KAERI

최신딥러닝 동향 및 기계공학분야의 딥러닝 응용

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2018.12.20

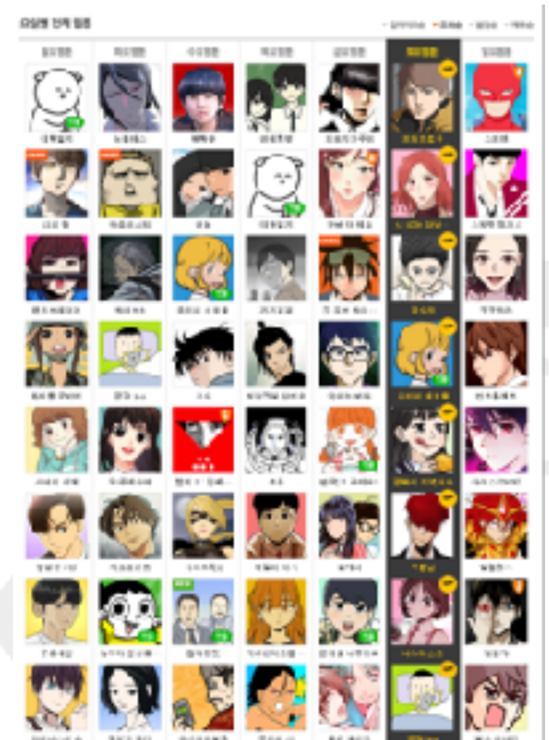
Korea Atomic Energy Research Institute

~~최신 딥러닝 동향~~

제가 재미있게 보고 있는 관심분야 + 핫한 논문

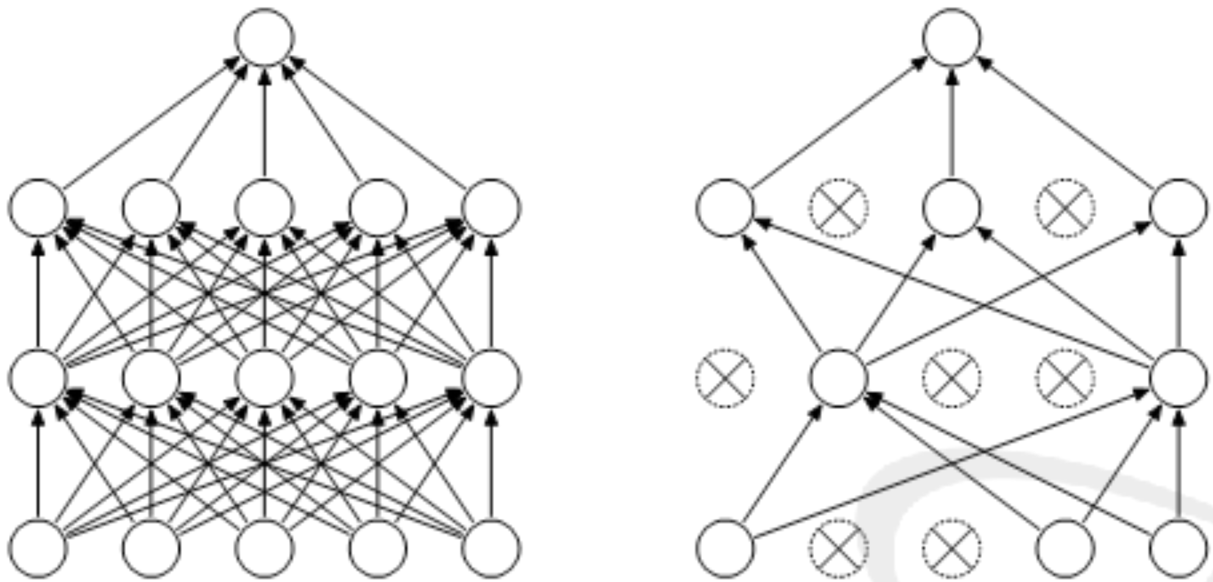
- Uncertainty
- Non-Euclidian (Geometric) DL
- Meta Learning
- Attention
- Model based RL
- Domain Adaptation
- Domain Transfer Network

- BERT
- World model
- Alpha Fold



Dropout as a Bayesian Approximation

Yarin Gal, Uncertainty in Deep Learning (2016)

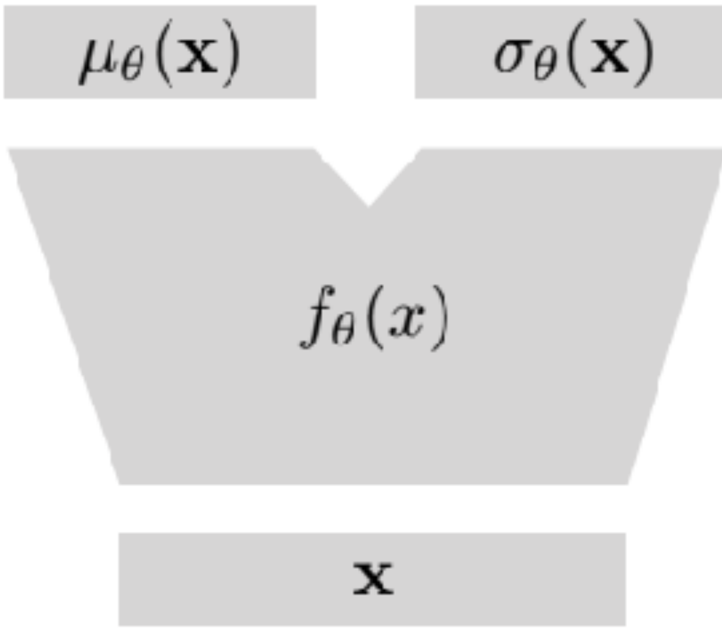


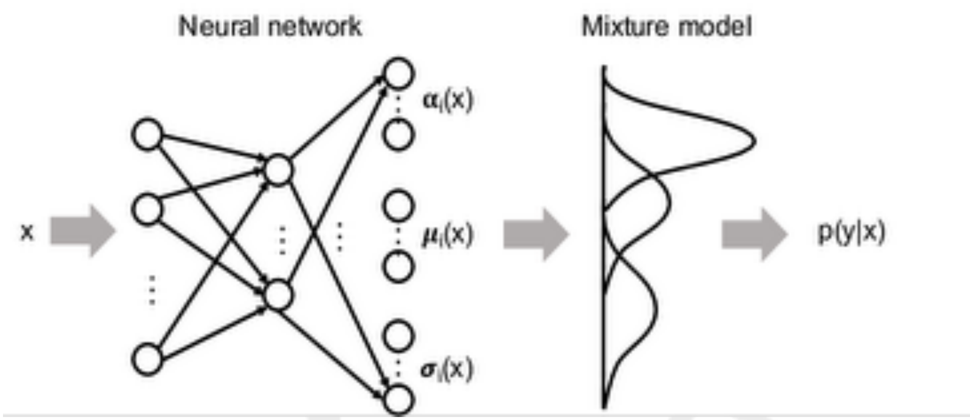
(a) Standard Neural Net (b) After applying dropout.

https://www.slideshare.net/sangwoomo7/dropout-as-a-bayesian-approximation

https://arxiv.org/abs/1703.04977

Simple and Scalable Predictive Uncertainty Estimation using Deep Ensembles, NIPS 2017

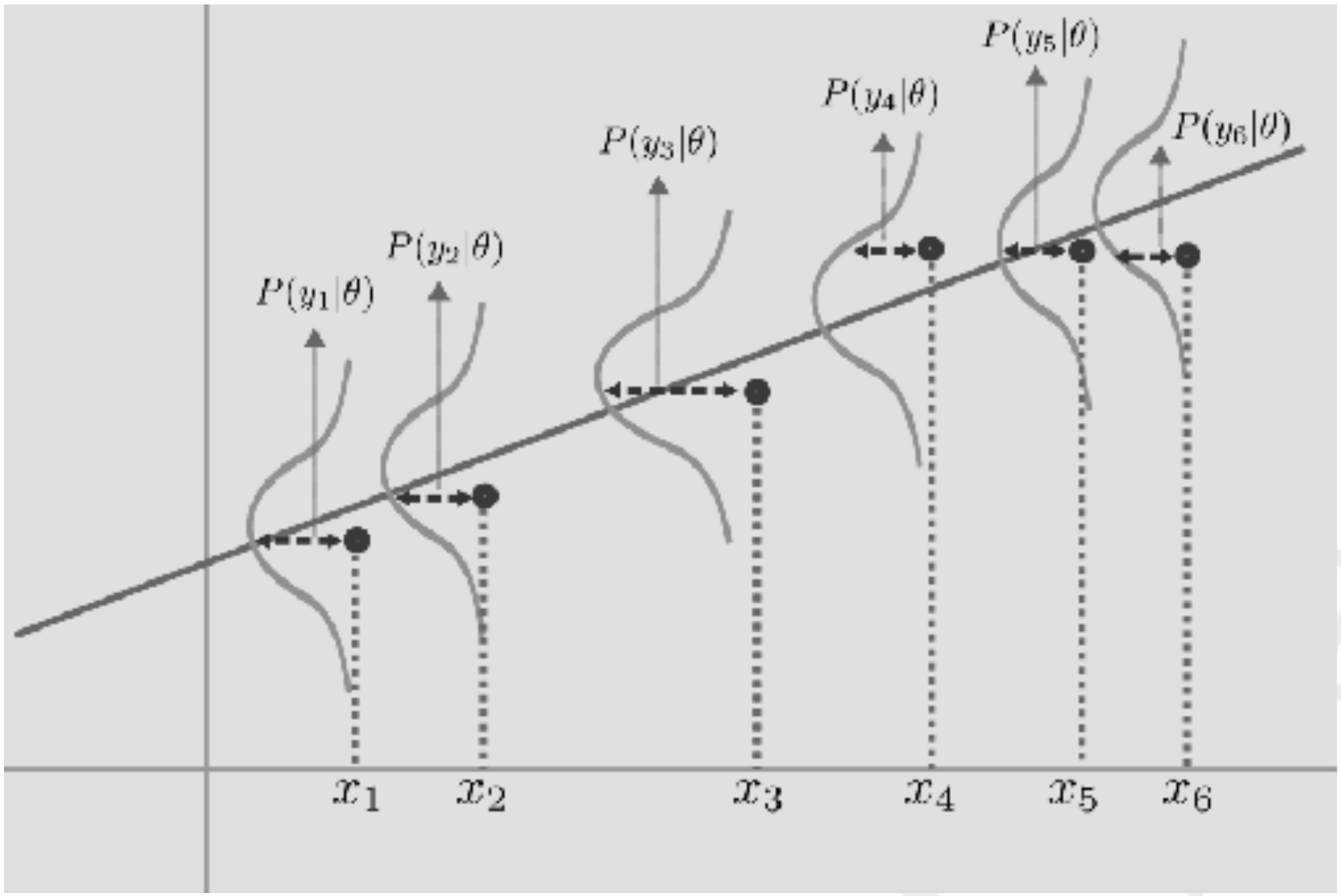




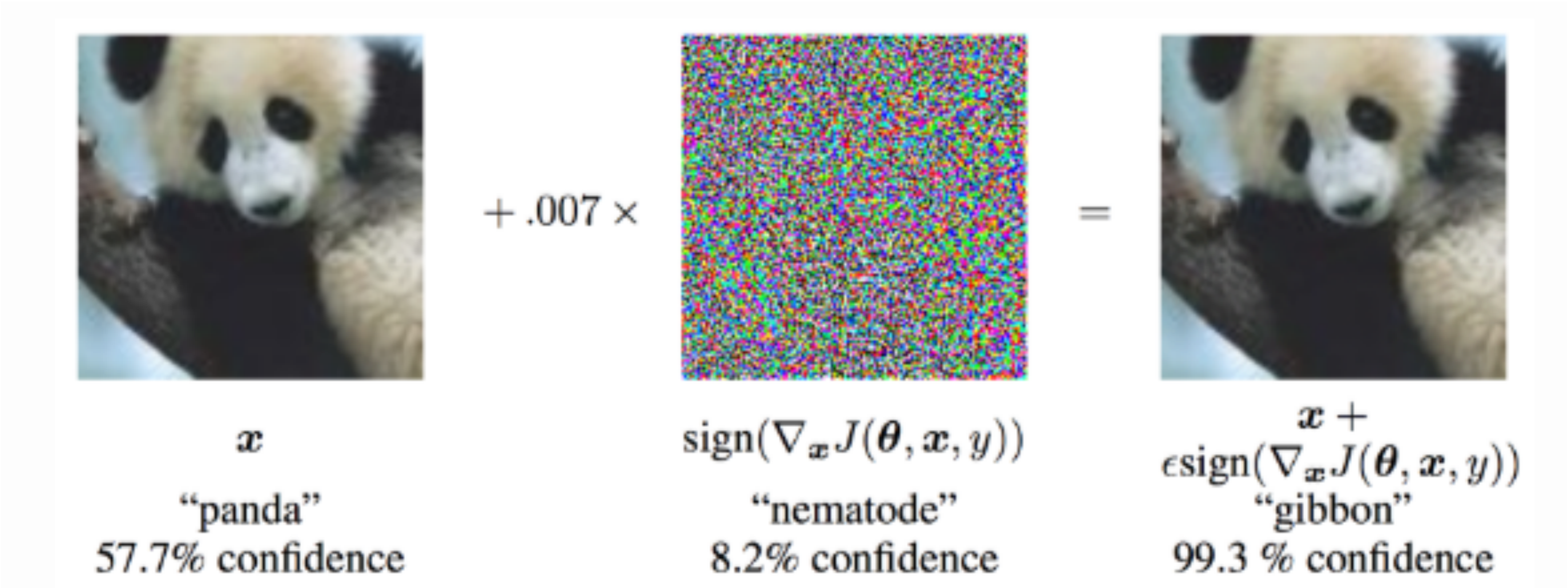
Density network

D. A. Nix and A. S. Weigend. Estimating the mean and variance of the target probability distribution. In IEEE International Conference on Neural Networks, **1994**

Simple and Scalable Predictive Uncertainty Estimation using Deep Ensembles, NIPS 2017



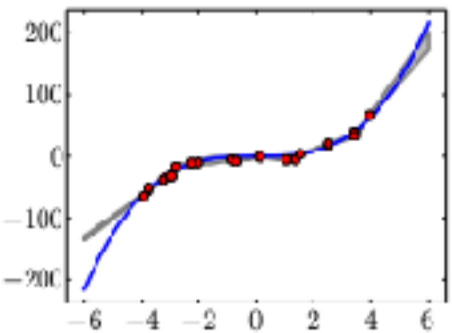
Simple and Scalable Predictive Uncertainty Estimation using Deep Ensembles



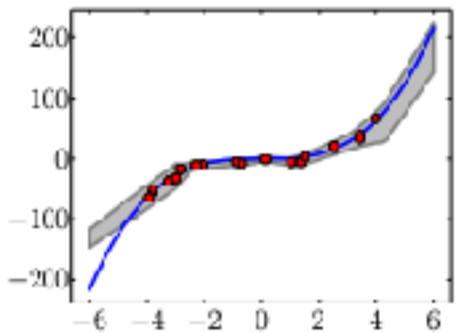
Adversarial Training

https://arxiv.org/abs/1703.04977

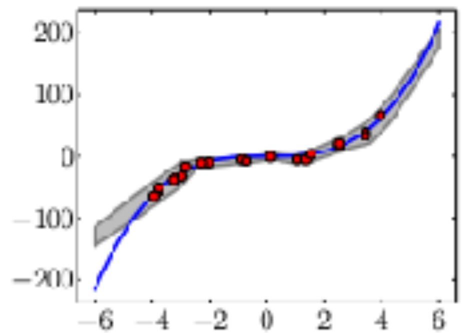
Simple and Scalable Predictive Uncertainty Estimation using Deep Ensembles



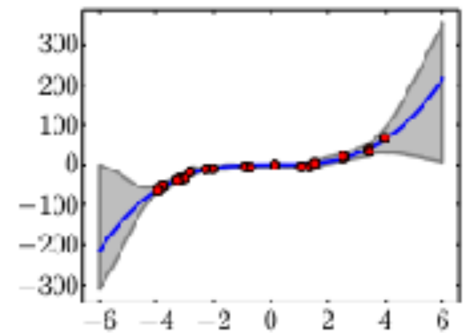
Empirical variance



Density Network

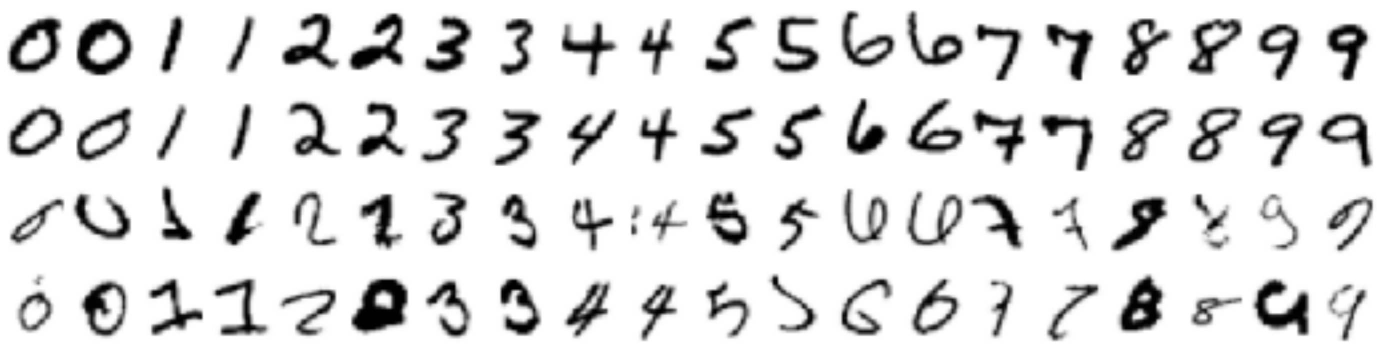


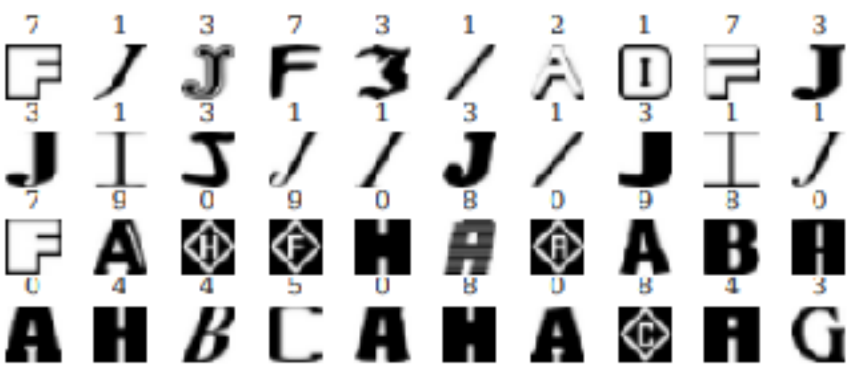
Adversarial training



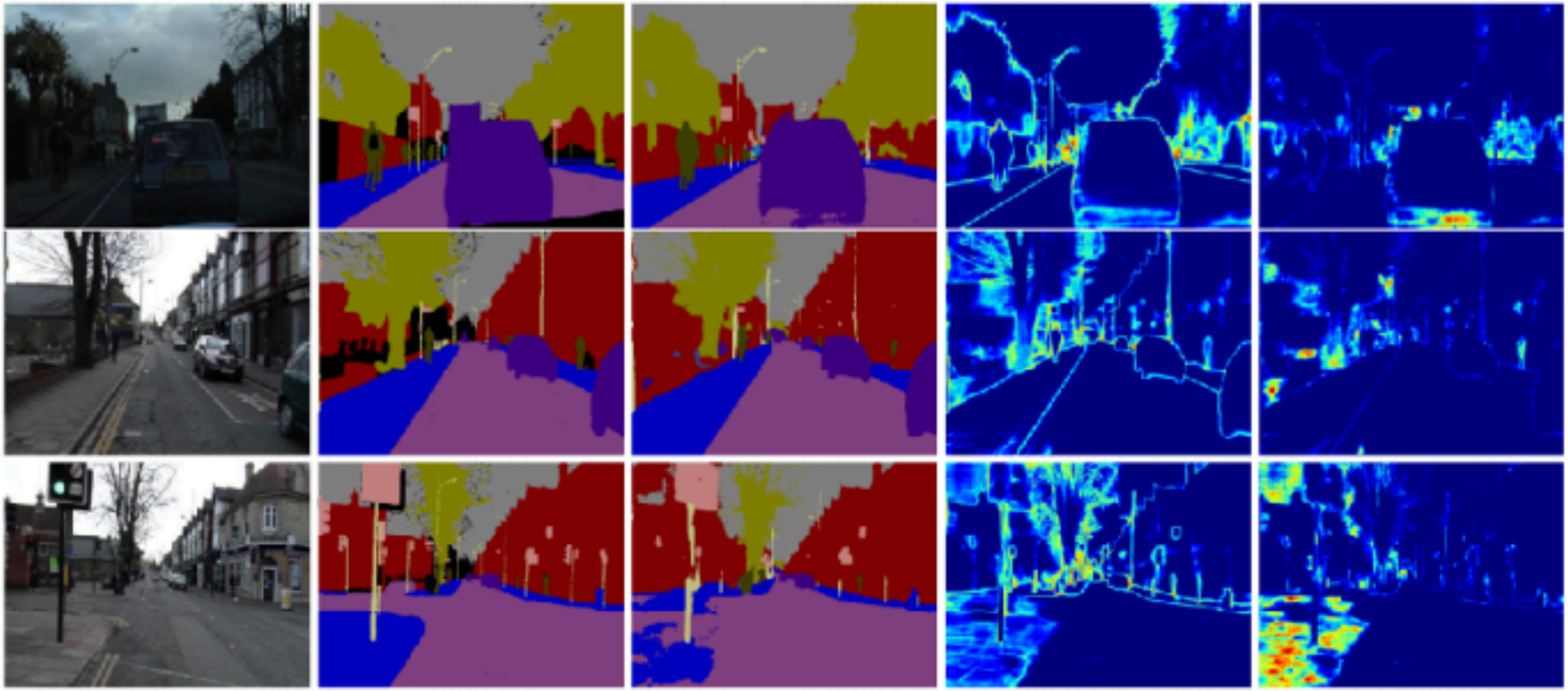
Deep ensemble

Simple and Scalable Predictive Uncertainty Estimation using Deep Ensembles





Aleatoric & Epistemic Uncertainty

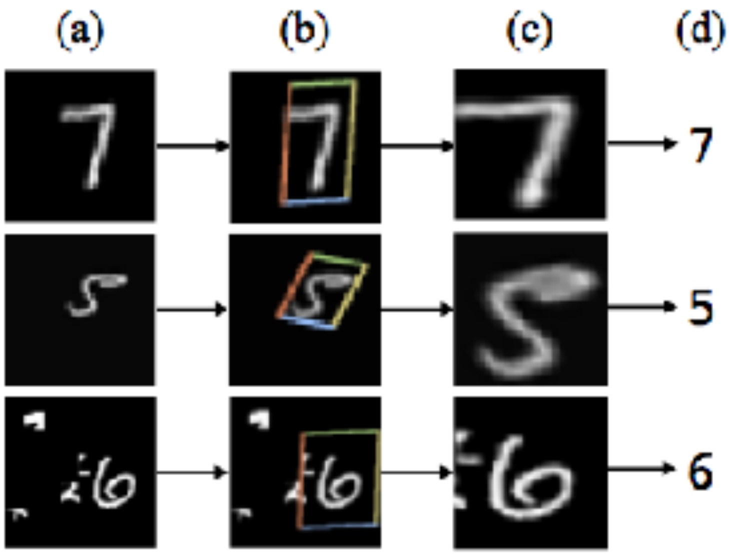


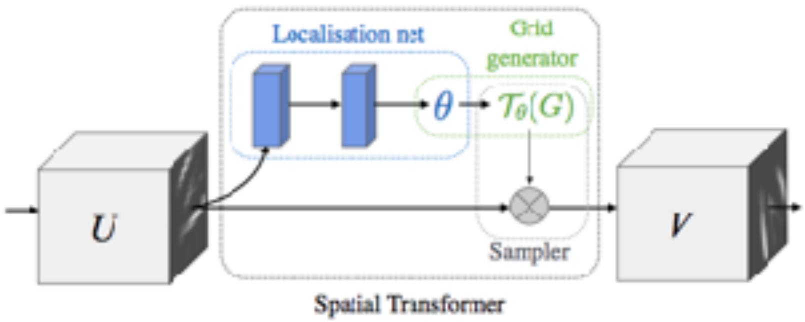
(a) Input Image (b) Ground Truth (c) Semantic Segmentation (d) Aleatoric Uncertainty (e) Epistemic Uncertainty

https://arxiv.org/abs/1703.04977

Visual Attention

- spatial transformer networks (2016)





Visual Attention

- spatial transformer networks (2016)

Model		R	RTS	P	E
		MNIST Distortion			
FCN		2.1	5.2	3.1	3.2
CNN		1.2	0.8	1.5	1.4
ST-FCN	Aff	1.2	0.8	1.5	2.7
	Proj	1.3	0.9	1.4	2.6
	TPS	1.1	0.8	1.4	2.4
ST-CNN	Aff	0.7	0.5	0.8	1.2
	Proj	0.8	0.6	0.8	1.3
	TPS	0.7	0.5	0.8	1.1

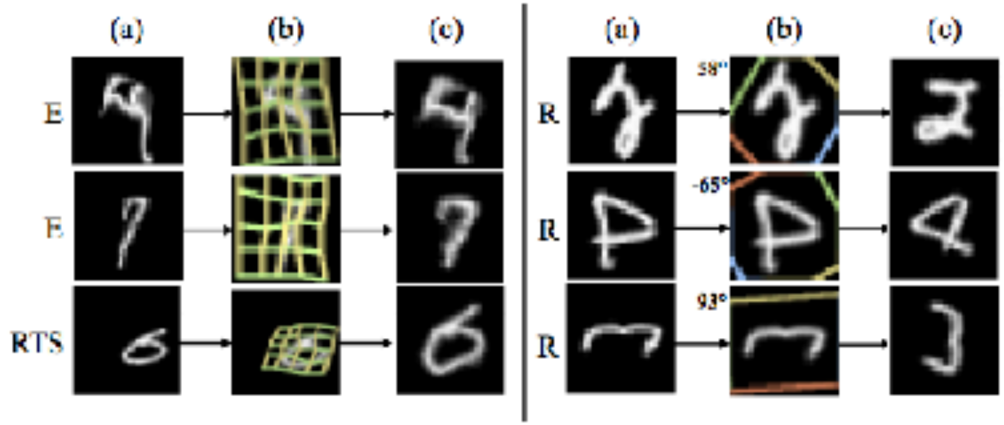
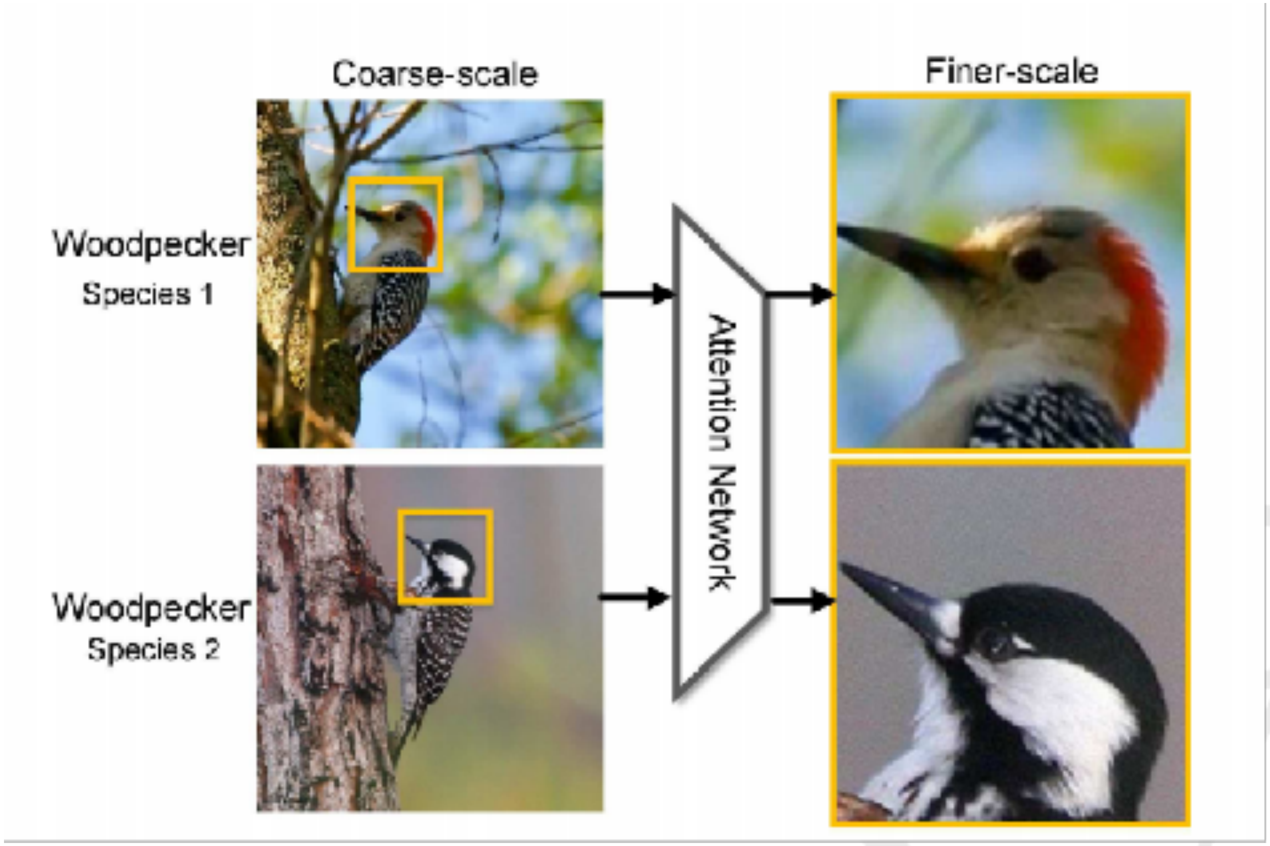


Table 1: *Left:* The percentage errors for different models on different distorted MNIST datasets. The different distorted MNIST datasets we test are TC: translated and cluttered, R: rotated, RTS: rotated, translated, and scaled, P: projective distortion, E: elastic distortion. All the models used for each experiment have the same number of parameters, and same base structure for all experiments. *Right:* Some example test images where a spatial transformer network correctly classifies the digit but a CNN fails. (a) The inputs to the networks. (b) The transformations predicted by the spatial transformers, visualised by the grid $T_\theta(G)$. (c) The outputs of the spatial transformers. E and RTS examples use thin plate spline spatial transformers (ST-CNN TPS), while R examples use affine spatial transformers (ST-CNN Aff) with the angles of the affine transformations given. For videos showing animations of these experiments and more see `https://goo.gl/qdEhUu`.

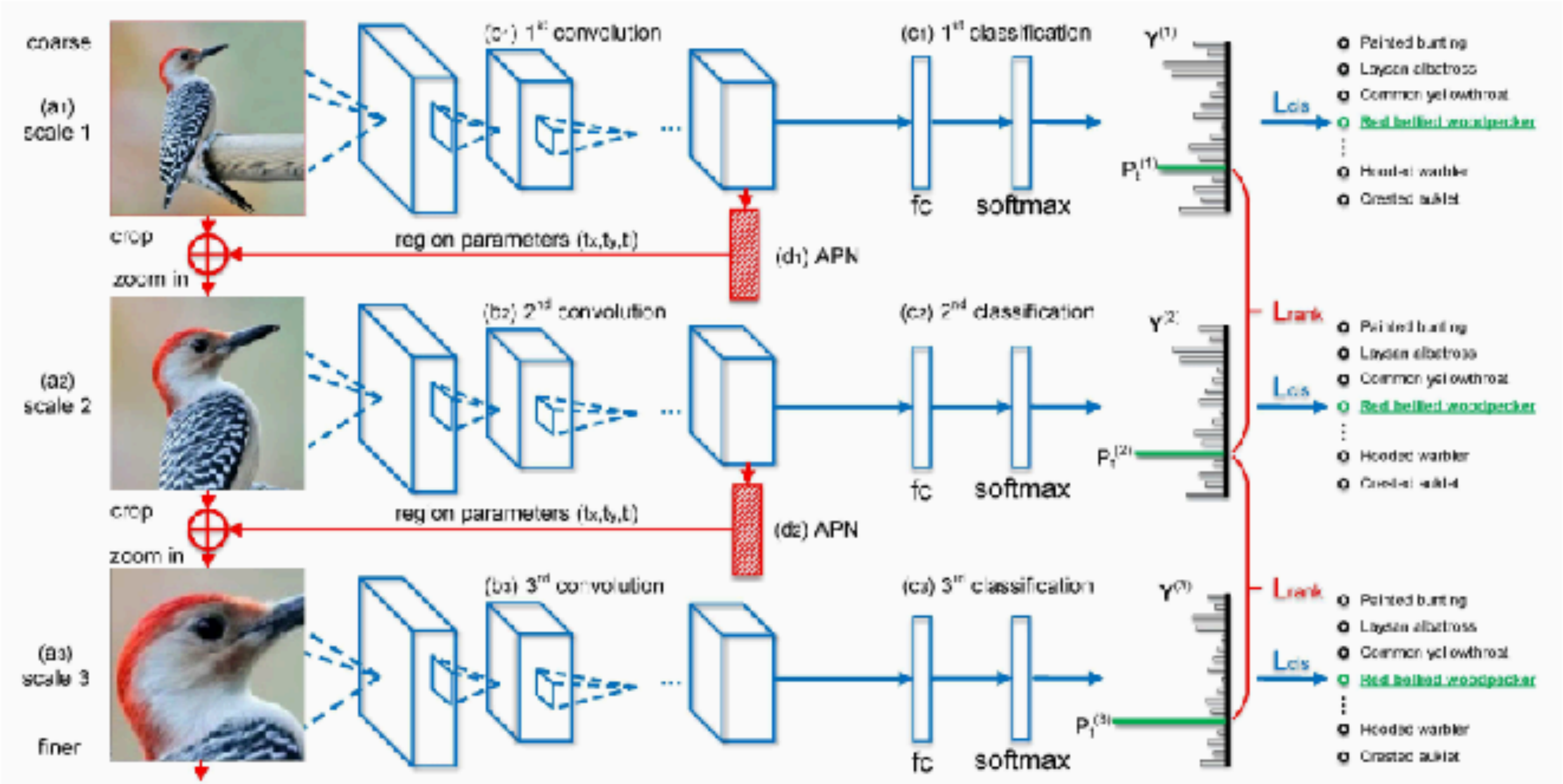
Visual Attention

- 주어진 문제를 더 효율적으로 더 좋은 성능을 해결
- 딥러닝이 블랙박스 모델인 것에 해석력 제공



Look Closer to See Better: Recurrent Attention Convolutional Neural Network for Fine-grained Image Recognition

Visual Attention



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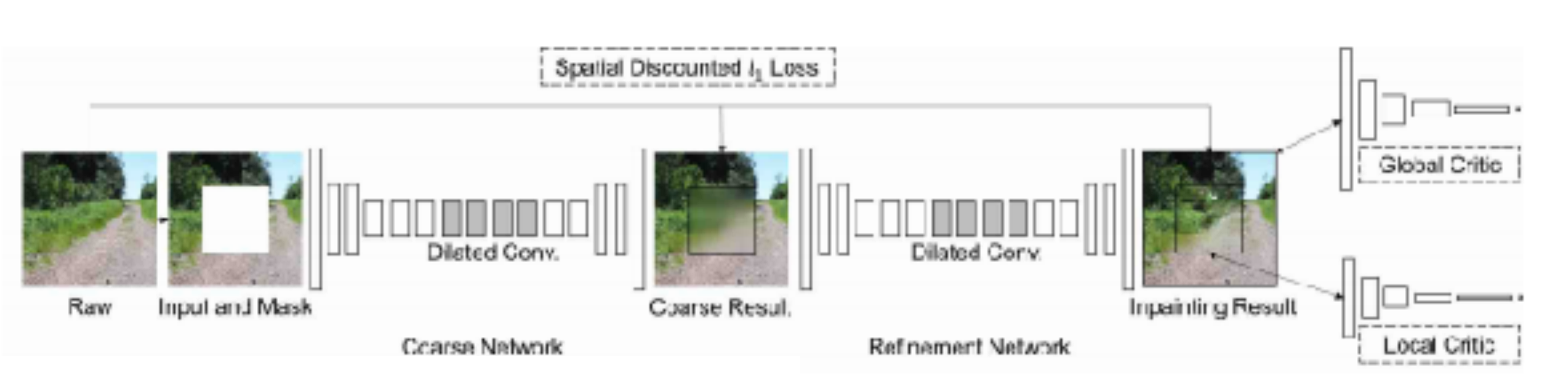
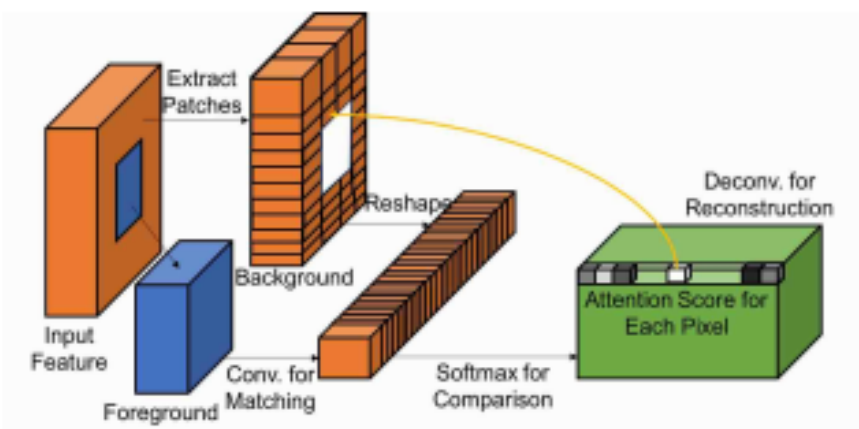
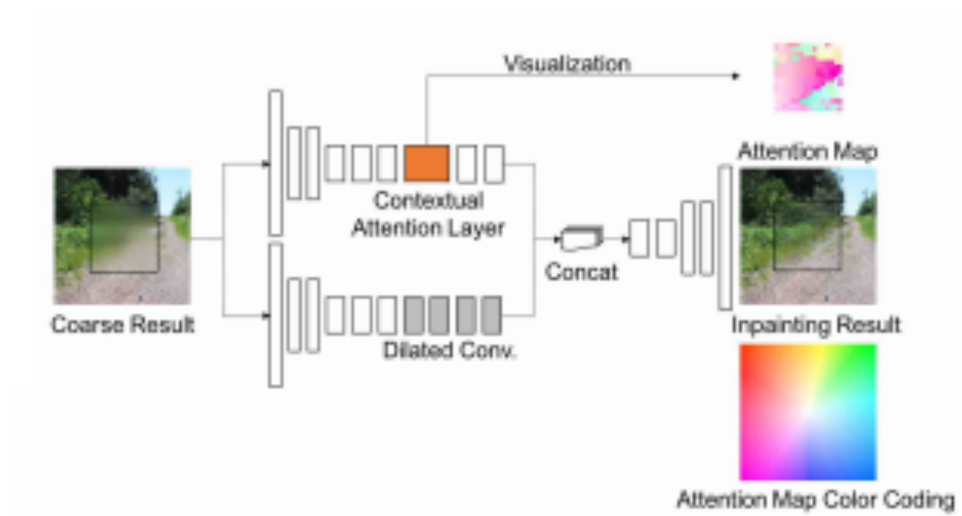
Generative Image Inpainting with Contextual Attention

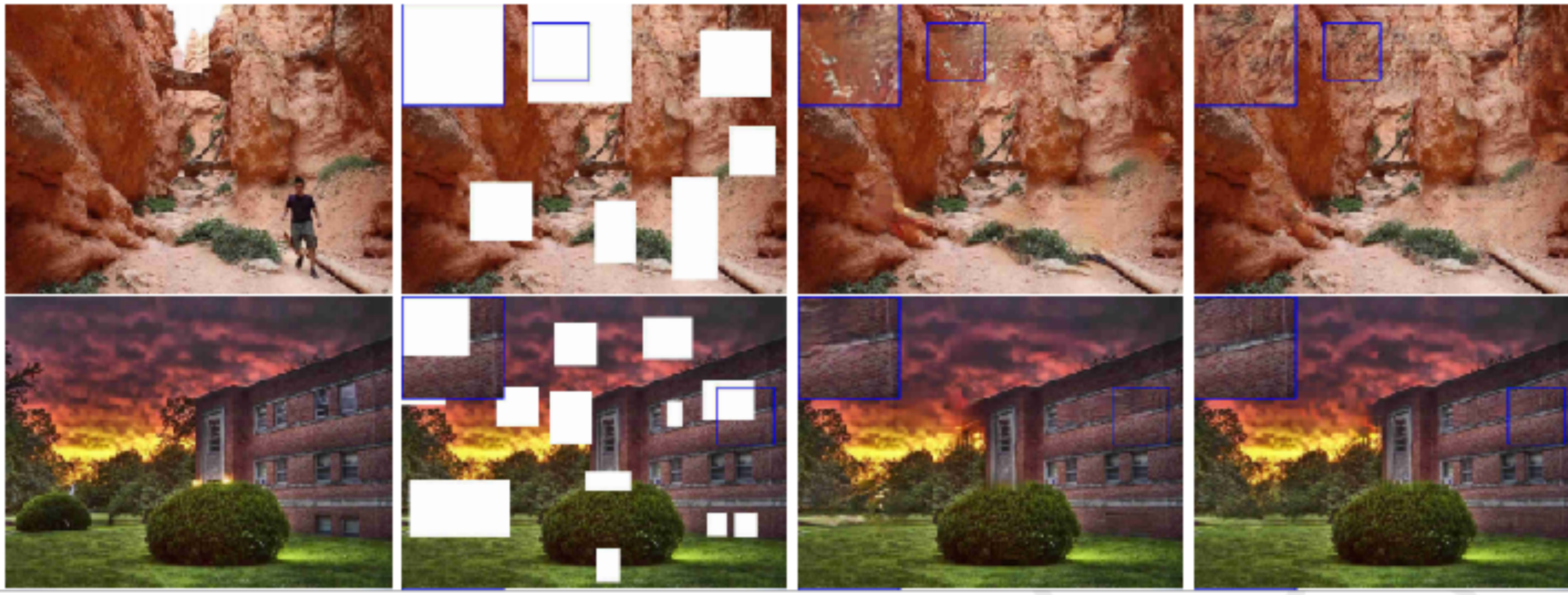
Generative Image Inpainting with Contextual Attention

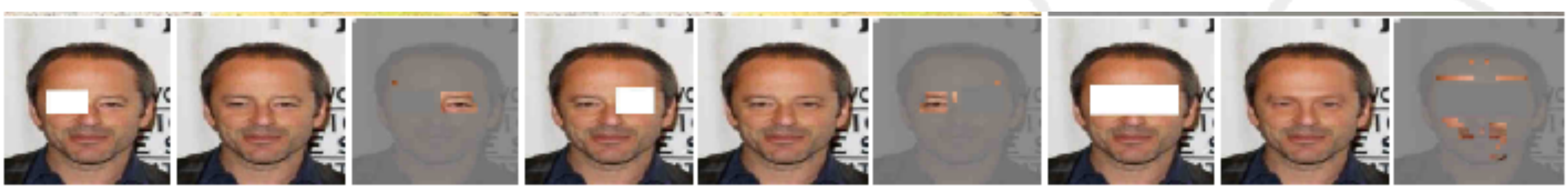






Generative Image Inpainting with Contextual Attention



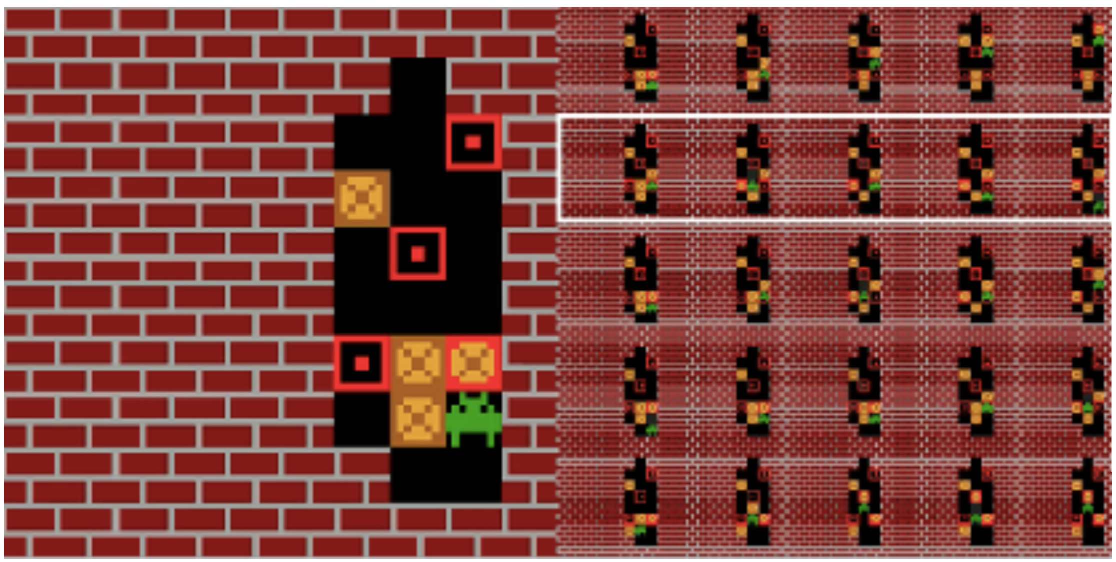


World Model

Simple random search provides a competitive approach to reinforcement learning

		Maximum average reward after # timesteps				
Task	# timesteps	ARS	SAC	DDPG	SQL	TRPO
Hopper-v1	$2.00 \cdot 10^6$	3306	$\approx$3000	$\approx$1100	$\approx$1500	$\approx$1250
HalfCheetah-v1	$1.00 \cdot 10^7$	5024	$\approx$11500	$\approx$6500	$\approx$8000	$\approx$1800
Walker2d-v1	$5.00 \cdot 10^6$	4205	$\approx$3500	$\approx$1600	$\approx$2100	$\approx$800
Ant-v1	$1.00 \cdot 10^7$	2072	$\approx$2500	$\approx$200	$\approx$2000	$\approx$0

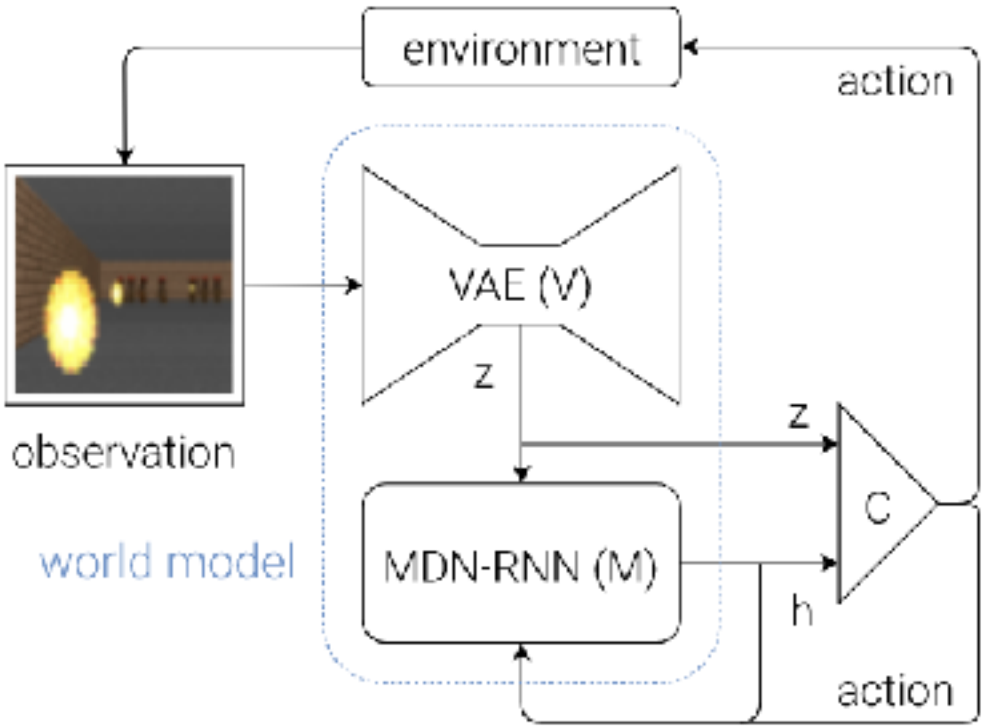
Imagination-Augmented Agents for Deep Reinforcement Learning (I2A)



I2A@87	∼ 1400
I2A MC search @95	∼ 4000
MCTS@87	∼ 25000
MCTS@95	∼ 100000
Random search	∼ millions

Table 1: Imagination efficiency of various architectures.

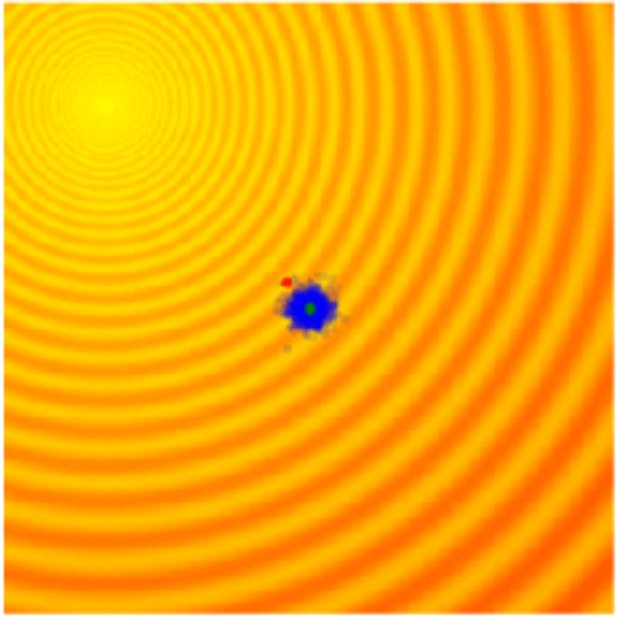
World Model

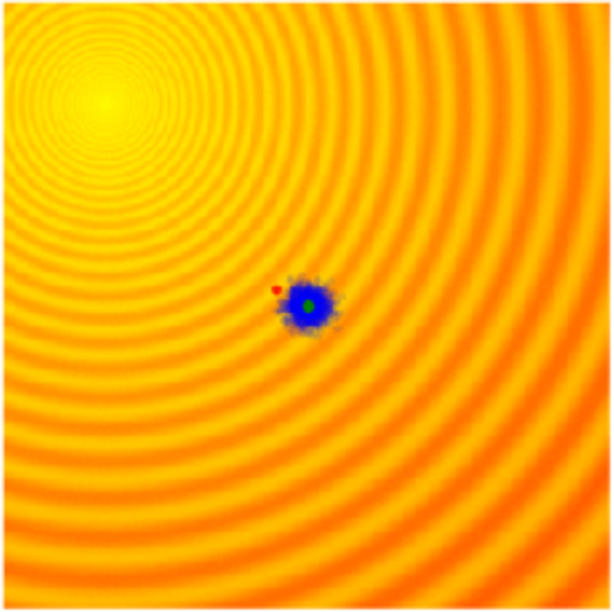


environment
action
VAE (V)
z
z
observation
C
world model
MDN-RNN (M)
h
action

100%
0%

World Model : CMA-ES

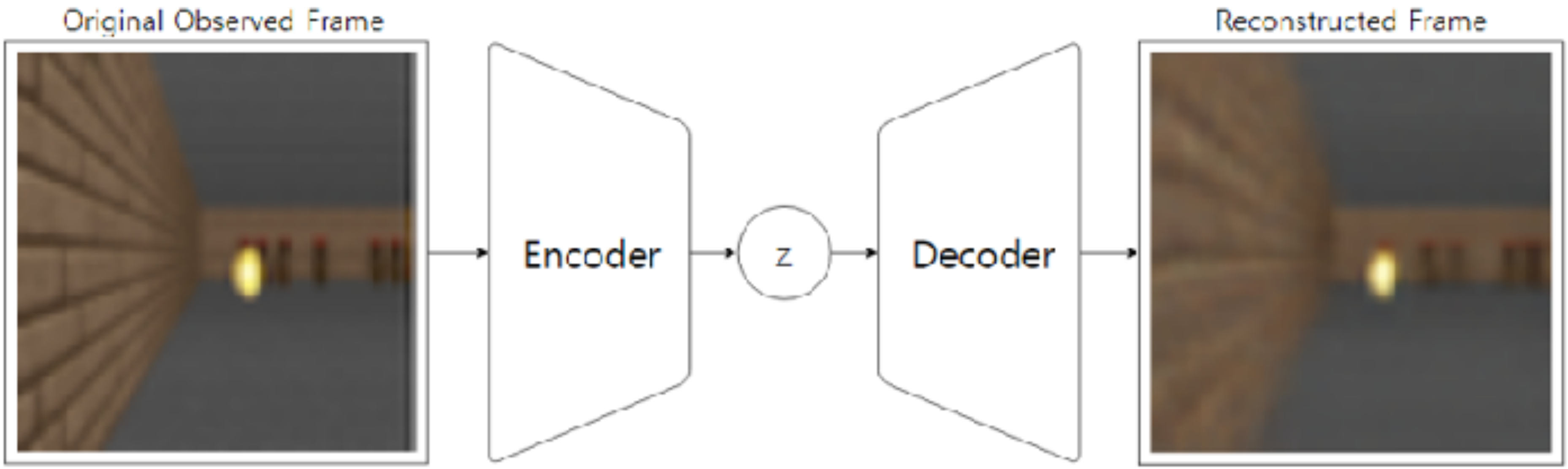




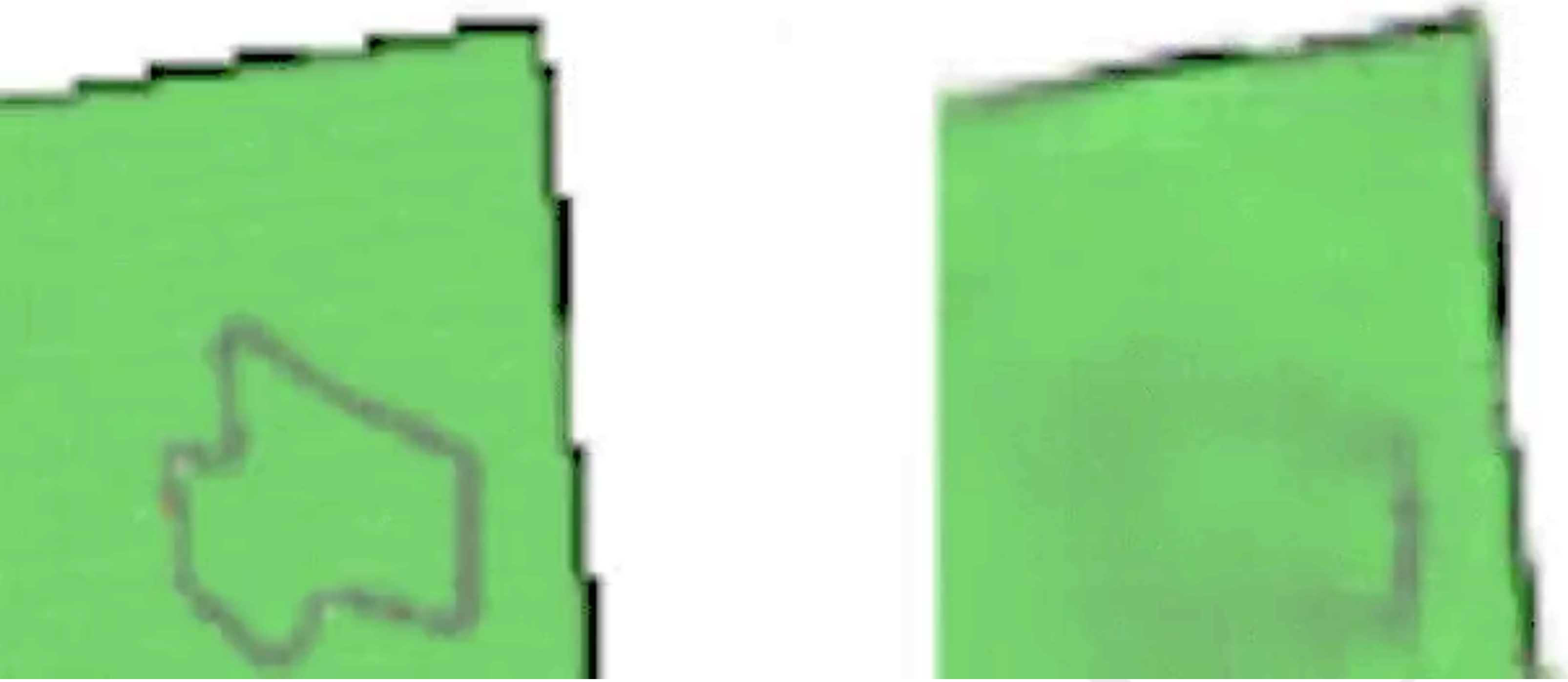
1. Calculate the fitness score of each candidate solution in generation (g).
2. Isolates the best 25% of the population in generation (g), in purple.
3. Using only the best solutions, along with the mean $\mu^{(g)}$ of the current generation (the green dot), calculate the covariance matrix $C^{(g+1)}$ of the next generation.
4. Sample a new set of candidate solutions using the updated mean $\mu^{(g+1)}$ and covariance matrix $C^{(g+1)}$.

http://blog.otoro.net/2017/10/29/visual-evolution-strategies/

World Model : Variational Autoencoder

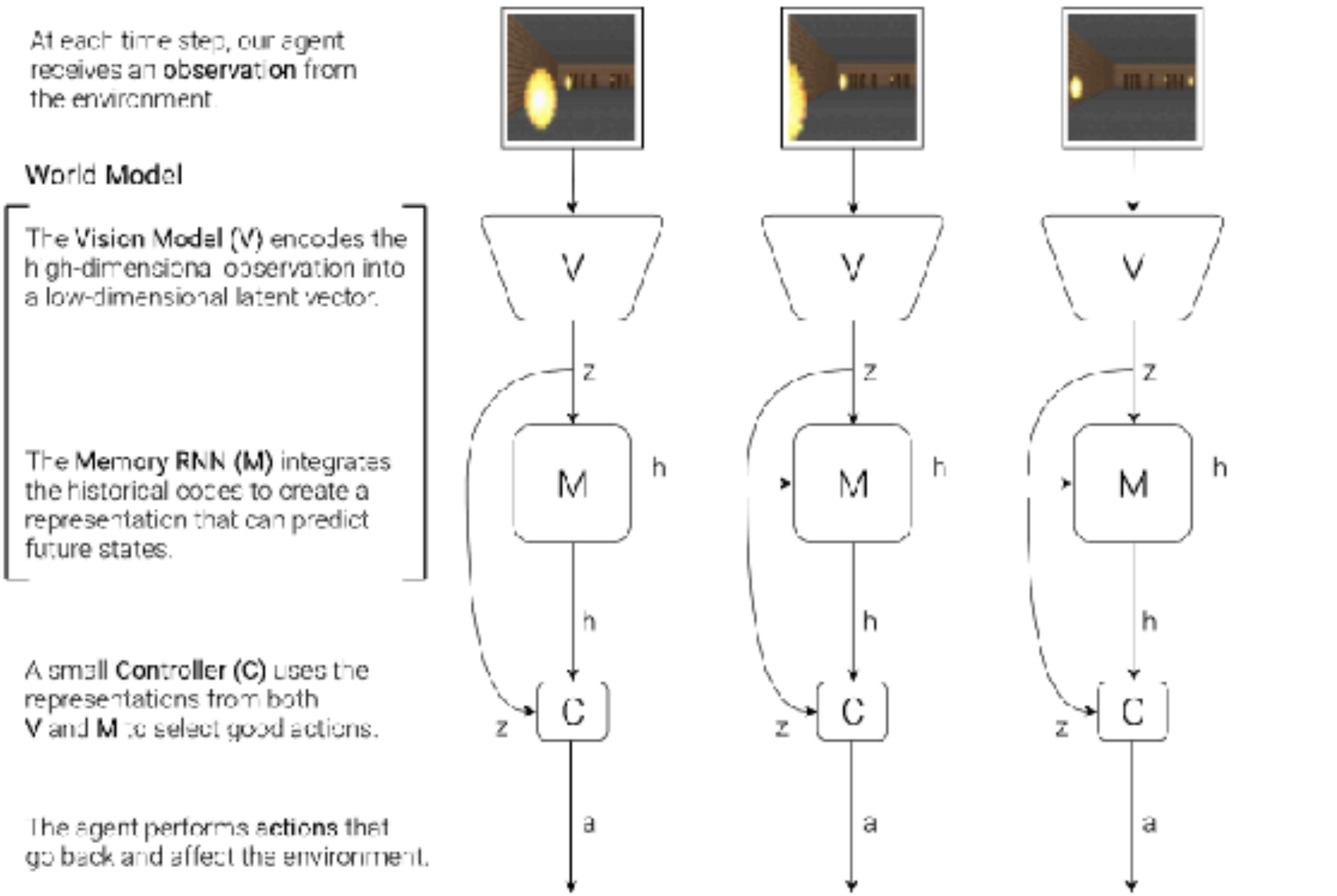


World Model : Variational Autoencoder

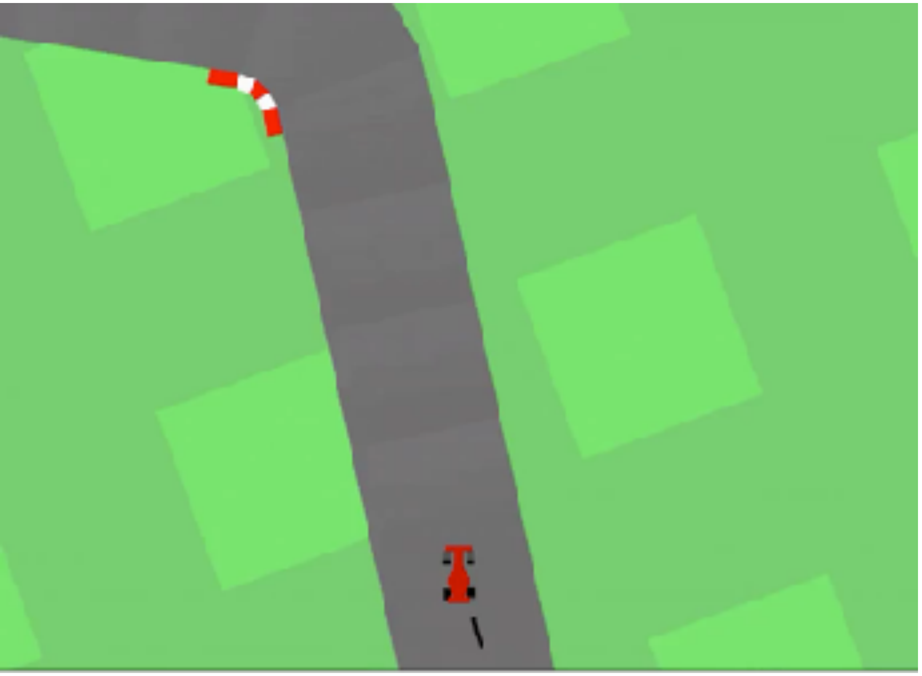


World Model: MDN – RNN (Sketch RNN)

World Model


At each time step, our agent receives an observation from the environment.
World Model
The Vision Model (V) encodes the high-dimensional observation into a low-dimensional latent vector.
The Memory RNN (M) integrates the historical codes to create a representation that can predict future states.
A small Controller (C) uses the representations from both V and M to select good actions.
The agent performs actions that go back and affect the environment.
V
z
M
h
h
C
z
a

World Model



Domain Transfer Network

Image-to-Image Translation with Conditional Adversarial Networks

Image-to-Image Translation with Conditional Adversarial Networks

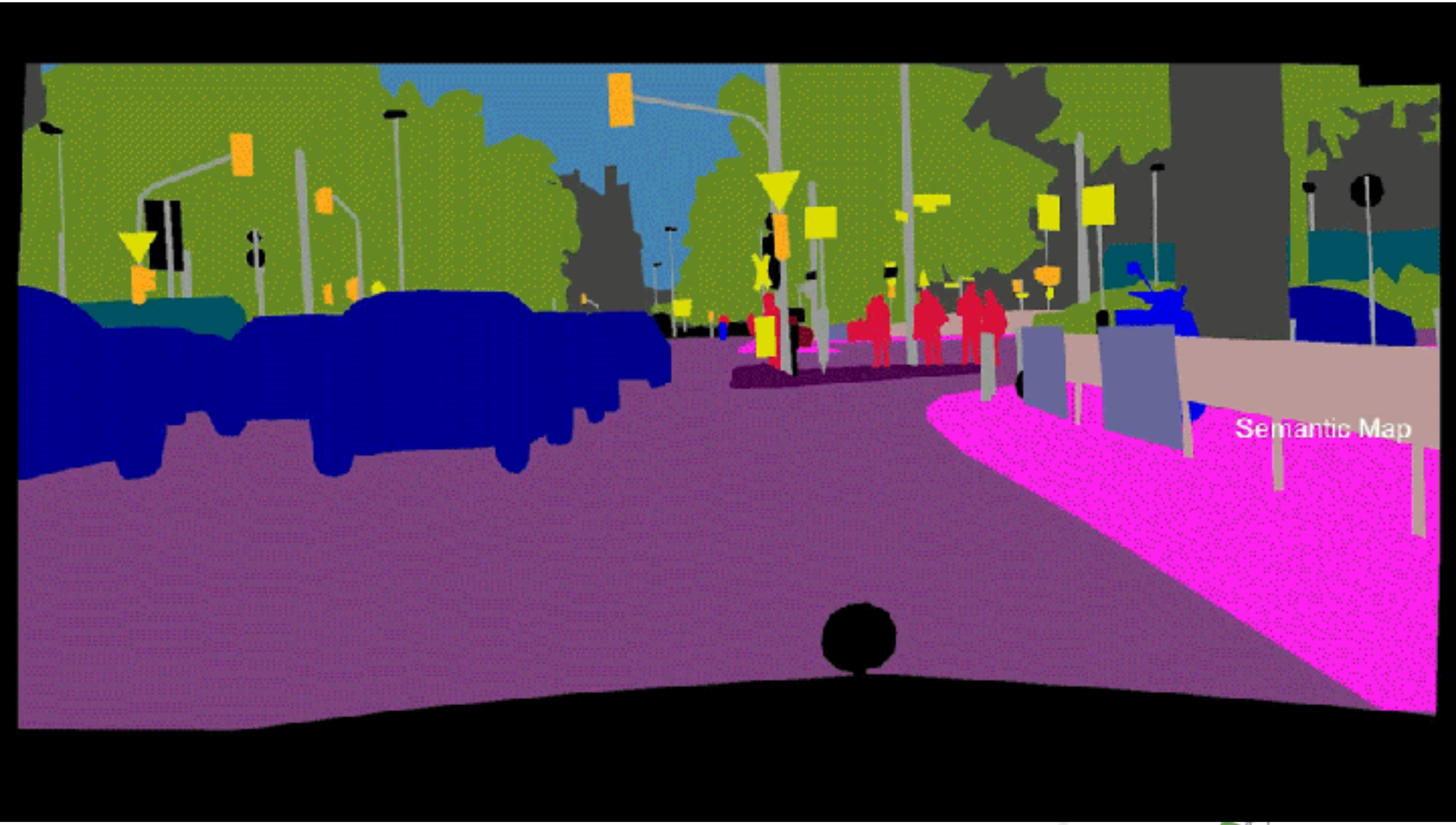
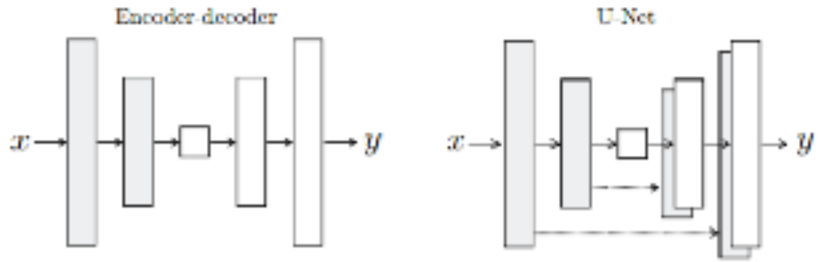


Image-to-Image Translation with Conditional Adversarial Networks



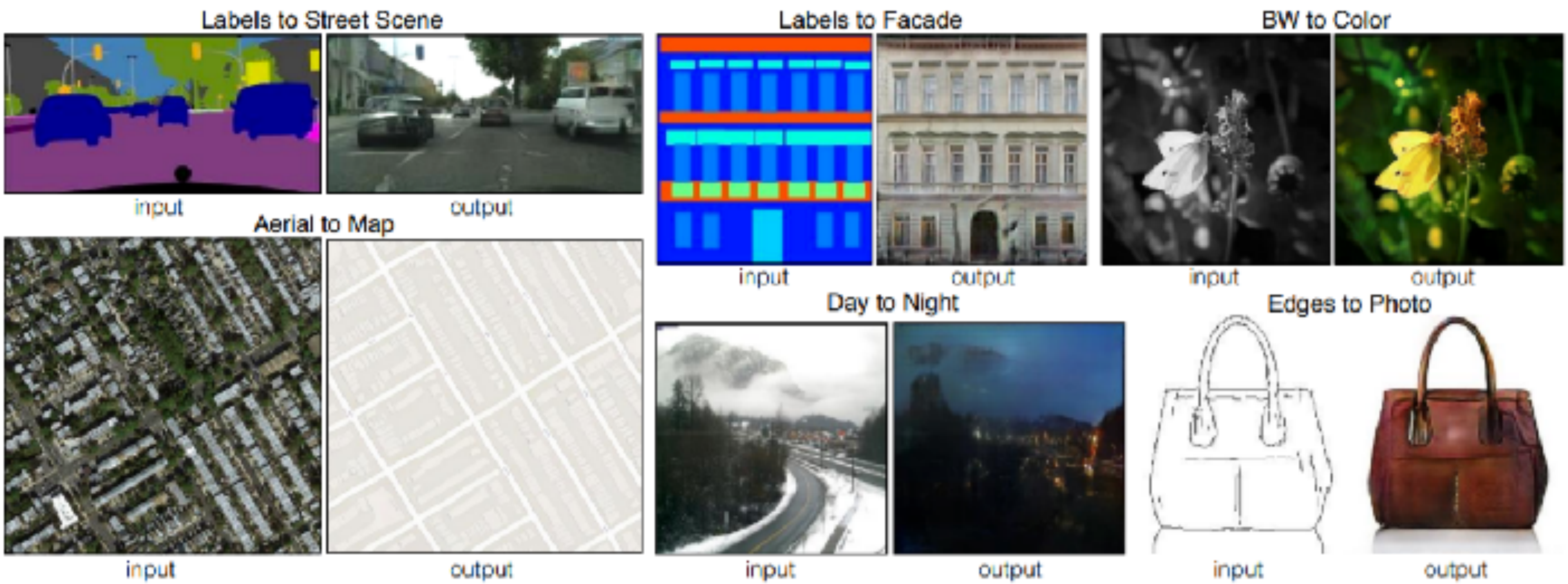


Image-to-Image Translation of Unpaired Dataset!

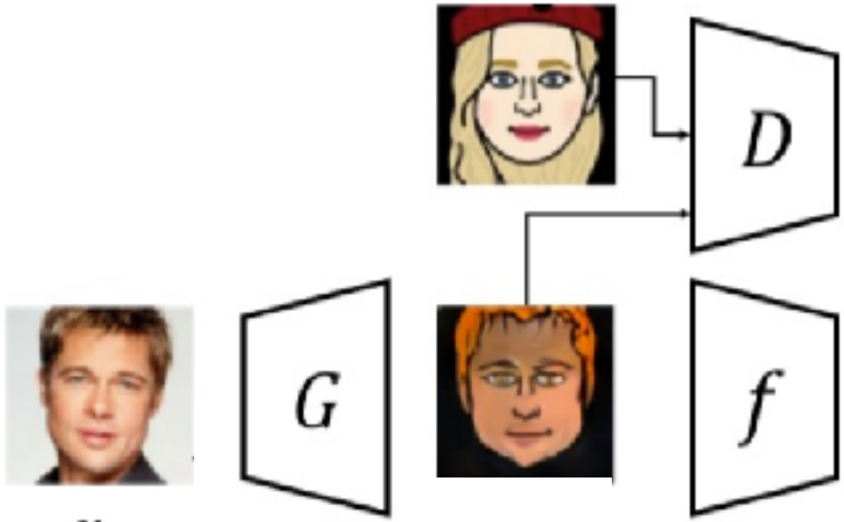
Unsupervised Cross-Domain Image Generation

같은정보
- 얼굴 윤곽
- 얼굴 특징

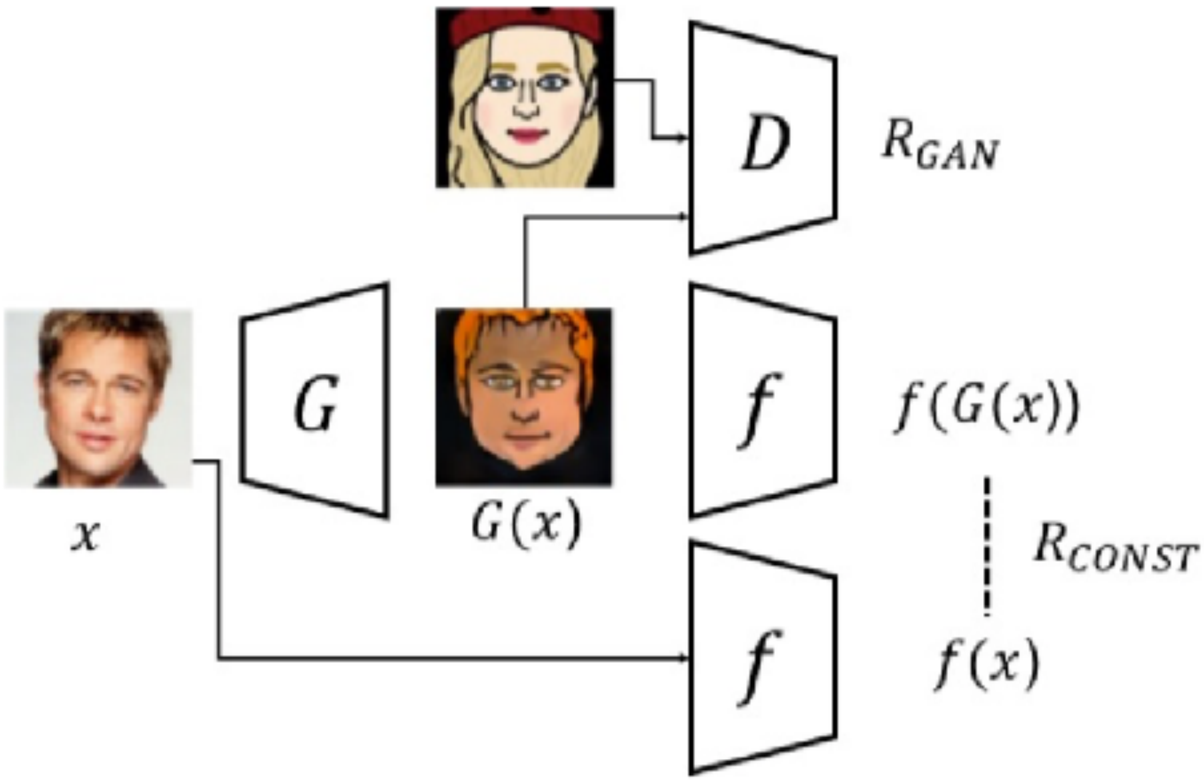
다른 정보
- 윤곽선 두께
- 색상복잡도

https://arxiv.org/abs/1611.02200

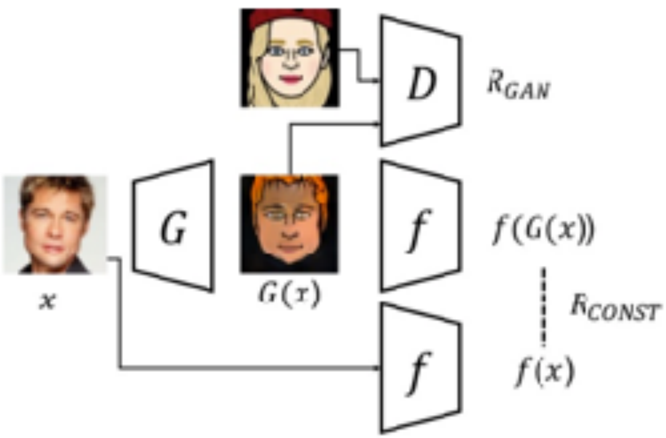
Unsupervised Cross-Domain Image Generation

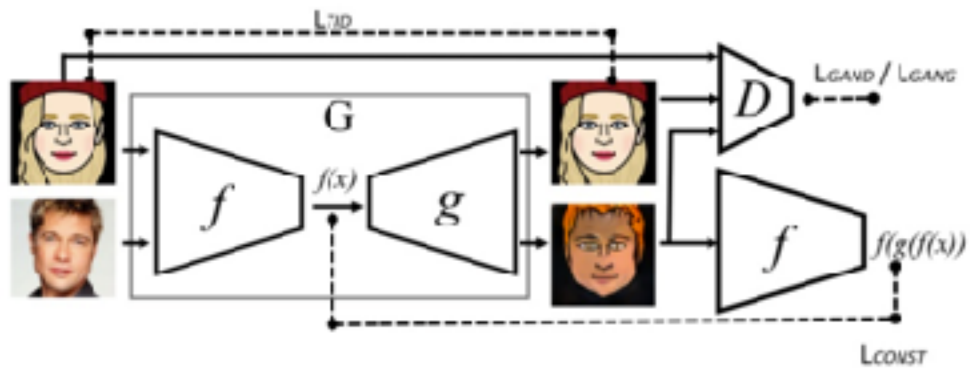


Unsupervised Cross-Domain Image Generation

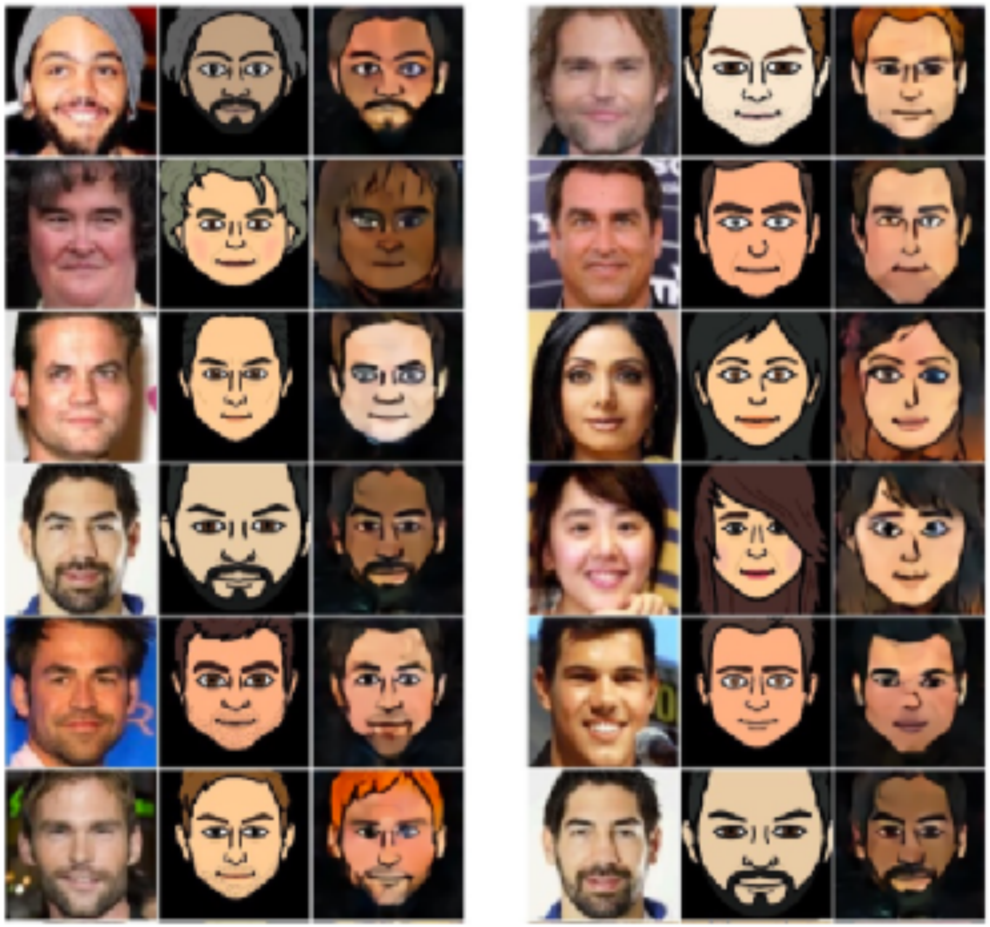


Unsupervised Cross-Domain Image Generation

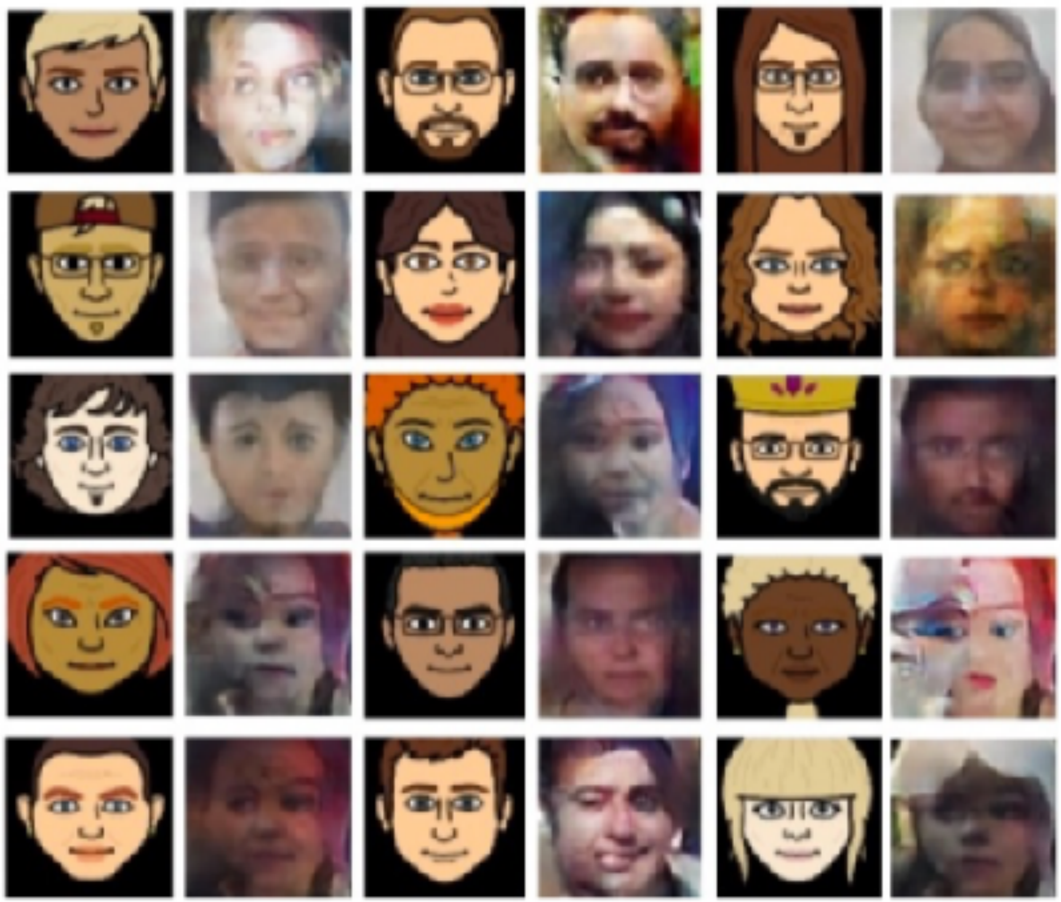




Unsupervised Cross-Domain Image Generation



Unsupervised Cross-Domain Image Generation



Cycle GAN (Disco GAN)

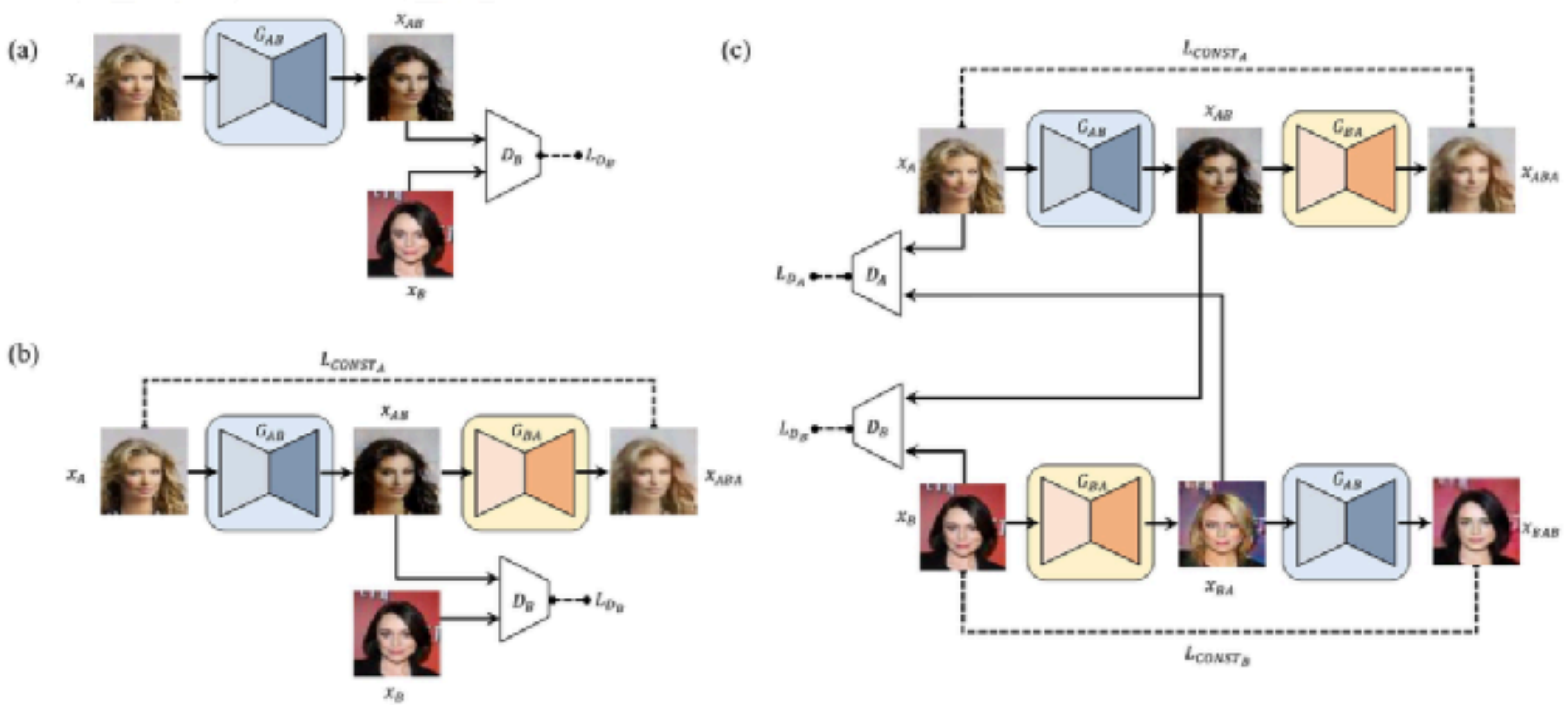
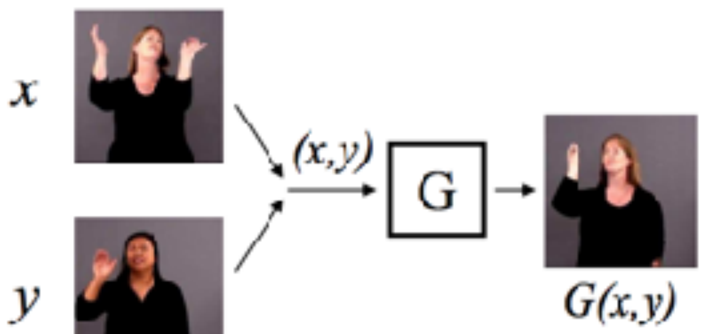
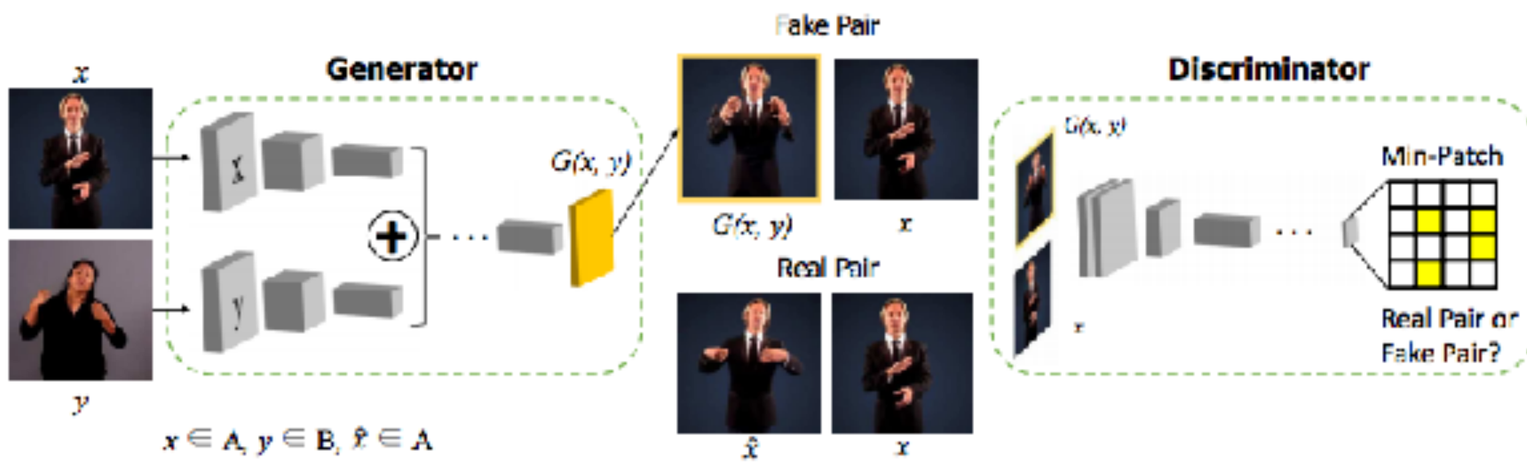


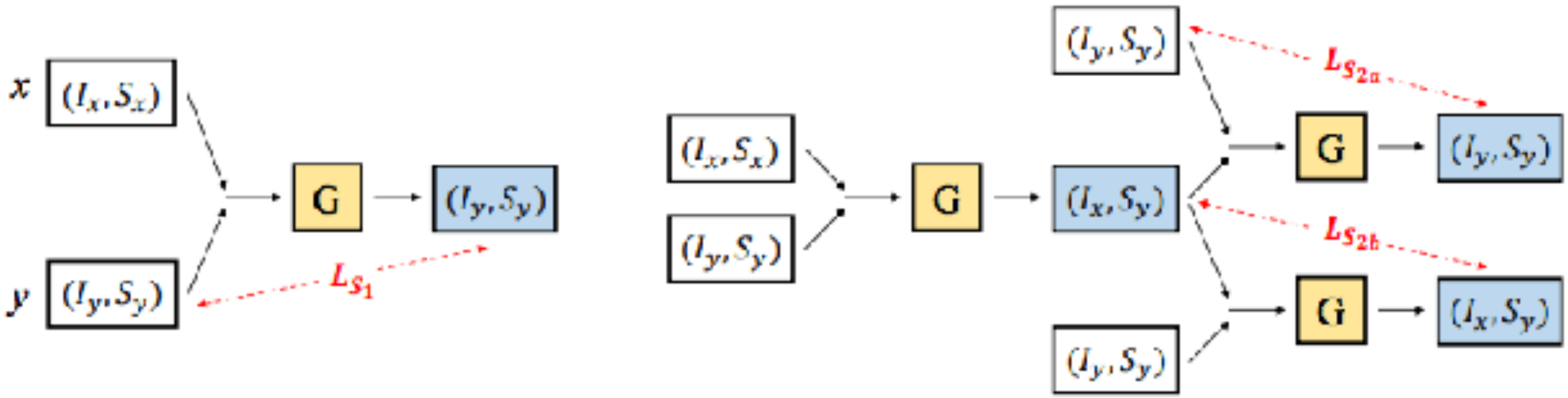
Figure 2. Three investigated models. (a) standard GAN (Goodfellow et al., 2014), (b) GAN with a reconstruction loss, (c) our **proposed model (DiscoGAN)** designed to discover relations between two unpaired, unlabeled datasets. Details are described in Section 3.

Generating a Fusion Image: One's Identity and Another's Shape





Generating a Fusion Image: One's Identity and Another's Shape



(a) Shape Loss L_{S_1} for $I_x = I_y$

(b) Shape Loss $L_{S_{2a}}$ *and* $L_{S_{2b}}$ for $I_x \neq I_y$

Figure 3. Illustration of *Shape Loss*. (a) Shape loss L_{S_1} is defined when $I_x = I_y$ (b) Shape loss $L_{S_{2a}}$ and $L_{S_{2b}}$ are defined when $I_x \neq I_y$. To achieve our goal, these shape losses should be minimized. In the figure, generator G is only one model (same weights), and blue images are the generated output images from the generator

Generating a Fusion Image: One's Identity and Another's Shape

Everybody Dance!

Everybody Dance!

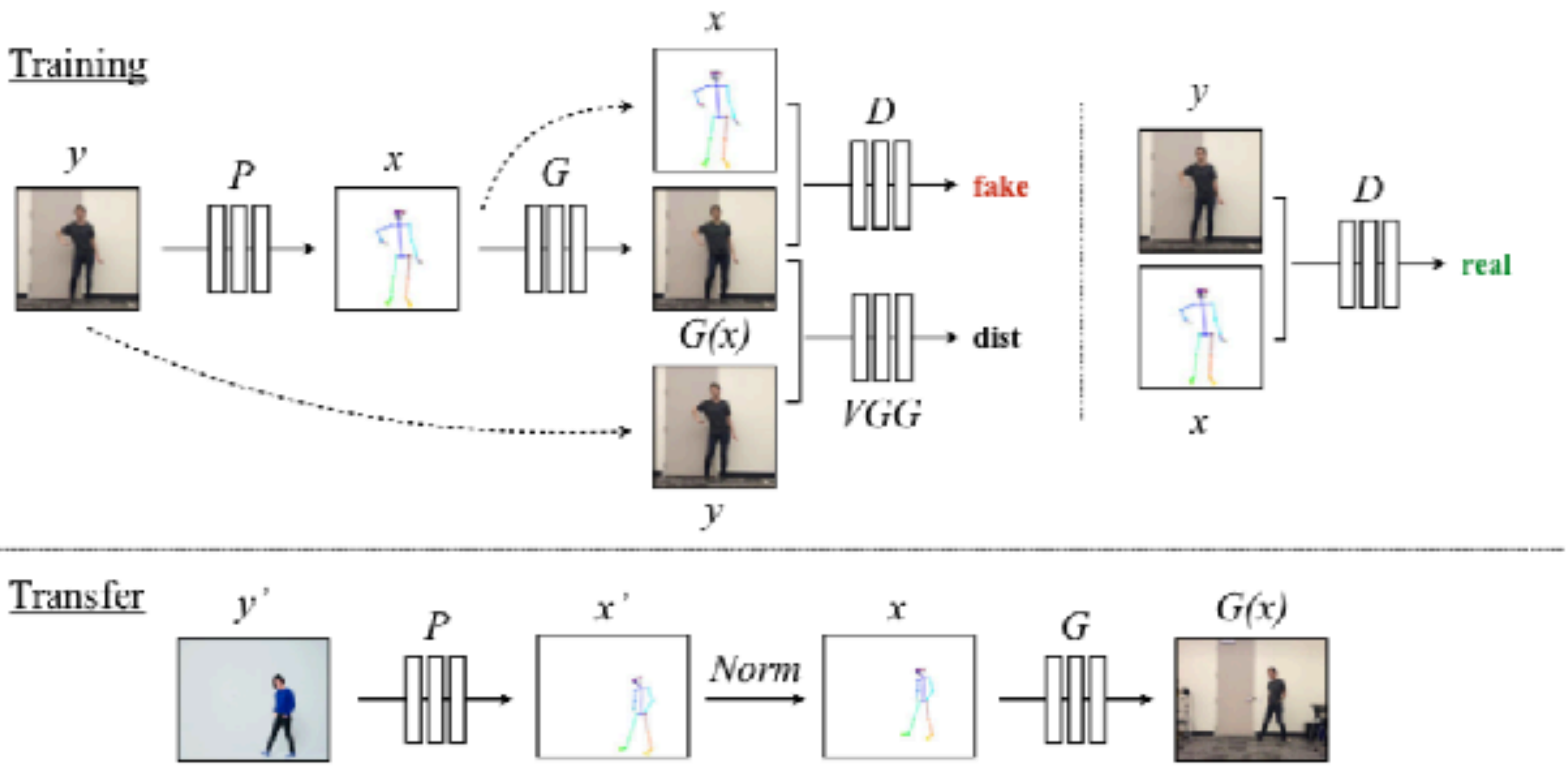
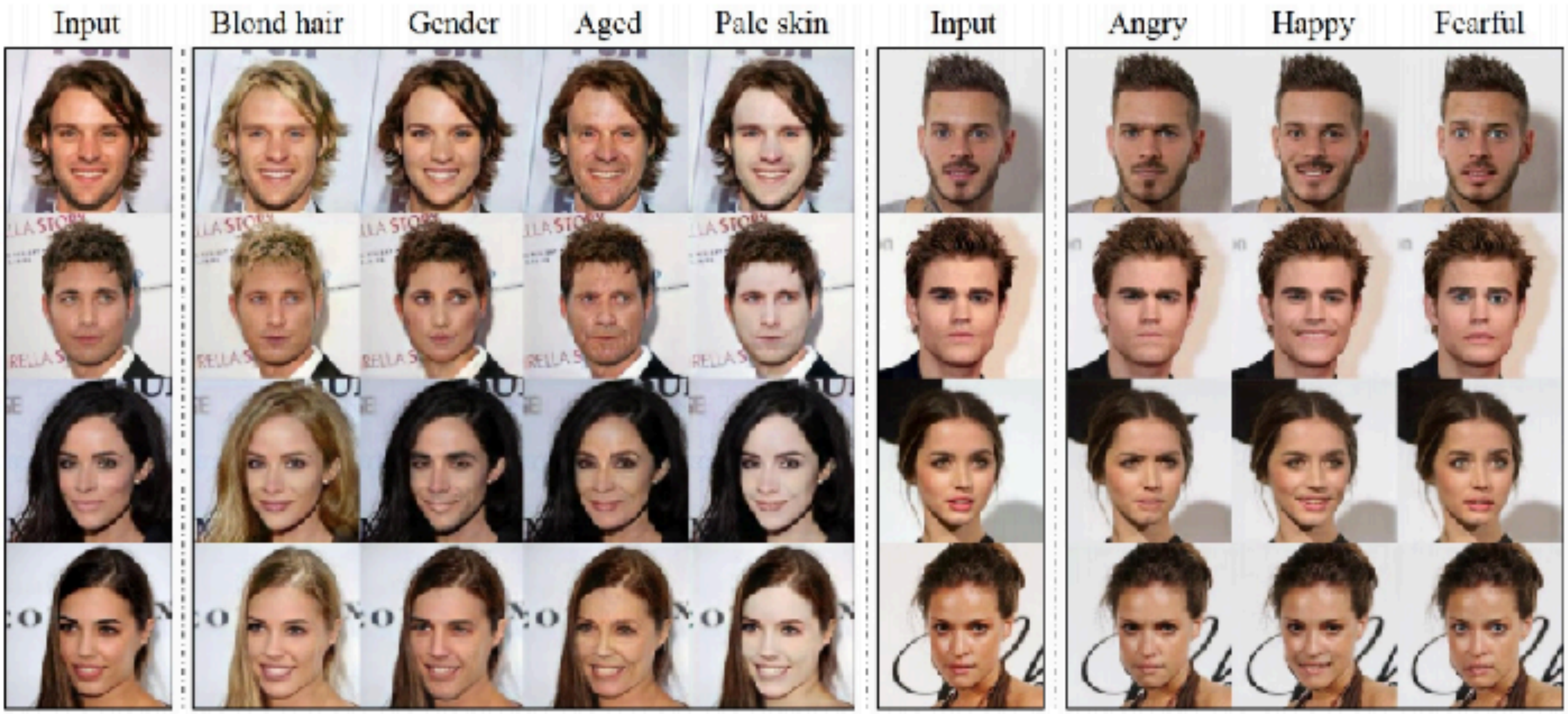


Fig. 3. (Top) **Training:** Our model uses a pose detector P to create pose stick figures from video frames of the target subject. During training we learn the mapping G alongside an adversarial discriminator D which attempts to distinguish between the "real" correspondence pair (x, y) and the "fake" pair $(G(x), y)$. (Bottom) **Transfer:** We use a pose detector $P : Y' \to X'$ to obtain pose joints for the source person that are transformed by our normalization process $Norm$ into joints for the target person for which pose stick figures are created. Then we apply the trained mapping G.

Multi modal Transfer



StarGAN

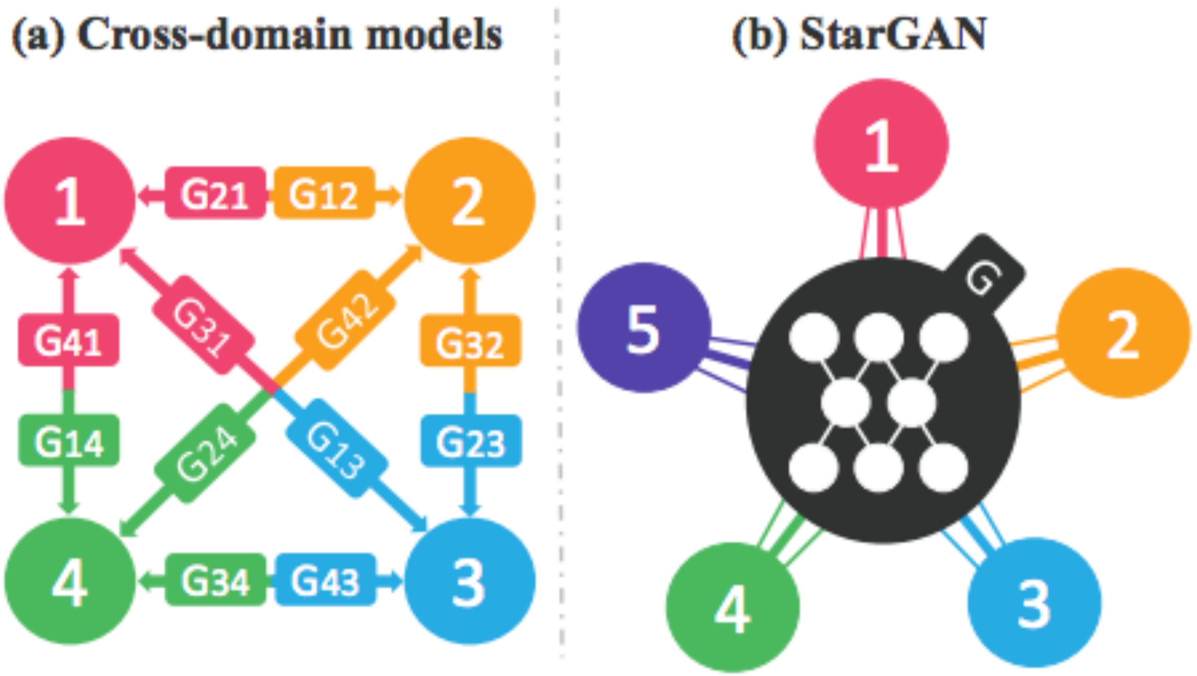
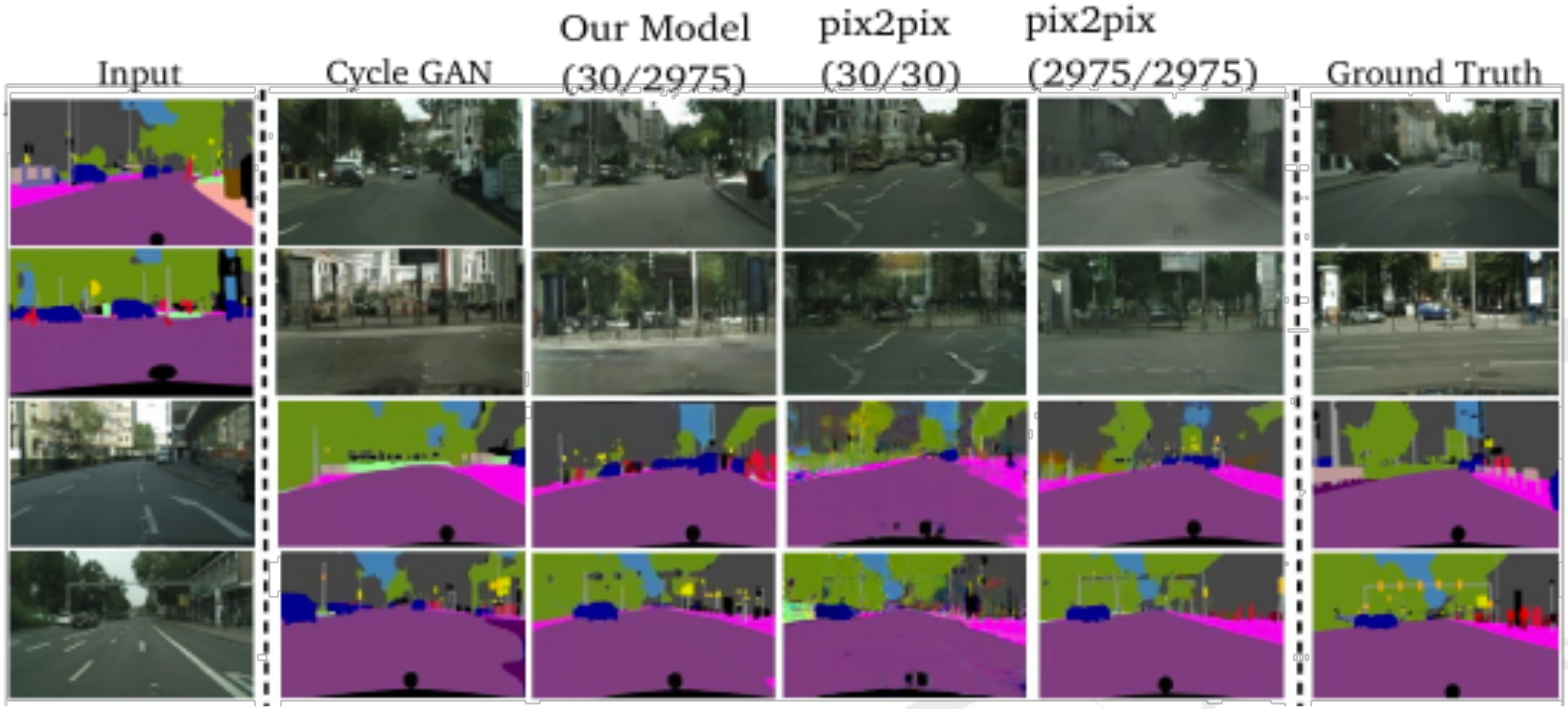

(a) Cross-domain models
(b) StarGAN
1
2
3
4
G21
G12
G41
G14
G31
G42
G24
G13
G32
G23
G34
G43
1
2
3
4
5
G

image-to-image translation using paired and unpaired training samples



https://arxiv.org/pdf/1805.03189.pd

TimbreTron: A WaveNet(CycleGAN(CQT(Audio))) Pipeline for Musical Timbre Transfer

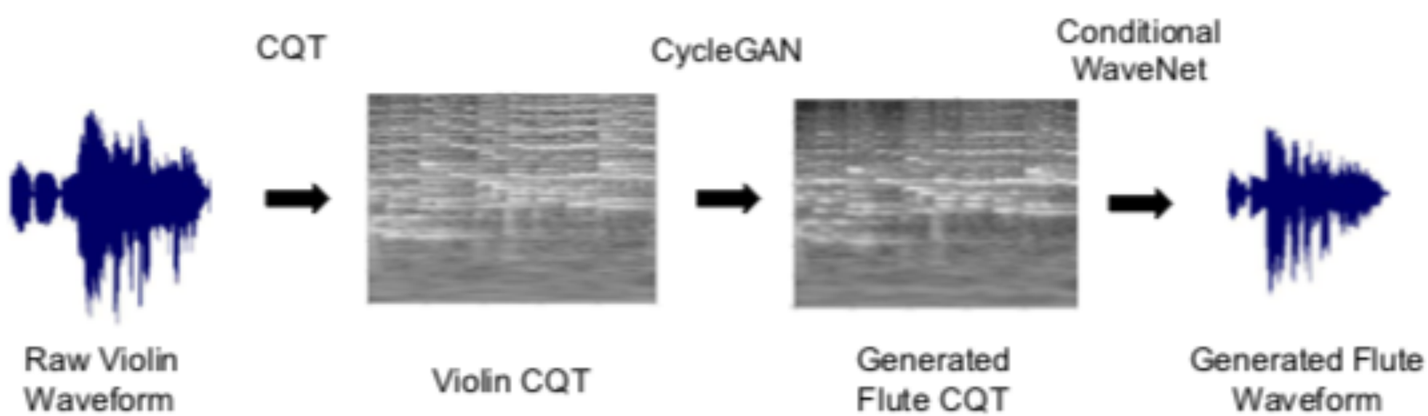


Figure 1: The TimbreTron pipeline that performs timbre transfer from Violin to Flute.

Domain for engineering?

- Signal / Noise ?
- Experiment / Simulation ?
- Small / Large ?
- Problem A / B
- Device A / B

기계공학에서의 인공지능

기계공학 분야의 인공지능

- 기기 진단 및 고장 예지
- 비파괴 검사
- 전산 역학
- 최적 설계
- 로봇 제어

가상 물리모델

전류

전압

전자기장

온도

토크

전자기, 유동, 마찰, 동역학......

너무 많은 노력이 필요...

가상 물리모델

전류

전압

전자기장

온도

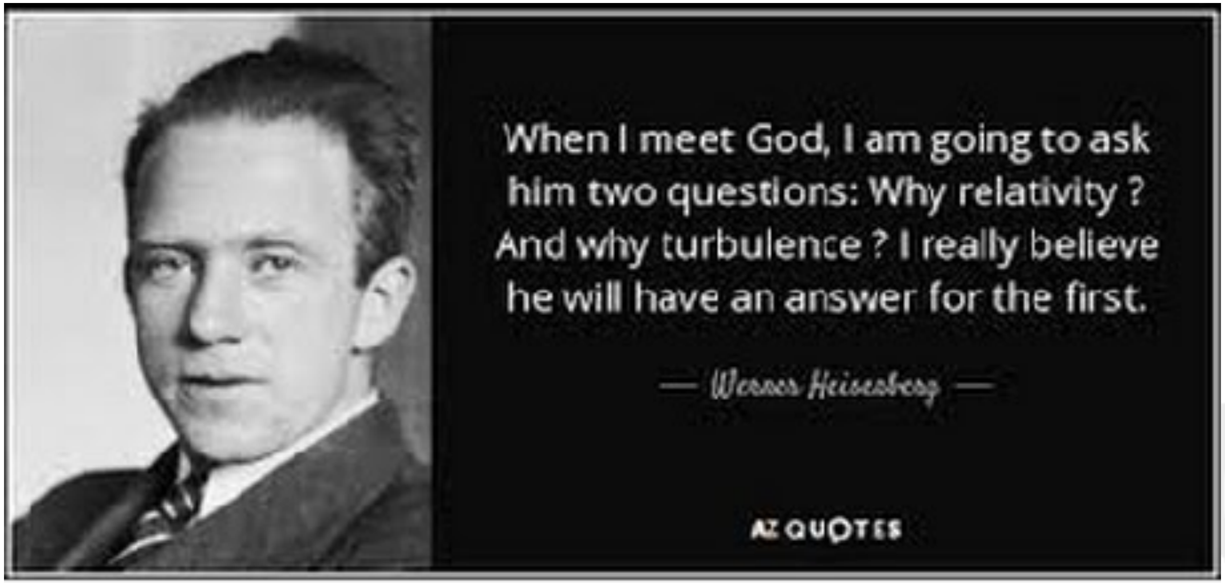
f

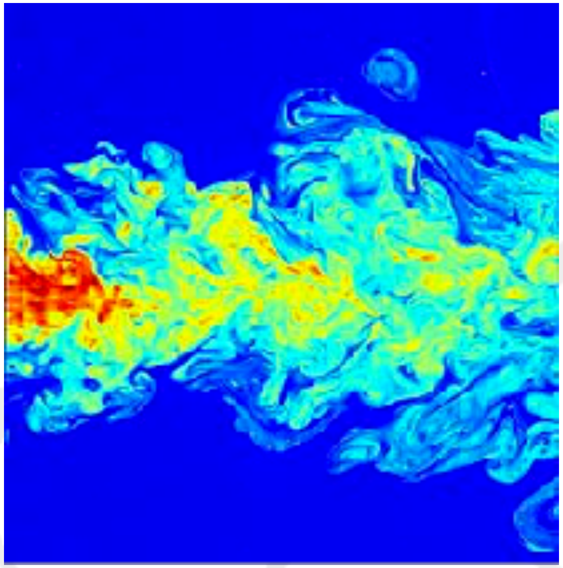
토크

정상, 고장

- 비정상 검출
- 수명 예측

Turbulence





https://ko.wikipedia.org/wiki/%EB%82%9C%EB%A5%98_(%EC%97%AD%ED%95%99)

Navier-Stokes Equation

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

change of velocity with time

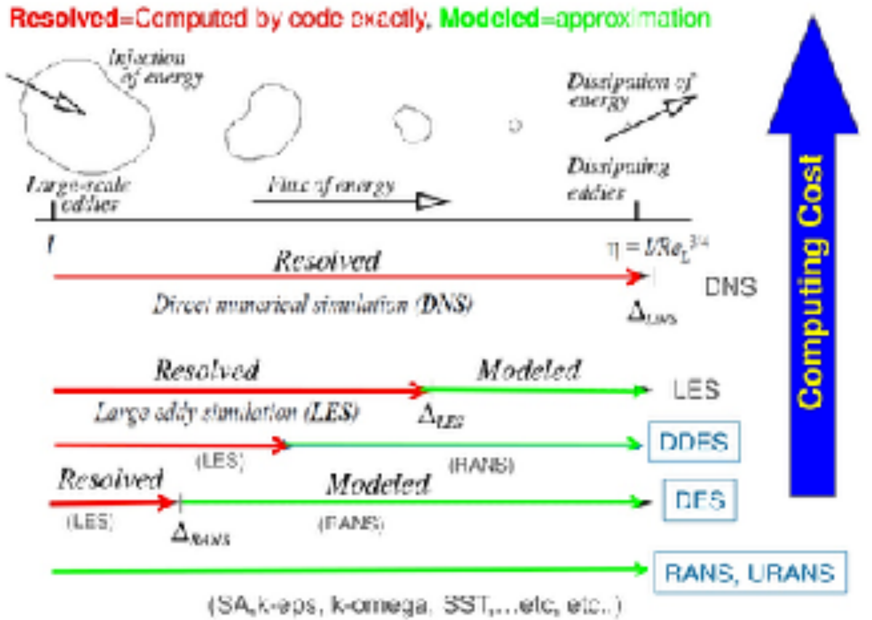
Convective term

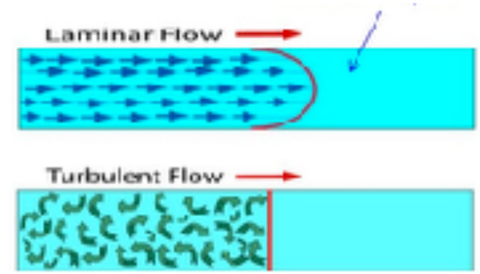
Pressure term: Fluid flows in the direction of largest change in pressure

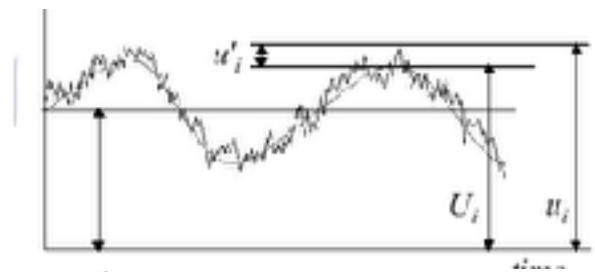
Body force term: external forces that act on the fluid (such as gravity, electromagnetic, etc.)

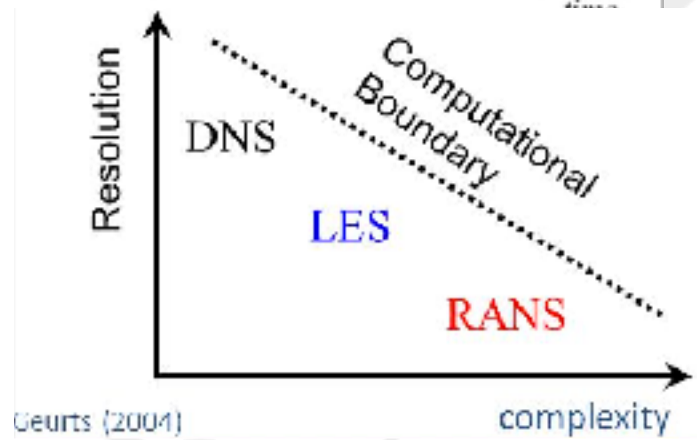
viscosity controlled velocity diffusion term

Accuracy vs. Cost



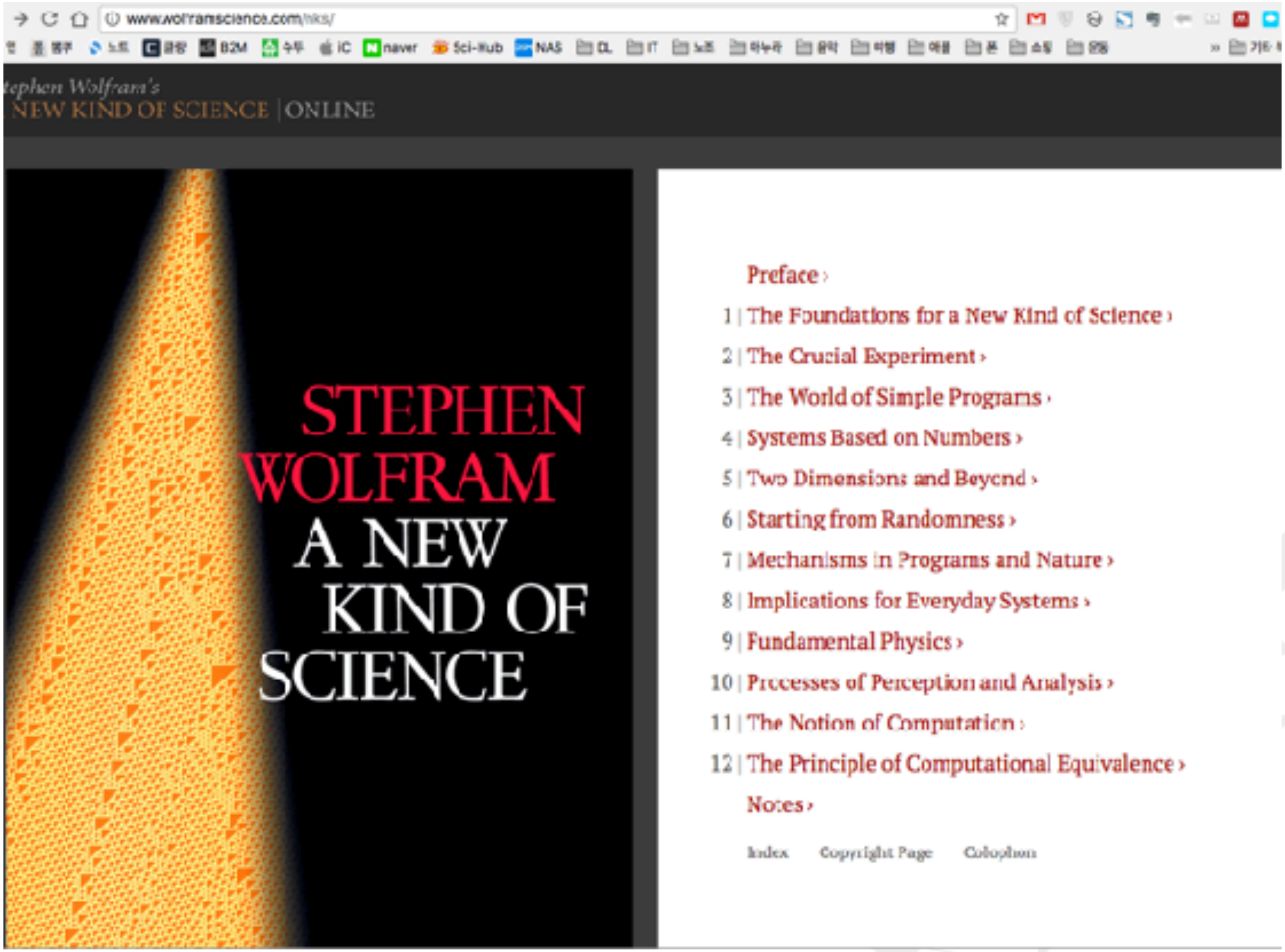






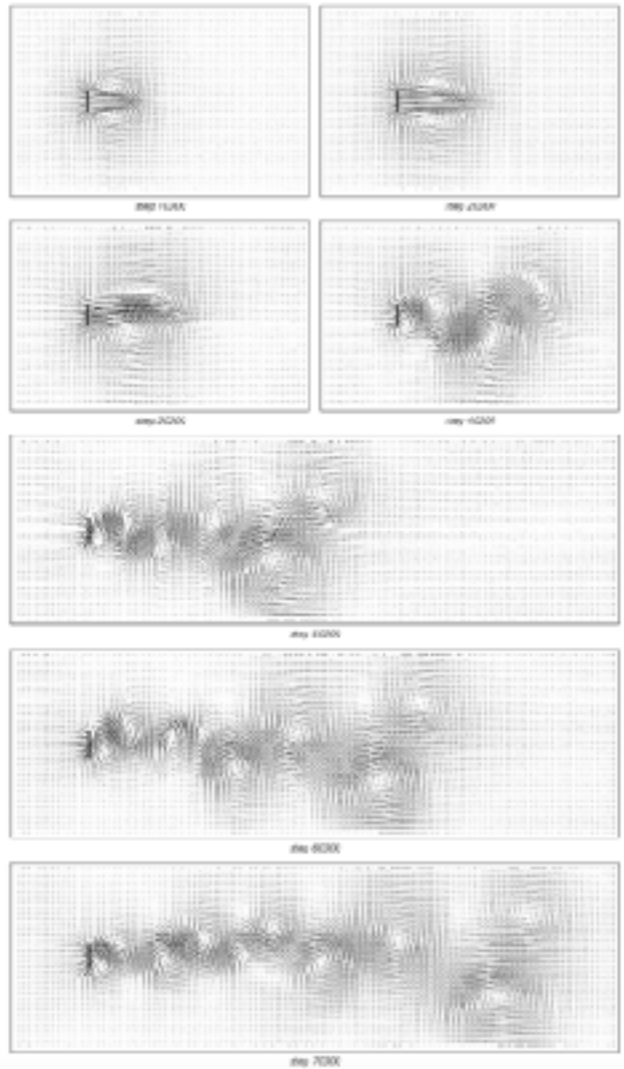
Intro to CFD and Multiphysics Simulations, https://www.slideshare.net/AltairHTC/s02-altair-cosgrove

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.



딥러닝으로 난류모델을 만들 수 있을까?!

Why does deep and cheap learning work so well?*

Henry W. Lin, Max Tegmark, and David Rolnick
Dept. of Physics, Harvard University, Cambridge, MA 02138
Dept. of Physics, Massachusetts Institute of Technology, Cambridge, MA 02139 and
Dept. of Mathematics, Massachusetts Institute of Technology, Cambridge, MA 02139

(Dated: July 21 2017)

We show how the success of deep learning could depend not only on mathematics but also on physics: although well-known mathematical theorems guarantee that neural networks can approximate arbitrary functions well, the class of functions of practical interest can frequently be approximated through "cheap learning" with exponentially fewer parameters than generic ones. We explore how properties frequently encountered in physics such as symmetry, locality, compositionality, and polynomial log-probability translate into exceptionally simple neural networks. We further argue that when the statistical process generating the data is of a certain hierarchical form prevalent in physics and machine-learning, a deep neural network can be more efficient than a shallow one. We formalize these claims using information theory and discuss the relation to the renormalization group. We prove various "no-flattening theorems" showing when efficient linear deep networks cannot be accurately approximated by shallow ones without efficiency loss; for example, we show that n variables cannot be multiplied using fewer than 2^n neurons in a single hidden layer.

Deep Learning in Computer Graphics

M. Chu, “Data-Driven Synthesis of Smoke Flows with CNN-based Feature Descriptors”, SIGGRAPH 2017

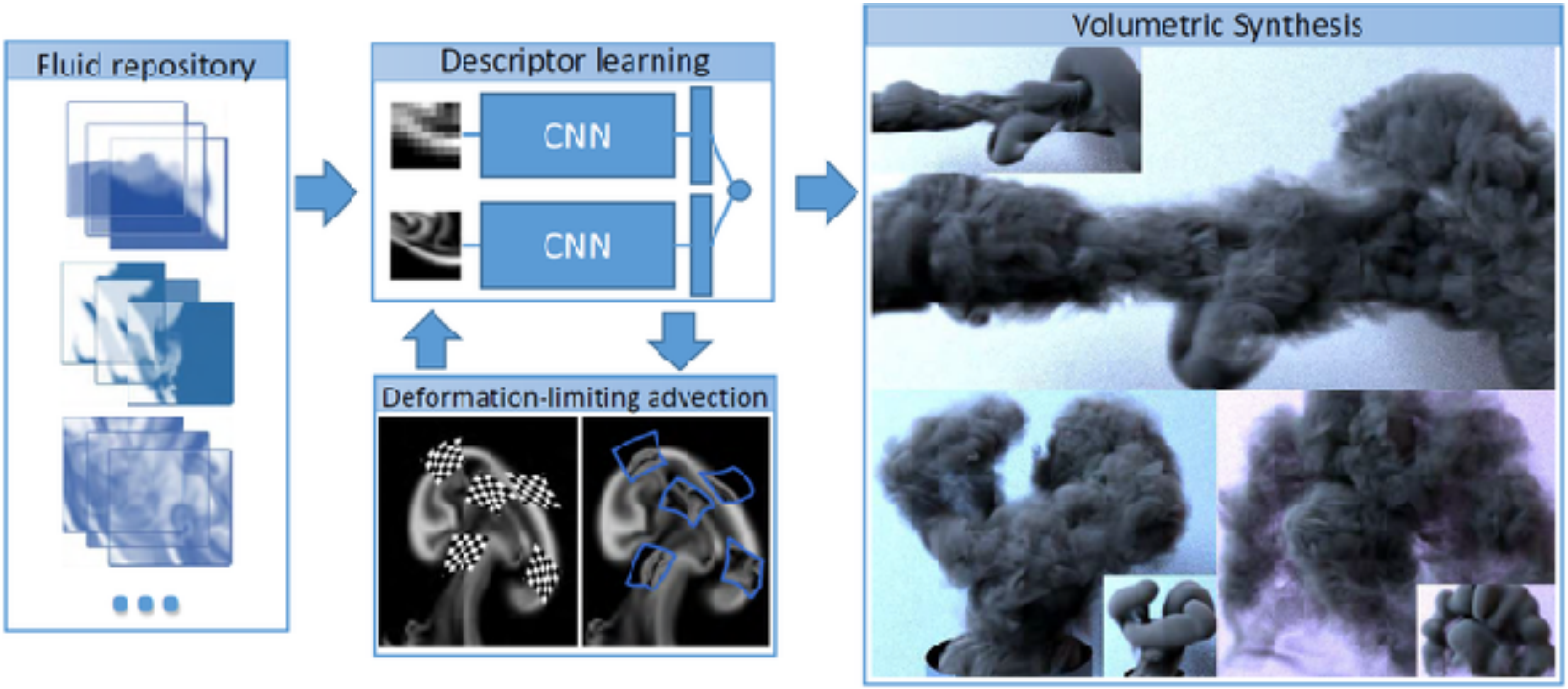
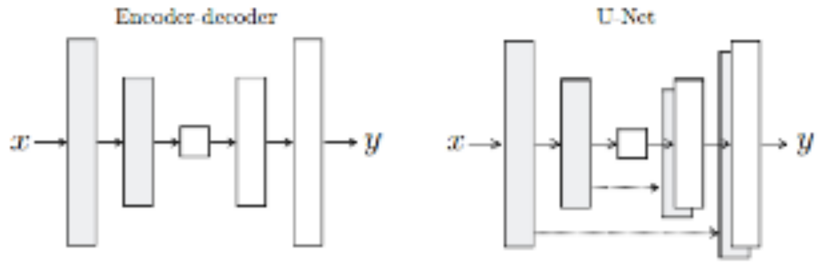
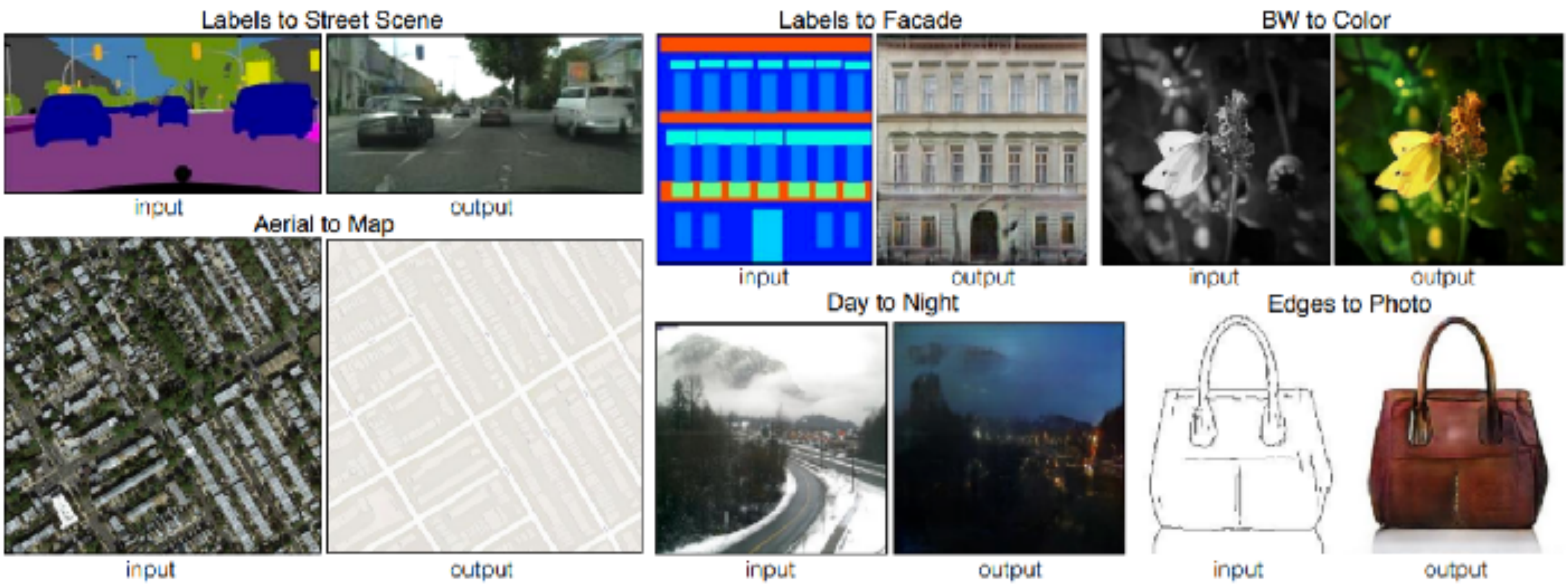
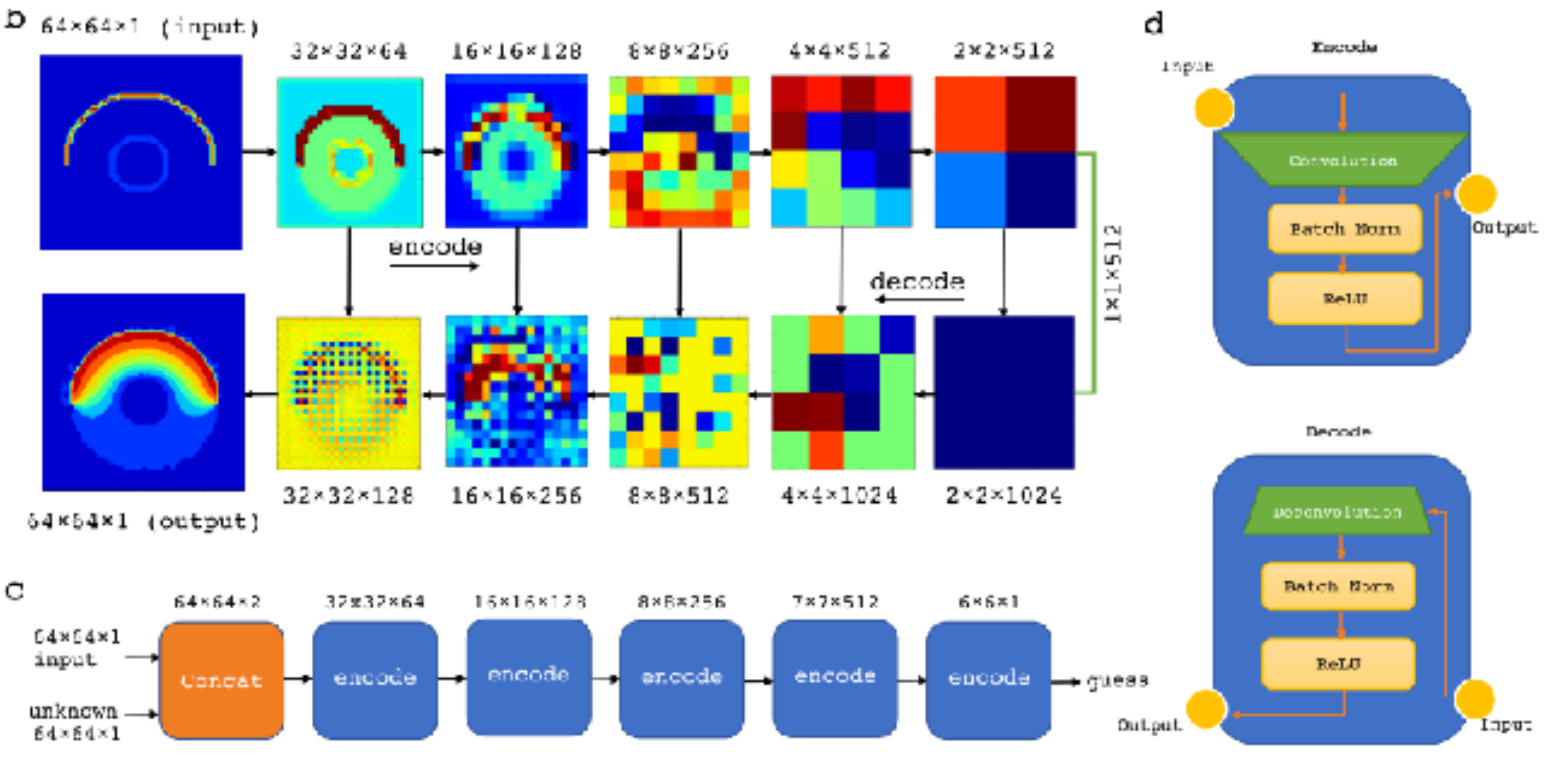


Image-to-Image Translation with Conditional Adversarial Networks

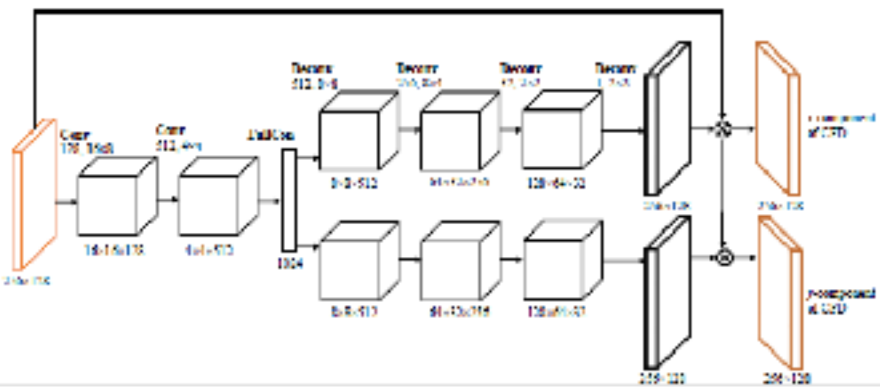


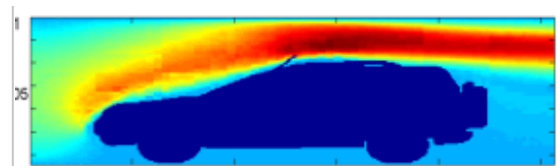


Deep Learning the Physics of Transport Phenomena

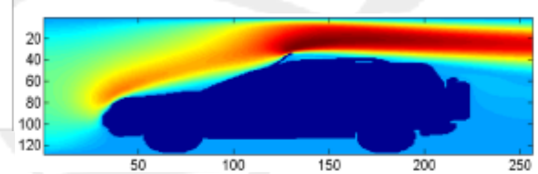


Convolutional Neural Networks for Steady Flow Approximation





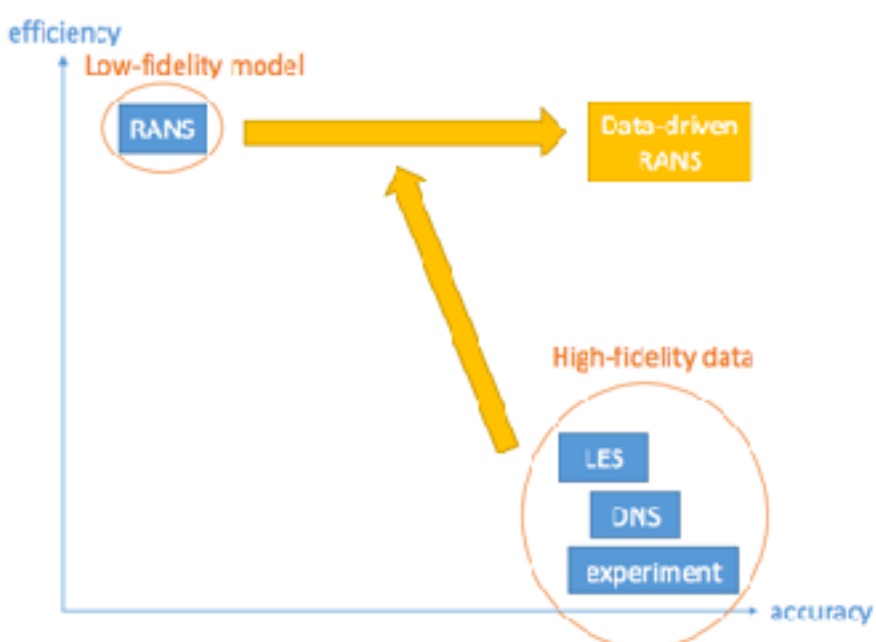
CNN Prediction

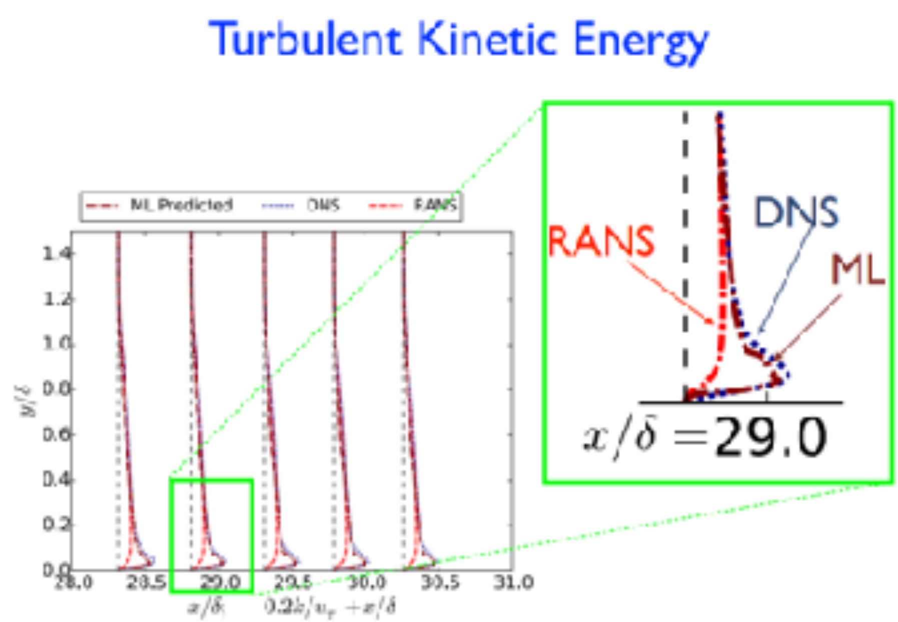


LBM

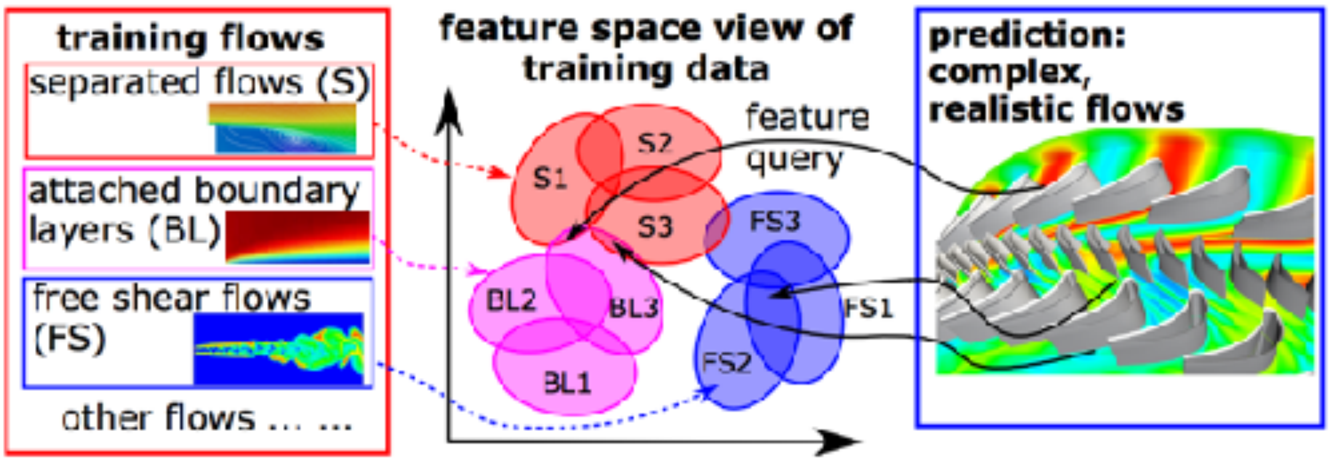
https://www.biorxiv.org/content/biorxiv/early/2017/12/30/240317.full.pdf

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





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

Solving the Quantum Many-Body Problem with Artificial Neural Networks, science 2017

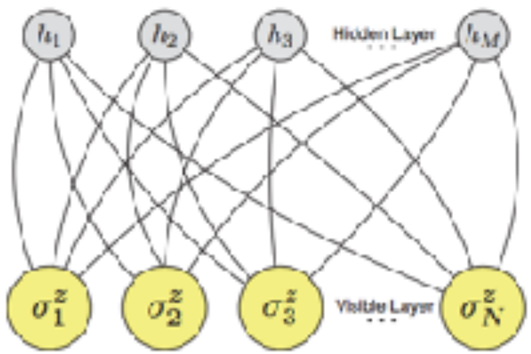
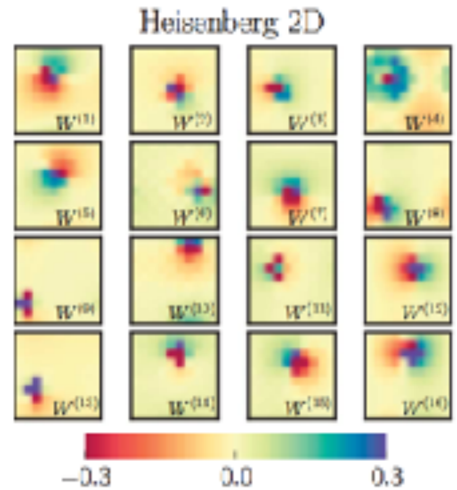


Fig. 1 Artificial neural network encoding a many-body quantum state of N spins. A restricted Boltzmann machine architecture that features a set of N visible artificial neurons (yellow dots) and a set of M hidden neurons (gray dots) is shown. For each value of the many-body spin configuration $S = (\sigma_1^z,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



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

Physics Equations…

$$v = \lambda f \qquad I \; \alpha \; \frac{1}{r^2} \qquad \beta = 10 \log_{10}\left(\frac{I}{I_0}\right) \qquad f_L = \left(\frac{v \pm v_L}{v \mp v_S}\right) f_S$$

$$f_{beat} = \left| f_1 - f_2 \right| \qquad \lambda_n = \frac{2L}{n} \qquad v = \sqrt{\frac{F_T}{\mu}}$$

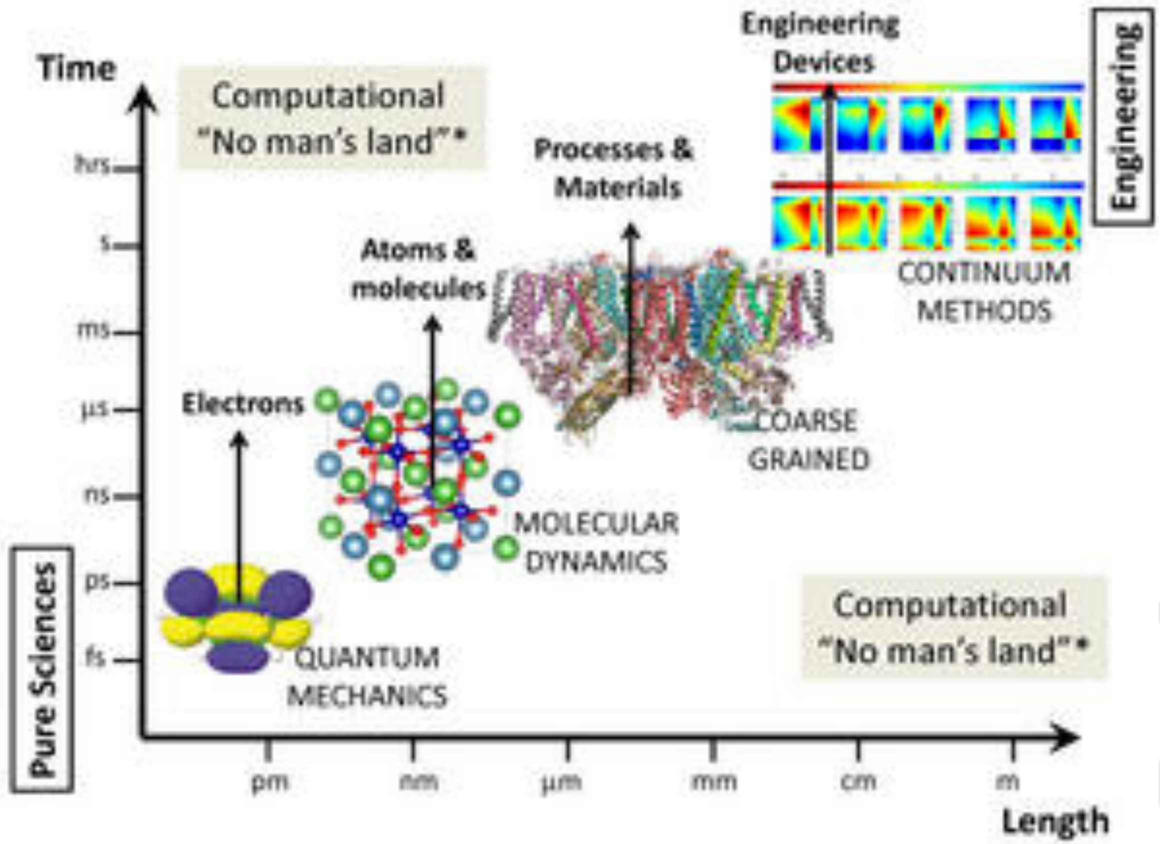
$$k = \frac{1}{4\pi\,\varepsilon_0} \approx 9.0 \times 10^9 \,\frac{N\,m^2}{C^2} \qquad \vec{E} = k\,\frac{q}{r^2}\,\hat{r} \qquad V = k\,\frac{q}{r}$$

$$\vec{E} = -\vec{\nabla} V \qquad \vec{F} = k\,\frac{q_1\,q_2}{r^2}\,\hat{r} \qquad U = k\,\frac{q_1\,q_2}{r}$$

$$\Phi_E = \frac{q_{enclosed}}{\varepsilon_0} \qquad \Phi_E = \oint \vec{E} \cdot d\vec{A}$$

https://tinycards.duolingo.com/decks/22o3FEEq/physics-equations

Quantum Mechanics to real worlds

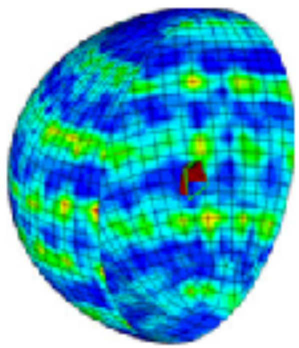


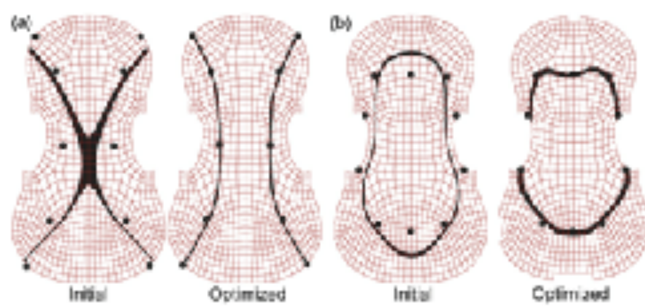
http://www.atomicarchive.com/Physics/Physics1.shtml

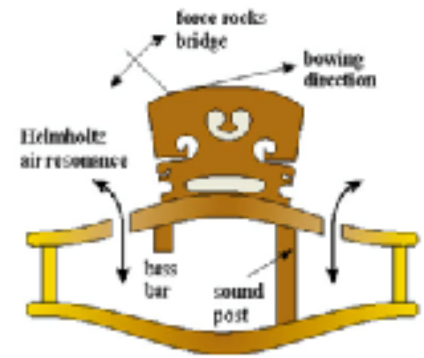
FB Group: Physics Informed Machine learning

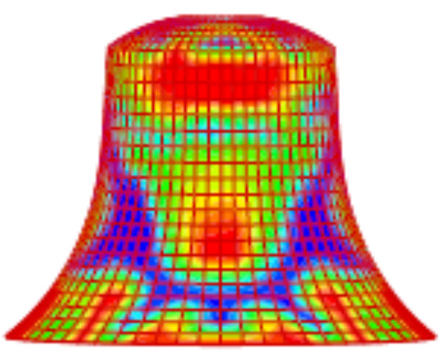
Deep Learning for Topology Optimization Design

박사학위 주제

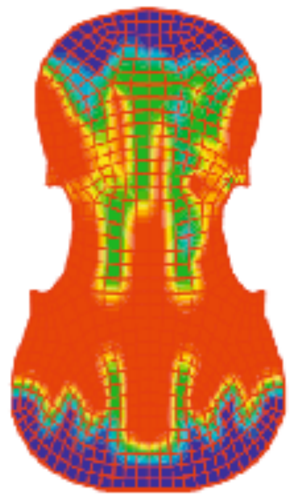




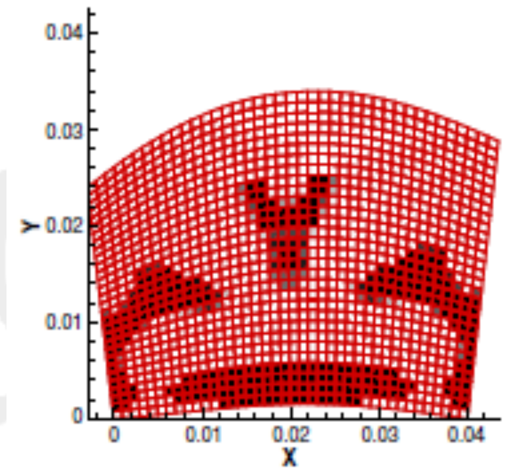




종의 최적설계
(Acoustical Damping &
Natural Frequency, 2011)

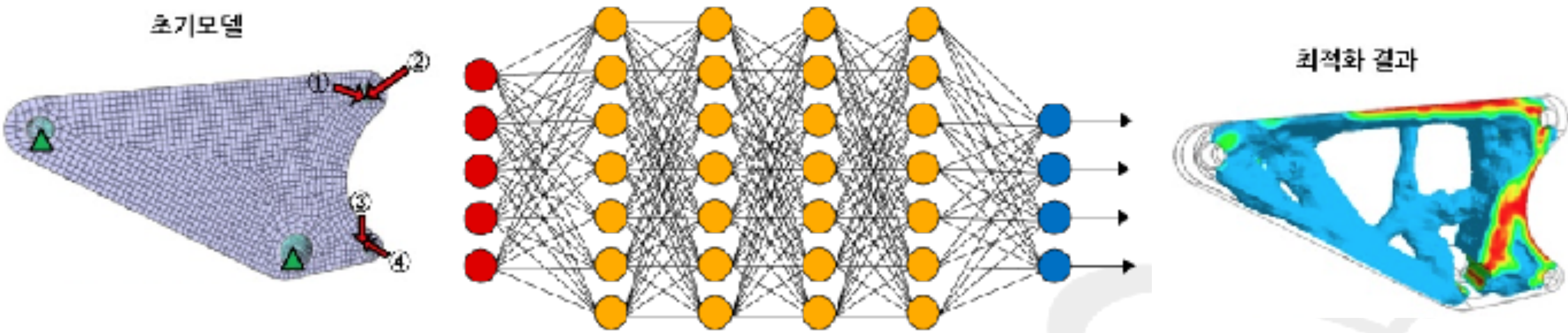


바이올린 상판의 최적설계
(Natural Frequency & Nodal Line,2010)



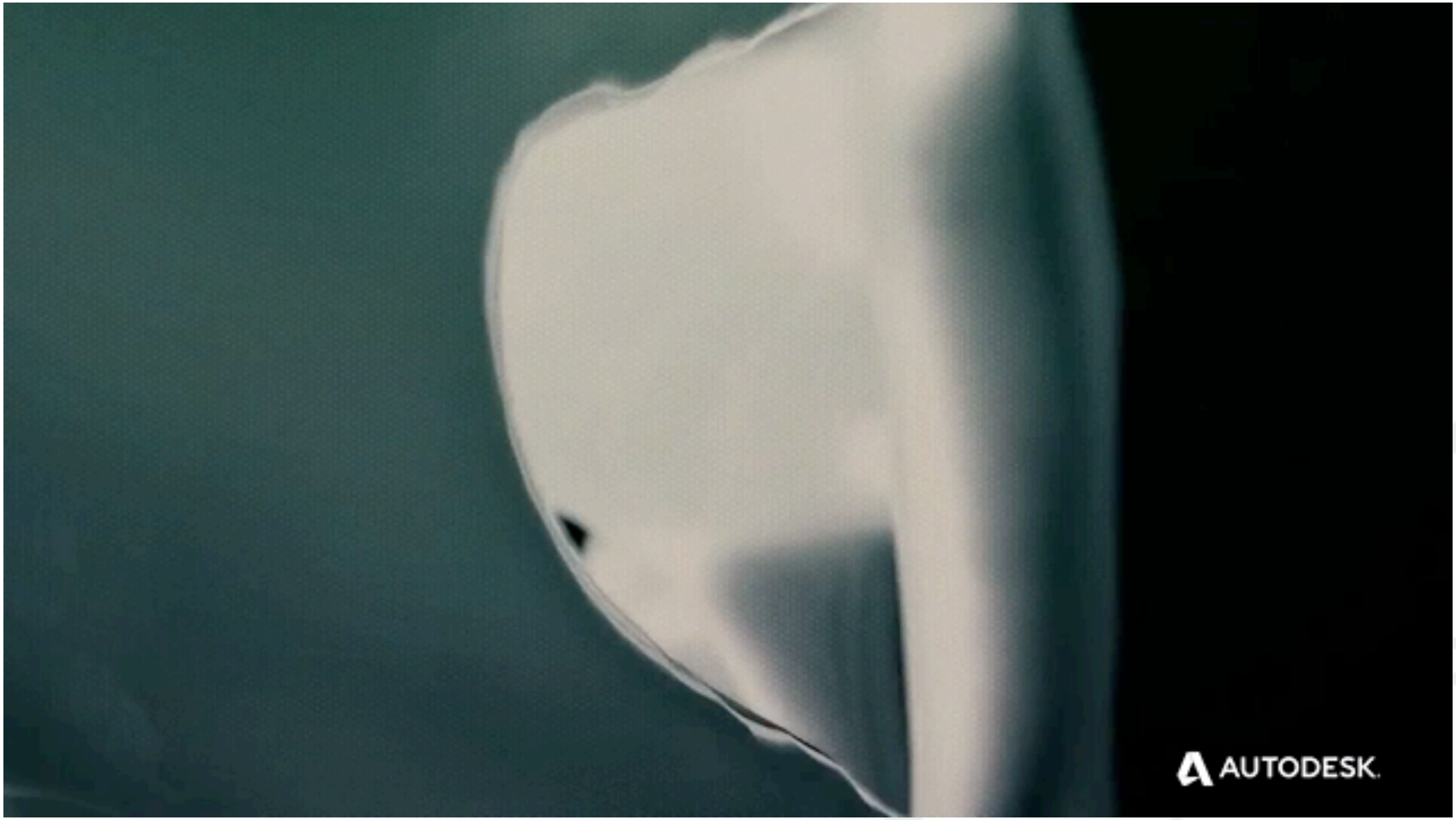
바이올린 브릿지의 위상최적설계
(Natural Frequency & 진동전달 효율,2013)

AI가 설계를 대신해줄 수 없을까?



Autodesk Generative Design

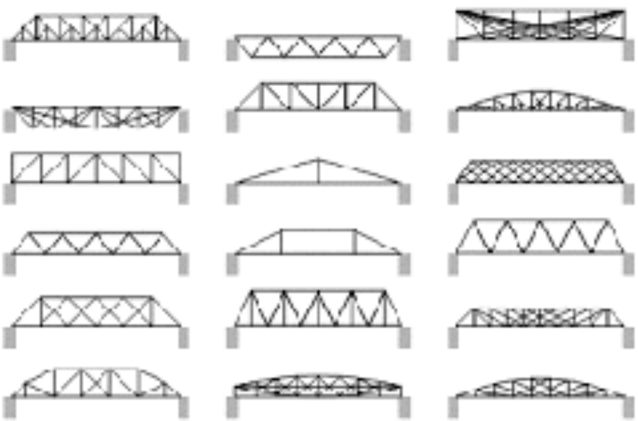
Autodesk Generative Design



최적설계를 인공지능이 대신할 수 있을까?

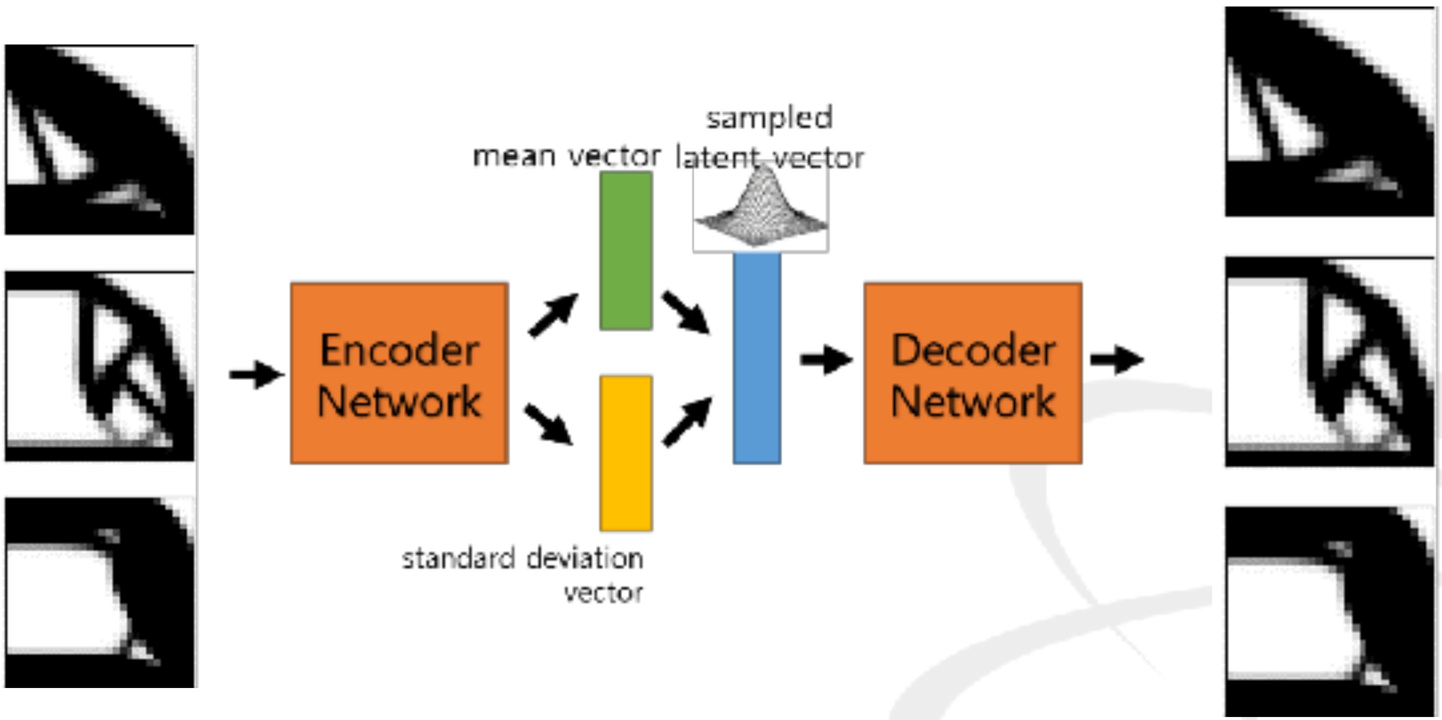
$$
\begin{aligned}
&\underset{x}{\text{minimize}} && F = F(\mathbf{u}(\rho), \rho) = \int_{\Omega} f(\mathbf{u}(\rho), \rho)\mathrm{d}V \\
&\text{subject to} && G_0(\rho) = \int_{\Omega} \rho \mathrm{d}V - V_0 \leq 0 \\
& && G_j(\mathbf{u}(\rho), \rho) \leq 0 \text{ with } j = 1, \ldots, m
\end{aligned}
$$

기존 설계로부터 설계의 원리를 배울 수 있지 않을까?

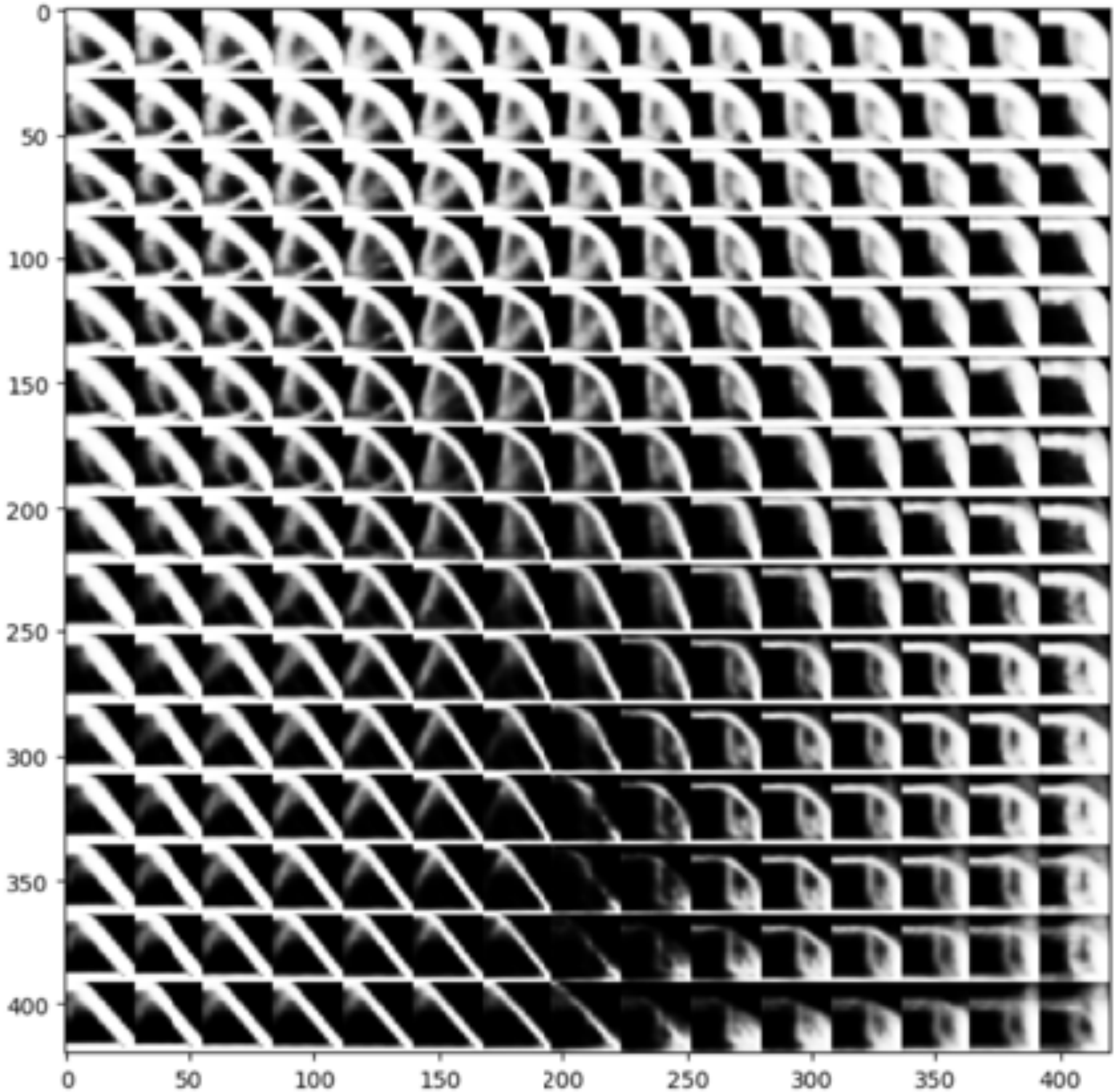


Unsupervised Learning of Topology Optimization Results

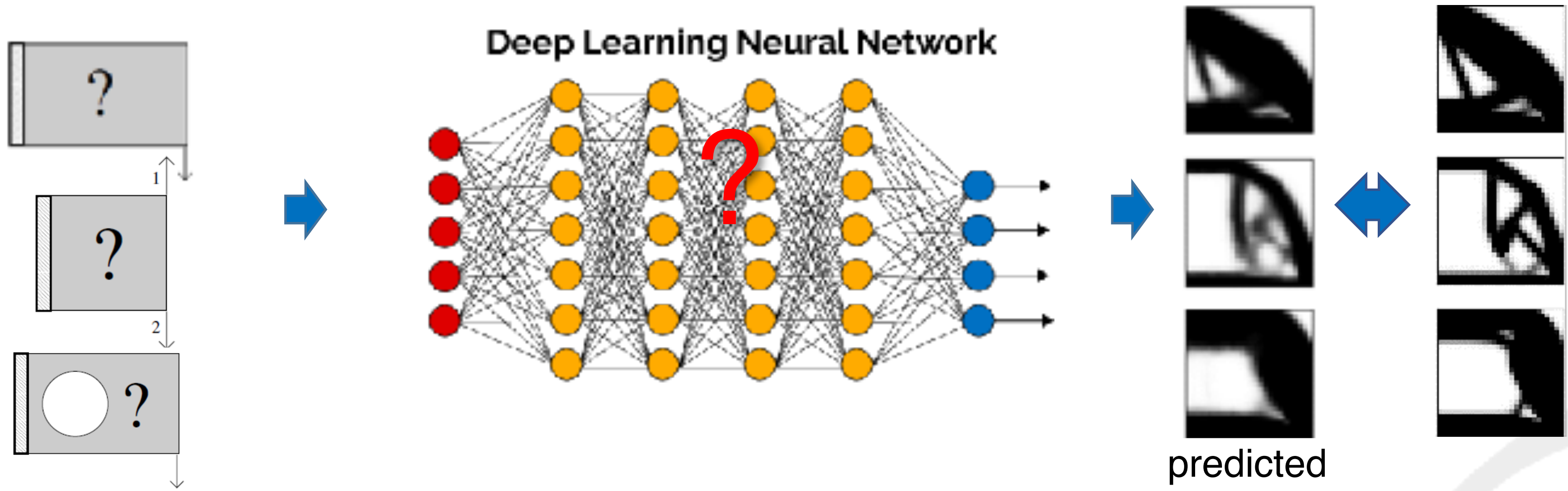
가능한 적은 수의 변수로 구조를 표현할 수 있는가?

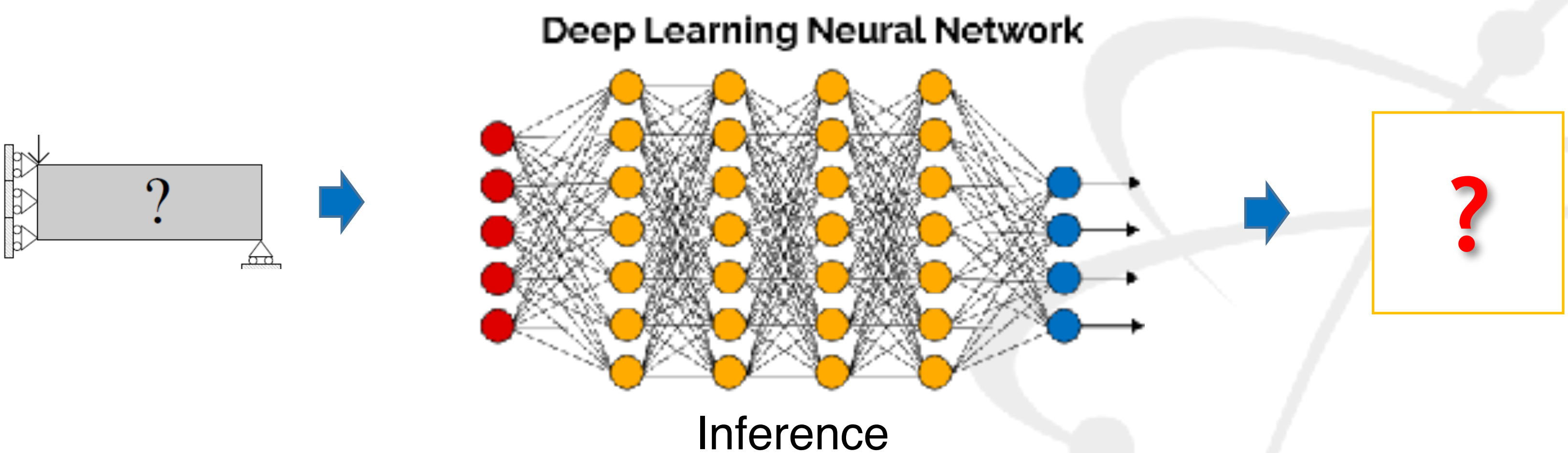


2개의 잠재변수로 표현한 구조

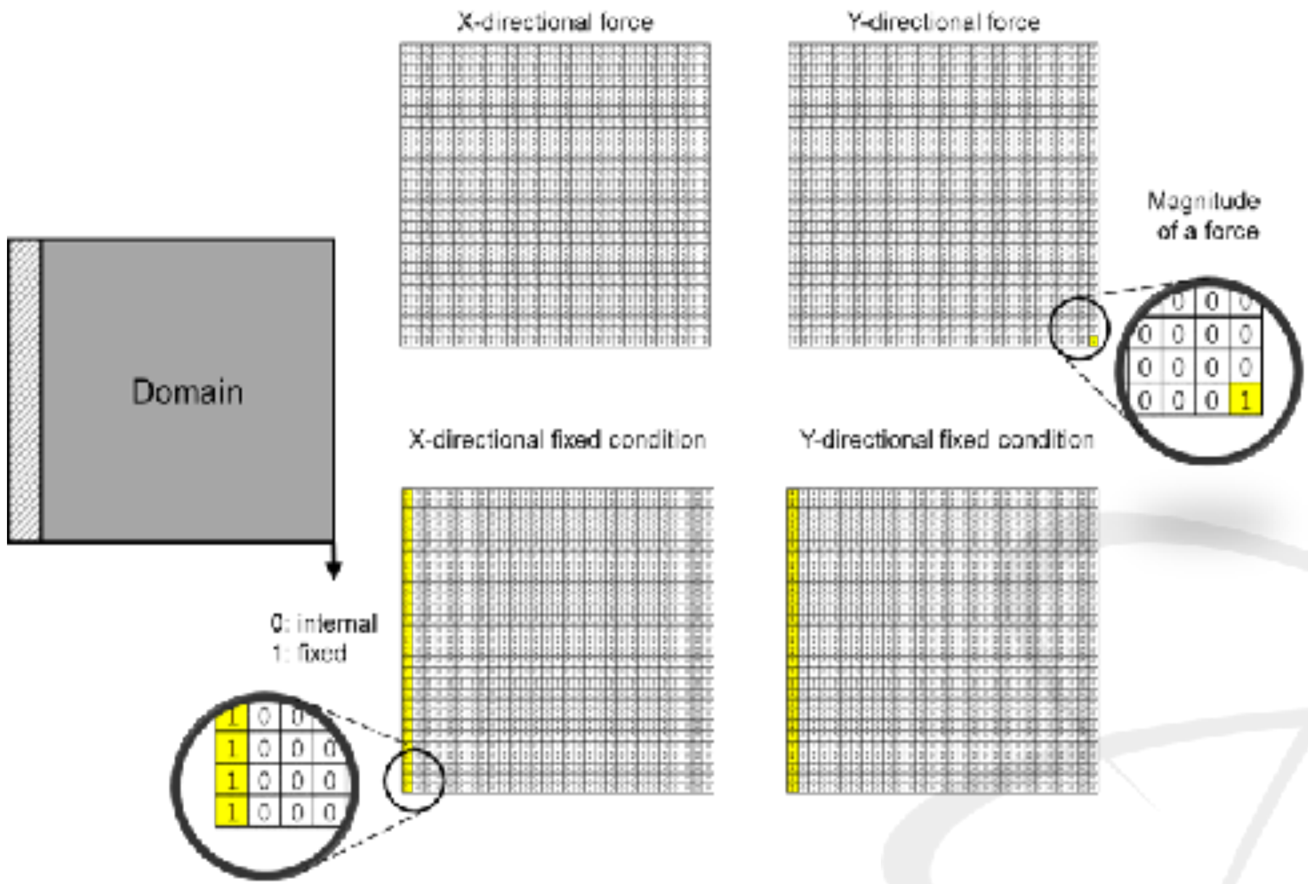


Deep Learning for Topology Optimization Design



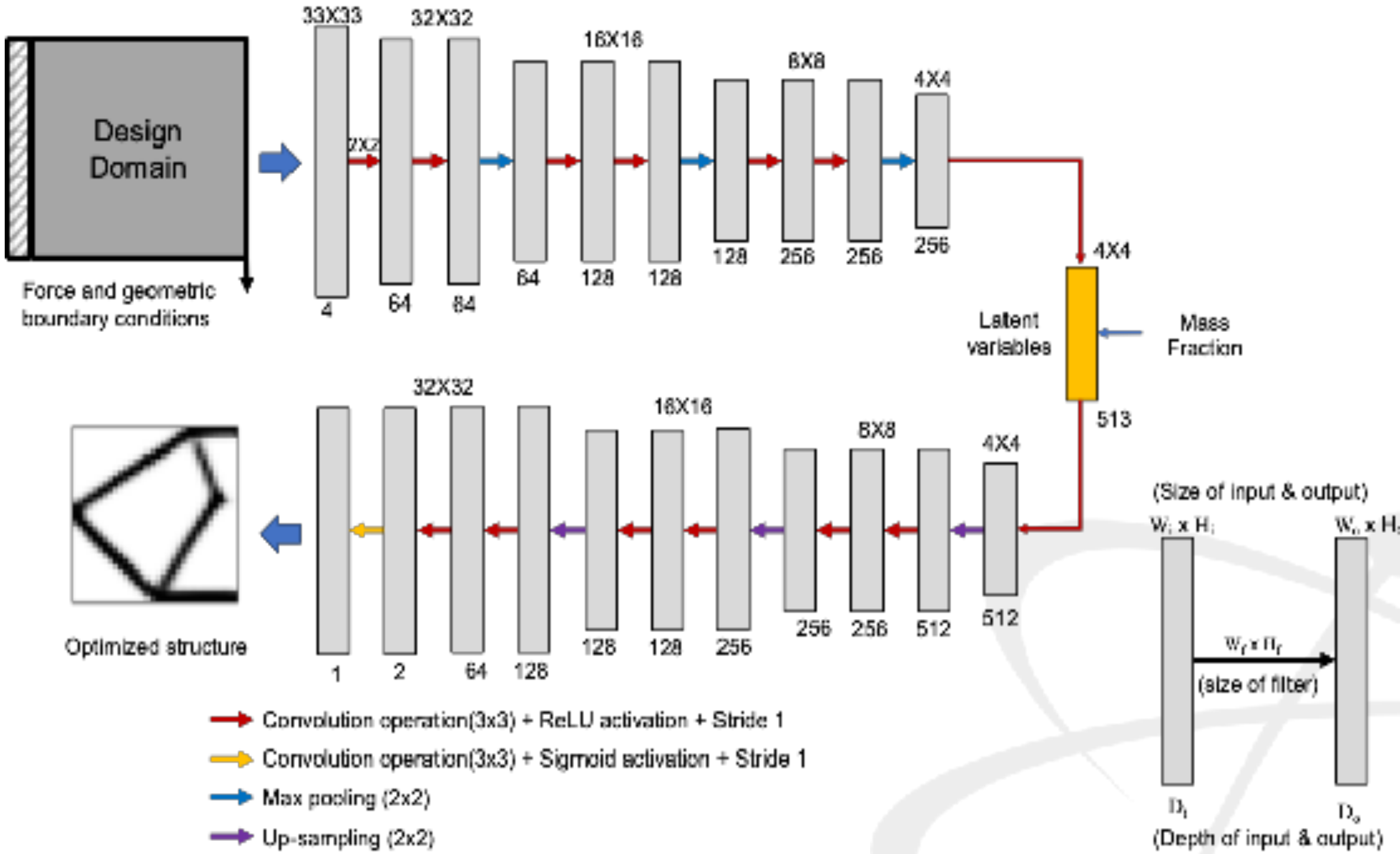


Deep Learning for Topology Optimization Design
: Discretization of boundary conditions



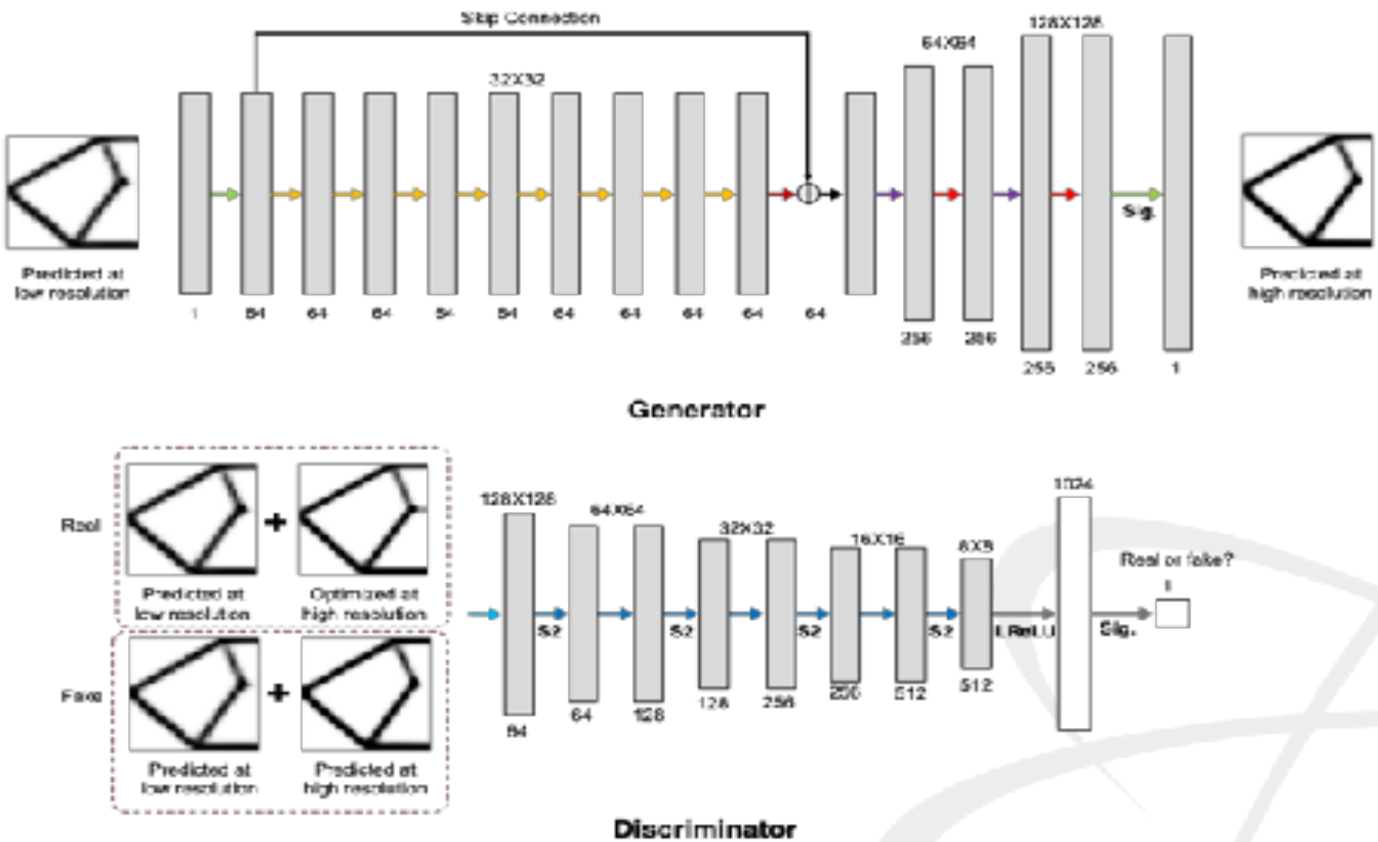
https://arxiv.org/abs/1801.05463

Deep Learning for Topology Optimization Design
: 1st Stage



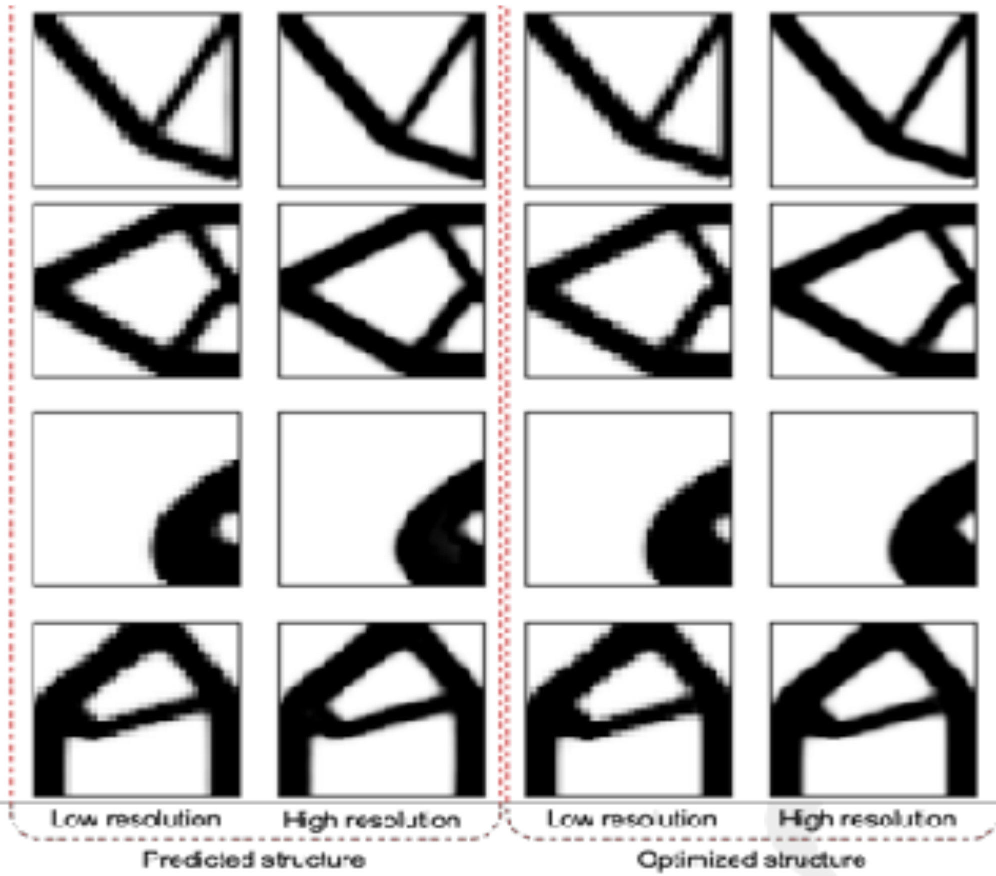
https://arxiv.org/abs/1801.05463

Deep Learning for Topology Optimization Design
: 2nd Stage



https://arxiv.org/abs/1801.05463

Deep Learning for Topology Optimization Design



https://arxiv.org/abs/1801.05463

Hybrid Approach?

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

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 Engineering

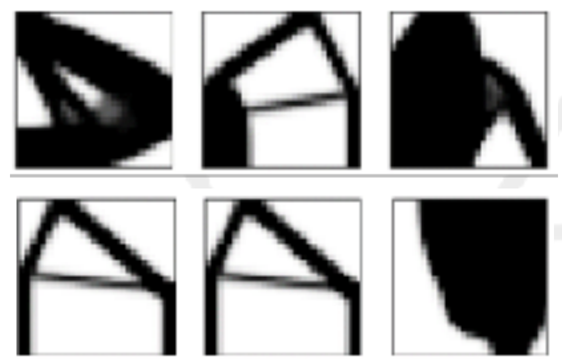
Hybrid Approach?

Optimization Scheduler

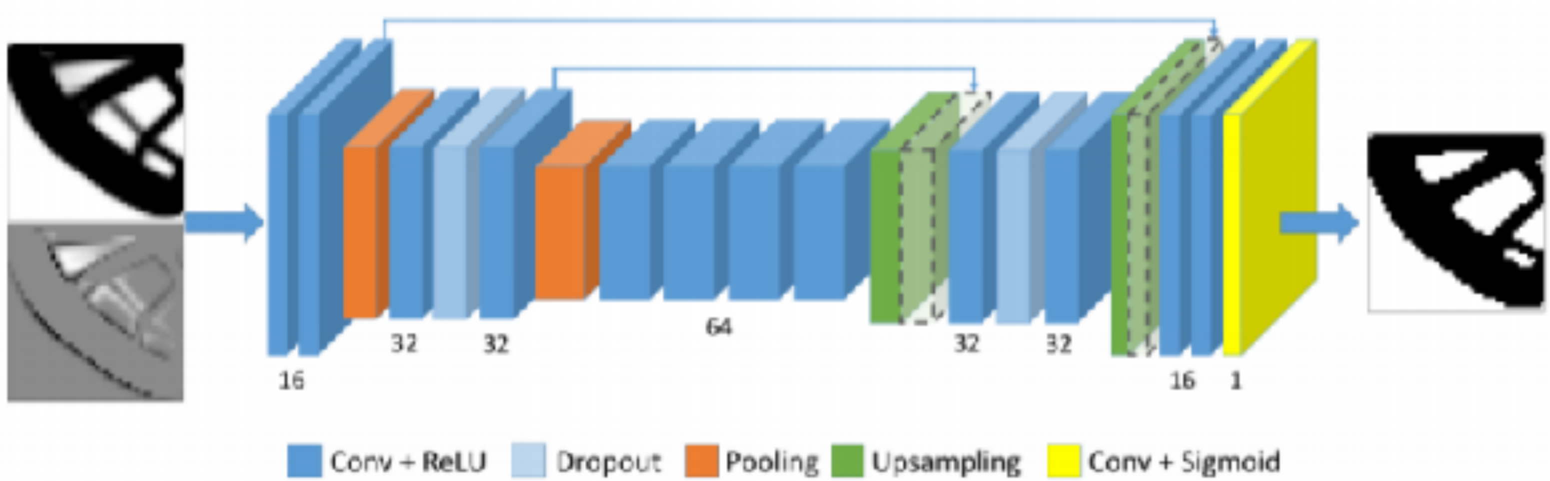
기존 최적설계

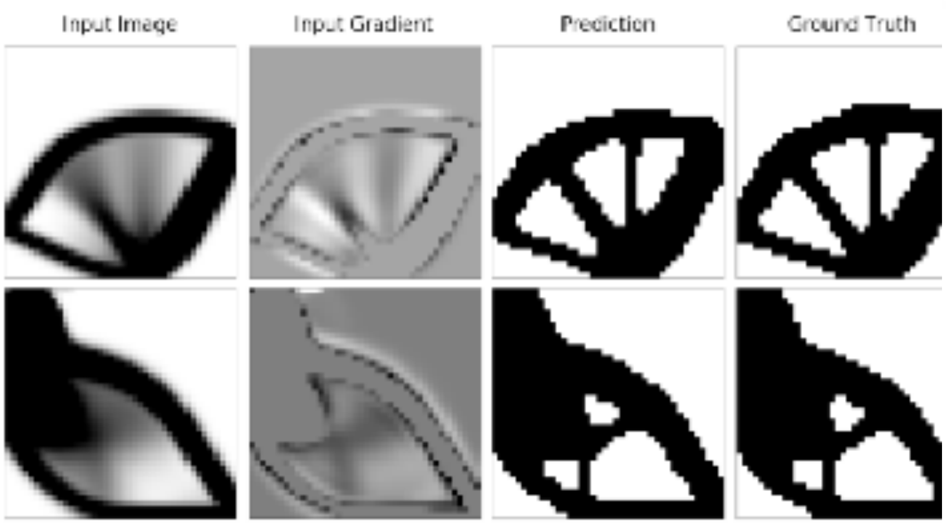
$$\frac{\partial c}{\partial x_e} = -p(x_e)^{p-1}\ \mathbf{u}_e^T\ \mathbf{k}_0\ \mathbf{u}_e$$

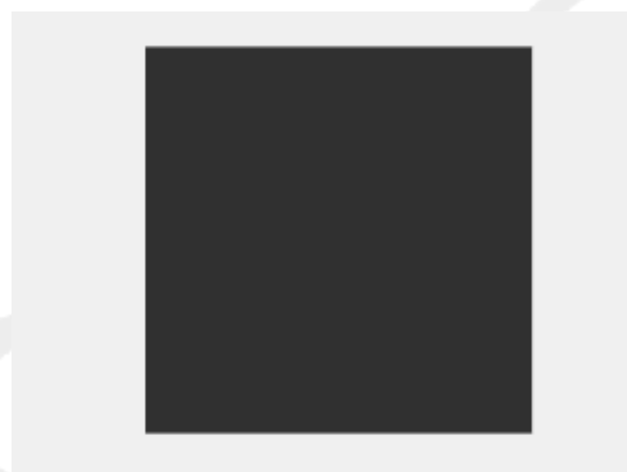
머신러닝 알고리즘



Neural networks for topology optimization





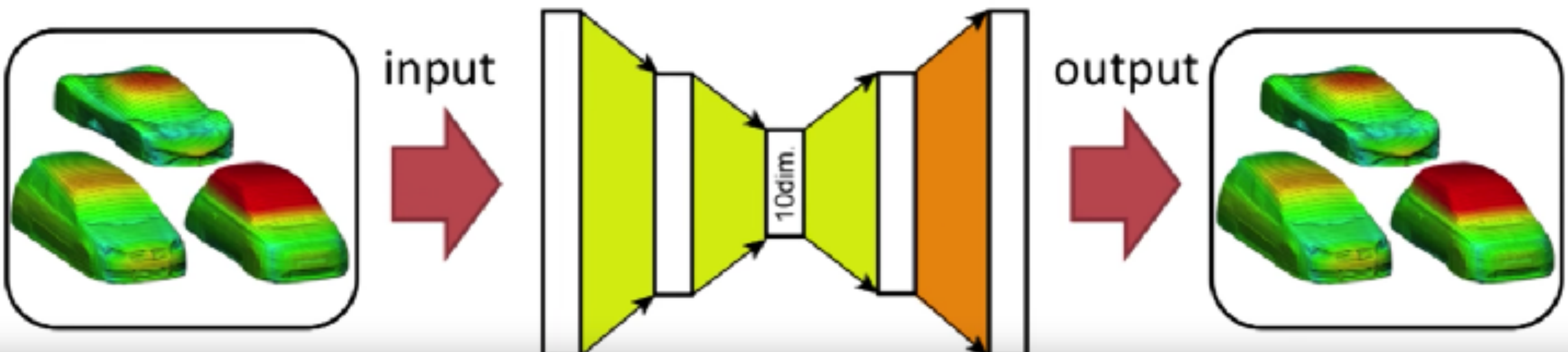


https://arxiv.org/abs/1709.095

Exploring Generative 3D Shapes Using Autoencoder Networks

Nobuyuki Umetani

AUTODESK RESEARCH



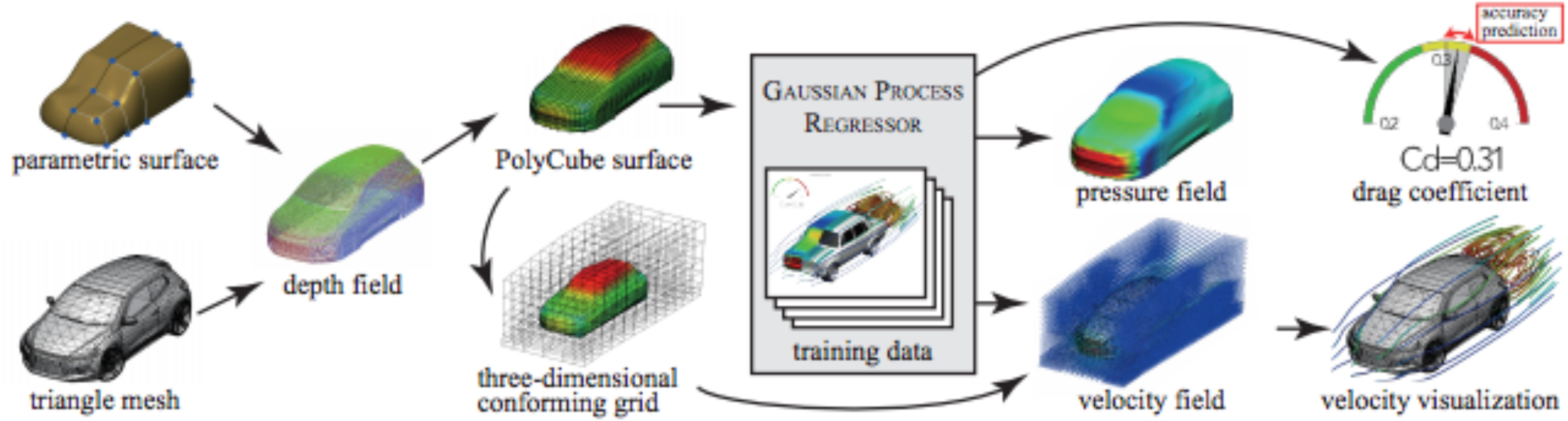
https://www.youtube.com/watch?v=25xQs0Hs1z0

Lea

Learning Three-Dimensional Flow for Interactive Aerodynamic Design

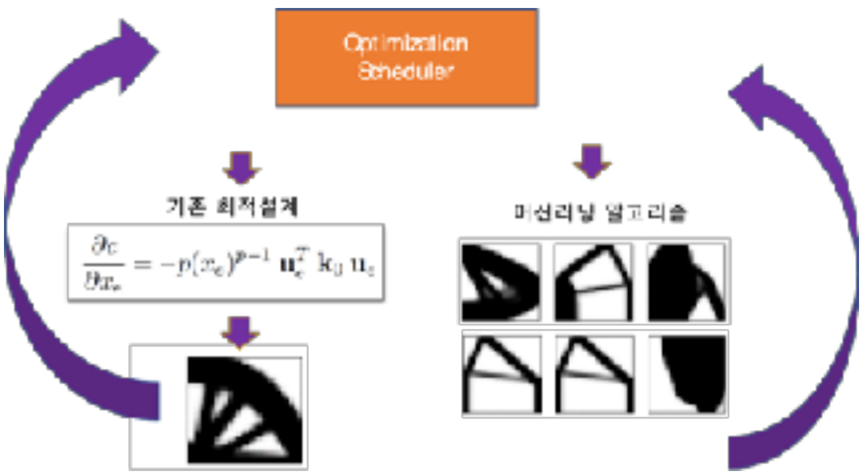
Nobuyuki Umetani[1] Bernd Bickel[2]

1. AUTODESK 2. IST AUSTRIA



인공지능을 활용한 최적설계

최적설계의 효율화

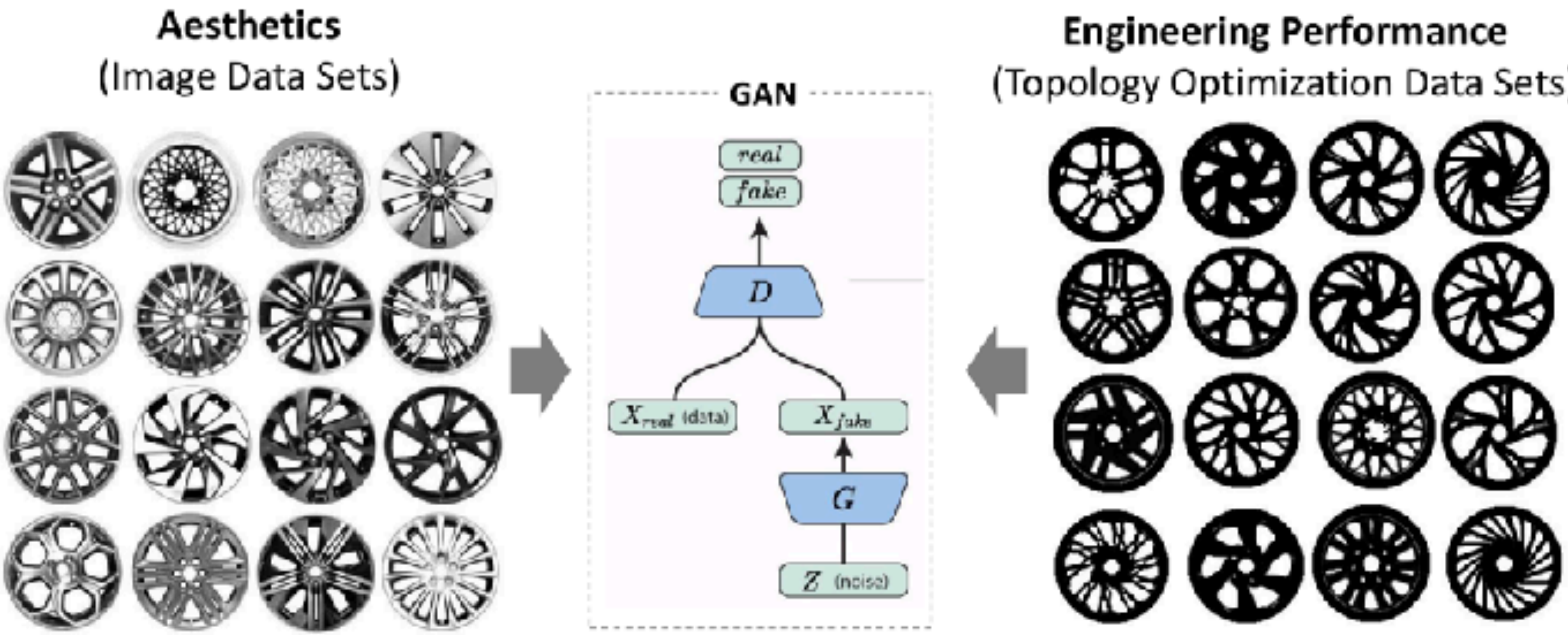


- 머신러닝 기술을 적용한 기존 최적설계 및 수치해석 방법론의 효율성 향상
- 설계자를 위한 빠른 해석 툴

감성의 메타모델

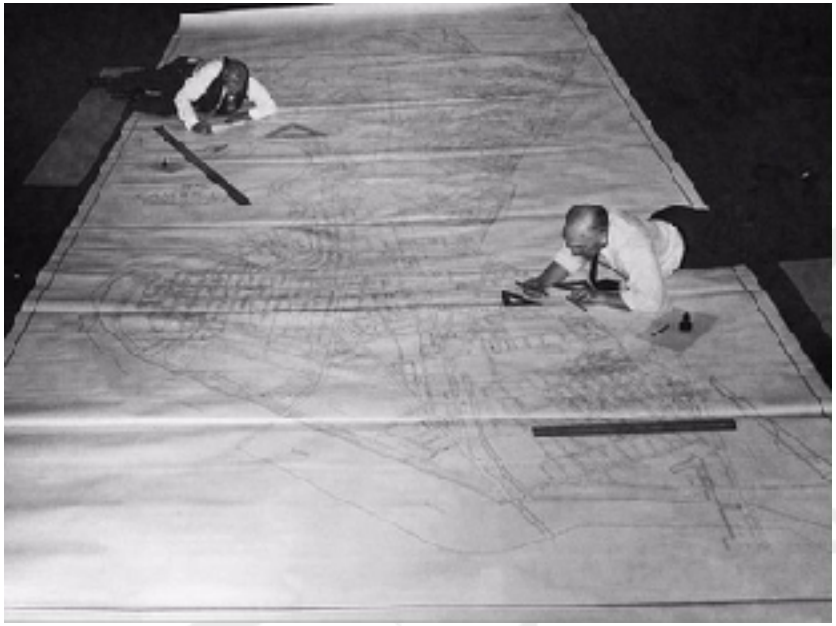
- 기존에 공학적으로 정의하기 힘들었던 것 (개인의 취향, 제작성, 심미성) 고려한 최적설계

디자인을 고려한 최적설계 (숙명여대 기계공학과 강남우 교수)



-Oh, S., Jung, Y., Lee, I., & Kang, N. (2018, August). Design Automation by Integrating Generative Adversarial Networks and Topology Optimization. In *ASME 2018 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference* (pp. V02AT03A008-V02AT03A008). American Society of Mechanical Engineers.

CAD가 발명되기 전…

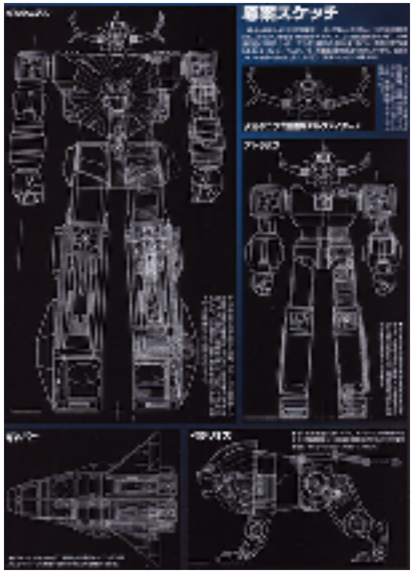


3D 프린트를 이용한 나만의 장난감

인공지능이 설계를 대신해 준다면?

멋진 로봇 만들어줘! 크기는 얼마고 3단합체가 되고, 날개가 달렸고.........

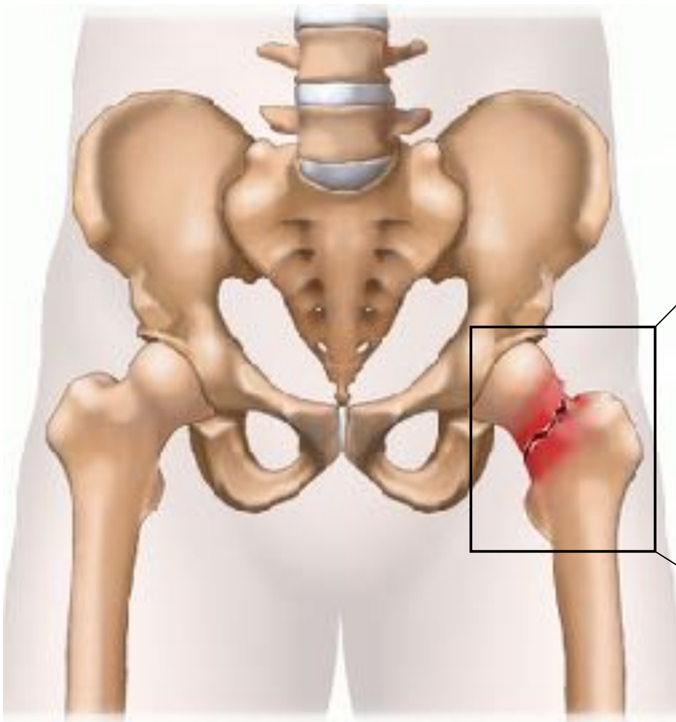
인공지능



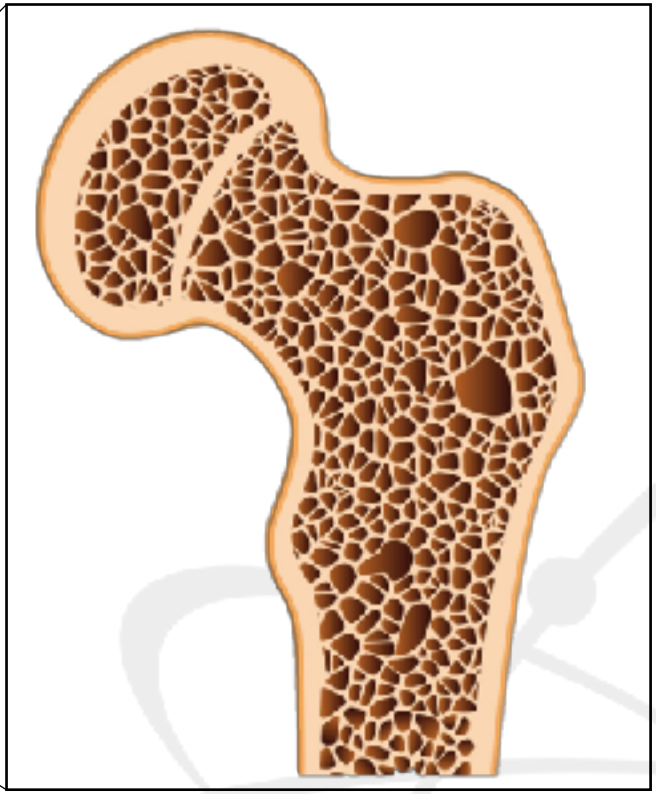
3D 프린터

Deep Learning based Bone Microstructure Reconstruction

골다공증 진단을 위한 뼈 CT 사진 고해상화



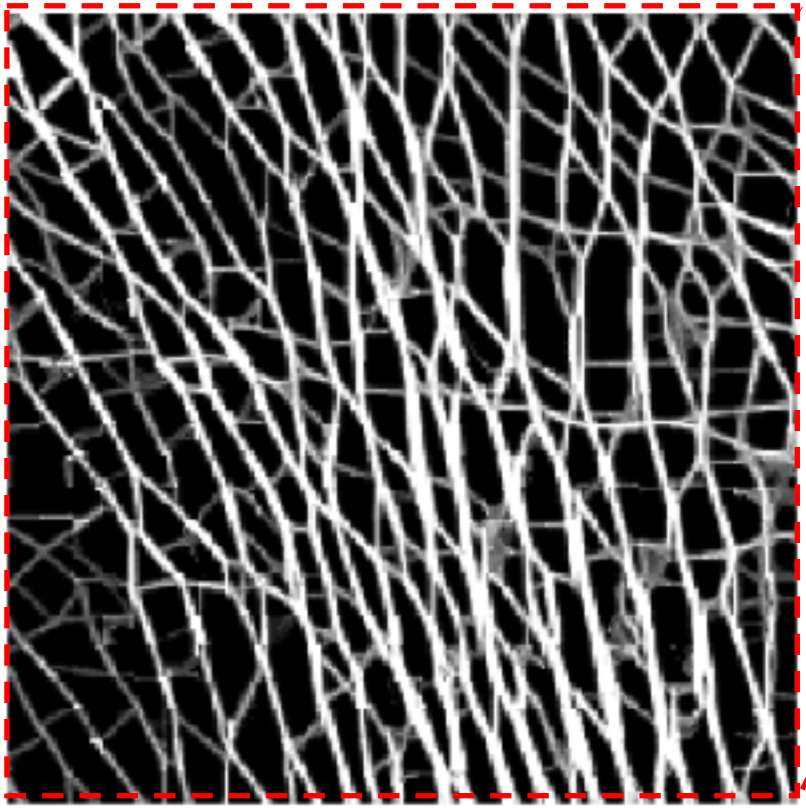
골다공증성 골절

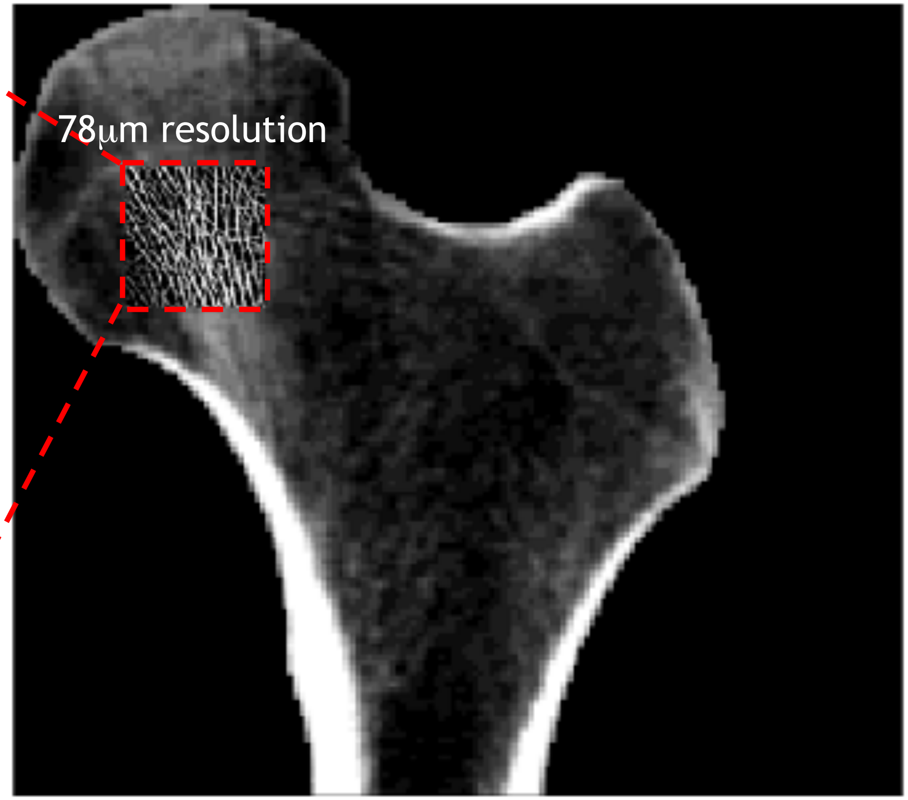


골다공증

골다공증 진단을 위한 뼈 CT 사진 고해상화

정확한 골다공증 진단을 위한 저선량 CT 사진 고해상화

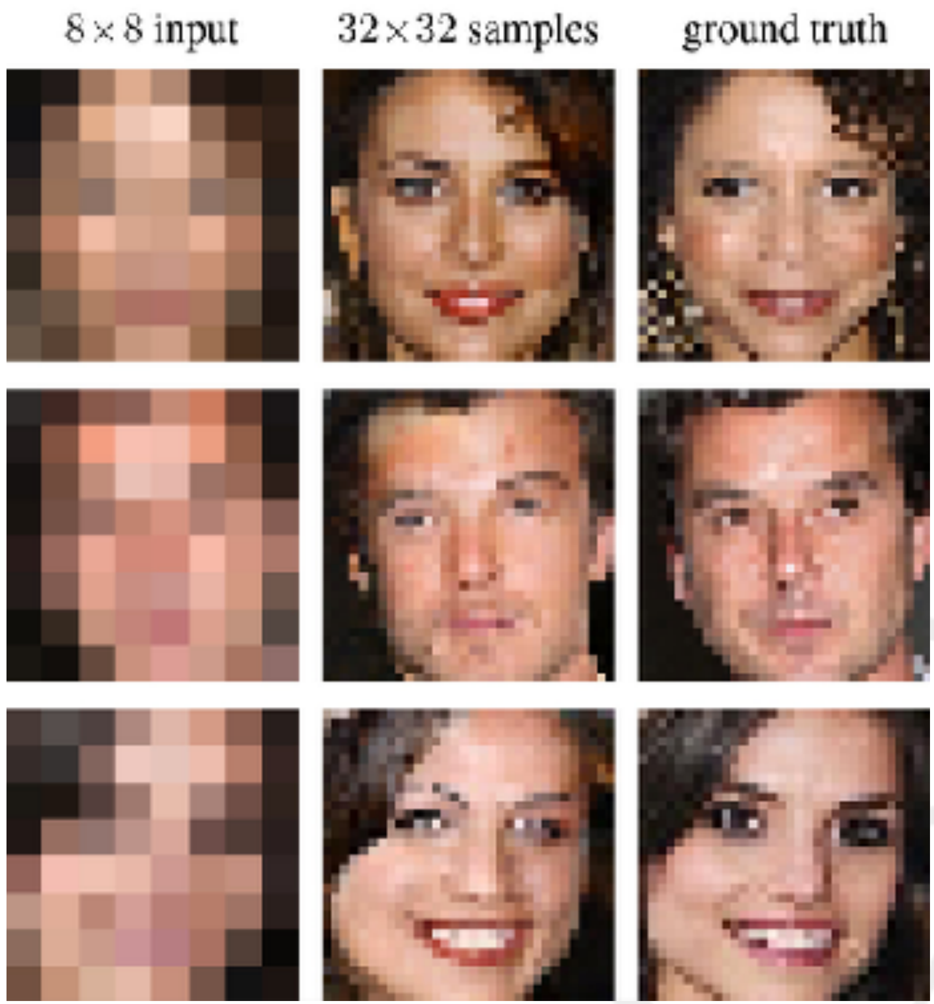




78μm resolution

625μm resolution

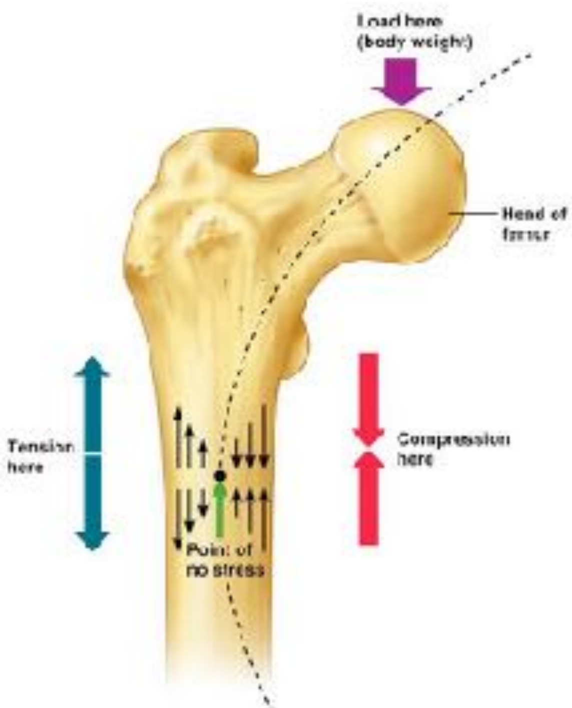
딥러닝 기반 영상 고해상화 기술 1



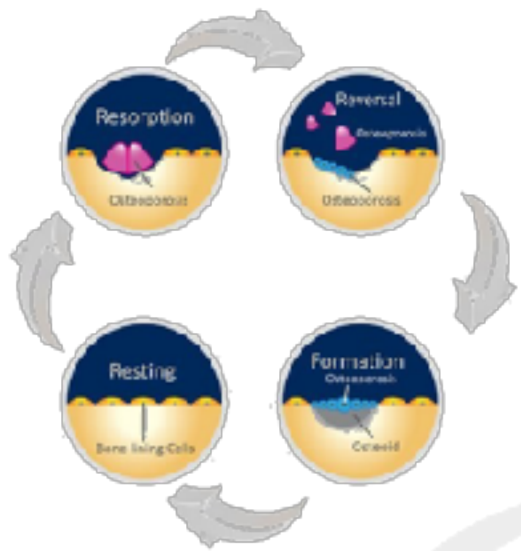
arXiv:1702.00783

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



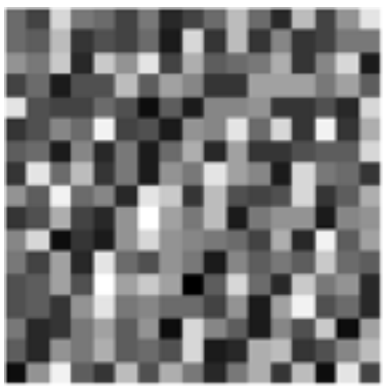
골재형성 과정

골 미세구조

골 재형성을 위한 위상최적화

골재형성
(Bone remodeling)

위상최적화
(Topology optimization)



저해상도의 의료 영상
(600 μm 수준)

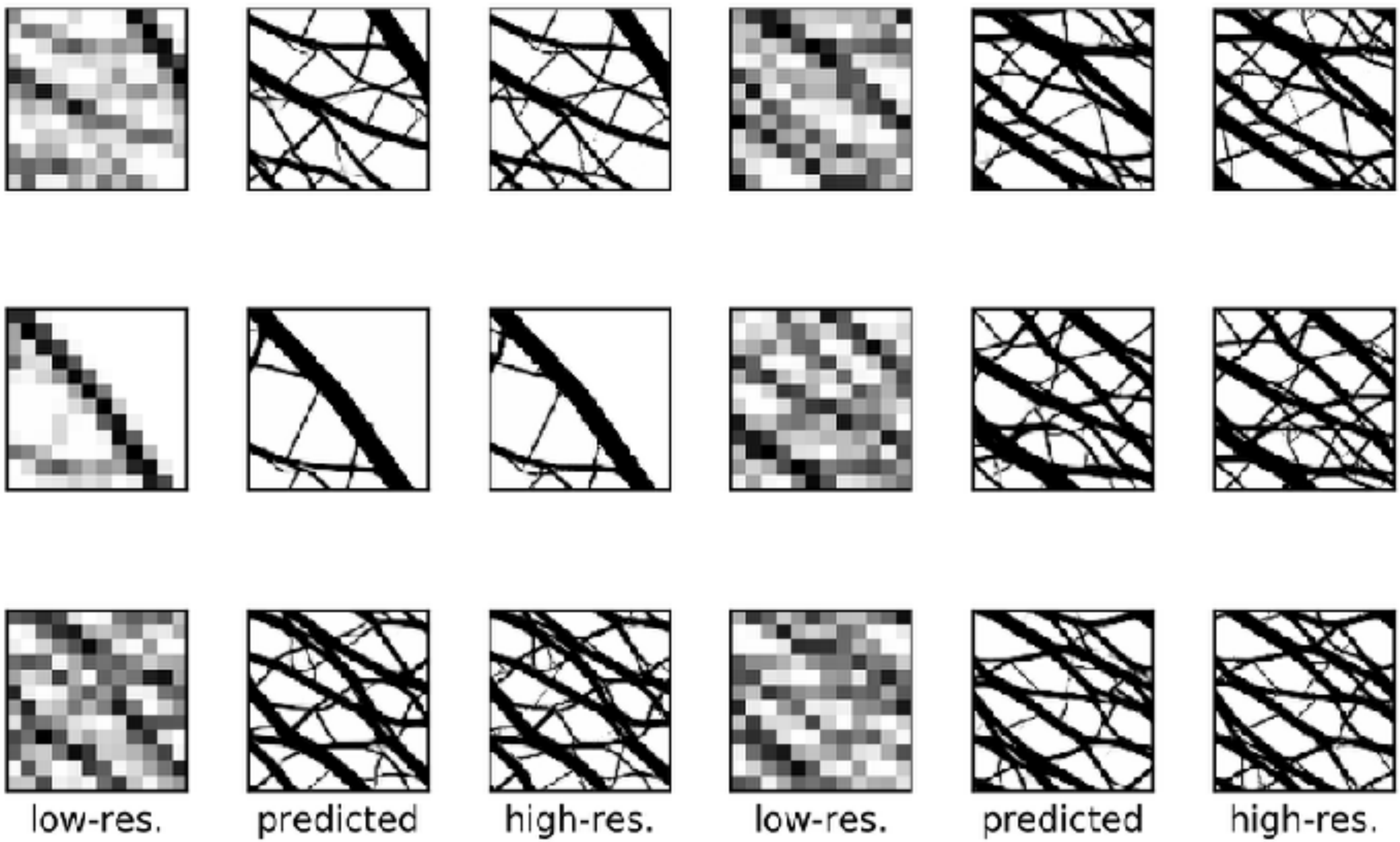
input

위상최적화

output

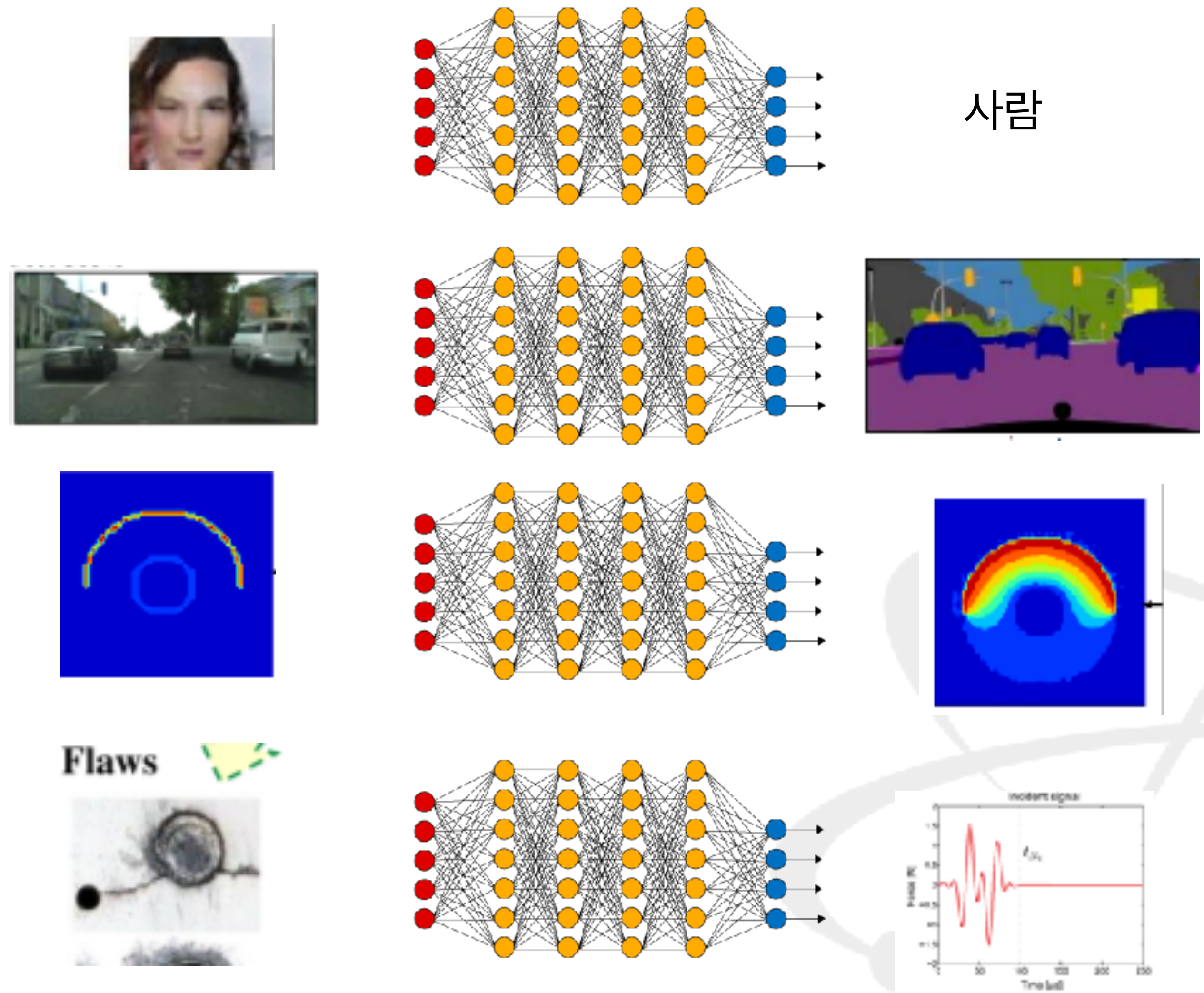
고해상도의 미세구조
(50 μm 수준)

고해상화 결과

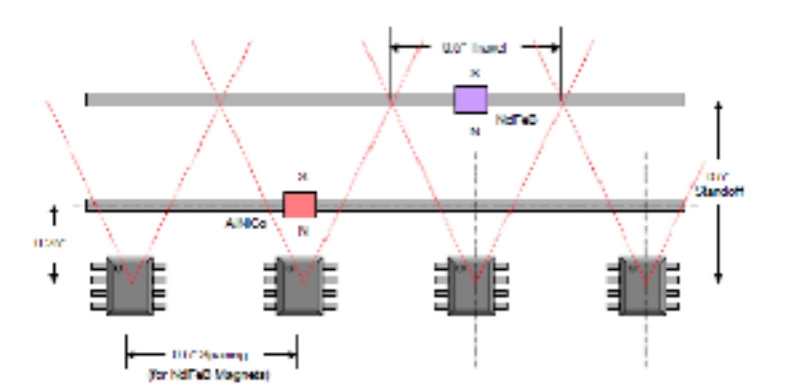


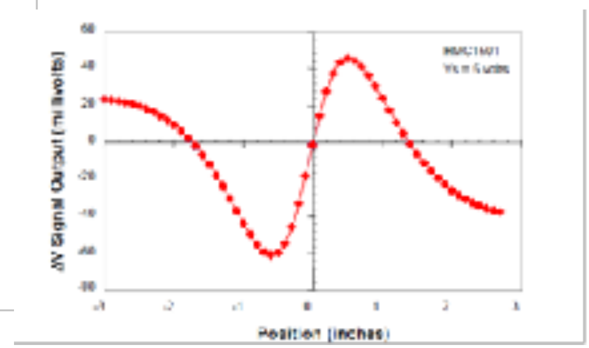
Deep Learning for Nuclear & Industrial Engineering

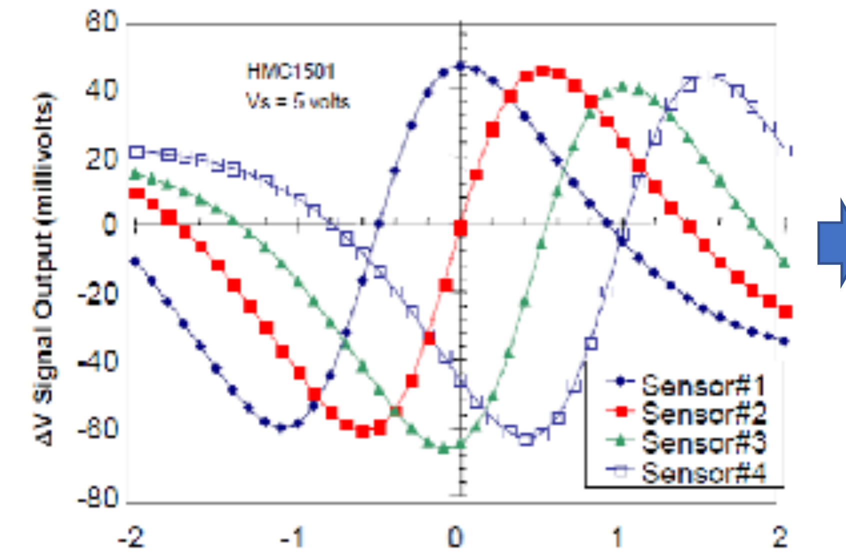
딥러닝이란?

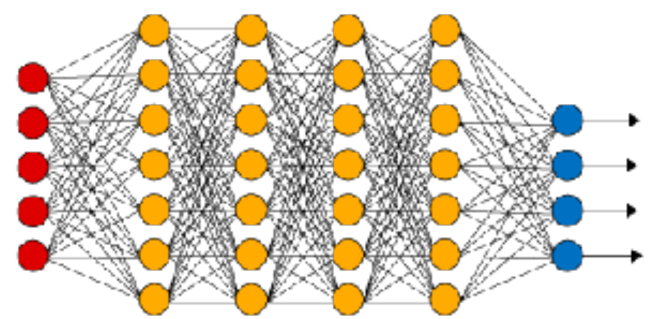


홀센서 기반 위치지시기 개발





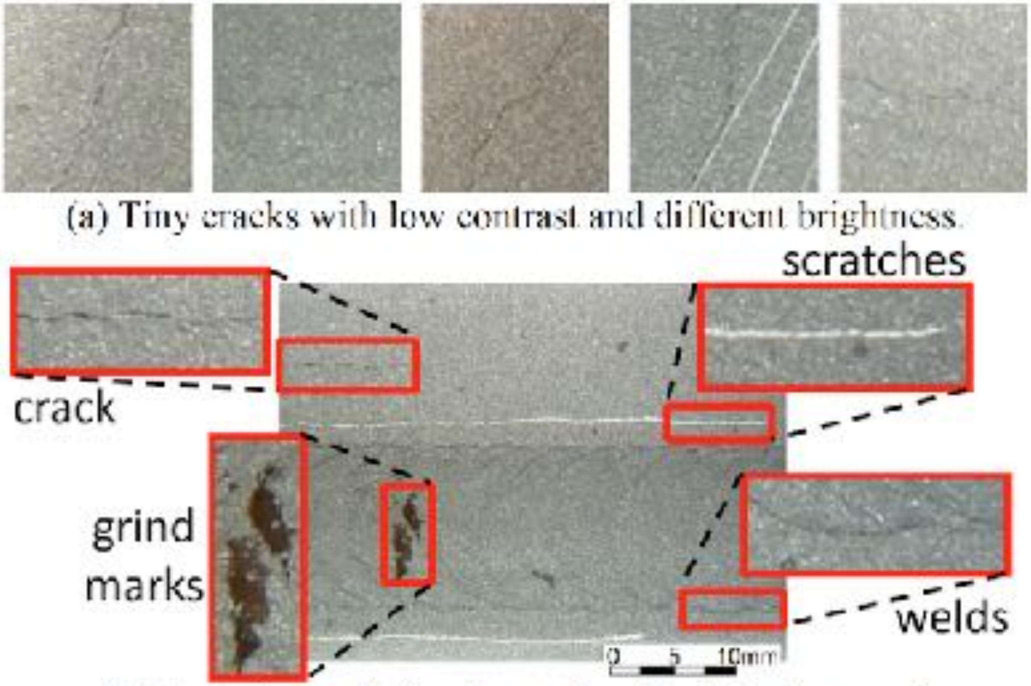




제어봉 위치

센서노이즈, 감도, 자력, 외부자장 고려

System automatically detects cracks in nuclear power plants



(a) Tiny cracks with low contrast and different brightness.

(b) Scratches, grind marks, and welds in background.

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

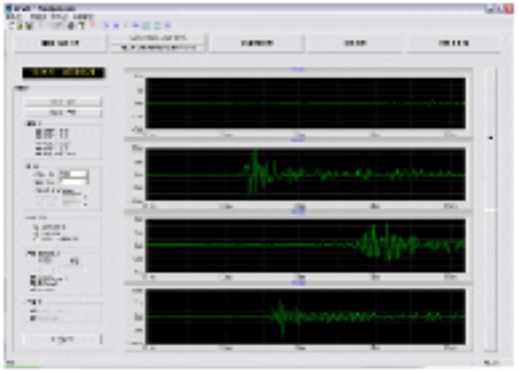
NSSS Integrity Monitoring system

*전력경제신문

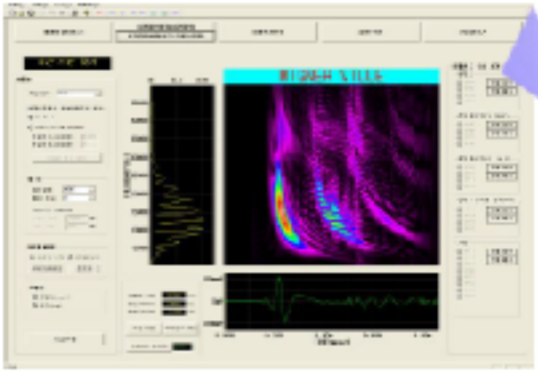
Loose part monitoring system (LPMS)

Mass Estimation [2]

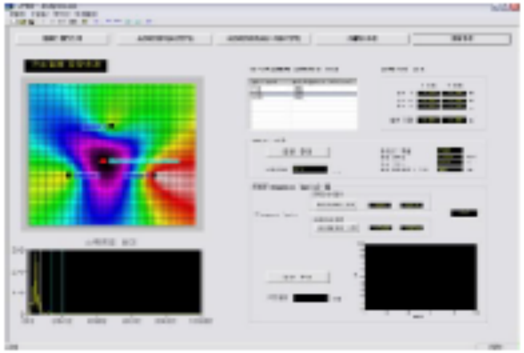
1. Measured signal



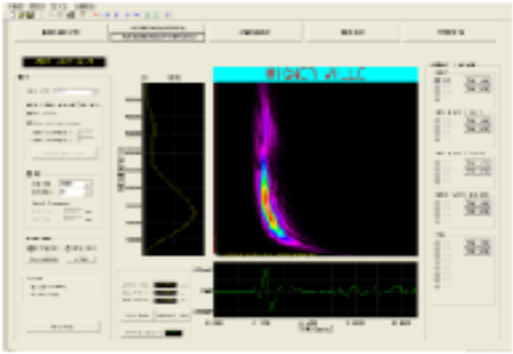
2. Eliminating reflected wave & noise



4. Mass estimation



3. Finding center frequency



LPMS 기존 방법

신기술

[2] D.-B. Yoon, J.H. Park et al, "Enhancement of Impact Mass Estimation Algorithm for a Plate Type Structure", Material Transactions, Vol. 48 no.06 (2007), pp. 1249-1253

*박진호, 원자로계통의 금속이물질 감시시스템, 2013 원전계측제어 심포지엄(NuPIC 2013)

후쿠시마 사고

The crisis at the Fukushima nuclear plant was "a profoundly man-made disaster", a Japanese parliamentary panel has said in a report.

The disaster "could and should have been foreseen and prevented" and its effects "**mitigated by a more effective human response**", it said.

BBC News (5 July 2012)

Fukushima fault: 'Man-made disaster' could have been prevented

Published time: 5 Jul, 2012 06:57
Edited time: 5 Jul, 2012 17:20

Get short URL

Members of the media and Tokyo Electric Power Co. (Tepco) employees look at the No. 4 reactor building (rear), amongst tsunami damage, at the company's Fukushima Dai-Ichi nuclear power plant in Okuma Town, Fukushima Prefecture. (AFP Photo / Tomohiro Ohsumi) / AFP

The disaster at the Fukushima power plant may have been triggered by a tsunami, **but it was human error that made it into one of the worst-ever nuclear accidents in human history**, a Japanese Parliamentary panel says. (RT news, 5 July 2012)

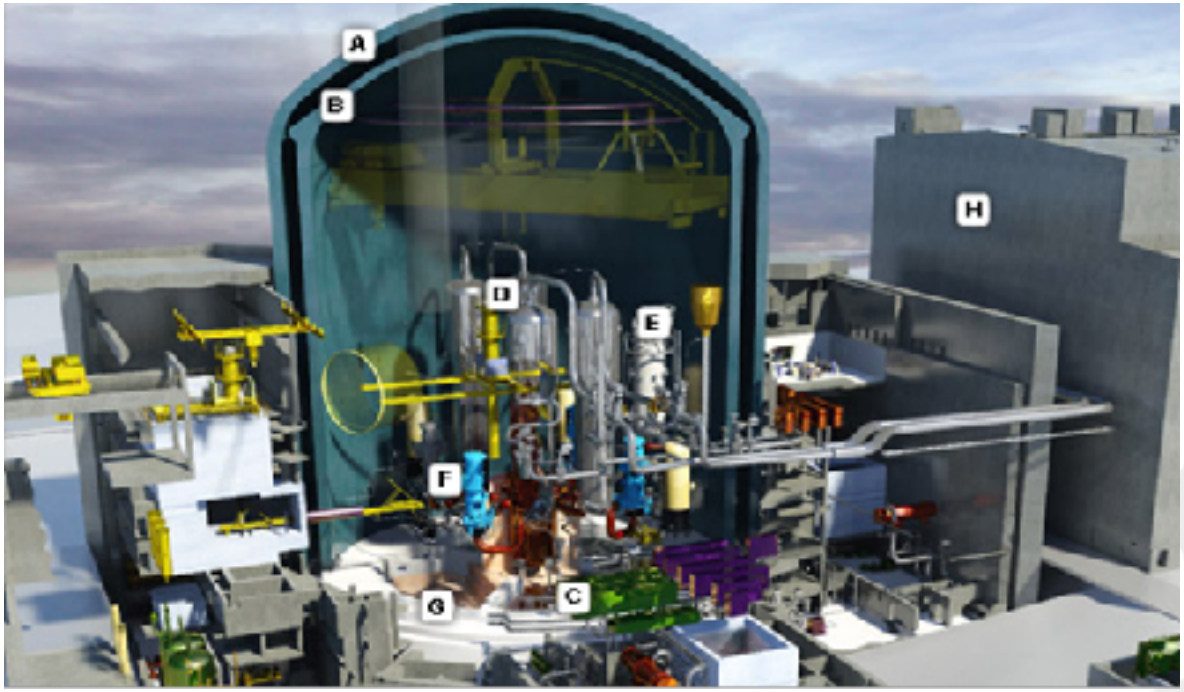
후쿠시마 사고 원인 (기술적 측면)

- 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

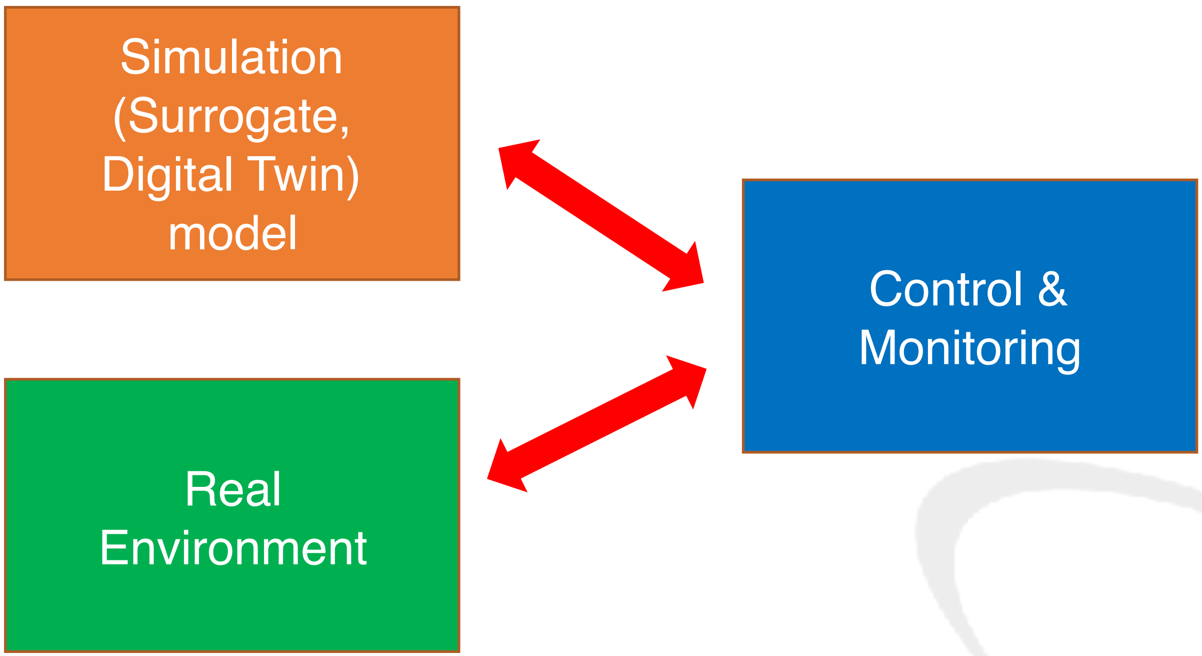
원자로의 Digital Twin을 이용한 사고 대응

- 후쿠시마 사고와 같은 상황에도 안전한 원자로



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

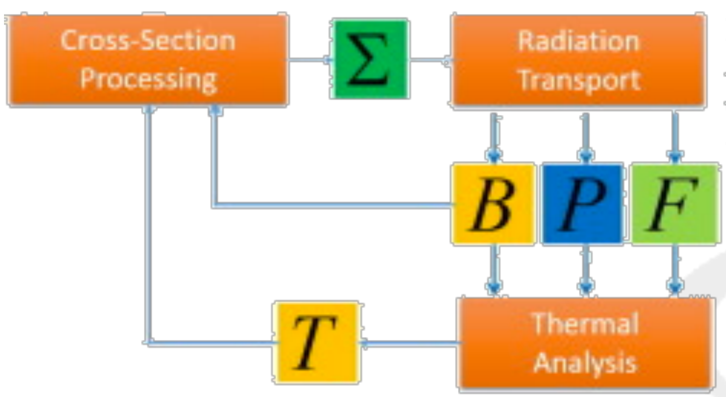
Surrogate (meta) modeling with machine learning



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

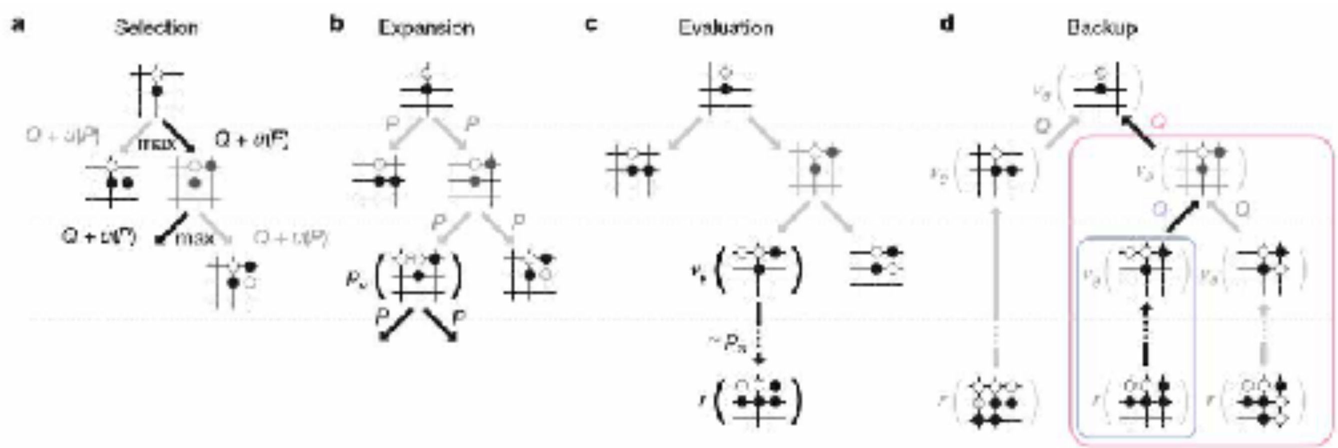
Dimensionality reducibility for multi-physics reduced order modeling

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.



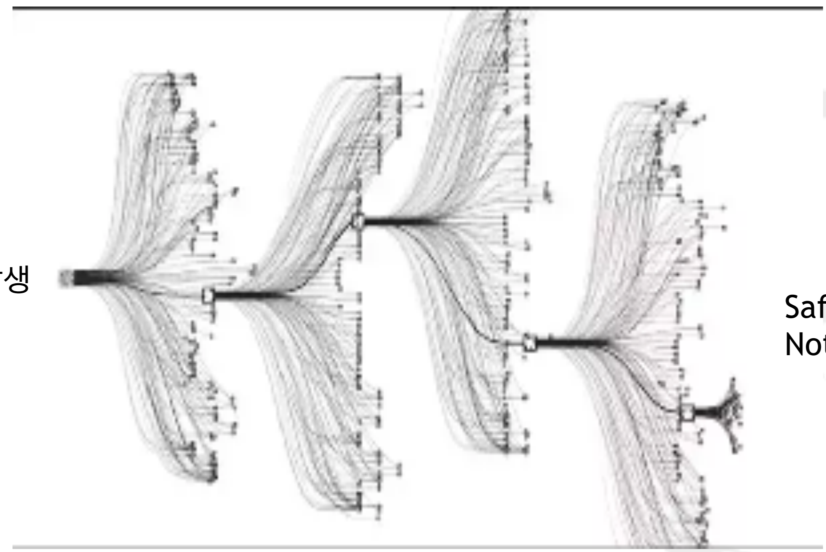
T: Temperature Distribution
Σ: Macroscopic Cross-Sections
P: Power Distribution
B: Burnup Distribution
F: Fission Rate Distribution

중대사고 대응 로직



Decision1 Decision2 Decision3 Decision4

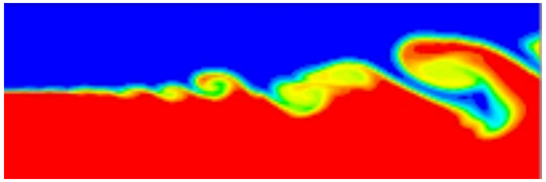
사고발생

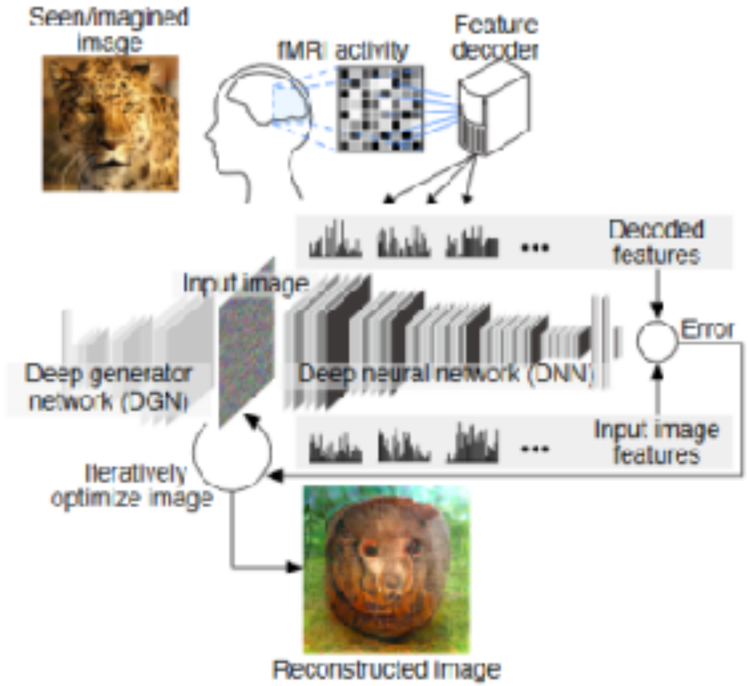


Safe or
Not ?

Korea Atomic Energy Research Institute

Rise of Data science





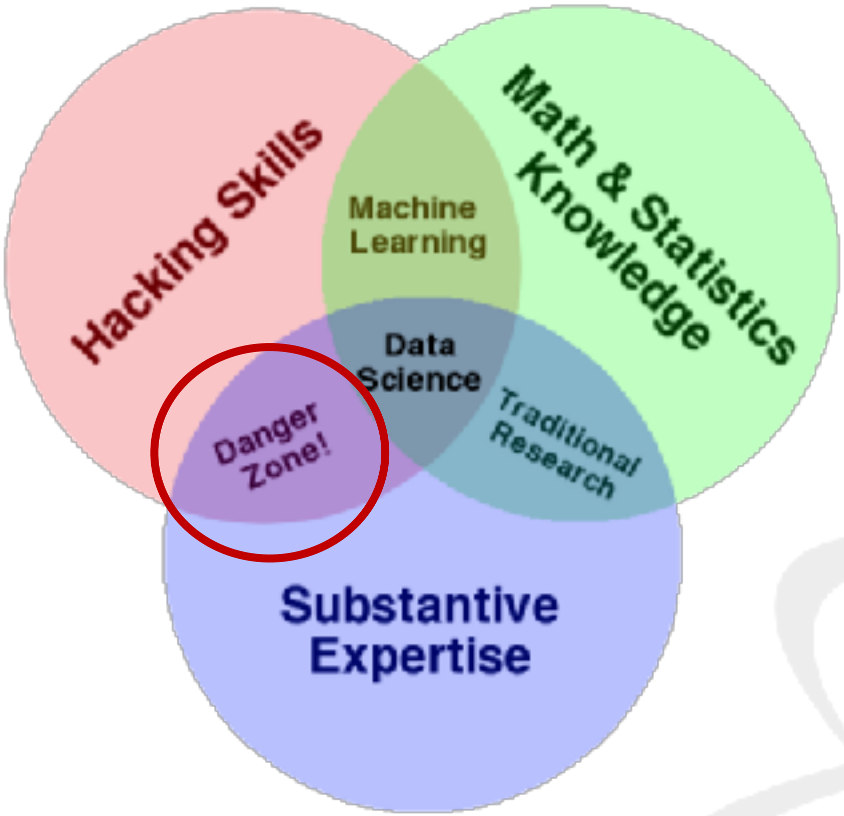
https://www.biorxiv.org/content/biorxiv/early/2017/12/30/240317.fu

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)

Data Science 을 위해서는?



From Drew Conway

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

[중앙일보] 입력 2018.01.25 05:00

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 명세한 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
어뢰간 쫓긴 '中 핵잠 굴욕'

태양광 관세 때리니 7만명 실직위기…
일자리 보호의 역설

맛있다는 한국 맥주, '몬고점' 유럽서 판매 금을 이유

마구르드 카드 만들다 '한국의 테슬라'
전기차 꿈꾼다

과학/공학에서 인공지능 기술의 의미?

- 기존에 찾지 못했던 어떤 물리법칙을 찾을 수 있지 않을까?
- Multi-scale & Multi-physics 문제를 잘 해결해줄 수 있지 않을까?
- 기존 수치해석 방법의 한계를 뛰어넘을 수 있지 않을까?
- 과학과 예술을 연결시켜주는 매개체?

THANK YOU

Acknowledgement

- 연구재단 신진연구, 딥러닝과 위상최적설계를 융합한 AI 설계 프레임워크 개발 (2018.3~2020.2)
- 원자력연구원 기관고유사업, 딥러닝과 위상최적설계 기술을 융합한 골격계 CT 사진 복원 기술 개발 (2018.11~2019.10)

KAERI Korea Atomic Energy Research Institute