Will AI and Health-IT make your life easier and work more interesting?

.....maybe....maybe not.!

Martin Than





WHAT'S NOT INCLUDED

- Robotics
- Virtual reality and augmented reality
- Health Informatics connectivity
- Ethics
- Omics
- 3D printing
- Drones

•TIME

• PEOPLE

• HUMANITY

• 1 TO 1



• 1 TO MANY

• 1 TO ONE

Prof. Francis Peabody (Harvard 1927)

• A task of the doctor is to transform...

"that case of mitral stenosis in the second bed on the left" into the complex problem of....

"Henry Jones, lying awake nights while he worries about his wife and children"

Will make the clinician's job more interesting as it decreases the tasks that are routine

Will make the visible – become invisible (task burden) also make the invisible – become visible (signals from data)

It is human + machine NOT human vs machine

like other technologies , will be hyped in the short term but deliver in the long term

We need to be patient-centric and have an awareness of inherent bias in AI

AI



Hype Cycle for Emerging Technologies, 2018



Time

gartner.com/SmarterWithGartner

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Hype Cycle for Emerging Technologies, 2018



gartner.com/SmarterWithGartner

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Source: Gartner (July 2008)



Hype Cycle for Emerging Technologies, 2018



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Source: Gartner (July 2008)

EXPONENTIAL TECHNOLOGY CONVERGENCE

- 1. BIG DATA
- 2. PROCESSING POWER
- 3. DATA SCIENCE TECHNIQUES / AI / MACHINE LEARNING

EMERGENCY MEDICINE IS AN ART OF MAKING RAPID VITAL DECISIONS WITH INCOMPLETE INFORMATION





Risk assessments made on available data by different people

Background logic – Our subliminal thought process





Risk assessments made on available data by AI

CLINICAL DECISION MAKING — Threshold theory

Test/no t thres		treatment reshold
No treat No test	Test	Treat No test
	Disease probability	

Pauker SG, Kassirer JP. The threshold approach to clinical decision making. N Engl J Med. 1980;3022:1109-1117.

Edaculator the ED ACS Calculator

Acute coronary syndrome risk score calculator based on the EDACS study



× ĉ

ohest pain Web Pages V 73 results found cont

24 results found contain Acuto Cheat Pain Chest Pain (Non-acuto Chest Pain Acuto Cheat Pain Mono Infusion Pulmonary Embolsm (C Maccolotikental Special Non-acuto Cardiology & Defeaturism Defeaturism Barn Ingaries

uges: 1 <u>2 3 4 5 6 7 8</u>

Calculate an EDACS score



- Pain[#] radiates to arm, shoulder, neck or jaw
- Pain[#] occurred or worsened by inspiration
- Pain[#] is reproduced by palpation
- #Pain that caused presentation to hospital



- At least 18 years old
- Chest pain consistent with acute coronary syndrome
- Normal vital signs
- No ongoing pain or crescendo presentation

Your score is 11

This is a low risk* score

*see explanatory notes for interpretation

ransfer to hospital via

loses as long as blood

<mark>pain</mark> relief.

aboratory for rapid

w risk. Consider Ione. rovide <mark>pain</mark> relief as

community. patients in the

Edaculate!

WHAT IS BIG DATA

There is no uniform definition of "big data" in health care, but it is often characterized by the 5 "Vs":

- VOLUME represents the size of a dataset, usually ranging from terabytes to zetabytes
- **VELOCITY** pertains to data in motion and the fast speed of the generation of new data
- VARIETY refers to data in various types and forms, and its resultant complexity
- VERACITY indicates the trustworthiness (? ambiguities due to data uncertainty and inconsistency
- VALUE refers to the additional worth that data can bring to generate knowledge

Patients like me

What if we could pool our clinical experience

Many predictors are not a dichotomous variable

• E.g. TROPONIN





Machine Learning in Radiology: EC: Choice Applications Beyond Image Interpretation SA-CME

Paras Lakhani, MD^a, Adam B. Prater, MPH, MD^b, R. Kent Hutson, MD^{c, b}, Kathy P. Andriole, PhD^d, Keith J. Dreyer, DO, PhD^e, Jose Morey, MD^{f,g,b}, Luciano M. Prevedello, MD, MPHⁱ, Toshi J. Clark, MD^j, J. Raymond Geis, MD^j, Jason N. Itri, MD, PhD^g, C. Matthew Hawkins, MD^b

NOVEMBER 15, 2017

Stanford algorithm can diagnose pneumonia better than radiologists

Stanford researchers have developed a deep learning algorithm that evaluates chest X-rays for signs of disease. In just over a month of development, their algorithm outperformed expert radiologists at diagnosing pneumonia.







SOME EXAMPLE TYPES OF MACHINE LEARNING

- Linear regression
- Logistic regression
- Linear Discriminant analysis
- Classification and regression trees
- Naive Bayes
- K-nearest neighbors
- Learning Vector Quantization
- Support vector machine
- LASSO
- Gradient Boosting
- Artificial neural network



O'REILLY®











Limitations to data sets

- Imaging,
- ICU,
- Process data

• 80% of medical data is UNSTRUCTURED

Model for MI³ Based on Boosting Method

$$\log \frac{p_1}{1 - p_1} = F_M(X) = F_0(X) + \sum_{i=1}^{M} a_i T_i(X)$$

 p_1 =probability of type 1 myocardial infarction and $T_i(X,\beta_i)$ is a decision tree of $X = (age \ category, sex \ category, high-sensitivity \ cardiac \ troponin \ I \ concentration \ at \ presentation, high-sensitivity \ cardiac \ troponin \ I \ concentration)$ characterized by parameters β_i , where M is the number of decision trees. a_i is the weighting for each decision tree.



ROC curves for the MI³ index and myocardial infarction



Training red: AUC 0.963 [95%CI: 0.956 - 0.971])

Testing blue: AUC 0.963 [95%CI: 0.957 - 0.968])

A mock-up of how the algorithm may be presented to physicians and patients


AIM TO COMBINE INTO ONE INTERFACE

- MEDICAL RECORD
- CLINICAL GUIDANCE
- PREDICTION OF PROBABILITIES

DECISION-AID PROTOTYPE LEAD DEVELOPER DR MARC GUTENSTEIN

ADVANTAGES

- Becomes the medical record and integrates with EHR
- Reduces error rate
- Prompts for other key differential diagnoses
- Will provide individualised probabilities
- Communication with patient create lay language discharge paperwork
- Facilitates nursing handover
- Constant collection of data
- MAKES LIFE EASIER FOR THE USER (e.g. experience of NZ police force)

Natural Language Processing (NLP)

- ALLOWS the computer to understand spoken as well as written human language
- USES techniques such as parsing,
 - which is the analysis of words in the sentence for grammar followed by a process of arranging the words that shows the proper relationship between these words.

- NLP COMPONENTS ARE:
 - natural language understanding (NLU) and
 - natural language generation (NLG)
- NLP is the intersection of AI and linguistics.



Journal of Health & Medical Informatics

Hurrell et al., J Health Med Informat 2017, 8:6 DOI: 10.4172/2157-7420.1000297

Case Report

Open Access

Use of Natural Language Processing to Identify Significant Abnormalities for Follow-up in a Large Accumulation of Non-delivered Radiology Reports

Michael Hurrell^{1*}, Alan Stein² and Sharyn MacDonald¹

¹Department of Radiology, Canterbury District Health Board, University of Otago, Christchurch, New Zealand ²Department of Radiology, Hewlett Packard Enterprise, Palo Alto, USA

WHERE IS EMERGENCY MEDICINE?

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Al will.....

• 1 TO 1



• 1 TO MANY

• 1 TO ONE

THANK YOU



Mundane tasks

- Results sign off
- Ordering
- Notes
- Task communication