Towards automatic essay scoring of Basque language texts from a rule-based approach based on curriculum-aware systems

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Abstract

Although the Basque Education Law mentions that students must finish secondary compulsory education at B2 Basque level and their undergraduate studies at the C1 level, there are no objective tests or tools that can discriminate between these levels. This work presents the first rule-based method to grade written Basque learner texts. We adapt the adult Basque learner curriculum based on the CEFR to create a rule-based grammar for Basque. This paper summarises the results obtained in different classification tasks by combining information formalised through CG3 and different machine learning algorithms used in text classification. Besides, we perform a manual evaluation of the grammar. Finally, we discuss the informativeness of these rules and some ways to further improve assisted text grading and combine rule-based approaches with other approaches based on readability and complexity measures.

1 Introduction

Text classification of writing and reading materials is laborious and sometimes hard to do manually. Teachers that do not have a linguistic background do not feel confident in this task, but in some languages, researchers can use automatic text classification tools to point to some objective measures (Type Token Ratio, POS-based measures...). However, this automatic task is difficult to address for low resourced-languages. The classification of essays is worthy of interest because even if Basque Education Law mentions that students must finish compulsory secondary education at the CEFR B2 level and their undergraduate studies at the C1 level, there are no objective tests or tools that can discriminate between these levels. Using deep learning-based methods could be difficult for teachers as these do not follow the language curriculum or the learning stage of the student. If automated systems could describe the curriculum or the learning stage of the student in a way that the teachers can understand or employ, this would be very useful, and teachers would have an additional source of information where they could offer more adapted materials and teaching.

This work aims to explore rule-based models to classify written learner texts. The motivation of this work is to lighten the burden on teachers in the correction task. We want to contribute to the area of tools or applications to carry out objective tests automatically to fundamentally discriminate between levels B2 and C1. In this line, previous work (Zupanc and Bosnic, 2016) emphasises the role of automatic systems to help teachers:

> Automated essay evaluation represents a practical solution to a time-consuming, labour-intensive and expensive activity of manual grading of student's essays.

Furthermore, this approach could help to define language-based classification criteria that follow HEOC, the adult Basque learner curriculum (HABE, 2015).

One of the difficulties of classifying and grading essays is represented by the perceived subjectivity of the grading process. This issue may be

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faced through the adoption of automated assessment tools for essays (Valenti et al., 2003).

There have been other studies of automatic classification for the Basque language but from different approaches (Castro-Castro et al., 2008; Zipitria et al., 2010, 2011; Azpillaga, 2022; Arrieta et al., 2023). We expand on these works and study how automatic text classifiers can benefit from Basque curricular grammar, a formalisation of the linguistic expressions described in the Basque curriculum.

Other similar works include a system for the Arabian language (Alqahtani and Alsaif, 2019) as well as feature-based machine learning approaches for Estonian (Vajjala and Loo, 2014) and monolingual, cross-lingual, and multilingual classification with three languages: German, Czech and Italian (Volodina et al., 2016). For Estonian, the best model reported by Vajjala and Loo (2014) reaches a prediction accuracy of 79%.

Regarding the automated essay-scoring task, Lim et al. (2021) conducted an automatic assessment using Automatic Essay Scoring systems. Gaillat et al. (2022), in their work, showed that early approaches were rule-based, but later systems relied on probabilistic models based on Natural Language Processing methods that exploit the corpus of learners. Their method exploits machine learning algorithms to classify learner writings with many metrics, including specifically-designed microsystem metrics. Microsystems are composed of several competing constructions (for instance the use of the article) grouped according to functional proximity. They can be defined as families of competing constructions in a unique paradigm. Results on internal data show that different microsystems help to classify essays from B1 to C2 levels (82% accuracy).

We follow a language- and curriculum-based approach: we formalise the expressions and linguistic phenomena described in the HEOC using CG3 (Bick and Didriksen, 2015), creating a level-informed grammar for Basque. The Basque CG3 Grammar contains 296 ADD rules that add language-level information. These rules are based on the linguistic indicators described for each level in the HEOC. We apply this grammar to the HABE-IXA Basque learner corpus (Arrieta et al., 2023), annotating the phenomena described by the curriculum. We use the information provided by the grammar to classify texts in binary and multi-class experiments and analyse which rules are relevant to discriminate different CEFR levels.

The paper is organised as follows: in Section 1, some background information on the Basque curriculum and text classification task is provided. Then our method to support essay classifying is described in Section 2. In this work, we evaluate and compare the results obtained using the CG3 grammar features with different algorithms. Detailed figures shall be shown in Section 3. After that, in the discussion, we propose some future lines of work, in Section 4. Finally, in Section 5 we sum up the main conclusions.

2 Method

We adapted the adult Basque learner curriculum based on the CEFR to create a rule-based grammar for Basque. First, we identified and defined phenomena and linguistic structures collected in HEOC that will be formalised for each level. The result of this task is what we call *Basque CG3 Grammar*.

The employed corpus contains essays written in official HABE (Basque Government Department for language certification) exams. It contains 480 texts (146,465 tokens) from the B1, B2, C1 and C2 CEFR levels. The corpus is balanced, it contains 120 essays of each level. These essays have been evaluated by at least two language expert testers. Following HABE's evaluation criteria, some of the texts have not obtained a passing grade for the exam, others have passed by a small margin and others have passed with good grades (see Table 1). It is available with CC BY-NC 4.0 license at: https://doi.org/10.23728/b2share.81433fddcd06405f8505c7606b29ff99

Lev.	Texts	Pass	Pass+	No pass	Tokens
B1	120	40	40	20	2,157
B2	120	40	40	20	28,319
C1	120	40	40	20	40,305
C2	120	30	17	73	56,271
All	480	150	137	133	146,465

Table 1: HABE-IXA corpus statistics (Arrieta et al., 2023)

To perform our curriculum-based classification approach, we have used the open-source grammar formalism VISL CG3 (Didriksen, 2003) which is compatible with other JAVA build systems such as CTAP (Chen and Meurers, 2016) by means of

Apache UIMA. This grammar was built by two expert linguists in CG3. The grammar contains 296 rules from A1 to C2 CEFR level, based on the HEOC (see Figure 1). These rules allow us to incorporate different types of linguistic information covering HEOC´s textual and language expressions as indicators of the development of linguistic competence and the development of the strategic competence that correspond to each level. After identifying these expressions, we annotate them with a custom tag corresponding to that rule. For example, for level C1 the following rule pays attention to the syntactic structures of completive sentences in which the subordinating particle (*ezen* stands for 'that') and the relation morpheme *-ela* appear, and adds the "C1_COMPLETIVES" tag:

ADD: C1_MAILAKO_MENDEKOAK (%C1_COMPLETIVES)

TARGET (KONPL)

IF (0 ADT OR ADL) (*-1 ("ezen"));

We apply our grammar in the morphologically annotated HABE-IXA corpus. Then, the results are filtered by removing linguistic instances that are either too common (the absolutive case, common nouns) or appear scarcely in this corpus (less than 10 total tags). The number of times each rule has been applied can be seen in Figure 1. It must be mentioned that the length of the essays in the corpus depends on its CEFR level, with B1 texts being the shortest and C2 the longest.

To evaluate this set of rules we have followed an intrinsic manual evaluation method checking whether the labels were applied correctly and an extrinsic automatic evaluation method where we use the annotation data to automatically classify texts depending on their CEFR level. For the latter, we want to see if the expressions identified by the CG3 rules encode relevant information about a text's level and complexity. We will perform the tasks of classification in two experiments:

- Binary classification (B2 or C1 level) using all rules and using the 10 most relevant rules.
- Multiclass classification (B1, B2, C1 or C2 level) using all rules and using the 10 most relevant rules.

3 Results

We evaluate the results through a detailed analysis consisting of an intrinsic and extrinsic evaluation.

	B1	B2	C1	C2	All
Total	198	284	259	148	889
Correct	188	273	247	120	828
%	94.94	96.13	95.37	81.08	93.14

Table 2: Results of the manual evaluation: precision of the Basque CG3 grammar.

Regarding the intrinsic manual evaluation method, we check manually if the labelled features were properly annotated using CG3 rules. The results in Table 2 show that in B1, B2 and C2 the precision is higher than 90%, and only C2 is below with 81.08% of accuracy.

During this evaluation, we realise that some rules are too general, so they are not informative, such as the use of common nouns, the use of absolutive case, the use of certain verbs tenses, and so on. Therefore, certain linguistic features of the HEOC are common at all levels and are very basic features that will have a greater presence in the texts, but from a qualitative point of view, they do not represent linguistic structures that help to determine a specific level. These common features will therefore be discarded in a future version because we will obtain this data by other means, for example using the Basque version of CTAP.

Regarding the extrinsic evaluation method, we proposed a classification task using only the CG3 rules: we use the data generated by our rule set to classify essays into a CEFR level. We want to see i) if the curriculum indicators that we have formalised as a ruleset allow us to determine the CEFR of an essay, and ii) which rules are most relevant for this classification.

We encode each text of the HABE-IXA corpus as a feature vector containing the extracted data of each rule as shown in Figure 2. We eliminate redundant information by filtering all the rule results that have a Pearson correlation higher than 0.95. Then, to avoid classification based on text length, we normalise each feature vector with the number of tokens in the text. Finally, we rescale the features to the same range (from 0 to 1) using a min-max scaler.

We split our data into training and evaluation sets (see Table 3), and we maintain this corpus split for all the experiments. For these classifica-

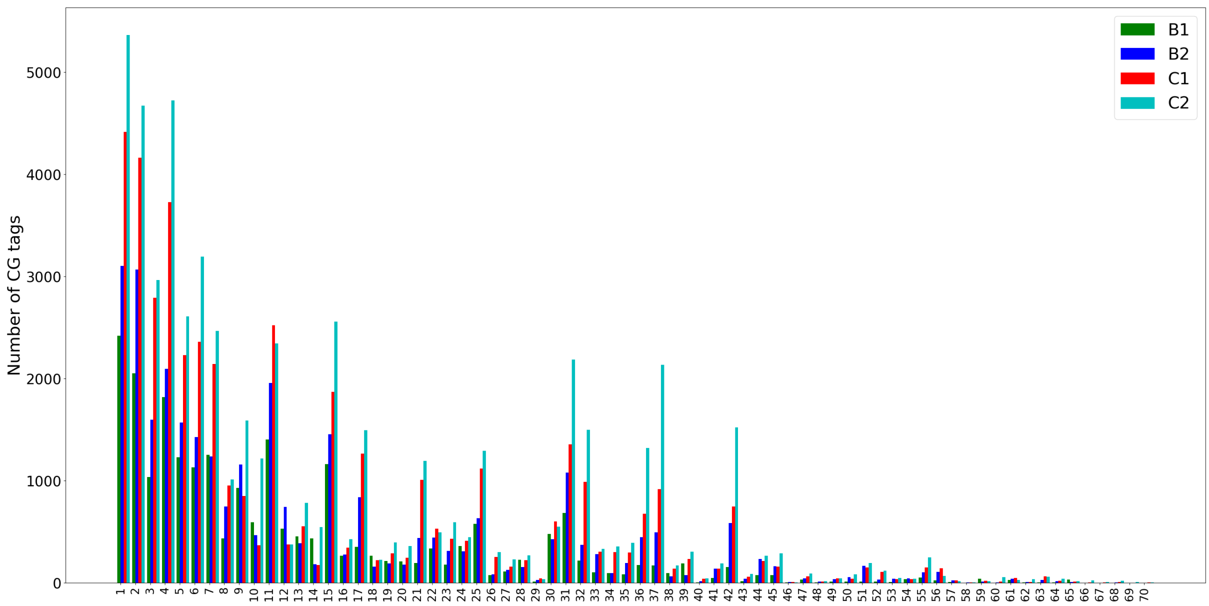

Figure 1: Each type of rule applied in the HABE-IXA corpus. Expressions in each of the levels of the corpus: B1, B2, C1 and C2. The complete list of rules is in the supplementary material.

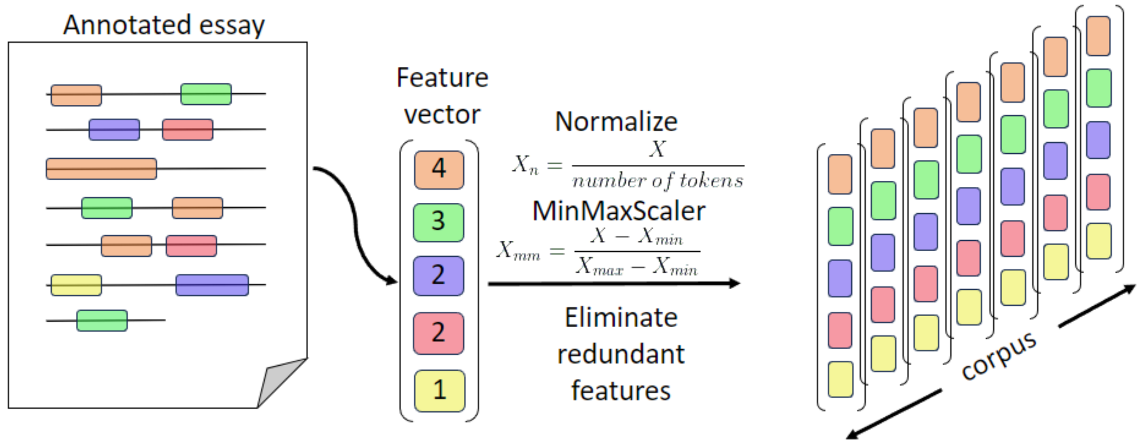

Figure 2: Preprocessing of the annotated texts and the feature vectors.

tion experiments, we use essays from the HABE-IXA corpus that passed their corresponding exam.

Classification	Train	Eval
Binary (B2-C1)	154	46
Multiclass	251	92

Table 3: Number of texts in training and evaluation sets.

To do so, we used Scikit-learn (Pedregosa et al., 2011) to train different types of machine learning models: $i)$ support vector machine (SVM, RBF kernel and C = 1), $ii)$ logistic regression classifier(LR), $iii)$ random forest classifier (RF) (100 estimators, depth = 8) and $iv)$ Naive Bayes classifier (NB). The results of these models are shown in Table 4.

	Binary			Multiclass		
	Train	Eval	Diff	Train	Eval	Diff
SVM	0.98	0.84	-0.14	0.97	**0.84**	-0.13
LR	0.95	0.76	-0.19	0.92	0.79	-0.13
RF	1.0	**0.87**	-0.13	1.0	0.80	-0.20
NB	0.85	0.82	-0.03	0.84	0.72	-0.12

Table 4: Evaluation set results of the CEFR level classifications, both binary (B1-C2) and multiclass (B1-B2-C1-C2), using all rules with different ML models.

As we can see in Table 4, the best results on the evaluation data were obtained by the RF in the binary task and SVM in the multiclass task. The RF seems to overfit on train data in both tasks, so parameter optimization should be done in future work to avoid memorization issues. Naive Bayes classifiers obtain lower results, but training and evaluation accuracy are similar, suggesting that this could be a model that generalises better than the others.

We grouped the CG3 rules into four categories and analysed the importance of these categories in the classification task. We used permutation feature importance (Altmann et al., 2010) to measure the contribution of each of the features to the score of the classifier. The PFI permutates one feature at a time and measures the drop in accuracy of the model. The higher the loss of accuracy, the more important this feature was for the model. We measured the importance of the rules in the multiclass classification task using SVM, which obtained the best results. We show these results in Figures 3 and 4.

We see that rules "genitive case" and "indirect/reported question" are the most relevant rules for declension[1] and syntax, respectively. In Figure 4, we show the results for different groups of rules sorted according to the curriculum from A1 indicators to higher-level C2 indicators.

We show that we have rules for each level grouped in Verb, Declension and Syntax for levels A1, A2, B1, B2 and C1, and rules for Discourse phenomena in levels C1 and C2. Note that for C2 we do not have rules in other categories, since the curriculum only describes discursive features at this level. As we can see in Figure 4, Declension is the category that helps the most in the classification task for A1, A2, B2 and C1, but there is a large variance from one rule to another. The 10 most important features for the multiclass task (SVM) are shown in Table 5.

Finally, we show in Table 6 the results of the best models using only annotations from the 10 most important rules obtained with the PFI method. From the 4 models (RF, SVM, NL and NB), we only retrained the models that had the best performance using the entire grammar (RF and SVM).

Table 6 shows some rules are enough to have a strong classifier, which means that almost 10 rules do more than 90% of the classification task (91.95% of binary classification and 94.05% of multiclass classification task). But these 10 features do not seem that they are not as informative as the multidimensional phenomenon (lexis, grammar, discourse, morphology...) in which language is acquired or developed, because these 10 features are those to describe basic language forms from A1 to B2, but we don't find any feature from C1 (such as discourse markers, some type of subordinate clauses, subjunctive verbs...). Most of the distinctive features of these 10 basic features pertain to the field of morphology: case markers such as possessive/spatiotemporal genitive and ergative; the use of some kind of POS, for instance, nouns, pronouns, adverbs, verbal nouns and indeterminate modifiers; and the use of perfective verb aspect. The remaining feature corresponds to the syntax: the use of indirect/reported questions.

[1] Declension is not appropriate to describe Basque language, which is an agglutinative language. We use this terminology here because we try to reflect the linguistic information collected in the HEOC.

Rule	PFI
A2. Possessive genitive declension	0.073
A2. Spatiotemporal genitive	0.048
B1. Subordination. Indirect/reported question	0.047
B2. Adverbs	0.046
A1. Ergative declension	0.045
B1. Indeterminate	0.043
A2. Syntax. Perfective aspect	0.043
B2. Pronouns	0.038
B1. Verbal noun	0.035
B2. Nouns	0.030

Table 5: The rules and permutation feature importances for the most relevant features for the SVM classifier in the multiclass task.

	All rules	10 Rules
Binary - RF	**0.87**	0.80
Multiclass - SVM	**0.84**	0.79

Table 6: The classifier results using the entire ruleset and only the 10 most relevant rules.

4 Discussion

In this section, we explain some issues that may help to better understand the results: the size of the corpus and the application/design of the CG3 rules.

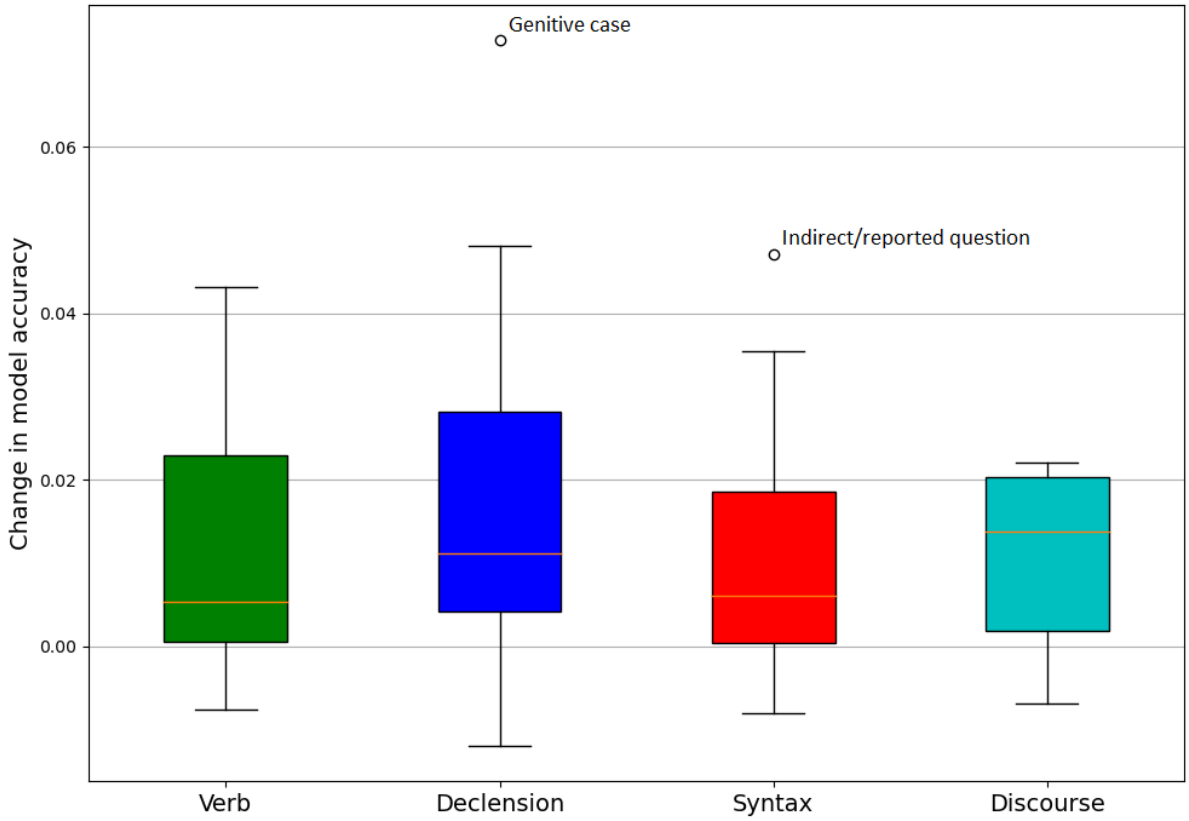

Figure 3: Permutation feature importance, measured as the change in the model's accuracy, for the different types of rules of the Basque CG3 Grammar. The outliers here represent the most relevant rule for each group.

The size of our corpus is one of the characteristics to take into account. The corpus is made up of 480 texts, 120 texts for each level (from B1 to C2). In total, there are 146,465 tokens in the corpus.

Compared to corpora with similar characteristics, our corpus is a bit smaller.

For example, Thewissen (2013) uses 223 texts with 150,000 tokens to study the evolution of errors through the different levels. Chen and Baker (2016) study lexical bundles in learner essays. The corpus used for that reason is bigger: it is made up of 585 essays and 202,154 tokens.

On the other hand, Lahuerta (2018) examines the texts of 100 Spanish EFL learners. The total number of tokens is 31,900. The corpus is used to study the accuracy and grammatical complexity. Yannakoudakis et al. (2018) want to predict proficiency levels in learner writing. To do this, they use two datasets: i) the learner output corpus (320 texts and 140,949 tokens) and ii) the expert input corpus (818 texts and 289,312 tokens).

As it has been observed, the size of our corpus is small compared to other similar works. Consequently, we have been able to find fewer errors, and this limits the accuracy of the results.

Apart from the size of the corpus, we think that it should be noted that the labels introduced by the rules indicate the level at which a given linguistic structure corresponds, this does not imply that they are only applied in texts corresponding to that level. For example, the labels of the most basic levels (A1, A2), such as common nouns, declension, verb tense and so on, also apply in texts of higher levels such as B2, C1, Basque C2... We can say that the grammar is coherent with the HEOC curriculum on which it is based. That means that each level meets all the features and linguistic phenomena of the levels below it.

Finally, from the grammarian perspective, the typology of these rules is varied (general phenomena and rules for specific constructions or words) and there have also been small differences in the way the labels are designed (for instance, for connectors we have general rule vs fine-grained rules). Therefore, it would be convenient to unify the criteria for creating rules for the next version.

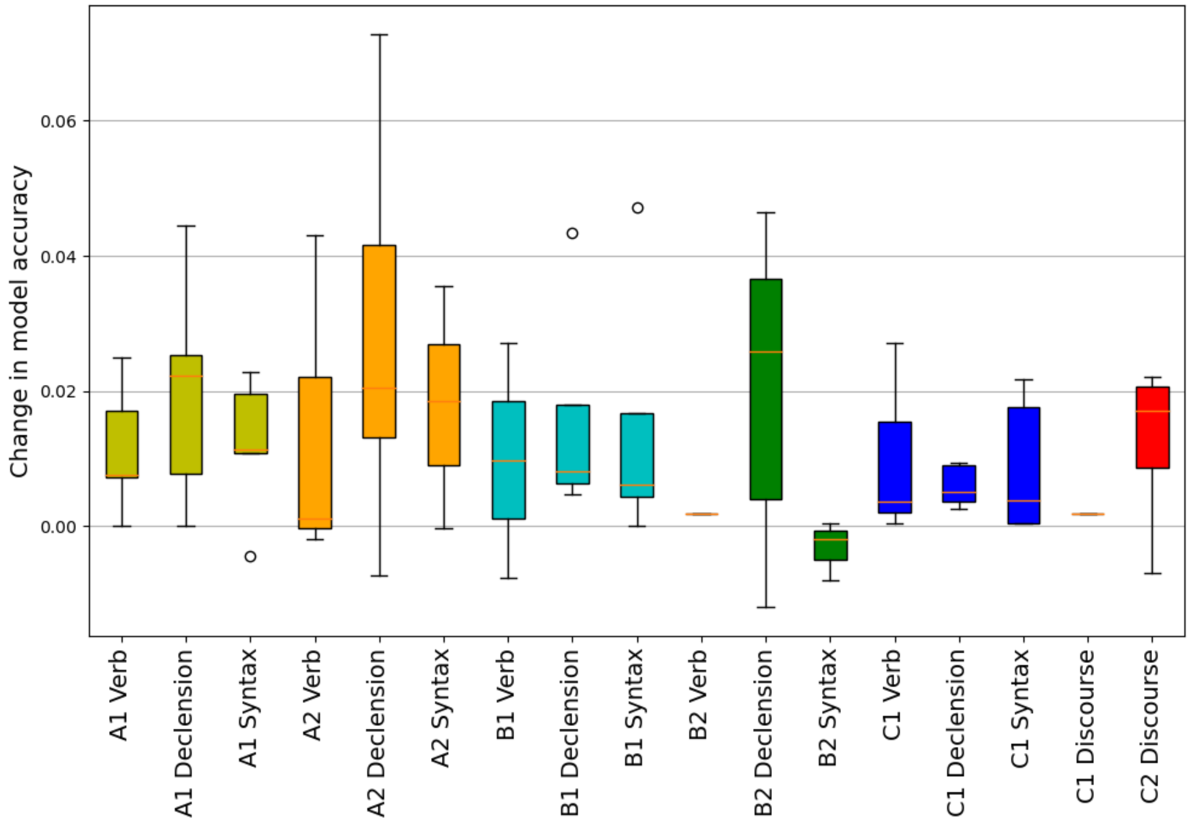

Figure 4: Permutation feature importance, measured as the change in the model's accuracy, for different groups of rules in the Basque CG3 Grammar, sorted according to the HEOC from A1 indicators to higher level C2 indicators.

5 Conclusion and future work

In this paper, we present the first CG3 version of the Basque grammar based on HEOC to grade written Basque students. The classification tasks performed on the experiments based on this first version show that the information provided by our rules is useful for discriminating different CEFR levels. There is a correlation between the greater the number of labels of different types, the higher the level of the text.

Our experimental results suggest that our approach has promising results, advancing the construction of automatic tools to test and discriminate between B2 and C1.

A more detailed analysis of the results shows also that the informativeness of these rules should be improved in the future. In that sense, we think that a redefinition of the principles for writing grammar benefits the explainability of the linguistic information added by the rules.

Finally, we believe that we will improve in assisted text grading by combining rule-based approaches with other approaches based on readability and complexity measures.

Acknowledgments

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Supplementary material

	Basque rule	Translation to English
1	A1. Sintaxia. Aditz trinkoa	A1. Syntax. Synthetic verb
2	B2. Zenbatzaileak	B2. Quantifiers
3	A2. Sintaxia. Aditz-izena	A2. Syntax. Verbal noun
4	A2. Sintaxia. Indikatiboko orainaldia	A2. Syntax. Present indicative
5	C1. ADT	C1. Synthetic verb
6	B1. Juntadura	B1. Coordination
7	B1. Aditza	B1. Verb
8	B1. Zehaztugabeak	B1. Indeterminates
9	A2. Sintaxia. Aspektu burutua	A2. Syntax. Perfective aspect
10	B2. Izena	B2. Nouns
11	B2. Izenordainak	B2. Pronouns
12	A1. Sintaxia. Indikatibo orainaldia	A1. Syntax. Past indicative
13	A1. Izena. Biziduna	A1. Noun. Animate
14	A1. Izena. Berezia	A1. Proper noun
15	A1. Aditz iragankorra	A1. Transitive verb
16	A1. Sintaxia. Gertakizuna	A1. Syntax. Future
17	A1. Izen funtziozko menderakuntza	A1. Noun subordinate clauses
18	A2. Deklnabidea. Soziatiboa	A2. Sociative declension
19	B2. Galdetzaileak	B2. Interrogatives
20	A1. Elkartuak. Aurkaritzakoa	A1. Adversative
21	B1. Aditz-izena	B1. Verbal noun
22	A2. Sintaxia. Bakuna, baiezkoa	A2. Simple sentence, affirmative
23	A1. Deklinabidea. Instrumentala	A1. Instrumental declension
24	A1. Galdetzailea. Zergatik	A1. Interrogative why
25	A2. Sintaxia. Aspektu ezburutua	A2. Syntax. Imperfective aspect.
26	A1. Elkartuak. Hautakaria	A1. Disjunctive
27	A1. Galdetzailea. Zer	A1. Interrogative what
28	A2. Deklinabidea. Adlatiboa	A2. Adlative declension
29	C1. Graduatzaileak	C1. Grade particles
30	B2. Adberbioak	B2. Adverbs
31	A2. Deklinabidea. Inesiboa	A1. Inessive declension
32	B1. Menderakuntza. Zehar galdera	B1. Subordination. Indirect/reported question
33	A2. Deklinabidea. Partitiboa	A2. Partitive declension
34	C1. ADL	C1. Auxiliary verb
35	C1. Deklinabidea	C1. Declension
36	A1. Deklinabidea. Ergatiboa	A1. Ergative declension
37	A2. Deklinabidea. Genitibo edutezkoa	A2. Possessive genitive declension
38	A1. Elkartuak. Baldintza	A1. Conditional
39	B2. Indartuak	B2. Strengthened forms
40	A2. Sintaxia. Al partikula	A2. Syntax. Al particle
41	B1. Adberbioak	B1. Adverbs
42	A2. Deklinabidea. Genitibo leku-denborazkoa	A2. Declension. Spatiotemporal genitive
43	C1. Postposizioak	C1. Postpositions
44	B2. Postposizioak	B2. Postpositions
45	A1. Deklinabidea. Ablatiboa	A1. Ablative declension
46	C2. Modalizazioa	C2. Modalization
47	B2. Partikulak	B2. Particles
48	B1. Puntua laburduretan	B1. Dot in abbreviations
49	C1. Juntagailuak	C1. Conjunctions
50	C2. Testu-markatzaileak	C2. Text markers
51	B1. Plural hurbila	B1. Close plural
52	C1. Determinatzaile zehaztugabea	C1. Indefinite determiner
53	C1. Indartuak	C1. Strengthened forms
54	A2. Deklinabidea. Destinatiboa	A2. Destination declension
55	C1. Aditzak	C2. Verbs
56	B1. Deiktiko pertsonalak	B1. Personal deictics
57	C1 Moduzkoak1	C1. Modal clauses1
58	C1. Moduzkoak2	C1. Modal clauses2
59	B1. Elkarkariak	B1. Reciprocality
60	C1. Moduzkoak3	C1. Modal clauses3
61	C2. Operatzaile argudiozkoak	C2. Argumentative operators
62	C1. Testu-antolatzaileak	C1. Discourse markers
63	C1. Helburuzkoak	C1. Final clauses
64	C1. Kontzetsiboak	C1. Concessive
65	A1. Sintaxia. Ahalera	A1. Syntax. Potential
66	C2. Berbaldi markatzaileak	C2. Discourse markers
67	B2. Menderakuntza. Galde-perpausa	B2. Subordination. Question sentence
68	C1. Aditzondoak	C1. Mood adverbs
69	B2. Aditz lokuzioak	B2. Verbal locution
70	C1. Mendekoak	C1. Subordination