AI in Support of People and Society

Eric Horvitz
Technical Fellow and Director
Microsoft Research-Redmond Lab
Artificial Intelligence

Study of computational mechanisms underlying thought & intelligent behavior
Artificial Intelligence

Study of computational mechanisms underlying thought & intelligent behavior

“..to find how to make machines…solve kinds of problems now reserved for humans…” (1955)
Artificial Intelligence

Study of computational mechanisms underlying thought & intelligent behavior

Multiple subdisciplines & research communities

- Computer Vision
- Speech & Dialog
- Decisions & Plans
- Robotics
- Perception
- Learning
- Reasoning
- Natural Language
Inflection Point

↑ Computation & memory

↑ Data via digital economy, devices, Web

↑ Learning & reasoning prowess

Opportunities, competitive landscape
Long-term R&D
Innovations Shared
Handwriting recognition
25 billion letters per year
100s of millions of dollars saved

(video)

Kim & Govindaraju (1997)
New Competencies & Experiences
New Competencies & Experiences
New Competencies & Experiences

Still in lab, but on way

(video)

Taylor, Bordeaux, Cashman, … Shotton, et al. (2016)
New Competencies & Experiences

Thumb & forefinger: foundation of civilization

Moving into computational realm

Taylor, Bordeaux, Cashman, ... Shotton, et al. (2016)
New Competencies & Experiences

Hybrid learning pipelines for language & vision

New Competencies & Experiences

Hybrid learning pipelines for language & vision

New Competencies & Experiences

Hybrid learning pipelines for language & vision

New Competencies & Experiences

Hybrid learning pipelines for language & vision

Broad Spectrum of Opportunities

Healthcare  Education  Governance
Sciences    Criminal justice
Transportation
Agriculture  Privacy & security
Sustainability  Emergency management
Data $\rightarrow$ Predictions $\rightarrow$ Decisions
People, Models, and Insights

Sensed data

Predictive model

Decision model

Data → Predictions → Decisions
AI & Healthcare: Long-term Dream

H., Shwe (1995)

Saria, Rajani, Gould, et al. (2010)
Broad Spectrum of Opportunities

Healthcare
Sciences
Transportation
Agriculture
Sustainability

Education
Governance
Criminal justice
Privacy & security
Emergency management
Example: Readmissions Challenge

Rehospitalizations among Patients in the Medicare Fee-for-Service Program

Stephen F. Jencks, M.D., M.P.H., Mark V. Williams, M.D., and Eric A. Coleman, M.D., M.P.H.

ABSTRACT

Background Reducing rates of rehospitalization has attracted attention from policymakers as a way to improve the quality of care and reduce costs. However, we have limited information on the frequency and patterns of rehospitalization in the United States to aid in planning the necessary changes.

Methods We analyzed Medicare claims data from 2003–2004 to describe the patterns of

- ~20% within 30 days
- ~35% in 90 days

➤ Estimated cost to Medicare (2004): $17.4 billion
Learning from Healthcare Data

Washington Hospital Center

20 years of data  30,000 variables

- Admissions, discharge, transfer (ADT)
- Chief complaint in free text
- Age, gender, demographics
- Diagnosis codes (ICD-9)
- Vital signs
- Lab results
- Medications
- Procedures
- Locations in hospital
- Admitting & attending MD codes
- Fees and billing

Readmissions Manager

Reducing Hospital Readmissions is an Impending Priority

Overview

One in five Medicare inpatients is readmitted within 30 days. The Centers for Medicare and Medicaid Services (CMS) considers 40%-75% of these readmissions to be preventable.

In October 2012, CMS will begin to track readmission and impose financial penalties on hospitals with higher-than-expected readmission rates for certain conditions. Other payers will certainly follow.

It is clear that hospital admissions and readmissions are becoming a critical parameter for tracking care delivery from both a financial and quality perspective.

Readmissions Manager for Microsoft Amalga is an innovative solution to help organizations address this very important business need.

Readmissions Manager Targets Avoidable Hospital Readmissions

<table>
<thead>
<tr>
<th>PROB_NUM_%</th>
<th>FACTORS_PRO_READMISSION</th>
</tr>
</thead>
<tbody>
<tr>
<td>37.9</td>
<td>Num past 6m visits = 6 to 10 / Patient had dx = Diabetes</td>
</tr>
<tr>
<td>32.72</td>
<td>stayed &lt;1 day in the hospital / Patient had dx = Diabetes</td>
</tr>
<tr>
<td>30.83</td>
<td>Patient had dx = Chronic renal failure / 44 &lt; Age &lt; 60</td>
</tr>
<tr>
<td>29.05</td>
<td>Patient had dx = Disorders of fluid, electrolyte, and acid-base balance</td>
</tr>
<tr>
<td>28.54</td>
<td>Patient had dx = Acute renal failure / Patient had dx = Diabetic nephropathy</td>
</tr>
<tr>
<td>27.36</td>
<td>Patient had dx = Other personal history presenting with symptoms</td>
</tr>
<tr>
<td>18.05</td>
<td>stayed &lt;1 day in the hospital</td>
</tr>
<tr>
<td>16.57</td>
<td>Patient had dx = Disorders of fluid, electrolyte, and acid-base balance</td>
</tr>
<tr>
<td>16.18</td>
<td>stayed &lt;1 day in the hospital / Ave gap of past yr visits</td>
</tr>
<tr>
<td>15.52</td>
<td>stayed &lt;1 day in the hospital / Patient had dx = Other personal history presenting with symptoms</td>
</tr>
<tr>
<td>14.53</td>
<td>stayed &lt;1 day in the hospital</td>
</tr>
<tr>
<td>14.42</td>
<td>stayed &lt;1 day in the hospital / Patient had dx = Other personal history presenting with symptoms</td>
</tr>
<tr>
<td>14.39</td>
<td>Patient had dx = Acute renal failure / 44 &lt; Age &lt; 60</td>
</tr>
<tr>
<td>13.59</td>
<td>stayed &lt;1 day in the hospital / 44 &lt; Age &lt; 60</td>
</tr>
<tr>
<td>13.36</td>
<td>stayed &lt;1 day in the hospital / Hour of visit = 00</td>
</tr>
<tr>
<td>12.44</td>
<td>stayed &lt;1 day in the hospital</td>
</tr>
</tbody>
</table>
From Predictions to Decisions

Units 5E/501/8E/9W/8ITCU

Baseline:
Discharges to home/homeward bound between 10/15/2011 - 4/29/2012
Readmissions Rate (all cases): 13%
Score ≥ 25: 27%
Average direct cost/readmission: $10,888

<table>
<thead>
<tr>
<th></th>
<th>Initial Pilot 4/30/2012 - 7/30/2012</th>
<th>1 Month Post engagement 9/1/2012 - 9/30/2012</th>
</tr>
</thead>
<tbody>
<tr>
<td>Readmissions Rate</td>
<td>12%</td>
<td>10%</td>
</tr>
<tr>
<td>Score ≥ 25</td>
<td>23%</td>
<td>20%</td>
</tr>
<tr>
<td># of Admissions Avoided</td>
<td>9</td>
<td>11</td>
</tr>
<tr>
<td>Follow up call completion</td>
<td>52%</td>
<td>61%</td>
</tr>
<tr>
<td>Follow up call not Completed</td>
<td>32%</td>
<td>21%</td>
</tr>
<tr>
<td>Total Annualized savings</td>
<td>$391,968</td>
<td>$1,448,104</td>
</tr>
</tbody>
</table>

↓ Total Readmission Rate by 3% and +$1.4M Savings
Special Intervention?

Data → Predictions → Decisions

Outcome? $p(\text{Readmit} \mid E)$

Intervene?

Special program ($$)

Standard care

Congestive Heart Failure
$800 intervention @ 35% efficacy?

31.4% readmissions ➔ $13.2%.
Insights

$1800 intervention @ 20% efficacy?

Value in Larger Ecosystem

Value in Larger Ecosystem

Preventable Errors and Deaths

44,000 - 98,000 per year → 440,000 per year

Institute of Medicine, 1999


Hospital Errors are the Third Leading Cause of Death in U.S., and New Hospital Safety Scores Show Improvements Are Too Slow

Washington, D.C., October 23, 2013 – New research estimates up to 440,000 Americans are dying annually from preventable hospital errors. This puts medical errors as the third leading cause of death in the United States, underscoring the need for patients to protect themselves and their families from harm, and for hospitals to make patient safety a priority.

James (2013)

To Err is Human: Building a Safer Health System, Inst. of Medicine (1999)
Preventable Errors and Deaths


- Cancer: 585k
- Heart disease: 611k
- COPD: 149k
- Suicide: 41k
- Motor vehicles: 34k
- Firearms: 34k
- Medical error: 251k

Based on our estimate, medical error is the 3rd most common cause of death in the US.

Makary & Daniel (2016)
Preventable Errors and Deaths

Based on our estimate, medical error is the 3rd most common cause of death in the US

Makary & Daniel (2016)
Promise of AI
AI as Safety Nets

Learn to detect anomalies with healthcare delivery

Hauskrecht, Batal, Valko, Visweswaran, Cooper, Clermont (2013)

Learning to predict expert will be surprised

“Significant likelihood of surprising outcome within 48 hours.”

Bayati, Koch, H.
Perception and Robotics in Healthcare
Perception and Robotics in Healthcare

Grammar of surgery
Recognize surgical actions & intentions

Perception and Robotics in Healthcare

Mix of human and machine initiatives

Broad Spectrum of Opportunities

Healthcare  Education
Sciences    Governance
Transportation  Criminal justice
Agriculture  Privacy & security
Sustainability  Emergency management
Cutting Through Complexity of Biology

Segal, Shapira, Regev, Pe'er, Botstein, Koller, Friedman, et al. (2003)
Cutting Through Complexity of Biology

- Biology’s control of differentiation of embryonic cells

**AI theorem prover**

**Regulatory program**
- 16 interactions
- 12 components
- 3 inputs!

Dunn, Martello, Yordanov, Emmott, Smith (2014)
Cutting Through Complexity of Biology

Biology’s control of differentiation of embryonic cells

Understanding biology’s languages, programs, protocols

Understanding & correcting programs gone awry: Cancer
Keeping up with the Literature

*AI for machine reading & comprehension*

**Biomedical studies**
1 million papers / year
2 new papers / minute
“Involvement of p70(S6)-kinase activation in IL-10 up-regulation in human monocytes by gp41 envelope protein of human immunodeficiency virus type 1 ...”

Poon, Toutanova, Quirk (2015)
Promising Design & Discovery Tools

Precision medicine via active, updated models

H. Poon, et al. (2016)
Broad Spectrum of Opportunities

Healthcare  Education
Sciences  Governance
Transportation  Criminal justice
Agriculture  Privacy & security
Sustainability  Emergency management
Toward Precision Agriculture

Symbiotic use of ground & air vehicles

Ideal team work on plans & information value

P. Tokekar, J. Vander Hook, D. Mulla, V. Isler
Toward Precision Agriculture

Tokekar, Vander Hook, D. Mulla, V. Isler
Toward Precision Agriculture

Construct soil nitrogen map

Tokekar, Vander Hook, D. Mulla, V. Isler
Toward Precision Agriculture

Apple yield estimation

Broad Spectrum of Opportunities

- Healthcare
- Sciences
- Transportation
- Agriculture
- **Sustainability**
- Education
- Governance
- Criminal justice
- Privacy & security
- Emergency management
Sustainability, Environment, Natural Resources, Wildlife

Supporting sensing, models, predictions, and decisions in support of world’s ecosystems
Guidance on Land Resources

Streaked Horned Lark          Taylor’s Checkerspot          Mazama Pocket Gopher

South Puget Sound region

Infer actions that maximize likelihood of survival

Dynamics of availability of reserve lands

Golovin, Krause, Gardner, Converse, Morey (2011)
Caltech, ETH, NCSU, USGS, USFWS
Guidance on Land Resources

Golovin, Krause, Gardner, Converse, Morey (2011)
Caltech, ETH, NCSU, USGS, USFWS
Bogunovic, Krause, Converse (2012)
Guidance on Land Resources

Golovin, Krause, Gardner, Converse, Morey (2011)

[Graph showing expected number of persisting species over rounds for different optimization methods: dynamic optimization, dynamic by area, random, and a priori optimization.]
Edward O. Wilson: “AI may be essential to the survival of life on our planet.”

- Oct. 2014

H., personal communication (2016)
Harnessing Legacy Data & Infrastructure
Example: Winds & Weather

NOAA: Winds Aloft

Thousands of Wind Sensors
Thousands of Wind Sensors
Windflow

Cloud Service:

http://windflow.azurewebsites.net/
Windflow

Cloud Service:

http://windflow.azurewebsites.net/
Windflow

Cloud Service:

http://windflow.azurewebsites.net/
Studies

Precision Planning for Routing

Beyond great circle routes
Interleaving of sensing, prediction, planning

Dey, Kolobov, Caruana, et al. (2014)
Precision Planning for Routing

Ideal routes via richer automated planning

Dey, Kolobov, Caruana, et al. (2014)
Example: Cell Towers as Sensors

Disruption, Reconnaisance, Recovery

Lac Kivu quake
Feb 3, 2008
5.9
Disruption, Reconnaissance, Recovery

3 years of logs of incoming & outgoing calls
140 cell towers, 6 days: 10,527,799 calls

Active Cell Towers on Feb 3 2008

Detecting Disruption

Outgoing Calls

Negative Loglikelihood

Days

Earthquake

Modeling & Inference

Transform existing infrastructure into sensor array

Inferring Epicenter

17.12 km
Inferring Epicenter
Infer Opportunities to Assist

Day 0

- Opportunities for Assistance
  - Cell Towers (Radius indicate % increase in calls)
  - True Epicenter
Infer Opportunities to Assist

Day 1
Infer Opportunities to Assist

Day 2

Opportunities for Assistance
- Cell Towers (Radius indicate % increase in calls)
- True Epicenter
Broad Spectrum of Opportunities

Healthcare  Education
Sciences  Governance
Transportation  Criminal justice
Agriculture  Privacy & security
Sustainability  Emergency management

Rich benefits for people and society
Aspirations & Goals

(video)

Mitchell, He, Tran, Koul, Shaikh, et al. (2016)
View from Stratosphere: Windflow test balloon