



# Big Data, AI and Deep Learning in Sepsis

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# Objectives

“Even though there are no ways of knowing for sure, there are ways of knowing for pretty sure.”

– **Lemony Snicket**

1. Why Sepsis and big data?
2. First steps
  - a. Few insights
  - b. Implications
3. Cautions

## Disclaimer

Wikipedia contains articles on many medical topics; however, **no warranty** is made that any of the articles are accurate. There is absolutely no assurance that any statement contained or cited in an article touching on medical matters is true, correct, precise, or up-to-date. The overwhelming majority of such articles are written, in part or in whole, **by non-professionals**. Even if a statement made about medicine is accurate, it may not apply to you or your symptoms. The medical information provided on Wikipedia is, at best, of a general nature and **cannot substitute for the advice of a medical professional** (for instance, a qualified doctor/physician, nurse, pharmacist/chemist, and so on). **Wikipedia is not a doctor.**

**I claim to know everything, but even my children doubt that. I am not a scientist, just a physician who does a bit of everything including research.**

**No one has been naive enough to sponsor me to present these findings**

# So Sepsis!

*Where we are at with Sepsis?*

Infection,  
Organ  
dysfn



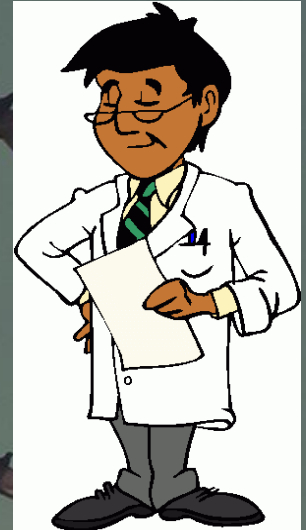
SIRS, Severe  
sepsis, Sepsis



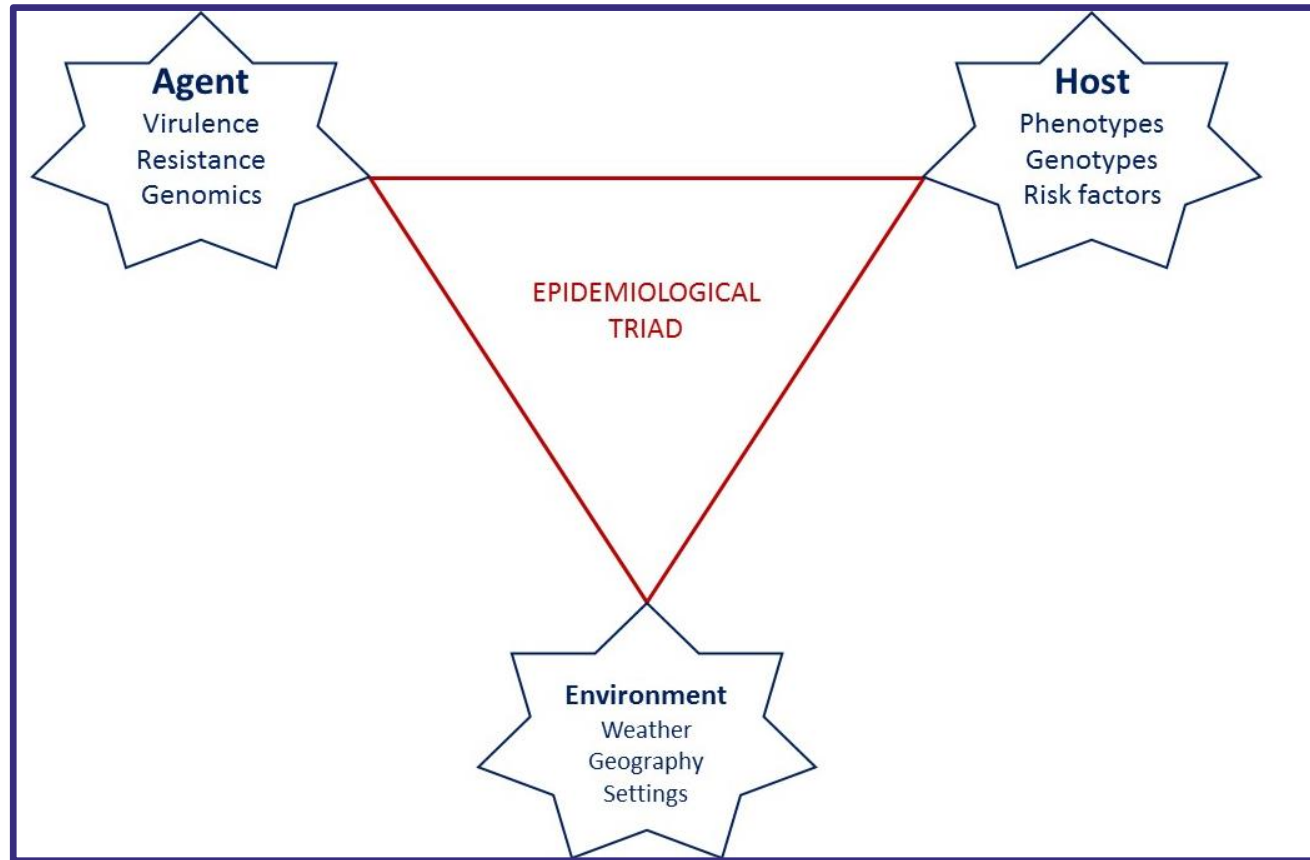
Antibiotics,  
Fluids, Steroids,  
EGDT...



AMS,  
Overuse,  
Incidents



# Outcomes of infection



# Hierarchy of Research design



Lobo, Michele A et al. "Research Design Options for Intervention Studies" Pediatric physical therapy : the official publication of the Section on Pediatrics of the American Physical Therapy Association vol. 29 Suppl 3,Suppl 3 IV STEP 2016 CONFERENCE PROCEEDINGS (2017): S57-S63.

# Traditional Research Methods

- Screening algorithms – derivation of variables and thresholds from patients with adverse outcomes
- Validation of logistic models based severity scores – transferability
- The double blind randomised controlled therapeutic trial challenge for sepsis
- Timelines of infection, sepsis, septic shock and adverse outcomes – Triage is not T0

Research mainly designed around interventions and causality and inference usually derived in retrospect.

# EM in Sepsis

Screening  
Stratification  
Diagnosis  
Management  
Disposition

- Personalizing of Screening algorithms - variability
- Static nature of variable thresholds – demographic SIRS variations
- ‘Diagnosis’ of Sepsis???
- Management
  - Antibiotics
  - Fluids
  - Adjuvants
- Safe discharge

WHEN IS IT SAFE, WHEN NOT TO DO, BALANCING RISK  
BENEFITS...



??????



CAN WE DO ANY BETTER?



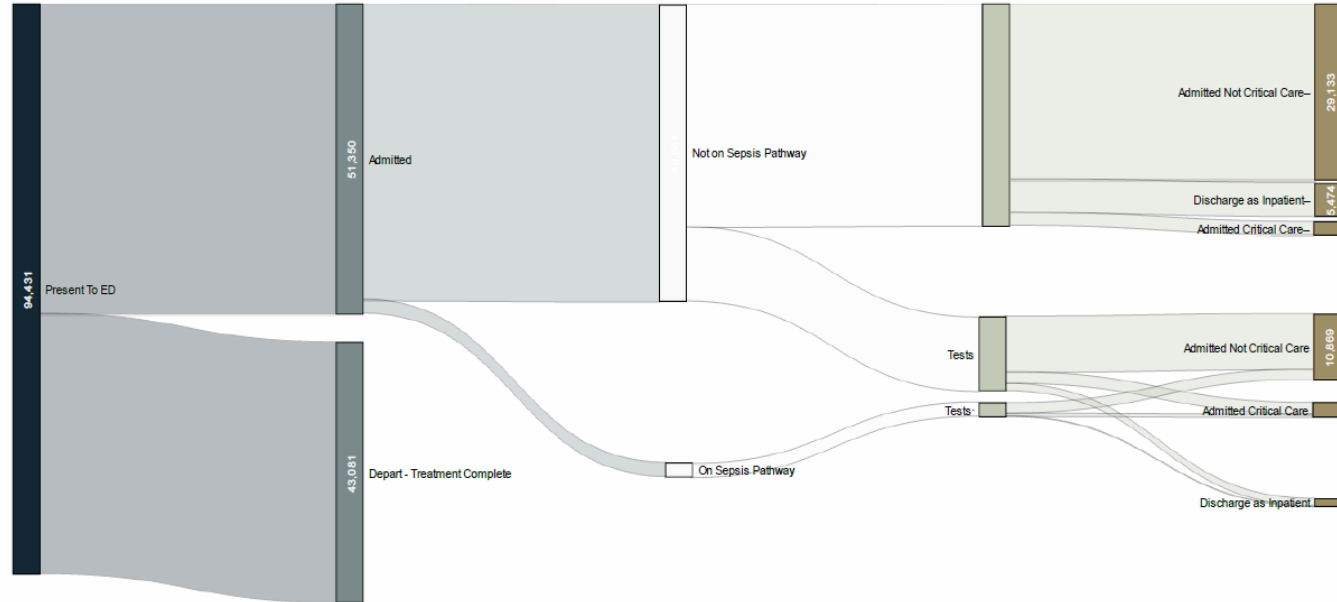
# Big Data

Is big data, augmented intelligence, artificial intelligence or deep learning the magic pill?

# Small Big data pilot

## Preliminary findings

- *Retrospective data linkage ED presentations n=94491 (2014-2015)*
- *Linked to blood gas results for all patients during time period n=35821*
- *In-hospital outcomes from inpatient admin CIS n=68138*
- *Sepsis pathway patients with linked pathology/ microbiology results n=4544*



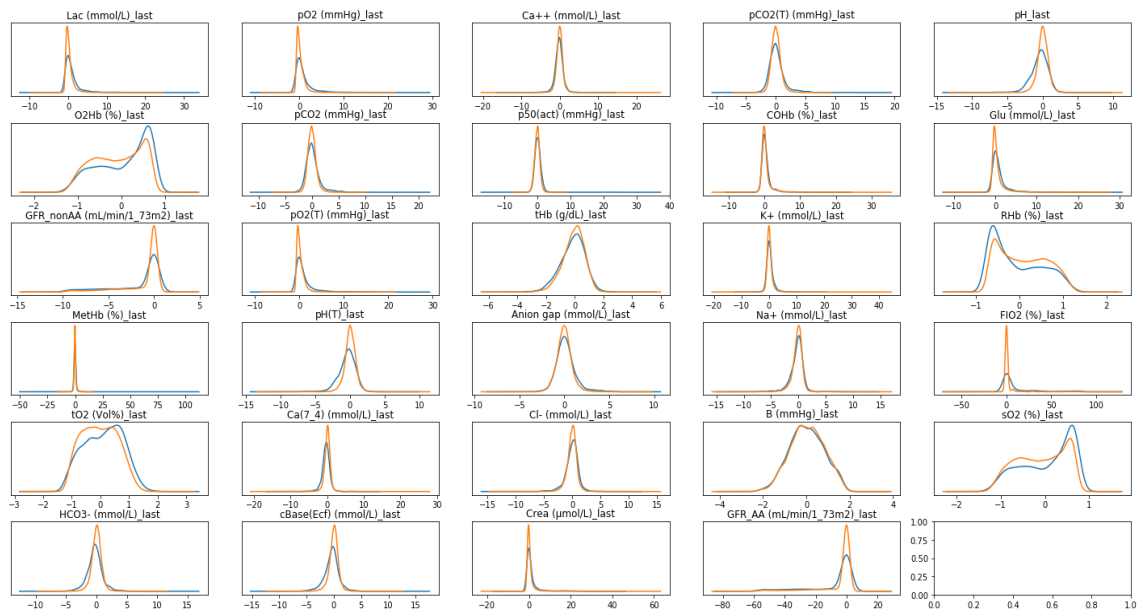
# Analysis Environment

- The data analysis was performed using Jupyter notebooks (python) and scikit-learn libraries



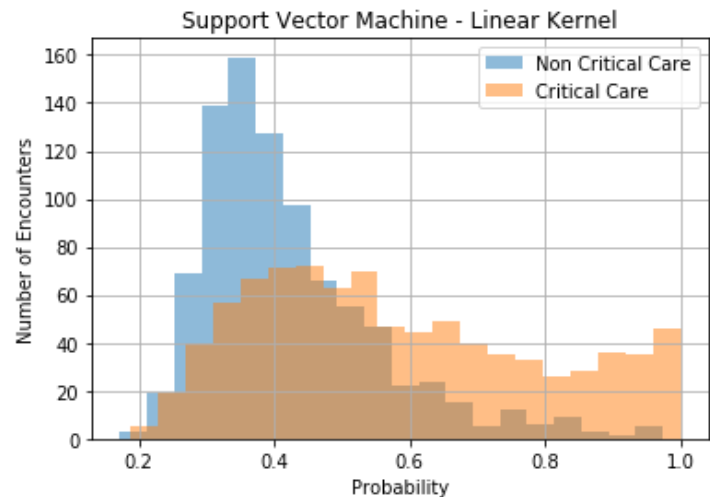
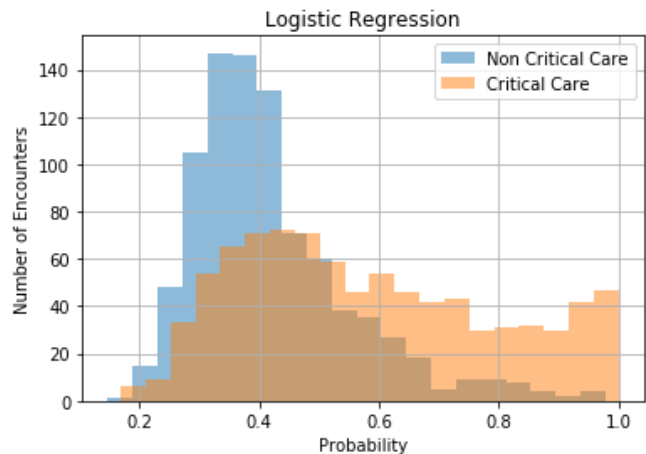
- Calan Holmes – Master of Data Science, School of Engineering IT, Sydney University
- Dr Aldo Saavedra - Senior Research Fellow,  
Centre for Translational Data Science, Sydney University  
Faculty of Health, Sydney University.  
eHealth NSW

# Overview of data

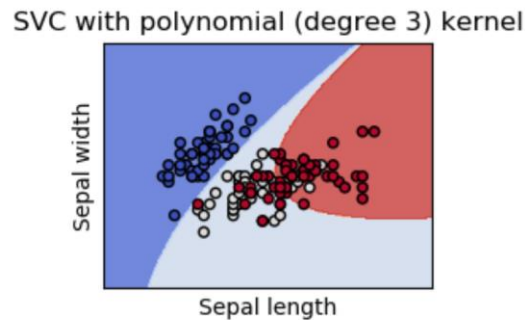
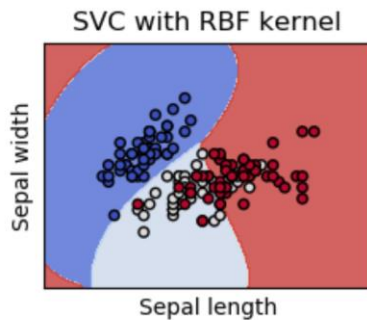
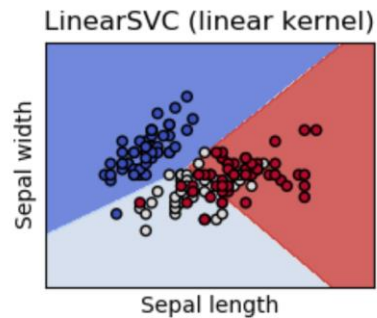
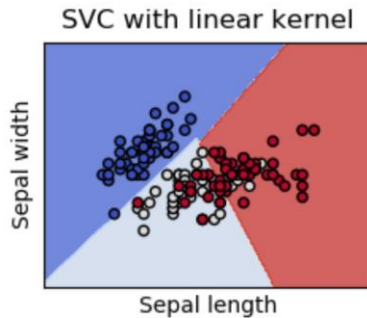


Critical care  
Non Critical care

# Model Predictions



# Illustration of boundaries defined by SVM models



Well known dataset with entries showing the width and length of sepals in flowers.

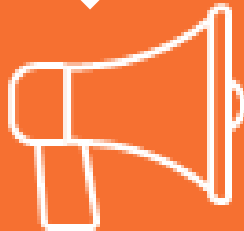


## CLINICAL DECISION SUPPORT

Triage  
information

SIRS  
algorithms

POC + Lab  
results



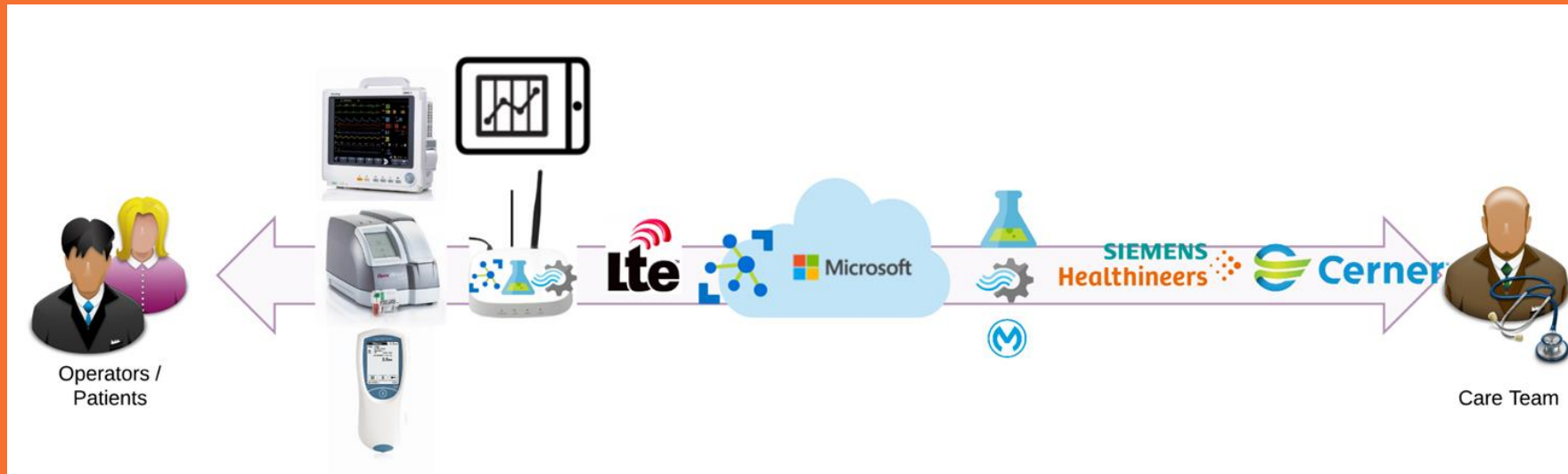
Clinical Decision  
Support

- 78 of 160 possible triage presenting problems
- Algorithms with SEPSIS KILLS static SIRS thresholds
- POC tests – lactate
- Lab tests – CRP, PCT, BC, viral testing
- Dual threshold alerts
- Clinician validation versus automation

## LEARNING SYSTEMS



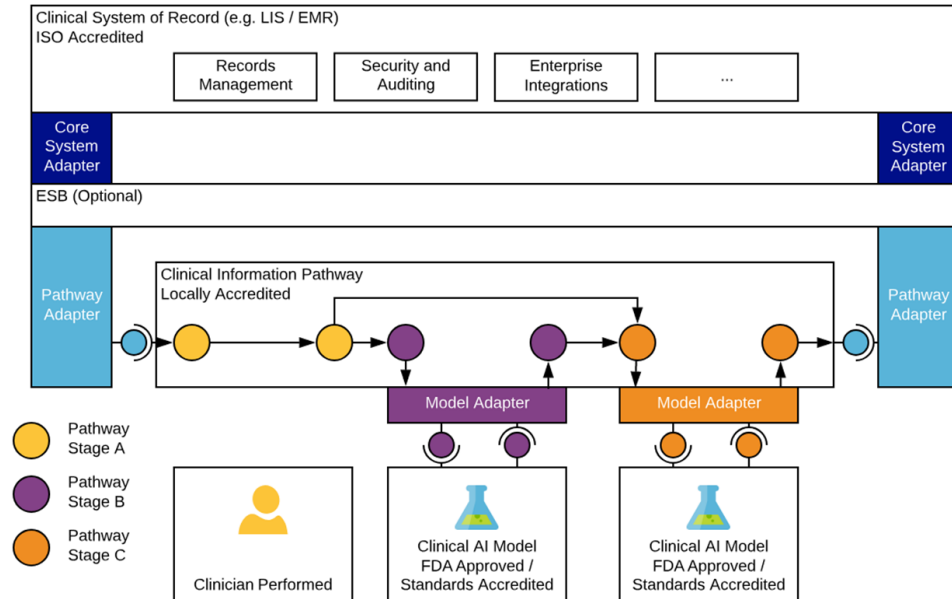
# Leveraging Existing architecture...



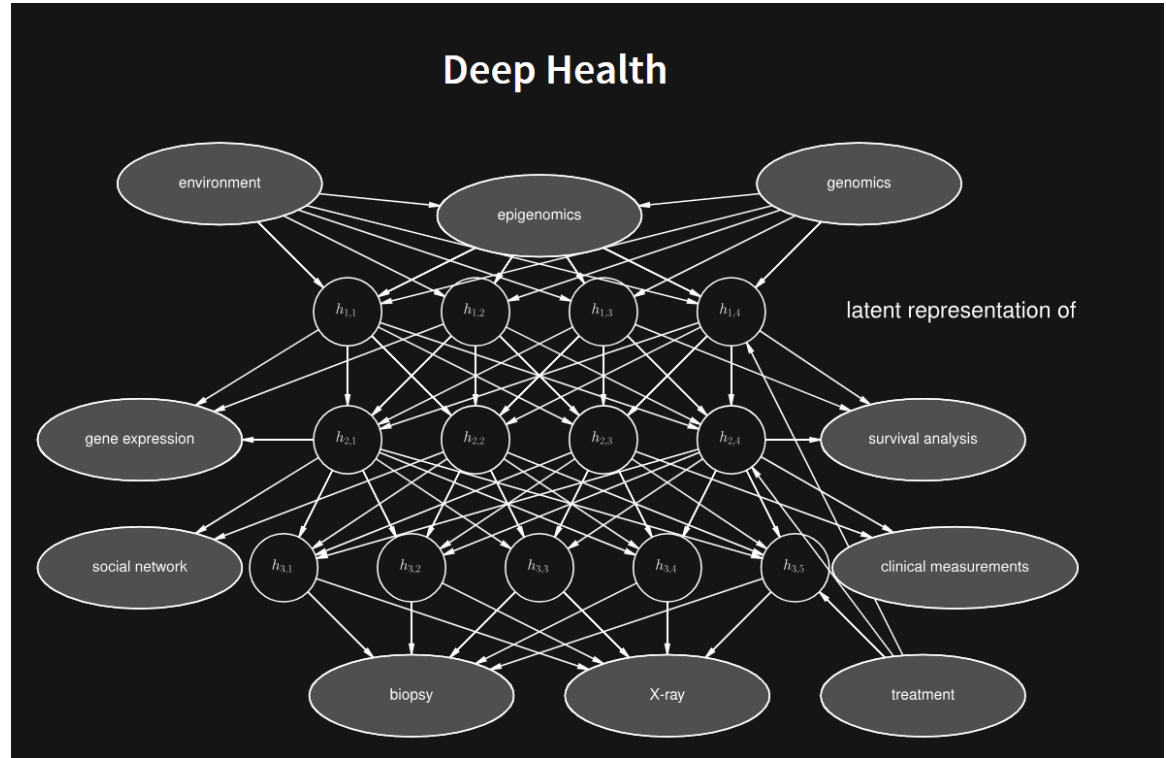
## Unlocking the EMR dependencies...

# Future directions

- *Replication of pathways at Westmead precinct sites – age-specific thresholds – MRFF SHP seed grant*
- *Alert based data-mapping and live datastream learning exercises*



# Learning networks



- Replicating health data and process networks to capture predictors and interventions

Steele, Scott et al. "Using machine-learned bayesian belief networks to predict perioperative risk of clostridium difficile infection following colon surgery" Interactive journal of medical research vol. 1,2 e6. 19 Sep. 2012, doi:10.2196/ijmr.2131

# Machine learning and Deep learning

## Machine learning

Machine learning uses algorithms to parse data, learn from that data, and make informed decisions based on what it has learned

## Deep learning

Deep learning structures algorithms in layers to create an “artificial neural network” that can learn and make intelligent decisions on its own



Deep learning is a subfield of machine learning. Deep learning is what powers the most human-like artificial intelligence



Collaborative team led design of future health infrastructure and health IT architecture is key to delivering solutions.

“

*To develop artificial intelligence  
networks in our clinical systems, we  
will first need to learn what  
intelligence in healthcare really  
means...*



Thank you very much  
for your time

# Discussion