Prolog

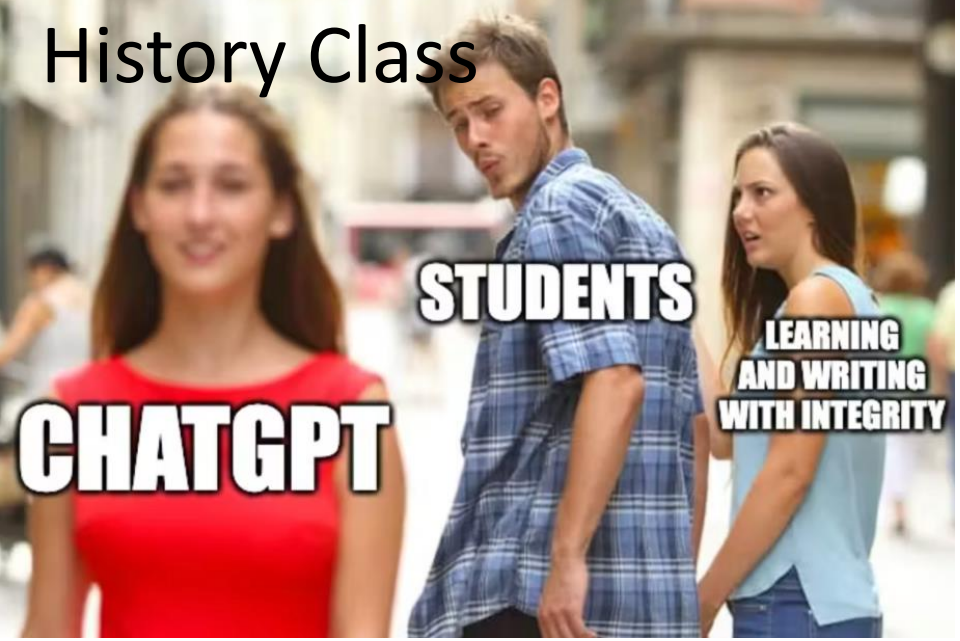
slido

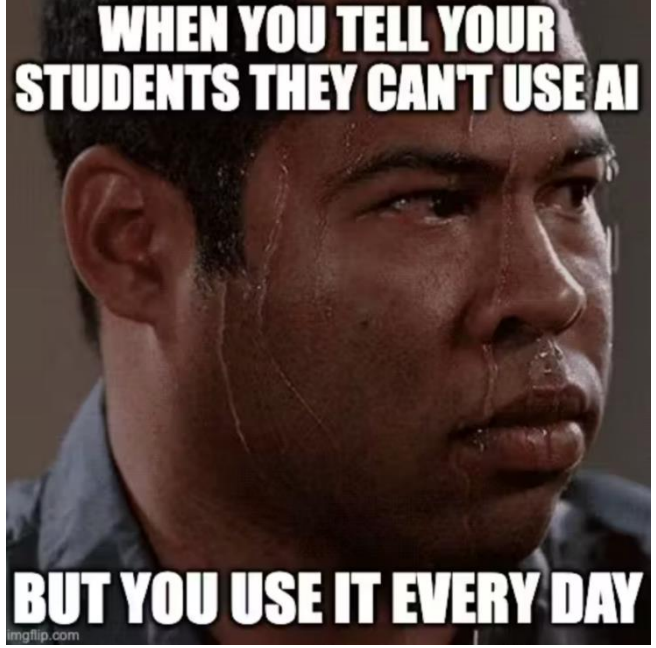
Please download and install the Slido app on all computers you use

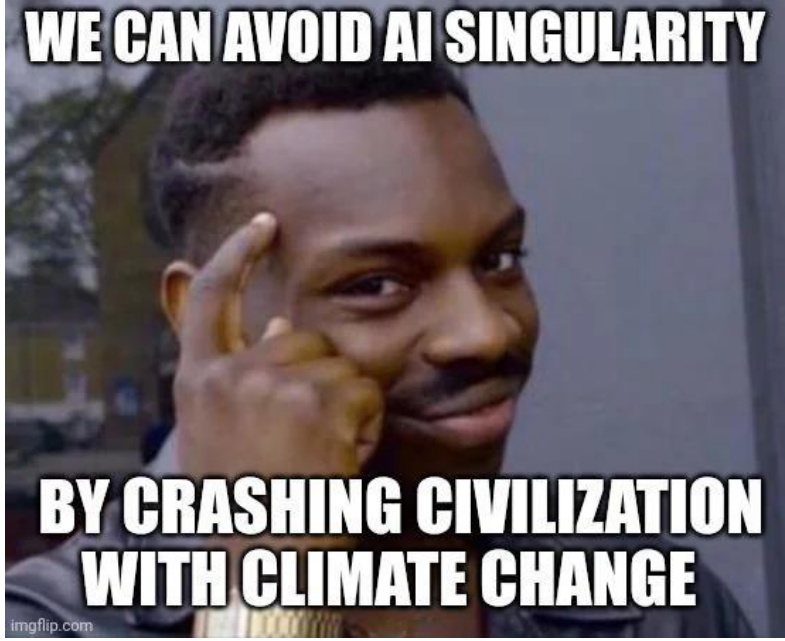


It is called DEEP learning, because ...

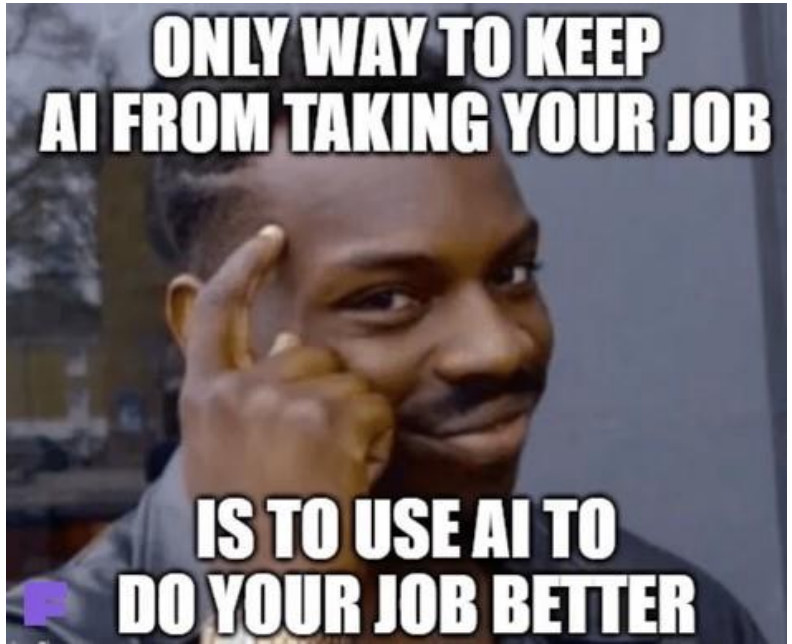
ⓘ Start presenting to display the poll results on this slide.

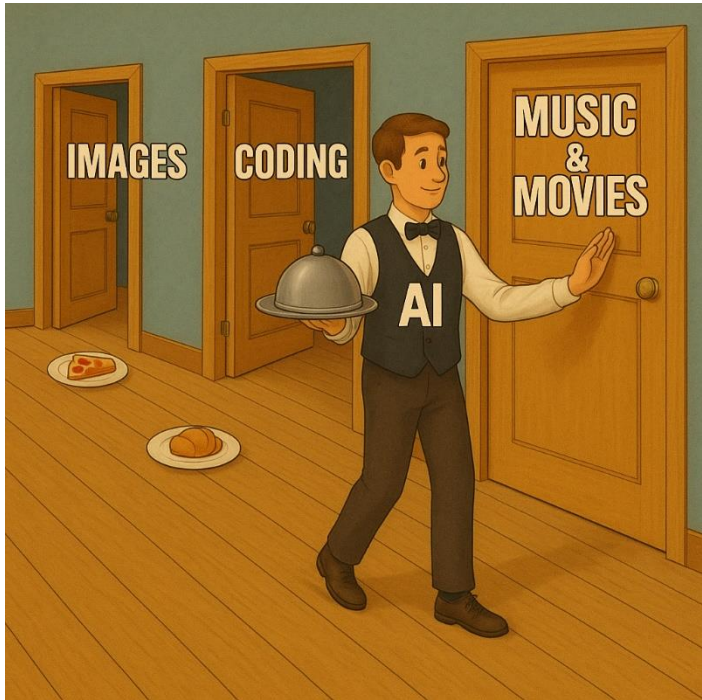

History Class
STUDENTS
LEARNING AND WRITING WITH INTEGRITY
CHATGPT


WHEN YOU TELL YOUR STUDENTS THEY CAN'T USE AI
BUT YOU USE IT EVERY DAY
imgflip.com

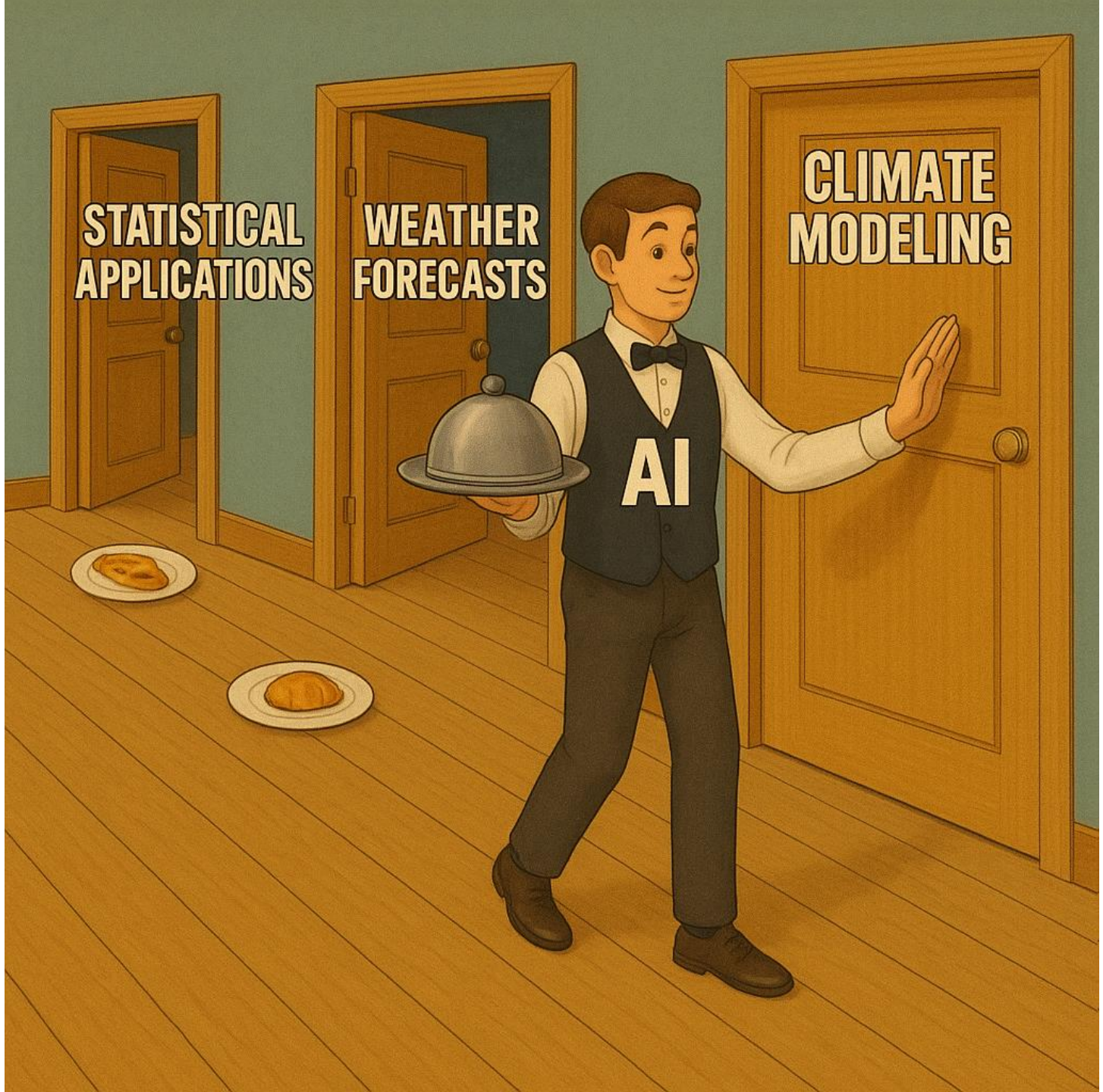

WE CAN AVOID AI SINGULARITY
BY CRASHING CIVILIZATION WITH CLIMATE CHANGE
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5000 YEARS OF ACCUMULATED HUMAN KNOWLEDGE AND KNOWHOW
CHATGPT
Prolog
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ONLY WAY TO KEEP AI FROM TAKING YOUR JOB
IS TO USE AI TO DO YOUR JOB BETTER


IMAGES
CODING
MUSIC & MOVIES
AI

DKRZ


STATISTICAL APPLICATIONS
WEATHER FORECASTS
CLIMATE MODELING
AI

Prolog

Machine Learning in Climate Science MSc Class in *Ocean and Climate Physics*
!Open for Computer Science!



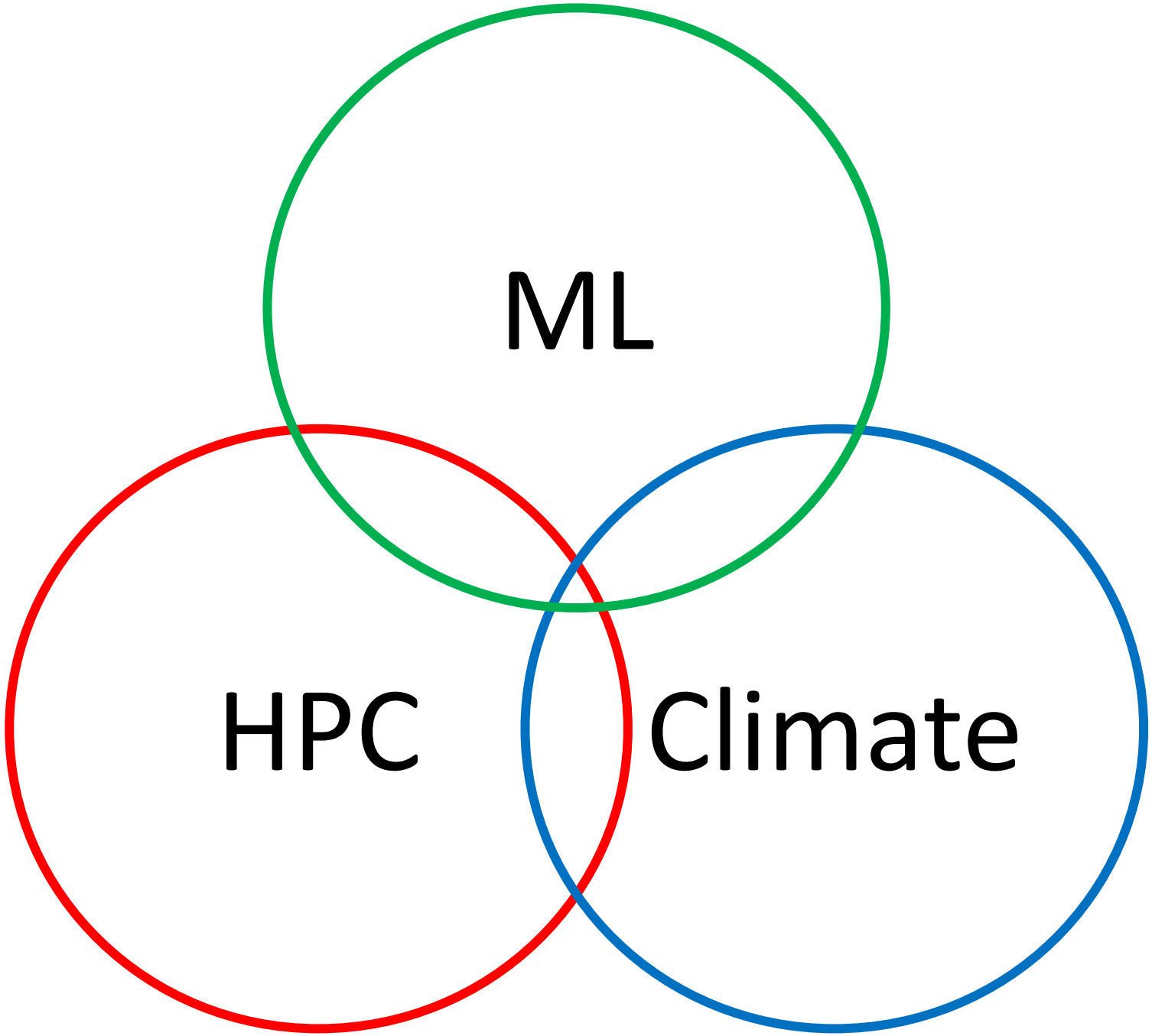
UHH Vorlesung „Hochleistungsrechnen“
Machine Learning in Climate Science on Super Computers
Introduction and Research

Christopher Kadow

German Climate Computing Center

DKRZ
DEUTSCHES KLIMARECHENZENTRUM

Class @ UHH
BSc/MSc Studies
Nov, 17 2026


ML
HPC
Climate

German Climate Computing Center

HLRE-3 – Mistral (2015-2021)



BULLX CPU **3.6 Pflops**

GPU-blades

21x VIS-GPGPU nodes (K80, M40, Quadro)
256-1024GB RAM 12GB VRAM

2x V100 512GB RAM 32GB VRAM

HLRE-4 – Levante (2022-202X)



ATOS CPU/GPU blades **17 Pflops**

GPU-blades

1 node: 2 AMD EPYC **+ 4 NVIDIA A100**

58x nodes 2x 512GB RAM 4x 40/80GB VRAM

2x nodes 2x 1024GB RAM 4x 40GB VRAM

1 node: **4 NVIDIA GH200** (4× Grace 72-core ARM + 4× Hopper GPU)

42x nodes 4x480 GB RAM 4× 96 GB VRAM

Agenda *Introduction and Research*



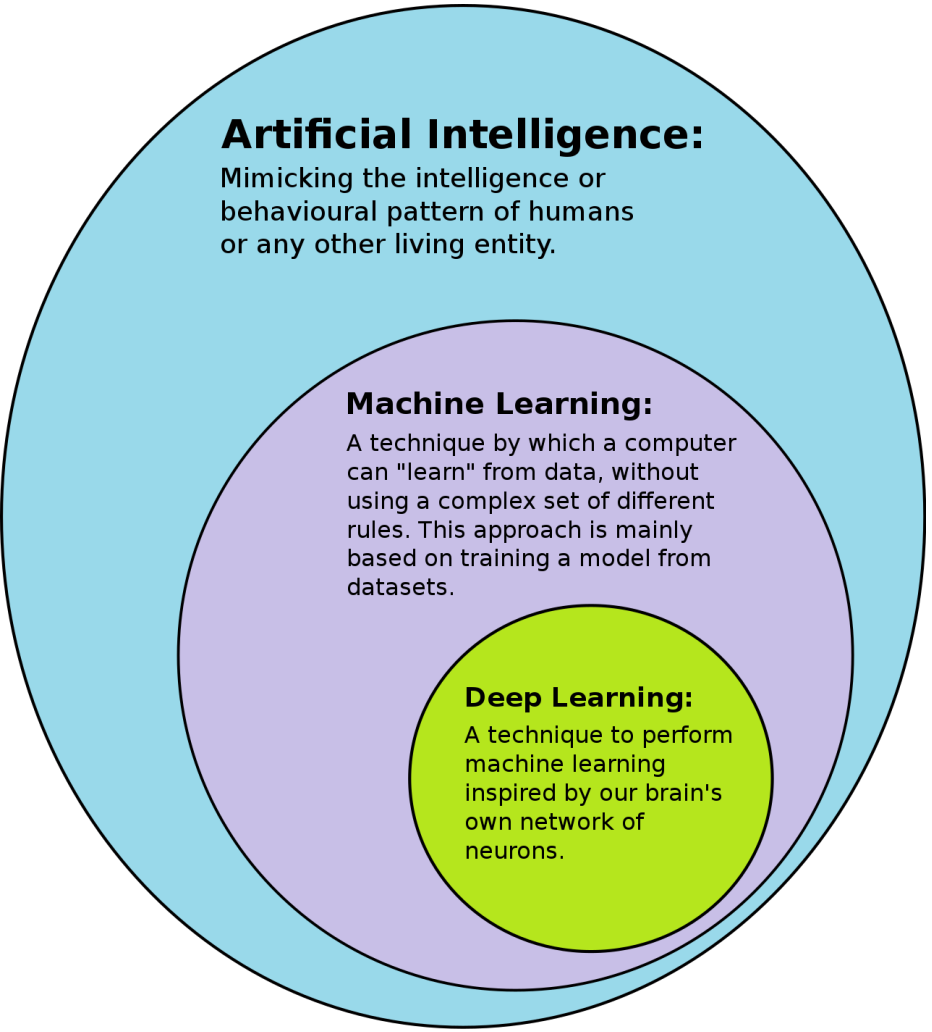
- General
  - DL, ML, AI? WTF? Literature?
  - What is a Neural Network?
- Methods & Networks
  - Supervised Learning, Unsupervised Learning, Reinforcement Learning
  - Convolutional Neural Network, Recurrent Neural Network, Generative Adversal Network
- Hardware & Software
  - PCs, HPCs, Clouds
  - Tools, Frameworks, Applications
- AI reconstructs missing Climate Information
  - A Research Journey
  - Transfer Learning
  - What is next?



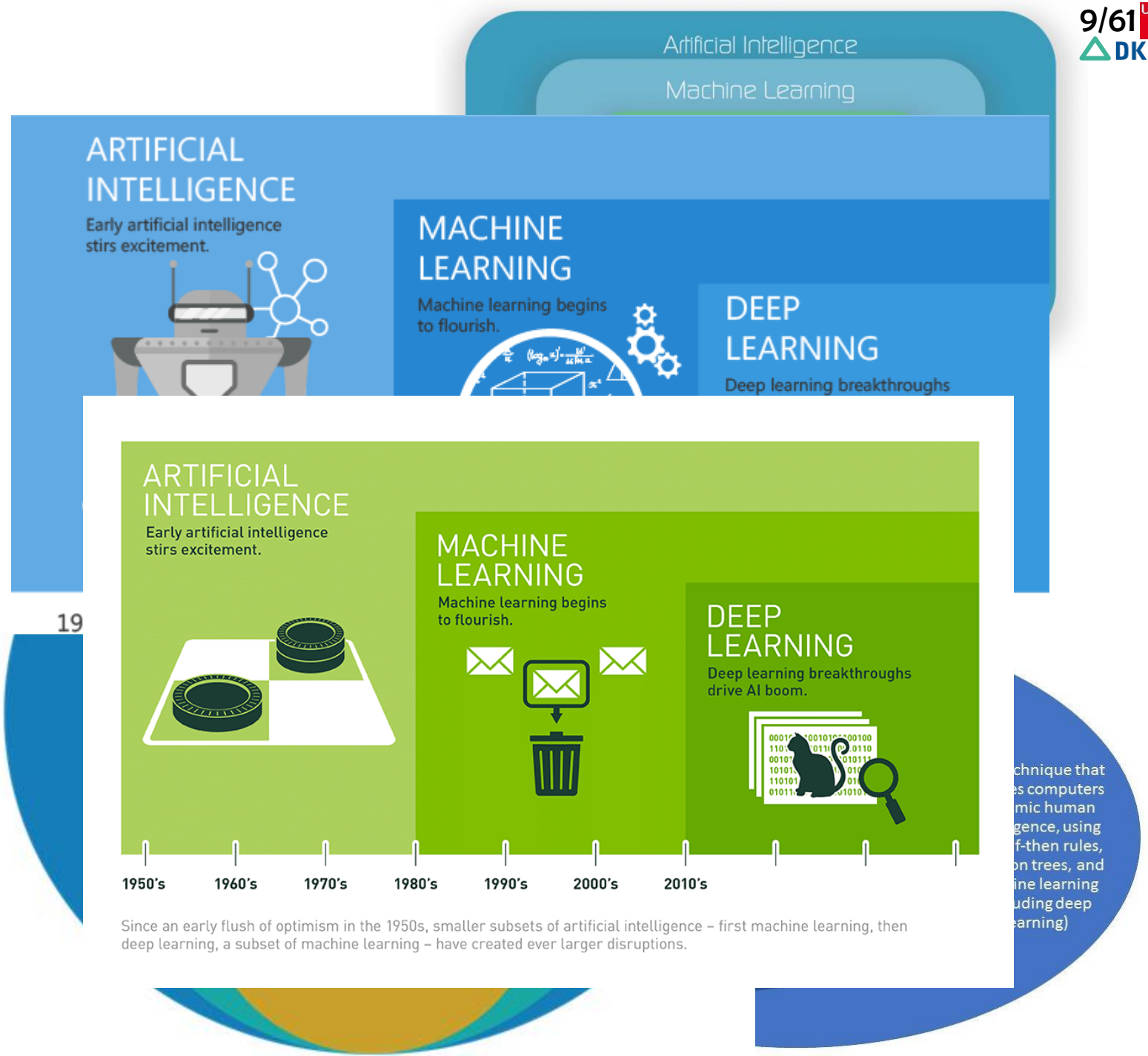


General

General



Wikipedia.com



General

Data Science

- Need of entire analytics universe
- Branch that deals with data
- Different operations related to data i.e.
  - Data Gathering
  - Data Cleaning
  - Data Subsetting
  - Data Manipulation
  - Data Insights [Data Mining]

Machine Learning

- Combination of Machine and Data Science
- Machines utilize Data Science techniques to learn about the data hence called as Machine Learning
- Model Building, Model Evaluation and Validation
- 3 Types:
  - Unsupervised Learning
  - Reinforcement Learning
  - Supervised Learning
- Most popular tools are Python, R and SAS

Deep Learning

- Specific branch of Machine Learning that deals with different flavours of Neural Network
- Examples
  - Simple Neural Network
  - Convolutional Neural Network
  - Recurrent Neural Network
  - Long Short Term Memory
- Mainly utilized in..
  - Object detection in Image and Video
  - Speech Recognition
  - Natural Language Processing and Understandings

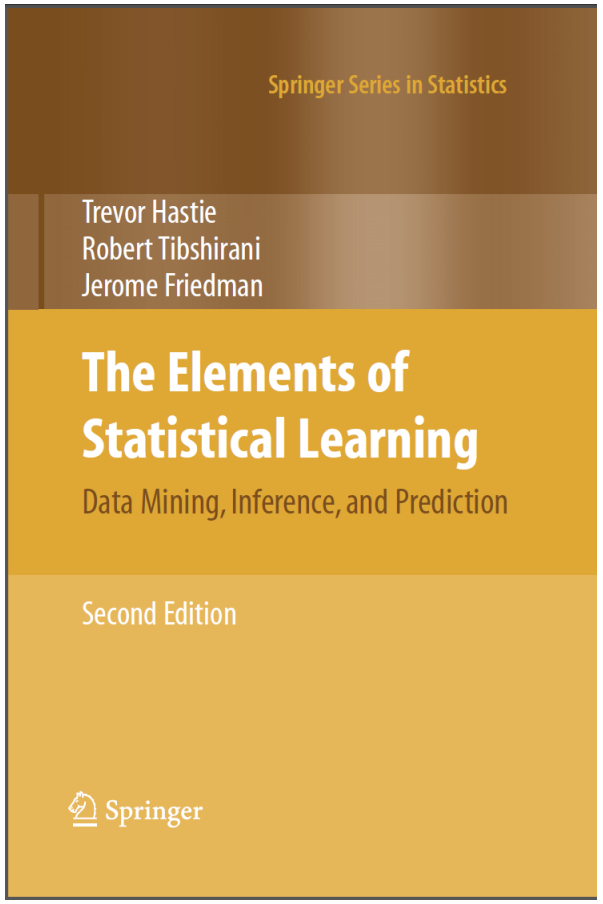
Artificial Intelligence

- Big Umbrella
- Empowering machines to take decisions on their own
- As the name suggest imparting humans' natural intelligence in machines
- Thus machines have ability to understand and react according to the situation

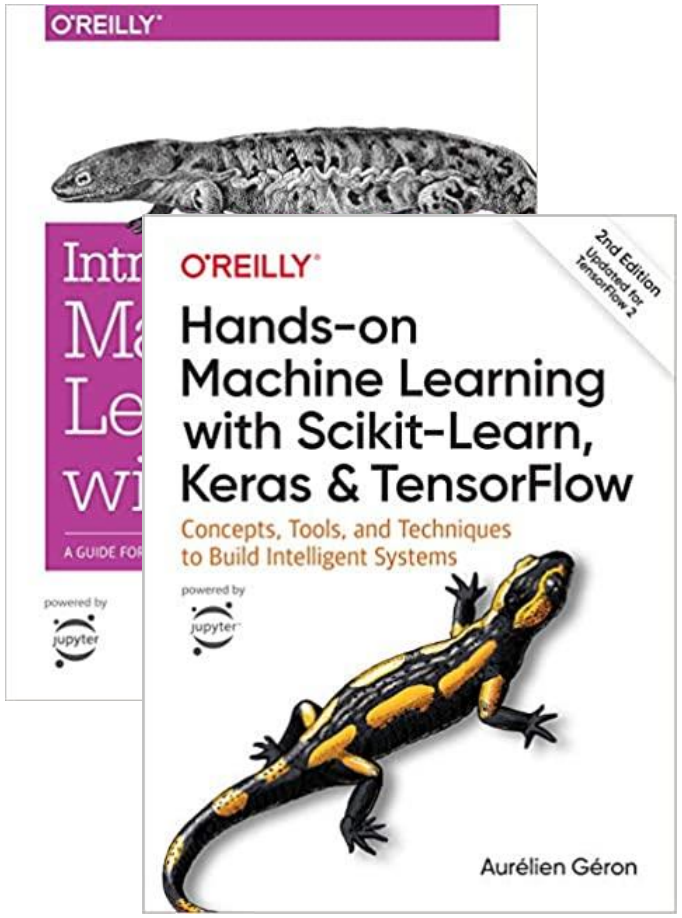
https://mc.ai

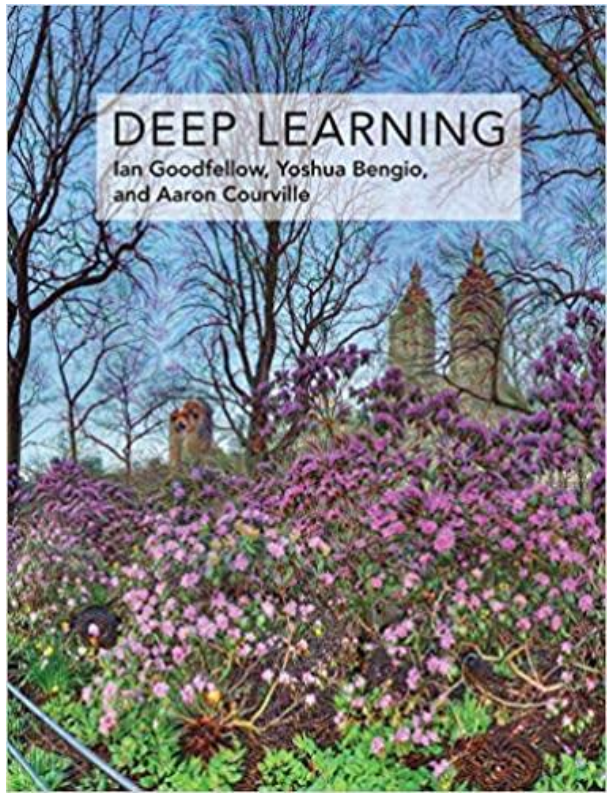
Literature

Books

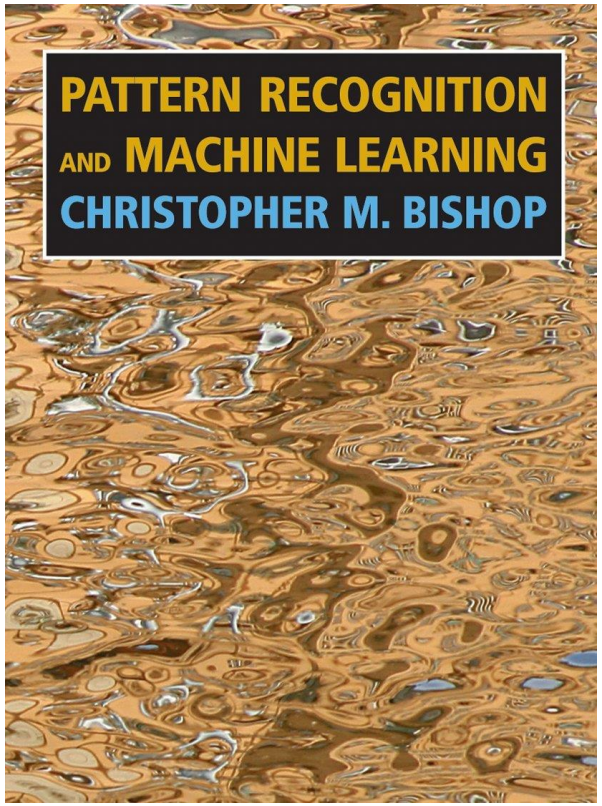


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General

Literature

German



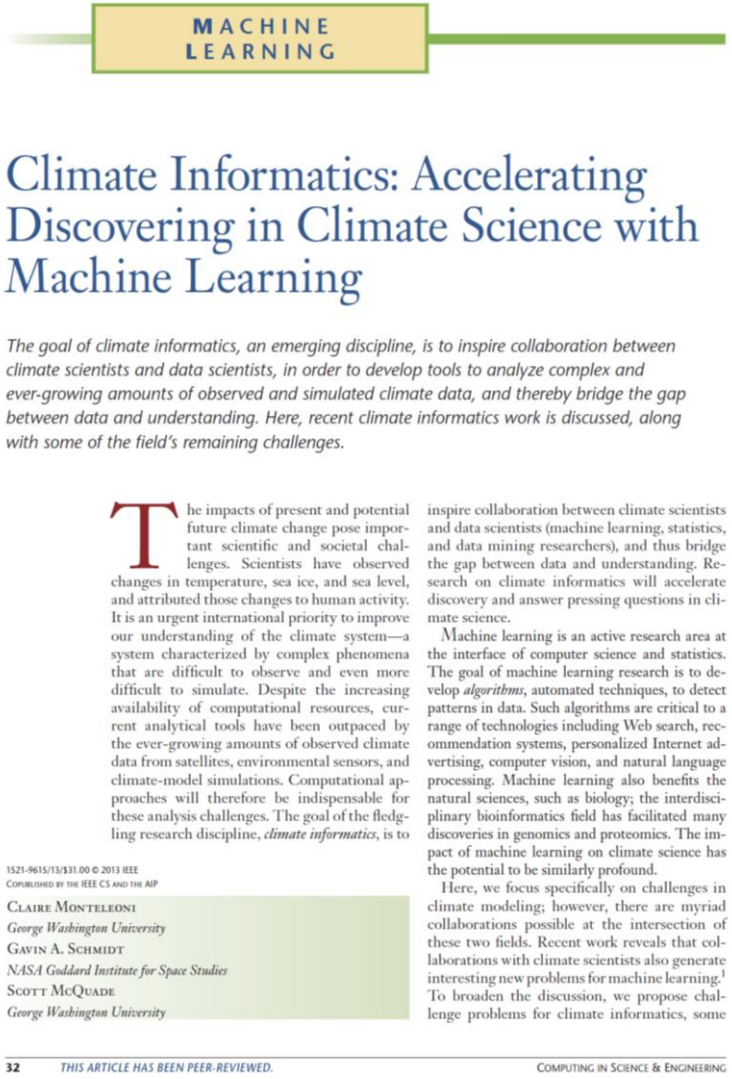
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PDF and Printed

PDF



MACHINE LEARNING

Climate Informatics: Accelerating Discovering in Climate Science with Machine Learning

The goal of climate informatics, an emerging discipline, is to inspire collaboration between climate scientists and data scientists, in order to develop tools to analyze complex and ever-growing amounts of observed and simulated climate data, and thereby bridge the gap between data and understanding. Here, recent climate informatics work is discussed, along with some of the field's remaining challenges.

The impacts of present and potential future climate change pose important scientific and societal challenges. Scientists have observed changes in temperature, sea ice, and sea level, and attributed those changes to human activity. It is an urgent international priority to improve our understanding of the climate system—a system characterized by complex phenomena that are difficult to observe and even more difficult to simulate. Despite the increasing availability of computational resources, current analytical tools have been outpaced by the ever-growing amounts of observed climate data from satellites, environmental sensors, and climate-model simulations. Computational approaches will therefore be indispensable for these analysis challenges. The goal of the fledgling research discipline, *climate informatics*, is to inspire collaboration between climate scientists and data scientists (machine learning, statistics, and data mining researchers), and thus bridge the gap between data and understanding. Research on climate informatics will accelerate discovery and answer pressing questions in climate science.

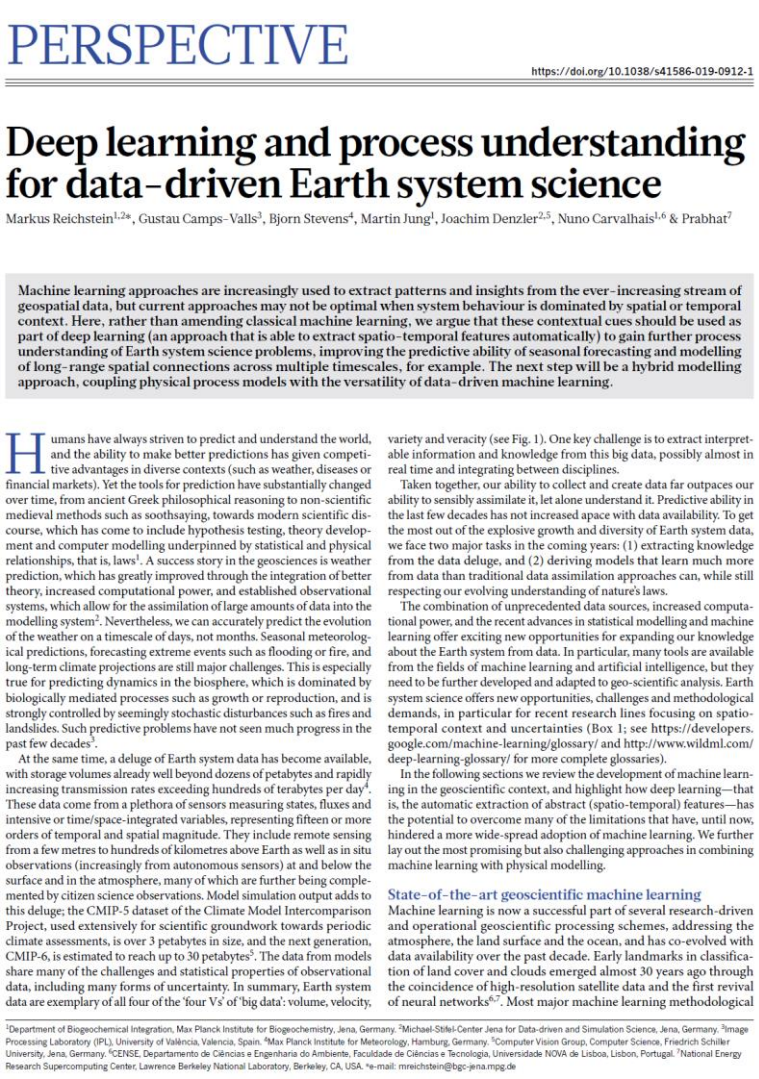
Machine learning is an active research area at the interface of computer science and statistics. The goal of machine learning research is to develop *algorithms*, automated techniques, to detect patterns in data. Such algorithms are critical to a range of technologies including Web search, recommendation systems, personalized Internet advertising, computer vision, and natural language processing. Machine learning also benefits the natural sciences, such as biology; the interdisciplinary bioinformatics field has facilitated many discoveries in genomics and proteomics. The impact of machine learning on climate science has the potential to be similarly profound.

Here, we focus specifically on challenges in climate modeling; however, there are myriad collaborations possible at the intersection of these two fields. Recent work reveals that collaborations with climate scientists also generate interesting new problems for machine learning.[1] To broaden the discussion, we propose challenge problems for climate informatics, some

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George Washington University

Monteleoni, C., G.A. Schmidt, and S. McQuade, 2013: Climate informatics: Accelerating discovering in climate science with machine learning. *Comput. Sci. Eng.*, **15**, 32-41, doi:10.1109/MCSE.2013.50.



PERSPECTIVE

https://doi.org/10.1038/s41586-019-0912-1

Deep learning and process understanding for data-driven Earth system science

Markus Reichstein[1,2]*, Gustau Camps-Valls[3], Bjorn Stevens[4], Martin Jung[1], Joachim Denzler[2,5], Nuno Carvalhais[1,6] & Prabhat[7]

Machine learning approaches are increasingly used to extract patterns and insights from the ever-increasing stream of geospatial data, but current approaches may not be optimal when system behaviour is dominated by spatial or temporal context. Here, rather than amending classical machine learning, we argue that these contextual cues should be used as part of deep learning (an approach that is able to extract spatio-temporal features automatically) to gain further process understanding of Earth system science problems, improving the predictive ability of seasonal forecasting and modelling of long-range spatial connections across multiple timescales, for example. The next step will be a hybrid modelling approach, coupling physical process models with the versatility of data-driven machine learning.

Humans have always striven to predict and understand the world, and the ability to make better predictions has given competitive advantages in diverse contexts (such as weather, diseases or financial markets). Yet the tools for prediction have substantially changed over time, from ancient Greek philosophical reasoning to non-scientific medieval methods such as soothsaying, towards modern scientific discourse, which has come to include hypothesis testing, theory development and computer modelling underpinned by statistical and physical relationships, that is, laws[1]. A success story in the geosciences is weather prediction, which has greatly improved through the integration of better theory, increased computational power, and established observational systems, which allow for the assimilation of large amounts of data into the modelling system[2]. Nevertheless, we can accurately predict the evolution of the weather on a timescale of days, not months. Seasonal meteorological predictions, forecasting extreme events such as flooding or fire, and long-term climate projections are still major challenges. This is especially true for predicting dynamics in the biosphere, which is dominated by biologically mediated processes such as growth or reproduction, and is strongly controlled by seemingly stochastic disturbances such as fires and landslides. Such predictive problems have not seen much progress in the past few decades[3].

At the same time, a deluge of Earth system data has become available, with storage volumes already well beyond dozens of petabytes and rapidly increasing transmission rates exceeding hundreds of terabytes per day[4]. These data come from a plethora of sensors measuring states, fluxes and intensive or time/space-integrated variables, representing fifteen or more orders of temporal and spatial magnitude. They include remote sensing from a few metres to hundreds of kilometres above Earth as well as in situ observations (increasingly from autonomous sensors) at and below the surface and in the atmosphere, many of which are further being complemented by citizen science observations. Model simulation output adds to this deluge; the CMIP-5 dataset of the Climate Model Intercomparison Project, used extensively for scientific groundwork towards periodic climate assessments, is over 3 petabytes in size, and the next generation, CMIP-6, is estimated to reach up to 30 petabytes[5]. The data from models share many of the challenges and statistical properties of observational data, including many forms of uncertainty. In summary, Earth system data are exemplary of all four of the 'four Vs' of 'big data': volume, velocity, variety and veracity (see Fig. 1). One key challenge is to extract interpretable information and knowledge from this big data, possibly almost in real time and integrating between disciplines.

Taken together, our ability to collect and create data far outpaces our ability to sensibly assimilate it, let alone understand it. Predictive ability in the last few decades has not increased apace with data availability. To get the most out of the explosive growth and diversity of Earth system data, we face two major tasks in the coming years: (1) extracting knowledge from the data deluge, and (2) deriving models that learn much more from data than traditional data assimilation approaches can, while still respecting our evolving understanding of nature's laws.

The combination of unprecedented data sources, increased computational power, and the recent advances in statistical modelling and machine learning offer exciting new opportunities for expanding our knowledge about the Earth system from data. In particular, many tools are available from the fields of machine learning and artificial intelligence, but they need to be further developed and adapted to geo-scientific analysis. Earth system science offers new opportunities, challenges and methodological demands, in particular for recent research lines focusing on spatio-temporal context and uncertainties (Box 1; see https://developers.google.com/machine-learning/glossary/ and http://www.wildml.com/deep-learning-glossary/ for more complete glossaries).

In the following sections we review the development of machine learning in the geoscientific context, and highlight how deep learning—that is, the automatic extraction of abstract (spatio-temporal) features—has the potential to overcome many of the limitations that have, until now, hindered a more wide-spread adoption of machine learning. We further lay out the most promising but also challenging approaches in combining machine learning with physical modelling.

State-of-the-art geoscientific machine learning

Machine learning is now a successful part of several research-driven and operational geoscientific processing schemes, addressing the atmosphere, the land surface and the ocean, and has co-evolved with data availability over the past decade. Early landmarks in classification of land cover and clouds emerged almost 30 years ago through the coincidence of high-resolution satellite data and the first revival of neural networks[6,7]. Most major machine learning methodological

[1]Department of Biogeochemical Integration, Max Planck Institute for Biogeochemistry, Jena, Germany. [2]Michael-Stifel-Center Jena for Data-driven and Simulation Science, Jena, Germany. [3]Image Processing Laboratory (IPL), University of València, Valencia, Spain. [4]Max Planck Institute for Meteorology, Hamburg, Germany. [5]Computer Vision Group, Computer Science, Friedrich Schiller University, Jena, Germany. [6]CENSE, Departamento de Ciências e Engenharia do Ambiente, Faculdade de Ciências e Tecnologia, Universidade NOVA de Lisboa, Lisbon, Portugal. [7]National Energy Research Supercomputing Center, Lawrence Berkeley National Laboratory, Berkeley, CA, USA. *e-mail: mreichstein@bgc-jena.mpg.de

Reichstein, M., Camps-Valls, G., **Stevens, B**. *et al.* Deep learning and process understanding for data-driven Earth system science. *Nature* **566,** 195–204 (2019). https://doi.org/10.1038/s41586-019-0912-1

General

Inputs

Source data fed into the neural network, with the goal of making a decision or prediction about the data.

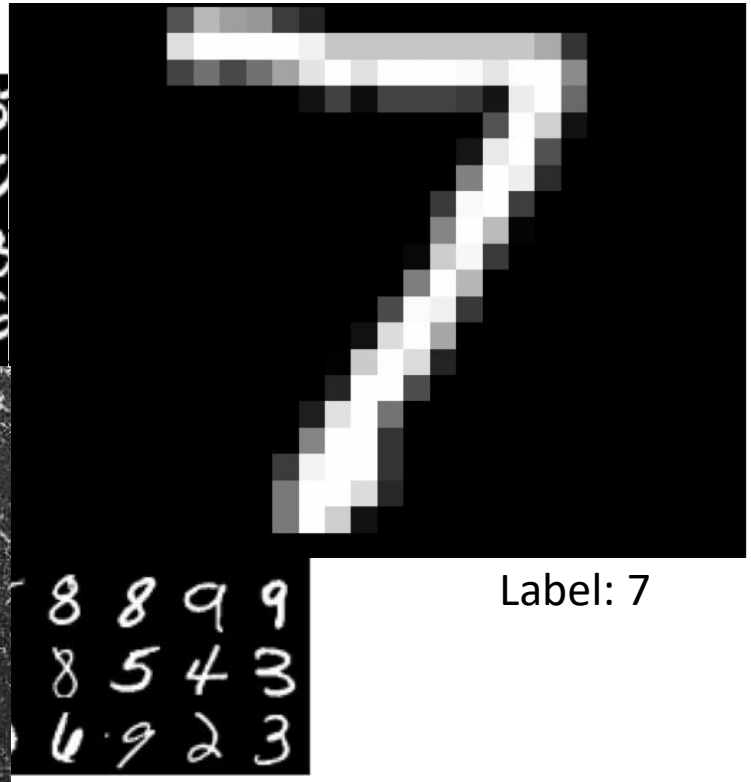


Label: Cat



IMAGENET





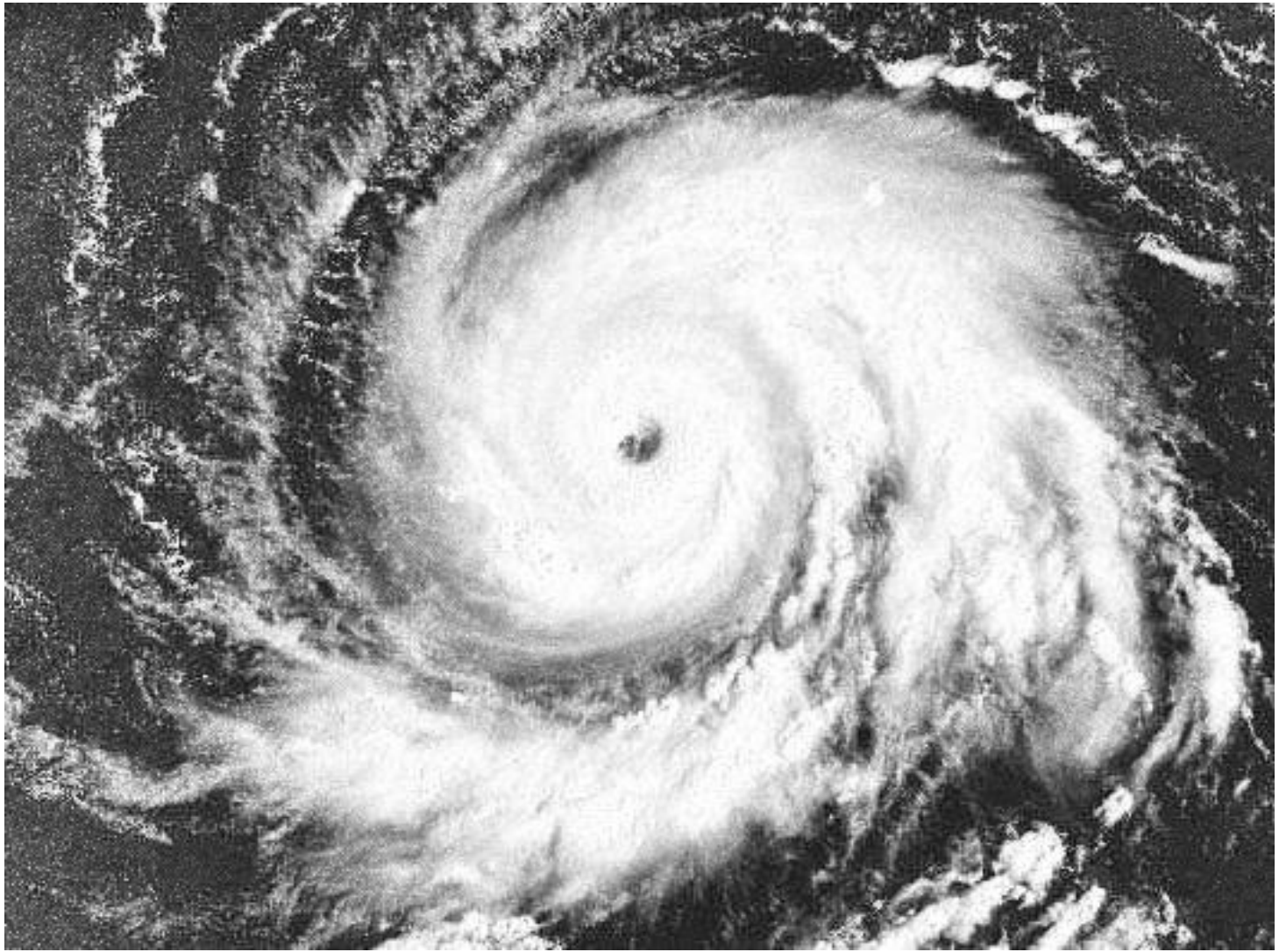
Label: 7

MNIST

General

Inputs

Source data fed into the neural network, with the goal of making a decision or prediction about the data.



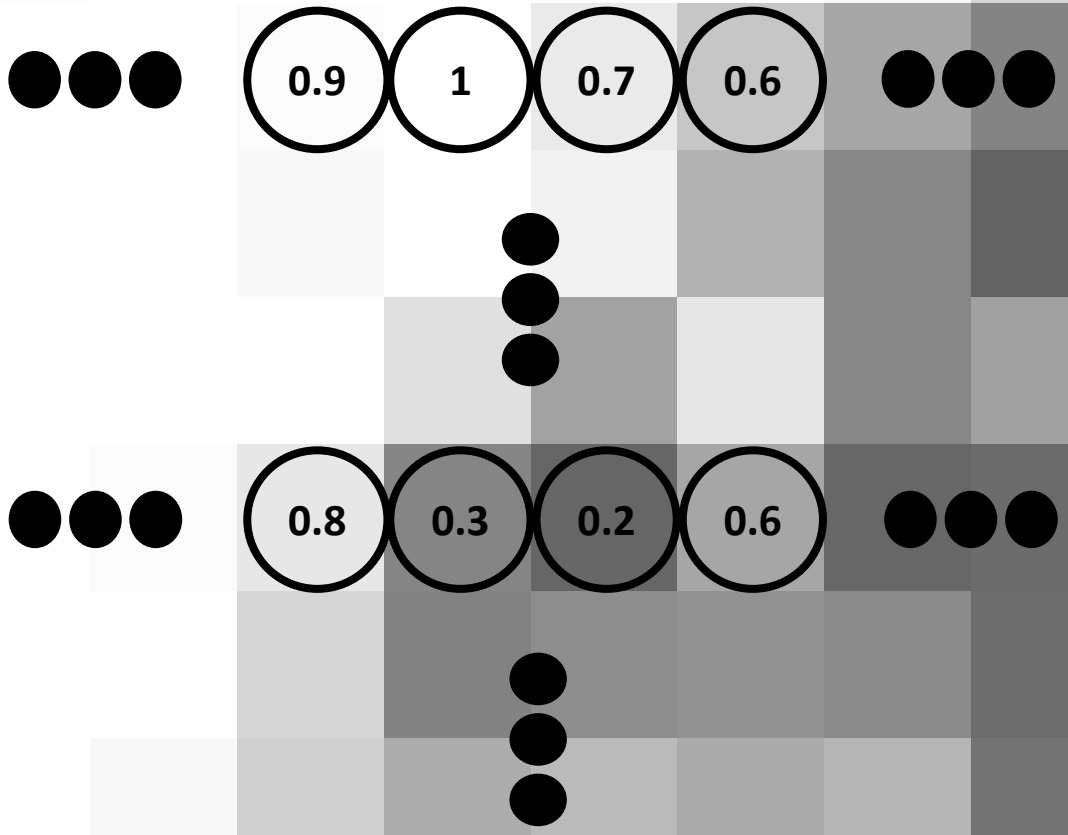
General

Inputs

Source data fed into the neural network, with the goal of making a decision or prediction about the data. The data is broken down into binary signals, to allow it to be processed by single neurons—for example an image is input as individual pixels.

Training, Validation, Test Set

A set of outputs for which the correct outputs are known, which can be used to train the neural networks.



General

Inputs

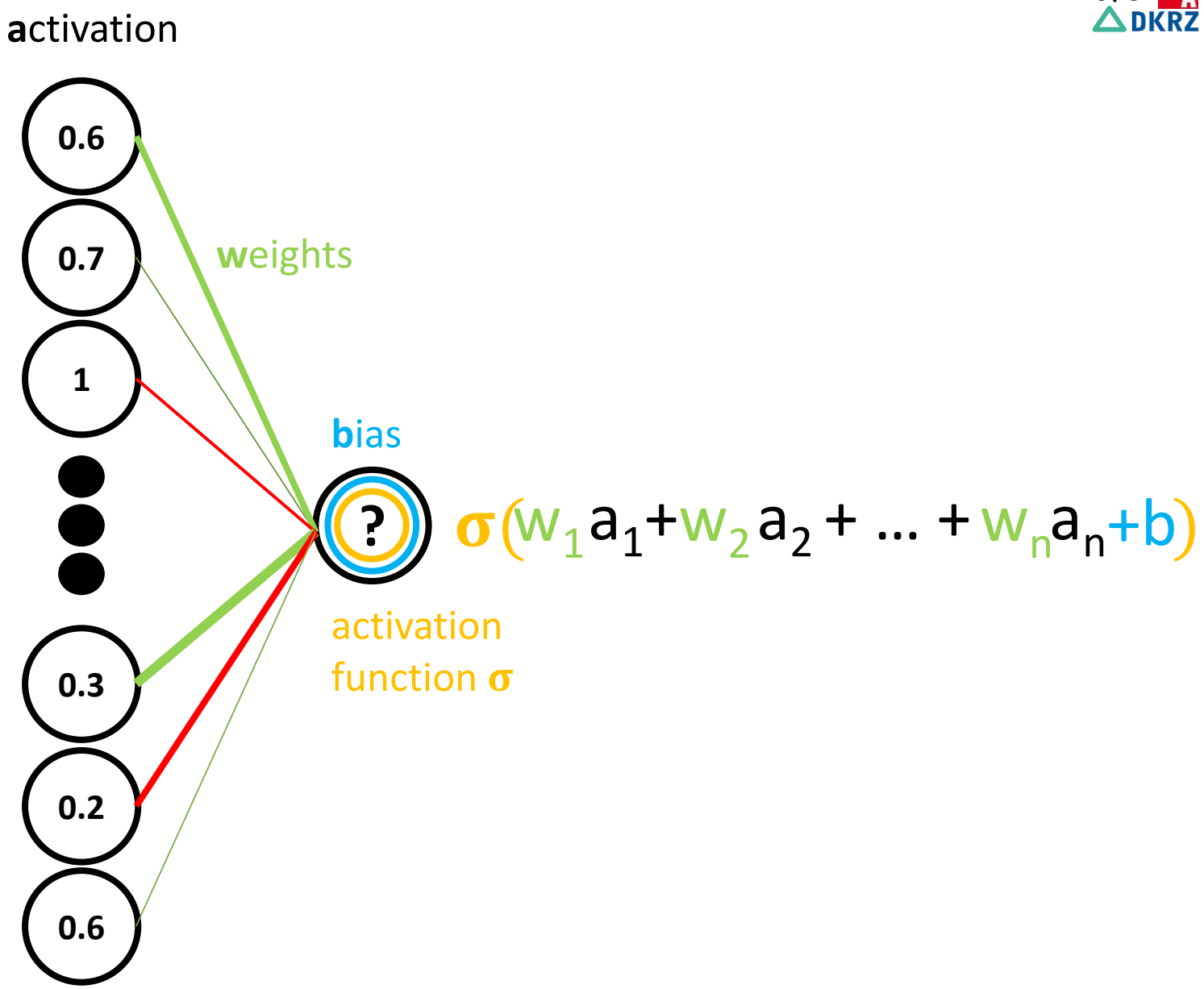
Training, Validation, Test Set

Initialization

Setting the weights at the beginning, before the model is trained. A typical strategy in neural networks is to initialize the weights randomly, and then start optimizing from there.

Activation Function

Each neuron accepts part of the input and passes it through the activation function. Commonly used functions are the sigmoid function, tanh and ReLu.



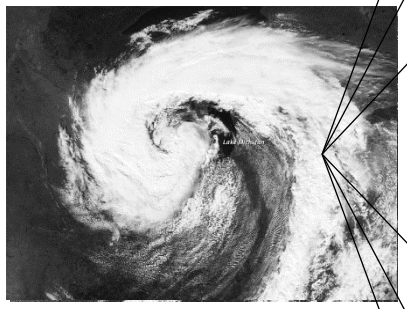
General

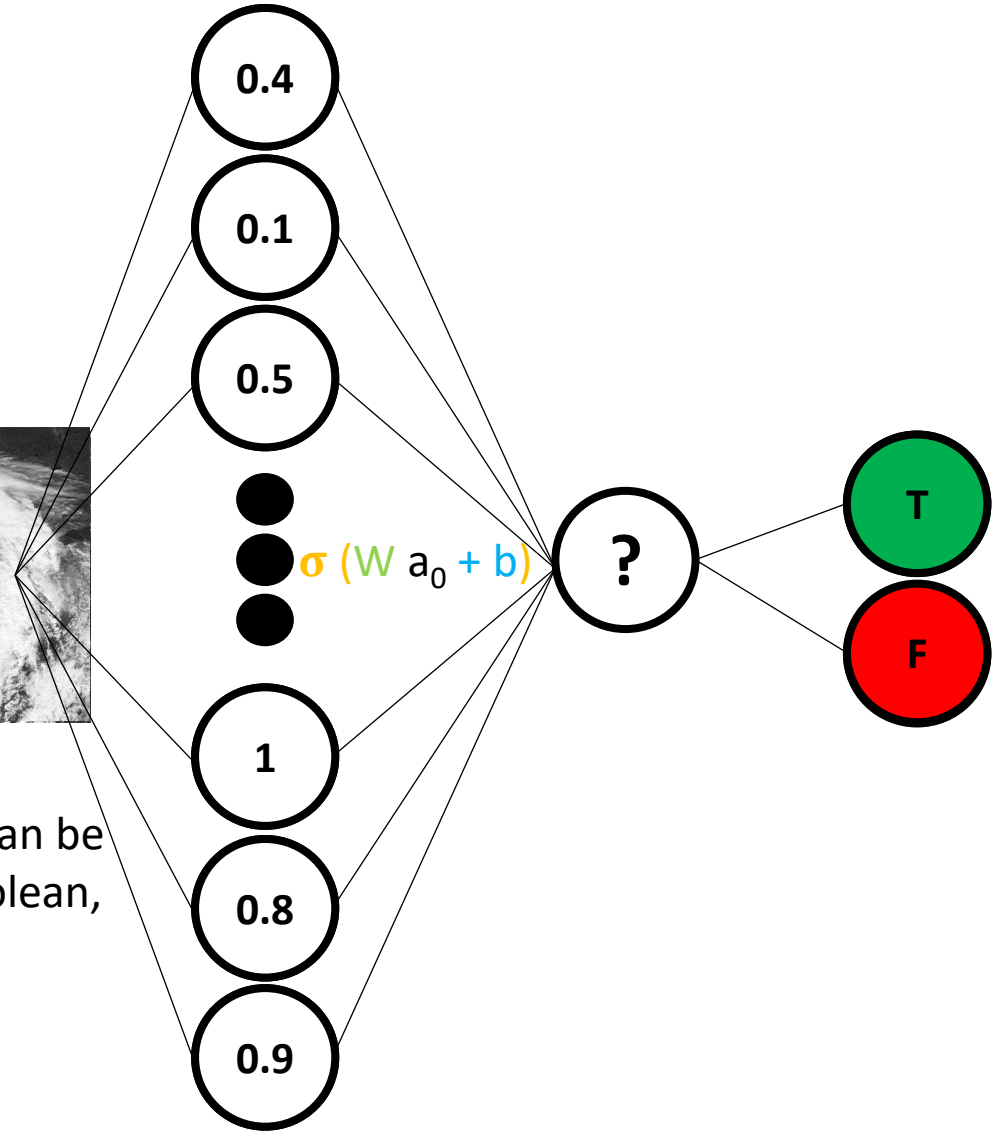
Inputs

Training, Validation, Test Set

Initialization

Activation Function





Outputs

The output of the neural network can be a real value between 0 and 1, a boolean, or a discrete value (for example, a category ID).

Weight Space

Each neuron is given a numeric weight. The weights, applied to the activation function, determine each neuron's output. In training of a deep learning model, the objective is to discover the weights that can generate the most accurate output.

General

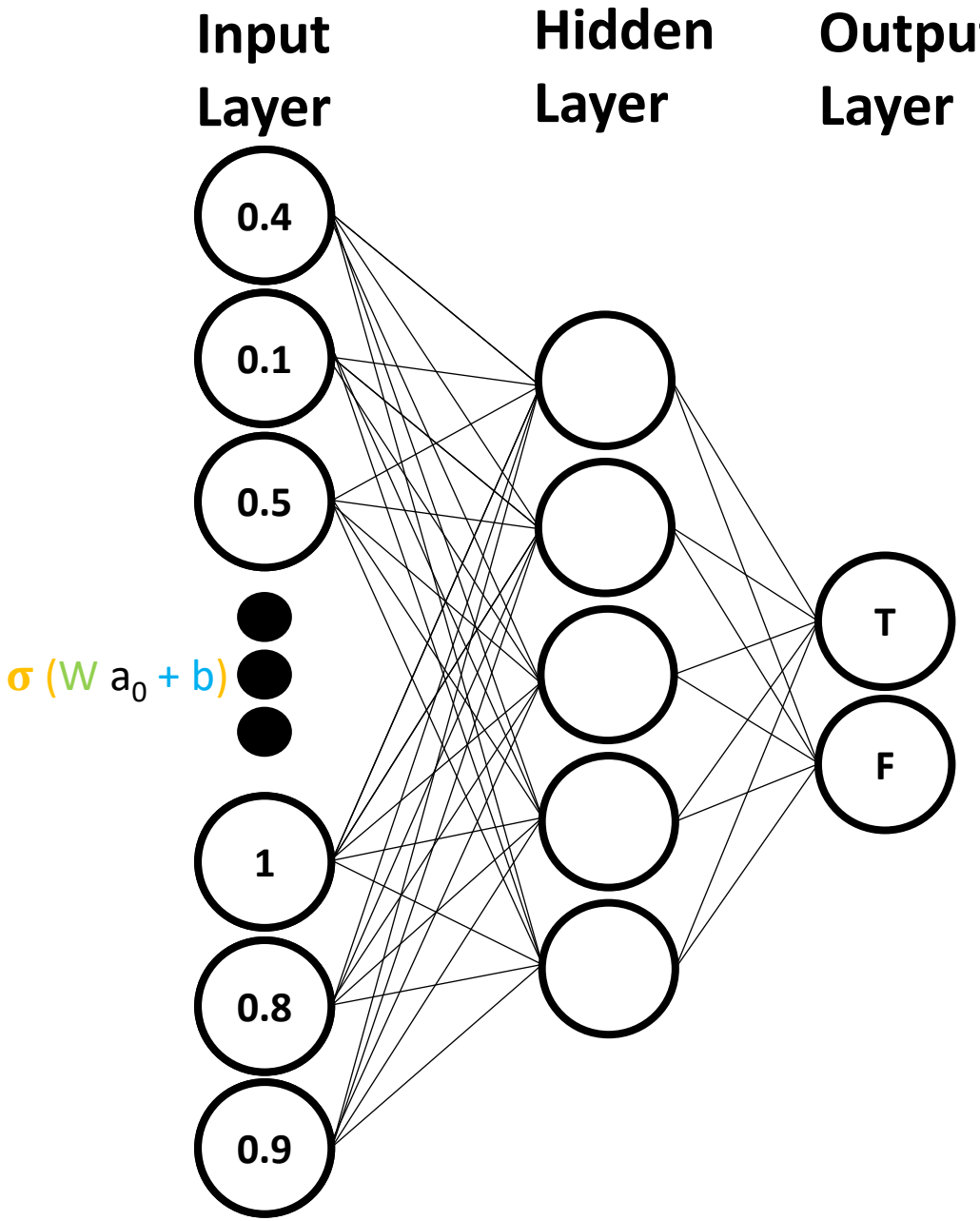
Inputs

Training, Validation, Test Set

Initialization

Activation Function

Outputs

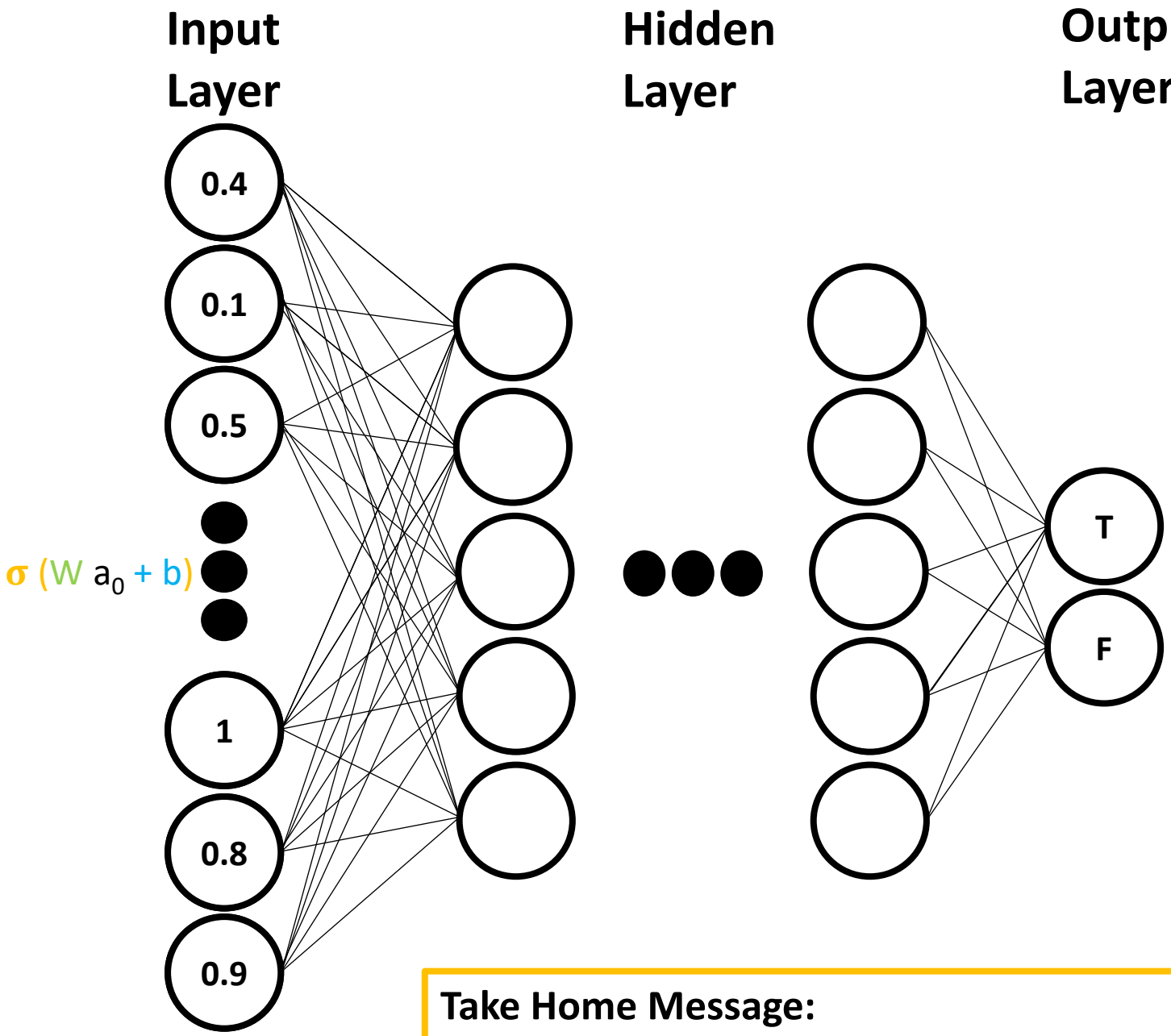


Weight Space

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General

- Inputs
- Training, Validation, Test Set
- Initialization
- Activation Function
- Outputs
- Weight Space



Take Home Message:

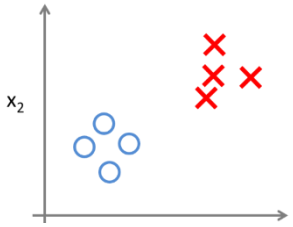
- *Neurons are mathematical functions*
- *Deep Learning* needs Hidden Layers

Adapted from missinglink.ai

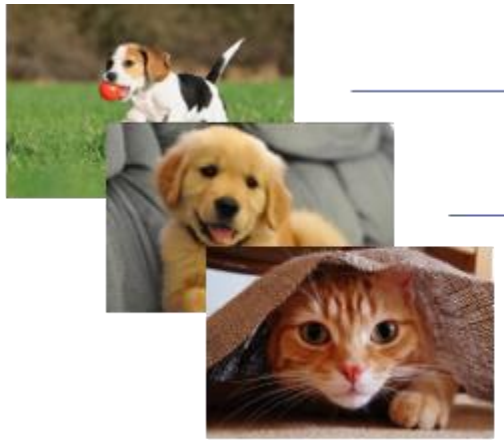
Methods

Methods

Machine Learning → Supervised Learning

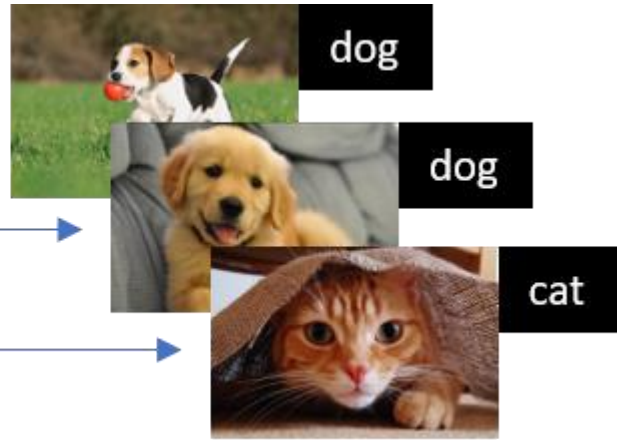


Example:

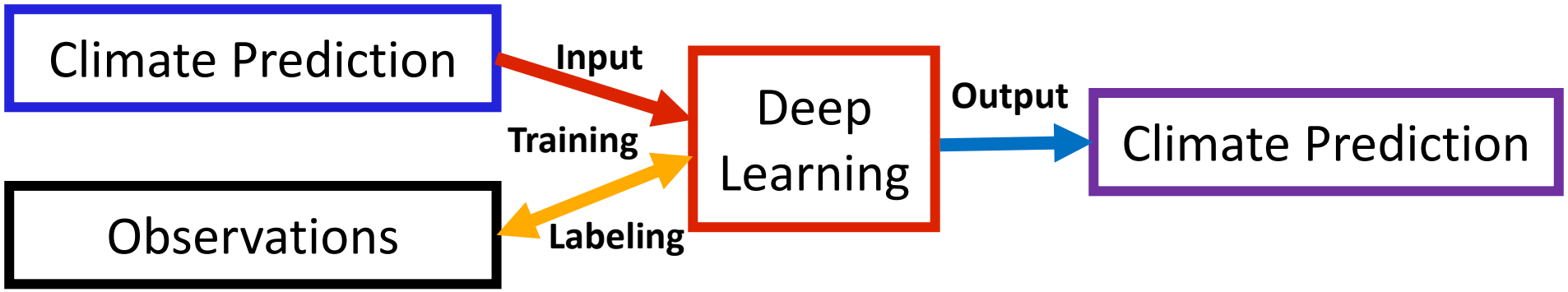


Supervised ML algorithm

allagora.wordpress.com



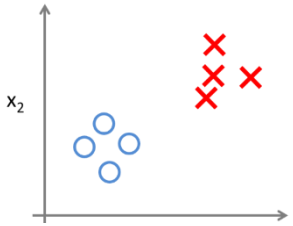
Research:



Methods

Machine Learning

Supervised Learning



TWO MINUTE PAPERS

YouTube

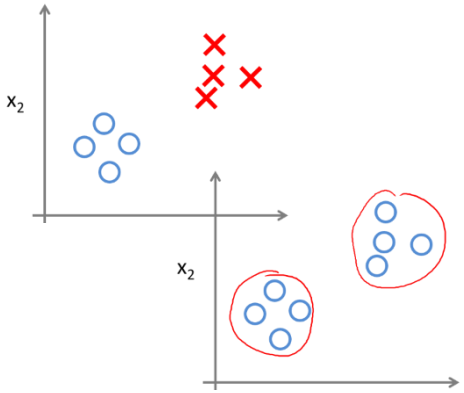




Methods

Machine Learning

- Supervised Learning
- Unsupervised Learning



Example:



Unsupervised ML algorithm





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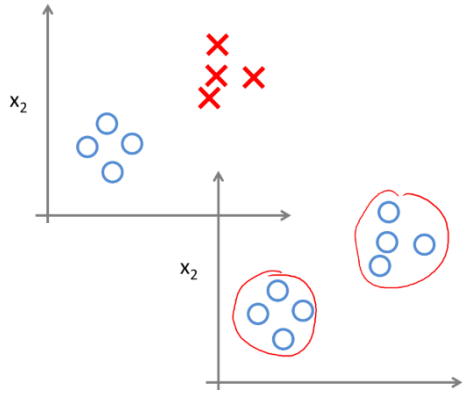
Research:

Climate Observation → **Input** → Deep Learning → Climate Observation / Climate Observation



Methods

- Machine Learning
  - Supervised Learning
  - Unsupervised Learning





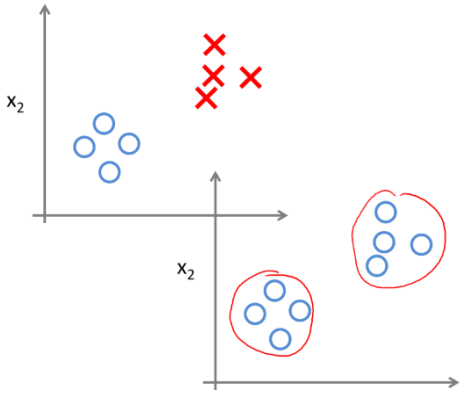
YouTube





Methods

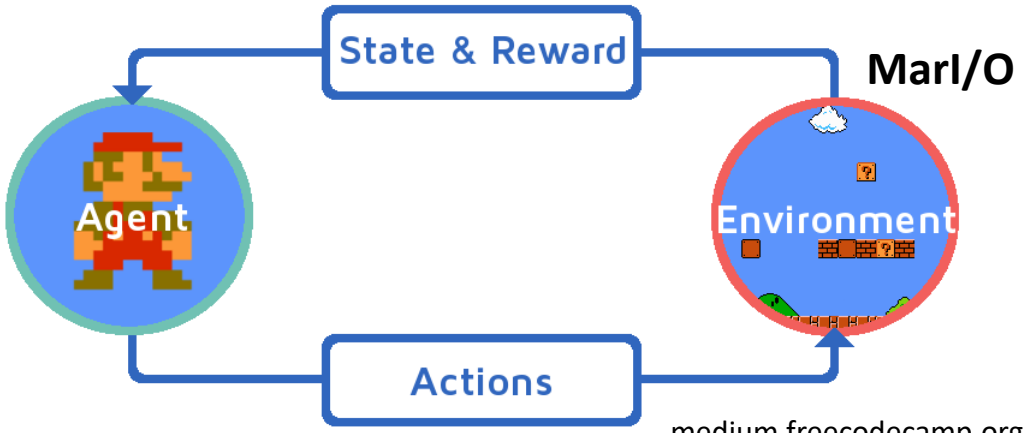
- Machine Learning
  - Supervised Learning
  - Unsupervised Learning
  - Reinforcement Learning



APE2010.de; www.coursera.org

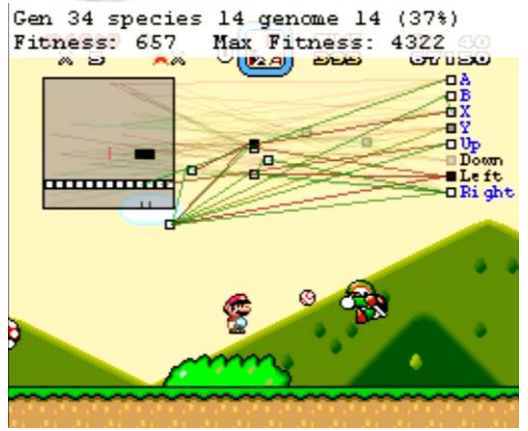


Example:



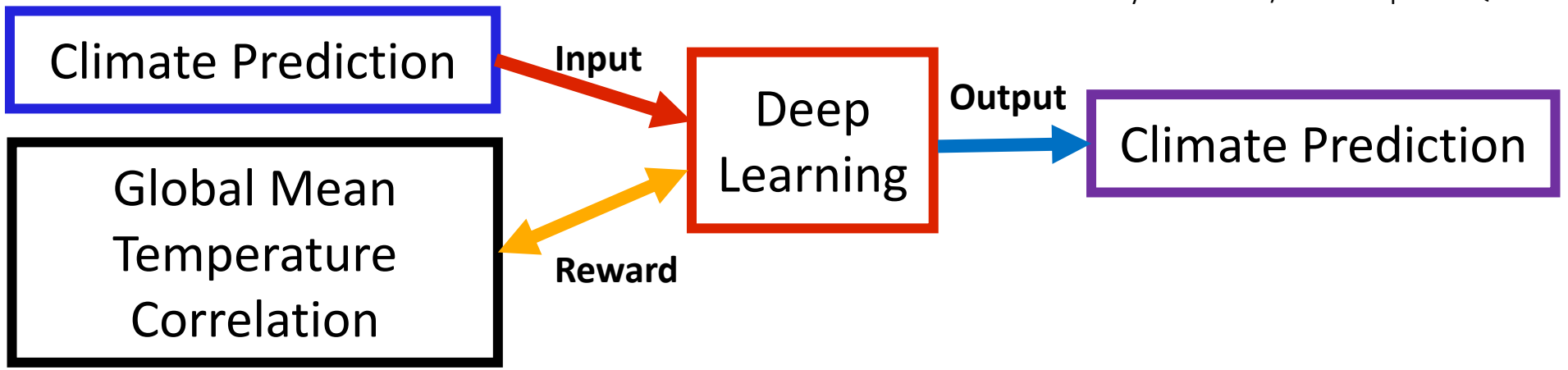
MarI/O

medium.freecodecamp.org



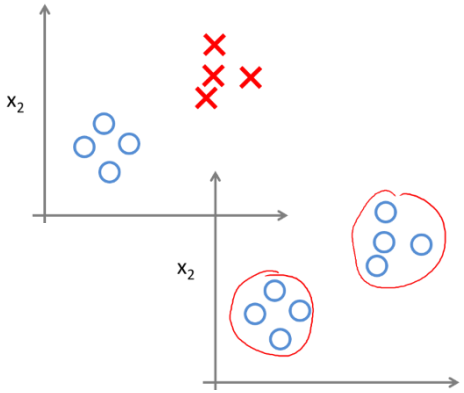
www.youtube.com/watch?v=qv6UVOQ0F44

Research:



Methods

- Machine Learning
  - Supervised Learning
  - Unsupervised Learning
  - Reinforcement Learning



APE2010.de; www.coursera.org



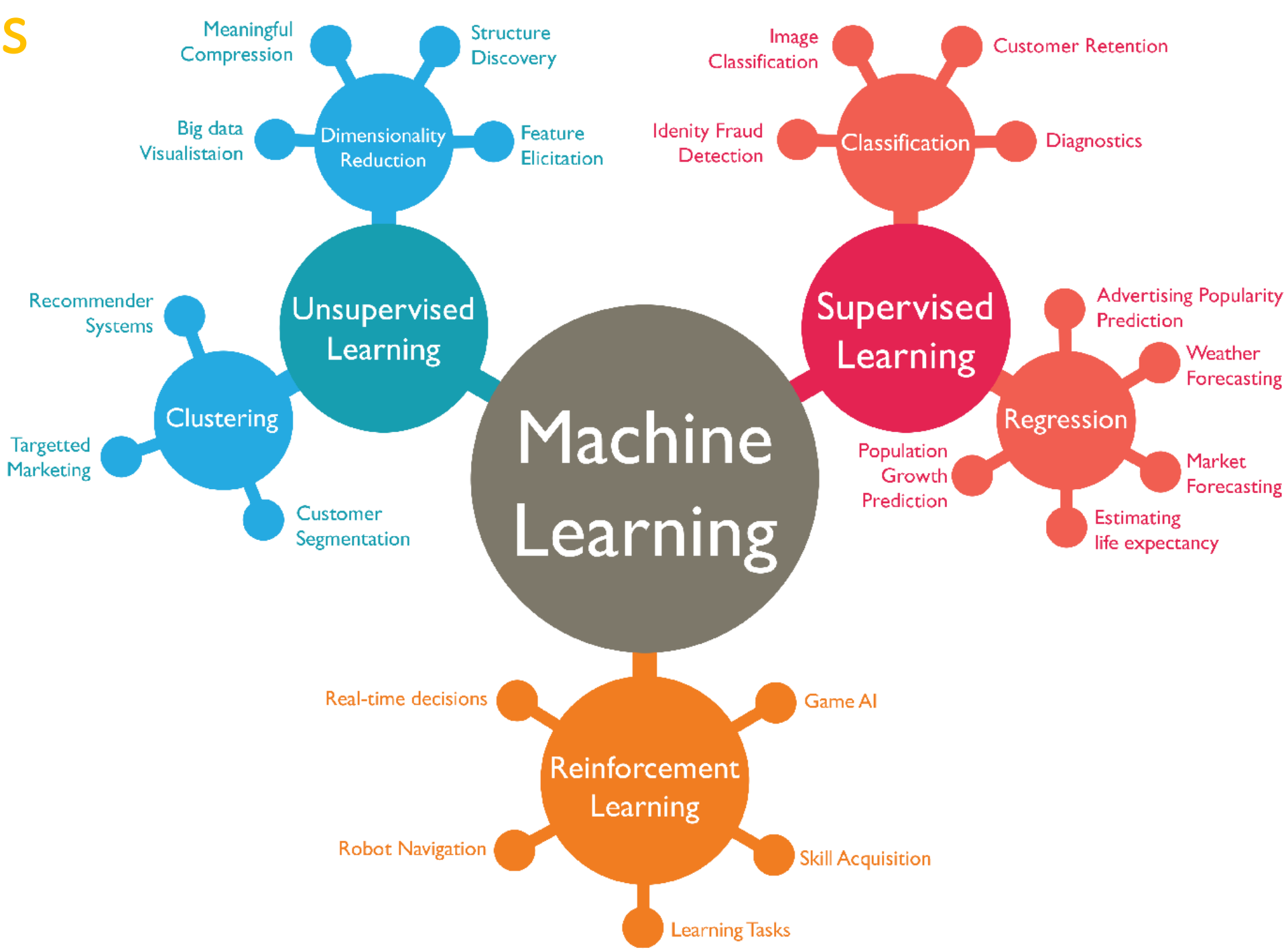
TWO MINUTE PAPERS

YouTube





Methods


Machine Learning
Unsupervised Learning
Supervised Learning
Reinforcement Learning
Dimensionality Reduction
Clustering
Classification
Regression
Meaningful Compression
Structure Discovery
Big data Visualistaion
Feature Elicitation
Recommender Systems
Targetted Marketing
Customer Segmentation
Image Classification
Customer Retention
Idenity Fraud Detection
Diagnostics
Advertising Popularity Prediction
Weather Forecasting
Population Growth Prediction
Market Forecasting
Estimating life expectancy
Real-time decisions
Game AI
Robot Navigation
Skill Acquisition
Learning Tasks

Hardware & Software

Hardware & Software

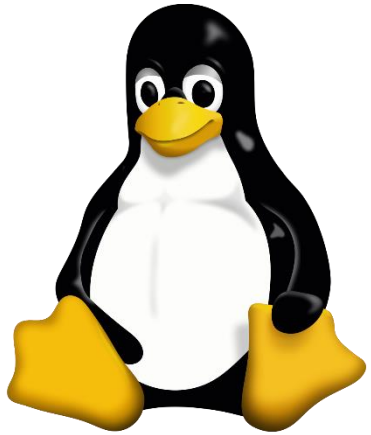
Great News: Deep Learning, Machine Learning, Artificial Intelligence is possible on **CPU, GPU and TPU**











Hardware & Software

Great News: Deep Learning, Machine Learning, Artificial Intelligence is possible on **CPU, GPU and TPU**



You can use bigger or high performance computer like DKRZ or UHH.

Or also you could use Amazon Web Services (AWS) or Google Cloud.

DKRZ DEUTSCHES KLIMARECHENZENTRUM

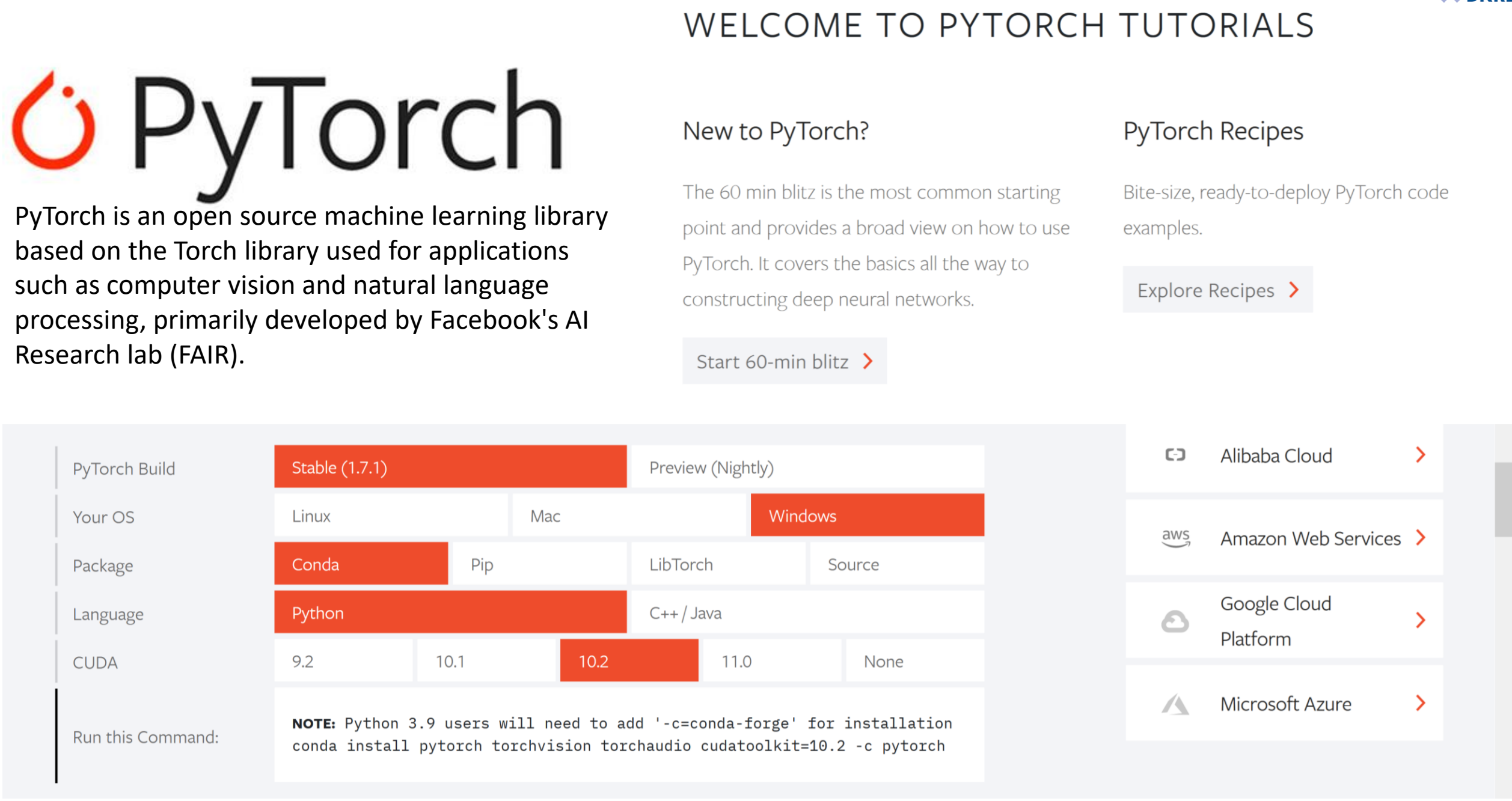
UHH

aws

Google Cloud

Hardware & Software

PyTorch is an open source machine learning library based on the Torch library used for applications such as computer vision and natural language processing, primarily developed by Facebook's AI Research lab (FAIR).

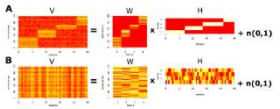


Applications

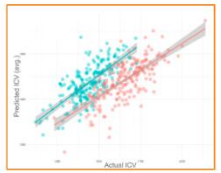
Applied Machine Learning

Dr. Kaustubh Patil

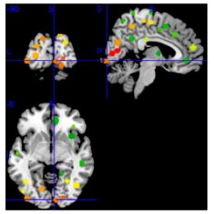
Gehirn- und Verhaltensdaten: strukturelle, funktionale, Diffusions- und kognitive Daten



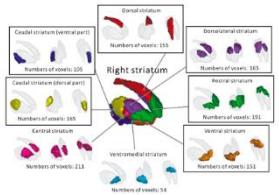
Maschinelle Lernmethoden:
Faktorisierung
Klassifizierung
Clustering



Vorhersage: Hirnalter und -größe; klinischer Zustand



Biologische Erkenntnisse von klinischer Relevanz und evolutionärem Ursprung



Multimodale Organisation bei Gesundheit und Erkrankung

Use of HPC: in all stages of the ML pipeline

- Data management: dynamic using DataLad
  - (all data does not fit in user folder)
- Preprocessing (CAT12): ~1hr/subject
  - (parallelized subject-wise on JURECA)
- Feature extraction:
  - Gray matter volume from thousands of brain regions
- Learning:
  - Traditional methods: SVM
  - Deep learning: multi-GPU using PyTorch

HPC

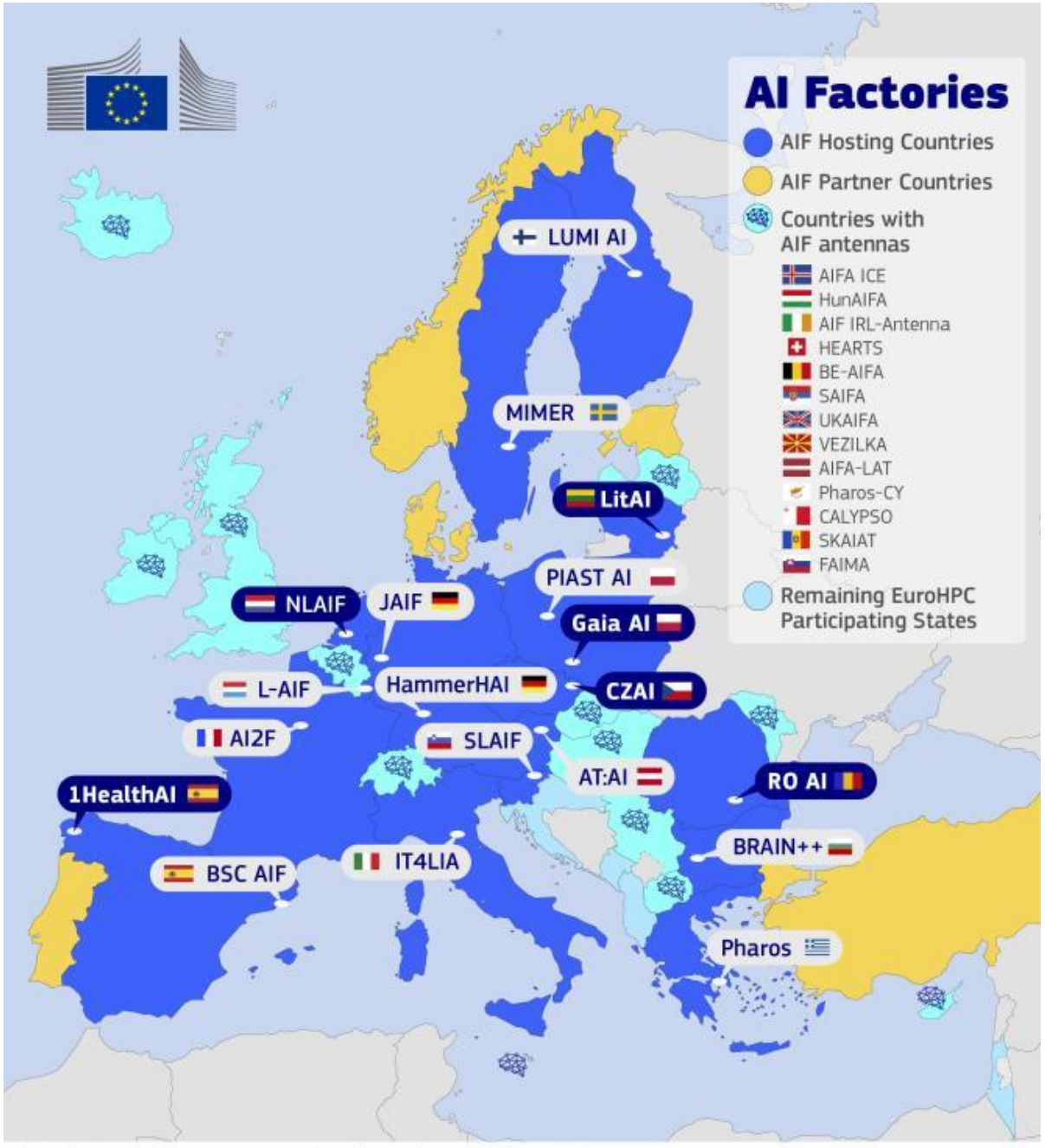


JUPITER | Der Start von Exascale in Europa

Das Forschungszentrum Jülich wird Standort des ersten europäischen Exascale-Rechners. Der Supercomputer soll als erster Rechner in Europa die Grenze von 1 Trillion Rechenoperationen pro Sekunde – einer „1" mit 18 Nullen – brechen.

Cores	122,768 CPU cores + 71.680 FP64 CUDA cores (GPUs in total)	44,928 CPU cores + 12,939,264 FP64 CUDA cores (GPUs in total)
Main Memory	total of 264 TB	total of 479 TB + total of 150 TB High Bandwidth Memory

Applications



HPC



JUPITER | Der Start von Exascale in Europa

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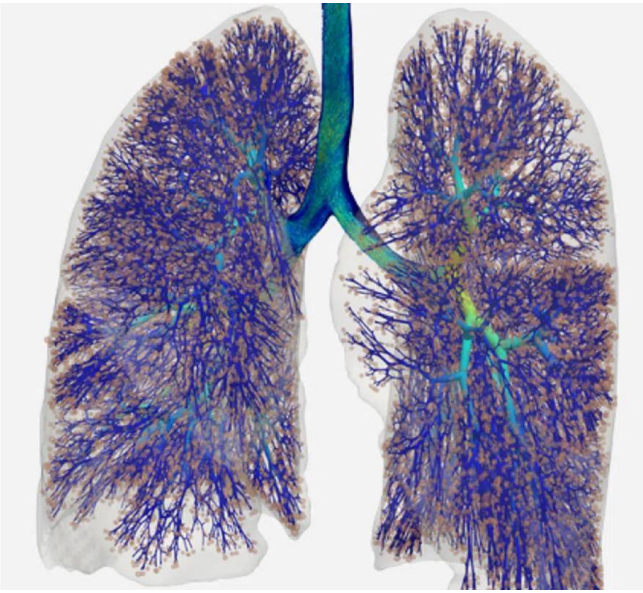
Cores	122,768 CPU cores + 71.680 FP64 CUDA cores (GPUs in total)	44,928 CPU cores + 12,939,264 FP64 CUDA cores (GPUs in total)
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Applications

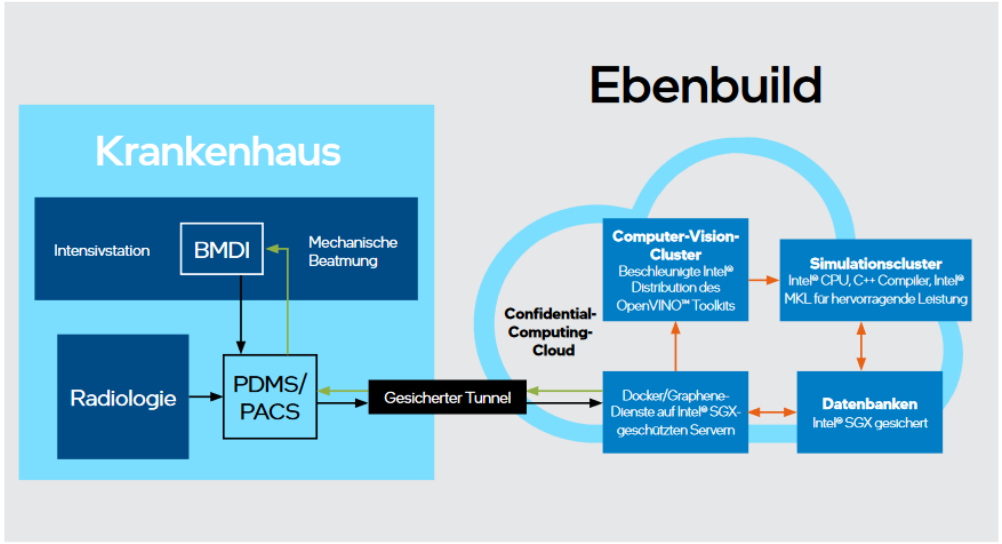
Buzzword: Digital Twin

HPC

Atemnotsyndrom (Acute Respiratory Distress Syndrome, ARDS)



Ebenbuild-Forschungsprogramm zielt darauf ab, Ärzten zum allerersten Mal **personalisierte digitale Zwillinge der menschlichen Lunge** zur Verfügung zu stellen.



Hardware of SuperMUC-NG

ComputeNodes	Thin Nodes	Fat Nodes	Total (Thin + Fat)
Processor	Intel Skylake Xeon Platinum 8174	Intel Skylake Xeon Platinum 8174	Intel Skylake Xeon Platinum 8174
Cores per Node	48	48	48
Memory per node (GByte)	96	768	NA
Number of Nodes	6,336	144	6,480
Number of Cores	304,128	6,912	311,040
PEAK @ nominal (PFlop/s)	26.3	0.6	26.9
Linpack (Pflop/s)	TBD	TBD	19.476
Memory (TByte)	608	111	719
Number of Islands	8	1	9
Nodes per Island	792	144	NA
Filesystems			
High Performance Parallel Filesystem	50 PB @ 500 GB/s		
Data Science Storage	20 PB @ 70 GB/s		
Home Filesystem	256 TB		



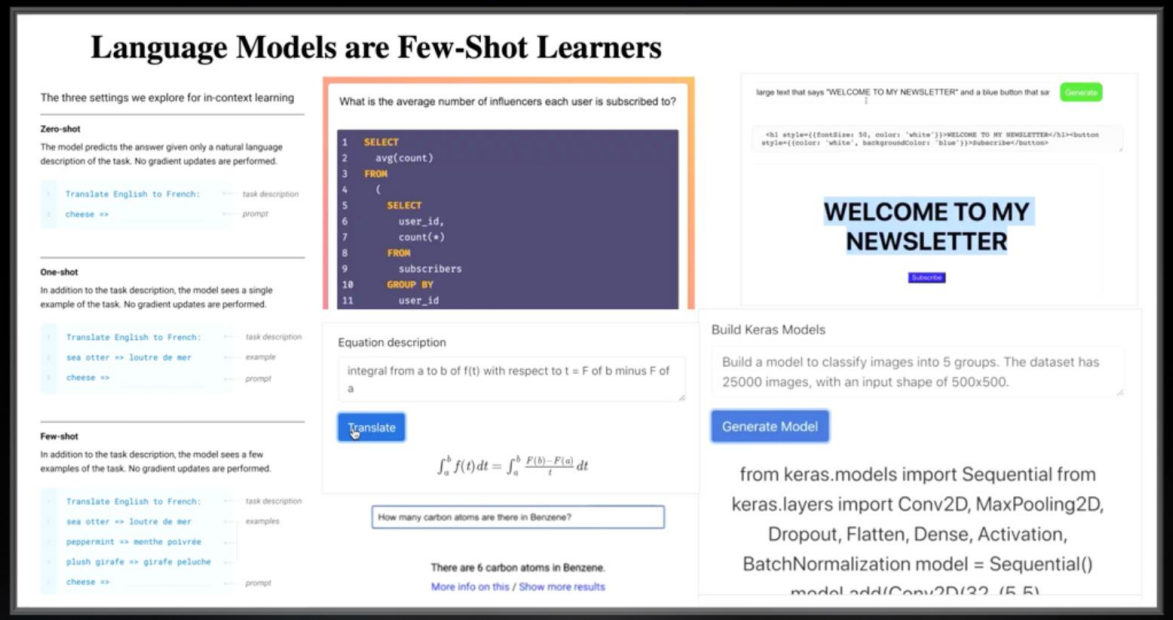
Damit soll eine **mechanische Beatmungstherapie** so passgenau angelegt werden können, dass sich die Überlebens- und Erholungsraten von Patienten mit ARDS deutlich verbessern.

Courtesy by INTEL and Ebenbuild

Applications

OPEN AI'S GPT-3: 175B PARAMS

(July 2020) A turning-point in large language models.



https://www.educative.io/blog/top-uses-gpt-3-deep-learning

61 NVIDIA

HPC

THE SELENE SUPERCOMPUTER

NVIDIA's DGX SuperPOD Deployment

#7 on TOP500 (27.6 PetaFLOPS HPL)

#2 on Green500 (20.5 GigaFLOPS/watt)

Fastest industrial system in the U.S. — 1+ ExaFLOPS AI

Built from the NVIDIA DGX SuperPOD Reference Architecture

- 2nd generation SuperPOD Reference Architecture
- NVIDIA DGX A100 and NVIDIA Mellanox InfiniBand network
- The blueprint for AI power and scale, infused with the knowhow from NVIDIA's decade plus of AI experience

Configuration:

- 2,240 NVIDIA A100 Tensor Core GPUs
- 280 NVIDIA DGX A100 systems
- 494 Mellanox 200G HDR InfiniBand switches
- 7 PB of all-flash storage

Courtesy by David M. Hall - NVIDIA

Image Inpainting - Restoration

Human Intelligence

Paintings



”Ground Truth“ ”Broken“ ”Restoration“

Sanctuary of Mercy church in Borja, Spain
https://en.wikipedia.org

Artificial Intelligence

Photos



”Ground Truth“ ”Broken“ ”Restoration“

Image Inpainting with Deep Learning
https://medium.com Tarun Bonu

Literature

Bertalmio, M., Sapiro, G. Caselles, V. & Ballester, C. **Image inpainting**. In *Proc. ACM Conf. Comp. Graphics (SIGGRAPH)* (eds Brown, J. R. & Akeley, K.) 417–424 (ACM/Addison-Wesley, 2000)

Image Inpainting

Marcelo Bertalmio and Guillermo Sapiro*
Electrical and Computer Engineering, University of Minnesota

Vicent Caselles and Coloma Ballester
Escola Superior Politecnica, Universitat Pompeu Fabra



Abstract

Inpainting, the technique of modifying an image in an undetectable form, is as ancient as art itself. The goals and applications of inpainting are numerous, from the restoration of damaged paintings and photographs to the removal/replacement of selected objects. In this paper, we introduce a novel algorithm for digital inpainting of still images that attempts to replicate the basic techniques used by professional restorators. After the user selects the regions to be restored, the algorithm automatically fills-in these regions with information surrounding them. The fill-in is done in such a way that isophote lines arriving at the regions' boundaries are completed inside. In contrast with previous approaches, the technique here introduced does not require the user to specify where the novel information comes from. This is automatically done (and in a fast way), thereby allowing to simultaneously fill-in numerous regions containing completely different structures and surrounding backgrounds. In addition, no limitations are imposed on the topology of the region to be inpainted. Applications of this technique include the restoration of old photographs and damaged film; removal of superimposed text like dates, subtitles, or publicity; and the removal of entire objects from the image like microphones or wires in special effects.

CR Categories: I.3.3 [Computer Graphics]: Picture/Image Generation—; I.3.4 [Computer Graphics]: Graphics Utilities—; I.4.4 [Image Processing and Computer Vision]: Restoration—; I.4.9 [Image Processing and Computer Vision]: Applications—;

(e.g., removal of stamped date and red-eye from photographs, the infamous "airbrushing" of political enemies [3]).

Digital techniques are starting to be a widespread way of performing inpainting, ranging from attempts to fully automatic detection and removal of scratches in film [4, 5], all the way to software tools that allow a sophisticated but mostly manual process [6].

In this article we introduce a novel algorithm for automatic digital inpainting, being its main motivation to replicate the basic techniques used by professional restorators. At this point, the only user interaction required by the algorithm here introduced is to mark the regions to be inpainted. Although a number of techniques exist for the semi-automatic detection of image defects (mainly in films), addressing this is out of the scope of this paper. Moreover, since the inpainting algorithm here presented can be used not just to restore damaged photographs but also to remove undesired objects and writings on the image, the regions to be inpainted must be marked by the user, since they depend on his/her subjective selection. Here we are concerned on how to "fill-in" the regions to be inpainted, once they have been selected.[1] Marked regions are automatically filled with the structure of their surrounding, in a form that will be explained later in this paper.

2 Related work and our contribution

We should first note that classical image denoising algorithms do not apply to image inpainting. In common image enhancement applications, the pixels contain both information about the real data

Elharrouss, O., Almaadeed, N., Al-Maadeed, S. & Akbari, Y. Image inpainting: a review. *Neural Process. Lett.* **51**, 2007–2028 (2019).

Neural Processing Letters (2020) 51:2007–2028
https://doi.org/10.1007/s11063-019-10163-0

Check for updates

Image Inpainting: A Review

Omar Elharrouss[1] · Noor Almaadeed[1] · Somaya Al-Maadeed[1] · Younes Akbari[1]

Published online: 6 December 2019
© Springer Science+Business Media, LLC, part of Springer Nature 2019

Abstract

Although image inpainting, or the art of repairing the old and deteriorated images, has been around for many years, it has recently gained even more popularity, because of the recent development in image processing techniques. With the improvement of image processing tools and the flexibility of digital image editing, automatic image inpainting has found important applications in computer vision and has also become an important and challenging topic of research in image processing. This paper reviews the existing image inpainting approaches, that were classified into three subcategories, sequential-based, CNN-based, and GAN-based methods. In addition, for each category, a list of methods for different types of distortion on images are presented. Furthermore, the paper also presents available datasets. Last but not least, we present the results of real evaluations of the three categories of image inpainting methods performed on the used datasets, for different types of image distortion. We also present the evaluations metrics and discuss the performance of these methods in terms of these metrics. This overview can be used as a reference for image inpainting researchers, and it can also facilitate the comparison of the methods as well as the datasets used. The main contribution of this paper is the presentation of the three categories of image inpainting methods along with a list of available datasets that the researchers can use to evaluate their proposed methodology against.

Keyword Image inpainting · Objects removal · Image repairing · CNN · GAN

Liu et al. 2018 Image Inpainting for **Irregular Holes** Using Partial Convolutions



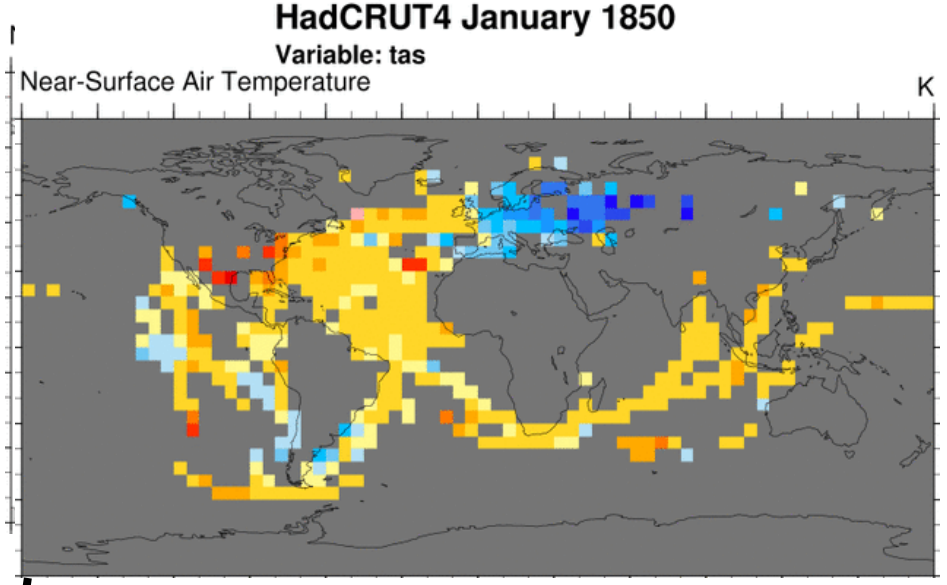
Transfer Learning



BUT HOW?

Climate Science?

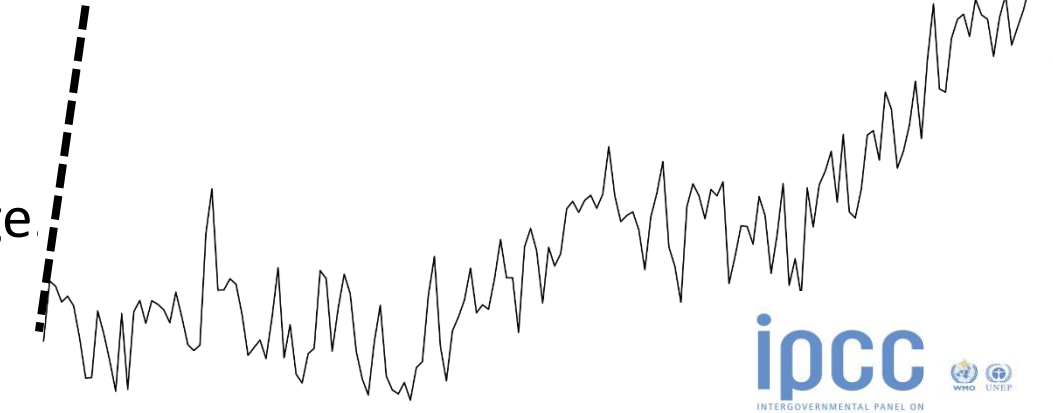
Observations Annual Mean HadCRUT4
Station, Ship, Boye based data



GRAY -> Missing Values

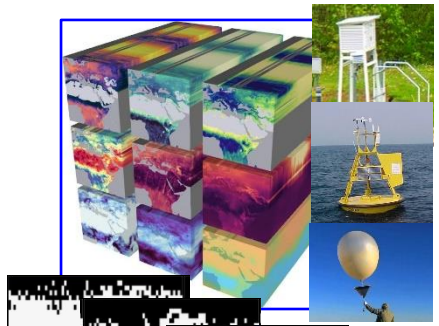
Youtube comment:

Google: Let's make AI that teaches itself to walk.
Facebook: Let's make AI that develop their own language.
Nvidia: Let's make Healing brush tool from Photoshop...



ipcc INTERGOVERNMENTAL PANEL ON climate change

Transfer Learning



20CR Reanalysis
1870-2009
1 Model (Atmos.)
55+1 Ens. Member

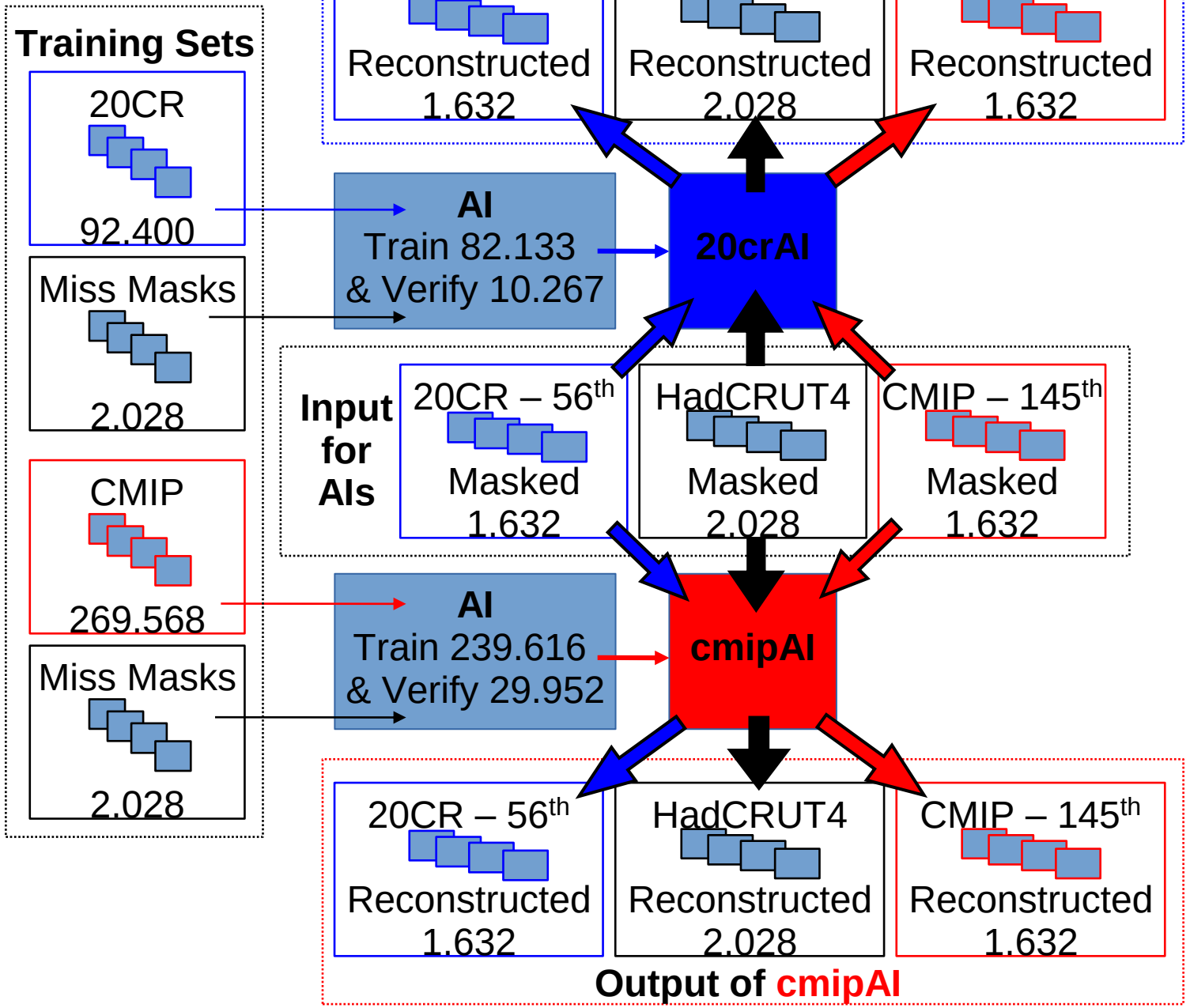
HadCRUT4
1850-2018



CMIP5 Historical
1850-2005
35 Models (ESMs)
144+1 Ens. Member

HadCRUT4
1850-2018

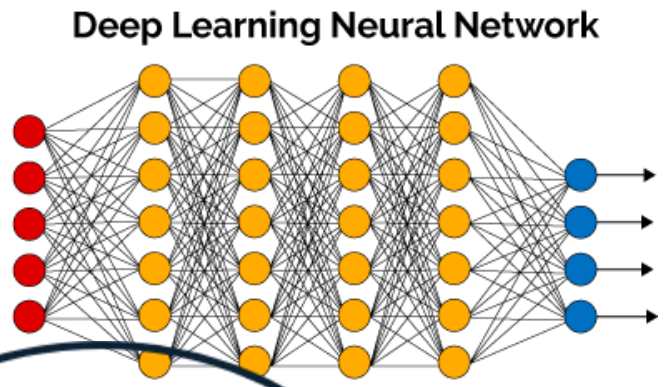
Setup of Machine Learning sets:
Training, Validation, Test
IMPORTANT: How to select each? Science and Evaluation! Don‘t cheat yourself.



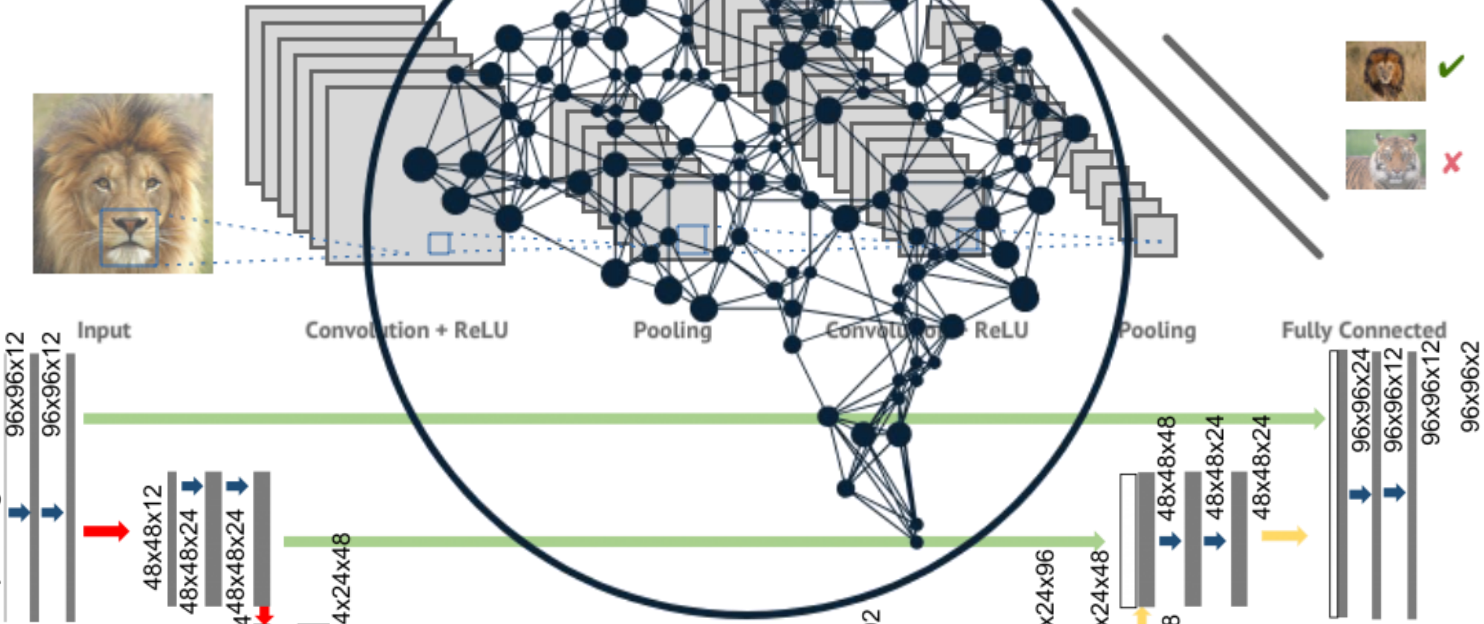
ML Techniques

Neural Networks

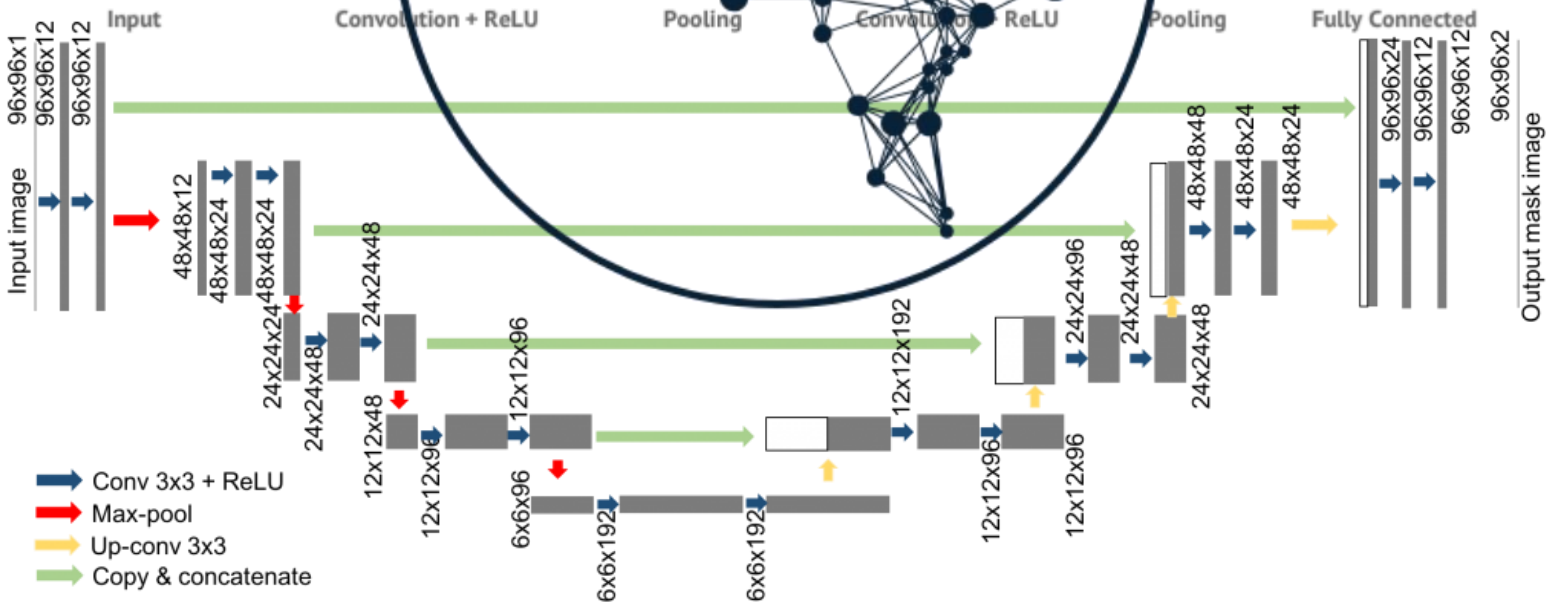
PyTorch,
Partial Convolution,
cuDNN CUDA-GPU accelerated



(Partial) Convolution



U-Net Architecture



Pre-Research

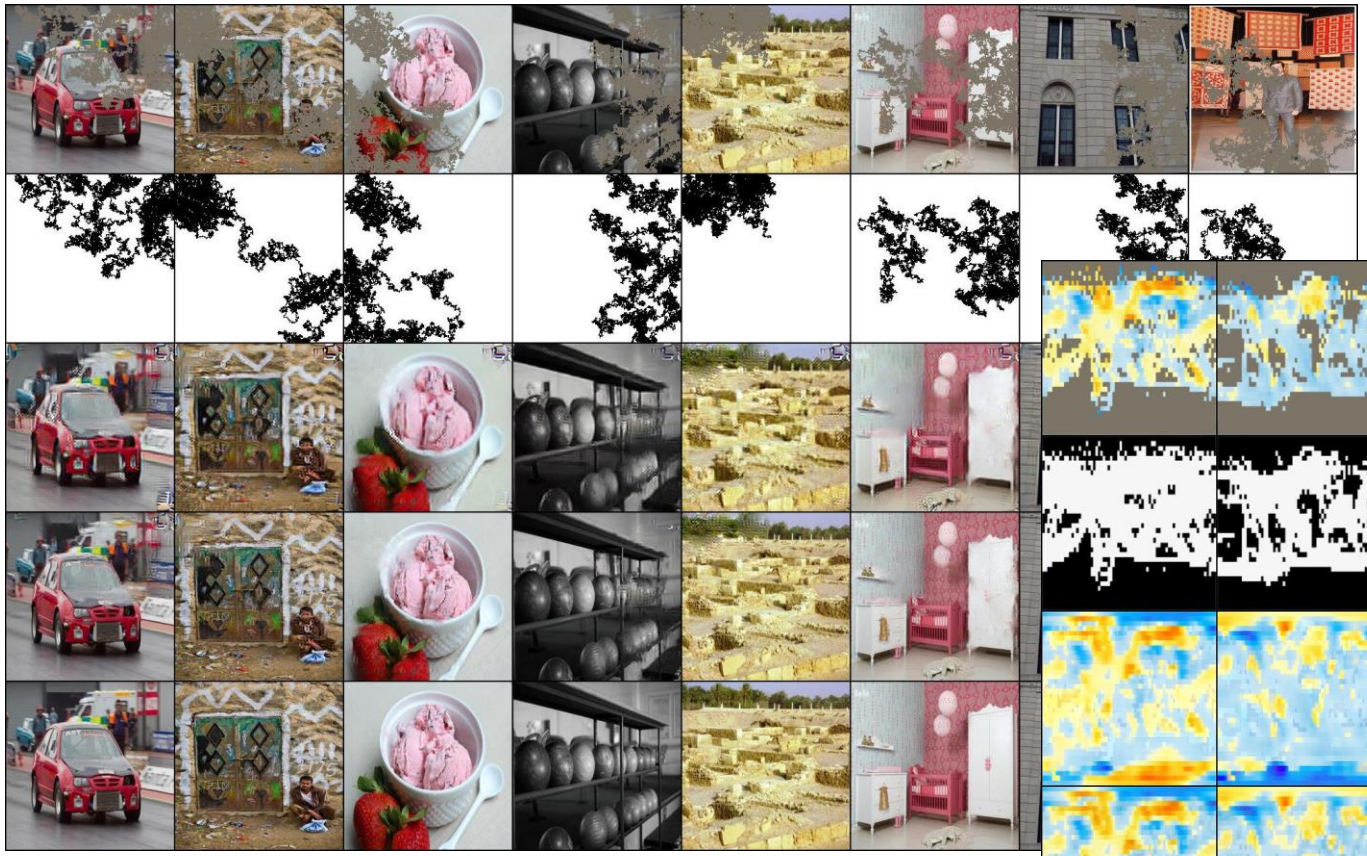
Find computer with GPUs
~1 day

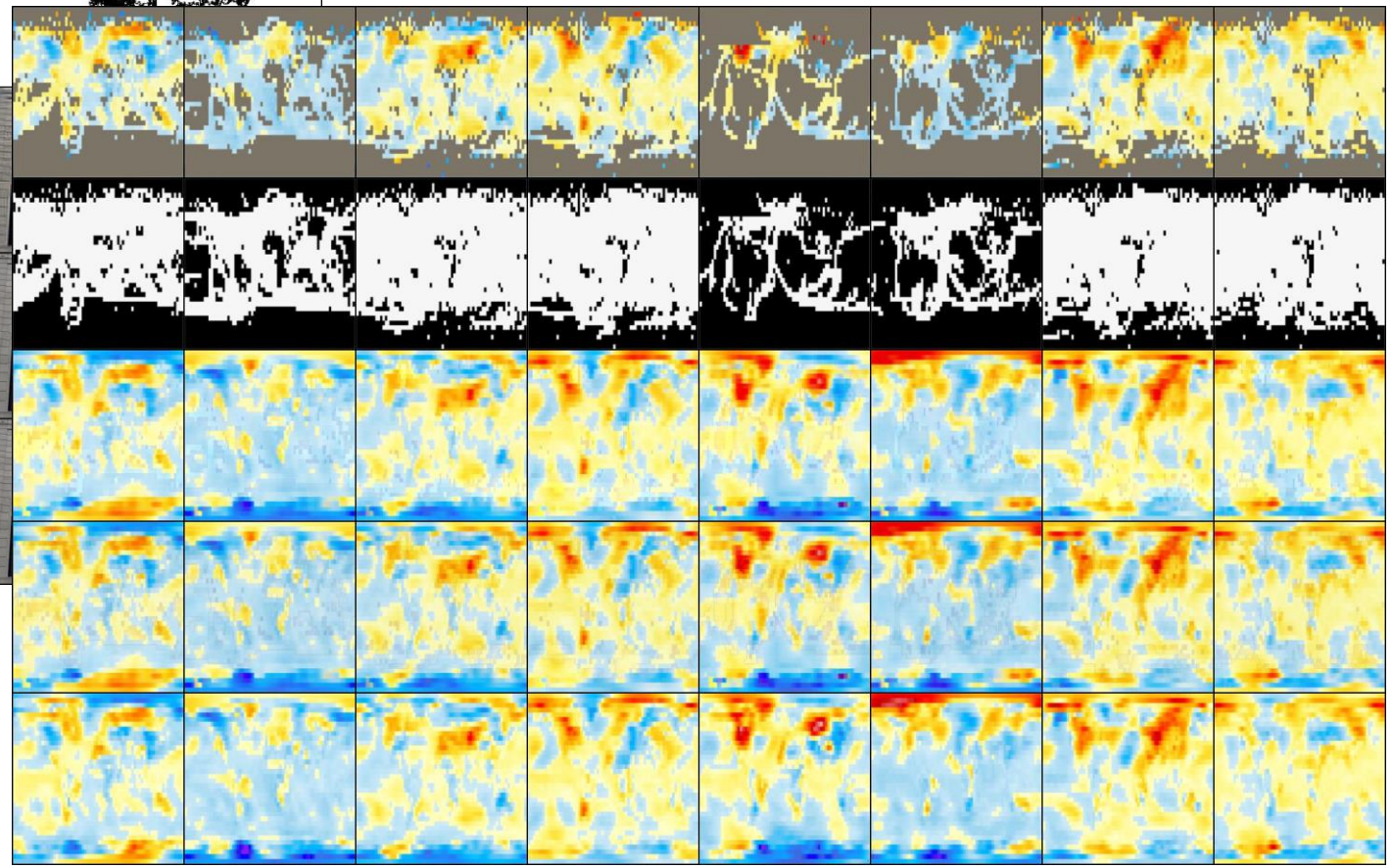
Install Software, Download Pics
~3 days

Run Software in its original mode
~2 days

Produce JPGs from Climate Data and run
~3 days

Change AI software to read climate data (NetCDF) and run and tune
~12 days





Pre-Research

Shown is the learning process, each square and step shows **50 iterations** in the neural network, to create a related (climate) pattern.
From
Kadow et al 2020

Entdecken

Einstellungen

Nature Geoscience
8.353 Tweets

Folgen

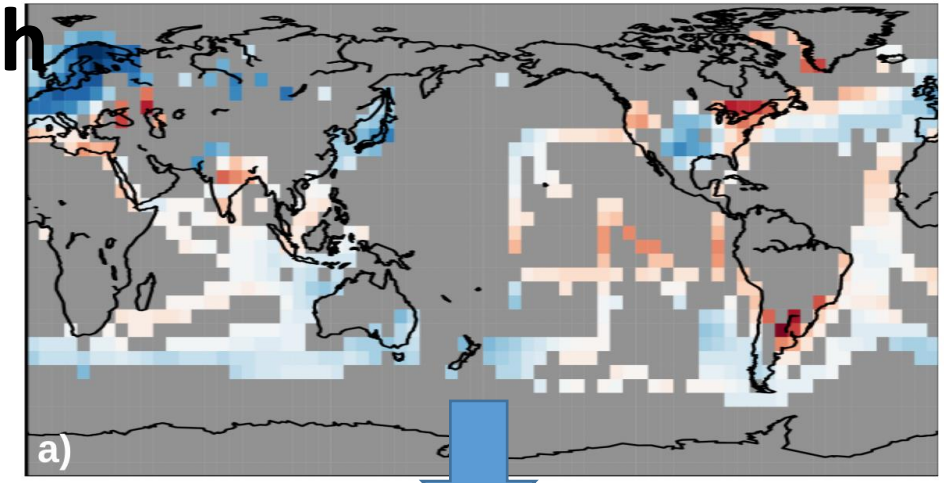
Nature Geoscience @NatureGeosci · 1. Juni

NGeo: Artificial intelligence can reconstruct missing historical temperature data

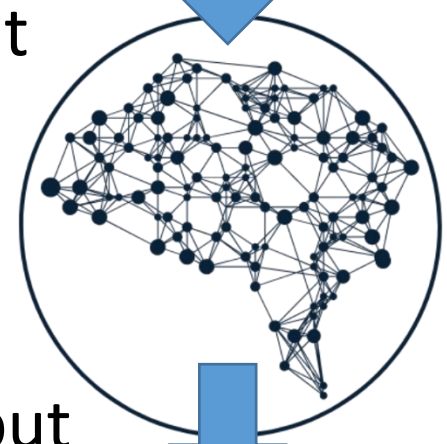
nature.com/articles/s4156...



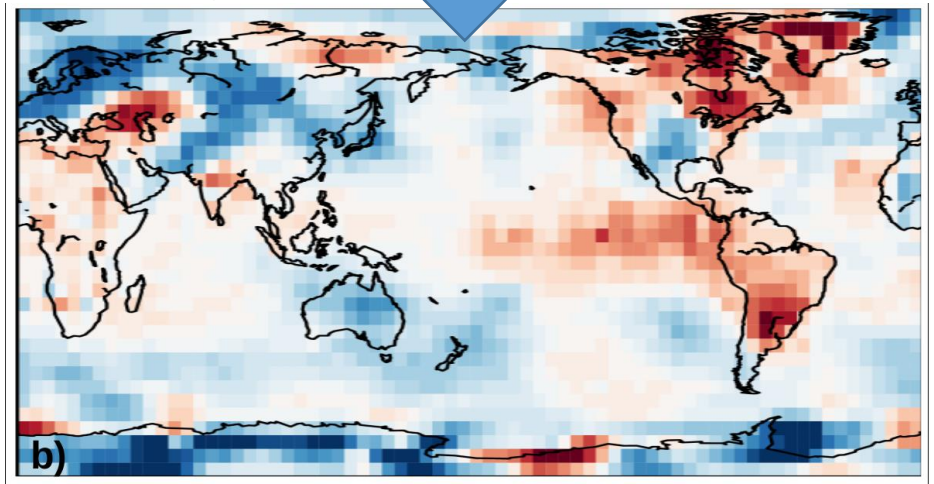
2 3



AI Input

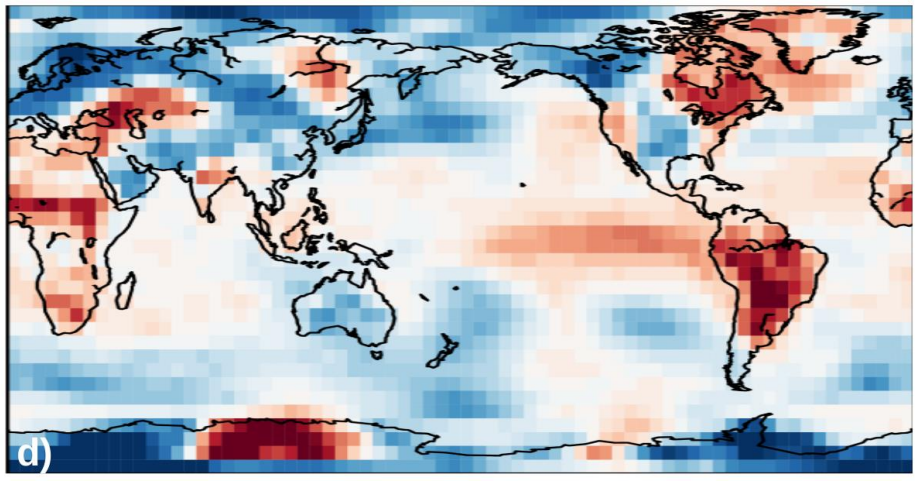


AI Output

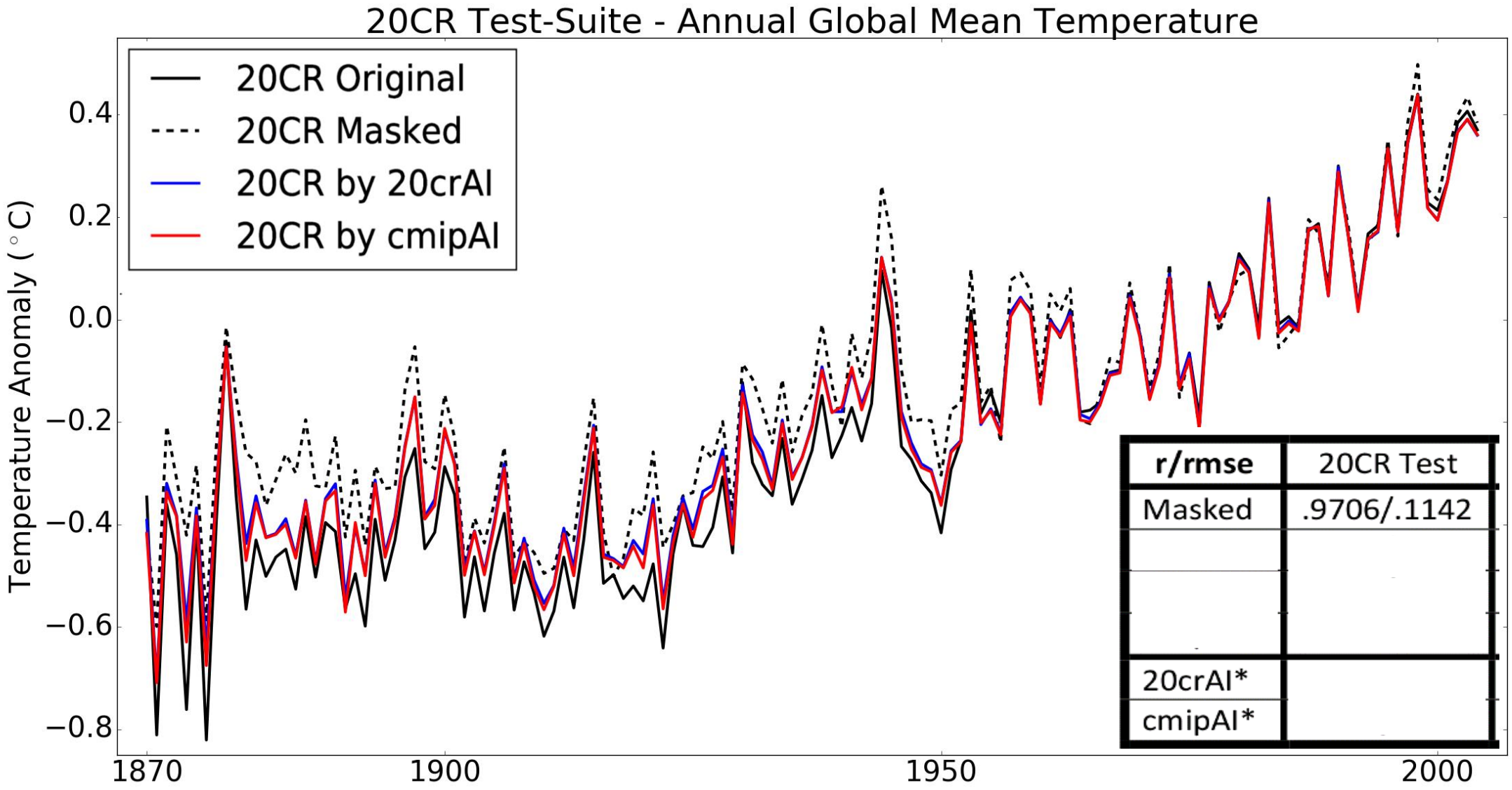


+ HadCRUT4
Miss Mask

Original - Temperature



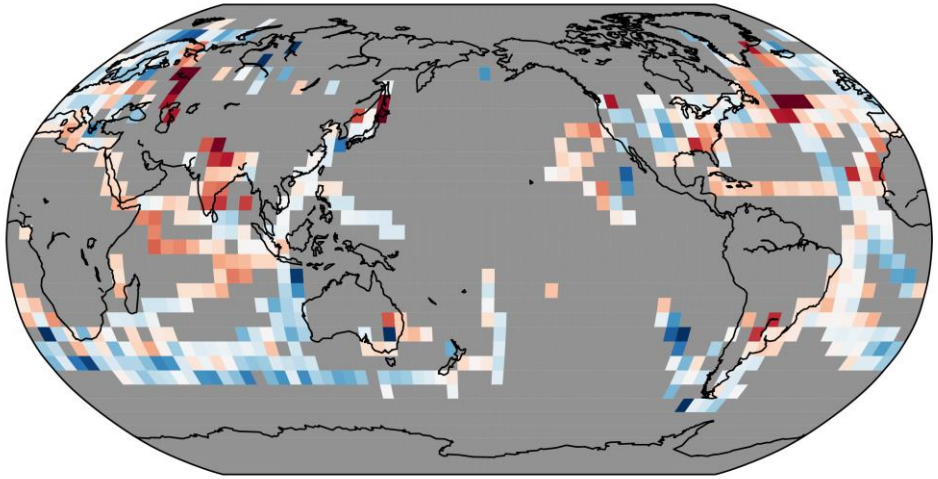
Research


20CR Test-Suite - Annual Global Mean Temperature
20CR Original
20CR Masked
20CR by 20crAI
20CR by cmipAI
Temperature Anomaly (°C)
0.4
0.2
0.0
−0.2
−0.4
−0.6
−0.8
1870
1900
1950
2000
r/rmse
20CR Test
Masked
.9706/.1142
20crAI*
cmipAI*

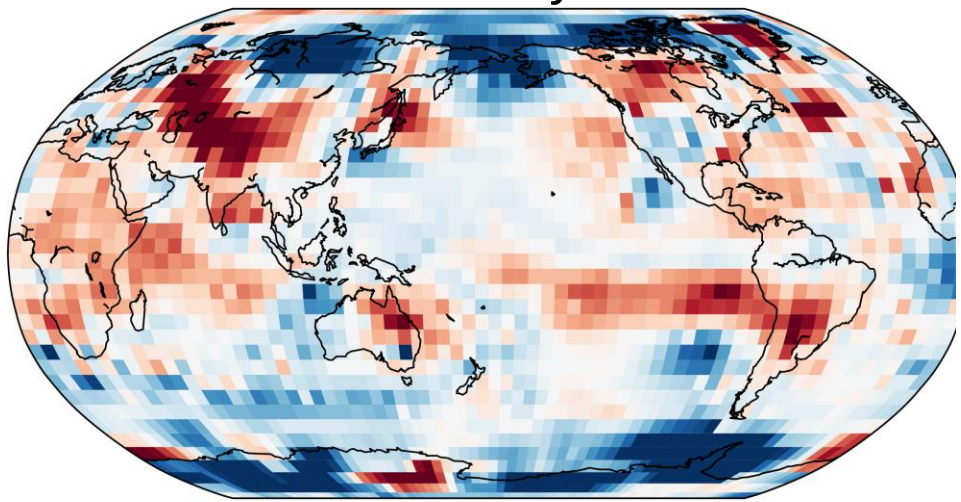
Temporal and Spatial – HadCRUT4

El Nino
July
1877

HadCRUT4 Original

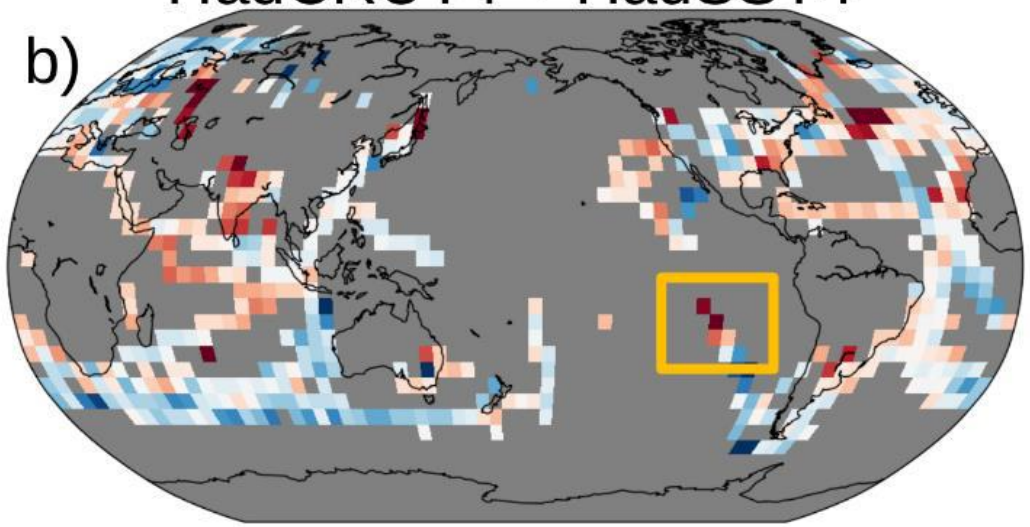


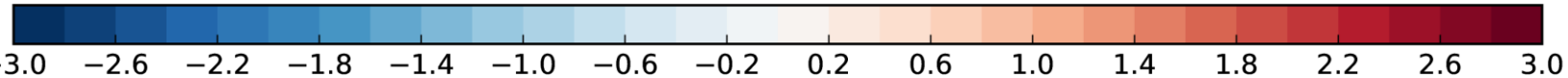
HadCRUT4 by 20crAI

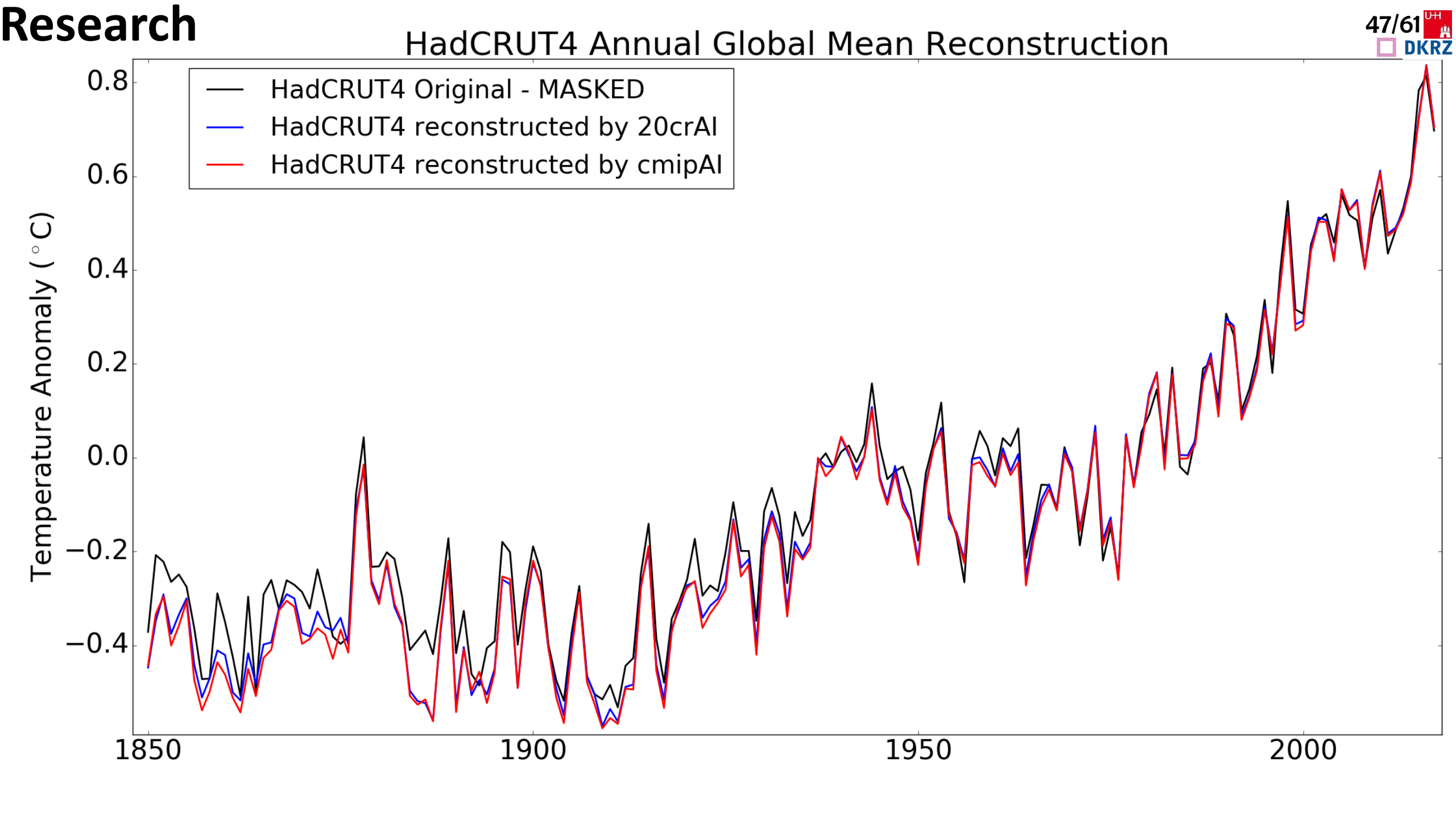


HadCRUT4 by Cowtan and Way

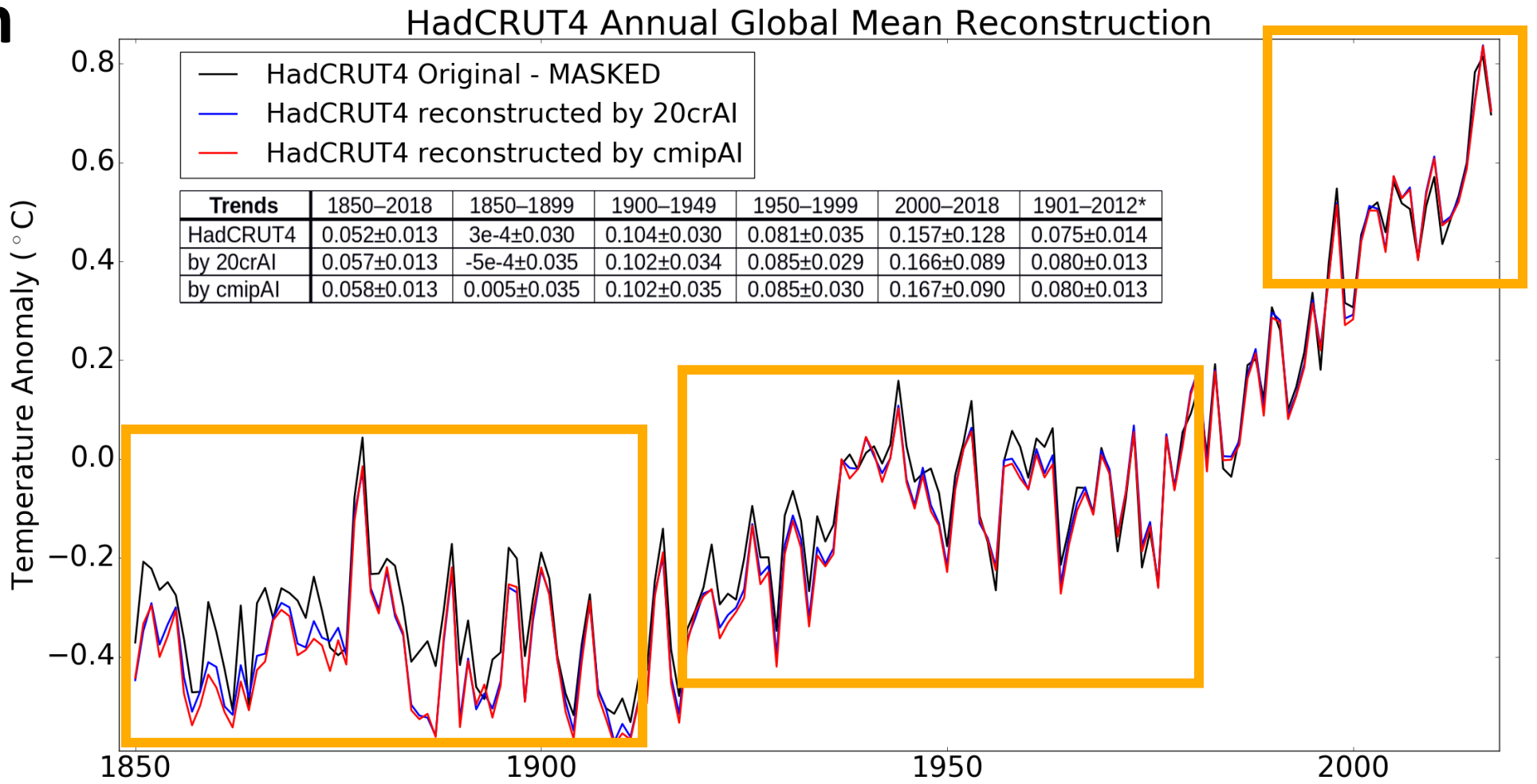
HadCRUT4 + HadSST4






HadCRUT4 Annual Global Mean Reconstruction
HadCRUT4 Original - MASKED
HadCRUT4 reconstructed by 20crAI
HadCRUT4 reconstructed by cmipAI
Temperature Anomaly (°C)
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
1850
1900
1950
2000

Research



Trends	1850–2018	1850–1899	1900–1949	1950–1999	2000–2018	1901–2012*
HadCRUT4	0.052±0.013	3e-4±0.030	0.104±0.030	0.081±0.035	0.157±0.128	0.075±0.014
by 20crAI	0.057±0.013	-5e-4±0.035	0.102±0.034	0.085±0.029	0.166±0.089	0.080±0.013
by cmipAI	0.058±0.013	0.005±0.035	0.102±0.035	0.085±0.030	0.167±0.090	0.080±0.013

- **cooler** global mean temperature from the **mid 19th to the early 20th century**
  - an **underestimation of** the global mean temperature **trend** between 1850 and 2018.
- The results of the AI reconstructions support other studies by also showing a **cooler** period in **the mid of the 20th century**.
- **Early 21th century**: Compared to HadCRUT4, both AIs agree on a **weaker hiatus** phase and a **stronger trend** including higher values for **2016**, the warmest year on record.

AI Reconstructs Photos with Realistic Results



2018

2020

ARTICLES
https://doi.org/10.1038/s41561-020-0582-5
nature geoscience
Check for updates

Artificial intelligence reconstructs missing climate information

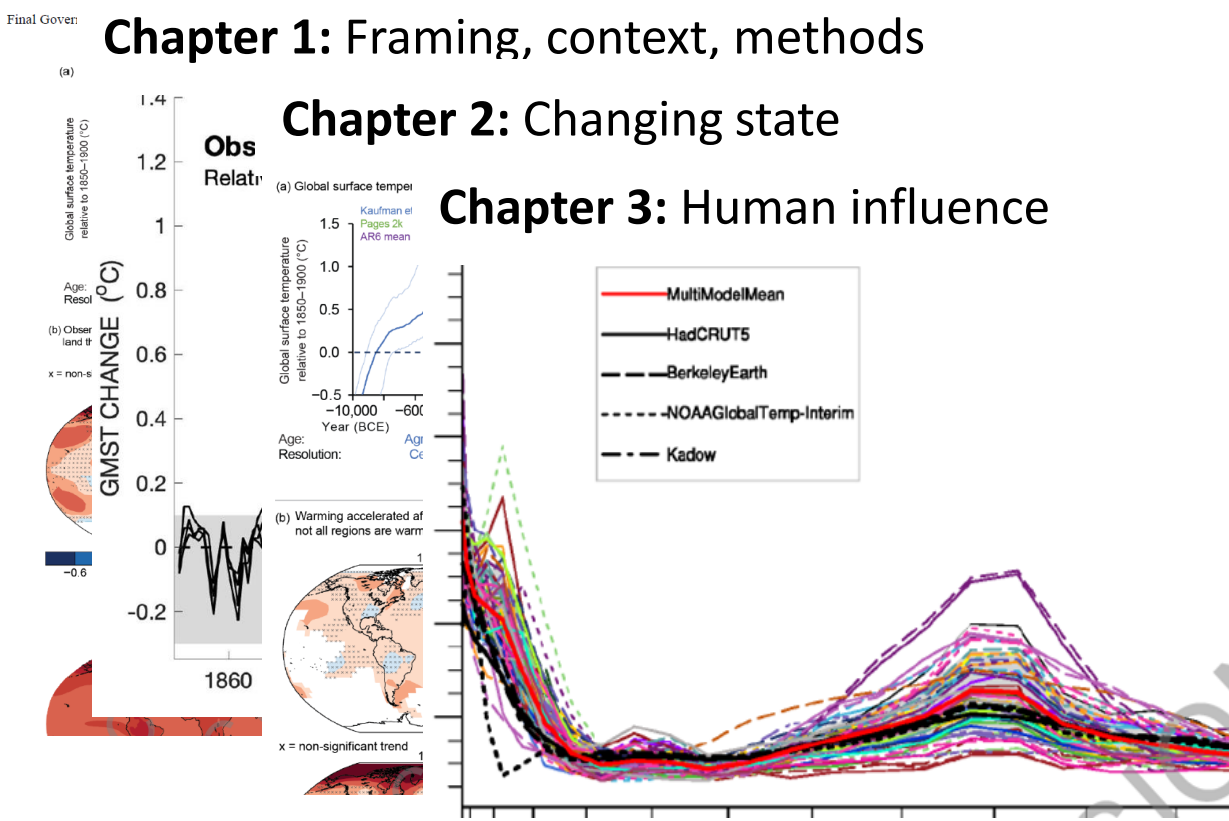
Christopher Kadow[1,2]✉, David Matthew Hall[3] and Uwe Ulbrich[2]

Historical temperature measurements are the basis of global climate datasets like HadCRUT4. This dataset contains many missing values, particularly for periods before the mid-twentieth century, although recent years are also incomplete. Here we demonstrate that artificial intelligence can skilfully fill these observational gaps when combined with numerical climate model data. We show that recently developed image inpainting techniques perform accurate monthly reconstructions via transfer learning using either 20CR (Twentieth-Century Reanalysis) or the CMIP5 (Coupled Model Intercomparison Project Phase 5) experiments. The resulting global annual mean temperature time series exhibit high Pearson correlation coefficients (≥0.9941) and low root mean squared errors (≤0.0547 °C) as compared with the original data. These techniques also provide advantages relative to state-of-the-art kriging interpolation and principal component analysis-based infilling. When applied to HadCRUT4, our method restores a missing spatial pattern of the documented El Niño from July 1877. With respect to the global mean tem-

+ Open Source Software and Data

2021

Technical Summary



Chapter 1: Framing, context, methods

Chapter 2: Changing state

Chapter 3: Human influence

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NVIDIA

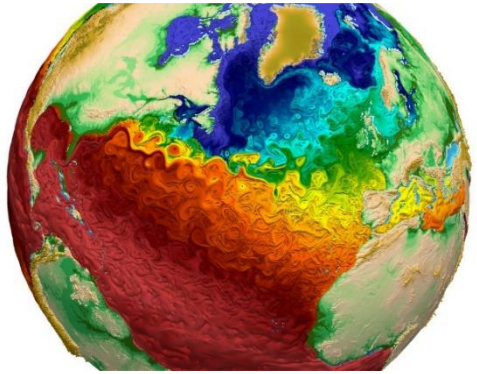
Freie Universität Berlin

ipcc INTERGOVERNMENTAL PANEL ON climate change

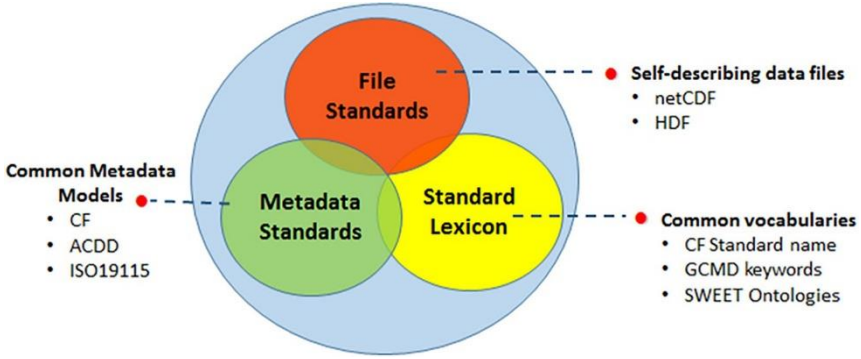
ar6

AI reconstructs missing Climate Information

HPC Modeling



HPC Processing



HPC AI/ML

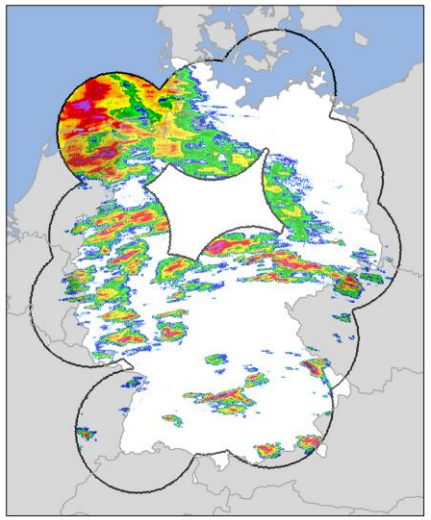


- **Successful combination** of climate modeling, observation and artificial intelligence -> on and thanks to HPCs
- At the moment, many groups (try to) improve models with AI, here it is **vice versa**
- Missing values introduce structual biases, which can be **reduced by AI**
- Other studies are confirmed (trends, hiatus, etc.), but this study shows an **added value** in terms of temperol (global mean) and spatial structures (e.g. El Nino 1877).
- Data and technology will be continously **prepared for the community (on GitHub)**

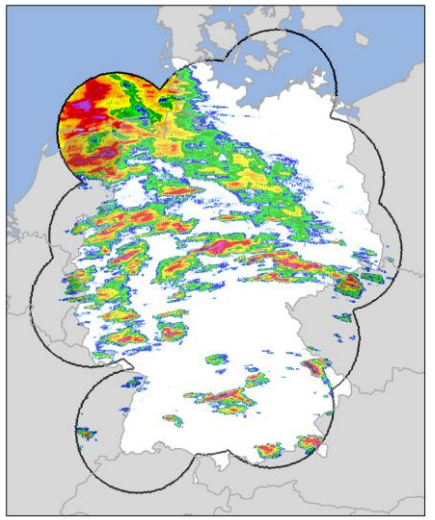
Research

Next steps with Inpainting technology:

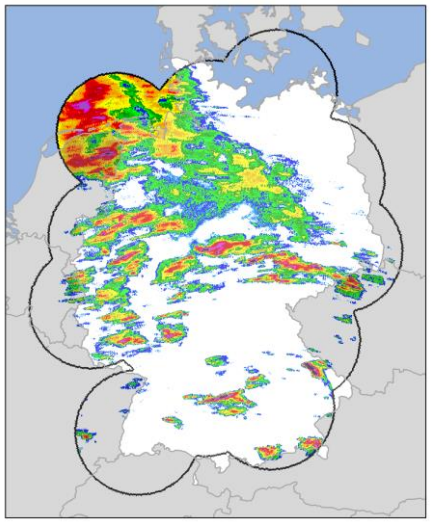
CLINT CLIMATE INTELLIGENCE CLIMXTREME Climate Change and Extreme Events	
Max-Planck-Institut für Meteorologie	
UH VOLIMPACT	
Helmholtz-Zentrum hereon	



Broken



Ground Truth



AI Infilled

Research

HPC

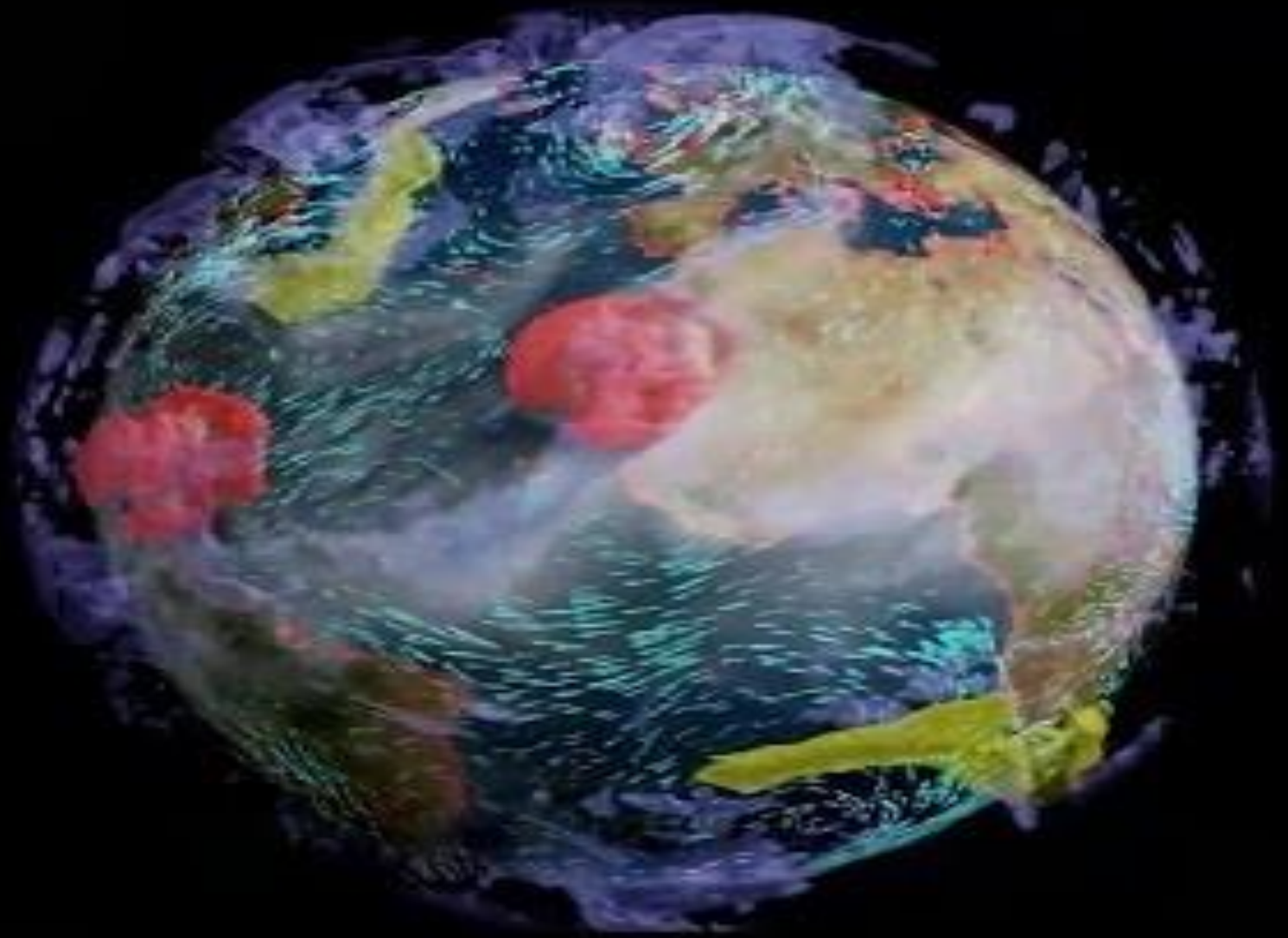
Benchmarks - Use As Is

OLD

NEW

Training 100K	Mistral	Levante	Speedup
Temperature (72x72)	17.2 Its/sec	55.6 Its/sec	x 3.2
Precipitation (512x512)	1.29 Its/sec (23h)	8.42 Its/sec (3h)	x 6.5

Infilling	Mistral	Levante	Speedup
Temperature (72x72)	46 sec	29 sec	x 1.6
Precipitation (512x512)	264 sec / 40% mem	174 sec / 20% mem	x 1.5

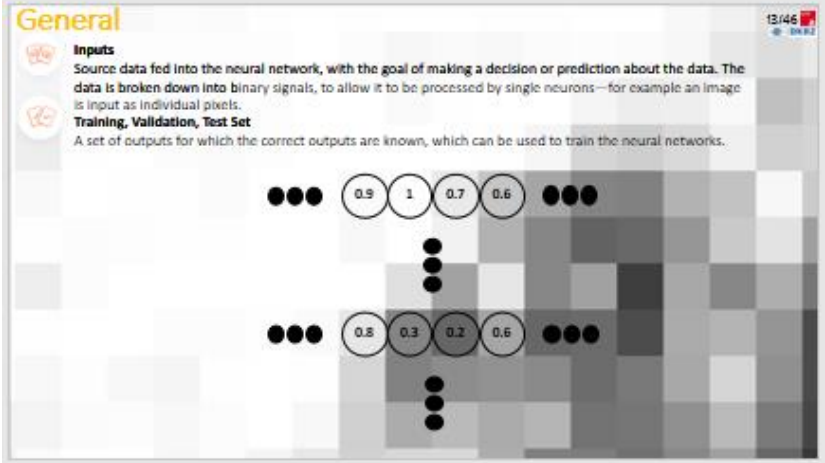


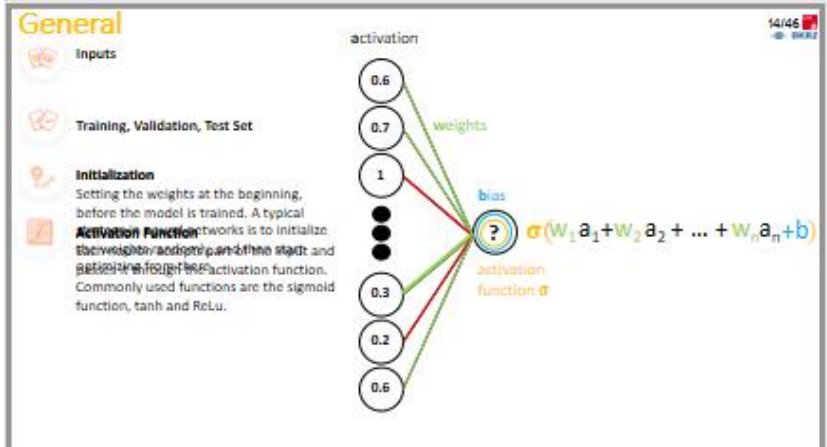
UHH Teaching – also for Informatics!

AI for Climate Science
Winter Semester 27/28

ML Introduction
Coding Examples incl Inpainting Paper
Research Seminar





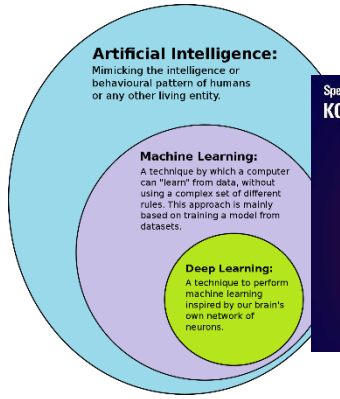


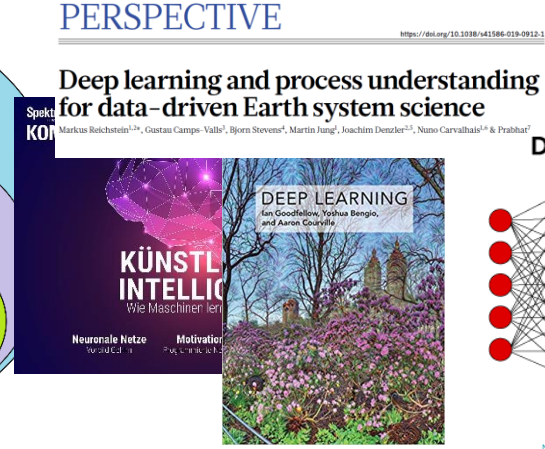
Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

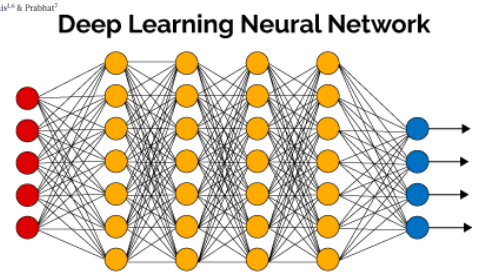
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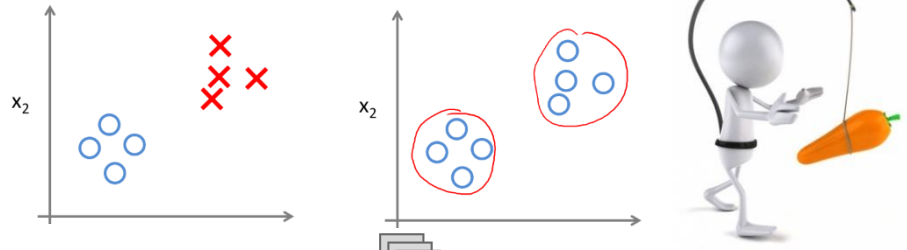
Summary

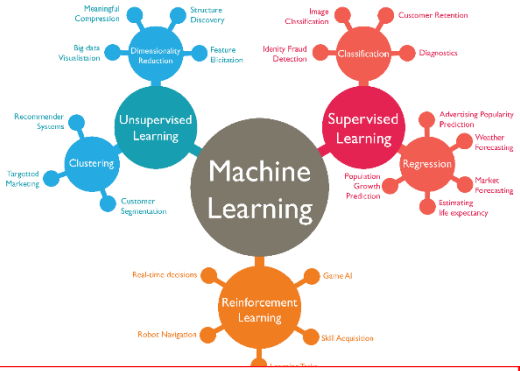
- General
  - DL, ML, AI? WTF? Literature
  - What is a Neural Network?
- Methods & Networks
  - Learning (UnSupervis, Reinforce)
  - Neural Nets (CNN, RNN, GAN)
- Hardware & Software
  - PCs, HPCs, Clouds
  - Tools, Frameworks, First Steps
  - Applications
- AI reconstructs missing Climate
  - Temperature and Precipitation
- ***Master***
  - ***Thesis on these topics?***
  - ***Class AI 4 Climate Science***

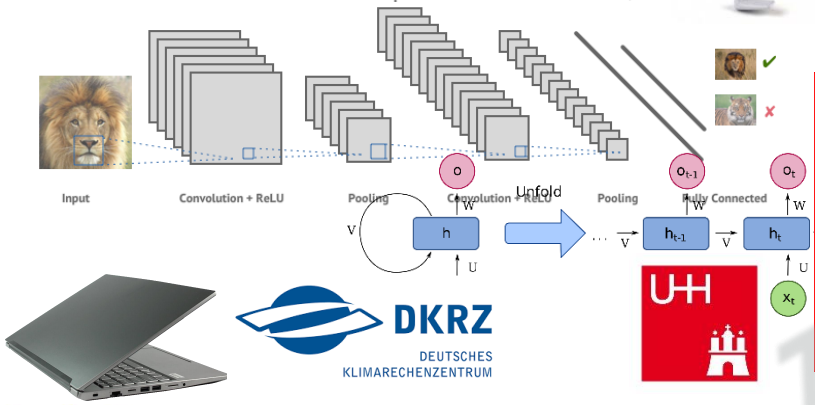


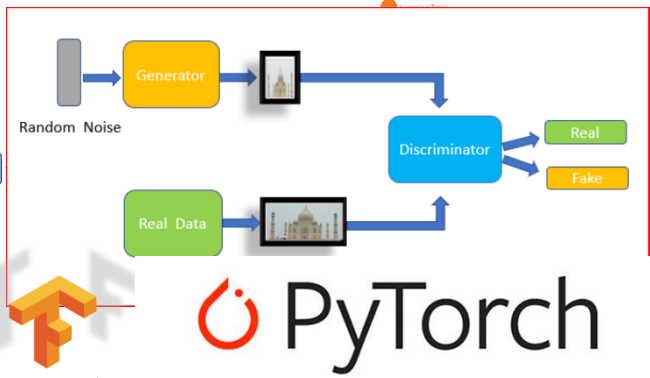












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