4 *Extrinsic Evaluation: Readability Assessment of English Texts*

In this Section we present an extrinsic evaluation of AzterTest in a readability assessment scenario for English texts. In this evaluation, we have tested various classifiers to detect three reading levels (elementary, intermediate, advanced) based on Coh-Metrix and AzterTest's output on an open licensed corpora. We compare our results to other systems, perform an error analysis and discuss the best features.

4.1 Corpus

In order to train and validate AzterTest, we have used the corpus OneStopEnglish corpus (Vajjala and Lucic, 2018). This corpus compiles newspaper articles aligned at text and sentence level across three reading levels (elementary, intermediate, advanced), targeting English as Second Language (ESL) learners. The corpus consists of 189 texts, each of them in three versions (567 in total). We have decided to use this corpus because it is one of the few available[9] and it is licensed under CC BY-SA 4.0. Moreover, this corpus demonstrates its usefulness for automatic readability assessment among others. Namely, Vajjala and Lucic (2018) obtained an accuracy of 78.13 % using features based on readability classification research with the Sequential Minimal Optimization (SMO) (Platt, 1998) classifier.

For our experimental purposes we have randomly divided the corpus (in total 567 texts) into 2 non-overlapping datasets: 456 texts (152 texts for each class) as the training set and 111 texts (37 texts for each class) as the test set.

4.2 Classifying Experiments and Results

In order to classify the texts according to their complexity level, we have trained several classifiers that are included in WEKA (Hall et al., 2009). To evaluate the classifiers we have used the 10-fold cross-validation and the test set.

In these experiments we have tested three tools: Coh-Metrix and two configurations of AzterTest. In the first configuration of AzterTest we have taken into account all the features (absolute numbers and ratios) while in the second, AzterTest-ratios, we have only selected features based on incidents, means or typical deviations. Regarding the features, first, we have tested all the Coh-Metrix, AzterTest and AzterTest-ratios features.

[9] https://zenodo.org/record/1219041

Secondly, in order to detect the best features to tag and automatically remove the noise ones, we have tested different sets of attributes (25, 50, 75 and 100). In this experiment, we have tested chi square using different sets of attributes: 25, 50, 75 and 100. We have used Flesch readability ease as baseline.

In Table 1 we present the accuracy of the classifiers (Class. column) for each tool [Baseline, Coh-Metrix (Coh), AzterTest (Azt) and AzterTest-ratios (Azt-r)] and using different features (Feat. column). For brevity, we only show the classifiers [*i*) Sequential Minimal Optimization (SMO) (Platt, 1998) and *ii*) Simple Logistic (SL) (Landwehr, Hall, and Frank, 2005)] and the feature sets (all, 50 and 25) that have obtained the best results. We have tested the classifiers with the defaults hyperparameters.

Tool	Class.	Feat.	Data	Accu.
Baseline	SMO	Flesch	Cross	49.78
			Test	54.95
Coh	SL	All	Cross	77.19
			Test	81.98
Coh	SL	50	Cross	**77.85**
			Test	**81.98**
Coh	SL	25	Cross	75.65
			Test	85.58
Azt	SMO	All	Cross	82.01
			Test	84.68
Azt	SMO	50	Cross	**82.01**
			Test	**90.09**
Azt	SMO	25	Cross	82.01
			Test	88.28
Azt-r	SMO	All	Cross	80.92
			Test	84.68
Azt-r	SMO	50	Cross	80.04
			Test	85.58
Azt-r	SMO	25	Cross	**81.35**
			Test	**84.68**

Table 1: Classification results of the three level readability assessment experiment

Respecting the classification results, the best classifier for Coh-Metrix is Simple Logistic, while it is SMO for AzterTest's two configurations and the baseline. The best results are obtained with the 50 most predictive features in Coh-Metrix and AzterTest, but with 25 in AzterTest-ratios. Moreover, all the results are lower when evaluating with 10 fold cross-validation.

In sum, looking at these results, the best model is the SMO classifier with 50 features of

AzterTest, namely 90.09 %. It is 4.16 points better than the best Coh-Metrix results using the cross-validation and 8.11 points using the test set. AzterTest is also better than the baseline in 32.23 points with the cross-validation and in 35.14 points with the test set. Therefore, in this scenario, AzterTest outperforms Coh-Metrix, the classical readability formula used as baseline and the results reported by Vajjala and Lucic (2018). However, AzterTest-ratios is not far from AzterTest, and outperforms Coh-Metrix when evaluating with cross-validation.

In addition to the all and selected features, we have also trained the classifiers with each type of linguistic/stylistic features that we described in section 3.2. In Table 2 we rank these results by type.

Feature Group	Data	Accu.
Syntactic	Cross	70.61
	Test	75.67
Lexical Density	Cross	65.13
	Test	72.07
Descriptive	Cross	65.13
	Test	67.56
Word Frequency	Cross	60.96
	Test	68.46
Vocabulary	Cross	55.92
	Test	60.36
Readability	Cross	53.50
	Test	59.45
Word Morphological	Cross	50.21
	Test	55.85
Word Semantic	Cross	50.21
	Test	49.54
Referential Cohesion	Cross	46.05
	Test	44.14
Discourse Connectives	Cross	38.59
	Test	34.23

Table 2: The results of the SMO classifier with specific linguistic features (only AzterTest's ratios)

Taking into account the different feature types, the syntactic features (complexity and pattern density together) performed best with an accuracy of 70.61 %; lexical features and descriptive features (65.13 %) performed almost equally well; word frequencies performed worse than lexical in cross-validation but similarly in the test and, finally, the accuracy of referential cohesion and discourse connectives is below 50 %.

Finally, we present the F measure for each text level of the best model. The F measure is 0.917 for the elementary level, 0.857 for the intermediate and 0.932 for the advanced. Comparing these results to the work for Brazilian Portuguese (Aluísio et al., 2010) that also classified into three levels, rudimentary (F measure 0.732), basic (F measure 0.483) and advanced level (F measure 0.913), we observe that our model is stronger across classes.

4.3 Error analysis

We have also carried out an error analysis, using the output of the best system, which is the SMO classifier incorporating the best 50 characteristics of AzterTest. We have checked manually the annotation results in the test. The test set comprised 111 instances and only 11 of them are errors. 3 instances have been erroneously classified as "intermediate" out of 37 "advanced" type instances. For the 37 "elementary" type, only 4 have been predicted to be "intermediate" and finally, concerning the 37 "intermediate" instances, the system has classified 2 of them as "advanced" and another 2 as "elementary". Under no circumstances has the system predicted an "advanced" instance to be "elementary" or vice versa.

4.4 Discussion: Best Feature Selection and Corpus Analysis

Using both absolute and ratio features results in a higher score (Table 1). However, we have decided to exclude absolute numbers for stylistic analysis of AzterTest, since they may hinder other linguistic and stylistic features. For example, the raw number of words is usually a predictive feature, but it depends on text length and not on its linguistic characteristics. That is, a short text can be simple or complex even though it is short. Measuring features independently of text length allows the user to compare different texts.

Following, in Table 3 we present the the linguistic/stylistic analysis of the corpus, where we show the average values of the 25 most predictive ratios. The abbreviations we use are: n.=number, i.=incidence (per 1000 words), m.=mean, s.=standard deviation, sent.=sentence, prop.=proposition, sub.=subordinate and w.=word.

We observe in this corpus, which compiles journalist texts adapted for ESL readers, that the key features to discriminate among

Feature	A	I	E
Word Frequency			
i. of rare verbs	18.38	11.63	7.57
m. of distinct rare content w.	18.22	13.99	10.73
m. of rare content w.	15.36	12.16	9.76
i. of rare adj.	13.22	10.09	6.51
Descriptive			
s. of w. per sent.	10.66	8.95	7.46
s. of w. per sent. without stop w.	7.47	6.34	5.31
m. of w. per sent.	21.11	18.83	16.14
i. of n. of sent.	48.50	53.90	62.34
m. of w. per sent. without stop w.	14.61	13.00	11.19
s. of letters in w.	2.55	2.49	2.34
Vocabulary			
i. of B2	32.66	27.39	18.42
i. of C1	10.97	7.37	4.30
Lexical Diversity			
Honoré	984.93	896.14	779.31
Maas	0.0506	0.0546	0.0621
MTLD	119.32	106.98	90.09
Syntactic Complexity			
m. of prop. per sent.	52.22	41.65	31.37
m. NP per sent.	6.82	6.18	5.42
m. of punc. per sent.	2.58	2.33	2.04
m. VP per sent.	3.18	2.88	2.55
m. depth per sent.	5.79	5.51	5.11
Syntactic Pattern Density			
i. gerund density	16.42	12.84	7.94
Readability			
Flesch-Kincaid	11.55	10.27	8.59
Flesch Ease	51.54	56.28	63.43
SMOG	8.64	8.04	7.07
Word Semantic			
m. hypernym of verbs	2.09	1.97	1.83

Table 3: Corpus analysis with the 25 best predictive ratios of AzterTest

the three linguistic levels are, a) concerning word frequency, distinct rare content words, particularly verbs and adjectives; b) regarding descriptive features, words per sentence with and without stopwords and letters per word; c) at vocabulary level, incidence of B2 and C1 words; d) and lexical diversity, Honoré, Maas measures and MTLD; e) at syntactic level, propositions, NPs, VPs and punctuation marks per sentence and sentence depth; f) regarding the classical readability formulae, Flesch-Kincaid, Flesch Ease and SMOG; and, finally, g) at semantic the level,the hypermyn verbs index.

All the values decrease from advanced to elementary level, except for the incidence of number of sentences, MAAS lexical density and Flesch Ease. In the case of the MAAS and Flesch Ease, higher scores indicate that the texts are simpler, which correlates to the rest of the features. The higher number of sentences can be explained because simpler texts have shorter sentences and less clauses, and therefore, more sentences are required to communicate the information in the texts.

5 *AzterTest: Web Tool and Source*

Additionally, AzterTest is a web tool that computes 153 features of the linguistic and discourse representations of a text, including descriptive, lexical diversity, readability, word morphological information, word frequency, vocabulary knowledge, syntactic complexity, syntactic pattern density, word semantic information, referential cohesion and connectives. Furthermore, AzterTest web tool classifies the text under three language levels of difficulty (elementary, intermediate and advanced). The tool can be tested in the following website http://178.128.198.190. In Figures 1 and 2 we show the home page of AzterTest and an excerpt of its analysis respectively.

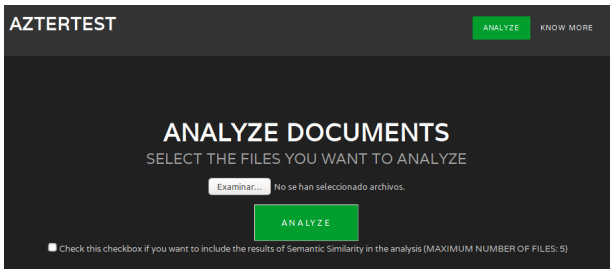
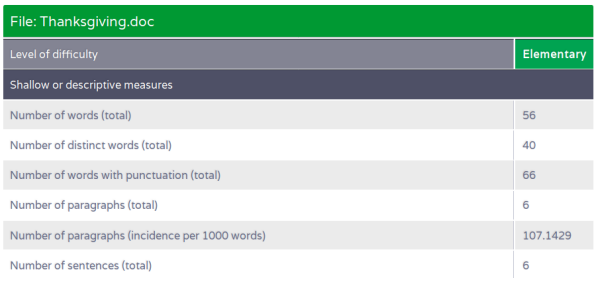


Figure 1: Main Page of AzterTest Web Tool

AzterTest source is implemented in Python and it is freely available from a public GitHub repository https://github.com/kepaxabier/AzterTest.

6 *Conclusions and future work*

In this paper, we have introduced AzterTest, an open source linguistic and stylistic analysis tool. AzterTest computes and takes into account 153



File: Thanksgiving.doc	
Level of difficulty	Elementary
Shallow or descriptive measures	
Number of words (total)	56
Number of distinct words (total)	40
Number of words with punctuation (total)	66
Number of paragraphs (total)	6
Number of paragraphs (incidence per 1000 words)	107.1429
Number of sentences (total)	6

Figure 2: Screenshot of AzterTest Result (Readability and Descriptive Features)

features, which are grouped into descriptive incidences, word frequencies, vocabulary knowledge, lexical diversity, morphological information, syntactic phenomena, classical readability formulae, semantic information and cohesion devices. The main contributions concerning features are related to new vocabulary and frequency.

Moreover, we have tested AzterTest in a readability assessment scenario for English texts, and using a set of 50 features and the classifier SMO we have obtained an accuracy of 90.09 %. This model outperforms the results obtained with Coh-Metrix's output in this task.

Furthermore, we have made the web application available to teachers so that they can assess the linguistic, stylistic and readability characteristics of their reading materials.

Considering that AzterTest is based on universal dependency parsers, in the future, we will adapt it for multiple languages, and we also plan to extend it with additional vocabulary related features. Additionally, we intend to perform a more extensive assessment of the tool with a group of potential users in order to gather information and adapt AzterTest at their suggestions. Finally, we also plan to use AzterTest for other textual analysis across genres and domains or specialised discourse (Parodi, 2006).

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