Contribution of Probabilistic Grammar Inference with k-Testable Language for Knowledge Modeling
Application on Aging People

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Abstract: We investigate the contribution of unsupervised learning and regular grammatical inference to respectively identify profiles of elderly people and their development over time in order to evaluate care needs (human, financial and physical resources). The proposed approach is based on k-Testable Languages in the Strict Sense Inference algorithm in order to infer a probabilistic automaton from which a Markovian model which has a discrete (finite or countable) state-space has been deduced. In simulating the corresponding Markov chain model, it is possible to obtain information on population ageing. We have verified if our observed system conforms to a unique long term state vector, called the stationary distribution and the steady-state.

1 INTRODUCTION

Demographic shifts in the population and the fact that people are living longer have created an awareness that the health care system is and will be increasingly difficult to control, organize and finance especially where the ageing population are concerned. The senior citizen population is increasing along with the diversity of their health backgrounds and medico-social needs which cannot be provided easily because of health aspects, social conventions and lifestyles that are intertwined with the ageing process. Long-term care is a variety of services that includes medical and non-medical care to people who have a chronic illness or disability. This illness or disability could include a problem with memory loss, confusion, or disorientation. This is called cognitive impairment and can result from conditions such as Alzheimer's disease. Care needs often progress as age or as chronic illness or disability progresses. Long-term care helps meet health or personal needs. Most long-term care is to assist people with support services such as activities of daily living like dressing, bathing, and using the toilet. Approximately 70% of individuals over the age of 65 will require at least some type of long-term care services during their lifetime. Over 40% will need care in a nursing home for some period of time. Nursing homes provide long-term care to people who need more extensive care, particularly those whose needs include nursing care or 24-hour supervision in addition to their personal care needs. We focus our interest on nursing homes. This project is being carried out in close collaboration with a French mutual benefit organization called "Mutualité Française de la Loire" which manages several nursing homes. The steps of the project consist in:

1. The specification of elderly people profiles in using unsupervised learning approach (Combes and Azéma, 2013),
2. The study of the development of these profiles over time in using a probabilistic graph of transitions between the clusters inferred by k-TSSI (k-Testable Languages in the Strict Sense Inference) algorithm. The objective is to deduce Markov process which has a discrete (finite or countable) state-space.
3. Discrete-time Markov chain simulation is used to forecast population ageing. It allows to identify the elderly people care needs and the

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workload in short-term, medium-term and long-term and to predict the future costs. An application is presented in (Combes et al., 2008).

This presentation is split up into seven sections. After an introduction describing the scope of the study, we introduce the characteristics of the collected data in section 2. In section 3, we describe the profiles of residents obtained in using cluster analysis. A brief review of previous works is presented in section 4. The section 5 treats the techniques used (regular probabilistic grammar inference) to model the automaton symbolizing the changing profiles and their development over time. Starting from this automaton, a Markov model is deduced. Thereby, it is possible to verify if our system is achieving a steady state. The section 6 presents the obtained results concerning the four medical nursing homes (called Bernadette, Soleil, Les Myosotis, Val Dorlay situated in France) and dementia disease and more particular, Alzheimer's disease. We conclude with some perspectives.

2 DATA COLLECTED

The quantitative data arises from the databases and the corresponding information system deals with the evaluation of autonomy/disability of elderly people. Dependence evaluation in France is carried out using a specific national scale called AGGIR: Autonomy-Gerontology-Group-Iso-Resources. The quantitative data concerns 628 residents and more than 2,200 observations of independence evaluations. The evaluations are made by the resident doctor in collaboration with the medical staff. An item can be evaluated using the four adverbs (see figure 1):

- Spontaneously corresponding to the letter ***S***,
- Entirely corresponding to the letter ***T***,
- Correctly corresponding to the letter ***C***,
- Usually corresponding to the letter ***H***.

The codification is the following. If all four adverbs are marked, the code is ***C***. If less than four adverbs are checked (three or two or one), the code is **B**. If no adverb is checked, the code is ***A***.

The proposed algorithm uses numerical data. So, the corresponding values are:

- 0 for code ***A*** meaning the person can do it alone,
- 1 for code ***B*** meaning the person can do partially it,
- 2 for code ***C*** meaning the person cannot do it alone.

The first step is to analyze the degree of autonomy-disability in order to identify clusters.

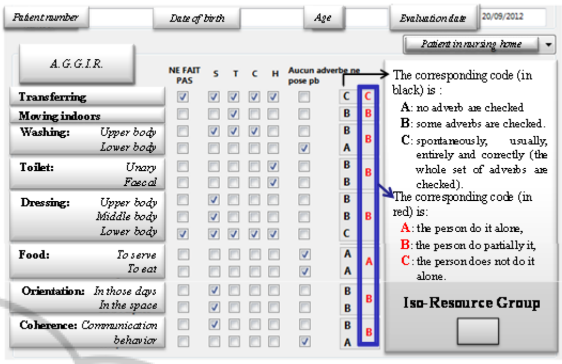


Figure 1: A.G.G.I.R scale.

3 IDENTIFICATION OF RESIDENTS' PROFILES

The aim is to find feature-patterns related to the autonomy-disability level of elderly people living in nursing homes. These levels correspond to profiles based on the people's ability to perform activities of daily living like being able to wash, dress and move. To achieve this aim, an unsupervised learning approach is proposed (Combes and Azéma, 2013). It based on principal component analysis technique to direct the determination of the clusters with self-organizing partitions. Cluster analysis is made on the 8 variables: Transferring to or from bed or chair, Moving indoors, Washing, Toilet, Dressing, Food, Orientation, Coherence. The cluster analysis identifies two kinds of patterns:

- The decline in executive functions regarding to motor and functional abilities called apraxia disorders,
- The cognitive impairment and neuropsychological deficits.

By combining clustering with a machine learning process, we could be able to predict the development of physical autonomy loss or mental autonomy loss in elderly people over time. To reach this objective, we use machine learning approach based on grammar inference in order to infer a probabilistic automaton. In the article, we only present the patients' profiles evolution regarding to upper function disorders (cognitive impairment).

4 RELATED WORKS

We want to obtain a probabilistic graph of transitions between states (clusters) with the length-of-stay in each state (temporal state representations). It is also interesting to study cluster succession of length *k* (for example, the 3 last states of resident's clusters, a *k* timed series). Probabilistic automata are used in various areas in pattern recognition or in fields to which pattern recognition is linked. Different concept learning algorithms have been developed for different types of concepts. The learning of deterministic finite automata (DFA), also called regular inference is based on acceptance of regular languages which allow to model the behaviour of systems. The aim consists in constructing a DFA from information about the set of words it accepts. There are many algorithms for regular inference (Angluin, 1987); (Garcia and Vidal, 1990a); (Rivest and Sphapire, 1993); (Balczar et al., 1997); (Parekh et al., 1998); (Parekh and Honavar, 2001); (Bugalho and Oliviera, 2005)...

A finite automaton with transition probabilities represents a distribution over the set of all strings defined over a finite alphabet. The articles presented by (Rico-Juan et al., 2000) and (Vidal et al., 2005) present a survey and a study of the relations and properties of probabilistic finite-automata and tree. (Dupont et al., 2005) clarify the links between probabilistic automata and hidden Markov models. In a first part of this work, the authors present:

– the probabilities distributions generated by these models,
– the necessary and sufficient conditions for an automaton to define a probabilistic language.

The authors show that one the one hand, probabilistic deterministic finite automata (PDFA) form a proper subclass of probabilistic non-deterministic automata (PNFA) and the other hand, PNFA and hidden Markov models are equivalent.

We assume that our problem could be modelled as a state transition graph (probabilistic deterministic finite automaton). Consequently, the pattern recognition of sequences and the corresponding probabilities could be inductively learned via an inference algorithm. The k-TSSI (k-Testable Languages in the Strict Sense Inference) algorithm (Garcia *et al.*, 1990a, 1990b) could be useful, convenient and suitable for two reasons: the simplicity of implementation and the possibility to take into account memory effects (timed macro-states). The inductive inference of the class of k – testable languages in the strict sense (*k*-TLSS) has been studied and adapted to local languages, N-grams and tree languages. A k-TLSS is essentially defined by a finite set of substrings of length *k* that are permitted to appear in the strings of then language. Given a size *k* of memory, the objective is to find an automaton for the language. This subclass of language called k-testable language has the property that the next character is only dependent on the previous *k-1* characters. In our case, it is interesting to be able to identify the substrings (memory) of length *k*. But, our goal is to infer a timed model and an automaton inferred by the k-TSSI algorithm does not take into account the timed-state. The interesting question is how to infer timed automata and very few works exist in the domain (Alur et al., 1990, 1991); (Alur and Dill, 1994); (Grinchtein et al., 2005); (Verwer et al., 2007, 2011). Timed automata correspond to finite state models where explicit notion of time is taken into account and is represented by timed events. Time can be modelled in different ways, e.g. discrete or continuous. The more recent works (Verwer *et al.*, 2007, 2011) propose an algorithm for learning simple timed automata, known as real-time automata where the transitions of real-time automata can have a temporal constraint on the time of occurrence of the current symbol relative to the previous symbol. The problem is also that it is difficult to take into account a set of substrings of length *k* *(k>1)* and the algorithm is not generalized to probabilistic timed-automata**.** In this section we propose a model in order to take into account the concept of time in the automaton inferred by the k-TSSI algorithm (i.e. the duration of time a resident spends in a particular cluster). In the next section, we present the implementation of the model.

5 DEVELOPMENT OF PATIENTS' PROFILES: MODEL IMPLEMENTATION

The method consists in:

1. Learning a deterministic finite automata (DFA) using k-TSSI algorithm.
2. Transforming this DFA into a probabilistic DFA.
3. Converting this probabilistic DFA in a Markov chain model.

5.1 Preliminaries

The aim of grammatical inference is to learn models of languages from examples of sentences of these languages. Sentences can be any structured composition of primitive elements or symbols, though the most common type of composition is the concatenation. So we infer a grammar and the corresponding representation is an automaton.

An automaton consists of:

- **Σ:** a finite input alphabet of symbols,
- **Σ*:** the set of all finite length strings generated from Σ,
- **L**: a sub-set of **Σ*** corresponding to the collected words,
- **Q**: a finite set of states with $\mathbf{q_0}$ as start state, **F** is a set of final states ($\mathbf{F} \subseteq \mathbf{Q}$),
- δ: a transition function of **Q×Σ→Q**. So that $q' = \delta(q,\sigma)$ returns a state for current state q and input symbol σ from Σ. Each transition is noted by 3-tuple (q,σ,q').

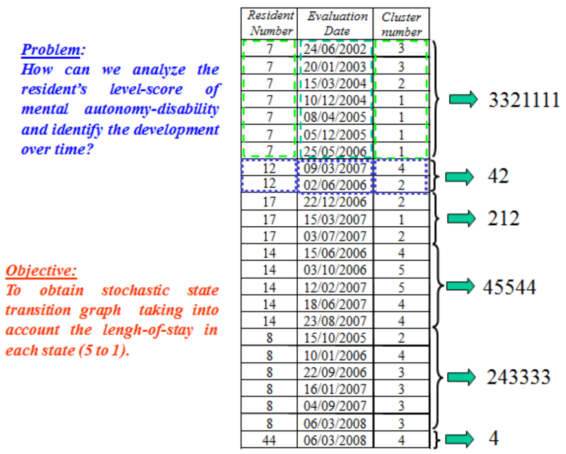
A finite automaton is a 5-tuple $(\mathbf{Q}, \Sigma, \delta, q_0, \mathbf{F})$. If for all $q \in \mathbf{Q}$ and for all $\sigma \in \Sigma$, $\delta(q, \sigma)$ corresponds to a unique state of **Q**, then the automaton is said to be a Deterministic Finite Automaton (DFA). Grammatical inference refers to the process of learning rules from a set of labelled examples. It belongs to a class of inductive inference problems (Angluin and Smith, 1983) in which the target domain is a formal language (a set of strings generated from some alphabet Σ) and the hypothesis space is a family of grammars. It is also often referred to as automata induction, grammar induction, or automatic language acquisition. The inference process aims at finding a minimum automaton (the canonical automaton) that is compatible with the examples. In regular grammar inference, we have a finite alphabet Σ and a regular language $L \subseteq \Sigma^*$. Given a set of examples that are in the language (I_+) and a (possibly empty) set of examples not in the language (I_-), the task is to infer a deterministic finite automaton A that accepts the examples in I_+ and rejects the examples in I_-.

5.2 k-TSS Inference Algorithm

The k-TSSI algorithm (Garcia and Vidal, 1990a) allows us to infer k-Testable Languages in the Strict Sense. The inductive inference of the class of k-Testable Languages in the Strict Sense is defined by a finite set of substrings of length k that are allowed to appear in the strings of the language. Given a positive sample $I_+ \in \mathbf{L}$ of strings of an unknown language, a deterministic finite-state automaton that recognizes the smallest k-TLSS containing I_+ is obtained. An automaton inferred by the k-TSSI algorithm is by its construction, non-ambiguous. Moreover, our choice is justified by the fact that k-testable (k > 1) can take into account a memory effect (ie N-gram). Indeed, we observed during data analysis that the change in evolution of the autonomy/disability state depends on the previous resident's states and their diseases (especially for chronic and disabling diseases such as osteoarticular degenerative diseases, anxio-depressive disorder, behavioural disorders…). To illustrate our approach and for the sake of simplicity, we will present in this article, the results obtained with 1-TSSL (the next state depends only on the previous states) in order to explain how we turn the time series into sequences. We choose to divide up the length-of-stay in the each cluster (for example, one discrete step = 30 days). Consequently, the corresponding automaton is a 6-tuple $(Q,\Sigma,\delta,q_0,F,d)$ where d corresponds to the length-of-stay in the states. In the following sections, we explain the implementation of the model through an example (on only six residents: 7, 12, 17, 14, 8, 44 corresponding to an excerpt of the collected data).

5.2.1 Setting Up the Alphabet

The assessment of elderly people's autonomy/disability allows us to classify residents into five levels of mental dependence situation (5 to 1 in decreasing order of severity). Figure 2 presents the data collected from the database.



Resident Number	Evaluation Date	Cluster number
7	24/06/2002	3
7	20/01/2003	3
7	15/03/2004	2
7	10/12/2004	1
7	08/04/2005	1
7	05/12/2005	1
7	25/05/2006	1
12	09/03/2007	4
12	02/06/2006	2
17	22/12/2006	2
17	15/03/2007	1
17	03/07/2007	2
14	15/06/2006	4
14	03/10/2006	5
14	12/02/2007	5
14	18/06/2007	4
14	23/08/2007	4
8	15/10/2005	2
8	10/01/2006	4
8	22/09/2006	3
8	16/01/2007	3
8	04/09/2007	3
8	06/03/2008	3
44	06/03/2008	4

Figure 2: Data and sequences.

The resident assessment is made on different dates. For example, resident number 7 was evaluated at level 3 (mental disorder) on the 06/24/2002. For all the assessments concerning resident number 7, we can deduce the sequence: ***3321111***. But this sequence does not express the amount of time the person spends in each state (level of mental disorder).

5.2.2 Preliminary Mapping of the Set of Strings (k-TSSI Algorithm)

The objective is to obtain a stochastic state transition graph taking into account the length-of-stay in each state.

The **first step** consists in the definition of the alphabet (the set Σ). The set Σ is based on an alphabet of 6 symbols - {***a,b,c,d,e,f***} which correspond to:

- ***a*** length-of-stay in cluster number 1 during a given period (example:30 days),
- ***b*** length-of-stay in cluster number 2 during a given period,
- etc (until the symbol ***e*** for cluster number 5).

The symbol ***f*** models the fact that a resident can leave the nursing home or corresponds to the last resident assessment during the last 30 days before the data extraction. It is only used when we want to deduce the Markov model. Consequently, in the following example, the symbol ***f*** does not exist in figure 3.

The ***second step*** concerns the identification of the words which corresponds to the translation of the initial sequence in order to take into account length of time spent in each cluster. Resident number **7** stayed in cluster number ***3*** from ***06/24/2002 to 03/15/2004*** (date at which the resident was evaluated and changed to cluster number 2). Thus resident number **7** stayed in cluster number ***3*** for about *22 periods* of *30 days*. The symbol modeling cluster number ***3*** for 30 days is ***c***, consequently the initial sequence "***33***" becomes "***cccccccccccccccccccccc***". The resident stayed in cluster number ***2*** for *9 periods*… and the corresponding word is:

ccccccccccccccccccccccbbbbbbbbbaaaaaaaaaa aaaaaaaa

So we obtain the set $L \subseteq \Sigma^*$. ***L*** corresponds to the learning set from which the automaton is inferred. The initial set of sequences (figure 2)

{3321111, 42, 212, 56656, 243333, 4}

becomes:

L=*{ccccccccccccccccccccccbbbbbbbbbaaaaaaa aaaaaaaaaa, ddb, bbbbbaaaab, ddddeeeeeeeeddee, bbbddddddcccccccccccccccc, dd}*

From the set ***L*** in using k-TSSI algorithm (to simplify, we present the case corresponding to *k*=1), we obtain the automaton described in figure 3. This algorithm consists in building the sets **Q, Σ, δ,q₀,F** by observation of the corresponding events in the training strings. From these sets, a finite-state automaton that recognizes the associated language is straightforwardly built. The detail of the algorithm is described in (Garcia *et al.*, 1990b).

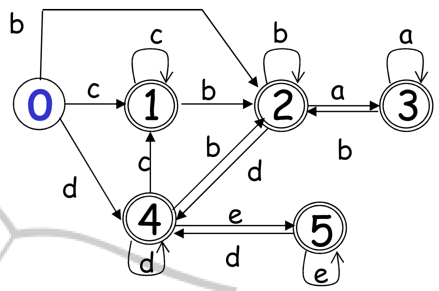


Figure 3: The automaton inferred by the algorithm k-TSSI with q_0 =0.

5.3 Computation of Probabilities

The automaton is inferred by the k-TSSI algorithm. We have to associate transition probabilities with states. In order to compute these probabilities, we use the learning set ***L***. From the words of set ***L,*** when they are recognized by the automaton inferred by k-TSSI, we count:

- The transition between two states for a given symbol (transition from the state ***q*** by the symbol ***σ***): $cp_{\delta(q,\sigma)}$,
- each transition in a state q: cp_q,
- if a state q is the final state (end of the words): cp_{q_final}.

For the algorithm, we use the three epochs-counts in order to estimate the probabilities. The algorithm computing the probabilities from a learning set is the following.

Input $I_+ = \{x_1,\ldots,x_{|I+|}\}$ *//collected sample*
A_k = **(Q, Σ, δ,q₀,F)** *//the inferred automaton*
Output $PA_k = \{p_{\delta(q,xij)}, p_{q\_final}\}$ *//the obtained probabilities*
Begin
For *i=1* **until** $|I_+|$ *//for all words x_i in I_+*
  $q \leftarrow q_0$
  For *j=1* **until** $|x_i|$ *//for all symbol x_{ij} of the word $x_i \in I_+$*
    $q' \leftarrow \delta(q,x_{ij})$ *//the corresponding transition*
    cp_q ++ *//epoch-count in passing state*
    $cp_{\delta(q,xij)}$ ++ *//epoch-count in passing transition*
    $q \leftarrow q'$
  EndFor
  cp_{q_final}++ *//epoch-count concerning the final states*

```
    cpq ++
EndFor
For all q ∈ Q
    pq_final= cpq_final / cpq      //Computation of final-state probabilities
EndFor
For all δ(q,σ)∈ δ
pδ(q,σ) = cpδ(q,σ)/ cpq          //Computation of transition probabilities
EndFor
Return PAk
```

The obtained results from the sample presented in figure 2 are:

- $cp_q = (6_{(0)}, 39_{(1)}, 19_{(2)}, 22_{(3)}, 17_{(4)}, 10_{(5)})$,
- $cp_{q\_final} = (0_{(0)}, 1_{(1)}, 2_{(2)}, 1_{(3)}, 1_{(4)}, 1_{(5)})$,
- $cp_{\delta(q,\sigma)} = (2_{\delta(0,b)}, 1_{\delta(0,c)}, 3_{\delta(0,d)}, 0_{\delta(0,e)}, 1_{\delta(1,b)}, 37_{\delta(1,c)}, 2_{\delta(2,a)}, 14_{\delta(2,b)}, 1_{\delta(2,d)}, 20_{\delta(3,a)}, 1_{\delta(3,b)}, 1_{\delta(4,b)}, 1_{\delta(4,c)}, 12_{\delta(4,d)}, 2_{\delta(4,e)}, 1_{\delta(5,d)}, 8_{\delta(5,e)})$.

And afterwards, we deduce *the probabilities:*

- $p_{q\_final} = (0/6_{(0)}, 1/39_{(1)}, 2/19_{(2)}, 1/22_{(3)}, 1/17_{(4)}, 1/10_{(5)})$,
- $p_{\delta(q,\sigma)} = (2/6_{\delta(0,b)}, 1/6_{\delta(0,c)}, 3/6_{\delta(0,d)}, 1/39_{\delta(1,b)}, 37/39_{\delta(1,c)}, 2/19_{\delta(2,a)}, 14/19_{\delta(2,b)}, 1/19_{\delta(2,d)}, 20/22_{\delta(3,a)}, 1/22_{\delta(3,b)}, 1/17_{\delta(4,b)}, 1/17_{\delta(4,c)}, 12/17_{\delta(4,d)}, 2/17_{\delta(4,e)}, 1/10_{\delta(5,d)}, 8/10_{\delta(5,e)})$.

So we obtain the probabilistic deterministic automaton where the time series are taken into account. The advantage of using 1-TSSL (k-TSSI algorithm with k=1) lies in the fact that one state corresponds to one symbol. We have added a new symbol $\boldsymbol{f}$ and a final state $\boldsymbol{q_6}$ in order to facilitate the translation of the probabilistic automaton into a Markov process. For all q states where $p_{q\_final}>0$, we add a transition $\delta(q,g)= q_6$, $p_{\delta(q,g)} = p_{q\_final}$ and $p_{q\_final} \leftarrow 0$. We note that $p_{q_6\_final} = 1$.

From patients' file living in Soleil nursing home and suffering from Alzheimer disease, the probability matrix of transitions between states and the corresponding automaton are respectively presented in the table 1 and in the figure 4.

Table 1: The corresponding probability matrix of transitions between states (figure 4).

To ⇨ From ⇩	Cluster 5	Cluster4	Cluster3	Cluster2	Cluster1	q_6
q_0	0.5072	0.0580	0.3333	0.0290	0.0725	
Cluster5	0.9738	0.0005	0.0009	0	0	0.0248
Cluster4	0.0629	0.9021	0.0210	0	0	0.0140
Cluster3	0.0229	0.0134	0.9408	0.0019	0.0019	0.0191
Cluster2	0	0.0299	0.0299	0.8955	0	0.0448
Cluster1	0	0	0.0122	0.0488	0.9268	0.0122

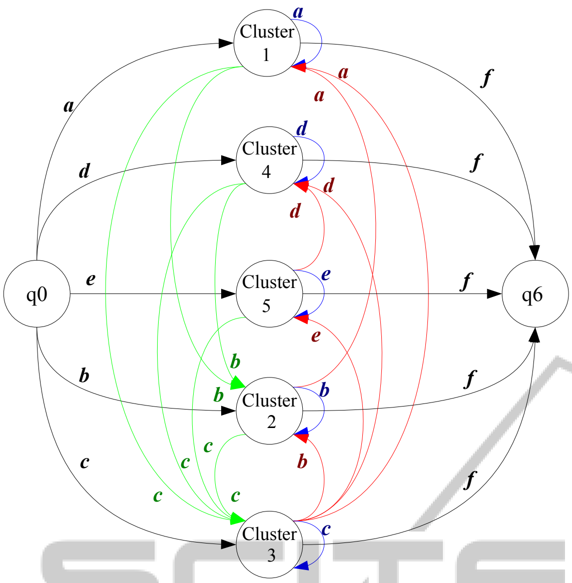


Figure 4: The automaton inferred by the algorithm k-TSSL (Soleil nursing home: residents suffering from dementia).

5.4 Markov Model

The final state q_6 not only represents the resident state when they left the system but also the last resident assessment (resident present in the system at the date of database extraction).

In order to obtain the Markov chain model, we have to compute the probabilities:

- Pe_i: Input probabilities (i.e. the initial resident assessments) in each $cluster_i$ (i=1..5),
- Psi: Output probabilities (i.e. the last resident assessments when residents leave the system) in being $cluster_i$ (i=1..5) after 30 days (corresponding to the equidistant discrete time).

We have also to modify the probabilities of staying in $cluster_i$ (i=1..5), regarding if the patient is staying in the nursing home at the at the date of database extraction (these evaluations are taken into account in the transition with the symbol f to q_6 in table 1). We add the number of evaluations in the corresponding $cluster_i$. It is the reason that the probability to be in *cluster1*, (initially is *0.9738* in table1) becomes *0.9902* in the Markov matrix.

When a resident leaves the system, he is immediately replaced by a new resident. Consequently, two other probabilities are taken into account *PE* and *PS*. The Markov matrix is presented in the table 2.

Table 2: The Markov matrix obtained from the collected data - Soleil Nursing home: patient suffering from dementia.

	Pe_i	Cluster5	Cluster4	Cluster3	Cluster2	Cluster1	PSS
PEE	0	0	0	0	0	0	1
Cluster5	0.0725	0.9390	0	0.0019	0	0	0
Cluster4	0.0290	0.0488	0.9403	0.0019	0	0	0
Cluster3	0.3333	0.0122	0.0299	0.9580	0.0210	0.0009	0
Cluster2	0.0580	0	0.0299	0.0134	0.9161	0.0005	0
Cluster1	0.5072	0	0	0.0229	0.0629	0.9902	0
Psi	0	0	0	0.0019	0	0.0084	0

Table 4: Evolution of patients' profiles in 2 years.

No Dementia	Cluster5	Cluster4	Cluster3	Cluster2	Cluster1	**Exit**
Cluster5	50.9%	16.0%	5.8%	1.6%	2.4%	23.3%
Cluster4	3.8%	56.0%	10.6%	3.4%	4.1%	22.2%
Cluster3	4.3%	4.0%	25.2%	9.1%	13.8%	43.6%
Cluster2	0.8%	0.9%	11.4%	29.4%	29.6%	27.9%
Cluster1	0.1%	0.6%	0.7%	1.3%	33.1%	64.2%

Dementia	Cluster5	Cluster4	Cluster3	Cluster2	Cluster1	**Exit**
Cluster5	9.7%	20.6%	27.1%	12.7%	19.4%	10.5%
Cluster4	0.5%	20.2%	32.4%	14.7%	20.0%	12.2%
Cluster3	0.6%	1.5%	21.8%	17.7%	34.1%	24.3%
Cluster2	0.1%	0.1%	1.9%	11.9%	31.7%	54.3%
Cluster1	0.2%	0.1%	1.5%	15.5%	64.8%	17.9%

We verify if the system reaches a steady state. Out of definition, an eigenvector $\boldsymbol{x}$ is associated to eigenvalue $\boldsymbol{l}$ if: $\boldsymbol{A*x = l*x}$

(A corresponding to the probabilities matrix presented in table 2)

If an eigenvector of $\boldsymbol{x}$ is associated to a unique eigenvalue 1, such a vector is called a ***steady state vector***. If we identify only one eigenvalue 1, then the distribution is said to be irreducible and aperiodic.

The eigenvector associated with the eigenvalue 1 has been computed. We have one eigenvalue 1 and the corresponding eigenvector $\boldsymbol{x}$ is the following:
0.00692 0.01263 0.01966 0.12108 0.03768 0.79510 0.00693

The interpretation of this eigenvector is that the system (ratio of the resident profiles without 0.69% of resident turnover of input/output in the nursing home) evolves towards a state where the percentages of population are:

- 1.28% are in cluster5,
- 1.99% are in cluster4,
- 12.28% are in cluster3,
- 3.82% are in cluster2,
- 80.63% are in cluster1.

6 EXPERIMENTS

The table 3 presents the steady state vectors from different samples. We see that the decline is more important for elderly people with dementia than non-demented elderly people.

Table 3: Steady state: population staying in medical nursing homes.

	4 Nursing Homes	Patient Without Dementia Disease	Patient Suffering from Dementia
Cluster5	3.57%	35.98%	0.32%
Cluster4	13.42%	27.00%	1.93%
Cluster3	27.80%	15.96%	5.21%
Cluster2	11.54%	5.65%	6.84%
Cluster1	43.66%	15.40%	85.69%

Now, we simulate the evolution over time in using transition matrix used to model the Markov chain concerning each population. The results concerning the patients' profiles in 2 years are presented in table 4.

If the patient does *not* suffer from *dementia* disease, if he is initially in cluster5, the probabilities that the patient will be staying in:

– Cluster5 is 50.9%,
– Custer4 is 16%,
– Cluster3 is 5.8% ...

and leaves the system with a probability near to 23%.

If the patient suffers of *dementia*, the probabilities that the patient which will be staying in:

– Cluster5 is 9.7%,
– Cluster4 is 20.6%,
– Cluster3 is 27.1%, ...

and leaves the system with a probability near to 10%.

7 CONCLUSIONS

An application of grammatical inference to the identification of the resident's autonomy-disability progress over time has been presented. From profiles identified in using clustering approach (Combes and Azéma, 2013), we propose preliminary results of an investigation where regular grammars are used for modeling the ageing people evolution over time. The finite automaton is inferred in using the k-TSSI algorithm and afterward modified in order to obtain a probabilistic graph of transitions between states (clusters) with the length-of-stay in each state. From this graph, we deduce automatically the corresponding Markov chain model. For the sake of simplicity, we only present in the article, the case where *k*=1. It is evident that in this case, we can use a bi-gram. But we have also study the evolution with *k=2..n*.

In perspective, we have to extend and to validate our approach on different models such that Hidden Markov Models which are widely used in many patterns recognition areas. We have to study in more details probabilistic automata and discrete hidden models in order to clarify the links between them (Dupont et al., 2005).

It could be interesting to study other classes of diseases. Approximately 1-1,5 % French population suffer from dementia and the causes of dementia are neurological disorders such as Alzheimer's disease (causes 50 percent to 70 percent of all dementia), blood flow-related (vascular) disorders such as multi-infarct disease, inherited disorders such as Huntington's disease, and infections such as HIV (Khachaturian, 2007). In fact, we would like to simulate the patient’s progress in order to forecast and to analyze the facility needs for long, medium and short-term care in order to dimension the human, financial and physical resources necessary in the future.

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