Temporal Pointwise Convolutional Networks for Length of Stay Prediction in the Intensive Care Unit

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Abstract

The pressure of ever-increasing patient demand and budget restrictions make hospital bed management a daily challenge for clinical staff. Most critical is the efficient allocation of resource-heavy Intensive Care Unit (ICU) beds to the patients who need life support. Central to solving this problem is knowing for how long the current set of ICU patients are likely to stay in the unit. In this work, we propose a new deep learning model based on the combination of temporal convolution and pointwise (1x1) convolution, to solve the length of stay prediction task on the eICU critical care dataset. The model – which we refer to as Temporal Pointwise Convolution (TPC) – is specifically designed to mitigate for common challenges with Electronic Health Records, such as skewness, irregular sampling and missing data. In doing so, we have achieved significant performance benefits of 18-51% (metric dependent) over the commonly used Long-Short Term Memory (LSTM) network, and the multi-head self-attention network known as the Transformer.

1 Introduction

In-patient length of stay (LoS) explains approximately 85-90% of inter-patient variation in hospital costs in the United States [42]. Extended length of stay is associated with increased risk of contracting hospital acquired infections [21] and mortality [29]. Hospital bed planning can help to mitigate these risks and improve patient experiences [2]. This is particularly important in the intensive care unit (ICU), which has the highest operational costs in the hospital [9] and a limited supply of specialist staff and resources. Such a bed management system would operate on data held in the Electronic Health Record (EHR) system, which contains patient data such as medical histories, diagnoses, medications, treatment plans, allergies, radiology images, laboratory tests and clinical notes.

At present, discharge date estimates are usually done manually by clinicians, but these rapidly become out-of-date and can be unreliable [32, 34]¹. Automated ICU LoS forecasting systems may reduce the administrative burden on clinicians as well as enable more sophisticated planning strategies e.g. scheduling high-risk elective surgeries on days with more availability predicted in the ICU [15].

In our work, the task is to predict the patients’ remaining ICU length of stay at hourly intervals during their stay using preceding data from the EHR (similar to Harutyunyan et al. [20]). We include

¹Mak et al. [32] found that the average error made by clinicians when predicting hospital length of stay at admission time was 3.82 days, with a standard deviation of 6.51 days.

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time series data (e.g. vital signs, nurse observations, ventilator logs and laboratory test results), non
time-varying (static) features (e.g. age and gender), and diagnoses data. When designing both the
architecture and pre-processing, we focus on mitigating for the effects of non-random missingness
due to irregular sampling, sparsity, outliers, skew, and other biases that are commonly present in EHR
data. We summarise the key contributions of our paper as follows:

1. A new model – Temporal Pointwise Convolution (TPC) – which combines the strengths of:
   • Temporal convolutional layers [26, 55], in capturing causal dependencies across the
time domain.
   • Pointwise convolutional layers [30], in computing higher level features from interac-
tions in the feature domain.

   We show that these methods complement each other by extracting different information. Our
model outperforms the commonly used Long-Short Term Memory (LSTM) network [23] and
the Transformer [56]. We justify why our approach may be more robust to missingness with
an extensive ablation study (particularly missingness from irregular and sparse sampling).

2. We develop a sophisticated data processing pipeline for the eICU database [38] that is
designed to i) mitigate some of the impact of sparsity (for the diagnoses) and missing data
(for time series) in the EHR and ii) extract a wide variety of features semi-automatically
such that the approach is generalisable to other EHR databases.

3. We make a case for using the mean squared logarithmic error (MSLE) loss function to train
LoS models, as it helps to mitigate the effects of skew.

4. We present a visualisation of the model’s performance to communicate its reliability to a
user as a function of time since admission and the predicted remaining LoS.

Our code is on GitHub: https://github.com/EmmaRocheteau/eICU-LoS-prediction.

2 Related Work

Despite its importance, the length of stay prediction task has received less attention than mortality
prediction. This is potentially due to its difficulty: there is increased dependence on operational
factors which may change depending on the time of day and month of the year, and there is significant
positive skew in the labels (shown in Figure 1). To simplify the task, LoS prediction has most
frequently appeared as a binary classification task, i.e. long vs. short stays\footnote{This limits the usefulness of the model as you can only plan over a pre-set timescale.} [17, 35, 41], or less
commonly as a regression task optimised with a mean squared error (MSE) loss function [40, 46].
Harutyunyan et al. [20] cast LoS prediction as a multi-class classification problem over LoS buckets,
by using unevenly sized bins, they were able to partially mitigate for the skew.

Previous work on LoS prediction covers a wide variety of methods including: multiple regression
analysis [1], random forest [14], hidden Markov models [49] and fully-connected neural networks
with autoencoder pre-training [60]. Owing to the centrality of time series in the EHR, LSTMs have been by far the most popular model for predicting length of stay and have achieved state-of-the-art results [20, 41, 46]. This reflects the prominence of LSTMs in other clinical prediction tasks such as predicting in-hospital adverse events including cardiac arrest [54] and acute kidney injury [53], forecasting diagnoses and medication codes [6, 31] and clinical interventions [51], missing-data imputation [4], and the classic task of mortality prediction [5, 20, 47]. The Transformer model [56] was originally designed for natural language processing (NLP), but it has marginally outperformed the LSTM on LoS [48]. Therefore, the LSTM and the Transformer were chosen as key baselines.

In this work we propose a new model for the task of length of stay prediction, exploiting pointwise convolutions and dilated temporal convolutions. We discuss in detail how the proposed architecture relates to prior methodological work throughout Section 3.

3 Methods

Model Overview Broadly, we want our model to extract both temporal trends and inter-feature relationships in order to capture the patient’s clinical state and make accurate LoS predictions. Consider a patient who is experiencing slowly worsening respiratory symptoms but is otherwise stable. As this patient is unlikely to be weaned from their ventilator in the near future, a clinician would likely anticipate a long remaining LoS, but how do they come to this conclusion? Intuitively, they are evaluating the trajectory of the patient, so they may ask themselves “is the respiratory rate getting better or deteriorating?”. Additionally, they might want to obtain a better indication of lung function by combining certain features e.g. the PaO₂/FiO₂ ratio. In short they focus on trends and feature interactions – so we aim to extract both of these with our model.

Formally, our task is to predict the remaining LoS at every timepoint \( y_1, \ldots, y_T \in \mathbb{R}_{>0} \) up to the discharge time \( T \), using the patients’ diagnoses, \( d \in \mathbb{R}^{D \times 1} \), static features, \( s \in \mathbb{R}^{S \times 1} \), and time series \( x_1, \ldots, x_T \in \mathbb{R}^{F \times 2} \). Note that initially, for every timepoint \( t \), there are two ‘channels’ per time series feature: \( F \) original features, \( x_t' \in \mathbb{R}^{F \times 1} \), and their corresponding decay indicators \( x_t'' \in \mathbb{R}^{F \times 1} \). In the following sections, we explain how we extract both temporal trends and inter-feature relationships using a novel combination of techniques.

Temporal Convolution Temporal Convolution Networks (TCNs) [26, 55] are a subclass of convolutional neural networks [13] that convolve over the time dimension. They operate on two key principles: the output is the same length as the input, and there can be no leakage from the future into the past. In other words, they only convolve on elements up to the current timepoint \( t \). We use stacked TCNs to extract temporal trends in our data. Unlike most implementations, we do not share the weights across features i.e. the weight sharing is only across time (like in Xception [7]) because our features differ sufficiently in their temporal characteristics to warrant specialised processing.

We define the temporal convolution operation for the \( i_{th} \) feature in the \( n_{th} \) layer as

\[
(f^{(n,i)} * h^{(n,i)})(t) = \sum_{j=1}^{k} f^{(n,i)}(j) h^{(n,i)}_{t-d(j-1)}
\]

where \( h^{(n,i)}_{1:t} \in \mathbb{R}^{C^{(n)} \times t} \) represents the temporal input to layer \( n \) at timepoint \( t \). It contains \( C^{(n)} \) channels for each feature \( i \). For the first layer, the input \( h^{(n,i)}_{1:t} \) is the same as the original data \( x_{1:t}^{(n,i)} \in \mathbb{R}^{2 \times t} \) and therefore \( C^{(1)} = 2 \). The convolutional filter \( f^{(n,i)} : \{1, \ldots, k\} \rightarrow \mathbb{R}^{Y \times C^{(n)}} \) corresponds to a tensor of \( Y \times C^{(n)} \times k \) parameters per feature, since it maps \( C^{(n)} \) input channels into \( Y \) output channels, while looking at \( k \) timesteps. The output takes the form \( (f^{(n,i)} * h^{(n,i)})(t)^\top \in \mathbb{R}^{1 \times Y} \). The dilation factor, \( d \), and the kernel size, \( k \), together determine the temporal receptive field or ‘time span’ of the filter: \( d(k-1) + 1 \) hours for a single layer. Note that the \( t - d(j-1) \) term ensures that we only look backwards in time \(^4\). The receptive field can be further increased by stacking multiple TCNs, especially when the dilation factor is increased with each layer (as in Wavenet [55] and ByteNet [26]). We increment the dilation by 1 with each layer i.e. \( d = n \).

\(^3\)The decay indicators tell the model how recently the observation \( x' \) was recorded. They are described in detail in Section 4.

\(^4\)To ensure that the output is always length \( T \), we add left-sided padding of size \( d(k-1) \) before every temporal convolution (not shown in equation 1).
We concatenate the temporal convolution outputs for each feature, $i$ as follows

$$
\left( f^{(n)} \ast h^{(n)} \right)(t) = \left[ \begin{array}{c} R^{(n)} \\
\| \begin{array}{c} f^{(n,i)} \ast h^{(n,i)}(t) \\
\| \end{array} \|_{i=1}^{d=1} \\
\end{array} \right]_{R^{(n)} \times Y} (2)
$$

We use $\|$ to denote concatenation i.e. $[\| a^{(1)} \| \ldots \| a^{(A)} \|]_{A \times 1}$ where $a^{(i)} \in \mathbb{R}^{1 \times 1}$. In this example, $A \times 1$ specifies the output dimensions (and therefore the axis of concatenation). In our case, the output dimensions are $R^{(n)} \times Y$, where $R^{(n)}$ is the number of temporal input features. Throughout this section we will label mathematical terms with numbers (1), (2) etc. which correspond to objects in Figure 3. We recommend the reader to follow Figure 3 alongside the equations.

**Pointwise Convolution**  
Pointwise convolution [30], also referred to as $1 \times 1$ convolution, is typically used to reduce the channel dimension when processing images [52]. It may be helpful to conceptualise pointwise convolution as a fully connected layer, applied separately to each timepoint (shown diagrammatically in Figure 2). Like in temporal convolution, the weights are shared across all timepoints; however, there is no information transfer across time i.e. the temporal receptive field is always 1 hour. Instead, we transfer information across the features to compute $Z$ interaction features from the pointwise input\footnote{We use a wider set of $P^{(n)}$ features for pointwise convolution, which includes features that are not appropriate for temporal convolution beyond just the first layer (decay indicators $x''$) or at all (static features $s$). Note that when $n = 1$, we omit $x''$ because the decay indicators are already included in $h^{(1)}$, so $P^{(1)} = 2F + S$.}, $p^{(n)}_i = (\bar{v}(h^{(n)}) \| s \| x''_i) \in \mathbb{R}^{P^{(n)} \times 1}$, where $P^{(n)} = (R^{(n)} \times C^{(n)}) + F + S$, and $b : A_{d_1 \times d_2 \ldots \times d_n} \rightarrow A_{d_1 \times d_2 \ldots \times d_n}$ represents the flatten operation. We define the pointwise convolution operation in the $n_{th}$ layer as

$$
\left( g^{(n)} \ast p^{(n)} \right)(t) = \sum_{i=1}^{P^{(n)}} g^{(n)}(i)p^{(n,i)} (3)
$$

where the pointwise filter is given by $g^{(n)} : \{1, \ldots, P^{(n)}\} \rightarrow \mathbb{R}^{Z \times 1}$, and the resulting convolution produces $Z$ output channels i.e. the output takes the form $(g^{(n)} \ast p^{(n)})(t) \in \mathbb{R}^{Z \times 1}$.

**Skip Connections**  
We propagate skip connections [22] to allow each layer to see the original data and the pointwise outputs from previous layers. This helps the network to cope with infrequently sampled data. For example, if we suppose that a particular blood test is taken once per day, but the frequency is not consistent enough to constrain to a periodicity (a real example is shown in Figure 5). In order to not lose temporal resolution, we forward-fill these data (Section 4) and convolve with increasingly dilated temporal filters until we find the appropriate width to capture the most useful trend. However, a problem arises if the smaller convolutional filters in previous layers (which did not see any useful temporal variation in the short-term) have polluted the original data with their re-weightings, making learning more difficult. Therefore, skip connections provide a consistent anchor to the original data. Note that they are concatenated (like in DenseNet [24], and
Figure 3: Left: The original time series, $x'$ (grey) and the decay indicators, $x''$ (orange) are processed by $N$ TPC layers before being combined with a diagnosis embedding $d^*$ (purple) and static features $s$ (yellow) along the feature axis. A two-layer pointwise convolution is applied to obtain the final predictions $\hat{y}$ (red). Right: In the $n_{th}$ TPC layer, the temporal and pointwise convolution operate in parallel. In the temporal branch, differently coloured convolutional filters indicate independent parameters. Left-sided padding of size $d(k - 1)$ (white) is added before each temporal convolution. The skip connections (light-blue and grey) are added in step (3).

are arranged in the shared-source connection formation [58]) as illustrated in Figure 2. The skip connections expand the feature dimension, $R(n) = F + Z(n - 1)$, to accommodate all the pointwise outputs, and also the channel dimension to fit the original data, $C(n) = Y + 1$ (except for $n = 1$, when $C(1) = 2$). The organisation of the skip connections is best visualised in Figure 3b.

**Temporal Pointwise Convolution** Our model – which we refer to as Temporal Pointwise Convolution (TPC) – combines temporal and pointwise convolution in a parallel architecture. Firstly, the temporal output is combined with all the skip connections to form $r^{(n)}_t$ (Step 3 in Figure 3b)

$$r^{(n)}_t = \left[ \begin{array}{c} \left( f^{(n)} \ast h^{(n)}_t \right) \\ \text{Temporal Output (2)} \\ \left. \left[ \prod_{n' = 1}^{n-1} \left( g^{(n')} \ast p^{(n')}_t \right) \right] \right]_{Z(n-1) \times 1} \right]_{R(n) \times (Y + 1)}$$

(4)

$r^{(n)}_t$ is then concatenated with the pointwise output after it has been repeated $Y + 1$ times (Step 6 in Figure 3b). We can therefore define the $n_{th}$ TPC layer as

$$h^{(n+1)}_t = \sigma \left[ \left. \left[ \prod_{i=1}^{Y+1} \left( g^{(n)} \ast p^{(n)}_t \right) \right] \right]_{Z \times (Y+1)} \right]_{R(n+1) \times (Y+1)}$$

(5)
where \( \sigma \) represents the ReLU activation function. The full model has \( N \) TPC layers stacked sequentially (9 in our hyperparameter optimised model). After \( N \) layers, the output \( \mathbf{h}^{(N)}_t \) is combined with the static features \( \mathbf{s} \in \mathbb{R}^{S \times 1} \), and a diagnosis embedding \( \mathbf{d}^* \in \mathbb{R}^{D^* \times 1} \) (the output of single fully connected layer). Two pointwise convolution layers then generate the predictions

\[
\hat{y}_t = \text{HardTanh}\left(\exp\left(\mathbf{g}'' \ast \mathbf{g}' \ast \mathbf{h}^{(N)}_t \parallel \mathbf{s} \parallel \mathbf{d}^*_{B \times 1}\right)\right) \tag{6}
\]

where \( B = R^{(N)} \times (Y + 1) + S + D^* \) and the final pointwise filters are \( \mathbf{g}' : \{1, \ldots, B\} \rightarrow \mathbb{R}^{X \times 1} \) and \( \mathbf{g}'' : \{1, \ldots, X\} \rightarrow \mathbb{R}^{1 \times 1} \). Note that if a baseline model were to be used instead of TPC, the output dimensions would be \( H \times 1 \) instead of \( B \times 1 \), where \( H \) is the LSTM hidden size or \( d_{model} \) in the Transformer. We apply an exponential function to allow the upstream model to predict \( \log(\text{LoS}) \) instead of \( \text{LoS} \). We hypothesised that this could help to circumvent a common issue seen in previous models (e.g. Harutyunyan et al. [20], as they struggle to produce predictions over the full dynamic range of length of stays). Finally, we apply a HardTanh function [18] to clip any predictions that are smaller than 30 minutes or larger than 100 days, which protects against inflated loss values.

\[
\text{HardTanh}(x) = \begin{cases} 
100, & \text{if } x > 100, \\
\frac{1}{48}, & \text{if } x < \frac{1}{48}, \\
x, & \text{otherwise.} 
\end{cases} \tag{7}
\]

We use batch normalisation [25] and dropout [50] throughout to regularise the model (as shown in Figure 3).

![Figure 4: The behaviour of squared logarithmic error (blue) and squared error (red) functions when the true LoS is 1 day.](image)

**Loss Function** The remaining LoS has a positive skew (shown in Figure 1) which makes the LoS prediction task more challenging. We partly circumvent this problem by replacing the commonly used mean squared error (MSE) loss with mean squared log error (MSLE).

\[
\mathcal{L} = \frac{1}{T} \sum_{t=1}^{T} (\log(\hat{y}_t - y_t))^2 \tag{8}
\]

MSLE penalises proportional over absolute error, which seems more reasonable when considering an error of 5 days in the context of a 2-day stay vs. a 30-day stay. The difference in behaviour can be seen in Figure 4. The HardTanh constraint bounds the predictions to the interval \([\frac{1}{48}, 100]\), which protects against infinite MSLE loss. It is worth noting that for bed management purposes it is particularly important not to harshly penalise over-predictions. The model will become overly cautious and regress its predictions towards the mean. This is counter-productive because long stay patients have a disproportionate effect on bed occupancy. We test our substitution of the loss function with an ablation study.
4 Data

eICU Database We use the eICU Collaborative Research Database [38], a multi-centre dataset collated from 208 hospitals in the United States. It comprises 200,859 patient unit encounters for 139,367 unique patients admitted to ICUs between 2014 and 2015.

Remaining Length of Stay Task We assign a remaining LoS target to each hour of the stay, beginning 5 hours after admission to the ICU and ending when the patient dies or is discharged. The remaining LoS is calculated by subtracting the time elapsed in the ICU from the total LoS. We only train on data within the first 14 days of any patient’s stay to protect against very long batches which would slow down training. This cut-off applies to 2.4% of patient stays, but it does not affect their maximum remaining length of stay values because these appear within the first 14 days. The total and remaining LoS distributions are shown in Figure 1.

Cohort and Feature Selection We selected all adult patients (>18 years) with an ICU LoS of at least 5 hours and at least one recorded observation. This produces a cohort of 118,534 unique patients and 146,666 ICU stays. We selected time series from the following tables: lab, nursecharting, respiratorycharting, vitalperiodic and vitalaperiodic. We used a semi-automatic process for feature selection: to be included, the variable had to be present in at least 12.5% of patient stays, or 25% of stays for lab variables. As can be seen in Figure 5, the lab variables tend to be sparsely sampled compared to the other time series. To help the model to cope with missing data, we forward-filled over the gaps\(^6\) and we added ‘decay indicators’ to each feature to specify where the data is stale. The decay was calculated as $0.75^j$, where $j$ is the time since the last recording. This is similar in spirit to the masking used by Che et al. [5].

We extracted diagnoses from the pasthistory, admissiondx and diagnoses tables, and 17 static features from the patient, apachepatientresult and hospital tables (see Tables 2 and 3 in the Appendix for the full list of time series and static features).

Further pre-processing details are included in Appendix A. After pre-processing, the data were divided such that 70% of patients were used for training, 15% for validation and 15% for testing.

\(^6\)This is preferable to interpolation because in realistic scenarios the clinician would only have the most recent value and its timestamp.
5 Experiments and Results

Baselines A certain level of performance is achievable ‘for free’ by predicting values that are close to the mean or median LoS (3.50 and 1.70 days respectively). We include ‘mean’ and ‘median’ models to benchmark this elemental performance. APACHE IV [62] is a severity scoring model for critically ill patients which includes a LoS forecast. It uses a smaller set of features, and is only evaluated once after 24 hours has passed in the ICU. Note that it cannot be compared directly, but we include it only as point of reference for a clinical model that is currently widely used in hospitals. We include a standard LSTM baseline which is very similar to Sheikhalishahi et al. [46]. We also include a channel-wise LSTM (CW LSTM) baseline similar to Harutyunyan et al. [20] which consists of a set of independent LSTMs which process each feature separately (note the similarity with the TPC model). Our Transformer [56] baseline is a multi-head self-attention model. Like the TPC model, it is not constrained to progress one timestep at a time; however, unlike TPC, it is not able to scale its receptive fields or process features independently. The hyperparameter search methodology and further implementation details for the transformer can be found in Appendix B.

Evaluation Metrics It is important to consider several metrics when evaluating length of stay. Bad models can ‘cheat’ particular metrics by virtue of being close to the mean or median value, or by never making long LoS predictions (which is undesirable for the purposes of bed management), whereas a good model should do well across all the metrics. We report on the following for each experiment: mean absolute deviation (MAD), mean absolute percentage error (MAPE), mean squared error (MSE), mean squared log error (MSLE), coefficient of determination (\(R^2\)) and Cohen Kappa Score. Further information about these metrics can be found in Appendix C.

Table 1: Performance of the TPC model compared to baseline models (a) and various ablation studies (b) and (c). Unless otherwise specified, the loss function is MSLE. For the first four metrics, lower is better. The error margins are 95% confidence intervals (CIs) calculated over 10 runs. (a) shows the baseline comparisons. Note that mean, median and APACHE are deterministic models so they have no error bars. *Note that the APACHE results cannot be compared directly to the other models (explained in ‘Baselines’). (b) compares the effect of the loss function on the TPC model. See Table 10 for the MSE results of LSTM, CW LSTM and Transformer. (c) shows various TPC ablation studies. WS refers to weight sharing. The best results are highlighted in blue. If the upper CI of another result exceeds the lower CI of the best result, then it is highlighted in light blue. The TPC (MSLE) result has been repeated in each subtable for ease of comparison.

| Model         | MAD (±)   | MAPE (±) | MSE (±)  | MSLE (±) | \(R^2\)  | Kappa (±) |
|---------------|-----------|----------|----------|----------|----------|-----------|
| Mean          | 3.21 ±0.00 | 395.7 ±0.02 | 29.5 ±0.02 | 2.87 ±0.02 | 0.00 ±0.02 | 0.00 ±0.02 |
| Median        | 2.76 ±0.00 | 184.4 ±0.02 | 32.6 ±0.02 | 2.15 ±0.02 | -0.11 ±0.02 | 0.00 ±0.02 |
| APACHE*       | 2.54 ±0.00 | 182.1 ±0.01 | 16.6 ±0.02 | 1.10 ±0.02 | -0.01 ±0.02 | 0.20 ±0.02 |
| (a) LSTM      | 2.39 ±0.00 | 118.2 ±1.10 | 26.9 ±0.10 | 1.47 ±0.01 | 0.09 ±0.00 | 0.28 ±0.00 |
| (a) CW LSTM   | 2.37 ±0.00 | 114.5 ±0.40 | 26.6 ±0.10 | 1.43 ±0.00 | 0.10 ±0.00 | 0.30 ±0.00 |
| (a) Transformer | 2.36 ±0.00 | 114.1 ±0.60 | 26.7 ±0.10 | 1.43 ±0.00 | 0.09 ±0.00 | 0.30 ±0.00 |
| (a) TPC       | 1.78 ±0.02 | 63.5 ±4.30 | 21.7 ±0.50 | 0.70 ±0.03 | 0.27 ±0.02 | 0.58 ±0.01 |
| (b) TPC (MSLE)| 1.78 ±0.02 | 63.5 ±4.30 | 21.7 ±0.50 | 0.70 ±0.03 | 0.27 ±0.02 | 0.58 ±0.01 |
| (b) TPC (MSE) | 2.21 ±0.02 | 154.3 ±10.1 | 21.6 ±0.20 | 1.80 ±0.10 | 0.27 ±0.01 | 0.47 ±0.01 |
| (c) TPC       | 1.78 ±0.02 | 63.5 ±3.80 | 21.8 ±0.50 | 0.71 ±0.03 | 0.26 ±0.02 | 0.58 ±0.01 |
| TPC           | 2.68 ±0.15 | 137.8 ±16.4 | 29.8 ±2.90 | 1.60 ±0.03 | -0.01 ±0.10 | 0.38 ±0.01 |
| TPC           | 1.91 ±0.01 | 71.2 ±1.10 | 23.1 ±0.20 | 0.86 ±0.01 | 0.22 ±0.01 | 0.52 ±0.01 |
| TPC           | 2.34 ±0.01 | 116.0 ±1.20 | 26.5 ±0.20 | 1.40 ±0.01 | 0.10 ±0.01 | 0.31 ±0.00 |
| TPC           | 1.93 ±0.01 | 73.9 ±1.90 | 23.0 ±0.20 | 0.89 ±0.01 | 0.22 ±0.01 | 0.51 ±0.01 |
| TPC           | 1.76 ±0.02 | 67.0 ±2.40 | 20.3 ±0.40 | 0.71 ±0.02 | 0.31 ±0.01 | 0.61 ±0.01 |
| TPC           | 1.77 ±0.02 | 65.6 ±4.10 | 21.5 ±0.50 | 0.71 ±0.03 | 0.27 ±0.02 | 0.59 ±0.01 |
| TPC           | 1.84 ±0.01 | 64.5 ±3.00 | 22.5 ±0.30 | 0.77 ±0.02 | 0.24 ±0.01 | 0.56 ±0.01 |
| (c) TPC (no decay) | 2.90 ±0.18 | 179.1 ±17.4 | 34.2 ±4.6 | 1.80 ±0.05 | -0.16 ±0.16 | 0.33 ±0.00 |

TPC Performance Table 1a shows that the TPC model has outperformed all of the baseline models on every metric – particularly those that are more robust to skewness: MAPE, MSLE and Kappa. Discounting APACHE, the best performing baselines are the Transformer and the channel-wise...
LSTM (CW LSTM), whose results are almost indistinguishable. Our results are highly consistent with Harutyunyan et al. [20] (for CW LSTM) and Song et al. [48] (for Transformers), who both found small improvements over the standard LSTM model.

**MSLE Loss Function** Table 1b shows that using the MSLE loss function rather than MSE leads to significantly improved behaviour in the TPC model, with large performance gains in MAD, MAPE, MSLE and Kappa, while conceding little in terms of MSE and $R^2$. The MSE results for the other baselines are shown in Table 10 in the Appendix; they show a similar pattern to the TPC model.

**Ablation Studies** To better understand the impact of our design choices for the TPC model, we perform a set of ablation studies on its components. In Table 1c we can see that the temporal-only model is superior to the pointwise-only model, but the TPC model outperforms them both. The temporal-only model performs much better than its weight sharing ablation, suggesting that having independent parameters per feature is important for the LoS task.

When we remove the skip connections, we can see that the performance is impaired by 5-25%. Unexpectedly, there is marginal improvement in some of the metrics when the exponential function is removed. However, when we examined the ‘TPC (no exp.)’ performance in patients who had a remaining LoS longer than 5 days vs. shorter than 5 days, we found that the improvement was limited to the short stay patients, so it seems that the exponential function is harmful when predicting in the short stay range\(^7\), which are very common in the dataset (Figure 1).

We also explored how different aspects of the EHR contribute to model performance. Perhaps surprisingly, we found that the exclusion of diagnoses does not seem to harm the model. This could be because the diagnoses that are most relevant for predicting LoS in the ICU (e.g. Acute Respiratory Distress Syndrome (ARDS), are discernible from the time series data alone e.g. PaO2, FiO2, PEEP, Tidal Volume etc.).

The decay indicators contribute a small (mostly non-significant) benefit to the TPC model of 2-8%. Their contribution is more obvious when we compare the pointwise-only model with and without decay indicators\(^8\). All of the metrics see improvements of 5-23%.

We performed ablations on the type of time series variable that we include: laboratory tests only (labs), which are infrequently sampled, and all other variables (other) which include vital signs, nurse observations, and automatically recorded variables (e.g. from ventilator machines). The results (shown in Appendix D.1) indicate that the TPC model is better able to exploit disparate EHR time series than the baselines. They also show that the advantage of the CW LSTM over the standard LSTM is only apparent when the model has to process different types of time series simultaneously.

**Visualisation** We noticed that the errors made by our model are not uniform across all inputs, and aggregate measures tend to mask this variability in model performance. We visualise MAPE (chosen for its interpretability) as a function of the time since admission and the predicted remaining LoS. The user knows this information at the time of prediction, so they can rapidly assess the reliability of the forecast they just received. Figure 6 shows an example for the TPC model. We can see that the model is generally reliable across a range of situations, but is notably unreliable when it predicts a long LoS during the first 1-2 days of admission. Additional investigation revealed these to be under-predictions. We believe that this is an effect of the skewness, since short stay patients are far more frequent than long stay patients, so the model requires 1-2 days to gather enough evidence to predict a long LoS.

**ICU Simulation** From the perspective of a bed manager, aggregate performance of the model is important. To investigate this, we performed a simulation study. We ran 500 ICU simulations by randomly selecting 16 examples from the test set to form a ‘virtual cohort’. The number 16 was chosen because US hospitals have, on average, 24 ICU beds [57] with an occupancy rate of 68% [19]. Figure 7 shows the number of patients remaining in the ICU (of the selected cohort; we do not visualise incoming ICU admissions) using their true remaining LoS (blue). We compute the error

\[\text{error} = \frac{\text{true LoS} - \text{predicted LoS}}{\text{true LoS}}\]

\(^7\)The model would need to produce an increasingly negative output as it attempts to predict shorter remaining LoS, because the model is effectively predicting log(LoS) until the output is exponentiated.

\(^8\)This could be because they provide insight into the temporal structure (e.g. the model could theoretically learn relationships between how many up-to-date measurements there are and the probability of a current deterioration)
Figure 6: Mean absolute percentage error as a function of days since admission and predicted remaining LoS.

Figure 7: ICU simulation. We show the number of patients remaining in the ICU over time from an initial cohort of 16 patients from 500 random simulations. The shaded regions show the standard deviation across the runs. Error is calculated from True minus Predictions.

We have shown that the TPC model outperforms all baseline models on the LoS task. We believe that there are several factors contributing to its success, which we discuss in turn below.

We start by examining the parallel architectures in the TPC model. Each has been designed to extract different information: trends from the temporal component and inter-feature relationships from the pointwise component. The ablation study shows that the temporal component is more important, but we know that their contributions are complementary because the best performance is only seen when they are used together. Therefore, the complementary architectures is a strength of our model.

Next, we highlight that the temporal-only model far outperforms its most direct comparison, the CW LSTM, on all metrics. Theoretically they are well matched because they both have feature-specific parameters and they are unable to compute cross-feature interactions until the final layers of the model. To begin to explain this, we can consider how the information flows through the model.
The temporal-only model can directly step across large gaps in time, whereas the CW LSTM is forced to progress one timestep at a time. This gives the CW LSTM the comparatively harder task of remembering information across a noisy EHR with distracting signals of varying frequency. In addition, the temporal-only model can easily tune its receptive fields for optimal processing of each feature thanks to the skip connections (which are not present in the CW LSTM). Even the hyperparameter search results (Appendix B) for the TPC model are interesting, because the best model was found to have 9 layers and a kernel size of 4. This means that the temporal convolutions in the final layer are learning relationships over a receptive field size of at least 28 hours\(^9\). This is long enough for single convolutions to span over more than one day to extract useful trends directly from lab results.

The difference in performance between the temporal-only model with and without weight sharing provides strong evidence that assigning independent parameters to each feature is important for the LoS task. Some EHR time series are irregularly and sparsely sampled, and can exhibit considerable variability in the temporal frequencies within the underlying data (this is evident in Figure 5). This presents a difficult challenge for any model, especially if it is constrained to learn one set of parameters to suit all features. The relative success of the CW LSTM over the standard LSTM when processing disparate time series – but not similar – also lends weight to this theory (Appendix D.1).

However, the assignment of independent parameters to each feature does not explain all the successes of the TPC model e.g. the TPC model can process disparate time series and gain more marginal performance than the CW LSTM. We need to consider that periodicity is a key property of EHR data\(^10\). The temporal component of the TPC model is the only architecture with an inherent periodic structure which makes it much easier to learn EHR trends. By comparison, a single attention head in the Transformer model does not look at timepoints a fixed distance apart, but can take an arbitrary form. This is a strength in the natural language processing domain, given the variety of sentence structures possible, but it does not help the Transformer to derive trend features e.g. how the gradient is changing over time. Learning to recognise these trends in patients is often crucial to the LoS task. For example, when spotting the deteriorating respiratory patient we introduced in Section 3.

Finally, we reiterate that using MSLE loss instead of MSE greatly mitigates for positive skew in the LoS task, and this benefit is not model-specific (all of the baselines perform better with MSLE). This demonstrates that careful consideration of the task – as well as the data and model – is an important step towards building useful tools for healthcare providers.

Limitations and Future Work Our work has important limitations. First of all, this is a retrospective study which brings with it a familiar set of limitations [12]. Furthermore, although it is widely believed that accurate LoS predictions can be used to improve bed planning [44], this is not a foregone conclusion and prospective trials are needed to demonstrate real-world impact [41]. Sendak et al. [45] go some way to address this gap in the literature by providing a detailed account of the steps to implement and evaluate their model ‘Sepsis Watch’ into practice.

Length of stay prediction is a particularly challenging task due to its dependence on both clinical and operational factors. The operational overhead of transfers depends on the time of day [16], and can change over time as practices change [27]. The eICU data has been collected over a short timespan from 2014 to 2015. It would be instructive to test whether the methods are robust on the MIMIC-III and AmsterdamUMCdb datasets. By reserving more recent data as a test set, these databases would permit experimentation on how quickly a LoS model becomes out-of-date [35]. We note that although we do not test our models on MIMIC-III, it is encouraging that our results – even hyperparameter values – are highly consistent with the work of Harutyunyan et al. [20] and Song et al. [48].

Previous work has found merit in a multitask approach to patient outcome prediction [20, 46]. We did not investigate this, but it is possible that it could have improved our predictions. Patients who die in the ICU or shortly after may exhibit very different clinical trajectories to those who survive.

\(^9\)The receptive field for a single layer can be calculated with \(d(k - 1) + 1\), where \(d\) is the dilation and \(k\) is the kernel size. For the final TPC layer this is \(9(4 - 1) + 1 = 28\) hours, since \(d = n\). In reality, the receptive field can capture much longer than 28 hours because the temporal convolutions are stacked on top of convolutions that can also look backwards in time and so on. Equally if the early layers are not found to be useful for this particular feature, they can be skipped.

\(^10\)This is true both in sampling patterns and in the underlying biological functions e.g. circadian variation with sleep, periodic responses to medication schedules etc.
The model should be able to predict a short remaining LoS when the patient is healthy enough to be discharged, but also when the patient is rapidly decompensating. It is likely that our model is inadvertently solving the mortality/decompensation problem as well, but the explicit training for multitask prediction might make the model more robust.

Lastly, there may be more sophisticated methods for filling in missing data than decay indicators (e.g. Gaussian Processes have previously shown promising performance benefits on EHR-based models [39], and recent methods exploiting differential equations have allowed RNNs to operate on irregularly sampled data [3, 43].

7 Conclusion

In this work we have shown that the TPC model is well-equipped to analyse EHR time series containing different frequencies, missingness and sparse sampling. We believe that the following four aspects contribute the most to its success:

1. The combination of two complementary architectures that are able to extract different features, both of which are important for patient assessment.
2. The ability to step directly over large gaps in time.
3. The capacity to specialise processing to each feature (including the freedom to select the appropriate receptive field size for each).
4. The rigid spacing of the temporal filters, making it easy to derive trends in the EHR.

From a clinical perspective, we have contributed to the advancement of LoS prediction models, a prerequisite for automated bed management tools. This will have important implications for cost reduction [19] and resource allocation [33] worldwide. From a computational perspective, we have provided key insights for retrospective EHR studies, particularly where LSTMs are the currently model of choice. In the broader context of machine learning for healthcare we have demonstrated that careful consideration of the complexities of health data is an important step towards building useful tools for healthcare providers.

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References

[1] Hyunyoung Baek, Minsu Cho, Seok Kim, Hee Hwang, Minseok Song, and Sooyoung Yoo. Analysis of Length of Hospital Stay using Electronic Health Records: A Statistical and Data Mining Approach. *PloS one*, 13(4):e0195901–e0195901, 2018.

[2] Mathias C. Blom, Karin Erwander, Lars M. Gustafsson, Mona Landin-Olsson, Fredrik Jonsson, and Kjell Ivarsson. The Probability of Readmission within 30 days of Hospital Discharge is Positively Associated with Inpatient Bed Occupancy at Discharge – A Retrospective Cohort Study. In *BMC Emergency Medicine*, 2015.

[3] Edward De Brouwer, Jaak Simm, Adam Arany, and Yves Moreau. Gru-ode-bayes: Continuous modeling of sporadically-observed time series. In *NeurIPS*, 2019.

[4] Wei Cao, Dong Wang, Jian Li, Hao Zhou, Lei Li, and Yitan Li. BRITS: Bidirectional Recurrent Imputation for Time Series. In *NeurIPS*, 2018.

[5] Zhengping Che, Sanjay Purushotham, Kyunghyun Cho, David Sontag, and Yan Liu. Recurrent Neural Networks for Multivariate Time Series with Missing Values. *Scientific Reports*, 8(1):6085, 2018.

[6] Edward Choi, Mohammad Taha Bahadori, Andy Schuetz, Walter F. Stewart, and Jimeng Sun. Doctor AI: Predicting Clinical Events via Recurrent Neural Networks. *JMLR workshop and conference proceedings*, 56:301–318, 2015.

[7] François Chollet. Xception: Deep Learning with Depthwise Separable Convolutions. *CoRR*, abs/1610.02357, 2016.

[8] Jacob Cohen. A Coefficient of Agreement for Nominal Scales. *Educational and Psychological Measurement*, 20(1):37–46, 1960.

[9] Deborah Dahl, Greg G Wojtal, Michael Breslow, Randy Holl, Debra Huguez, David Stone, and Gloria Korpi. The High Cost of Low-Acuity ICU Outliers. *Journal of healthcare management / American College of Healthcare Executives*, 57:421–434, 2012.

[10] Thuppahi Sisira De Silva, Don MacDonald, Grace Paterson, Khokan C. Sikdar, and Bonnie Cochrane. Systematized Nomenclature of Medicine Clinical Terms (SNOMED CT) to Represent Computed Tomography Procedures. *Comput. Methods Prog. Biomed.*, 101(3):324–329, 2011.

[11] A Elixhauser, C Steiner, and L Palmer. Clinical Classifications Software, 2015.

[12] A M Euser, C Zoccali, K J Jager, and F W Dekker. Cohort Studies: Prospective versus Retrospective. *Nephron Clinical Practice*, 113(3):c214–c217, 2009.

[13] Kunihiko Fukushima. Neocognitron: A Self-Organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position. *Biological Cybernetics*, 36(4):193–202, 1980.

[14] Cheng Gao, Abel N Kho, Catherine Ivory, Sarah Osmundson, Bradley A Malin, and You Chen. Predicting Length of Stay for Obstetric Patients via Electronic Medical Records. *Studies in health technology and informatics*, 245:1019–1023, 2017.

[15] T. Gentimis, A. J. Alnaser, A. Durante, K. Cook, and R. Steele. Predicting Hospital Length of Stay Using Neural Networks on MIMIC III Data. In *2017 IEEE 15th Intl Conf on Dependable, Autonomic and Secure Computing*, pages 1194–1201, 2017.

[16] C. Goldfrad and K. Rowan. Consequences of Discharges from Intensive Care at Night. *The Lancet*, 355(9210):1138–1142, 2000.

[17] Jen J. Gong, Tristan Naumann, Peter Szolovits, and John V. Guttag. Predicting Clinical Outcomes Across Changing Electronic Health Record Systems. In *KDD*, 2017.

[18] Çaglar Gülçehre, Marcin Mozulsoki, Misha Denil, and Yoshua Bengio. Noisy Activation Functions. *CoRR*, abs/1603.00391, 2016.
[19] Neil A Halpern and Stephen M Pastores. Critical Care Medicine Beds, Use, Occupancy, and Costs in the United States: A Methodological Review. *Critical care medicine*, 43(11):2452–2459, 2015.

[20] Hrayr Harutyunyan, Hrant Khachatrian, David C. Kale, Greg Ver Steeg, and Aram Galstyan. Multitask Learning and Benchmarking with Clinical Time Series Data. *Scientific Data*, 6(96), 2019.

[21] Mahmud Hassan, Howard Tuckman, Robert Patrick, David Kountz, and Jennifer Kohn. Hospital Length of Stay and Probability of Acquiring Infection. *International Journal of Pharmaceutical and Healthcare Marketing*, 4:324–338, 2010.

[22] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep Residual Learning for Image Recognition. *CoRR*, abs/1512.03385, 2015.

[23] Sepp Hochreiter and Jürgen Schmidhuber. Long Short-Term Memory. *Neural computation*, 9(8):1735–1780, 1997.

[24] Gao Huang, Zhuang Liu, Laurens van der Maaten, and Kilian Q Weinberger. Densely connected convolutional networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2017.

[25] Sergey Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In *Proceedings of the 32nd International Conference on International Conference on Machine Learning - Volume 37*, ICML’15, pages 448–456. JMLR, 2015.

[26] Nal Kalchbrenner, Lasse Espeholt, Karen Simonyan, Aäron van den Oord, Alex Graves, and Koray Kavukcuoglu. Neural Machine Translation in Linear Time. *CoRR*, abs/1610.10099, 2016.

[27] Amit D. Kalra, Robert S Fisher, and Peter Axelrod. Decreased Length of Stay and Cumulative Hospitalized Days despite Increased Patient Admissions and Readmissions in an Area of Urban Poverty. *J Gen Intern Med.*, 25(9):920–935, 2010.

[28] Kevin B. Laupland, Andrew W. Kirkpatrick, John B. Kortbeek, and Danny J. Zuege. Long-term Mortality Outcome Associated With Prolonged Admission to the ICU. *Chest*, 129(4):954 – 959, 2006.

[29] Min Lin, Qiang Chen, and Shuicheng Yan. Network In Network, 2013.

[30] Zachary Chase Lipton, David C. Kale, Charles Elkan, and Randall C. Wetzel. Learning to Diagnose with LSTM Recurrent Neural Networks. *CoRR*, abs/1511.03677, 2015.

[31] Gregory Mak, William D. Grant, James C McKenzie, and John B. McCabe. Physicians’ Ability to Predict Hospital Length of Stay for Patients Admitted to the Hospital from the Emergency Department. In *Emergency medicine international*, 2012.

[32] Kusum S Mathews and Elisa F Long. A Conceptual Framework for Improving Critical Care Patient Flow and Bed Use. *Annals of the American Thoracic Society*, 12(6):886–894, 2015.

[33] Antonio Paulo Nassar and Pedro Caruso. ICU Physicians are Unable to Accurately Predict Length of Stay at Admission: A Prospective Study. *Journal of the International Society for Quality in Health Care*, 28 1:99–103, 2016.

[34] Bret Nestor, Matthew B. A. McDermott, Geeticka Chauhan, Tristan Naumann, Michael C. Hughes, Anna Goldenberg, and Marzyeh Ghassemi. Rethinking Clinical Prediction: Why Machine Learning must Consider Year of Care and Feature Aggregation. *CoRR*, abs/1811.12583, 2018.

[35] NHS Digital. DCB0084: OPCS-4.9 Requirements Specification, 2019.
[37] Adam Paszke, Sam Gross, Francisco Massa, et al. PyTorch: An Imperative Style, High-Performance Deep Learning Library. In *Advances in Neural Information Processing Systems 32*, pages 8024–8035. Curran Associates, Inc., 2019.

[38] Tom J Pollard, Alistair E W Johnson, Jesse D Raffa, Leo A Celi, Roger G Mark, and Omar Badawi. The eICU Collaborative Research Database, A Freely Available Multi-Center Database for Critical Care Research. *Scientific Data*, 5(1):180178, 2018.

[39] Niranjani Prasad, Li-Fang Cheng, Corey Chivers, Michael Draugelis, and Barbara E. Engelhardt. A Reinforcement Learning Approach to Weaning of Mechanical Ventilation in Intensive Care Units. *CoRR*, abs/1704.06300, 2017.

[40] S. Purushotham, C. Meng, Z. Che, and Y. Liu. Benchmarking Deep Learning Models on Large Healthcare Datasets. *Journal of Biomedical Informatics*, 83:112–134, 2018.

[41] Alvin Rajkomar, Eyal Oren, Kai Chen, et al. Scalable and Accurate Deep Learning with Electronic Health Records. In *npj Digital Medicine*, 2018.

[42] John Rapoport, Daniel Teres, Yonggang Zhao, and Stanley Lemeshow. Length of Stay Data as a Guide to Hospital Economic Performance for ICU Patients. *Medical Care*, 41:386–397, 2003.

[43] Yulia Rubanova, Ricky T. Q. Chen, and David Duvenaud. Latent odes for irregularly-sampled time series. *NeurIPS*, abs/1907.03907, 2019.

[44] Robert Schmidt, Sandra Geisler, and Cord Spreckelsen. Decision Support for Hospital Bed Management Using Adaptable Individual Length of Stay Estimations and Shared Resources. *BMC Medical Informatics and Decision Making*, 13(1):3, 2013.

[45] Mark Sendak, Madeleine Clare Elish, Michael Gao, Joseph Futoma, William Ratliff, Marshall Nichols, Armando Bedoya, Suresh Balu, and Cara O’Brien. “the human body is a black box”: Supporting clinical decision-making with deep learning. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, FAT* ’20, page 99–109, New York, NY, USA, 2020. Association for Computing Machinery.

[46] Seyedmostafa Sheikhalishahi, Eevake Balaraman, and Venet Osmani. Benchmarking Machine Learning Models on eICU Critical Care Dataset, 2019.

[47] Benjamin Shickel, Tyler J. Loftus, Lasith Adhikari, Tezcan Ozrazgat-Baslanti, Azra Bihorac, and Parisa Rashidi. DeepSOFA: A Continuous Acuity Score for Critically Ill Patients using Clinically Interpretable Deep Learning. In *Scientific Reports*, 2019.

[48] Huan Song, Deepta Rajan, Jayaraman J. Thiagarajan, and Andreas Spanias. Attend and Diagnose: Clinical Time Series Analysis using Attention Models. In 32nd AAAI Conference on Artificial Intelligence, AAAI 2018, pages 4091–4098. AAAI press, 2018.

[49] Mani Sotoodeh and Joyce C. Ho. Improving Length of Stay Prediction using a Hidden Markov Model. *AMIA Joint Summits on Translational Science*, 2019:425–434, 2019.

[50] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Dropout: A Simple Way to Prevent Neural Networks from Overfitting. *Journal of Machine Learning Research*, 15:1929–1958, 2014.

[51] Harini Suresh, Nathan Hunt, Alistair E. W. Johnson, Leo Anthony Celi, Peter Szolovits, and Marzyeh Ghassemi. Clinical Intervention Prediction and Understanding with Deep Neural Networks. In *MLHC*, 2017.

[52] Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott E. Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. Going Deeper with Convolutions. *CoRR*, abs/1409.4842, 2014.

[53] Nenad Tomašev, Xavier Glorot, Jack W Rae, et al. A Clinically Applicable Approach to Continuous Prediction of Future Acute Kidney Injury. *Nature*, 572(7767):116–119, 2019.
[54] Sana Tonekaboni, Mjaye Mazwi, Peter Laussen, Danny Eytan, Robert Greer, Sebastian D. Goodfellow, Andrew Goodwin, Michael Brudno, and Anna Goldenberg. Prediction of Cardiac Arrest from Physiological Signals in the Pediatric ICU. In MLHC, 2018.

[55] Aäron van den Oord, Sander Dieleman, Heiga Zen, Karen Simonyan, Oriol Vinyals, Alex Graves, Nal Kalchbrenner, Andrew W. Senior, and Koray Kavukcuoglu. WaveNet: A Generative Model for Raw Audio. CoRR, abs/1609.03499, 2016.

[56] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, undefinedukasz Kaiser, and Illia Polosukhin. Attention is all you need. In Proceedings of the 31st International Conference on Neural Information Processing Systems, NIPS’17, page 6000–6010. Curran Associates Inc., 2017.

[57] David J. Wallace, Derek C. Angus, Christopher W. Seymour, Amber E. Barnato, and Jeremy M. Kahn. Critical Care Bed Growth in the United States. A Comparison of Regional and National Trends. American Journal of Respiratory and Critical Care Medicine, 191(4):410–416, 2015. PMID: 25522054.

[58] Zhongyuan Wang, Peng Yi, Kui Jiang, Junjun Jiang, Zhen Han, Tao Lu, and Jiayi Ma. Multi-memory convolutional neural network for video super-resolution. IEEE Transactions on Image Processing, PP:1–1, 12 2018. doi: 10.1109/TIP.2018.2887017.

[59] World Health Organisation. ICD-10: International Statistical Classification of Diseases and Related Health Problems, volume 10th Revision. World Health Organisation, 2011.

[60] Tahmina Zebin, Shahadate Rezvy, and Thierry Chaussalet. A Deep Learning Approach for Length of Stay Prediction in Clinical Settings from Medical Records. In 2019 IEEE Conference on Computational Intelligence in Bioinformatics and Computational Biology (CIBCB), pages 1–5, 2019.

[61] David Zimmerer, Jens Petersen, Gregor Köhler, Jakob Wasserthal, Tim Adler, Sebastian Wirkert, and Tobias Ross. trixi - Training and Retrospective Insight eXperiment Infrastructure. https://github.com/MIC-DKFZ/trixi, 2017.

[62] Jack E Zimmerman, Andrew A Kramer, Douglas S McNair, and Fern M Malila. Acute Physiology and Chronic Health Evaluation (APACHE) IV: Hospital Mortality Assessment for Today’s Critically Ill Patients. Read Online: Critical Care Medicine | Society of Critical Care Medicine, 34(5), 2006.
A Feature Pre-processing

A.1 Static Features

The 17 static features are shown in Table 2. Discrete and continuous variables were scaled to the interval [-1, 1], using the 5th and 95th percentiles as the boundaries, and absolute cut offs were placed at [-4, 4]. This was to protect against large or erroneous inputs, while avoiding assumptions about the variable distributions. Binary variables were coded as 1 and 0. Categorical variables were converted to one-hot encodings.

Table 2: Static features. Age >89, Null Height and Null Weight were added as indicator variables to indicate when the age was more than 89 but has been capped, and when the height or weight were missing and have been imputed with the mean value.

| Feature              | Type     | Source Table |
|----------------------|----------|--------------|
| Gender               | Binary   | patient      |
| Age                  | Discrete | patient      |
| Hour of Admission    | Discrete | patient      |
| Height               | Continuous | patient      |
| Weight               | Continuous | patient      |
| Ethnicity            | Categorical | patient      |
| Unit Type            | Categorical | patient      |
| Unit Admit Source    | Categorical | patient      |
| Unit Visit Number    | Categorical | patient      |
| Unit Stay Type       | Categorical | patient      |
| Num Beds Category    | Categorical | hospital     |
| Region               | Categorical | hospital     |
| Teaching Status      | Binary   | hospital     |
| Physician Speciality | Categorical | apachepatientresult |
| Age >89              | Binary   |              |
| Null Height          | Binary   |              |
| Null Weight          | Binary   |              |

A.2 Diagnoses

Like many EHRs, diagnosis coding in eICU is hierarchical. At the lowest level they can be quite specific e.g. “neurologic | disorders of vasculature | stroke | hemorrhagic stroke | subarachnoid hemorrhage | with vasospasm”. To maintain the hierarchical structure within a flat vector, we assigned separate features to each hierarchical level and use binary encoding. This produces a vector of size 4,436 with an average sparsity of 99.5% (only 0.5% of the data is positive). We apply a 1% prevalence cut-off on all these features to reduce the size of the vector to 293 and the average sparsity to 93.3%. If a disease does not make the cut-off for inclusion, it is still included via any parent classes that do make the cut-off (in the above example we record everything up to “subarachnoid hemorrhage”). We only included diagnoses that were recorded before the 5th hour in the ICU, to avoid leakage from the future.

Many diagnostic and interventional coding systems are hierarchical in nature: ICD-10 classification [59], Clinical Classifications Software [11], SNOMED CT [10] and OPCS Classification of Interventions and Procedures [36], so this technique is generalisable to other coding systems present in EHRs.

A.3 Time Series

For each admission, 87 time-varying features (Table 3) were extracted from each hour of the ICU visit, and up to 24 hours before the ICU visit. The variables were processed in the same manner as the static features. In general, the sampling is very irregular, so the data was re-sampled according to one hour intervals and forward-filled. After forward-filling is complete, any data recorded before the ICU admission is removed. Decay indicators are added as described in Section 4.
Table 3: Time Series features. ‘Time in the ICU’ and ‘Time of day’ were not part of the tables in eICU but were added later as helpful indicators to the model.

| Source Table | lab | respiratory charting |
|--------------|-----|----------------------|
| -basos | MPV | glucose  | Exhaled MV |
| -eos | O2 Sat (%) | lactate | Exhaled TV (patient) |
| -lymphs | PT | magnesium | LPM O2 |
| -monos | PT - INR | pH | Mean Airway Pressure |
| -polys | PTT | paCO2 | Peak Insp. Pressure |
| ALT (SGPT) | RBC | paO2 | PEEP |
| AST (SGOT) | RDW | phosphate | Plateau Pressure |
| BUN | WBC x 1000 | platelets x 1000 | Pressure Support |
| Base Excess | albumin | potassium | RR (patient) |
| FiO2 | alkaline phos. | sodium | SaO2 |
| HCO3 | anion gap | total bilirubin | TV/kg IBW |
| Hct | bedside glucose | total protein | Tidal Volume (set) |
| Hgb | bicarbonate | troponin - I | Total RR |
| MCH | calcium | urinary specific gravity | Vent Rate |
| MCHC | chloride | | |
| MCV | creatinine | | |
| nursecharting | | | |
| Bedside Glucose | cvp | noninvasediastolic | Time in the ICU |
| Delirium Scale/Score | heartrate | noninvasivemean | Time of day |
| Glasgow coma score | respiration | noninvasivesystolic | |
| Heart Rate | s2o | | |
| Invasive BP | st1 | | |
| Non-Invasive BP | st2 | | |
| O2 Admin Device | st3 | | |
| O2 L/% | systemicdiastolic | | |
| O2 Saturation | systemicmean | | |
| Pain Score/Goal | systemicsystolic | | |
| Respiratory Rate | | | |
| Sedation Score/Goal | | | |
| Temperature | | | |

B Hyperparameter Search Methodology and Implementation Details

Our model and its baselines have hyperparameters that can broadly be split into three categories: time series specific, non-time series specific and global parameters (shown in more detail in Tables 4, 5 and 6). The hyperparameter search ranges have been included in Table 7. First, we ran 25 randomly sampled hyperparameter trials on the TPC model to decide the non-time series specific parameters (diagnosis embedding size, final fully connected layer size, batch normalisation strategy and dropout rate) keeping all other parameters fixed. These parameters then remained fixed for all the models which share their non-time series specific architecture. We ran 50 hyperparameter trials to optimise the remaining parameters for the TPC, standard LSTM, and Transformer models. To train the channel-wise LSTM and the temporal model with weight sharing, we ran a further 10 trials to re-optimise the hidden size (8 per feature) and number of temporal channels (32 channels shared across all features) respectively. For all other ablation studies and variations of each model, we kept the same hyperparameters where applicable (see Table 1 for a full list of all the models). The number of epochs was determined by selecting the best validation performance from a model trained over 50 epochs. This was different for each model: 8 for LSTM, 30 for CW LSTM, and 15 for the Transformer and TPC models. We noted that the best LSTM hyperparameters were similar to that found in Sheikhhalishahi et al. [46].

All deep learning methods were implemented in PyTorch [37] and were optimised using Adam [28]. The data (including decay indicators) and the non-time series components of the models were the
same as in TPC (Figure 3a). We used trixi to structure our experiments and easily compare different hyperparameter choices [61]. The experiments were performed using resources provided by the Cambridge Tier-2 system operated by the University of Cambridge Research Computing Service (www.hpc.cam.ac.uk) funded by EPSRC Tier-2 capital grant EP/P020259/1.

Table 4: The TPC model has 11 hyperparameters (Main Dropout and Batch Normalisation have been repeated in the table because they apply to multiple parts of the model). We allowed the model to optimise a custom dropout rate for the temporal convolutions because they have fewer parameters and might need less regularisation than the rest of the model. The best hyperparameter values are shown in brackets. Hyperparameters marked with * were fixed across all of the models.

| TPC Specific       | Pointwise Specific |
|--------------------|--------------------|
| Temp. Channels (12)| Point. Channels (13)|
| Temp. Dropout (0.05)| Main Dropout* (0.45)|
| Kernel Size (4)    | Batch Normalisation* (True)|
| No. TPC Layers (9) |                    |

| Non-TPC Specific       | Global Parameters |
|------------------------|-------------------|
| Diag. Embedding Size* (64)| Batch Size (32) |
| Main Dropout* (0.45)    | Learning Rate (0.00226)|
| Final FC Layer Size* (17)| Batch Normalisation* (True)|

Table 5: The LSTM model has 9 hyperparameters. We allowed the model to optimise a custom dropout rate for the LSTM layers. Note that batch normalisation is not applicable to the LSTM layers. The best hyperparameter values are shown in brackets. Hyperparameters marked with * were fixed across all of the models.

| LSTM Specific       | Non-LSTM Specific  | Global Parameters |
|--------------------|--------------------|-------------------|
| Hidden State (128) | Diag. Embedding Size* (64)| Batch Size (512) |
| LSTM Dropout (0.2) | Main Dropout* (0.45)    | Learning Rate (0.00129)|
| No. LSTM Layers (2)| Final FC Layer Size* (17)| Batch Normalisation* (True)|

B.1 Transformer

Table 6: The Transformer model has 12 hyperparameters. We allowed the model to optimise a custom dropout rate for the Transformer layers. The positional encoding hyperparameter is binary; it determines whether or not we used the original positional encodings proposed by Vaswani et al. [56]. They were not found to be helpful (perhaps because we already have a feature to indicate the position in the time series (Section A.3)). Note that batch normalisation is not applicable to the Transformer layers (the default implementation uses layer normalisation). The best hyperparameter values are shown in brackets. Hyperparameters marked with * were fixed across all of the models.

| Transformer Specific | Non-Transformer Specific | Global Parameters |
|----------------------|--------------------------|-------------------|
| No. Attention Heads (2) | Diag. Embedding Size* (64)| Batch Size (32) |
| Feedforward Size (256) | Main Dropout* (0.45)    | Learning Rate (0.00017)|
| $d_{model}$ (16)      | Final FC Layer Size* (17)| Batch Normalisation* (True)|
| Positional Encoding (False) |                      |                   |
| Transformer Dropout (0) |                          |                   |
| No. Transformer Layers (6) |                          |                   |

The Transformer is a multi-head self-attention model, originally designed for sequence-to-sequence tasks in natural language processing. It consists of both an encoder and decoder, however we only
use the former because the LoS task is regression. Our implementation is the same as the original encoder in Vaswani et al. [56], except that we add temporal masking to impose causality\(^\text{11}\), and we omit the positional encodings because they were not helpful for the LoS task.

Table 7: Hyperparameter Search Ranges. We took a random sample from each range and converted to an integer if necessary. For the kernel sizes (not shown in the table) the range was dependent on the number of TPC layers selected (because large kernel sizes combined with a large number of layers can have an inappropriately wide range as the dilation factor increases per layer). In general the range of kernel sizes was around 2-5 (but it could be up to 10 for small numbers of TPC Layers).

| Hyperparameter                             | Lower | Upper | Scale  |
|--------------------------------------------|-------|-------|--------|
| Batch Size                                 | 4     | 512   | log\(_2\) |
| Dropout Rate (all)                         | 0     | 0.5   | Linear |
| Learning Rate                              | 0.0001| 0.01  | log\(_{10}\) |
| Batch Normalisation                        | True  | False |        |
| Positional Encoding                       | True  | False |        |
| Diagnosis Embedding Size                   | 16    | 64    | log\(_2\) |
| Final FC Layer Size                        | 16    | 64    | log\(_2\) |
| Channel-Wise LSTM Hidden State Size        | 4     | 16    | log\(_2\) |
| Point. Channels                            | 4     | 16    | log\(_2\) |
| Temp. Channels                             | 4     | 16    | log\(_2\) |
| Temp. Channels (weight sharing)            | 16    | 64    | log\(_2\) |
| LSTM Hidden State Size                     | 16    | 256   | log\(_2\) |
| \(d_{\text{model}}\)                      | 16    | 256   | log\(_2\) |
| Feedforward Size                           | 16    | 256   | log\(_2\) |
| No. Attention Heads                        | 1     | 12    | Linear |
| No. TPC Layers                             | 1     | 4     | Linear |
| No. LSTM Layers                            | 1     | 10    | Linear |

C Evaluation Metrics

The metrics we use are: mean absolute deviation (MAD), mean absolute percentage error (MAPE), mean squared error (MSE), mean squared loss error (MSLE), coefficient of determination (\(R^2\)) and Cohen Kappa Score. We modify the MAPE metric slightly so that very small true LoS values do not produce unbounded MAPE values. We place a 4 hour lower bound on the divisor i.e.

\[
\text{Absolute Percentage Error} = \frac{|y_{\text{true}} - y_{\text{pred}}|}{\max \left( \frac{y_{\text{true}}}{4}, \frac{4}{24} \right)} \times 100
\]

MAD and MAPE are improved by centering predictions on the median. Likewise, MSE and \(R^2\) are bettered by centering predictions around the mean. They are more affected by the skew. MSLE is a good metric for this task, indeed, it is the loss function in most experiments, but is less readily-interpretable than some of the other measures. Cohen’s linear weighted Kappa Score [8] is intended for ordered classification tasks rather than regression, but it can effectively mitigate for skew if the bins are chosen well. It has previously provided useful insights in Harutyunyan et al. [20], so we use the same LoS bins: 0-1, 1-2, 2-3, 3-4, 4-5, 5-6, 6-7, 7-8, 8-14, and 14+ days. As a classification measure, it will treat everything falling within the same classification bin as equal, so it is fundamentally a coarser measure than the other metrics.

To illustrate the importance of using multiple metrics, consider that the mean and median models are in some sense equally poor (neither has learned anything meaningful for our purposes). Nevertheless, the median model is able to better exploit the MAD, MAPE and MSLE metrics, and the mean model fares better with MSE, but the Kappa score betrays them both. A good model will perform well across all of the metrics.

\(^{11}\)The processing of each timepoint can only depend on current or earlier positions in the sequence
D Additional Investigations

D.1 Time Series Ablation

Table 8: Performance of the TPC model and its baselines when only some of the time series are included. The indicator ‘(labs)’ means that the model has been trained exclusively on laboratory tests, ‘(other)’ refers to everything except labs: vital signs, nurse observations and machine logged variables. The metric acronyms, colour scheme and confidence interval calculation is described in the legend to Table 1. The percentage impairment when compared to the complete dataset is shown in grey underneath the absolute values. They are calculated with respect to the best value for the metric: 0 for MAD, MAPE, MSE and MSLE, and 1 for $R^2$ and Kappa. A large percentage impairment means that the model does much better with complete data i.e. it has a high ‘percentage gain’ from the combination of both data types compared to the ablation case.

| Model      | MAD    | MAPE   | MSE    | MSLE   | $R^2$ | Kappa  |
|------------|--------|--------|--------|--------|-------|--------|
| LSTM       | 2.39 ± 0.00 | 118.2 ± 1.1 | 26.9 ± 0.1 | 1.47 ± 0.01 | 0.09 ± 0.00 | 0.28 ± 0.00 |
| LSTM (labs)| 2.43 ± 0.00 | 123.8 ± 1.2 | 27.3 ± 0.1 | 1.57 ± 0.00 | 0.08 ± 0.00 | 0.27 ± 0.00 |
| LSTM (other)| 2.41 ± 0.00 | 120.2 ± 0.7 | 27.3 ± 0.1 | 1.49 ± 0.00 | 0.07 ± 0.00 | 0.27 ± 0.00 |
| CW LSTM    | 2.37 ± 0.00 | 114.5 ± 0.4 | 26.6 ± 0.1 | 1.43 ± 0.00 | 0.10 ± 0.00 | 0.30 ± 0.00 |
| CW LSTM (labs)| 2.42 ± 0.00 | 124.4 ± 0.7 | 27.0 ± 0.1 | 1.57 ± 0.00 | 0.08 ± 0.00 | 0.28 ± 0.00 |
| CW LSTM (other)| 2.41 ± 0.00 | 120.6 ± 0.8 | 27.1 ± 0.1 | 1.51 ± 0.00 | 0.08 ± 0.00 | 0.29 ± 0.00 |
| Transformer| 2.36 ± 0.00 | 114.1 ± 0.6 | 26.7 ± 0.1 | 1.43 ± 0.00 | 0.09 ± 0.00 | 0.30 ± 0.00 |
| Transformer (labs)| 2.42 ± 0.00 | 121.0 ± 0.7 | 27.3 ± 0.1 | 1.56 ± 0.00 | 0.07 ± 0.00 | 0.27 ± 0.00 |
| Transformer (other)| 2.40 ± 0.00 | 118.3 ± 0.6 | 27.3 ± 0.1 | 1.50 ± 0.00 | 0.07 ± 0.00 | 0.27 ± 0.00 |
| TPC        | 1.78 ± 0.02 | 63.5 ± 4.3 | 21.7 ± 0.5 | 0.70 ± 0.03 | 0.27 ± 0.02 | 0.58 ± 0.01 |
| TPC (labs) | 1.85 ± 0.01 | 72.0 ± 2.2 | 22.5 ± 0.2 | 0.81 ± 0.01 | 0.24 ± 0.01 | 0.55 ± 0.00 |
| TPC (other)| 1.81 ± 0.02 | 68.5 ± 4.7 | 21.8 ± 0.3 | 0.77 ± 0.03 | 0.26 ± 0.01 | 0.57 ± 0.01 |

We performed ablations on the type of time series variable that we include: laboratory tests only (labs), which are infrequently sampled, and all other variables (other) which include vital signs, nurse observations, and automatically recorded variables (e.g. from ventilator machines). This shows how well each model can cope with time series exhibiting different periodicity and sampling frequencies. The results are shown in Table 8.

The TPC model has the largest percentage gain when the labs and other variables are combined (this is synonymous with the greatest percentage impairment in the ablations). Next are the CW LSTM and Transformer, followed by the LSTM. This suggests that the TPC model is best able to exploit EHR time series with different temporal properties.

When examining the results for LSTM and CW LSTM in more detail, we can see that the CW LSTM only has an advantage when the model has to combine the data types. This supports the hypothesis that the CW LSTM is better able to cope when there are varying frequencies in the data, as it can tailor the processing to each. When the inter-feature variability is small (the same type of time series) they perform similarly.

It is unsurprising that the Transformer does better than the LSTM when combining data types, as it can directly skip over large gaps in time to extract a trend in lab values, while simultaneously attending to recent timepoints for the processing of other variables.

The TPC is the most successful model; its inherent periodic structure helps it to extract useful information from all of the variables. The CW LSTM and Transformer do not have this in their architectures, making the derivation more obscure. The importance of periodicity is discussed in more detail in Section 6.
D.2 Training Data Size

Researchers may wish to know how large their training data should be to benefit from using the TPC model. We tested the TPC, LSTM, CW LSTM, and Transformer models with 6.25%, 12.5%, 25%, 50%, and 100% of the training data. TPC maintains the best test performance on all data sizes, with an increasing benefit for larger data. Figure 8 shows the effect on MSLE. Table 9 shows the full results for all metrics.

Figure 8: The effect of changing the size of the training data on the LSTM, CW LSTM, Transformer, and TPC model performance. Only the mean squared logarithmic error (MSLE) is shown for clarity, however the other metrics are shown in Table 9. Note that the performance of the CW LSTM and Transformer models are so similar that the curves are superimposed.

Table 9: The effect of changing the size of the training data on the LSTM, CW LSTM, Transformer, and TPC model performance. A hundred percent of the training set represents 102,712 ICU stays, 50% is 51,356, 25% is 25,678, 12.5% is 12,839, and 6.25% is 6,420 stays.

| Model (% train data) | MAD ± | MAPE ± | MSE ± | MSLE ± | $R^2$ ± | Kappa ± |
|----------------------|-------|--------|-------|--------|--------|---------|
| LSTM (100)           | 2.39  | 118.2  | 26.9  | 1.47   | 0.09   | 0.28    |
| LSTM (50)            | 2.41  | 129.9  | 26.2  | 1.52   | 0.11   | 0.31    |
| LSTM (25)            | 2.44  | 126.8  | 27.2  | 1.58   | 0.08   | 0.27    |
| LSTM (12.5)          | 2.48  | 137.4  | 27.4  | 1.65   | 0.07   | 0.27    |
| LSTM (6.25)          | 2.52  | 135.9  | 28.0  | 1.71   | 0.05   | 0.26    |
| CW LSTM (100)        | 2.37  | 114.5  | 26.6  | 1.43   | 0.10   | 0.30    |
| CW LSTM (50)         | 2.40  | 123.4  | 26.5  | 1.48   | 0.10   | 0.31    |
| CW LSTM (25)         | 2.44  | 119.8  | 27.2  | 1.54   | 0.08   | 0.29    |
| CW LSTM (12.5)       | 2.50  | 134.7  | 27.7  | 1.63   | 0.06   | 0.28    |
| CW LSTM (6.25)       | 2.58  | 129.8  | 29.0  | 1.73   | 0.02   | 0.25    |
| Transformer (100)    | 2.36  | 114.1  | 26.7  | 1.43   | 0.09   | 0.30    |
| Transformer (50)     | 2.39  | 120.1  | 26.5  | 1.48   | 0.10   | 0.31    |
| Transformer (25)     | 2.43  | 117.9  | 27.2  | 1.54   | 0.08   | 0.28    |
| Transformer (12.5)   | 2.48  | 128.1  | 27.9  | 1.62   | 0.06   | 0.26    |
| Transformer (6.25)   | 2.52  | 139.7  | 27.8  | 1.69   | 0.06   | 0.26    |
| TPC (100)            | 1.78  | 63.5   | 21.7  | 0.70   | 0.27   | 0.58    |
| TPC (50)             | 1.95  | 72.0   | 23.8  | 0.87   | 0.19   | 0.51    |
| TPC (25)             | 2.09  | 89.0   | 24.8  | 1.09   | 0.16   | 0.45    |
| TPC (12.5)           | 2.28  | 101.4  | 27.0  | 1.36   | 0.08   | 0.35    |
| TPC (6.25)           | 2.49  | 139.9  | 28.0  | 1.64   | 0.05   | 0.28    |
Table 10: The effect of training with the mean squared logarithmic error (MSLE) loss function when compared to mean squared error (MSE). This is an extension to Table 1 (refer to its legend for definitions of the metric acronyms, detailed of CI calculations and meaning of the colour scheme).

| Model            | MAD    | MAPE   | MSE    | MSLE   | $R^2$   | Kappa   |
|------------------|--------|--------|--------|--------|---------|---------|
| LSTM (MSLE)      | 2.39±0.00 | 118.2±1.1 | 26.9±0.1 | 1.47±0.01 | 0.09±0.00 | 0.28±0.00 |
| LSTM (MSE)       | 2.57±0.03 | 235.2±6.2 | 24.5±0.2 | 1.97±0.02 | 0.17±0.01 | 0.28±0.02 |
| CW LSTM (MSLE)   | 2.37±0.00 | 114.5±0.4 | 26.6±0.1 | 1.43±0.00 | 0.10±0.00 | 0.30±0.00 |
| CW LSTM (MSE)    | 2.56±0.01 | 218.5±4.0 | 24.2±0.1 | 1.84±0.02 | 0.18±0.00 | 0.34±0.01 |
| Transformer (MSLE)| 2.36±0.00 | 114.1±0.6 | 26.7±0.1 | 1.43±0.00 | 0.09±0.00 | 0.30±0.00 |
| Transformer (MSE)| 2.51±0.01 | 212.7±5.2 | 24.7±0.2 | 1.87±0.03 | 0.16±0.01 | 0.28±0.01 |
| TPC (MSLE)       | 1.78±0.02 | 63.5±4.3  | 21.7±0.5 | 0.70±0.03 | 0.27±0.02 | 0.58±0.01 |
| TPC (MSE)        | 2.21±0.02 | 154.3±10.1| 21.6±0.2 | 1.80±0.10 | 0.27±0.01 | 0.47±0.01 |