ELMED219 - 2022

Fri Jan 21st, 10:15-12

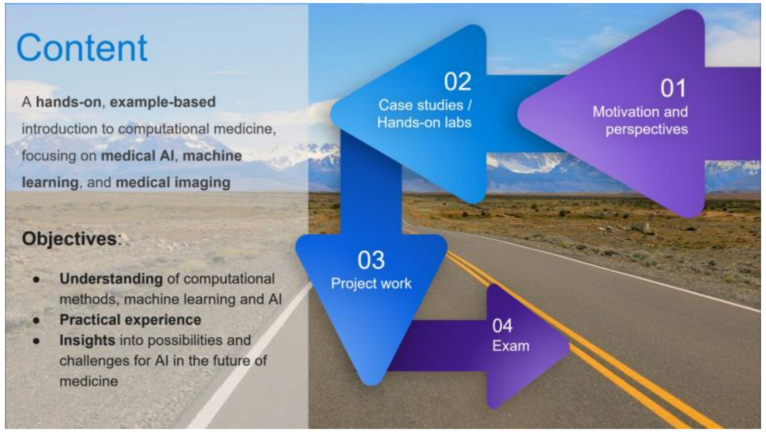
Perspectives on medical AI: innovation, education, epistemology, ethics and impact

Objectives

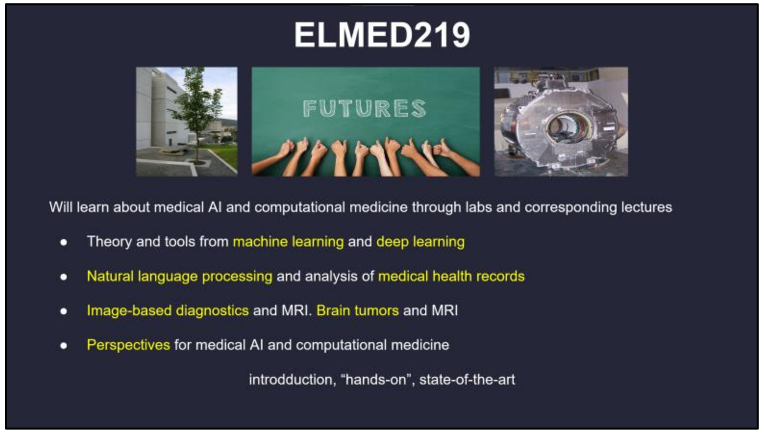
- *A very* ***quick overview*** *of what we've discussed so far in ELMED219*
- *A look at some* ***challenges and limitations*** *of current AI systems*
- *Also*

Innovation, education, epistemology, ethics and impact

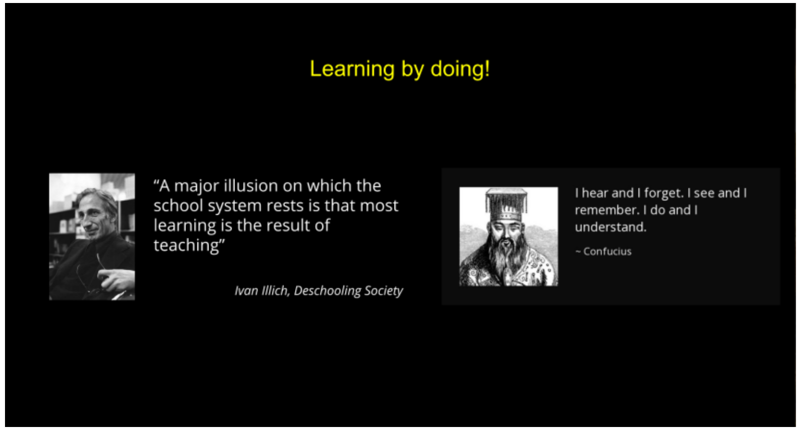
$$y \approx f(x;\ \theta)$$



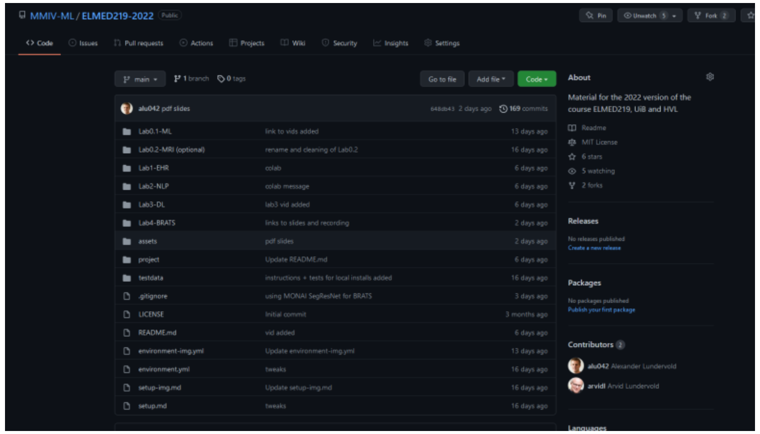
Content
A hands-on, example-based introduction to computational medicine, focusing on medical AI, machine learning, and medical imaging
Objectives:
Understanding of computational methods, machine learning and AI
Practical experience
Insights into possibilities and challenges for AI in the future of medicine
01 Motivation and perspectives
02 Case studies / Hands-on labs
03 Project work
04 Exam



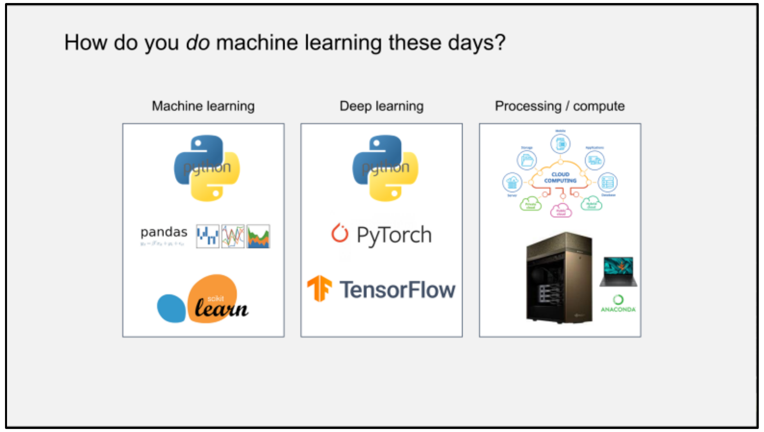
ELMED219
FUTURES
Will learn about medical AI and computational medicine through labs and corresponding lectures
Theory and tools from machine learning and deep learning
Natural language processing and analysis of medical health records
Image-based diagnostics and MRI. Brain tumors and MRI
Perspectives for medical AI and computational medicine
introdduction, "hands-on", state-of-the-art



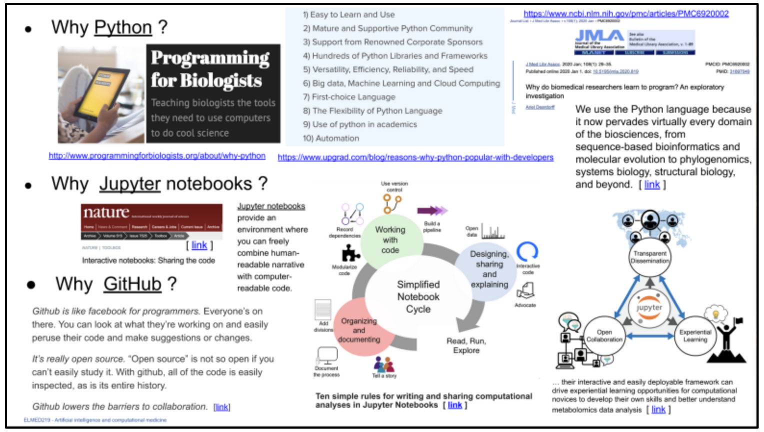
Learning by doing!
"A major illusion on which the school system rests is that most learning is the result of teaching"
Ivan Illich, Deschooling Society
I hear and I forget. I see and I remember. I do and I understand.
~ Confucius



MMIV-ML / ELMED219-2022 Public
Pin
Unwatch 5
Fork 2
Code
Issues
Pull requests
Actions
Projects
Wiki
Security
Insights
Settings
main
1 branch
0 tags
Go to file
Add file
Code
alu042 pdf slides
648db43 2 days ago
169 commits
Lab0.1-ML link to vids added 13 days ago
Lab0.2-MRI (optional) rename and cleaning of Lab0.2 16 days ago
Lab1-EHR colab 6 days ago
Lab2-NLP colab message 6 days ago
Lab3-DL lab3 vid added 6 days ago
Lab4-BRATS links to slides and recording 2 days ago
assets pdf slides 2 days ago
project Update README.md 6 days ago
testdata instructions + tests for local installs added 16 days ago
.gitignore using MONAI SegResNet for BRATS 3 days ago
LICENSE Initial commit 3 months ago
README.md vid added 6 days ago
environment-img.yml Update environment-img.yml 13 days ago
environment.yml tweaks 16 days ago
setup-img.md Update setup-img.md 16 days ago
setup.md tweaks 16 days ago
About
Material for the 2022 version of the course ELMED219, UiB and HVL
Readme
MIT License
6 stars
5 watching
2 forks
Releases
No releases published
Create a new release
Packages
No packages published
Publish your first package
Contributors 2
alu042 Alexander Lundervold
arvidl Arvid Lundervold
Languages



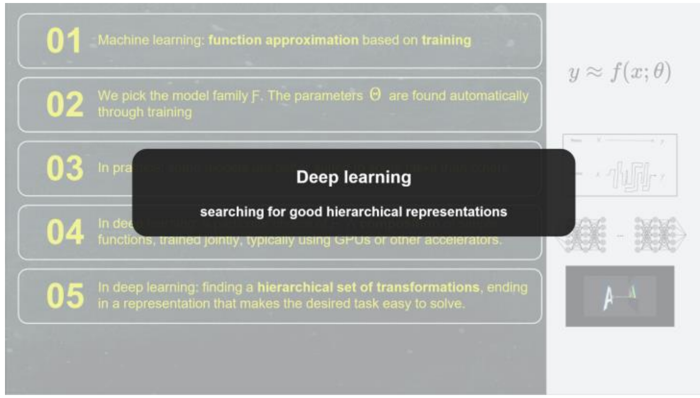
How do you do machine learning these days?
Machine learning
Deep learning
Processing / compute
pandas
learn
PyTorch
TensorFlow
CLOUD COMPUTING
ANACONDA

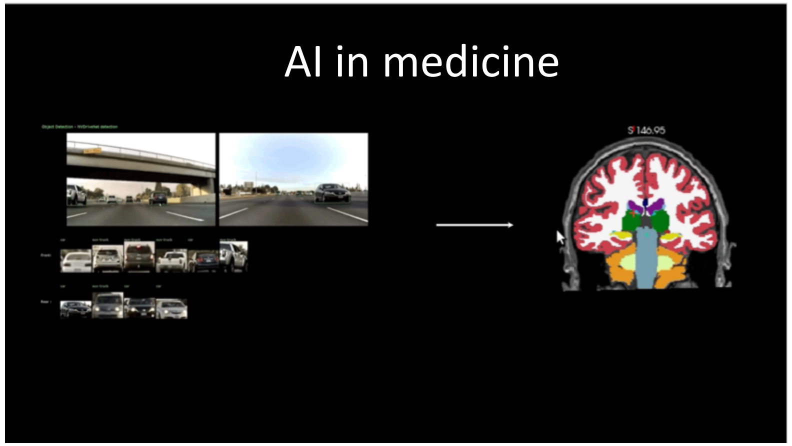


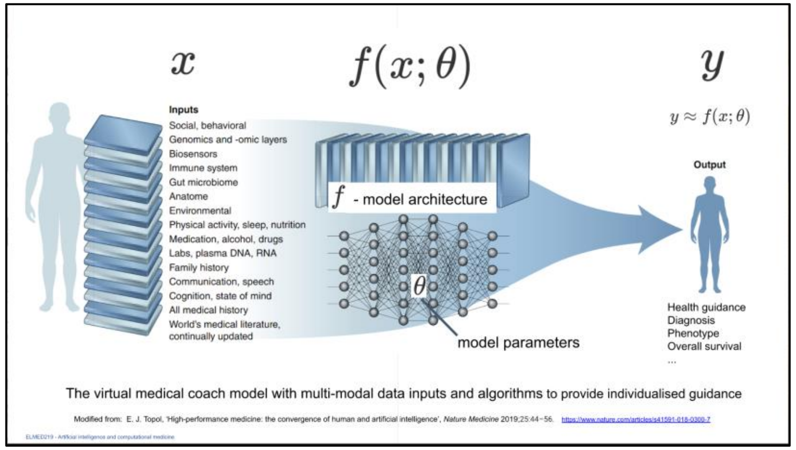
Why Python ?
Programming for Biologists
Teaching biologists the tools they need to use computers to do cool science
1) Easy to Learn and Use
2) Mature and Supportive Python Community
3) Support from Renowned Corporate Sponsors
4) Hundreds of Python Libraries and Frameworks
5) Versatility, Efficiency, Reliability, and Speed
6) Big data, Machine Learning and Cloud Computing
7) First-choice Language
8) The Flexibility of Python Language
9) Use of python in academics
10) Automation
https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6920002
JMLA
Why do biomedical researchers learn to program? An exploratory investigation
We use the Python language because it now pervades virtually every domain of the biosciences, from sequence-based bioinformatics and molecular evolution to phylogenomics, systems biology, structural biology, and beyond. [link]
http://www.programmingforbiologists.org/about/why-python
https://www.upgrad.com/blog/reasons-why-python-popular-with-developers
Why Jupyter notebooks ?
nature
[link]
Interactive notebooks: Sharing the code
Jupyter notebooks provide an environment where you can freely combine human-readable narrative with computer-readable code.
Use version control
Record dependencies
Build a pipeline
Working with code
Open data
Modularize code
Designing, sharing and explaining
Interactive code
Advocate
Simplified Notebook Cycle
Add divisions
Organizing and documenting
Read, Run, Explore
Document the process
Tell a story
Ten simple rules for writing and sharing computational analyses in Jupyter Notebooks [link]
Transparent Dissemination
jupyter
Open Collaboration
Experiential Learning
... their interactive and easily deployable framework can drive experiential learning opportunities for computational novices to develop their own skills and better understand metabolomics data analysis [link]
Why GitHub ?
Github is like facebook for programmers. Everyone's on there. You can look at what they're working on and easily peruse their code and make suggestions or changes.
It's really open source. "Open source" is not so open if you can't easily study it. With github, all of the code is easily inspected, as is its entire history.
Github lowers the barriers to collaboration. [link]
ELMED219 - Artificial intelligence and computational medicine

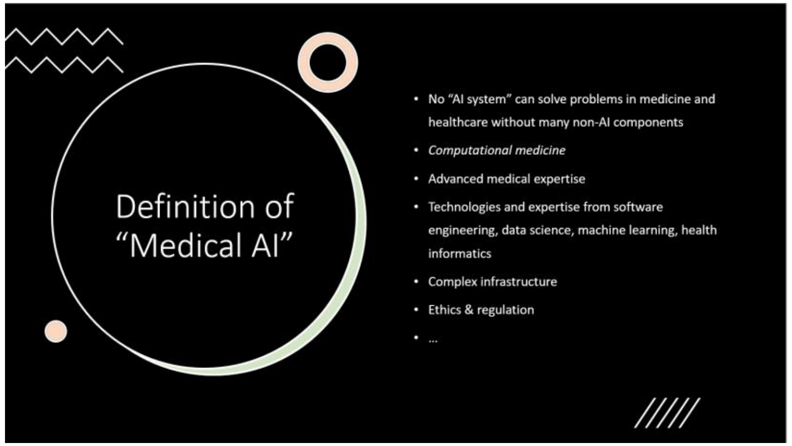

DIABETES
Petal
Sepal
Machine learning
Two (very) simple examples

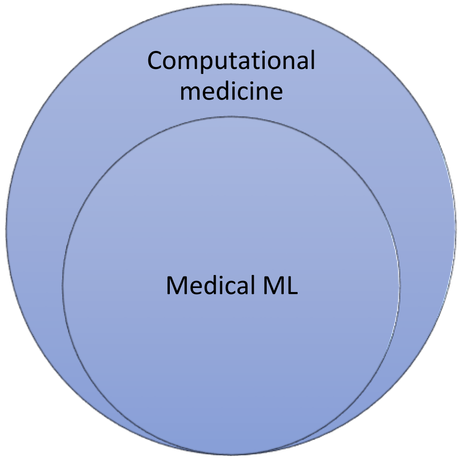

Patient ID
ML models learn from *features* / *representations* of data
No diabetes
No diabetes
Diabetes

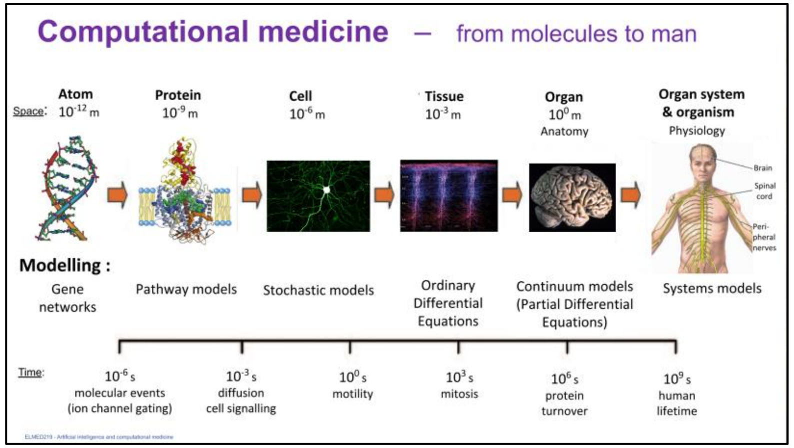

01 Machine learning: **function approximation** based on **training**
02 We pick the model family F. The parameters θ are found automatically through training
03 In pra
04 In dee
functions, trained jointly, typically using GPUs or other accelerators.
05 In deep learning: finding a **hierarchical set of transformations**, ending in a representation that makes the desired task easy to solve.
Deep learning
searching for good hierarchical representations
$y \approx f(x;\theta)$

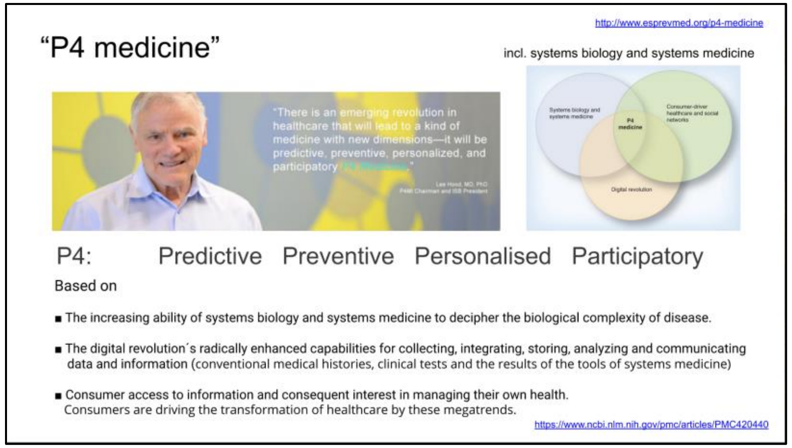

AI in medicine

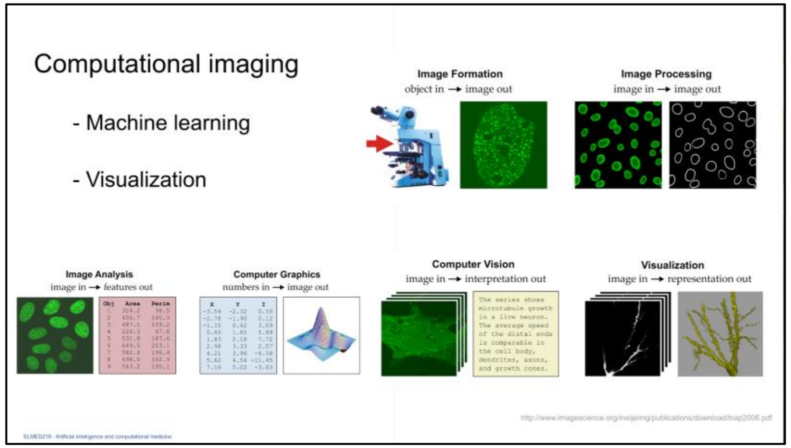

x
$f(x;\theta)$
y
$y \approx f(x;\theta)$
Inputs
Social, behavioral
Genomics and -omic layers
Biosensors
Immune system
Gut microbiome
Anatome
Environmental
Physical activity, sleep, nutrition
Medication, alcohol, drugs
Labs, plasma DNA, RNA
Family history
Communication, speech
Cognition, state of mind
All medical history
World's medical literature, continually updated
f - model architecture
θ
model parameters
Output
Health guidance
Diagnosis
Phenotype
Overall survival
...
The virtual medical coach model with multi-modal data inputs and algorithms to provide individualised guidance
Modified from: E. J. Topol, 'High-performance medicine: the convergence of human and artificial intelligence', Nature Medicine 2019;25:44–56.

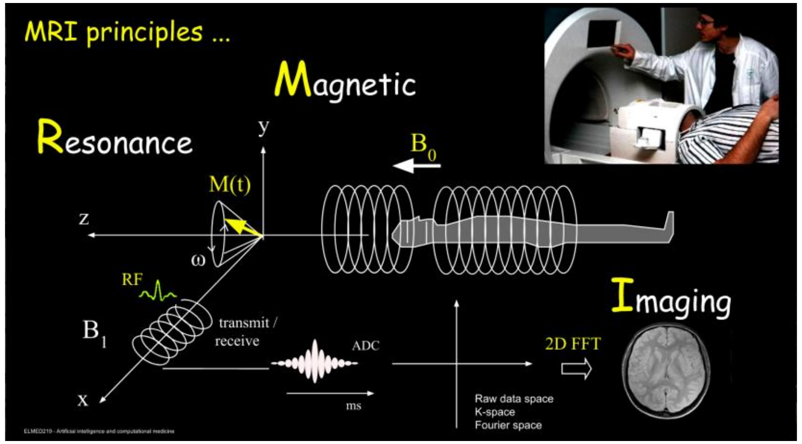

Definition of "Medical AI"
• No "AI system" can solve problems in medicine and healthcare without many non-AI components
• *Computational medicine*
• Advanced medical expertise
• Technologies and expertise from software engineering, data science, machine learning, health informatics
• Complex infrastructure
• Ethics & regulation
• ...


Computational medicine
Medical ML

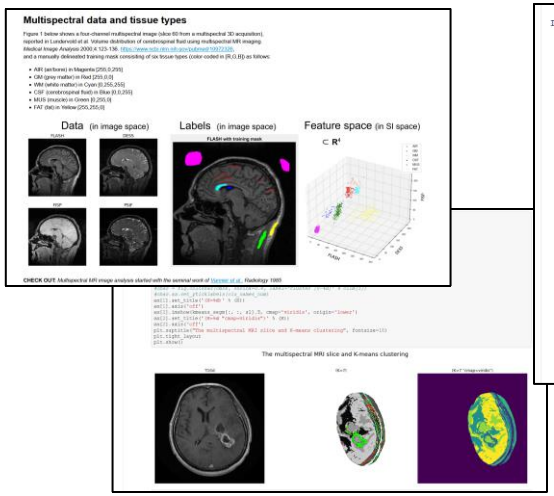

Computational medicine – from molecules to man
Space: Atom 10^{-12} m
Protein 10^{-9} m
Cell 10^{-6} m
Tissue 10^{-3} m
Organ 10^{0} m Anatomy
Organ system & organism Physiology
Brain
Spinal cord
Peri-pheral nerves
Modelling :
Gene networks
Pathway models
Stochastic models
Ordinary Differential Equations
Continuum models (Partial Differential Equations)
Systems models
Time:
10^{-6} s molecular events (ion channel gating)
10^{-3} s diffusion cell signalling
10^{0} s motility
10^{3} s mitosis
10^{6} s protein turnover
10^{9} s human lifetime

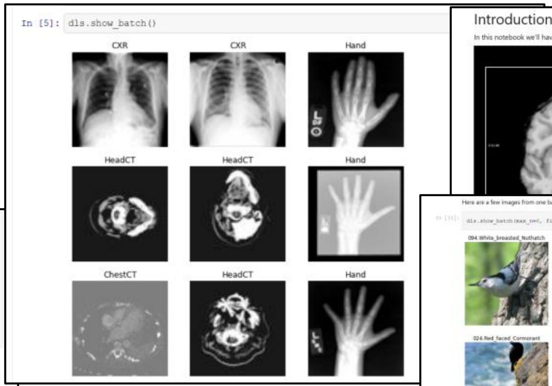

http://www.esprevmed.org/p4-medicine
"P4 medicine"
incl. systems biology and systems medicine
"There is an emerging revolution in healthcare that will lead to a kind of medicine with new dimensions—it will be predictive, preventive, personalized, and participatory"
P4: Predictive Preventive Personalised Participatory
Based on
The increasing ability of systems biology and systems medicine to decipher the biological complexity of disease.
The digital revolution´s radically enhanced capabilities for collecting, integrating, storing, analyzing and communicating data and information (conventional medical histories, clinical tests and the results of the tools of systems medicine)
Consumer access to information and consequent interest in managing their own health. Consumers are driving the transformation of healthcare by these megatrends.
https://www.ncbi.nlm.nih.gov/pmc/articles/PMC420440

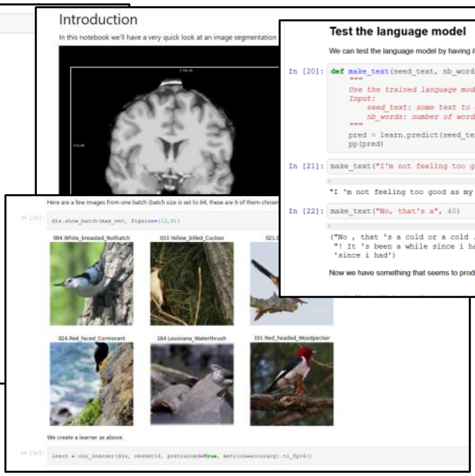

Computational imaging
- Machine learning
- Visualization
Image Formation
object in → image out
Image Processing
image in → image out
Image Analysis
image in → features out
Computer Graphics
numbers in → image out
Computer Vision
image in → interpretation out
Visualization
image in → representation out

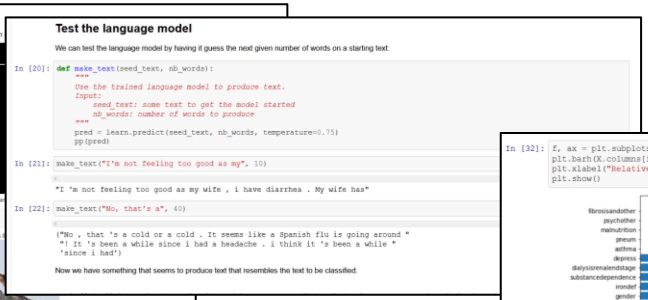

MRI principles ...
Magnetic
Resonance
Imaging
M(t)
B_0
B_1
RF
transmit / receive
ADC
ms
2D FFT
Raw data space
K-space
Fourier space

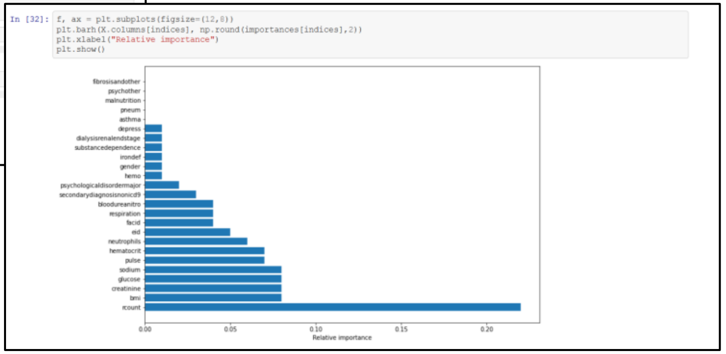

Electronic health records
Patient Master


Multispectral data and tissue types
Data (in image space)
Labels (in image space)
Feature space (in SI space)
The multispectral MRI slice and K-means clustering


In [5]: dls.show_batch()
CXR
CXR
Hand
HeadCT
HeadCT
Hand
ChestCT
HeadCT
Hand


Introduction


Test the language model
We can test the language model by having it guess the next given number of words on a starting text
In [20]: def make_text(seed_text, nb_words):
Use the trained language model to produce text.
pred = learn.predict(seed_text, nb_words, temperature=0.75)
In [21]: make_text("I'm not feeling too good as my", 10)
"I 'm not feeling too good as my wife , i have diarrhea . My wife has"
In [22]: make_text("No, that's a", 40)
Now we have something that seems to produce text that resembles the text to be classified.

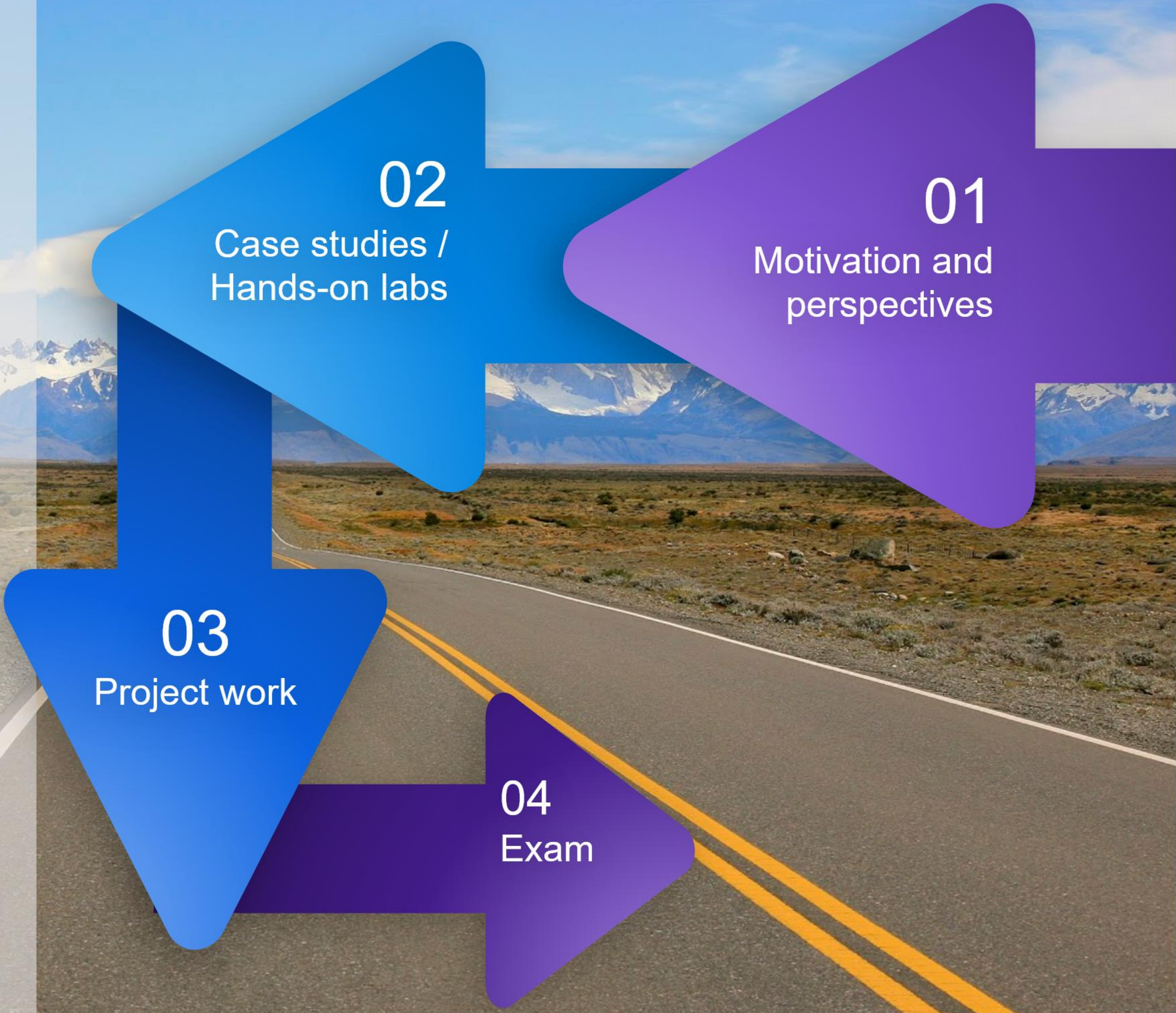

In [32]: f, ax = plt.subplots(figsize=(12,8))
plt.xlabel("Relative importance")
plt.show()
Relative importance

Content

A **hands-on**, **example-based** introduction to computational medicine, focusing on **medical AI**, **machine learning**, and **medical imaging**

Objectives:

- **Understanding** of computational methods, machine learning and AI
- **Practical experience**
- **Insights** into possibilities and challenges for AI in the future of medicine



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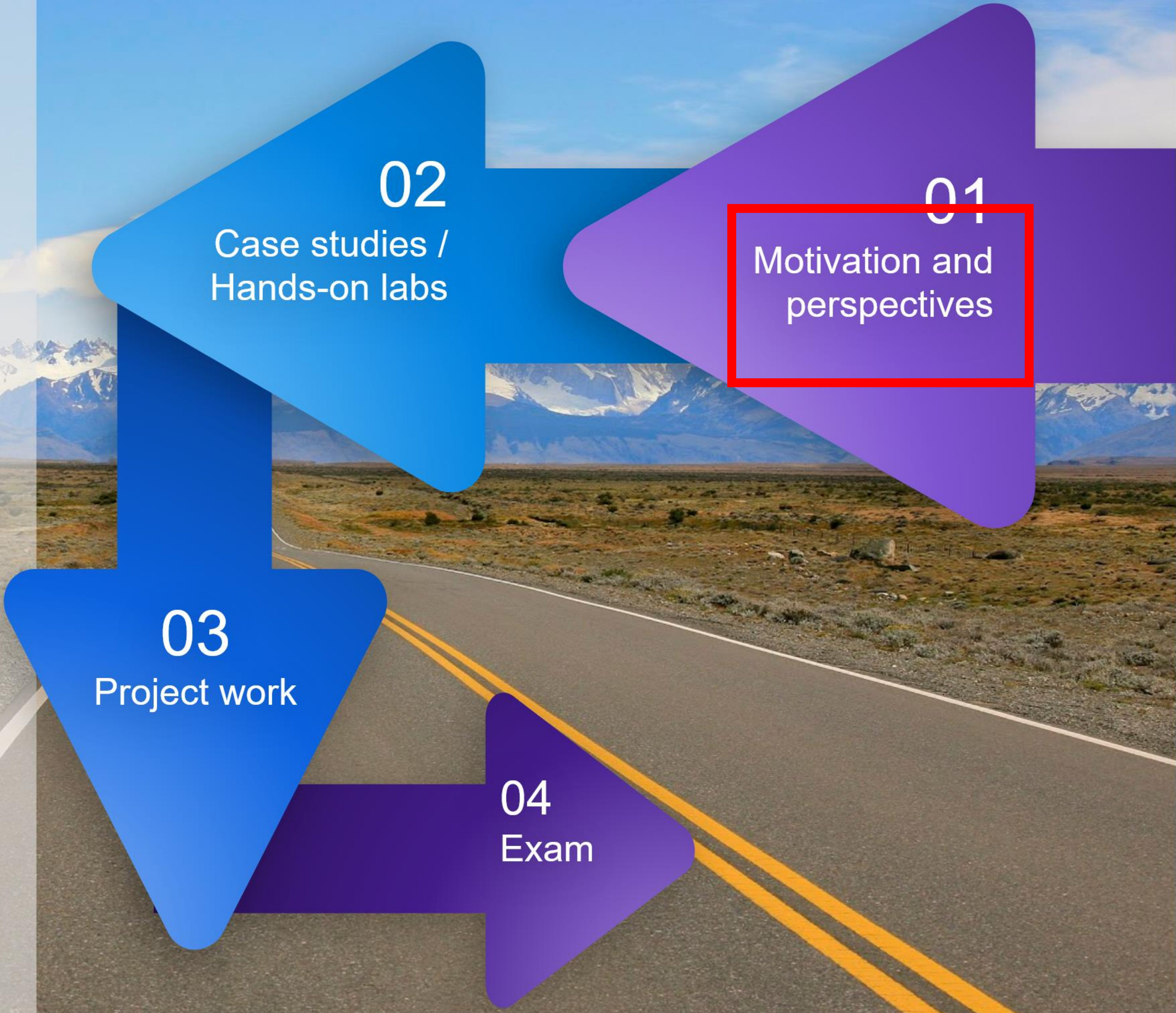
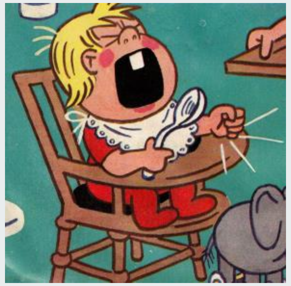


Some challenges for medical AI, especially systems based on deep learning

Data hungry!



Black box

“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?

Privacy

Data access

Law

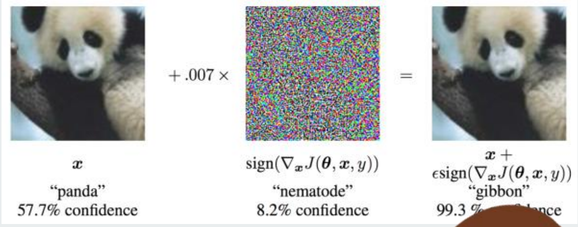
Data labeling

Protecting data

De-anonymization-angrep

Model inversion
Membership attack

Adversarial examples



Fairness

Reproducibility

And more...

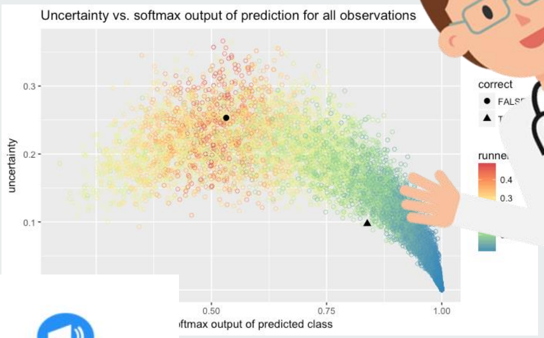
Differential privacy

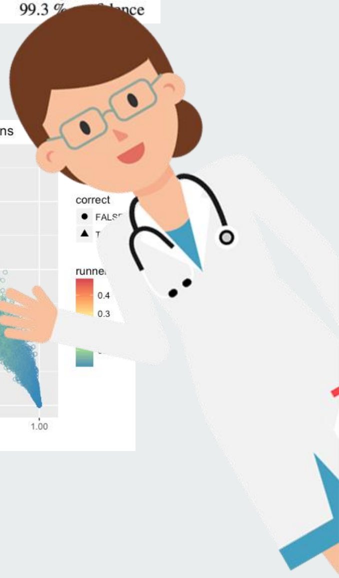
Lack of theory

Models lack of understanding

Trust

Uncertainty





What makes one model better than another?

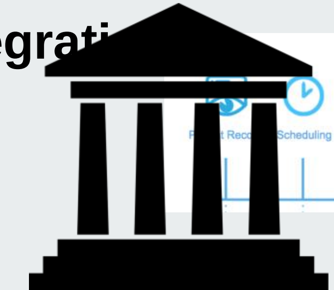
Clinical validation!

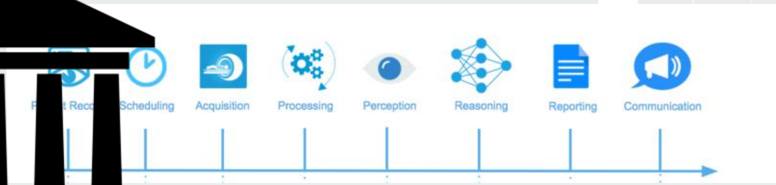
Education

Software engineering best practices

deployment, maintenance, unit testing, hidden technical debt, ...

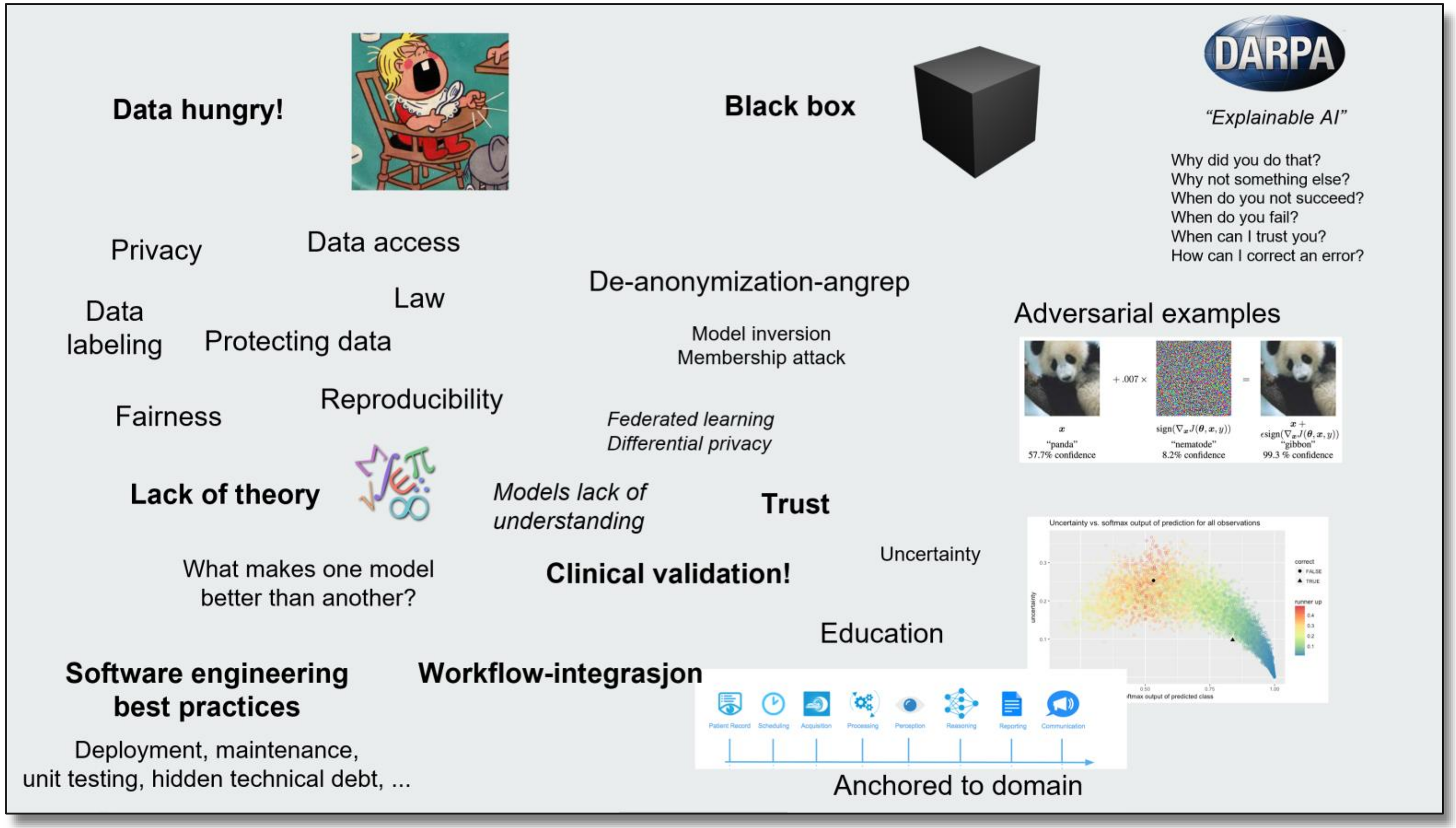
Workflow integration



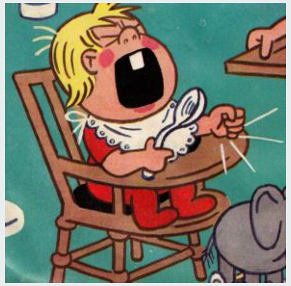


Anchored to domain

- *«Explainability»*
- Fairness, bias, resource allocation
- Responsibility
- Skewed incentives
- *"Quality metrics"* and commercial interests versus patient care
- The hippocratic oath
- "Best practices" constantly in flux
- Robustness
- Causality
- *Human-in-the-loop, patient-in-the-loop*?
- Data management, governance & provenance
- Responsible research and innovation
- Medical, cultural and professional community with a rich history and considerable societal impact.
- ...



Data hungry!



Black box

DARPA

"Explainable AI"

Why did you do that?
Why not something else?
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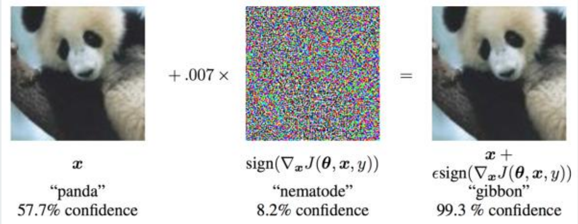
Adversarial examples



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Federated learning
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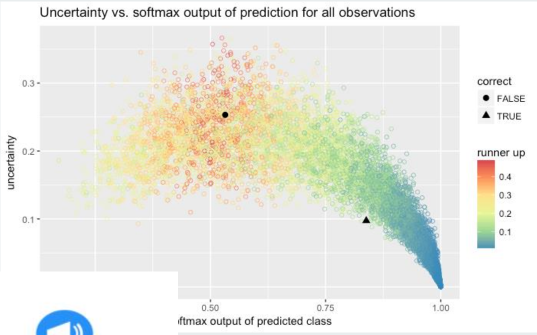
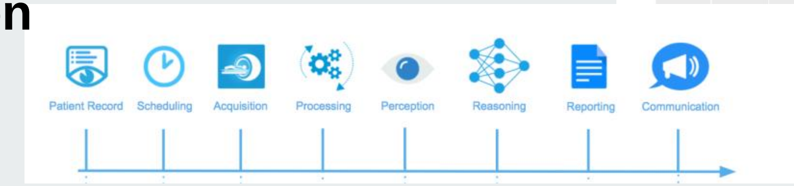


Education

Software engineering best practices

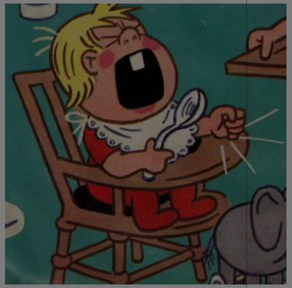
Deployment, maintenance,
unit testing, hidden technical debt, ...

Workflow integration



Anchored to domain

Data hungry!



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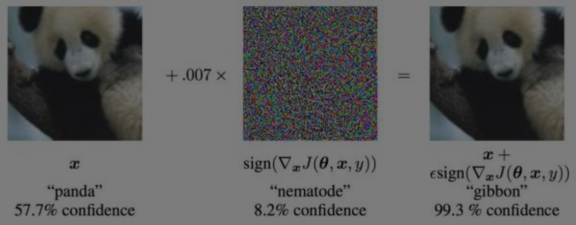


Lack of theory

What makes one model better than another?

Software engineering best practices

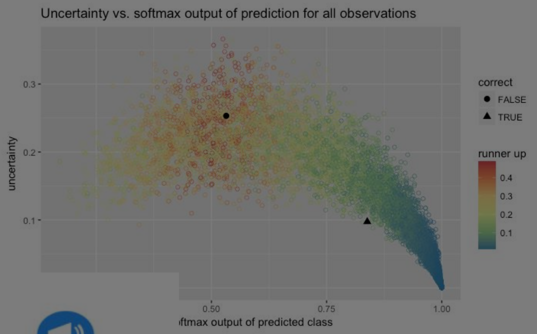
Deployment, maintenance,
unit testing, hidden technical debt, ...

Models lack of understanding

Trust

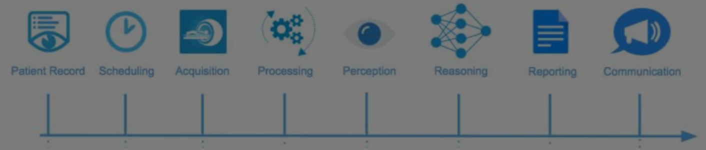
Clinical validation!

Uncertainty

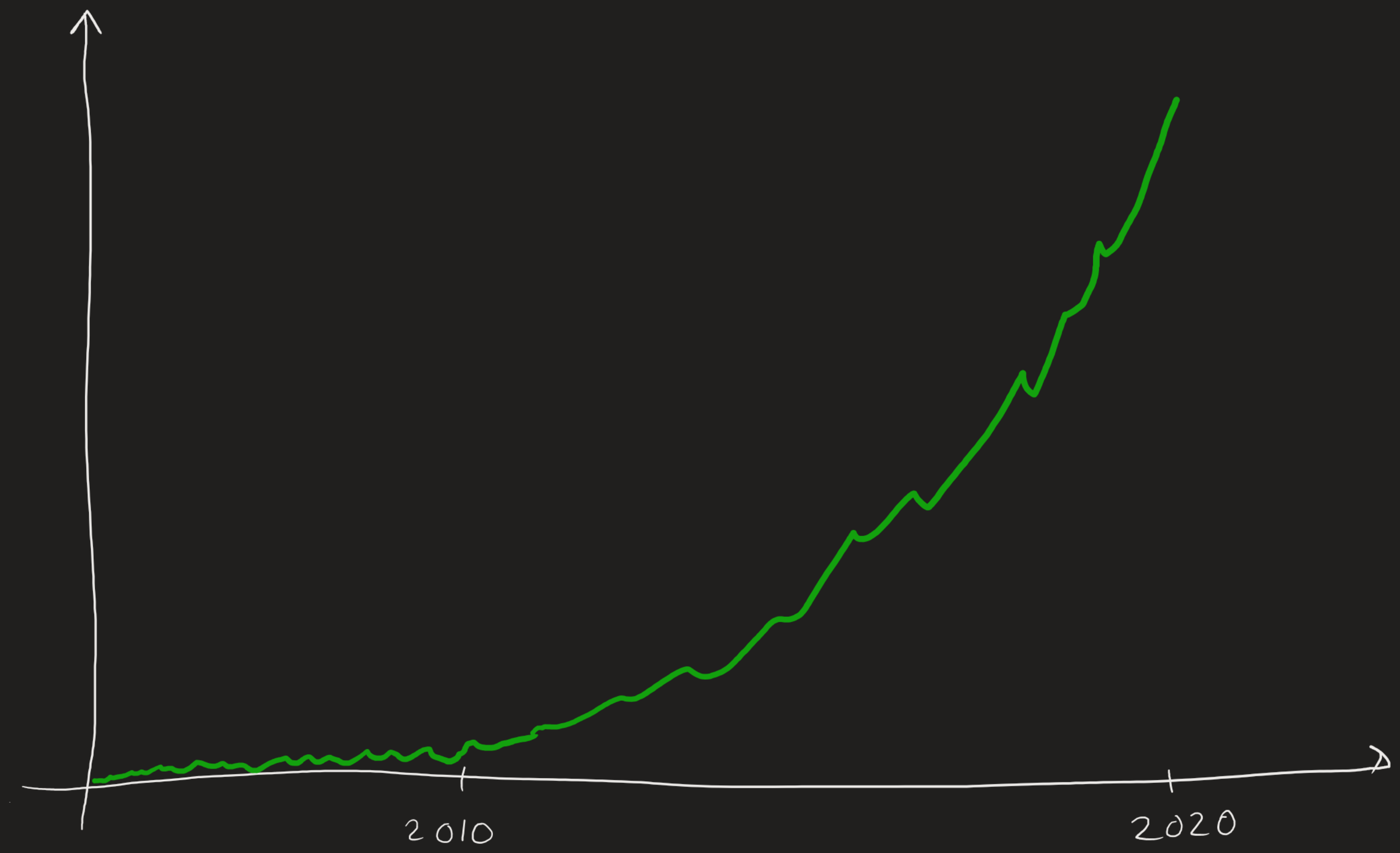


Education

Workflow integration



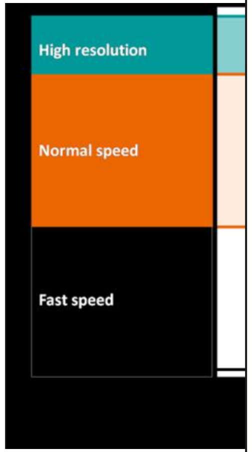
Anchored to domain


2010
2020


Theory
Research
Practice
Patient care
The "proof-of-concept-to-production-gap"

Siemens Biogra

are: Edison



AI for Radiology
an implementation guide

Products | Companies | Project AIR | Blogs | About | Contact

Products

Find the artificial intelligence based software for radiology that you are looking for.
All products listed are available for the European market (CE marked).

Subspeciality: All | Modality: All | CE: All | CE class: All | FDA class: All

Search... Search

185/185 results

AI4MedImaging

AI4MedImaging

AI4CMR

Heart ventricles segmentation, quantification of ventricular volumes, myocardial mass, and ejection ...

The AI4CMR software performs a automatic cardiac segmentation and interpretation of Cardiac Magnetic Resonance (CMR), allowing quantification of various parameters without the need for intervention ...

Subspeciality: Cardiac
Modality: MR

Read more

CE: Class IIa - MDR
FDA:
Information source: Vendor
Certification verified: Yes

SIEMENS Healthineers

Siemens Healthineers

AI-Rad Companion Brain MR

brain volume quantification, segmentation, normative comparison, report generation

AI-Rad Companion Brain MR performs an automatic segmentation of the different brain areas, including an individual volumetric analysis. It compares the different volumes to a normative database and ...

Subspeciality: Neuro
Modality: MR

Read more

CE: Class IIa - MDR
FDA: Class II
Information source: Vendor
Certification verified: Yes

SIEMENS Healthineers

Siemens Healthineers

AI-Rad Companion Chest CT

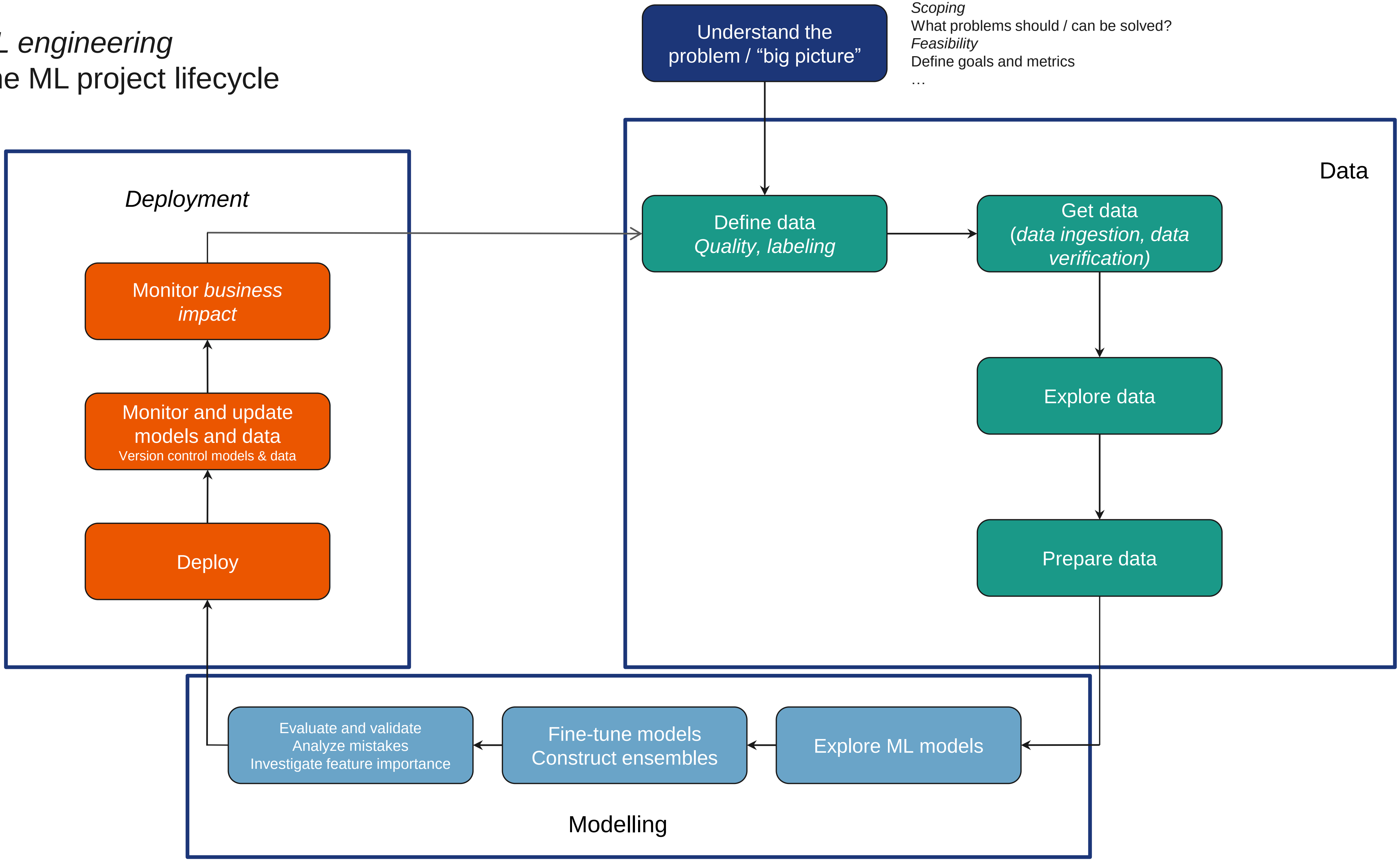
Segmentation and volume quantification of lungs, lung lobes, lung lesions, heart, thoracic aorta, ...

CE: Class IIa - MDR
FDA: Class II

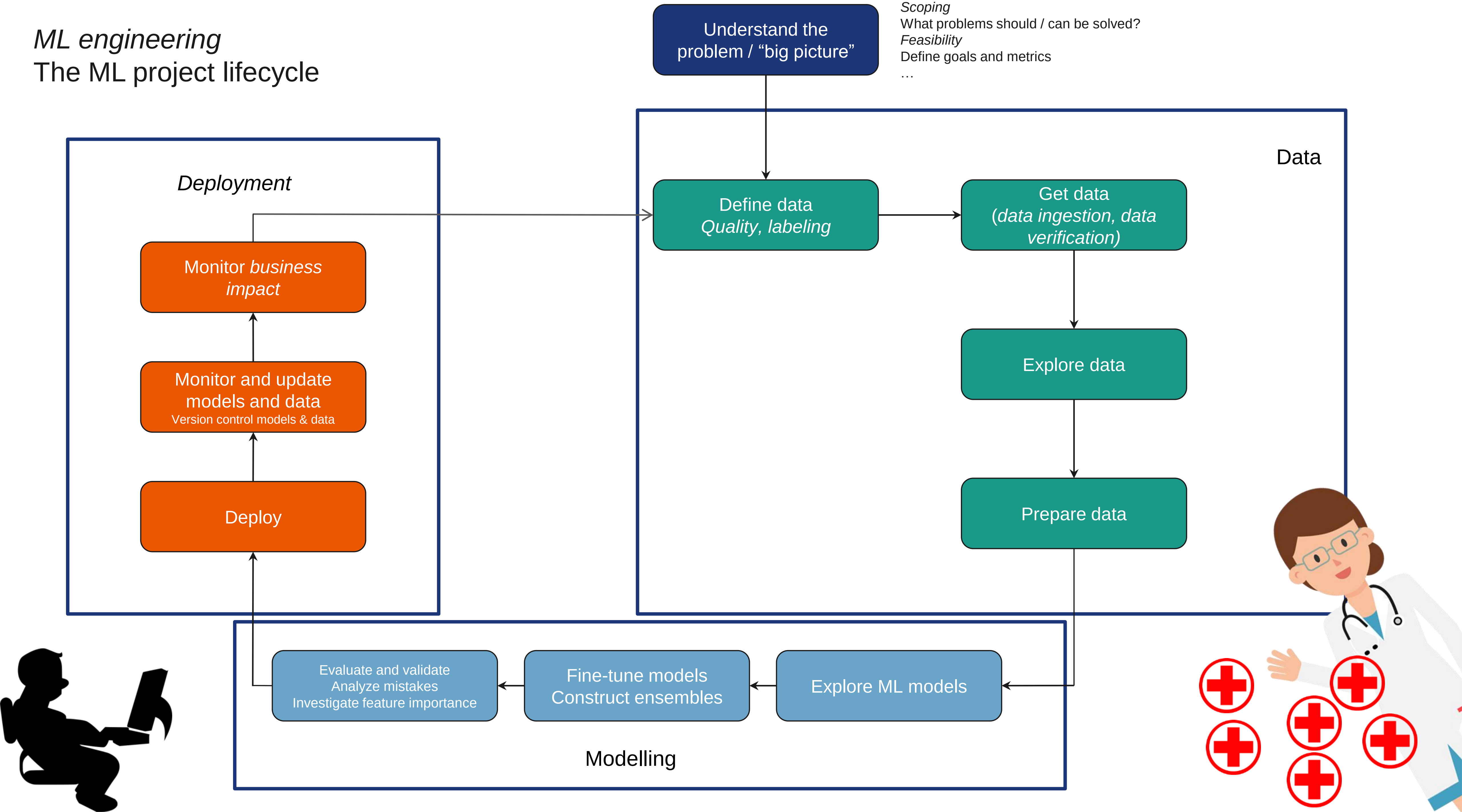

Theory
Research
Practice
Patient care
The “proof-of-concept-to-production-gap”

How do you create machine learning solutions?

ML engineering
The ML project lifecycle



ML engineering
The ML project lifecycle

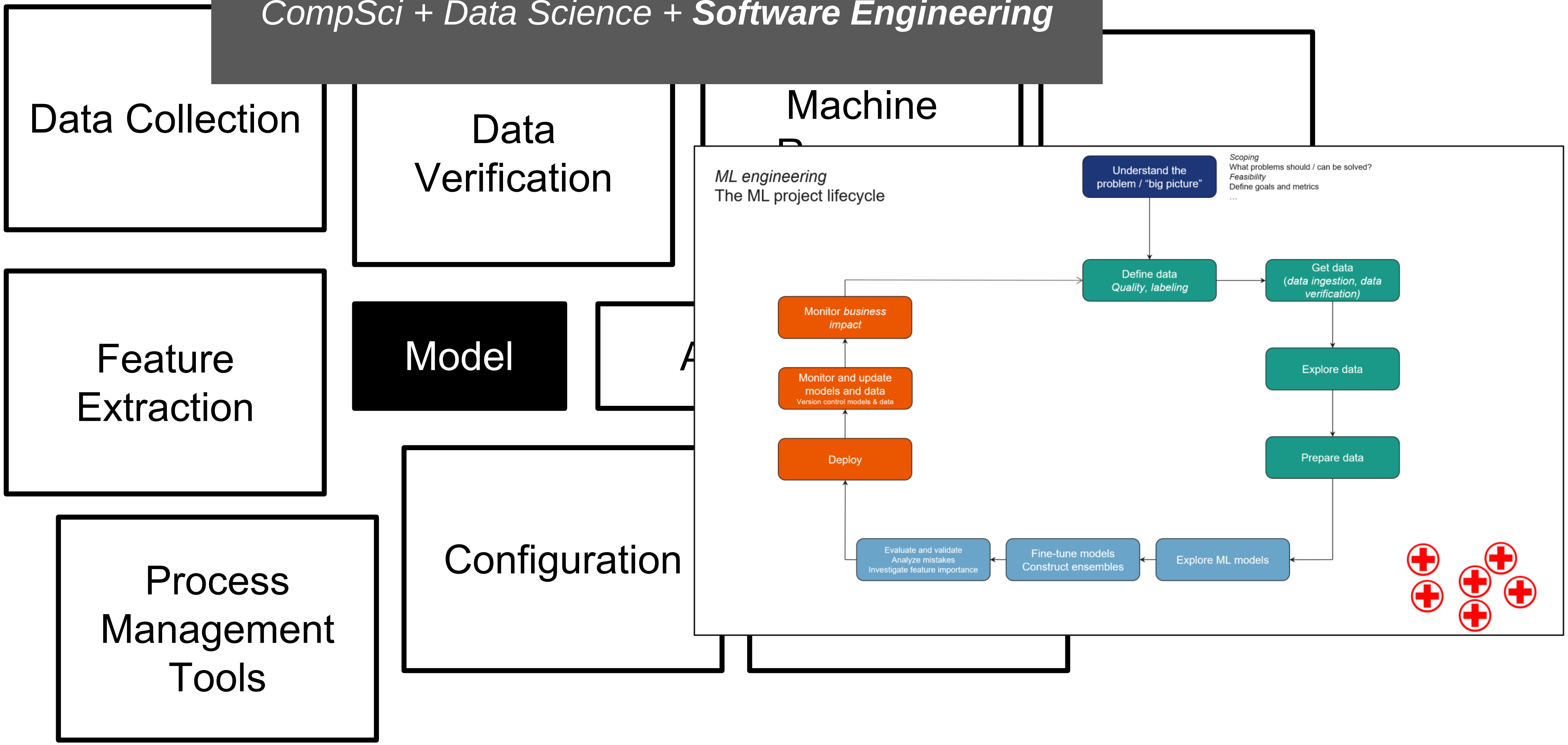


Model

Machine learning engineering

~

CompSci + Data Science + ***Software Engineering***

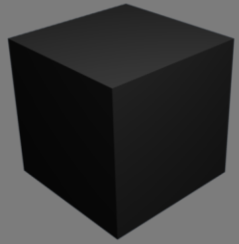


Sculley, David, et al. "Hidden technical debt in machine learning systems." *Advances in neural information processing systems* 28 (2015): 2503-2511.

5 min break

Data hungry!

Black box



"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?

Privacy

Data access

Law

Data labeling

Protecting data

Reproducibility

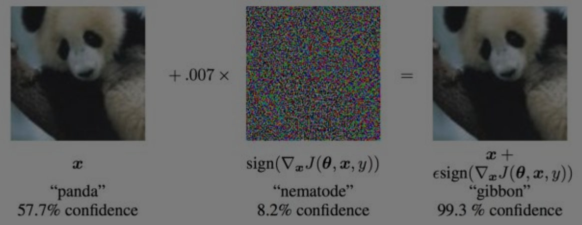
Fairness

De-anonymization-angrep

Model inversion
Membership attack

Federated learning
Differential privacy

Adversarial examples



Lack of theory

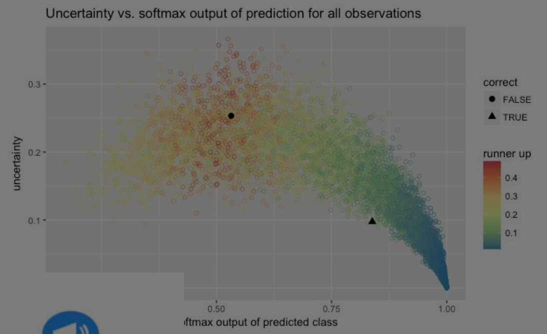
What makes one model better than another?

Models lack of understanding

Trust

Uncertainty

Clinical validation!

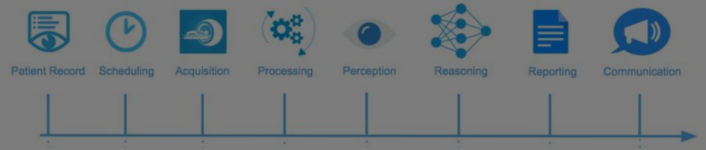


Education

Software engineering best practices

Deployment, maintenance, unit testing, hidden technical debt, ...

Workflow integration



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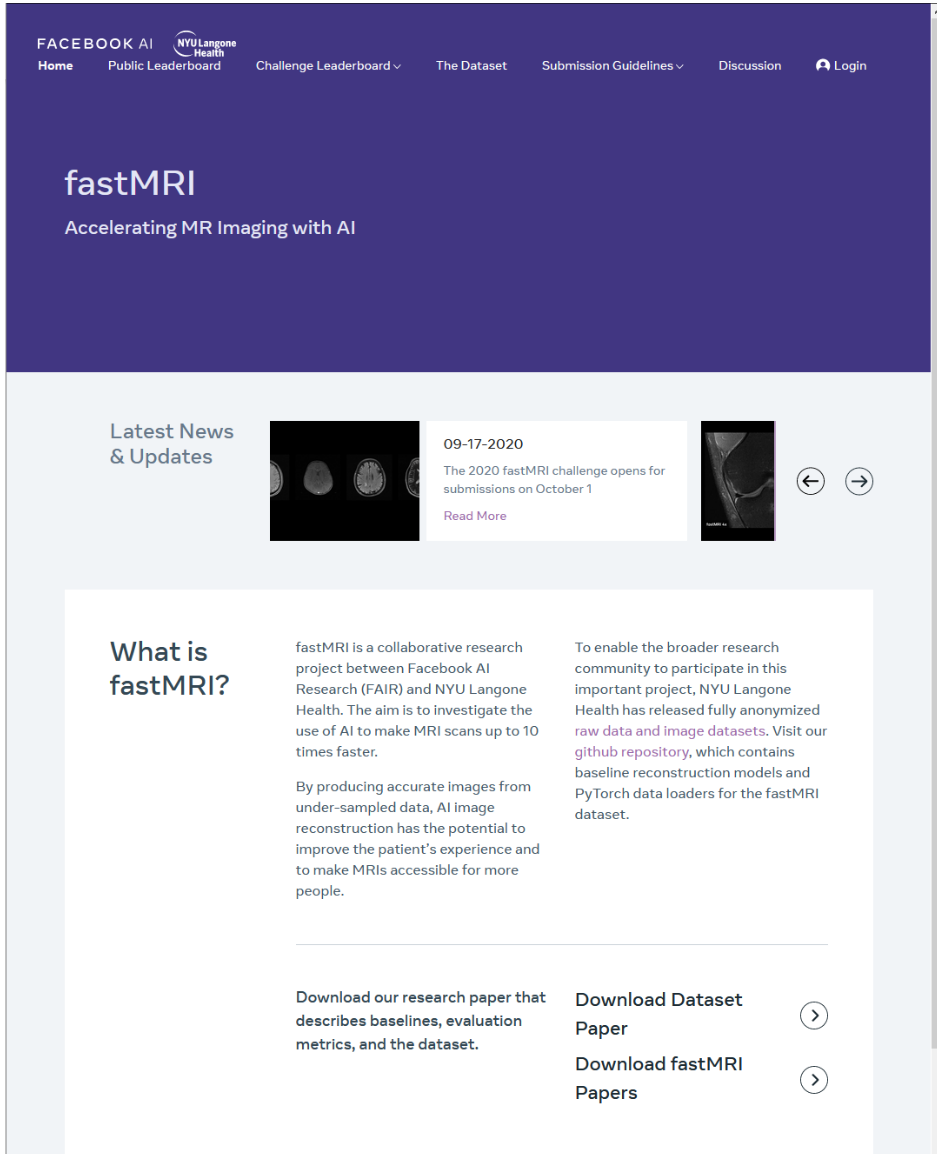

FACEBOOK AI NYU Langone Health

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fastMRI

Accelerating MR Imaging with AI

Latest News & Updates

09-17-2020

The 2020 fastMRI challenge opens for submissions on October 1

Read More

What is fastMRI?

fastMRI is a collaborative research project between Facebook AI Research (FAIR) and NYU Langone Health. The aim is to investigate the use of AI to make MRI scans up to 10 times faster.

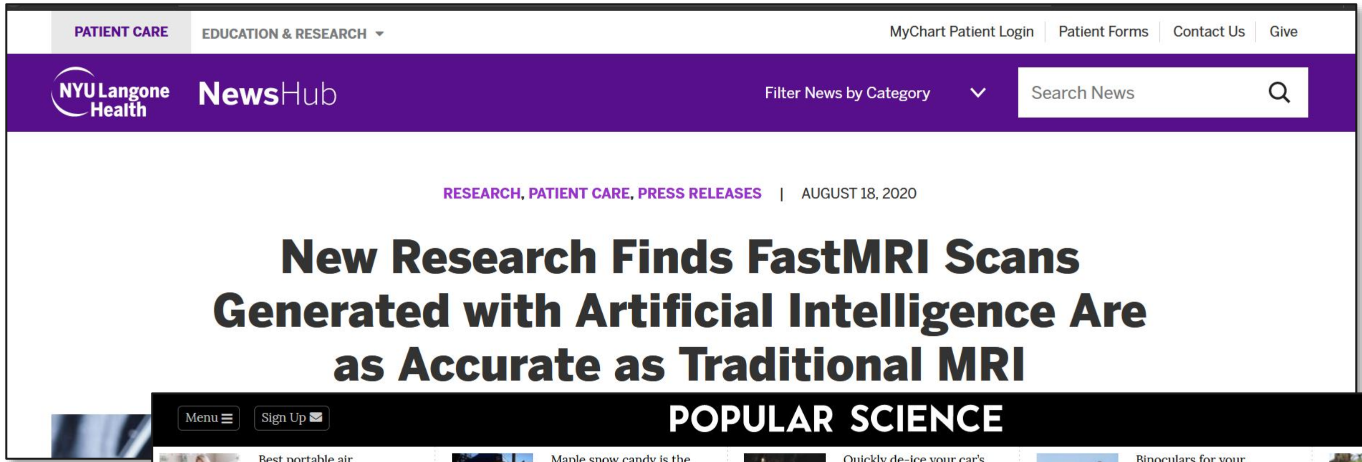
By producing accurate images from under-sampled data, AI image reconstruction has the potential to improve the patient's experience and to make MRIs accessible for more people.

To enable the broader research community to participate in this important project, NYU Langone Health has released fully anonymized raw data and image datasets. Visit our github repository, which contains baseline reconstruction models and PyTorch data loaders for the fastMRI dataset.

Download our research paper that describes baselines, evaluation metrics, and the dataset.

Download Dataset Paper

Download fastMRI Papers



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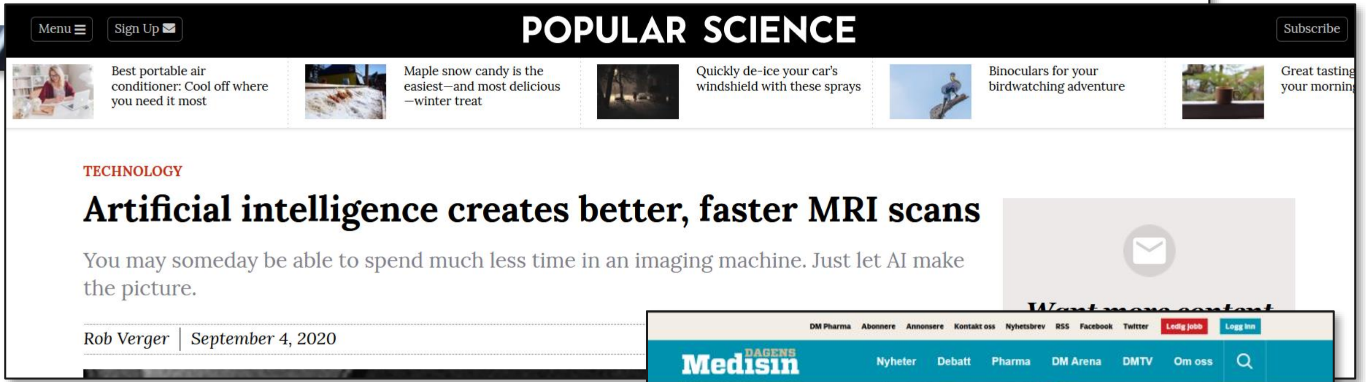
RESEARCH, PATIENT CARE, PRESS RELEASES | AUGUST 18, 2020

New Research Finds FastMRI Scans Generated with Artificial Intelligence Are as Accurate as Traditional MRI



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TECHNOLOGY

Artificial intelligence creates better, faster MRI scans

You may someday be able to spend much less time in an imaging machine. Just let AI make the picture.

Rob Verger | September 4, 2020

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FORSIKTIG OPTIMIST: Helga Brøgger, overlege ved OUS og leder for Norsk radiologisk forening håper resultatene holder mål og mener det er positivt for videre forskning og utvikling at det brukes åpen kildekode.
Foto: Vidar Sandnes

Håper MR-funn kan bidra til å fjerne en flaskehals

Challenge Leaderboard
ging with AI
Latest News & Updates

On instabilities of deep learning in image reconstruction and the potential costs of AI

Vegard Antun[a], Francesco Renna[b], Clarice Poon[c], Ben Adcock[d], and Anders C. Hansen[a,e,1]

[a]Department of Mathematics, University of Oslo, 0316 Oslo, Norway; [b]Instituto de Telecomunicações, Faculdade de Ciências, Universidade do Porto, Porto 4169-007, Portugal; [c]Department of Mathematical Sciences, University of Bath, Bath BA2 7AY, United Kingdom; [d]Department of Mathematics, Simon Fraser University, Burnaby, BC V5A 1S6, Canada; and [e]Department of Applied Mathematics and Theoretical Physics, University of Cambridge, Cambridge CB3 0WA, United Kingdom

Edited by David L. Donoho, Stanford University, Stanford, CA, and approved March 12, 2020 (received for review June 4, 2019)

Deep learning, due to its unprecedented success in tasks such as image classification, has emerged as a new tool in image reconstruction with potential to change the field. In this paper, we demonstrate a crucial phenomenon: Deep learning typically yields unstable methods for image reconstruction. The instabilities usually occur in several forms: 1) Certain tiny, almost undetectable perturbations, both in the image and sampling domain, may result in severe artefacts in the reconstruction; 2) a small structural change, for example, a tumor, may not be captured in the

AI and deep learning have already changed the field of computer vision and image classification (16–19), where the performance is now referred to as super human (20). However, the success comes with a price. Indeed, the methods are highly unstable. It is now well established (21–25) that high-performance deep learning methods for image classification are subject to failure given tiny, almost invisible perturbation of the image. An image of a cat may be classified correctly; however, a tiny change, invisible to the human eye, may cause the algorithm to change its

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ML engineering
The ML project lifecycle

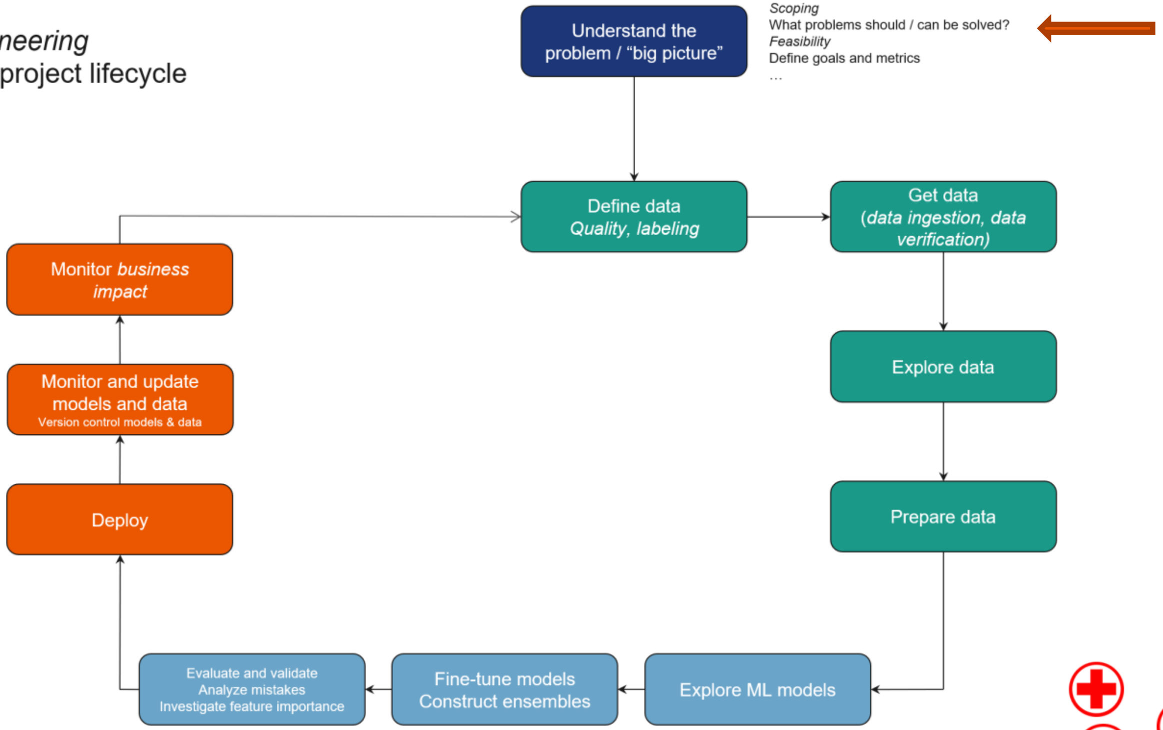

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Foto: Vidar Sandnes

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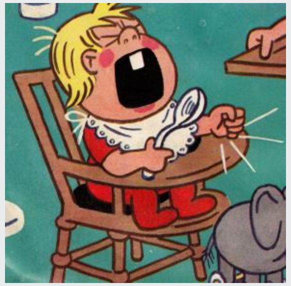
Data hungry!



Black box

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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?

Privacy

Data access

Law

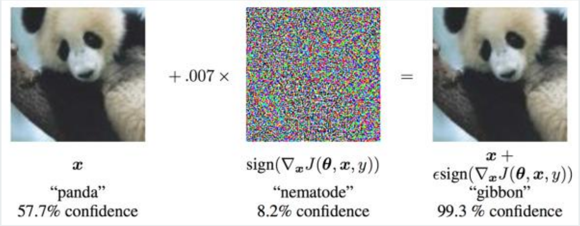
Data labeling

Protecting data

De-anonymization-angrep

Model inversion
Membership attack

Adversarial examples



Fairness

Reproducibility

Federated learning
Differential privacy

Lack of theory

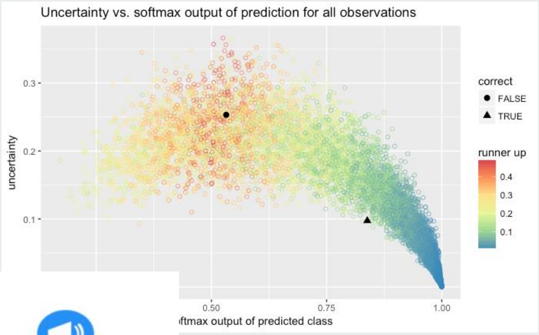
Models lack of understanding

Trust

What makes one model better than another?

Clinical validation!

Uncertainty

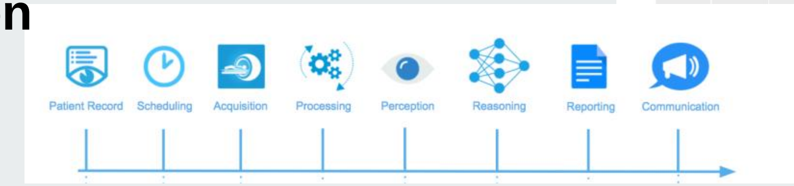


Education

Software engineering best practices

Deployment, maintenance,
unit testing, hidden technical debt, ...

Workflow integration



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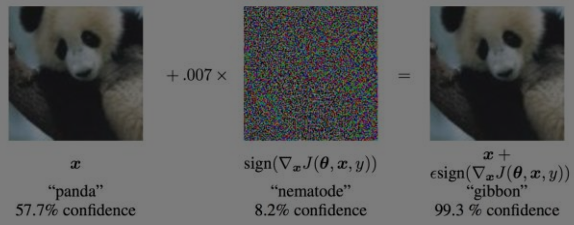

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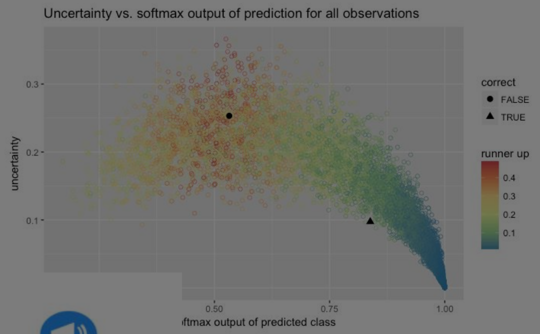

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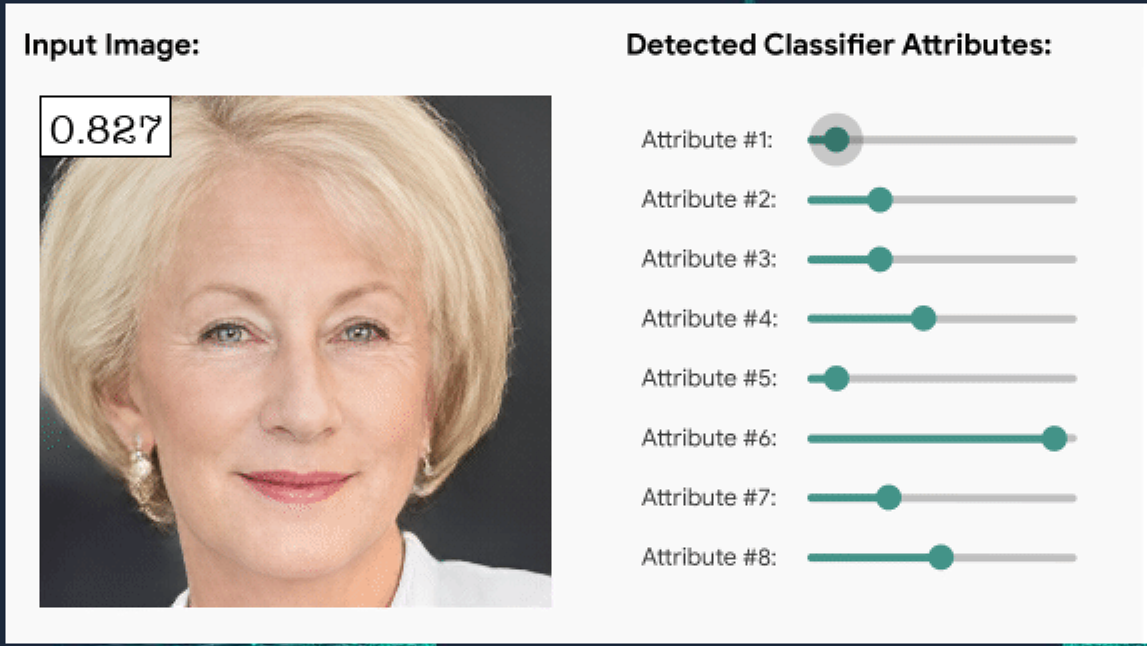


$y \approx f(x;\, \theta)$

image → young vs. old

Explaining in Style: Training a GAN to explain a classifier in StyleSpace

Sept. 2021

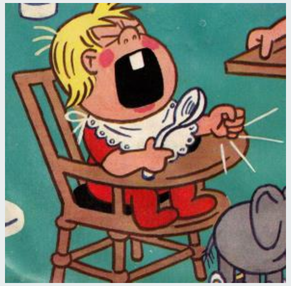
Oran Lang[*1] Yossi Gandelsman[*1] Michal Yarom[*1] Yoav Wald[*1,2]
Gal Elidan[1] Avinatan Hassidim[1] William T. Freeman[1,3] Phillip Isola[1,3]
Amir Globerson[1,4] Michal Irani[1,5] Inbar Mosseri[1]

[1] Google Research [2] Hebrew University [3] MIT [4] Tel Aviv University [5] Weizmann Institute of Science

*The current kind of **artificial intelligence***
*requires some kind of **artificial neuroscience***

Break

Data hungry!



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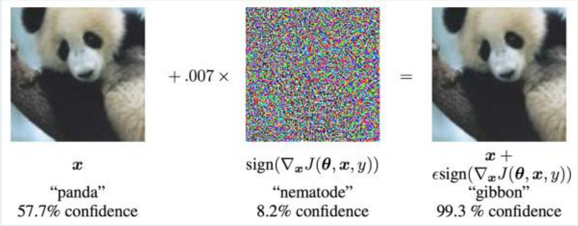

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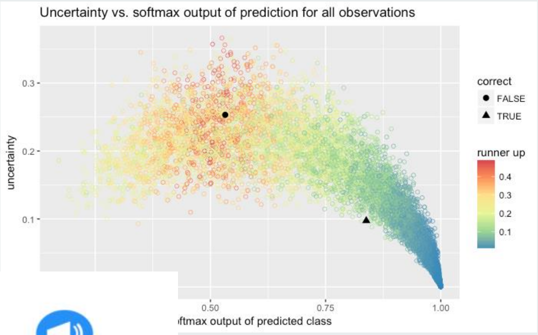

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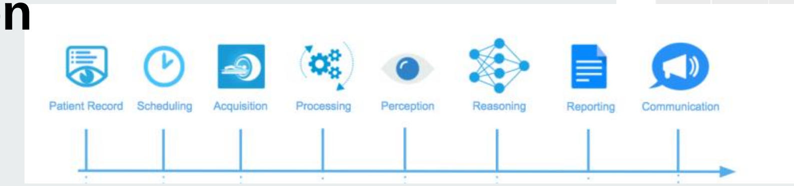

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BIAS

AI and machine learning is showing up in more and more areas in society

Who gets a mortgage?
Who’s hired?
Who’s convicted?
Who gets what news?

Who gets what?

There are some obvious problems with this, based on the systems strengths and weaknesses..


Bobby Vankavelaar
EXCLUSIVE
TAKING ACTION FOR YOU
INVESTIGATION FOCUSED ON TESLA AUTOPILOT
abc ACTION NEWS
11:02
83°

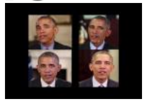
Chinese authorities collecting DNA from all residents of Xinjiang

Officials build database of iris scans and blood types of everyone aged 12 to 65 in region home to 11 million Muslim Ughurs

The New York Times

Facial Recognition Is Accurate, if You're a White Guy

AI Could Set Us Back 100 Years When It Comes to How We Consume News



Fake videos could become so convincing that we may have to get used to getting our news without them.

China's Huawei tested A.I. software that could identify Uighur Muslims and alert police, report says

PUBLISHED WED, DEC 9 2020-4:39 AM EST | UPDATED WED, DEC 9 2020-11:07 PM EST

Questioning AI: does artificial intelligence need an off switch? - Science Weekly podcast

Judges Now Using Artificial Intelligence to Rule on Prisoners

Chinese police are using facial recognition sunglasses to track citizens

The glasses are being used by officers in police stations to oversee travelers during the Lunar New Year

By James Vincent | @jjvincent | Feb 8, 2018, 4:51am EST

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Amazon scraps secret AI recruiting tool that showed bias against women

NOAH SHACHTMAN SECURITY 10.18.2007 09:00 AM

Robot Cannon Kills 9, Wounds 14

We're not used to thinking of them this way. But many advanced military weapons are essentially robotic — picking targets out automatically, slewing into position, and waiting only for a human to pull the trigger. Most of the time. Once in a while, though, these machines start firing mysteriously on their own. The South African [...]

Facebook looks to AI to monitor harmful behaviours

January 24, 2018

AI Could Trigger WWIII, Alibaba CEO Warns

Alex Woodie

UK PM seeks 'safe and ethical' artificial intelligence

New national security unit set up to tackle fake news in UK

…but one can encounter problems even *with no ill intent!*

“If we let algorithms decide then society becomes more just. Everyone’s treated the same, with the same result.”

Not necessarily!

Machine learning systems are trained on data collected from “the real world”.

The real world is unfair!

With no bad intentions one can easily end up designing unfair AI systems

“Dog”

“Dog”

```
[ 5.12695312e-02 -2.23388672e-02 -1.72851562e-01  1.61132812e-01
 -8.44726562e-02  5.73730469e-02  5.85937500e-02 -8.25195312e-02
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 -2.75390625e-01  2.61718750e-01  2.46093750e-01 -4.71191406e-02
  6.25000000e-02  4.16015625e-01 -3.55468750e-01  2.22656250e-01]
```
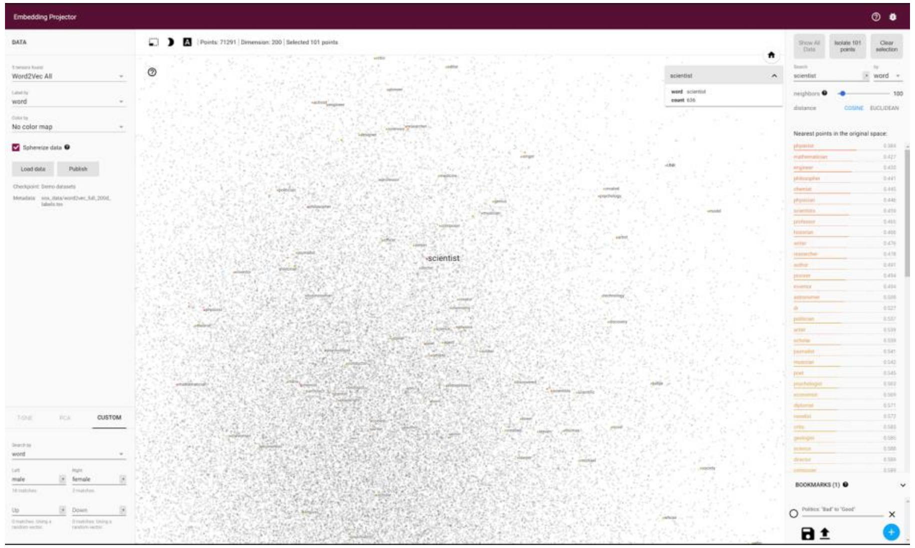

Word embeddings

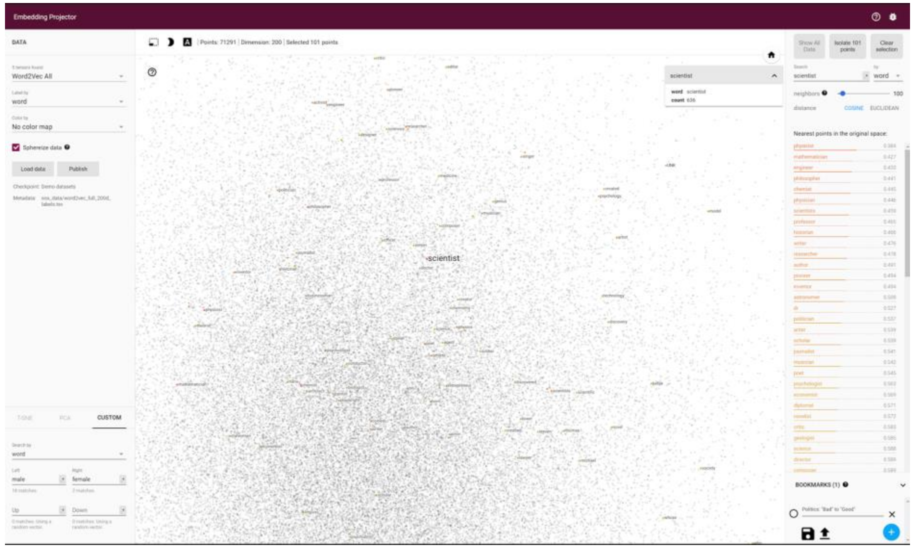
word → vector of numbers

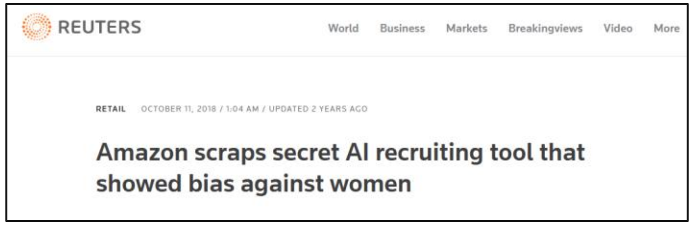
Similar things can be said for other representations of language used in AI



http://projector.tensorflow.org

Data genereated in our societies contain **stereotypes** and **cultural bias**





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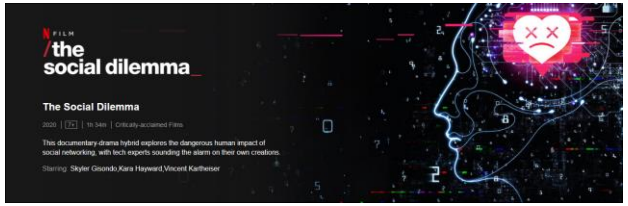

Facebook's response to Netflix documentary

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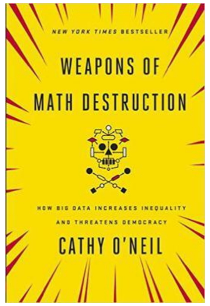
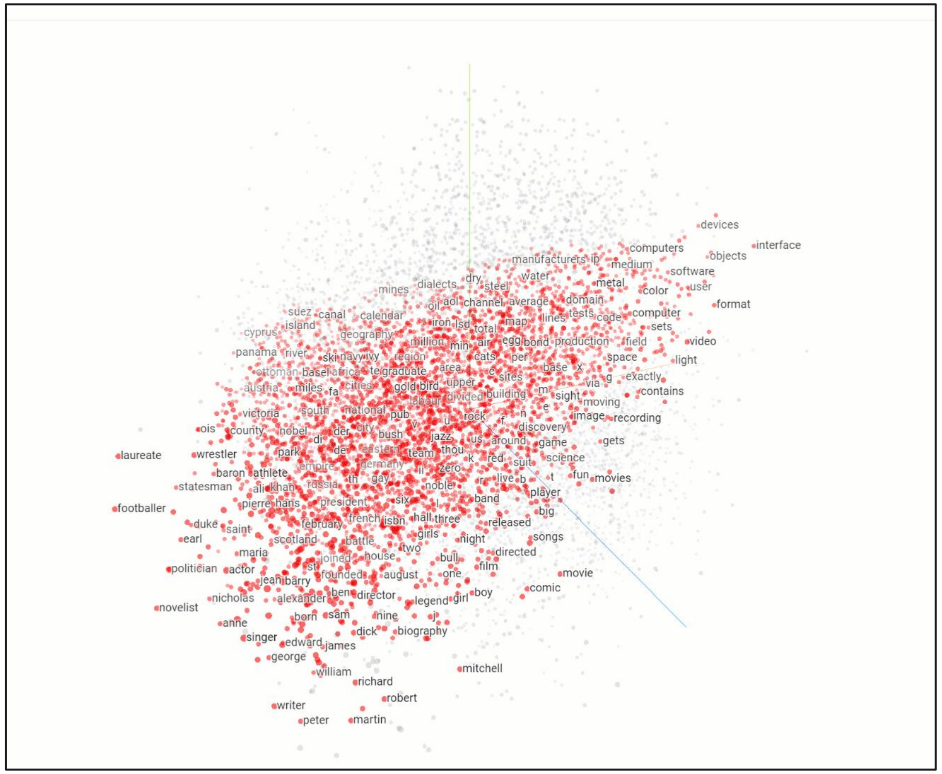
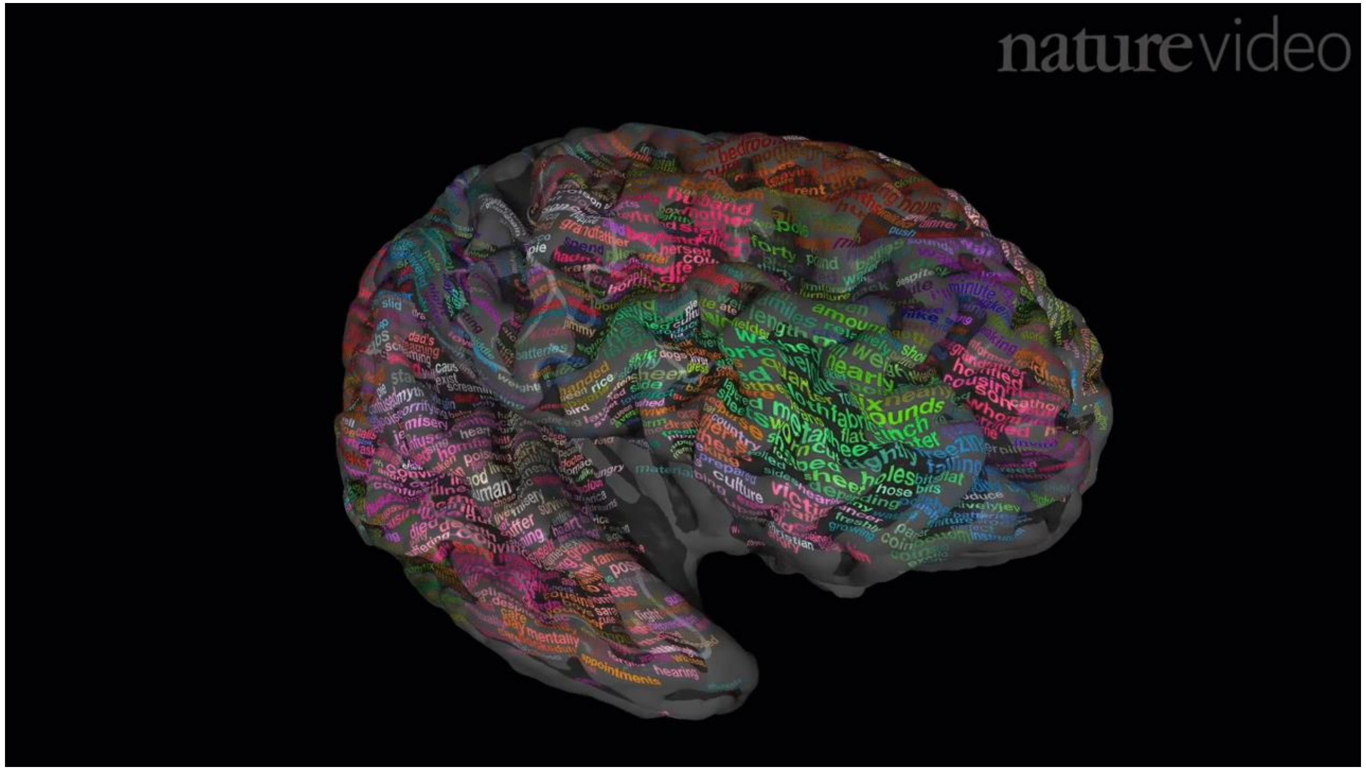


Break





Natural speech reveals the semantic maps that tile human cerebral cortex, Nature, April 2016

Data hungry!

Black box

"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?

Privacy

Data access

Law

Data labeling

Protecting data

Reproducibility

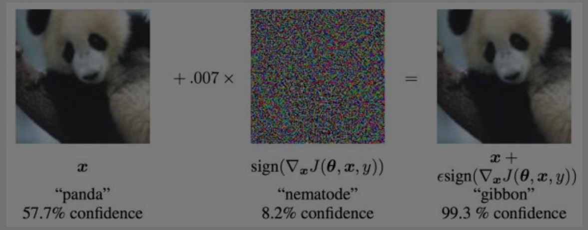
Fairness

De-anonymization-angrep

Model inversion
Membership attack

Federated learning
Differential privacy

Adversarial examples

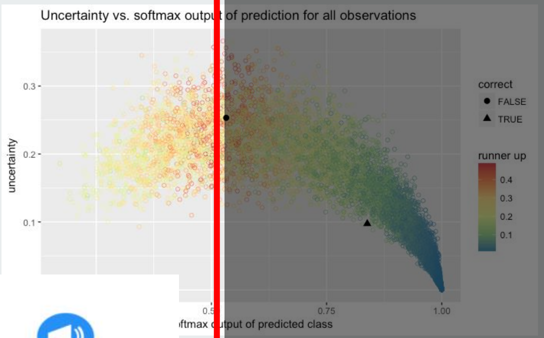


Lack of theory

Models lack of understanding

Trust

Uncertainty



What makes one model better than another?

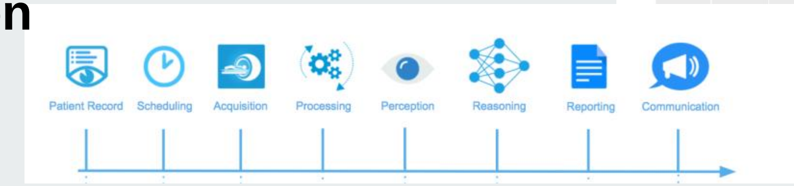
Clinical validation!

Education

Software engineering best practices

Deployment, maintenance, unit testing, hidden technical debt, ...

Workflow integration



Anchored to domain

What's the status of medical AI?

How much is "things in the pipeline" versus close to clinical implementation?

nature medicine
REVIEW ARTICLE
https://doi.org/10.1038/s41591-021-01614-0
Check for updates

AI in health and medicine

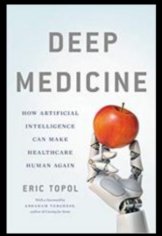
20.01.2022 (yesterday)

Pranav Rajpurkar[1,4], Emma Chen[2,4], Oishi Banerjee[2,4] and Eric J. Topol[3]

Eric Topol, MD

«almost every type of clinician [...] will be using AI technology, and in particular deep learning, in the future»

Eric Topol, Nat. Medicine, Jan 7 2019



What's the status of medical AI?

How much is "things in the pipeline" versus close to clinical implementation?

- *In the years ahead, AI is poised to **broadly reshape medicine***
- *Today, the deployment of medical AI systems in routine clinical care presents an important **yet largely unfulfilled opportunity***
- ***Randomized controlled trials** and prospective studies can bridge this gap between theory and practice*
- *Despite the potential of the field, **major technical and ethical questions** remain for medical AI.*
- *a need for bold imagination. […] hope to see even more **creative, out-of-the-box approaches** to medical AI*

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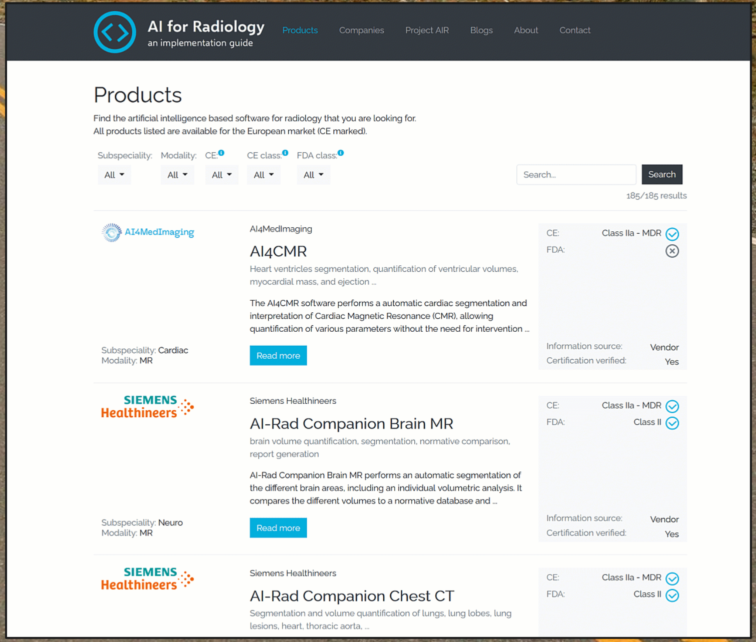

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REVIEW ARTICLE | FOCUS
https://doi.org/10.1038/s41591-018-0300-7
nature medicine

High-performance medicine: the convergence of human and artificial intelligence

Eric J. Topol

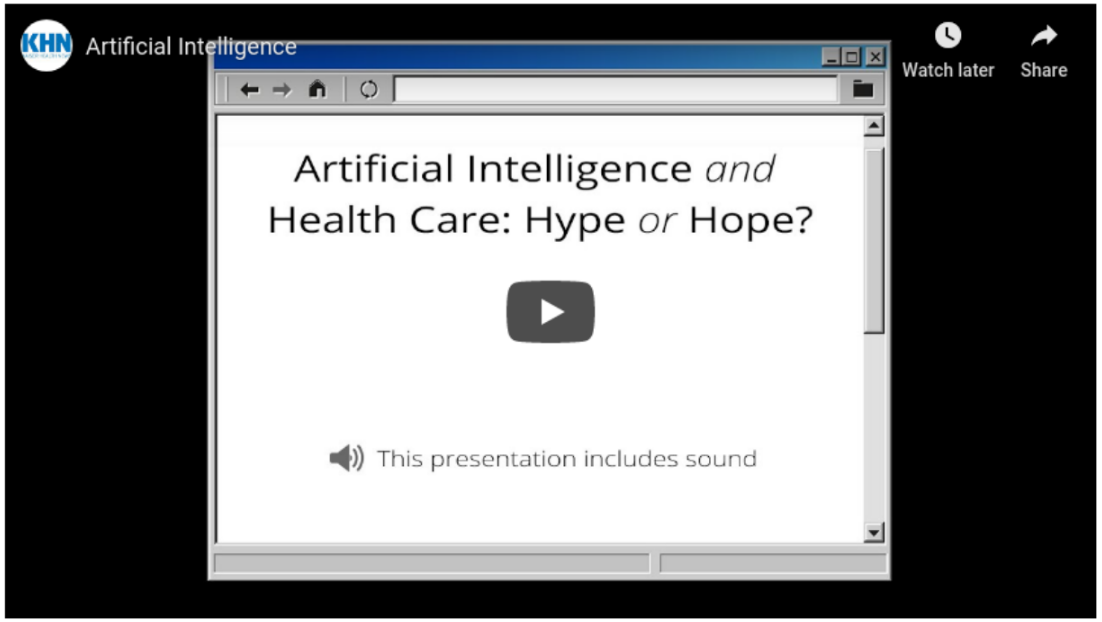
07.01.2019

KHN
KAISER HEALTH NEWS

A Reality Check On Artificial Intelligence: Are Health Care Claims Overblown?

Dec. 2019

By Liz Szabo 1 week ago



Health products powered by artificial intelligence, or AI, are streaming into our lives, from virtual doctor apps to wearable

Time to reality check the promises of machine learning-powered precision medicine

Sept. 2020

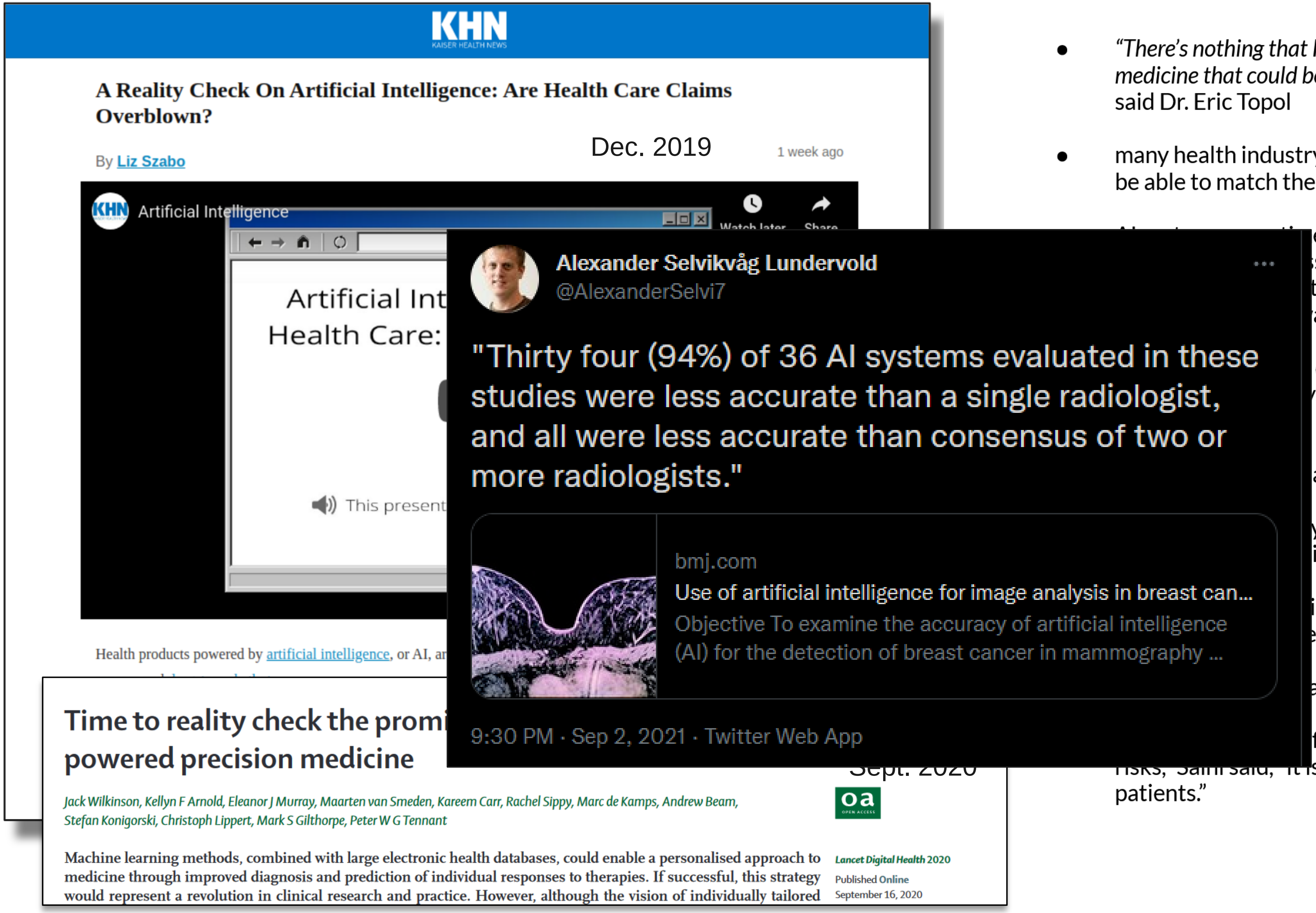
Jack Wilkinson, Kellyn F Arnold, Eleanor J Murray, Maarten van Smeden, Kareem Carr, Rachel Sippy, Marc de Kamps, Andrew Beam, Stefan Konigorski, Christoph Lippert, Mark S Gilthorpe, Peter W G Tennant

Machine learning methods, combined with large electronic health databases, could enable a personalised approach to medicine through improved diagnosis and prediction of individual responses to therapies. If successful, this strategy would represent a revolution in clinical research and practice. However, although the vision of individually tailored

Lancet Digital Health 2020
Published Online
September 16, 2020

- *"There's nothing that I've seen in my 30-plus years studying medicine that could be as impactful and transformative"* as AI, said Dr. Eric Topol
- many health industry experts fear AI-based products won't be able to match the hype.
- AI systems sometimes learn to make predictions based on factors that have less to do with disease than the **brand of MRI machine** used, the **time a blood test is taken** or whether a patient was **visited by a chaplain.**

  [Or learn] to tell the difference between that hospital's portable chest X-rays with those taken in the radiology department
- "Most AI products have little evidence to support them"
- AI models are mostly tested on computers, not in hospitals or other medical facilities
- Systems developed in one hospital often flop when deployed in a different facility
- Relaxing standards at the FDA (510(k))
- "While it is the job of entrepreneurs to think big and take risks," Saini said, "it is the job of doctors to protect their patients."



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1 week ago

Artificial Intelligence

Watch later Share

Artificial Int

Health Care:

This present

Health products powered by artificial intelligence, or AI, ar

Alexander Selvikvåg Lundervold
@AlexanderSelvi7

"Thirty four (94%) of 36 AI systems evaluated in these studies were less accurate than a single radiologist, and all were less accurate than consensus of two or more radiologists."

bmj.com
Use of artificial intelligence for image analysis in breast can...
Objective To examine the accuracy of artificial intelligence (AI) for the detection of breast cancer in mammography ...

9:30 PM · Sep 2, 2021 · Twitter Web App

Time to reality check the promi
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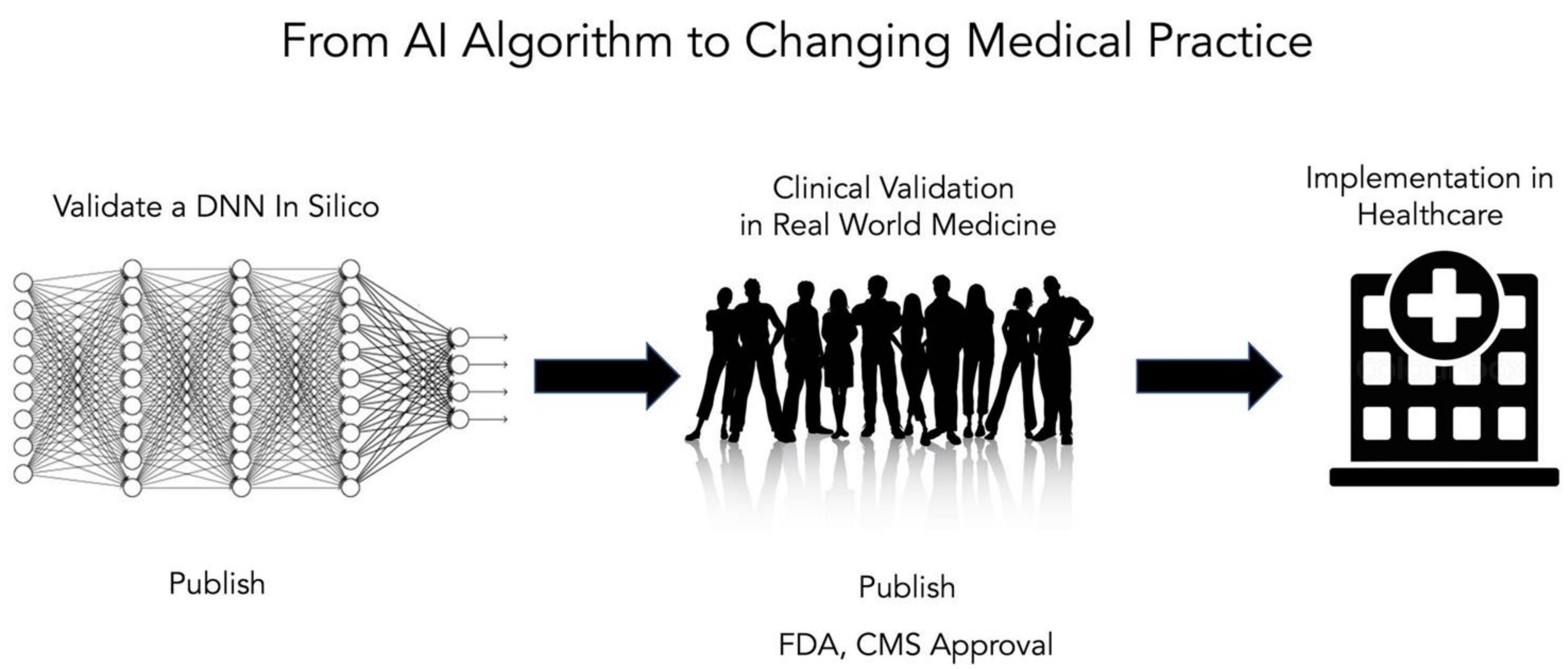

but on our way here…

Modified from Eric Topol

What's the status of medical AI?

RSNA Journals

Radiology

Algorithm to Changing Me

Clinical Validation
in Real World Medici

Communications
From the Editor

Free Access

Assessing Radiology Research on Artificial Intelligence: A Brief Guide for Authors, Reviewers, and Readers—From the *Radiology* Editorial Board

David A. Bluemke, Linda Moy, Miriam A. Bredella, Birgit B. Ertl-Wagner, Kathryn J. Fowler, Vicky J. Goh, Elkan F. Halpern, Christopher P. Hess, Mark L. Schiebler, Clifford R. Weiss

but on our way here...

Key Considerations for Authors, Reviewers, and Readers of AI/ML Manuscripts in *Radiology*

Key Considerations
Are all three image sets (training, validation, and test sets) defined?
Is an *external* test set used for final statistical reporting?
Have multivendor images been used to evaluate the AI algorithm?
Are the sizes of the training, validation, and test sets justified?
Was the AI algorithm trained using a standard of reference that is widely accepted in our field?
Was preparation of images for the AI algorithm adequately described?
Were the results of the AI algorithm compared with radiology experts and/or pathology?
Was the manner in which the AI algorithm makes decisions demonstrated?
Is the AI algorithm publicly available?

Note.—AI = artificial intelligence, ML = machine learning.

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28.06.2021

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Health informatics
Protocol

Developing a reporting guideline for artificial intelligence-centred diagnostic test accuracy studies: the STARD-AI protocol

PDF | XML

Viknesh Sounderajah[1,2], Hutan Ashrafian[1,2], Robert M Golub[3], Shravya Shetty[4], Jeffrey De Fauw[5], Lotty Hooft[6,7], Karel Moons[6,7], Gary Collins[8], David Moher[9], Patrick M Bossuyt[10], Ara Darzi[1,2], Alan Karthikesalingam[11], Alastair K Denniston[12,13,14,15], Bilal Akhter Mateen[16], Daniel Ting[17], Darren Treanor[18], Dominic King[19], Felix Greaves[20], Jonathan Godwin[5], Jonathan Pearson-Stuttard[21], Leanne Harling[1], Matthew McInnes[22], Nader Rifai[23], Nenad Tomasev[5], Pasha Normahani[1], Penny Whiting[24], Ravi Aggarwal[1,2], Sebastian Vollmer[16], Sheraz R Markar[1], Trishan Panch[25], Xiaoxuan Liu[12,13,14,15] On behalf of the STARD-AI Steering Committee

From the Editor

World Health Organization

Health Topics | Countries | Newsroom | Emergencies | Data | About WHO

Home / Publications / Overview / Generating Evidence for Artificial Intelligence Based Medical Devices: A Framework for Training Validation and Evaluation

Generating Evidence for Artificial Intelligence Based Medical Devices: A Framework for Training Validation and Evaluation

Including a use-case study for Cervical Cancer Screening

17 November 2021 | Publication

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Note.—AI = artificial intelligence, ML = machine learning.

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

Who defines the ground truth?
Is there a ground truth?

The development of medical AI should happen with the health-care sector in the driver's seat *

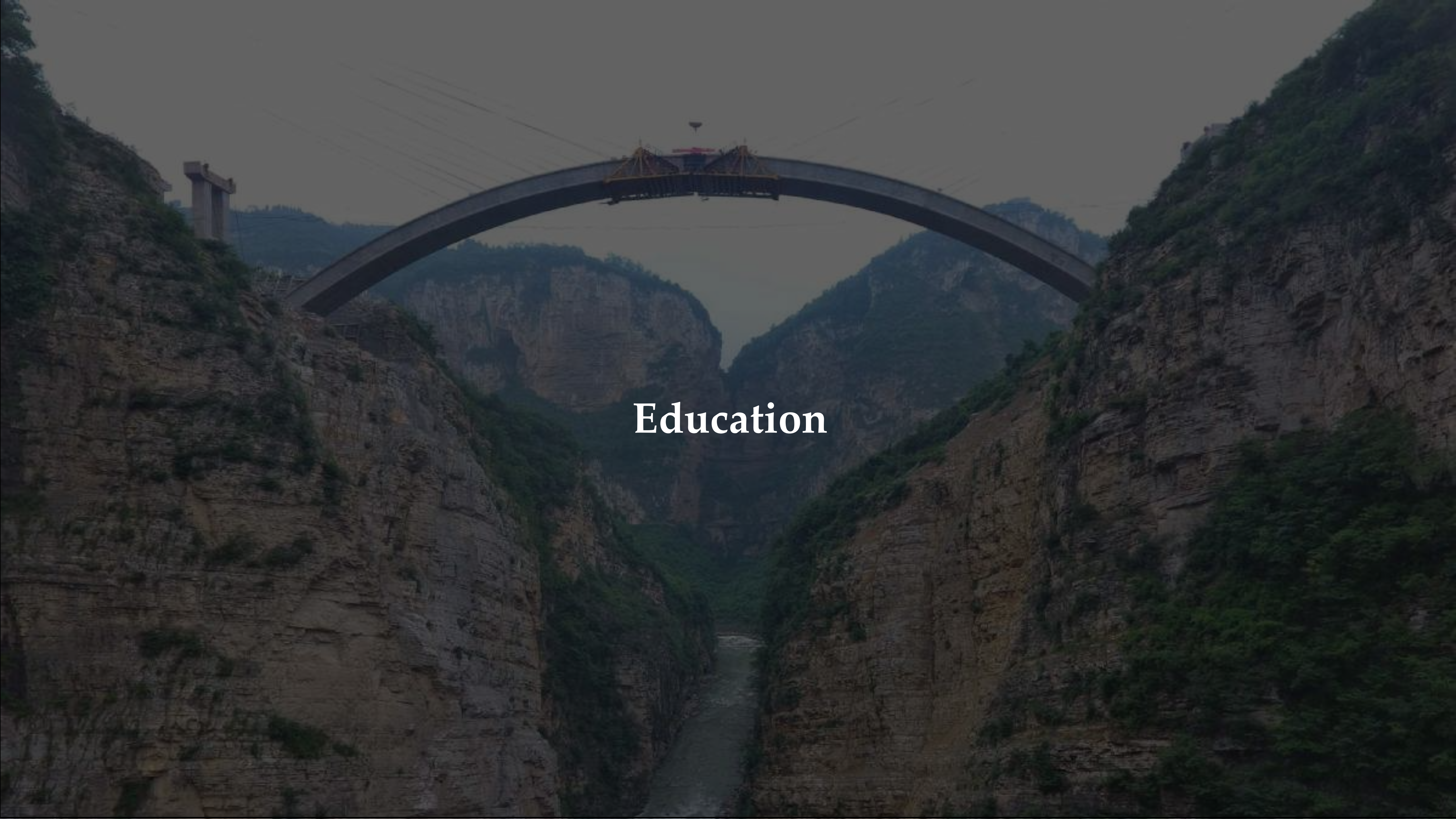
applications, **methods**, and **infrastructure**

Well-placed to ***research***, ***evaluate***, ***implement*** and ***innovate***

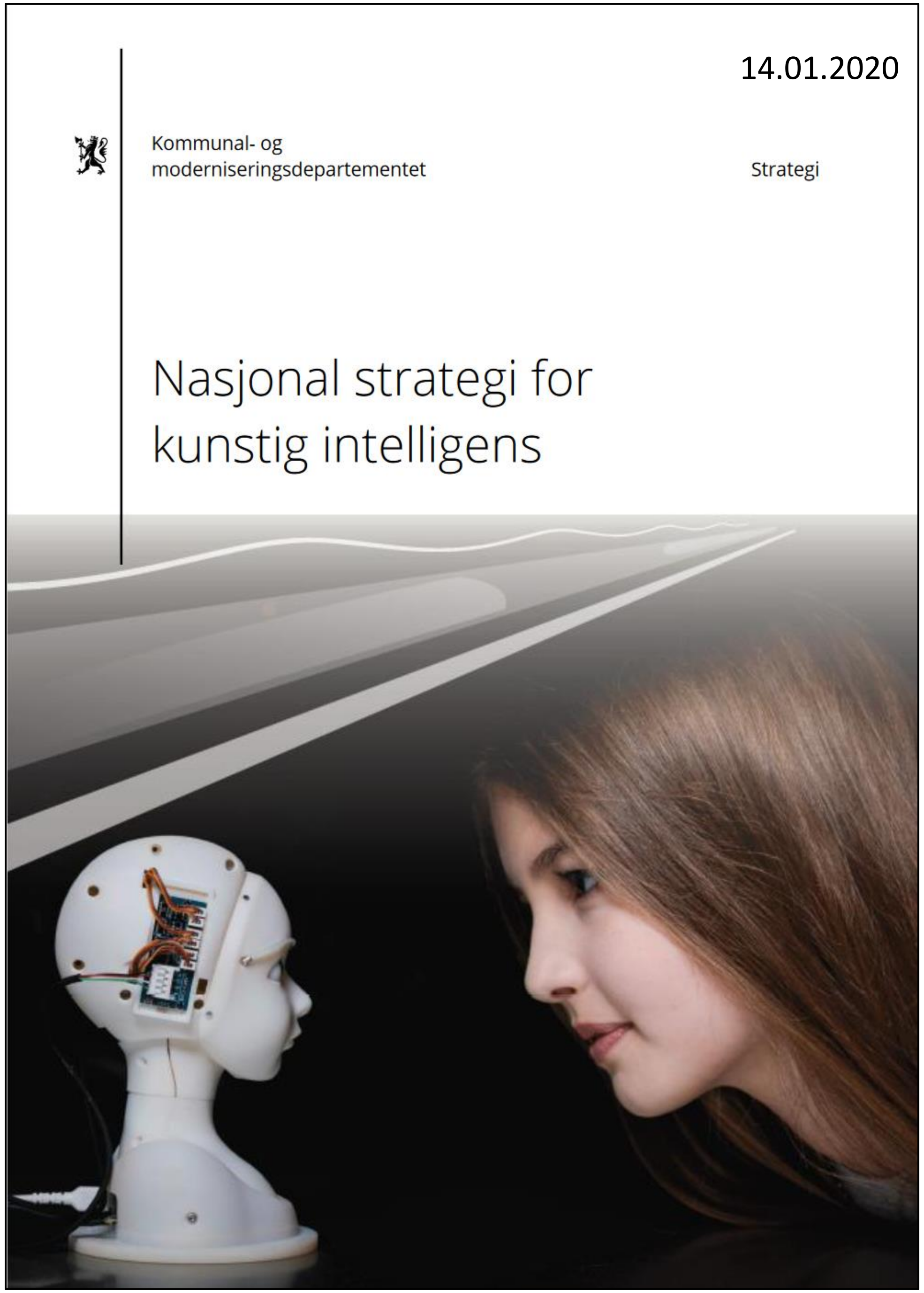
* at least in the front seat

IMMIV

Break



Education



Institutions of higher education ought to evaluate how topics with relevance to artificial intelligence can be integrated into their programmes in areas that will be affected by artificial intelligence in the coming years.

Need for interdisciplinarity

Knowledge of artificial intelligence, and related fields such as ethics and data protection associated with AI applications, will be important in study programmes oriented towards the educational sector, health, crime prevention, law and several other fields. For example, an introductory course in artificial intelligence has been established at the University of Bergen, in which students of medicine and bioengineering learn about how AI can be used in clinical practice. One of the aims is to promote interdisciplinary cooperation between physicians and engineers. The universities of Bergen and Oslo also offer courses in artificial intelligence and machine learning oriented towards social scientists.

https://www.regjeringen.no/no/dokumenter/nasjonal-strategi-for-kunstig-intelligens/id2685594

AMA Journal of Ethics

Illuminating the Art of Medicine

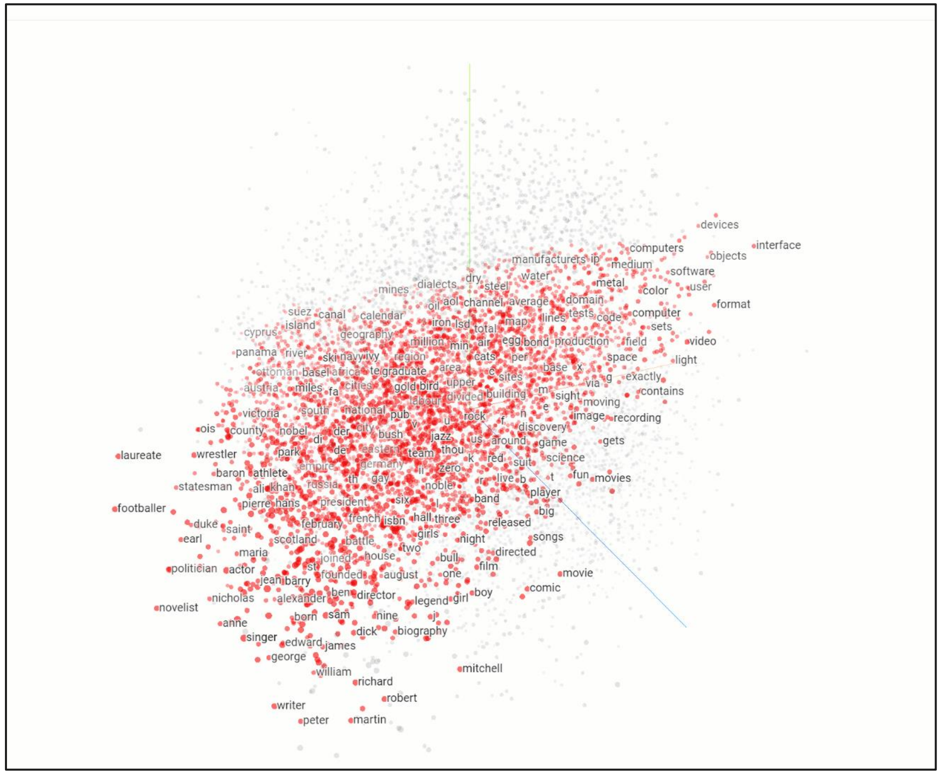
Information Overload

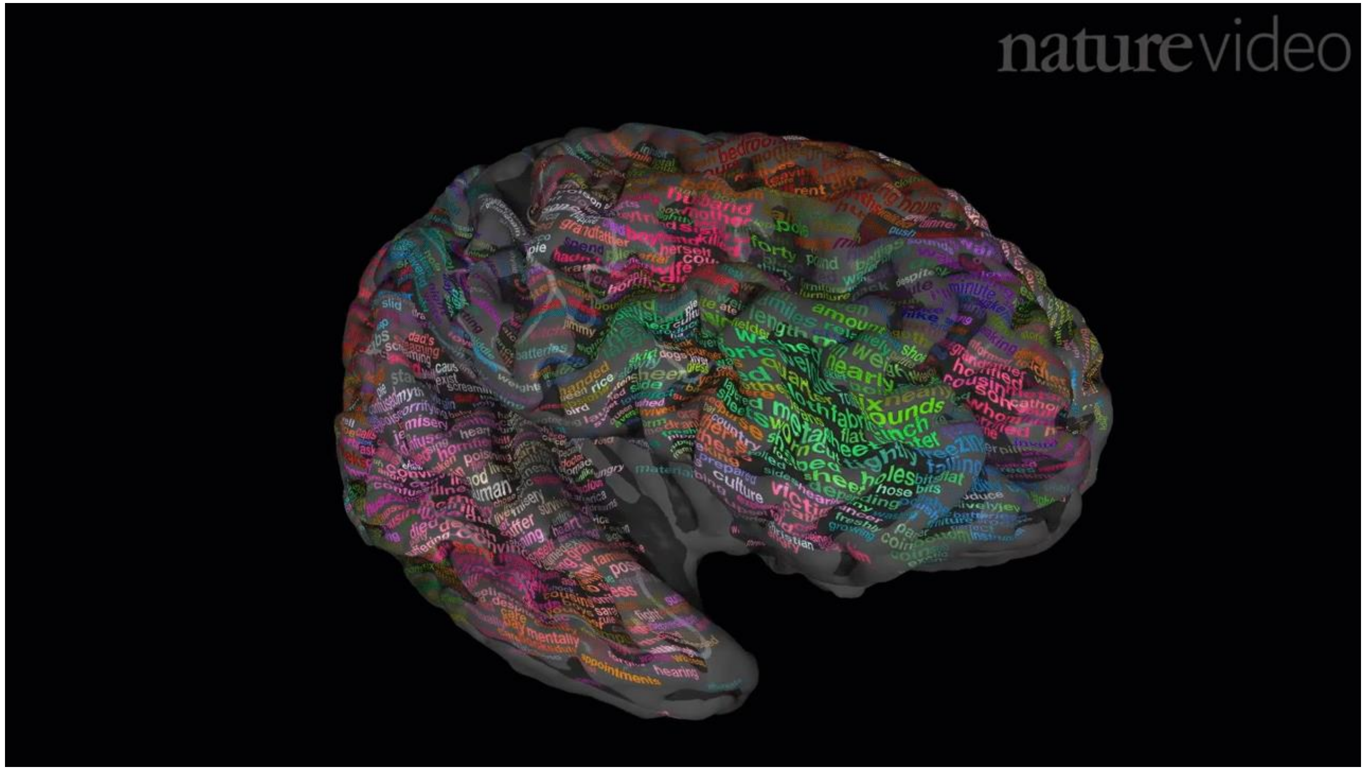
The system for educating medical students is approaching a crisis driven by 2 compelling forces: growing externalization of available medical knowledge outside the minds of physicians and stress-induced mental illness among learners.[2-5]

Information Overload

The system for educating medical students is approaching a crisis driven
available medical knowledge outside the minds of physicians and stress-

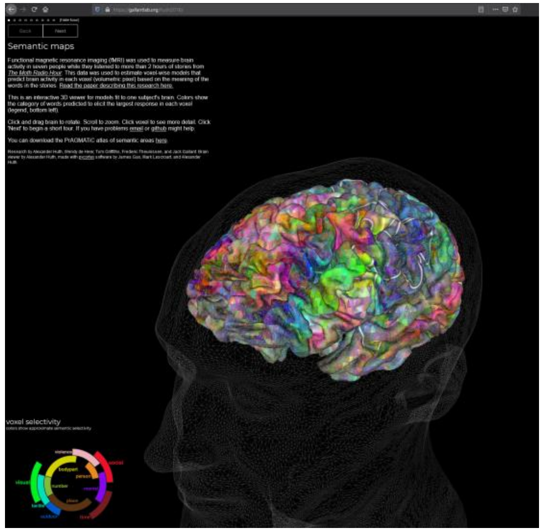
Epistemology



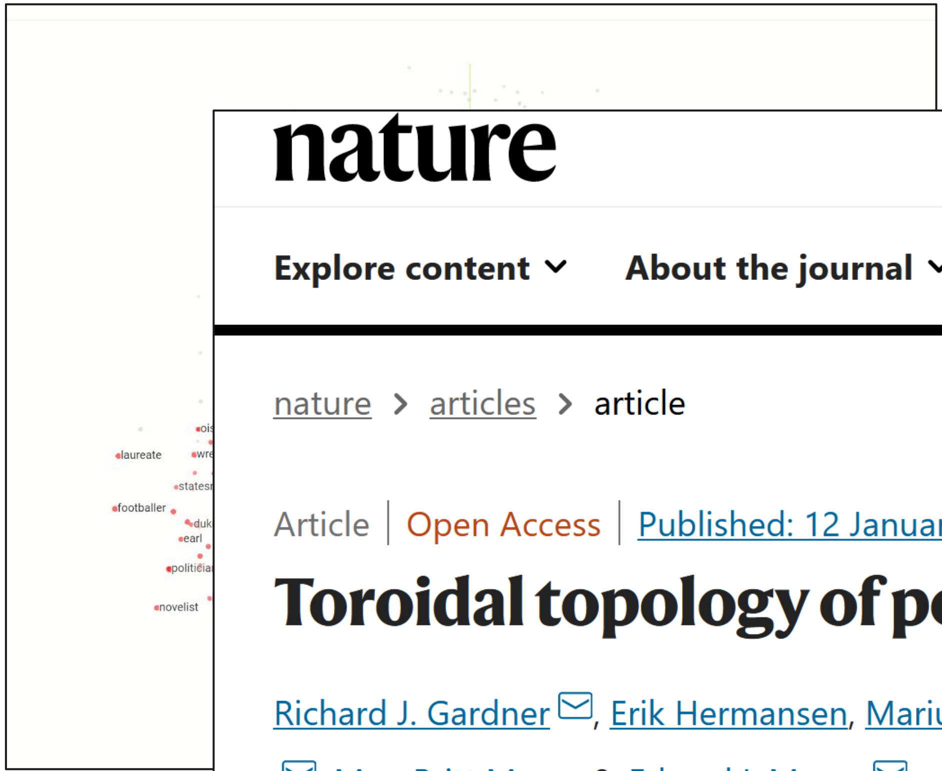


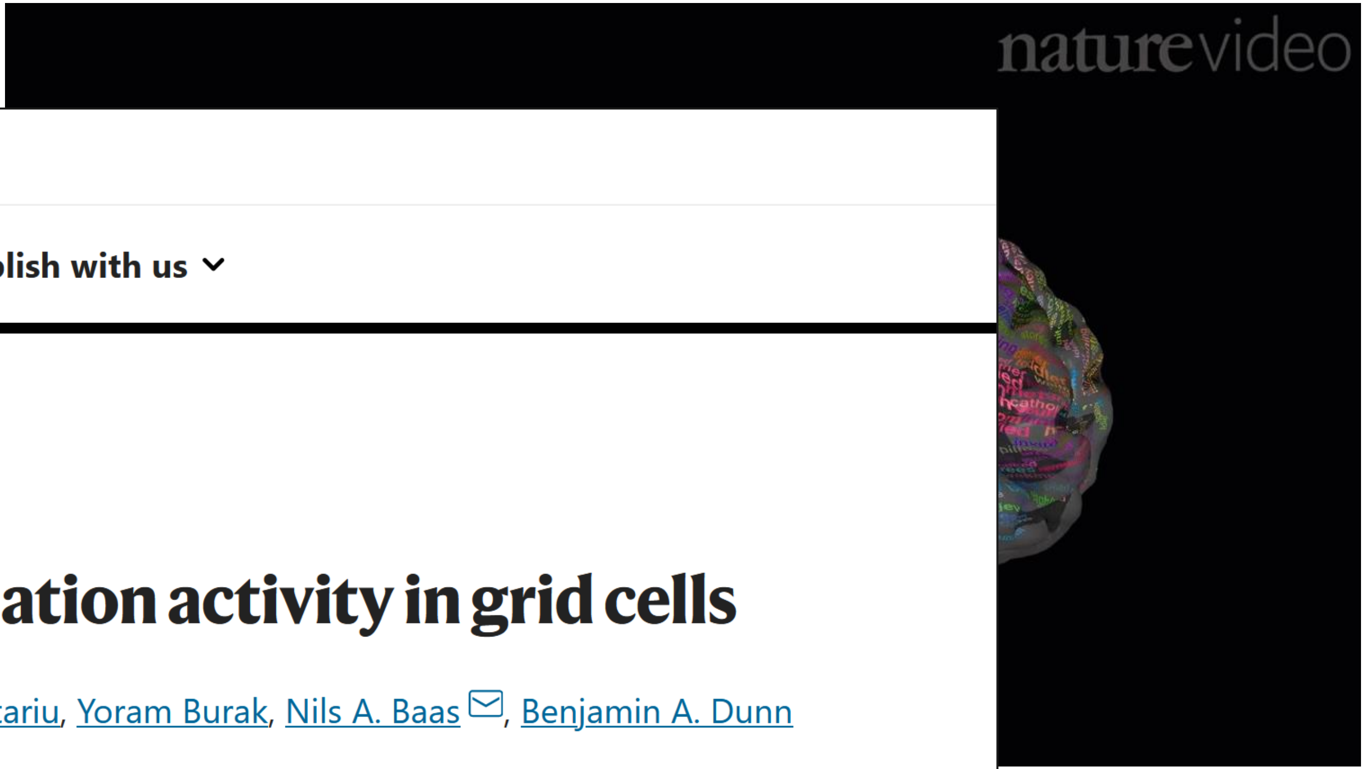
Natural speech reveals the semantic maps that tile human cerebral cortex, Nature, April 2016

Representations in brain and machine



https://gallantlab.org/huth2016





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Article | Open Access | Published: 12 January 2022

Toroidal topology of population activity in grid cells

Richard J. Gardner, Erik Hermansen, Marius Pachitariu, Yoram Burak, Nils A. Baas, Benjamin A. Dunn, May-Britt Moser & Edvard I. Moser

Nature (2022) Cite this article

https://github.com/erikher/GridCellTorus

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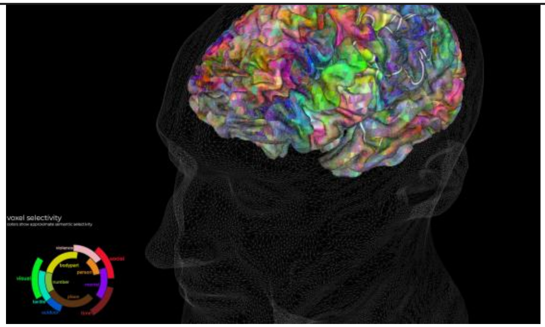
lature, April 2016

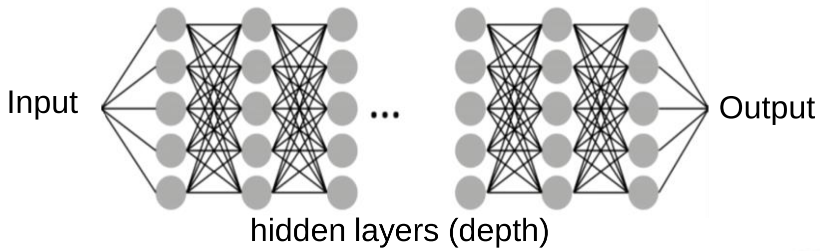
Represen
brain and



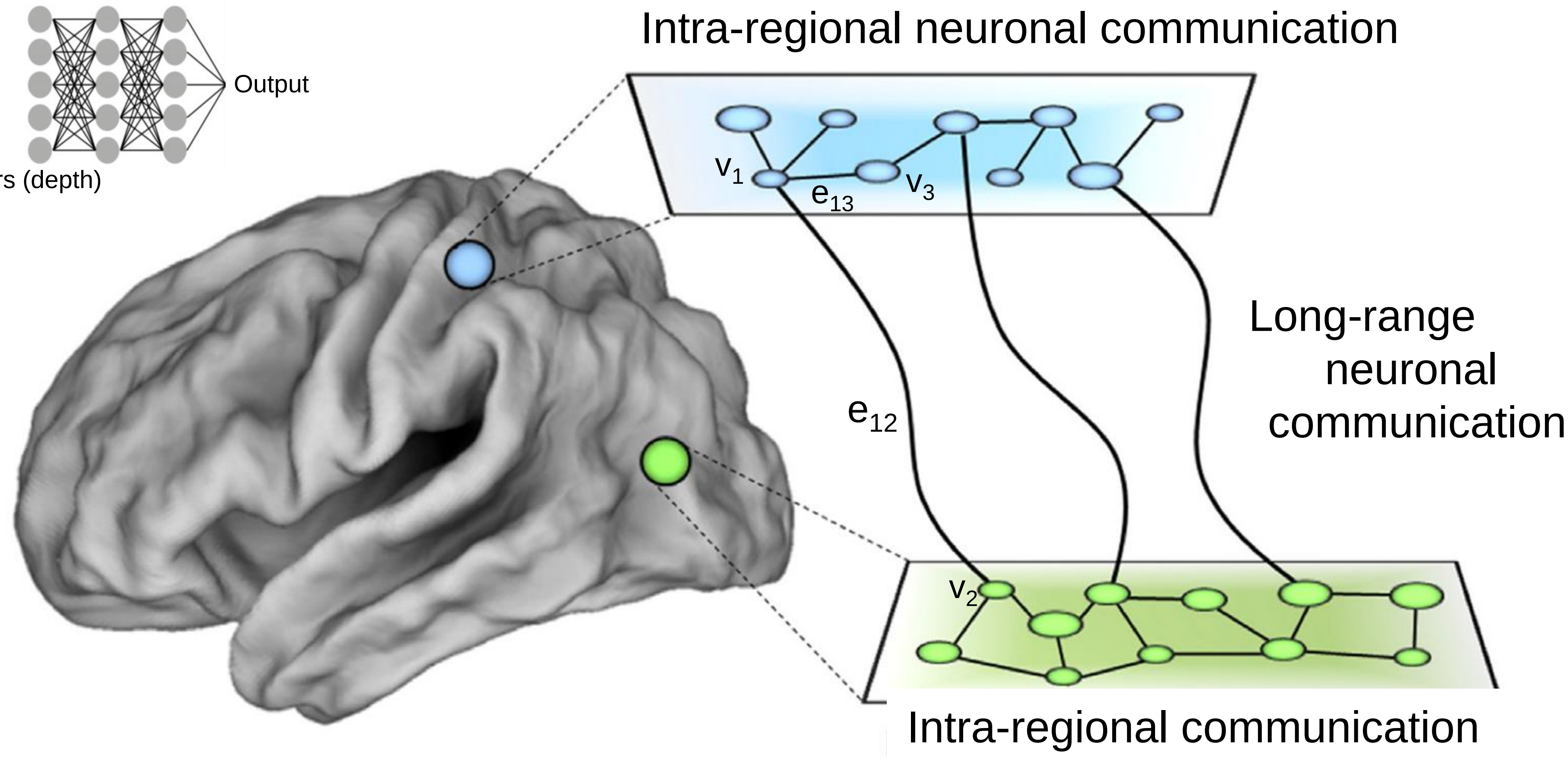
https://gallantlab.org/huth2016

Neural networks in brain and machine

in machine:



in brain:

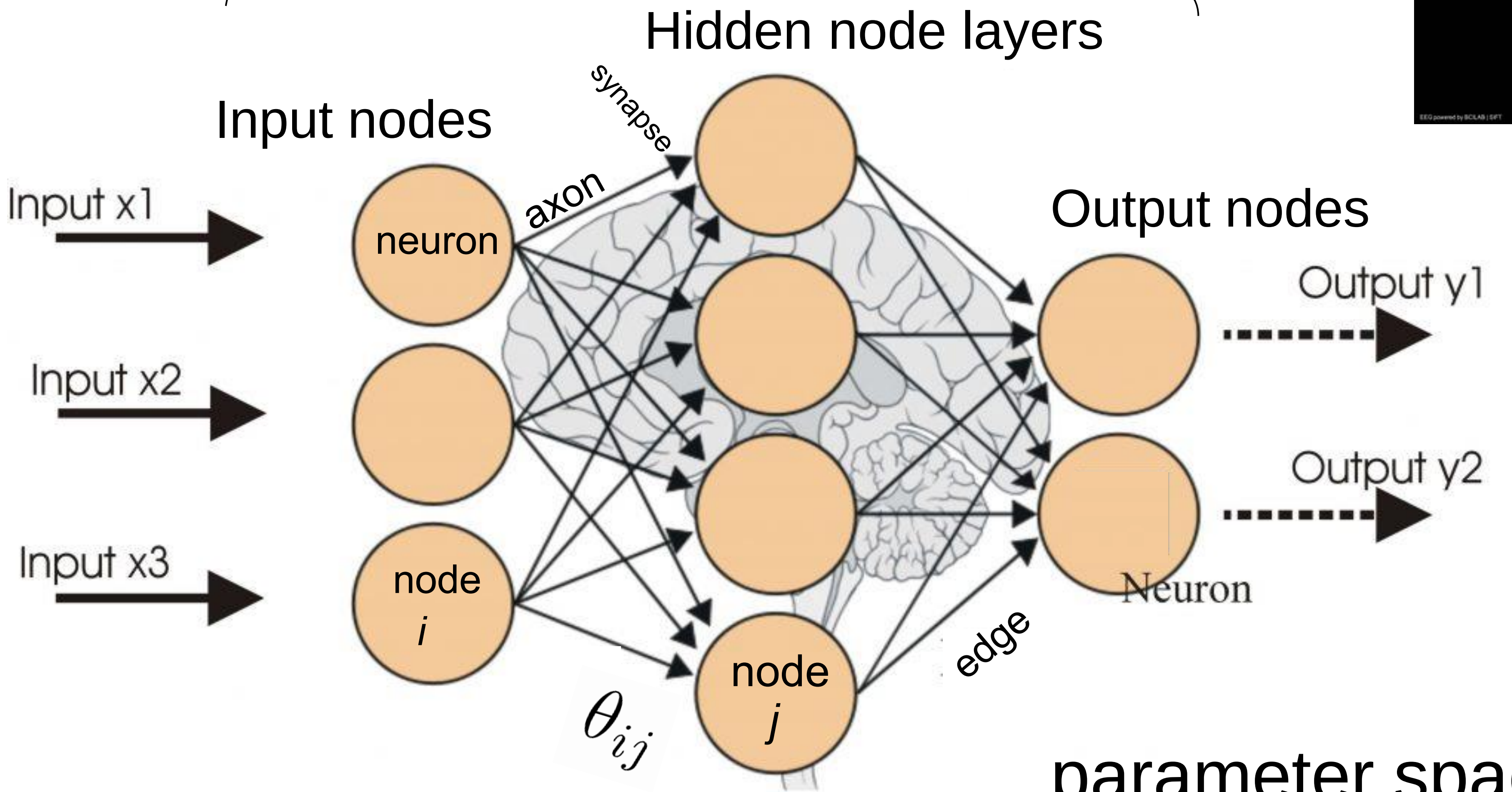


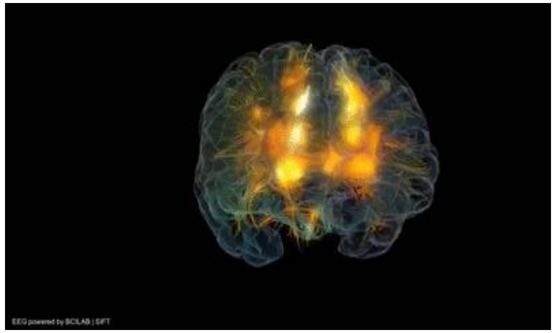
Graph theory:

A **graph** G is an ordered pair $G=(V,E)$ where V denote a set of **vertices** (nodes) and $E \subseteq V \times V$ are the **edges** (arcs, connections) of the graph

e.g. v1, v2, v3 $\in$ V and (v_1,v_2), (v_1,v_3) $\in$ E

$\overbrace{\hspace{6cm}}^{\text{f (model)}}$





Network activity

- learning
- inference

$\boldsymbol{X}$
(data)

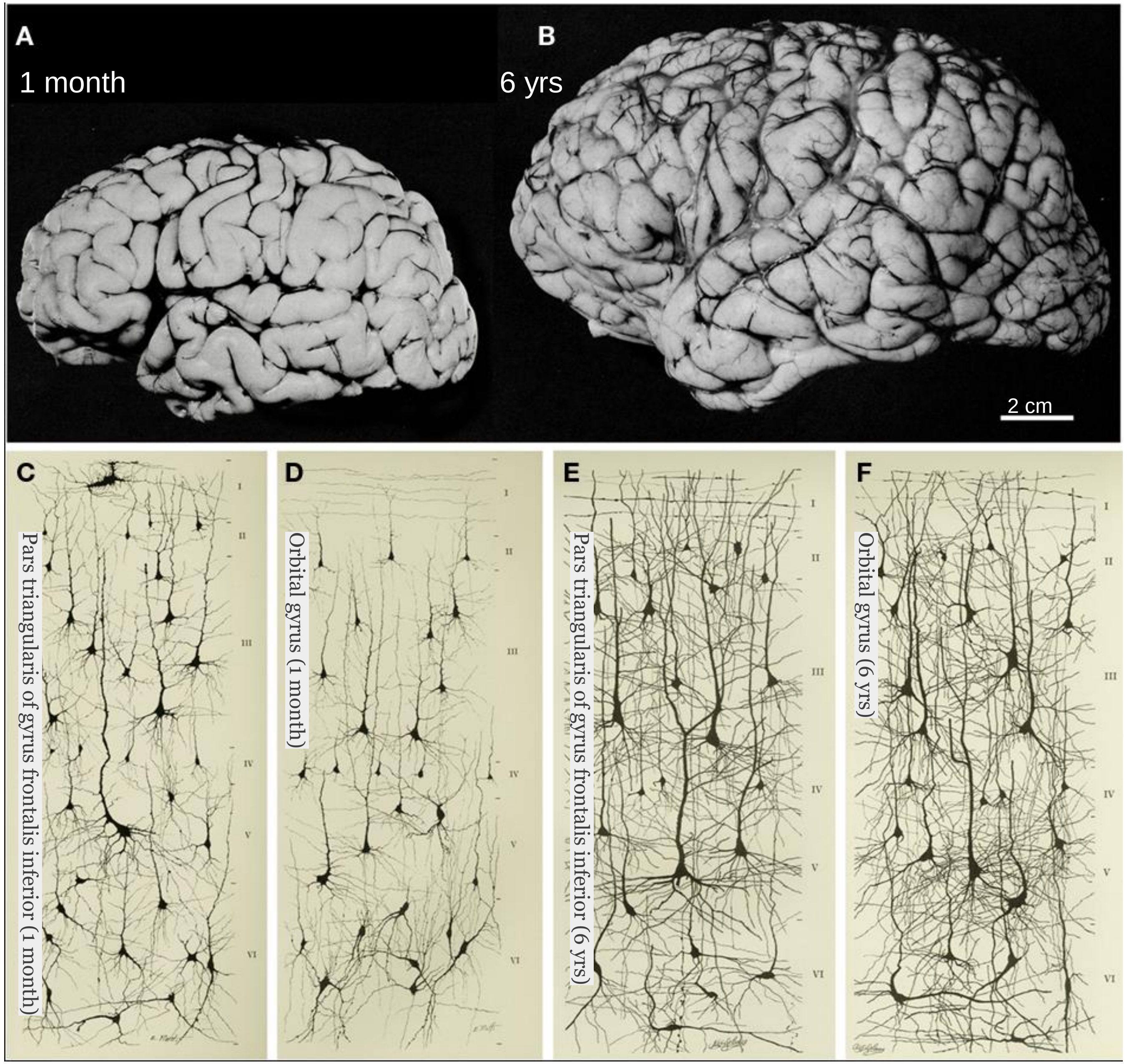
$\mathbb{R}^n$

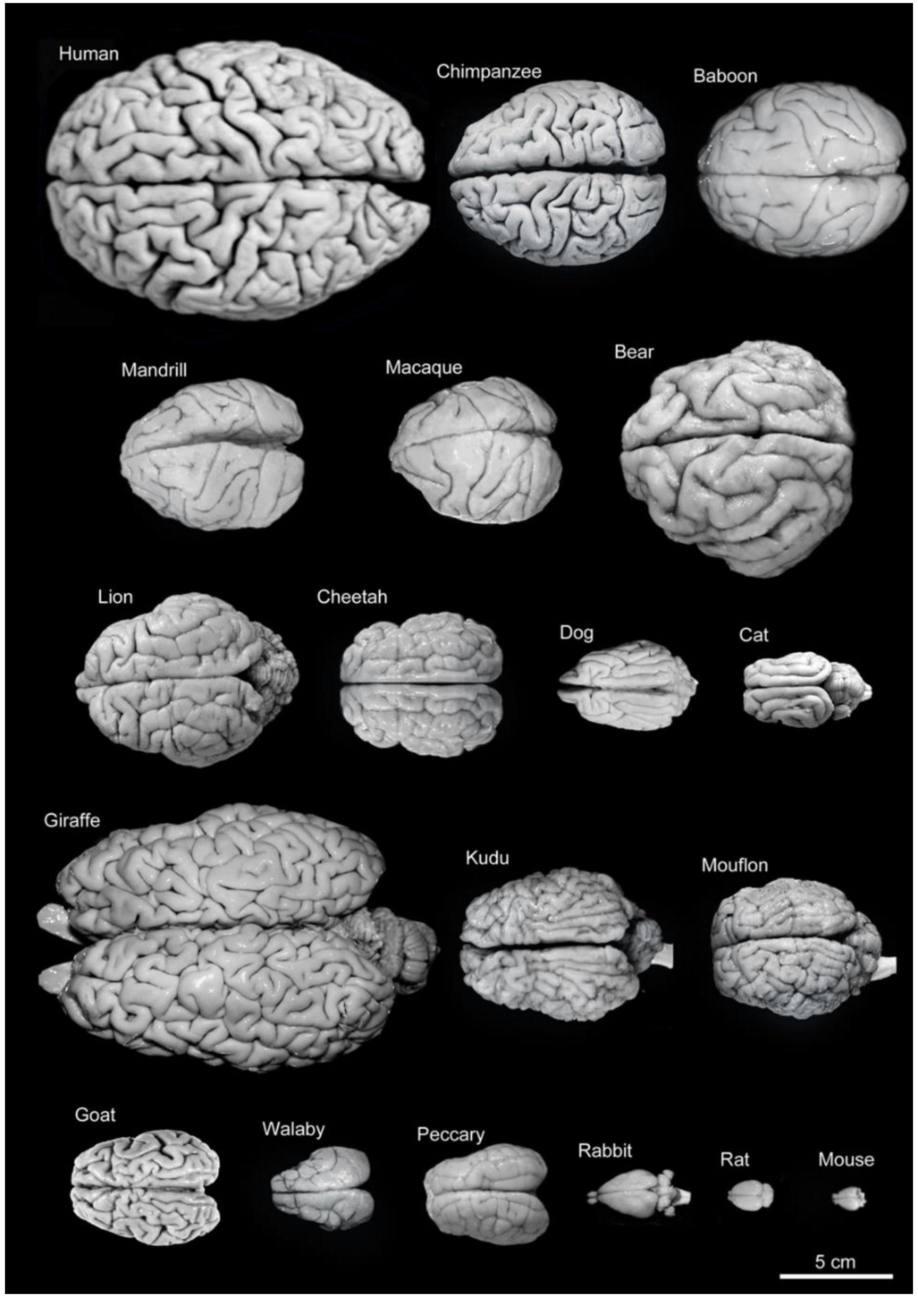
y
(output)

parameter space $\subset \mathbb{R}^p$

$$y \approx f(\boldsymbol{X}; \theta)$$

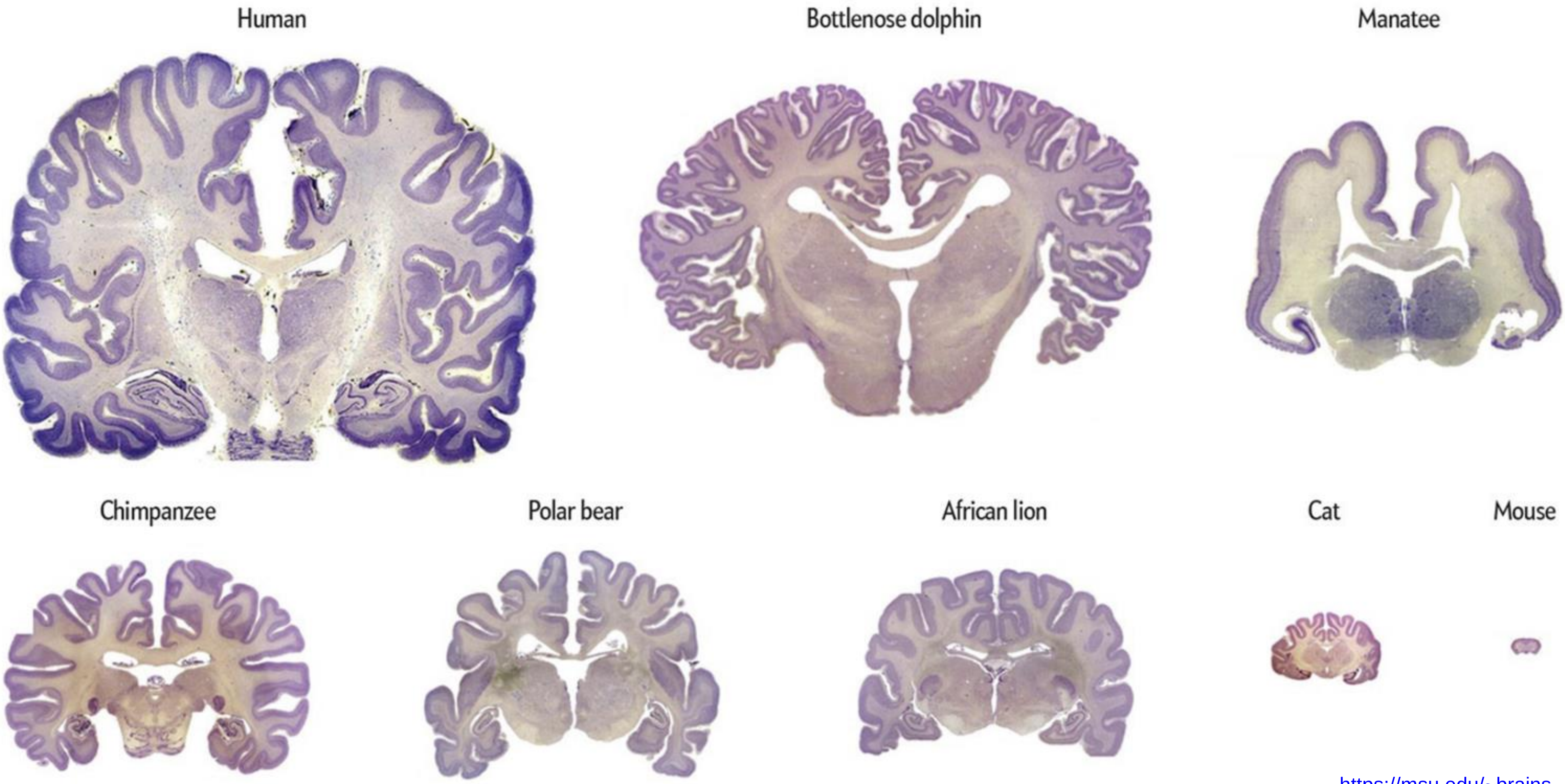
J. DeFelipe. The evolution of the brain, the human nature of cortical circuits, and intellectual creativity



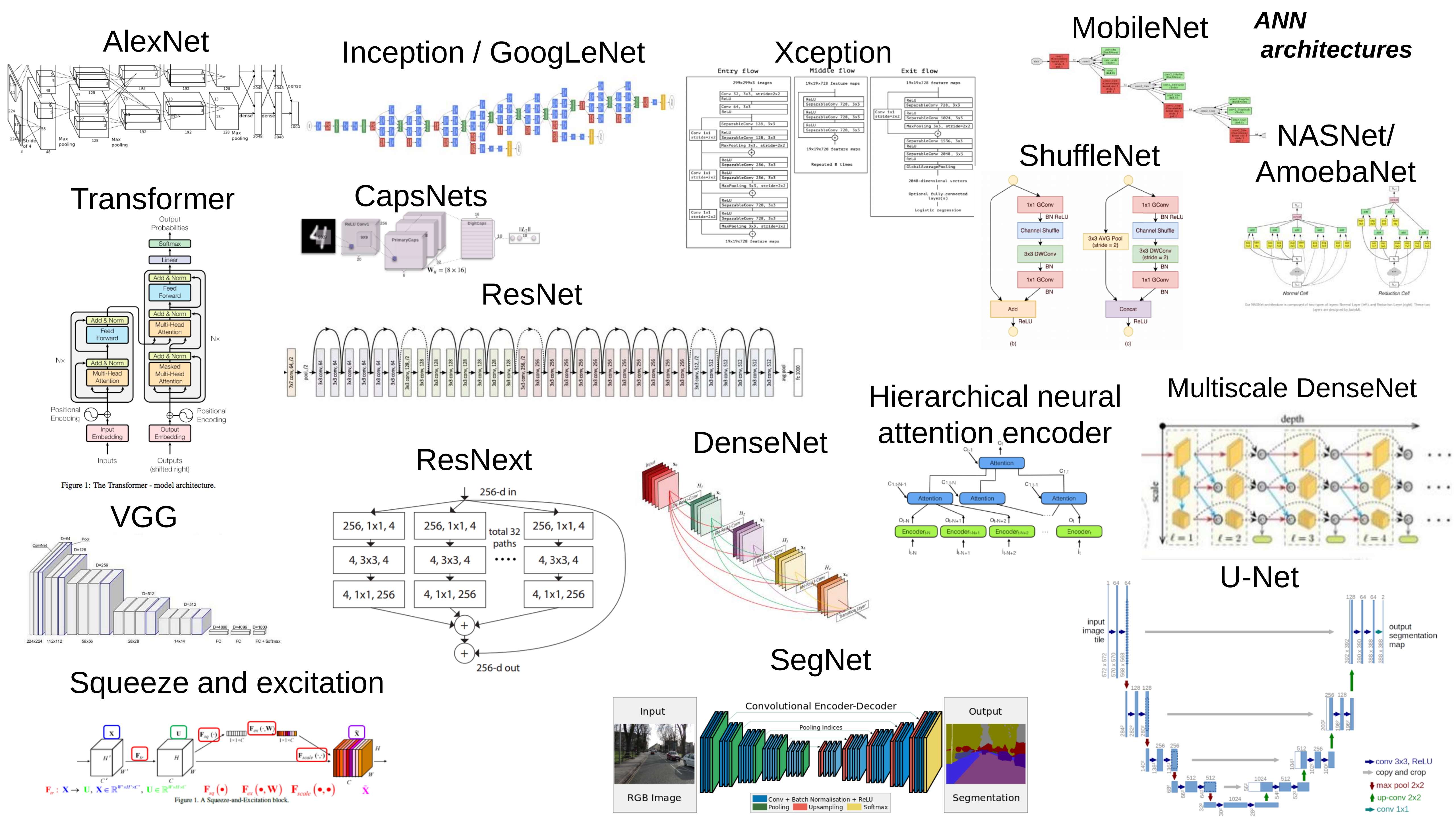


Frontiers in Neuroanatomy 16 May 2011 https://doi.org/10.3389/fnana.2011.00029

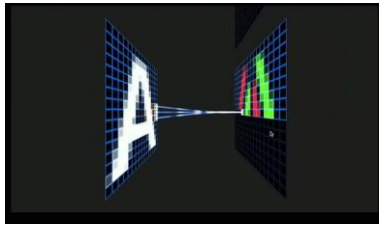
J. DeFelipe. The evolution of the brain, the human nature of cortical circuits, and intellectual creativity (2011)

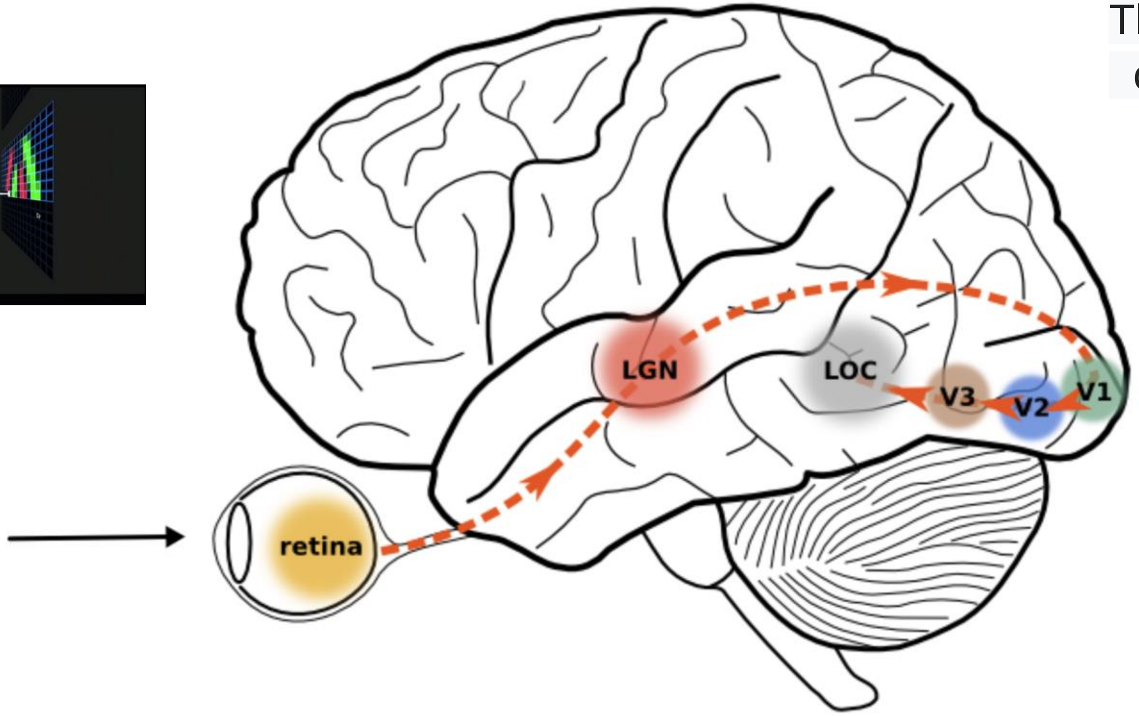


https://msu.edu/~brains

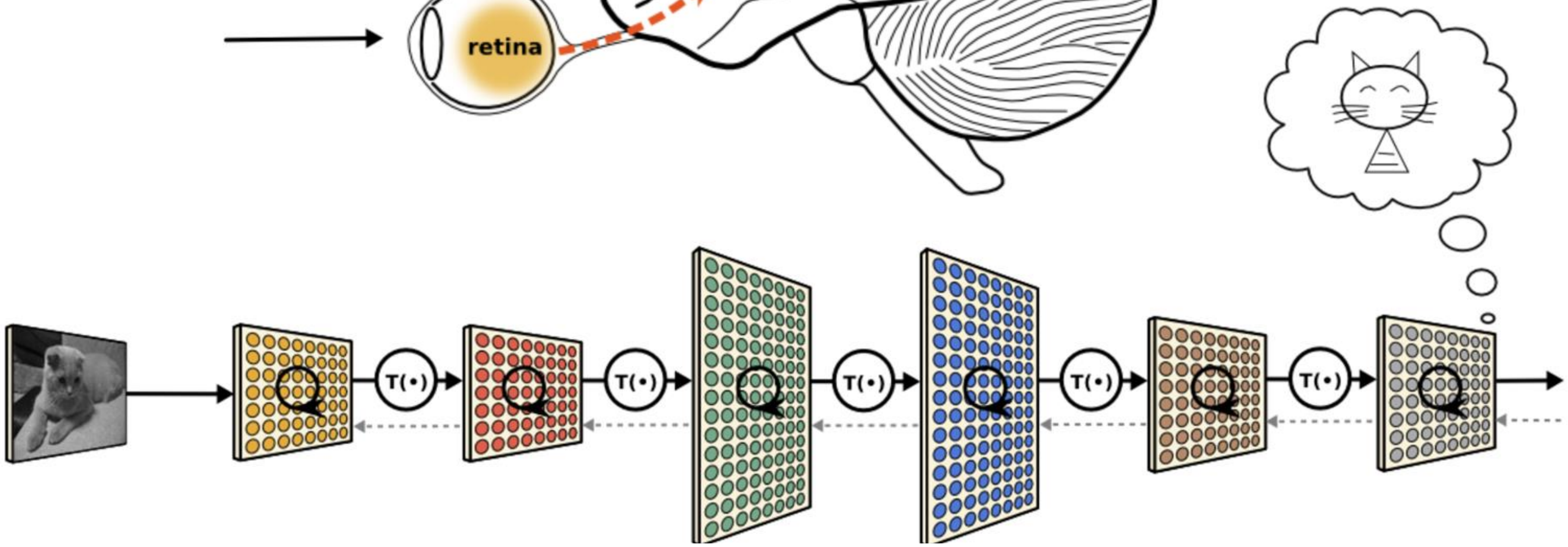

ANN architectures
AlexNet
Inception / GoogLeNet
Xception
Entry flow
Middle flow
Exit flow
MobileNet
NASNet/
AmoebaNet
Normal Cell
Reduction Cell
ShuffleNet
1x1 GConv
BN ReLU
Channel Shuffle
3x3 DWConv
BN
Add
ReLU
3x3 AVG Pool
(stride = 2)
3x3 DWConv
(stride = 2)
Concat
(b)
(c)
Transformer
Output
Probabilities
Softmax
Linear
Add & Norm
Feed
Forward
Multi-Head
Attention
Masked
Multi-Head
Attention
Nx
Positional
Encoding
Input
Embedding
Output
Embedding
Inputs
Outputs
(shifted right)
Figure 1: The Transformer - model architecture.
CapsNets
ReLU Conv1
PrimaryCaps
DigitCaps
ResNet
Hierarchical neural
attention encoder
Attention
Multiscale DenseNet
depth
scale
VGG
DenseNet
Input
Transition Layer
ResNext
256-d in
256, 1x1, 4
4, 3x3, 4
4, 1x1, 256
total 32
paths
256-d out
U-Net
input
image
tile
output
segmentation
map
conv 3x3, ReLU
copy and crop
max pool 2x2
up-conv 2x2
conv 1x1
SegNet
Input
Convolutional Encoder-Decoder
Pooling Indices
Output
RGB Image
Segmentation
Conv + Batch Normalisation + ReLU
Pooling
Upsampling
Softmax
Squeeze and excitation
Figure 1. A Squeeze-and-Excitation block.

Signal pathways from the retina to object detection in the lateral occipital cortex





The human brain has **deep architecture**, where the cortex seems to have a **generic approach to learning**.



A given input is perceived at several **levels of abstraction**. Each level corresponds to a new area of the cortex. We process information in a hierarchical way, with **transformation and representation on several levels**.

Therefore, we learn simple concepts first and then put them together.

This structure of understanding can perhaps be seen most clearly in the human visual system. As shown in the figure, the signaling pathway goes from the retina to the lateral occipital cortex (LOC), which eventually recognizes the object.

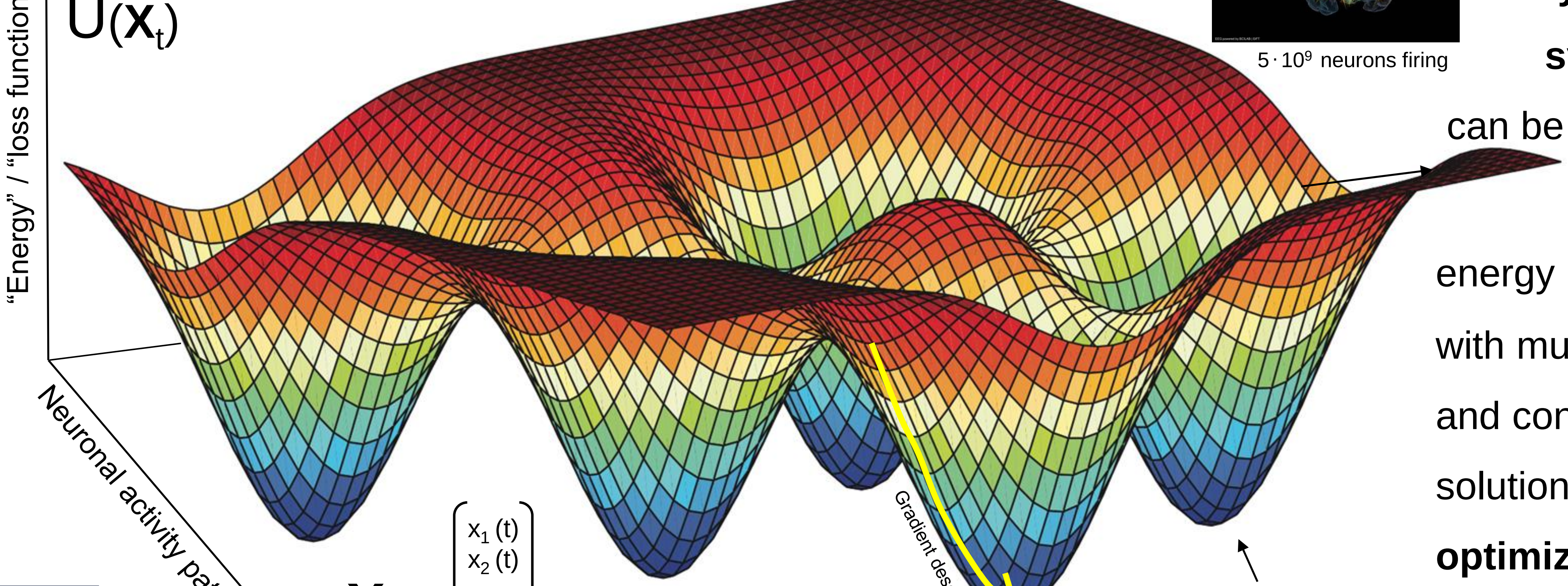
The ventral visual cortex (V1, V2, V3) encompasses a set of areas that process images in increasingly abstract ways, from *edges*, *corners* and *contours*, *shapes*, *object-parts* to *object*, so that we can learn, recognize and categorize three-dimensional objects from arbitrary two-dimensional images that hit the retina.

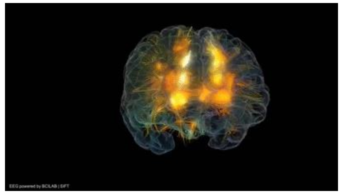
LGN = lateral geniculate nucleus V1 = primary visual cortex LOC = lateral occipital cortex

https://neuwritesd.org/2015/10/22/deep-neural-networks-help-us-read-your-mind

Neural networks & neurodynamics in brain and machine

… the shape of the landscape (manifold) embedded in $\mathbf{R}^n$ is dependent of the fitness or loss function and the synaptic weights (learning)





$5 \cdot 10^9$ neurons firing

The dynamics of a **multistable dynamical system** can be visualized as a **descent** in a energy landscape $U(\mathbf{X}_t)$ with multiple "valleys", and considered as a solution of an **optimization problem**

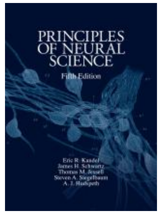
$$\mathbf{X}_t = \begin{pmatrix} x_1(t) \\ x_2(t) \\ . \\ . \\ . \\ x_n(t) \end{pmatrix}$$

Vector space spanned by all possible neuronal states, $\mathbf{x}(t)$

$n \sim 5 \cdot 10^9$ neurons

"attractor"

- a **memory**, a **percept**, a **decision**



Neuron
Review
CellPress

Neuroscience-Inspired Artificial Intelligence

Demis Hassabis,[1,2,*] Dharshan Kumaran,[1,3] Christopher Summerfield,[1,4] and Matthew Botvinick[1,2]
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[2]Gatsby Computational Neuroscience Unit, 25 Howland Street, London, UK
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http://dx.doi.org/10.1016/j.neuron.2017.06.011

The fields of neuroscience and artificial intelligence (AI) have a long and intertwined history. In more recent times, however, communication and collaboration between the two fields has become less commonplace. In this article, we argue that better understanding biological brains could play a vital role in building intelligent machines. We survey historical interactions between the AI and neuroscience fields and emphasize current advances in AI that have been inspired by the study of neural computation in humans and other animals. We conclude by highlighting shared themes that may be key for advancing future research in both fields.

In recent years, rapid progress has been made in the related fields of neuroscience and artificial intelligence (AI). At the dawn of the computer age, work on AI was inextricably intertwined with neuroscience and psychology, and many of the early pioneers straddled both fields, with collaborations between these disciplines proving highly productive (Churchland and Sejnowski, 1988; Hebb, 1949; Hinton et al., 1986; Hopfield, 1982; McCulloch and Pitts, 1943; Turing, 1950). However, more recently, the interaction has become much less commonplace, as both subjects have grown enormously in complexity and disciplinary boundaries have solidified. In this review, we argue for the critical and ongoing importance of neuroscience in generating ideas that will accelerate and guide AI research (see Hassabis commentary in Brooks et al., 2012).

We begin with the premise that building human-level general AI (or "Turing-powerful" intelligent systems; Turing, 1936) is a daunting task, because the search space of possible solutions is vast and likely only very sparsely populated. We argue that this therefore underscores the utility of scrutinizing the inner workings of the human brain— the only existing proof that such an intelligence is even possible. Studying animal cognition and its neural implementation also has a vital role to play, as it can provide a window into various important aspects of higher-level general intelligence.

The benefits to developing AI of closely examining biological intelligence are two-fold. First, neuroscience provides a rich source of *inspiration* for new types of algorithms and architectures, independent of and complementary to the mathematical and logic-based methods and ideas that have largely dominated traditional approaches to AI. For example, were a new facet of biological computation found to be critical to supporting a cognitive function, then we would consider it an excellent candidate for incorporation into artificial systems. Second, neuroscience can provide *validation* of AI techniques that already exist. If a known algorithm is subsequently found to be implemented in the brain, then that is strong support for its plausibility as an integral component of an overall general intelligence system. Such clues can be critical to a long-term research program when determining where to allocate resources most productively. For example, if an algorithm is not quite attaining the level of performance required or expected, but we observe it is core to the functioning of the brain, then we can surmise that redoubled engineering efforts geared to making it work in artificial systems are likely to pay off.

Of course from a practical standpoint of building an AI system, we need not slavishly enforce adherence to biological plausibility. From an engineering perspective, what works is ultimately all that matters. For our purposes then, biological plausibility is a guide, not a strict requirement. What we are interested in is a systems neuroscience-level understanding of the brain, namely the algorithms, architectures, functions, and representations it utilizes. This roughly corresponds to the top two levels of the three levels of analysis that Marr famously stated are required to understand any complex biological system (Marr and Poggio, 1976): the goals of the system (the computational level) and the process and computations that realize this goal (the algorithmic level). The precise mechanisms by which this is physically realized in a biological substrate are less relevant here (the implementation level). Note this is where our approach to neuroscience-inspired AI differs from other initiatives, such as the Blue Brain Project (Markram, 2006) or the field of neuromorphic computing systems (Esser et al., 2016), which attempt to closely mimic or directly reverse engineer the specifics of neural circuits (albeit with different goals in mind). By focusing on the computational and algorithmic levels, we gain transferrable insights into ge eral mechanisms of brain function, while leaving roo accommodate the distinctive opportunities and ch that arise when building intelligent machines *in si*

The following sections unpack these points by past, present, and future of the AI-neurosci Before beginning, we offer a clarification. Throughou we employ the terms "neuroscience" and "AI." We u terms in the widest possible sense. When we say neurosci we mean to include all fields that are involved with the study the brain, the behaviors that it generates, and the mechanisms by which it does so, including cognitive neuroscience, systems neuroscience and psychology. When we say AI, we mean work

nature neuroscience
FOCUS | PERSPECTIVE
https://doi.org/10.1038/s41593-019-0520-2

A deep learning framework for neuroscience

Blake A. Richards[1,2,3,4,42*], Timothy P. Lillicrap[5,6,42], Philippe Beaudoin[7], Yoshua Bengio[1,4,8], Rafal Bogacz[9], Amelia Christensen[10], Claudia Clopath[11], Rui Ponte Costa[12,13], Archy de Berker[7], Surya Ganguli[14,15], Colleen J. Gillon[16,17], Danijar Hafner[15,18,19], Adam Kepecs[20], Nikolaus Kriegeskorte[21,22], Peter Latham[23], Grace W. Lindsay[22,24], Kenneth D. Miller[22,24,25], Richard Naud[26,27], Christopher C. Pack[3], Panayiota Poirazi[28], Pieter Roelfsema[29], João Sacramento[30], Andrew Saxe[31], Benjamin Scellier[1,8], Anna C. Schapiro[32], Walter Senn[13], Greg Wayne[5], Daniel Yamins[33,34,35], Friedemann Zenke[36,37], Joel Zylberberg[4,38,39], Denis Therien[7,42] and Konrad P. Kording[4,40,41,42]

Systems neuroscience seeks explanations for how the brain implements a wide variety of perceptual, cognitive and motor tasks. Conversely, artificial intelligence attempts to design computational systems based on the tasks they will have to solve. In artificial neural networks, the three components specified by design are the objective functions, the learning rules and the architectures. With the growing success of deep learning, which utilizes brain-inspired architectures, these three designed components have increasingly become central to how we model, engineer and optimize complex artificial learning systems. Here we argue that a greater focus on these components would also benefit systems neuroscience. We give examples of how this optimization-based framework can drive theoretical and experimental progress in neuroscience. We contend that this principled perspective on systems neuroscience will help to generate more rapid progress.

Major technical advances are revolutionizing our ability to observe and manipulate brains at a large scale and to quantify complex behaviors[1,2]. How should we use this data to develop models of the brain? When the classical framework for systems neuroscience was developed, we could only record from small sets of neurons. In this framework, a researcher observes neural activity, develops a theory of what individual neurons compute, then assembles a circuit-level theory of how the neurons combine their operations. This approach has worked well for simple computations. For example, we know how central pattern generators control rhythmic movements[3], how the vestibulo-ocular reflex promotes gaze stabilization[4] and how the retina computes motion[5]. But can this classical framework scale up to recordings of thousands of neurons and all of the behaviors that we may wish to account for? Arguably, we have not had as much success with the classical approach in large neural circuits that perform a multitude of functions, like the neocortex or hippocampus. In such circuits, researchers often find neurons with response properties that are difficult to summarize in a succinct manner[6,7].

The limitations of the classical framework suggest that new approaches are needed to take advantage of experimental advances. A promising framework is emerging from the interactions between neuroscience and artificial intelligence (AI)[8–10]. The rise of deep learning as a leading machine-learning method invites us to revisit artificial neural networks (ANNs). At their core, ANNs model neural computation using simplified units that loosely mimic the integration and activation properties of real neurons[11]. Units are implemented with varying degrees of abstraction, ranging from

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Ethics

The AI HLEG is an independent expert group that was set up by the European Commission in June 2018. Contact Nathalie Smuha - AI HLEG Coordinator E-mail CNECT-HLG-AI@ec.europa.eu European Commission B-1049 Brussels Document made public on 8 April 2019.

Trustworthy AI has **three components**, which should be met throughout the system's entire life cycle:

1. it should be **lawful**, complying with all applicable laws and regulations
2. it should be **ethical**, ensuring adherence to ethical principles and values
3. it should be **robust**, both from a technical and social perspective, since, even with good intentions, AI systems can cause unintentional harm.

https://ec.europa.eu/futurium/en/ai-alliance-consultation/guidelines

Ethical Principles in the Context of AI Systems

i. Respect for human autonomy

Humans interacting with AI systems must be able to keep **full and effective self-determination over themselves**, and be able to partake in the democratic process. The allocation of functions between humans and AI systems should follow **human-centric design principles** and leave meaningful opportunity for human choice.

ii. Prevention of harm

AI systems should neither cause nor exacerbate harm or otherwise adversely affect human beings. This entails the protection of **human dignity** as well as **mental and physical integrity**. Vulnerable persons should receive greater attention and be **included in the development, deployment** and use of AI systems. Preventing harm also entails consideration of the **natural environment** and all living beings.

iii. Fairness

Ensuring equal and just distribution of both benefits and costs, and ensuring that **individuals and groups are free from unfair bias**, **discrimination** and **stigmatisation**. Equal opportunity in terms of **access to education**, goods, services and technology should also be fostered.

iv. Explicability

This means that processes need to be **transparent** (incl. **traceability**), the capabilities and purpose of AI systems openly communicated, and decisions – to the extent possible – **explainable** to those directly and indirectly affected. The degree to which explicability is needed is highly dependent on the context and the severity of the consequences if that output is erroneous or otherwise inaccurate.

https://ec.europa.eu/futurium/en/ai-alliance-consultation/guidelines

How can this be implemented in a concrete medical domain?

Ethics of AI in Radiology

European and North American Multisociety Statement

•Ethics of AI in Radiology. European and North America Multisociety Statement 2019 [https://www.acr.org/-/media/ACR/Files/Informatics/Ethics-of-AI-in-Radiology-European-and-North-American-Multisociety-Statement--6-13-2019.pdf]

Key Considerations for Authors, Reviewers, and Readers of AI/ML Manuscripts in *Radiology*

Key Considerations
Are all three image sets (training, validation, and test sets) defined?
Is an *external* test set used for final statistical reporting?
Have multivendor images been used to evaluate the AI algorithm?
Are the sizes of the training, validation, and test sets justified?
Was the AI algorithm trained using a standard of reference that is widely accepted in our field?
Was preparation of images for the AI algorithm adequately described?
Were the results of the AI algorithm compared with radiology experts and/or pathology?
Was the manner in which the AI algorithm makes decisions demonstrated?
Is the AI algorithm publicly available?

Note.—AI = artificial intelligence, ML = machine learning.

Ethics of AI in Radiology: European and North American Multisociety Statement

Search or jump to... /

Pulls Issues Marketplace Explore

The Institute for Ethical Machine Learning

The Institute for Ethical Machine Learning is a think-tank that brings together with technology leaders, policymakers & academics to develop standards for ML.

United Kingdom http://ethical.institute @EthicalML a@ethical.institute

Overview | Repositories 16 | Packages | People | Projects

Search or jump to... /

Pulls Issues Marketplace

The Institute for Ethical Machine Lea

The Institute for Ethical Machine Learning is a think-tank that br
policymakers & academics to develop standards for ML.

United Kingdom http://ethical.institute @EthicalML

Pro

1. Human augmentation

I commit to assess the impact of incorrect predictions and, when reasonable, design systems with human-in-the-loop review processes

2. Bias evaluation

I commit to continuously develop processes that allow me to understand, document and monitor bias in development and production.

3. Explainability by justification

I commit to develop tools and processes to continuously improve transparency and explainability of machine learning systems where reasonable.

4. Reproducible operations

I commit to develop the infrastructure required to enable for a reasonable level of reproducibility across the operations of ML systems.

5. Displacement strategy

I commit to identify and document relevant information so that business change processes can be developed to mitigate the impact towards workers being automated.

6. Practical accuracy

I commit to develop processes to ensure my accuracy and cost metric functions are aligned to the domain-specific applications.

7. Trust by privacy

I commit to build and communicate processes that protect and handle data with stakeholders that may interact with the system directly and/or indirectly.

8. Data risk awareness

I commit to develop and improve reasonable processes and infrastructure to ensure data and model security are being taken into consideration during the development of machine learning systems.

README.md

Awesome production machine learning

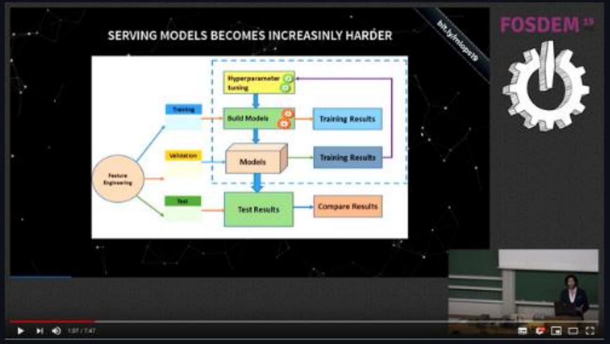
This repository contains a curated list of awesome open source libraries that will help you deploy, monitor, version, scale, and secure your production machine learning 🚀

Quick links to sections in this page

🔍 Explaining predictions & models	🔒 Privacy preserving ML	📜 Model & data versioning
🏁 Model Training Orchestration	💪 Model Serving and Monitoring	🤖 Neural Architecture Search
📓 Reproducible Notebooks	📊 Visualisation frameworks	🔠 Industry-strength NLP
🧵 Data pipelines & ETL	🏷️ Data Labelling	🗞️ Metadata Management
📡 Functions as a service	🗺️ Computation distribution	📥 Model serialisation
🧮 Optimized computation frameworks	💸 Data Stream Processing	🔴 Outlier and Anomaly Detection
🌀 Feature engineering	🎁 Feature Stores	⚔️ Adversarial Robustness
💰 Commercial Platforms	💾 Data Storage Optimization	

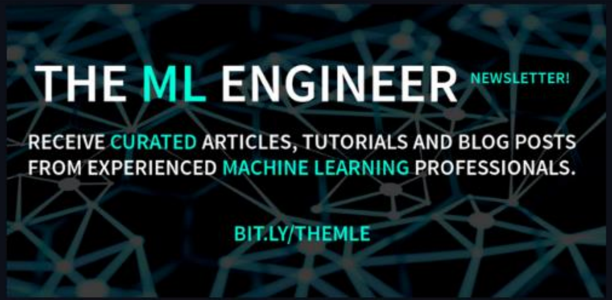
10 Min Video Overview

This 10 minute video provides an overview of the motivations for machine learning operations as well as a high level overview on some of the tools in this repo.



Want to receive recurrent updates on this repo and other advancements?

You can join the Machine Learning Engineer newsletter. You will receive updates on open source frameworks, tutorials and articles curated by machine learning professionals.



The objectives of ELMED219

- **Understanding** of computational methods, machine learning and AI
- **Practical experience**
- **Insight** into possibilities and challenges for AI in the future of medicine

README.md

ELMED219-2022 (team-based project)

Precision medicine and quantitative imaging in glioblastoma

Description

Imagine that you are a group of established successful scientists that will team up to tackle an important biomedical and medical challenge. There is an open call for research proposals under a new umbrella program entitled “Artificial intelligence and computational (bio)medicine”, where your multidisciplinary group are aiming for a project on “Precision medicine and quantitative imaging in glioblastoma - a multiscale approach”.

The focus of the assignment is **(i)** description of relevant imaging technologies and modalities - possibly at different scales, **(ii)** proposal of imaging-derived biomarkers for glioblastoma, **(iii)** machine learning techniques for segmentation, classification, treatment stratification and prediction, **(iv)** the novelty and expected impact of your approach, and **(v)** the evaluation of the ethics of your project together with a data management plan (and not so much the basic science of brain tumors per se).

Organization of your report

Fri, Jan 21	
10:15-12:00	Perspectives on medical AI: innovation, education, epistemology, ethics and impact
	Arvid Lundervold / Alexander Selvikvåg Lundervold
Mon, Jan 24	
--- 17:00 ---	Team project report due
Wed, Jan 26	
10:15-12:00	Team project presentations (15 min) *“**Why** should this project be funded?”*
Fri, Jan 28	
09:00-11:00	Digital home exam (using Inspera)

Eksamen

Digital hjemme-eksamen på Inspera.

Fredag 28. januar klokken 9 til 11.

Mulige eksamsoppgaver

8 Ubalanserte klasser

Anta du skal løse et binært klassifikasjonsproblem med svært ubalanserte klasser. Den hyppigst forekommende klasse opptrer i 99 % av treningsdata. Modellen din viser 99 % korrekthet (accuracy) etter prediksjon på testdata. Hvilket av følgende utsagn er riktig i dette tilfellet?

1. Accuracy-metrikken er ikke godt egnet i situasjoner med ubalanserte klasser
2. Accuracy er godt egnet i situasjoner med ubalanserte klasser
3. Presisjon (precision) og gjenkalling (recall) er godt egnet ved ubalanserte klasser
4. Precision og recall er ikke velegnede metrikker i situasjoner med ubalanserte klasser

Velg ett alternativ

- ○ Alternativ 2 og 4
- ○ Alternativ 2 og 3
- ○ Alternativ 1 og 3
- ○ Alternativ 1 og 4

23 Generalisering

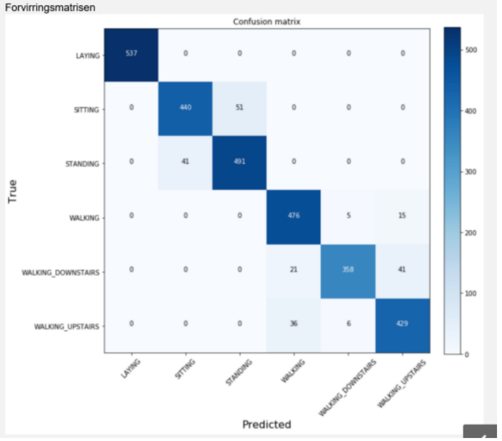
En maskinlæringsmodell kan ha **generaliseringsevne** ("generalization").
Hva innebærer dette? (velg det svar du synes er mest korrekt)

Velg ett alternativ

- ○ Oppnå perfekt accuracy på treningsdata
- ○ Ha god ytelse på nye usette data
- ○ Overtilpasse treningsdata
- ○ Kunne brukes i både styrt og ikke-styrt læring, samt i reinforcement learning

27 Forvirringsmatrise 2

Forvirringsmatrisen



20 Dry lab

Angi svaralternativet som best dekker begrepet "dry lab" (tørr-lab) i kontekst av ELMED219.

Velg ett alternativ

- ○ Laboratorium med tørt inneklima, forenlig med drift av servere og tungt datautstyr
- ○ Laboratorium for fotografisk fremstilling (photo printing) uten bruk av "våte" kjemikalier
- ○ Laboratorium som utfører analyse, modellering og computer-basert simulering av biologiske eller fysiske målinger og systemer
- ○ Laboratorium som ikke tar i bruk kjemikalier eller "våte" reagenser i eksperimentelle studier, men bruker elektroniske sensorer (chips) til sekvensering, imaging o.l.

32 Explainable AI

Utdyp begrepet "explainable AI" (XAI) og gi eksempler relevant i medisinske anvendelser.

Skriv ditt svar her Hjelp

Format

Words: 0

ELMED219 - 2022

Talk to you on Discord and see you for the team project presentations on Wednesday Jan 26 at 10.15

Perspectives on medical AI: innovation, education, epistemology, ethics and impact