Course introduction: why machine learning in healthcare?

BIODS388/BIOMED388

Matthew Lungren MD MPH

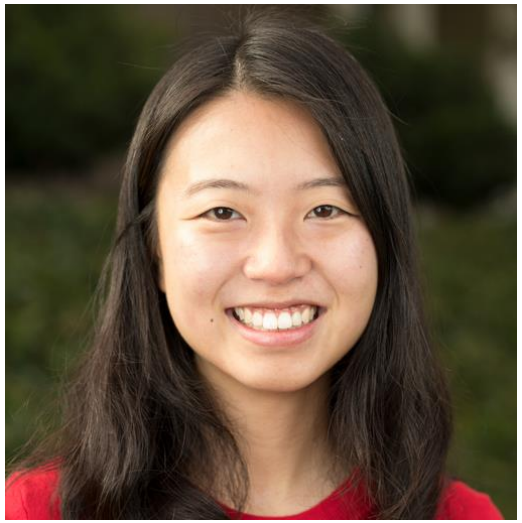
9/17/2020

Agenda

- Who we are
- Who you are
- Course syllabus
- Assignments
- Walkthrough
- Questions
- Why machine learning in healthcare?

Who we are

Matt Lungren MD MPH



Serena Yeung PhD

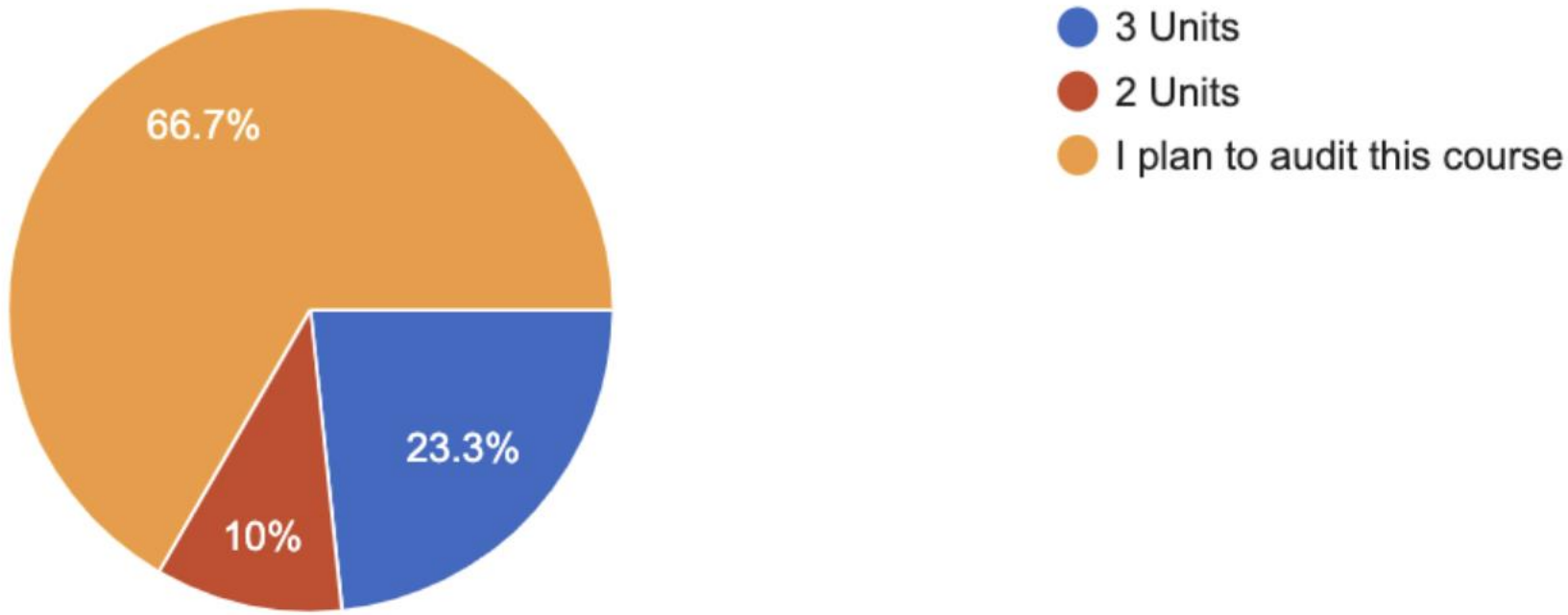
Anuj Pareek MD

Mars Huang MS

Who you are

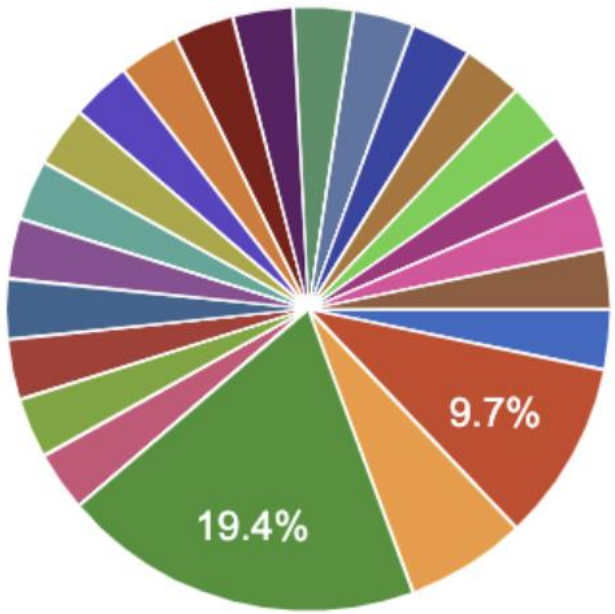
How many units do you plan to take this course for? (for more information, refer to Logistics - Grading: http://web.stanford.edu/class/biods388/logistics.html)

30 responses



What is your degree program? *

31 responses

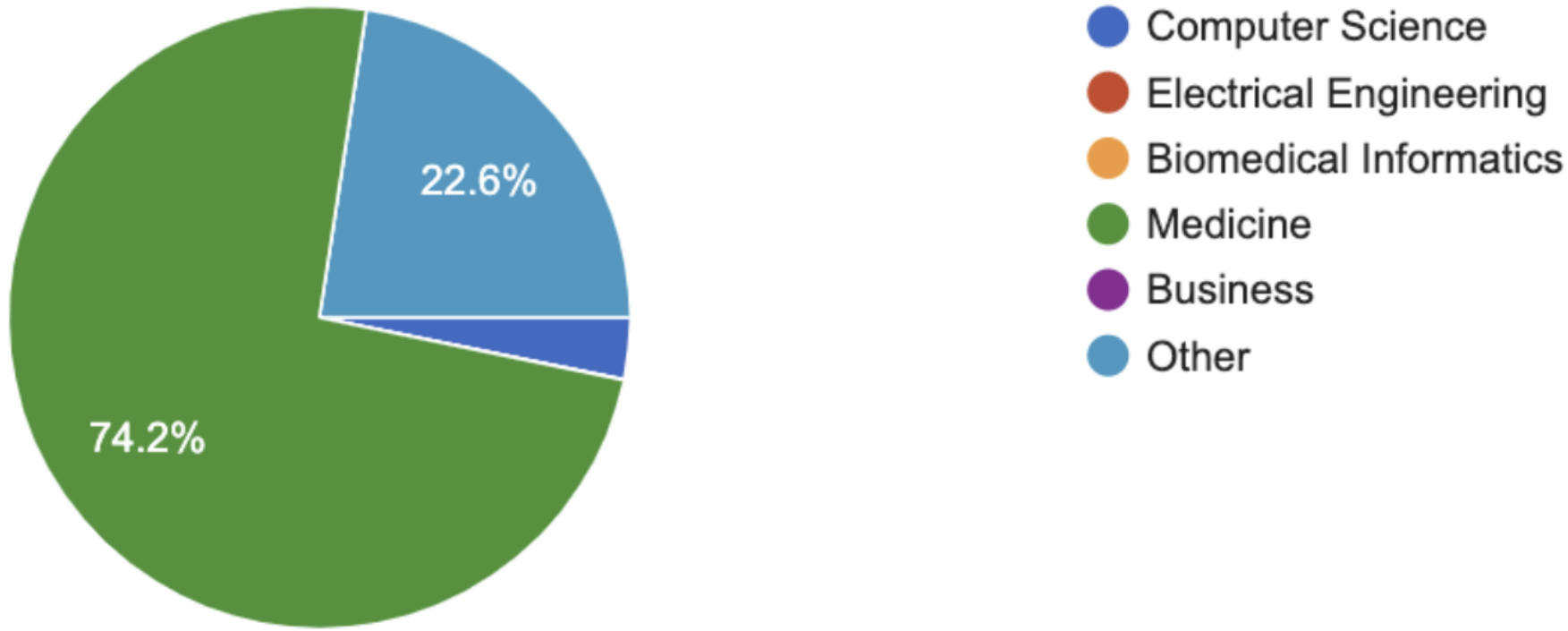


Undergraduate
Masters
PhD
MD
MBA
JD
none
Research Scholar in Biomedical Scien…

1/4

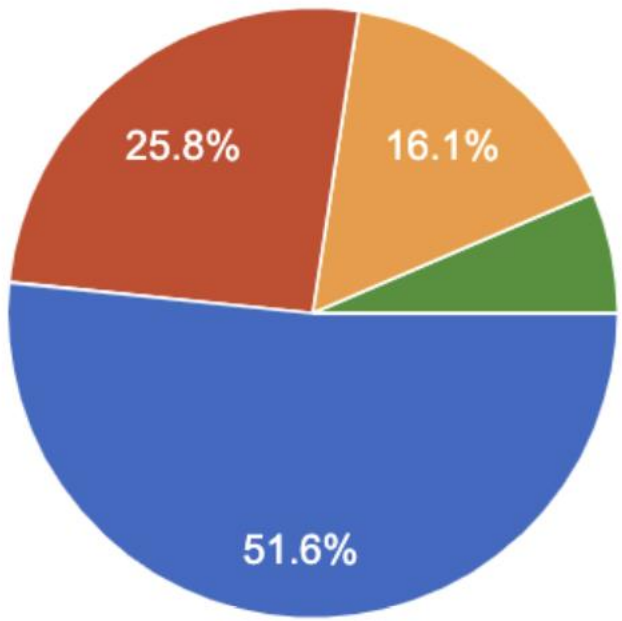
What is your department?

31 responses



How would you describe your background in deep learning?

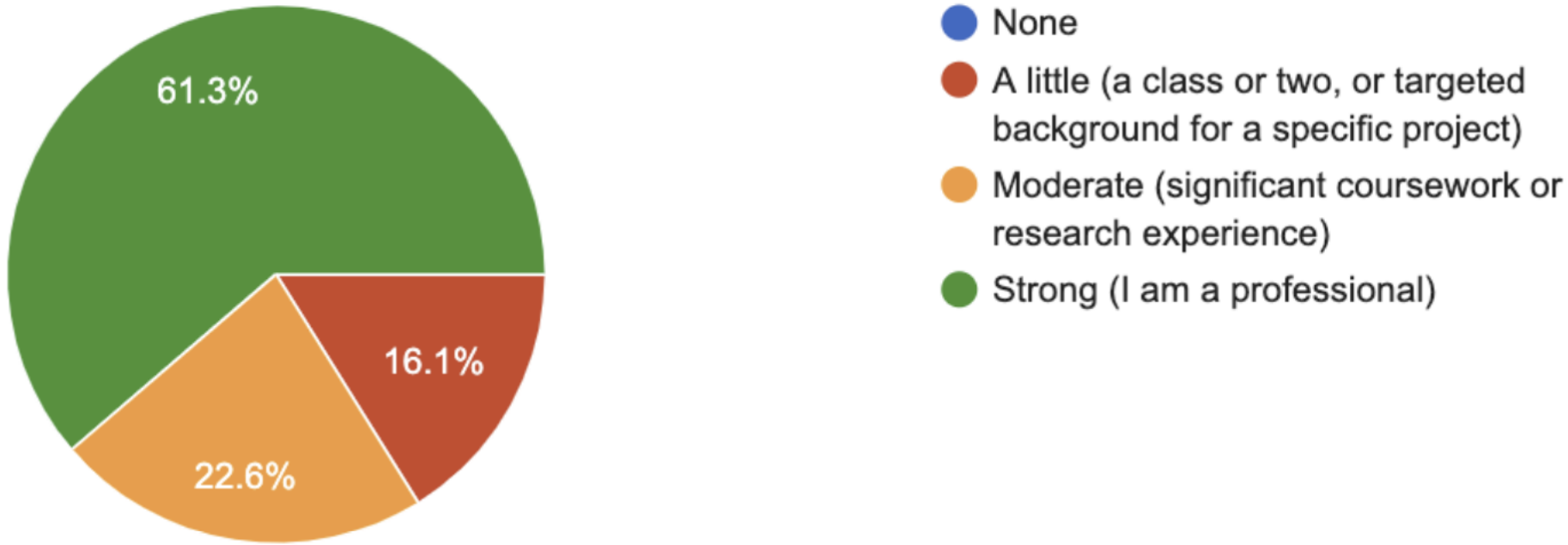
31 responses



- None -- no experience in machine learning or deep learning
- A little (have trained a deep learning / machine learning model before)
- Moderate (am comfortable with using deep learning)
- Strong (deep knowledge of cutting edge and/or research experience)

How would you describe your background in Medicine/Biology/Biomedicine?

31 responses



Assignments

2 credit

- Reflections 20%
  - 10 classes = 8 reflections (drop 2 lowest grades)
- Scientific paper review 1: 40%
- Scientific paper review 2: 40%

3 Credit

- Reflections 20%
  - 10 classes = 8 reflections (drop 2 lowest grades)
- Scientific paper review 1: **20%**
- *Research paper for clinical journal (in collaboration with BIODS 220 engineering students): **60%**

Logistics

- Yes there are **four** websites – welcome to the future ☺
  1. Course website: **BIODS388.stanford.edu**
  2. Piazza: for **office hours with TAs, discussions**, and announcements
  3. Canvas: **mainly for zoom link**s to class and announcements
  4. Gradescope: for turning in / grading **assignments**

Live Walkthrough Course Websites and How to Navigate

15 second Classmate Introductions (on Piazza)

1. Your name
2. Your day job/major
3. Home town
4. Why you are taking this course
5. You **have to** sing karaoke. What song do you pick?
6. What is your absolute dream job?

Questions

Why Machine Learning In Healthcare

The NEW ENGLAND JOURNAL of MEDICINE

SPECIAL ARTICLE

MEDICINE AND THE COMPUTER

The Promise and Problems of Change

WILLIAM B. SCHWARTZ, M.D.*

Abstract Rapid advances in the information sciences, coupled with the political commitment to broad extensions of health care, promise to bring about basic changes in the structure of medical practice. Computing science will probably exert its major effects by augmenting and, in some cases, largely replacing the intellectual functions of the physician. As the "intellectual" use of the computer

care, it will also inevitably exact important social costs — psychologic, organizational, legal, economic and technical. Only through consideration of such potential costs will it be possible to introduce the new technology in an effective and acceptable manner. To accomplish this goal will require new interactions among medicine, the information sciences and the management sciences, and the de-

"Computing Science will probably exert its major effects by augmenting and in some cases largely replacing the intellectual functions of the physician"

foundly change the nature of medical manpower recruitment and medical education — in short, the possibility that the health-care system by the year 2000 will be basically different from what it is today. This article explores that possibility and exam-

nities. Even less do they give hope of dealing with the difficult challenge of maintaining a high level of physician competence in the face of a continued expansion of medical knowledge that tends to widen progressively the gap between what a doctor

"…address fundamental problems of the healthcare system - the increasing shortage of physicians …"

velopments in the area of "housekeeping" activities offer considerable hope for the improvement of both

of medical care and efforts to enlarge medical-school capacity and create new classes of "doctor's assistants," the physician shortage promises to be with us for decades and to pose a serious obstacle

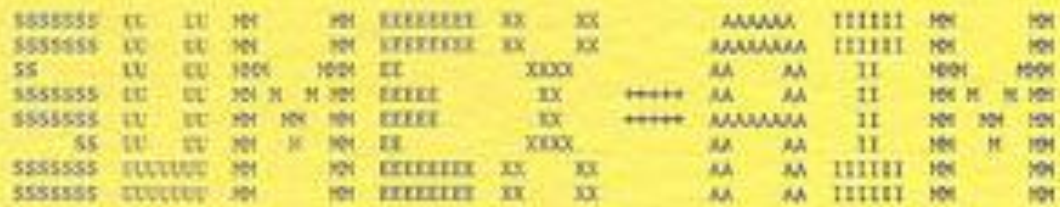
*From the Department of Medicine, Tufts University School of Medicine, and the Medical Service of the New England Medical Center Hospitals (address reprint requests to D

Dec. 3, 1970

Harry Truman

33rd president of the US

> The only thing that's new in the world is the history you don't know



SUMEX-AIM* DEDICATION
November 14, 1974
Stanford University

February

25 Cents

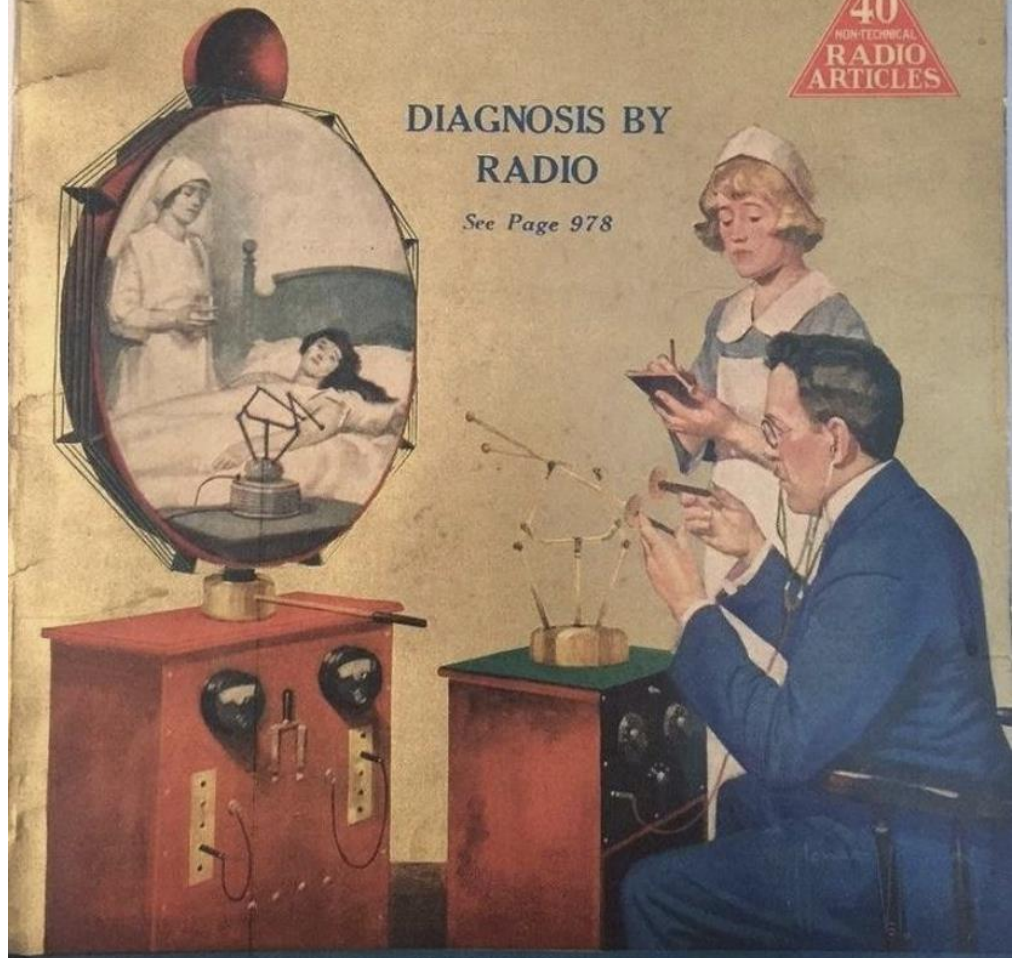
Science and Invention

IN PICTURES

40 NON-TECHNICAL RADIO ARTICLES

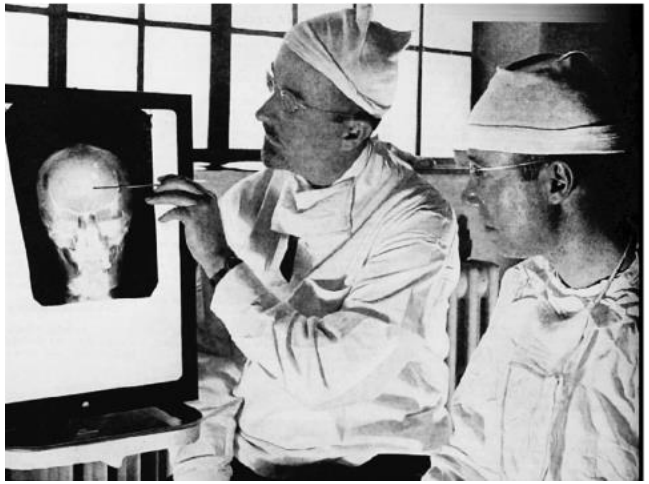
DIAGNOSIS BY RADIO

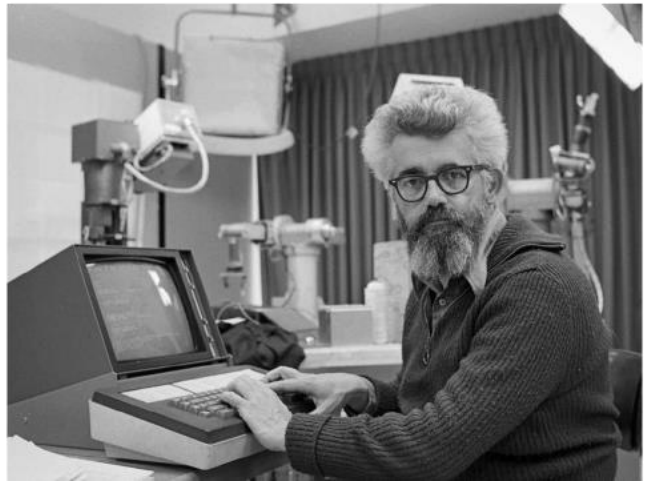
See Page 978



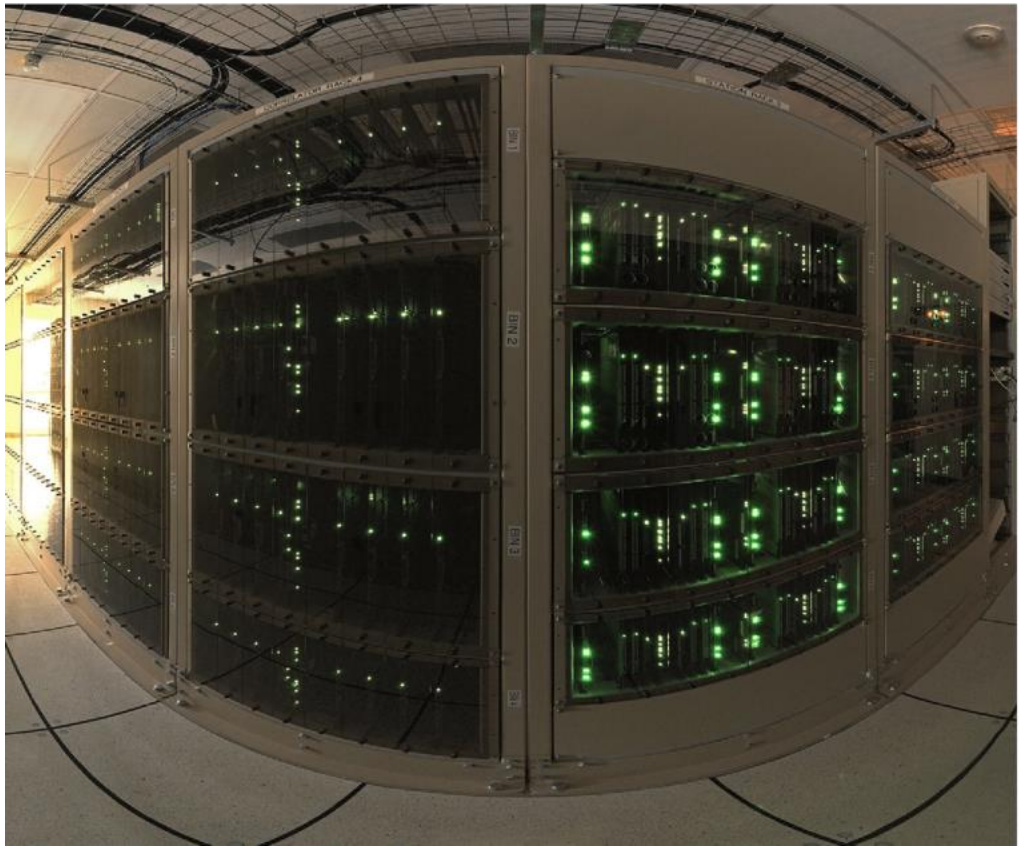
EXPERIMENTER PUBLISHING COMPANY, NEW YORK, PUBLISHERS OF
RADIO NEWS - SCIENCE & INVENTION - THE EXPERIMENTER - MOTOR CAMPER & TOURIST


IBM
Data Processing
Division



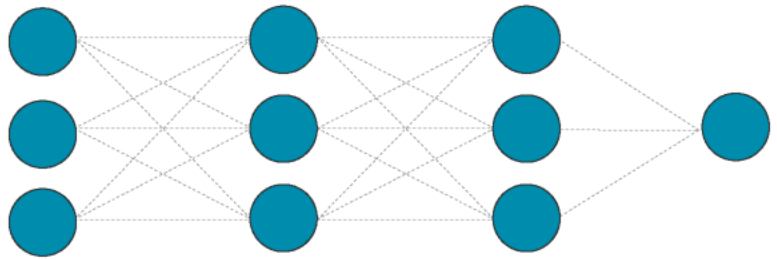



CONTROL DATA
6600



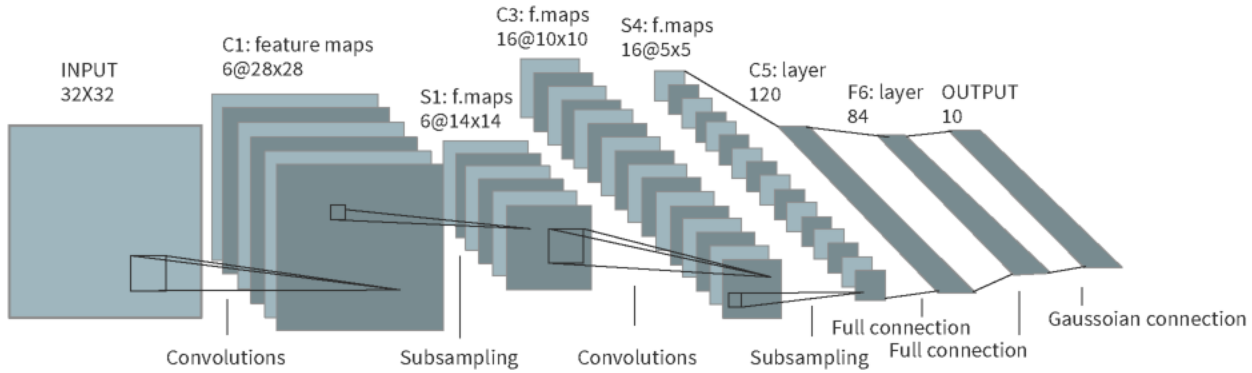

OAK RIDGE
National Laboratory
IBM
summit

MAJOR CLASSES OF NEURAL NETWORK ARCHITECTURES



Fully connected neural networks

(fully connected layers, good for structured data inputs)

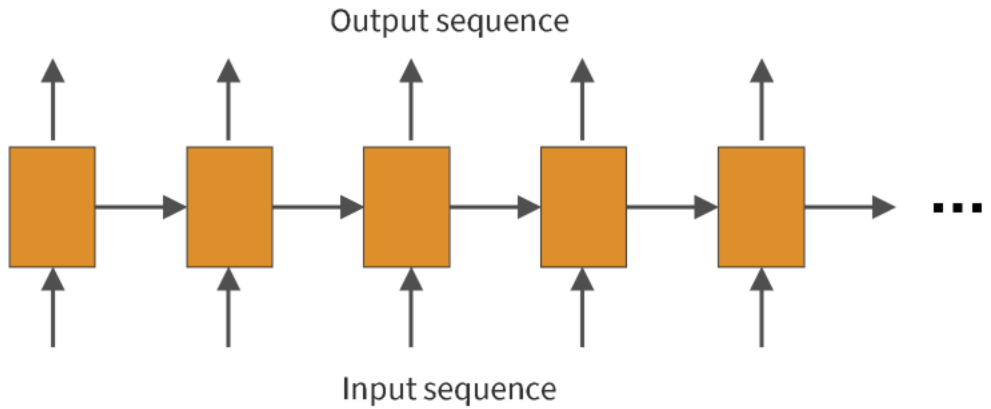


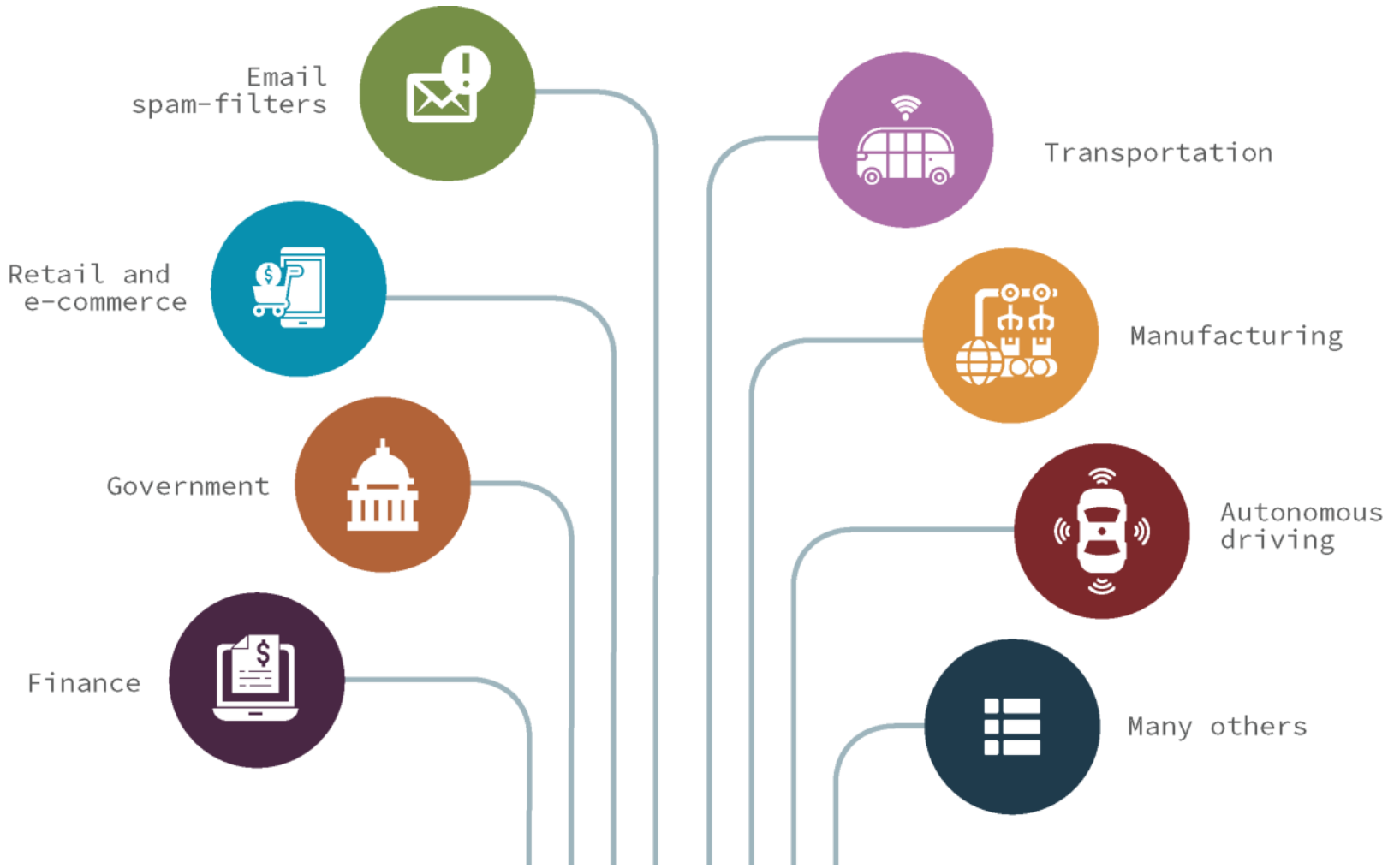
Convolutional neural networks

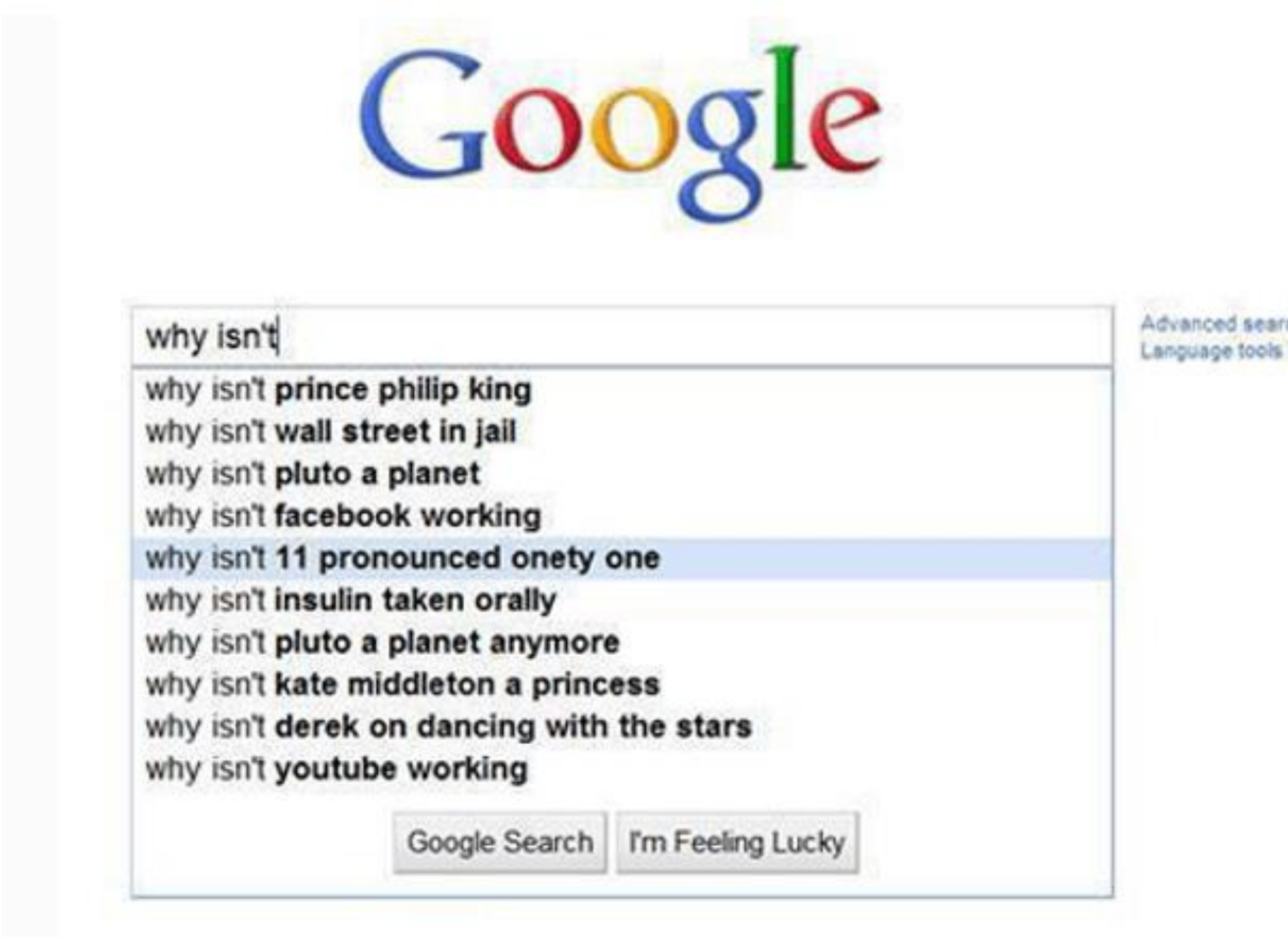
(convolutional layers, good for image inputs)

Recurrent neural networks

(fully connected layers modeling recurrence relation across sequence, good for sequence inputs)




Email
spam-filters
Retail and
e-commerce
Government
Finance
Transportation
Manufacturing
Autonomous
driving
Many others


Google
why isn't
why isn't prince philip king
why isn't wall street in jail
why isn't pluto a planet
why isn't facebook working
why isn't 11 pronounced onety one
why isn't insulin taken orally
why isn't pluto a planet anymore
why isn't kate middleton a princess
why isn't derek on dancing with the stars
why isn't youtube working
Google Search
I'm Feeling Lucky
Advanced search
Language tools


@teenybiscuit

PRACTICALLY LIMITLESS APPLICATIONS

screening and diagnosis

adaptive clinical trials

operations research

global health

precision medicine

home health and wearables

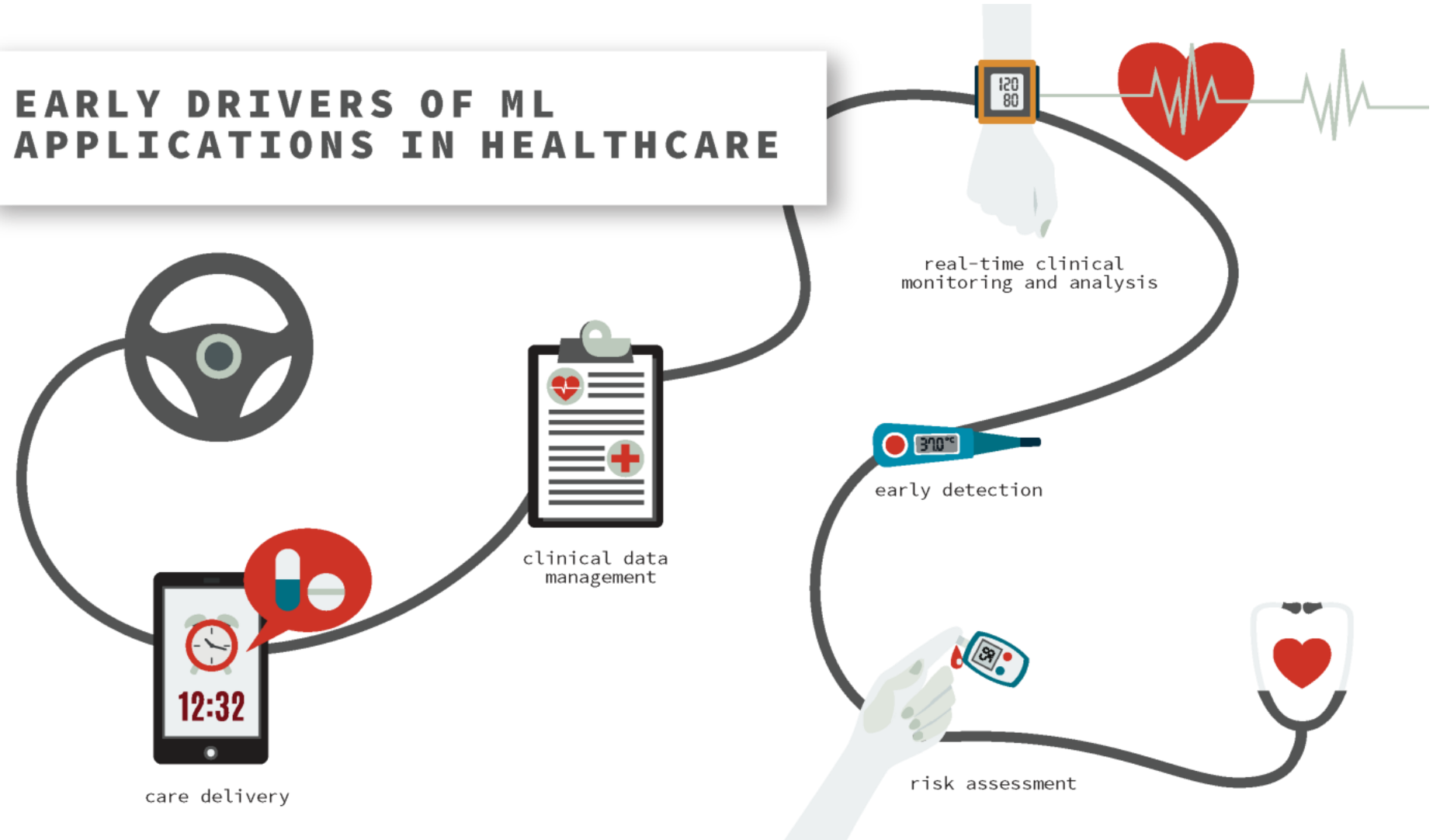
genomic analysis

drug discovery and design

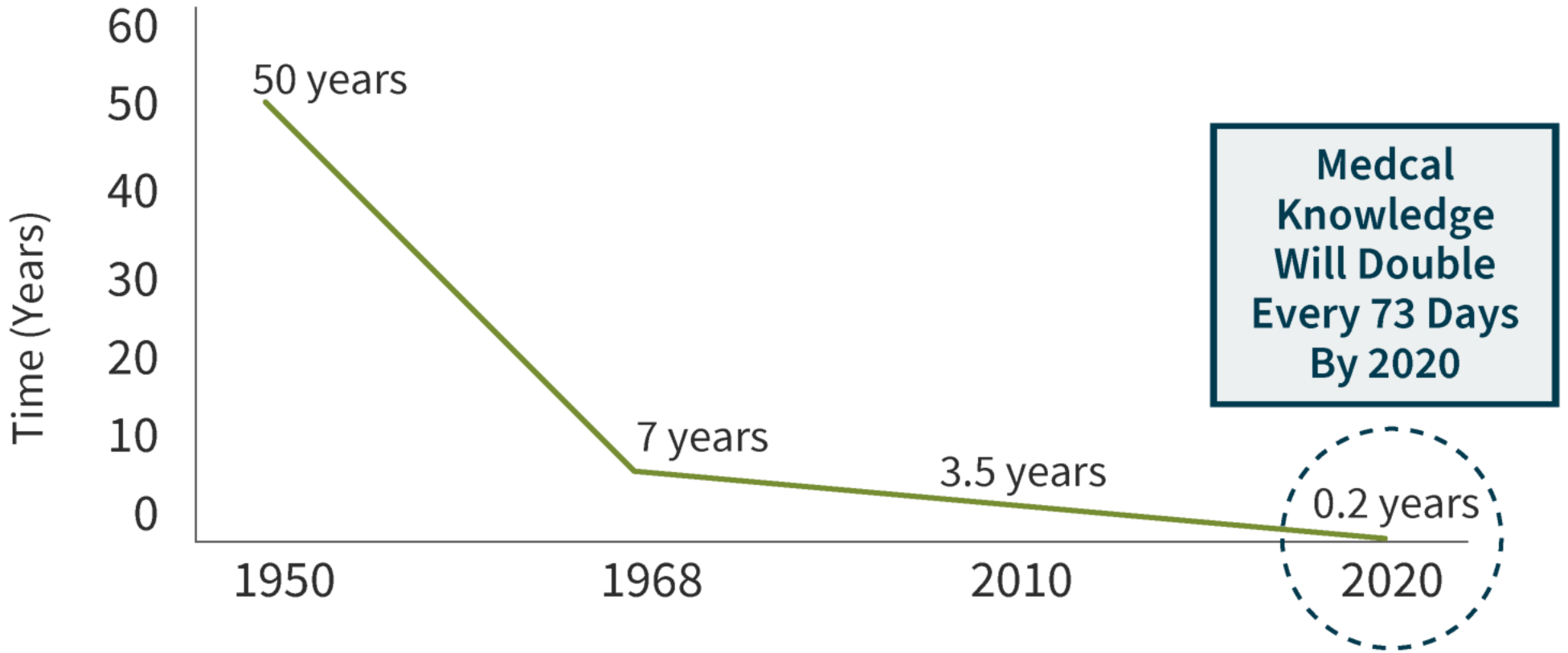
robotics

and many many more.

EARLY DRIVERS OF ML APPLICATIONS IN HEALTHCARE

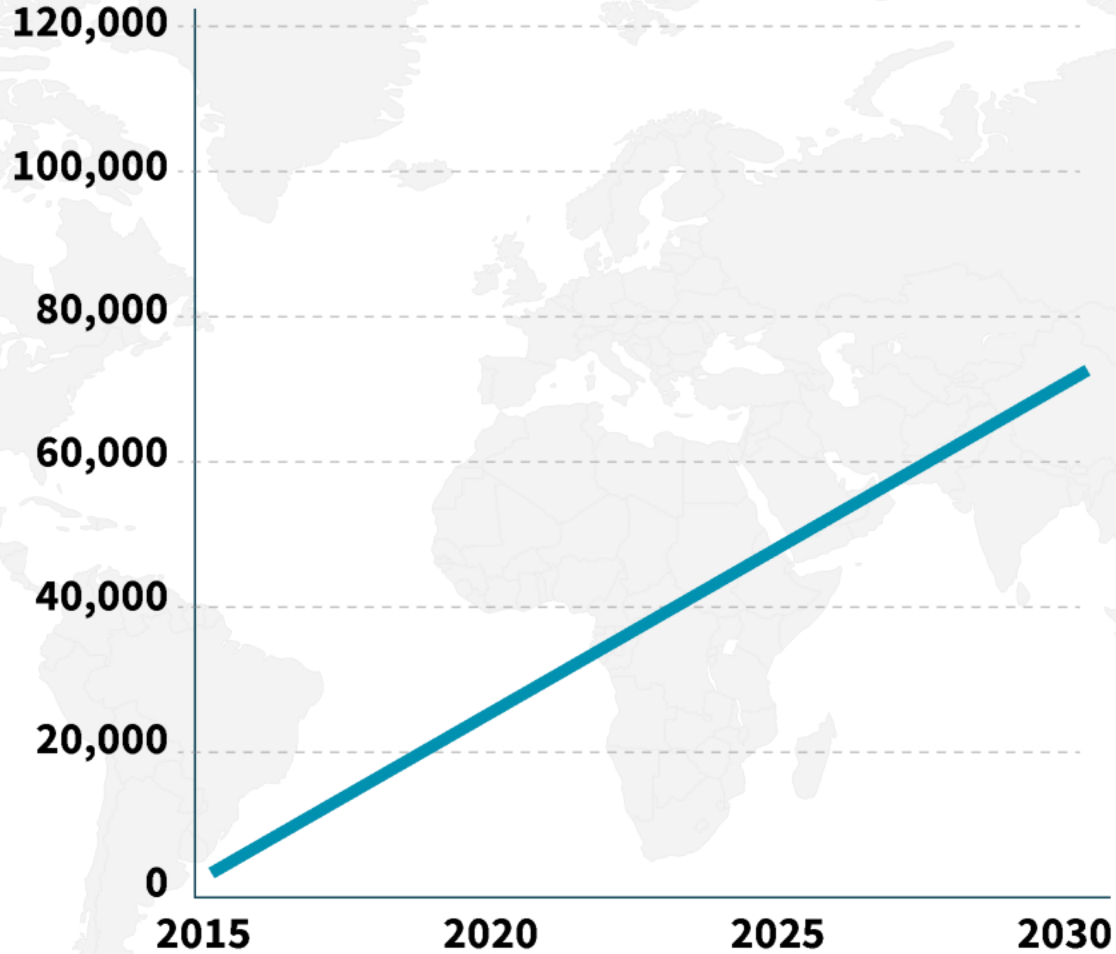


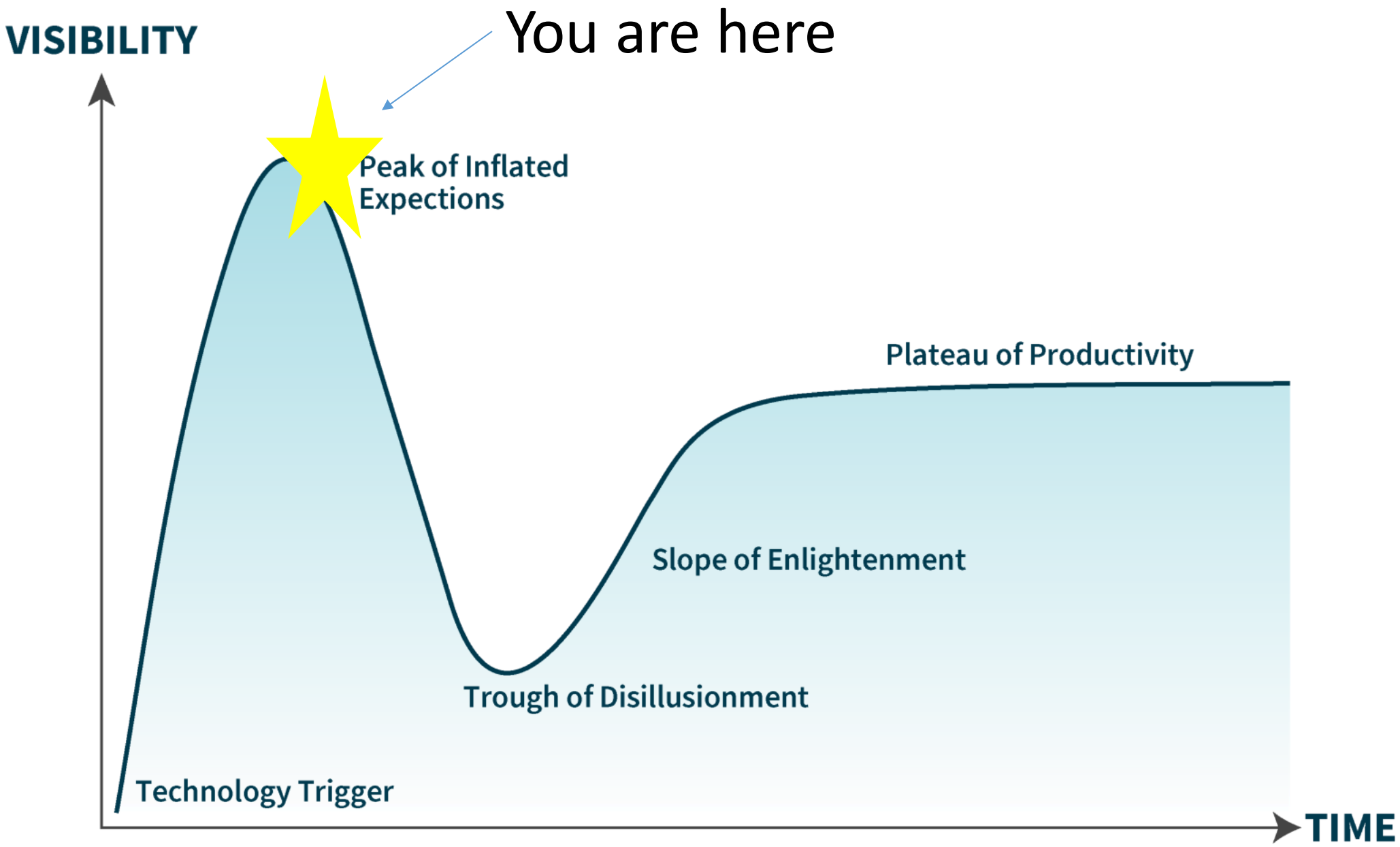
TIME TO DOUBLE MEDICAL KNOWLEDGE IS DECREASING



Graphic source, NCBI, “Challenges and opportunities facing medical eduction”
Peter Densen, MD,2011

PROJECTED PHYSICIAN SHORTFALL




You are here
VISIBILITY
Peak of Inflated Expections
Plateau of Productivity
Slope of Enlightenment
Trough of Disillusionment
Technology Trigger
TIME


SMART REPORTING
Therapixel
Medexprim
商汤 sensetime
median
OSIMIS
QLARITY IMAGING
image biopsy lab
12sigma TECHNOLOGIES
CuraCloud
enlitic
QMENTA
PaxeraHealth
qure.ai
SENO MEDICAL INSTRUMENTS INC.
quibim
zebra
ai analysis inc.
Blackford
CureMetrix
JLK INSPECTION
WEKA.IO
teraRecon
VAREX IMAGING
ADVANTIS MEDICAL IMAGING
ANYMEDI
BOLD BRAIN VENTURES
FLYWHEEL
INTELLIGENT ULTRASOUND
PHILIPS Healthcare
CORTECHS Labs
Better insight through quantitative imaging.
DNP Dai Nippon Printing Co.,Ltd.
VARIAN
imbio
PVmed
Sorna
aidence human sense in artificial intelligence
CAIDE Systems
DDH
TOMTEC
Perspectum Diagnostics
SUBTLE MEDICA
aidoc
Cercare Medical
DEEP VOXEL
Yitu Healthcare 依图医疗
INCEPTO
Quantib
AIRS
circle CARDIOVASCULAR IMAGING
viz.ai
FOVIA
inferVISION
DEEP NOID
Google Cloud Platform
KHEIRON MEDICAL TECHNOLOGIES
Rad AI
ONEMEDNET
DIA IMAGING ANALYSIS
COGNEX
GE Healthcare
koios
OXIPIT
PURESTORAGE
VUNO
ARTERYS
BAYER
HEALTHMYNE
MEDICVision IMAGING SOLUTIONS
RADLogics
iCAD
DeepRadiology
COMBINOSTICS
VIDA
DeepTek
BioMind
onyx
SOPHiA
BALZANO ARTIFICIAL INTELLIGENCE ENGINEERS
contextflow
densitas
IBM Watson
mirada
RADIOBOTICS
数坤科技 SHUKUN
Fraunhofer MEVIS
icometrix IMAGING BIOMARKER EXPERTS
macadamian
COLLECTIVE MINDS RADIOLOGY
深睿医疗 deepwise
Lunit
mim SOFTWARE
NUANCE

Arthur C. Clarke

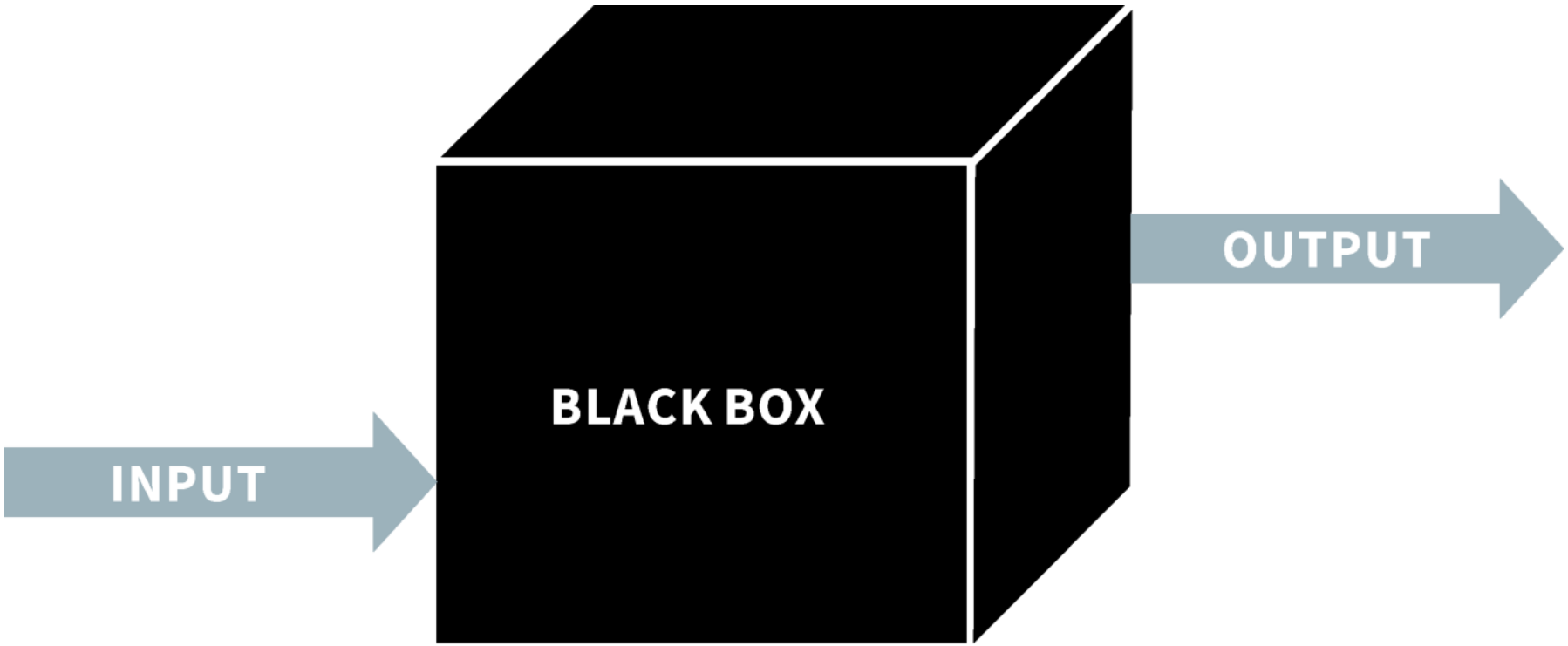
Professional Fiction Writer

> Any sufficiently advanced technology is indistinguishable from magic.

INPUT

OUTPUT

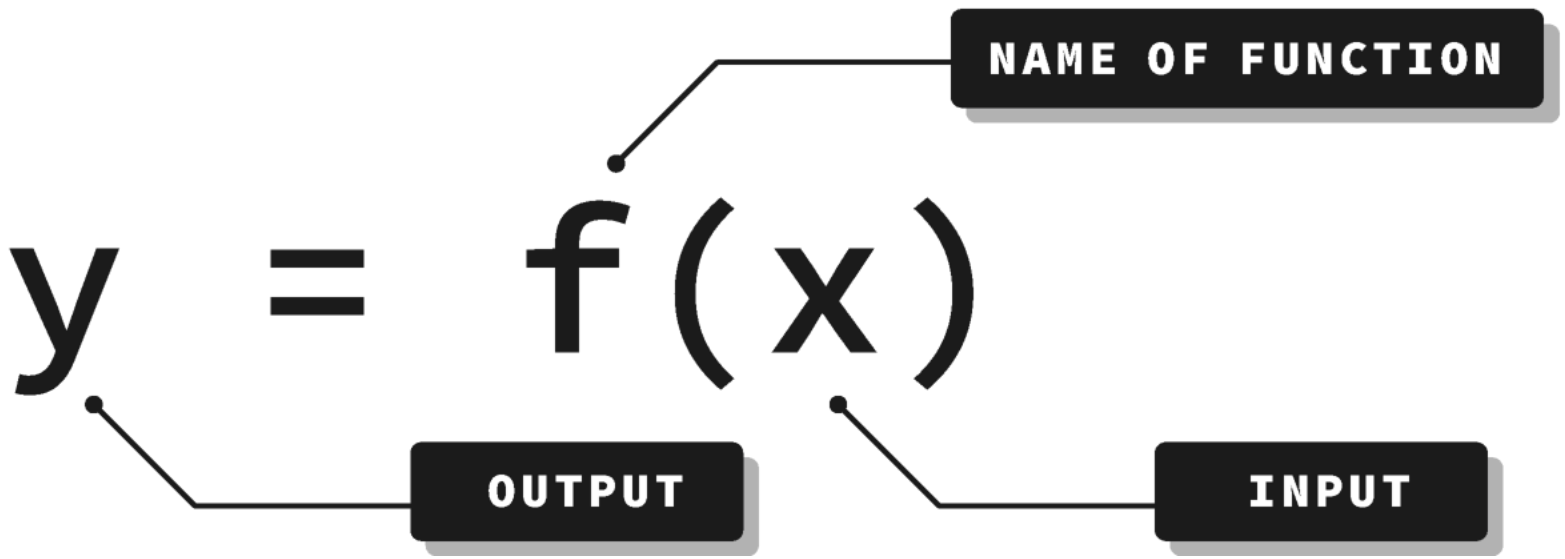
The “function value”



Internal behavior of the code is unknown

function

SOME CALCULATIONS



Processing

INPUT

Function

OUTPUT

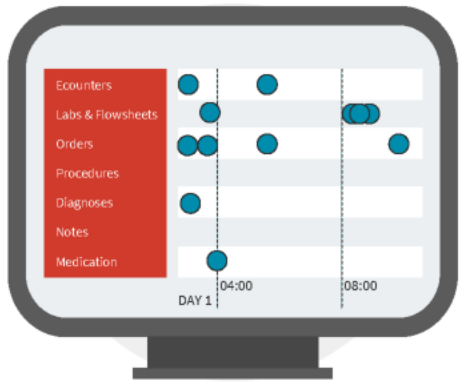
X

Function
square
input

Y

Function
visually
analyze
input

ST elevation myocardial infarction (heart attack)



Electronic health record data

Learned Function

Mortality, readmission, diagnosis labels

Chest radiographs

Learned Function

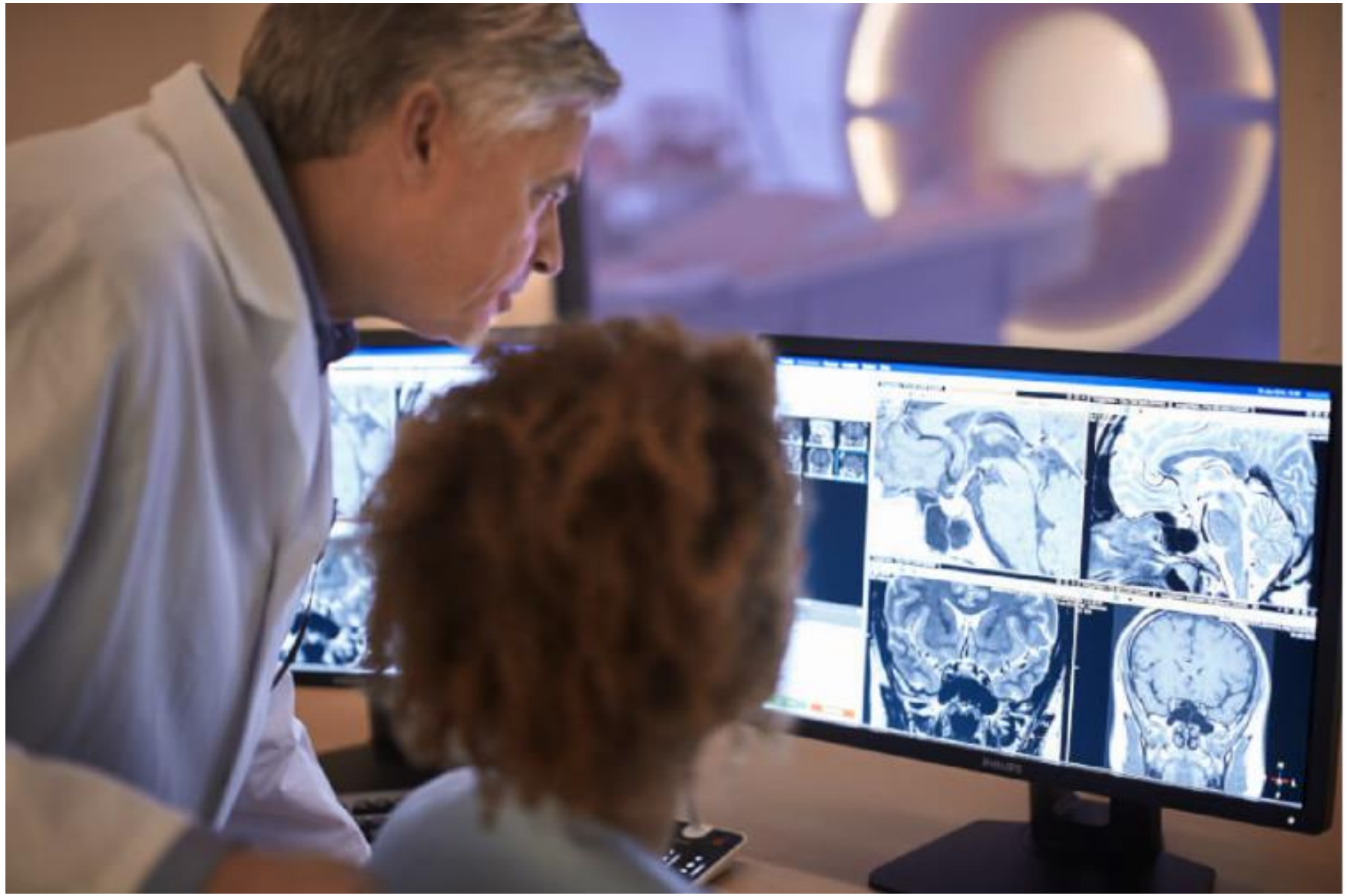
Presence of 14 conditions

HEALTHCARE ECOSYSTEM

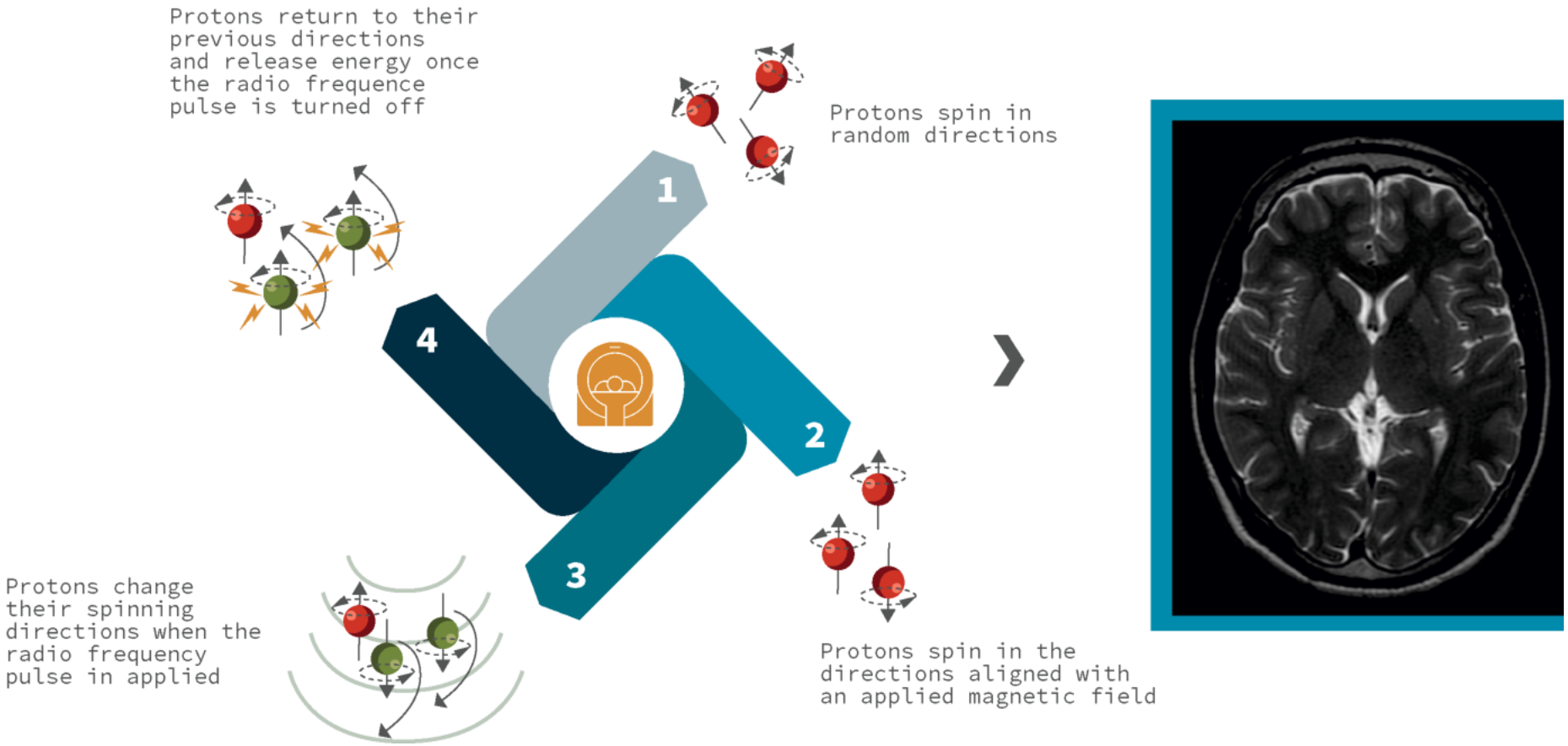
Barriers

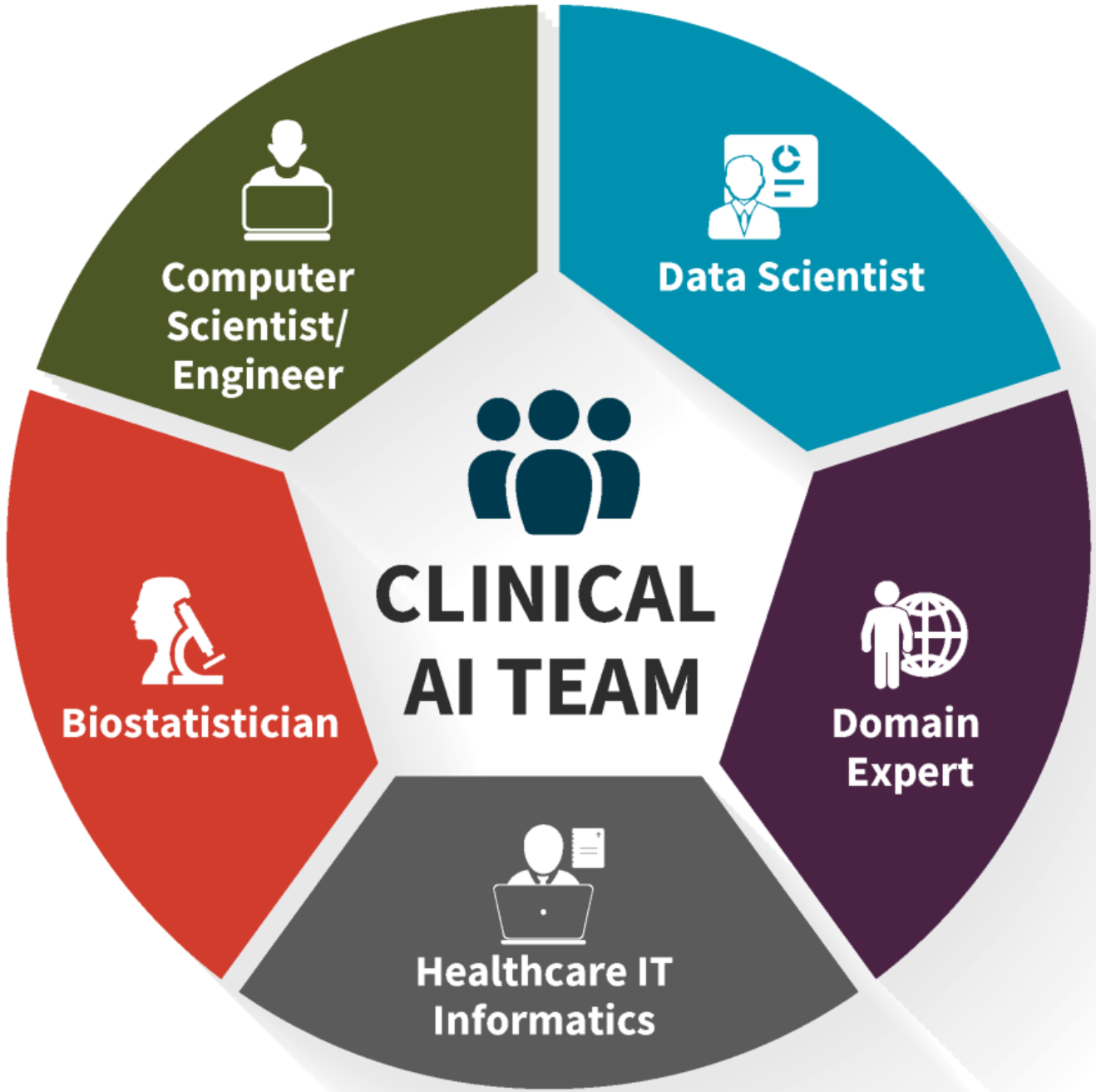
- $W^{[i]} = [w_1^{[i]}, w$ $1]$
- $b^{[i]} = {}^T[b_1^{[i]}, b_2^{[i]}$
- $\mathcal{Z}^{[i]} = {}^T[z_1^{[i]}, z_2^{[}$
- $\mathcal{A}^{[i]} = \psi^{[i]}(\mathcal{Z}^{[i]}$ $)]$

Um No.




PATIENT
SIEMENS
10.0t


Protons return to their previous directions and release energy once the radio frequence pulse is turned off
Protons spin in random directions
1
2
3
4
Protons change their spinning directions when the radio frequency pulse in applied
Protons spin in the directions aligned with an applied magnetic field


Computer Scientist/ Engineer
Data Scientist
CLINICAL AI TEAM
Biostatistician
Domain Expert
Healthcare IT Informatics

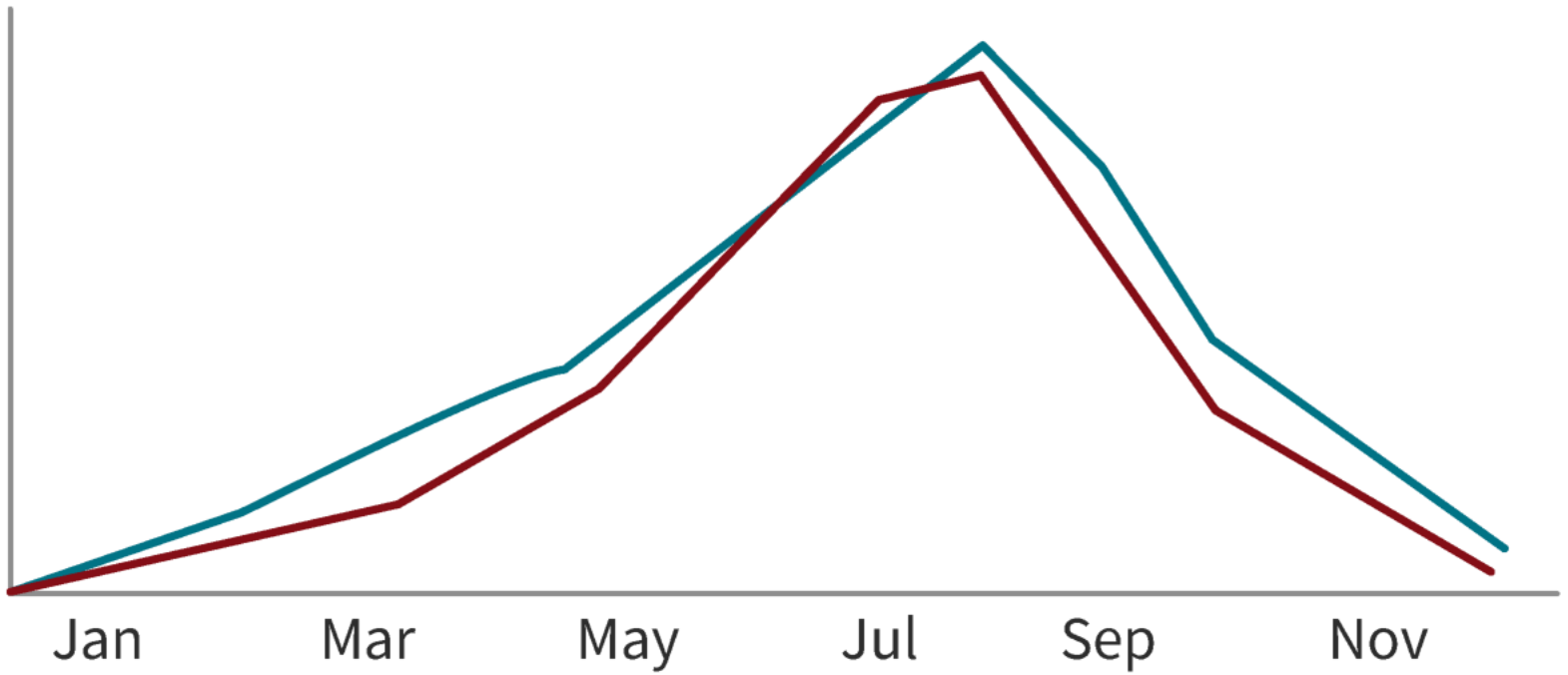
> Ultimately, this course is meant to empower YOU in your journey toward mastering the fundamentals of machine learning in healthcare

Machines are not perfect

Machines are not inherently logical or rational

Shortcut learning is principle behind most failures and bias

CORRELATION IS NOT CAUSATION!



Both ice cream sales and shark attacks increase when the weather is hot and sunny, but they are not caused by other (they are caused by good weather, with lots of people at the beach, both eating ice cream and having a swim in the sea)

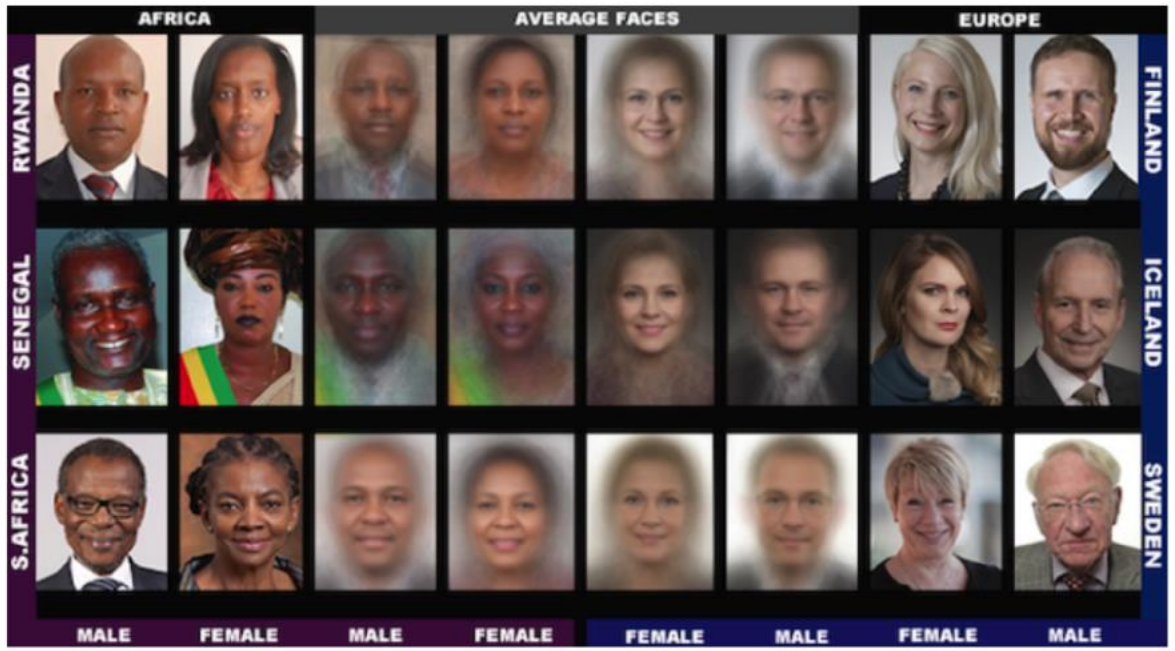
MODEL ACCURACY:

100% when tested with thousands of images of tanks

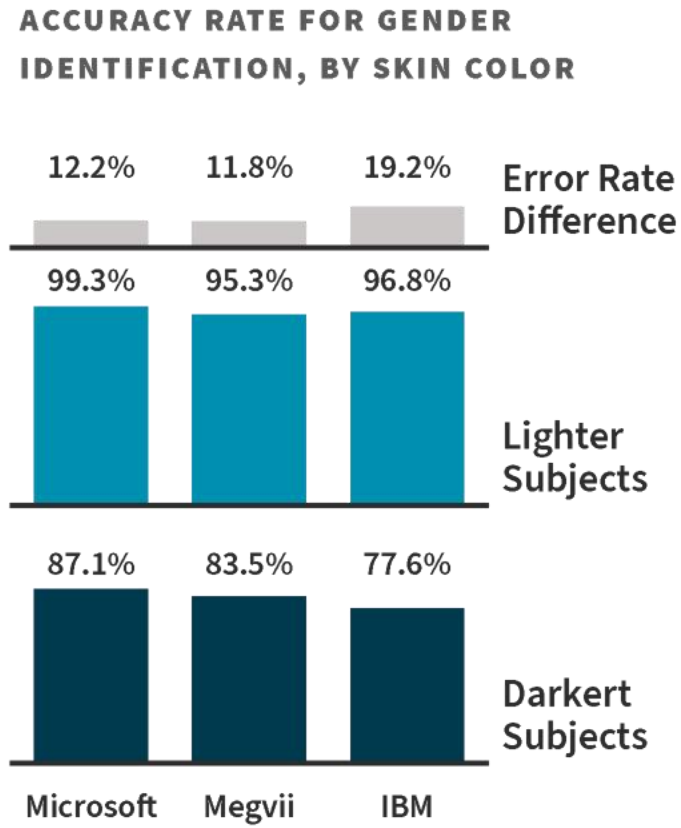
50% when tested live with tanks in a field

The model was focused on the background.

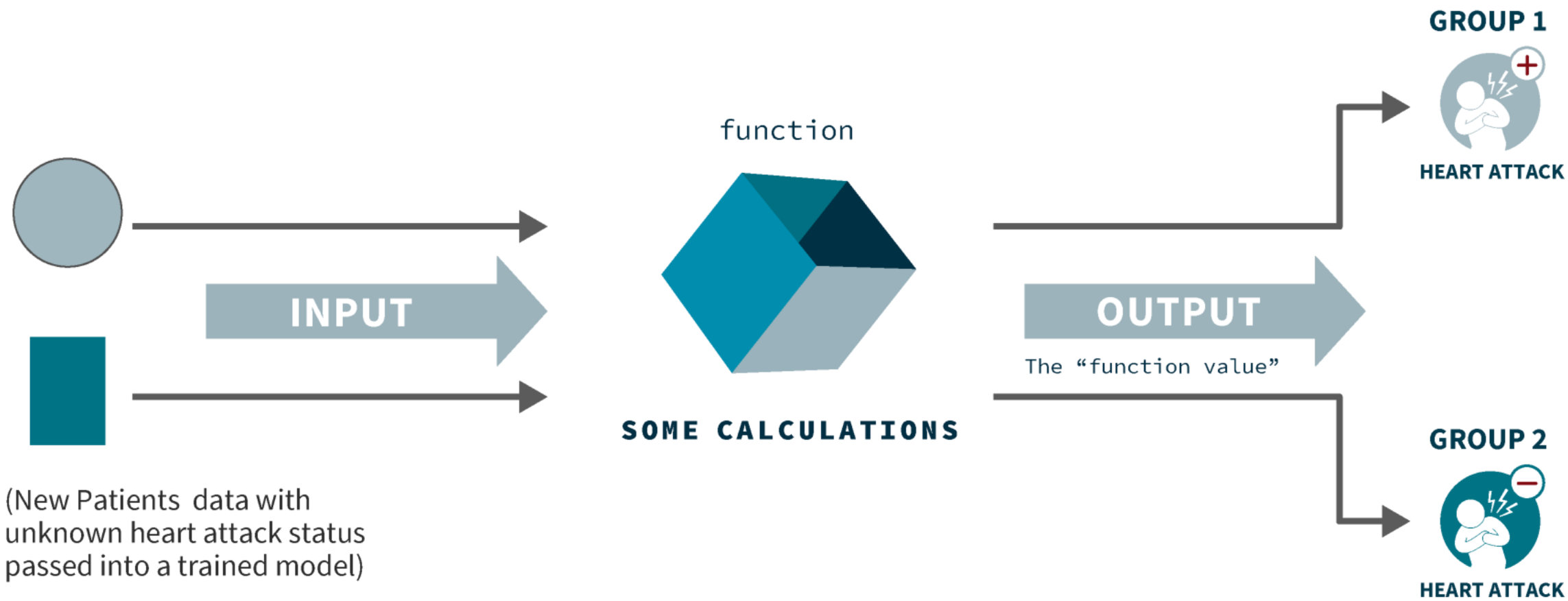
MACHINE LEARNING SYSTEMS ARE NOT INHERENTLY NEUTRAL



Pilot Parliaments Benchmark

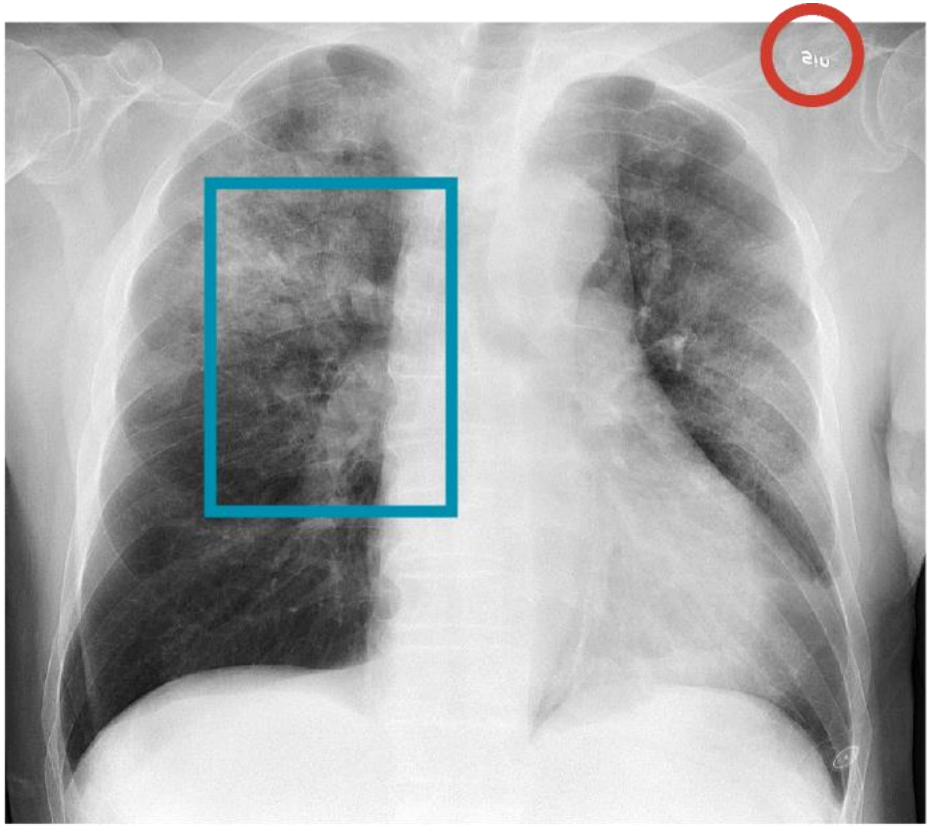


Sample images and average faces from the Pilot Parliaments Benchmark dataset. Credit: Joy Buolamwini and Timnit Gebru



(New Patients data with unknown heart attack status passed into a trained model)

(The new model correctly classified them - but used the correlation of patient hair color)

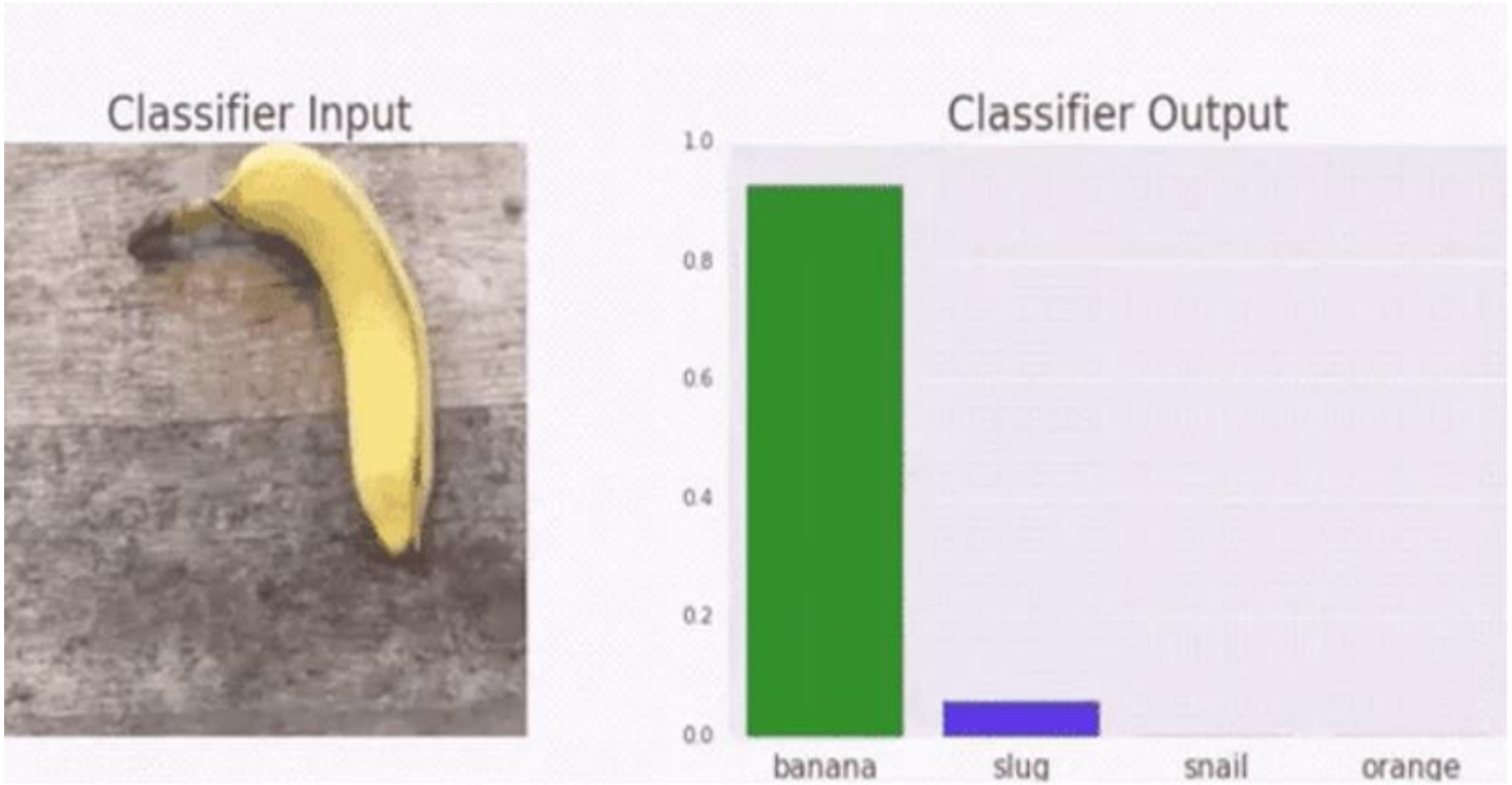


HOSPITAL A

1% pneumonia prevalence in data

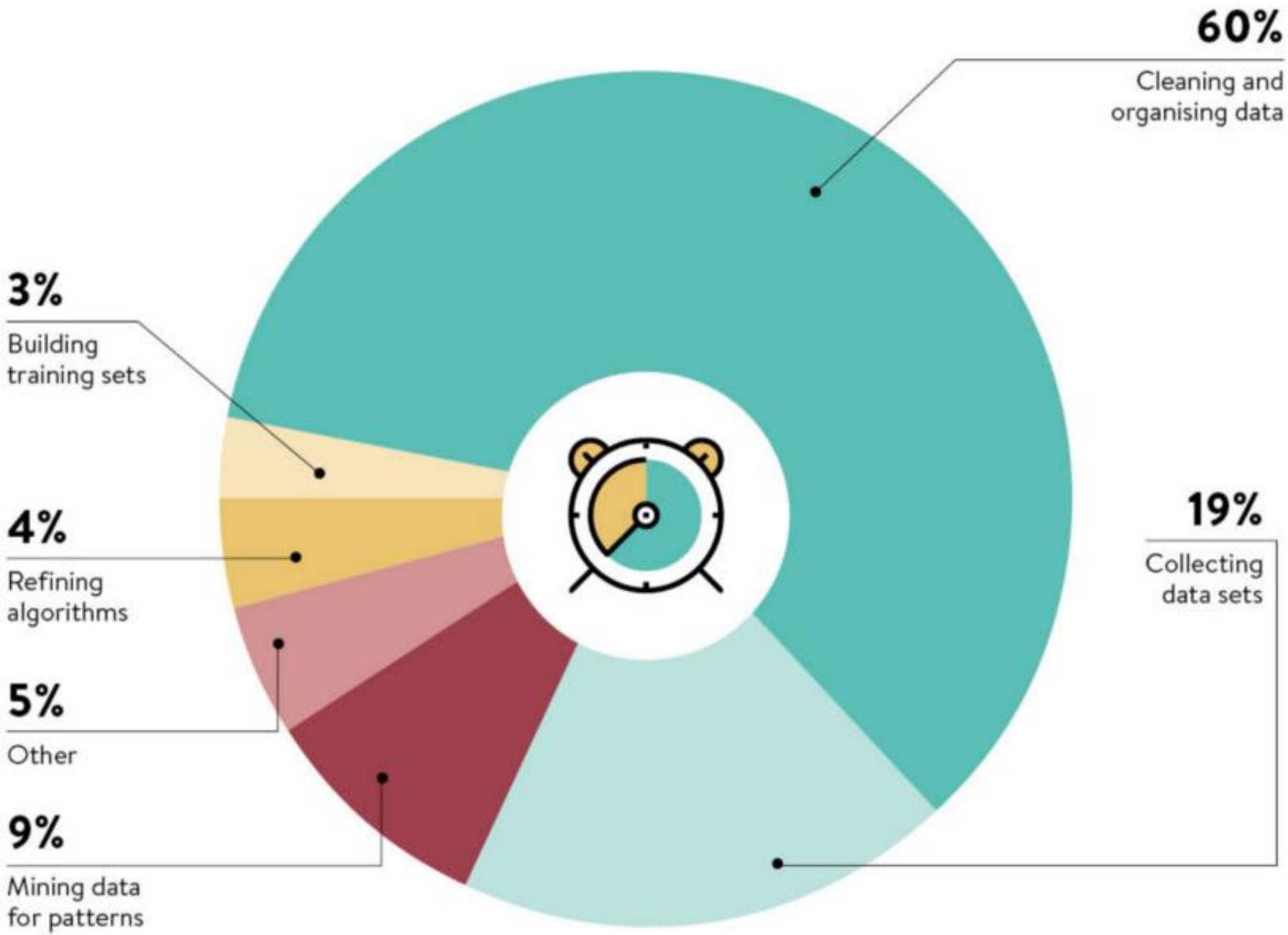
HOSPITAL B

35% pneumonia prevalence in data



Robust Physical-World Attacks on Machine Learning Models, Evtimov et al. https://arxiv.org/abs/1707.08945

The secret to success is the data



Source: CrowdFlower 2016

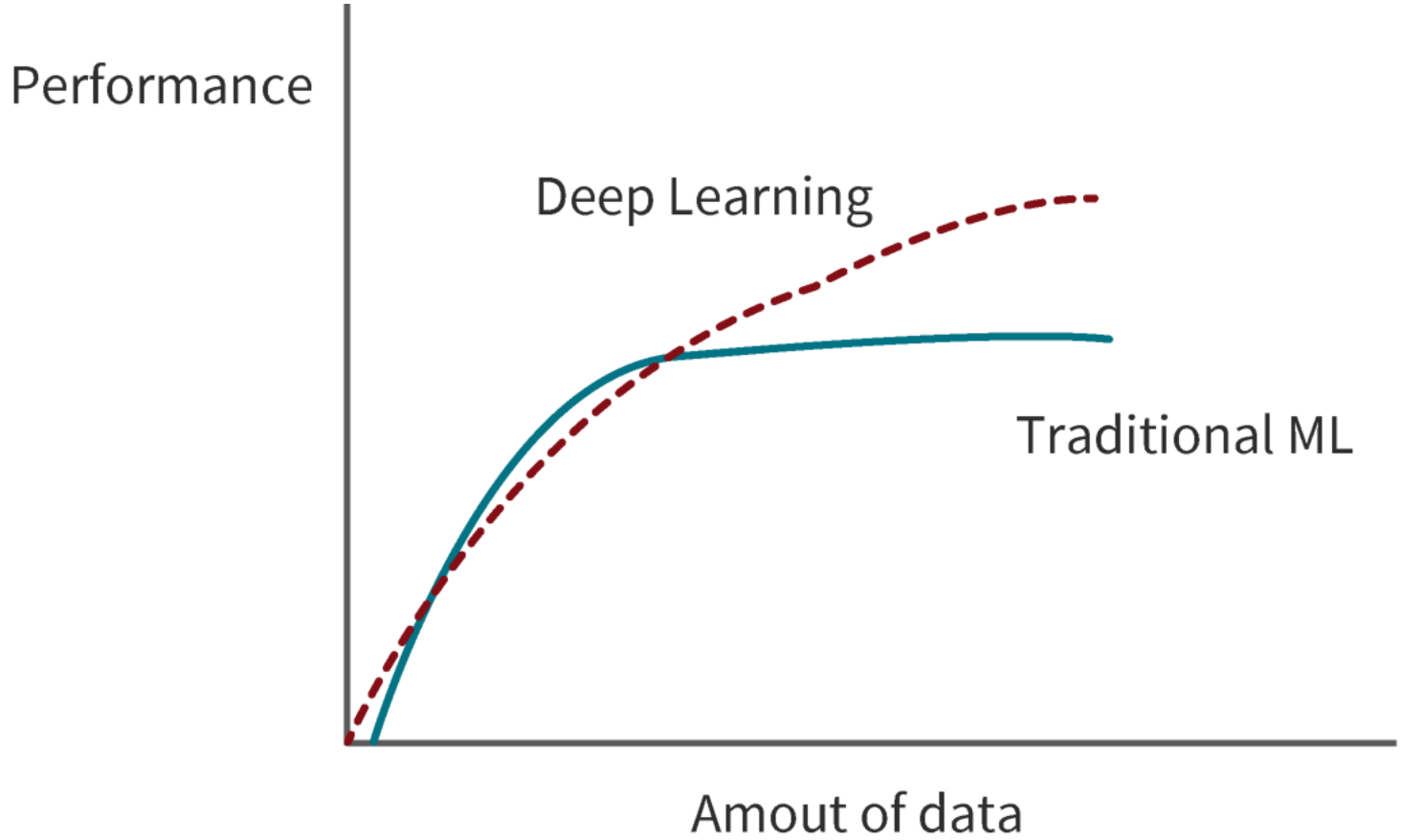
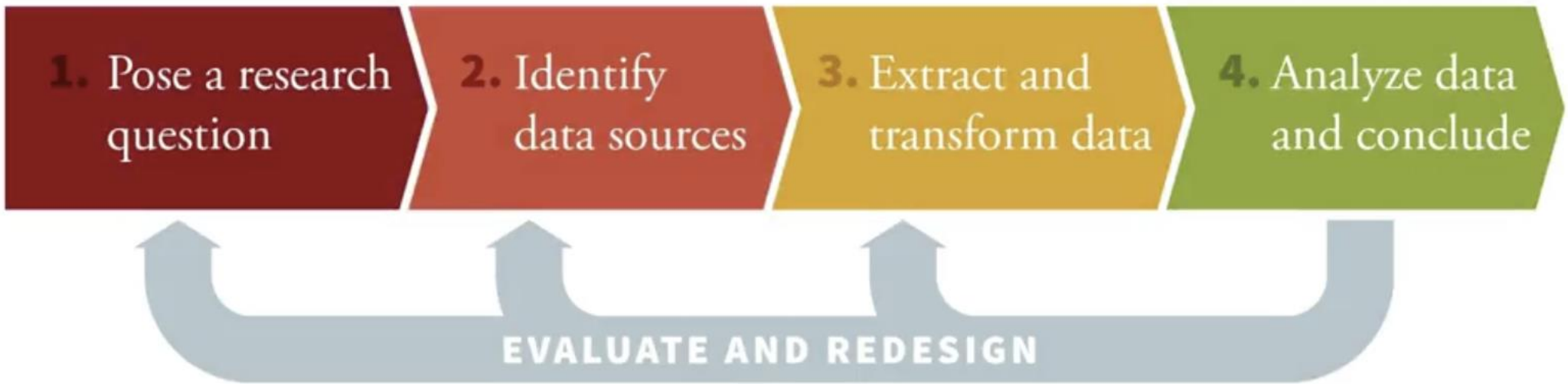
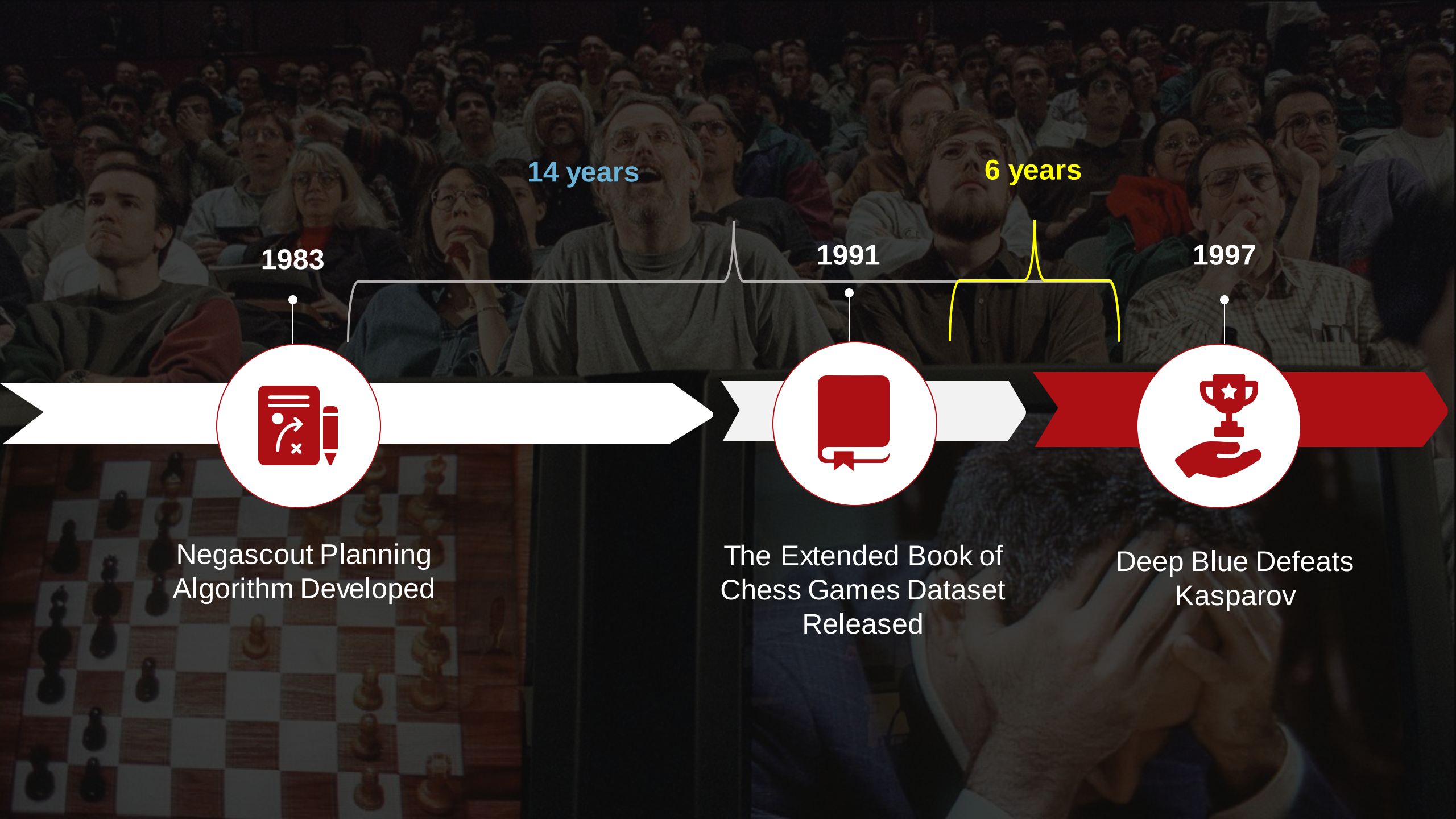


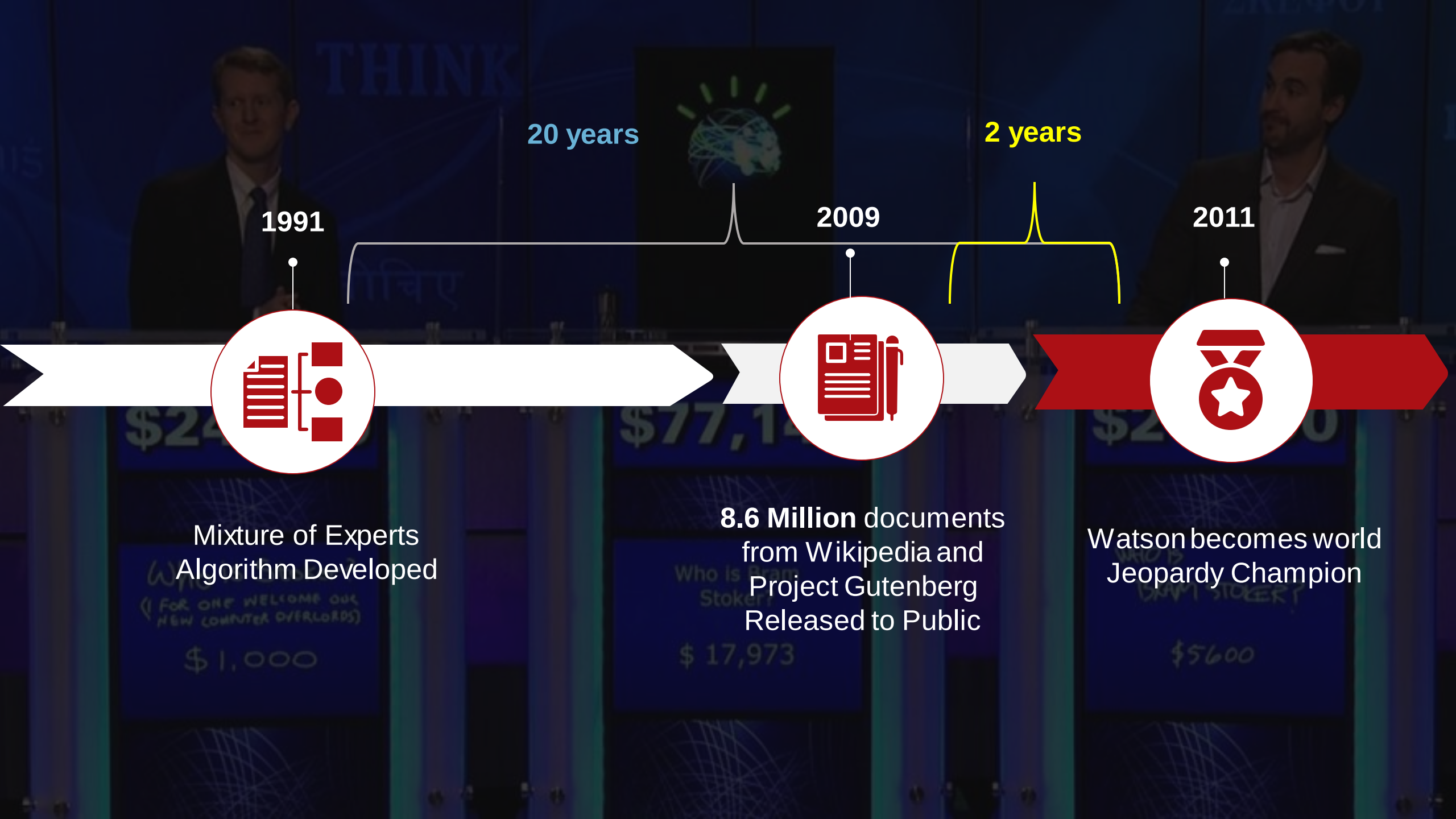
Figure shows how the performance of machine learning algorithms changes with increasing data size in the case of traditional machine learning algorithms (regression, etc.) and in the case of deep learning.
Specifically, for traditional machine learning algorithms, performance grows according to a power law and then reaches a plateau. This plateau is often higher with deep learning approaches for certain tasks and is one of the reasons for widespread use for applications with large data availability

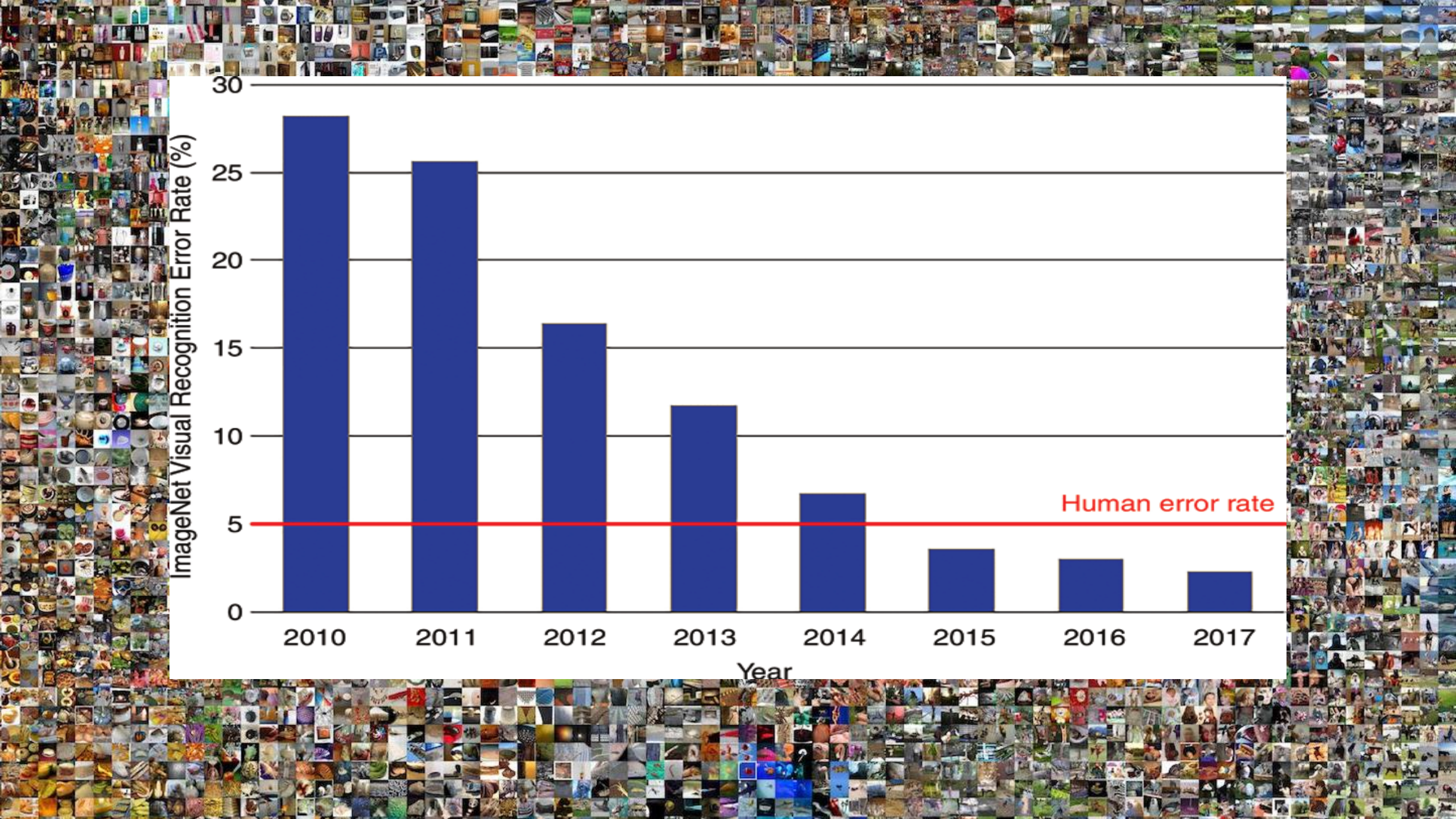
DATA MINING WORKFLOW

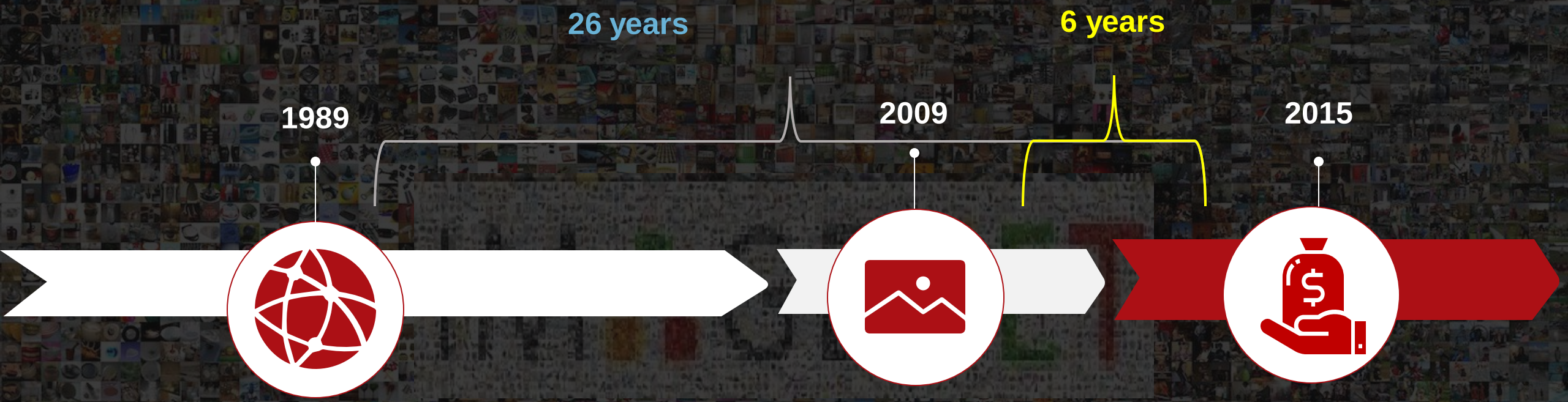



14 years
6 years
1983
1991
1997
Negascout Planning Algorithm Developed
The Extended Book of Chess Games Dataset Released
Deep Blue Defeats Kasparov


THINK
$24,000
Who is Stoker?
(I FOR ONE WELCOME OUR NEW COMPUTER OVERLORDS)
$1,000
$77,147
Who is Bram Stoker?
$ 17,973
$21,600
WHO IS BRAM STOKER?
$5600


20 years
2 years
1991
2009
2011
Mixture of Experts Algorithm Developed
8.6 Million documents from Wikipedia and Project Gutenberg Released to Public
Watson becomes world Jeopardy Champion


ImageNet Visual Recognition Error Rate (%)
30
25
20
15
10
5
0
Human error rate
2010
2011
2012
2013
2014
2015
2016
2017
Year

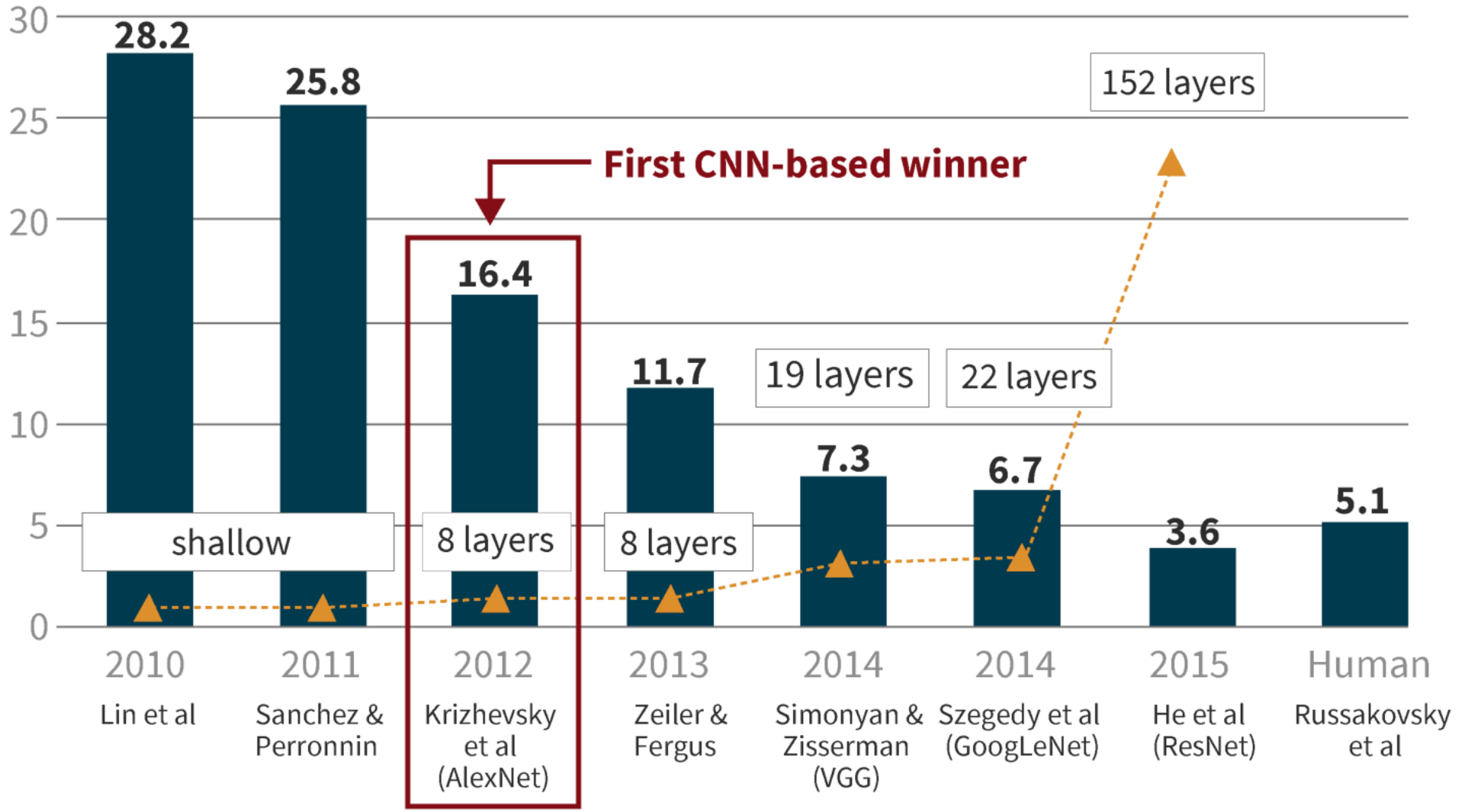


Convolutional Neural Network Created

1.5 Million classified images with 1,000 object categories released to public

Microsoft Research surpasses human recognition performance

IMAGENET LARGE SCALE VISUAL RECOGNITION CHALLENGE (ILSVRC) WINNERS



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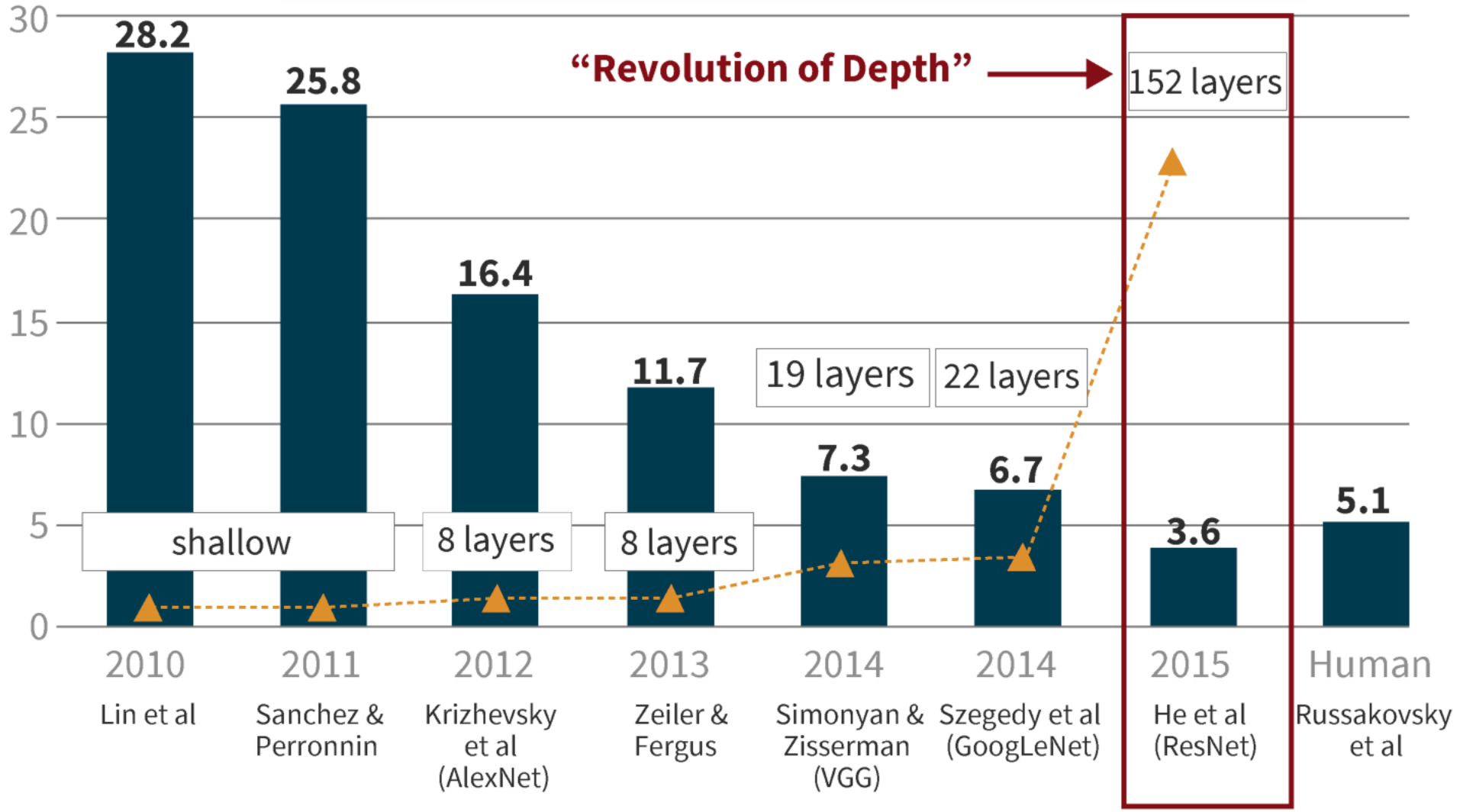


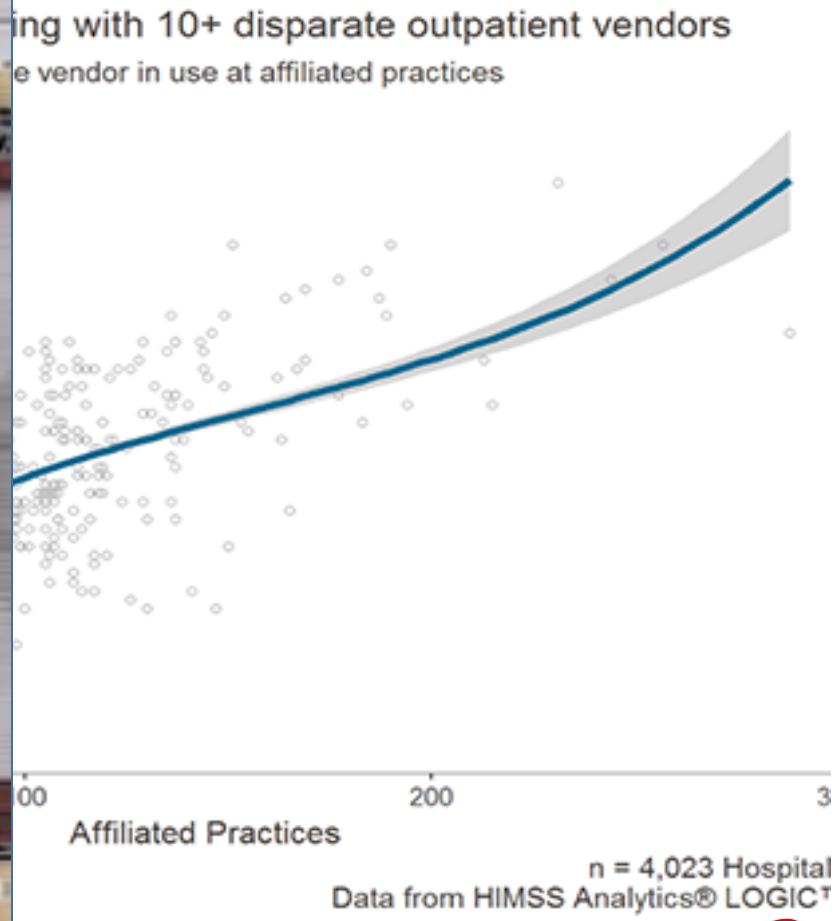

Big Data Market Size Revenue For
(in billion U
100
80
60
volume in billion U.S. dollars
th Korea's unfinished revolution
me in France
banking

Oil extraction is messy

AIMI
STANFORD CENTER FOR ARTIFICIAL INTELLIGENCE IN MEDICAL IMAGING

Medical data is messy

- Descriptive unstructu
- Imaging studies are la
- Up to 20% of significa
  in healthcare occur on



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DATA are not Traditional Form of Property

Not divided or consumed and easily replicated

“Ownership” of data is an **imprecise concept**

- **Rights to control access**
- **Rights to share of profit**

Value of data and information is relative

- **Exclusive access to data may give relative advantage**
- Advantage negated when others have access to the same data

People With Cancer By State Email/Postal/Phone Mailing List

The People With Cancer By State mailing list consists of individuals who suffer from different types of cancer, and would be great prospects for health products, treatments, medications, and much more. These active, opt-in consumers yield proven results for a wide variety of direct marketing campaigns. This list is the ideal tool to effectively build relationships with your unique audience.

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MARKET:	CONSUMER
CHANNELS:	✉ ☎
SOURCE:	COMPILED LISTS, INTERNET/ON-LINE
PRIVACY:	CONFIRMED OPT-IN
DMA?:	NO
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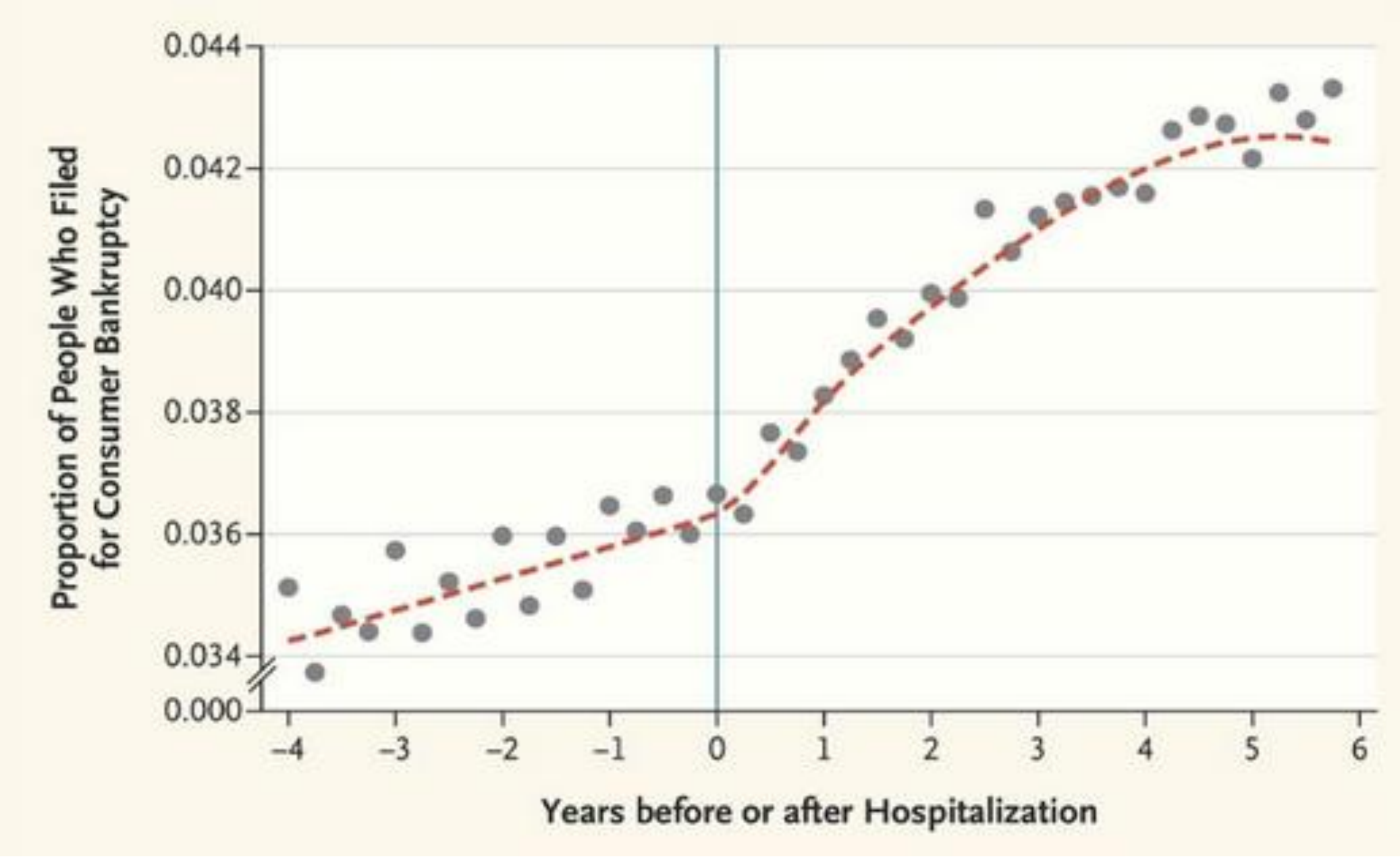
GEO:	USA

DESCRIPTION

About Exact Data's Consumer Database:

but… MEDICAL DATA ARE PEOPLE



Solving the right problems is everything

FINDING PROBLEMS WORTH SOLVING

	SCIENCE	PRACTICE	DELIVERY
CLASSIFY	Finding sybtypes of heart failure with preserved injection fraction	Who might be at high risk for a thromboembolism?	Who is burnt out?
PREDICT	Estimating the disease risk conferred by genetic variations	Which patients are at risk of dying in the next 3-12 months?	Who will be a no show?
ACT/TREAT	XYZ solid tumors can be treated by allogeneic chimeric antigen receptor T-cell By	What is a good second line drug to manage diabetes after metformin?	Request four back up nurses on Wed, for the Ortho OR.

USE CASE: *AI MODEL FOR SEPSIS IN THE ICU*

	SCIENCE	PRACTICE	DELIVERY
CLASSIFY	Use EMR data to classify ICU patients into different sepsis risk categories for future work in other factors and signals that may signify future sepsis treatments		
PREDICT			
ACT/TREAT			

USE CASE: *AI MODEL FOR SEPSIS IN THE ICU*

	SCIENCE	PRACTICE	DELIVERY
CLASSIFY			
PREDICT			
ACT/TREAT			Use historical ICU data to inform adjustment of par quantities for relevant sepsis medications, staff, and equipment

USE CASE: *AI MODEL FOR SEPSIS IN THE ICU*

	SCIENCE	PRACTICE	DELIVERY
CLASSIFY			
PREDICT		Real-time patient EMR data, and then predict the patients likely to develop sepsis at the point of care.	
ACT/TREAT			

EDUCATION FOR THE HEALTHCARE WORKFORCE

- Principles and impacts of machine learning
- How to interpret the model recommendations
- The flaws and biases
- How to identify unintended consequences of machine learning system behavior

Course introduction: why machine learning in healthcare?

Machine learning framework: terms, definitions, and jargon

Supervised machine learning and traditional approaches

Fundamentals of deep learning and neural networks

Common neural network architectures for different clinical applications

Evaluation metrics for machine learning in healthcare

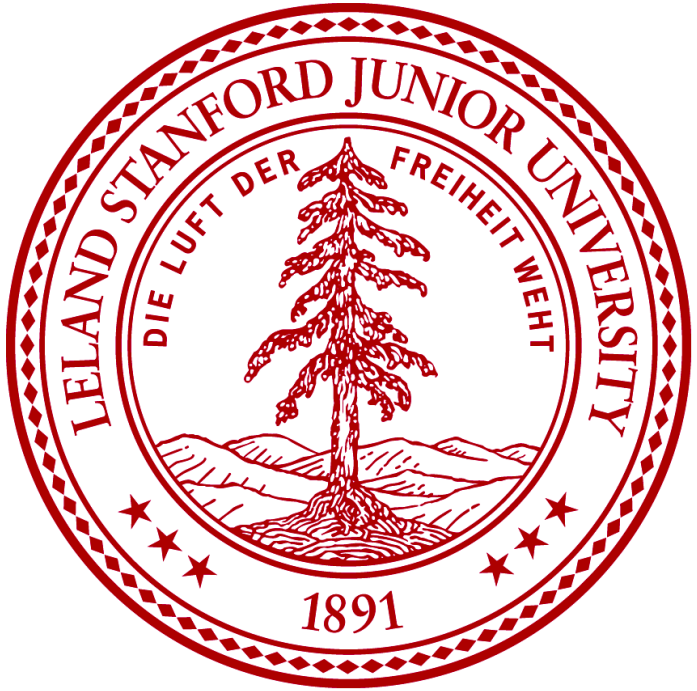
Strategies, challenges, and the black box

Data considerations for clinical machine learning

Team-based design and evaluation of clinical machine learning applications

Course conclusion: the future of clinical work in the era of machine learning

Thank You



Matthew P Lungren MD MPH

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Associate Director
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- Anesthesia
- Bioengineering
- Biomedical Data Science
- Cardiothoracic Surgery
- Computer Science
- Dermatology
- Emergency Medicine
- Genetics
- Medicine
- Neurology & Neurological Sciences
- Neurosurgery
- Ophthalmology
- Pathology
- Pediatrics
- Psychiatry & Behavioral Sciences
- Psychology
- Radiation Oncology
- Radiology
- Surgery
- Urology

Stanford AIMI

Center for Artificial Intelligence in Medicine and Imaging

Stanford MEDICINE

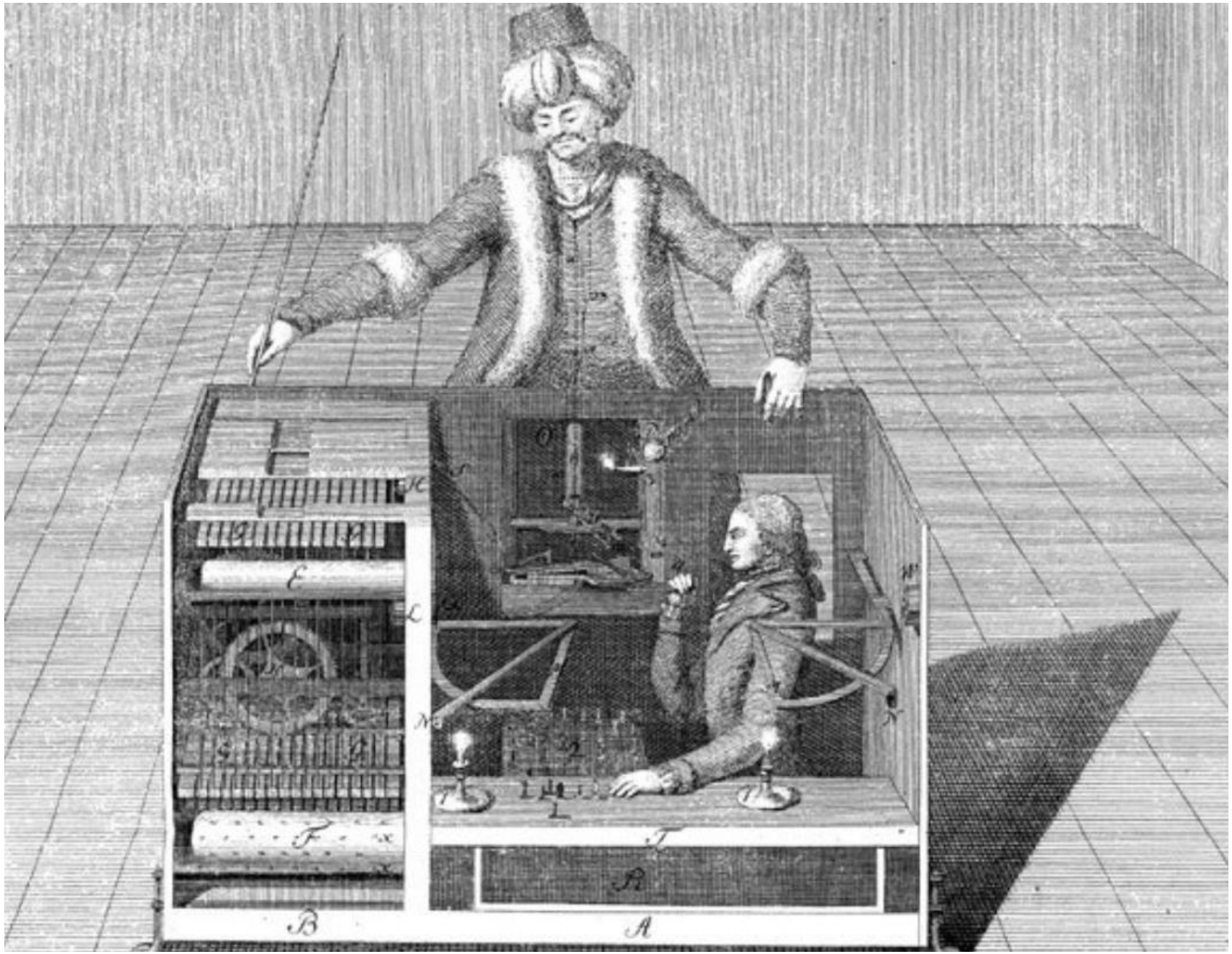
ENGINEERING

Key Computer Science Faculty Collaborators

Fei Fei Li, PhD
Creator of ImageNet

Chris Manning, PhD
Stanford AI Lab Director

Andrew Ng, PhD
Deep Learning Pioneer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L
F
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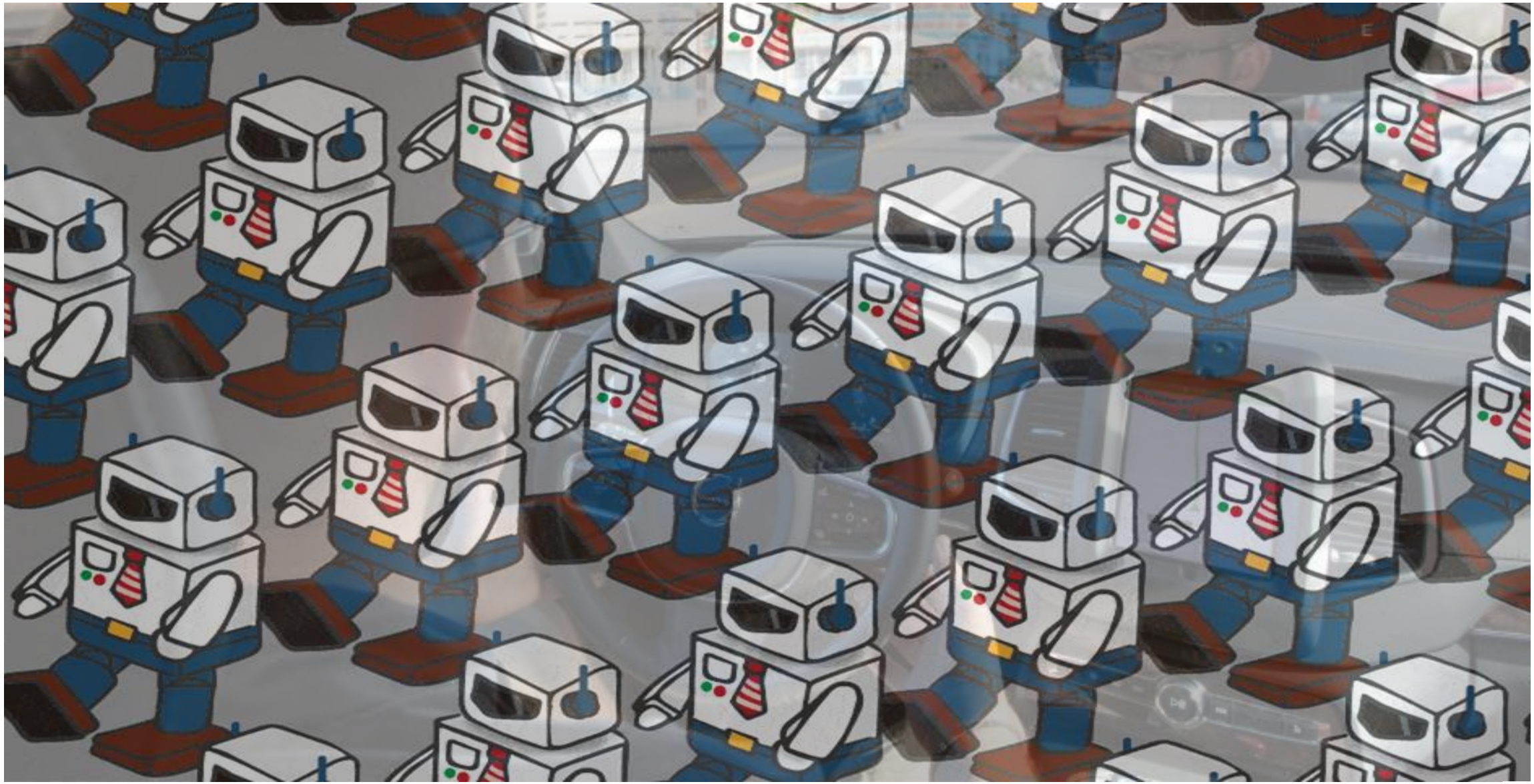

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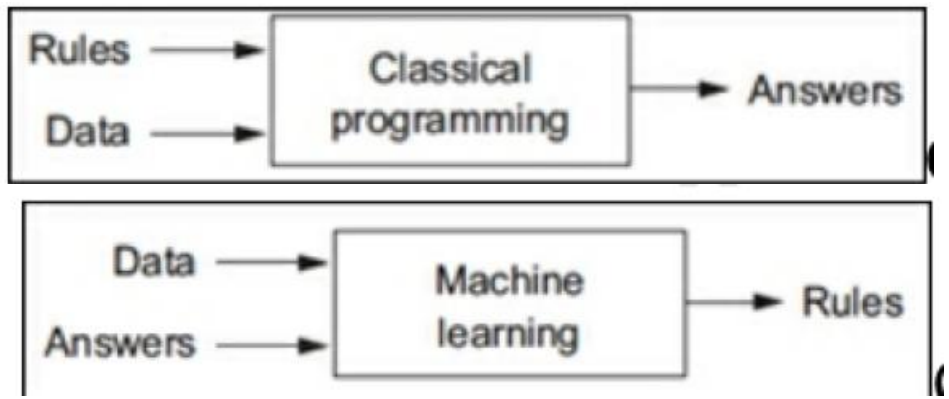
HUMAN SKILLS UNLIKELY TO BE REPLACED

- complex reasoning
- judgment
- analogy-based learning
- abstract problem solving
- physical interactions
- empathy and communication
- counseling
- implicit observation

COMMON SPECIALTIES OF PRIMARY CARE PROVIDERS

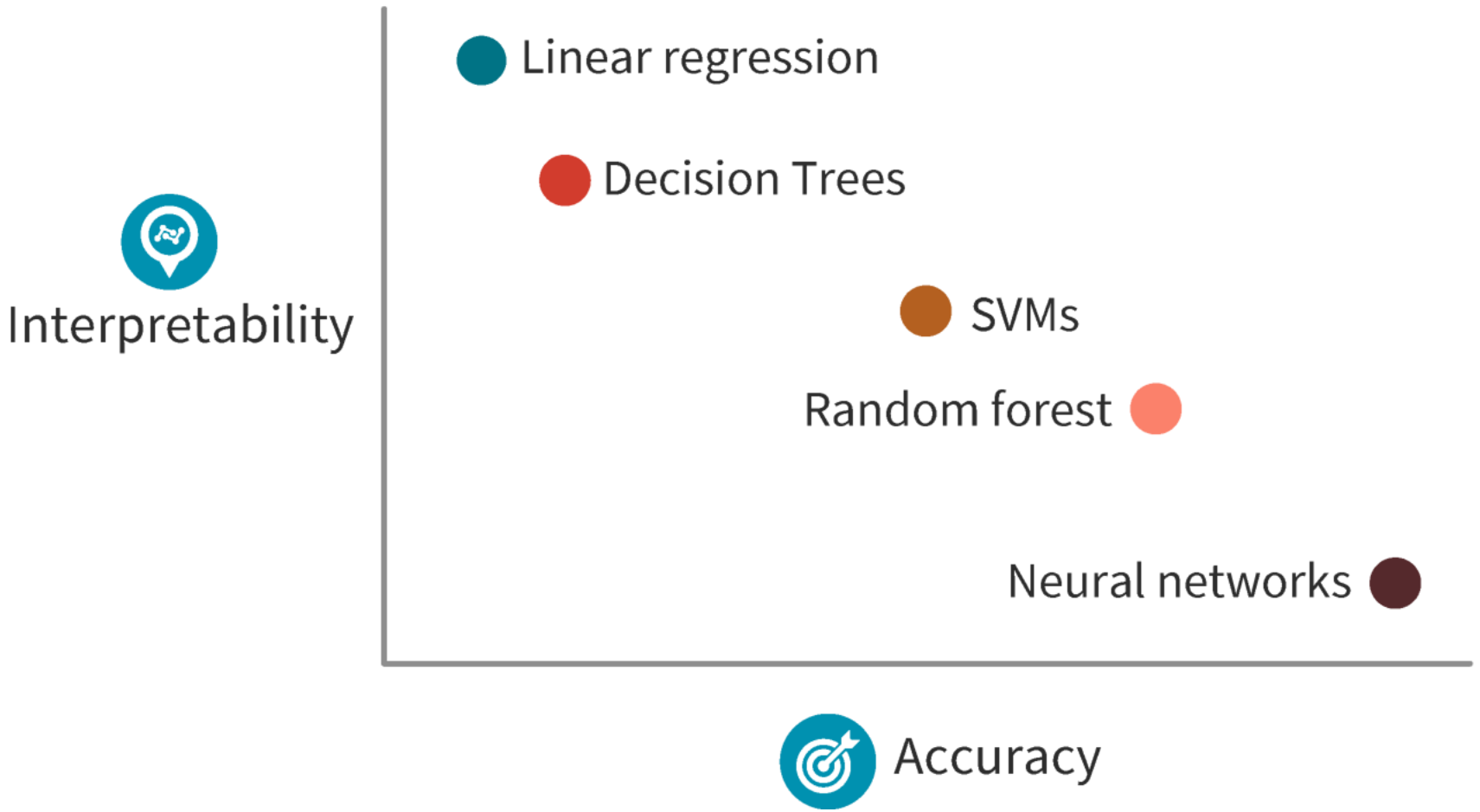
- transcribing clinical documentation
- image analysis
- billing and coding
- practice management
- staffing and resource optimization
- prior authorization forms
- triaging routine diagnosis


Rules
Data
Classical programming
Answers
Data
Answers
Machine learning
Rules

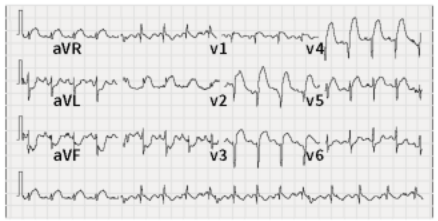
“The simplest solution is most likely the right one”

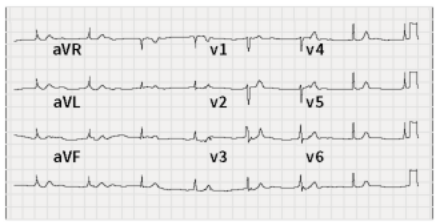
“Never attribute to malice that which is adequately explained by stupidity"

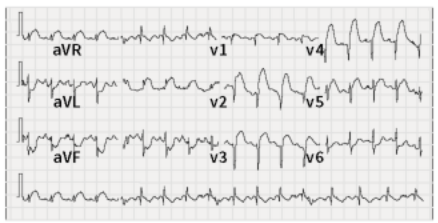
TENSION BETWEEN BLACK BOX AND INTERPRETABLE ALGORITHMS



ECG examples







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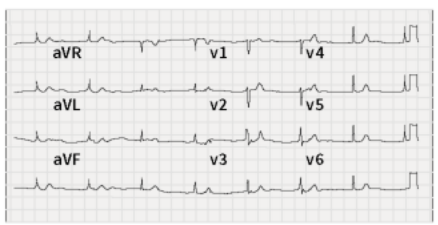
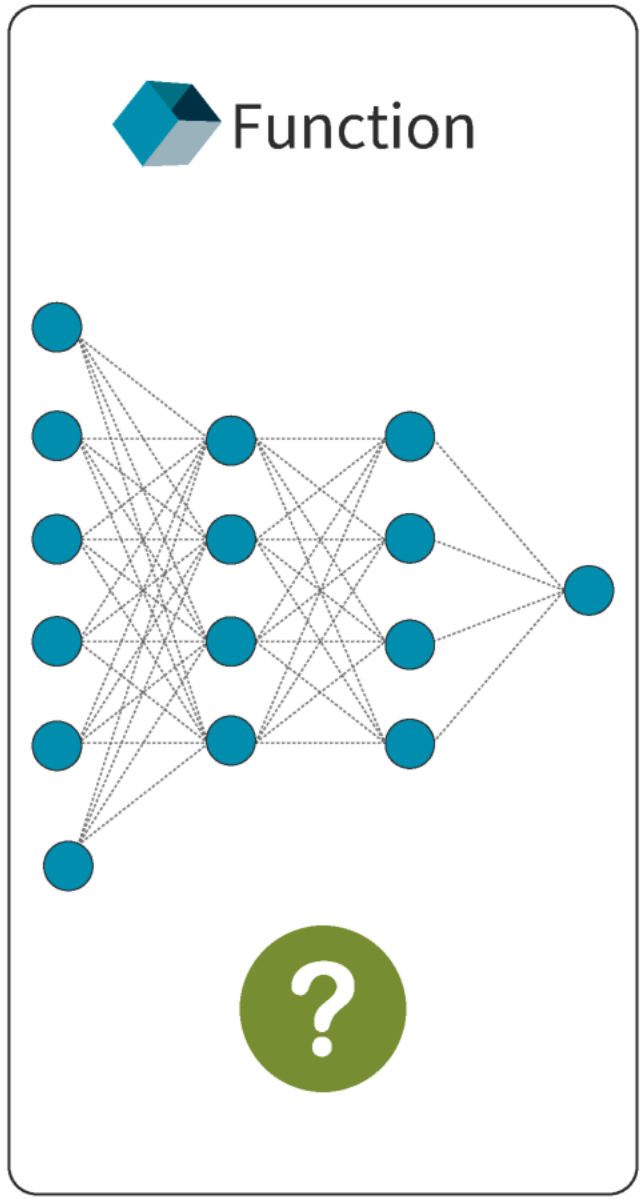




Heart attack?

YES

YES

NO

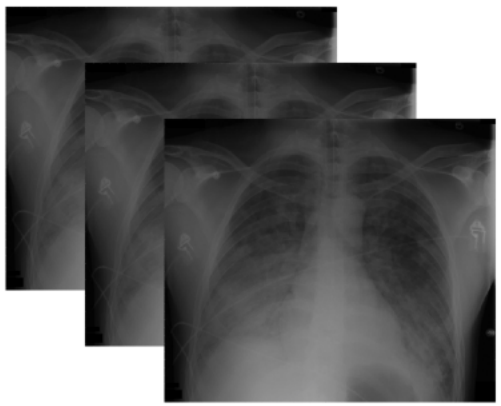
YES

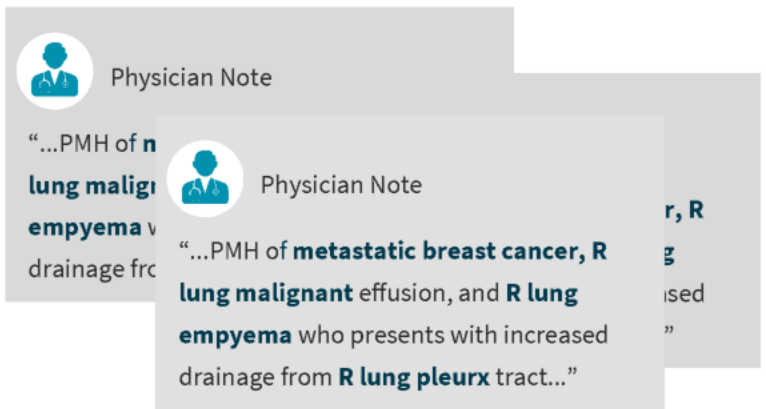
NO

Features

Models

Labels





Function

Function

Function

Sepsis = yes
Sepsis = No
Sepsis = No
Sepsis = yes

Pneumonia = yes
Pneumonia = No
Pneumonia = No
Pneumonia = yes

Readmission = yes
Readmission = No
Readmission = No
Readmission = yes

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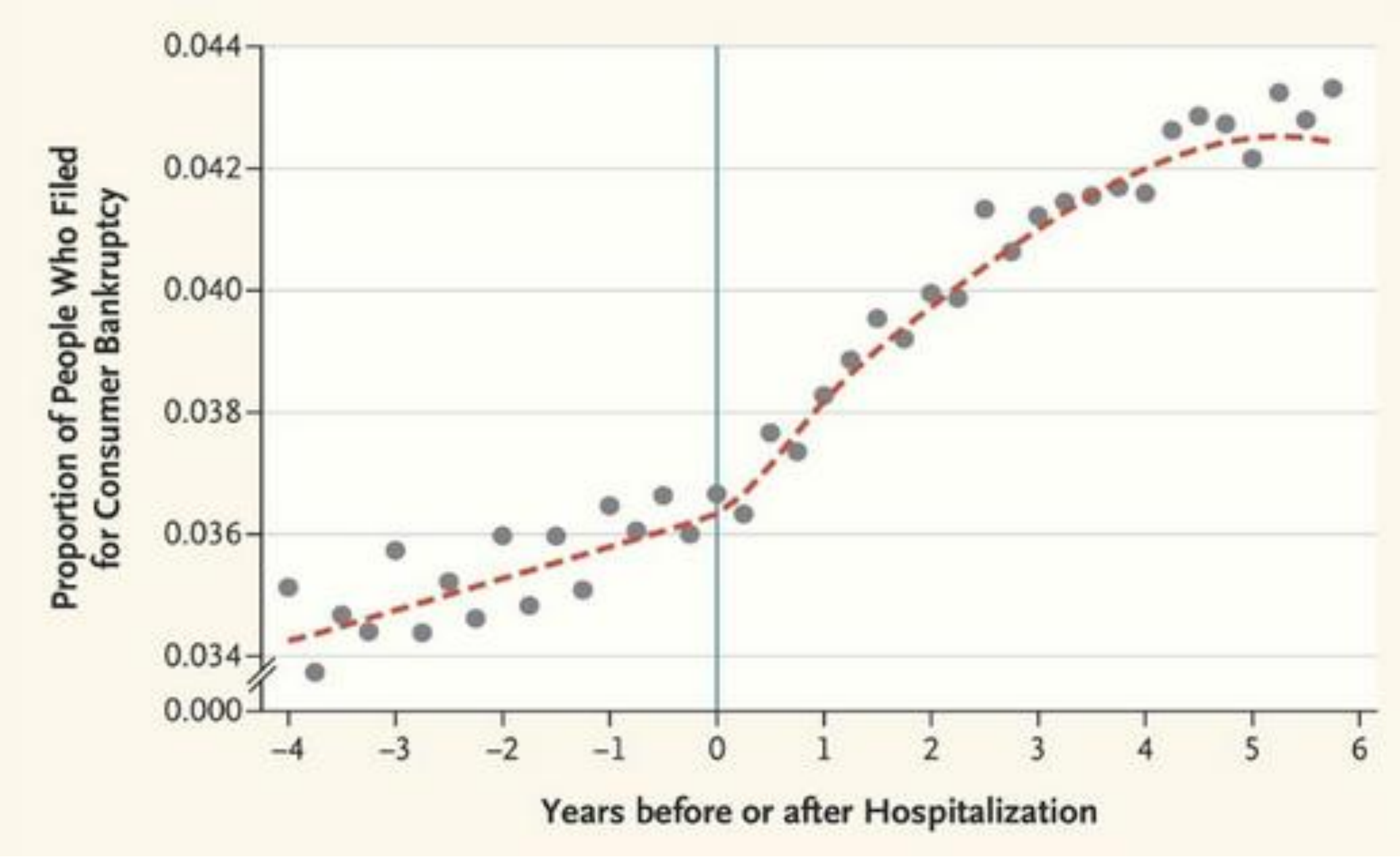


Patients own the data, should not be shared without their explicit consent

Providers own data, which can be bought and sold like any other commodity

All who interact with and use the data are "data stewards" with a fiduciary responsibility to both patients and society

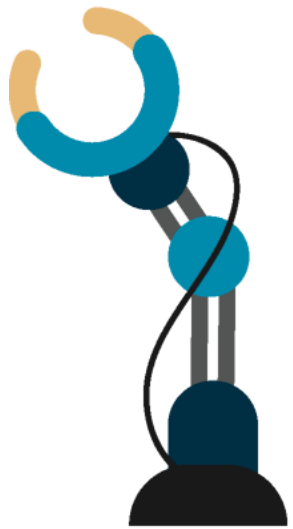
Credit: David Larson MD MBA

Our position:

Once clinical data have been used to provide care,
the primary purpose for acquiring the data is fulfilled.

For secondary use: **clinical data should be treated as a form of public good used for the benefit of all thorough open source research and education**

Credit: David Larson MD MBA

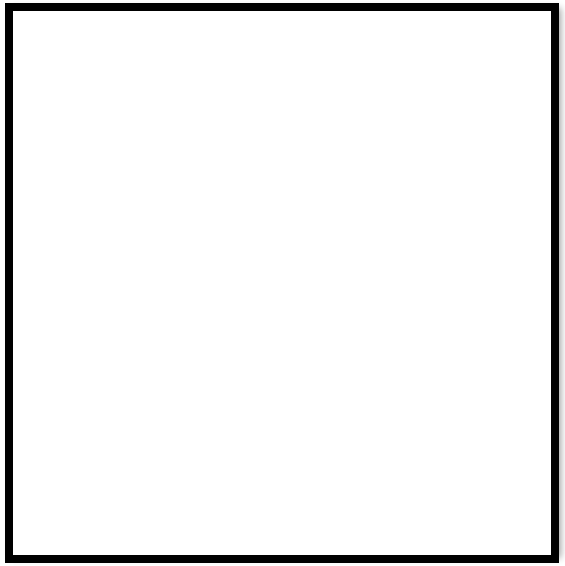


MACHINE
LEARNING

ARTIFICIAL
INTELLIGENCE

Loigistics

COURSE LOGISTICS



Title

Heading

Text