# Temporal Pointwise Convolutional Networks for Length of Stay Prediction in the Intensive Care Unit Paper Reproduction Study

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Presentation link: TODO-youtube_link
Code link: https://github.com/weicheng113/DL4H-Project

## 1 Introduction

In this project we aim to replicate the paper "Temporal Pointwise Convolutional Networks for Length of Stay Prediction in the Intensive Care Unit" by Emma Rocheteau, Pietro Liò and Stephanie Hyland [1]. The original paper proposes a new model architecture named Temporal Pointwise Convolution (TPC) that combines temporal convolution and pointwise convolution, to predict the remaining length of stay of ICU patients in the eICU and MIMIC-IV datasets.

The authors claim that TPC mitigates many common challenges with Electronic Health Records, such as skewness, irregular sampling and missing data which results in significant improvement over traditional timeseries models like LSTM and Transformer.

## 2 Scope of reproducibility

Finetuned pretrained TPC model will have higher accuracy than a LSTM/transformer model trained on the eICU dataset.

### 2.1 Addressed claims from the original paper

The following claims will be tested:

- TPC has anywhere from 18% to 68% performance gain over the commonly used Long-Short Term Memory (LSTM) network, and the multi-head self-attention network known as the Transformer.

- Using mean-squared logarithmic error (MSLE) as the loss function to train length of stay models vastly increases the accuracy of the models as it deals more naturally with positively-skewed labels.

## 3 Methodology

### 3.1 Model descriptions

The task of the TPC model is to predict the length of stay of a patient in the ICU at different time points using the time series data such as heart-rate, diagnosis data such as blood glucose and other static features such as age and demographics.

The first part of TPC is the temporal convolution network where the output is the same length as input and it is casual which means for a given output index, it can only make use of inputs before that index. Temporal convolution outputs for each feature are concatenated.

The second part is the pointwise convolution which is a fully connected layer applied seperately to each timepoint. Here, weights are shared across all timepoints but there is no information transfer across time.

The image below shows the two parts of TPC:

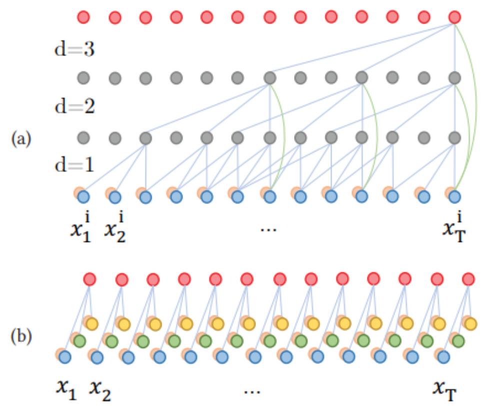


Figure 1: (a) Temporal convolution (b) Pointwise convolution.

This figure shows a layer of the TPC model:

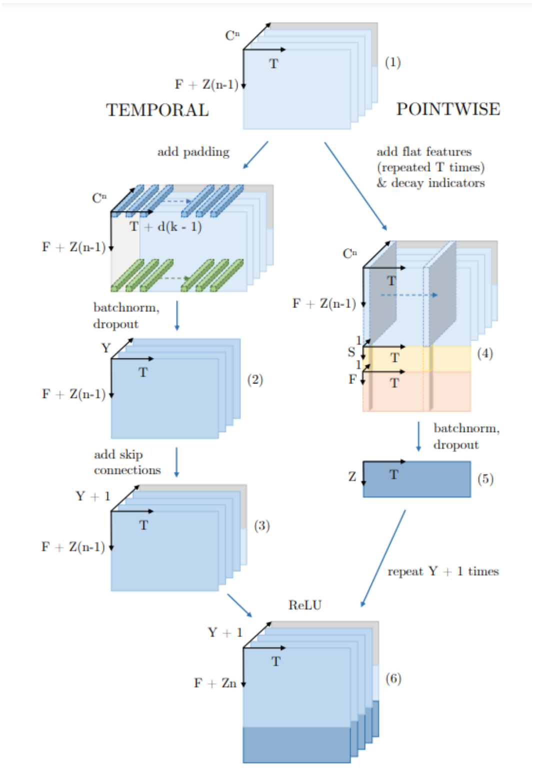


Figure 2: A layer of the TPC model.

The table below lists the parameters used by the TPC model and their default values:

| Parameter | Default value |
|---|---|
| Number of layers | 9 |
| Kernel size | 4 |
| No temporal kernels | 12 |
| Point size | 13 |
| Share weights | False |
| No skip connections | False |

Table 1: Default parameter values for the TPC model.

### 3.2 Data descriptions

We used the eICU Collaborative Research Database[2] which comprises of 200,859 patient unit encounters for 139,367 unique patients admitted to ICUs between 2014 and 2015. The following preprocessing steps were taken prior to using this data for model training:

- Adult patients (≥18 years) with an ICU length of stay of at least 5 hours and at least one recorded observation were selected.
- 87 time series were selected from the following tables: lab, nursecharting, respiratorycharting, vitalperiodic and vitalaperiodic.
- For a variable to be selected it had to be present in at least 12.5 % of patient stays, or 25% for lab variables.
- Missing data in time series data was forward-filled over the gaps.
- ‘decay indicators’ were added to specify where the data is stale.The decay was calculated as $0.75^j$ , where j is the time since the last recording .
- Diagnoses data was extracted from the pasthistory, admissiondx and diagnoses table and 17 static features from the patient, apachepatientresult and hospital tables.

The patients were divided as follows:

- Training set - 70%
- Validation set - 15%
- Testing set = 15%

The table below shows the cohort summary for the eICU dataset:

| | eICU |
|---|---|
| Number of patients | 118,535 |
| Train | 82,973 |
| Validation | 17,781 |
| Test | 17,781 |
| Number of stays | 146,671 |
| Train | 102,749 |
| Validation | 22,033 |
| Test | 21,889 |
| Gender (% male) | 2 54.1% |
| Age (mean) | 63.1 |
| LoS (mean) | 3.01 |
| LoS (median) | 1.82 |
| Remaining LoS (mean) | 3.47 |
| Remaining LoS (median) | 1.67 |
| In-hospital mortality | 9.25% |
| Number of input features | 104 |
| Time series | 87 |
| Static | 17 |

Table 2: Cohort summary for the eICU dataset.

### 3.3 Hyperparameters

TODO

### 3.4 Implementation

For the paper reproduction, we chose to use the author's code and made minor changes where necessary to make it run efficiently without any errors.

### 3.5 Computational requirements

We used AWS EC2 g4dn.2xlarge NVIDIA T4 GPU 16GB, 8 vCPUs and 16 GB memory for this project. It took about 4 hours to create the eICU database in PostgreSQL and required 60GB disk space to store it and an additional 8 hours to execute the preprocessing scripts. The size of the processed dataset is 21GB. We trained the TPC model on this processed data with a batch size of 64 for 15 epochs and it took about 8 to 10 hours.

## 4 Results

We trained the TPC model on the eICU dataset for 15 epochs and computed the evaluation metrics on the test dataset. It is compared with the values in the original paper. We were able to get the evaluation metrics within 10% of the authors values in this initial test run of the model.

| Paper | MAD | MAPE | MSE |
|---|---|---|---|
| Original | 1.78±0.02 | 63.5±4.3 | 21.7±0.5 |
| Replication | 1.968 | 57.354 | 24.152 |

Table 3: Result comparison for TPC model on eICU test data.

| Paper | MSLE | $R^2$ | KAPPA |
|---|---|---|---|
| Original | 0.70±0.03 | 0.27±0.02 | 0.58±0.01 |
| Replication | 0.665 | 0.311 | 0.601 |

Table 4: Result comparison for TPC model on eICU test data.

### 4.1 Result 1

TODO

### 4.2 Result 2

TODO

### 4.3 Additional results not present in the original paper

TODO

## 5 Discussion

TODO.

### 5.1 What was easy

TODO

### 5.2 What was difficult

TODO

### 5.3 Recommendations for reproducibility

TODO

## 6 Communication with original authors

TODO

## References


[1] Emma Rocheteau, Pietro Liò, and Stephanie Hyland. 2021. Temporal Pointwise Convolutional Networks for Length of Stay Prediction in the Intensive Care Unit. In ACM Conference on Health, Inference, and Learning (ACM CHIL '21), April 8–10, 2021, Virtual Event, USA. ACM, New York, NY, USA, 19 pages. https://doi.org/10.1145/3450439.3451860

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