Integrating Physiological Time Series and Clinical Notes with Deep Learning for Improved ICU Mortality Prediction

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Abstract
Intensive Care Unit Electronic Health Records (ICU EHRs) store multimodal data about patients including clinical notes, sparse and irregularly sampled physiological time series, lab results, and more. To date, most methods designed to learn predictive models from ICU EHR data have focused on a single modality. In this paper, we leverage the recently proposed interpolation-prediction deep learning architecture (Shukla and Marlin 2019) as a basis for exploring how physiological time series data and clinical notes can be integrated into a unified mortality prediction model. We study both early and late fusion approaches, and demonstrate how the relative predictive value of clinical text and physiological data change over time. Our results show that a late fusion approach can provide a statistically significant improvement in mortality prediction performance over using individual modalities in isolation.

1 Introduction
Electronic health records (EHRs) store multimodal data related to individual medical history including clinical notes, physiological measurements, lab results, radiology images, and more. Intensive Care Unit Electronic Health Records (ICU EHRs) are particularly interesting as they contain measurements of multiple physiological variables through time. The analysis of these data has the potential to improve care via the creation of improved decision support tools based on machine learning and data mining techniques. However, the complexity of the data has led to a focus on analyzing single data modalities in isolation (Marlin et al. 2012; Lipton, Kale, and Wetzel 2016; Che et al. 2018; Putoma et al. 2017).

In this paper, we explore the predictive value of integrating physiological time series data and clinical text into a unified mortality prediction model. Specifically, we leverage the content of clinical notes through time and fuse the information they contain with physiological time series data. We build on the recently proposed interpolation-prediction deep learning architecture as a framework for modeling sparse and irregularly sampled physiological time series data (Shukla and Marlin 2019). We study several methods for representing the clinical text, along with both early and late fusion approaches to integrating the two data modalities (Kiela and Bottou 2014; Fiterau et al. 2017).

We begin by presenting related work on physiological time series modeling, clinical text, and fusion approaches. We next present the proposed approach including a brief review of interpolation-prediction networks. Finally, we present mortality prediction experiments on the MIMIC-III data set (Johnson et al. 2016) demonstrating how the relative predictive value of clinical text and physiological data change during the first 48 hours after admission. We show that the late fusion approach can provide a significant improvement over using individual modalities in isolation.

2 Related Work
The problem of interest in this work is learning supervised machine learning models by fusing clinical time series with unstructured clinical text data. In this section, we review related work on modeling and analysis of both clinical text and sparse and irregularly sampled physiological time series, as well as related work on fusion approaches.

2.1 Clinical text
With increasing access to clinical notes over the last several years, there has been significant progress in understanding clinical text data and using these data to improve prediction of clinical outcomes. Natural language processing and information extraction techniques have been successfully applied to tasks including clinical concept extraction (Boag et al. 2015), relation extraction (Savova et al. 2010), question-answering (Uzuner, Solti, and Cadag 2010), predictive modeling (Ghassemi et al. 2012) and more.

Methods for using narrative notes to predict clinical outcomes include medical concept extraction using rule based (Savova et al. 2010) or machine learning techniques (Boag et al. 2015). However, such methods can require a substantial amount of work in rule construction, keyword selection, text annotation or feature engineering for supervised machine...
learning. Unsupervised methods such as topic modeling can be used to solve this problem. Topic modeling (Ghassemi et al. 2012) methods rely on extracting topic features from clinical text data. Lehman et al. (2012) combined both topic modeling and medical concept extraction approaches for predicting in-hospital mortality.

Inspired by the recent success of word embedding methods including word2vec and GloVe (Pennington, Socher, and Manning 2014) in numerous natural language processing tasks, Minarro Gimenez, Marin Alonso, and Samwald (2014) learned an embedding model for medical text data. De Vine et al. (2014) used journal abstracts to train the embeddings. Choi, Yi-I Chiu, and Sontag (2016) evaluated the efficiency of word embeddings in capturing relations between medical concepts. Boag et al. (2018) compared the clinical notes representation generated by Bag of Words (BoW), word2vec and the final hidden layer of a learned LSTM for downstream clinical prediction tasks. Their results showed that there is no simple winning representation. BoW and word2vec achieved similar performance in predicting in-hospital mortality. In other recent work, Ghassemi et al. (2015) used Gaussian processes to model sequences of clinical notes as time series of topics.

In this work, we consider clinical notes as sequences of words or sentences and use recurrent networks to predict in-hospital mortality. We generate sentence embeddings using simple averages (Pennington, Socher, and Manning 2014) as well as weighted averages of word embeddings (Arora, Liang, and Ma 2017). Similar to Boag et al. (2018), we compare with Bag-of-Words and GloVe models. Finally, similar to Kalchbrenner, Grefenstette, and Blunsom (2014), we also use a convolutional model for prediction where the clinical notes are represented in terms of word embeddings.

2.2 Irregularly sampled physiological time-series

A sparse and irregularly sampled time series is a sequence of samples with large and irregular intervals between their observation times. Such data commonly occur in electronic health records where they can represent a significant problem for both supervised and unsupervised learning methods (Marlin et al. 2012). A closely related problem is performing supervised learning in the presence of missing data (Little and Rubin 2014). Indeed, the problem of analyzing sparse and irregularly sampled data can be converted into a missing data problem (typically with loss of information or inference efficiency) by discretizing the time axis and indicating that intervals with no observed samples are missing. This is the approach taken to deal with irregular sampling by Marlin et al. (2012) as well as Lipton, Kale, and Wetz5e (2016). Learning is generally harder as the amount of missing data increases, so choosing a discretization interval length must be dealt with as a hyper-parameter of such a method.

The alternative to pre-discretization is to construct models with the ability to directly use an irregularly sampled time series as input. For example, Lu et al. (2008) present a kernel-based method that can be used to produce a similarity function between two irregularly sampled time series. Li and Marlin (2015) subsequently provided a generalization of this approach to the case of kernels between Gaussian process models. Li and Marlin (2016) showed how a deep neural network model (feed-forward, convolutional, or recurrent) could instead be stacked on top of a Gaussian process layer with end-to-end training, while Futoma et al. (2017) showed how this approach could be generalized from the univariate to the multivariate setting.

An important property of the above models is that they allow for incorporating all of the information from all available time points into a global interpolation model. A separate line of work has looked at the use of more local interpolation methods while still operating directly over continuous-time inputs. For example, Che et al. (2018) presented several methods based on gated recurrent unit (GRU) networks (Chung et al. 2014) combined with simple imputation methods including mean imputation and forward filling with past values. Che et al. (2018) additionally considered an approach that takes as input a sequence consisting of both the observed values and the timestamps at which those values were observed. The previously observed input value is decayed over time toward the overall mean. In another variant, the hidden states are similarly decayed toward zero. Yoon, Zame, and van der Schaaf (2017) presented another similar approach based on a multi-directional RNN, which operates across streams in addition to within streams.

In this work, we use the recently proposed interpolation-prediction network to model sparse and irregularly sampled physiological time series (Shukla and Marlin 2019). This framework addresses some difficulties with prior approaches including the complexity of the Gaussian process interpolation layers used in Li and Marlin (2016) and Futoma et al. (2017), and the lack of modularity in the approach of Che et al. (2018). We describe this framework in more detail in Section 3.2.

2.3 Fusion models

Learning multimodal representations is a fundamental research problem. Canonical correlation analysis (Hotelling 1935) has been widely used for modeling multimodal data (Hardoon, Szedmak, and Shawe-taylor 2004; Klein et al. 2015). It learns a subspace to maximize the correlation between multiple modalities. Ngiam et al. (2011) introduced a multimodal deep learning framework to combine video and audio for speech recognition. Multimodal learning with language and vision subspaces has been used to improve the performance of image captioning tasks (Karpathy, Joulin, and Fei-Fei 2014; Socher et al. 2014). Srivastava and Salakhutdinov (2012) used fused representations of multiple modalities (text and images) as input for discriminative tasks. Siboner and Lapata (2014) use stacked autoencoders for fusing multimodal data while Kiela and Bontou (2014) adopt a simple concatenation strategy and achieve empirical improvements using convolutional models for extracting visual features and skip-gran models for text.

A separate line of work has looked at combining time-series data and textual information. Tang, Yang, and Zhou (2009) analyzed news reports to improve the prediction of stock prices, while Rodrigues, Markou, and Pereira (2018) use a simple concatenation approach to combine time-series data and text to improve prediction performance.
and textual data for taxi demand prediction by learning their latent representations.

Within the clinical data space, Fiterau et al. (2017) showed how combining structured information like age, gender, height, etc., with time series data can improve performance. Xu et al. (2018) developed clinical predictive models by integrating continuous monitoring data with discrete clinical event sequences. Rajkomar et al. (2018) combined multiple modalities such as demographics, provider orders, diagnoses, procedures, medications, laboratory values, clinical text data and vital signs and showed improved performance on multiple tasks. Jin et al. (2018) combined unstructured clinical text data with physiological time-series data for in-hospital mortality prediction, similar to the present work. Relative to that work, we consider multiple clinical text representations, base our time series model on interpolation-prediction networks (Shukla and Marlin 2019), and focus on how the relative value of clinical text and physiological data vary through time. Further, we consider both early and late fusion approaches, expanding on the prior work of Kiela and Bottou (2014) and Fiterau et al. (2017).

3 Proposed Fusion Model Framework

In this section, we present the proposed fusion modeling framework. We begin by presenting notation and a description of the models used for clinical text and physiological time series, followed by a discussion of fusion approaches.

3.1 Notation

We let \( D = \{(s_n, v_n, y_n)\}_{n=1}^N \) represent a data set containing \( N \) data cases. An individual data case consists of a single target value \( y_n \) (discrete in the case of classification), a \( D \)-dimensional, sparse and irregularly sampled multivariate physiological time series \( s_n \), and the unstructured text data present in the clinical notes \( v_n \), represented as a sequence of words. We note that different dimensions \( d \) of the multivariate time series \( s_n \) can have observations at different times, as well as different total numbers of observations \( k_{dn} \). Thus, we represent time series \( d \) for data case \( n \) as a tuple \( s_{dn} = (t_{dn}, x_{dn}) \) where \( t_{dn} = [t_{1dn}, \ldots, t_{L_{dn}dn}] \) is the list of time points at which observations are defined and \( x_{dn} = [x_{1dn}, \ldots, x_{L_{dn}dn}] \) is the corresponding list of observed values.

3.2 Time Series Model

We briefly review the interpolation-prediction network framework that Shukla and Marlin (2019) proposed to model sparse and irregularly sampled time series data. The architecture is based on the use of several semi-parametric interpolation layers organized into an interpolation network, followed by the application of a prediction network that can leverage any standard deep learning model. Figure 1 shows the architecture of the interpolation-prediction model.

The interpolation network interpolates the multivariate, sparse, and irregularly sampled input time series against a set of reference time points \( r = [r_1, \ldots, r_T] \). A two-layer interpolation network is used where the first layer separately transforms each of \( D \) univariate input time series, creating several intermediate interpolants. The second interpolation layer merges information across all time series at each reference time point by taking into account learnable correlations across all time series. The interpolation network outputs a total of \( C = 3 \) components for each dimension of the input time series: a smooth, cross-channel interpolant to capture smooth trends, a transient component to capture transients, and an intensity function to capture information about where observations occur in time. We define \( f_\theta(s_n) \) to be the function computing the output \( \hat{s}_n \) of the interpolation network. The output \( \hat{s}_n \) is a fixed-sized array with dimensions \((DC) \times T\).

The second component, the prediction network, takes the output of the interpolation network \( \hat{s}_n \) as its input and produces a prediction \( \hat{y}_n = g_\omega(s_n) = g_\omega(f_\theta(s_n)) \) for the target variable \( y_n \). The prediction network can consist of any standard supervised neural network architecture (fully-connected feedforward, convolutional, recurrent, etc.).

We learn the parameters of this model using a composite objective function consisting of a supervised component and an unsupervised component (an autoencoder loss). The objective function is listed below. More details can be found in Shukla and Marlin (2019). In the fusion case, we use this objective to pre-train the interpolation-prediction network parameters in isolation.

\[
\theta_s, \omega_s = \underset{\theta, \omega}{\text{argmin}} \sum_{n=1}^N \ell_P(y_n, g_\omega(f_\theta(s_n))) + \delta_R \sum_{n=1}^N \ell_I(s_n, \hat{s}_n) + \delta_F \|\theta\|_2^2 + \delta_G \|\omega\|_2^2
\]

where \( \ell_P \) is the loss for the prediction network and \( \ell_I \) is the interpolation network autoencoder loss.

3.3 Text Models

We consider several different approaches to modeling unstructured text including approaches based on bag-of-words and word embedding representations. We describe each text representation approach below.

- TF-IDF: Each text document is first represented using TF-IDF features computed from a bag-of-words representation. We remove stop words and select a vocabulary consisting of the top 6,000 most frequent remaining words. We apply a one hidden layer (1NN) fully connected network of size 128 on top of the TF-IDF inputs, followed by the rest of the prediction network.
- Word Embedding (WE): Each document is first represented as a matrix where rows are words in the document and columns are word embedding dimensions. Word embeddings are computed using a standard, pre-trained 300-dimensional GloVe model (Pennington, Socher, and Manning 2014). We then apply a convolutional neural network model with one 1D convolution and one pooling layer, followed by a fully-connected layer of size 128 connected to the rest of the prediction network. Stop words and words with no embeddings are removed. All documents are zero-padded to match the length of the longest
document. We select the number of convolution kernels on a validation set.

- Unweighted Sentence Embedding (USE): Each document is first represented as a matrix where rows are sentences in the document and columns are the sentence embedding dimensions. The sentence embeddings are computed by averaging the GloVe embeddings (Pennington, Socher, and Manning 2014) of their constituent words. We then apply a GRU model (Chung et al. 2014) to the sequence of sentence embeddings, followed by a fully-connected layer of size 128 connected to the rest of the prediction network. We consider GRU models with between 32 and 512 hidden units and select the best on a validation set.

- Weighted Sentence Embedding (WSE): Each document is represented as a matrix where rows are sentences in the document and columns are the sentence embedding dimensions. We compute the sentence embedding by weighting the GloVe word embeddings (Pennington, Socher, and Manning 2014) based on their unigram probability in the entire corpus as described in Arora, Liang, and Ma (2017). The remainder of this approach matches the unweighted case as described above.

In all cases, the text representations described above are connected to the remainder of a prediction network via a 128-dimensional hidden layer. Recalling that \( v_n \) represents the raw, unstructured text data available as input for data case \( n \), we can view each of the methods described above as a different approach to computing a fixed, 128-dimensional embedding \( \hat{v}_n = h_\phi(v_n) \). To learn the parameters \( \phi \) for each approach, we use a supervised pre-training approach. We directly connect the text embedding layer \( \hat{v}_n \) to the prediction target, and minimize a prediction loss. In this work, we focus on in-hospital mortality prediction and use binary cross entropy as the loss function during pre-training.

### 3.4 Fusion Approaches

In this section, we present fusion architectures that combine the interpolation-prediction network described in Section 3.2 with the embedding-based models for representing unstructured text described in Section 3.3. In particular, we present two prediction network architectures that accept as input the interpolants produced by the interpolation network and the text embeddings produced by the unstructured text models. Both architectures are shown in Figure 2 and are described below.

- Late Fusion: In this approach, the prediction network uses the same GRU architecture used by Shukla and Mirali (2019) to extract a fixed-dimensional latent representation of the physiological time series data. This representation is concatenated with the text embedding layer and the combined latent representation is connected to the prediction target using a linear layer. This architecture is shown in Figure 2 (left).
- **Early Fusion**: We also consider a deeper integration of the information contained in both physiological time series and clinical notes. In this method, our prediction network has access to the clinical text data prior to incorporating physiological time series data via a GRU layer, as shown in Figure 2 (right).

In both fusion architectures, the prediction network takes as input the time series interpolants \( \hat{s}_n = f_\theta(s_n) \) (where \( f_\theta \) denote the interpolation network) as well as the text embedding \( \hat{v}_n = h_\phi(v_n) \) and outputs a prediction \( \hat{y}_n = g_\omega(\hat{s}_n, \hat{v}_n) = g_\omega(f_\theta(s_n), h_\phi(v_n)) \). As described above, we use supervised pre-training of all of the model parameters by training the interpolation-prediction and text embedding networks in isolation. During the fusion stage, we freeze the text embedding parameters \( \phi \), and fine-tune the interpolation and prediction network parameters \( \theta \) and \( \omega \).

The learning objective for the fusion framework requires specifying a loss \( \ell_F \) for the prediction network (we use cross-entropy loss for classification). We let \( \ell_I \) be the interpolation network autoencoder loss as described in Section 3.2. We also include \( \ell_2 \) regularizers for all the network parameters, \( \delta_F, \delta_G, \) and \( \delta_R \) are hyper-parameters that control the trade-off between the components of the objective function. The full objective is shown below.

\[
\theta_*, \omega_* = \arg\min_{\theta, \omega} \sum_{n=1}^{N} \ell_I(y_n, g_\omega(f_\theta(s_n), h_\phi(v_n))) \\
+ \delta_R \sum_{n=1}^{N} \ell_I(s_n, \hat{s}_n) + \delta_F \|\theta\|^2_2 + \delta_G \|\omega\|^2_2 \tag{2}
\]

Note again that we leverage a pre-trained text embedding model, thus the text embedding model parameters \( \phi \) are fixed to their optimal pre-trained values \( \phi_* \). The parameters of the fusion model (as well as all other models used in this work) are learned using the Adam optimization method in TensorFlow with gradients provided via automatic differentiation.

## 4 Experiments and Results

In this section, we present experiments and results. Our experiments focus on the relative predictive performance of text-only models, time-series-only models, and fusion models for the problem of in-hospital mortality prediction. The prediction output is a single binary variable representing the occurrence of in-hospital mortality more than 48 hours after admission. The time series inputs to the prediction task are sparse and irregularly sampled physiological time series. We consider making predictions using physiological time series data available between 6 and 48 hours after admission. The text inputs to the prediction task consists of text content known at the time of admission and progress notes available between 6 and 48 hours after admission. We begin by briefly describing the data set used, followed by the set of baseline and comparison models, the empirical protocols used, and finally the results.

### 4.1 Dataset

Our experiments are based on the publicly available MIMIC-III dataset (Johnson et al. 2016). This data set contains sparse and irregularly sampled physiological signals, discharge summaries, progress notes, medications, diagnostic codes, in-hospital mortality, length of stay, demographics information and more. It consists of approximately 58,000 hospital admission records. We focus on predicting in-hospital mortality using both the clinical text and time series data. We start with the data set used in Shukla and Marlin (2019) which consists of hospital admission records with hospital admission-to-discharge length of stay more than 48 hours. From that dataset, we obtained 42,984 records for our experiments after removing newborns and hospital admission records containing no clinical notes. A hospital admission may correspond to zero or multiple ICU episodes. In this paper, we only consider the data cases that were admitted to ICU at least once during their hospital stay.

Similar to Shukla and Marlin (2019), we extract 12 standard physiological variables from each of the records. Table 1 shows the variables and sampling rates (per hour). We use text data known at the time of admission such as chief complaints, past medical history and history of present illness. We take care in extracting this information from discharge summaries in order to avoid any information leak. We also extract progress notes from non-discharge reports such as respiratory, ECG, echo, radiology, and nursing reports. We use the date and time stamps on these reports to create a set of notes available between 6 and 48 hours after admission. Note that the physiological data and clinical notes are aligned in a conservative manner. If a clinical note has both a date and time associated with it, we assume that information was available at the specified time. For notes that have dates but not times available, we assume that information was available at the end of the indicated day. The happens for some ECG and Echo reports in the data set.

| feature | Sampling Rate | feature | Sampling Rate |
|---------|--------------|---------|--------------|
| SpO2   | 0.80         | TGCS    | 0.14         |
| HR     | 0.90         | CR      | 0.06         |
| RR     | 0.48         | UO      | 0.20         |
| SBP    | 0.59         | FiO2    | 0.06         |
| DBP    | 0.60         | Glucose | 0.10         |
| Temp   | 0.19         | pH      | 0.04         |

Table 1: Features extracted from MIMIC III

### 4.2 Baseline Models

We compare fusion models with a number of baseline approaches that model the physiological time series or the clinical text data individually. Shukla and Marlin (2019) show that the interpolation-prediction network outperforms a range of baseline and recently proposed models on both classification and regression tasks for sparse and irregularly sampled time series. Hence, we use interpolation-prediction networks as our time series-only baseline model. We use the

https://github.com/mlsd-lab/interp-net
pre-trained text-only models described in Section 3.3 to provide text-only baselines.

### 4.3 Empirical Protocols

Each unique hospital admission-to-discharge episode for a patient is assigned a unique ID in the MIMIC-III data set. The data in each episode are treated as being independent. In the train-test split, we divide the data based on the hospital admission ID (i.e. 80% (27510) of IDs are used for training and 20% (8597) are used for testing). We set aside another 20% (6877 data cases) from the training set to use as a validation set. Since we only use data from within individual hospital-to-discharge episodes, the data cases we construct are temporally non-overlapping. Again, this is consistent with how the MIMIC-III data set has been used in past research (Shukla and Marlin 2019; Che et al. 2018).

All models are trained to minimize the cross entropy loss. For all of the models, we independently tune the hyper-parameters - number of hidden layers, hidden units, convolutional filters, filter-size, learning rate, dropout rates and regularization parameters on the validation set. For TF-IDF-based models, we also tune the number of TF-IDF features. The neural network models are learned using the Adam optimizer. Early stopping is used on the validation set. The final outputs of the hidden layers are used in a logistic layer that predicts the class. We evaluate all the models using an estimate of generalization performance computed on the test set. We report the performance on the test set in terms of the area under the ROC curve (AUC score).

### 4.4 Results

In this section, we present the results of the mortality prediction experiments. We begin with text-only and time series-only baseline results, followed by fusion model results.

**Text-Only Baselines:** Table 2 shows the classification performance for the text-only models described in Section 3.3. We evaluate all models in the case of text data available at the time of admission. These results show that the TF-IDF-based model performs significantly better than the embedding methods. This may be due to the fact that health-specific concepts are not well represented in the standard Glove embeddings used. Another possible reason could be the use of abbreviated terms, which are quite common in clinical notes. For this reason, we only consider the TF-IDF model when making predictions based on all the progress notes available after admission. We can see that prediction performance using the TF-IDF model increases significantly as more text data become available over time.

**Time Series-Only Baseline:** Table 3 assesses the predictive performance of the time-series-only interpolation-prediction network described in Section 3.2. As expected, predictive performance increases as the amount of observed physiological data increases. We note that the results reported here are different from that in Shukla and Marlin (2019) because of additional data filtering required for removing hospital admission records containing no clinical notes and neonates data. Comparing to the results in Table 2, we can see that the predictive value of the clinical text available at the time of admission exceeds that of the available physiological data until near the end of the 42 hour period following admission. The next set of experiment aims to assess whether these two modalities can result in improved performance when fused.

**Fusion Approaches:** Based on the observed success of the TF-IDF-based model in the text-only baseline experiments, we examine the performance of fusion approaches using the TF-IDF-based model to embed the clinical text data. We begin by assessing the performance of a fusion approach that only has access to the clinical text data available at the time of admission, but increasing amounts of physiological time series data up to the end of the 48 hour period following admission. Table 3 shows the classification performance of the early and late fusion models under this experimental scenario. Figure 4 shows the performance of early and late fusion relative to the time series-only and text-only baselines. We can see that the late fusion approach achieves better performance than the early fusion approach in the first 30 hours after admission, while both significantly improve on the time

| Text Model     | Hours from Admission | Time Series-Only AUC | Early Fusion AUC | Late Fusion AUC |
|----------------|----------------------|----------------------|------------------|-----------------|
| WE / CNN       | 0                    | 0.7106               | 0.7850           | 0.8027          |
| WSE / RNN      | 0                    | 0.7380               | 0.7916           | 0.8161          |
| USE / RNN      | 0                    | 0.7645               | 0.8046           | 0.8138          |
| TF-IDF / 1-NN  | 0                    | 0.7759               | 0.8126           | 0.8256          |
| TF-IDF / 1-NN  | 6                    | 0.7902               | 0.8284           | 0.8324          |
| TF-IDF / 1-NN  | 18                   | 0.7958               | 0.8291           | 0.8320          |
| TF-IDF / 1-NN  | 36                   | 0.8023               | 0.8380           | 0.8376          |
| TF-IDF / 1-NN  | 48                   | 0.8245               | 0.8427           | 0.8453          |

Table 2: Text-only baselines.

Table 3: Performance of Time Series-Only baseline, Early and Late Fusion approach with notes available at admission time and increasing amount of physiological signals.
Figure 3: Performance comparison on the mortality prediction task with text available at admission only but increasing amounts of physiological time series.

series-only baseline. However, we see that all three models that incorporate physiological data increase in predictive performance as the amount of physiological data increases. Further, we see that the performance gap between fusion and time series-only models decreases over time, which indicates that the advantage provided by the initial fusion with text data available at time of admission decreases over time as that information becomes less relevant. Finally, we note that the late fusion model outperforms the text-only baseline at all times while the early fusion model initially exhibits lower performance than the text-only TF-IDF baseline, but goes on to match and then outperforms the text-only baseline.

Next, we consider the fusion process as increasing volumes of text data become available through time, as well as increasing volumes of physiological data. For this experiment, we consider only the TF-IDF-based text embedding model and limit the discussion to the late fusion approach as these models have achieved the best performance in our experiments to date. We consider incorporating text data known at admission at time 0, followed by the text of all notes known between 6 and 48 hours following admission. The results of this experiment are shown in Figure 4. We can see the predictive performance of progress notes is significantly better than physiological time series data. We can also see that the performance of the fused model always exceeds that of the corresponding text-only baseline at a given point in time, with performance generally rising as additional physiological/text data become available. By comparing with Figure 3, we can see that the addition of progress notes past admission results in a final fused model that significantly outperforms models that only have access to text data from the time of admission.

To verify the statistical significance of the gap between the late fusion approach and the single-modality approaches, we perform a five-fold random resampling assessment of the test AUC by randomly generating 5 train-validation-test splits. We run the complete hyper-parameter selection and learning pipeline for each approach on each of the five data sets. Figure 4 shows the mean with 95% confidence interval for all the baselines. Further, we performed a paired t-test on the resulting collection of AUC values for the late fusion approach compared to the single modality approaches. The results show that the improvement in mean AUC shown in Figure 4 is highly statistically significant ($p < 0.001$).

5 Discussion and Conclusions

In this paper, we have developed methods for investigating the relative predictive value of the content of clinical notes and physiological time series data in ICU EHRs. We have considered models based on clinical text only, models based on physiological time-series only, and a novel fusion approach that combines both modalities. Our experiments have focused on using this methodology to assess the relative predictive value of clinical text and physiological data as a function of time since admission. We have focused on the task of predicting in-hospital mortality events which take place more than 48 hours after admission.

Our results show that the relative value of information in text records known at the time of admission decreases over time as more physiological data are observed. However, incorporating newly available text data can significantly boost predictive performance. Finally, our results strongly support the conclusion that fusing both data modalities result in the best overall predictive performance.

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