RELATIONAL MULTI-INSTANCE LEARNING FOR CONCEPT ANNOTATION FROM MEDICAL TIME SERIES

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ABSTRACT

Recent advances in computing technology and sensor design have made it easier to collect longitudinal or time series data from patients, resulting in a gigantic amount of available medical data. Most of the medical time series lack annotations or even when the annotations are available they could be subjective and prone to human errors. Earlier works have developed natural language processing techniques to extract concept annotations and/or clinical narratives from doctor notes. However, these approaches are slow and do not use the accompanying medical time series data. To address this issue, we introduce the problem of concept annotation for the medical time series data, i.e., the task of predicting and localizing medical concepts by using the time series data as input. We propose Relational Multi-Instance Learning (RMIL) - a deep Multi Instance Learning framework based on recurrent neural networks, which uses pooling functions and attention mechanisms for the concept annotation tasks. Empirical results on medical datasets show that our proposed models outperform various multi-instance learning models.

1 INTRODUCTION

Clinicians have limited time (e.g., only a few minutes (Howie et al., 1999)) to study and treat each patient. However, they are overloaded with a lot of patient data from multiple sources and in various formats, such as patient medical history and doctor's notes in free-flowing text, vitals and monitoring data which are captured as time series, and prescriptions and drugs which appear as medical codes including ICD-9 (Organization & Corporation, 1998), LOINC codes (Forrey et al., 1996)), etc. This rich information should be summarized and available to clinicians in easily digestible format for faster diagnosis and treatment. Graphical visualizations (Plaisant et al., 1998) are a popular approach to show patient data to doctors. However, recent studies have shown that graphical visualisations are not always helpful for clinicians' decision-making (Law et al., 2005; Van Der Meulen et al., 2010). Text summaries on the other hand are widely embraced and are usually adopted in practice (Scott et al., 2013). Most existing systems use natural language processing techniques (Afantenos et al., 2005; Giordano et al., 2015) to generate summaries from doctor notes which include test results, discharge reports, observational notes, etc. While these systems are useful, they only use one source of data, i.e., doctor's notes which might have noisy and erroneous entries, for text summarization. On the other hand, electronic health records have other sources of patient data such as vital signs, monitoring sensors, lab results in the form of multivariate time-series, which can be more accurate and may contain rich information about patient's conditions. Few existing patient summarization systems actually extract information directly from these time series for concept prediction and/or summarization. Generating simple text summaries such as trends from time series has been investigated before (Sripada et al., 2003) but is marginally useful since these trends are not mapped to the medical concepts which can be understood by the clinicians. Recent works (Pham et al., 2016; Choi et al., 2016a;b; Lipton et al., 2015; Che et al., 2016) have successfully shown that clinical events and outcomes can be predicted using medical codes or clinical time series data. However, directly obtaining medical concept annotations and summaries from the time series data is still an open question.

In this work, we introduce the concept annotation task as the problem of predicting and localizing the medical concepts by modeling the related medical time series data. Figure 1 illustrates a concept annotation example where medical time series data such as heart rate, pH and blood gas pressure are given, and the goal is to predict the time series of concepts such as intubation, extubation and

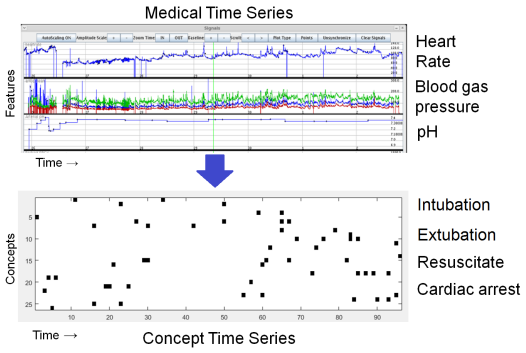


Figure 1: Medical time series to concept annotations.

resuscitate. To solve concept annotation problem, we formulate it as a Multi-Instance Learning (MIL) problem (Dietterich et al., 1997) and propose a deep learning based framework called Relational Multi-Instance Learning (RMIL). RMIL uses Recurrent Neural Networks (RNNs) to model multivariate time series data, leverages instance relations via attention mechanisms, and provides concept predictions using pooling functions.

The main contributions of our work are the following. We present a unified view of the MIL approaches for time series data using RNN models with different pooling functions and attention mechanisms. We show that our RMIL model is capable of learning a good classifier for concept detection (bag label predictions) and concept localization tasks (instance label prediction), even though it is only trained using bag labels. We demonstrate that RMIL obtains promising results on real-world medical datasets and outperforms popular MIL approaches.

The rest of the paper is structured as follows. In the following section, we briefly discuss the related works. Afterwards, we describe MIL framework and describe how RNN can be combined with multi-instance learning framework to obtain our proposed RMIL. In Sections 4 and 5, we present experimental results and conclusions respectively. In the appendix, we demonstrate anomaly detection as another application of our RMIL framework.

2 Related Work

Discovering concept annotations from the multivariate time series is a relatively new problem in medical domain with limited prior work. In this section, we will first highlight the related works on annotation tasks and then review related works on multi-instance learning.

Concept Annotation In medical domain, concept annotation is usually addressed in the clinical narrative mining and biomedical text mining literature (Aggarwal & Zhai, 2012; Cohen & Hersh, 2005; Zweigenbaum et al., 2007; Vincze et al., 2008). In other domains such as web-mining and computer vision, the concept annotation is usually analogous to semantic annotation (Kiryakov et al., 2004), image annotation (Jeon et al., 2003), object localization (Lampert et al., 2008) and image captioning (Karpathy et al., 2014).

Clinical Narratives Mining Automated discovery of temporal relations from clinical narratives (Savova et al., 2009; Zhou et al., 2006; Albright et al., 2013) and doctor notes (Plaisant et al., 1996) to uncover the patterns of disease progression is an important research problem in clinical informatics. Recent efforts such as SemEval competitions (Bethard et al., 2016) have been conducted to study this problem and evaluate/benchmark clinical information extraction systems (Xu et al., 2010). These competitions focus on discrete, well-defined tasks which allow for rapid, reliable and repeatable evaluations. However, they only consider identifying and extracting temporal relations from clinical notes and do not use the accompanying medical time series data.

Image Annotation and Captioning Successful object recognition systems have been developed in the past few decades for image annotation, object detection and localization in images and videos. ImageNet (Deng et al., 2009) and PASCAL challenges (Everingham et al., 2010) have greatly

accelerated the research in this area. Image captioning and visual-to-text translation, which are more generalized image annotation tasks, have been recently studied in several works (Karpathy et al., 2014; Kojima et al., 2002; Mao et al., 2014; Yu et al., 2016) where the goal is to find a text caption for a given image. Deep learning models such as RNN and sequence-to-sequence models (Sutskever et al., 2014) have achieved excellent results for image annotation/captioning tasks.

Multi-Instance Learning Multi-Instance Learning (MIL), a well known researched topic in machine learning, was first introduced by Dietterich et al. (1997) as a form of weakly supervised learning for drug activity prediction. MIL frameworks have since been applied to many other domains including image and text annotations (Chen & Wang, 2004; Soleimani & Miller, 2017). Andrews et al. (2003) adapted Support Vector Machines (SVM) to the MIL framework and introduced miSVM and MISVM for optimizing instance-level and bag-level classifications respectively. Zhou & Zhang (2007) further extended MIL and proposed MIMLSVM for tackling multi-label problems. Zhou et al. (2009) introduced miGraph and MIGraph to model the structure in each bag. Zhang et al. (2011); Guan et al. (2016) also proposed MIL framework for structure data by leveraging the relational structures at the bag and instance levels. Generative model based MIL frameworks such as Multi-Instance Mixture Model (MIMM)(Foulds & Smyth, 2011), and Dirichlet Process Mixture of Guassians (DPMIL) (Kandemir & Hamprecht, 2014) have also been proposed for binary multi-instance classification. Guan et al. (2016) used an autoregressive hidden Markov model and proposed an MIL framework for activity recognition in time-series data. Garcez & Zaverucha (2012) used recurrent neural networks to combine instance-level preprocessing and bag-level classification in MIL setting. Comprehensive reviews of MIL approaches are provided in Amores (2013); Herrera et al. (2016); Soleimani & Miller (2017). Recently, deep learning models have been successfully applied for MIL framework (Zhu et al., 2017; Wu et al., 2015; Huang et al., 2013; Yan et al., 2016; Kotzias et al., 2014; Kraus et al., 2016) and these approaches are generally termed as deep multi-instance learning models. Most of these works use either convolutional neural networks or deep neural networks in their MIL framework for image annotation, labeling, segmentation or classification tasks. Despite the popularity of deep models for MIL, there are few works which have extended deep MIL models for multivariate time series data. The goal of this paper is to propose and study deep multi-instance learning models for multivariate time series data.

3 METHODS

In this section, we will first describe the Multi-instance learning framework, and then present our problem formulation and our proposed relational multi-instance learning models.

3.1 MULTI-INSTANCE LEARNING

Multi-instance learning (MIL) is a form of weakly supervised learning where the training data is arranged in sets called *bags*, and a label is provided for the entire bag. The data points inside a bag are referred to as *instances*. In the MIL framework, instance labels are not provided during training. The main goal of MIL is to learn a model based on the instances in the bag and the label of the bag - to make bag-level and instance-level predictions. In this work, we only focus on the classification task in MIL, leaving out other learning tasks such as regression. Generally, two broad assumptions are considered to model the relationship between instance label and bag label. In the standard MIL assumption (Dietterich et al., 1997), the bag label is negative if all the instances in the bag have a negative label, and the bag label is positive if at-least one of the instances in the bag has a positive label. Following the notations of Carbonneau et al. (2017), let X denote a bag with N feature vector instances i.e., $X = \{x_1, ..., x_N\}$. Let each instance x_i in feature space $\mathcal{X}$ be mapped to a class by some process $f : \mathcal{X} \rightarrow \{0, 1\}$, where 0 and 1 correspond to negative and positive labels respectively. The bag classifier, also know as the aggregator function, $g(X)$ is defined by:

$$g(X) = \begin{cases} 1 & \text{if } \exists x \in X : f(X) = 1; \\ 0 & \text{otherwise} \end{cases}$$

The standard assumption is quite restrictive for some problem settings, where the positive bags cannot be identified by a single instance. Thus, this assumption can be relaxed to a collective assumption

which says that several positive instances in a bag are necessary to assign a positive label to that bag. In this case, a bag classifier is given by:

$$g(X) = \begin{cases} 1 & \text{if } \sum_{x \in X} f(X) \geq \theta; \\ 0 & \text{otherwise} \end{cases}$$

where θ is a threshold which indicates the minimum number of instances with positive labels that should be present in a bag to assign a positive label to that bag. As discussed in section 2, a plethora of works have adapted machine learning models to the MIL setting to optimize instance-level and/or bag-level predictions.

3.2 Problem Formulation

We formulate the concept annotation task as the detection and localization of concepts given the medical time series data. Let each patient $i \in \{1, .., N\}$ be associated with a medical time series (also referred to as feature time series) denoted by $\boldsymbol{X}_i \in \mathbb{R}^{T \times D}$, where D denotes the number of features (such as heart rate, blood pressure) and T denotes the length of time series observations (i.e., amount of time a patient is monitored). Let $\mathcal{C}$ denote the set of all the concepts associated with the N patients, and $\boldsymbol{Y}_i \in \{0, 1\}^K$ denote the concepts associated with i^{th} patient where $K = |\mathcal{C}|$. Let $\boldsymbol{C}_i \in \{0, 1\}^{T \times K}$ denote the concept time series of $\boldsymbol{X}_i$ with $C_i^{jk} = 1$ when concept k is present at time-stamp j. In multi-instance learning settings, we treat each time series $\boldsymbol{X}_i$ as one bag, and the observation at each time step j i.e. $\boldsymbol{X}_i^j \in \mathbb{R}^D$ as an instance in that bag. We are interested in the following tasks:

- Concept prediction task: for patient i, given $\boldsymbol{X}_i$, predict $\boldsymbol{Y}_i$.
- Concept localization task: for patient i, given $\boldsymbol{X}_i$, predict $\boldsymbol{C}_i$.

Notice that during training phase, only the input $\boldsymbol{X}_i$ and prediction label $\boldsymbol{Y}_i$ are available. Though $\boldsymbol{C}$ is not known, we usually have some assumptions about the relationship of prediction and localization labels. In this work, $Y_i^k = \mathcal{I}\left(\sum_{1 \leq j \leq T} C_i^{jk} \geq \eta\right)$, where $\mathcal{I}$ is an indicator function and η is a constant which depends on the MIL assumption. For example, in our concept annotation tasks we make the standard assumption, i.e we assume $\eta = 1$, i.e. the time series label (bag label) for a concept is positive if that concept is present at any one time-stamp (at-least one instance has positive label).

3.3 Relational Multi-Instance Learning Framework

Inspired by the recent success of recurrent neural networks in sequence modeling Bahdanau et al. (2014); Sutskever et al. (2014) and classification tasks Krizhevsky et al. (2012); Simonyan & Zisserman (2014), we adapt these models to the MIL framework to model multivariate time series data for concept annotation tasks. We denote all the variables at every time step as an instance and the entire multivariate time series as a bag. Unlike the traditional MIL setting, where the instances within a bag are independent of each other, in our case, the instances have relationships (namely temporal dependencies) among them. To model these dependencies, we propose to combine RNN models such as Long-Short Term Memory Neural Networks (LSTM) and Sequence-to-Sequence models with MIL, and propose our **R**elational **M**ulti-**I**nstance **L**earning framework, abbreviated as **RMIL**. RMIL takes in multivariate time series as input and outputs concept annotations. In RMIL, the outputs of RNN model provide the instance label predictions (i.e. solution for concept localization task) and the aggregation of the instance labels using aggregators such as pooling layer provides the bag label predictions (i.e. solution for concept prediction task). We propose different pooling functions and attention mechanisms which can be easily incorporated into our RMIL to improve the concept annotations.

Pooling Layers for RMIL The bag-level prediction is obtained by using an aggregation gathering on all instance-level predictions. The aggregator function $g(\cdot) : [0, 1]^T \mapsto [0, 1]$ in RMIL can be modeled using the pooling layers. Without loss of generality we assume that RNN model computes a mapping from the feature time series to the concept time series for each of the concept $k \in \mathcal{C}$. Let us denote the probability of an instance j belonging to concept k as p_{jk}. Then, the bag level probability for a concept k is given by $P_k = g(p_{1k}, p_{2k}, \ldots, p_{Tk})$. The role of aggregator function

$g(\cdot)$ is to combine the instance probabilities from each class specific feature map $\{p_{jk}\}$ into a single bag probability P_k. Several pooling mechanisms shown in Table 1 have been introduced in MIL and deep learning literature which can be used in our RMIL. In table 1, r, a, b_k, and r_k are parameters which can be fixed or are learned during training, and $\sigma(\cdot)$ denotes the sigmoid function.

Table 1: Pooling functions for RMIL.

Pooling Functions	
Noisy-OR pooling (Zhang et al., 2006)	$P_k = g\left(\{p_{jk}\}\right) = 1 - \prod_j (1 - p_{jk})$
Log-sum-exponention (LSE) (Ramon & De Raedt, 2000)	$P_k = g\left(\{p_{jk}\}\right) = \frac{1}{r} \log\left(\frac{1}{T} \sum_j \exp\left(r p_{jk}\right)\right)$
Generalized Mean (GM) (Keeler et al., 1991)	$P_k = g\left(\{p_{jk}\}\right) = \left(\frac{1}{T} \sum_j p_{jk}^r\right)^{1/r}$
Integrated segmentation and recognition (ISR) (Keeler et al., 1991)	$P_k = g\left(\{p_{jk}\}\right) = \sum_j \frac{p_{jk}}{1-p_{jk}} / \left(1 + \sum_j \frac{p_{jk}}{1-p_{jk}}\right)$
Noisy-AND pooling (Kraus et al., 2016)	$P_k = g\left(\{p_{jk}\}\right) = \frac{\sigma\left(a\left(\sum_j p_{jk}/T - b_k\right)\right) - \sigma(-ab_k)}{\sigma(a(1-b_k)) - \sigma(-ab_k)}$
Max pooling	$P_k = g\left(\{p_{jk}\}\right) = \max_j \left(p_{jk}\right)$
Softmax pooling	$P_k = g\left(\{p_{jk}\}\right) = \sum_j p_{jk} \cdot softmax\left(\{p_{jk}\}\right)_j = \frac{\sum_j p_{jk} \exp(r_k p_{jk})}{\sum_j \exp(r_k p_{jk})}$

Attention Mechanism for RMIL Instances within each bag have temporal relations between them. We can use attention mechanism to focus on some of the instances and their relations to improve their instance-level predictions. In order to make predictions at time j, the hidden state $\boldsymbol{h}_j \in \mathbb{R}^Q$ of RNN can be used, where Q is the hidden state dimension. However, relevant information may be captured by hidden states at other time steps as well. Thus, we may want to introduce an attention vector or matrix ($\boldsymbol{a}$) to leverage information of hidden states $\boldsymbol{H} = (\boldsymbol{h}_1, \cdots, \boldsymbol{h}_T)^\top \in \mathbb{R}^{T \times Q}$ from all time steps. Let us denote the output after attention as $\tilde{\boldsymbol{H}} \in \mathbb{R}^{T \times Q}$. The attention matrix can then be modeled using $\tilde{\boldsymbol{H}}$ in various ways as listed below.

Feature-based Attention One idea is to design the attention matrix based on the feature and its time-stamp. Let us define a feature-based attention matrix as $\boldsymbol{A} = (\boldsymbol{a}_1, \cdots, \boldsymbol{a}_T)^\top \in \mathbb{R}^{T \times Q}$. For each $j = 1, \cdots, T$, we have

$$\boldsymbol{a}_j = \left(\exp\left({\boldsymbol{w}_j}^\top \boldsymbol{H}\right)\right) \oslash \left(\sum_{1 \le j' \le T} \exp\left({\boldsymbol{w}_{j'}}^\top \boldsymbol{H}\right)\right)$$

and $\tilde{\boldsymbol{H}} = \boldsymbol{A} \odot \boldsymbol{H}$, where $\odot$ and $\oslash$ are element-wise multiplication and division, respectively and $\boldsymbol{W} = (\boldsymbol{w}_1, \cdots, \boldsymbol{w}_T)^\top \in \mathbb{R}^{T \times T}$ is the weight matrix which can be learned during training. We call this *Attention-F* mechanism. We can simplify this attention by averaging the attentions for all hidden dimensions by taking $a_{jq} \leftarrow 1/Q \cdot \sum_{1 \le q' \le Q} a_{jq'}$. We will denote this as *Attention-FS* mechanism.

Time-based Attention Attention model (Ma et al., 2017) can be designed to capture the relation between the current time step j and previous time steps $j' \le j$, by solely relying on previous hidden states $\boldsymbol{h}_{j'}$. We can define a time-based attention matrix as $\boldsymbol{A} \in \mathbb{R}^{T \times T}$. For each j and j' in $[1, \cdots, T]$, we have

$$a_{j,j'} = \begin{cases} \left(\exp\left(\boldsymbol{w}^\top \boldsymbol{h}_{j'}\right)\right) / \left(\sum_{1 \le j'' \le j} \exp\left(\boldsymbol{w}^\top \boldsymbol{h}_{j''}\right)\right), & j' \le j; \\ 0, & \text{otherwise.} \end{cases}$$

and $\tilde{\boldsymbol{H}} = \boldsymbol{A} \cdot \boldsymbol{H}$, where $\boldsymbol{w} \in \mathbb{R}^D$ is the weight vector to learn. We use *Attention-T* to represent Time-based attention mechanism.

Interaction-based Attention The time-based attention can be further improved by considering both the previous and current hidden states $\boldsymbol{h}_{j'}$ and $\boldsymbol{h}_j$ (Ma et al., 2017). In this case, we have

$$a_{j,j'} = \begin{cases} \left(\exp\left(\boldsymbol{v}^\top \tanh(\boldsymbol{W_1}\boldsymbol{h}_j + \boldsymbol{W_2}\boldsymbol{h}_{j'})\right)\right) / \left(\sum_{1\leq j''\leq j} \exp\left(\boldsymbol{v}^\top \tanh(\boldsymbol{W_1}\boldsymbol{h}_j + \boldsymbol{W_2}\boldsymbol{h}_{j''})\right)\right), & j' \leq j; \\ 0, & \text{otherwise} \end{cases}$$

and similarly $\tilde{\boldsymbol{H}} = \boldsymbol{A} \cdot \boldsymbol{H}$. Here, we need to learn $\boldsymbol{v} \in \mathbb{R}^S, \boldsymbol{W_1} \in \mathbb{R}^{S\times Q}, \boldsymbol{W_2} \in \mathbb{R}^{S\times Q}$, and we choose $S = Q/2$. A simplified version of interaction-based attention can be obtained if we use vector $\boldsymbol{w_1} \in \mathbb{R}^Q, \boldsymbol{w_2} \in \mathbb{R}^Q$ instead of matrices $\boldsymbol{W_1}, \boldsymbol{W_2}$ and by setting $\boldsymbol{v} = \boldsymbol{1}$ in the above equation. We use *Attention-I* and *Attention-IS* to represent Interaction-based attention mechanism and simplified version of interaction-based attention mechanism respectively.

The above attention mechanisms usually help both prediction and localization tasks.

4 EXPERIMENTS

Here, we demonstrate the performance of our proposed RMIL models on concept annotation tasks i.e. concept prediction and localization tasks, using a real-world health-care dataset and compare its performance to the popular multi-instance learning approaches. In addition, we discuss the impact of using pooling functions and attention mechanism in our RMIL framework.

4.1 DATASET DESCRIPTIONS AND EXPERIMENTAL DESIGN

To evaluate our RMIL, we ran experiments on MIMIC-III RESP dataset whose statistics is shown in Table 2.

Table 2: MIMIC-III RESP dataset.

	MIMIC-III RESP
# of samples (N)	2014
# of variables (D)	21
# of time steps	4
# of concepts	26

MIMIC-III RESP Dataset MIMIC-III is a public dataset (Johnson et al., 2016) which has deidentified clinical care data collected at Beth Israel Deaconess Medical Center from 2001 to 2012. It contains over 58,000 hospital admission records of 38,645 adults and 7,875 neonates. For our work, we extracted 21 feature time series from more than 2,000 adult patients who were diagnosed with a respiratory disorder such as Acute Hypoxemic Respiratory Failure (AHRF) (Khemani et al., 2009) at the time of admission. These 21 features are respiratory based features such as peak inspiratory pressure (PIP) and arterial partial pressure of oxygen (PaO2) and were collected during the first 3 days after admission. The feature time series has 4 time stamps and the first time stamp corresponds to the admission time. We denote this dataset as MIMIC-III RESP dataset.

Concept Annotations The medical time series data of MIMIC-III dataset does not come with the concept annotations, however the medical concepts are available in the doctor notes of the MIMIC-III database. To obtain the concept annotations, we extract the concept time series from the doctor notes using the `NOTEEVENTS` table of MIMIC-III database. The total number of doctor notes is 2,083,180, out of which 98.15% of notes (2,044,634 notes) have no timestamp and 1.85% of notes (38,546 notes) have timestamps associated with them. The total number of unique concepts in the doctor notes in the first 3 days data is 6,197. To obtain concept time series for each patient with respiratory disorder such as AHRF, we first identified respiratory-related concepts from the medical literature (Antonelli et al., 2001; Khemani et al., 2009), and obtained their medical codes from the Unified Medical Language System (UMLS) dictionary (Bodenreider, 2004). Then, we mined the patient's doctor notes from `NOTEEVENTS` table to extract all the possible medical concepts related to the respiratory system and its disorder. In total, we chose top 26 respiratory concepts to annotate the feature time series, and generated the concepts time series for 4 time-stamps (first 3 days after admission) for each patient.

4.2 COMPARISON AND IMPLEMENTATION DETAILS

We compare the performance of our proposed models to the popular MIL models such as MISVM (Andrews et al., 2003) and DPMIL (Kandemir & Hamprecht, 2014). We categorize all the evaluated methods into two groups:

Table 3: Concept annotation results on MIMIC-III RESP dataset. Max-pooling function was used in all RMIL models.

		Prediction		Localization	
		AUROC	**AUPRC**	**AUROC**	**AUPRC**
RMIL Models	S2S	0.858	0.756	0.788	0.431
	S2S with Attention I	0.858	0.758	0.793	0.433
	LSTM	0.860	0.763	0.795	0.444
	LSTM with Attention I	0.862	0.766	0.797	0.444
	Bi-LSTM	0.864	0.769	0.789	0.415
	Bi-LSTM with Attention I	0.864	0.769	0.796	0.420
MIL Models	DPMIL	0.531	0.222	0.516	0.148
	MISVM	0.751	0.613	0.706	0.333

1. *Multi-Instance Learning models (MIL)*: We treat MISVM and DPMIL as our baseline MIL models.
2. *Relational Multi-Instance Learning models (RMIL)*: We evaluate the following deep learning models as part of our RMIL framework:
   (a) Long Short-Term Memory neural networks (LSTM) (Hochreiter & Schmidhuber, 1997)
   (b) Bi-directional LSTM (Bi-LSTM) (Graves et al., 2013)
   (c) Sequence to Sequence models (S2S) (Sutskever et al., 2014)
   (d) The above three RMIL models with different attention mechanisms
   (e) The above RMIL models with different pooling functions

For LSTM models, we use two LSTM layers and two dense layers. For S2S models, we use two LSTM layers for both the encoder and the decoder. For Bi-LSTM models, we use two bi-directional LSTM layers. All the models were constructed to have a comparable number of parameters. We train all the Deep learning models with the RMSProp optimization method and we use early stopping to find the best weights on the validation dataset. For baseline MIL models, we follow the suggestions of the corresponding papers to fine-tune the parameters. All the input variables in the training data are normalized to be 0 mean and 1 standard deviation. The inputs to all the models is the same feature time series data. We used Keras (Chollet, 2017) and Python to run the deep models and MISVM models. Matlab code from the original authors was used to obtain DPMIL results. We use the area under ROC (AUROC) and area under precision-recall curve (AUPRC) scores as our evaluation metrics and report the results from 5-fold cross validation for all the evaluated methods.

4.3 Quantitative Results

Table 3 shows the concept annotation results on the MIMIC-III RESP dataset. From this table, we see that RMIL models outperform the non-deep multi-instance learning models by at least 8-10% for concept localization task, and by at least 10-15% for concept prediction tasks in terms of AUROC and AUPRC. Among all the RMIL models, we find that LSTM model obtains slightly better overall results compared to the other models for localization task.

To study the impact of pooling and attention, we trained and evaluated LSTM models with different pooling functions and different attention mechanisms, which are described in Section 3. Tables 4 and 5 show the comparison results. From these tables, we observed that (i) all the attention mechanisms except feature-based attention perform similar to each other especially for the prediction task, and (ii) all the pooling functions other than ISR and Noisy-OR obtain similar overall performance. This demonstrates that choice of attention does not matter but choice of pooling has some impact in our RMIL framework.

4.4 Discussions

We can study the interpretability of concept localization by looking at the localization results of our RMIL models, even though the model is trained without the labels for localization. Figure 2 shows the ground truth annotations of two respiratory concepts - intubation and extubation concepts, and the prediction probabilities of these concepts obtained by our RMIL attention-based LSTM models. From figure 2(a) we can make the following observations, (i) intubation usually happens before

Table 4: Results on RMIL LSTM models with different pooling functions and with Attention-I mechanism.

	Prediction		Localization	
	AUROC	**AUPRC**	**AUROC**	**AUPRC**
LSTM with ISR Pooling	0.862	0.765	0.733	0.375
LSTM with Noisy-AND Pooling	0.863	0.767	0.779	0.431
LSTM with Generalized Mean Pooling	0.863	0.767	0.796	0.450
LSTM with LSE Pooling	0.863	0.767	0.792	0.452
LSTM with Softmax Pooling	0.863	0.767	0.790	0.450
LSTM with Noisy-OR Pooling	0.860	0.762	0.703	0.318
LSTM with Max Pooling	0.862	0.766	0.797	0.444

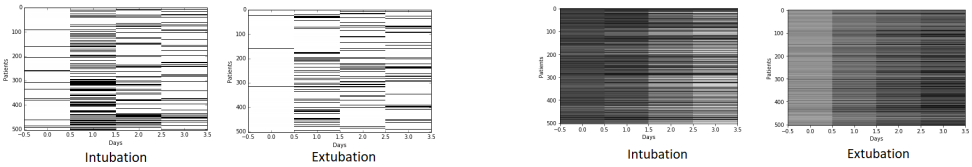
Table 5: Results on RMIL LSTM models with different attention mechanisms and with max pooling.

	Prediction		Localization	
Model	**AUROC**	**AUPRC**	**AUROC**	**AUPRC**
LSTM with Attention-T	0.864	0.768	0.796	0.445
LSTM with Attention-IS	0.862	0.767	0.798	0.446
LSTM with Attention-I	0.862	0.766	0.797	0.444
LSTM with Attention-FS	0.861	0.765	0.796	0.417
LSTM with Attention-F	0.861	0.764	0.780	0.408
LSTM with no attention	0.860	0.763	0.795	0.444

extubation for the same patient, (ii) intubation and extubation could happen on the same day, and (iii) intubation and extubation occur commonly within the 1st 24 hours of admission. From the figure 2(b), we see that our RMIL attention based LSTM predicts that the probability of intubation happening on the first day of admission is higher (draker gray means higher probability of concept occurrence) and the probability of extubation happening within first day is lower. This indicates that the model has correctly learnt that intubation should appear before extubation. This also implicitly implies that the RMIL attention-based LSTM models have correctly learnt the instance-level relationships from the medical time series data with only bag-level labels.

5 SUMMARY

In this paper, we presented Relational Multi-Instance Learning - a deep multi-instance learning framework using recurrent neural networks for concept annotation from the medical time series data. Empirical results on medical dataset demonstrated that our proposed models outperform the popular state-of-the-art multi-instance learning approaches. Experiments with different pooling and attention mechanisms showed that while attention mechanism does not have a significant impact on model's performance, certain pooling functions such as ISR and Noisy-OR can negatively impact the instance prediction results.



(a) Ground truth annotations of intubation and extubation concepts.

(b) Intubation and extubation concept prediction probabilities identified by attention-based LSTM.

Figure 2: Ground truth and predicted concept annotation comparison. In 2(a) white block corresponds to absence of a concept and black block corresponds to presence of a concept. In 2(b), darker gray value indicates higher chance for presence of a concept. X-axis represents time steps, Y-axis corresponds to different patients.

REFERENCES

Stergos Afantenos, Vangelis Karkaletsis, and Panagiotis Stamatopoulos. Summarization from medical documents: a survey. *Artificial intelligence in medicine*, 33(2):157–177, 2005.

Charu C Aggarwal and ChengXiang Zhai. *Mining text data*. Springer Science & Business Media, 2012.

Daniel Albright, Arrick Lanfranchi, Anwen Fredriksen, William F Styler IV, Colin Warner, Jena D Hwang, Jinho D Choi, Dmitriy Dligach, Rodney D Nielsen, James Martin, et al. Towards comprehensive syntactic and semantic annotations of the clinical narrative. *Journal of the American Medical Informatics Association*, 20(5):922–930, 2013.

Jaume Amores. Multiple instance classification: Review, taxonomy and comparative study. *Artificial Intelligence*, 201:81–105, 2013.

Stuart Andrews, Ioannis Tsochantaridis, and Thomas Hofmann. Support vector machines for multiple-instance learning. In *Advances in neural information processing systems*, pp. 577–584, 2003.

M Antonelli, G Conti, ML Moro, A Esquinas, G Gonzalez-Diaz, M Confalonieri, P Pelaia, T Principi, C Gregoretti, F Beltrame, et al. Predictors of failure of noninvasive positive pressure ventilation in patients with acute hypoxemic respiratory failure: a multi-center study. *Intensive care medicine*, 2001.

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. *arXiv preprint arXiv:1409.0473*, 2014.

Steven Bethard, Guergana Savova, Wei-Te Chen, Leon Derczynski, James Pustejovsky, and Marc Verhagen. Semeval-2016 task 12: Clinical tempeval. *Proceedings of SemEval*, pp. 1052–1062, 2016.

Olivier Bodenreider. The unified medical language system (umls): integrating biomedical terminology. *Nucleic acids research*, 32(suppl_1):D267–D270, 2004.

Alessandro Camerra, Themis Palpanas, Jin Shieh, and Eamonn Keogh. isax 2.0: Indexing and mining one billion time series. In *Data Mining (ICDM), 2010 IEEE 10th International Conference on*, pp. 58–67. IEEE, 2010.

Ricardo JGB Campello, Davoud Moulavi, Arthur Zimek, and Jörg Sander. Hierarchical density estimates for data clustering, visualization, and outlier detection. *ACM Transactions on Knowledge Discovery from Data (TKDD)*, 10(1):5, 2015.

Marc-Andre Carbonneau, Veronika Cheplygina, Eric Granger, and Ghyslain Gagnon. Multiple instance learning: A survey of problem characteristics and applications. *Pattern Recognition*, 2017.

Philip K Chan and Matthew V Mahoney. Modeling multiple time series for anomaly detection. In *Data Mining, Fifth IEEE International Conference on*, pp. 8–pp. IEEE, 2005.

Varun Chandola, Arindam Banerjee, and Vipin Kumar. Anomaly detection: A survey. *ACM computing surveys (CSUR)*, 41(3):15, 2009.

Varun Chandola, Arindam Banerjee, and Vipin Kumar. Anomaly detection for discrete sequences: A survey. *IEEE Transactions on Knowledge and Data Engineering*, 24(5):823–839, 2012.

Zhengping Che, Sanjay Purushotham, Kyunghyun Cho, David Sontag, and Yan Liu. Recurrent neural networks for multivariate time series with missing values. *arXiv preprint arXiv:1606.01865*, 2016.

Yixin Chen and James Z Wang. Image categorization by learning and reasoning with regions. *Journal of Machine Learning Research*, 5(Aug):913–939, 2004.

Edward Choi, Mohammad Taha Bahadori, Elizabeth Searles, Catherine Coffey, Michael Thompson, James Bost, Javier Tejedor-Sojo, and Jimeng Sun. Multi-layer representation learning for medical concepts. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 1495–1504. ACM, 2016a.

Youngduck Choi, Chill Yi-I Chiu, and David Sontag. Learning low-dimensional representations of medical concepts. *AMIA Summits on Translational Science Proceedings*, 2016:41, 2016b.

François Chollet. Keras (2015). *URL http://keras. io*, 2017.

Aaron M Cohen and William R Hersh. A survey of current work in biomedical text mining. *Briefings in bioinformatics*, 6(1):57–71, 2005.

Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on*, pp. 248–255. IEEE, 2009.

Thomas G Dietterich, Richard H Lathrop, and Tomás Lozano-Pérez. Solving the multiple instance problem with axis-parallel rectangles. *Artificial intelligence*, 89(1):31–71, 1997.

Mark Everingham, Luc Van Gool, Christopher KI Williams, John Winn, and Andrew Zisserman. The pascal visual object classes (voc) challenge. *International journal of computer vision*, 88(2): 303–338, 2010.

Arden W Forrey, Clement J Mcdonald, Georges DeMoor, Stanley M Huff, Dennis Leavelle, Diane Leland, Tom Fiers, Linda Charles, Brian Griffin, Frank Stalling, et al. Logical observation identifier names and codes (loinc) database: a public use set of codes and names for electronic reporting of clinical laboratory test results. *Clinical Chemistry*, 42(1):81–90, 1996.

James Foulds and Padhraic Smyth. Multi-instance mixture models and semi-supervised learning. In *Proceedings of the 2011 SIAM International Conference on Data Mining*, pp. 606–617. SIAM, 2011.

AS d'Avila Garcez and Gerson Zaverucha. Multi-instance learning using recurrent neural networks. In *Neural Networks (IJCNN), The 2012 International Joint Conference on*, pp. 1–6. IEEE, 2012.

Daniela Giordano, Isaak Kavasidis, and Concetto Spampinato. Automatic summary creation by applying natural language processing on unstructured medical records. In *International Conference on Computer Analysis of Images and Patterns*, pp. 383–393. Springer, 2015.

Alex Graves, Abdel-rahman Mohamed, and Geoffrey Hinton. Speech recognition with deep recurrent neural networks. In *Acoustics, speech and signal processing (icassp), 2013 ieee international conference on*, pp. 6645–6649. IEEE, 2013.

Xinze Guan, Raviv Raich, and Weng-Keen Wong. Efficient multi-instance learning for activity recognition from time series data using an auto-regressive hidden markov model. In *International Conference on Machine Learning*, pp. 2330–2339, 2016.

Fabio Guigou, Pierre Collet, and Pierre Parrend. The artificial immune ecosystem: a bio-inspired meta-algorithm for boosting time series anomaly detection with expert input. In *European Conference on the Applications of Evolutionary Computation*, pp. 573–588. Springer, 2017.

Manish Gupta, Jing Gao, Charu C Aggarwal, and Jiawei Han. Outlier detection for temporal data: A survey. *IEEE Transactions on Knowledge and Data Engineering*, 26(9):2250–2267, 2014.

Francisco Herrera, Sebastián Ventura, Rafael Bello, Chris Cornelis, Amelia Zafra, Dánel Sánchez-Tarragó, and Sarah Vluymans. Introduction. In *Multiple Instance Learning*, pp. 1–16. Springer, 2016.

Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8): 1735–1780, 1997.

Victoria Hodge and Jim Austin. A survey of outlier detection methodologies. *Artificial intelligence review*, 22(2):85–126, 2004.

John GR Howie, David J Heaney, Margaret Maxwell, Jeremy J Walker, George K Freeman, and Harbinder Rai. Quality at general practice consultations: cross sectional survey. *Bmj*, 319(7212): 738–743, 1999.

Yan Huang, Wei Wang, Liang Wang, and Tieniu Tan. Multi-task deep neural network for multi-label learning. In *Image Processing (ICIP), 2013 20th IEEE International Conference on*, pp. 2897–2900. IEEE, 2013.

Jiwoon Jeon, Victor Lavrenko, and Raghavan Manmatha. Automatic image annotation and retrieval using cross-media relevance models. In *Proceedings of the 26th annual international ACM SIGIR conference on Research and development in informaion retrieval*, pp. 119–126. ACM, 2003.

AEW Johnson, TJ Pollard, L Shen, L Lehman, M Feng, M Ghassemi, B Moody, P Szolovits, LA Celi, and RG Mark. Mimic-iii, a freely accessible critical care database. *Scientific Data*, 2016.

Michael Jones, Daniel Nikovski, Makoto Imamura, and Takahisa Hirata. Exemplar learning for extremely efficient anomaly detection in real-valued time series. *Data Mining and Knowledge Discovery*, 30(6):1427–1454, 2016.

Melih Kandemir and Fred A Hamprecht. Instance label prediction by dirichlet process multiple instance learning. In *UAI*, pp. 380–389, 2014.

Andrej Karpathy, George Toderici, Sanketh Shetty, Thomas Leung, Rahul Sukthankar, and Li Fei-Fei. Large-scale video classification with convolutional neural networks. In *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, pp. 1725–1732, 2014.

James D Keeler, David E Rumelhart, and Wee Kheng Leow. Integrated segmentation and recognition of hand-printed numerals. In *Advances in neural information processing systems*, pp. 557–563, 1991.

Robinder G Khemani, David Conti, Todd A Alonzo, Robert D Bart, and Christopher JL Newth. Effect of tidal volume in children with acute hypoxemic respiratory failure. *Intensive care medicine*, 35 (8):1428–1437, 2009.

Atanas Kiryakov, Borislav Popov, Ivan Terziev, Dimitar Manov, and Damyan Ognyanoff. Semantic annotation, indexing, and retrieval. *Web Semantics: Science, Services and Agents on the World Wide Web*, 2(1):49–79, 2004.

Atsuhiro Kojima, Takeshi Tamura, and Kunio Fukunaga. Natural language description of human activities from video images based on concept hierarchy of actions. *International Journal of Computer Vision*, 50(2):171–184, 2002.

Dimitrios Kotzias, Misha Denil, Phil Blunsom, and Nando de Freitas. Deep multi-instance transfer learning. *arXiv preprint arXiv:1411.3128*, 2014.

Oren Z Kraus, Jimmy Lei Ba, and Brendan J Frey. Classifying and segmenting microscopy images with deep multiple instance learning. *Bioinformatics*, 32(12):i52–i59, 2016.

Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, pp. 1097–1105, 2012.

Stephen C Kurachek, Christopher J Newth, Michael W Quasney, Tom Rice, Ramesh C Sachdeva, Neal R Patel, Jeanne Takano, Larry Easterling, Mathew Scanlon, Ndidiamaka Musa, et al. Extubation failure in pediatric intensive care: a multiple-center study of risk factors and outcomes. *Critical care medicine*, 31(11):2657–2664, 2003.

Christoph H Lampert, Matthew B Blaschko, and Thomas Hofmann. Beyond sliding windows: Object localization by efficient subwindow search. In *Computer Vision and Pattern Recognition, 2008. CVPR 2008. IEEE Conference on*, pp. 1–8. IEEE, 2008.

Anna S Law, Yvonne Freer, Jim Hunter, Robert H Logie, Neil McIntosh, and John Quinn. A comparison of graphical and textual presentations of time series data to support medical decision making in the neonatal intensive care unit. *Journal of clinical monitoring and computing*, 19(3): 183–194, 2005.

Jessica Lin, Eamonn Keogh, Stefano Lonardi, and Bill Chiu. A symbolic representation of time series, with implications for streaming algorithms. In *Proceedings of the 8th ACM SIGMOD workshop on Research issues in data mining and knowledge discovery*, pp. 2–11. ACM, 2003.

Zachary C Lipton, David C Kale, Charles Elkan, and Randall Wetzell. Learning to diagnose with lstm recurrent neural networks. *arXiv preprint arXiv:1511.03677*, 2015.

Fenglong Ma, Radha Chitta, Jing Zhou, Quanzeng You, Tong Sun, and Jing Gao. Dipole: Diagnosis prediction in healthcare via attention-based bidirectional recurrent neural networks. In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 1903–1911. ACM, 2017.

Junhua Mao, Wei Xu, Yi Yang, Jiang Wang, Zhiheng Huang, and Alan Yuille. Deep captioning with multimodal recurrent neural networks (m-rnn). *arXiv preprint arXiv:1412.6632*, 2014.

World Health Organization and Practice Management Information Corporation. *ICD-9-CM: International Classification of Diseases, 9th Revision: Clinical Modification*, volume 1. PMIC (Practice Management Information Corporation), 1998.

Trang Pham, Truyen Tran, Dinh Phung, and Svetha Venkatesh. Deepcare: A deep dynamic memory model for predictive medicine. In *Advances in Knowledge Discovery and Data Mining*, pp. 30–41. Springer, 2016.

Catherine Plaisant, Brett Milash, Anne Rose, Seth Widoff, and Ben Shneiderman. Lifelines: visualizing personal histories. In *Proceedings of the SIGCHI conference on Human factors in computing systems*, pp. 221–227. ACM, 1996.

Catherine Plaisant, Rich Mushlin, Aaron Snyder, Jia Li, Daniel Heller, and Ben Shneiderman. Lifelines: using visualization to enhance navigation and analysis of patient records. In *Proceedings of the AMIA Symposium*, pp. 76. American Medical Informatics Association, 1998.

Jan Ramon and Luc De Raedt. Multi instance neural networks. In *Proceedings of the ICML-2000 workshop on attribute-value and relational learning*, pp. 53–60, 2000.

Adrienne G Randolph, David Wypij, Shekhar T Venkataraman, James H Hanson, Rainer G Gedeit, Kathleen L Meert, Peter M Luckett, Peter Forbes, Michelle Lilley, John Thompson, et al. Effect of mechanical ventilator weaning protocols on respiratory outcomes in infants and children: a randomized controlled trial. *Jama*, 288(20):2561–2568, 2002.

Guergana Savova, Steven Bethard, Will Styler, James Martin, Martha Palmer, James Masanz, and Wayne Ward. Towards temporal relation discovery from the clinical narrative. In *AMIA annual symposium proceedings*, volume 2009, pp. 568. American Medical Informatics Association, 2009.

Donia Scott, Catalina Hallett, and Rachel Fettiplace. Data-to-text summarisation of patient records: Using computer-generated summaries to access patient histories. *Patient education and counseling*, 92(2):153–159, 2013.

Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*, 2014.

Hossein Soleimani and David J Miller. Semisupervised, multilabel, multi-instance learning for structured data. *Neural computation*, 2017.

Somayajulu G Sripada, Ehud Reiter, Jim Hunter, and Jin Yu. Generating english summaries of time series data using the gricean maxims. In *Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining*, pp. 187–196. ACM, 2003.

Ilya Sutskever, Oriol Vinyals, and Quoc V Le. Sequence to sequence learning with neural networks. In *Advances in neural information processing systems*, pp. 3104–3112, 2014.

Marian Van Der Meulen, Robert H Logie, Yvonne Freer, Cindy Sykes, Neil McIntosh, and Jim Hunter. When a graph is poorer than 100 words: A comparison of computerised natural language generation, human generated descriptions and graphical displays in neonatal intensive care. *Applied Cognitive Psychology*, 24(1):77–89, 2010.

Veronika Vincze, György Szarvas, Richárd Farkas, György Móra, and János Csirik. The bioscope corpus: biomedical texts annotated for uncertainty, negation and their scopes. *BMC bioinformatics*, 9(11):S9, 2008.

Xing Wang, Jessica Lin, Nital Patel, and Martin Braun. A self-learning and online algorithm for time series anomaly detection, with application in cpu manufacturing. In *Proceedings of the 25th ACM International on Conference on Information and Knowledge Management*, pp. 1823–1832. ACM, 2016.

Brigham C Willis, Alan S Graham, Eunice Yoon, Randall C Wetzel, and Christopher JL Newth. Pressure-rate products and phase angles in children on minimal support ventilation and after extubation. *Intensive care medicine*, 31(12):1700–1705, 2005.

Jiajun Wu, Yinan Yu, Chang Huang, and Kai Yu. Deep multiple instance learning for image classification and auto-annotation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 3460–3469, 2015.

Hua Xu, Shane P Stenner, Son Doan, Kevin B Johnson, Lemuel R Waitman, and Joshua C Denny. Medex: a medication information extraction system for clinical narratives. *Journal of the American Medical Informatics Association*, 17(1):19–24, 2010.

Zhennan Yan, Yiqiang Zhan, Zhigang Peng, Shu Liao, Yoshihisa Shinagawa, Shaoting Zhang, Dimitris N Metaxas, and Xiang Sean Zhou. Multi-instance deep learning: Discover discriminative local anatomies for bodypart recognition. *IEEE transactions on medical imaging*, 35(5):1332–1343, 2016.

Haonan Yu, Jiang Wang, Zhiheng Huang, Yi Yang, and Wei Xu. Video paragraph captioning using hierarchical recurrent neural networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 4584–4593, 2016.

Cha Zhang, John C Platt, and Paul A Viola. Multiple instance boosting for object detection. In *Advances in neural information processing systems*, pp. 1417–1424, 2006.

Dan Zhang, Yan Liu, Luo Si, Jian Zhang, and Richard D Lawrence. Multiple instance learning on structured data. In *Advances in Neural Information Processing Systems*, pp. 145–153, 2011.

Li Zhou, Genevieve B Melton, Simon Parsons, and George Hripcsak. A temporal constraint structure for extracting temporal information from clinical narrative. *Journal of biomedical informatics*, 39 (4):424–439, 2006.

Zhi-Hua Zhou and Min-Ling Zhang. Multi-instance multi-label learning with application to scene classification. In *Advances in neural information processing systems*, pp. 1609–1616, 2007.

Zhi-Hua Zhou, Yu-Yin Sun, and Yu-Feng Li. Multi-instance learning by treating instances as non-iid samples. In *Proceedings of the 26th annual international conference on machine learning*, pp. 1249–1256. ACM, 2009.

Wentao Zhu, Qi Lou, Yeeleng Scott Vang, and Xiaohui Xie. Deep multi-instance networks with sparse label assignment for whole mammogram classification. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pp. 603–611. Springer, 2017.

Pierre Zweigenbaum, Dina Demner-Fushman, Hong Yu, and Kevin B Cohen. Frontiers of biomedical text mining: current progress. *Briefings in bioinformatics*, 8(5):358–375, 2007.

6 Appendix

6.1 MIMIC-III Concept List

Table 6 show the concept list of the MIMIC-III RESP dataset used in our experiments.

Table 6: MIMIC-III respiratory concept list.

Concept Number	Concept Name
1	Respiratory rate
2	Biomedical tube device
3	Analysis of arterial blood gases and ph
4	Ventilation, function (observable entity)
5	Medical history
6	Injury wounds
7	Body weights
8	Tidal volume
9	Inspired fraction of oxygen
10	Intubation
11	Positive end-expiratory pressure
12	Artificial airways
13	Bicarbonates
14	Tracheal extubation
15	Chest radiograph
16	Mean blood pressure
17	Oxygen measurement, partial pressure, arterial
18	Cardiac arrest
19	Peak inspiratory pressure
20	Biomechanical compliance
21	Tachycardia ventricular
22	Scoliosis
23	Acute lung injury
24	Partial pressure of carbon dioxide in arterial blood
25	Resuscitate
26	Sudden onset

6.2 Anomaly Detection for Time Series

Here, we will demonstrate anomaly detection from medical time series data as an use case application of our RMIL framework.

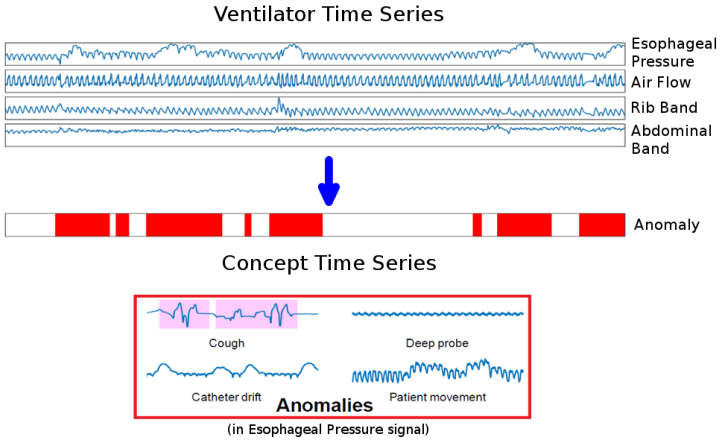


Figure 3: Anomaly detection from ventilator time series data.

6.2.1 Motivation and Related Work

Each year, more than 1,000,000 US adults and children are put on mechanical ventilation during their stays in ICU. However, lack of effective tools to aid with ventilator weaning and extubation (removal of the breathing tube) readiness assessment results in nearly half of the patients spending unnecessary days on ventilators (Randolph et al., 2002), and up to 20% of them having ventilators discontinued too soon (Kurachek et al., 2003). Spending unnecessary days on ventilators can lead to hospital-acquired infections while having ventilators discontinued too soon could require painful reintubation. A work-of-breathing measure called Pressure-Rate Product (PRP), calculated from esophageal pressure, has shown potential to be used as a guideline for ventilator weaning and extubation readiness assessment (Willis et al., 2005). However, PRP calculations are susceptible to sensor artifacts and breathing pattern anomalies. These anomalies limit realtime use of PRP for clinical decision making. Our goal is to automatically detect and remove these anomalies by using our proposed Relational Multi-instance learning models, thereby enabling real-time clinical decision making. Figure 3 shows the example of anomaly detection from the ventilator time series data. Here, anomalies appear due to patient factors (cough, movement) and instrument factors (probing, catherter drift), and should be automatically detected from the ventalitor monitoring time series data.

There is a long history and a rich body of research work on anomaly detection in time series data. See Hodge & Austin (2004); Chandola et al. (2009) for a quick survey on generic anomaly detection algorithms. Gupta et al. (2014) also author a survey on anomaly detection for time series data. In their follow-up survey, Chandola et al. (2012) gave a summary on discrete sequence anomaly detection algorithms. Unfortunately, techniques for time series anomaly detection are quite domain-specific. This is due to highly-varied nature of time series characteristics. In Chan & Mahoney (2005), a set of k minimum bounding rectangles between each time step is used as a model of normal data generating distribution. In Camerra et al. (2010); Lin et al. (2003), continuous time series are converted to ordinal symbolic representation, allowing faster approximation of Euclidean distance between time series windows and early pruning. Then, anomaly detection can be performed by setting a threshold on distance value. Recently, Wang et al. (2016) proposes a self-learning method that learns clusters of constrained grammars based on ordinal symbolic approximation of time series value. Guigou et al. (2017) proposes incorporating experts into anomaly detection in a method inspired by immune system. In Jones et al. (2016), the authors propose extracting exemplars from Euclidean pairwise distance as a way to speed up anomaly detection algorithm. Most of these techniques for time series anomaly detection are quite domain-specific, and few of them model the anomaly detection problem in Multi-instance learning setting.

6.2.2 Problem Formulation

We formulate the anomaly detection as concept annotation problem in MIL setting, where the bag corresponds to the medical time series data $\boldsymbol{X}_i$ and an instance is the features at a time-stamp, and

the anomaly corresponds to a concept. Thus, the prediction (predicting $\boldsymbol{Y}_i$) and localizaton tasks (predicting $\boldsymbol{C}_i$) correspond to predicting the presence and location of the anomalies in the time series data. For anomaly detection, we assume $Y_i^k = \mathcal{I}\left(\sum_{1 \leq j \leq T} C_i^{jk} \geq \eta\right)$, where η is chosen as $\eta = 0.2T$ and T is the number of time series windows within the bag.

6.2.3 EXPERIMENTS

We conduct anomaly detection experiments on a PICU dataset described below.

PICU Dataset This dataset consists of 1,530 recorded 5-minute 200-Hz sensor readings from 385 subjects collected at a leading children's hospital by a team of research clinicians. Statistics of the dataset is shown in Table 7. The recordings are made on mechanically-ventilated patients in pediatrics ICU ward. Medical time series data collected from four sensors are used: flow volume spirometry, esophageal pressure sensor, and dual band respiratory inductance plethysmography. Each subject can be under one of four breathing conditions: ventilated with Continuous Positive Airway Pressure (CPAP), ventilated with Pressure Support (PS), 5 minutes after extubation, and 60 minutes after extubation. Along with the 4 sensor signals, clinician verified binary anomaly label generated using hard-crafted state-of-the-art breathing anomaly detection algorithm is provided as ground truth.

Table 7: PICU dataset statistics.

	PICU
# of samples (N)	1530
# of variables (D)	80
# of time steps	60
# of concepts	1

We annotate the concept of breathing anomaly in MIL framework by processing the dataset as follows. The sensor recordings are split into non-overlapping 5-second windows. In MIL framework, each window becomes an instance and each recording becomes a bag. For each sensor signal of each window, we extract 20 Mel-Frequency Cepstral Coefficients (MFCCs) to be used as features of each instance; thus, each instance has 80 features in total. For each instance, its anomaly label is set to positive if at least 20% of the window are labeled as anomaly. The bag anomaly label is set to positive if at least 60% of its instances are labeled as anomaly.

Results Table 8 shows the anomaly detection results using our RMIL models. We observe that (i) RMIL models mostly outperform the non-deep MIL models on both tasks, (ii) LSTM and Bi-LSTM based RMIL models obtain better overall results compared to the sequence-to-sequence models, and (iii) the attention mechanism does not help for localization task but sometimes obtains better results for the prediction task.

Table 8: Anomaly detection results on PICU dataset with different attention mechanisms and with max pooling.

		Prediction		**Localization**	
		AUROC	**AUPRC**	**AUROC**	**AUPRC**
RMIL Models	S2S	0.741	0.797	0.532	0.707
	S2S with Attention-I	0.732	0.787	0.511	0.694
	S2S with Attention-F	0.730	0.789	0.519	0.689
	LSTM	0.708	0.763	0.543	0.712
	LSTM with Attention-I	0.690	0.767	0.513	0.682
	LSTM with Attention-F	0.712	0.776	0.522	0.690
	Bi-LSTM	0.729	0.784	0.562	0.725
	Bi-LSTM with Attention-I	0.711	0.769	0.535	0.708
	Bi-LSTM with Attention-F	0.736	0.790	0.539	0.704
MIL Models	Cluster-MIL*	-	-	0.530	0.670
	MISVM	0.572	0.647	0.542	0.606

Remark: Cluster-MIL* is a HDBSCAN clustering (Campello et al., 2015) based approach for anomaly detection. It uses both instance and bag labels for training, while other models only use bag labels for training.