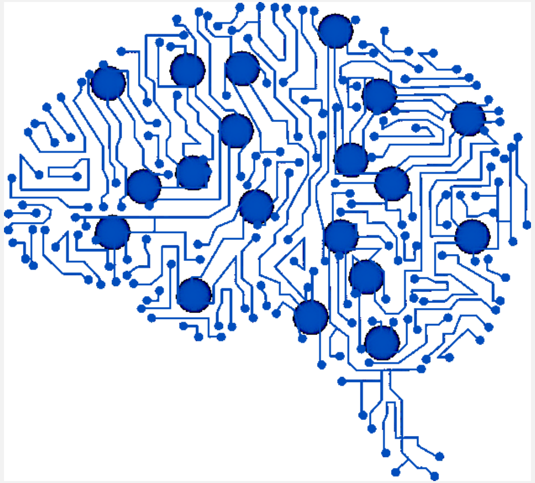
제51회
2019 춘계학술발표대회

튜토리얼 1

Deep Learning Basics and Representative Models

김중헌 교수 (중앙대학교)



Deep Learning Basics and Representative Models (KIPS, May 10th, 2019)

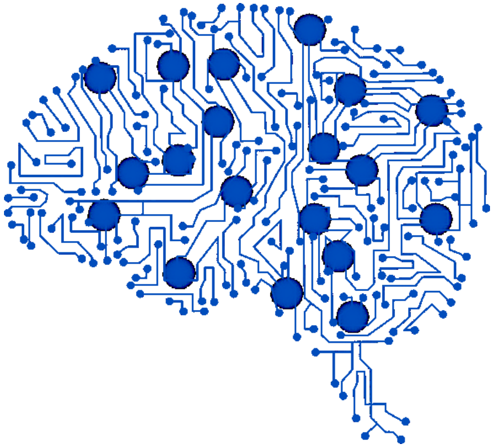
Prof. Joongheon Kim
Chung-Ang University (CAU), Seoul, Korea
https://sites.google.com/site/joongheonkim/
joongheon@gmail.com

Deep Learning Basics

Representative Models and Applications

Distributed Computing Research

Conclusions and Future Work



Geoffrey E Hinton

Yoshua Bengio

Yann LeCun

FATHERS OF THE DEEP LEARNING REVOLUTION RECEIVE ACM A.M. TURING AWARD

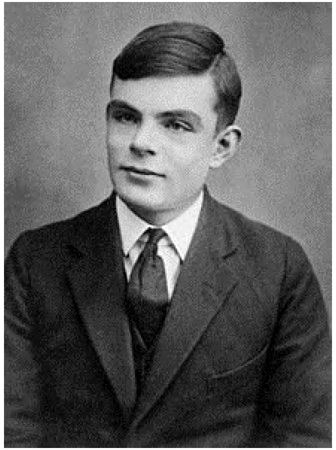
Bengio, Hinton, and LeCun Ushered in Major Breakthroughs in Artificial Intelligence

ACM named Yoshua Bengio, Geoffrey Hinton, and Yann LeCun recipients of the 2018 ACM A.M. Turing Award for conceptual and engineering breakthroughs that have made deep neural networks a critical component of computing. Bengio is Professor at the University of Montreal and Scientific Director at Mila, Quebec's Artificial Intelligence Institute; Hinton is VP and Engineering Fellow of Google, Chief Scientific Adviser of The Vector Institute, and University Professor Emeritus at the University of Toronto; and LeCun is Professor at New York University and VP and Chief AI Scientist at Facebook.

Working independently and together, Hinton, LeCun and Bengio developed conceptual foundations for the field, identified surprising phenomena through experiments, and contributed engineering advances that demonstrated the practical advantages of deep neural networks. In recent years, deep learning methods have been responsible for astonishing breakthroughs in computer vision, speech recognition, natural language processing, and robotics—among other applications.

While the use of artificial neural networks as a tool to help computers recognize patterns and simulate human intelligence had been introduced in the 1980s, by the early 2000s, LeCun, Hinton and Bengio were among a small group who remained committed to this approach. Though their efforts to rekindle the AI community's interest in neural networks were initially met with skepticism, their ideas recently resulted in major technological advances, and their methodology is now the dominant paradigm in the field.

The ACM A.M. Turing Award, often referred to as the "Nobel Prize



Alan Turing (1912-1954)
Father of Computer Science

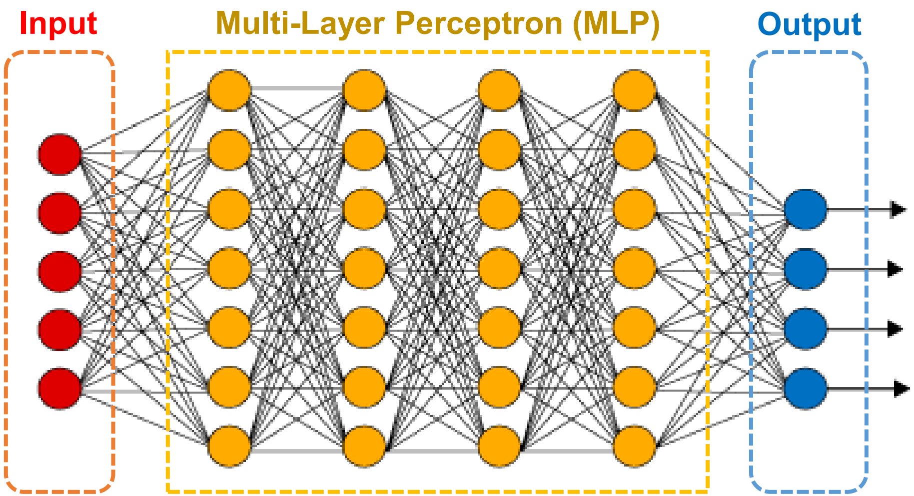
https://amturing.acm.org/

- How Deep Learning Works?
  - Deep Learning Computation Procedure

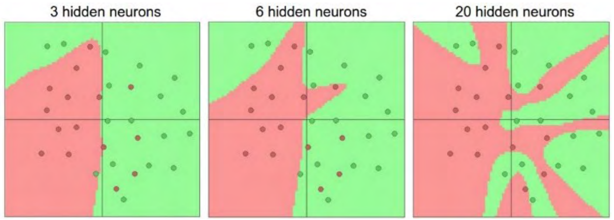
Deep Learning Model Setup
- MLP, CNN, RNN, GAN, or Customized
- # Hidden Layers, # Units, Input/Output, …
- Cost Function / Optimizer Selection

Training (with Large-Scale Dataset)
- Input: Data, Output: Labels
- Learning → Weights Updates for Cost Function Minimization

Inference / Testing (Real-Word Execution)
- Input: Real-World Input Data
- Output: Interference Results based on Updated Weights in Deep Neural Networks



Non-Linear Training (Weights Updates) for Cost Minimization: GD, SGD, Adam, etc.



- How Deep Learning Works?
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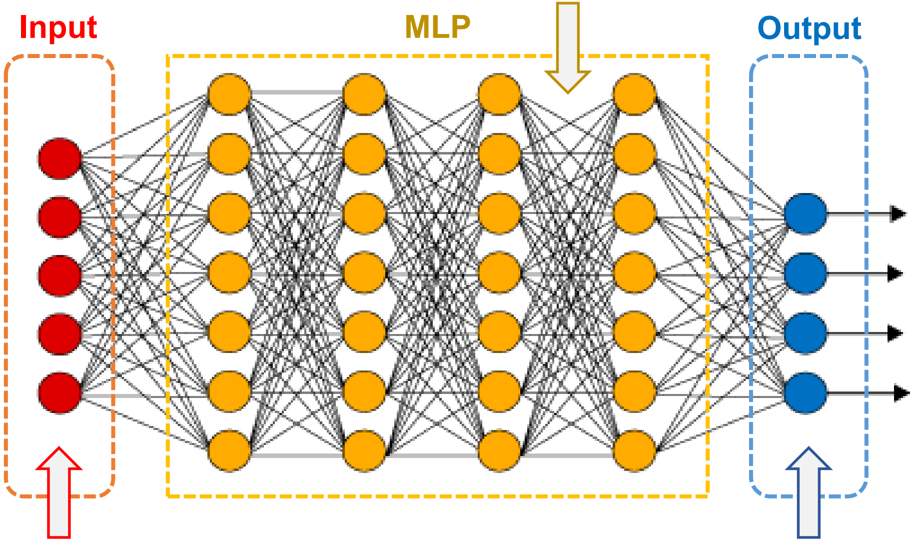
All weights in units are trained/set (under cost minimization)



INPUT: Data
- One-Dimension Vector

OUTPUT: Labels
- One-Hot Encoding

We need a lot of training data for generality (otherwise, we will suffer from overfitting problem).

- How Deep Learning Works?
  - Deep Learning Computation Procedure

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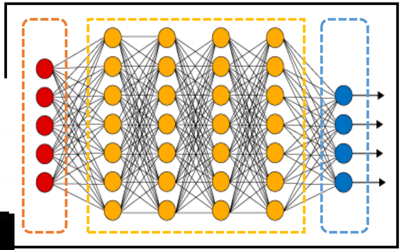
Trained Model



Intelligent Surveillance Platforms

INPUT: Real-Time Arrivals

OUTPUT: Inference
- Computation Results based on (i) INPUT and (ii) trained weights in units (trained model).

- How Deep Learning Works?
  - Issue - **Overfitting**

What if we do not have enough data for training (not enough to derive Gaussian/normal distribution)?

Deep Learning Model Setup
- MLP, CNN, RNN, GAN, or Customiz...
- # Hidden Layers, # Units, Input/Output, …
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Inference / Testing (Real-Word Execution)
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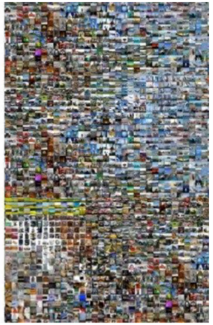
Situation becomes worse when the model (with insufficient training data) accurately fits on training data.

To Combat the Overfitting
- More training data
- Autoencoding (or variational auto-encoder (VAE))
- Droupout
- Regularization

Key Success Factors in Deep Learning Revolution

Our **labeled datasets** were **too small**.

IMAGENET
14.2 million images



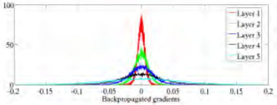
Big-Data

Our **computers** were millions of times **too slow**.

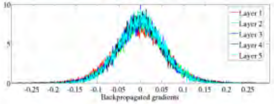
GPU

We **initialized** the weights **in a stupid way.**

Normalized Initiation

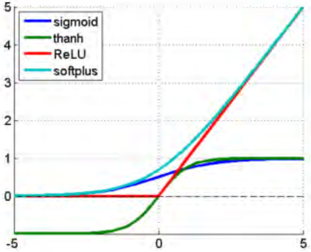


Initiation by Pre-trained Model



We used the **wrong type of non-linearity (activation function).**

Using ReLU for solving Gradient Vanishing Problem



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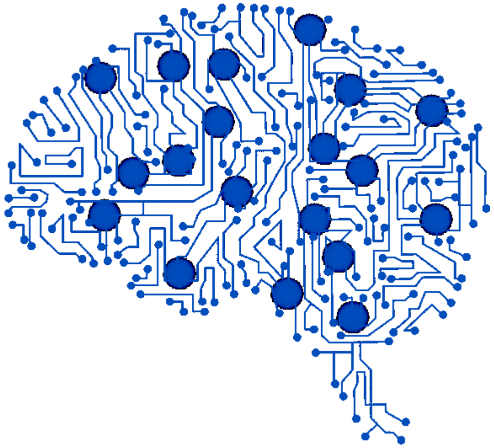
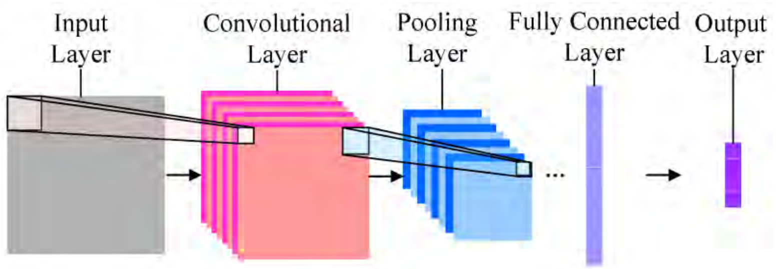
Conclusions and Future Work



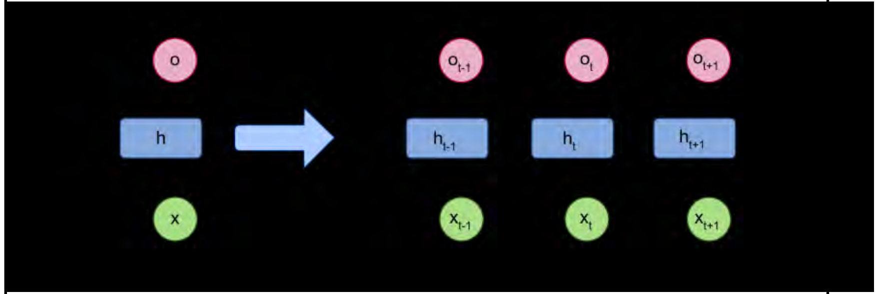
- Two Major Deep Learning Models → CNN vs. RNN

Convolutional Neural Network (CNN)



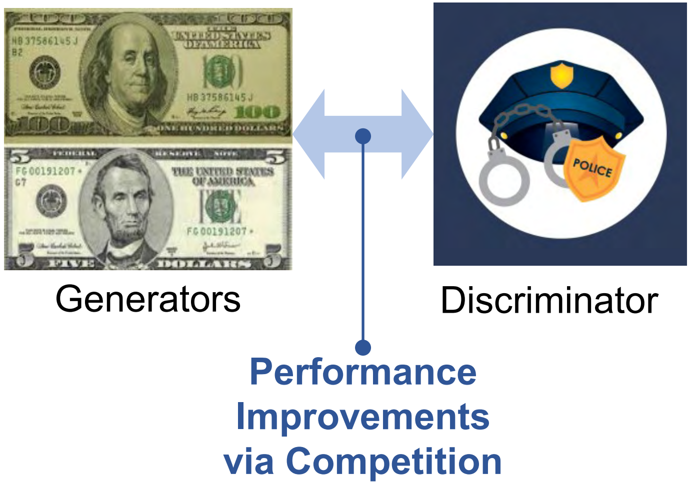
- In conventional neural network architectures, the input should be one-dimensional vector.
- In many applications, the input should be multi-dimensional (e.g., 2D for images). Thus, we need architectures in order to recognize the features in high-dimensional data.
- Mainly used for **visual information learning**

Recurrent Neural Network (RNN)



- In conventional neural network architectures, there is no way to introduce the concept of time.
- The time index can be represented as the chain of neural network models.
- The representative models are LSTM and GRU.
- Mainly used for **time-series information learning**

- An Emerging Direction, Generative Adversarial Network (GAN)
  - Training both of **generator** and **discriminator**; and then generates samples which are similar to the original samples.

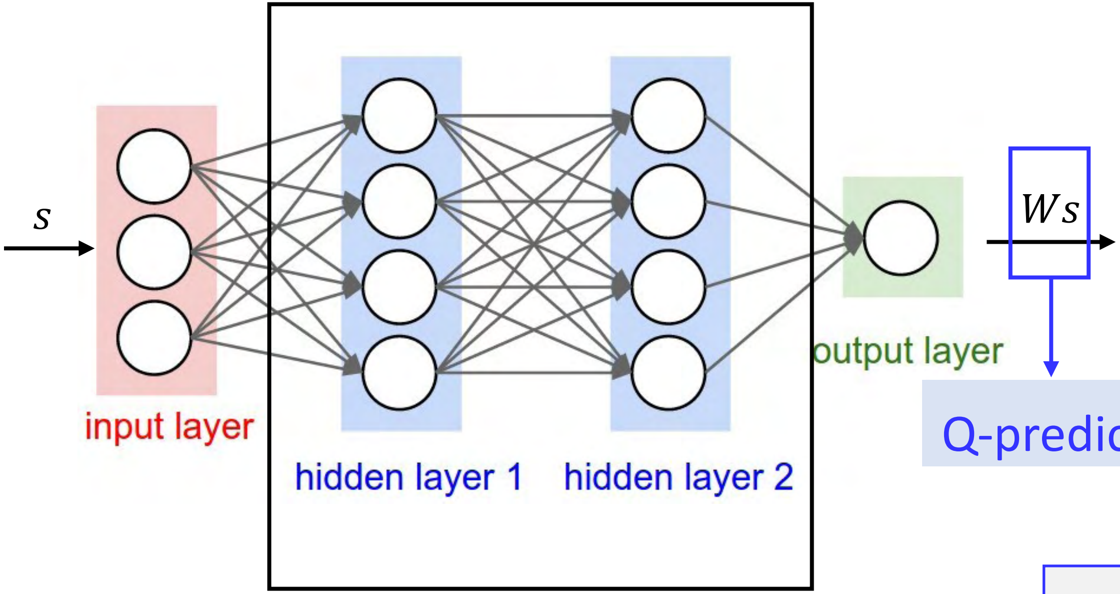


- Deep Q-Network (DQN)

$$\text{Cost}(W) = (Ws - y)^2$$

$$y = r + \gamma \max Q(s')$$

Q^*



Q-predict: $\hat{Q}$

Weights, θ

Approximating Q^* using θ

$$Ws = \hat{Q}(s, a|\theta) \approx Q^*(s, a)$$

- Imitation Learning

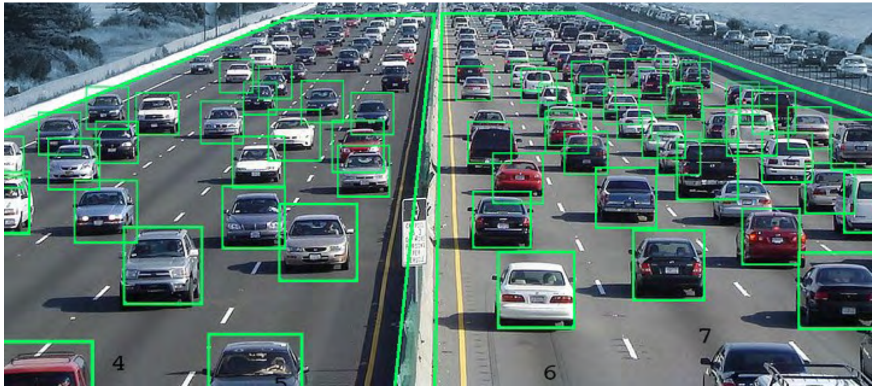
Pro-Gamer

Trained Agent

The goal of Imitation Learning is to train a policy to mimic **the expert's demonstrations**

Deep Learning Applications: Vision

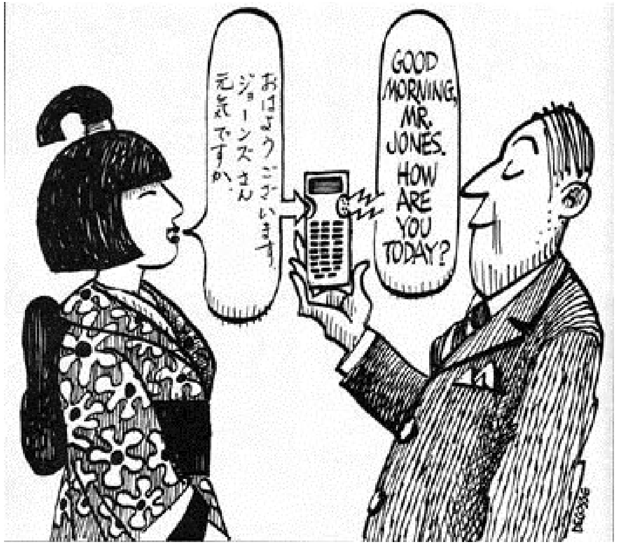
Visual Learning
- Object Recognition
- Style Transfer
- Deblurring and Denoising
- Super-Resolution
- …



Deep Learning Applications: Speech and Languages

Speech/Language Learning

- Speech Recognition
- Machine Translation
- Information Retrieval
- …



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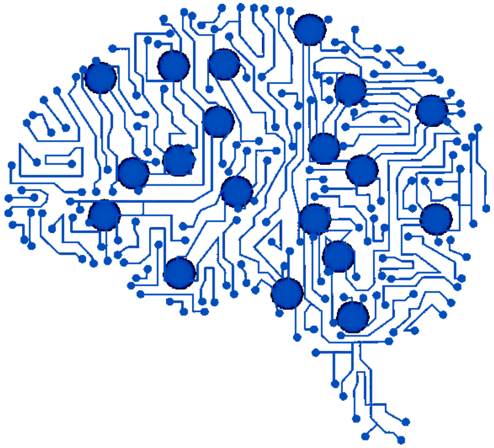
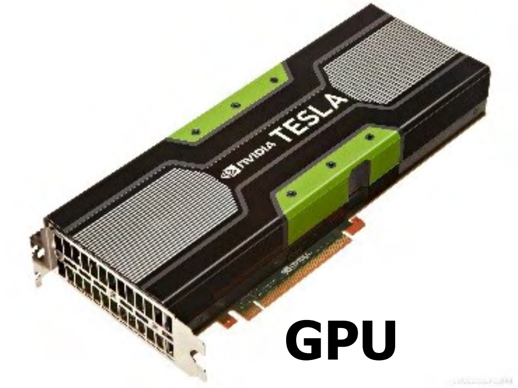
Concluding Remarks



- Distributed?

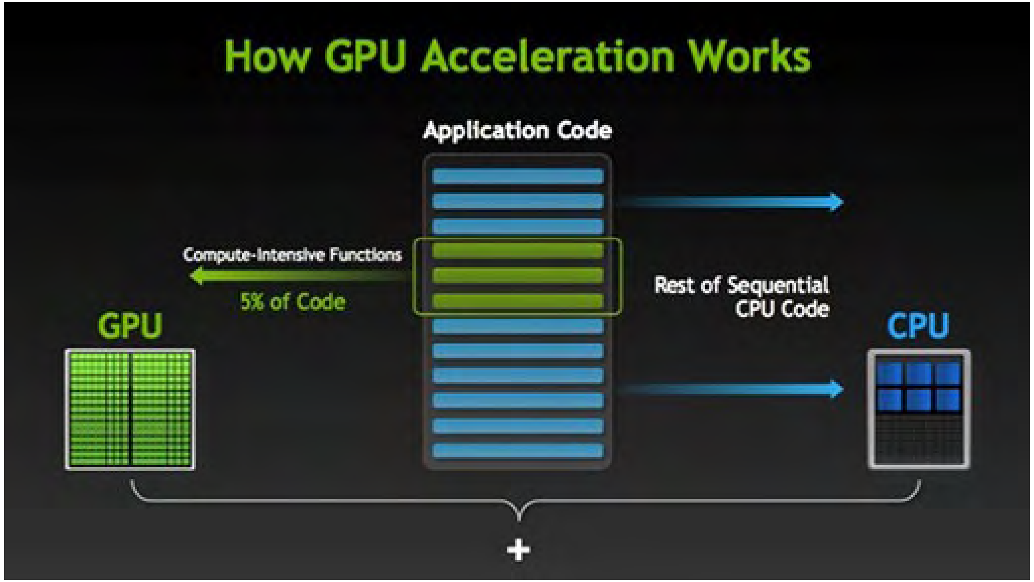
Supercomputer

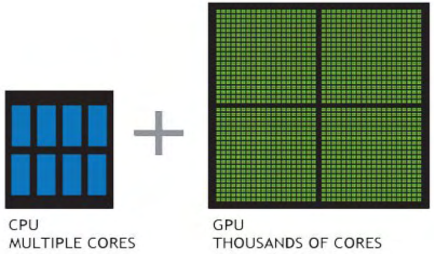


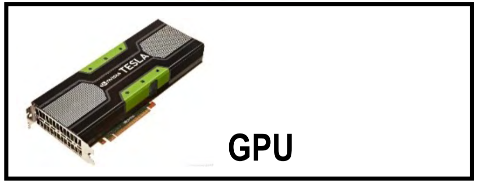
GPU

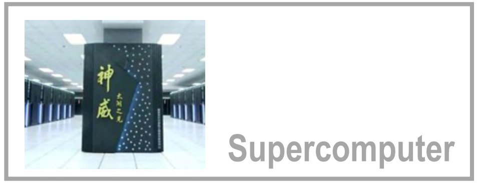
Geo-Distributed Computing

Introduction: GPU





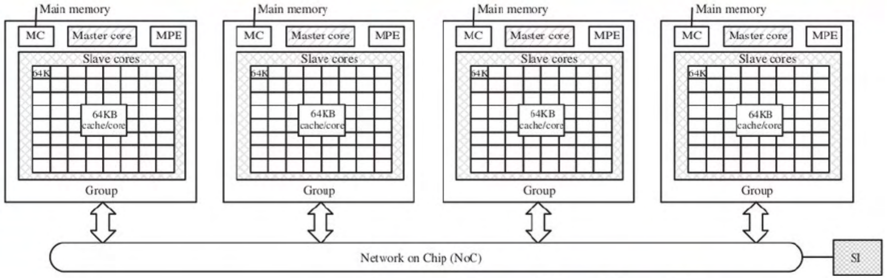


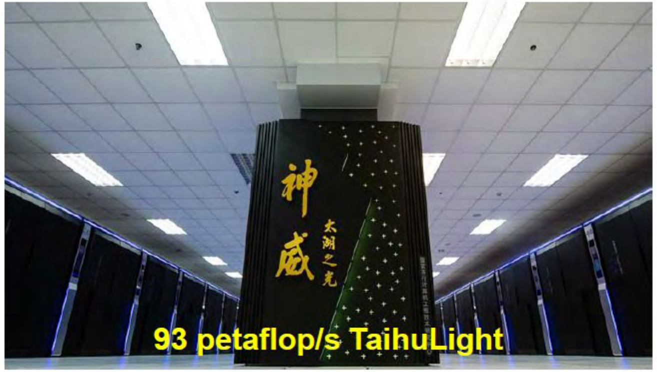


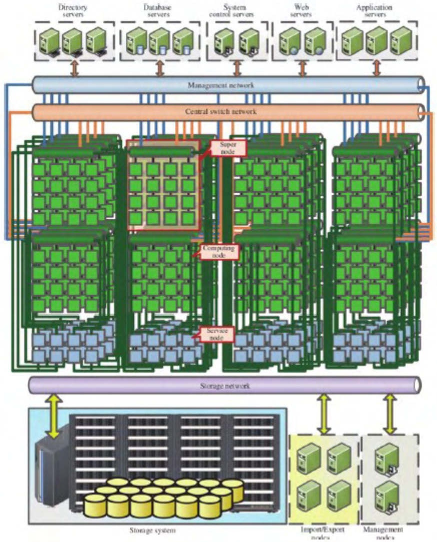
References)

- https://kr.nvidia.com/object/what-is-gpu-computing-kr.html
- https://www.youtube.com/watch?time_continue=51&v=-P28LKWTzrI

256 cores/Sunway SW26010 processor × 40,960 = 10,485,760 cores





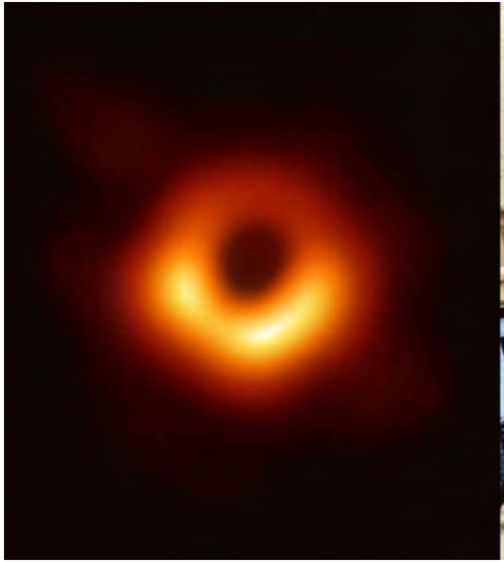


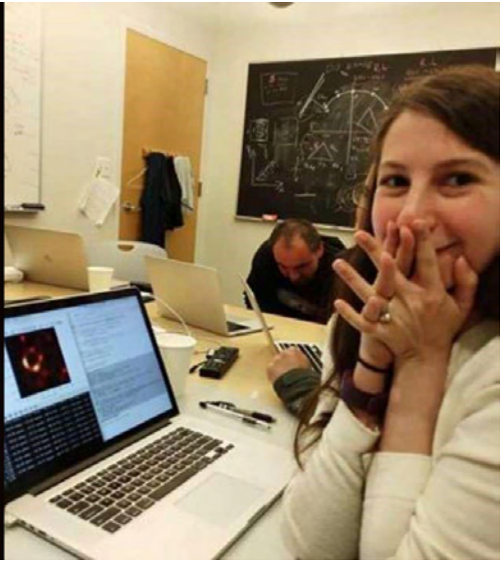
GPU

Supercomputer

Geo-Distributed Computing

Reference)
- http://cacs.usc.edu/education/cs653-lecture.html





Bouman posing with data collected by the Event Horizon Telescope project.
Image: Flora Graham

GPU

Supercomputer

Geo-Distributed Computing

Reference) How to take a picture of a black hole, Katie Bouman (MIT)

- https://www.youtube.com/watch?v=BIvezCVcsYs&feature=youtu.be

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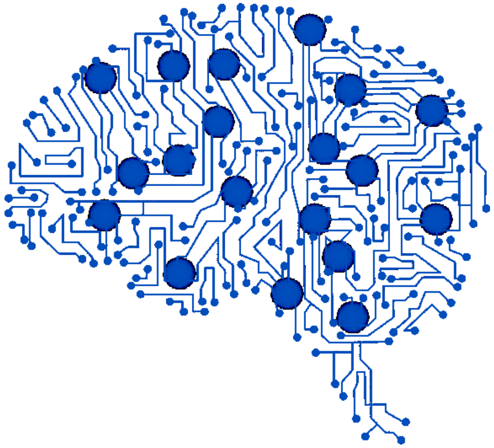


Concluding Remarks and Q&A

- Deep Learning Revolution is Real.
- Models: CNN, RNN, GAN, DRL, IL, ...
- Distributed Computing: GPU, Supercomputing, and Geo-Distributed

- More questions?
  - joongheon@gmail.com
  - joongheon@cau.ac.kr
- More details?
  - https://sites.google.com/site/joongheonkim/
  - http://prof.cau.ac.kr/~joongheon

제51회
2019 춘계학술발표대회

튜토리얼 2

AI 기술을 이용한 참과 거짓의 경계에 대한 연구 사례

강장묵 교수 (남서울대학교)

AI 기술을 이용한 참과 거짓의 경계에 대한 연구 사례

drakerjmjung@gmail.com

공학(정보보호, 2005) 박사

정치학(정치법학, 2009) 박사

가. 행 사 명 : 2019년 춘계학술발표대회
나. 개최일자 : 2019년 5월 10일(금) ~ 11일(토)
다. 개최장소 : 숭실대학교
라. 앙청내용 : 강창묵 교수(남서울대학교) 튜토리얼 발표
마. 강연시간 : 2019년 5월 10일(금) 14:00 ~ 14:50(50분간)
* 세부 시간은 프로그램 구성상 약간 변경될 수 있음

Prof. Kang, Jang Mook

출처: https://doooj.tistory.com/187

Ph. D. Kang, Jang Mook

1. 2017년 과기정통부, 사회현안문제 해결형 챌린저 인공지능 R&D 경진대회 종합 2위(장관상 수상)

2. 2018년 과기정통부, 가짜뉴스 찾기 경진대회 종합 1위 (정확도 3%대로 일위 선정), 15억 과제 수주

3. 2019년 1월 1일-12월 31일까지 '인공지능 기반 가짜뉴스를 판단하는 알고리즘 설계 및 소프트웨어 모델링' 사업 총괄 책임 수행
(총 연구인원 30명 내외, 참여 기업 2곳, 참여 학교 자문 포함 5곳, 2019년 예산 누적 총 25억원)

Professor
남서울대학교
빅데이터산업보안학과 조교수
빅데이터산업보안센터 센터장

동영상 Play: https://www.youtube.com/watch?v=jm2Og9ncxuM

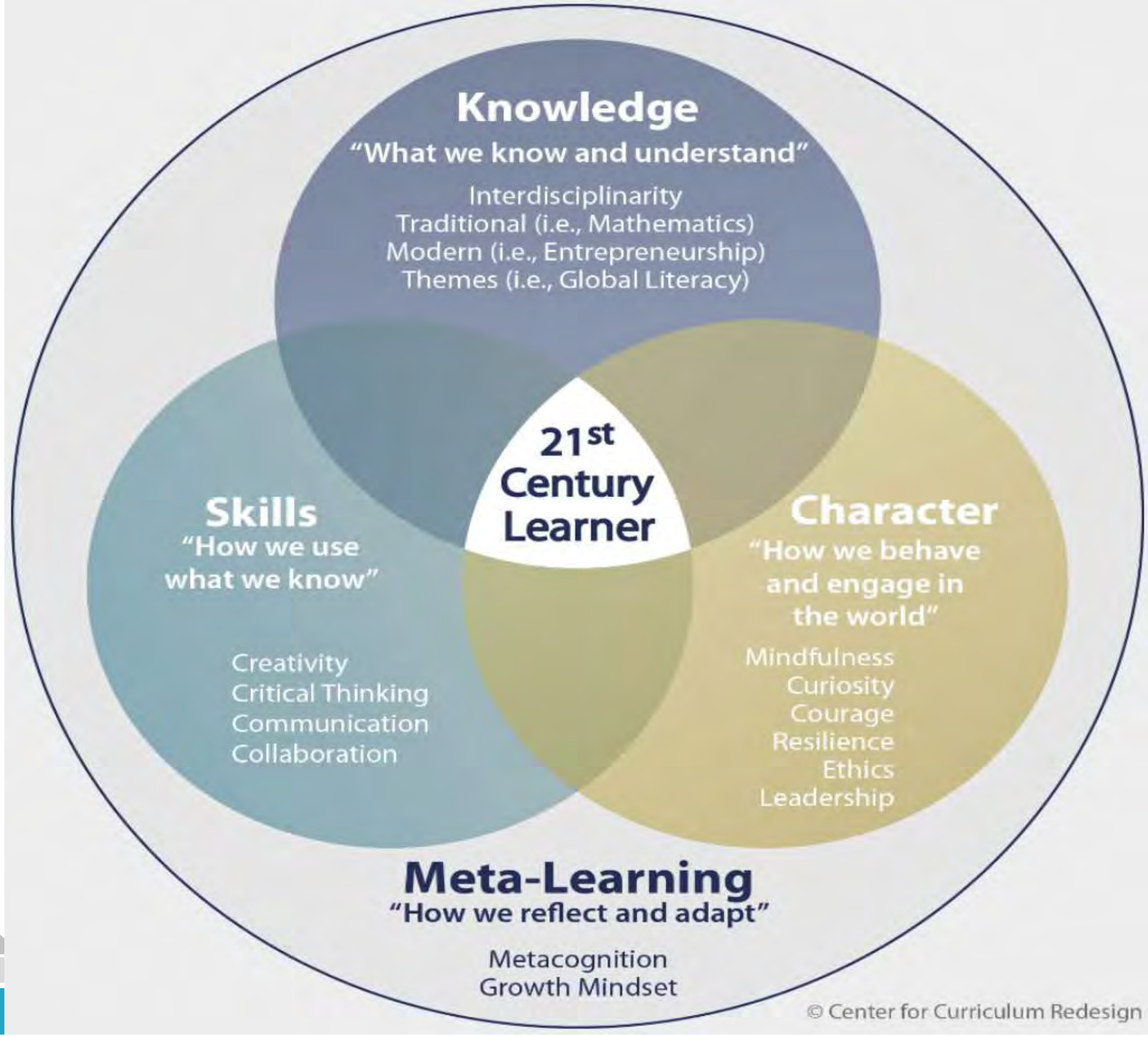
4 차 산업 혁명의 성공은 데이터
(아래 소개 자료를 보면서 어떤 데이터일지 그려보자)

- JTBC 개요 - https://youtu.be/jYJuQCe0RMc
- YTN1 사물인터넷 - https://youtu.be/WZwMNsHWd1o
- YTN2 맞춤형 헬스케어 - https://youtu.be/-3QG_DTYAGM
- YTN3 로봇 - https://youtu.be/vTuCI3RgIYU
- YTN4 인공지능 - https://youtu.be/wOVEjffL3zI
- YTN5 가상현실 - https://youtu.be/SOnnJsHM_1Y
- YTN6 자율주행 - https://youtu.be/0Kk7qNT1eFI
- YTN7 웨어러블 - https://youtu.be/fL4QvQHzq2Q
- YTN8 에너지 신산업 - https://youtu.be/BepOnBHwgpo
- YTN9 드론 - https://youtu.be/kI_58cOW4Ho
- YTN10 스마트 시티 - https://youtu.be/o2q-7iXEueE

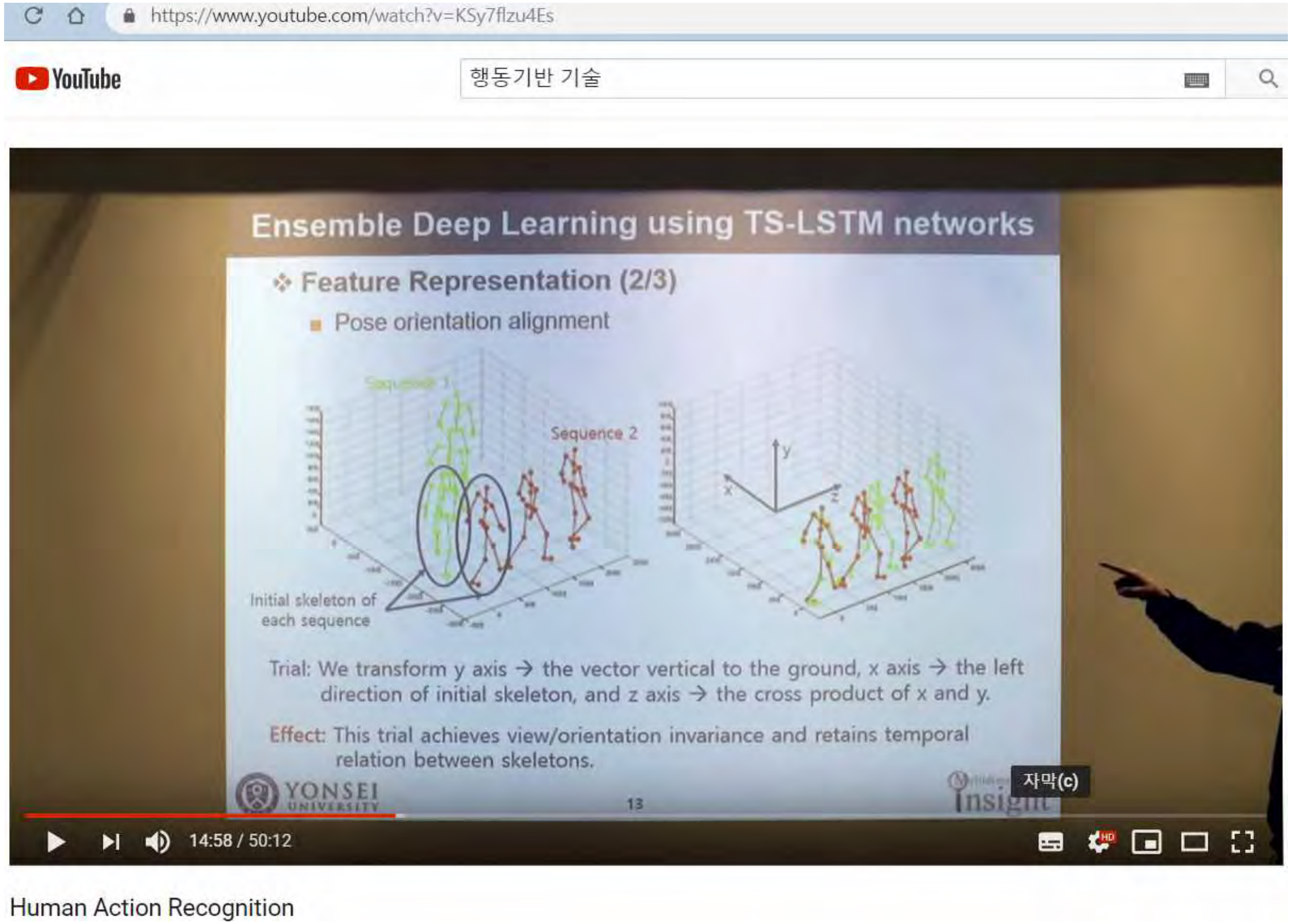
https://www.youtube.com/watch?v=iqTi2LIkWn8

출처: 최만, 4차산업혁명과 미래교육, 2017

데이터의 중심 Meta, 학습의 중심 역시 Meta(색인화? 라벨링?)



시작하는 글 : 확장성, 속도, 행동기반



개론 수준으로 이해할 분 : https://www.youtube.com/watch?v=KSy7flzu4Es

AI에 밑천

사물인터넷

빅데이터

인공지능

여기서 사물-데이터 찾아보기

그림 인용: https://www.slideshare.net/honest72/4-110090866?qid=6b29ed9c-c689-4966-9fbe-87ef73cab17f&v=&b=&from_search=3

센싱-데이터-비정형-빅데이터

- 침대에 올라온 시간
- 잠에 든 시간
- 일어난 시간

잠을 잔 시간

- 코를 곤 횟수
- 코골이 소리 크기
- 침대에 쉬를 한 횟수
- 매트리스의 온도, 습도

그림 인용: https://www.slideshare.net/honest72/4-110090866?qid=6b29ed9c-c689-4966-9fbe-87ef73cab17f&v=&b=&from_search=3

빅데이터-기계학습-심화학습-신경망이론

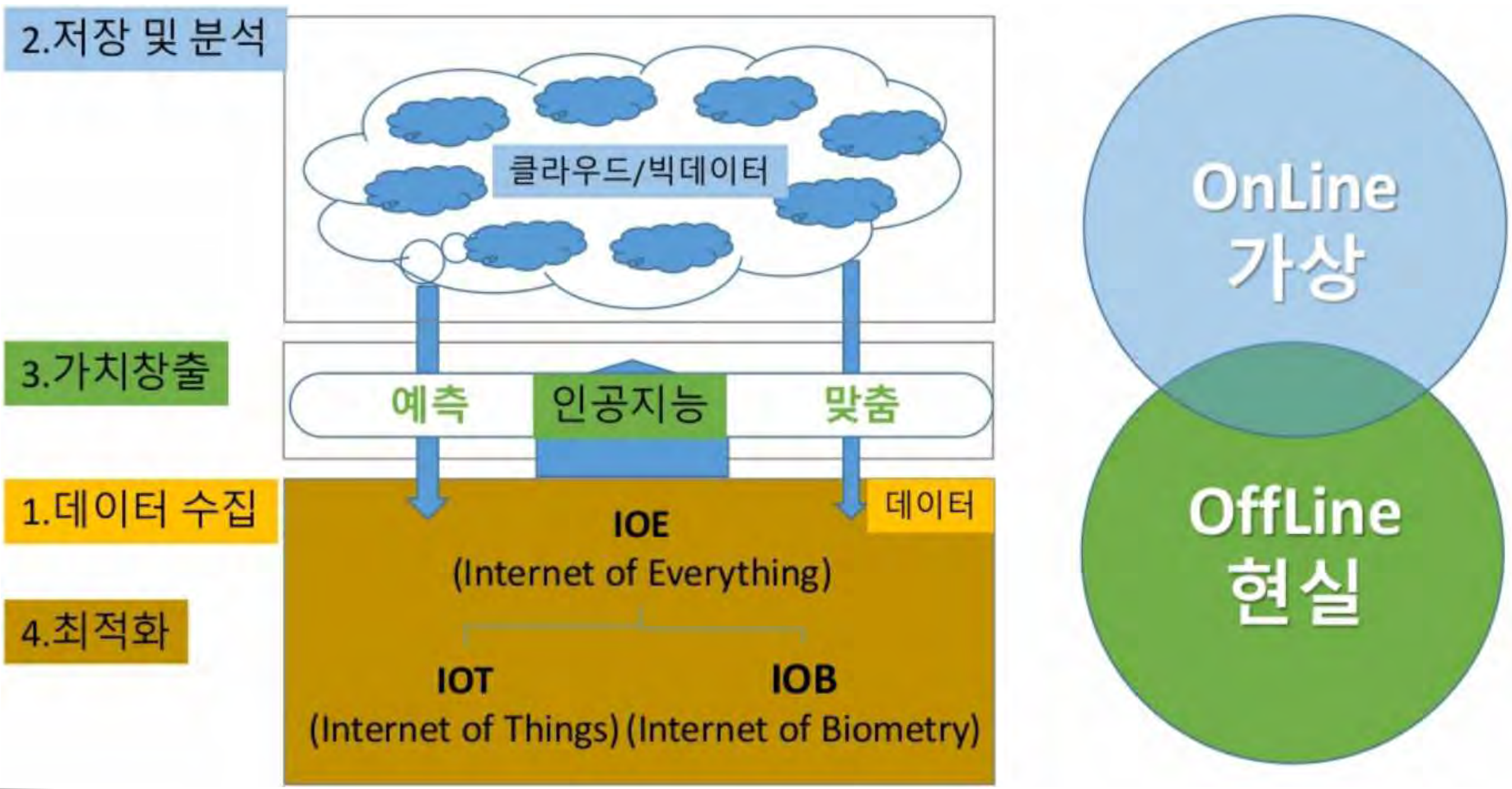
인공지능이라는 소프트웨어가
빅데이터에서 반복적인 규칙을 찾아냄

- 침대에 올라온 시간 : 10시 전후
- 잠에 든 시간 : 10시 20분 전후
- 일어난 시간 : 7시 30분 전후
- 코를 곤 횟수 : 하루 평균 3번
- 코골이 소리 크기 : 115dB (아주 큼)
- 침대에 쉬를 한 횟수 : 지금까지 7번
- 매트리스의 온도, 습도 : 평균 28도, 45%

그림 인용: https://www.slideshare.net/honest72/4-110090866?qid=6b29ed9c-c689-4966-9fbe-87ef73cab17f&v=&b=&from_search=3

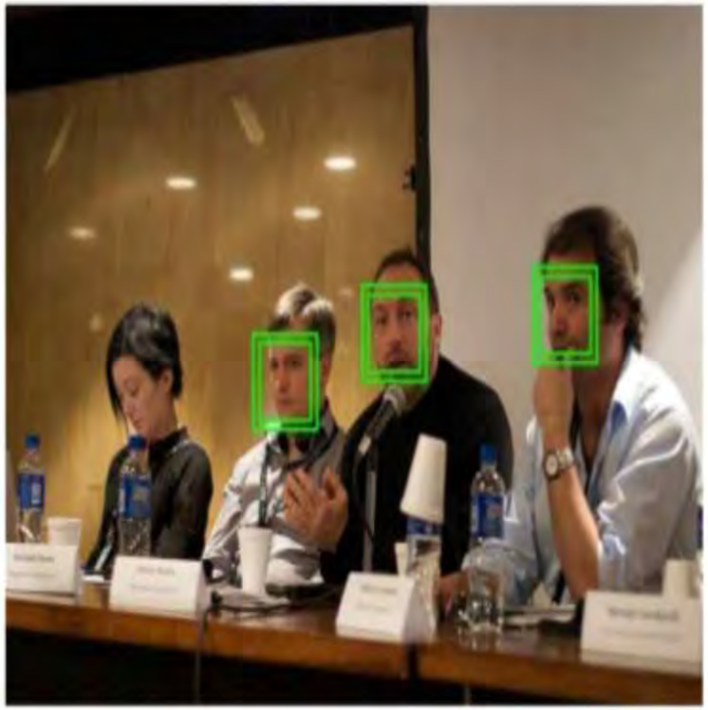
융복합 데이터, 데이터를 이해해야 Ai 모델링도 잘 한다.

제4차 산업혁명의 3대 키워드	데이터 관점
지능	데이터를 통한 지능화
융합	데이터의 융합
연결	연결이라는 데이터가 흐르는 상태



인용: https://www.slideshare.net/ssuserbd0159/4-76192521?qid=6608467b-0d9d-4394-82d4-7b74e5b8eb96&v=&b=&from_search=5
https://www.slideshare.net/brucedong/4-170720v12?qid=9f033488-8049-48d1-86ab-91b265fac1ff&v=&b=&from_search=9

AI의 대표적인 분야



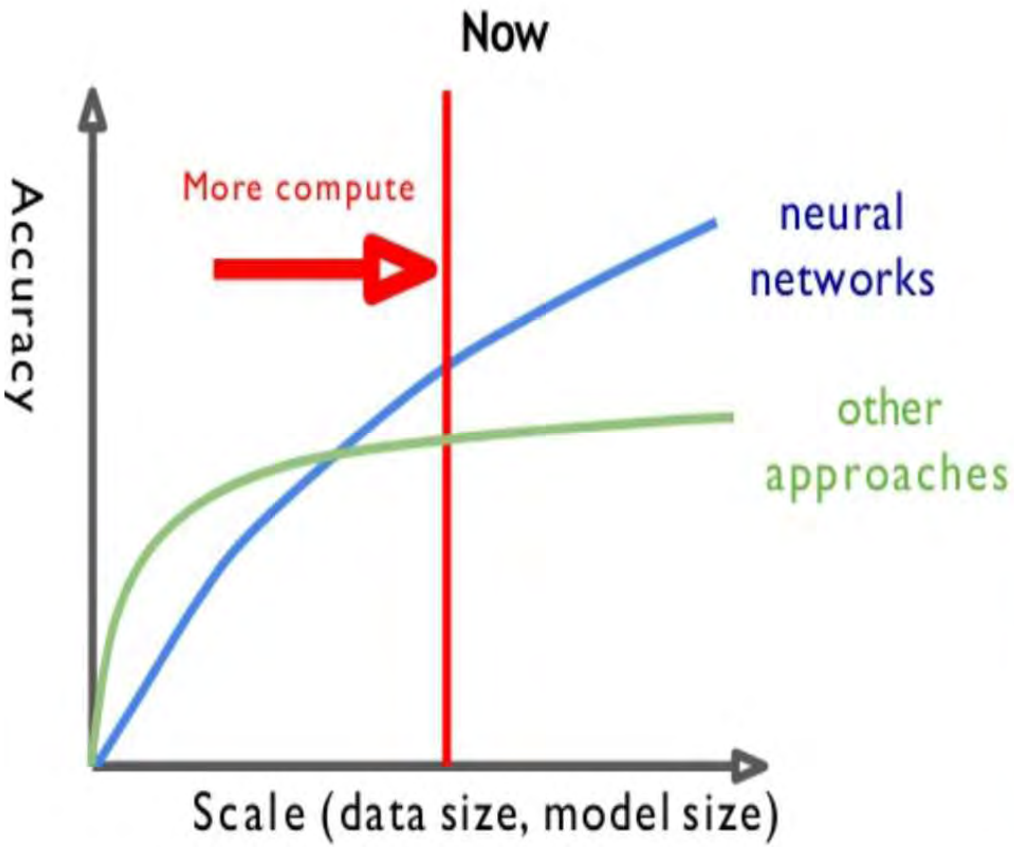
이미지

자연어

자율주행

인용: https://www.slideshare.net/hanpark/ss-65217681

5%의 Classification 능력, 어려운 문제



인용: https://www.slideshare.net/awskorea/amazon-ai-deep-learning-on-aws?qid=820e9768-edab-421b-8fef-b9ac01a7f41c&v=&b=&from_search=6

강장묵 연구팀의 작은 성과 (자연어 분야)

2017년: 에트리 팀, 카이스트, 서울대, 고려대, 줌 검색 회사 등과 소수점 3자리점의 차이

인공지능 R&D 챌린지 장관상 수상

인용: http://www.gukjenews.com/news/articleView.html?idxno=838345

강장묵 연구팀의 작은 성과 (자연어 분야)

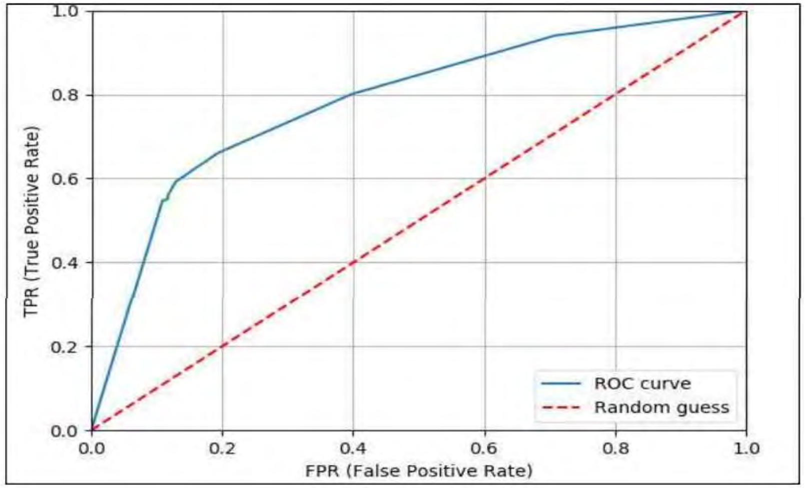
2017년: 에트리 팀, 카이스트, 서울대, 고려대, 줌 검색 회사 등과 소수점 3자리점의 차이

2018년: 3%로 2017년 1등한 팀을 이기고 종합 일위 차지 (국가공인시험평가 결과)

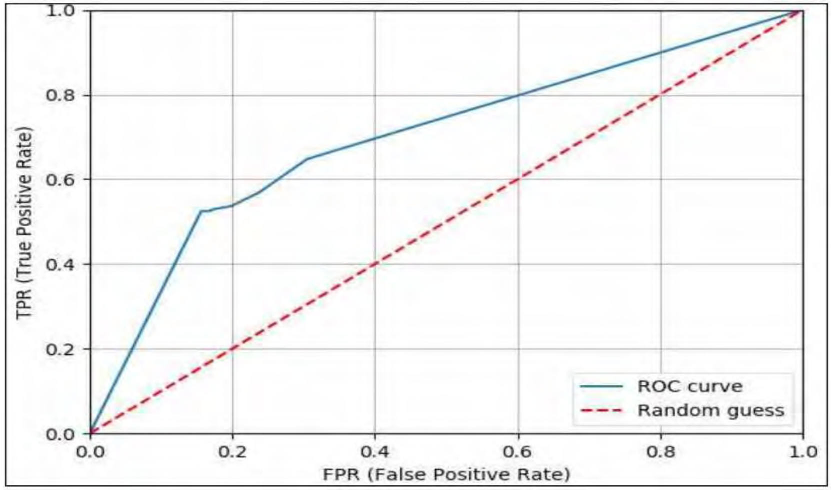
항목	1차년도 목표	결과
임무1	75%	78.46%
임무2	65%	69.87%
평균	70%	74.16%

참여 A사	참여 B사	비고
80.4%	70.6%	
61.5%	66.2%	
70.9%	68.4%	

* 상기 내용은 정량 평가 최종 결과 임



[임무1 ROC Curve]



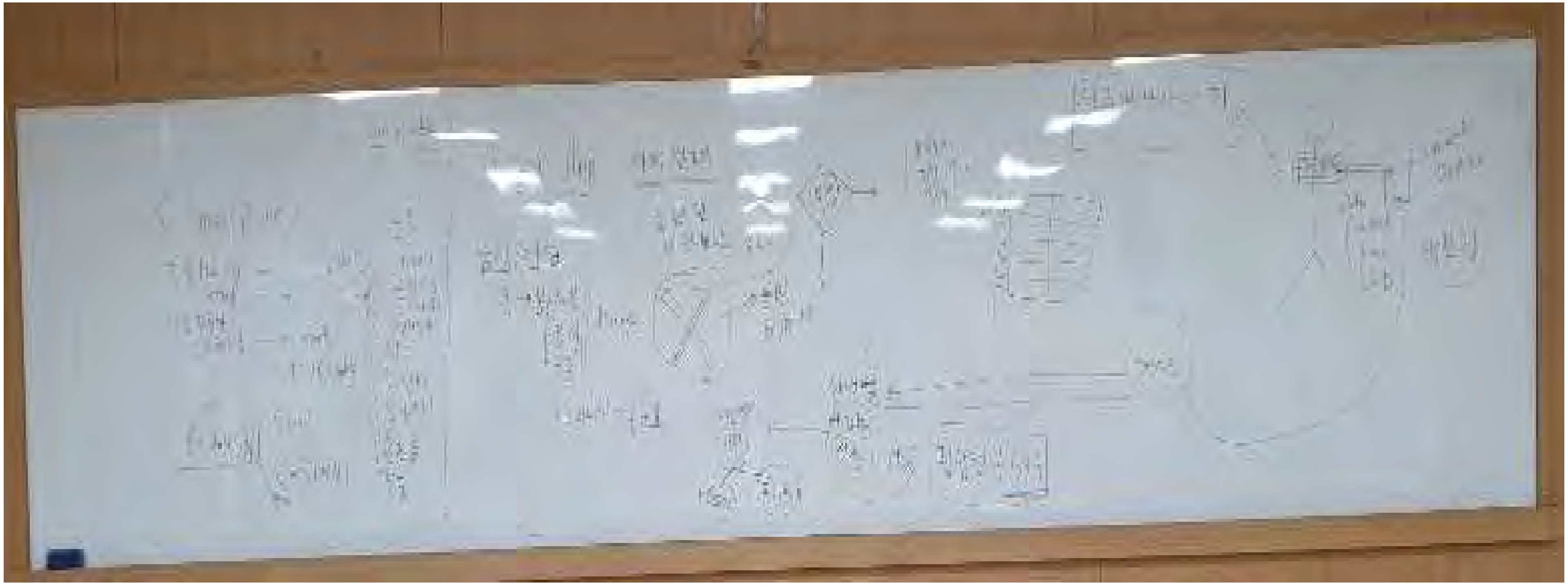
[임무2 ROC Curve]

인용: https://www.slideshare.net/hanpark/ss-65217681

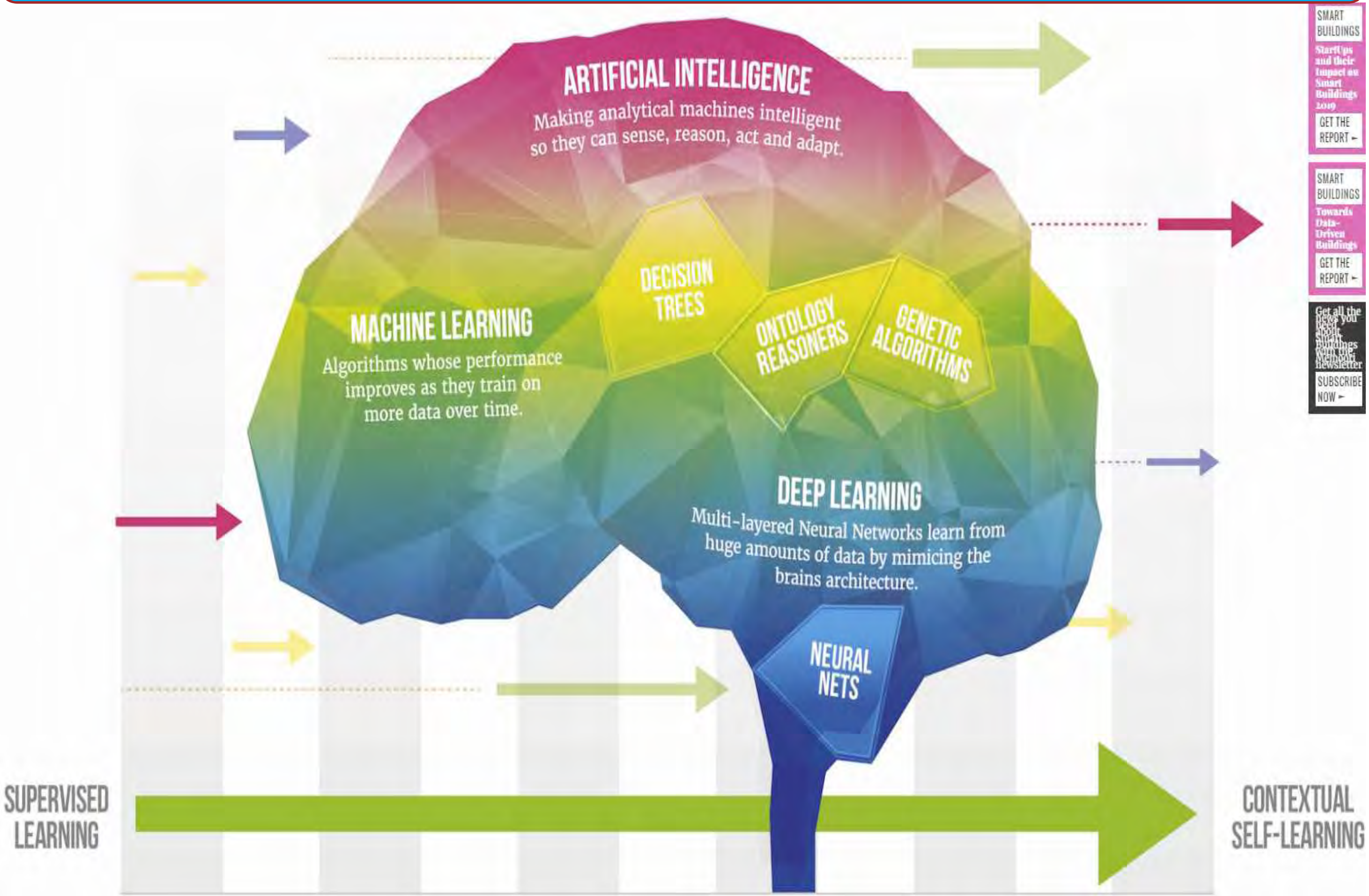
사진 인용: http://dawsoncrossfit.com/crossfit-kids-break-time/

직접 그리고 생각하기

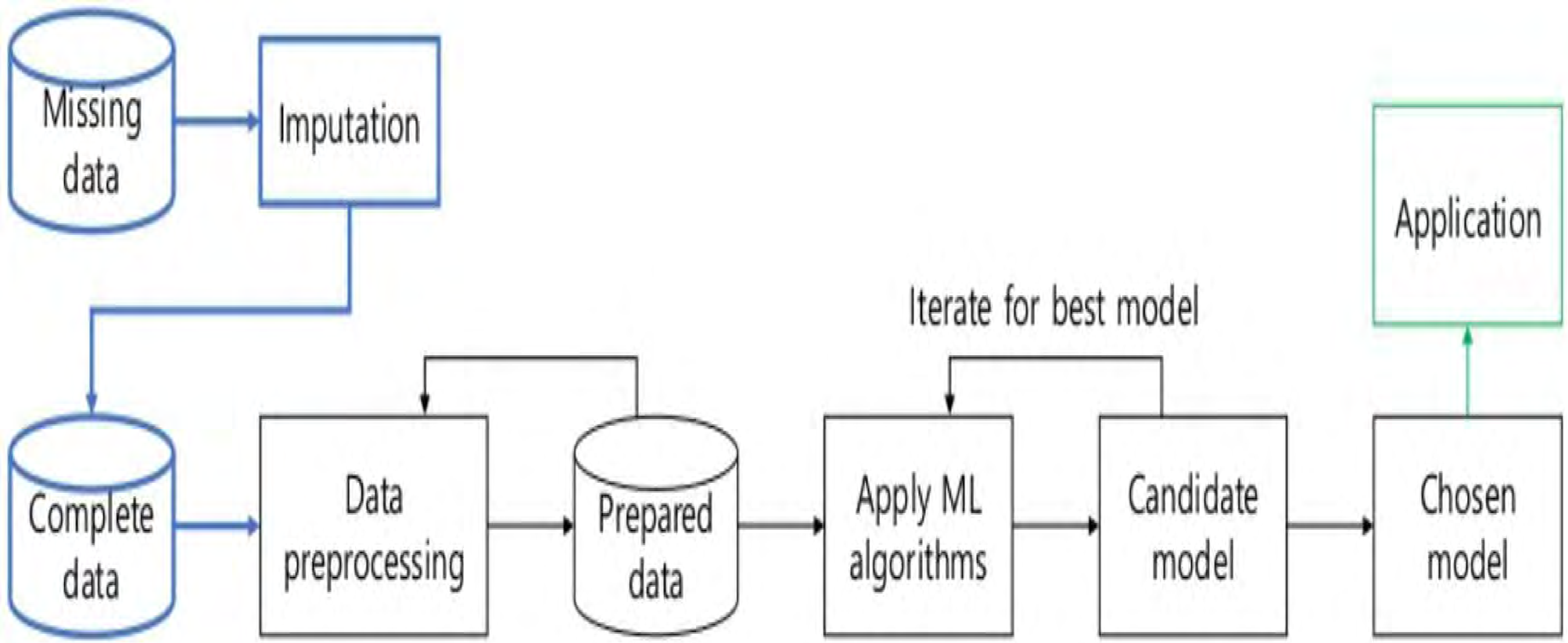
"AI 서비스 설계하기 구상하기"



AI의 가벼운 이해(쉬었다가 다시 몸풀기)



AI와 학습 데이터 구축



Imputation(대체) 모델 이용
Model의 Overfitting 또는 Underfitting이 발생
알고리즘의 입력 값에 맞는 데이터 변형 과정 필요

성공적인 데이터 소사이어티가 되기 위해

선순환 구조의 이해

AI의 아킬레스건(엄밀하게는 빅데이터)

1. 개인정보보호의 문제
2. 실제 예측력이나 정확도가 떨어지는 문제
3. 비용이 많이 드는 문제(전처리, 후처리)
4. 전문가 부재(인문/사회과학을 이해한 데이터 과학자)

○ de-identification은 anonymization와 pseudonymization를 포함하는 과정(절차)에 해당

○ anonymization와 pseudonymization은 de-identification의 단계에 해당

○ Anonymous data : 관련된 개인을 식별할 수 없게끔 특정 정보를 처리한 상태

not single out, not linkable, not inferred

○ Pseudonymous data : 특정 정보에서 식별자를 pseudonym(가명)으로 대체하여 관련된 개인과의 연결성을 제거한 상태

single out, but not linkable, not inferred

○ 번역

- de-identification : 비식별화 / 익명화
- anonymization : 익명화 / 비식별화
- pseudonymization : 가명처리 / 중간개인정보

인용: https://www.slideshare.net/ssuserbd0159/ss-62079304?qid=d075d52b-266f-44bd-8dd9-b00ec7bd293d&v=&b=&from_search=10

재식별화의 위험

[단독] 복지부 빅데이터의 위험성…개인정보 암호화해도 풀 수 있다

등록 :2016-09-25 16:50 수정 :2016-09-25 21:58

f 🐦 ➦ ★ 🖶

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한국 처방전 데이터의 주민번호
하버드대 연구팀 "암호화 해제"
복지부 의료데이터 민간개방에 경고

국회 보건복지위원회 소속 정춘숙 의원(더불어민주당)이 25일 번역해 공개한 미국 하버드대학교 라타냐 스위니 교수 연구팀의 2015년 논문 '처방전 데이터상 공유되는 대한민국 주민등록번호의 익명성 해제'를 보면, 연구팀은 한국인 사망자 2만3163명의 처방전 데이터의 암호화된 주민등록번호를 전부 해제하는 데 성공한 것으로 나타났다. 연구팀은 암호화된 주민등록번호를 논리적 추론 방식과 자동탐색실험, 두 가지 방식으로 모두 해제했다. 논리적 추론 방식은 각각의 자리에서 발견되는 문자의 빈도를 통해 어떤 자리의 어떤 수가 어느 문자로 치환됐는지를 추론하는 방식인데, 논문은 한국의 주민등록번호는 임의번호가 아닌 생년월일과 성별 등 인구통계학적 개인정보를 담고 있기 때문에 더 쉽게 풀 수 있었다고 밝혔다.

인용: https://www.youtube.com/watch?v=lQyaWqGYDzE

라타냐 스위니 교수

하바드 대 라타냐 스위니 교수와의 미팅

보스턴

비식별화와 재식별화

Technology Science

...how technology impacts humans.

De-anonymizing South Korean Resident Registration Numbers Shared in Prescription Data

처방전 데이터의 주민등록번호 익명성 해제 연구 </p> <p class=MsoSubtitle>Latanya Sweeney, Ji Su Yoo

Abstract

Introduction

Background

Methods

Results

Discussion

References

Download

Authors

Citation

Data

Suggestions

Letter	Number
a	1
b	2
c	3
d	4
e	5
f	6
g	7
h	8
i	9
j	0

Odd-digit

Letter	Number
f	0
g	9
h	8
i	7
j	6
k	5
l	4
m	3
n	2
o	1

Even-digit

- South Korea's national identifier, the Resident Registration Number (RRN) includes encoded demographic information and a checksum with a publicly-known pattern
- We conducted two de-anonymization experiments on 23,163 encrypted RRNs from prescription data of South Koreans
- We demonstrate the data's vulnerability to de-anonymization by revealing all 23,163 unencrypted RRNs in both experiments

Coding table that replaced digits of South Korean national identifiers with letters in shared

AI 튜트리올에 대한 결어

A라는 분야에 B라는 방법이 성공했다고 해서, C라는 분야에서 성공할 보장이 없음
그래서 google, IBM, Apple, Facebook 등의 AI 접근이 많이 다름
AI의 진수는 응용에 있음
사회에 파급효과가 커서 비기술적 요소(규범, 경제, 법제 등)에 대한 이해도 필요함
현재 AI 기술은 성능이 향상된 것이지 실수가 없어진 것은 아님
(자율주행차도 사고가 남, 로봇 수술도 아주 드문 실수를 함)

디지털 사회혁신을 위해
AI 기술로 단순 기능직인 오퍼레이터의 실업이 아닌
AI변호사, AI판사, AI 기자, AI 회계사, AI 전문가를 꾸준하게 개발하는 노력이 필요

인용: https://techscience.org/a/2015092901/


Thank Q
drakerjmjung@gmail.com
The followings were made to supplement
my shabby presentation.
When you need anything,
please e-mail me at this address at any time.

튜토리얼 3

AI-Assisted Pathological Diagnosis

곽태영 CTO (㈜딥바이오)

AI-assisted pathological diagnosis

Kwak, Tae-Yeong @ Deep Bio Inc.

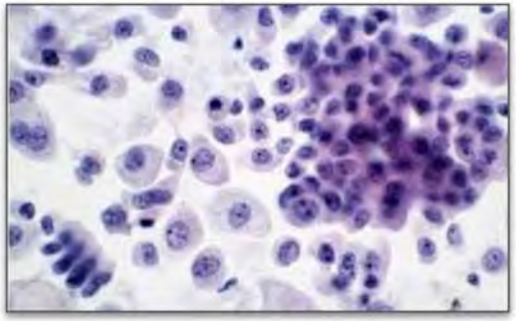
deep bio

Pathological diagnosis

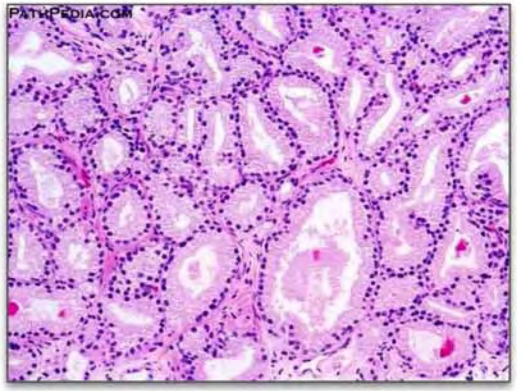
Diagnosis based on the pathological knowledge, including

- Morphological changes in cells and tissues
- Proliferation of specific antigen, antibody, protein, ...

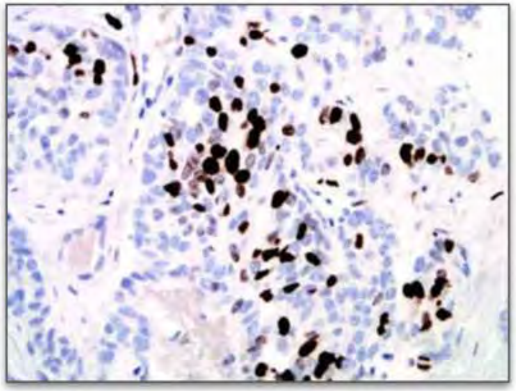
Cytopathology



Histopathology



Molecular pathology



Digital pathology

Transforms from glass slides to digital slide images

- Changes in storage, education, consultation, etc.

Using light microscope is still the major approved diagnosis method

- Digital slide images generated by regulation-cleared scanners can be used for the primary diagnosis

Light microscope

(from: Leica Microsystems)

Microscope camera

(from: News-Medical site)

Whole-slide scanner

(from: Leica Biosystems)

Applying automated image analysis on pathological diagnosis

Segmentation

Segmenting tubule structures in pathological images for further diagnosis

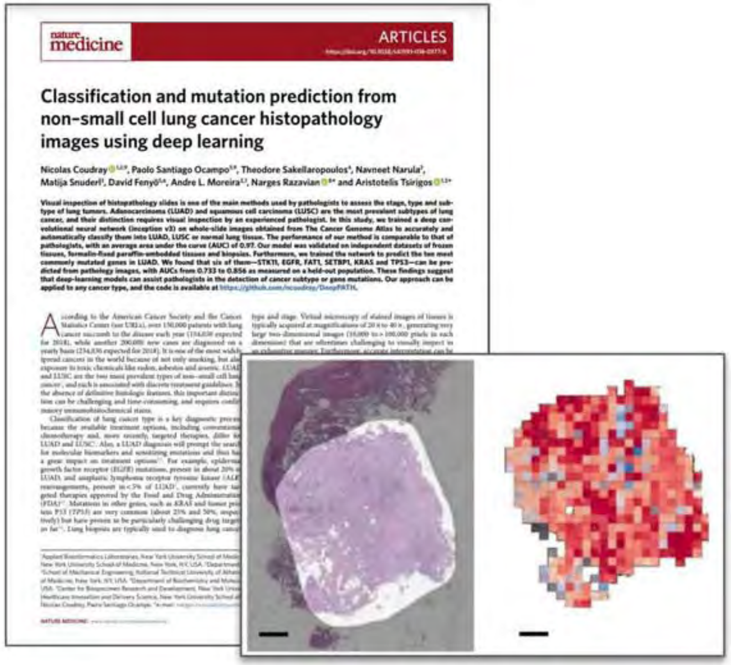
Detection

Finding lymph node metastasis for breast cancer staging

Janowczyk A, Madabhushi A, *Deep learning for digital pathology image analysis: A comprehensive tutorial with selected use cases.* J Pathol Inform. 2016; 7: 29.
Litjens G *et al. Deep learning as a tool for increased accuracy and efficiency of histopathological diagnosis.* Sci Rep. 2016; 6: 26286.

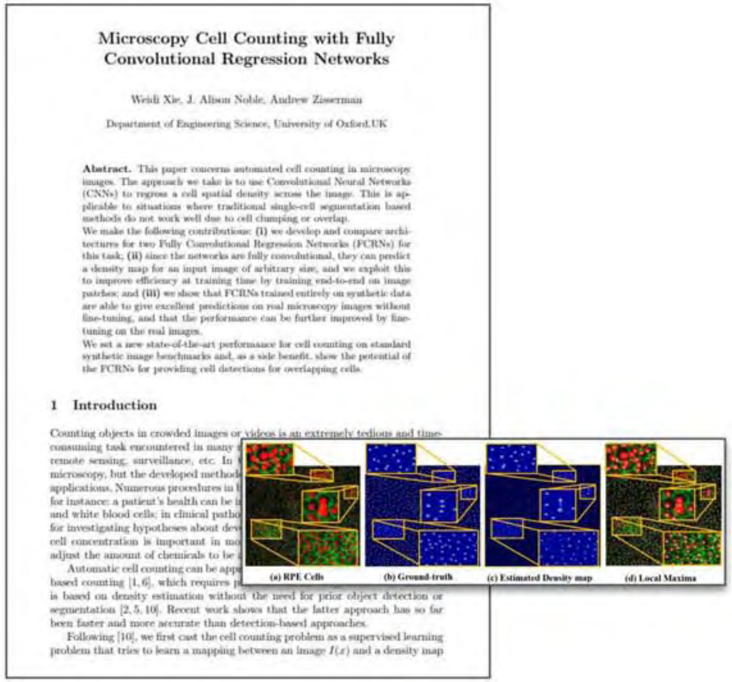
Applying automated image analysis on pathological diagnosis

Classification



Classifying lung cancer subtype:
adenocarcinoma vs. squamous cell carcinoma

Counting



Counting specific cells to get some pathological quantity

Coudray N *et al. Classification and mutation prediction from non–small cell lung cancer histopathology images using deep learning*, Nat Med. 2018; 24(10): 1559-1567.
Xie W *et al. Microscopy cell counting and detection with fully convolutional regression networks.* Comput Methods Biomech Biomed Eng Imaging Vis 2016; 6(3): 283-292.

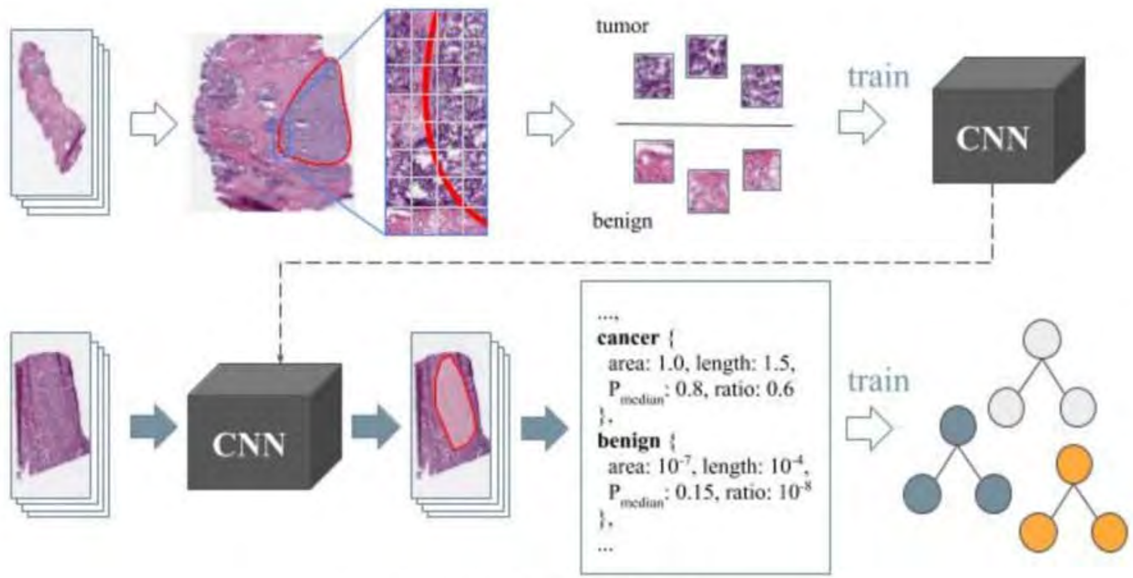
Dealing with: large digital whole-slide images (WSIs)

Scanning 2cm x 3cm at 400x magnification, where typical pixel length 0.25 μm

→ 80,000 x 120,000 pixels (~ 10 G pixels = 30 GB at no compression level)

2-step approach:

- Create a *patch-wise* classifier
- Create a *WSI-level* classifier using the *patch-wise* one



(from: Chang HY *et al.*, JPTM 2019)

Chang HY *et al. Artificial Intelligence in Pathology*, J Pathol Transl Med. 2019; 53(1): 1-12.

Dealing with: limited annotation data

Annotation should be done by the experienced pathologists

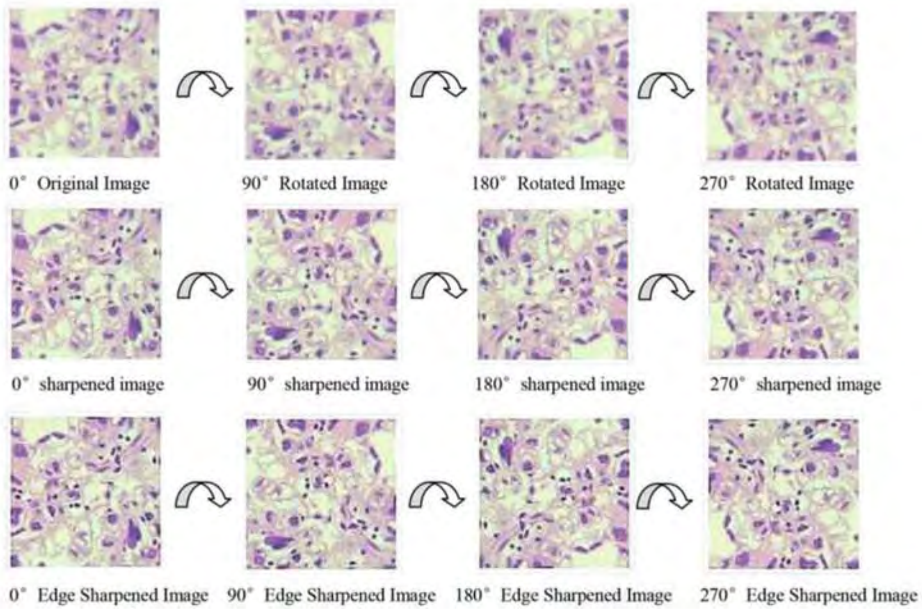
→ typically less than 1,000 handmade annotations available

Data *augmentation*:

- Flip
- Rotate
- Blur
- Sharpen

Data *curation*:

- More samples from *decision boundaries*



(from: Wu M *et al.*, Biosci Rep. 2018)

Wu M *et al. Automatic classification of ovarian cancer types from cytological images using deep convolutional neural networks.* Biosci Rep. 2018; 38(3): BSR20180289.

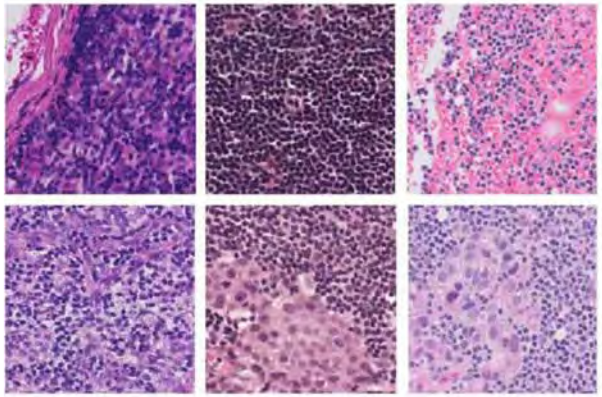
Dealing with: stain color variation

Variations affecting stain color:

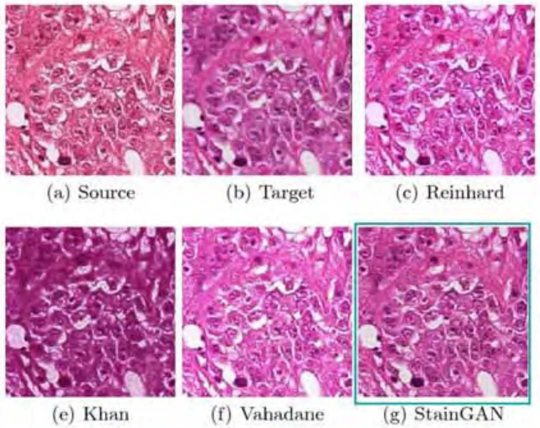
- Tissue thickness (3 μm ~ 10 μm)
- Staining process (amount of dye, staining duration, dye maker, etc.)
- Optical characteristics of digital slide scanners

Color *alteration*:

- Normalization
- Randomization (*Color jittering*)



(from: Cho H *et al.*, arXiv 2017)



(from: Shaban MT *et al.*, arXiv 2018)

Cho H *et al. Neural Stain-Style Transfer Learning using GAN for Histopathological Images.* arXiv 2017; arXiv:1710.08543.
Shaban MT *et al. StainGAN: Stain Style Transfer for Digital Histological Images.* arXiv 2018; arXiv:1804.01601.

deep bio

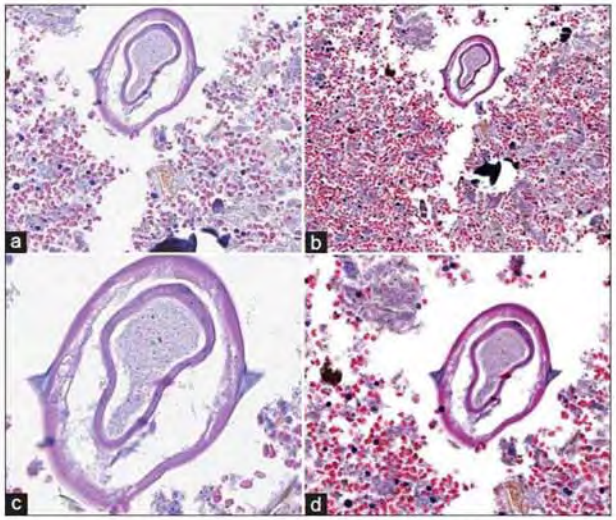
Dealing with: image resolution variation

Variations affecting actual pixel length:

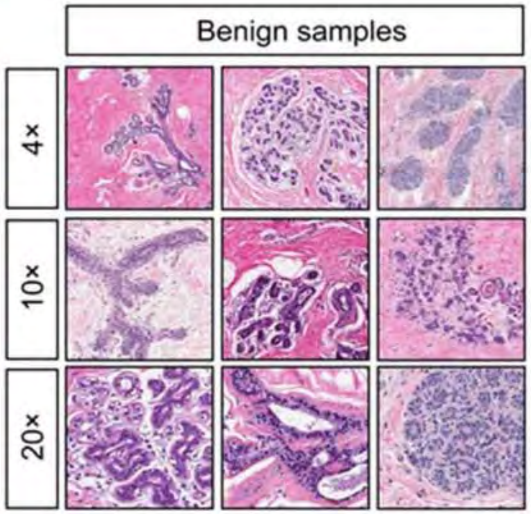
- Optical characteristics of digital slide scanners
- Magnification level (5x, 10x, 20x, 40x, ...)

Pixel length *alteration*:

- Normalization
- Randomization (*Random resizing*)



(from: Sellaro TL *et al.*, J Pathol Inform 2013)



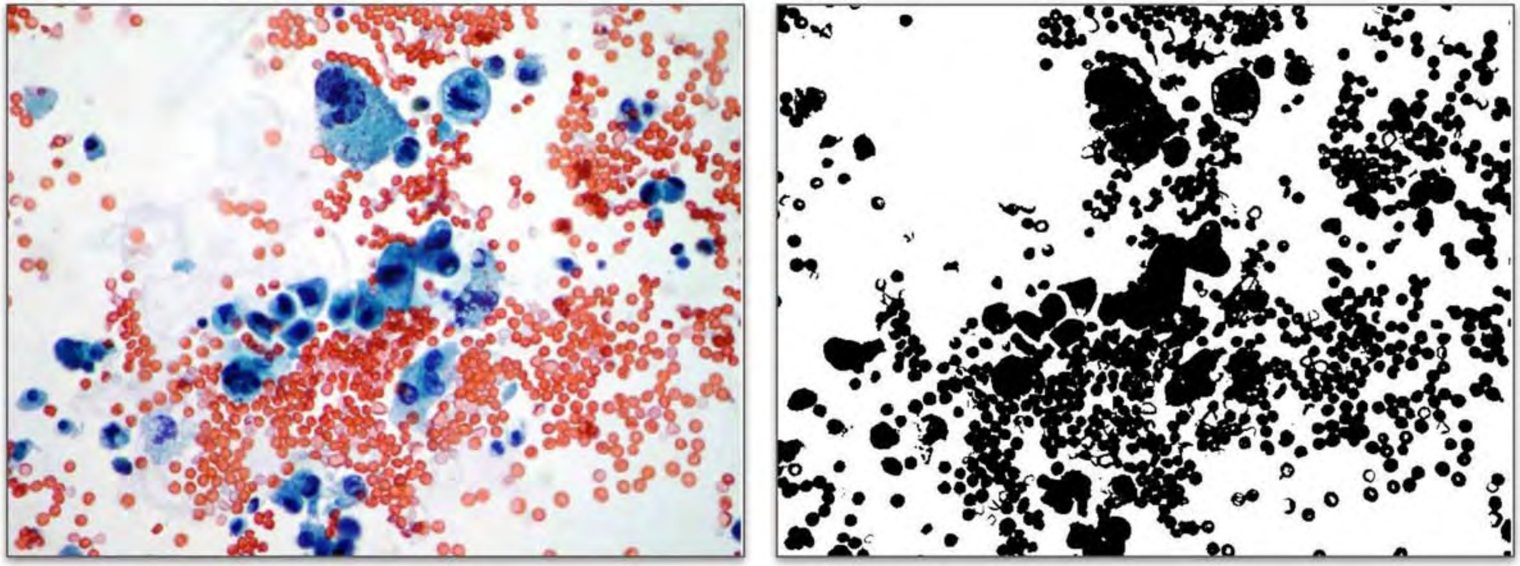
(from: Levenson RM *et al.*, PLoS ONE 2015)

Sellaro TL *et al. Relationship between magnification and resolution in digital pathology systems.* J Pathol Inform 2013; 4: 21.
Levenson RM *et al. Pigeons (Columba livia) as Trainable Observers of Pathology and Radiology Breast Cancer Images.* PLoS ONE 2015; 10(11): e0141357.

Region-of-interest (ROI) detection

Detecting and removing out-of-interest area from whole-slide image:

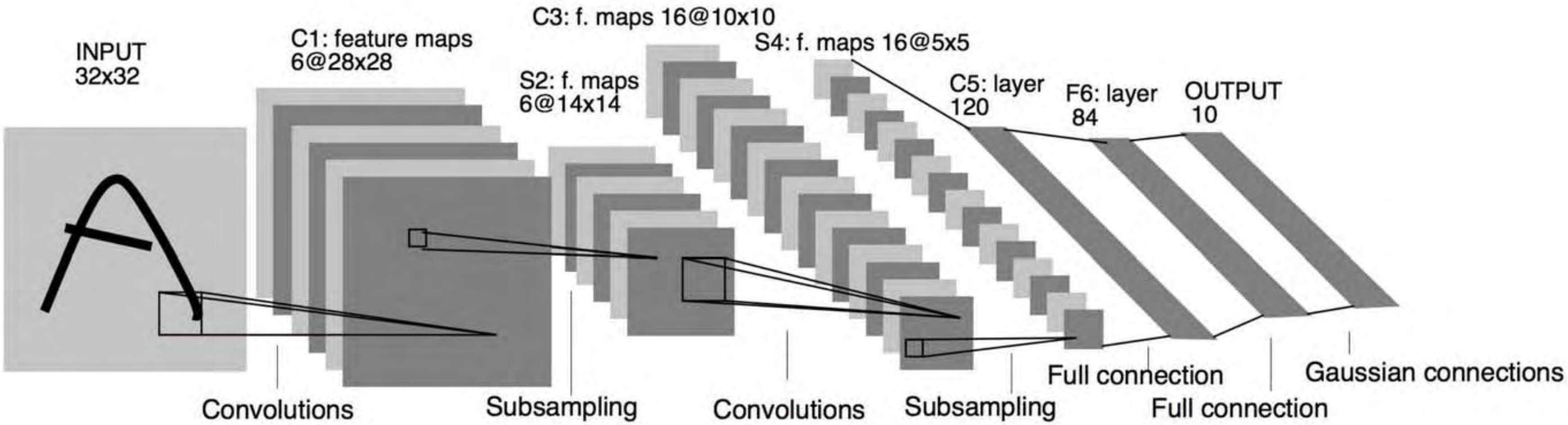
- Image transformation + thresholding
- Pixel- or patch-wise classifier (CNN)



Otsu N. *A threshold selection method from gray-level histograms.* IEEE Trans Syst Man Cybern 1979; 9: 62-6.

Convolutional neural networks (CNNs)

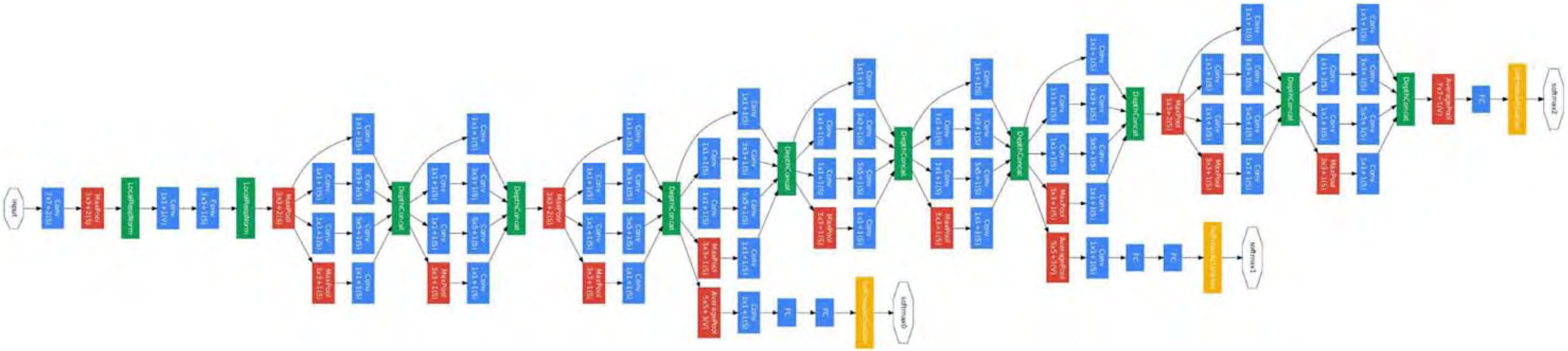
Learns important visual features

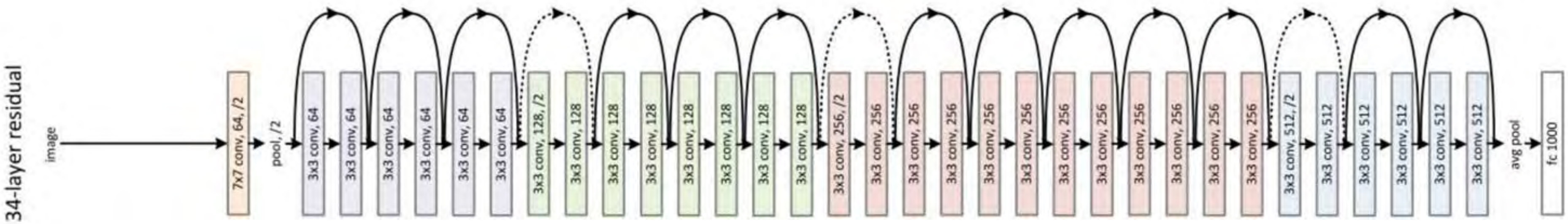


Modern CNNs have more complex structures, including *branching*, *merging*, *residual connections*, etc.

LeCun Y et al. *Gradient-Based Learning Applied to Document Recognition.* Proc. of IEEE 1998; 86(11): 2278-2324.

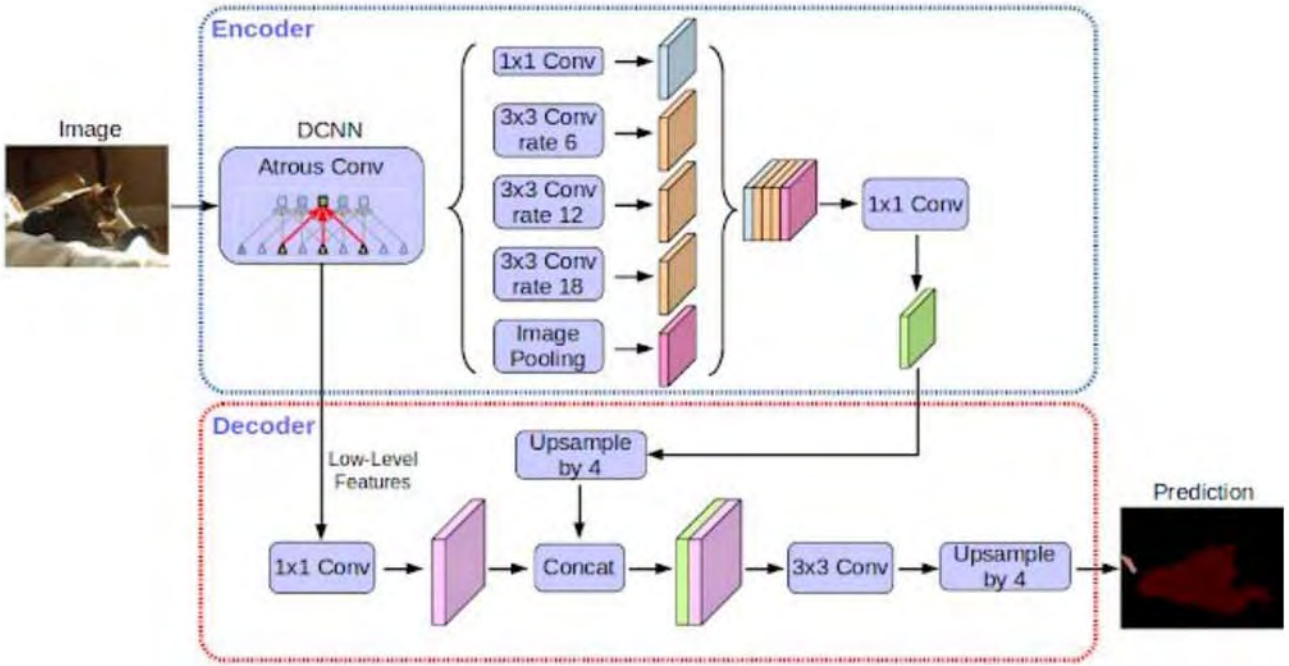
CNNs for object recognition





Szegedy C *et al. Going deeper with convolutions*, IEEE CVPR 2015.
He K *et al. Deep Residual Learning for Image Recognition*, IEEE CVPR 2016.

CNNs for image segmentation



Chen L-C *et al. Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation*, arXiv 2018; arXiv:1802.02611

Part of pathological AI researches...

Author (year)	Disease	Data	Task	Model	Augmentation	Performance
Garud *et al.* (2017)[46]	Breast cancer	FNA cytology/175 (images)	Decision Benign/cancer	CNN	None	Image level decision acc. 89.7%
Li and Ping (2018)[47]	Lymph node metastasis	CAMELYON16/400 (WSIs)	Decision Yes/no	CNN + CRF	Color jitter, rotation, etc.	Patch level decision acc. 93.8%
Rannen Triki *et al.* (2018)[48]	Breast cancer	Frozen section OCT/4,921 (frames)	Decision Benign/cancer	CNN	None	Patch level decision acc. 94.96%
Ehteshami Bejnordi *et al.* (2018)[49]	Breast cancer	BREAST Stamp/2,387 (WSIs)	Decision Benign/cancer	CNN + CNN	None	WSI level decision AUC 0.962
Litjens *et al.* (2016)[50]	Lymph node metastasis	Lymph node specimen/271 (samples)	Decision Yes/no	CNN	None	Sample level decision AUC 0.90
Cireşan *et al.* (2013)[51]	Breast cancer	MITOS/300 mitosis in 50 images	Mitosis detection	CNN	Rotation, flip, etc.	Detection F1-score 0.782
Teramoto *et al.* (2017)[52]	Lung cancer	FNA cytology/298 (images)	Classification Adeno-Squamous cell Small cell	CNN	Rotation, flip, etc.	Overall classification acc. 71.1%
Yu *et al.* (2016)[53]	Lung cancer	TCGA-LUAD/1,074 TCGA-LUSC/1,111 Stanford TMA/294 (samples)	Decision Benign/cancer Survival analysis	SVM	None	Patch level decision AUC 0.85
Coudray *et al.* (2018)[54]	Lung cancer	TCGA lung cancer/1,635 (samples)	Classification Adeno- Squamous cell Benign Multi-task decision Gene mutation	CNN	None	Overall classification AUC 0.97 STK11 mutation decision AUC 0.85
Campanella *et al.* (2018)[55]	Prostate cancer	Needle biopsy/12,160 (samples)	Decision Benign/cancer	CNN (MIL)	None	Sample level decision AUC 0.979
Arvaniti *et al.* (2018)[56]	Prostate cancer	TMA/886 (samples)	Classification Gleason score	CNN+scoring rule	Rotation, flip, color jitter	Model-pathologist Cohen's kappa 0.71
Zhou *et al.* (2017)[57]	Prostate cancer	TCGA-PRAD/368 (cases)	Decision 3+4/4+3	CNN	None	Sample level decision acc. 75%
Nagpal *et al.* (2018)[58]	Prostate cancer	TCGA-PRAD+others/train 1,226, test 331 (slides)	Classification Gleason group Survival analysis	CNN+k-NN	None	Overall classification acc. 70% C-index 0.697
Litjens *et al.* (2016)[50]	Prostate cancer	Needle biopsy / 225 (WSIs)	Decision Benign/cancer	CNN	None	Slide level decision AUC 0.99
Ertosun and Rubin (2015)[59]	Brain cancer	TCGA-GBM & LGG (unknown size)	Classification GBM LGG grade 2 LGG grade 3	CNN + CNN	Color transform to H&E	GBM/LGG decision acc. 96% LGG grade decision acc. 71%
Mobadersany *et al.* (2018)[60]	Brain cancer	TCGA-GBM & LGG/1,061 (samples)	Survival analysis	CNN	Rotation, normalization	C-index 0.754
Wu *et al.* (2018)[61]	Ovarian cancer	Biopsy/7,392 (images)	Classification Subtypes	CNN	Rotation, image enhancement	Overall classification acc. 78.2%
Zhang *et al.* (2017)[62]	Cervix cancer	HEMLBC/1,978 Herlev/917 (images)	Decision Benign/cancer	CNN	Rotation, translation,	Image level decision AUC 0.99
Xu *et al.* (2017)[63]	Sickle cell disease	Red-blood cell/7,206 (patches)	Classification Cell types	CNN	Rotation, flip, translation, etc.	Cell level classification acc. 87.5%
Meier *et al.* (2018)[64]	Gastric cancer	TMA/469 (samples) CD8/Ki67 IHC	Survival analysis	CNN	None	Stratification by risk successful (p<.01)
Xie *et al.* (2016)[65]	-	Synthetic fluorescence microscopy cell/ 200 (images)	Cell counting	CNN	None	Mean absolute error < 2%
Tuominen *et al.* (2010)[66]	-	IHC stained breast cancer slides/100	Cell counting	Comp. vision	None	Correlation coefficient 0.98

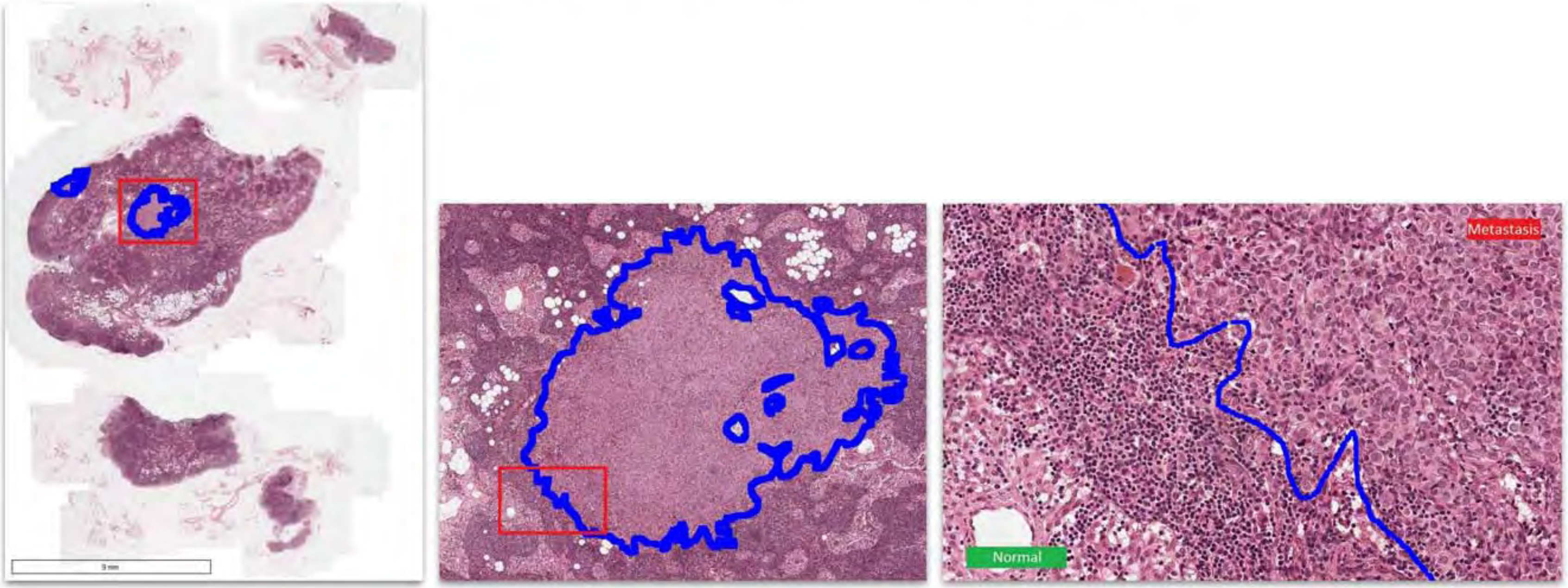
Chang HY *et al.* *Artificial Intelligence in Pathology*, J Pathol Transl Med. 2019; 53(1): 1-12.

deepbio

Lymph node metastasis detection

Important in patient prognosis after surgery

- Distant metastasis occurs after lymph-node metastasis
- Pathologists inspect H&E stained lymph node slides with light microscopes



https://camelyon17.grand-challenge.org/Background/

Lymph node metastasis detection challenge (CAMELYON)

CAMELYON16: detection of metastasis

- Macro-metastasis > 2.0 mm
- Micro-metastasis > 0.2 mm (or 200 cells)
- Isolated tumor cells (ITC)

CAMELYON17: decision of pN-stage

- pN0 = no metastasis
- pN0(i+) = only ITCs
- pN1mi = only micro-metastases
- pN1 = metastases in 1~3 nodes w/ macro-
- pN2 = metastases in 4~9 nodes w/ macro-

JAMA | Original Investigation

Diagnostic Assessment of Deep Learning Algorithms for Detection of Lymph Node Metastases in Women With Breast Cancer

Babak Ehteshami Bejnordi, MS; Mitko Veta, PhD; Paul Johannes van Diest, MD, PhD; Bram van Ginneken, PhD; Nico Karssemeijer, PhD; Geert Litjens, PhD; Jeroen A. W. M. van der Laak, PhD; and the CAMELYON16 Consortium

IMPORTANCE Application of deep learning algorithms to whole-slide pathology images can potentially improve diagnostic accuracy and efficiency.

OBJECTIVE Assess the performance of automated deep learning algorithms at detecting metastases in hematoxylin and eosin–stained tissue sections of lymph nodes of women with breast cancer and compare it with pathologists' diagnoses in a diagnostic setting.

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Related articles page 2211 and page 2250
Supplemental content
CME Quiz at jamanetwork.com/learning and CME Questions page 2252

From Detection of Individual Metastases to Classification of Lymph Node Status at the Patient Level: The CAMELYON17 Challenge

36 Author(s) Péter Bándi ; Oscar Geessink ; Quirine Manson ; Marcory Van Dijk ; Maschenka ··· View All Authors

Abstract
Document Sections
I. Introduction
II. Materials
III. Methods

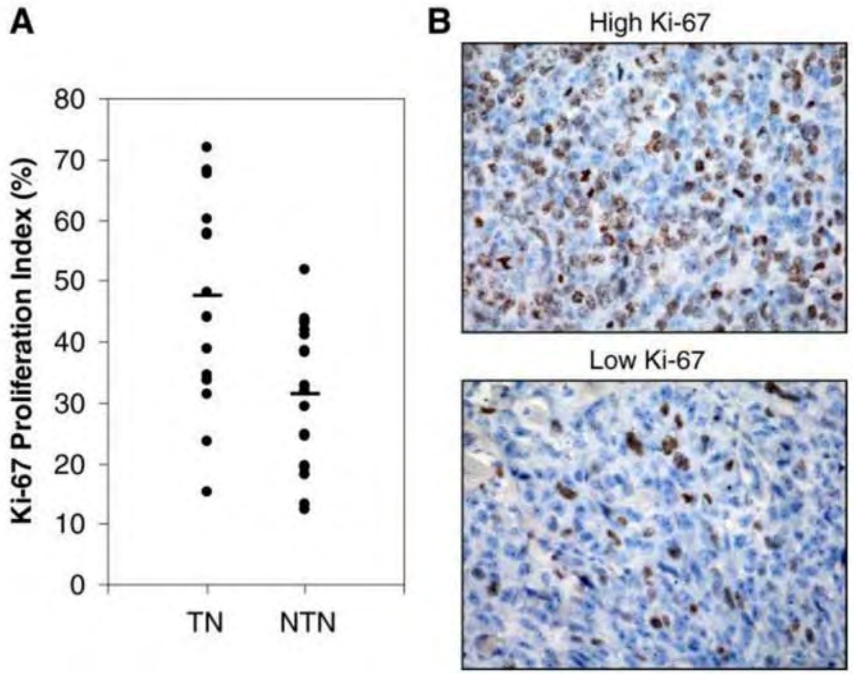
Abstract:
Automated detection of cancer metastases in lymph nodes has the potential to improve the assessment of prognosis for patients. To enable fair comparison between the algorithms for this purpose, we set up the CAMELYON17 challenge in conjunction with the IEEE International Symposium on Biomedical Imaging 2017 Conference in Melbourne. Over 300 participants registered on the challenge website, of which 23 teams submitted a total of 37 algorithms before the initial deadline. Participants were provided with 899 whole-slide images (WSIs) for developing their algorithms. The developed algorithms were evaluated based on the test set encompassing 100 patients and 500 WSIs.

Bejnordi BE *et al. Diagnostic Assessment of Deep Learning Algorithms for Detection of Lymph Node Metastases in Women With Breast Cancer.* JAMA. 2017; 318(22): 2199-2210.
Bandi P *et al. From Detection of Individual Metastases to Classification of Lymph Node Status at the Patient Level: The CAMELYON17 Challenge.* IEEE Trans on Medical Imaging; 38(2): 550-560.

Ki-67 proliferation index computation

Important in patient prognosis after surgery

- High Ki-67 proliferation in tumor cells means that cancers are growing
- Pathologists inspect IHC-stained tissue slides to measure the ratio of DAB-stained cells (brown) over H-stained cells (purple)
- Only cancerous cells should be counted

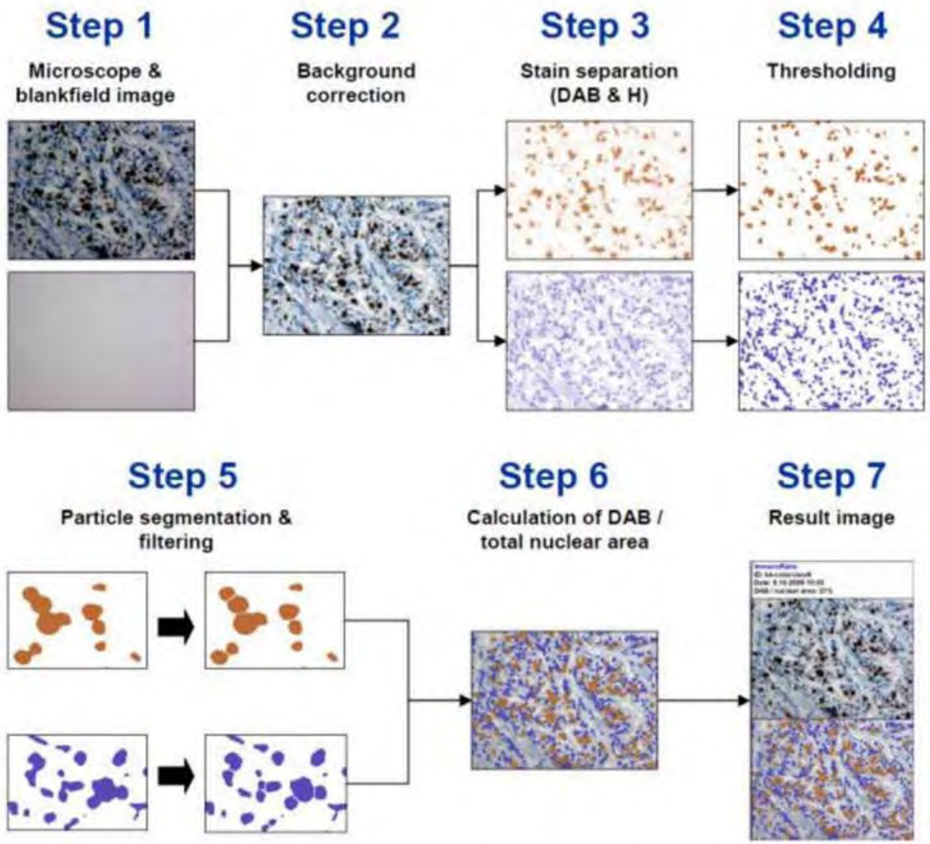


Pillai SKK *et al. Triple-negative breast cancer is associated with EGFR, CK5/6 and c-KIT expression in Malaysian women.* BMC Clinical Pathology 2012; 12: 18.

Ki-67 proliferation index computation: good old method

ImmunoRatio

- Cell-wise segmentation
  - Color channel separation
  - Thresholding to get cell area of interest
- Cell counting
  - Actually, count all pixels in concern (area)
- Prone to color variation

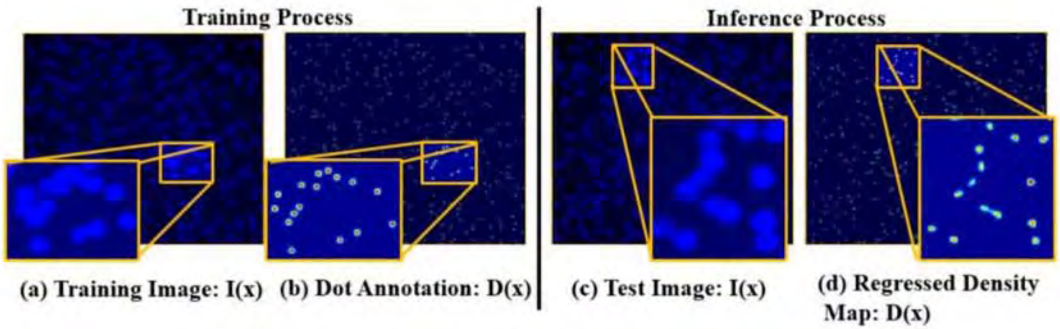


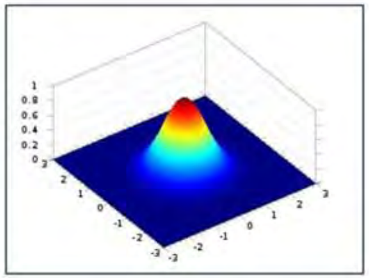
Tuominen VJ *et al. ImmunoRatio: a publicly available web application for quantitative image analysis of estrogen receptor (ER), progesterone receptor (PR), and Ki-67*. Breast Cancer Res. 2010; 12(4): R56

Ki-67 proliferation index computation: deep-learning based

Using fully convolutional regression networks

- Modeling cell images as the mixture of 2D Gaussians
- Structure similar to deep auto-encoder





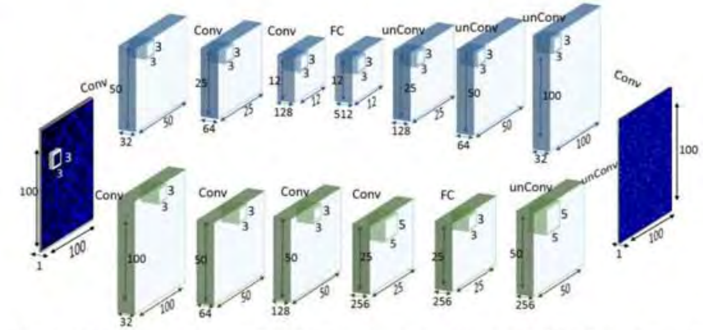


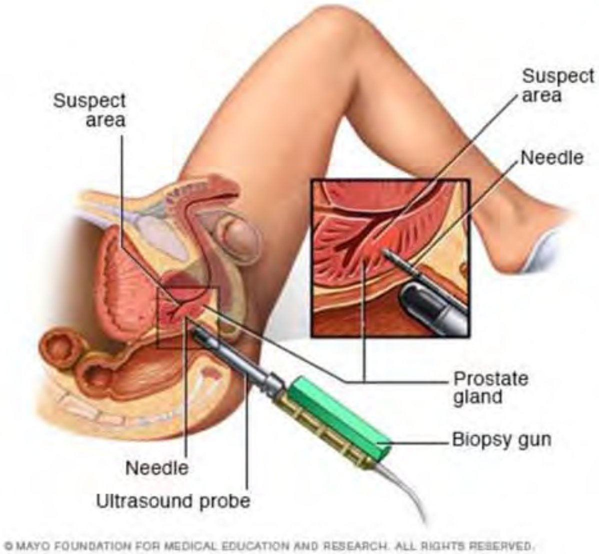
Fig. 2: *Network Structures:* FCRN-A is shown in **blue** & FCRN-B is shown in **green**. In both architectures, we first map the input image to feature maps with dense representation, and then recover the spatial span by bilinear upsampling. **FC** – Fully Connected Layer (Implemented as convolution); **Conv** – Convolutional Layer + ReLU (+ Max Pooling); **unConv** – Upsampling + ReLU + Convolution;

Xie W *et al. Microscopy cell counting and detection with fully convolutional regression networks.* Comput Methods Biomech Biomed Eng Imaging Vis 2016; 6(3): 283-292.

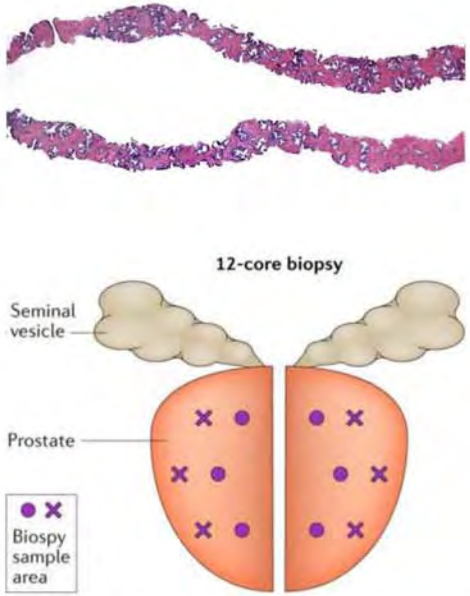
Gleason system based cancer grading

Important in patient treatment decision

- Pathologists inspect H&E stained prostate biopsy slides with light microscopes

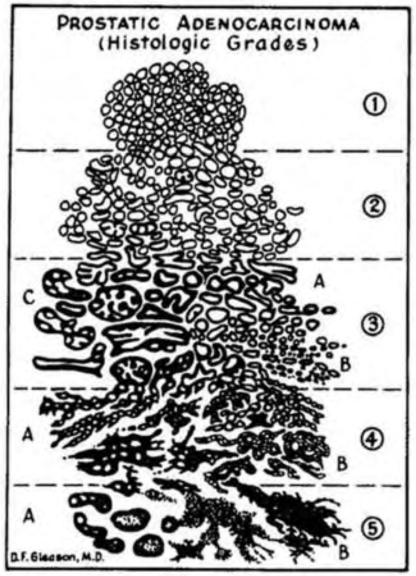


(from: Mayo Clinic homepage)



(from: Sathianathen NJ *et al.*, Nat Rev Urol. 2018)

Gleason Grade



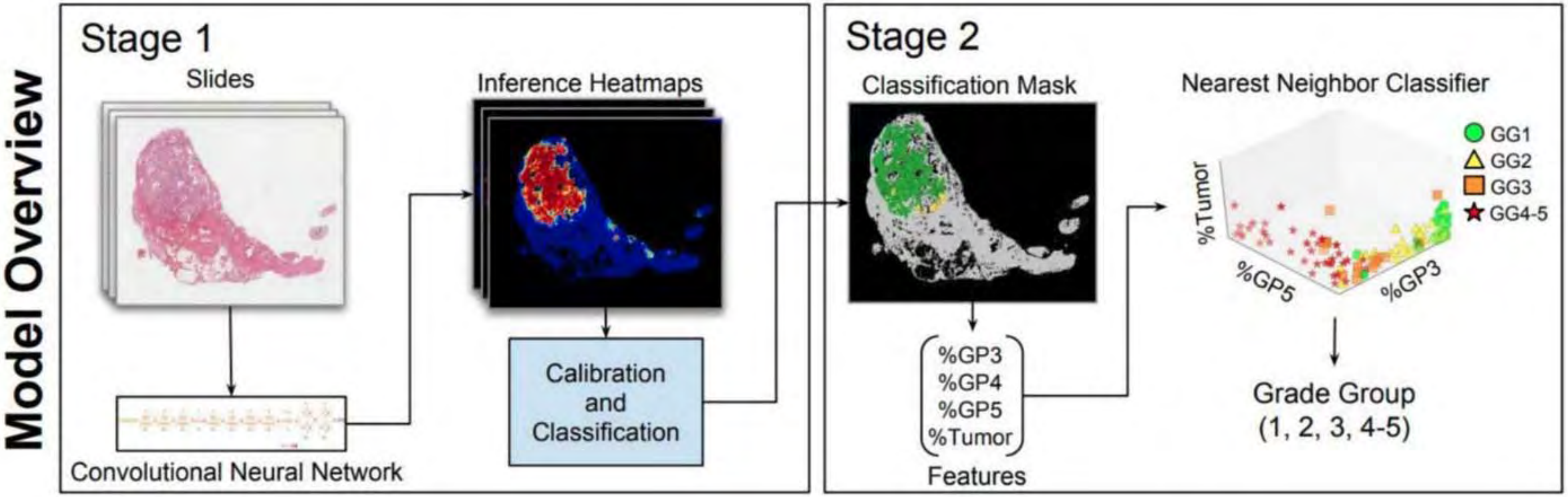
(from: American Urological Association)

Sathianathen *et al.* *Landmarks in prostate cancer*. Nat Rev Urol. 2018; 15(10): 627-642.

Gleason system based cancer grading

Typical approaches

- 1st step: patch-wise cancer area detection
- 2nd step: core-wise decision using the result of 1st step



Nagpal K *et al. Development and Validation of a Deep Learning Algorithm for Improving Gleason Scoring of Prostate Cancer.* arXiv 2018; arXiv:1811.06497.

Take-home message

Pathological diagnosis is very important in the patient treatment.

Digital pathology is largely due to the advance of digital technology;
it can free pathologists from the tedious microscopy work.

Deep learning based pathological diagnosis is a recent research topic.

It is challenging to develop good deep learning models for digital pathology image.

Great results exist for some diseases and tasks, but the future is beyond.

Thank You !!

deep bio