Parallel universes to improve the diagnosis of cardiac arrhythmias (extended abstract)

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Abstract

We are interested in using parallel universes to learn interpretable models that can be subsequently used to automatically diagnose cardiac arrhythmias. In our study, parallel universes are heterogeneous sources such as electrocardiograms, blood pressure measurements, phonocardiograms etc. that give relevant information about the cardiac state of a patient. To learn interpretable rules, we use an inductive logic programming (ILP) method on a symbolic version of our data. Aggregating the symbolic data coming from all the sources before learning, increases both the number of possible relations that can be learned and the richness of the language. We propose a two-step strategy to deal with these dimensionality problems when using ILP. First, rules are learned independently in each universe. Second, the learned rules are used to bias a new learning process from the aggregated data. The results show that this method is much more efficient than learning directly from the aggregated data. Furthermore the good accuracy results confirm the benefits of using multiple sources when trying to improve the diagnosis of cardiac arrhythmias.

1 Problem description

To improve the quality of cardiac monitoring systems and in particular, the automated diagnosis of cardiac arrhythmias, we want to benefit from the presence of multiple complementary sources such as electrocardiograms, blood pressure measurements, phonocardiograms etc.. Each source is a parallel universe from which we can extract relevant information about the cardiac state of a patient.

We are interested in learning, across all those universes, temporal rules that could be used in a diagnosis scheme. To learn this kind of rules, a relational learning system that uses Inductive Logic Programming (ILP) [3] is well-adapted. ILP not only enables to learn relations between specific events occurring in all universes but also provides rules that are understandable by doctors since the representation method relies on first order logic.

One possible way to combine information coming from different universes is simply, to aggregate all the learning data and then, to learn as if having one rich universe. However, in such a large universe, the amount of data and the expressiveness of the language, can increase dramatically with the number of

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sources and with them, the computation time of ILP algorithms and the size of the hypothesis search space. Many methods have been proposed in ILP to cope with the search space dimensions, one of them is using a declarative bias [4]. This bias aims either at narrowing the search space or at ranking hypotheses to consider first the better ones for a given problem. Designing an efficient bias to learn across all universes is a difficult task.

We propose a divide-and-conquer strategy (called biased multisource learning) where first, symbolic rules are learned independently from each universe. Then, we use the learned rules to automatically create a bias that can restrict the large and rich universe composed by the aggregation of the data of every smaller universes.

2 Biased multi-source learning

To describe the method, we focus on learning from two universes. Both universes contain specific events that can be described in terms of logic predicates.

For each cardiac arrhythmia, a discriminating set of rules (H_1 and H_2) are learned in each universe independently. From these set of rules, we create a strong declarative bias to learn another set of rules from the rich universe composed by the aggregation of the data coming from those two smaller universes 1 and 2. The language L defined by the bias contains only predicates that occurs in H_1 and H_2. To further constrain the learning process, we compute from the sets H_1 and H_2 all relevant sequences of events across both universes and impose these sequences as a syntactic bias. Relevant sequences are physiologically possible sequences that maintain the relative order of the events computed in rules H_1 and H_2.

To efficiently compute rules across the universes with the biased multisource method, the rules learned a priori in each universe must contain common relational predicates (here, the temporal succession relation). If it is not the case, there is no possible layout between events occurring in the different universes. In the latter case, the biased multisource method behaves as a voting method and learns the best single-universe rules from H_1 and H_2. This is also true when data from the different sources are redundant. On the contrary, when the universes are really complementary, the biased multisource method gives very good results compared to learning from a single universe.

3 Results

We use data from MIMIC database (Multi-parameter Intelligent Monitoring for Intensive Care [2]) which contains 72 patients files recorded in the CICU of the Beth Israel Hospital Arrhythmia Laboratory. Seven cardiac rhythms (corresponding to seven classes) are investigated in this work: normal rhythm (*sr*), ventricular extra-systole (*ves*), bigeminy (*bige*), ventricular doublet (*doub*),

	ECG only (a)		ABP only (b)		rich univ (c)		biased rich (d)	
	Nodes	Time	Nodes	Time *	Nodes	Time	Nodes	Time
sr	2544	176.64	2679	89.49	18789	3851.36	243	438.55
ves	2616	68.15	5467	68.04	29653	3100.00	657	363.86
bige	1063	26.99	1023	14.27	22735	3299.43	98	92.74
doub	2100	52.88	4593	64.11	22281	2417.77	1071	290.17
vt	999	26.40	3747	40.01	8442	724.69	30	70.84
svt	945	29.67	537	17.85	4218	1879.71	20	57.58
af	896	23.78	972	21.47	2319	550.63	19	63.92
TOT	11163	404.51	19018	315.24	108437	15823.59	2138	1377.66

Table 1: Number of nodes visited for learning and computation times.

ventricular tachycardia (*vt*), supra-ventricular tachycardia (*svt*) and atrial fibrillation (*af*).

Table 1 gives an idea of the computational complexity of four different learning processes: from each universe separately (a and b); from one rich universe composed by the aggregated data without using a bias (c); from one rich universe composed by the aggregated data using the biased multisource method (d). All universes are synchronized. They describe in parallel the cardiac state of the patient. In the following experiments, universes are one lead of an electrocardiogram (ECG) and a blood pressure measurement (ABP). *Nodes* is the number of nodes explored in the search space and *Time* is the learning computation time in CPU seconds on a Sun Ultra-Sparc 5. On average, from 5 to 10 times more nodes are explored when learning from (c) than when learning from (a) and (b) and about 500 to 1000 times less nodes are explored during (d) multisource learning than during (c). However the computation time does not grow linearly with the number of explored nodes because the covering tests (determining whether an hypothesis is consistent with the examples) are more complex for (c) and (d). Biased multisource learning (d) computation times take into account the necessary time to first learn the rules in each universe separately. They are still very much smaller (8 to 35 times less) than when learning on the rich universe without using the bias (c).

We give accuracy results obtained with a leave-one-out cross validation method when learning on each universe separately and when learning across the universe using the biased method. The universes are complementary: the lead V of an electrocardiogram without information on the shape of the waves and the arterial blood pressure channel without information on the diastole. The results of this study are given in Table 2. The table shows that the accuracy is really improved by using multiple universes not only during the learning process but also, in most cases, during the test step.

More results on these data can be found in [1].

	ECG (c)		ABP (b)		biased multisource (d)	
	PrecAp	PrecT	PrecAp	PrecT	PrecAp	PrecT
rs	0.48	0.44	1	0.98	1	1
esv	0.52	0.46	0.928	0.80	0.942	0.76
bige	0.98	0.90	0.997	0.84	0.999	0.88
doub	0.85	0.78	0.98	0.86	0.99	0.88
tv	0.88	0.72	0.93	0.82	0.97	0.8
tsv	0.96	0.96	0.96	0.82	0.99	0.96
fa	0.977	0.9	0.978	0.78	0.98	0.82

Table 2: ross validation results when learning in each universe separately and when learning in the rich universe using the biased method

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