Disruptive Technology in Healthcare: Artificial Intelligence and Robots

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UTHealth
Outline

- The Age of Acceleration
- The Age of Disruption
- The AI Revolution
- Examples: Disruptive Technology in Healthcare
- Conclusion
Today – The Age of Acceleration

Data

Cell Phone Adoption

EHR Adoption

Computing Speed

World Population

Old Stone Age
New Stone Age
Bronze Age
Iron Age
Modern Age
Middle Ages
TODAY: AI Revolution

Agricultural Revolution

Industrial Revolution

Internet Revolution

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Today - The Age of Disruption

“The past 20 or 30 years, and the next 20 or 30 years—really is historically unique. It is arguably the **largest economic disruption in recorded human history.**”

(Ben Sasse, US Senator, WSJ, April 21, 2017)

The biggest companies in these industries are all IT companies today.
Three Drivers for the AI Revolution

Healthcare

Mobile Internet
- Smart phones
- Sensors
- Internet of things
- 5G Connectivity

Computing
- Parallel Computing
- Cloud
- Edge Computing
- Machine Learning & AI

Big Health Data
- Clinical
- Genomic & biological
- Environmental
- Behavioral
- Social & Economic

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The Many “Revolutions” of Artificial Intelligence

1956 Dartmouth
1969 MIT
1986 UCSD Backpropagation
1997 IBM Deep Blue
2011 IBM Watson
2012 ImageNet
2017 Google AlphaGo

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Speak now

This Is Us

this is a strategically

this is a strategic retreat

this is a strategic Retreat session footage

this is a strategic Retreat session for the University

this is a strategic Retreat session for the University of Texas Health Science Center at Houston
Autonomous Vehicle
(NVidia CES 2018 Demo)

- 1.25 million lives could be saved per year
- 157 hours commute time per person per year
- $150 B fuel cost saving in US in one year
https://www.youtube.com/watch?v=68F-UUU_Ff4
Impact of AI on Global GDP (PwC)

Figure 1: Where will the value gains come from with AI?

Source: PwC analysis
### Impact of AI on Healthcare (McKinsey)

<table>
<thead>
<tr>
<th>Highest-ranked use cases, based on survey responses</th>
<th>Use case type</th>
<th>Impact</th>
<th>Data richness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diagnose known diseases from scans, biopsies, audio, and other data</td>
<td>Predictive analytics</td>
<td>1.4</td>
<td>0.3</td>
</tr>
<tr>
<td>Predict personalized health outcomes to optimize recommended treatment</td>
<td>Radical personalization</td>
<td>1.2</td>
<td>1.3</td>
</tr>
<tr>
<td>Optimize labor staffing and resource allocation to reduce bottlenecks</td>
<td>Resource allocation</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td>Identify fraud, waste, and abuse patterns in diverse clinical and operations data</td>
<td>Discover new trends/anomalies</td>
<td>0.6</td>
<td>0.3</td>
</tr>
<tr>
<td>Predict individual hospital admission rates using historical and real-time data</td>
<td>Forecasting</td>
<td>0.5</td>
<td>0.7</td>
</tr>
<tr>
<td>Triage patient cases during hospital admission using patient data, audio, and video</td>
<td>Predictive analytics</td>
<td>0.5</td>
<td>0.3</td>
</tr>
</tbody>
</table>
Examples of Disruptive Technology in Healthcare

- Imaging
- Natural Language Processing (NLP)
- Computational Phenotyping
- Prediction
- Computational Biomarker
- Population Health
- Precision Medicine
- Medical Education
- Physician Robot Companion
AI to medicine today is like microscope to life sciences in 1600s:

REEXAMINE AND REDISCOVER EVERYTHING ANEW
Imaging

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; et al.

Author Affiliations  |  Article Information

### Computational Phenotyping from EHR Data

31,816 Patients x 169 Diagnoses x 471 Medications

<table>
<thead>
<tr>
<th>Hyperlipidemia</th>
<th>Moderate Hypertension</th>
<th>Uncomplicated Diabetes</th>
<th>Mild Hypertension</th>
<th>Chronic Respiratory Inflammation/Infection</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Phenotype 1</strong> (41.6% of patients)</td>
<td><strong>Phenotype 2</strong> (31.5% of patients)</td>
<td><strong>Phenotype 3</strong> (17.6% of patients)</td>
<td><strong>Phenotype 4</strong> (31.1% of patients)</td>
<td><strong>Phenotype 5</strong> (36.7% of patients)</td>
</tr>
<tr>
<td>Other Endocrine, Metabolic, and Nutritional Disorders</td>
<td>Hypertension</td>
<td>Diabetes with No or Unspecified Complications</td>
<td>Hypertension</td>
<td>Other Ear, Nose, Throat, and Mouth Disorders</td>
</tr>
<tr>
<td>HMG CoA Reductase Inhibitors</td>
<td>Beta Blockers Cardio-Selective</td>
<td>Sulfonylureas</td>
<td>ACE Inhibitors</td>
<td>Viral and Unspecified Pneumonia, Pleurisy</td>
</tr>
<tr>
<td>Intestinal Cholesterol Absorption Inhibitors</td>
<td>Angiotensin II Receptor Antagonists</td>
<td>Biguanides</td>
<td>Thiazides and Thiazide-Like Diuretics</td>
<td>Significant Ear, Nose, and Throat Disorders</td>
</tr>
<tr>
<td>Fibrin Acid Derivatives</td>
<td>Loop Diuretics</td>
<td>Diagnostic Tests</td>
<td>Cough/Cold/Allergy Combinations</td>
<td>Cephalosporins - 2nd Generation</td>
</tr>
<tr>
<td>Antihyperlipidemics - Combinations</td>
<td>Potassium</td>
<td>Insulin Sensitizing Agents</td>
<td>Azithromycin</td>
<td>Cephalosporins - 1st Generation</td>
</tr>
<tr>
<td>Nicotinic Acid Derivatives</td>
<td>Nitrates</td>
<td>Diabetic Supplies</td>
<td>Fluoroquinolones</td>
<td>Expectorants</td>
</tr>
<tr>
<td>Bile Acid Sequestrants</td>
<td>Alpha-Beta Blockers</td>
<td>Meglitinide Analogues</td>
<td>Sympathomimetics</td>
<td></td>
</tr>
<tr>
<td>Oil Soluble Vitamins</td>
<td>Vasodilators</td>
<td>Antidiabetic Combinations</td>
<td>Penicillin Combinations</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Antitussives</td>
<td></td>
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<td></td>
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<td></td>
<td>Glucocorticosteroids</td>
<td></td>
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<td></td>
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<td></td>
<td>Tetracyclines</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>Anti-infective Misc. - Combinations</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>Clarithromycin</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>Cephalosporins - 2nd Generation</td>
<td></td>
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<td></td>
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<td></td>
<td>Cephalosporins - 1st Generation</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>Expectorants</td>
<td></td>
</tr>
</tbody>
</table>

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Limestone: High-throughput candidate phenotype generation via tensor factorization

Joyce C. Ho, Joydeep Ghosh, Steve R. Steinhubl, Walter F. Stewart, Joshua C. Denny, Bradley A. Malin, Jimeng Sun

Journal of Biomedical Informatics
Volume 52, December 2014, Pages 199-211
Prediction 1: Temporal Disease Trajectories
(6.2 million patients in Denmark)

(Jensen et al., 2014, Nature Communications)
Prediction 2: Risk Calculators from EHR Data

<table>
<thead>
<tr>
<th>Prediction</th>
<th>Unhealthy Person</th>
<th>Healthy Person</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>65 years</td>
<td>65 years</td>
</tr>
<tr>
<td>Sex</td>
<td>Female</td>
<td>Male</td>
</tr>
<tr>
<td>Smoker</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Total cholesterol</td>
<td>300 mg/dL</td>
<td>150 mg/dL</td>
</tr>
<tr>
<td>HDL cholesterol</td>
<td>20 mg/dL</td>
<td>60 mg/dL</td>
</tr>
<tr>
<td>Systolic BP</td>
<td>160 mm Hg</td>
<td>120 mm Hg</td>
</tr>
<tr>
<td>Blood pressure being treated with medicines</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

47.4% **Unhealthy Person**
10-year risk of MI or death.

7.3% **Healthy Person**
10-year risk of MI or death.

Can machine-learning improve cardiovascular risk prediction using routine clinical data?

Stephen F. Weng, Jenna Reps, Joe Kai, Jonathan M. Garibaldi, Nadeem Qureshi
Published: April 4, 2017 • https://doi.org/10.1371/journal.pone.0174944
**Prediction 3: Sepsis**

New Machine Learning Algorithms for 4 Hour **Prediction** of Severe Sepsis:

- **Performance (AUC)**
  - Status Quo: 0.85
  - Ongoing: 0.92

Effect of a machine learning-based severe sepsis prediction algorithm on patient survival and hospital length of stay: a randomised clinical trial

- **BMJ Open Respiratory Research 2017**

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**Figure 2** Decrease in average hospital and ICU length of stay with the use of the machine learning algorithm. The error bars represent one standard error above and below the mean length of stay. ICU, intensive care unit.
Computational Biomarker: Sensors

Sleep Pattern Monitor

Ingestible Sensors (Proteus Digital)

Vital Sign Tracker

Contact Lens for Glucose

Apple Watch

Fertility Thermometer

Bio Stamp for Vital Signs
Computational Biomarker: AF Detection

Smartphone device beat Holter for post-stroke AF detection

Publish date: October 18, 2018
By Mitchel L. Zoler; Clinical Neurology News
Computational Biomarker: Typing for Parkinson's

Typing data

\[\downarrow\]

Low dimensional representation

\[\downarrow\]

Automatic Classifier/Regressor

\[\downarrow\]

Parkinson’s Disease Typing Phenotype

Heart Rate Variability, Deep Learning, and Disease Prediction

- Diabetes: 0.85 AUC
- Sleep apnea: 0.80 AUC
- Hypertension: 0.80 AUC
- High cholesterol: 0.67 AUC

Population Health
- Chronic Disease Registry at UT Physicians

Interactive Graphs

Hwang, Bernstam, Johnson at UTHealth
Precision Medicine
- Cancer Clinical Trials Matching System

• UT MD Anderson and UTHealth
  • Dr. Funda Meric-Bernstam and Dr. Elmer Bernstam

• Using patient’s genetic and clinical information to select the most appropriate clinical trials
Test Result

- Total Points: 600
- Passing Points: 360
- Robot: 456
- Top 5% among human takers

What is in the “Brain”

- Dozens of medical textbooks
- 2 million medical records
- 400,000 literature

Chinese robot becomes world's first machine to pass medical exam

By Ma Si and Cheng Yu | chinadaily.com.cn | Updated: 2017-11-10 15:32

iFlytek's AI-enabled robot sits the test of China's national medical licensing examination. [Photo provided to China Daily]
Before a patient sees the doctor
Conclusion
- Human Technology Integration

- Knowledge and Process in Technology
- Increasing exponentially
- Informatics, Data Science, and AI

- Knowledge and Process in Brain
- Unchanged
- Cognitive Science

(Graph is from William Stead)
Thank you!

At UTHealth School of Biomedical Informatics,

We Are