Healthcare Denmark visit to UCSF

The UCSF/GE partnership on Artificial Intelligence

10th March 2018
<table>
<thead>
<tr>
<th>Time</th>
<th>Topic</th>
<th>Presenter</th>
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<tbody>
<tr>
<td>9:00-9:20</td>
<td>Welcome</td>
<td>Henrik Krogen (GE DK)</td>
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<tr>
<td></td>
<td>• Introductions</td>
<td>Dr Hammond</td>
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<td></td>
<td>• Review agenda and objectives</td>
<td>Tours de table</td>
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<tr>
<td>9:20-9:40</td>
<td>The Danish HC-Situation and AI Perspectives</td>
<td>Eric Jylling, Danish Regions</td>
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<td>9:40 -10:45</td>
<td>The GE and USCF story: Partnering to define the future of AI through industry and academic partnership</td>
<td>Dr Hammond (UCSF)</td>
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<td>• The shared vision</td>
<td>Dr Calcutt (UCSF)</td>
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<td></td>
<td>• Product roadmap: from ideas to regulatory approval</td>
<td>Dr Austin (GE HC)</td>
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<td>10:45-11:30</td>
<td>Discussion</td>
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<td>• Q&amp;A</td>
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<td>• Collaboration opportunities</td>
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<td>• Action items</td>
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Objectives

1. Learn about Denmark’s HC situation + AI interest/strategy

2. Overview of the GE and UCSF partnership – an example of an Academic-Industrial collaboration

3. Understand GE’s and UCSF’s shared vision for artificial intelligence solutions

4. Explore possible collaboration opportunities UCSF-GE- Regions of Denmark
The HC Denmark Perspective
HC Denmark Perspective

Erik Jylling. Executive Vice President Health Politics at Danish Regions
The healthcare case for AI
UCSF Launches Deep Learning Partnership with GE Healthcare

The partnership will produce a library of deep learning algorithms that will empower clinicians around the world to make faster and more effective decisions for some of the most complex medical conditions, all at the point of care.
Possible Solution Suites

**Neuro suite**
- Acute Stroke Management
- Neuro MR Suite (Pediatrics/Adult)
- ...

**Chest Suite**
- Pneumothorax
- Tubes and lines
- ...

**Knee Suite**
- Tissue Segmentation
- Anomaly detection
- ...

- **Neurology**
- **Oncology**
- **Cardiovascular**
- **Critical Care**
- **Musculoskeletal**
- **Endocrinology**
- **Ophthalmology**
- **Pulmonology**
Investment in AI is increasing

**Investment**
Venture capital funding in healthcare companies surpassed $5B.

**Revenue from AI & Cognitive compute in healthcare by 2021**
6 – 10 $B
Medical Science is embracing both AI and DL

Scientific Publications

Artificial Intelligence 1991-2016

Deep Learning 1991-2016

SOURCE: Pubmed search: Artificial Intelligence & Medicine, Deep Learning & Medicine
The Productivity Challenge

**Fluctuating Demand**
Average annual growth in past 7 years

- MR = 1.6% (2.1% CAGR)
- Card Cath = 5.6% (1.1% CAGR)

**Radiologist Burnout**
Mean % of radiologists reporting “burnout symptoms” (‘15)

- ~ 49%

**Rad Shortages Globally**

- 1,123 - 1,458³ est no. of rads needed by 2020
- 8.5%⁴ of posts unfilled in 2016
- 4.3⁵ X workload

**Source:**
The Quality Challenge

Real-Time Error Rated

Average real-time, day-to-day error rate, averages

~ 3–5%

Numbers in the Literature

<table>
<thead>
<tr>
<th>Author (year)</th>
<th>Modality</th>
<th>Reported Error Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Muhm et al. (1983)</td>
<td>CXR</td>
<td>90% of Lung Ca seen on retrosp. CXRs</td>
</tr>
<tr>
<td>Markus (1990)</td>
<td>Ba enema</td>
<td>30% of visible lesions missed</td>
</tr>
<tr>
<td>Harvey et al. (1993)</td>
<td>Mammo</td>
<td>41% of cancers seen in previous study</td>
</tr>
<tr>
<td>Robinson (1999)</td>
<td>ED Xrays</td>
<td>3–6% error per observer</td>
</tr>
<tr>
<td>Quekel et al. (1999)</td>
<td>CXR</td>
<td>19% missed diagnosis rate (NSCL Ca)</td>
</tr>
<tr>
<td>Tudor et al (1999)</td>
<td>Xrays</td>
<td>Mean accuracy 77% (without clinical info; 80% with clinical information.)</td>
</tr>
<tr>
<td>Goddard (2001)</td>
<td>Various</td>
<td>Clinically significant error rate 2-20%</td>
</tr>
<tr>
<td>Siewart et al (2008)</td>
<td>Oncol CT</td>
<td>Discordant read: 31-37% with change in staging (19%) &amp; treatment (23%)</td>
</tr>
<tr>
<td>Briggs et al. (2007)</td>
<td>Neuro CT</td>
<td>13% major &amp; 21% minor discrepancy</td>
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</table>

Retrospective Error Rates

Average retrospective error rate among radiologic studies

~ 30%

Worldwide, an estimated 40M radiologic errors occur per annum.

The Quality Challenge isn’t just about the read

**Analysis and Prioritization of Near-Miss Adverse Events in a Radiology Department**

**OBJECTIVE:** The purpose of this study is to describe a method for the evaluation and prioritization of near-miss events in a radiology department.

**MATERIALS AND METHODS:** Every consecutive near-miss event occurring between 2007 and 2008 was retrospectively identified, classified by error type, and scored for its severity associated with risk. The highest severity generally associated with each event was multiplied and scored on a standardized SQUIRE scale. Six near-miss events were then assigned to each severity level. The product of individual scores, ranging from 1 to 8, was then the total score. Events were categorized by error type, patient type, and event type.

**RESULTS:** The most common error type was the use of incorrect patient information, and 98% of these errors originated outside the radiology department. More than 40% of the events were assigned a severity score, with 65% of the errors having occurred in the radiology department.

**CONCLUSION:** The method was constructed from standardized definitions of outcome severity for the ability of near-miss events to mitigate adverse near-miss adverse events.

**TABLE 4: Error Types Associated With 62 Radiologic Near-Miss Events**

<table>
<thead>
<tr>
<th>Error Type</th>
<th>No. (%) of Events</th>
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<tbody>
<tr>
<td>Order entry error</td>
<td>20 (32)</td>
</tr>
<tr>
<td>Care or service coordination</td>
<td>12 (19)</td>
</tr>
<tr>
<td>Incorrect patient identity information</td>
<td>10 (16)</td>
</tr>
<tr>
<td>Contraindication to planned procedure</td>
<td>5 (8)</td>
</tr>
<tr>
<td>Failure of electronic information transfer</td>
<td>2 (3)</td>
</tr>
<tr>
<td>Hazard related to equipment</td>
<td>2 (3)</td>
</tr>
<tr>
<td>Hazard related to environment</td>
<td>2 (3)</td>
</tr>
<tr>
<td>Other failure to follow policy</td>
<td>2 (3)</td>
</tr>
<tr>
<td>Wrong protocol</td>
<td>2 (3)</td>
</tr>
<tr>
<td>Error of image interpretation</td>
<td>2 (3)</td>
</tr>
<tr>
<td>Patient allergy</td>
<td>2 (3)</td>
</tr>
<tr>
<td>Medication stocking error</td>
<td>1 (2)</td>
</tr>
</tbody>
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UCSF – description + AI ambitions
UCSF Descriptive
Public University Structure

430,000 Jobs
Million patient records  Among the largest granular patient repositories
Publically owned

**Facilities:** 10+ Campuses
5 Medical Centers
3 National Laboratories

**Research:** Top in NIH Funding; Clinical + ResearchData

The University of California at San Francisco (UCSF) is one of the top research funded academic medical centers:
- 1600 Active UCSF Inventions
- 1,000 Products From UCSF Technologies
- 5 Nobel Laureates

The Center for Digital Health Innovation (CDHI) collaborates with Industry and UCSF scientific innovators to envision and realize new solutions to improve the lives of providers and patients.

**SmarterHealth**

Courtesy of UCSF’s Center for Digital Health Innovation’s SmarterHealth Program.
SmarterHealth: Leveraging medical context and patient data within a scalable AI platform to support the delivery of the right treatment to the right patient at the right time

Courtesy of UCSF's Center for Digital Health Innovation's SmarterHealth Program.
SmarterHealth Components

Research Priorities & Methodology → Computation → Discovery → Applications

Feedback Loop
Enables rapid cycle, continuous improvement

Courtesy of UCSF's Center for Digital Health Innovation's SmarterHealth Program.
What We Are Addressing with AI

- Predict Disease Trajectories
- Expedite Clinical Workflow
- Design Therapies
- Define Next Generation Treatment Pathways
- Automate Triage
- Automate Individual Patient Context

Courtesy of UCSF’s Center for Digital Health Innovation's SmarterHealth Program.
Discovery & Validation Platform

Connotes novel components within the treatment context.

Courtesy of UCSF’s Center for Digital Health Innovation’s SmarterHealth Program.
Agnostic, Multi Use Case Platform

Targeted Use Case

Multi Modal Data Streams

Features
• Secure environment
• Longitudinal, enhanced patient data set
• Blurs the line between gold standard medical and health data

Courtesy of UCSF’s Center for Digital Health Innovation’s SmarterHealth Program
Advanced Computational Platform

Enhanced Patient Data Repository

- Multi-tenancy Research Interface
- ML, Deep Learning, AI, Advanced Analytics
- Preclinical Proof of Concept Clinical Decision Support or Digital Therapeutics

Courtesy of UCSF's Center for Digital Health Innovation's SmarterHealth Program
Current AI Discovery Efforts

- Trauma/ICU
- Radiology
- Orthopedic
- Neurology
- Oncology
- Internal Medicine
  - Cardiology

Note: All funding provided through commercial co-development agreements, including GE.
The GE Collaboration

• 10-Year Master Agreement
• 5-Year Initial funding to produce a minimum of 8 algorithms

• Currently on trajectory to deliver a minimum of 26:
  • Statement of Work (SOW) #1- Pneumothorax & NG Tube (2)
  • SOW #2 – FAST Free Fluid Detection (1)
  • SOW #3 - Knee Segmentation & Anomaly Detection (14)
  • SOW #4 – Chest X-ray Suite ET Tube Placement (3)
  • SOW #5 – Chest X-ray Suite Pneumoperitoneum (1)
  • SOW #6 - Chest X-ray Suite NG Tube Placement (5)
  • SOW #7 – PENDING APPROVAL – Mitral Calcification (3)

Courtesy of UCSF’s Center for Digital Health Innovation’s SmarterHealth Program
Detecting Pneumothorax
Clinical Decision Support to Expedite Workflow and Optimize Outcomes
Detecting Correct/Incorrect Tube Placement
Clinical Decision Support to Expedite Workflow and Optimize Outcomes

Courtesy of UCSF's Center for Digital Health Innovation's SmarterHealth Program
Technology in development. Not cleared or approved by any regulatory body for commercial availability.
Our Collaboration with GE

- Cultural - Commercial, for-profit entity vs a publicly owned, not-for-profit academic medical research institution
- Communication – Commercial timelines vs research and discovery
- Structural – Product management process vs research plan driven
- People – Critical component
The need for partners

Though GE HC is deeply entrenched into HC (since 1896) – we need the real patient perspective included.
Which is why we are partnering with top orgs to develop high quality, AI-enabled workflows that are safe and deliver outcomes.

Develop a library of deep learning algorithms to empower clinicians to make faster decisions about some of the most complex medical conditions.

Develop and commercialize technologies to advance the diagnosis and treatment of childhood diseases.

Develop imaging systems that improve clinician reading confidence and productivity through the integration of artificial intelligence into the imaging workflow.

Develop an AI platform and applications aimed to improve clinician productivity and patient outcomes across multiple care areas and medical specialties.