



Beth Israel Deaconess
Medical Center

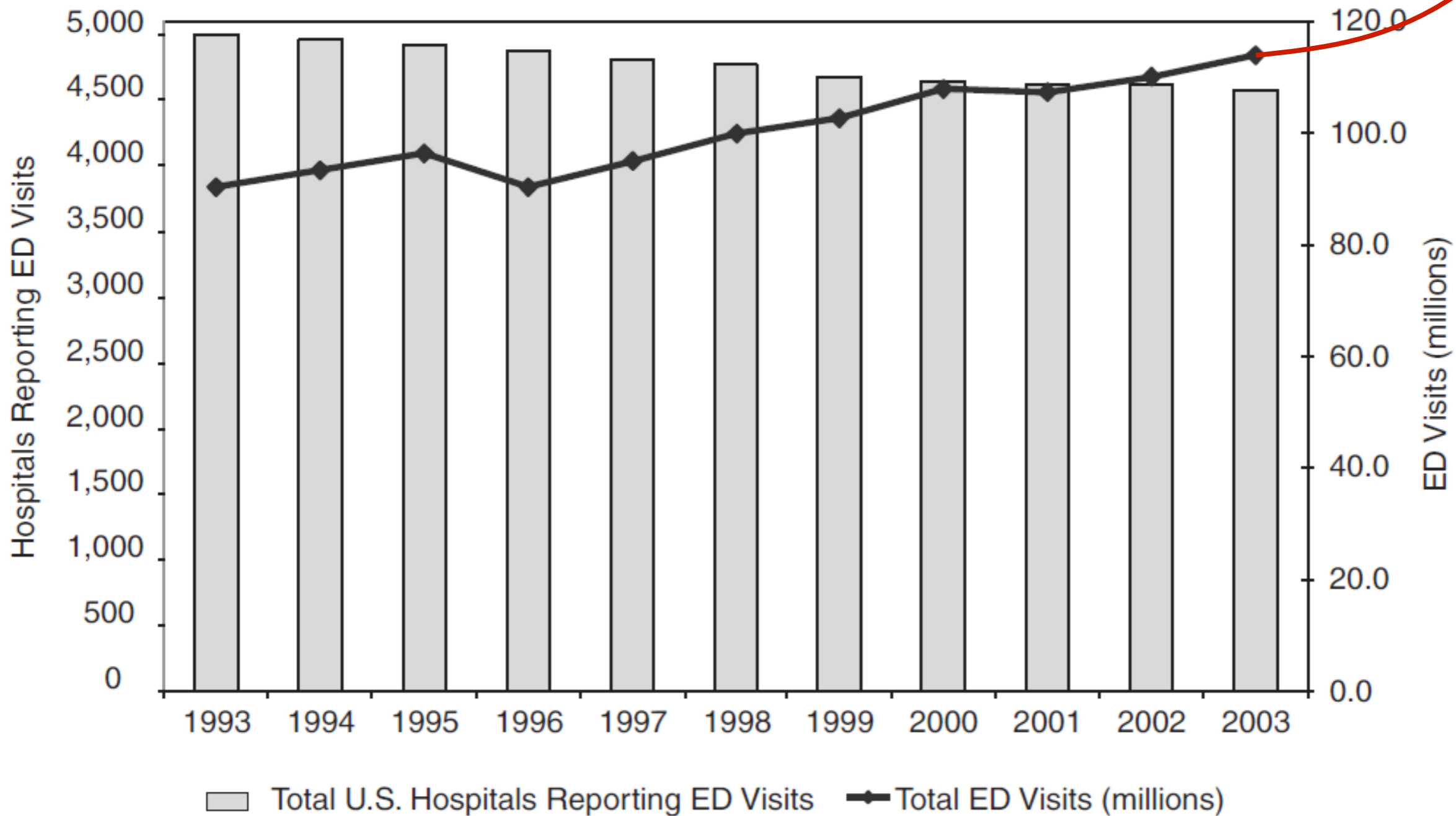


A teaching hospital of
Harvard Medical School

Machine Learning at BIDMC: *augmenting clinical workflows*

Steven Horng, MD MMSc FACEP
Clinical Lead for Machine Learning
June 25, 2019

Increasing ED visits

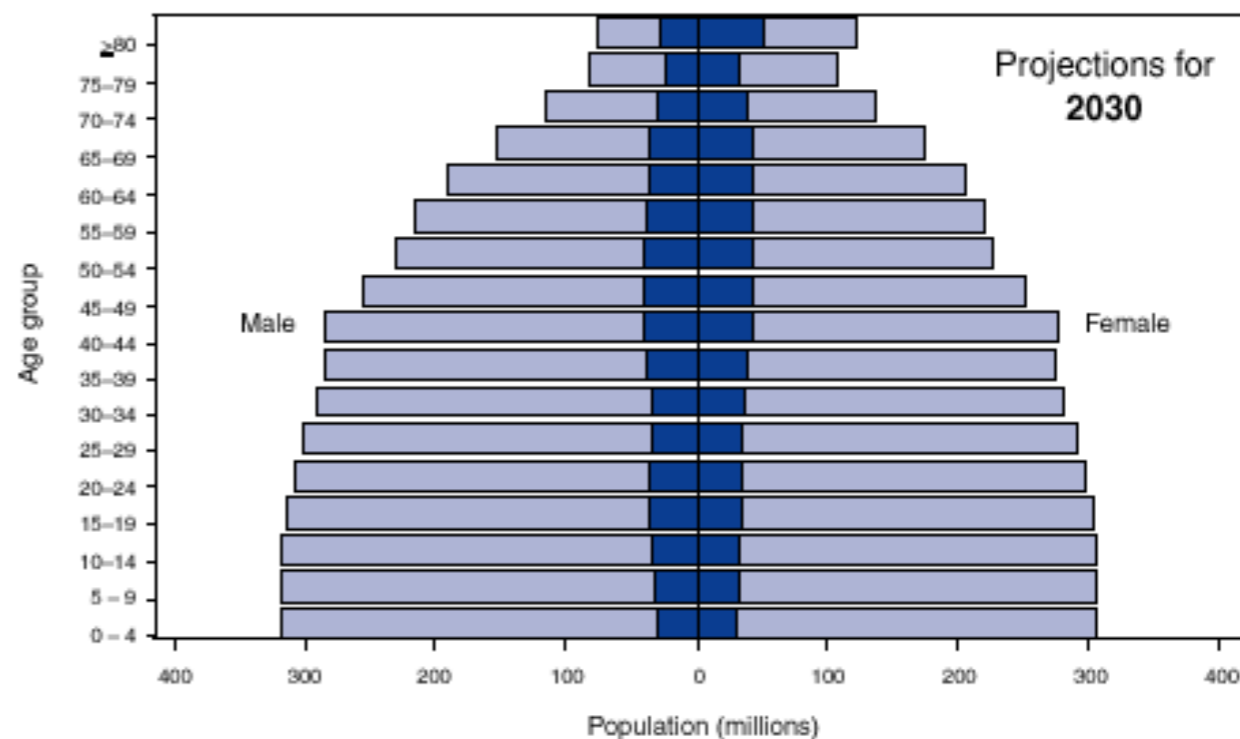
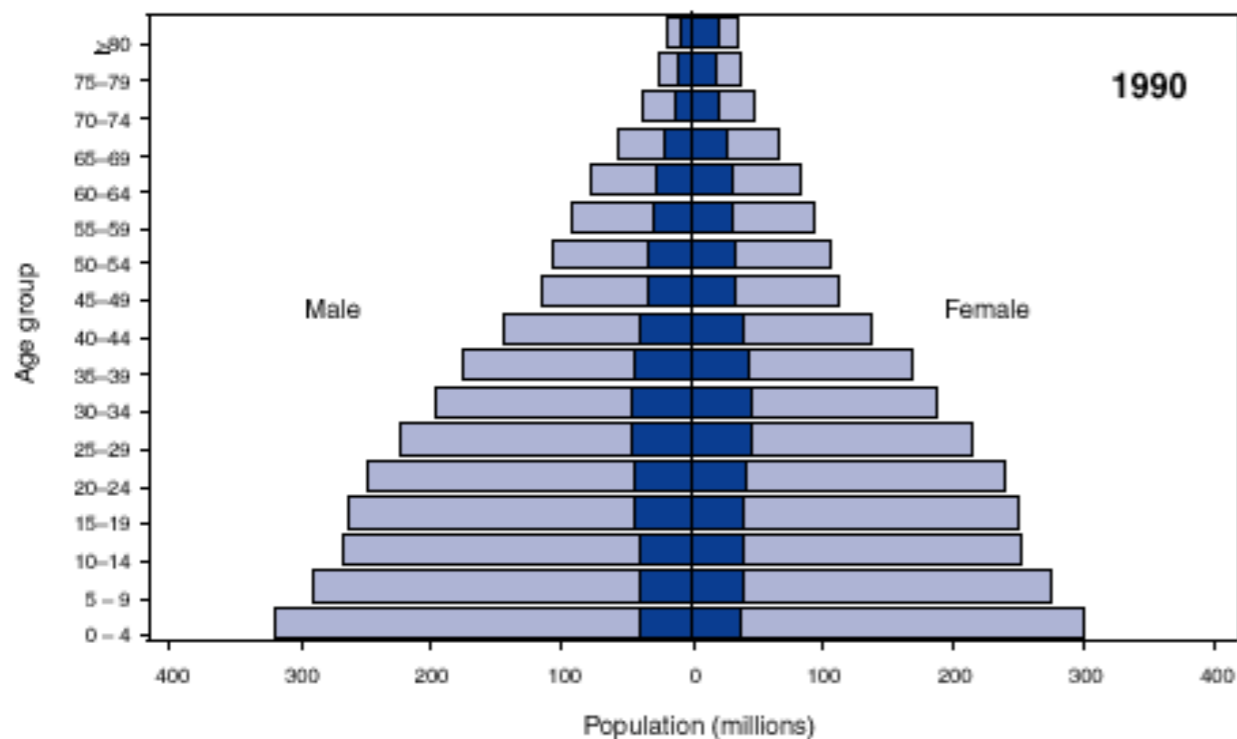


↑ Life Expectancy

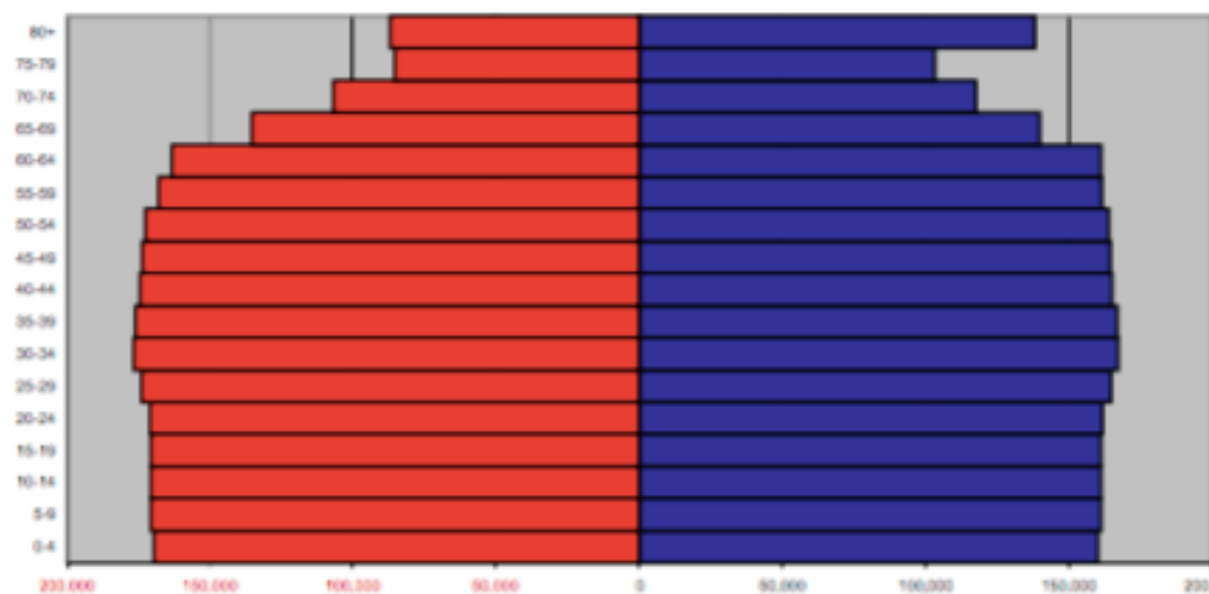
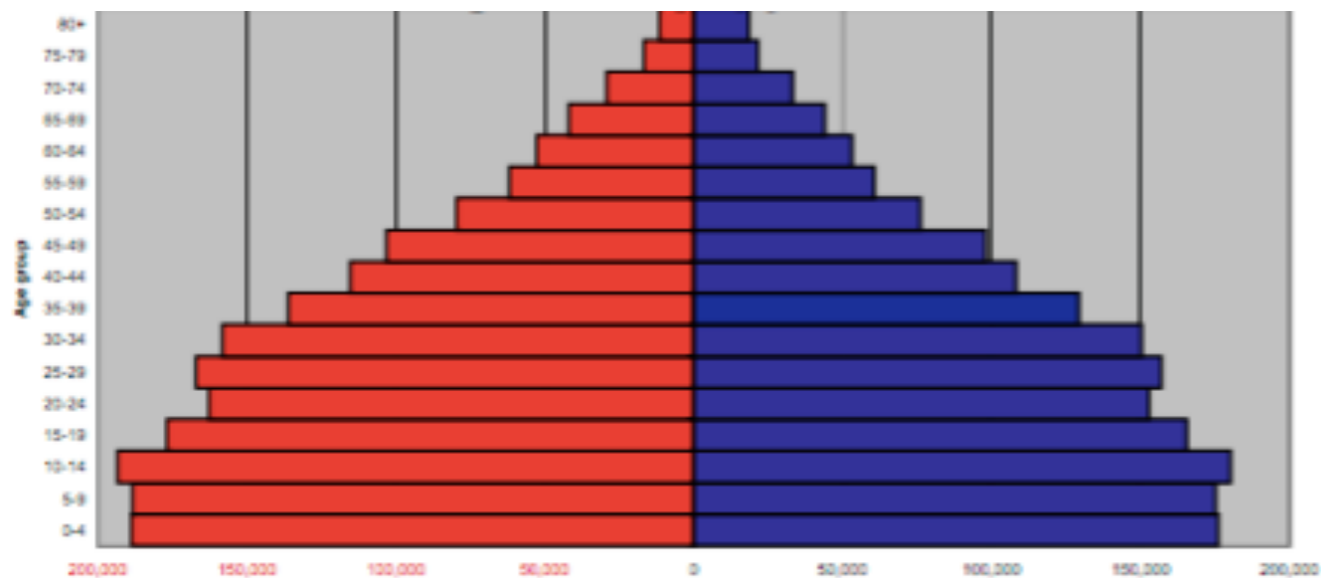
↓ Fertility Rate

Shifting Age Demographic

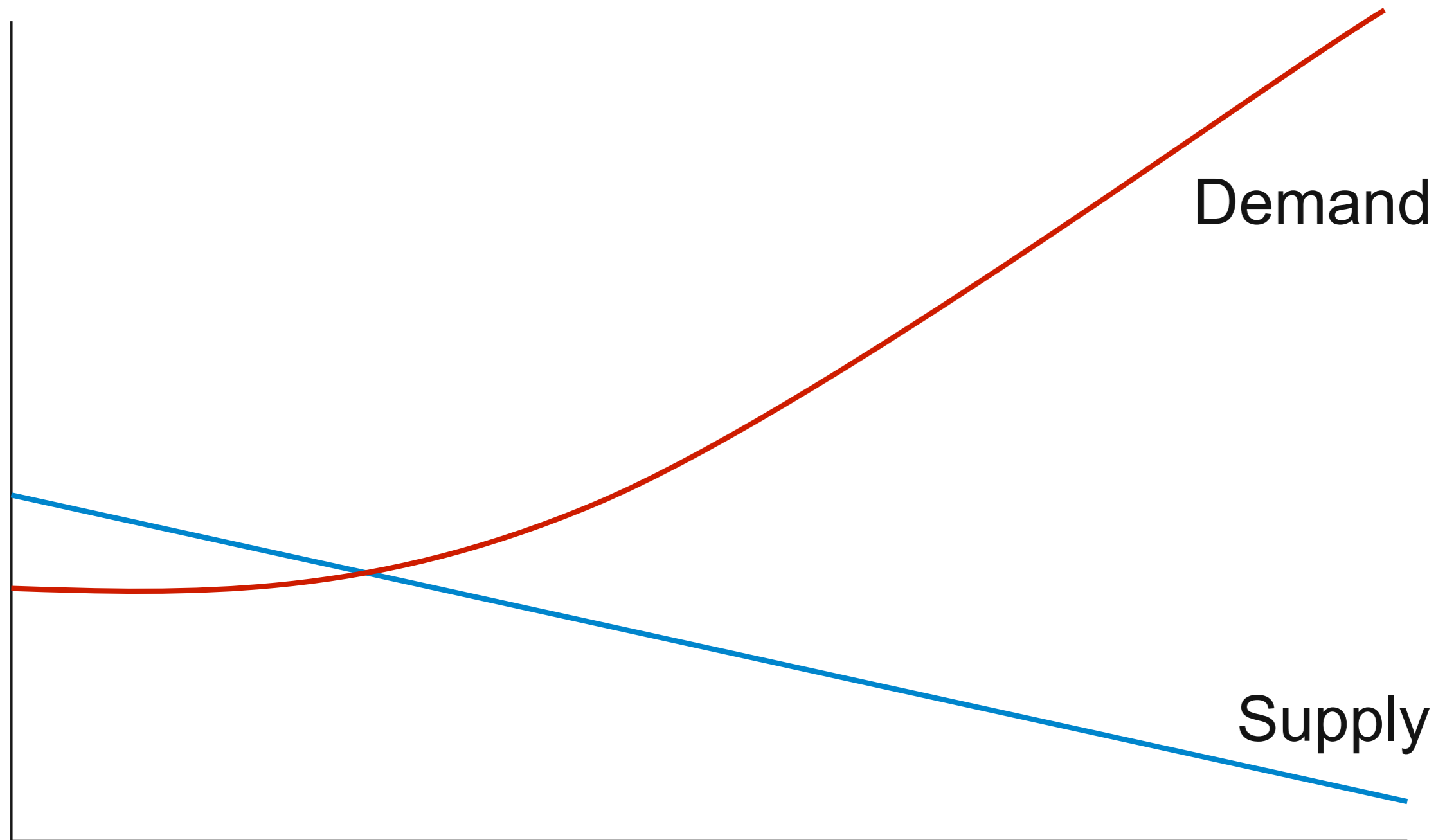
USA

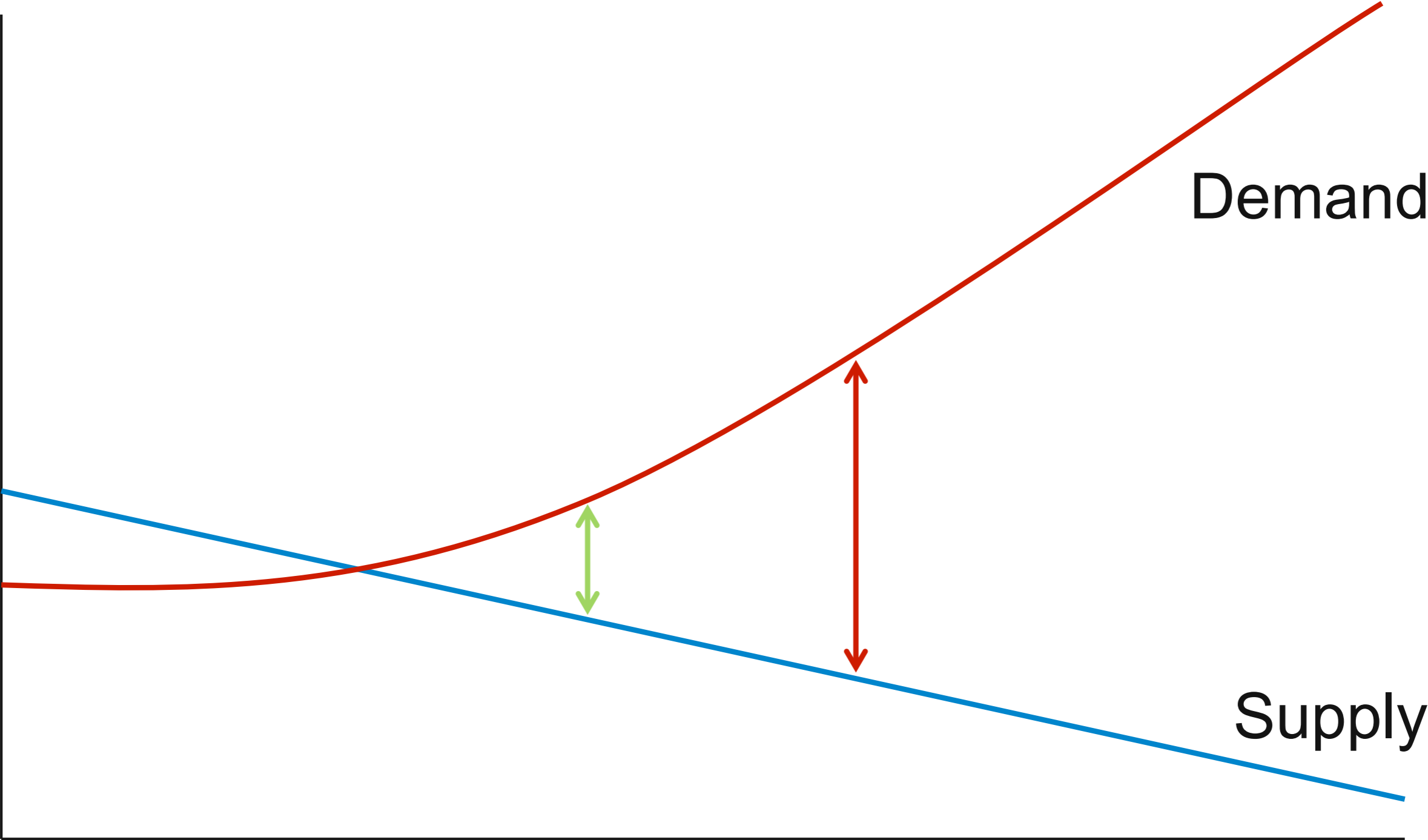


Asia



Supply - demand mismatch





Need to fundamentally
change our care processes

Recent Advances in Machine Learning

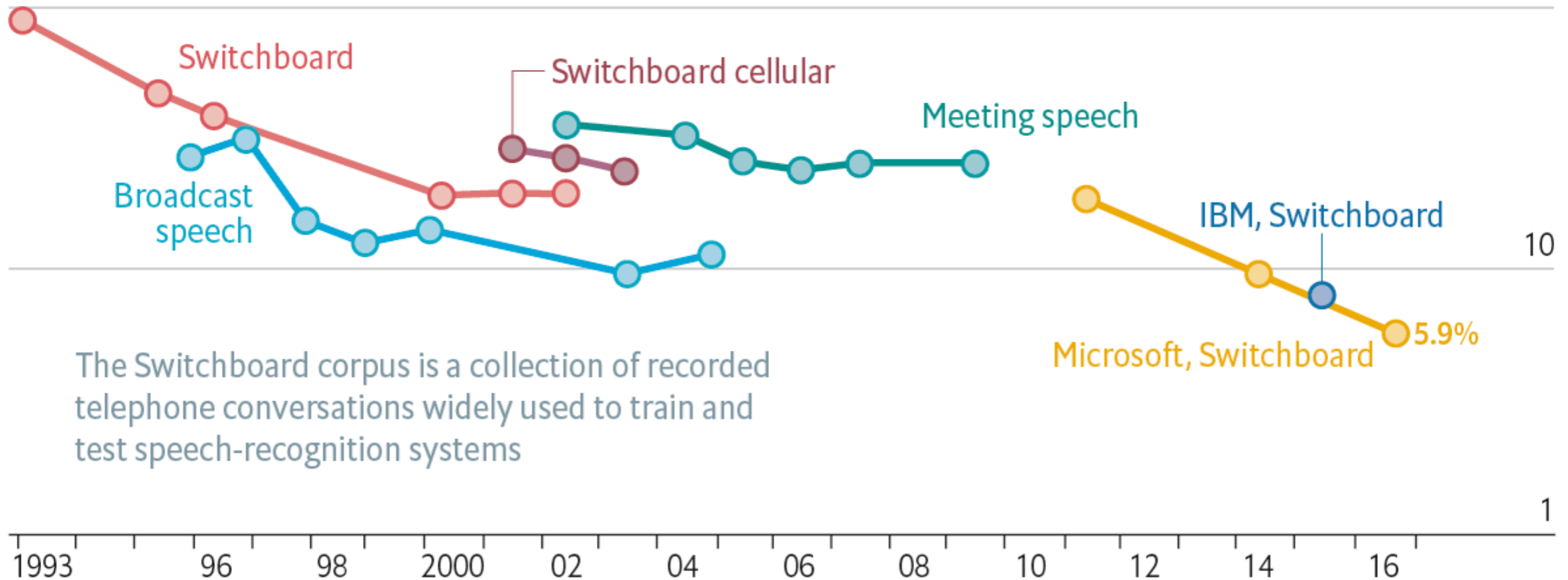
Speech Recognition

Loud and clear

Speech-recognition word-error rate, selected benchmarks, %

Log scale

100

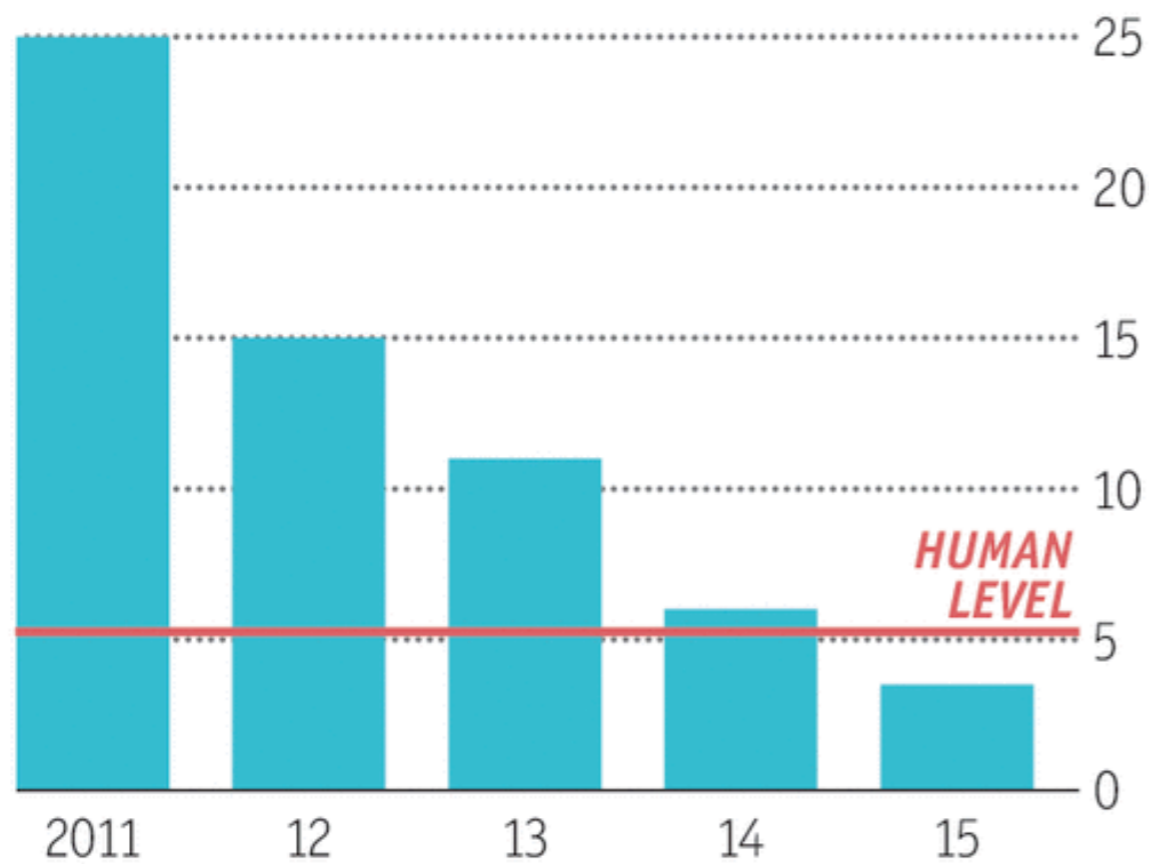


The Switchboard corpus is a collection of recorded telephone conversations widely used to train and test speech-recognition systems

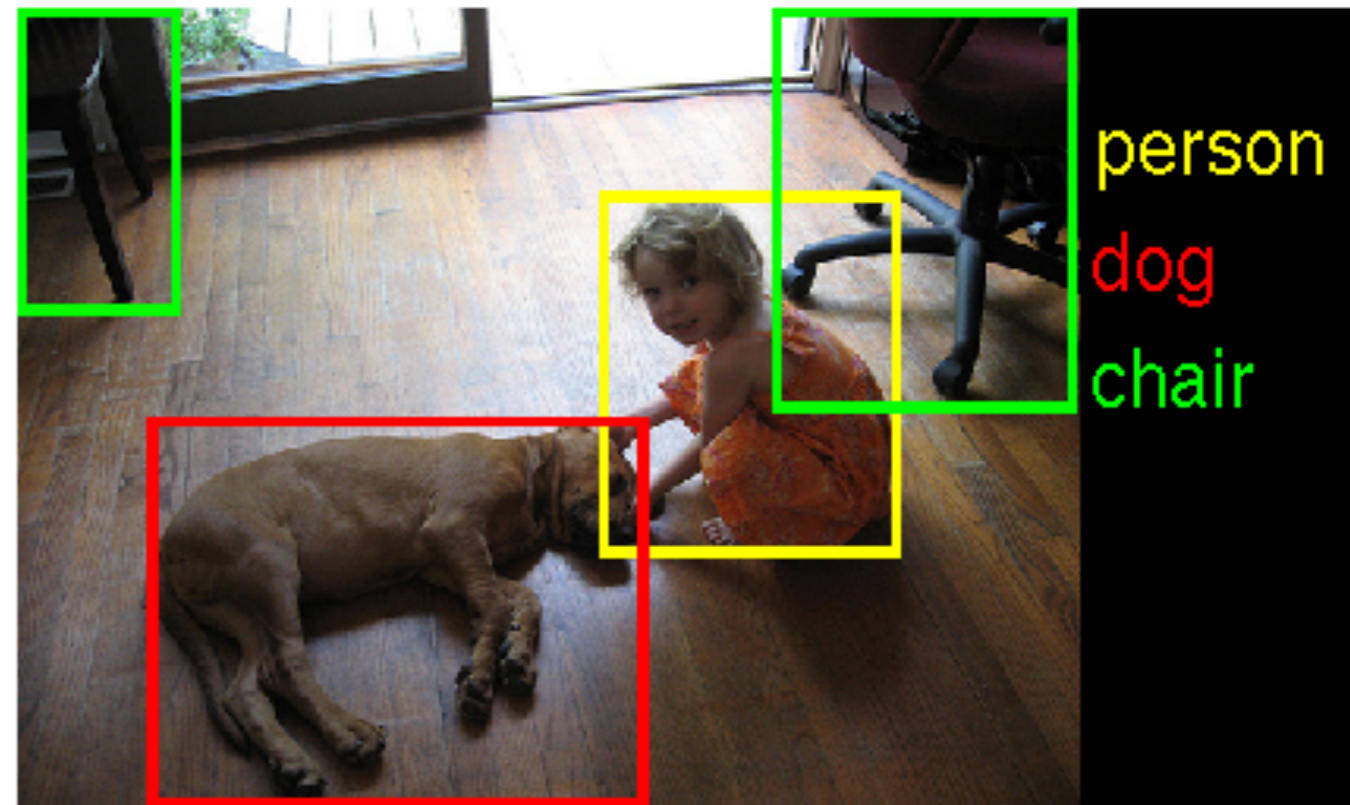
Image Recognition

Ever cleverer

Error rates on ImageNet Visual Recognition Challenge, %



Sources: ImageNet; Stanford Vision Lab

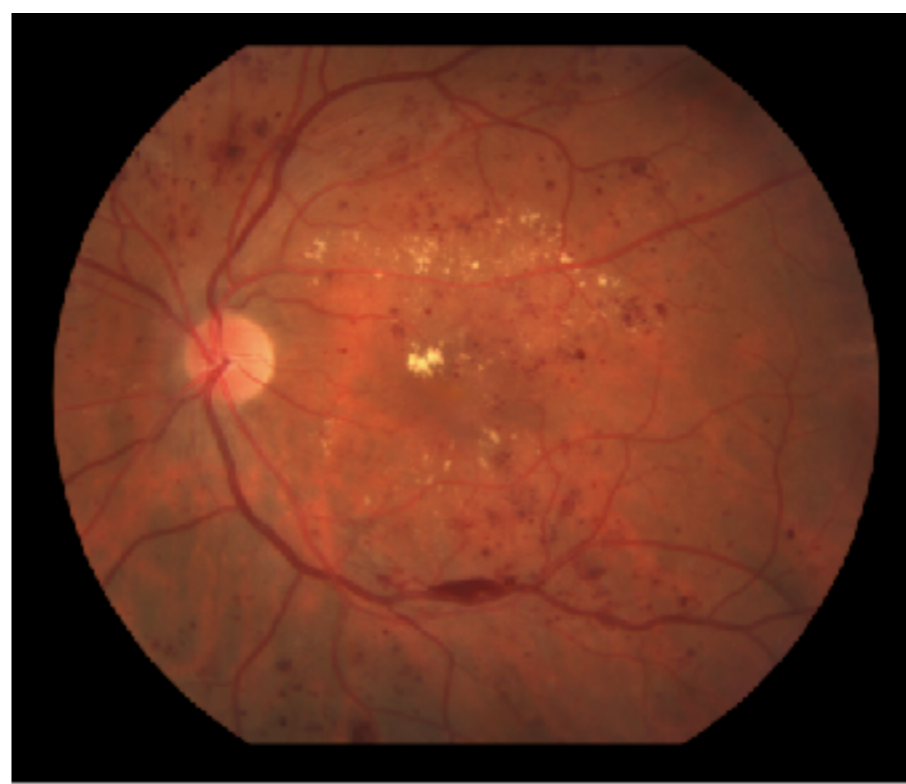


Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs

Varun Gulshan, PhD; Lily Peng, MD, PhD; Marc Coram, PhD; Martin C. Stumpe, PhD; Derek Wu, BS; Arunachalam Narayanaswamy, PhD; Subhashini Venugopalan, MS; Kazumi Widner, MS; Tom Madams, MEng; Jorge Cuadros, OD, PhD; Ramasamy Kim, OD, DNB; Rajiv Raman, MS, DNB; Philip C. Nelson, BS; Jessica L. Mega, MD, MPH; Dale R. Webster, PhD



Normal






Diabetic Retinopathy



Letter

Dermatologist-level classification of skin cancer with deep neural networks

Andre Esteva , Brett Kuprel , Roberto A. Novoa , Justin Ko, Susan M. Swetter, Helen M. Blau & Sebastian Thrun 

Nature **542**, 115–118 (02 February 2017)

doi:10.1038/nature21056

[Download Citation](#)

Diagnosis

Machine learning

Skin cancer

Received: 28 June 2016

Accepted: 14 December 2016

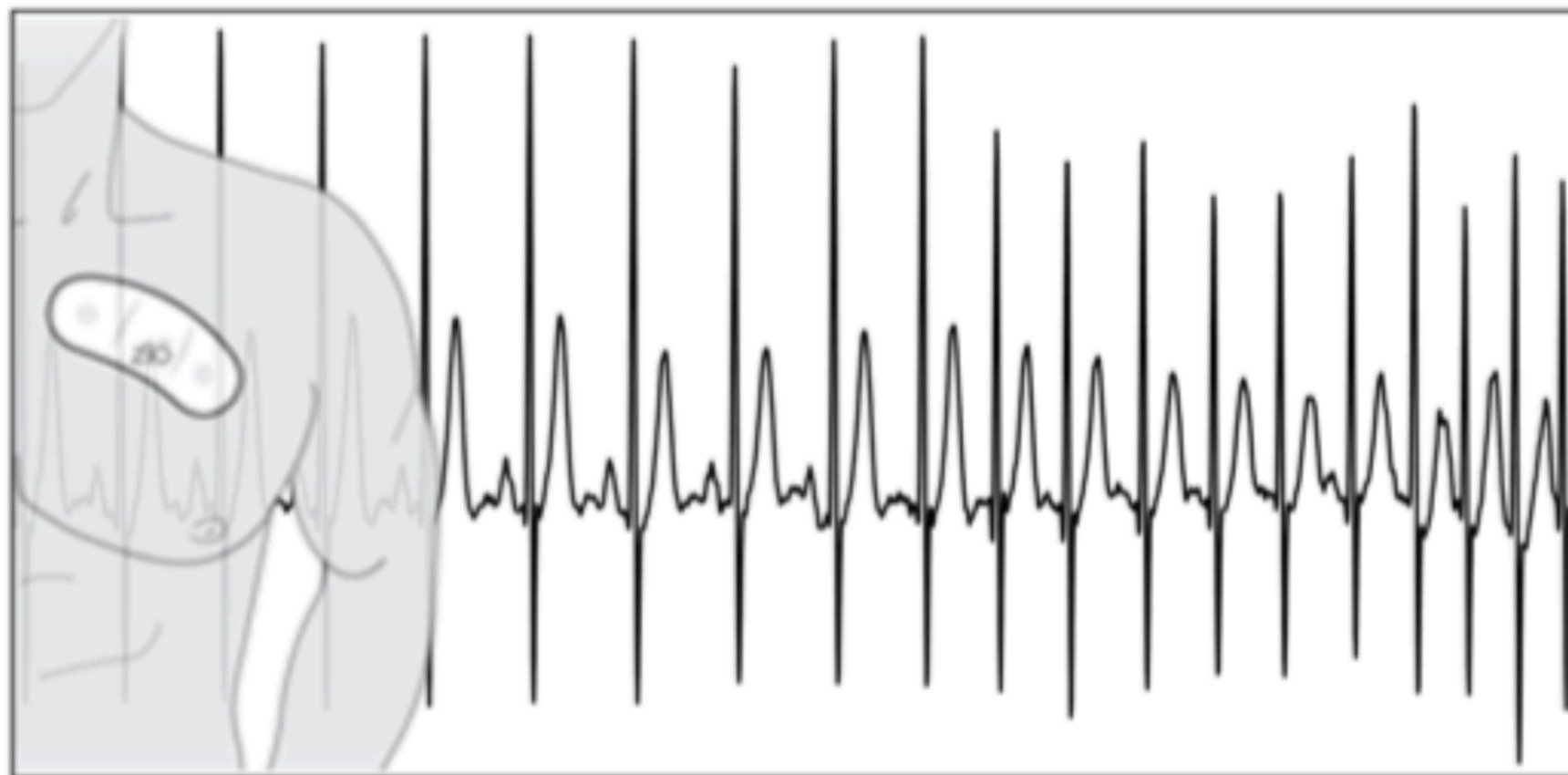
Published online: 25 January 2017

Corrigendum: 28 June 2017

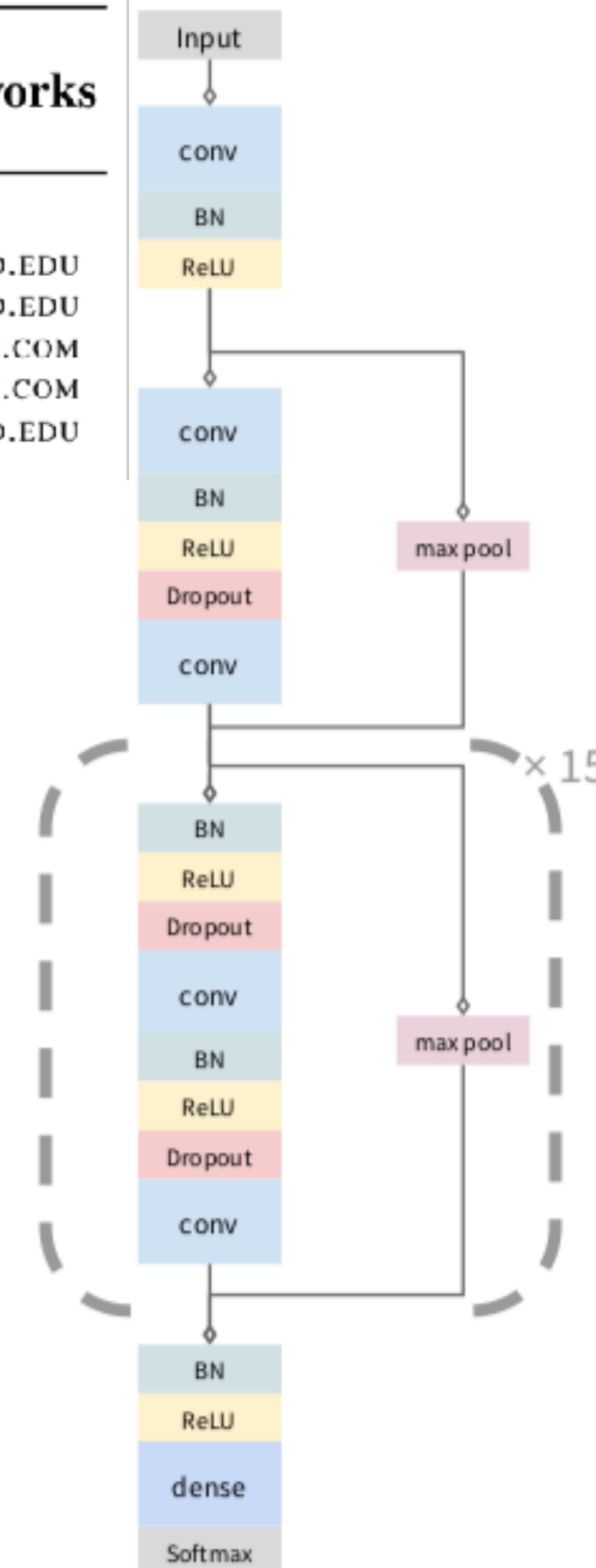
Cardiologist-Level Arrhythmia Detection with Convolutional Neural Networks

Pranav Rajpurkar*
Awni Y. Hannun*
Masoumeh Haghpanahi
Codie Bourn
Andrew Y. Ng

PRANAVSR@CS.STANFORD.EDU
AWNI@CS.STANFORD.EDU
MHAGHPANAHI@IRHYTHMTECH.COM
CBOURN@IRHYTHMTECH.COM
ANG@CS.STANFORD.EDU



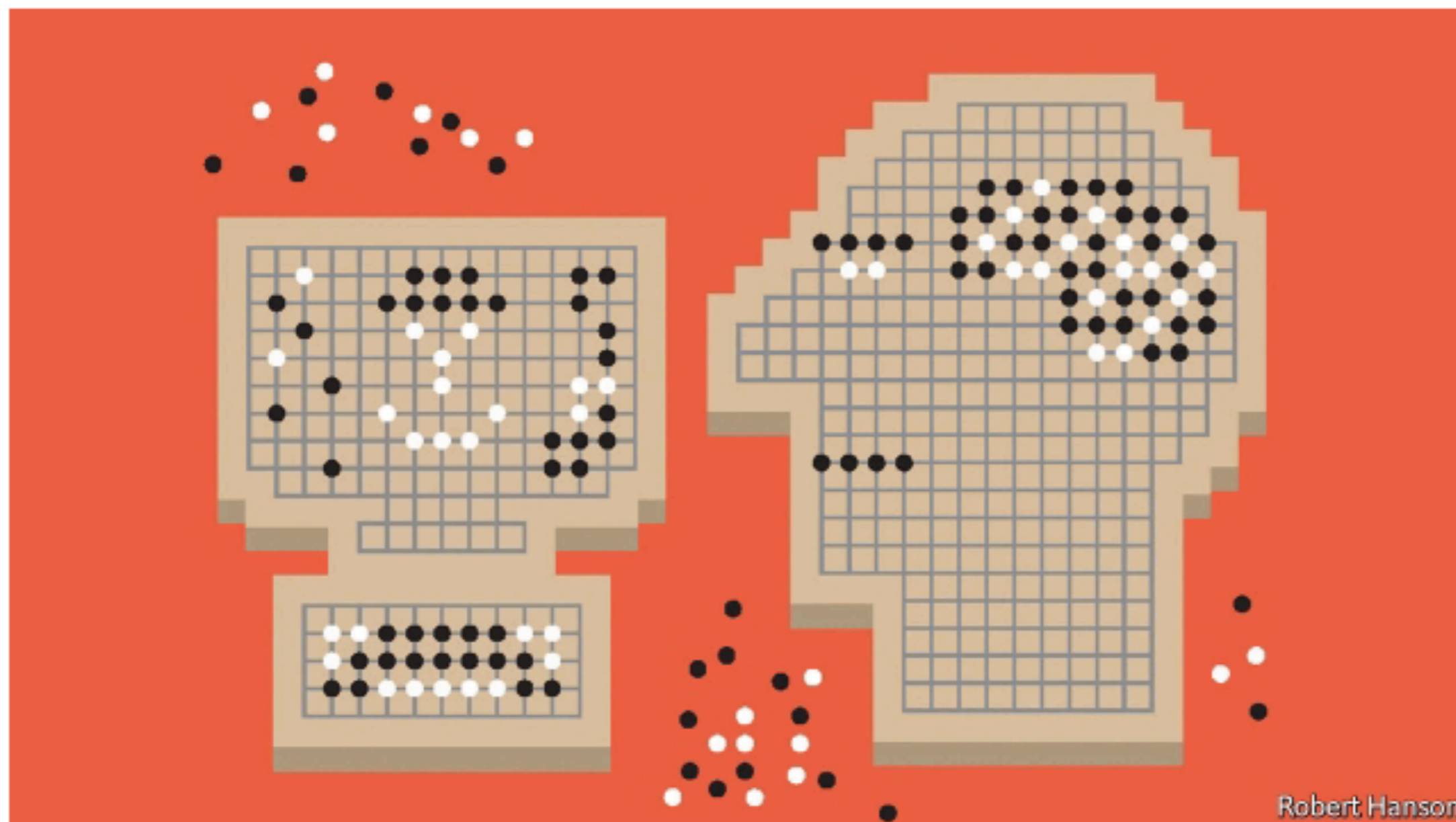
34-layer Convolutional
Neural Network



Artificial intelligence

The latest AI can work things out without being taught

Learning to play Go is only the start



Why the sudden jump?

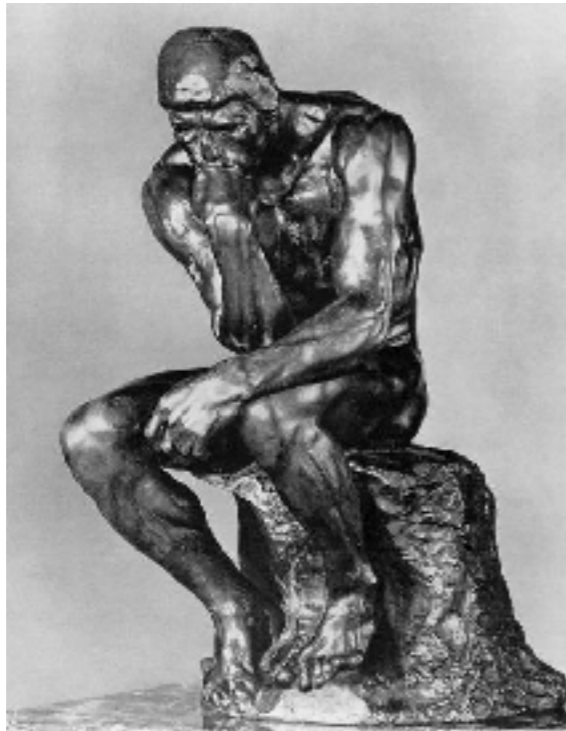
- Better at math?
- Large amounts of Data
- Increased Computational Capacity

Do we really need
doctors?

Do doctors really need
computers?

How do we get computers
to **help us** and **not hurt us**?

What are **humans** really good at?



What are **computers** really good at?



$$\begin{aligned} P(\mathbf{Z}, \mathbf{W}; \alpha, \beta) &= \int_{\boldsymbol{\theta}} \int_{\boldsymbol{\varphi}} P(\mathbf{W}, \mathbf{Z}, \boldsymbol{\theta}, \boldsymbol{\varphi}; \alpha, \beta) d\boldsymbol{\varphi} d\boldsymbol{\theta} \\ &= \int_{\boldsymbol{\varphi}} \prod_{i=1}^K P(\varphi_i; \beta) \prod_{j=1}^M \prod_{t=1}^N P(W_{j,t} | \varphi_{Z_{j,t}}) d\boldsymbol{\varphi} \int_{\boldsymbol{\theta}} \prod_{j=1}^M P(\theta_j; \alpha) \prod_{t=1}^N P(Z_{j,t} | \theta_j) d\boldsymbol{\theta}. \end{aligned}$$

Old Paradigm

New Paradigm

Capture Once, Use Once

Capture Once, Use Many Times

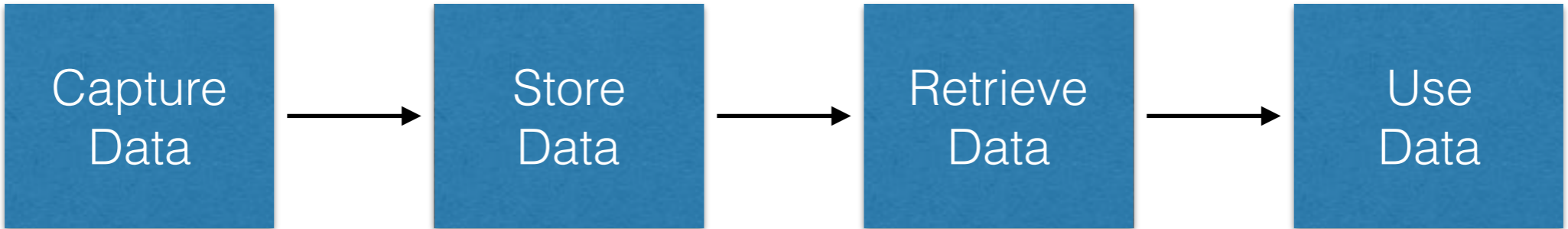
Know exactly how data will be used

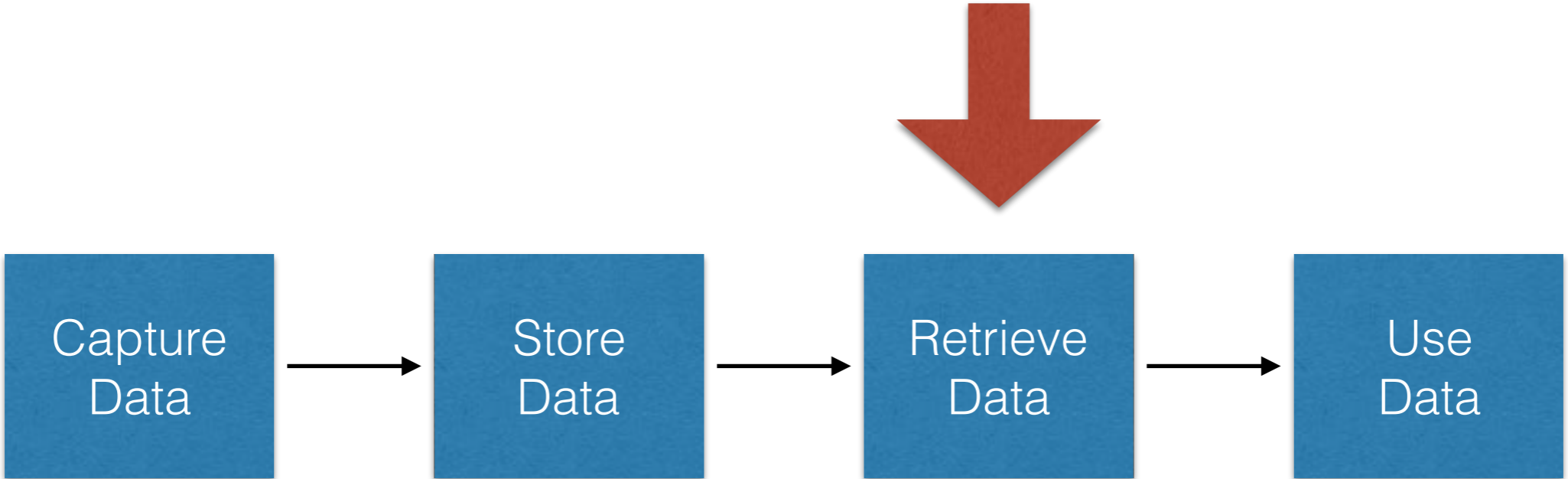
Can not anticipate future secondary
use of data

Schema on Write
(highly structured data)

Schema on Read
(less structured data)

Can't just be about storage
Needs to **provide value**





All 761 omr 740 ops 21

TESTING

94 search results. (0.0106 seconds)

1. Followup (Progress note) omr

06/10/2015 Ayad Hamdan (Hematology/Oncology)

or thrush. Heart: Regular rate and rhythm. Normal S1, S2. No **murmurs**, rubs, or gallops. Lungs: Clear to auscultation bilaterally without rhonchi, rales

2. CHRONIC OBSTRUCTIVE PULMONARY DISEASE (Initial note) omr

06/02/2015 Douglas Beach (Pulmonary)

lymphadenopathy. Chest: Wheezing on exam Cardiac: Normal s1 and s2. No **murmurs** appreciated. No accentuated second heart sound or RV heave. Extremities: No edema

3. Discharge Summary (Disch Sum) ops

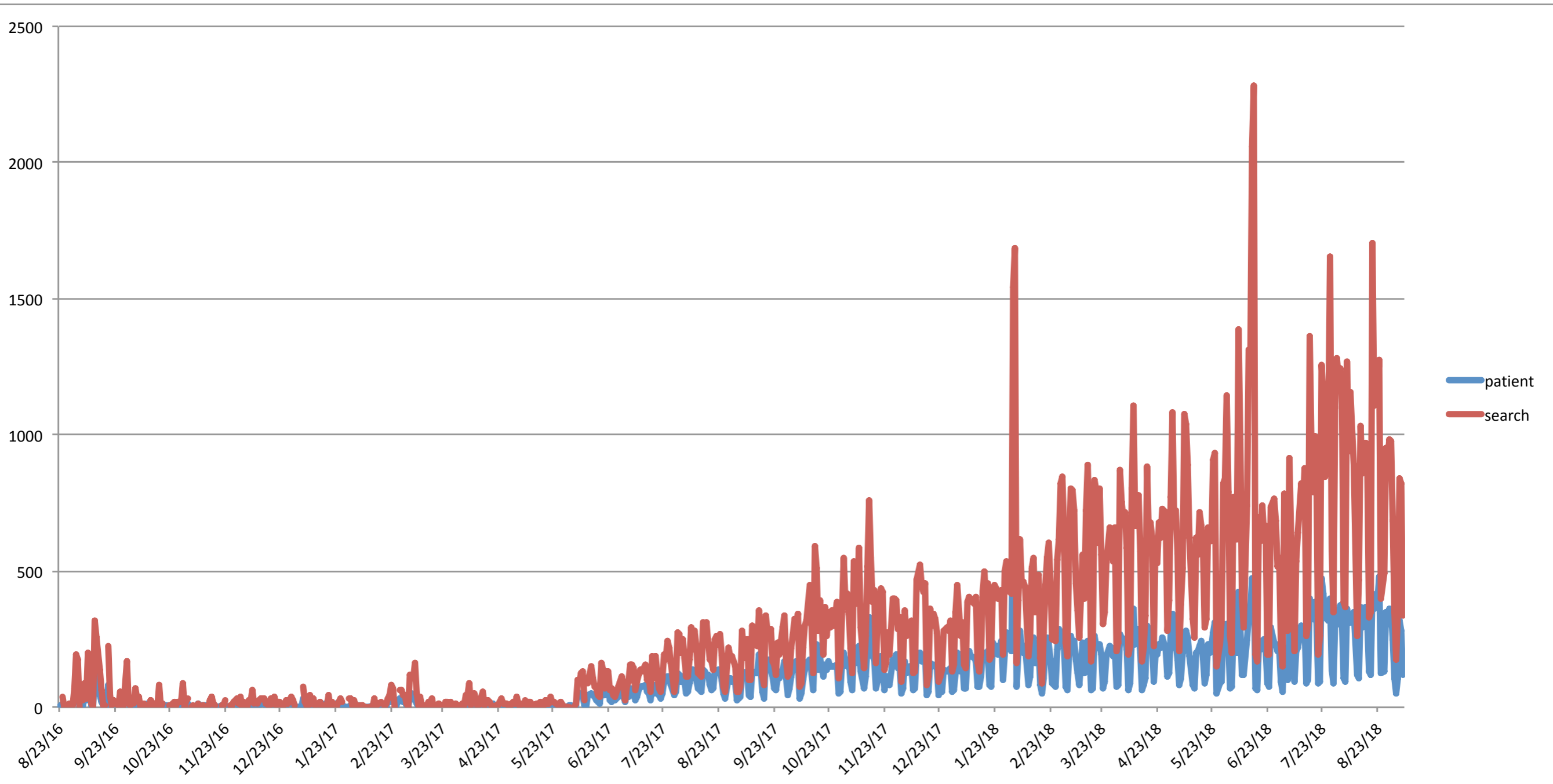
04/21/2015 Meghan J Campo (unknown)

to assess due to body habitus CARDIAC: tachycardic, S1/S2, no **murmurs**, gallops, or rubs LUNG: Diffusely wheezing ABDOMEN: nondistended, +BS, nontender...cough compred to prior CV: Regular rate and rhythm, normal S1 + S2, no **murmurs**, rubs, gallops Abdomen: soft, non-tender, non-distended, no pain on deep palpation

4. Follow-up (Progress note) omr

09/10/2014 Ayad Hamdan (Hematology/Oncology)

or adenopathy. Heart: Regular rate and rhythm. Normal S1, S2. No **murmurs**, rubs, or gallops. Lungs: Clear to auscultation bilaterally without rhonchi, rales



Contextual Information Retrieval

- Cardiac Info (10)

DM: metformin

HTN: metoprolol tartrate

Tobacco: None

FH: Father w/ hx of etoh abuse, passed away from MI @ 70s, first one in 50s. Paternal grandmother with CVA and paternal grandfather with MI in the 70s. mother with OCD. [12/19/2014 17:13]

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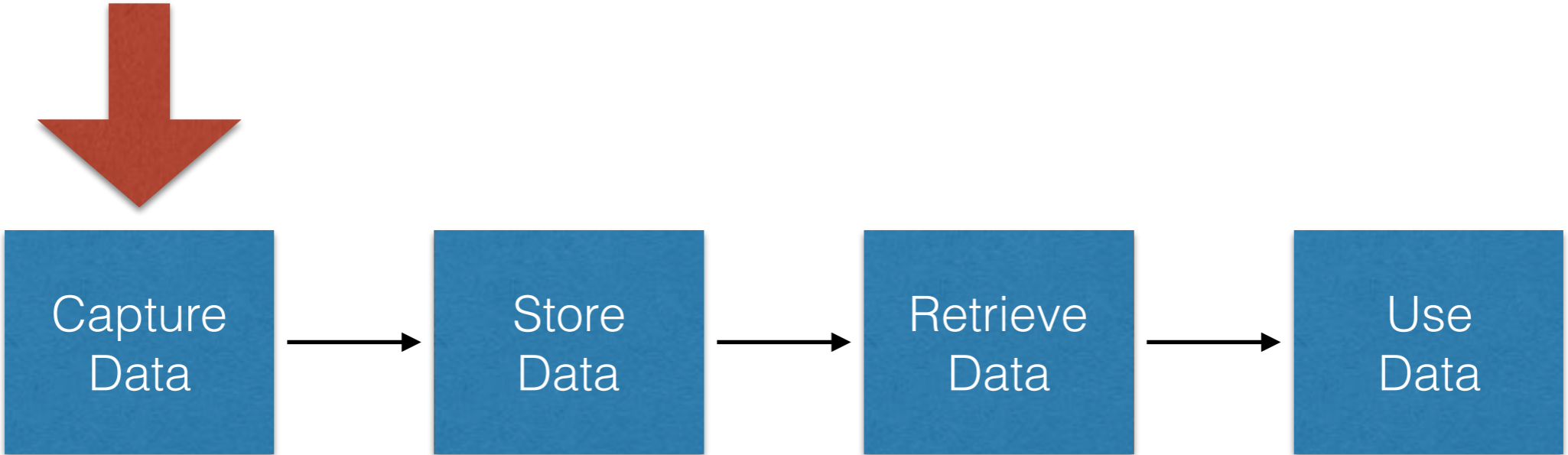
08/19/2004 Echo

05/25/2004 Cath

1. Coronary angiography of this right dominant circulation revealed single vessel CAD. The LMCA had no significant stenoses. The LAD had minor luminal irregularities. The LCX had a 90% hazy lesion of a large OM1 with TIMI 2 flow. The RCA had no obstructive disease. 2. Resting hemodynamics showed elevated LV filling pressures. 3. Left ventriculography showed no wall motion abnormalities and an EF of 56%. 4. Successful stenting of the OM1 with 2.5 x 20 mm Taxus DES at 14 atms and successful PTCA of the mid OM1 with 2.0 x 15 mm open sail balloon at 6 atms with no residual stenosis in the stented segment, 25% residual stenosis in the mid OM1, no dissection and timi 3 flow. See PTCA comments.

05/25/2004 Echo

03/30/2004 NUCLEAR



Structured Chief Complaints

- Almost always entered as free text
- Structured chief complaints have great utility
 - Clinical Decision support
 - Research
 - QA
 - Epidemiology

Standard vocabulary / ontology

Small vocabulary

Large vocabulary

Easy to learn and use

Difficult to learn and use

Reproducible

Quality dependent on user training and motivation

Too general, often times not accurately representing the chief complaint

Very specific, well representing the chief complaint if used properly

Probabilistic Inference for Chief Complaint UI

- **Essentially a Diagnosis Problem**
- Probabilistic Inference based on all available data(Age, Sex, Vital signs, Emergency Severity Index, Medical Problems, labs, etc.)
- Implemented as Contextual Auto-complete

Chief Complaint UI

The image displays two side-by-side screenshots of a medical software interface, likely for a hospital's Emergency Department (ED). Both screenshots show the same patient information and interface elements, but the right-hand screenshot has a dropdown menu open for the 'Chief Complaints' field.

Page Header: BIDMC ED PORTAL - Session # 300111322 - *** TEST SYSTEM *** - Google Chrome

Navigation: Help, LifeImage

Patient Information: KERMIT,F [69 / M]

Vitals: Temp 99 HR 102 BP 150/70 RR 24 O2sat 99%

History: 69 y/o M Patient with severe intermittent RUQ pain. Began soon after eating. Also is a heavy drinker.

Chief Complaints:

Options:

- RUQ abdominal pain
- Allergic reaction
- L Knee pain
- Rectal pain
- Right sided abdominal pain

Transfer:

- MCI

Buttons: Enter, Cancel

Right Screenshot Dropdown Menu:

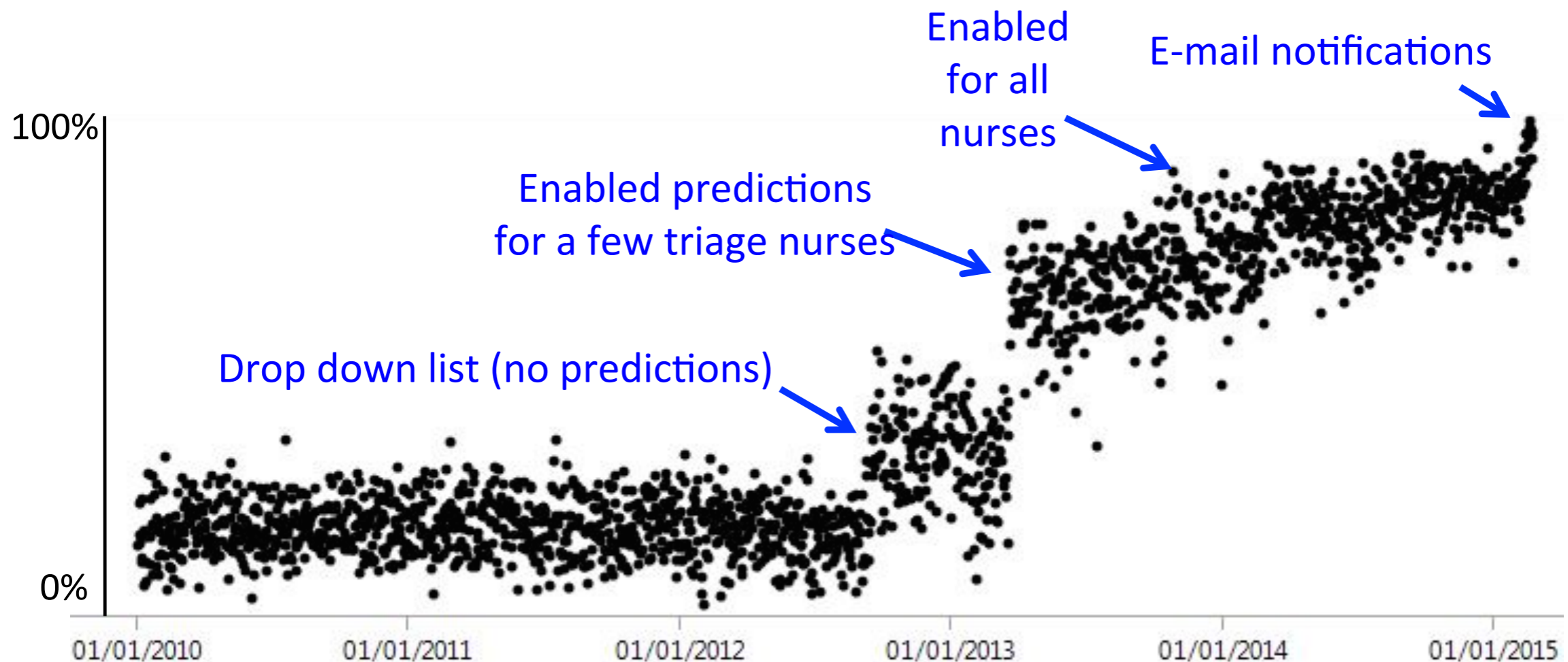
- RIGHT UPPER QUADRANT PAIN
- RUQ ABDOMINAL PAIN
- RUQ PAIN
- ALLERGIC REACTION
- L KNEE PAIN
- RECTAL PAIN
- RIGHT SIDED ABD PAIN
- RIGHT SIDED ABDOMINAL PAIN
- L WRIST PAIN
- RIGHT SIDED CHEST PAIN
- TESTICULAR PAIN
- KNEE PAIN
- ELBOW PAIN
- RIB PAIN
- L ELBOW PAIN
- HAND PAIN
- VAGINAL PAIN

Chief Complaint UI Performance Characteristics

Multiclass SVM	
Best-5	0.757
Best-10	0.825
Discounted Cumulative Gain	0.613

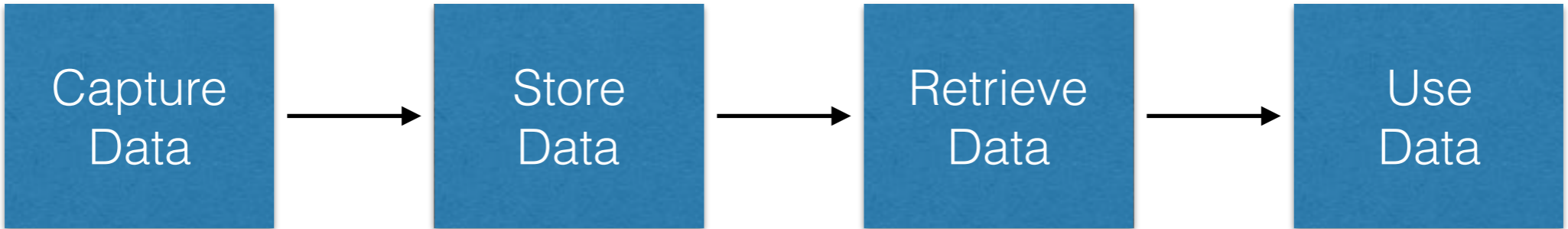
Compliance

- Structured chief complaint went from ~35% to ~95% ($p < 0.001$)
- Nurses don't realize it's there



Can be applied to usage for any standard ontology

- Snomed CT
- ICD10
- CPT



Automated Triggering

- Clinical pathways
- Decision Support
- Order Sets
- Research eligibility screening

Benefits of Automated Triggers

- Doesn't rely on user knowing that a function exists (important given our large number of transient users)
- Independent of user's knowledge and motivation

Clinical State	Description	Value	Anchors	State	Reasoning
chestpain_acute	cardiac chest pain	.81		<input type="text" value=""/>	# chest pain
cardiac_acute		.07		<input type="text" value=""/>	also in ddx is angina or mi
cancer_history		.04		<input type="text" value=""/>	collins is a simnum year old female with a history of htn , mdd , and asthma who presents to the ed for chest pain and shortness of breath
abdominalpain_acute	acute abdominal pain	.03		<input type="text" value=""/>	chest pain
infection_acute		.03		<input type="text" value=""/>	cxr
asthma-copd_acute	active asthma/copd	.02		<input type="text" value=""/>	acute onset chest pressure with dyspnea possibly related to history of asthma and could be an exacerbation however she is not wheezy on exam
diabetes_history	diabetes	.02		<input type="text" value=""/>	age_63
syncope_acute		.02		<input type="text" value=""/>	she was also so uncomfortable that she had to get out of bed and lay on the floor
uti_acute		.01		<input type="text" value=""/>	ms
backpain_acute	acute back pain	.01		<input type="text" value=""/>	# chest pain
allergicreaction_acute	acute allergic reaction	.01		<input type="text" value=""/>	acute onset chest pressure with dyspnea possibly related to history of asthma and could be an exacerbation however she is not wheezy on exam
chf_acute		.01		<input type="text" value=""/>	# dyspnea :
psych_acute	acute psychiatric condition	0		<input type="text" value=""/>	she was also so uncomfortable that she had to get out of bed and lay on the floor
headache_acute	active headache	0		<input type="text" value=""/>	a / p :

OPEN

Learning a Health Knowledge Graph from Electronic Medical Records

Maya Rotmensch¹, Yoni Halpern², Abdulhakim Tlimat³, Steven Horng^{3,4} & David Sontag ^{5,6}

Demand for clinical decision support systems in medicine and self-diagnostic symptom checkers has substantially increased in recent years. Existing platforms rely on knowledge bases manually compiled through a labor-intensive process or automatically derived using simple pairwise statistics. This study explored an automated process to learn high quality knowledge bases linking diseases and symptoms directly from electronic medical records. Medical concepts were extracted from 273,174 de-identified patient records and maximum likelihood estimation of three probabilistic models was used to automatically construct knowledge graphs: logistic regression, naive Bayes classifier and a Bayesian network using noisy OR gates. A graph of disease-symptom relationships was elicited from the learned parameters and the constructed knowledge graphs were evaluated and validated, with permission, against Google's manually-constructed knowledge graph and against expert physician opinions. Our study shows that direct and automated construction of high quality health knowledge graphs from medical records using rudimentary concept extraction is feasible. The noisy OR model produces a high quality knowledge graph reaching precision of 0.85 for a recall of 0.6 in the clinical evaluation. Noisy OR significantly outperforms all tested models across evaluation frameworks ($p < 0.01$).

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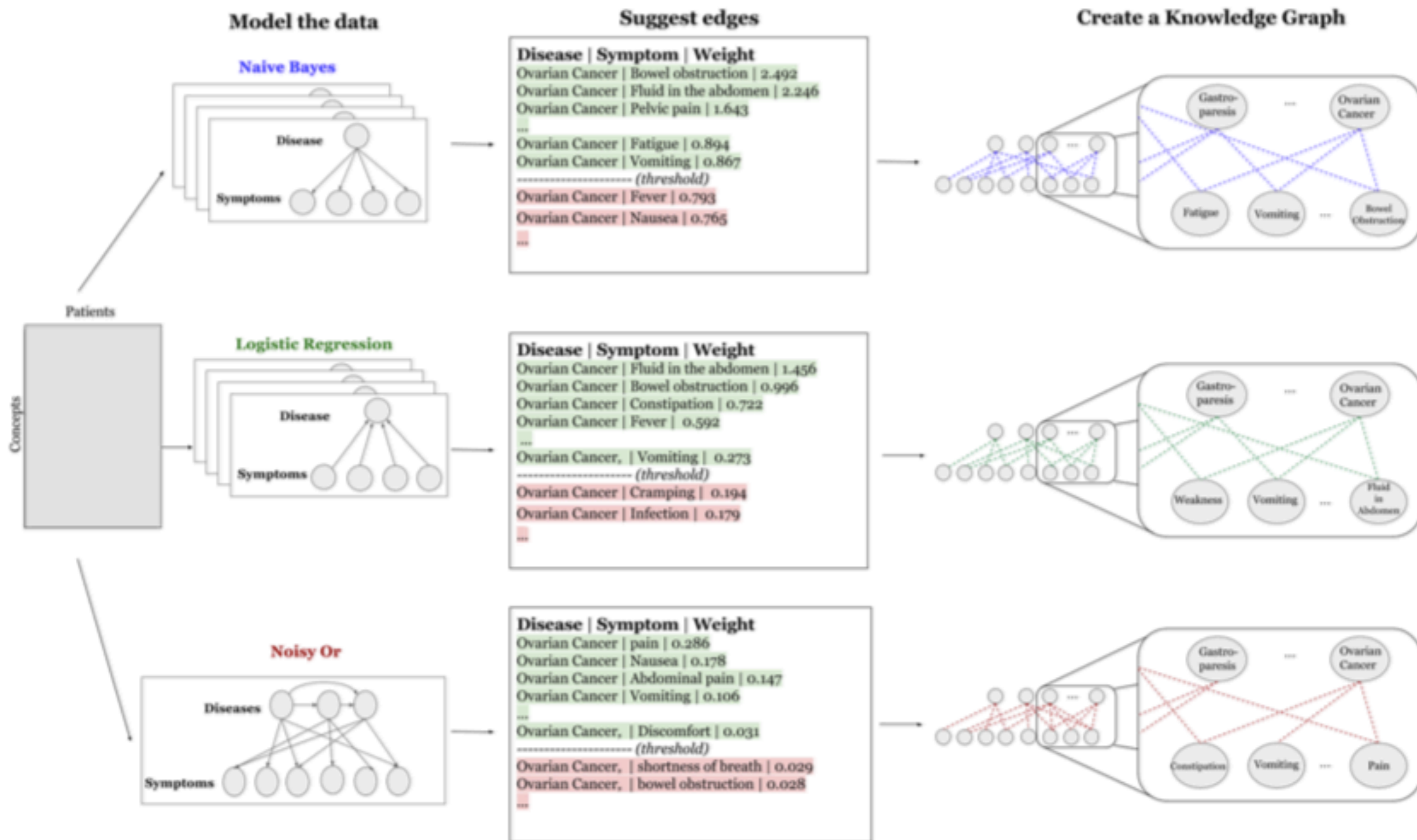


Figure 2. Workflow of modeling the relationship between diseases and symptoms and knowledge graph construction, for each of our 3 models (naive Bayes, logistic regression and noisy OR).

- Cardiac CP Order Set

To be drawn immediately Add-on

Initial

- IVs: Place IV (saline lock);
flush per protocol
- Noninvasive Patient Monitoring: Continuous Cardiac monitoring
- Noninvasive Patient Monitoring: Continuous Pulse oximetry

EKG (pick 1)

- EKG (to be performed): Indication: Chest Pain
- EKG (to be performed): Indication: Dyspnea

Laboratory

- CBC + Diff
- + Chem-7
- Troponin

Aspirin (pick 1)

- Aspirin 243 mg PO *Allergy
- Aspirin 324 mg PO *Allergy
- Aspirin taken before arrival

Imaging

- XR Chest PA & Lateral
- XR Chest AP Portable

Stress

- Exercise Stress Test (ETT) ⁱ
- Stress Echo ⁱ
- Myocardial Perf with Exercise ⁱ
- Myocardial Perf with Pharm Stress ⁱ

+ Other

[Order More](#)

[Order+Sign](#)

Contextual Information Retrieval

- Cardiac Info (10)

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Tobacco: None

FH: Father w/ hx of etoh abuse, passed away from MI @ 70s, first one in 50s. Paternal grandmother with CVA and paternal grandfather with MI in the 70s. mother with OCD. [12/19/2014 17:13]

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05/25/2004 Echo

03/30/2004 NUCLEAR

Checklists

- Unstructured Data
- Scanned Images (consent forms, DNR/DNI, etc.)

Risk Stratification

Triage waiting room sorting

- Triage is most necessary when demand > supply
- Same time when very difficult to allocate additional resources to re-prioritize / monitor patients
- Automated methods using already collected data would be helpful

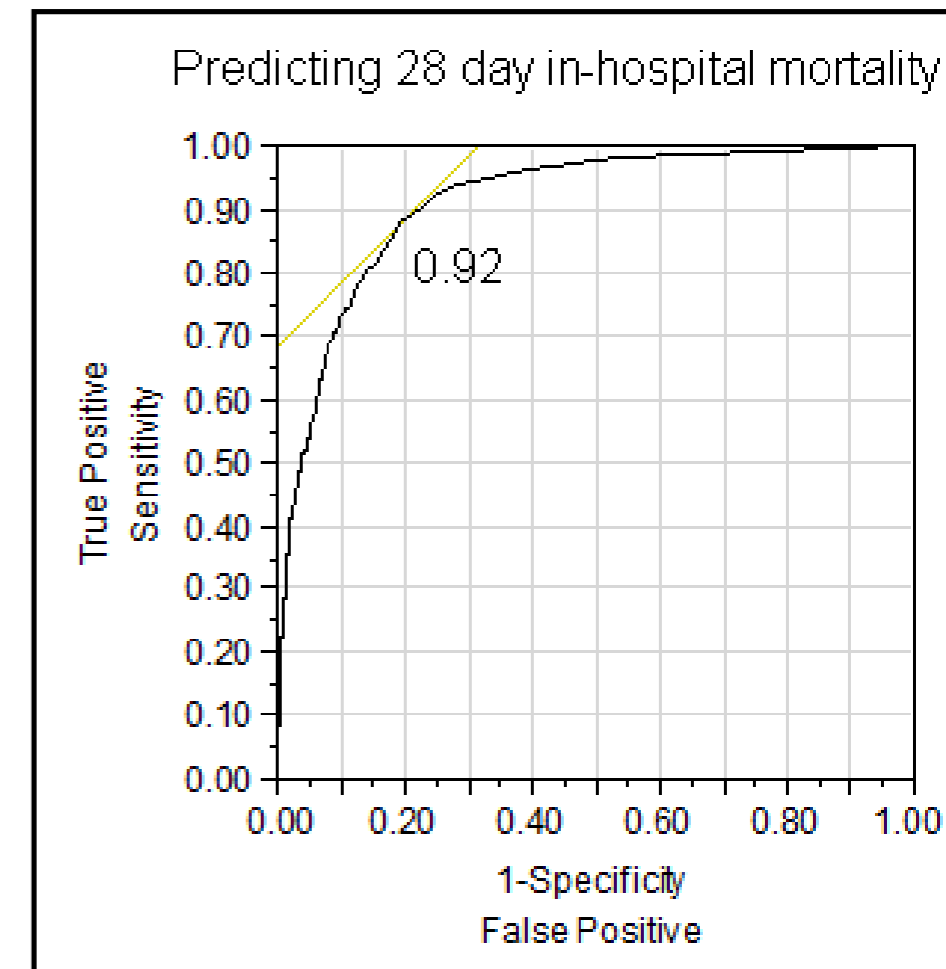


Probabilistic Inference for Triage Rack Sorter

- **Essentially a Risk Stratification Problem**
- Probabilistic Inference based on all available data(Age, Sex, Vital signs, Emergency Severity Index, Medical Problems, labs, etc.)
- Implemented as graphical risk stratification meter

Risk Stratification

Outcome	Algorithm AUC	
	<u>derivation</u> <i>(n=75,992)</i>	<u>Validation</u> <i>(n=18,981)</i>
<u>All ED Patients</u>		
Infection	0.88	0.88
28 day mortality	0.94	0.92
ICU admission	0.91	0.90



Triage

eRack (7)									
TIR	TID	Age	Rm	Name	Chief Complaint	Att	Res	Nur	Mortality
1409d	10:34	77	7	Corporan-Can...	Sob, Cough, Vom	LarryN		Deth	
1430d	10:11	23	5	Lin, B	Sob, Throat Closing	Alden		no rob	
917d	8:15	84	2	Bissell, P	Black Stools	LarryN			
1176d	08:14:5h	56	21	Mills, M	Treat Fwd2 Hisc2 R C				
1436d	11:35	64	23b	Post Franken...	Melena	Hurry		nic rob	
1409d	9:15	60	22a	Pullano, H	1 Inr, Fever,			MA	
1430d	10:30	73	32	Uyeno, J	Fever, c/p Sinus Sur			Yolo	

Temp 97.3 HR 96 BP 104/69 RR 24 O2sat 100%

88 y/o M pt from coolidge house with past few days of altered mental status, lethargic, fevers. o2sat today 88% ra. also with INR>10, Na=161. triggered to room 21)

Time	Pain	Temp	HR	BP	RR	Pox	Glucose
+ Triage 13:12	u/c	97.3	96	104/60	24	100% NRE	

30 day mortality: 71% [Go to Patient View -->](#)

Quantification of
pulmonary edema as a
surrogate for **fluid status**

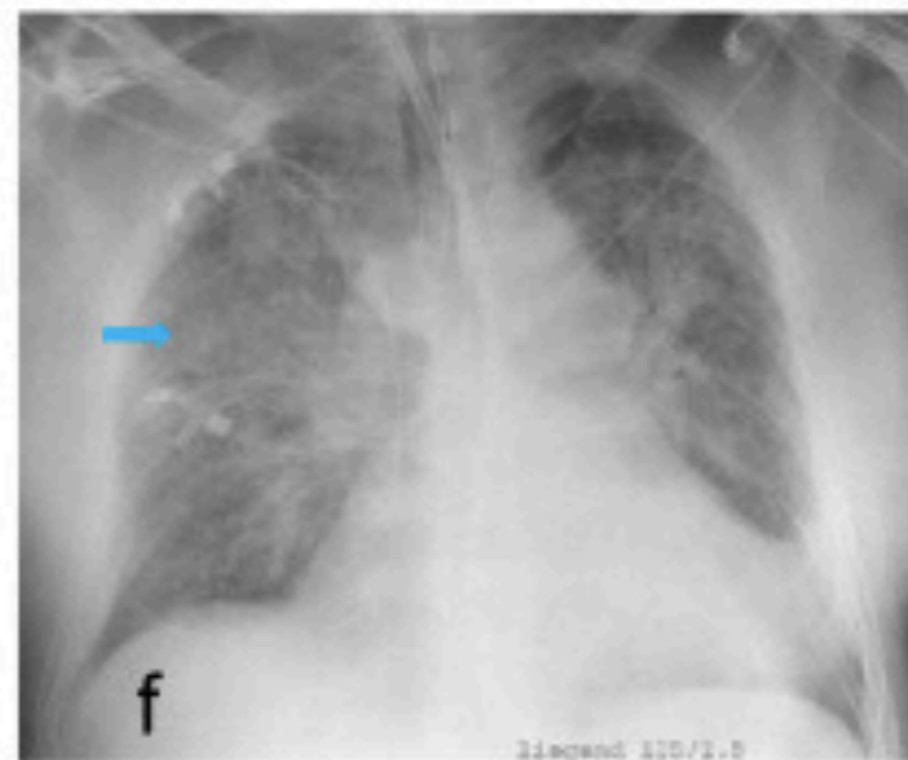
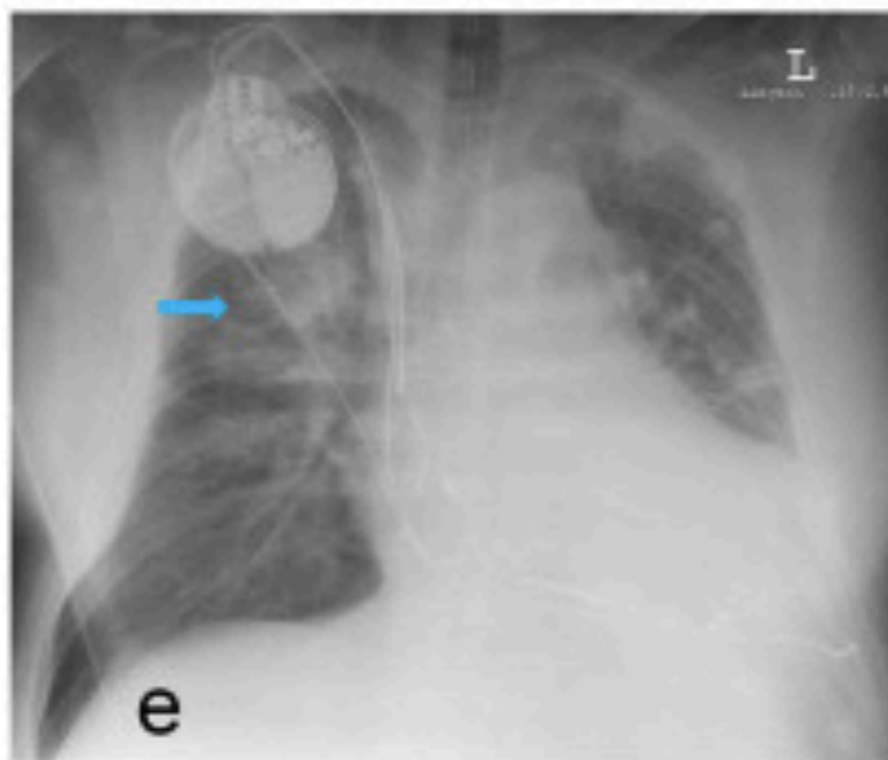
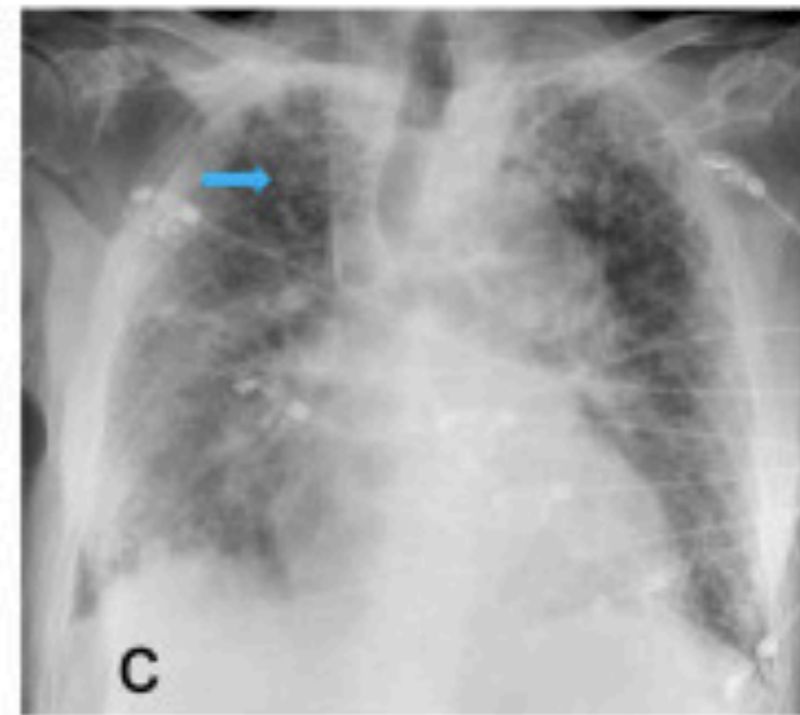
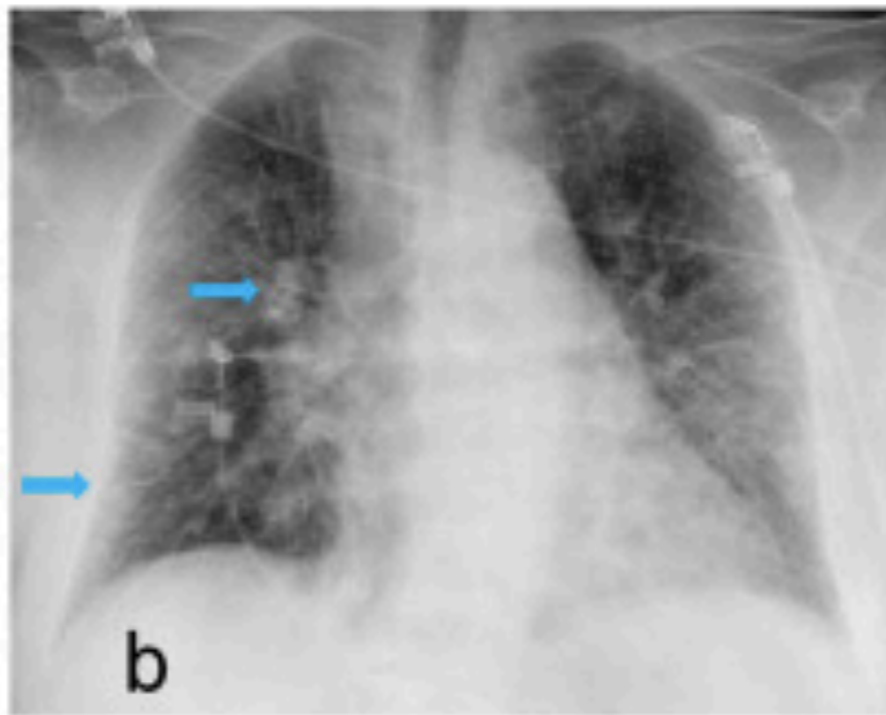
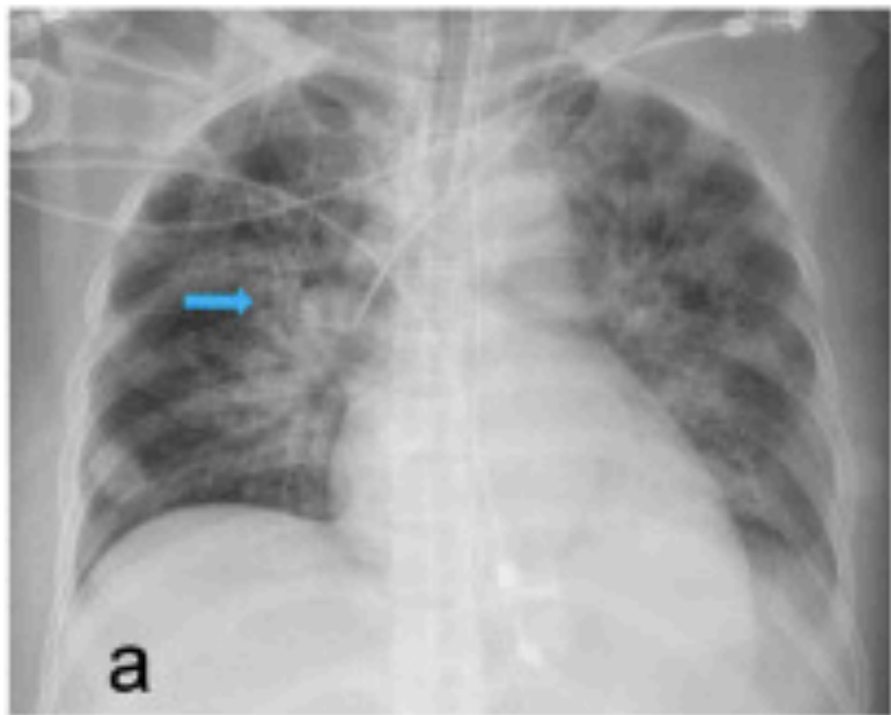
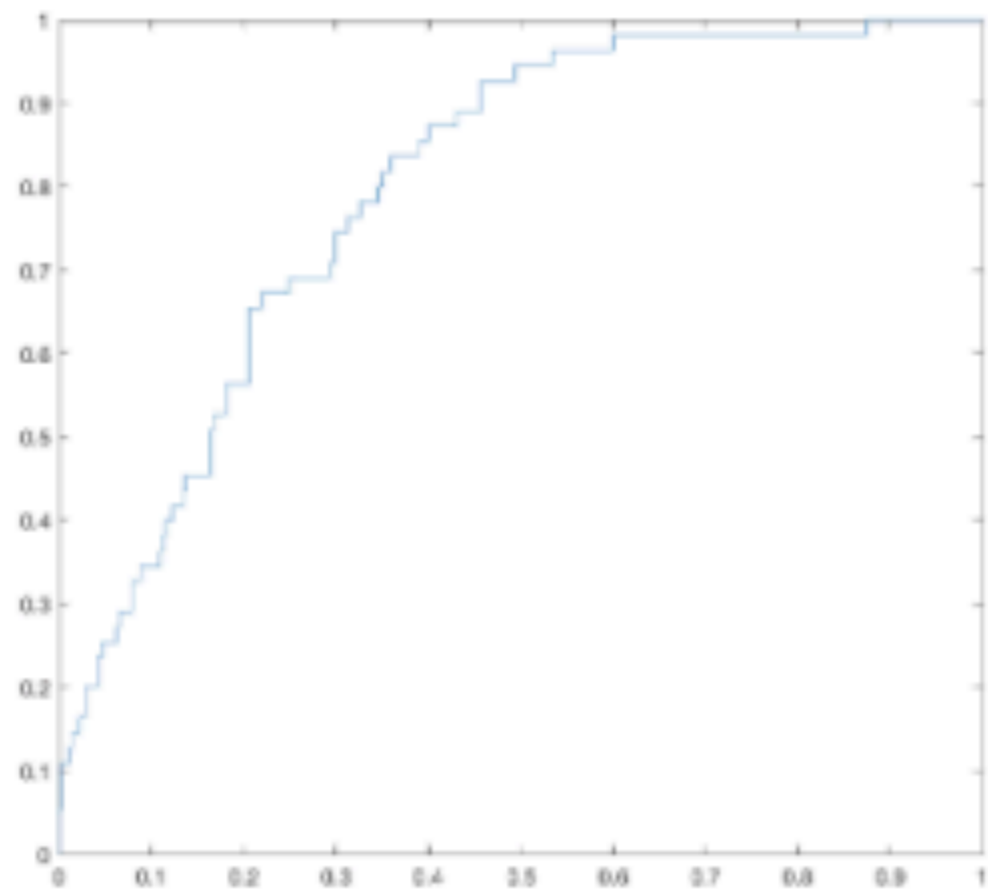


Table 1**Radiologic scoring of pulmonary edema on bedside chest radiographs**

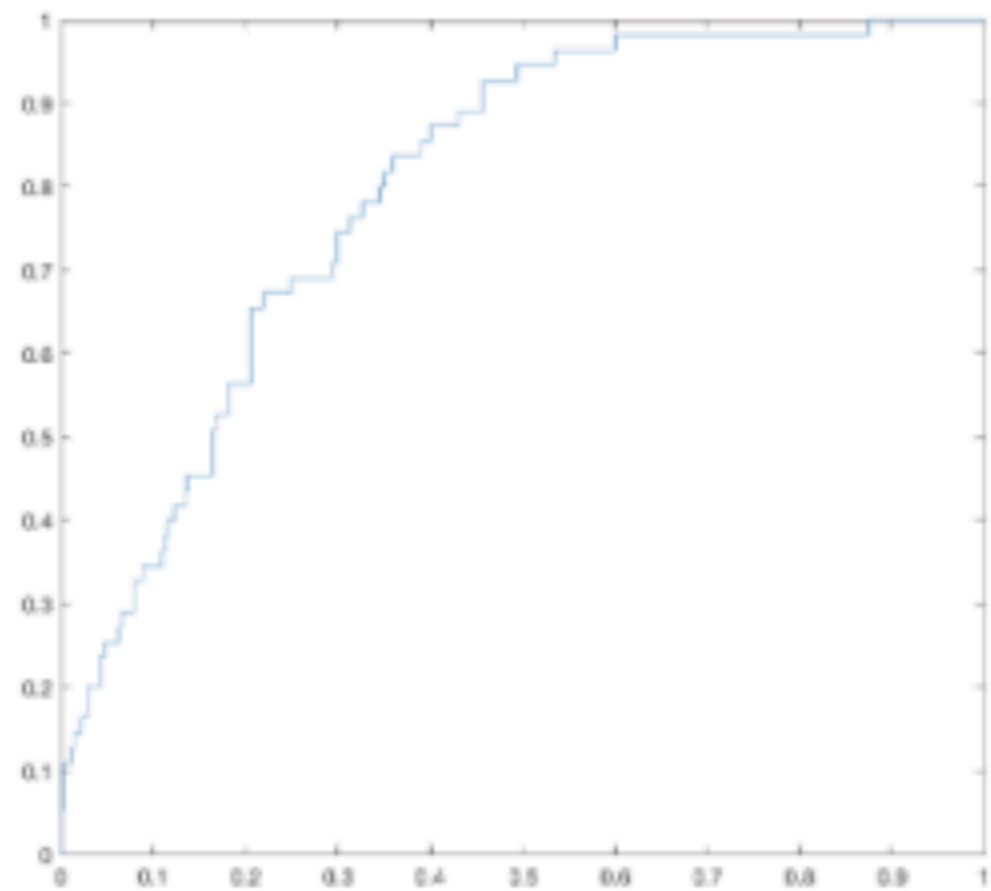
Variables		Score		
		Mild	Moderate	Severe
Hilar vessels	Enlarged	1	2	3
	Increased in density	2	4	6
	Blurred	3	6	9
Kerley B lines		4	-	8
Micronoduli		4	-	8
Widening of interlobular fissure		4	8	12
Peribronchial and perivascular cuffs		4	8	12
Extensive perihilar haze		5	10	15
Diffuse increase in density		5	10	15

kappa 0.68



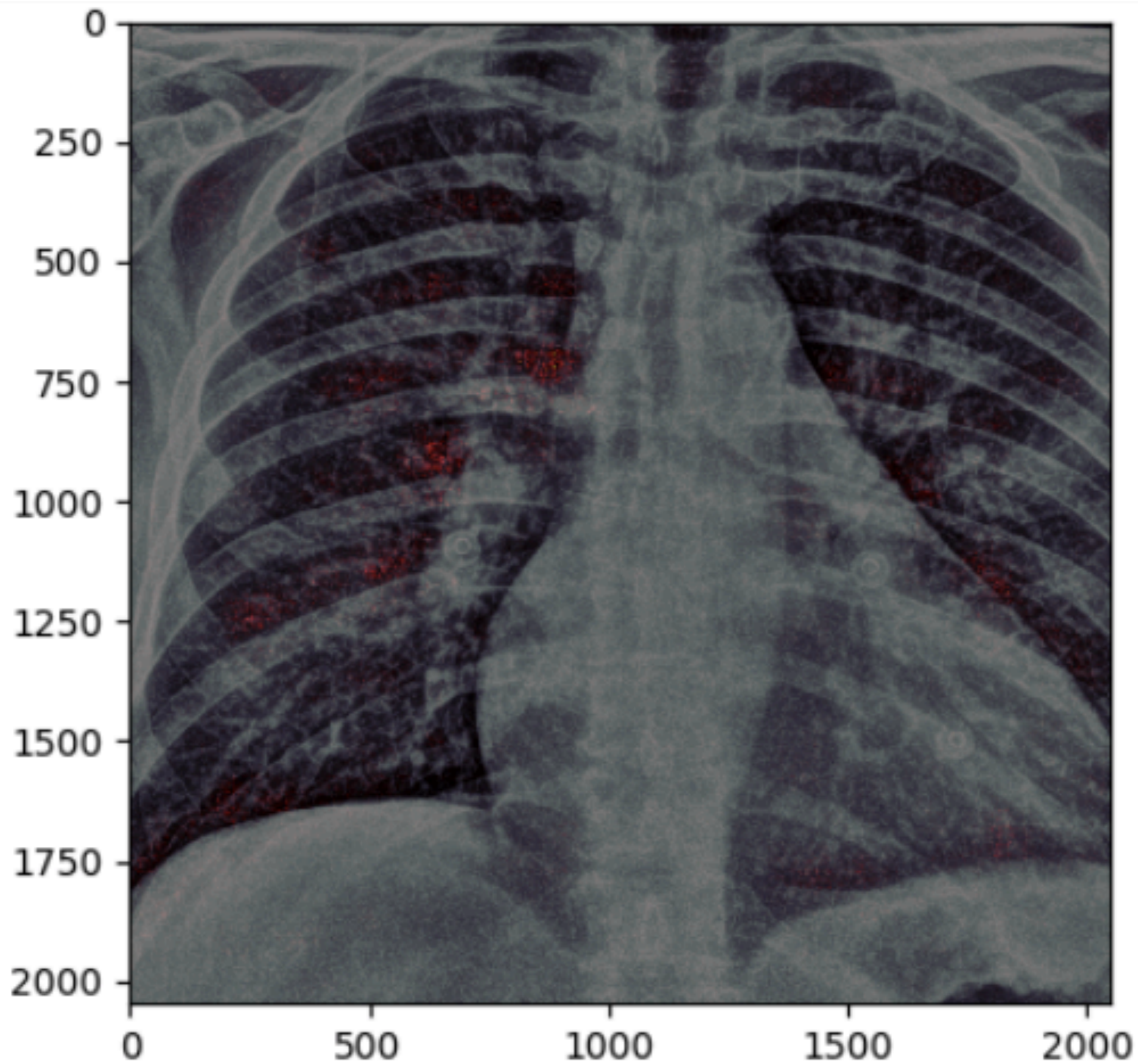
AUC=0.75

No Edema vs. Mild/Moderate/Severe edema



AUC=0.80

No/Mild Edema vs Moderate/Severe Edema



Summary

- Big data / Machine Learning will help us leverage the data already being generated
- Right information at the right time
- Design for the user (save time, facilitate workflow)
- Build decision support directly into the user interfaces