KAERI

원자로 안전 감시 및 제어를 위한 인공지능 기반 기술

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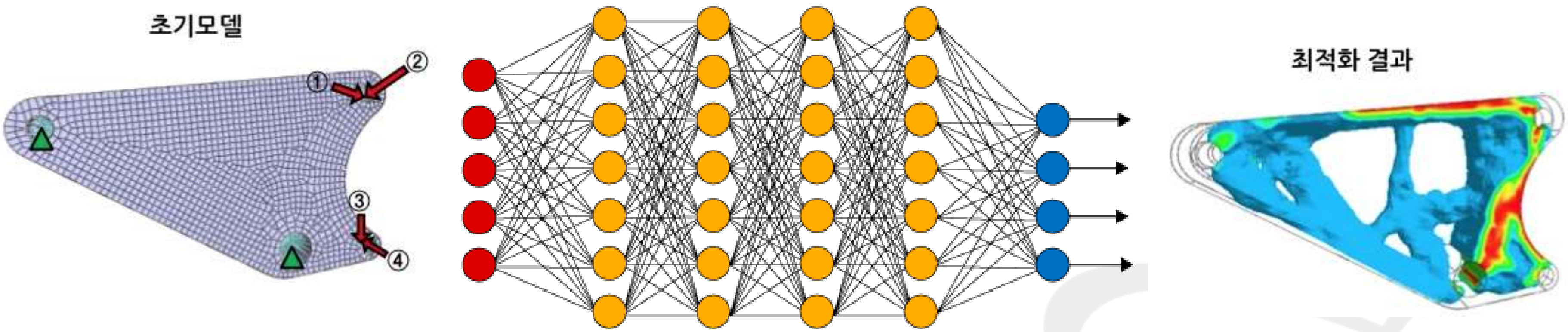
2018.05.16

Korea Atomic Energy Research Institute

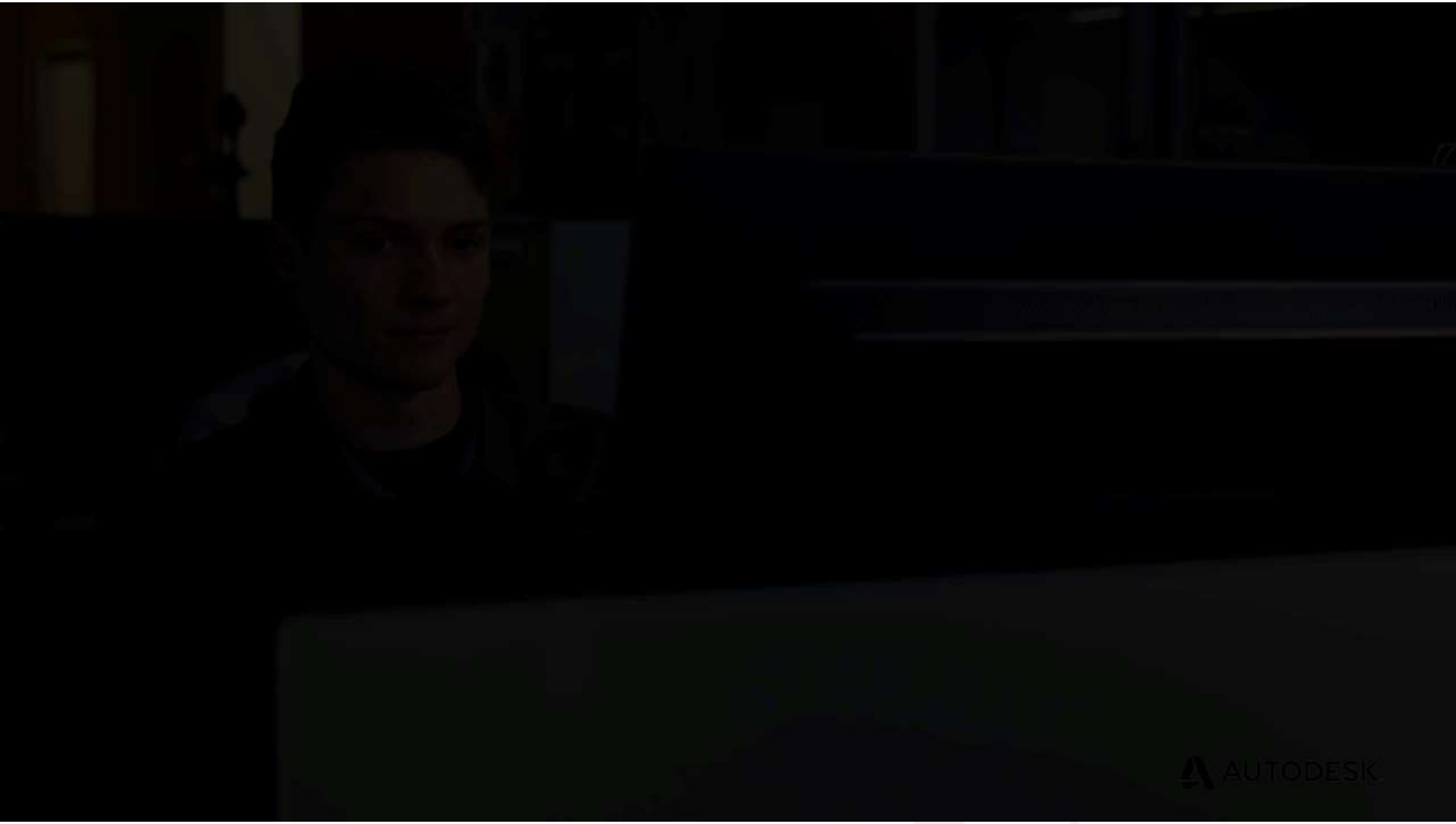
Applications of Deep Learning

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

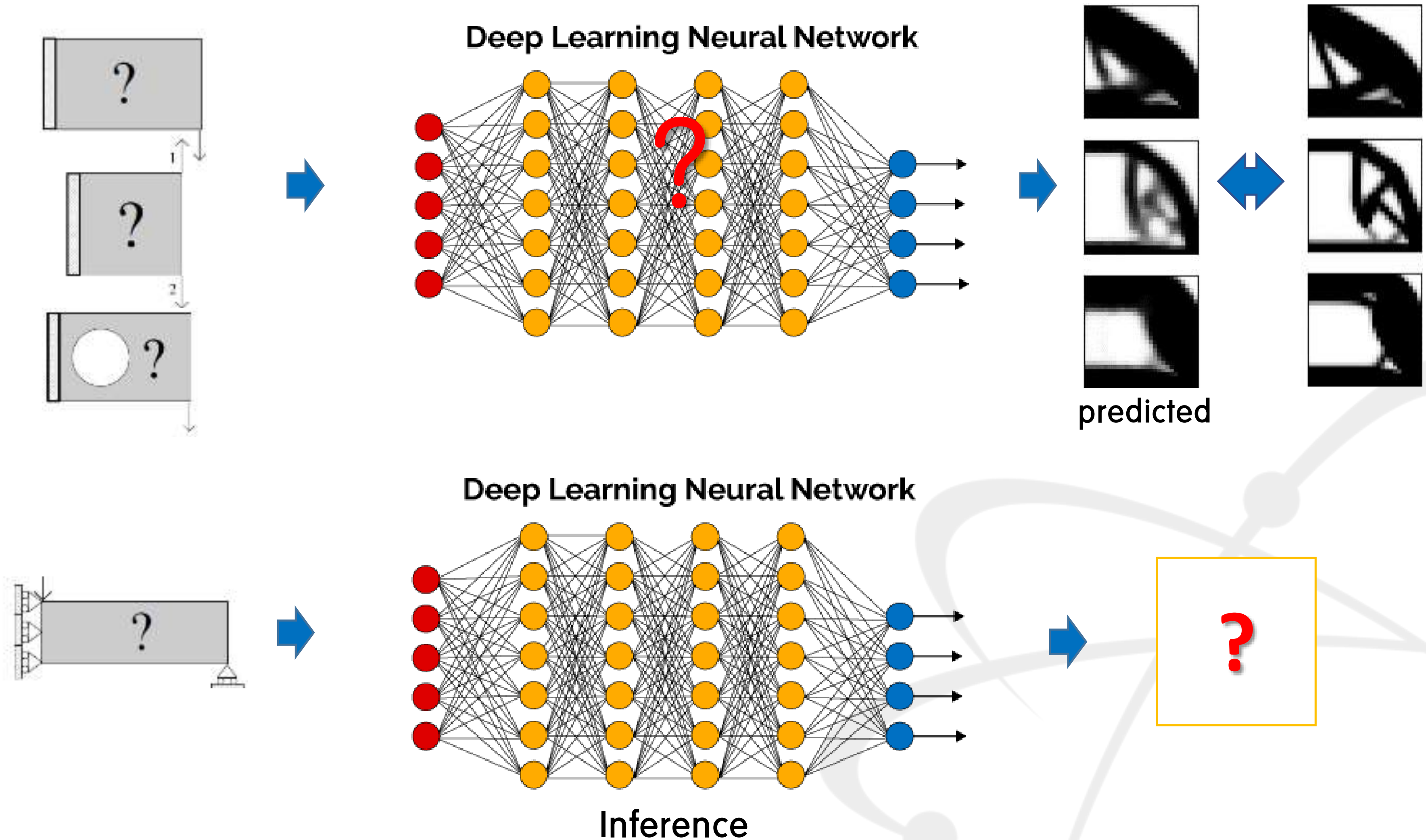
AI가 설계를 대신해줄 수 없을까?



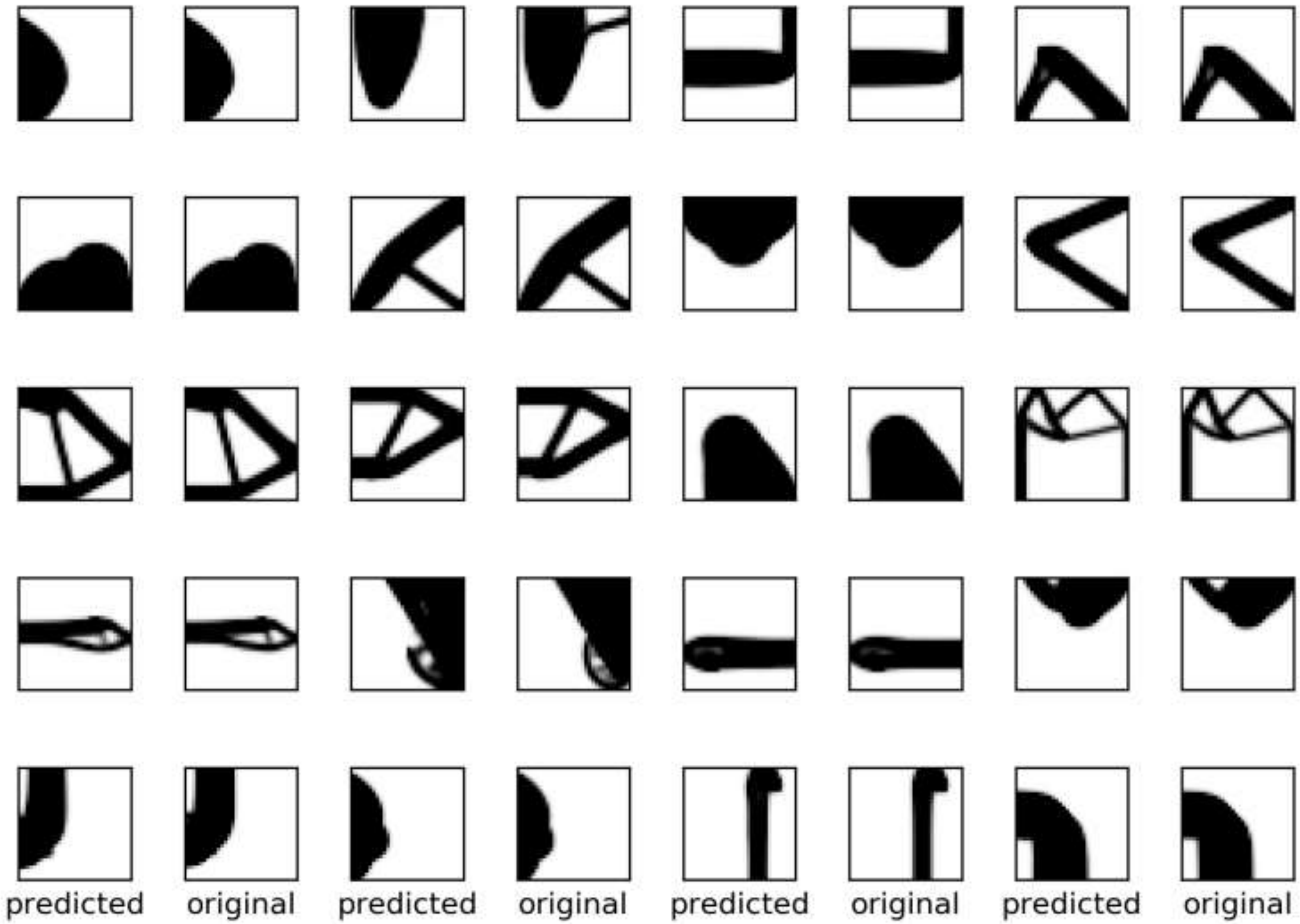
Autodesk Generative Design



Deep Learning for Topology Optimization Design



Deep Learning for Topology Optimization Design



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 Engineering

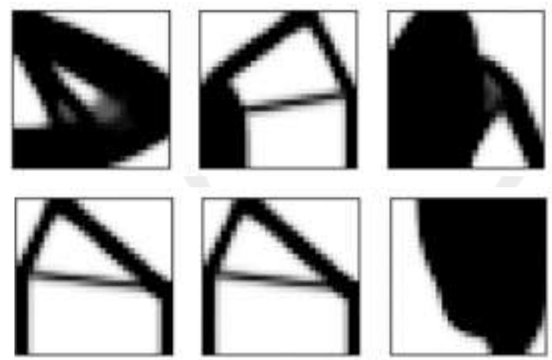
Hybrid Approach?

Optimization Scheduler

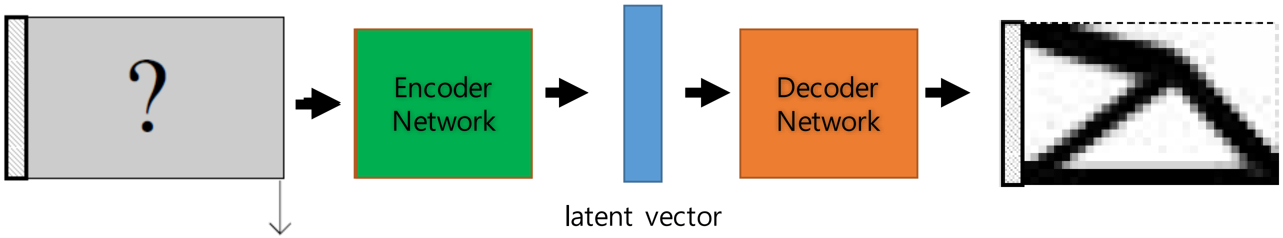
기존 최적설계

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

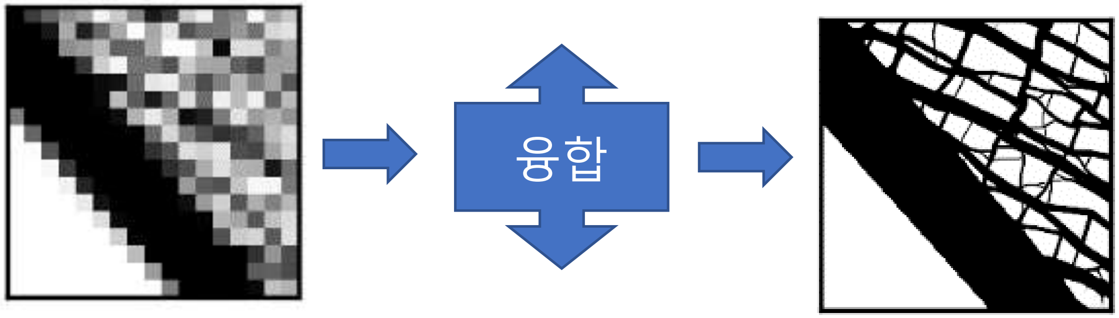
머신러닝 알고리즘



연구 개념



딥러닝 기반 위상최적설계



딥러닝 기반 영상 고해상화

인공지능은 무엇인가요?

Korea Atomic Energy Research Institute

인공지능인가요?


GoldStar
인공지능
저소음이라 조용하다!
OK
인공지능
금성 OK 세탁기


GoldStar
세계가 놀랐다!
카오스세탁기 탄생
금세기 제3의 물리학혁명, 카오스이론-
세계의 유명 전자회사들보다 앞서
금성이 카오스이론으로 세탁기를 만들었습니다.
차세대 전자기술의 핵심이 될 카오스이론
금성 카오스세탁기

인공지능인가요?

인공지능 (artificial Intelligence)

From The Quest for Artificial Intelligence, Nils John Nilsson

Artificial Intelligence is that activity devoted to machines intelligent, and intelligence it that quality that enables an entity to function appropriately and with foresight in its environment

For these reasons, I take a rather generous view of what constitutes AI. That means that my history of the subject will, at times, include some control engineering, some electrical engineering, some statistics, some linguistics, some logic, and some computer science.

둘다 인공지능이다!

당시 기술으로 뭔가 신기해보이면 인공지능이다!

https://brunch.co.kr/@flatdesign/23

머신러닝 (machine learning)

From Arthur Samuel

Field of study that gives computers the ability to learn without being explicitly programmed

From Tome Mitchell

T : Task (특정 과제에 대해)

E : Experience (경험을 통해)

P : Performance (성능을 향상)

How?

- 데이터 마이닝, 자동 탐색, 데이터베이스 업데이팅, 프로그래밍

Feedback methods

- Supervised Learning, Unsupervised Learning, Reinforcement Learning

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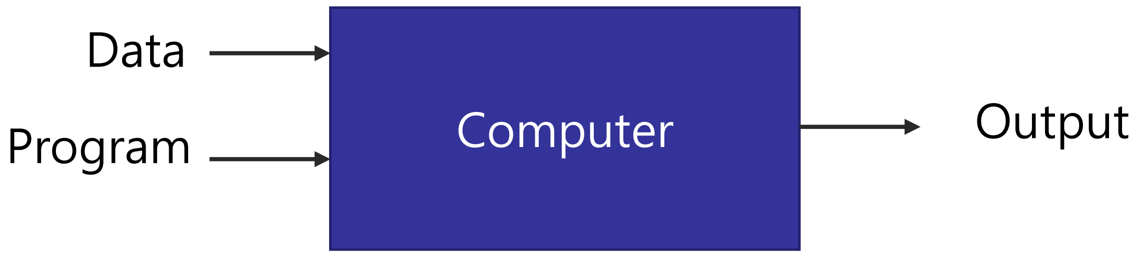
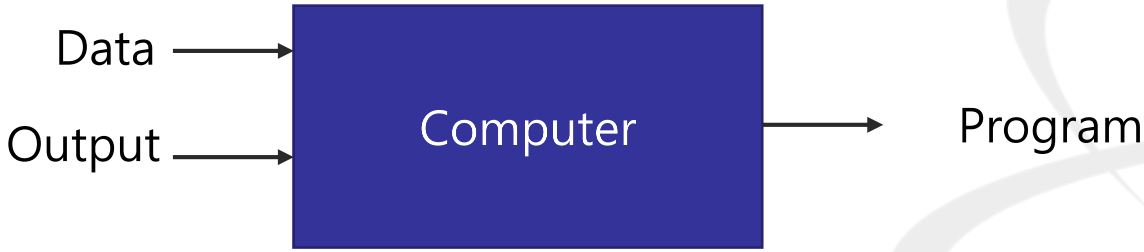
Machine Learning

Traditional Programming

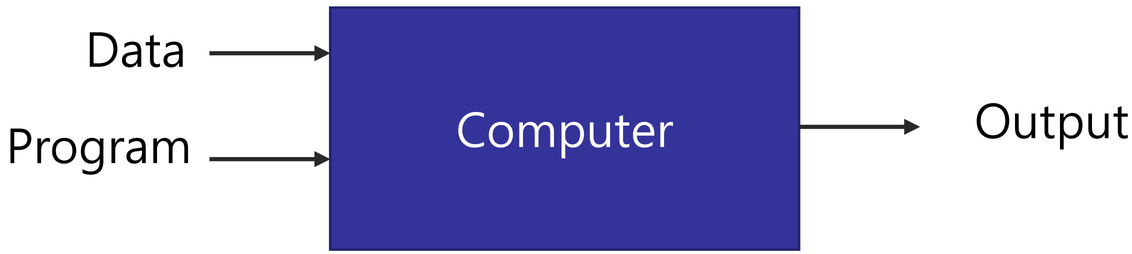


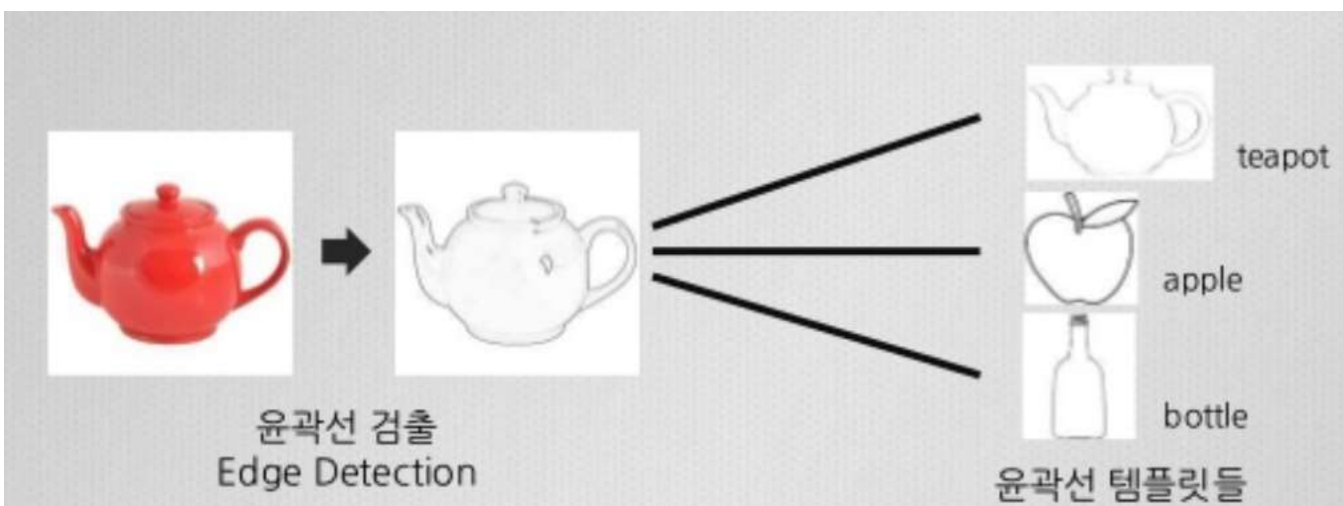
Machine Learning



Machine Learning

Traditional Programming





https://www.slideshare.net/yonghakim900/ss-60252533

Machine Learning

Machine Learning

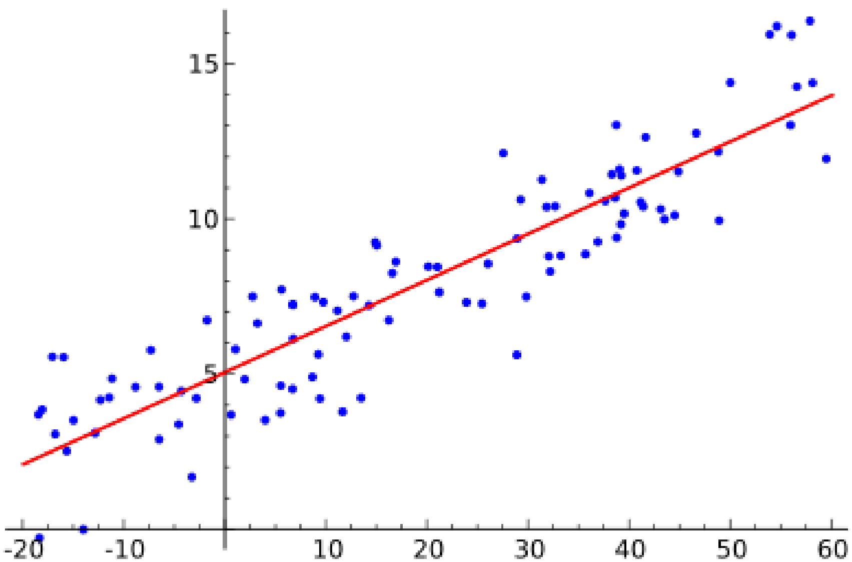
→ CAT

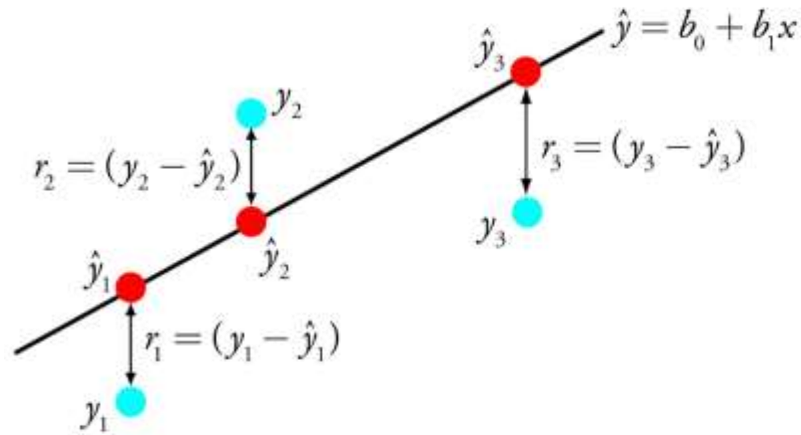
고전적으로 컴퓨터가 고전했던
고도의 인식 문제를
컴퓨터가 계산할 수 있는 계산문제로 치환
>> 통계학

Machine Learning

Regression model

$$Y = W \cdot X$$





$$\theta = (X^T X)^{-1} X^T Y$$

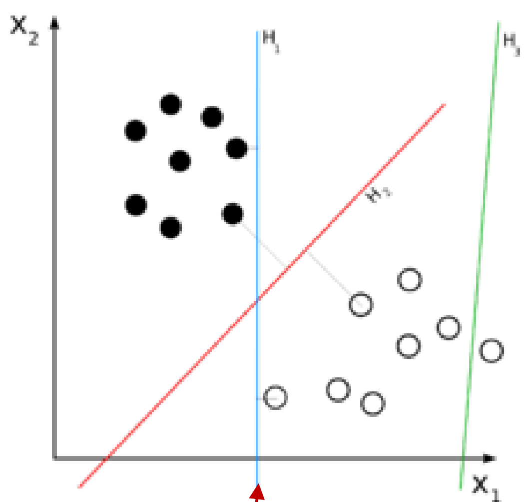
MIN $J(\theta) = \frac{1}{2}\sum_{i=0}^{m}(h_\theta(x^{(i)}) - y^{(i)})^2$

https://en.wikipedia.org/wiki/Linear_regression

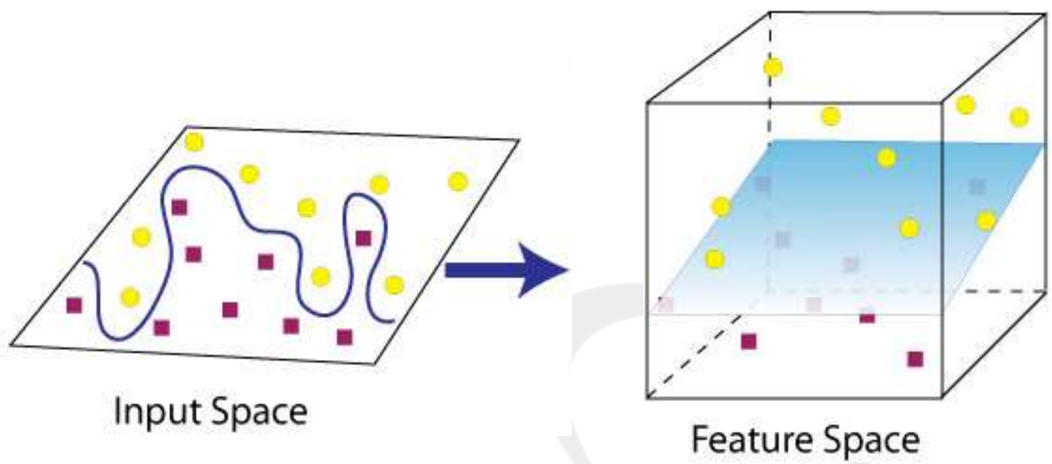
https://towardsdatascience.com/simple-linear-regression-2421076a5892

Machine Learning

Classification model



Support vector machine(SVM)

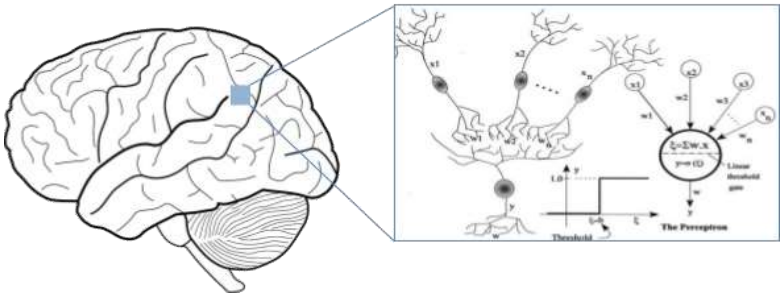


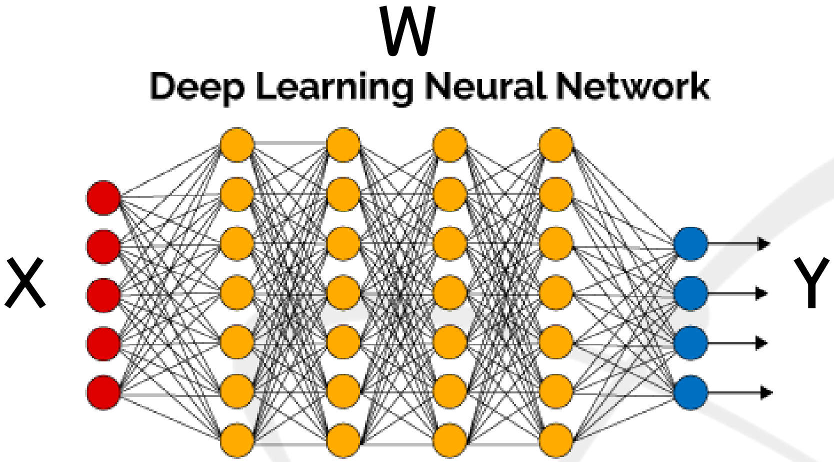
원공간의 데이터를 선형분류가 가능한 고차원 공간으로 매핑

https://ratsgo.github.io/machine%20learning/2017/05/30/SVM3/

Deep Learning

$$Y = W(X)$$

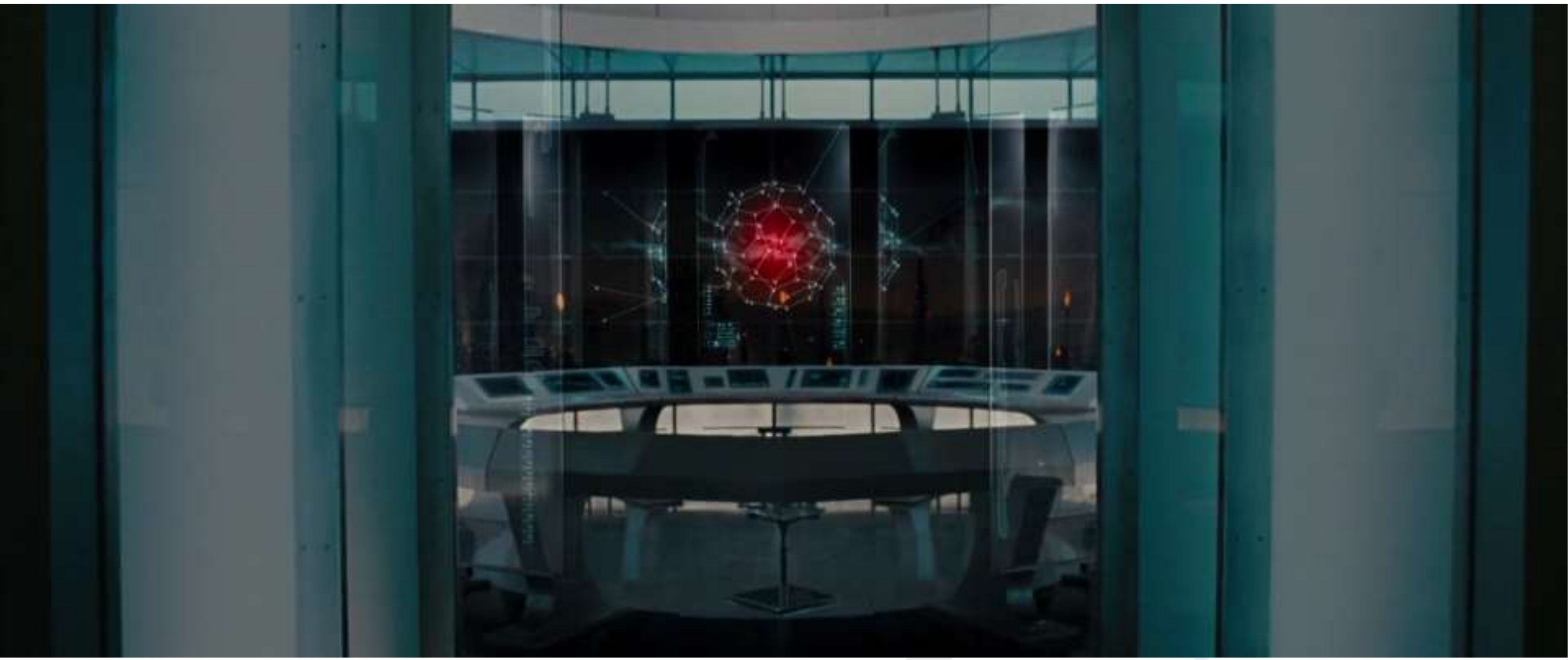




http://blog.daum.net/ygyung/15996778

https://hackernoon.com/log-analytics-with-deep-learning-and-machine-learning-20a1891ff70e

스카이넷 (터미네이터)



Neural Networks

François Chollet
@fchollet

부적절한 명칭

"Neural networks" are a sad misnomer. They're neither neural nor even networks. They're chains of differentiable, parameterized geometric functions, trained with gradient descent (with gradients obtained via the chain rule). A small set of highschool-level ideas put together

4:58 AM - Jan 13, 2018

3,412 1,421 people are talking about this

Francois Chollet- one of the pioneers of Deep Learning, author of the Keras framework

Neural Networks

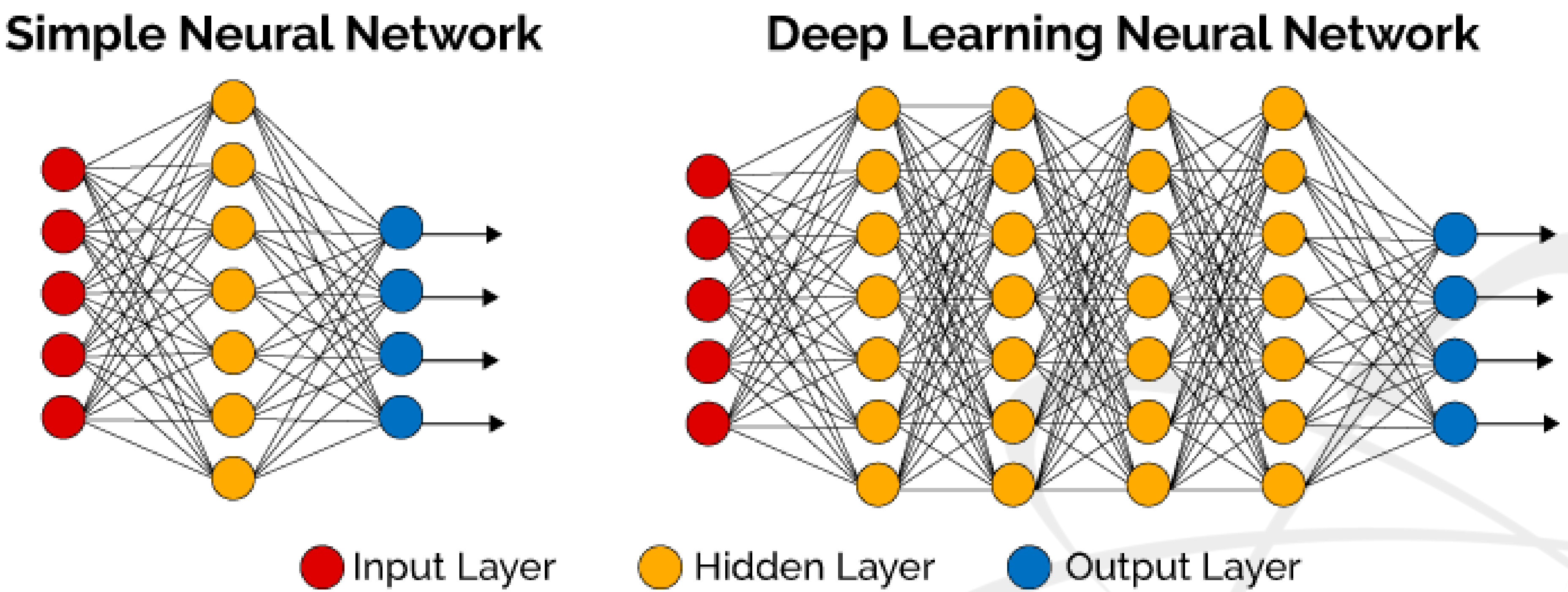
From The Elements of Statistical Learning

*The term **neural network** has evolved to encompass a large class of models and learning methods. Here we describe the most widely used "vanilla" neural net, sometimes called the single hidden layer back-propagation network, or single layer perceptron. There has been a **great deal of hype surrounding** neural networks, making them seem **magical** and **mysterious**. As we make clear in the section, they are **just nonlinear statistical models**, much like the projection pursuit regression model discussed above.*

뉴럴 네트워크(NN: 인공신경망)를 둘러싼 막대한 양의 과장 광고가 있었고, 그들(NN)을 마법적이고 신비롭게 보이도록 만들었다.

여기서 분명히 하건데, 그들은 위에 설명한 PPR 모델 만큼이나 그저 비선형 통계 모델일 뿐이다.

인공신경망이 왜 Good Approximator 인가?



Universal Approximation Theorem

Universal approximation theorem

From Wikipedia, the free encyclopedia

In the mathematical theory of artificial neural networks, the **universal approximation theorem** states[1] that a feed-forward network with a single hidden layer containing a finite number of neurons (i.e., a multilayer perceptron), can approximate continuous functions on compact subsets of $\mathbb{R}^n$, under mild assumptions on the activation function. The theorem thus states that simple neural networks can *represent* a wide variety of interesting functions when given appropriate parameters; however, it does not touch upon the algorithmic learnability of those parameters.

One of the first versions of the theorem was proved by George Cybenko in 1989 for sigmoid activation functions.[2]

Kurt Hornik showed in 1991[3] that it is not the specific choice of the activation function, but rather the multilayer feedforward architecture itself which gives neural networks the potential of being universal approximators. The output units are always assumed to be linear. For notational convenience, only the single output case will be shown. The general case can easily be deduced from the single output case.

Contents [hide]

1 Formal statement
2 See also
3 References
4 External links

Formal statement [edit]

The theorem[2][3][4][5] in mathematical terms:

Let $\varphi(\cdot)$ be a nonconstant, bounded, and monotonically-increasing continuous function. Let I_m denote the m-dimensional unit hypercube $[0,1]^m$. The space of continuous functions on I_m is denoted by $C(I_m)$. Then, given any $\varepsilon > 0$ and any function $f \in C(I_m)$, there exist an integer N, real constants $v_i, b_i \in \mathbb{R}$ and real vectors $w_i \in \mathbb{R}^m$, where $i = 1, \cdots, N$, such that we may define:

$$F(x) = \sum_{i=1}^{N} v_i \varphi\left(w_i^T x + b_i\right)$$

as an approximate realization of the function f where f is independent of φ; that is,

$$|F(x) - f(x)| < \varepsilon$$

for all $x \in I_m$. In other words, functions of the form $F(x)$ are dense in $C(I_m)$.

This still holds when replacing I_m with any compact subset of $\mathbb{R}^m$.

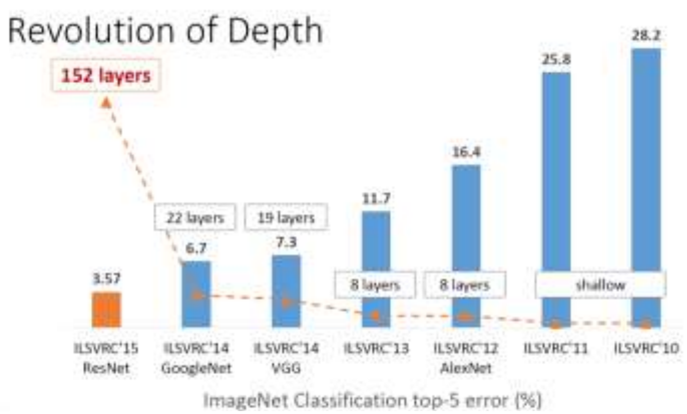
Why does deep and cheap learning work so well?*

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.

VGG Network



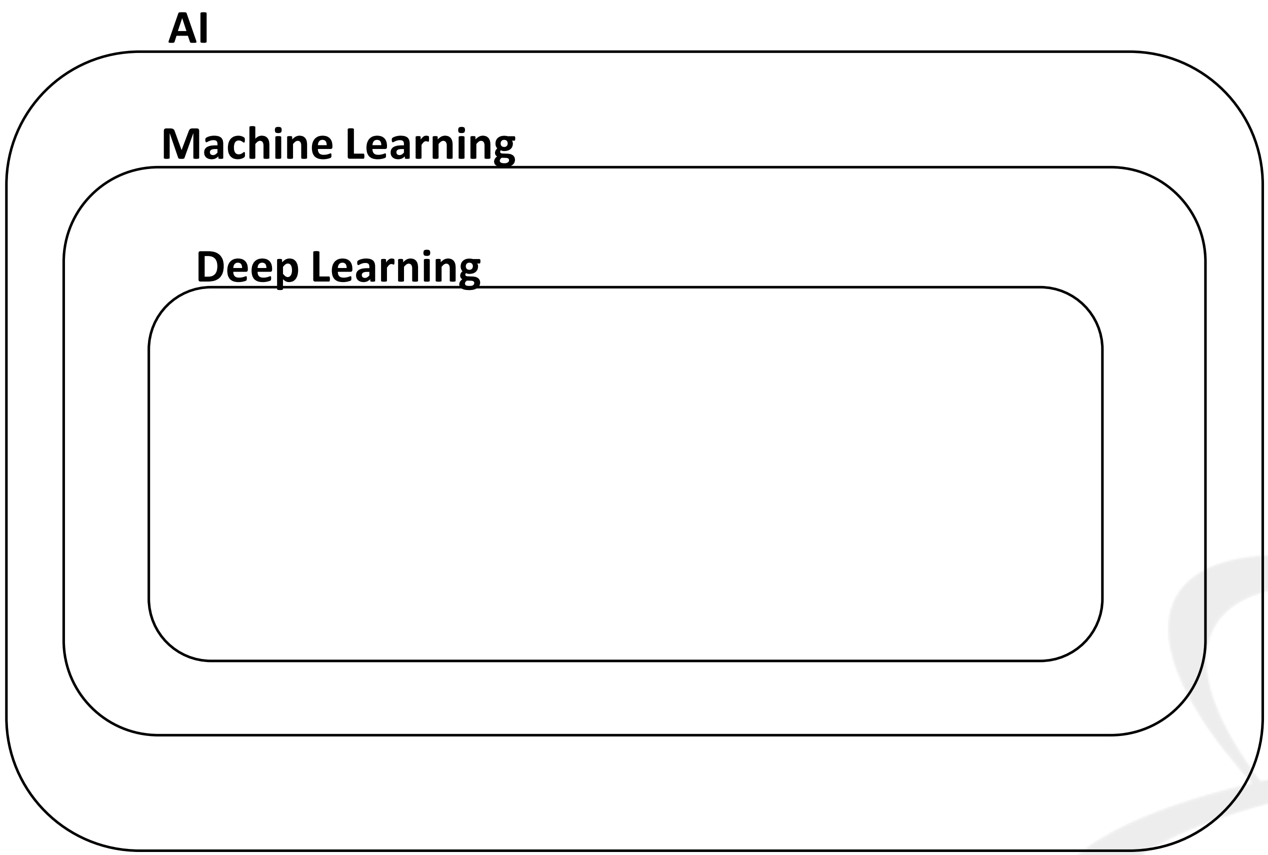

```
# 오리지날 VGG16 모델
def VGG_16():
    model = Sequential()
    model.add(Lambda(vgg_preprocess, input_shape=(3,224,224)))

    ConvBlock(2, model, 64)
    ConvBlock(2, model, 128)
    ConvBlock(3, model, 256)
    ConvBlock(3, model, 512)
    ConvBlock(3, model, 512)

    model.add(Flatten())
    FCBlock(model)
    FCBlock(model)
    model.add(Dense(1000, activation='softmax'))
    return model

model = VGG_16()
model.compile(optimizer=Adam(lr=0.001),
              loss='categorical_crossentropy', metrics=['accuracy'])
```

```
def ConvBlock(layers, model, filters):
    for i in range(layers):
        model.add(ZeroPadding2D((1,1)))
        model.add(Convolution2D(filters, 3, 3,
                                activation='relu'))
    model.add(MaxPooling2D((2,2), strides=(2,2)))
```

```
def FCBlock(model):
    model.add(Dense(4096, activation='relu'))
    model.add(Dropout(0.5))
```

하용호, 딥러닝을 인스톨시켜주마

인공지능 / 머신러닝 / 딥러닝



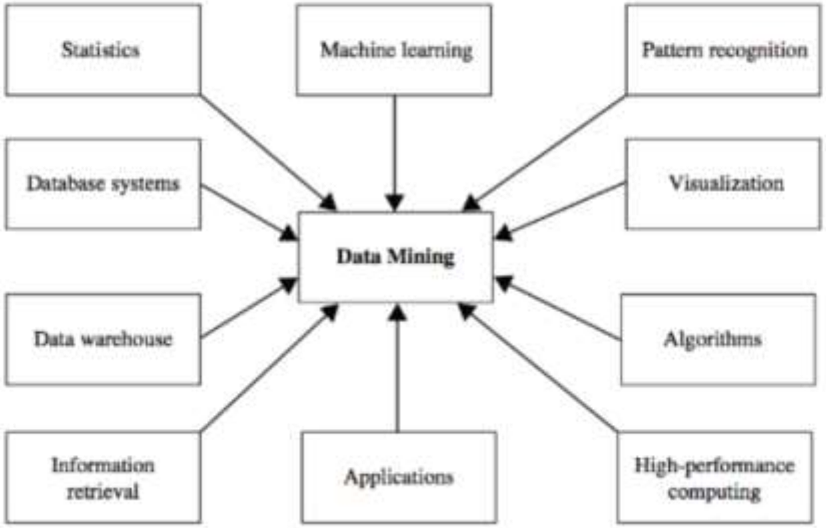
데이터 마이닝 (Data mining)

From Data mining : Concepts and Techniques, Jiawei Han

Searching for knowledge – interesting patterns in data

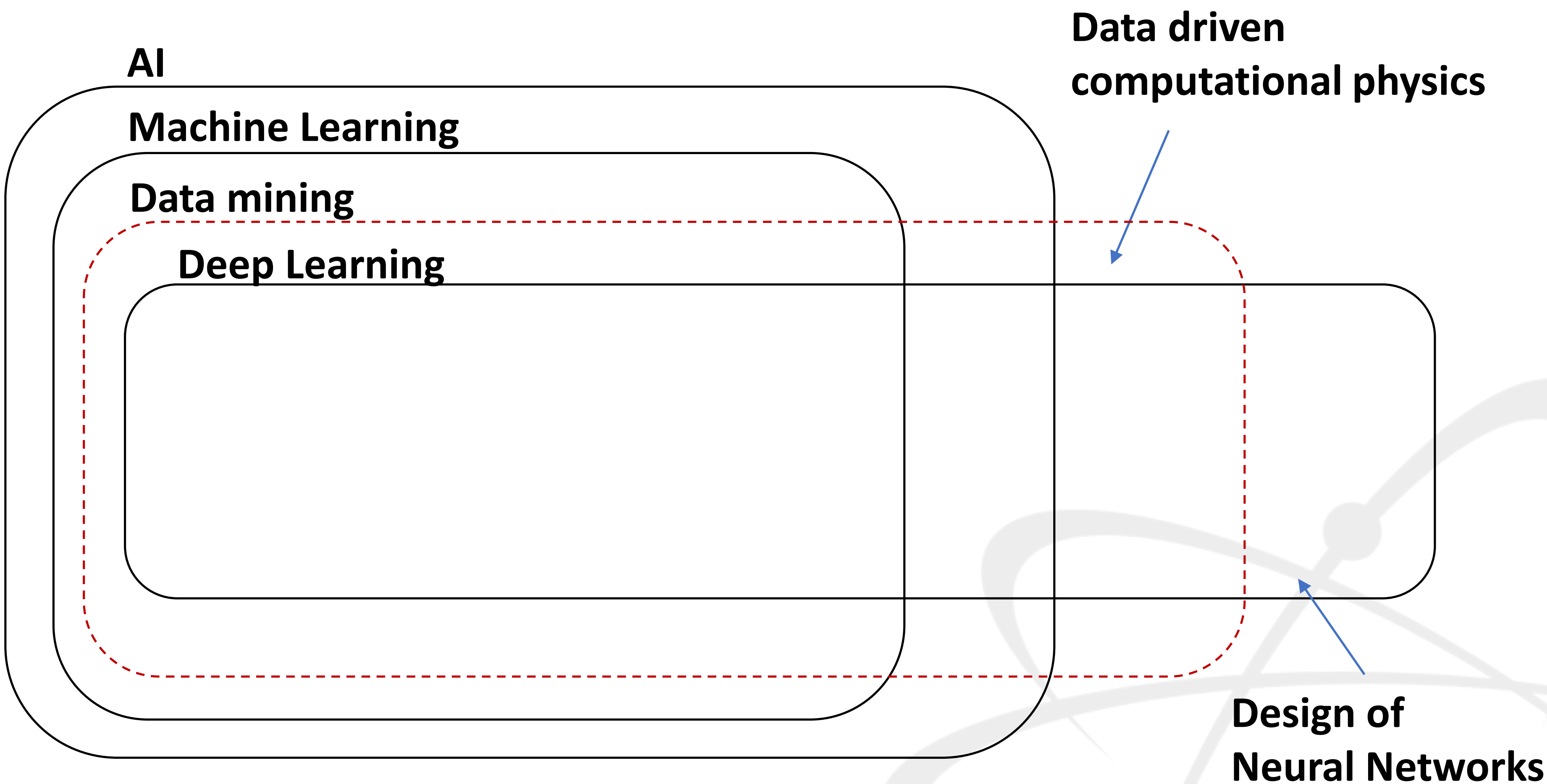
Extraction of interesting patterns or knowledge from huge amount of data

Classification, Regression, Outliner analysis, Clustering,
Associate rule discovery, Pattern discovery

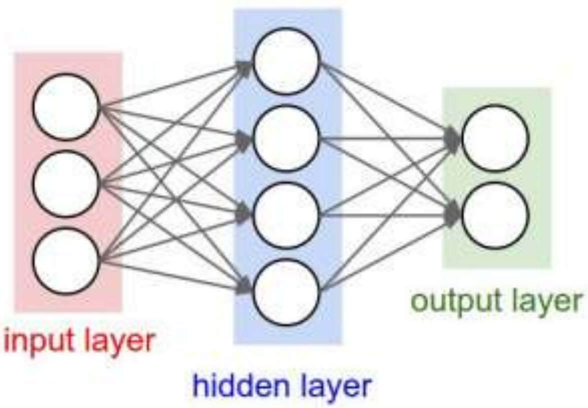


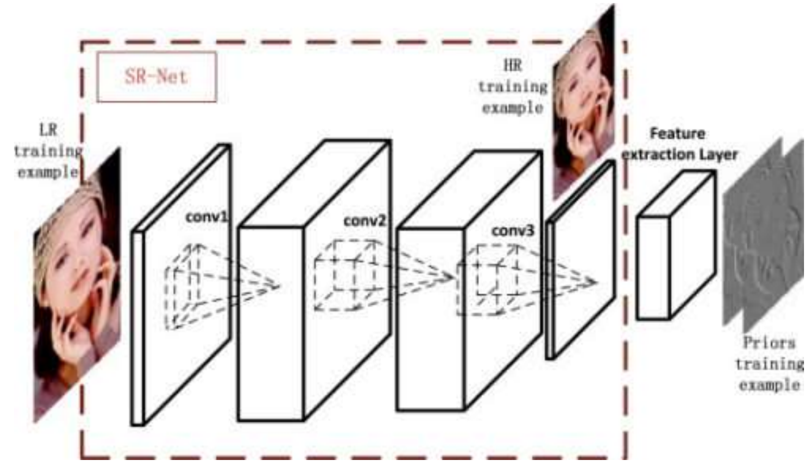
https://brunch.co.kr/@flatdesign/23

인공지능 / 머신러닝 / 딥러닝

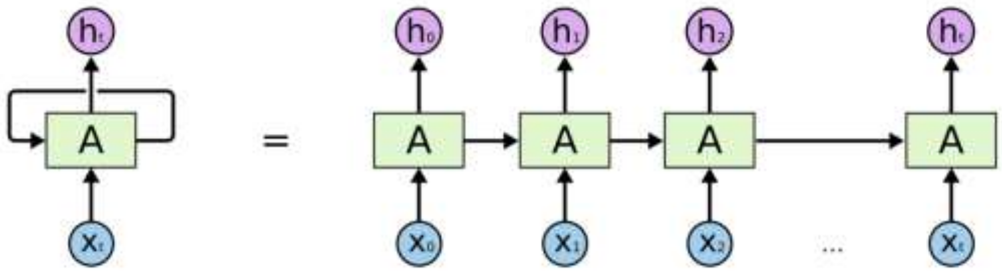


Neural Network 의 발전





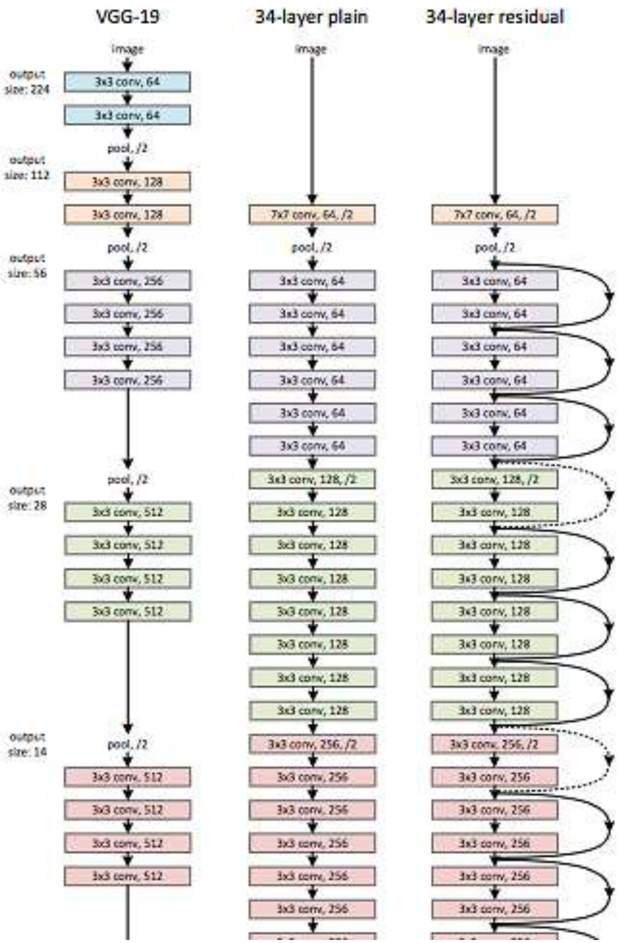
Convolution Neural Network



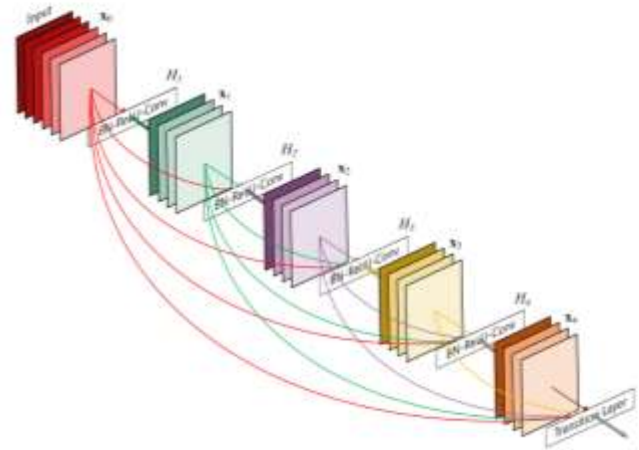
Recurrent Neural Network

http://www.mtechprojects.org/deep-convolutional-neural-networks-projects.html

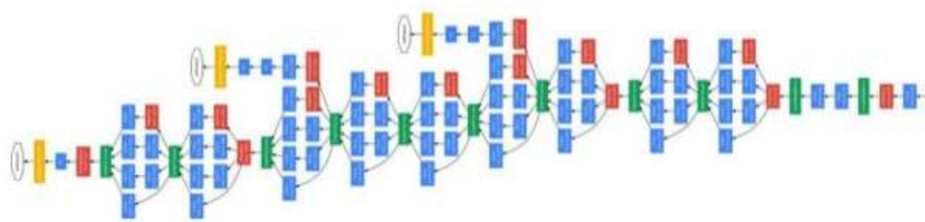
Neural Network 구조의 응용



VGG Net & Resnet

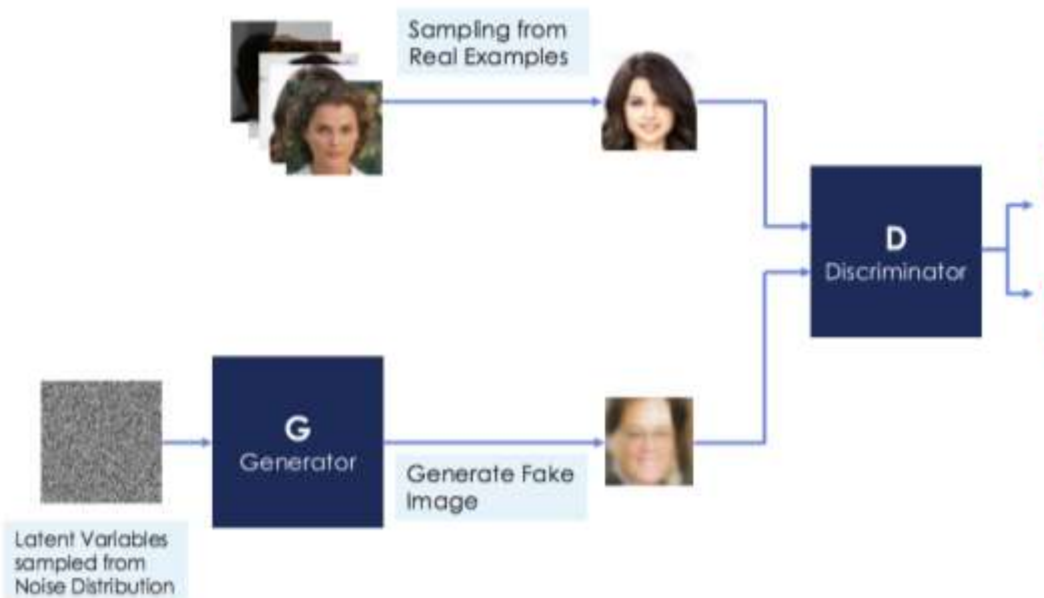


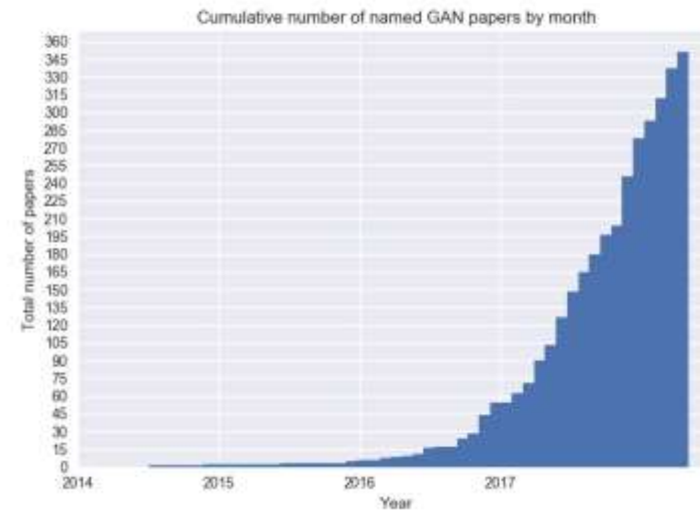
Densnet



GoogleNet

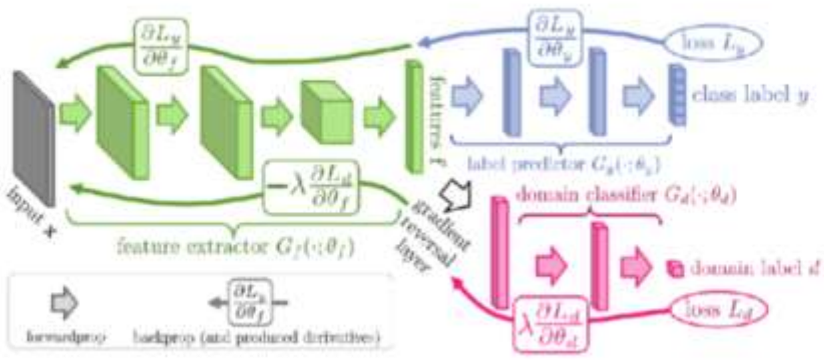
Generative Adversarial Networks



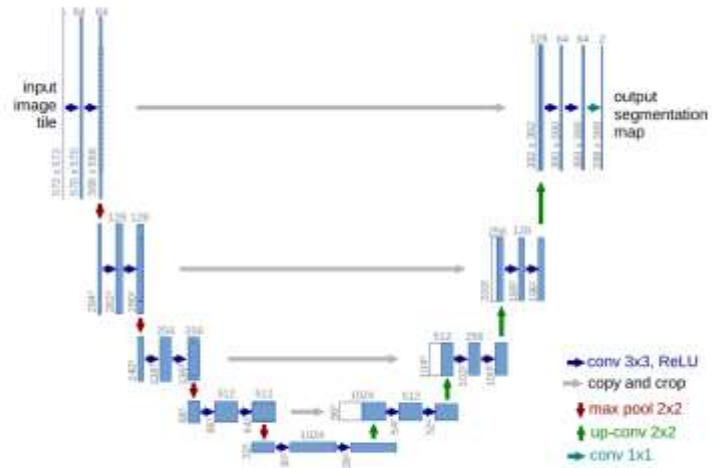


http://solarisailab.com/archives/2482

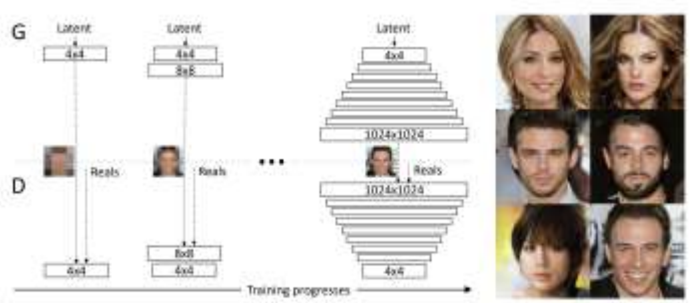
Variants…



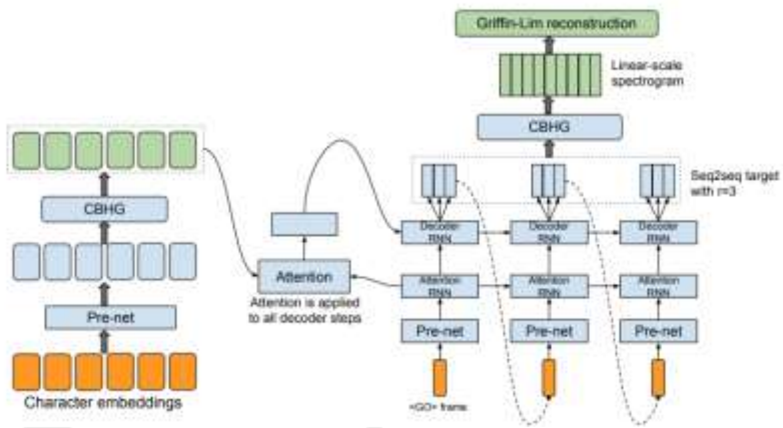
DANN https://arxiv.org/abs/1505.07818



UNET https://arxiv.org/abs/1505.04597

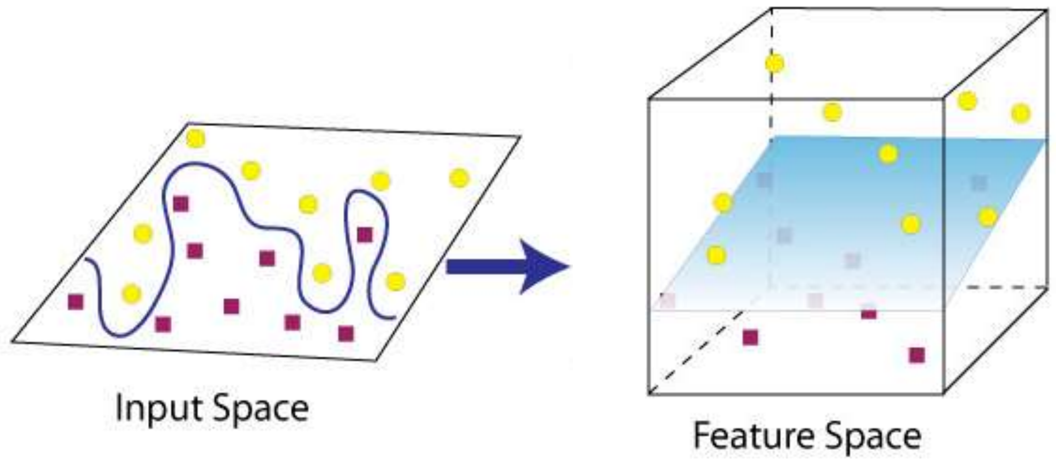


PG-GAN https://arxiv.org/pdf/1710.10196.pdf

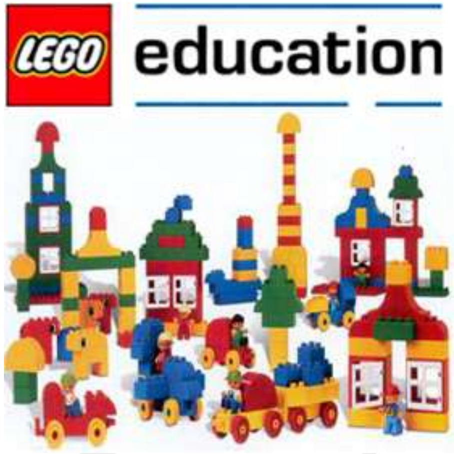


Tacotron https://arxiv.org/pdf/1703.10135.pdf

Playing LEGO!



Machine Learning



Deep Learning

하고싶은 싶은 말?

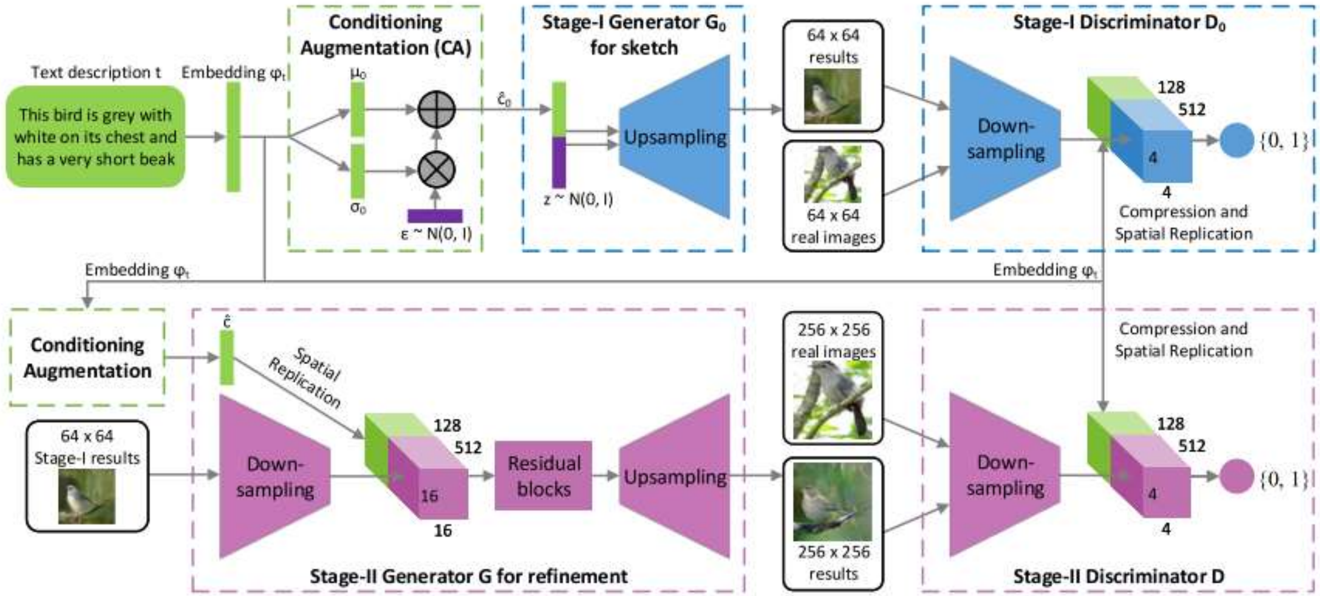
- 머신러닝은 본질적으로 데이터를 이용한 확률모형이다.
  - 통계학, 수학!!
  - 블랙박스인가?

- 뉴럴넷이 머신러닝의 폭발적인 발전을 이끌었다.
  - 단지 Kernel 함수에 지나지 않는다.
  - 과거 수십년동안 발전해온 머신러닝 학문을 이해해야 한다.
  - 머신러닝의 새로운 패러다임.

- 공유문화가 핵심이다?!
  - 소스코드 공유(깃헙)
  - 논문 공유(아카이브)
  - 공개된 데이터셋

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

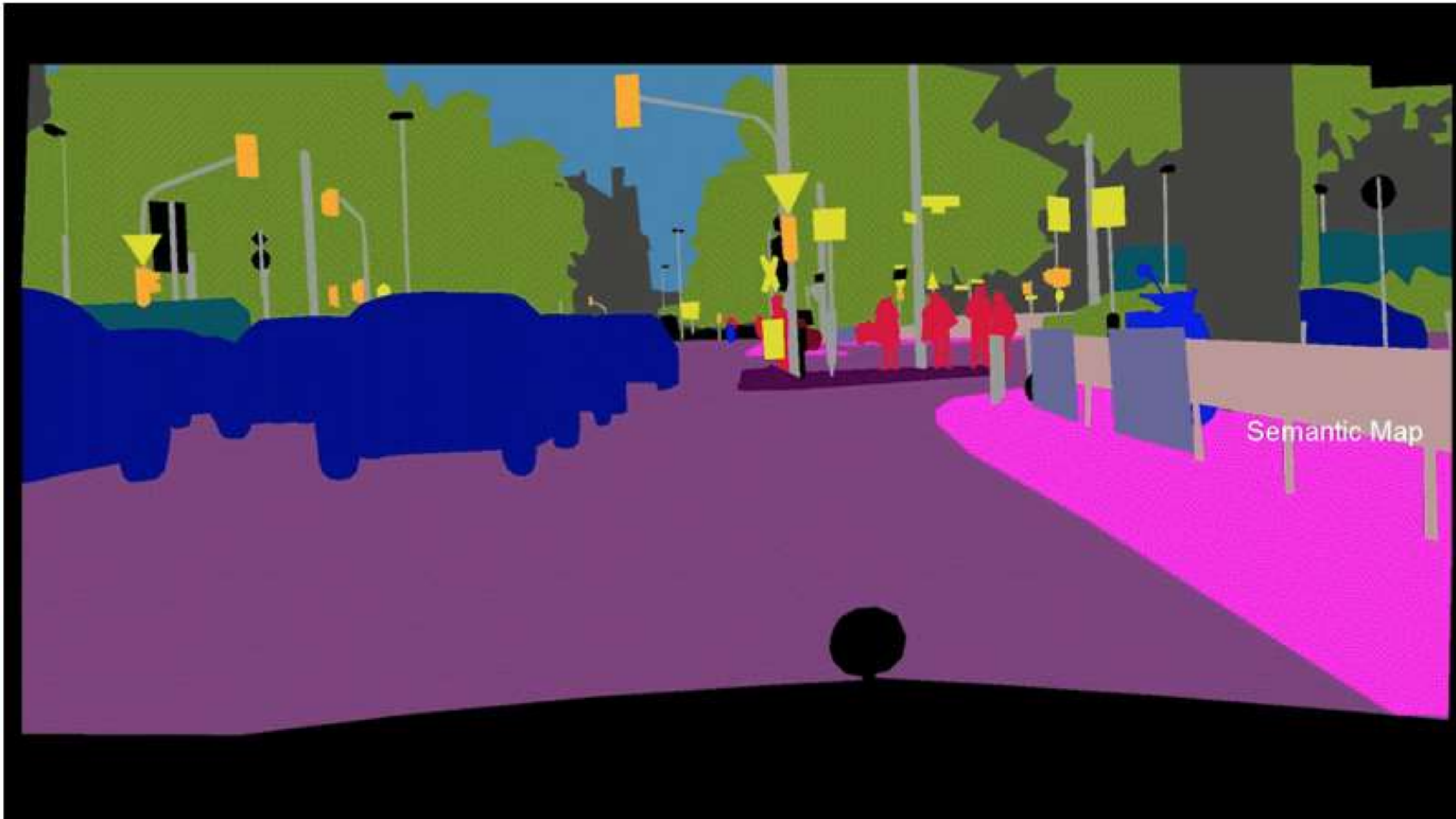
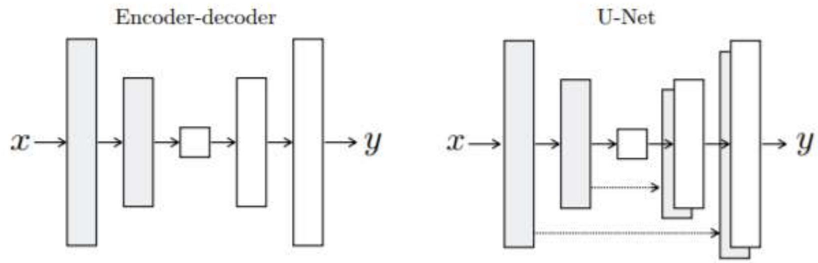
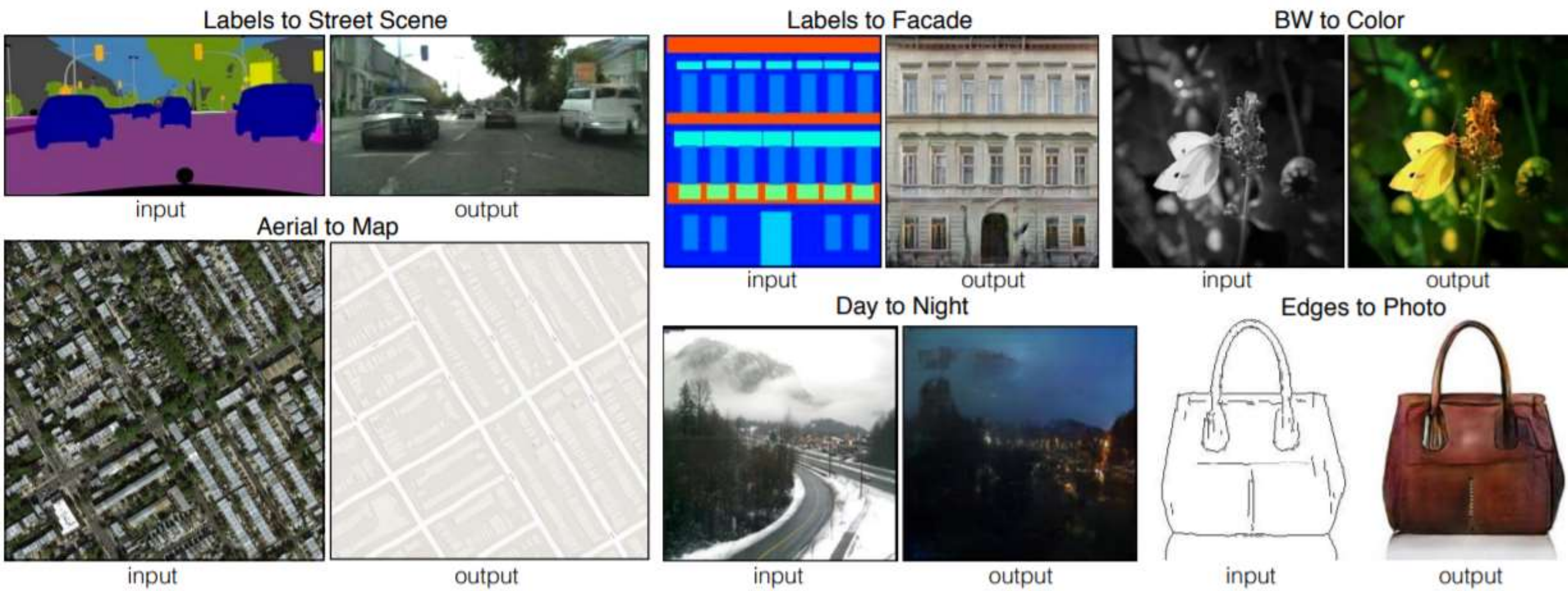


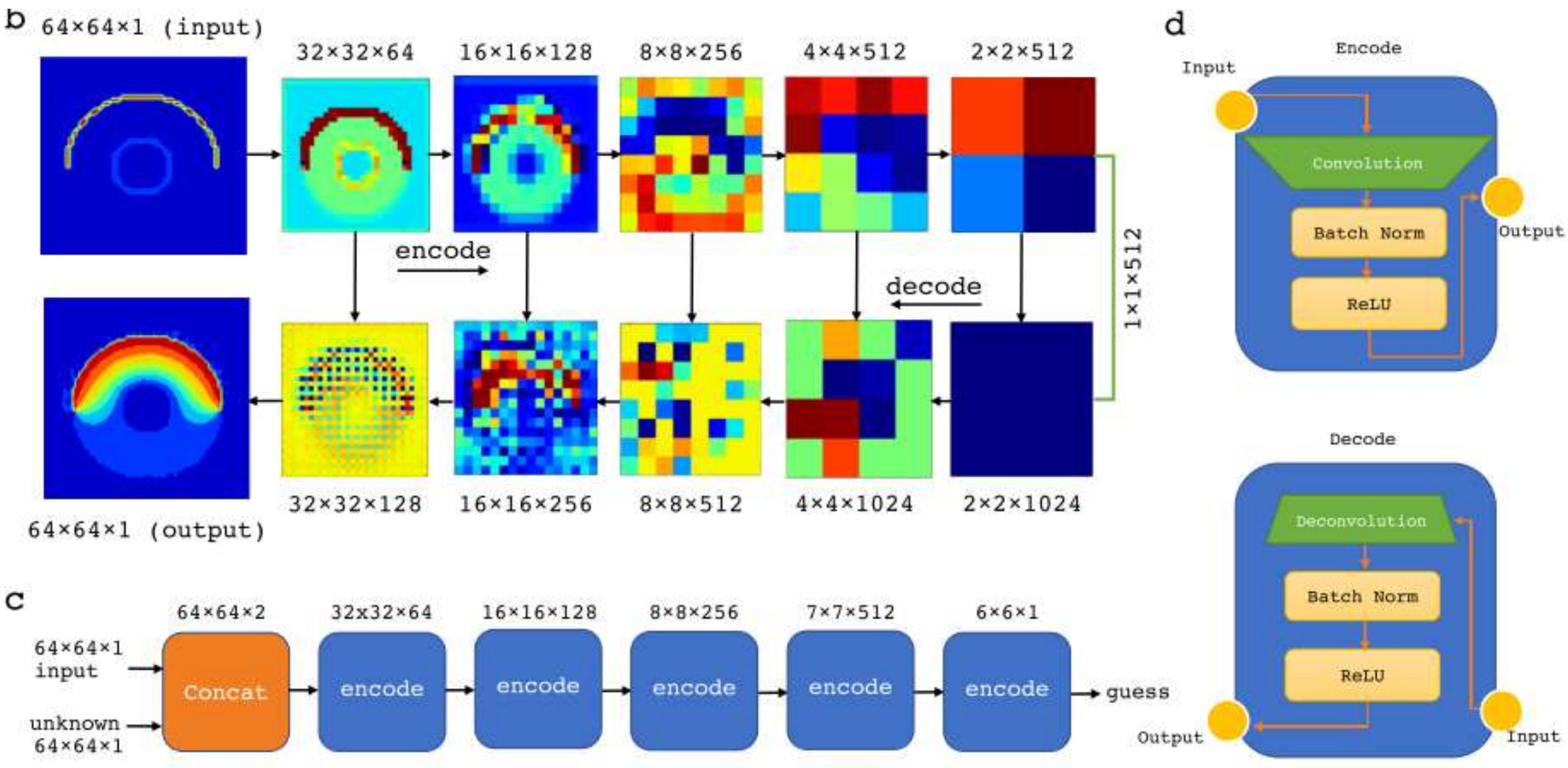
Image-to-Image Translation with Conditional Adversarial Networks

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

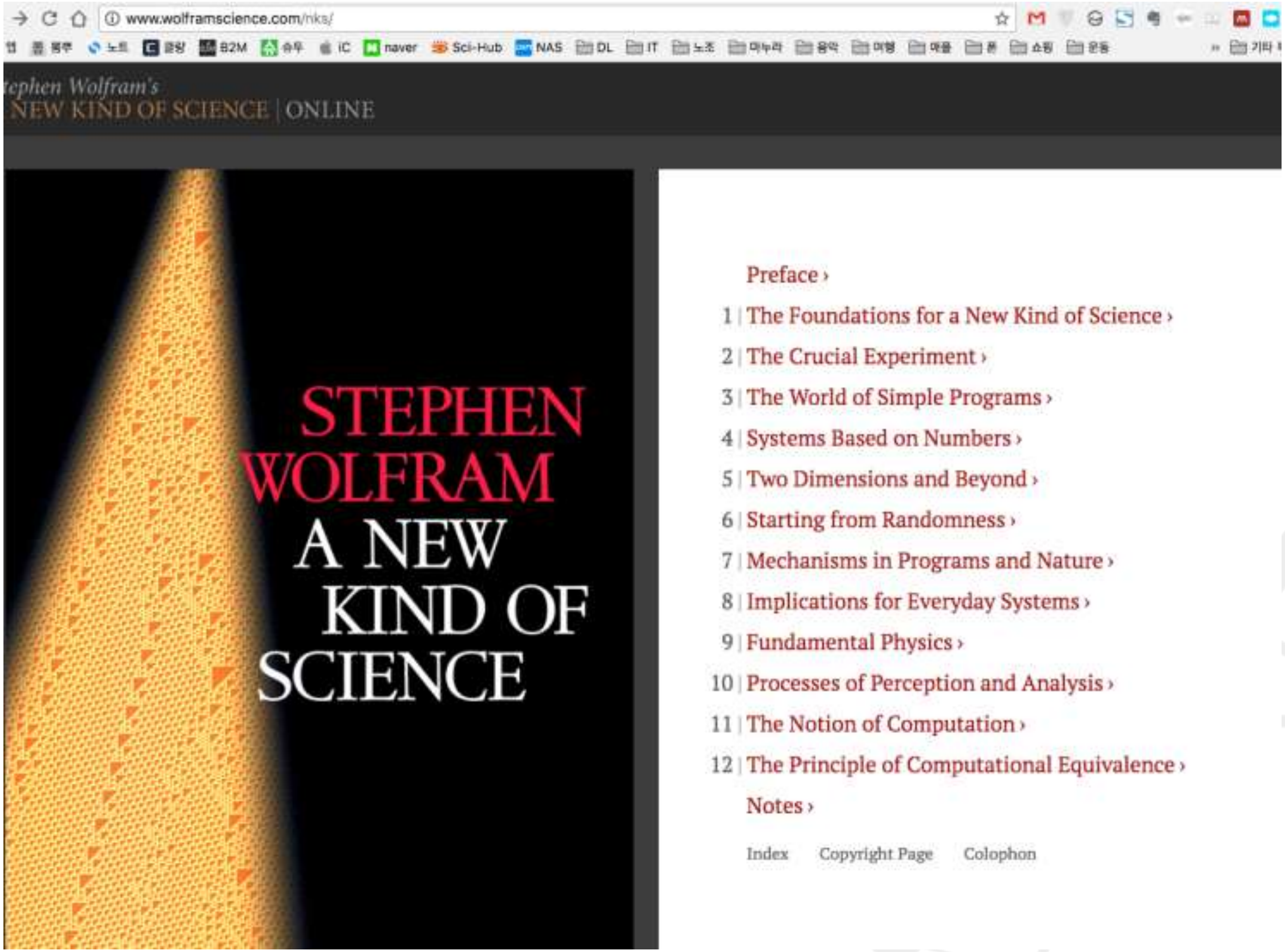
Convective term

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.)

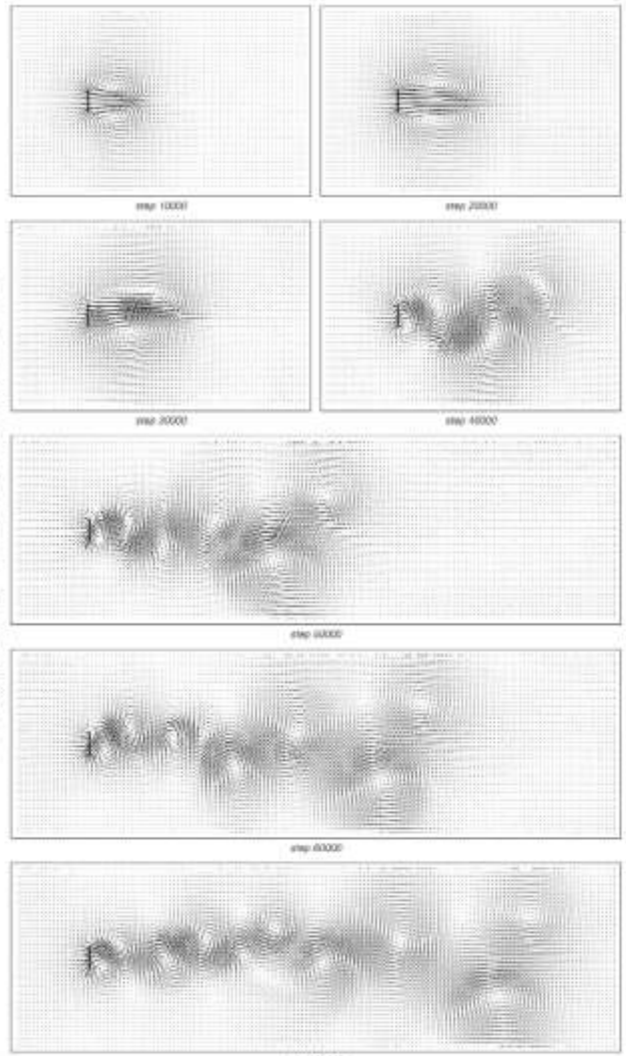
viscosity controlled velocity diffusion term

A New kind of science, Stephen Wolfram

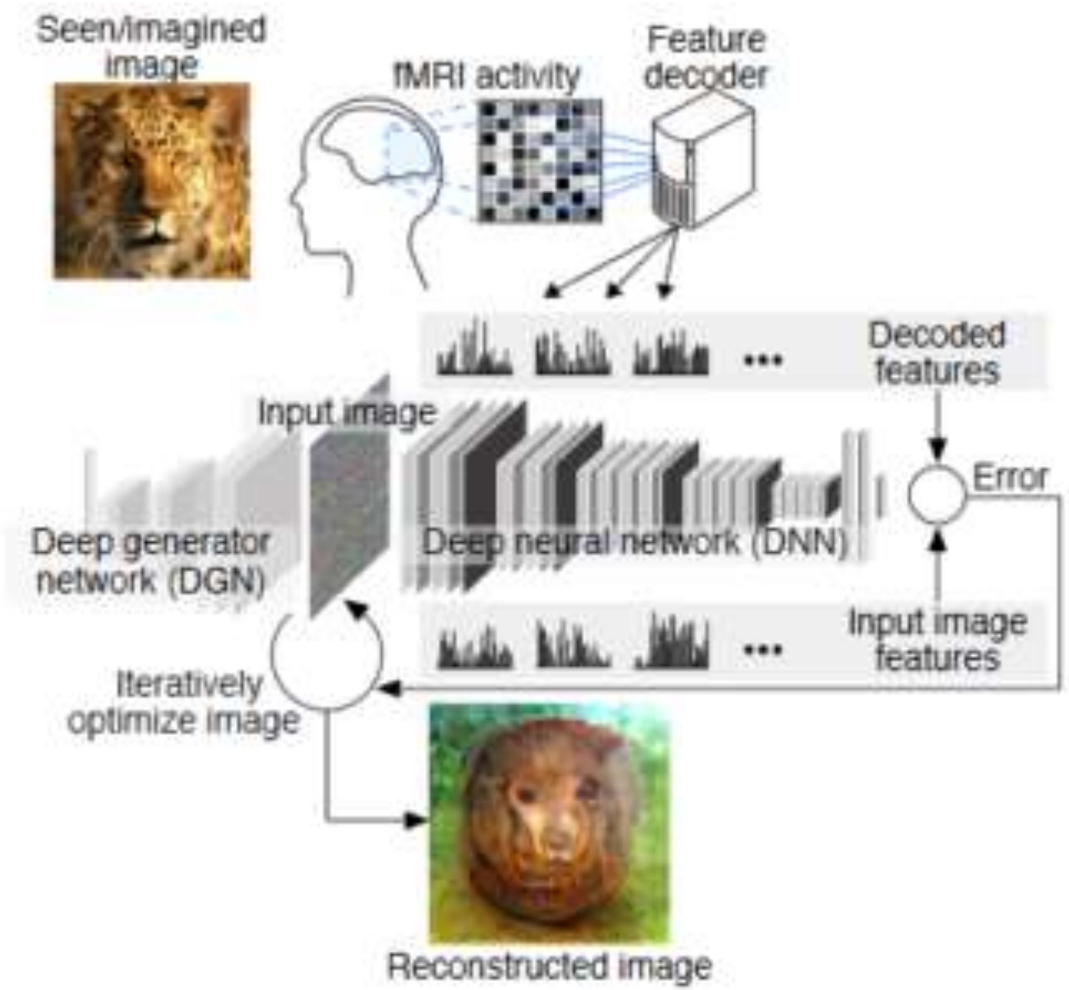


A New kind of science, Stephen Wolfram

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.



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

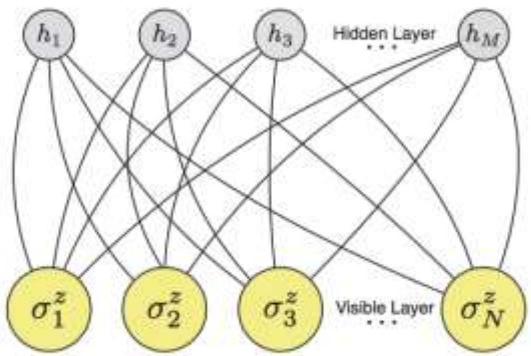
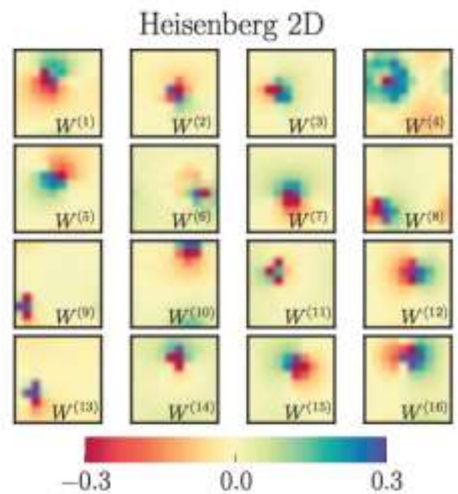


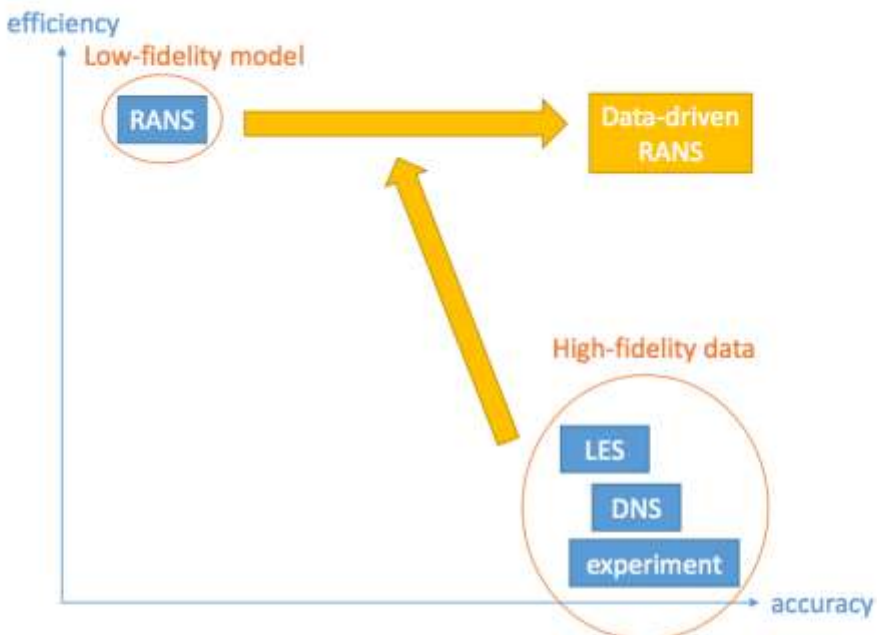
Fig. 1. Artificial neural network encoding a many-body quantum state of *N* spins. A restricted Boltzmann machine architecture that features a set of *N* visible artificial neurons (yellow dots) and a set of *M* hidden neurons (gray dots) is shown. For each value of the many-body spin configuration $S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

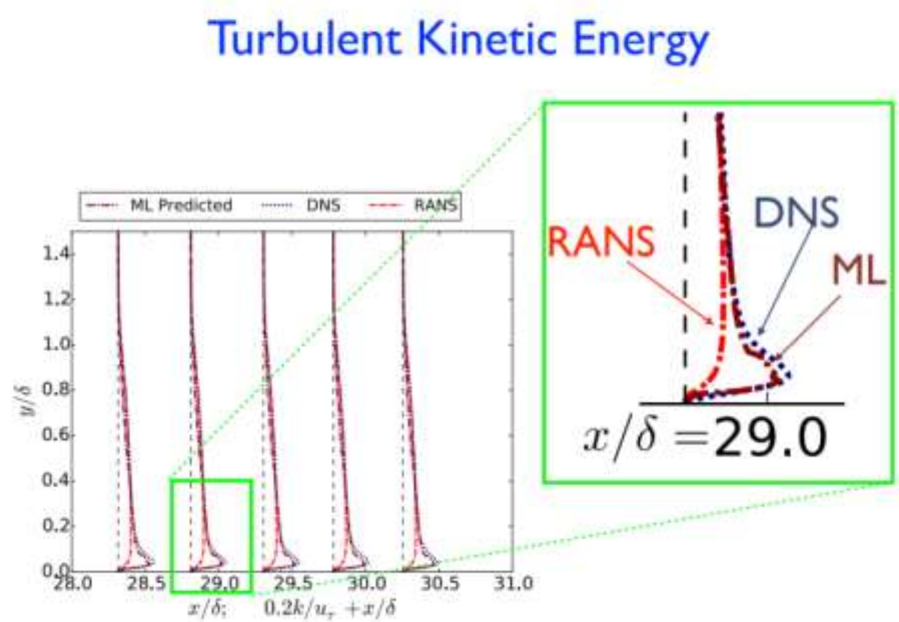


- 물질의 양자상태(스핀 등)가 어떻게 되는지 시뮬레이션하는 것은 물질 구성에 좀 더 깊은 이해를 줌.
- 기본적으로 물질은 Many-body System인데, 이들 사이의 상호작용으로 나타는 물질의 상태를 시뮬레이션하는 것은 시간과 컴퓨팅 파워가 무척이나 많이 필요함.
- Deep learning을 이용하여 물질의 양자상태에 대한 시뮬레이션을 진행.

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

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

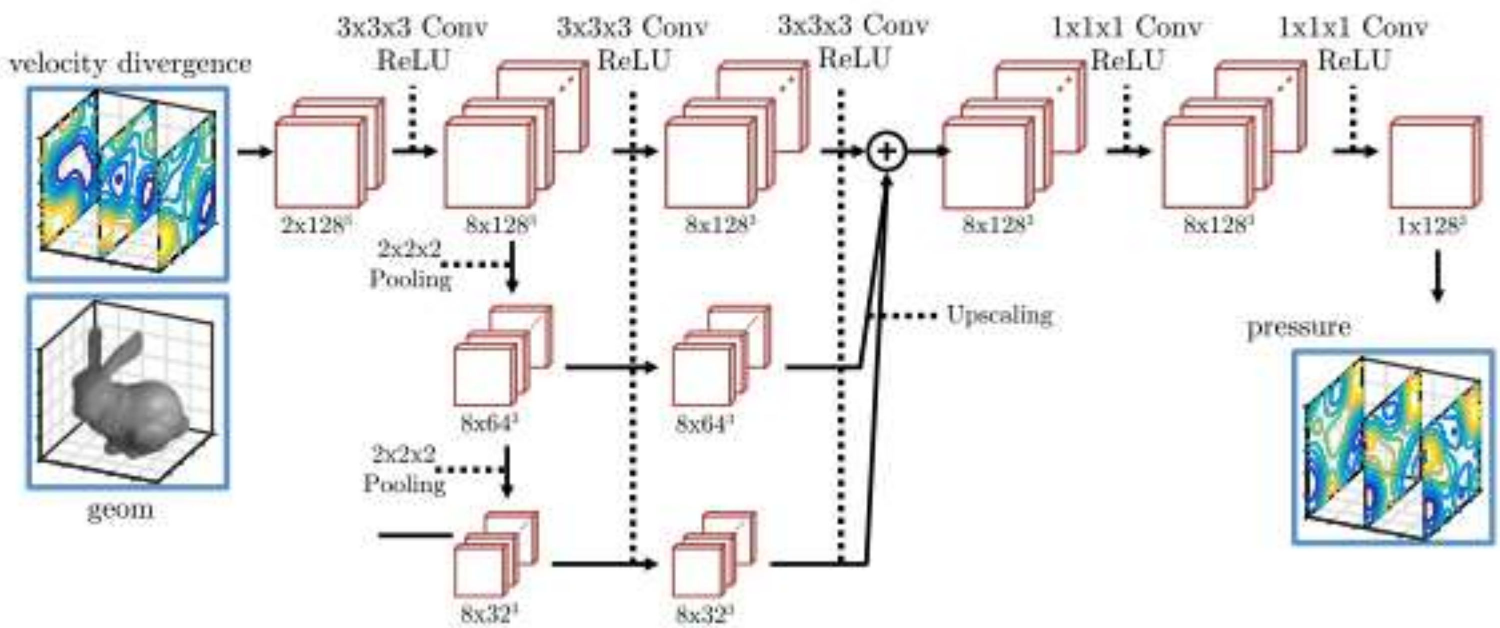




38

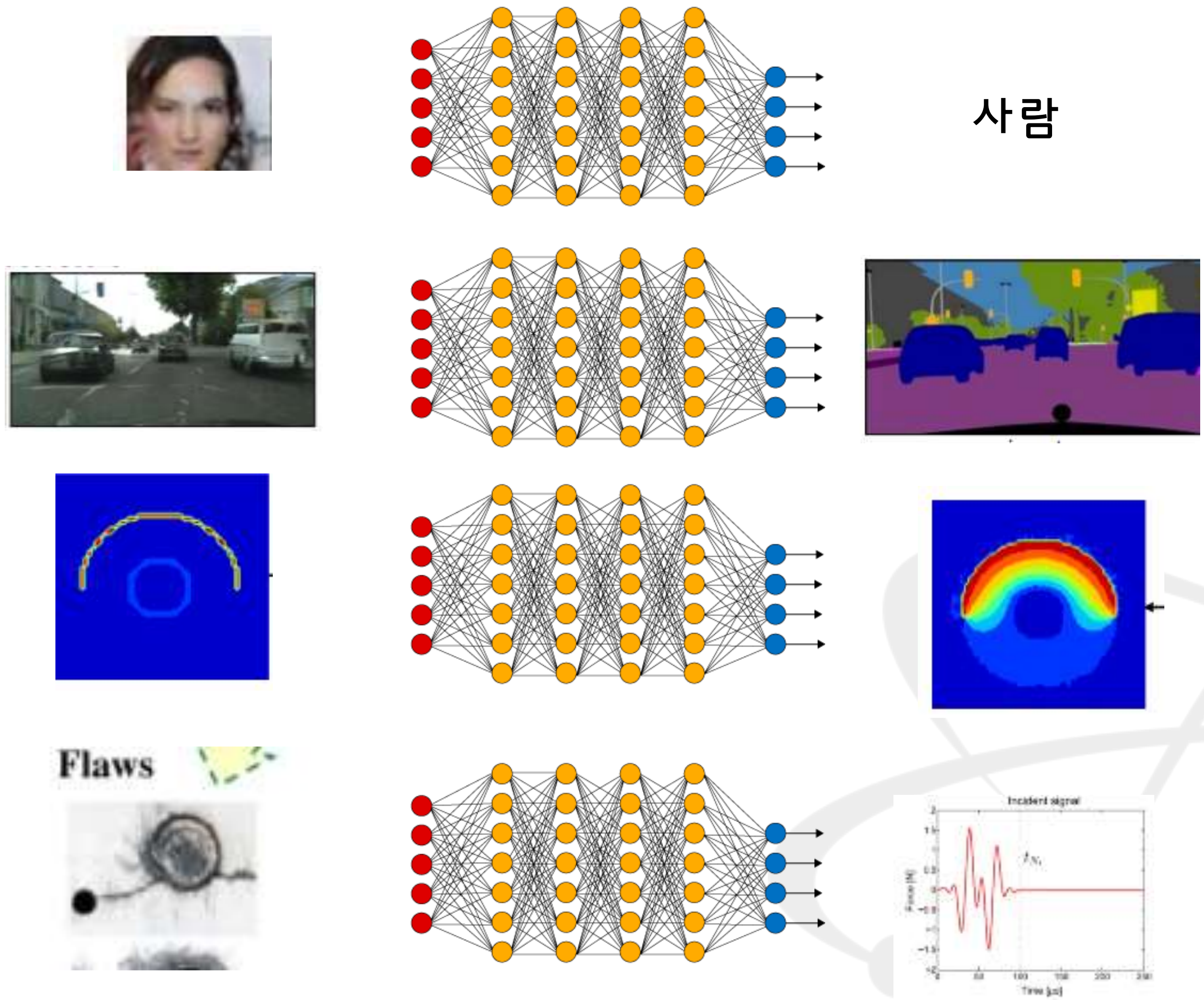
J. Tompson, Accelerating Eulerian Fluid Simulation with Convolutional Networks

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



Deep Learning for Nuclear & Industrial Engineering

딥러닝이란?



Deep Learning for Nuclear & Industry Engineering

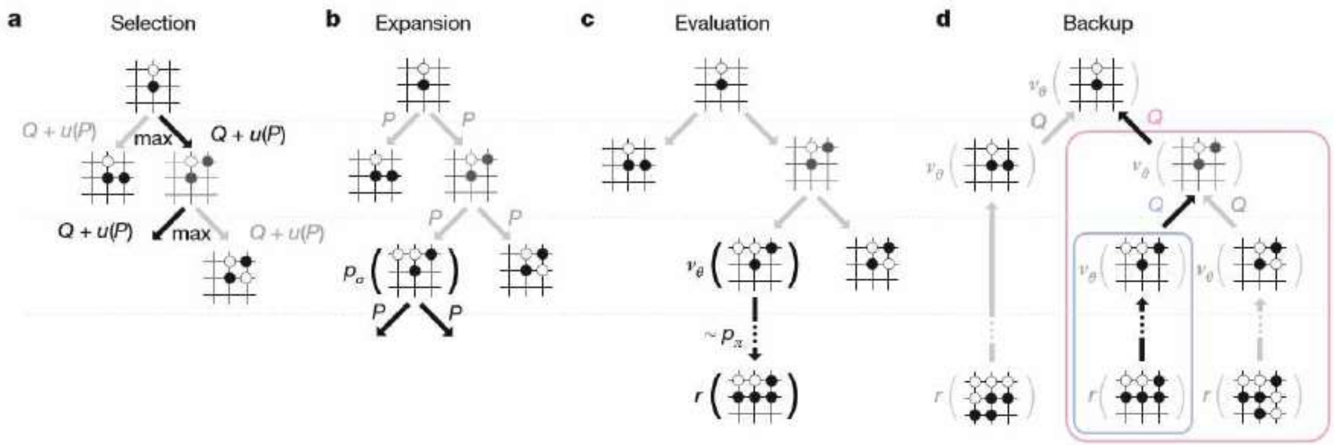
- Anomaly Detection
- Non destructive Test
- Health monitoring
  - Pump LPMS, Acoustic alarm
- Uncertainty Evaluation
- Digital Twin
- Automation
  - Normal condition, Emergency condition
- Structural Optimization
- Materials Science

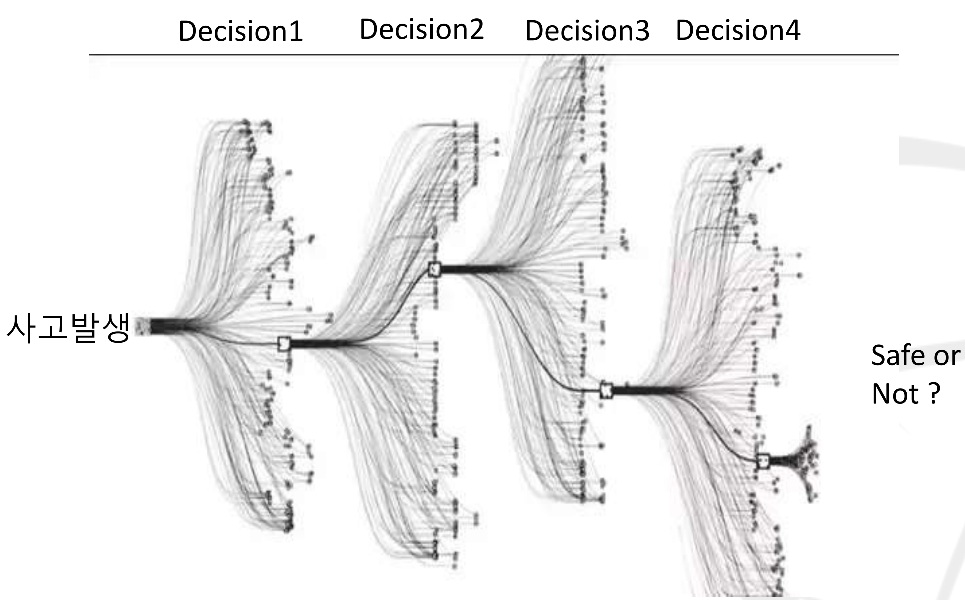
후쿠시마 사고 원인 (기술적 측면)

- 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

중대사고 대응 로직


a
Selection
max
Q + u(P)
b
Expansion
P
c
Evaluation
d
Backup
Q


Decision1
Decision2
Decision3
Decision4
사고발생
Safe or
Not ?

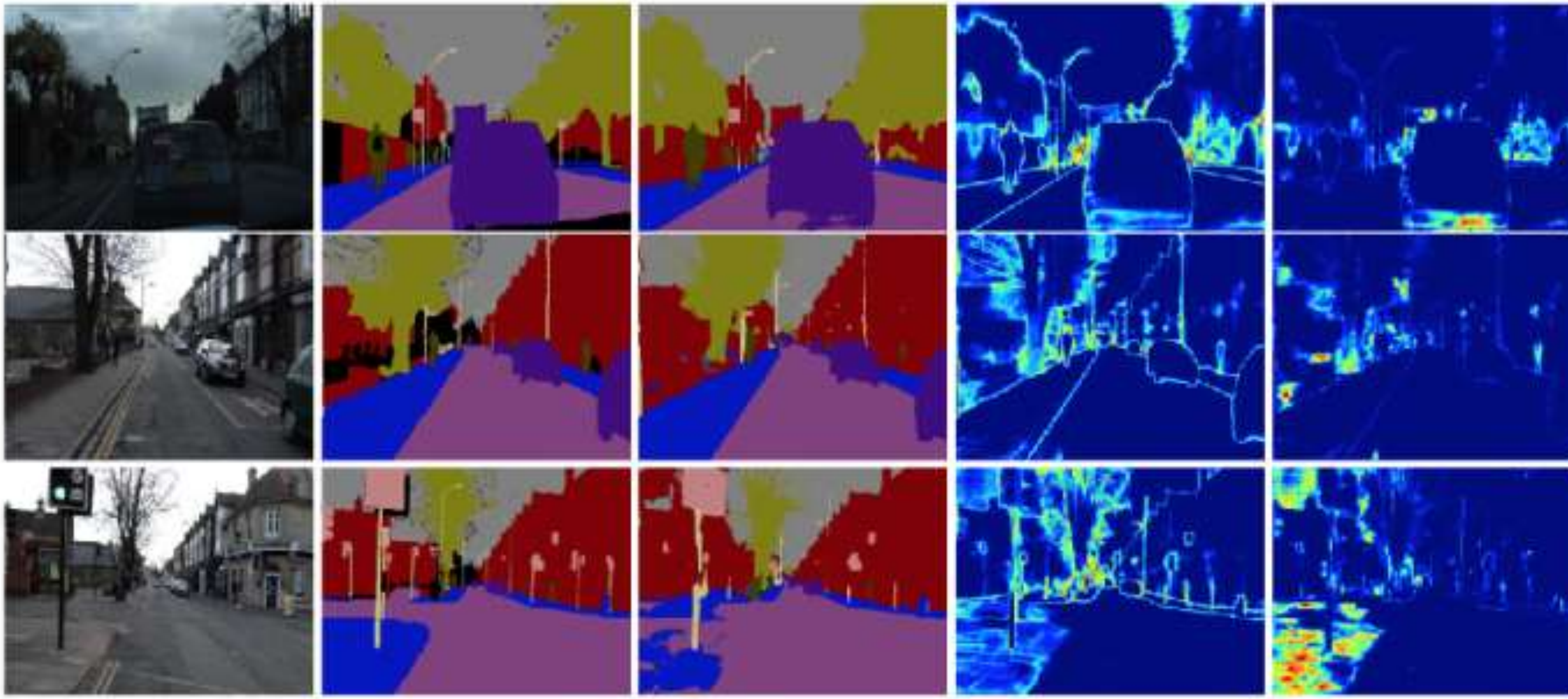
그 밖의 아이템..

- 자율운전??
- 수소취하 사진을 분석한 물성 예측
- 감시시스템
  - 화재 및 운전원 감시
  - Acoustic monitoring system
- 배관 감육 진단
- Digital Twin
- Multi-physics calculations

무엇이 어렵나?

- 증명할 수 있는가? 불확실도는 얼마인가?
- 데이터 부족
- 라벨 만들기
  - 비용
  - 난이도
- 정상데이터에 편중

Aleatoric & Epistemic Uncertainty



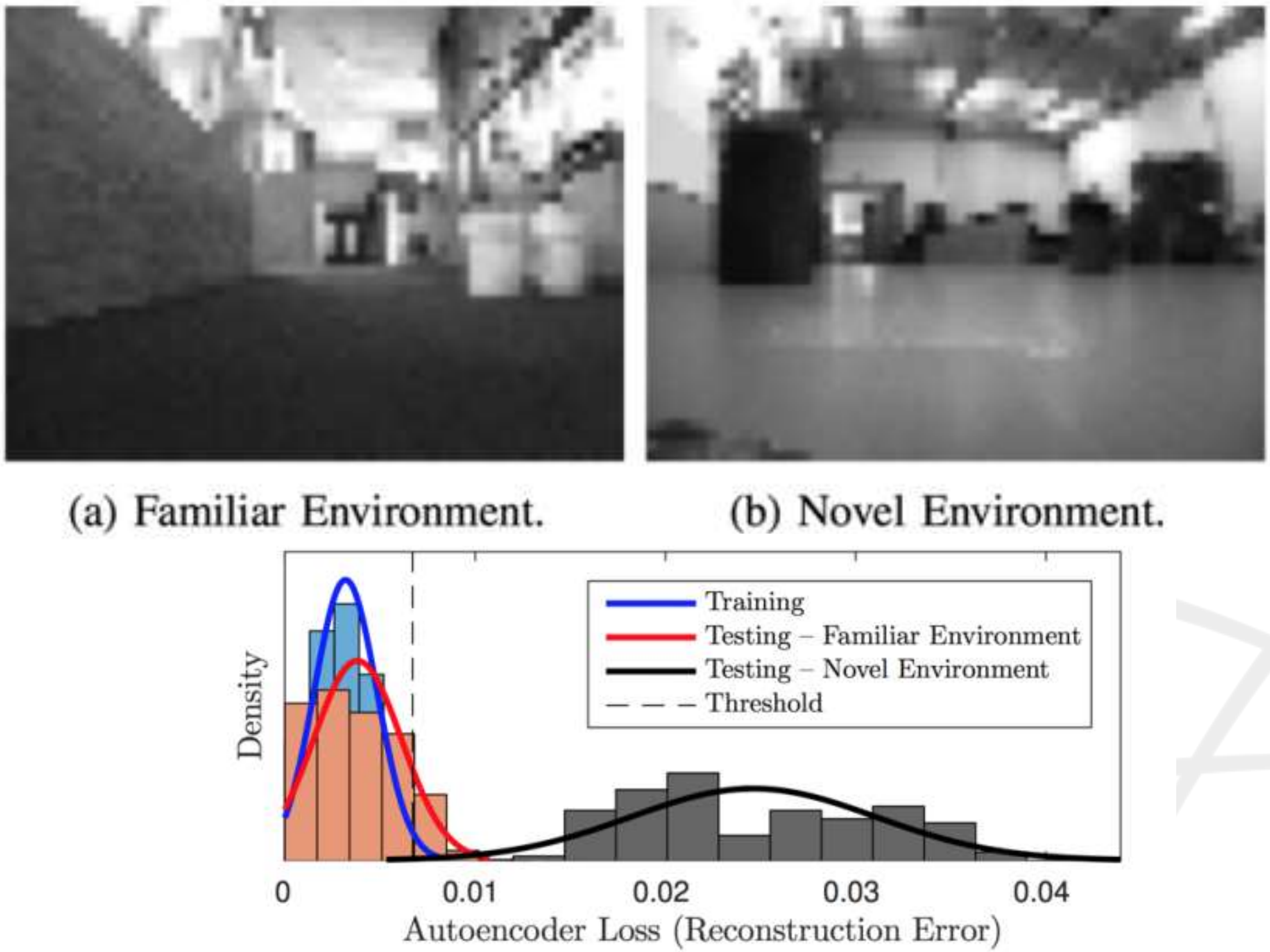
(a) Input Image (b) Ground Truth (c) Semantic Segmentation (d) Aleatoric Uncertainty (e) Epistemic Uncertainty

https://arxiv.org/abs/1703.04977

Anomaly Detection

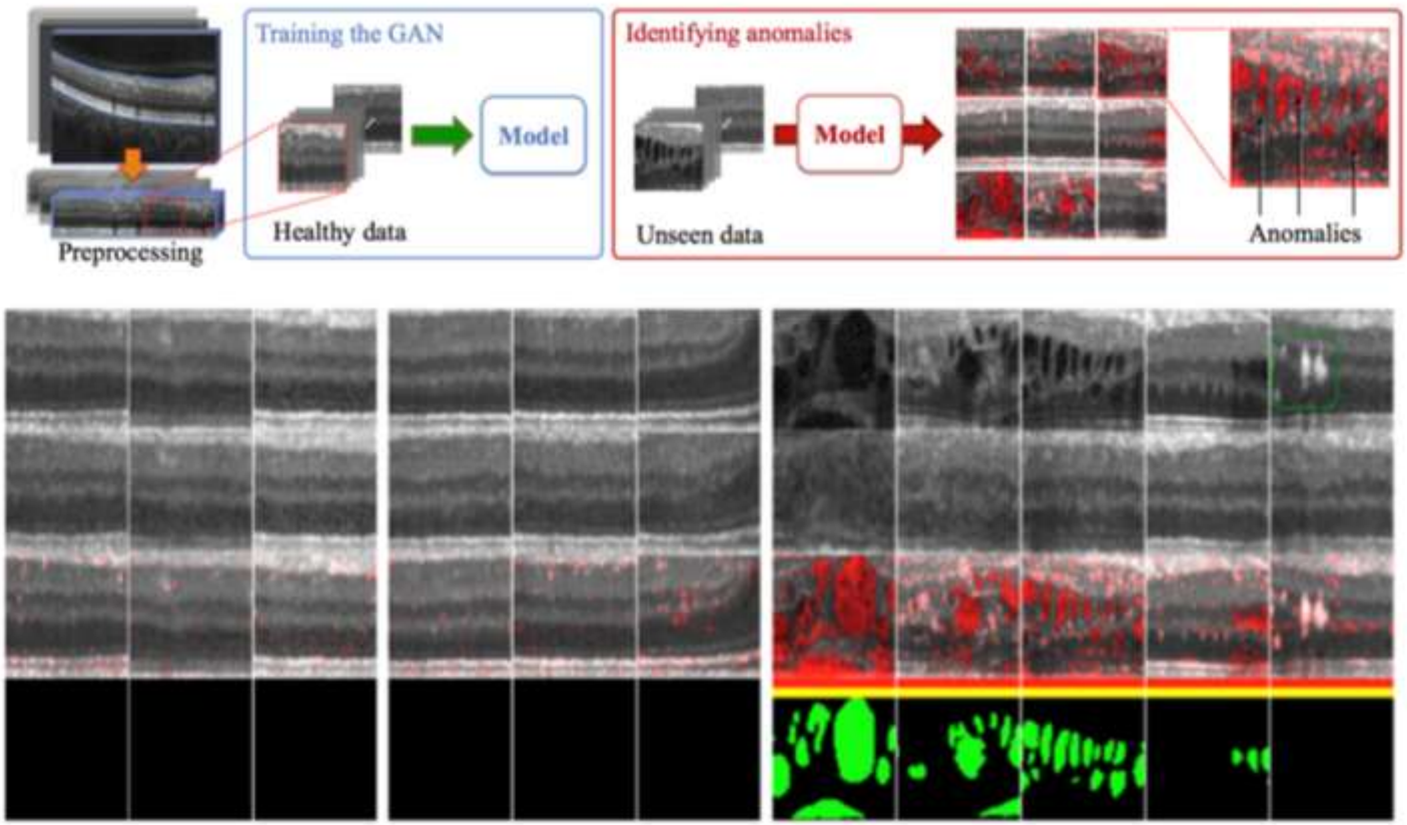
*Romit’s blog: romitsblog.wordpress.com

Anomaly Detection with VAE



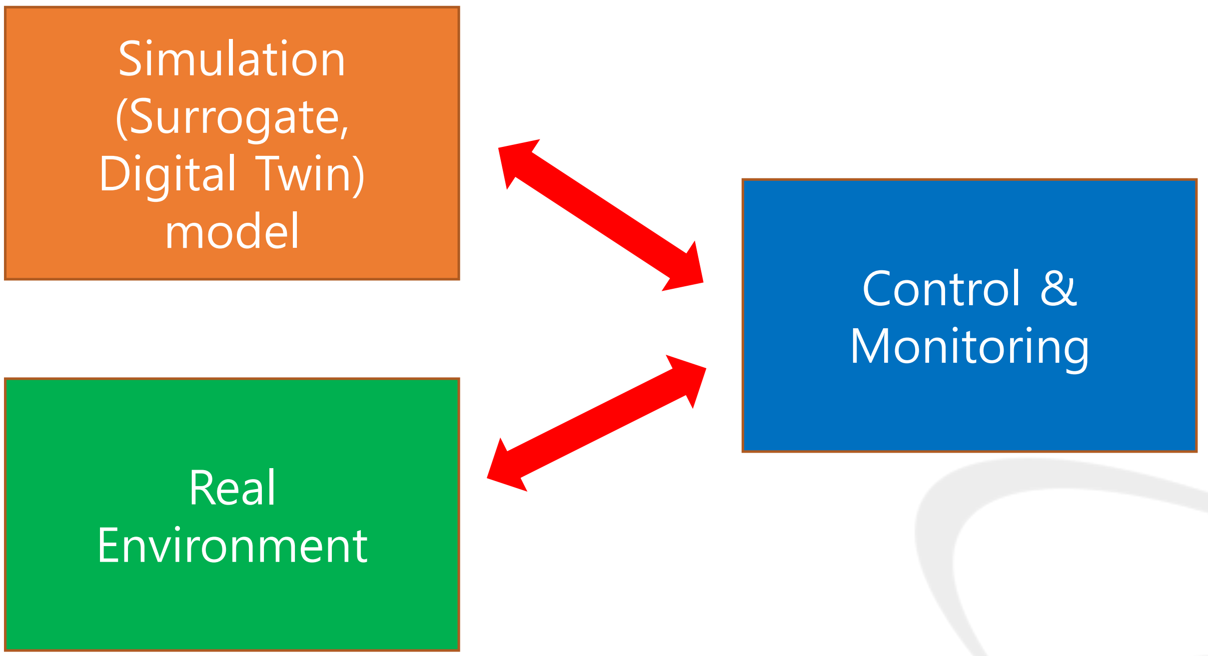
*C. Ritcher and N. Roy, Safe Visual Navigation via Deep Learning and Novelty Detection

AnoGAN



*Arxiv: 1703.05921

Surrogate (meta) modeling with machine learning



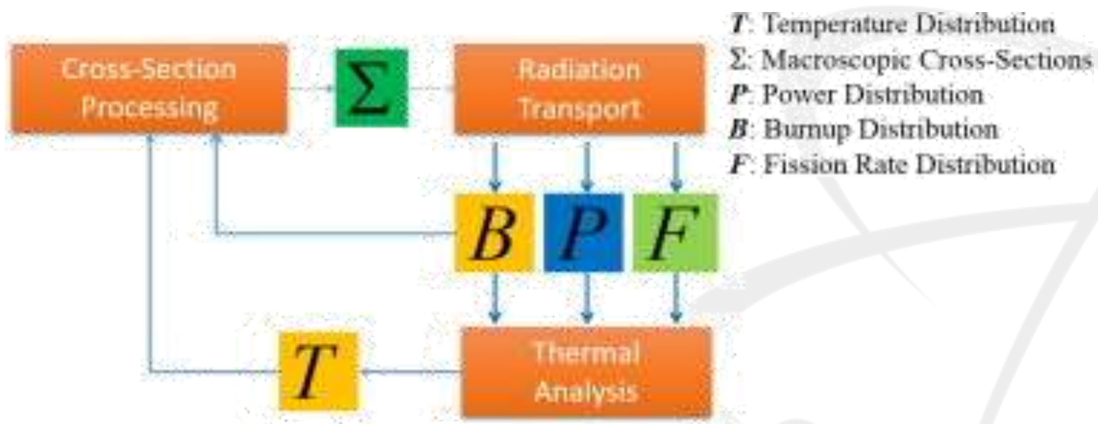
- 복잡한 다물리 현상을 빠르게 모사할 수 있는가?
- 어떤 데이터를 생성할 것인가?
- 실제 데이터와 차이는?

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

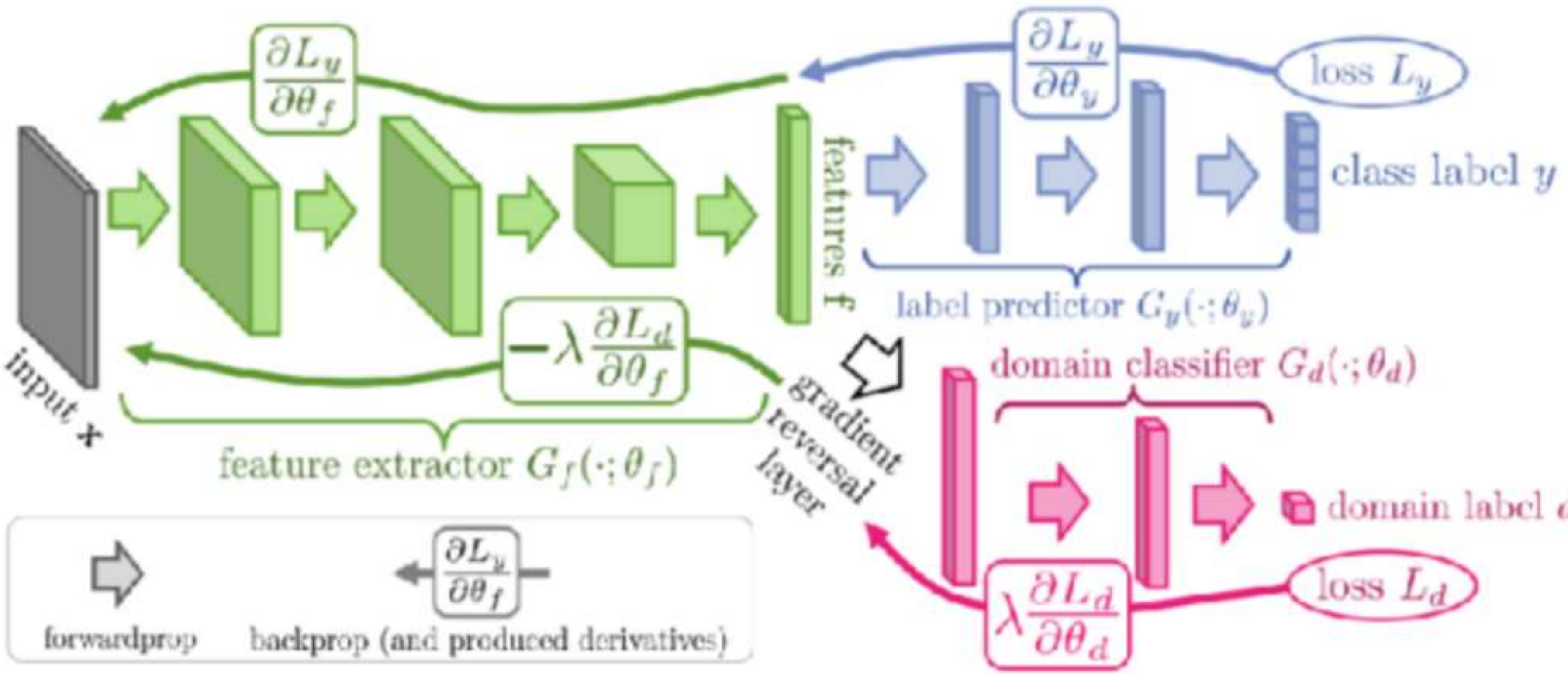
- PCA offers the potential to automate the selection of an optimal basis for representing the manifolds

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

Domain Adaptation

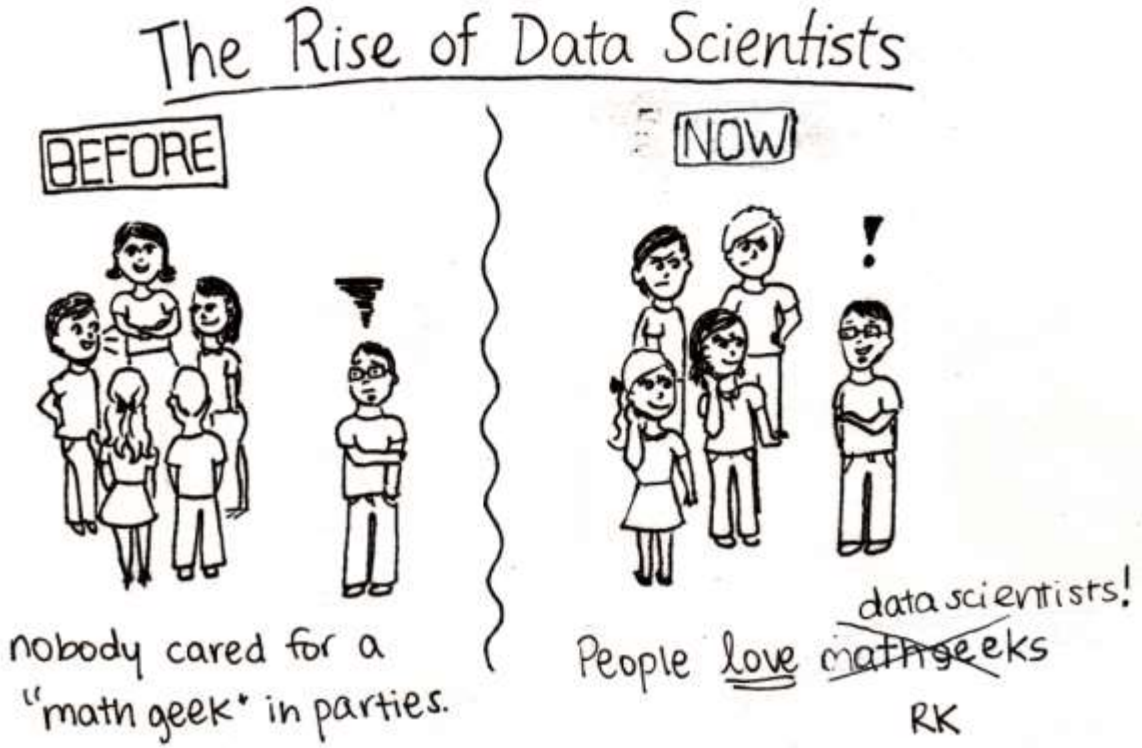
최성준, 딥러닝 최신동향, https://tykimos.github.io/2018/01/04/ISS_Recent_Trends_in_Deep_Learning/

Domain Adversarial Neural Network



https://arxiv.org/abs/1505.07818

Ending…



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)

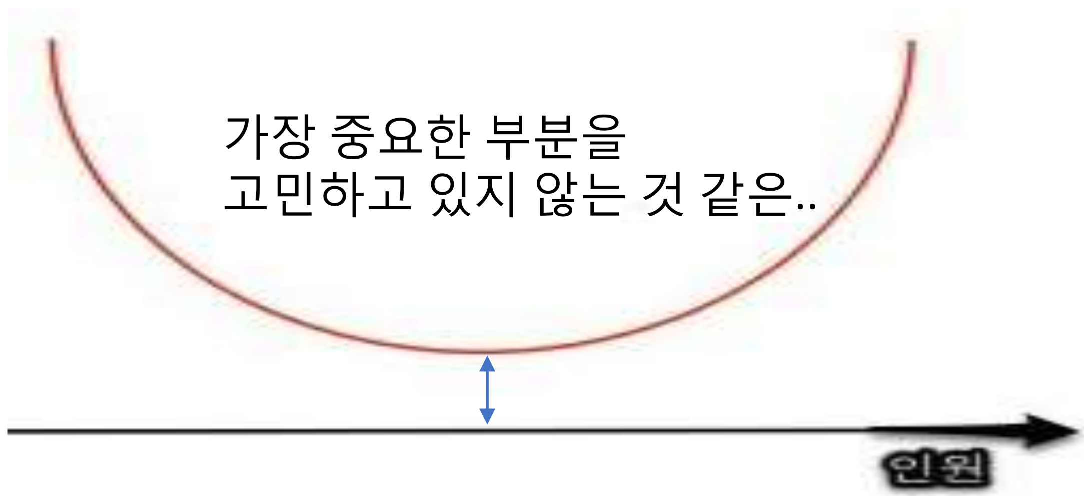
심각한 오해

인공지능 학계

- 도메인 지식 없이도 모든 문제를 잘푸는 인공지능을 개발했다!

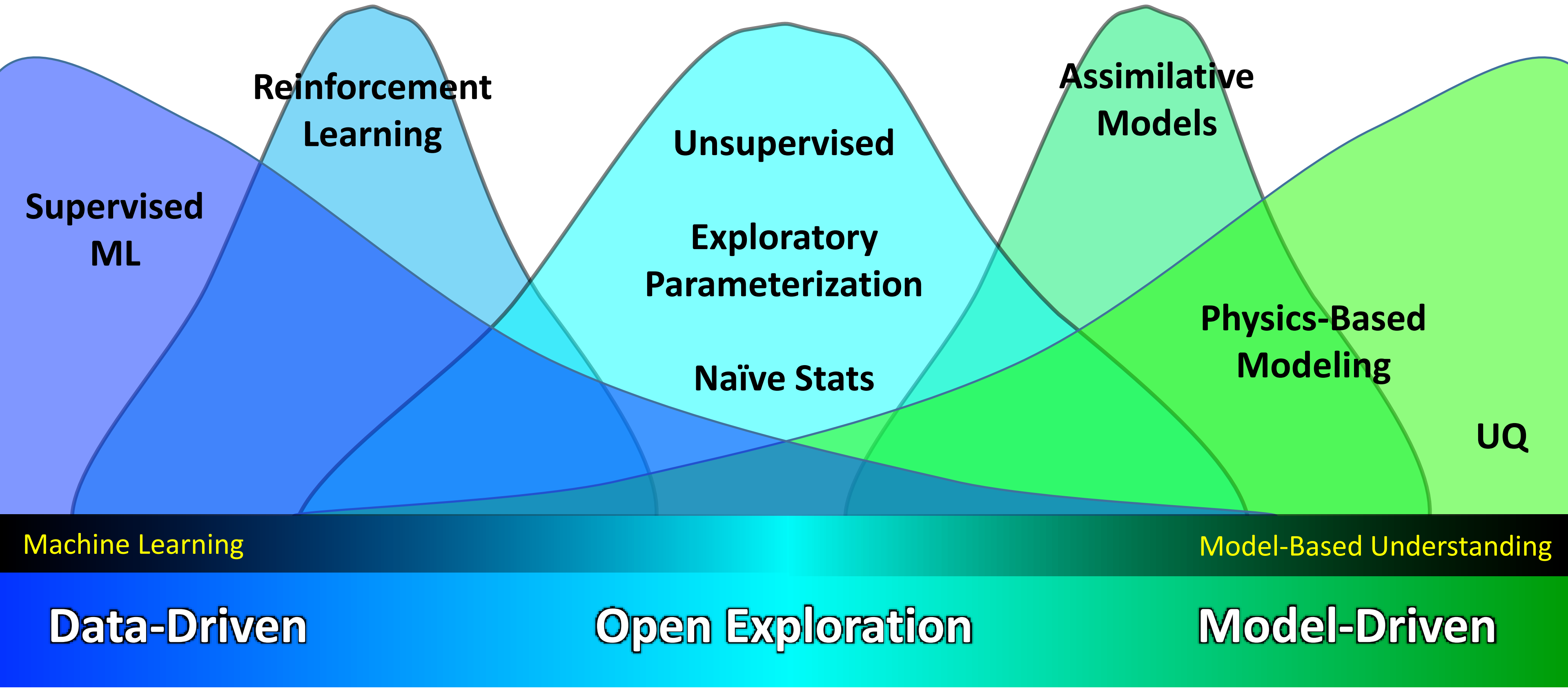
응용분야

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



Data Science Technology Spectrum

Real-world systems often combine several techniques

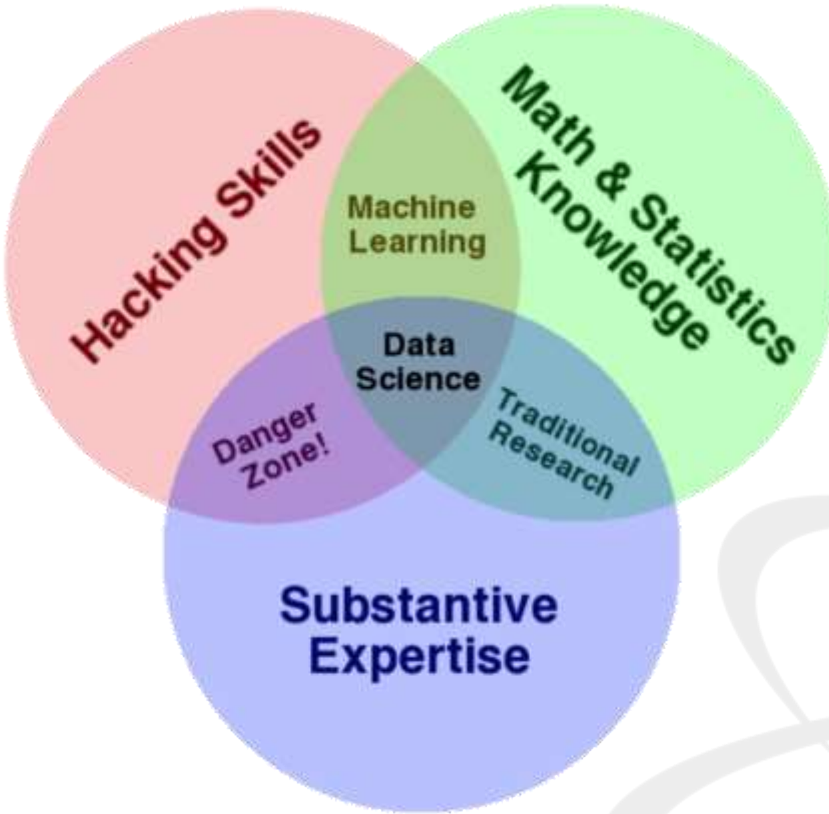


Expert Knowledge in Data + Labels
Model (mostly) determined by D + L

Expert Knowledge in Model Details
Data refines model parameters

* Lukas Mandrake, Machine Learning & Autonomy

Drew Conway, the Data Science Venn Diagram



Data Science 전문가가 원자력계에 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) 관련 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

데이터 역량 시험 도입해

사내자격증으로 공식 인정

高레벨 받은 직원에겐 포상

하고싶은 말을 많으나..

- 딥러닝, 머신러닝 기술을 단순히 적용하는 것이 아니라
  어떻게 적용할 지에 대하여 한단계 더 고민을 더 해봐야 한다.
  - Uncertainty evaluation, Explainable AI
  - Domain adaptation
- 딥러닝이 만능이 아니다.
  - End to End 는 비효율!
  - 기존 머신러닝 알고리즘과 융합.
  - Domain 지식으로 탐색 공간을 줄이자.
  - 문제에 맞는 methods가 필요하다.
- Domain + machine learning 전문가가 극히 부족
  - 협업 필요.
  - 타분야의 연구 케이스 스터디.
    원자로를 사람으로 바꾸면 의료와 고민하는 것이 똑같다.
- 한번에 대박은 없다. 차근차근. 쉬운 문제 부터 풀어나가야 한다.
- 아주 작은 문제라도 의미있게 잘푼다면 대박!
  원자력계 뿐만 아니라 인공지능 학계에서도 지대한 관심을 가질 것임.

THANK YOU

Acknowledgement

- 연구재단 신진연구, 딥러닝과 위상최적설계를 융합한 AI 설계 프레임워크 개발 (2018.3~2020.2)
- KISTI 연구지원사업, 딥러닝과 위상최적설계를 융합한 AI 설계 프레임워크 개발 (2018.1~6)
- 원자력연구원 기관고유사업, 딥러닝과 위상최적설계 기술을 융합한 뼈 CT 사진 복원 기술 개발 (2018.3~9)

KAERI Korea Atomic Energy Research Institute