Current/Past Research conducted on freely available multi-center (eICU)/single-center (MIMIC's) databases for critical care research

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Databases

Freely accessible critical care databases from Philips

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   - Current version (v2.0 (17 May 2018))
   - 200,859 patient between 2014 – 2015, from 335 units at 208 hospitals.

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2. Medical Information Mart for Intensive Care databases(MIMIC's (1996, 2011, 2016))
   - ★ I – 121 records, II – 32,000 records, III – 53,423 records between 2001 – 2012 from Beth Israel Deaconess Medical Center in Boston
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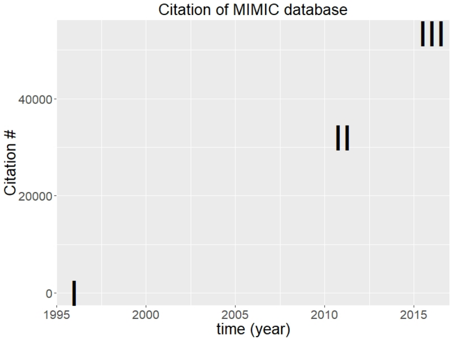
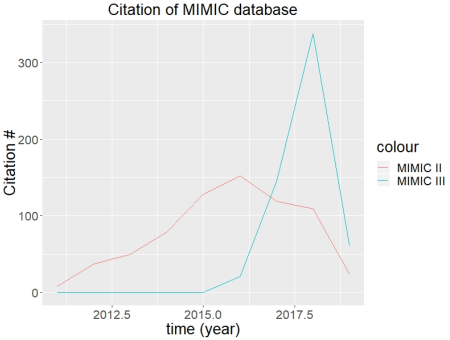
3. MIMIC-III and eICU-CRD are independent

What's the deal here?

Citation & Data Magnitude





Areas

1. Medical Research
2. Engineering/Computer Science (ECS)
3. Other general focused area
   - E.g. Testing the quality of the data
4. Not so many on other fields such as in Statistics

Published Journals

Medical Journal

- Critical Care series (e.g. Critical Care Medicine)
- Journal of Electrocardiology
- The Lancet
- Computing in Cardiology
- Nature series
- and many more...

Medical Research

Questions

1. Choice of covariates
2. Mortality prediction
3. What's the characteristic of the data?
4. e.g. Do we have better prediction rate by including BMI index in the predictive model? (Kramer 2019)

Procedure

1. Processing Data
2. Analyzing Data
3. Displaying in Table + Explanation
4. Using Medical models (e.g. APACHE (Acute Physiologic Assessment and Chronic Health Evaluation) and OASIS (Outcome and Assessment Information Set) models, etc)
5. Sensitive test, evaluation using statistical measures (e.g. ROC (Receiver operating characteristic))

Published Journals

ECS

- IEEE series (e.g. IEEE journal of biomedical and health informatics/transactions on Biomedical Engineering/Computing in Cardiology, etc)
- Many conferences/proceedings (e.g. EMBC/EMBC/AAAI)
- Journal of the ACM

Questions and Motivation

Various different topics

1. From medical research
2. Privacy/Security concern
3. Data Reliability
4. Save money/time/patients
5. Auto-detection system
6. and many more

Some main Research areas

ECS

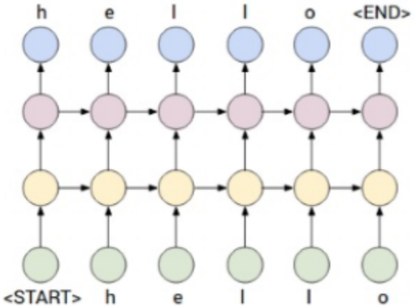
- Data Generation
- Classification & Detection
- Clustering – Finding Treatment
- Prediction – Mortality rate

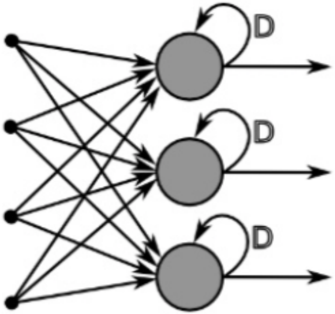
Data Generation

- To prevent privacy concern
- E.g. Dernoncourt et. al. (2016),
  - De-identification of Patient Notes
  - Conditional random field (CRF) model (RNN)
  - Optimized to maximize the likelihood of the labels
- E.g. Esteban et. al. (2017)
  - Generative Adversarial Networks (GANs) with RNN, conditioned on auxiliary information Synthetic data

What are Recurrent Neural Networks

1. In their simplest form (RNNs), they are just Neural Networks with a feedback loop
2. The previous time step's hidden layer and final outputs are fed back into the network as part of the input to the next time step's hidden layers.





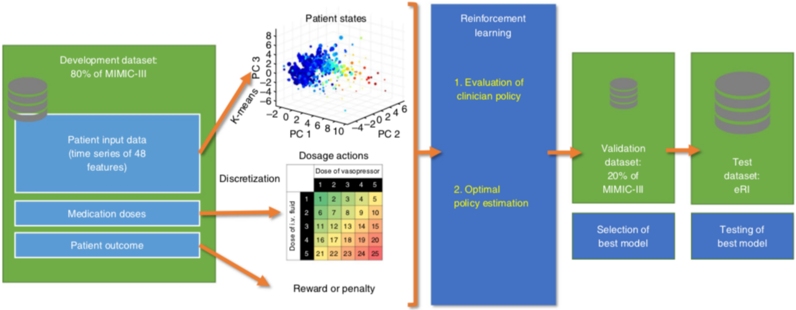
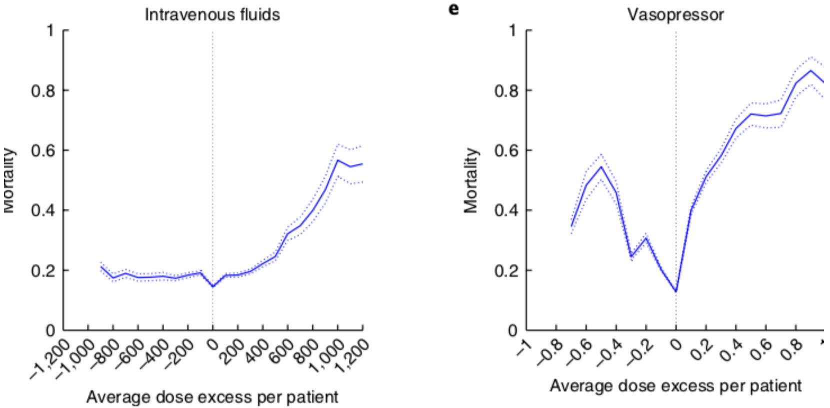


Fig. 1 | Data flow of the AI Clinician. Eighty percent of the MIMIC-III dataset was used to define the elements of the MDP. Time series of patient data were clustered into finite states. The dose of intravenous (i.v.) fluids and vasopressors were discretized into 25 possible actions. Patient survival at 90 d after ICU admission defined reward. Reinforcement learning was used to estimate optimal treatment strategies—the AI policy. The remaining 20% of MIMIC-III data was used to identify the best model among 500 candidates, which was then tested on an independent dataset from the eRI database.


Intravenous fluids
Mortality
Average dose excess per patient
e
Vasopressor
Mortality
Average dose excess per patient

Detection

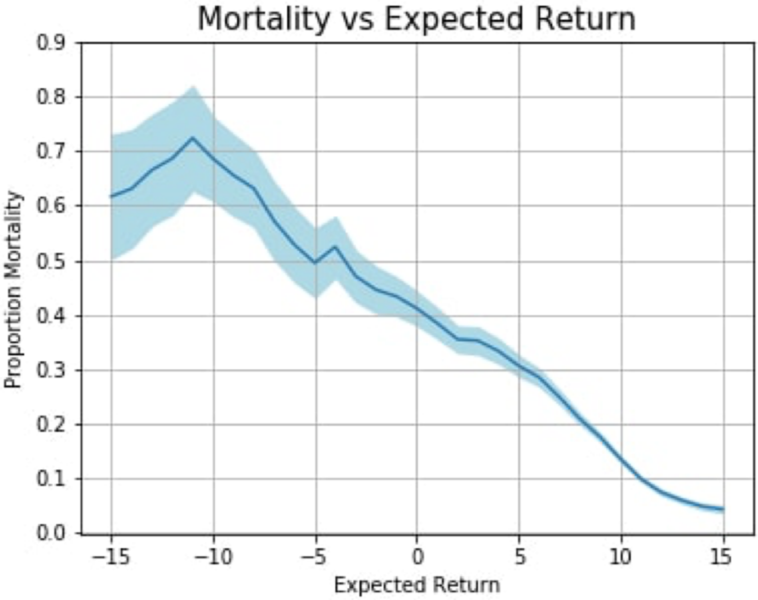
- Komorowski et. al. (2018), The Artificial Intelligence Clinician learns optimal treatment strategies for sepsis in intensive care
  - Markov decision process (MDP), deploy the AI clinician to solve the MDP and predict outcomes of treatment strategies
  - 1. Evaluation of clinician policy; 2. Optimal policy estimation
  - The AI policy – Time series of patient data were clustered into finite states, then apply RL to estimate optimal treatment strategies -
  - Random forest used, temporal difference learning etc.
- A machine learning approach to intensive care discharge.
  - Decision support tool for inpatient discharge process using LC/RF with cross-validation
  - ROC (Receiver-operator-characteristic) and PRC (Precision recall) craves

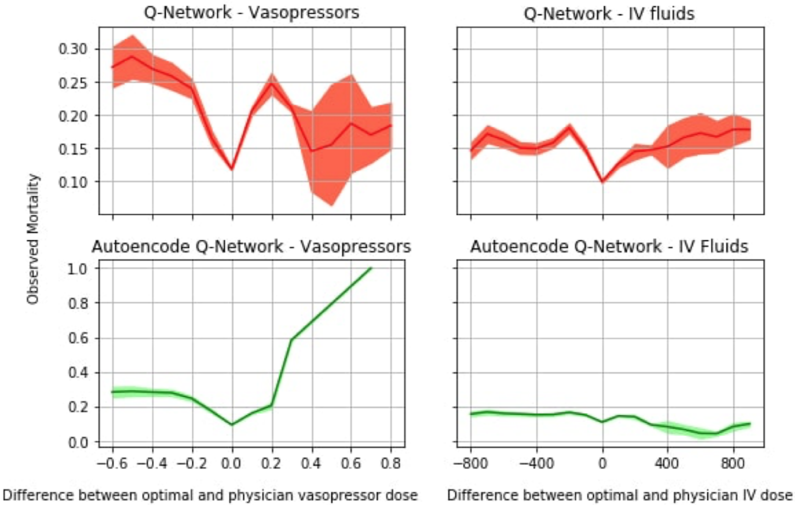
Patient	NLD	NLD_{opt}	RF	LC	NLD fails	Notes
1034 (FP)	0.010 (1.0)	0.010 (1.0)	0.071 (0.784)	0.096 (0.765)	-	Patient admitted to ICU post surgery (primary lung tumour). Discharge to ward. Readmitted within 24 hours with bacterial pneumonia.
10783 (FP)	0.010 (1.0)	0.010 (1.0)	0.035 (0.819)	0.163 (0.716)	-	Patient admitted to ICU with secondary hepatic tumour. Appears to be RFD at 96 hours prior to callout.
4065 (TN)	1.0 (0.467)	0.464 (0.702)	0.368 (0.494)	0.395 (0.450)	R2, R4, C0, P, B1, B3, B4	Patient admitted to ICU with intracranial abscess. Not ready for discharge at 72 hours prior to callout.
4065 (TP)	0.010 (1.0)	0.010 (1.0)	0.077 (0.780)	0.047 (0.812)	-	Same patient as above. RFD at time of callout.
868 (FN)	0.113 (0.867)	0.046 (0.939)	0.080 (0.777)	0.054 (0.806)	C0, T	Patient admitted with malignant large bowel tumour. Appears NRFD at time of callout. Positive outcome.

Clustering

Finding the optimal treatment for patients

- Raghu et. al. (2017)
- To find optimal treatment of Sepsis
- SSM – probabilistic dependence between the latent state variable and the observed measurement


Mortality vs Expected Return
Proportion Mortality
Expected Return
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
−15
−10
−5
0
5
10
15


Q-Network - Vasopressors
Q-Network - IV fluids
Autoencode Q-Network - Vasopressors
Autoencode Q-Network - IV Fluids
Observed Mortality
0.30
0.25
0.20
0.15
0.10
1.0
0.8
0.6
0.4
0.2
0.0
−0.6 −0.4 −0.2 0.0 0.2 0.4 0.6 0.8
−800 −400 0 400 800
Difference between optimal and physician vasopressor dose
Difference between optimal and physician IV dose

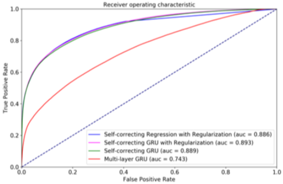
Prediction

- Rajkomar et. al. (2018),
  - Electronic health record (EHR)
  - EHR -> input container of FHIR specification -> in temporal order -> high precision
- Nemati et. al. (2018), An Interpretable Machine Learning Model for Accurate Prediction of Sepsis in the ICU
- Pan et. al. (2019),
  - Prediction of acute kidney injury (AKI)
  - Based on Recurrent Neural networks (RNN), to be dependent on the previous predicted output and corresponding label
  - Incorporate with prediction and estimation errors

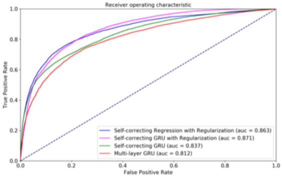
Pan et. al.

Model	MIMIC (testing)	MIMIC (training)	eICU (testing)	eICU (training)
Multi-layer GRU (baseline)	0.743	0.777	0.812	0.836
Self-correcting RNN*	0.889	0.892	0.837	0.875
Self-correcting Regression with Regularization*	0.886	0.891	0.861	0.894
Self-correcting RNN with Regularization*	0.893	0.897	0.871	0.899

Table 1: AUC of the four models on MIMIC-III and eICU. * Proposed methods.



(a)

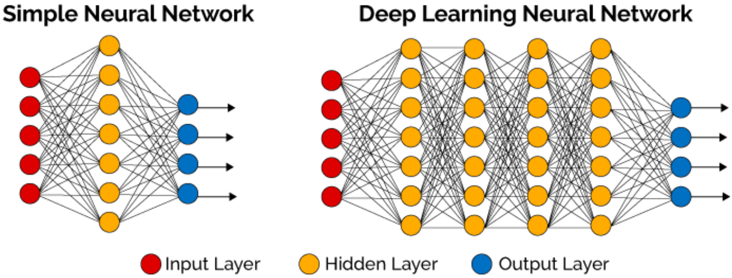


(b)

Figure 5: ROC of the four comparing models (a) on the MIMIC-III dataset for time steps $t > 6$, and (b) on the eICU dataset for time steps $t > 6$. The red line indicates the baseline RNN model, and the other lines are ones for our proposed methods.

Methodologies

Methodologies



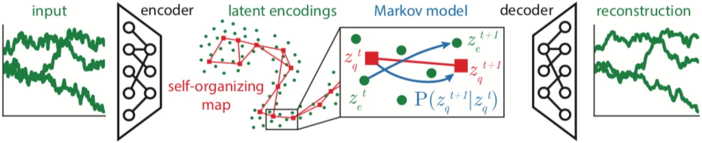
Methodologies

Mainly on Machine Learning/AI literature

1. Variations of Neural Network
2. GA, RNN, Auto-encoder, Long-Short Term Memory
3. LSTM – well-suited to classifying, processing and making predictions based on time series data,
4. Rarely, Logistic classifier or Random Forest
5. Biomedical text mining/bioNLP techniques

Representation

Representation



Some statistical methods used

- Cross-validation
- AUROC

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- Cross-validation
- AUROC
- Bahadori et. al. (2017) – Causal Regularization
- Sow et. al. (2010), – ARIMA model
- Johnson et. al. (2012) uses Bayesian Network/Learning
- Pirracchio et. al. (2015) – GLM
- Mayaud et. al. (2013), Li-wei et. al. (2013) – Bootstrap

Remarks:

1. The difference between eICU and MIMIC's
2. Interpretability – from statistics point of view
3. Almost no related publications on statistical journals, yet!
4. Might be missing some earlier works
5. Data cleaning procedure

Reading Break

Reading Break

THANK YOU!

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