Automatic Annotation of Sensor Data Streams using Abductive Reasoning

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Abstract: Fast growing structured knowledge in machine processable formats such as RDF/OWL provides the opportunity of having automatic annotation for stream data in order to extract meaningful information. In this work, we propose a system architecture to model the process of stream data annotation in an automatized fashion using public repositories of knowledge. We employ abductive reasoning which is capable of retrieving the best explanations for observations given incomplete knowledge. In order to evaluate the effectiveness of the framework, we use multivariate data coming from medical sensors observing a patient in ICU (Intensive Care Unit) suffering from several diseases as the ground truth against which the eventual explanations (annotations) of the reasoner are compared.

1 INTRODUCTION

With increasingly large sensor networks whose data is available online, more and more effort is required to interpret the data in order to extract meaningful information. An inherent part of this interpretation is the ability to annotate the signals and in particular to annotate interesting events with plausible explanations. Further, for multivariate time-series data, the annotation process should take into account eventual dependencies which exist between signals. While, data mining and analysis techniques are useful to reveal the structures in the data and identify regions of interest e.g. events, human supervision is still required to provide a mapping to meaningful symbolic labels.

In this paper, we attempt to automate the labelling process by mining the relevant knowledge from available online sources. This work puts special attention to multivariate data where codependencies between signals exist. Instead of manually defining rules with which a priori explanations for events are deduced (causes to effects reasoning), we utilize a posteriori model (effects to causes reasoning) in terms of finding the best explanation for the observations. Such reasoning mechanisms are well suited where intermixed cause and effect relations exist (such as diagnostic problems). Therefore, the framework is based on abductive reasoning inferring its final results with no predefined deductive rules.

To evaluate this work, we choose the medical domain due to the wealth of open-linked knowledge in medicine. The sensor data supposed to be annotated are 12-hours multivariate ICU (Intensive Care Unit) data coming from medical sensors monitoring a patient. At the end, in order to measure the effectiveness of the framework, the eventual annotations are compared to the list of diseases that the patient is suffering from.

The structure of the paper is as follows. In Section 2 we outline a survey on related works in stream data annotation and differentiate each of them with our model. The paper then proceeds to concentrate on details of the framework in Section 3. Afterwards, Section 4 begins with a short introduction to the data set followed by illustrative results showing how the reasoning induces intelligible explanations from ontological concepts for the real sensor data. The paper ends with the conclusion and the future works which are mainly about the enhancements required for both data and knowledge levels.

2 RELATED WORKS

The root of sensor data annotation is in data fusion where the main task of fusion methods is keeping the different types of data coming from various sensors synchronised (Joshi and Sanderson, 1999). The focus of these methods is on raw data consolidation for the sake of data interpretation, however, without any integration with higher level of data (symbolic knowledge). For exploiting labelled data sets, works such as (Belkacem et al., 2011) and (Alirezaie and Loutfi, 2012) use data driven approaches to classify events that are detected on signals. The annotation process of these works is defined as assigning a predefined label to those parts of the signal holding the behaviour matched with this label. Although the later work, despite the lack of structured knowledge related to its sensor data retrieves more informative annotations for signals, these two works are stringently dependent to the labels manually provided for their data set. However, in our framework, in spite of the fact that the event detection process is similarly based on parameters set by the expert, the process is not strictly dependent to these labels and the expert can change them as he/she prefers.

Increasing in developing sensors and consequently in interests on context awareness has pushed the research towards symbolic knowledge integration to numeric data (Abowd et al., 1999). For example, in robotics with focus on the human robot interaction, many works are principally working on mapping the perception of robot into relevant concepts. The focus of works such as (Coradeschi et al., 2013) and (Loutfi et al., 2005) is on the process of creating and then maintaining the relations between a symbol and raw data which are readings of sensors that observe an object in the environment. The foundation of these works is the background knowledge by which the relations in anchoring or more general, in grounding process, are formed. Often, an ad-hoc knowledge representation mechanism is used with the background knowledge modelled in the form of first order production rules (Daoutis et al., 2009).

In addition, making use of ontologies research works such as (Henson et al., 2011a) and (Perera et al., 2012) benefit from the interleaved structures of ontologies for provisioning a more efficient mapping of observation into perception. The later one whose domain of work is the same as ours, enriches the domain knowledge about sensors for healthcare by comparing it with the real data sources. These works, however, use the initial base of knowledge which are modelled in a non or semi automatic way whereas our model considers the results of data analysis and uses abductive reasoning with a posteriori knowledge acquired automatically.

The necessity of a posteriori model implied by the automatic knowledge acquisition approach has recently emerged in the area of sensor data processing. The work (Thirunarayan et al., 2009) applies abductive reasoning over sensor data which are interpreted based on predefined knowledge. Other works such as (Henson et al., 2012) and (Henson et al., 2011b), model a system that makes it possible to infer explanations from an incomplete set of observations which are not necessarily sensor data. The reasoning framework in these works is based on Parsimonious Covering Theory (PCT) (Reggia and Peng, 1986) which is also used in this paper. Nonetheless, since the PCT in these works is based on OWL, it is not able to provide an explanation containing more than one cause for the observations. Consequently, in this paper, we model the proposed framework in Java-OWL to ensure the communication with RDF-OWL implemented repositories and to overcome the constraints of pure OWL for PCT for abductive reasoning.

3 FRAMEWORK

In this section we introduce all the components of the framework. Loosely speaking, our model regardless of occurred events, retrieves the relevant entities from knowledge repositories (top-down) and subsequently sifts through knowledge using observations coming from data (bottom-up). Depicted in Fig. 1, this framework is composed of four components and a ***Reasoner*** module. The *Reasoner* needs to have three inputs, namely ***Causes***, ***Relations*** and ***Observations*** which are provided by components *Cause_Generator*, *Relation_Generator* and *Observation_Generator*, respectively. The output of the system is produced by the module called the ***Explanations***. In the following subsections we explain the details of the required inputs for the reasoning module which turns out the best explanations for the observed situations.

3.1 Initialization

The initialization component labelled in Fig. 1 contains the ***Configuration*** module which is a text file containing settings related to signal data and their abnormalities. This file is filled by the expert of the domain and contains settings such as phenomena (i.e. heart) being observed by sensors along with their properties (i.e. rate). Figure 2 shows two examples of the configuration file. Inspired from the *SSN* ontology (Compton and et al, 2012), the setting terms are specified by ”feature_of_interest” and ”property”. In addition, other properties related to the signal behaviours clarifying situations in which events are most likely to occur, can be set in the ”Behaviours” section of the

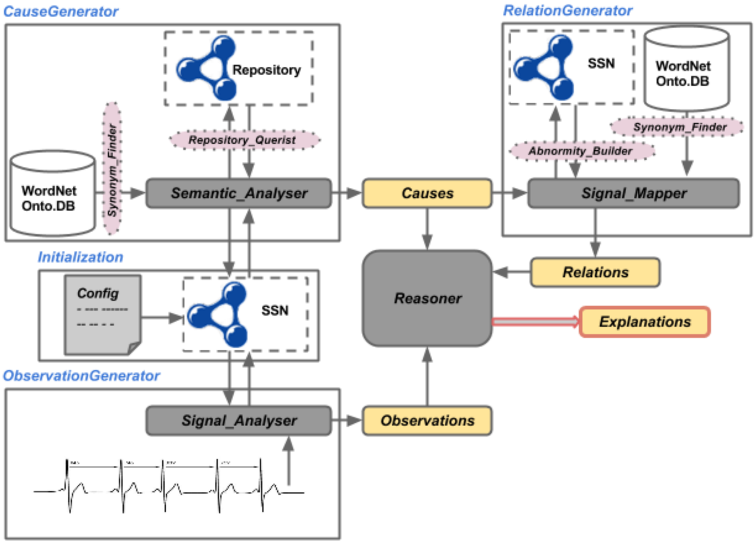


Figure 1: The Stream Data Annotation Framework.

file. Although it may seem that the process is dependent to the manually set parameters, the eventual annotations of signals are not literally dependent to the terms that the expert entered. In other words, regardless of the terms that the expert uses to explain the abnormal behaviour of a sensor, the final annotation will be unique.

The ***SSN*** ontology which is populated with the content of the *Configuration* file is applied to disconnect the remaining parts of the framework from this manually populated file. In this way, different components of the system can use ontological methods to acquire information in the *Configuration*. For example, all values of the *feature_of_interest* keys in the *Configuration* file are transferred to the *SSN* ontology and saved there as subclasses of the ”FeatureOfInterest”[1] class. Moreover, all property keys in the file are similarly copied as subclasses of the ”Property” class in the ontology which are connected to the ”FeatureOfInterest” subclasses via the ”has-Property” object property.

The *SSN* ontology, in addition, creates a subclass of its ”Observation” class in order to reify each ”Behaviours” section in the *Configuration* file providing the numerical details of an abnormal behaviour in a signal. As we will see later, during the signal analysis (*Observation_Generator* component), once such an abnormal behaviour is detected, an instance for this subclass is spontaneously created. Shown in Fig. 1, the other components transform the data independent of the *Configuration* file.

3.2 Generating Causes

The annotation process stems from the *Cause_Generator* component labelled in Fig. 1 which also contains the ***Semantic_Analyser*** module. This component is in addition composed of two main interfaces, *Repository_Querist* and the *Synonym_Finder* providing the ability of collaboration with high level knowledge.

The *Repository_Querist* interface is supposed to search through a repository and return a hierarchy of related concepts formatted in RDF/OWL. Considering the medical domain of this work, the *NCBO BioPortal* is used as a repository with more than 300 linked biomedical ontologies and RDF terminologies (Salvadores et al., 2012). Therefore, the *Repository_Querist* is implemented alongside of the OntoCAT package (Adamusiak et al., 2011) which provides high level abstraction for interacting with public ontologies in repositories including the *NCBO BioPortal*.

As mentioned above, we are aiming to annotate medical signals that might contain abnormal behaviours, namely symptoms of diseases. Given the search term ”symptom”, the *Repository_Querist* draws all ontologies containing this term. 15 out of 21 returned ontologies have the same domain address and refer to different concepts of the ”Symptom Ontology” which is ranked first in the returned list. This ontology includes well-categorized medical symptoms in terms of the body part names so that it provides an easy way to find the specific symptom type. In other words, since the annotation in this domain refers to a kind of disease symptom, analysing

[1] A feature of interest can be any real-world object the properties of which are observed by a sensor (Compton and et al, 2012).

the content of the Symptom Ontology as a reference ontology is sufficient.

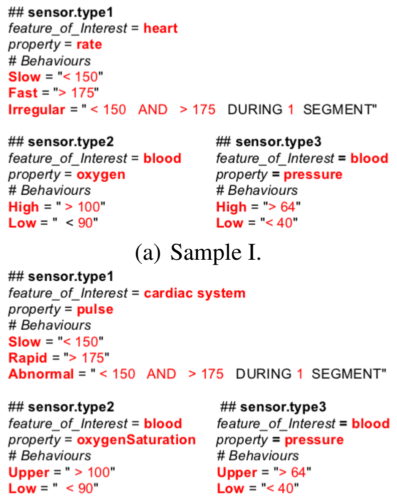
Having the categorized list of symptoms, the *Semantic_Analyser* first tokenizes[2] each item into its tokens and then passes each token through a stemming [3] process. This process is followed by calling the *Semantic_Analyser*'s second interface, the *Synonym_Finder*. Before going to the further details, it is worth mentioning that the tokenizing process preserves all elements of a sentence (e.g. subject, object, verb, etc.) in order to lessen the risk of information losing.

The *Synonym_Finder* interface using the RiTa.WordNet[4], is independently tasked to retrieve the set of synonyms of a single term defined in the *WordNet* ontology. Given a token, this interface then returns a related synonym list. Each symptom (split into its tokens) is consequently assigned with multiple synonym lists corresponding to its tokens. We are particularly interested to find those symptoms that are related to parts of the body (phenomena) observed by sensors (i.e. heart). For this, the *Semantic_Analyser* counts the number of times that the label of each phenomenon (which is already a subclass of the ”FeatureOfInterest” class in the *SSN* ontology) appears in the synonym list of each token. As a result, the symptom item whose tokens have the total highest number, is selected as the candidate and then its subclasses in the Symptom Ontology are returned.

Briefly speaking, the *Semantic_Analyser* uses the *Synonym_Finder* for sifting the resulted hierarchy of concepts and admitting those that are more pertinent in terms of their ranks in semantic similarities. The final ***Causes*** list shown in Fig. 1 is the union of all subclasses of a candidate returned per each phenomenon. The details of this process are further illustrated in Section 4.

3.3 Generating Relations

Labelled in Fig. 1, the *Relation_Generator* contains the ***Signal_Mapper*** module which as such has two interfaces, *Abnormity_Builder* and *Synonym_Finder*. This component is responsible for bridging the gap between knowledge drawn from repositories and sensor observations. Defining the possible abnormal situations, the *Abnormity_Builder* interface works based on the ”Behaviour” section of the *Configuration* file which are already transferred into the *SSN* ontology[5]. It means that this interface works with the *SSN* ontology rather than the file.



```
## sensor.type1
feature_of_Interest = heart
property = rate
# Behaviours
Slow = "< 150"
Fast = "> 175"
Irregular = " < 150   AND   > 175   DURING 1  SEGMENT"

## sensor.type2                    ## sensor.type3
feature_of_Interest = blood        feature_of_Interest = blood
property = oxygen                  property = pressure
# Behaviours                       # Behaviours
High = " > 100"                    High = "> 64"
Low = "  < 90"                     Low = "< 40"
```

(a) Sample I.

```
## sensor.type1
feature_of_Interest = cardiac system
property = pulse
# Behaviours
Slow = "< 150"
Rapid = "> 175"
Abnormal = " < 150   AND   > 175   DURING 1  SEGMENT"

## sensor.type2                       ## sensor.type3
feature_of_Interest = blood           feature_of_Interest = blood
property = oxygenSaturation           property = pressure
# Behaviours                          # Behaviours
Upper = " > 100"                      Upper = "> 64"
Low = "  < 90"                        Low = "< 40"
```

(b) Sample II.

Figure 2: Configuration File Samples. (The red parts are entered by the expert).

Shown in Fig. 2(a), for example, possible behaviours for a specific signal are defined as ”fast”, ”slow” and ”irregular”. Combining these trends with their observed phenomenon, this module results in a list of possible abnormalities in the signals. In other words, this interface has the task of concatenating the combination of the values of ”feature_of_interest” and ”property” keys (i.e. heart rate) with the aforementioned trends (i.e irregular). The final outcome is the list of phrases such as ”irregular heart rate”, ”low oxygen saturation”, etc.

With its *Synonym_Finder* interface, the *Signal_Mapper* module provides the possibility of linking data behaviours to symptoms of diseases. As we will see later, each cause coming from the *Casue_Generator* can be either a single term or a phrase. For each single term cause, the *Synonym_Finder* retrieves its definitions from the Symptom Ontology or from the WordNet Ontology (in case the former returns nothing) and replaces the term with this definition.

At the next step, the *Signal_Mapper* creates an $n \times m$ similarity matrix S, where n and m are the length of the items in the *Causes* list and the number of phrases built by the *Abnormity_Builder*, respectively. As the details are represented in Algorithm 1 the matrix S which is initialized to the zero matrix, holds the similarity values between these two lists.

[2] The process of splitting a sequence of strings into its elements called tokens.

[3] The process of reducing inflected words to their stem, base or root form.

[4] http://www.rednoise.org/rita

[5] As the subclass of the Observation class in the *SSN* ontology (Compton and et al, 2012)

Algorithm 1: Similarity Matrix

```
Data: Causes, AbnormalList
Result: S
/* The Similarity Matrix                    */
begin
    $n \leftarrow getLength$(Causes)
    $m \leftarrow getLength$(AbnormalList)
    S $\leftarrow getZeroMatrix(n, m)$
    for $i \leftarrow 1$ to $n$ do
        $tree \leftarrow getGrammaticalTree$(Cause[i])
        foreach NN in the tree do
            $JJ \leftarrow tree.getAdjective(NN)$
            $mainNN \leftarrow tree.getMainNoun(NN, JJ)$
            for $j \leftarrow 1$ to $m$ do
                if $getProperty(AbnormalList[j]) \in$
                $getSynonyms(NN)$ and
                $getBehaviour(AbnormalList[j]) \in$
                $getSynonyms(JJ)$ and
                $getFeatureOfInterest(AbnormalList[j]) \in$
                $getSynonyms(mainNN)$ then
                    S$[i, j] \leftarrow 1$
                end
            end
        end
    end
end
```

To measure the similarity values, the *Signal_Mapper* needs to perform operations about grammatical processing over the *Causes* items addressing the rows of the matrix *S*. To set the value of the element $s_{i,j}$ of the matrix *S*, the *Signal_Mapper* using the StanfordParser (Marneffe et al., 2006), reads the i^{th} cause and builds its grammatical structure tree. During this process, each word of the cause item finds its own grammatical role such as noun (labelled by ”NN”) or adjective (labelled by ”JJ”) in the sentence. Afterwards, all nodes of the tree having the noun role are retrieved. For each ”NN”, the *Signal_Mapper* collaborating with its *Synonym_Finder* obtains the synonym list. Moreover, the j^{th} column is referring to the abnormal behaviour that is composed by a feature of interest (noun), behaviour (adjective) and a property (noun). Therefore, if the synonym list of the ”NN” contains the property name of the current column, the process goes further as described below, otherwise it switches to the next ”NN”.

Following the process, the *Signal_Mapper* reads the adjective of the ”NN” from the tree which is labelled by ”JJ” and similarly retrieves its synonym set. If the ”behaviour” part of the j^{th} column is also found in the recent synonym list, and if the combination of ”JJ” and ”NN” is related to another ”NN” (by a proposition) which is a synonym of the ”feature of interest” part of the column j, the $s_{i,j}$ is set to 1.

Proceeding the above process for all elements of the matrix *S*, the *Signal_Mapper* nominates all non zero elements as its output. These non zero elements show the relations existing between the causes and an abnormal behaviours. In other words, the row-column of each candidate is considered as an item in the ***Relations*** list. The resulted *Relations* list is regarded as the second input of the *Reasoner* (Fig. 1).

3.4 Generating Observations

The *Observation_Generator* is lastly needed to add the information of captured events to the reasoner. Shown in Fig. 1, it has one module called ***Signal_Analyser*** doing the event detection process over the signal. This module works based on threshold values defined by the expert in order to localize the events over a signal with their time points. Likewise as Section 3.3, the module of this component works with the *SSN* populated with information about the behaviour of signals including the ranges of their values. For example, in Fig. 2(a), the *”Behaviours”* section related to the ”heart” shows the range of the heart rate which is equivalent to an ”irregular” behaviour.

The signal analysis method in this component works based on segmentation (Fig.4). In other words, in an iterative process it looks for an anomaly over one signal. Once an anomaly is found, it defines a time interval around this. Considering the situations of other signals during this interval, it defines a segment whose borders are set based on several parameters including the number of observations (detected abnormal behaviours) around the detected anomaly over each signal and their average values as well.

Although the role of anomaly detection in data annotation process is non trivial, the details of this method is out of the scope of this paper. In fact, any data driven event detection method would work with this framework. Having signals labelled at time points of anomalies, the *Signal_Analyser* adds an item to the *Observations* list for each type of anomaly detected at each segment.

3.5 Reasoner

The *Reasoner* module is based on abductive reasoning whose basis is on the Set theory in mathematics, with the goal of finding the best possible *Explanations* for the *Observations*. Given three input lists (*Causes*, *Relations* and *Observations*), the *Reasoner* calculates the power set[6] of the *Causes* list to find the best explanation. In other words, the items of the final *Ex-*

[6] The power set of a set is the set of all its subsets.

planations are subsets of the *Causes* list chosen based on the reasoner principles.

Precisely speaking, the abductive reasoning module of this framework is based on the Parsimonious Covering Theory (PCT) (Reggia and Peng, 1986). According to this theory, the best explanation is defined within two criteria: Covering and Minimality. With the former criterion as shown in (1), the reasoner nominates those subsets of the *Causes* list whose items are related to all the observations detected in a particular segment of signals:

$$covering = \{c \subseteq Causes \quad | \quad \forall o \in Observations \rightarrow (o,c) \in Relations\} \quad (1)$$

Furthermore, the minimality criterion which is also called irredundancy (2) considers the size of the aforementioned selected subset. In this way, the reasoner is able to choose those covering subsets of the *Causes* list that are minimal in terms of the cardinality.

$$irredundancy = \{c \in covering \quad | \quad \nexists d \subset c \quad and \quad d \in covering\} \quad (2)$$

Algorithm 2: Abductive Reasoning

```
Data: Causes, Observations, Relations
Result: Explanations
begin
    /* Heuristic I: Removing
       non-participant causes                */
    Causes← getActiveList(Causes, Relations)
    Explanations←null
    powerSet ← getPowerSet(Causes)
    foreach ps in the powerSet do
        if isCovering(ps, Observations) then
            if isIrredundant(ps, Observations)
            then
                addExplanation(ps, Explanations)
            else
                /* Heuristic II: Removing
                   the supersets of ps       */
                removeSuperSet(ps, powerSet)
            end
        end
    end
```

The reasoner takes above criteria into account for each member of the power set, namely a subclass of the *Causes* list. Once these two criteria hold, the reasoner adds the subclass to the final *Explanations* list of a segment. Algorithm 2 shows the details of the reasoner.

However, due to the exponential growth of the power set, the reasoning process is intractable and having a heuristic to resolve its complexity is well advised. For this, the reasoning process applies two heuristics: First, before calculating the power set, it passes the *Causes* list through a filter to remove those items that have not participated in any relation (in the *Relations* list). Second, during the iterative process, once the irredundancy of an element of the power set does not hold, all other elements of the power set which are the superset of this element are removed. As we will see in Section 4, these heuristics reduce the size of the *Causes* list and as a result the size of its power set drastically.

Eventually, since each segment of signals is independently analysed and separately labelled with explanations, at its final step, the *Reasoner* calculates the occurrence probability of each type of disease appearing in all *Explanations* lists. The most probable explanations which are basically a cause or a symptom of a disease (or a disease per se) are reported to the expert.

4 EXPERIMENTS

This section first introduces the data set used in this work and proceeds with the results obtained from each part of the framework.

4.1 Data Set

Following the approach of data annotation, we need to evaluate the final drawn *Explanations* for the *Observations*. For this reason, we make use of a labelled data set which is the ICU data package provided for use in 1994 AI in Medicine symposium submissions (Bache and Lichman, 2013). This data set contains 12-hours time-series data come from sensors measuring ”Heart Rate”, ”Arterial Pressure”, and ”Arterial O_2 Saturation” of a 8.5 month old female infant suffering from ”multiple liver abscesses”, ”portal hypertension” and ”E. Coli sepsis”.

In the following, we examine our frameworks to see how relevant the final explanations are to the diseases of the aforementioned patient.

4.2 Results

Considering the signal data, the expert of the domain initially fills the *Configuration* file based on his/her idea in monitoring the patient. As mentioned before, the process is not literally dependent to the parameters set by the expert. For example, since the internal processes of the framework are basically based on synonyms of terms, for two different configurations

Table 1: List of Symptoms

symptom category	heart	blood
abdominal symt	0	0
head & neck symt	0	0
musculoskeletal system symt	0	0
neurological & physiological symt	0	0
reproductive system symt	0	0
skin & integumentary tissue symt	0	0
digestive system symt	0	0
cardiovascular system symt	1	0
hemic system symt	0	1
nervous system symt	0	0
nutrition, metabolism symt	0	0
respiratory system & chest symt	0	0
urinary system symt	0	0

shown in Fig. 2, the reasoner results in the same final explanations. In this scenario (Fig. 2(a)), the expert fills the file for 3 sensors monitoring the ”heart” and ”blood” of the patient, with their properties such as the ”rate” (rate of heart), ”pressure” (pressure of blood) and ”oxygen” (oxygen of blood).

After initializing the *SSN* ontology, the annotation process starts from the *Cause_Generator* component. Given the term ”symptom” *Semantic_Analyser* module using its *Repository_Querist* interface, retrieves relevant concepts of the ”Symptom Ontology” from the *NCBO BioPortal* repository. Table 1 shows all returned symptoms categorized based on the body parts’ names.

In order to single out those symptoms that are more likely to be seen in our observations, each item in Table 1 needs to be tokenized and then stemmed. The *Synonym_Finder* interface is called for each pruned token and returns its synonyms list. Each symptom item in Table 1 is consequently assigned with multiple synonym lists corresponding to its tokens. As mentioned in Section 3.2, the number of times that two terms ”heart” and ”blood” appear separately in the synonym lists can rank the symptoms in terms of their relevance to each of these phenomena (”feature_of_interest”). Using this criterion, the ”cardiovascular system symptom” and the ”hemic system symptom” due to their highest similarity values are chosen (Table 1). The output of the *Cause_Generator*, as partially listed in Table 2, are the 30 and 32 (totally 62) concepts being in subsumption relation with the ”cardiovascular” and ”hemic” system symptoms, respectively. This list is considered as the *Causes* list of the framework (Fig. 1).

Table 2: List of Causes

#	Cause	Symptom Group
1	arrhythmia	Cardiovascular System
2	atrial fibrillation	Cardiovascular System
3	postphlebitic ulcer	Cardiovascular System
...	...	...
61	cyanosis	Hemic System
62	hypoxemia	Hemic System

In order to provide the second input list of the *Reasoner*, the *Signal_Mapper* module in *Relation_Generator* component is required to create all possible abnormal behaviours in signals based on what the expert has mentioned. As it is shown in Fig. 2, each sensor type has its own behaviour section indicating the probable abnormal behaviours. Therefore, using its *Abnormity_Builder* interface, this module create the list of all observable events in the environment by concatenating each behaviour with the combination of its ”feature_of_interest” and ”property” values. Table 3 itemizes 7 behaviours as the result of this process.

Table 3: Possible Abnormal Behaviours

#	Abnormal Behaviour
1	irregular heart rate
2	fast heart rate
3	slow heart rate
4	high blood pressure
5	low blood pressure
6	high blood oxygen
7	low blood oxygen

Proceeding the flow of the *Relation_Generator*, the process reaches to the phase of creating the similarity matrix *S*. Each cause in Table 2 can be a single term (i.e.”arrhythmia”) or a phrase (i.e.”atrial fibrillation”). The first step in building the matrix is replacing each single term cause with its definition retrieved from the symptom ontology (and in case of undefined term, from the WordNet ontology). For example, the term ”arrhythmia” is replaced with its definition: ”*an abnormal rate of muscle contractions in the heart*”.

The *Signal_Mapper* module first initializes the 62×7 matrix *S* to the zero matrix and then embarks to set its elements’ values. Due to the big size of this matrix, we cannot completely demonstrate it here. However, we concisely mention that, for instance, the element $s_{1,1}$ addressing the ”arrhythmia” and ”irregu-

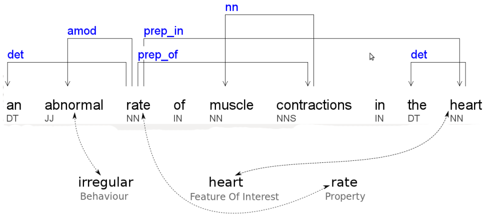


Figure 3: Grammatical Parsing Tree (arrhythmia).

lar heart rate" in its row and column, respectively, is passed to the dependency parsing module which extracts the grammatical structure of the sentence (the definition of the "arrhythmia") shown in Fig. 3. Following Algorithm 1, we see the term "abnormal" is identified as the adjective (JJ) of the term "rate" (NN) which is related to the term "heart" (NN) (by a proposition). This structure is quite matched with "irregular heart rate" phrase in the column so that the adjective "irregular" is also found in the synonym list of the word "abnormal" and so on. Therefore the value of the element $s_{1,1}$ is switched to 1.

At the end of this phase, considering the non-zero value criterion at each column, this component totally retrieves 18 relations (as the second input of the *Reasoner*) from the matrix S. Table 4 partially depicts the *Relations* list. Counting the unique causes in Table 4, we find that only 11 causes have participated in the *Relations* list. It means that instead of analysing the 2^{62} elements of the power set, the reasoner using the aforementioned heuristic iterates through 2^{11} elements.

Table 4: Relations between Causes and Abnormal Behaviours

#	Cause	Abnormal Behaviour
1	arrhythmia	irregular heart rate
2	bradycardia	slow heart rate
	...	...
10	hypotension	low blood pressure
	...	...
17	hyperemia	low blood pressure
18	hypoxemia	low blood oxygen

Moreover, in *Observation_Generator* component, the *Signal_Analyser* discovers observations, namely abnormal behaviours over the signals. The signal processing method as depicted in Fig. 4, has defined 8 segments over 12-hours signal data. Each labelled (starred) time point is regarded as an observation. To prepare the *Observations* list, similar observations at each segment are concatenated to one. For example, for the first segment where the heart rate signal is holding 4 similar anomalies (Fig. 4), 1 observation is extracted as the candidate of this anomaly type in the segment.

Given the *Observations* of each segment along with the *Causes* and the *Relations* sets, the *Reasoner* module following Algorithm 2 looks for the best explanation for the segment.

Table 7 summarizing the Fig. 4 presents the detected observations at each segment. In addition, the *Explanations* list of each segment which is eventually inferred by the reasoner is also given. It can be seen that the *Reasoner* has totally assigned 6 disease types to the 12-hours of observation. Counting the number of each disease appearances (not the observation), we can calculate its emerging probability.

Table 5: Disease Emerging Probability (I)

#	Disease	Appearance	Probability
1	hypertension	31	39.2%
2	septicShock	10	12.67%
3	palpitation	10	12.67%
4	tachycardia	10	12.67%
5	hyperemia	9	11.4%
6	hypoxemia	9	11.4%

Table 6: Disease Emerging Probability (II)

#	Disease	Appearance	Probability
1	hypertension	21	30.4%
2	Sepsis	20	29%
3	palpitation	10	14.5%
4	hyperemia	9	13.05%
5	hypoxemia	9	13.05%

Among 6 diseases listed in Table 5, the first (hypertension) and second (Septic shock) ones are addressing the patient profile who is suffering from "portal hypertension" and "E. Coli sepsis". Although the rest of discovered annotations are not reported in the data set, they are related to mentioned ones. For example, in some references such as (Graves and Rhodes, 1984) "tachycardia" along with the "hypertension" are known as a sign of "Sepsis". It means that if occurring the combination of the first and forth diseases is also considered as a symptom of Sepsis, the probability of Sepsis will increase (Table 6). Furthermore, the undiscovered disease of the patient, "multiple liver abscesses" (Section 4.1), is obviously related to the liver system which might need more specific sensors to be diagnosed.

Table 7: Observations shown in Fig.4

Segment#	Observations	Explanations
1	”fast heart rate” ”low blood oxygen” ”high blood pressure”	(hypertension,hypoxemia,palpitation) (hypertension, palpitation,hyperemia) (hypertension,hypoxemia,septicShock) (hypertension,hyperemia,septicShock) (hypertension,hypoxemia,tachycardia) (hypertension,hyperemia,tachycardia)
2	”fast heart rate” ”high blood pressure”	(hypertension,palpitation) (hypertension,septicShock) (hypertension,tachycardia)
3	same as segment 1	same as segment 1
4	”high blood pressure”	(hypertension)
5	same as segment 2	same as segment 2
6	same as segment 2	same as segment 2
7	same as segment 1	same as segment 1
8	same as segment 2	same as segment 2

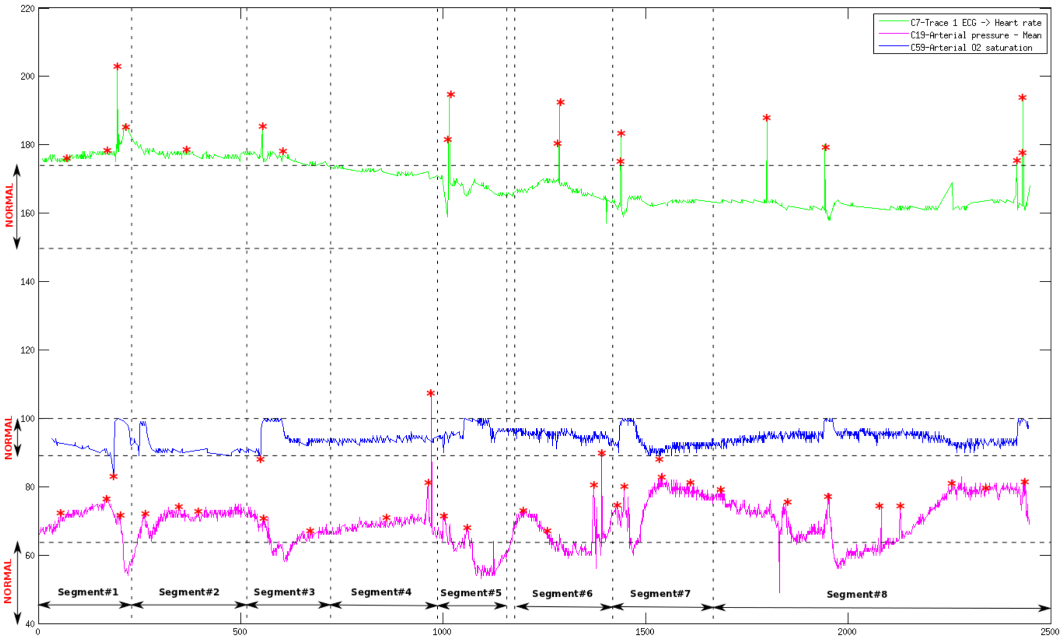


Figure 4: Segmentation Result Over 12-Hours Data.

5 CONCLUSION

In this paper, we introduced a framework for the task of automatic medical sensor data annotation which are probable causes of detected events. Because of its top-down view, this framework avoids to lose the relevant cases and considers all possible causes for anomalies observed. At the same time, its bottom-up view helps as a sifter to remove irrelevant causes and reduces the complexity of the reasoning process.

The only manually created module in this framework is the *Configuration* file. Although the annotation process introduced in this work is literally independent to this file and the expert is free to explain the behaviour of abnormal values with his/her own words, the final explanation are drawn based on the meaning of concepts written there. Moreover, in some situations where definition of abnormal behaviours is not straightforward, it can be cumbersome to populate the *Configuration*. Therefore, as one of the major future steps, we are interested to replace the data analysis method of this framework with an unsupervised data processing method which automatically extracts features of the signal and the expert can give up on filling the *Configuration* file.

The framework has been designed to be as domain independent as possible. Nevertheless, an important prerequisite is to have available knowledge in forms of linked-data. Due to the lack of structured knowledge, for example, in life science, agriculture, etc., we need to customize the framework for different domains. For instance, in this work we used the search term "symptom" which has to change in other domains. Moreover, the evaluation part of this work would be more enriched if we examined the framework for different domains. For this, as the extension of this work, we look for different multivariate signal data for which public linked knowledge is available.

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