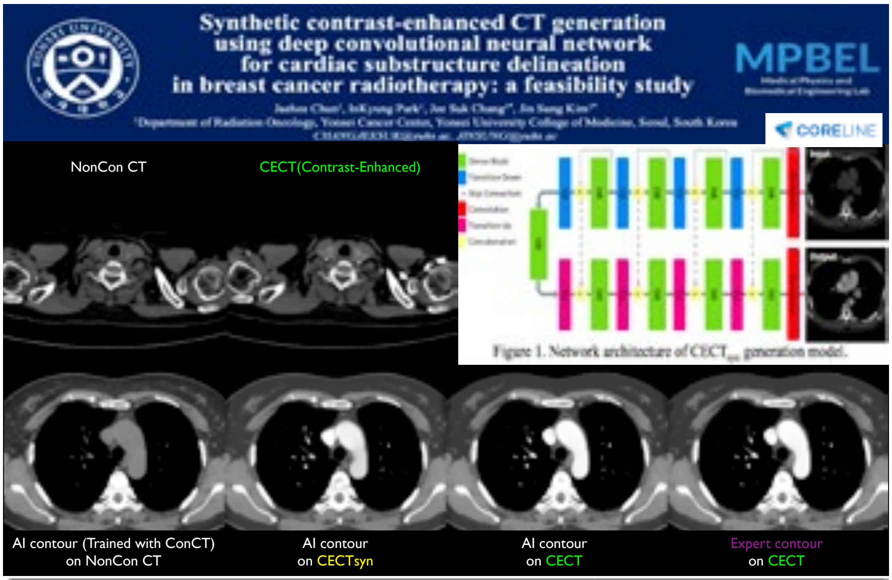
https://doi.org/10.1038/s41467-020-19449-7 OPEN

Deep learning-enabled multi-organ segmentation in whole-body mouse scans

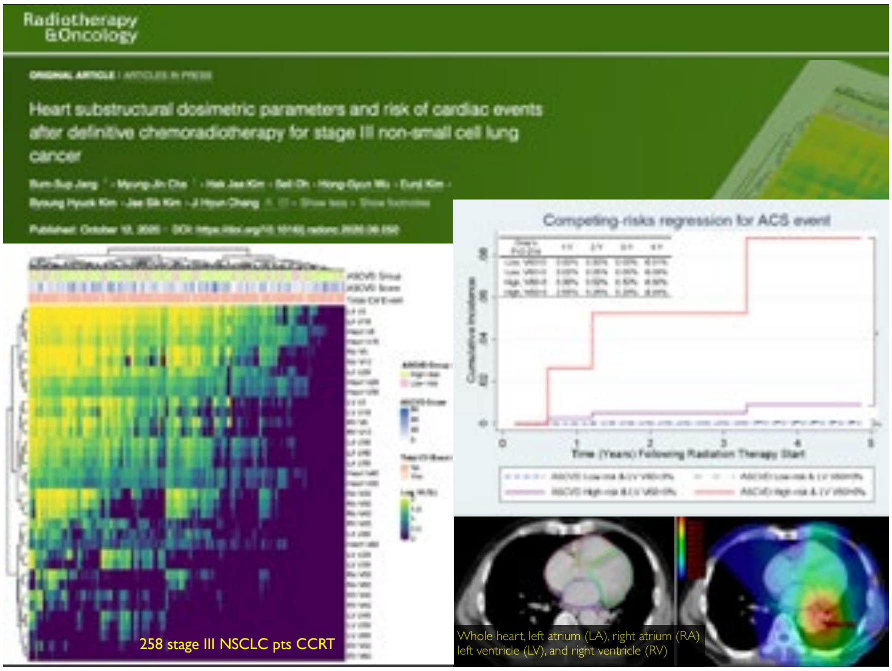
Oliver Schoppe[1,2,3], Chenchen Pan[3,4], Javier Coronel[1,2], Hongcheng Mai[3,4], Zhouyi Rong[3,4], Mihail Ivilinov Todorov[3,4,5], Annemarie Müskes[6], Fernando Navarro[1,2], Hongwei Li[1], Ali Ertürk[3,4,7] & Bjoern H. Menze[1,2,8,9]

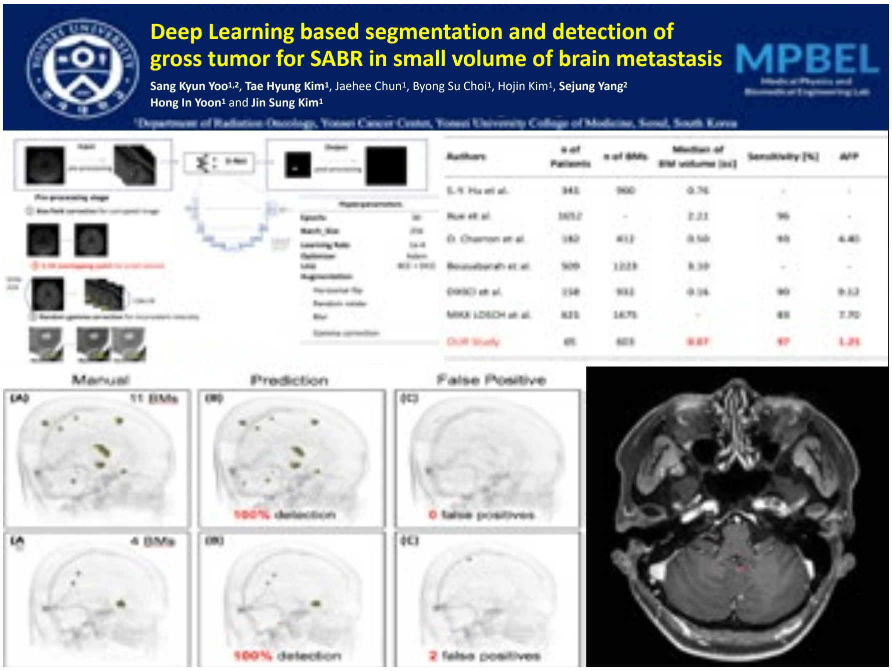


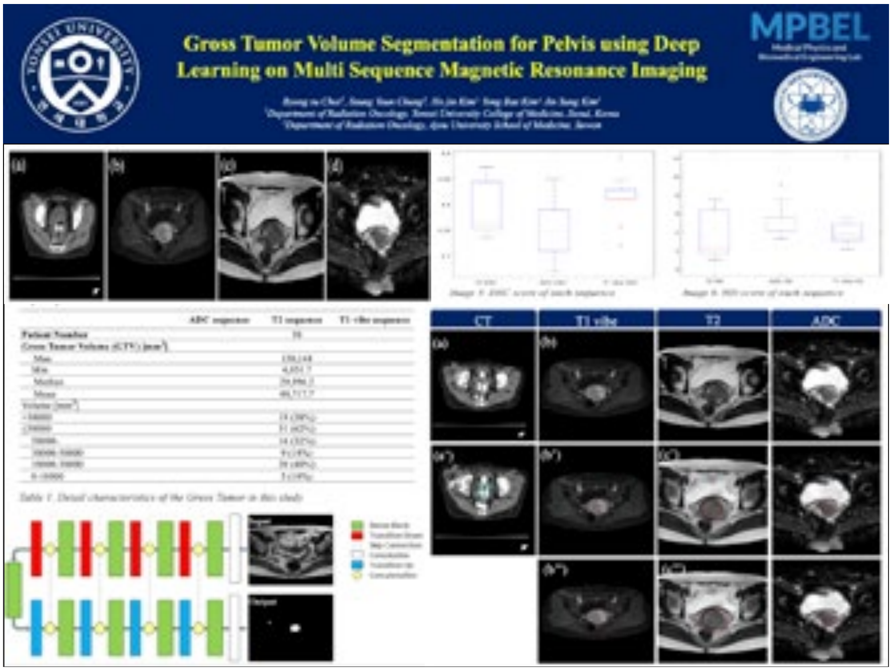




	Heart	Lt_ventricle	Lt_atrium	Rt_ventricle	Rt_atrium	LAD	RCA	Average
NCT_{real}	0.965	0.101	0.000	0.117	0.311	0.059	0.083	0.234
$CECT_{syn}$	0.949	0.914	0.877	0.834	0.791	0.422	0.106	0.699
$CECT_{real}$	0.974	0.965	0.953	0.912	0.863	0.591	0.317	0.796

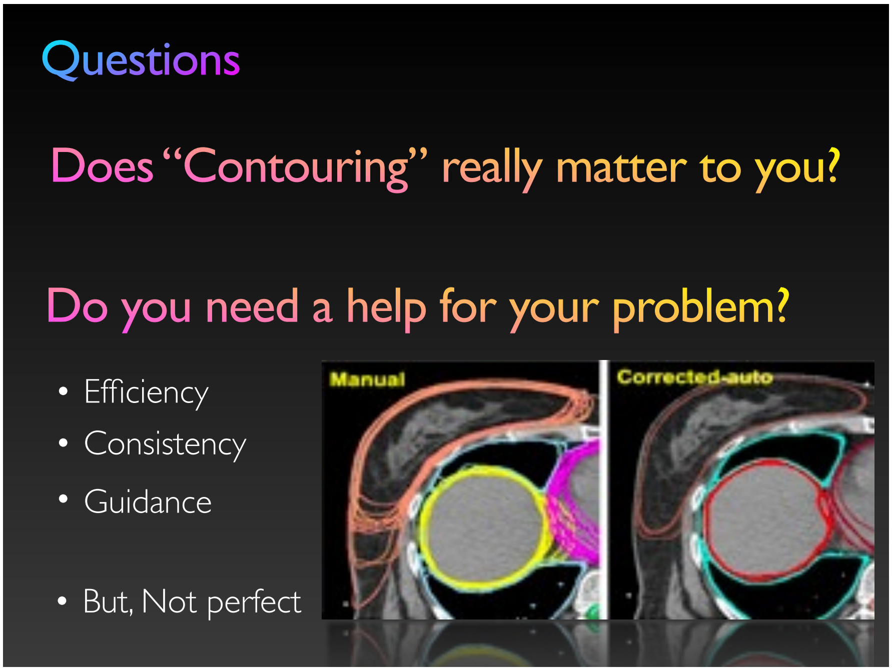

Radiotherapy & Oncology
Heart substructural dosimetric parameters and risk of cardiac events after definitive chemoradiotherapy for stage III non-small cell lung cancer
Competing-risks regression for ACS event
Time (Years) Following Radiation Therapy Start
258 stage III NSCLC pts CCRT
Whole heart, left atrium (LA), right atrium (RA)
left ventricle (LV), and right ventricle (RV)

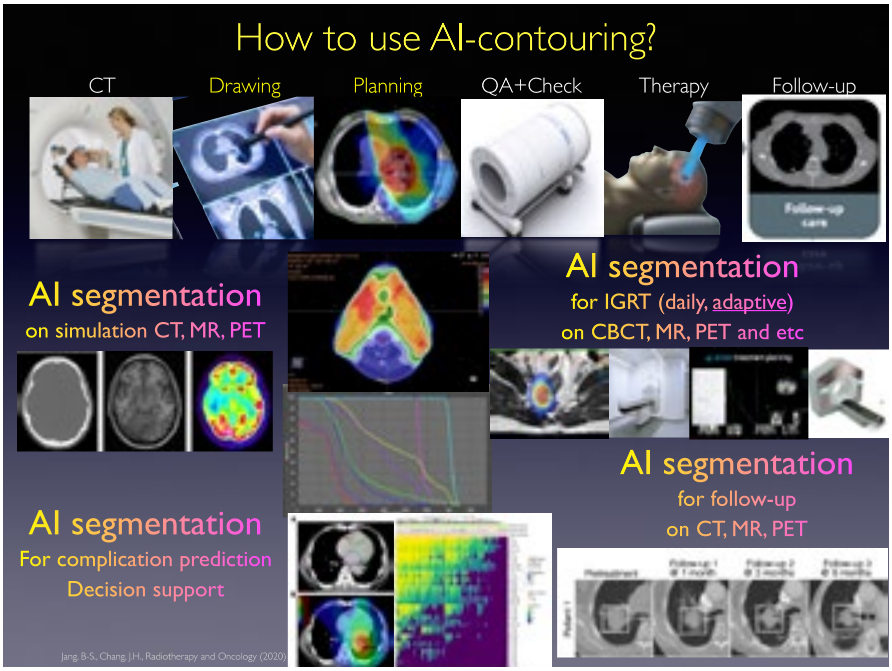

Deep Learning based segmentation and detection of gross tumor for SABR in small volume of brain metastasis
Sang Kyun Yoo[1,2], Tae Hyung Kim[1], Jaehee Chun[1], Byong Su Choi[1], Hojin Kim[1], Sejung Yang[2]
Hong In Yoon[1] and Jin Sung Kim[1]
MPBEL
Manual
Prediction
False Positive
11 BMs
4 BMs
100% detection
0 false positives
100% detection
2 false positives



Future

AI Research & RadOnc


Questions
Does "Contouring" really matter to you?
Do you need a help for your problem?
• Efficiency
• Consistency
• Guidance
• But, Not perfect
Manual
Corrected-auto


How to use AI-contouring?
CT
Drawing
Planning
QA+Check
Therapy
Follow-up
AI segmentation
on simulation CT, MR, PET
AI segmentation
for IGRT (daily, adaptive)
on CBCT, MR, PET and etc
AI segmentation
for follow-up
on CT, MR, PET
AI segmentation
For complication prediction
Decision support
Jang, B-S., Chang, J.H., Radiotherapy and Oncology (2020)

Deployment Barriers of AI in Clinical RadOnc

- AI solutions are beyond just a set of ML models, should be designed and implemented together as a system including people(users), processes and technologies
  - Clinical use is beyond a research paper
- We still have some barriers for AI research in clinical practice
  - Dataset size
  - Data heterogeneity
  - Data curation
  - Lack of ground truth
  - Clinical data quality
  - Model explainability
  - Model robustness

Summary

- AI will support Radiation Oncology!
  - ML / DL / Reinforcement Learning !!!
- AI-powered segmentation will be a key baseline for radiation therapy and cancer management
- Clinical AI-based segmentation needs "Clinicians" & physicists!
  - Data curation - contouring generation, inspection
  - Clinical commissioning, clinical evaluation, improvement
  - Real-time adaptive radiation therapy
  - Toxicity prediction, dose modeling and etc
  - No pain, No gain
- We need to make a "new tool" clinical, practical and robust together in our daily workflow for our patients and us.

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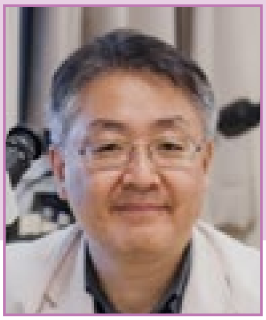
송상용

성균관의대 삼성서울병원



EDUCATION

2000	서울대학교, 박사, 의학
1992	서울대학교, 석사, 의학
1988	서울대학교, 학사, 의학

CAREER

1995 – 1996	미국 NIH / Visiting Fellow, 메트리젤 / 전이모델
2011 – 2012	미국 피츠버그대학병원 / 방문교수, 바이오뱅킹 / 디지털병리
1996 –	삼성서울병원 / 전문의, 병리 진단
1997 –	성균관대학교 / 교수, 병리 교육

Artificial intelligence in digital pathology intelligence

The role of artificial intelligence (AI) in pathology has been slowly introduced but is actively settling down with digital to revolutionize current and future medicine in the coming years. Radiology, a medical specialty partly similar to and partly different from pathology has been relatively rapid to adopt AI with digital whereas pathology (particulary histo- and cyto-pathology) is just on the starting line, especially in Korea. Pathology armed with AI promises to play a crucial role in precision medicine in cancer health care. In this lecture, the current issues of pathology in Korea followed by a brief history of Korean digital pathology and AI research, the global results of pathology AI researches and obstacles of Korean pathology and AI settlement are described. AI has the potential to change the practice of pathology by ensuring rapid and accurate classification or counting features automatically without fatigue and enabling pathologists to focus on higher level thinking and diagnostic conclusions, especially integrating clinical, morphological and molecular information to make more accurate diagnosis and in this way contribute to better health care in future medicine.

4

Recent Issues of Medical AI

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이 지 형

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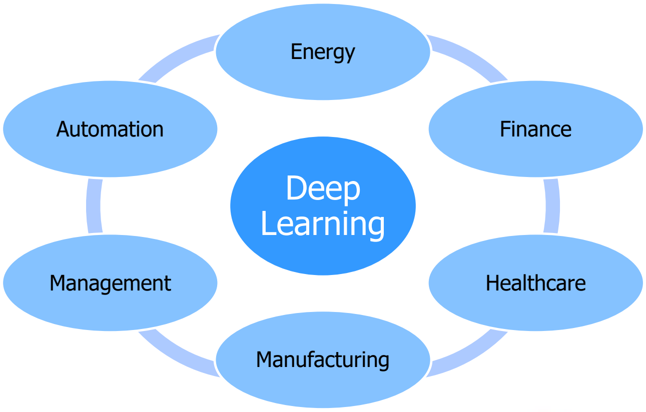
CAREER

2019 – 2021	한국정보과학회 인공지능연구회 위원장
2000 – 2002	SRI International, International Fellow
2017 –	성균관대학교 지능정보융합원 부원장
2019 –	성균관대학교 인공지능학과 학과장

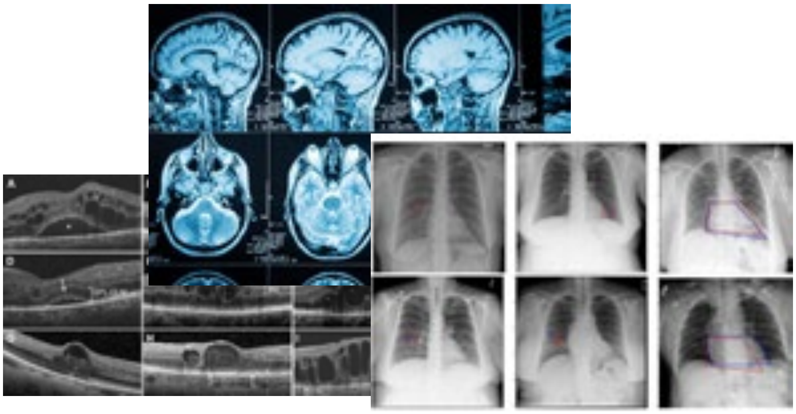
Algorithm robustness and confidence

Deep Learning Era



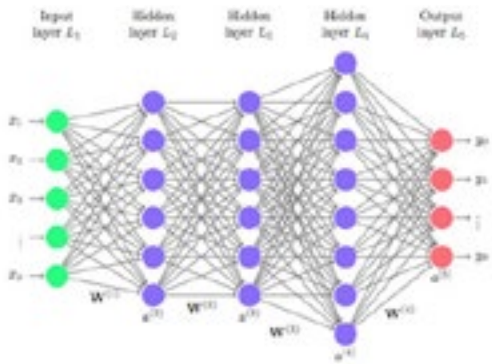
Deep Learning Era

- **Medical Image Analysis**



Deep Learning

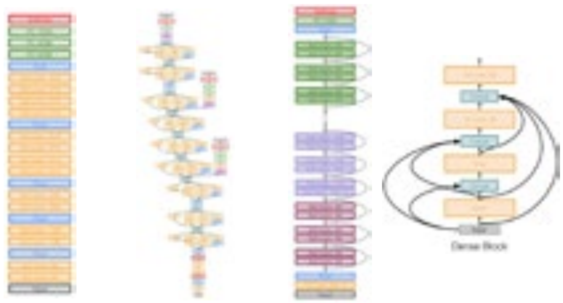
- **What is it?**



https://towardsdatascience.com/its-deep-learning-times-a-new-frontier-of-data-a1e9ef9fe9a8

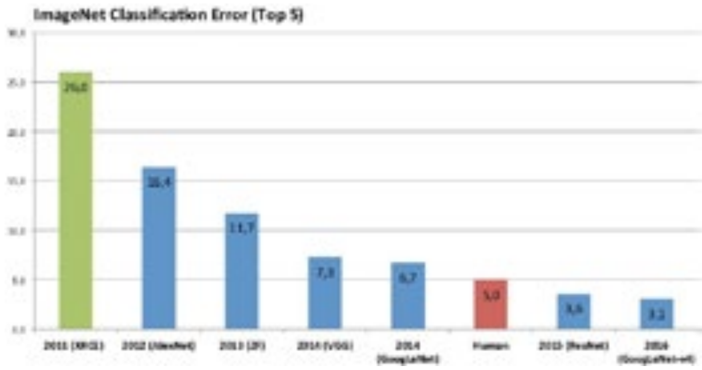
Deep Learning

- **Various deep neural network structures have been proposed**
  - They are applied in innumerous application domains



Deep Learning

- **It has shown astonishing accuracies**



https://devopedia.org/imagenet

Deep Learning

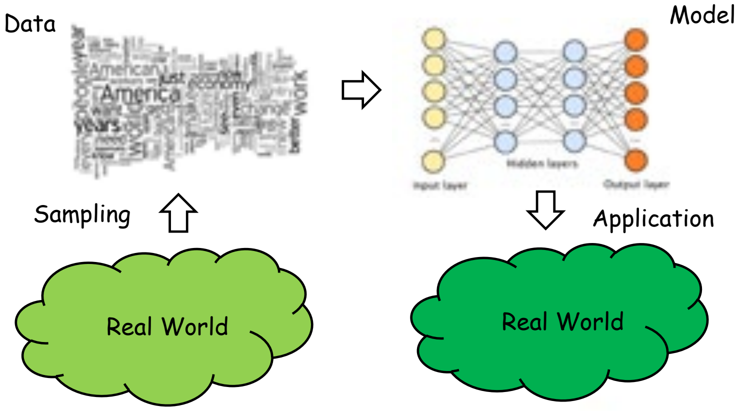
- **Is the deep learning model really useful?**

- **Unfortunately, Performance is measured with GIVEN training and testing dataset!!**
  - They are not all of the world.

- **What possibly happens when deep neural networks meet the REAL world**

Data Driven Approach

- **Model built from Data**



Potential Problems related with Data

- **Data Distribution Change**
  - Covariate Shift
  - Label Shift
- **Adversarial Sample**
- **Out-of-distribution**

Data Distribution Change

Covariate Shift

Label Shift

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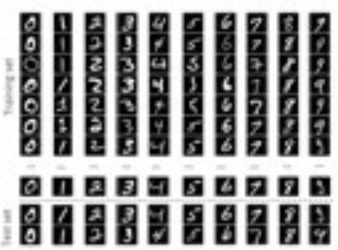
Unique Origin Unique Future

Data Distribution

- **Deep learning assume distributions of training set and test set**



https://medium.com/merantix/applying-deep-learning-to-real-world-problems-ba2d86ac5837

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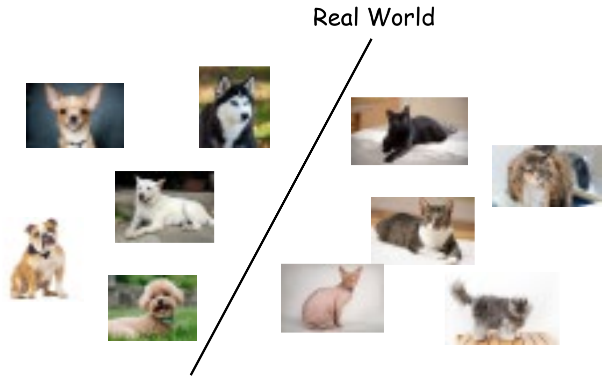
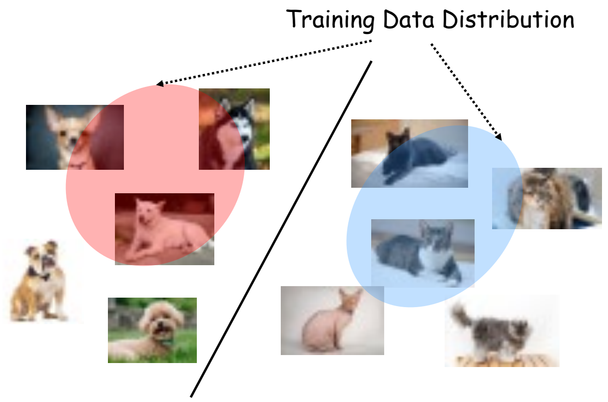
Data Distribution Change

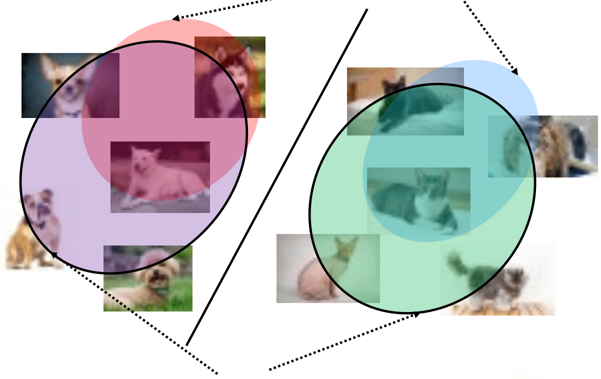


Images from google search

Covariate Shift

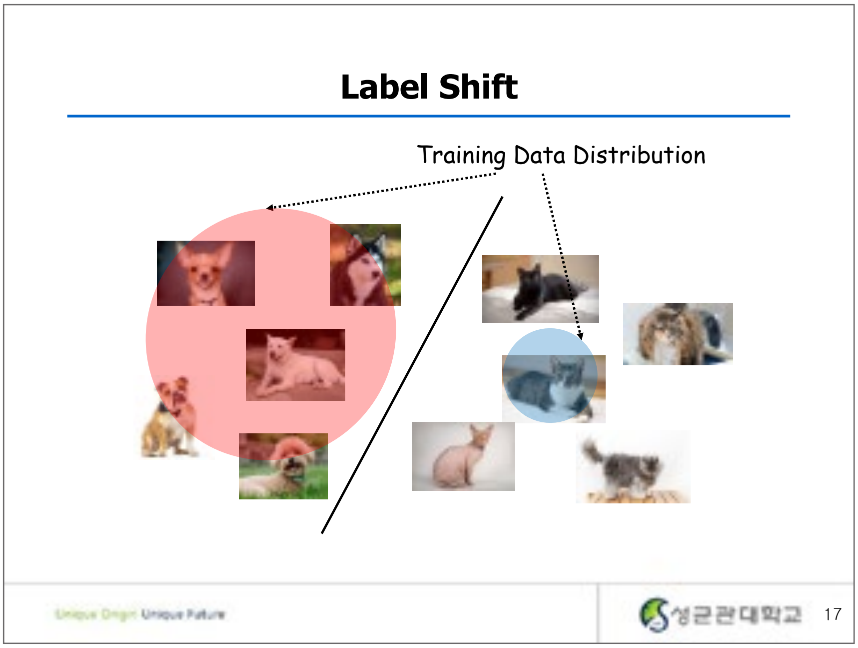


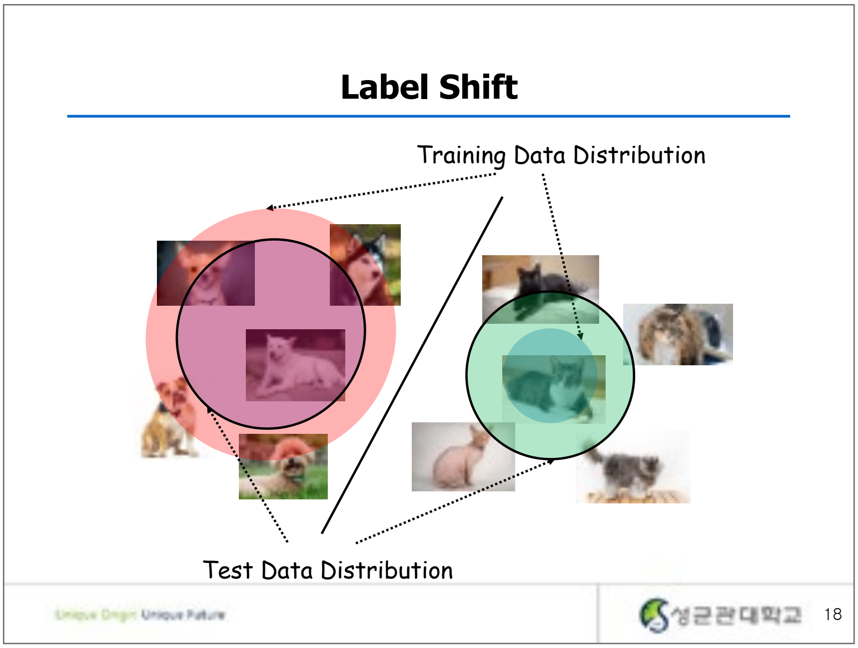
Covariate Shift



Covariate Shift

- **Medical diagnosis**
  - Training with images from A device
  - Testing with images from B device
- **Speech recognition**
  - Training - West coast accent
  - Testing - Non-native speaker
- **Language**
  - Training - 'James, bring me a soda'
  - Testing - 'John, bring me a coke


Label Shift
Training Data Distribution
17


Label Shift
Training Data Distribution
Test Data Distribution
18

Label Shift

- **Can a model learn to differentiate?**

Images from google search

Label Shift

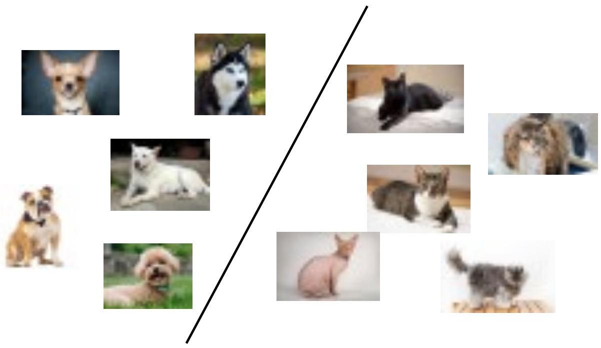
- **Medical diagnosis**
  - Train on data with few sick patients in regular season
  - Test on data during flu season
- **Text Analysis**
  - Train on news data before election
  - Test on news data after election (new topics, names, discussions, but still same language)

Adversarial Sample

Unique Origin Unique Future

Ideal Training Dataset

- **No Data Shift**



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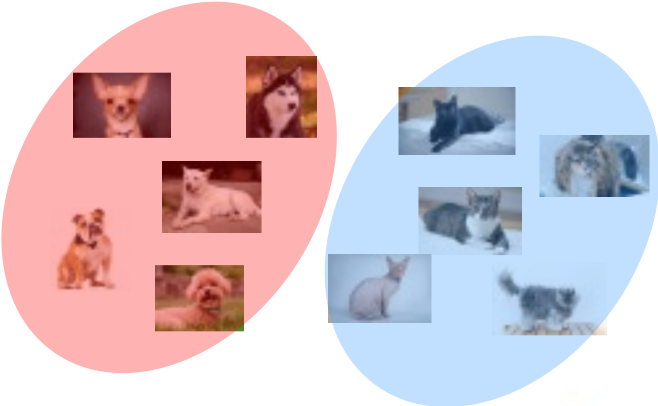
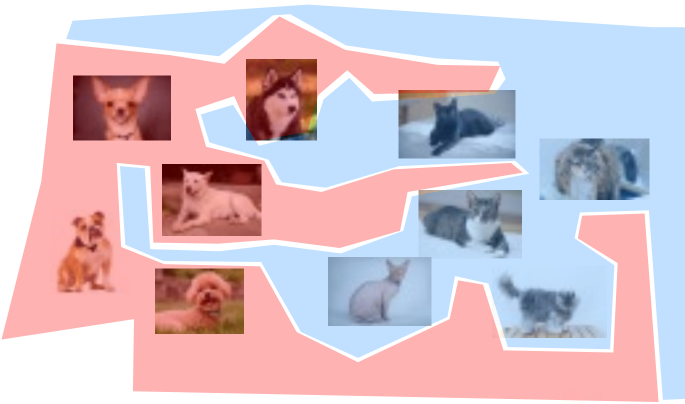
How about Models?

- Clean and Simple Models?



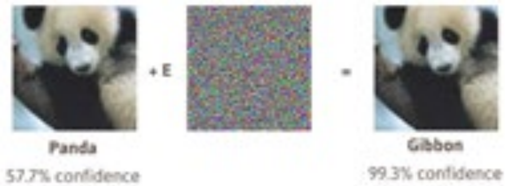
How about Models?

- Or.. Clumsy Model



Adversarial Sample

- **Does deep neural network guarantee the same answers?**



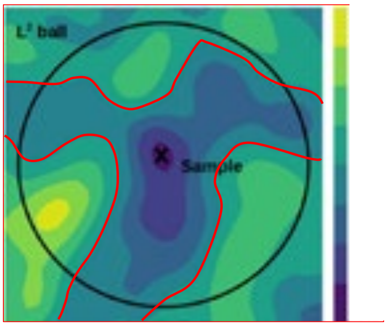
True image Adversarial image

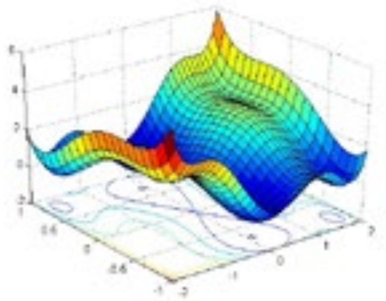
Goodfellow, Ian J., Jonathon Shlens, and Christian Szegedy. "Explaining and harnessing adversarial examples."

Adversarial Sample

- **Security concern for machine learning models**
  - An attack created to fool one network also fools other networks
  - Attacks also work in the physical world
  - It is very easy to generate adversarial examples
  - Many defense strategies have been proposed, they all fail against strong attacks

Why it happens?





https://algorithmia.com/blog/introduction-to-loss-functions
https://towardsdatascience.com/know-your-enemy-7f7c5038bdf3

Defense Approaches

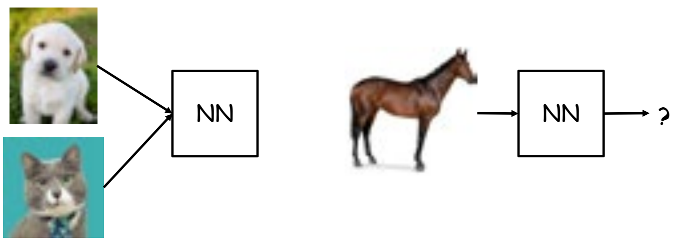
- **Adversarial Training**
  - Train model using adversarial examples as well as natural data
- **Filtering/Detecting**
  - Learning pattern of adversarial examples or perturbations
  - Reject adversarial samples without classifying them using a specialized side model
- **Denoising (Preprocessing)**
  - Reduce noise in the input using denoiser

Out-of-Distribution Detection

Unique Origin Unique Future

Can you say "I don't know"?

- **In the World, there are many instances which we never expect they are given.**
  - Does deep neural network can say "I don't know" ?



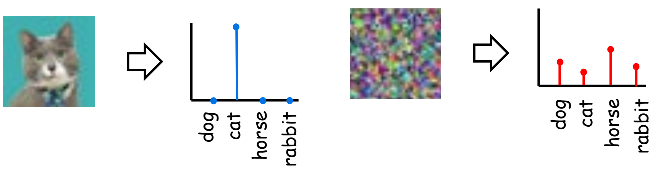
Out of distribution

Can you say “I don’t know”?

- **Deep Learning is not so Reliable**

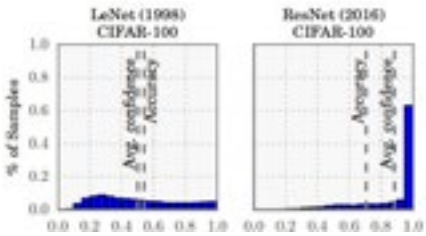
Confidence of Output

- **A Simple Way**
  - We choose the maximum of softmax for classification
    - For an image in domain, softmax will produce a sharp output
    - For an image out of domain, softmax will produce rather a vague output
  - Let’s check the value of the maximum



Confidence of Output

- **Over Confidence**
  - Modern NN tends to output overconfident prediction
    - Confidence : Max softmax probability
  - NN returns prediction with high confidence for noise image



Guo, Chuan, et al. "On calibration of modern neural networks." *Proceedings of the 34th International Conference on Machine Learning-Volume 70*. JMLR. org, 2017.

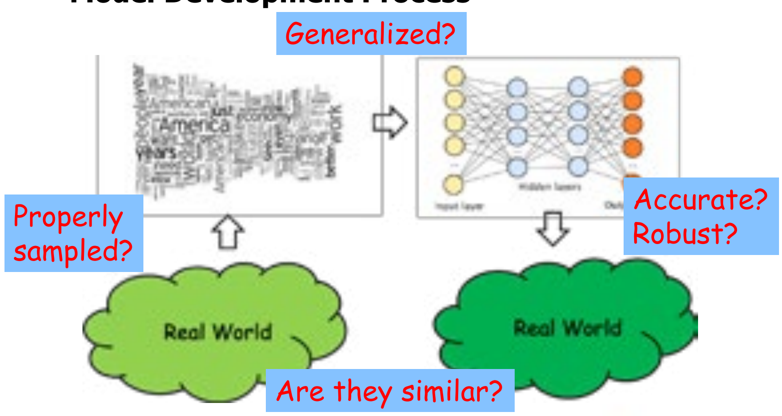
Defense Approaches

- **Outlier Detection**
  - Learning what is normal and then reject what does not seem normal
- **Confidence Calibration**
  - Train the Neural Network to confidently answer to what it confidently believe
- **Variance-based Detection**
  - Verify variance of Neural Networks

Summary

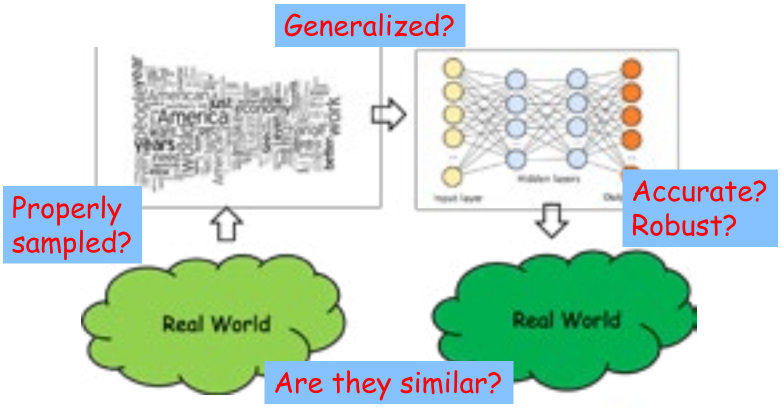
Deep Learning

- **Model Development Process**



Deep Learning

- **Model Development Process**



MEMO

CURRICULUM VITAE

한경화

연세의대 세브란스병원

EDUCATION	2006	숙명여자대학교 통계학 학사
	2008	연세대학교 의학통계학 석사
	2015	연세대학교 의학통계학 박사
CAREER	2006 – 2008	연세대학교 의학통계학과 조교
	2008 – 2012	연세대학교 의과대학 연구부 통계지원실 조교
	2012 – 2015	연세대학교 의과대학 강남의생명연구센터 통계지원실 조교
	2015 –	연세대학교 의과대학 영상의학교실 방사선의과학연구소 연구조교수

임상 AI validation의 실제

의학 영상 분야의 의료인공지능의 활용 사례는 진단에 대한 분류(classification)나 영상 분할(segmentation)을 목적으로 하는 딥러닝 알고리즘을 개발 및 적용하는 경우가 많다. 최근 이렇게 개발된 딥러닝 또는 그 외 인공지능 기술을 활용한 소프트웨어에 대한 임상 검증 연구가 많이 발표되고 있다. 본 강의에서는 적절한 임상적 검증을 위해 필요한 요소들 중 특히 통계학적 고민이 필요한 부분을 다루고자 한다.

의료인공지능의 임상 검증 연구를 계획할 때 먼저 검증 자료의 대상자 또는 영상의 개수의 선정 문제에 부딪히게 되는데, 이 단계에서 평가할 성능 지표의 적절한 형태, 이에 대응되는 연구 설계, 질병 스펙트럼, 유병률 등을 고려해야 한다.

기존의 인공지능 이전 기술 또는 또다른 인공지능 기술에 기반한 방식과의 비교를 수행하는 연구에서는 그 비교의 목적에 따라 연구 설계와 통계학적 방법을 달리해야 한다. 참조 표준으로 삼을만한 결과가 없는 경우에는 결과 간 비교를 일치도 분석으로 수행하게 되고, 평가자 간 주관적인 요소를 반영하기 위해 여러 평가자가 개입한 결과를 활용하기도 한다. 참조 표준이 있는 경우에는 진단 정확도를 평가하는 목적 하에 연구를 진행할 수 있고, 이 경우에도 인공지능 기술을 활용했을 때 얻을 수 있는 추가적인 효과를 평가하기 위해 여러 평가자가 개입할 수 있다. 최근에는 적절한 평가자의 수와 대상자 수를 조율하여 적정 통계학적 검정력을 얻을 수 있는 효

율성을 높인 디자인도 제안된 바 있다.

기술적 측면에서의 타당성 검증 또는 진단 정확도 평가를 수행한 후에는 실제적인 임상 검증을위해 임상적 유효성 (effectiveness) 또는 임상적 유용성 (utility)을 평가하기 위한 연구가 필요하다. 본 강의에서는 이러한 연구에서 고려할 검증 지표의 종류, 연구 설계, 사례 등을 소개하고자 한다.

MEMO

CURRICULUM VITAE

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	2014	The University of Texas, Austin Ph.D.
CAREER	2006 – 2009	KT 전임 연구원
	2014 – 2016	IBM T.J. Watson Research Center, Yorktown Heights, Research Staff Member
	2016 –	KAIST 교수
	2016 -	NeurIPS, ICML 등 인공지능/ 기계학습 top conference area chair 등 정보과학회 인공지능소사어티 학술부회장, 편집부회장,이사 등

Federated learning : recent improvements and challenges

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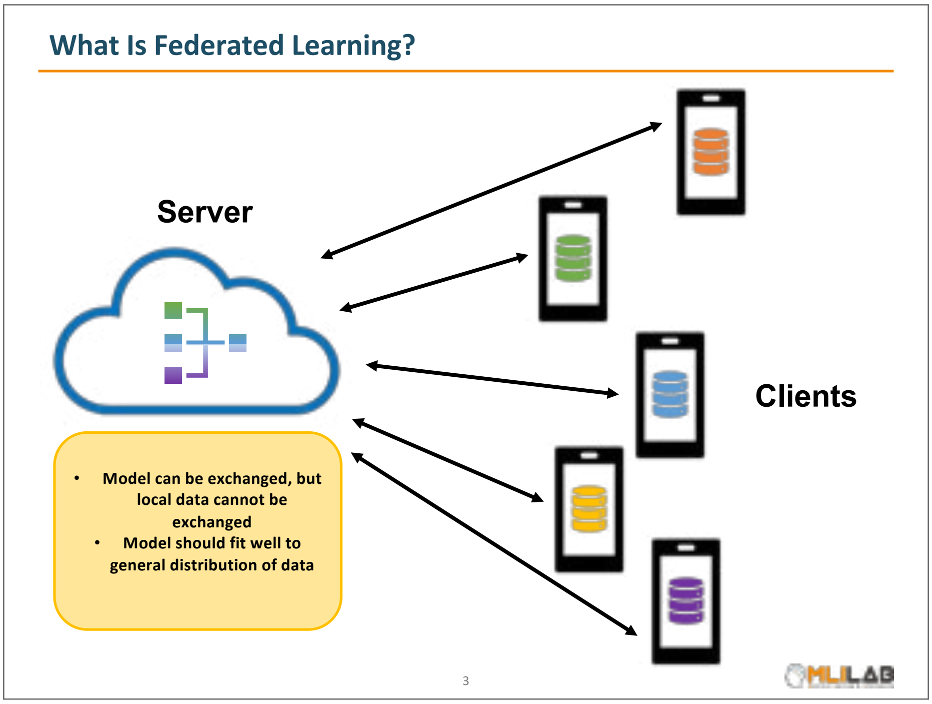
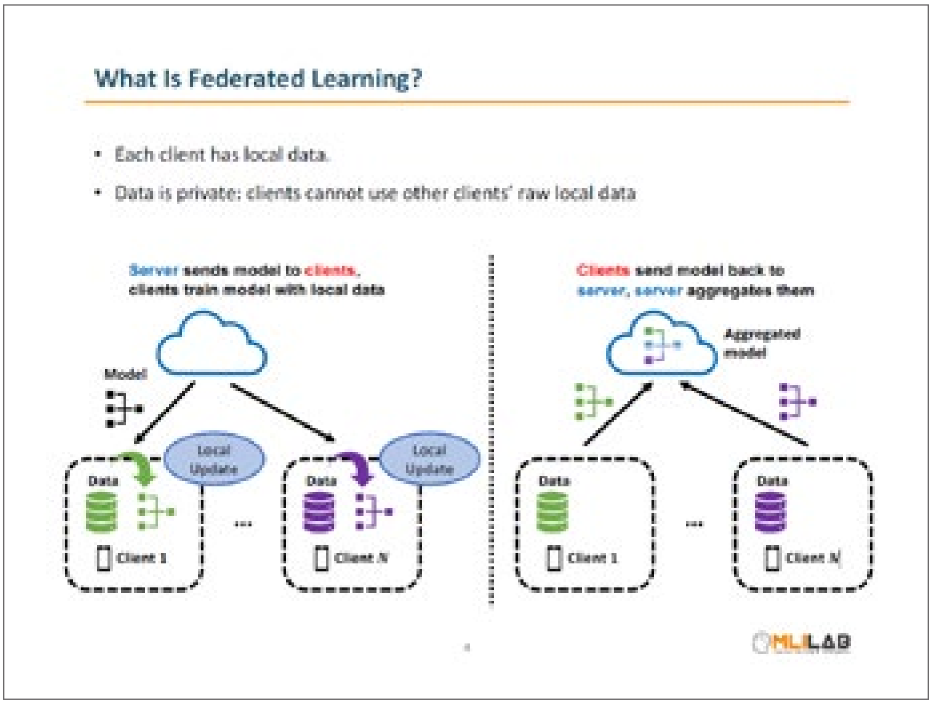

What Is Federated Learning?
Server
Clients
Model can be exchanged, but local data cannot be exchanged
Model should fit well to general distribution of data
3
MLILAB


What Is Federated Learning?
Each client has local data.
Data is private: clients cannot use other clients' raw local data
Server sends model to clients, clients train model with local data
Model
Local Update
Local Update
Data
Data
Client 1
Client N
Clients send model back to server, server aggregates them
Aggregated model
Data
Data
Client 1
Client N
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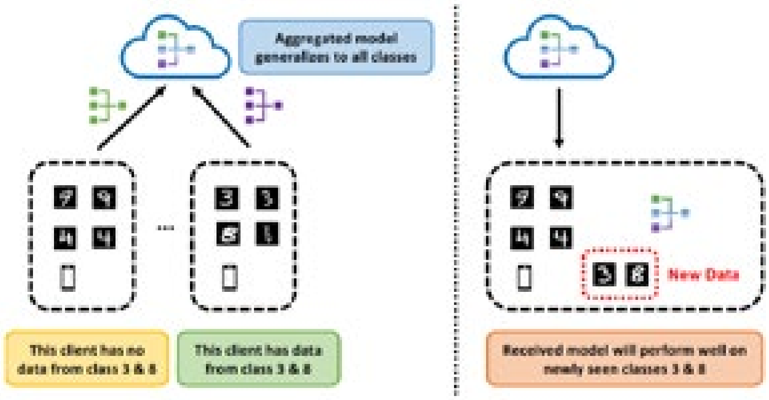
FL Can Improve Generalization of Local Models

- Under FL, each device can learn a model that generalizes well to unseen data
  - Ex) MNIST



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FL and Distributed Learning

Properties	Federated Learning	Distributed Learning
Dataset	Local, often **heterogeneous**	Random
Accessibility	Inaccessible across clients (**privacy**)	Always allowed
Availability	Only a fraction of clients	Always every client
Primary Cost	**Communication** cost	Computation cost

- Federated Learning is similar to distributed learning, but has a number of limitations that makes it distinct.
  - If model is sent to server after every single update, it is analogous to large-batch distributed learning (FedSGD).
  - However, due to reasons above, FedSGD is highly inaccurate and inefficient.

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FedAvg

- **FedAvg** (McMahan et al., 2016) performs ***weighted averaging*** of locally trained (SGD) model parameters by each client.

$$\boldsymbol{w}_t = \sum_{k=1}^{n} p_k \boldsymbol{w}_t^k, p_k = \frac{N_k}{N}$$

  - Usually weighted by data size proportion p_k
  - Local $\boldsymbol{w}_t^k$ is trained with local data of client k with given number of local epochs (E), starting from global model parameter $\boldsymbol{w}_{t-1}$

- FedAvg has been the basic foundation of most modern FL algorithms!
  - Much better than FedSGD (McMahan et al., 2016)

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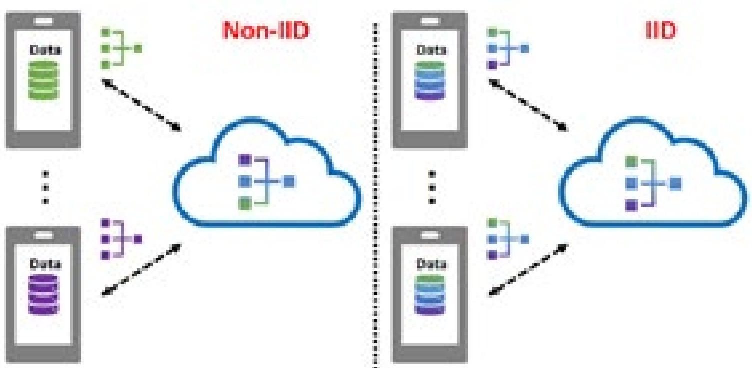
Challenges of FL: Non-IID Settings

- In most realistic settings, local data for each device is ***heterogeneous***: not identically and independently distributed (***Non-IID***).
- FedAvg shows decreased performance and slower learning in such situations



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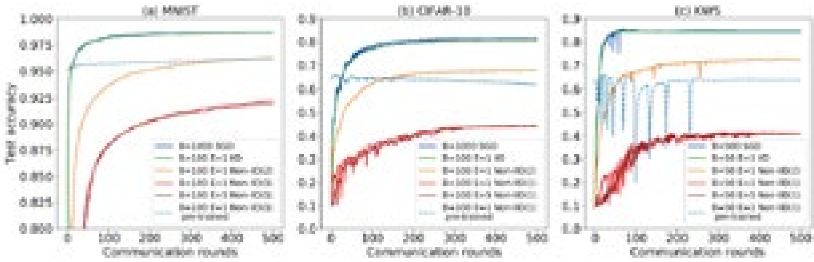
Does FedAvg Converge?

- It is not immediately trivial that FedAvg will converge.
  - In case of ***IID*** (identical and independently distributed), proved by Zhou and Cong, 2017
  - For ***non-IID***, it was only recently shown by Li et al., 2020
    - Also showed for partial participation (fraction of clients trained per round)
- However, current FL algorithms are much slower to converge compared to ordinary deep learning, for non-IID. (Zhao et al., 2018)



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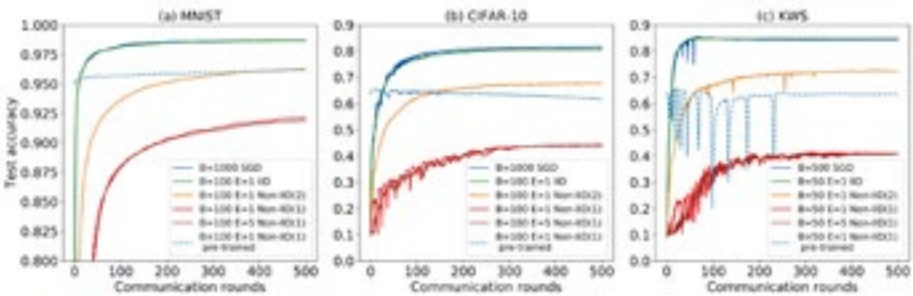

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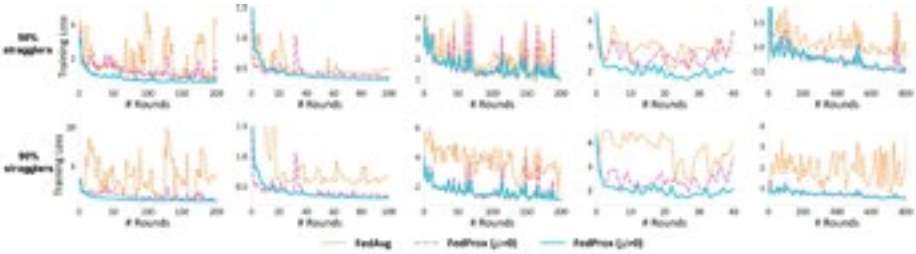
FedProx

- FedProx (Li et al., 2020) utilizes proximal term during local training:

$$\ell_{\mathrm{FedProx}} = \ell_{\mathrm{SGD}} + \frac{\mu}{2}\|w - w_t\|^2$$

- FedProx has better stability and performance for heterogeneous settings.



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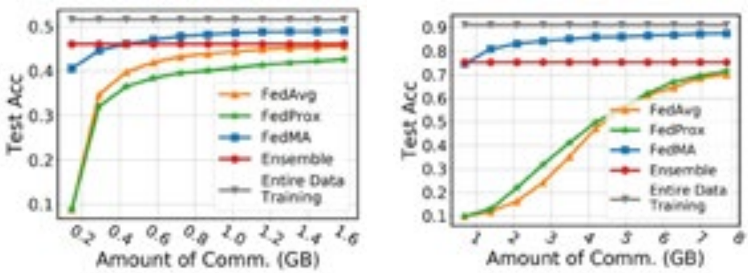
Challenges of FL: Communication Efficiency

- Under typical federated learning environments, **communication bottleneck** exists.
  - *Limited* communication bandwidth but *high* model dimension
  - CoCoA (Smith et al., 2018) and PFNM (Yurochkin et al., 2019) improves communication efficiency
  - FedMA (Wang et al., 2020) also works for more complex (ex. VGG) models



(a) LSTM, Shakespeare; message size

(c) VGG-9, CIFAR-10; message size

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Challenges of FL: Fairness

- If clients have differently distributed data, for some clients the global model will particularly not fit well (**unfair**)
  - Agnostic Federated Learning (AFL) (Mohri et al., 2019) learns on client with highest loss
  - q-FFL (Li et al., 2019) uses aggregated loss related to α-fairness

Dataset	Objective	Average (%)	Worst 10% (%)	Best 10% (%)	Variance
Synthetic	$q = 0$	80.8 $\pm$ .9	18.8 $\pm$ 3.0	100.0 $\pm$ 0.0	724 $\pm$ 72
	$q = 1$	79.0 $\pm$ 1.2	**31.1** $\pm$ 1.8	100.0 $\pm$ 0.0	**472** $\pm$ 14
Vehicle	$q = 0$	87.3 $\pm$ .5	43.0 $\pm$ 1.0	**95.7** $\pm$ 1.0	291 $\pm$ 18
	$q = 5$	87.7 $\pm$ .7	**69.9** $\pm$ .6	94.0 $\pm$ .9	**48** $\pm$ 5
Sent140	$q = 0$	65.1 $\pm$ 4.8	15.9 $\pm$ 4.9	100.0 $\pm$ 0.0	697 $\pm$ 132
	$q = 1$	66.5 $\pm$ .2	**23.0** $\pm$ 1.4	100.0 $\pm$ 0.0	**509** $\pm$ 30
Shakespeare	$q = 0$	51.1 $\pm$ .3	39.7 $\pm$ 2.8	**72.9** $\pm$ 6.7	82 $\pm$ 41
	$q = .001$	52.1 $\pm$ .3	**42.1** $\pm$ 2.1	69.0 $\pm$ 4.4	**54** $\pm$ 27

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Problem Setting

- We suggest a novel algorithm such that:
  - Performs (relatively) well on non-IID settings
  - Imposes very small additional communication cost and privacy concerns

- Thus, we propose:
  - **MAFL** (mean augmented federated learning), which is a novel FL framework that alters exchange of variables that has small negative effect in communication efficiency and privacy

  - **FedMix**, which is a novel algorithm operating under MAFL, that particularly improves performance on heterogeneous data distribution.

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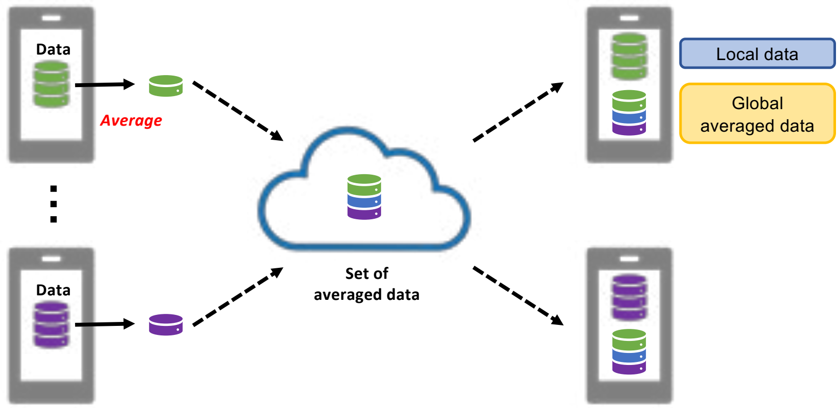
MAFL (Mean Augmented Federated Learning)

- **MAFL** (Mean Augmented Federated Learning) is a modified FL framework where:
  - ***Averaged input data*** are exchanged across clients (via server)
    - e.g. Averaged image pixels, averaged language embedded vectors



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Algorithms – MAFL

Algorithm 1: Mean Augmented Federated Learning (MAFL)

Input: $\mathbb{D}_k = \{X_k, Y_k\}$ for $k = 1, \dots, N$
M_k: number of data instances used for computing average $\bar{x}, \bar{y}$

Initialize w_0 for global server
for $t = 0, \dots, T-1$ **do**
  for *client k with updated local data* **do**
    Split local data into M_k sized batches
    Compute $\bar{x}, \bar{y}$ for each batch
    Send all $\bar{x}, \bar{y}$ to server
  end
  $\mathbb{S}_t \leftarrow K$ clients selected at random
  Send w_t to clients $k \in \mathbb{S}_t$
  if *updated* **then**
    Aggregate all $\bar{x}, \bar{y}$ to X_g, Y_g
    Send X_g, Y_g to clients $k \in \mathbb{S}_t$
  end
  for $k \in \mathbb{S}_t$ **do**
    $w_{t+1}^k \leftarrow LocalUpdate(k, w_t; X_g, Y_g)$
  end
  $w_{t+1} \leftarrow \frac{1}{K} \sum_{k \in \mathbb{S}_t} p_k w_{t+1}^k$
end

Averaged data sent to server
(only required when local data change)

Server sends averaged data
to selected clients

Communication Cost Analysis in MAFL

- MAFL imposes additional communication cost by exchange of averaged data

- However, in most cases,
  - Exchanging model parameters each round costs $2p_m$ per client (p_m: # of model parameters)
  - Exchanging averaged data costs $2d_i$ per client (d_i: input dimension) for maximum M_k each time
  - Since $p_m \gg d_i$ in most deep learning scenarios, we conclude that ***additional communication cost imposed by MAFL is negligible.***
    - Especially if exchange of averaged data does not happen every round

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Privacy Analysis in MAFL

- Degree of privacy concerns by MAFL depends on M_k and # of data per client (N_k)
  - Privacy is ensured as M_k is larger
  - Concerns
    - Ownership of averaged data and subsequent exposure of local distribution from each averaged entry
    - Individual added data detected by changes in averaged data
    - Upper limit of M_k if N_k is small enough

  - Possible modifications
    - Random shuffling, and further averaging among already-averaged data in global server
    - Upper limit on averaged data updates depending on data changed percentage
    - Lower limit on N_k for the client to send averaged data
  - Such modifications are able since the framework is flexible enough to accept such changes!

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Mixup

- Mixup (Zhang et al., 2018)
  - Linearly combines both input and output:

$$\tilde{\boldsymbol{x}} = \lambda \boldsymbol{x}_i + (1-\lambda)\boldsymbol{x}_j$$
$$\tilde{y} = \lambda y_i + (1-\lambda) y_j$$
$$\lambda \in [0,1]$$

- **Global Mixup** will likely result in ideal performance
  - But *invalid* for federated learning: disallowed access to other client's $(\boldsymbol{x}_j, y_j)$

$$\ell_{\text{Global}} = \ell\left(f\left((1-\lambda)\boldsymbol{x}_i + \lambda \boldsymbol{x}_j\right), (1-\lambda) y_i + \lambda y_j\right)$$

- **Local Mixup** is a possible implementation:
  - $(\boldsymbol{x}_i, y_i)$, $(\boldsymbol{x}_j, y_j)$ always from same client's local data

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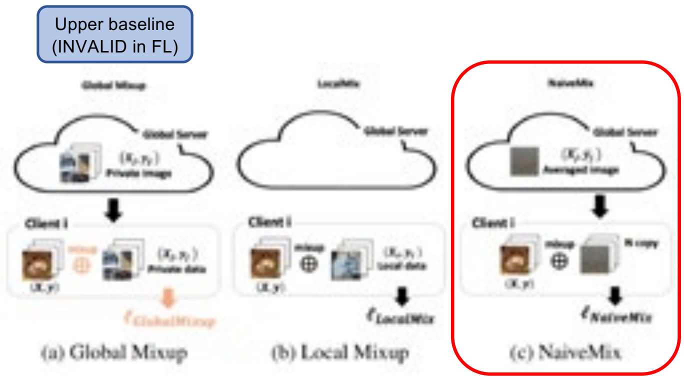
NaiveMix: A Simple Mixup Algorithm under MAFL

- NaiveMix: Mixup is performed between local client data and averaged data

$$\ell_{\text{NaiveMix}} = \ell\left(f\left((1-\lambda)\boldsymbol{x}_i + \lambda \overline{\boldsymbol{x}_j}\right), (1-\lambda) y_i + \lambda \overline{y_j}\right)$$



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FedMix: Approximation of Global Mixup Loss

- Since global Mixup is impossible under FL, *we suggest a novel algorithm,* ***FedMix****, that approximates global Mixup loss without access to individual data* $(\boldsymbol{x}_j, y_j)$
- Global Mixup batch loss (batch set J):

$$\frac{1}{|J|}\sum_{j\in J}\ell\left(f\left((1-\lambda)\boldsymbol{x}_i+\lambda\boldsymbol{x}_j\right),(1-\lambda)y_i+\lambda y_j\right)$$

- This loss could be approximated for $\lambda \ll 1$ into:

$$\begin{aligned}\ell_{\text{FedMix}} = &(1-\lambda)\ell\big(f((1-\lambda)\boldsymbol{x}_i),y_i\big)\\ &+\lambda\ell\big(f((1-\lambda)\boldsymbol{x}_i),\underline{\overline{y}_j}\big)\\ &+\lambda\boxed{\frac{\partial\ell}{\partial\boldsymbol{x}}}\underline{\overline{\boldsymbol{x}}_j}\end{aligned}$$

The algorithm only uses $(\overline{\boldsymbol{x}}_j,\overline{y}_j)$!

$((1-\lambda)\boldsymbol{x}_i, y_i)$

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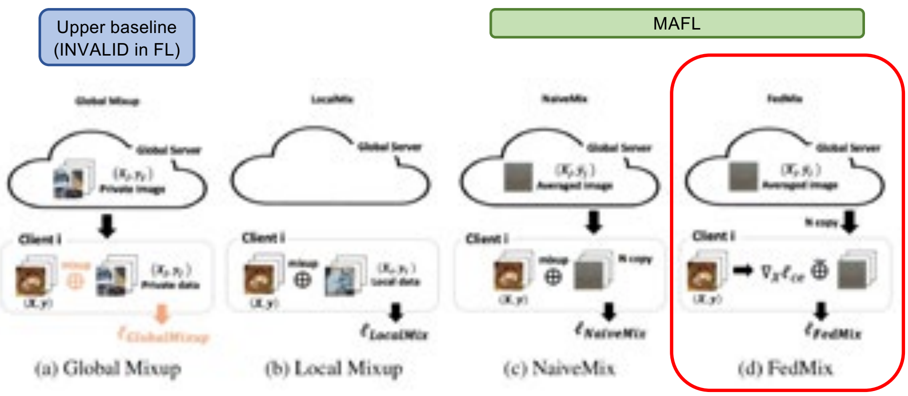
Overview



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Algorithms – FedMix

Algorithm 2: FedMix

LocalUpdate$(k, \boldsymbol{w}_t; \boldsymbol{X}_g, \boldsymbol{Y}_g)$ under MAFL (Algorithm 1):

$\boldsymbol{w} \leftarrow \boldsymbol{w}_t$

for $e = 0, \ldots, E-1$ **do**

  Split $\mathbb{D}_k$ into batches of size B

  for $batch(\boldsymbol{X}, \boldsymbol{Y})$ **do**

    Select an entry $\boldsymbol{x}_g, \boldsymbol{y}_g$ from $\boldsymbol{X}_g, \boldsymbol{Y}_g$

    $\ell_1 = (1-\lambda)\ell\big(f((1-\lambda)\boldsymbol{X}; \boldsymbol{w}), \boldsymbol{Y}\big)$

    $\ell_2 = \lambda\ell\big(f((1-\lambda)\boldsymbol{X}; \boldsymbol{w}), \boldsymbol{y}_g\big)$

    $\ell_3 = \lambda \frac{\partial \ell_1}{\partial \boldsymbol{x}} \cdot \boldsymbol{x}_g$

    (derivative calculated at $\boldsymbol{x} = (1-\lambda)\boldsymbol{x}_i$ and $y = y_i$ for each of $\boldsymbol{x}_i, y_i$ in $\boldsymbol{X}, \boldsymbol{Y}$)

    $\ell = \ell_1 + \ell_2 + \ell_3$

    $\boldsymbol{w} \leftarrow \boldsymbol{w} - \eta_{t+1}\nabla\ell$

  end

end

return $\boldsymbol{w}$

Instead of local SGD loss

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Experimental Settings

- Benchmark image classification: FEMNIST, CIFAR10, CIFAR100
  - FEMNIST (Caldas et al., 2019)
    - Non-IID: Each client has images written by different writer
    - Model: LeNet-5

  - CIFAR10 and CIFAR100
    - Non-IID: Each client has limited number of different classes
      - e.g. 2 classes per client for CIFAR10, 20 classes for CIFAR100
      - Model: VGG-9

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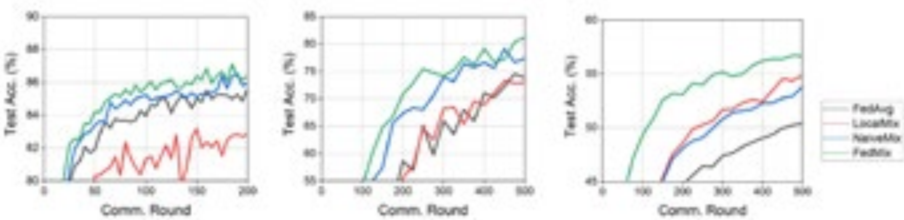
FedMix in Non-IID settings

- FedMix performs best (on non-IID settings)



(a) FEMNIST (b) CIFAR10 (c) CIFAR100

Algorithm	FEMNIST		CIFAR10		CIFAR100	
	test acc. (200)	rounds (80%)	test acc. (500)	rounds (70%)	test acc. (500)	rounds (40%)
Global Mixup	88.2	8	88.2	85	61.4	54
FedAvg	85.3	26	73.8	283	50.4	101
LocalMix	82.8	28	73.0	267	54.8	91
NaiveMix	85.9	23	77.4	198	53.8	85
FedMix	**86.5**	**18**	**81.2**	**162**	**56.7**	**34**

Models in Combination with FedProx

- FedMix combined with FedProx outperforms other algorithms also combined with FedProx
  - Does not necessarily improve over vanilla FedMix

Algorithm	FEMNIST		CIFAR10		CIFAR100	
	test acc. (200)	rounds (80%)	test acc. (500)	rounds (70%)	test acc. (500)	rounds (40%)
FedProx	84.6	**29**	77.3	266	51.2	79
FedProx + LocalMix	84.1	39	74.1	314	54.0	90
FedProx + **NaiveMix**	85.7	37	76.7	230	53.1	74
FedProx + **FedMix**	**86.0**	32	**78.9**	**223**	**54.5**	**63**

Effect of λ and M_k on FedMix

- FedMix does not show decline of performance with increase in M_k

	M_k	5	10	20	50	All
FEMNIST	NaiveMix	85.7	**86.3**	86.2	86.1	85.9
	FedMix	**86.0**	85.7	**86.4**	**86.2**	**86.5**
CIFAR10	NaiveMix	79.6	77.9	79.1	77.1	77.4
	FedMix	**81.4**	**79.9**	**80.4**	**79.5**	**81.2**

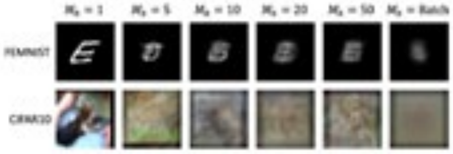


Figure 3: Performance of MAFL-based algorithms for various M_k values (left), and samples of averaged images from EMNIST/CIFAR10 for various M_k values (right).

- FedMix is best on small value of λ

λ	**0.05**	**0.1**	**0.2**	**0.5**
Global Mixup	79.4	80.4	81.1	63.6
FedMix	81.2	80.5	77.7	67.1

FedMix Excels as Heterogeneity Increases

- FedMix declines less as heterogeneity increases
- FedMix declines less as fewer clients are selected per round

Table 6: Test accuracy after 500 rounds on CIFAR10, under varying number of classes per client.

Algorithm	class/client **2**	**3**	**5**	**10 (iid)**
Global Mixup	88.2	90.7	90.9	91.4
FedAvg	73.8	84.2	86.8	89.3
Localmix	73	83.3	86.4	89.1
NaiveMix	77.4	84.5	87.7	**89.4**
FedMix	**81.2**	**85.1**	**87.9**	89.1

Table 7: Test accuracy after 500 rounds on CIFAR10, under varying number of clients trained per communication round.

Algorithm	K/N **0.1**	**0.15**	**0.25**	**0.5**	**1.0**
Global Mixup	89.3	89.7	88.2	91.2	90.7
FedAvg	63.3	73.2	73.8	76.3	83.1
Localmix	64.7	64.5	73	77.9	79.8
NaiveMix	73.6	74.7	77.4	81.4	83.5
FedMix	**74.7**	**76.9**	**80.5**	**82.1**	**84.3**

FedMix on NLP Task

- Dataset: *The Complete Works of William Shakespeare* (abbrv. Shakespeare)
- Task: Next character prediction
  - Non-IID: One speaking role for each client
  - Model: 2-layer LSTM
- Mixup is performed for embedded vectors

- MAFL algorithms show highest performance

Table 2: Test accuracy after 50 rounds on Shakespeare dataset.

Algorithm	Global Mixup	FedAvg	FedProx	LocalMix	NaiveMix	FedMix
Test Acc. (%)	54.4	54.7	54.4	53.7	**56.9**	**56.9**

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2021
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