THE QUANTUM PATIENT:
ADVANCED AND PREDICTIVE ANALYTICS IN HEALTH CARE

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“While the individual man is an insoluble puzzle, in the aggregate he becomes a mathematical certainty”

Sherlock Holmes
A central tenet of SAS’ industry strategy is the concept of convergence.

SAS understands that transformations needed in the life science and healthcare industries require shared data and insights across previously siloed markets (payers, providers, and pharma) – an era of collaboration around analytics.

Outcomes | Quality | Value
CHALLENGES

DATA, DATA, EVERYWHERE...

Patient

Thanks to Stan Huff at Intermountain Healthcare
CHALLENGES ADOPTING ADVANCED ANALYTICS IN HEALTHCARE

- Data Access
- Data Quality/Integrity
- Unstructured/Text
- Universal Healthcare Exchange Language
- Interoperability
- Privacy and Anonymization
- Analytic Maturity
- Easy of Use
DATA  \hspace{1cm} \text{…ONE MORE THING ABOUT COMPLEXITY}

- Medicine is a probabilistic science
- Data quality, completeness, reliability
- Capacity to describe unexpected events
- Multi dimensional data

Dealing with complexity instead of fighting it!

CHRISTIAN LOVIS, MD MPH
Professor of Clinical Informatics, University of Geneva
Head of Medical Information Sciences, Geneva University Hospitals
Geneva, SWITZERLAND
IS THIS THE FUTURE IN THE US?

• Millions of American consumers will have their first video consults

• Prescribed their first health apps

• Use their smartphones as diagnostic tools for the first time.

• Higher deductibles create opportunities to manage medical expenses with new tools and services from insurance companies, healthcare providers, banks and other new entrants.

• Shift by shift, visit by visit, nurses doctors and other clinicians learn to work in new ways, incorporation insights gleaned from data analysis into their treatment plan.

How Telemedicine Is Transforming Health Care
The revolution is finally here—raising a host of questions for regulators, providers, insurers and patients
By MELINDA BECK
June 26, 2016

THE WALL STREET JOURNAL
“It is predicted that digital electronic computers will assume an increasingly important role in medicine…

William R. Best, M.D. (1962)

“Since the earliest days of computers, health professionals have anticipated the day when machines would assist in the diagnostic process”


Computer Programs to Support Clinical Decision Making—Reply

“In Brazil and India, machines are already starting to do primary care, because there’s no labor to do it. They may be better than doctors. Mathematically, they will follow evidence—and they’re much more likely to be right.”

Robert Kocher, M.D. (2013)
Mathematical models out-perform doctors in predicting cancer patients' responses to treatment

"If models based on patient, tumour and treatment characteristics already out-perform the doctors, then it is unethical to make treatment decisions based solely on the doctors' opinions. We believe models should be implemented in clinical practice to guide decisions."

Cary Oberije, Ph.D.
MAASTRO Clinic
Maastricht University Medical Center, Maastricht, The Netherlands.

2nd Forum of the European Society for Radiotherapy and Oncology (ESTRO).
Abstract no: OC-0140, "Clinical 2 – Lung and Head & Neck cancer"
Geneva, Switzerland 19-23 April 2013
Maturity of advanced and predictive analytics to address many complex issues in health care

Growth in the digitization and availability of health care data

Changes in social, economic and legislative considerations related to availability, access and quality of care

- Automation
- Insight
- Knowledge
- Optimization
- Simulation
HYBRID ANALYTIC APPROACH FOR COMPLEX PROBLEMS

Enterprise Data

Known Patterns

- Rules
  - Rules to surface known issues
    - Relevant diagnosis code recorded
    - Prescription not filled

Unknown Patterns

- Anomaly Detection
  - Algorithms to surface unusual behaviors
    - New symptom presents
    - # patients with event exceeds expected

Complex Patterns

- Predictive Models
  - Identify patterns and relationships to anticipate future events
    - Patterns of patient behavior for known issues
    - Drivers for high cost

Unstructured Data

- Text Mining
  - Enhance analytic methods with unstructured data
    - Extract knowledge from clinical narrative
    - Integration of rich case file information

Associative Linking

- Network Analysis
  - Associative discovery thru automated link analysis across heterogeneous data
    - Linked highly diverse elements
    - Connected network of adverse events with contributing factors

HYBRID APPROACH

Proactively applies combinations of techniques at entity and network levels
Making our medical records open for sharing will save 100,000 lives a year, Google CEO Larry Page told the TED conference in Vancouver today.

"Wouldn't it be amazing if everyone's medical records were available anonymously to research doctors?" Page said. "We'd save 100,000 lives this year.

We’re not really thinking about the tremendous good which can come from people sharing information with the right people in the right ways."

Larry Page
19 March 2014
GOOGLE WANTS TO DEFINE A HEALTHY HUMAN

Google is "exploring ways to make it easy for participants to share their health information and habits with researchers on a routine basis."
CEO Roundtable on Cancer’s Life Sciences Consortium (LSC)

- LSC founded 2004
- Mission: “Bold and Venturesome”
- Accomplish together what no single company might consider alone
PDS: Open Access Cancer Data-Sharing Platform

- Voluntary, not-for-profit platform
  - Broadly share, integrate, and analyze cancer data
  - Sophisticated analytic tools
  - Free, easy-to-use, with favorable IP
  - Industry and NCI-NCTN comparator-arm phase III trials
  - De-identified patient data, dictionary, protocols & CRFs

- To benefit cancer patients
- **Public Launch:** April 8, 2014
A cloud-based, big data platform powered by a library of clinical, social and behavioral analytics. That will help doctors, nurses and other health care providers better understand each patient and tailor care to improve health while reducing costs.

Analytics will allow Dignity Health to assign a probability to future events like the risk of readmission, the likelihood of sepsis or kidney failure, and then apply best practices to intervene early and reduce the possibility of avoidable future complications and costs.

**USE CASE**

- Dignity Health’s pilot sepsis bio-surveillance program helped reduce sepsis mortality at 16 facilities.

- Dignity Health enabled health care providers to proactively manage potential risks, resulting in reduced mortality, shorter length of stay in the intensive care unit and an overall reduction in costs.

- On average, 69,000 lives a month were monitored during the initial rollout of the program

- Average mortality rate for sepsis patients decreased by 7.25 percent

- Average severe sepsis rate decreased by 14.9 percent

- Physician response time with sepsis bundle orders was reduced by nearly 51 percent

*Dignity Health, one of the US’s largest health systems, is a 20-state network of nearly 9,000 physicians, 55,000 employees and more than 380 care centers, including hospitals, urgent and occupational care, imaging centers, home health and primary care clinics.*
Informed predictions save lives
Advanced statistical tools enhance detection of life-threatening sepsis cases

Challenge
To more accurately predict the severity of sepsis in a patient.

Solution
A team of researchers used JMP® Genomics software from SAS to study data sets with tens of thousands of compounds. The researchers are not statisticians, but the software enabled them to examine complex data sets quickly and accurately. Statisticians validated their analysis results.

Results
The software helped the team develop a blood test that can distinguish between mild and severe cases of sepsis, alerting doctors to cases requiring immediate hospitalization. This research may also lead to more effective treatment of other infections.

An integrated clinico-metabolomic model improves prediction of death in sepsis
Sci Transl Med. 2013 Jul 24; 5(195):
Our latest collaboration, May 4, 2016

Duke Clinical Research Institute and SAS open heart-disease data to researchers

- New collaboration will give more researchers access to the largest and oldest cardiovascular database in the world.
- The DCRI and analytics leader SAS will provide researchers worldwide with data management and analytics tools to explore 45 years of cardiovascular patient data collected by the Duke University Health System.

“Open science is good for researchers, good for innovation, and good for patients and the public. The question at the center of the open-science discussion is not whether data should be shared, but how we can usher in responsible methods for doing so. Our collaboration with SAS will allow data to be shared for the advancement of public health worldwide.”

DCRI Executive Director Eric Peterson, MD, MPH
IOT IMPROVING PATIENT MANAGEMENT

BUSINESS ISSUE
• Detect relevant patterns in patient real-time data to alert critical care teams
• Monitoring
• Patient vital statistics from various sensors across different equipment
• Incoming lab results joined with real time sensor data

RESULTS
• Monitor data to trigger actions based upon detected patterns
• Send messages across email and SMS
• Alert immediately appropriate critical care teams
• Send immediate recommendation to remote patient
RESULTS  LENGTH OF STAY

• Figures represent length of stay in the nursing wards for a schedule that was generated for a single operating room in a two-week period

• This simulation assumes that the nursing wards were empty on the first day and gradually fill up.

Optimized schedule creates a much more steady buildup in occupancy, demonstrated on day 2.

At end of end of the second week, there are numerous discharges in both plans. Buildup is more stable as related to manual scheduling.
A ‘Small’ Application of Big Data Analytics in Healthcare

- Create a discrete-event simulation model for a NICU's patient mix (SAS® Simulation Studio)
- More accurate nurse scheduling
- Better match between nursing ratios and acuity
- Better preparation for changes in status
- Optimize balance between cost and quality
Duke Hospital NICU Staffing needs:

- Three Neonatal Fellows
- Four Attending Neonatologists
- Five Pediatric Residents
- Five Respiratory Therapists
- Nine Neonatal Nurse Practitioners
- OVER SIXTY NURSES...
DATA SIMULATION INPUTS

• Number and Type of Admissions per Day
  • Inborn / Transfer and Gestational Age (GA)
• Predicted Length of Stay (LOS) / Model Exit
• Probability envelopes for major morbidities
• Timing of events
• Affect on LOS
• Temporal affect on acuity
• Model Exit
  • Death
  • Discharge
  • Transfer
• Constraints
  • Number/type of beds, number/availability of transfer beds, number of nurses
PROBABILITY ENVELOPES

PREDICTED LENGTH OF STAY (LOS) / MODEL

- Exit
- Probability envelopes for major morbidities
- Timing of events
- Affect on LOS
- Temporal affect on acuity

- Model Exit
  - Death
  - Discharge
  - Transfer
- Constraints
  - Number/type of beds, number/availability of transfer beds, number of nurses
## Simulation Validation

<table>
<thead>
<tr>
<th></th>
<th>Model Mean (95th% CI)</th>
<th>Actual Data N or Mean (95th% CI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Admissions</td>
<td>845 (840, 851)</td>
<td>792 (732, 851)</td>
</tr>
<tr>
<td>Admissions &lt;28 Weeks</td>
<td>126 (123, 128)</td>
<td>119 (109, 129)</td>
</tr>
<tr>
<td>Average Daily Census</td>
<td>57 (56, 58)</td>
<td>57 (54, 61)</td>
</tr>
<tr>
<td>LOS (days)</td>
<td>26 (25, 26)</td>
<td>26 (25, 28)</td>
</tr>
<tr>
<td>LOS &lt;28 Weeks (Days)</td>
<td>78 (77, 79)</td>
<td>86 (81, 91)</td>
</tr>
<tr>
<td>Deaths</td>
<td>35 (34, 37)</td>
<td>38 (34, 43)</td>
</tr>
</tbody>
</table>
• Contrary to the current belief that reduction of ALOS implies a reduction in hospital resource utilization due to improved care, the exact opposite appears to be true.

• Hospital administrators should seriously consider high fidelity modeling before initiating a ‘one size fits all’ approach to cost containment strategies.
OBJECTIVES

Optimizing Surgery Schedules to Save Resources, and to Save Lives

CHALLENGE FORMULA

• Minimize the maximum number of beds needed in two-weeks time to reduce the total number of beds in specific ward

• Balance the number of incoming patients (from OR) and outgoing patients (e.g. leave home) on each day.
• Tremendous interest in accessing and using unstructured data to enhance data driven decision making related to patient safety, quality and outcomes.

• Interest not limited to internal/CROM data
FDA PATIENT PREFERENCE INITIATIVE


The Food and Drug Administration (FDA) is announcing the following public workshop entitled “The Patient Preference Initiative: Incorporating Patient Preference Information into the Medical Device Regulatory Processes”.

The purpose of this workshop is to discuss ways to incorporate patient preferences on the benefit-risk trade-offs of medical devices into the full spectrum of the Center for Devices and Radiological Health (CDRH) regulatory decision making. It also aims to advance the science of measuring treatment preferences of patients, caregivers, and health care providers.
The objective of this requirement is to provide FDA with the resources needed to use social media to inform and evaluate FDA risk communications. Specifically, the objective is to provide FDA with:

• Analyses of social media that provide baselines on consumer sentiment prior to FDA communication and that depict changes in social media buzz following FDA communications

• In-house capability for social media monitoring; and Surveillance through social media listening for early detection of adverse events and food-borne illness.

• The scope of work includes social media buzz reports, a social media dashboard, and quarterly surveillance reports related to specific product classes.
A Patient Reported Outcome is any report of the status of a patient’s health condition that comes directly from the patient, without interpretation of the patient’s response by a clinician or anyone else.

Guidance for Industry
Patient-Reported Outcome Measures: Use in Medical Product Development to Support Labeling Claims
U.S. Department of Health and Human Services
Food and Drug Administration 2009

Any outcome evaluated directly by the patient himself and based on patient’s perception of a disease and its treatment(s) is called patient-reported outcome (PRO).

Reflection Paper on the Regulatory Guidance for the use of Health Related Quality of Life (HRQL) Measures in the Evaluation of Medicinal Products
European Medicines Agency 2005
OBJECTIVE
FROM INFINITY TO SAS TABLES
DATA

ON LINE DATA SOURCES

Healthyplace.com

ncbi.nlm.nih.gov/pubmed/

Epilepsyfoundatio.org

Epilepsy.com

http://www.accessdata.fda.gov

Vnsmessageboard.com
How to build a “Lie Detector” for the internet;

- Semantic Field Normalization/Contextualization for Self-Reported Symptom-Treatment-Outcome Measurement in Web-based Media Sources
- Adaptation of “Semantic Nets” to Establish Veracity of Symptom-Treatment Outcome Reports in Health Related Web Interactions
- Behavioral context as a pathway to crafting semantic field normalization mappings in Clinician/Patient Reported Outcomes Data (C/PROM)
“Ab silico ad salus; Interactive Visualization of Network Phenomena in Highly Heterogeneous and Voluminous Data”

Can visualization and temporal network analysis help explain and predict therapeutic and safety related issues in medical products and procedures using automated analysis of large amounts of structured and unstructured data from diverse data sources including social media?

OBJECTIVE

- Between 1964 and 2012 we identified 2181 Abstracts of interest.
- 78 unique Labeled AE terms were identified for a total of 2312 counts.

- Between 1994 and 2012 we identified 13,878 unique reports related to the product of interest.
- 89 Labeled AE terms were identified for a 10417 counts.
- 55 reports contained 10 or more Labeled AE’s.

DATA SOURCES

<table>
<thead>
<tr>
<th>Website</th>
<th>Document Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Epilepsy.com</td>
<td>5,353</td>
</tr>
<tr>
<td>Epilepsyfoundation.org</td>
<td>8,653</td>
</tr>
<tr>
<td>vsnmessageboard.com</td>
<td>13,115</td>
</tr>
<tr>
<td>Healthyplace.com</td>
<td>11,272</td>
</tr>
<tr>
<td>pubmed/medline</td>
<td>2,180</td>
</tr>
<tr>
<td>MAUDE</td>
<td>17,162</td>
</tr>
<tr>
<td>TOTAL</td>
<td>57,726</td>
</tr>
</tbody>
</table>
Patient preferences considered for the first time in FDA decision to approve first-of-kind obesity device

RTI Health Solutions partnered with the FDA to conduct a study on patients’ preferences which contributed to the Agency’s regulatory decision to approve a first-of-kind device to treat obesity.

This was the first time a patient preference study impacted a new device approval.

Incorporating patient-preference evidence into regulatory decision making

Surgical Endoscopy
January 2015
Martin P. Ho, Juan Marcos Gonzalez, Herbert P. Lerner, Carolyn Y. Neuland, Joyce M. Whang, Michelle McMurry-Heath, A. Brett Hauber, Telba Irony
Harness Patient Preference from Social Media

"Identify and Incorporate the Patient Voice into Our Decision-making on Medical Devices" – FDA Voice

Emily McRae, Cheyanne Baird, Joe Boland, Pat Dougherty, Martin Ho, Tetsu Iwamoto, Mimi Nguyen, Kathryn O’Callaghan, Michaela Wallis, Mark Wolff, Anindita Saha

SAS Institute Inc., Cary, NC / Center for Devices and Radiological Health, Food and Drug Administration, Silver Spring, MD

Objectives
- Explore the feasibility of collecting patient preference information from a variety of social media sources on selected topics.
- Apply sentiment scoring methods to reveal content-specific sentiment levels related to medical device treatments.

Background
- Social media has became a popular medium for individuals to express their opinions.
- After conducting a patient preferences survey on weight loss devices, CDHR explored sentiment analysis to harness patient preference from unstructured posts of social media for comparison with the survey results.

Sentiment analysis is an evolving technology that applies text analytics to analyze a document and infer the author’s sentiment about a topic of interest, such as a medical treatment.

CDHR and SAS collaborated to capture web-based patient sentiments on the benefits, risks, and other attributes of medical treatment to treat obesity and epilepsy.

Material and Methods
- Identified most popular websites on treatments of obesity (surgery, sleeve, band, balloon) and epilepsy (RNS, VNS, DBS, AEDs)
- Veracity Scoring (Signal to noise reduction)
- Segmentation and Data Cleaning
- Sentiment Analysis
- Visualization and Exploration
- Incremental data crawling for real-time sentiment analysis compared to baseline

Patient Forums

- Epilepsy
  - http://epilepsyfoundation.org/
  - http://forum.epilepsysociety.org.uk/
- Obesity
  - http://www.bariatrical.com/
  - http://www.obesityhelp.com/
  - http://weightlosssurgery.preboards.com/
  - www.wlsurgery.com/

Results

Patient Preference Attributes

<table>
<thead>
<tr>
<th>Obesity</th>
<th>Epilepsy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clarity</td>
<td>Clarity</td>
</tr>
<tr>
<td>Efficacy</td>
<td>Efficacy</td>
</tr>
<tr>
<td>Duration</td>
<td>Duration</td>
</tr>
<tr>
<td>Quality of Life</td>
<td>Quality of Life</td>
</tr>
<tr>
<td>Weight Loss</td>
<td>Seizure Reduction</td>
</tr>
<tr>
<td>Safety</td>
<td>Safety</td>
</tr>
<tr>
<td>Adverse Events</td>
<td>Adverse Events</td>
</tr>
<tr>
<td>Device Malfunction</td>
<td>Device Malfunction</td>
</tr>
<tr>
<td>Hospitalization</td>
<td>Hospitalization</td>
</tr>
<tr>
<td>Usage</td>
<td>Usage</td>
</tr>
<tr>
<td>Daily Life Impact</td>
<td>Daily Life Impact</td>
</tr>
</tbody>
</table>

An Example of Sentiment Analysis

Epilepsy: Thanks for sending this thread. I had my surgery on 10/27. My surgery went well. I did take longer in recovery than most but I don’t really remember that to much. I was on my pain drip and I used it every time the light turned green. I didn’t feel pain but they had said it is to stay ahead of the pain so that is what I did. I was up and walking around 9pm on the 1st day I had surgery. My surgery was at 2pm. My husband stayed the whole time he was in the hospital and that was a huge help. I just felt more comfortable with him there. I went home Tuesday around supportive and I needed my pain medicine at all once I got home. And by that first weekend I was getting in my protein and my liquids. I was surprised by that. My incisions were all good and my pain much healed up now. I walked everyday and most days I did get my tour in. It did make me feel better! I am sure of that. I have been back to the gym and working on getting my stamina back. I had a good 2 week post op appointment and was happy about that. Everything I introduced in the soft food stage has gone well. So for that I am grateful. So I am running my doctors orders and doing two shakes a day and one small meal. I usually have my meal at dinner time with my family. I haven’t bothered me to eat for my family and they eat my little bit of whatever. There is no way I want to mess this up. I didn’t get thru all this to not follow the rules and so far following the rules has been working.

Epilepsy Domain Dashboard

Obesity Domain Dashboard

Obesity Device Sentiment Overtime

Epilepsy Device Sentiment Overtime

Conclusions

Developed upon advanced text analytics, sentiment analysis is a powerful method to harness timely patient preference information from unstructured yet increasingly big data in the social media to complement data collected from other sources.

Acknowledgments

The authors would like to acknowledge Division of Reproductive, Endocrine, and Metabolic Disease and Division of Neurological and Physical Medicine Devices for their input on certain preference attributes and dashboard design.
“When schemes are laid in advance, it is surprising how often the circumstances fit in with them.”

Sir William Osler, New York Academy of Medicine in 1897