

# Artificial Intelligence in Clinical Medicine

## Artificial Intelligence in Clinical Medicine

Shyam Visweswaran, MD, PhD  
Professor of Biomedical Informatics  
University of Pittsburgh

Department of  
Biomedical Informatics

Pitt CTSI



1

## Applications of Artificial Intelligence (AI) in Medicine

- **For biomedical discovery**
  - AI is used especially for big data, heterogeneous data, and combination of experimental and observational data
- **For clinical decision support**
  - CDS *provides clinicians, patients or public health officials with knowledge and person-specific information, intelligently filtered or presented at appropriate times, to enhance health and health care*<sup>1</sup>
  - AI can make CDS more effective
- In this session I will focus on AI and clinical decision support

<sup>1</sup>Medicare and Medicaid Programs: Electronic Health Record Incentive Program. Vol 75 FR 44313; 4435, Washington DC, 2010, Centers for Medicare and Medicaid Services.

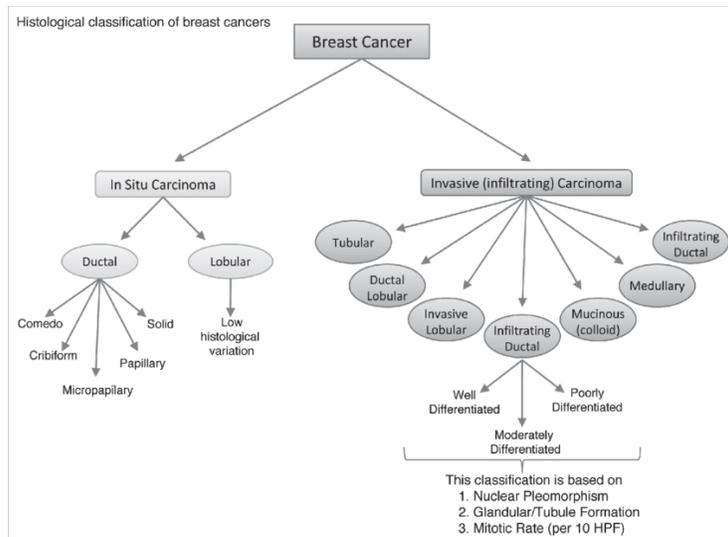
2

## Clinical Challenges

1. **Knowledge overload** – Growing **medical knowledge** threatens to overwhelm human memory capacity (e.g., rise of molecular classification of disease is adding new rapidly changing medical knowledge)

3

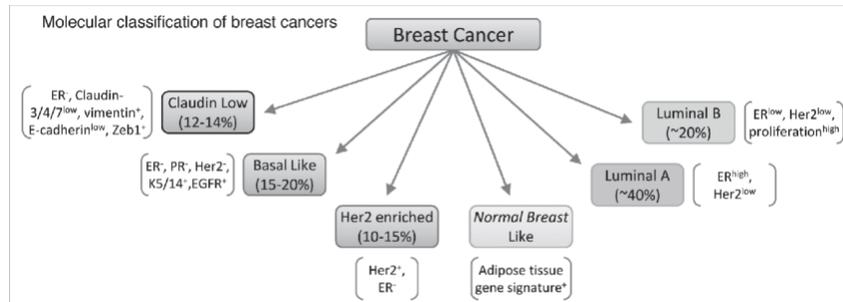
## Histological Classification of Breast Cancers



Malhotra GK, Zhao X, Band H, Band V. Histological, molecular and functional subtypes of breast cancers. *Cancer biology & therapy*. 2010 Nov 15;10(10):955-60.

4

## Molecular Classification of Breast Cancers



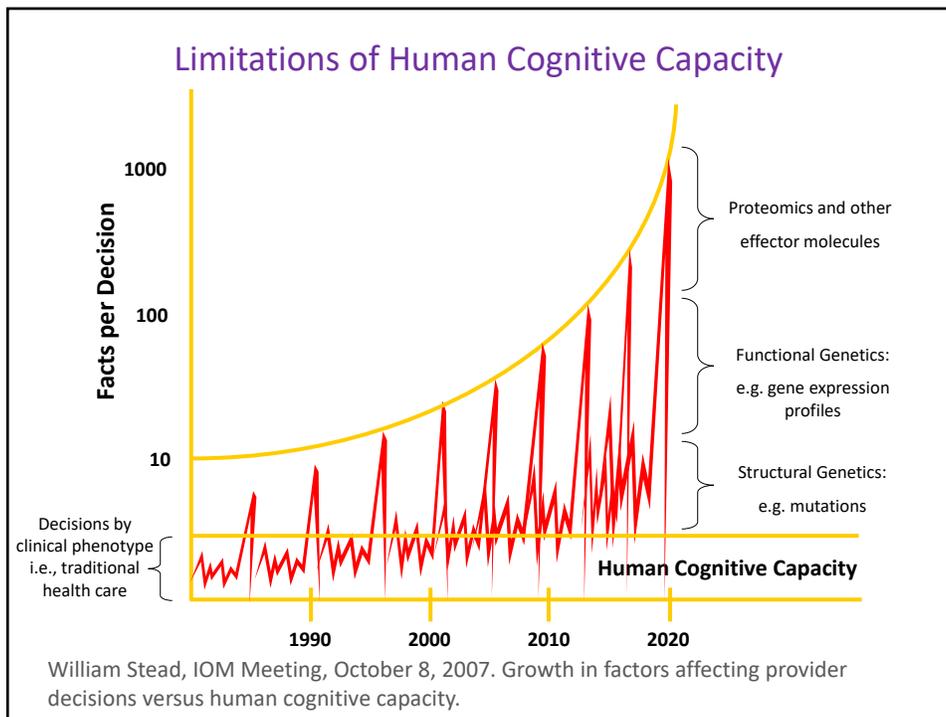
Malhotra GK, Zhao X, Band H, Band V. Histological, molecular and functional subtypes of breast cancers. *Cancer biology & therapy*. 2010 Nov 15;10(10):955-60.

5

## Clinical Challenges

1. **Knowledge overload** – Growing **medical knowledge** threatens to overwhelm human memory capacity (e.g., rise of molecular classification of disease is adding new rapidly changing medical knowledge)
2. **Data overload** – Increasing **clinical data per patient** threatens to overwhelm human cognitive ability to process (e.g., 1,400 new data points per patient per day in critical care)

6

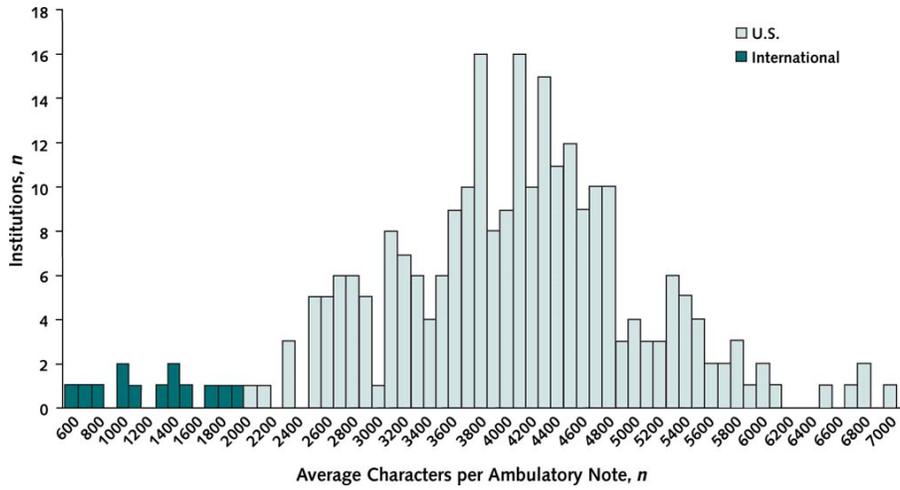


7

- ### Clinical Challenges
1. **Knowledge overload** – Growing **medical knowledge** threatens to overwhelm human memory capacity (e.g., rise of molecular classification of disease is adding new rapidly changing medical knowledge)
  2. **Data overload** – Increasing **clinical data per patient** threatens to overwhelm human cognitive ability to process (e.g., 1,400 new data points per patient per day in critical care)
  3. **Process overload** – Rising length of time to **review results or enter information** in the electronic health record (EHR) system threatens clinician burnout (e.g., 6 hours in a 11-hour day for documenting in the EHR system)

8

## Increasing Clinical Documentation



Downing NL, Bates DW, Longhurst CA. Physician burnout in the electronic health record era: are we ignoring the real cause? *Annals of internal medicine*. 2018 Jul 3;169(1):50-1.

9

## Overview of AI

10

## Artificial Intelligence (AI)

- “**General AI**” – goal is to create intelligent machines that can successfully perform any intellectual task that a human being can.
- “**Narrow AI**” – goal is to create software or computing resource that can accomplish specific problem solving or reasoning tasks.
- The field of AI field draws upon computer science, computer engineering, mathematics, statistics, psychology, linguistics, philosophy, and neuroscience.

11

## “Narrow AI” has been quite successful

Some of the most successful applications of AI are those in which the **AI is embedded like raisins in a loaf of raisin bread**: the raisins do not occupy much space, but they often provide the principal source of nutrition.<sup>1</sup>



<sup>1</sup>Esther Dyson, Industrial analyst

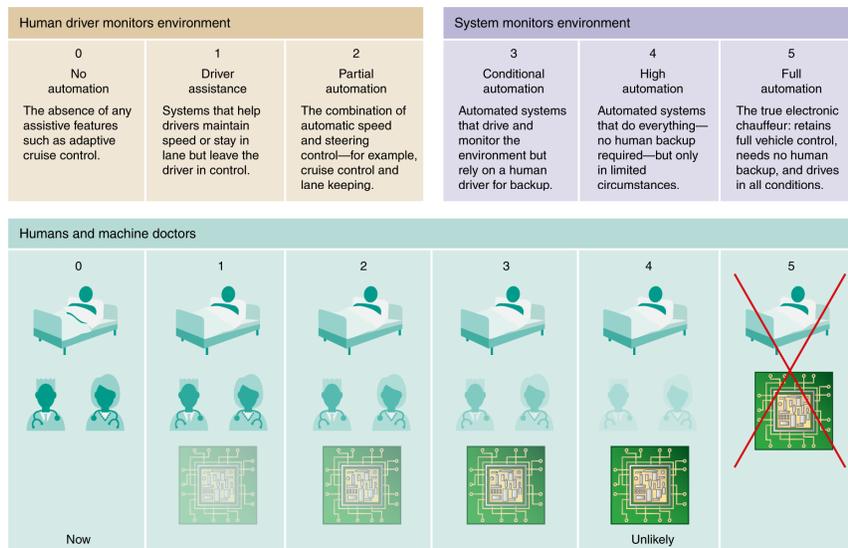
12

## Autonomous AI vs. Intelligence Augmentation (IA)

- **Autonomous AI** – goal is to create intelligent machines that replace human beings at a task.
  - Human-out-of-the-loop systems
  - Creating Autonomous AI is very hard
- **Intelligence Augmentation (IA)** – goal is to use AI to enable humans perform better at a task.
  - Human-in-the-loop systems or decision support systems
  - Creating IA is less hard

13

## Analogy Between Self-Driving Cars and Medicine



Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. *Nature medicine*. 2019 Jan;25(1):44.

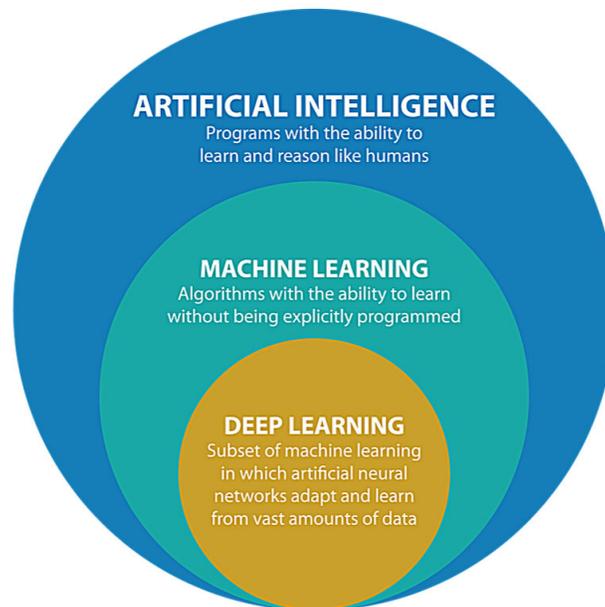
14

## Advantages and Disadvantages of AI

- **Advantages**
  - Fast, efficient, never forgets
  - Can handle large amounts of data, can easily identify trends in data
  - Can enable standardization of decisions
  - Potentially updatable quickly with new knowledge
- **Disadvantages**
  - Errors may be hard to uncover and can propagate quickly
  - Automation bias – clinician becomes unduly dependent
  - Opaque; does not reason in a medical framework

15

## Types of AI



16

## Types of Machine Learning

- **Supervised Learning** – e.g., **predict** a clinical outcome
- **Unsupervised Learning** – e.g., **cluster** patient clinical presentations into subphenotypes
- **Natural Language Processing (NLP)** – e.g., identify relevant information in a clinical **note**
- **Image processing** – e.g., identify relevant findings in a clinical **image**

17

## Prediction: Severe Outcome in 30 days

### PSI

### PNEUMONIA SEVERITY INDEX

FINE MJ ET AL: A PREDICTION RULE TO IDENTIFY LOW-RISK PATIENTS WITH COMMUNITY ACQUIRED PNEUMONIA. NEJM 1997;336:243

Demographics	Co-morbidities	Physical exam / vital signs	Laboratory / imaging
<ul style="list-style-type: none"> <li>• Age (1 point per year)</li> <li>Male Yr</li> <li>Female Yr -10</li> <li>• Nursing home residency +10</li> </ul>	<ul style="list-style-type: none"> <li>• Neoplasia +30</li> <li>• Liver disease +20</li> <li>• CHF +10</li> <li>• Cerebrovascular disease +10</li> <li>• Renal disease +10</li> </ul>	<ul style="list-style-type: none"> <li>• Mental confusion +20</li> <li>• Respiratory rate +20</li> <li>• SBP +20</li> <li>• Temperature +15</li> <li>• Tachycardia +15</li> </ul>	<ul style="list-style-type: none"> <li>• Arterial pH +30</li> <li>• BUN +20</li> <li>• Sodium +20</li> <li>• Glucose +10</li> <li>• Hematocrit +10</li> <li>• Pleural effusion +10</li> <li>• Oxygenation +10</li> </ul>

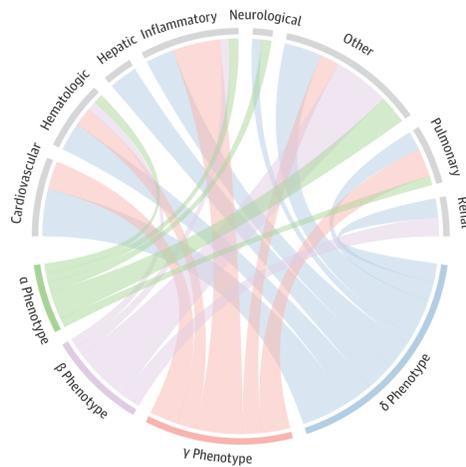
Risk class (Points)	Mortality (%)	Recommended site of care
I (<50)	0.1	Outpatient
II (51–70)	0.6	Outpatient
III (71–90)	2.8	Outpatient or brief inpatient
IV (91–130)	8.2	Inpatient
V (>130)	29.2	Inpatient

as a site-of-care tool. BUN, blood urea nitrogen; CHF, chronic heart failure; SBP, systolic blood pressure.

Fine MJ, Auble TE, Yealy DM, et. al. A prediction rule to identify low-risk patients with community-acquired pneumonia. N Engl J Med. 1997; 336:243-250.

18

## Clustering: Sepsis Phenotypes



Seymour CW, Kennedy J, Wang S, Chang C-CH, Elliot CF, Xu Z, Berry S, Clermont G, Cooper G, Gomez H, Huang DT, Kellum JA, Mi Q, Opal SM, Talisa V, Poll T, Visweswaran S, Vodovotz Y, Weiss JC, Yealy DM, Yende S, Angus DC. Derivation, validation, and potential treatment implications of novel clinical phenotypes for sepsis. *Jama*. 2019 May 28;321(20):2003-17.

19

## NLP: Identify Incidental Findings in CT Report

### Technique:

Contiguous helical images were obtained from the thoracic inlet to the upper thigh after the uneventful administration of 100 cc of Isovue-370. Coronal and sagittal reconstructions were obtained.

### Findings:

#### Chest:

Dependent atelectasis is mild. The lungs are otherwise clear. There is no pneumothorax or pleural effusion. A 4 mm pulmonary nodule is in the left upper lobe (series 6, image 45). The tracheobronchial tree is patent.

The heart size is normal with no pericardial effusion. No mediastinal hematoma is identified. No enlarged lymph nodes are in the thorax. The visualized thyroid and esophagus are normal.

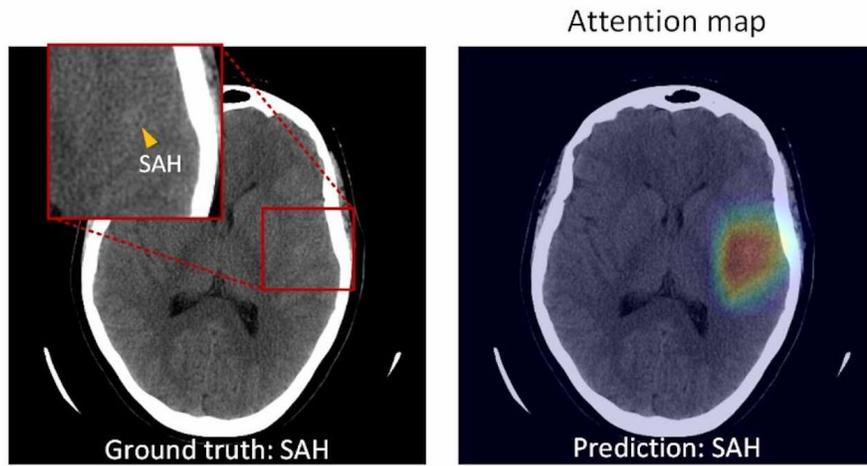
#### Abdomen/pelvis:

The liver, gallbladder, spleen, pancreas, adrenal glands, and kidneys are normal. The bowel is normal in caliber with no bowel wall thickening or obstruction. The rectum, prostate, urinary bladder are normal. There is no free or loculated fluid. No lymphadenopathy is identified. No acute injury to the abdomen or pelvis is identified.

Trivedi G, Hong C, Dadashzadeh ER, Handzel RM, Hochheiser H, Visweswaran S. Identifying incidental findings from radiology reports of trauma patients: An evaluation of automated feature representation methods. *International journal of medical informatics*. 2019 Sep 1;129:81-7.

20

## Image Processing: Identify SAH in CT Scan



Lee H, Yune S, et al. An explainable deep-learning algorithm for the detection of acute intracranial haemorrhage from small datasets. *Nature Biomedical Engineering*. 2019 Mar;3(3):173.

21

## Clinical Decision Support for Knowledge Overload

22

## Diagnostic Support System

Henderson EJ, Rubin GP. The utility of an online diagnostic decision support system (Isabel) in general practice: a process evaluation. *JRSM Short Rep.* 2013 Apr 4;4(5):31.

23

## Pharmacogenomics Decision Support

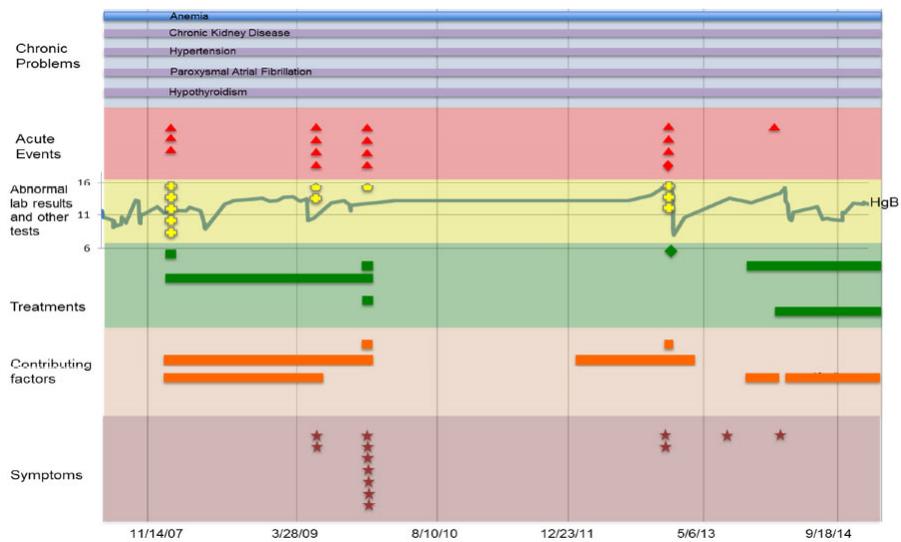
Nishimura AA, Shirts BH, Dorschner MO, Amendola LM, Smith JW, Jarvik GP, Tarczy-Hornoch P. Development of clinical decision support alerts for pharmacogenomic incidental findings from exome sequencing. *Genetics in Medicine.* 2015 Mar 5;17(11):939.

24

## Clinical Decision Support for Data Overload

25

### Problem-Oriented Patient Record Summarization

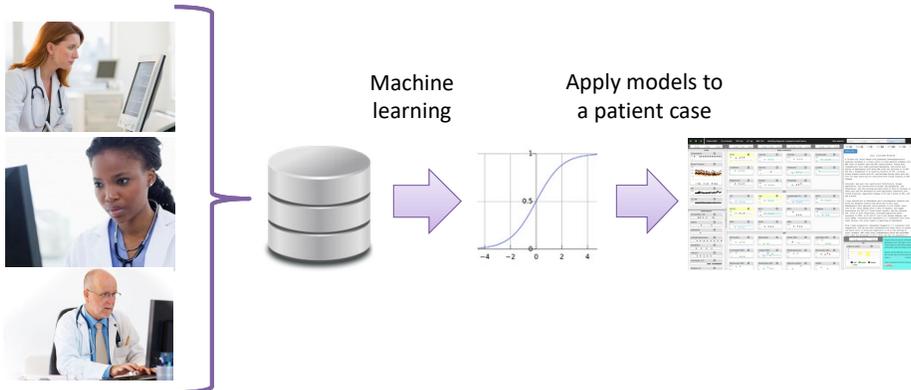


Devarakonda, M. Watson cognitive computing for Electronic Medical Records. AMIA Joint Summits 2016.

26

## Identify and Highlight Relevant Data in EHRs

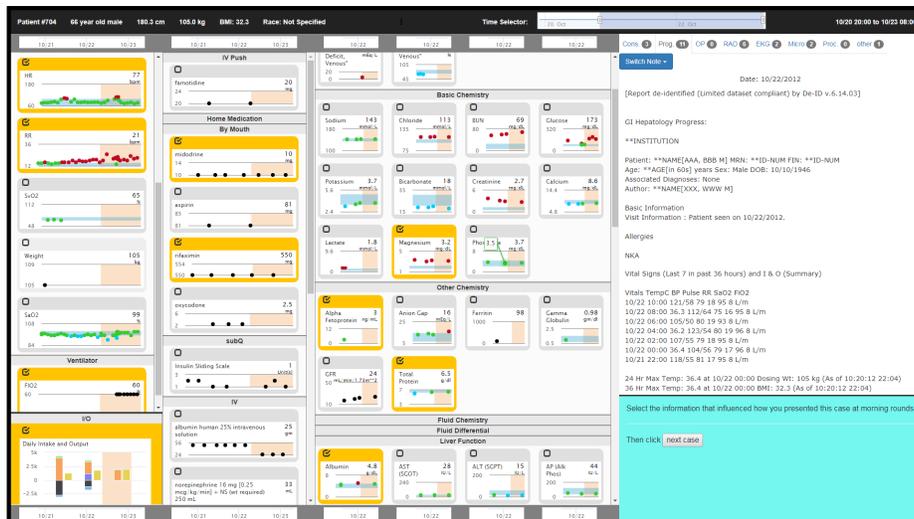
Observe and store  
EMR usage patterns



King AJ, Cooper GF, Hochheiser H, Clermont G, Visweswaran S. Development and preliminary evaluation of a prototype of a Learning Electronic Medical Record System. AMIA Annu Symp Proc. 2015 Nov 5;2015:1967-75.

27

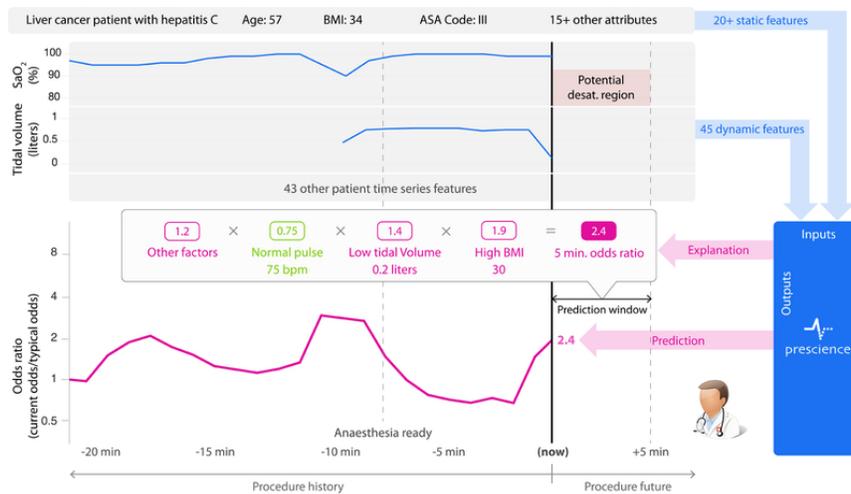
## Learning Electronic Medical Record System



King AJ, Cooper GF, Hochheiser H, Clermont G, Visweswaran S. Development and preliminary evaluation of a prototype of a Learning Electronic Medical Record System. AMIA Annu Symp Proc. 2015 Nov 5;2015:1967-75.

28

## Predicting Future Intraoperative Hypoxaemia



Lundberg SM, Nair B, Vavilala MS, Horibe M, Eisses MJ, Adams T, Liston DE, Low DK, Newman SF, Kim J, Lee SI. Explainable machine-learning predictions for the prevention of hypoxaemia during surgery. *Nature biomedical engineering*. 2018 Oct;2(10):749-60.

29

## Clinical Decision Support for Process Overload

30

## Virtual Medical Scribe



31

## Question Answering on Electronic Medical Records

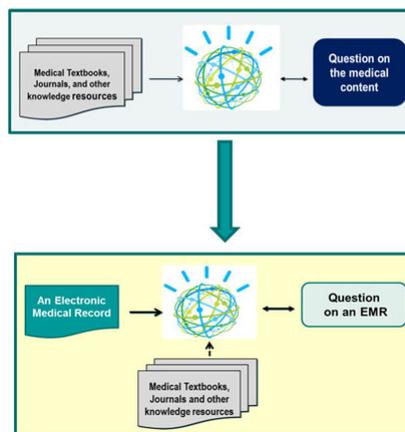
### Why was *Sitagliptin* stopped?

```

;td65 year old male
Wants to discuss the results of the MRI - has arteros
Also results of his labs.

He was unable to get Januvia he is not on it.
Cost is also very expensive
His DM control is improved -
Will hold off starting it at this point
Has lost about 6-8 lb since last time as he is doing
    
```

Question Type	Num. of questions	Example
yes/no	91	Is the substance abuse problem ongoing or resolved?
what	53	What are the results of the urine tox screen?
temporal-when	17	When was non-insulin-dependent diabetes mellitus diagnosed?
reason - why, how	16	Why did he get malignant tumor of colon at this age?



Raghavan, P, Patwardhan, S. Question answering on Electronic Medical Records. AMIA Joint Summits on Translational Science, Podium Presentation, 2016.

32

## NLP: Identify Incidental Findings in CT Report

### Technique:

Contiguous helical images were obtained from the thoracic inlet to the upper thigh after the uneventful administration of 100 cc of Isovue-370. Coronal and sagittal reconstructions were obtained.

### Findings:

#### Chest:

Dependent atelectasis is mild. The lungs are otherwise clear. There is no pneumothorax or pleural effusion. **A 4 mm pulmonary nodule is in the left upper lobe (series 6, image 45).** The tracheobronchial tree is patent.

The heart size is normal with no pericardial effusion. No mediastinal hematoma is identified. No enlarged lymph nodes are in the thorax. The visualized thyroid and esophagus are normal.

#### Abdomen/pelvis:

The liver, gallbladder, spleen, pancreas, adrenal glands, and kidneys are normal. The bowel is normal in caliber with no bowel wall thickening or obstruction. The rectum, prostate, urinary bladder are normal. There is no free or loculated fluid. No lymphadenopathy is identified. No acute injury to the abdomen or pelvis is identified.

Trivedi G, Hong C, Dadashzadeh ER, Handzel RM, Hochheiser H, Visweswaran S. Identifying incidental findings from radiology reports of trauma patients: An evaluation of automated feature representation methods. International journal of medical informatics. 2019 Sep 1;129:81-7.

33

## AI in Clinical Medicine: Ethical Aspects

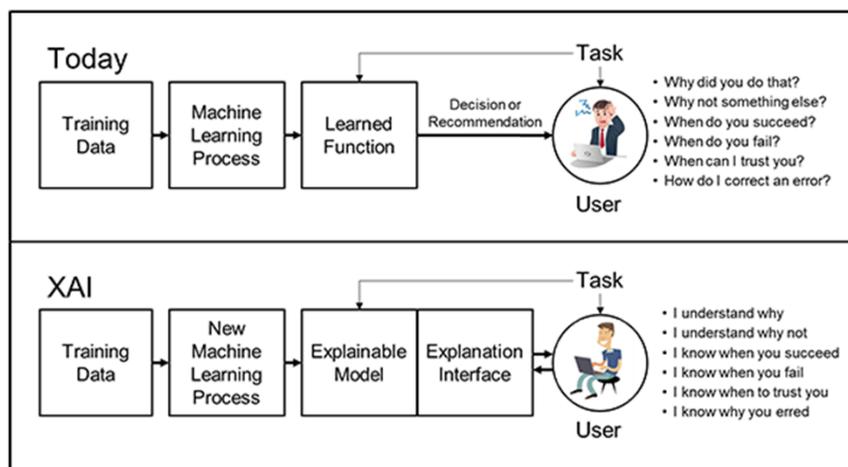
34

## Ethical Issues



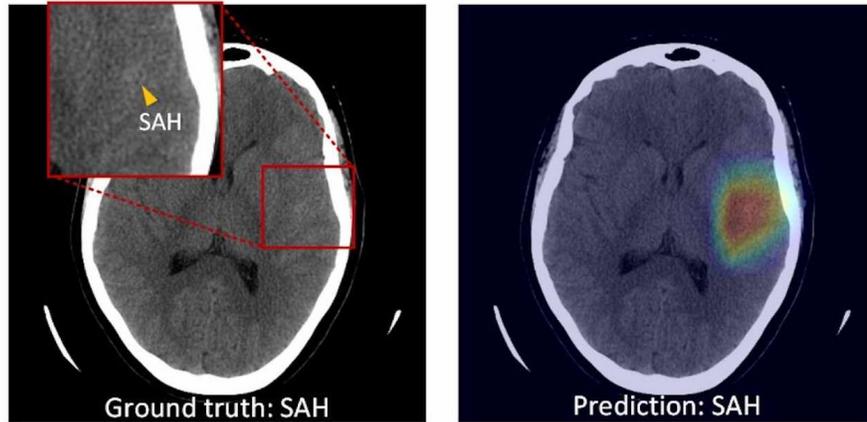
35

## Transparency: Explanation in AI



36

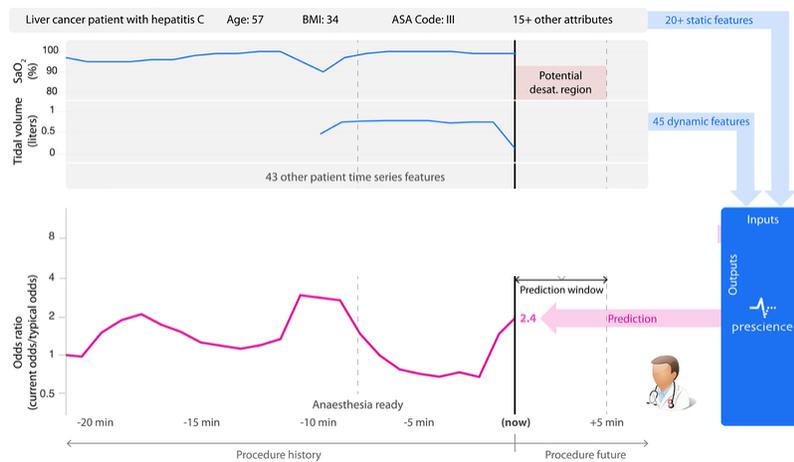
## Attention Maps as Explanations



Lee H, Yune S, et al. An explainable deep-learning algorithm for the detection of acute intracranial haemorrhage from small datasets. *Nature Biomedical Engineering*. 2019 Mar;3(3):173.

37

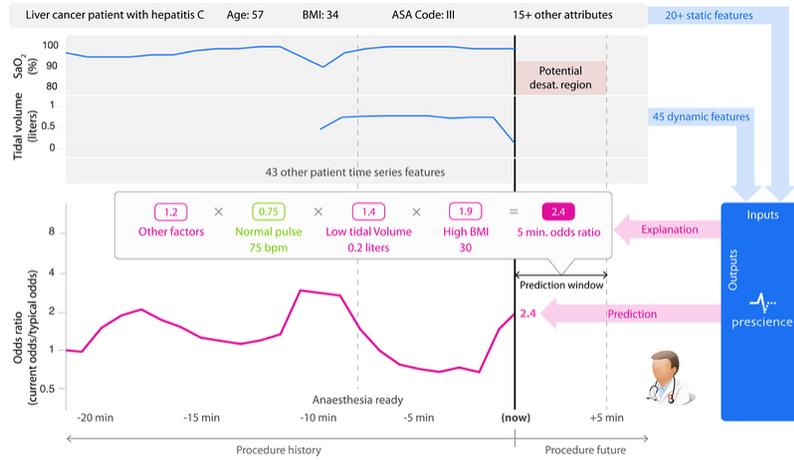
## Prediction



Lundberg SM, Nair B, Vavilala MS, Horibe M, Eisses MJ, Adams T, Liston DE, Low DK, Newman SF, Kim J, Lee SI. Explainable machine-learning predictions for the prevention of hypoxaemia during surgery. *Nature biomedical engineering*. 2018 Oct;2(10):749-60.

38

## Key Variables as Explanations



Lundberg SM, Nair B, Vavilala MS, Horibe M, Eisses MJ, Adams T, Liston DE, Low DK, Newman SF, Kim J, Lee SI. Explainable machine-learning predictions for the prevention of hypoxaemia during surgery. *Nature biomedical engineering*. 2018 Oct;2(10):749-60.

39

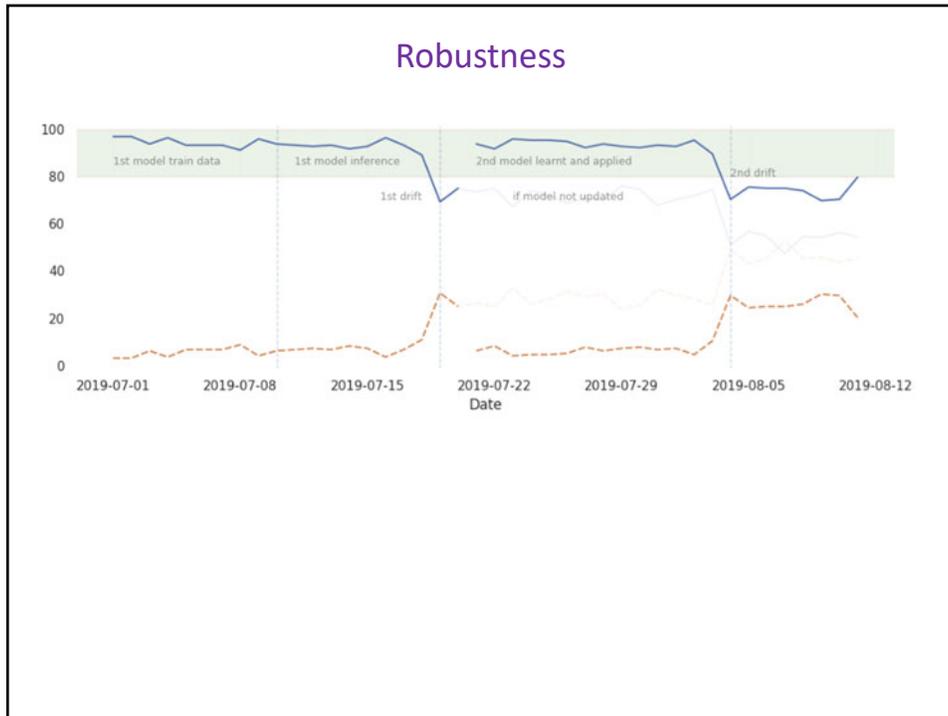
## Fairness

Gender Classifier	Darker Male	Darker Female	Lighter Male	Lighter Female	Largest Gap
Microsoft	94.0%	79.2%	100%	98.3%	20.8%
FACE++	99.3%	65.5%	99.2%	94.0%	33.8%
IBM	88.0%	65.3%	99.7%	92.9%	34.4%



Buolamwini J, Gebru T. Gender shades: Intersectional accuracy disparities in commercial gender classification. *InConference on fairness, accountability and transparency 2018 Jan 21* (pp. 77-91).

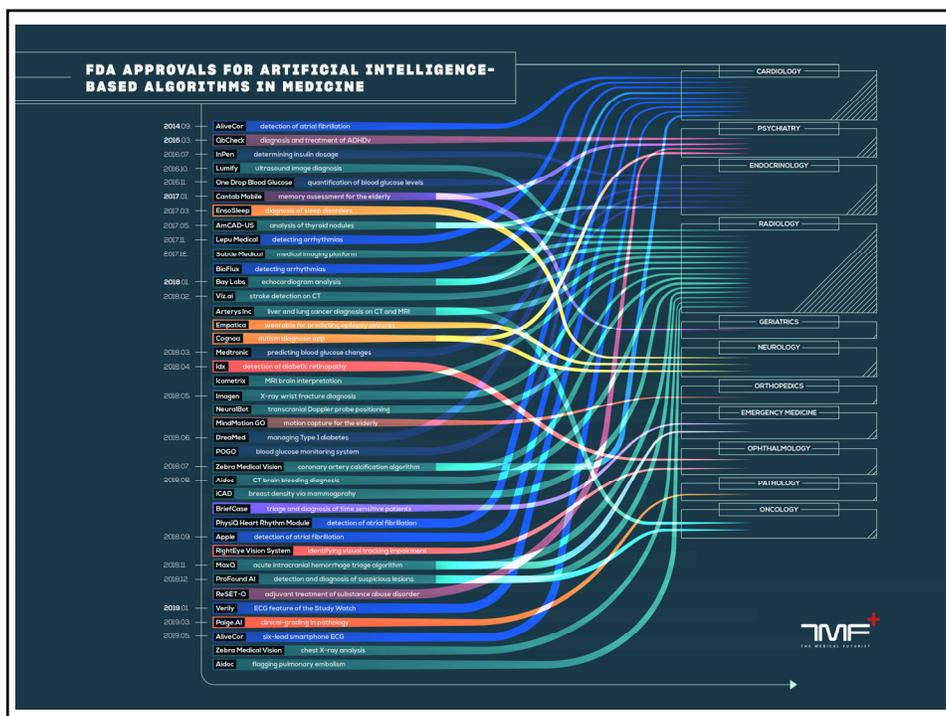
40



41

Where is AI Making Inroads in the  
Near Term (next 5 years)?

42



43

## Clinical Imaging

- Clinical imaging is used in many specialties
  - Radiology, pathology, dermatology, ophthalmology, cardiology, etc.
- Biggest effect of AI is in radiology
  - Largest number of FDA approved algorithms approved
  - Over 10 years, publications on AI in radiology have increased from 100–150 per year to 700–800 per year
  - Neuroradiology appears as the most involved subspecialty
- Example AI applications
  - Prioritization of reporting: automatic selection of findings deserving faster action
  - Comparison of current and previous examinations, especially in oncologic follow-up
  - Quick identification of negative studies
- Uneasiness about AI is highest among radiologists
  - Parallels reluctance among pilots to embrace autopilot technology in the early days of automated aircraft aviation

Pesapane F, Codari M, Sardaneli F. Artificial intelligence in medical imaging: threat or opportunity? Radiologists again at the forefront of innovation in medicine. *European radiology experimental*. 2018 Dec 1;2(1):35.

44

## Monitoring

- Acute care monitoring
  - Alerting on physiological monitoring in ICU and OR
  - Neurophysiological monitoring in the OR
- Ambulatory monitoring
  - Holter monitoring
- Home monitoring
  - Risk of falls
- Mobile devices monitoring
  - Cardiac arrhythmias

45

## In This Decade...

- Diffusion of AI in clinical medicine will be incremental
- Most AI will function to enable clinicians rather than replace them
- Clinicians will be involved in various aspects of AI – development, data curation, policy making, evidence generation, etc.

46