Multi-view Integration Learning for Irregularly-sampled Clinical Time Series

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Abstract

Electronic health record (EHR) data is sparse and irregular as it is recorded at irregular time intervals, and different clinical variables are measured at each observation point. In this work, we propose a multi-view features integration learning from irregular multivariate time series data by self-attention mechanism in an imputation-free manner. Specifically, we devise a novel multi-integration attention module (MIAM) to extract complex information inherent in irregular time series data. In particular, we explicitly learn the relationships among the observed values, missing indicators, and time intervals between the consecutive observations, simultaneously. The rationale behind our approach is the use of human knowledge such as what to measure and when to measure in different situations, which are indirectly represented in the data. In addition, we build an attention-based decoder as a missing value imputer that helps empower the representation learning of the inter-relations among multi-view observations for the prediction task, which operates at the training phase only. We validated the effectiveness of our method over the public MIMIC-III and PhysioNet challenge 2012 datasets by comparing with and outperforming the state-of-the-art methods for in-hospital mortality prediction.

1 Introduction

Electronic health record (EHR) data is a collection of patients’ health data such as coded diagnoses, vital signs, and lab test results, procedures, and textual narratives, etc. Over the last decade, there has been significant progress on developing deep learning models using multivariate EHR time series owing to its abundance of health big datasets. However, learning appropriate EHR representations is challenging for many classical machine learning models, due to the nature of EHR that is irregularly sampled, where observations are measured at different time points determined by the type of measurement, the patient’s health status, and the availability of clinical staff. Different number of observations and a lack of temporal alignment across data invalidate the use of machine learning models that assume a fixed-dimensional feature space.

The classical machine learning approaches for handling the irregularly sampled time series are mostly based on convolutional neural network (CNN), recurrent neural network (RNN), and more recently attention-based methods, showing their superiority in healthcare target tasks. Specifically, CNN is usually applied to capture the local temporal characteristics of clinical data using the predefined kernel on a small chunk of EHR features for identifying local motifs, i.e., co-occurrences of diseases [Nguyen et al., 2017], and patients similarity [Suo et al., 2017]. But those works have limitations on modeling local temporal dependencies in the predefined kernel size, not global ones.

RNN-based methods have been the de-facto solution to deal with clinical time series data, as RNNs can manage various lengths of sequential data. But conventional RNN methods are designed to handle data with a constant time interval between consecutive time series, thus leading to sub-optimal performance for irregular time interval. To address this challenge, the widely-used approach is to convert irregularly sampled time series data into regularly sampled time series, i.e., temporal discretization [Lipton et al., 2016; Futoma et al., 2017] and feed this fixed-dimensional vector to RNNs. Nonetheless, it requires ad-hoc choices on the window size and the aggregation function that deals with values falling within the same window. Similar to discretization methods, interpolation methods [Futoma et al., 2017; Shukla and Marlin, 2019] require specifying discrete reference time points. Instead of using all available observations in the input to replace the interpolants at these time points, it may inevitably introduce additional noise or information loss due to assumption of a fixed time interval.

A better approach for handling irregular time series is to directly model the unequally spaced original data. Compared to the conventional RNN that relies on discrete time, ordinary differential equation (ODE)-based recurrence models [Lechner and Hasani, 2020] were proposed to handle non-uniform time intervals and remove the need to aggregate observations into equally spaced intervals by generalizing hidden state transitions in RNN to continuous time dynamics by ODEs. Another alternative is to exploit the source of missingness

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such as missing indicators and time interval for modeling informative missingness pattern. The existing works [Che et al., 2018; Lipton et al., 2016; Baytas et al., 2017; Zhang, 2019; Tan et al., 2020] used either missing indicators or time interval, and applied the heuristic decaying function such as a monotonically non-increasing function, without learning representations for missingness.

More recently, attention-based methods [Choi et al., 2016; 2017; Ma et al., 2018; Song et al., 2018; Horn et al., 2020] have been used to deal with irregular sampling. In particular, self-attention models [Vaswani et al., 2017] offered computational advantages over RNNs due to their fully parallelized sequence processing. Several works based on self-attention mechanism have applied a simple modified self-attention such as a masked attention [Song et al., 2018], or replaced the positional encoding with time encoding and concatenated encoding vector and missing indicators [Horn et al., 2020].

To address the aforementioned challenges and limitations, this paper proposes a novel method to jointly learn deep representations of multi-view features from irregular multivariate time series data by using the self-attention mechanism in an imputation-free manner. Specifically, we devise a novel multi-view integration attention module (MIAM) to learn complex missing patterns by integrating missing indicators and time interval, and further combine observation and missing pattern in the representation space through a series of self-attention blocks. On top of the MIAM module, we build an attention-based decoder as a missing data imputer that helps empower the representation learning of the interrelations among multi-view observations for the prediction task, which operates at the training phase only. As a result, model complexity is reduced, while removing the need to impute missing data at the same time. We showed that our proposed method outperformed state-of-the-art methods for in-hospital mortality prediction on real-world EHR datasets: MIMIC-III and PhysioNet 2012 challenge datasets.

2 Related Work

Irregular Time Series Modeling

In order to accommodate irregularly sampled time series data, the widely-used approach is to discretize time into consecutive, non-overlapping uniform intervals, i.e., temporal discretization [Lipton et al., 2016; Futoma et al., 2017], which enables the use of models that operate on fixed-dimensional vectors. In the meantime, discretization reduces the problem from irregular time series data modeling into missing data imputation. The simple imputation approaches range from simple zero imputation and forward filling to more sophisticated deep learning approaches [Cao et al., 2018] including generative adversarial network (GAN) [Yoon et al., 2018] and variational autoencoder (VAE) [Fortuin et al., 2020; Jun et al., 2019], etc. However, this explicit imputation of missing data during discretization mostly depends on heuristic or unsupervised method that will not be universally applicable, and further needs to consider uncertainty [Jun et al., 2020] for application of downstream clinical tasks.

Similar to discretization methods, interpolation methods require specifying discrete reference time points. A multi-task Gaussian process (MGP-RNN) model [Futoma et al., 2017] conducted a probabilistic interpolation by transforming irregular time series into a more uniform representation on evenly spaced reference time points, and feeding the latent function values into RNNs. While it provides uncertainty, there are limitations on a predefined time interval between reference time points and limited expressiveness of the model from a sum of separable kernel function. Instead, the interpolation-prediction network (IPNet) [Shukla and Marlin, 2019] learned an optimal time interval for deterministic interpolation. The interpolation network first interpolated irregular time series for each variable, and then merged all time series across every variable. However, IPNet may unavoidably introduce additional noise or information loss because it was also expected to assume fixed time interval.

Accordingly, recent interest of irregularity-based methods is learning representations directly from multivariate sparse and irregularly sampled time series as input without the need for imputation [Zaheer et al., 2017; Horn et al., 2020]. To this end, ODE-LSTM model [Lechner and Hasani, 2020] was proposed to generalize hidden state transitions in RNN to continuous time dynamics by ODEs, compared to conventional RNN that depends on discrete time. In this way, it deals with continuous time observations within the LSTM network, enabling cells to handle non-uniform time intervals and remove the need to aggregate observations into equally spaced intervals.

Missing Patterns Modeling

For modeling informative missingness, [Che et al., 2018] added a temporal decay derived from time interval to the input variables and hidden states, and directly included both observation and masking indicators inside the GRU architecture. Also, [Lipton et al., 2016] used hand-engineered features derived from the response indicator such as mean and standard deviation of missing indicators for each time series. [Baytas et al., 2017] proposed a time-aware LSTM (T-LSTM) that decomposes the cell memory into short and long-term memories and decays the short-term memory by weights transformed from time intervals, while retaining the long-term memories. Specifically, a monotonically non-increasing function is heuristically chosen as a decaying function. Similarly, ATTAIN [Zhang, 2019] decayed short-term memory by using both time intervals and weights generated from the attention mechanism by considering several previous events, not just one previous event. DATA-GRU [Tan et al., 2020] also introduced a time-aware mechanism to a GRU for handling irregular time interval, and further devised a dual attention mechanism to deal with missing values in both data-quality and medical-knowledge views.

Attention Mechanism in Irregular Time Series Modeling

Several recent models have leveraged attention mechanisms as their fundamental approach to dealing with irregular sampling. For example, RETAIN [Choi et al., 2016] learned an interpretable representation of irregularly sampled time series by two-level RNNs, generating visit-level and variable-level attentions. To learn robust representations of EHR data, [Choi
et al., 2017] introduced a graph-based attention method. Similarly, [Ma et al., 2018] proposed a knowledge-based attention mechanism to learn embeddings for nodes in the knowledge graph. Based on the self-attention [Vaswani et al., 2017], [Song et al., 2018] proposed a SAnD model that uses a masked self-attention specifying how far the attention model looks into the past and a dense interpolation for capturing masked self-attention specifying how far the attention model looks into the past and a dense interpolation for capturing temporal dependencies. In addition, [Horn et al., 2020] replaced the positional encoding with time encoding and concatenated encoding vector and missing indicators.

3 Method

In this section, we present the proposed method for multi-view features integration learning of irregular multivariate EHR time series for in-hospital mortality prediction task. First, we introduce the notations for multivariate time series data, and then describe our proposed method that consists of (i) input and time embedding, (ii) multi-view integration learning, (iii) mortality prediction as a binary classification, and (iv) auxiliary imputation for masked missing data. The overall architecture is shown in Figure 1.

3.1 Data Representation

For each subject \( n \), given a set of \( D \)-dimensional multivariate time series in \( t^{(n)} = [t_1, ..., t_j, ..., t_{T_n}] \) time points of length \( T_n \), we denote an observation time series as \( X^{(n)} = [x_{t_1}^{(n)}, ..., x_{t_j}^{(n)}, ..., x_{t_{T_n}}^{(n)}]^\top \in \mathbb{R}^{T_n \times D} \), where \( x_{t_j}^{(n)} \in \mathbb{R}^D \) represents the \( t_j \)-th observation of all variables, and \( x_{t_j,d}^{(n)} \) is the element of the \( d \)-th variable in \( x_{t_j}^{(n)} \). In this setting, since the time series \( X^{(n)} \) includes missing values, we introduce the masking vector across time series, \( M^{(n)} = [m_{t_1}^{(n)}, ..., m_{t_j}^{(n)}, ..., m_{t_{T_n}}^{(n)}]^\top \in \mathbb{R}^{T_n \times D} \), which has the same size of \( X^{(n)} \) to mark which variables are observed or missing. Specifically, we have \( m_{t_j,d}^{(n)} = 1 \) if \( x_{t_j,d}^{(n)} \) is observed, otherwise, \( m_{t_j,d}^{(n)} = 0 \). If the observation is missing, the input is set to zero for that dimension. For each variable \( d \), we also present the time interval \( \Delta^{(n)} = [\delta_{t_1}^{(n)}, ..., \delta_{t_j}^{(n)}, ..., \delta_{t_{T_n}}^{(n)}]^\top \in \mathbb{R}^{T_n \times D} \), where \( \delta_{t_j,d}^{(n)} \in \mathbb{R} \) is defined as:

\[
\delta_{t_j,d}^{(n)} = \begin{cases} 
    t_j - t_{j-1} + \delta_{t_{j-1},d}^{(n)}, & t_j > 1, m_{t_{j-1},d}^{(n)} = 0 \\
    t_j - t_{j-1}, & t_j > 1, m_{t_{j-1},d}^{(n)} = 1 \\
    0, & t_j = 1.
\end{cases}
\]

In this paper, given a clinical time series dataset \( D = \{X^{(n)}, M^{(n)}, \Delta^{(n)}\}_{n=1}^N \) for \( N \) subjects, we construct a mapping function to predict the mortality labels \((y_1, \cdots, y_N)\) in the binary classification problem.

For uncluttered, we will use functional notation that represents information about a particular patient, omitting superscript \( (n) \) for \( n \)-th subject.

3.2 Multi-view Integration Learning

The key feature of missing data is that there may be information conveyed by missingness itself, and ignoring this dependence may lead incorrect predictions. The existing works [Che et al., 2018; Lipton et al., 2016; Baytas et al., 2017; Zhang, 2019; Tan et al., 2020] leveraged these sources of missingness, i.e., missing indicators and time interval, and applied the heuristic decaying function for their use without learning its representation. However, using inappropriate modeling for missingness may lead to unreliable assessment of feature importance and model that is not robust to measurement changes.

Motivated by this observation, in this work, we learn a deep representation of irregular time series data by effectively leveraging both missing indicators and time interval. We consider these sources of missingness as a human knowledge such as to what to measure and when to measure in different situations, which are indirectly represented in the data. In this context, we regard the representations of missing indicators and time interval as multi-view features of irregularly-sampled observation. Specifically, we propose a multi-view features integration learning for modeling the inter-relationships among multi-view observations. This is achieved by using the self-attention mechanism, where the inner product of representations often reflects relationship such as similarity.

Input and Time Embedding

Given the \( D \) measurements at every time step, the first step is to learn the respective input embeddings for observation,
missing indicators and time interval. Compared to [Vaswani et al., 2017] that only considered sequence order rather than temporal patterns in positional encoding, in this work, we employ a time embedding as a variant of positional encoding that takes continuous time values as input, and convert them into an encoding vector representation. This approach deals with irregularly-sampled time series by considering the exact time points and their time interval. For time embedding (TE), sine and cosine functions proposed in [Vaswani et al., 2017] are modified as follows:

\[
\text{TE}_{(t, 2d)} = \sin \left( \frac{t}{l_{\text{max}}^2/d_{\text{model}}} \right) \sqrt{d_k} \tag{2}
\]

\[
\text{TE}_{(t, 2d+1)} = \cos \left( \frac{t}{l_{\text{max}}^2/d_{\text{model}}} \right) \sqrt{d_k} \tag{3}
\]

where \(t\), \(d\), \(d_{\text{model}}\), and \(l_{\text{max}}\) denote the exact time point, variable index, the dimension of model, and the maximum time length of data, respectively. The time embeddings are added to the learned input embeddings.

**Self-attention**
The basic building block is based on multi-head self-attention (MHA), where a scaled dot-product attention is calculated on a set of queries (Q), keys (K), and values (V) as follows:

\[
\alpha(Q, K, V) = \sigma \left( \frac{QK^\top}{\sqrt{d_k}} \right) V \tag{4}
\]

where \(\alpha\) denotes the attention function, \(\sigma\) is softmax activation function, \(d_k\) is the dimension of the key vector.

**Multi-view Integration Attention**
Based on the MHA block, we learn the attention representations of multi-view irregular time series including observation, masking indicators, and time interval. Specifically, each input set \((X, M, \Delta)\) learns its own representation \((H^X, H^M, H^\Delta)\) through self-attention, where each data is fed corresponding to Q, K, and V.

In this work, we devise a novel multi-view integration attention module (MIAM) that consists of two submodules: (i) an integration module that relies mostly on the self-attention mechanism, and (ii) a position-wise fully connected feed-forward network (FFN) module. Integration module aims to learn complex missing pattern by integrating missing indicators and time interval, and further combine observation and the learned missing pattern in the representation space. While the most works in the literature [Che et al., 2018; Lipton et al., 2016; Baytas et al., 2017; Zhang, 2019; Tan et al., 2020] exploited either missing indicators or time interval, and applied the heuristic decaying function for its use, we effectively learn informative missing pattern by using both missing indicators and time interval in the representation space. We argue that learning the underlying representation from missingness itself removes the need to impute values, and does not require specifying any heuristic function.

In the integration module, there are two integration steps, i.e., missingness integration and observation-missingness integration. In the missingness integration step, we incorporate the representation of missing indicators with that of time interval by MHA block in Eq. (5), resulting into the representation of missing pattern \((H^M^*)\).

\[
H^M^* = \alpha(H^\Delta, H^M, H^M) = \sigma \left( \frac{H^\Delta H^M^\top}{\sqrt{d_k}} \right) H^M \tag{5}
\]

Similarly, in the observation-missingness integration step, the representation of observation is combined with that of missing pattern by computing another MHA block in Eq. (6).

\[
H^X^* = \alpha(H^M^*, H^X, H^X) = \sigma \left( \frac{H^M^* H^X^\top}{\sqrt{d_k}} \right) H^X \tag{6}
\]

This final attention output is the jointly learned deep representations that model the relation between irregular observation data and missing pattern. Then FFN module is applied to each time point identically for modeling the dependency among variables. For more powerful deep representations, the MIAM modules are stacked \(L\) times, and the output obtained at the end of the MIAM becomes \(H^X\) again. The final representation \(H^X^*\) is leveraged for the downstream prediction and auxiliary imputation tasks.

### 3.3 In-hospital Mortality Prediction
To predict the probability of in-hospital mortality, given the time series representation \(H^X^*\), we conduct average pooling over timestamps, which results into a final pooled representation \(\tilde{h}\), and apply a multi-layer perceptron (MLP), followed by a sigmoid activation function as follows:

\[
p(y = 1|\tilde{h}) = \varphi_2(\varphi_1(\tilde{h}W_1 + b_1)W_2 + b_2) \tag{7}
\]

where \(\{W_1, b_1, W_2, b_2\}\) are parameter matrices for classification, and \(\varphi_1\) and \(\varphi_2\) are a LeakyReLU activation and sigmoid activation function, respectively.

Furthermore, to handle poor classification performance problem in highly imbalanced data found in healthcare dataset, we employ focal loss [Lin et al., 2017; Jun et al., 2020] as the objective function to calculate the classification loss between the target mortality label \(y\) and the predicted label \(\hat{y}\) or each patient:

\[
\mathcal{L}_{cls} = \sum_{n=1}^{N} -\beta(1 - \hat{y}(n))^\gamma \log(\hat{y}(n)) \tag{8}
\]

where \(N\) is the total number of patients, \(\gamma\) is a focusing parameter for a minority class, and \(\beta\) is a weighting factor to balance the importance between classes.

### 3.4 Auxiliary Missing Data Imputation
On top of the MIAM module, we also build an attention-based decoder as a missing data imputer that aims to enhance representational power of the inter-relations among multi-view observations for the prediction task. To investigate the masked imputation loss, we randomly masked 10% of non-missing values and predicted them. From a self-supervised learning perspective, it can be regarded as similar to a masked language modeling task used by BERT [Devlin et al., 2018] that randomly masks some tokens in a text sequence, and then independently recovers the masked tokens to learn language representations. By taking a similar
approach, we learn the inter-relations between corrupted values and context, which further contributes to learning the inter-relations among multi-view observations. It should be noted that the proposed method is basically an imputation-free method since imputation only operates in the training phase, not the test phase. Therefore, it has the advantage of reducing model complexity, while not facing the existing imputation-related problems mentioned earlier.

In the attention-based decoder, we further apply an attention block between the final representation of the MIAM module (\( \mathbf{H}^{\mathrm{X}} \)) as query and observation representation (\( \mathbf{H}^{\mathrm{X}} \)) as key and value, followed by FFN. The output layer maps the output of FFN to the target time sequence by the learned embedding, and results into the imputed data (\( \mathbf{X} \)).

Given another masking vector \( \mathbf{M}_{\text{imp}} \) introduced for the purpose of marking the masked values, the imputation loss \( \mathcal{L}_{\text{imp}} \) is calculated by masked mean squared error (MSE) between the original sample \( \mathbf{X} \) as the ground truth and the imputed sample \( \hat{\mathbf{X}} \) for the marked values only by \( \mathbf{M}_{\text{imp}} \) as:

\[
\mathcal{L}_{\text{imp}} = \frac{1}{N} \sum_{n=1}^{N} \left( \mathbf{X}^{(n)} \odot \mathbf{M}_{\text{imp}}^{(n)} - \hat{\mathbf{X}}^{(n)} \odot \mathbf{M}_{\text{imp}}^{(n)} \right)^2. 
\]

By adding imputation loss to the objective function, the imputer provides auxiliary information to achieve the optimal prediction result.

### 3.5 Loss Function

The composite loss is defined by accumulating the prediction and imputation losses as \( \mathcal{L} = \mathcal{L}_{\text{imp}} + \lambda_{\text{cls}} \mathcal{L}_{\text{cls}} \), where \( \lambda_{\text{imp}} \) and \( \lambda_{\text{cls}} \) are hyper-parameters that control the ratio between two losses. We optimize all the parameters of our model in an end-to-end manner via the composite loss \( \mathcal{L} \).

### 4 Experiment

In this section, we evaluated our proposed method for the in-hospital mortality prediction on two publicly available datasets: the Medical Information Mart for Intensive Care III (MIMIC-III), and the PhysioNet 2012 challenge dataset. We reported the average results of the area under the ROC curve (AUC) and the area under the precision–recall curve (AUPRC) from 5-fold cross validation, comparing with other state-of-the-art (SOTA) methods in the literature. In addition, we conducted extensive ablation studies to evaluate the effect of multi-view integration module and our auxiliary imputer.

### Dataset and Preprocessing

We conducted experiments on two datasets: MIMIC-III and PhysioNet 2012 challenge datasets. MIMIC-III consists of medical records of 13,998 patients collected at Beth Israel Deaconess Medical Center. We used 99 different time series measurements for each patient. The selected time series was scarcely observed leading to a missing rate of approximately 90%. For the in-hospital mortality label, the ratio between 1,181 positive (dead in hospital) and 12,817 negative (alive in hospital) was approximately 1:10.8. The number of irregular time points ranges from 1 to 247 (\( m \pm \sigma : 49.29 \pm 35.90 \)).

PhysioNet 2012 challenge consists of 35 different time-series measurements and 5 general descriptors for 4,000 critical care patients with at least 48 hours of hospital stay. We used 35 time-series variables without the general descriptor of 3,997 patients with at least one observation time. The missing rate is approximately 80.5%, and the mortality labels are imbalanced at a ratio of approximately 1:6 between 554 positive and 3,443 negative cases. The number of irregular time points ranges from 1 to 202 (\( m \pm \sigma : 73.87 \pm 23.06 \)).

In terms of data preprocessing, because each variable has a different range, all inputs were first Winsorized for removing outliers and then z-normalized using the global mean and standard deviation from the entire training set to achieve a zero mean and unit variance in a variable-wise manner.

### Experimental Settings

We trained our models using the Rectified Adam (RAdam) optimizer [Liu et al., 2019] with an initial learning rate of 0.005 and a multiplicative decay of 0.2 every 10 epochs for 60 epochs using minibatches of 64 samples. We chose the final optimal model based on the performance of the validation set.

For MIMIC-III dataset, the model achieved its best performance at two-layered MHA with 8 heads of \( \beta \) and \( \gamma \) in focal loss were chosen 7 and 0.15, respectively, and \( \lambda_{\text{imp}} \) and \( \lambda_{\text{cls}} \) in the composite loss were 0.1 and 7, respectively.

We validated the efficacy of our proposed method by comparing it with SOTA methods categorized as recurrence-based method, interpolation-based method, and attention-based method as shown in Table 1.

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1Available at https://mimic.physionet.org/.

2Available at https://physionet.org/content/challenge-2012/.
Table 2: Results of ablation studies in terms of the multi-view integration ($m \pm \sigma$ from 5-fold cross-validation). Among the methods, the bold text indicates the proposed approach.

| Dataset     | Method          | AUC  | AUPRC |
|-------------|-----------------|------|-------|
| MIMIC-III   | Single (X)      | 0.7943 ± 0.0008 | 0.3044 ± 0.0091 |
| MIMIC-III   | Double (X + M)  | 0.8273 ± 0.0058 | 0.3385 ± 0.0170 |
| MIMIC-III   | Double (X + Δ)  | 0.8458 ± 0.0051 | 0.3577 ± 0.0155 |
| MIMIC-III   | Triple (X + M + Δ) | 0.8534 ± 0.0071 | 0.3565 ± 0.0133 |
| PhysioNet   | Single (X)      | 0.7816 ± 0.0381 | 0.4195 ± 0.0345 |
| PhysioNet   | Double (X + M)  | 0.8131 ± 0.0292 | 0.4475 ± 0.0452 |
| PhysioNet   | Double (X + Δ)  | 0.8142 ± 0.0175 | 0.4501 ± 0.0225 |
| PhysioNet   | Triple (X + M + Δ) | 0.8231 ± 0.0221 | 0.4730 ± 0.0477 |

5 Results

Performance Comparison

Table 1 compares the results of our proposed method with those of the competing methods for mortality prediction on MIMIC-III and PhysioNet 2012 challenge datasets. For both datasets, our model achieved the best classification performance. Overall performance of recurrence-based methods and attention-based methods were similar, and interpolation methods showed relatively lower performance than the others. Among the recurrence-based methods, ODE-LSTM [Lechner and Hasani, 2020] demonstrated a competitive performance, which is a continuous time LSTM-based model that takes irregularly-sampled time series as input and simultaneously handles time intervals. It suggests the need for directly modeling irregularly sampled time series and a more sophisticated use of missing indicators and time interval. These experimental results validated the efficacy of our proposed method that learns the multi-view representation of irregular time series data and their deep integration with the self-attention mechanism, and further builds the auxiliary missing data imputer, showing its superior performance in the downstream task.

Ablation Study

In this study, we conducted extensive ablation studies to investigate the influence of different experimental design options in terms of multi-view integration module and auxiliary imputer in our method. Table 2 shows the results of investigating the effectiveness of multi-view integration through four scenarios: single view (X), double views (X + M, X + Δ), and triple views (X + M + Δ). It can be seen that integrating observation and sources of missingness was better than using observation only, and that the result of integration for triple views was the highest in both MIMIC-III and PhysioNet 2012 datasets, which shows the effectiveness of incorporating observation and sources of missingness. In the double view cases, the scenario of (X + Δ) achieved slightly better performance than that of (X + M) in both datasets.

In addition, we explored the effect of the attention-based imputer, as shown in Table 3. The results showed that the proposed model built with the attention-based imputer achieved higher performance than w/o imputer in both datasets, indicating that our auxiliary imputer helps enhance representational power of the inter-relationships among multi-view observations for the prediction task.

Furthermore, we examined the necessity of using explicit imputation data in the prediction task in Table 4. In this regard, we compared our proposed approach with the case of using the imputed data by BRITS imputer [Cao et al., 2018] as the SOTA imputation method and our auxiliary imputer. In these cases, the imputation (dotted line in Figure 1) is also conducted in the test phase. The result of using the imputed data by our auxiliary imputer (Auxiliary Imputation+MIAM) is comparable to that of the proposed approach (No Imputation+MIAM) and that of (BRITS Imputation+MIAM).

These results indicate that using explicit imputation data contributes to the improvement of prediction task performance to some extent rather than without imputation, but its effect is insignificant. Thus, our proposed approach of using the auxiliary imputer in the training phase only suffices to deal with modeling irregular time series data.

6 Conclusion

In this work, we proposed a method to directly learn the integrated representations of multi-view features from irregular multivariate time series data by using the self-attention mechanism without imputation. Specifically, we devised a novel multi-integration attention module (MIAM) to extract complex missing pattern by integrating missing indicators and time interval, and further combine observation and missing pattern in the representation space through a series of self-attention blocks. In addition, we built an attention-based decoder as a missing value imputer that helps empower the representation learning of the inter-relationships among multi-view observations for prediction task, which operates at the training phase only. We validated the effectiveness of our method over the public MIMIC-III and PhysioNet challenge 2012 datasets by comparing with and outperforming the state-of-the-art methods for in-hospital mortality prediction.
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