

AI in Healthcare

Ying Ding

AI Health Lab

School of Information

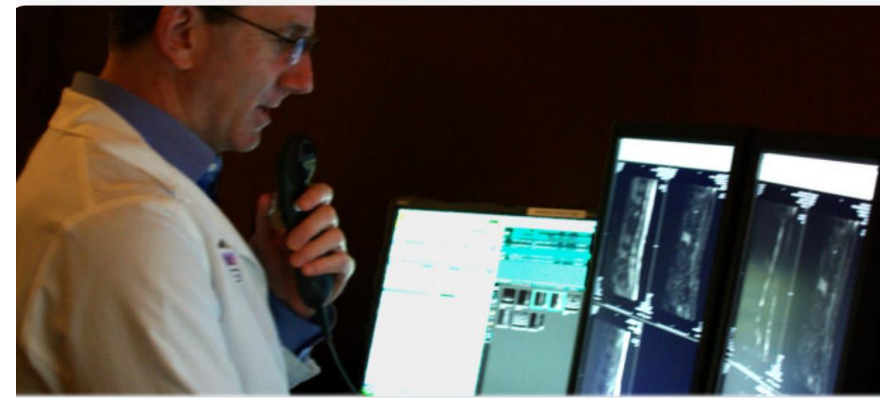
Dell Medical School

UT Austin

Disclosure

- Co-founder of Data2Discovery
- Co-founder of Merkouri.ai

Too fast, or too late



Director's Message



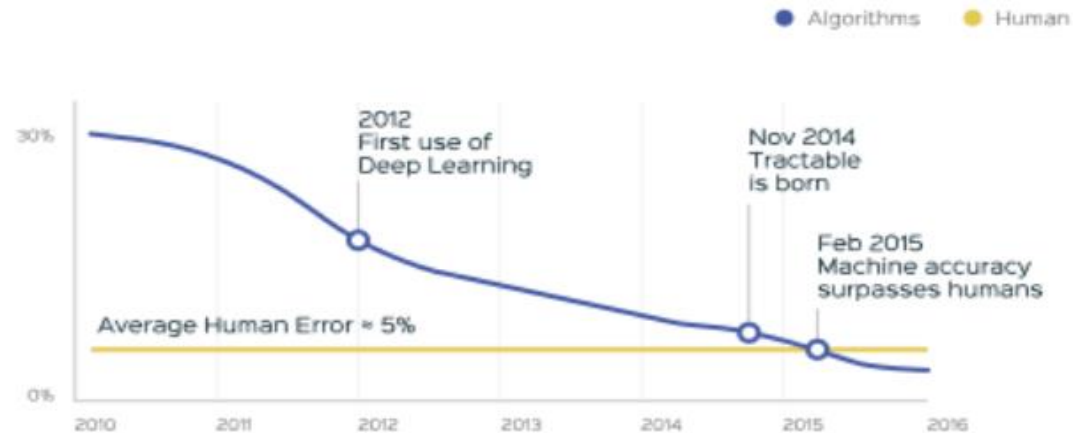
Back in 2017, I tweeted “radiologists who use AI will replace radiologists who don’t.” The tweet has taken on a life of its own, perhaps because it has a double meaning.

Curt Langlotz, Director of AI in health and imaging at Stanford

Many doctors complain that things are moving too fast, but the pace of AI in health has grown exponentially. If you do not deal with it now, it will be too late.

The message also intends to promote the idea that all radiologists will eventually adopt AI, thereby replacing their former selves. But regardless of which replacement scenario seems more likely, no one doubts that AI will transform how imaging professionals practice medicine.

AI Versus Human Image Recognition Error Rates

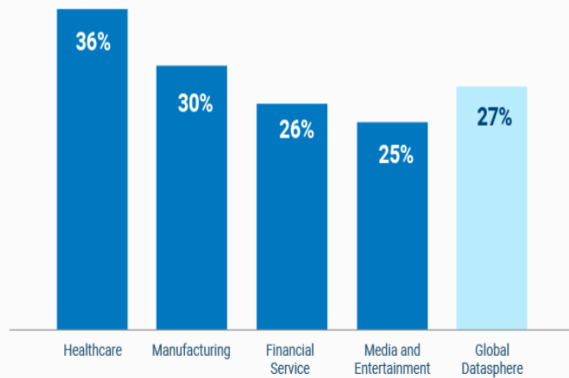


With estimates of average diagnostic error rates ranging from 3% to 5%, there are approximately 40 million diagnostic errors involving imaging annually worldwide.

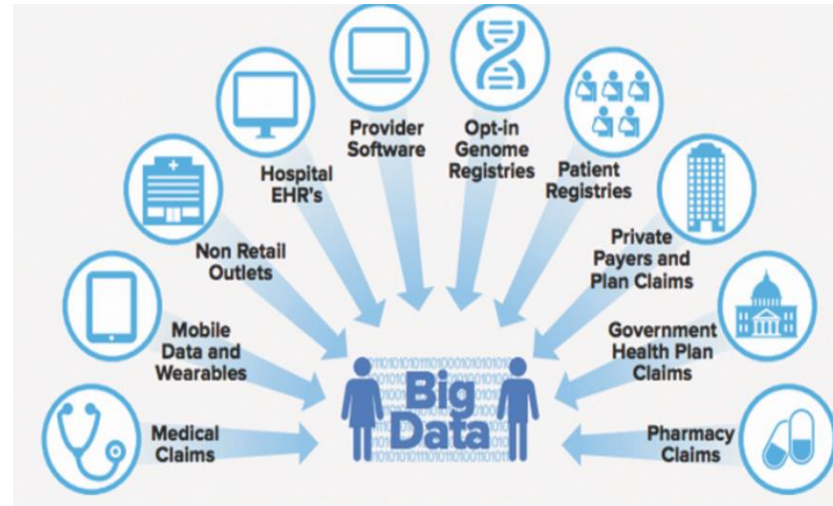
Source: Unpacking the AI-Productivity Paradox,"
By Erik Brynjolfsson et al., *MIT Sloan Management Review*, January 2018
sloanreview.mit.edu

Healthcare Data World

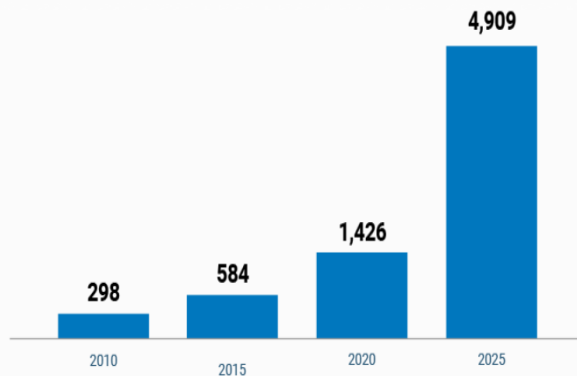
2018-2025 Data – Compound Annual Growth Rate (CAGR)



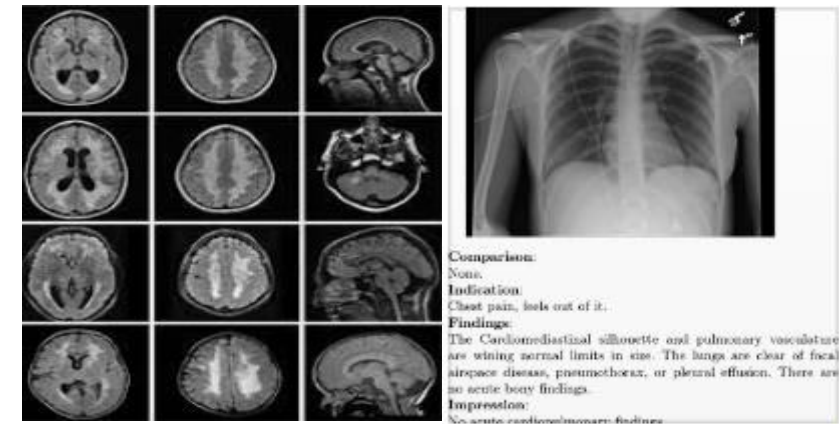
Source: Coughlin et al Internal Medicine Journal article "Looking to tomorrow's healthcare today: a participatory health perspective". IDC White Paper, Doc# US44413318, November 2018. The Digitization of the World – From Edge to Core.



The Number of Digital Device Interactions / Capita / Day



Source: Coughlin et al Internal Medicine Journal article "Looking to tomorrow's healthcare today: a participatory health perspective". IDC White Paper, Doc# US44413318, November 2018. The Digitization of the World – From Edge to Core.



	PatientID	Admission ID	CodingSystem	PrimaryDiagnosisCode	DiagnosisCodeDescription
3	A1234-B456	34	ICD-9	E11.64	Type 2 diabetes mellitus with hypoglycemia
4	A1234-B456	34	ICD-9	I25.812	Atherosclerosis of bypass graft of coronary ar...
5	A1234-B456	34	ICD-9	I25.10	Atherosclerotic heart disease of native corona...
6	A1234-B456	34	ICD-9	780.96	Generalized Pain
7	A1234-B456	34	ICD-9	784.0	Dizziness and giddiness
17	B1234-C456	34	ICD-9	M05.59	Rheumatoid polyneuropathy with rheumatoid arth...
18	B1234-C456	34	ICD-9	Z13.85	Encounter for screening for nervous system dis...

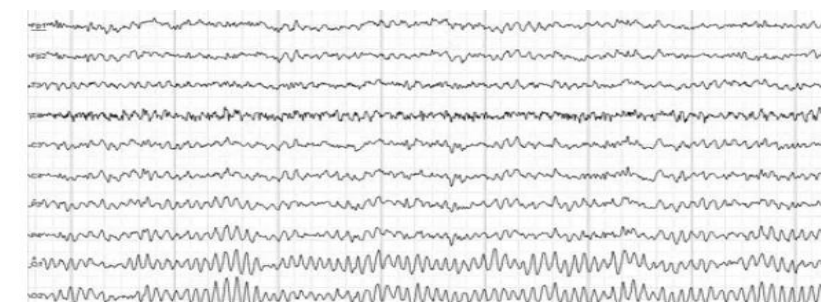
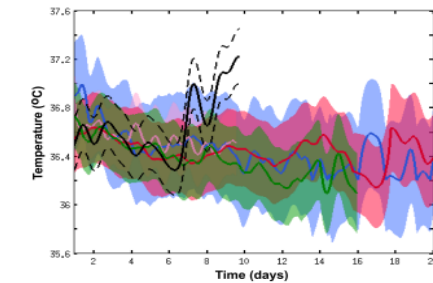
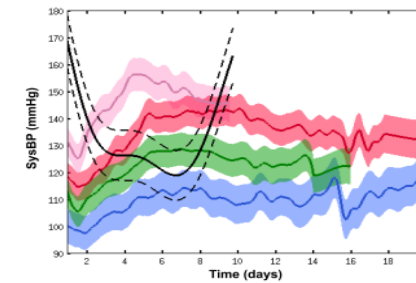
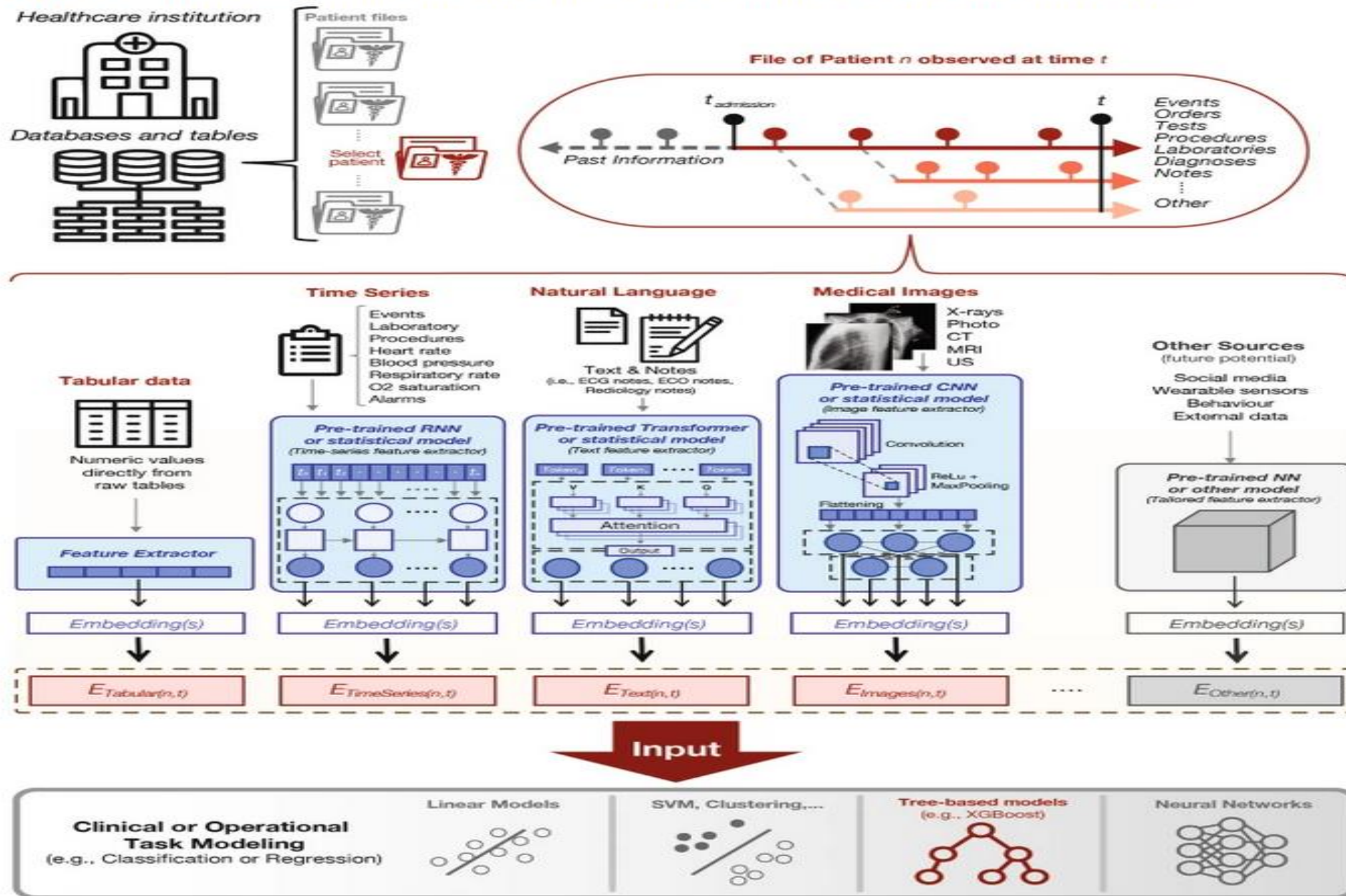
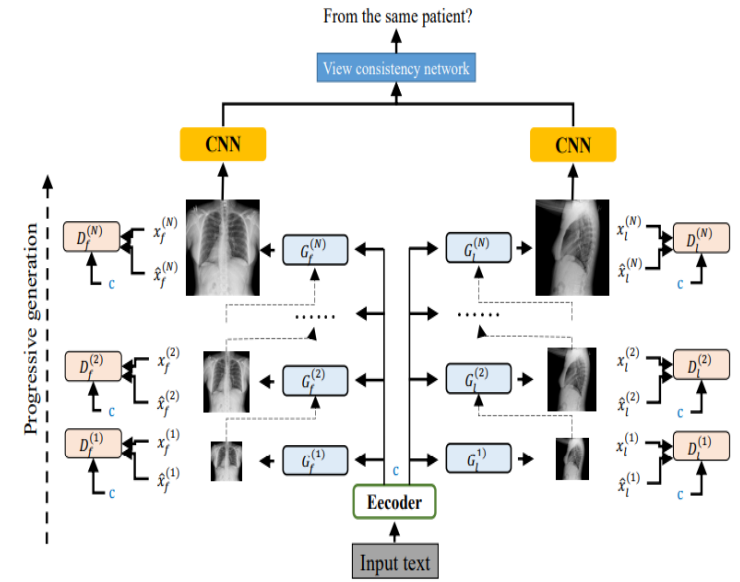
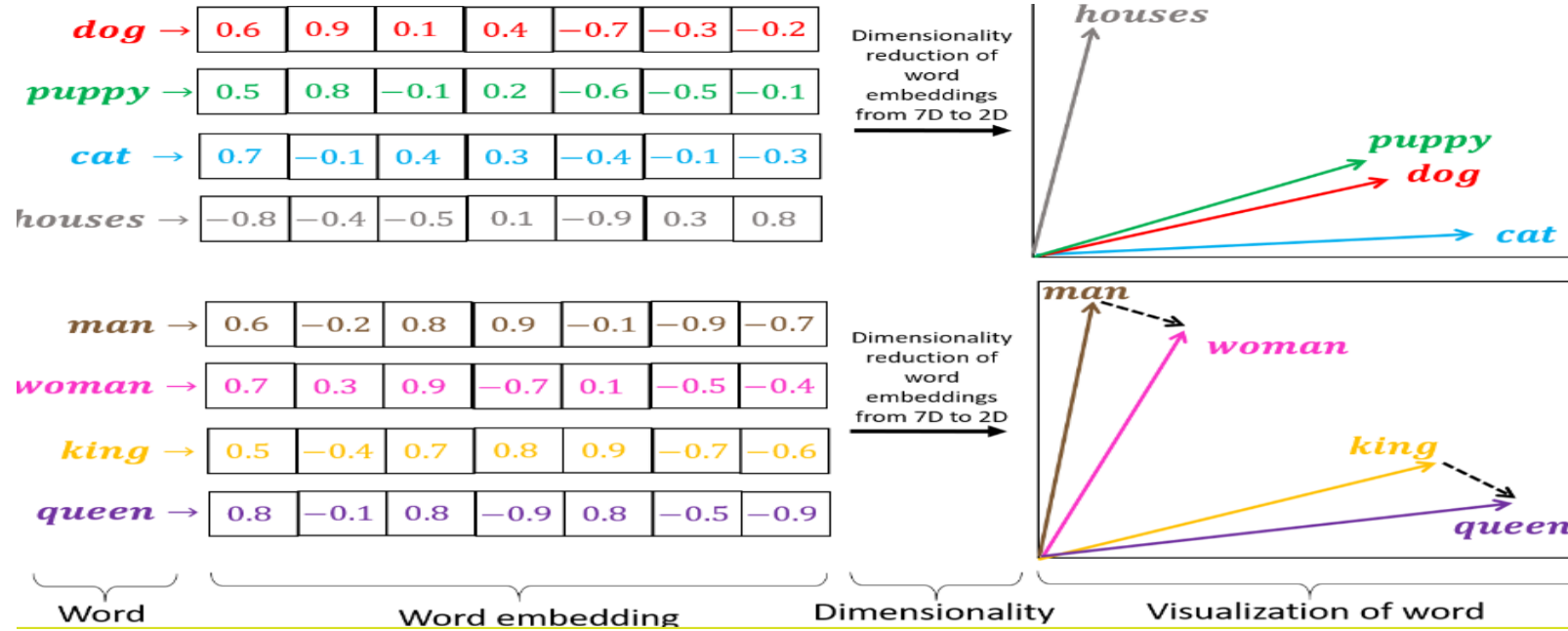


Fig. 1: Holistic Artificial Intelligence in Medicine (HAIM) framework.

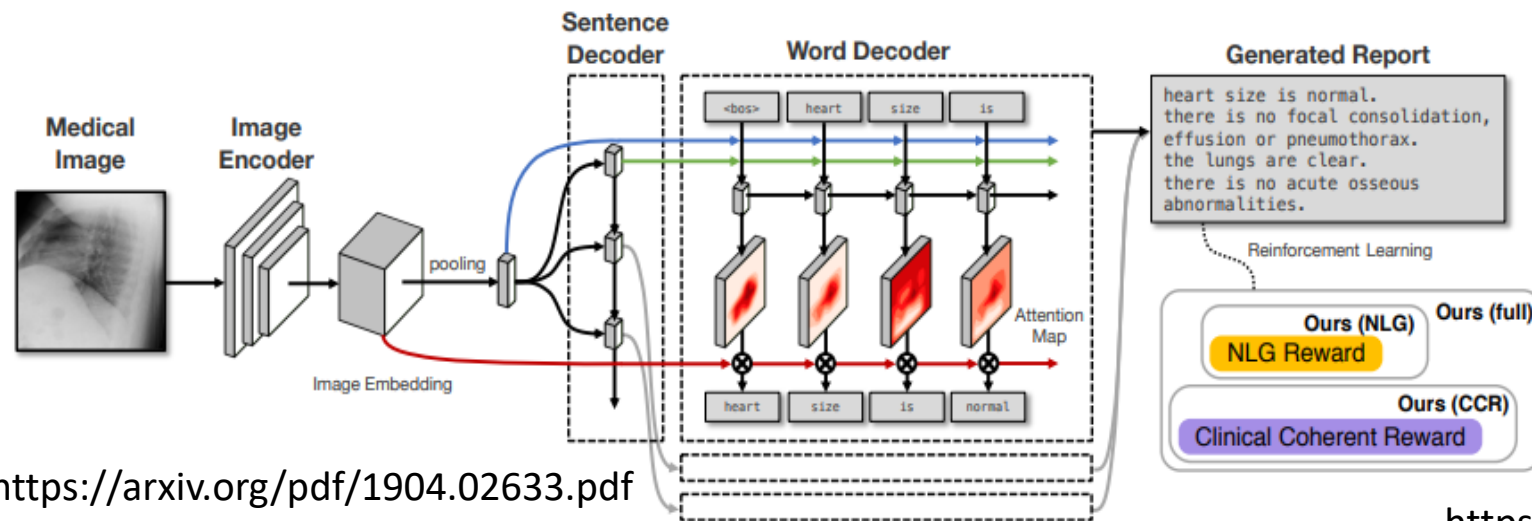


Deep Learning:
The best way to deal with complex cross modality healthcare data

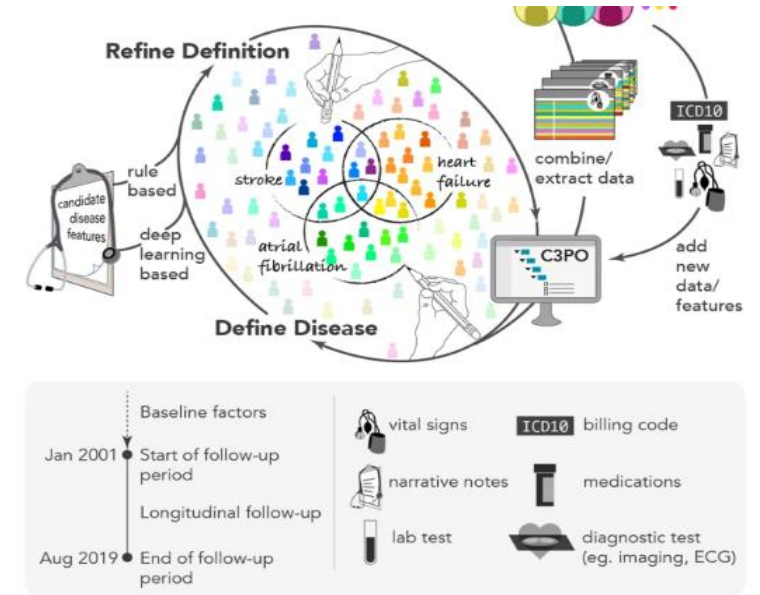
Embedding is the magic language for AI



<https://arxiv.org/pdf/2006.10552v1.pdf>



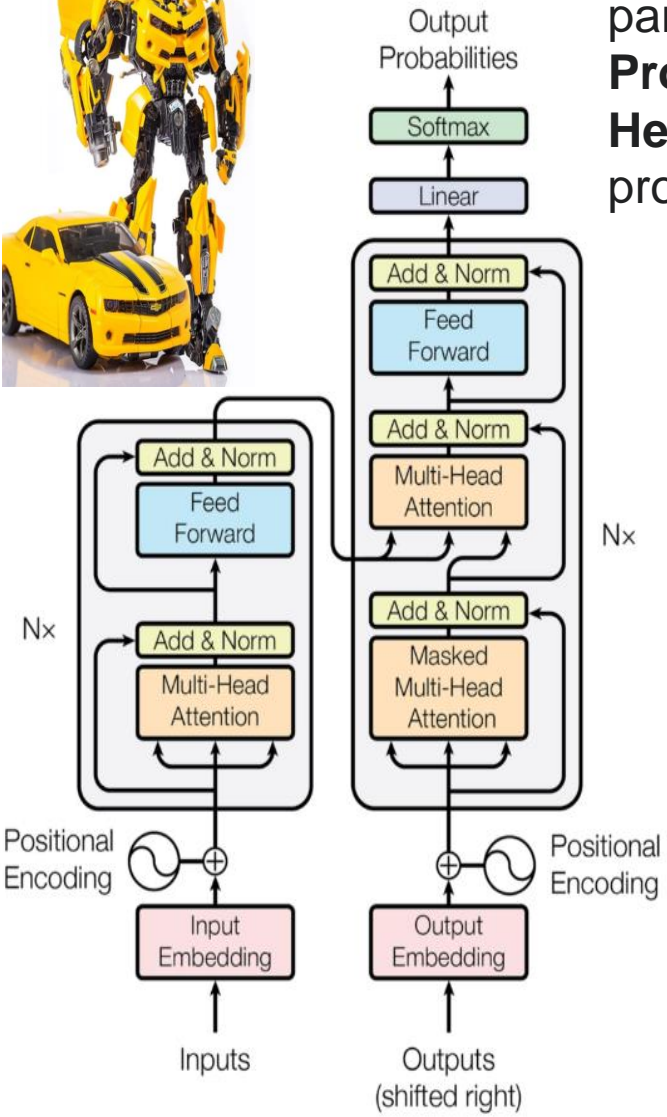
<https://arxiv.org/pdf/1904.02633.pdf>



<https://www.nature.com/articles/s41746-022-00590-0>

Transformer: the Power of AI

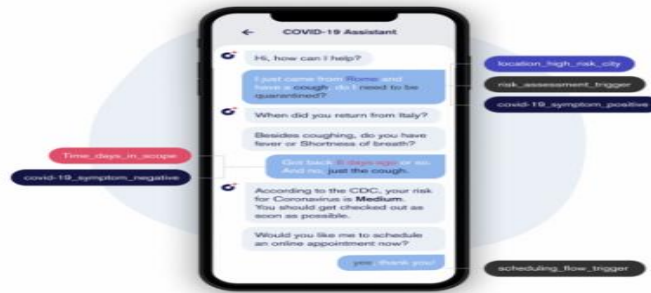
BEHRT (BERT for EHR)



Theory: adopting the mechanism of self-attention, weighting the significance of each part of the input data.

Project December: GPT-3 to create hyper-realistic chatbots

Health Risk Prediction: Predicting the end of life, surgical procedure (surgery), the probability of hospitalization



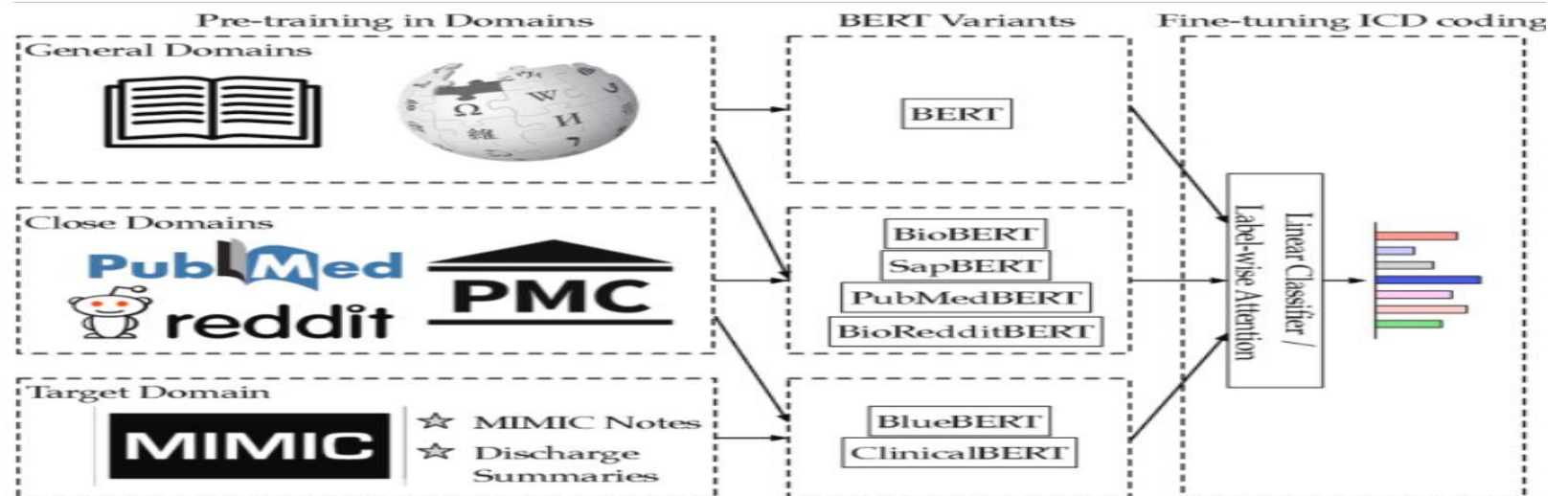
THE OFFERING

We're providing a free COVID-19 virtual assistant

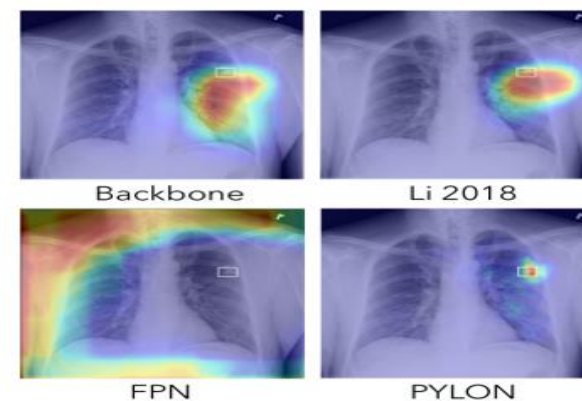
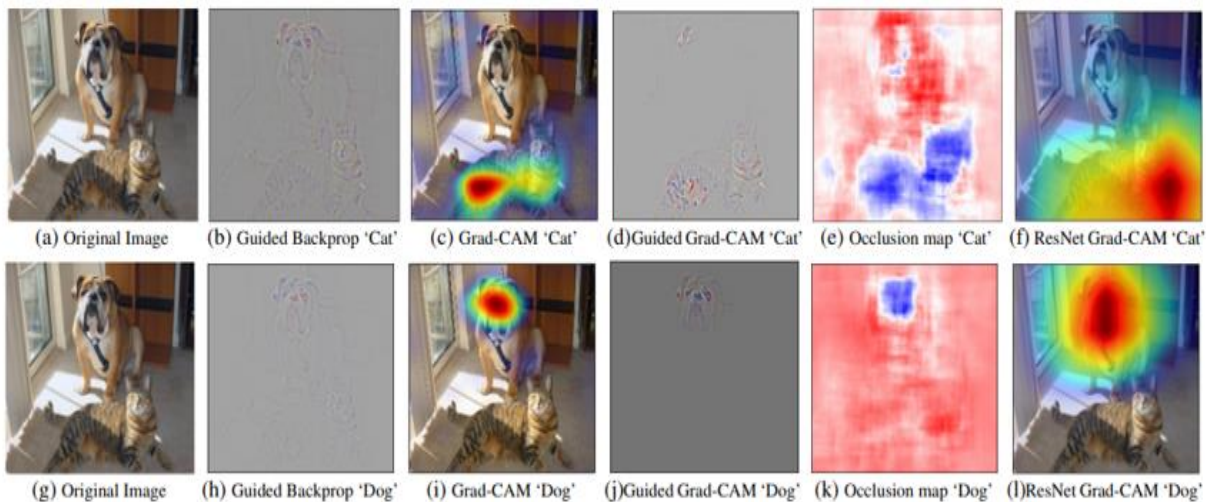
- Answer FAQs
- Navigate patients to Coronavirus-related content
- Triage symptoms
- Deliver information from WHO, CDC and other verified sources

Work Email

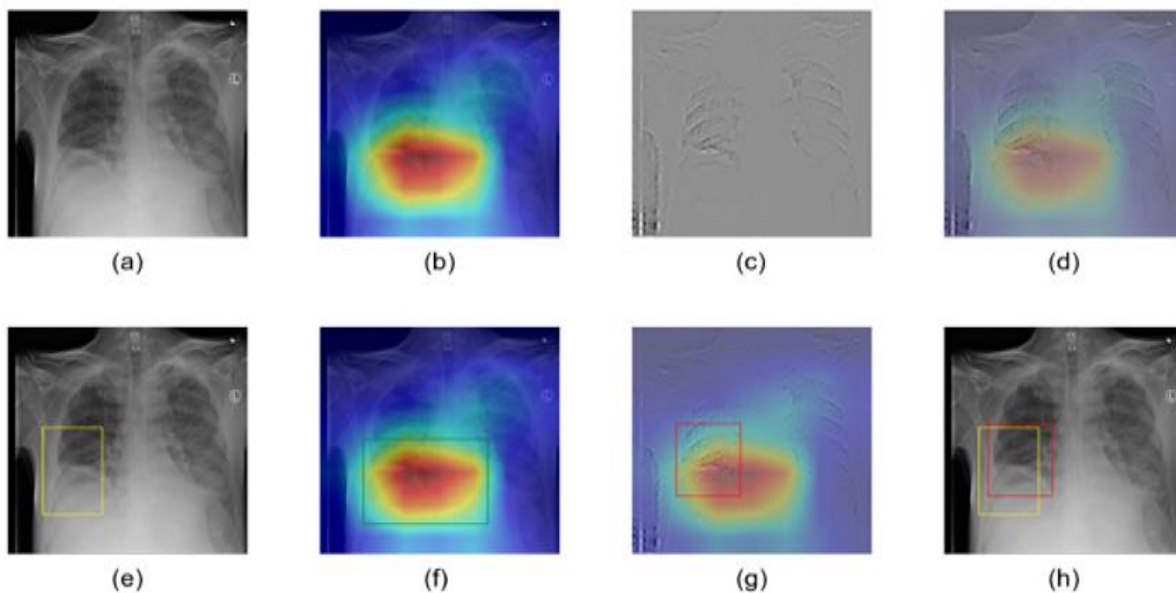
Get the COVID-19 Assistant



Explainable AI in Health



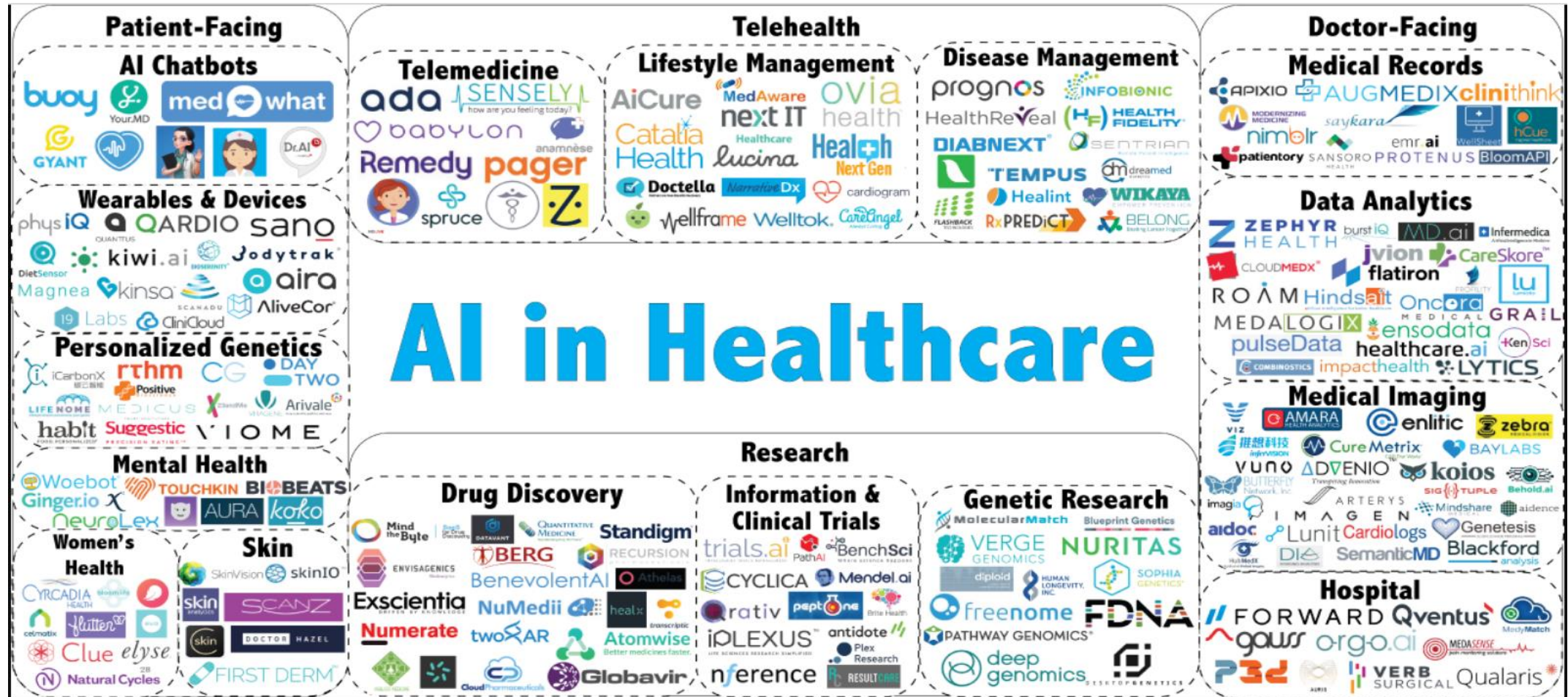
<https://ieeexplore.ieee.org/document/8237336>



Name	Atelectasis	Cardiom.	Effusion	Infiltration	Mass	Nodule	Pneumonia	Pneumoth.	Weighted avg.
IoU > 0.25 or IoR > 0.25									
Backbone	0.39 ± 0.02	1.0 ± 0.0	0.47 ± 0.04	0.67 ± 0.01	0.48 ± 0.02	0.01 ± 0.0	0.74 ± 0.02	0.17 ± 0.02	0.53 ± 0.01
Li2018	0.36 ± 0.02	0.99 ± 0.01	0.54 ± 0.02	0.73 ± 0.02	0.41 ± 0.05	0.04 ± 0.03	0.72 ± 0.04	0.23 ± 0.03	0.54 ± 0.01
PYLON (ours)	0.63 ± 0.02	1.0 ± 0.01	0.65 ± 0.01	0.81 ± 0.03	0.71 ± 0.04	0.49 ± 0.05	0.8 ± 0.03	0.2 ± 0.02	0.68 ± 0.01
IoU > 0.5 or IoR > 0.5									
Backbone	0.17 ± 0.01	1.0 ± 0.0	0.2 ± 0.03	0.36 ± 0.02	0.3 ± 0.02	0.0 ± 0.0	0.48 ± 0.04	0.12 ± 0.01	0.35 ± 0.01
Li2018	0.11 ± 0.01	0.97 ± 0.03	0.22 ± 0.01	0.44 ± 0.02	0.2 ± 0.03	0.0 ± 0.0	0.52 ± 0.05	0.13 ± 0.02	0.35 ± 0.01
PYLON (ours)	0.42 ± 0.03	0.99 ± 0.01	0.48 ± 0.03	0.59 ± 0.03	0.61 ± 0.04	0.35 ± 0.04	0.7 ± 0.03	0.15 ± 0.01	0.55 ± 0.01

<https://arxiv.org/pdf/2010.11475.pdf>

AI in Health Competitive Ecosystem



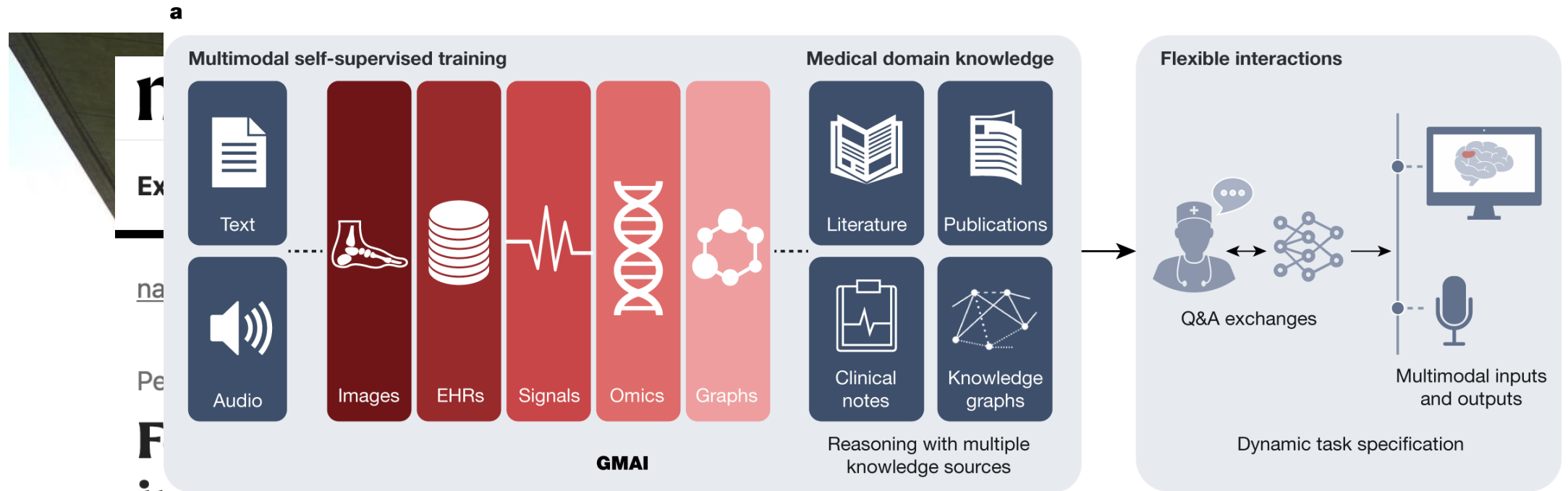
- Expertise, wisdom, human attitude, care, empathy, mutual understanding, and support lie at the very base of the medical profession and cannot be automated.

https://www.google.com/books/edition/Artificial_Intelligence_in_Medical_Imagi/ss6FDwAAQBAJ?hl=en&gbpv=1

LLM in Healthcare

Foundation models

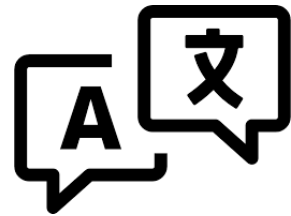
Large and reusable AI model trained on enormous quantities of unlabeled data and generalized to any tasks



Regulations: Application approval; validation; audits; community-based challenges; analyses of biases, fairness and diversity

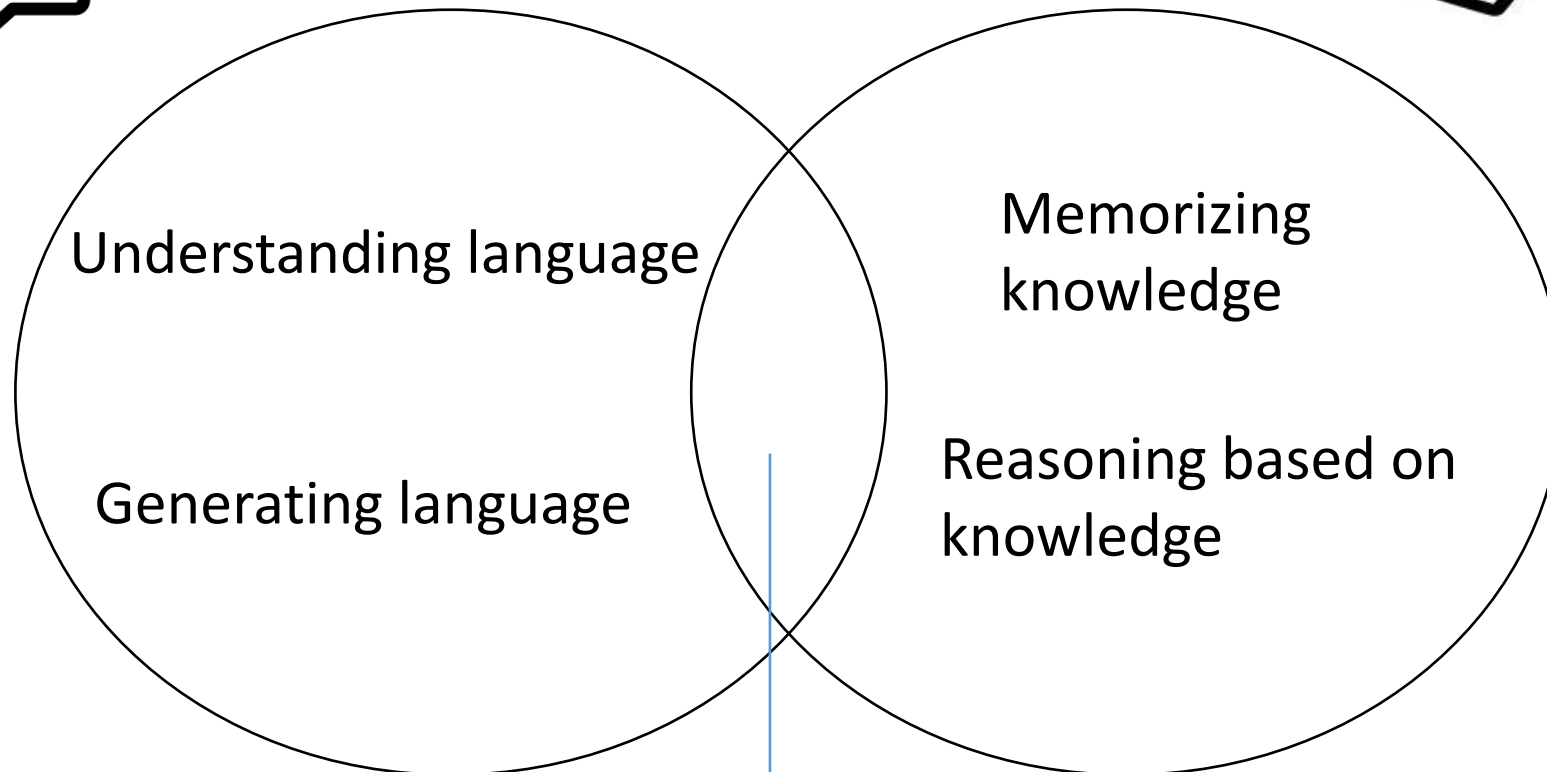
<https://www.nature.com/articles/s41586-023-05881-4>

What does Large Language Model (LLM) do?



Language

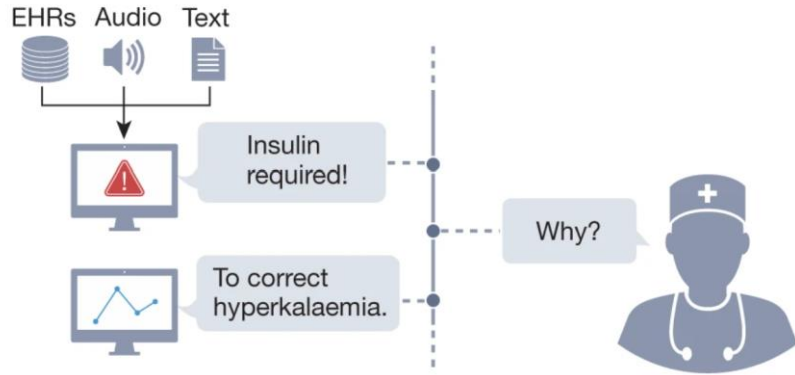
Knowledge



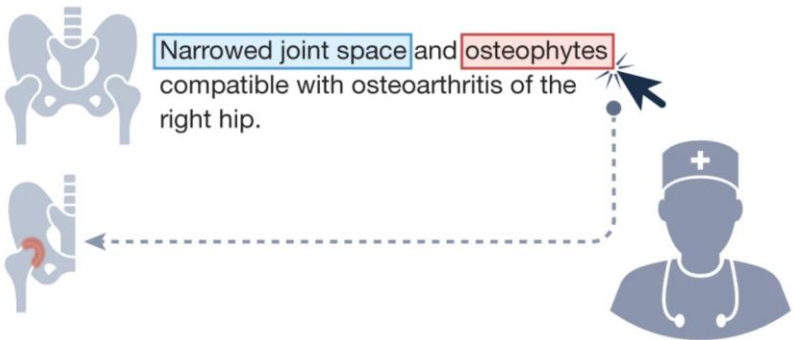
Talk like knowledgeable human, such as a doctor!

<https://arxiv.org/abs/2304.13712>

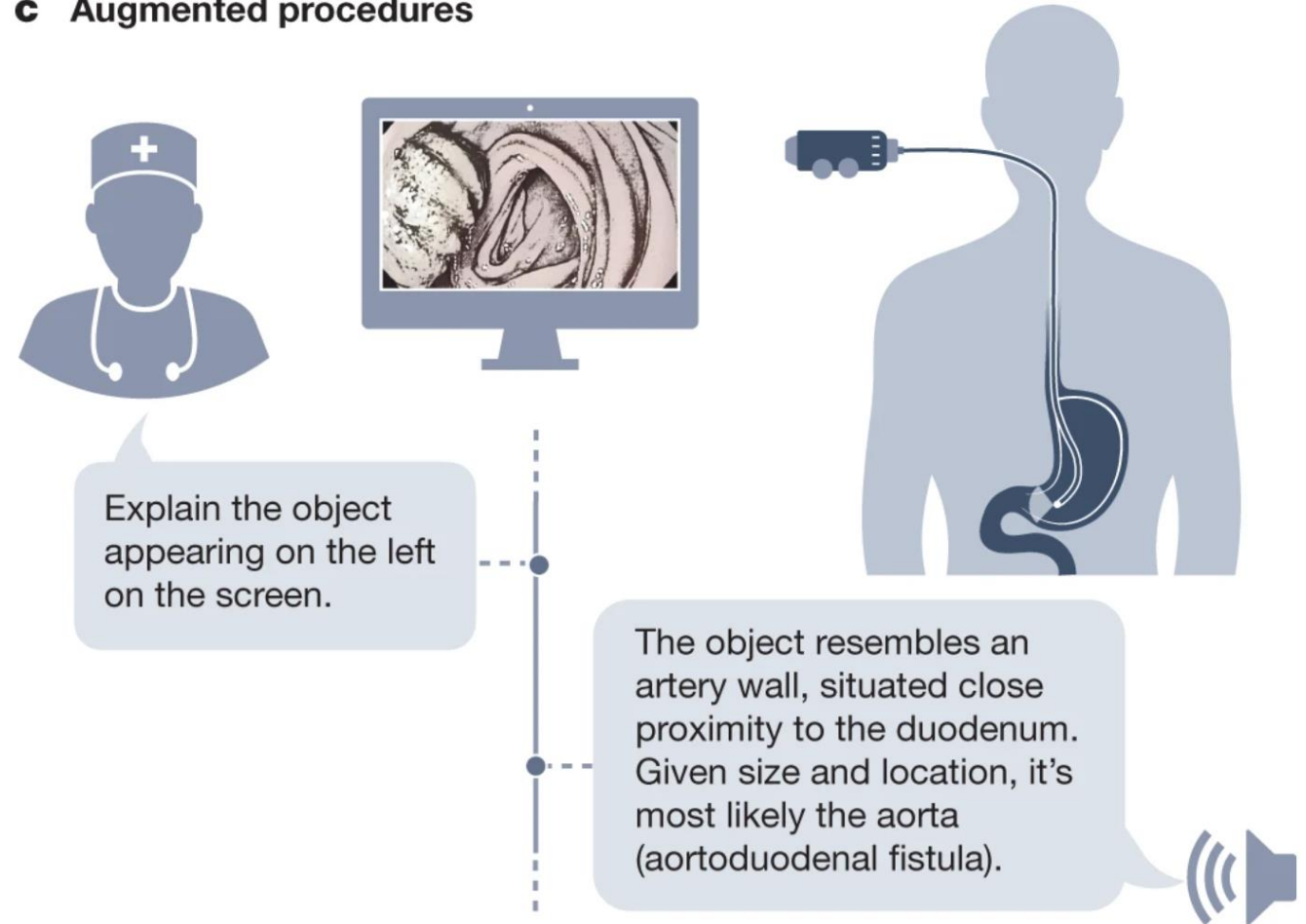
a Bedside decision support



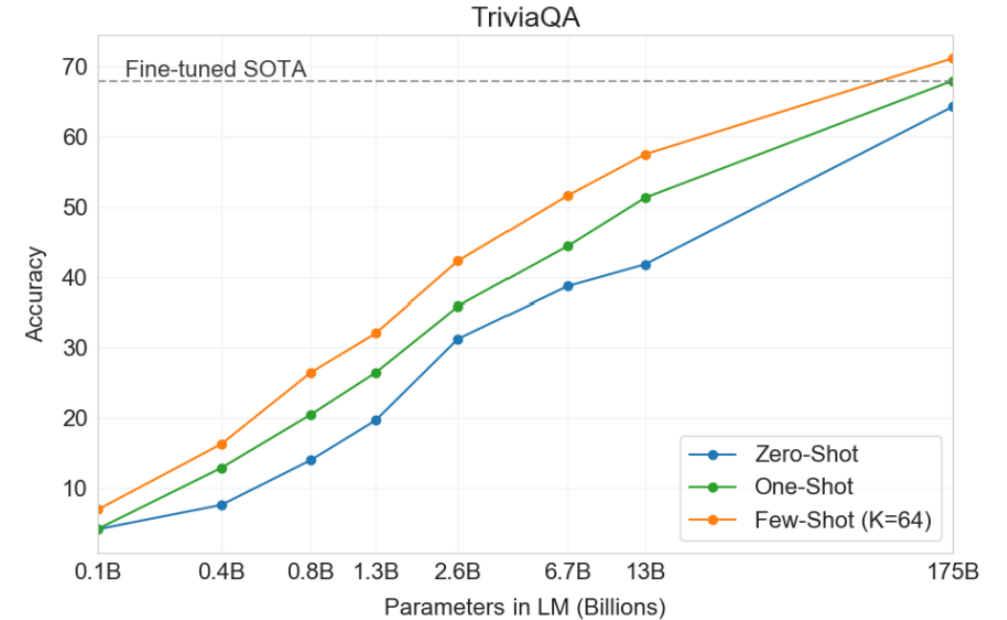
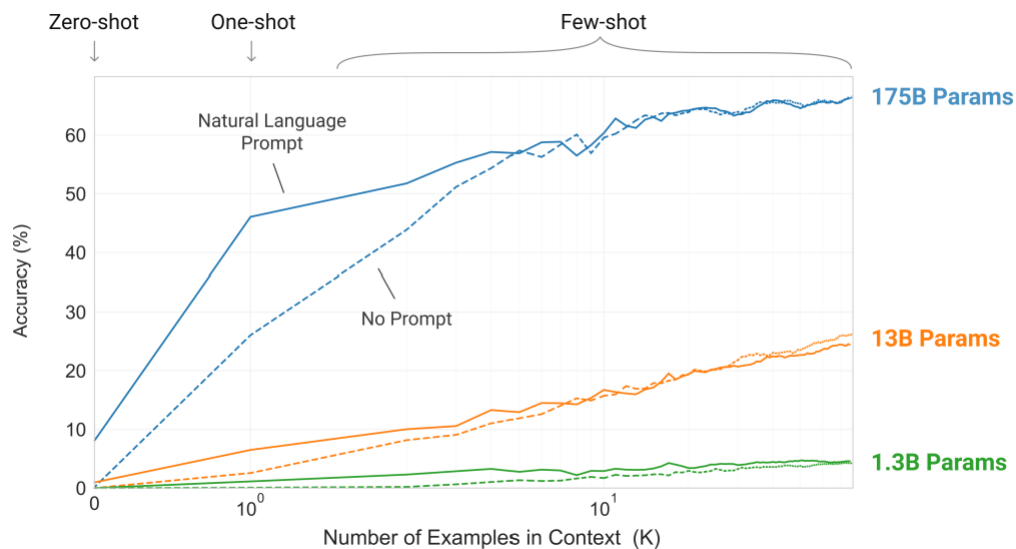
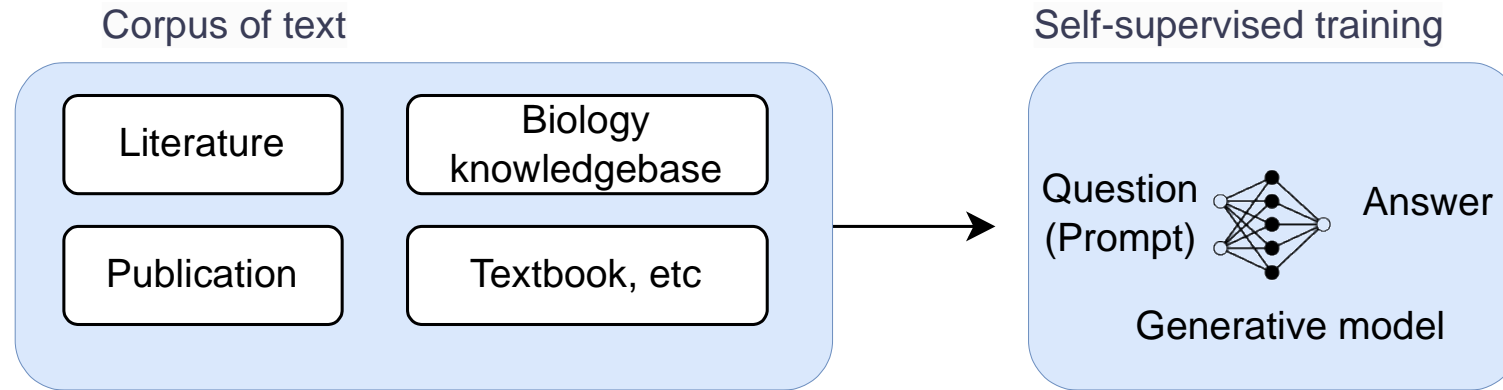
b Grounded radiology reports



c Augmented procedures



Large Language Models are Few-shot Learners



LLM in Medicine

Medical Knowledge


Medical Communication: patient care, simplification, translation, monitoring, medical literacy, mental health, substance abuse, clinical trial

Medical Documentation: discharge summaries, authorization letters, radiology report, medical notes,

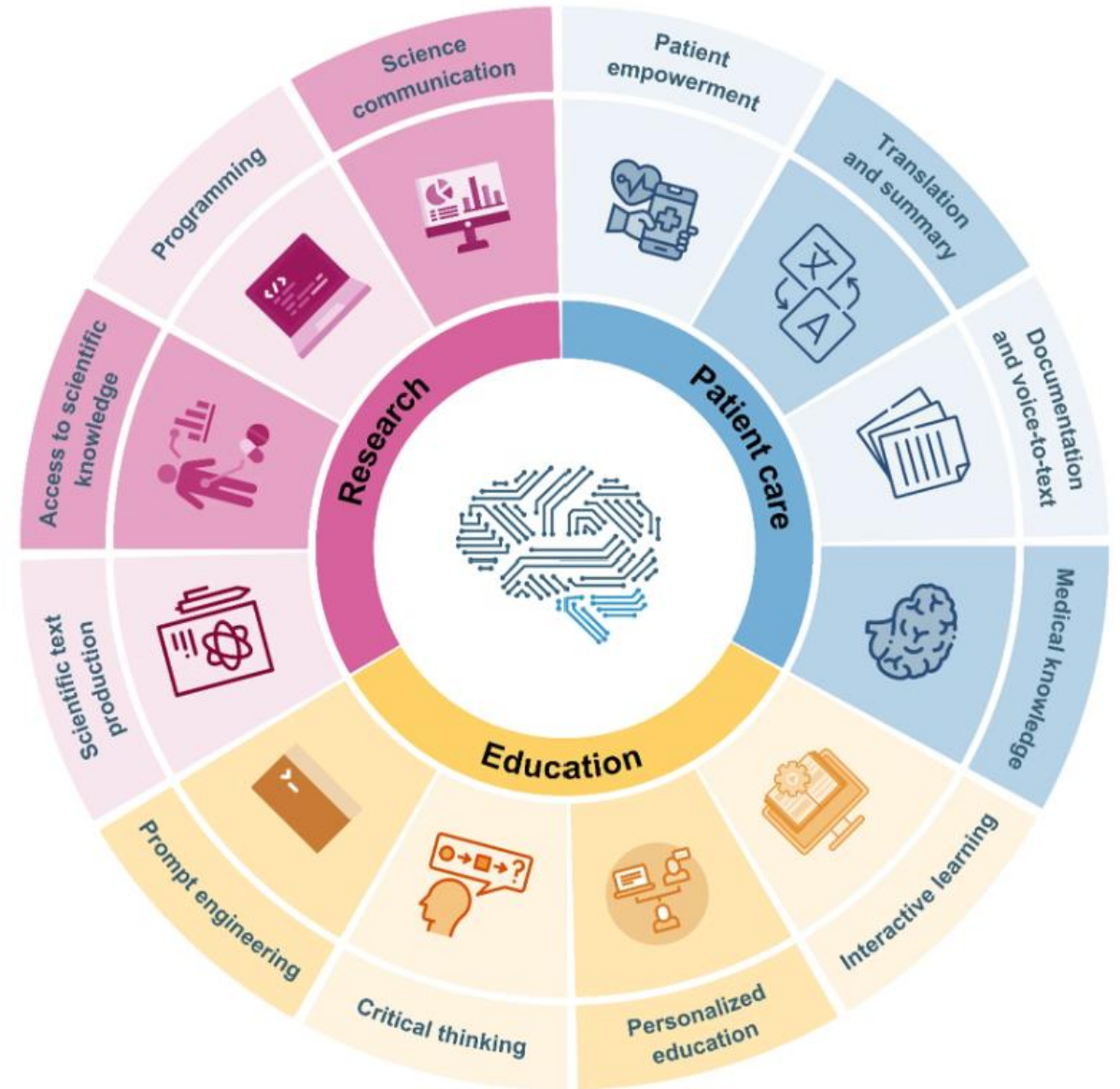
Medical Diagnosis: facilitate clinical decision support, access/summarize patient history, retrieve medical knowledge and new discoveries

Medical Training: workforce training, interactive learning/summarizing, translational, personalized, medical research/literature review

The future landscape of large language models in medicine

[Jan Clusmann](#), [Fiona R. Kolbinger](#), [Hannah Sophie Muti](#), [Zunamys I. Carrero](#), [Jan-Niklas Eckardt](#), [Narmin Ghaffari Laleh](#), [Chiara Maria Lavinia Löffler](#), [Sophie-Caroline Schwarzkopf](#), [Michaela Unger](#), [Gregory P. Veldhuizen](#), [Sophia J. Wagner](#) & [Jakob Nikolas Kather](#) 

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LLM powered Medical Annotation for SDoHs

Social History:

lives at home with wife and daughter. Planning to visit other daughter abroad in [**Name (NI) 311**] in [**Name (NI) 547**]. works as psychologist. No tobacco, occasional EtOH, no other drugs "since the 60s."

- **Community Presence**
- Education Level
- Joblessness
- Homelessness
- Alcohol Use
- Tobacco Use
- Drug Use

SDoH	Training Set (2048)	Accuracy	AUROC	Cost
Community Presence (1 Example)	Human Annotated	0.924	0.975	\$508.16
	GPT-Annotated	0.903	0.960	\$1.41
Joblessness (2 Examples)	Human Annotated	0.94	0.977	\$508.16
	GPT-Annotated	0.893	0.945	\$2.92
Alcohol Use (1 Example)	Human Annotated	0.913	0.966	\$508.16
	GPT-Annotated	0.864	0.924	\$1.04
Tobacco Use (2 Examples)	Human Annotated	0.935	0.976	\$508.16
	GPT-Annotated	0.926	0.961	\$3.81

Pathology with LLM

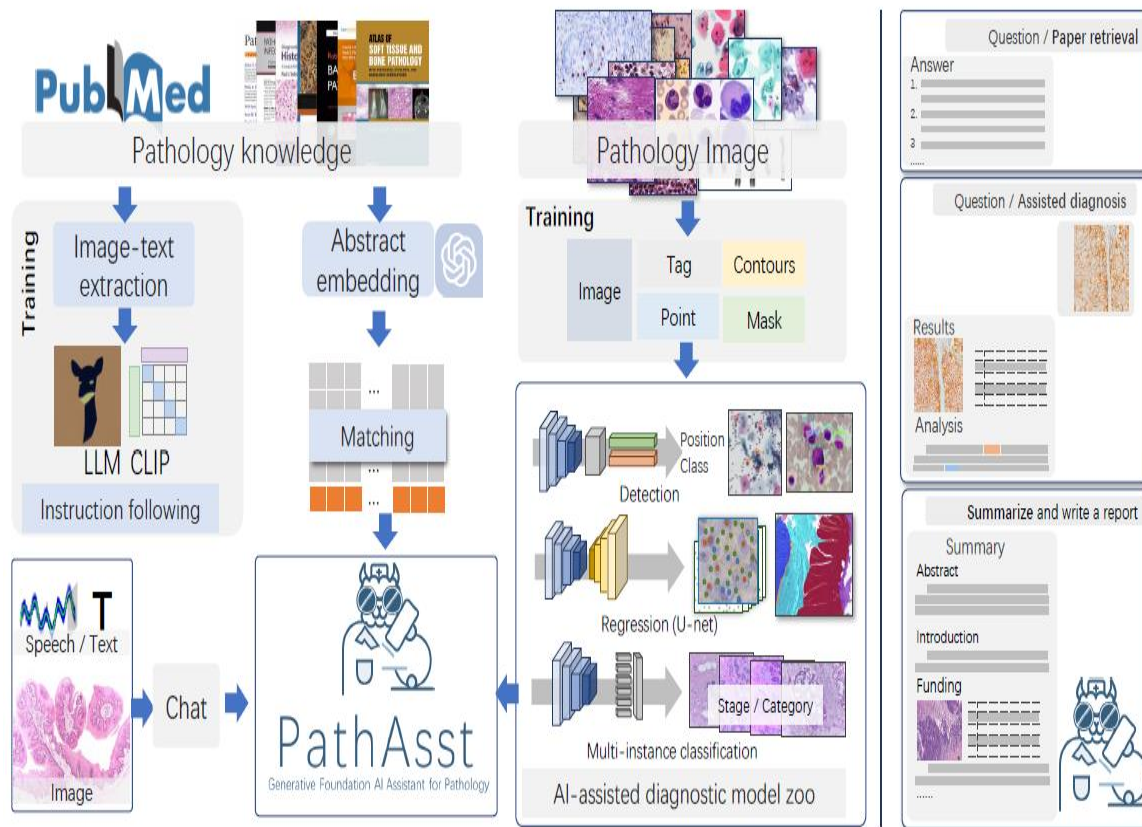
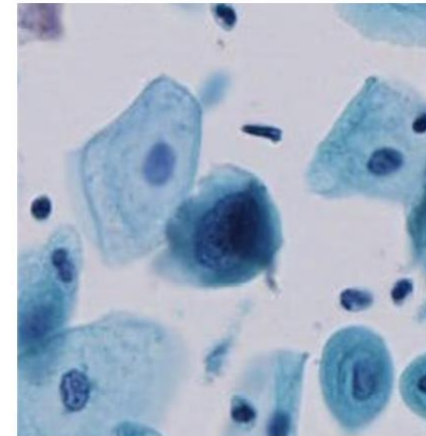


Figure 3: PathAsst network architecture.

Visual input example:



User
PathAsst

What do you notice about this image?

Upon examining the provided image patch, I notice the following observations:

1. The nucleus of these cells appears enlarged 2.5-3 times
2. The nuclear membrane appears irregular
3. The cells appear to be abnormal, possibly atypical squamous cells of undetermined significance (ASC-US)

Based on these observations, I would recommend further testing to confirm the presence of abnormal cells. An abnormal cervical Pap test result may indicate a high-risk for cervical cancer. It's important to follow up with your healthcare provider for further evaluation and treatment.

User
LLaVA [21]

What do you notice about this image?

The image is a close-up view of a blue substance, possibly ink or a dye, dispersed in water. The blue particles are evenly distributed throughout the water, creating a visually striking scene. The blue substance appears to be in the form of small spheres or shapes, which are spread across the entire image. The contrast between the blue particles and the water makes the scene quite captivating, as the blue elements stand out prominently.

User
MiniGPT-4 [48]

What do you notice about this image?

The image shows a group of cells, which are microscopic in size, arranged in a pattern. The cells are blue and have a round shape. Some of the cells have small black dots on them, which could be the nuclei. The cells appear to be arranged in a grid-like pattern, with some cells connected to others. The cells are suspended in a clear liquid, which could be a solution. The image is likely a microscopic view of a sample of cells.

Thank You!



IFML Institute for Foundations of
MACHINE LEARNING

<https://aihealth.ischool.utexas.edu/>

