Bayesian Networks for Identifying Semantic Relations in a Never-Ending Learning System

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Abstract. A new paradigm of Machine Learning named Never-Ending Learning has been proposed through a system known as NELL (Never-Ending Language Learning). The major idea of this system is to learn to read the web better each day and to store the gathered knowledge in a knowledge base (KB), continually and incrementally. This paper proposes a new method that can help NELL populating its own KB using Bayesian Networks (BN). More specifically, we use facts (knowledge) already stored in NELL's KB as input for a BN learning algorithm named VOMOS (Variable Ordering Multiple Offspring Sampling) by aiming at representing the acquired knowledge by NELL system. In addition, we propose to use the BN induced by VOMOS for identifying new semantic relations to be added to NELL's KB, expanding thus its initial ontology.

Keywords: Bayesian Networks, Never-Ending Learning, Machine Learning.

1 Introduction

Machine Learning [1] is a research area that has received a lot of attention within the Artificial Intelligence and Computer Science in general. This fact has contributed for a great advance and progress in results obtained by methods and algorithms from this research area in recent decades. Currently, however, there are not yet many computer systems able to learn cumulatively, forever, in a never-ending learning fashion. More important, there are not many systems that use the knowledge acquired yesterday to improve their ability of learning today, in a continuous and never-ending process.

The first never-ending learning system reported in literature is named NELL (Never-Ending Language Learning) [2, 3]. NELL is a computer system that runs 24 hours per day, 7 days per week, extracting information from web text to populate and extend its own knowledge base. The main goal of the system is to learn to read the web better each day, and to store the gathered knowledge in a never-ending growing knowledge base (KB). The system takes advantage of many different components like CPL [4], CSEAL [5], Prophet [6], OntExt [7], and Conversing Learning [8], in order to be self-supervised and avoid semantic drifting [9, 10]. Semantic drifting is expected to happen in semi-supervised systems after too many iterations without supervision. NELL's key principle to minimize semantic drifting is to couple many different views and many different tasks, in a multi-view [11] and multi-task [12] learning approach. The idea is combining different components with different approaches aiming to obtain a confident learning and minimize the semantic drifting. NELL's KB is represented by an ontology-based structure characterized by categories, relations and their instances. In [3], an extended version of the prototype reported in [2] is presented with the currently subsystems (modules or components).

Since NELL's KB continuously grows each day, it does not contain all instances of every category, neither all instances of every relation described in the ontology [13]. The main idea behind the work described in this paper is to show how we can help NELL populating its own knowledge base using Bayesian Networks (BN) [15]. In this paper, we use facts (knowledge) already stored in NELL's KB as input for a BN learning algorithm named VOMOS (Variable Ordering Multiple Offspring Sampling) [16] aiming to discover new relations (Relation Discovery - RD), as well as to extract new instances for relations (Relation Extraction – RE) that NELL was not able to obtain from web text before.

Related works focus on the same task of RD and RE using NELL's KB, as well as other KB's. In [17], the authors propose the use of association rules in order to populate NELL's KB with instances and generalized association rule to investigate how useful they can be to extend the relations between the KB categories. In [14] a very similar idea is proposed, but based on Bayesian Sets (BS). However, developing methodologies to help both, extending and populating such KB and improving their coverage is still a challenge. In this paper we are interested in starting to explore Bayesian Networks (BN) to help in such tasks.

BN are probabilistic models that allow inference and may be used to discover relationships between variables, thus the methods and algorithms applied to induce the BN structure may also be used to guide NELL's ontology automatic extension and population. To do so, we propose to use VOMOS, a hybrid adaptive algorithm based on MOS approach [18] and designed for improving the process of inducing a BN structure from data. The main idea behind VOMOS is to explore the power of different evolutionary operators to search for suitable variable orderings.

Therefore, this paper presents, as specific goals, i) the application of VOMOS to induce a BN capable of representing the acquired knowledge by NELL and allow inference (based on such representation); ii) explore VOMOS induced BN to identify new semantic relations to be added to NELL's KB (expanding the initial ontology).

The remainder of this paper is organized as follows. Section 2 provides a brief overview of BN and it also presents VOMOS algorithm. Section 3 shows how VOMOS has been applied to NELL's knowledge base to induce a BN and to identify new semantic relations. Section 3 also presents some experiments with the proposed approach. Finally, Section 4 brings the concluding remarks and points out some future work.

2 Bayesian Networks

Bayesian Networks (BN) [15] are graphical representations of multivariate joint probability distributions. They are described by directed acyclic graphs in which the nodes represent the variables and the arcs represent probabilistic dependencies between connected nodes (variables). The strength of each dependence is given by the conditional probability $P(x_i \mid \pi_{x_i})$, where x_i and π_{x_i} are the i-th variable and the set of parents of x_i in the graph, respectively. The use of conditional independence is the key to the ability of BN to provide a general-purpose compact representation for complex probability distributions.

Computational methods for learning BN may be seen as a manner to identify a probabilistic model which describes the dependence (and independence) among variables from a given domain [19]. Thus, BN learning algorithms may be used as a tool for the discovery of relationships among variables and therefore they are suitable for the purposes of this work.

Among several BN learning algorithms available in the literature, this work applies a specific method named VOMOS [16]. This method, presented in Subsection 2.1, has important characteristics for the solution of the problem of identifying semantic relations in NELL's knowledge base.

2.1 VOMOS (Variable Ordering Multiple Offspring Sampling)

VOMOS [16] is a Multi-Off-Spring (MOS) algorithm [18] aiming at optimizing the learning of Bayesian network structure by searching for a suitable Variable Ordering (VO). The basic idea of VOMOS is to use a hybrid adaptive algorithm (MOS) that simultaneously handles several evolutionary approaches and dynamically adjusts the participation of each one of them in the overall search process, as described in [18].

The main characteristics of the general evolutionary strategy employed by VOMOS are the following. Each individual of the population represents a possible VO. The variable identification (ID) is coded as an integer number. Therefore, for a problem described by M variables, V_1, V_2, …, V_M having as ID the integers 1, 2, …, M respectively, there are M! possible VO and therefore M! possible individuals.

Fig. 1 presents VOMOS algorithm pseudo-code; the input for the algorithm is the training dataset. MOS starts the search process by generating the initial population randomly (P_0) and evaluating each individual. The individuals are evaluated by the fitness function and the best ones are then selected to generate the next generation. The new individuals will be created using a set of recombination operators (crossover and/or mutation operators). Each set of these operators create their own individuals $O_i^{(j)}$ (i is the generation and j is the set of recombination operators).

The idea of using this set of operators embedded in MOS is to explore the potential of each one collectively. In this sense, we are interested in approaching the variable ordering problem integrating previously defined evolutionary operators. The idea of integrating different methods and algorithms in order to enhance the results in a specific problem has shown good results in works related to Ensembles of Classifiers [20], as well as in the “Never-Ending Learning” paradigm [2]. Therefore it motivated us to explore these integration principles by using the evolutionary approach given in MOS [18].

According to empiric results presented in literature [16][21], VOMOS is able to induce good BNs which can be used for identifying relationships among variables from given domain. Thus, VOMOS seems suitable for the search of semantic relations between variables from NELL’s knowledge base.

Algorithm: VOMOS Algorithm
{Input: training dataset.}
{Output: Best_VO, Best_BN.}
begin
  Create initial global population of candidate solutions P_0.
  Evaluate initial population P_0.
  while termination criterion not reached **do**
    for every crossover operator **do**
      for every mutation operator **to** (if there are any)
        Create new individuals from current population P_i.
        Evaluate new individuals.
        Add new individuals to an auxiliary population $O_i^{(j)}$.
      end
    end
    Combine populations $O_i^{(j)}$ and P_i according to a pre-established criterion to generate P_{i+1}.
  end
end

Fig. 1. VOMOS algorithm pseudo-code (extracted from [16]).

3 VOMOS Algorithm applied to NELL’s Knowledge Base

This paper aims at to apply VOMOS algorithm to NELL’s KB. The BN structure induced by VOMOS allows identifying the semantic relations existing in the KB. Thus, it will be possible to discover new relations that may be identified through BN structure and inserted in the knowledge base in the future, expanding the NELL’s initial ontology.

Since VOMOS seeks a suitable variable ordering for the BN structure learning, when it is applied to NELL’s KB, it may identify the correct relationships (of dependence and independence) among the variables from the specific domain. Thus the BN induced by VOMOS allows, as direct consequence, a representation of NELL’s functional relations in a representation structure that enables inference.

3.1 Preparation of the datasets

NELL's KB was initially pre-processed. This data pre-processing is very important because the data format stored in the KB is not suitable for BN learning algorithms. The pre-processing procedure allowed building a dataset containing only the NELL's functional relations, named DataSet1. Thus, VOMOS was ran using DataSet1 as input to induce a BN able to allow inference in NELL's KB and identify new semantic relations.

NELL's complete KB is available at http://rtw.ml.cmu.edu/rtw/resources. To aply the pre-processing step, we have used the tab-separated-value file with every belief in the KB, one per line. The accessed file was a subset built from iteration 945. The tab-separated-value file has thirteen columns (or variables), of which only the first three were used: Entity, Relation and Value (forming a kind of SPO, Subject-Predicate-Object, triple). The variable Relation presents relations existing between two categories stored in Entity and Value. Table I shows two examples of instances for these three variables. The first instance brings the relation *teamplaysinleague* that allowed learning two new values for the categories *sporteam* (in Entity) and *sportsleague* (in Value). This line in Table I means that *Montana_tech_orediggers* is a sport team which plays in league *ncaa*. Similarly, the second instance stores the value *hunterdon*, learnt for the category *county* (in Entity) and the value *raritan*, learnt for the category *river* (in Value). Both values were learnt from relation *cityliesonriver.*

Table I. Examples of instances for the variables *Entity, Relation, Value*, provided in NELL's KB.

Entity	Relation	Value
concept:sportsteam:montana_tech_orediggers	concept:teamplaysinleague	concept:sportsleague:ncaa
concept:county:hunterdon	concept:cityliesonriver	concept:river:raritan

The dataset for VOMOS was built from values of those three variables provided in NELL's KB. It can also be noticed, in examples shown in Table 1, that data still need to be cleaned before being used (e.g., in *concept:river:raritan*, it might be that we are only interested in *raritan*). Thus, the dataset for VOMOS is composed of variables (that represent categories) and their values which form semantic relations in NELL's KB. For example, the relation *teamplaysinleague* (see Table I) provides both variables *team* (*sportsteam*) and *league* (*sportsleague*) to compose the dataset for VOMOS; their values (*montana_tech_orediggers* and *ncaa*) are also stored. From this dataset, VOMOS may induce a BN able to represent the relation *teamplaysinleague* through a directed arc between variables *team* and *league*, existing in induced BN structure, reinforcing NELL's belief that this relation is correct.

3.2 Experiments and Analysis of Results

This section describes the experiments performed using VOMOS algorithm having as input datasets obtained from a relation set and values which were stored in NELL's knowledge base (KB). The main goal described here is to induce Bayesian networks (BN) able to represent the semantic relations existing in NELL's KB and identify new relations not present yet. VOMOS algorithm was chosen to carry out these experiments mainly because of its properties of being able to find a suitable variable ordering (VO) to optimize BN's learning. Thus, the induced BN structure may be considered the most probable to represent the semantic relations existing in NELL's KB, given a set of explored VO.

Two datasets were built based on DataSet1, described in Subsection 3.1. These two new datasets have their characteristics summarized in Table II. The first dataset called *DataSet_NELLValues* has 6 variables and 31000 instances which were obtained from relations representing knowledge about sports. In each line of this dataset, the conjunction of the values of all variables represents a true knowledge, as shown in Table III. Notice that the first line in Table III brings the following true information: *ahman_green* (athlete) is a *football* (sport) player that plays for *texans* (team), as a *running_back* (sportposition), having fans in *germany* (country of fans) and uses *cleats* (equipment). In this case, this dataset tends to present relationships among all variables aiming to check if VOMOS can represent these relationships in a BN.

The second dataset called *DataSet_Relations* has 10 variables and 100000 instances and, like the first dataset, it has data regarding sports. However, unlikely the first dataset, the instances do not clearly suggest the relationships among every variable. In this scenario, we are interested in assessing the ability of the VOMOS algorithm to find new relationships among distinct variables from NELL's data.

Table II. Datasets used in experiments.

Dataset names	Number of attributes	Number of instances
DataSet_NELLValues	6	31000
DataSet_Relations	10	100000

Table III. Examples of two instances existing in *DataSet_NELLValues*.

Variables	Athlete	sport	team	sportposition	countryOfFans	equipment
Instances	ahman_green	football	texans	running_back	Germany	cleats
	yogi_berra	baseball	yankees	Catcher	Japan	uniform

As previously mentioned in Subsection 2.1, VOMOS is an evolutionary algorithm and it was applied here following the same setting and methodology described in [16]. Each individual (representing a possible variable ordering) is evaluated by an objective function. The objective function, which expresses the quality of the BN structures, used here is the natural logarithm of a posteriori probability of the database of cases, given the structure to be evaluated, following the definition given by Cooper and Herskovits (g function) [19]. The initial population has 100 individuals. The new individuals are created using different combinations of crossover and mutation operators. Each combination is applied to same population. The crossover rate was defined as 0.9 and the mutation rate as 0.1. For the stopping criterion, it was defined a maximal number of 5 generations without improvements. These parameter values were empirically defined.

Next, the VOMOS algorithm was run for the two datasets. Since the algorithm has stochastic nature, more than one run is necessary to verify the final solution. For this reason, VOMOS was run 35 times for each dataset. Table IV presents the average Bayesian score (g function) obtained by VOMOS. Since the two datasets have few variables, the VOMOS algorithm converged fast. As soon in first generation, in all runs, for two datasets, VOMOS has already obtained the best result. This result suggests that VOMOS is more adequate for larger datasets, with more variables, as already stated in [16].

In addition, and aiming at conducting a more robust comparative analysis, the datasets were also used as input to run the K2 algorithm [19], considered an efficient algorithm when a suitable VO is supplied. Since it is not possible to know such ordering in this case, K2 was performed using a random VO. The results obtained by K2 are also shown in Table IV.

Table IV. Bayesian score (g function) for VOMOS and K2 (random VO).

Dataset Names	VOMOS	K2 (random VO)
DataSet_NELLValues	-329686.72	- 336145.49
DataSet_Relations	-1156046.51	- 1158252.47

Considering the results presented in Table IV, some observations are possible. Taking into consideration the assessed datasets, the Bayesian scores obtained with VOMOS are better than the ones achieved when using the K2 algorithm. As the Bayesian score reflects the quality of the induced BN structure, it is possible to state that VOMOS tends to induce the best BN.

Fig. 2 (a) and Fig. 2 (b) present the BN structures induced by VOMOS, when applying it to data sets *DataSet_NELLValues* and *DataSet_Relations*, respectively. Observing the induced structures, it is possible to take some conclusions. These BN structures demonstrate the capacity of the VOMOS algorithm for representing the functional relations from NELL's KB.

Observing Fig. 2 (a), it is possible to notice that VOMOS identified the dependence relationships among the variable from *DataSet_NELLValues*, which has been built based on some functional relations existing in NELL's KB. Thus, VOMOS demonstrates the ability to represent these relations in a BN structure. VOMOS has identified, for example, the relationship between variables *sport* and *team*, which is represented through an arc in the structure, as can be seen in Fig. 2 (a). This arc in the structure reinforces the belief of NELL's system on the relation *teamplayssport* to be correct and so it can learn true values.

The BN structure shown in Fig. 2 (b) supports further our thesis that VOMOS may represent functional relations existing in NELL's KB. Notice that *DataSet_Relations* has more variables than *DataSet_NELLValues* and the conjunction of the values of all variables do not suggest relationships among the variables, as done in *DataSet_NELLValues*. Therefore, the structure induced by VOMOS from

DataSet_Relations reflects its ability in representing dependence relationships among variables from data of the functional relations in NELL's KB. Another interesting issue is that *country* has been the only variable that is not connected in the BN structure (see Fig. 2 (b)). This suggests that *country* has no relationship with other variables, according in *DataSet_Relations*. Actually, there is no functional relation defined between *country* and other variables in the subset of NELL's KB used in these experiments. However, our concern is also to verify whether VOMOS could induce a BN structure to represent some functional relations, which did not exist in NELL's KB. As an example, we can analyze the arc in Fig. 2 (b) between *fan* and *equipment* variables. This arc represents a functional relation not existing in NELL's KB that makes sense. Thus, VOMOS has found a new functional relation that may be inserted in NELL's ontology and that will allow the system to expand its knowledge on both categories. Other example is shown by the arcs between *team* and *athlete* and *athlete* and *startposition*. The arcs indirectly suggest a new functional relation. This same relation is directly represented in structure of the Fig. 2 (a) through arc between team and *sportposition*. This will be investigated later.

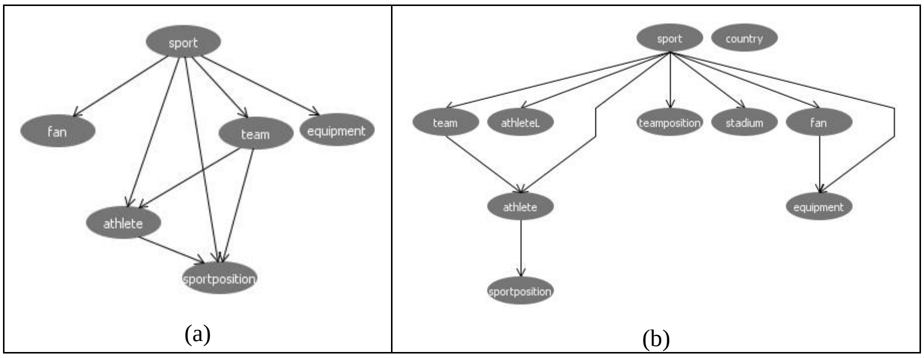

Fig. 2. (a) BN structure induced by VOMOS from the *DataSet_NELLValues* dataset. (b) BN structure induced by VOMOS from the *DataSet_Relations* dataset.

These results show initial promising empirical evidence on the feasibility of using Bayesian Networks as a tool for representation of knowledge stored through semantic relations in NELL's KB. From this representation, it is still possible to discover new relations to expand its initial ontology. We intend, in sequence, to augment the number of variables in datasets, aiming at to represent and identify different knowledge areas learnt by NELL system.

4 Conclusions and Future Works

This paper proposes a new method for representing and identifying semantic relations from knowledge base on a never-ending system named NELL. This new method employs a Bayesian network learning algorithm called VOMOS aiming to induce

Bayesian Networks that identify dependence relationships among variables and thus representing the semantics relations.

The presented results show the feasibility of application of VOMOS for NELL`s knowledge base (KB). In the performed experiments, a subset of NELL's KB was pre-processed for providing datasets to VOMOS. Some relations existing in NELL's KB are drawn and their variables and values form two datasets that serve as input to run VOMOS. From these datasets, VOMOS induced Bayesian Network structures that represent the dependence relationships among the variables that form the semantic relations. The initial experiments have shown the ability of VOMOS to learn a Bayesian Network capable of identifying the semantic relations existing in NELL's ontology. Besides, VOMOS has been able to find new functional relations that may allow expanding the NELL's initial ontology.

Based on these initial results, we intend to investigate new Bayesian Network learning algorithms (based on VO [22], or not) for being applied to NELL's KB. We also pretend to study inference algorithms aiming at inferring new facts which can populate NELL's KB. In addition, new experiments will be run in future from NELL's KB in Portuguese [13].

Another very interesting line of investigation for future work is to explore relational (and first order) approaches to Bayesian Networks [23], such as the more recent approaches proposed in [24, 25].

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