Bringing Big Data to the Bedside

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Stanford Children’s Health

Located in Palo Alto, CA
Opened in 1991
311 bed pediatric/obstetric quaternary-care facility

Hospital statistics
– 400,000 Patient Visits
– 13,000 Discharges
566 alarm-related deaths over 5 years

Machines that go 'ping'
Stanford Children’s baseline alarm data

Frequency of alarms on acute medical/surgical wards
– ~2300 per day
– One alarm every 1.5 minutes

*85-99% of bedside alarms don’t require clinical intervention*
© Typical vital sign parameters

- Not evidence based
  - Often derived from small populations of healthy children

- Recent publication found that hospitalized children have vital signs very different from most reference ranges
Data-Driven Vital Sign Parameters

Extracted heart rate (HR) and respiratory rate (RR) data from the LPCH clinical data warehouse to create percentile tables stratified by patient age.

7,202 unique patients & 62,508 vital sign measurements.
HR Parameter change

RR Parameter change
Pilot unit HR alarm results

~30% reduction in HR alarms

Goel V., Poole S., Kipps A., Palma J., Platchek T., Pageler N., Longhurst C., Sharek P. Implementation of Data-Driven Heart Rate and Respiratory Rate Parameters on a Pediatric Acute Care Unit. Stud Health Technol Inform. 2015; 216:918. PMID: 26262220.
Hospital-wide Implementation Aug 25

- ~250 bedside monitor profile changes
- Largest EHR order set change since go-live
- Nursing feedback:
  - They love the new profiles
  - Report fewer alarms
True positive alarms in a sick patient
Avoid false positive alarms in a well patient
Next steps: Linking physiologic and EHR data

Vital sign waveforms

Electronic Health Records (EHRs)

Over 2 million hours of data
Almost 20,000 unique pediatric patients
1. Develop a framework to incorporate physiologic context into the alarm system

2. Establish data-driven alarm thresholds at admission time using similar patients

3. Incorporate the patient’s own data to revise vital sign alarm thresholds over time
“The green button, representing real-time use of big data to create personalized cohorts of similar patients, will be a resource for both bedside decision making and the prioritization of unanswered questions for point-of-care randomization.”
**Problem:** A lot of medical care is educated guesses

**Opportunity:** Decisions influenced by what happened to people like you.

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**My Patient**
A 55 year old female of Vietnamese heritage with known asthma presents to her physician with new onset moderate hypertension

**Intervention**
Antihypertensives

**Outcome**
Diastolic pressure < 90 mm Hg

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Diastolic BP with Drug A: 245
Diastolic BP with Drug B: 989

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**Variables associated with Outcome**
- Drug A
- Asthma
- Ethnicity
- HDL
- HbA1c > 10%

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**Green button**

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*Health Affairs, July 2014*
Bringing cohort studies to the bedside: framework for a ‘green button’ to support clinical decision-making

“...future EHR systems will bring querying, visualization and decision support functions together to allow individualized virtual cohorts of similar patients to be assembled and used in real-time to support treatment selection and planning”

It is important to develop methods to support these personalized observational studies at the point-of-care, to understand when these methods may provide valid results, and to validate and integrate these findings with those from clinical trials.

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Just as health professionals and organizations have an obligation to learn, patients have an obligation to contribute to, participate in, and otherwise facilitate learning.
Achieving a Nationwide Learning Health System

Charles P. Friedman,* Adam K. Wong, David Blumenthal
Published 10 November 2010; Volume 2 Issue 57 57cm29

We outline the fundamental properties of a highly participatory rapid learning system that can be developed in part from meaningful use of electronic health records (EHRs). Future widespread adoption of EHRs will make increasing amounts of medical information available in computable form. Secured and trusted use of these data, beyond their original purpose of supporting the health care of individual patients, can speed the progression of knowledge from the laboratory bench to the patient’s bedside and provide a cornerstone for health care reform.

According to conventional wisdom, 17 years elapse before a new element of validated clinical knowledge finds its way into routine clinical practice in the United States (1). Although there is undoubtedly considerable variance around this estimate, the latency between biomedical discovery and care implementation information will be stored in electronic form (4). At the same time, achievement of meaningful use of these EHRs will enable this clinical information to flow securely from the site where it was collected to a different location where the information has an authorized use. In practice settings that achieve meaningful
Continuously Learning Health Care System
Alarm thresholds for similar patients

**Input**
- Age
- Gender
- Weight
- Height
- Ethnicity
- Diagnosis
- Medications
- Test results
- ...

Features known at admission

**Output**

Vital sign metrics

Using similar patients
"The importance of those who have clinical backgrounds and work in IT settings is increasingly acknowledged by leaders in health IT."

1. The consensus is driven by the recognition of the value that electronic health record (EHR) and health information exchange (HIE) across traditional business boundaries can potentially provide. Recent actions such as the

2. Expanding the role of clinicians and researchers for the modern age, Dr. Hersh describes the need for a workforce necessary to sustain the systems to improve the quality, safety, and cost-effectiveness of care.
How do we ensure our healthcare system learns from every patient, at every visit, every time?
Thank you
Questions/Comments?
vgoeil@lpch.org
Home monitoring for kids with type 1 diabetes

- Diabetes management is highly data-driven, but physician access to patient data is inefficient and largely restricted to clinic visits
- Technology-enabled:
  - Apple announces HealthKit, which allows iOS apps to exchange health data
  - Epic MyChart app is HealthKit-enabled
  - Dexcom continuous glucose monitors are HealthKit-enabled
Innovation

- Using Apple HealthKit with Epic MyChart and Dexcom glucose monitors to enable home monitoring for children with diabetes
• Outcomes (Kumar et al. under review at JAMIA)
  - Pilot of 10 patients Spring/Summer 2015 shows improved MD efficiency, patient satisfaction, and revenue generation (through CGM review codes)
  - Expanded in Fall 2015 to include all patients with type 1 diabetes using Dexcom CGM monitor (now covered by payors)
  - Stanford Children’s developed app for viewing CGM data (q5min data points = 288 data points / 24 hours) now available publicly at http://gluvue.stanfordchildrens.org
Evidence-Based Medicine in the EMR Era

Jennifer Frankovich, M.D., Christopher A. Longhurst, M.D., and Scott M. Sutherland, M.D.

Any physicians take great pride in the practice approach, using the data captured

Results of Electronic Search of Patient Medical Records (for a Cohort of 98 Pediatric Patients with Lupus) Focused on Risk Factors for Thrombosis Relevant to Our 13-Year-Old Patient with Systemic Lupus Erythematosus.

<table>
<thead>
<tr>
<th>Outcome or Risk Factor</th>
<th>Keywords Used to Conduct Expedited Electronic Search</th>
<th>Prevalence of Thrombosis no./total no (%)</th>
<th>Relative Risk (95% CI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outcomes — thrombosis</td>
<td>“Thrombus,” “Thrombosis,” “Blood clot”</td>
<td>10/98 (10)</td>
<td>Not applicable</td>
</tr>
<tr>
<td>Thrombosis risk factor</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Heavy proteinuria (~2.5 g per deciliter)</td>
<td>“Nephrosis,” “Nephrotic,” “Proteinuria”</td>
<td>8/36 (22)</td>
<td>7.8 (1.7–50)</td>
</tr>
<tr>
<td>Present at any time</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Present &gt;60 days</td>
<td>“Urine protein”</td>
<td>7/23 (30)</td>
<td>14.7 (3.3–96)</td>
</tr>
<tr>
<td>Pancreatitis</td>
<td>“Pancreatitis,” “Lipase”</td>
<td>5/8 (63)</td>
<td>11.8 (3.8–27)</td>
</tr>
<tr>
<td>Antiphospholipid antibodies</td>
<td>“Aspirin”</td>
<td>6/51 (12)</td>
<td>1.0 (0.3–3.7)</td>
</tr>
</tbody>
</table>

* In all cases, the sentences surrounding the keywords were manually reviewed to determine their relevance to our patient. Pancreatitis was defined as an elevated lipase level (twice the upper limit of normal) coexisting with abdominal pain. We used the word “aspirin” as a proxy for antiphospholipid antibodies, since it is standard practice at our institution to give all patients with these antibodies aspirin; if “aspirin” was found in the chart, antiphospholipid-antibody status was confirmed by investigating the laboratory results.

We recently found ourselves in such a situation as we admitted to our service a 13-year-old girl so to speak — was equally fruitless and failed to produce a consensus.

Of the 98 patients in our pediatric lupus cohort, 10 patients developed thrombosis, documented