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Computational Cognitive Modeling for the Diagnosis of Specific Language Impairment

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Abstract. Specific Language Impairment (SLI), as many other cognitive deficits, is difficult to diagnose given its heterogeneous profile and its overlap with other impairments. Existing techniques are based on different criteria using behavioral variables on different tasks. In this paper we propose a methodology for the diagnosis of SLI that uses computational cognitive modeling in order to capture the internal mechanisms of the normal and impaired brain. We show that machine learning techniques that use the information of these models perform better than those that only use behavioral variables.

Keywords. Language impairment, machine learning, automatic diagnosis, computational cognitive modeling.

Introduction

The characterization and diagnosis of cognitive impairments is, in most cases, problematic. There are two main reasons for this fact: heterogeneity and overlap. Specific Language Impairment (SLI) is an example of cognitive impairment that presents these two problems. SLI is usually defined as a developmental disorder of the language ability in the absence of factors that typically affect language learning such as hearing impairments, low non-verbal intelligence or neurological damage [1]. SLI individuals usually show wide differences in the severity of disorder and the factors affected by the disorder [1]. This fact has led to the definition of different SLI subgroups [2] and even different definitions for each individual profile inside SLI. The other main difficulty is the high overlap of SLI with other cognitive impairments. SLI co-occurs with some other disorders [2, 3, 4] and, moreover, this impairment is not restricted to language. There are many other cognitive functions that are impaired such as working memory or some motor skills. This high heterogeneity and overlap makes very difficult to differentiate SLI from other cognitive impairments and to distinguish between different subcategories grouped under the SLI profile. Therefore, there is no unified account for the particular developmental profile of SLI and there are no standardized tests to identify impaired children. The general approach is to use vocabulary based scales or processing-dependent measures [5]. The first type of

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measures identifies SLI with the children on the tail of the scores distribution on various vocabulary-related tasks. Processing dependent scales use alternative measures not related to vocabulary. Besides, machine learning techniques have been used for the diagnosis of SLI [6] with promising results but still failing to find a standardized method applicable to SLI. All these approaches have in common that they are based on behavioral observations but, as stated before, SLI behavioral patterns are highly heterogeneous and are also found in some other disorders. Given these conditions, behavior does not seem to be enough. Our proposal is that having access to the processes that underlie normal and impaired behavior could help the diagnosis process. And we propose that computational cognitive modeling could be a useful tool to get access to those processes.

In this paper we propose a methodology for the diagnosis of SLI. The idea is to build a computational cognitive model of a task in which impaired children show differences with normal children and use the different parameters of the model to train machine learning algorithms for the diagnosis. We applied the methodology on an existing database of Spanish-speaking children. The results show that the information obtained from the computational cognitive models is very useful in the diagnosis process. Also it is important to note that this methodology is easily extended to other languages and even to other cognitive impairments not necessarily related to language.

1. Method

As commented in the previous section, the diagnosis of many cognitive impairments is complicated by two main factors: overlap and heterogeneity. In order to avoid these two problems, any methodology for the diagnosis of cognitive impairments should have two main features: generality and individualization. The methodology should be adequate to diagnose various different cognitive impairments and, at the same time, it should take into account the individual differences that are usually present on these impairments. Here we present a methodology that achieves these two objectives and we apply it to the particular case of SLI. The different stages of the methodology are explained below:

1.1. Define target task

In this stage we have to find a task or set of tasks in which the patients show some kind of difficulties and behavioral differences with respect to the normal individuals. In our case, it is well know that SLI children have problems with verbal morphology. So we decided to choose a verb inflection task. Given the infinitive of many different verbs, the model has to inflect them with different combinations of mood, tense, aspect, number and person and acquire the correct inflections through development.

1.2. Computational cognitive modeling

The next step is to build a computational cognitive model for the target task. The psychological plausibility of the model is a key point. The model should be able to show the normal and the impaired behavior but it is also highly relevant how the model produces these behaviors because that information is going to be used on the diagnosis process. The better the model mimics human behavior, the more useful would be the information obtained from it.

In our case, we built a computational cognitive model using the cognitive architecture ACT-R [7]. A more detailed description of the model can be found in [8]. We describe below its main features:

- Mechanisms: The model is based on two general strategies: memory retrieval and analogy. Using these two initial mechanisms, the model is able to acquire the regular rules and the irregular exceptions just using the examples from the input vocabulary.
- Parameters: The mechanisms of the model are controlled by a series of parameters that give shape to its behavior. These parameters form three main groups: declarative memory parameters that control the retrieval of learned facts from memory, procedural memory parameters that control the learning and execution of rules and grammatical processing parameters that control how the model deals with the different grammatical features.
- Representation: The model uses semantic and morphological information. Each verb form is represented by its meaning and some grammatical features such as conjugation, number, person, mood, tense or aspect.
- Input vocabulary: We used the Spanish Verb Inventory (accessible at http://crl.ucsd.edu/experiments/svi) [9] that contains frequencies for the present and past tense forms of 50 of the earliest acquired Spanish verbs.

1.3. Subject modeling

Given the great heterogeneous profile of many cognitive impairments, any diagnosis methodology should take into account the individual differences. Our proposal is to obtain for each individual the set of parameter values of the computational cognitive model that better fit the behavior of that individual. Therefore, this stage of the methodology requires the use of an optimization algorithm for the parameter values. In this case we used an evolutionary strategy with Gaussian mutation, an intermediate crossover operator and a 1:5 ratio for the parent population and the offspring sizes.

1.4. Application of machine learning techniques

The final stage of the methodology is to apply different machine learning techniques using the information derived from the computational cognitive model.

We used a database of 48 Spanish-speaking children (24 with typical language development (TLD) and 24 with language impairment (LI)) used in [10]. The two groups were age matched (TLD 4;6, LI 4;5). Children produced narratives based on two different wordless picture books and the transcripts were analyzed to obtain different grammatical measures. Of particular interest for our study on the inflectional task are those related to verb morphology: omissions, substitutions of person, number and tense and over-generalizations.

We applied the previous steps of the methodology to obtain the best set of parameter values and so, the best model for each of the 48 individuals and built three different classifiers for the diagnosis: an SVM, a Naïve Bayes classifier and a Neural Network. We used as reference method the one used by Simon-Cerejeido & Gutiérrez

Clellen [10] in a previous work with this same database: a Linear Discriminant Analysis (LDA) using only behavioral data. In order to evaluate the performance of the methods we performed a leave-one-out cross validation (LOOCV) and compute the sensitivity, specificity and Area Under Curve (AUC).

Moreover, we also used three different feature sets in order to analyze the importance of the different information sources. The first feature set is made only by the observable variables captured in the database (a total of 15 variables). The second feature set is made only by the internal variables of the model (i.e. the parameter values obtained from the individualized computational models (a total of 10 parameters). And the third feature set is a combination of the two previous sets.

2. Results

Table 1 shows the results obtained by the four classification methods with the three complete feature sets. The results shown for LDA with the *observable set* are different from the ones reported in [10] because we used a LOOCV method to evaluate all the classifiers. All the classifiers but the Neural Network performed better (ANOVA, $p < 0.01$) than the reference method in terms of sensitivity and AUC with all three feature sets. However there were almost no significant differences in terms of specificity. Note that, in this case, it is more important to obtain good results in terms of sensitivity because it is much more problematic to diagnose as normal an impaired children than the opposite.

The second analysis revealed significant differences (ANOVA, $p < 0.01$) between the three feature sets in terms of sensitivity. All of the classifiers improved their sensitivity with the use of the internal variables of the model. Probably the most important result is that the use of the "observable+internal" feature set produced a significant improvement (ANOVA, $p < 0.01$) as compared to the other two feature sets in all cases in terms of sensitivity, specificity and AUC.

Table 1. Sensitivity, specificity and AUC for the different methods and feature sets.

	Observable			**Internal**			**Observable + Internal**		
	Sensit.	**Specif.**	**AUC**	**Sensit.**	**Specif.**	**AUC**	**Sensit.**	**Specif.**	**AUC**
SVM	0.67	0.86	0.79	0.79	0.81	0.85	0.88	0.86	0.89
Naïve Bayes	0.73	0.85	0.80	0.78	0.78	0.83	0.87	0.83	0.85
Neural Net	0.67	0.81	0.76	0.73	0.75	0.77	0.80	0.83	0.81
LDA	0.58	0.81	0.71	0.73	0.77	0.75	0.79	0.87	0.80

3. Discussion

In this paper we present a general methodology for the diagnosis of cognitive impairments and we apply it to the particular case of SLI. Typical approaches to SLI diagnosis are based on behavioral observations but, as stated before, SLI behavioral patterns are highly heterogeneous and are found also in some other disorders. Our proposal is to use computational cognitive modeling as a tool to have some kind of access to the processes that underlie normal and impaired behavior and use this information in the diagnosis process. The results show that the information obtained from the computational cognitive models is extremely useful for the diagnosis process.

Looking at the results, the first observation is that machine learning techniques clearly outperform the reference method even using only observable variables. This fact shows, like some other previous works [6], that the use of machine learning techniques can be of great interest for the diagnosis of cognitive impairments and, in particular, for the diagnosis of SLI.

The key proposal of this work is that the diagnosis of cognitive impairments could be improved by using some clue about the cognitive processes that underlie normal and impaired behavior. This idea is reinforced by the obtained results. All methods improved their sensitivity with the information of the internal variables. As stated before, sensitivity is the most important measure to optimize. Moreover, the results obtained combining both sources of information (behavioral variables and the internal variables of the model) are extremely good, reaching sensitivity rates higher than 88 % and AUC near 90%. These two results show that the combination of machine learning techniques with the information obtained through computational cognitive modeling could be a helpful methodology to support the diagnosis of SLI.

Finally, it is important to note that this methodology is easily extended to other languages and even to other cognitive impairments not necessarily related to language.

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