Project Proposal for CS598 DL4H in Spring 2023

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1 Cite the original paper

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2 State the general problem the paper aims to solve

It is a central task in hospital operation and resources planning to reliably predict the length of stay for hospitalized patients, especially for those critically ill patients staying in the Intensive Care Unit (ICU). This paper aims to build a novel and reliable deep-learning predictive model for the length of stay in the ICU.

3 Describe the new and specific approach taken by the paper. Discuss why it is interesting or innovative

Historically, the two most popular models used for the length of stay prediction are LSTMs and Transformers due to the centrality of time series in the EHR (Sheikhalishahi et al., 2019; Song et al., 2018). More recently Temporal Convolutional Networks (TCN) were developed as a variation of CNN to handle sequential data (Bai et al., 2018). The key feature of TCNs is a structure of causal convolutions and dilated convolutions that enable possessing of very long history sizes. Compared to traditional RNNs, TCNs can be done in parallel and achieve more flexible receptive field sizes, while avoiding the problem of exploding/vanishing gradients.

Our selected paper described a novel Temporal Pointwise Convolution (TPC) model, which is based on the combination of temporal convolution networks and pointwise (1x1) convolution to predict ICU length of stay. The new model is specifically designed to handle common challenges with EHR, such as skewness, irregular sampling, and missing data. Of interest, the use of TCNs is to capture temporal trends of input features, while pointwise convolution models aim to characterize inter-feature relationships. Different than prior studies, the temporal convolution filters in this paper do not share parameters between features, therefore allowing the model to optimize the process despite heterogeneity and missing data in the temporal characteristics. The model also enables flexible selection of temporal receptive field sizes (independently for each feature) because of the skip connections.

4 Identify the specific hypotheses we plan to verify in your reproduction study

1. The TPC model significantly outperforms the commonly used LSTM and Transformer models for ICU length of stay prediction by margins of 18-68%.

2. The use of mean-squared logarithmic error (MSLE) loss function instead of commonly used mean squared error (MSE) loss will lead to better model performance, as the former handles positively-skewed labels more naturally.

3. The data processing pipeline developed by the authors for the eICU and MIMIC-IV databases could mitigate the common problems of sparsity and missing data in the EHR and the approach is generalizable to other EHR databases.

5 Outline any additional ablations we plan to do and explain why they are interesting

1. We plan to explore whether certain differences in model architecture would impact its performance. In particular, we plan to compare the performance of the TPC model, temporal-only model, pointwise-only model, temporal-only model with weight sharing, and TPC model without skip connections. Such analysis would be interesting as it would demonstrate the true key components leading to performance improvement in the TPC model, while also shed light on the model's interpretability.

2. We plan to test the model when training on datasets of different sizes that include various input features. This analysis is interesting as in the real life of hospital operation, ICU length of stay is a clinical question for physicians to answer based on several relevant diagnostic information, therefore inclusion of different features (relevant or not) might notably impact model performance.

6 Explain how we have access to the necessary data

The paper used the eICU Collaborative Research Database v2.0 and MIMIC-IV v0.4 Database, both available through PhysioNet. We have got access to the datasets by following these steps:

1. Complete the required training CITI "Data or Specimens Only Research" course.

2. Request accesses to the eICU Collaborative Research Database/MIMIC-IV Database.
   - eICU: https://physionet.org/content/eicu-crd/2.0/
   - MIMIC-IV: https://physionet.org/content/mimiciv/0.4/

3. Download csv tables and set up local Postgres databases to access them by leveraging existing codes.
   - eICU: https://github.com/MIT-LCP/eicu-code/tree/master/build-db/postgres
   - MIMIC-IV: https://github.com/EmmaRocheteau/MIMIC-IV-Postgres

7 Discuss the computational feasibility of your proposed work

The paper did not explicitly mention the computational resources and training time used, except for the mention of utilizing resources provided by the Cambridge Tier-2 system.

However, we have experienced slow processing and limited memory issues using our own laptops. The storage requirement for the eICU and MIMIC-IV4 databases is around 60 GB, and running a test of the basic TPC model on a laptop without GPU takes approximately 2.5 days.

To overcome these limitations, we plan to utilize free computing resources such as Google Colab, AWS, and others. By taking advantage of the powerful GPUs and TPUs available on these platforms, we hope to significantly reduce our model's training time and enable us to experiment with more complex models and larger datasets. If our datasets exceed the free resources available after preprocessing or the runtime exceeds the free limit, we may need to limit our sample size or consider other paid services.

8 Specify if we will be re-using existing code and provide a link to it, or if we will implement the code yourself

To preprocess the data, we intend to make use of the code provided by the author (https://github.com/EmmaRocheteau/TPC-LoS-prediction). After conducting preliminary testing on our local machine, we have determined that the existing code requires some refactoring to be fully functional.

As for the new experiments on top of TPC model, we plan to write new code that work in synergy with existing code. We have already established communication with the first author.

In addition, we must ensure that our code is optimized for parallel computing to make efficient use of the available resources.

References

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