KAERI

딥러닝과 함께하는 최적설계와 시뮬레이션, 원자력분야의 적용사례

한국원자력연구원 유 용균
(ygyu@kaeri.re.kr, yoyogo@gmail.com)

2018.06.22

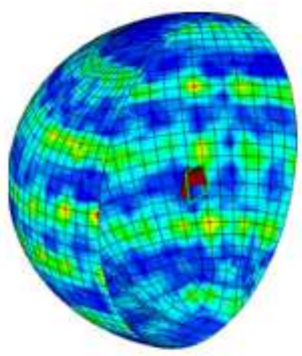
Korea Atomic Energy Research Institute

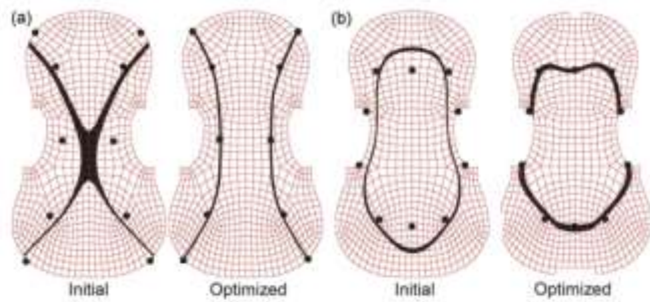
덕업일치를 꿈꾸며..

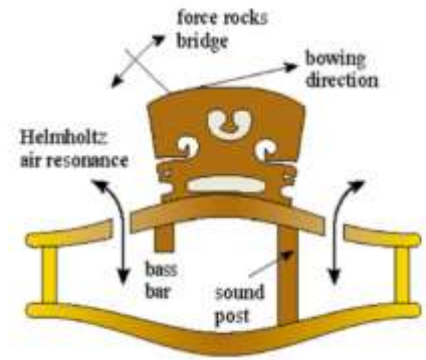
Deep learning for topology optimization design
-연구재단 신진연구과제(2018.3~2020.2)
-KISTI 연구지원사업 (2018.1.1~6.30)
Deep learning based bone microstructure reconstruction
-원자력연구원 기관고유사업(2018.3.21~9.20)
Hall sensor 신호를 이용한 제어봉구동장치 위치지시기 개발

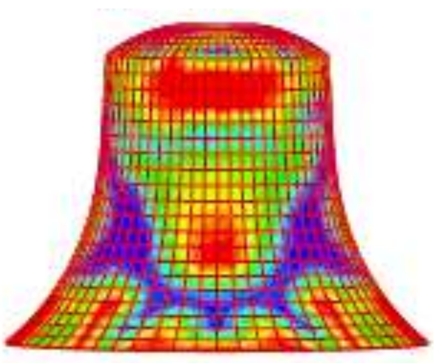
출처:네이버 웹툰 '호랭총각'

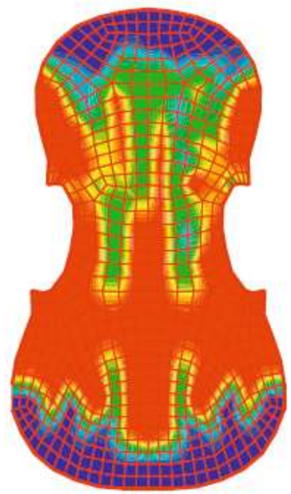
박사학위 주제 (~2010)

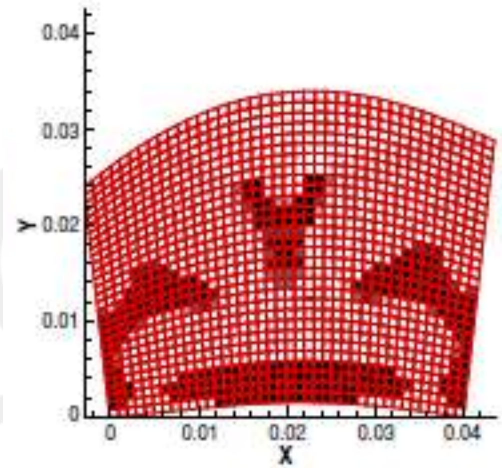












종의 최적설계
(Acoustical Damping & Natural Frequency, 2011)

바이올린 상판의 최적설계
(Natural Frequency & Nodal Line,2010)

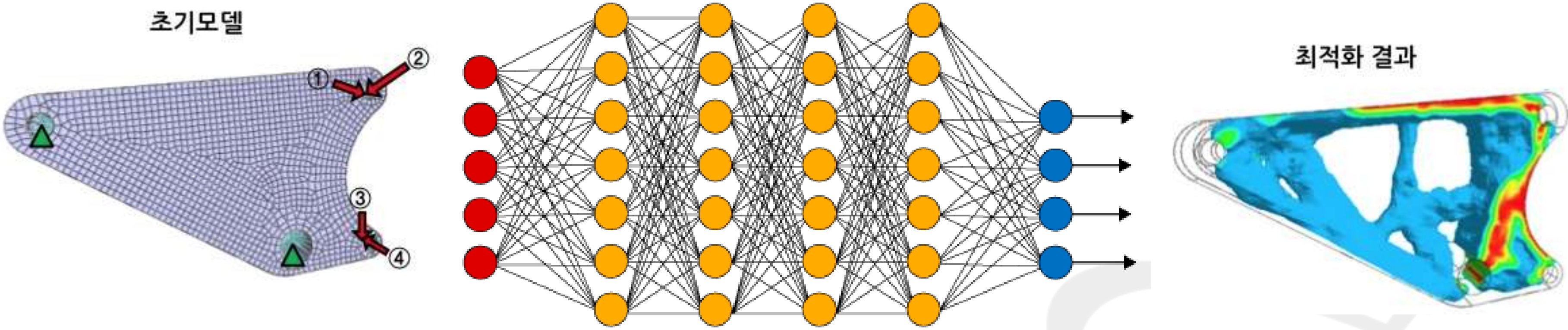
바이올린 브릿지의 위상최적설계
(Natural Frequency & 진동전달 효율,2013)

원자력연구원 (2012~)

Applications of Deep Learning

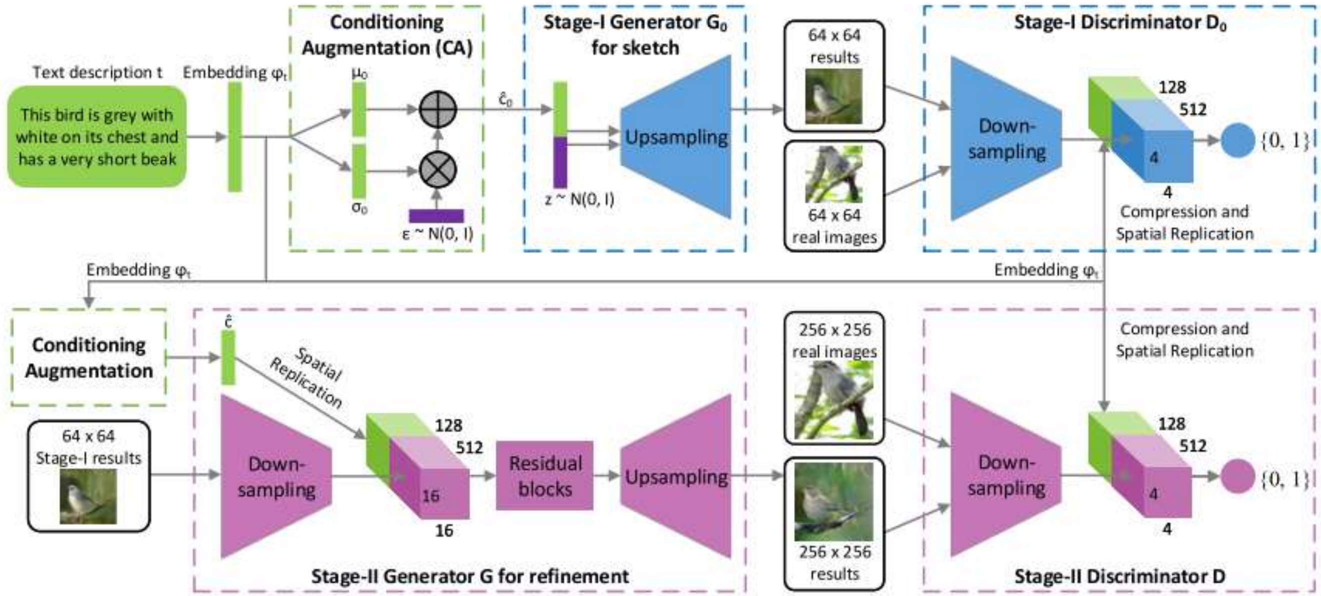
LipNet
(https://www.youtube.com/watch?v=fa5QGremQf8)

AI가 설계를 대신해줄 수 없을까?



Physics Informed Machine Learning

Stack-GAN



Text description	This bird is blue with white and has a very short beak	This bird has wings that are brown and has a yellow belly	A white bird with a black crown and yellow beak	This bird is white, black, and brown in color, with a brown beak	The bird has small beak, with reddish brown crown and gray belly	This is a small, black bird with a white breast and white on the wingbars.	This bird is white black and yellow in color, with a short black beak

Stage-II images

Image-to-Image Translation with Conditional Adversarial Networks

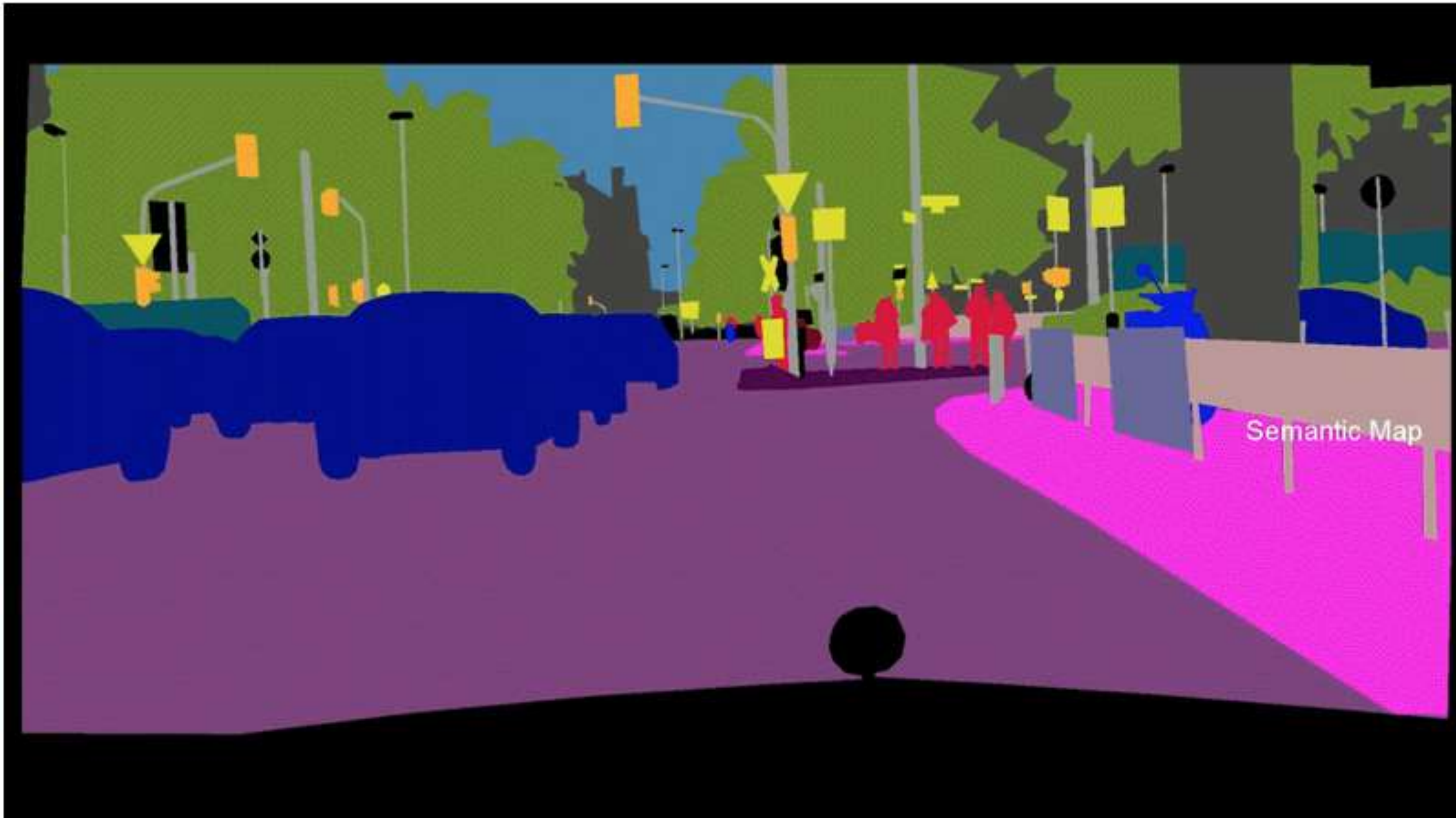
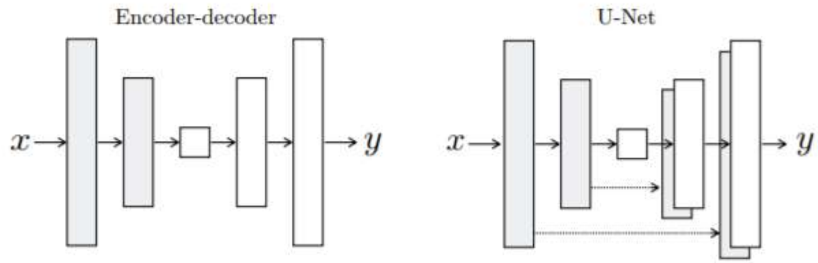
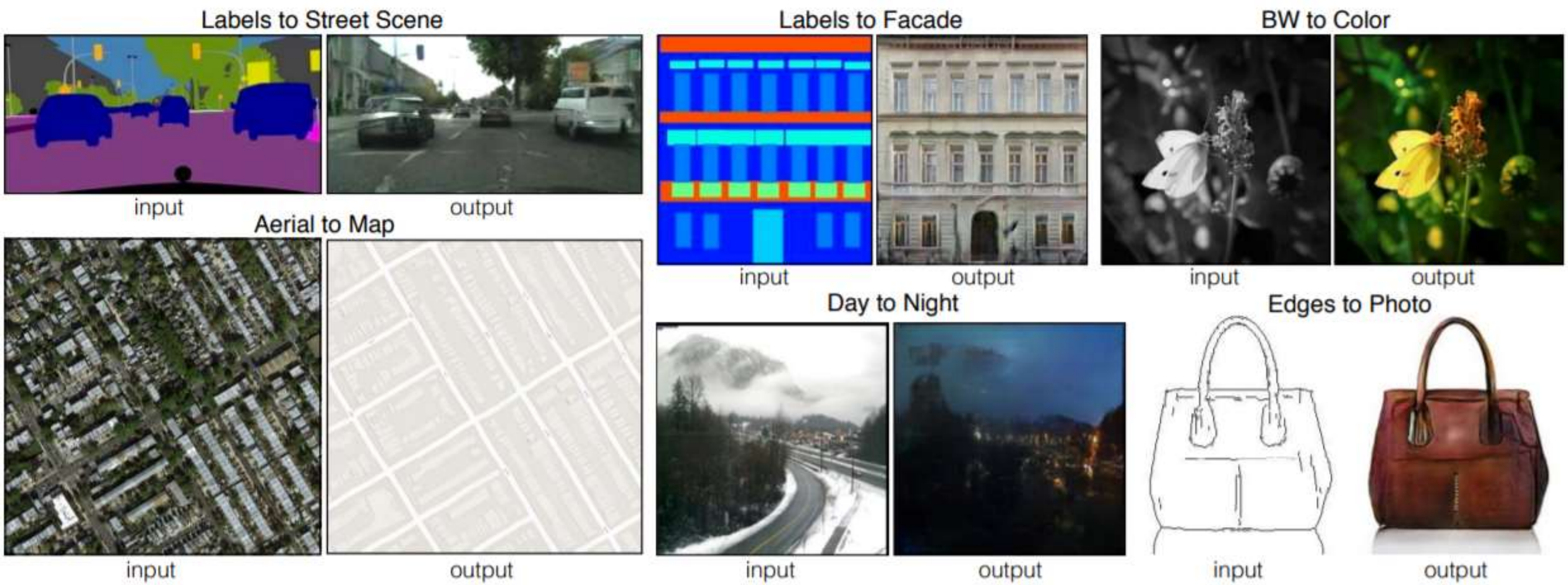


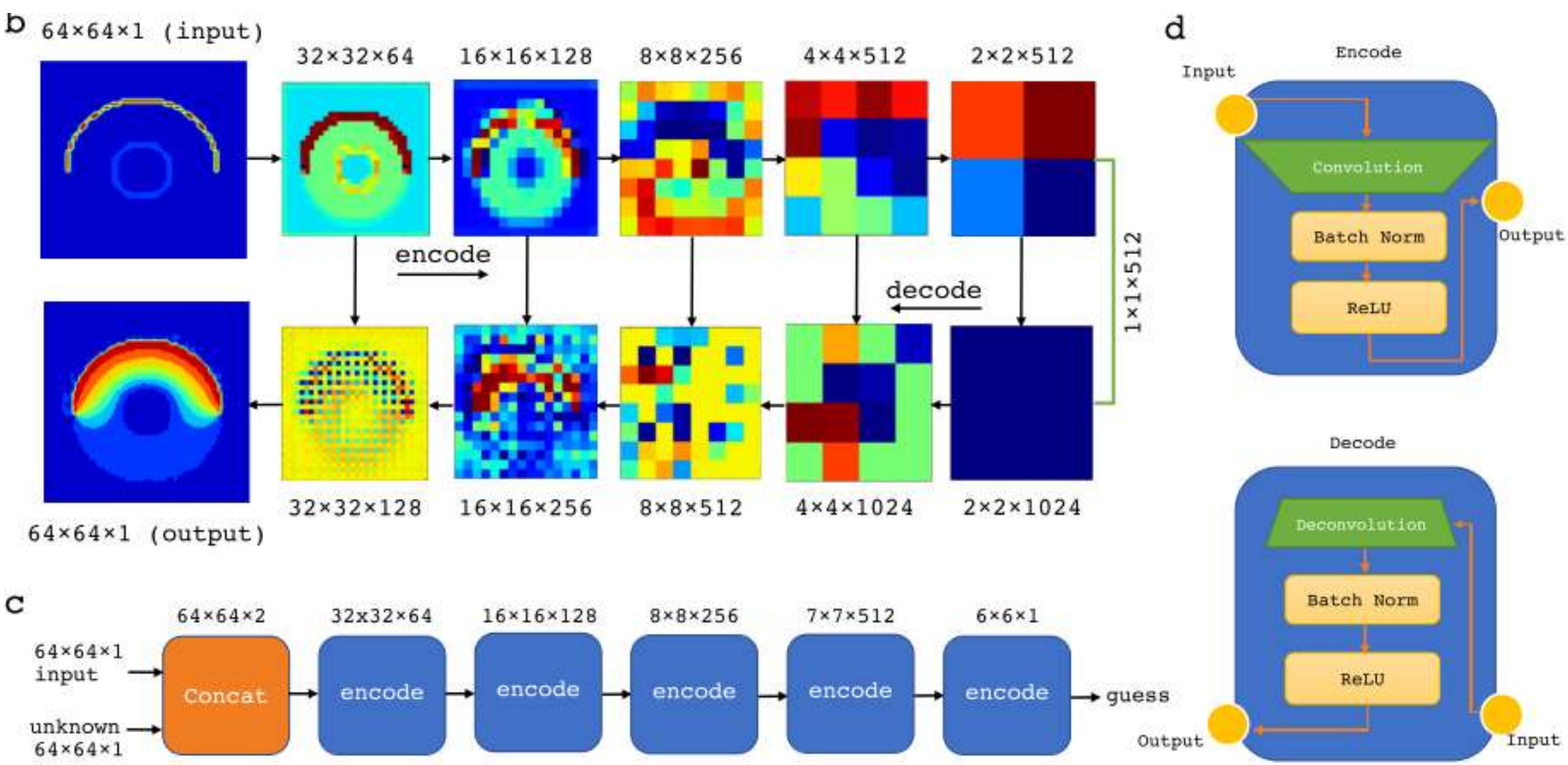
Image-to-Image Translation with Conditional Adversarial Networks

Image-to-Image Translation with Conditional Adversarial Networks





Deep Learning the Physics of Transport Phenomena



Navier-Stokes Equation

$$\rho[\frac{\partial V}{\partial t} + (V.\nabla)V] = -\nabla P + \rho g + \mu\nabla^2 V$$

change of velocity with time

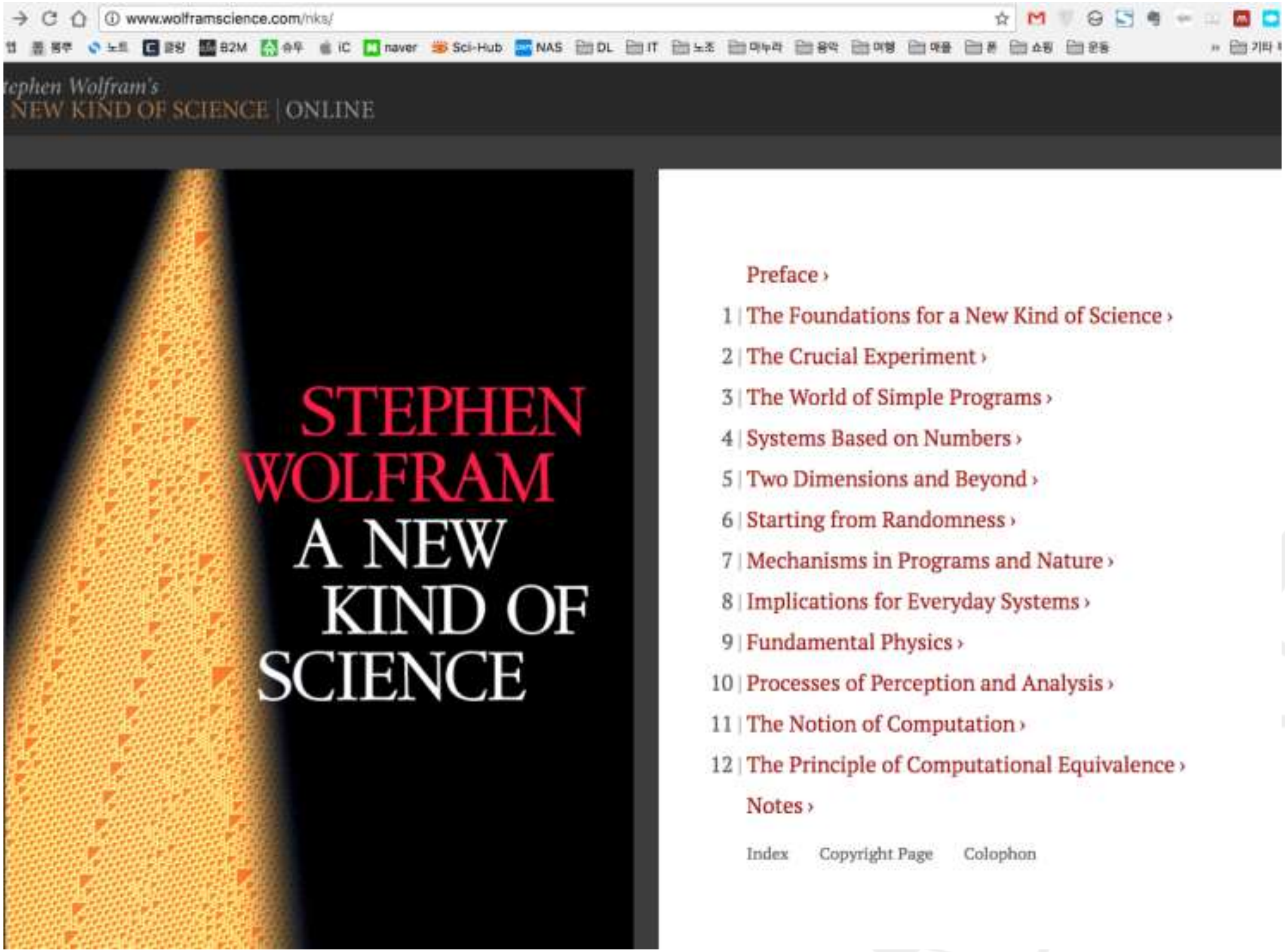
Convective term

Pressure term: Fluid flows in the direction of largest change in pressure

Body force term: external forces that act on the fluid (such as gravity, electromagnetic, etc.)

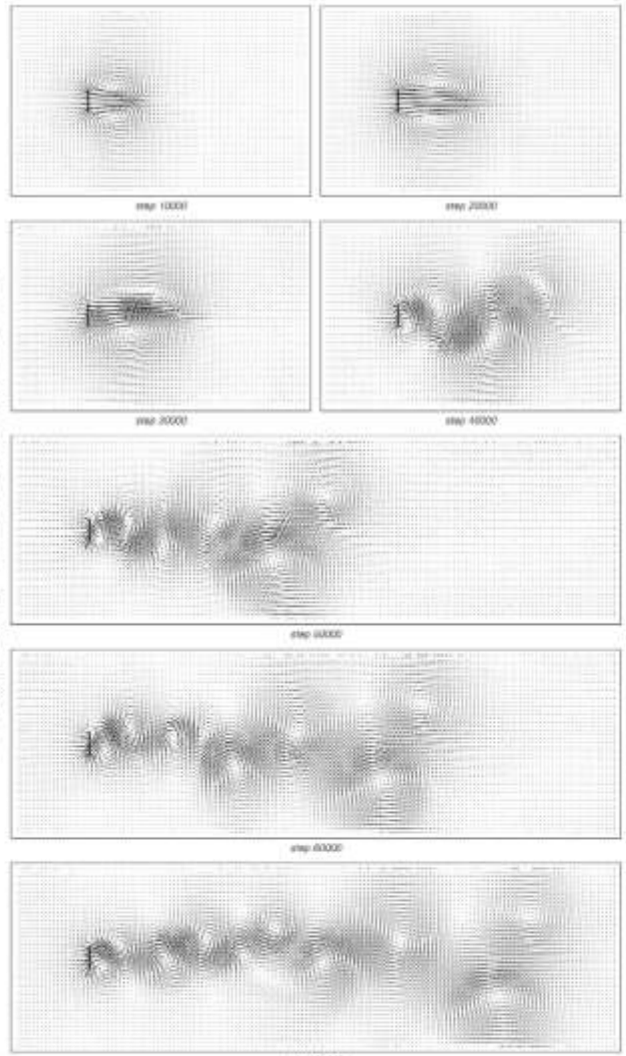
viscosity controlled velocity diffusion term

A New kind of science, Stephen Wolfram

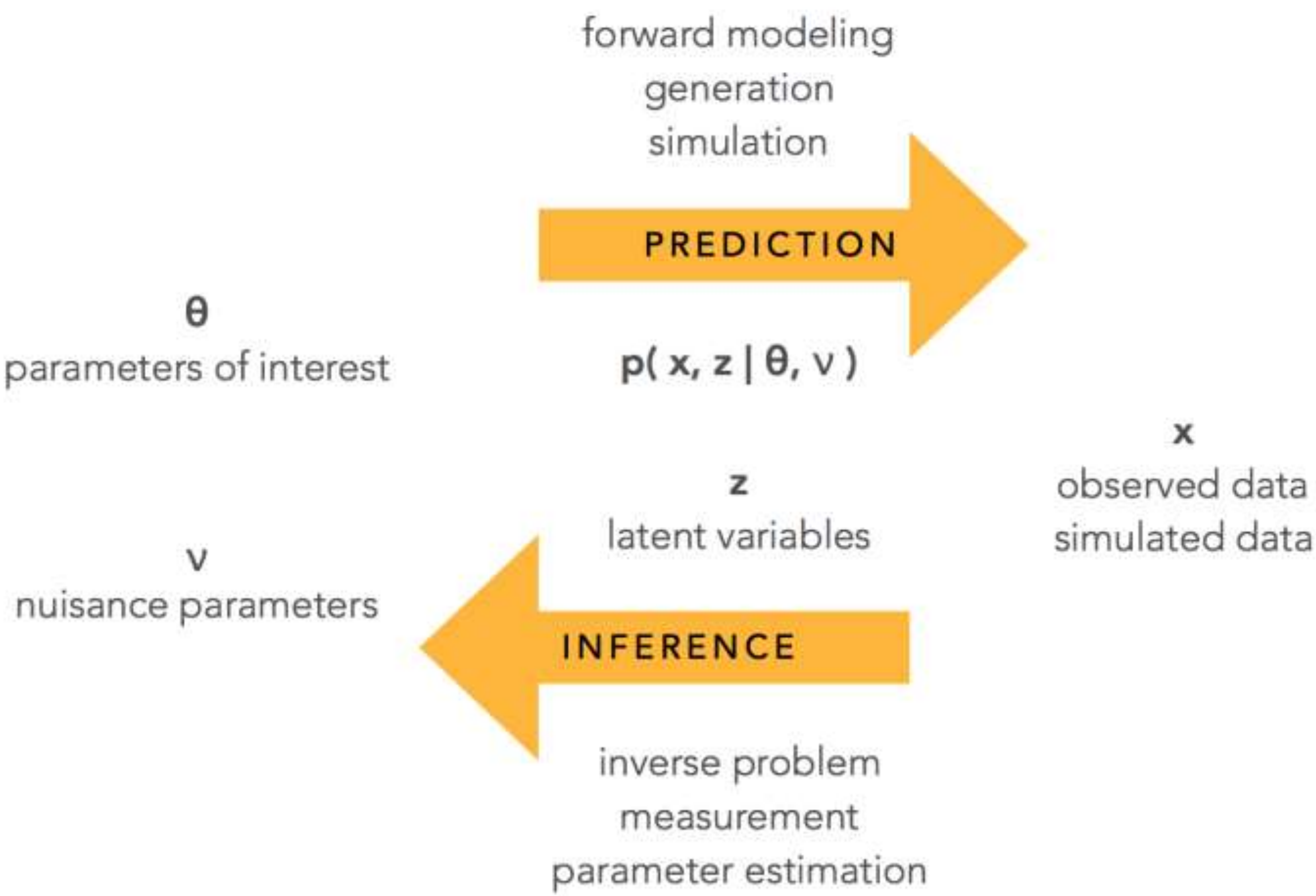


A New kind of science, Stephen Wolfram

A larger example of the cellular automaton system shown on the previous page. In each picture there are a total of 30 million underlying cells. The individual velocity vectors drawn correspond to averages over 20 × 20 blocks of cells. Particles are inserted in a regular way at the left-hand end so as to maintain an overall flow speed equal to about 0.4 of the maximum possible. To make the patterns of flow easier to see, the velocities shown are transformed so that the fluid is on average at rest, and the plate is moving. The underlying density of particles is approximately 1 per cell, or 1/6 the maximum possible—a density which more or less minimizes the viscosity of the fluid. The Reynolds number of the flow shown is then approximately 100. The agreement with experimental results on actual fluid flows is striking.

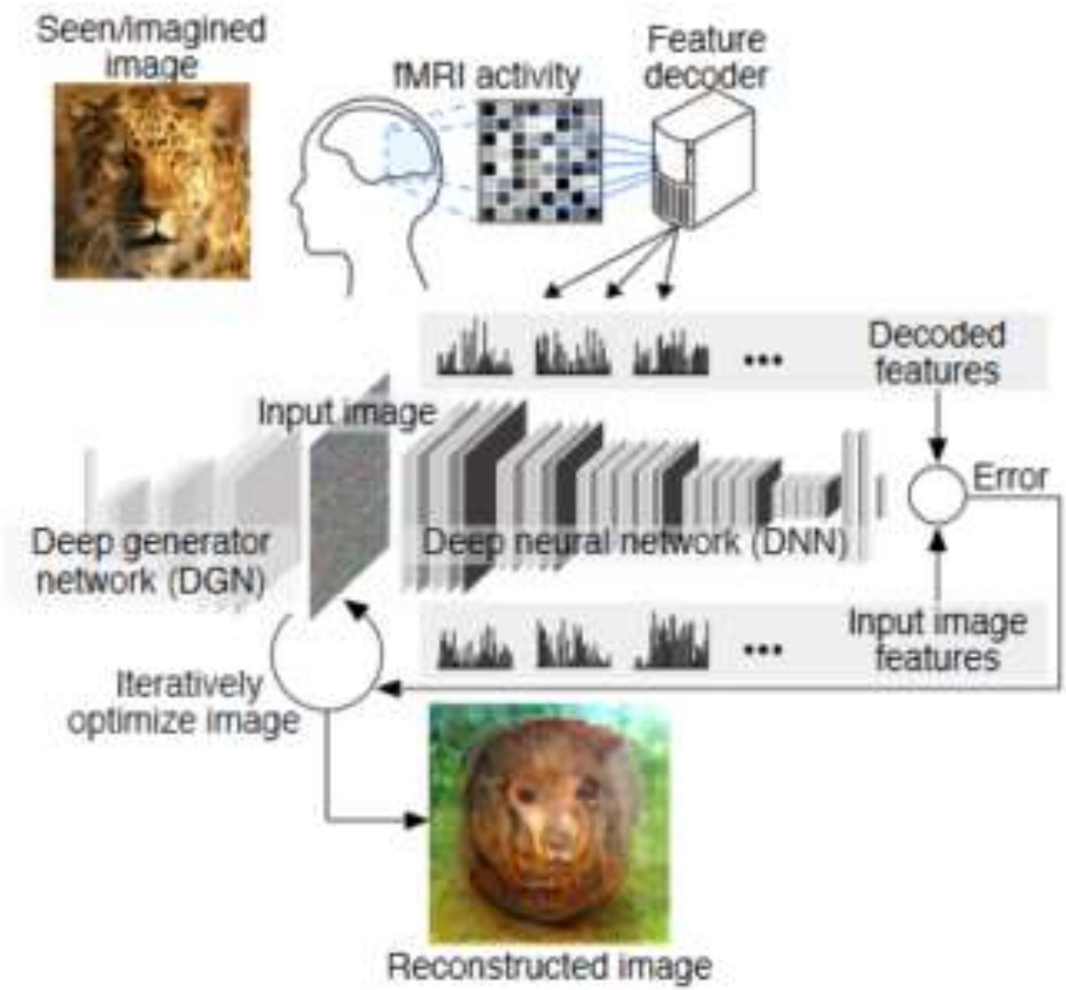


딥러닝을 이용한 물리현상 분석



http://helper.ipam.ucla.edu/publications/dlt2018/dlt2018_14649.pdf

fMRI to Image



뇌의 동작
원리를 꼭
알아야 할까요?

https://www.biorxiv.org/content/biorxiv/early/2017/12/30/240317.full.pdf

Solving the Quantum Many-Body Problem with Artificial Neural Networks

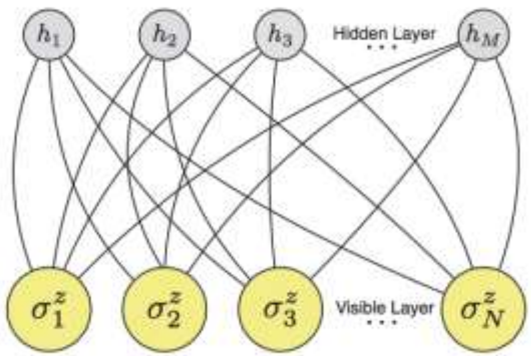
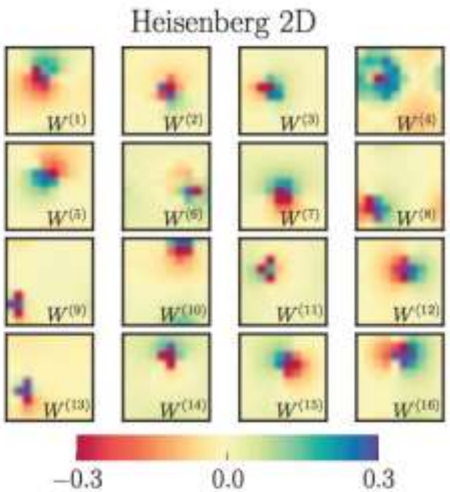


Fig. 1. Artificial neural network encoding a many-body quantum state of N spins. A restricted Boltzmann machine architecture that features a set of N visible artificial neurons (yellow dots) and a set of M hidden neurons (gray dots) is shown. For each value of the many-body spin configuration $\mathcal{S} = (\sigma_1^z, \sigma_2^z, \ldots, \sigma_N^z)$, the artificial neural network computes the value of the wave function $\Psi(\mathcal{S})$.



- 물질의 양자상태(스핀 등)가 어떻게 되는지 시뮬레이션하는 것은 물질 구성에 좀 더 깊은 이해를 줌.
- 기본적으로 물질은 Many-body System인데, 이들 사이의 상호작용으로 나타는 물질의 상태를 시뮬레이션하는 것은 시간과 컴퓨팅 파워가 무척이나 많이 필요함.
- Deep learning을 이용하여 물질의 양자상태에 대한 시뮬레이션을 진행.

Physics & Machine Learning

< physics | machine learning >

Articles News Papers

Papers

The following are recent papers combining the fields of physics—especially quantum mechanics—and machine learning. Please email Roger Melko or Miles Stoudenmire if you would like to see a paper added to this page.

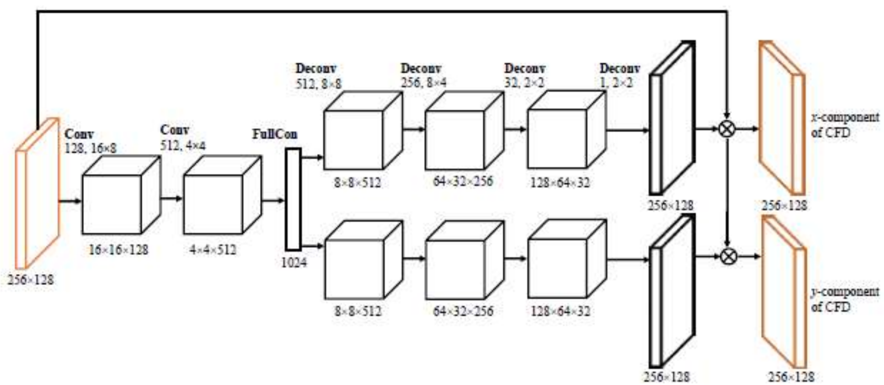
Applying Machine Learning to Physics

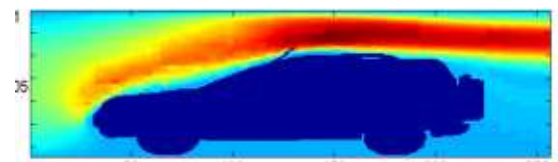
- "Bypassing the Kohn-Sham equations with machine learning", Felix Brockherde, Leslie Vogt, Li Li, Mark E. Tuckerman, Kieron Burke & Klaus-Robert Müller, Nature Comm. 8 872, Oct 2017
- "Learning Disordered Topological Phases by Statistical Recovery of Symmetry", Nobuyuki Yoshioka, Yutaka Akagi, Hosho Katsura, arxiv:1709.05790, Sept 2017
- "Restricted-Boltzmann-Machine Learning for Solving Strongly Correlated Quantum Systems", Yusuke Nomura, Andrew Darmawan, Youhei Yamaji, Masatoshi Imada, arxiv:1709.06475, Sept 2017
- "Identifying Product Order with Restricted Boltzmann Machines", Wen-Jia Rao, Zhenyu Li, Qiong Zhu, Mingxing Luo, Xin Wan, arxiv:1709.02597, Sept 2017
- "Machine learning & artificial intelligence in the quantum domain", Vedran Dunjko, Hans J. Briegel, arxiv:1709.02779, Sept 2017
- "Phase Diagrams of Three-Dimensional Anderson and Quantum Percolation Models by Deep Three-Dimensional Convolutional Neural Network", Tomohiro Mano, Tomi Ohtsuki, arxiv:1709.00812, Sept 2017
- "Machine Learning Spatial Geometry from Entanglement Features", Yi-Zhuang You, Zhao Yang, Xiao-Liang Qi, arxiv:1709.01223, Sept 2017
- "Machine Learning Topological Invariants with Neural Networks", Pengfei Zhang, Huitao Shen, Hui Zhai, arxiv:1708.09401, Aug 2017
- "Extensive deep neural networks", Iryna Luchak, Kyle Mills, Kevin Ryczko, Adam Domurad, Isaac Tamblyn, arxiv:1708.06686, Aug 2017
- "Learning Fermionic Critical Points", Natanael C. Costa, Wenjian Hu, Z. J. Bai, Richard T. Scalettar, Rajiv R. P. Singh, arxiv:1708.04762, Aug 2017
- "Deep Learning the Ising Model Near Criticality", Alan Morningstar, Roger G. Melko, arxiv:1708.04622, Aug 2017
- "Spectral Learning of Restricted Boltzmann Machines", Aurélien Decelle, Giancarlo Fissore, Cyril Furtlehner, arxiv:1708.02917, July 2017
- "Solving the Bose-Hubbard model with machine learning", Hiroki Saito, arxiv:1707.09723, July 2017
- "Quantum dynamics in transverse-field Ising models from classical networks", Markus Schmitt, Markus Heyl, arxiv:1707.06656, July 2017
- "Learning the Einstein-Podolsky-Rosen correlations on a Restricted Boltzmann Machine", Steven Weinstein, arxiv:1707.03114, July 2017
- "Quantum phase recognition via unsupervised machine learning", Peter Broecker, Fakher F. Assaad, Simon Trebst, arxiv:1707.00663, July 2017
- "Deep neural networks for direct, featureless learning through observation: the case of 2d spin models", K. Mills, I. Tamblyn, arxiv:1706.09779, June 2017
- "Inverse Ising inference by combining Ornstein-Zernike theory with deep learning", Alpha A. Lee, arxiv:1706.08466, June 2017
- "Machine Learning Studies of Frustrated Classical Spin Models", Ce Wang, Hui Zhai, arxiv:1706.07977, June 2017
- "Self-Learning Phase Boundaries by Active Contours", Ye-Hua Liu, Evert P.L. van Nieuwenburg, arxiv:1706.08111, June 2017
- "Machine-learning-assisted correction of correlated qubit errors in a topological code", P. Baireuther, T. E. O'Brien, B. Tarasinski, C. W. J. Beenakker, arxiv:1705.07855, May 2017
- "Self-Learning Monte Carlo Method: Continuous-Time Algorithm", Yuki Nagai, Huitao Shen, Yang Qi, Junwei Liu, Liang Fu, arxiv:1705.06724, May 2017
- "Criticality & Deep Learning I: Momentum Renormalisation Group", Dan Oprisa, Peter Toth, arxiv:1705.11023, May 2017
- "Construction of Hamiltonians by machine learning of energy and entanglement spectra", Hiroyuki Fujita, Yuya O. Nakagawa, Sho Sugiura, Masaki

https://physicsml.github.io/pages/papers.html

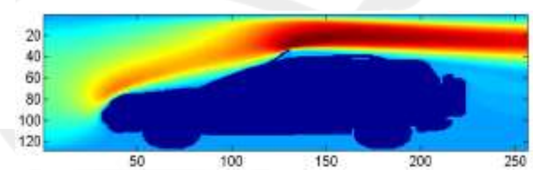
Convolutional Neural Networks for Steady Flow Approximation

$$y=f'(x)$$





CNN Prediction

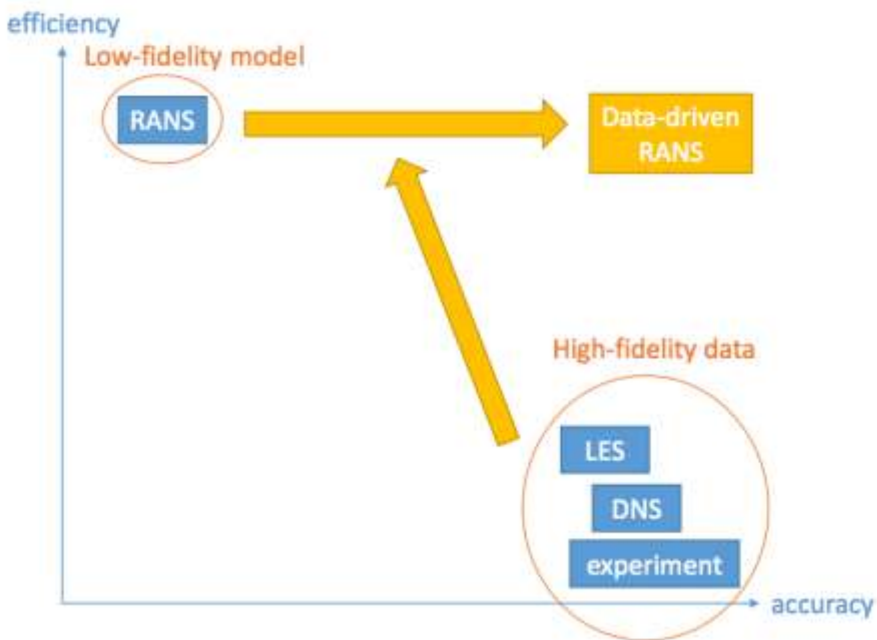


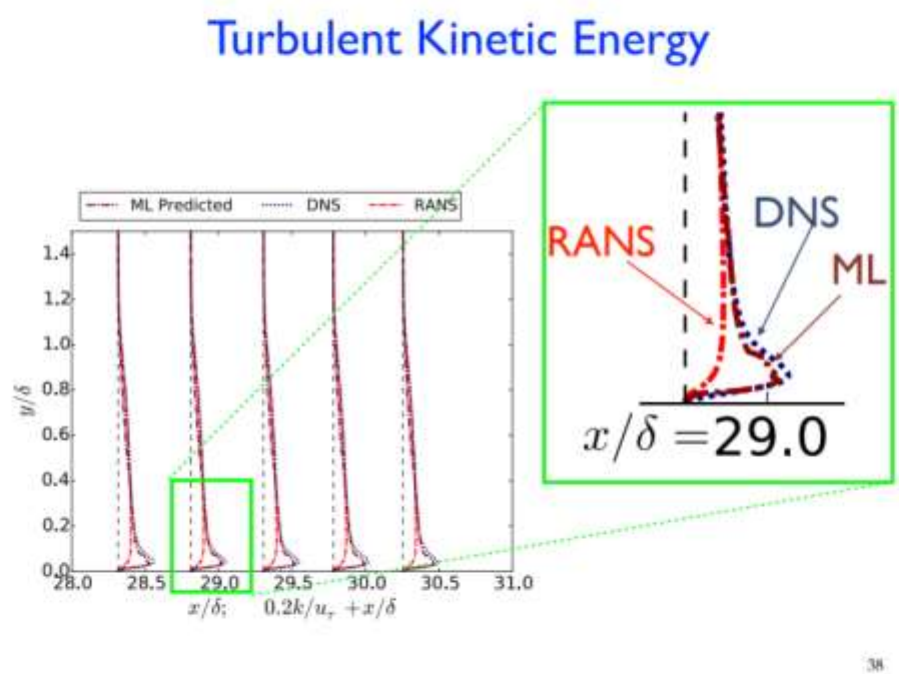
LBM

https://www.biorxiv.org/content/biorxiv/early/2017/12/30/240317.full.pdf

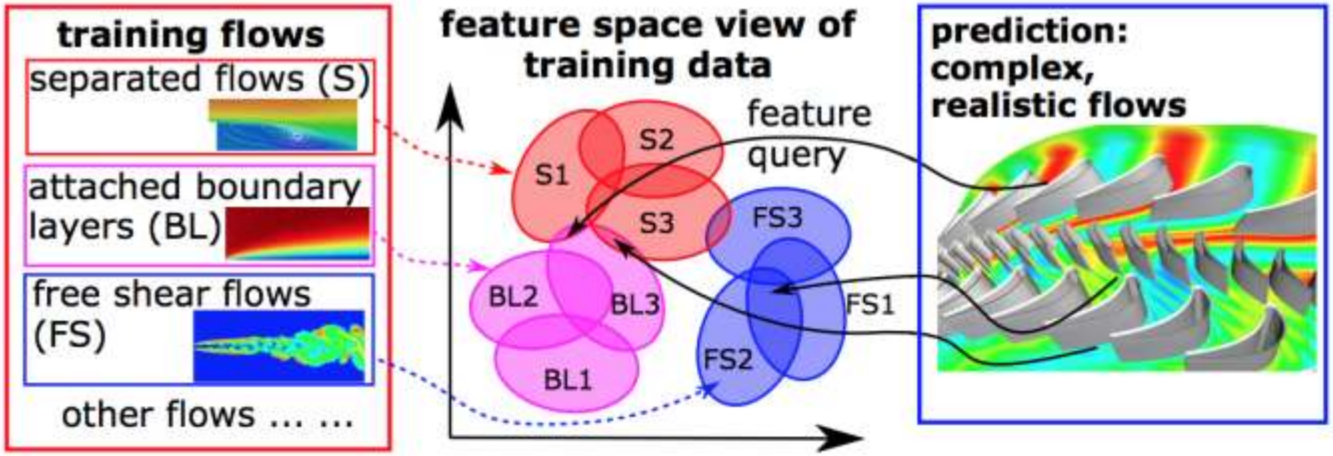
Duraisamy, A comprehensive physics-informed machine learning framework for predictive turbulence modeling

$$y = f(x) + f'(x)$$





Feature Space View



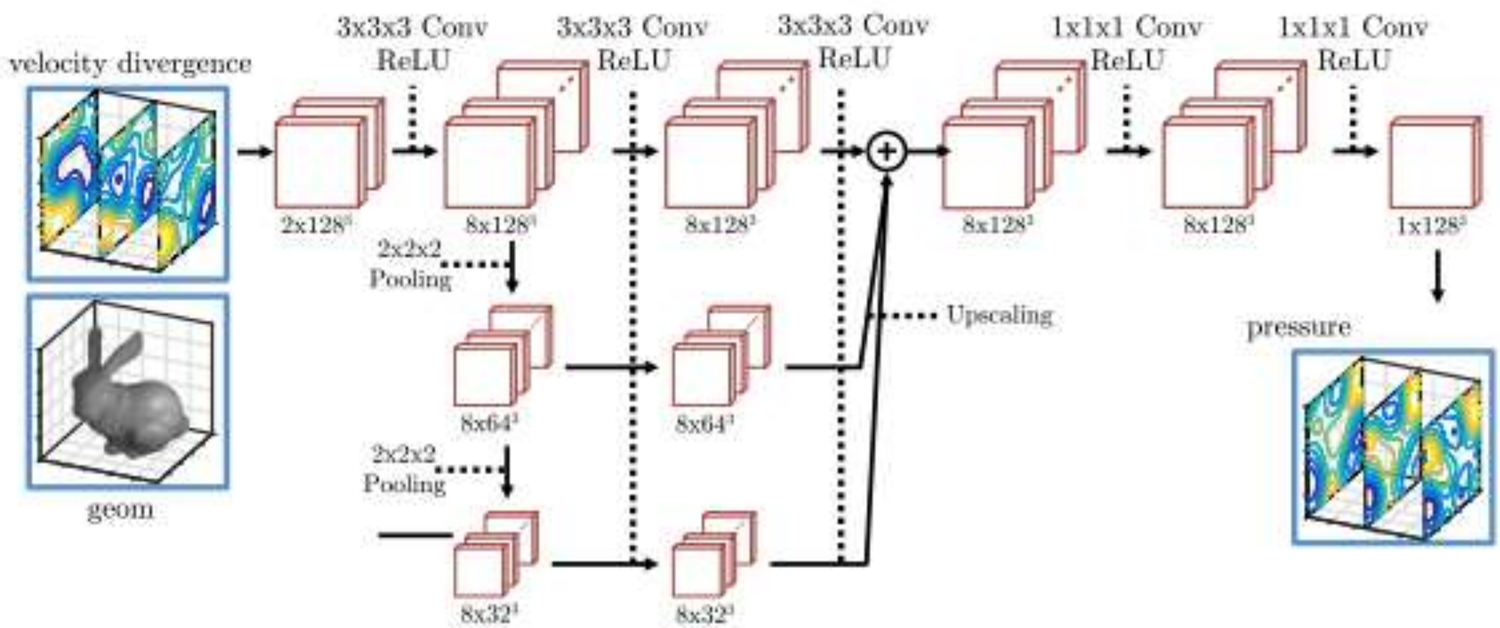
Addressing Dr. Menter's concerns on ML:

- Data-driven models are constructed as "add-on" (patch) for traditional models, by developers.
- The database and the machine learning are built into the model; not constructed by the users.

Heng Xiao and Jinlong Wu , Towards A Physics-Informed Machine Learning Framework for Predictive Turbulence Modeling

Accelerating Eulerian Fluid Simulation with Convolutional Networks

$$y = g(f'(x))$$



Machine Learning + Computational Mechanics

Archives of Computational Methods in Engineering (I.F > 5.0!!!)

<u>Special Issue :</u> Machine Learning in Computational Mechanics

11 Result(s) for '"S.I.: Machine Learning in Computational Mechanics"'

Sort By Relevance | Date Published

Article

Big Data in Experimental Mechanics and Model Order Reduction: Today's Challenges and Tomorrow's Opportunities

Since the turn of the century experimental solid mechanics has undergone major changes with the generalized use of images. The number of acquired data has literally exploded and one of today's challenges is re...

Jan Neggers, Olivier Allix, François Hild... in *Archives of Computational Methods in Engin...* (2018)

Article

Nonlinear Shape-Manifold Learning Approach: Concepts, Tools and Applications

In this paper, we present the concept of a "shape manifold" designed for reduced order representation of complex "shapes" encountered in mechanical problems, such as design optimization, springback or image co...

Liang Meng, Piotr Breitkopf... in *Archives of Computational Methods in Engin...* (2018)

Article

A Manifold Learning Approach to Data-Driven Computational Elasticity and Inelasticity

Standard simulation in classical mechanics is based on the use of two very different types of equations. The first one, of axiomatic character, is related to balance laws (momentum, mass, energy, ...), whereas...

Rubén Ibañez, Emmanuelle Abisset-Chavanne... in *Archives of Computational Methods in Engin...* (2018)

Article

Background Information of Deep Learning for Structural Engineering

Since the first journal article on structural engineering applications of neural networks (NN) was published, there have been a large number of articles about structural analysis

사회

세종대 이승혜 교수, '딥러닝 논문' 세계적 공학저널 등재 쾌거

건축분야에 '딥러닝 기법' 도입 방법 연구해 성과 인정받아

홍승표 기자

승인 2017.07.25 17:59:03

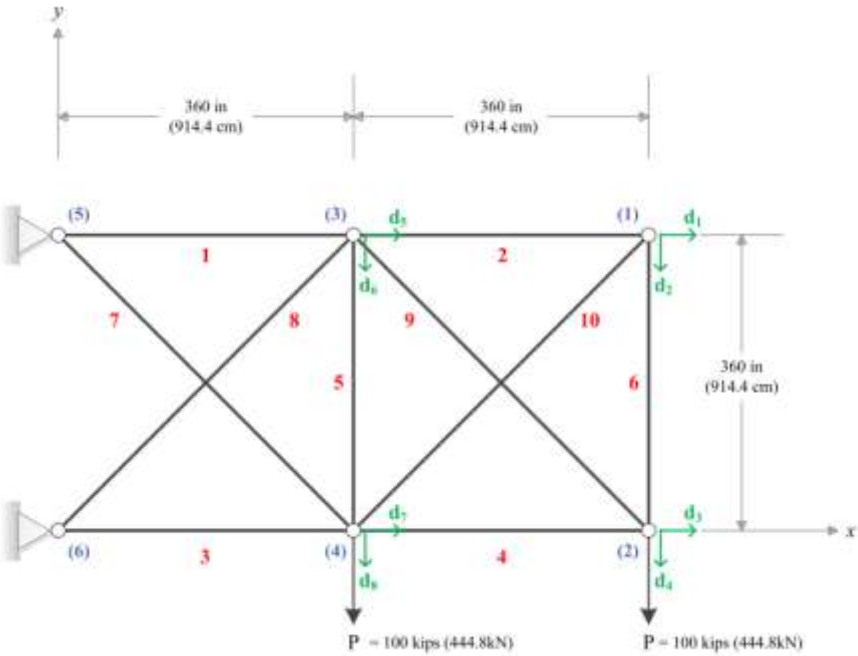
(서울=국제뉴스) 홍승표 기자 = 세종대학교 이승혜 교수(건축공학과)의 연구논문이 세계적인 융합수학분야 저널에 게재되는 쾌거를 이뤘다.

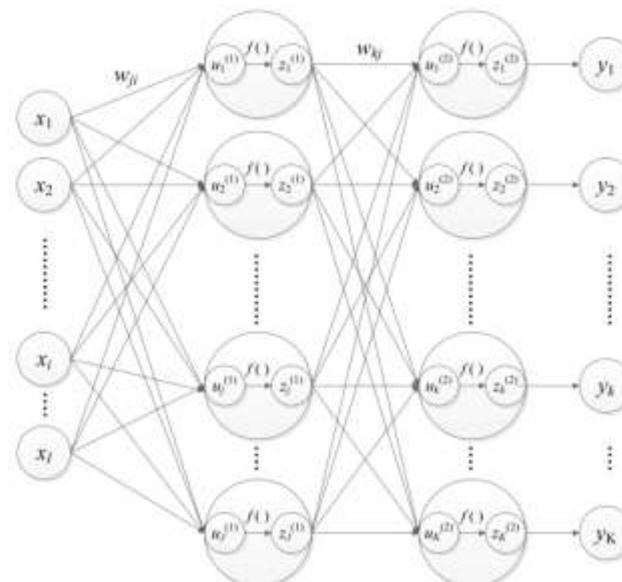
▲ 세종대학교 건축공학과 이승혜 교수 <사진제공/세종대학교>

세종대 측은 "이승혜 교수의 논문인 '구조공학을 위한 딥러닝 기법의 기반 정보(Background Information of Deep Learning for Structural Engineering)'가 지난 3월 '전산기법 공학 저널(Archives of Computational Methods in Engineering)'에 온라인으로 게재됐다"고 밝혔다.

전산기법 공학 저널은 캐나다의 세계적 지식정보 서비스 그룹인 '톰슨로이터'에서 제공하는 'JCR Impact Factor' 기준 융합수학분야 100개 저널 가운데 최고로 꼽히는 저널이다.

Lee, et. al, Background Information of Deep Learning for Structural Engineering





https://link.springer.com/search?query=%22S.I.%3A+Machine+Learning+in+Computational+Mechanics%22

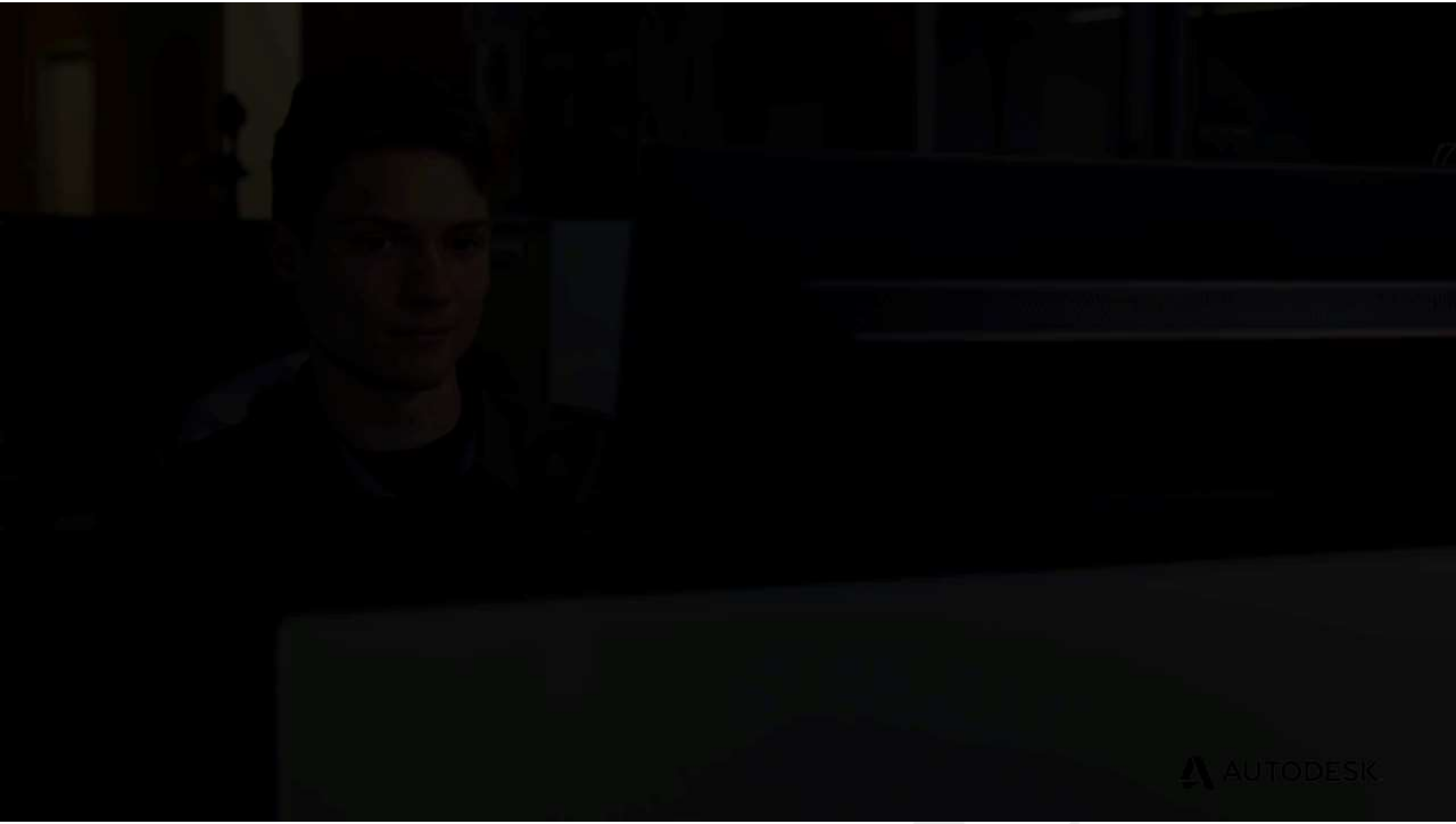
Deep Learning for Topology Optimization Design

Where Is AI Headed in 2018?

"딥러닝은 엔지니어링 시뮬레이션 및 설계 혁명을 일으킬 것이다." - GE 리서치 수석 정보 과학자 마크 에드가(Marc Edgar)

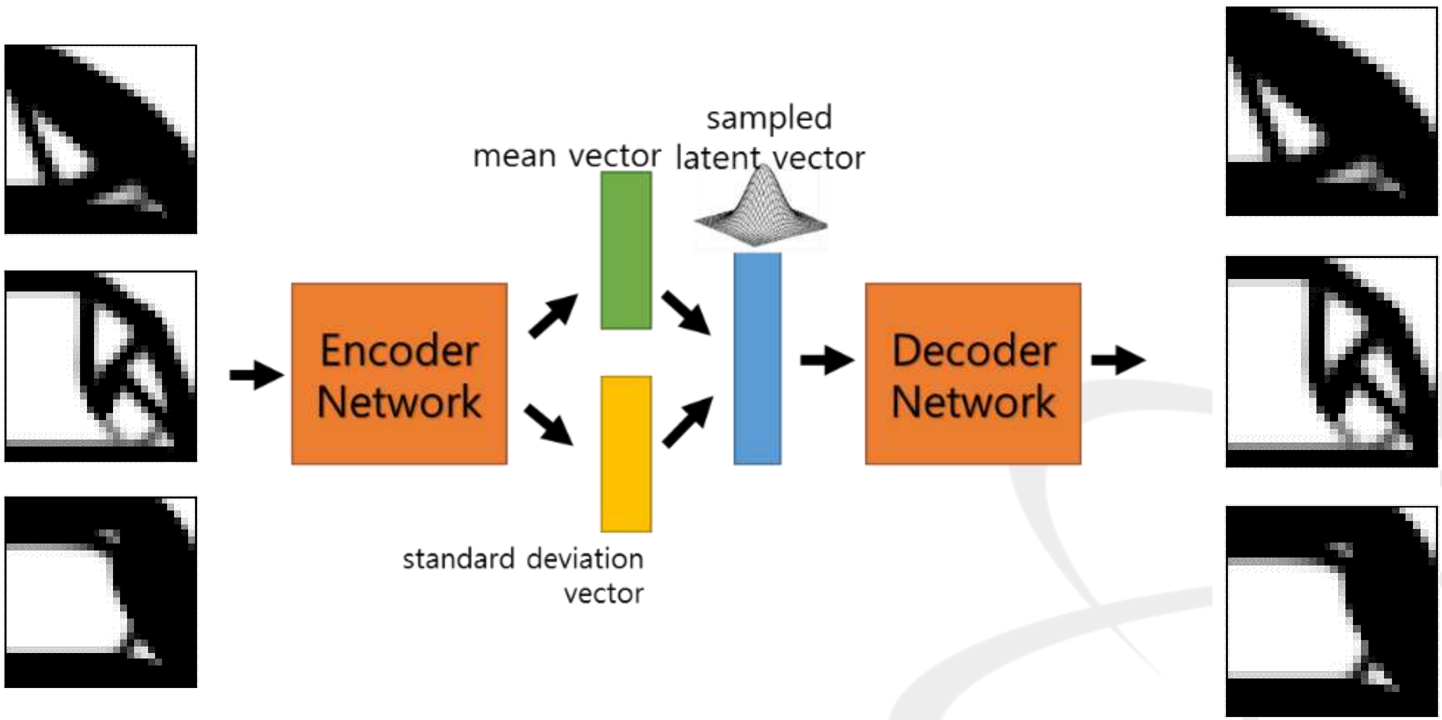
2018 년은 엔지니어링 시뮬레이션 및 설계의 혁신을 시작하는 한해가 될 것이다. 향후 3 ~ 5 년 동안 딥러닝은 제품의 기능, 성능 및 비용 면에서 혁신적인 패러다임을 창출하기 위해 수년에서 수개월 걸리던 제품 개발을 수 주 또는 수일 만에 가속화 할 것이다.“

Autodesk Generative Design

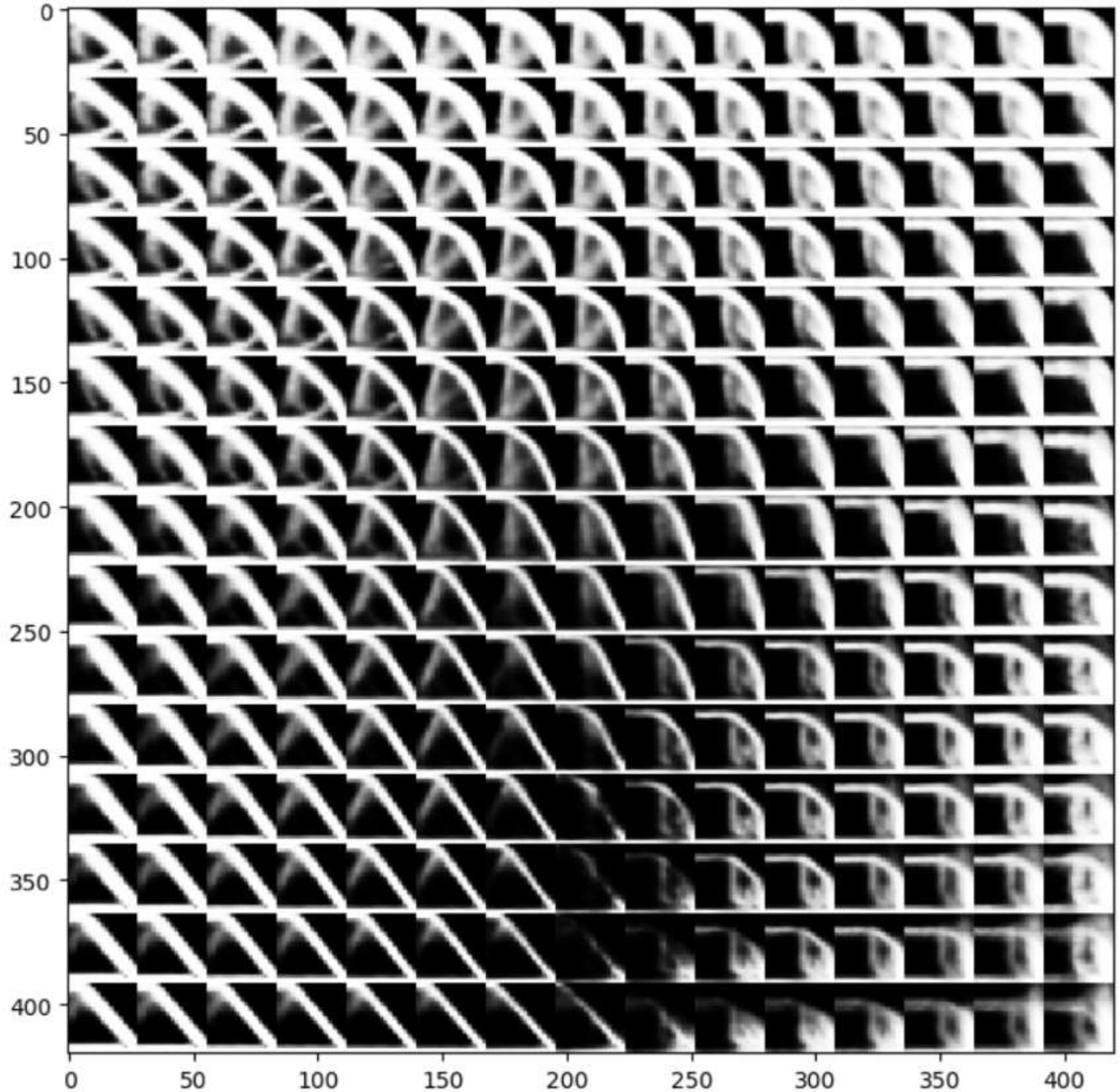


Unsupervised Learning of Topology Optimization Results

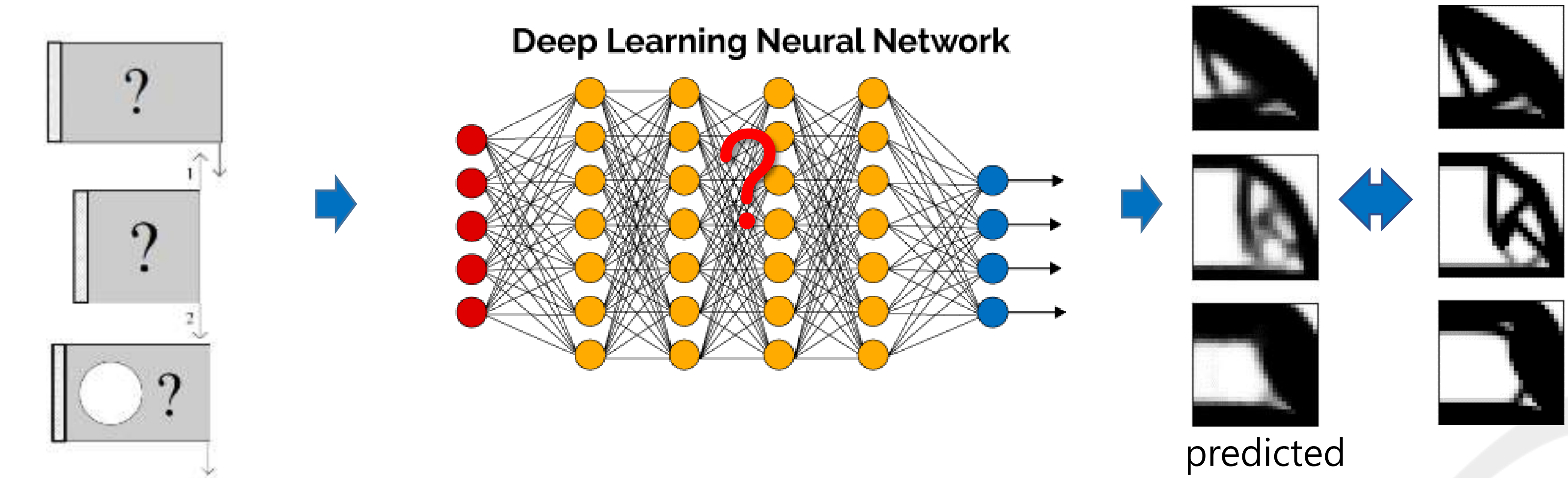
가능한 적은 수의 변수로 구조를 표현할 수 있는가?

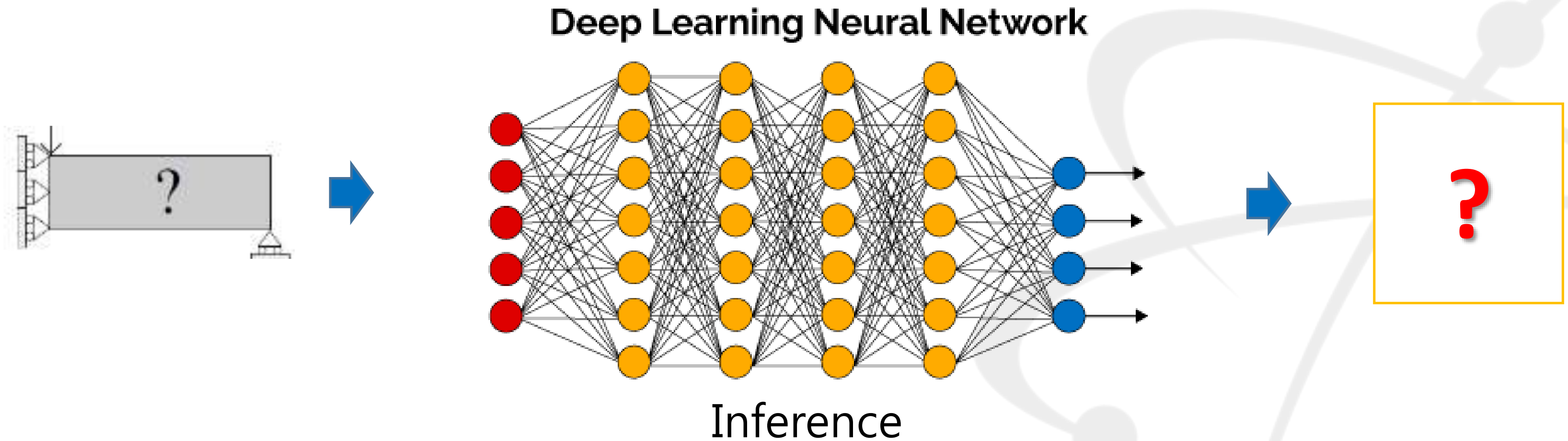


2개의 잠재변수로 표현한 구조

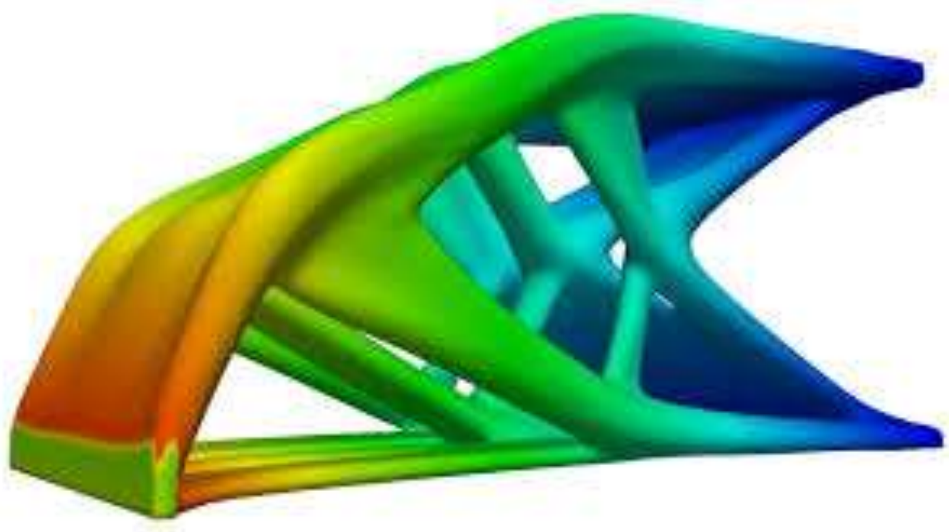


Deep Learning for Topology Optimization Design





Deep Learning for 3D Topology Optimization Design



https://www.math.uni-trier.de/~schmidt/gputop.html#./gputop_files/cantilever.jpg

Hybrid Approach?

$$y=g(x) \quad \Leftrightarrow \quad y=g'(x)$$

Conventional Modeling	Data-driven modeling
Differential equation	Functions trained with data
Numerical simulation	Training time required
Slow, large memory	Faster, small memory
Difficult non-linear modeling	Non-linear modeling
Difficult to optimize	Easy Optimization

박문규, Simulation Environment, Big Data and Ai in Nuclear Enginee

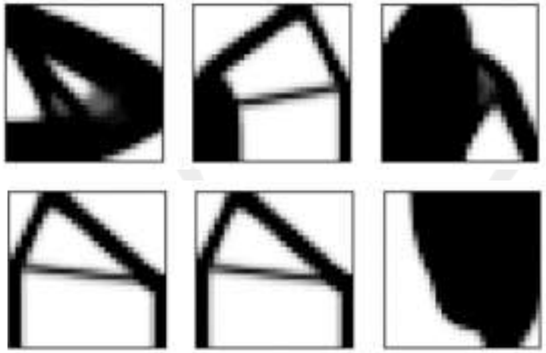
Hybrid Approach?

Optimization Scheduler

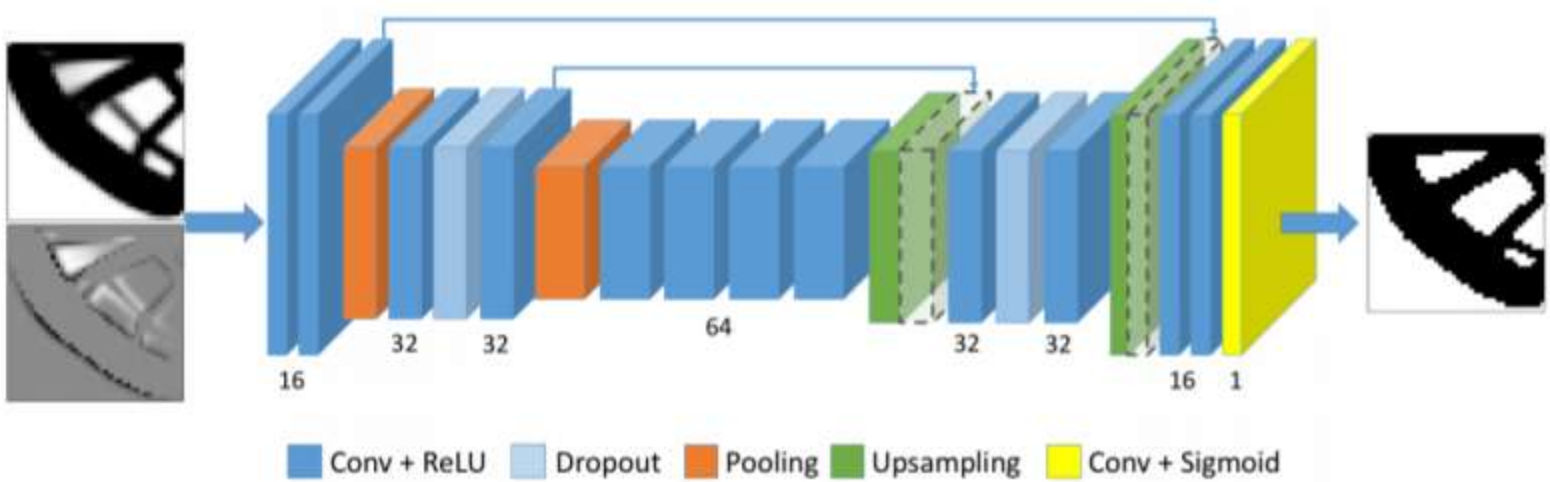
기존 최적설계

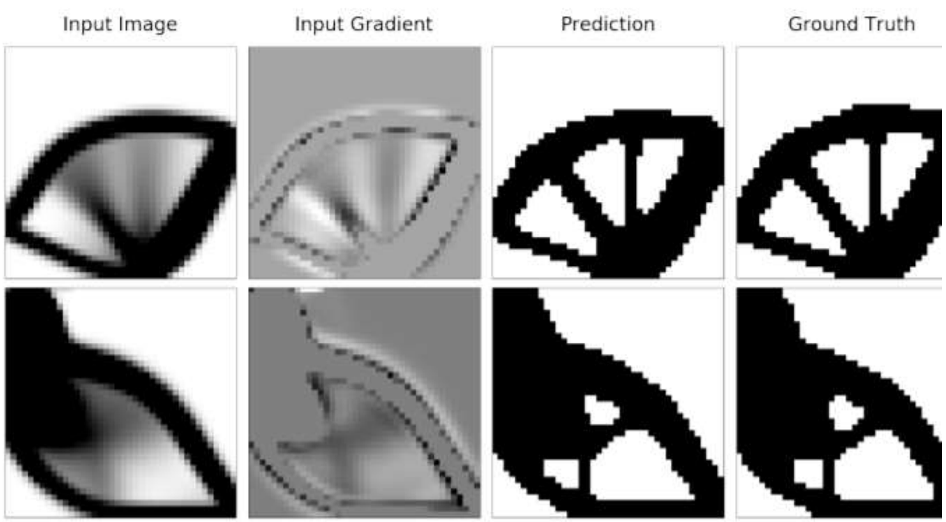
$$\frac{\partial c}{\partial x_e} = -p(x_e)^{p-1}\, \mathbf{u}_e^T\, \mathbf{k}_0\, \mathbf{u}_e$$

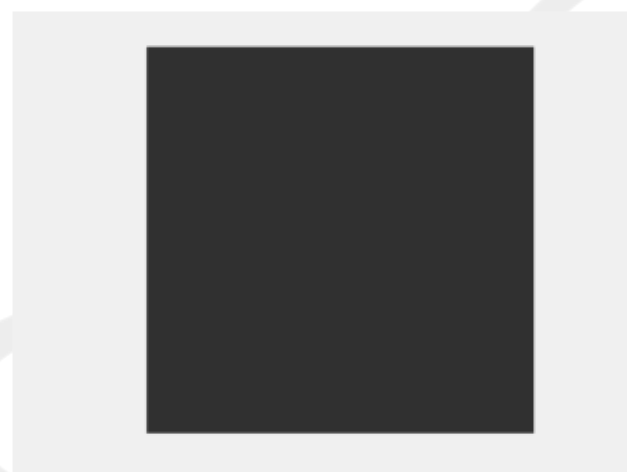
머신러닝 알고리즘



Neural networks for topology optimization



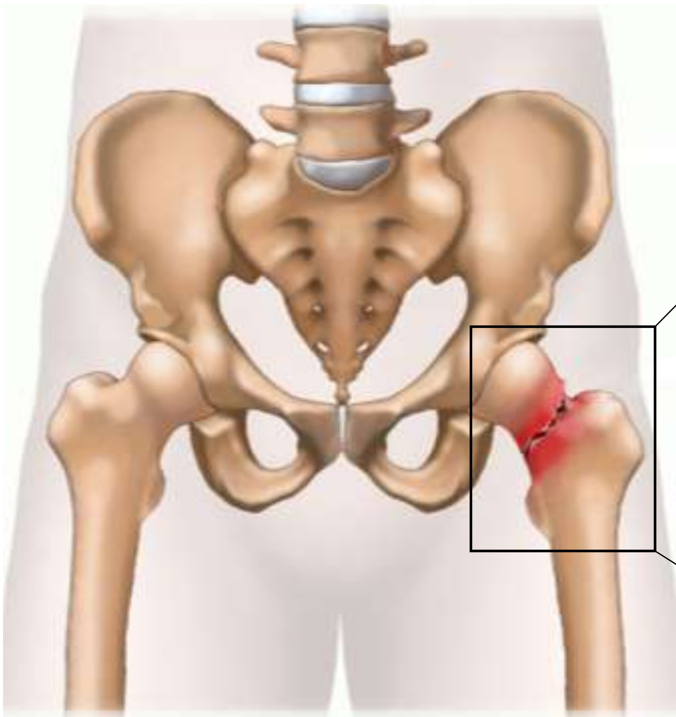




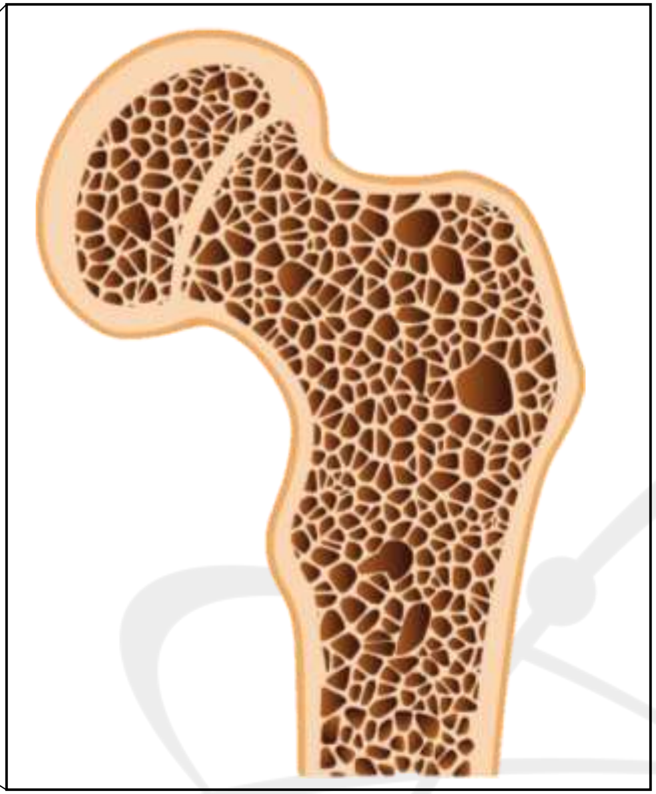
https://arxiv.org/abs/1709.09578

Deep Learning based Bone Microstructure Reconstruction

골다공증 진단을 위한 뼈 CT 사진 고해상화



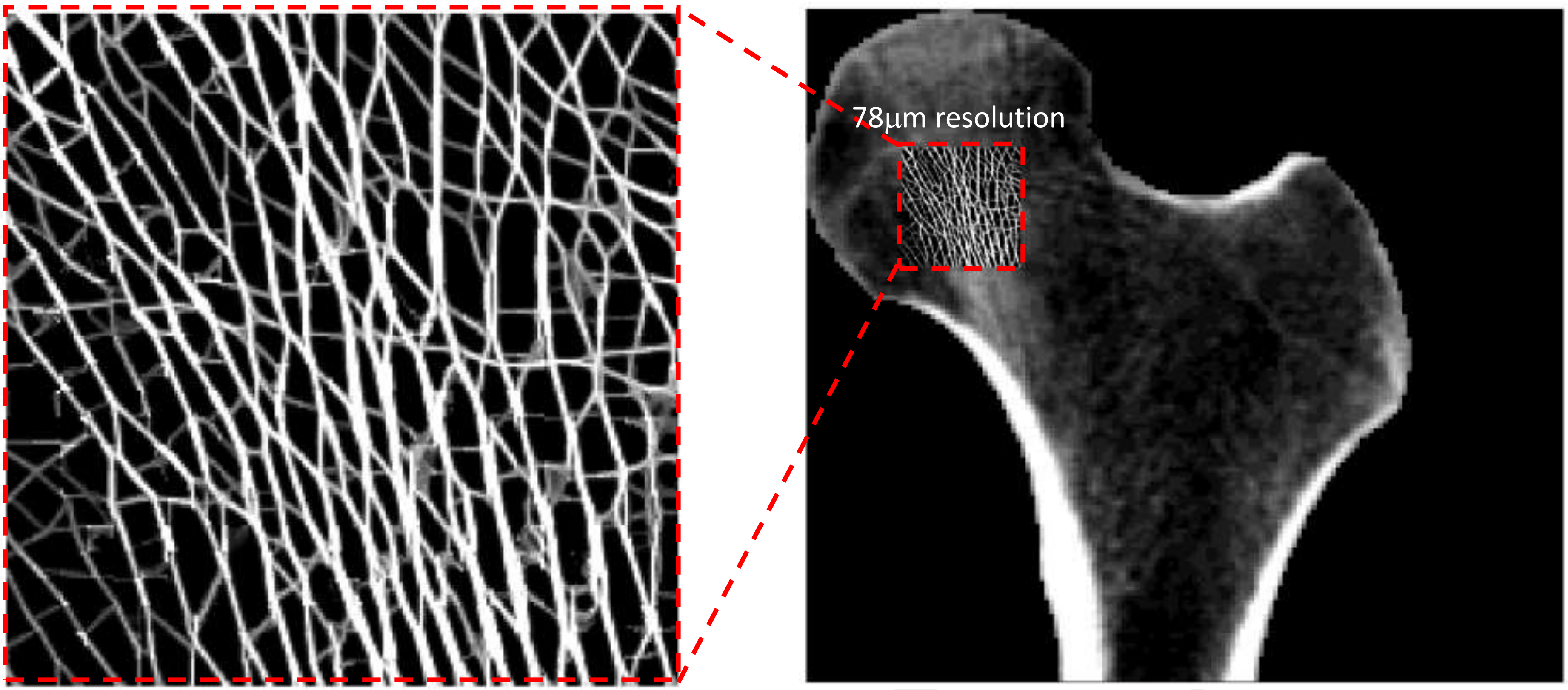
골다공증성 골절



골다공증

골다공증 진단을 위한 뼈 CT 사진 고해상화

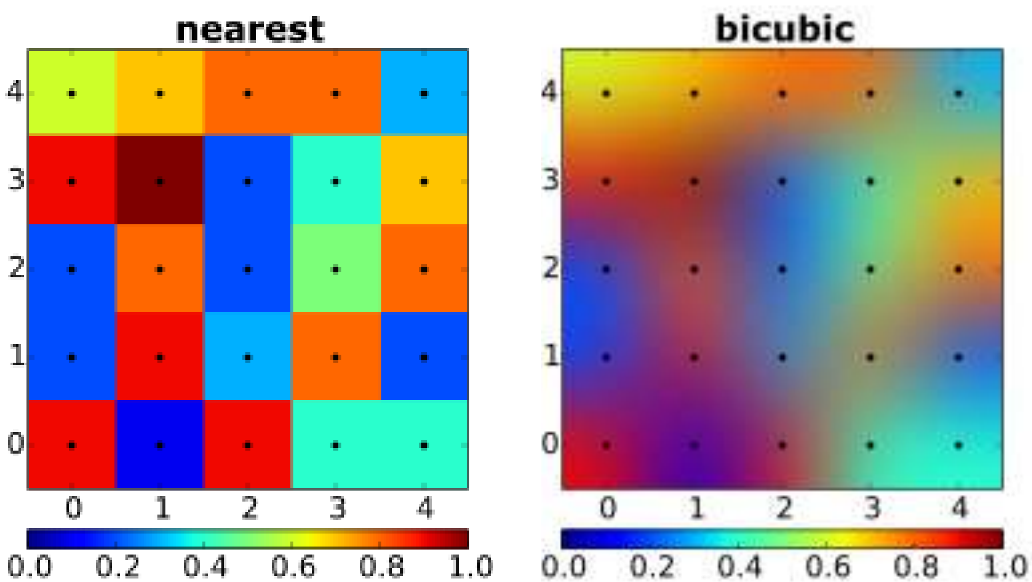
정확한 골다공증 진단을 위한 저선량 CT 사진 고해상화

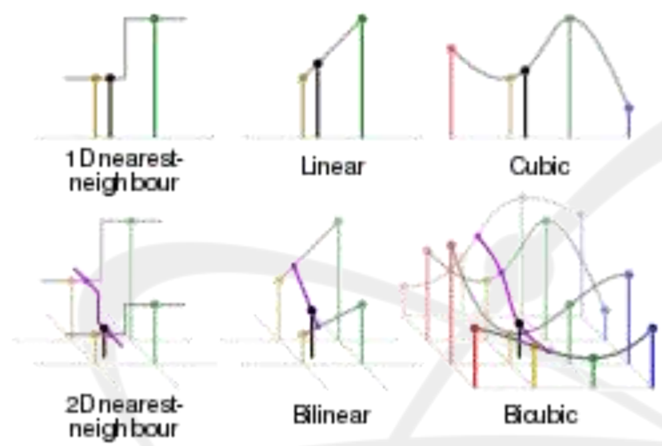


78μm resolution

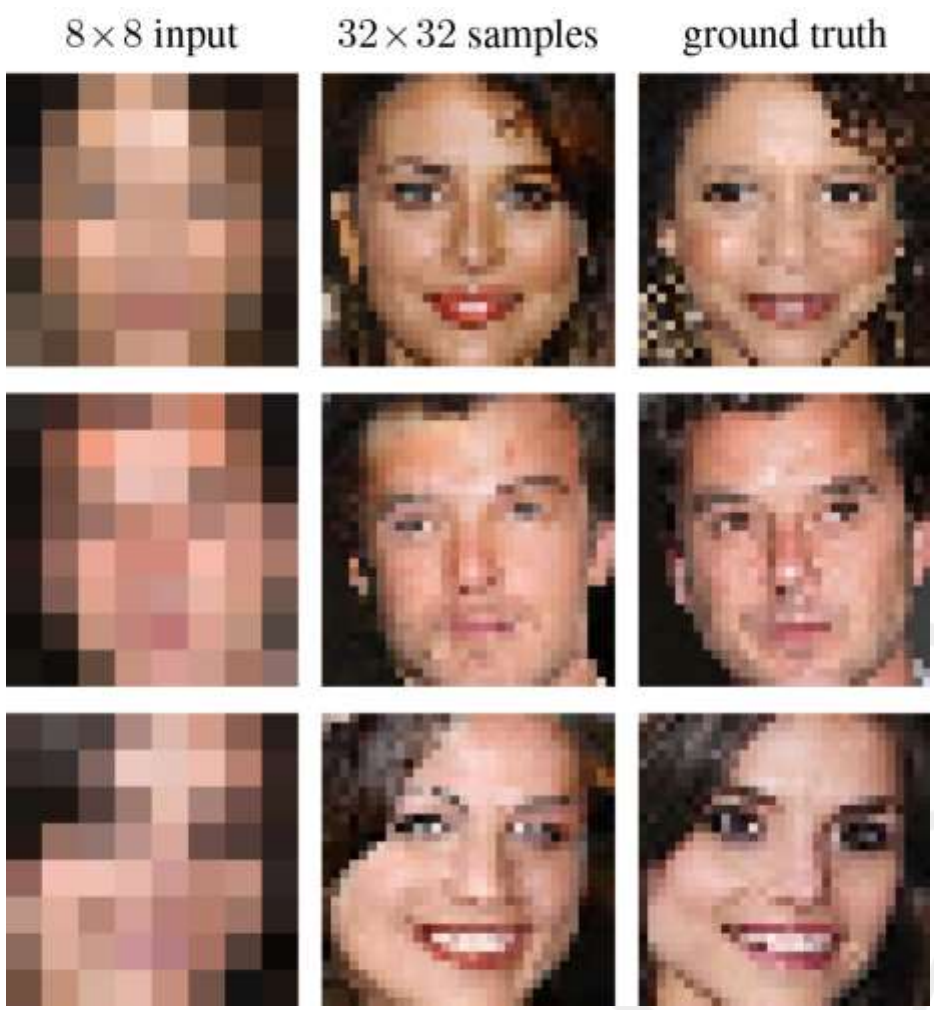
625μm resolution

기존 영상 고해상화 기술


nearest
bicubic
0.0 0.2 0.4 0.6 0.8 1.0


1D nearest-neighbour
Linear
Cubic
2D nearest-neighbour
Bilinear
Bicubic

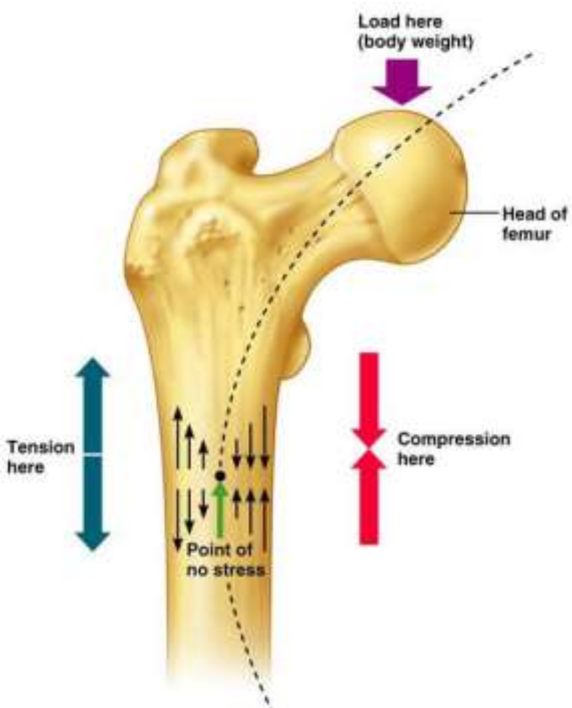
딥러닝 기반 영상 고해상화 기술 1



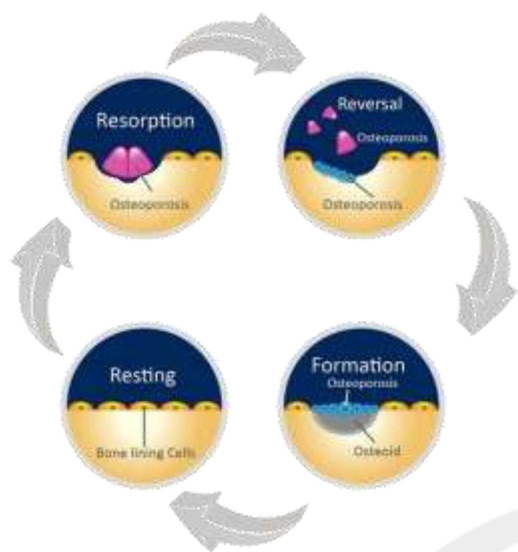
arXiv:1702.00783

골 재형성

- 골 재형성 과정은 **최소의 골량**으로 주어진 기계적 자극에 대해 **최대의 기계적 효율**을 얻는 골 미세구조를 생성함 (Wolff's law, 1892)



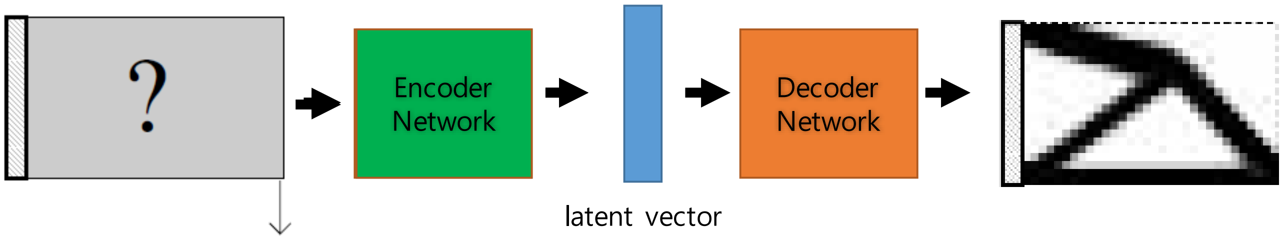
기계적 자극



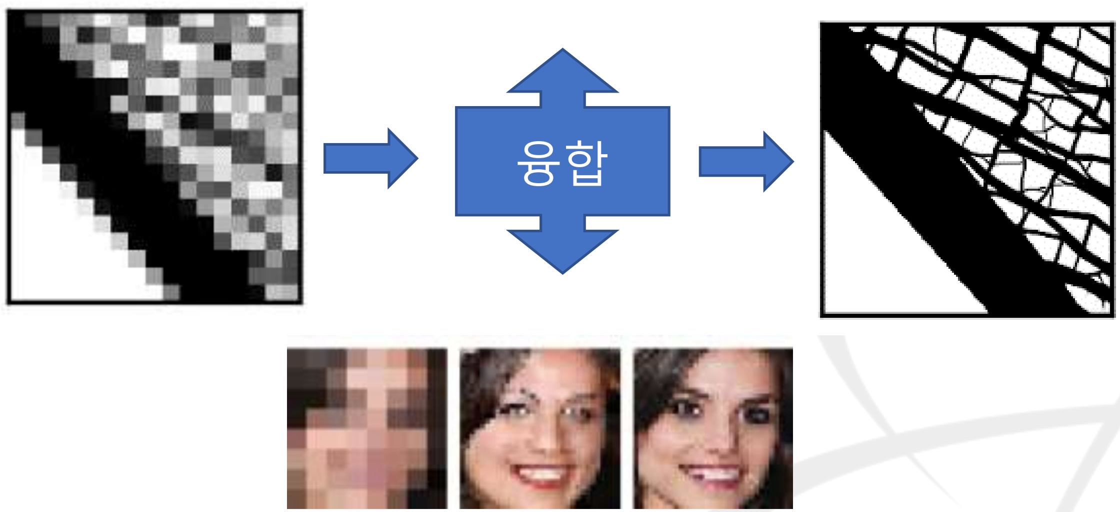
골재형성 과정

골 미세구조

연구 개념



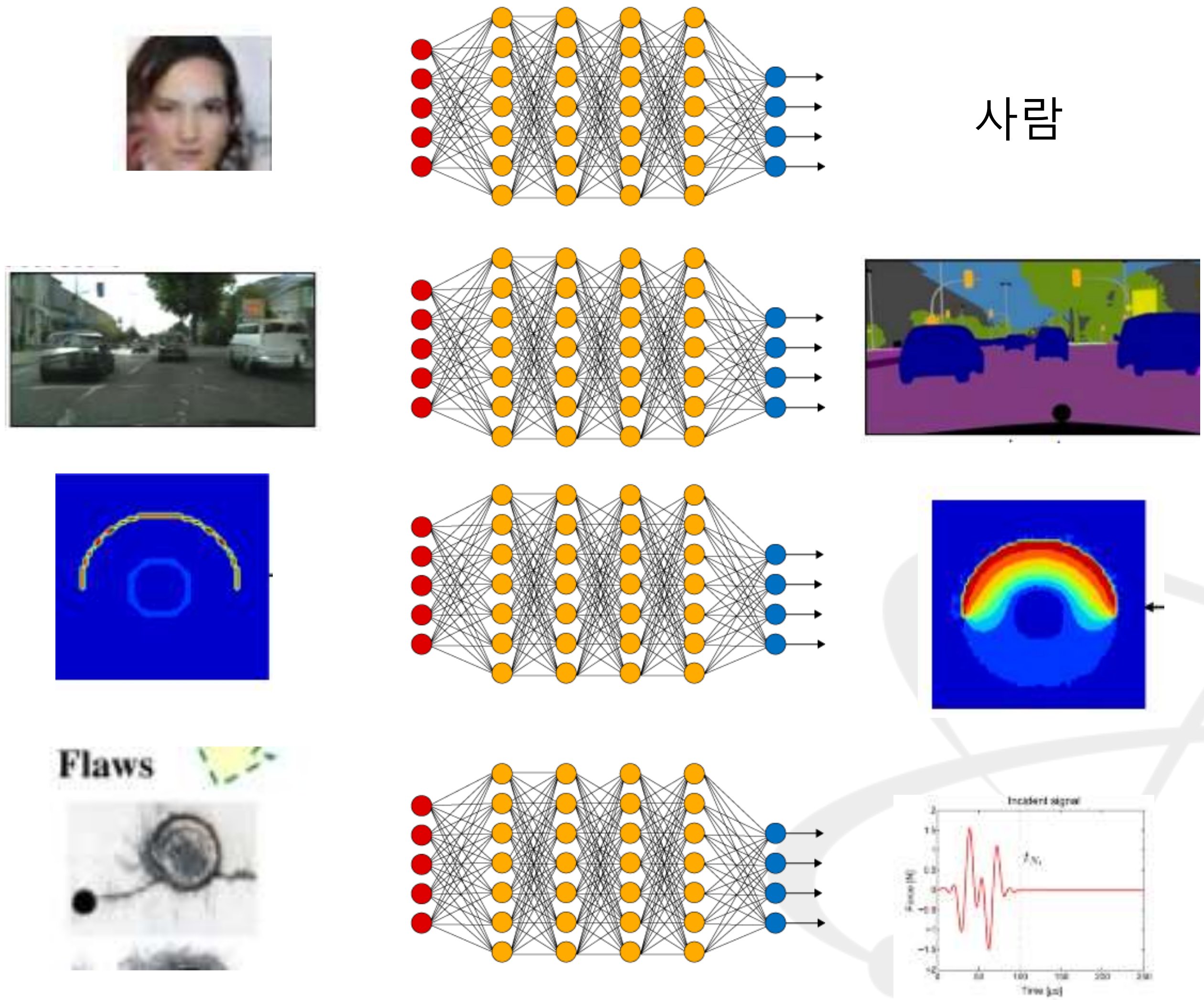
딥러닝 기반 위상최적설계



딥러닝 기반 영상 고해상화

Deep Learning for Nuclear & Industrial Engineering

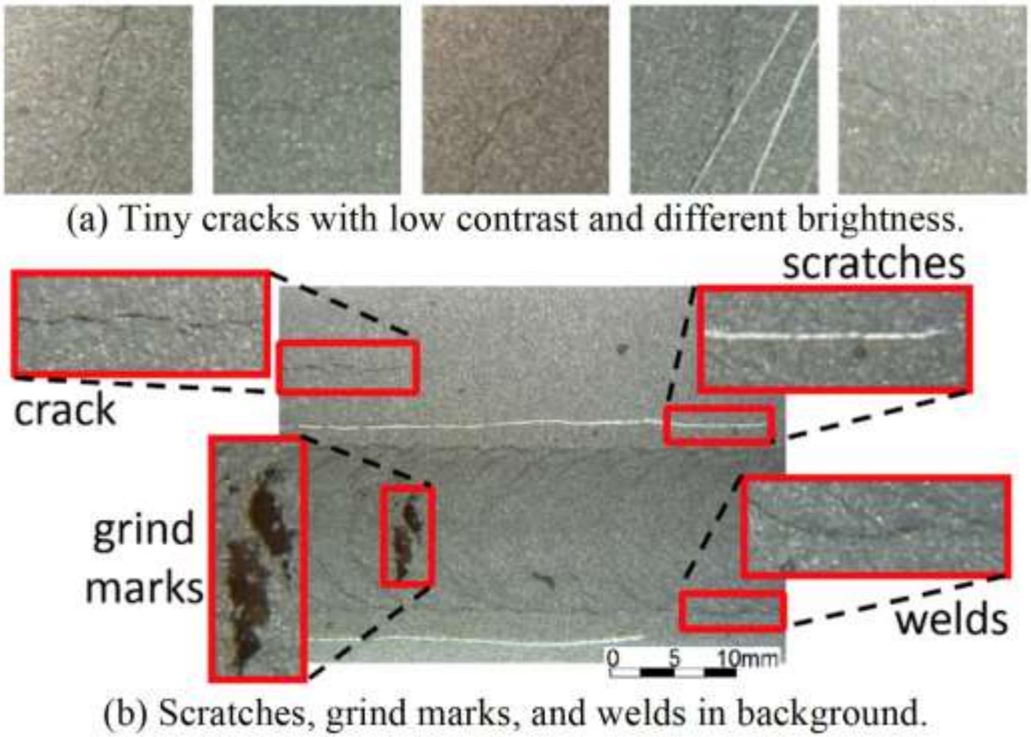
딥러닝이란?



Deep Learning for Nuclear & Industry Engineering

- Anomaly Detection
- Non destructive Test
- Health monitoring
  - Pump LPMS, Acoustic alarm
- Uncertainty Evaluation
- Digital Twin
- Automation
  - Normal condition, Emergency condition
- Structural Optimization
- Materials Science

System automatically detects cracks in nuclear power plants



https://www.purdue.edu/newsroom/releases/2017/Q1/system-automatically-detects-cracks-in-nuclear-power-plants.html

핵연료봉 수소화물(Hydride) 특성 예측

김재용, AI를 이용한 HR 특성예측

NSSS Integrity Monitoring system

*전력경제신문

증기발생기 와전류 탐상

*김길유, 증기발생기 U-Tube ECT 전문가시스템, Physics Informed Machine Learning 포럼, 2017, 충남대

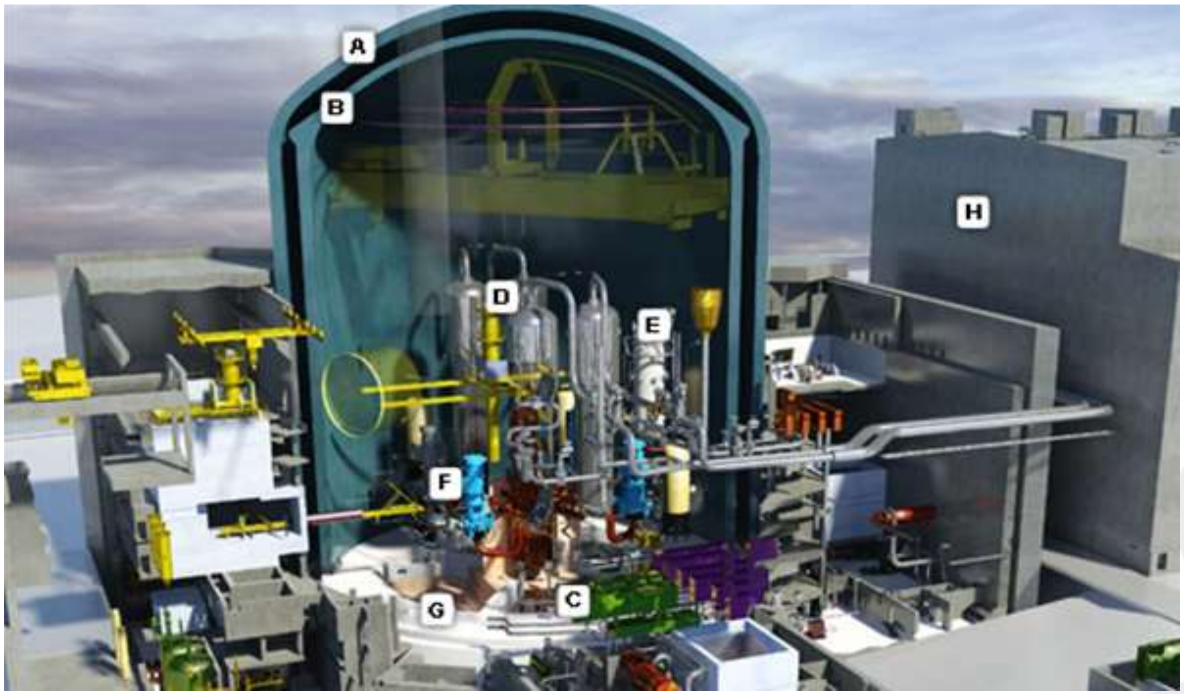
후쿠시마 사고

후쿠시마 사고 원인 (기술적 측면)

- 초대형 쓰나미에 대한 무방비
  - 설계기준 쓰나미 설정 + 설계기준 초과 쓰나미 대책
- 중대사고 대응 대책 미흡
  - 1980년대 이후 잘 알려진 Mark-I 격납용기의 취약성 보완 미흡
  - 중대사고 대응 대책(설비, 절차서, 교육 훈련 등) 부족
- 지진과 쓰나미에 의해 악화된 작업 환경
  - 복구 설비 이동에 제약
  - 끊임없는 여진 문제
- 사고 진행 과정에서의 부적절한 대응
  - 1호기 비상응축기 작동상태 오인, 3호기 고압주입계통 수동 중단, 격납용기 배기밸브 개방 지연, 보고체계 혼선 등
- 원전 내부 상태에 대한 정보 부족
  - 원자로 내부 상태에 대한 부정확한 이해/추정
- 중대사고가 다수 호기에서 동시에 전개

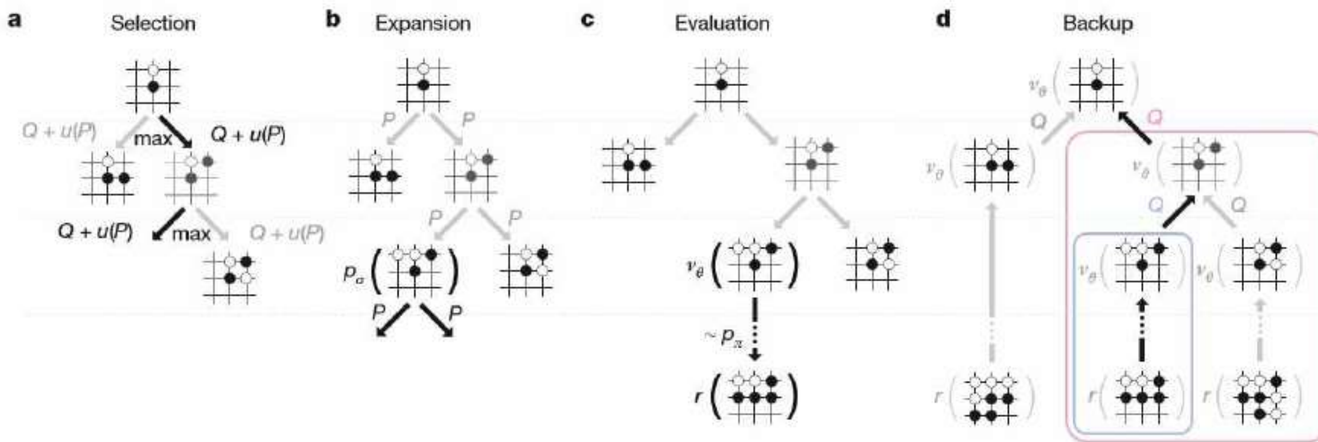
*백원필, 원자력 이용 현황, 후쿠시마 사고 및 지속 이용을 위한 도전과제, 부산대학교 세미나

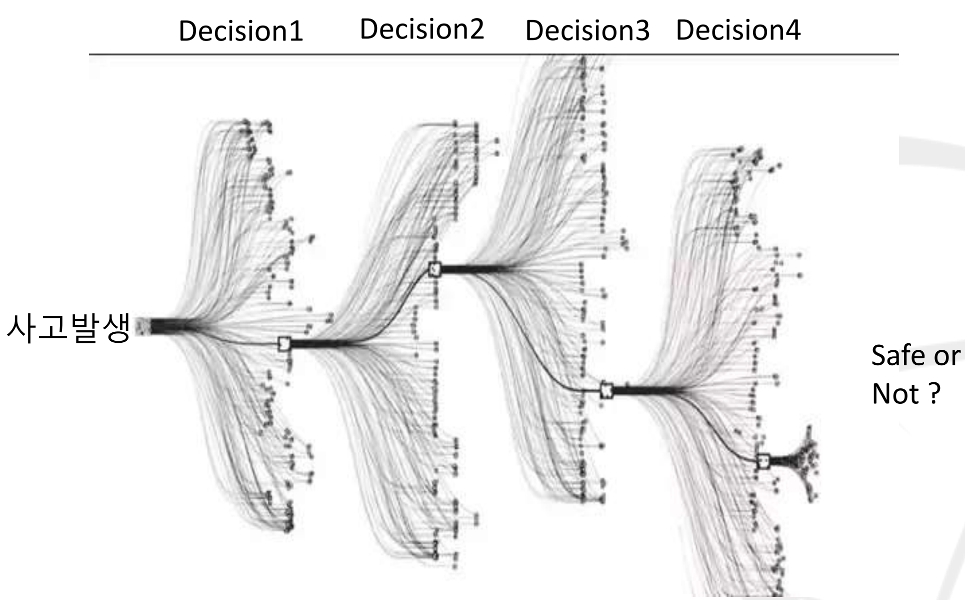
Digital Twin



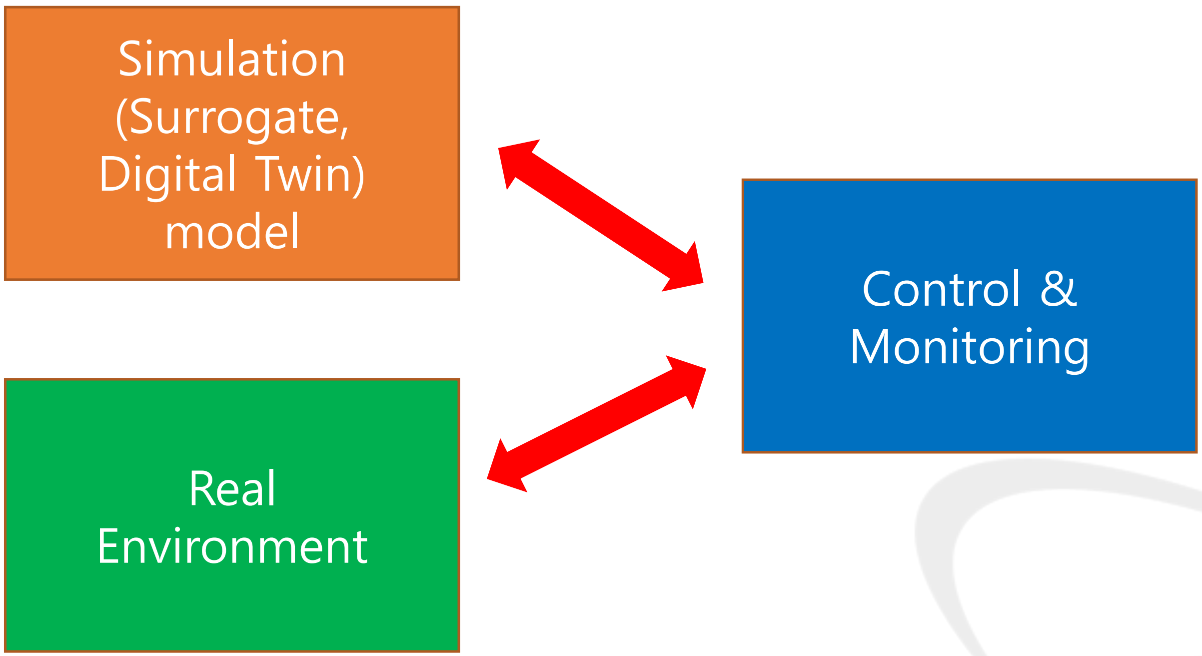
http://www.corys.com/en/steps/article/digital-twin-challenge-nuclear-power-plants

중대사고 대응 로직


a
Selection
$Q + u(P)$
max
$Q + u(P)$
$Q + u(P)$
max
$Q + u(P)$
b
Expansion
P
P
P
P
p_σ
P
P
c
Evaluation
v_θ
$\sim p_\pi$
r
d
Backup
v_θ
Q
Q
v_θ
v_θ
Q
Q
v_θ
v_θ
r
r
r


Decision1
Decision2
Decision3
Decision4
사고발생
Safe or
Not ?

Surrogate (meta) modeling with machine learning



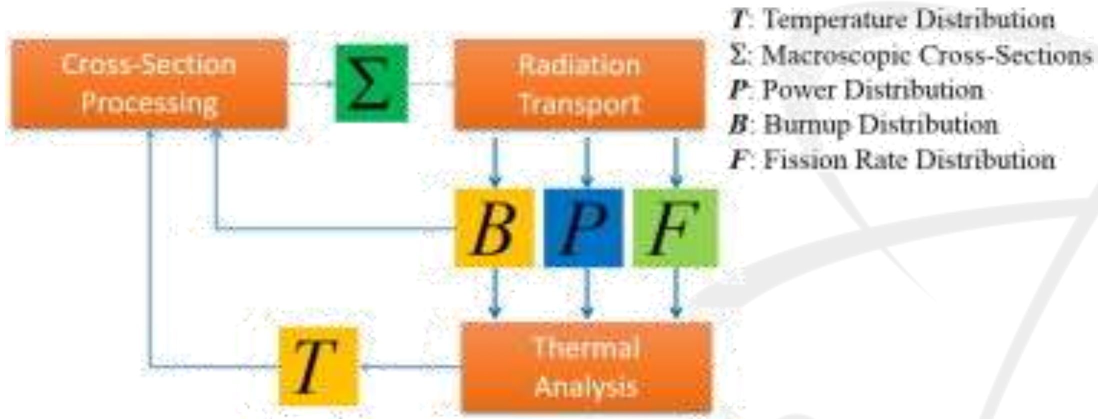
- 복잡한 다물리 현상을 빠르게 모사할 수 있는가?
- 어떤 데이터를 생성할 것인가?
- 실제 데이터와 차이는?

Dimensionality reducibility for multi-physics reduced order modeling

The final goal of this study is to construct a surrogate model for the coupled Rattlesnake-BISON models

The computational cost needed for the construction of surrogate models for a multi-physics model can be significantly reduced if one employs dimensionality reduction to identify the effective DOF.

Another important conclusion of this study is that while fine mesh simulation is highly needed to accurately describe the multi-physics nature of system behavior, it comes at a great cost.



Combustion modeling using principal component analysis

- Direct numerical simulation of combustion systems is impossible
  - Resolution requirement
  - Number of equations to be solved
    - Ex) 53 species and 325 reactions
    - 57 strongly coupled PDE

- PCA offers the potential to automate the selection of an optimal basis for representing the manifolds

$$\mathbf{X} \approx \boldsymbol{\eta} \mathbf{A}^{\mathsf{T}} \quad \rho \frac{\mathrm{D}(\boldsymbol{\Phi})}{\mathrm{D}t} = -\nabla \cdot (\mathbf{j}_{\boldsymbol{\Phi}}) + (s_{\boldsymbol{\Phi}}) \qquad \rho \frac{\mathrm{D}}{\mathrm{D}t}(\boldsymbol{\eta}) = -\nabla \cdot (\mathbf{j}_{\eta}) + (s_{\eta});$$

그 밖의 아이템..

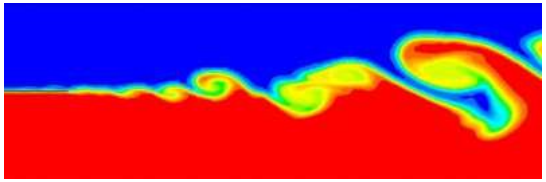
- 자율운전
- 감시시스템
  - 화재 및 운전원 감시
  - 핵물질 유출 감시 (CCTV, neutron detector)
- 배관 감육 진단

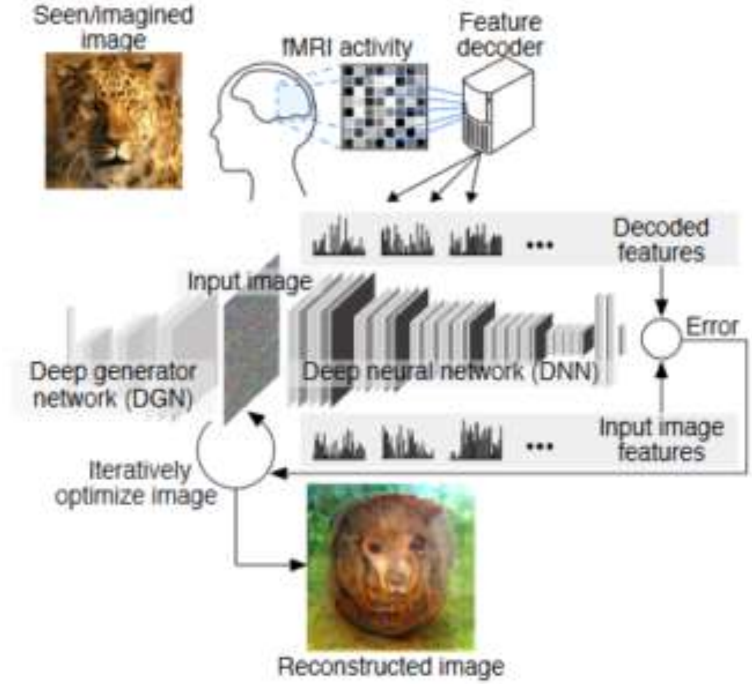
아주 조금만 기술적으로 들어갑시다

- 증명할 수 있는가? 불확실도는 얼마인가?
- 데이터 부족
- 라벨링의 비용 및 난이도
- 정상데이터에 편중
- 시뮬레이션으로 데이터 생성시
  - 시뮬레이터 해석 시간
  - 시뮬레이터와 실제 상황과의 차이

Ending…

Rise of Data science





https://www.biorxiv.org/content/biorxiv/early/2017/12/30/240317.full.pdf

Conventional Modeling	Data-driven modeling
Differential equation	Functions trained with data
Numerical simulation	Training time required
Slow, large memory	Faster, small memory
Difficult non-linear modeling	Non-linear modeling
Difficult to optimize	Easy Optimization

박문규, Simulation Environment, Big Data and Ai in Nuclear Engineering

Hidden Figures (2017)

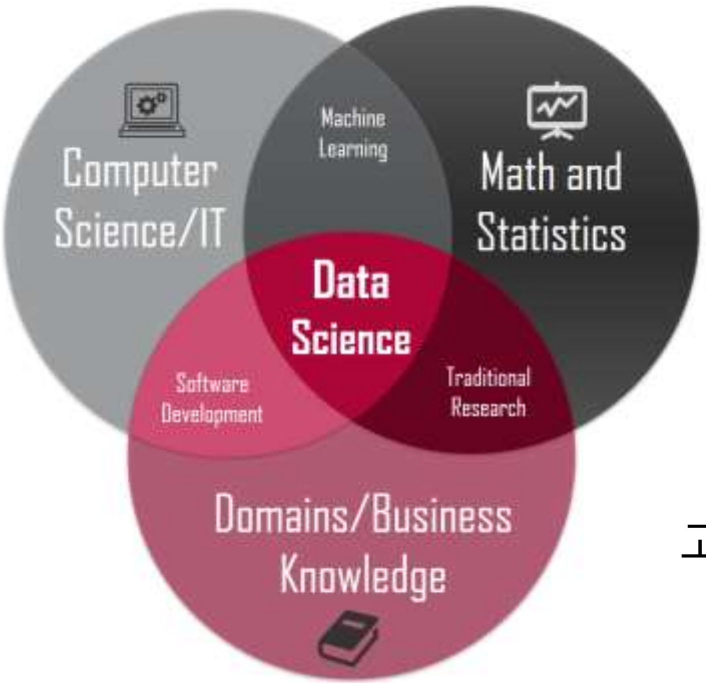
심각한 오해

인공지능 학계

- 도메인 지식 없이도 모든 문제를 잘푸는 인공지능을 개발했다!

응용분야

- 응 그래? 그럼 가져다 쓰면 되겠네?
- 알파고 제로 가지고 와서 적용하면 뭔가 잘되겠지.
- 잘 안되잖아! (예전처럼) 사기야!

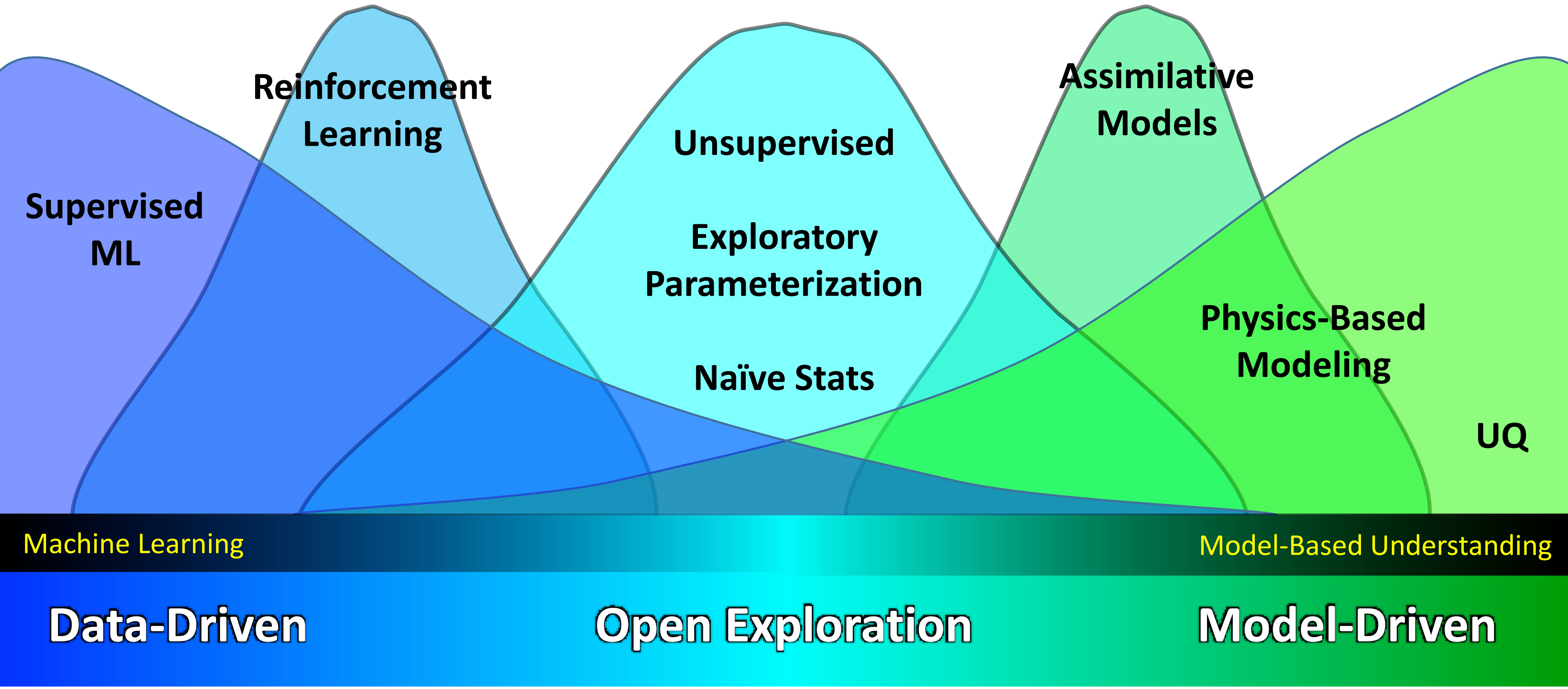


가장 중요한 부분을 고민하고 있지 않는 것 같은..

https://www.stoodnt.com/blog/top-universities-for-ms-in-data-science-in-usa/

Data Science Technology Spectrum

Real-world systems often combine several techniques



Expert Knowledge in Data + Labels
Model (mostly) determined by D + L

Expert Knowledge in Model Details
Data refines model parameters

* Lukas Mandrake, Machine Learning & Autonomy

1인 기업이 만든 바둑 AI '돌바람', 어떻게 일본 딥젠고 꺾고 우승했나

[중앙일보] 입력 2018.01.25 05:00

가 가

손해용 기자

지난 18일 인터넷 바둑사이트 타이젬을 통해 열린 한국의 '돌바람'과 일본의 '딥젠고' 간의 인공지능(AI) 특별대국 제4국. 딥젠고가 불리한 형세를 인정하고 돌을 던지자 돌바람을 개발한 임재범(48) 돌바람네트워크 대표는 주먹을 불끈 쥐었다. 돌바람이 최종 전적 3승 1패로 우승을 확정 짓는 순간이었다.

> **돌바람 개발자 임재범 대표 인터뷰**
> **1998년 '바둑이'로 출발…정부·기업 후원 없이 혼자서 개발**
> **돌바람이 한때 정상 근접, 그러나 알파고 등장 후 약체 전락**
> **지난해 딥러닝 탑재후 예전 알파고 수준으로 기력 급상승**

돌바람과 딥젠고의 대결은 바둑계에서 다윗과 골리앗의 싸움으로 여겨졌다. 딥젠고는 알파고의 은퇴 이후 중국의 바둑 인공지능 '줴이'(絶藝)와 세계 1위 · 2위를 다투는 강호. 반면 돌바람은 지난해 세계대회 최고 성적이 8강에 불과한 약체였다. 특히 딥젠고는 일본 소프트웨어업체 드왕고와 도쿄대 · 일본기원으로부터 대대적인 지원을 받고 있다. 반면 돌바람의 개발사는 임씨가 대표인 영세한 1인 중소업체에 불과했다.

임 대표는 24일 중앙일보와의 인터뷰에서 "지난해 딥젠고와 두 차례 대국을 펼쳐 모두 패했는데, 설욕을 하고 나니 정말 기쁘더라"며 "아직 딥젠고를 앞섰다고 말할 정도는 아니지만 적어도 동등한 실력이 됐다는 것은 확실하다"고 말했다.

추천기사

北, 평창 전날 대규모 열병식 평양 한복판 5만명 동원한다

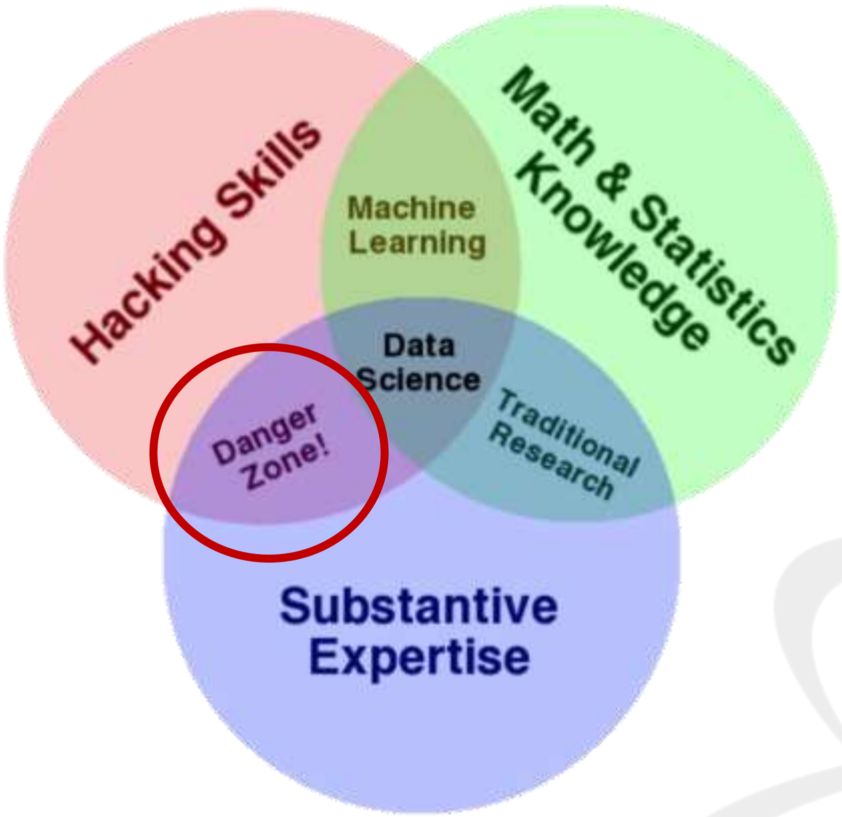
시끄러워 일본에 발각됐다 이틀간 쫓긴 '中핵잠 굴욕'

태양광 관세 때리니 2만명 실직위기… 일자리 보호의 역설

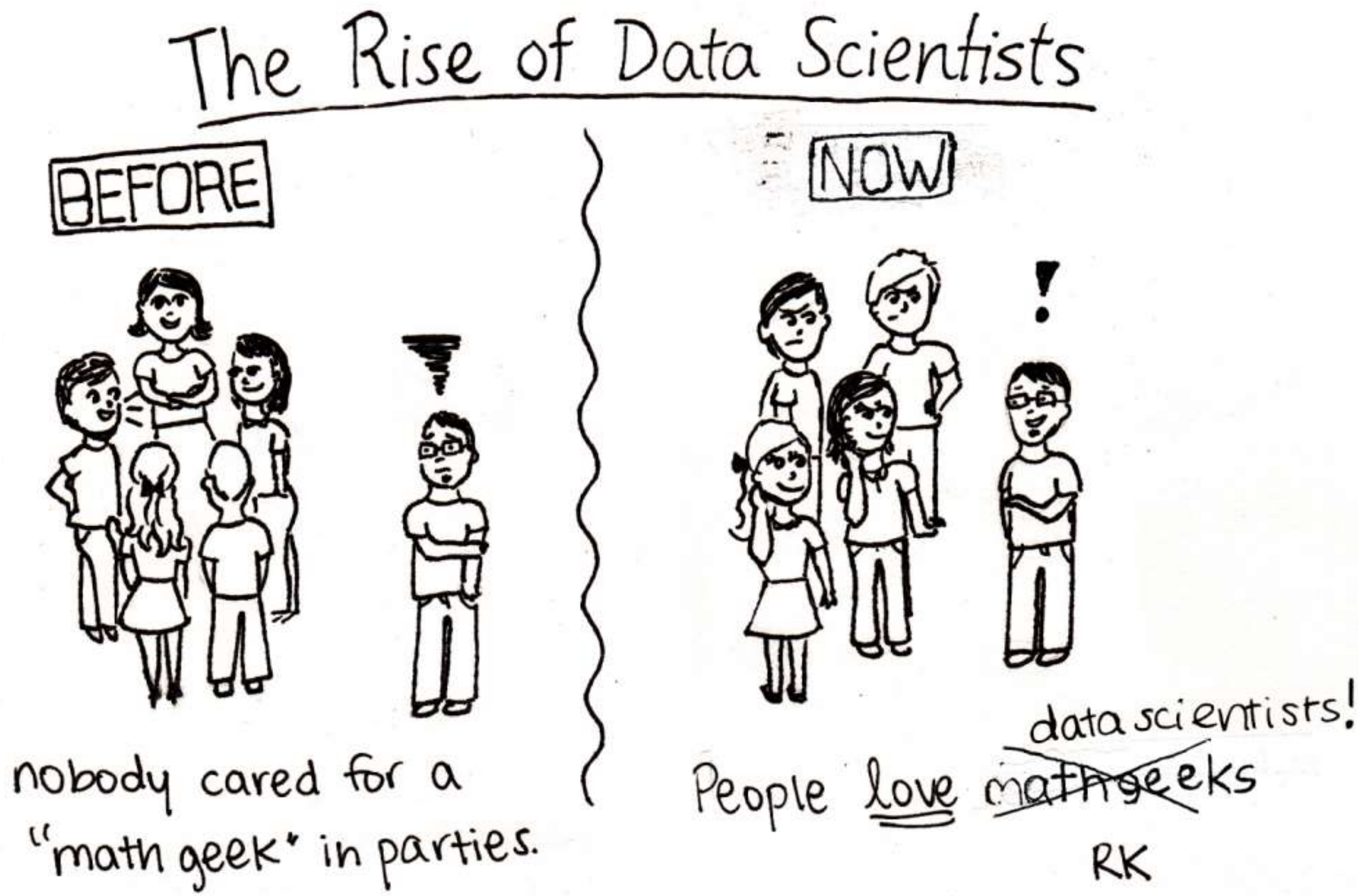
맛없다는 한국 맥주, '본고장' 유럽서 판매 급증 이유

야쿠르트 카트 만들다 '한국의 테슬라' 전기차 꿈꾼다

Data Science 을 위해서는?



From Drew Conway



https://www.techjuice.pk/how-to-become-a-data-scientist-for-free/

출연연에는 Data Science 전문가 집단이 필요합니다.

매일경제

✓PiCK

[Case Study] SK하이닉스 역대급 실적 뒤엔…`데이터 사이언스` 조직 있었네

기사입력 2018-02-09 04:05 기사원문 스크랩 본문듣기 · 설정

13 3 요약봇 가

SK하이닉스의 데이터 전문 조직 `데이터 사이언스`. [사진 제공 = SK하이닉스]

데이터 시대가 도래했다고 하지만 데이터 활용은 특정 산업에 편중되고 있는 모습이다.
전문적인 데이터 분석 역량을 갖춘 인재들 역시 제조업보다는 금융과 정보기술(IT) 관
련 분야로 진출하는 경우가 많은 것으로 나타나고 있다.

ficial-intel

2016년 30여 명 규모로 신설

매년 전문인력 두 배로 확충
현장과 원활한 연계 위해
반도체 엔지니어도 배치

생산성 향상 1등 공신

먼지 한 톨도 용납 안 될 만큼
매우 까다로운 반도체 공장
공정 과정서 나오는 데이터
수집·가공해 현장이슈 대응

그룹 차원 데이터 역량 강화

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