Data to Insights and Actions: Enabling Evidence-Based Healthcare
Hippocrates (c. 460 B.C. - c. 370 B.C.)

On diseases, make a habit of two things—to help, or at least to do no harm.


…it is worth learning from everyone; for people do not discover these by reasoning but by chance, and experts not more than laymen.


**Attaining dream of evidence-based reasoning through advances in computer science.**
Fueling Pursuit of the Dream

Significant advances made possible via long-term funding by prescient federal agencies

- Critical NIH, NSF, ONR, DARPA support for decades
- AI in Medicine (AIM) in 1980s → Core CS
  - Ignited veritable revolution in machine intelligence
  - Core advances in context of AIM: representation, inference, decision making, machine learning for medical applications.
Exciting Times

Learning & reasoning prowess
Sensing, interaction, ubiquity
Computation & connectivity
Data capture → learning, decisions
Wrestling with a Bottleneck

- Learning & reasoning prowess
- Sensing, interaction, ubiquity
- Computation & connectivity
- Data capture → learning, decisions
Enabling Evidence-Based Medicine

- Diagnosis, actions, policies
- Wellness and prevention
- Discovery

Data capture $\rightarrow$ learning, decisions
Advances in Representation & Reasoning

- e.g., Probabilistic graphical models

(From I. Beinlich, et al)
Microsoft Pregnancy and Child Care

Microsoft Health Preview
Pregnancy and Child Care

What's New
Click here for this month's highlights in Microsoft Pregnancy and Child Care.

Library
To browse through illustrated articles on pregnancy, birth, and early child care, click here.

Find By Word
If you know what you're looking for, click here to search the Library by keywords.

Find By Symptom
Click here to find useful information in the Library related to children's symptoms.

Community Center
Have a story to share? Want to send us mail? Click here to access our community bulletin boards.
Describe the child
in the drop-down boxes at the right. Relevant information will appear below.

Age: Toddler, Sex: Female

Complaint: Abdominal pain

Localized pain: Can the child localize, or point to, the site of the pain?
- No, unable to localize
- Below the navel to the child's left
- Above the child's navel
- Either of the child's sides
- Below the navel to the child's right
- Above the navel to the child's right
- Above the navel to the child's left
- Don't Know

Results so far

<table>
<thead>
<tr>
<th>Disorder</th>
<th>Relevance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Viral gastroenteritis</td>
<td></td>
</tr>
<tr>
<td>Psychosomatic pain</td>
<td></td>
</tr>
<tr>
<td>Urinary tract infection</td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td></td>
</tr>
</tbody>
</table>

Start Over, Review, Next>> Finish
Learning Predictive Models from Data

- New access to large amounts of data
- Procedures for learning predictive models
Best actions via analysis of costs & benefits under uncertainty.

- Case library
- Predictive Model
- Decision Model
- Data
- Predictions
- Decisions
Example: Reducing Hospital Readmissions

Bayati, Braverman, Gillam, Koch, Singh, Smith, H.
Costly Challenge

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

- Estimated cost to Medicare in 2004: $17.4 billion
Learning from a Case Library

- Washington Hospital Center hospital system (DC)
- All visits during the years 2001 to 2009 (e.g., ~300,000 ED visits)
  - Admissions, discharge, transfer (ADT)
  - Chief complaint in free text
  - Age, gender, demographics
  - Diagnosis codes (ICD-9)
  - Lab results and studies
  - Medications
  - Vital signs
  - Procedures
  - Locations in hospital
  - Admitting and attending MD codes
  - Fees and billing

~25,000 variables considered in dataset
Building a Predictive Model for Readmission
Performance of Classifier for Readmission

![Graph showing the relationship between true positive rate and false positive rate.

- True positive rate
  - 10%
  - 20%
  - 30%
  - 40%
  - 50%
  - 60%
  - 70%
  - 80%
  - 90%
  - 100%

- False positive rate
  - 10%
  - 20%
  - 30%
  - 40%
  - 50%
  - 60%
  - 70%
  - 80%
  - 90%
  - 100%

Train and Test sections indicated with different colors.

- Train: Larger section
- Test: Smaller section

The graph illustrates the trade-off between true positive and false positive rates, typically used in evaluating classifier performance.
# Identifying Evidential Relevance

<table>
<thead>
<tr>
<th>Weight</th>
<th>Feature Description</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.68398</td>
<td>Dx0-&gt;2 = Excessive vomiting in pregnancy</td>
<td>0.31%</td>
</tr>
<tr>
<td>0.61306</td>
<td>Dx3-&gt;2 = Personal history of malignant neoplasm</td>
<td>0.28%</td>
</tr>
<tr>
<td>0.58281</td>
<td>Dx0-&gt;2 = Heart failure</td>
<td>0.30%</td>
</tr>
<tr>
<td>0.56708</td>
<td>Dx0-&gt;1 = Nephritis, nephrotic syndrome, and nephrosis</td>
<td>0.09%</td>
</tr>
<tr>
<td>0.56649</td>
<td>Dx3-&gt;2 = Heart failure</td>
<td>0.28%</td>
</tr>
<tr>
<td>0.54663</td>
<td>Complaint sentence contains &quot;suicidal&quot;</td>
<td>0.17%</td>
</tr>
<tr>
<td>0.48415</td>
<td>Dx1-&gt;2 = Disorders of function of stomach</td>
<td>0.07%</td>
</tr>
<tr>
<td>0.47257</td>
<td>Dx5-&gt;0 = Diseases Of The Genitourinary System</td>
<td>0.15%</td>
</tr>
<tr>
<td>0.46136</td>
<td>Dx0-&gt;2 = Chronic airway obstruction, not elsewhere classified</td>
<td>0.10%</td>
</tr>
<tr>
<td>0.44555</td>
<td>Dx4-&gt;2 = Depressive disorder, not elsewhere classified</td>
<td>0.10%</td>
</tr>
<tr>
<td>0.44257</td>
<td>Stayed 14 hours in the ER</td>
<td>0.10%</td>
</tr>
<tr>
<td>0.43890</td>
<td>Dx0-&gt;1 = Other psychoses</td>
<td>0.32%</td>
</tr>
<tr>
<td>0.43513</td>
<td>Dx0-&gt;0 = Diseases Of The Blood And Blood-Forming Organs</td>
<td>0.46%</td>
</tr>
<tr>
<td>0.42582</td>
<td>Complaint sentence contains &quot;dialysis&quot;</td>
<td>0.19%</td>
</tr>
<tr>
<td>0.41888</td>
<td>Dx0-&gt;2 = Depressive disorder, not elsewhere classified</td>
<td>0.27%</td>
</tr>
<tr>
<td>0.41302</td>
<td>Dx1-&gt;1 = Nephritis, nephrotic syndrome, and nephrosis</td>
<td>0.29%</td>
</tr>
<tr>
<td>0.38506</td>
<td>Complaint sentence contains &quot;fluid&quot;</td>
<td>0.10%</td>
</tr>
<tr>
<td>0.37474</td>
<td>69 &lt; Age</td>
<td>9.22%</td>
</tr>
</tbody>
</table>
Interventions are costly but promise reduced likelihood of readmission

- Post-discharge care coordination
- Patient education
- Scheduled outpatient visits
- Telemedicine, connected health

Experiences with costs and efficacies reported in literature.
Analysis of Value of Decision System

- Predictive model, 2004-2007, test cases from 2008
- Costs, efficacy from studies

For 2008:
- 62,000 visits to ED
- 2,200 readmissions within 30 days
- Est. cost of readmissions: ~$44,000,000
Analysis of Value of Decision System

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Toward Site-Specific Trials

“Clinical trials” of sensing & intervention strategies

Local learning cycle for hospital centers, e.g., CHF
Readmissions Manager for Microsoft Amalga
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%–70% 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
Engineering: Tractability and Tradeoffs

The figure shows the performance of different feature sets on a ROC curve. The curves represent the trade-off between true positive rate and false positive rate for various feature sets. Each curve is labeled with its corresponding AUC and number of features:

- V1: AUC = 0.758, #feat = 463
- V1: AUC = 0.752, #feat = 323
- V1: AUC = 0.736, #feat = 107
- V1: AUC = 0.731, #feat = 66
- V2: AUC = 0.715, #feat = 57
- V2: AUC = 0.709, #feat = 23

The AUC values indicate the accuracy of the classification, with higher AUC values indicating better performance.
Predictive Platform Goes Live...
Learning from In-World Application

Automation ↔ expert handholding?

- Data differences → universal schema
- Local train and test cycle
- Quality assurance

Predictive Modeling Research
Example: Reducing Medical Errors & Injuries
Deaths attributed to medical error:

44,000 - 98,000 / year U.S., preventable errors.

“To Err is Human,” Inst. of Medicine, 2000

Adverse medical events:

13.5% of hosp. Medicare patients, 44% preventable.

Levinson, 2010

Costs of errors:

$17 to $29 billion per year in U.S.

Thomas, et al., 1999
Medical Errors & Injuries in the News

The New York Times

WORLD | U.S. | N.Y. / REGION | BUSINESS | TECHNOLOGY | SCIENCE | HEALTH

Report Finds Most Errors at Hospitals Go Unreported

WASHINGTON — Hospital employees recognize and report only one out of seven errors, accidents and other events that harm Medicare patients while they are hospitalized, federal investigators say in a new report.

Yet, even after hospitals investigate preventable injuries and infections that have been reported, they rarely change their practices to prevent repetition of the “adverse events.”

Leslie S. McSwiney, inspector general of the Health and Human Services.

In the report, being issued on Friday, hospitals are criticized for not properly monitoring and analyzing patient events, analyzing their causes” and improving patient safety. It said that the government should require the same kind of investigation that occurs after an airline crash.

CMS Issues Medicare Final Payment Rule; Strengthens Tie Between Payment and Quality Improvement

August 2, 2011
Direction: Learn to Detect Anomalies

Identify errors of omission & commission
→ Train on 4,486 cardiac patients; 30,828 episodes

Hauskrecht, Valko, Batal, Clermont, Visweswaran, Cooper
Direction: Learn to Detect Anomalies

- Identify errors of omission & commission
  → Train on 4,486 cardiac patients; 30,828 episodes

Predictive model:
patient state \( x \) → actions \( a \)

Current patient
State \( x^* \)

Observed action \( a^* \)

Hauskrecht, Valko, Batal, Clermont, Visweswaran, Cooper
Direction: Forecast Surprises

- Infer likelihood that physician will be surprised.
- Predicts patient will return to ED and be \textit{admitted with unforeseen diagnosis}.
Direction: Learn to Predict Infection

- Healthcare-related infections: 1 in 20 hospital visits
- 5% result in death (top 10 cause of death in US)
- Care costs: ~$20 billion annually

*Predicting MRSA < 48 hrs*
Prob Patient acquires C. Difficile?

- diabetes = TRUE
- history of C. Diffi = TRUE
- hospital service = gsg (general surgery)
- meds = acetylcysteine (n-acetylcys)
- meds = lidocaine hcl
- meds = clindamycin phosphate
- platelet count = G (thrombocytosis)
- unit = 2g
- albumin = L (hypoalbuminemia)
- admission source = transfer
- attending MD = XXXXXX
- unit = 2d
- CO2 = L (hypocapnea)
- city = Hyattsville
- employer name = Not Employed
- monocyte percent = H
- 70<=age<80
- wbc = H (white blood cell count)
- admission procedure = catheterization
- admission complaint = gastrointestinal
- last visit meds = fentanyl citrate
- meds = hydromorphone hcl

Insights about deeper mechanisms & causality

Richer Models & Interventions

Spatiotemporal models

Causality?
Susceptibility \((t)\) → Exposure \((t)\) → Infection, \(t\)

Space & time

<table>
<thead>
<tr>
<th>Location Unit, Room</th>
<th>(T_{ii})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cardiac Cath Unit, 4Axx-P</td>
<td>8/15</td>
</tr>
<tr>
<td>Medicine Patient CU, 4NxxE</td>
<td>8/15</td>
</tr>
<tr>
<td>Main OR, MRxx-P</td>
<td>8/17</td>
</tr>
<tr>
<td>Cardiac Intensive CU, CRxx-P</td>
<td>8/17</td>
</tr>
<tr>
<td>Surgical Patient CU, 4Fxx-B</td>
<td>8/18</td>
</tr>
<tr>
<td>Surgical Patient CU, 4Fxx-A</td>
<td>8/24</td>
</tr>
</tbody>
</table>
New pattern recognition methods to predict sudden cardiac death from ECG data.
(Syed, et al. 2011)

Fusion of immunological & clinical data to elucidate links between environmental exposure and pediatric asthma.
(Simpson, et al. 2010)

New image analyses linking histologic features to prognosis in breast cancer.
(Beck, et al. 2011)

New temporal reasoning to predict NICU outcomes from physiological signals.
(Saria, et al. 2010)
CS Advances and Data Capture in Medicine

Andy Wilson and Hrvoje Benko
CS Advances and Data Capture in Medicine

Hinckley, Pahud, Yatani, et al.
Data capture: workflow, directed vs. ambient, new sources (devices, online activities, etc.)

Data sharing and access: legal, technical

Richer models: time, space, physiology, psychology

Causal influences: from suspicion to cause

User modeling: display, interaction, intention

Active learning: offline & real time

Transfer learning: time & space

Fusing genomic, epigenetic, & clinical data
Multiple scientific challenges ahead
Data capture & availability as key bottleneck
Criticality of multiple threads of CS research
Feasibility of enhanced quality at lower cost

On being faithful to the Hippocratic Oath…