Big Data Analytics: One Health System’s Experience

Rob Fassett, MD
Chief Medical Informatics Officer
Oracle Health Sciences
Don’t Kill Don

Don Berwick, MD

RFP: Replace Don’s Right Knee

• Don’t kill Don
• Don’t hurt Don
• Minimize Don’s pain
• Don’t make Don feel helpless
• Don’t make Don wait
• Don’t waste money

Annals of Internal Medicine

My Right Knee

Donald M. Berwick, MD, MPP

Ann Intern Med. 18 January 2005;142(2):121-125
Take Don’s Advice

Don Berwick, MD
How can information technologies like data warehousing and analytics accelerate the pace of care quality improvement?
Data: The Essential Substrate

Circle Area Suggests the Relative Volume of Healthcare-Relevant Data on a Given Person

- + EMR
- + HIE
- + PHR
- + Social
- + Omics + Sensor
- Claims
More Data Than Stars
Big Data

In 2010 we humans generated more bits of information than there are stars in the knowable universe.

In 2009 humanity created more data than we have in all of human history.

Twitter captures about 8 terabytes of data every day.

- "Big Data" Defined
  - Volume
  - Velocity
  - Variety
  - Value

- Big Data Analytics
  - New opportunities
  - New challenges
  - New tools
Quality Analytics at the Level of a Single Health System

How does a given health system ... use Big Data analytics ... ... to take great care of Don?
Analytics Throughout the Quality Improvement Cycle

Health Data From All Sources

Big Data Warehouse

Data Discovery

Find Patients (Cohort Identification)

Hypothesis Generation & Comparative Effectiveness (Data Mining)

Safety & Outcomes Measurement

Enterprise Healthcare Analytics

Patient Engagement Analytics (Innovation in Data Visualization)

Point of Care Tools (e.g. Predictive Analytics, Care Gaps, Bedside Data Mining)

Performance Management (Reporting, Alerting, Nextgen Scorecarding)
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5. Safety & Outcomes Measurement

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Phenotyping Algorithms

- Example: how do you find your patients with rheumatoid arthritis?
- Relying on billing codes not sufficient in the EMR era – miss many patients
- EMR problem lists are often not reliable by themselves – need better curation
- Phenotyping algorithms combine codes, NLP, labs, meds, et cetera to yield higher sensitivity, specificity, PPV.
- Phenotyping algorithms can be “portable” across different health systems

### Table

<table>
<thead>
<tr>
<th>Model</th>
<th>Sens by algorithm or criteria</th>
<th>Sens (95% CI)</th>
<th>Spec (95% CI)</th>
<th>Diff (95% CI)</th>
<th>NPL</th>
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<td>94 (91.96)</td>
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<td>56 (54.60)</td>
<td>5 (3.80)**</td>
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<td>Published administrative codified criteria</td>
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<td>≥3 ICD9 RA</td>
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<td>≥3 ICD9 RA + DMARD</td>
<td>77.69</td>
<td>45 (37.33)</td>
<td>68 (57.75)</td>
<td>49 (40.57)**</td>
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</table>
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Enterprise Healthcare Analytics
Bedside Data Mining

Evidence-Based Medicine in the EMR Era
Jennifer Frankovich, M.D., Christopher A. Longhurst, M.D., and Scott M. Sutherland, M.D.

1) One Pediatric Patient with Systemic Lupus Erythematosus At High Risk for Thrombosis

- Nephrotic-range proteinuria
- Anti-phospholipid antibodies
- Pancreatitis

2) Should we anti-coagulate?

- Significant risk of stroke
- Anti-coagulants also have risks

3) There was no expert consensus and no definitive literature. So they consulted the clinical data warehouse.

- Queried the Stanford STRIDE data warehouse and found 98 similar patients
- 10 of those 98 SLE patients had thrombosis
- This patient was given anti-coagulation based on this data warehouse query
- She did just fine – no thrombosis, no adverse events from anti-coagulation.

- Decision based on information, not hunches – this is the future of healthcare.

Frankovich, J, Longhurst, CA, Sutherland, SM. NEJM (2011) 365:1758-1759
Molecular Decision Support

Nickolas Volker

- Treating each patient as if they are the “average human” is often not effective
- Must combine phenotype and genotype in the exam room
- Treating each person based on their uniqueness is a truly big data analytics challenge
- New tools are required for safe, high quality, cost effective, personalized medicine

Making a definitive diagnosis: Successful clinical application of whole exome sequencing in a child with intractable inflammatory bowel disease

Elizabeth A. Worthley, PhD1,2, Alan N. Mazer, MD, PhD3,4, Grant D. Syverson, MD2, Daniel Holibility, BSc2, Reneeia B. Boulacca, MSc2, Brennan Dockor, BSc2, Jaime M. Serpe, BSc2, Trivikram Dasg, PhD2, Michael R. Tschanner, BSc2, Regan L. Vetil, MSc2, Monica J. Breshore, PhD1, Ulrich Broeckel, M.D. PhD2,3,1, Kay Tomato Mitchell, PhD1,2,1, Margarita J. Arte, MD2,3, James T. Casper, MD2,3, David A. Margolis, MD2,3, David P. Bick, MD2,3,1, Martin J. Heuas, PhD2,3, John M. Rantet, MD2,3, James W. Verbly, MD, PhD2,3, Howard J. Jacob, PhD2,3,4, and David P. Dammock, MD2,3,4
### Align Data by Patient Event

**Patient ID:** AI  
**Align By:** Diagnosis: Glioblastoma NOS (9440/3)

#### Result Summary:
Data is plotted relative to start of event: Diagnosis: Glioblastoma NOS (9440/3)

<table>
<thead>
<tr>
<th>Patient ID</th>
<th>Event</th>
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<tbody>
<tr>
<td>20075</td>
<td>Diagnosis</td>
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<td>20046</td>
<td>Diagnosis</td>
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<tr>
<td>20046</td>
<td>Procedure</td>
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<td>Procedure</td>
</tr>
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</tr>
<tr>
<td>20071</td>
<td>Diagnosis</td>
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<tr>
<td>20071</td>
<td>Procedure</td>
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<td>Procedure</td>
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<td>Procedure</td>
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<td>Procedure</td>
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<td>Procedure</td>
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</table>
Nicholas Volker After Treatment

- X-linked immunodeficiency
- Mutation in a gene coding for an apoptosis inhibitor
- Received an allogenic cord blood transfusion
- Living large: back to school and playing baseball & riding ATVs
- This is Big Data analytics in action at the bedside when it really matters!

http://www.jsonline.com/features/health/111224104.html
Analytics Throughout the Quality Improvement Cycle

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- Health Data From All Sources
- Big Data Warehouse
- Data Discovery
- Safety & Outcomes Measurement
- Patient Engagement Analytics (Innovation in Data Visualization)
- Point of Care Tools (e.g. Predictive Analytics, Care Gaps, Bedside Data Mining)

ORACLE

Enterprise Healthcare Analytics

PeopleSoft, ORACLE

Medtronic, Apple, Allscripts, Siemens, McKesson, Epic, Cerner, Twitter, Medtronic, Allscripts, Siemens, McKesson, Epic, Cerner, Twitter

ORACLE HEALTH SCIENCES
Oracle Care Management Analytics

• What is Care Management Analytics?
  – Show the Accountable Care team how their individual patients
  – Roll up this individual patient view to create a population view

• Target Users
  – Individual Physicians
  – The coordinated Accountable Care team
  – Clinical and Executive Leadership

• Simultaneously Optimize:
  – Care Quality & Outcomes
  – Cost Effectiveness
  – Patient Satisfaction
  – Operational Efficiency
### Patient Summary - Process Measures

<table>
<thead>
<tr>
<th>Category Of Care</th>
<th>All Patients</th>
<th>Patients On Guideline</th>
<th>Patients Off Guideline</th>
<th>Patients Almost Off Guideline</th>
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<tbody>
<tr>
<td>Anticoagulation</td>
<td>40</td>
<td>6</td>
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<td>Asthma Treatment</td>
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<td>COPD</td>
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<tr>
<td>Diabetes</td>
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<td>10</td>
<td>90</td>
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<tr>
<td>Hypertension</td>
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<td>3</td>
<td>59</td>
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<td>Lipid Control</td>
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<td>8</td>
<td>78</td>
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<tr>
<td>MI</td>
<td>16</td>
<td>1</td>
<td>15</td>
<td>1</td>
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<tr>
<td>Wellness</td>
<td>301</td>
<td>28</td>
<td>273</td>
<td>27</td>
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<tr>
<td><strong>Total</strong></td>
<td><strong>805</strong></td>
<td><strong>74</strong></td>
<td><strong>731</strong></td>
<td><strong>72</strong></td>
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</table>

Metric Summary is not applicable for Current Status

- On Guideline
- Off Guideline
- Almost Off Guideline
# Galen Health Systems

## Clinical Care Analytics

**Home >> Diabetes >> Almost Off Guideline Patients**

**Timeframe: Current Status**

### Diabetes - Process Measures - Almost Off Guideline Patients

<table>
<thead>
<tr>
<th>Patient Name</th>
<th>Gender</th>
<th>Age</th>
<th>BMI</th>
<th>Type</th>
<th>Overall Process</th>
<th>Overall Outcomes</th>
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<tr>
<td>Jim Hughes</td>
<td>M</td>
<td>48</td>
<td>3614</td>
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<td>☐</td>
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<tr>
<td>Melody Anderson</td>
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<td>Dick Brown</td>
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<td>9864</td>
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</tbody>
</table>

- ☐: On Guideline
- ☐: Off Guideline
- ☐: Almost Off Guideline
- ☐: Not Applicable
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Democratizing Analytics

Analytics are increasing having an impact at the point of care and beyond
Patient Engagement Analytics

Russ Bessette, MD

Director, Louisville Informatics Institute
Univ of Louisville

• Dr. Bessette used data mining to identify key indicators of disease progression for dialysis patients
• Used innovative visual analytic techniques to help dialysis patients understand their health and get engaged
• Training nurse “Knowledge Workers” and community-based “Health Coaches” to use these tool to help underserved patients get engaged in their care
• Dr. Bessette’s effort has gained momentum with hospitals, physician groups, and payers across the state.

Deploying innovative visual analytics to help traditionally underserved patients in Kentucky get engaged in their health and wellness.
Analytics are Vital to HC Transformation

HC Transformation requires much more than just an EMR. It requires integrated clinical, financial, administrative, and research data from across the Provider Enterprise and analytics.
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