

Computational cognitive modeling of inflectional verb morphology in Spanish-speakers for the characterization and diagnosis of Alzheimer's Disease

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Abstract

Alzheimer's Disease, as other mental and neurological disorders, is difficult to diagnose since it affects several cognitive abilities shared with other impairments. Current diagnostic mainly consists of neuropsychological tests and history obtained from the patient and relatives. In this paper we propose a methodology for the characterization of probable AD based on the computational cognitive modeling of a language function in order to capture the internal mechanisms of the impaired brain. Parameters extracted from the model allow a better characterization of this illness than using only behavioral data.

1 Introduction

Document "Dementia. A public health priority" by the World Health Organization¹ defines dementia as a syndrome, usually of a chronic or progressive nature, caused by a variety of brain illnesses that affect memory, thinking, orientation, comprehension, calculation, learning capacity, language, and judgment leading to an inability to perform everyday activities. Current data estimate over 35.6 million people worldwide affected by dementia and this number will double by 2030 and more than triple by 2050². Dementia is among the seven pri-

ority mental and neurological impairments¹. Although dementia is a collective concept including different possible causes or diseases (vascular, Lewy bodies, frontotemporal degeneration, Alzheimer), there are broad similarities between the symptoms of all them. Alzheimer's Disease (AD) is the most common cause of dementia. Its early diagnosis may help people to have information in the present for making decisions about their future and to receive treatment as soon as possible.

Clinical diagnosis of dementia happens after subjects realize memory loss or language difficulties affecting their everyday activities. Usually, the therapist takes note of these subjective impairments coupled with objective information given by some relative and then performs a battery of neuropsychological tests. Besides, neuroimaging techniques (MRI, PET) and biomarkers tests can strengthen the diagnosis process by discarding any other pathology. The drawback of these last techniques is their high cost. So, a key point in detecting this syndrome is to research about noninvasive and low cost diagnosis techniques whose application could be extended to everybody at a very early stage even before appearing any subjective or observable symptom.

One of the most common functions affected in dementia is language production (Hart and Semple, 1990). Many of the structures and processes involved in language processing are shared by different cognitive capacities. So, it would be possible to identify any cognitive impairment not directly

¹ www.who.int/mental_health/publications/

² www.who.int/mental_health/neurology/dementia/

related to language at an early stage by analyzing language processing.

The loss of communicative capability is detected in 80% of people at the first development stage of AD. Most research works relating AD and language have mainly focused their efforts on the lexical-semantics area (Cherkow and Bub, 1990) although there are also several studies showing linguistic problems in areas like phonology, syntax, pragmatics and inflectional morphology and how these problems evolve along the disease's stages (Taller and Philips, 2008).

The majority of these works have been carried out in English but their results can be extended to other languages such as Spanish. An exhaustive analysis of linguistic processing in Spanish was performed by Cuetos et al. (2003) covering phonological, syntactical and semantic areas. However, there is no study dealing with verbal morphology in Spanish. The closest reference work examining the effects of AD in past-participle and present-tense production of real regular and irregular verbs as well as novel verbs of the two first morphological classes is in Italian (Walenski et al. 2009). The pattern found is the same as in English inflection: dementia patients are impaired at inflecting real irregular verbs but not real regular verbs for both tenses or novel verbs (Ullman, 2004).

Although there exist many neuropsychological tests used to diagnose dementia (Pasquier, 1999), like MMSE (Mini-Mental State Examination) (Folstein et al., 1975), they have a low sensibility at early stages and do not provide an individual and distinguishing measure of the disease. Language tests have proven to be very useful tools in identifying different types of mental disorders (Stevens et al., 1996).

In (Cuetos et al., 2003) the authors build a support model for the diagnosis of probable AD from the results of tasks belonging to phonological, syntactic and semantics areas by using a linear regression analysis. Other research work (Bucks et al., 2000) finds the predictive markers of probable AD by Principal Component Analysis (PCA) from measures of spontaneous narrative speech. The same kind of measures were processed by different machine learning methods resulting in classification models with a high predictive power (Thomas et al., 2005), which were able to detect the type of disorder even in pre-symptomatic subjects (Jarrod et al., 2010). These works demonstrate, on the one

hand, the role of language use as a behavioral measure; on the other, the potential value of the computational analysis of language as a characterization and diagnostic means and, specifically, the capability of machine learning techniques to develop descriptive and predictive models of mental disorders from language use.

In other cognitive impairments related to language production (Oliva et al., 2014), the performance of classification models obtained with machine learning techniques have shown to be better than statistical methods like regression or lineal discriminant analyses. Nevertheless, to the best of our knowledge, there is no study about modeling by machine learning methods the behavior of native Spanish-speakers with dementia by using measures extracted from verbal morphology tests.

As stated before, there exist different types of dementia as a consequence of diverse diseases that share similar symptoms and behavioral patterns. A deeper knowledge about the specific structural or functional causes of this syndrome and so about the underlying disease can be gained by neuroimaging techniques. But these techniques are expensive and their use is not generally extended. The efficacy of a therapy or treatment depends on how the disease affects the patient individually. However, most studies present a profile of average behavior behind disorders. A novel way to overcome this lack of personalized information about the patient can be supplied by computational modeling of individual patients' behavior when patients perform a certain cognitive task.

A cognitive architecture is a general framework to develop behavior computational models about human cognition (Anderson and Lebiere, 1998). This type of architecture must take into account the abilities (i.e. memory, learning, perception, motor action) and the boundaries (i.e. forgetting) of the human being. As a general theory about the structure and function of a complete cognitive system, a cognitive architecture determines the way perceptual, cognitive and motor processes interact in producing behavior. The framework provided by a cognitive architecture allows the computational models supported by it to be neurologically and psychologically plausible. Computational modeling is an integral procedure for obtaining indirect measurements about structures and processes involved when people accomplish a cognitive task (Iglesias et al., 2012; Serrano et al., 2009). A good

subject’s model must fit the behavior of such a subject, that is, it must generate statistically equivalent data to the subject’s data. A well-known cognitive architecture is ACT-R (Anderson, 2007). Its application to a language function as the task of acquiring verbal morphology in English (Taagten and Anderson, 2002) is based on the dual-mechanism theory (Pinker and Prince, 1988), which posits that irregular forms of verbs are stored in memory as entries in the mental lexicon while regular forms are computed by rules. This same paradigm has been used to model the acquisition of a highly inflected verbal system like Spanish (Oliva et al., 2010) and the behavior of children with Specific Language Impairment (SLI) (Oliva et al., 2013).

This paper presents a methodology for the characterization and diagnosis of probable AD (pAD) for native-Spanish speakers based on the computational cognitive modeling of the subjects’ behavior when they perform verb inflection tasks. The set of variable values of each model are presented to supervised machine learning algorithms to learn a classification and predictive model of data. The results of the preliminary study that we have carried out show that the variables obtained from the computational cognitive models are very informative for the diagnosis process. Also it is important to note that this methodology can be easily extended to other languages and even to other cognitive impairments not necessarily related to language.

2 Method

As commented in the previous section, AD can present overlapping symptoms with other types of dementia and exhibit more deficits other than language use. So, any methodology for the diagnosis of cognitive or mental impairments should have two main goals: generality and individualization. The methodology should be adequate to diagnose 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 applied to the particular case of pAD consisting mainly in: i) finding the task that exhibits behavioral differences between healthy and impaired subjects, ii) preparing the computational cognitive architecture with the knowledge to deal with the selected task, iii) mod-

eling the individual subject’s behavior to obtain the parameters of the architecture specific to each participant, and iv) applying machine learning techniques on the information given by the cognitive models to learn the classification model that supports impairment diagnosis. Next, the different steps of the methodology are explained and applied to characterize and diagnose pAD.

2.1 Participants

Twenty-two native-Spanish speakers were initially selected to take part in this preliminary study by the Centro de Referencia Estatal de Discapacidad y Dependencia (CRE) de León, Spain, distributed into twelve patients of pAD (six men, six women) and ten healthy control subjects (five men, four women) age-matched. pAD participants were identified by the MEC (Lobo et al., 1979) and Barcelona tests (Peña-Casanova et al. 2005) for Spanish speakers.

Three participants with pAD were discarded due to two of them have a low educational level and the third one was not originally from Spanish. The final participants’ demographic features can be seen in Table 1.

	pAD	control
Participants	9	10
Avg. Age (SD)	69.33 (6.42)	67.3 (2.58)
Sex	4F / 5M	5F / 5M

Table 1. Participants’ demographic features. SD stands for Standard Deviation.

2.2 Define target task

The task to be carried out intends to reflect behavioral differences between pAD patients and control healthy individuals. Since patients with pAD have shown deficits with verbal morphology in English and Italian, we have selected a task of verb inflection consisting of two sets with 40 pairs of sentences. In selecting the sentences’ verbs, we have avoided reflexive, recent and onomatopoeic verbs. In the first set, devoted to present tense, all the sentences were presented at first person, singular and together a frequency adverb to denote that the action is usually performed. An example of this set is: a) *A mí me gusta llevar pantalones vaqueros* (I like to wear jeans) and b) *Así que todos los días*

... *pantalones vaqueros* (So I ... jeans every day). In the second set, devoted to simple past, all sentences were presented at third person, singular and together the adverb “*ayer*” (“yesterday”) to denote that the action was done in the past. An example of this set is: a) *A Lola le gusta comer temprano* (Lola likes to eat early) and b) *Así que ayer Lola ... temprano* (So Lola ... early yesterday).

In the two sets, 20 regular and 20 irregular verbs were used, respectively. These verbs were retrieved from the Reference Corpus of Current Spanish³ and matched in frequency (regular = 44.79, irregular = 44.33, $p = 0.98$). All regular verbs, except one (“*comer*”-“to eat”), belonged to the first morphological class, or first conjugation, finishing the infinitival form of the verb with “-*ar*”. Irregular verbs belonged to the second and third conjugation, finishing with “-*er*” and “-*ir*”, respectively. Both regular and irregular matched in orthographical (Number of letters: Infinitive form: regular = 6.4, irregular = 5.85, $p = 0.29$; Inflected form: regular = 5.48, irregular = 5.58, $p = 0.74$) and phonological length (Number of syllables: Infinitive form: regular = 2.4, irregular = 2.25, $p = 0.41$; Inflected form: regular = 2.4, irregular = 2.35, $p = 0.69$), and consonant density (Infinitive form: regular = 1.62, irregular = 1.57, $p = 0.62$; Inflected form: regular = 1.18, irregular = 1.24, $p = 0.43$) in order to avoid phonological factors biasing results.

2.3 Behavioral profile

Next, the procedure performed to collect this kind of data and the results obtained are briefly described.

Procedure: 80 pairs of sentences were randomly sorted and presented to all the participants. Every participant had to read each sentence pair slowly and to fill the gap in the second sentence with the suited inflected form of the verb in the first sentence. The answers of each participant are categorized as follows: 1) Correct answers, 2) Overregularization or Irregularization errors, occurring when the expected form was irregular or regular, respectively, 3) Number or Person (NP) errors, when fails the number or person affix, 4)

Mood, Tense or Aspect (MTA) errors, when fails the mood or tense or aspect affix, and 6) Other errors, not included in the previous categories.

Results: People with pAD made more mistakes when inflecting both past and present tenses. The results obtained show a clear deficit in producing irregular forms both in past and present tense in participants with pAD compared with controls, as seen in languages such as English (Ullman, 2004) and Italian (Walenski et al., 2009). Table 2 presents these results. Other types of errors made by participants with pAD holding statistical differences with the control group are overregularization ones in present tense and substitution errors of mood, tense or aspect. According to the dual-mechanism theory (Pinker and Prince, 1988), errors in irregular forms and MTA errors are focused on declarative memory fails since this memory stores irregular verb forms

		pAD	control
Regular Forms	Correct	0.983	0.995
	Irregularization	0	0
	NP Errors	0	0
	MTA Errors	0.006	0
	Other Errors	0.013	0.005
Present Tense			
Irregular Forms	Correct	0.911**	0.985
	Irregularization	0.028*	0.01
	NP Errors	0	0
	MTA Errors	0.039*	0
	Other Errors	0.022	0.005
Regular Forms	Correct	0.978	0.99
	Irregularization	0	0
	NP Errors	0	0
	MTA Errors	0.011	0.005
	Other Errors	0.011	0.005
Past Tense			
Irregular Forms	Correct	0.9**	0.98
	Irregularization	0.039	0.02
	NP Errors	0.006	0
	MTA Errors	0.033**	0
	Other Errors	0.022*	0

Table 2. Behavioral results.

and their abstract grammatical features. In the same way, overregularization errors are predicted by this mechanism due to the application by proce-

³ RAE. 2012. Real Academia Española: Banco de datos (CREA). Corpus de Referencia del Español Actual. <http://www.rae.es>.

dural memory of a regular rule to produce an irregular form when this form is not found in the declarative memory.

2.4 Computational Cognitive Modeling

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

Each individual computational cognitive model is obtained from a dual-mechanism cognitive architecture for the acquisition of verbal morphology in highly inflected languages like Spanish along children’s development. A more detailed description of this architecture can be found in (Oliva et al., 2010). We describe below the instantiation of this architecture to fit adults’ features and behavior in the verb inflection task:

- **Mechanisms:** The architecture is based on two general strategies: memory retrieval and analogy. Using these two initial mechanisms, the architecture is able to use the regular rules and the irregular exceptions just using the examples from the input vocabulary.
- **Parameters:** The mechanisms of the architecture 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 (RT-retrieval threshold, ANS-noise introduced into the memory retrieval process, BLL-forgetting factor, A_0 -initial activation); procedural memory parameters that control the learning and execution of rules (α) and the noise in the process of selecting a rule to execute (EGS); and grammatical processing parameters that control how the architecture deals with the different grammatical features (γ_m , controls the noise introduced into the perception of morphological features, C-PM, NP-PM

and MTA-PM, which control the sensitivity of the model to each grammatical feature as conjugation, number-person and mood-time-aspect, respectively) when retrieving a verb form from memory.

- **Representation:** The architecture 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 in the declarative memory.
- **Input vocabulary:** The architecture uses the same 20 regular verbs and 20 irregular verbs in present and past tense, retrieved from the Reference Corpus of Current Spanish (RAE, 2012) and engaged in the target task.

The procedure used to make the architecture mimic participants’ behavior lies in presenting to it randomly each of the 40 verbs in infinitive form and to ask for the present tense of the first person of singular or the past tense of the third person of singular, depending on the sentence pair.

2.5 Subject modeling profile

Our proposal is to obtain for each participant the set of parameter values of the computational cognitive architecture that best fit the behavior of that participant.

Type	Attribute	Range
Declarative Memory	RT	$-0.02 \pm (5*0.62)$
	ANS	$0.43 \pm (5*0.34)$
	BLL	$0.40 \pm (5*0.31)$
	A_0	$-0.02 \pm (5*0.62)$
Procedural Memory	α	$0.20 \pm (5*0.03)$
	EGS	$0.13 \pm (5*0.46)$
Grammatical Processing	γ_m	0.1 ± 0.5
	Conj-PM	-2.8 ± 5
	NP-PM	-3.6 ± 5
	MTA-PM	-3.0 ± 5

Table 3. Attributes and their range of values in the search space.

Procedure: This stage of the methodology requires the use of an optimization algorithm for obtaining the architecture’s parameter values that adjust to the user’s behavior. We used an evolutionary strategy (Beyer and Schwefel, 2002), where the genotype consists of the 9 parameters of the cognitive architecture mentioned above. To constrain the search space to psychologically plausible values we used the database proposed by (Wong et al., 2010) shown in Table 3.

Subset	Type	Attribute	Index
Behavioral data	Present Regular	% Correct-PresReg	1
		% Irregul-PresReg	2
		% NP-PresReg	3
		% MTA-PresReg	4
		% Other-PresReg	5
	Present Irregular	% Correct-PresReg	6
		% Irregul-PresReg	7
		% NP-PresReg	8
		% MTA-PresReg	9
		% Other-PresReg	10
	Past Regular	% Correct-PresReg	11
		% Irregul-PresReg	12
		% NP-PresReg	13
		% MTA-PresReg	14
		% Other-PresReg	15
	Past Irregular	% Correct-PresReg	16
		% Irregul-PresReg	17
		% NP-PresReg	18
		% MTA-PresReg	19
		% Other-PresReg	20
Cognitive data	Declarative Memory	RT	21
		ANS	22
		BLL	23
		A ₀	24
	Procedural Memory	α	25
		EGS	26
	Grammatical Processing	γ_m	27
		Conj-PM	28
		NP-PM	29
		MTA-PM	30

Table 4. Attributes used by machine learning methods.

In order to model individuals with impairment, the range allowed for each of the parameters is de-

finied as the average value \pm five standard deviations (Thomas et al., 2003). Since dementia is an impairment happening in adulthood, when most verbs have been yet acquired, verbs in declarative memory have associated a default activation value equal to the forgetting factor (RT). The fitness function used was the minimum mean square error between the participant’s error rate vector and the model’s error rate vector and the operators were Gaussian mutation, an intermediate crossover operator and 1:5 ratio for the parent population and the offspring sizes.

Results: The behavioral profile of every participant at inflecting verb forms was modeled by the architecture. The parameter values for each participant’s model were computed as the average value for 10 runs of the evolutionary strategy, with a stop criterion of 200 generations. The global correlation between the participants’ and models’ error vectors was of 0.92, showing a very high fitting degree. The values of these personalized cognitive model data could aid to determine the status of specific cognitive structures and processes. The efficiency of the modeling process is not taken account since time is not an important constraint in this application.

2.6 Application of machine learning techniques

The final stage of the methodology has a two-fold goal: a) applying different machine learning techniques to both the behavioral and cognitive model data and analyzing their respective informative and discriminant power, and b) comparing both kind of data and the combination of them in the diagnosis process. Variables used by machine learning techniques are shown in Table 4.

Variable weighting: Cognitive model data provided further information than behavioral data for discriminating between pAD and control participants. First, variables of both behavioral profile and cognitive model sources were ordered by five attribute weighting methods, given by RapidMiner (Mierswa et al, 2006), which weight variables according to different criteria. Table 5 presents the ranking, computed by each method (Information Gain (I.G), Correlation (C.), Chi-square (Chi-sq.), Rule weighting (R-W), SVM weighting (SVM-W)), and the average ranking for every variable. From this, we also calculated the average ranking

for each information source and the global average ranking, seeking for statistical differences between sources.

Figure 1 shows these average rankings with their standard deviations. In this figure, the variables related to cognitive model data have been indexed from 1 to 10 referring indexes from 20 to 30 in Table 4.

Index	I.G.	C.	Chi ²	R-W	SVM-W	Avg.
1	11	12	13	14	16	13.2
2	27	26	30	25	28	27.2
3	28	25	26	30	26	27.0
4	26	20	25	24	25	24.0
5	16	19	20	19	17	18.2
6	10	13	15	12	14	12.8
7	2	3	9	5	7	5.2
8	29	27	28	26	29	27.8
9	7	2	4	6	8	5.4
10	21	28	21	29	23	24.4
11	17	10	8	7	4	9.2
12	30	29	27	28	30	28.8
13	25	24	29	27	27	26.4
14	22	14	17	12	12	15.4
15	23	30	18	21	21	22.0
16	9	4	3	8	9	6.6
17	12	15	10	13	13	12.6
18	24	23	19	23	22	22.2
19	1	5	2	2	11	4.2
20	18	16	14	22	15	17.0
21	4	9	1	1	2	3.4
22	5	6	11	4	3	5.8
23	8	17	17	15	20	15.4
24	14	8	7	11	6	9.2
25	19	18	23	20	24	20.8
26	13	11	14	10	10	11.6
27	3	1	6	3	1	2.8
28	15	22	16	16	18	17.4
29	20	21	22	21	19	20.6
30	6	7	5	9	5	6.4

Table 5. Attributes sorted by 5 different attributes weighting methods and average rank (Avg.). The Index field refers to attributes' index in Table 4.

Behavioral data show that the most relevant variables are mood, tense and aspect substitutions both in present and past tense forms of irregular verbs, overregularization in present tense and the percentage of correct past tense forms of irregular verbs. The group of behavioral data achieves an average ranking significantly lower ($p < 0.05$) than cognitive model data using a two-tailed t-test.

As can be seen in Figure 1, among the group of cognitive model data, the four variables with the

lowest ranks present an average ranking of 4.6 that stand out on the six remaining variables, which have an average ranking of 15.83.

Two of these four variables are related to the declarative memory (RT and ANS, with indexes 1 and 2 in abscises of Fig. 1, respectively) and the other two to the grammatical processing (γ_m and MTA-PM, with indexes 7 and 10 in abscises of Fig. 1, respectively). These results indicate that the major differences between pAD and controls rely on internal structures and mechanisms involving declarative memory affecting the retrieval of irregular forms and of their grammatical features as predicted in (Ullman, 2001).

Predictive power: The full set of combined data had better performance metrics than individual data sets to correctly classify pAD. We evaluated the predictive power of data by four machine learning algorithms.

The algorithms are applied on the behavioral data, cognitive model data and the combined set of behavioral and cognitive model data to assess the informative and discriminant role of every information source in the classification performance. The cognitive model feature set is made only by the internal variables of the model (9 parameters). The behavioral feature set consists of the variables collected from participants (20 parameters corresponding to six error categories for four combinations tense-form). The third feature set is a combination of the two previous sets.

Subset	Metric	SVM	NB	DT	NN
Behavioral data	Sensitivity	0.61	0.65	0.50	0.54
	Specificity	0.64	0.73	0.54	0.63
	PR+	1.69	2.41	1.09	1.46
	PR-	0.61	0.48	0.93	0.73
	AUC	0.62	0.68	0.52	0.60
Cognitive data	Sensitivity	0.71	0.68	0.62	0.61
	Specificity	0.77	0.77	0.63	0.74
	PR+	3.09	2.96	1.68	2.35
	PR-	0.38	0.42	0.60	0.53
	AUC	0.73	0.72	0.62	0.68
Full set	Sensitivity	0.86	0.75	0.71	0.85
	Specificity	0.81	0.79	0.79	0.81
	PR+	4.53	3.57	3.38	4.47
	PR-	0.17	0.32	0.37	0.19
	AUC	0.58	0.76	0.76	0.82

Table 6. Sensitivity, Specificity, Positive Probability Rate (PR+), Negative Probability Rate (PR-) and AUC results obtained by the four classification algorithms and the three feature sets.

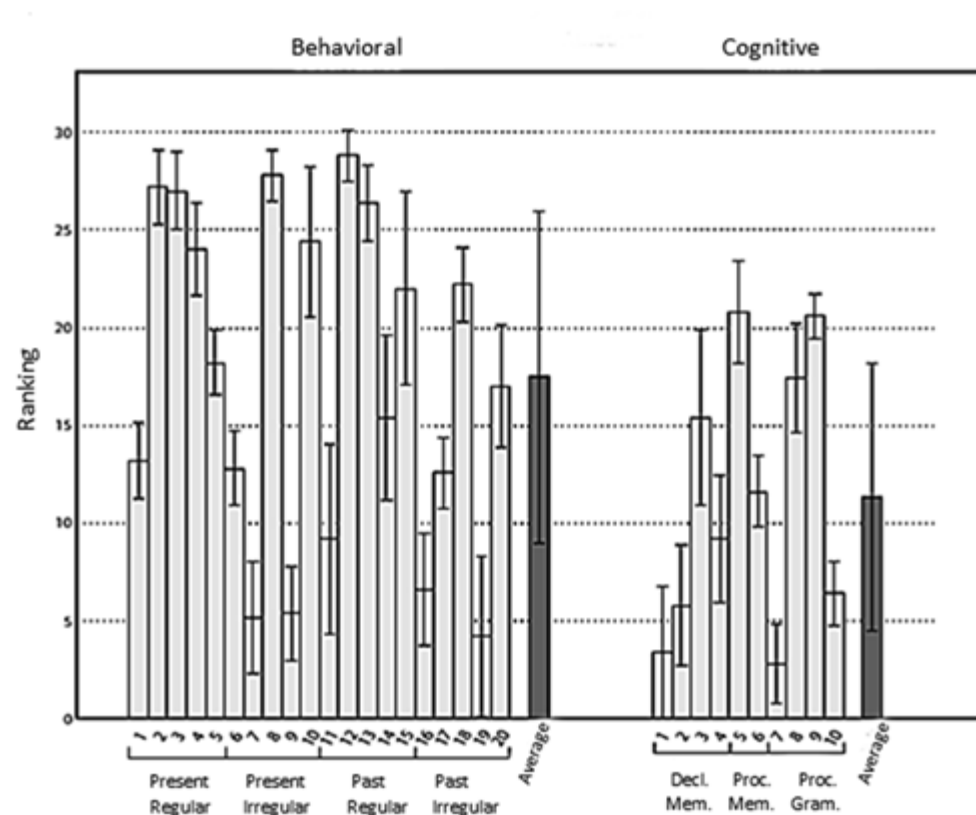


Figure 1. Average ranking and standard deviation for each attribute of the two attribute sets.

The classifiers used are a Support Vector Machine (SVM), a Naïve Bayes classifier (NB), a Neural Network (NN) and a Decision Tree (DT) (Mitchell, 1997). All the experiments were run under RapidMiner with its default parameter configuration (Mierswa et al, 2006). To evaluate each algorithm's performance, a leave-one-subject-out cross validation (LOOCV) was carried out and the sensitivity, specificity, positive and negative probability rates, and the Area Under Curve (AUC) metrics were computed.

Table 6 shows the results obtained for each one of the four classifiers and each feature set. A detailed analysis of all metrics confirms the importance of cognitive model data either alone or combined with behavioral features.

A one-way ANOVA test was carried out to check the differences among the performance of every classifier applied on each one of the three features set. Note that, given the preliminary nature of this study, the statistical power of them could be low. The SVM and DT classifiers improved statistically their sensitivity results ($p < 0.05$) with the use of cognitive model variables regarding behav-

ioral variables. Besides, DT and NN improved statistically their specificity results ($p < 0.05$) with this feature set. The results are also better in sensitivity, specificity and AUC metrics for all classifiers with the use of complete feature set as compared to only behavioral feature set ($p < 0.05$). The SVM and NN classifiers achieve sensitivity and specificity values higher than 80%, exceeding the threshold whereby a classification method can be considered a diagnosis support method (Plante and Vance, 1994). All these results confirm the relevant role of cognitive model variables supporting the diagnosis of pAD.

3 Discussion

In this paper we present a general methodology for the diagnosis of cognitive impairments when an inflectional verb task is carried out and we apply it to the particular case of pAD. The performed study corroborates the underlying hypothesis that computational cognitive modeling of a subject performing that inflection task provides a more characteristic and discriminant information than

only behavioral information extracted from neuropsychological tests. In spite of the low number of patients and types of verbs used, the results obtained in this preliminary study allow to identify significant differences useful for analyzing the relation between pAD and the verb morphology in Spanish. Beside, computational cognitive modeling could be a useful tool to have some kind of access to the processes that underlie normal and impaired behavior and this information could support the diagnosis process.

The average results of the five attribute weighting techniques rank informative ability of cognitive modeling variables above behavioral variables for discriminating pAD from control subjects when all of them perform an inflectional verb task. Besides, the full set of both cognitive modeling and behavioral variables lead to classifiers that improve sensitivity, specificity and AUC in comparison to only behavioral variables. All the results confirm the cross-linguistic generality of the pattern found in English and Italian: pAD patients are spared at processing regular inflected forms but impaired at irregular forms.

The methodology allows an individualized cognitive modeling for each subject and the parameter values obtained from the model can provide some clues about the underlying areas or mechanisms affected by the disease and their level of effects. The methodology has shown its successful application to cognitive impairments directly related to language like SLI (Oliva et al., 2013) as well as non-specific language impairment like pAD.

We conclude 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 pAD. Finally, it is important to note that this methodology is easily extensible to other languages, based on the language-independent nature of the mechanisms, parameters, representation and input vocabulary of the computational cognitive architecture used.

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