

인공지능을 활용한 기상/기후 예측

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Intelligent Remote sensing and geospatial

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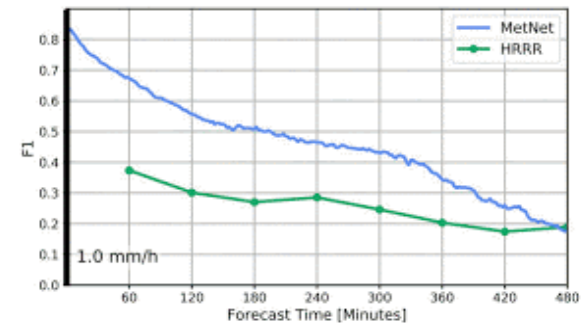
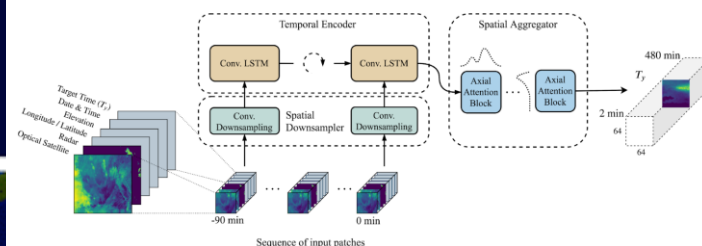
IRIS LAB
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인공지능 (Artificial Intelligence)



Google AI (<https://ai.googleblog.com>)

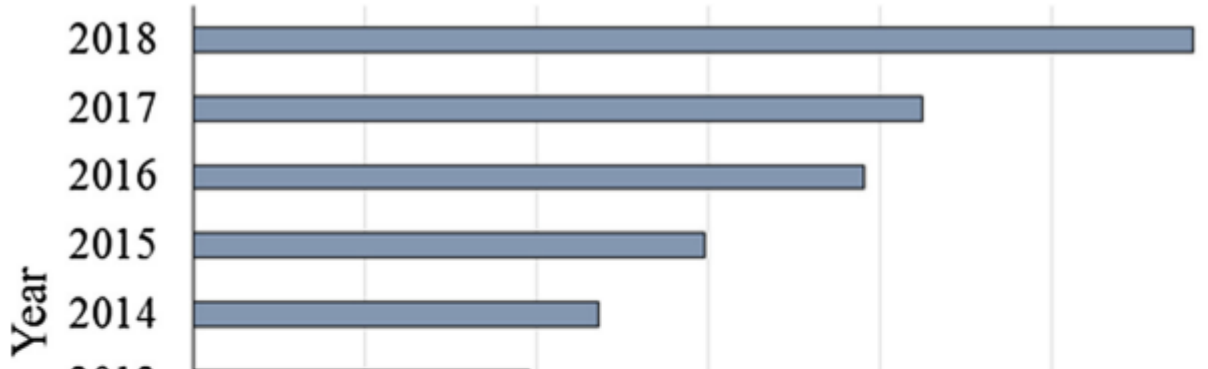


인공지능을 활용한 기상/기후 연구



기상기후분야의 AI 활용 트렌드

Ardabili et al., 2019



The 2nd NOAA Workshop on Leveraging AI in Environmental Sciences
Exploiting Space and Ground-Based Observations and Enhancing Earth System Predictions

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30 July 2020 - 25 February 2021
NOAA Center for Weather and Climate Prediction
5830 University Research Court
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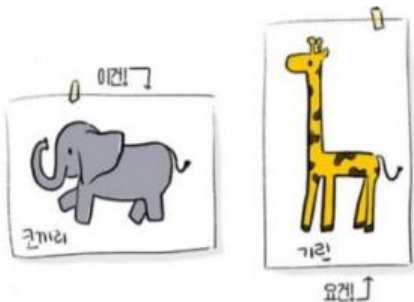
인공지능 종류 : 학습방법에 따른



인공지능 종류

인공지능 Artificial Intelligence

지도 학습
Supervised Learning

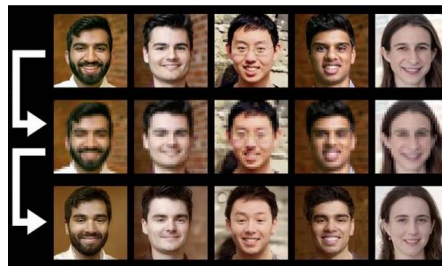


비지도 학습
Unsupervised Learning

비지도 학습은 답을 가르쳐주지 않고 공부를 시키는거야.



자기지도 학습
Self-supervised Learning



강화 학습
Reinforcement Learning

강화 학습은 일종의 게임 같이 보상해주는거야



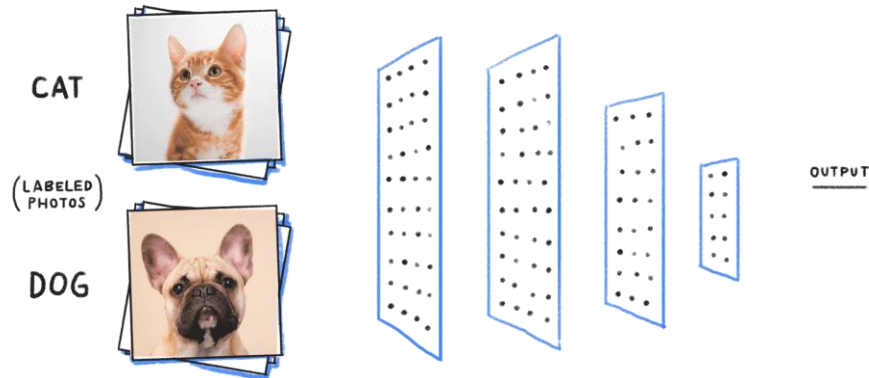
인공지능 종류



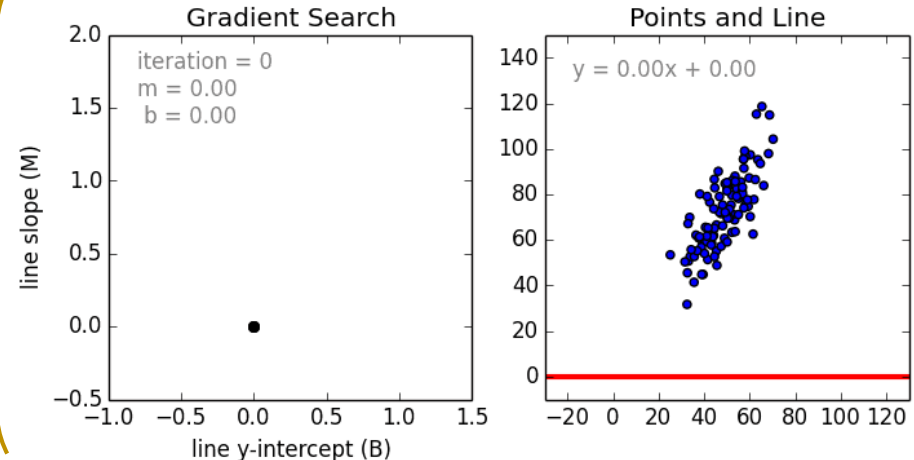
Supervised Learning (지도 학습)

- 데이터에 대한 명시적 정답인 레이블이 주어진 상태에서 학습시키는 방법
- 분류 (Classification) 및 회귀 (Regression)에 주로 활용됨
- 대표적인 알고리즘: Logistic Regression, Random Forest, Support Vector Machine 등

Classification



Regression

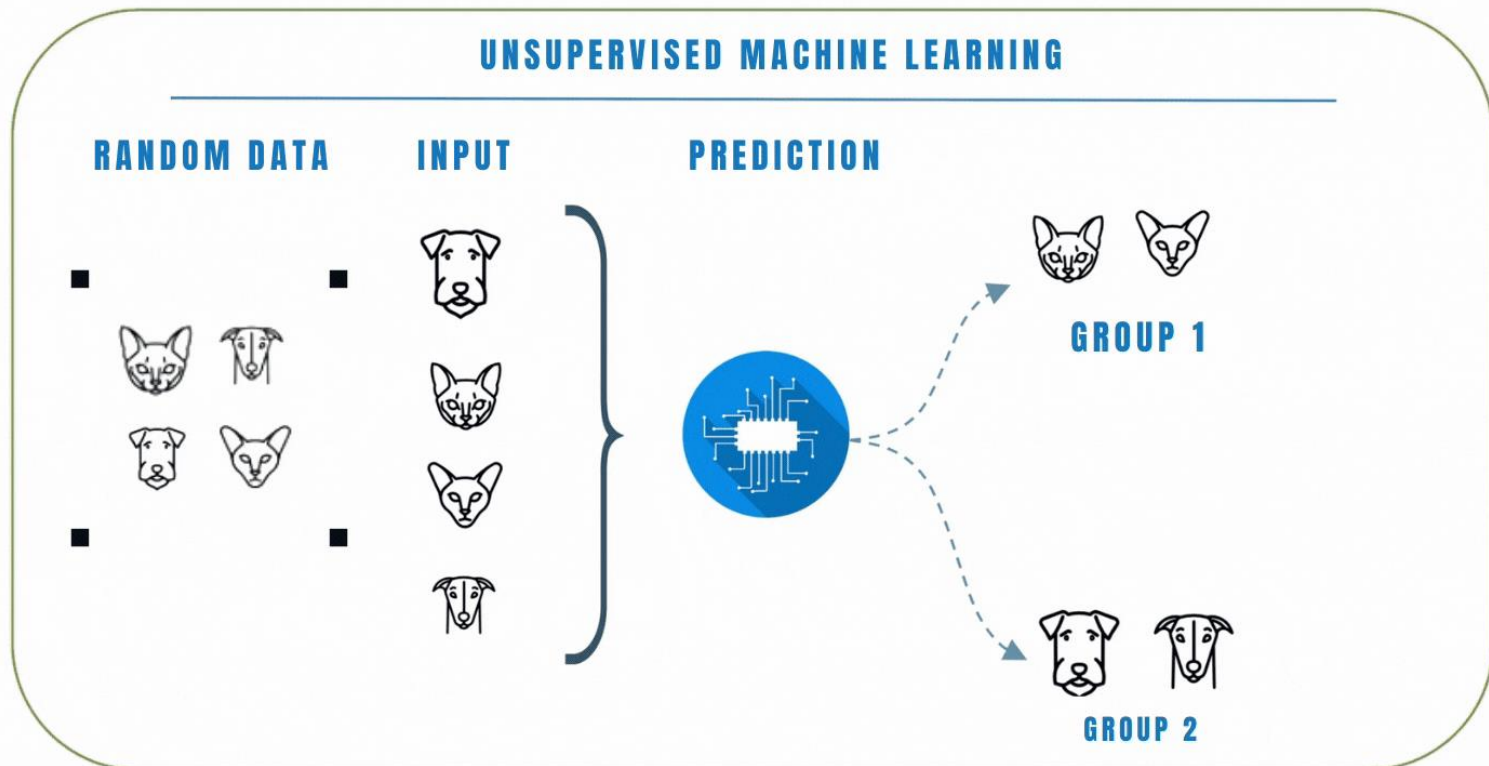


인공지능 종류



Unsupervised Learning (비지도 학습)

- 데이터에 대한 레이블이 주어지지 않은 상태에서 학습시키는 방법
- 데이터의 구성 또는 특징을 밝히는 목적으로 활용됨
- 대표적인 알고리즘: Self-Organizing Map, Hierarchical Clustering, Density Estimation 등

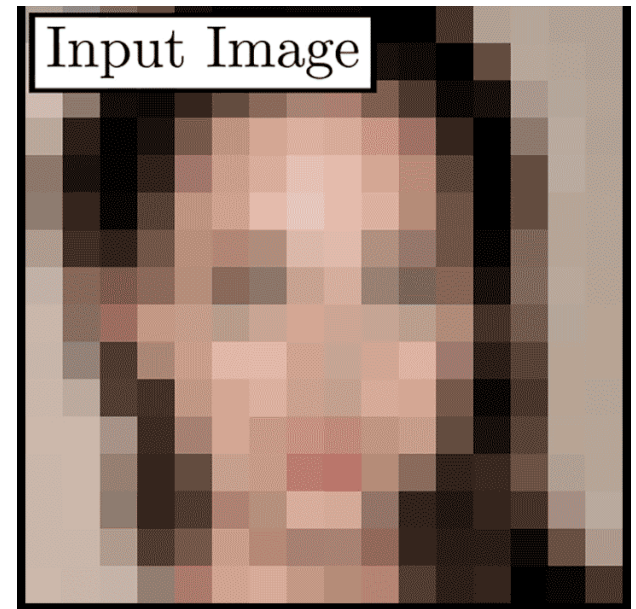


인공지능 종류



Self-supervised Learning (자기지도 학습)

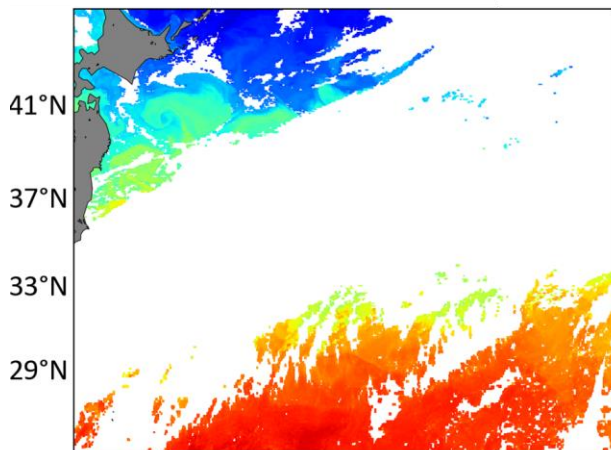
- 지도학습과 달리, 다량의 레이블이 없는 원데이터로부터 데이터 부분들의 관계를 통해 레이블을 자동으로 생성하여 지도학습에 이용
- 데이터의 부분 데이터나 손상된 부분으로부터 생성 및 재건
- 대표적인 알고리즘: Autoencoder, Self-supervised GAN 등



인공지능 종류 | Self-supervised Learning (자기지도 학습)

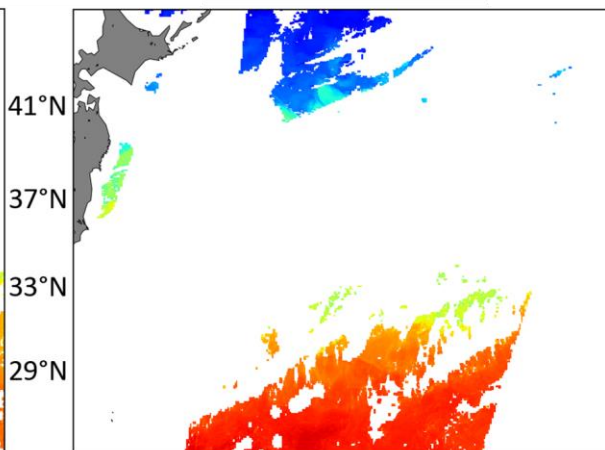


원본 MODIS



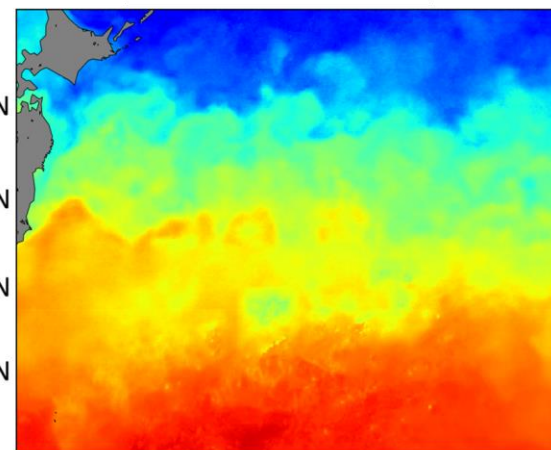
145°E 150°E 155°E 160°E 165°E

검증 MODIS



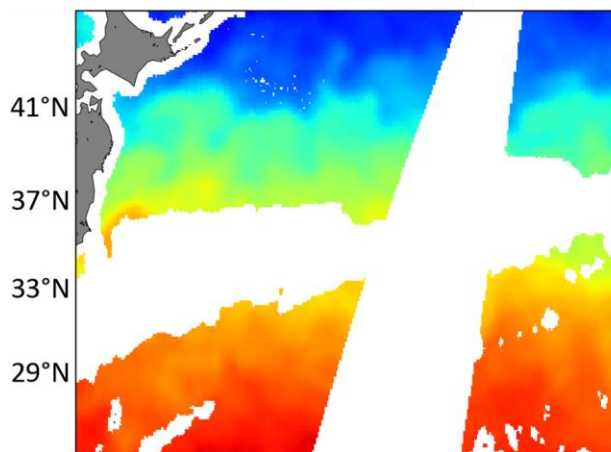
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보간 MODIS



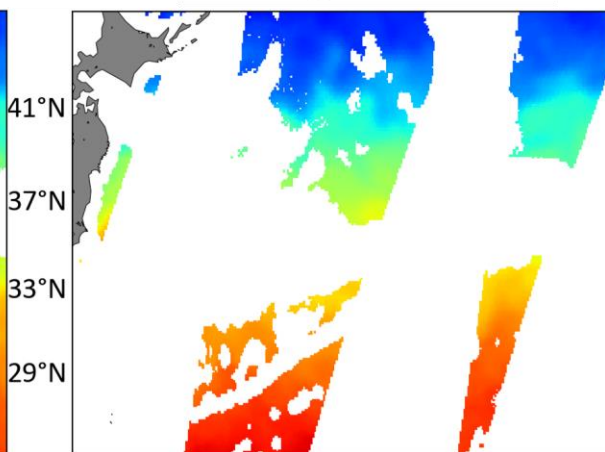
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원본 AMSR2



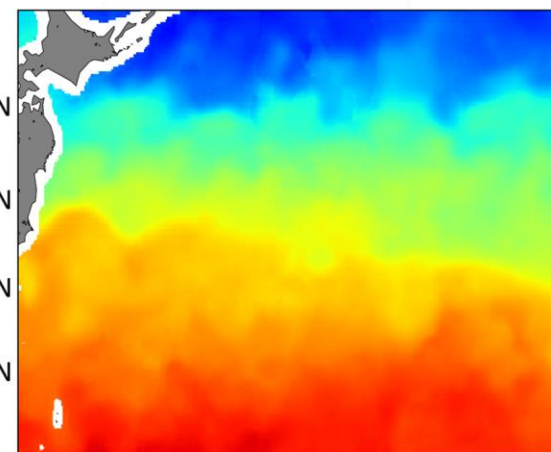
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검증 AMSR2



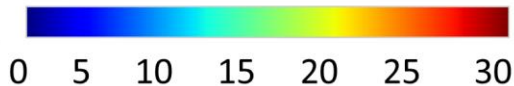
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보간 AMSR2



145°E 150°E 155°E 160°E 165°E

SST (°C)



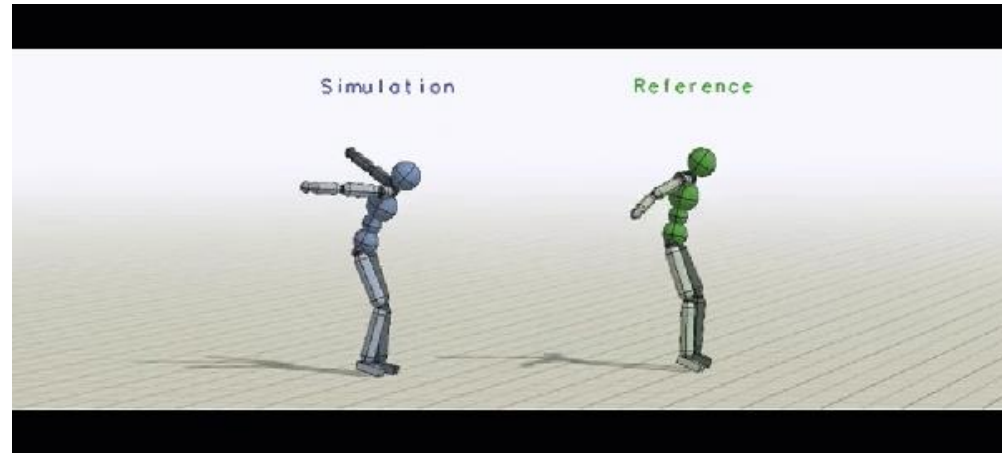
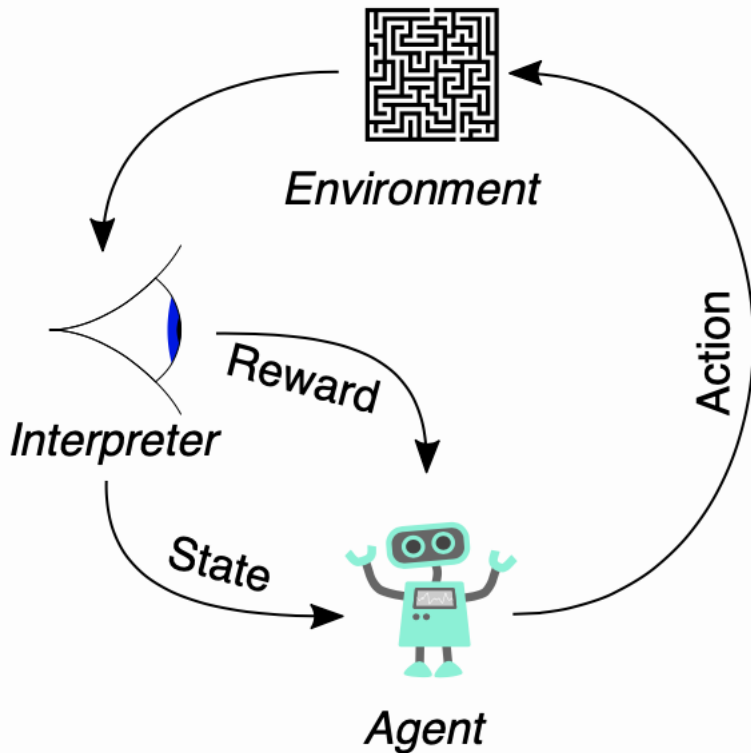
인공지능 종류



이미지 출처: <https://riptutorial.com/machine-learning/example/32668/reinforcement-learning>

Reinforcement Learning (강화 학습)

- 많은 시뮬레이션을 통해, 현재의 선택으로 미래의 보상이 최대가 되도록 학습시키는 방법
- 의사결정을 위한 최적의 액션 선택을 목적으로 활용됨
- 대표적이지 않으나, Monte Carlo Methods, Q-Learning, Markov Decision Process



출처

air.berkeley.edu/blog/2018/04/10/virtual-stuntman/

towardsdatascience.com/getting-started-with-reinforcement-q-learning-77499b1766b6



인공지능 알고리즘 훈련



인공지능 훈련 방법 (Hyperparameter Tuning Process)

Original Dataset

- 학습에 사용될 훈련자료와 최종 성능 평가를 위한 독립된 테스트 자료 구분

Training Set

Test Set

- 훈련 자료에서 최종 모델 선정을 위한 validation 자료 구분

Training Set

Validation Set

Test Set

Training tuning and

Ma

Offline Model vs. Real-time Learning Model

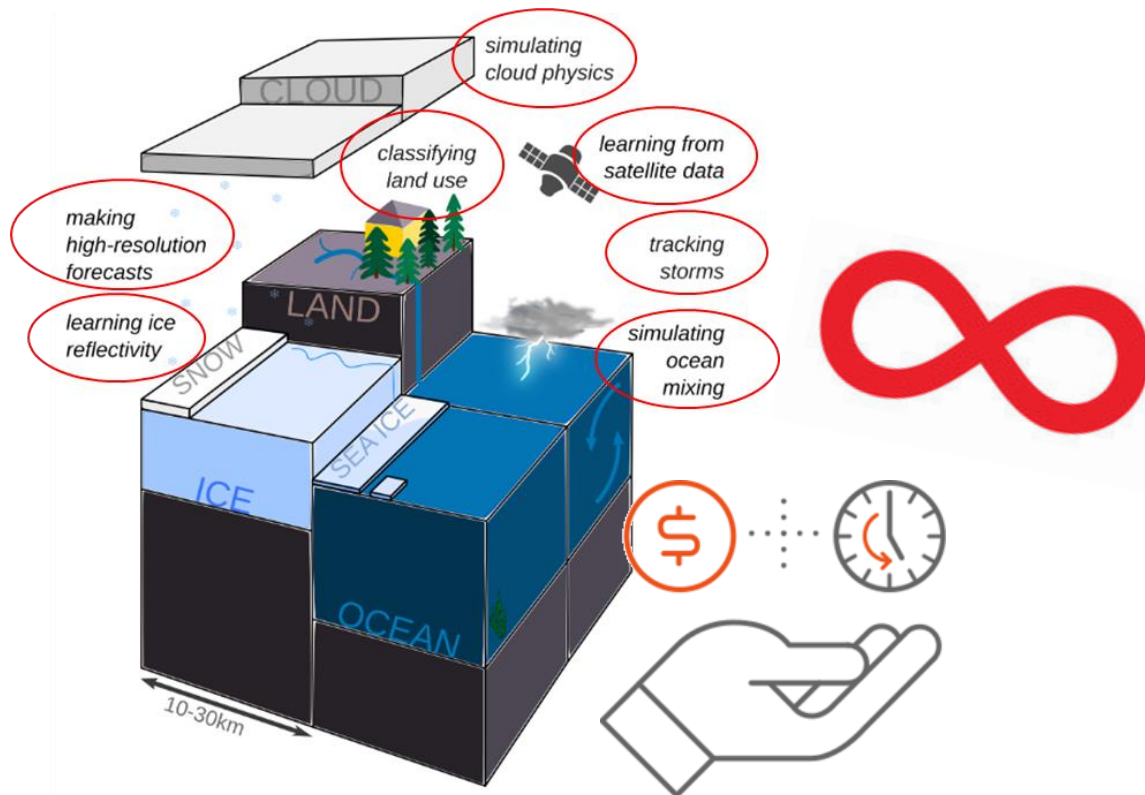
Predictive Model

테스트 자료를 통한 최종 성능 평가

인공지능을 활용한 기상/기후 예측



인공지능을 활용한 기상/기후 예측

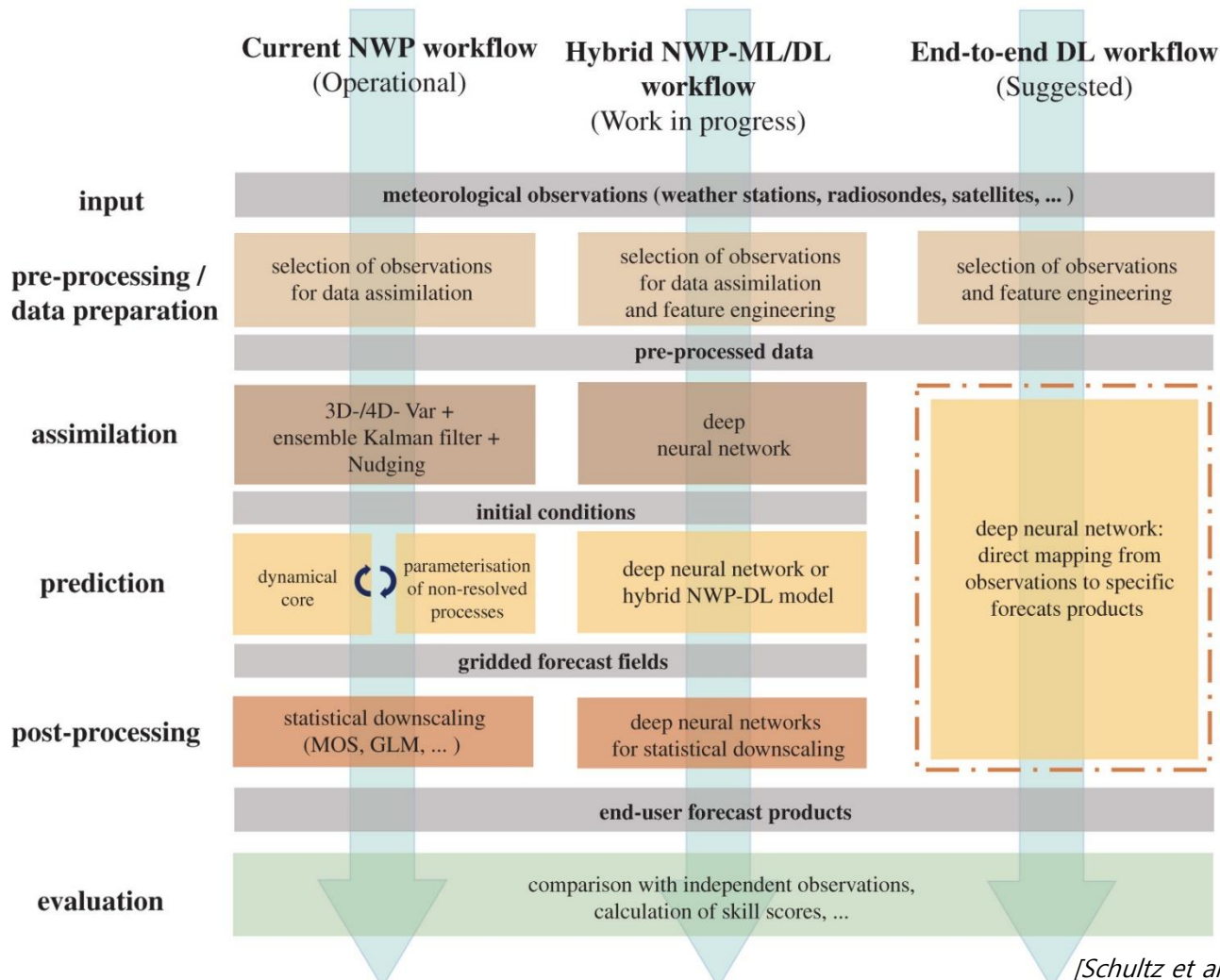


- 상대적으로 빠른 학습(모델링) 장점으로 최근 기상기후분야에 적극 이용되기 시작함

인공지능을 활용한 기상/기후 예측



인공지능을 활용한 기상/기후 예측 방법



[Schultz et al., 2021]



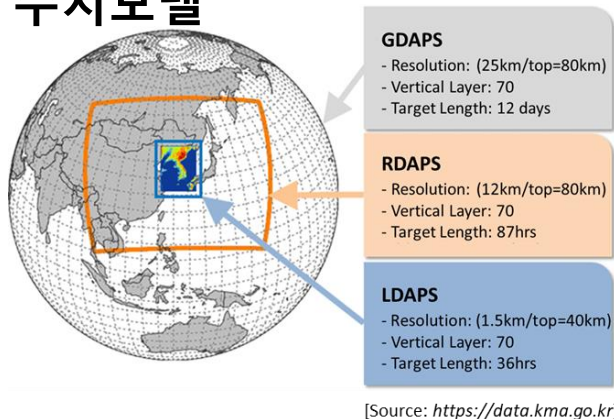
인공지능을 활용한 기상/기후 예측



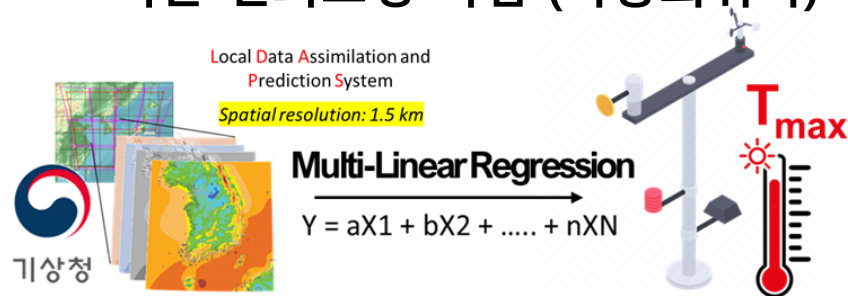
기상예측 정확도 향상을 위한 수치예보모델 후처리 보정

- 수치모델의 예측 산출물에 존재하는 계통적 오차를 통계적으로 보정하는 방법

수치모델



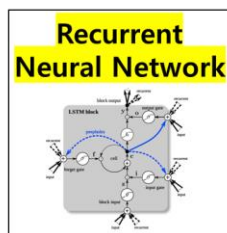
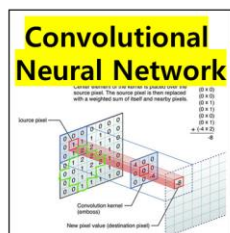
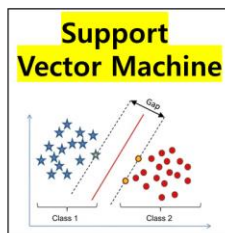
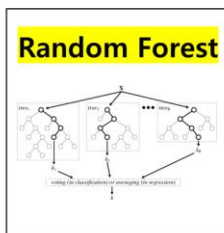
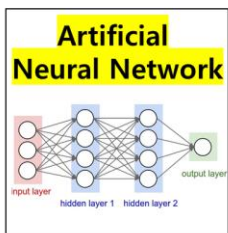
기존 편의보정 기법 (다중회귀식)



LDAPS forecast (X)

Observation data (Y)

제시되는 인공지능 기법



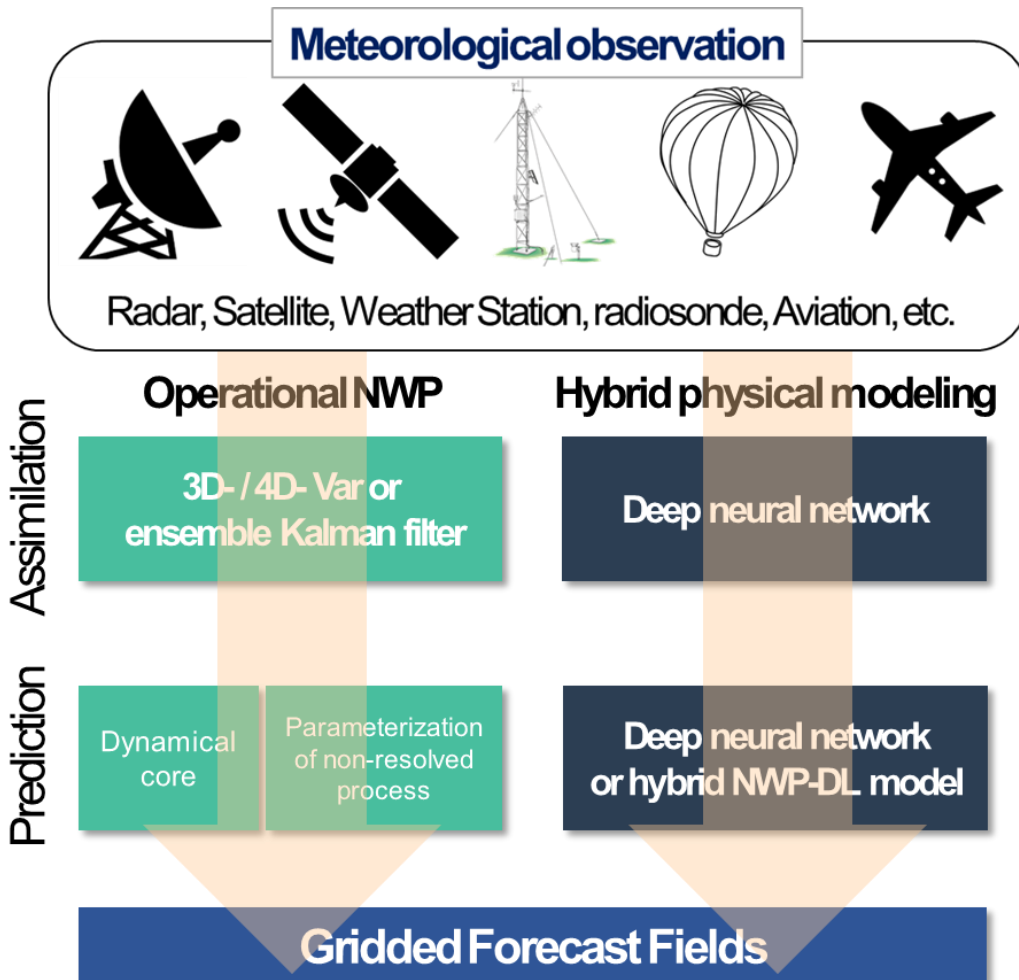
- 장점:** 후처리 보정을 통해 수치모델의 예측 자료 정확도를 효과적으로 높일 수 있음
- 단점:** 후처리 보정은 계통적 오차만을 보정할 수 있기 때문에, 수치모델에 존재하는 무작위 오차 (random error)를 개선하기 힘들

인공지능을 활용한 기상/기후 예측



수치모델과 인공지능 기법 결합 (Hybrid physical modeling)

- 수치 모델의 Data assimilation 과정을 딥러닝으로 대체하는 방법



- 장점:** Data assimilation 정확도를 높임으로써 예측 자료 정확도를 높일 수 있음

- 단점:** 예기치 않은 불안정성이 나타날 수 있으며, 수치모델과 인공지능 코드를 하나의 인터페이스에서 구현하기 복잡함

인공지능을 활용한 기상/기후 예측



데이터기반 인공지능을 활용한 기상/기후 예측 (Data-driven modeling)

- 초기장(관측자료)을 기반으로 딥러닝을 활용하여 기상/기후 예측하는 방식

Table 1
List of Variables Contained in the Benchmark Data Set

Long name	예단 변수	Short name	Description
Geopotential		z	Proportional to the height of a pressure level
Temperature		t	Temperature
Specific_humidity		q	Mixing ratio of water vapor
Relative_humidity		r	Humidity relative to saturation
u_component_of_wind		u	Wind in x/longitude-direction
v_component_of_wind		v	Wind in y/latitude direction
Vorticity		vo	Relative horizontal vorticity
Potential_vorticity		pv	Potential vorticity
2m_temperature		t2m	Temperature at 2 m height above surface
10m_u_component_of_wind		u10	Wind in x/longitude-direction at 10 m height
10m_v_component_of_wind		v10	Wind in y/latitude-direction at 10 m height
total_cloud_cover		tcc	Fractional cloud cover
total_precipitation		tp	Hourly precipitation
toa_incident_solar_radiation		tisir	Accumulated hourly incident solar radiation
Constants			<i>File containing time-invariant fields</i>
land_binary_mask		lsm	Land-sea binary mask
soil_type		slt	Soil-type categories
orography		orography	Height of surface
latitude		lat2d	2-D field with latitude at every grid point
longitude		lon2d	2-D field with longitude at every grid point

✓ 과거 날씨 데이터를 학습한 AI 모델이 높은 계산 비용을 필요로 하는 물리모델을 능가할 수 있을지에 초점



JAMES | Journal of Advances in Modeling Earth Systems

RESEARCH ARTICLE
10.1029/2020MS002203

WeatherBench: A Benchmark Data Set for Data-Driven Weather Forecasting

Stephan Rasp¹, Peter D. Duesen², Sebastian Scher³, Jonathan A. Weyn⁴, Soukayna Moutadid⁵, and Nils Thuerey⁶

Abstract Data-driven approaches, most prominently deep learning, have become powerful tools for prediction in many domains. A natural question to ask is whether data-driven methods could also be used to predict global weather patterns days in advance. First studies show promise but the lack of a common data set and evaluation metrics make intercomparison between studies difficult. Here we present a benchmark data set for data-driven medium-range weather forecasting (specifically 3-5 days), a topic of high scientific interest for atmospheric and computer scientists alike. We provide data derived from the ERA5 archive that has been processed to facilitate the use in machine learning models. We propose simple and clear evaluation metrics which will enable a direct comparison between different methods. Further, we provide baseline scores from simple linear regression techniques, deep learning models, as well as purely physical forecasting models. The data set is publicly available at <https://github.com/pangeo-data/WeatherBench> and the companion code is reproducible with tutorials for getting started. We hope that this data set will accelerate research in data-driven weather forecasting.

Plain Language Summary WeatherBench provides a new benchmark to test data-driven approaches to weather forecasting. Traditional weather models are based on the discretized equations governing the atmosphere. They perform very well for many tasks but are still found lacking for some others. Data-driven approaches, such as deep learning, directly learn from the best available observations and could potentially produce better forecasts. In this paper, we define a benchmark task—predicting pressure and temperature across the globe 3 and 5 days ahead—which will hopefully lead to progress in data-driven weather prediction and foster collaboration across disciplines.

1. Introduction

Deep learning, a branch of machine learning based on multilayered artificial neural networks, has proven to be a powerful tool for a wide range of tasks, most notably image recognition and natural language processing (LeCun et al., 2015). More recently, deep learning has also been used in many fields of natural science. Much of the success of deep learning is based on the ability of neural networks to recognize patterns in high-dimensional spaces. A natural question to ask then is whether deep learning can also be used to predict future weather patterns.

Currently, weather (and climate) predictions are based on purely physical computer models, in which the governing equations, or our best approximation thereof, of the atmosphere and ocean are solved on a discrete numerical grid (Bauer et al., 2015). Overall, this approach has been very successful. However, today's numerical weather prediction (NWP) models still have shortcomings for many important applications, for example, forecasting mesoscale convective systems over Africa (Vogel et al., 2018). Furthermore, huge amounts of computing power are required, especially for creating probabilistic forecasts which are usually limited to 50 ensemble members or less. For these reasons and the growing popularity of machine learning (ML) there has been a growing interest to improve and speed up NWP with data-driven approaches.

ML can be applied to weather prediction in many different ways. Two long-standing applications of ML are postprocessing—the correction of statistical biases in the output of physical models—and statistical

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RASP ET AL. 1 of 17

[Rasp et al., 2020]



인공지능을 활용한 기상/기후 예측



데이터기반 인공지능을 활용한 기상/기후 예측 (Data-driven modeling)

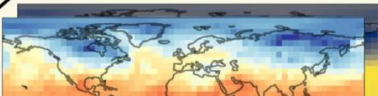
- 제시되는 딥러닝 모델 디자인

[Rasp et al., 2020]

(a) Direct prediction

Channels =
Variables x
Levels

t = 0



t = 5 days

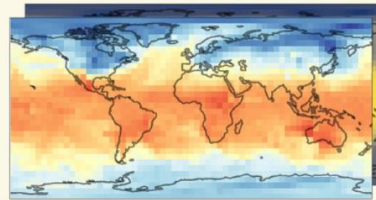


Table 1
RMSE for 3–5 days Forecast Time

Model	Latitude-weighted RMSE (3 days/5 days)			
	Z500 [m ² s ⁻²]	T850 [K]	T2M [K]	PR [mm]
Persistence	936/1,033	4.23/4.56	3.00/3.27	3.23/3.24
Climatology	1,075	5.51	6.07	2.36
Weekly climatology	816	3.50	3.19	2.32
IFS T42	489/743	3.09/3.83	3.21/3.69	–
IFS T63	268/463	1.85/2.52	2.04/2.44	–
Operational IFS	154/334	1.36/2.03	1.35/1.77	2.36/2.59
Weyn et al. (2020)	373/611	1.98/2.87	–	–
Direct (ERA only)	314/561	1.79/2.82	1.53/2.32	2.03/2.35
Direct (CMIP only)	323/561	2.09/2.82	1.90/2.32	2.30/2.39
Direct (pretrained)	268/523	1.65/2.52	1.42/2.03	2.16/2.30
Continuous (ERA only)	331/545	1.87/2.57	1.60/2.06	2.22/2.32
Continuous (CMIP only)	330/548	2.12/2.75	2.24/2.59	2.29/2.38
Continuous (pretrained)	284/499	1.72/2.41	1.48/1.92	2.23/2.33

Note. All forecasts evaluated at 5.625° resolution. Best physical and data-driven methods are highlighted.

Abbreviations: IFS, integrated forecasting system; RMSE, root mean squared error.

- Advanced Approach 적용 논문

JAMES | Journal of Advances in Modeling Earth Systems

RESEARCH ARTICLE
10.1029/2020MS002199

Improving Data-Driven Global Weather Prediction with Deep Convolutional Neural Networks on a Cubed Sphere

Jonathan A. Weyn¹, Dule R. Durran¹, and Rich Caron²

¹Department of Atmospheric Sciences, University of Washington, Seattle, WA, USA; ²Microsoft Research, Redmond, WA, USA

Abstract We present a significantly improved data-driven global weather forecasting framework using a deep convolutional neural network (CNN) to forecast several basic atmospheric variables on a cubed-sphere grid. New developments in this framework include an off-line volume-conservative mass cubed-sphere grid, improvements to the CNN architecture and the minimization of the low-frequency multiple steps in a prediction sequence. The cubed-sphere remapping minimizes the distortion of cube faces on which convolution operations are performed and provides natural boundary condition padding in the CNN. Our improved model produces weather forecasts that are indistinguishable from realistic weather patterns at lead times of several weeks and longer. For short- to medium-range forecasting, our model significantly outperforms persistence, climatology, and a coarse-resolution dynamical numerical weather prediction (NWP) model. Unsurprisingly, our forecasts are weaker from a high-resolution state-of-the-art operational NWP system. Our data-driven model is able to forecast complex surface temperature patterns from low temporal atmospheric state variables. On a time scale, our model produces a realistic seasonal cycle driven solely by the prescribed variation of atmospheric solar forcing. Although currently does not compete with operational weather forecasting models, our data-driven CNN executes much faster than these models, suggesting the learning could prove to be a valuable tool for large ensemble forecasting.

Plain Language Summary Recent work has begun to explore building global weather prediction models using only machine learning techniques trained on large amounts of atmospheric data. We develop a newly improved machine learning algorithm capable of operating like traditional models and predicting several fundamental atmospheric variables, including near-surface temperature. While our model does not yet compete with the state-of-the-art in numerical weather prediction, our model produces realistic forecasts that perform well and execute extremely quickly, offering a potential for future development in probabilistic weather forecasting.

1. Introduction

Though still in its infancy, the application of machine learning (ML) to various aspects of weather forecasting is receiving increasing attention and yielding promising results. ML has been used to output from numerical weather prediction (NWP) models in attempts to improve forecasts. W. Roberts (NWS) has been used for many years to postprocess NWP output (e.g., Chapman & Dawson, 2016; Kalogirou & Barnes, 2016). Recent advances in data and computation have led to successful ensemble probabilistic postprocessing of NWP (Rasp & Lerch, 2018; McKeown et al., 2019) demonstrated the ability of deep NMs to denoise the output of general circulation models (GCMs) to higher horizontal resolution, and Scher and Mesinger (2018) used NMs to estimate the 10-day weather forecasts. ML methods have also been used to identify extreme weather and climate observed and modeled atmospheric states (Kurtz et al., 2019; Legras et al., 2019; Liu et al., 2019) and extreme weather events (e.g., Heram & Schumacher, 2018), and to provide operational grid risk assessment for severe weather (McEvoy et al., 2017; Lorenz et al., 2019). Development of extra spatial patterns in precipitation from gridded atmospheric fields, while Chappin et al. (2018) demonstrated the ability of deep NMs can skillfully predict extreme low-frequency rainfall with real-time input information. Another ML effort has focused on the improvement of physics parameterizations in NWP models (Lorenz et al., 2019; Legras et al., 2019).

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WEYN ET AL.

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RESEARCH ARTICLE
10.1029/2020MS002183

Data Driven Medium Range Weather Prediction With a ResNet Pretrained on Climate Simulations: A New Model for WeatherBench

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Abstract Numerical weather prediction has traditionally been based on the models that describe the dynamical and physical equations of the atmosphere. Recently, however, the rise of deep learning has created increased interest in purely data-driven medium-range weather forecasting with few studies exploring the feasibility of such an approach. To accelerate progress in this area, the WeatherBench benchmark challenge was defined. Here, we train a deep residual convolutional neural network (ResNet) to predict geopotential, temperature and precipitation at 6252 resolution up to 5 days ahead. To avoid overfitting and improve forecast skill, we train the model using historical climate model output before learning on reanalysis data. The resulting forecast outperforms previous submissions to WeatherBench and are comparable in skill to a physical baseline at similar resolution. We also analyze how the neural network captures its predictions and find that, for the case studies analyzed, the model has learned physically reasonable correlations. Finally, we perform scaling experiments to estimate the potential skill of such an approach for medium-range weather forecasting. In particular, some researchers were skeptical of such an approach for medium-range weather forecasting.

Plain Language Summary Weather forecasts are created by running highly complex computer simulations that encompass our knowledge of how the atmosphere works. This approach has served us well but is there a different way? The paradigm of machine learning proposes learning an algorithm from data rather than building it from physical principles. For several areas like computer vision and natural language processing this has worked exceedingly well, so it just makes sense to try it as well for weather forecasting. This paper presents the latest attempt at training a machine learning weather forecasting model. It is shown that the learned model produces reasonable forecasts, approximately on par with traditional models run on much lower resolution. However, there is still a large gap to current state-of-the-art high-resolution weather models that is unlikely to be closed with a purely data-driven approach because not enough training data exist.

1. Introduction

Current numerical weather prediction (NWP) is based on physical models of the atmosphere and the ocean, in which the governing equations are discretized and sub-grid processes are parameterized (Kutub, 2005). Continued refinement of these models along with increasing computing power and better observations to create initial conditions has led to steady increases in forecast skill over the last decades (Bauer et al., 2015). The improvements in the model components and the tuning of the parameters is, in a large majority of cases, guided by scientific expertise rather than using a statistical method (Brennan et al., 2017). In the current operational weather forecasting chain, the only component that includes a learning algorithm is post-processing, the correction of statistical errors from NWP output. Most commonly, post-processing is done using simple linear techniques (model output statistics) but in recent years more modern machine learning techniques, such as random forests and neural networks, have been explored (Grigoriev et al., 2010; McEvoy et al., 2017; Rasp & Lerch, 2018; Tsalikis et al., 2018).

With the apparent successes of deep learning in modeling high-dimensional data in other domains such as computer vision and natural language processing, a natural question to ask is whether numerical weather models can also be learned purely from data. This question opens some debate over initial studies (Dobson & Bauer, 2018; Scher, 2018; Scher & Mesinger, 2018; Weyn et al., 2019) showed the general feasibility of such an approach for medium-range weather forecasting. In particular, some researchers were skeptical

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RASP AND THUREY

[Weyn, 2020]

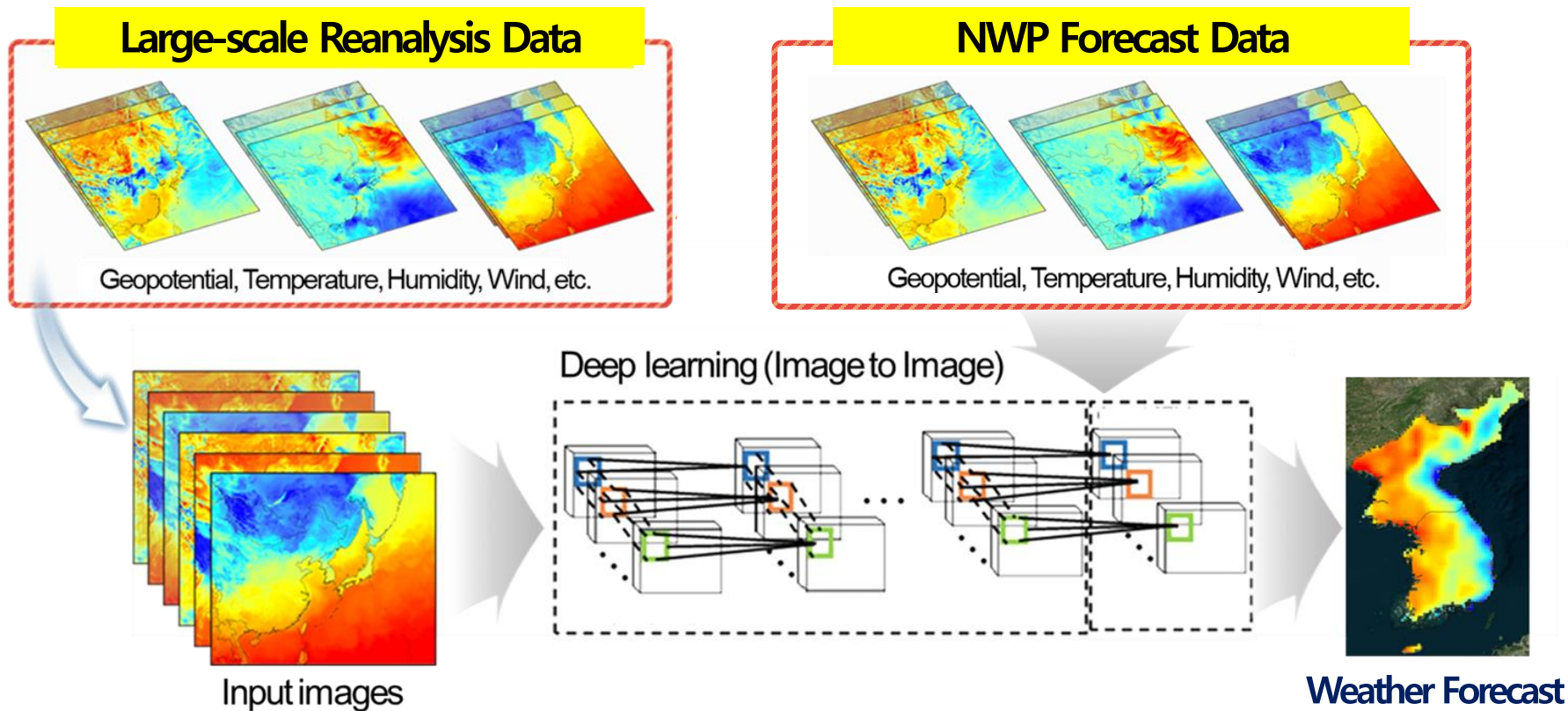
[Rasp and Thuerey, 2021]

인공지능을 활용한 기상/기후 예측



Proposed hybrid approach (Data-driven modeling + NWP forecast output)

- Data-driven 접근 방식과 수치예보모델의 예측산출물을 결합하여 예측하는 방법



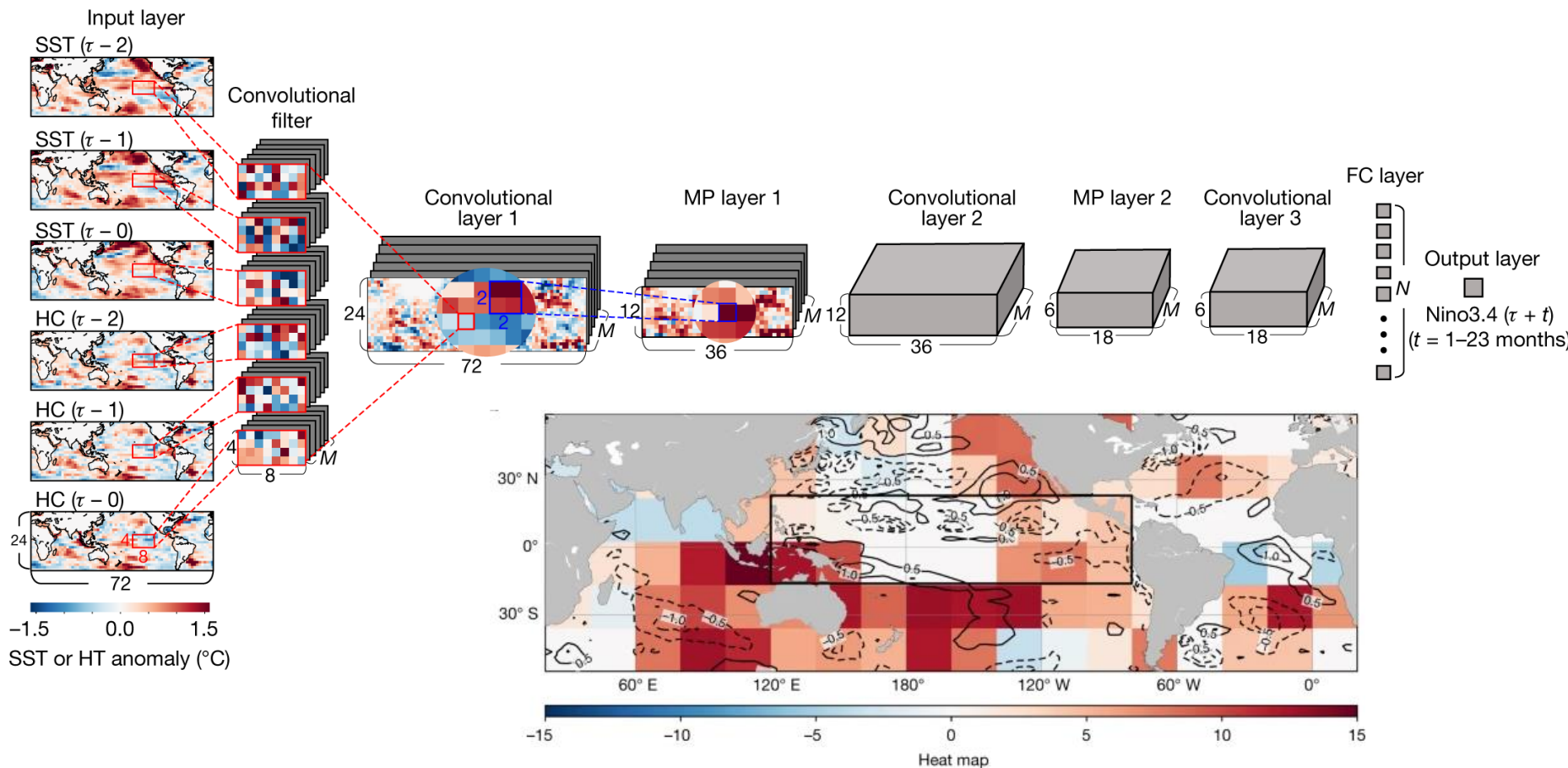
- 수치모델의 의존성을 벗어난 Data-driven 기법과 수치예보 모델 산출물을 함께 이용하여 예측 정확도가 향상될 것으로 기대

(eg, Temperature, Humidity or other meteorological variables)

인공지능을 활용한 기상/기후 예측



인공지능을 활용한 기상/기후 예측 방법

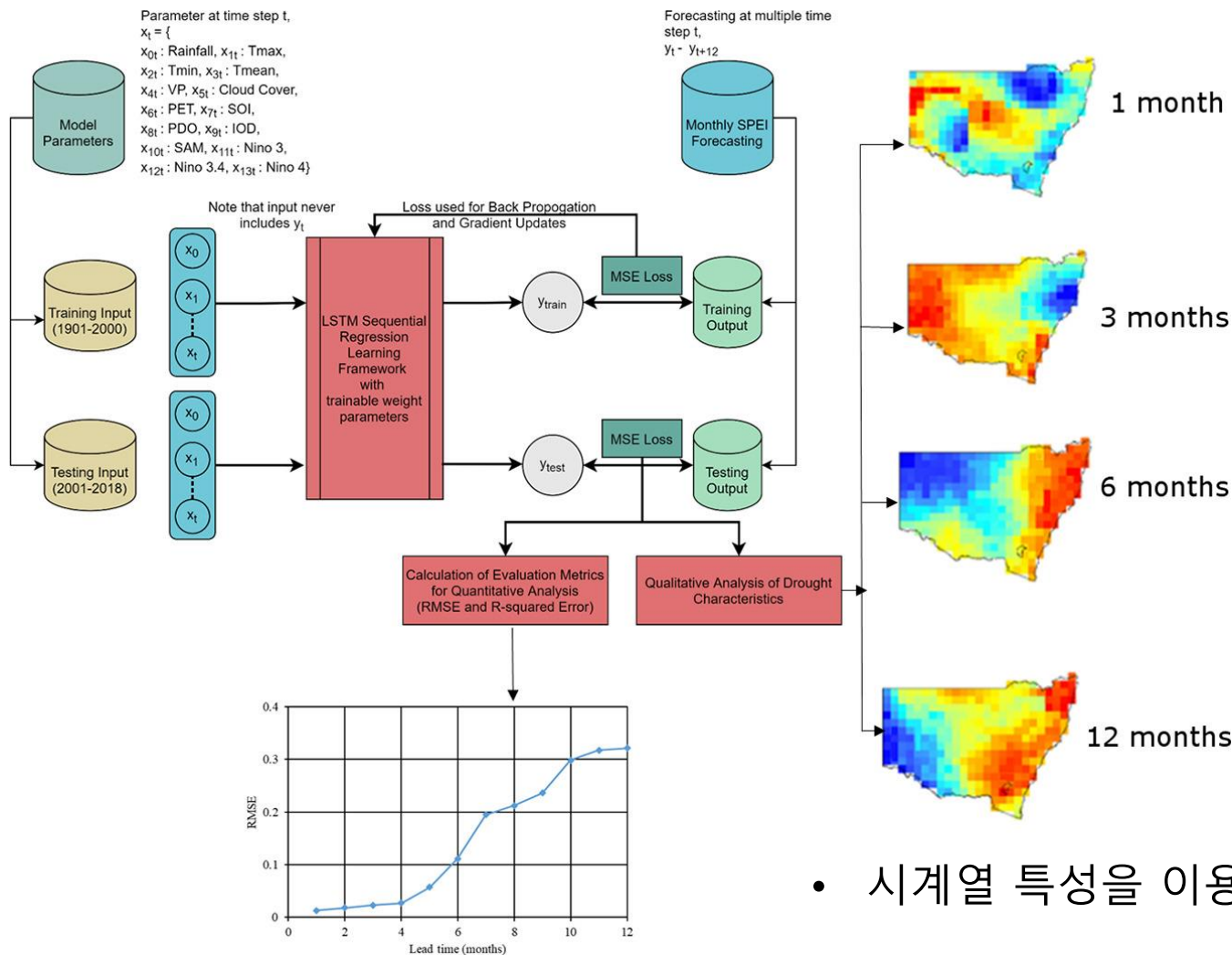


- 공간정보를 이용한 Convolutional neural network 기반 ENSO 예측

인공지능을 활용한 기상/기후 예측



인공지능을 활용한 기상/기후 예측 방법



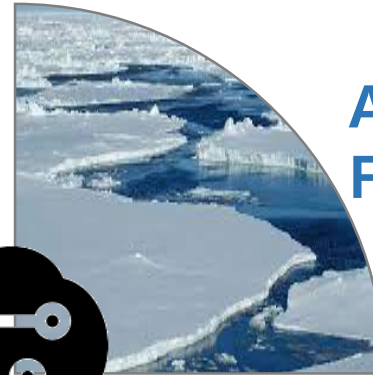
- 시계열 특성을 이용한 가뭄 예측



인공지능을 활용한 기상/기후 예측 사례 연구



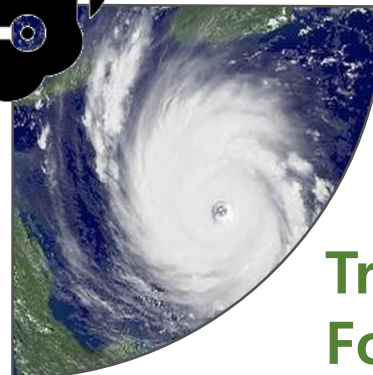
**Drought
Forecasts**



**Arctic sea ice
Forecasts**



**Rainfall
Forecasts**



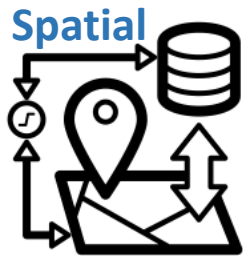
**Tropical cyclone
Forecasts**



연구에 사용한 대표적인 딥러닝 기법



Convolutional Neural Network (CNN)



1 _{x-1}	1 _{x0}	1 _{x1}	0	0
0 _{x0}	1 _{x1}	1 _{x0}	1	0
0 _{x1}	0 _{x0}	1 _{x1}	1	1
0	0	1	1	0
0	1	1	0	0

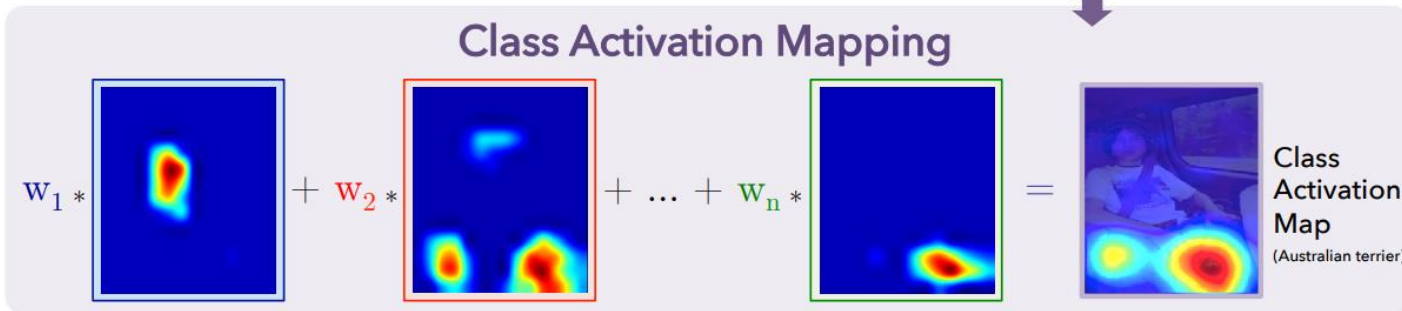
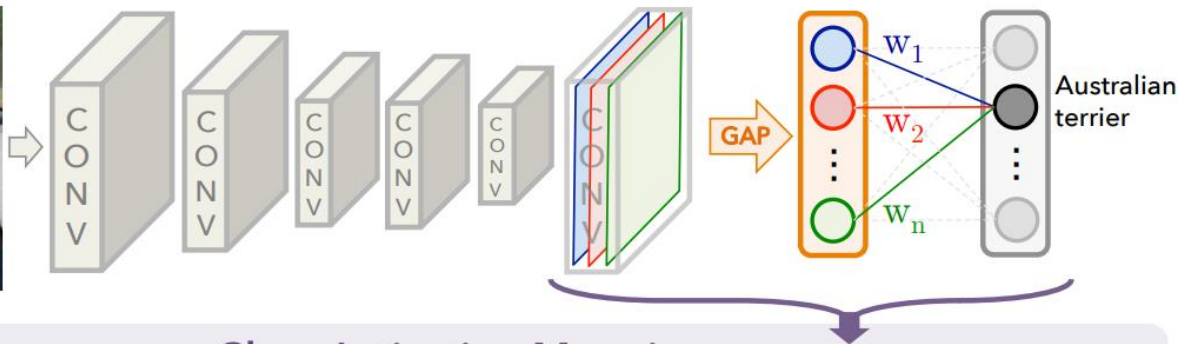
Image

4		

Convolved Feature



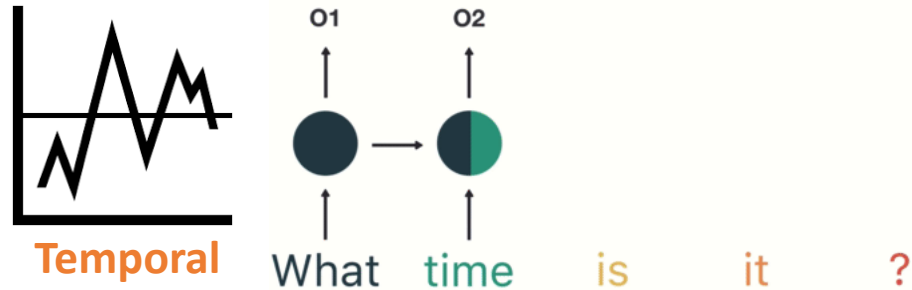
Input



연구에 사용한 대표적인 딥러닝 기법

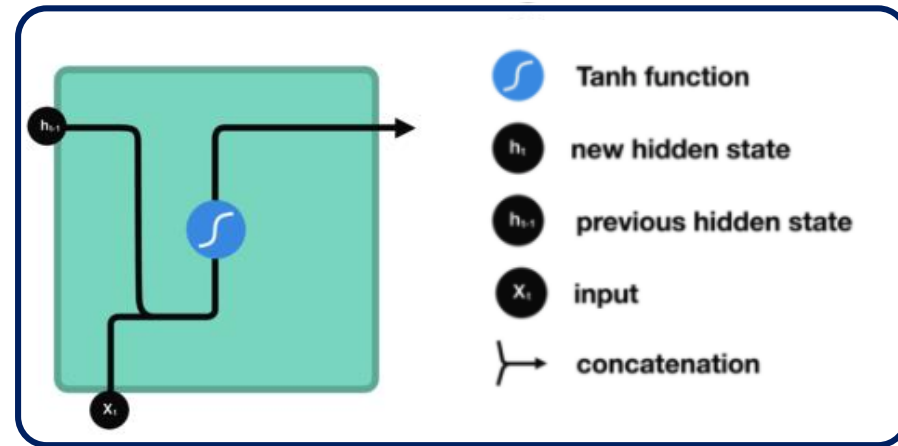


<https://codlingual.tistory.com/87>

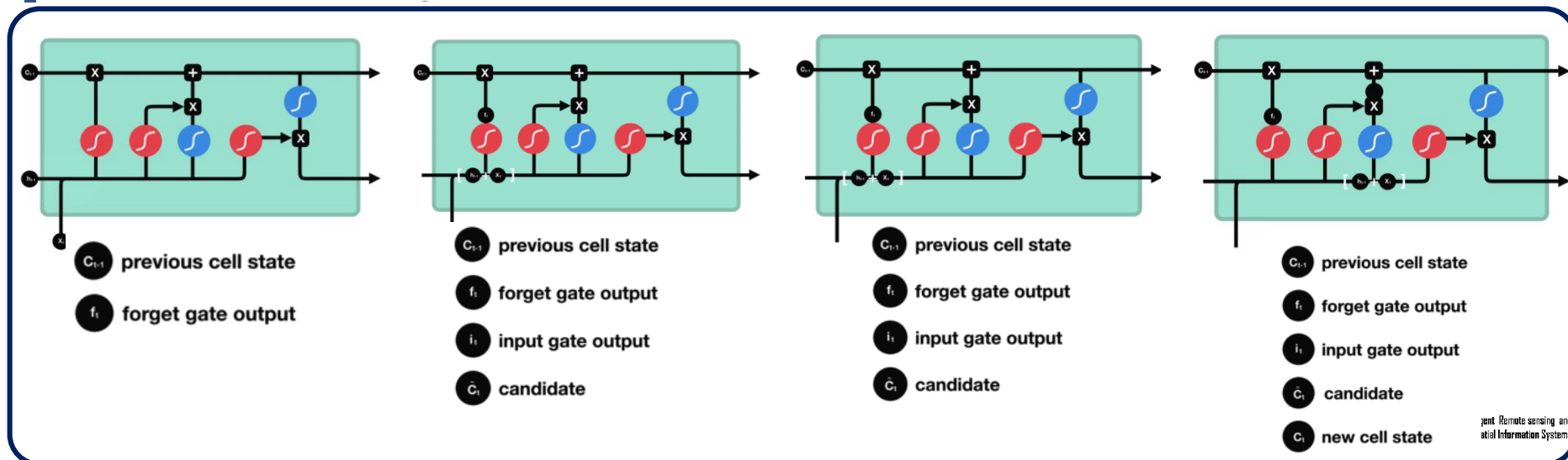


- 시계열 패턴을 고려하여 예측
- 시계열 특성이 있는 분야에 사용가능

Recurrent Neural Network (RNN)



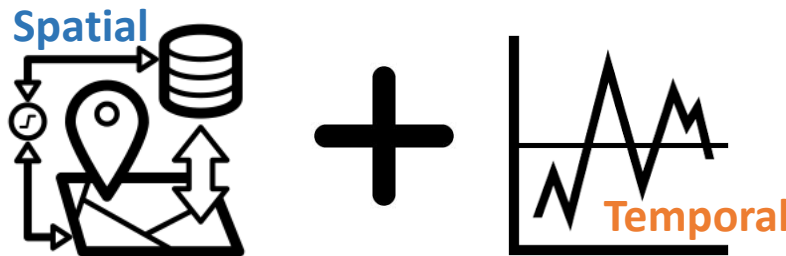
Long Short Term Memory (LSTM)



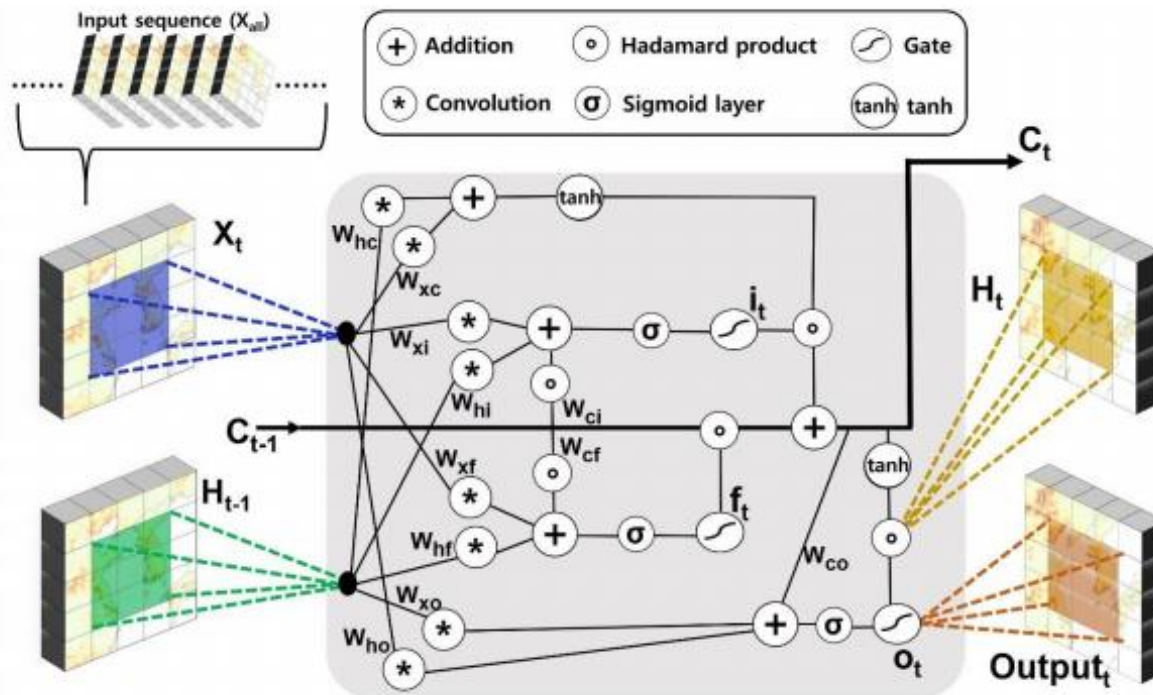
연구에 사용한 대표적인 딥러닝 기법



Convolutional Long Short Term Memory (ConvLSTM)



- 공간의 특성과 시계열 특성을 동시에 고려할 수 있다는 장점이 있음



$$i_t = \sigma(W_{xi} * X_t + W_{hi} * H_{t-1} + W_{ci} \circ C_{t-1} + b_i)$$

$$f_t = \sigma(W_{xf} * X_t + W_{hf} * H_{t-1} + W_{cf} \circ C_{t-1} + b_f)$$

$$C_t = f_t \circ C_{t-1} + i_t \circ \tanh(W_{xc} * X_t + W_{hc} * H_{t-1} + b_c)$$

$$O_t = \sigma(W_{xo} * X_t + W_{ho} * H_{t-1} + W_{co} \circ C_t + b_o)$$

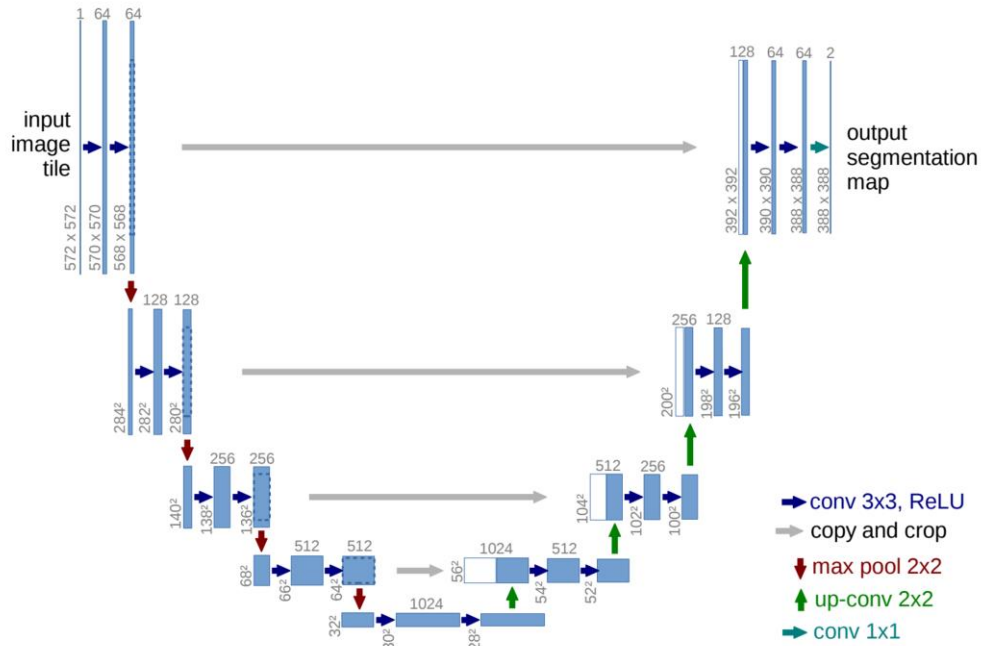
$$H_t = O_t \circ \tanh(C_t)$$



연구에 사용한 대표적인 딥러닝 기법



U-Net



- Fully connected layer를 사용하지 않고 convolution 연산으로만 이뤄져 있는 fully convolutional network (FCN)의 일종
 - 입력 크기와 동일한 크기의 출력 생성 가능
 - 모든 filter를 전체 영역에 공유하므로 메모리의 효율성
- Encoder-decoder 구조를 통해 feature 추출
- Skip connection을 통해 깊은 구조에서도 원본 이미지의 고해상도 정보 손실을 보완함

• 수축경로(Contracting Path)

점진적으로 넓은 범위의 의미정보 추출

• 확장경로(Expanding Path)

의미정보를 픽셀 위치 정보와 결합하여 픽셀마다 어떤 객체에 속하는지 구분

• 전환구간 (Bottle Neck)

인공지능을 활용한 기상/기후 예측



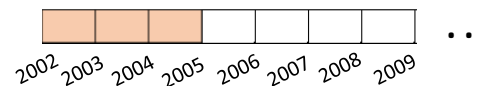
동아시아 가뭄 단기예측

- 위성기반의 가뭄지수의 시공간적 패턴변화와 단기 기상예측자료(수치 모델)을 이용하여 기계학습 (random forest)을 포함한 딥러닝 (ConvLSTM) 기반의 동아시아 가뭄을 단기 예측함

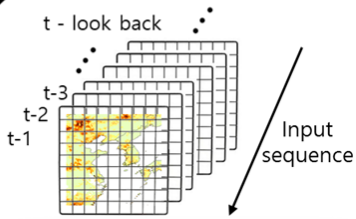


Convolutional LSTM (step 1)

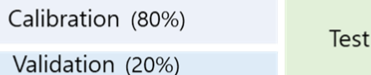
Real-time learning



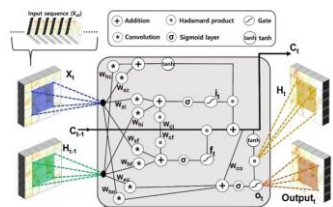
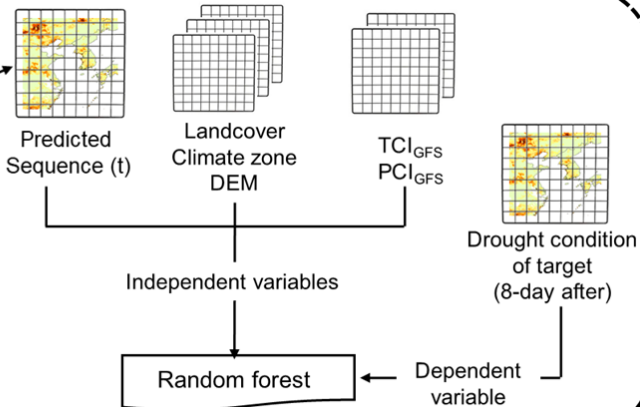
Step1. Convolutional LSTM (historical patterns)



Random forest (step 2)



Step2. Random forest applying numerical model



- 가뭄의 단기(8일 뒤) 예측
- 위성자료 + 수치예보모델 융합
- ConvLSTM + Random forest
- 지형자료 이용
- 실시간학습(online model)

Park, S. et al. (2020). Short-Term Forecasting of Satellite-Based Drought Indices Using Their Temporal Patterns and Numerical Model Output. Remote Sensing, 12(21), 3499.

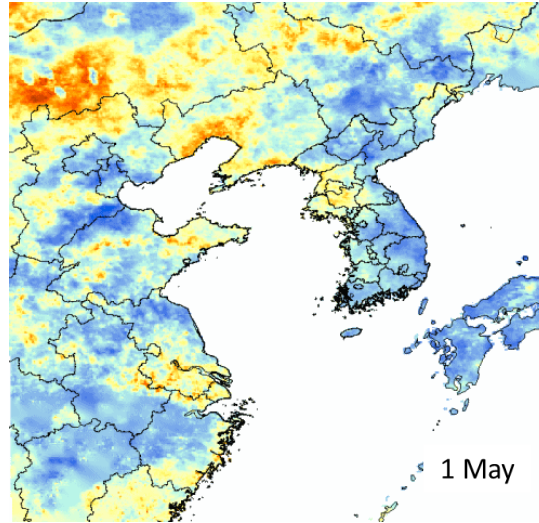
인공지능을 활용한 기상/기후 예측



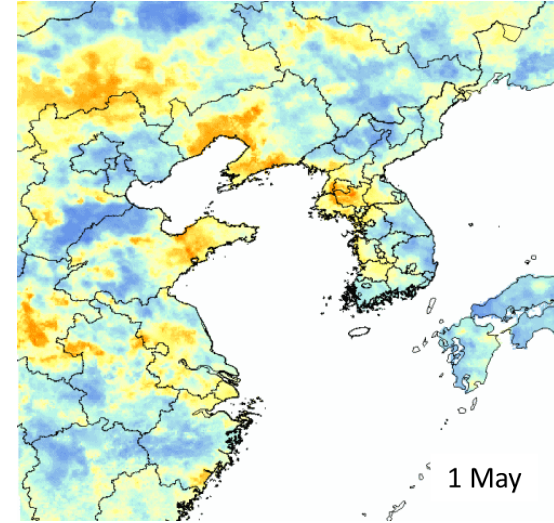
동아시아 가뭄 단기예측



기존 가뭄 지수

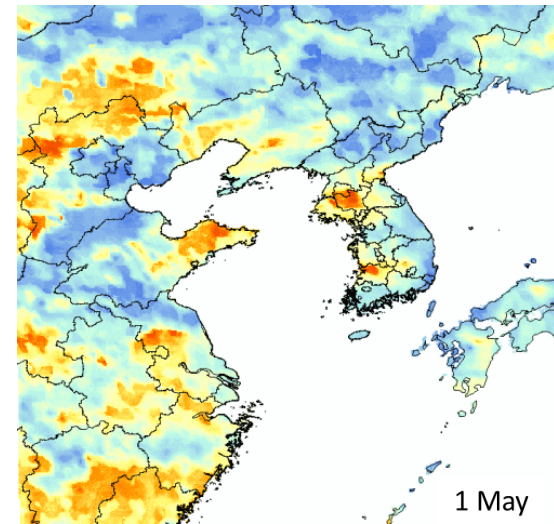
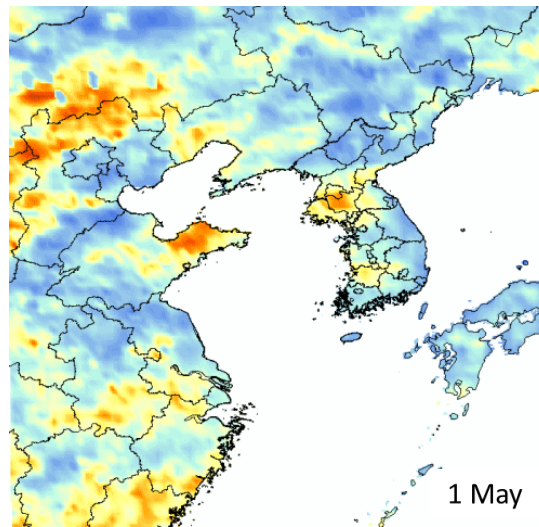


예측된 가뭄지수



SDCI
가뭄지수

SPI
가뭄지수

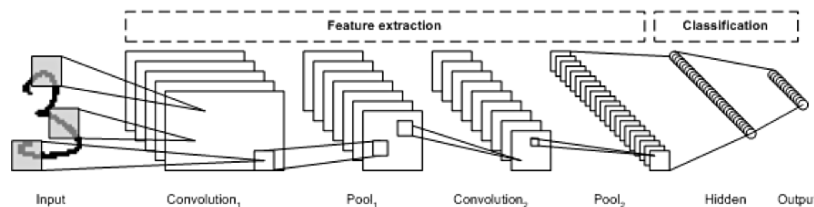
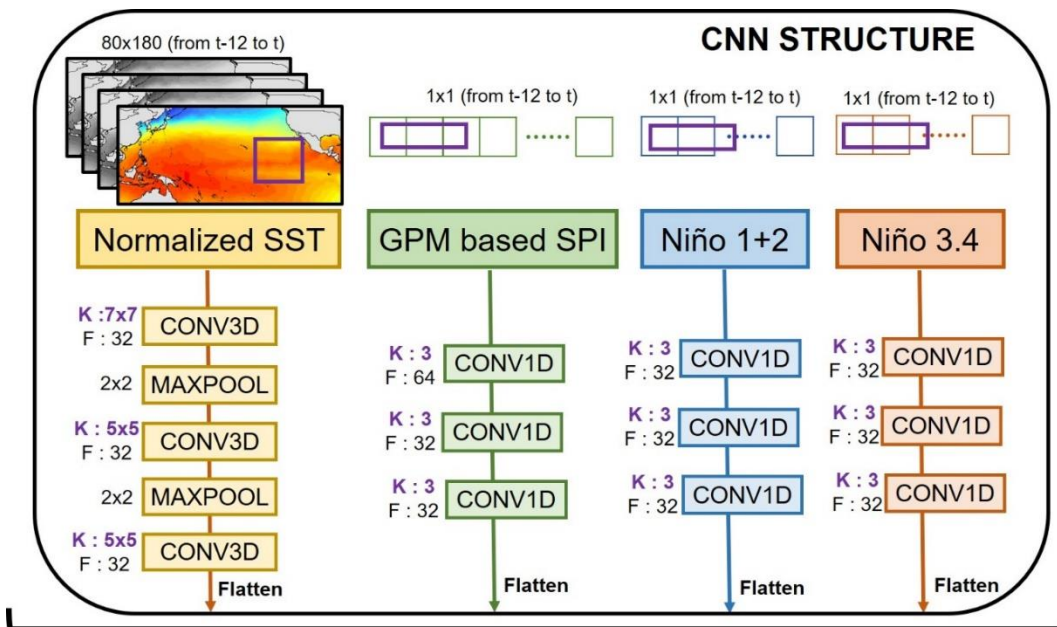


인공지능을 활용한 기상/기후 예측



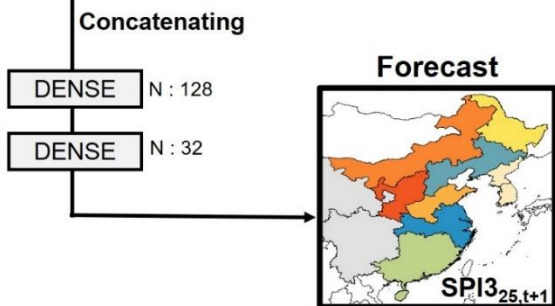
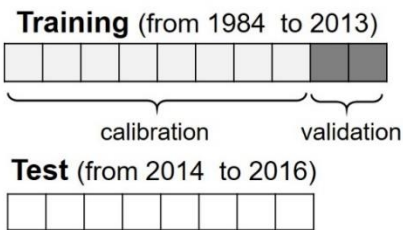
SST 원격상관을 이용한 동아시아 가뭄 예측(1-3개월)

- 위성기반의 SST의 원격상관 및 가뭄의 시계열 패턴을 고려하여 CNN 기반의 동아시아 가뭄을 장기 예측함



- CNN을 이용하여 과거 12개월의 SST의 시공간적 패턴 정보를 추출함
- 과거 가뭄패턴+ 기후인자 융합

* K : Kernel size, F : #Filter, N : #node

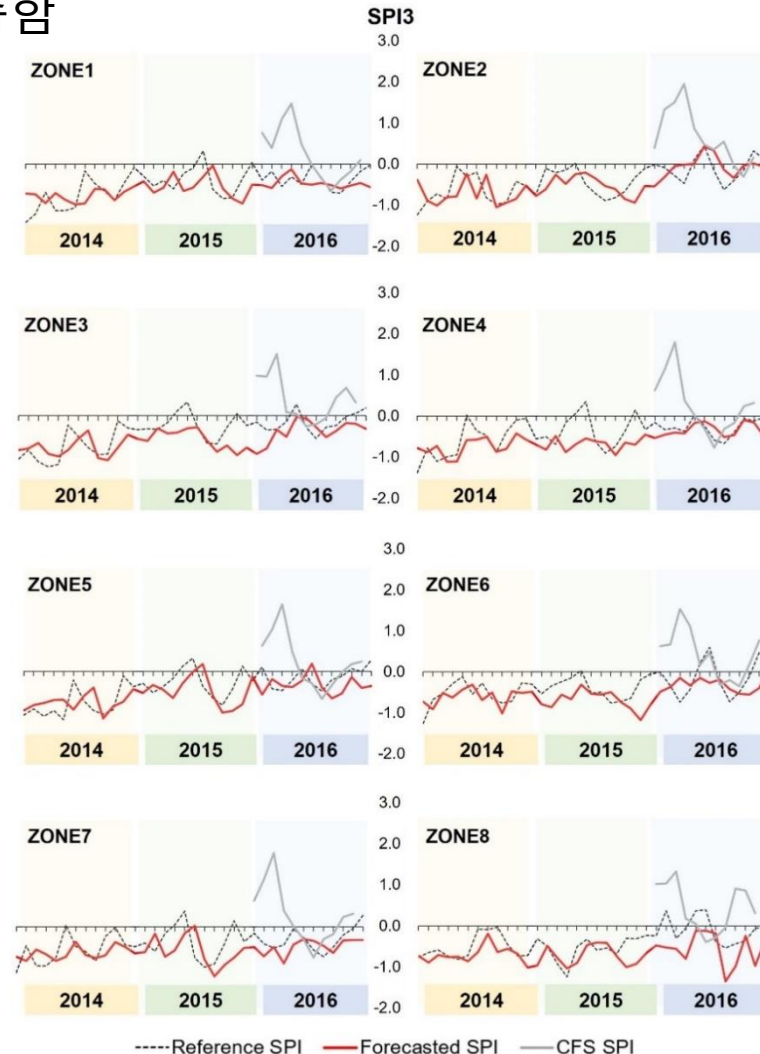
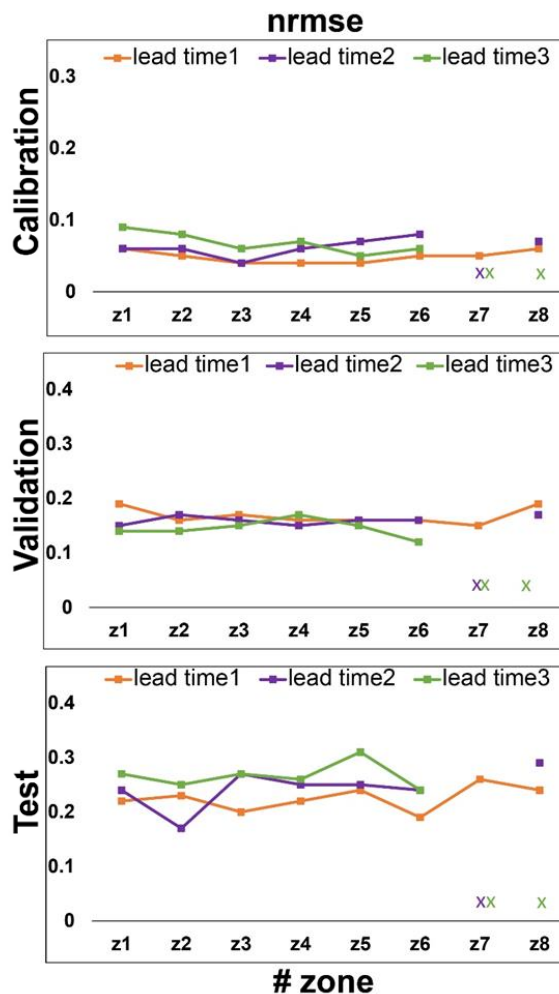
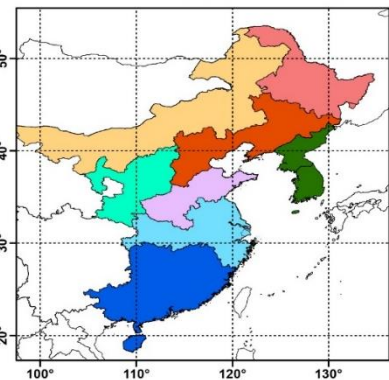


인공지능을 활용한 기상/기후 예측



SST 원격상관을 이용한 동아시아 가뭄 예측(1-3개월)

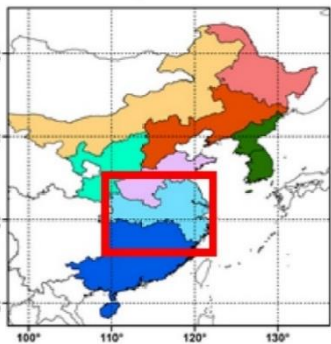
- 위성기반의 SST의 원격상관 및 가뭄의 시계열 패턴을 고려하여 CNN 기반의 동아시아 가뭄을 장기 예측함



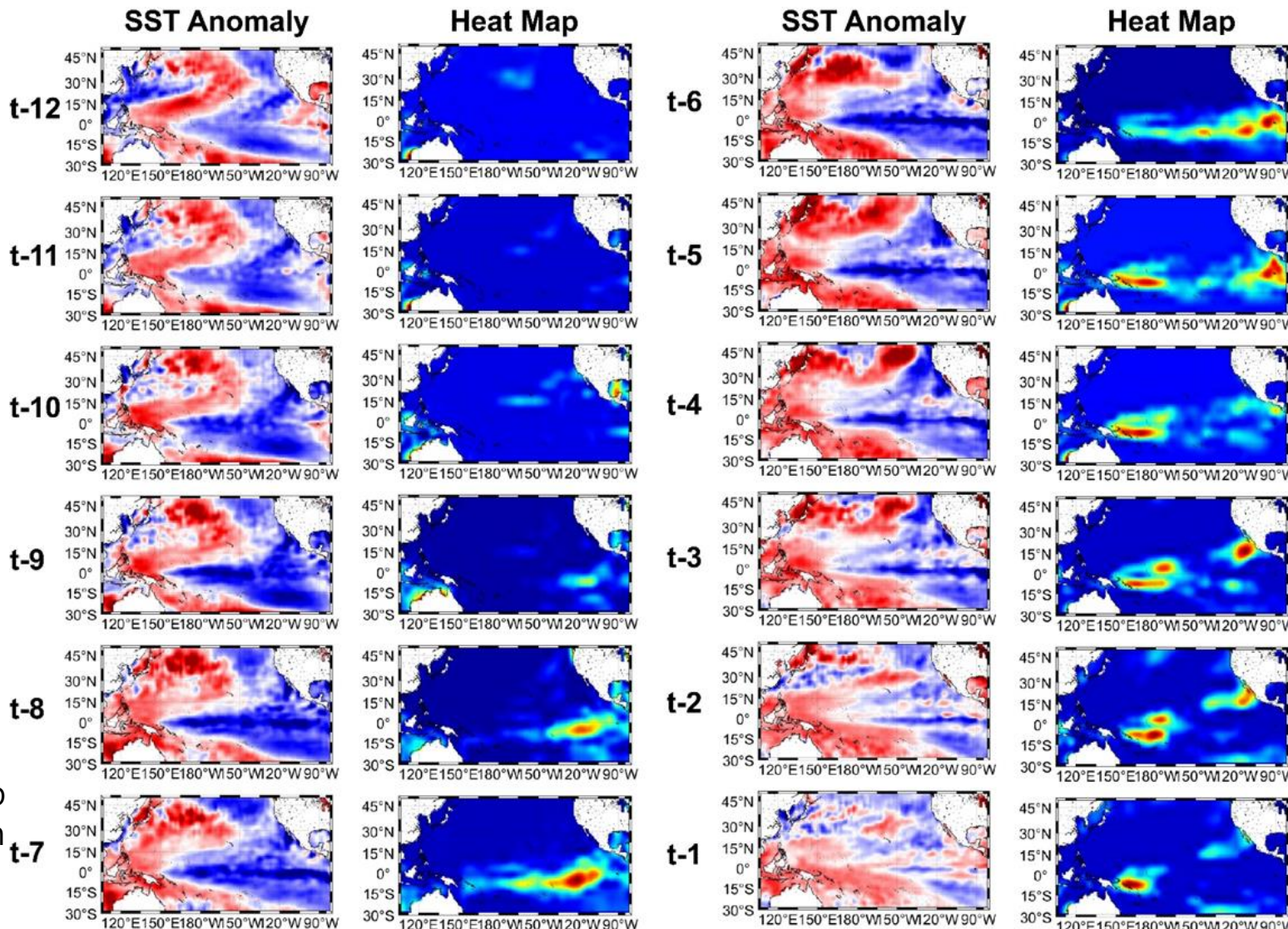
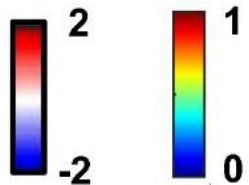
인공지능을 활용한 기상/기후 예측



SST 원격상관을 이용한 동아시아 가뭄 예측(2011년 5월 케이스)



SST Anomaly Heat Map



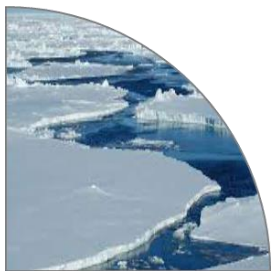
The SST anomaly (left) and Heat map (right) derived from the CNN model

인공지능을 활용한 기상/기후 예측

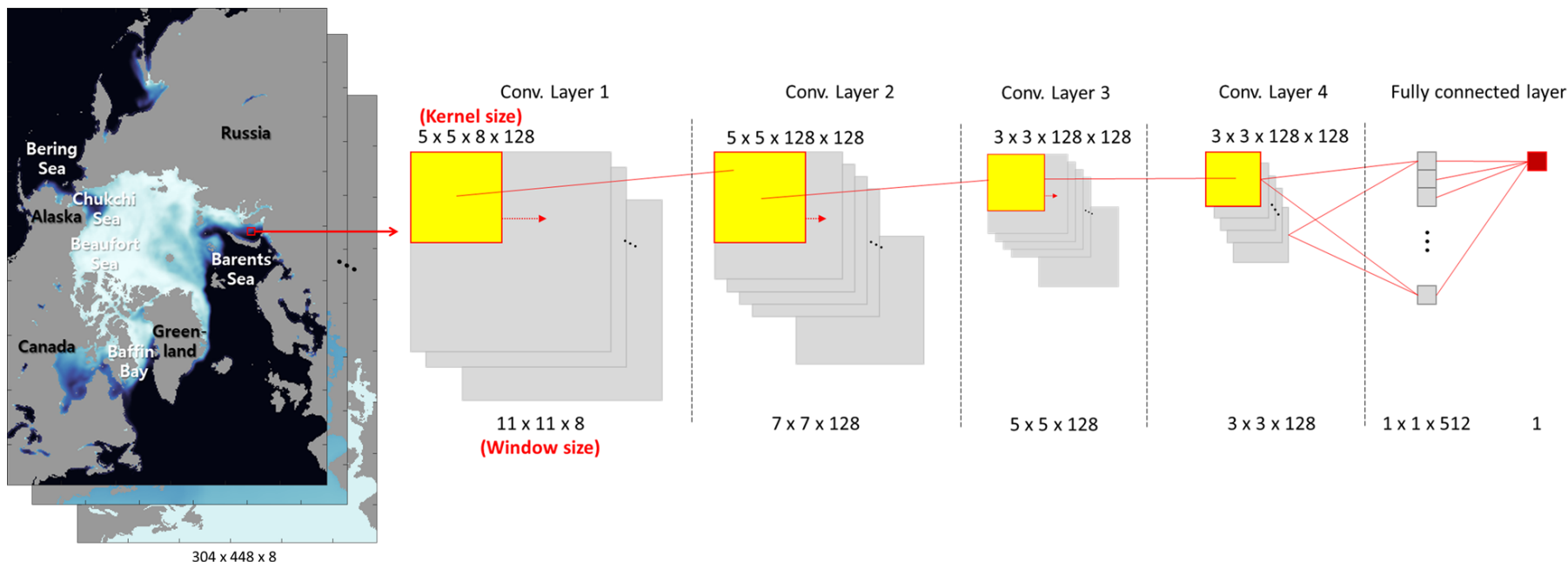


북극 해빙 농도 장기예측

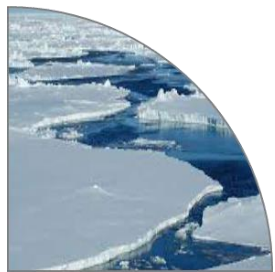
- CNN 기법을 활용한 여름철 북극 해빙 3, 6, 9개월 예측 모델 개발



	variables
과거 해빙농도 (4)	<ul style="list-style-type: none"> 현재 해빙 농도 1년 전 해빙 농도 과거 해빙 농도 변화 패턴 (5, 10년)
과거 해빙농도 이상치 (4)	<ul style="list-style-type: none"> 현재 해빙농도 이상치 1년 전 해빙농도 이상치 과거 해빙농도 이상치 변화 패턴 (5, 10년)

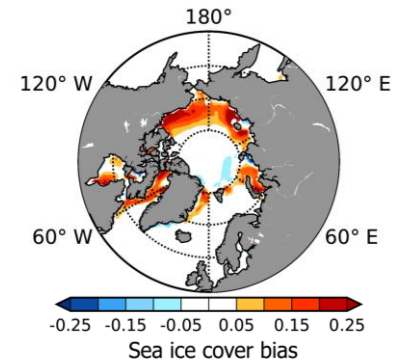


인공지능을 활용한 기상/기후 예측



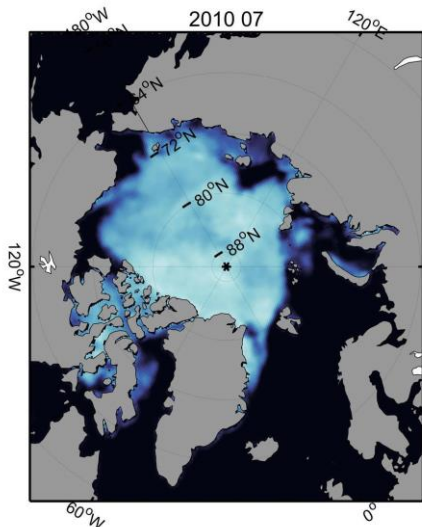
북극 해빙 농도 장기예측

- CNN 기법 활용한 7월 북극 해빙 장기 예측 결과 (25km, 2010-2019)
- 3 ~ 9개월 예측 모델 모두 10% 이하의 RMSE
- ECMWF SEAS5 예측 모델 기준, 6-8월 1개월 해빙 농도 예측결과, 10% 이상의 예측 오차를 보임

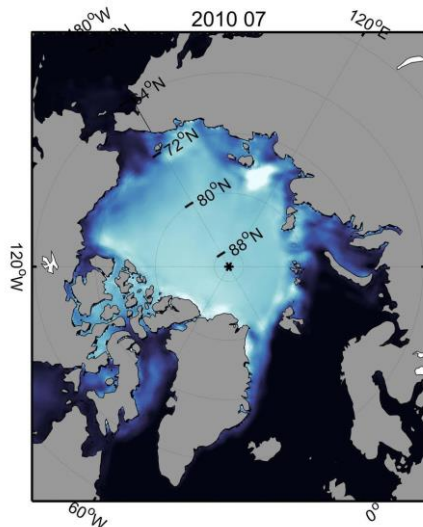


ECMWF SEAS5 1개월 예측 오차 (Johnson et al., 2019)

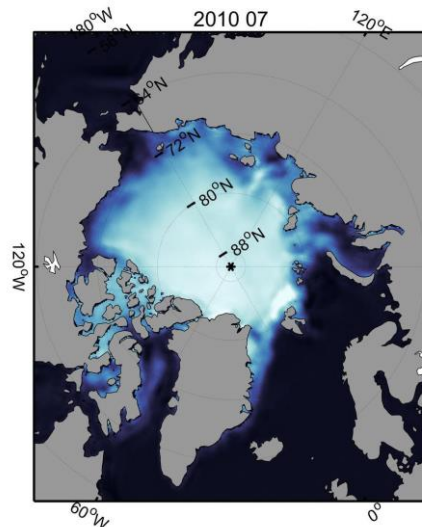
7월 해빙 농도
(2010-2019)



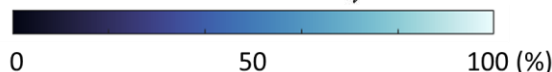
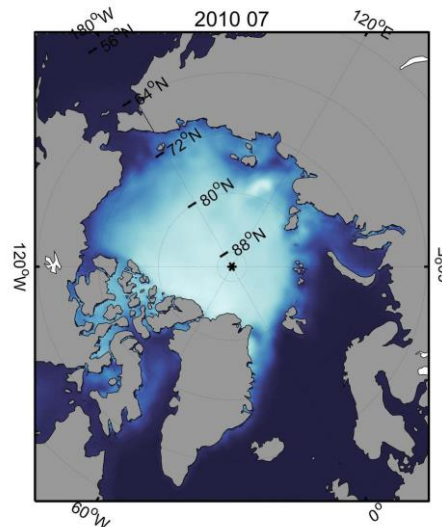
3개월 예측 결과
(RMSE = 7.08%)



6개월 예측 결과
(RMSE = 7.87%)



9개월 예측 결과
(RMSE = 8.06%)



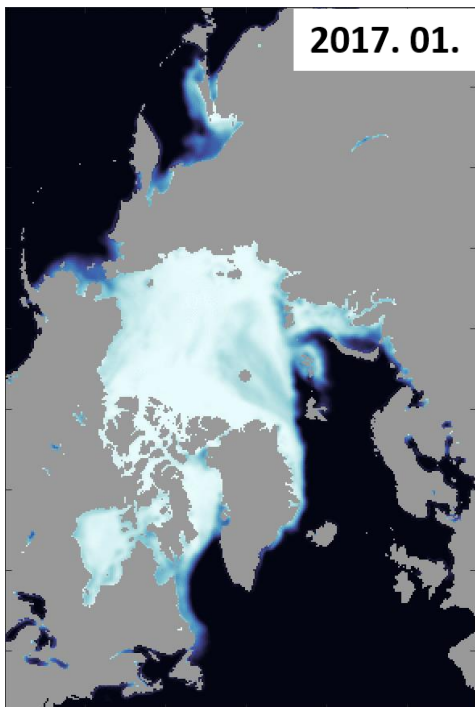
인공지능을 활용한 기상/기후 예측



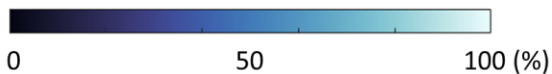
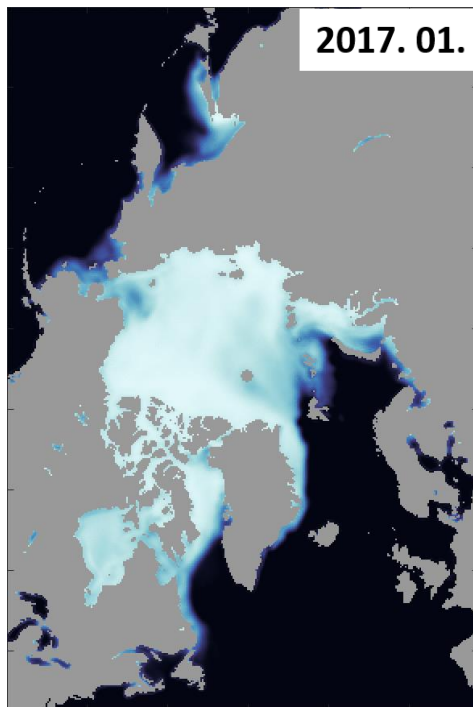
북극 해빙 농도 단기 예측

- CNN 기법 활용한 북극 해빙 1개월 단기 예측
- 현재 및 과거 해빙 특성, 해양 및 대기 변수 활용 예측 모델 개발
- 전체 예측 기간에 대하여 5.76%의 RMSE를 보였으며, **과거 해빙 농도 특성이 가장 중요한 예측 변수로 나타났으며, 뒤이어 해수면 온도가 중요한 것으로 나타남**

2017년 월별 해빙



1개월 예측 결과



상대적 변수 중요도

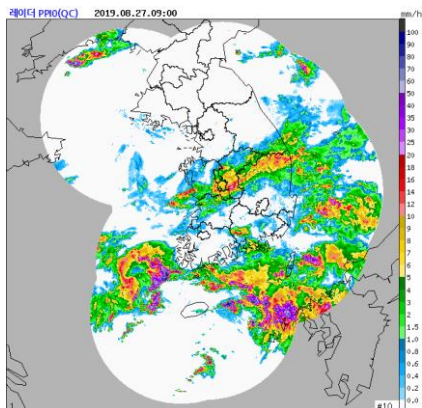
변수	1년 전 SIC	SIC	1년 전 SIC anomaly	SIC anomaly
변수 중요도	1.134	1.029	1.095	1.012
변수	해수면 온도	대기 온도	알베도	풍속 (v-wind)
변수 중요도	1.035	1.005	1.006	1.008

인공지능을 활용한 기상/기후 예측

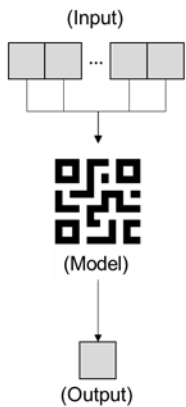


초단기 강수 예측

- 실시간으로 레이더 강수 패턴을 딥러닝 모델 (CNN)에 학습하여 초단기 (0-1시간) 강수 예측을 수행함

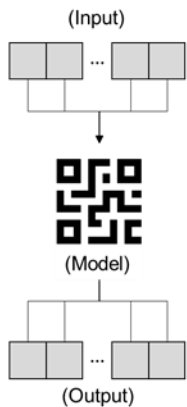


Single-target

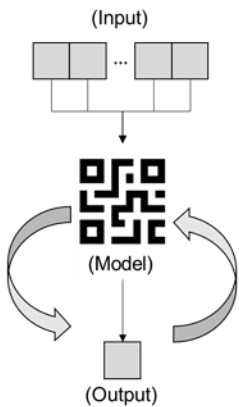


N개의 개별 모델 필요

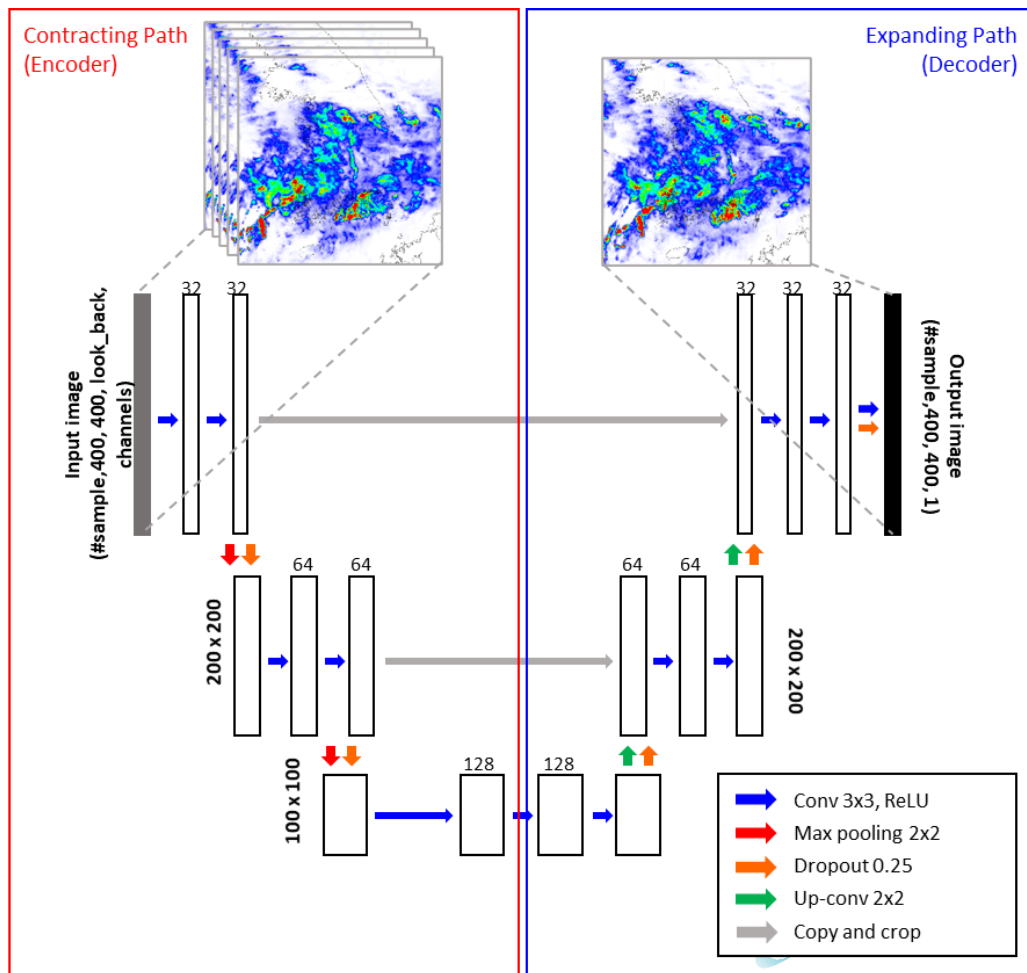
Multi-target



Recursive



반복적인 예측



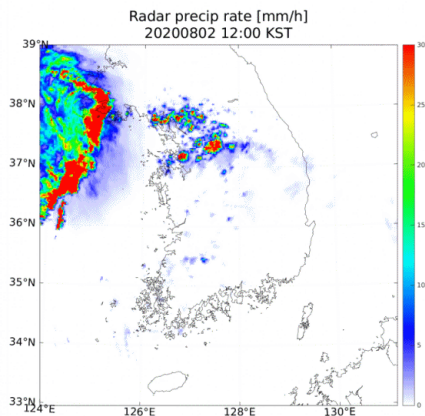
인공지능을 활용한 기상/기후 예측



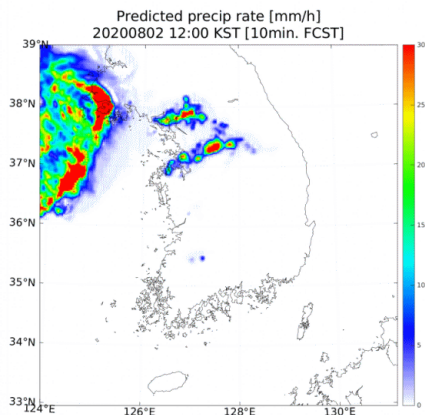
초단기 강수 예측 - 예측 시간에 따른 결과



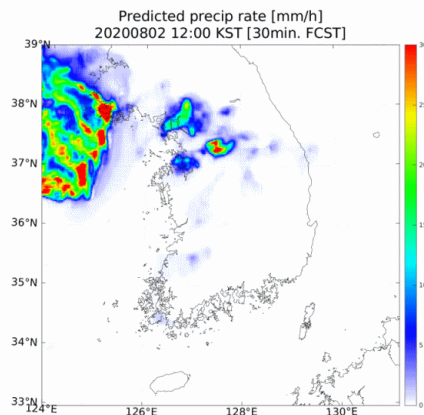
Multi-target



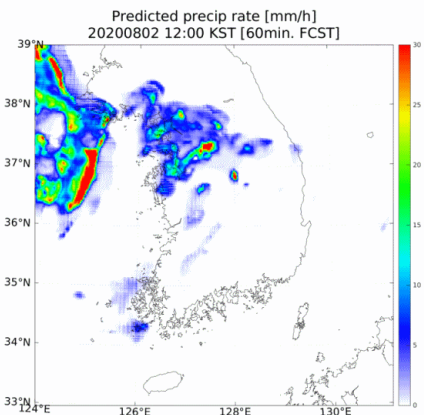
Recursive



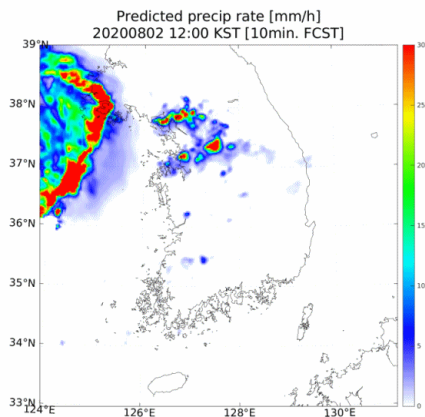
Fc+ 10min



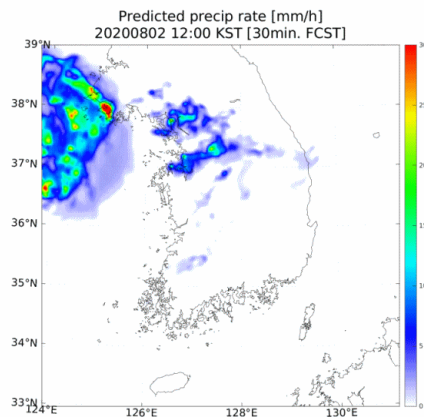
Fc+ 30min



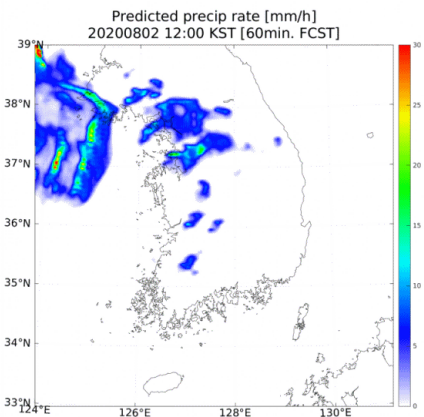
Fc+ 60min



Fc+ 10min



Fc+ 30min



Fc+ 60min

인공지능을 활용한 기상/기후 예측



초단기 강수 예측 - LDAPS 수치모델과의 비교

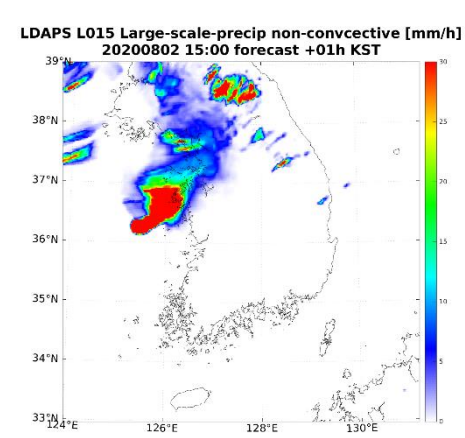
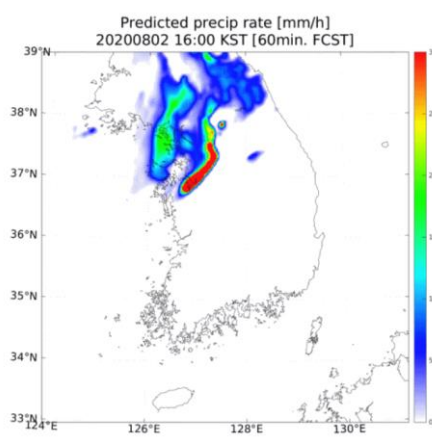
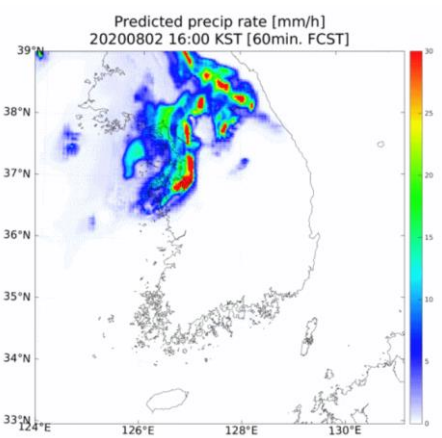
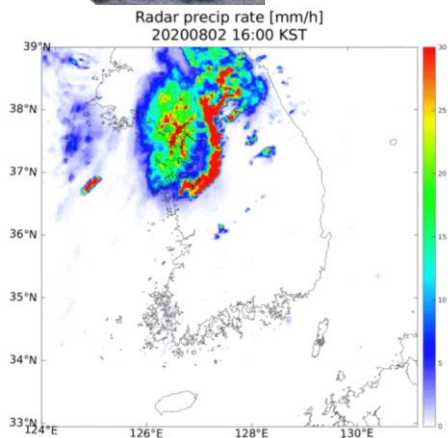


레이더 16:00

Mutli-target +01hr

Recursive +01hr

LDAPS +01hr

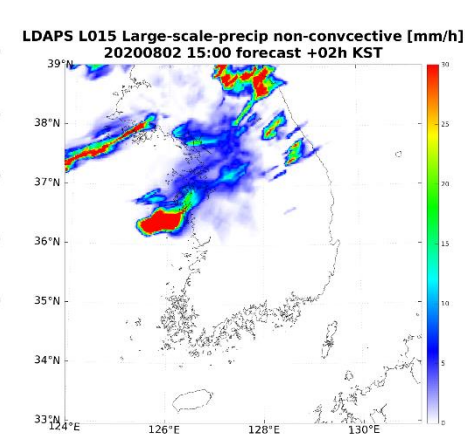
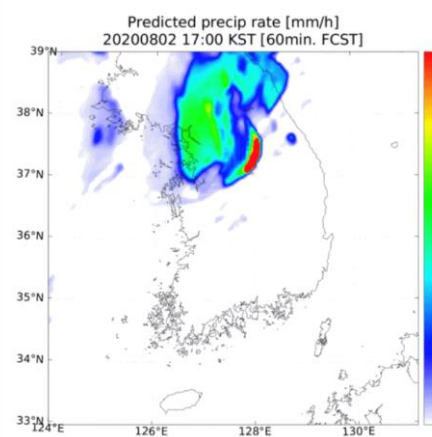
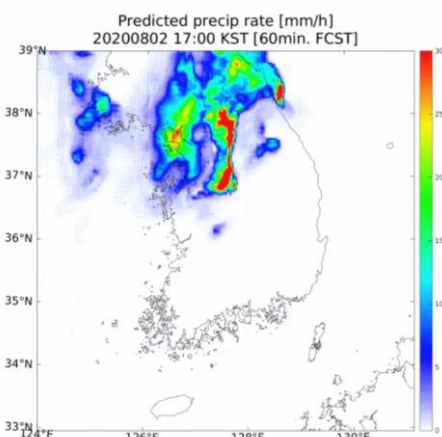
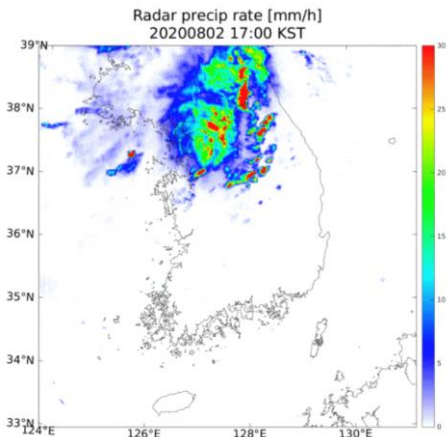


레이더 17:00

Mutli-target +01hr

Recursive +01hr

LDAPS +02hr

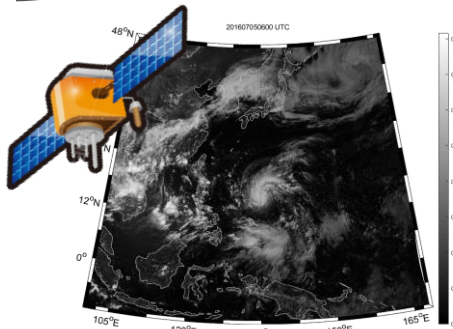
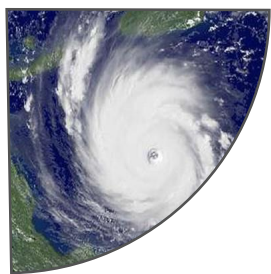


인공지능을 활용한 기상/기후 예측

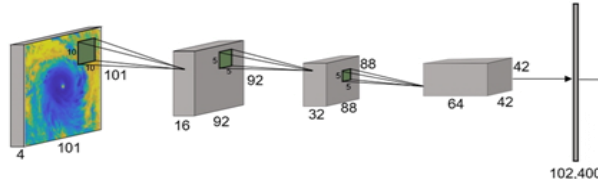


딥러닝 기반 태풍 강도 추정

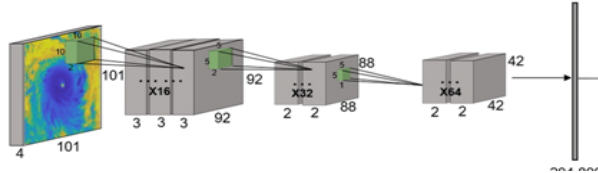
- 정지궤도 기상위성기반 태풍 관측자료의 적외채널별 패턴을 딥러닝 (2D-/3D-CNNs)을 통해 분석하여 해당 태풍의 강도를 객관적으로 추출함



(a) 2D CNN architecture

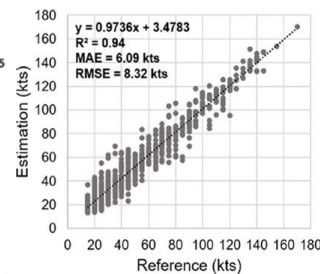


(b) 3D CNN architecture

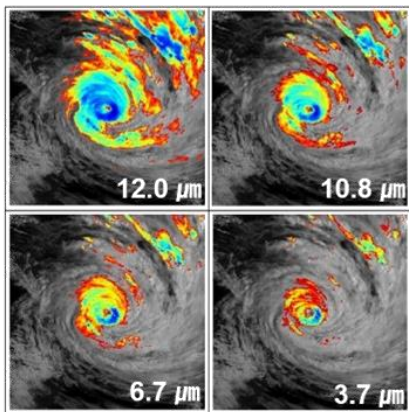
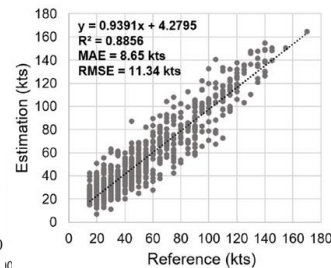


Training 2D/3D-CNNs using collected TC references

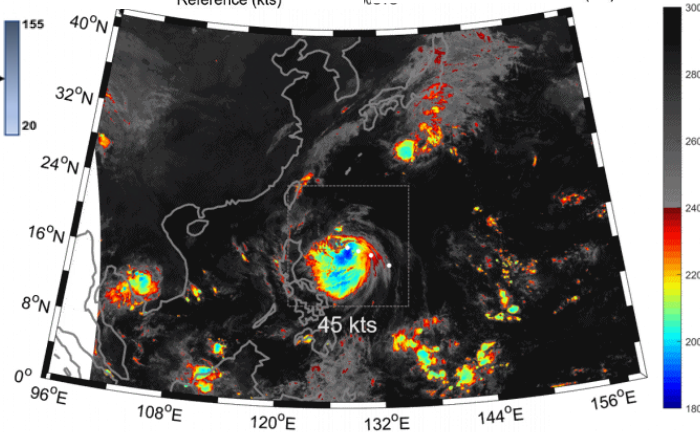
2D-CNNs based estimation results
8.32 kts RMSE



3D-CNNs based estimation results
11.34 kts RMSE

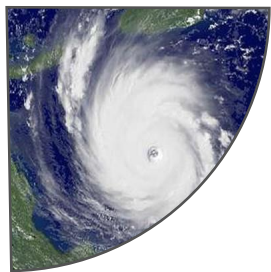


Multi spectral channels-based TC observations using geostationary satellite



Geostationary satellite-based TC intensity estimation every 10 min

인공지능을 활용한 기상/기후 예측

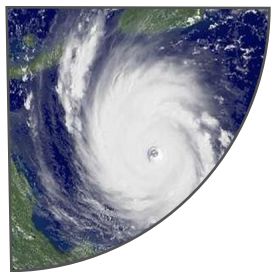


딥러닝 기반 태풍 강도 추정

- 정지궤도 기상위성기반 태풍 관측자료의 적외채널별 패턴을 딥러닝 (2D-/3D-CNNs)을 통해 분석하여 해당 태풍의 강도를 객관적으로 추출함

태풍 강도	딥러닝 모델 기반 태풍의 형태 분석		예보관 학습 자료	태풍 강도	딥러닝 모델 기반 태풍의 형태 분석		예보관 학습 자료
20 (Weak Topical depression)				90 (Category 2)			
30 (Tropical depression)				105 (Category 3)			
35 (Tropical Storm)				115 (Category 4)			
65 (Category 1)				145 (Category 5)			

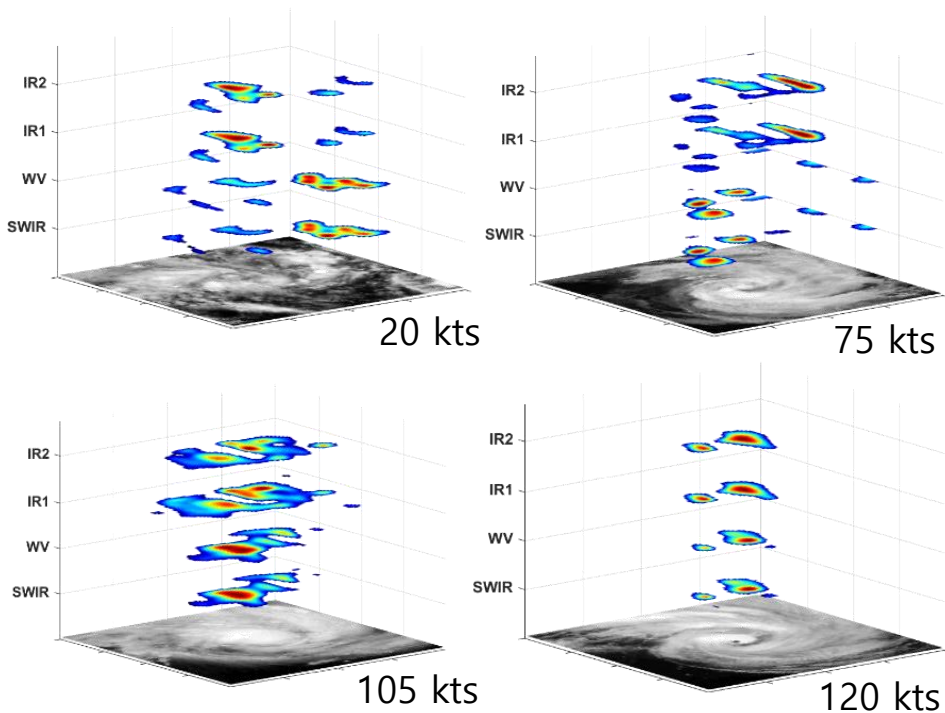
인공지능을 활용한 기상/기후 예측



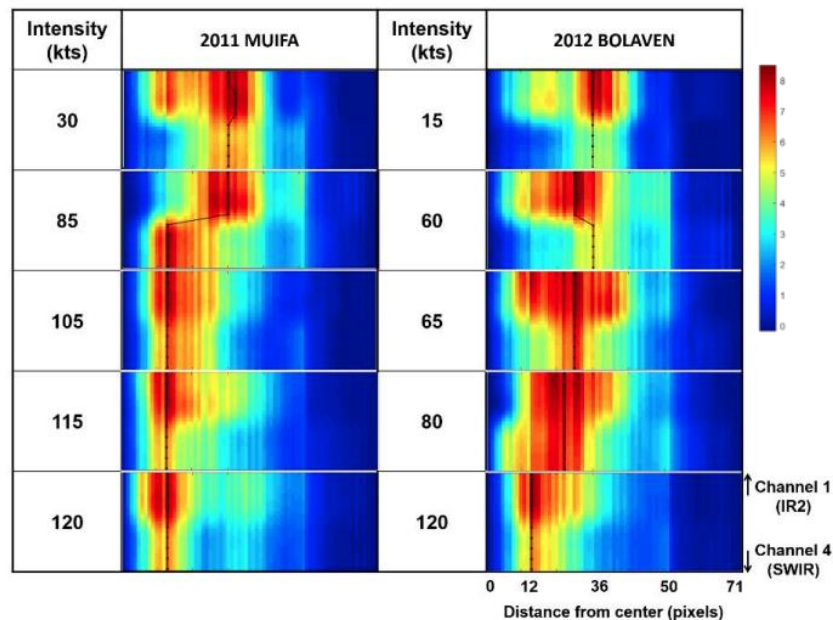
딥러닝 기반 태풍 강도 추정

- 정지궤도 기상위성기반 태풍 관측자료의 적외채널별 패턴을 딥러닝 (2D-/3D-CNNs)을 통해 분석하여 해당 태풍의 강도를 객관적으로 추출함

태풍 강도 별
다중 적외 채널 간 Heat map 분포의 차이



2011 MUIFA, 2012 BOLAVEN 의
강도 별 태풍의 Heat map 분포 분석



인공지능의 한계와 도전 방향



- ❖ AI is not a panacea
- ❖ Require multidisciplinary approaches
- ❖ Knowledge engineers for AI vs. domain experts
- ❖ Limitations of AI
 - Require too much data → no more training data
 - Causation vs. correlation → ExAI (Explainable AI)
 - Limited capacity of transfer; not transparent
 - Not good at modeling unstable situations
 - Locality → Generalization (Expandability)
- ❖ Based on my experience,
 - Good at modeling relatively static environment such as land cover classification
 - Has high uncertainty for modeling dynamic parameters especially when input variables are not well identified in relation with the target variable.
 - Representation is a key to successful AI applications.

인공지능의 한계와 도전 방향

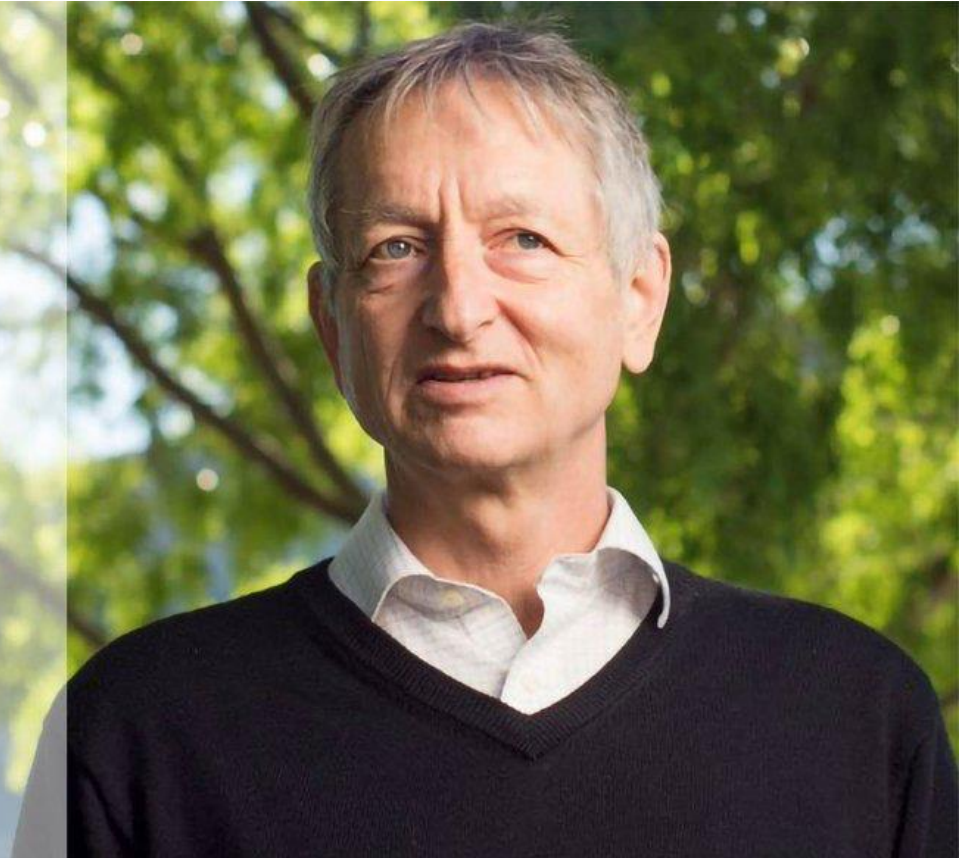


- “Science progresses one funeral at a time.”

“

The future depends on some graduate student who is deeply suspicious of everything I have said.

~ Geoffrey Hinton





Thank you

Questions?
ersgis@unist.ac.kr

