

AI in Health

Ying Ding

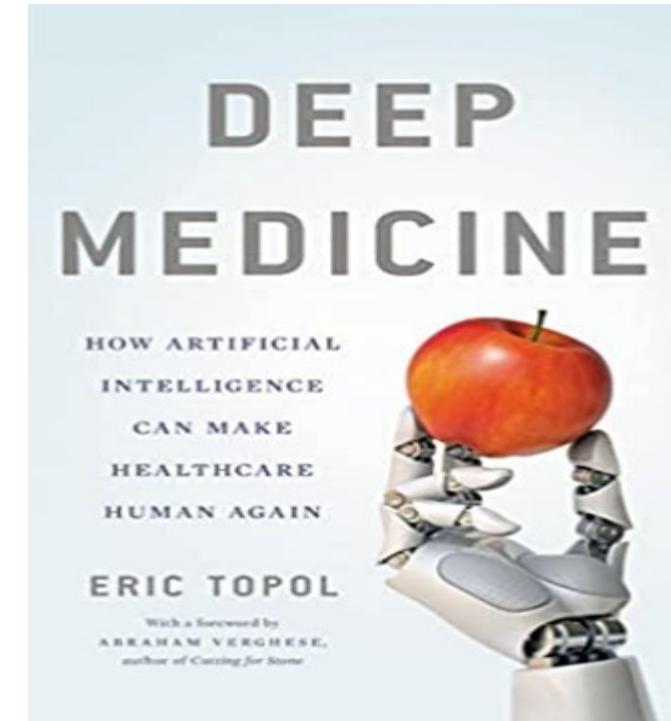
AI Health Lab

School of Information

Dell Medical School

Outlandish Expectations for AI in Healthcare

- Outperform doctors at all tasks
- Diagnose the undiagnosable
- Treat the untreatable
- See the unseeable on scans, slides
- Predict the unpredictable
- Classify the unclassifiable
- Eliminate workflow inefficiencies
- Eliminate hospital admissions and readmissions
- Eliminate the surfeit of unnecessary jobs
- 100% medication adherence
- Zero patient harm
- Cure cancer



Eric Topol, Deep Medicine, 2019



Eric Topol, MD

Executive VP, Scripps Research
Professor, Molecular Medicine, Scripps Research
Director & Founder, Scripps Research Translational Institute
Department of Molecular Medicine

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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.

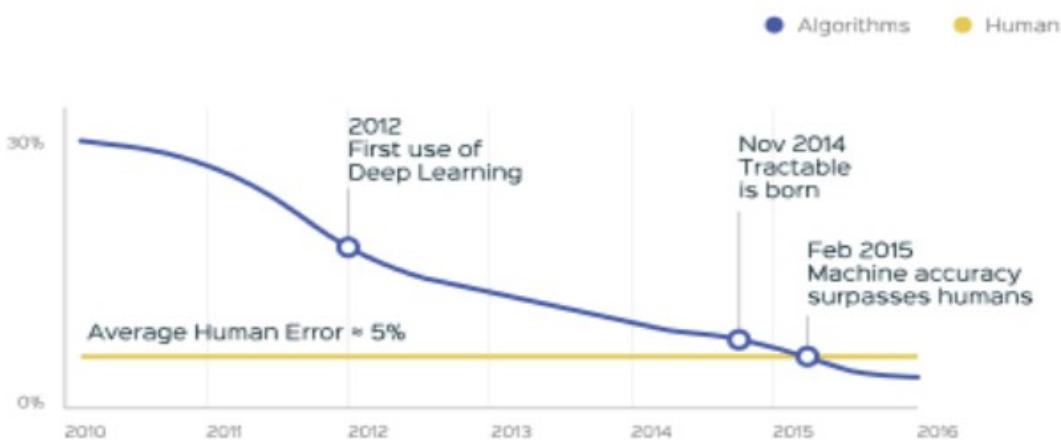
Curt Langlotz, Director of AI in health and imaging at Stanford



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.

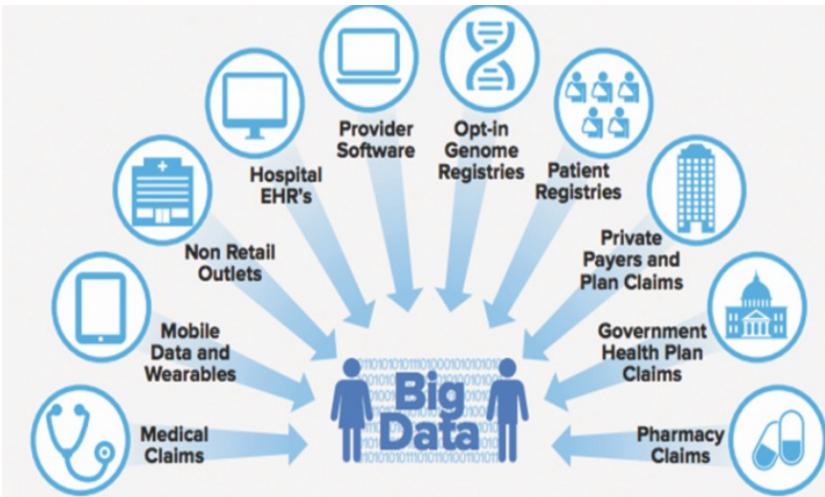
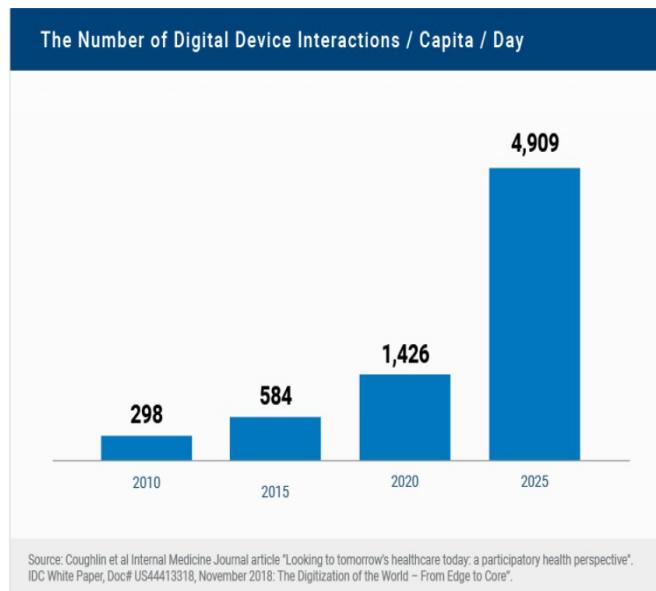
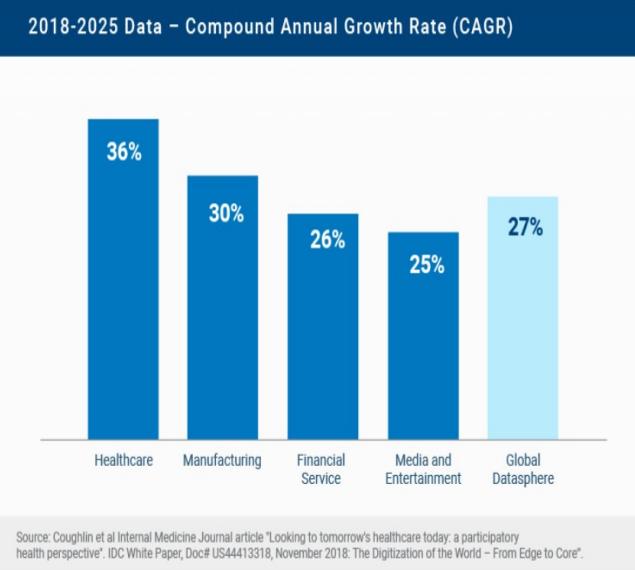
The message also intends to promote the idea that all radiologists will eventually adopt AI, thereby replacing their former selves. But regardless of which replacement scenario seems more likely, no one doubts that AI will transform how imaging professionals practice medicine.

AI Versus Human Image Recognition Error Rates

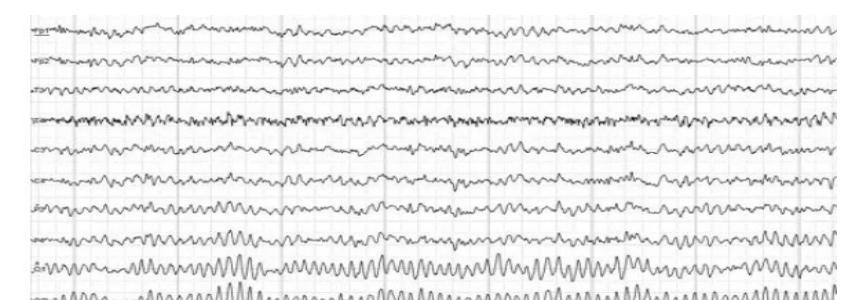
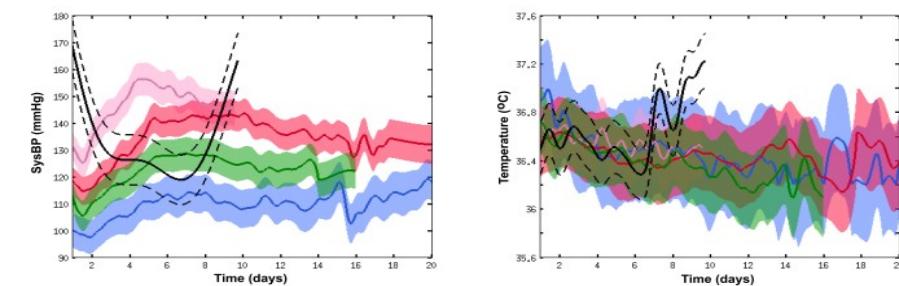


With estimates of average diagnostic error rates ranging from 3% to 5%, there are approximately 40 million diagnostic errors involving imaging annually worldwide.

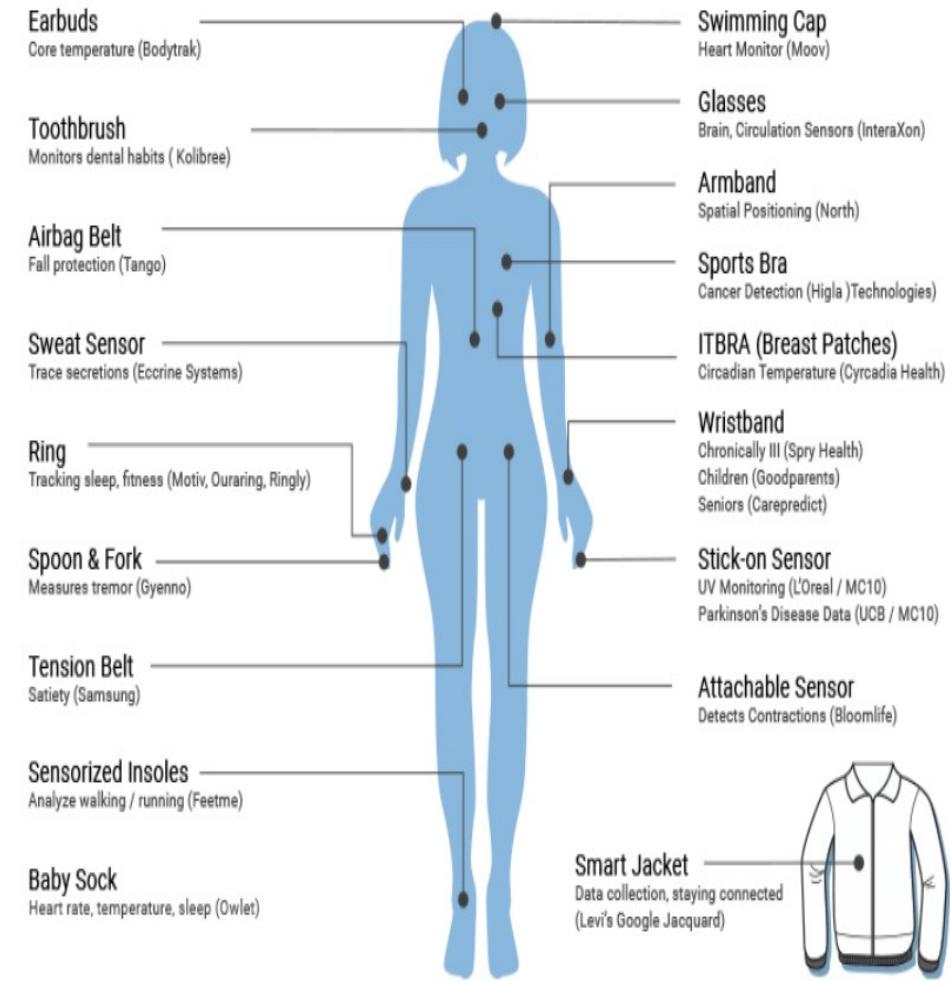
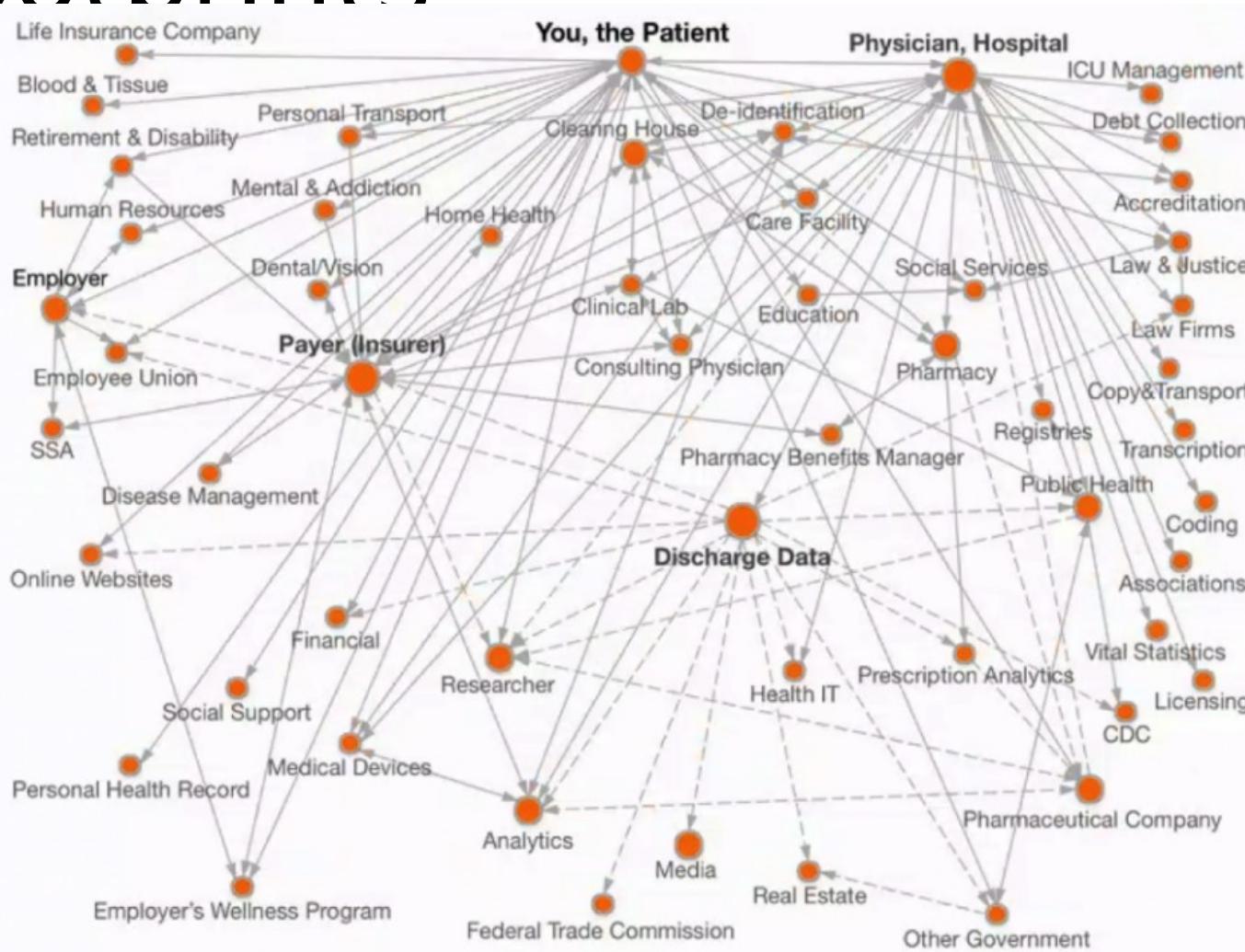
Healthcare Data World



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...

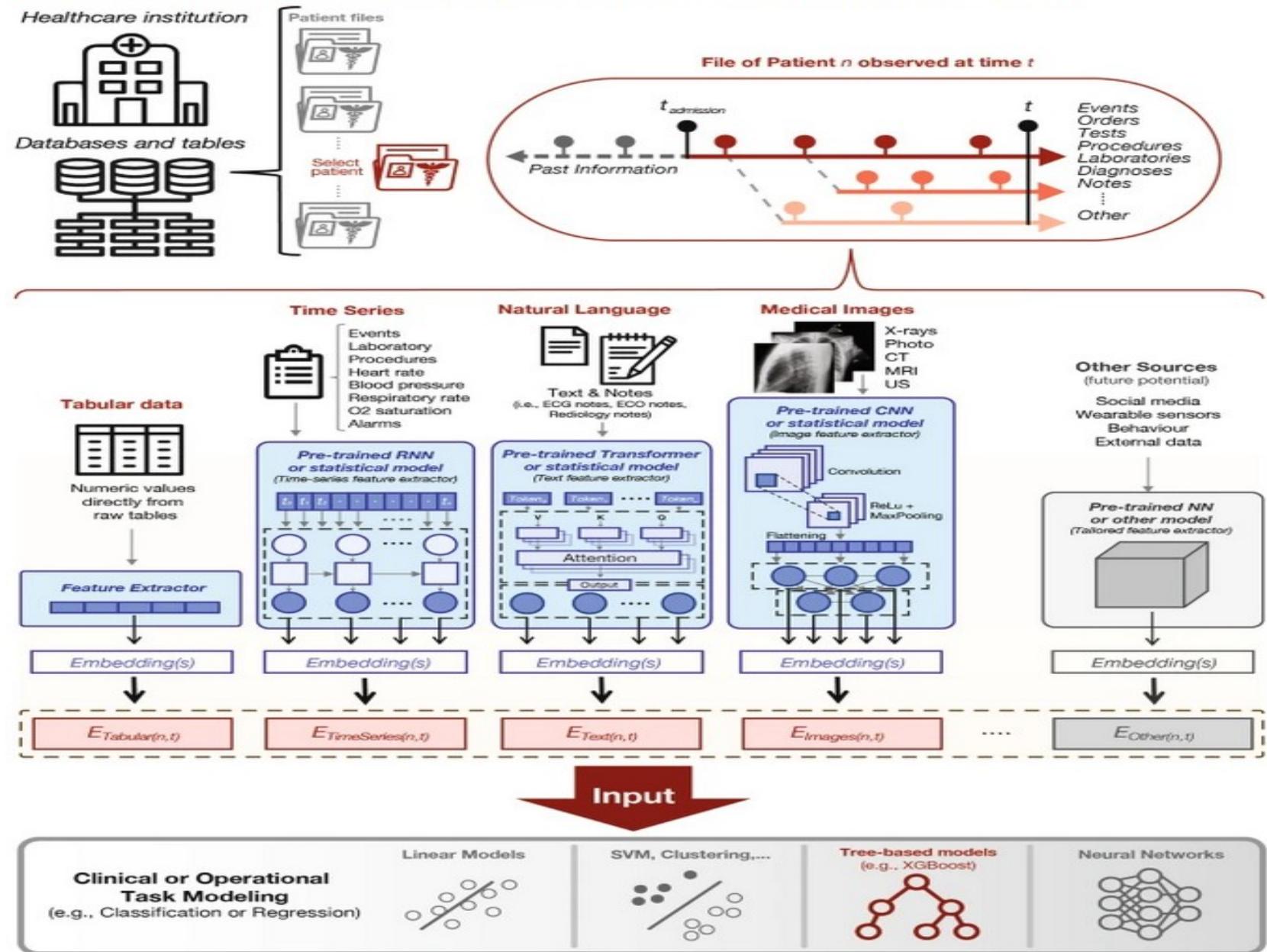


Patient-Centered Digital Footprints

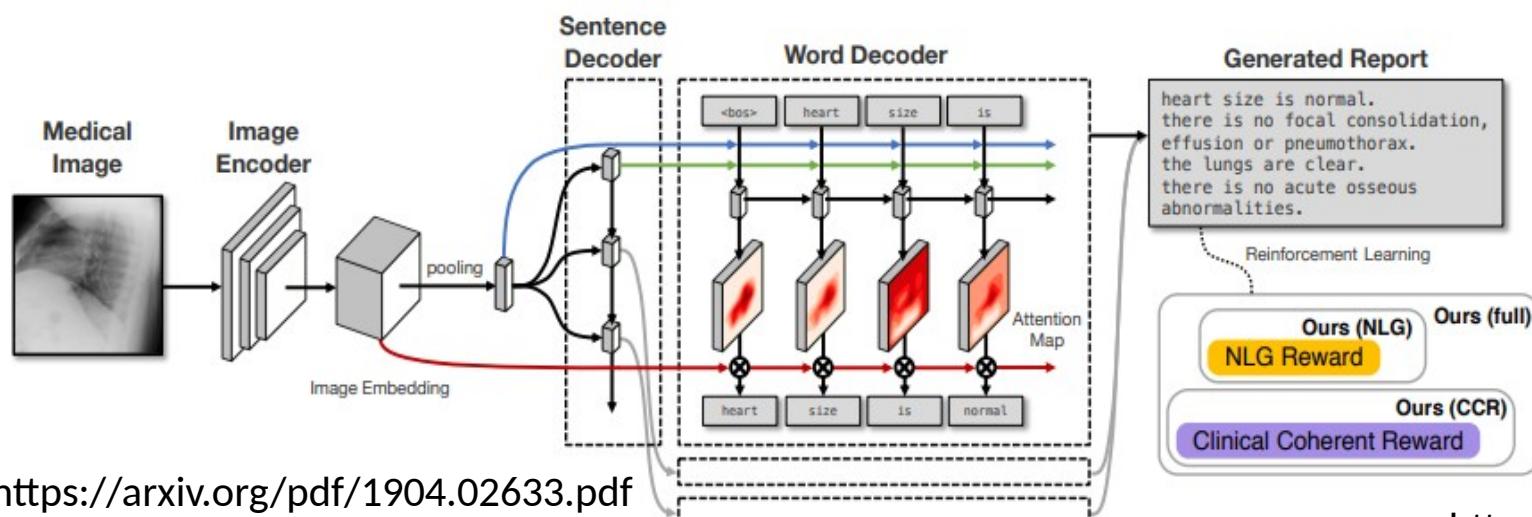
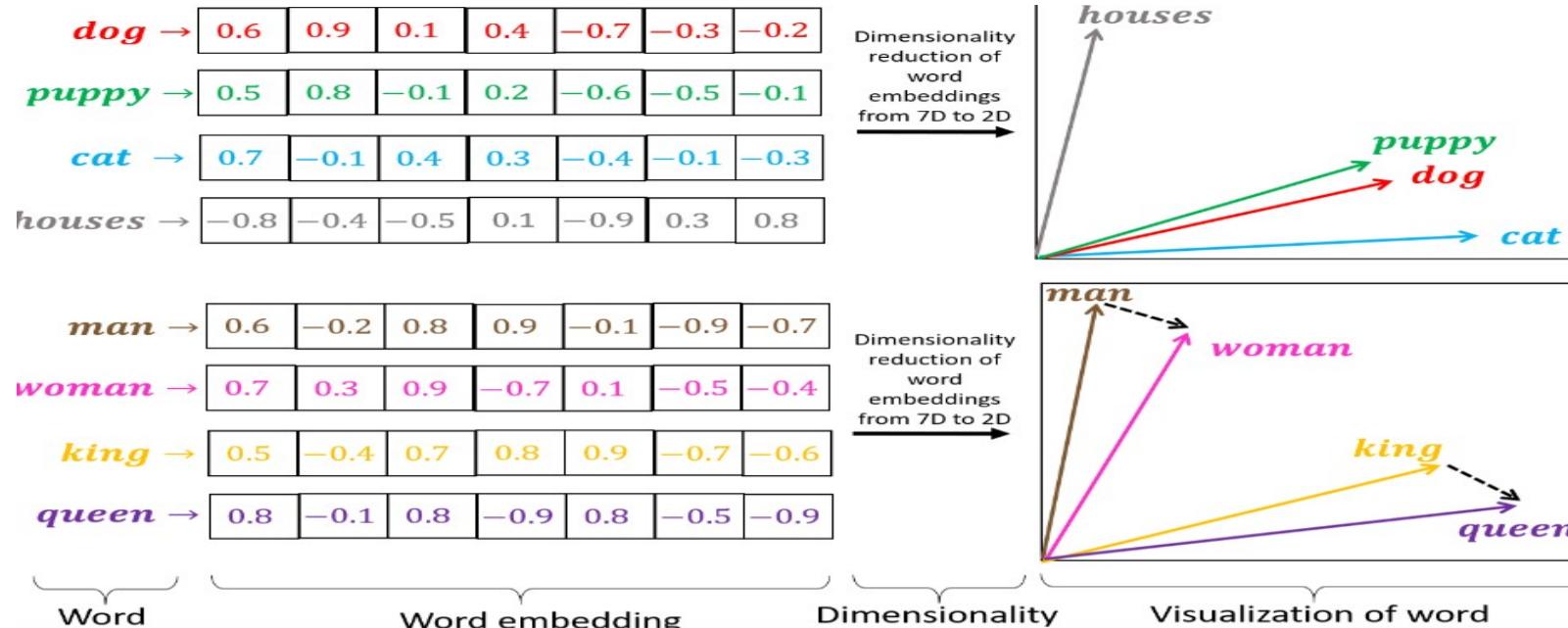


Deep Learning: The best way to deal with complex cross modality healthcare data

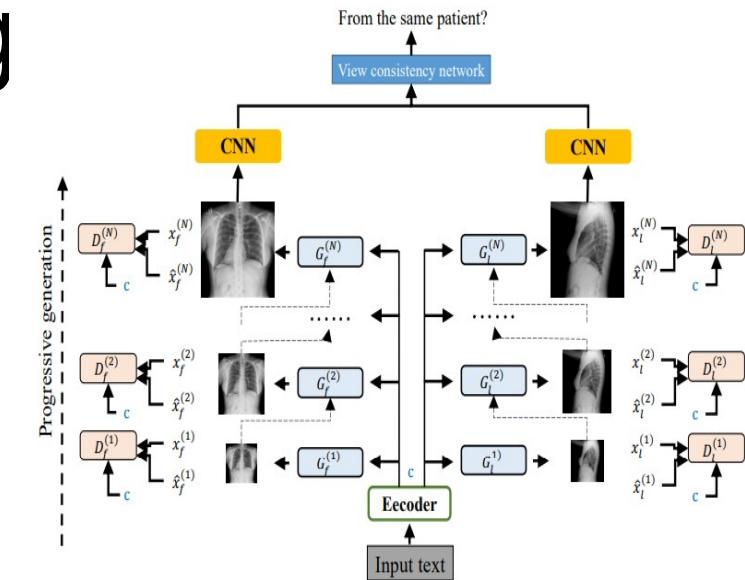
Fig. 1: Holistic Artificial Intelligence in Medicine (HAIM) framework.



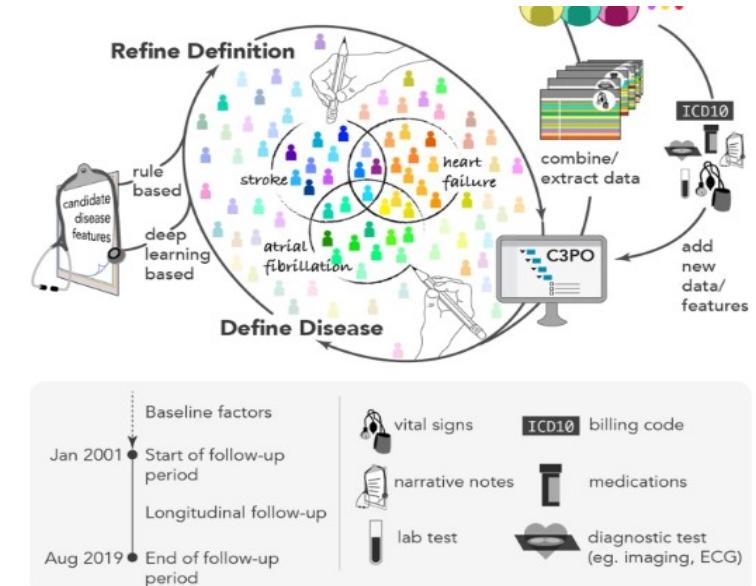
Embedding is the magic language



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



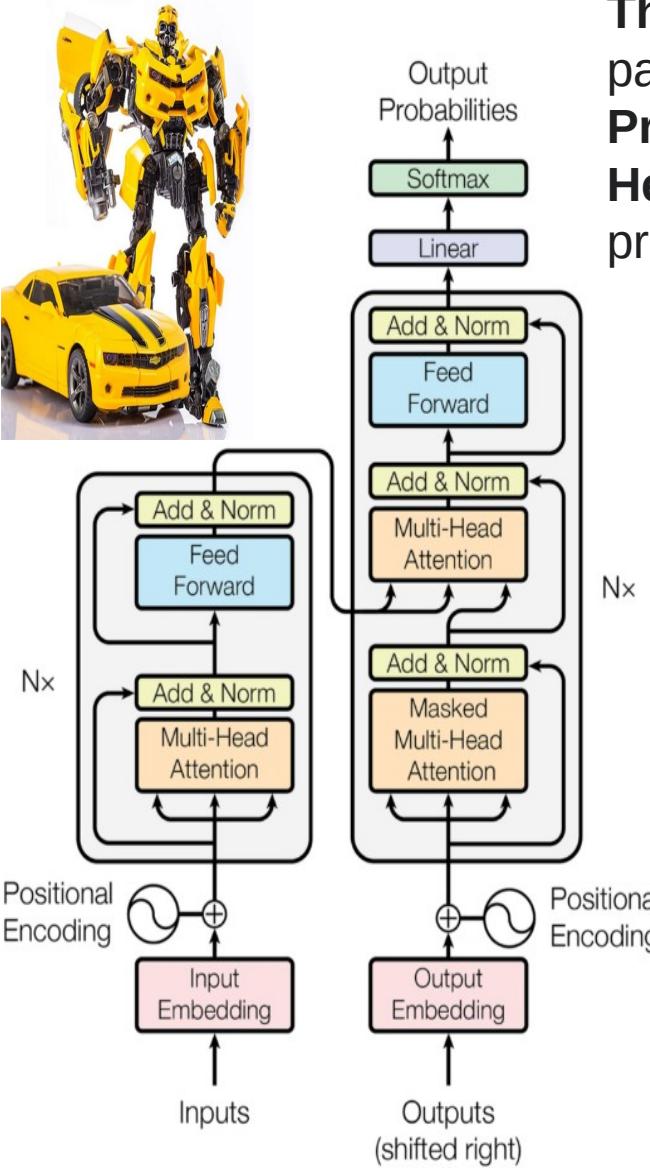
<https://arxiv.org/pdf/2006.10552v1.pdf>



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

Transformer: the Power of AI

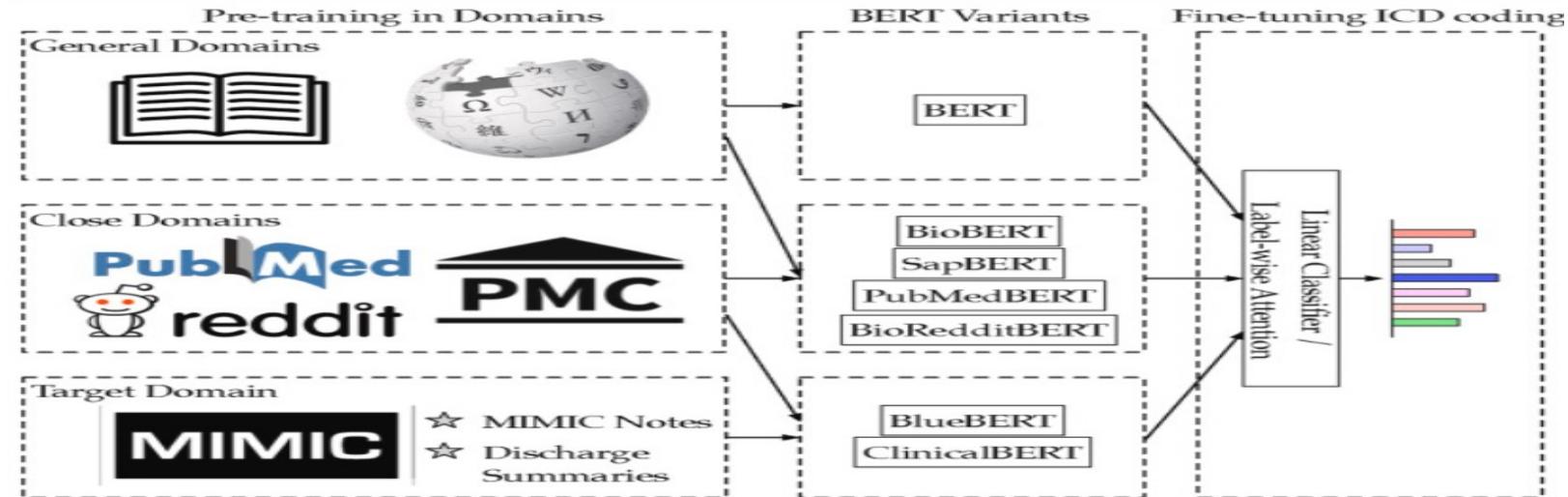
BEHRT (BERT for EHR)



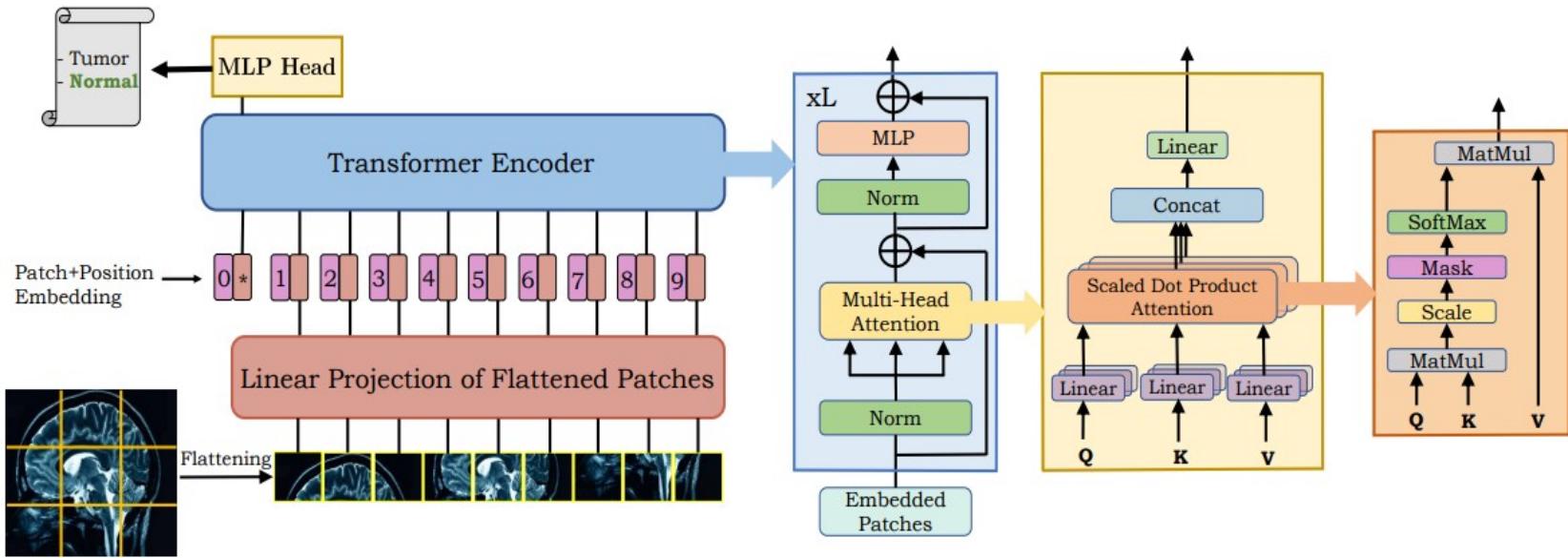
Theory: adopting the mechanism of self-attention, weighting the significance of each part of the input data.

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

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



Transformer: the Power of AI



<https://arxiv.org/abs/2010.11929>

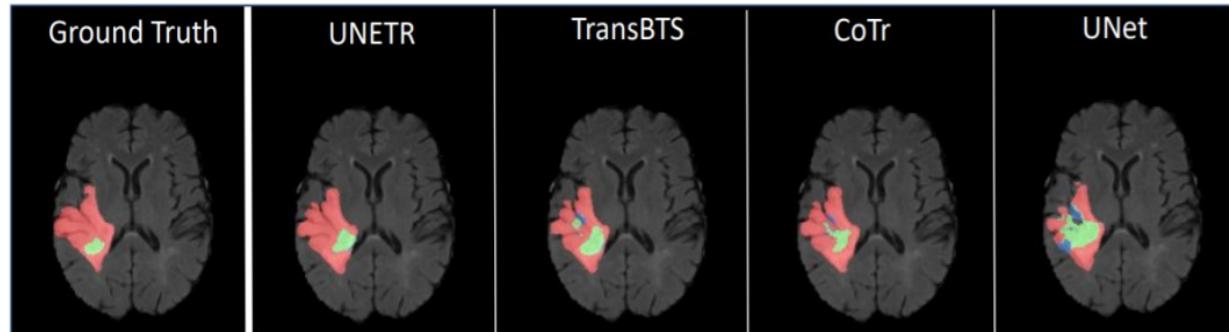
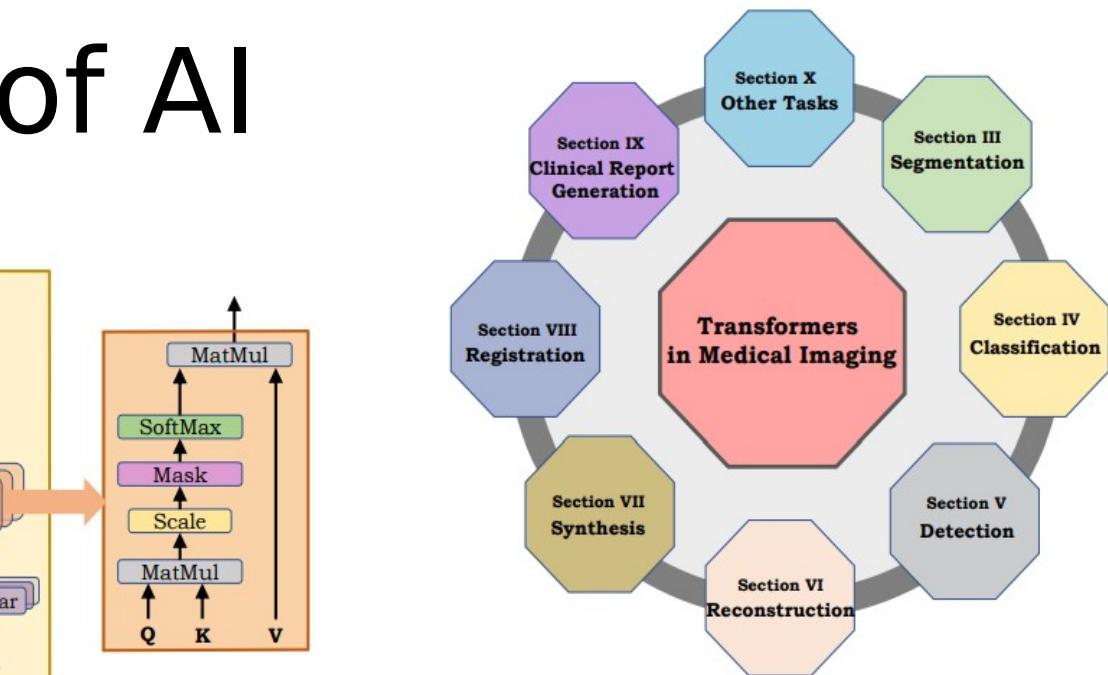
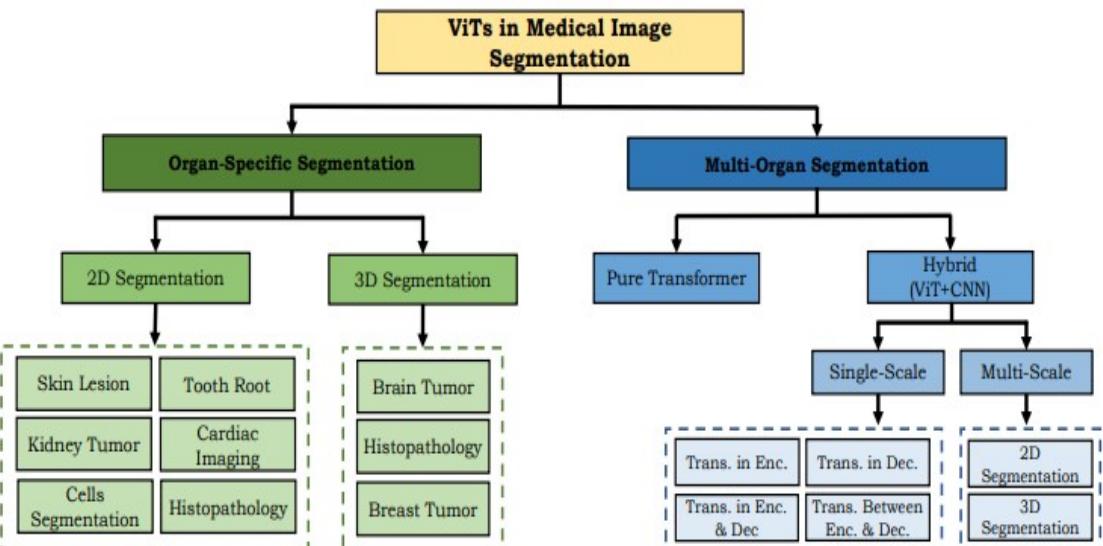


Figure 10: Qualitative results of brain tumor segmentation task using transformer. From left to right: Ground truth image, UNETR [35] (ViT-based), TransBTS [138] (ViT-based), CoTr [200] (ViT-based), and UNet [114] (CNN based). Note that transformer-based approaches demonstrate better performance in capturing the fine-grained details of brain tumors as compared to CNN-based method. Image courtesy [35].

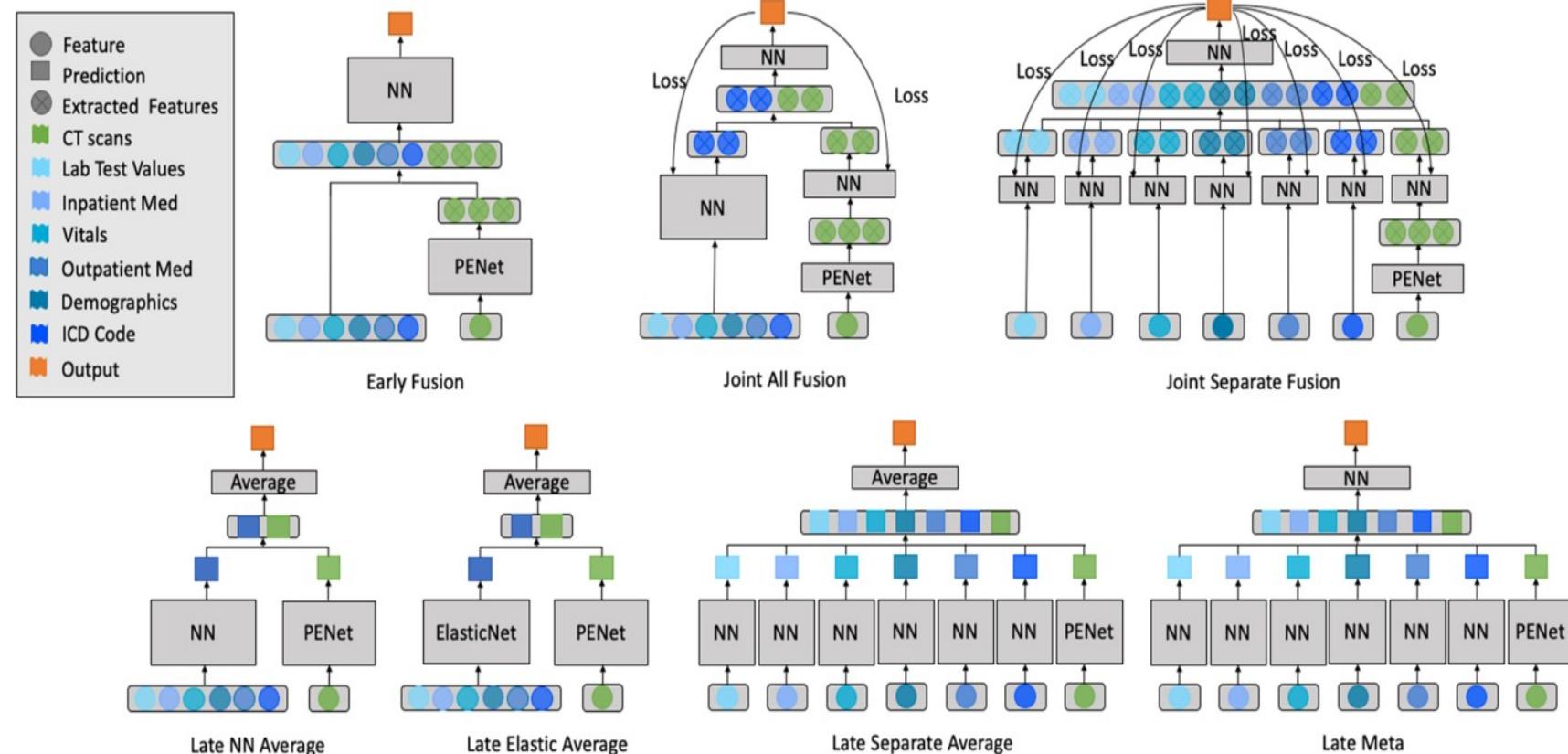
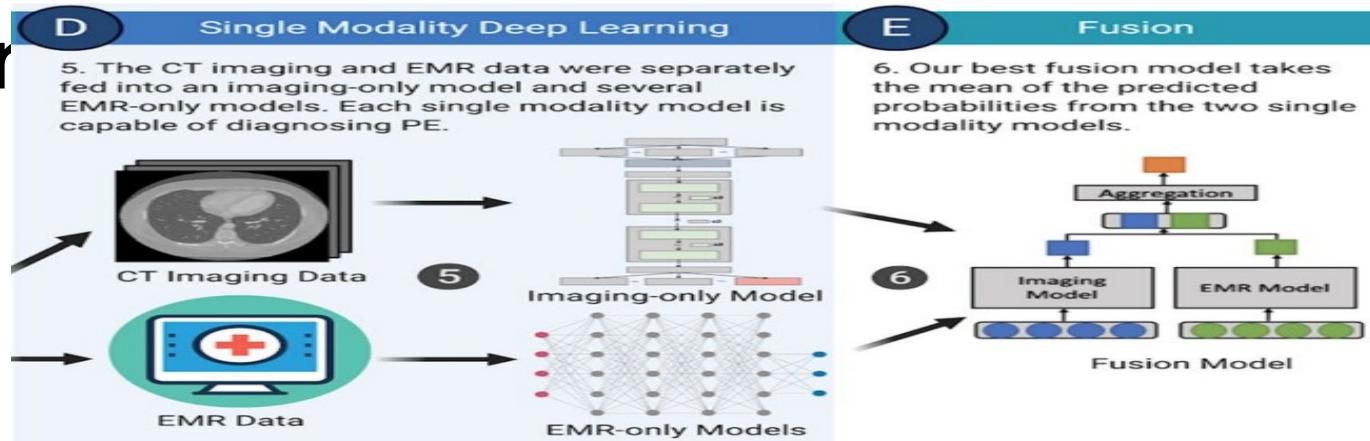


<https://arxiv.org/pdf/2201.09873.pdf>

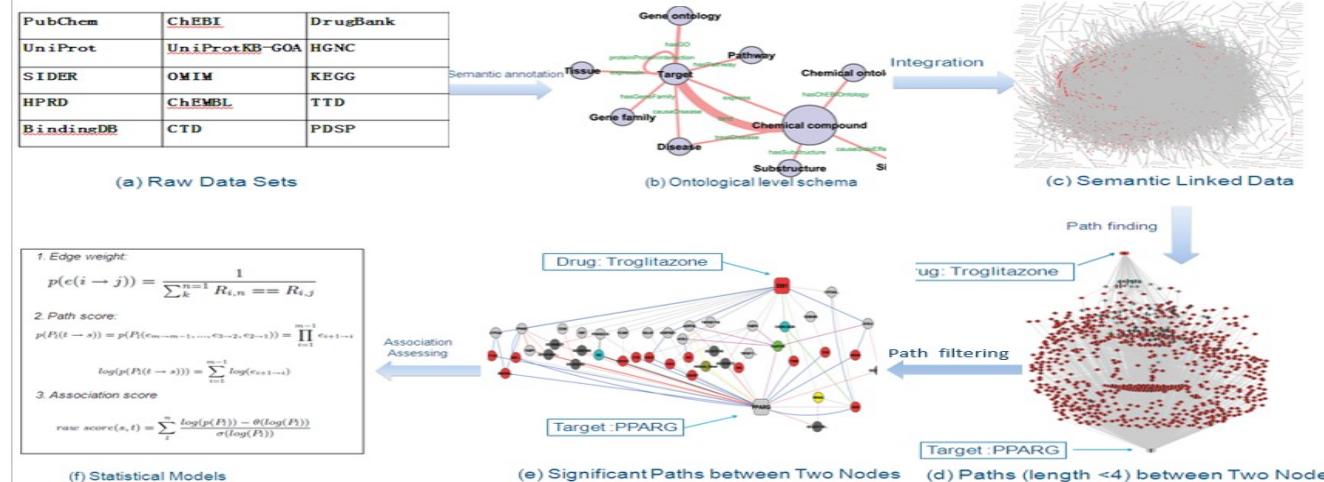


Multimodal Fusion Learning

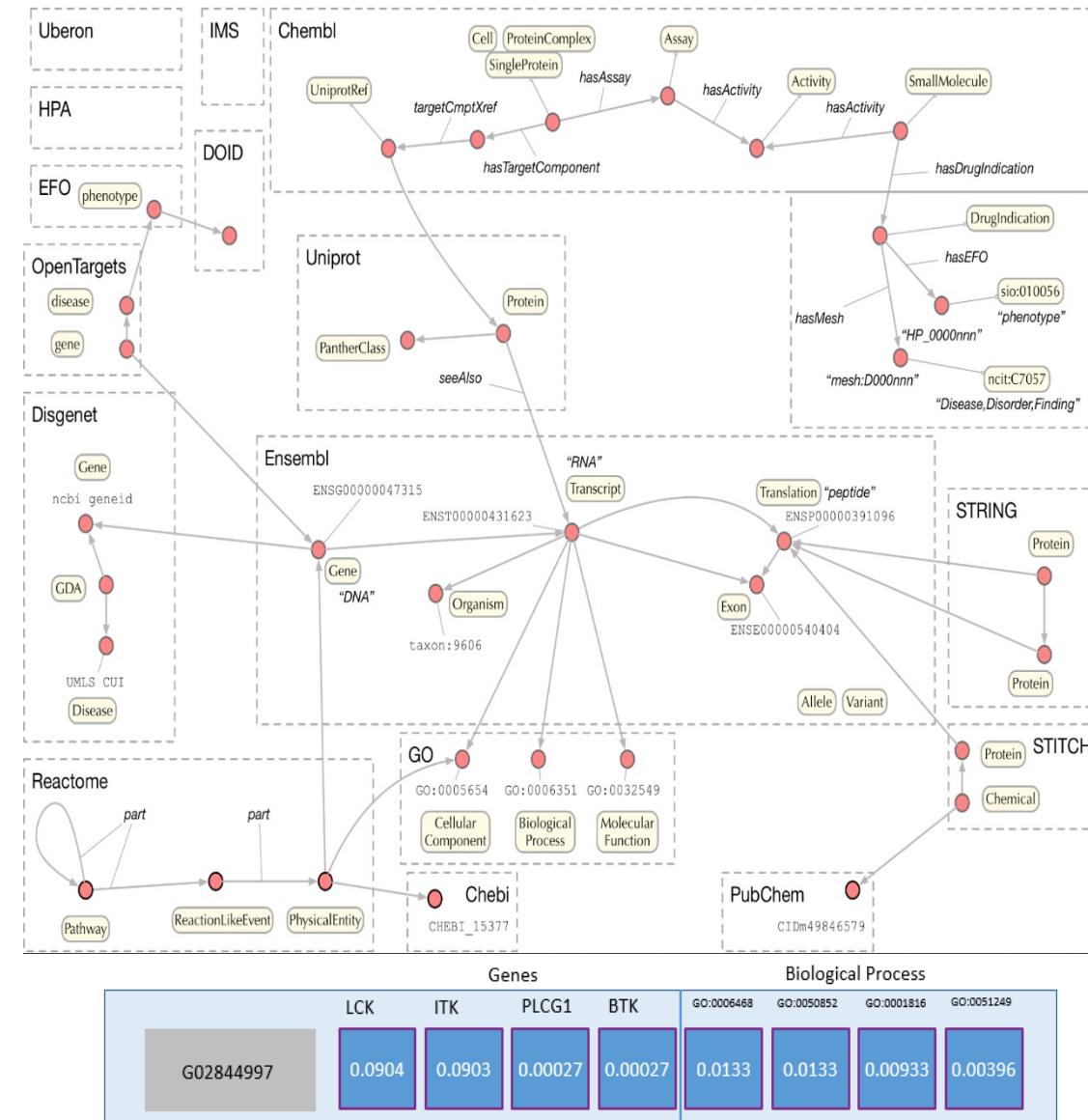
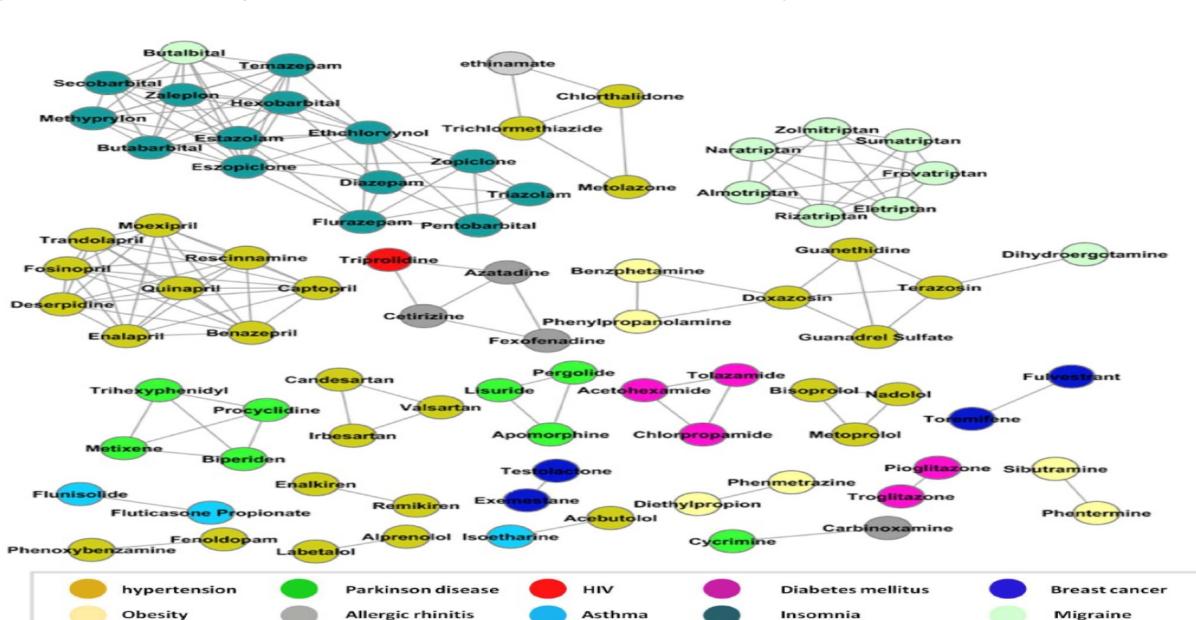
Multimodal fusion model architectures that are capable of utilizing both pixel data from volumetric Computed Tomography Pulmonary Angiography(CTPA) scans and clinical patient data from the EMR to automatically classify Pulmonary Embolism (PE) cases. The best performing multimodality model is a late fusion model that achieves an AUROC of 0.947, outperforming imaging-only and EMR-only single modality models.



Knowledge Graph: The Connected Health

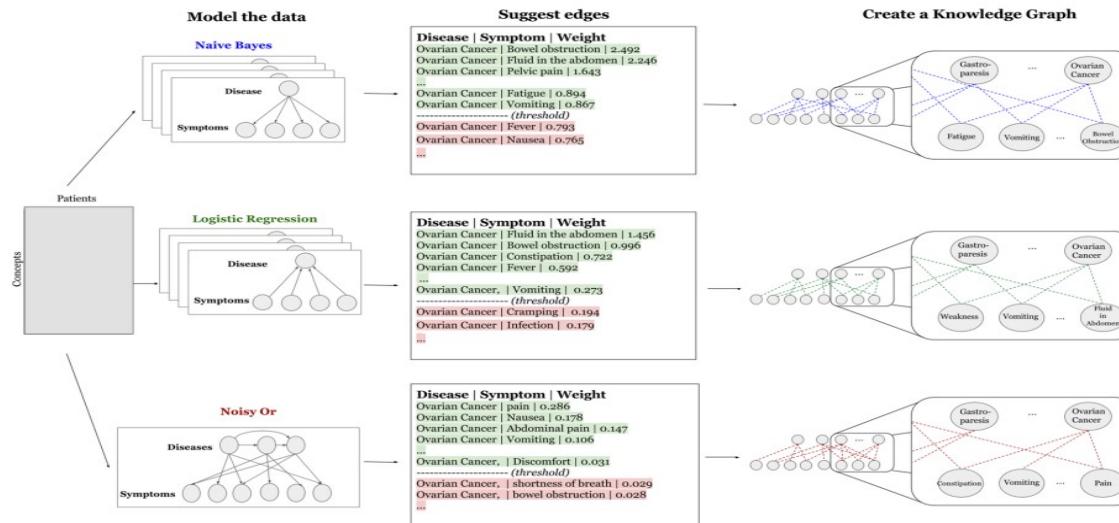


<https://journals.plos.org/ploscompbiol/article?id=10.1371/journal.pcbi.1002574>

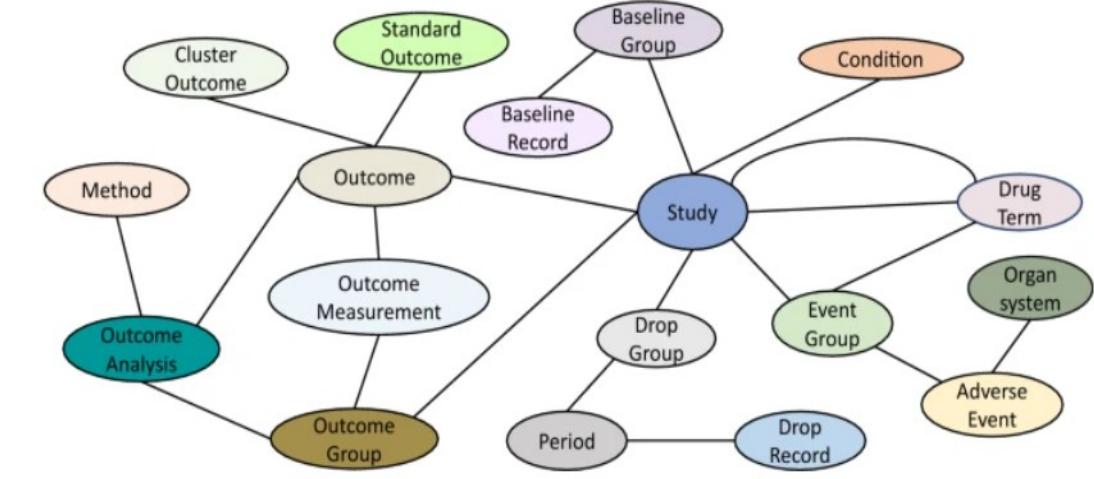
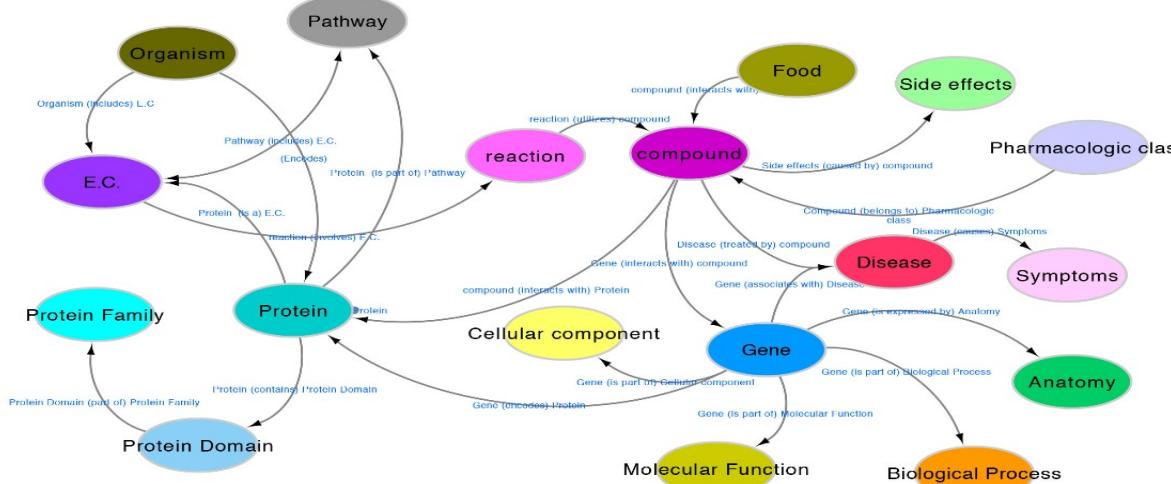


<https://bmcbioinformatics.biomedcentral.com/>

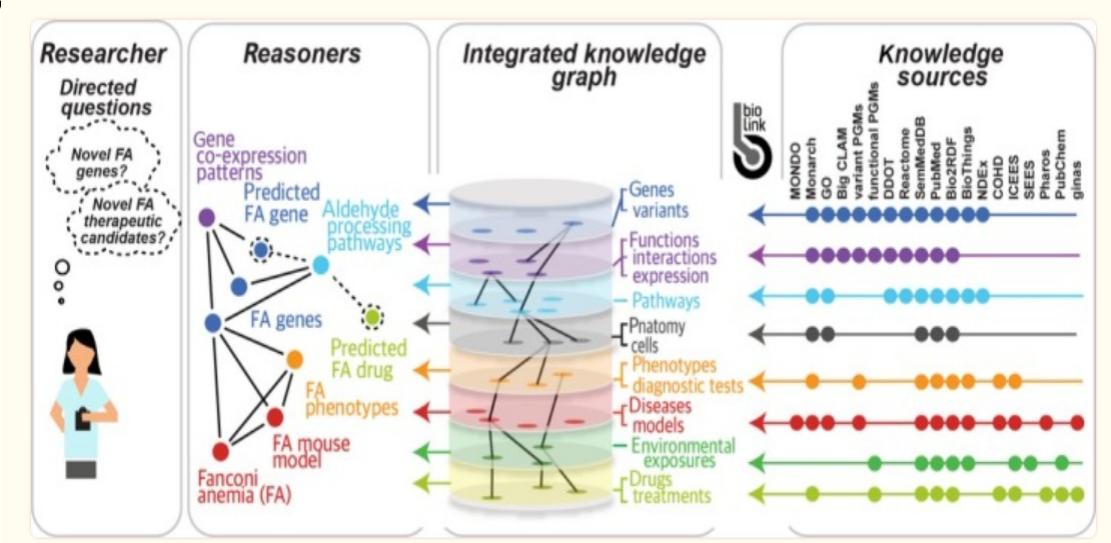
Knowledge Graph: The Connected Health



Disease-Symptom KG: <https://www.nature.com/articles/s41598-017-0577>



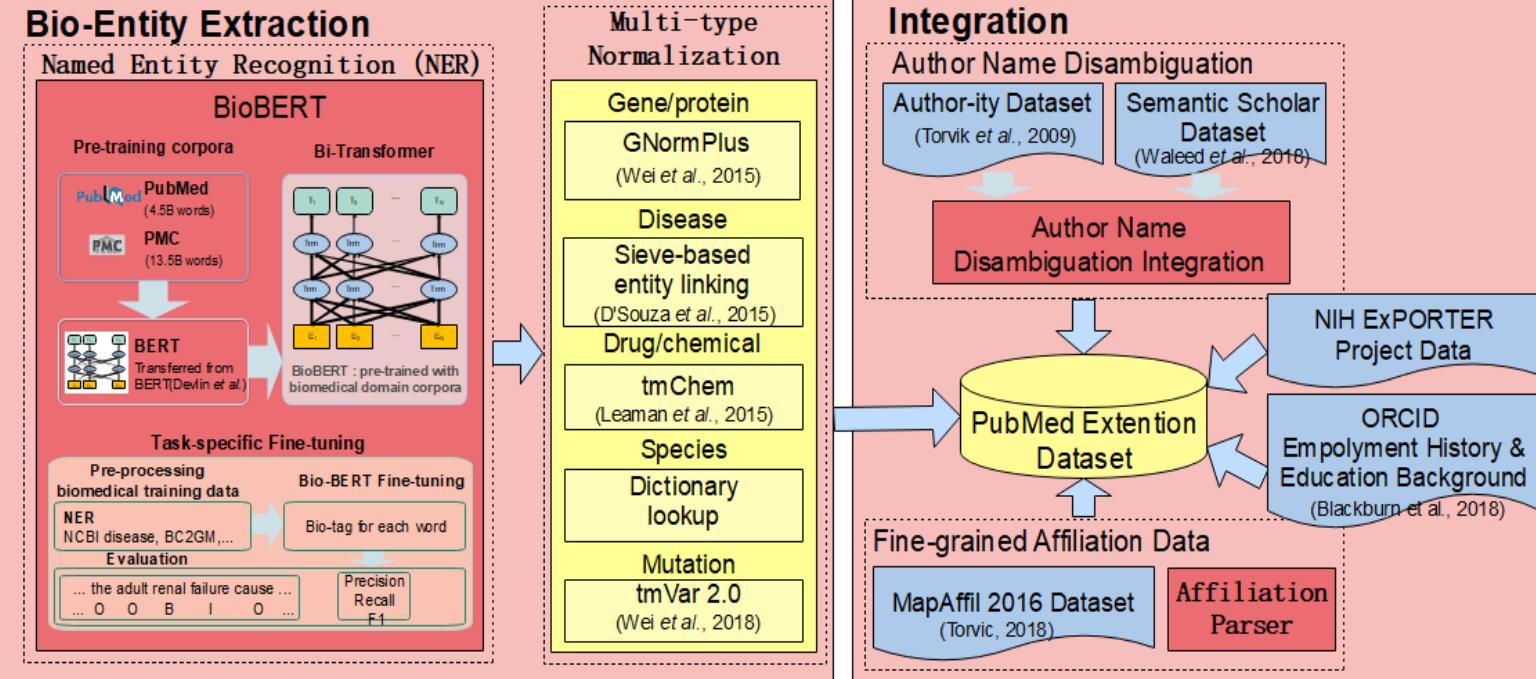
Clinical Trail KG: <https://github.com/ninglab/CTKG>



NIH-NCATS: Biomedical data translator:
<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6440568/>

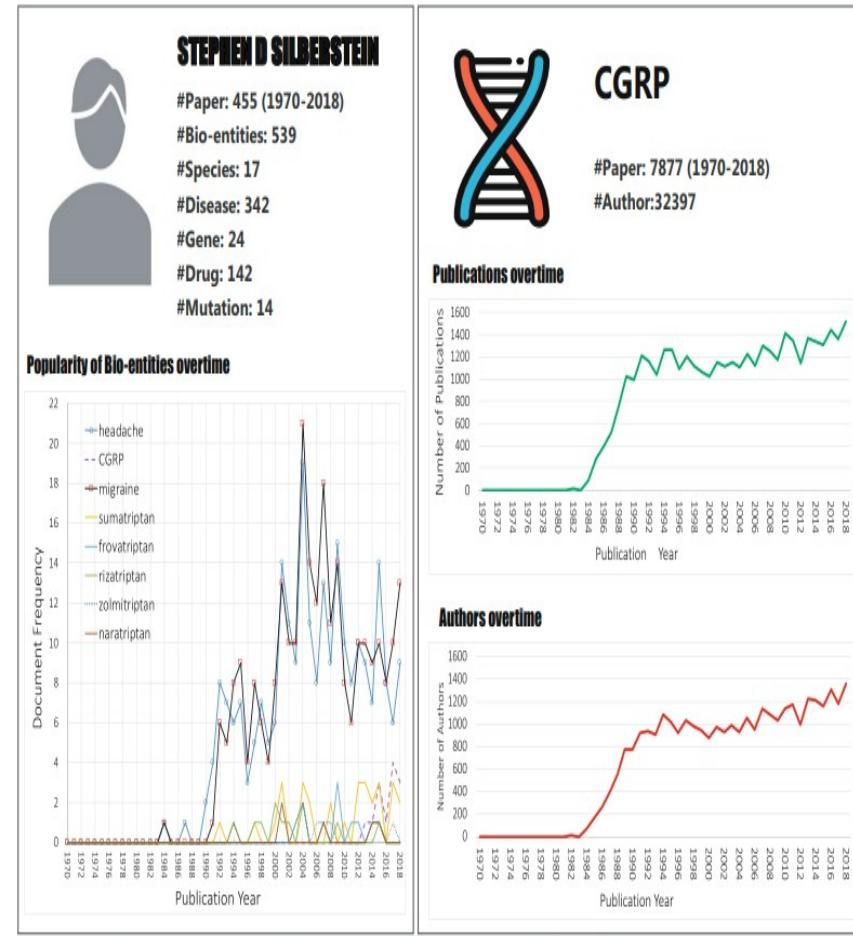
SPOKE: <https://spoke.ucsf.edu/>

Knowledge Graph about PubMed



File	# of Lines	# of Distinct PMIDs	# of Distinct AND IDs
Author_List	114,345,178	28,510,300	14,830,461
Bio-entities_Main	330,394,494	18,361,409	-
Bio-entities_Mutation	1,388,341	312,099	-
Affiliations	46,065,099	19,601,383	8,300,984
Researcher_Employment	532,356	-	276,483
Researcher_Education	512,267	-	268,610
NIH_Projects	12,340,431	1,790,949	102,070

	Precision	Recall	F1 score
Author-ity	99.43%	96.92%	98.16%
Semantic Scholar	96.24%	97.66%	96.94%
AND Integration	98.62%	97.56%	98.09%



(a) Researcher-centric activity

(b) Bio-entity-centric activity

<https://www.nature.com/articles/s41597-020-0543-2>

Graph convolutional neural network for bigger graphs (pre-clinical+clinical+PubMed)

Closed Loop of Pre-clinical and Clinical Data

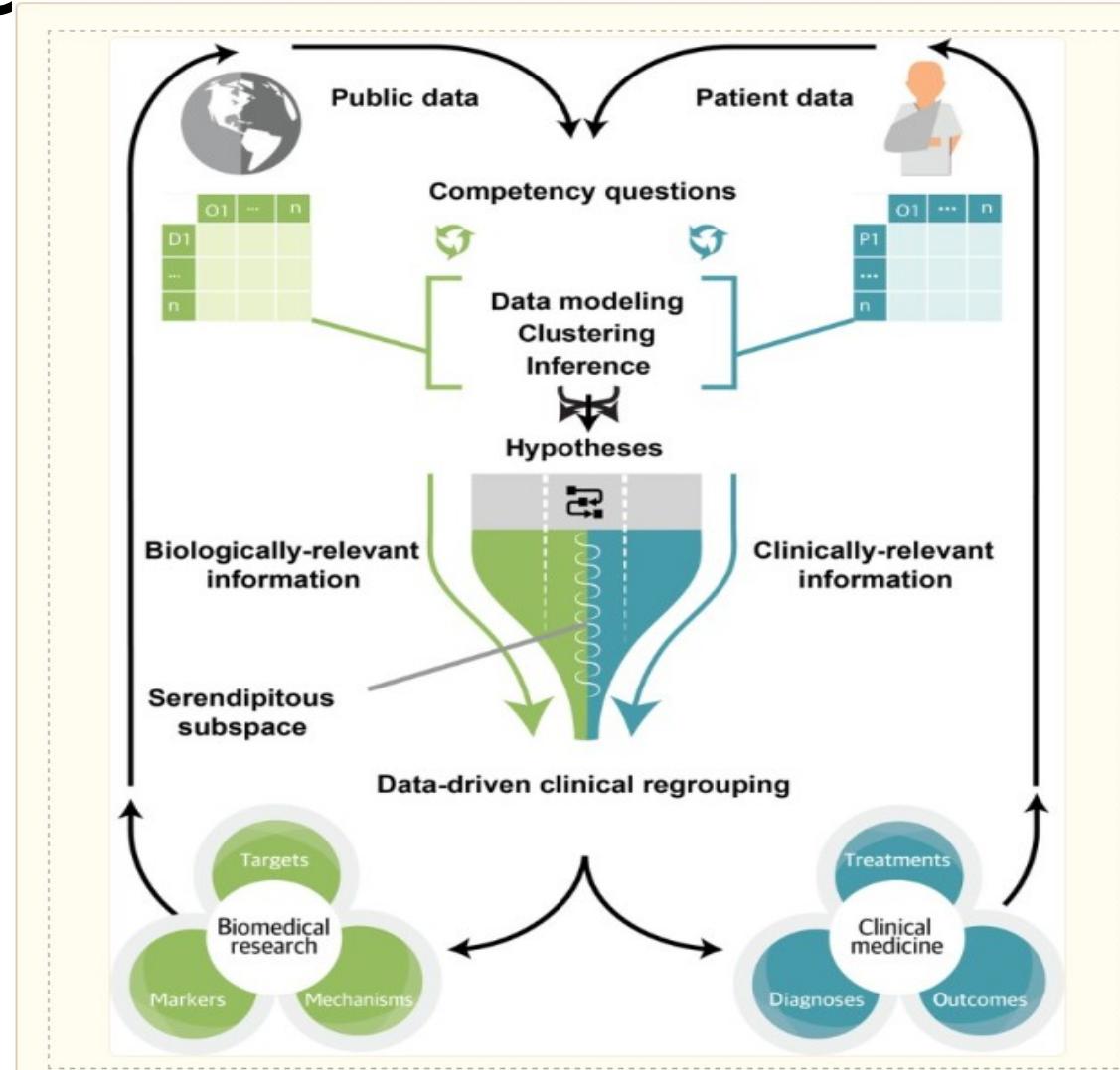
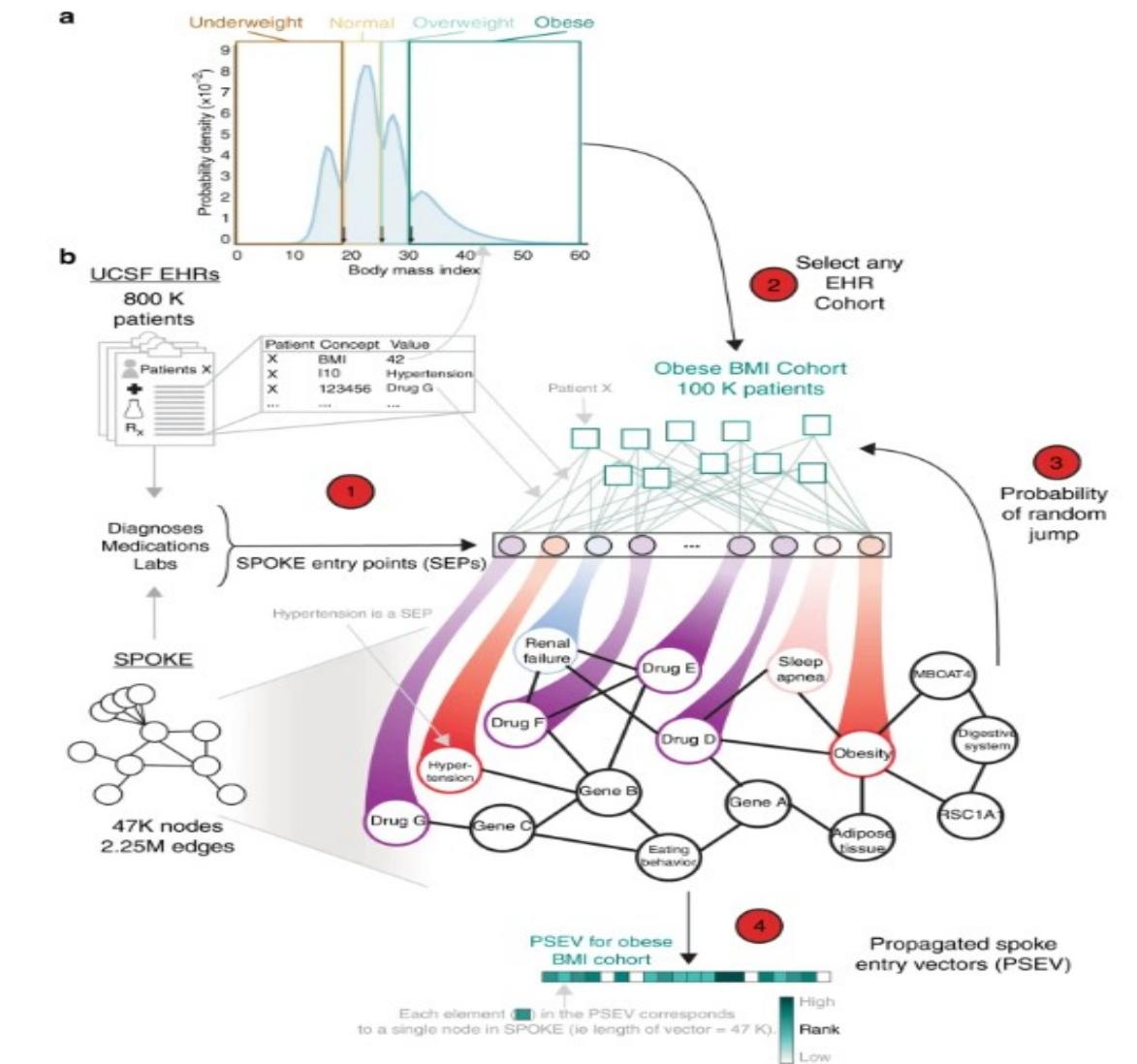
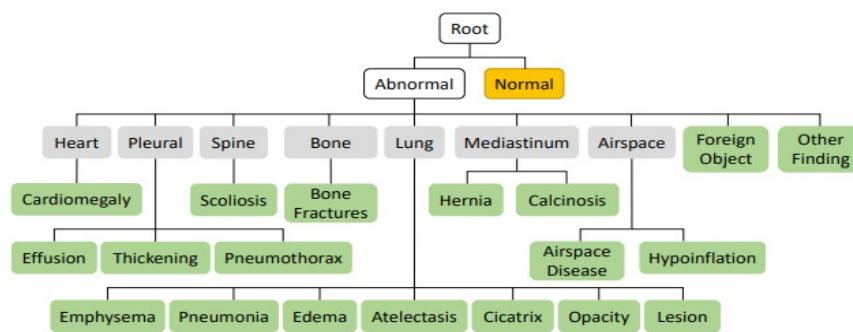
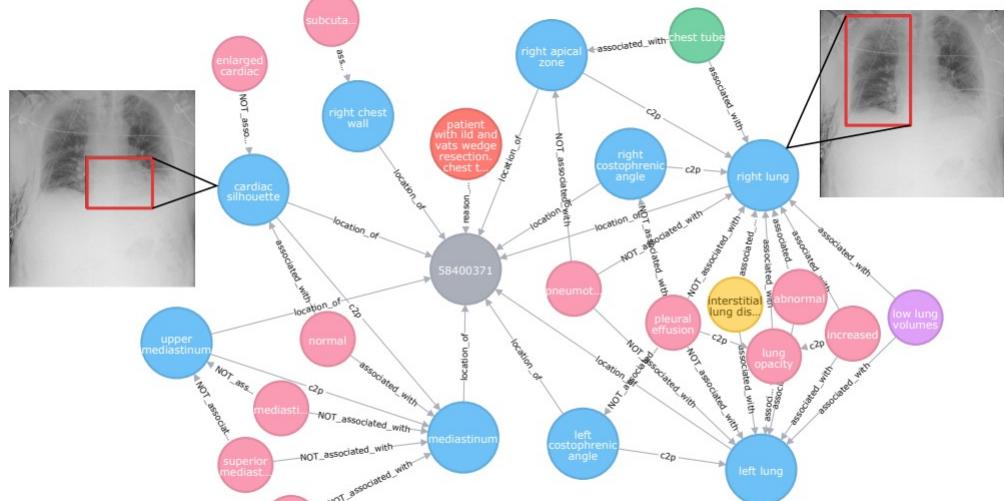


Fig. 1

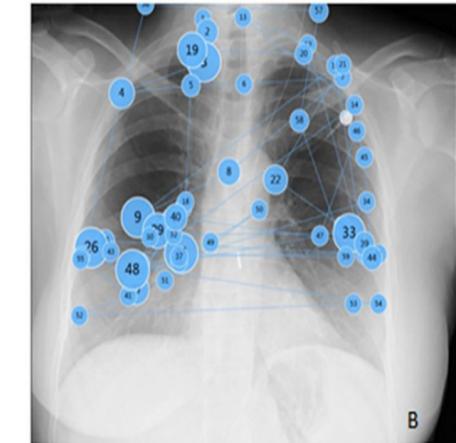
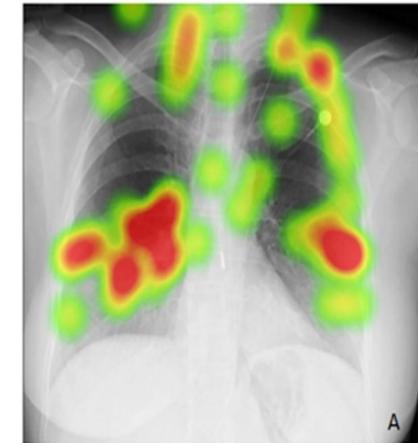
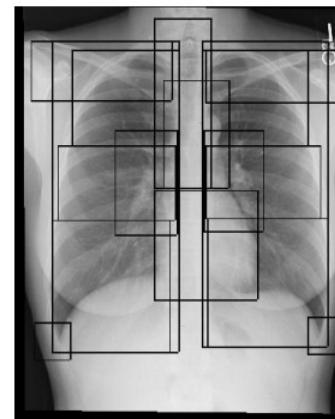


Knowledge Graph in Chest X-Ray

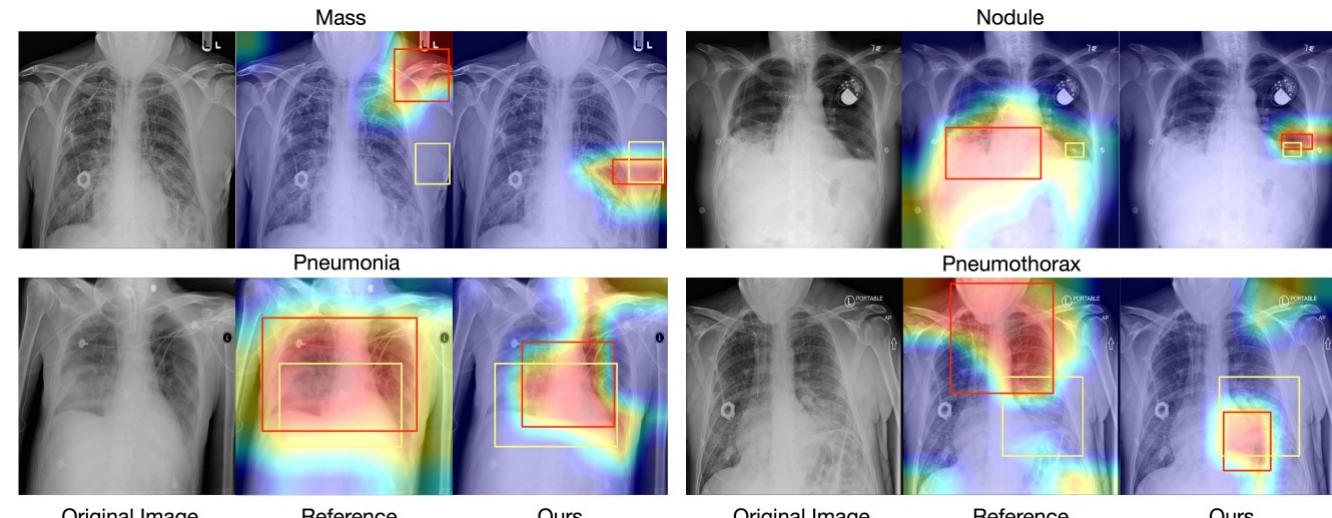


<https://arxiv.org/pdf/2108.00316.pdf>

REFLACX, a dataset of reports and eye-tracking data for localization of abnormalities in chest x-rays



<https://www.nature.com/articles/s41597-022-01441-z>

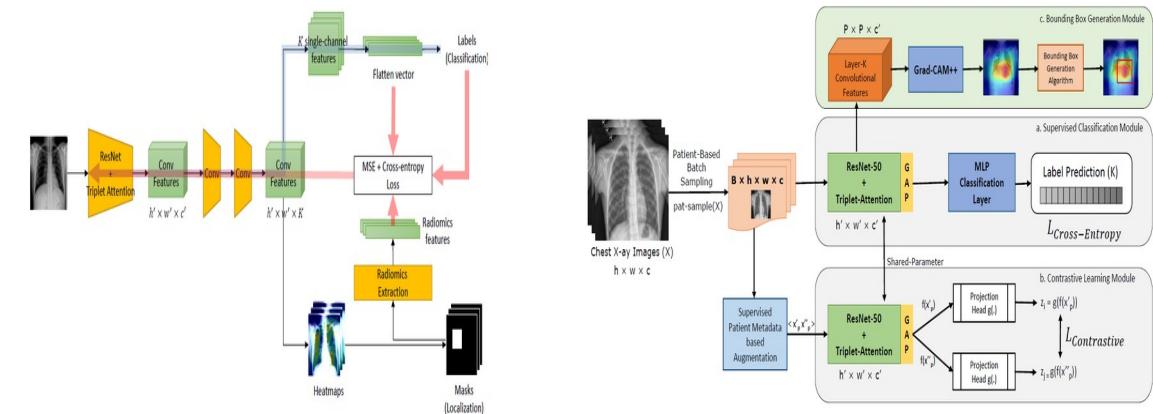


https://openaccess.thecvf.com/content/WACV2022/papers/Han_Knowledge-Augmented_Contrastive_Learning_for_Abnormality_Classification_and_Localization_in_Chest_WACV_2022_paper.pdf

Research Highlight: Human-Centered AI for Medical Imaging Diagnosis

Project goals:

- Develop the novel methods to add doctors' prior knowledge to enable better human-centered AI approaches for medical imaging diagnosis
- Develop novel contrastive learning methods by proposing using patient metadata as data augmentation methods to generate positive samples for a given image.

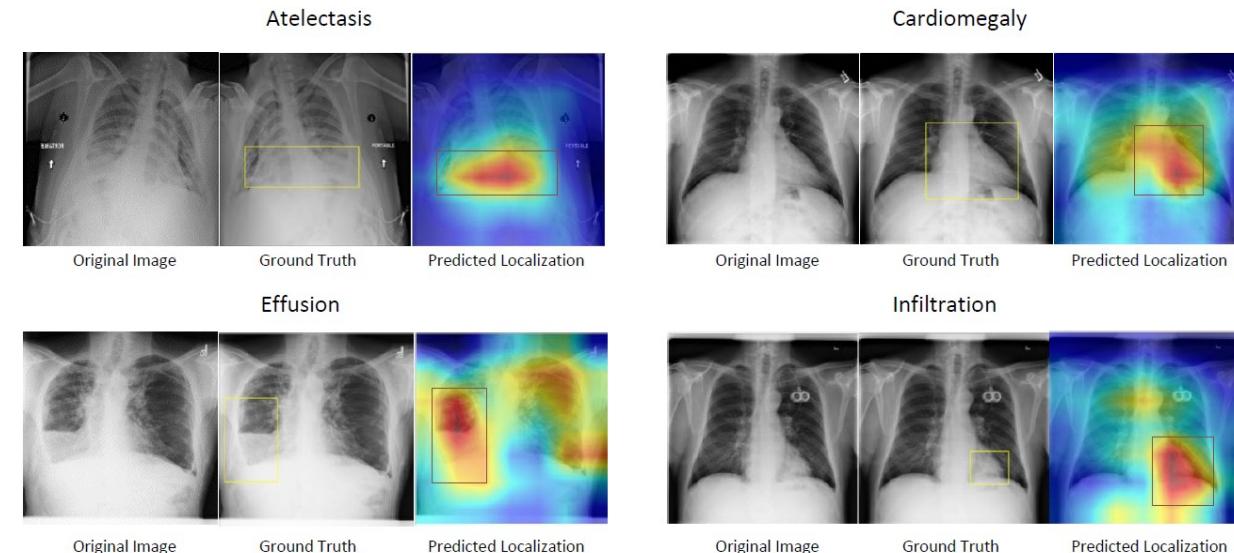


- Barriers: adding radiologist's prior knowledge (radiomics) into deep learning methods is challenging.
- Output: Our ChexRadiNet outperforms the state-of-the-art on both disease detection (0.843 in AUC) and localization (0.679 in $T(\text{IoU}) = 0.1$).

SCALP outperforms existing baselines with significant margins in both classification and localization tasks. Specifically, the average classification AUCs improve from 82.8% (SOTA using DenseNet-121) to 83.9% (SCALP using ResNet-50), while the localization results improve on average by 3.7% over different IoU thresholds

Han, Y., Chen, C., Tewfik, A., Glicksberg, B., Ding, Y., Peng, Y., & Wang, Z. (2022). Knowledge-Augmented Contrastive Learning for Abnormality Classification and Localization in Chest X-rays with Radiomics using a Feedback Loop. **WACV2022**

Jaiswal, A., Li, H., Zander, C., Han, Y., Rousseau, J., Peng, Y., & Ding, Y. (2021). SCALP - Supervised Contrastive Learning for Cardiopulmonary Disease Classification and Localization in Chest X-rays using Patient Metadata, **ICDM 2021**



Research Highlight: Trustworthy Assertion Classification Through Prompting

Project goals:

- Classify the assertion status of clinical diagnoses or conditions being present, absent, or possible in medical notes. It is critical for automated clinical reasoning
- Present a prompt-based assertion classification method, to correctly identify the assertion status of an entity in the unstructured clinical notes.
- Introduce two rationale faithfulness metrics: comprehensiveness and sufficiency.

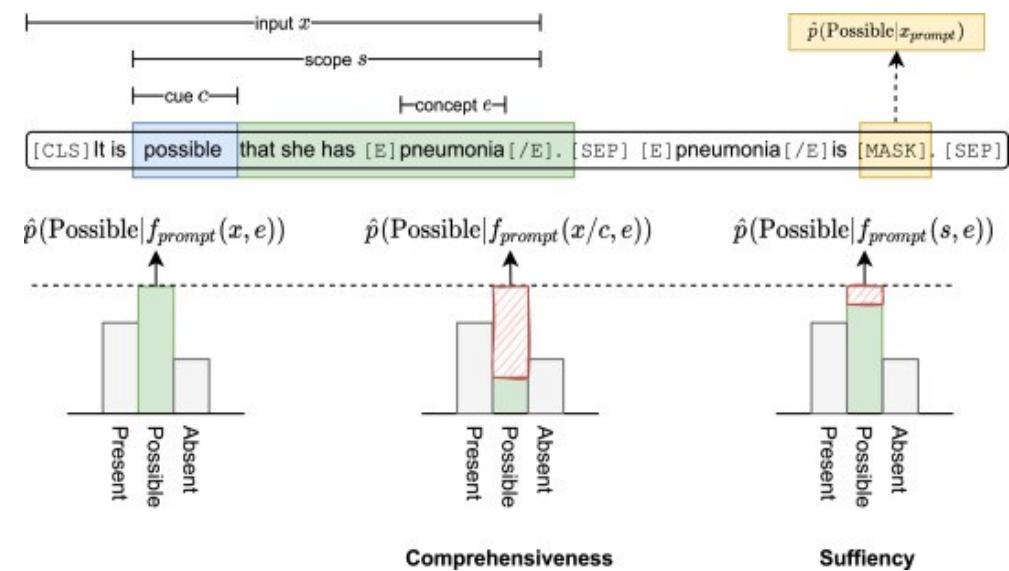
Result:

- We evaluated the model on six datasets. Our prompt-based method achieved a micro-averaged F-1 of 0.954 on the i2b2 2010 assertion dataset, with $\sim 1.8\%$ improvements over previous works.
- In particular, our model showed excellence in detecting classes with few instances (few-shot).
- Evaluations on five external datasets showcase the outstanding generalizability of the prompt-based method to unseen data.

Table 1

Examples of assertion types. Concepts are italicized.

Assertion type	Example
Present	Severe <i>systolic HTN</i> is noted.
Absent	There is no <i>pericardial effusion</i> .
Possible	High CO and low SVR suggestive of <i>sepsis</i> .
Conditional	Narcotics can cause <i>constipation</i> .
Hypothetical	Return to the emergency room if he experiences any <i>chest pain</i> .
Not Associated	Father had <i>MI</i> at 42.



Wang, S., Tang, L., Majety, A., Rousseau, J.F., Shih, G., Ding, Y., & Peng, Y. (2022) Trustworthy Assertion Classification through Prompting. *Journal of Biomedical Informatics* (IF 6.317), p104139.

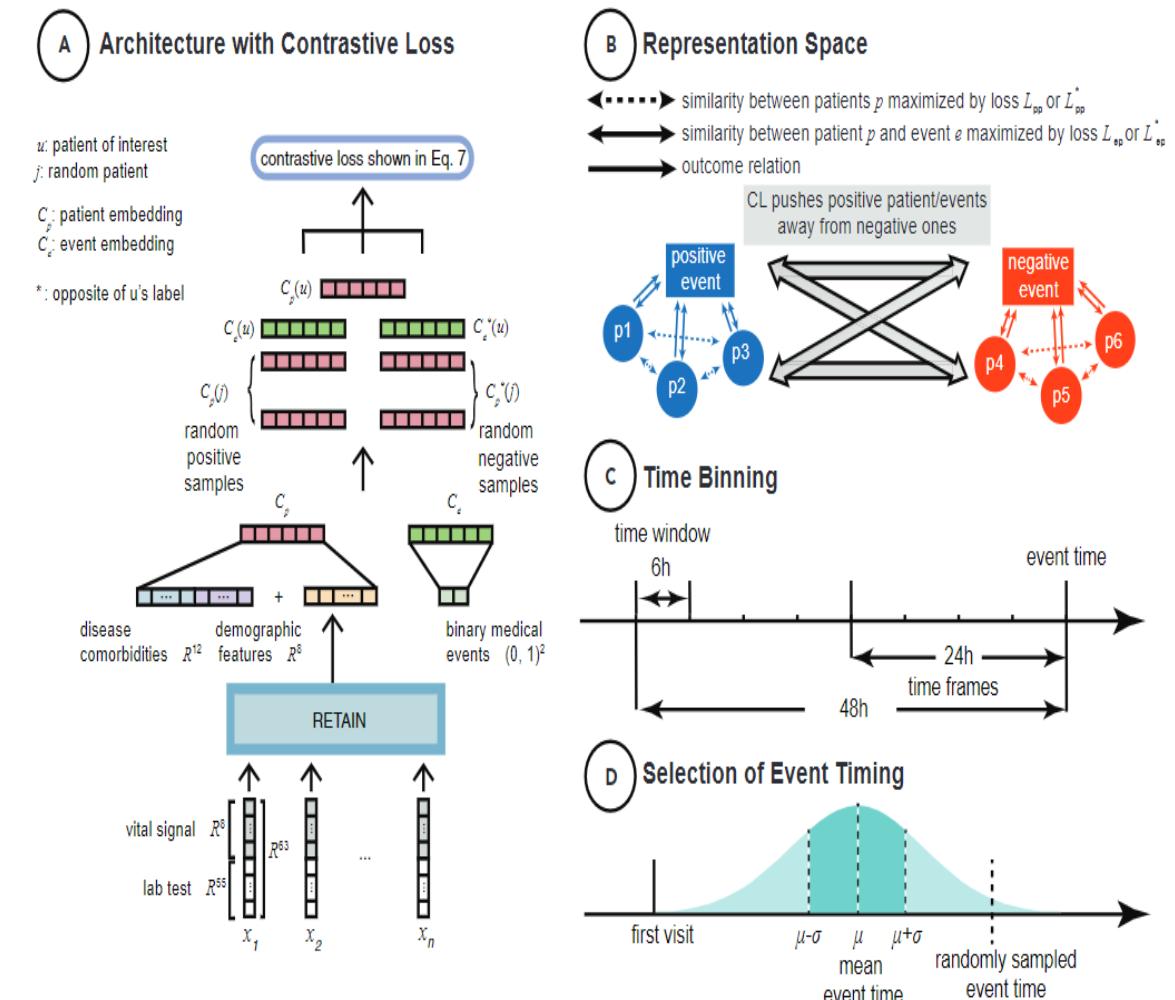
Research Highlight: COVID-19 Patient Health Risk Prediction

Project Goals:

- Deep learning (DL) models typically require large-scale data, but COVID data are highly class imbalanced. Conventional approaches in DL use cross-entropy loss (CEL), which often suffers from poor margin classification.
- we develop and refine a new model architecture based on the recently proposed contrastive deep learning.

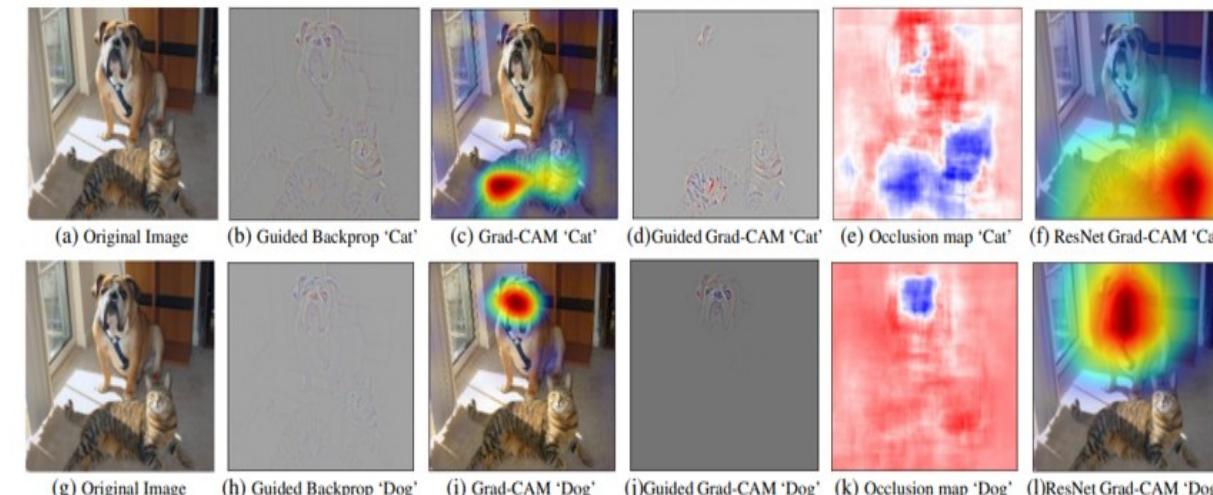
Output:

- CL models consistently outperform CEL models, with differences ranging from 0.04 to 0.15 for area under the precision and recall curve (AUPRC) and 0.05 to 0.1 for area under the receiver-operating characteristic curve (AUROC).
- As a relevant use case, we demonstrate the power of this framework for predicting critical events in COVID-19 patients as well as an enhanced ability to identify important features.
- Our work shows promise for datasets with high missingness and outcome imbalance that normally hinders performance

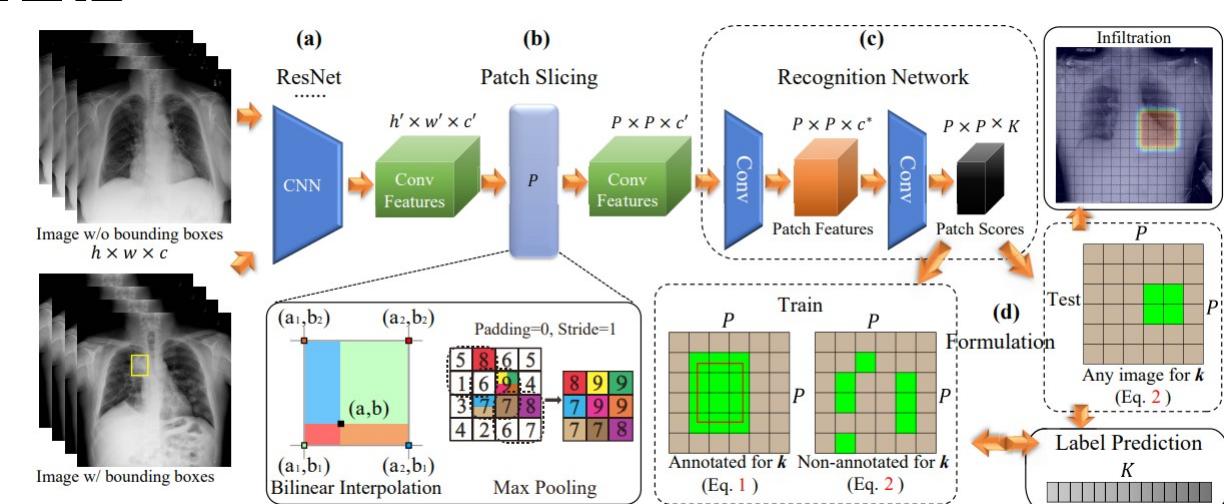
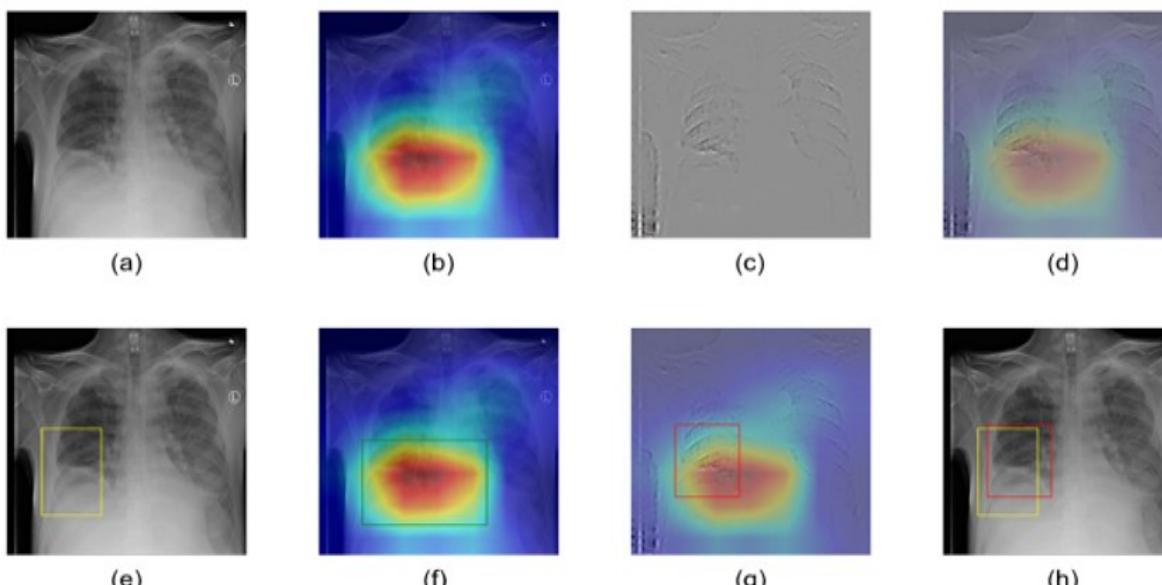


Wanyan, T., Honarvar, H., Jaladanki, S.K., Zang, C., Naik, N., Soman, S., De Freitas, J. K., Paranjpe, I., Vaid, A., Zhang, J., Miotto, R., Wang, Z., Nadkarni, G. N., Zitnik, M., Azad, A., Wang, F., Ding, Y., & Glicksberg, B. (2021). Contrastive learning improves critical event prediction in COVID-19 patients. *Patterns*, 2(12): 100389.

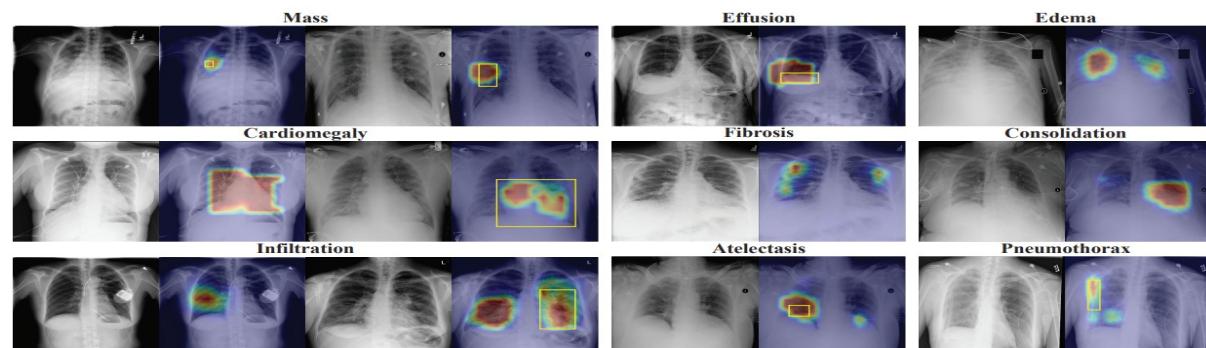
Explainable AI in Health



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

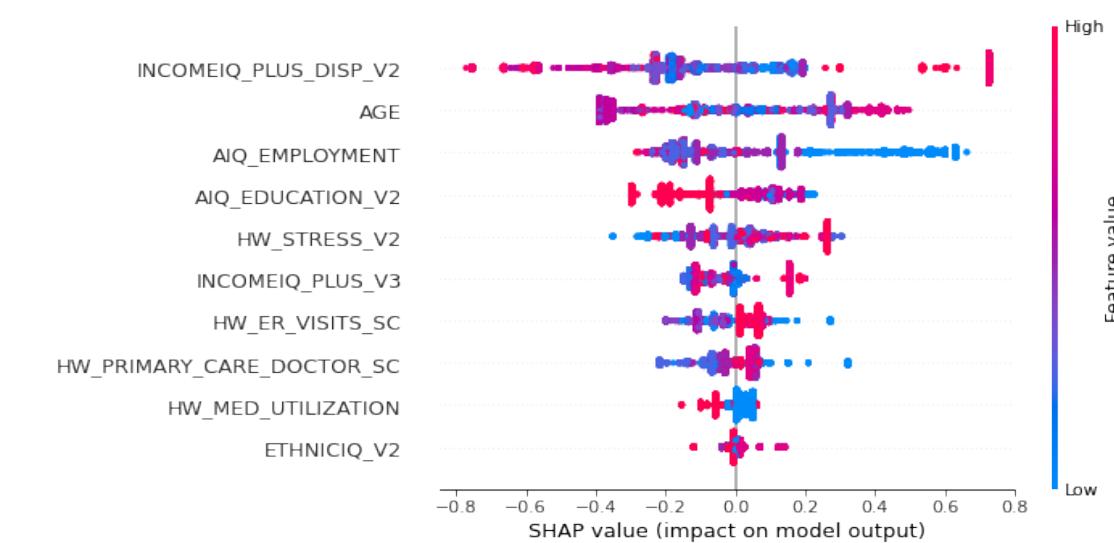
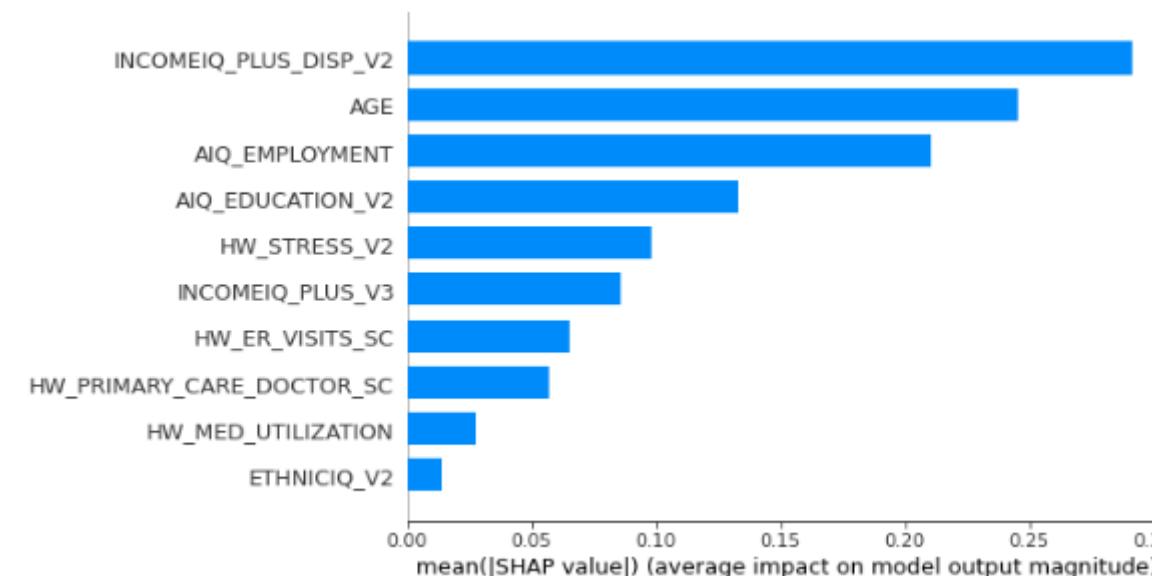


T(IoU)	Model	Atelectasis	Cardiomegaly	Effusion	Infiltration	Mass	Node	Pneumonia	Pneumothorax
0.1	ref.	0.69	0.94	0.66	0.71	0.40	0.14	0.63	0.38
	ours	0.71 ± 0.05	0.98 ± 0.02	0.87 ± 0.03	0.92 ± 0.05	0.71 ± 0.10	0.40 ± 0.10	0.60 ± 0.11	0.63 ± 0.09
0.2	ref.	0.47	0.68	0.45	0.48	0.26	0.05	0.35	0.23
	ours	0.53 ± 0.05	0.97 ± 0.02	0.76 ± 0.04	0.83 ± 0.06	0.59 ± 0.10	0.29 ± 0.10	0.50 ± 0.12	0.51 ± 0.08
0.3	ref.	0.24	0.46	0.30	0.28	0.15	0.04	0.17	0.13
	ours	0.36 ± 0.08	0.94 ± 0.01	0.56 ± 0.04	0.66 ± 0.07	0.45 ± 0.08	0.17 ± 0.10	0.39 ± 0.09	0.44 ± 0.10
0.4	ref.	0.09	0.28	0.20	0.12	0.07	0.01	0.08	0.07
	ours	0.25 ± 0.07	0.88 ± 0.06	0.37 ± 0.06	0.50 ± 0.05	0.33 ± 0.08	0.11 ± 0.02	0.26 ± 0.07	0.29 ± 0.06
0.5	ref.	0.05	0.18	0.11	0.07	0.01	0.01	0.03	0.03
	ours	0.14 ± 0.05	0.84 ± 0.06	0.22 ± 0.06	0.30 ± 0.03	0.22 ± 0.05	0.07 ± 0.01	0.17 ± 0.03	0.19 ± 0.05
0.6	ref.	0.02	0.08	0.05	0.02	0.00	0.01	0.02	0.03
	ours	0.07 ± 0.03	0.73 ± 0.06	0.15 ± 0.06	0.18 ± 0.03	0.16 ± 0.06	0.03 ± 0.03	0.10 ± 0.03	0.12 ± 0.02
0.7	ref.	0.01	0.03	0.02	0.00	0.00	0.00	0.01	0.02
	ours	0.04 ± 0.01	0.52 ± 0.05	0.07 ± 0.03	0.09 ± 0.02	0.11 ± 0.06	0.01 ± 0.00	0.05 ± 0.03	0.05 ± 0.03



<https://arxiv.org/pdf/1711.06373.pdf>

Explainable AI in Health



	Method	Admin. data	Diagnosis	Vital signs	Prescriptions	Notes	3 day window		7 day window		14 day window	
							Accuracy	AUC	Accuracy	AUC	Accuracy	AUC
*	RF (Baseline)	x	x	x	x		0.733 (0.004)	0.750 (0.004)	0.755 (0.010)	0.804 (0.011)	0.863 (0.004)	0.820 (0.011)
1	RNN	x	x	x	x	x	0.749 (0.008)	0.775 (0.005)	0.774 (0.004)	0.831 (0.005)	0.868 (0.002)	0.850 (0.009)
2	RNN	x	x	x	x		0.746 (0.003)	0.768 (0.007)	0.772 (0.006)	0.827 (0.005)	0.867 (0.002)	0.843 (0.011)
3	RNN	x	x	x		x	0.745 (0.008)	0.771 (0.007)	0.773 (0.005)	0.827 (0.008)	0.867 (0.003)	0.851 (0.008)
4	RNN	x	x		x	x	0.740 (0.008)	0.756 (0.006)	0.755 (0.005)	0.796 (0.007)	0.863 (0.004)	0.806 (0.008)
5	RNN	x	x	x			0.750 (0.006)	0.775 (0.007)	0.771 (0.003)	0.824 (0.006)	0.869 (0.002)	0.856 (0.006)



ChatGPT: Clinical Note

- 50 year old female presents after having fallen in the bathtub 4 days ago and hitting the back of her head. Since then she has had a massive headache which did not resolve with Tylenol. She states that she has a high threshold for pain and did not realize how bad it was during the day while at work but then when she got home at night she noticed it. The patient noticed ""silvery specs"" in her vision and she had trouble with some simple tasks like finding the tags on the back of her clothing in the morning. She reported that she had to check several times to make sure she did not put her clothes on backwards. She has had some dizziness, but no nausea or vomiting. Her speech has not been affected.

ChatGPT: Clinical Note



A 50-year-old female had a fall in the bathtub four days ago and hit the back of her head. She has been experiencing a severe headache that did not improve with Tylenol. The patient has noticed some changes in her vision and difficulty with simple tasks, such as finding the tags on her clothing. She also reported some dizziness, but no nausea or vomiting. Her speech has not been affected.

To laymen



A woman fell in the bathtub and hit her head. Since then, she has a big headache that won't go away, even after taking medicine. She is also seeing things differently, like sparkly specks, and having trouble with easy tasks, like putting on her clothes the right way. She feels dizzy sometimes, but she is not throwing up or having trouble talking.

To a five year old

ChatGPT: Clinical Note

Y

can you extract SNoMED CT terms from this note



I'm sorry, but I cannot extract SNOMED CT terms from the medical note you provided.

SNOMED CT is a clinical terminology that provides a standardized way of representing health information, and requires specific training and tools to extract relevant terms.

Additionally, the note you provided is not detailed enough to identify specific SNOMED CT codes.

Y

is headache a snomed CT term



Yes, "headache" is a term that is included in the SNOMED CT terminology. In SNOMED CT, the concept of "headache" is represented by the code "25064002". This code can be used to describe a patient's headache symptoms, location, intensity, and duration, and to support the documentation of a diagnosis. ED CT provides a standardized vocabulary that can help improve the accuracy, consistency, and interoperability of health

Regenerate response

ChatGPT for Healthcare

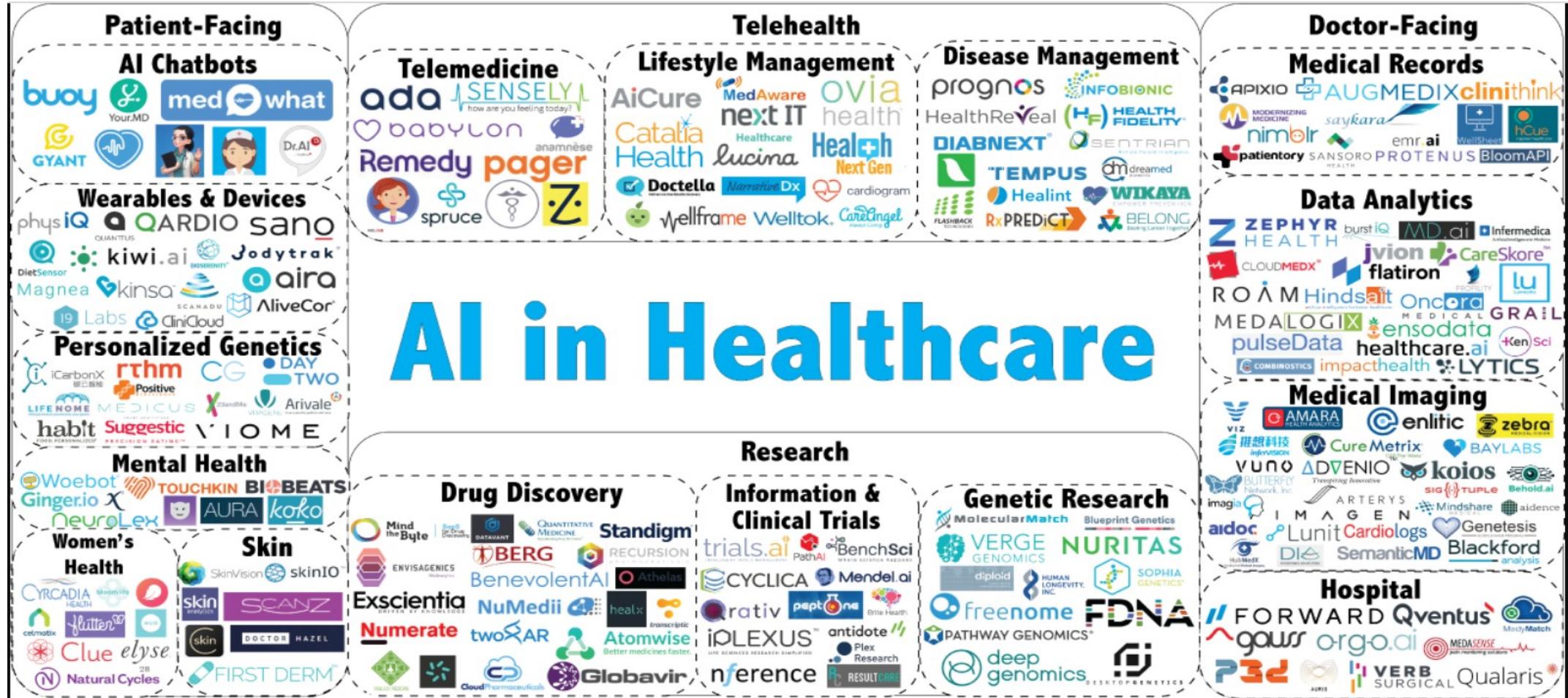
ChatGPT can play a valuable role in healthcare in several ways:

1. Medical Information and Education: ChatGPT can provide accurate and up-to-date information about medical conditions, symptoms, treatment options, medications, and more. It can help answer questions from patients, caregivers, or even healthcare professionals seeking quick references.
2. Symptom Checker and Triage: ChatGPT can assist in triaging patients by asking relevant questions about their symptoms and providing initial assessments. While it cannot replace a doctor's diagnosis, it can offer general guidance and suggest appropriate next steps, such as seeking urgent care or scheduling a non-emergency appointment.
3. Mental Health Support: ChatGPT can offer support for mental health concerns by providing general information about common conditions, coping strategies, and self-care practices. It can also act as a listening ear and offer emotional support by engaging in conversations that promote empathy and understanding.

4. Health Monitoring and Tracking: ChatGPT can integrate with health monitoring devices and apps to help users track their health metrics, interpret results, and provide personalized insights. It can remind users to take medication, monitor their progress, and offer tips for maintaining a healthy lifestyle.
5. Healthcare Workflow Assistance: ChatGPT can assist healthcare professionals by automating administrative tasks, such as scheduling appointments, updating patient records, and answering routine inquiries. This can save time and allow healthcare providers to focus on patient care.
6. Health Promotion and Patient Education: ChatGPT can engage in conversations that promote healthy behaviors, encourage preventive care, and educate patients about lifestyle choices that can improve their overall well-being. It can provide personalized recommendations based on individual health profiles and preferences.
7. Language Assistance and Translation: ChatGPT can bridge language barriers by offering translation services to facilitate communication between patients and healthcare providers. It can also assist in generating patient education materials or translating medical documents into different languages.

It's important to note that while ChatGPT can provide valuable information and support, it is not a substitute for professional medical advice. In cases of medical emergencies or complex conditions, it's crucial to consult with qualified healthcare professionals.

AI in Health Competitive Ecosystem

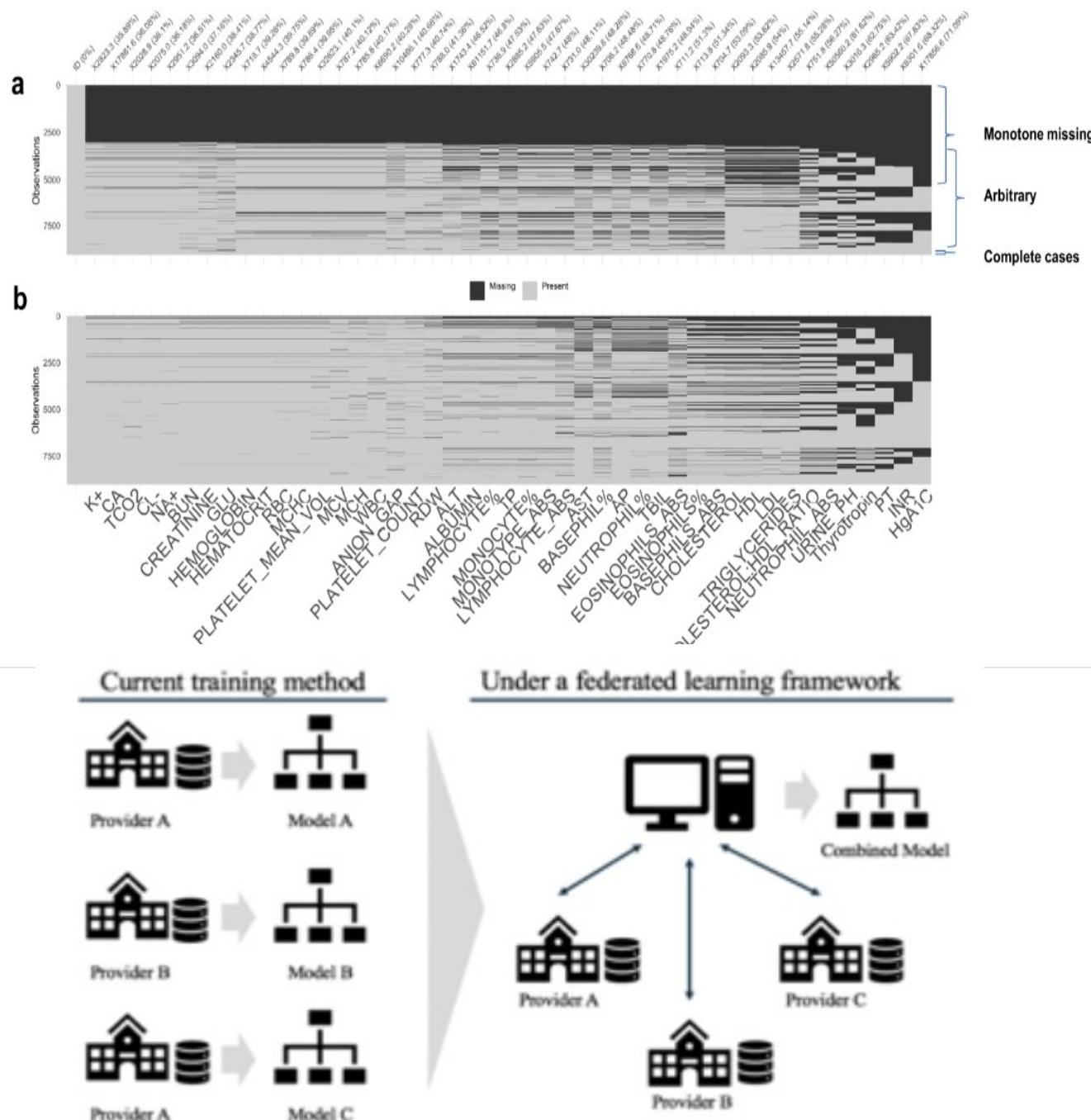


- Expertise, wisdom, human attitude, care, empathy, mutual understanding, and support lie at the very base of the medical profession and cannot be automated.

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

Challenges

- Missing Data: Data Imputation, VAE
 - Data Distribution Shift: Fairness AI
 - Sharing data: Federated Learning
 - Lack of labelled data as training datasets: transfer learning
 - Data imbalance: Few-shot learning, contrastive learning





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