Artificial Intelligence in Medicine

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John McCarthy, Dartmouth, 1956:

"...every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it."

1. Build systems that think exactly like humans do ("strong AI")

2. Just get systems to work without figuring out how human reasoning works ("weak AI")

3. Use human reasoning as a model but not necessarily the end goal

Encyclopedia Britannica:

"the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings"

Amazon: the field of computer science dedicated to solving cognitive problems commonly associated with human intelligence, such as learning, problem solving, and pattern recognition

Machine learning is required

IDx-DR AI diagnostics

Designed to detect severe diabetic retinopathy

AI algorithm analyzes retinal images

Images uploaded to a cloud server

Delivers a positive or negative result

First device that doesn't need physician interpretation



FDA approves AI-powered diagnostic that doesn't need a doctor's help

Viz LVO diagnostic Al

Designed to detect stroke

AI algorithm analyzes CT scan brain images

Automatically notifies a neurologic specialist

Involve specialists sooner than normally possible

Notification by cellphone



Al in dermatology

Several products directed at the consumer level

Diagnosis of skin lesions by smartphone photo/app

AI driven chatbot makes recommendations about skin products

May be driven in part by human advisors







Stanford CheXNet

Deep AI machine learning

Detect 14 lung conditions based on chest x-ray

Outperformed human radiologic interpretation

Learning based on dataset of >100,000 chest x-rays



Input Chest X-Ray Image

CheXNet 121-layer CNN

Output Pneumonia Positive (85%)



















3.37



What's the "cost" of this difference?



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Propagate backwards









From: Grant Sanderson, 3blue1brown website: https://www.3blue1brown.com and Neural Networks and Deep Learning (online book) by Michael Nielsen

	え	5	0	Ч		9	Avera all train	age over ning data
w_0	-0.08	+0.02	-0.02	+0.11	-0.05	-0.14	••••	-0.08
w_1	-0.11	+0.11	+0.07	+0.02	+0.09	+0.05	••• →	+0.12
w_2	-0.07	-0.04	-0.01	+0.02	+0.13	-0.15	••••	-0.06
•	•	•	•	•	•	•	·	÷
$w_{13,001}$	+0.13	+0.08	-0.06	-0.09	-0.02	+0.04	••••	+0.04

The limit of the universe is the output

Nothing in the universe is not the output

Any input can produce any programmed output



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Nothing in the universe is not the output

Any input can produce any programmed output



More artificial than intelligent?

"Deep learning" - over a hundred neural net levels

What are all those levels doing? Even the engineers don't know

Will the network always make the right call? MIT Technology Review

Intelligent Machines

The Dark Secret at the Heart of AI

No one really knows how the most advanced algorithms do what they do. That could be a problem.

by Will Knight April 11, 2017

Is there any way to have oversight?





adversarial example

Non-Targeted "5"



 $\langle \rangle$

The left side is the non-targeted adversarial exampele (a 28 X 28 pixel image). The right side plots the activations of the network when given the image.

Source: Machine Learning at Berkeley blog

adversarial example

Targeted "6" [x_target=2]



The left side is the targeted adversarial example (a 28 X 28 pixel image). The right side plots the activations of the network when given the image.

Source: Machine Learning at Berkeley blog



"I keep sounding the alarm bell but until people see robots going down the street killing people, they don't know how to react because it seems so ethereal." - Elon Musk



 Core public agencies, such as those responsible for criminal justice, healthcare, welfare, and education (e.g "high stakes" domains) should no longer use "black box" Al and algorithmic systems. This includes the unreviewed or unvalidated use of pre-trained models, AI systems licensed from third party vendors, and algorithmic processes created in-house. The use of such systems by public agencies raises serious due process concerns, and at a minimum they should be available for public auditing, testing, and review, and subject to accountability standards. Genomics, drug discovery, oncology

Oncology – lots of data and treatments



Watson – "reads" literature, protocols, patient charts

Treatment plans concordant with tumor board 93% of breast cancer cases



Let's tall

Oncology and Genomics

Bringing confident decisionmaking to oncology

Provide evidence-backed cancer care to each patient, by understanding millions of data points

Some published studies are erroneous

Some published studies cannot be reproduced

Some published studies are fraudulent

Algorithms can be taught to make biased decisions

Frequent auditing will probably be needed

AI Treatment



MD Anderson fallout: \$39M loss

Requires costly, wellorganized data input

Data input requires lots of time and labor

Can only draw conclusions on the data it is trained on

No recent system updates





Let's talk

Oncology and Genomics

Bringing confident decisionmaking to oncology

Provide evidence-backed cancer care to each patient, by understanding millions of data points

"Human intelligence outperforms machinelearning applications in complex decision making routinely required during the course of care, because machines do not yet possess mature capabilities for perceiving, reasoning, or explaining."

HealthAffairs

TOPICS JOURNAL BLOG

INNOVATIONS IN CARE DELIVERY

Four Lessons In The Adoption Of Machine Learning In Health Care

Ernest Sohn, Joachim Roski, Steven Escaravage, Kevin Maloy

MAY 9, 2017

HEALTH AFFAIRS BLOG

10.1377/hblog20170509.059985



"... machine learning can be effectively deployed today to reduce more routine, time-consuming, and resource-intensive tasks, allowing freedup personnel to be redeployed to support higher-end work."



HEALTH AFFAIRS BLOG

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AI embedded in workplace messaging system

Prompts managers to solicit feedback from workers stress level

Suggests reading material

IBM Watson Tone Analyzer

Analyzes emails for negative language



Features



Physician burnout is skyrocketing

EMRs don't help

Solution? Digital scribes!

Fill out the EMR through voice recognition

Suggest diagnoses

Health How Tech Has Undermined—and May Now Save—the Doctor-Patient Relationship



Educational tool

AI software with voice recognition

Simplifies patient note preparation

Shares note to the cloud

Allows MD more face time with patients

Interacts with EMR for orders, lab trends



Al software

Gets an email account and EMR sign-in

Checks patient insurance eligibility against online portals

Reduced insurance denials

Reduced days in AR

Scheduling, orders, patient engagement



Geared toward Medicare Advantage

Al identification of diagnosis codes from patient chart

PDF, EMR, scanned files

Improve risk adjustment and reimbursement



Research?





Conclusions

Powerful technology

Existent or likely:

diagnostics digital scribes chart mining call centers treatment design **Too early:** complex clinical decision making

BUSINESS 02.01.18 09:22 AM

THE WIRED GUIDE TO ARTIFICIAL INTELLIGENCE

Supersmart algorithms won't take all the jobs, but they are learning faster than ever, doing everything from medical diagnostics to serving up ads.

BY TOM SIMONITE

ARTIFICIAL INTELLIGENCE IS overhyped—there, we said it. It's also incredibly important.