UNIVERSITY OF CAMBRIDGE

Predicting Length of Stay in the ICU with Temporal Pointwise Convolutional Networks

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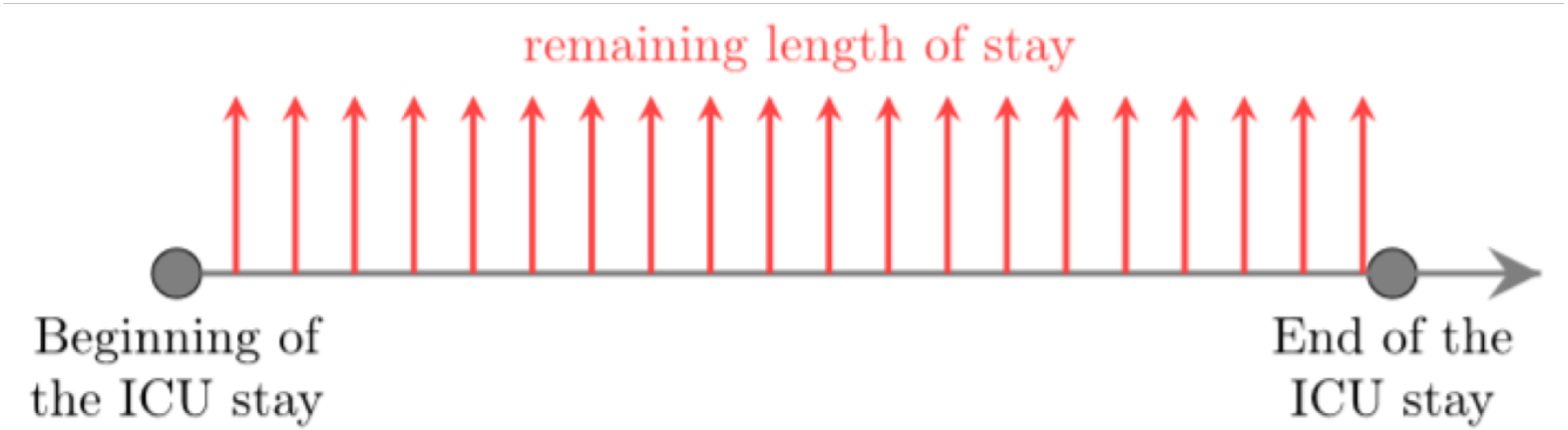
Length of Stay

Why Length of Stay?

- It's a key determinant of hospital costs.
- Long stays increase the risk of hospital acquired infections.

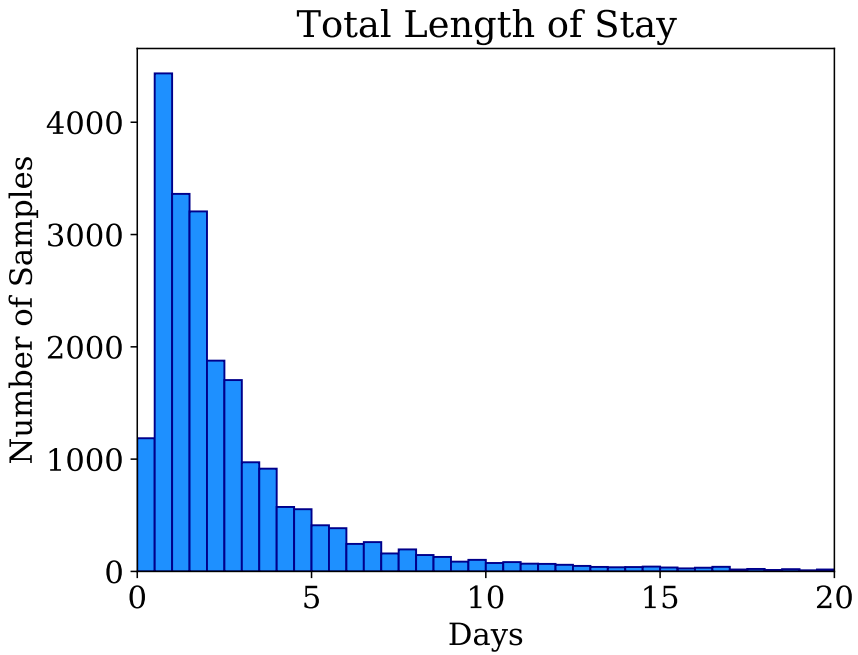
Efficient bed management could mitigate costs and risk. We need to know how long the patients are going to remain in the ICU.

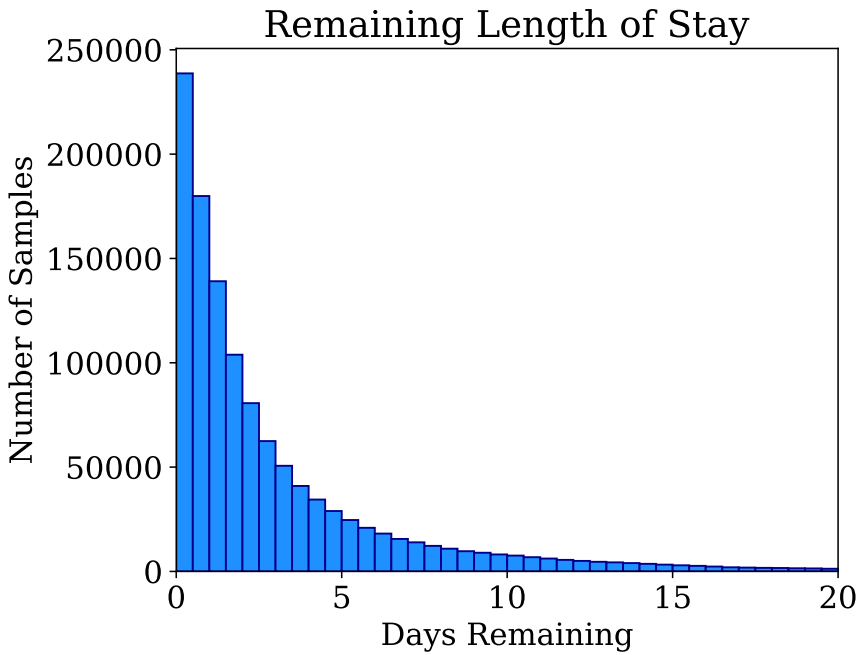
Remaining Length of Stay Prediction



Harutyunyan et al. 2019

Length of Stay Labels



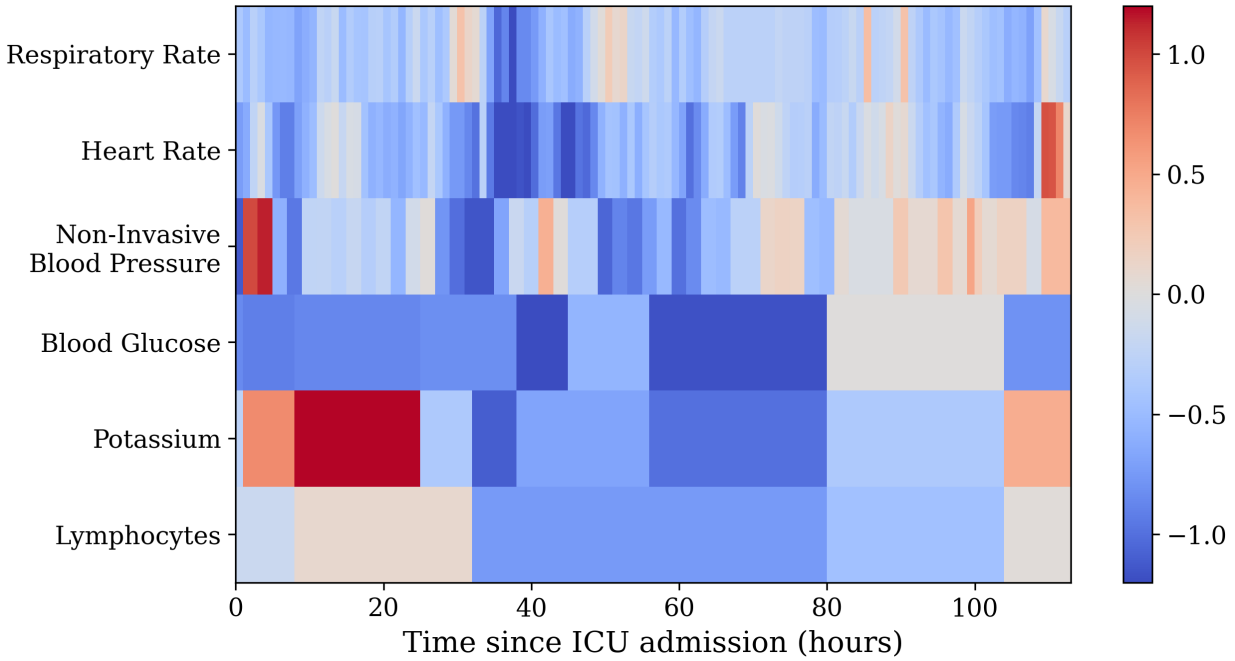


Data: Electronic Health Records in Intensive Care

eICU

- 200,859 ICU stays from 208 different hospitals across the US.
- Contains:
  - Time Series e.g. heart rate, blood pressure
  - Lab Results e.g. blood glucose
  - Demographics e.g. age, gender, ethnicity
  - Diagnoses
  - Medications

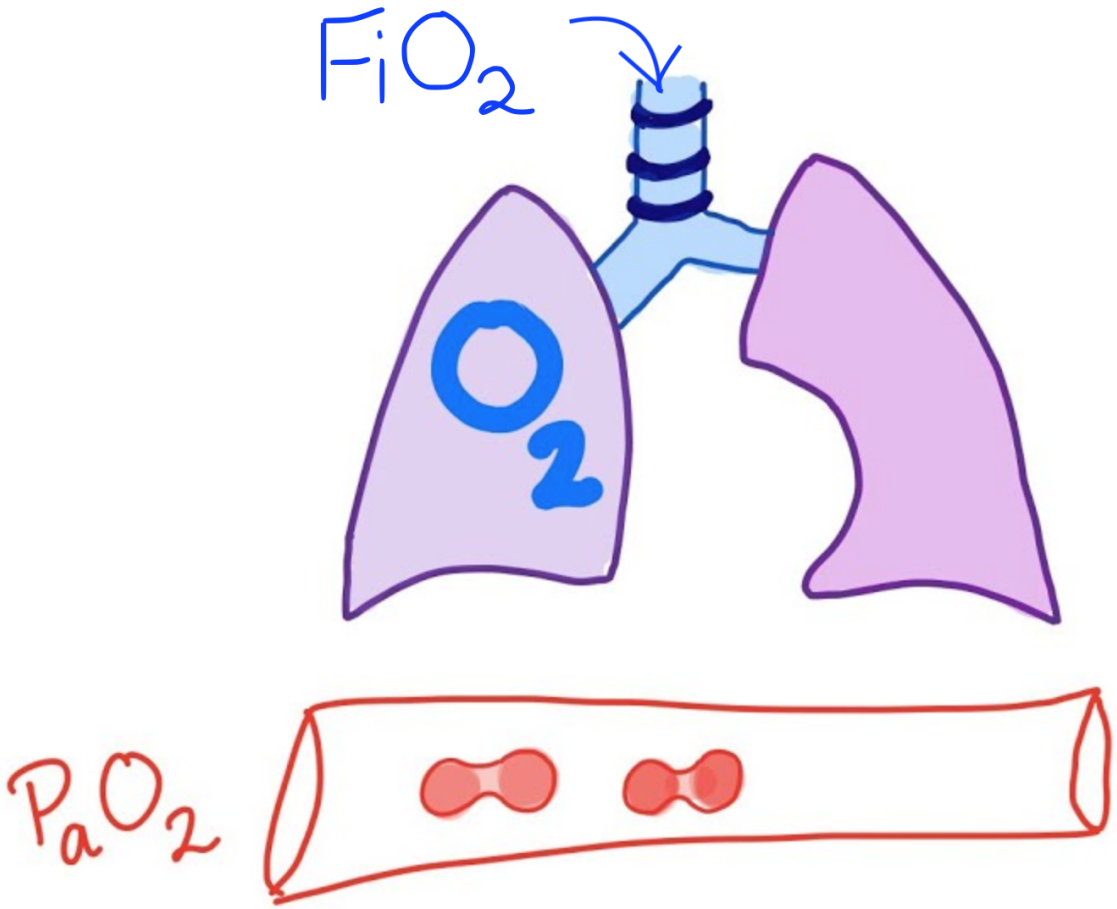
Example


Respiratory Rate
Heart Rate
Non-Invasive Blood Pressure
Blood Glucose
Potassium
Lymphocytes
0
20
40
60
80
100
Time since ICU admission (hours)
1.0
0.5
0.0
−0.5
−1.0

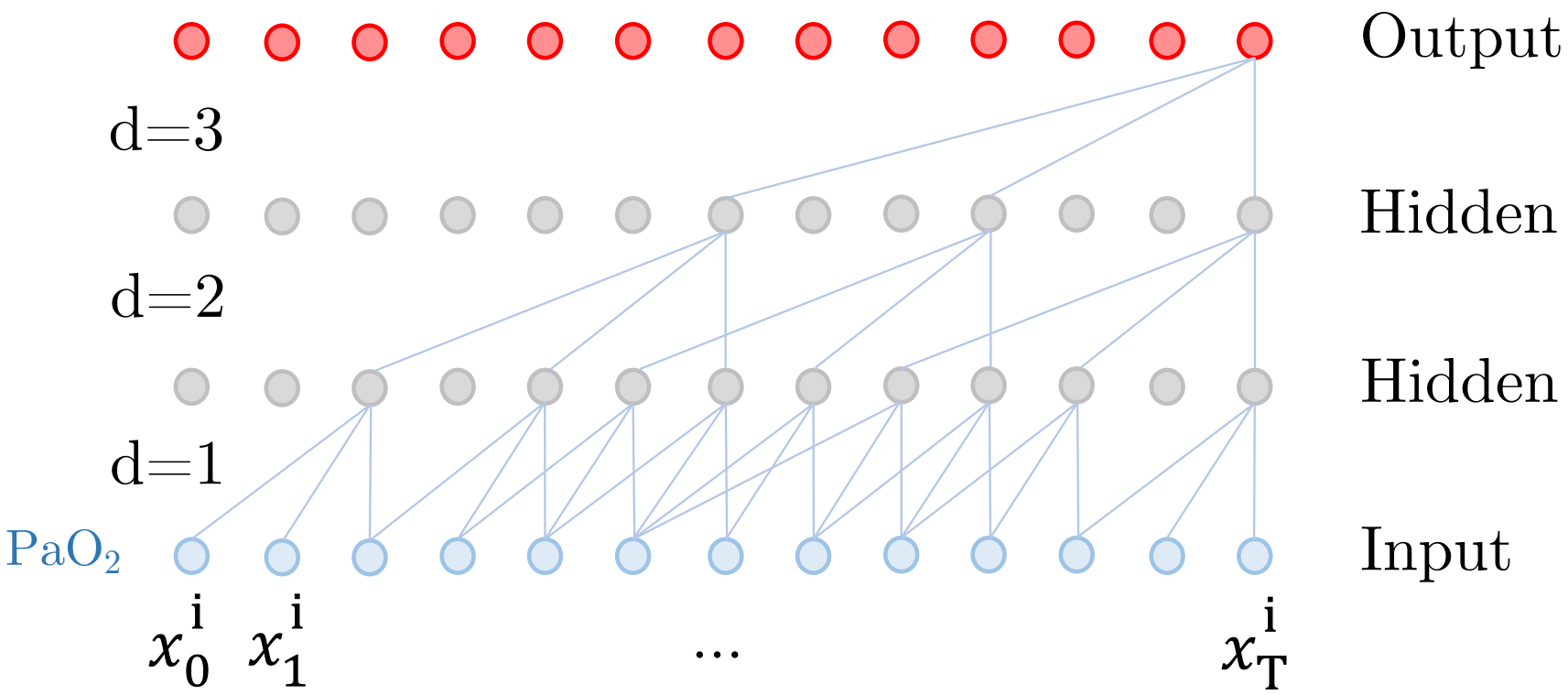
What do we want the model to extract?

- Temporal trends
- Inter-feature relationships

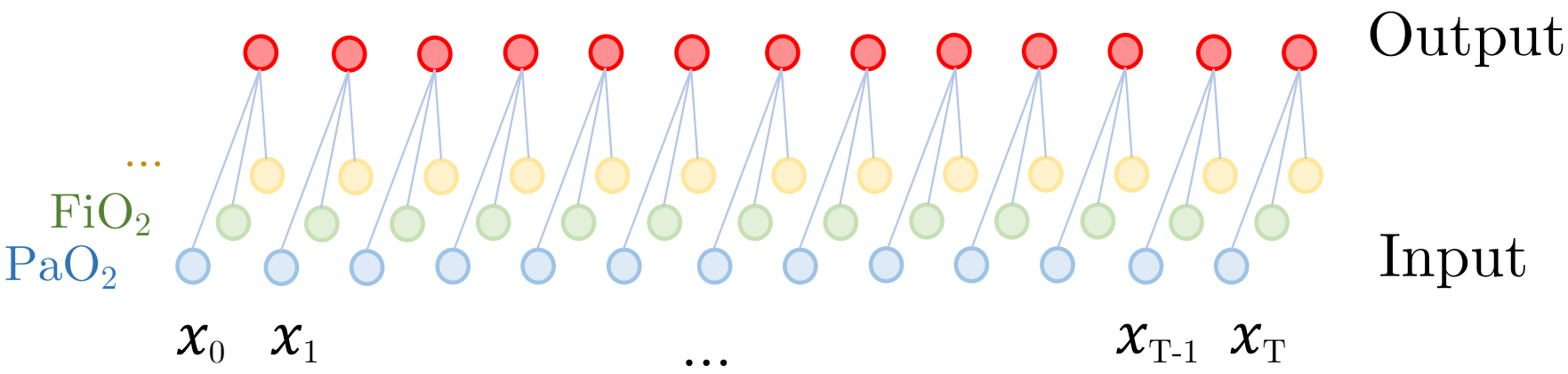
Example



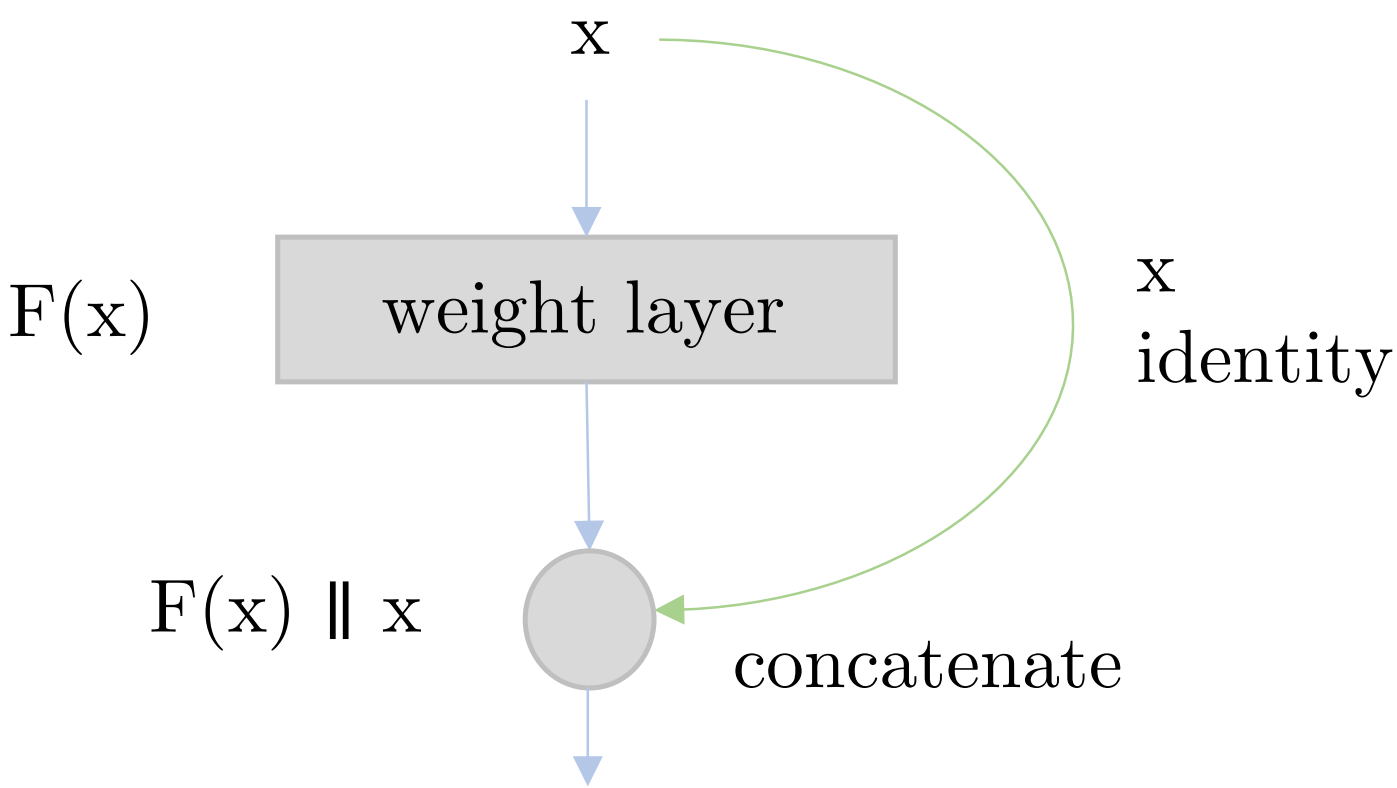
Temporal Convolution



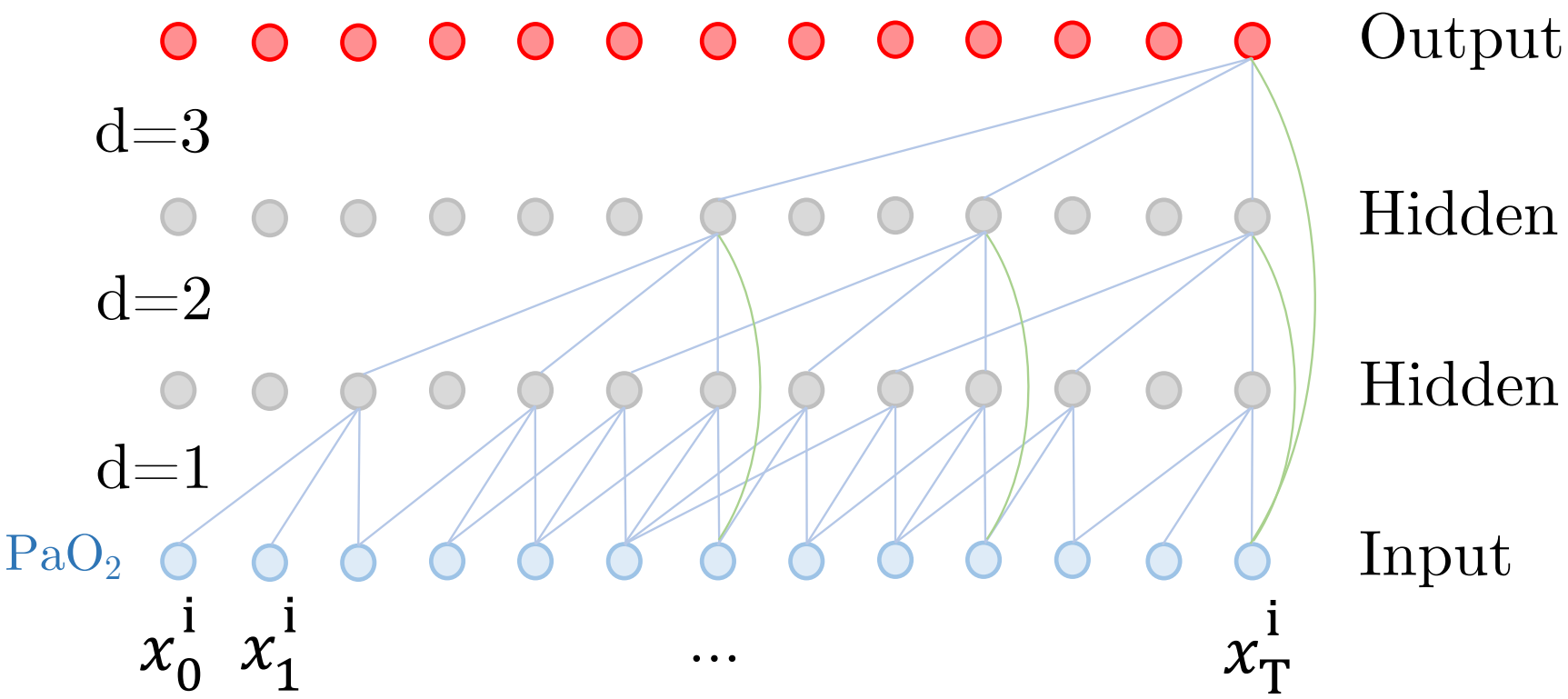
Pointwise Convolution



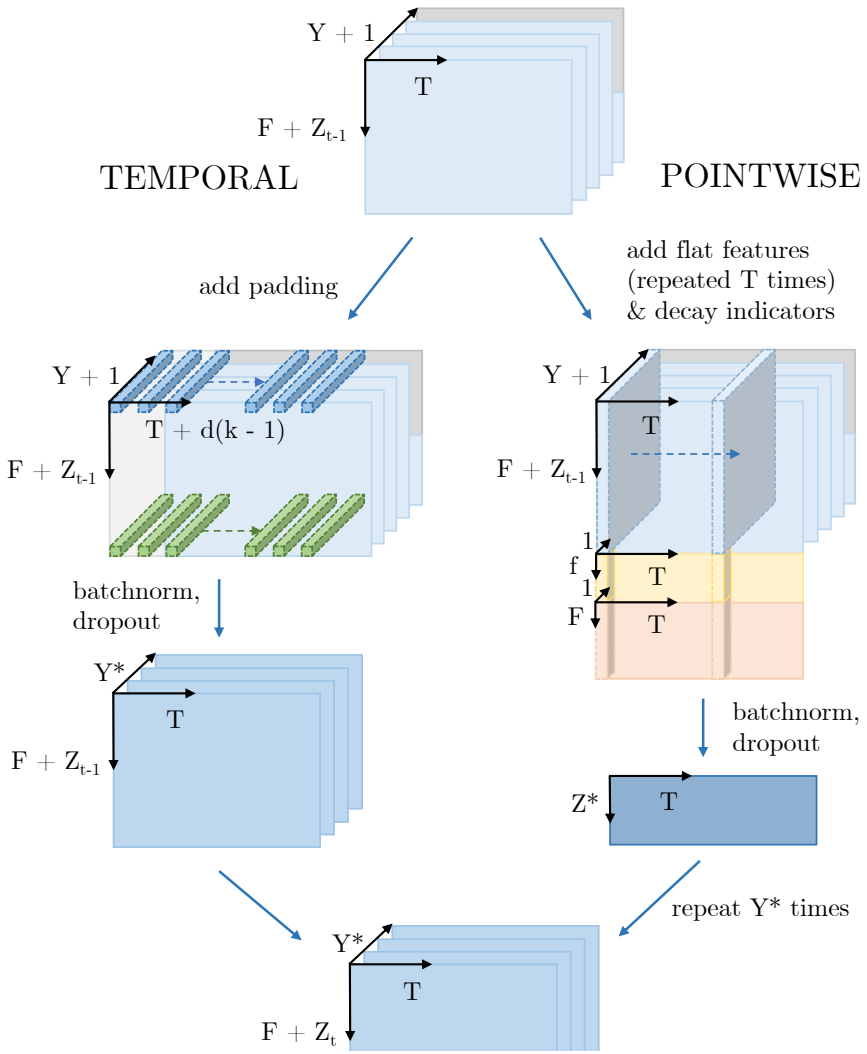
Skip Connections



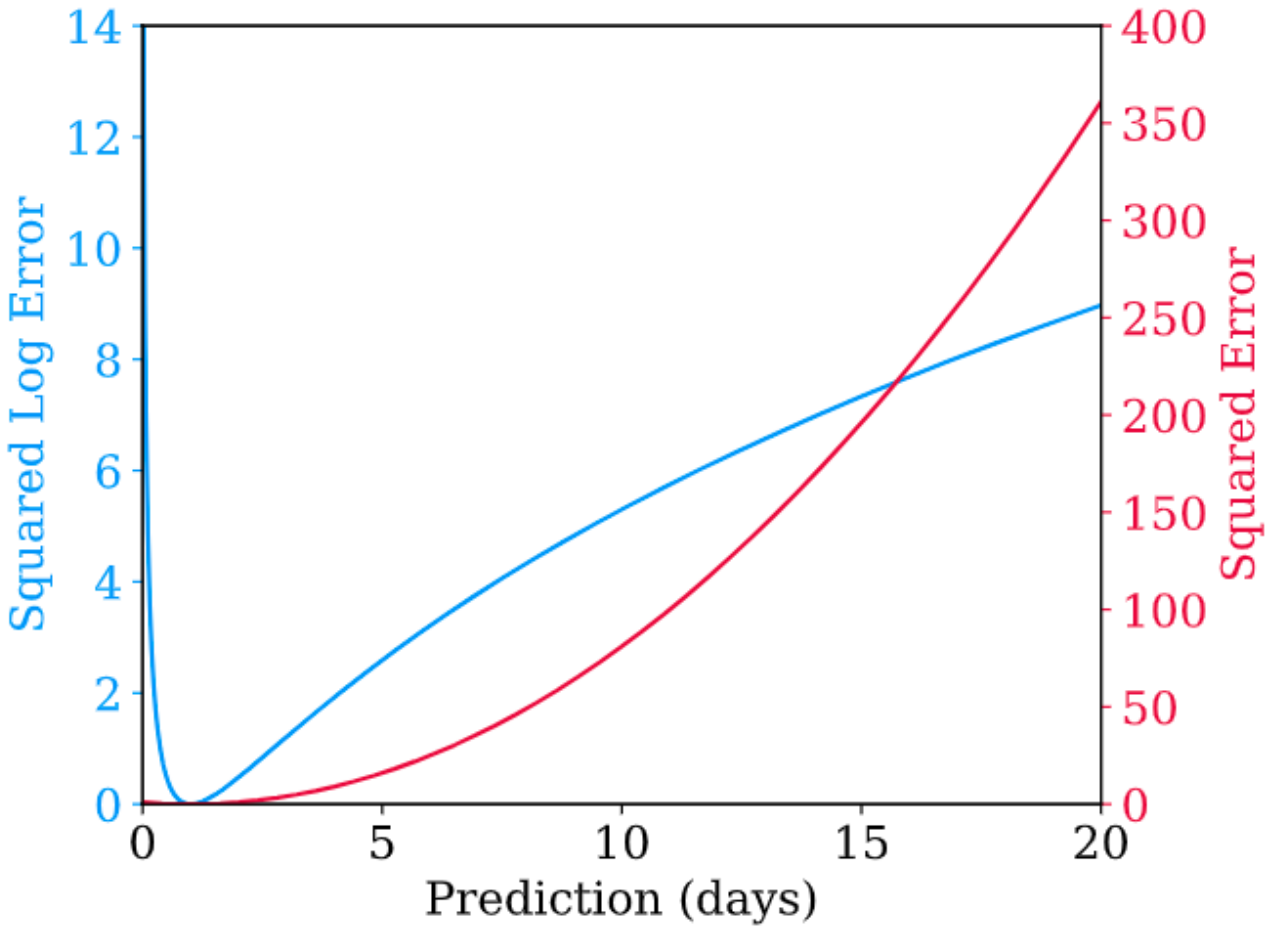
Temporal Receptive Fields



Model


Y + 1
T
F + Z$_{t-1}$
TEMPORAL
POINTWISE
add padding
add flat features
(repeated T times)
& decay indicators
Y + 1
T + d(k - 1)
F + Z$_{t-1}$
Y + 1
T
F + Z$_{t-1}$
1
f
1
F
T
T
T
batchnorm,
dropout
Y*
T
F + Z$_{t-1}$
batchnorm,
dropout
Z*
T
repeat Y* times
Y*
T
F + Z$_t$

Loss Function

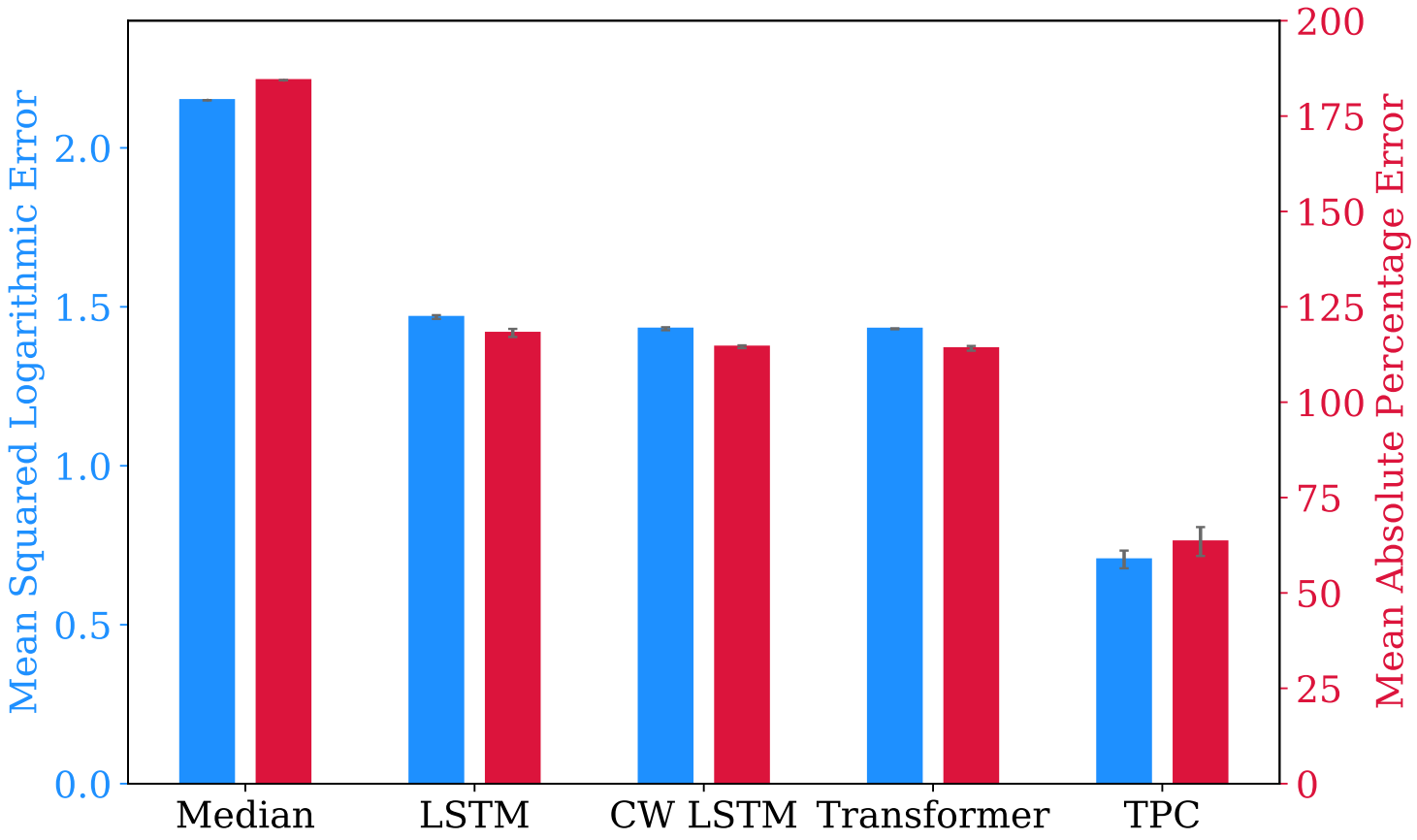


Why do we expect TPC to do well on LoS?

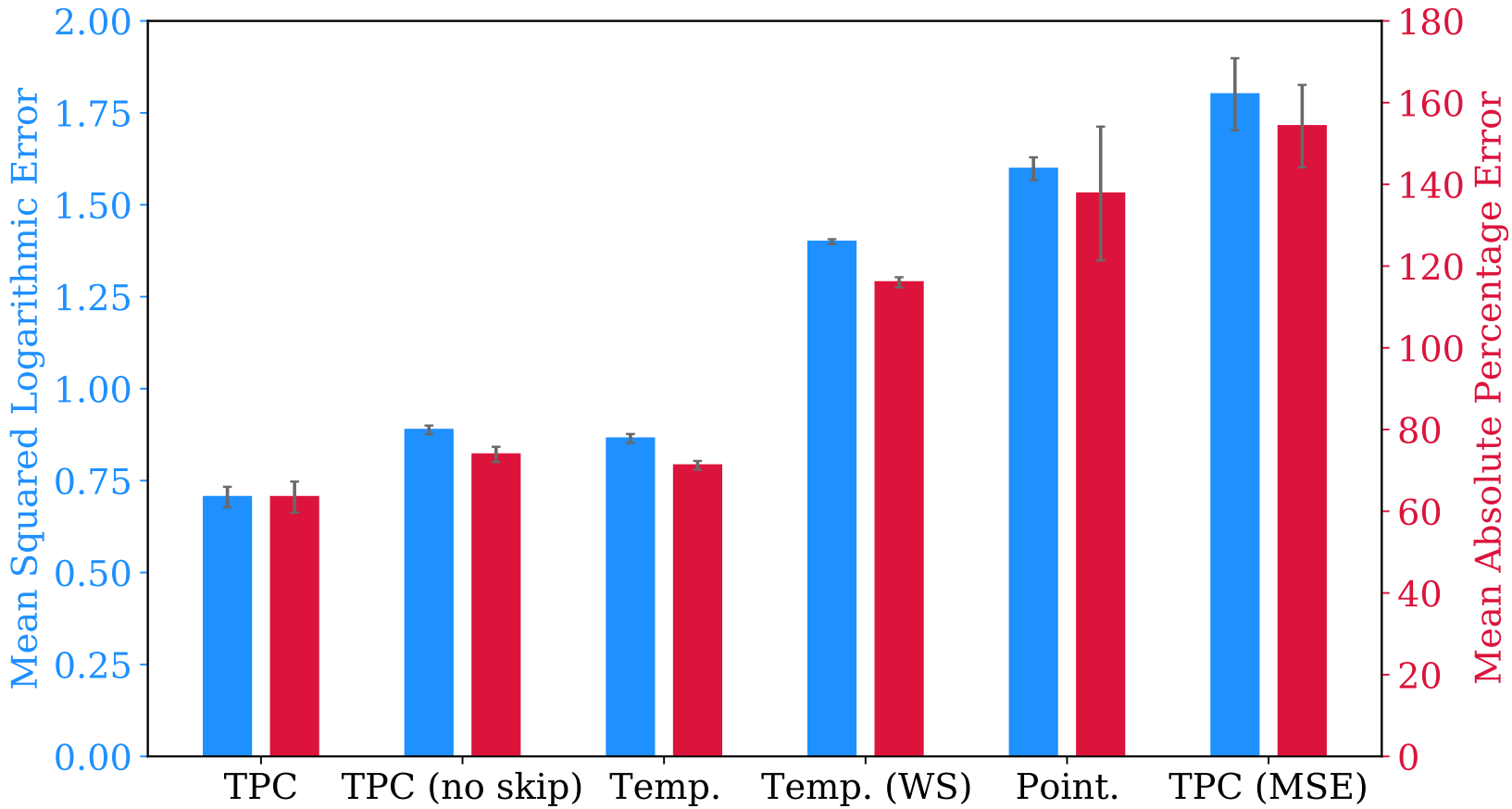
- It has been specifically designed to be able to extract trends and inter-feature relationships.

- It can theoretically choose it's own temporal receptive field sizes (independently for each feature) because of the skip connections.

Results


Mean Squared Logarithmic Error
0.0
0.5
1.0
1.5
2.0
Mean Absolute Percentage Error
0
25
50
75
100
125
150
175
200
Median
LSTM
CW LSTM
Transformer
TPC

Ablation Study



Any Questions?

Please do email me with any questions!
ecr38@cam.ac.uk

Or if you would like a copy of the full length paper straight away (it is ‘on hold’ for arxiv)

Thank you!

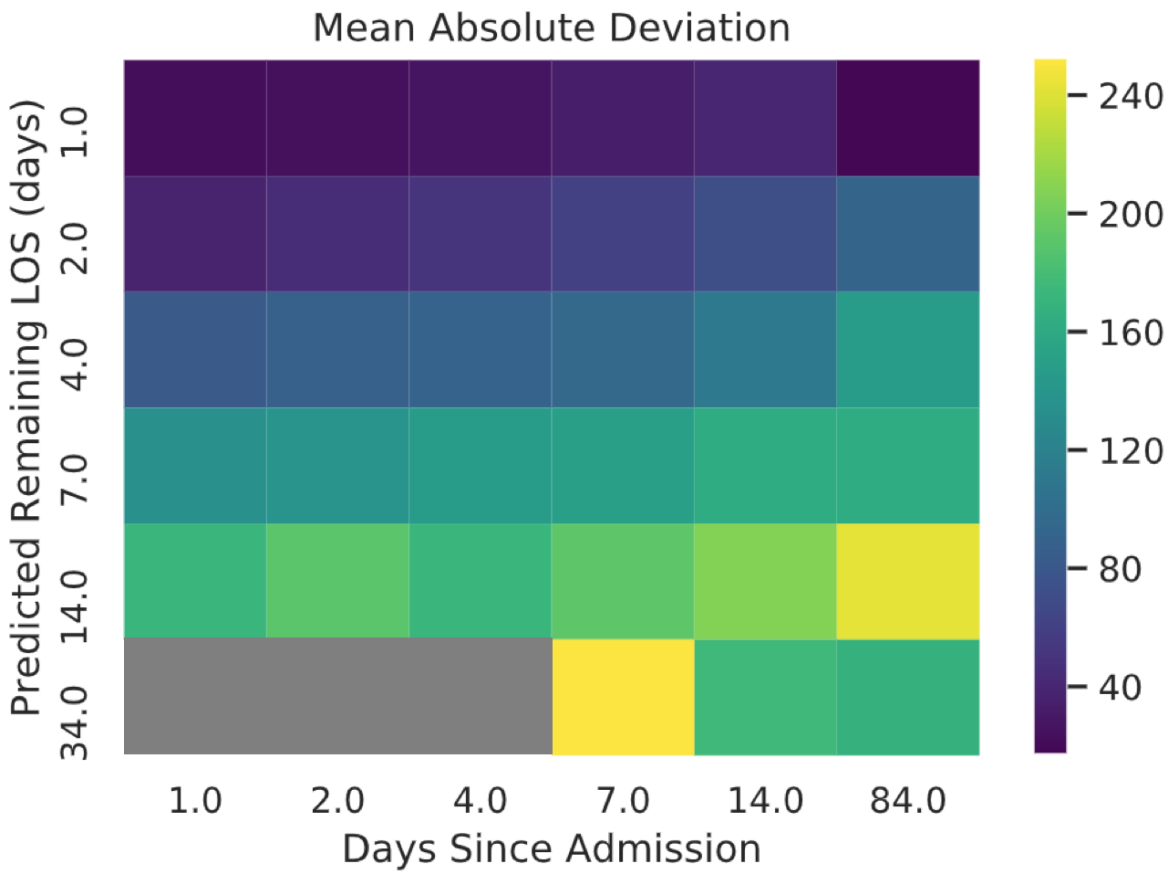
To my funders:

- The Armstrong Fund
- The Frank Elmore Fund
- The Clinical School

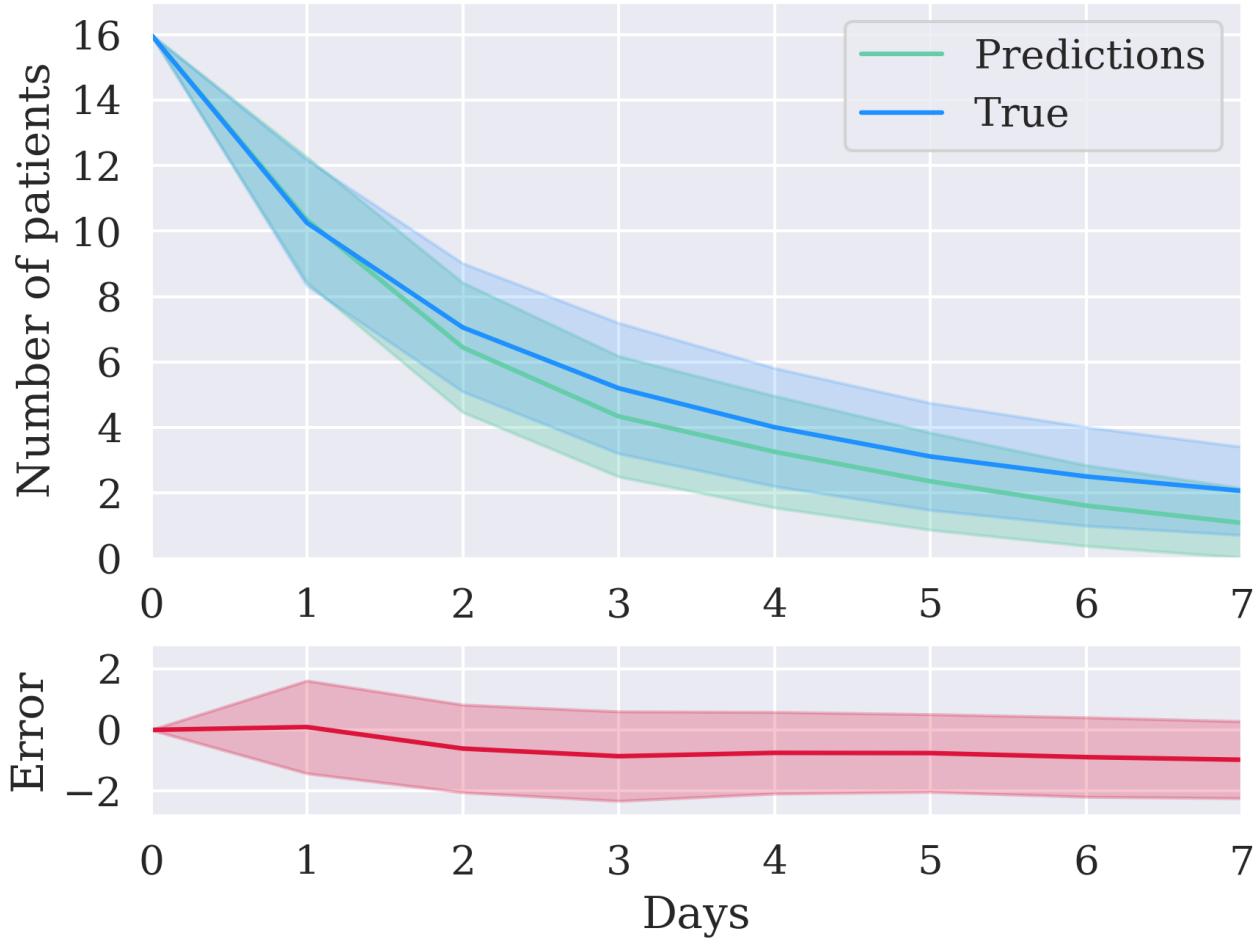
To my supervisor/mentor:

Prof. Pietro Lio and Dr Stephanie Hyland

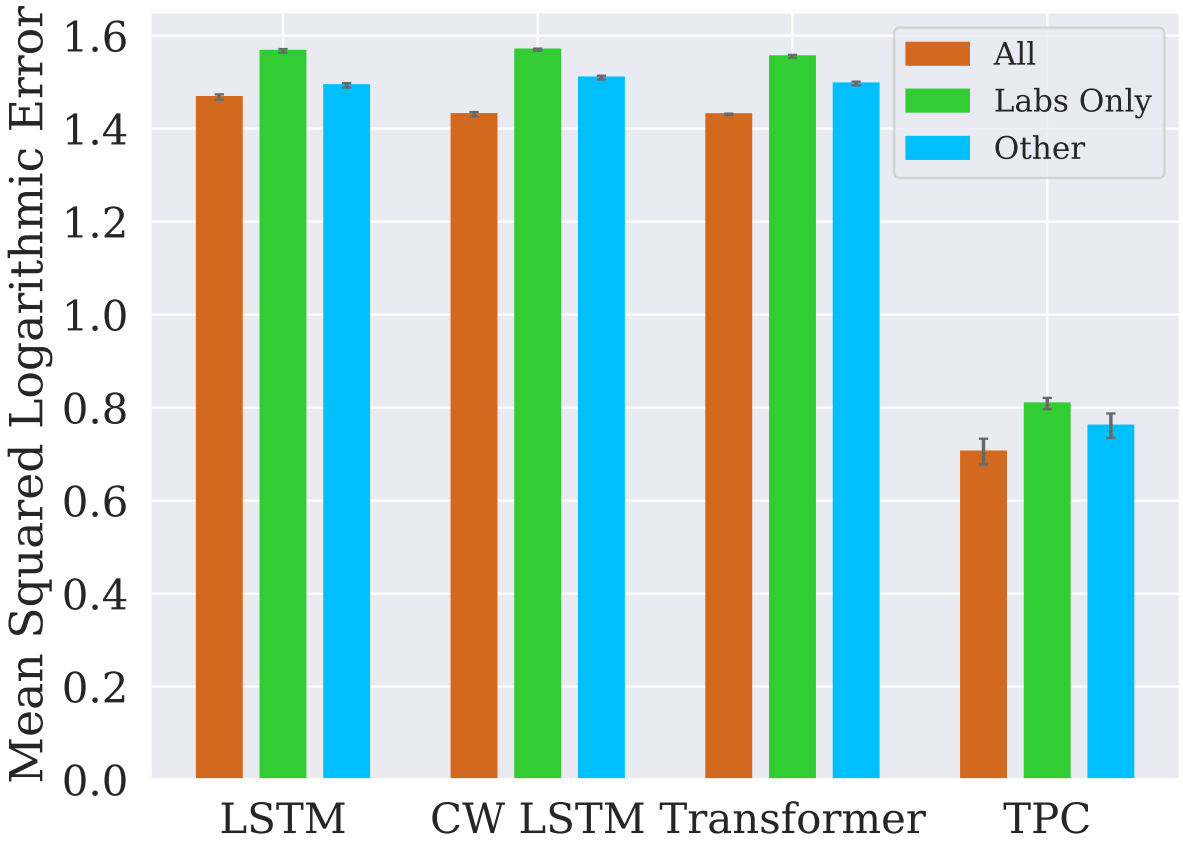
Model Reliability



ICU Simulation Study



Data Type Ablation



Training Data Size