SELF-SUPERVISED PREDICTIVE CODING AND MULTIMODAL FUSION ADVANCE PATIENT DETERIORATION PREDICTION IN FINE-GRAINED TIME RESOLUTION

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ABSTRACT

In the Emergency Department (ED), accurate prediction of critical events using Electronic Health Records (EHR) allows timely intervention and effective resource allocation. Though many studies have suggested automatic prediction methods, their coarse-grained time resolutions limit their practical usage. Therefore, in this study, we propose an hourly prediction method of critical events in ED, i.e., mortality and vasopressor need. Through extensive experiments, we show that both 1) bi-modal fusion between EHR text and time-series data and 2) self-supervised predictive regularization using \(L_2\) loss between normalized context vector and EHR future time-series data improve predictive performance, especially the far-future prediction. Our uni-modal/bi-modal/bi-modal self-supervision scored 0.846/0.877/0.897 (0.824/0.855/0.886) and 0.817/0.820/0.858 (0.807/0.81/0.855) with mortality (far-future mortality) and with vasopressor need (far-future vasopressor need) prediction data in AUROC, respectively.

Index Terms— Self-supervision, predictive coding, multi-modal fusion, EHR, time-series prediction

1. INTRODUCTION

In the emergency department (ED) and intensive care unit (ICU), early prediction of clinically critical events is crucial to make timely interventions for deteriorating patients. Particularly, early mortality event prediction can produce precise prioritization of high-risk patients followed by an efficient resource allocation [1]. Early prediction of vasopressor need can help clinicians efficiently prepare for an urgent vasopressor administration [2]. As a result, many studies have reported their early prediction systems using Electronic Health Records (EHR) [1,2,3].

Reported studies, however, make predictions in coarse-grained time resolution: 1) predicting vasopressor need within 24/48 hour [4,5] and within 6-10 hours [6] and 2) predicting mortality within 24/48 hours [4] and within the whole hospitalization period [1,7]. Prediction over a coarse-grained time resolution can be impractical where timely decision-making and rapid intervention are crucial.

Other studies utilized multi-modal EHR data, such as Wang et al. [1] with physiological index, treatment records, and hospitalization records to predict mortality or Suresh et al. [6] with demographic data, vital signs/lab tests, and clinical notes for intervention prediction. However, the benefit of the adding modalities was uncertain, since these studies reported the performance of the multi-modal model without comparing it to the uni-modal model.

Our main contributions are as follows: 1) to predict the mortality and vasopressor need of urgent patients, we propose a fine-grained time deterioration prediction method for the first time in the literature; 2) we explore various future encoding methods and losses for self-supervised learning (SSL) predictive coding for deterioration prediction (Fig.2); 3) through an extensive experiment, we show that both multimodal fusion and SSL predictive coding regularization using \(L_2\) loss and normalized context vector improve the predictive performance, especially far-future prediction, which is crucial but more challenging than near-future prediction [2,8].

2. METHODS

Fig.1 illustrates the overall scheme of our network. We conduct four different studies: 1) selecting a uni-modal (numeric) model, 2) selecting a bi-modal (numeric + text) fusion strategy, 3) comparing various SSL losses, and 4) selecting the method to encode the future EHR numeric data for SSL. For each study, we select the best-performing one and fix it for the remaining studies to assess the efficacy of the added component, e.g., additional modality or SSL loss (Fig. 3). We conduct every study for both mortality and vasopressor need prediction data. For a fair comparison, we fix all Transformer-based models to equally have 8 transformer layers, 4 multi-heads, and 256 feature dimensions (Fig.1(b)).

2.1. Electronic Health Record Data

To simulate an urgent hospital environment, we used the MIMIC-ED and MIMIC-IV (Medical Information Mart for Intensive Care in Emergency Department and IV) datasets [9,10]. Since both datasets share the same patients, we merged chief complaints from MIMIC-ED (text data) and
a total of 18 different time-series features from MIMIC-IV (numeric data), i.e., vital signs, lab-test results, and demographic features (age and gender). Vital-sign includes heart rate, respiration rate, and 4 other items. Lab-tests includes Hematocrit, Platelet, and 8 more items. We labeled the occurrence of mortality and vasopressor usage in binary. The sampling frequency for the time-series data is 1 hour, and we applied carry-forward imputation for missing features. The input time length varies from 3 to 24 hours to 1) challenge the prediction for patients shortly after admission and 2) simulate varying ED environments [11]. We used zero-padding to fix the input data length as 24 hours and only considered patients who had ICU stays of 15 to 1440 hours.

To select the best-performing model for the four studies (Table 2), we used the averaged validation area under the receiver operating characteristic (AUROC) from 5-fold cross-validation (CV). To assess the efficacy of the additional component, i.e. text data and SSL, we compared the averaged test AUROC from the 5-fold CV of the best-performing uni-modal, bi-modal, and the model trained with SSL (Fig. 3).

Table 1: Data statistics with patient numbers for mortality prediction and vasopressor need prediction tasks.

| Tasks       | Mortality | Vasopressor |
|-------------|-----------|-------------|
| Data Split  | Train / Test | Train / Test |
| Positive Subjects | 2544 / 262 | 5827 / 606 |
| Negative Subjects | 24492 / 2836 | 21941 / 2580 |

2.2. Uni-modal Model for EHR Numeric Data

We explored four different models: GRU-D [12], LSTM, Transformer [13], and Graph Transformer [7]. All four models map time-series numeric data (vital-signs, lab tests, demographics) $x_{\leq t} \in \mathbb{R}^{18 \times T_i}$, ($T_i = 24$ in our study) into a context vector $c_t \in \mathbb{R}^{256}$, which is then mapped to 12 probabilities for our 12-hour fine-grained time prediction. For mapping, we use 12 distinct 2-layer MultiLayer perceptron (MLP) with batch normalization and ReLU non-linearities between the 2 linear layers, followed by a sigmoid function. Both GRU-D and LSTM receive the raw input $x_{\leq t}$, whereas both Transformer and Graph Transformer receive the encoded input $z_{\leq t}$, which is $x_{\leq t}$ encoded by the 2-layer MLP with Layer Normalization (LN) and ReLU activation, to output the context vector $c_t$ (CLS token vector) (Fig. 1(a)).

2.3. Bi-modal Fusion Strategy for EHR Text Data

Alike the best-performing uni-modal model (Table 2), we use the vanilla Transformer with BERT tokenization [14] for EHR text data. We fuse the outcomes of the $L_f$-th layer of the text and numeric Transformers (Fig. 1(b)); we refer the early and mid fusion to the fusions that occur after the 0-th (before Transformer) and 4-th layer of the Transformers of text and numeric data (Fig. 1(b)). Note that we rigorously explore the early and mid fusion due to the poor performance of the late fusion (fusion after 9-th layer) during our preliminary experiment. Moreover, we experimented with three different types of fusion methods: 1) Multimodal Bottleneck Transformer (MBT) [15], 2) Multimodal-Transformer (MT) [15], 3) Bi-Cross Modal Attention Transformer (BCMAT) [16]. MBT, MT, and BCMAT respectively utilize the fusion bottleneck (FSN) tokens [15], concatenation, and attention fusion after the $L_f$-th layer. Specifically, MBT creates and lets two Transformers share four new FSN tokens after the $L_f$-th layer of the text and numeric Transformers. MT concatenates the outcomes of the $L_f$-th layer of both Transformers. BCMAT uses two parallel attention fusions; after $L_f$-th layer, one Transformer uses its outcome as both the key and value and the outcome of the other Transformer as the query, and vice versa for the other fusion.
2.4. Self-supervised Regularization

For time-series data, Oord et al. [17] introduced Contrastive Predictive Coding (CPC) which self-supervises networks to encourage capturing global information, i.e. ‘slow feature’, using Noise Contrastive Estimation (NCE). Moreover, Wanyan et al. [4] and Zang et al. [18] proposed to regularize networks by adding a SSL loss to the supervision loss. Motivated by these studies, we regularize our bi-modal network using CPC whose loss can be described as Eq. 1:

$$\mathcal{L}_{\text{NCE}} = -E_x \left[ \log \frac{\exp(z_{t+k}^T W_k c_t)}{\sum_{j > t} \exp(z_j^T W_k c_t)} \right]$$  (1)

$$\mathcal{L}_{\text{cosine}} = -\frac{\|z_{t+k}\|_2 \cdot \|W_k c_t\|_2}{\|z_{t+k}\|_2 \cdot \|W_k c_t\|_2}$$  (2)

$$\mathcal{L}_{L_2} = ||z_{t+k} - W_k c_t||_2$$  (3)

However, since we add supervision loss to SSL loss (NCE), we assume the model will not converge to a trivial solution (model collapse) even if the SSL loss does not contain negative pairs. Therefore, we also implement cosine (Eq. 2) and $L_2$ loss (Eq. 3) alongside NCE. In the equations above, $c_t$ refers to the context vector (Fig. 1-(a)) from the bi-modal fusion Transformer. We use linear transformation $W_k c_t$ for SSL prediction where different $W_k$ is used for different time step $k$. In this study, we use 12 distinct $W_k$ to concurrently predict 12 encoded future numeric $z_{t+1}$, $z_{t+2}$, ..., $z_{t+12}$. Note that, the encoder for the past numeric $x_{<t}$ encodes 12 distinct future numeric $x_{>t}$ as well. Since we maximize the mutual information (MI) between linearly transformed context vectors and 12 distinct $z_{>t}$, which share the same encoder, the encoder is encouraged to learn the information shared across all time points; we assume this ‘slow feature’ encourages far-future prediction. For $L_2$ loss of $MT_{\text{early}}$ (mortality prediction), we explore additional LN to normalize $c_t$, because $L_2$ loss from unnormalized $c_t$ is large in its value compared to supervision loss ($MBT_{\text{early}}$ does not need additional LN since its context vector is already normalized).

2.5. Encoding Future Numeric Data for Self-supervision

The original CPC paper proposes to maximize MI between context vector $c_t$ and encoded future numeric $z_{t+k}$ (Fig. 2(b)) instead of using raw future numeric $x_{t+k}$ (Fig. 2(a)). Its aim is to avoid modeling the high dimensional distribution of the raw data $x_{t+k}$. However, our raw data $x_{t+k}$ has lower dimensions than the encoded data $z_{t+k}$. Therefore, we hypothesized that modeling the raw future numeric may outperform modeling the encoded future numeric. We also experimented encouraging similarity between the context vectors of the past and future (Fig. 2(c)). We compare the performance of these three SSL structures (Fig. 2) in Sec. 3.3.

3. RESULTS AND DISCUSSION

3.1. Transformer works better than other alternatives for learning EHR numeric data

As shown in Table 2, the vanilla Transformer outperforms all other alternatives to predict mortality and vasopressor need in a fine-grained time course. Note that the vanilla Transformer excels over the Graph Transformer suggesting that learning temporal relationships is more important than learning inter-feature relationships. All four models show gradual degradation in performance when predicting further in the future, which reflects the difficulty in far-future prediction.

3.2. EHR text enhances far-future mortality prediction

Early fusion of EHR text data improves both tasks though more improvement is shown in mortality prediction (Table 2). Specifically, feature concatenation (MT) benefits mortality prediction the most, whereas MBT improves the vasopressor need task the most. Note that by fusing EHR text data for mortality prediction, more improvement is made as prediction time gets further in the future, which is consistent throughout all six fusion strategies. We assume that since the chief complaint is not temporal but informative, it improves learning global features for mortality prediction [17].

3.3. Self-supervised predictive regularization using $L_2$ loss with normalized context vector is crucial

As shown in Table 2, SSL regularization using $L_2$ loss with normalized context vector $c_t$ by LN performs the best for both prediction tasks with consistent performance escalation in far-future prediction. In particular, the performance gap between
Table 2: Validation AUROC of 1) uni-modal, 2) bi-modal, 3) self-supervision loss, and 4) different future numeric encoding methods for self-supervision. Best performing option (bold) is selected and applied to the remaining studies to assess the efficacy of an additional feature. * indicates additional normalization (Sec. 2.4). RFN, EFN, and FC refer to the different future numeric data encoding methods for SSL (Fig. 2).

| Models               | 0~1h | 1~2h | 2~3h | 3~4h | 4~5h | 5~6h | 6~7h | 7~8h | 8~9h | 9~10h | 10~11h | 11~12h | Avg. |
|----------------------|------|------|------|------|------|------|------|------|------|-------|--------|-------|-----|
| MTearly              | 0.91 | 0.87 | 0.88 | 0.87 | 0.86 | 0.85 | 0.84 | 0.83 | 0.82 | 0.81  | 0.8  | 0.8  | 0.82 |
| MTL              | 0.91 | 0.88 | 0.88 | 0.87 | 0.86 | 0.85 | 0.84 | 0.83 | 0.82 | 0.81  | 0.8  | 0.8  | 0.83 |
| MTmid               | 0.91 | 0.88 | 0.87 | 0.86 | 0.85 | 0.84 | 0.83 | 0.82 | 0.81 | 0.81  | 0.8  | 0.8  | 0.83 |
| MTmid               | 0.91 | 0.88 | 0.87 | 0.86 | 0.85 | 0.84 | 0.83 | 0.82 | 0.81 | 0.81  | 0.8  | 0.8  | 0.83 |
| BCMATearly        | 0.91 | 0.88 | 0.87 | 0.86 | 0.85 | 0.84 | 0.83 | 0.82 | 0.81 | 0.81  | 0.8  | 0.8  | 0.83 |
| BCMATmid     | 0.91 | 0.88 | 0.87 | 0.86 | 0.85 | 0.84 | 0.83 | 0.82 | 0.81 | 0.81  | 0.8  | 0.8  | 0.83 |

| MTearly + NCEEFN  | 0.93 | 0.88 | 0.87 | 0.86 | 0.85 | 0.84 | 0.83 | 0.82 | 0.81 | 0.81  | 0.8  | 0.8  | 0.83 |
| MTearly + CosineEFN | 0.91 | 0.9 | 0.87 | 0.87 | 0.86 | 0.85 | 0.84 | 0.83 | 0.82 | 0.81  | 0.8  | 0.8  | 0.83 |
| MTearly + L2EFN   | 0.69 | 0.56 | 0.75 | 0.79 | 0.67 | 0.72 | 0.73 | 0.57 | 0.64 | 0.67  | 0.69 | 0.67 | 0.67 |
| MTearly + L2EFN   | 0.92 | 0.97 | 0.89 | 0.88 | 0.89 | 0.88 | 0.89 | 0.87 | 0.87 | 0.87  | 0.87 | 0.87 | 0.87 |
| MTearly + L2EFN   | 0.92 | 0.94 | 0.89 | 0.89 | 0.89 | 0.88 | 0.88 | 0.87 | 0.87 | 0.87  | 0.87 | 0.87 | 0.87 |
| MTearly + L2EFN   | 0.92 | 0.94 | 0.88 | 0.87 | 0.86 | 0.85 | 0.84 | 0.84 | 0.83 | 0.83  | 0.82 | 0.82 | 0.82 |
| MTearly + L2EFN   | 0.92 | 0.94 | 0.88 | 0.87 | 0.86 | 0.85 | 0.84 | 0.84 | 0.83 | 0.83  | 0.82 | 0.82 | 0.82 |

3.4. Mortality and Vasopressor Need Prediction

Fig. 3 shows 1) both additional components (i.e., EHR text data and SSL with normalized c2) improve an hourly predictive performance of both tasks and 2) the difference between the two tasks. Specifically, adding EHR text data by bi-modal fusion improves overall/far-future (11-12h) prediction of the uni-modal model (baseline) by 0.031/0.031 in mortality prediction and by 0.004/0.003 in vasopressor need prediction. Additional SSL loss further improves overall/far-future prediction of the bi-modal model by 0.020/0.031 in mortality prediction and by 0.038/0.045 in vasopressor need prediction. In mortality prediction, though predictive performance degrades much as prediction time gets further in the future, both bi-modal fusion and SSL significantly moderate the performance degradation.

4. CONCLUSION

This paper proposes an hourly deterioration prediction method for urgent patients in the ED/ICU. With extensive experiments, we show that both multi-modal fusion and SSL regularization effectively improve the performance of mortality and vasopressor need prediction in a fine-grained time-res-
olution; in mortality prediction, both multi-modal fusion and SSL regularization specifically improve the far-future prediction. In addition, we show the importance of context vector normalization for $L_2$ loss in SSL predictive coding regularization. We believe our method will advance timely intervention and effective resource allocation in the ED/ICU.

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