# Discussion of "Dynamic Mortality Risk Predictions in Pediatric Critical Care Using Recurrent Neural Networks" by Aczon et al.

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# Overview of paper

- Applies recurrent neural nets (RNN) to the problem of predicting mortality in the ICU (i.e., pediatric populations)
- Dynamic prediction using time-dependent clinical data pulled from the EMR

# Background: Predicting Mortality/Illness Severity

- An important problem to critical care doctors in both adult and pediatric settings
- Well-studied problem: dates back to the 1980s
- Adult critical care: APACHE, SAPS
  1. Uses physiological measurements and deviations from “normal” values
  2. “Static” model
- Pediatric critical care: PIM, PRISM
- Recently, new versions of these scoring systems have come out

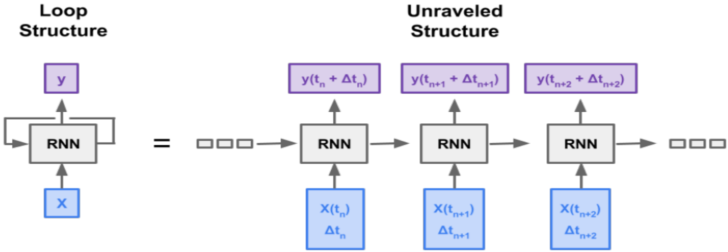
# Properties of scoring systems

- Classification/Discrimination
- Calibration

# Model

- Authors use a recurrent neural network to predict survival
  1. Allows to process sequential data
  2. Feedback loop to tie to data at previous time points
  3. Different from neural networks such as GoogleNet, Inception, ResNet that have been used for image data
- Survival is at fixed time point $t_0$ ($= 1$ if dead at $t_0$, $= 0$ if alive at $t_0$)
- Goal: predict mortality in ICU for pediatric patients

# Recurrent Neural Network schematic



# Neural nets: approximation properties

- Some background: Neural networks studied in the 1980s and 1990s
- Theoretical appeal due to
  1. their ability to approximate many continuous functions
  2. their ability to approximate many dynamical systems
- Authors exploit property 2. in this article

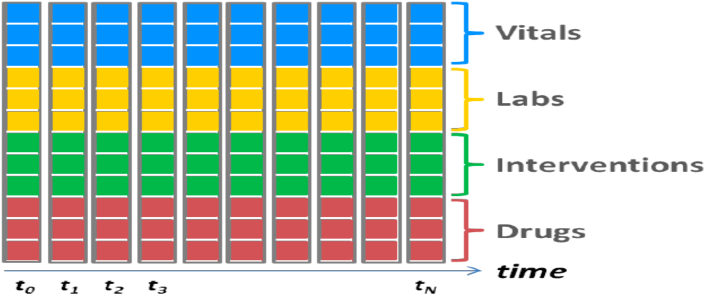
# Dynamical Systems

- Dynamical system: model for measurement(s)/outcome(s) that evolves over time
- Here, they model $P(t) = [\text{vitals,labs,drugs,interventions}]^T$ through the dynamical system:

$$\frac{dP(t)}{dt} = F\{P(t)\}, \qquad P(t_0) = P_0,$$

where $F$ denotes unknown function and $P_0$ is value of variables at initial state

# Measurements



# Dynamical Systems and Neural Networks

- Approximate differential equation by

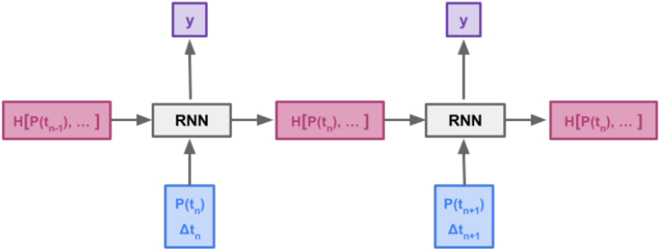
$$P(t_n + \Delta t_n) = G\left[P(t_n), \Delta t_n, H[P(t_{n-1}, \ldots, P(t_{n-k})]\right]$$

- Researchers (Hornik et al., 1989, Funahashi, 1989) show that RNN can approximate $G$
- This leads to

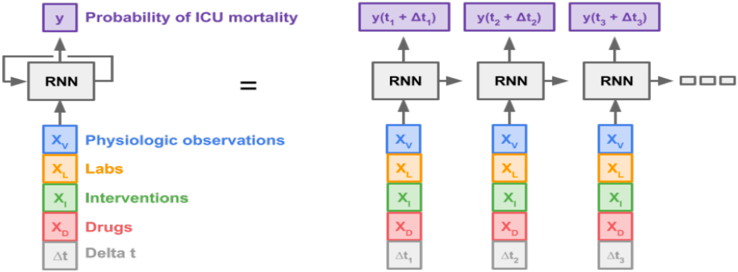
$$P(t_n + \Delta t_n) = RNN\left[P(t_n), \Delta t_n, H[P(t_{n-1}, \ldots, P(t_{n-k})]\right],$$

where $H$ represents the hidden state

# Recurrent Neural Network diagram



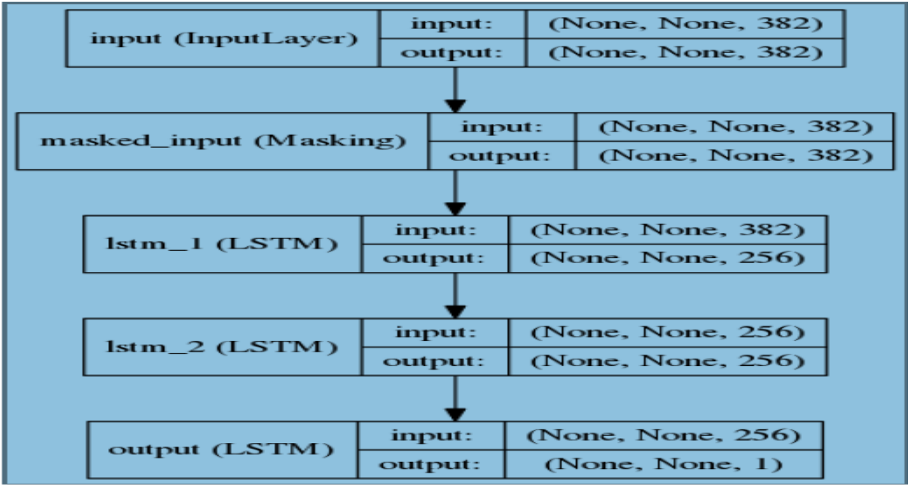
# RNN applied to data



# Modelling choices

- Architecture of RNN
- Order of the RNN

# LSTM architecture



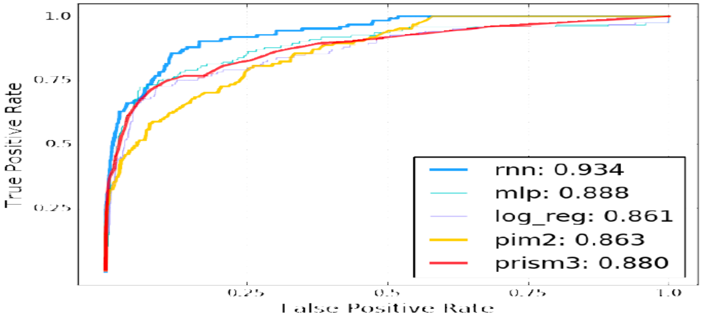
# Data description

- Data pulled on 16559 patient encounters from 12020 patients over a 10-year period
- 75% put in training, 25% in test set
- Issues:
    1. Irregularity, Sparsity and asynchronicity of measurements
    2. Repeated encounters from same patient

# Data Preprocessing

- Pooling of similar biological/physiological measurements
- Aggregation "resulted in approximately 300 different physiologic and treatment variables"
- Imputation
- No age normalization for any measurements

# Comparison of ROC curves



# Take home points

- Proof of concept
- EHR data: messy!!!
- Preprocessing steps matter
- No consideration of calibration
- No formal comparison of methods (DeLong et al., 1988)
- RNN approximating dynamical system: COOL!!!