Medical AI: developing, applying, and evaluating AI used in medicine

PRESIMAL 2022

AUTUMN RESEARCH SCHOOL

AI IN MEDICAL IMAGING

15.09.22

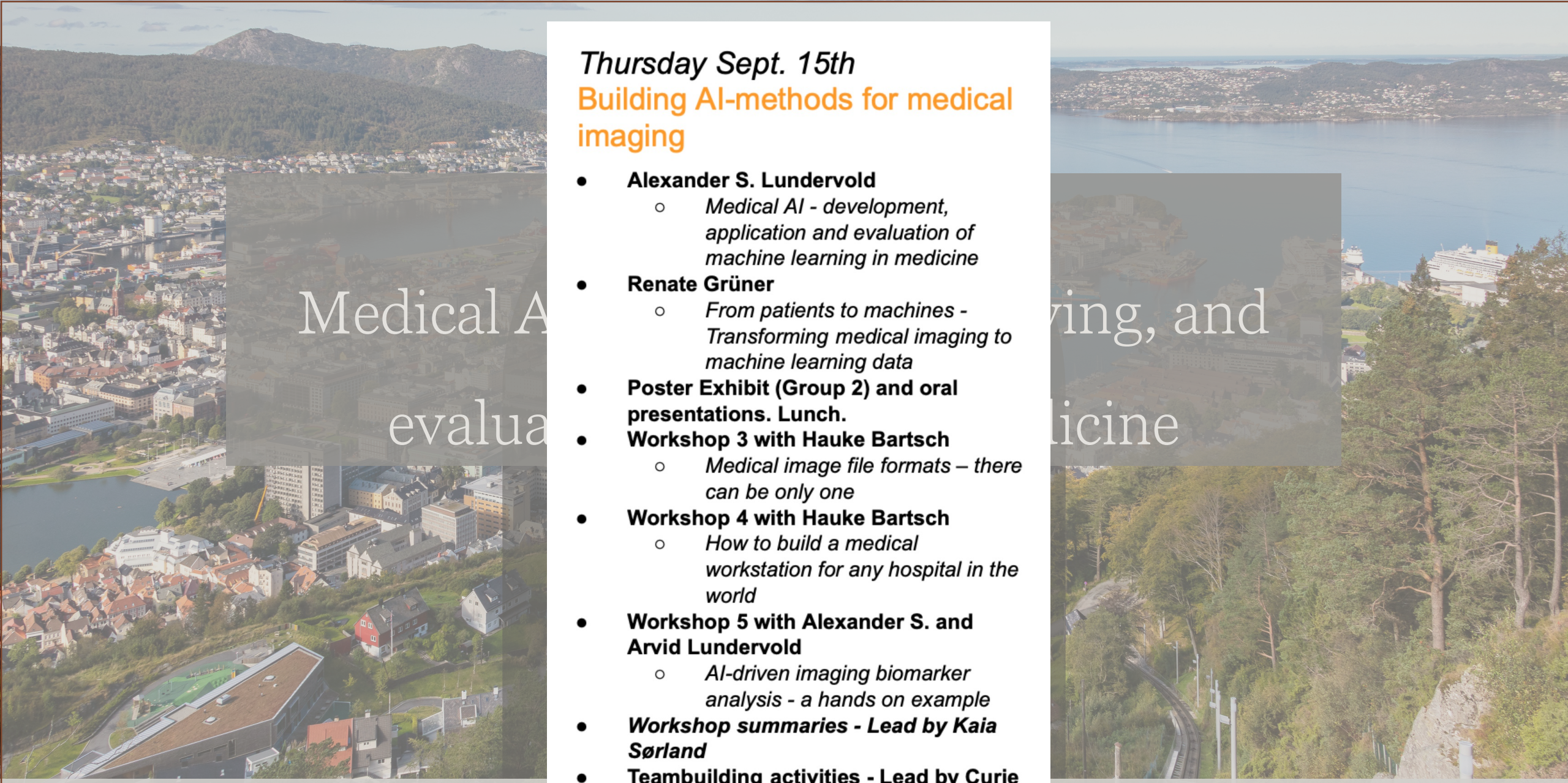
Western Norway University of Applied Sciences

MMIV

Haukeland University Hospital

Alexander Selvikvåg Lundervold

allu@hvl.no; lundervold.net



Medical A… …ying, and evalua… …licine

Thursday Sept. 15th

Building AI-methods for medical imaging

- **Alexander S. Lundervold**
  - *Medical AI - development, application and evaluation of machine learning in medicine*
- **Renate Grüner**
  - *From patients to machines - Transforming medical imaging to machine learning data*
- **Poster Exhibit (Group 2) and oral presentations. Lunch.**
- **Workshop 3 with Hauke Bartsch**
  - *Medical image file formats – there can be only one*
- **Workshop 4 with Hauke Bartsch**
  - *How to build a medical workstation for any hospital in the world*
- **Workshop 5 with Alexander S. and Arvid Lundervold**
  - *AI-driven imaging biomarker analysis - a hands on example*
- ***Workshop summaries - Lead by Kaia Sørland***
- **Teambuilding activities - Lead by Curie**
- **Dinner**

Western Norway University of Applied Sciences

MMIV

Haukeland University Hospital

Alexander Selvikvåg Lundervold

allu@hvl.no; lundervold.net

Medical AI: developing, applying, and evaluating AI used in medicine

PRESIMAL 2022

AUTUMN RESEARCH SCHOOL

AI IN MEDICAL IMAGING

15.09.22

Western Norway University of Applied Sciences

IMMIV

Haukeland University Hospital

Alexander Selvikvåg Lundervold

allu@hvl.no; lundervold.net

Medical AI: developing, applying, and evaluating AI used in medicine

PRESIMAL 2022

AUTUMN RESEARCH SCHOOL

AI IN MEDICAL IMAGING

15.09.22

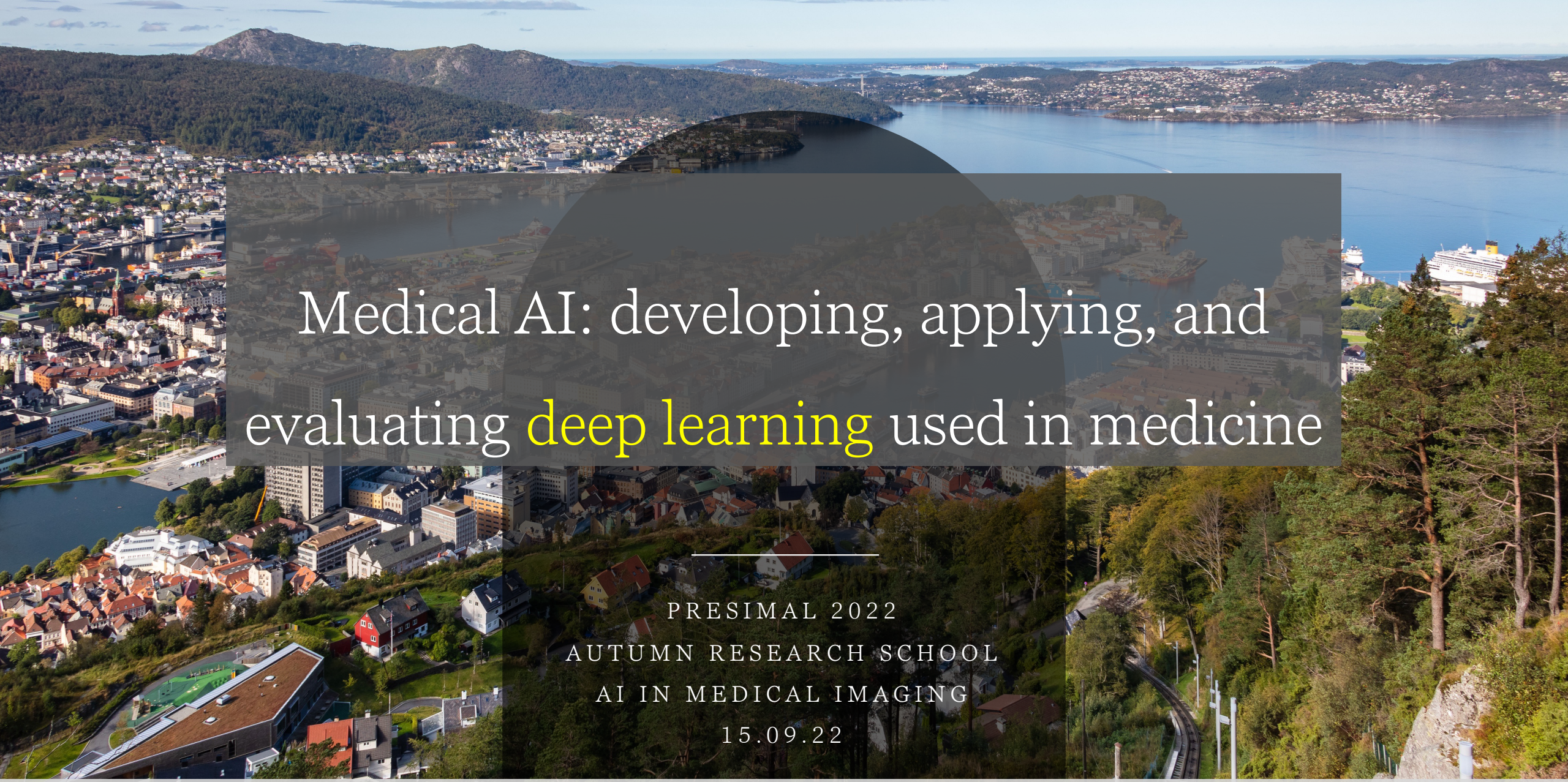
Western Norway University of Applied Sciences

IMMIV

Haukeland University Hospital

Alexander Selvikvåg Lundervold

allu@hvl.no; lundervold.net



Medical AI: developing, applying, and evaluating deep learning used in medicine

PRESIMAL 2022

AUTUMN RESEARCH SCHOOL

AI IN MEDICAL IMAGING

15.09.22

Western Norway University of Applied Sciences

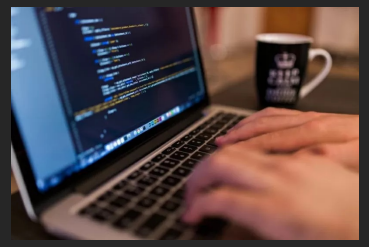
IMMIV

Haukeland University Hospital

Alexander Selvikvåg Lundervold

allu@hvl.no; lundervold.net

Plan



Hands-on workshop later today

What *is* deep learning?

How do you *do* deep learning?

Some perspectives, opportunities and challenges

Plan

Will only have time for a quick peek at the field!

Objectives:

(i) to *demystify*

(ii) make sure everyone understands what deep learning is about at a fundamental level, and get a sense of how you *do* deep learning as a practitioner

(iii) hopefully trigger some ideas and potentially a desire to explore further

de

learning?

opportunities and challenges

First...

- **Michael Riegler**
  - *AI in medical imaging - Challenges and opportunities*

What *is* deep learning?

How do you *do* deep learning?

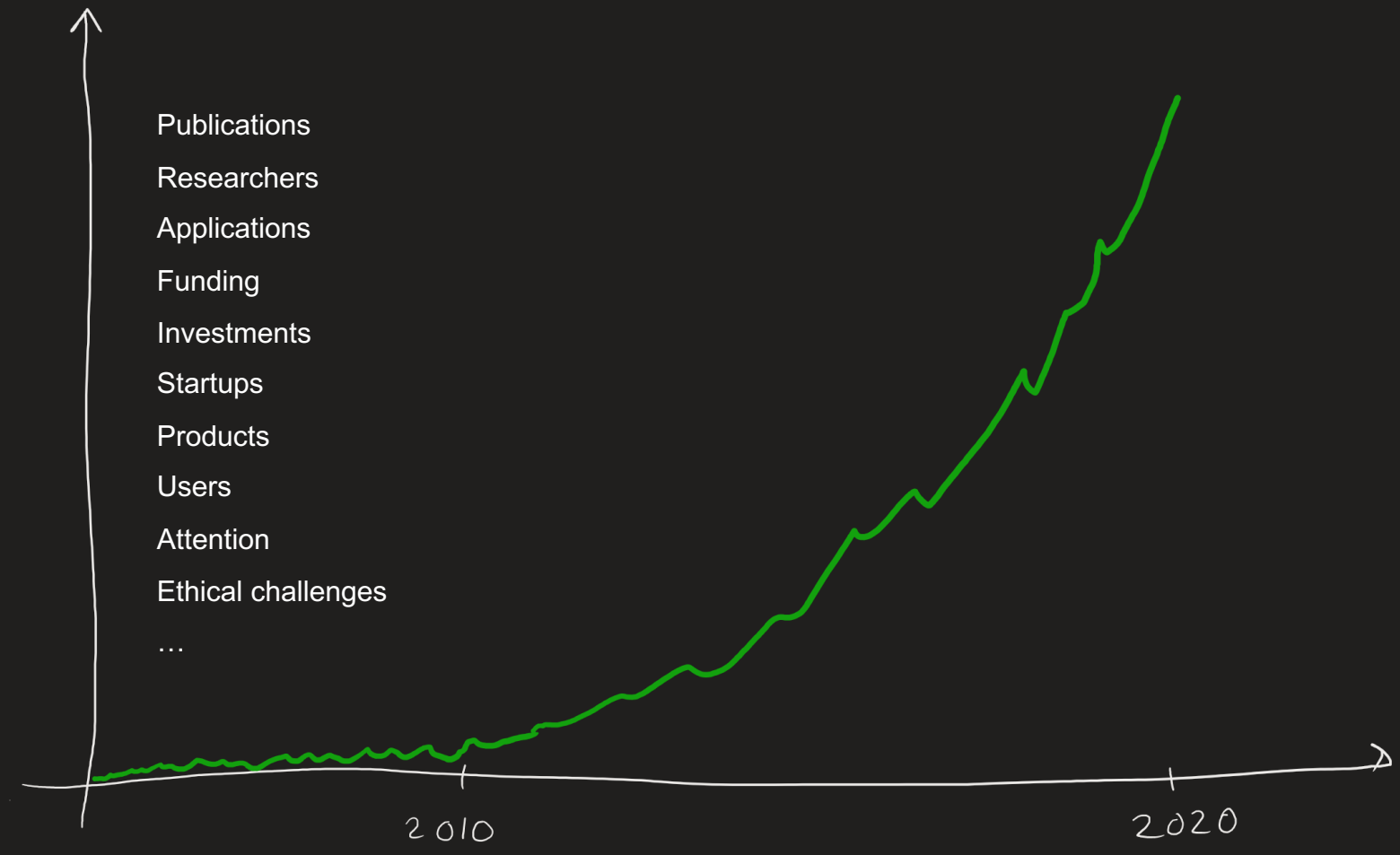
Some perspectives, opportunities and challenges

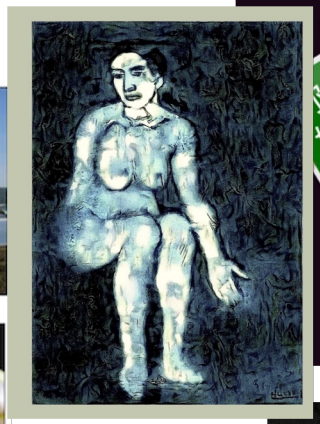
Artificial intelligence

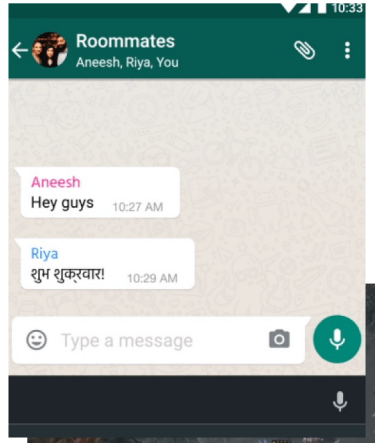
Machine learning

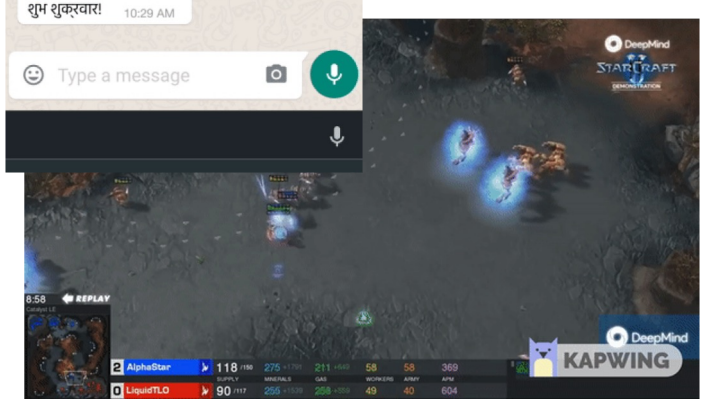
Deep learning

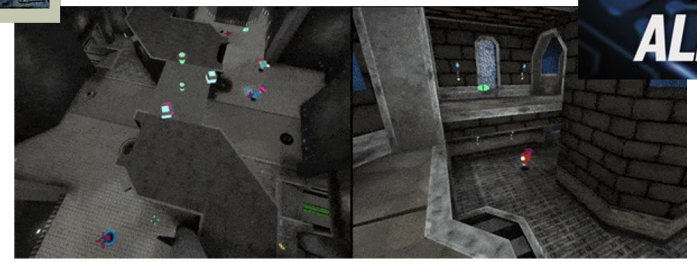
Representation learners











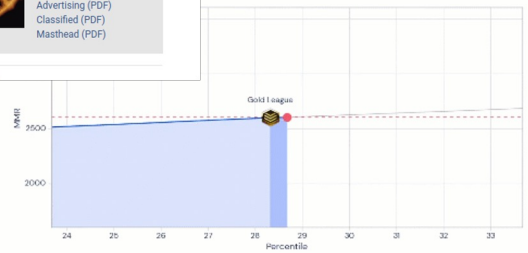
SHARE RESEARCH ARTICLE

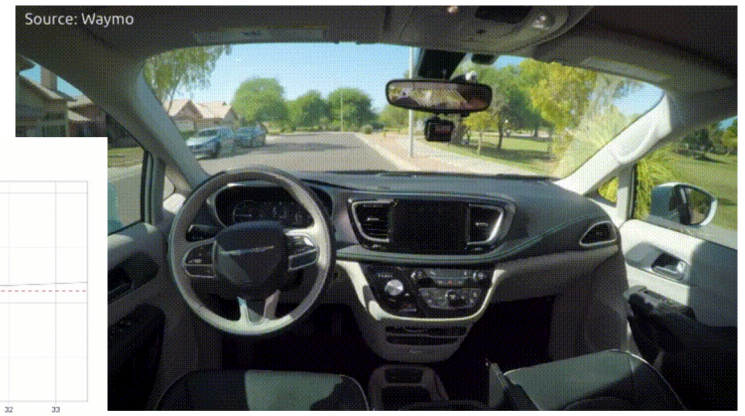
Human-level performance in 3D multiplayer games with population-based reinforcement learning

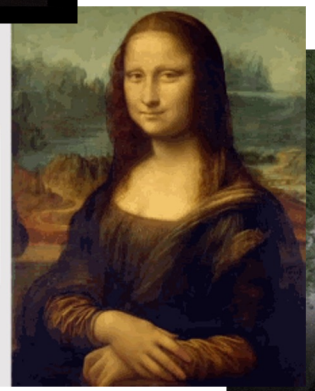
Max Jaderberg*,†, Wojciech M. Czarnecki*,†, Iain Dunning†, Luke Marris, Guy Lever, Antonio Garcia Castañeda, Charles Beat…
+ See all authors and affiliations

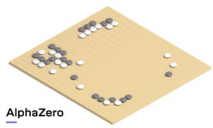
Science 31 May 2019:
Vol. 364, Issue 6443, pp. 859-865
DOI: 10.1126/science.aau6249

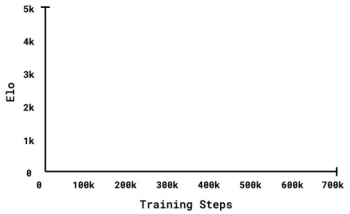
Science
Vol 364, Issue 6443
31 May 2019
Table of Contents
Print Table of Contents
Advertising (PDF)
Classified (PDF)
Masthead (PDF)











Skin cancer can't hide from deep-learning diagnostics

May 21, 2019 | Dave Pearson | Diagnostics

FDA Approves AI Tool That Can Detect Wrist Fractures

The FDA has approved a new tool that can improve the accuracy of wrist fracture diagnosis.

By Jessica Miley
May 28th, 2018

Deep learning improves detection of polyps during colonoscopy

November 07, 2018 | Matt O'Connor | Artificial Intelligence

Nevit Dilmen/Wikimedia Commons

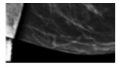
Deep learning predicts OCT measures of diabetic macular thickening

Exudates in the macula showing clinically significant macular edema (CSME) can be deceiving for the diagnosis of abnormal macular thickening. Left: Color fundus photo shows exudates indicating CSME, with associated CST <250 um. Right: CFP shows no CSME, but has associated CST >250 um. (Images courtesy of Jeffrey Wilks, MD, PhD)

Deep learning detects ACL tears on MRI si

May 17, 2019 | Matt O'Connor | Artificial Intelligence

By Steve Lenier
May 21, 2019



Novel Molecules Designed by Artificial Intelligence May Accelerate Drug Discovery

TOPICS: Artificial Intelligence Biotechnology InSilico Medicine

NEWS CAREERS JOURNALS

News Home All News

ME > NEWS > ALL NEWS > AI CRACKS THE CODE OF PROTEIN COMPLEXES—PROVIDI

WS | BIOLOGY

AI cracks the code of prote -providing a road map for

oftware maps thousands of the partnered proteins

NOV 2021 · 2:00 PM · BY ROBERT F. SERVICE

Results

tein complex prediction with AlphaFold-Multimer

chard Evans, Michael O'Neill, Alexander Pritzel, Natasha Antropova, Andre
m Green, Augustin Žídek, Russ Bates, Sam Blackwell, Jason Yim, Olaf R
bastian Bodenstein, Michal Zielinski, Alex Bridgland, Anna Potapenko, Andrew
athryn Tunyasuvunakool, Rishub Jain, Ellen Clancy, Pushmeet Kohli, John
emis Hassabis

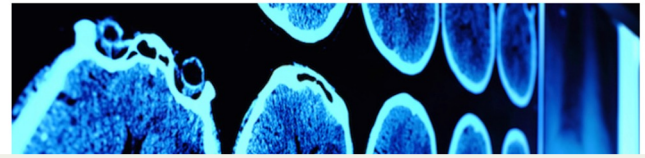
https://doi.org/10.1101/2021.10.04.463034

rticle is a preprint and has not been certified by peer review [what does this mean?].

Science LOG IN

Deep Learning Tool Identifies Disease Markers of Alzheimer's

A deep learning tool was able to rapidly detect markers of Alzheimer's disease in human brain tissue.



NOVEMBER 15, 2017

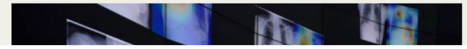
Stanford algorithm can diagnose pneumonia better than radiologists

Stanford researchers have developed a deep learning algorithm that evaluates chest X-rays for signs of disease. In just over a month of development, their algorithm outperformed expert radiologists at diagnosing pneumonia.

BY TAYLOR KUBOTA

Stanford researchers have developed an algorithm that offers diagnoses based off chest X-ray images. It can diagnose up to 14 types of medical conditions and is able to diagnose pneumonia better than expert radiologists working alone. A paper about the algorithm, called CheXNet, was published Nov. 14 on the open-access, scientific preprint website arXiv.

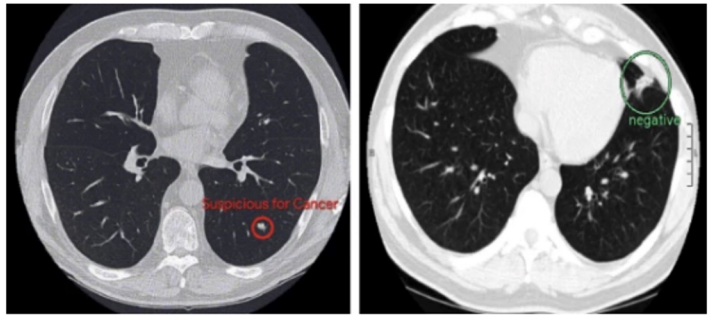
"Interpreting X-ray images to diagnose pathologies like



AI

Google's lung cancer detection AI outperforms 6 human radiologists

KHARI JOHNSON @KHARIJOHNSON MAY 20, 2019 8:00 AM

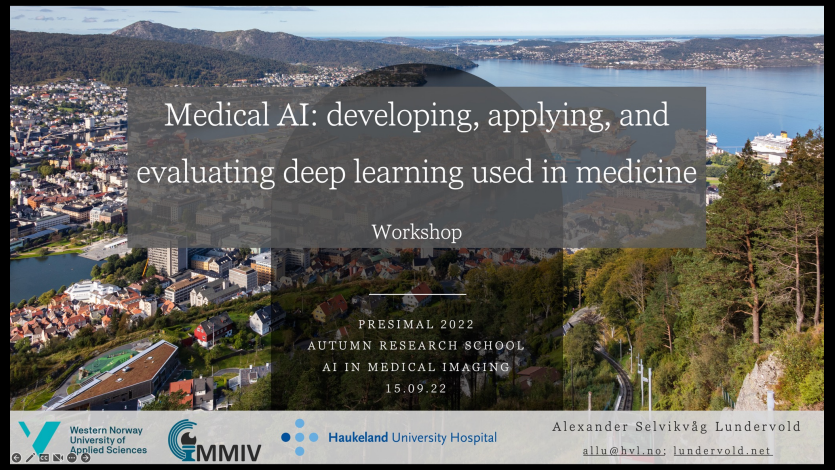


What is deep learning?

Deep learning

searching for good hierarchical geometric representations

Workshop at 15.15



Deep learning

***searching** for good hierarchical geometric representations*

Deep learning

searching for good hierarchical geometric representations

Deep learning

searching for good hierarchical geometric representations

Deep learning

searching for good hierarchical geometric representations

01

02

03

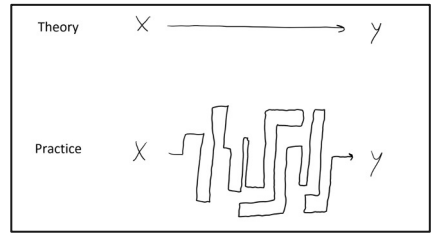
04

05

01 Machine learning: **function approximation** based on **training**

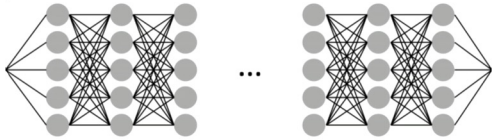
$$y \approx f(x;\theta)$$

02 We pick the model family f. The parameters θ are found automatically through training

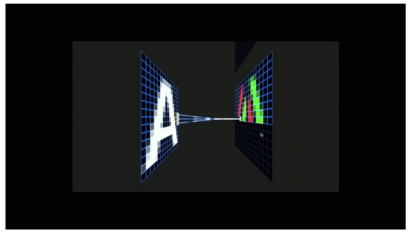


03 In practice: some models are better suited to some tasks than others.

04 In deep learning: a particular choice of f. A **composition** of simple functions, trained jointly, typically using GPUs or other accelerators.



05 In deep learning: finding a **hierarchical set of geometric transformations**, ending in a representation that makes the desired task easy to solve.



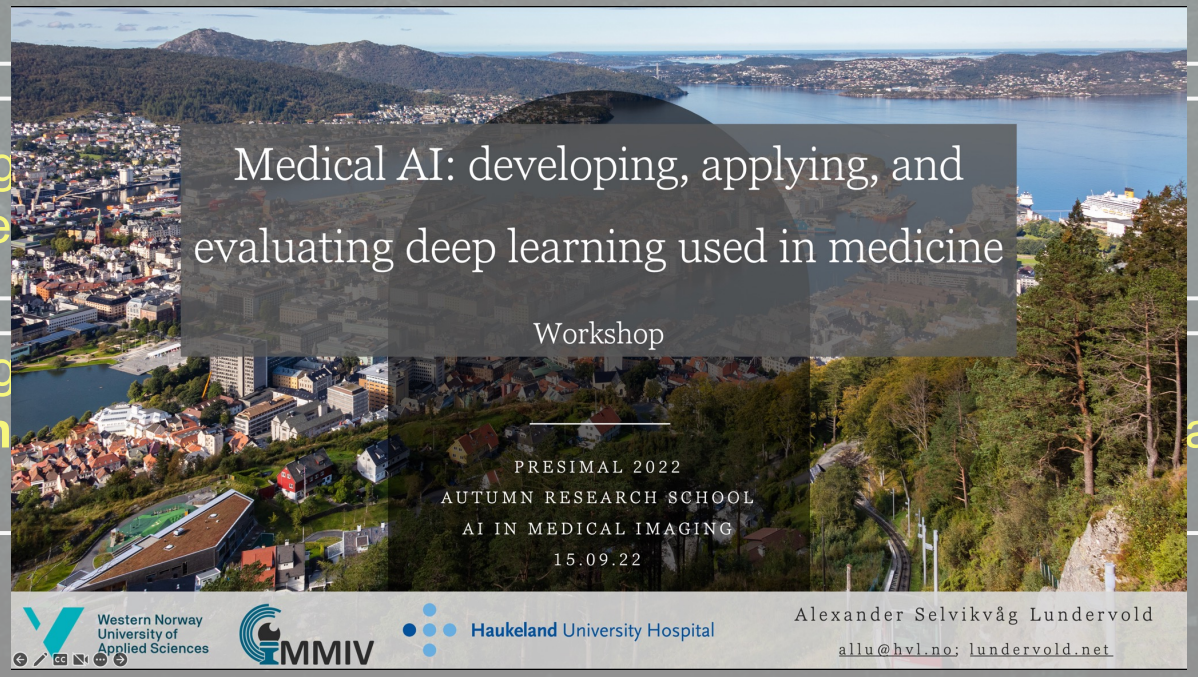
01 Machine learning: **function approximation** based on **training**

02 We pick the model family $\mathcal{F}$. The parameters Θ are found automatically through training

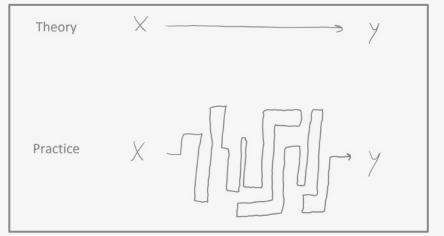
03 In practice: some models Workshop at 15.15 n others.

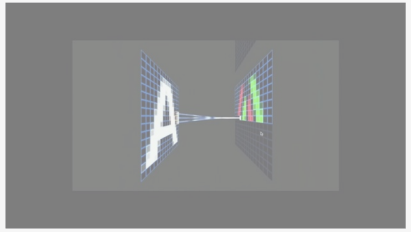
04 In deep learning functions, traine

05 In deep learning **transformation** easy to solve. ask



$$y \approx f(x;\theta)$$





Plan

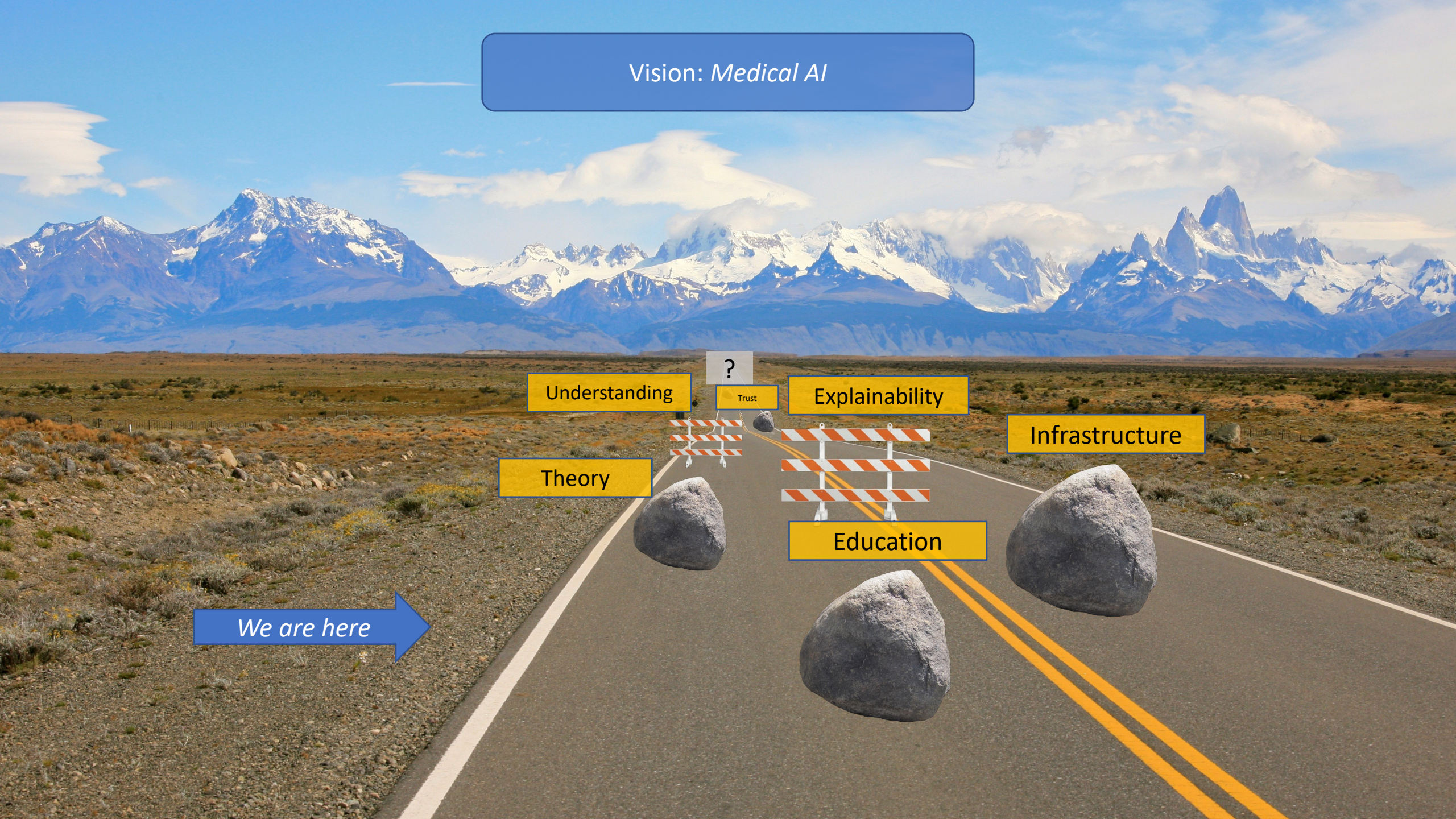
What *is* deep learning?

How do you *do* deep learning?

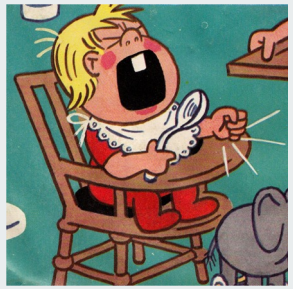
Some perspectives, opportunities and challenges

Challenges for deep learning in medicine

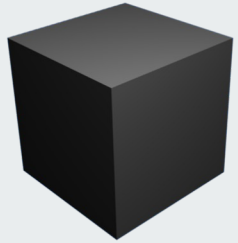
- **Michael Riegler**
  - *AI in medical imaging - Challenges and opportunities*


Vision: *Medical AI*
?
Understanding
Trust
Explainability
Infrastructure
Theory
Education
We are here

Data hungry!



Black box



DARPA

"Explainable AI"

Why did you do that?
Why not something else?
When do you not succeed?
When do you fail?
When can I trust you?
How can I correct an error?

Overuse

Spurious patterns

Privacy

Data access

De-anonymization attacks

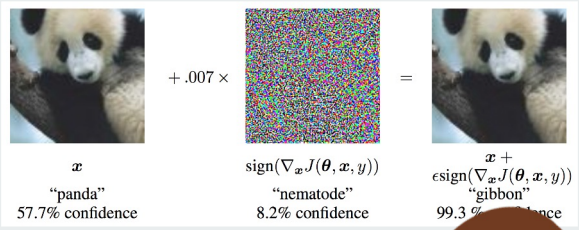
Law

Data labeling

Protecting data

Model inversion
Membership attack

Adversarial examples



Fairness

Reproducibility

And more...

Differential privacy

Lack of theory

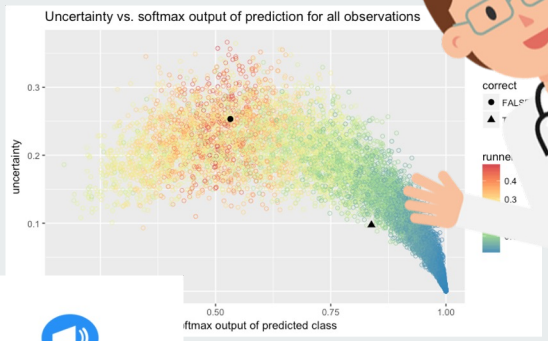
Models lack of understanding

Trust

Instability

Underspecification

Uncertainty



Clinical validation

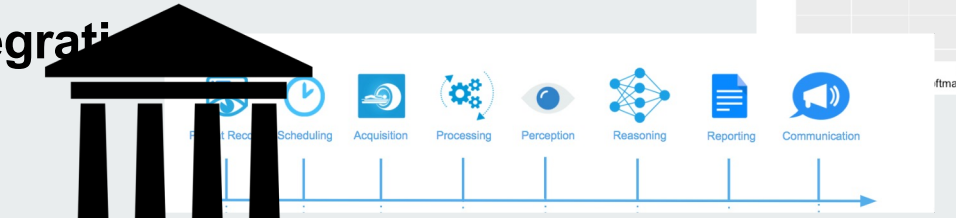
What makes one model better than another?

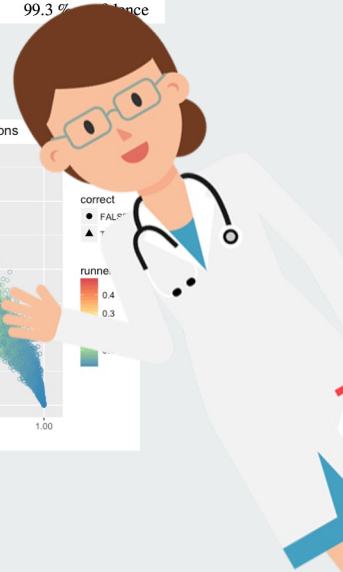
Causality

Education

Software engineering best practices

Workflow integrati

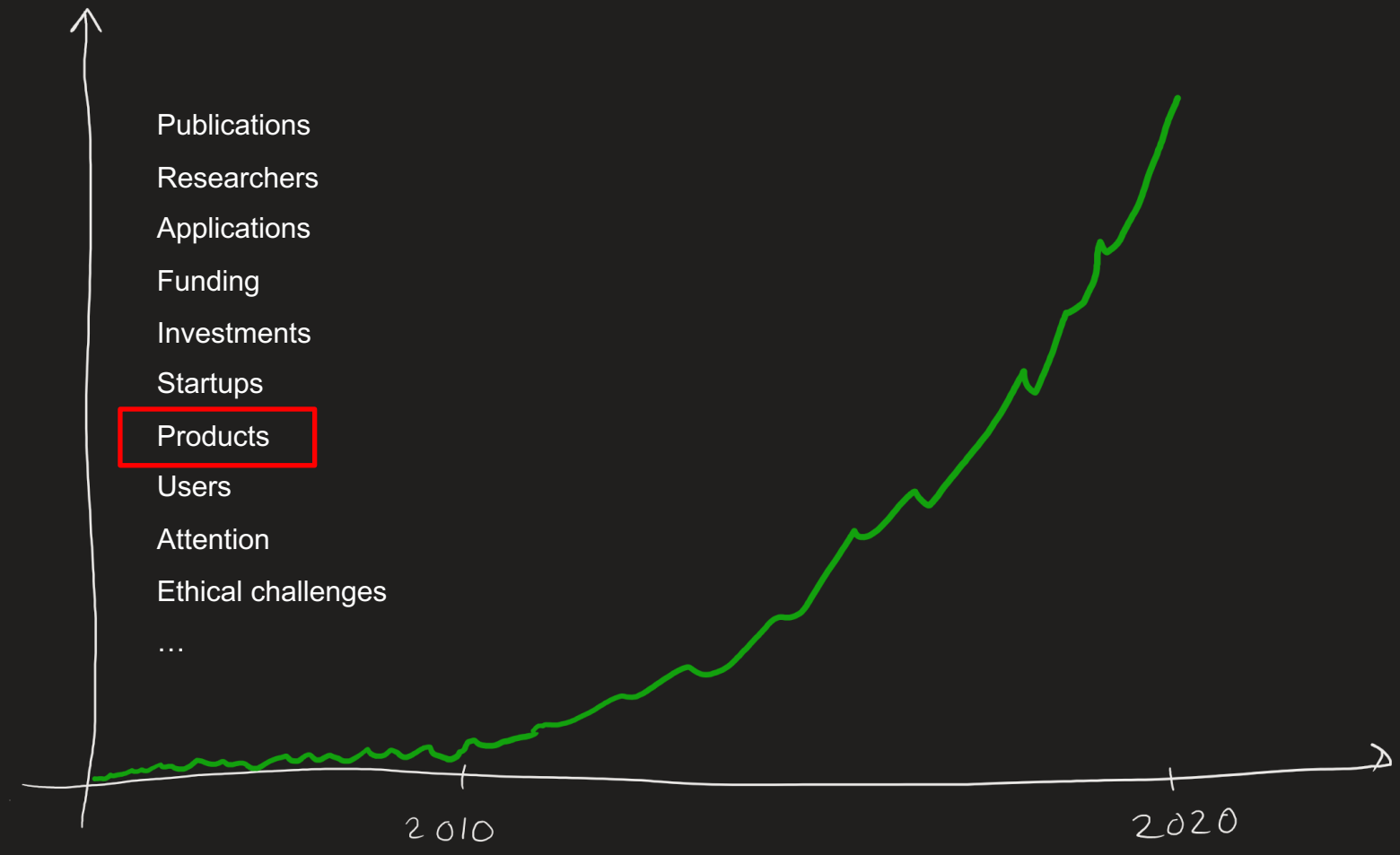




ployment, maintenance,
g, hidden technical debt, ...

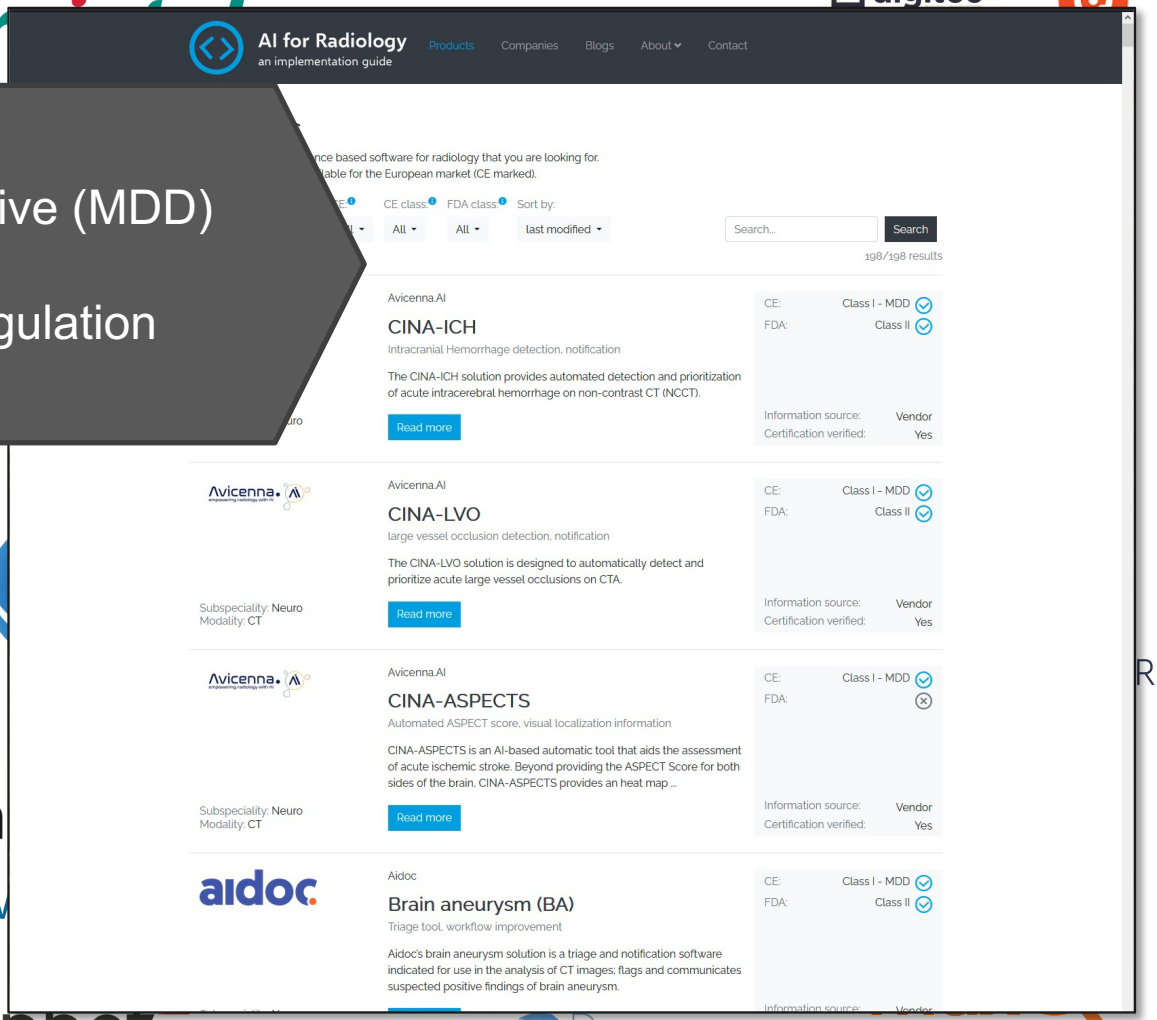
Anchoring to domain

Artificial intelligence Machine learning **Deep learning**



All of these are available on the European market per May 2022 (CE marked)

OBS:
Medical Device Directive (MDD)
versus
Medical Device Regulation
(MDR)



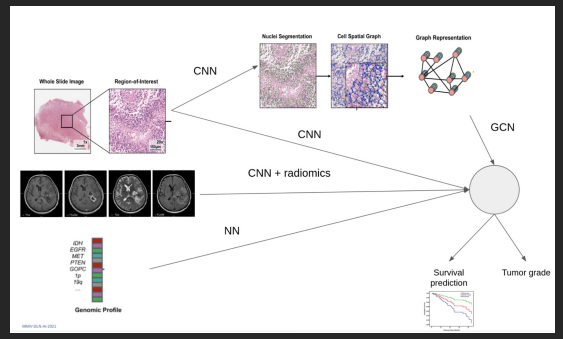

Tasks
Modalities
Anatomical regions
...
Narrow
Data availability
Competency availability
Medical feasibility
Technical feasibility
Organizational feasibility
Regulatory feasibility
Theoretical limitations
Incentives
...

The research side is somewhat broader...

...trying to investigate how to integrate heterogeneous data about patients and disease processes.

Two examples:

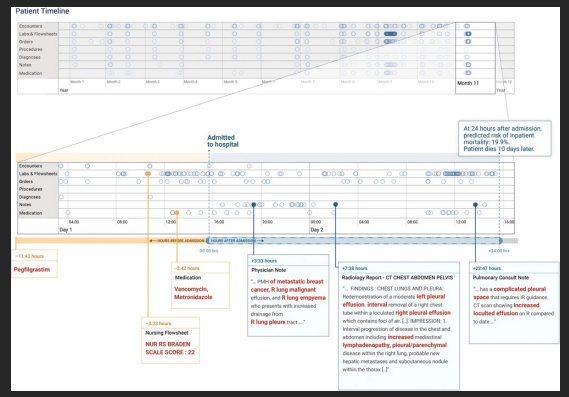
Integrated diagnostics



From brain tumor imaging and genetics to survival prediction

Chen et.al. IEEE Trans Med Imaging, 2022, 10.1109/TMI.2020.3021387

Deep learning and electronic health records



From EHR to length-of-stay and in-hospital mortality

Rajkomar et.al., NPJ Digit Med, 2018, 10.1038/s41746-018-0029-1

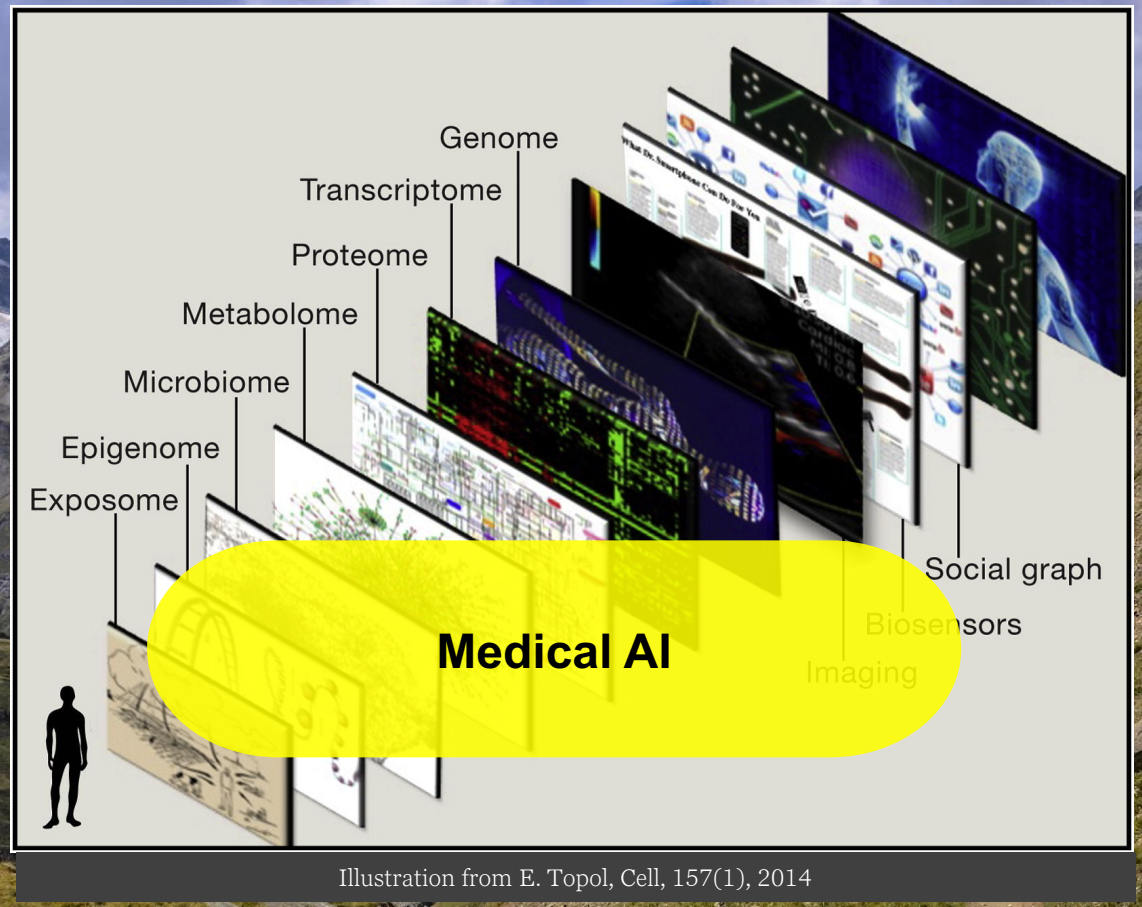
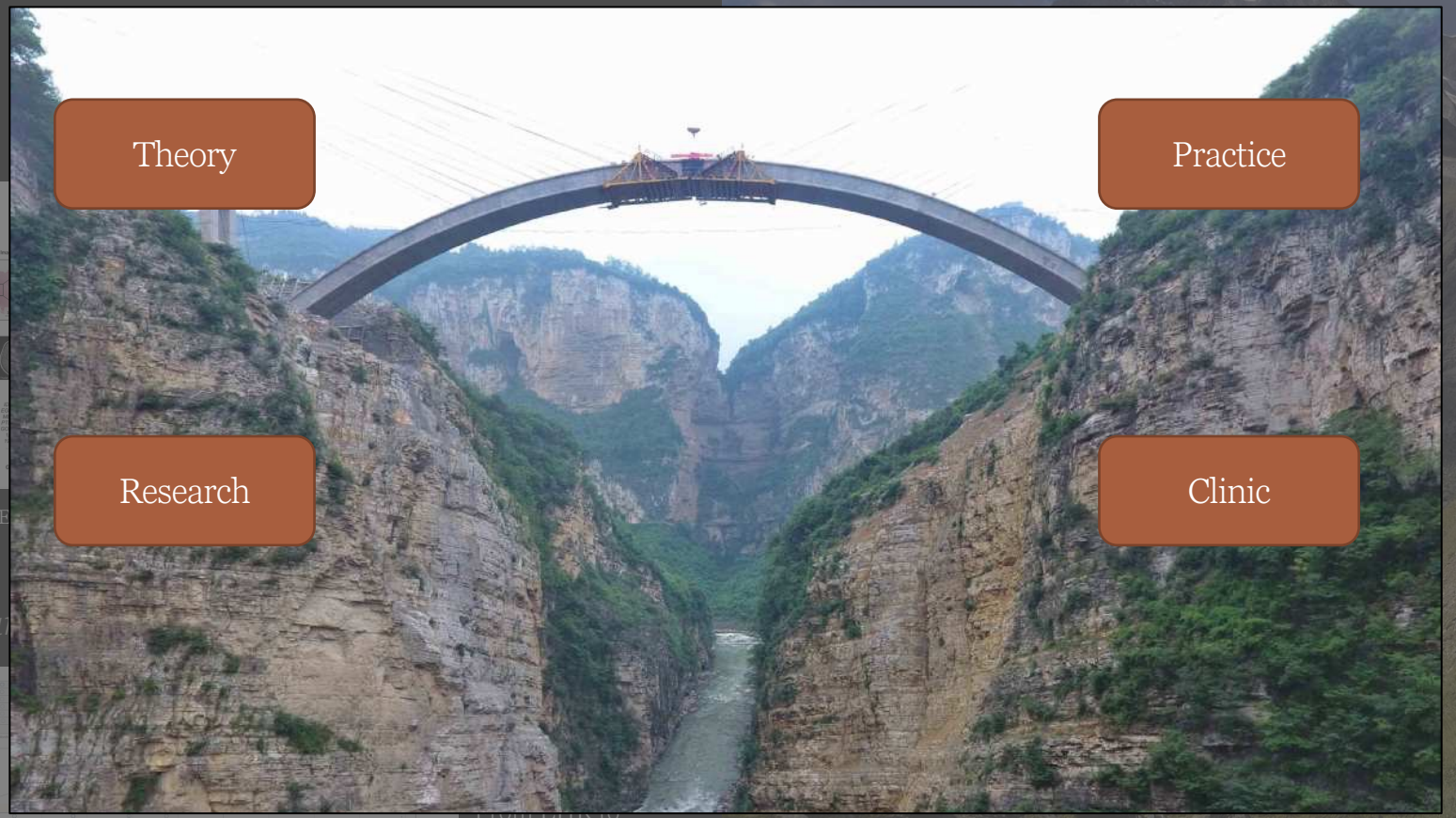


Illustration from E. Topol, Cell, 157(1), 2014

The research side is somewhat broader...

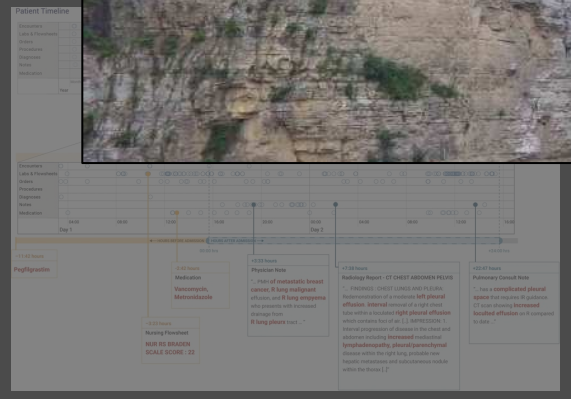
...trying to investigate how to integrate heterogeneous data about patients and disease processes.

Two examples:



Chen et.al. IE

Deep lea



length-of-stay and
in-hospital mortality

Rajkomar et.al., NPJ Digit Med, 2018, 10.1038/s41746-018-0029-1


Machine learning in medicine


Practical machine learning
&
Machine learning engineering

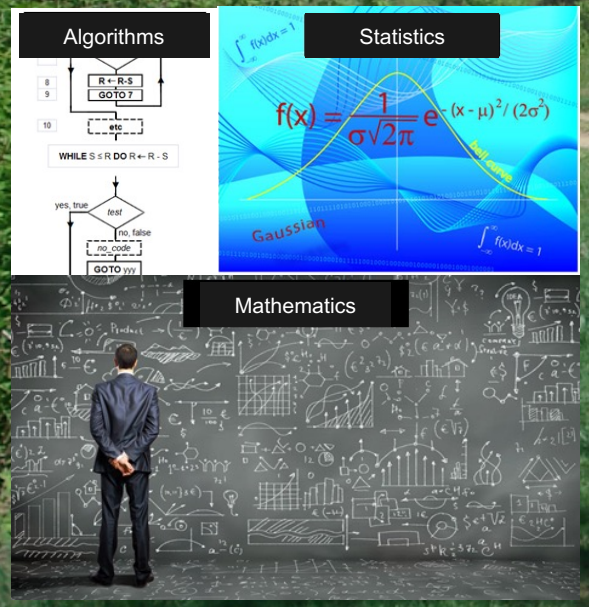

Machine learning
Machine learning
Machine learning

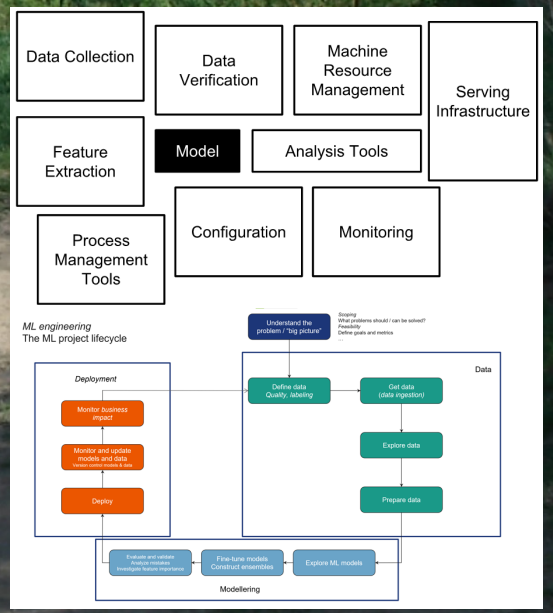

Machine learning
Machine learning models
Machine learning engineering

Machine learning

Machine learning models

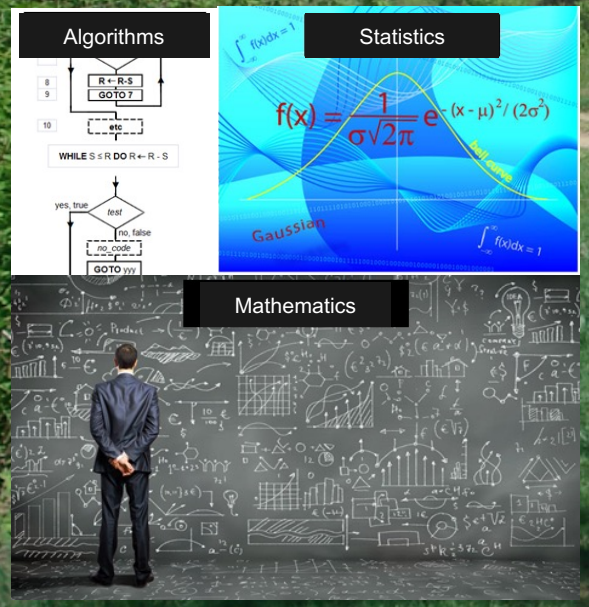
Machine learning engineering

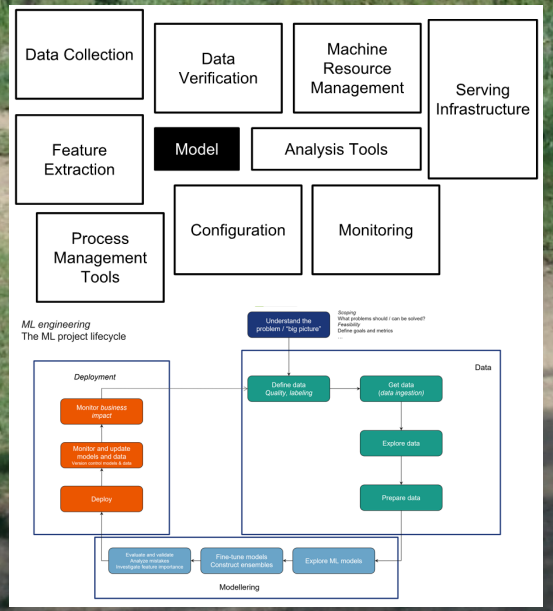




Machine learning models

Machine learning engineering

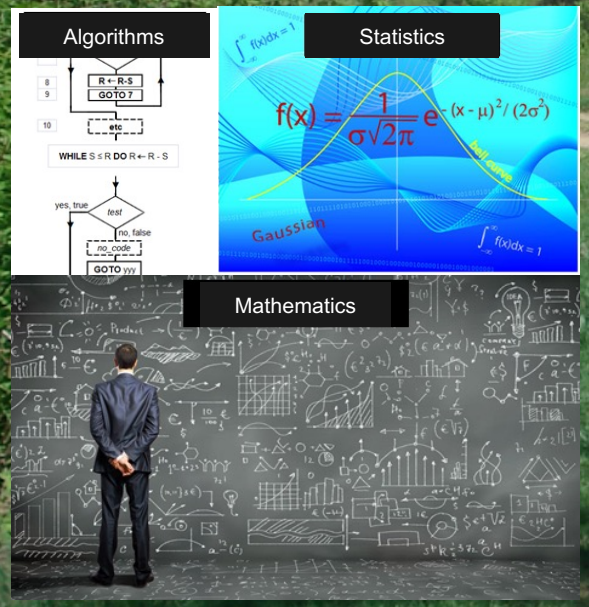


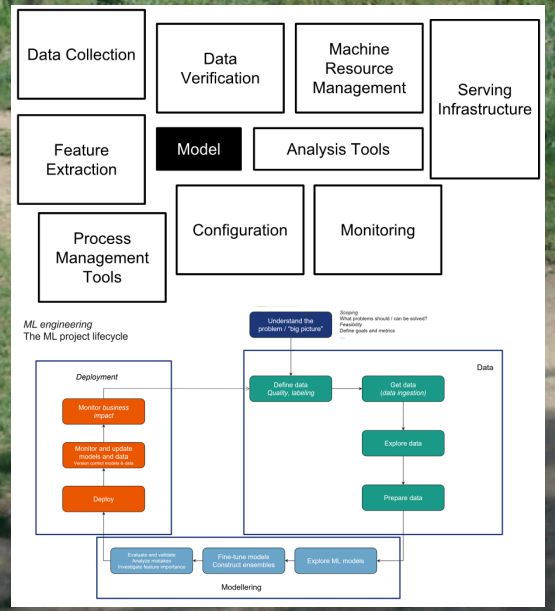


Machine learning models

Machine learning engineering

Data and society

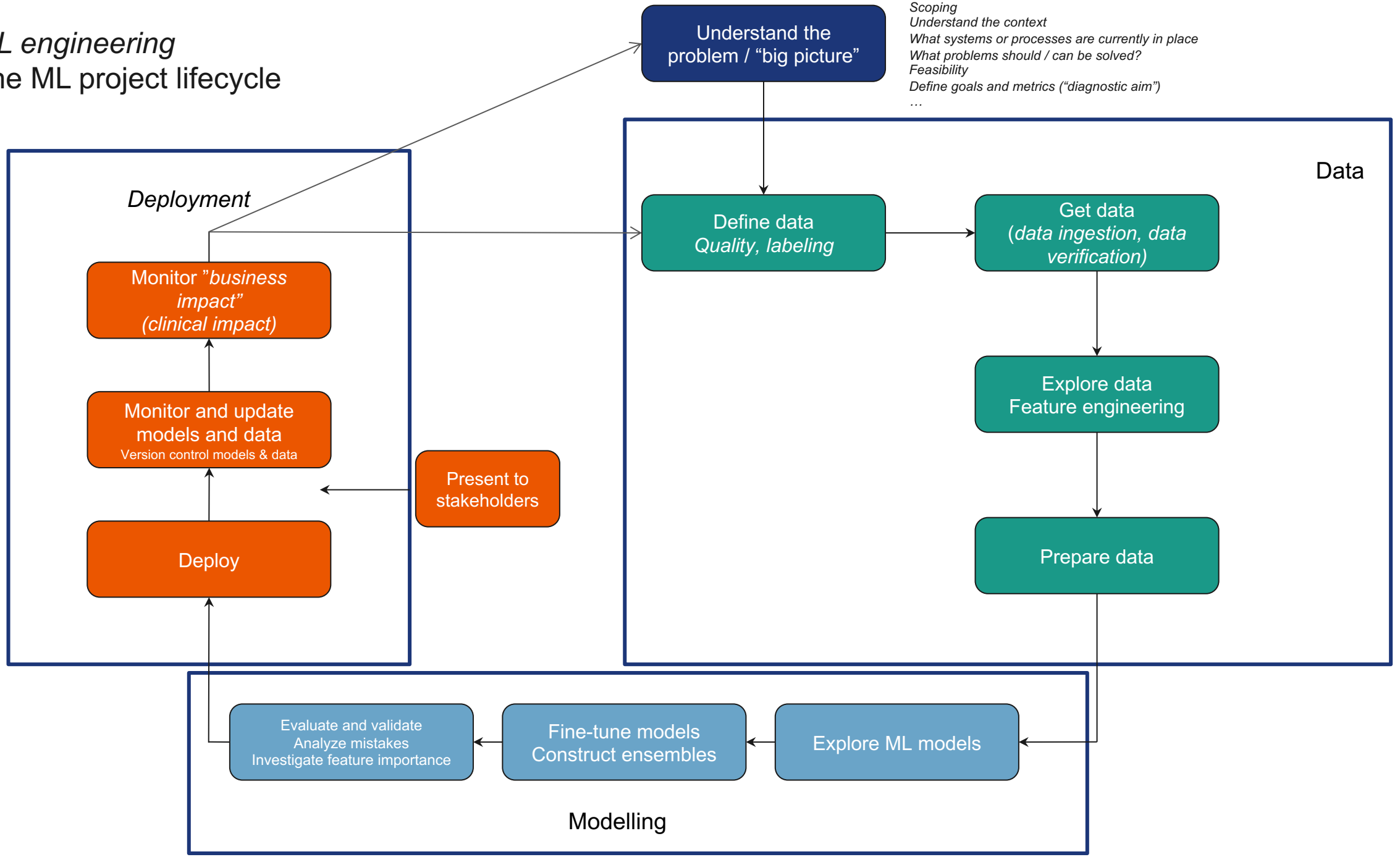




How do you make a machine learning-based solution?

ML engineering

The ML project lifecycle



ML engineering

The ML project lifecycle

Understand the problem / "big picture"

Scoping
Understand the context
What systems or processes are currently in place
What problems should / can be solved?
Feasibility
Define goals and metrics ("diagnostic aim")

Data

Define data
Quality, labeling

Get data
(data ingestion, data verification)

Explore data
Feature engineering

Prepare data

Explore ML models

Fine-tune models
Construct ensembles

Evaluate and validate
Analyze mistakes
Investigate feature importance

Modelling

Deployment

Present to stakeholders

Deploy

Monitor and update models and data
Version control models & data

Monitor "*business impact*"
(clinical impact)

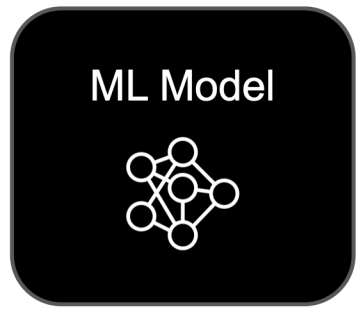


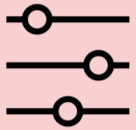
Illustration based on https://developers.google.com/machine-learning/testing-debugging/pipeline/overview

Analysis Tools

Data Verification

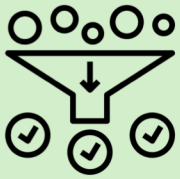
Process Management Tools

Configuration

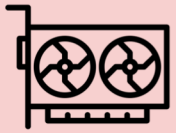


ML Model

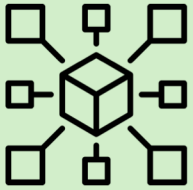
Feature Extraction



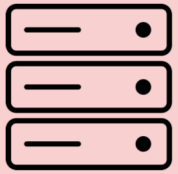
Machine Resource Management



Data Collection



Serving Infrastructure



Monitoring

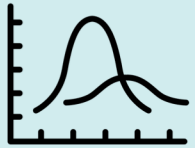
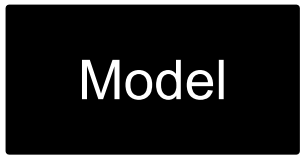
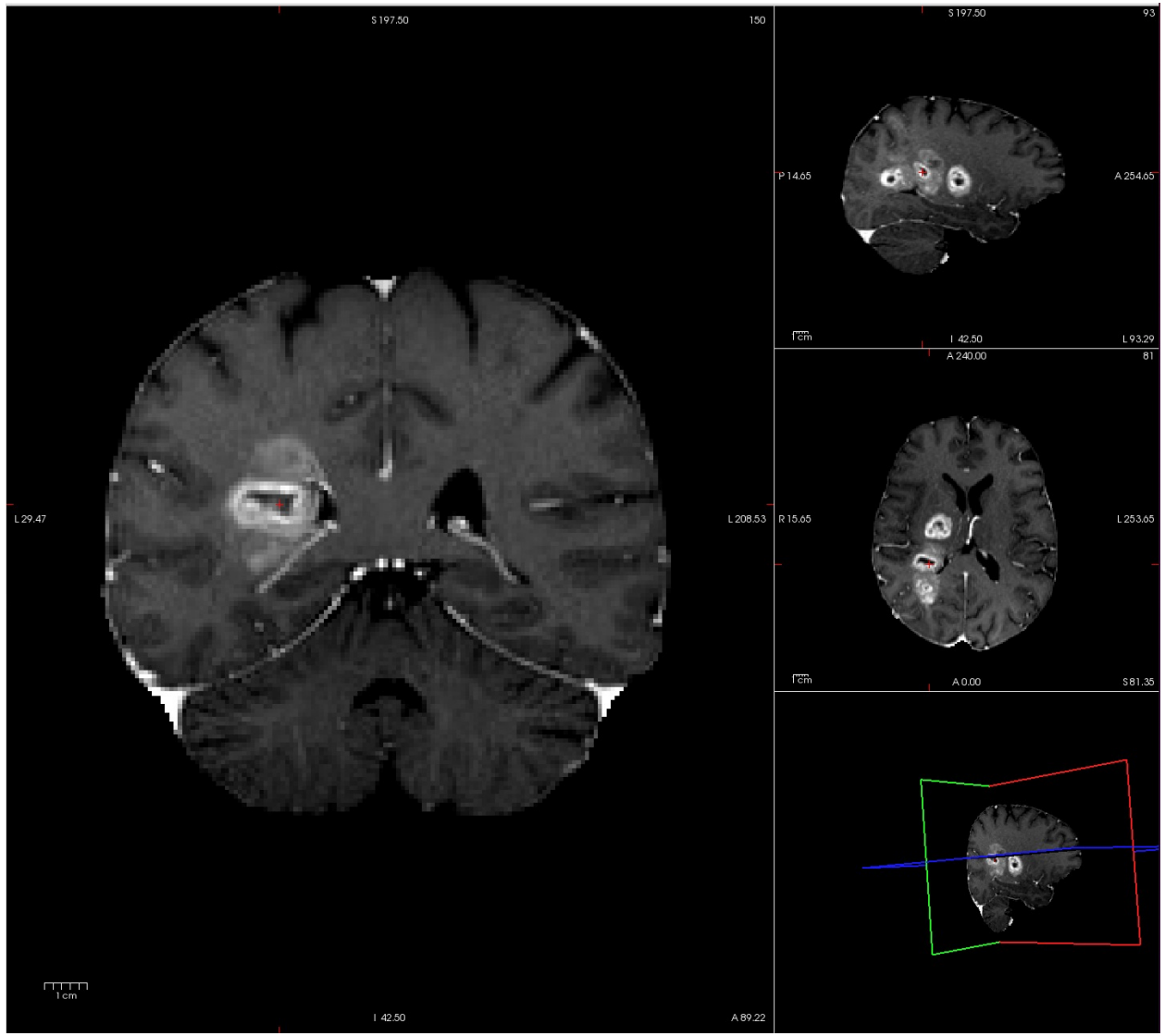


Illustration based on https://developers.google.com/machine-learning/testing-debugging/pipeline/overview

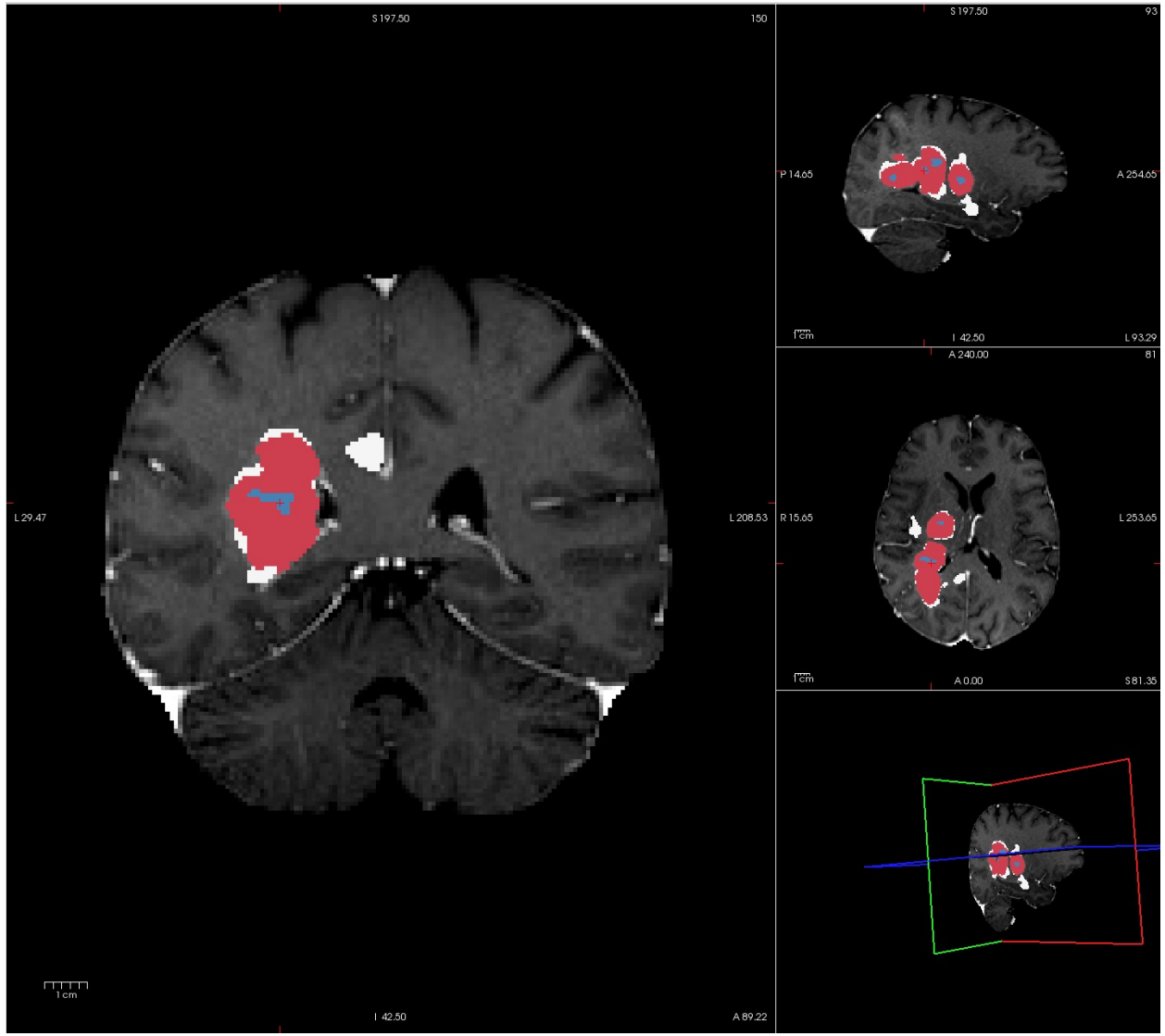

Machine learning in medicine


Model

Model


S 197.50
150
L 29.47
L 208.53
I 42.50
A 89.22
S 197.50
93
P 14.65
A 254.65
I 42.50
L 93.29
A 240.00
81
R 15.65
L 253.65
A 0.00
S 81.35

Model


S 197.50
150
L 29.47
L 208.53
I 42.50
A 89.22
1 cm
S 197.50
93
P 14.65
A 254.65
I 42.50
L 93.29
A 240.00
81
R 15.65
L 253.65
A 0.00
S 81.35

Pattern Recognition
Volume 110, February 2021, 107562

Cross-modality deep feature learning for brain tumor segmentation

Dingwen Zhang [a], Guohai Huang [a], Qiang Zhang [a], Jungong Han [b], Junwei Han [c], Yizhou Yu [d]

Biomedical Signal Processing and Control
Volume 55, January 2020, 101641

RescueNet: segmentati

Shubhangi Nema [a, b], Aka

Show more

Add to Mendeley

Computer Communications
Volume 153, 1 March 2020, Pages 196-207

Modality-Pairing Learning for Brain Tumor Segmentation

Yixin Wang, Yao Zhang, Feng Hou, Yang Liu, Jiang Tian, Cheng Zhong, Yang Zhang & Zhiqiang He

Conference paper | First Online: 27 March 2021

877 Accesses | 4 Citations

Part of the Lecture Notes in Computer Science

Expert Systems with Applications
Volume 170, 15 May 2021, 114566

ERV-Net: An efficient 3D residual neural network for brain tumor segmentation

Xinyu Zhou [a, 1], Xuanya Li [b, 1], Kai Hu [a], Yuan Zhang [a], Zhineng Chen [c], Xieping Gao [a, d]

Show more

Add to Mendeley | Share | Cite

https://doi.org/10.1016/j.eswa.2021.114566

Get rights and content

Physics in Medicine & B

PAPER

Brain tumor segmenta dynamic susceptibility

Jiwoong Jeong[1,2], Yang Lei[1], Sha Hui Mao[3,4] and Xiaofeng Yang[1,4]

Published 14 September 2020 • © 2020

Articles

Automated quantitative tumour response assessment of MRI in neuro-oncology with artificial neural networks: a multicentre, retrospective study

Philipp Kickingereder, Fabian Isensee*, Irada Tursunova, Jens Petersen, Ulf Neuberger, David Bonekamp, Gianluca Brugnara, Marianne Schell, Tobias Kessler, Martha Foltyn, Inga Harting, Felix Sahm, Marcel Prager, Martha Nowosielski, Antje Wick, Marco Nolden, Alexander Radbruch, Jürgen Debus, Heinz-Peter Schlemmer, Sabine Heiland, Michael Platten, Andreas von Deimling, Martin J van den Bent, Thierry Gorlia, Wolfgang Wick, Martin Bendszus†, Klaus H Maier-Hein†*

Summary

Background The Response Assessment in Neuro-Oncology (RANO) criteria and requirements for a uniform
have been introduced to standardise assessment of MRI scans in both clinical trials and clinical practice. I
these criteria mainly rely on manual two-dimensional measurements of contrast-enhancing (CE) target les
thus restrict both reliability and accurate assessment of tumour burden and treatment response. We aimed to
a framework relying on artificial neural networks (ANNs) for fully automated quantitative analysis of MRI i
oncology to overcome the inherent limitations of manual assessment of tumour burden.

Lancet Oncol 2019; 20: 728–740
Published Online
April 2, 2019
http://dx.doi.org/10.1016/S1470-2045(19)30098-1

*Joint first authors
†Joint senior authors

Neurocomputing
Volume 392, 7 June 2020, Pages 305-313

Brain tumor segmentation with deep convolutional symmetric neural network

Workshop at 15.15

TransBTS: Multimodal Brain Tumor Segmentation Using Transformer

Wenxuan Wang, Chen Chen, Meng Ding, Hong Yu, Sen Zha & Jiangyun Li

Conference paper | First Online: 21 September 2021

7535 Accesses | 15 Citations

Part of the Lecture Notes in Computer Science book series (LNIP,volume 12901)

frontiers in Computational Neuroscience

Brain Tumor Segmentation Ensemble of 3D U-Nets and Survival Prediction Using Ra Features

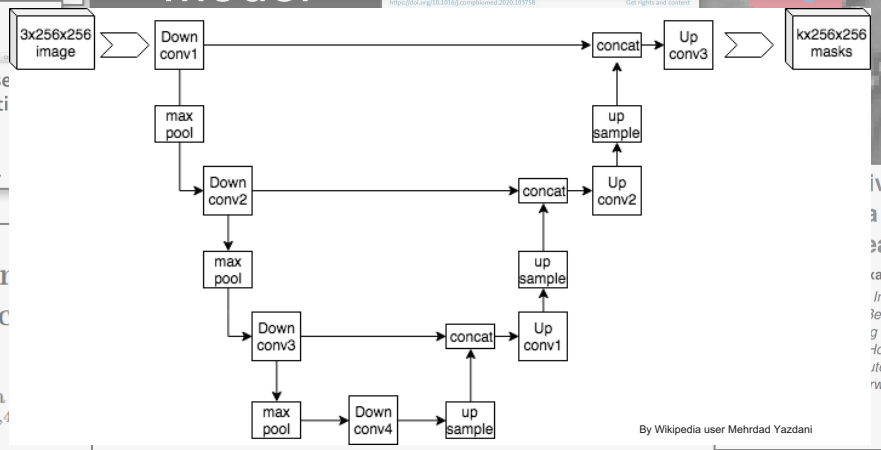
Xue Feng*, Nicholas J. Tustison, Sohil H. Patel and Craig H. Me

scientific reports

OPEN

Brain tumor segmentation base on deep learning and an attenti mechanism using MRI multi-modalities brain images

Ramin Ranjbarzadeh[1], Abbas Bagherian Kasgari[2], Saeid Jafarzadeh Ghoushchi[3], Shokofeh Anari[4], Maryam Naseri[5] & Malika Bendechache[6]



Brain tumor segmentation from multiparar MRI using a multi-encoder U-Net architec

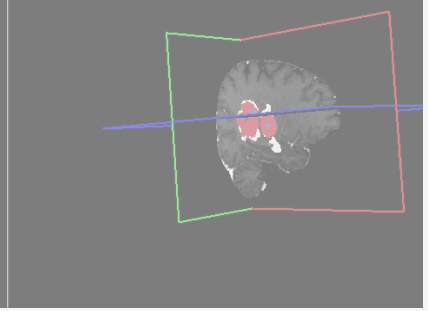
Saruar Alam[1,2], Bharath Halandur[2,3], P.G.L. Porta Mana[2,4], Dorota Arvid Lundervold[1,2], and Alexander Selvikvåg Lundervold[2,4]

[1] Department of Biomedicine, University of Bergen, Norway
[2] Mohn Medical Imaging and Visualization Centre (MMIV), Department of Radiology, Haukeland University Hospital, Bergen, Norway
[3] Department of Clinical Science, University of Bergen, Norway
[4] Department of Computer science, Electrical engineering and Mathematical sciences, Western Norway University of Applied Sciences, Bergen, Norway
[5] Department of Oncology, Haukeland University Hospital, Bergen, Norway

Connected Convolutional Networks*

Saruar Alam[1,2], Arvid Lundervold[1,2], and Alexander Selvikvåg Lundervold[2,3]

[1] Department of Biomedicine, University of Bergen, Norway
[2] Mohn Medical Imaging and Visualization Centre (MMIV), Department of Radiology, Haukeland University Hospital, Bergen, Norway
[3] Department of Computer science, Electrical engineering and Mathematical sciences, Western Norway University of Applied Sciences, Bergen, Norway



ML Model

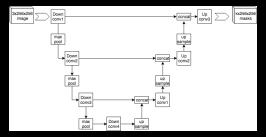


Illustration based on https://developers.google.com/machine-learning/testing-debugging/pipeline/overview

Analysis Tools

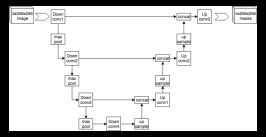
Data Verification

Process Management Tools

In radiology, solutions must be compatible with existing infrastructure!

Configuration

ML Model



Feature Extraction

Machine Resource Management

Data Collection

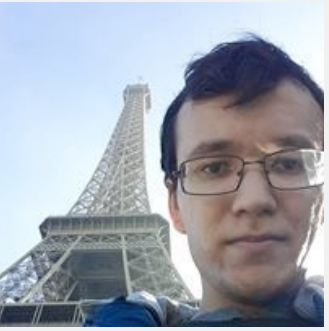
Serving Infrastructure

Monitoring

Illustration based on https://developers.google.com/machine-learning/testing-debugging/pipeline/overview

In radiology, solutions must be compatible with existing infrastructure!

Hauke Bartsch
Computer Science



Zhanbolat Satybaldinov
Software engineering

Research Information System for the Western Norway Regional Health Authorities

medical research data in Helse Førde, Bergen, Fonna, and Stavanger

Partners

MMIV
HELSE BERGEN Haukeland universitetssjukehus
HELSE VEST IKT
Forskningsrådet

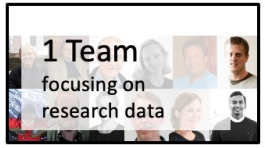
Researchers – Mohn Medical Imaging and Visualization
Healthcare professionals – Radiology
Technologists – Helse Vest IKT
Funding – The Research Council of Norway

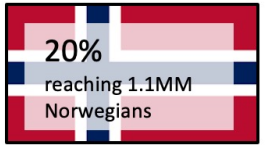
Features

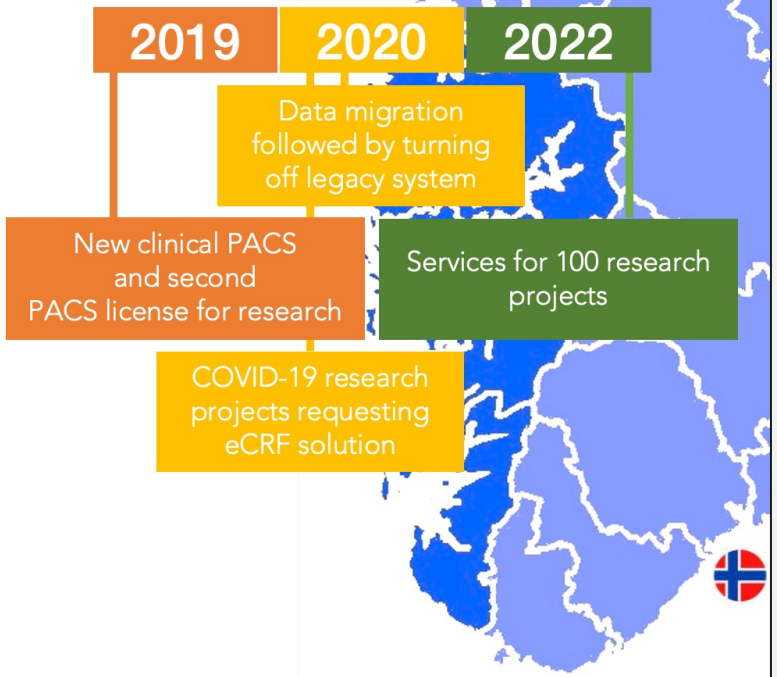
Data migration, anonymization, exchange, and data processing
Commercial image archiving and viewing platform
Electronic data capture (eCRF)

Hospital infrastructure for research

Connects 4 major hospitals and 30 treatment centers







https://github.com/mmiv-center/Research-Information-System

Illustration from https://developers.google.com/machine-learning/testing-debugging/pipeline/overview

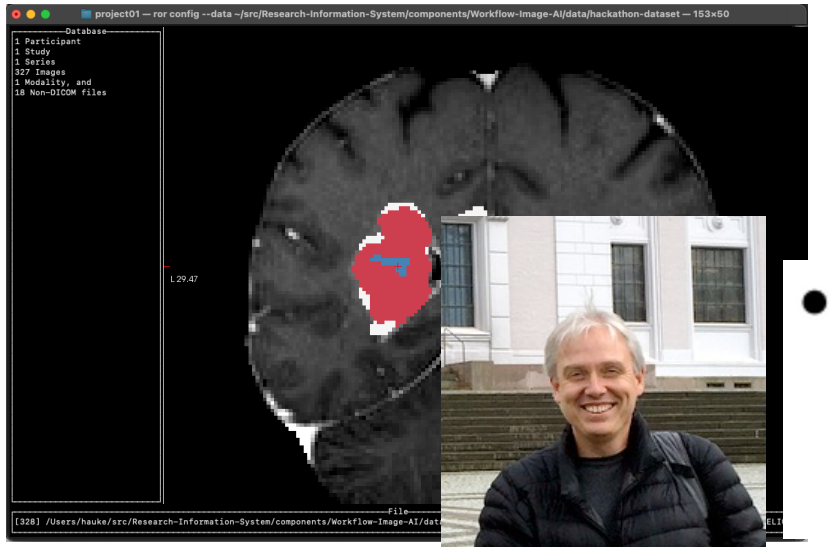
Slide by Hauke Bartsch

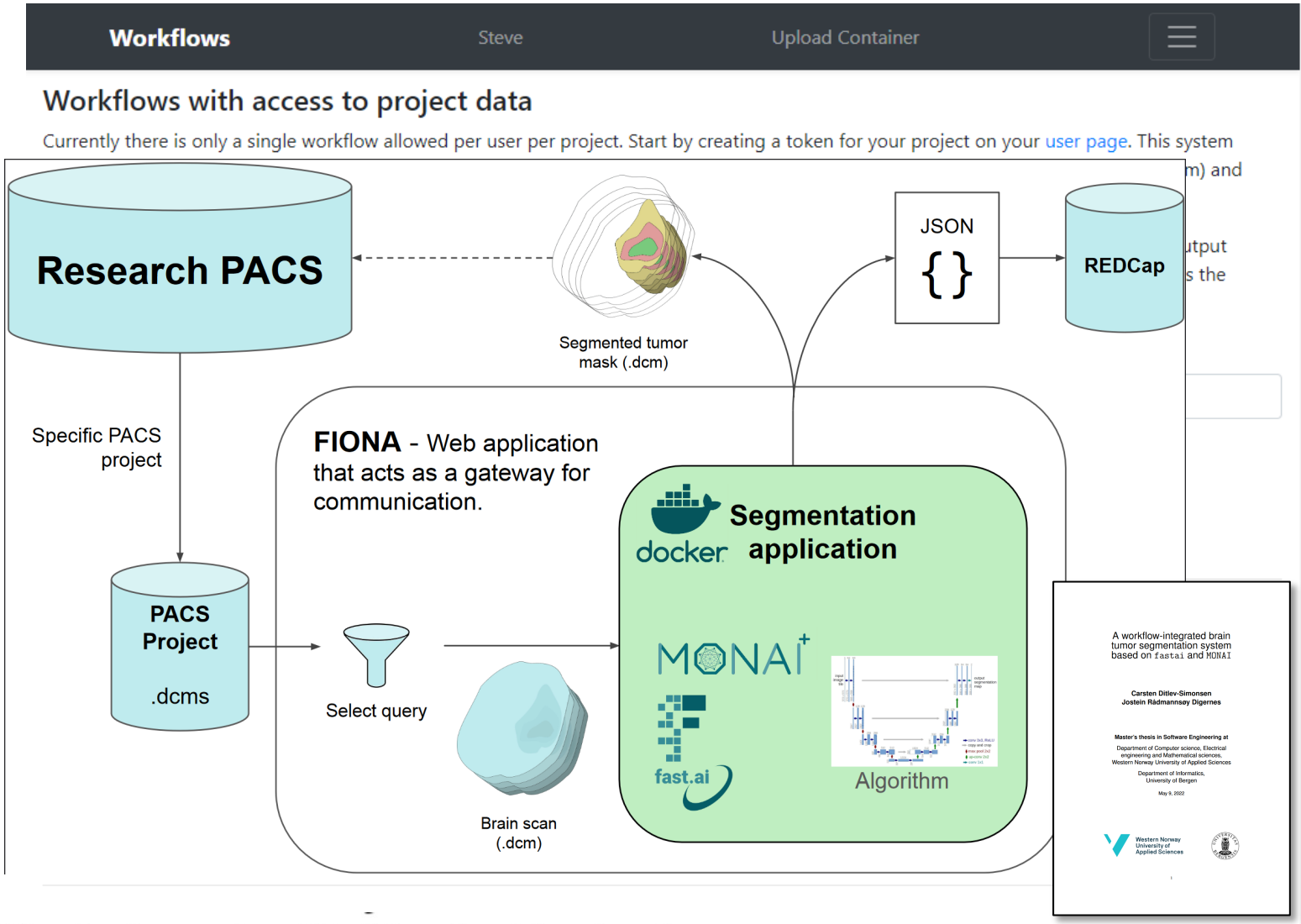
AI workflows

User driven activity supporting deep learning on medical images with training and prediction inside the hospital system.

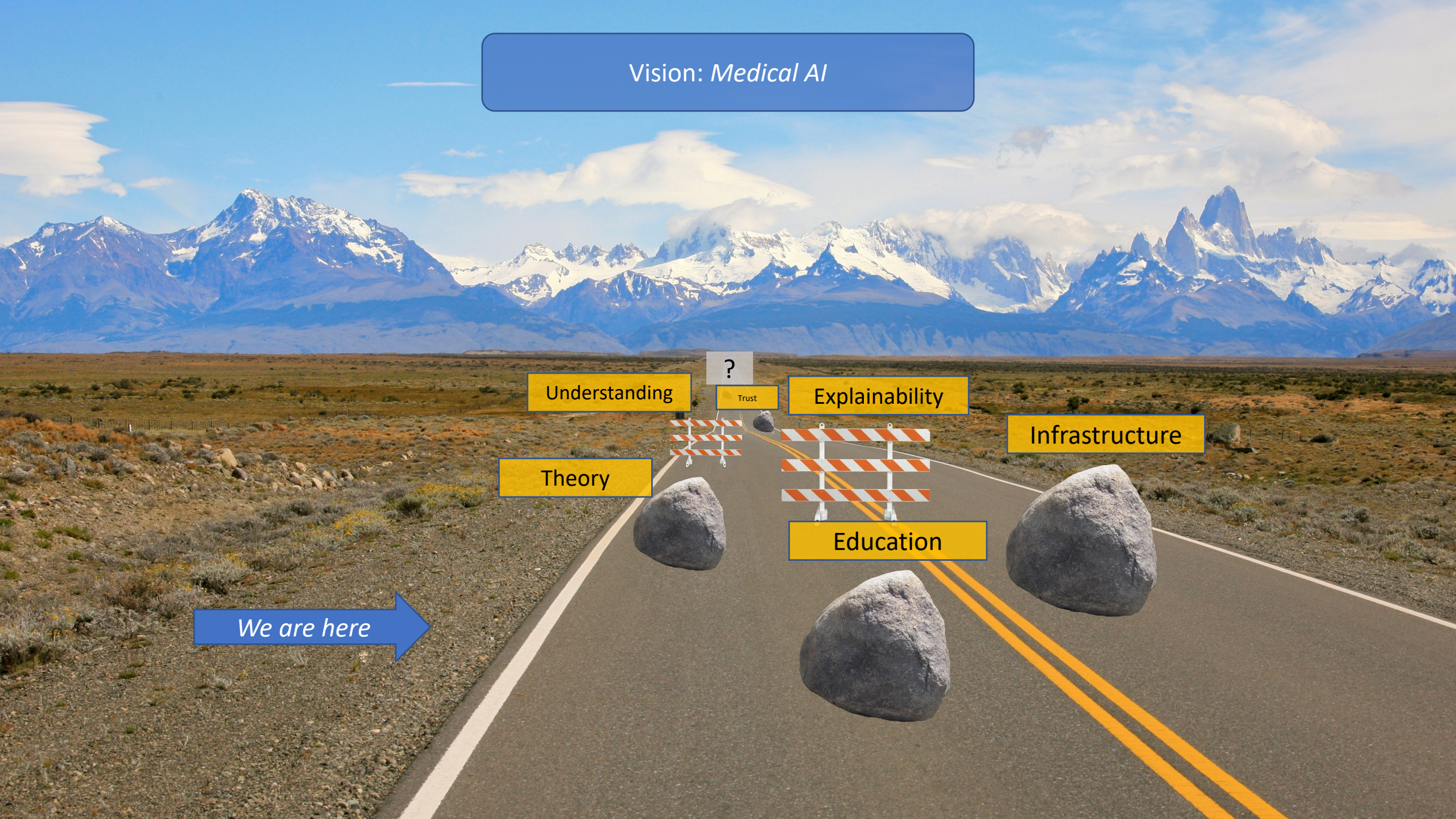
Open-source code development see:

`github.com / mmiv-center / Research-Information-System / tree / master / components / Workflow-Image-AI`





- **Workshop 4 with Hauke Bartsch**
  - *How to build a medical workstation for any hospital in the world*


Vision: *Medical AI*
?
Understanding
Trust
Explainability
Infrastructure
Theory
Education
We are here

Vision: *Medical AI*

The development of Medical AI should happen with medical experts in the driver's seat *

in tight collaboration with (all the right kind of) scientists and technologists

Infrastructure

Theory

Education

We are here

* at least in the front seat

Vision: *Medical AI*

The development of Medical AI should happen with medical experts in the driver's seat *

in tight collaboration with (all the right kind of) scientists and technologists (i.e., *you!*)

Infrastructure

Education

We are here

* at least in the front seat

Vision: *Medical AI*

The development of Medical AI should happen with medical experts in the driver's seat *

in tight collaboration with (all the right kind of) scientists and technologists (i.e., *you!*)

We are here

Western Norway University of Applied Sciences

MMIV

Haukeland University Hospital

Alexander Selvikvåg Lundervold

allu@hvl.no; lundervold.net