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A regression tree of the aptitudes, personality, and academic performance relationship

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ABSTRACT

This study suggests regression trees as a complementary tool to regression and SEM to respond to questions related with the influence of intelligence, personality, and their interplay on academic performance. Data from 818 secondary education students (402 girls and 416 boys) in aptitudes, personality, and academic performance in four learning areas: language (Catalan and Spanish) and science (Natural and Mathematics) were modelled with this technique. Two hypotheses articulated the presentation of this methodology. Aptitudes were much more relevant than personality to explain variance in academic performance. Verbal aptitude was particularly more relevant for girls than for boys.

1. Introduction

The motivation of scholars to investigate individual differences related with academic performance (AP) in diverse learning levels and domains has increased outstandingly. Personality, intelligence and vocational interests have been put forward as key determinants of intellectual human development, with meta-analytic results indicating considerable common variance between them (Ackerman, 1996; Ackerman & Heggestad, 1997). From this standpoint, personality and intelligence would be likely to determine the probability of success in a given task, whereas vocational interests would determine the motivation to attempt a given task. Therefore, the interest in the past few years has shifted towards the combination of intelligence and personality to predict AP. Several works have suggested complex associations between both constructs (Aluja & Blanch, 2004; Beaujean et al., 2011; Beier, Campbell, & Crook, 2010; Chamorro-Premuzic & Arteche, 2008; Chamorro-Premuzic & Furnham, 2004; Farsides & Woodfield, 2003; Heaven & Ciarrochi, 2012; Laidra, Pullmann, & Allik, 2007; Noftle & Robins, 2007; O'Connor and Paunonen, 2007; Poropat, 2009). Some conclusions derived from this body of research suggested that a better knowledge of the factors influencing AP would aid to predict the performance of individuals in academic programs, to provide more guidance, and to design academic curricula tailored to specific learning needs (O'Connor and Paunonen, 2007).

Most of these research works have based their implications in data derived from regression analyses and structural equation modelling (SEM). However, given the significance and multidimensionality of this problem, the prediction of AP from individual differences in intelligence and personality could also be complemented from a more diverse set of techniques such as regression trees (Breiman, Friedman, Olshen, & Stone, 1984). The regression tree (RT) is a particular case in tree-based methods with some useful peculiarities to analyze the relationship of individual differences with AP. RT is a conceptually simple non-parametric technique, thus, it does not impose normality assumptions to data. It is also a versatile technique that handles well continuous, categorical or both types of variables, and missing data. Moreover, although it performs satisfactorily with several variables it includes only the predictive variables in an eventual final model. However, some drawbacks of RT imply the need for large sample sizes and its instability when small changes in the data result in high levels of variability (Hastie, Tibshirani, & Friedman, 2008). RTs might be superior to regression and by extension perhaps to SEM, in exploratory research. In addition, RTs could be better suited to study interactions or non-linear relations among variables when large sample sizes are available (Armstrong & Andress, 1970; Lemon, Roy, Clark, Friedmann, & Rakowski, 2003).

The focus of this work was to describe the general use of RTs to address questions of relevance within AP research. Past research has used RTs to assess the relationship of personality and intelligence with outcomes such as suicidal ideation and justice contacts,

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respectively (Kerby, 2003; Levine, 2008). First, we summarize the primary architecture and use of RTs. Secondly, we assessed two hypotheses to provide an example of the contribution of RTs to elucidate the relationships between aptitudes, personality and AP. Aptitudes are the skills or potential that a person can materialize or not in a variety of fields, and that may be advantageous to succeed in learning situations (Juan-Espinosa, 1997; Snow & Lohman, 1984).

1.1. Regression trees (RTs)

The main objective of an RT is to model a response variable (AP) from a number of explanatory variables (aptitudes and personality). This can be represented as a binary tree, a hierarchical structure formed by nodes and edges, the latter representing some sort of information flow between adjacent nodes (see Fig. 1). An edge from nodes A to B, means that A is the predecessor of B, and B is the descendant of A. The root of the tree has no predecessors (node A). The leaves of the tree have no descendants (nodes D, E, F and G). Brother nodes have the same predecessor (nodes B and C, or nodes F and G). The level or depth of a node is the length in edges from the root. The height of a tree (h) is its amount of levels. Similar binary trees have the same shape. Equivalent trees are similar and their nodes contain the same information. All the nodes in a complete binary tree but their leaves have two descendants. The number of nodes in a complete binary tree is $2^h - 1$.

The algorithm to build an RT considers recursive partitions of the data space, by dividing successively each part into smaller data portions. Explanatory variables determine these partitions by yielding the best separation of the data at each stage with observed cut-off scores within each explanatory variable (c_n)

$$Y = \sum_{n=1}^{n} c_n(X_1, X_2 \in R_n) \tag{1}$$

where Y is the response variable, X_1 and X_2 are two explanatory variables, and R_n is the full data space with n partitions (Hastie et al., 2008). For each partition with observation i, the mean response variable and the residual sum of squares (RSSs) are calculated to determine the optimal chosen partition at each step, which is the one that minimizes RSS. For a given RT with $|T|$ leaves, its RSS is the expression in (2), whereas a coefficient of determination for RT is shown in (3).

$$\mathrm{RSS}(T) = \sum_{n=1}^{|T|} \sum_{x_i \in R_n} (y_i - \hat{y}_n)^2 \tag{2}$$

$$R^2(T) = \frac{\mathrm{TSS} - \mathrm{RSS}(T)}{\mathrm{TSS}} \qquad \mathrm{TSS} = \sum_{i=1}^{n} (y_i - \bar{y})^2 \tag{3}$$

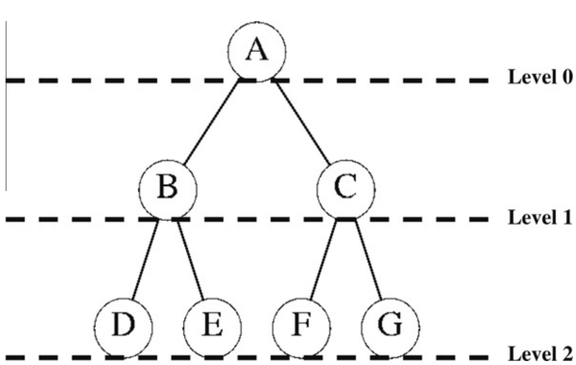

Fig. 1. A complete binary tree with four leaves (D, E, F, and G) and height (h) = 3.

Model specification proceeds in two stages: growing and pruning. First, an RT is grown with an estimated complexity parameter (cp) for each node. The cp is indicative of the most adequate balance between tree size and predictive accuracy. Simpler trees with a lower number of nodes have higher cp's. Second, the tree is pruned by estimating the tree again with the cp set at the value matching the lower relative error found at the growing stage. This procedure aims to obtain an optimal number of tree levels, to avoid drawing spurious relationships that might impair the use of the prediction tree for new data sets (overfitting), and to guarantee a fair predictive power (Torgo, 2003). The regression tree selects the more relevant variables and is read from the root on. The left branch of each node contains the values below the explanatory variable cut-off score, and the right branch contains the values above the explanatory variable cut-off score. The recursive splits proceed through the left branches when the cut-off or stated condition is true. The leaves of the tree contain its predictions, showing the average value of the response variable and the sample size at each prediction.

1.2. Specific hypotheses

Evidence regarding the interaction of intelligence and personality to predict AP is mixed and inconclusive. Some research works have indicated complex associations between both domains in predicting AP (Ackerman & Heggestad, 1997; Beaujean et al., 2011; Chamorro-Premuzic & Arteche, 2008; Farsides & Woodfield, 2003; Heaven & Ciarrochi, 2012). However, intelligence has also been suggested as the strongest predictor of AP independently of personality (Laidra et al., 2007), even though personality traits mainly involved with Conscientiousness could also explain variance in AP above intelligence (O'Connor and Paunonen, 2007). It has been suggested though that personality and AP correlations might be attenuated at younger ages because of the interaction of age and academic level, lower construct validity of personality measures for children, or the increasing importance of grading practices at higher academic levels (Poropat, 2009). Therefore, the first hypothesis in the present research is that aptitudes will be the most influential predictors of AP over and above personality across different learning areas.

Sex differences are likely to arise frequently among intelligence and personality, they might appear early and be stable across age groups, and also extensible to other cultures and countries (Ackerman & Heggestad, 1997; Halpern, 1997). Average scores in cognitive abilities for females might be higher in phonological and semantic information processing, elaboration of prose, fine psychomotor skills, and perceptual speed, while average scores for males might be higher in visual-spatial abilities and fluid reasoning in mathematical and science areas (Halpern, 1997; Steinmayr, Beauducel, & Spinath, 2010). The verbal advantage of girls over boys could also be due to their calmer behavior, higher memorizing abilities for verbally presented information, or better writing skills (Aluja, Ballesté, & Torrubia, 1999; Deary, Strand, Smith, & Fernandes, 2007). Thus, the second hypothesis in this study is that verbal aptitudes will be of greater importance in the prediction of AP across different learning areas for girls than for boys.

2. Method

2.1. Participants and procedure

There were 402 girls (M = 13.44, SD = .63) and 416 boys (M = 13.50, SD = .61) enrolled at 29 secondary education public schools in Catalonia (Spain). Mean age of all participants was 13.47 years (SD = .62) and were of Caucasian ethnicity. After a formal written consent from parents and school authorities, volunteer participants fulfilled the assessment questionnaire in 2 h sessions. There were no expected differences with non-volunteering participants. A group of trained undergraduate educational psychology students collected the data in classrooms during school-time. Participants were not paid but a brief report summarizing individual outcomes was provided to those students who requested it.

2.2. Measures

2.2.1. Personality measures

Personality was assessed with the High School Personality Questionnaire (Cattell & Cattell, 1988), a 142 multiple-choice items self-report instrument for children and adolescents tapping 14 personality characteristics: Warmth, Intelligence, Emotional Stability, Excitability, Dominance, Cheerfulness, Conformity, Boldness, Sensitivity, Withdrawal, Apprehension, Self-Sufficiency, Self-Discipline, and Tension. There were three response options (a–c) scored with either 1 or 2 points, but for the Intelligence dimension which was scored with only one point. Short-term test–retest reliability of the instrument lies within .70–.80 (Cattell & Cattell, 1988).

2.2.2. Aptitudes

Aptitudes were evaluated with the level 2 Test of Educational Ability TEA-2 (Seisdedos, De la Cruz, Cordero, & González, 1994; Thurstone & Thurstone, 1954). The instrument includes three subscales: verbal reasoning, abstract reasoning, and calculation. The authors of the Spanish adaptation reported Pearson correlation coefficients for global criterion validity ranging from .54 (12-year-olds) to .36 (14-year-olds). This instrument has a .93 Spearman–Brown reliability coefficient (Seisdedos et al., 1994).

2.2.3. Academic performance

There were four achievement measures collected from school records for the two last years within the language (Spanish and Catalan) and science (Natural and Mathematics) areas of typical school learning curricula. These measures ranged from two to six, with lower scores indicating a poorer performance in each learning area.

2.3. Data analyses

All data analyses were done with R software (R Development Core Team, 2011). There were mean comparisons in the study variables between boys and girls, correlations of personality and aptitudes with achievement, and d effect sizes computation (Cohen, 1988). RTs implemented with the `rpart` library allowed the modelling of the four response variables, AP in language (Catalan and Spanish) and science areas (Natural and Mathematics), from the aptitudes and personality variables more strongly related with each AP variable (Breiman et al., 1984; Kerby, 2003). All variables were standardized ($M = 0$, SD = 1). First, a large tree was

Table 1
Personality and aptitudes.

Variable	Girls	Boys	*d* Effect size (95% CI)	Correlation coefficients							
				Girls (*N* = 402)				Boys (*N* = 416)			
	Mean (*Sd*)	Mean (*Sd*)		Cat	Sp	Na	Ma	Cat	Sp	Na	Ma
Warmth (A)	12.53	10.16	.75	.13	.16	.14	.11	.08	.14	.11	.12
	(3.32)	(3.00)	(.61, .89)	.09	.07	.07	.08	.08	.09	.11	.11
Intelligence (B)	6.39	6.04	.23	**.33**	**.32**	**.31**	**.31**	**.38**	**.40**	**.38**	**.37**
	(1.48)	(1.53)	(.09, .37)	**.32**	**.32**	**.32**	**.31**	**.39**	**.40**	**.42**	**.43**
Emotional stability (C)	10.62	11.72	−.36	.15	.14	.11	.12	.10	.13	.13	.16
	(3.10)	(2.94)	(−.50, −.23)	.18	.10	.11	.09	.12	.09	.14	.15
Excitability (D)	9.73	9.63	.03	−.10	−.07	−.04	−.09	−.09	−.07	−.13	−.13
	(3.19)	(3.11)	(−.11, .17)	−.04	−.01	−.10	−.07	−.08	−.07	−.11	−.10
Dominance (E)	6.77	10.14	−1.18	−.07	−.07	−.01	−.04	−.07	−.06	−.01	−.01
	(2.77)	(2.94)	(−1.33, −1.03)	−.07	−.09	−.05	−.05	−.06	−.07	.01	−.05
Cheerfulness (F)	9.90	10.92	−.33	−.18	−.15	−.12	−.14	−.12	−.08	−.07	−.09
	(3.23)	(2.90)	(−.47, −.19)	−.20	−.19	−.17	−.17	−.17	−.17	−.09	−.12
Conformity (G)	12.09	11.19	.31	**.21**	**.16**	**.17**	**.18**	**.22**	**.17**	**.19**	**.14**
	(2.87)	(2.89)	(.17, .45)	**.19**	**.22**	**.17**	**.18**	**.22**	**.22**	**.21**	**.20**
Boldness (H)	9.63	10.63	−.27	.02	.04	.05	.03	.11	.14	.17	.18
	(3.73)	(3.65)	(−.41, −.13)	−.04	−.04	−.02	−.05	.11	.13	.18	.14
Sensitivity (I)	12.64	7.03	1.65	.13	.11	.10	.09	−.03	−.01	−.07	−.10
	(3.37)	(3.45)	(1.48, 1.80)	.14	.19	.13	.13	.00	.00	−.06	−.07
Withdrawal (J)	8.39	9.06	−.23	−.01	.02	.00	−.01	−.08	−.06	−.06	−.05
	(2.89)	(2.89)	(−.37, −.09)	.01	.00	.02	.02	−.05	−.05	−.06	−.08
Apprehension (O)	9.63	9.24	.12	−.04	−.05	−.10	−.09	−.14	−.14	−.14	−.16
	(3.24)	(3.19)	(−.02, .26)	−.07	−.01	−.06	−.04	−.15	−.10	−.14	−.12
Self-sufficiency (Q2)	7.53	9.00	−.49	−.04	−.06	−.04	−.04	−.04	−.02	−.04	−.04
	(3.05)	(2.98)	(−.63, −.35)	.02	.03	.03	.03	.01	.01	−.02	.00
Self-discipline (Q3)	10.53	9.75	.27	**.18**	**.17**	**.16**	**.17**	**.16**	**.19**	**.20**	**.18**
	(2.91)	(2.93)	(.13, .40)	**.17**	**.16**	**.16**	**.15**	**.20**	**.17**	**.16**	**.16**
Tension (Q4)	10.91	9.77	.35	−.06	−.10	−.09	−.10	−.07	−.08	−.10	−.12
	(3.38)	(3.18)	(.21, .49)	−.04	−.04	−.05	−.03	−.07	−.05	−.11	−.06
Verbal	9.47	9.45	.01	.47	.46	.46	.42	.34	.37	.32	.31
	(2.85)	(2.95)	(−.13, .14)	.39	.39	.46	.43	.35	.36	.39	.36
Abstract reasoning	14.98	14.67	.07	.40	.40	.40	.40	.42	.40	.40	.43
	(4.20)	(4.48)	(−.07, .21)	.37	.33	.39	.39	.45	.42	.42	.46
Calculation	16.11	17.57	−.25	.37	.39	.40	.41	.41	.42	.44	.41
	(5.67)	(6.11)	(−.38, −.11)	.39	.34	.42	.45	.45	.45	.45	.45

Note: Correlations ⩾±.10 are significant at the $p < 0.05$ level; Correlations ⩾±.14 are significant at the $p < 0.01$ level; Correlations ⩾±.17 are significant at the $p < 0.001$ level. Top and bottom lines for correlation coefficients correspond to the first and second assessed academic years, respectively. Cat = Catalan Language; Sp = Spanish language; Na = Natural science; Ma = Mathematics.

Table 2
Achievement measures.

Measure	Girls M (*Sd*)	Boys M (*Sd*)	*t*	*d* Effect size (95% CI)
Catalan 1	4.25 (1.14)	3.80 (1.17)	5.57***	.39 (.25, .53)
Spanish 1	4.20 (1.22)	3.76 (1.19)	5.22***	.36 (.23, .50)
Natural science 1	4.12 (1.24)	3.89 (1.24)	2.62**	.19 (.05, .32)
Mathematics 1	4.03 (1.24)	3.78 (1.22)	2.91**	.20 (.07, .34)
Catalan 2	4.19 (1.16)	3.62 (1.20)	6.90***	.48 (.34, .62)
Spanish 2	4.13 (1.23)	3.57 (1.22)	6.54***	.46 (.32, .60)
Natural science 2	4.04 (1.27)	3.74 (1.26)	3.91***	.24 (.10, .37)
Mathematics 2	3.90 (1.29)	3.57 (1.27)	3.69***	.26 (.12, .40)

** $p < 0.01$.
*** $p < 0.001$.

grown, and their predictive performance was estimated in terms of its complexity parameter (cp = 0.01). Second, the same tree was run again by fixing cp to the lower relative error found at the first stage. Coefficients of determination were determined by applying expressions (2) and (3) to each final RT.

3. Results

Table 1 shows means, standard deviations, effect sizes, and the correlation coefficients of personality and aptitude measures with the four achievement measures for boys and girls at the first (top line) and second (bottom line) assessed academic years. The strongest correlations of personality variables with AP are in boldface ($p < .01$ significance level). Table 2 shows that girls scored higher than boys did in the four achievement measures for the two assessment years, with *d* effect sizes ranging from .19 at the first year in natural science, to .48 at the second year in Catalan language. Girls outperformed boys in languages, with smaller differences in natural sciences and mathematics.

RTs were estimated for boys and girls with AP in language and science areas as the response variables, and the strongest correlates with AP as explanatory variables (personality: G and Q3; aptitudes: verbal, abstract reasoning, and calculation). This strategy can be helpful to build simpler tree models with only a few explanatory variables in relation to the number of available observations. The personality variable labelled as intelligence (b) was excluded because of its redundancy with aptitudes. Figs. 2 and 3 show the final tree-plots for girls and boys. The top four plots in each figure show the results for the language area, whereas the bottom four plots in each figure show the results for the science area. Complexity parameters (*cp*) in tree pruning and coefficients of determination are at the bottom of each plot. The root nodes in all trees were aptitudes, indicating that they were the most important variables in predicting achievement in all academic areas.

Verbal aptitude was the most important to predict AP for girls in the language area (Catalan and Spanish) at the first year, although it was calculation at the second year. Conformity (G) appeared only in the second measurement year of both, Catalan and Spanish languages, at the lowest level of the tree hierarchy. Calculation aptitude was the most important predictor for girls in the science area (Natural and Mathematics), although verbal aptitude was the root node in first year Natural science, and it appeared also at the very immediate level from the initial calculation split in the rest AP areas. No personality variables intervened in the prediction of AP in the science area. The two trees for Natural were similar, whereas the two trees for Mathematics were nearly equivalent. Coefficients of determination explained a fair amount of AP variance due to the explanatory variables included in each tree (.23–.33).

Reasoning and calculation were the most important predictors of AP for boys in the language area in Catalan and Spanish, respectively. Besides, conformity (G) was also present in all trees' right branch for the four language AP areas, indicating a more prominent influence than for girls. The Catalan 1 tree was the deepest one with $h = 5$. Calculation aptitude was the most important in predicting AP in the science areas for boys, but for the abstract reasoning aptitude at Mathematics 2. Conformity (G) also influenced all science AP areas, appearing at the second level of the trees' right branches for Natural 1 and at the third level for the rest AP's. Trees

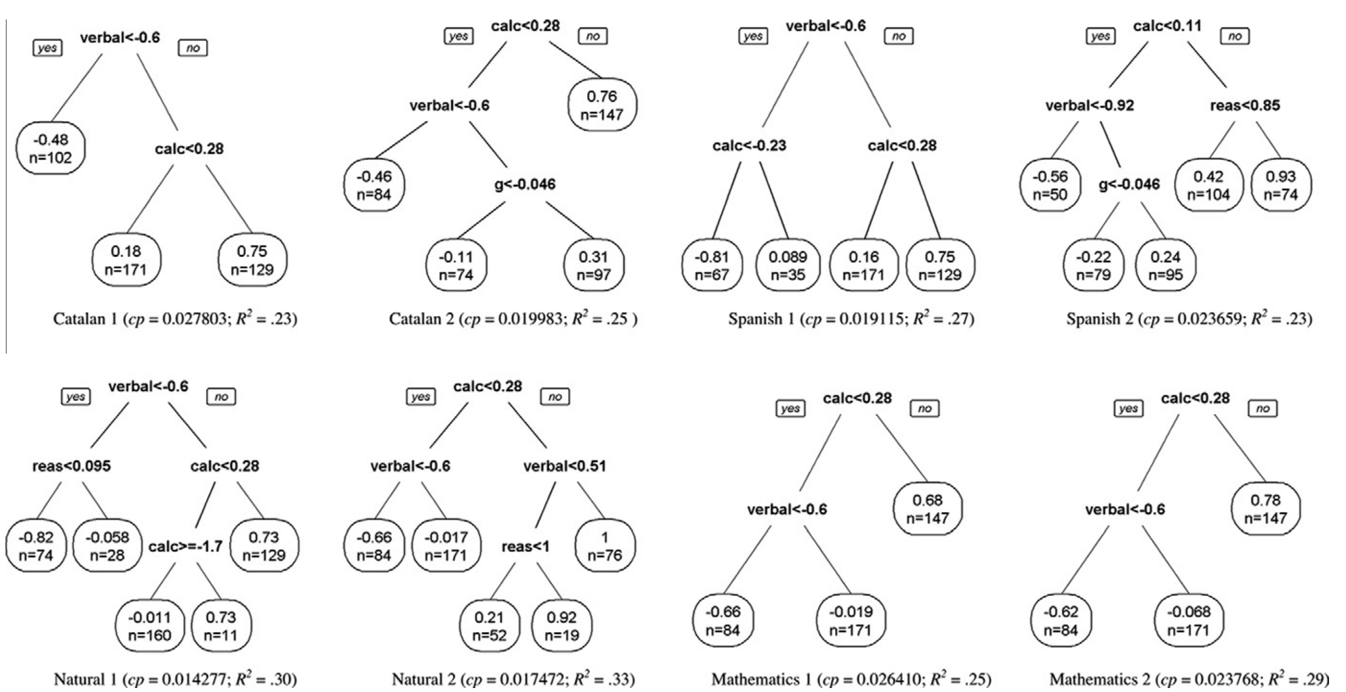

Fig. 2. Tree-plots for girls ($N = 402$; calc: calculation; reas: reasoning; g: conformity). Move to the left branch when the stated condition is true.

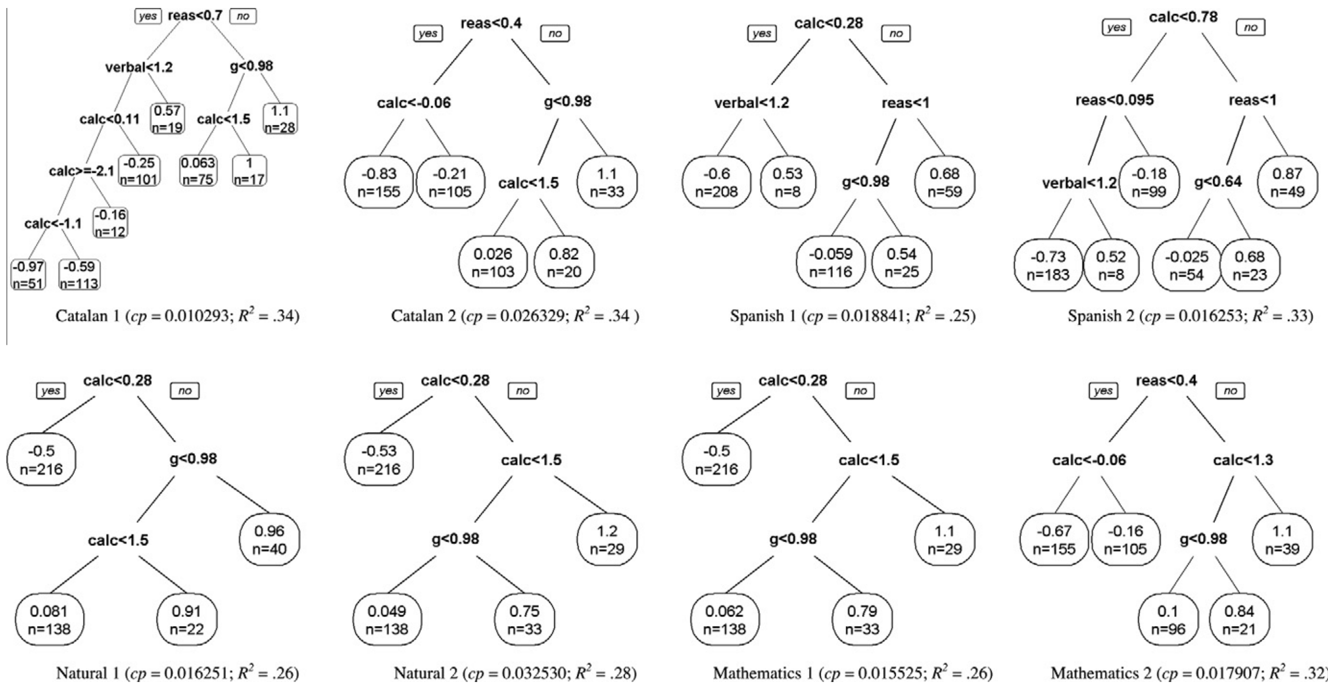

Fig. 3. Tree-plots for boys ($N = 416$; calc: calculation; reas: reasoning; g: conformity). Move to the left branch when the stated condition is true.

for Catalan 2 and Spanish 1, and Natural 1, 2, and Mathematics 1 were similar. In addition, trees for Natural 2 and Mathematics 1 were nearly equivalent. Coefficients of determination to explain AP variance lay within .25 and .34.

4. Discussion

The current study sought to expose the capabilities of RTs to analyze a timely issue such as the individual differences determinants of AP. The use of this application was guided by the formulation of two hypotheses. The outcomes derived from the RT technique provided partial support for the hypothesized relationships.

Aptitudes were more determinant predictors of AP than personality for girls (verbal and calculation), and for boys (abstract reasoning and calculation). These aptitudes were located at the root nodes and upper level nodes of each RT for the eight learning areas, indicating their greater predictive power concerning each response variable (AP). However, personality was also particularly influential in boys' performance in all learning areas, but only Catalan 2 and Spanish 2 in the case of girls. In addition, this variable was topologically located under the root left branch for girls, but under the root right branch for boys, suggesting that low scores in Conformity (G) might impair specific AP in Catalan 2 and Spanish 2 for girls, while high scores in Conformity (G) enhanced AP for boys in every studied learning area. This outcome is in accordance with the reported stronger predictive power of AP concerning the broad big five Conscientiousness factor, as the narrower Conformity (G) variable would fall within that broad domain (O'Connor and Paunonen, 2007; Poropat, 2009).

Verbal aptitude was clearly more relevant for girls than for boys. While verbal aptitude appeared in all trees for girls at their first (Catalan 1, Spanish 1, Natural 1) or second levels (Catalan 2, Spanish 2, Natural 2, Mathematics 1 and 2), it was nearly missing in the trees for boys (only in Catalan 1 and Spanish 1). This fact could support somehow the reported larger representation in the right tail of the distribution, for girls in verbal abilities and for boys in mathematical and science reasoning (Wai, Cacchio, Putallaz, & Makel, 2010). These outcomes support the notion of sex differences in cognitive abilities at early ages, which was clearly apparent from the obtained RTs in different curricular learning areas (Halpern, 1997). It is remarkable that verbal aptitude was fully absent from trees in the science area for boys, whereas it appeared within all trees in the science area for girls. Thus, girls and boys might perform equally well in the same knowledge domain, although applying a very different set of cognitive abilities. In fact, girls outperformed boys in all learning areas in the present research. The topological similitude and partial equivalence of the studied RTs when predicting the performance in different learning areas reinforced somehow the schema of different cognitive abilities for girls and boys.

A shortcoming in the present study is that the cross-validation of these outcomes was not performed because of space limitations. The results from RTs should be cross-validated with a secondary sample or within the same data set by dividing it into a training and a test sample. There are two main approaches. The initial tree building begins with the training sample (75% of participants), whereas the test sample (25% of participants) re-evaluates its shape, conveyed information, and global predictive value. Alternatively, in a k-fold cross-validation the data set is analyzed in k subsets, the tree is estimated for all data except for one k' subset, and subsequently applied to k'. This process can be repeated by alternating the k' group, which allows one to select the tree with the lowest misclassification rate (Efron & Tibshirani, 1991; Lemon et al., 2003). Large sample sizes can contribute positively to cross-validation and important parameters in RTs. For instance, lower predictive deviances were found for sample sizes of 2000 and 6000, but higher for sample sizes of 250 and 500 when related with tree complexity and learning rate (Elith, Leathwick, & Hastie, 2008).

In the past few years, the study of the psychological determinants of AP has become an outstanding issue for both, scholars and practitioners. Information regarding the potential influences of individual differences on AP is crucial for decision makers concerning the design and general management of educational activities. RTs possess some key features as a learning method that might be important to study the determinants of AP. These range from the natural handling of mixed data (quantitative and qualitative) and missing values, the robustness to outliers, its insensitiveness to transformations of inputs, and its ability to deal with irrelevant inputs (Hastie et al., 2008). In addition, this methodology allows one to contrast specific a priori hypotheses in basic research. This methodology can complement regression analyses and SEM, by representing the primary topology of the assessed relationships within particular circumstances. For instance, RTs may eventually be useful in practical settings such as a primary or secondary school for decision-makers in educational administration, and perhaps more illustrative about the particular configurations of predictive individual differences that determine AP for different groups (i.e., girls and boys) or in different learning areas, such as those described in this work.

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